Data Foundation & The ML Framework

Understanding Data and How Machines Learn

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Recap: What Did We See Last Week?

AI is everywhere:

- AlphaFold solving protein folding
- AI writing code, music, art
- Self-driving cars, medical diagnosis

The key insight:

> Machine Learning = Learning patterns from DATA

Today: What IS this data? How does learning actually work?

Today's Learning Goals

By the end of this lecture, you will be able to:

1. **Distinguish** traditional programming from machine learning
2. **Identify** the three learning paradigms (supervised, unsupervised, RL)
3. **Differentiate** classification from regression problems
4. **Explain** why train/test split is essential
5. **Apply** the sklearn API pattern to any ML problem

Part 1: The ML Framework

How Machines Learn

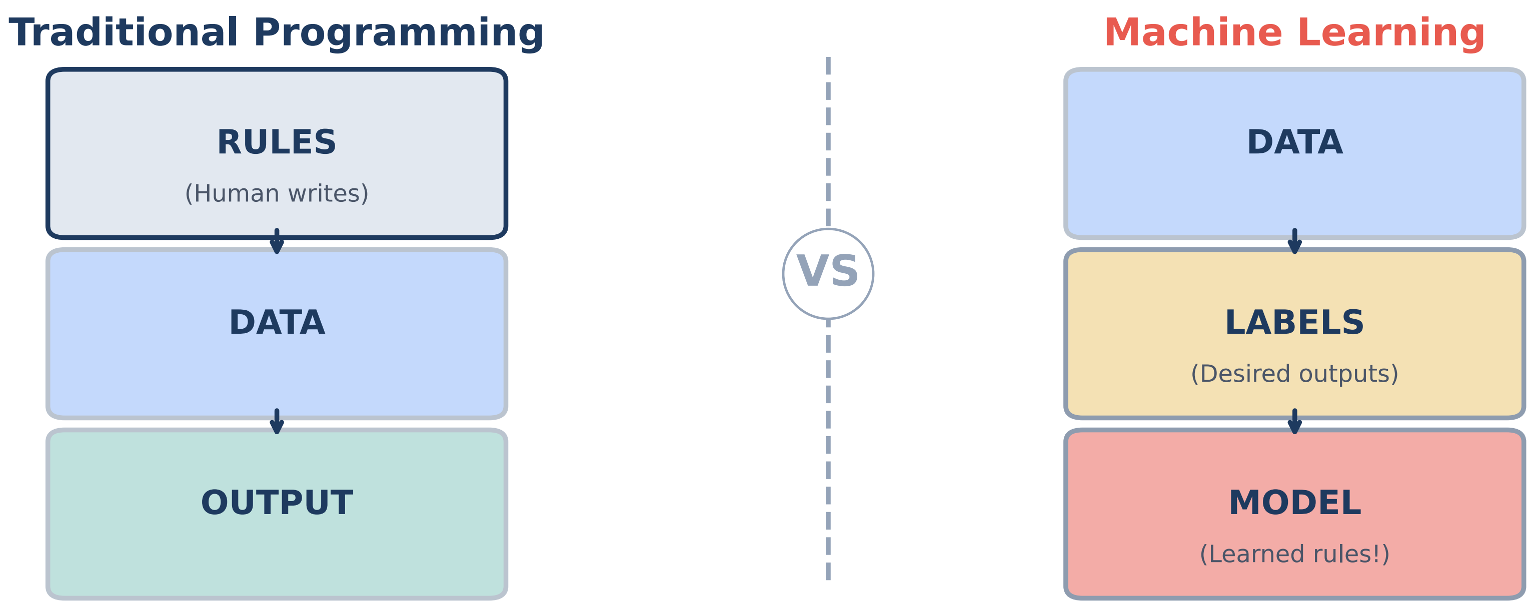
The Big Question

Every AI/ML system answers **one fundamental question**:

> **"Given some input, what should the output be?"**

Input	Output	System
Email text	Spam or Not Spam	Spam Filter
Image	"Cat" or "Dog"	Image Classifier
"The capital of France is"	"Paris"	Language Model
House features	Price ($)	Price Predictor

Traditional Programming vs ML



The Paradigm Shift

Traditional Programming

```
┌──────────┐
│  RULES   │  ← Human writes
│(if/else) │
└────┬─────┘
     │
┌────▼─────┐
│   DATA   │
└────┬─────┘
     │
┌────▼─────┐
│  OUTPUT  │
└──────────┘
```

Explicit programming

Machine Learning

```
┌──────────┐
│   DATA   │
└────┬─────┘
     │
┌────▼─────┐
│  LABELS  │  ← Desired outputs
└────┬─────┘
     │
┌────▼─────┐
│  MODEL   │  ← Learned rules!
└──────────┘
```

Learning from examples

Why This Matters

Scenario	Traditional	ML
Spam changes tactics	Rewrite rules	Retrain on new examples
1000 new categories	1000 new rule sets	Same algorithm, new data
Complex patterns	Impossible to specify	Model discovers them
Human bias	Encoded in rules	(Can still exist in data)

> ML excels when patterns are complex or rules are hard to specify explicitly.

Example: Spam Detection

Traditional Approach:

```python
def is_spam(email):
    if "FREE" in email:
        return True
    if "winner" in email:
        return True
    if "click here" in email:
        return True
    if sender not in contacts:
        if num_links > 5:
            return True
    # ... 1000 more rules
    return False
```

What about "Fr33" or "w1nner"?

What if rules conflict?

ML Approach:

```python
# Just give it examples!
X = [email1, email2, ...]
y = [spam, not_spam, ...]

model = SpamClassifier()
model.fit(X, y)

# Model learns patterns itself!
model.predict(new_email)
```

It learns to generalize!

Handles variations automatically

The Power of Generalization

Training data has: "FREE money!!!"

Model learns: Unusual capitalization + exclamation marks + money words = suspicious

New email: "EARN ca$h NOW!!!" → **Spam** (never seen before, but pattern matches)

> Good ML models learn the **underlying pattern**, not just memorize examples.

Three Learning Paradigms

SUPERVISED	UNSUPERVISED	REINFORCEMENT
Data + Labels	Data only	Actions + Rewards
↓	↓	↓
Predict labels	Find structure	Maximize reward
Ex: Spam detection	*Ex: Customer segments*	*Ex: Game playing*

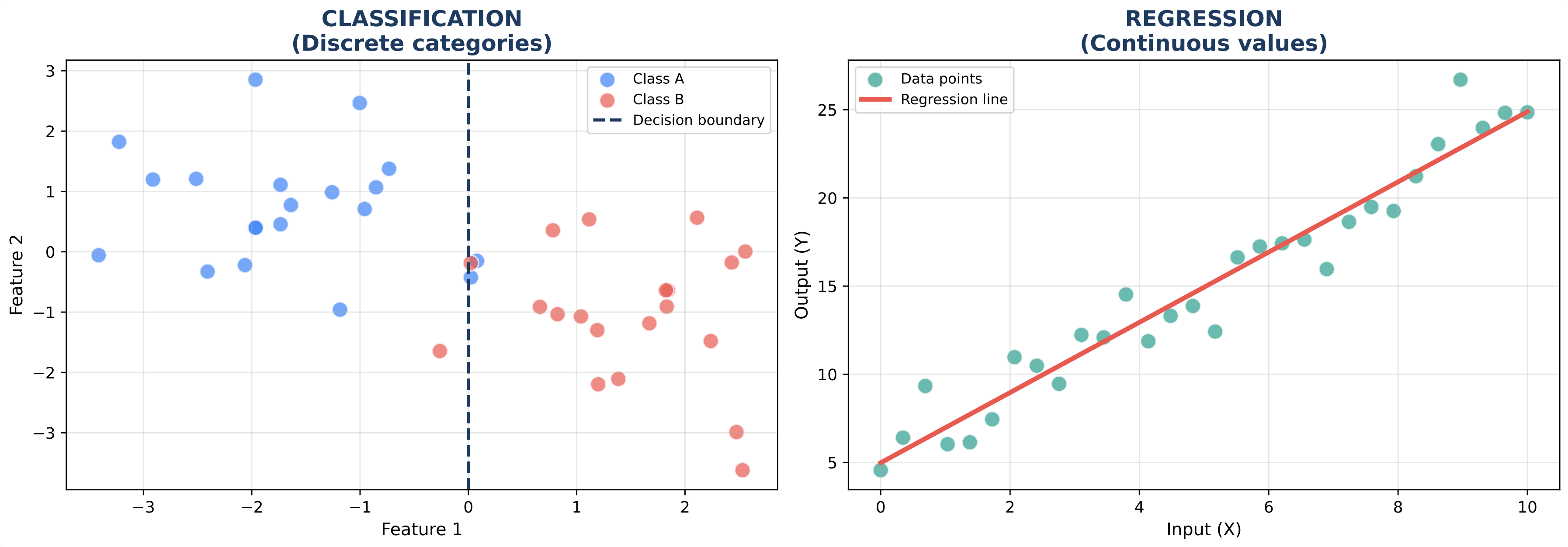
Paradigm Comparison

Aspect	Supervised	Unsupervised	Reinforcement
Data	X + y (labels)	X only	States + Actions
Goal	Predict labels	Find structure	Maximize reward
Feedback	Correct answers	None	Reward signals
Example	Spam detection	Customer segments	Game playing

Supervised Learning: The Teacher Analogy

```
┌──────────────────────────────────────────────────────────────┐
│                    SUPERVISED LEARNING                        │
├──────────────────────────────────────────────────────────────┤
│                                                               │
│   Student (Model)          Teacher (Training Data)           │
│                                                               │
│   "Is this spam?"    ──→   "Yes, that's spam."               │
│                             "No, that's legitimate."          │
│                             "Yes, that's spam."               │
│                             ...                               │
│                                                               │
│   After many examples, student learns the patterns!          │
│                                                               │
└──────────────────────────────────────────────────────────────┘
```

Supervised Learning: Two Types



Classification: Discrete Outputs

Goal: Assign input to one of K categories

Type	K	Example
Binary	2	Spam / Not Spam
Multi-class	K > 2	Cat, Dog, Bird, Fish
Multi-label	Multiple	[Action, Comedy] for a movie

```
# Binary: One probability
model.predict_proba(email)  # → [0.15, 0.85] = 85% spam

# Multi-class: K probabilities (sum to 1)
model.predict_proba(image)  # → [0.70, 0.20, 0.05, 0.05]
                            #     Cat   Dog   Bird  Fish
```

Classification Examples

Task	Input	Classes	Real-World Use
Spam Detection	Email text	Spam, Not Spam	Gmail, Outlook
Medical Diagnosis	Symptoms, tests	Disease A, B, Healthy	Hospital systems
Image Recognition	Photo pixels	1000 ImageNet classes	Google Photos
Sentiment Analysis	Review text	Positive, Negative, Neutral	Brand monitoring
Fraud Detection	Transaction	Fraud, Legitimate	Credit card companies
Face Recognition	Face image	Person 1, 2, ..., N	iPhone unlock

Regression: Continuous Outputs

Goal: Predict a numerical value

```
# Output can be ANY number
model.predict(house_features)  # → 425,000.00
model.predict(face_image)      # → 27.3 (years old)
model.predict(stock_data)      # → 152.47 (price)
```

Classification: "Which bucket?" | Regression: "How much?"

Regression Examples

Task	Input	Output	Range	Real-World Use
House Pricing	Size, location	Price ($)	$100K - $10M	Zillow, Redfin
Age Estimation	Face image	Years	0 - 100	Age verification
Demand Forecasting	History, season	Units	0 - ∞	Amazon inventory
Energy Prediction	Weather, time	kWh	0 - ∞	Power grid
Stock Prediction	Historical data	Price	0 - ∞	Trading
Salary Estimation	Resume features	Salary	$0 - $1M	LinkedIn

Quick Check: Classification or Regression?

Task	Answer
"Will it rain tomorrow?"	Classification (Yes/No)
"How many mm of rain?"	Regression (continuous)
"What genre is this movie?"	Classification (Action, Comedy, ...)
"What rating will user give?"	Could be both! (1-5 stars)
"Which digit is written?"	Classification (0-9)
"How confident is the prediction?"	Regression (0.0 - 1.0)

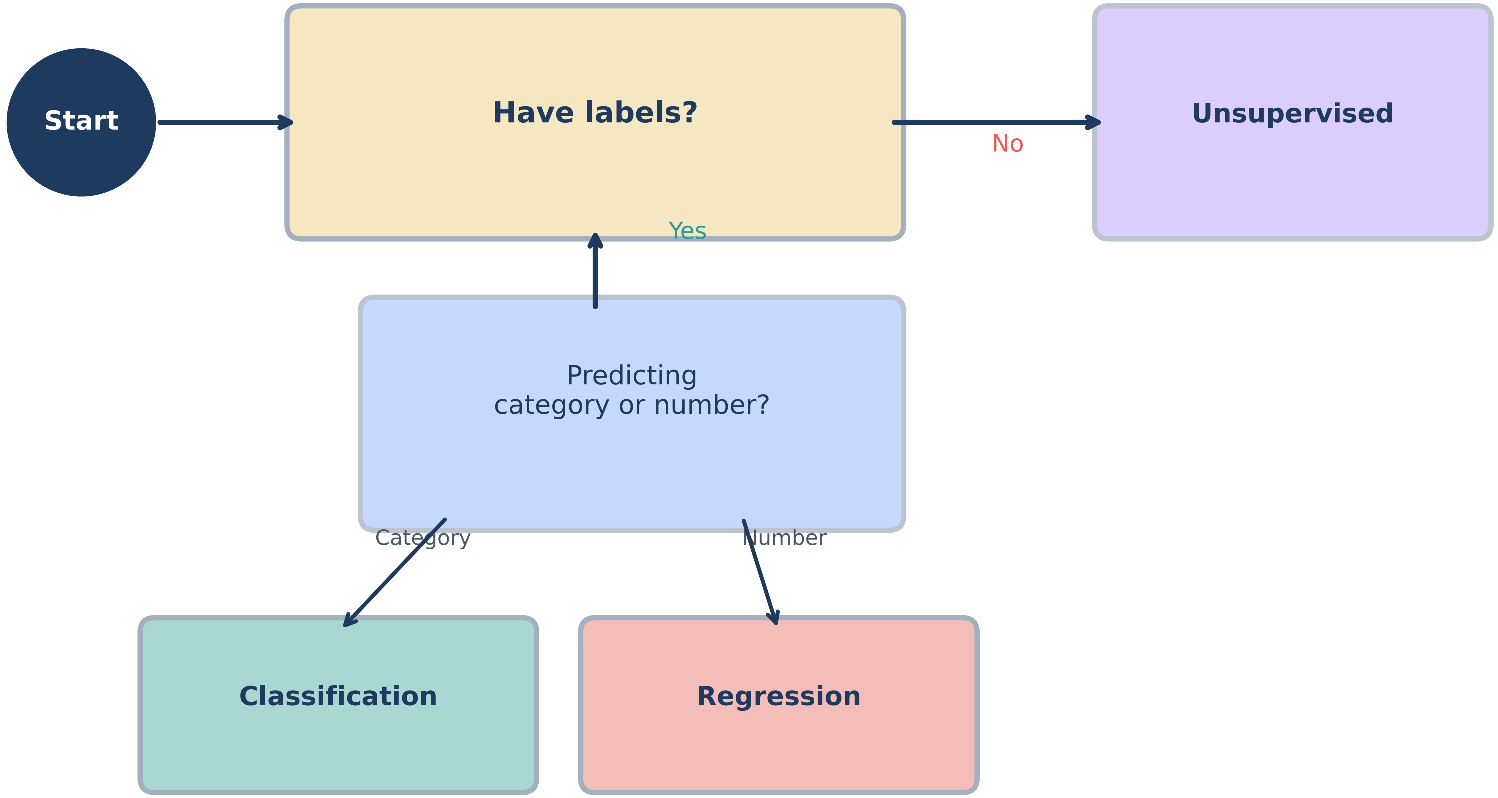
The In-Between: Ordinal Data

Some data is **ordered categories**:

Rating	As Classification	As Regression
⭐	Class 0	1.0
⭐⭐	Class 1	2.0
⭐⭐⭐	Class 2	3.0
⭐⭐⭐⭐	Class 3	4.0
⭐⭐⭐⭐⭐	Class 4	5.0

Both approaches can work! Regression might predict 3.7 stars.

ML Tasks: The Decision Flowchart



Computer Vision Task Hierarchy

More Information →

Classification	Detection	Segmentation	Pose
"What is it?"	*"What & where?"*	*"Exact shape?"*	*"Keypoints?"*
→ Cat	→ Boxes	→ Masks	→ Skeleton

NLP Task Hierarchy

Task	Input → Output	Example	Complexity
Classification	Text → Category	"Great movie!" → Positive	⭐
NER	Text → Tagged entities	"[Sundar Pichai]_PERSON visited [Google]_ORG"	⭐⭐
Seq2Seq	Sequence → Sequence	English → French	⭐⭐⭐
Generation	Prompt → Text	"Write a poem..." → Poem	⭐⭐⭐⭐

Part 2: Understanding Data

The Fuel for Machine Learning

"Data is the New Oil"

"Data is the new oil. Like oil, data is valuable, but if unrefined it cannot really be used."
— Clive Humby (2006)

Oil Industry	ML Industry
Extract crude oil	Collect raw data
Refine into gasoline	Clean and process data
Powers engines	Powers models
Pollution issues	Bias issues

What IS Data in ML?

Features (X) | **Label (y)**

sqft	beds	baths	garage	price
1500	3	2	Yes	$300K
2000	4	3	Yes	$450K
1200	2	1	No	$200K

Anatomy of a Dataset

```
                     Features (X)                            Label (y)

            ┌────────┬───────┬────────┬─────────┬────────┐  ┌─────────┐
            │  sqft  │ beds  │ baths  │ garage  │  year  │  │  price  │
            ├────────┼───────┼────────┼─────────┼────────┤  ├─────────┤
   Row 1 →  │  1500  │   3   │   2    │   Yes   │  1990  │  │ 300,000 │
   Row 2 →  │  2000  │   4   │   3    │   Yes   │  2005  │  │ 450,000 │
   Row 3 →  │  1200  │   2   │   1    │   No    │  1975  │  │ 200,000 │
   Row 4 →  │  1800  │   3   │   2    │   Yes   │  2010  │  │ 350,000 │
            └────────┴───────┴────────┴─────────┴────────┘  └─────────┘

            n_samples = 4 (rows)
            n_features = 5 (columns in X)
```

Features: The Inputs

Features = Information about each example

Good Features

- Relevant to prediction
- Measurable/computable
- Available at prediction time
- Not too correlated with each other

Feature Examples

Domain	Features
House	sqft, beds, zip code
Email	word counts, sender
Image	pixel values
Customer	age, purchases, clicks

Types of Features

Numerical	Categorical	Binary	Ordinal	Text
25, 3.14, -5	*Red, Blue, Green*	*Yes/No, 0/1*	*S < M < L*	*"Hello world"*

Feature Type Details

Type	Values	Example	Encoding
Numerical	Any number	Age: 25, Price: $50.99	Use directly
Categorical	Unordered set	Color: Red, Blue, Green	One-hot encoding
Binary	2 values	Has garage: Yes/No	0 or 1
Ordinal	Ordered set	Size: S < M < L < XL	Integer encoding
Text	String	"Great product!"	Embedding
Date/Time	Timestamp	2024-01-15	Extract features

One-Hot Encoding Example

Problem: Models need numbers, but "Red" isn't a number!

Solution: Create binary columns for each category

Color	is_Red	is_Blue	is_Green
Red	1	0	0
Blue	0	1	0
Green	0	0	1
Blue	0	1	0

```
pd.get_dummies(df['color'])  # Does this automatically!
```

Labels: The Outputs

Label = What we want to predict

Supervised Task	Label Type	Examples
Binary classification	0 or 1	spam/not spam
Multi-class	Integer (0 to K-1)	digit (0-9)
Regression	Float	price ($)
Multi-label	Binary vector	[action, comedy, drama]

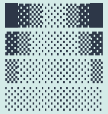
Unsupervised learning has NO labels! That's what makes it "unsupervised."

Types of Data Structures

Tabular

A	B
1	2

Image



Text

"The quick
brown fox
jumps..."

Time Series

Tabular Data (Most Common)

```python
import pandas as pd

df = pd.DataFrame({
    'sqft': [1500, 2000, 1200],
    'beds': [3, 4, 2],
    'price': [300000, 450000, 200000]
})

#    sqft  beds   price
# 0  1500     3  300000
# 1  2000     4  450000
# 2  1200     2  200000

X = df[['sqft', 'beds']]  # Features
y = df['price']            # Labels
```

Image Data

```python
import numpy as np

# Grayscale image: Height × Width
mnist_digit = np.zeros((28, 28))  # 784 pixels

# Color image: Height × Width × 3 (RGB)
photo = np.zeros((224, 224, 3))   # 150,528 values

# Batch of images: Batch × Height × Width × Channels
batch = np.zeros((32, 224, 224, 3))  # 32 images
```

```
┌──────────────────────────┐
│ 0   0   0   23  155  0   │
│ 0   0   89  254 254  0   │  ← Each cell = pixel brightness
│ 0   0   155 254 178  0   │    (0 = black, 255 = white)
│ ...                      │
└──────────────────────────┘
```

Text Data

Raw text needs preprocessing:

```
text = "I love this movie! It's great."

# Step 1: Tokenize (split into words/pieces)
tokens = ["I", "love", "this", "movie", "!", "It", "'s", "great", "."]

# Step 2: Convert to numbers (vocabulary index)
indices = [23, 156, 45, 892, 2, 56, 78, 234, 3]

# Step 3: (Optional) Convert to embeddings
embeddings = model.embed(indices)  # Shape: (9, 768)
```

Time Series Data

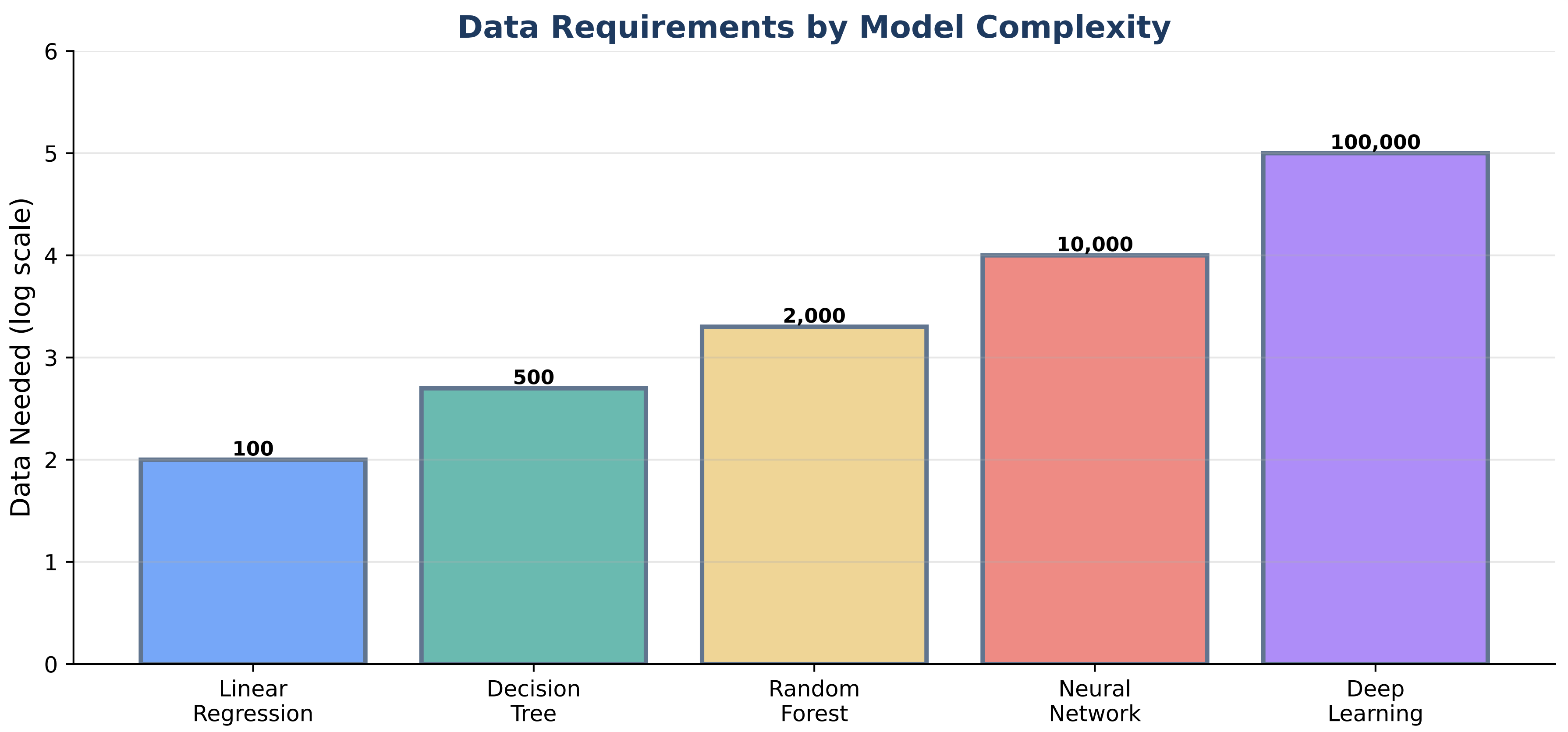
```python
# Stock prices over time
dates = pd.date_range('2024-01-01', periods=100)
prices = [100.0, 101.5, 99.8, 102.3, ...]  # 100 values

# Key characteristic: ORDER MATTERS!
# Shuffling destroys the patterns
```

```
Price
  │    /\
  │   /  \  /\
  │  /    \/  \
  │ /          \
  └──────────────────► Time

    t1  t2  t3  t4
```

How Much Data Do You Need?

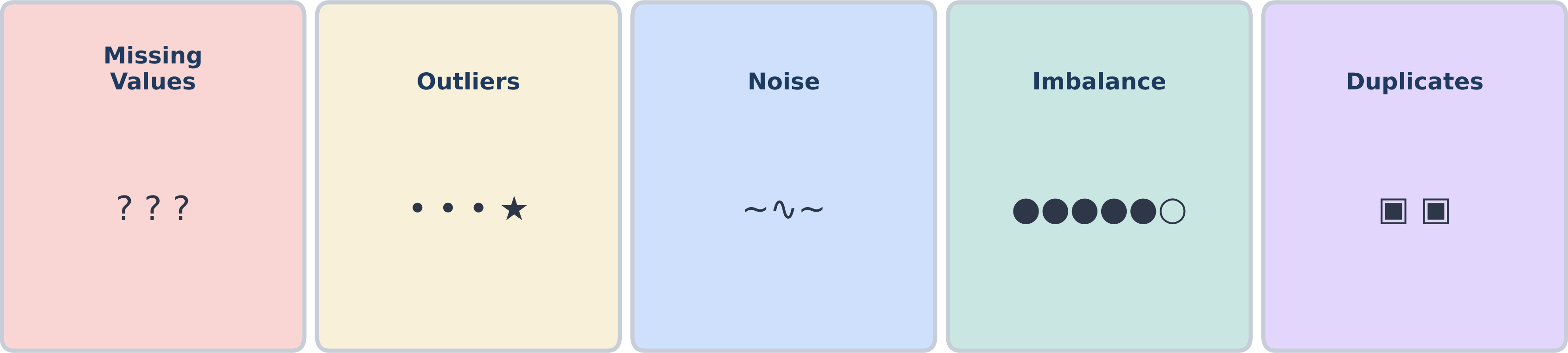


The Data Scaling Laws

Model Complexity	Minimum Data	Sweet Spot	Diminishing Returns
Linear Regression	50	500	5,000
Decision Tree	100	1,000	10,000
Random Forest	500	5,000	50,000
Neural Network (small)	1,000	10,000	100,000
Deep Learning	10,000	100,000	1,000,000+
LLMs	1B tokens	1T tokens	10T+ tokens

More data almost always helps, but there are diminishing returns. Quality > Quantity!

Data Quality Issues



Missing Values

```python
# Original data
df = pd.DataFrame({
    'age': [25, None, 35, 42, None],
    'salary': [50000, 60000, None, 80000, 55000]
})

# Option 1: Drop rows with missing values
df.dropna()  # Lose 3 rows!

# Option 2: Fill with mean/median
df['age'].fillna(df['age'].mean())  # Fill with 34

# Option 3: Fill with mode (categorical)
df['color'].fillna(df['color'].mode()[0])
```

Outliers

```
Normal distribution:      With outlier:

     ╭───────╮                ╭───────╮
    /         \              /         \              •
   /           \            /           \           (outlier)
  /             \          /             \
 /               \        /               \
────────────────────     ────────────────────────────────

  μ = 50                   μ = 50        outlier = 500

Mean without outlier: 50
Mean with outlier: 95  ← Heavily skewed!
```

Detection: Z-score > 3, IQR method, visual inspection

Class Imbalance

Scenario: Fraud detection (1% fraud, 99% legitimate)

Approach	Model Prediction	Accuracy
Naive model	"All legitimate"	99%!
Smart model	Tries to detect	97%

The 99% model is USELESS! It never detects fraud.

Solutions:

- Oversample minority class (SMOTE)
- Undersample majority class
- Use class weights
- Different metrics (precision, recall, F1)

The Data Lifecycle

1. Collect → 2. Clean → 3. Explore → 4. Transform → 5. Split → 6. Use

Data Lifecycle in Code

```python
# 1. COLLECT
df = pd.read_csv('raw_data.csv')

# 2. CLEAN
df = df.dropna()  # Handle missing
df = df[df['age'] < 120]  # Remove outliers

# 3. EXPLORE
df.describe()  # Statistics
df.hist()  # Visualize

# 4. TRANSFORM
df['log_price'] = np.log(df['price'])  # Transform
X = pd.get_dummies(df[features])  # Encode

# 5. SPLIT
X_train, X_test, y_train, y_test = train_test_split(X, y)

# 6. USE
model.fit(X_train, y_train)
```

Part 3: Train/Test Split

The Most Important Concept

The Exam Analogy

Practice Questions

Q1, Q2, Q3, Q4, Q5

(Study material)

→

Exam Questions

Q6, Q7, Q8, Q9, Q10

(Never seen before!)

Two Study Strategies

Strategy A: Memorize

```
Q: "What is 2+3?"
A: "5" (memorized)

Q: "What is 2+4?"
A: "???" (never seen!)
```

Result: Fails on new questions

Strategy B: Learn

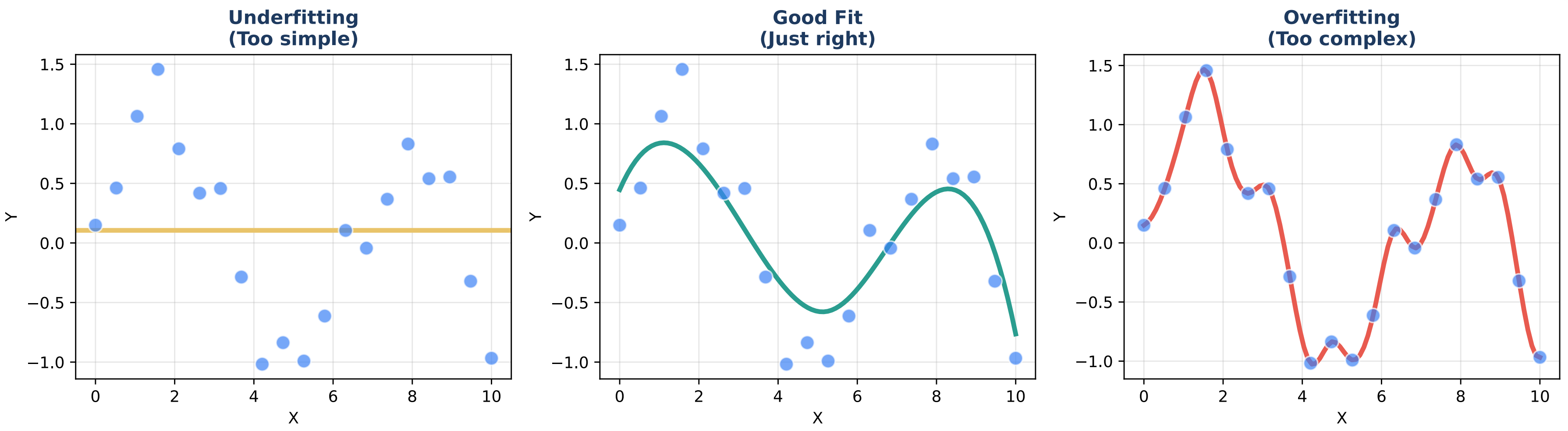
```
Q: "What is 2+3?"
A: "5" (understands addition)

Q: "What is 2+4?"
A: "6" (applies principle)
```

Result: Works on any question

> We want ML models to LEARN, not MEMORIZE!

What is Overfitting?



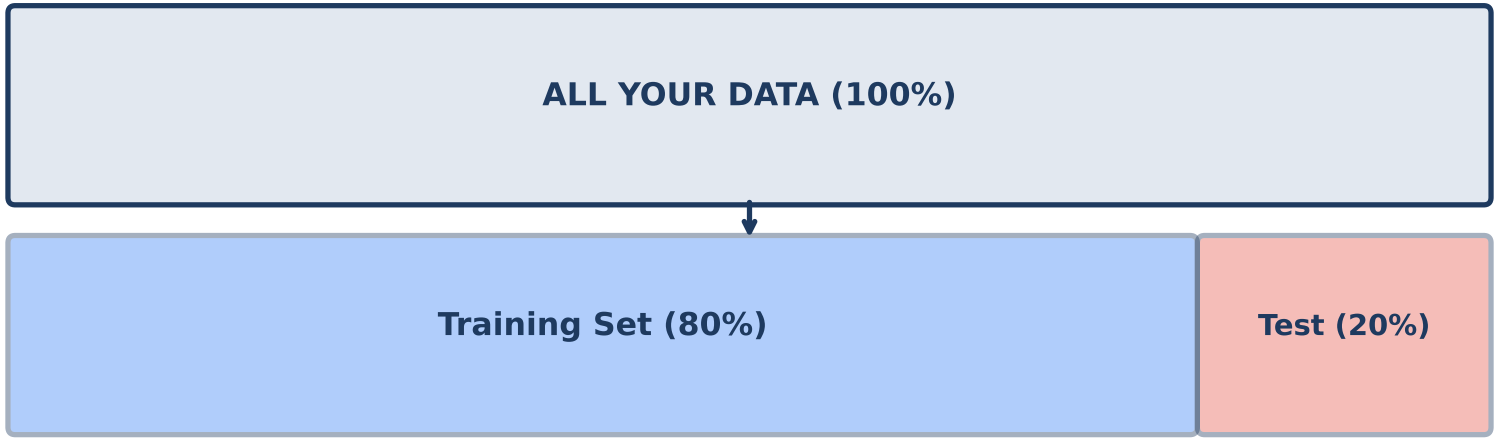
Overfitting in Detail

Definition: Model performs well on training data but poorly on new data

Metric	Overfitting	Good Fit
Training Accuracy	99%	92%
Test Accuracy	60%	90%
Gap	39%	2%

The model memorized the training data!

The Train/Test Split



Why Split Works

```
THE RULES

1. Model trains ONLY on training data

2. Model NEVER sees test data during training

3. After training, evaluate on test data

4. Test performance = Expected real-world performance
```

The Golden Rule

NEVER PEEK AT TEST DATA!

If you use test data for:

- Choosing which model to use → **Data leakage**
- Tuning hyperparameters → **Data leakage**
- Feature selection → **Data leakage**

Your accuracy estimate will be **too optimistic** and your model will **fail in production**.

Train/Test Split in Code

```python
from sklearn.model_selection import train_test_split

# The sacred split
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
    stratify=y           # Keep class proportions (classification)
)

print(f"Training samples: {len(X_train)}")  # 800
print(f"Test samples: {len(X_test)}")       # 200

# NOW: Only touch X_train, y_train until final evaluation
```

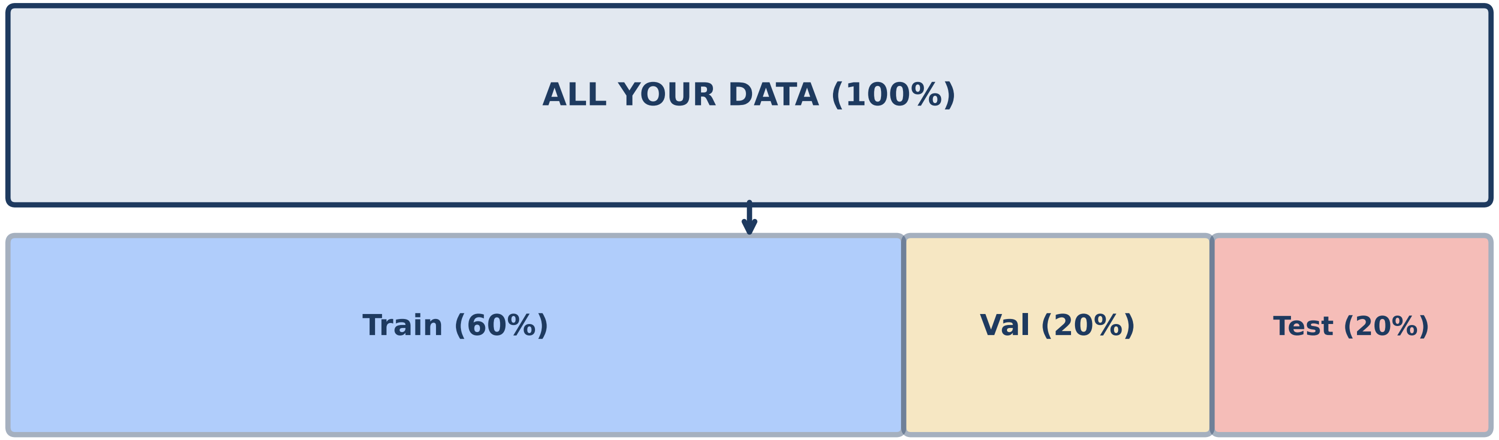
Choosing Split Ratio

Dataset Size	Train %	Test %	Reasoning
< 1,000	70%	30%	Need enough test samples
1,000 - 10,000	80%	20%	Standard split
10,000 - 100,000	90%	10%	Plenty of test data
> 100,000	95%	5%	Even 5% is thousands

> With huge datasets, even a small percentage gives reliable estimates.

The Three-Way Split

For model selection, you need **three** sets:



Three-Way Split Explained

Set	Purpose	When Used
Training (60%)	Learn parameters	During `model.fit()`
Validation (20%)	Tune hyperparameters	Choosing model, settings
Test (20%)	Final evaluation	Once, at the very end

```
# First split: separate test
X_temp, X_test, y_temp, y_test = train_test_split(X, y, test_size=0.2)

# Second split: separate validation
X_train, X_val, y_train, y_val = train_test_split(X_temp, y_temp, test_size=0.25)
# 0.25 of 0.8 = 0.2 of total
```

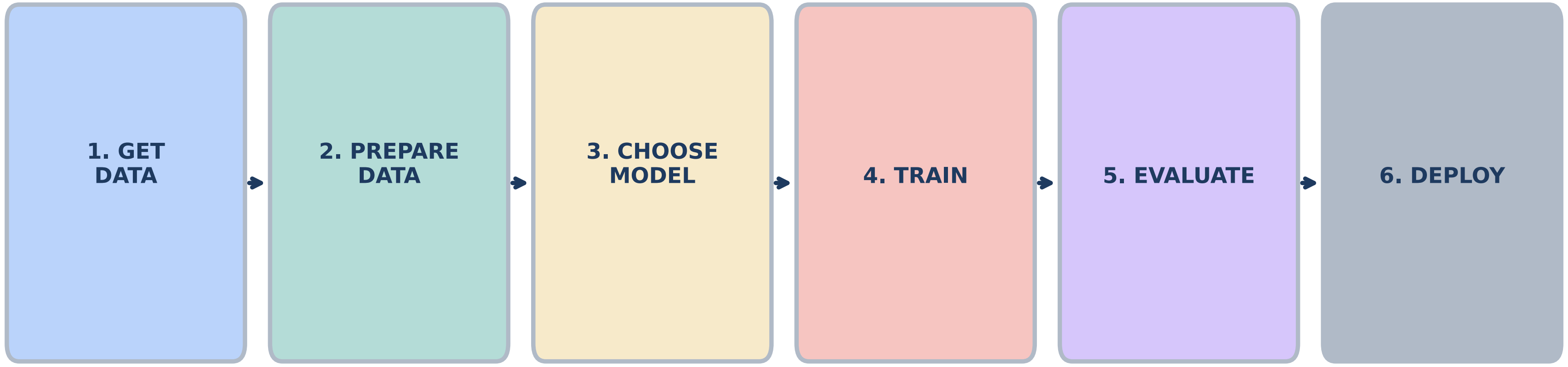
Common Mistakes

Mistake	Why It's Bad	Fix
Training on all data	Can't detect overfitting	Always split first
Peeking at test data	Optimistic estimates	Lock away test data
Tuning on test	Indirect training	Use validation set
Small test set	High variance	Use at least 20%
No random state	Non-reproducible	Set `random_state=42`
Data leakage	False confidence	Check processing order

Part 4: The ML Recipe

Putting It All Together

The Universal ML Recipe



Step 1: Get Data

```python
import pandas as pd
from sklearn.datasets import load_iris

# Option 1: Load from file
df = pd.read_csv('houses.csv')
X = df[['sqft', 'beds', 'baths']]
y = df['price']

# Option 2: Use sklearn datasets
iris = load_iris()
X, y = iris.data, iris.target

# Option 3: Create manually
X = [[1500, 3, 2], [2000, 4, 3], [1200, 2, 1]]
y = [300000, 450000, 200000]
```

Step 2: Prepare Data

```python
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

# 1. Split first! (before any processing)
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42
)

# 2. Scale features (fit ONLY on train!)
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)  # fit + transform
X_test_scaled = scaler.transform(X_test)        # only transform!
```

Always fit scaler on training data only! Otherwise: data leakage.

Step 3: Choose a Model

Model Selection Guide

Start Here →	**Linear/Logistic Regression**
Need Explanation →	**Decision Tree**
General Purpose →	**Random Forest**
Maximum Accuracy →	**XGBoost / Neural Net**

Model Complexity Ladder

Model	Complexity	Interpretability	When to Use
Linear/Logistic	⭐	High	Start here, baseline
Decision Tree	⭐⭐	High	Need explanations
Random Forest	⭐⭐⭐	Medium	General purpose
XGBoost	⭐⭐⭐⭐	Low	Competitions
Neural Network	⭐⭐⭐⭐⭐	Very Low	Images, text, lots of data

Always start simple! Only add complexity if needed.

Step 4: Train (Fit)

```python
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeClassifier

# For regression
reg_model = LinearRegression()
reg_model.fit(X_train, y_train)

# For classification
clf_model = DecisionTreeClassifier(max_depth=5)
clf_model.fit(X_train, y_train)

# What happens inside:
# 1. Model sees (X, y) pairs
# 2. Adjusts internal parameters
# 3. Minimizes prediction error
# 4. Stores learned patterns
```

What Happens During Training?

```
Iteration 1:  Predictions: [350K, 400K, 250K]
              Actual:      [300K, 450K, 200K]
              Error:       Large!
              Action:      Adjust parameters ↓

Iteration 2:  Predictions: [320K, 430K, 220K]
              Actual:      [300K, 450K, 200K]
              Error:       Smaller
              Action:      Keep adjusting...

...

Iteration N:  Predictions: [305K, 445K, 198K]
              Actual:      [300K, 450K, 200K]
              Error:       Small enough!
              Action:      Stop, save parameters
```

Step 5: Evaluate

```python
# Make predictions on TEST data (never seen before!)
predictions = model.predict(X_test)

# Compare predictions to actual values
from sklearn.metrics import mean_squared_error, accuracy_score

# Regression
rmse = np.sqrt(mean_squared_error(y_test, predictions))
print(f"RMSE: ${rmse:,.0f}")  # RMSE: $25,000

# Classification
accuracy = accuracy_score(y_test, predictions)
print(f"Accuracy: {accuracy:.1%}")  # Accuracy: 94.5%
```

Step 6: Deploy

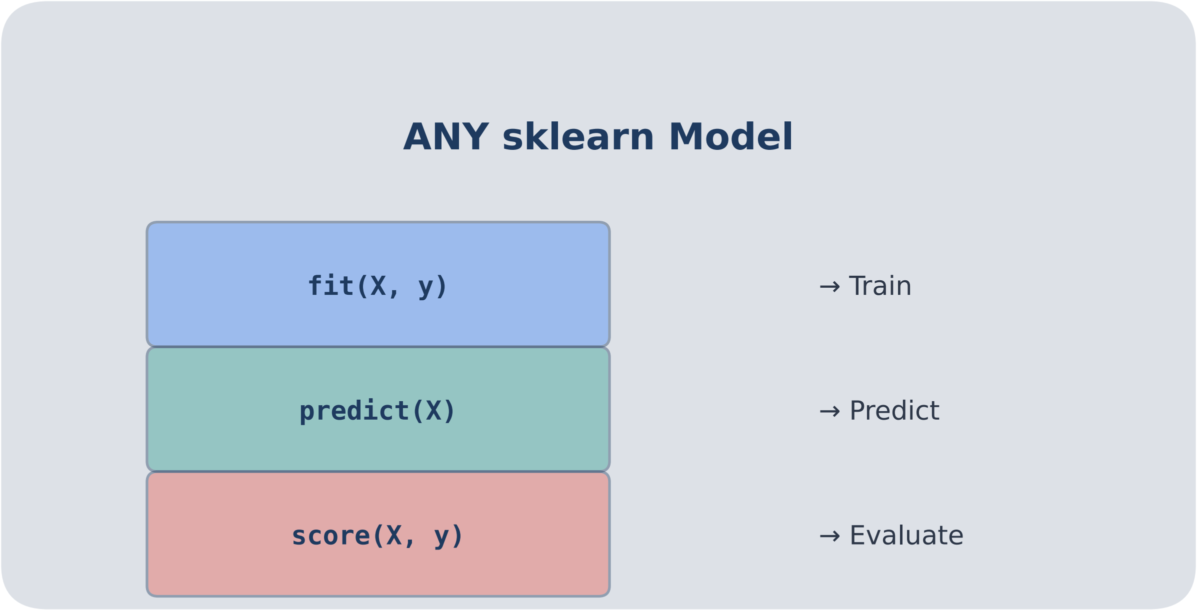
```python
import joblib

# Save the trained model
joblib.dump(model, 'house_price_model.pkl')
joblib.dump(scaler, 'scaler.pkl')

# Later, in production...
model = joblib.load('house_price_model.pkl')
scaler = joblib.load('scaler.pkl')

# New house comes in
new_house = [[1800, 3, 2]]  # sqft, beds, baths
new_house_scaled = scaler.transform(new_house)
predicted_price = model.predict(new_house_scaled)
print(f"Predicted price: ${predicted_price[0]:,.0f}")
```

The sklearn API Pattern



The Beauty of Consistent APIs

```python
# ALL sklearn models follow the same pattern!

# Linear Regression
from sklearn.linear_model import LinearRegression
model = LinearRegression()
model.fit(X_train, y_train)
model.predict(X_test)

# Random Forest
from sklearn.ensemble import RandomForestClassifier
model = RandomForestClassifier()
model.fit(X_train, y_train)
model.predict(X_test)

# Neural Network
from sklearn.neural_network import MLPClassifier
model = MLPClassifier()
model.fit(X_train, y_train)
model.predict(X_test)

# Same 3 methods: fit(), predict(), score()
```

Complete Example: Classification

```python
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, classification_report

# 1. Load data
iris = load_iris()
X, y = iris.data, iris.target

# 2. Split
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42
)

# 3. Train
model = DecisionTreeClassifier(max_depth=3)
model.fit(X_train, y_train)

# 4. Evaluate
y_pred = model.predict(X_test)
print(f"Accuracy: {accuracy_score(y_test, y_pred):.1%}")
print(classification_report(y_test, y_pred, target_names=iris.target_names))
```

Complete Example: Regression

```python
from sklearn.datasets import fetch_california_housing
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
import numpy as np

# 1. Load data
housing = fetch_california_housing()
X, y = housing.data, housing.target

# 2. Split
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42
)

# 3. Train
model = LinearRegression()
model.fit(X_train, y_train)

# 4. Evaluate
y_pred = model.predict(X_test)
print(f"RMSE: ${np.sqrt(mean_squared_error(y_test, y_pred))*100000:,.0f}")
print(f"R² Score: {r2_score(y_test, y_pred):.3f}")
```

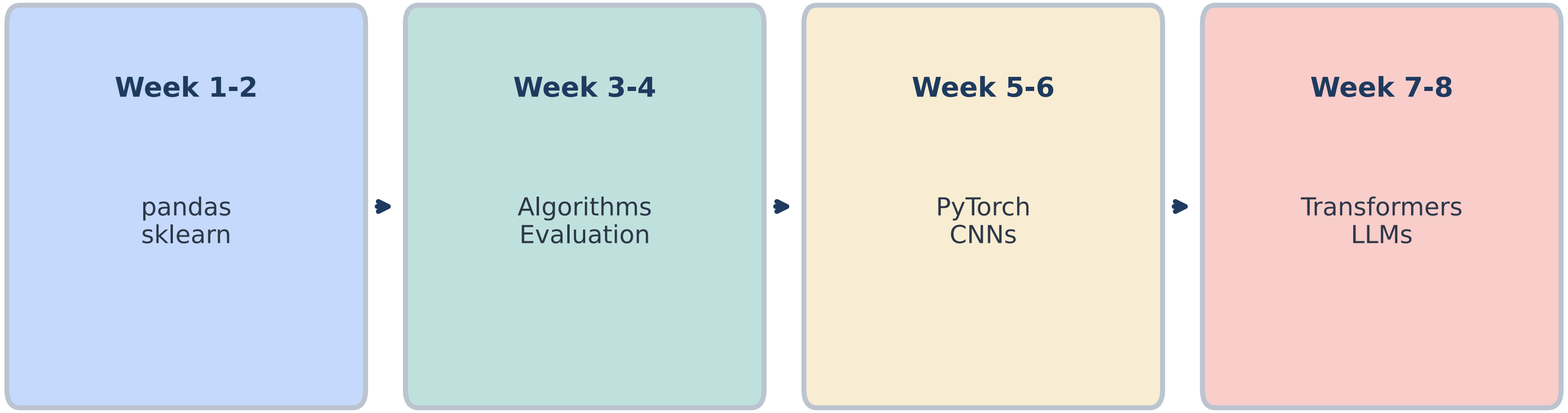
Part 5: Course Roadmap

What's Coming Next

Your Journey Through AI

Week	Topic	Big Question	You'll Learn
1	Introduction	What can AI do?	Motivation, capabilities
2	Data Foundation	What is ML?	Framework, data, split
3	Supervised Learning	How do algorithms work?	LR, Trees, KNN
4	Model Selection	How to choose?	CV, tuning, ensembles
5	Neural Networks	What is deep learning?	Backprop, PyTorch
6	Computer Vision	How do machines see?	CNNs, YOLO
7	Language Models	How do LLMs work?	Transformers
8	Generative AI	How do machines create?	Diffusion, APIs

Skills You'll Build



Key Takeaways

Framework

1. ML learns from DATA
2. Three paradigms: Supervised, Unsupervised, RL
3. Classification vs Regression

Data

4. Features (X) + Labels (y)
5. Quality > Quantity
6. Train/Test split is SACRED

Practice

7. The sklearn pattern: `fit()` → `predict()` → `score()`
8. Start simple, add complexity only if needed

Ready to Build!

Next: Supervised Learning Deep Dive

Lab this week: Your first ML models with sklearn

"In God we trust. All others must bring data."
— W. Edwards Deming

Questions?