Data Foundation & ML Framework

The Building Blocks of Machine Learning

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Where We Are

Lecture	Topic
1	What is AI? (videos, demos)
2	**How does ML work? (today!)**
3 onwards	Building specific models

Today: The foundation everything else builds on!

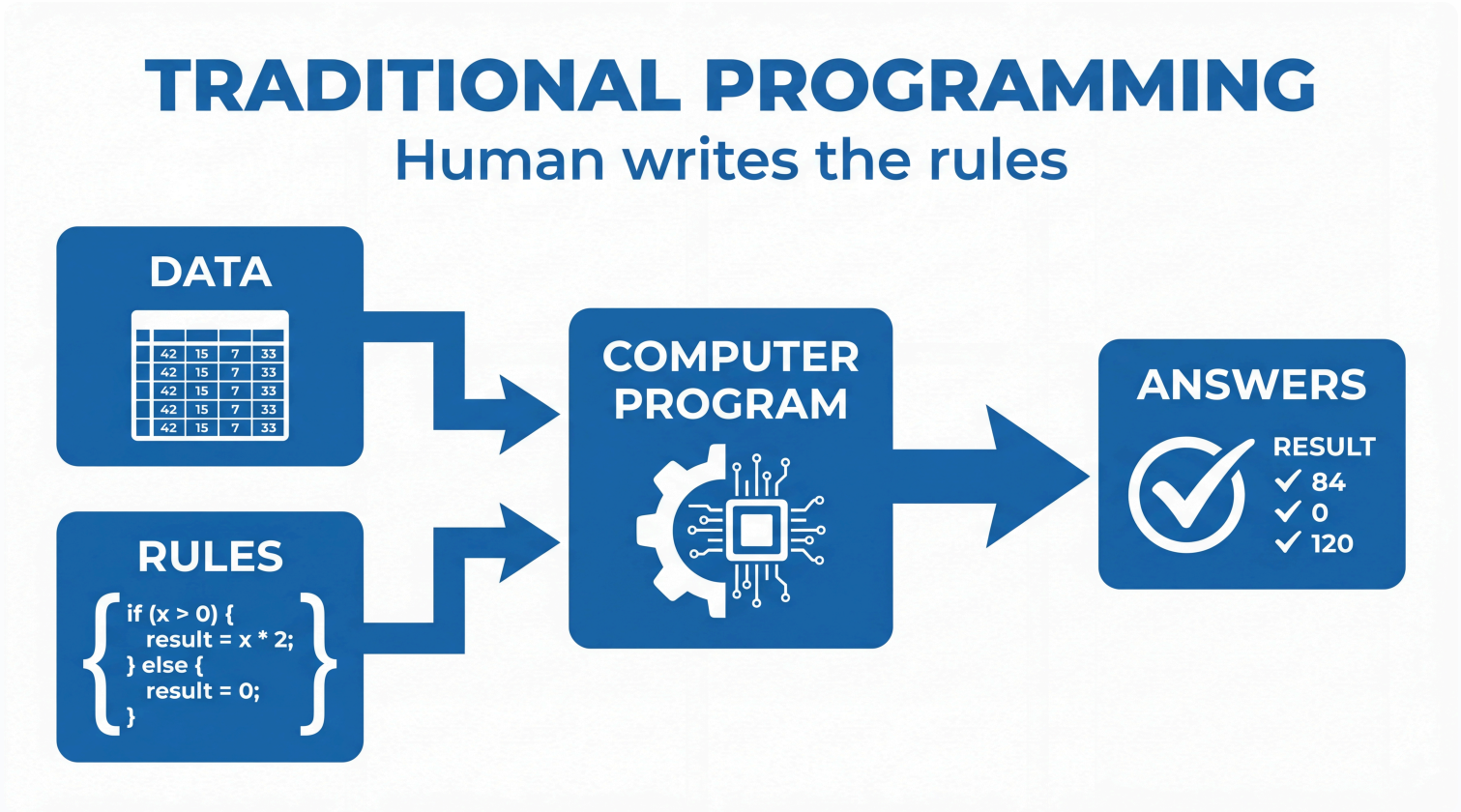
Today's Big Questions

1. What makes ML different from regular programming?
2. What are the different ways machines can learn?
3. How do we represent data for computers?
4. How do we know if our model is good?

Part 1: The ML Mindset

A New Way of Programming

Traditional Programming



You provide data and rules → Computer gives answers

Example: Spam Detection Rules

```
Problem: Determine if an email is spam

Your Rules:
  IF email contains "FREE MONEY" → Spam
  IF email contains "You've won" → Spam
  IF sender is unknown AND has attachment → Spam
  ...
```

You must think of every possible pattern!

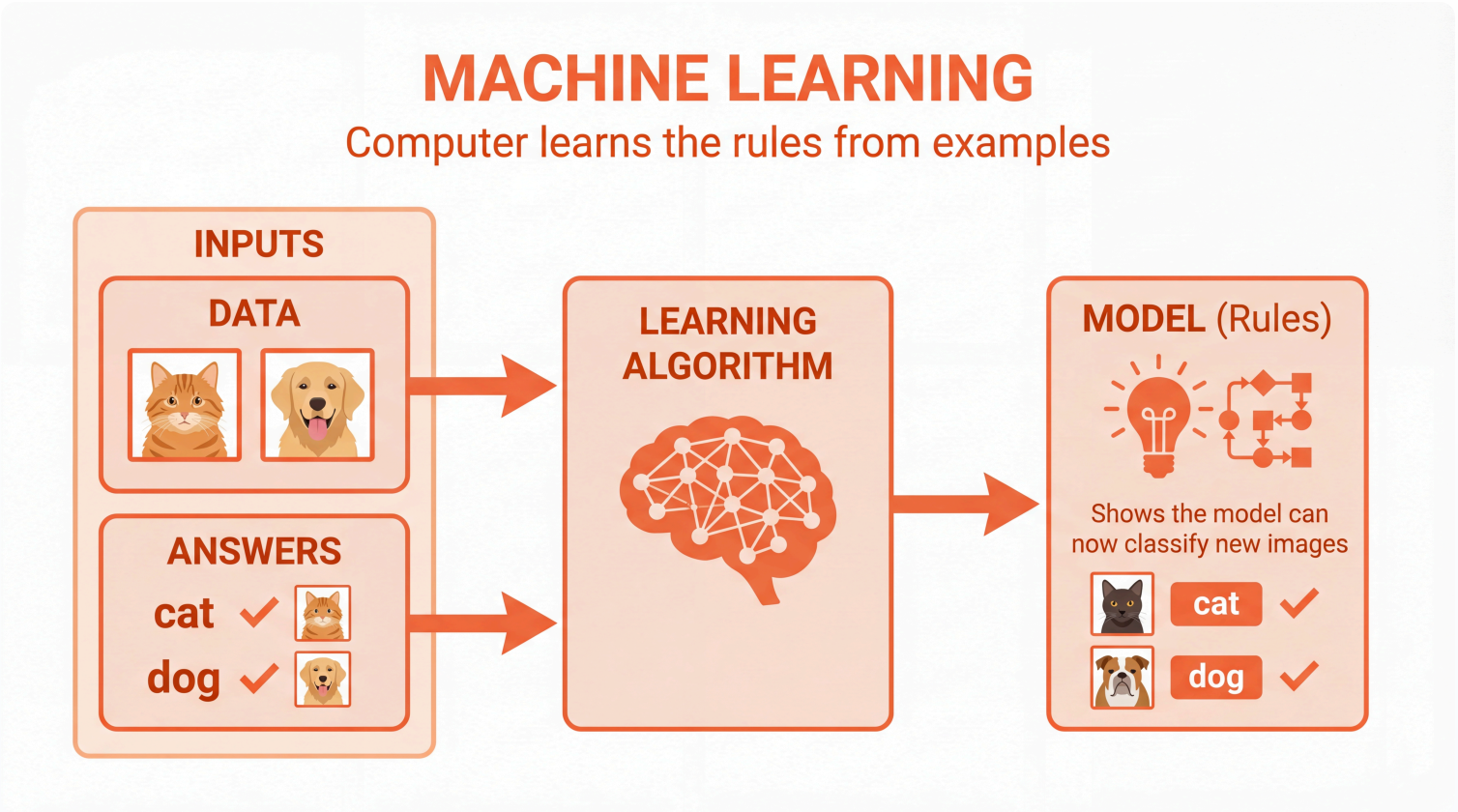
The Problem with Rules

What about these?

Email	Your Rule	Reality
"FR33 M0N3Y!!!"	Not spam	Spam!
"Won tickets to concert"	Spam	Actually legit!
"Free lunch in cafeteria"	Spam	Not spam!

Spammers adapt. Rules break.

The ML Approach



You provide data and answers → Computer learns the rules!

ML in Code

```
# You provide examples (data + answers)
emails = ["FREE MONEY!!!", "Meeting at 3pm", ...]
labels = ["spam", "not spam", ...]

# Computer learns patterns
model.learn(emails, labels)

# Now it can classify NEW emails
model.predict("FR33 M0N3Y")  # → "spam"
```

The model learned to handle variations it never saw!

The Key Difference

Traditional Programming	Machine Learning
Human writes rules	Computer learns rules
Rules are explicit	Rules are implicit (in the model)
Doesn't improve	Improves with more data
Breaks on edge cases	Generalizes to new cases

When to Use ML?

ML is great when:

Scenario	Example
Rules are complex	Face recognition
Rules change over time	Stock prediction
Rules are unknown	Medical diagnosis
There's lots of data	Language translation

ML is NOT needed when:

- Rules are simple and fixed (calculator)
- Data is scarce (rare diseases)

The Formal Definition

> "A computer program is said to **learn** from **experience E** with respect to some class of **tasks T** and **performance measure P** if its performance at tasks in T, as measured by P, improves with experience E."
> — Tom Mitchell

Breaking Down the Definition (with Example!)

Let's make this concrete with a spam filter:

Breaking Down the Definition

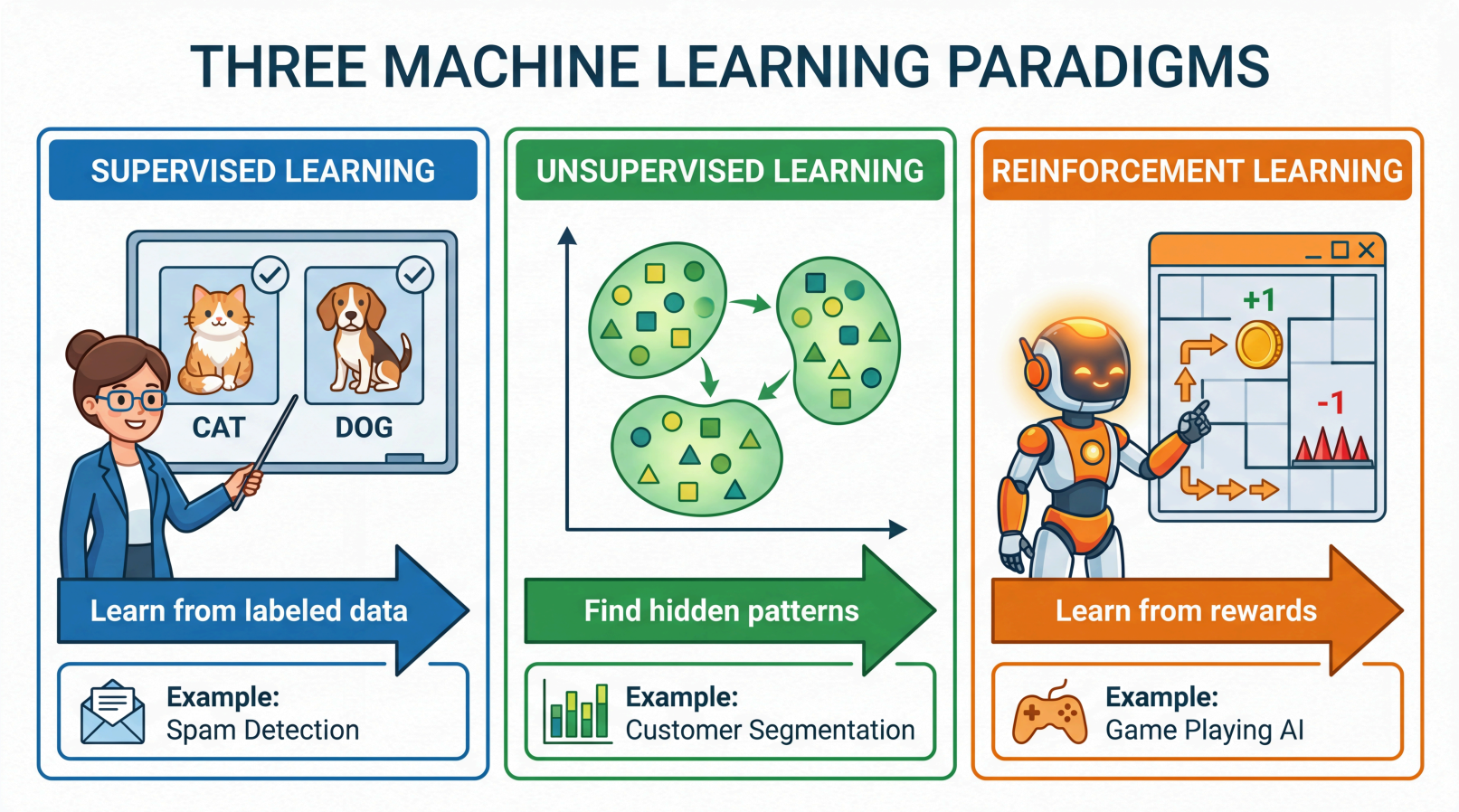
Component	Spam Filter Example
Task (T)	Classify emails as spam/not spam
Experience (E)	Database of labeled emails
Performance (P)	% of correctly classified emails

Learning = Performance improves with Experience!

Part 2: How Machines Learn

Three Learning Paradigms

Three Ways to Learn



This course focuses on supervised learning — learning from labeled examples!

Supervised Learning

Like learning with a teacher who tells you right/wrong

```
Teacher shows examples:
  "This email is spam"
  "This email is not spam"
  "This email is spam"

Student (model) learns patterns...

Later, student predicts on new email:
  "I think this is spam!" (hopefully correct!)
```

> This course focuses primarily on supervised learning!

Real Supervised Learning Examples

Task	Input	Output (label)
Spam detection	Email text	Spam / Not spam
Medical diagnosis	X-ray image	Disease / No disease
House pricing	House features	Price (₹)
Credit scoring	Customer info	Approve / Reject
Weather	Historical data	Rain / No rain

Unsupervised Learning

No labels! Find hidden patterns on your own

```
Data: Purchase histories of 10,000 customers

Algorithm discovers groups:
  "Group A seems to buy electronics"
  "Group B mostly buys groceries"
  "Group C buys luxury items"

Nobody TOLD it these groups exist!
```

Examples: Customer segmentation, anomaly detection

Reinforcement Learning

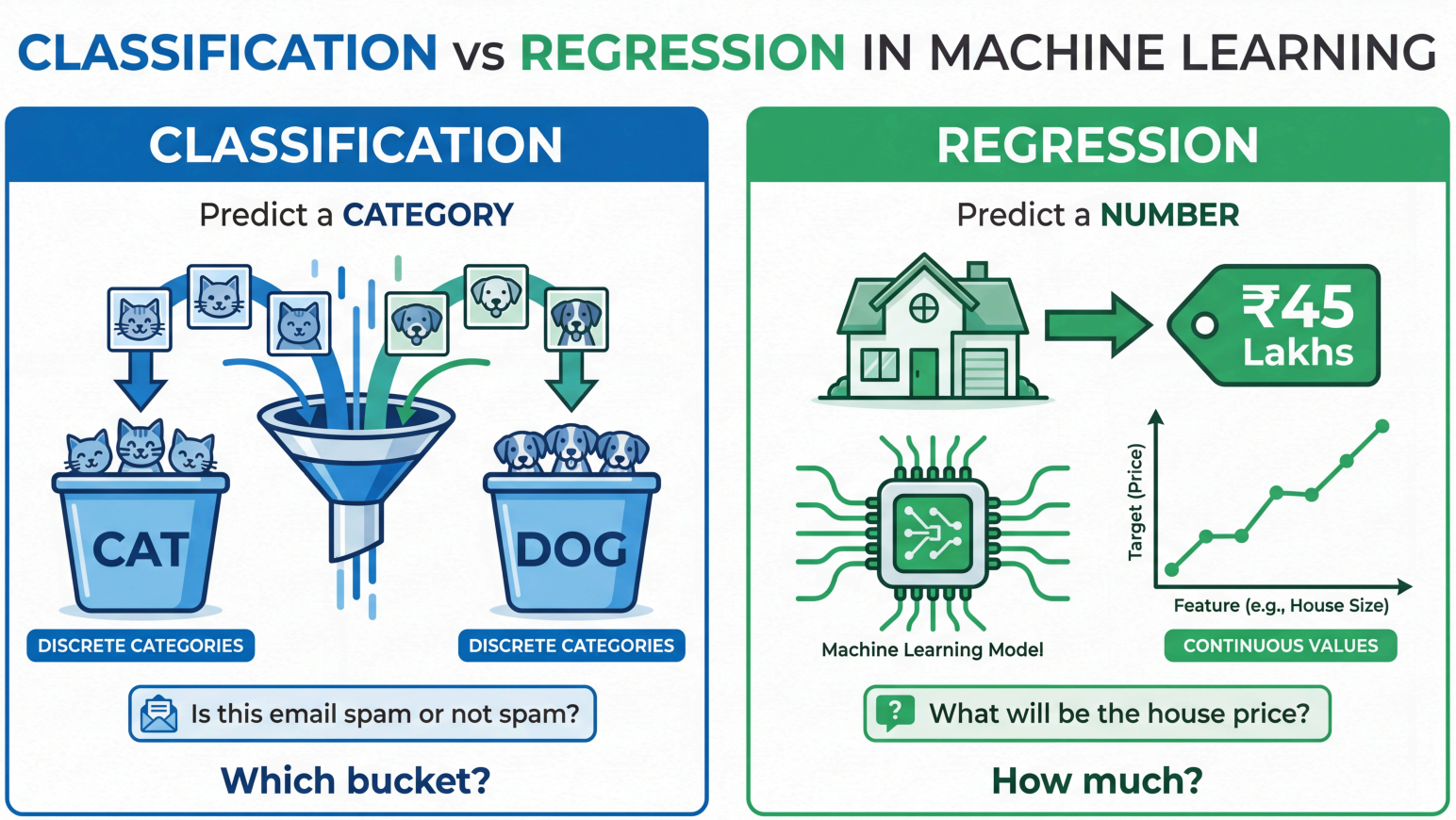
Learn by trial and error with rewards

```
Game-playing AI:
  Move left → +1 point (good!)
  Move right → -10 points (fell in pit!)
  Jump → +100 points (reached goal!)

Over time, learns: "Don't move right near pits"
```

Examples: AlphaGo, Self-driving cars, Robotics

Our Focus: Supervised Learning



Simple rule: Classification = "Which bucket?" | Regression = "How much?"

Classification Examples

Predict a category/class

Input	Output	Classes
Email	Spam or Not	2 classes (binary)
Image	Cat, Dog, Bird	3+ classes (multi-class)
Handwritten digit	0, 1, 2, ..., 9	10 classes
Movie review	Positive, Neutral, Negative	3 classes

Regression Examples

Predict a continuous number

Input	Output	Range
House features	Price	₹0 to ∞
Patient data	Blood pressure	60 - 180 mmHg
Weather history	Temperature	-20°C to 50°C
Image	Person's age	0 - 100 years

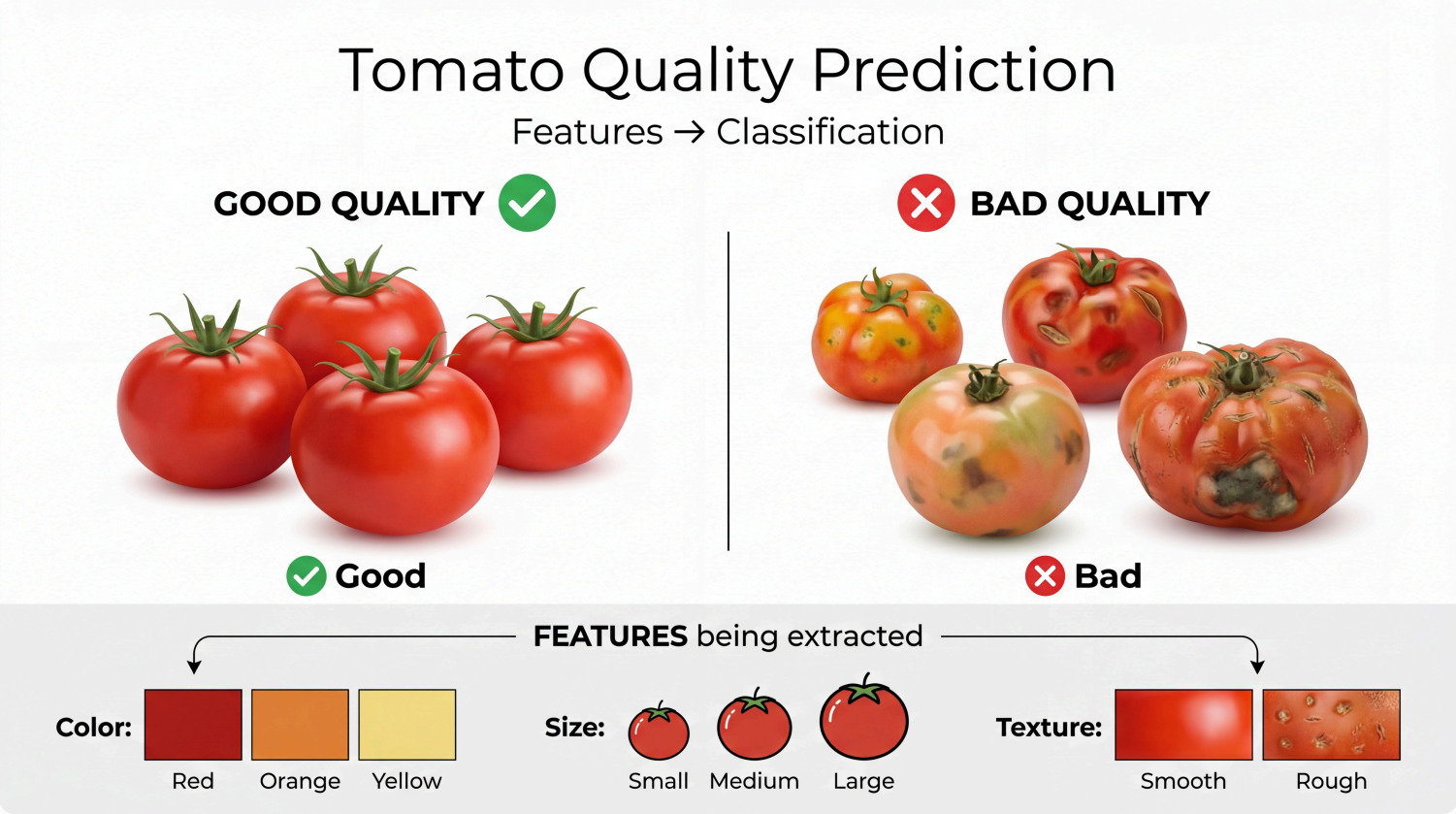
Quick Quiz: Classification or Regression?

Task	Type	Why?
Will it rain tomorrow?	Classification	Yes/No
How many mm of rain?	Regression	A number
What rating (1-5 stars)?	Either!	Ordered categories or continuous
Which digit (0-9)?	Classification	10 discrete categories

Part 3: Representing Data

Features, Labels, and Notation

A Concrete Example: Tomato Quality



These characteristics are called **features** (inputs to our model).

Our Tomato Dataset

Color	Size	Texture	Quality
Orange	Small	Smooth	Good
Red	Small	Rough	Good
Orange	Medium	Smooth	Bad
Yellow	Large	Smooth	Bad

Features (X): Color, Size, Texture

Label (y): Quality (what we want to predict)

Features vs Labels

Features (X)	Label (y)
What we observe	What we want to predict
Input to the model	Output of the model
Multiple columns	Usually one column
Color, Size, Texture	Good/Bad

Important: What Makes a Good Feature?

Good features:

- Color, Size, Texture → Related to quality!

Bad features:

- Sample number (1, 2, 3, 4) → Just an ID, meaningless!
- Day of week you measured → Probably irrelevant

> **Bad features confuse models.** Think about what's actually relevant!

Mathematical Notation

We need consistent symbols for ML

Symbol	Meaning	Example
n	Number of samples	4 tomatoes
d	Number of features	3 (Color, Size, Texture)
$\mathbf{X}$	Feature matrix (all data)	4 rows × 3 columns
$\mathbf{y}$	Label vector	[Good, Good, Bad, Bad]
$\mathbf{x}_i$	Single sample's features	Orange, Small, Smooth
y_i	Single sample's label	Good

The Convention

Bold UPPERCASE = Matrix: $\mathbf{X}$, $\mathbf{W}$
Bold lowercase = Vector: $\mathbf{x}$, $\mathbf{y}$, $\mathbf{w}$
Regular = Scalar: n, d, y_i

Why this matters: When you read ML papers or code, everyone uses these conventions!

The Dataset Notation

$$\mathcal{D} = \{(\mathbf{x}_i, y_i)\}_{i=1}^{n}$$

In English:

"Dataset $\mathcal{D}$ is a collection of n pairs, where each pair is (features, label)"

Example: $(\mathbf{x}_1, y_1)$ = (Orange, Small, Smooth, Good)

But Wait... Computers Need Numbers!

Problem: "Orange" and "Small" aren't numbers!

Solution: Convert categories to numbers (encoding)

Color	Encoded
Red	[1, 0, 0]
Orange	[0, 1, 0]
Yellow	[0, 0, 1]

This is called **one-hot encoding**.

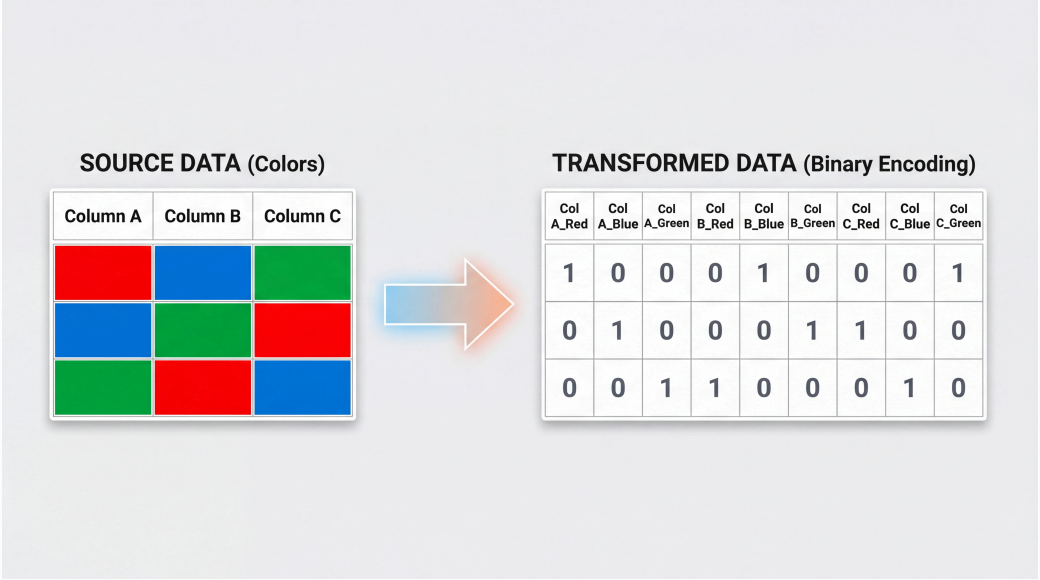
Why One-Hot Encoding?

Bad idea: Red=1, Orange=2, Yellow=3

Problem: This implies Orange is "between" Red and Yellow!

One-hot is better: Each color gets its own column

```
pd.get_dummies(df['Color'])
#    Red  Orange  Yellow
# 0    0       1       0
# 1    1       0       0
```



One-Hot: The Intuition

Think of it like a survey checkbox:

Question	Red?	Orange?	Yellow?
Tomato 1	☐	☑	☐
Tomato 2	☑	☐	☐

Each category is independent!

- No artificial ordering
- Model learns: "If Orange=1, then [something]"
- Categories with 100 options? 100 columns! (but sparse)

Part 4: Data Quality

Garbage In, Garbage Out!

Data Quality

Your model is only as good as your data!

Issue	Problem	Example
Missing values	Incomplete information	Empty cells in spreadsheet
Outliers	Extreme values	Age = 500 years
Imbalanced classes	One class dominates	99% healthy, 1% sick
Biased data	Unrepresentative sample	Only urban customers

> **Garbage In, Garbage Out!** No algorithm can fix fundamentally bad data.

For more: See ML class materials on data preprocessing.

Missing Values

What to do when data is incomplete?

Strategy	When to Use
Drop rows	Few missing values, lots of data
Fill with mean/median	Numerical features
Fill with mode	Categorical features
Use "Unknown" category	When missingness is meaningful

```
# In pandas
df['age'].fillna(df['age'].median(), inplace=True)
```

Outliers

Extreme values can mislead your model

Example	Normal Range	Outlier
Age	0-100	500
Salary	₹10K-₹1Cr	₹100Cr
Height	1.4m-2.1m	5m

Solutions:

- Remove if clearly errors
- Cap at percentiles (e.g., 1st and 99th)
- Use robust models (trees are less sensitive)

Imbalanced Classes

When one class dominates:

Class	Count	Problem
Not Fraud	99,900	Model just predicts "Not Fraud" always!
Fraud	100	Gets 99.9% accuracy but catches nothing

Solutions:

- Collect more minority class data
- Oversample minority class
- Undersample majority class
- Use class weights in training

Data Bias

Your data reflects the world it came from

Bias Type	Example
Selection bias	Only surveying English speakers
Historical bias	Past hiring data reflects past discrimination
Measurement bias	Different hospitals use different equipment

Biased data → Biased model → Unfair predictions!

Real-World Example: Biased Hiring AI

What happened:

- A company trained a hiring model on 10 years of data
- Historical data reflected existing biases in who got hired
- AI learned to replicate those biased patterns!

Result: Model unfairly penalized candidates from underrepresented groups

> **Lesson:** Always check your data for hidden biases before training!

Part 5: Train/Test Split

The Most Important Concept!

The Exam Analogy

Two study strategies:

Strategy A: Memorize	Strategy B: Learn
Memorize "2+3=5"	Understand addition
Exam: "2+3=?" → 5	Exam: "2+3=?" → 5
Exam: "2+4=?" → ???	Exam: "2+4=?" → 6

We want models to LEARN patterns, not MEMORIZE examples!

Why This Matters: A Story

You train a spam classifier on 1000 emails.

Method	Training Accuracy	On NEW emails
Memorize all 1000	100%	???
Learn patterns	95%	93%

The memorizer fails because:

- New spam uses different words
- New legitimate emails look different
- Real world is messier than training data

The learner succeeds because:

- Learned "lots of exclamation marks = suspicious"
- This PATTERN transfers to new emails!

The Problem

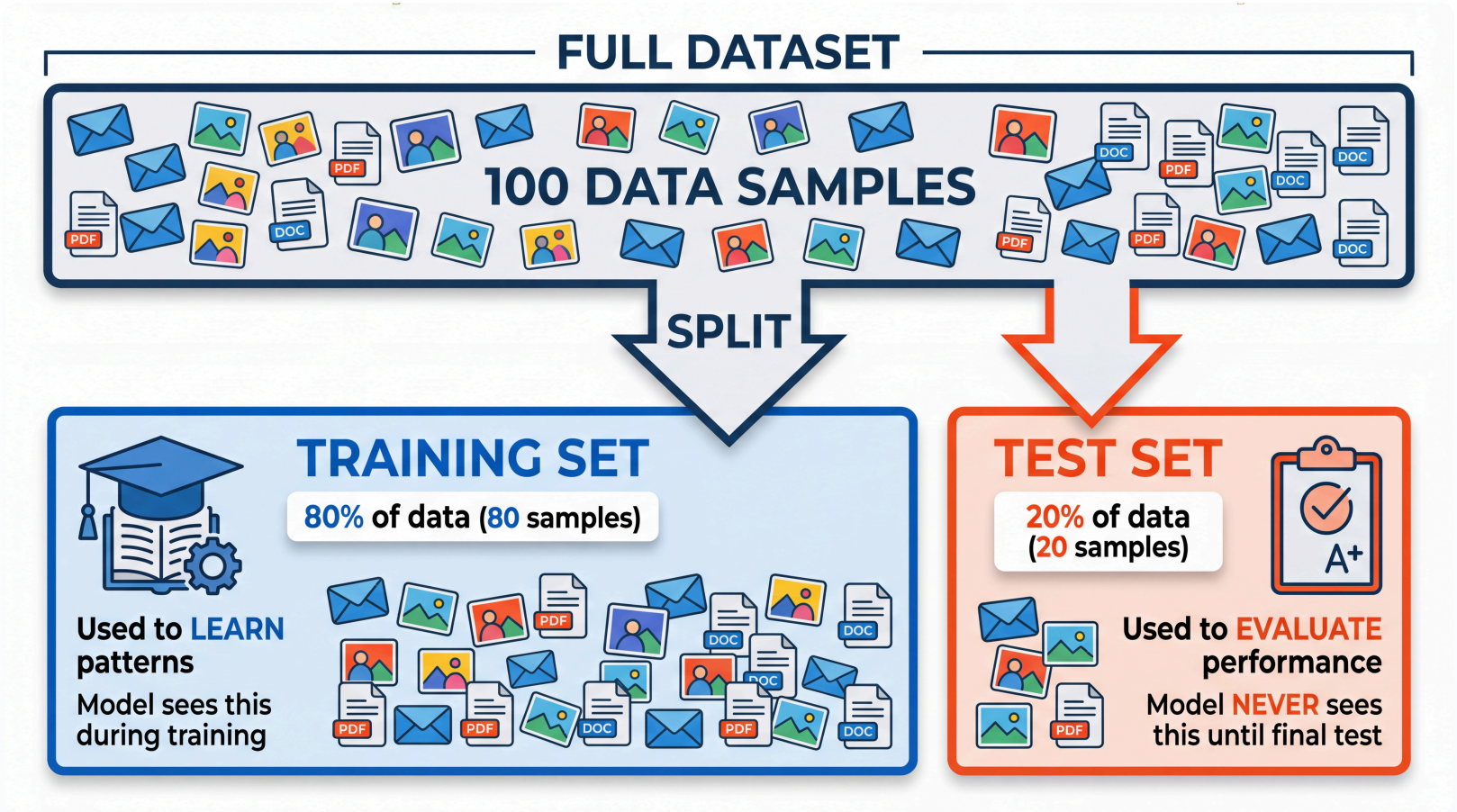
You train a model on 100 emails. You test on the SAME 100 emails.

What Happened	Score
Training accuracy	100%
Accuracy on NEW emails	60%

The model memorized the answers instead of learning patterns!

How do we detect this? We need a separate test set.

The Solution: Split Your Data



Don't test on data you trained on!

In Python

```
from sklearn.model_selection import train_test_split

# Split: 80% train, 20% test
X_train, X_test, y_train, y_test = train_test_split(
    X, y,
    test_size=0.2,      # 20% for testing
    random_state=42     # For reproducibility
)

# Train ONLY on training data
model.fit(X_train, y_train)

# Evaluate on test data (never seen!)
accuracy = model.score(X_test, y_test)
```

Why This Works

Scenario	Training Acc	Test Acc	Status
Good model	90%	88%	Learned!
Memorized	100%	60%	Overfitting
Too simple	65%	63%	Underfitting

The test accuracy tells you real-world performance!

The Golden Rule

> **NEVER peek at the test data during training!**

If you use test data to make decisions (choosing models, tuning parameters), you're cheating — your "test" accuracy becomes meaningless.

Part 5: Evaluation Metrics

How Do We Measure "Good"?

Accuracy: The Obvious Metric

$$\text{Accuracy} = \frac{\text{Correct Predictions}}{\text{Total Predictions}}$$

Example: 85 out of 100 correct → 85% accuracy

Sounds perfect, right?

When Accuracy Fails

Scenario: Cancer screening — 1000 patients

Reality	Count
Healthy	990
Cancer	10

Dumb model: Always predict "Healthy"

Metric	Value	Looks...
Accuracy	990/1000 = **99%**	Amazing!
Cancer cases caught	**0 out of 10**	Useless!

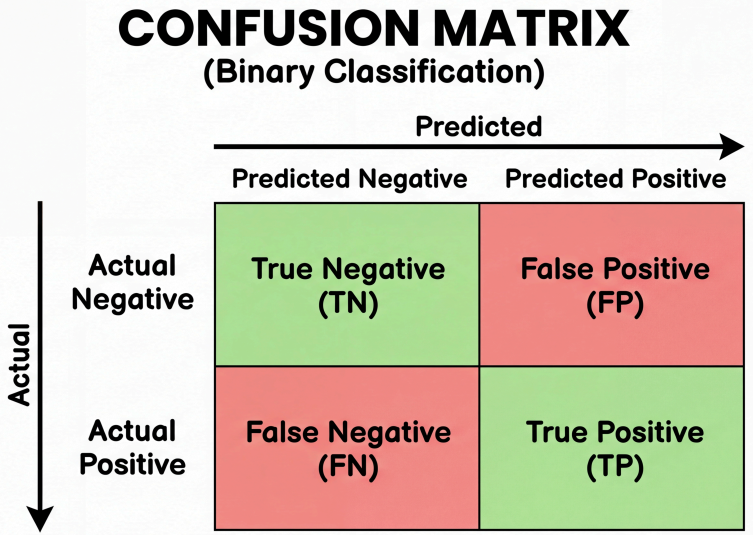
High accuracy can be completely misleading with imbalanced data!

The Confusion Matrix

The confusion matrix shows all four possible outcomes:

- **True Positive (TP):** Correctly caught cancer
- **True Negative (TN):** Correctly said healthy
- **False Positive (FP):** Said cancer but was healthy (false alarm)
- **False Negative (FN):** Said healthy but had cancer (MISSED!)

> The diagonal shows correct predictions; off-diagonal shows errors.



Reading a Confusion Matrix

Example: Cancer screening model tested on 1000 people:

	Predicted: Cancer	Predicted: Healthy
Actually: Cancer	85 (TP)	15 (FN)
Actually: Healthy	50 (FP)	850 (TN)

What does this tell us?

- Model catches 85/100 = 85% of cancer cases (Recall)
- When it says "cancer", it's right 85/135 = 63% (Precision)
- Overall: (85+850)/1000 = 93.5% accuracy

But is 15 missed cancers acceptable? That's the key question!

Precision: "When I Say Cancer, Am I Right?"

$$\text{Precision} = \frac{TP}{TP + FP}$$

From our confusion matrix: TP=85, FP=50

	Predicted: Cancer	Predicted: Healthy
Actually: Cancer	**85 (TP)**	15
Actually: Healthy	**50 (FP)**	850

$$\text{Precision} = \frac{85}{85 + 50} = \frac{85}{135} = 63\%$$

"When I say cancer, I'm right 63% of the time"

Recall: "Of All Cancers, How Many Did I Catch?"

$$\text{Recall} = \frac{TP}{TP + FN}$$

From our confusion matrix: TP=85, FN=15

	Predicted: Cancer	Predicted: Healthy
Actually: Cancer	85 (TP)	15 (FN)
Actually: Healthy	50	850

$$\text{Recall} = \frac{85}{85 + 15} = \frac{85}{100} = 85\%$$

"I catch 85% of all cancer cases (but miss 15%)"

Precision vs Recall Trade-off

You usually can't have both perfect!

Scenario	Prioritize	Why
Spam filter	Precision	Don't mark important emails as spam
Cancer screening	Recall	Don't miss any cancer cases
Criminal justice	Precision	Don't convict innocent people
Fire alarm	Recall	Don't miss any real fires

Trade-off: Increasing one often decreases the other!

The Precision-Recall Knob

Imagine adjusting a threshold:

Threshold	Precision	Recall	Behavior
Very high	99%	10%	Only flag when VERY sure
Medium	80%	80%	Balanced
Very low	30%	99%	Flag everything suspicious

You choose based on the cost of errors!

What's worse?	Choose...
Missing a real threat	Low threshold (high recall)
Many false alarms	High threshold (high precision)

F1 Score: The Balance

$$\text{F1} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Harmonic mean of precision and recall.

Precision	Recall	F1
100%	0%	0%
80%	80%	80%
100%	100%	100%

F1 is high only when BOTH are high!

Your Turn: Compute F1!

A spam filter tested on 200 emails:

	Predicted: Spam	Predicted: Not Spam
Actually: Spam	40	10
Actually: Not Spam	20	130

Try computing these (then we'll check together):

Metric	Formula	Your Answer
Precision	TP / (TP + FP)	? / (? + ?) = ?
Recall	TP / (TP + FN)	? / (? + ?) = ?
F1	2 × P × R / (P + R)	?
Accuracy	(TP+TN) / Total	?

Solution: F1 Worked Out

From the confusion matrix: TP=40, FP=20, FN=10, TN=130

Metric	Calculation	Result
Precision	40 / (40+20) = 40/60	**66.7%**
Recall	40 / (40+10) = 40/50	**80.0%**
F1	2 × 0.667 × 0.8 / (0.667 + 0.8)	**72.7%**
Accuracy	(40+130) / 200	**85.0%**

Notice: Accuracy (85%) looks great, but precision is only 67% — 1 in 3 "spam" flags is wrong!

Matthews Correlation Coefficient (MCC)

$$\text{MCC} = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}$$

Why MCC is useful:

- Ranges from -1 (worst) to +1 (best), 0 = random
- Works well even with **imbalanced classes**
- Considers all four quadrants of confusion matrix

Your Turn: Compute MCC!

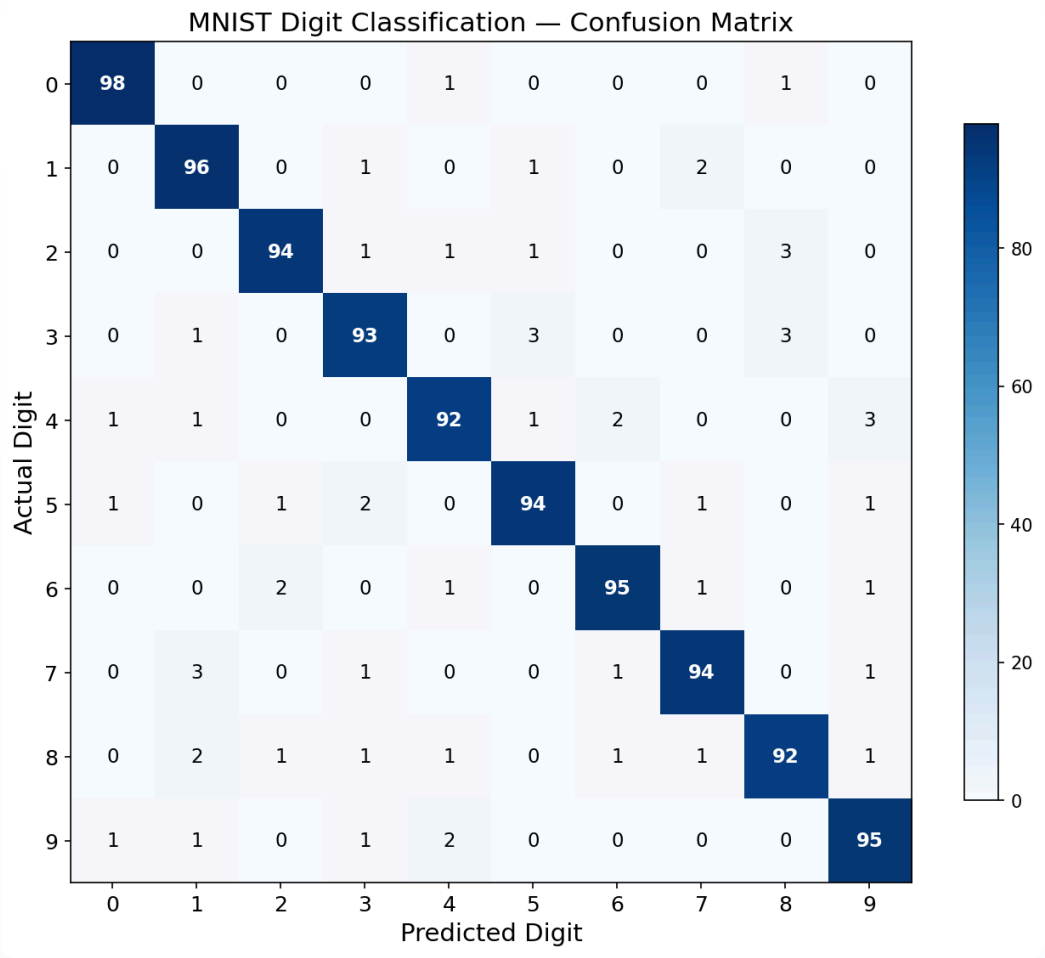
Same spam filter: TP=40, FP=20, FN=10, TN=130

$$\text{MCC} = \frac{40 \times 130 - 20 \times 10}{\sqrt{(40+20)(40+10)(130+20)(130+10)}}$$

Step	Calculation
Numerator	40×130 - 20×10 = 5200 - 200 = **5000**
Denominator	$\sqrt{60 \times 50 \times 150 \times 140}$ = $\sqrt{63{,}000{,}000}$ = **7937**
MCC	5000 / 7937 = **0.63**

MCC = 0.63 — a good (not great) classifier. Compare: the "always predict healthy" model gets MCC = 0!

Multi-Class Confusion Matrix



Reading the 10x10 Matrix

What can you spot?

Pattern	What It Means
Bright diagonal	Model is mostly correct
4 confused with 9	They look similar (closed loops)
3 confused with 5, 8	Curved digits are tricky
7 confused with 1	Both have vertical strokes

The confusion matrix tells you WHERE your model struggles!

This helps you decide: "Should I collect more training examples of 4s and 9s?"

Multi-Class: A 3x3 Example

A model classifies animals: Cat, Dog, Bird

	Pred: Cat	Pred: Dog	Pred: Bird
Actual: Cat	8	1	1
Actual: Dog	2	6	2
Actual: Bird	0	1	9

Per-class metrics (treat each class as binary):

Class	TP	FP	FN	Precision	Recall	F1
Cat	8	2	2	8/10=0.80	8/10=0.80	0.80
Dog	6	2	4	6/8=0.75	6/10=0.60	0.67
Bird	9	3	1	9/12=0.75	9/10=0.90	0.82

Multi-Class F1: Three Approaches

From our Cat/Dog/Bird example:

Approach	Calculation	Result
Macro F1	(0.80 + 0.67 + 0.82) / 3	0.76
Weighted F1	Weighted by class count (10 each here)	0.76
Micro F1	Pool: TP=23, FP=7, FN=7 → 23/26.5	0.77

```
from sklearn.metrics import f1_score

f1_score(y_true, y_pred, average='macro')
f1_score(y_true, y_pred, average='weighted')
f1_score(y_true, y_pred, average='micro')
```

Verify with Code!

```
import numpy as np
from sklearn.metrics import f1_score, classification_report

y_true = ['Cat']*10 + ['Dog']*10 + ['Bird']*10
y_pred = (['Cat']*8 + ['Dog']*1 + ['Bird']*1 +
          ['Cat']*2 + ['Dog']*6 + ['Bird']*2 +
          ['Cat']*0 + ['Dog']*1 + ['Bird']*9)

print(classification_report(y_true, y_pred))
```

Run this in the notebook and verify your hand calculations match!

Regression Metrics

For regression (predicting numbers), we measure "how far off":

Metric	Formula	Intuition
MAE	$\frac{1}{n}\sum \lvert y_i - \hat{y}_i \rvert$	Average error
MSE	$\frac{1}{n}\sum (y_i - \hat{y}_i)^2$	Penalizes big errors more
RMSE	$\sqrt{MSE}$	Same units as y

Regression Example

Actual Price	Predicted	Error
₹50 lakhs	₹48 lakhs	₹2 lakhs
₹30 lakhs	₹35 lakhs	₹5 lakhs
₹40 lakhs	₹40 lakhs	₹0

MAE = (2 + 5 + 0) / 3 = ₹2.33 lakhs

"On average, we're off by ₹2.33 lakhs"

Part 6: The sklearn Pattern

Your First ML Code

The Universal Pattern

ALL sklearn models follow the same pattern:

```
# 1. Create model
model = SomeModel()

# 2. Train (fit) on training data
model.fit(X_train, y_train)

# 3. Predict on new data
predictions = model.predict(X_test)

# 4. Evaluate
score = model.score(X_test, y_test)
```

Learn this once, use it forever!

Complete Example

```
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score

# 1. Split data
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2
)

# 2. Create and train model
model = DecisionTreeClassifier()
model.fit(X_train, y_train)

# 3. Predict and evaluate
predictions = model.predict(X_test)
print(f"Accuracy: {accuracy_score(y_test, predictions):.1%}")
```

Different Models, Same API!

Model	What It Does	Best For
`LinearRegression`	Fits a straight line	Predicting numbers
`LogisticRegression`	Fits a decision boundary	Yes/No classification
`DecisionTreeClassifier`	Learns if-else rules	Easy to interpret
`KNeighborsClassifier`	Finds similar examples	Small datasets
`MLPClassifier`	Mini neural network	Complex patterns

But they ALL use the exact same 3 methods!

The Universal sklearn Pattern

```
model = AnyModel()          # 1. Create
model.fit(X_train, y_train) # 2. Train
model.predict(X_test)       # 3. Predict
```

Want to try a different model? Just change line 1!

```
model = DecisionTreeClassifier()  # swap this line
model.fit(X_train, y_train)       # same
model.predict(X_test)             # same
```

Learn this pattern once, use it forever!

Summary: Key Concepts

Concept	Key Insight
ML vs Programming	ML learns rules from examples
Three Paradigms	Supervised (with labels), Unsupervised, RL
Classification	Predict categories
Regression	Predict numbers
Features & Labels	Inputs (X) and outputs (y)
Train/Test Split	Never test on training data!
Evaluation	Accuracy isn't everything (precision, recall, F1)

What's Next?

Lecture	Topic
3	**Supervised Learning:** Linear & Logistic Regression
4	**Model Selection:** How to choose and evaluate models
5	**Neural Networks:** The foundation of deep learning

Questions?

Next Lecture: Supervised Learning

Linear Regression, Logistic Regression, and Gradient Descent