Announcements

- Project Milestone 3 due **Friday, December 8 at 8pm**
  - 2 day extension
- Final exam is **Thursday, December 14 from 3-5pm in Chem 102**
  - Example final exam has been released

Final Exam Logistic

- 2 hours (aim for ~1.5 hours of material)

- What you can use
  - Pen + paper (no coding)
  - Closed book
  - **Calculator**
  - **1-page cheat sheet**

- You shouldn't need calculator or cheat sheet

Final Exam Content

- Focus on **understanding of concepts**

- For each model family
  - How do design decisions/hyperparameters affect bias-variance tradeoff?
  - What does the decision boundary look like?
  - Is optimization guaranteed to converge to the global optimum?

- Also, concepts such as exploration in reinforcement learning

- There will be questions about backpropagation

Lecture 26: Ethics

CIS 4190/5190

Fall 2023

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

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Group Fairness

- **Problem setup**
  - Sensitive attribute A
  - ML model R mapping input features X to prediction $\hat{Y} = R(X)$
  - True outcome Y (typically binary, and $Y = 1$ is the “good” outcome)

- **Example:** Insurance risk prediction
  - $A = \text{age}$
  - $R = \text{predicted cost}$
  - $Y = \text{true cost}$

Group Fairness

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

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

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

- What if lower age groups in fact behave more riskily?

Group Fairness

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

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

  - 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

Group Fairness

- **Sufficiency:** Outcome should be independent of risk score given age:

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

  - Intuitively, risk score tells us everything we need to know about the true outcome with respect to age

Group Fairness

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

Group Fairness

- Three notions are incompatible!

Proposition 2. *Assume that A and Y are not independent. Then sufficiency and independence cannot both hold.*

Proposition 3. *Assume Y is binary, A is not independent of Y, and R is not independent of Y. Then, independence and separation cannot both hold.*

Proposition 5. *Assume Y is not independent of A and assume $\hat{Y}$ is a binary classifier with nonzero false positive rate. Then, separation and sufficiency cannot both hold.*

- Thus, need carefully choose what kinds of fairness we ask for

Solon Barocas, Moritz Hardt, Arvind Narayanan, “Fairness and Machine Learning”

Algorithms for Ensuring Fairness

- Given a notion of fairness, there are a few ways of achieving it

- **Example:** Independence
  - **Pre-processing:** Adjust features to be uncorrelated with sensitive attribute
  - **Training constraints:** Impose the constraint during training
  - **Post-processing:** Adjust the learned classifier so its predictions are uncorrelated with the sensitive attribute

- **Goodhart's law:** "When a measure becomes a target, it ceases to be a good measure" – Marilyn Strathern
  - Do not blindly impose fairness, need to carefully examine predictions

Human-in-the-Loop Fairness

- **Potential solution:** Have domain experts weigh in on what performance metrics result in fair model selection/training

- **Challenges**
  - Experts may not understand limitations of ML models (e.g., does a judge using a system understand that it only has 60% accuracy?)
  - Potential for selective enforcement based on human biases

Human-in-the-Loop Fairness

- **Example:** In bail decision-making, judges selectively follow model
  - Less lenient against younger defendants, especially minorities
  - Younger defendants are actually more risky, but judges may have been lenient due to societal norms (e.g., “second chance”)
  - Judges followed algorithm less and less over time

https://www.washingtonpost.com/business/2019/11/19/algorithms-were-supposed-make-virginia-judges-more-fair-what-actually-happened-was-far-more-complicated/

Agenda

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Misinformation about ML

6.1 The public predicts a 54% likelihood of high-level machine intelligence within 10 years

Respondents were asked to forecast when high-level machine intelligence will be developed. High-level machine intelligence was defined as the following:

> We have high-level machine intelligence when machines are able to perform almost all tasks that are economically relevant today better than the median human (today) at each task. These tasks include asking subtle common-sense questions such as those that travel agents would ask. For the following questions, you should ignore tasks that are legally or culturally restricted to humans, such as serving on a jury.[13]

Respondents were asked to predict the probability that high-level machine intelligence will be built in 10, 20, and 50 years.

Comparison: Experts predicts in the ~50-year (may be optimistic)

Example: Self-Driving Without LIDAR

Example: Resume Evaluation

How to persuade a robot that you should get the job

Do mere human beings stand a chance against software that claims to reveal what a real-life face-to-face chat can't?

Stephen Buranyi

Sat 3 Mar 2018 19.05 EST

James Ball
@jamesrbuk

Vision: algorithms will make hiring better as they don't discriminate

Reality: "One HR employee for a major technology company recommends slipping the words "Oxford" or "Cambridge" into a CV in invisible white text, to pass the automated screening."

7:16 AM · Mar 4, 2018 · Twitter for iPhone

2.2K Retweets **3.5K** Likes

Based on slides by Arvind Narayanan

Agenda

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Feedback Loops in ML Systems

- ML models are often part of a larger system

- **Example:** Feedback loop in PredPol (used to predict crime)
  - This kind of approach is “especially nefarious” because police can say: “We’re not being biased, we’re just doing what the math tells us.” And the public perception might be that the algorithms are impartial. – Samuel Sinyangw

To predict and serve?

Kristian Lum, William Isaac

Rise of the racist robots – how AI is learning all our worst impulses

Feedback Loops in ML Systems

- **Recommender systems:** "A system for predicting the click through rate of news headlines on a website likely relies on user clicks as training labels, which in turn depend on previous predictions"

- **Potential for adversarial feedback**
  - Tricking a resume screening system by entering keywords like "Oxford"
  - **Anecdotal:** Computer vision systems to predict poverty and (semi-) automate global aid allocation decisions lead to people switching off their night lights and dressing up concrete roofs as thatched roofs

Satellite images used to predict poverty
By Paul Rincon
Science editor, BBC News website

Machine Learning: The High Interest Credit Card of Technical Debt
D. Sculley, Gary Holt, Daniel Golovin, Eugene Davydov, Todd Phillips, Dietmar Ebner, Vinay Chaudhary, Michael Young
SE4ML: Software Engineering for Machine Learning (NIPS 2014 Workshop)

Extreme Example: “Future Features”

- **Scenario**
  - Build a highly complex classifier with 99% accuracy for a time-series problem
  - Later, build a new classifier with 98.5% accuracy, runs $1000\times$ faster
  - Catastrophic failure when deployed!
- **Problem**
  - Training data included classifier’s prediction from previous step as input
  - **New classifier:** “Recycles” the prediction from the previous step (i.e., just use that single feature as the prediction!)
  - Works fine when previous prediction was already accurate
  - No longer the case after deployment!

Potential Solution

- **DAGGER algorithm**
  - Originally designed for imitation learning (i.e., RL from expert data)
  - Continuously collect new labels and add to training set

- $Z \leftarrow \text{Initial dataset}$
- For $t \in \{1,2,\dots\}$:
  - Train f_β on D and use to make decisions on new examples X_t
  - Observe (or collect) ground truth labels Y_t for X_t
  - $Z \leftarrow Z \cup \{(X_t, Y_t)\}$

- Use multi-armed bandits when there is partial feedback

Drew Bagnell, Feedback in Machine Learning, https://www.youtube.com/watch?v=XRSvz4UOpo4

More Challenging Feedback Loops

- **Example:** Hiring ads
  - Women tend to click on job ad with second-highest salary
  - ML model learns that women do not click on highest salary job ad, so it stops recommending it
  - Second-highest salary job ad → Highest salary job ad
  - Women click on new second-highest salary job ad!

- No substitute for manual analysis of ML models in projection
  - You’ll never be out of a job (at least for the foreseeable future)!

Lambrecht & Tucker. Algorithmic Bias? An Empirical Study of Apparent Gender-Based Discrimination in the Display of STEM Career Ads

Agenda: Ethics

- Dataset issues
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- Misinformation about ML
- Feedback in ML systems
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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?

Based on material from The Institute for Ethical AI and ML

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 27: Review Part 1

CIS 4190/5190

Fall 2023

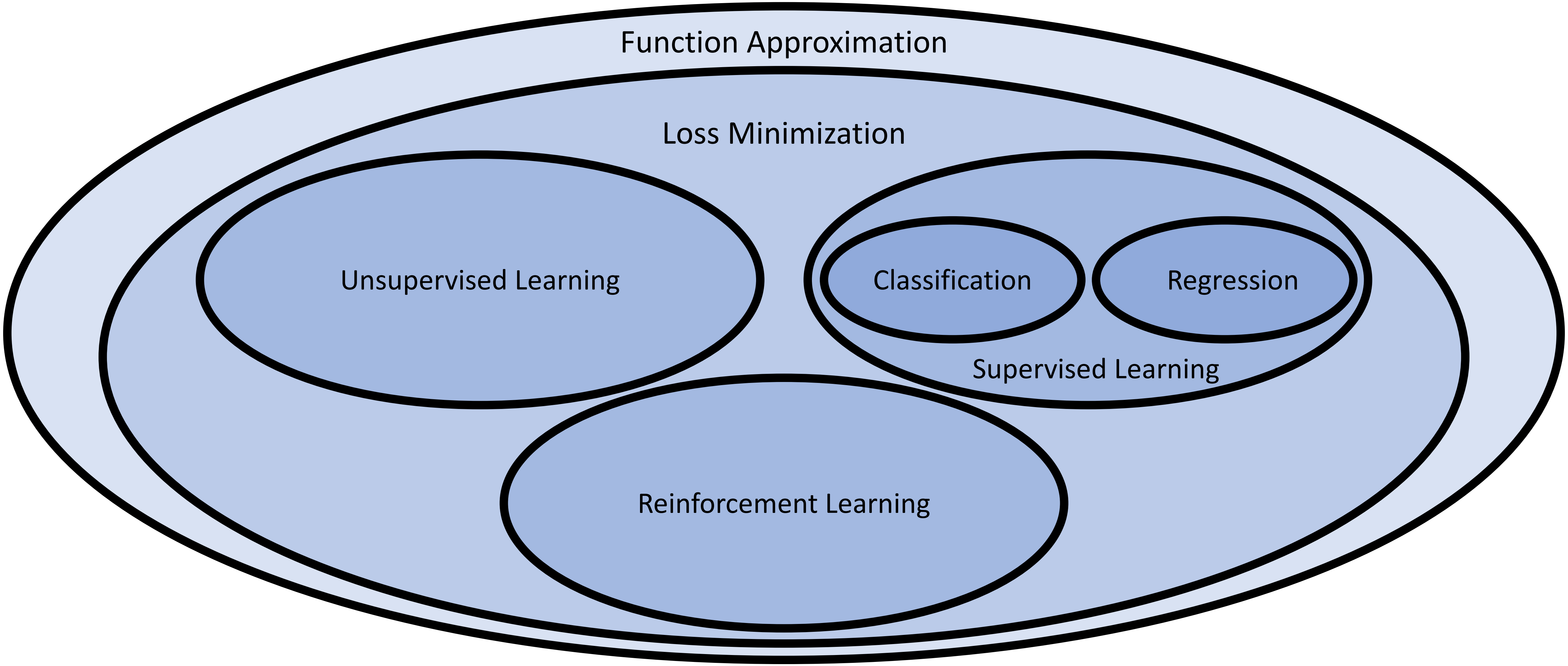
Concepts & Algorithms

- **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?

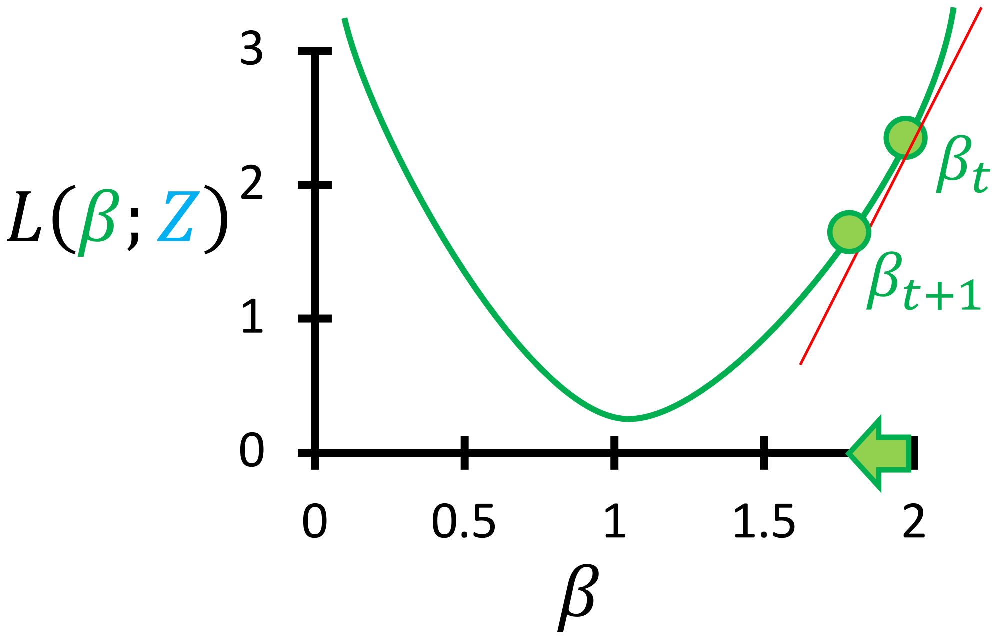
Algorithm: Linear Regression

- **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

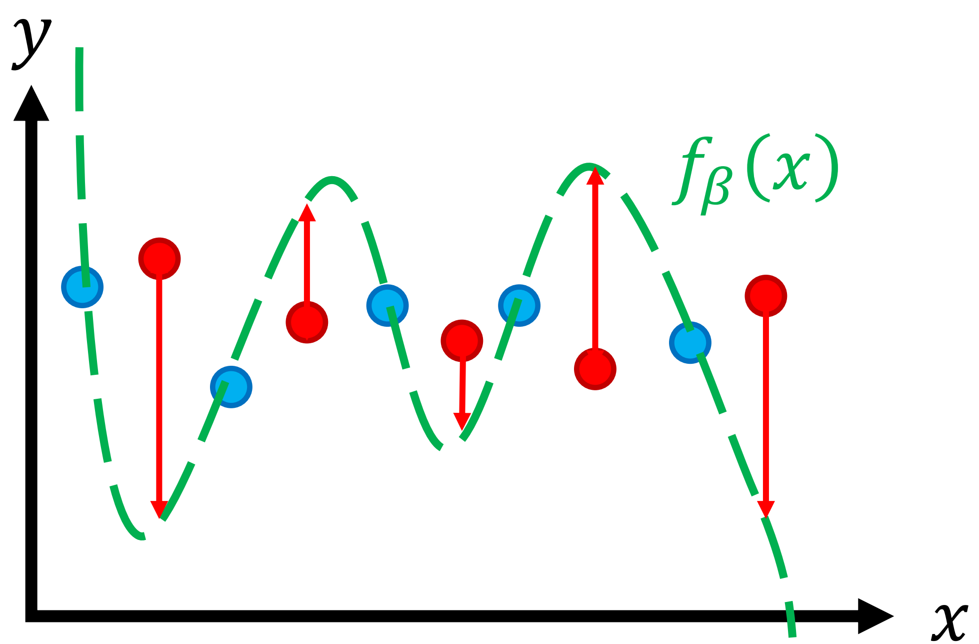
- **Polynomial features**
  - $\phi(x) = \beta_1 + \beta_2 x_1 + \beta_3 x_2 + \beta_4 x_1^2 + \beta_5 x_1 x_2 + \beta_6 x_2^2 + \cdots$
  - Quadratic features are very common; capture "feature interactions"
  - Can use other nonlinearities (exponential, logarithm, square root, etc.)

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

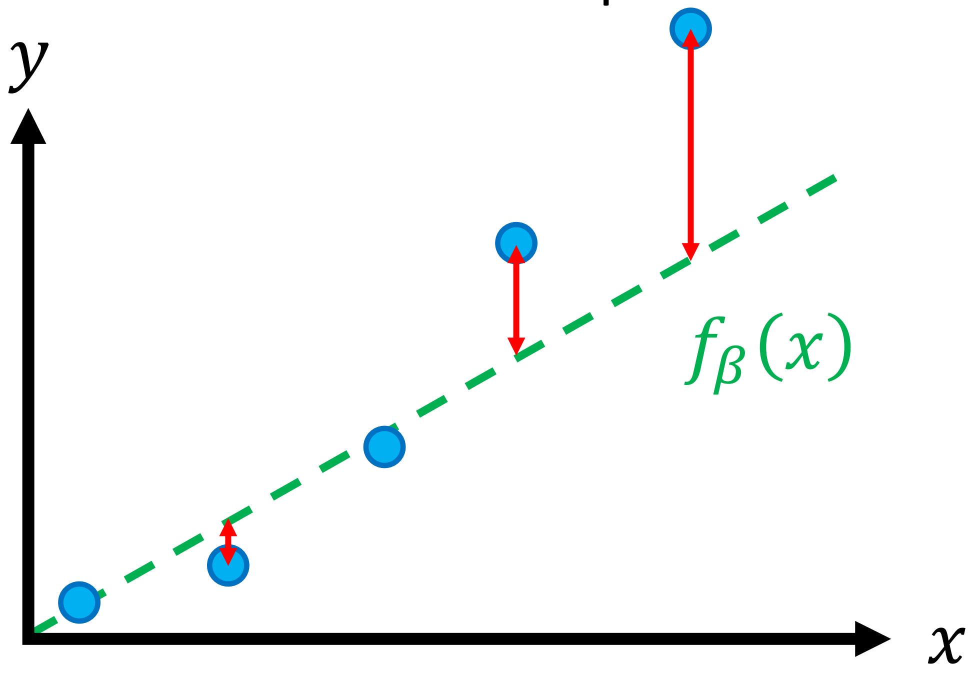
- **Encoding non-real inputs**
  - E.g., $x =$ "the food was good" and $y = 4$ stars
  - $\phi(x) = [1(\text{"good"} \in x) \quad 1(\text{"bad"} \in x) \quad \dots]^\top$

Concept: Bias-Variance Tradeoff

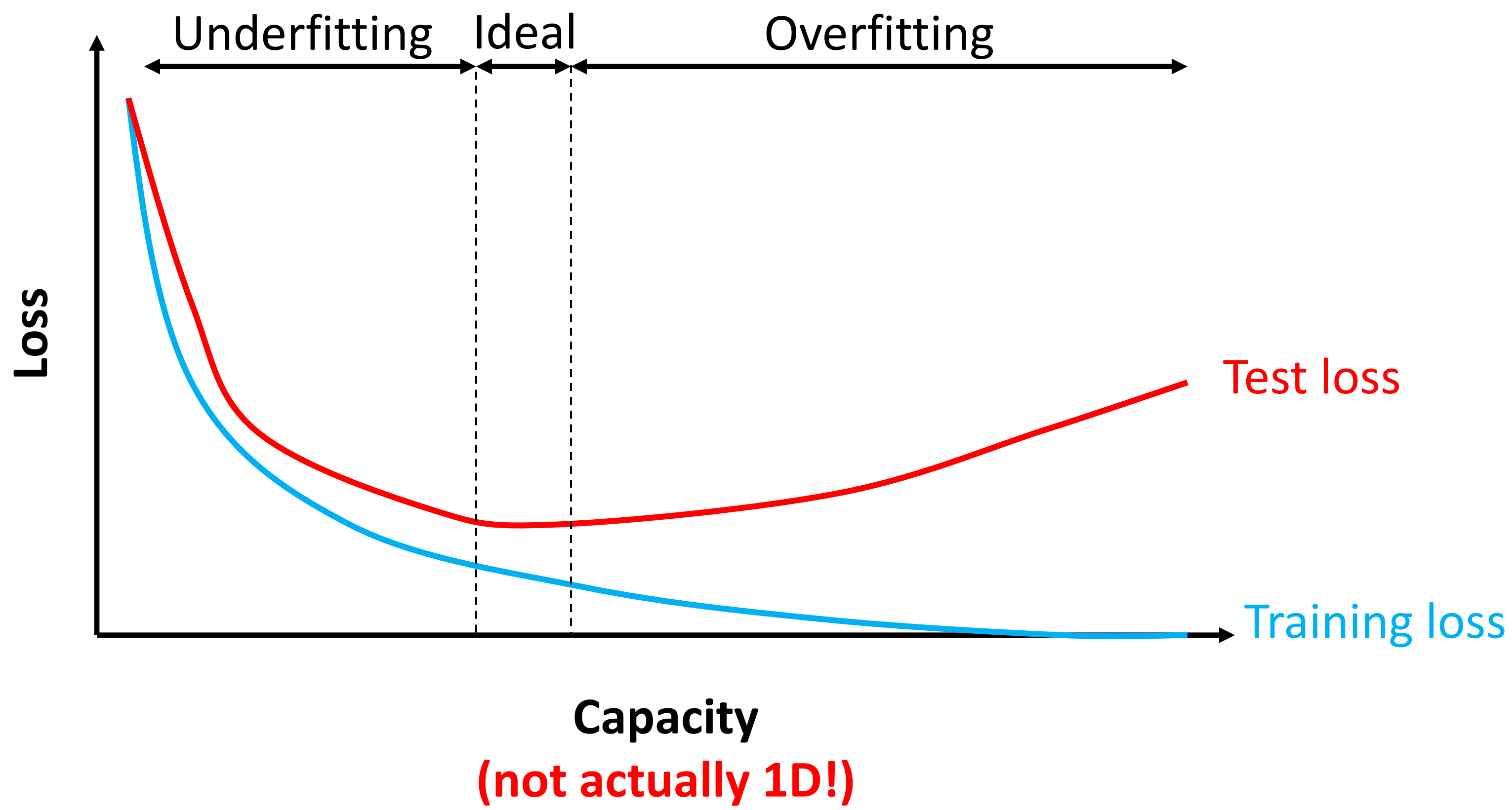
- **Overfitting (high variance)**
  - High capacity model capable of fitting complex data
  - Insufficient data to constrain it



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

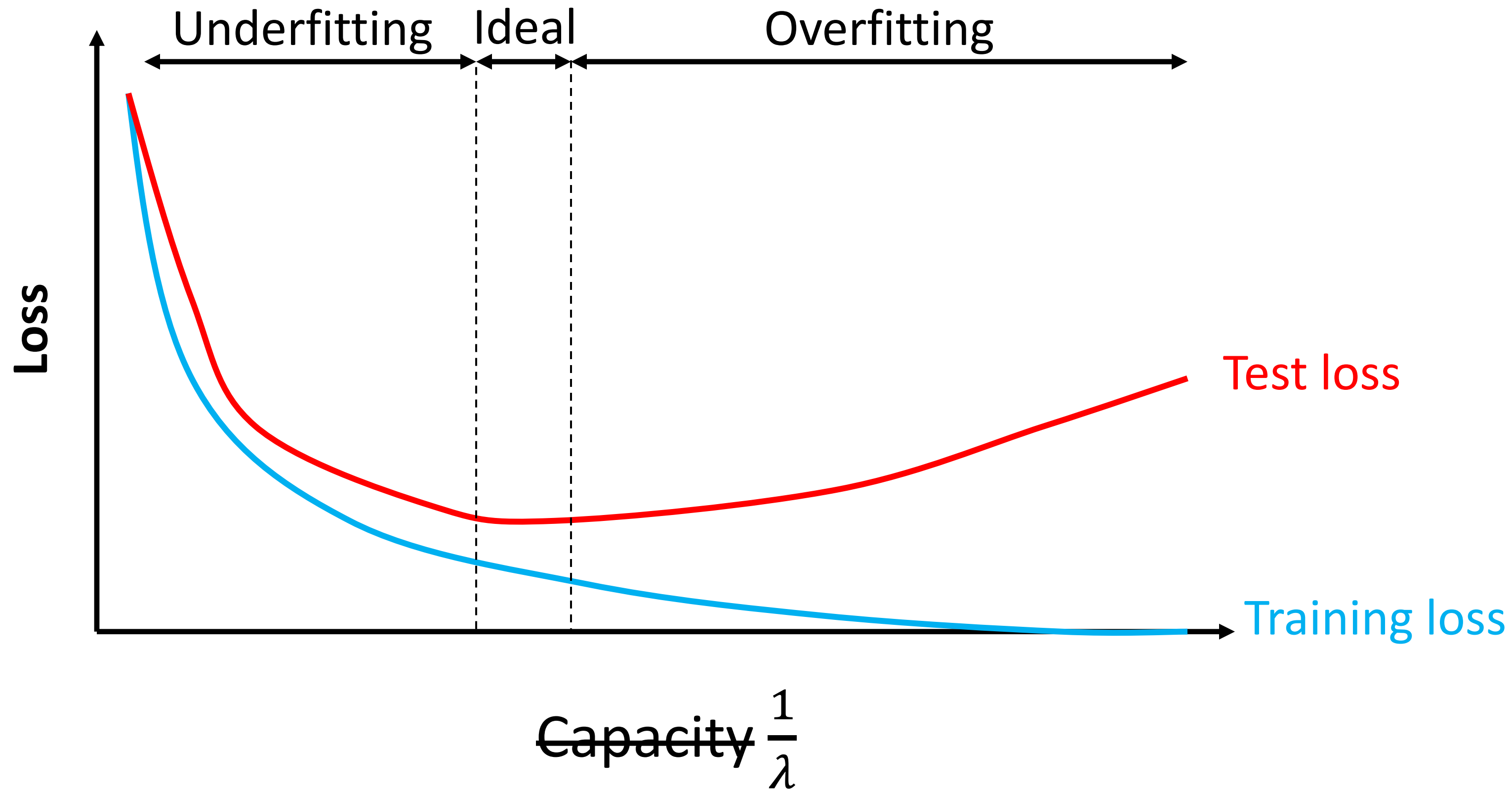


Concept: Bias-Variance Tradeoff



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_2regularization on β with $\lambda = \frac{1}{2\sigma^2}$

Algorithm: Sensitivity vs. Specificity

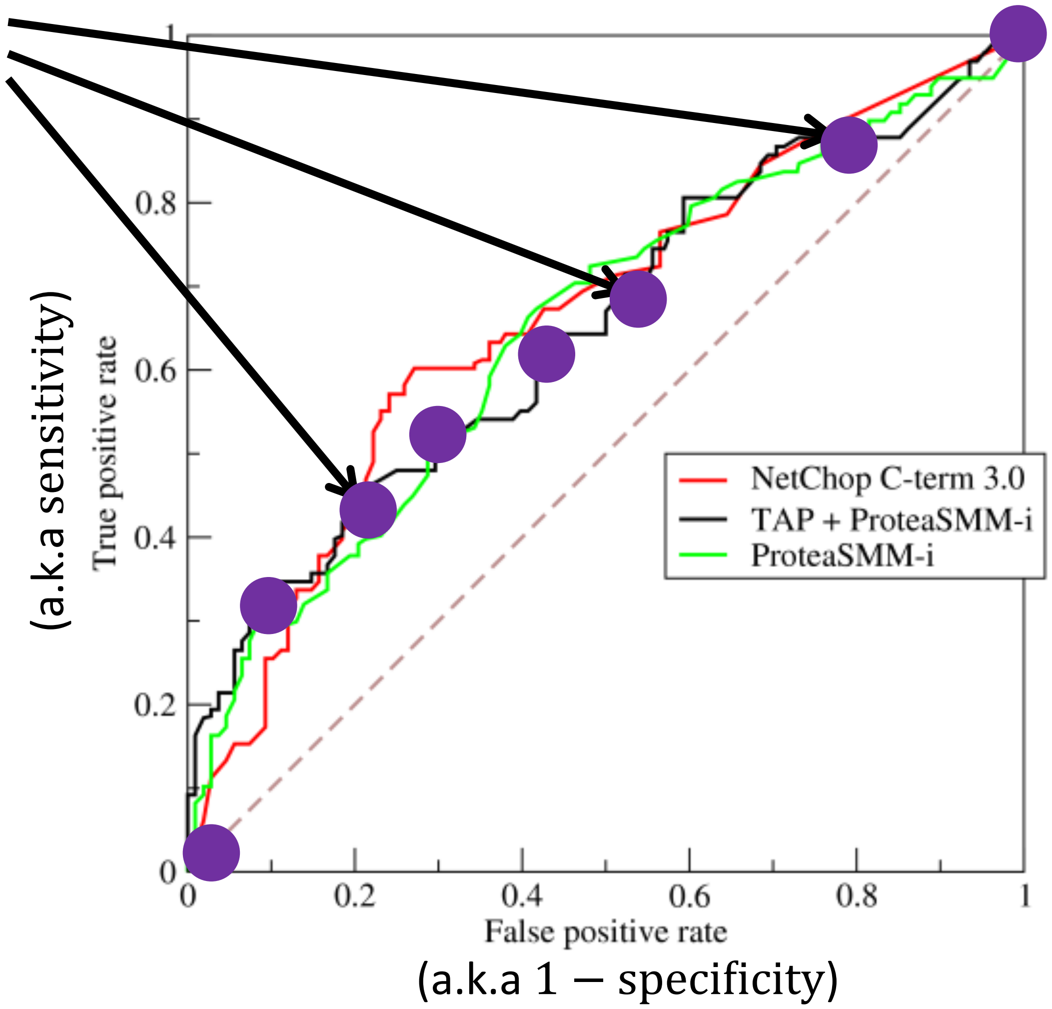
		Predicted Class	
		Yes	No
Actual Class	Yes	TP	FN
	No	FP	TN

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

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

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 $\hat{\beta}(Z)$

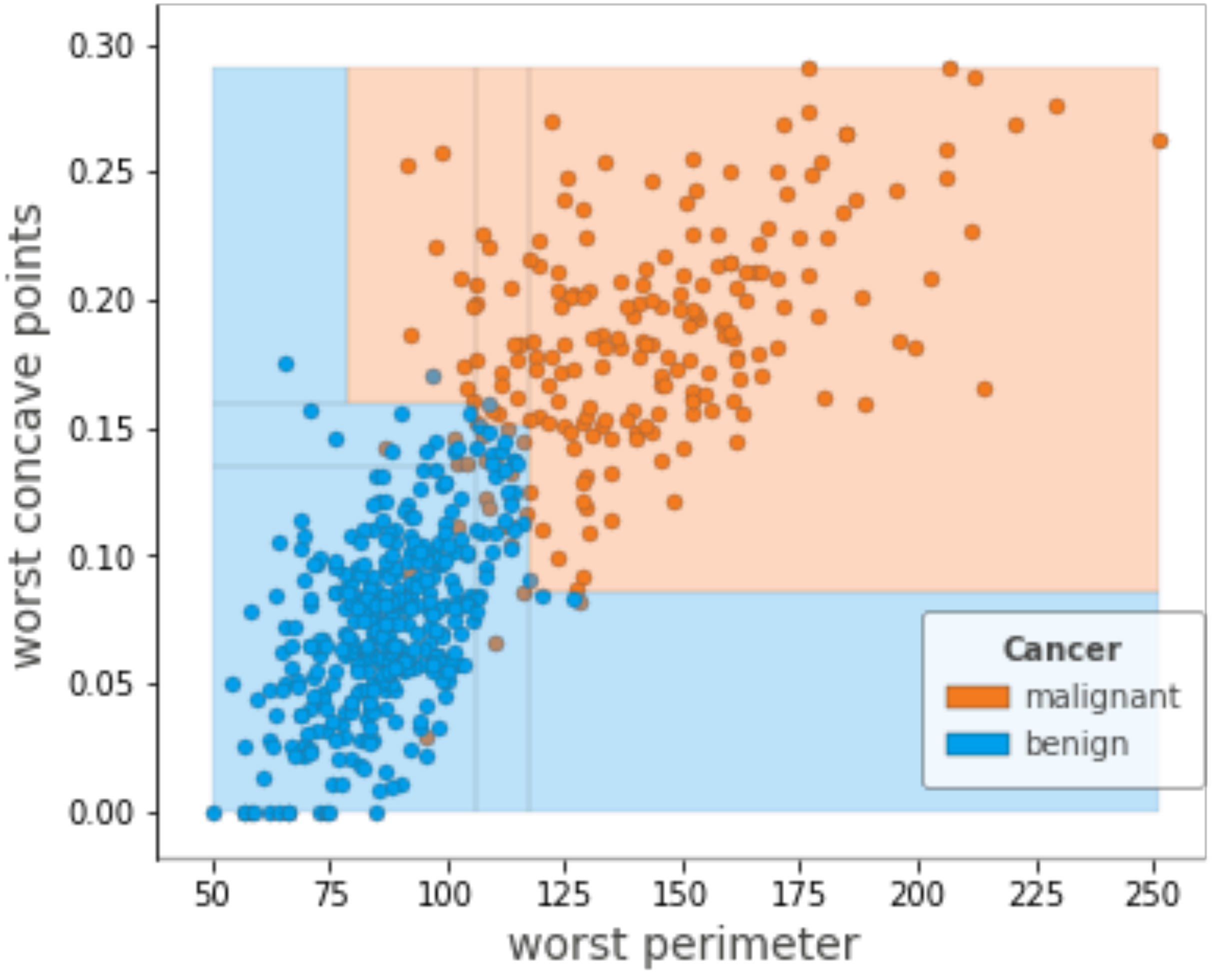
Algorithm: KNN

- **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

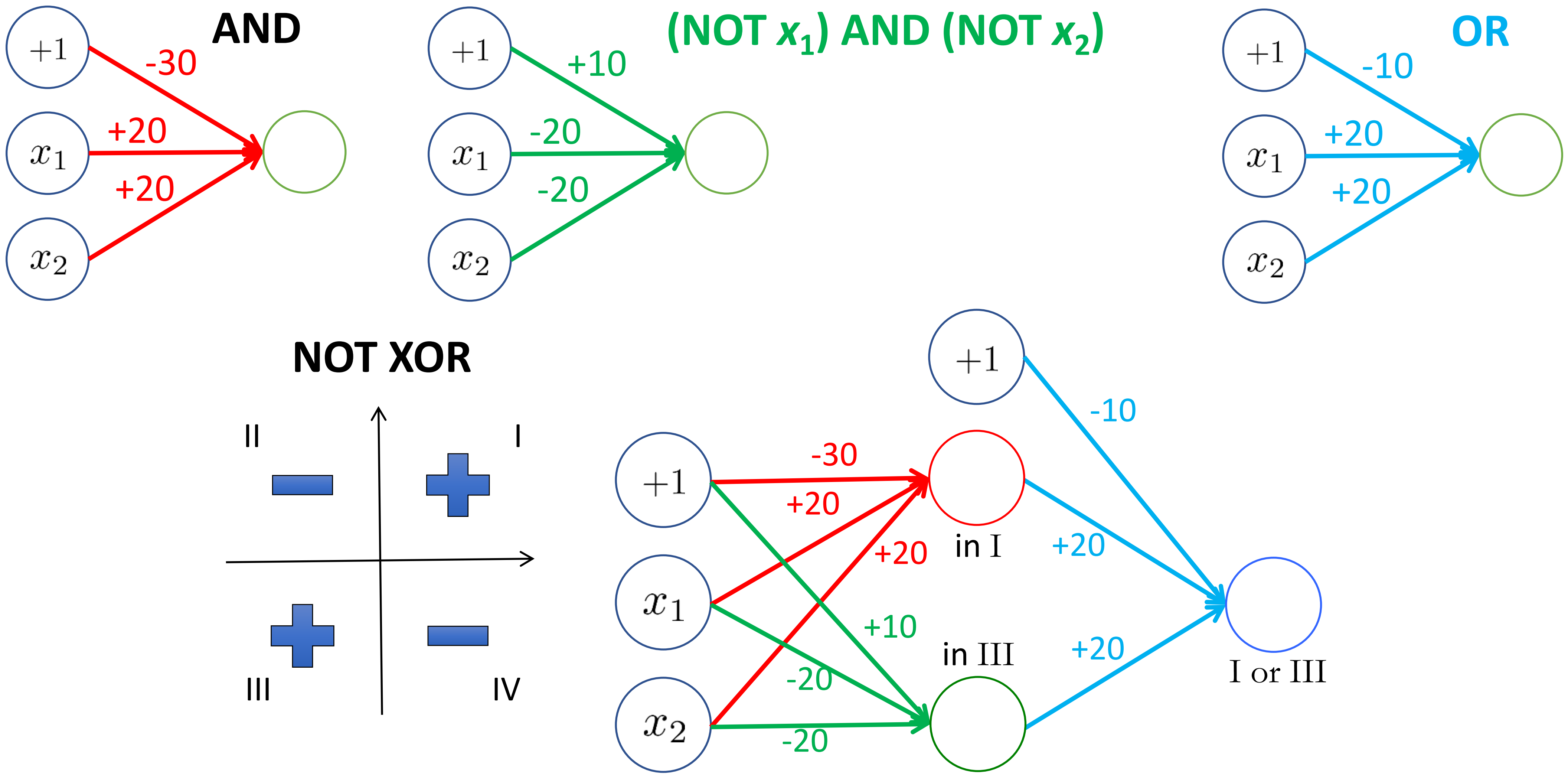
Algorithm: Gradient Boosted Decision Trees

- **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

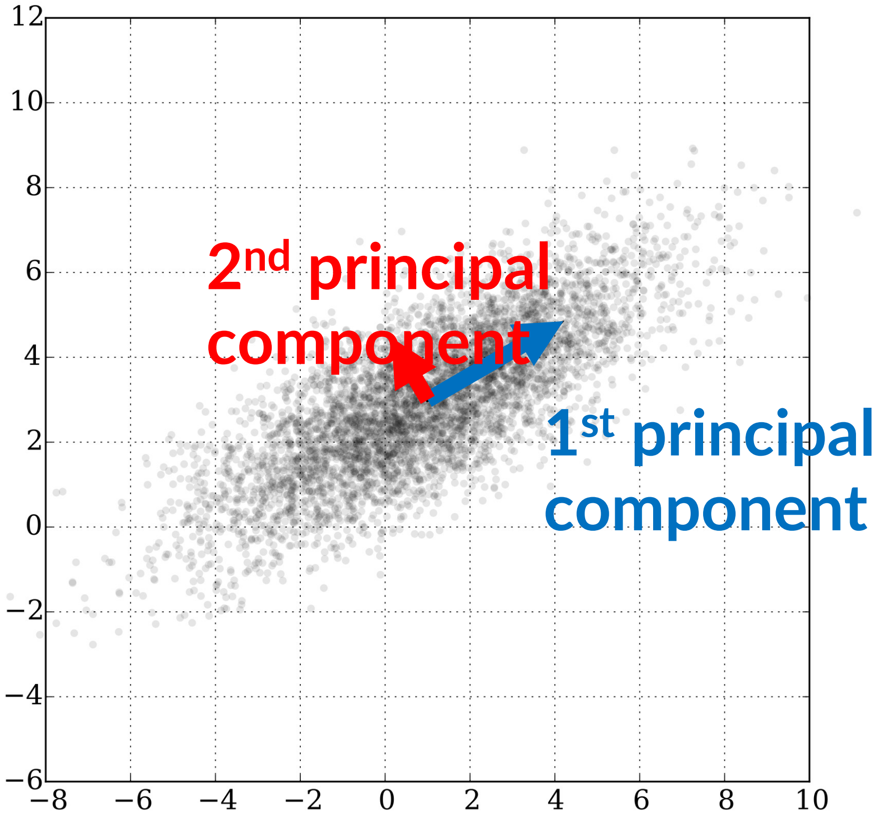
Algorithm: K-Means Clustering

- **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

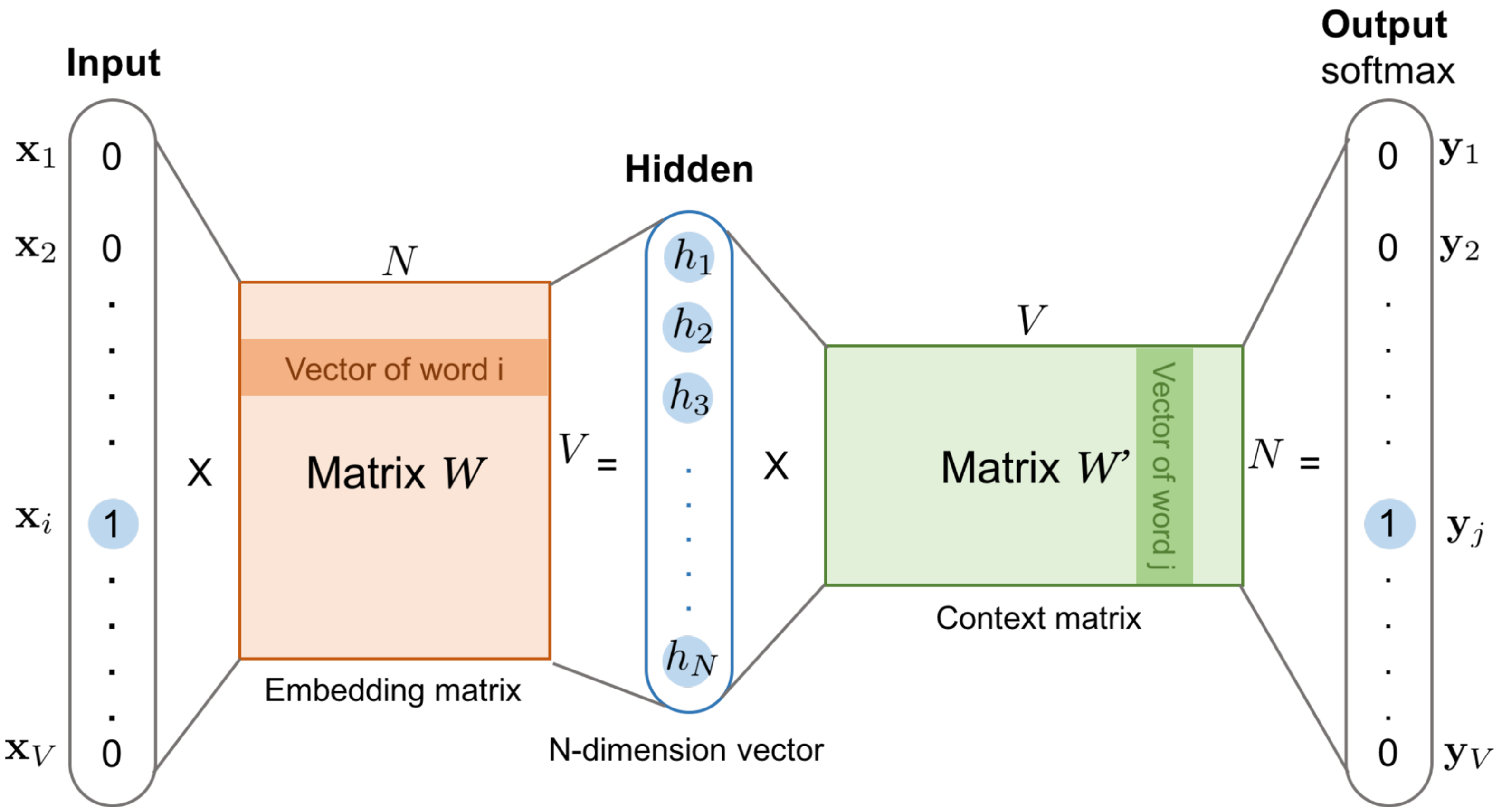
Algorithm: PCA



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

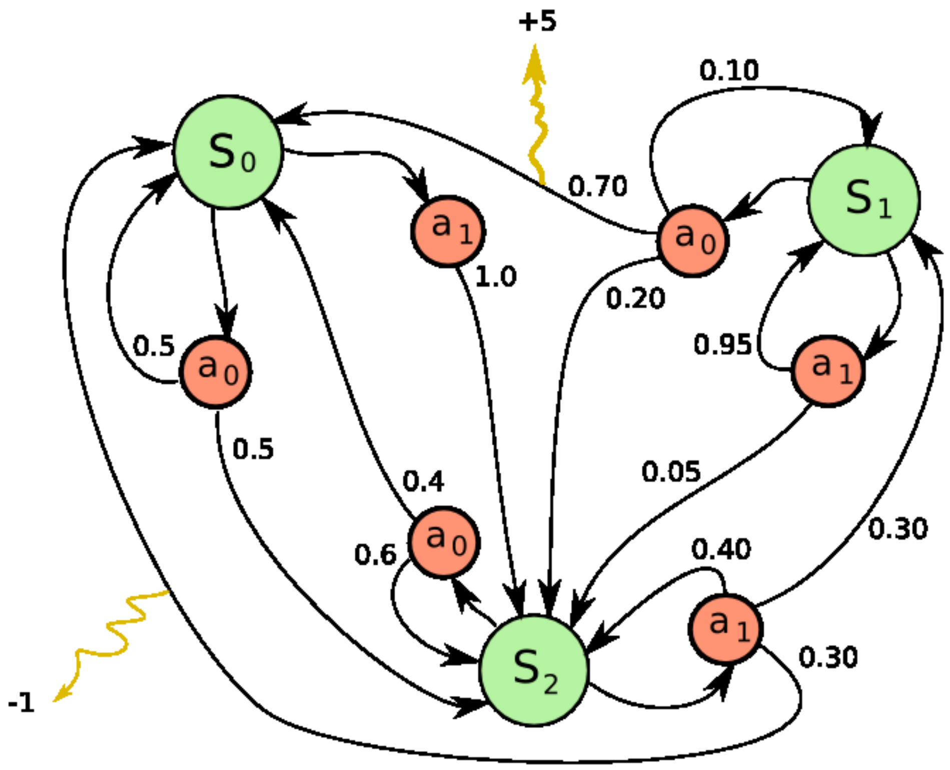


Algorithm: Bayesian Networks

- **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?