Text as Data

Meeting 5: Supervised Machine Learning

Petro Tolochko

Machine Learning

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  - Focus on prediction

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  - Text regression (scaling)

Dictionary vs. Supervised Machine Learning

Dictionary-based Methods

Supervised Machine Learning

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$\rightarrow$ *Dictionary methods encode human theory; supervised ML discovers patterns from data.*

Supervised ML Pipeline

- Create a labeled dataset
- Apply a function that maps features $\rightarrow$ outcome (ML step)
- Assess performance

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- **Goal:** learn a function $f(X) \to Y$ that generalizes to unseen documents.

Labeled Dataset

- How:
  - Human coders annotate parts of the corpus
  - Found data (e.g., self-reported profession in users' profile)
- Considerations:
  - Sampling should be representative for the corpus (e.g., Random, Stratified sample e.g., across time and source)
  - Quality of human coding matters (Assess the intercoder reliability)
  - Number of documents

Labeled Dataset

- Number of documents
  - the higher the number of categories and the lower the reliability of the coders, the higher the number of documents (Barberá et al., 2021)
- increase the sizes of manually coded validation dataset as large as possible (e.g., more than 1% of all data to be examined), assuming acceptable reliability (equal to or higher than .7) (Song et al., 2021)

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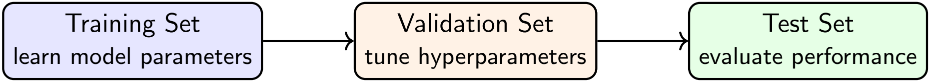
- Test Data
  - The subset that is used to evaluate the final performance
  - Not used for learning

Train–Validation–Test Split



Used during model development → Final evaluation only

The validation set guides learning; the test set measures generalization.

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- Repeat k times, each time with a different validation fold.
- Average performance across folds $\Rightarrow$ robust estimate of generalization.

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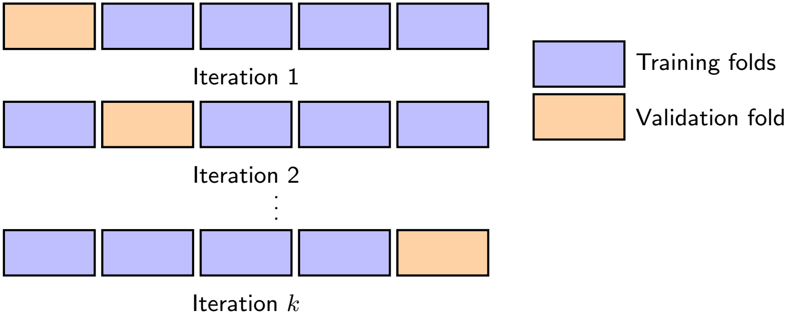

Each fold is used once for validation and $k-1$ times for training.

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- Apply the model to *learn* which features in X (extracted from raw text) matter to recover Y (i.e., labels from the training data)

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Naive Bayes

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Bayesian idea: update prior beliefs with new evidence.

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$\rightarrow$ *The classifier picks the class with the highest posterior probability.*

How Priors and Likelihoods Combine

$$\underset{\text{(Prior)}}{P(C)} \longrightarrow \underset{\text{(Likelihood)}}{P(X \mid C)} \longrightarrow \underset{\text{(Posterior)}}{P(C \mid X)}$$

Posterior = Prior × Likelihood (then normalized).

Naive Bayes picks the class with the highest posterior.

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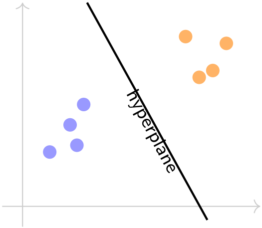
- Interpretation: each class is a simple *language model* — choose the one most likely to have generated the document.

Questions?

Support Vector Machines

What is a Hyperplane?



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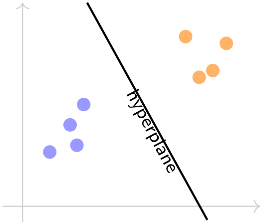

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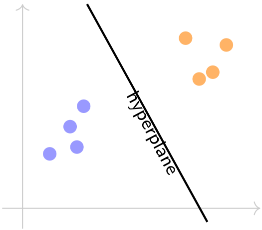

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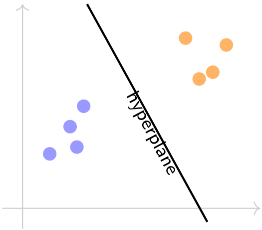

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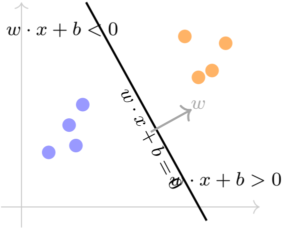
The Hyperplane Equation

Hyperplane: $w \cdot x + b = 0$

Decision rule: $\hat{y} = \text{sign}(w \cdot x + b)$



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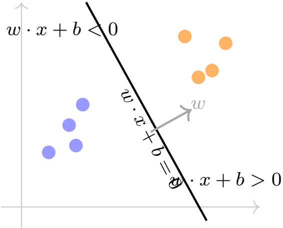
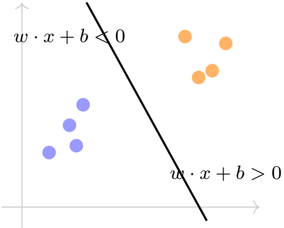


The hyperplane is the boundary where $w \cdot x + b = 0$.

Classification Rule

$$\text{Hyperplane: } w \cdot x + b = 0$$

$$\text{Prediction: } \hat{y} = \begin{cases} +1, & \text{if } w \cdot x + b > 0 \\ -1, & \text{if } w \cdot x + b < 0 \end{cases}$$



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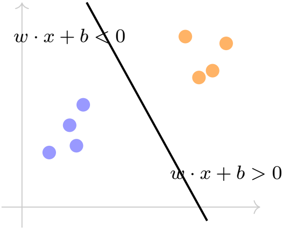
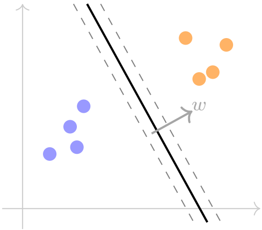


The sign of $(w \cdot x + b)$ *determines on which side of the hyperplane a point lies.*

Distance to the Hyperplane

Signed distance: $d_i = \dfrac{w \cdot x_i + b}{\|w\|}$

Margin: distance between supporting hyperplanes $= \dfrac{2}{\|w\|}$



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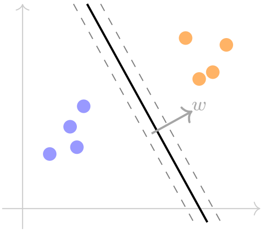
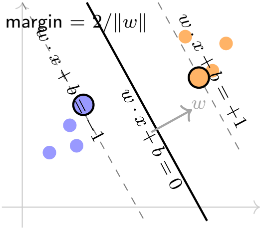


SVM chooses the hyperplane that maximizes this margin.

Support Vectors and the Margin



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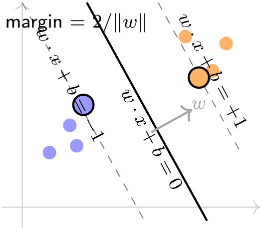

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$$w \cdot x + b = \pm 1$$

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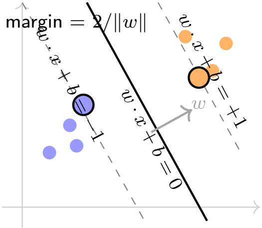

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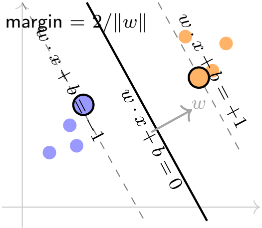

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- SVM maximizes the distance between these two margin planes.

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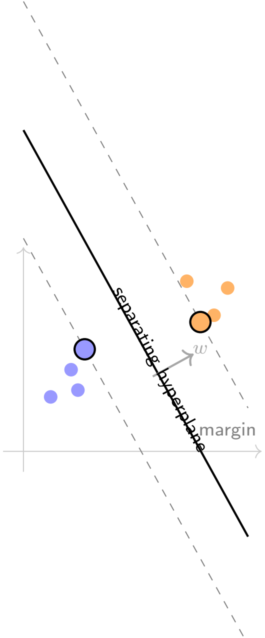

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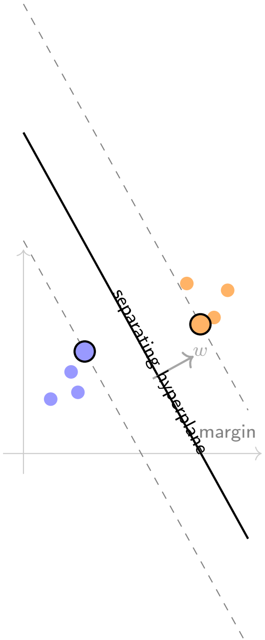

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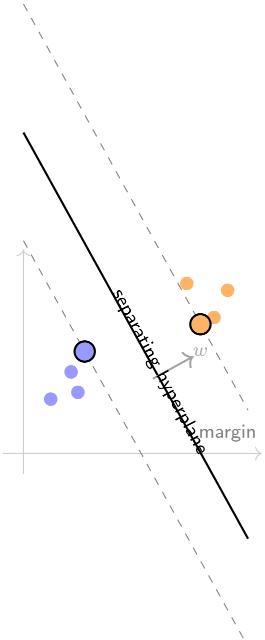

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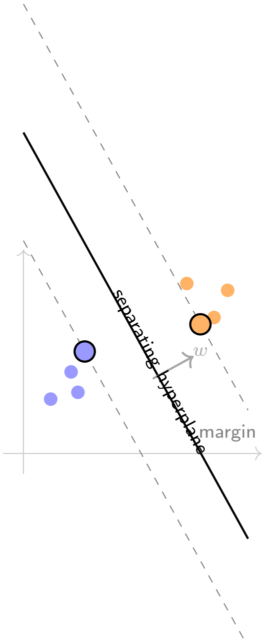

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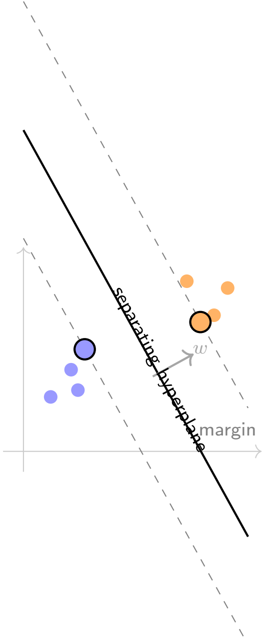

Support Vector Machines (SVMs)

- Represent each document as a feature vector (e.g., TF–IDF)
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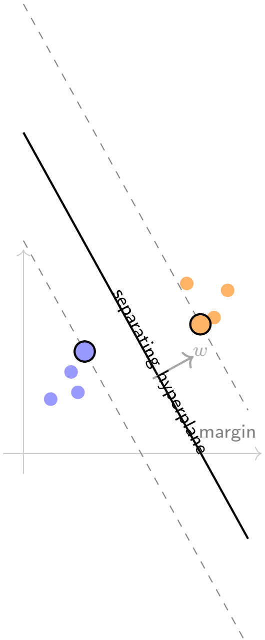

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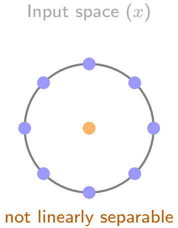

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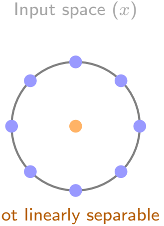

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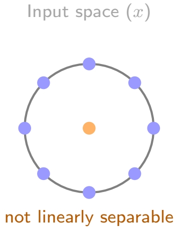

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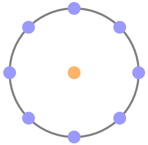

No linear hyperplane in 2D can separate these points.

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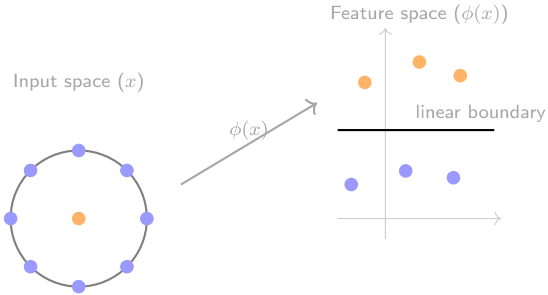
- This is called the **kernel trick**, we get all the benefits of high-dimensional geometry without ever leaving the original feature space.

The Kernel Trick

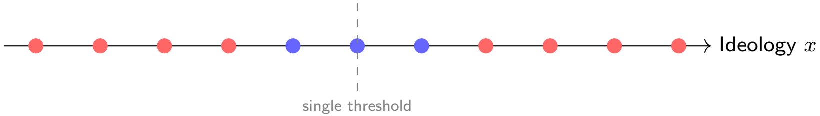


Common Kernel Functions

Kernel	Formula	Intuition
Linear	$K(x_i, x_j) = x_i \cdot x_j$	Measures direct similarity (no transformation).
Polynomial	$K(x_i, x_j) = (x_i \cdot x_j + c)^d$	Captures feature interactions (e.g., word pairs).
RBF / Gaussian	$K(x_i, x_j) = e^{-\gamma \|x_i - x_j\|^2}$	Distance-based similarity; very flexible and smooth.
Sigmoid	$K(x_i, x_j) = \tanh(\alpha\, x_i \cdot x_j + c)$	Behaves like a neural network activation.

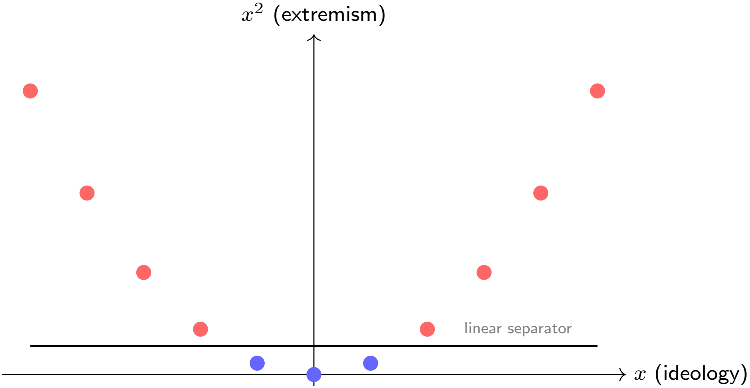
Kernels measure similarity in an implicit feature space —
they let SVMs handle nonlinear patterns without explicit transformation.

Ideology in 1D: Not Linearly Separable



Extremes (red) lie on both sides of the center — one cut on a line can't separate them from moderates (blue).

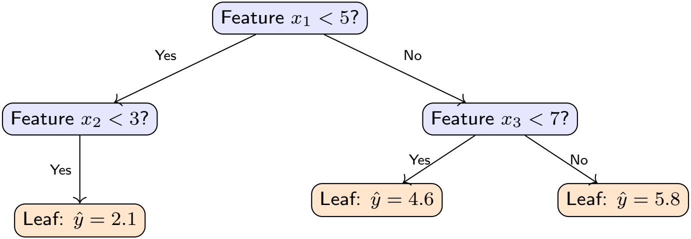
Nonlinear Map $\phi(x) = (x,\, x^2)$: Now Linearly Separable



After $\phi(x)$, a horizontal linear boundary separates extremes (red) from moderates (blue).

Decision Trees

- Trees split the feature space into regions where target values are similar.



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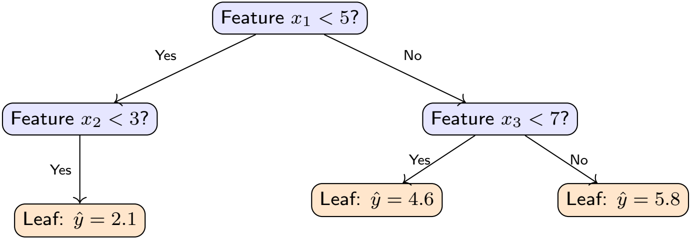

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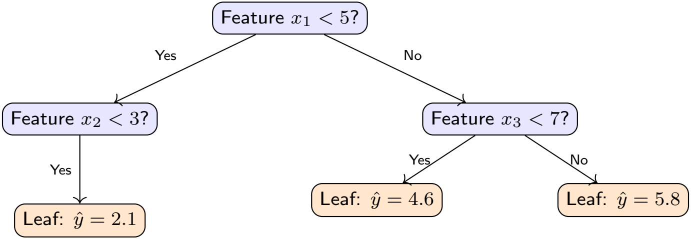

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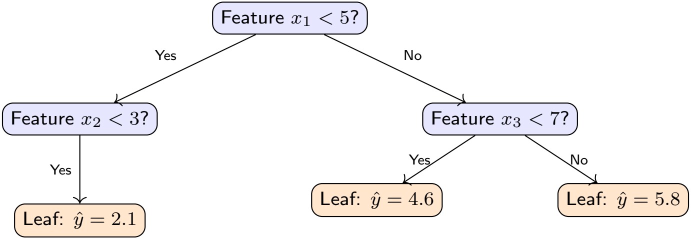
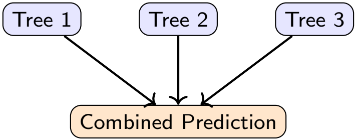
- The goal is to minimize a loss function over all splits (e.g., MSE or Gini impurity).



Questions?

From Trees to Ensembles

- A single tree is a weak learner — high variance and easy to overfit.



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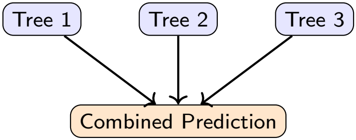

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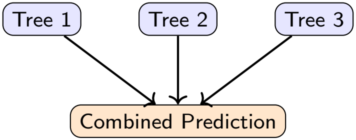

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- **Bagging:** average many independent trees (e.g., Random Forests).
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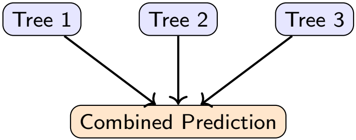
- Ensemble prediction combines all trees' outputs for a stronger model.



Gradient Boosting: Learning from Residuals

- We want to minimize a loss function $\mathcal{L}(y, F(x))$.

Residuals $r_i = -(\partial\ell/\partial F(x_i))$ $\longrightarrow$ Fit Tree $f_t(x)$ $\longrightarrow$ Update Model $F_t = F_{t-1} + \eta f_t$

Each new tree points in the direction that most reduces the loss — gradient descent in function space.

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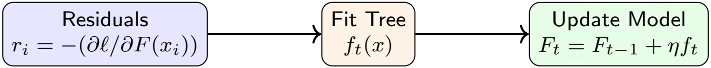

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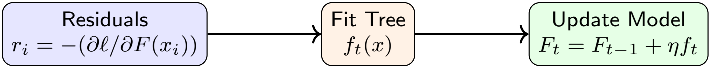

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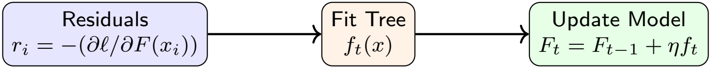

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- After T iterations, the final model is the sum of all trees:

$$F_T(x) = \sum_{t=1}^{T} \eta f_t(x)$$

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