Announcements

- Project Milestone 3 due **Friday, December 9 at 8pm**
  - 2 day extension

- Final exam is **Thursday, December 22 from 6-8pm**
  - Review sessions today and Monday
  - Example final exam has been released

Agenda: Ethics

- Dataset issues
- Fairness/discrimination in ML models
- Misinformation about ML
- Feedback in ML systems
- Practical principles for ethical ML

Recap: Data Collection Issues

- Need to gather representative sample
- Need to ensure labels are unbiased
- Need to think carefully about whether to include sensitive attributes

Agenda: Ethics

- Dataset issues
- Fairness/discrimination in ML models
- Misinformation about ML
- Feedback in ML systems
- Practical principles for ethical ML

Recap: Group Fairness

Non-discrimination criteria		
Independence	Separation	Sufficiency
$R \perp A$	$R \perp A \mid Y$	$Y \perp A \mid R$

Recap: Group Fairness

- **Independence:** Risk score distribution should be equal across ages:

$$P(\text{risk score} \mid \text{age}) = P(\text{risk score})$$

  - E.g., equal proportion of low risk customers for young vs. old people
  - Often called demographic parity

- If lower age groups in fact behave more riskily, algorithm is forced to make false negatives young people or false positives older people

Recap: Group Fairness

- **Separation:** Risk score should be independent of age given outcome:

$$P(\text{risk score} \mid \text{age}, \text{true outcome}) = P(\text{risk score} \mid \text{true outcome})$$

  - Equivalent to saying the true positive rate and false positive rate are equal across subgroups

- **Example:** Both of the following hold:
  - Fraction of young, low-insurance-usage people correctly identified as low-risk = Fraction of old low-insurance-usage people correctly identified as low-risk
  - Fraction of young high-insurance-usage people wrongly identified as low-risk = Fraction of old high-insurance-usage people wrongly identified as low-risk

Agenda: Ethics

- Dataset issues
- Fairness/discrimination in ML models
- Misinformation about ML
- Feedback in ML systems
- Practical principles for ethical ML

Ethical Issues

- When you build ML models, you are responsible for how it is eventually deployed
  - Face classifier may be used by an authoritarian government to track people or target minority subgroups
  - Technology may be used in safety critical settings without sufficient validation

Best Practices for Ethical ML

- Human augmentation
- Bias evaluation
- Explainability and justification
- Displacement strategy

Human Augmentation

- Assess the impact of incorrect predictions and, when reasonable, design systems with human-in-the-loop review processes

- Especially important in domains with significant impact on human lives (e.g. justice, health, etc.)
  - All stakeholders' values and perspectives should be accounted for during algorithm design
  - Domain experts as human-in-the-loop reviewers of ML decisions

Bias Evaluation

- **Use tools to understand bias in ML models**
  - No standard strategy, need to careful consider potential sources of bias for the domain you are working in
  - Requires continuous monitoring, not one-time effort

Explainability and Justification

- **Use tools to explain ML predictions**
  - Even though accuracy may decrease, the explainability may be significant
  - Important for end users to be able to understand ML predictions
  - Especially important due to hype and misinformation about ML

- **Challenges**
  - Potential leaking of sensitive data
  - Easy to game, e.g., “adversarial feedback”
  - Loss of competitive advantage
  - Sometimes hard to interpret, even for experts

Samuele Lo Piano, “Ethical Principles …” 2020

Explainability and Justification

- **Legal considerations**
  - France’s Digital Republic Act gives the right to an explanation as regards decisions on an individual made by algorithms
  - How and to what extent the algorithm was used, which data was processed and its source, etc.
  - Other countries considering similar laws

Displacement Strategy

- Identify and document relevant information so that business change processes can be developed to mitigate the impact on workers being automated

- Ensure all stakeholders are brought on board and develop a change-management strategy before automation

- Often, the workers are asked to do labor (e.g., generating training data) that will help automate themselves. Are the appropriately compensated?

Accountability

- **Question:** Should a passenger in automated car be able to command it to go 80 MPH on a 55 MPH road?

- **Reasons for "No"**
  - It's illegal and can endanger others
  - Who is liable for accidents? Driver? Manufacturer? Insurance company?

- **Reasons for "Yes"**
  - Many exceptions!
  - Rushing someone to the hospital, escaping a tornado, etc.

Other Challenges

- The ethics of ML and AI systems is an urgent topic **now**, not because of speculative future scenarios
  - Open and active area of research, involves scholars from law, social sciences, etc., as well as domain experts
  - Law moves slowly, and legal frameworks have much to catch up to

- **Looking forward**
  - **AI safety**: How can we make AI without unintended negative consequences?
  - **AI alignment:** How can AI make decisions that align with our values?

Useful Tools

- IBM AI Fairness 360: https://aif360.mybluemix.net/
- Google ML Fairness Gym: https://github.com/google/ml-fairness-gym
- Facebook Fairness Flow: https://venturebeat.com/2021/03/31/ai-experts-warn-facebooks-anti-bias-tool-is-completely-insufficient/

Lecture 26: Review

CIS 4190/5190

Fall 2022

Concepts & Algorithms

- **Concepts**
  - Know these well
  - Especially bias-variance tradeoff!

- **Algorithms**
  - What does the model family look like?
  - What does the loss function measure?
  - How does the optimizer work?
  - What is the effect of each design decision and hyperparameter on bias-variance tradeoff and/or optimization?

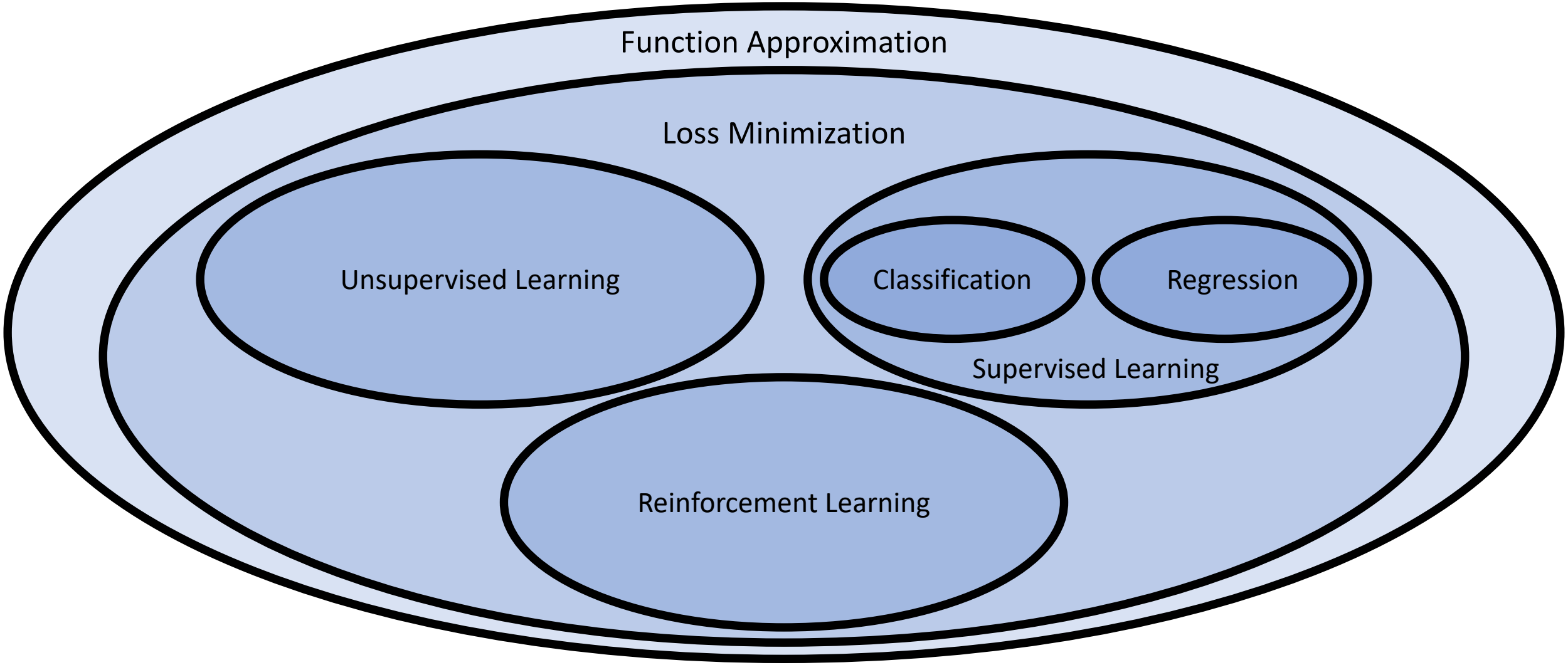
Concept: Types of Learning

- **Supervised learning**
  - Predict unknown output given a new input
  - Most common task

- **Unsupervised learning**
  - Infer structure in unlabeled data
  - Automatically learn features, visualize data, etc.

- **Reinforcement learning**
  - Sequential decision-making in unknown environment
  - Robotics, control, etc.

Concept: Types of Learning



Concept: Loss Minimization View

- **Model family:** What are the candidate models f?
- **Loss function:** How to define “approximating”?
- **Optimizer:** How do we minimize the loss?

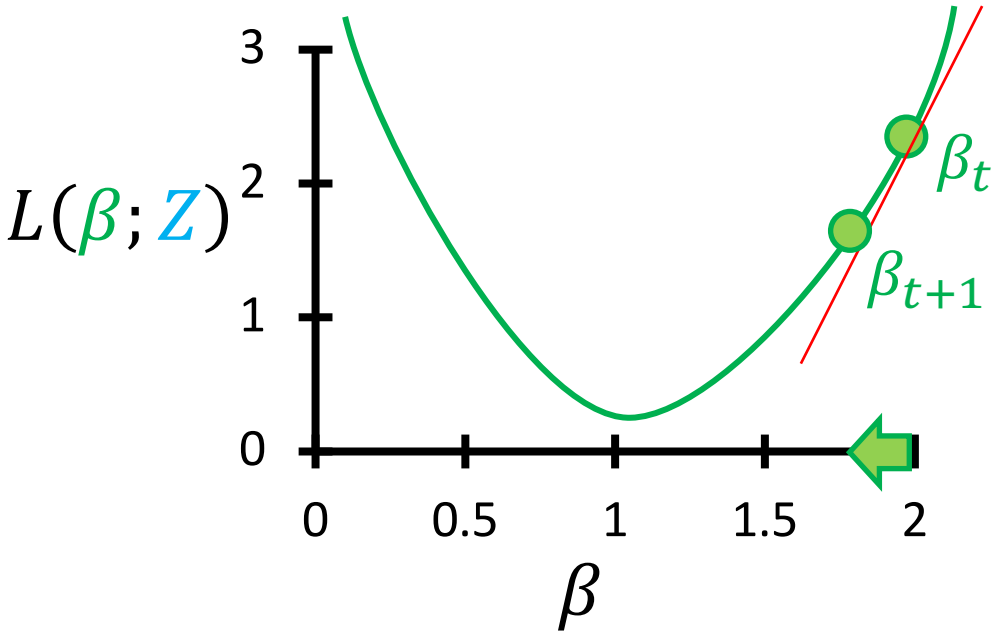
Algorithm: Linear Regression

- **Type:** Supervised learning
- **Model family:** Linear functions $f_\beta(x) = \beta^\top x$
- **Loss function:** MSE $L(\beta; Z) = \frac{1}{n}\sum_{i=1}^{n}(y_i - \beta^\top x_i)^2$
- **Optimizer:** Gradient descent
- **Hyperparameters:** Learning rate α, convergence threshold ϵ

Algorithm: Linear Regression

- Initialize $\beta_1 = \vec{0}$
- Repeat until $\|\beta_t - \beta_{t+1}\|_2 \leq \epsilon$:

$$\beta_{t+1} \leftarrow \beta_t - \alpha \cdot \nabla_\beta L(\beta_t; Z)$$



Algorithm: Linear Regression with Features

- **Type:** Supervised learning
- **Model family:** Linear functions $f_\beta(x) = \beta^\top \phi(x)$
- **Loss function:** MSE $L(\beta; Z) = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \beta^\top \phi(x_i)\right)^2$
- **Optimizer:** Gradient descent
- **Hyperparameters:** Feature map ϕ

Algorithm: Linear Regression with Features

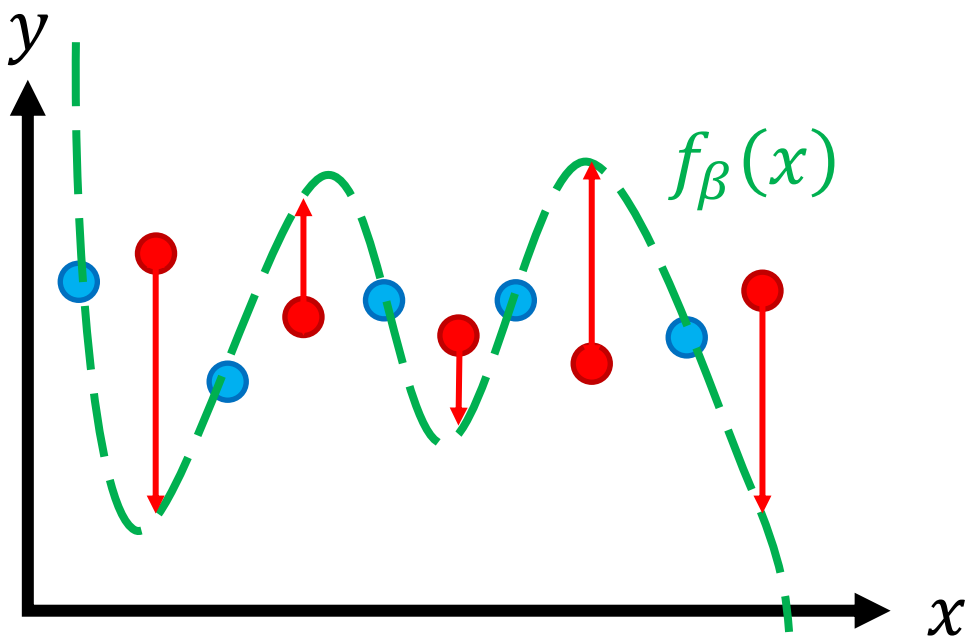
- **Polynomial features**
  - $\phi(x) = \beta_1 + \beta_2 x_1 + \beta_3 x_2 + \beta_4 x_1^2 + \beta_5 x_1 x_2 + \beta_6 x_2^2 + \cdots$
  - Quadratic features are very common; capture "feature interactions"
  - Can use other nonlinearities (exponential, logarithm, square root, etc.)

- **Intercept term**
  - $\phi(x) = [1 \quad x_1 \quad \dots \quad x_d]^\top$
  - Almost always used; captures constant effect

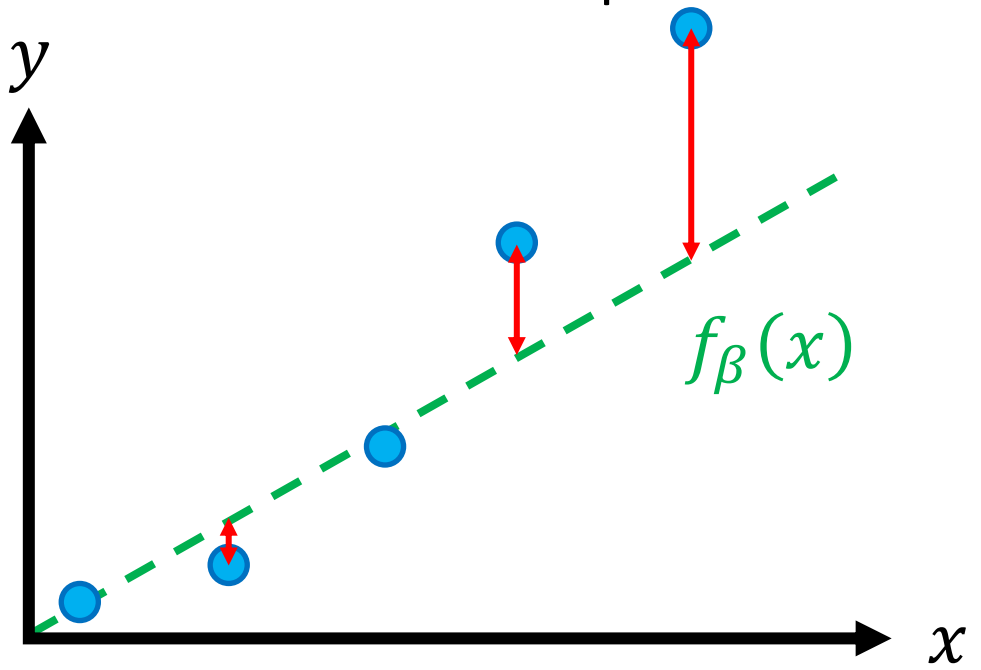
- **Encoding non-real inputs**
  - E.g., $x =$ "the food was good" and $y = 4$ stars
  - $\phi(x) = [1(\text{“good”} \in x) \quad 1(\text{“bad”} \in x) \quad \dots]^\top$

Concept: Bias-Variance Tradeoff

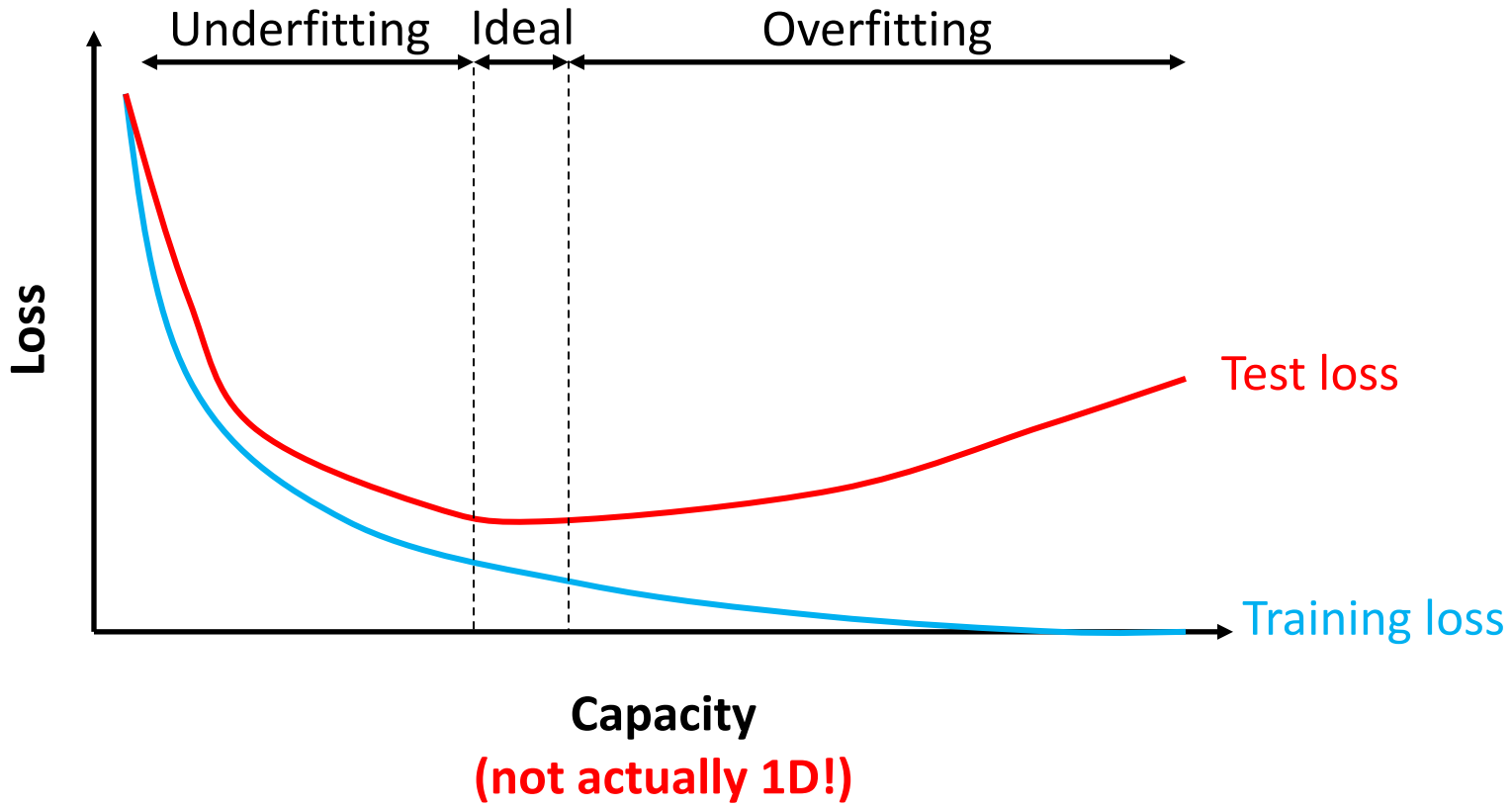
- **Overfitting (high variance)**
  - High capacity model capable of fitting complex data
  - Insufficient data to constrain it



- **Underfitting (high bias)**
  - Low capacity model that can only fit simple data
  - Sufficient data but poor fit

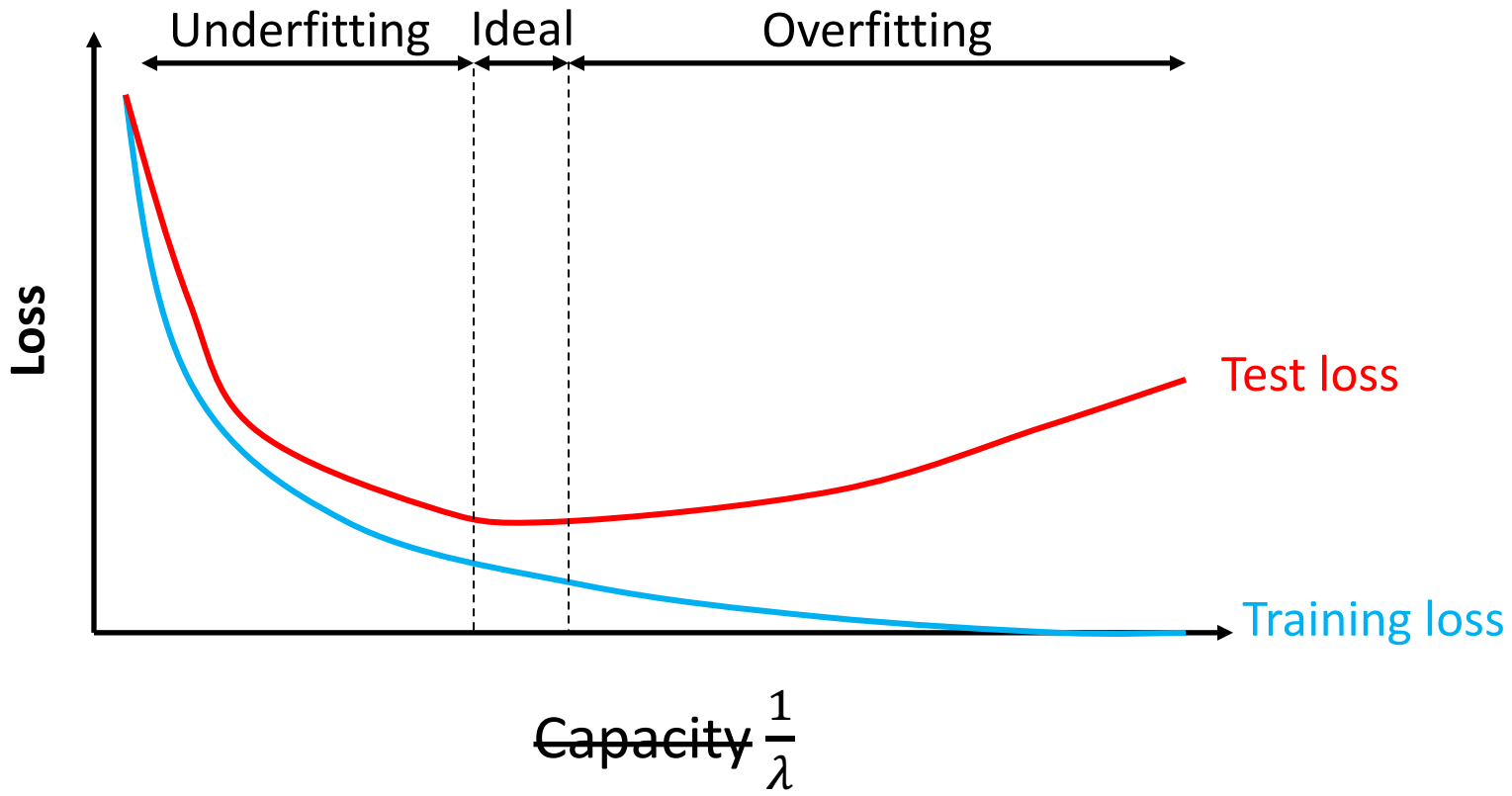


Concept: Bias-Variance Tradeoff



Slide by Padhraic Smyth, UCIrvine

Concept: Bias-Variance Tradeoff



Algorithm: L_2 Regularized Linear Regression

- **Type:** Supervised learning
- **Model family:** Linear functions $f_\beta(x) = \beta^\top x$
- **Loss function:** MSE $L(\beta; Z) = \frac{1}{n}\sum_{i=1}^{n}(y_i - \beta^\top x_i)^2 + \lambda \cdot \|\beta\|_2^2$
- **Optimizer:** Gradient descent
- **Hyperparameters:** Regularization weight λ

Concept: Maximum Likelihood Estimation

- **Model family:** What is the likelihood $p(y \mid x)$?
- **Optimizer:** How do we minimize the negative log likelihood (NLL)?

Concept: Maximum Likelihood Estimation

- **Model family:** Most likely label

$$f_\beta(x) = \arg\max_y p_\beta(y \mid x)$$

- **Loss function:** Negative log likelihood (NLL)

$$\ell(\beta; Z) = -\sum_{i=1}^{n} \log p_\beta(y_i \mid x_i)$$

Algorithm: Linear Regression

- **Likelihood:** A Gaussian distribution

$$p_\beta(y \mid x) = N(y; \beta^\top x, 1) = \frac{1}{\sqrt{2\pi}} \cdot e^{-\frac{(\beta^\top x - y)^2}{2}}$$

- **Optimizer:** Gradient descent

Algorithm: Linear Regression

- **Model family:**

$$f_\beta(x) = \beta^\top x$$

- **Negative log likelihood:**

$$\ell(\beta; Z) = \frac{n \log(2\pi)}{2} + \sum_{i=1}^{n} (\beta^\top x_i - y_i)^2$$

Algorithm: Logistic Regression

- **Likelihood:** Bernoulli distribution with

$$p_\beta(Y = 1 \mid x) = \frac{1}{1 + e^{-\beta^\top x}} = \sigma(\beta^\top x)$$

$$p_\beta(Y = 0 \mid x) = 1 - \sigma(\beta^\top x)$$

- **Optimizer:** Gradient descent

Algorithm: Logistic Regression

- **Model family:**

$$f_\beta(x) = 1(\beta^\top x \geq 0)$$

- **Negative log likelihood:**

$$\ell(\beta; Z) = -\sum_{i=1}^{n} y_i \log\big(\sigma(\beta^\top x_i)\big) + (1 - y_i) \log\big(1 - \sigma(\beta^\top x_i)\big)$$

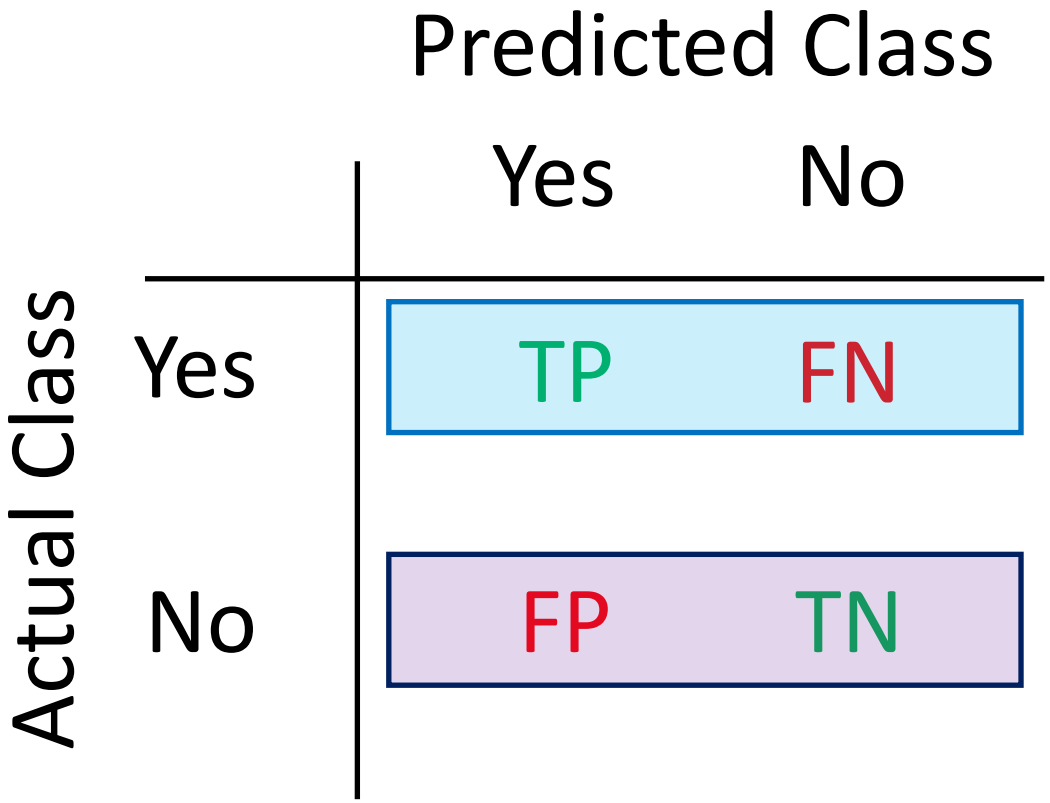
Concept: Regularization as a Prior

- What if we assume $\beta \sim N(0, \sigma^2 I)$?
- Consider the modified NLL

$$\ell(\beta; Z) = -\sum_{i=1}^{n} \log p_\beta(y_i \mid x_i) + \underbrace{\log \sigma\sqrt{2\pi}}_{\text{constant}} + \underbrace{\frac{\|\beta\|_2^2}{2\sigma^2}}_{\text{regularization}}$$

- Obtain L_2 regularization on β with $\lambda = \frac{1}{2\sigma^2}$

Algorithm: Sensitivity vs. Specificity

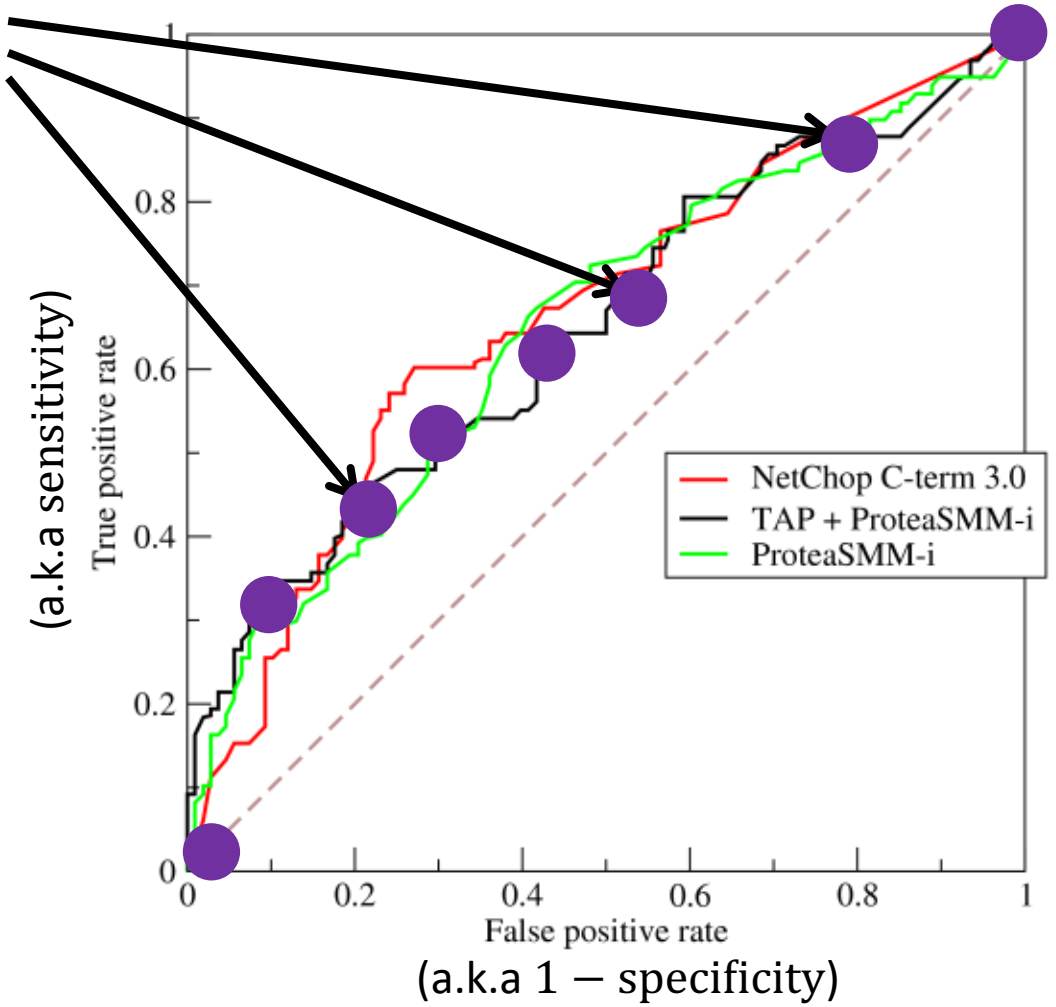


$$\text{sensitivity} = \frac{TP}{TP + FN}$$

$$\text{specificty} = \frac{TN}{TN + FP}$$

Algorithm: Sensitivity vs. Specificity

Each point on this curve corresponds to a choice of τ



Aside: Area under ROC curve is another metric people consider when evaluating $\hat{\beta}(Z)$

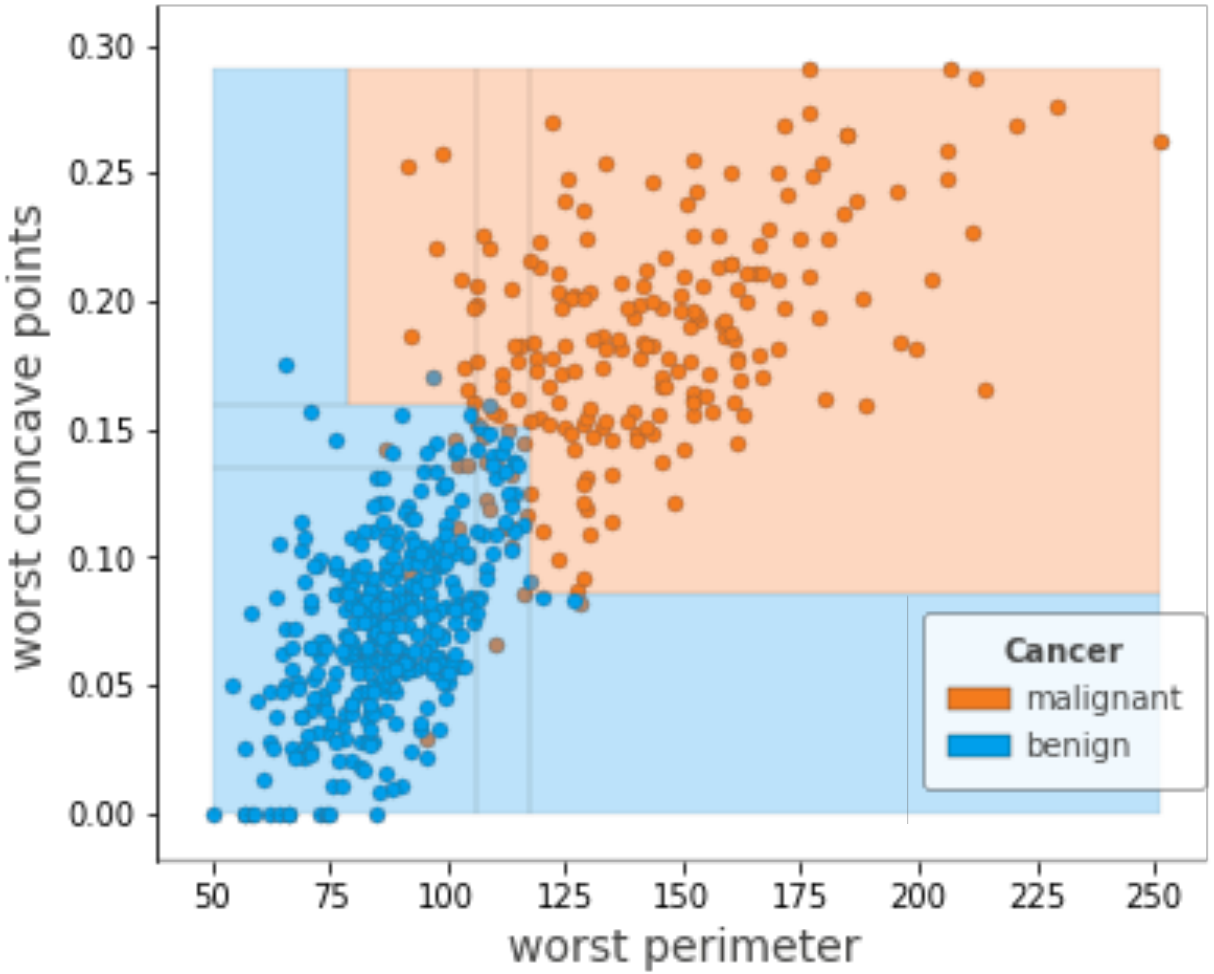
Algorithm: KNN

- **Type:** Supervised
- **Model family:** Aggregate labels of k nearest points
  - Parameters are the dataset (“nonparametric”)
- **Loss function:** MSE, accuracy, etc.
- **Optimizer:** N/A
- **Hyperparameters:** Aggregation/distance functions, k

Algorithm: Decision Trees

- **Type:** Supervised
- **Model family:** Decision trees ($x_i = c$ for categorical, $x_i \leq t$ for real)
- **Loss function:** MSE, accuracy, etc.
- **Optimizer:** CART algorithm
  - Recursively choose nodes based on split that maximizes information gain
  - Early stopping (e.g., minimum gain) or prune using validation set
- **Hyperparameters:** Gain metric, maximum depth, minimum gain

Algorithm: Decision Trees



Concept: Ensemble Design Decisions

- How to learn the base models?
  - **Bagging:** Sub-sample dataset and features
  - **Boosting:** Iteratively upweight incorrectly classified examples
  - **Gradient boosting:** Train next base model on residual labels

- How to combine the learned base models?
  - Average, majority vote, etc.
  - Train a supervised learning model using base models as “features”

Algorithm: Random Forests

- **Type:** Supervised
- **Model family:** Average of decision trees
  - For classification, average predicted probabilities
- **Loss function:** MSE or accuracy
- **“Optimizer”:** Bagging
  - **Intuition:** Learn overfit decision trees and then “average away” variance
- **Hyperparameters:** Number of trees, bagging strategy, decision trees

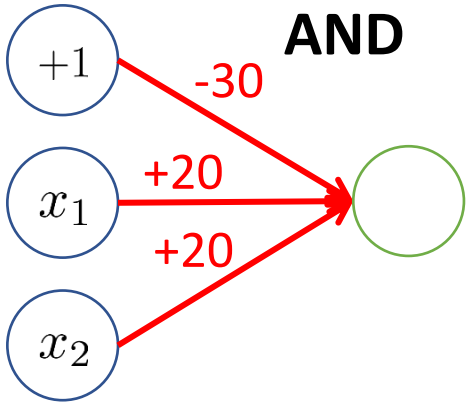
Algorithm: Gradient Boosted Decision Trees

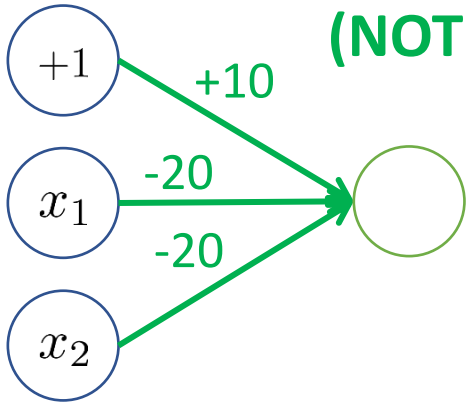
- **Type:** Supervised
- **Model family:** Weighted sum of decision trees
- **Loss function:** MSE or accuracy
- **"Optimizer":** Boosting
  - **Intuition:** Train many shallow decision trees
- **Hyperparameters:** Number of trees, decision trees

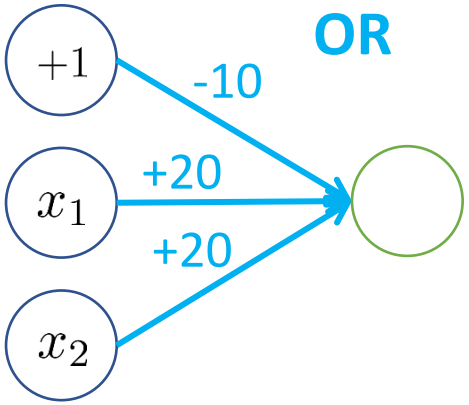
Algorithm: Neural Networks

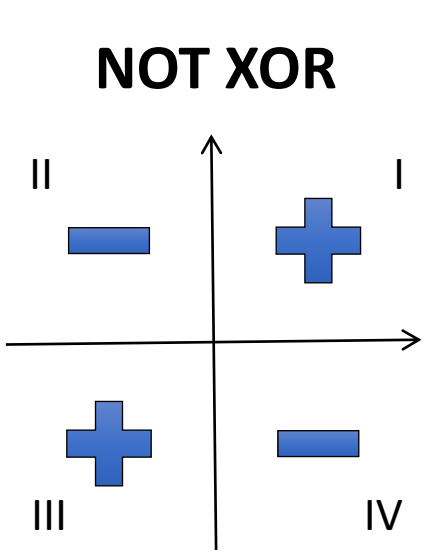
- **Type:** Supervised, unsupervised
- **Model family:** Custom composition of parametric layers
  - Nonlinearities
  - Linear/fully-connected, convolution, pooling, recurrent, self-attention
- **Loss function:** Any differentiable loss
- **Optimizer:** Gradient descent (compute gradient via backpropagation)
  - **Tweaks:** Momentum, adaptive learning rates, schedules, residual connections, initialization, batch normalization, dropout, early stopping
  - Make sure you know how to take partial derivatives!

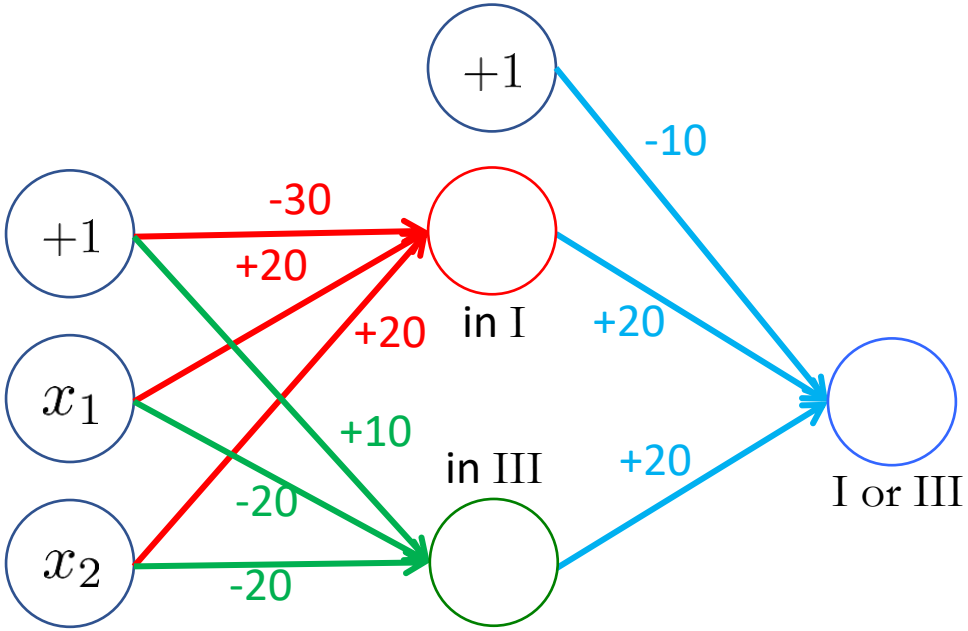
Algorithm: Neural Networks











Based on slide and example by Andrew Ng

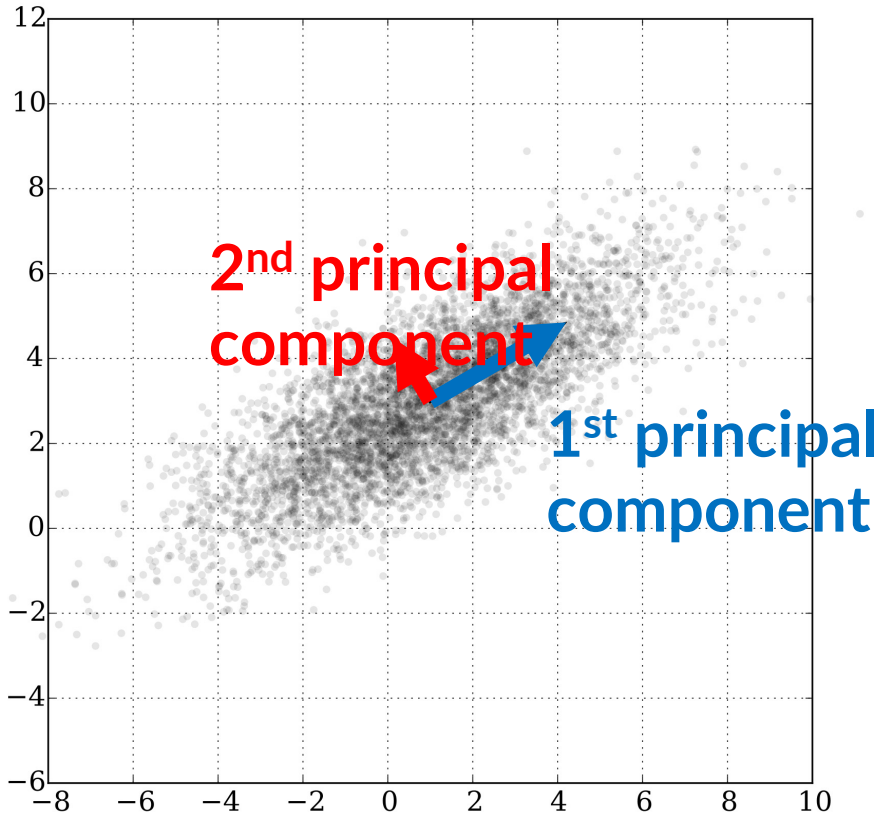
Algorithm: K-Means Clustering

- **Type:** Unsupervised learning
- **Model family:** K centroids, cluster is nearest centroid
- **Loss:** Average distance to nearest centroid
- **Optimizer:** Alternating minimization
  - **Step 1:** Given centroids, compute the cluster of each point
  - **Step 2:** Given clusters, compute the best centroids for each cluster
- **Hyperparameters:** Distance function, initialization strategy, k

Algorithm: PCA

- **Type:** Unsupervised learning
- **Model family:** K principal components (project point onto PCs)
- **Loss:** Approximation quality (e.g., MSE)
- **Optimizer:**
  - Center data and compute covariance matrix
  - Choose top k eigenvectors with largest eigenvalues
- **Hyperparameters:** k

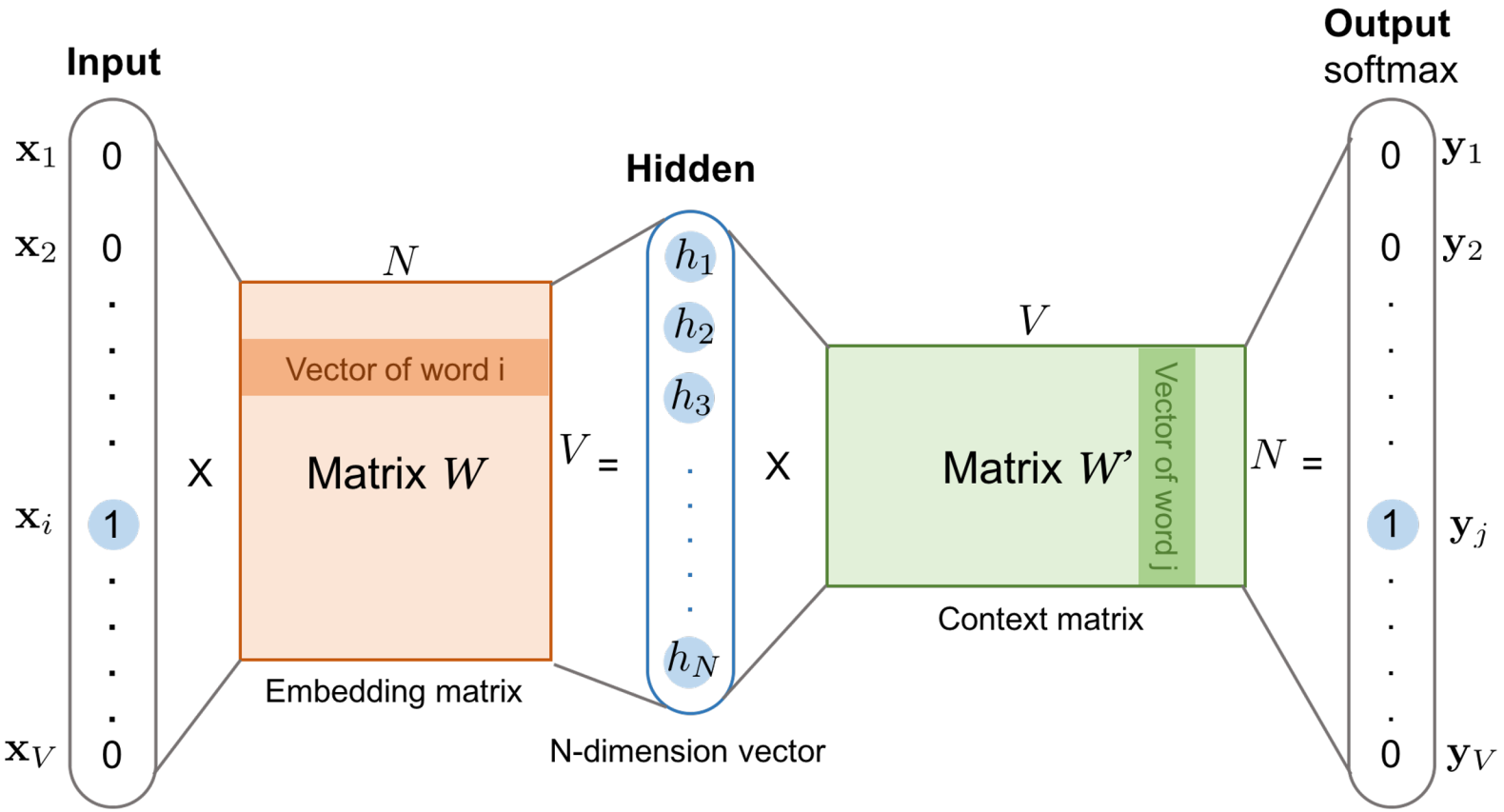
Algorithm: PCA



Algorithm: Word Vectors

- **Type:** Unsupervised (also called “self-supervised”)
- **Model family**
  - Neural network with a single hidden layer
  - Next word (and/or previous word)
- **Loss:** Softmax loss
- **Optimizer:** Gradient descent
- **Hyperparameters:** Hidden layer dimension

Algorithm: Word Vectors

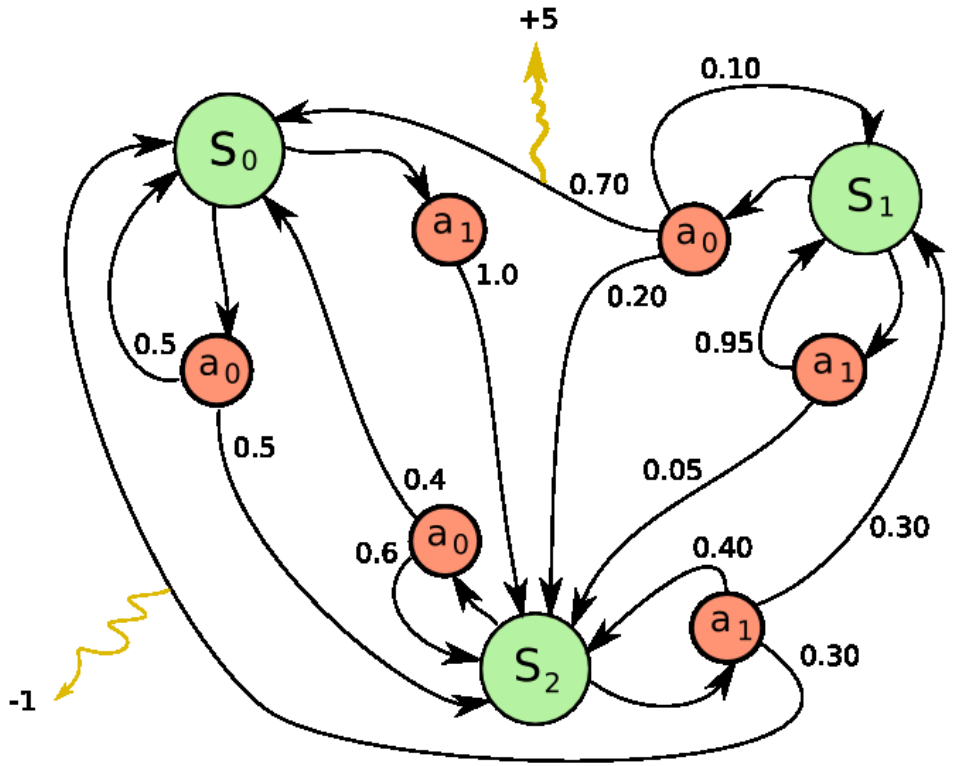


Algorithm: Bayesian Networks

- **Type:** Supervised, unsupervised
- **Model family:** Parametric family of joint distributions $P(X_1, \ldots, X_k)$
  - Imposes constraints on structure of joint distribution
  - Need to perform inference to compute original joint distribution
- **Loss:** NLL: $-\sum_{i=1}^{n} \log P\left(X_1 = x_{1,1}, \ldots, X_k = x_{i,k}\right)$
- **Optimizer:** Gradient descent
- **Hyperparameters:** Graph structure

Concept: MDP

- Set of states $s \in S$
- Set of actions $a \in A$
- Transition function $P(s' \mid s, a)$
- Reward function $R(s, a, s')$
- Discount factor $\gamma < 1$



Algorithm: Q Iteration

- **Type:** Reinforcement learning (to be precise, planning)
- **Model family:** Table of Q values $Q(s, a)$
  - Can use function approximation (use gradient update in optimizer)
- **Loss:** Cumulative expected reward
- **Optimizer:** Iteratively update Q values using Bellman equation
- **Hyperparameters:** Number of iterations, discount?

Algorithm: Q Learning

- **Type:** Reinforcement learning
- **Model family:** Table of Q values $Q(s, a)$
  - Can use function approximation (use gradient update in optimizer)
- **Loss:** Cumulative expected reward
- **Optimizer:** Iteratively update Q using approximate Bellman equation
- **Hyperparameters:** Learning rate, exploration strategy, discount?

Algorithm: Collaborative Filtering

- **Type:** Recommender system (between supervised and unsupervised)
- **Model family:** Predict ratings X_{ik} of user i for content k
  - Many choices, e.g., KNN using partial rating vectors
- **Loss:** MSE
- **Optimizer:** Model-dependent
- **Hyperparameters:** Distance/aggregation functions

Algorithm: Content-Based Recommendations

- **Type:** Recommender system (supervised)
- **Model family:** Predict ratings X_{ik} of user i for content k
  - Any supervised learning algorithm, e.g., linear regression
- **Loss:** MSE
- **Optimizer:** Model-dependent
- **Hyperparameters:** Item-content features

Concept: Ethics

- Dataset issues
- Fairness/discrimination in ML models
- Misinformation about ML
- Feedback in ML systems
- Practical principles for ethical ML

Concepts & Algorithms

- **Concepts**
  - Know these well
  - Especially bias-variance tradeoff!

- **Algorithms**
  - What does the model family look like?
  - What does the loss function measure?
  - How does the optimizer work?
  - What is the effect of each design decision and hyperparameter on bias-variance tradeoff and/or optimization?