MY474: Applied Machine Learning for Social Science

Lecture 1: Getting Started, Brief Introduction to Machine Learning

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18 January 2023

Agenda

1. Motivations
2. Logistics
3. What is machine learning?
4. A real-world example
5. Which model do we choose?
6. Quiz review

Motivations

Learning from Data

- **Fact:** The amount of data and information collected and stored is constantly increasing, due to advances in data collection, computerization of many aspects of life and breakthroughs in storage technology.
- **Consequence:** Statistical problems have increased both in size and complexity.
- **The data analyst's job:** make sense of all these data! Identify patterns and trends, uncover interesting relationships among the variables and/or the observations, predict future behavior.
- Machine learning can help us process and understand these data.

Learning from Data

- Technology helps
  - Faster computers $\rightarrow$ more flexible and thus more powerful techniques $\rightarrow$ fewer modeling assumptions
  - New capabilities from graphical processing units (GPUs)
- But not always: Faster computers do not solve all problems
  - Some problems are inherently computationally intractable
  - "Easy" black-box data analysis can lead to a lot of misuse and misunderstanding
  - Flexible models can overfit (too much of a good thing)
  - Understanding underlying assumptions and interpreting conclusions correctly remains as important as ever

Major concepts

- **Bias/Variance Tradeoff:** How complex should our model be? How closely should we fit the model to our data?
- **Generalization:** How can we measure if a model will generalize well to new data?
- **Cross-validation:** How do we estimate generalization error without throwing out data?
- **Regularization:** How do we home in on important features in our data?
- **Feature engineering:** How can we best represent the data for our specific task?
- **Model selection:** How do we select a model in a principled way?

Methods and tools

- **Estimation:** gradient descent, stochastic gradient descent, maximum likelihood, expectation maximization (EM)
- **Linear Models:** Logistic regression, linear discriminant analysis, support vector machines, perceptron
- **Regularization:** cost-complexity pruning, lasso regression, ridge regression, elasticnet
- **Non-parametric methods:** k-nearest neighbors (KNN), decision trees, random forests, gradient boosted trees
- **Dimension reduction:** principal component analysis (PCA)
- **Clustering:** k-means, hierarchical clustering

Social science implications of the rise of ML

- **Governance**
  - How do ML tools affect the durability of democracies/autocracies?
  - How can we ensure that critical ML systems are transparent?
  - How do we hold organizations/governments accountable for misuse of ML systems?
- **Social Impact**
  - How do we avoid algorithmic bias and ensure fairness of ML systems?
  - How can we avoid negative externalities of ML systems (violence, discrimination, false news, misinformation)?

Social science implications of the rise of ML

- **Privacy**
  - How are ML systems used by states and corporations for mass surveillance?
  - How can we maintain control over our data and privacy in the age of surveillance capitalism?
- **Interpretability**
  - How do we identify and address negative social externalities of extremely complex ML systems?
  - How can we uncover and mitigate latent biases in human-generated training data?

Logistics

About Me

- **Assistant Professor in Computational Social Science at the Methodology Department, LSE**
- Previously at **Dartmouth College**
- PhD in Political Science and Scientific Computing, **University of Michigan**
- My research:
  - Chinese politics, and authoritarian politics
  - Information control (censorship, propaganda, etc.), information and mobilization of violence
  - Applied machine learning for text data
- **Contact:**
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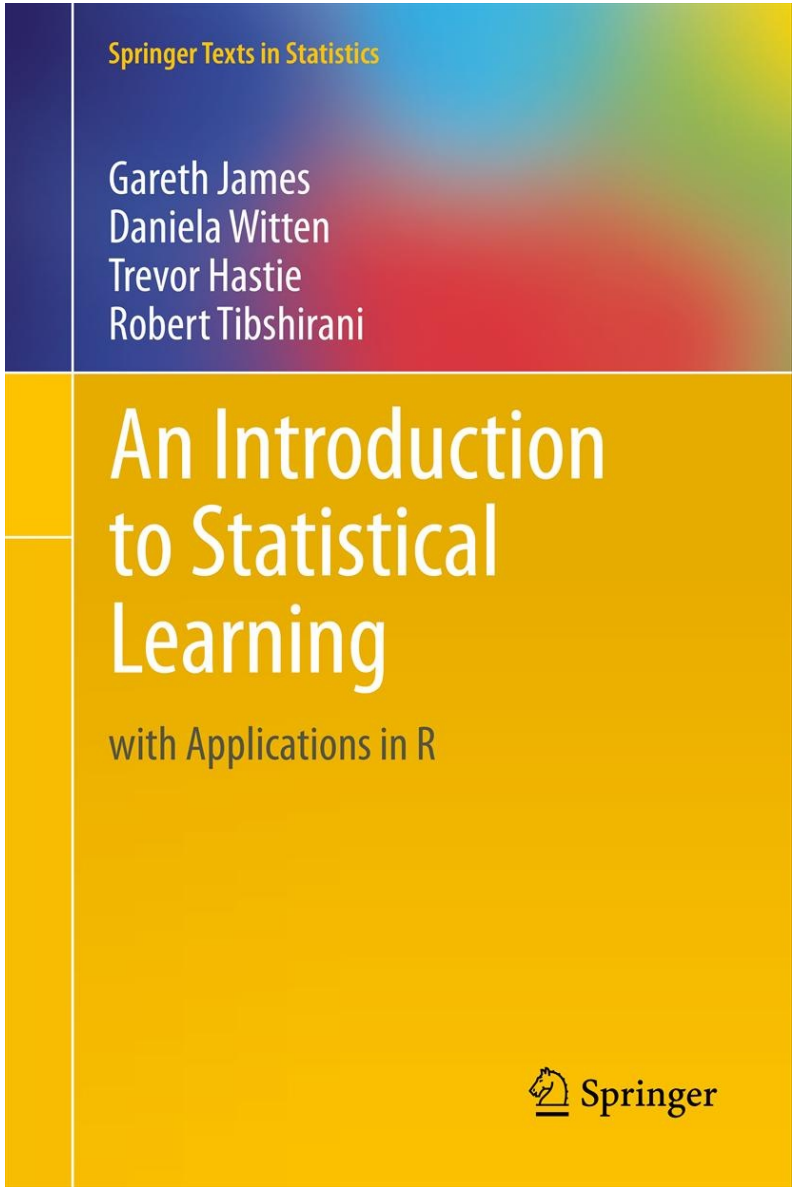
  - `www.blakeapm.com`
  - Office hours: book through Student Hub

Books



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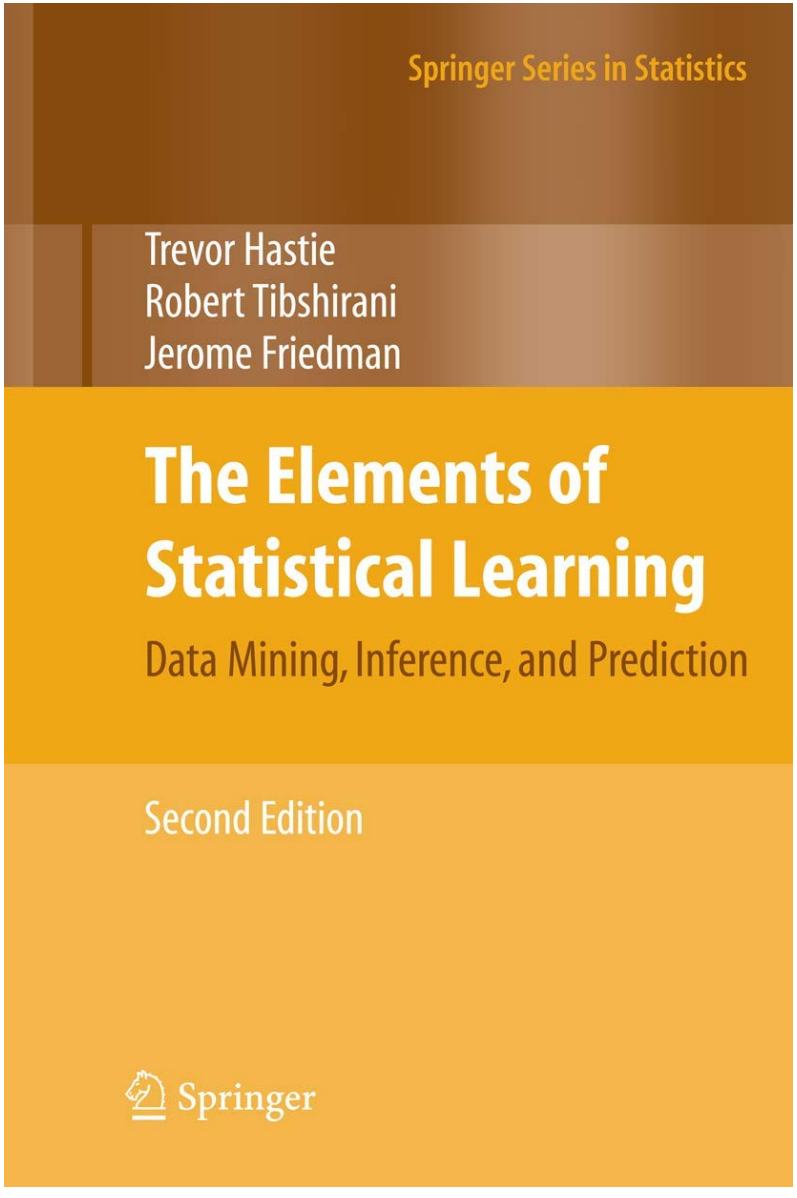
Books



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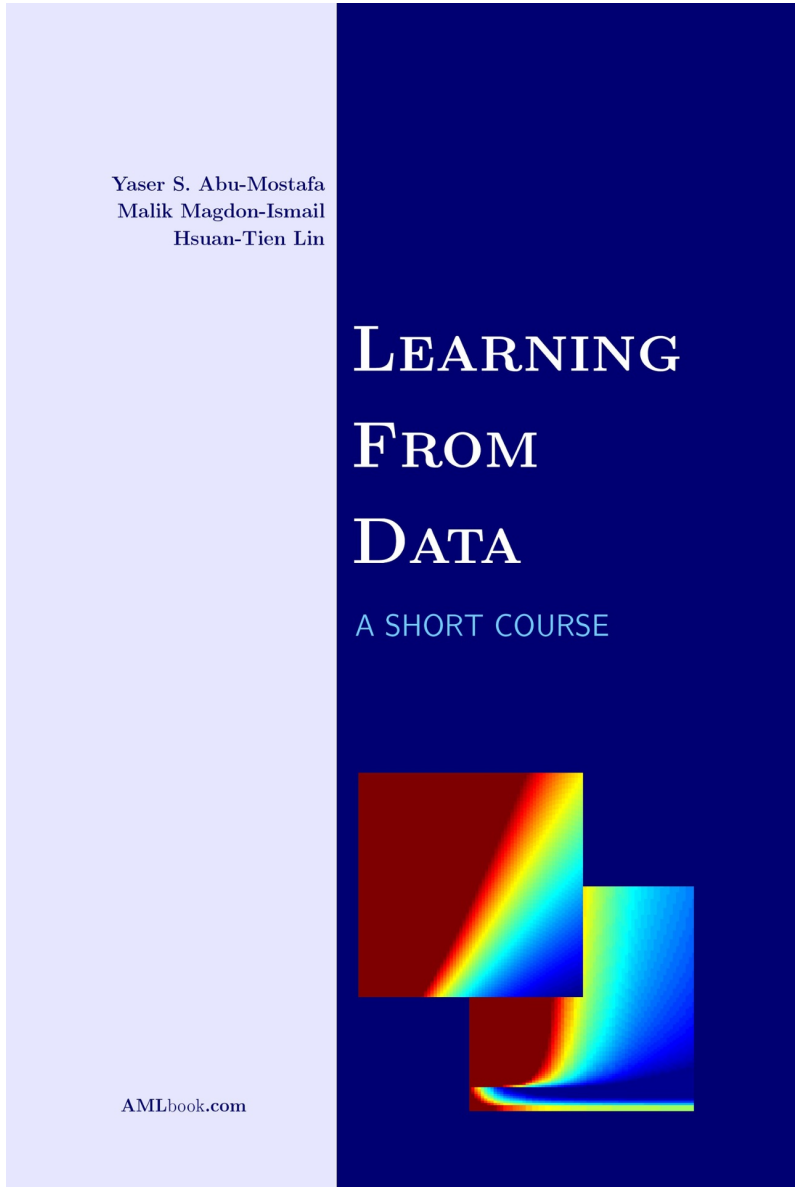


Download scan of ch. 1 on Moodle

Resources

- Course website: lse-my474.github.io
  - Class description
  - Course schedule
  - Slides from class
  - Readings list
  - Links to exercises and datasets
  - Submission links for homeworks
- Moodle page
  - Supporting materials
  - Links to Zoom meetings
- Readings
  - Mainly textbook chapters from ISLR
  - Complement content covered in lectures and seminars

Course schedule

- Lectures: Wednesday 9:00-11:00, CBG.G.01.
- Classes weeks 2, 4, 7, 9, 11, STC.S018:
  - Wednesdays 16:00-18:00
  - Thursdays 09:00-11:00
  - Thursdays 15:00-19:00
- No lectures or classes during Reading Week (week 6)

Evaluation

Formative coursework

- One problem set (LT)

Summative coursework

- Four problem sets, building upon content of lab sessions (LT)
  - 60% of course grade
  - Submitted via GitHub classroom (please create an account before first lab session)
- Quizzes (LT):
  - 40% of course grade
  - Timed online quiz
  - Based on lecture, seminars, and readings.

Assessment criteria (written work)

- **70–100**: Very Good to Excellent (Distinction).
  - Perceptive, focused use of a good depth of material with a critical edge. Original ideas or structure of argument.
- **60–69**: Good (Merit)
  - Perceptive understanding of the issues plus a coherent well-read and stylish treatment though lacking originality
- **50–59**: Satisfactory (Pass)
  - A "correct'' answer based largely on lecture material. Little detail or originality but presented in adequate framework. Small factual errors allowed.
- **30–49**: Unsatisfactory (Fail)
- **0–29**: Unsatisfactory (Bad fail)
  - Based entirely on lecture material but unstructured and with increasing error component. Concepts are disordered or flawed. Poor presentation. Errors of concept and scope or poor in knowledge, structure and expression.

What is machine learning?

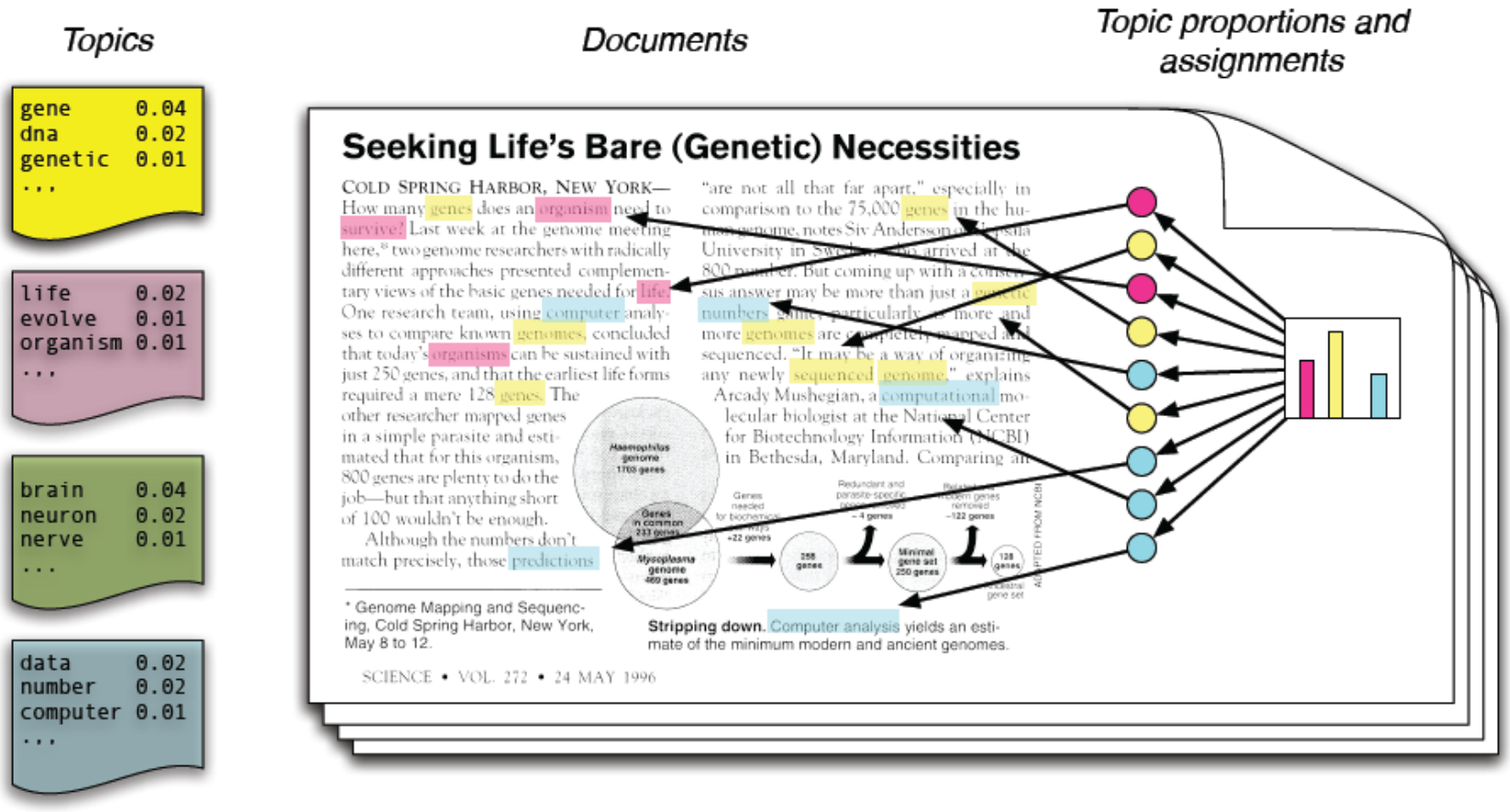
Machine learning is many things

- A method of mining data for **patterns** or unobserved **latent variables**
- A method of **approximating unknown functions** using available data
- A predictive framework for forecasting future events
- A framework for **augmenting** and **automating** human decisions or tasks

Unsupervised Learning

- **Objective:** Find patterns and structure among inputs $\mathbf{x}$ in the data $\mathcal{D}$.
- Types of unsupervised learning:
  - **Clustering:** Given data $\mathbf{X}$, identify clusters of objects that balance within-cluster similarity and distinctness between clusters.
  - **Dimension Reduction:** Given data $\mathbf{X}$, identify manifolds or underlying factors that represent the data in fewer dimensions
- Training data does not contain any outputs $\mathbf{y}$. Structure is instead learned from underlying patterns and structure of the inputs $\mathbf{x}$.

Unsupervised Example: Topic Modeling

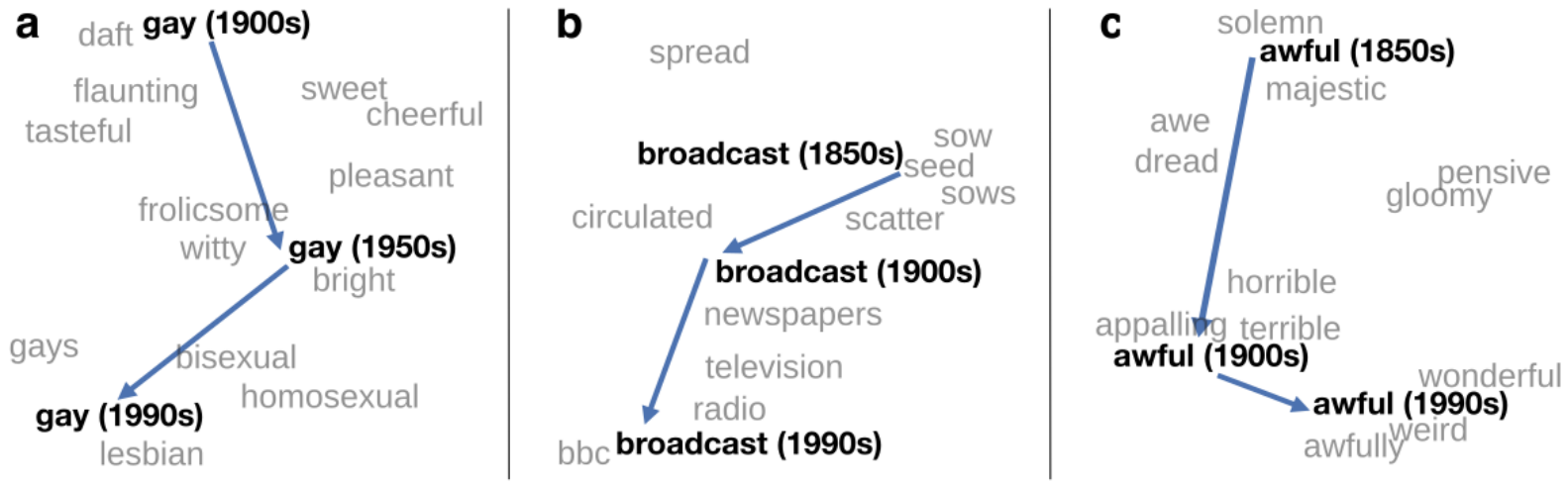


Source: David Blei

Unsupervised Example: Topic Modeling

- Data: a corpus of documents (e.g. all New York Times articles from 2020)
- Each document is represented as a vector of counts of all words that appear in the corpus $\mathbf{x}$ (features/inputs). This can be a vector of hundreds of thousands of words.
- There is no response/outcome $\mathbf{y}$, only inputs/features $\mathbf{x}$.
- Goal: build an algorithm to assign each document to a topic cluster (e.g. politics, business, finance, entertainment, etc.) using patterns in word use and word context across documents.

Unsupervised Example: Word Embeddings



Source: HistWords Project

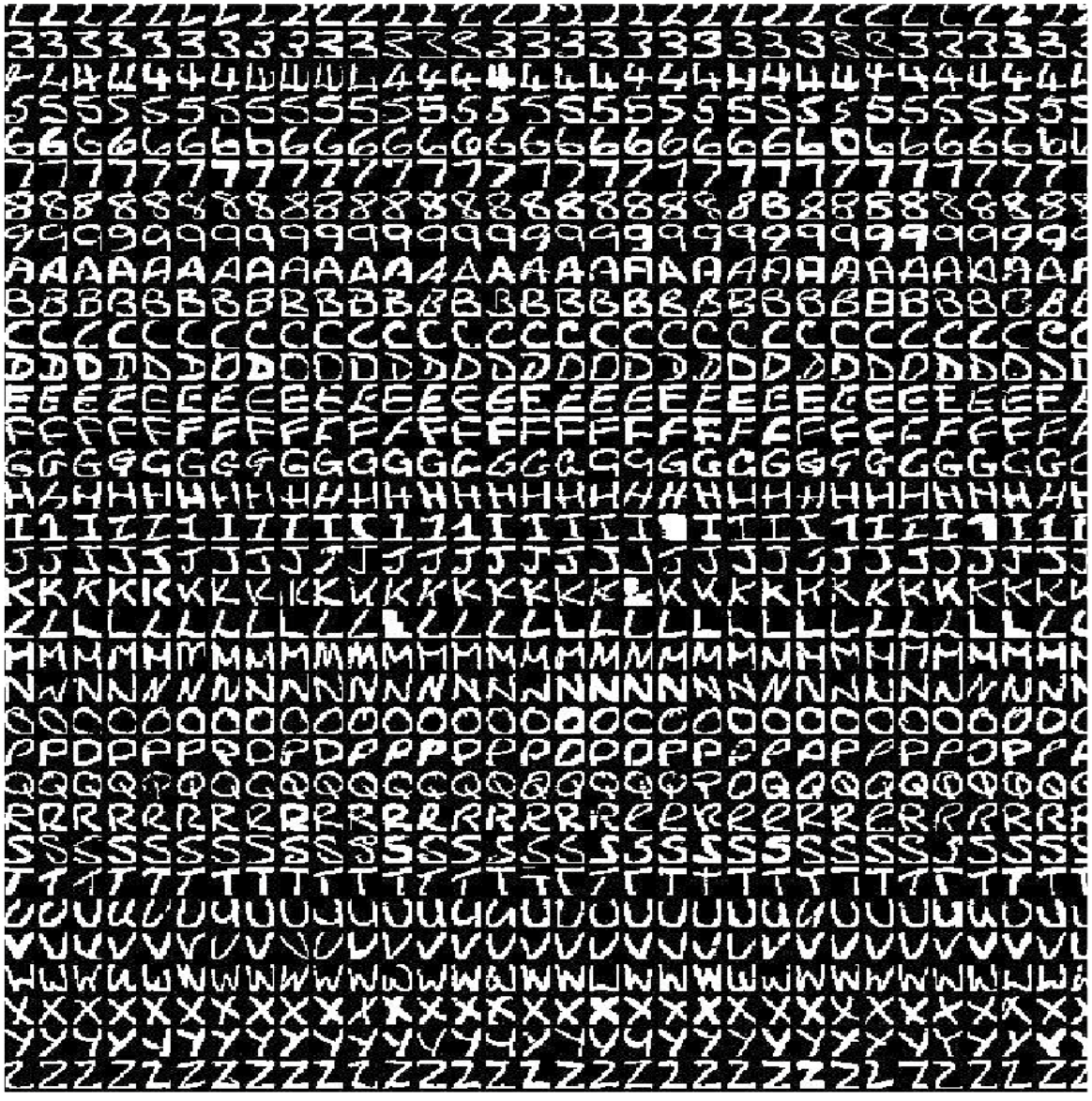
Unsupervised Example: Word Embeddings

- Data: a corpus of documents (e.g. all New York Times articles from 2020)
- Words are represented as fixed-dimensional vectors.
- There is no response/outcome, only inputs/features (words, word sequences).
- Goal: build an algorithm to represent each word as a fixed-dimensional vector that captures semantic information
- Word embeddings quantify semantic similarities between words by learning from the contexts in which words appear; words with similar meaning will appear in similar contexts.

Supervised Learning

- **Objective:** learn an approximation $g(x)$ of an unknown **target function** $f : \mathcal{X} \rightarrow \mathcal{Y}$ from data $\mathcal{D}$
  - $\mathcal{X}$ represents the input space of all possible inputs $\mathbf{x}$ (also called predictors, regressors, covariates, features, independent variables)
  - $\mathcal{Y}$ represents the output space of all possible outputs $\mathbf{y}$ (also called dependent variable, response, target, outcome).
- **Regression:** $\mathbf{y}$ is quantitative (e.g GDP, unemployment measures, vote counts, # of COVID cases)
- **Classification:** $\mathbf{y}$ is a value in a finite, unordered set (e.g. $y_i \in \{\text{ordinary}, \text{bot}, \text{troll}, \text{cyborg}\}$)
- **Data:** $\mathcal{D}$, a set of input-output examples $\{(\mathbf{x_1}, y_1) \ldots (\mathbf{x_N}, y_N)\}$.

Supervised Example: Optical Character Recognition (OCR)



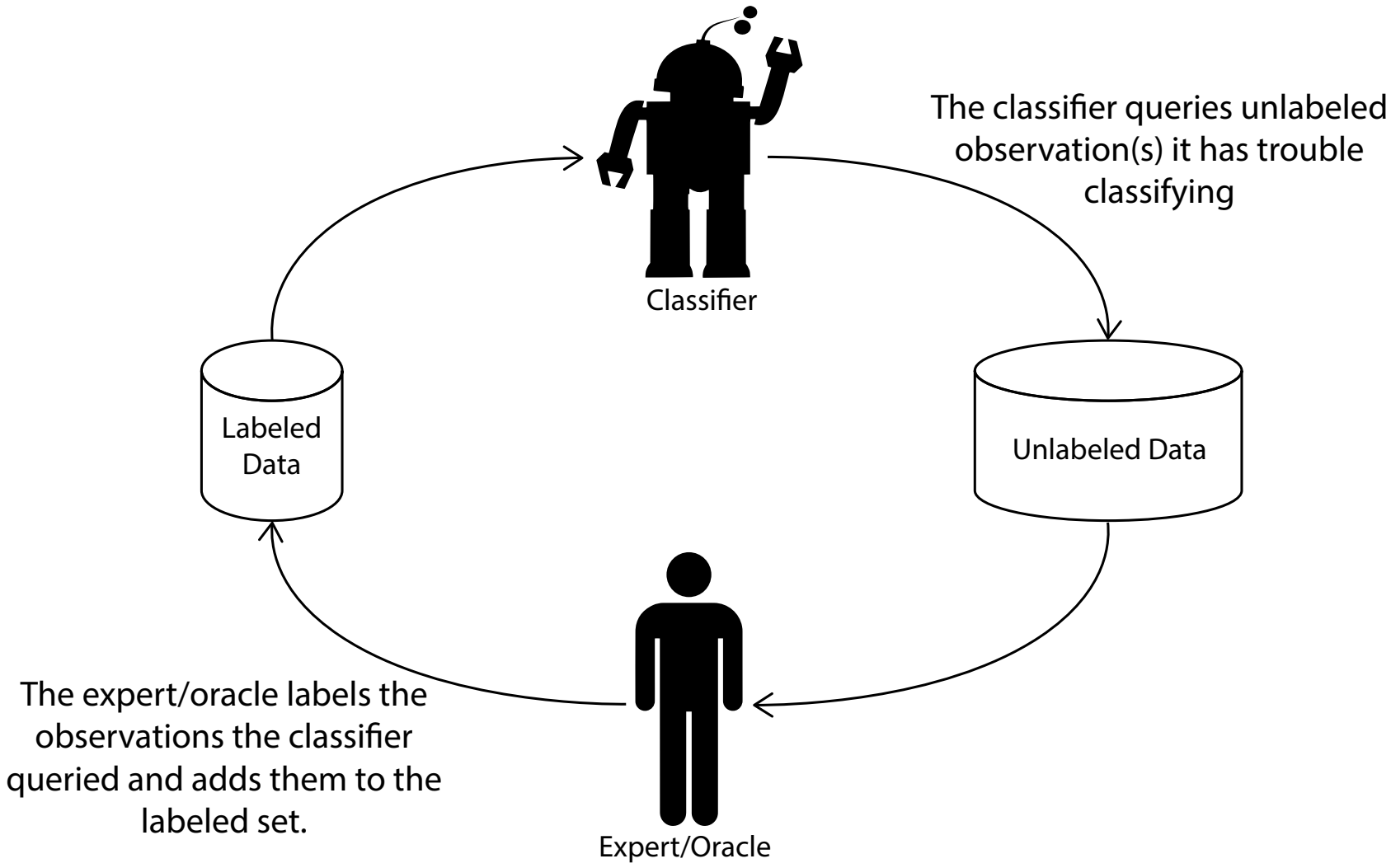
Supervised Example: Optical Character Recognition (OCR)

- Data: images of single handwritten letters and digits
- Each image is 20×16 pixels, with pixel intensities from 0 to 255. This vector of 320 quantitative variables is $\mathbf{x}$ (features/inputs).
- Response/outcome: the identity of each image $y_i \in \{A, B, ..., Z, 0, 1, ..., 9\}$. This categorical variable with 36 levels is $\mathbf{y}$.
- Goal: build an algorithm (classifier, learner) to predict the identity $\mathbf{y}$ from pixel values $\mathbf{x}$ using a dataset of labelled images

Supervised Example: Hate Speech Detection

Source: Google/Jigsaw

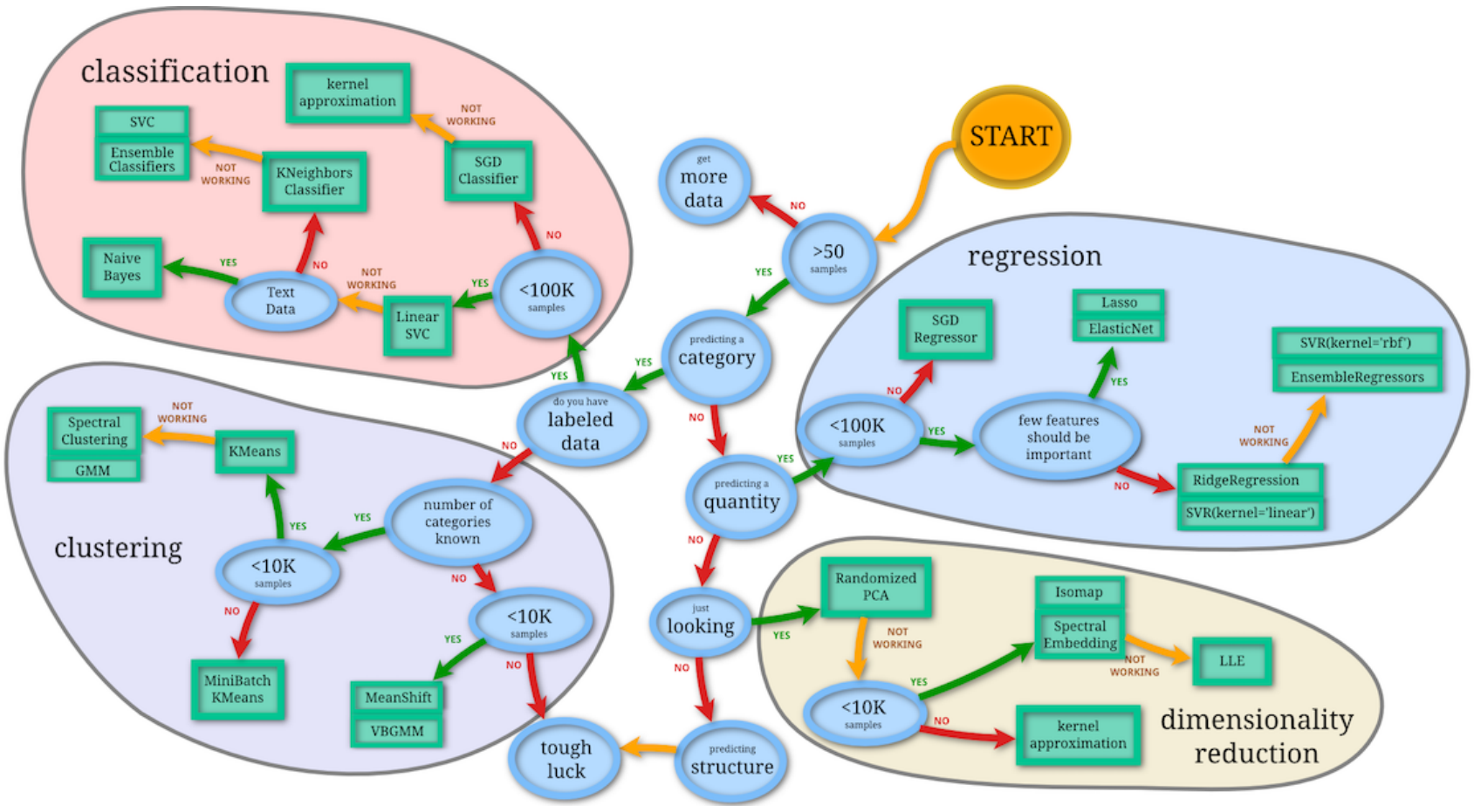
Active Learning



Reinforcement Learning

Source: DeepMind

A Cheet Sheet



Source: scikit-learn

A real world example

A real world example

Which of these Wikipedia Talk Page comments are insults?

1. "I HATE your freakin guts!!"
2. "YOU ARE AN IDIOT!!!!"
3. "Before we can accept this change, we need a citation for this second claim."
4. "I'm afraid I reverted your change. You erased all of the existing discussion there; we want to keep that."
5. "STOP YOUR DAMN NONSENSE!!!!! YOU HAVE DONE NOTHING TO IMPROVE THESE ARTICLES!!! ASSHOLE!!"

A real world example

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How did you solve this problem?

- What **features** of each comment were informative?
- Could we make this process more explicit?

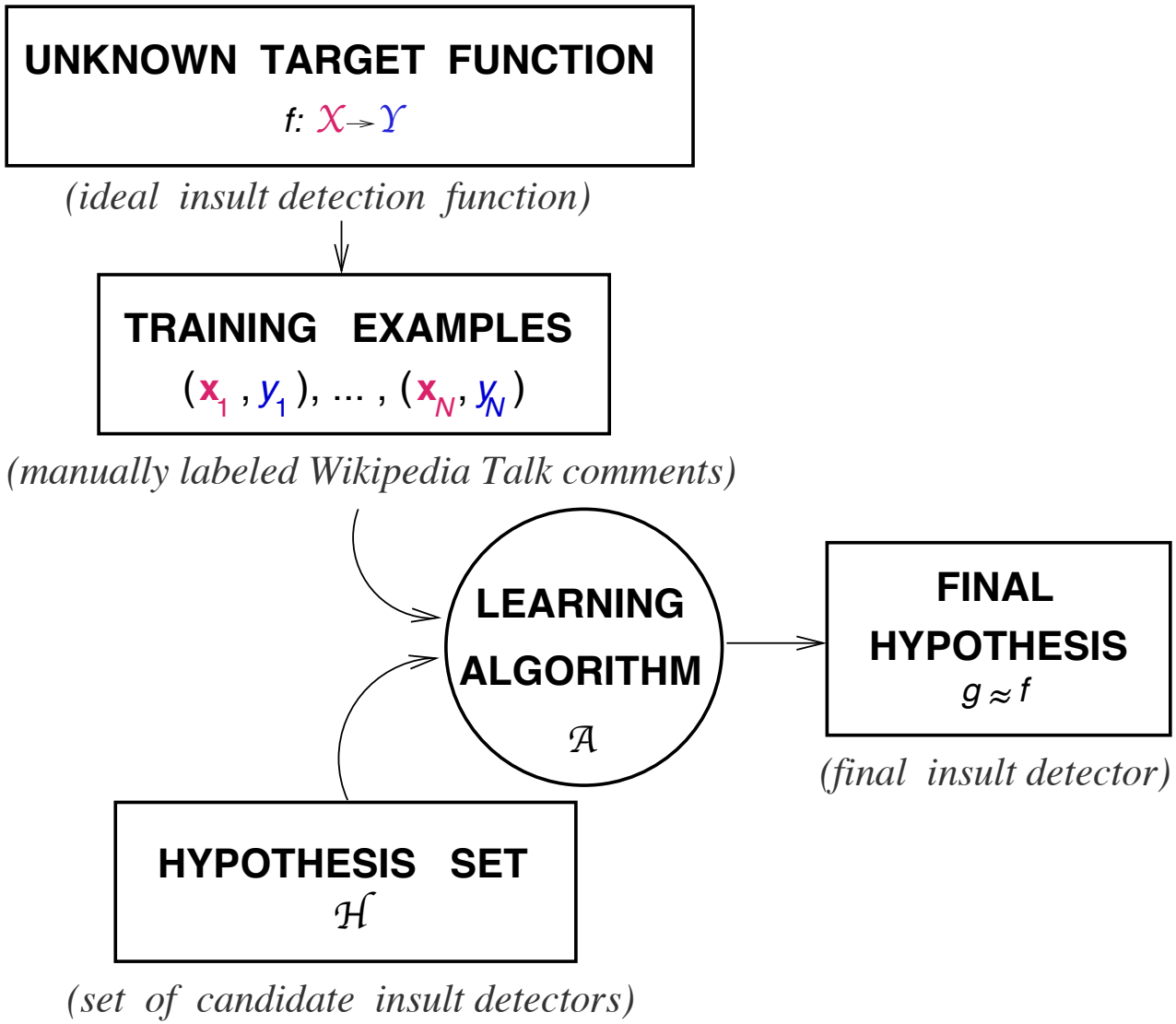
Formalizing the Problem of Insult Classification

- Unknown **target function** $f : \mathcal{X} \rightarrow \mathcal{Y}$ (What is an insult on Wikipedia Talk Pages)
  - $\mathcal{X}$ represents the input space of all possible inputs $\mathbf{x}$ (word/phrase/character/capital letter counts from Wikipedia Talk comments)
  - $\mathcal{Y} = \{\text{insult}, \neg\text{insult}\}$ represents the output space
- Data $\mathcal{D}$, a set of input-output examples $\{(\mathbf{x_1}, y_1) \dots (\mathbf{x_N}, y_N)\}$.

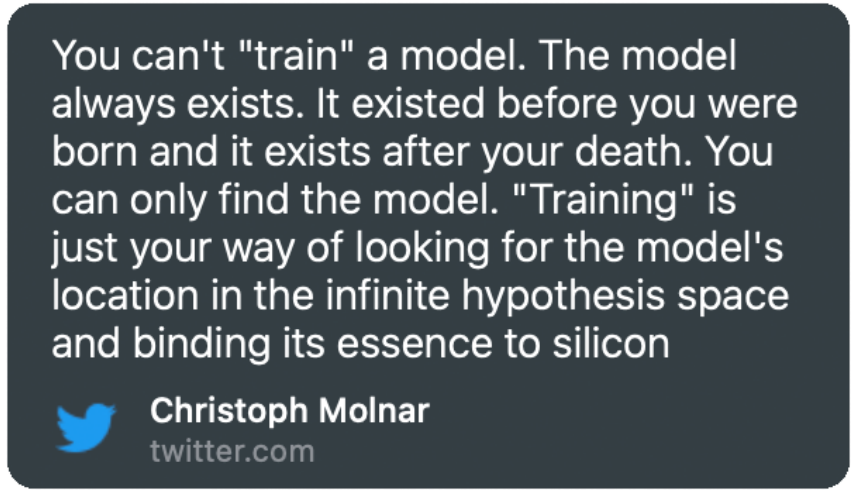
	"change"	"idiot"	"!"	# caps	y_i
1	0	0	2	5	insult
2	0	1	4	13	insult
3	1	0	0	1	¬insult
4	1	0	0	2	¬insult
5	0	0	10	60	insult

Formalizing the Problem of Insult Classification

- Using the dataset $\mathcal{D}$, approximate f with $g : \mathcal{X} \to \mathcal{Y}$
- g is chosen from the **hypothesis set** $\mathcal{H}$



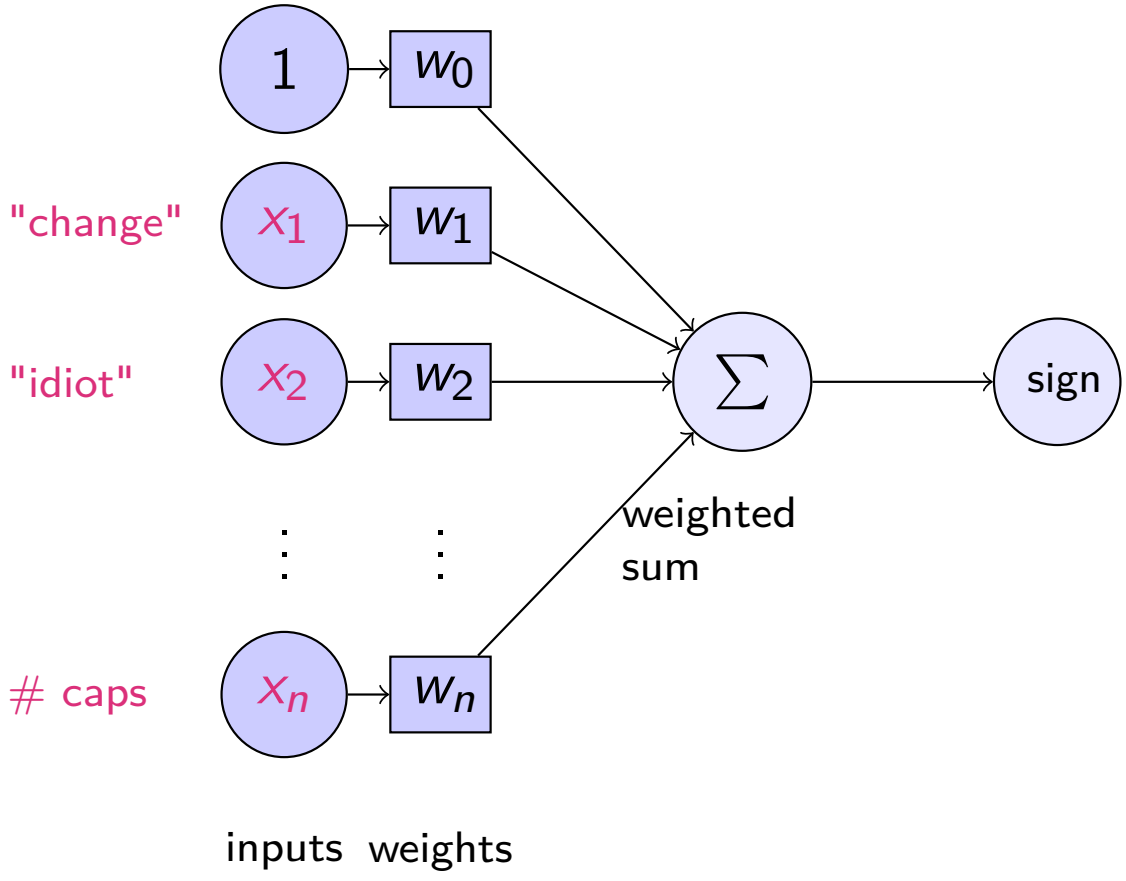
What is the hypothesis set $\mathcal{H}$



A silly but relevant tweet on ML theory :)

- All hypotheses $h \in \mathcal{H}$ share the same functional form.
- The functional form is determined by the **learning model**
- The best hypothesis $g \in \mathcal{H}$ is chosen by the **learning algorithm**
- In this lecture we will discuss two new learning models we could use to classify insults:
  1. **Perceptron**
  2. **K-Nearest Neighbors**

The Perceptron Learning Model



- We operationalize $\mathcal{Y} = \{\text{insult}, \neg\text{insult}\}$ as $\mathcal{Y} = \{1, -1\}$
- Weights w_i correspond to each input x_i (w_0 is the bias)
- The output of our learning model is $h(\mathbf{x}) = sign(\mathbf{w}'\mathbf{x})$

The Perceptron Learning Algorithm

Algorithm 1: Perceptron Learning Algorithm

$P \leftarrow$ inputs with label 1;
$N \leftarrow$ inputs with label -1;
Initialize $\mathbf{w}$ randomly;
while *any input is misclassified* **do**
    Choose random $\mathbf{x} \in P \cup N$;
    if $x \in P$ *and* $\mathbf{w} \cdot \mathbf{x} < 0$ **then**
        $\mathbf{w} = \mathbf{w} + \mathbf{x}$;
    end
    if $x \in N$ *and* $\mathbf{w} \cdot \mathbf{x} \geq 0$ **then**
        $\mathbf{w} = \mathbf{w} - \mathbf{x}$;
    end
end

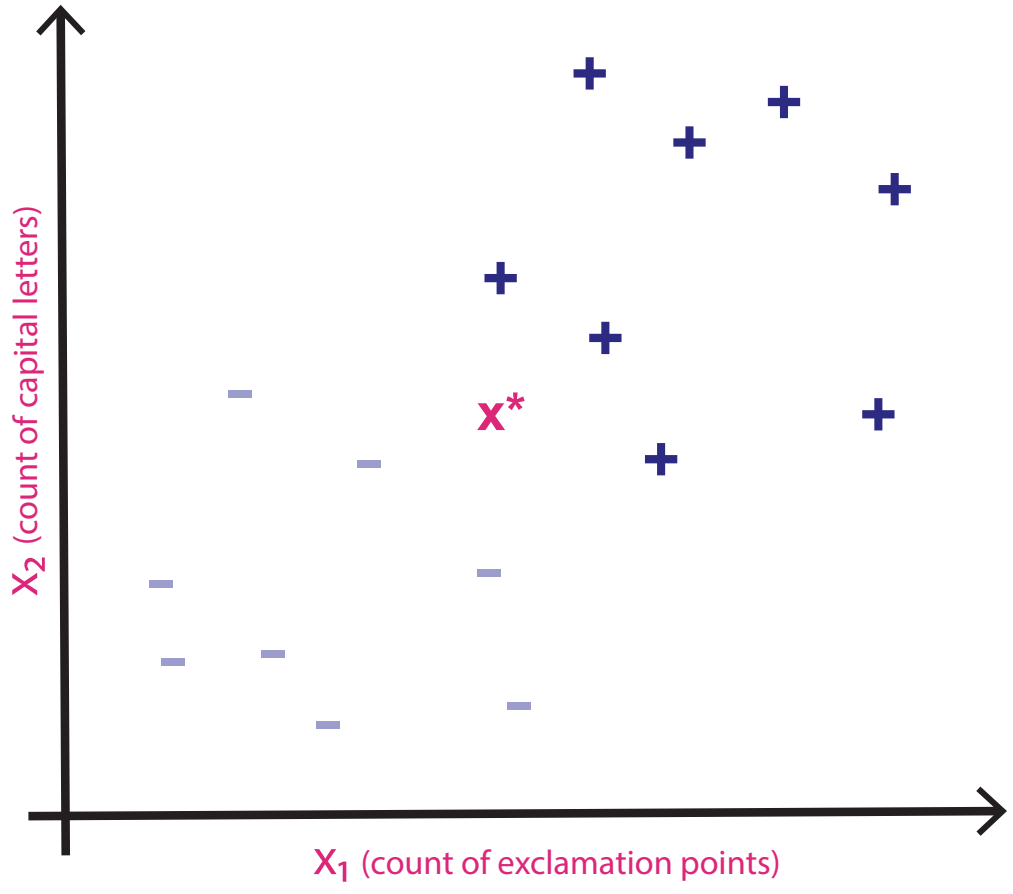
K-Nearest Neighbors (KNN)

- The KNN learning model is the entire training dataset $\mathcal{D}$; there is no learning required, just memorization
- Instead of learning weights or parameters, each x_i is loaded into memory
- KNN is a simple example of a **non-parametric model** where the model structure is determined from the dataset with no assumptions about the underlying data distribution.
- KNN does not work well in high dimensions unless data lie on or close to a low-dimensional subspace (manifold)
- The KNN learning model simply returns the majority class of the k nearest x_i in the dataset $\mathcal{D}$:

$$h(\mathbf{x}) = sign\left(\frac{1}{k}\sum_{x_i \in N_k(\mathbf{x}^*)} y_i\right) \quad y_i \in \{-1, 1\}$$

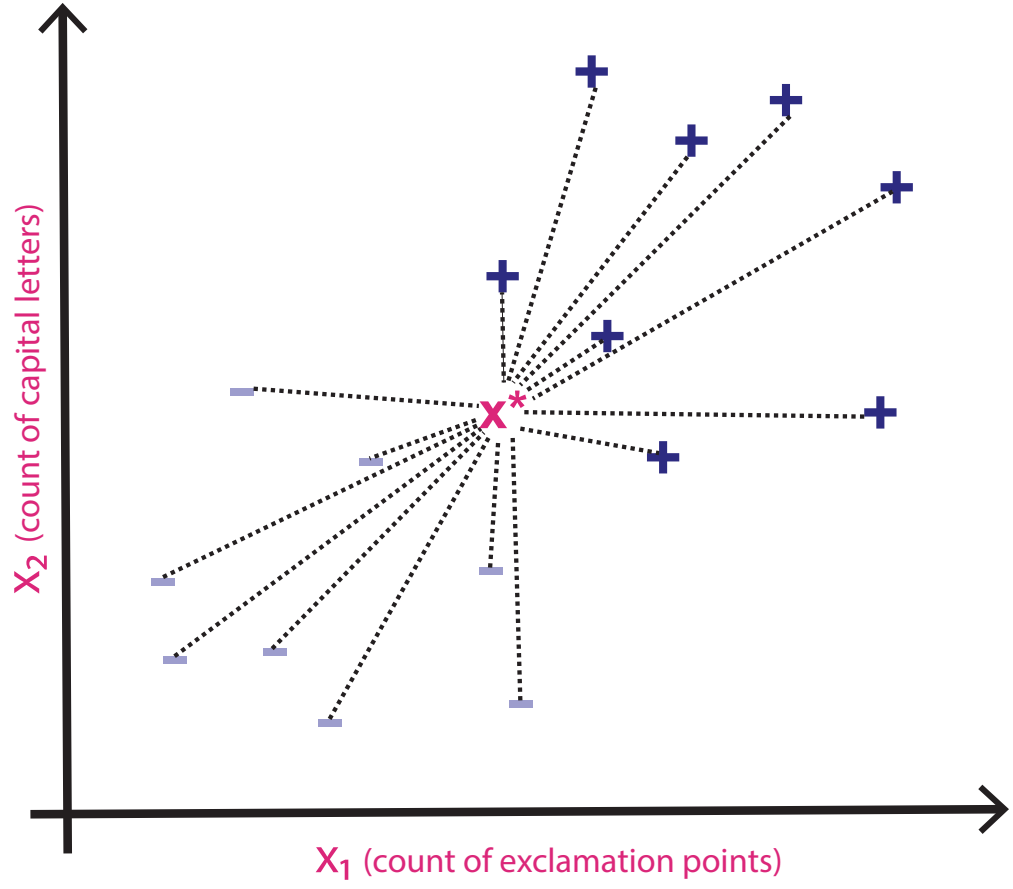
- $N_k(\mathbf{x}^*)$ consists of the k closest points to reference point x^* in the training data (k-nearest neighborhood).

K-Nearest Neighbors (KNN) Visualized



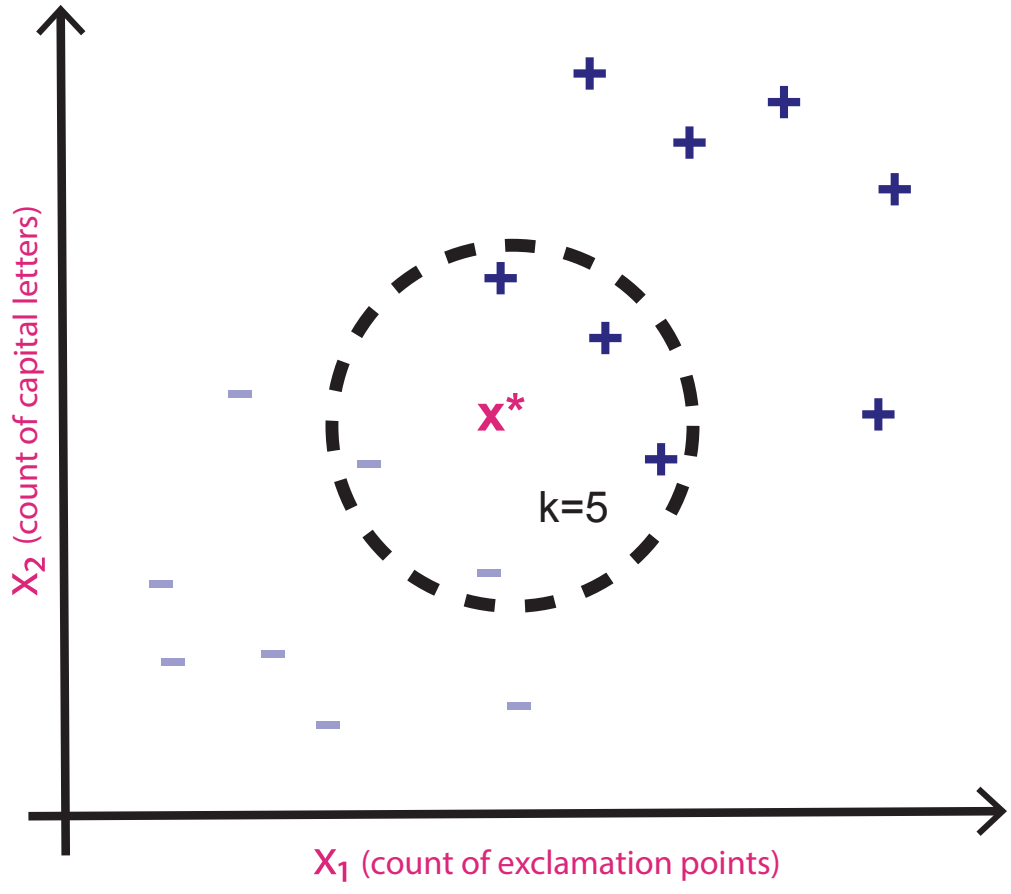
1. Calculate the distance between each x_i and reference point x^*
2. Find the k closest neighbors to x^*
3. Return the majority class of $y_i \in N_k(\mathbf{x}^*)$

K-Nearest Neighbors (KNN) Visualized



1. **Calculate the distance between each x_i and reference point x^***
2. Find the k closest neighbors to x^*
3. Return the majority class of $y_i \in N_k(\mathbf{x}^*)$

K-Nearest Neighbors (KNN) Visualized



1. Calculate the distance between each x_i and reference point x^*
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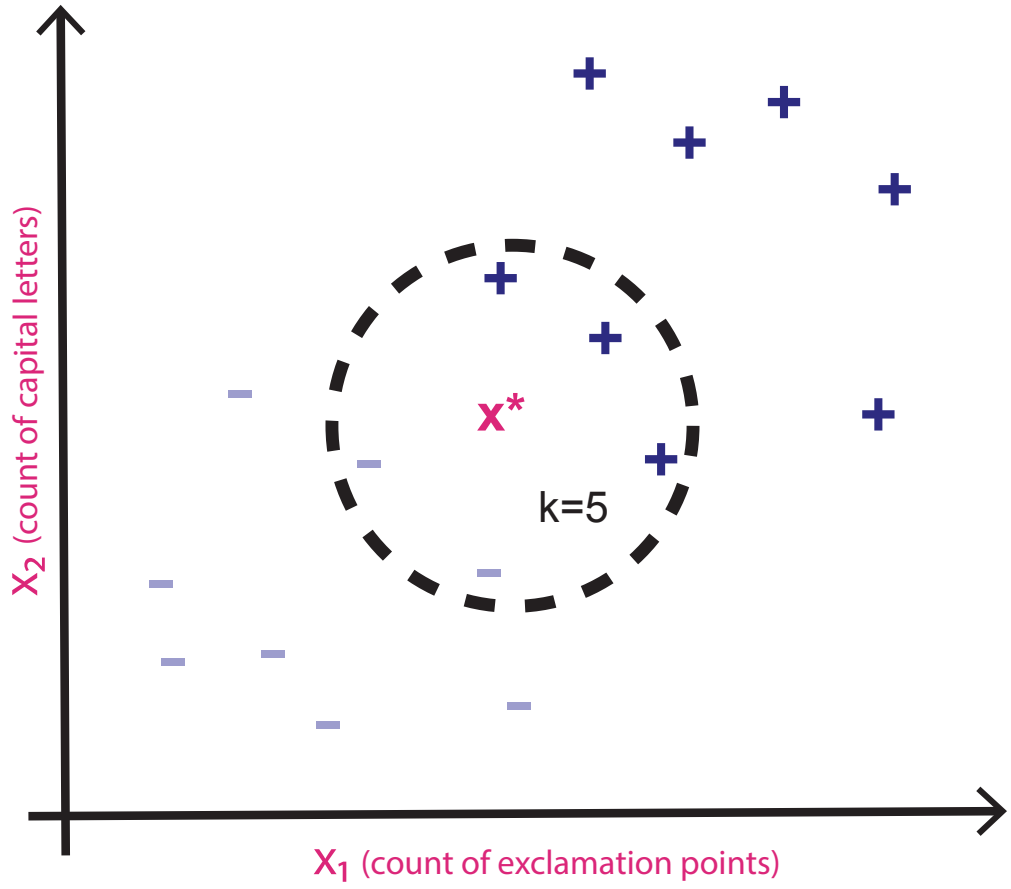
3. Return the majority class of $y_i \in N_k(\mathbf{x}^*)$

K-Nearest Neighbors (KNN) Visualized



1. Calculate the distance between each x_i and reference point x^*
2. Find the k closest neighbors to x^*
3. **Return the majority class of** $y_i \in N_k(\mathbf{x}^*)$
   - 3 votes insult, 2 votes ¬insult
   - This means x^* is an insult according to KNN

OLS Regression in a ML Framework

- In the case of **ordinary least squares (OLS) regression**, we assume $f(\cdot)$ is linear on coefficients β and has an additive separable stochastic component ε

$$\mathbf{y} = \mathbf{X}\beta + \varepsilon, \quad \varepsilon \sim \mathcal{N}_n(0, \sigma^2 \mathbf{I}_n)$$

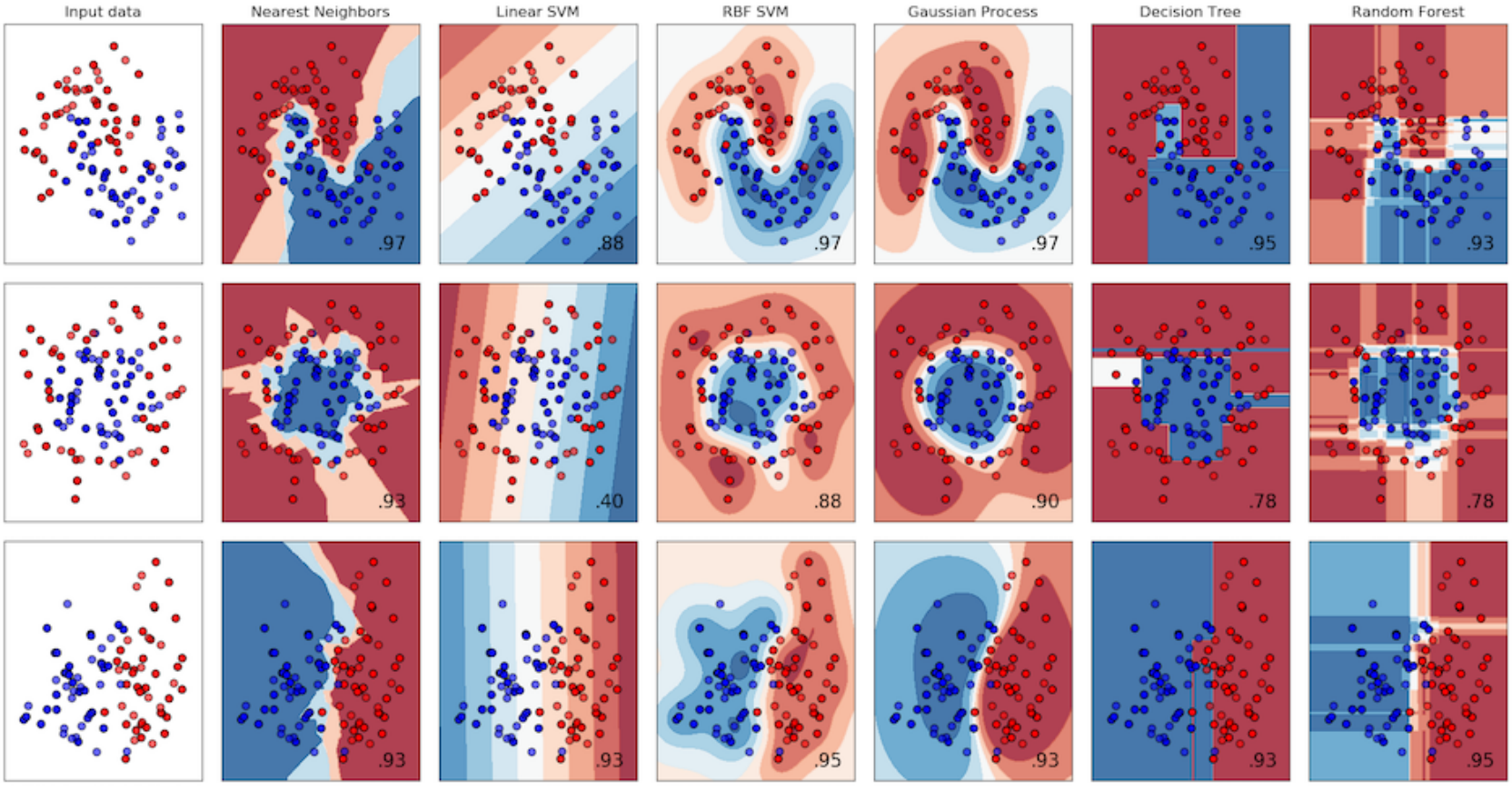
- For OLS, our learning model would have a hypothesis set containing all possible linear functions in the form

$$h(\mathbf{X}) = \mathbf{X}\hat{\beta}$$

- In this example $g(\mathbf{x}) \in \mathcal{H}$ is usually identified using the least squares **learning algorithm** which estimates parameters β with $\hat{\beta}$
- $g(\mathbf{x})$ is the best representation of the data in $\mathcal{H}$ because it minimizes the *residual sum of squares*

Which model do we choose?

Which model do we choose?

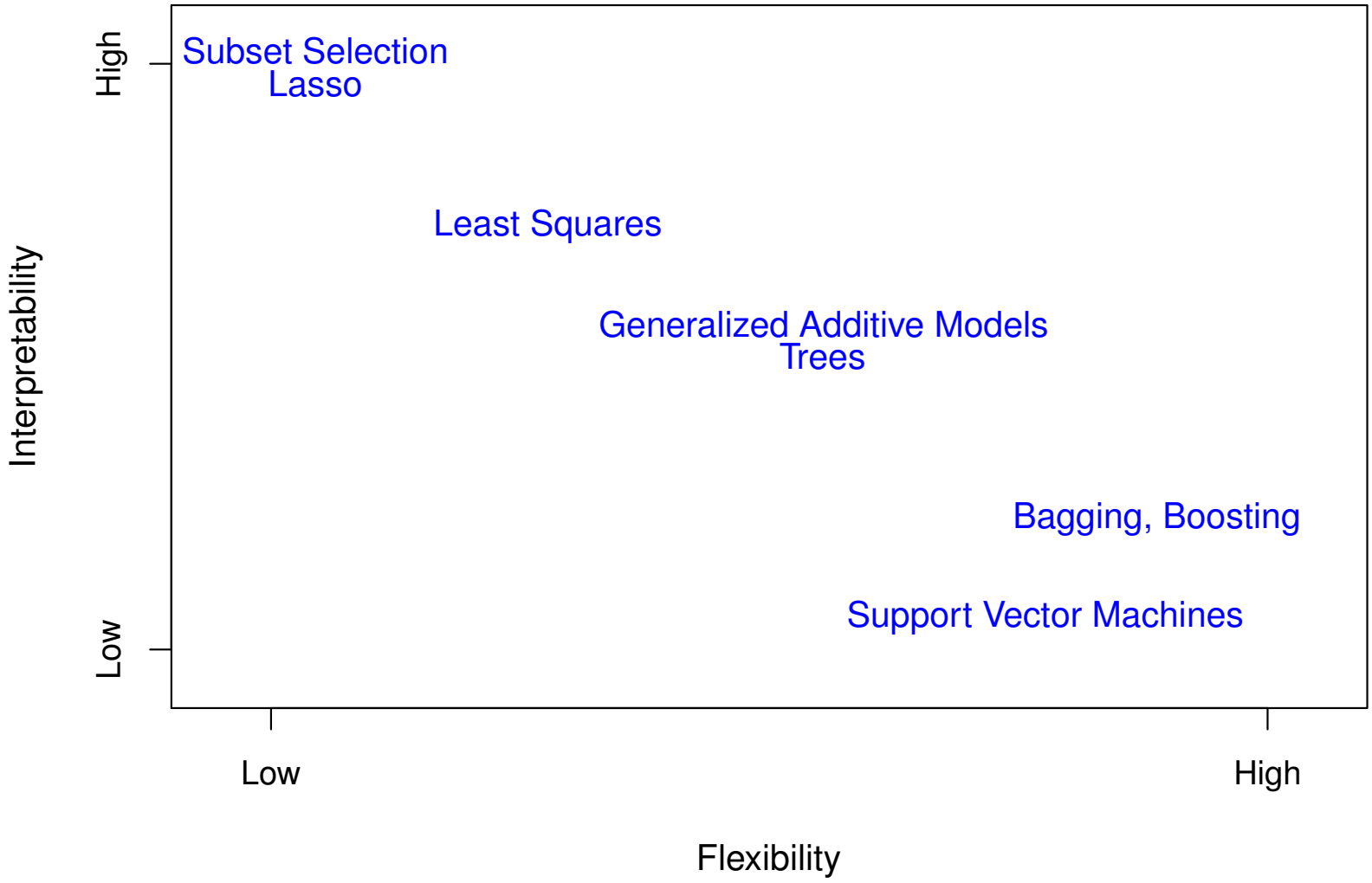


Which model works best really depends on the task and the data ("no free lunch"). (source: sklearn.org)

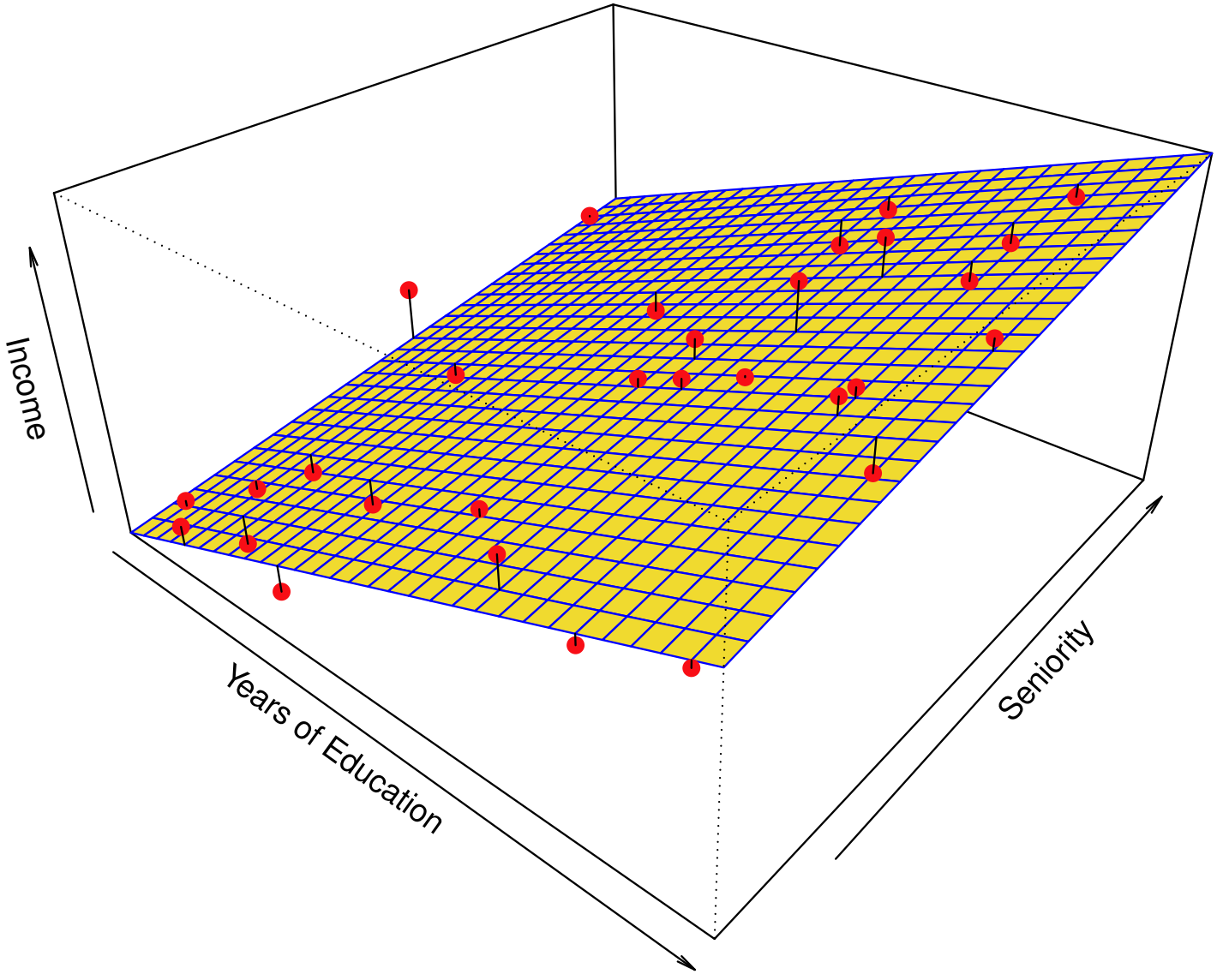
Types of Models

- Machine learning models come in many forms, each differing in the assumptions it makes about f
- **Parametric models** learn parameters that define the shape of f (e.g. $\hat{\beta}$ in OLS regression)
- **Non-parametric models** make few assumptions about f, instead fitting to the data with a certain degree of "smoothness"
- **Interpretable** models allow us to easily dissect and understand how outputs are estimated
- **Black box** models may have millions of parameters or a complicated model structure that make it difficult to understand how outputs are estimated.

The Trade-Off Between Prediction Accuracy and Model Interpretability



Parametric models

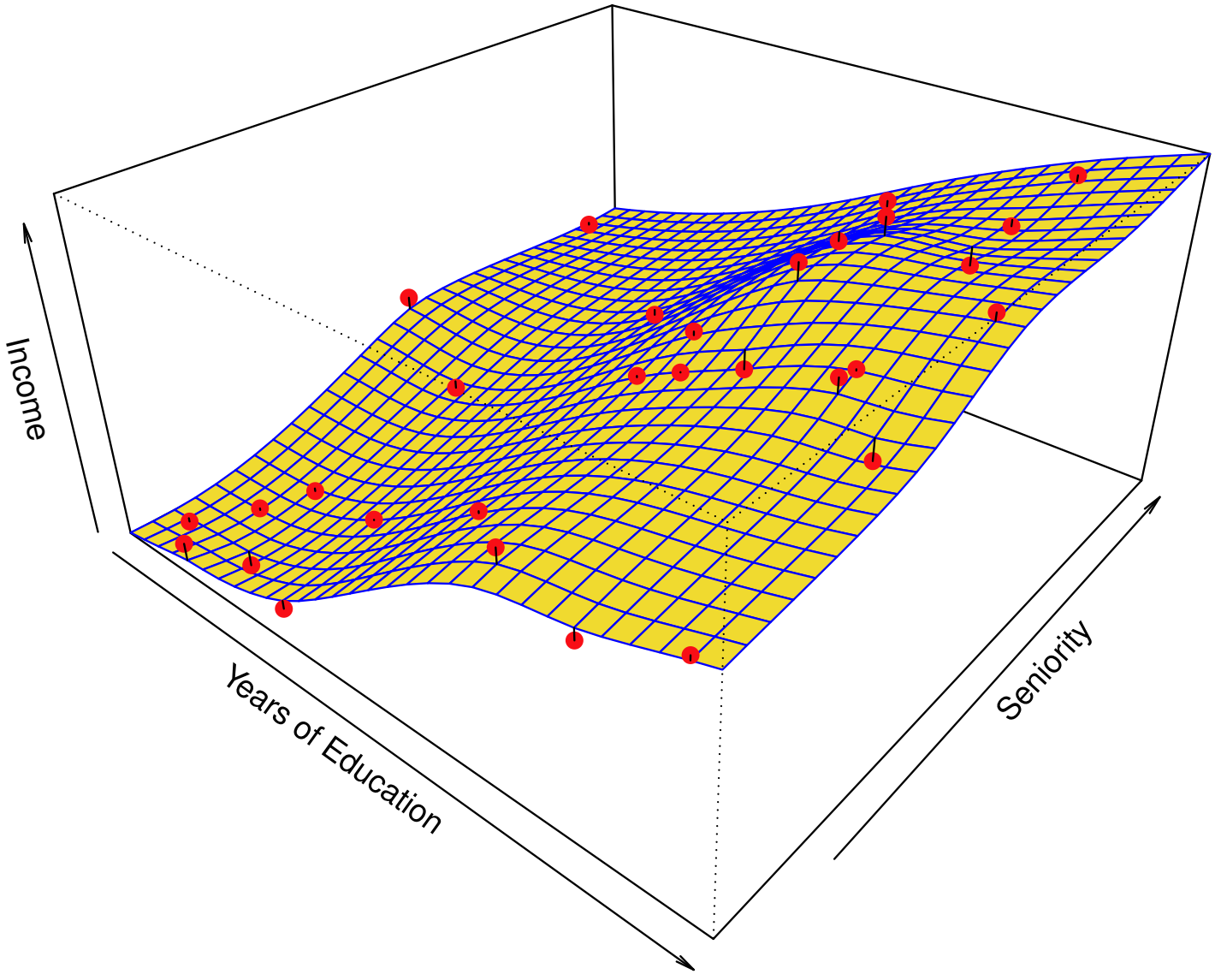


The number of parameters remains fixed, regardless of N.

Parametric models

- Objective: Estimate parameters such as $\hat{\beta}$ from training data
- Examples: OLS, discriminant analysis, logistic regression, neural networks
- Assumptions about the functional form (i.e. function is linear)
- Pros: More interpretable, faster, usually better for inference, require less data
- Cons: Unlikely to closely match the underlying function

Non-parametric models



The number of "parameters" increases as N increases.

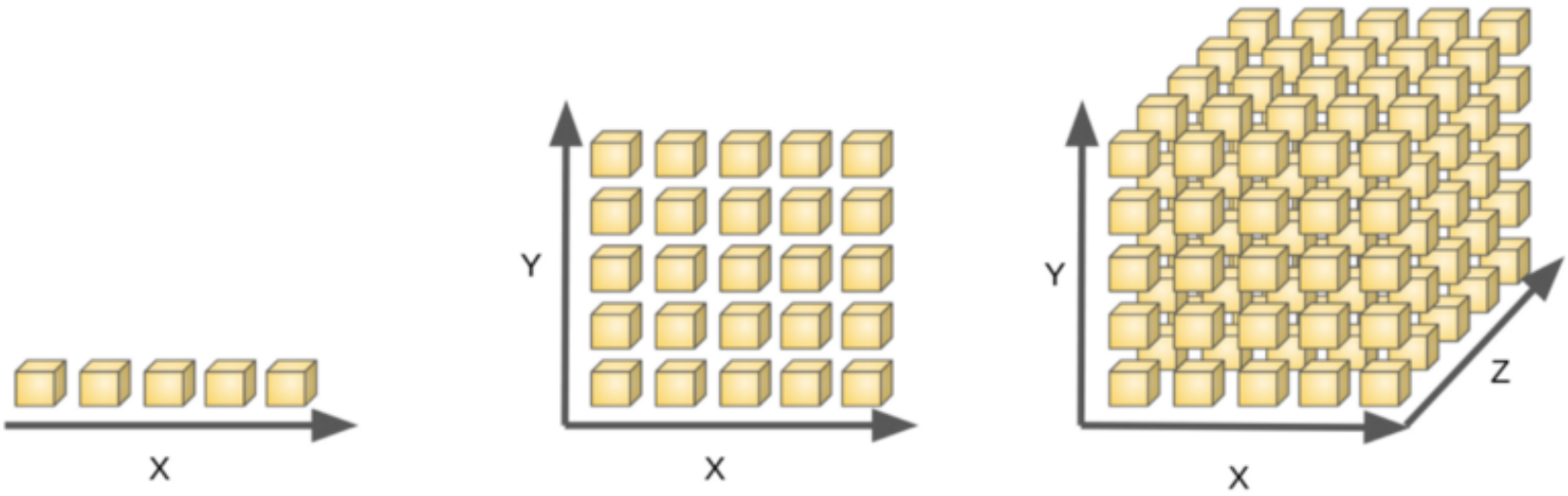
Non-parametric models

- Objective: Get as close as possible to the data
- Examples: decision trees, KNN, splines
- Fewer assumptions about the functional form
- Pros: Fewer assumptions about the underlying functional form, sometimes more accurate
- Cons: slow, prone to **overfitting**, **curse of dimensionality**, require a lot more data

Non-Parametric Models in High Dimensions

- Non-parametric models such as KNN often fail in high dimensions
- This is called the **curse of dimensionality**
- Reason: it is difficult to find enough observations close to a target point x
- If we smooth too much (e.g. increase the number of nearest neighbors k), the estimates become severely biased

Illustration: Searching for Treasure



Imagine searching a set of boxes for N pieces of treasure. With d = 1, there are only 5 boxes to search. With d = 2, there are now 25 boxes; and with d = 3, there are 125 boxes to search. As n gets bigger, it becomes difficult to sample all the boxes. This makes the treasure harder to find — especially as many of the boxes are likely to be empty! Source: FreeCodeCamp

Where does the "curse" come from?

- Suppose points $x_1, \ldots, x_n$ are uniformly distributed in a d-dimensional unit cube
- We wish to construct a hypercube neighborhood of x to capture a fraction ρ of the observations
- How big should the cube be? Since the volume is $\ell^d = \rho$, we need edge length $\ell^d = \rho^{1/d}$
- For example:
  - When $d = 1$: If $\rho = 0.01$, $\ell = 0.01$ and $\rho = 0.1$, $\ell = 0.1$.
  - When $d = 10$: If $\rho = 0.01$, $\ell = 0.63$ and $\rho = 0.1$, $\ell = 0.8$.

The Unit Cube Illustration

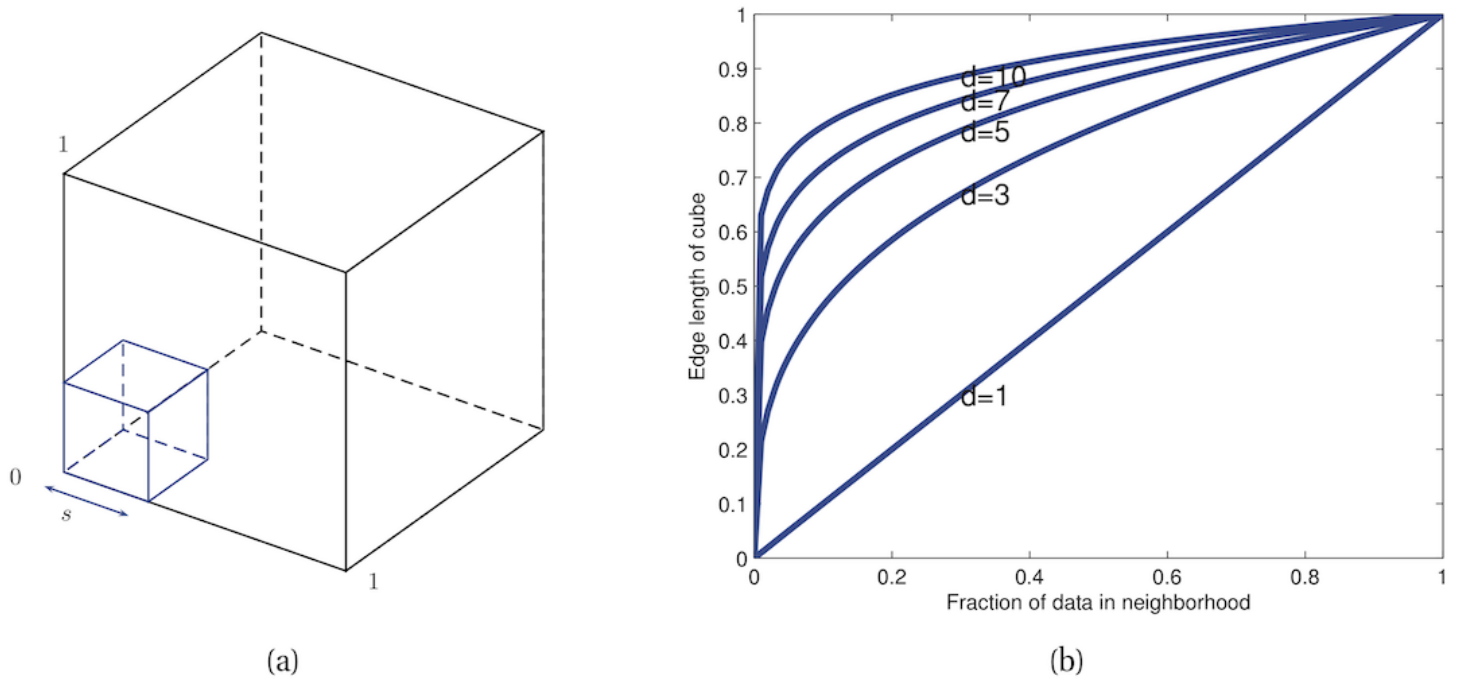


Figure 1.16 Illustration of the curse of dimensionality. (a) We embed a small cube of side s inside a larger unit cube. (b) We plot the edge length of a cube needed to cover a given volume of the unit cube as a function of the number of dimensions. Based on Figure 2.6 from (Hastie et al. 2009). Figure generated by `curseDimensionality`.

Source: *Machine Learning: A Probabilistic Perspective*

Implications of the curse of dimensionality

- "Local" methods are no longer local when the dimension p increases.
- If n points are sufficient to estimate a function in $\mathbb{R}^1$, n^p are needed to achieve similar accuracy in $\mathbb{R}^p$.
- Fortunately, in practice most data are not sampled uniformly from a cube (structure effectively reduces dimension), so the "curse" is not as pronounced as it is in the cube illustration.

Some quick crowdsourcing

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Quiz Study Guide

Concepts to Know

- Curse of dimensionality
- "No free lunch"
- KNN, perceptron
- Interpretability
- Parametric vs. non-parametric
- Unknown target function
- Hypothesis set, learning model, learning algorithm
- Unsupervised vs. supervised learning

Review Questions

1. What is the difference between a learning model and a learning algorithm?
2. Why is KNN considered a non-parametric model? Why is the perceptron model considered a parametric model?
3. In what scenarios might the perceptron model out-perform the KNN model?
4. What are some examples of supervised learning problems?
5. What are some examples of unsupervised learning problems?

Review Questions (continued)

6. What if we gathered some more Wikipedia Talk comments? How well would the models trained using our intial dataset **generalize** to new data?

- "You are an old cougar! You are an old cougar!"
- "You're full of crap. . . . . and you know it."
- "In this case there's been little editing activity so it will probably work."
- "THANK YOU!!! This is section looks great now! The last paragraph is missing a few citations, though."