



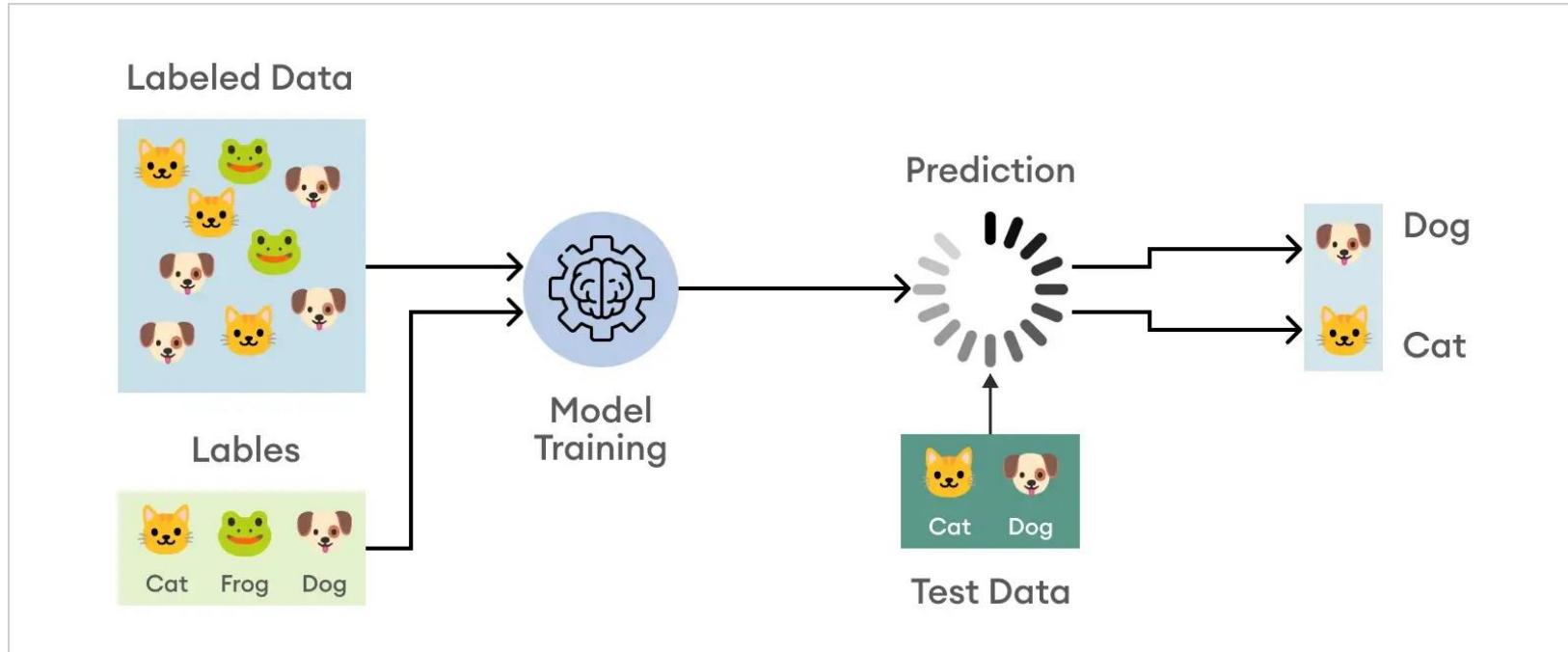
ML Classification Algorithms

Classification

Embedded ML



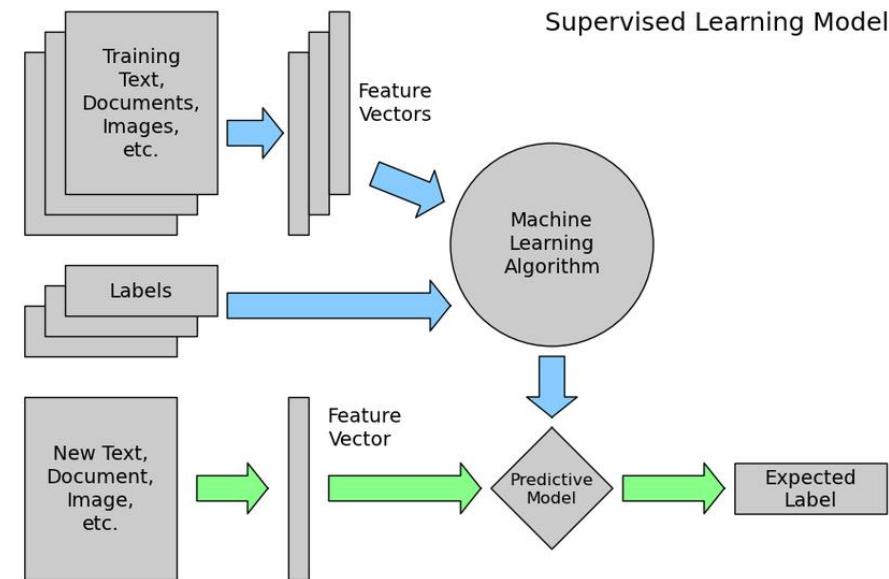
- **Classification** is a **supervised machine learning task** where a model learns to assign an input to **one of several discrete categories (classes)** based on labeled examples.



Classification



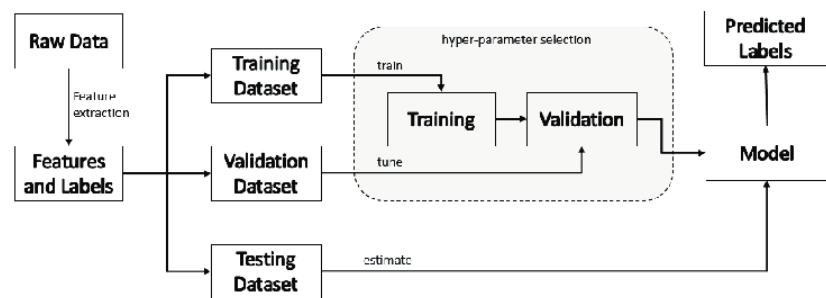
- Goal: Learn a mapping from **input features (X) to class labels (y)**
- Requires **labeled training data**
- Output: discrete class (e.g., walk / run / sit)
- Common applications:
 - Human Activity Recognition (IMU)
 - Gesture recognition
 - Fault detection
 - Audio / image classification
- Algorithms covered:
 - Decision Tree
 - Random Forest
 - Support Vector Machine (SVM)
 - Multi-Layer Perceptron (MLP)



Classification Pipeline



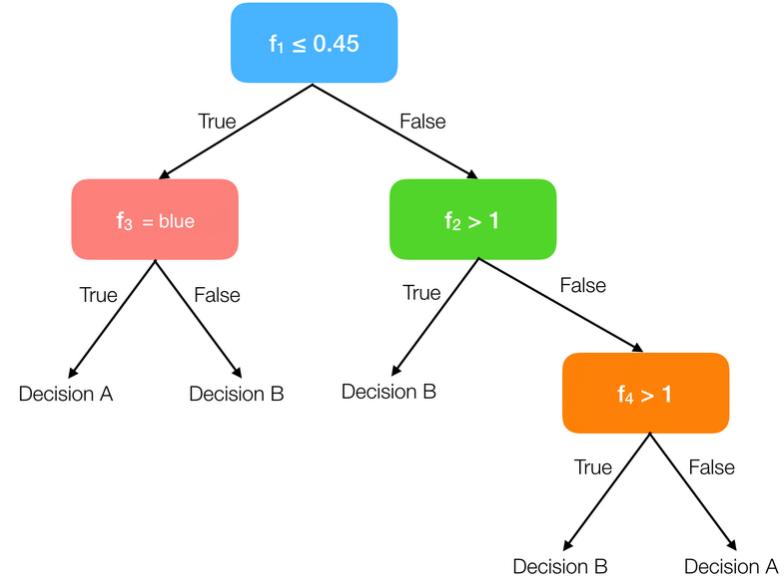
- Data collection (sensors, logs, datasets)
- Feature extraction (statistical, spectral, embeddings)
- Train / validation / test split
- Model training
- Evaluation metrics:
 - Accuracy
 - Precision / Recall
 - Confusion Matrix
 - F1-score
- Deployment (Edge / Cloud)





Decision Tree (DT)

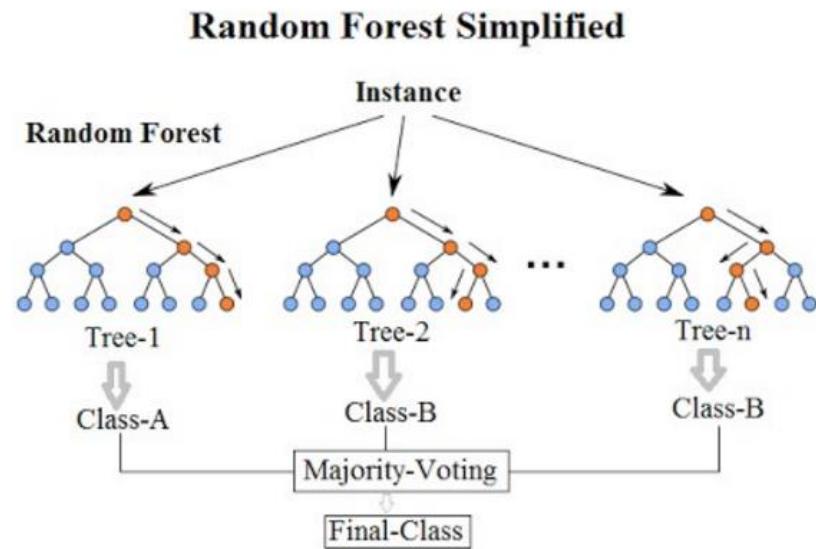
- Tree-structured model using **if-else rules**
- Splits data using feature thresholds
- Nodes: decision rules
- Leaves: class labels
- Popular splitting criteria:
 - Gini impurity
 - Entropy (Information Gain)
- **Advantages**
 - Easy to understand & visualize
 - No feature scaling required
 - Fast inference (good for embedded)
- **Limitations**
 - Overfitting on noisy data
 - Unstable to small data changes





Random Forest (RF)

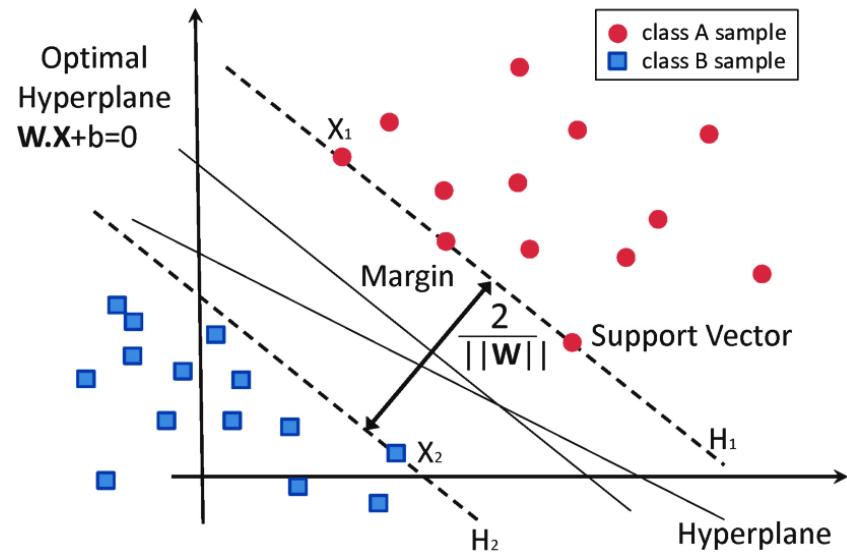
- Ensemble of **multiple decision trees**
- Each tree:
 - Trained on random subset of data
 - Uses random subset of features
- Final prediction = majority vote
- **Advantages**
 - High accuracy
 - Reduces overfitting
 - Works well with sensor data
- **Limitations**
 - Larger memory footprint
 - Less interpretable than single tree



Support Vector Machine (SVM)



- Finds an **optimal separating hyperplane**
- Maximizes margin between classes
- Can use **kernel functions**:
 - Linear
 - Polynomial
 - RBF (Gaussian)
- **Advantages**
 - Strong performance on small datasets
 - Effective in high-dimensional spaces
- **Limitations**
 - Sensitive to parameter tuning
 - Computationally expensive for large datasets
 - Less suitable for real-time embedded inference

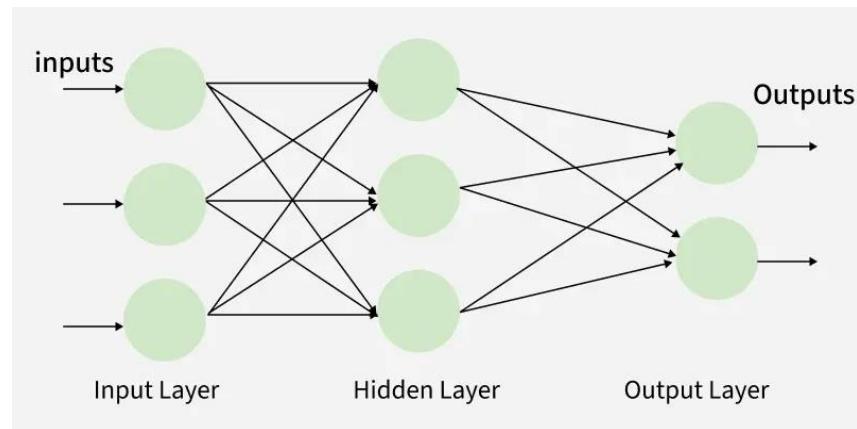


Multi-Layer Perceptron (MLP NN)

Embedded ML



- Fully connected **feed-forward neural network**
- Consists of:
 - Input layer
 - One or more hidden layers
 - Output layer
- Learns nonlinear decision boundaries
- **Advantages**
 - Very flexible
 - Learns complex feature interactions
 - Foundation for deep learning
- **Limitations**
 - Requires more data
 - Needs careful tuning
 - Harder to interpret



Backpropagation in Neural Networks

Embedded ML



- **Backpropagation** is the algorithm used to **train neural networks**
- It computes how much each **weight contributes to the prediction error**
- Uses **gradient descent** to update weights and minimize loss
-

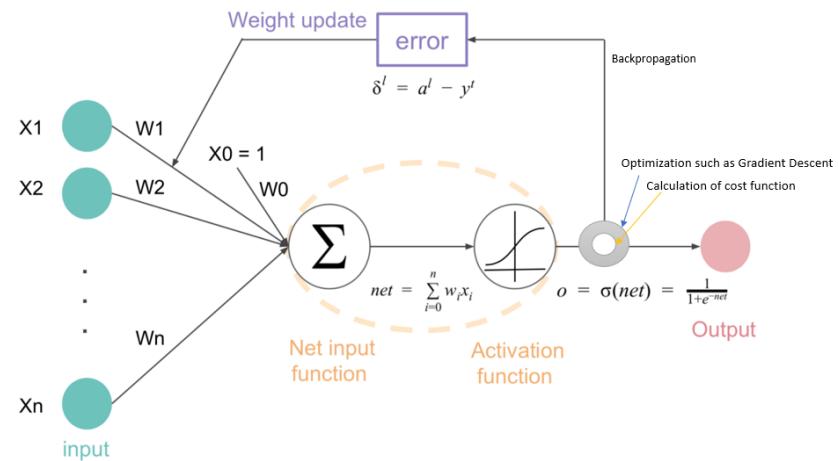
- **Two Phases of Training**

- 1 Forward Propagation**

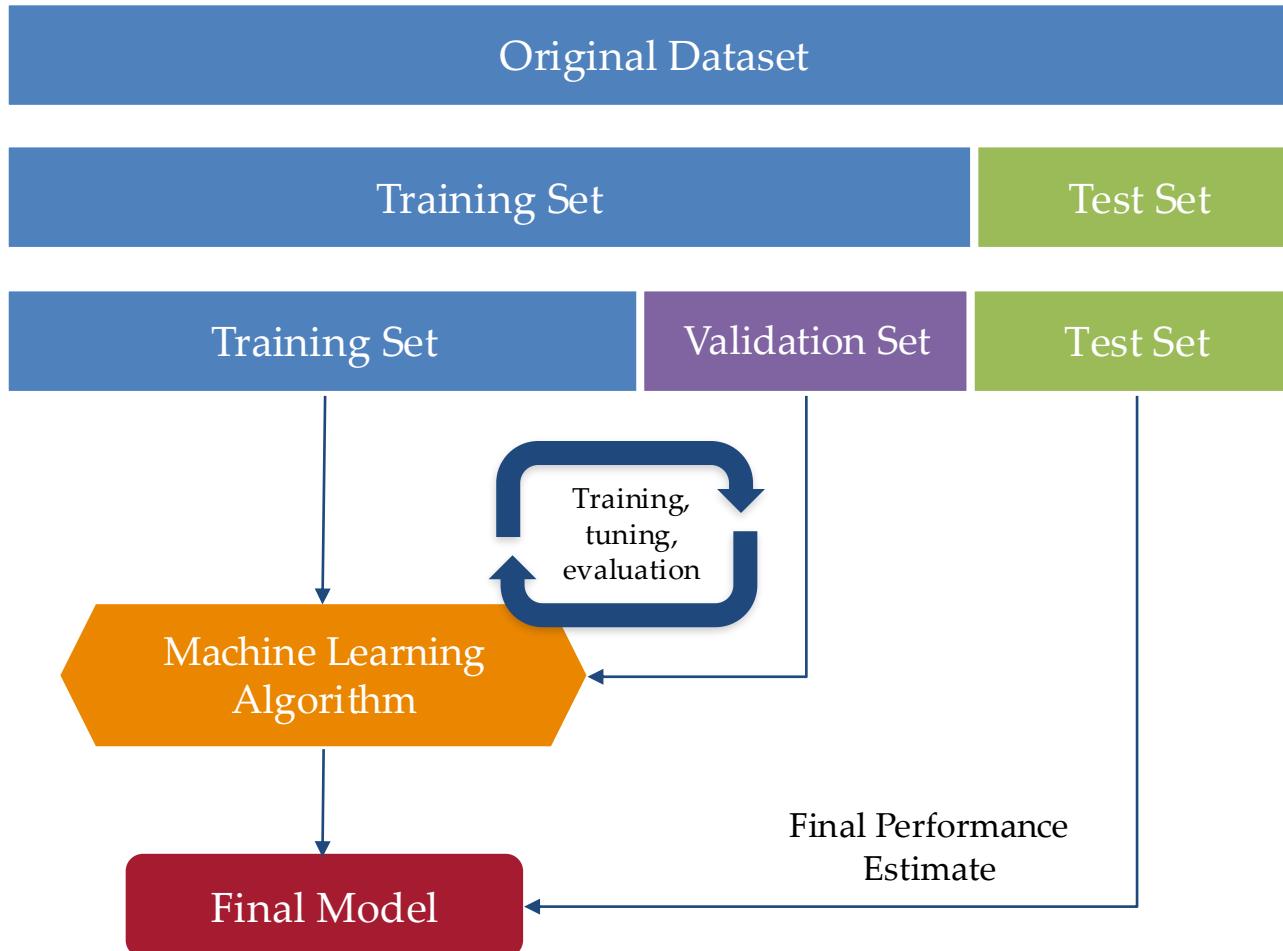
- Input features → hidden layers → output
- Network produces prediction \hat{y}

- 2 Backward Propagation**

- Compute loss:
- $L(y, \hat{y})$
- Propagate error **backwards**
- Update weights using gradients



ML Dataset Modeling



- Training data: labeled (ground truth - expected algorithm result; expensive!)
- Training: Algorithm uses labels to evaluate its accuracy on training data.

Holdout Validation (Train/Test Split)

Embedded ML



- **Concept:**

The dataset is divided into two disjoint subsets:

- **Training set:** Used to fit the model (e.g., 70–80%).
- **Test set:** Used to evaluate performance (e.g., 20–30%).

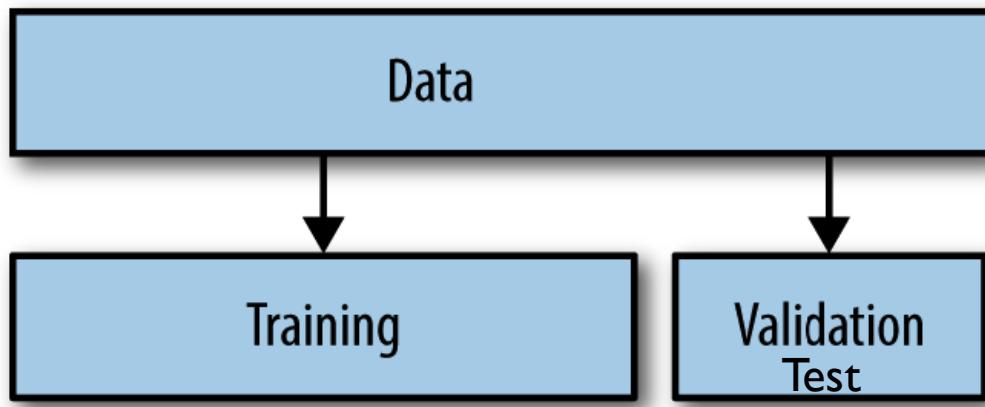
- **Advantages:**

- Simple and fast to implement.
- Useful for **large dataset**.

- **Disadvantages:**

- high variance depends on how the data is split.

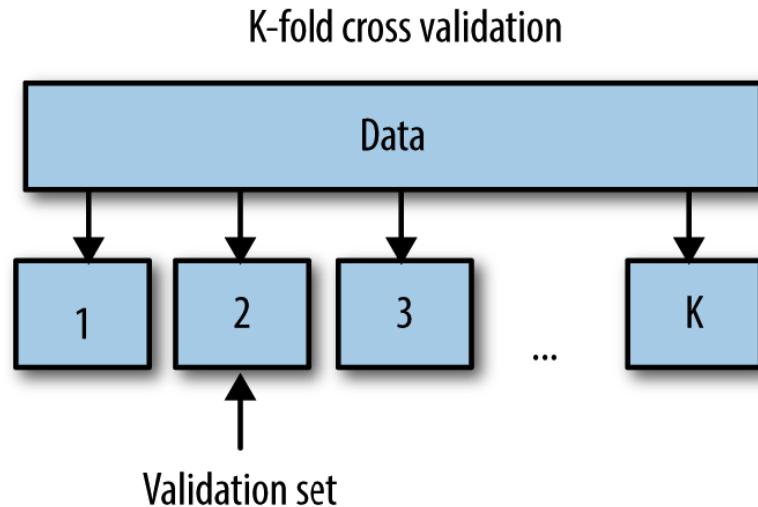
Hold-out validation



K-Fold Cross Validation



- **Concept:**
 - The dataset is divided into **K equal-sized folds** (commonly K=5 or 10).
 - For each iteration, one fold is used as the **validation set**, and the remaining K-1 folds are used for **training**.
 - The process repeats K times, each time with a different validation fold.
 - Final performance = **average of all K validation scores**.
- **Advantages:**
 - Reduces variance.
 - more reliable estimate of performance.
- **Disadvantages:**
 - Computationally more expensive (train model K times).
 - slow for large datasets/models.
- **Variations:**
 - **pure K-Fold CV**, there is **no separate test set**.
 - Best practice - **final holdout test set** (never touched during K-Fold CV) is used to evaluate the model



What to consider for time series data?



Scheme	Preserves Order	Handles Drift	Computation	Best For
Holdout Split	✓	✗	Low	Large, stable data
Expanding Window	✓	Partial	Medium	Periodic retraining
Sliding/Rolling Window	✓	✓	Medium	Non-stationary data
Walk-Forward Validation	✓	✓	High	Short-term forecasts
Time Series CV (Blocked)	✓	✗	Medium	Hyperparameter tuning
Nested CV	✓	Partial	Very High	Fair evaluation + tuning



Sampling

- If dataset has 70% Class A and 30% Class B, How do you split the dataset? Avoid imbalance in split.

Method	When to Use	API
Random Sampling	Baseline, assumes data is independent and identically distributed.	<code>train_test_split(X, y, test_size=0.2, shuffle=True)</code>
Stratified Sampling	Classification, imbalanced data	<code>train_test_split(..., stratify=y)</code>
Cluster Sampling	Data grouped by clusters (e.g., patients, machines)	<code>GroupKFold / GroupShuffleSplit</code>
Group-wise CV	Ensure all samples from a group stay together	<code>GroupKFold,</code> <code>LeaveOneGroupOut</code>
Time Series Splits	Ordered data, no shuffling allowed	<code>TimeSeriesSplit</code> , or custom expanding/rolling splits
Nested CV	Model selection + final evaluation	Outer KFold + inner CV inside outer loop
Bootstrap Sampling	Estimate confidence intervals, robust metrics	<code>sklearn.utils.resample</code> (sampling with replacement)

Evaluation Metrics (Classification)



- **Accuracy:** overall correctness
- **Precision:** correctness of positive predictions
- **Recall:** ability to find all positives
- **F1-Score:** balance of precision & recall
- **Confusion Matrix:**
 - Shows per-class performance
 - Reveals misclassification patterns

		Predicated Class		Sensitivity TP (TP+FN)	Specificity TN (TN+FP)
		Positive	Negative		
Actual Class	Positive	True Positive	False Negative Type II Error		
	Negative	False Positive Type I Error	True Negative		
	Precision TP (TP+FP)	Negative Predictive Value TN (TN+FN)	Accuracy TP (TP+TN+FP+FN)		

Precision, Recall, and Accuracy

Embedded ML



- Precision (predictive accuracy)
 - Percentage of positive labels that are correct
 - $\text{Precision} = (\# \text{ true positives}) / (\# \text{ true positives} + \# \text{ false positives})$
- Recall (sensitivity)
 - Percentage of positive examples that are correctly labeled
 - $\text{Recall} = (\# \text{ true positives}) / (\# \text{ true positives} + \# \text{ false negatives})$
- Accuracy
 - Percentage of correct labels
 - $\text{Accuracy} = (\# \text{ true positives} + \# \text{ true negatives}) / (\# \text{ of samples})$
- F1-score
 - Harmonic mean of precision and recall. Provides a balance between the two.

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

Improving Metrics



Metric	Condition for Good Classifier	If Low → How to Optimize
Precision	High → Few False Positives	<ul style="list-style-type: none">• Increase decision threshold• Better feature selection• Regularization to reduce noise
Recall	High → Few False Negatives	<ul style="list-style-type: none">• Lower decision threshold• Oversample minority class (SMOTE)• Use class weighting
Accuracy	High → Overall correctness (balanced classes)	<ul style="list-style-type: none">• Check class imbalance• Use resampling techniques• Improve model generalization (features, tuning)
F1-Score	High → Balanced Precision & Recall	<ul style="list-style-type: none">• Identify weak component (Precision or Recall)• Adjust threshold• Tune with F1 as scoring metric

Bias & Variance

Embedded ML

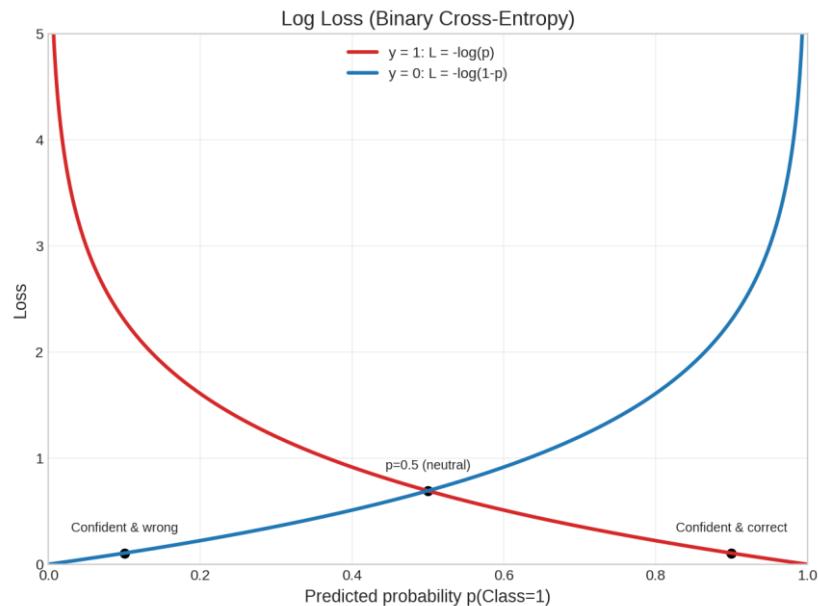
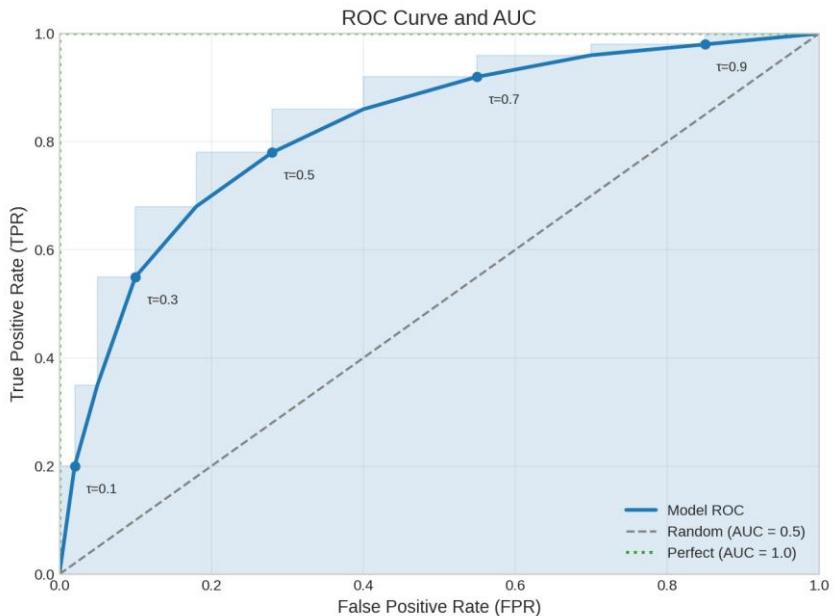


- Bias & Variance
 - bias and variance both indicate how well a model is likely to perform on new unseen data.
- Bias
 - expected difference between model's prediction and truth
- Variance
 - how much the model differs among training sets
- Model Scenarios
 - High Bias (underfitting): Model makes inaccurate predictions on training data
 - High Variance (overfitting): Model does not generalize to new datasets
 - Low Bias: Model makes accurate predictions on training data
 - Low Variance: Model generalizes to new datasets

Other KPI for classification

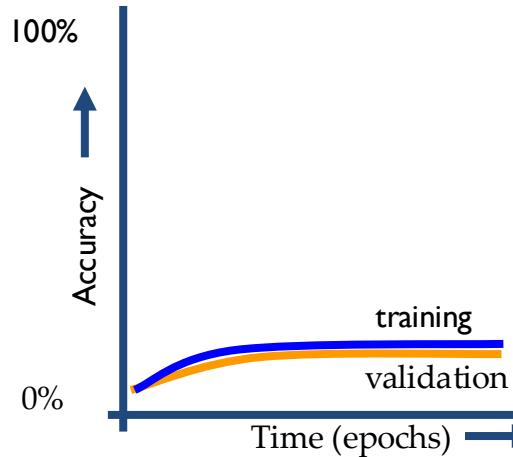


- **ROC-AUC:** The probability that the model ranks a randomly chosen positive higher than a negative.
- **Log Loss:** A measure of classification error that penalizes confident but wrong predictions.

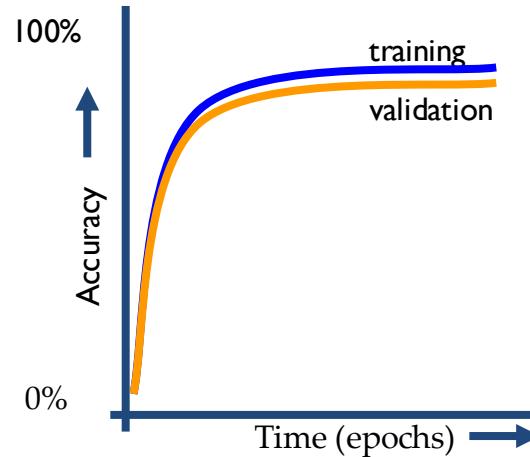




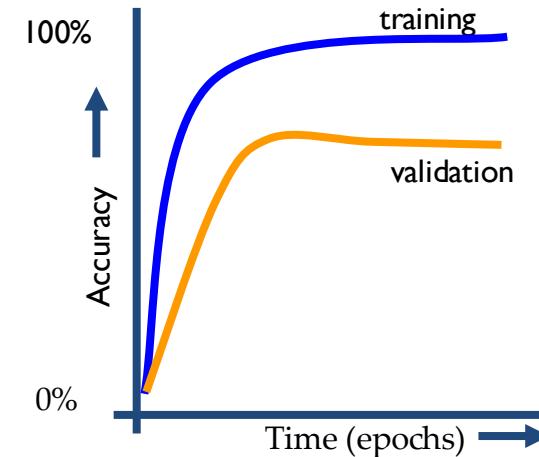
Spotting Underfitting and Overfitting



Underfit: Model performs poorly on training and validation data



Good fit: Model generalizes well from training to validation data



Overfit: Model predicts training data well but fails to generalize to validation data

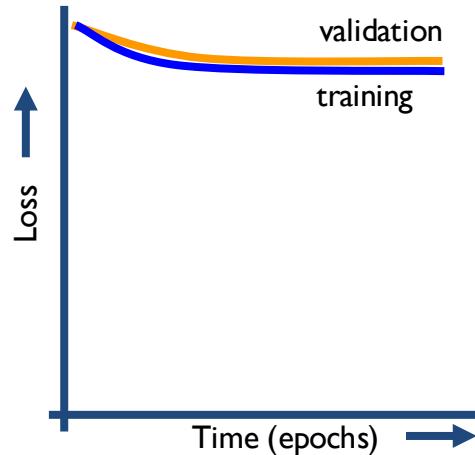
Accuracy = proportion of correctly classified samples.

$$\text{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total predictions}}$$

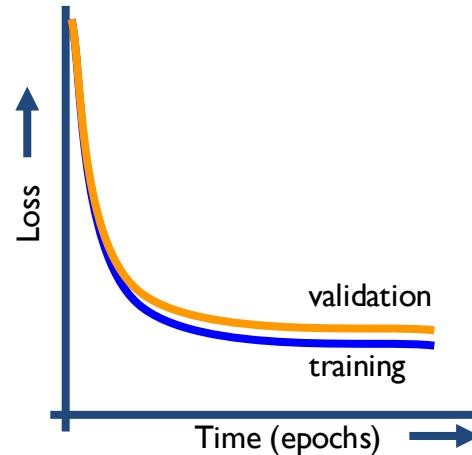
Only applies to **classification tasks** (not regression).



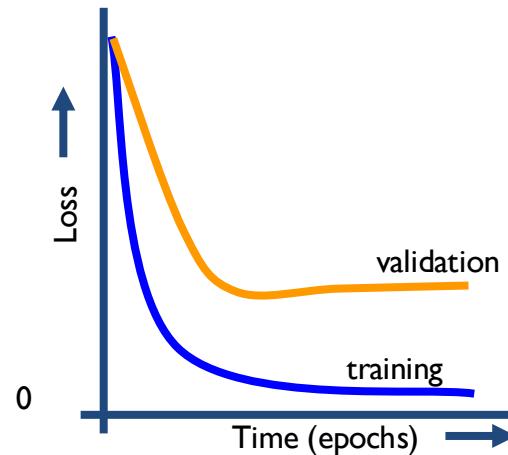
Spotting Underfitting and Overfitting



Underfit: Model performs poorly on training and validation data



Good fit: Model generalizes well from training to validation data



Overfit: Model predicts training data well but fails to generalize to validation data

- **Loss** is a number computed from a **loss function** (e.g., MSE for regression, cross-entropy for classification).
- It measures the **error** between predicted outputs and true labels.
- The goal of training = **minimize loss**.

Fix Overfitting and Underfitting

Embedded ML



Issue	Symptoms	Fixes
Overfitting	High training accuracy, low test accuracy	<ul style="list-style-type: none">• Simplify model (reduce layers, tree depth)• Apply regularization (L1/L2, dropout)• Early stopping• Data augmentation• Cross-validation• Reduce noisy features
Underfitting	Low accuracy on both training & test sets	<ul style="list-style-type: none">• Increase model complexity (more layers, deeper trees)• Add informative features• Reduce regularization strength• Train longer (more epochs)• Hyperparameter tuning