Learning to generate

Distributions, autoencoders and VAEs, built from one handwritten 3



A 3 turns into a 7. Every frame is decoded from a point on a straight line through the code space of the VAE we train today.

Nipun Batra · IIT Gandhinagar

START WITH A QUESTION

Who are these people?



Look closely: skin, hair, glasses, lighting, background. Anything odd?

Karras, Laine & Aila, *A Style-Based Generator Architecture for GANs* (StyleGAN), 2019 · CC BY-NC 4.0

START WITH A QUESTION

Who are these people?



No one. Each face is a random vector of 512 numbers pushed through a trained network.

Karras, Laine & Aila, *A Style-Based Generator Architecture for GANs* (StyleGAN), 2019 · CC BY-NC 4.0

YOUR TURN TO BE THE JUDGE

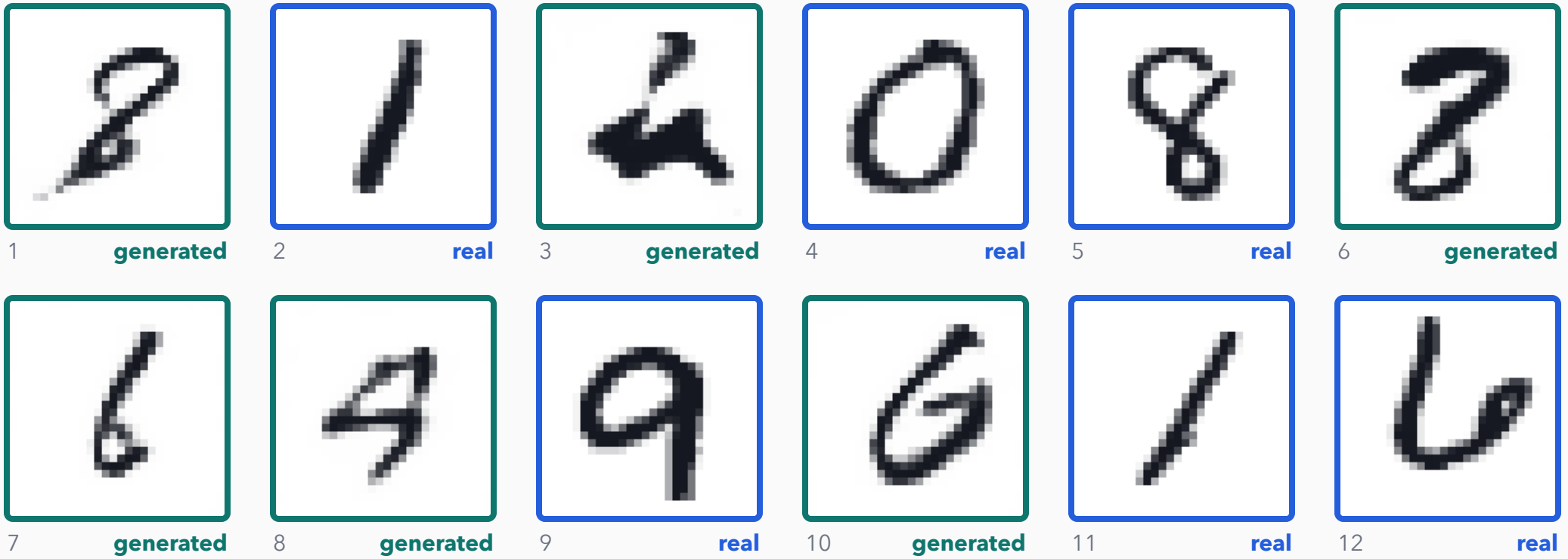
Real or generated?



Six are MNIST test digits, six come from a network. Write down which six are fake.

YOUR TURN TO BE THE JUDGE

Real or generated?

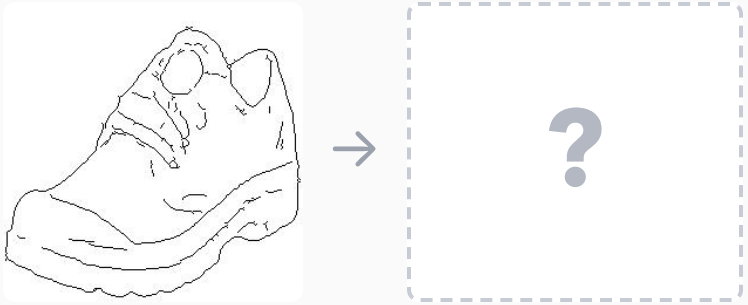


Generated: 1, 3, 6, 7, 8, 10 (teal frames). Six from a small GAN, trained in about 9 minutes: the topic of the next lecture.

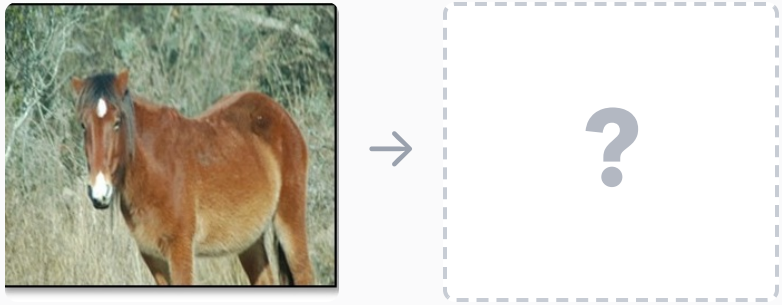
GENERATION IS NOT ONLY "MAKE A RANDOM PICTURE"

Predict the output, then look

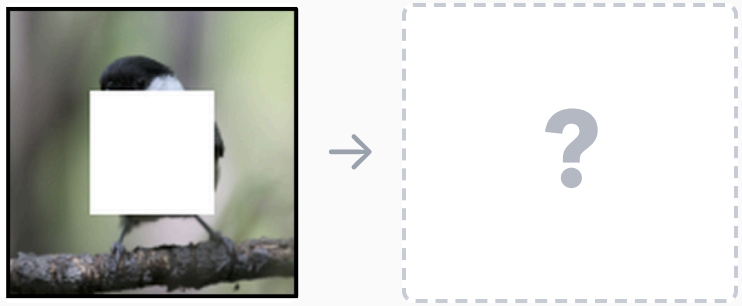
a sketch → a photo



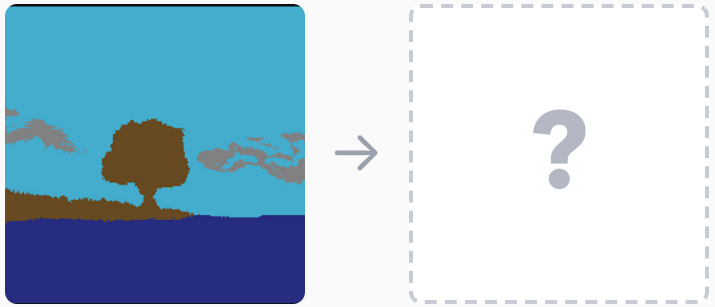
a horse → a zebra



fill a hole



a label map → a landscape



What should come out on the right? Is there exactly one right answer?

pix2pix (Isola et al. 2017) · CycleGAN (Zhu et al. 2017) · Context Encoders (Pathak et al. 2016) · SPADE (Park et al. 2019). All published model outputs.

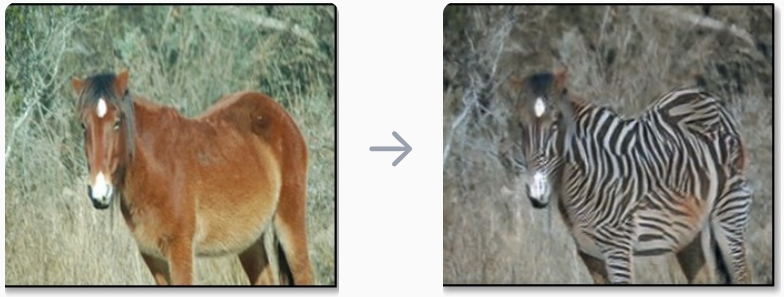
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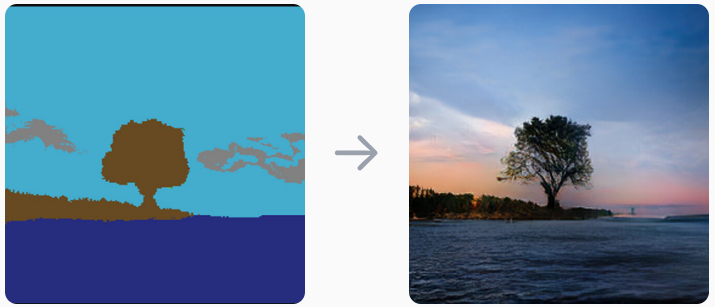
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fill a hole



a label map → a landscape



> **Each input allows many plausible outputs. A generator must pick one that looks real.**

pix2pix (Isola et al. 2017) · CycleGAN (Zhu et al. 2017) · Context Encoders (Pathak et al. 2016) · SPADE (Park et al. 2019). All published model outputs.

ONE INPUT, MANY ANSWERS

The same label map, three different photographs



the condition

SPADE / GauGAN, Park et al. 2019, teaser figure: here the variation comes from a style image given to the generator.

ONE INPUT, MANY ANSWERS

The same label map, three different photographs



the condition

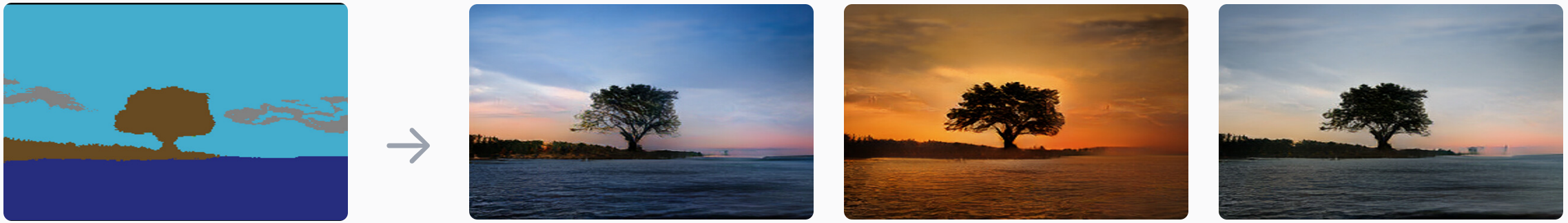


sample 1

SPADE / GauGAN, Park et al. 2019, teaser figure: here the variation comes from a style image given to the generator.

ONE INPUT, MANY ANSWERS

The same label map, three different photographs



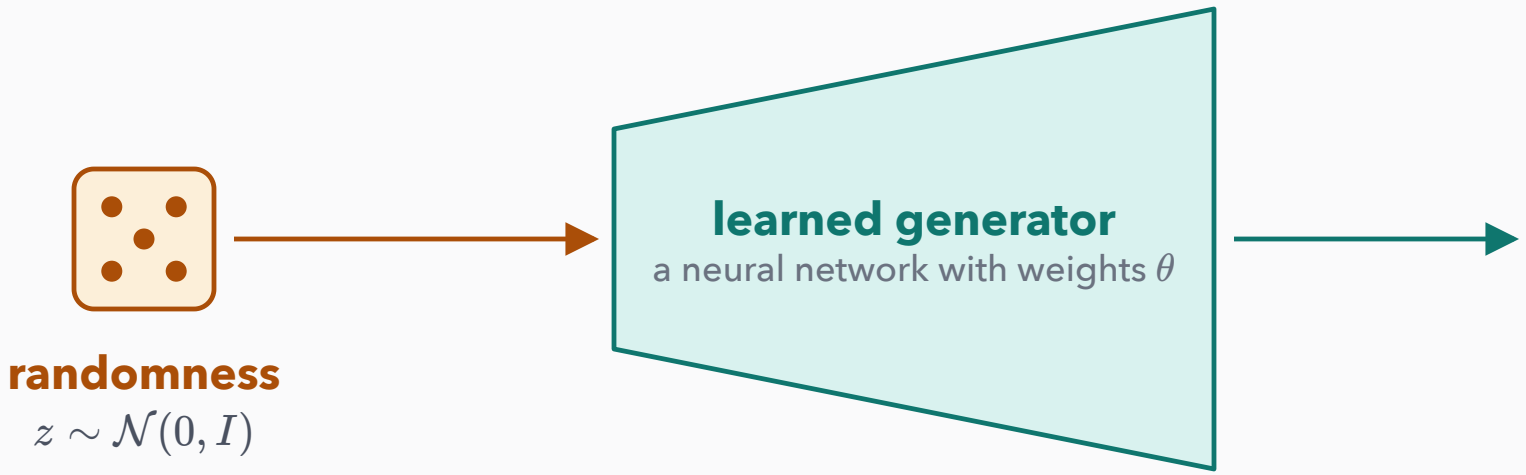
the condition | sample 1 | sample 2 | sample 3

A generator does not learn one answer. It learns a distribution of answers and draws from it.

SPADE / GauGAN, Park et al. 2019, teaser figure: here the variation comes from a style image given to the generator.

WHAT ALL OF THESE SHARE

Randomness in, a learned network, a sample out



Training means: adjust θ until the samples look like the data. But what is the loss?

WHAT ALL OF THESE SHARE

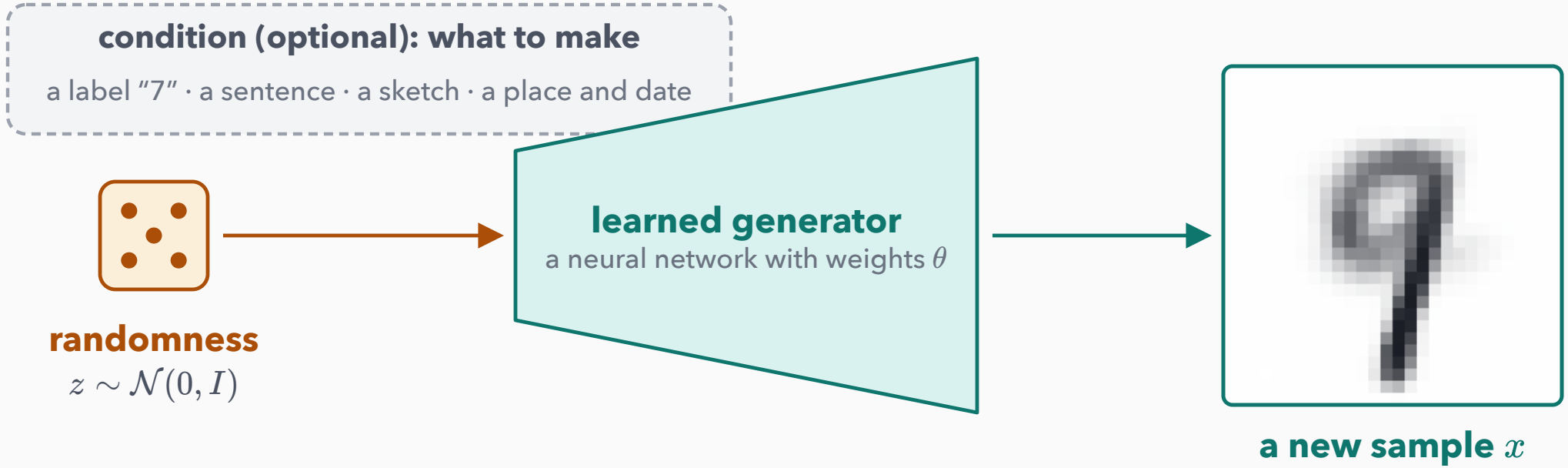
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Training means: adjust θ until the samples look like the data. But what is the loss?

WHAT CAN THE CONDITION BE?

Tell the generator what you want

a label $c = 7$



our own conditional VAE: eight different random z, all asked for a 7

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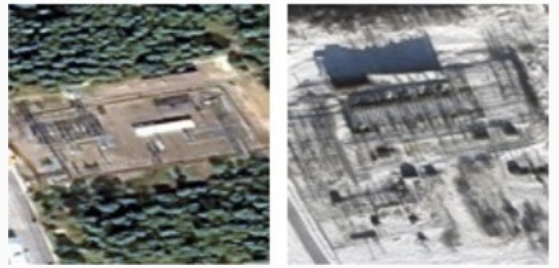
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our own conditional VAE: eight different random z, all asked for a 7

a sentence + a date "`a satellite image of an electric substation in Finland`", August vs January



DiffusionSat (Khanna et al., 2024): same caption, only the month changes

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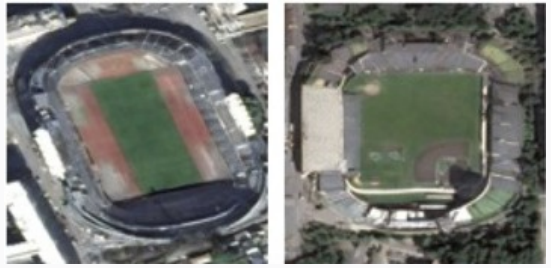
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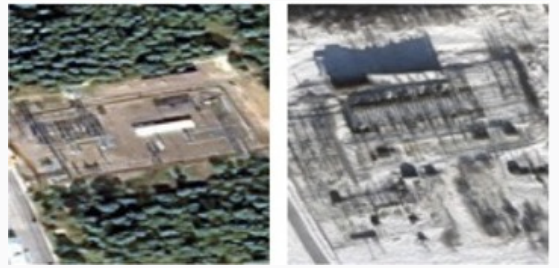
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a sentence + a place "`a satellite image of a stadium`", France vs USA coordinates



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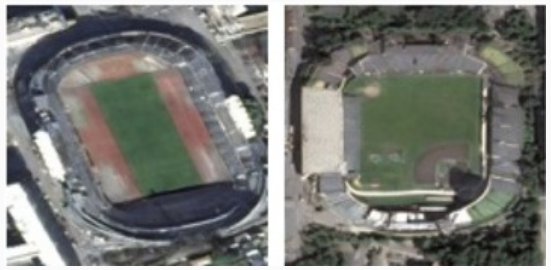
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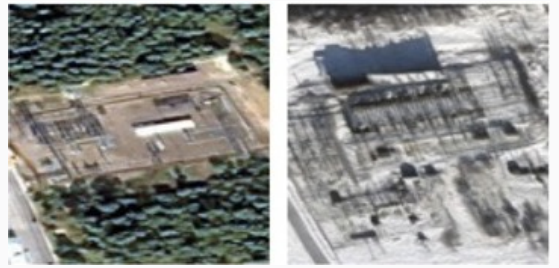
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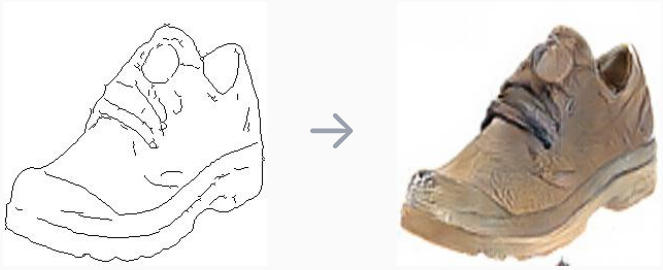
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an image a sketch, a label map, a photo with a hole



pix2pix, from the earlier slide

> **The condition fixes *what*; the randomness still decides *which one* of the many matching outputs you get.**

OUR CONDITIONAL VAE, ALL LABELS AT ONCE

The label picks the digit; the random z picks the style

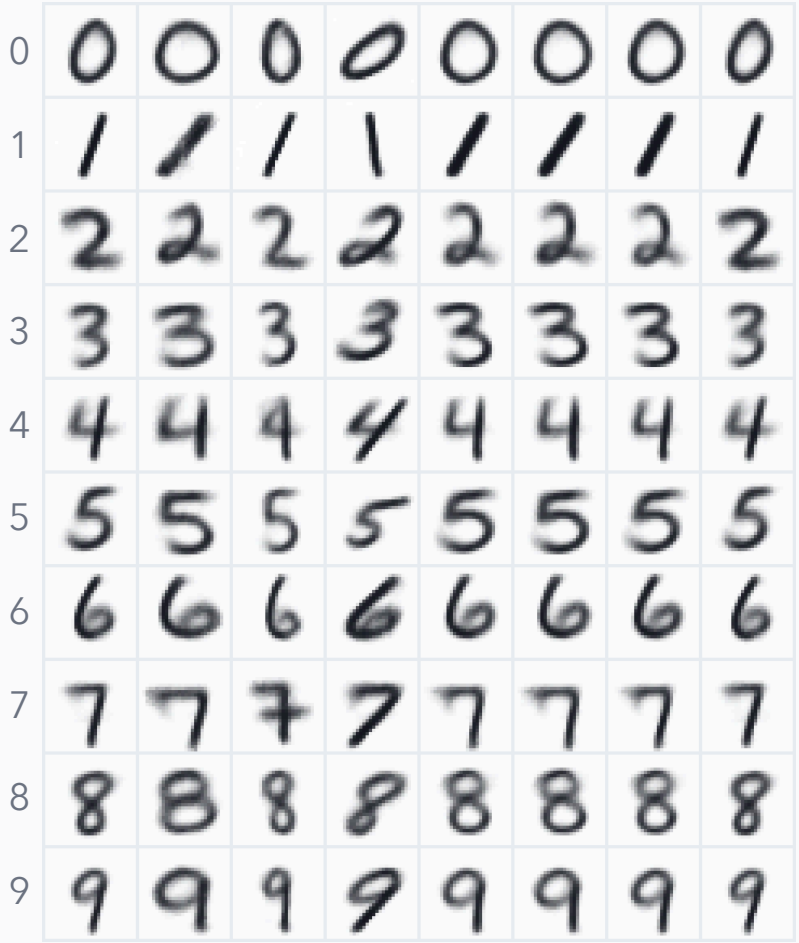


Each **row**: one label c, from 0 to 9.

Each **column**: one random z, the same all the way down.

OUR CONDITIONAL VAE, ALL LABELS AT ONCE

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Each **row**: one label c, from 0 to 9.

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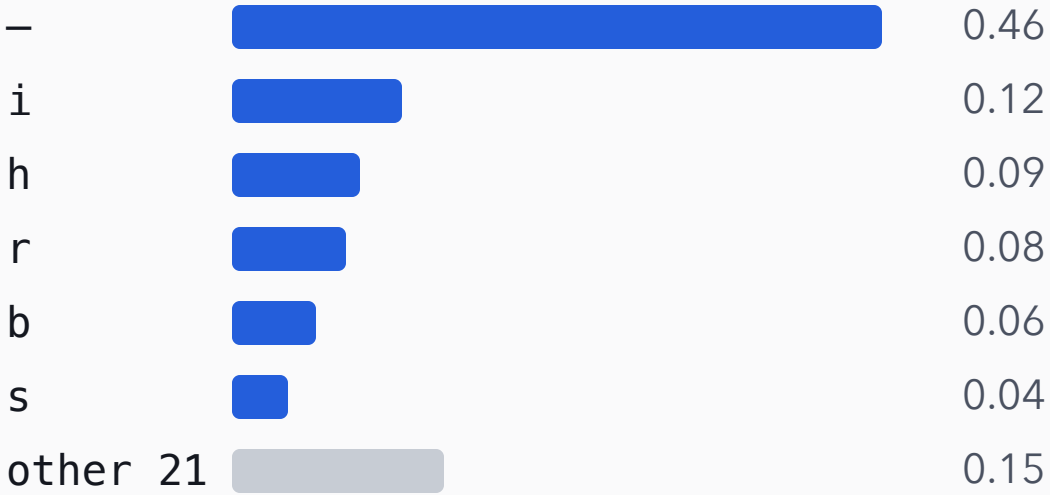
Read down a column: every digit is written with the same slant and thickness. The code z carries the handwriting; the label carries the identity.

EARLIER IN THIS COURSE

You have already built a generator

Our name model reads three characters and gives a probability for every next character.

after `a a b`, the trained model says:



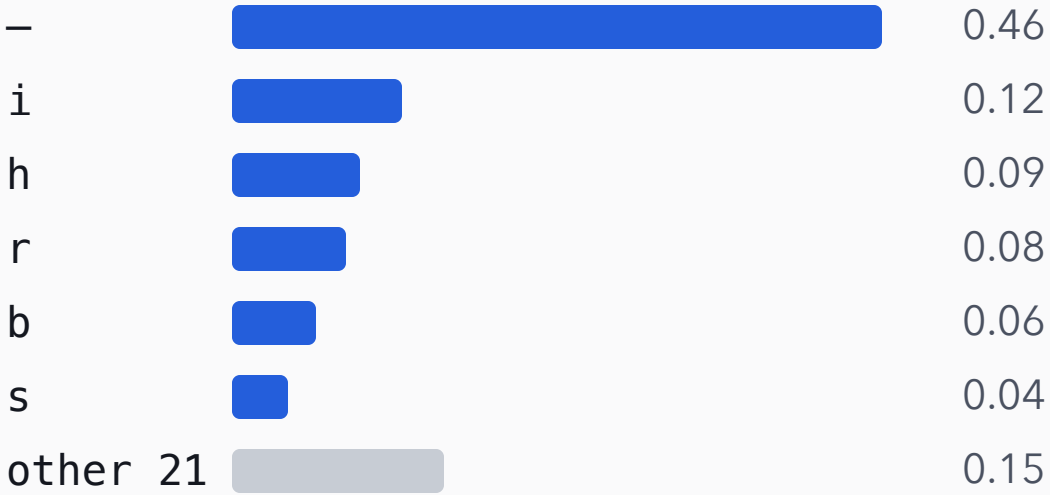
Same idea today: learn a distribution, then sample from it. Only now the samples are images.

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Generate: sample a character, append it, repeat.



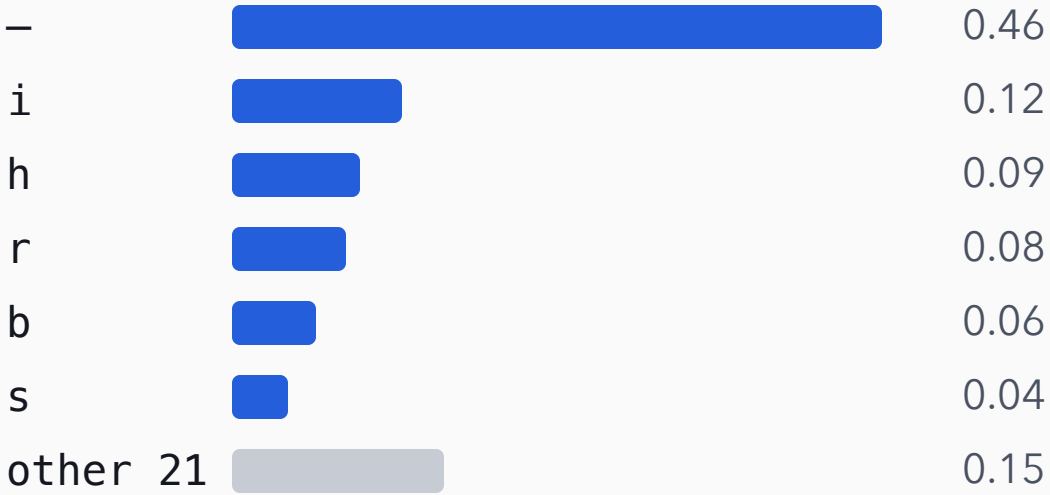
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Generate: sample a character, append it, repeat.



A different random draw at any step gives a different name. That is a generative model: it gives probabilities, and we sample from them.

Same idea today: learn a distribution, then sample from it. Only now the samples are images.

EARLIER IN THIS COURSE

A whole name gets one probability

context	next	probability	−log p
– – –	a	0.08	2.53
– – a	a	0.08	2.53
– a a	b	0.02	3.91
a a b	i	0.12	2.12
a b i	d	0.09	2.41
b i d	–	0.23	1.47

EARLIER IN THIS COURSE

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aabid		**3.2×10^{-7}**	**14.96**

$$p_\theta(\text{aabid}) = \prod_t p_\theta(x_t \mid x_{<t}) \qquad -\log p_\theta(\text{aabid}) = \sum_t -\log p_\theta(x_t \mid x_{<t})$$

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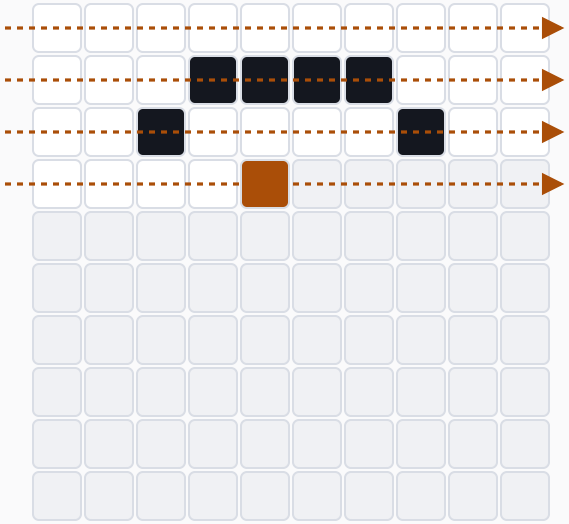
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> **Training made this number large for every name in the data. That is maximum likelihood, and it is what we want for images too.**

Two ways to generate a 28 × 28 digit

A · one pixel at a time

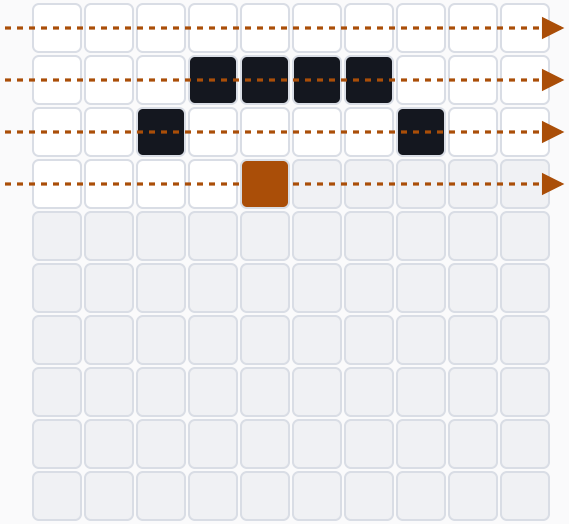


784 predictions in a row, like our names

$$p(x) = \prod_i p(x_i \mid x_{<i})$$

Two ways to generate a 28 × 28 digit

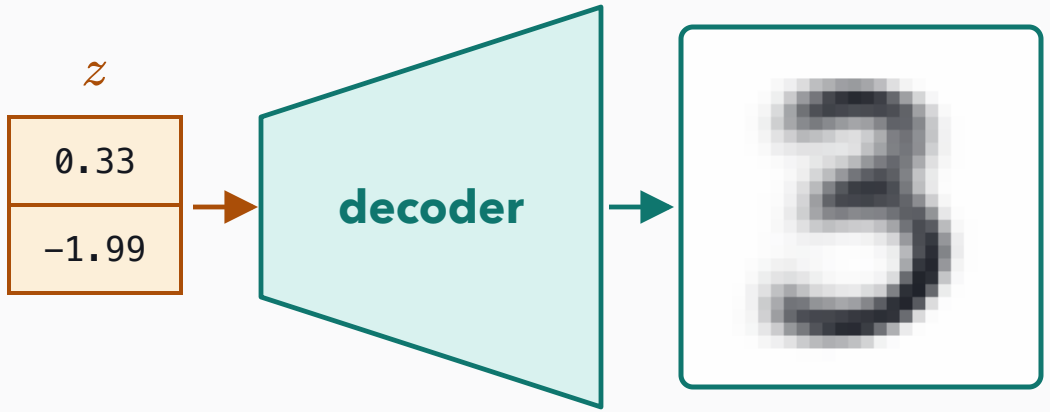
A · one pixel at a time



784 predictions in a row, like our names

$$p(x) = \prod_i p(x_i \mid x_{<i})$$

B · all pixels from one random vector



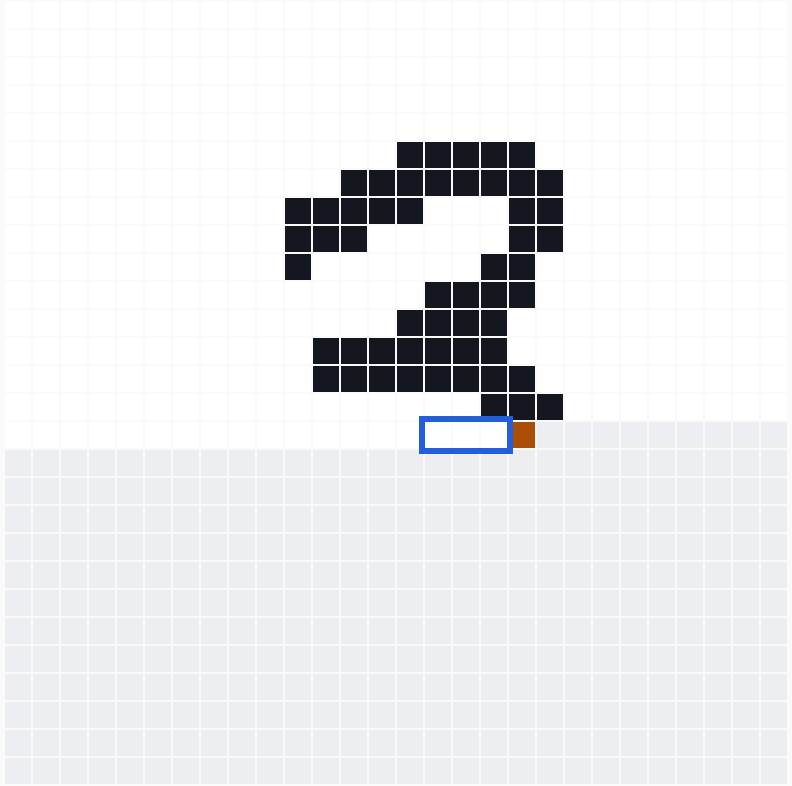
one pass: 2 numbers in, 784 pixels out

$$x = \text{decoder}(z)$$

Today: route B. Two questions: where does z come from, and how do we train a decoder when no one tells us the right z?

ROUTE A, THE WAY OUR NAME MODEL WORKED

Predict each pixel from the pixels already drawn

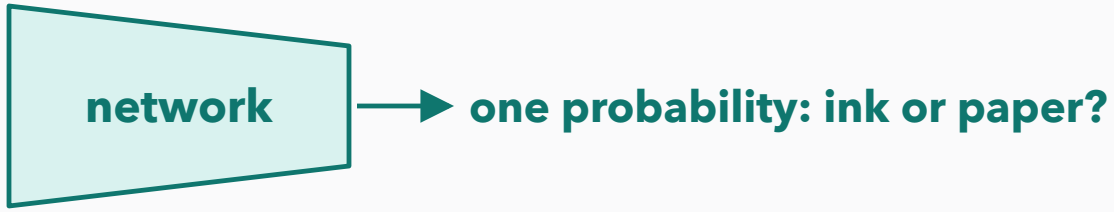


drawn so far · next pixel (orange) · not yet drawn (grey)

context: the 3 previous pixels

(the name model read 3 previous characters)

$$p(x_i = \text{ink} \mid 3 \text{ pixels}) = 0.24$$

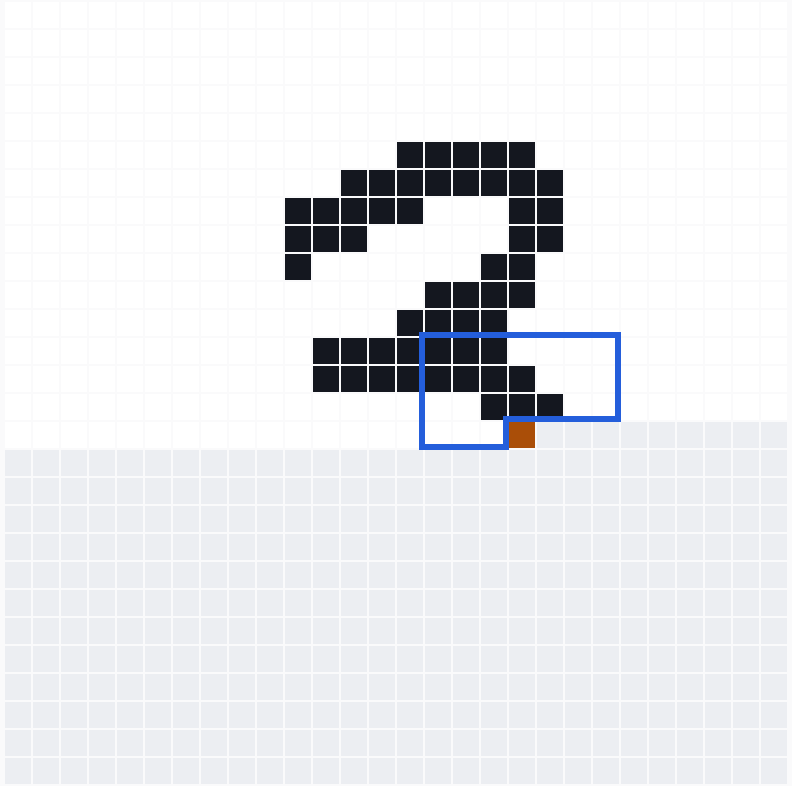


Repeat for all 784 pixels, one after another:

$$p(x) = \prod_{i=1}^{784} p(x_i \mid x_{<i})$$

ROUTE A, THE WAY OUR NAME MODEL WORKED

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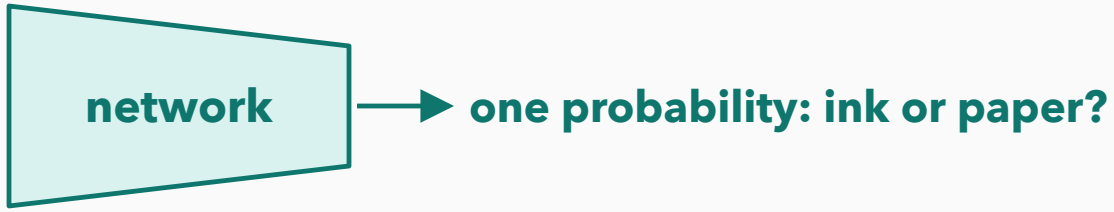


drawn so far · next pixel (orange) · not yet drawn (grey)

context: 3 rows above + 3 to the left

24 pixels the model may look at

$$p(x_i = \text{ink} \mid 24 \text{ pixels}) = 0.89$$



Repeat for all 784 pixels, one after another:

$$p(x) = \prod_{i=1}^{784} p(x_i \mid x_{<i})$$

ROUTE A, TRAINED ON MNIST

What these two pixel-by-pixel models generate



context: 3 previous pixels · $\log p(\text{our } 3) = -123.7$

ROUTE A, TRAINED ON MNIST

What these two pixel-by-pixel models generate



context: 3 previous pixels · $\log p(\text{our } 3) = -123.7$



context: 24 pixels above and left · $\log p(\text{our } 3) = -69.4$

More context, better strokes. And route A gives an exact $\log p(x)$: just add the 784 log-probabilities.

SO WHY ROUTE B TODAY?

Two routes, different strengths

	A · pixel by pixel	B · one code, one pass
generate one image	784 network calls, in order	1 network call

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a short summary z	none	**yes**: 2 to 100 numbers you can move, mix, edit

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used today in	language models; image models over image tokens	VAEs, GANs, and the latent space of diffusion models

> **Route A is the name model you already know. Today is route B: what the code is, and how to train a decoder when nobody tells us the right code.**

THE PLAN

Today's route, in two sessions

SESSION 1

1. **Distributions and fitting**
   a 1-D toy: fit, sample, how many bumps
2. **Autoencoders**
   plain, denoising, sparse, contractive; why they cannot generate
3. **The probabilistic view**
   prior, likelihood, an intractable posterior

SESSION 2

4. **KL divergence**
   how far apart are two distributions?
5. **Variational inference and the ELBO**
   a loss that never computes $p(x)$
6. **Reparameterisation**
   backprop through a random draw
7. **The VAE on MNIST**
   one digit, end to end, with real numbers

> **One running image throughout: test digit #90, a handwritten 3. GANs get their own lecture.**

PART 1 OF 7

Learn a distribution from examples, then sample from it

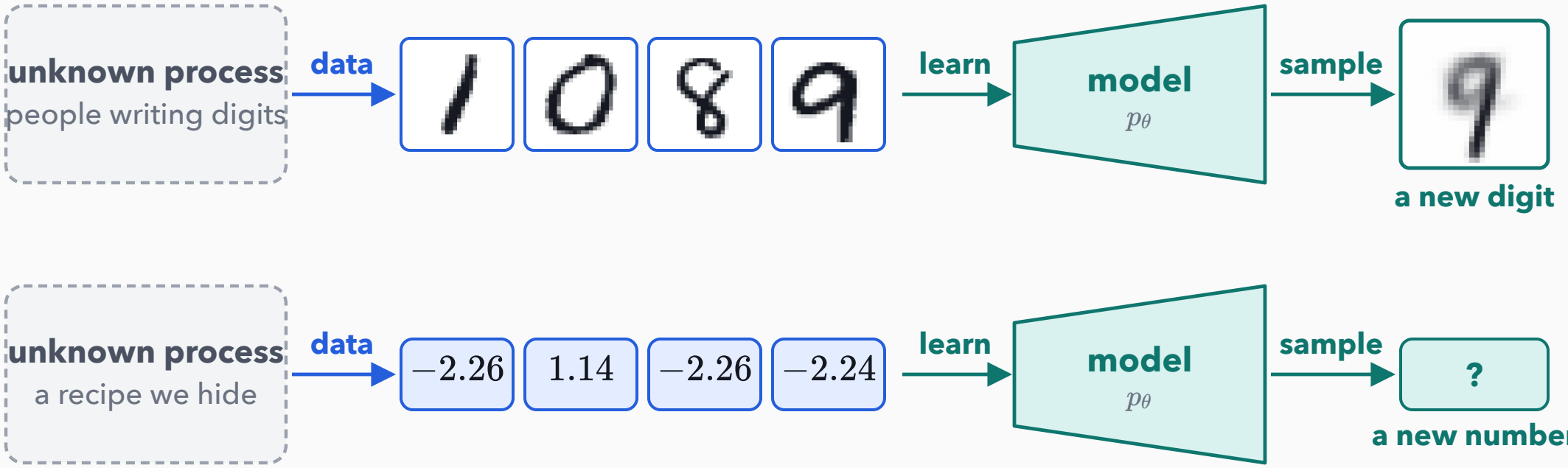
We have seen what generators can do. Before any network, the whole idea on **one number**: what does "learning" mean, and how do we then make new samples?

1 **Distributions and fitting**
2 Autoencoders
3 The probabilistic view
4 KL divergence
5 Variational inference and the ELBO
6 Reparameterisation
7 The VAE on MNIST

Examples in, a model out, new examples from the model

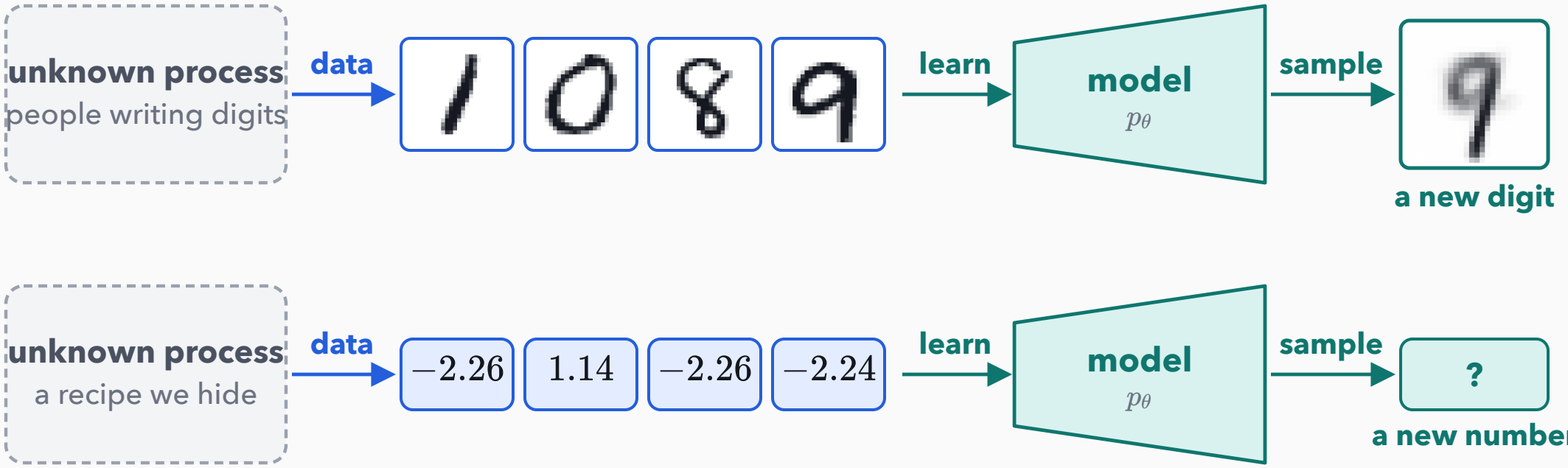


Examples in, a model out, new examples from the model



WHAT ARE WE TRYING TO DO?

Examples in, a model out, new examples from the model



1 · Learn

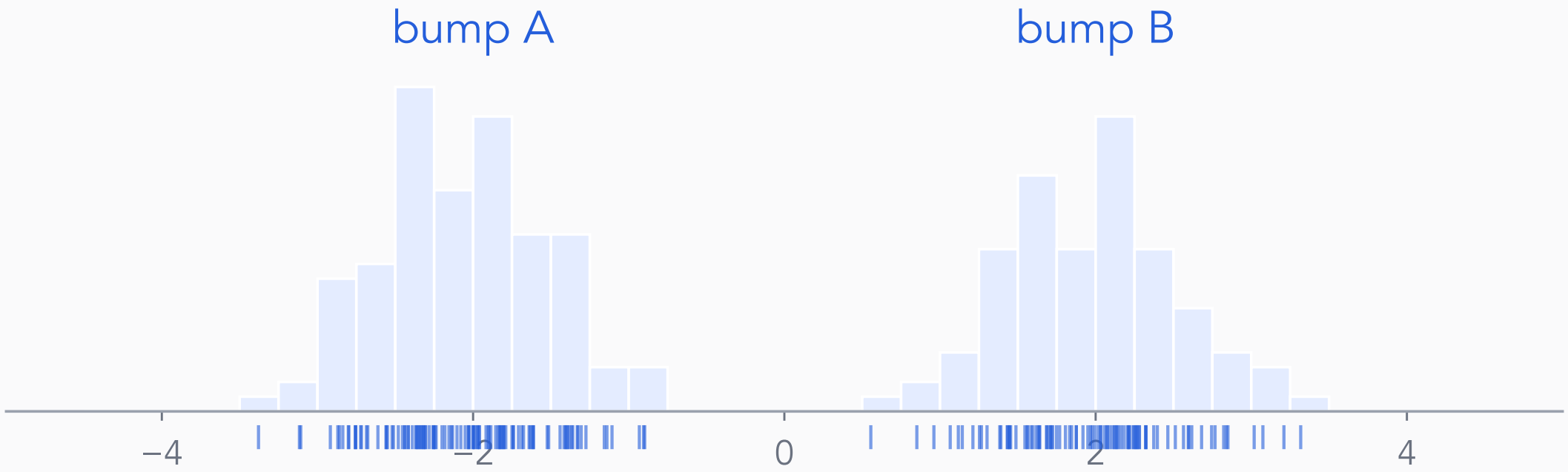
Choose the model's parameters θ so that the examples we have are **probable** under it.

2 · Generate

Draw **new** samples from the learned model p_θ.

OUR TOY DATA

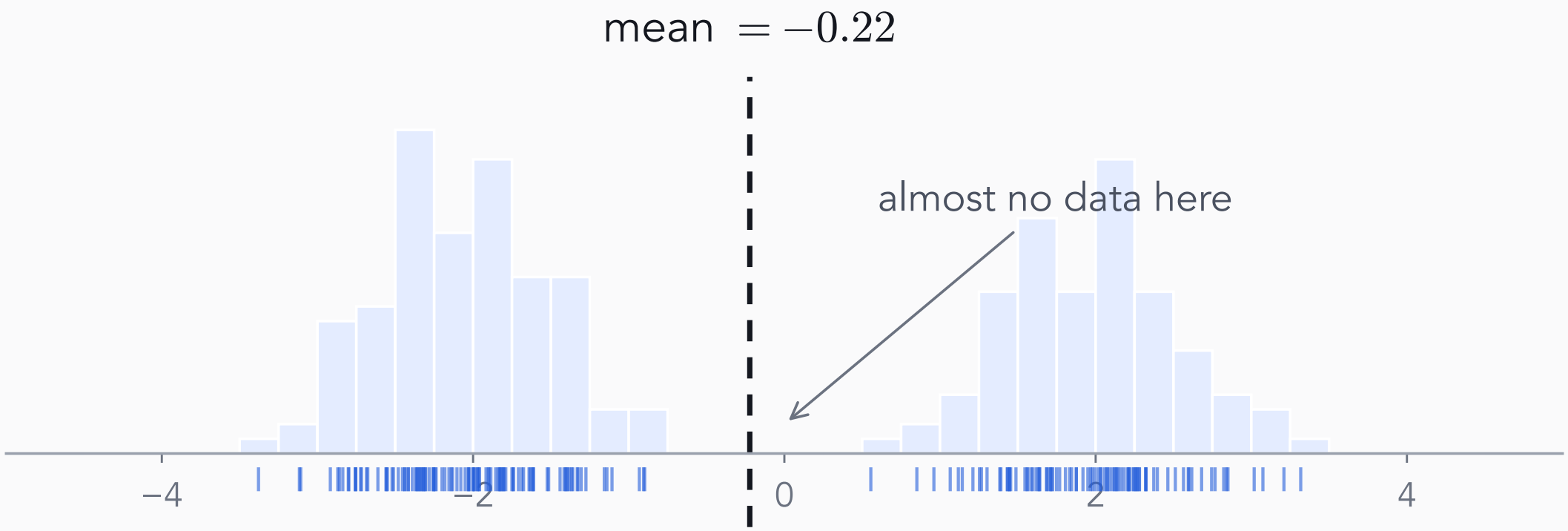
200 numbers from a recipe we keep hidden



> The model sees only these 200 numbers, not the recipe. Goal: learn from them, then produce a 201st that looks like it belongs.

A TEMPTING ANSWER

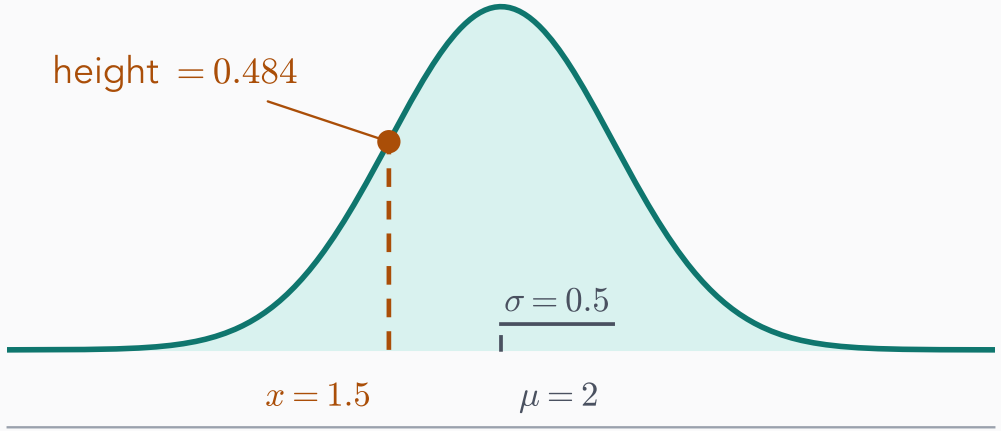
The average is a terrible sample



> **The mean is a number that almost never occurs. Generating needs the whole spread of the data, not one summary of it.**

How probable is $x = 1.5$ under a bump at 2?

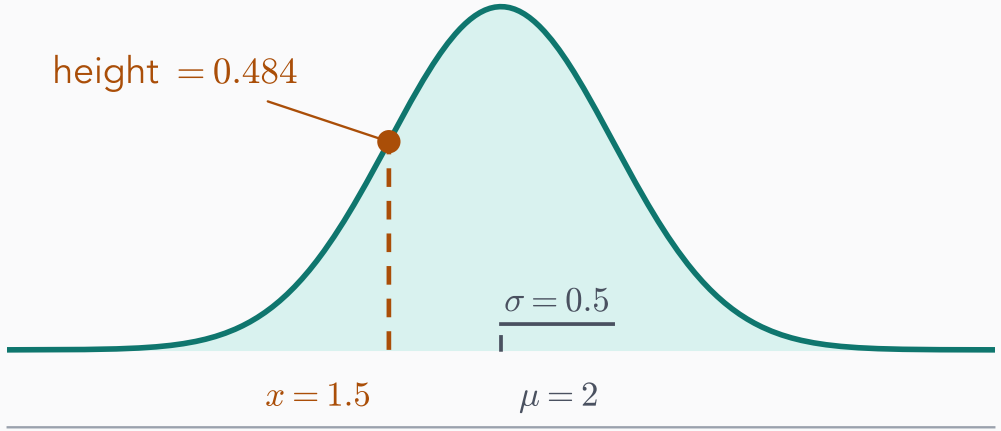
$$\mathcal{N}(x; \mu, \sigma^2) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2} \right)$$



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$$\frac{x-\mu}{\sigma} = \frac{1.5-2}{0.5} = -1$$

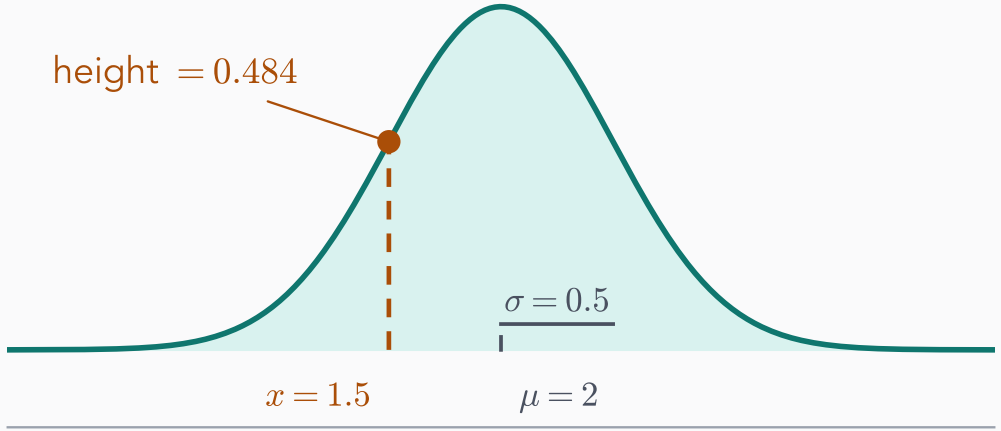


How probable is $x = 1.5$ under a bump at 2?

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$$\exp\Big(-\tfrac{1}{2}\cdot(-1)^2\Big) = e^{-0.5} = 0.607$$



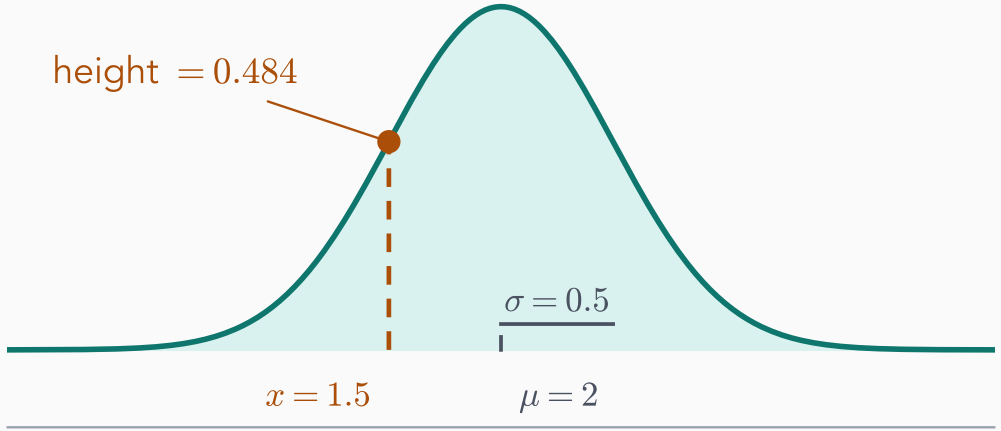
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$$\exp\Big(-\tfrac{1}{2}\cdot(-1)^2\Big) = e^{-0.5} = 0.607$$

$$\frac{1}{0.5\sqrt{2\pi}} = 0.798 \qquad \Rightarrow \qquad 0.798 \times 0.607 = \mathbf{0.484}$$



> The model's two parameters, μ and σ, decide how high the curve is at every x. Higher means more probable.

STEP 1 · LEARN

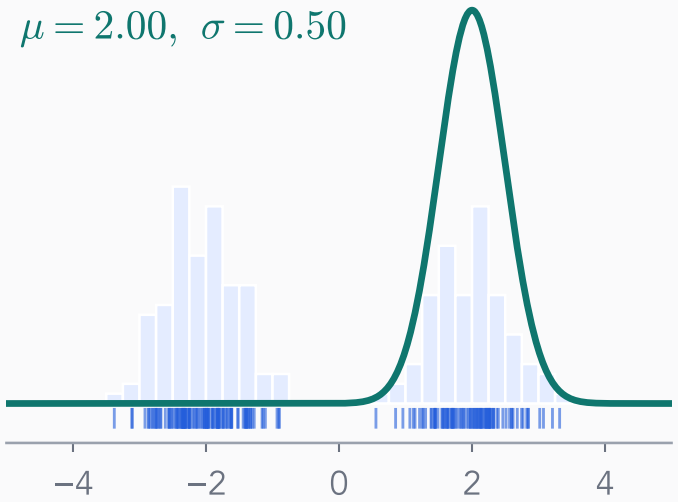
Score a choice of μ, σ on all 200 numbers

$$\log p_\theta(\text{data}) = \sum_{i=1}^{200} \log \mathcal{N}(x_i; \mu, \sigma^2), \qquad \theta = (\mu, \sigma)$$

STEP 1 · LEARN

Score a choice of μ, σ on all 200 numbers

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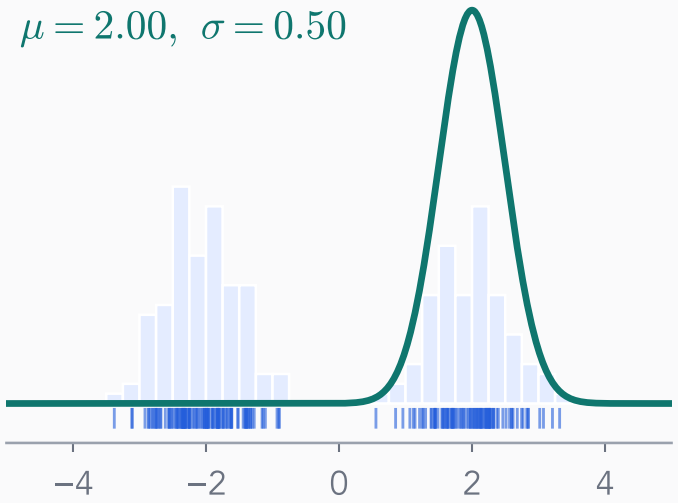


$$\log p = -3746.0$$

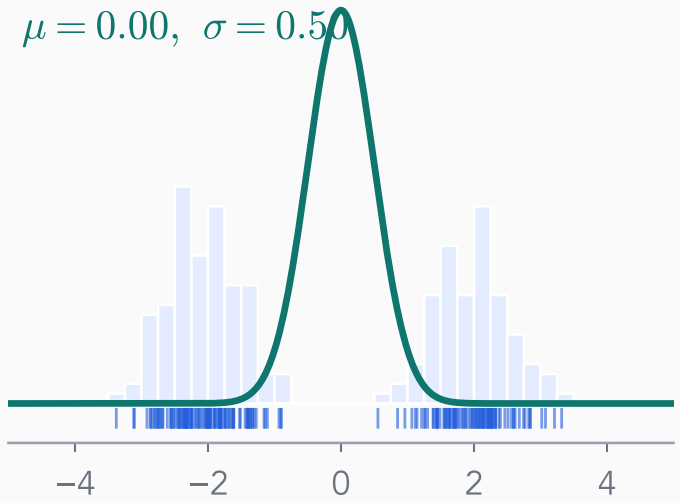
STEP 1 · LEARN

Score a choice of μ, σ on all 200 numbers

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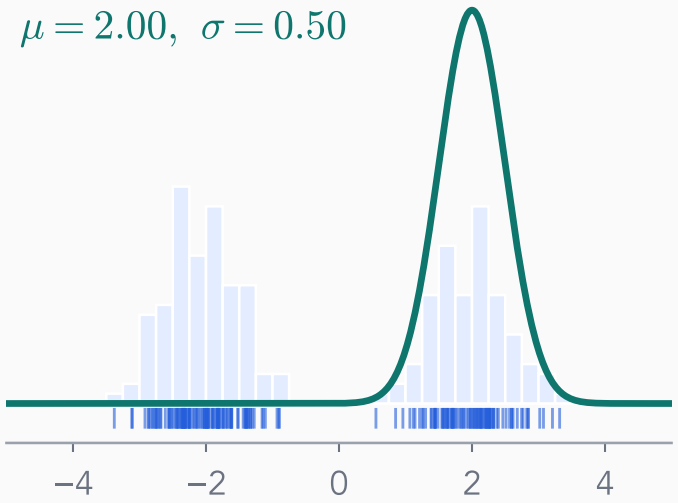


$\log p = -1790.0$

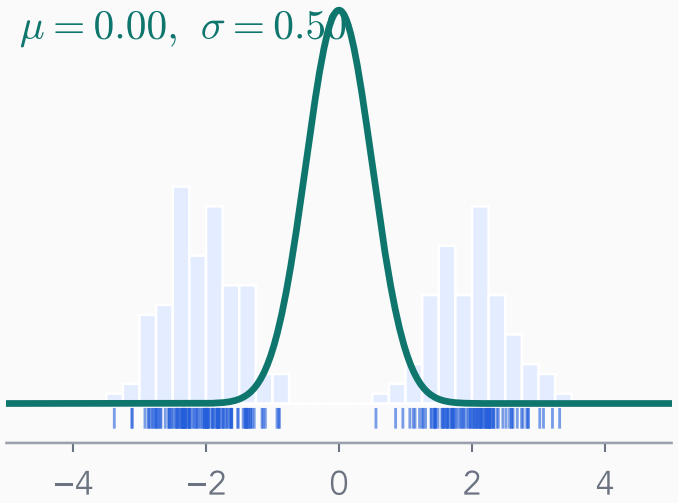
STEP 1 · LEARN

Score a choice of μ, σ on all 200 numbers

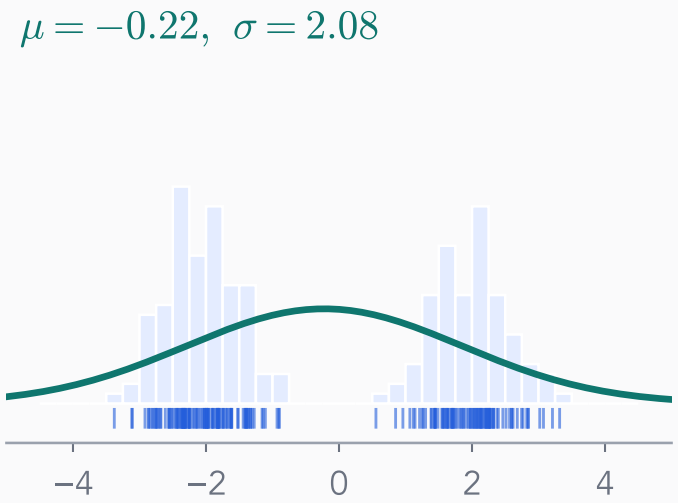
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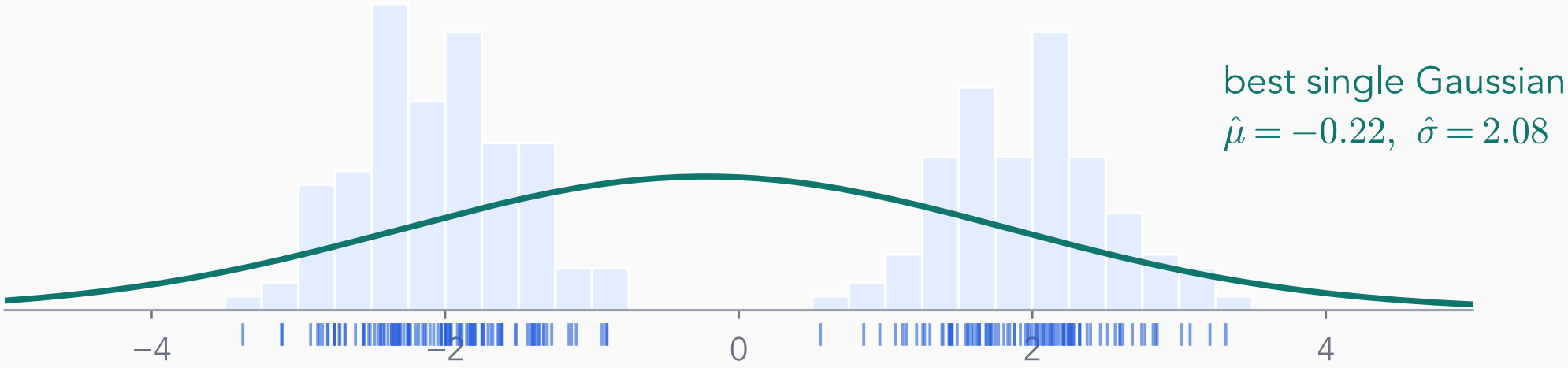
$\log p = -1790.0$



$\log p = -430.0$

> Learning = keep the θ with the highest score. That is **maximum likelihood**, the same rule that trained the name model.

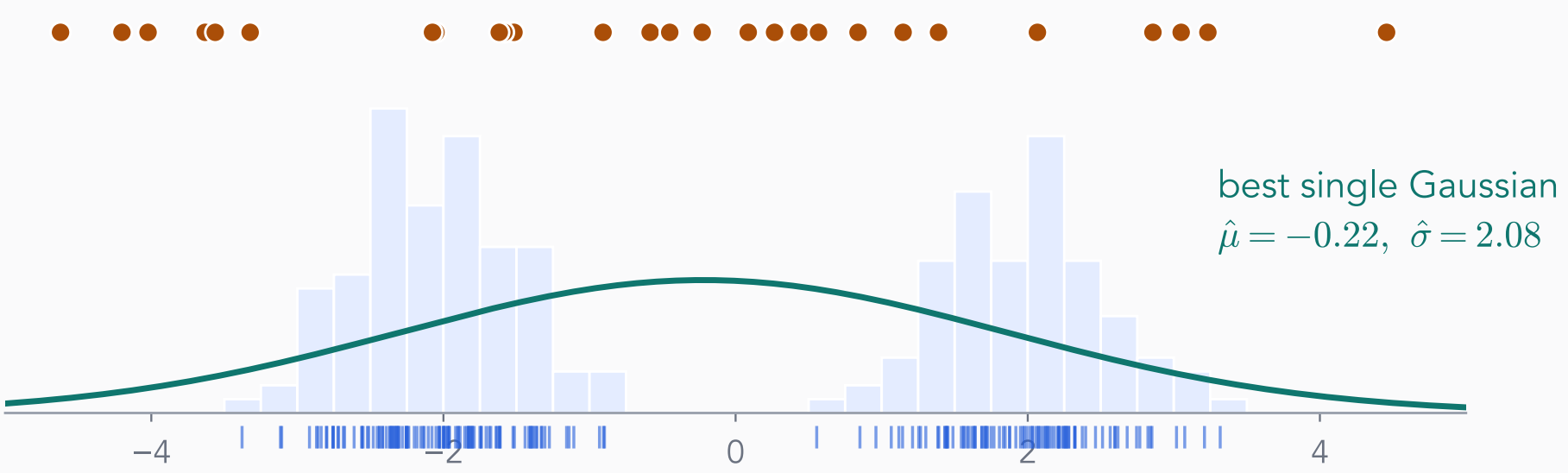
The best Gaussian has a formula; then we sample from it



$$\hat{\mu} = \frac{1}{N}\sum_{i=1}^{N} x_i = -0.22 \qquad \hat{\sigma}^2 = \frac{1}{N}\sum_{i=1}^{N}(x_i - \hat{\mu})^2 = 4.31$$

Setting the derivative of the score to zero gives these two numbers: the same answer as the third candidate.

The best Gaussian has a formula; then we sample from it



$$\hat{\mu} = \frac{1}{N}\sum_{i=1}^{N} x_i = -0.22 \qquad \hat{\sigma}^2 = \frac{1}{N}\sum_{i=1}^{N}(x_i - \hat{\mu})^2 = 4.31 \qquad x_{\text{new}} = \hat{\mu} + \hat{\sigma}\,\varepsilon, \quad \varepsilon \sim \mathcal{N}(0,1)$$

Step 2: 11 of 30 samples land in the empty gap. Learning worked; the model was too simple.

THE SAME FIT, IN PYTORCH

Learning = gradient descent on the negative log-likelihood

```
x = torch.tensor(data)                    # the 200 numbers
mu        = torch.tensor(1.0, requires_grad=True)
log_sigma = torch.tensor(0.0, requires_grad=True)
opt = torch.optim.Adam([mu, log_sigma], lr=0.05)

for step in range(300):
    dist = Normal(mu, log_sigma.exp())
    loss = -dist.log_prob(x).mean()
    opt.zero_grad(); loss.backward(); opt.step()

x_new = dist.sample((30,))                # step 2: generate
```

The parameters $\theta = (\mu, \log \sigma)$, started anywhere. We learn $\log \sigma$ so that $\sigma = e^{\log \sigma}$ is always positive.

THE SAME FIT, IN PYTORCH

Learning = gradient descent on the negative log-likelihood

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x_new = dist.sample((30,))                # step 2: generate
```

The loss is the score from the last slide with a minus sign, averaged: $-\frac{1}{N}\sum_i \log \mathcal{N}(x_i; \mu, \sigma^2)$.

THE SAME FIT, IN PYTORCH

Learning = gradient descent on the negative log-likelihood

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x_new = dist.sample((30,))              # step 2: generate
```

The update: nudge μ and $\log \sigma$ downhill, 300 times. The same loop trains every network in this course.

THE SAME FIT, IN PYTORCH

Learning = gradient descent on the negative log-likelihood

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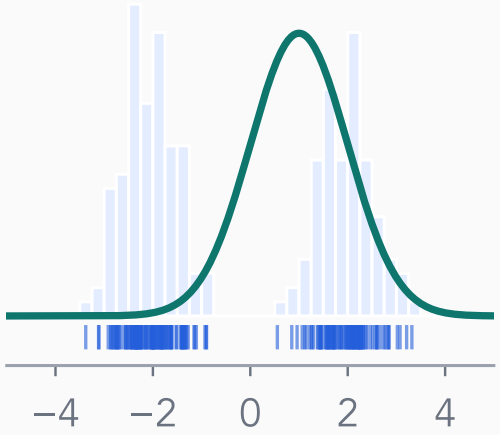
Result: $\mu = -0.22$, $\sigma = 2.08$, exactly the formula's answer. Then `sample` is step 2.

WATCH THE FIT HAPPEN

Four moments of that loop

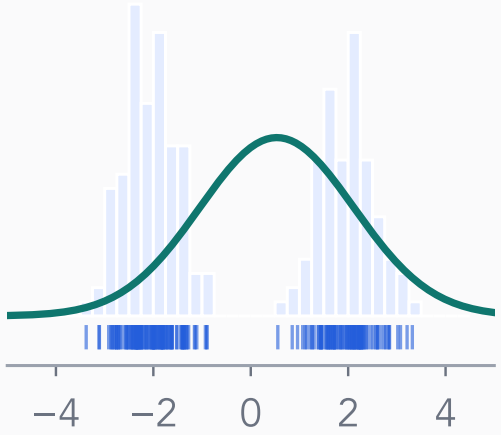
step 0: $\mu = 1.00,\ \sigma = 1.00$

loss $= 3.82$



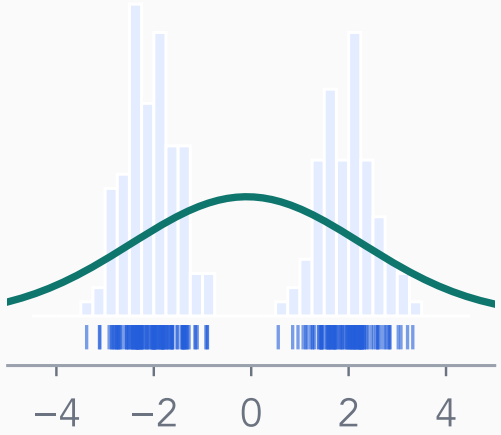
step 10: $\mu = 0.54,\ \sigma = 1.59$

loss $= 2.35$



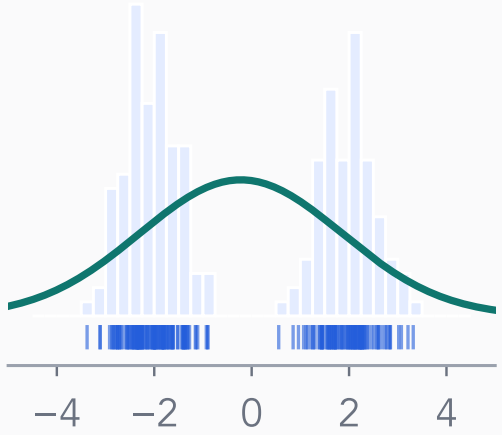
step 40: $\mu = -0.09,\ \sigma = 2.37$

loss $= 2.17$



step 300: $\mu = -0.22,\ \sigma = 2.08$

loss $= 2.15$



The curve starts in the wrong place, widens to cover both clumps, and stops at the best single bump. The loss falls from 3.82 to 2.15.

CHECKPOINT

So far: learn and generate work; one bump is not enough

	what we did	result
Learn	chose μ, σ to maximise $\log p_\theta(\text{data})$	$\hat{\mu} = -0.22,\ \hat{\sigma} = 2.08$
Generate	sampled $x = \hat{\mu} + \hat{\sigma}\varepsilon$	many samples in the gap

CHECKPOINT

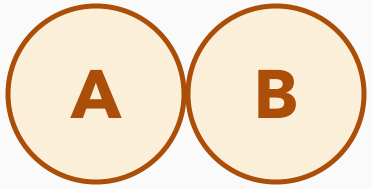
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	what we did	result
Learn	chose μ, σ to maximise $\log p_\theta(\text{data})$	$\hat{\mu} = -0.22,\ \hat{\sigma} = 2.08$
Generate	sampled $x = \hat{\mu} + \hat{\sigma}\varepsilon$	many samples in the gap
Fix	a richer model that can make two clumps	next slide

A RICHER MODEL: TELL A STORY

Hidden choice first, then the number

step 1 · hidden choice



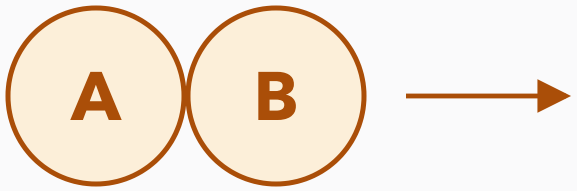
flip a fair coin:

$$p(z{=}\mathrm{A}) = p(z{=}\mathrm{B}) = \tfrac{1}{2}$$

> This is how we will generate: run the two steps. The coin is never written down in the data, so it is a hidden (latent) variable z.

Hidden choice first, then the number

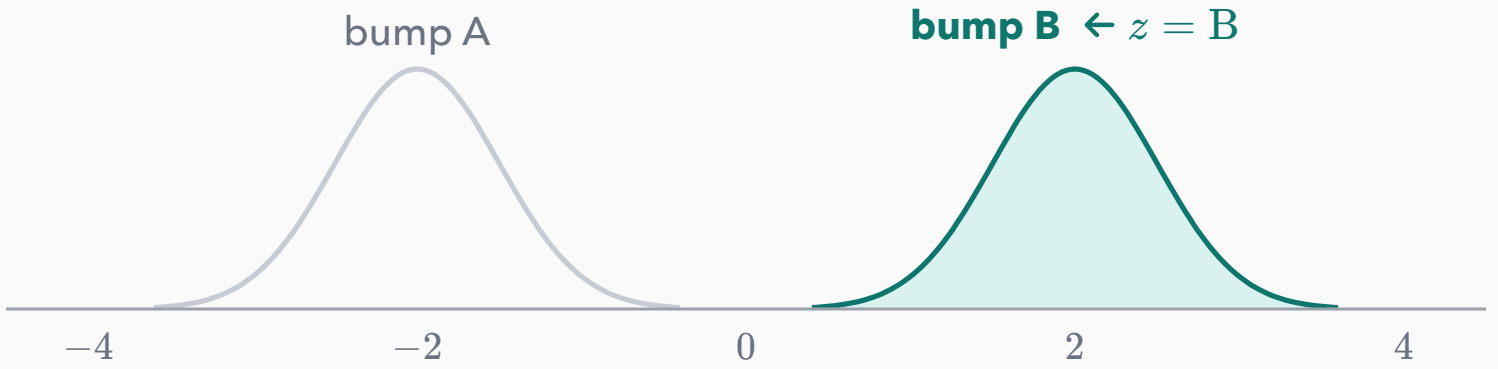
step 1 · hidden choice



flip a fair coin:

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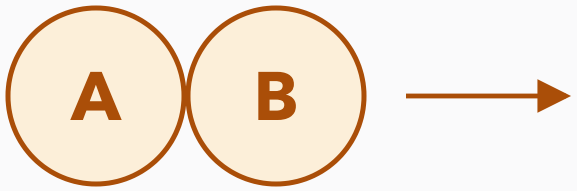
step 2 · draw x from the chosen bump



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Hidden choice first, then the number

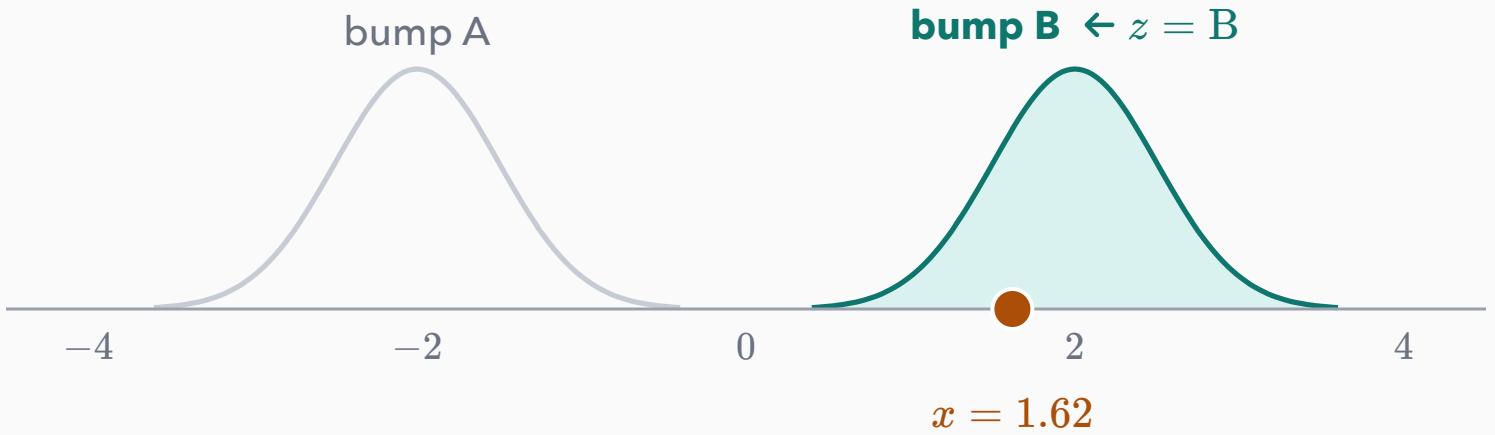
step 1 · hidden choice



flip a fair coin:

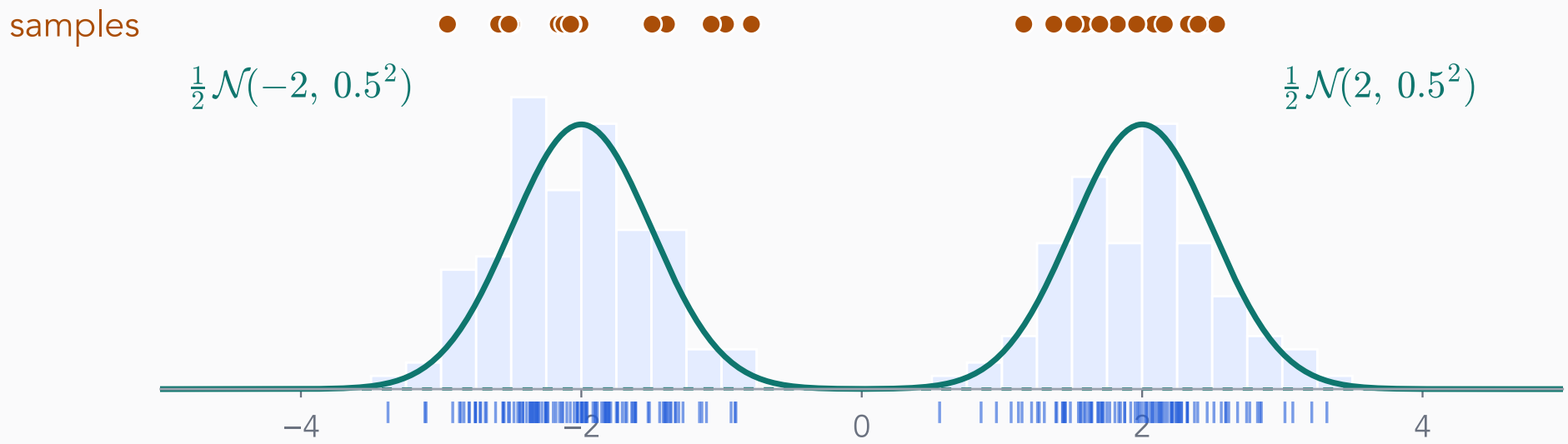
$p(z{=}\mathrm{A}) = p(z{=}\mathrm{B}) = \frac{1}{2}$

step 2 · draw x from the chosen bump



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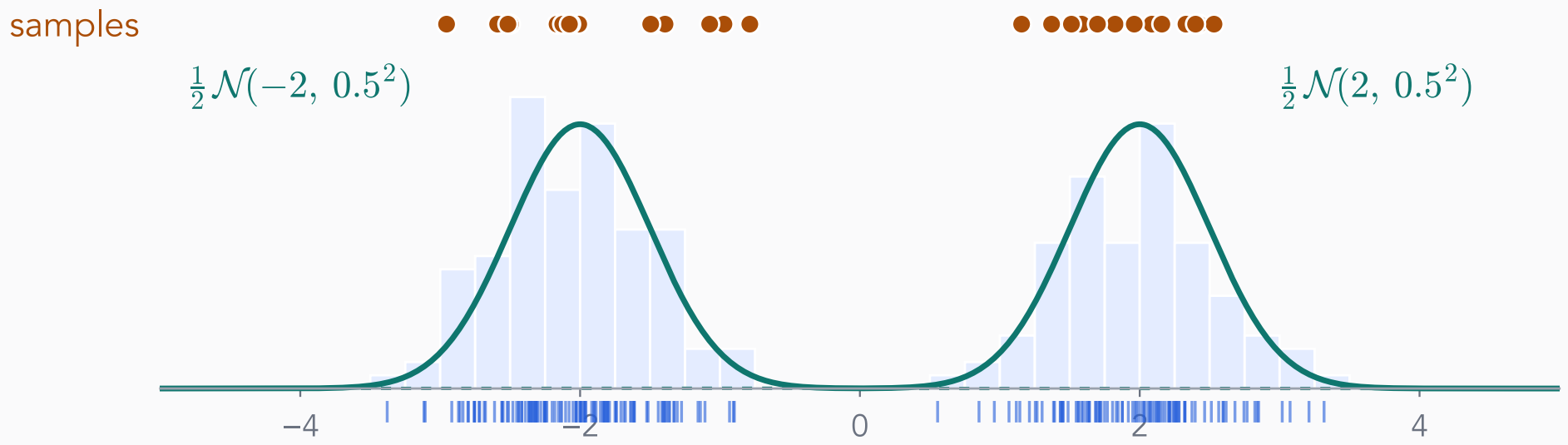
To score x, add up every way it could have been made



$$p(x) = \underbrace{\tfrac{1}{2}\,\mathcal{N}(x;\,-2, 0.5^2)}_{\text{made by bump A}} + \underbrace{\tfrac{1}{2}\,\mathcal{N}(x;\,2, 0.5^2)}_{\text{made by bump B}} = \sum_z p(z)\,p(x \mid z)$$

> One hidden coin flip made the model rich enough: the samples now fall in the bumps, not in the gap.

To score x, add up every way it could have been made



$$p(x) = \underbrace{\tfrac{1}{2}\,\mathcal{N}(x;\,-2, 0.5^2)}_{\text{made by bump A}} + \underbrace{\tfrac{1}{2}\,\mathcal{N}(x;\,2, 0.5^2)}_{\text{made by bump B}} = \sum_z p(z)\,p(x \mid z)$$

$$\text{at } x = 1.5: \quad \tfrac{1}{2}\cdot 0.000 + \tfrac{1}{2}\cdot 0.484 = 0.242$$

> One hidden coin flip made the model rich enough: the samples now fall in the bumps, not in the gap.

Same loop, a richer `log_prob`

```
logits = torch.zeros(K, requires_grad=True)   # bump weights
means  = torch.randn(K, requires_grad=True)
log_sd = torch.zeros(K, requires_grad=True)

def log_p(x):                                 # log p(x), shape [N]
    comp = Normal(means, log_sd.exp()).log_prob(x[:, None])   # [N, K]
    return torch.logsumexp(log_softmax(logits) + comp, dim=1)

loss = -log_p(x).mean()        # then the same 3-line update
```

Three parameters per bump: a weight, a centre, a width. `softmax` turns the weights into probabilities that sum to 1.

Same loop, a richer `log_prob`

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loss = -log_p(x).mean()        # then the same 3-line update
```

Every number under every bump: $\log p(x_i \mid z = k)$ for all i and k, a table of $N \times K$ log-densities.

Same loop, a richer `log_prob`

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    return torch.logsumexp(log_softmax(logits) + comp, dim=1)

loss = -log_p(x).mean()        # then the same 3-line update
```

The sum over the hidden choice: $\log \sum_k p(k)\, p(x \mid k)$. `logsumexp` does it without underflow.

Same loop, a richer `log_prob`

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logits = torch.zeros(K, requires_grad=True)   # bump weights
means  = torch.randn(K, requires_grad=True)
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    return torch.logsumexp(log_softmax(logits) + comp, dim=1)

loss = -log_p(x).mean()          # then the same 3-line update
```

Training is unchanged. With $K = 2$ it finds centres -2.06 and 1.98, widths 0.52 and 0.54.

STEP 2 · GENERATE, FROM THE TWO-BUMP FIT

Sampling runs the story: choose a bump, then a number

```
weights = softmax(logits)
k = torch.multinomial(weights, 1000,
                      replacement=True)    # the coin
x_new = means[k] + log_sd.exp()[k] * torch.randn(1000)
```

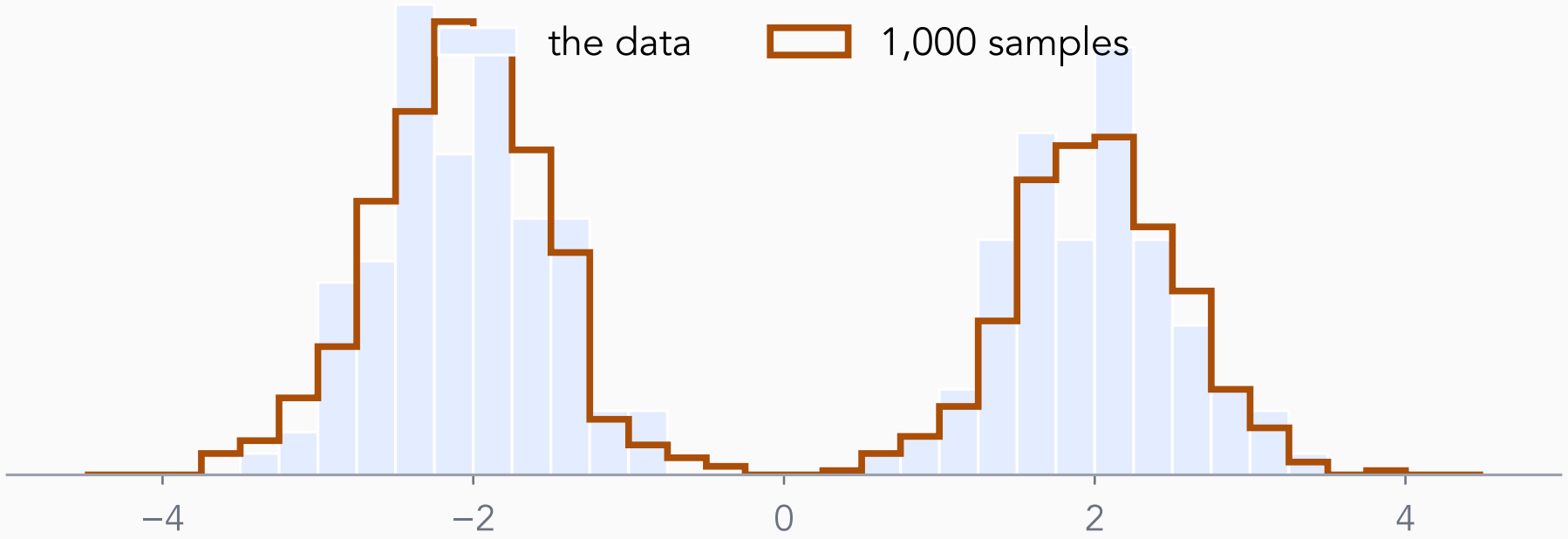
Step 1: pick a bump for each sample, with the learned weights.

STEP 2 · GENERATE, FROM THE TWO-BUMP FIT

Sampling runs the story: choose a bump, then a number

```
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k = torch.multinomial(weights, 1000,
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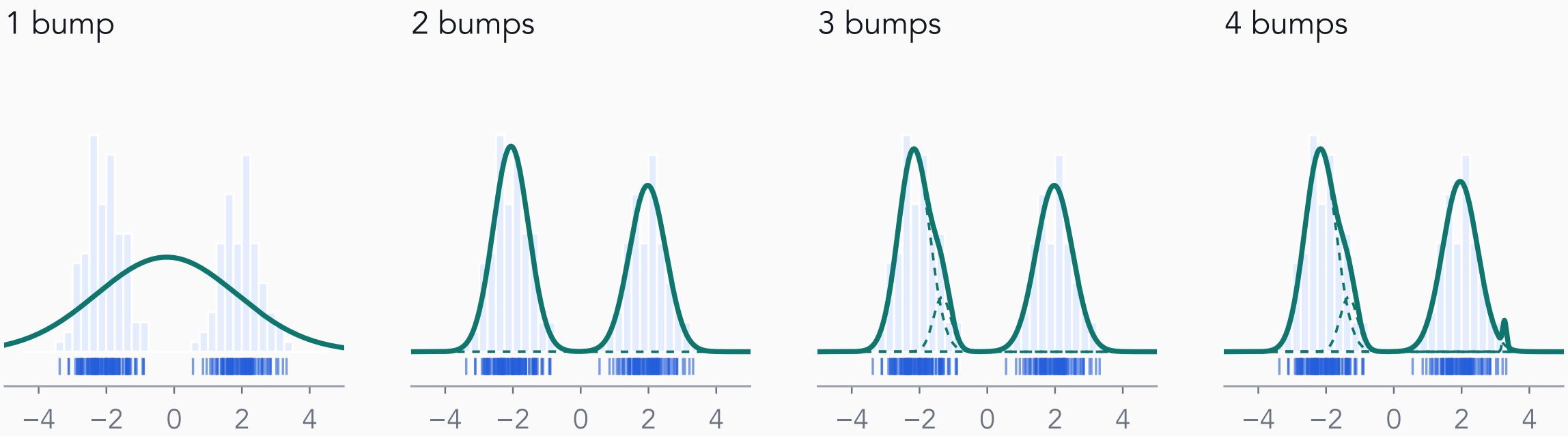
Step 2: draw a number from that bump: its centre plus its width times standard noise.



1,000 new numbers that follow the data, and none of them is a copy of a training number.

BUT HOW MANY BUMPS SHOULD WE FIT?

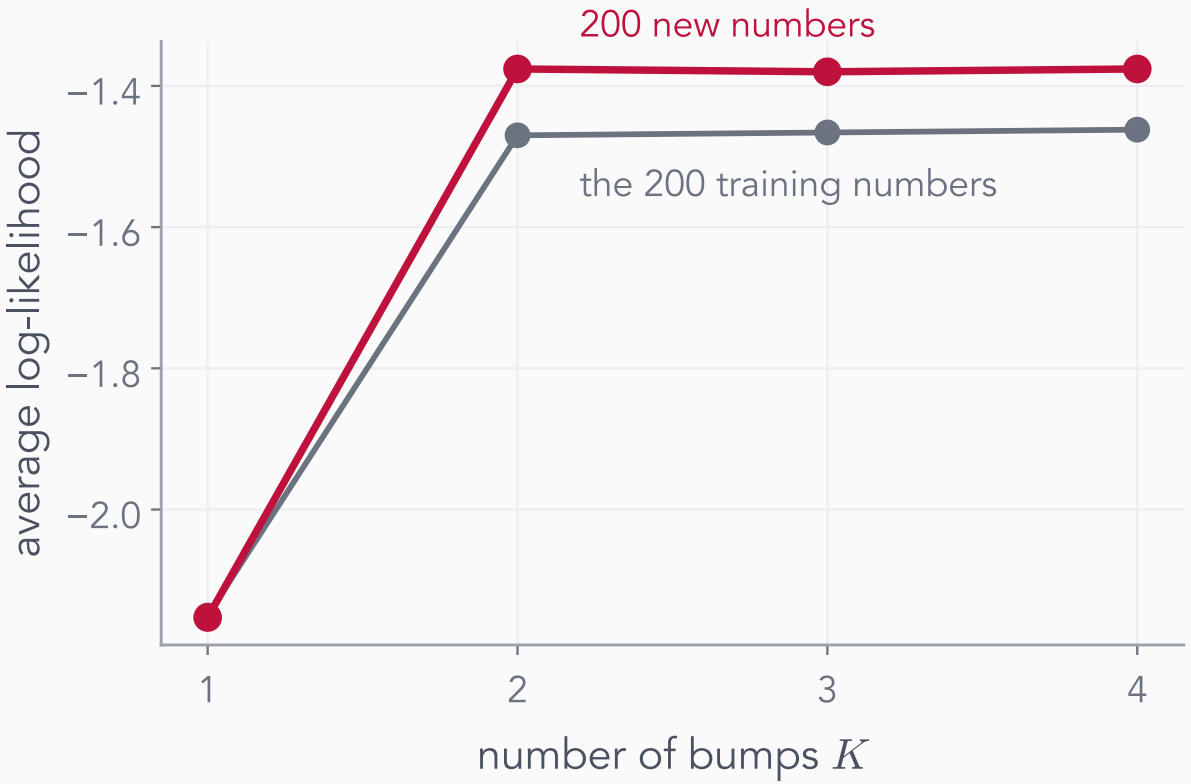
More bumps always fit the training data better



1, 2, 3, 4 bumps, each fitted with the same loop. The training score rises every time. So which one do we keep?

SCORE ON DATA THE FIT HAS NEVER SEEN

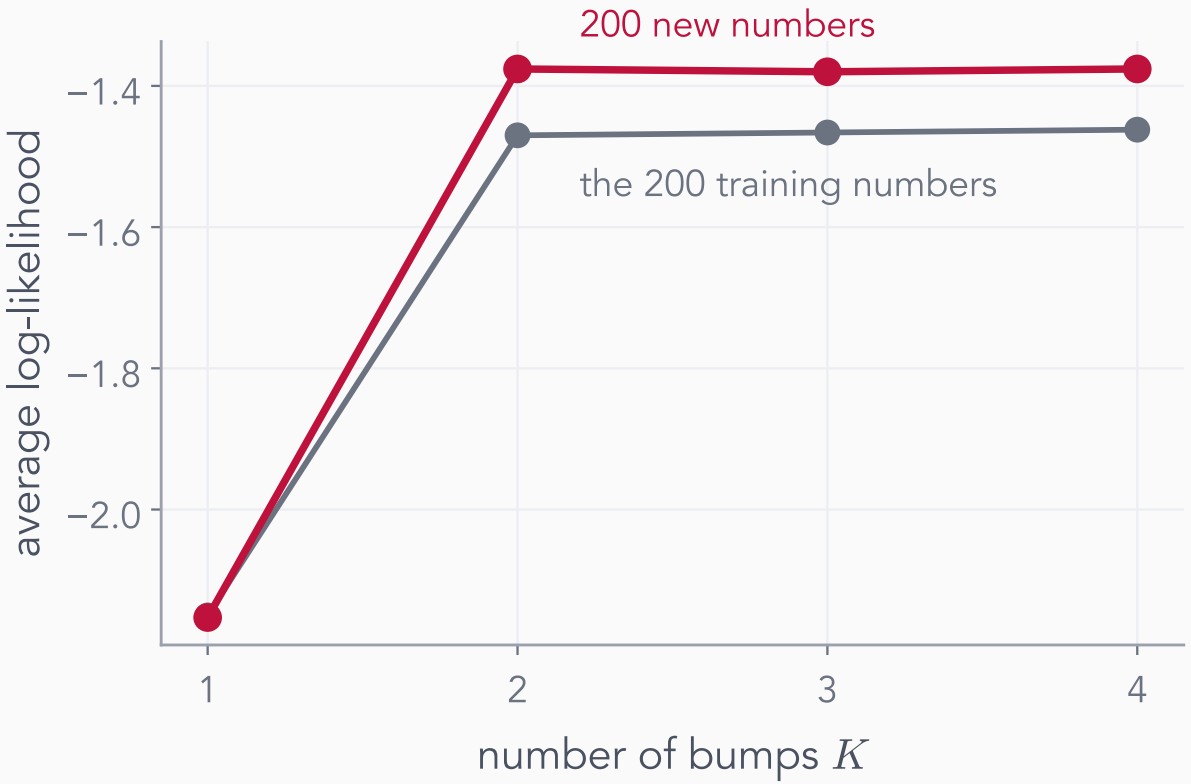
New data decides: two bumps



Draw **200 new numbers** from the same hidden recipe and score each fit on them.

SCORE ON DATA THE FIT HAS NEVER SEEN

New data decides: two bumps

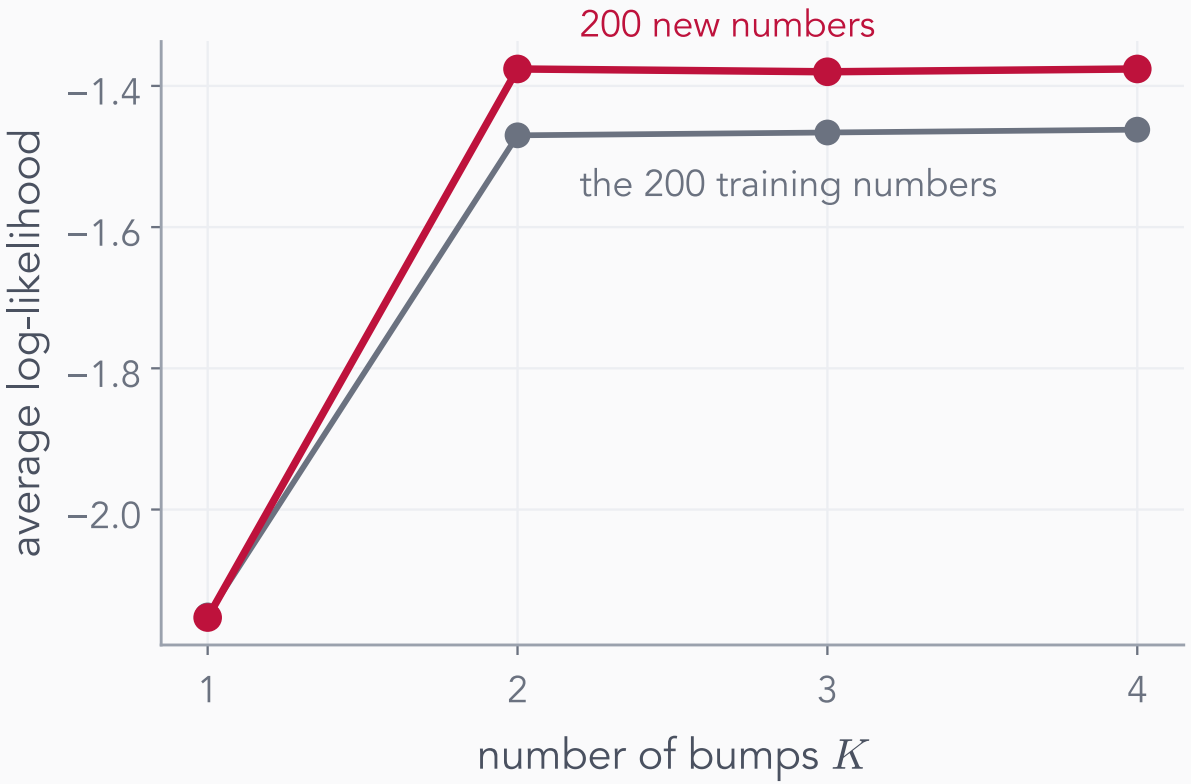


Draw **200 new numbers** from the same hidden recipe and score each fit on them.

1 → 2 bumps: $-2.153 \rightarrow -1.376$ per number. A real improvement.

SCORE ON DATA THE FIT HAS NEVER SEEN

New data decides: two bumps



Draw **200 new numbers** from the same hidden recipe and score each fit on them.

1 → 2 bumps: $-2.153 \rightarrow -1.376$ per number. A real improvement.

3 or 4 bumps: the training score creeps up, the new-data score does not. The extra bumps fit noise in the 200 training numbers.

> **Choose the size of a model by how well it scores data it has not seen. That holds for bumps, and for networks.**

STEP 1 · LEARN, LOOKED AT CLOSELY

Hidden in the fit: which bump made each point?

If we knew the coin for every point

fitting is easy: average the A-points for bump A's centre, the B-points for bump B's.

STEP 1 · LEARN, LOOKED AT CLOSELY

Hidden in the fit: which bump made each point?

If we knew the coin for every point

fitting is easy: average the A-points for bump A's centre, the B-points for bump B's.

We don't, so ask for each point

given this x, how probable is it that bump B made it? That is $p(\mathrm{B} \mid x)$.

STEP 1 · LEARN, LOOKED AT CLOSELY

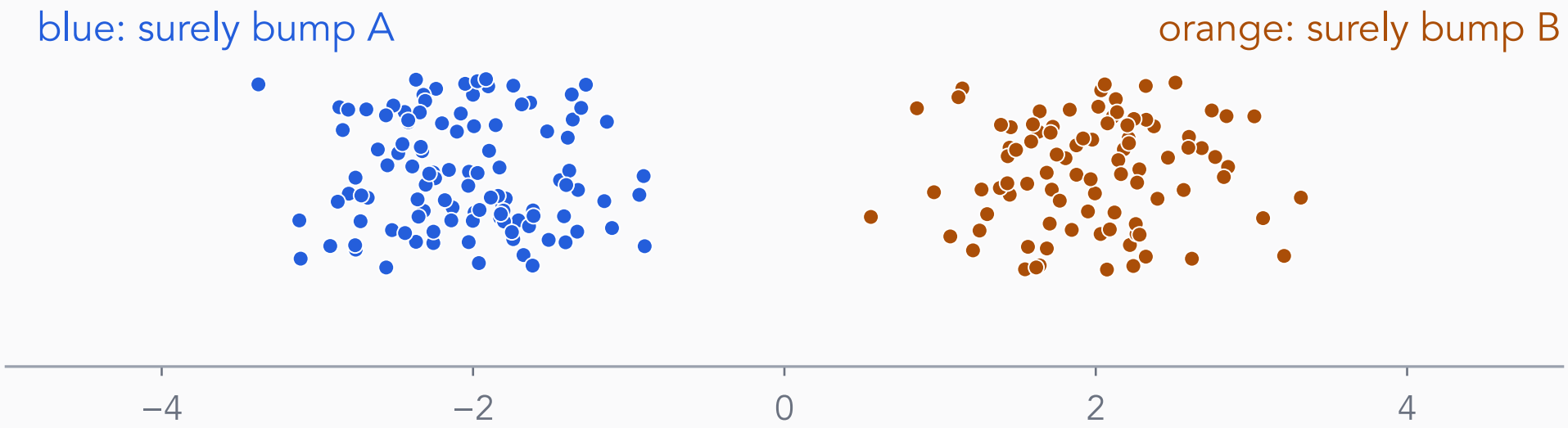
Hidden in the fit: which bump made each point?

If we knew the coin for every point

fitting is easy: average the A-points for bump A's centre, the B-points for bump B's.

We don't, so ask for each point

given this x, how probable is it that bump B made it? That is $p(\mathrm{B} \mid x)$.



Running the story backwards, from a number to its likely hidden cause, is called inference. The gradient descent we just ran was doing it all along: four slides on, we will see where.

THE BACKWARDS STEP, WORKED BY HAND

You see $x = 0.1$. Which bump made it?

bump z	prior $p(z)$	likelihood $p(x \mid z)$	prior × likelihood	÷ total = posterior
A, centre -2	0.5			
B, centre 2	0.5			

THE BACKWARDS STEP, WORKED BY HAND

You see $x = 0.1$. Which bump made it?

bump z	prior $p(z)$	likelihood $p(x \mid z)$	prior × likelihood	÷ total = posterior
A, centre -2	0.5	1.18×10^{-4}		
B, centre 2	0.5	5.84×10^{-4}		

THE BACKWARDS STEP, WORKED BY HAND

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bump z	prior $p(z)$	likelihood $p(x \mid z)$	prior × likelihood	÷ total = posterior
A, centre -2	0.5	1.18×10^{-4}	5.89×10^{-5}	
B, centre 2	0.5	5.84×10^{-4}	2.92×10^{-4}	

THE BACKWARDS STEP, WORKED BY HAND

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bump z	prior $p(z)$	likelihood $p(x \mid z)$	prior × likelihood	÷ total = posterior
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total $= p(x)$			3.51×10^{-4}	

THE BACKWARDS STEP, WORKED BY HAND

You see $x = 0.1$. Which bump made it?

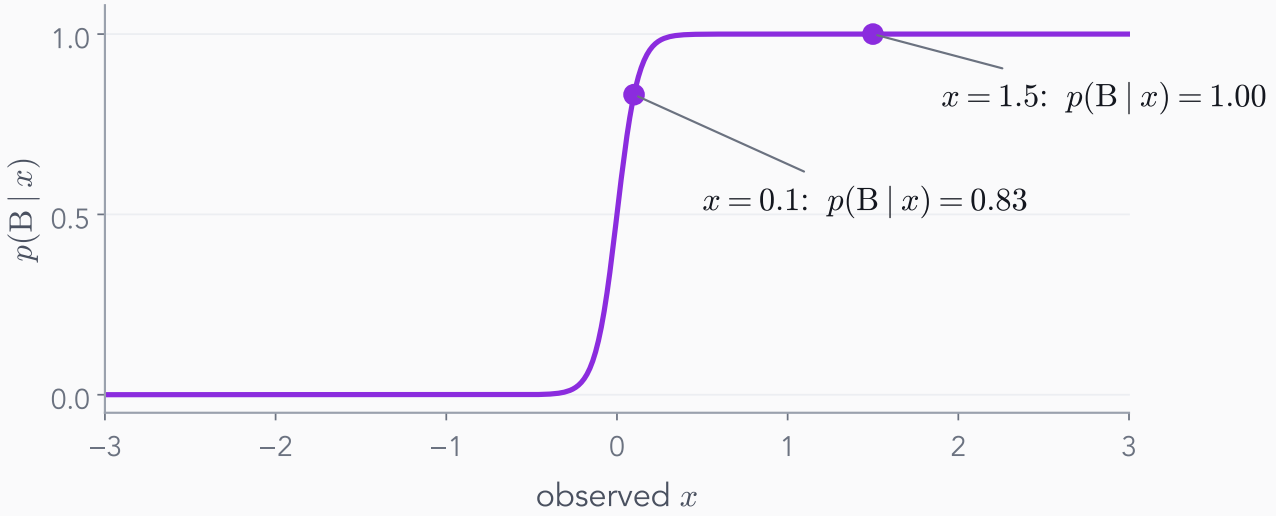
bump z	prior $p(z)$	likelihood $p(x \mid z)$	prior × likelihood	÷ total = posterior
A, centre -2	0.5	1.18×10^{-4}	5.89×10^{-5}	0.168
B, centre 2	0.5	5.84×10^{-4}	2.92×10^{-4}	**0.832**
total $= p(x)$			3.51×10^{-4}	**1.000**

$$p(\mathrm{B} \mid x) = \frac{p(\mathrm{B})\, p(x \mid \mathrm{B})}{p(x)} = 0.832$$

> **Bayes' rule is just this table: multiply, then divide by the total. Note the total is exactly the $p(x)$ of the two-bump formula.**

DO IT FOR EVERY x

The backwards step, as a curve

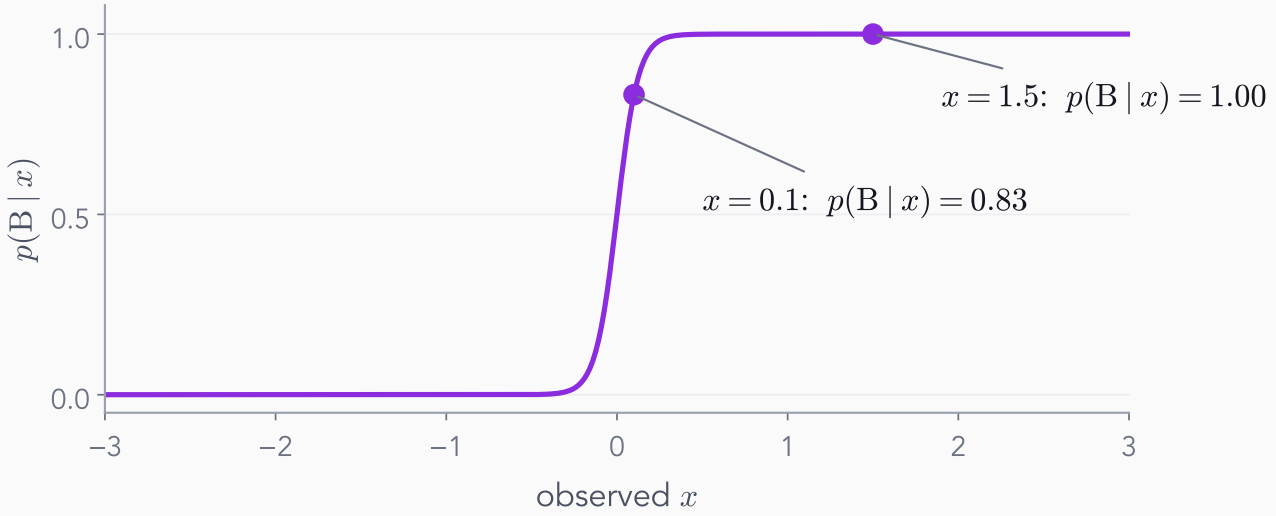


Repeat the table for every x and plot $p(\mathrm{B} \mid x)$.

These are the colours on the 200 points two slides ago.

DO IT FOR EVERY x

The backwards step, as a curve



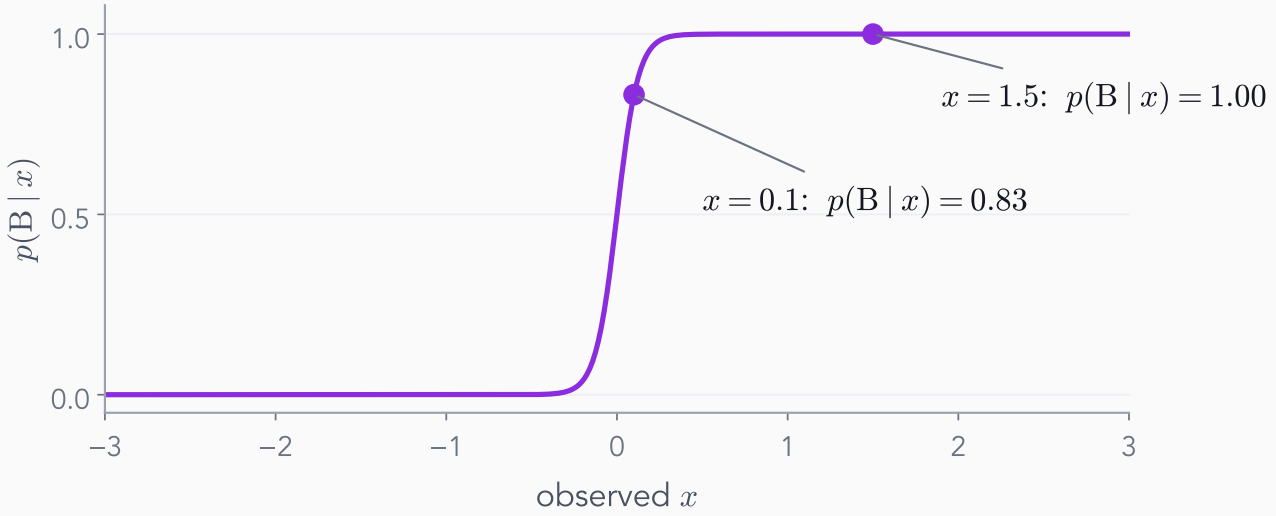
Repeat the table for every x and plot $p(\mathrm{B} \mid x)$.

Far right: certainly B. Far left: certainly A. Near 0: unsure.

These are the colours on the 200 points two slides ago.

DO IT FOR EVERY x

The backwards step, as a curve



Repeat the table for every x and plot $p(\mathrm{B} \mid x)$.

Far right: certainly B. Far left: certainly A. Near 0: unsure.

For these two bumps the curve is exactly $\mathrm{sigmoid}(16x)$: a logistic regression in disguise.

These are the colours on the 200 points two slides ago.

THE BACKWARDS STEP, IN ONE LINE

Posterior = softmax of (log prior + log likelihood)

```
log_joint = log_softmax(logits) + Normal(means, log_sd.exp()).log_prob(x)   # [K]
posterior = softmax(log_joint)                  # divide by the total: Bayes
```

THE BACKWARDS STEP, IN ONE LINE

Posterior = softmax of (log prior + log likelihood)

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log_joint = log_softmax(logits) + Normal(means, log_sd.exp()).log_prob(x)   # [K]
posterior = softmax(log_joint)                    # divide by the total: Bayes
```

With the fitted bumps, at $x = 0.1$: $p(\mathrm{A} \mid x) = 0.094$, $p(\mathrm{B} \mid x) = 0.906$. (With the true recipe it was 0.832: the fitted bumps are slightly different.)

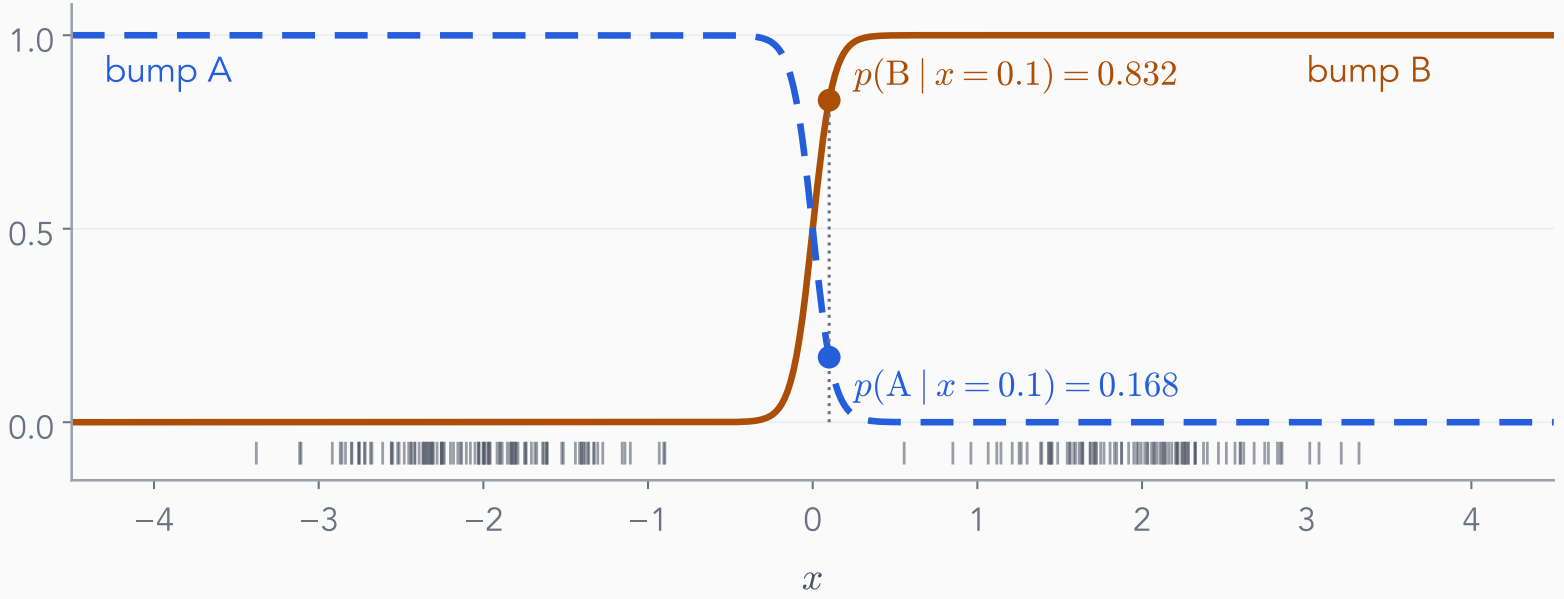
Softmax is "exponentiate, then divide by the total": exactly the last column of the Bayes table.

The gradient of $\log p(x)$ is weighted by the posterior

$$\frac{\partial \log p(x)}{\partial \mu_k} = p(k \mid x) \cdot \frac{x - \mu_k}{\sigma_k^2}$$

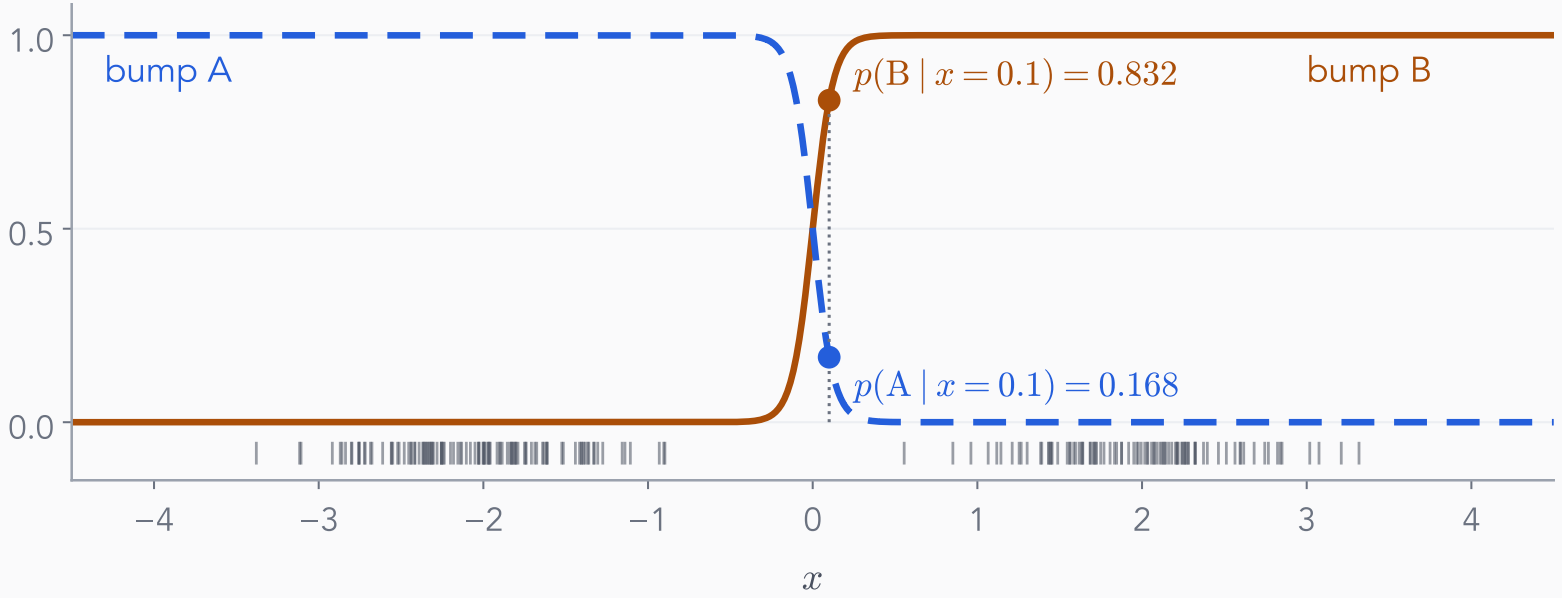
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The gradient of $\log p(x)$ is weighted by the posterior

$$\frac{\partial \log p(x)}{\partial \mu_k} = p(k \mid x) \cdot \frac{x - \mu_k}{\sigma_k^2}$$



At $x = 0.1$: bump B's centre is pulled by $0.832 \times (0.1 - 2)/0.25 = -6.32$, bump A's by $0.168 \times (0.1 + 2)/0.25 = 1.41$.

Each point pulls each bump in proportion to how likely that bump made it. Learning needs the posterior for every point: a 2-row table here, an intractable patch for images.

FOUR WORDS FOR THE REST OF THE LECTURE

Prior, likelihood, evidence, posterior

name	symbol	question it answers	at $x = 0.1$
prior	$p(z)$	what do we believe about z before seeing x?	0.5, 0.5

FOUR WORDS FOR THE REST OF THE LECTURE

Prior, likelihood, evidence, posterior

name	symbol	question it answers	at $x = 0.1$
prior	$p(z)$	what do we believe about z before seeing x?	0.5, 0.5
likelihood	$p(x \mid z)$	if z were known, how probable is this x?	5.84×10^{-4} for B

FOUR WORDS FOR THE REST OF THE LECTURE

Prior, likelihood, evidence, posterior

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prior	$p(z)$	what do we believe about z before seeing x?	0.5, 0.5
likelihood	$p(x \mid z)$	if z were known, how probable is this x?	5.84×10^{-4} for B
evidence	$p(x)$	how probable is x overall, summing over z?	3.51×10^{-4}

FOUR WORDS FOR THE REST OF THE LECTURE

Prior, likelihood, evidence, posterior

name	symbol	question it answers	at $x = 0.1$
prior	$p(z)$	what do we believe about z before seeing x?	0.5, 0.5
likelihood	$p(x \mid z)$	if z were known, how probable is this x?	5.84×10^{-4} for B
evidence	$p(x)$	how probable is x overall, summing over z?	3.51×10^{-4}
posterior	$p(z \mid x)$	having seen x, which z explains it?	B: 0.832

Generating uses the prior and the likelihood. Learning needs the evidence and the posterior.

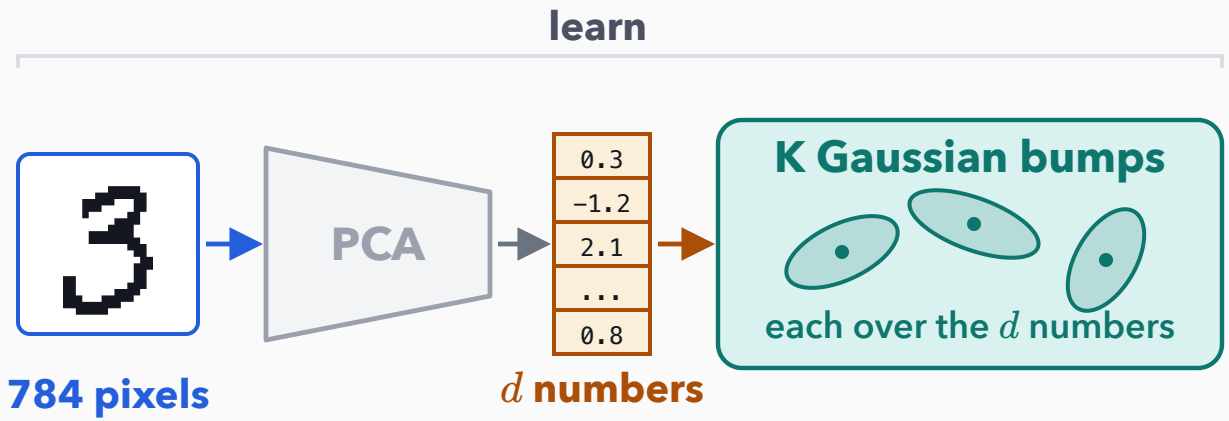
PART 1, SECOND HALF

The same recipe, on real images

Learn a distribution, then sample from it: can Gaussian bumps generate handwritten digits? How far does this simple toolkit get us, and where does it run out?

THE PLAN, AS A PICTURE

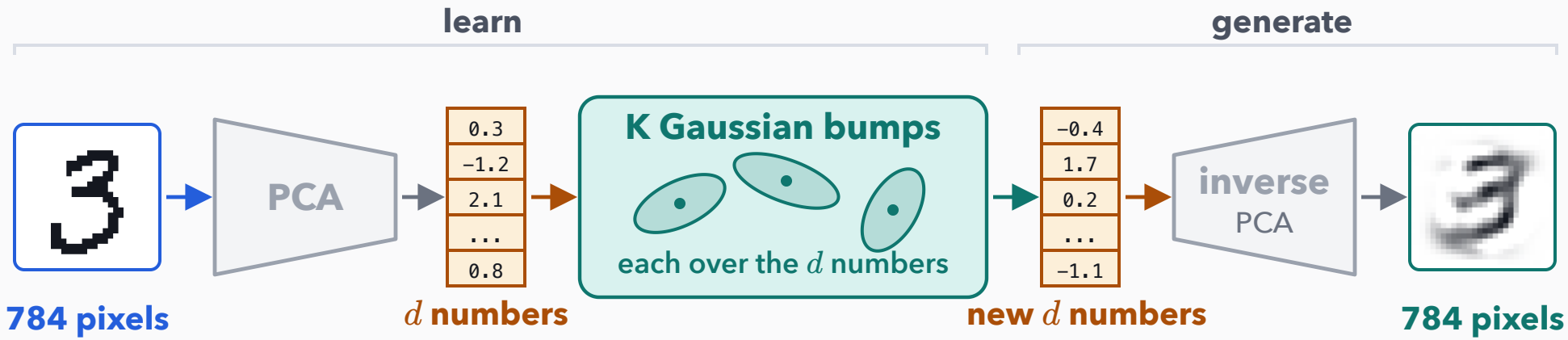
Squeeze, fit bumps, sample, un-squeeze



$z = V^\top (x - \bar{x})$ weight + centre (d) + covariance ($d(d+1)/2$)

THE PLAN, AS A PICTURE

Squeeze, fit bumps, sample, un-squeeze



Two questions before any code: each bump is a Gaussian over **what**? And how many bumps?

WHICH DIMENSION IS EACH GAUSSIAN?

One bump, three possible sizes

each bump is a Gaussian over	centre	covariance	numbers per bump, with its weight
1 number (the toy)	1	1 (a width)	3

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784 pixels, every pixel on its own	784	784 widths	1,569



Samples from one 784-pixel Gaussian with independent pixels: each pixel jitters on its own, so you get static around the average digit. Strokes need pixels that move **together**.

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784 pixels, every pixel on its own	784	784 widths	1,569
784 pixels, with all pixel pairs	784	307,720	308,505
50 PCA numbers (what we fit)	**50**	**1,275**	**1,326**



Samples from one 784-pixel Gaussian with independent pixels: each pixel jitters on its own, so you get static around the average digit. Strokes need pixels that move **together**.

> **Keep the covariance, shrink the dimension: a full Gaussian over 50 numbers costs about 230 times less than one over 784 pixels.**

PCA and inverse PCA: generation needs both

PCA, image to d numbers: coordinates along the d directions in which digits vary most.

$$\underbrace{z}_{d} = \underbrace{V^\top}_{d \times 784} (\underbrace{x - \bar{x}}_{784})$$

PCA and inverse PCA: generation needs both

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Inverse PCA, d numbers back to an image: add the directions back onto the mean digit.

$$\underbrace{\hat{x}}_{784} = \bar{x} + \underbrace{V}_{784 \times d} \underbrace{z}_{d}$$

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top: test digits, our 3 among them · bottom: PCA to 50 numbers, then inverse PCA

> **The bumps only ever see z. Every generated sample is d numbers until the inverse PCA turns it into pixels. With $d = 50$, 82.5% of the variation survives the round trip.**

SQUEEZE ALL THE WAY TO 2 NUMBERS

In 2-D you can see every bump

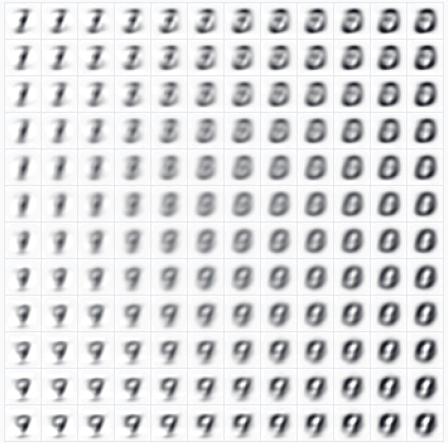


4,000 test digits by their 2 PCA numbers, coloured by label (the model never saw labels). Black: 10 fitted bumps, 1 and 2 widths. Red ×: 24 samples.

In 2-D you can see every bump



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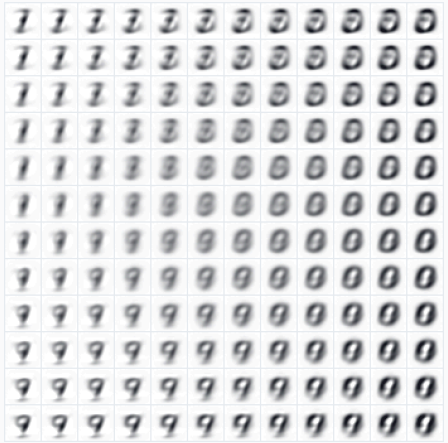
Inverse PCA of a grid over the plane: every point is a blend of a few blurry shapes.

SQUEEZE ALL THE WAY TO 2 NUMBERS

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4,000 test digits by their 2 PCA numbers, coloured by label (the model never saw labels). Black: 10 fitted bumps, 1 and 2 widths. Red ×: 24 samples.



Inverse PCA of a grid over the plane: every point is a blend of a few blurry shapes.



the 24 red × after inverse PCA

2 numbers keep only 16.8% of the variation. Every bump is visible, every sample is a ghost: interpretable is not the same as good.

THE TWO-BUMP CODE, SCALED UP

PCA, fit K bumps, sample, inverse PCA

```
x = mnist_train.flatten(1)                  # [60000, 784], grey levels
mean = x.mean(0)
_, _, Vt = torch.linalg.svd(x - mean, full_matrices=False)
V = Vt[:d].T                               # [784, d]
z = (x - mean) @ V                          # PCA: [60000, d]

gmm = MixtureSameFamily(Categorical(logits=logits),
                        MultivariateNormal(means, scale_tril=L))
loss = -gmm.log_prob(z_batch).mean()        # the same 3-line update

z_new = gmm.sample((24,))                   # step 2: generate
x_new = (mean + z_new @ V.T).clamp(0, 1)    # inverse PCA: [24, 784]
```

PCA: one SVD gives the directions; each image becomes d numbers.

THE TWO-BUMP CODE, SCALED UP

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```

The mixture: `logits` [K], `means` [K, d], `L` [K, d, d] lower-triangular, so each covariance $LL^\top$ is always valid.

THE TWO-BUMP CODE, SCALED UP

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```

Learning: the loop that fitted the two bumps, unchanged: minus the average log-probability, Adam.

THE TWO-BUMP CODE, SCALED UP

PCA, fit K bumps, sample, inverse PCA

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x_new = (mean + z_new @ V.T).clamp(0, 1)    # inverse PCA: [24, 784]
```

Generating: pick a bump by its weight, draw d numbers from it, inverse PCA to 784 pixels.

TRY IT: EVERY COMBINATION BELOW WAS FITTED

Slide the dimension and the number of bumps

PCA numbers d

50

bumps K

100

variation kept by d numbers: **82.5%**
parameters: **132,599**
score on new images: **−16.5**
new images prefer K = **100** at this d



test digits

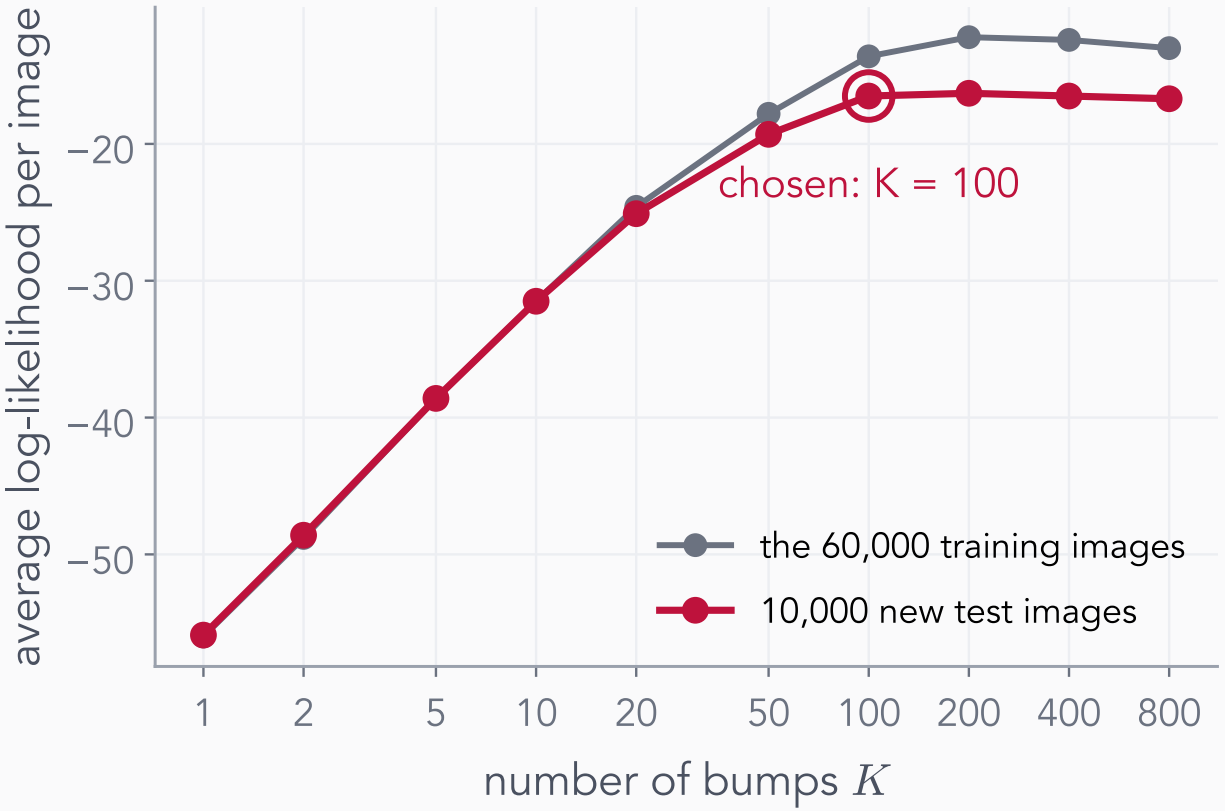


after PCA to d numbers and back



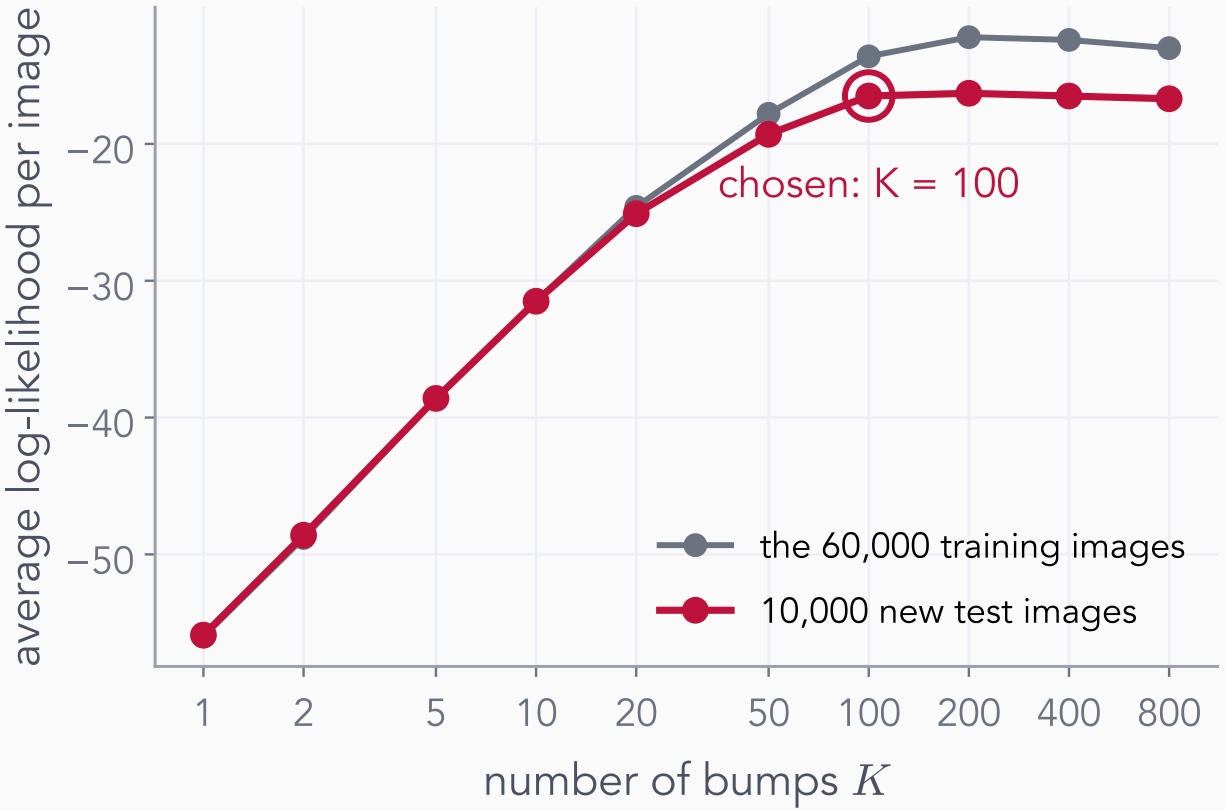
24 samples from the K-bump fit, after inverse PCA

The toy's rule: score on images the model has not seen



$d = 50$. Fit K = 1, 2, 5, 10, 20, 50, 100, 200, 400, 800 bumps to the 60,000 training images.

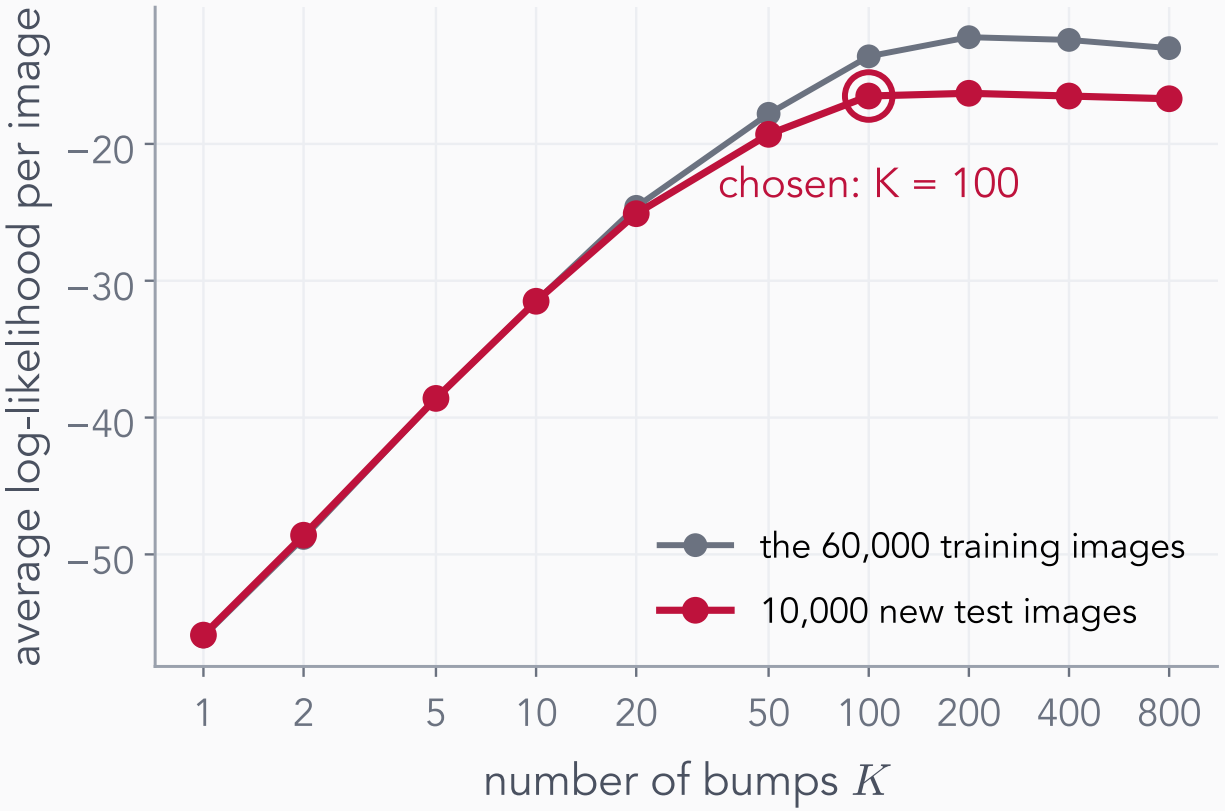
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Training images: more bumps fit them better, as with the toy.

The toy's rule: score on images the model has not seen



$d = 50$. Fit K = 1, 2, 5, 10, 20, 50, 100, 200, 400, 800 bumps to the 60,000 training images.

Training images: more bumps fit them better, as with the toy.

10,000 new test images: the score stops improving at $K = 100$. Doubling to 200 bumps changes the score by +0.2 nats. At 800 even the training score drops: that many bumps are more than 2,000 steps can fit.

Pick the smallest K that does as well as any on new images: $K = 100$, 132,599 parameters, each bump a Gaussian over 50 numbers.

AIC and BIC: charge for every parameter

$$\mathrm{AIC} = 2p - 2\log L \qquad\qquad \mathrm{BIC} = p\,\log N - 2\log L$$

$\log L$: the training log-likelihood, summed over all N = 60,000 images · p: the number of parameters · smaller is better

AIC and BIC: charge for every parameter

$$\mathrm{AIC} = 2p - 2\log L \qquad\qquad \mathrm{BIC} = p\,\log N - 2\log L$$

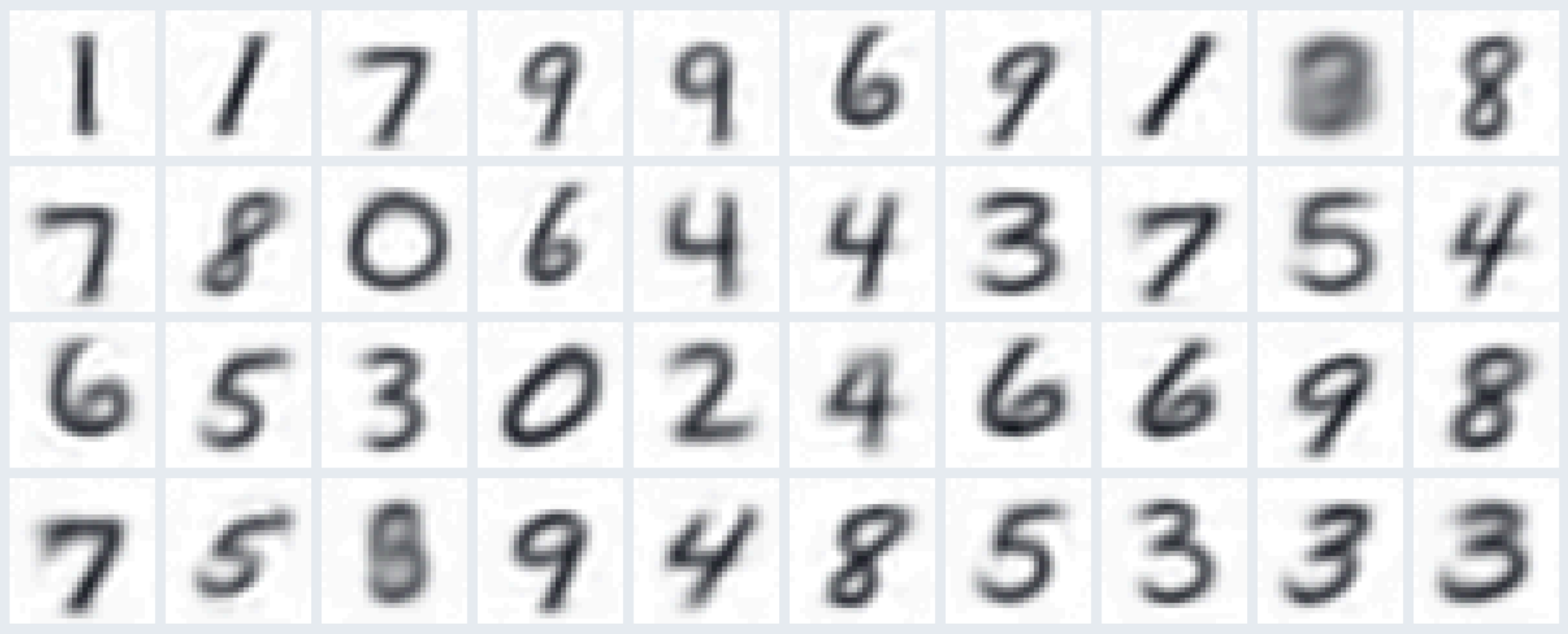
$\log L$: the training log-likelihood, summed over all N = 60,000 images · p: the number of parameters · smaller is better

rule	needs	price per parameter	picks
score on new images	10,000 extra images	none, it is measured	$K = 100$
AIC	training data only	2	$K = 100$
BIC	training data only	$\log 60{,}000 = 11.0$	$K = 50$

New images and AIC agree on $K = 100$; BIC, which charges more per parameter, keeps only 50. With plenty of data, measure on new data; with little, AIC or BIC.

WHAT THE BUMPS LEARNED

Each bump's centre is a style of digit



the centres of the 100-bump fit, after inverse PCA, heaviest bump first (the heaviest has weight 3.9%)

> **The hidden coin now has 100 sides, one prototype each, found without the labels. The backwards step $p(z \mid x)$ is still just a 100-row table.**

STEP 2 · GENERATE

Samples, as the number of bumps grows

1 bump: a single Gaussian over the 50 numbers of every digit



STEP 2 · GENERATE

Samples, as the number of bumps grows

1 bump: a single Gaussian over the 50 numbers of every digit



10 bumps



STEP 2 · GENERATE

Samples, as the number of bumps grows

1 bump: a single Gaussian over the 50 numbers of every digit



10 bumps



100 bumps, the size chosen on new images



OR SKIP PCA: MODEL THE 784 PIXELS DIRECTLY

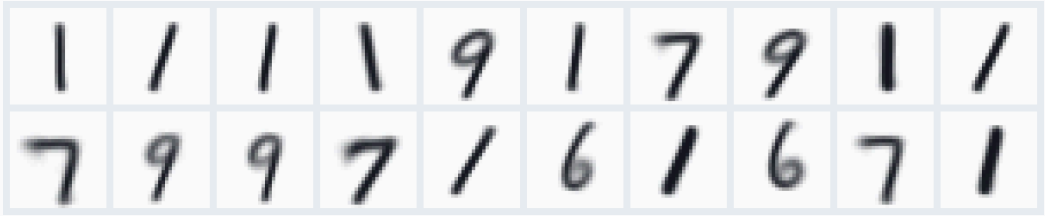
A mixture of Bernoullis: each bump is 784 ink probabilities

$$\log p(x \mid k) = \sum_{i=1}^{784} \Big[x_i \log \pi_{ki} + (1 - x_i) \log(1 - \pi_{ki}) \Big]$$

OR SKIP PCA: MODEL THE 784 PIXELS DIRECTLY

A mixture of Bernoullis: each bump is 784 ink probabilities

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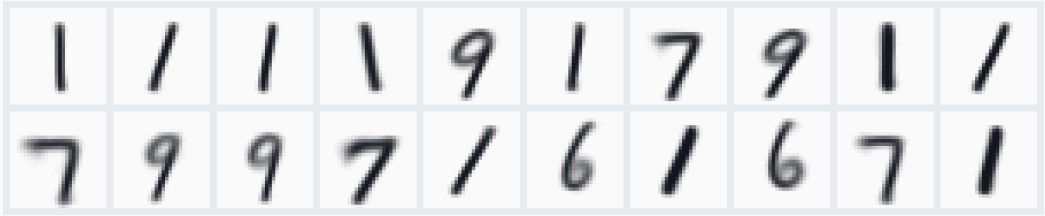


the 20 heaviest of 200 bumps: π_k, ink probability per pixel

OR SKIP PCA: MODEL THE 784 PIXELS DIRECTLY

A mixture of Bernoullis: each bump is 784 ink probabilities

$$\log p(x \mid k) = \sum_{i=1}^{784} \Big[x_i \log \pi_{ki} + (1 - x_i) \log(1 - \pi_{ki}) \Big]$$



the 20 heaviest of 200 bumps: π_k, ink probability per pixel



samples: pick a bump, flip each pixel's coin

> **Inside a bump every pixel is on its own, so samples are speckled; only the choice of bump ties pixels together. Same lesson as the 784-pixel Gaussian.**

AN HONEST LOOK

New digits, not copies, and not yet sharp



top: 8 samples · bottom: the closest of the 60,000 training images

AN HONEST LOOK

New digits, not copies, and not yet sharp



top: 8 samples · bottom: the closest of the 60,000 training images

What worked

The Part 1 loop, unchanged, learns a distribution over images and samples digit-like shapes, close to real digits but not copies of them.

AN HONEST LOOK

New digits, not copies, and not yet sharp



top: 8 samples · bottom: the closest of the 60,000 training images

What worked

The Part 1 loop, unchanged, learns a distribution over images and samples digit-like shapes, close to real digits but not copies of them.

What did not

Blur from the straight-line squeeze, and each bump can only stretch its template along fixed directions, not bend a stroke.

WHY WE CANNOT STOP HERE

This recipe does not scale

image	numbers	covariance per bump
MNIST, 28 × 28 grey	784	307,720

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MNIST, 28 × 28 grey	784	307,720
32 × 32 colour	3,072	4.7 million
64 × 64 colour face	12,288	75.5 million
256 × 256 colour photo	196,608	19.3 billion

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Squeeze first? A straight-line squeeze needs more and more numbers for richer images, and still blurs.

More bumps? Each bump is one template plus a Gaussian wiggle. Every pose, style and lighting needs its own templates.

Nothing is shared: the bump for a slanted 7 learns nothing from the bump for an upright 7.

> **We need a squeeze that can bend, learned by a network, and parts that are shared. Part 2: the autoencoder.**

END OF PART 1

What we did, and what comes next

WHAT WE DID

1. **Learn** = choose parameters that make the data probable.
2. **Generate** = sample from the learned model.
3. One bump was too simple; a hidden coin z fixed it.
4. Scoring x sums over z; learning needs the backwards step $p(z \mid x)$.
5. In code: one loop, `loss = -log_p(x).mean()`; choose the size on new data.
6. On MNIST: PCA to 50 numbers, 100 Gaussian bumps over them, inverse PCA: digit-like samples, but blurry, and the recipe does not scale.

END OF PART 1

What we did, and what comes next

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NEXT: IMAGES

PCA squeezed each image along straight lines. Next, learn the squeeze with a network: encode each image into a few numbers and rebuild it. That is the autoencoder.

Part 3 returns to this probabilistic story, with a code z in place of the coin.

PART 2 OF 7

From PCA to the autoencoder

Part 1 ended with PCA: squeeze an image to a few numbers along straight lines, then rebuild it. An **autoencoder** learns the squeeze with a network instead, so it can bend. First, the bridge: PCA is already one.

✓ Distributions and fitting

2 **Autoencoders**

3 The probabilistic view

4 KL divergence

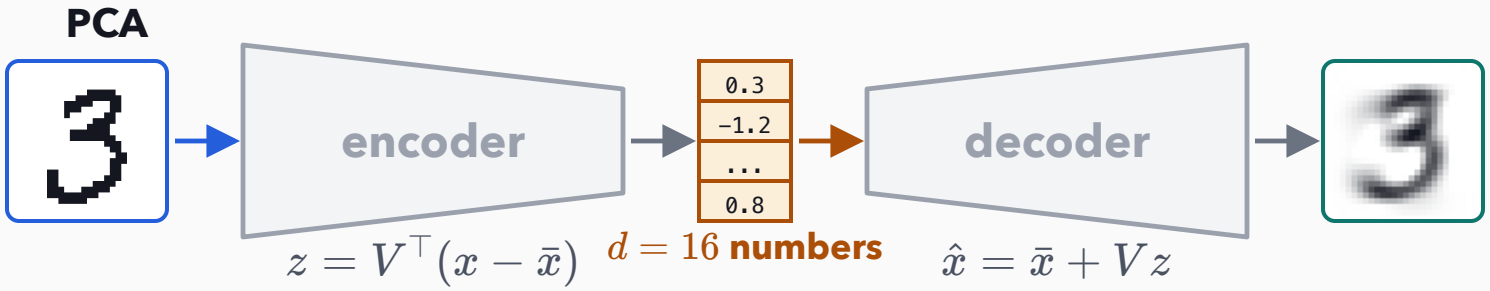
5 Variational inference and the ELBO

6 Reparameterisation

7 The VAE on MNIST

THE BRIDGE FROM PART 1

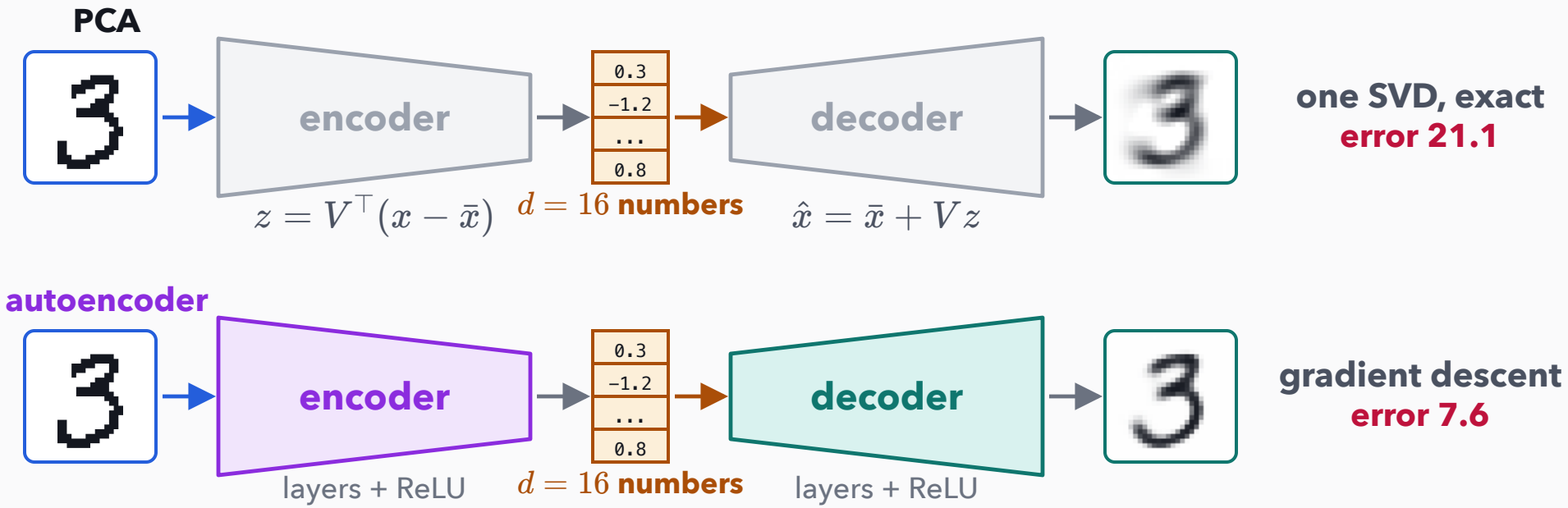
PCA was an autoencoder all along



one SVD, exact
error 21.1

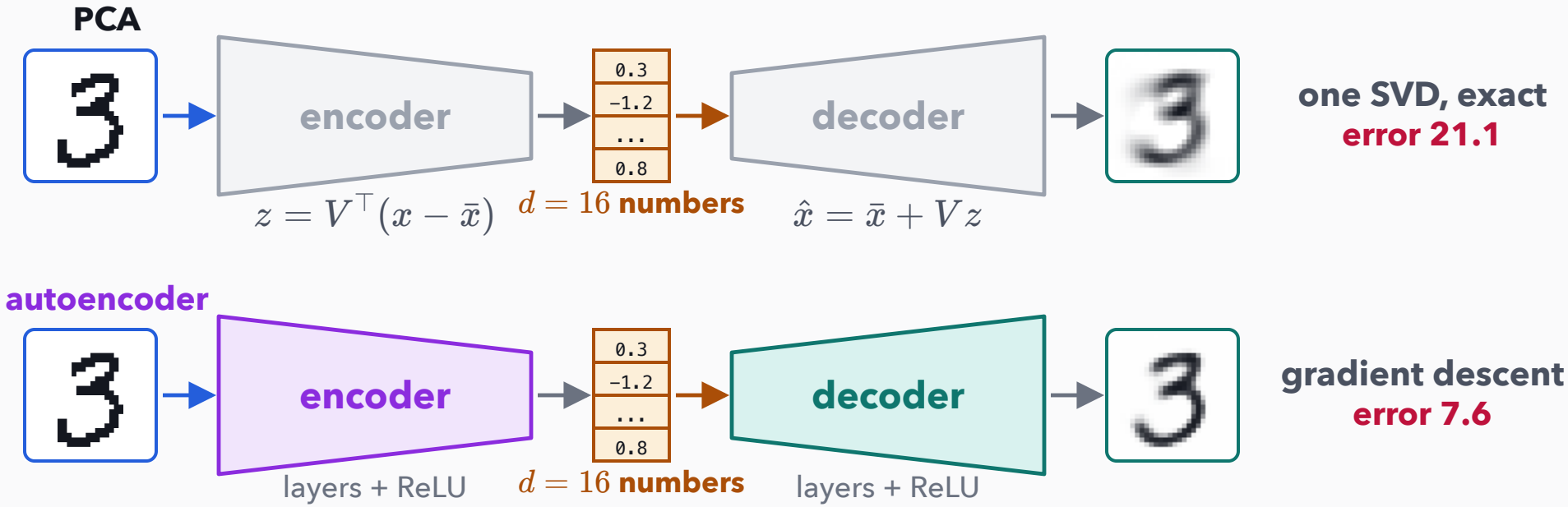
THE BRIDGE FROM PART 1

PCA was an autoencoder all along



THE BRIDGE FROM PART 1

PCA was an autoencoder all along



Both learn by making $\|x - \hat{x}\|^2$ small, summed over the 784 pixels. PCA is the best straight-line answer.

TRAIN THE STRAIGHT-LINE VERSION BY GRADIENT DESCENT

A linear autoencoder rediscovers PCA

```
enc = nn.Linear(784, d)       # no activation
dec = nn.Linear(d, 784)

x_hat = dec(enc(x))
loss = ((x_hat - x)**2).sum(1).mean()
```

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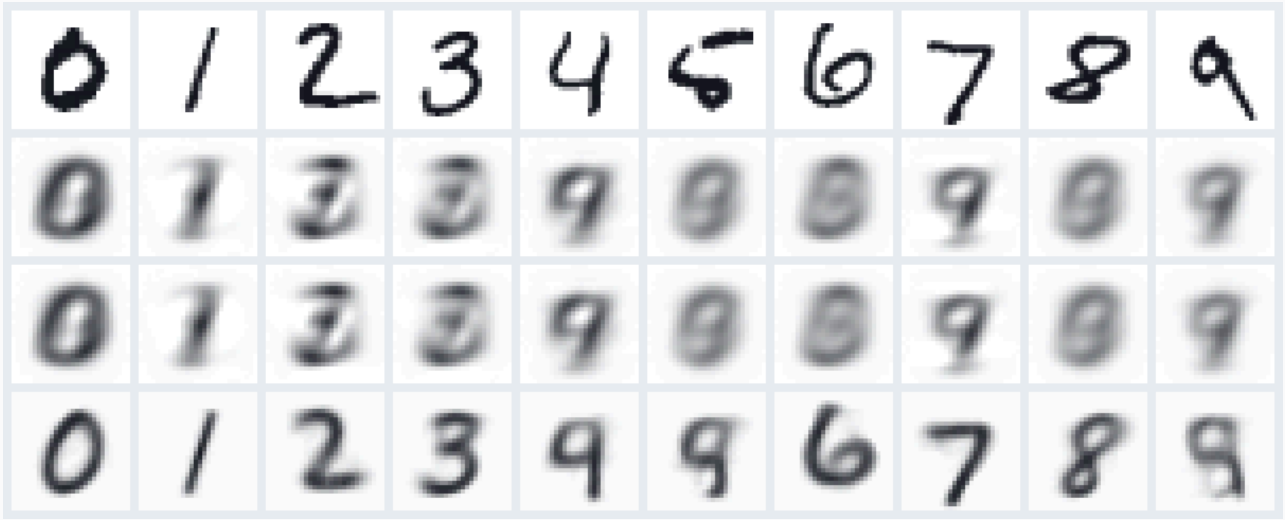
d	PCA, one SVD	linear AE, Adam	same directions?
2	43.6	43.6	1.0
16	21.1	21.1	1.0

error: squared error per test image, summed over 784 grey pixels · last column: 1 means the decoder spans exactly PCA's directions

Gradient descent finds exactly PCA's error and PCA's directions. Only the individual vectors may differ: any rotation of the same directions rebuilds just as well.

NOW LET IT BEND

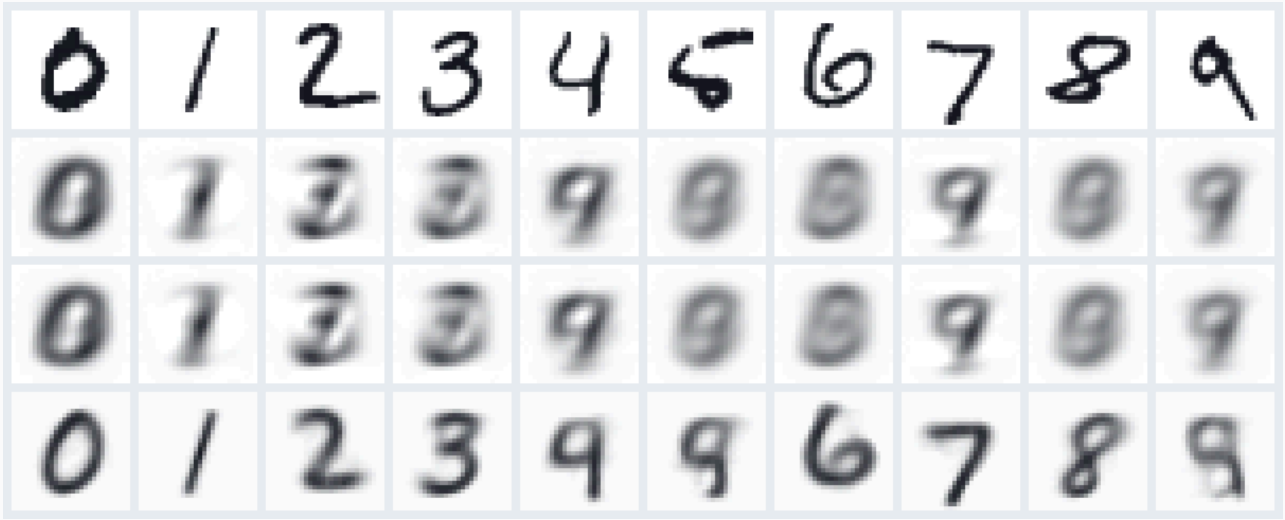
Same 2 numbers, add layers and ReLUs



rows: test digits · PCA · linear autoencoder · MLP autoencoder, each squeezing to **2** numbers

NOW LET IT BEND

Same 2 numbers, add layers and ReLUs



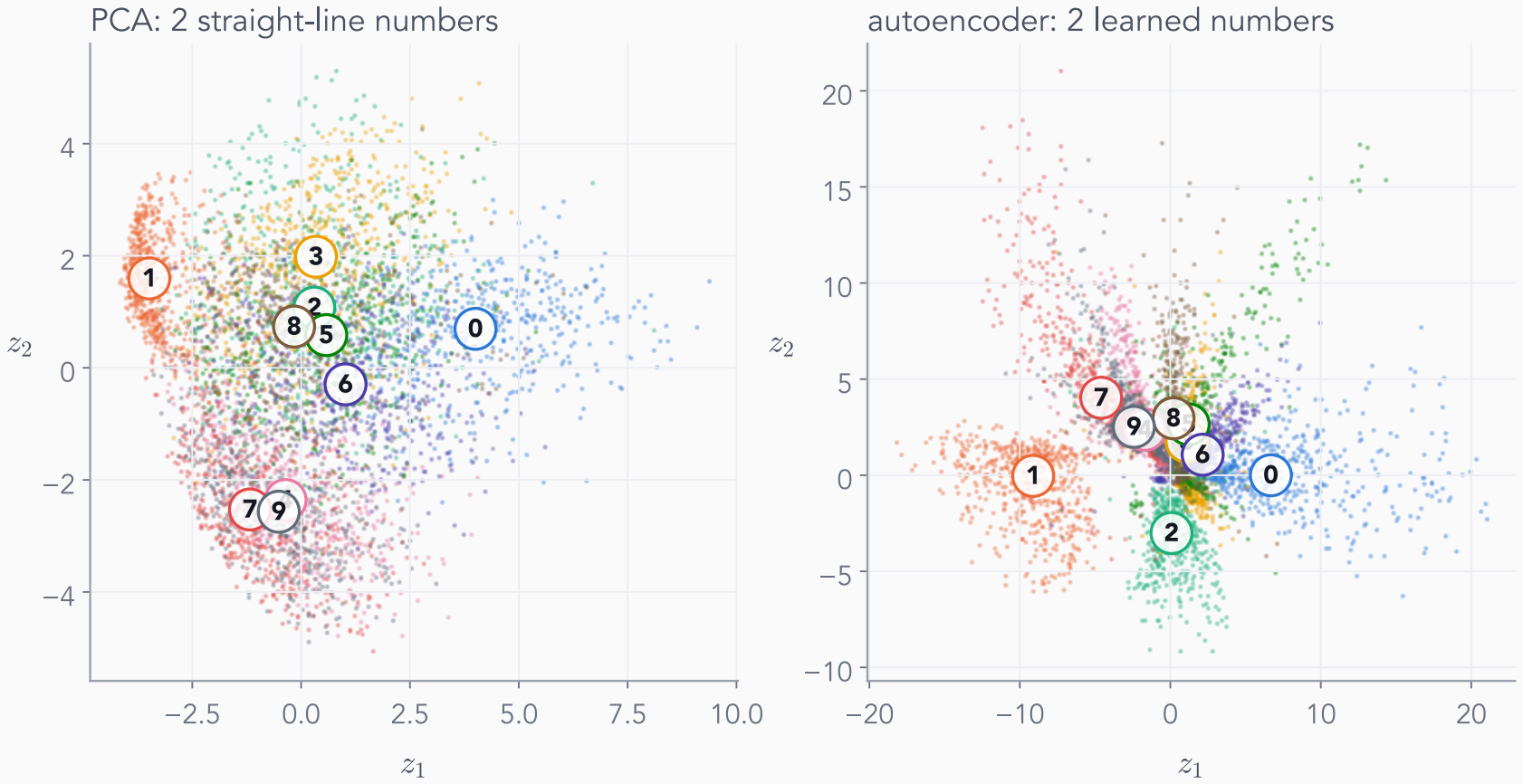
rows: test digits · PCA · linear autoencoder · MLP autoencoder, each squeezing to **2** numbers

error	$d = 2$	$d = 16$
PCA	43.6	21.1
linear AE	43.6	21.1
MLP AE	**29.3**	**7.6**

> **With only 2 numbers, the straight-line squeeze keeps a blurry average; the bendy one keeps which digit it was. Same idea, more flexible maps.**

WHAT THE 2 NUMBERS LOOK LIKE

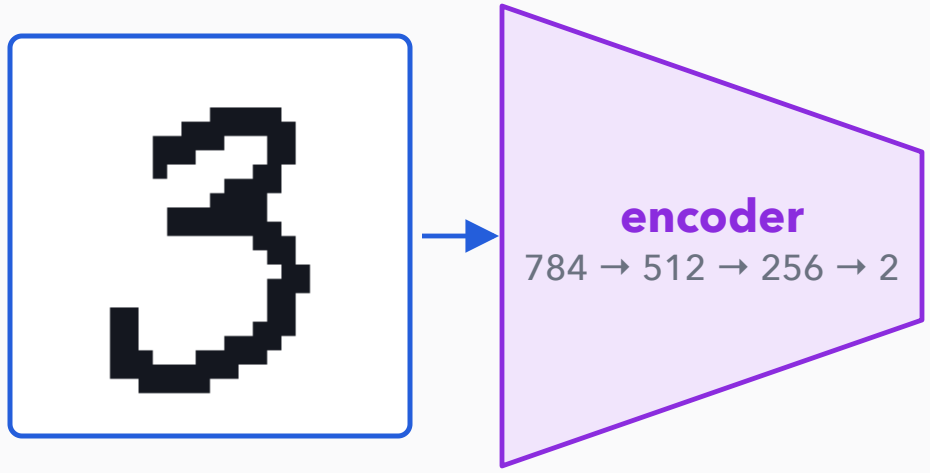
Straight-line codes overlap; learned codes pull digits apart



5,000 test digits, coloured by label (neither model saw labels). The autoencoder's squeeze bends to keep different digits apart.

SQUEEZE, THEN REBUILD

An autoencoder on our 3

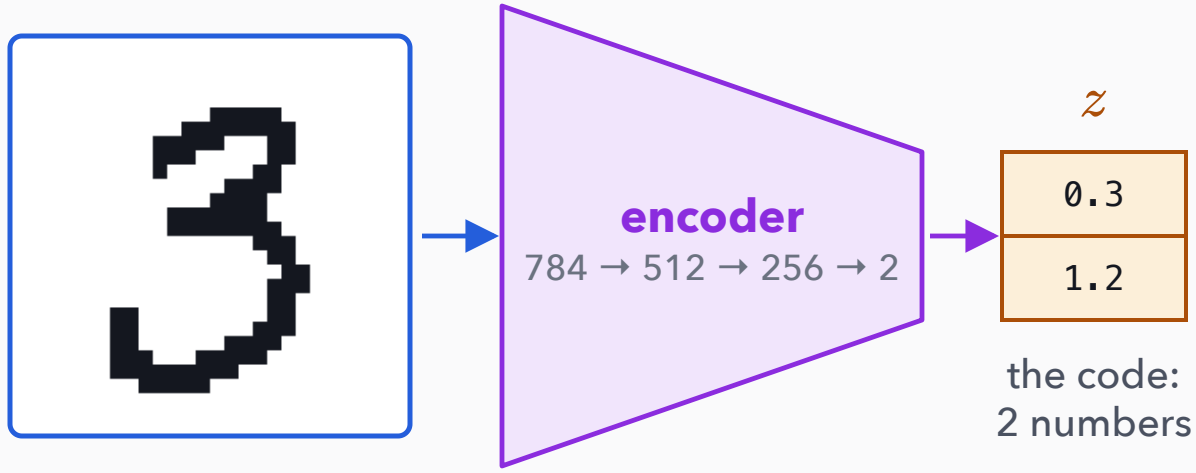


x: 28 × 28 = 784 pixels

> No labels needed: the image is its own target. The 2 numbers in the middle are all the decoder gets.

SQUEEZE, THEN REBUILD

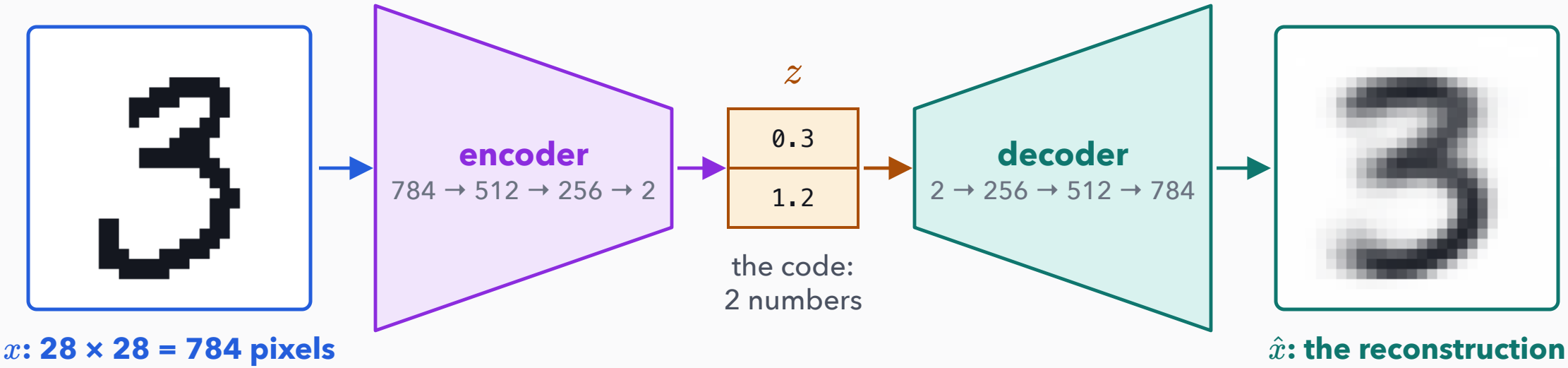
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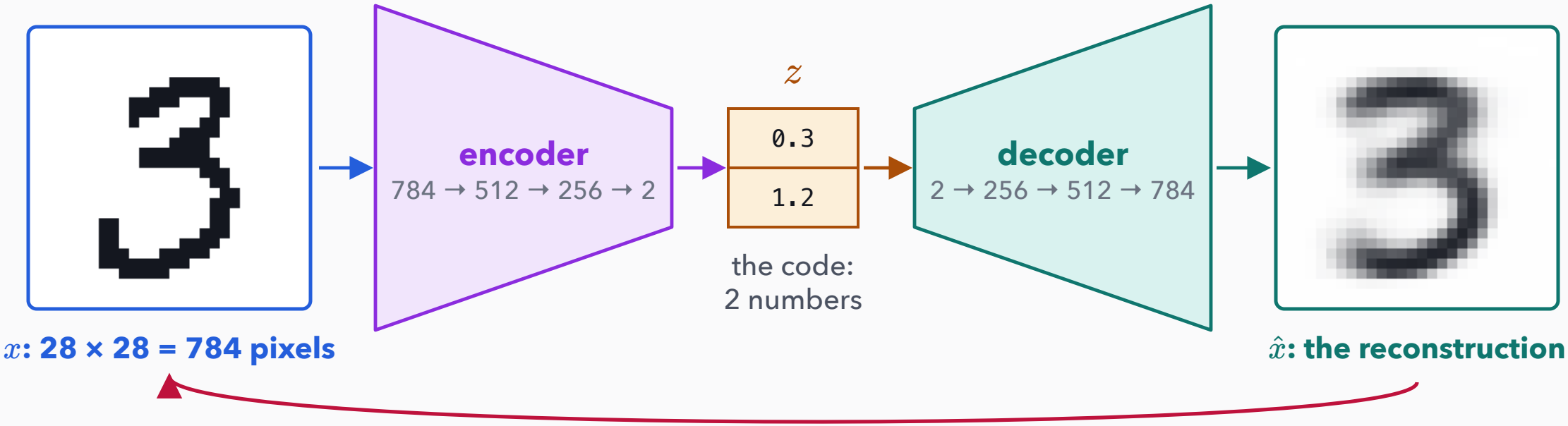
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COMPARING THE REBUILD WITH THE ORIGINAL

Binary cross-entropy, one pixel at a time

$$\text{loss}(x, \hat{x}) = -\sum_{i=1}^{784} \Big[x_i \log \hat{x}_i + (1 - x_i) \log(1 - \hat{x}_i) \Big]$$

pixel	true value	predicted	loss
ink, predicted well	1	0.90	$-\log 0.90 = 0.11$

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pixel	true value	predicted	loss
ink, predicted well	1	0.90	$-\log 0.90 = 0.11$
paper, predicted well	0	0.10	$-\log 0.90 = 0.11$
ink, missed	1	0.20	$-\log 0.20 = 1.61$

Pixels are 0 or 1 here (we binarise MNIST). Later we will see this is exactly a log-likelihood.

Two small networks and one loss

```
encoder = nn.Sequential(nn.Flatten(),
    nn.Linear(784, 512), nn.ReLU(),
    nn.Linear(512, 256), nn.ReLU(), nn.Linear(256, d))
decoder = nn.Sequential(nn.Linear(d, 256), nn.ReLU(),
    nn.Linear(256, 512), nn.ReLU(), nn.Linear(512, 784))

z      = encoder(x)                    # [B, d]   the code
logits = decoder(z)                    # [B, 784] one per pixel
loss = F.binary_cross_entropy_with_logits(
          logits, x.flatten(1), reduction="none").sum(1).mean()
```

Encoder: 784 pixels in, d numbers out. Each layer narrower than the last.

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```

Decoder: the mirror image, d numbers back up to 784.

Two small networks and one loss

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    nn.Linear(512, 256), nn.ReLU(), nn.Linear(256, d))
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loss = F.binary_cross_entropy_with_logits(
          logits, x.flatten(1), reduction="none").sum(1).mean()
```

Forward pass: image to code to one logit per pixel; sigmoid of a logit is the probability of ink.

Two small networks and one loss

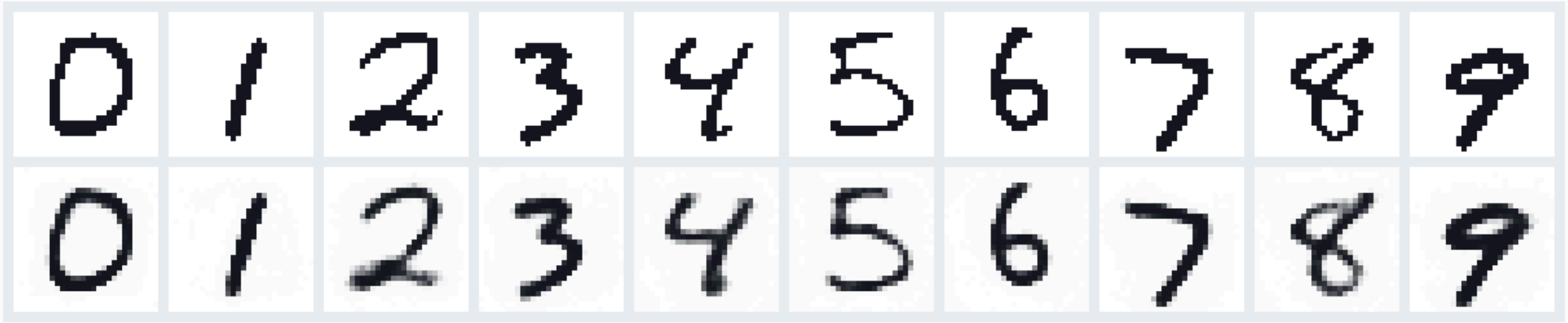
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logits = decoder(z)                    # [B, 784] one per pixel
loss = F.binary_cross_entropy_with_logits(
          logits, x.flatten(1), reduction="none").sum(1).mean()
```

Loss: binary cross-entropy summed over the 784 pixels of each image, then averaged over the batch. Train with the same three-line update as the bumps.

TRAINED ON 60,000 DIGITS

It reconstructs very well



top: test digits it never saw

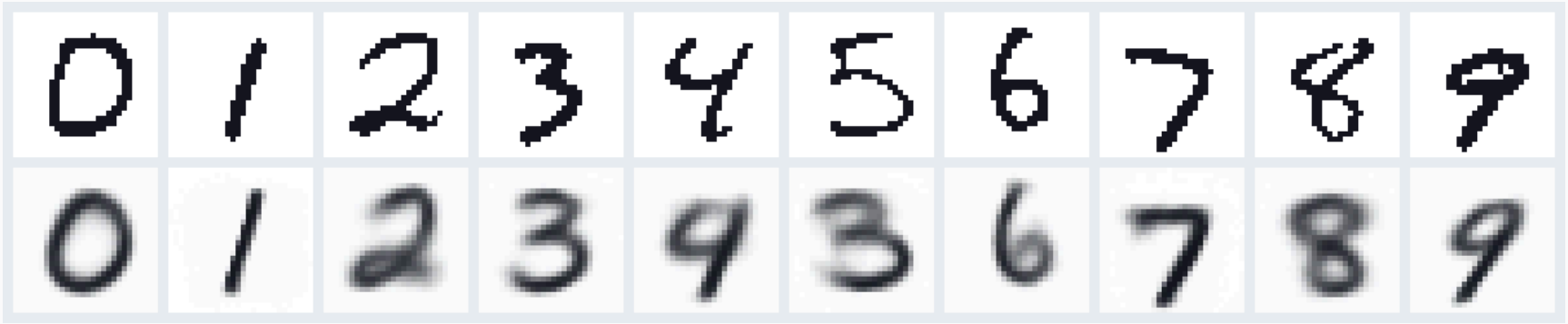
bottom: decoded from a 16-number code

> **784 pixels squeezed into 16 numbers and back. Average loss 44.9 nats per image. Can we now make new digits?**

HOW NARROW CAN THE MIDDLE BE?

2 numbers or 16 numbers per image

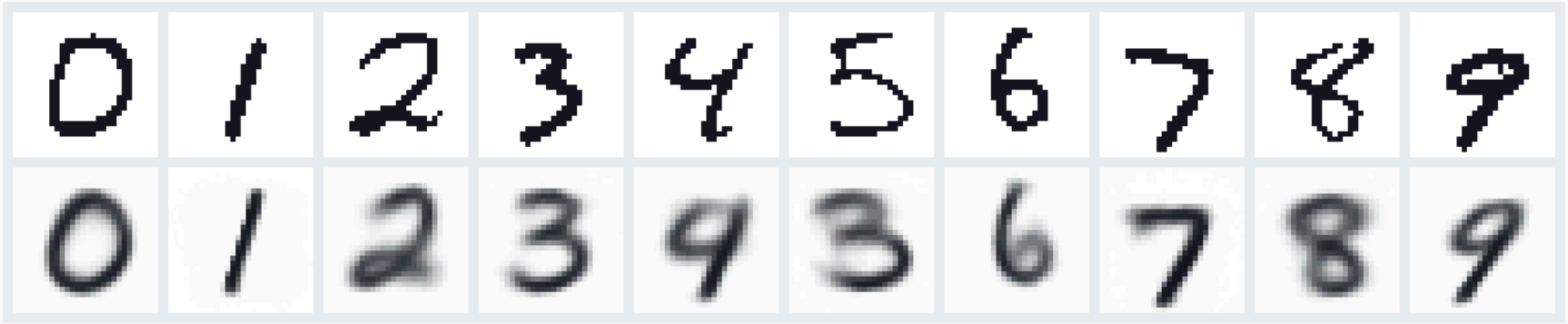
a 2-number code · loss 128.1 nats per image



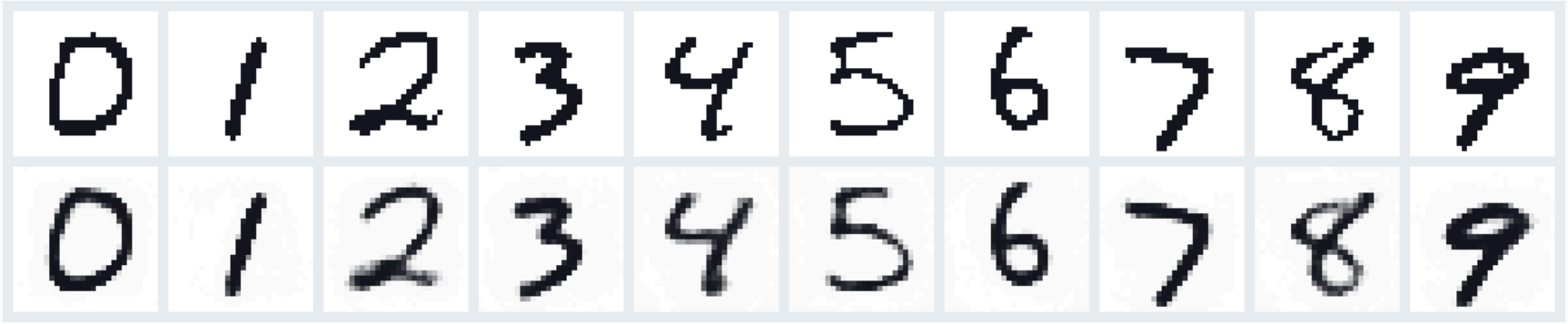
HOW NARROW CAN THE MIDDLE BE?

2 numbers or 16 numbers per image

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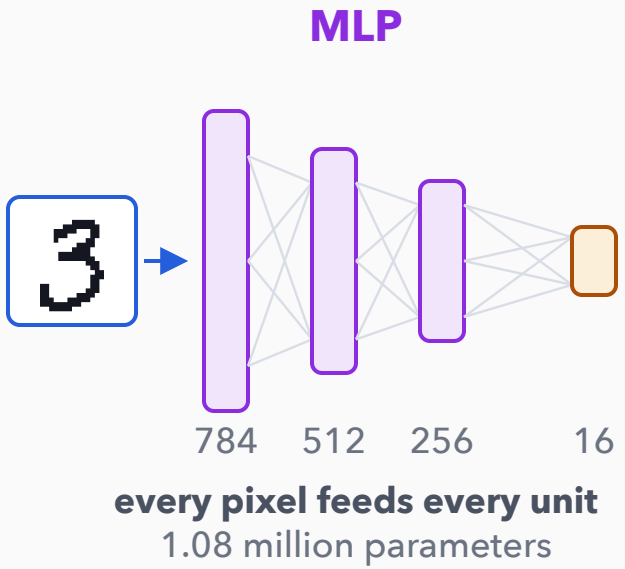


a 16-number code · loss 44.9 nats per image



Each pair of rows: test digits on top, reconstructions below. Two numbers keep the digit's identity; sixteen also keep its slant and stroke.

MLP, CNN or ViT: three ways to squeeze



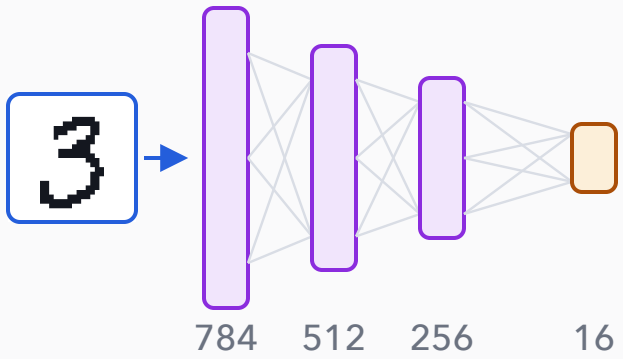
every pixel feeds every unit

1.08 million parameters

THE ENCODER AND DECODER CAN BE ANY NETWORK

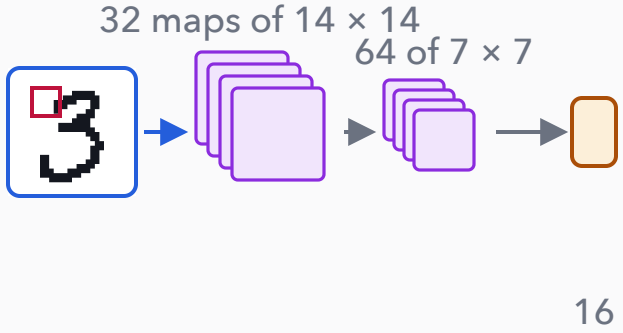
MLP, CNN or ViT: three ways to squeeze

MLP



every pixel feeds every unit
1.08 million parameters

CNN



small filters slide over the image
170 thousand parameters

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MLP, CNN or ViT: three ways to squeeze

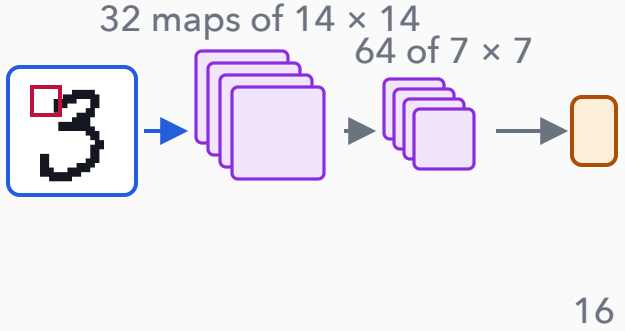
MLP



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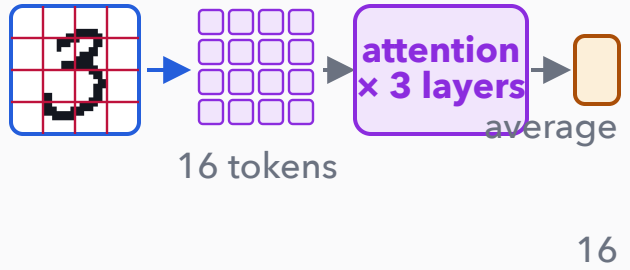
CNN



small filters slide over the image

170 thousand parameters

ViT

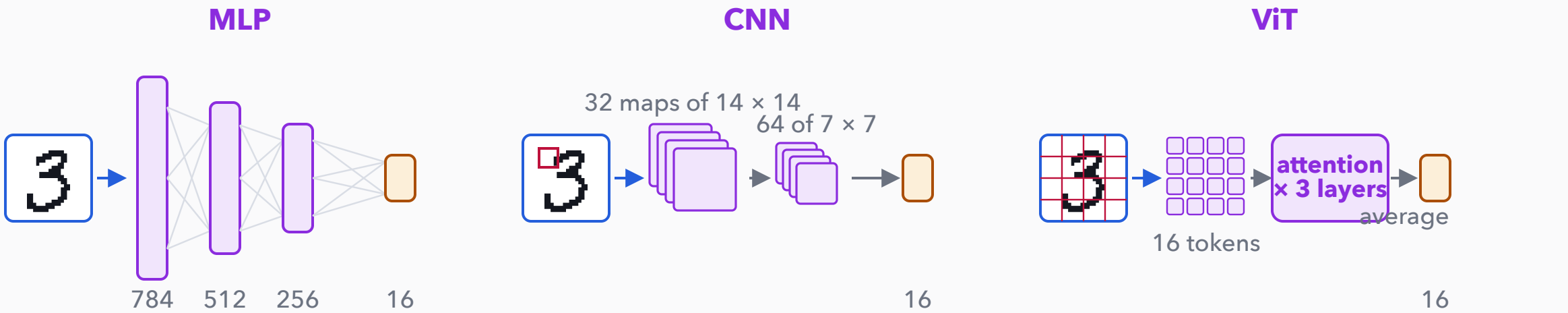


patches become tokens that attend to each other

228 thousand parameters

THE ENCODER AND DECODER CAN BE ANY NETWORK

MLP, CNN or ViT: three ways to squeeze



every pixel feeds every unit
1.08 million parameters

small filters slide over the image
170 thousand parameters

patches become tokens that attend to each other
228 thousand parameters

Same 16-number code, same squared-error loss. Each decoder mirrors its encoder back to 28 × 28.

> **An autoencoder is a recipe, not an architecture: anything that maps 784 numbers to 16 and back, and can be trained.**

IN PYTORCH

Only the encoder changes; the training loop does not

MLP

```
enc = nn.Sequential(
  nn.Flatten(),
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  nn.Linear(256, 16))
```

CNN

```
enc = nn.Sequential(
  nn.Conv2d(1, 32, 4, 2, 1), nn.ReLU(),  # 14x14
  nn.Conv2d(32, 64, 4, 2, 1), nn.ReLU(), # 7x7
  nn.Flatten(),
  nn.Linear(64*7*7, 16))
```

IN PYTORCH

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ViT

```
t = embed(patches(x)) + pos  # [B,16,64]
t = transformer(t)          # 3 layers
z = to_code(t.mean(1))       # [B,16]
```

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```

```
x_hat = dec(enc(x))                        # the same for all three
loss = ((x_hat - x)**2).sum(1).mean()
```

SAME DATA, SAME LOSS, SAME 16 NUMBERS

How the three compare on MNIST



rows: test digits · MLP · CNN · ViT, each through 16 numbers

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How the three compare on MNIST



rows: test digits · MLP · CNN · ViT, each through 16 numbers

	parameters	test error	training
MLP	1,075,488	7.6	9.0 s
CNN	170,193	7.3	23.0 s
ViT	227,713	8.6	65.0 s
PCA	13,328	21.1	one SVD

Lowest error: the CNN (7.3), with 6× fewer parameters than the MLP. Networks built for images use the pixel layout; the MLP has to learn it.

ONE IDEA, SEVERAL VARIATIONS

The autoencoder family

variant	what changes	what it encourages
plain	nothing: compress, rebuild	a short code that keeps what matters

Following Lilian Weng, "From Autoencoder to Beta-VAE" (2018)

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contractive	penalty: the code barely moves when the input moves a little	smooth, robust codes
variational	each image becomes a **cloud** of codes near $\mathcal{N}(0, I)$	a code space you can **sample** from

> **The first four change the loss or the input. The last one changes what a code is, and it is where today is going.**

Following Lilian Weng, "From Autoencoder to Beta-VAE" (2018)

VARIANT 1 · DENOISING AUTOENCODER

Feed it a damaged image, ask for the clean one

input: 20% of pixels flipped



```
noisy = flip_pixels(x, rate=0.2)                    # the only new line
loss  = bce_with_logits(decoder(encoder(noisy)), x)  # target: the CLEAN x
```

VARIANT 1 · DENOISING AUTOENCODER

Feed it a damaged image, ask for the clean one

input: 20% of pixels flipped

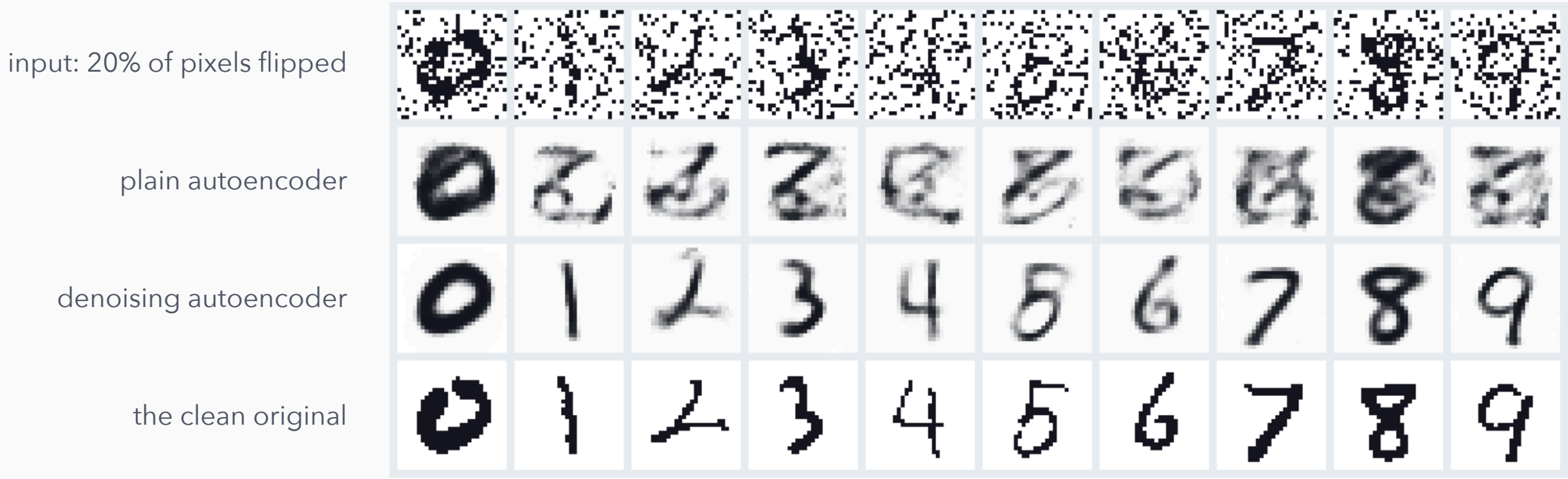
plain autoencoder



```
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```

VARIANT 1 · DENOISING AUTOENCODER

Feed it a damaged image, ask for the clean one




```
noisy = flip_pixels(x, rate=0.2)                    # the only new line
loss  = bce_with_logits(decoder(encoder(noisy)), x)  # target: the CLEAN x
```

The plain autoencoder copies the noise. Trained to undo damage, the code must hold the digit, not the specks.

VARIANT 2 · SPARSE AUTOENCODER

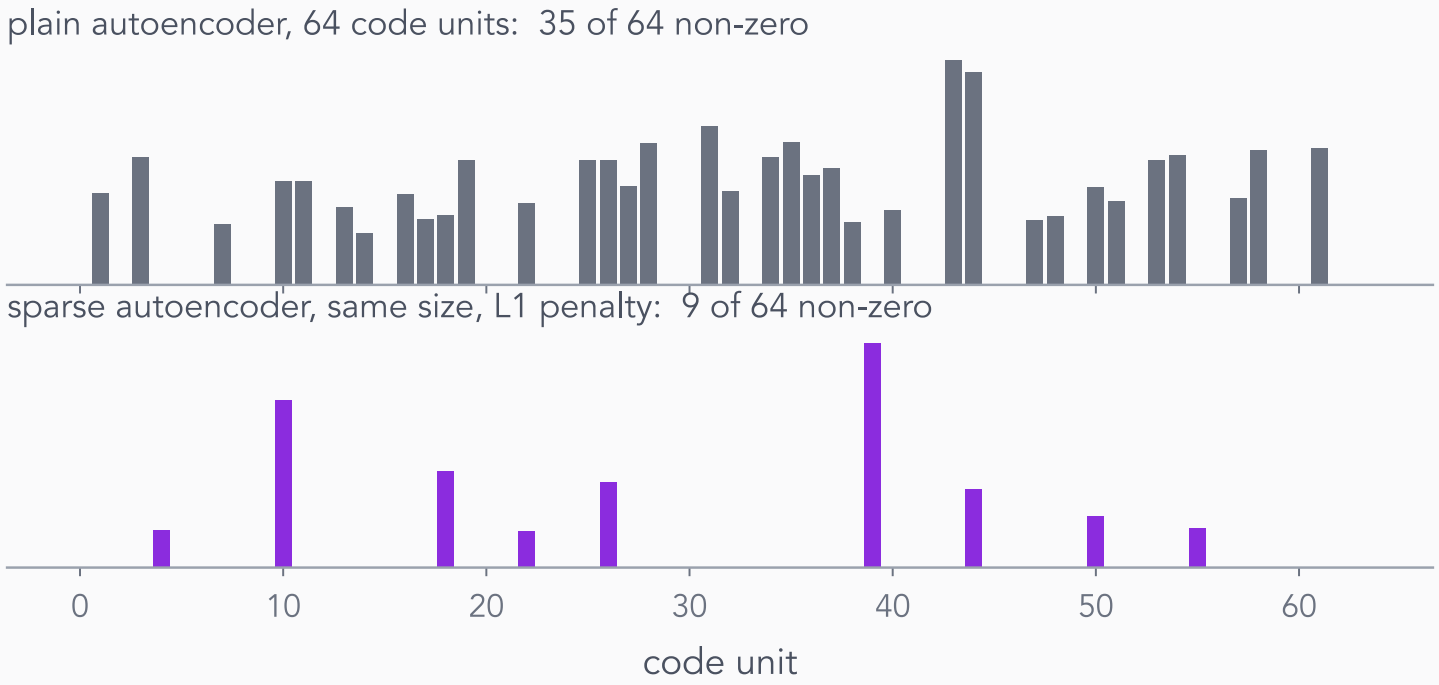
A wide code, but only a few units allowed on

$$\text{loss} = \text{reconstruction} + \lambda \sum_{j=1}^{64} |h_j|, \qquad h = \text{ReLU}(\text{encoder}(x))$$

VARIANT 2 · SPARSE AUTOENCODER

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The 64-number code of our 3. Averaged over test digits: 34.9 units on without the penalty, 8.8 with it.

VARIANT 3 · CONTRACTIVE AUTOENCODER (NOT TRAINED HERE)

Nudge the input; the code should barely move

$$\text{loss} = \text{reconstruction} + \lambda \left\| \frac{\partial h}{\partial x} \right\|_F^2 = \text{reconstruction} + \lambda \sum_{j,i} \left(\frac{\partial h_j}{\partial x_i} \right)^2$$

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Read the penalty

for every code unit h_j and every pixel x_i: how much does h_j change if x_i changes a little? Add up the squares.

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What it buys

two slightly different 3s get almost the same code. Nearby inputs, nearby codes: a first step towards a smooth code space.

WHAT AUTOENCODERS ARE USED FOR

Compress, clean, search, and spot the odd one out

Compress: 784 pixels → 16 numbers, 49× fewer.

Clean: the denoising slide.

Search: similar images have nearby codes, so search the codes.

WHAT AUTOENCODERS ARE USED FOR

Compress, clean, search, and spot the odd one out

Compress: 784 pixels → 16 numbers, 49× fewer.

Clean: the denoising slide.

Search: similar images have nearby codes, so search the codes.

Spot anomalies: an image the model has never seen anything like gets a large reconstruction error.



top: typical test digits, loss ≈ 40.5

bottom: the 8 worst of 10,000, loss up to 218.0

Useful, all of it. But none of it generates a new image. Can the decoder do that on its own?

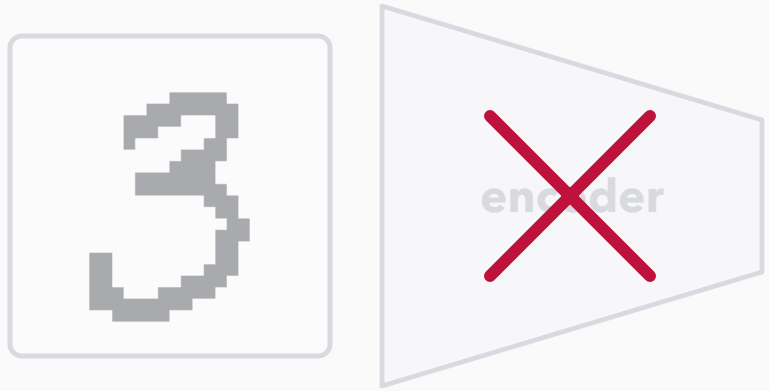
PART 2, SECOND HALF

Can an autoencoder generate?

The decoder turns codes into digits. If we pick a code ourselves, do we get a new digit?

THE OBVIOUS IDEA

Keep the decoder, feed it a random code

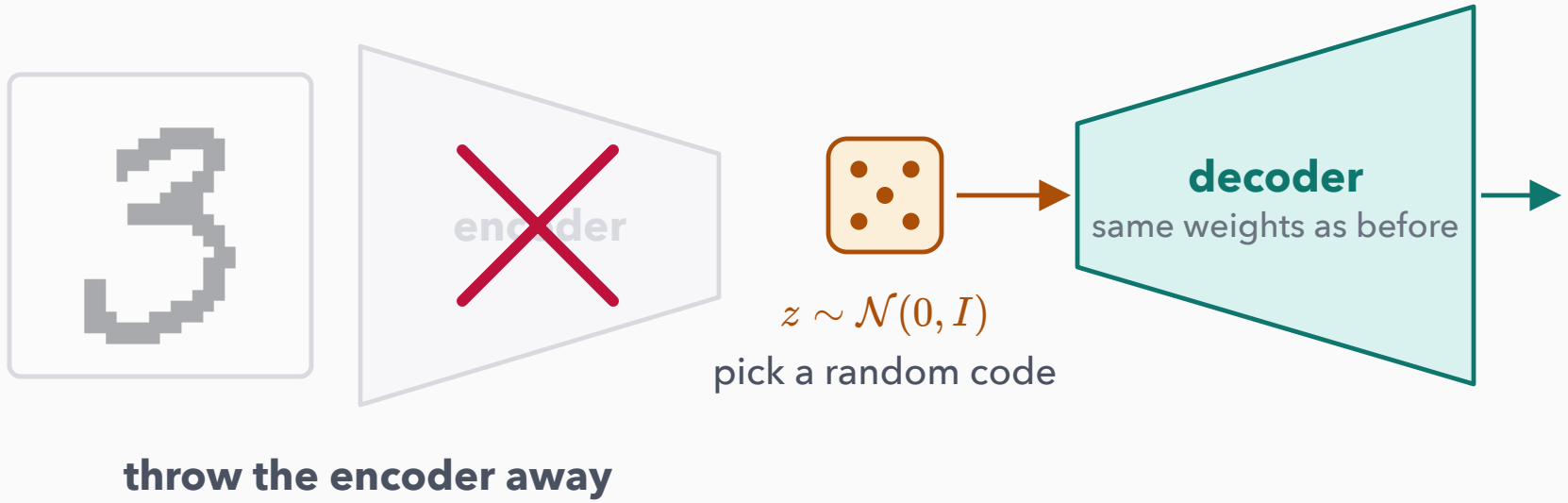


throw the encoder away

> The decoder turns codes into digits. So a random code should give a random digit. Right?

THE OBVIOUS IDEA

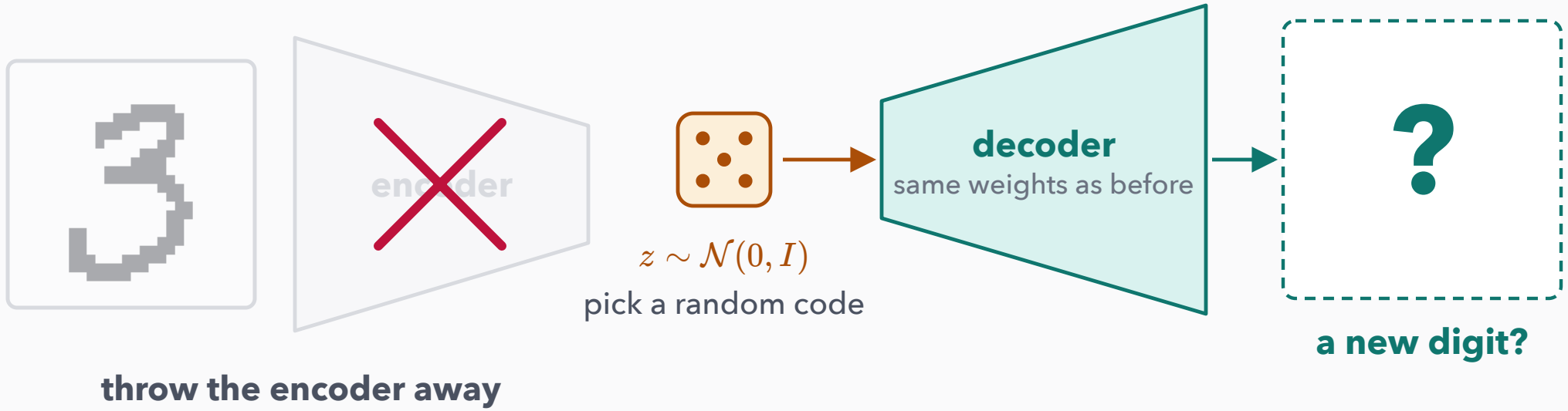
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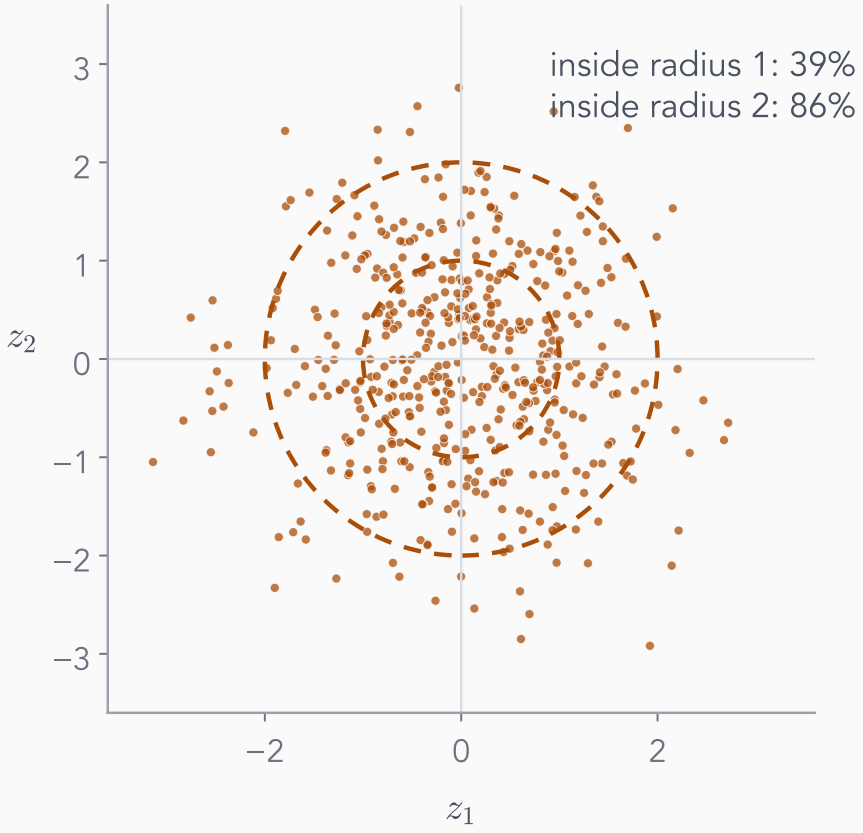
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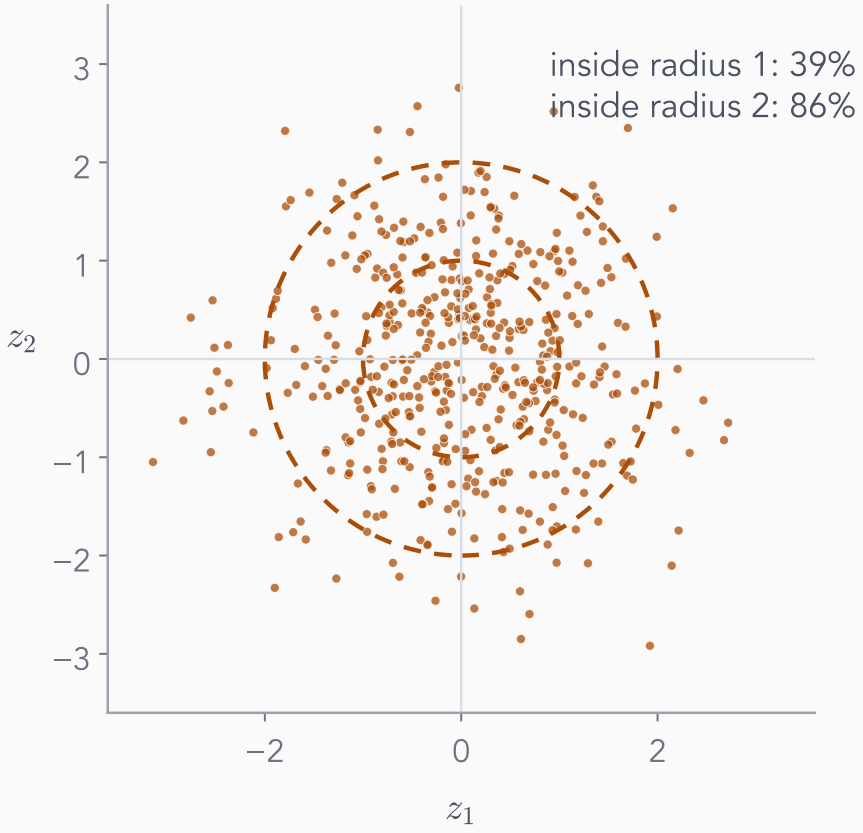
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$z \sim \mathcal{N}(0, I)$: two independent bell curves



Draw z_1 from a standard bell curve $\mathcal{N}(0, 1)$: mean 0, spread 1. Draw z_2 the same way, independently.

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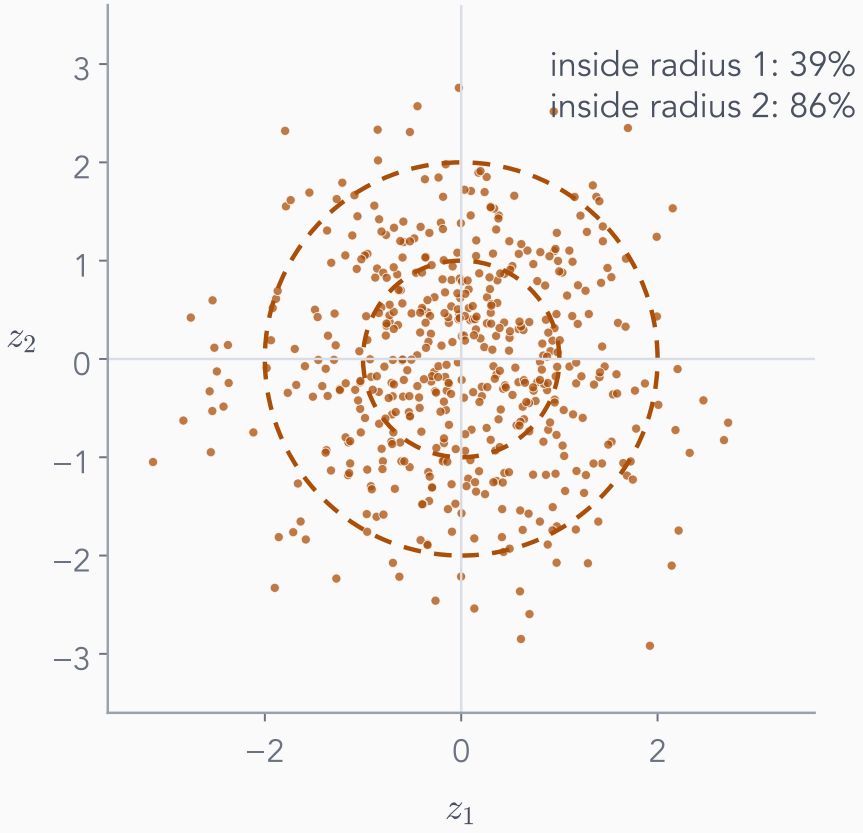


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Together that is written $\mathcal{N}(0, I)$: the **0** says the centre is $(0, 0)$; the **I** (identity matrix) says each number has spread 1 and the two do not depend on each other.

WHAT IS A "RANDOM CODE"?

$z \sim \mathcal{N}(0, I)$: two independent bell curves



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500 draws, plotted: most land within 2 of the origin, almost none beyond 3.

> **Why this choice? It is the simplest distribution we can sample from. The decoder, though, was never told about it.**

WHAT ACTUALLY COMES OUT

Random codes give scribbles

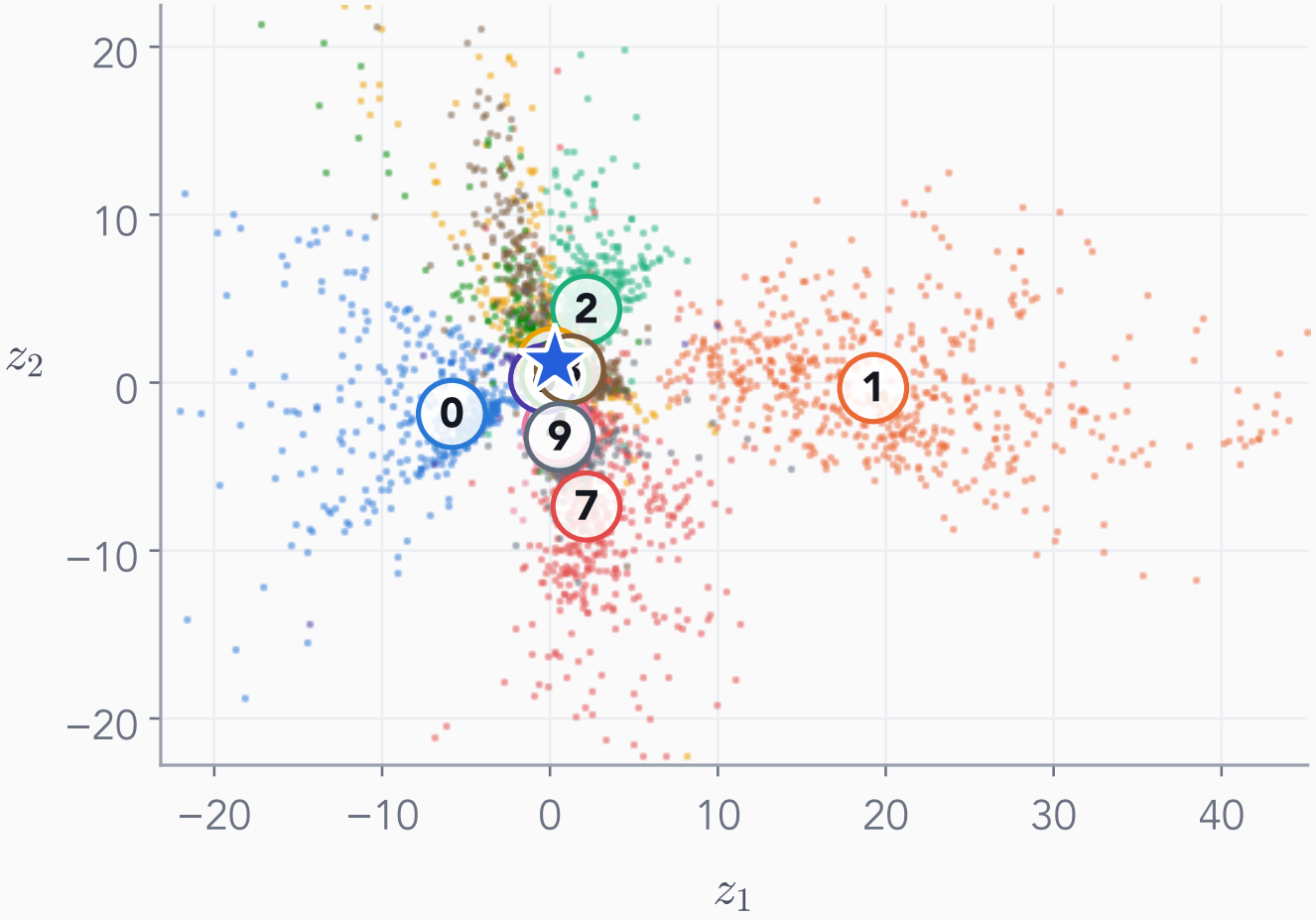


ten codes drawn from $\mathcal{N}(0, I)$ in 16 dimensions, through the trained decoder

The decoder only ever saw codes made by the encoder. Where do those codes live?

LOOK INSIDE (2-NUMBER VERSION)

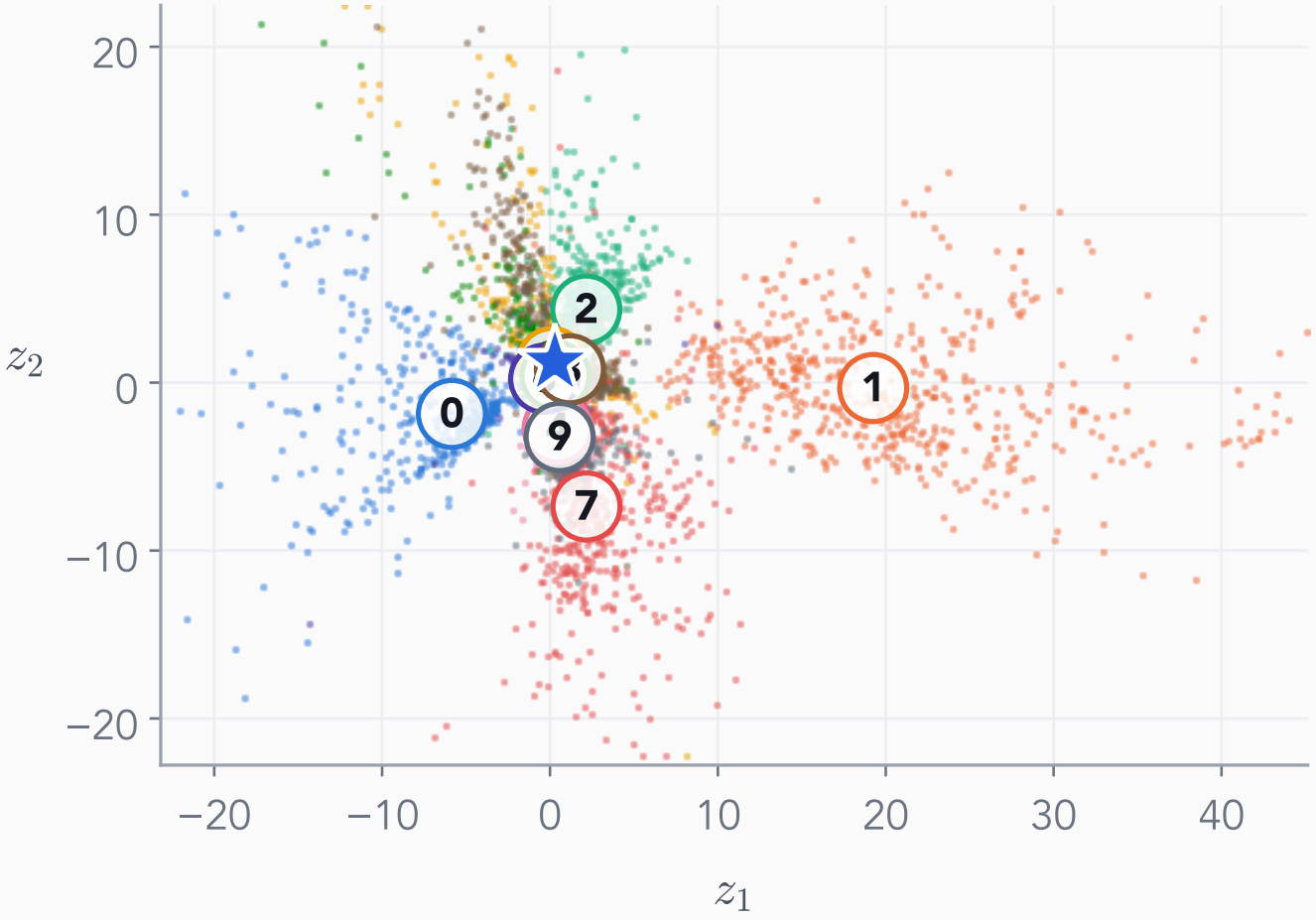
Where 5,000 test digits land



Each dot is one test digit's code, coloured by its true label. The star is our 3.

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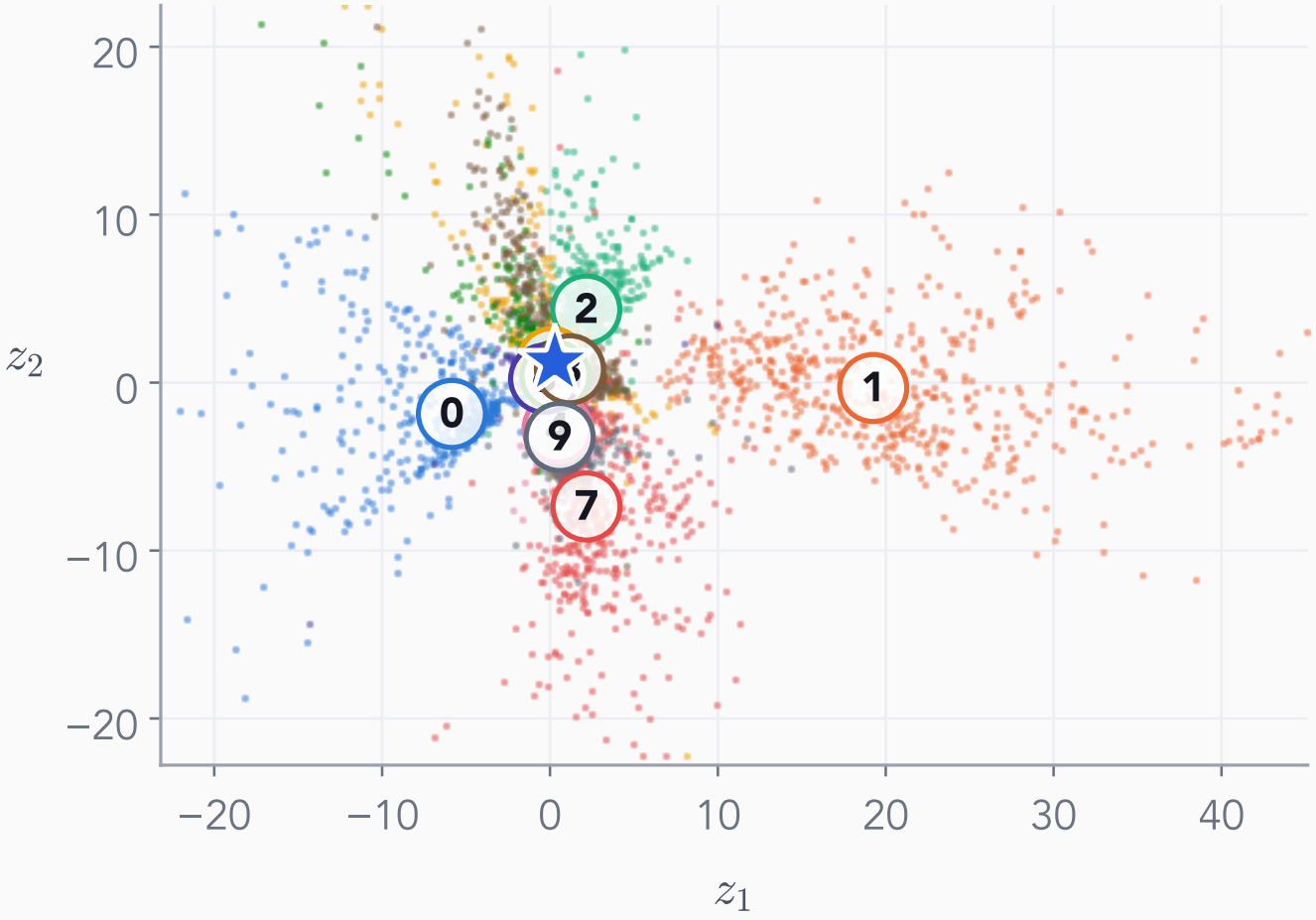


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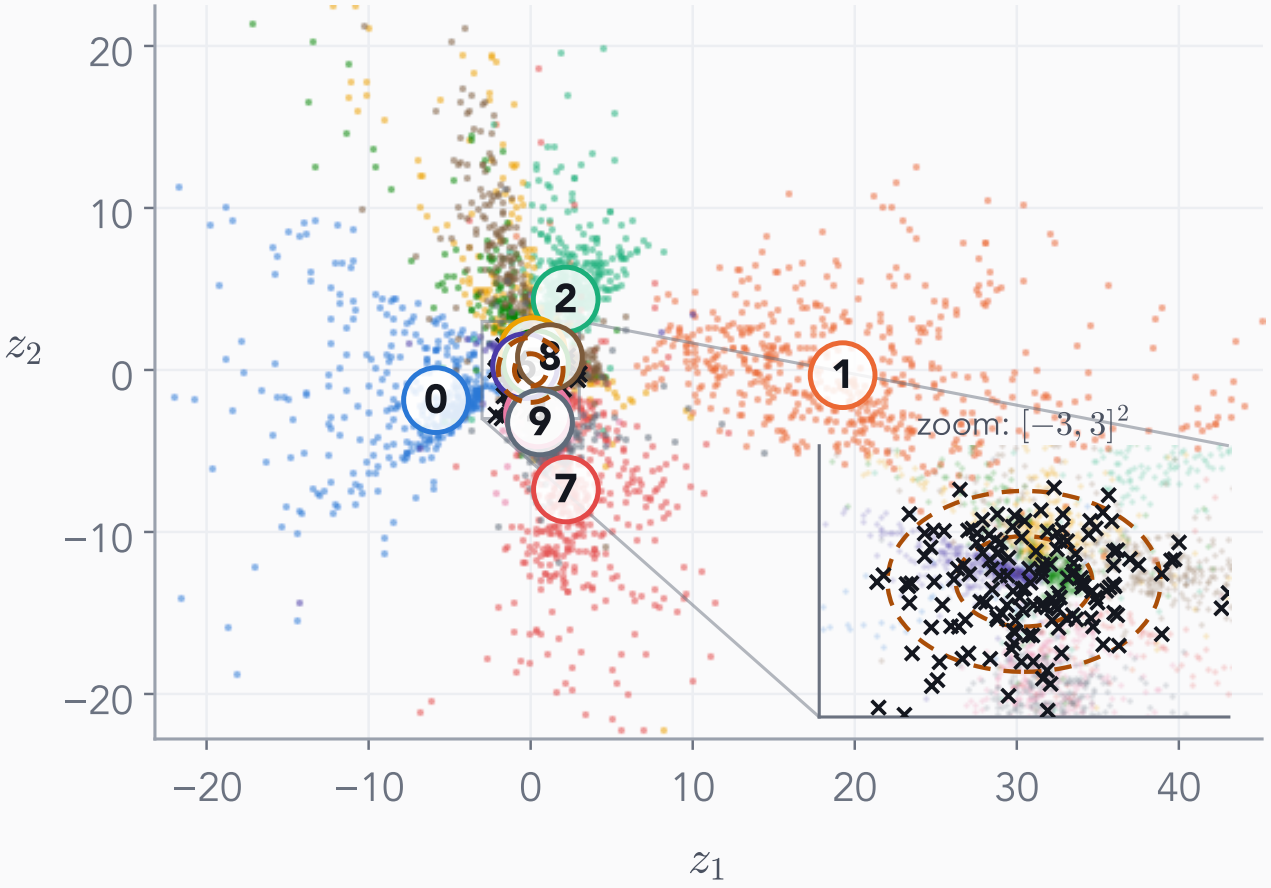
Same digits cluster together. Nobody asked for that; it just helps reconstruction.

Look at the axes: z_1 runs from −18.5 to 40.4, z_2 from −19.7 to 19.4. Nothing made the codes stay near the origin.

The code space has an arbitrary shape, scale and position.

OVERLAY RANDOM CODES

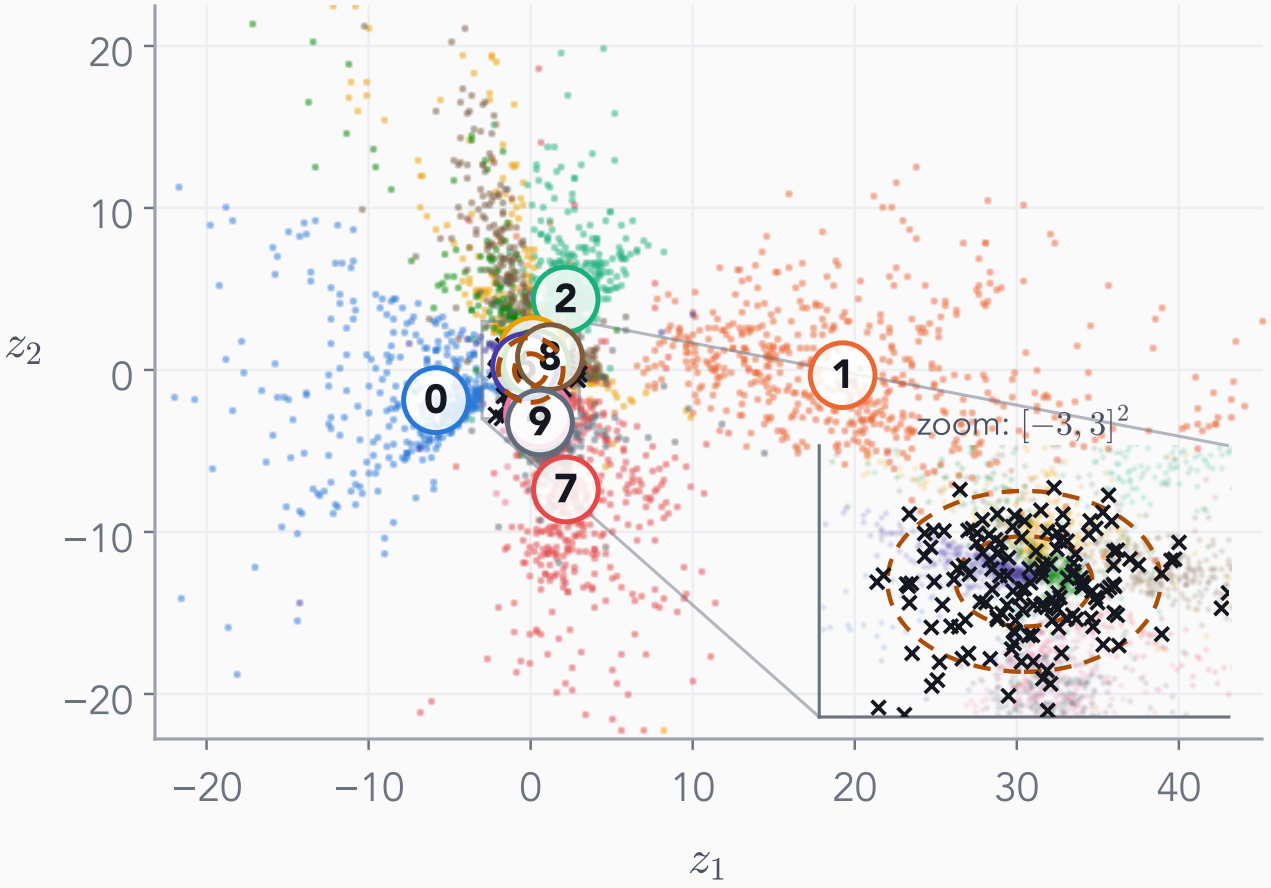
Random draws all land in one small spot



Now add 150 random codes from $\mathcal{N}(0, I)$ (black ×), the kind we fed the decoder two slides ago. Dashed circles: radius 1 and 2. On this map they all fall into one small crowded patch (zoomed, bottom right).

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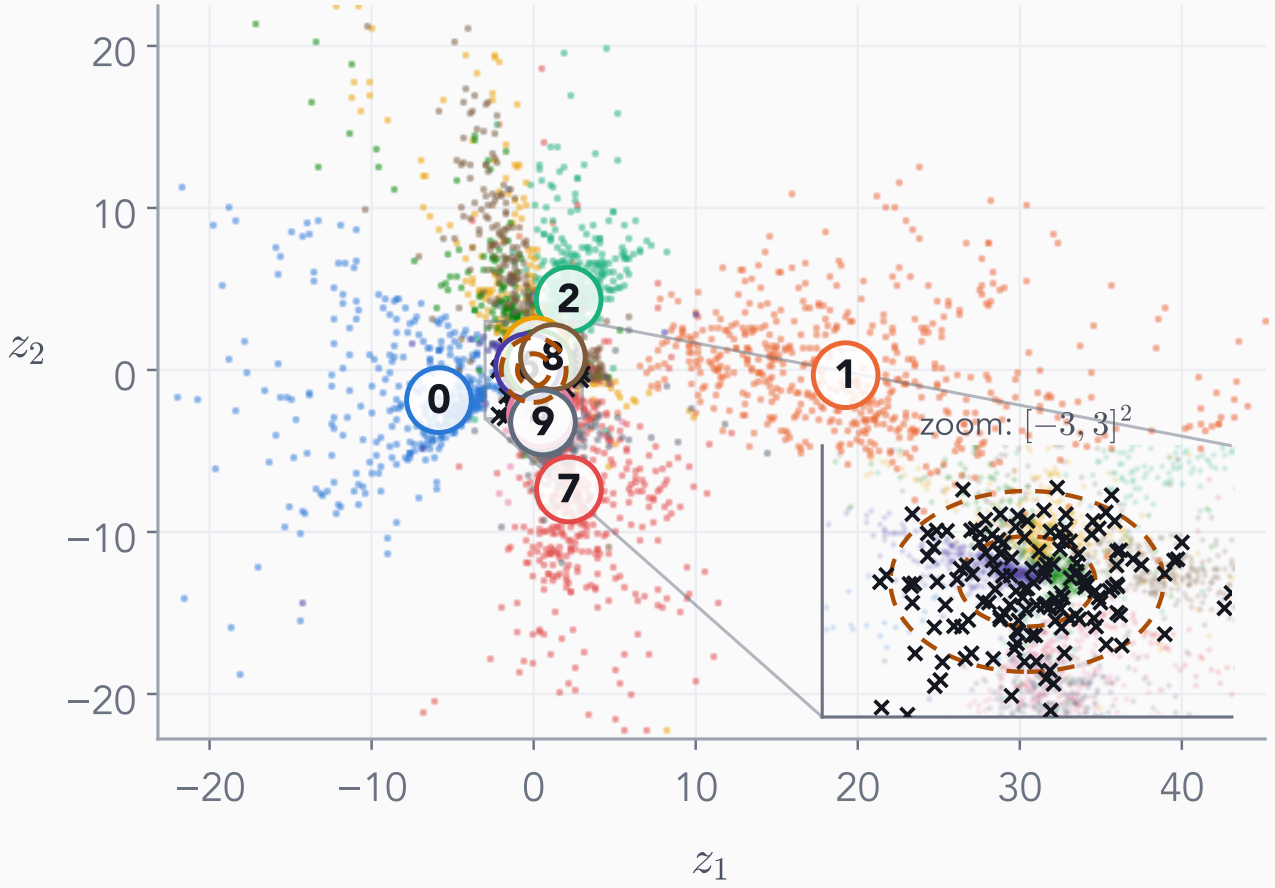
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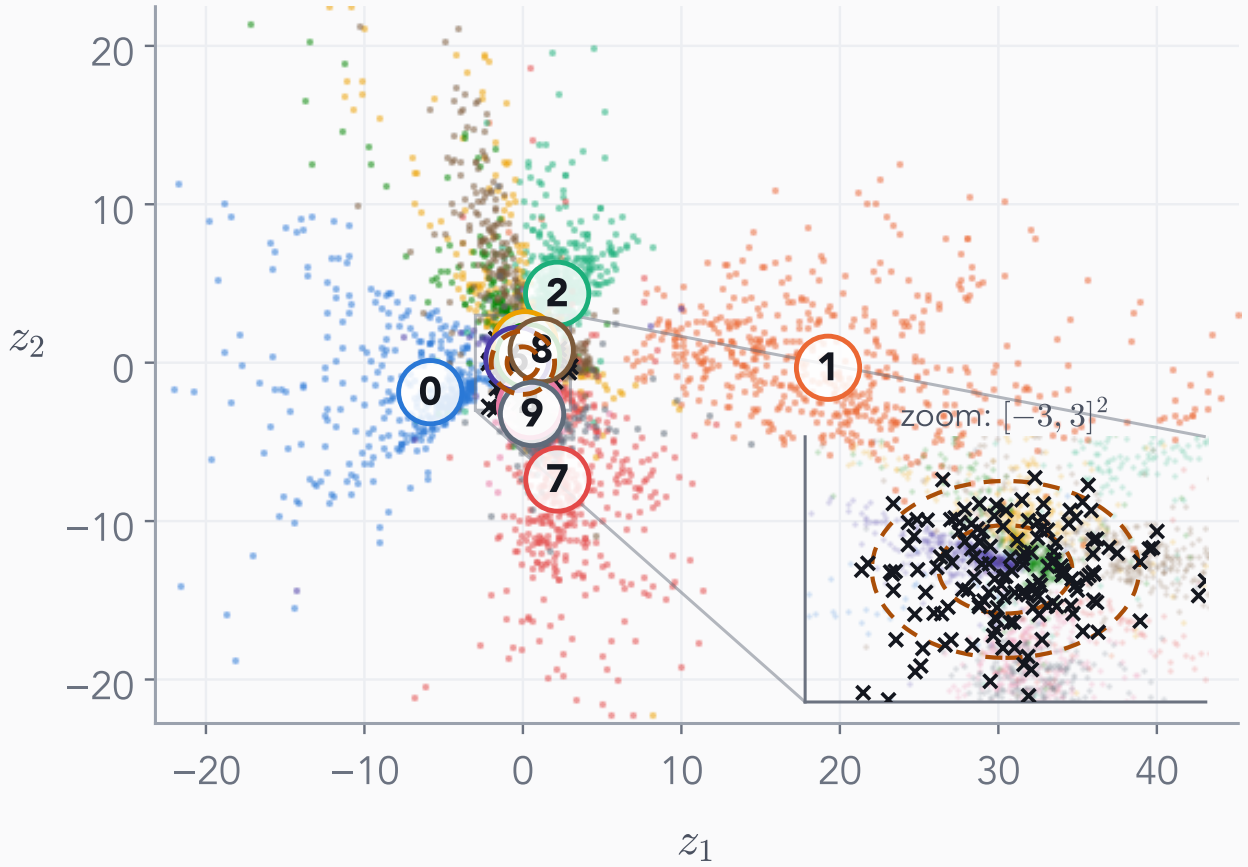
ten of them decoded: some digits, some smudges

And we can never generate a 1: the 1s live near $z_1 \approx 20$.

To sample, we need to know where the codes are, and every point there must decode to something sensible.

TRY IT: THE TRAINED AUTOENCODER, IN YOUR BROWSER

Pick a code, any code, and decode it

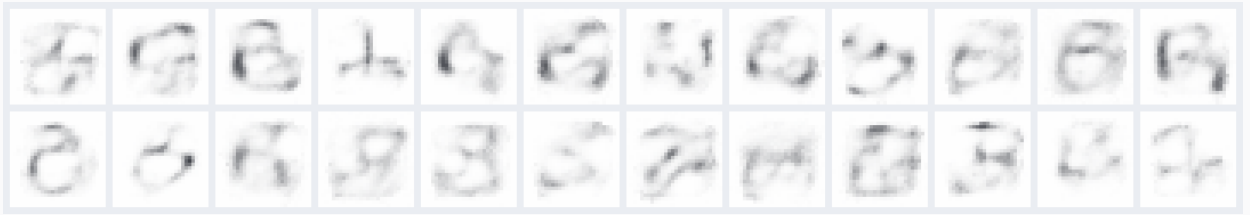


A real digit's code decodes well. A random code usually gives a smudge: the decoder only learned the dotted regions.

PART 1'S TOOL, ON THE AUTOENCODER'S CODES

Fit bumps to where the codes actually are

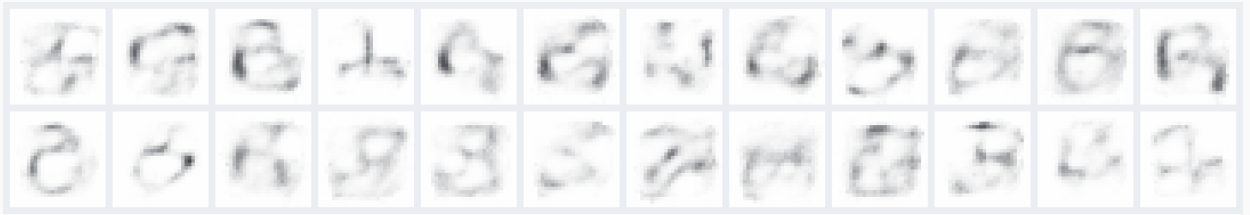
random codes from $\mathcal{N}(0, I)$, decoded by a 16-number autoencoder



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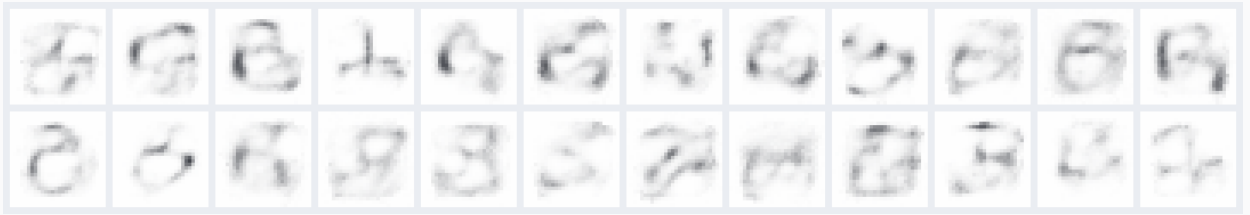
50 Gaussian bumps fitted to PCA's 16 numbers, sampled, inverse PCA



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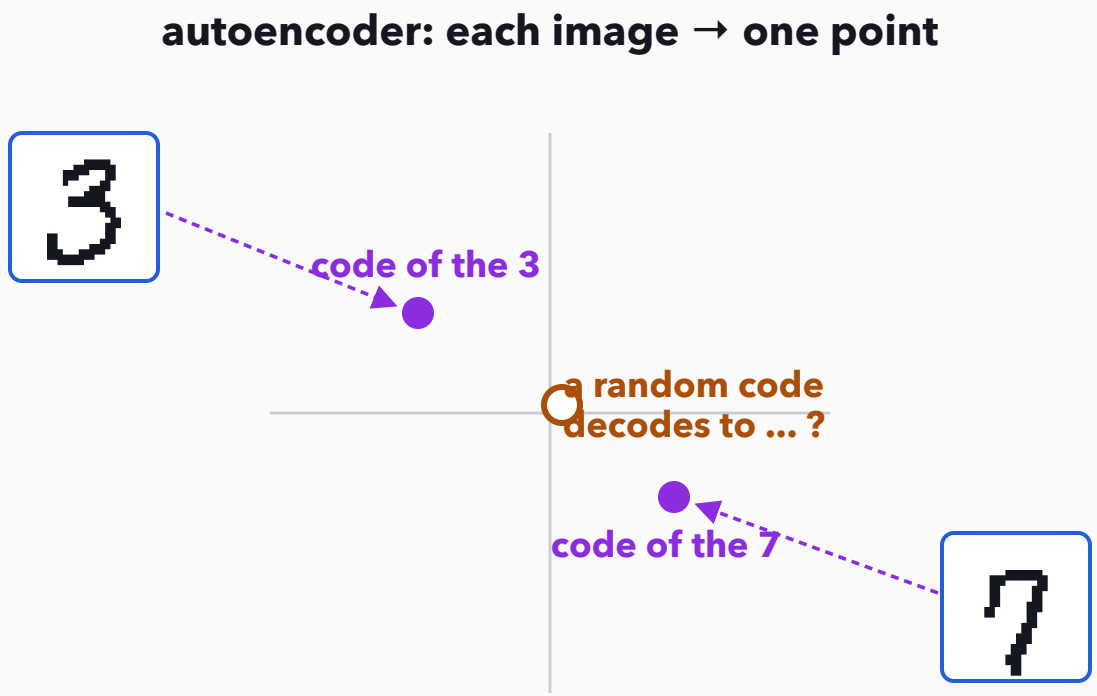
50 Gaussian bumps fitted to the autoencoder's 16 numbers, sampled, decoded



Bolting a density onto the codes works, and a better squeeze gives better samples. The VAE goes one step further: it shapes the codes during training, so that $\mathcal{N}(0, I)$ itself is the right density.

WHAT WE WANT INSTEAD

Encode to a cloud, not a point

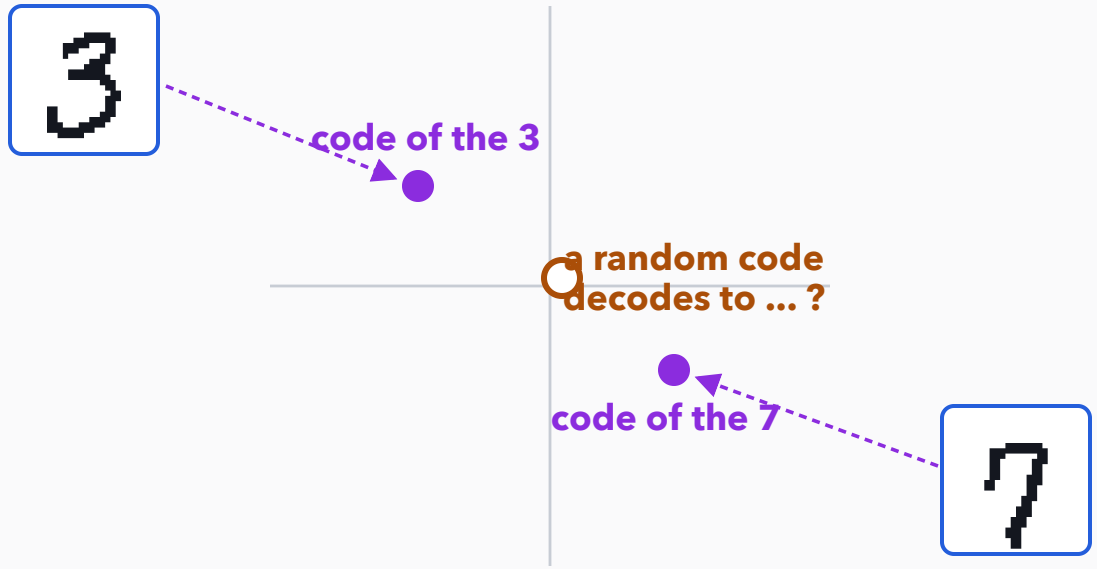


training only ever used the two purple points

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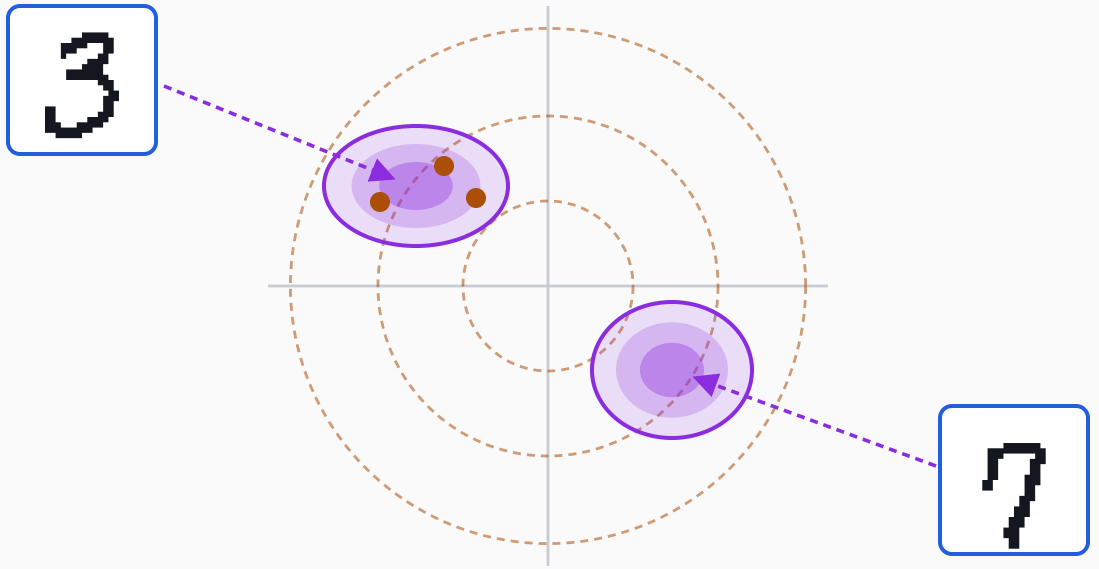
Encode to a cloud, not a point

autoencoder: each image → one point



training only ever used the two purple points

VAE: each image → a small cloud



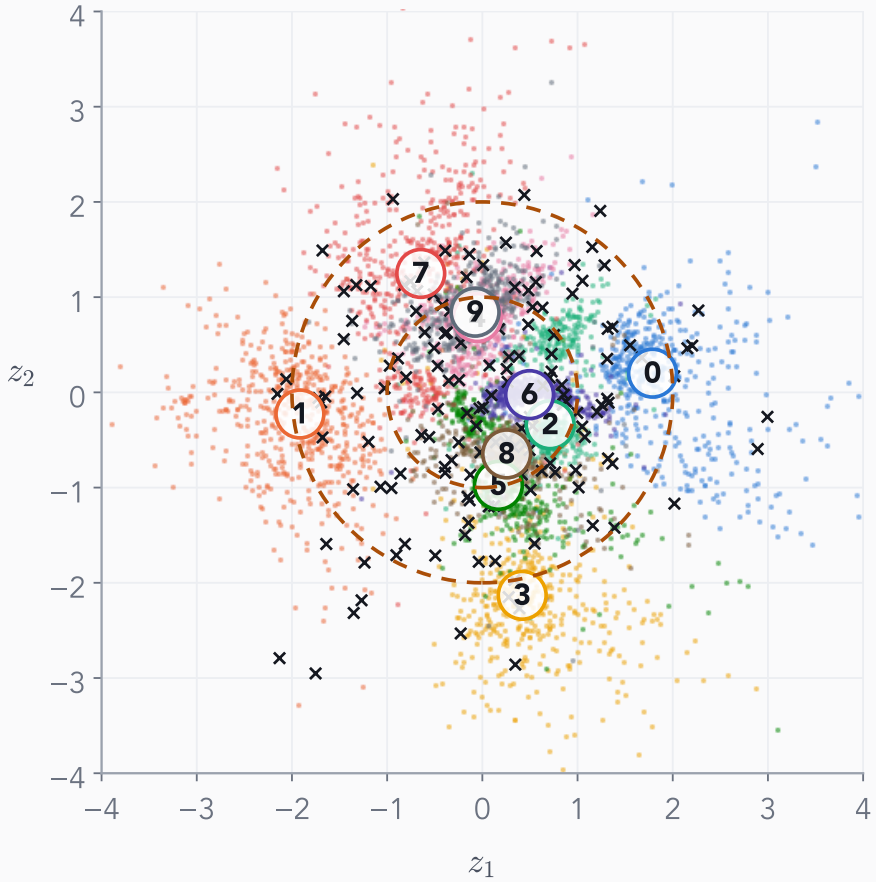
training: every code in the 3's cloud must decode back to the 3

Known: pull every cloud towards $\mathcal{N}(0, I)$, so random draws land on real codes.

Smooth: every point in a cloud must decode to that image, so neighbourhoods are meaningful.

A PREVIEW OF WHERE WE ARE GOING

The same plot for a VAE

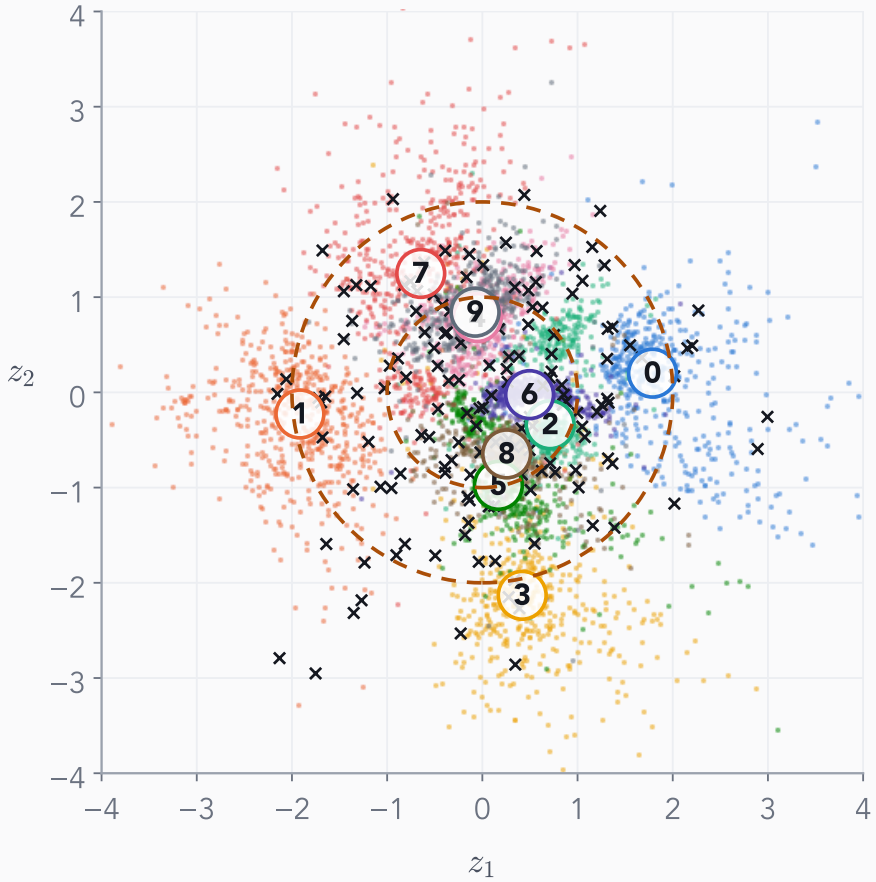


Same data, same 2-number code, same random draws. Now the codes sit inside $\mathcal{N}(0, I)$.

> **To get here: make the model probabilistic (Part 3), measure how close two distributions are (Part 4), and derive the loss (Part 5).**

A PREVIEW OF WHERE WE ARE GOING

The same plot for a VAE



Same data, same 2-number code, same random draws. Now the codes sit inside $\mathcal{N}(0, I)$.



the same kind of random codes, decoded

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END OF PART 2

What we did, and what comes next

WHAT WE DID

1. An encoder squeezes an image into a short code; a decoder rebuilds it. The image is its own target.
2. Random codes from $\mathcal{N}(0, I)$ decode to scribbles.
3. The codes spread over an arbitrary range, and the decoder never saw the space between them.
4. Variants change the input (denoising) or add a penalty (sparse, contractive).
5. The wish: encode each image to a **cloud**, and keep every cloud near $\mathcal{N}(0, I)$.

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NEXT: THE PROBABILISTIC VIEW

Turn the decoder into a probability model with a prior over codes, and ask what it would take to train it by maximum likelihood, as in Part 1.

PART 3 OF 7

The probabilistic view: a decoder is a likelihood

The autoencoder could not generate because nothing said where codes live. Part 1 had exactly what is missing: a **prior** over the hidden choice. Put Part 1's story and Part 2's decoder together.

✓ Distributions and fitting

✓ Autoencoders

3 **The probabilistic view**

4 KL divergence

5 Variational inference and the ELBO

6 Reparameterisation

7 The VAE on MNIST

Same story, bigger pieces

	two bumps (so far)	images (from now on)
hidden z	a coin: A or B	
$p(x \mid z)$	a bump at -2 or $+2$	
observed x	one number	
sum over z	2 terms	

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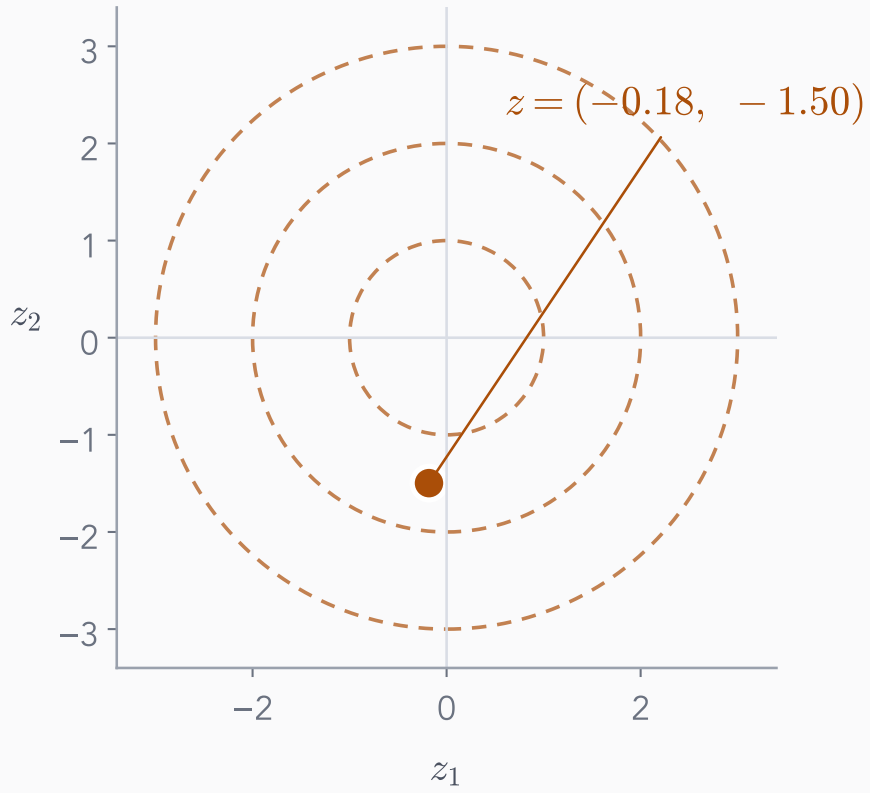
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observed x	one number	784 pixels, each ink (1) or paper (0)
sum over z	2 terms	every point in a plane: infinitely many

Next three slides: generate one image this way, one step at a time.

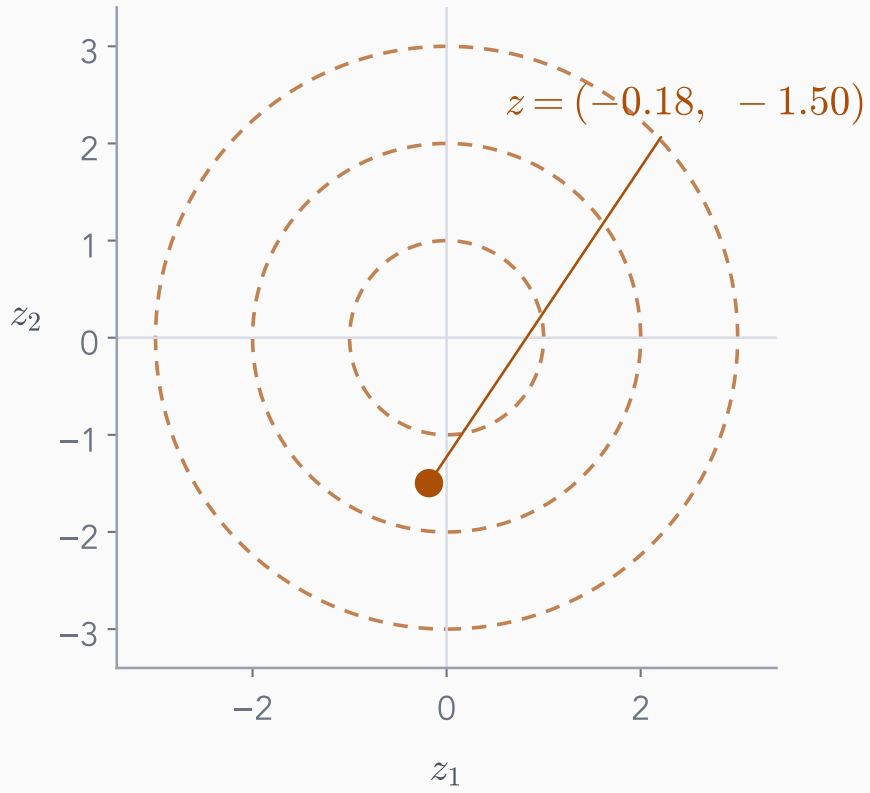
Draw a code



$$z \sim \mathcal{N}(0, I)$$

Two numbers, each from a standard bell curve: like flipping the coin, but the "coin" can land anywhere in the plane.

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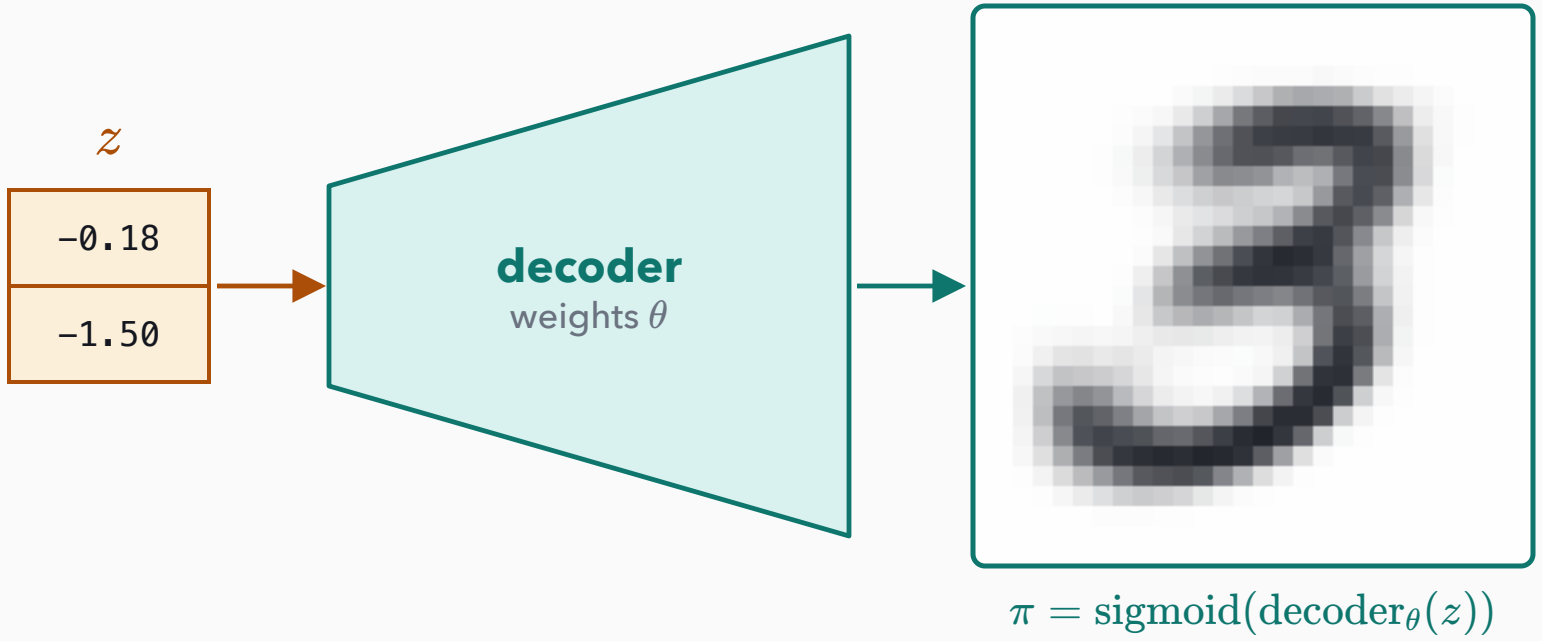
Two numbers, each from a standard bell curve: like flipping the coin, but the "coin" can land anywhere in the plane.

This draw: $z = (-0.18, \ -1.5)$.

On its own, z means nothing. The decoder will give it meaning.

GENERATING AN IMAGE · STEP 2 OF 3

Decode it into 784 pixel probabilities



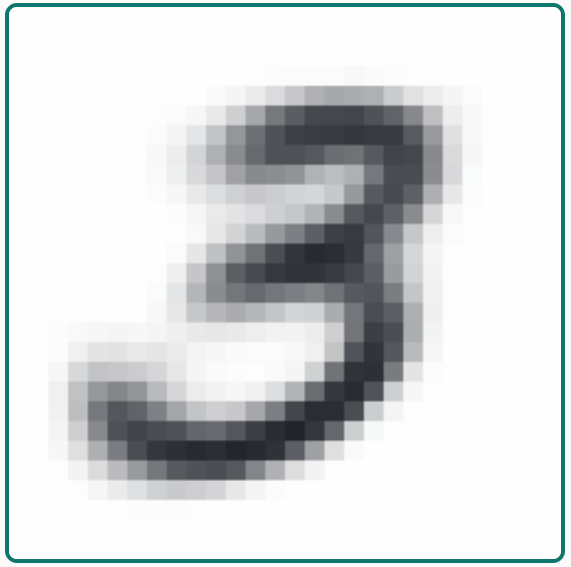
each π_i is between 0 and 1

π_i = probability that pixel i is ink

π_i is the probability that pixel i is ink. Dark grey = probably ink; white = probably paper.

GENERATING AN IMAGE · STEP 3 OF 3

Flip one coin per pixel



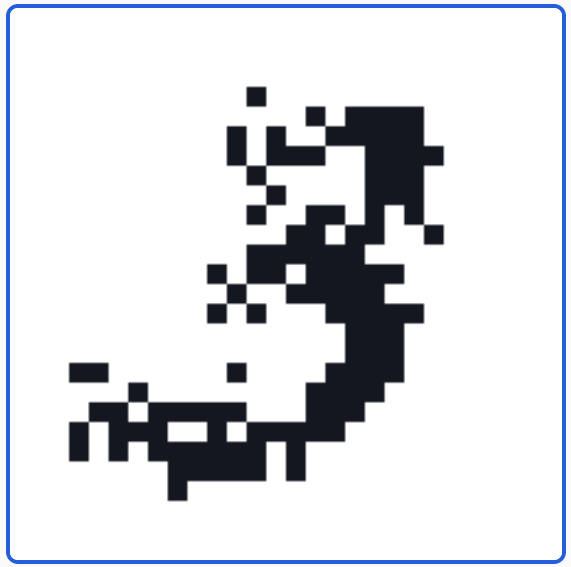
probabilities π

GENERATING AN IMAGE · STEP 3 OF 3

Flip one coin per pixel



probabilities π



one sample x

$$x_i \sim \text{Bernoulli}(\pi_i)$$

Each pixel independently: ink with probability π_i.

That is a generated image. In practice we usually display π itself, because it looks cleaner.

THE SAME TWO STEPS AS BEFORE

Generating is easy. Learning is the catch.

Generate ✓

draw $z \sim \mathcal{N}(0, I)$, decode, flip pixels. Three slides, done.

THE SAME TWO STEPS AS BEFORE

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Learn ?

choose the decoder's weights θ to make the training images probable:

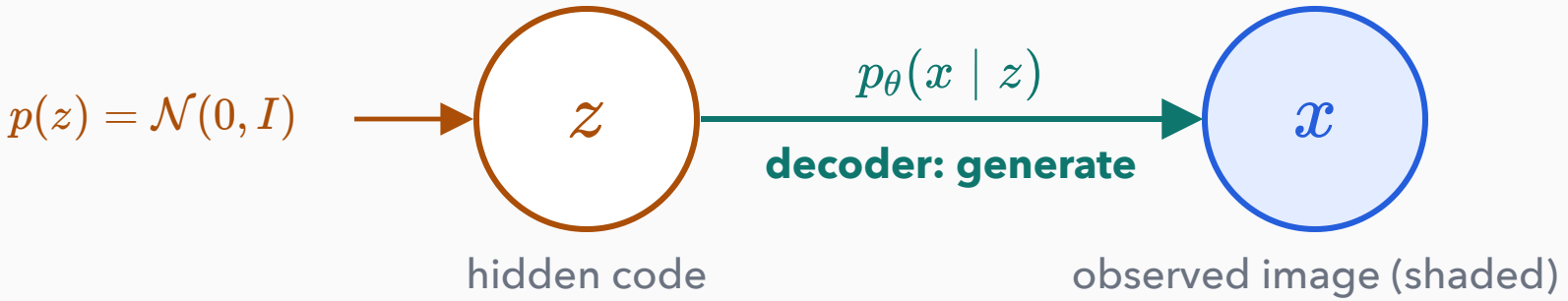
$$p_\theta(x) = \int p(z)\, p_\theta(x \mid z)\, dz$$

the two-bump sum, now over every code in the plane.

The rest of this part: why this integral is so hard, and the three ways people get around it.

THE MODEL, AS A PICTURE

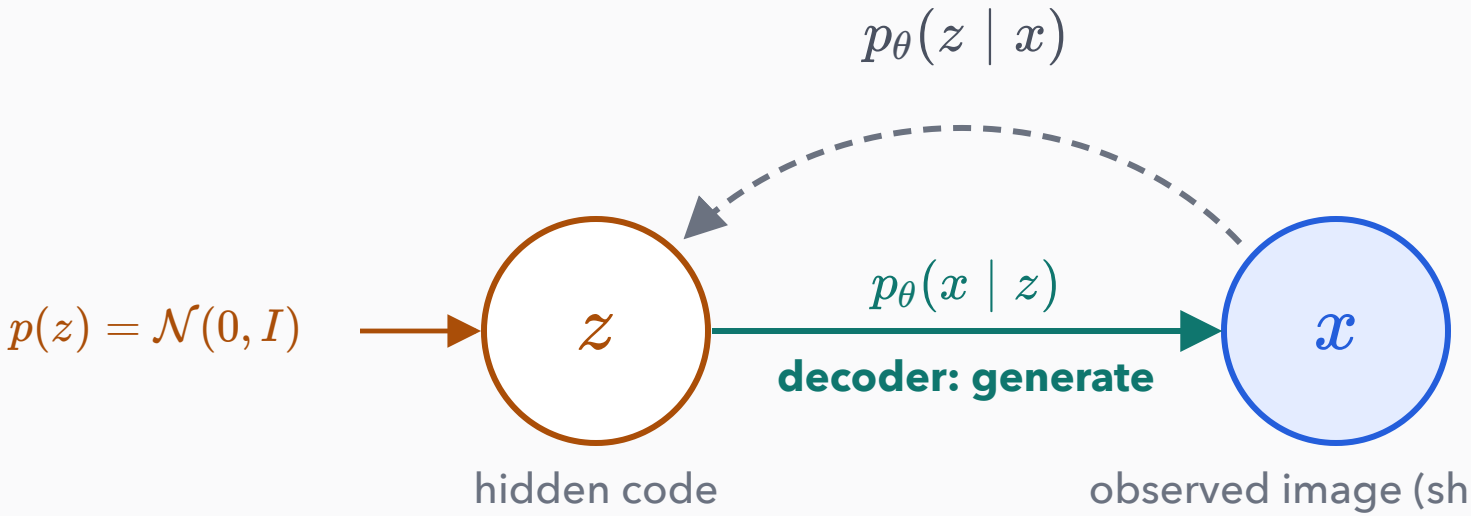
Two arrows: generate down, infer up



$$p_\theta(x, z) = p(z)\, p_\theta(x \mid z)$$

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Two arrows: generate down, infer up

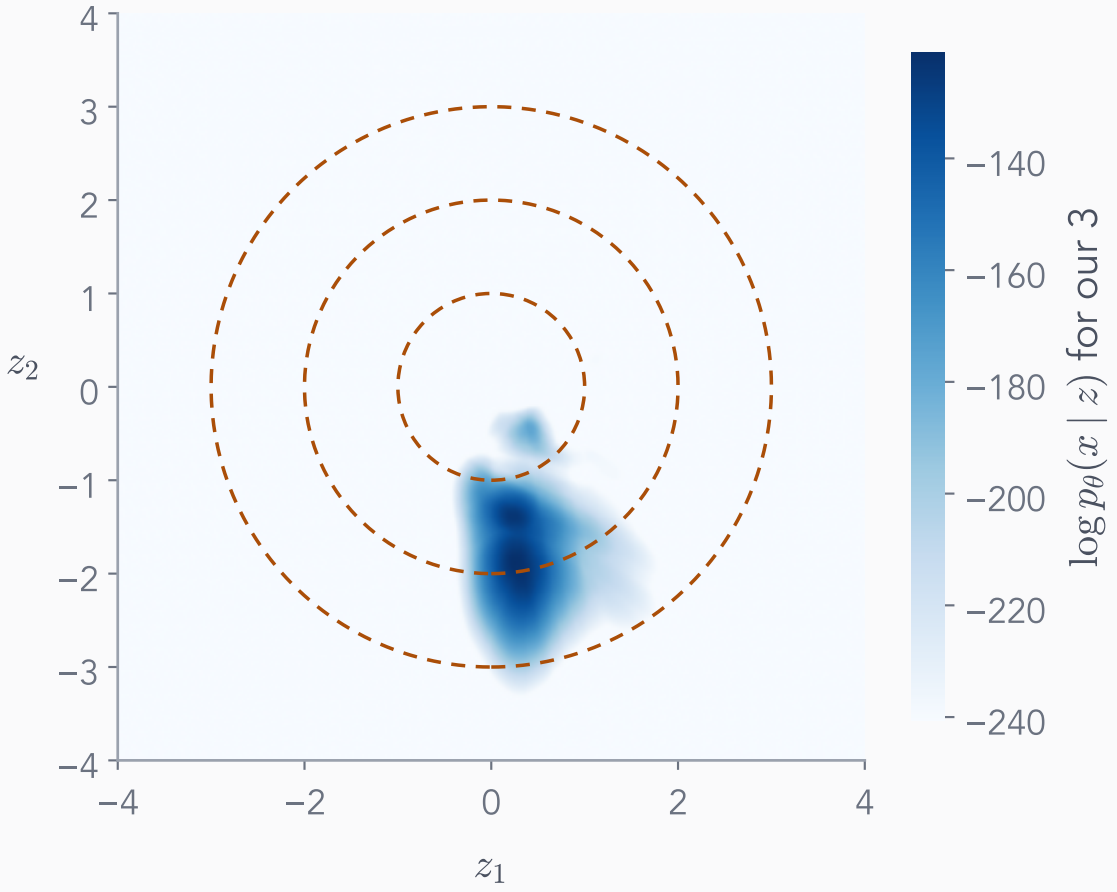


infer: which z made this x? Bayes, but it divides by $p_\theta(x)$ (dashed: out of reach)

$$p_\theta(x, z) = p(z)\, p_\theta(x \mid z)$$

MAXIMUM LIKELIHOOD FOR OUR 3

How probable is our 3 under the model?

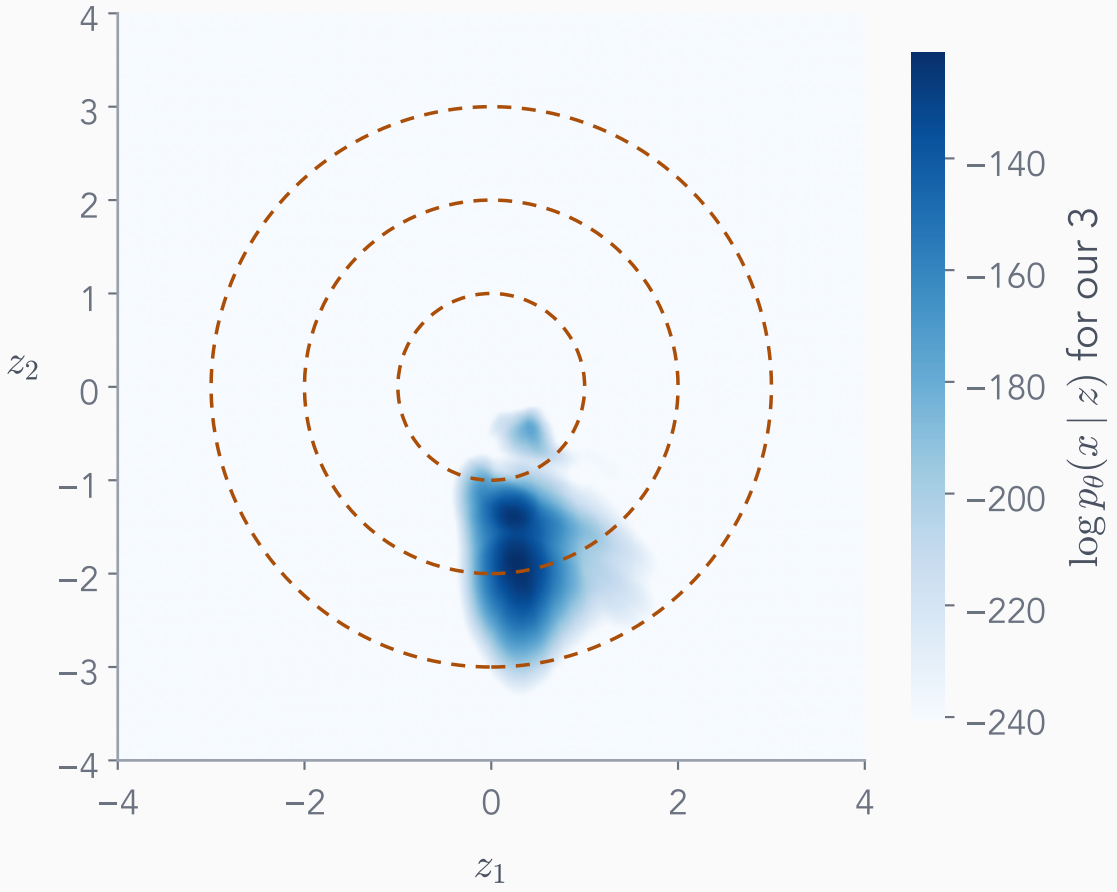


With the coin we summed over two values:

$$p(x) = \sum_{z \in \{\mathrm{A},\mathrm{B}\}} p(z)\, p(x \mid z)$$

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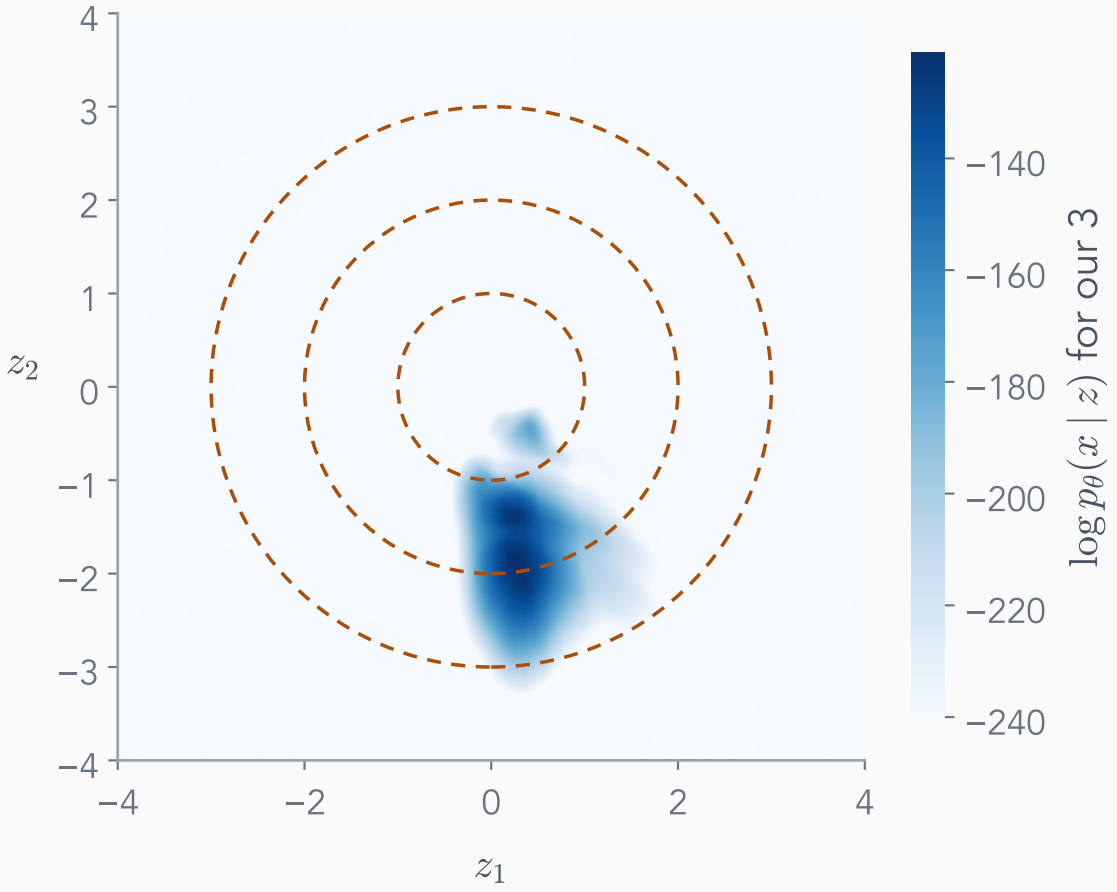
$$p(x) = \sum_{z \in \{\mathrm{A},\mathrm{B}\}} p(z)\, p(x \mid z)$$

A code can be any point in the plane, so the sum becomes an integral:

$$p_\theta(x) = \int p(z)\; p_\theta(x \mid z)\, dz$$

MAXIMUM LIKELIHOOD FOR OUR 3

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2 numbers per code, so we can afford a 901 × 901 grid of decoder calls: $\log p_\theta(x) = -128.7$ nats.

WHY NOT JUST COMPUTE $p_\theta(x)$?

The integral is intractable

No formula. With two bumps, $p(x)$ was a sum of 2 terms. Here it is $\int p(z)\, p_\theta(x \mid z)\, dz$ with a neural network inside: no algebra gives the answer.

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Too many terms to add up. Put a grid of 901 points on every axis of the code and add up the decoder's answers:

numbers in z	decoder calls
1	901
2 (our 3)	8.1×10^5 · a second
4	6.6×10^{11} · a week
8	4.3×10^{23}
16	1.9×10^{47}

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"Intractable" means exactly this: no formula, and far too many terms to sum.

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1	901
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16	1.9×10^{47}

> **And we need $p_\theta(x)$ for every image, at every training step.**

IDEA: ESTIMATE THE INTEGRAL BY SAMPLING

Random codes almost never hit the right patch

$$p_\theta(x) = \underbrace{\mathbb{E}_{z \sim p(z)}\left[\, p_\theta(x \mid z) \,\right]}_{\text{the average over codes from the prior}} \approx \frac{1}{S} \sum_{s=1}^{S} p_\theta(x \mid z_s)$$

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random codes $z_s \sim \mathcal{N}(0, I)$

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land within 2 widths of our 3's patch

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land within 2 widths of our 3's patch

−363.9

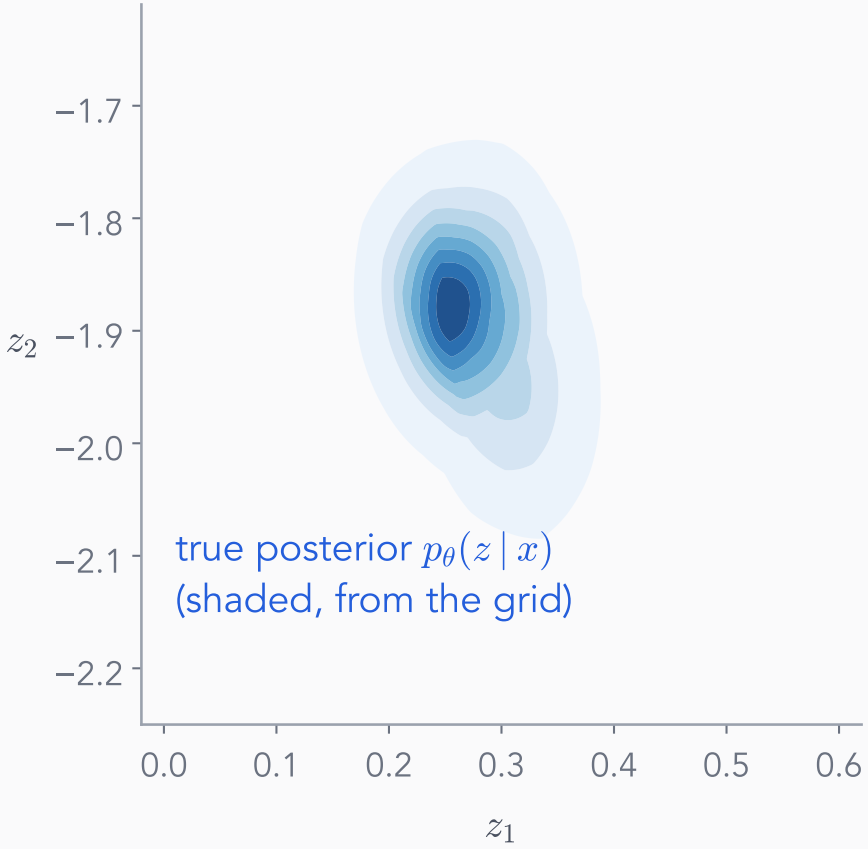
median $\log p(x \mid z)$ of a random code

−121.0

the best of the 100,000: $\log p(x \mid z)$

> **A typical random code makes our 3 about e^{243} times less probable than the best code. Blind sampling wastes almost every draw.**

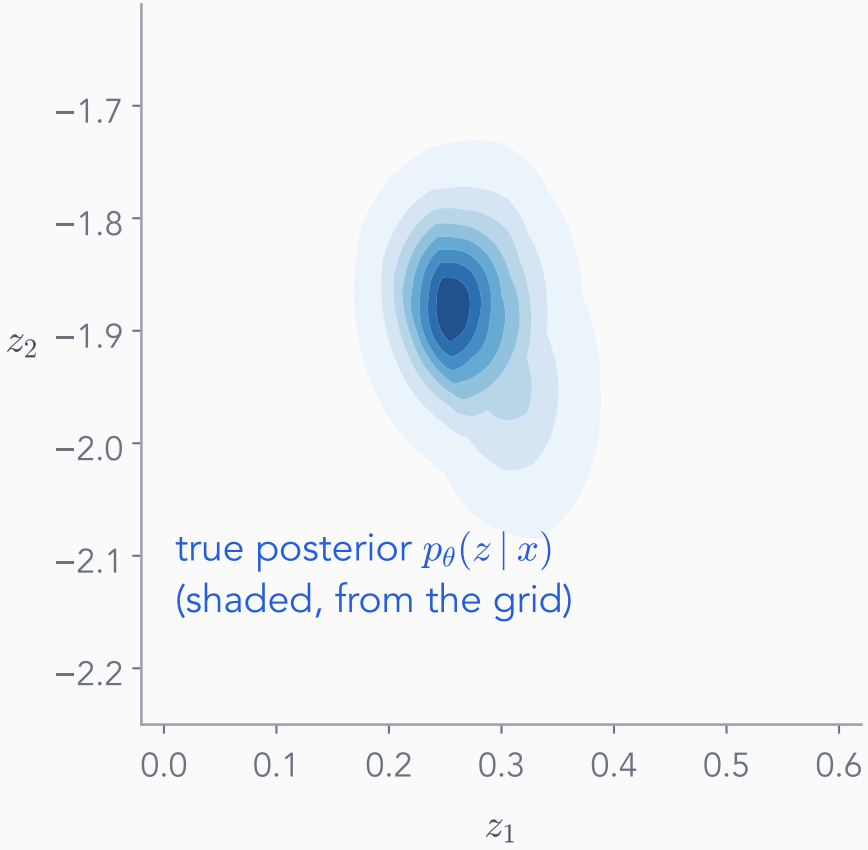
The backwards step: which codes could have made our 3?



Part 1's Bayes table, with a plane of codes instead of two bumps:

$$p_\theta(z \mid x) = \frac{p(z)\, p_\theta(x \mid z)}{p_\theta(x)}$$

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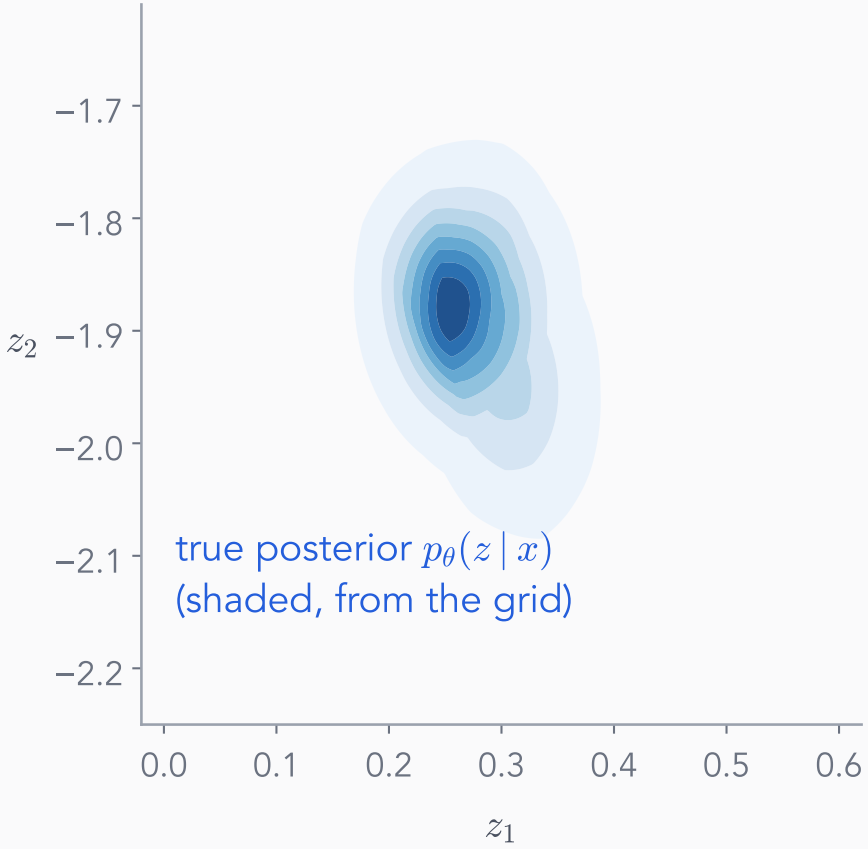


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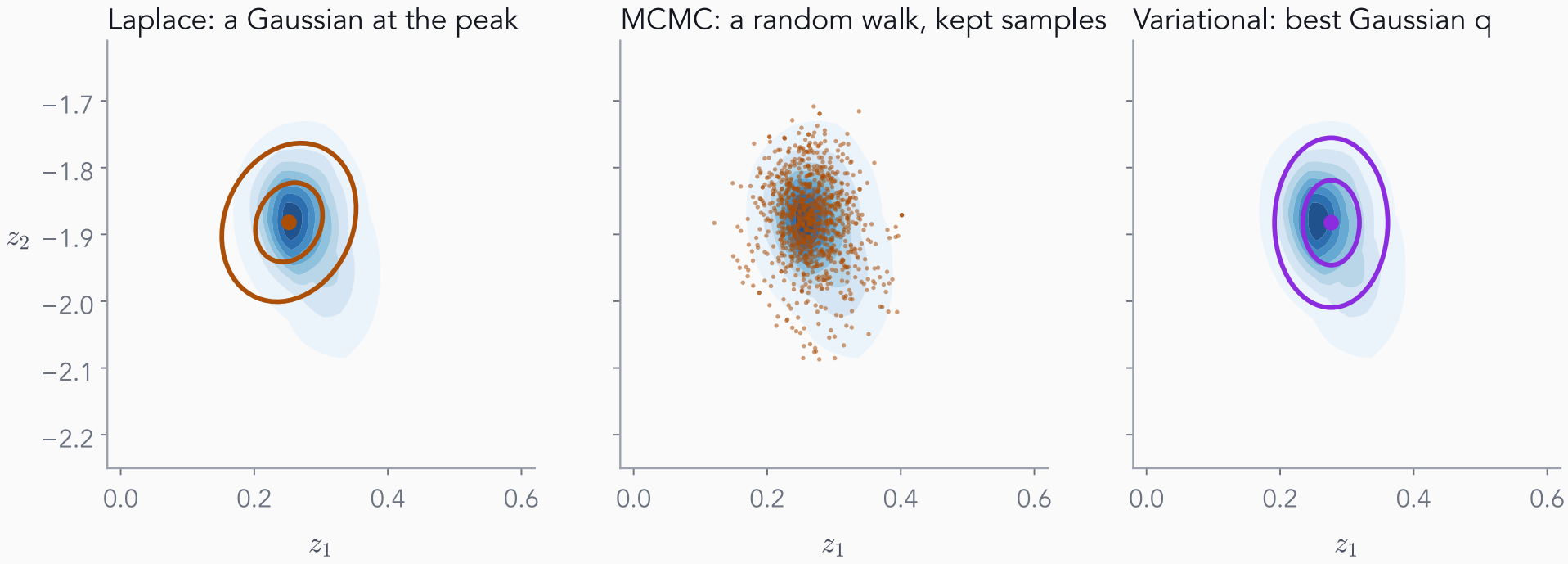
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The bottom is the evidence: the same impossible integral. So the posterior is out of reach too.

From the 2-number grid we can still look at it: a small, slightly tilted patch near $(0.25,\ -1.88)$, about 0.05 wide. The prior is 1 wide: one image pins its code down tightly.

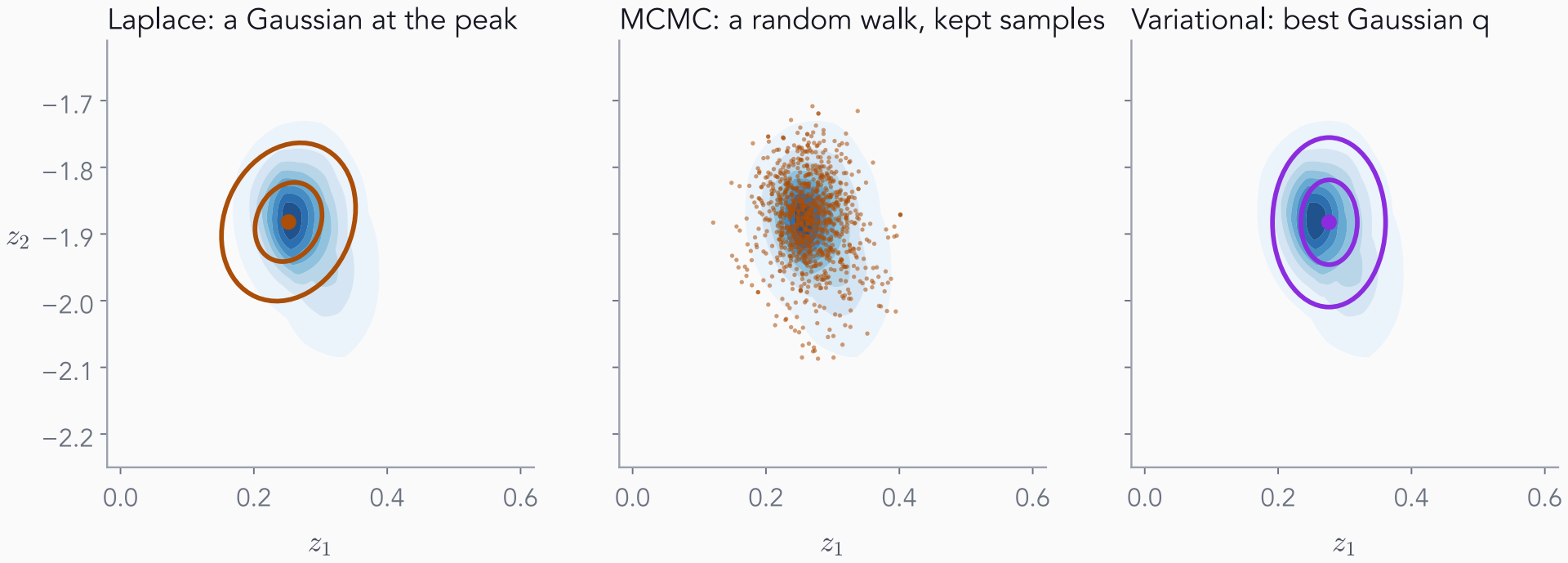
> **Training needs this patch for every image. Next: three ways to approximate a posterior we cannot compute.**

Three ways, all run on our 3's real posterior



Laplace: find the peak, fit a Gaussian to the curvature there. Fast, local.

Three ways, all run on our 3's real posterior

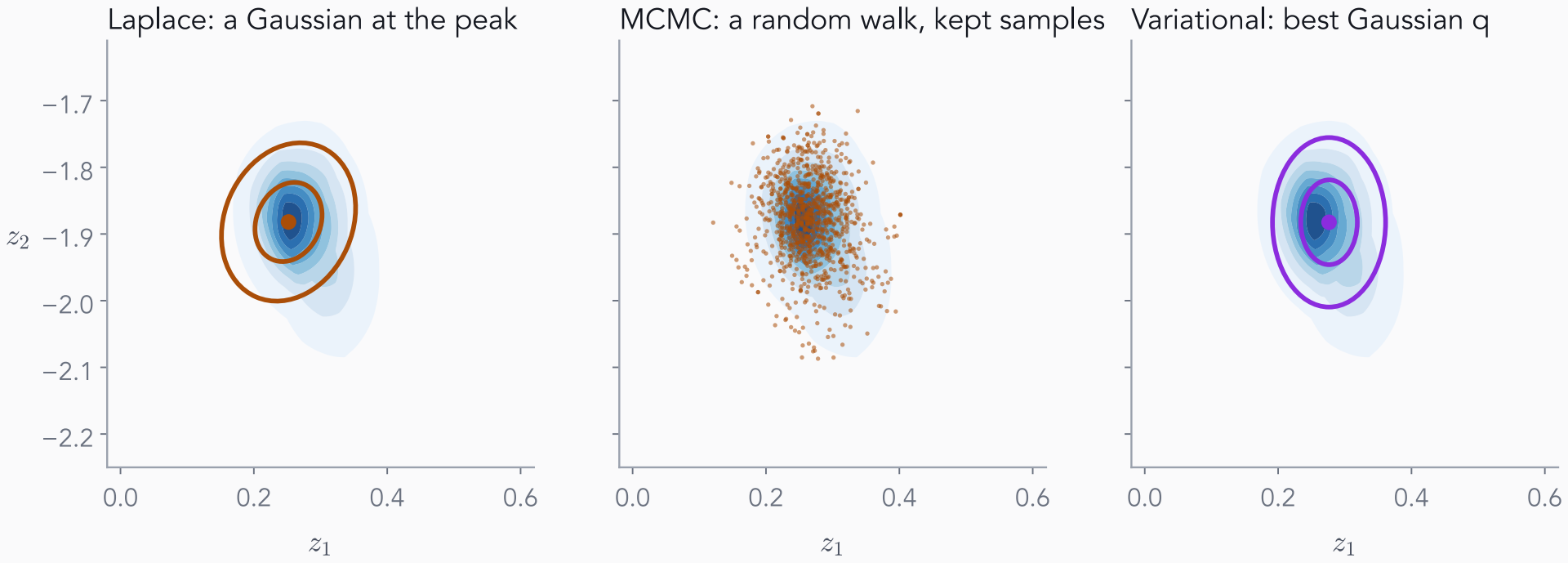


Laplace: find the peak, fit a Gaussian to the curvature there. Fast, local.

MCMC: a random walk that visits regions in proportion to the posterior. Exact in the long run, slow.

WHEN THE POSTERIOR CANNOT BE COMPUTED, APPROXIMATE IT

Three ways, all run on our 3's real posterior



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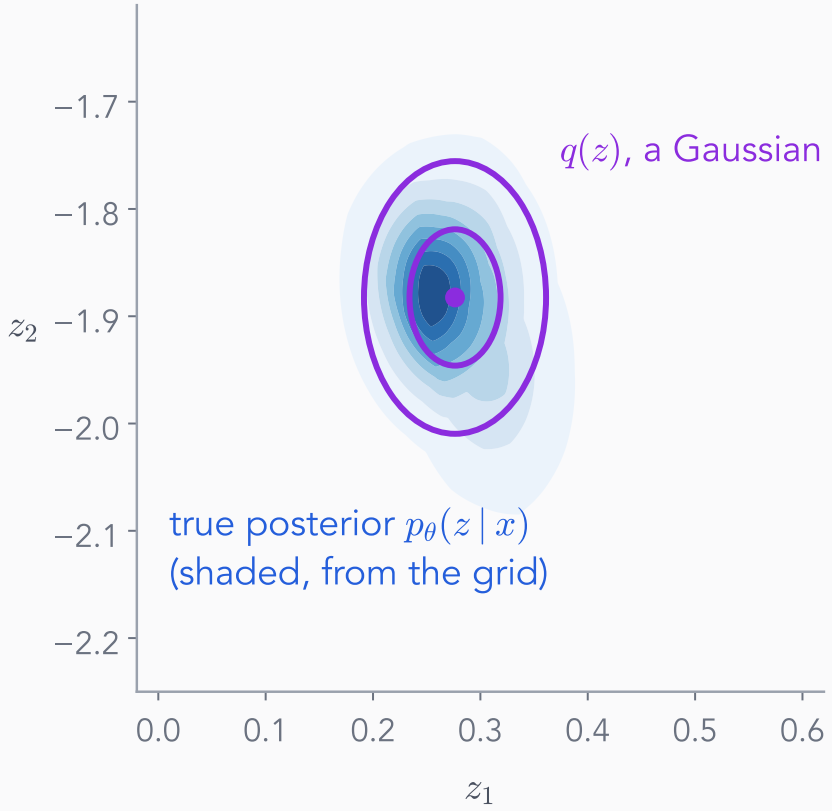
MCMC: a random walk that visits regions in proportion to the posterior. Exact in the long run, slow.

Variational: choose a simple family q and optimise it to be as close as possible. Fast, trainable.

> **Today: only the variational one. It turns inference into optimisation, which is what neural networks are good at.**

THE VARIATIONAL IDEA, FOR OUR 3

Propose a simple q, then pull it towards the true posterior

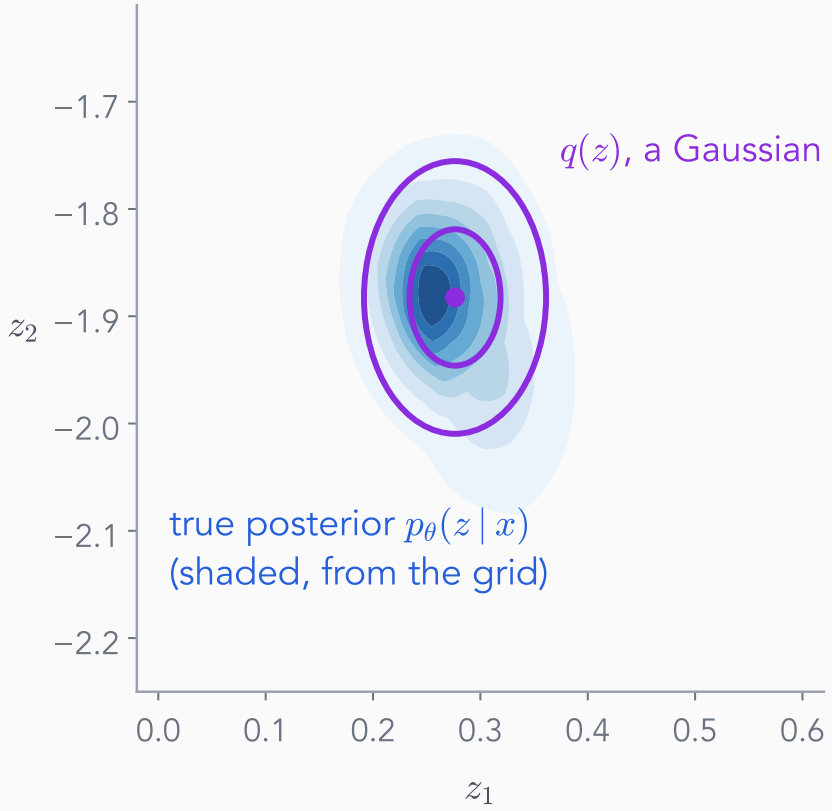


$$q(z) = \mathcal{N}\big(m,\ \mathrm{diag}(s_1^2, s_2^2)\big)$$

Four numbers to choose: a centre $m = (m_1, m_2)$ and two widths s_1, s_2.

THE VARIATIONAL IDEA, FOR OUR 3

Propose a simple q, then pull it towards the true posterior



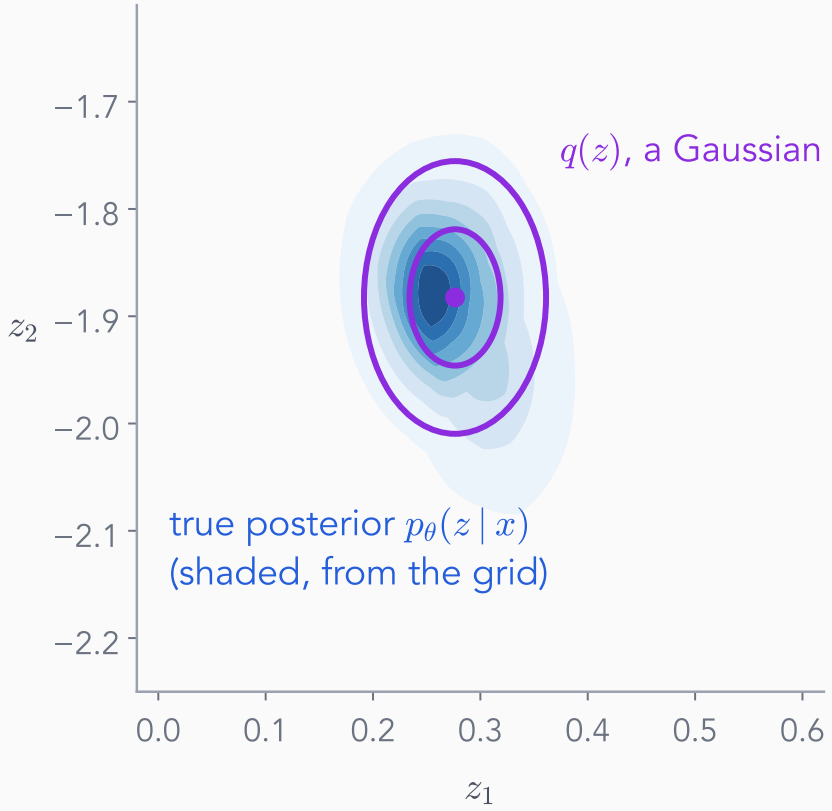
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Goal: make $q(z)$ as close as possible to $p_\theta(z \mid x)$, the shaded patch.

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"As close as possible" needs a **number** for how far apart two distributions are.

That number is the KL divergence: the first thing in Session 2.

END OF PART 3 · END OF SESSION 1

What we did, and what comes next

WHAT WE DID

1. Learn = make the data probable; generate = sample. Code: one loop.
2. Autoencoders compress and rebuild (plain, denoising, sparse, contractive), but cannot generate.
3. As a probability model: prior $p(z) = \mathcal{N}(0, I)$, likelihood $p_\theta(x \mid z)$ from the decoder.
4. Training needs $p_\theta(x)$ and the posterior $p_\theta(z \mid x)$: both intractable.
5. Variational idea: a simple q, pulled close to the posterior.

END OF PART 3 · END OF SESSION 1

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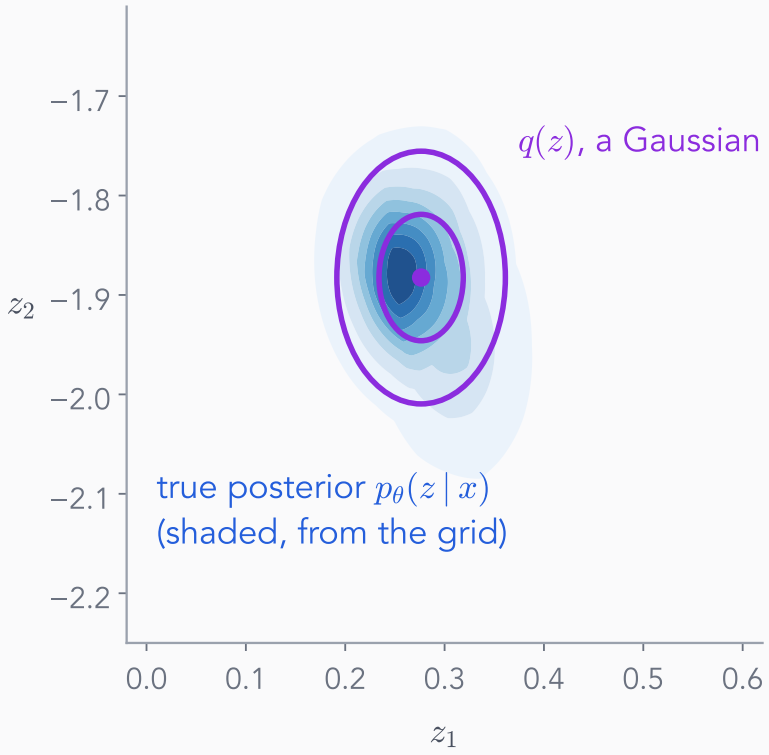
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SESSION 2

A distance between distributions (KL), the loss that pulls q close without ever computing $p_\theta(x)$ (the ELBO), gradients through random draws, and the VAE on MNIST.

Last time: we need q close to a posterior we cannot compute



A decoder plus a prior is a probability model: $p(z)\, p_\theta(x \mid z)$.

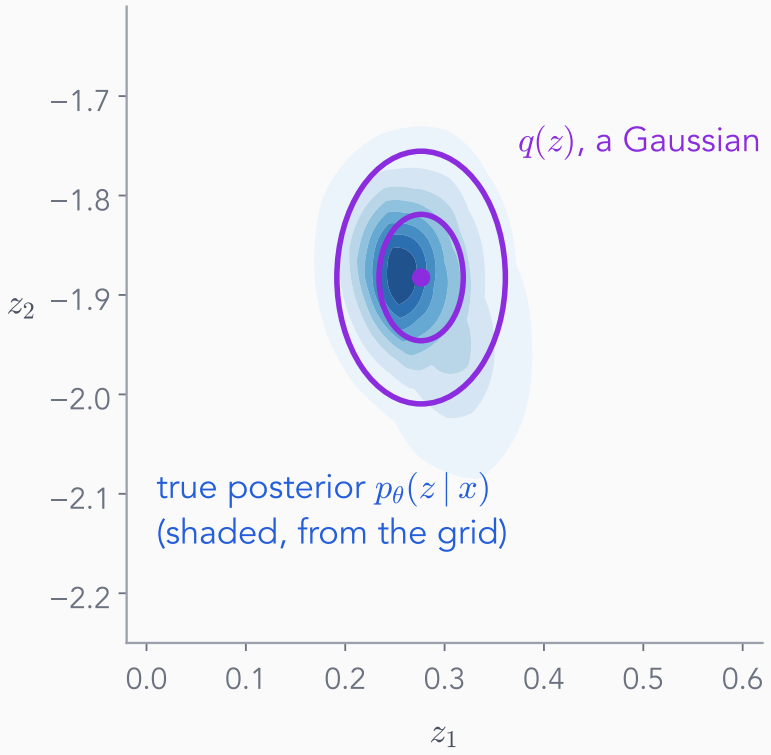
Training it needs $p_\theta(x) = \int p(z)\, p_\theta(x \mid z)\, dz$: intractable.

So does the posterior $p_\theta(z \mid x)$, the shaded patch for our 3.

Variational idea: a simple Gaussian q (purple), pulled close to it.

SESSION 2 · WHERE WE STOPPED

Last time: we need q close to a posterior we cannot compute



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The VI lecture's two lines:
$\log p(D) = \mathrm{ELBO}(q) + \mathrm{KL}\big(q \,\|\, p(\theta \mid D)\big)$ for every q
$z = \mu + \sigma \cdot \varepsilon$: a random draw with a gradient

Today: those two lines for our 3, then one network that applies them to every image: the VAE.

PART 4 OF 7

KL divergence, recalled for our 3's code

We want q **close** to the posterior. The VI lecture built "close" from scratch (its Part 2). Here: the facts we need from it, and the one formula every VAE loss uses, a cloud against the prior $\mathcal{N}(0, I)$.

✓ Distributions and fitting
✓ Autoencoders
✓ The probabilistic view
4 **KL divergence**
5 Variational inference and the ELBO
6 Reparameterisation
7 The VAE on MNIST

FROM THE VI LECTURE, PART 2

KL is an average of log-ratios, under its first argument

$$\mathrm{KL}\big(q \,\|\, p\big) = \mathbb{E}_{z\sim q}\big[\log q(z) - \log p(z)\big]$$

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Never negative

$\mathrm{KL} \geq 0$, and $= 0$ only when $q = p$: the log lies below its tangent.

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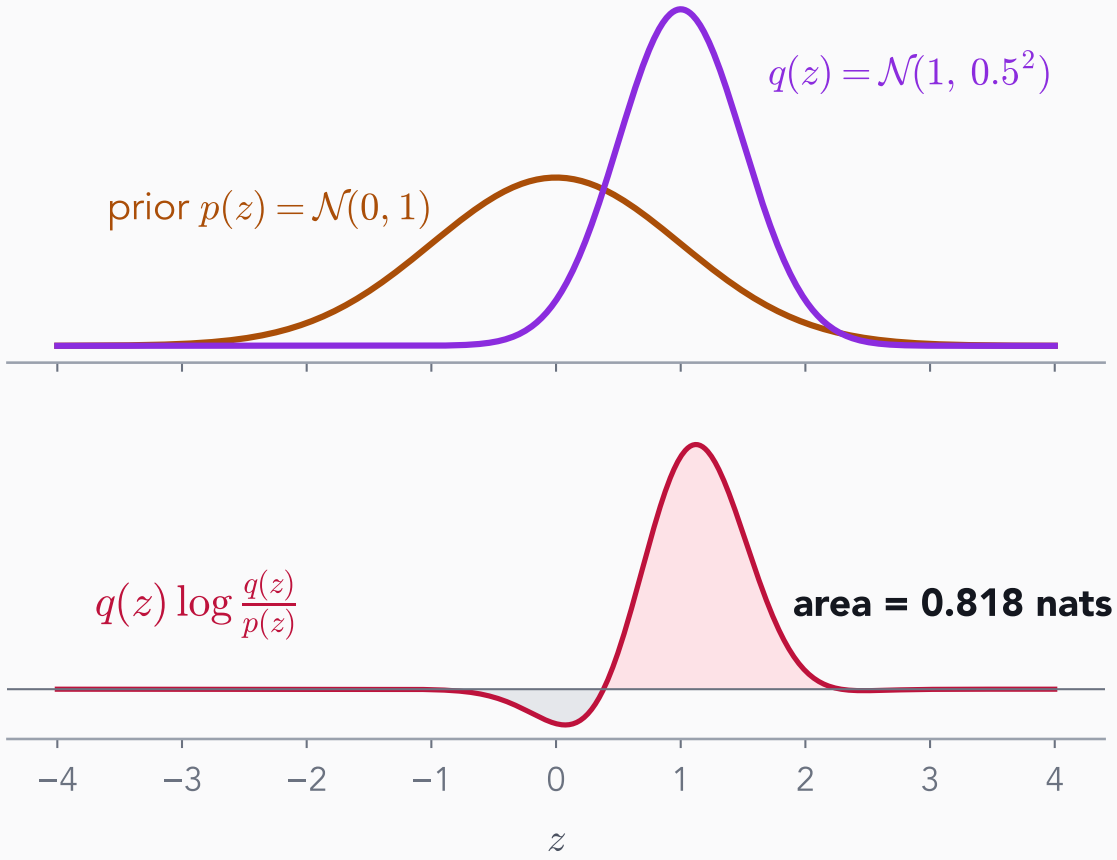
$\mathrm{KL}(q\|p) \neq \mathrm{KL}(p\|q)$. Which one we minimise changes the answer.

VI uses $\mathrm{KL}(q \,\|\, \text{posterior})$

An average under q, which we can draw from. The price: q seeks one mode and comes out too narrow.

> **Our 3's posterior is a single small patch, so there is only one mode to seek. What a diagonal q cannot do is tilt with it.**

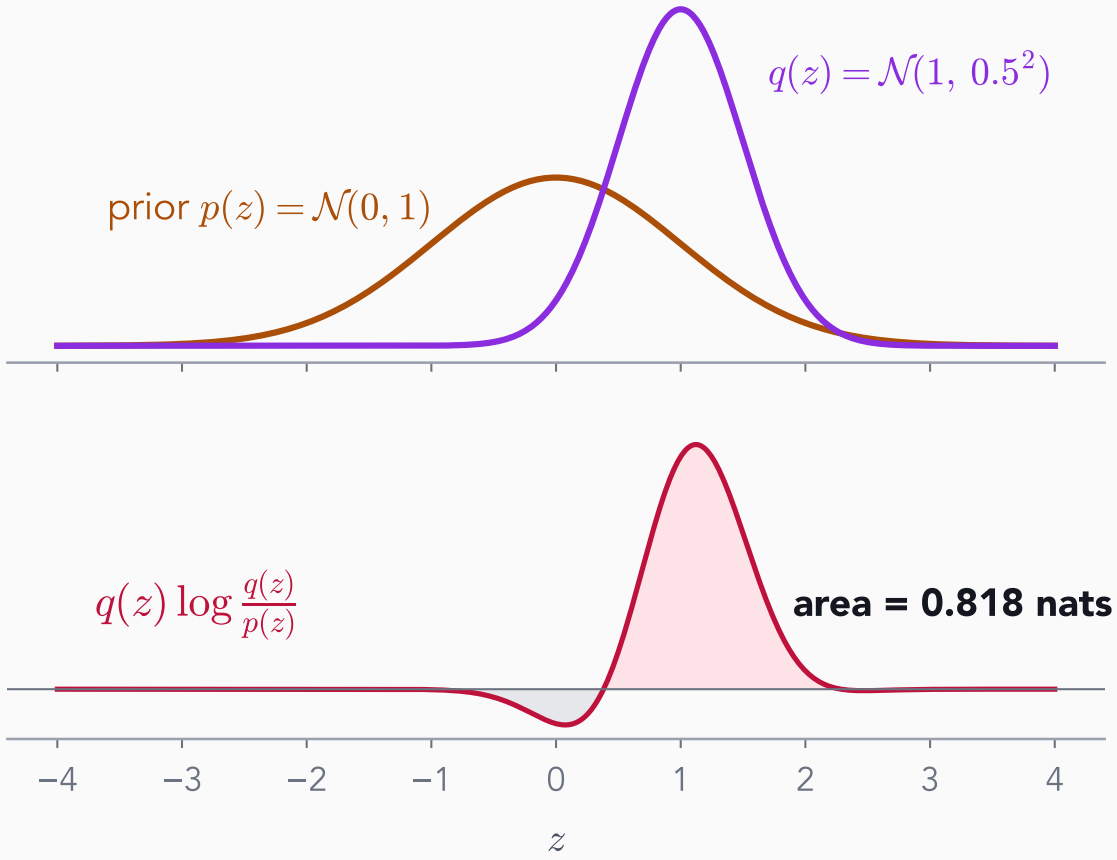
A Gaussian cloud against the prior $\mathcal{N}(0, 1)$



The VI lecture's formula for two Gaussians:

$$\mathrm{KL}(q \,\|\, p) = \frac{1}{2}\left[\log \frac{\sigma_p^2}{\sigma_q^2} - 1 + \frac{\sigma_q^2 + (\mu_q - \mu_p)^2}{\sigma_p^2}\right]$$

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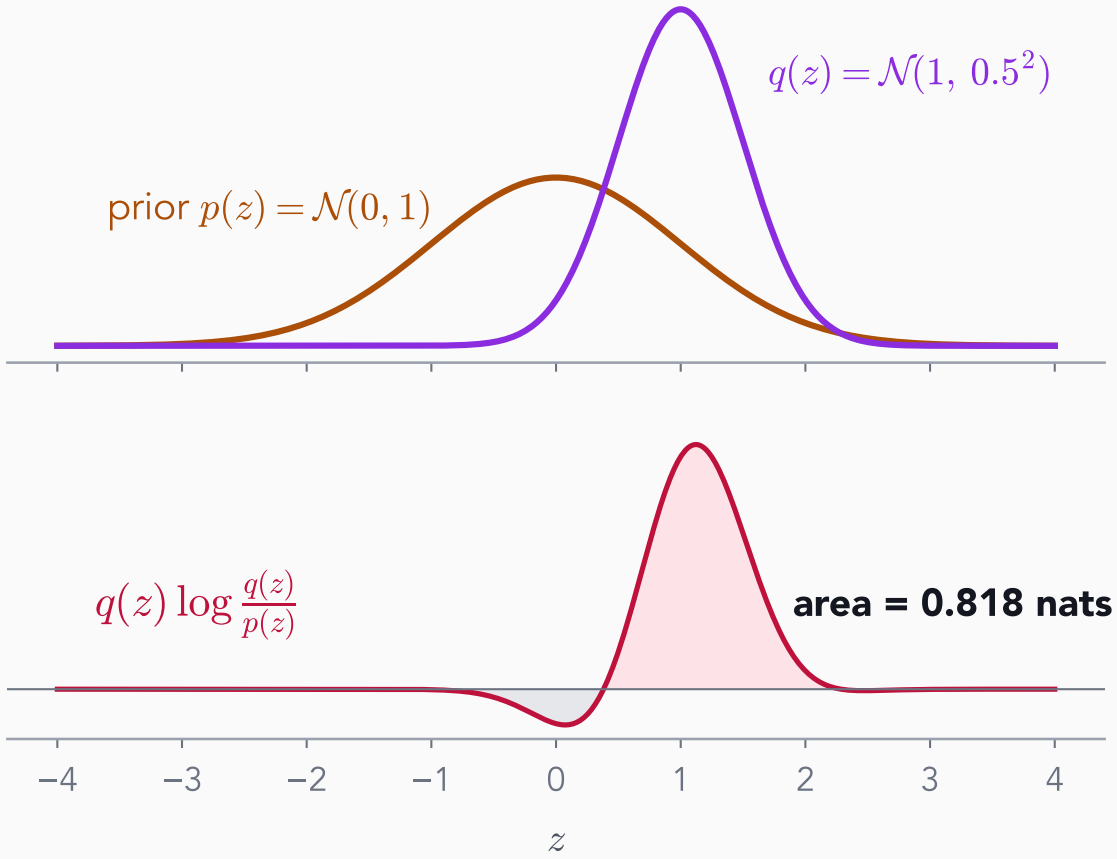
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Put in the prior, $\mu_p = 0$ and $\sigma_p = 1$:

$$\mathrm{KL}\big(q \,\|\, \mathcal{N}(0,1)\big) = \frac{1}{2}\big(\mu^2 + \sigma^2 - 1 - \log \sigma^2\big)$$

VI lecture (vi.html), Part 2: derive the Gaussian KL · the answer, and torch's `kl_normal_normal`

A Gaussian cloud against the prior $\mathcal{N}(0,1)$



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Check on the toy cloud $q = \mathcal{N}(1, 0.5^2)$, the shaded area:

$$\tfrac{1}{2}\big(1 + 0.25 - 1 + 1.386\big) = 0.818 \checkmark$$

A code with several coordinates and a diagonal q: one such term per coordinate, added. Moving a centre costs $\frac{1}{2}\mu^2$; a width other than 1 costs $\frac{1}{2}(\sigma^2 - 1 - \log \sigma^2)$.

END OF PART 4

What we did, and what comes next

WHAT WE DID

1. From the VI lecture: $\mathrm{KL}(q\|p)$ is an average under q, never negative, not symmetric.
2. VI minimises $\mathrm{KL}(q \,\|\, \text{posterior})$ because we can draw from q; q seeks a mode.
3. Against the prior: $\frac{1}{2}(\mu^2 + \sigma^2 - 1 - \log\sigma^2)$ per coordinate, added.

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NEXT: MAKE q CLOSE TO THE POSTERIOR

$\mathrm{KL}(q \,\|\, p_\theta(z \mid x))$ contains the intractable $p_\theta(x)$. The VI lecture's ELBO removes it; Part 5 runs it on our 3, then hands the job to an encoder.

PART 5 OF 7

Variational inference for our 3, then for every image

The VI lecture turned "make q close to the posterior" into a loss we can compute, the ELBO, and fitted a coin with it (its Part 6). Here the unknown is our 3's code: run the same loss on it, read the numbers, and see why doing this image by image leads to an encoder.

✓ Distributions and fitting

✓ Autoencoders

✓ The probabilistic view

✓ KL divergence

5 **Variational inference and the ELBO**

6 Reparameterisation

7 The VAE on MNIST

FROM THE VI LECTURE, PART 6, WITH AN IMAGE IN PLACE OF THE COIN

The same identity, written for one image

$$\log p_\theta(x) = \underbrace{\mathbb{E}_{z\sim q}\big[\log p_\theta(x,z) - \log q(z)\big]}_{\mathrm{ELBO}(q)} + \underbrace{\mathrm{KL}\big(q \,\|\, p_\theta(z \mid x)\big)}_{\geq 0}$$

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VI lecture	here
θ, **the unknown**	z, our 3's code
D, **the data**	x, our 3
prior $p(\theta)$	$p(z) = \mathcal{N}(0, I)$
likelihood $p(D \mid \theta)$	decoder $p_\theta(x \mid z)$

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The ELBO needs only the joint, $p_\theta(x,z) = p(z)\,p_\theta(x \mid z)$: prior times decoder. No $p_\theta(x)$, no posterior.

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The ELBO needs only the joint, $p_\theta(x,z) = p(z)\,p_\theta(x \mid z)$: prior times decoder. No $p_\theta(x)$, no posterior.

$\log p_\theta(x)$ does not move when q does, so whatever the ELBO gains, the KL to the posterior loses.

> **Careful with one letter: there, θ was the unknown; here it names the decoder's weights, and the unknown is z.**

THE LOWER BOUND, MEASURED ON OUR 3

The KL is never negative, so the ELBO sits below $\log p_\theta(x)$

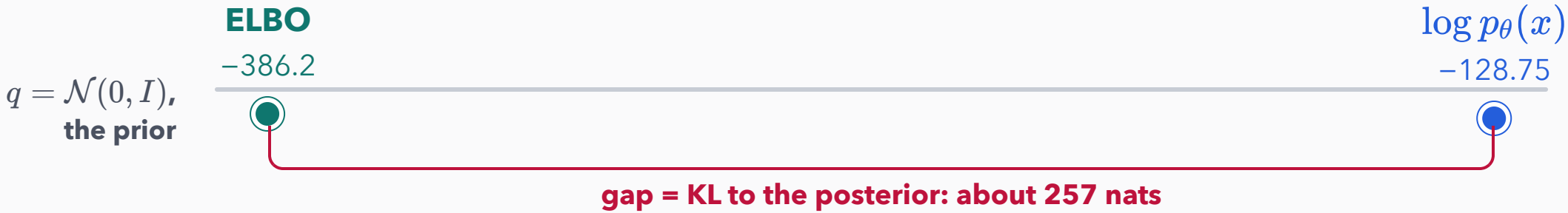
$$\log p_\theta(x) = \mathrm{ELBO}(q) + \underbrace{\mathrm{KL}\big(q \,\|\, p_\theta(z \mid x)\big)}_{\geq 0} \;\geq\; \mathrm{ELBO}(q)$$

THE LOWER BOUND, MEASURED ON OUR 3

The KL is never negative, so the ELBO sits below $\log p_\theta(x)$

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Our 3, two choices of q. The right end, $\log p_\theta(x)$, is fixed by the model; it does not move when q changes.



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Our 3, two choices of q. The right end, $\log p_\theta(x)$, is fixed by the model; it does not move when q changes.



> **The total cannot move, so raising the ELBO must shrink the KL: maximise the ELBO and q approaches the posterior, without ever computing $p_\theta(x)$.**

THE VI LECTURE'S SECOND FORM, FOR AN IMAGE

The ELBO, in symbols and in words

$$\text{ELBO} = \mathbb{E}_q\big[\log p_\theta(x \mid z) + \log p(z) - \log q(z)\big]$$

$$\text{ELBO} = \underbrace{\mathbb{E}_{z\sim q}\big[\log p_\theta(x \mid z)\big]}_{\text{rebuild } x \text{ from codes in its cloud}} - \underbrace{\mathrm{KL}\big(q(z) \,\|\, p(z)\big)}_{\text{keep the cloud near } \mathcal{N}(0,I)}$$

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First term: the autoencoder's reconstruction score, with the code drawn from the cloud.

Second term: the Gaussian KL to the prior from Part 4, in closed form.

The two wishes from the end of Part 2, derived rather than invented: rebuild well, and keep codes where the prior can find them.

VARIATIONAL INFERENCE BY HAND, FOR OUR 3

Four numbers, gradient ascent on the ELBO

```
x = our_3                                  # 784 pixels, fixed
m     = torch.zeros(2, requires_grad=True)   # q's centre
log_s = torch.zeros(2, requires_grad=True)   # q's log-widths
opt = torch.optim.Adam([m, log_s], lr=0.03)

for step in range(800):
    z = m + log_s.exp() * torch.randn(64, 2)    # 64 draws from q
    rec = -bce(decoder(z), x).sum(1).mean()    # E_q[log p(x|z)]
    kl  = 0.5 * (m**2 + (2*log_s).exp() - 1 - 2*log_s).sum()
    loss = -(rec - kl)                           # minus the ELBO
    opt.zero_grad(); loss.backward(); opt.step()
```

Only q is learned. The decoder is a trained one, kept fixed; x is our 3. Start at $q = \mathcal{N}(0, I)$: $m = 0$, $s = 1$.

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```

Draw codes from q: centre plus width times standard noise: the VI lecture's reparameterised draw (its Part 5), so gradients reach `m` and `log_s`.

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```

The two terms: reconstruction, averaged over the 64 draws; the KL to the prior by the Gaussian formula from Part 4.

VARIATIONAL INFERENCE BY HAND, FOR OUR 3

Four numbers, gradient ascent on the ELBO

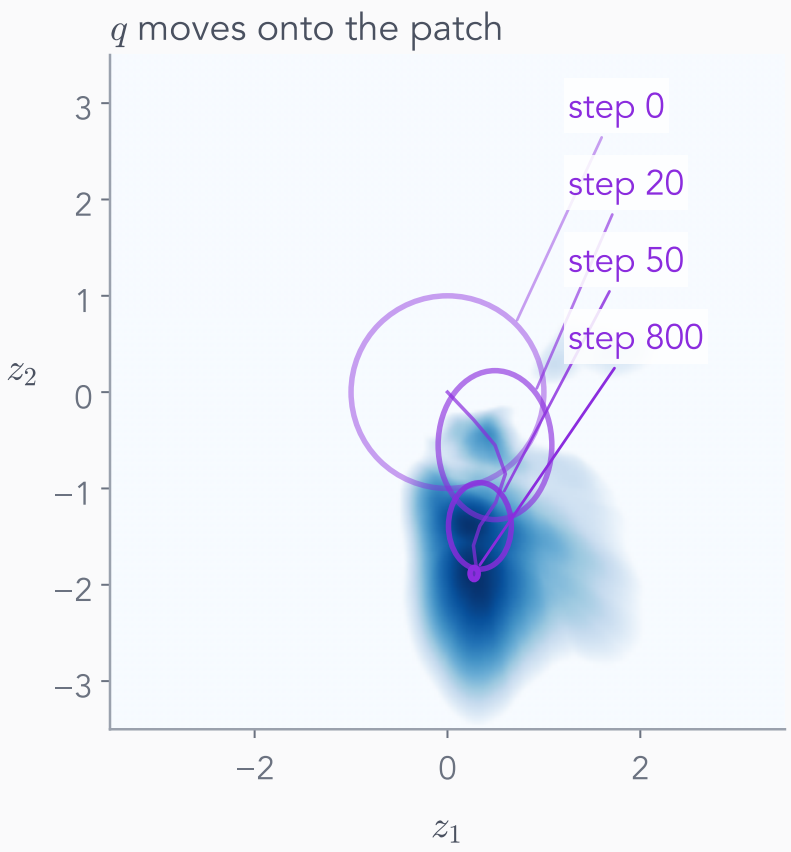
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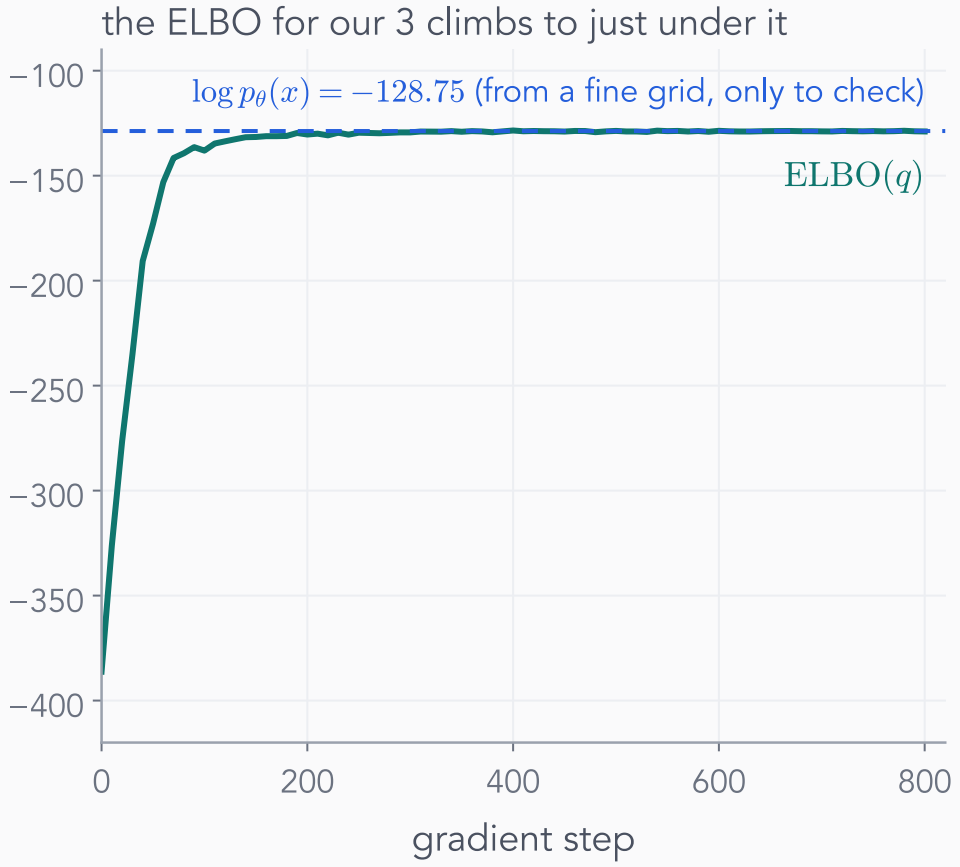
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```

The same three-line loop as fitting one Gaussian in Part 1. The ELBO rises from −386.0 to −128.8.

WATCH q TRAVEL

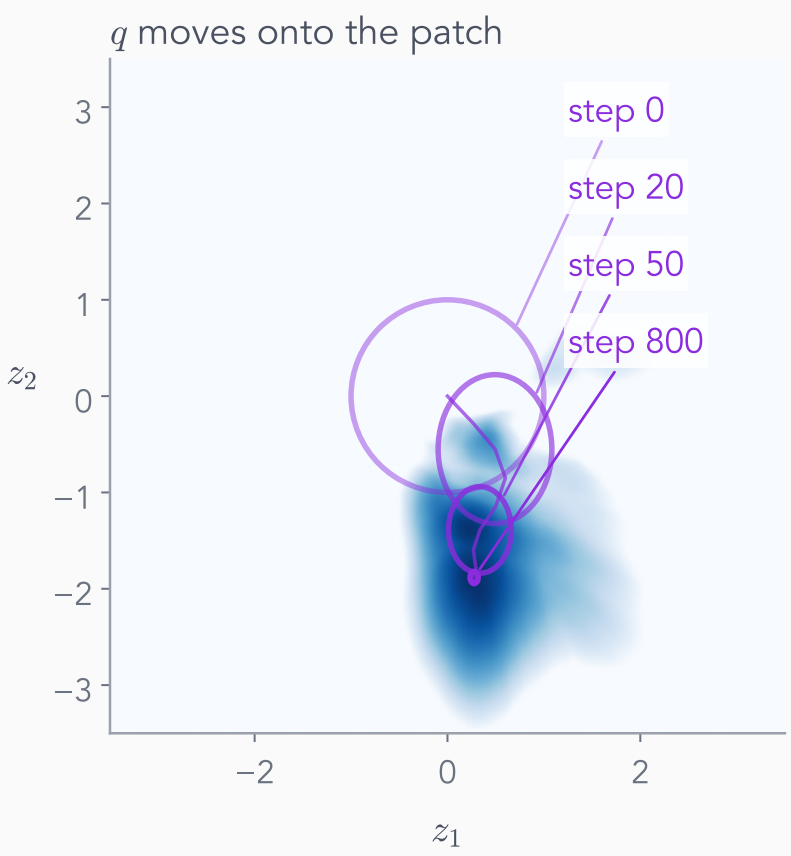
From $\mathcal{N}(0, I)$ to our 3's patch in 800 steps

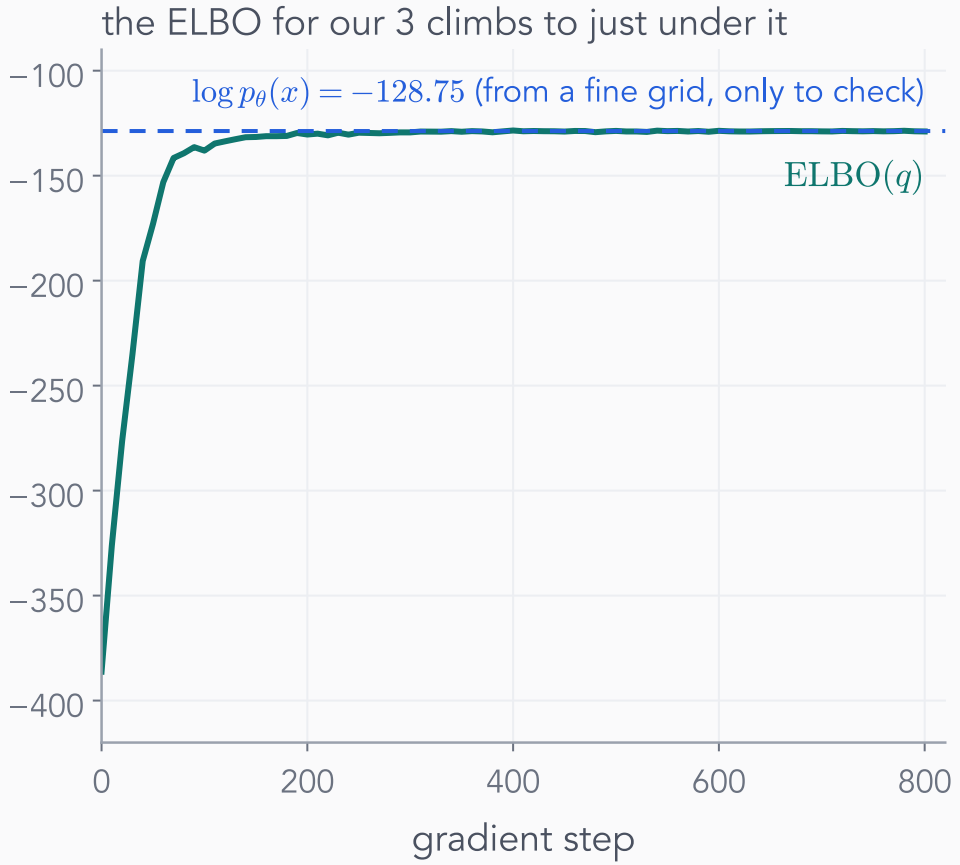




WATCH q TRAVEL

From $\mathcal{N}(0, I)$ to our 3's patch in 800 steps





Final ELBO −128.83, just under $\log p_\theta(x) = -128.75$. The gap, $\mathrm{KL}(q \,\|\, \text{posterior})$, is 0.08 nats: q is almost exactly right.

INSIDE THOSE 800 STEPS

The two terms pull against each other

step	reconstruction $\mathbb{E}_q[\log p_\theta(x \mid z)]$	$-\,\mathrm{KL}(q \,\|\, \text{prior})$	ELBO
$0 \cdot q$ is the prior	−386.2	— 0.0	−386.2

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800	**−122.2**	**— 6.73**	**−128.9**

Reconstruction gains about 264 nats: codes from q now decode to our 3.

The KL to the prior grows from 0 to 6.73: a narrow cloud far from the origin costs something.

The ELBO is a trade: a q precise enough to rebuild the image, no more precise than it needs to be.

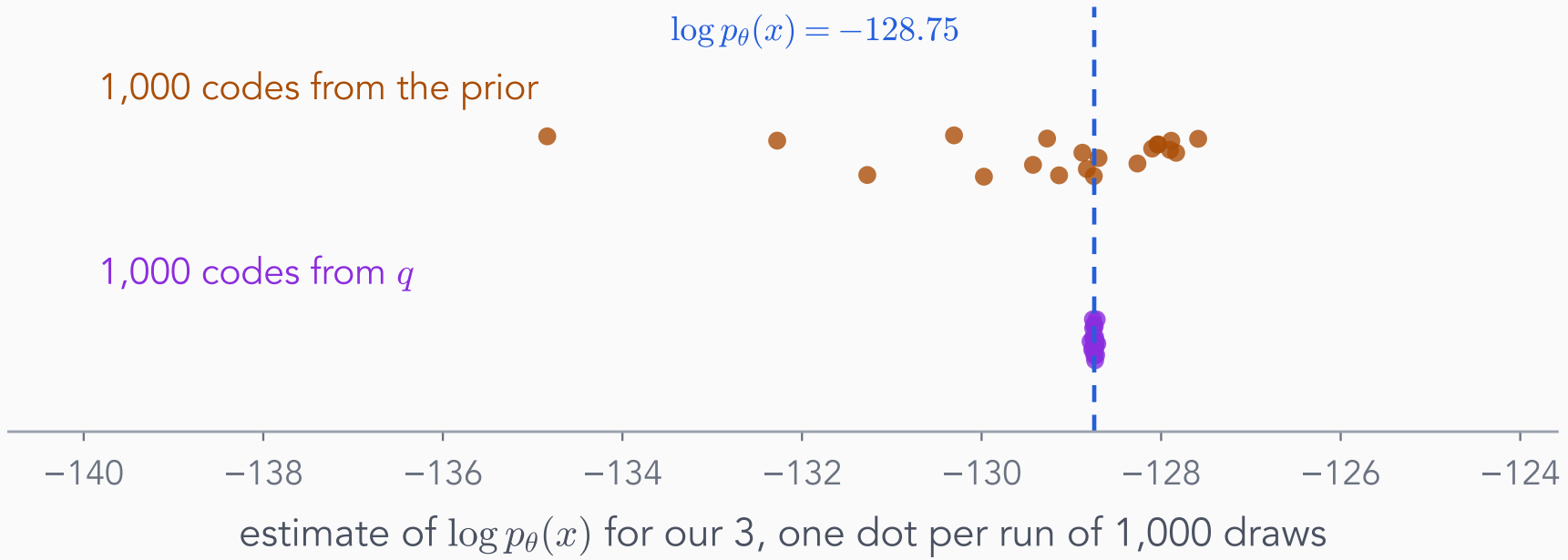
Sample codes where the patch is, then reweight

$$p_\theta(x) = \int q(z)\,\frac{p(z)\,p_\theta(x \mid z)}{q(z)}\,dz = \mathbb{E}_{z\sim q}\left[\frac{p_\theta(x,z)}{q(z)}\right] \approx \frac{1}{S}\sum_{s=1}^{S}\frac{p_\theta(x,z_s)}{q(z_s)}$$

A BONUS: WITH q, EVEN $p_\theta(x)$ BECOMES EASY TO ESTIMATE

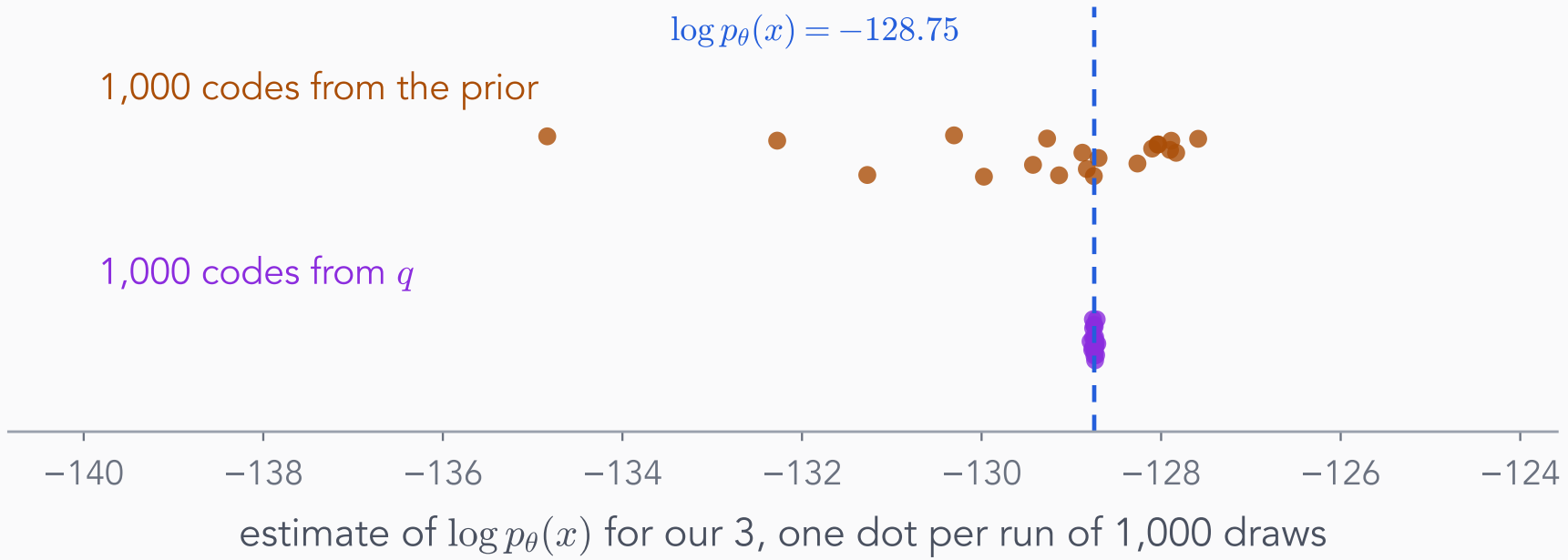
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20 runs of 1,000 draws each. From the prior, the estimates scatter from −134.8 to −127.6. From q: −128.74, give or take 0.017.

800 STEPS FOR ONE IMAGE

Amortised inference: learn to predict q

VI by hand: one optimisation per image



× 60,000 training images, redone each time the decoder changes, and again for every new image

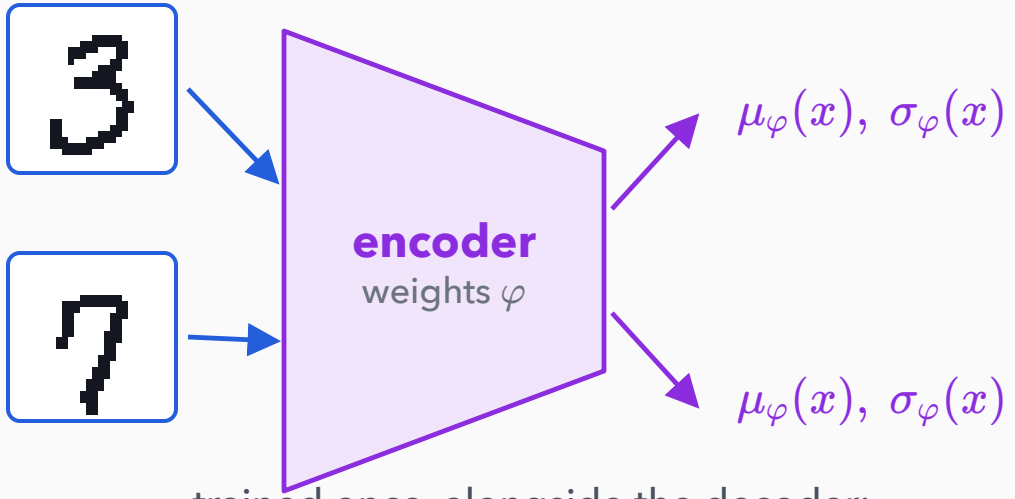
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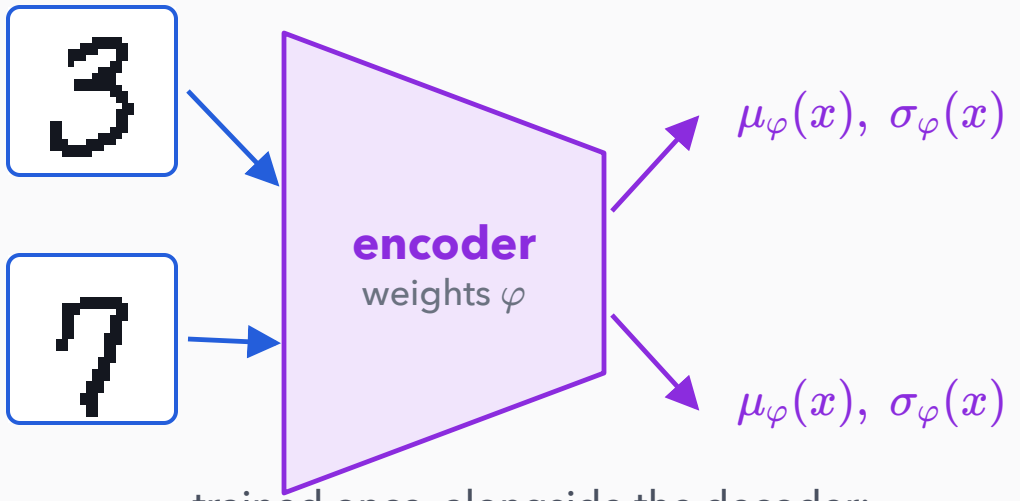
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> Our 3: ELBO −128.83 by hand in 800 steps, −129.3 from the encoder in one pass. Pay once during training; a little worse, thousands of times cheaper.

PUT THE PIECES TOGETHER

Encoder + decoder + ELBO = the variational autoencoder

$$\max_{\theta,\varphi} \sum_{i=1}^{N} \left(\mathbb{E}_{z \sim q_\varphi(z|x_i)} \left[\log p_\theta(x_i \mid z) \right] - \mathrm{KL}\left(q_\varphi(z \mid x_i) \,\|\, p(z) \right) \right)$$

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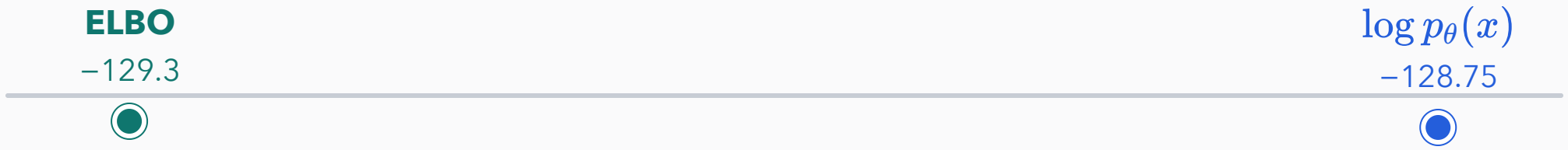
Trained together

Pushing on θ raises the ELBO mostly by making the data more probable: a better model. Pushing on φ shrinks the gap: a better q.

> **Kingma & Welling (2014) and Rezende et al. (2014): one network for the likelihood, one for the posterior, one loss for both.**

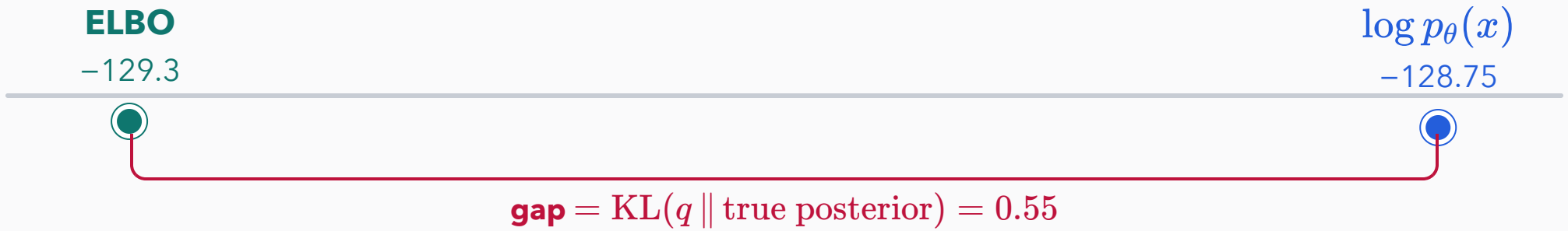
THE GAP FOR THE ENCODER'S q, MEASURED ON OUR 3

Two different KLs, two different jobs



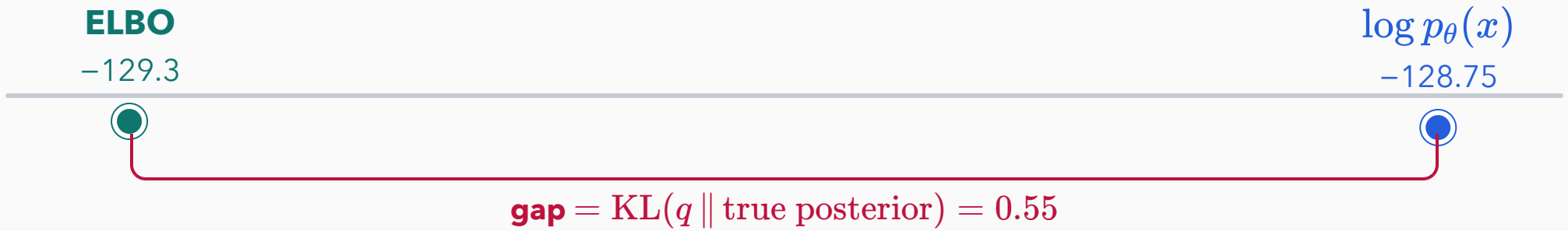
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Two different KLs, two different jobs



In the loss: $\mathrm{KL}(q \,\|\, \text{prior}) = 6.97$ nats.
Computable by formula.

In the gap: $\mathrm{KL}(q \,\|\, \text{true posterior}) = 0.55$ nats.
Needs $p_\theta(x)$; we only got it from the grid.

> **VI by hand closed the gap to 0.08 nats in 800 steps; the encoder's single pass leaves 0.55. That small loss is the price of amortising.**

END OF PART 5

What we did, and what comes next

WHAT WE DID

1. Our 3: $\log p_\theta(x) = \mathrm{ELBO} + \mathrm{KL}(q \,\|\, \mathrm{posterior})$, as in the VI lecture.
2. ELBO = reconstruction $-\ \mathrm{KL}(q \,\|\, \mathrm{prior})$: both computable.
3. VI by hand fits our 3's q in 800 steps and leaves a gap of 0.08 nats.
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NEXT: GRADIENTS THROUGH A RANDOM DRAW

The loss draws z from the encoder's cloud. Part 6: the VI lecture's reparameterisation, with μ and $\log \sigma^2$ coming out of a network.

PART 6 OF 7

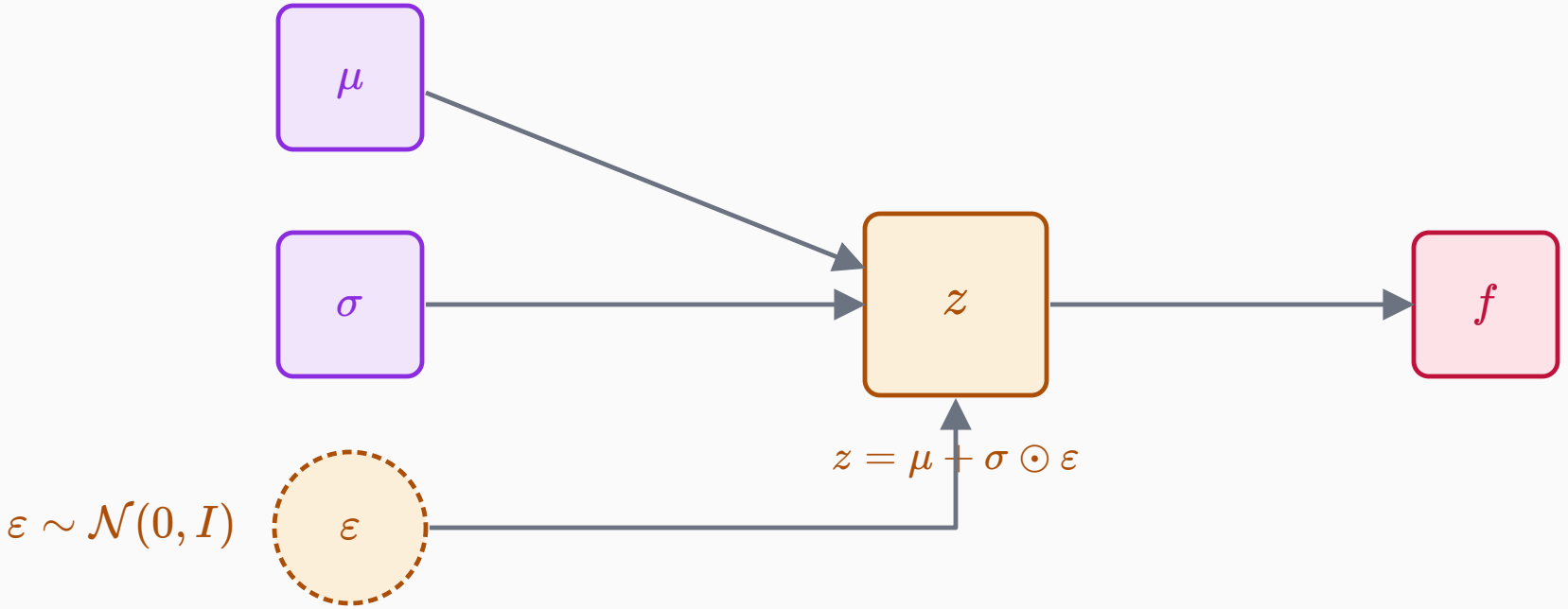
Backpropagating through the encoder's random draw

VI by hand drew each code as $m + s \cdot \varepsilon$ and backpropagated through it: the VI lecture's reparameterisation trick (its Part 5). The VAE does the same, except that μ and σ come out of the encoder, as $\log \sigma^2$. One recalled picture, one more link in the chain, and three lines of PyTorch.

✓ Distributions and fitting
✓ Autoencoders
✓ The probabilistic view
✓ KL divergence
✓ Variational inference and the ELBO
6 **Reparameterisation**
7 The VAE on MNIST

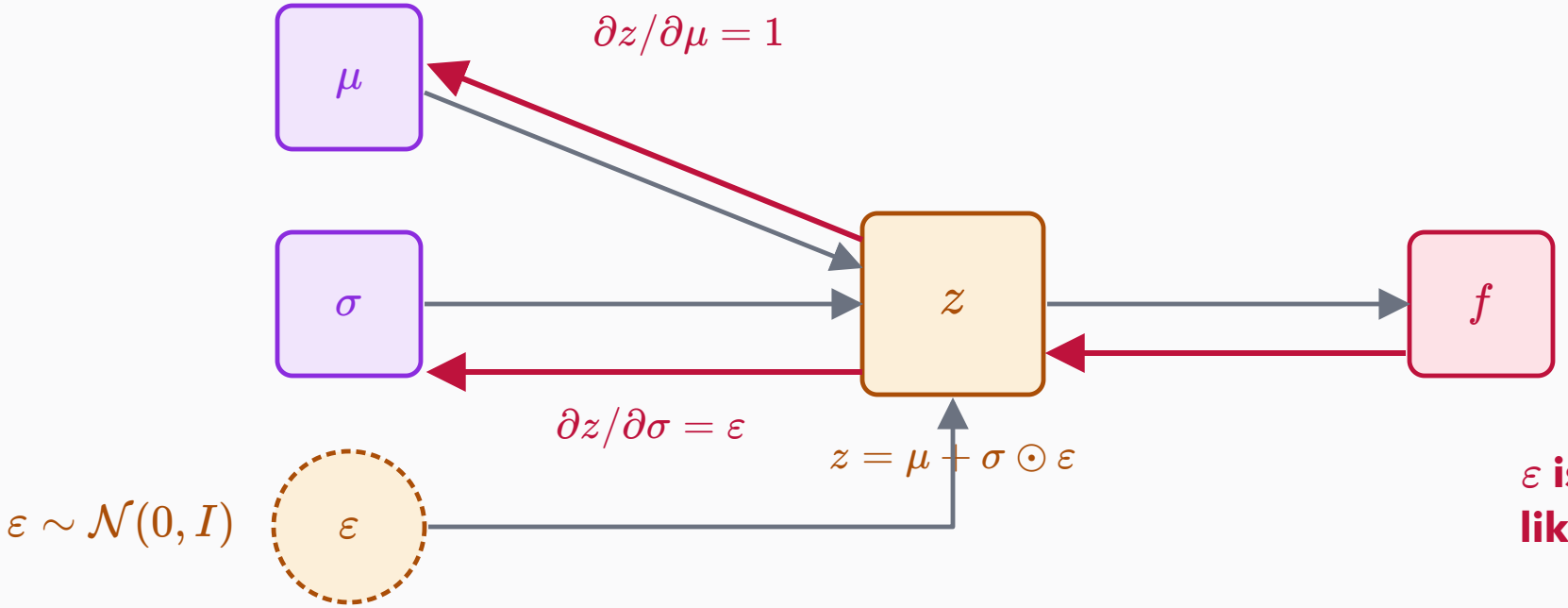
FROM THE VI LECTURE, PART 5, WITH THE ENCODER IN FRONT

Draw ε first, and the path back to μ and σ is arithmetic



FROM THE VI LECTURE, PART 5, WITH THE ENCODER IN FRONT

Draw ε first, and the path back to μ and σ is arithmetic



> As the VI lecture showed, `sample()` would cut the graph at z. Each draw gives a noisy gradient; on average it is exact.

The encoder outputs $v = \log \sigma^2$, not σ

$$\sigma = e^{v/2}$$

v can be any real number; σ is always positive

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derivative of $e^{v/2}$

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one more chain-rule factor after $\partial z / \partial \sigma = \varepsilon$

$$\frac{\partial z_1}{\partial v_1} = 0.62 \times \frac{0.047}{2} = 0.015$$

our 3: $v_1 = -6.11$, so $\sigma_1 = 0.047$; this draw's $\varepsilon_1 = 0.62$

Autograd adds this factor for us: in code it is the one line `std = torch.exp(0.5 * logvar)`.

IN PYTORCH

Three lines

```
# encoder outputs, shape [B, 2] each
mu, logvar = encoder(x)
std = torch.exp(0.5 * logvar)     # sigma = exp(v / 2)
eps = torch.randn_like(std)       # standard normal, no grad
z   = mu + std * eps              # differentiable in mu, std
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`Normal(mu, std).rsample()` does the same thing, as in the VI lecture; `.sample()` drops the gradient.

For our 3: $\mu = (0.3,\ -1.93)$, $\varepsilon = (0.62,\ -1.15)$ gives $z = (0.33,\ -1.99)$.

END OF PART 6

What we did, and what comes next

WHAT WE DID

1. From the VI lecture: sampling z directly cuts the gradient path; $z = \mu + \sigma\varepsilon$ with $\varepsilon \sim \mathcal{N}(0, I)$ keeps it.
2. $\partial z/\partial \mu = 1$ and $\partial z/\partial \sigma = \varepsilon$; one draw is noisy, the average is exact.
3. The encoder outputs $v = \log \sigma^2$: one more factor, $\partial \sigma/\partial v = \sigma/2$.
4. In PyTorch: three lines, or `rsample()`.

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NEXT: EVERYTHING TOGETHER

Encoder, cloud, reparameterised sample, decoder, ELBO: train it on MNIST and follow our 3 through every step.

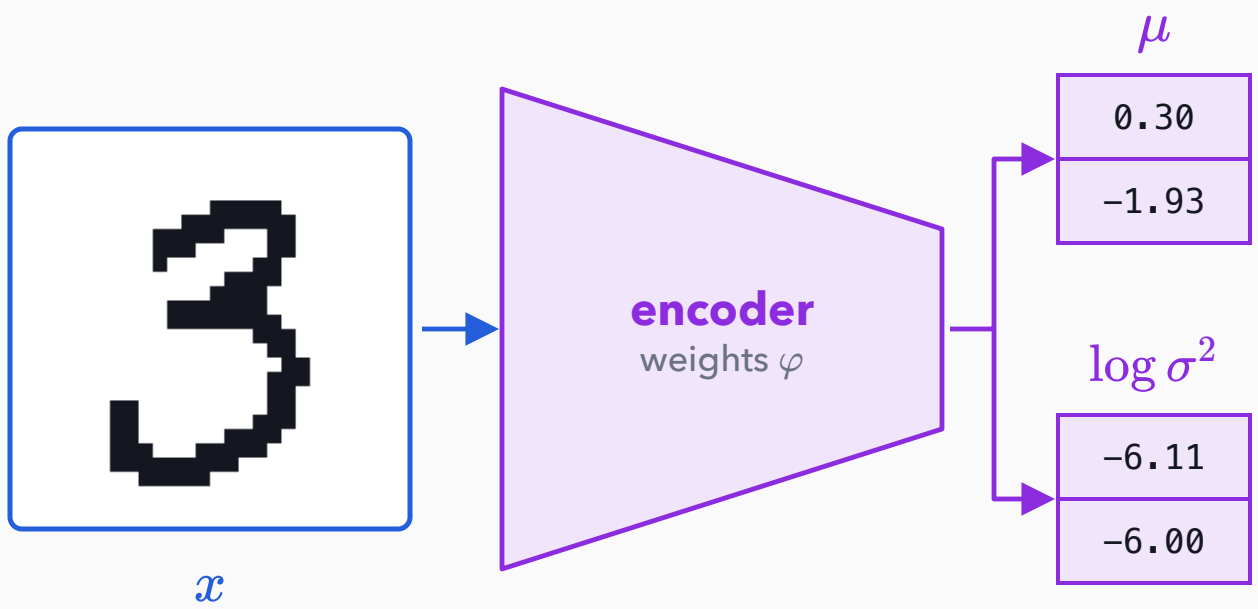
PART 7 OF 7

The variational autoencoder, end to end

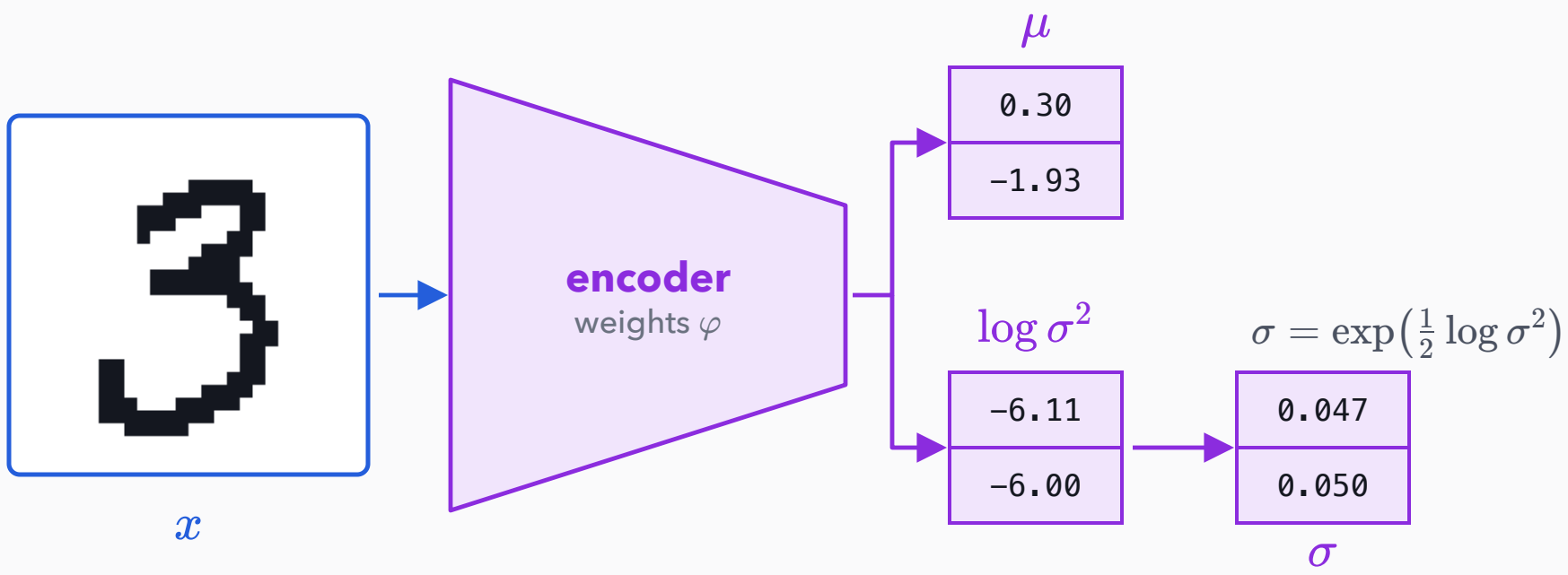
Every piece is in place: encoder, cloud, KL, ELBO, reparameterisation. Follow our 3 through the trained network, then generate.

- ✓ Distributions and fitting
- ✓ Autoencoders
- ✓ The probabilistic view
- ✓ KL divergence
- ✓ Variational inference and the ELBO
- ✓ Reparameterisation
- 7 **The VAE on MNIST**

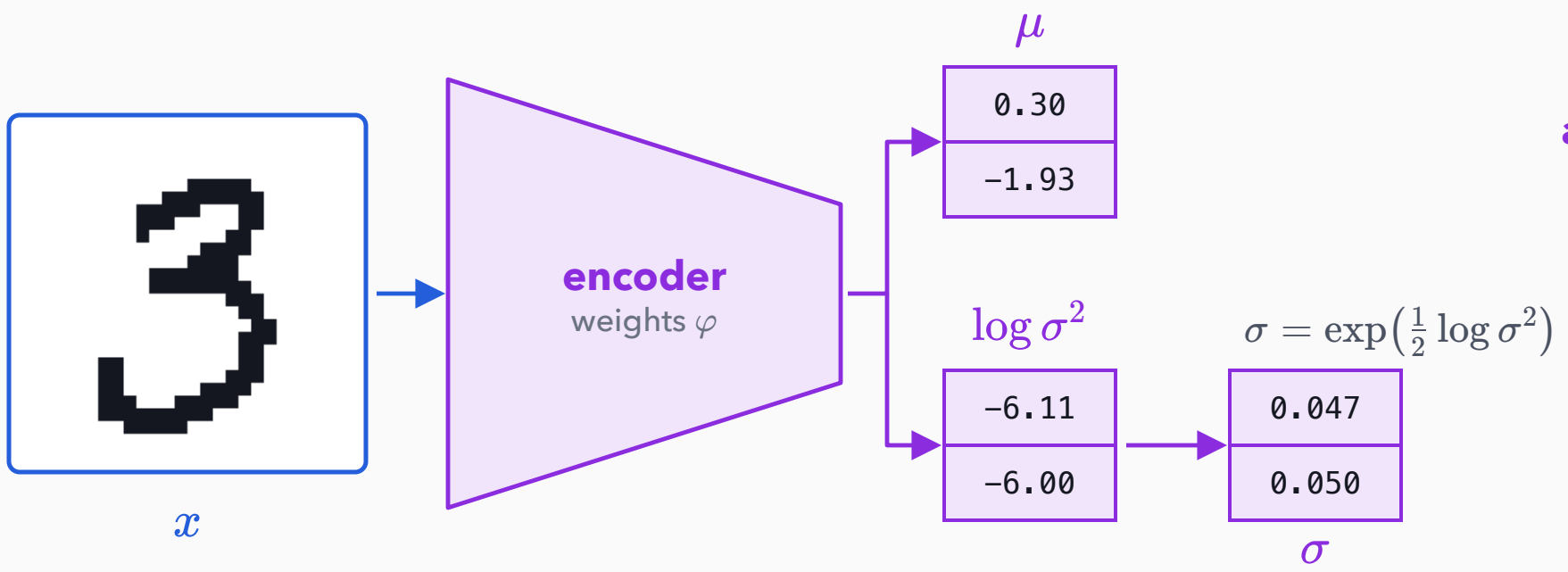
Encode: the image becomes a cloud



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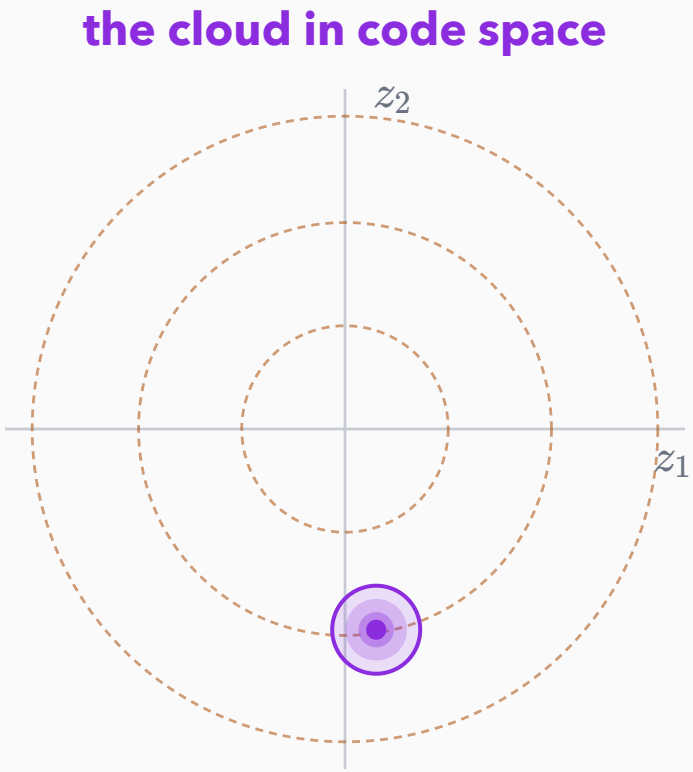


a cloud centred at μ with width σ:

$$q_\varphi(z \mid x) = \mathcal{N}(\mu, \sigma^2)$$

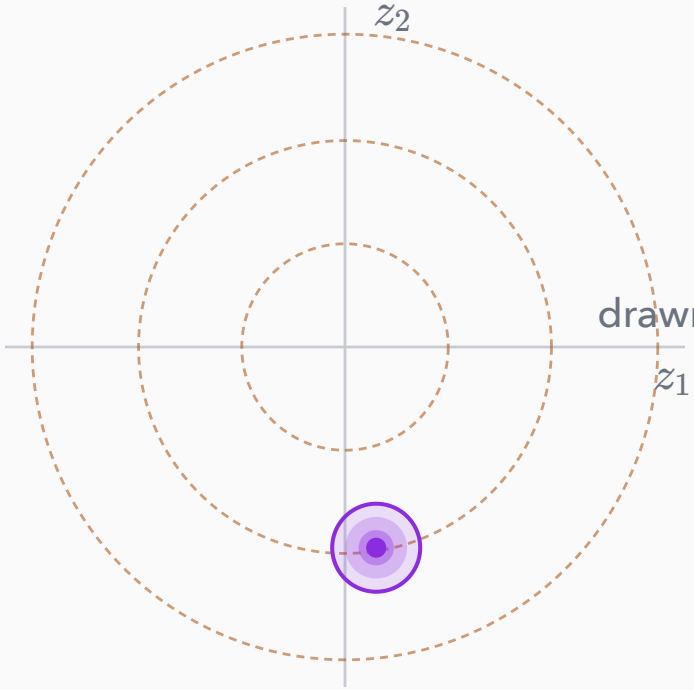
$\sigma \approx 0.05$ against the prior's $\sigma = 1$: the encoder is very sure where our 3 belongs.

Sample: one code from inside the cloud



Sample: one code from inside the cloud

the cloud in code space



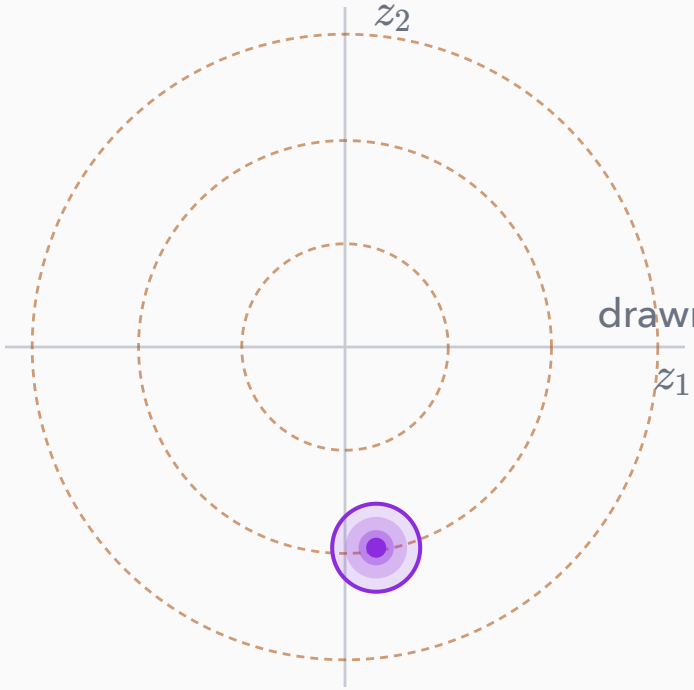


$\varepsilon = (0.62,\ -1.15)$

drawn from a standard normal once

Sample: one code from inside the cloud

the cloud in code space



ε

$\varepsilon = (0.62,\ -1.15)$

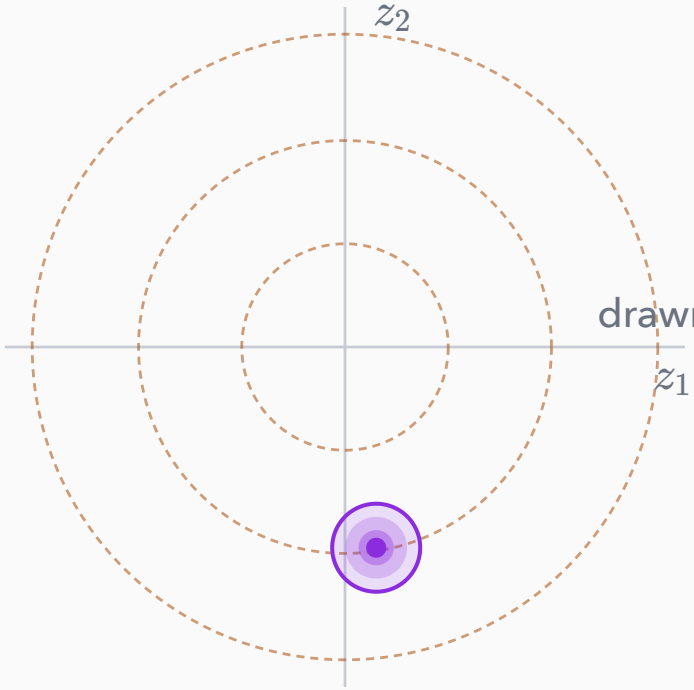
drawn from a standard normal once

$$z_1 = \mu_1 + \sigma_1 \varepsilon_1$$

$$= 0.30 + 0.047 \times 0.62 = 0.33$$

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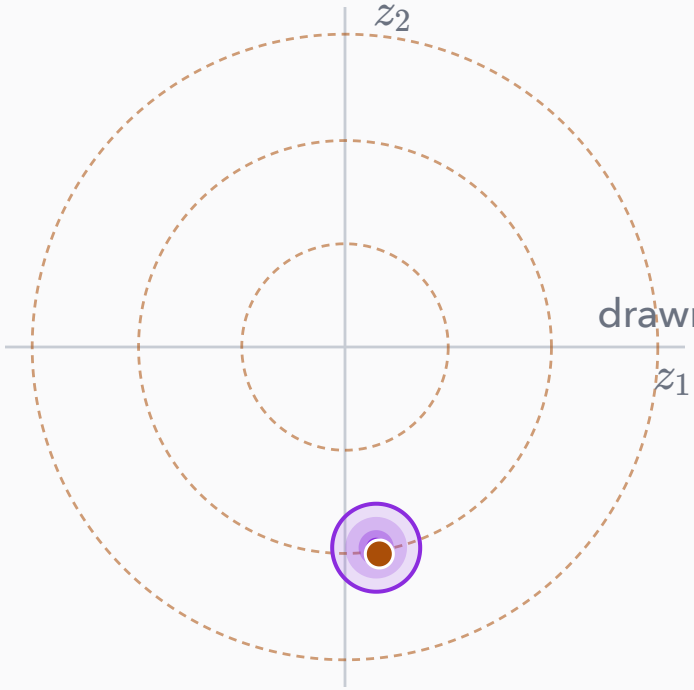
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$$z_1 = \mu_1 + \sigma_1 \varepsilon_1$$
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$$z_2 = \mu_2 + \sigma_2 \varepsilon_2$$
$$= -1.93 + 0.050 \times (-1.15) = -1.99$$

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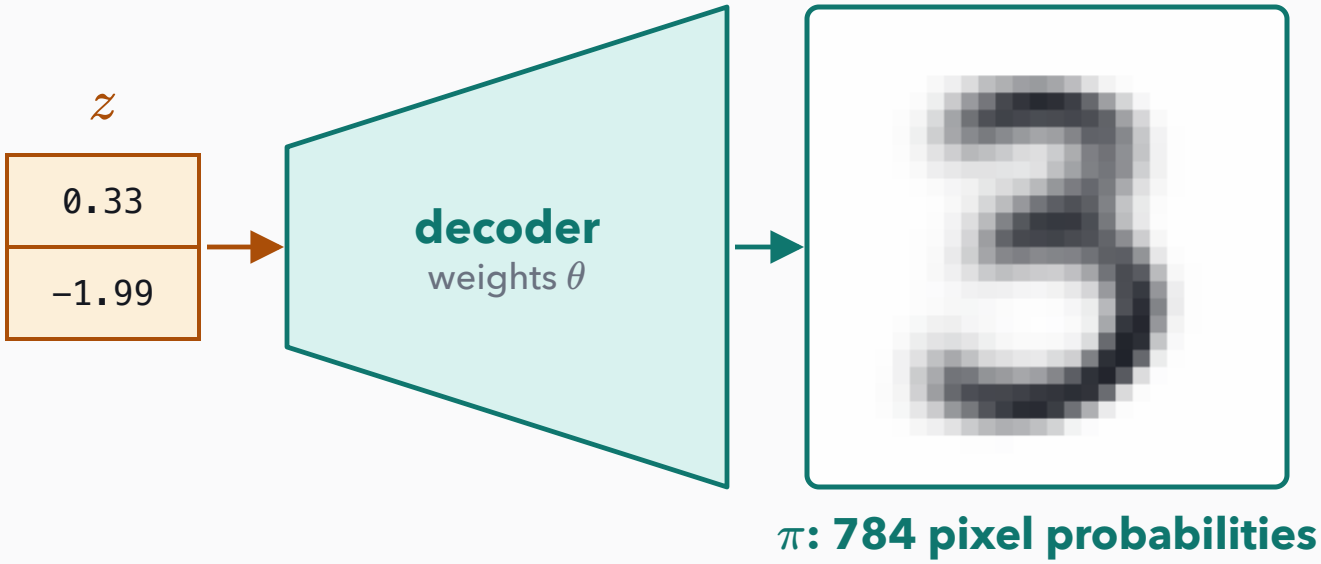
$$z_2 = \mu_2 + \sigma_2 \varepsilon_2$$
$$= -1.93 + 0.050 \times (-1.15) = -1.99$$

$z =$

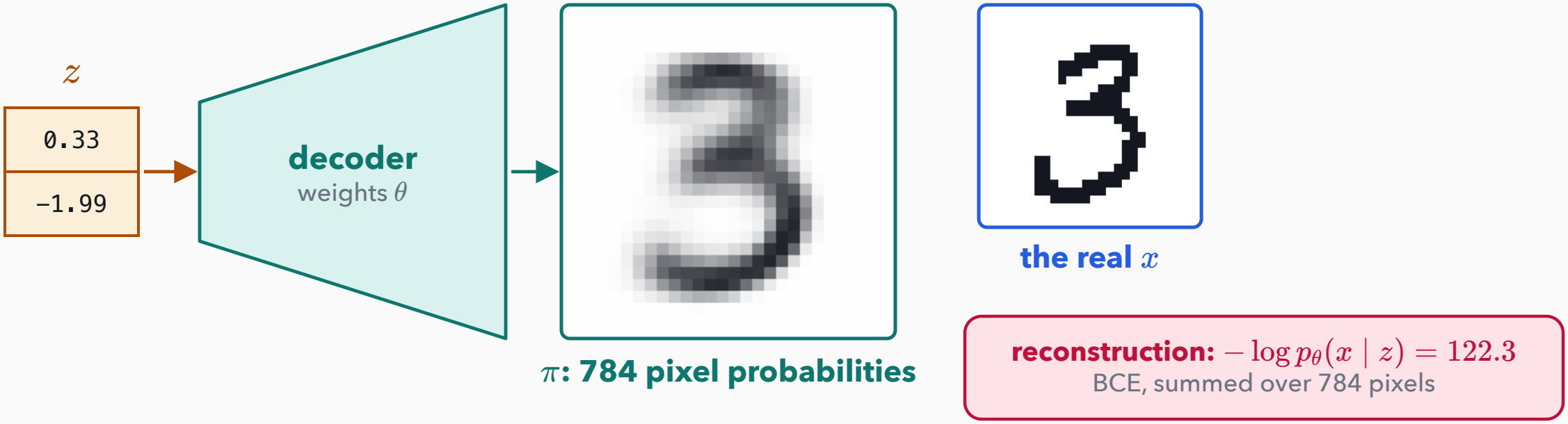
0.33	-1.99

one code from inside the cloud

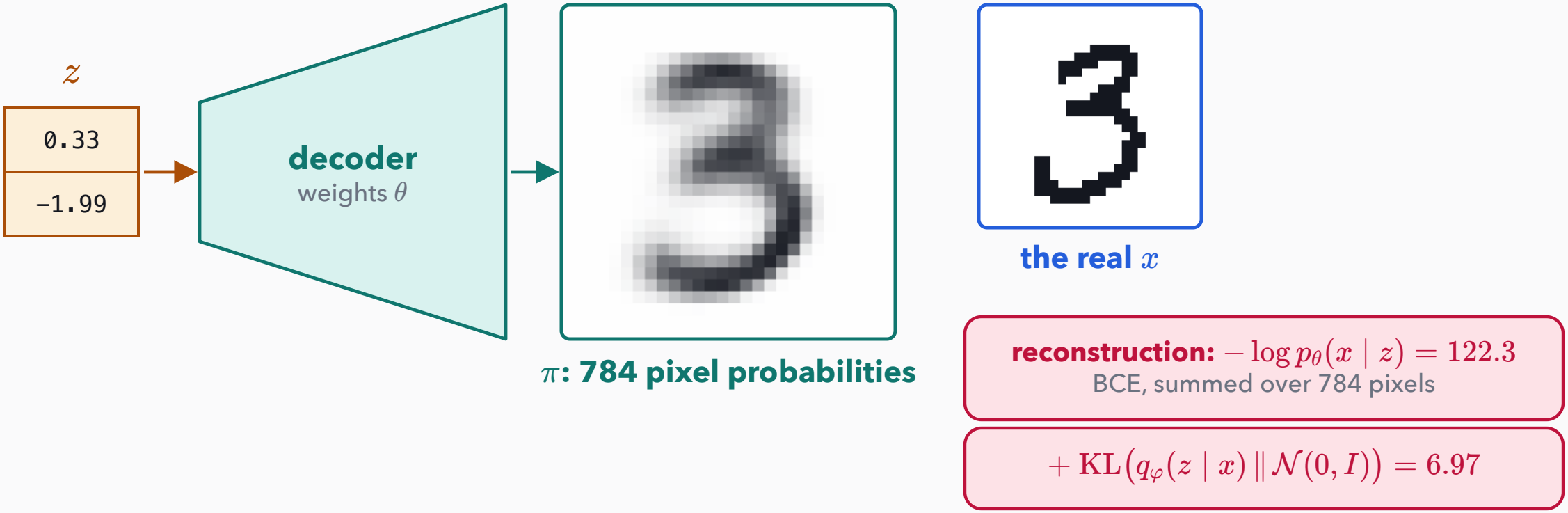
Decode, then score against the real 3



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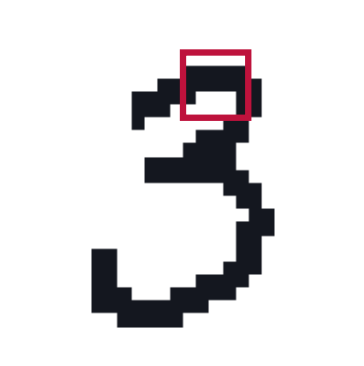
Decode, then score against the real 3



Loss for our 3: $122.3 + 6.97 = 129.3$ **nats. Backpropagate it into both** θ **and** φ**.**

STEP 3, ZOOMED IN: THE RECONSTRUCTION TERM

Each pixel is a coin flip with probability π_i



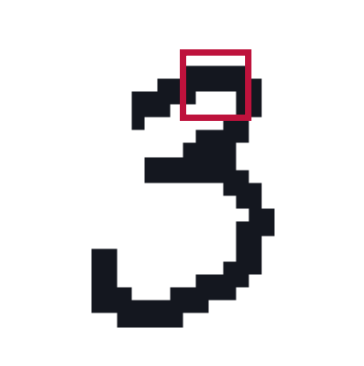
our 3, one 5 × 5 patch

observed x_i

0	0	0	0	0
1	1	1	1	1
1	1	1	1	1
1	0	0	0	1
0	0	0	0	1

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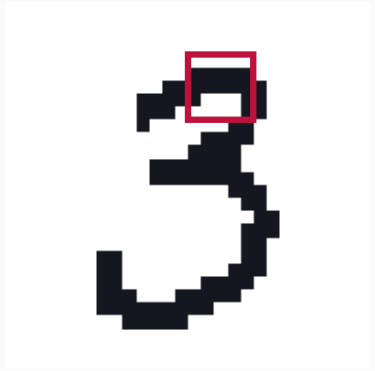
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1	1	1	1	1
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decoder's π_i

0.38	0.28	0.13	0.05	0.02
0.89	0.82	0.65	0.41	0.18
0.77	0.79	0.76	0.67	0.40
0.41	0.52	0.67	0.66	0.51
0.22	0.35	0.55	0.60	0.48

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0.41	0.52	0.67	0.66	0.51
0.22	0.35	0.55	0.60	0.48

$-\log p(x_i \mid z)$

0.48	0.33	0.14	0.05	0.02
0.12	0.20	0.43	0.89	1.71
0.26	0.24	0.27	0.40	0.92
0.89	0.73	1.11	1.08	0.67
0.25	0.43	0.80	0.92	0.73

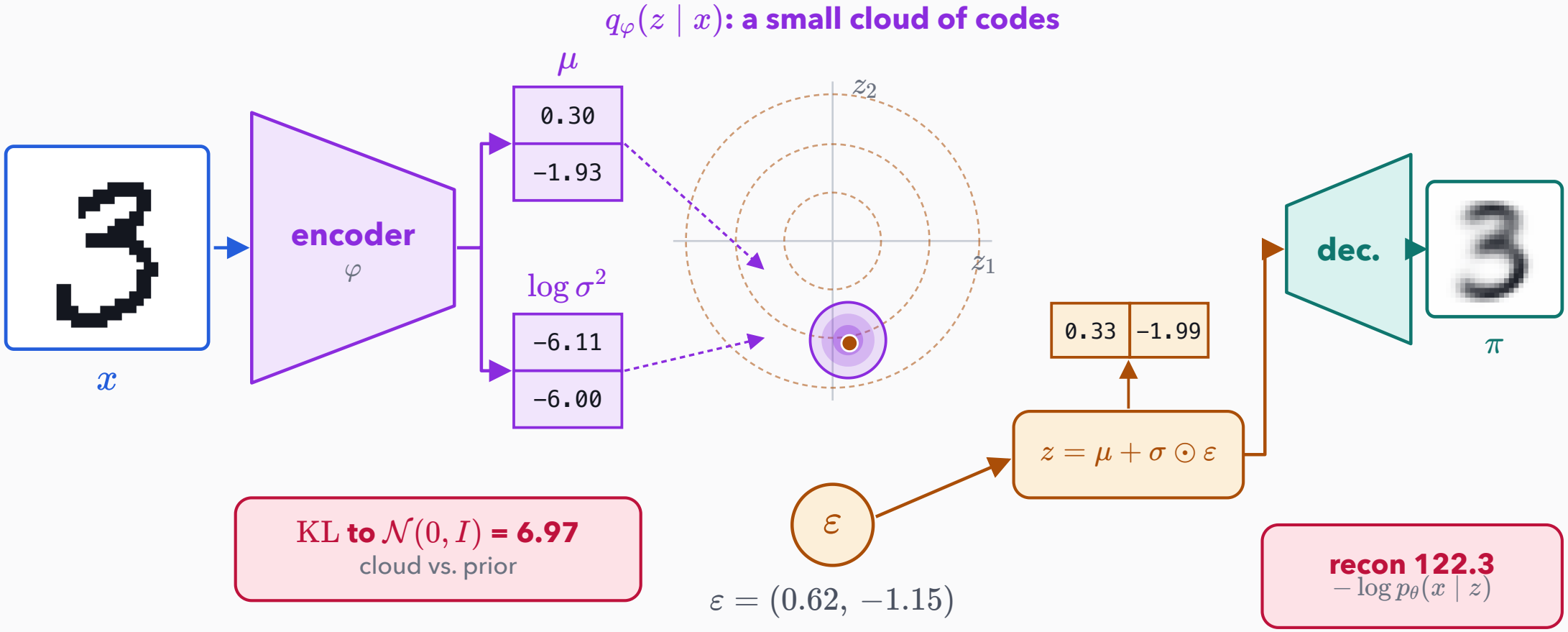
this 5 × 5 patch: 14.1 nats

$$-\log p_\theta(x \mid z) = -\sum_{i=1}^{784} \Big[x_i \log \pi_i + (1 - x_i) \log(1 - \pi_i) \Big] = 122.3 \text{ nats}$$

> **Binary cross-entropy is not a design choice: it is the Bernoulli log-likelihood. Gaussian pixels would give squared error.**

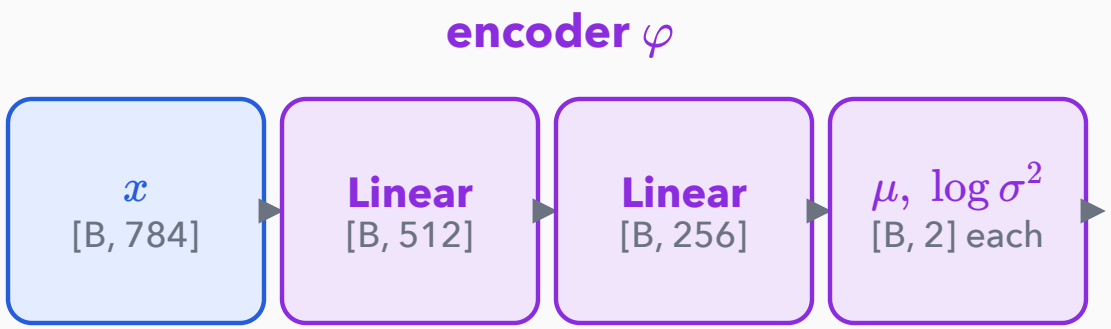
ALL THREE STEPS ON ONE PAGE

The whole VAE, for our 3



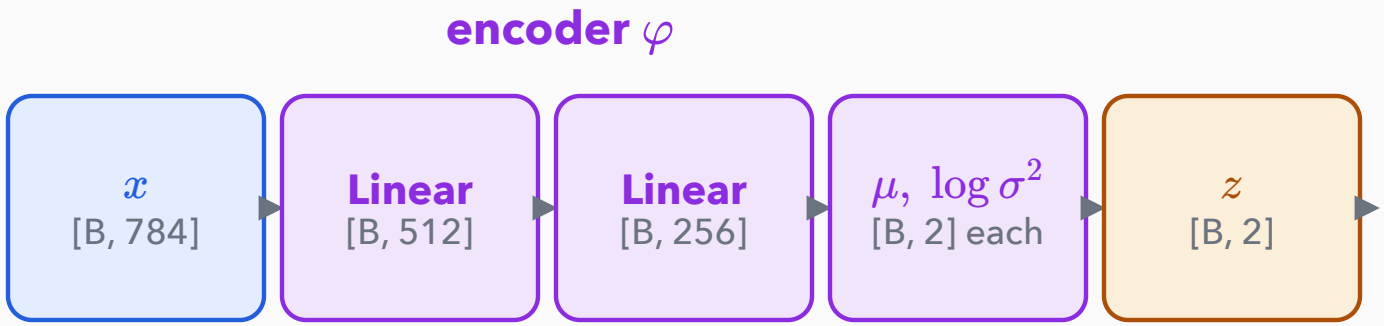
THE SAME NETWORK AS TENSORS

Shapes, layer by layer



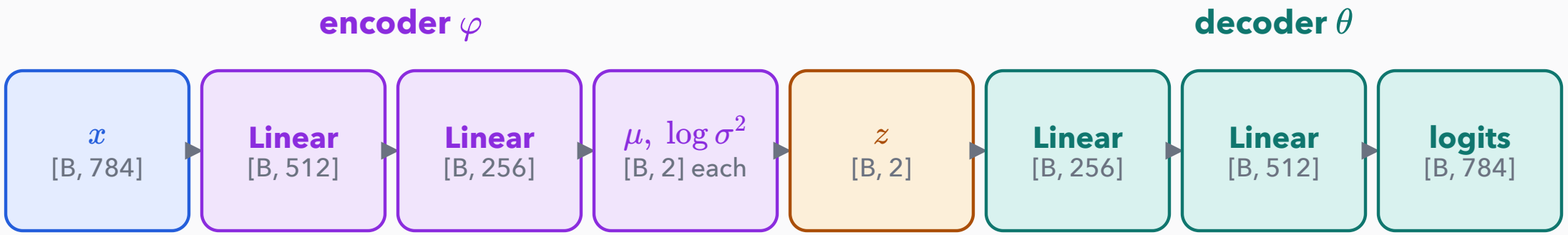
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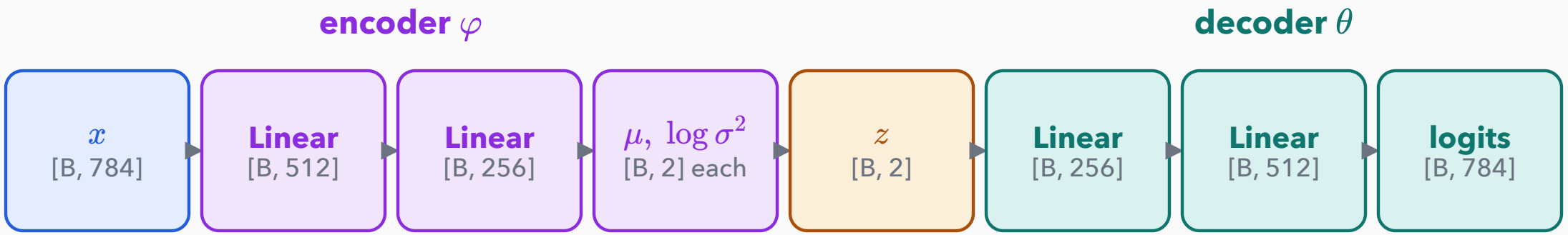
THE SAME NETWORK AS TENSORS

Shapes, layer by layer



THE SAME NETWORK AS TENSORS

Shapes, layer by layer



B = batch size. Only the 2 in the middle is the code; ε has the same shape as μ.

Loss per image: BCE summed over 784 pixels + KL summed over 2 coordinates.
Then average over the B images in the batch.

THE KL TERM FOR OUR 3

A tight cloud is expensive

$$\mathrm{KL} = \tfrac{1}{2} \sum_{j} \left(\mu_j^2 + \sigma_j^2 - 1 - \log \sigma_j^2 \right)$$

coordinate	μ_j	σ_j	μ_j^2	$\sigma_j^2 - 1$	$-\log \sigma_j^2$	$\frac{1}{2}(\text{sum})$

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z_1	0.3	0.047	0.09	-1.00	6.11	**2.6**

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z_2	−1.93	0.05	3.72	-1.00	6.00	**4.37**
total						**6.97 nats**

$$-\log\sigma_1^2 = -\log(0.047^2) = -\log 0.0022 = 6.11$$

> **Most of the cost is $-\log\sigma^2$: the price of being precise. Reconstruction wants precision; the KL resists.**

ONE TRAINING STEP

The whole algorithm fits on a slide

```
mu, logvar = model.encoder(x)              # [B,2], [B,2]
z = mu + torch.exp(0.5*logvar) * torch.randn_like(mu)
logits = model.decoder(z)                  # [B,784]
recon = F.binary_cross_entropy_with_logits(
          logits, x.flatten(1), reduction="none").sum(1)
kl = 0.5 * (mu**2 + logvar.exp() - 1 - logvar).sum(1)
loss = (recon + kl).mean()                 # per image, then batch
opt.zero_grad(); loss.backward(); opt.step()
```

Encode, reparameterise, decode.

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```

Sum the BCE over all 784 pixels of each image.

ONE TRAINING STEP

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loss = (recon + kl).mean()                 # per image, then batch
opt.zero_grad(); loss.backward(); opt.step()
```

Sum the KL over the 2 code coordinates of each image.

ONE TRAINING STEP

The whole algorithm fits on a slide

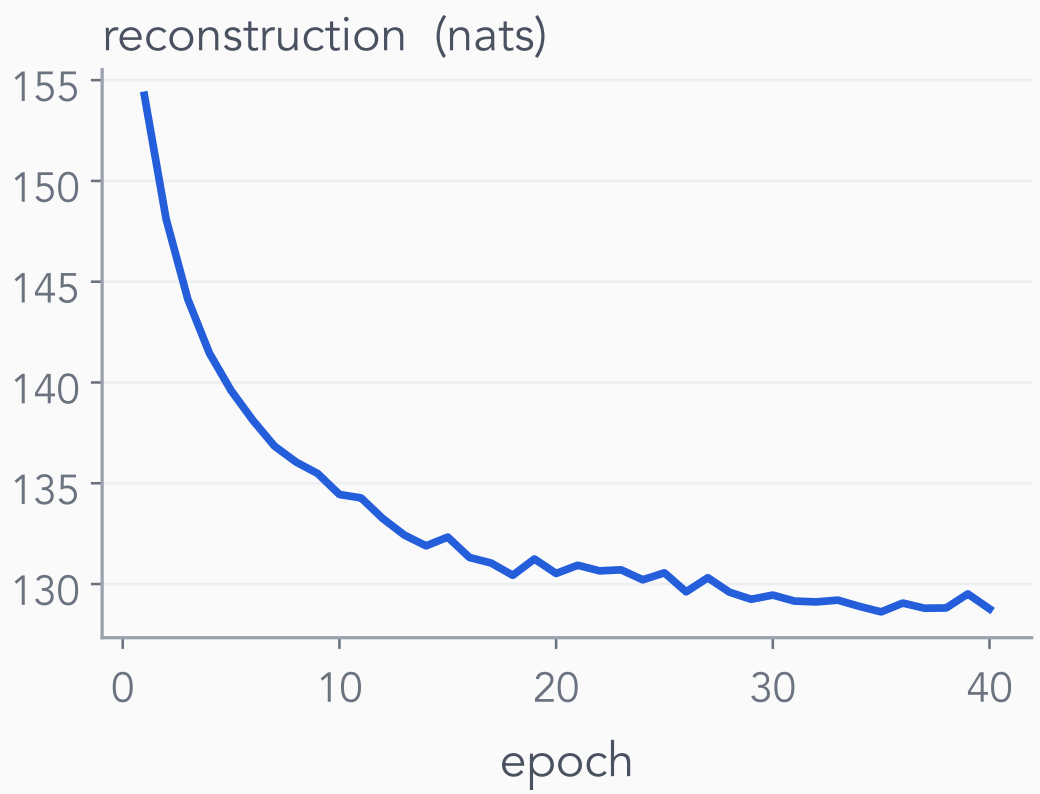
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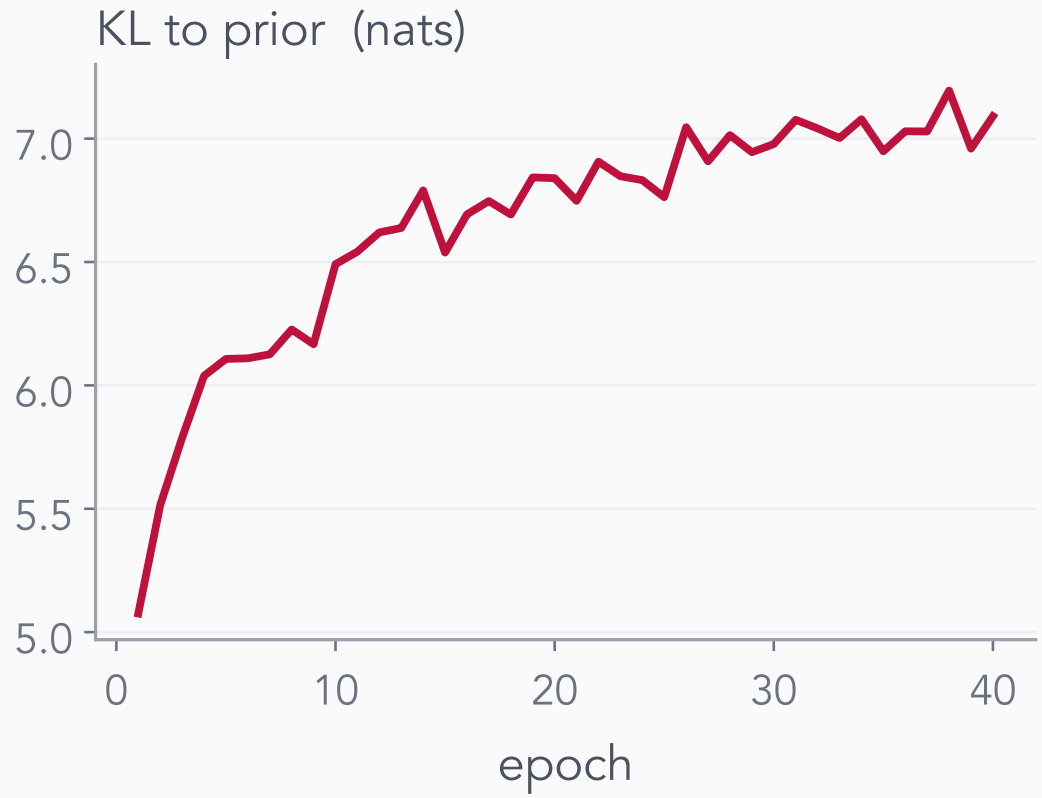
Add per image, average over the batch, step both encoder and decoder.

Averaging BCE over pixels instead of summing silently makes the KL 784× stronger.

TRAINING RUN, TEST SET

Reconstruction falls, KL rises, then both settle

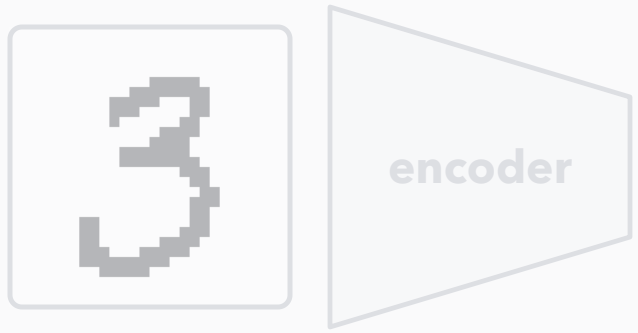




After 40 epochs: reconstruction 128.8 + KL 7.1 = 135.9 nats per test image.

THE PAYOFF

Generate: random code → decoder. No encoder.

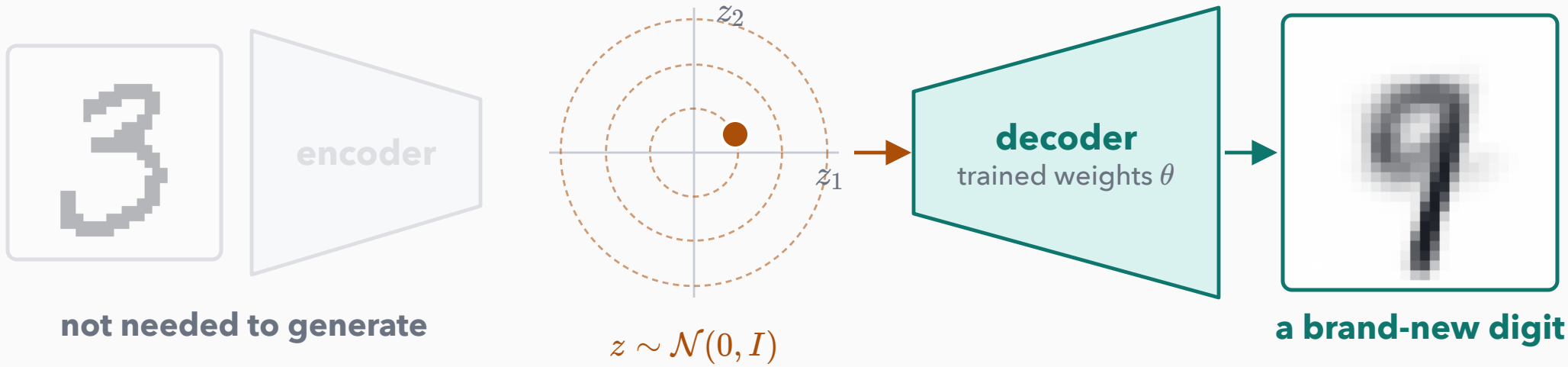


not needed to generate

> This is the whole generator. The encoder was scaffolding for training.

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This is the whole generator. The encoder was scaffolding for training.

48 RANDOM CODES EACH

Samples from two VAEs



2-number code · reconstruction 128.8

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Samples from two VAEs



2-number code · reconstruction 128.8

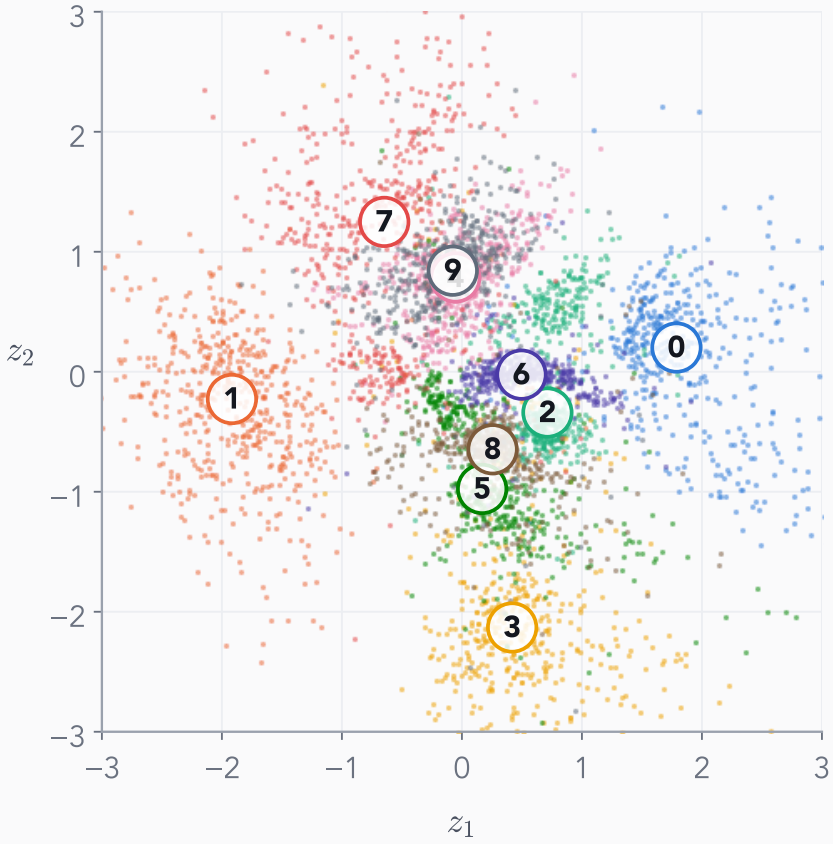


16-number code · reconstruction 57.8

More code dimensions: sharper and more varied, but some samples are odd. Neither is perfect.

BECAUSE THE CODE IS 2-D, WE CAN DRAW THE WHOLE MAP

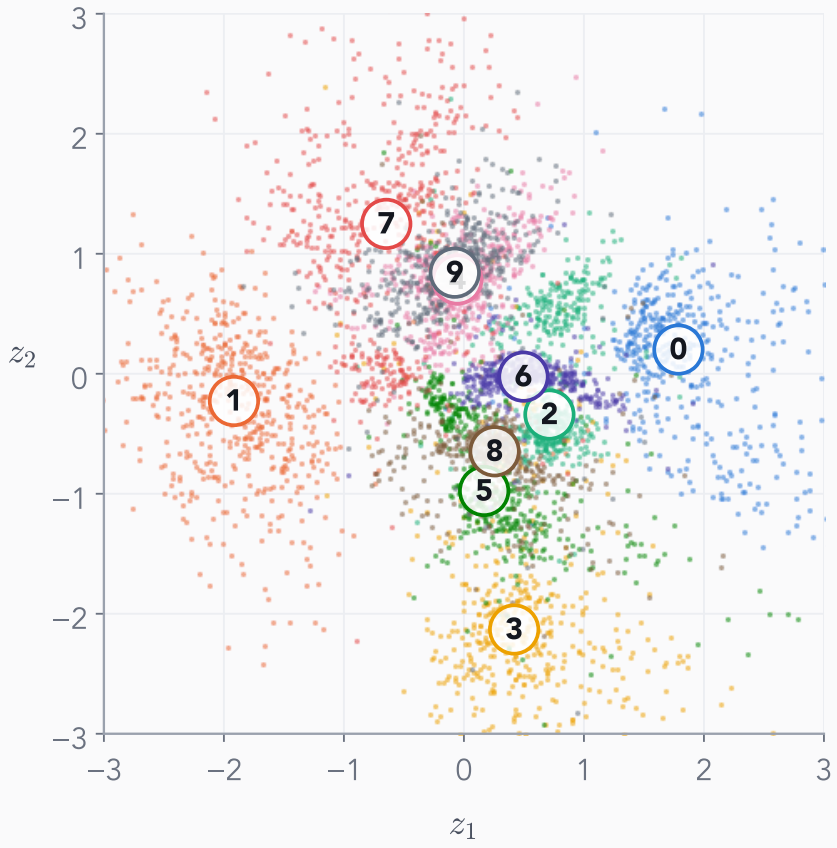
Every point in the code space is a digit



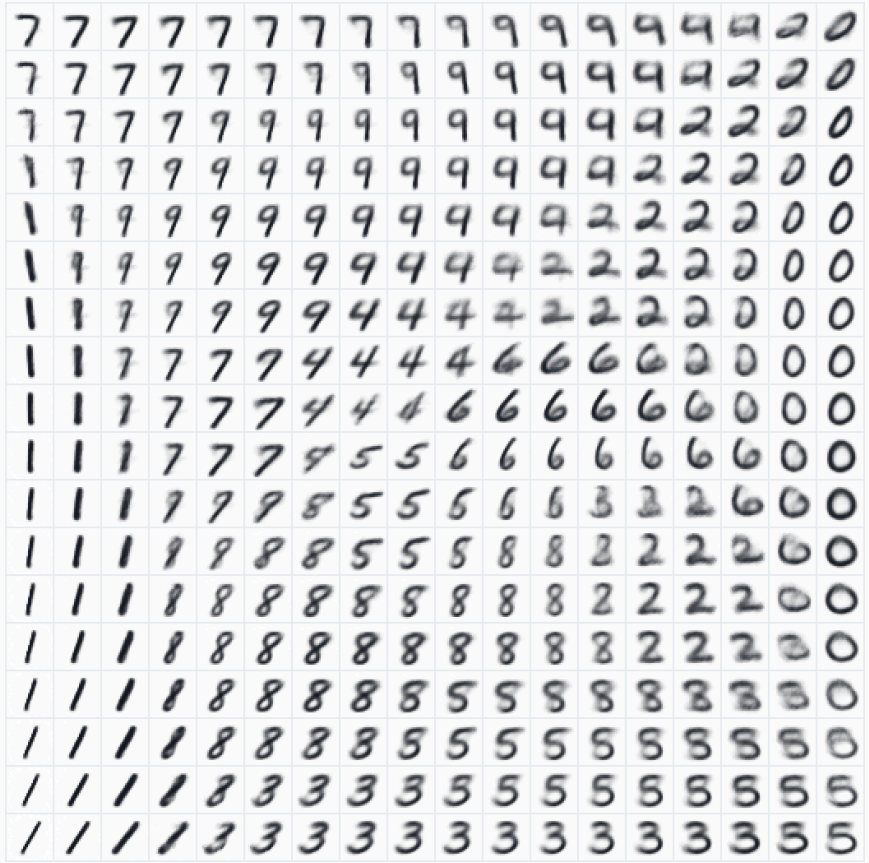
where test digits land

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where test digits land

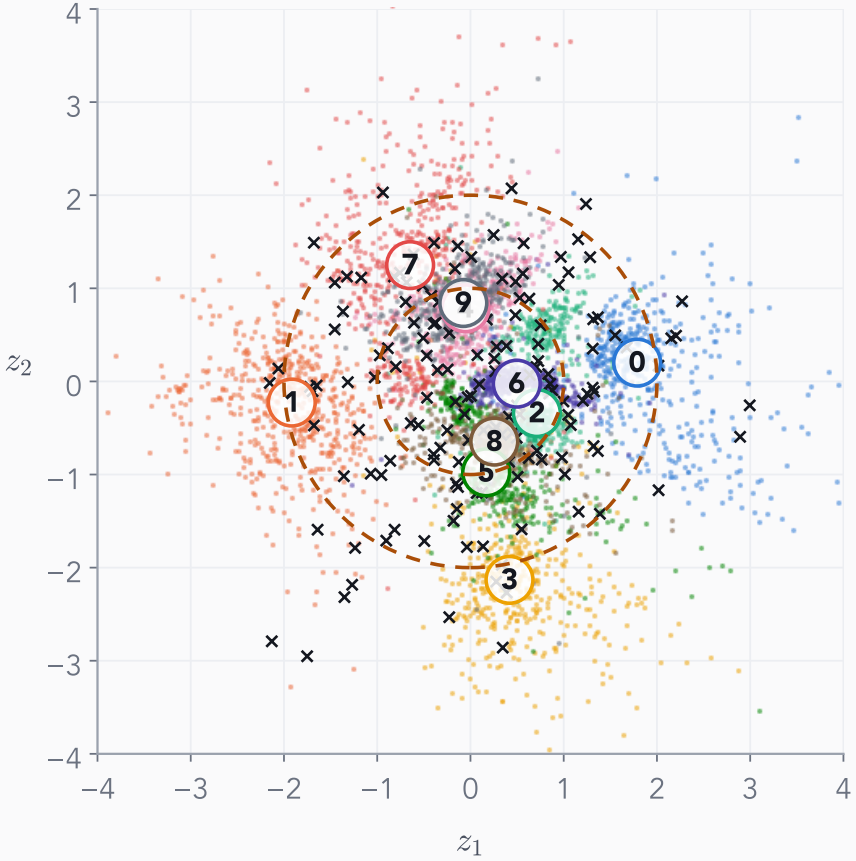


decoded on an 18 × 18 grid, spaced by quantiles of $\mathcal{N}(0, 1)$

Neighbouring codes give similar digits, and every region decodes to something plausible.

TRY IT: THE TRAINED VAE, IN YOUR BROWSER

The same app, now for the VAE



Now random codes from $\mathcal{N}(0, I)$ land among the dots, and almost every one decodes to a digit.

THE COVER, EXPLAINED

Walk in a straight line from our 3 to a 7



encode both, take 12 evenly spaced points between their μ's, decode each (16-number VAE)

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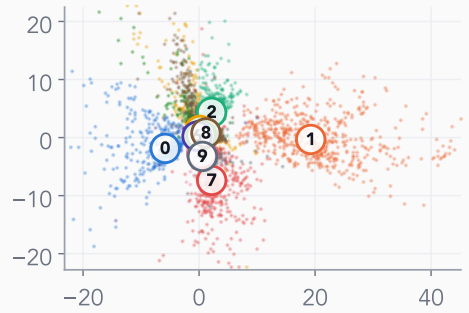


the same walk in the 2-number VAE: the line passes through the 5, 8, 4 and 9 regions on the map

THE TUG OF WAR, MADE VISIBLE

No KL, normal KL, too much KL

autoencoder (no KL)



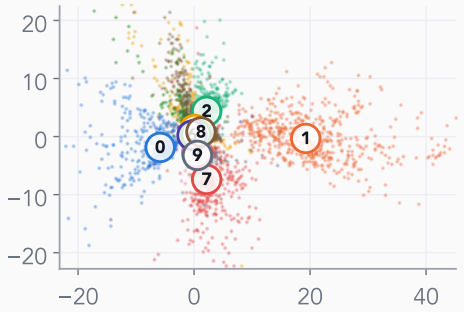


recon 128.1 · no KL term

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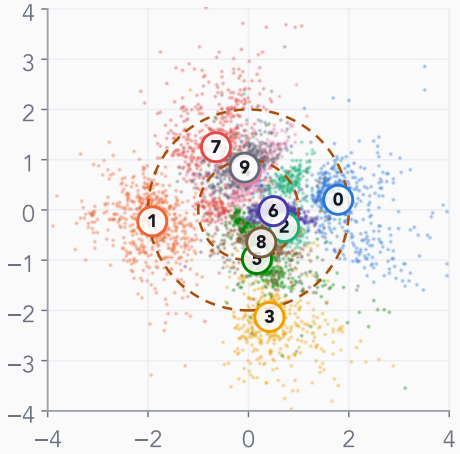
autoencoder (no KL)





recon 128.1 · no KL term

VAE, loss = recon + KL



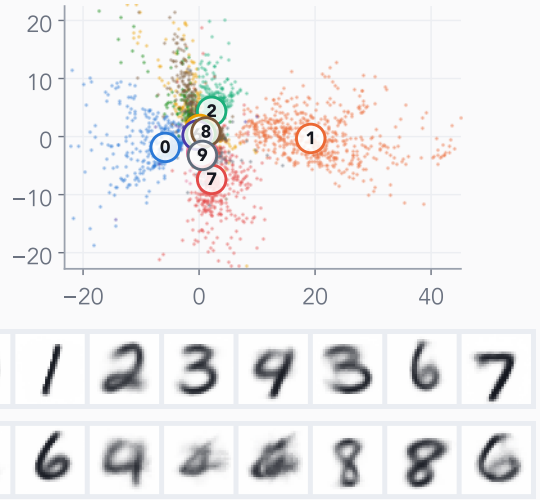


recon 128.8 · KL 7.1

THE TUG OF WAR, MADE VISIBLE

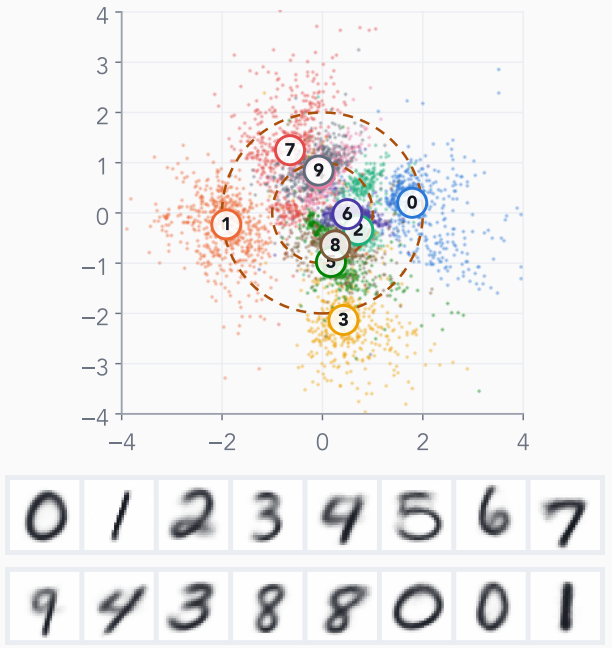
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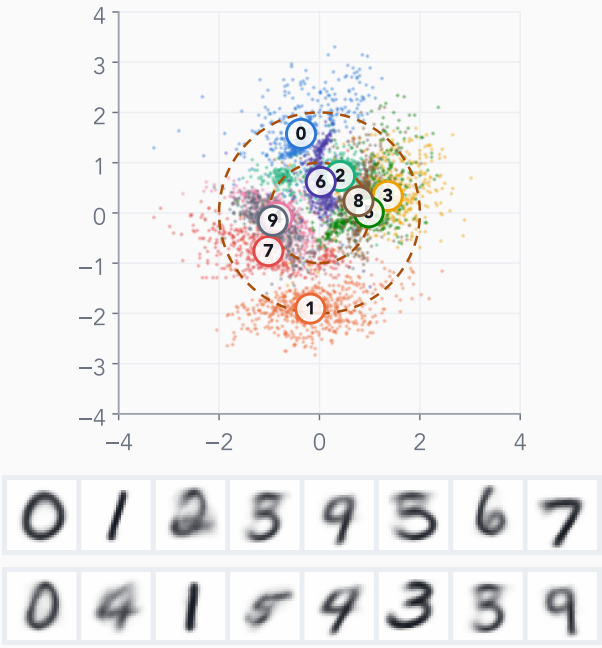
recon 128.1 · no KL term

VAE, loss = recon + KL



recon 128.8 · KL 7.1

recon + 8 × KL



recon 140.4 · KL 3.9

> **Rows: code space · reconstructions · random samples. Too little KL: samples fail. Too much: everything blurs together.**

AN HONEST LOOK

Why are VAE samples blurry?

1. It fits $\mathrm{KL}(\text{data} \,\|\, \text{model})$. Like the wide Gaussian on our bumps, it must cover every training digit, so when unsure it spreads probability.



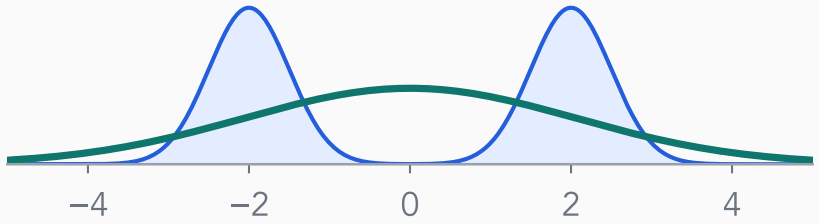
AN HONEST LOOK

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best $q = \mathcal{N}(0.0,\ 2.06^2)$



AN HONEST LOOK

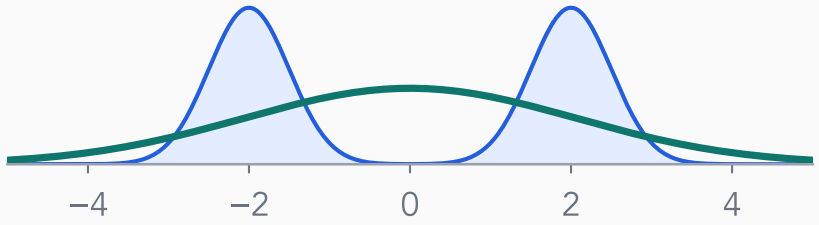
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3. We show π, the mean, not a sample. A sample would be speckled instead of grey.

best $q = \mathcal{N}(0.0,\ 2.06^2)$





π (the mean)



a sample

Not a law of nature: bigger codes, better decoders and better likelihoods all sharpen VAEs.

END OF PART 7

What we did, and what comes next

WHAT WE DID

1. Our 3: encode to a cloud, sample a code, decode, score: loss $= 129.3$.
2. Training: reconstruction falls, KL rises, both settle.
3. Generation needs only the prior and the decoder.
4. The KL weight trades sharp reconstructions against a usable code space; samples blur.

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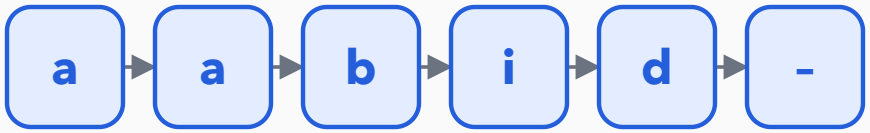
NEXT LECTURE: A DIFFERENT IDEA

VAEs maximise a bound on $p_\theta(x)$. GANs skip $p_\theta(x)$ entirely: a second network learns to judge real from fake.

THREE WAYS TO GENERATE

Same goal, three different training signals

autoregressive
one token at a time

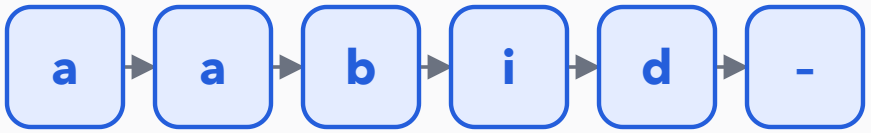


exact likelihood
slow sampling

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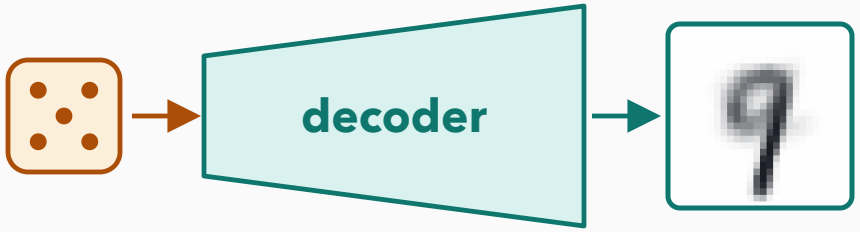
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exact likelihood
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VAE
random z, decode once

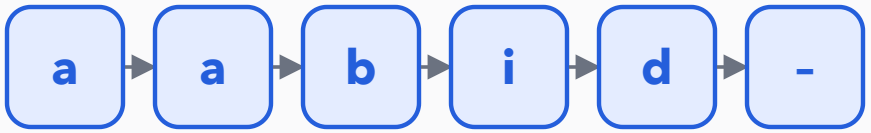


trained on the ELBO
tends to blur

THREE WAYS TO GENERATE

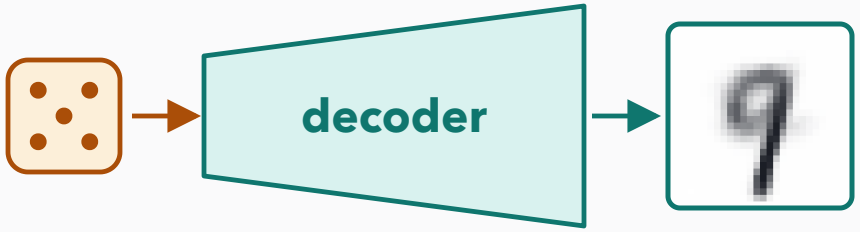
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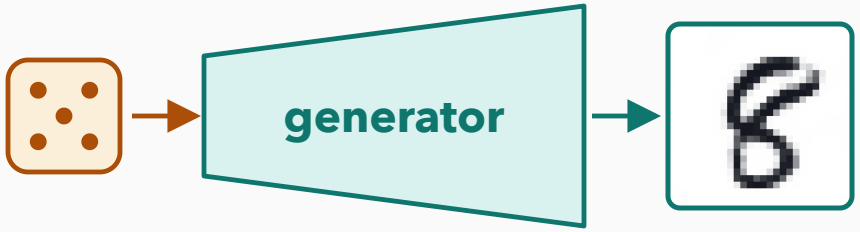
exact likelihood
slow sampling

VAE
random z, decode once



trained on the ELBO
tends to blur

GAN
random z, generate once



next lecture
trained against a judge

RETURN TO THE OPENING

What you can now explain



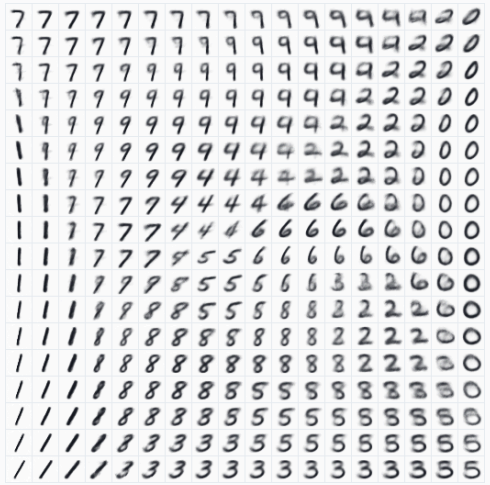
the cover: encode a 3 and a 7, walk a straight line between their codes, decode each point.

RETURN TO THE OPENING

What you can now explain



the cover: encode a 3 and a 7, walk a straight line between their codes, decode each point.



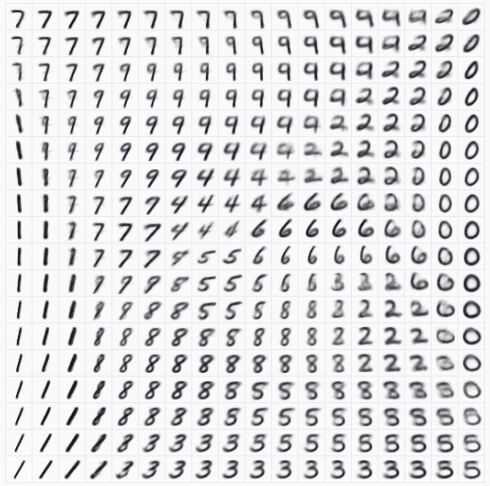
every code in $\mathcal{N}(0, I)$ decodes to a digit: recon + KL, derived from $\mathrm{KL}(q \,\|\, \text{posterior})$.

RETURN TO THE OPENING

What you can now explain



the cover: encode a 3 and a 7, walk a straight line between their codes, decode each point.



every code in $\mathcal{N}(0, I)$ decodes to a digit: recon + KL, derived from $\mathrm{KL}(q \,\|\, \text{posterior})$.



a conditional VAE: give the label to the encoder and the decoder, and choose which digit to draw.

BEFORE YOU LEAVE

Three exit questions

1. To generate a new digit with a trained VAE, which parts of the network do you use?

2. Two different KL divergences appear in the VAE story. What does each compare, and which one is in the loss?

3. We never compute $p_\theta(x)$. Why does maximising the ELBO still pull q towards the true posterior?

BEFORE YOU LEAVE

Three exit questions

1. To generate a new digit with a trained VAE, which parts of the network do you use?

   The prior and the decoder only: $z \sim \mathcal{N}(0, I)$, then decode. The encoder is for training.

2. Two different KL divergences appear in the VAE story. What does each compare, and which one is in the loss?

   $\mathrm{KL}(q \,\|\, \text{prior})$ is in the loss (6.97 for our 3). $\mathrm{KL}(q \,\|\, \text{true posterior})$ is the gap between the ELBO and $\log p_\theta(x)$ (0.55).

3. We never compute $p_\theta(x)$. Why does maximising the ELBO still pull q towards the true posterior?

   $\log p_\theta(x) = \mathrm{ELBO} + \mathrm{KL}(q \,\|\, \text{posterior})$, and the left side does not depend on q. Whatever the ELBO gains, the KL loses.

AFTER THE GAN LECTURE

What if we generate by removing noise, a little at a time?



our 3 → add a little Gaussian noise, again and again → pure noise

> **Adding noise is easy and gives free training pairs. Can a network learn to undo one small step, then walk all the way back from pure noise?**

APPENDIX

A second route to the ELBO

The VI lecture (its Part 6) reached the ELBO from $\mathrm{KL}(q \,\|\, \text{posterior})$. Many textbooks reach it from $\log p_\theta(x)$ with Jensen's inequality instead. Same bound, one more tool.

Start from what we want

$$\log p_\theta(x) = \log \int p_\theta(x, z)\, dz$$

Maximum likelihood wants this number large for our 3, and for every image in the data. The integral over all codes is the part we cannot compute.

A second route to the bound of Part 5, starting from $\log p_\theta(x)$ instead of the KL.

Multiply and divide by the encoder's cloud

$$\log \int p_\theta(x, z)\, dz$$

$$= \log \int q_\varphi(z \mid x)\, \frac{p_\theta(x, z)}{q_\varphi(z \mid x)}\, dz$$

Multiply and divide by the encoder's cloud

$$\log \int p_\theta(x, z)\, dz$$

$$= \log \int q_\varphi(z \mid x)\, \frac{p_\theta(x, z)}{q_\varphi(z \mid x)}\, dz$$

Multiplying and dividing by the same positive number changes nothing. We are free to choose any q; we choose the encoder's Gaussian, which is positive everywhere.

Why bother? Because the next move turns this integral into an average under q, and q knows where the patch is.

Read the integral as an average under q

$$\log \int q_\varphi(z \mid x)\, \frac{p_\theta(x, z)}{q_\varphi(z \mid x)}\, dz$$

$$= \log \mathbb{E}_{z \sim q_\varphi(z|x)} \left[\frac{p_\theta(x, z)}{q_\varphi(z \mid x)} \right]$$

Read the integral as an average under q

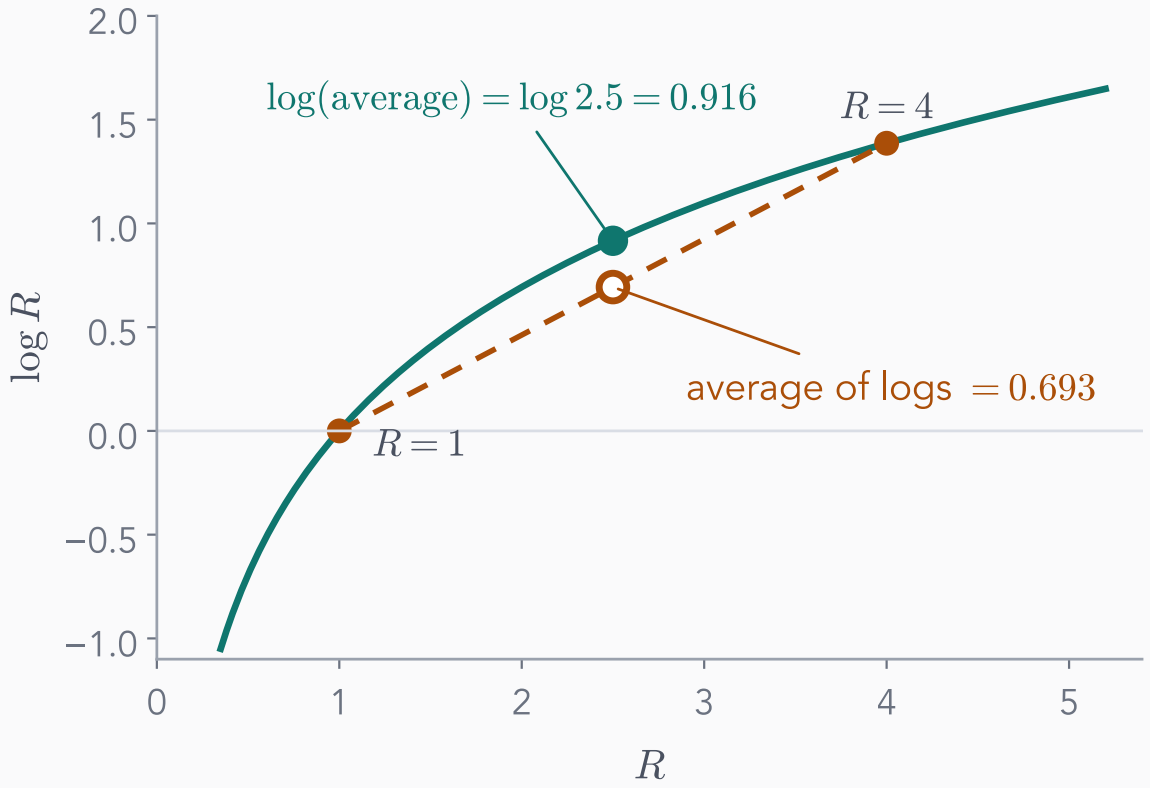
$$\log \int q_\varphi(z \mid x)\, \frac{p_\theta(x, z)}{q_\varphi(z \mid x)}\, dz$$

$$= \log \mathbb{E}_{z \sim q_\varphi(z|x)} \left[\frac{p_\theta(x, z)}{q_\varphi(z \mid x)} \right]$$

An integral against q is an average under q: $\int q(z)\, f(z)\, dz = \mathbb{E}_{z \sim q}[f(z)]$. Here $f(z)$ is the ratio $p_\theta(x, z)/q_\varphi(z \mid x)$: one number for each code.

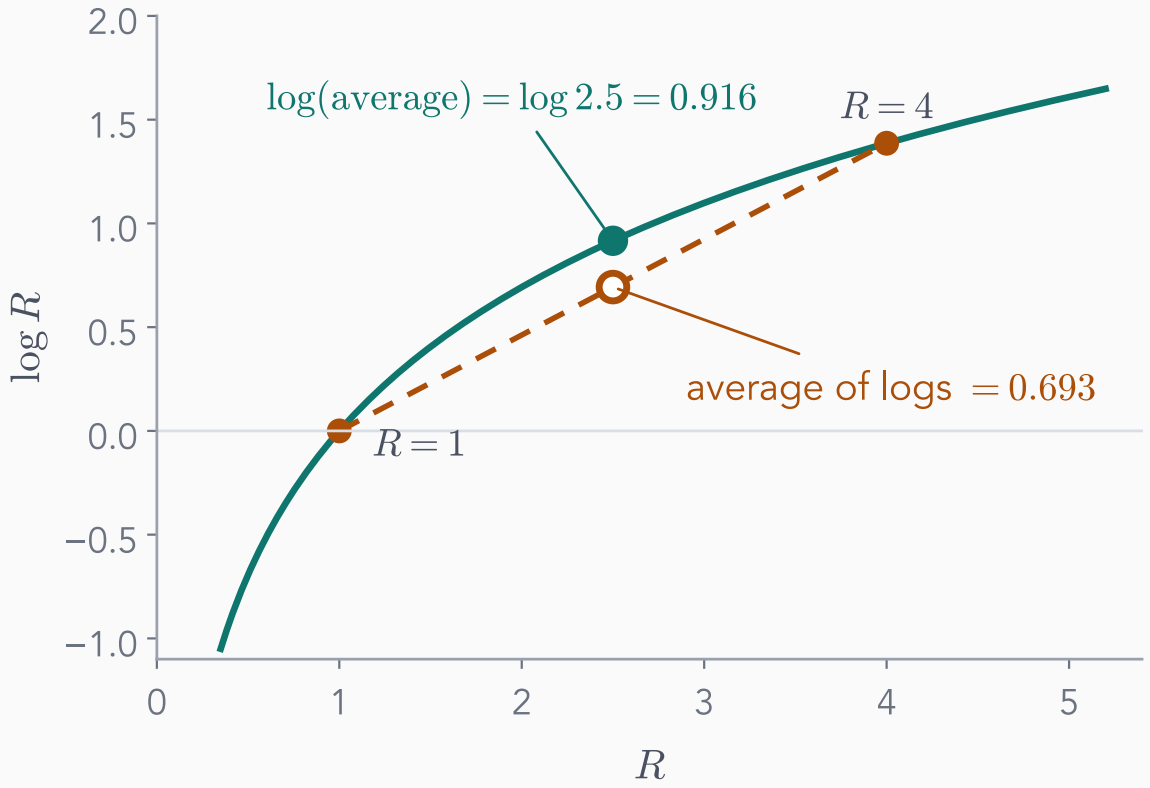
Still exact. We now average over codes drawn from the encoder's cloud, right where the patch is.

Jensen's inequality, in one picture



log curves downwards (it is concave), so every chord lies below the curve.

Jensen's inequality, in one picture

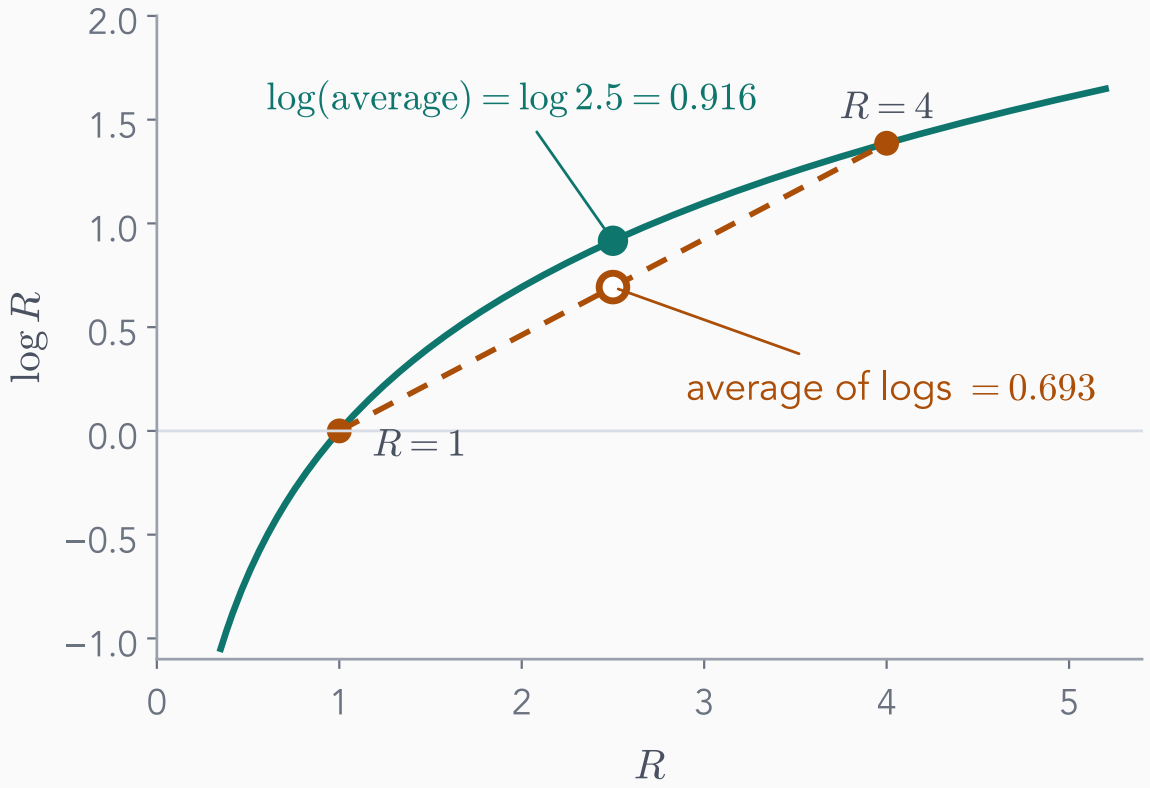


log curves downwards (it is concave), so every chord lies below the curve.

Two values, $R = 1$ and $R = 4$:

$$\underbrace{\log 2.5}_{\log \text{ of the average}} = 0.916 \geq \underbrace{\tfrac{1}{2}(0 + 1.386)}_{\text{average of the logs}} = 0.693$$

Jensen's inequality, in one picture



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$$\log \mathbb{E}[R] \geq \mathbb{E}[\log R]$$

Swap the log and the average: the only inequality

$$\log p_\theta(x) = \log \mathbb{E}_q\left[\frac{p_\theta(x,z)}{q_\varphi(z \mid x)}\right]$$

$$\log p_\theta(x) \geq \mathbb{E}_q\left[\log \frac{p_\theta(x,z)}{q_\varphi(z \mid x)}\right] =: \mathrm{ELBO}$$

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Jensen with $R = p_\theta(x,z)/q_\varphi(z \mid x)$. The right side is the **E**vidence **L**ower **BO**und: it can never exceed $\log p_\theta(x)$.

The same ELBO as Part 5. This route shows it is a bound; the KL route (the VI lecture's Part 6) also shows the gap is $\mathrm{KL}(q \,\|\, \text{posterior})$.

FURTHER READING

Where to go next

- Lilian Weng, *From Autoencoder to Beta-VAE* (lilianweng.github.io): the autoencoder family of Part 2
- Jaan Altosaar, *Tutorial: what is a variational autoencoder?*: the neural-network and probability views side by side
- Kingma & Welling, *Auto-Encoding Variational Bayes*, arXiv 1312.6114
- Blei, Kucukelbir & McAuliffe, *Variational Inference: A Review for Statisticians*, arXiv 1601.00670
- Bishop, *Pattern Recognition and Machine Learning*, §10.1: the ELBO + KL picture of Part 5
- The VI lecture (`vi.html`): KL, the ELBO and reparameterisation on toys; and three YouTube videos on KL divergence (video ids sjgZxuCm_8Q, KHVR587oW8I, tXE23653JrU)
- Stanford CS236 notes on VAEs (deepgenerativemodels.github.io)
- This lecture's code: `scripts/train_models.py` (all models), `scripts/make_figures.py` and `make_figures_extra.py` (every number on the slides)