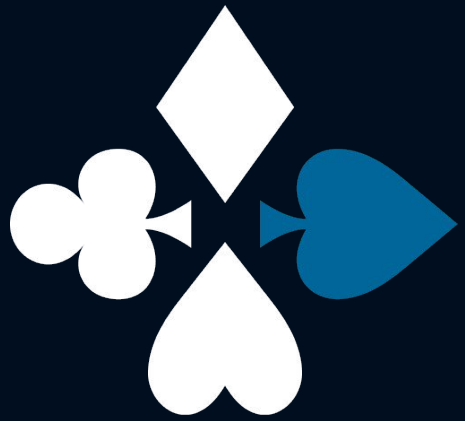


Pokerbots 2025

Lecture 5: Machine Learning

Sponsors

CITADEL | CITADEL Securities

Announcements

reference-4-2025

- Coding demo from yesterday available on GitHub
- Jupyter, Numpy, Matplotlib
- Recording link in readme

Make-up Progress Reports due Tonight

- As per syllabus, if your team missed the Week 1 bot submission deadline, a progress report is required to earn credit
- Reports are half a page and must list team name and members
- Submit via email to pokerbots@mit.edu by 11:59pm Tonight

Hackathon Tomorrow!

- Sponsored by **Codeium**
- Wednesday night (1/15)
- 32-044, 7pm -- LATE
- Show up and grind
- Dinner provided
- Snacks, fun, and games
- Prizes for challenges and those that stick around
- Details will be announced on Piazza

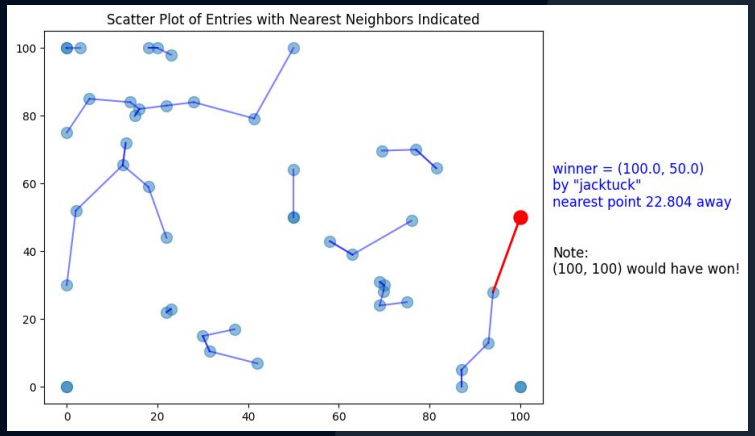
No Class Thursday

Cancelled in light of Hackathon the night before and Codeium Tech Talk at 11:30am

Giveaways!

Distance Game: **pkr.bot/dist**

- Pick a point (x, y), x and y are reals from 0-100
- Winner is whoever's the furthest from anyone else's guess (maximum distance to nearest neighbor)
- Prize: Nintendo Switch



from last year^

*Banned kerbs that participated in yesterday's wager are ineligible to win

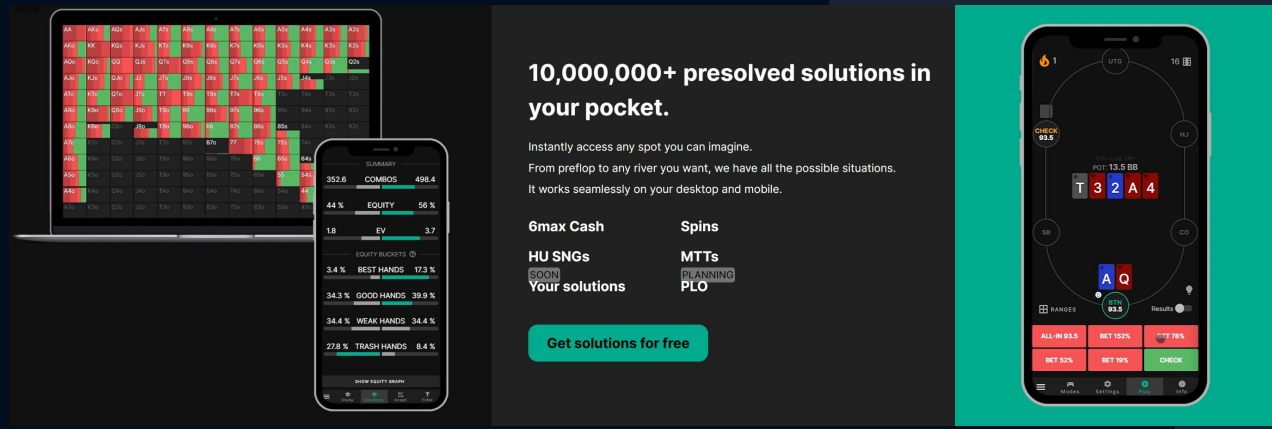
Survey Raffle: **pkr.bot/survey**

Class is halfway through (sort of)... help us improve it!

Winner selected at random

Prize:
One year's worth of GTO Wizard Full Subscription

*EVERYONE eligible to win



Machine Learning

Agenda for Today

- Machine Learning Basics
- Problem Setting for Supervised Learning
- Foundational Algorithms
- Creating a Good Model

Basics

What is Machine Learning (ML)?

- Using a machine (computation) to find patterns in data
- Found patterns can be applied without explicit programming
- Key idea: *generalize* instead of *memorize*
- Typically utilize large amounts of data
- Used for prediction, data compression, automation, decision-making

ML Workflow Overview

- Acquire dataset
- Create model(s)
- Evaluate model(s)
- Hopefully have good model via selection and improvement
- Deploy!

Types of Learning

- Supervised Learning
  - Dataset has examples of correct behavior
  - “Questions with answers”
  - Prediction tasks
- Unsupervised Learning
  - Dataset has no notion of good behavior
  - Task is to find patterns to represent dataset
  - Clustering, compression, generative modeling
- Reinforcement Learning (RL)
  - Environment with feedback (rewards), but no correct target
  - Sequential decision making, control, pokerbots!

Questions?

Problem Setting

Example

- Supervised learning setting (which we will focus on today)
- We love cats and birds!
- We want our algorithm to take a photo and tell us if it’s a cat or a bird
- We have example photos and labels of both

Example

Data

“Cat”

“Cat”

“Cat”

Labels

Example

“Bird”

“Bird”

“Bird”

Example

Cat or Bird?

Key Variables in Supervised Learning

- data example contains
  - “input” properties called *features*
  - “output” property called *label*
- *dataset* is a collection of these examples
- an *algorithm* that takes as an input an incomplete example with only features, and outputs a label to complete the example.

Types of Prediction

Classification

- Predict a category
- Example: “cat or bird”

Regression:

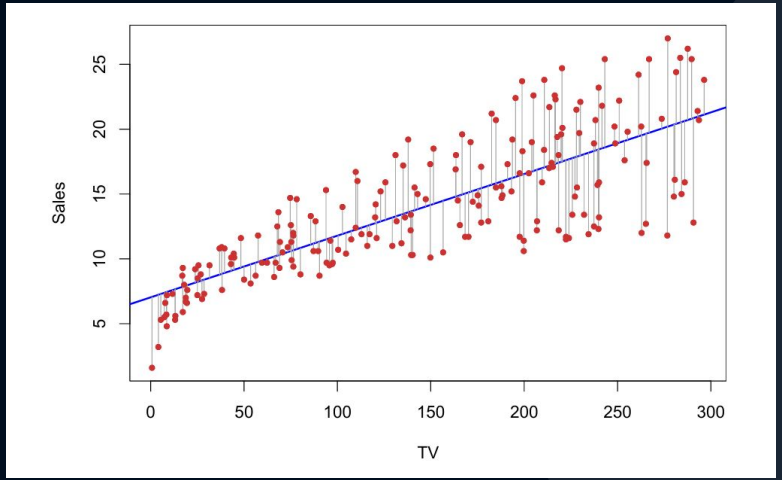
- Predict continuous value aka real number(s)
- Example: giveaway estimations

Questions?

Foundational Algorithms

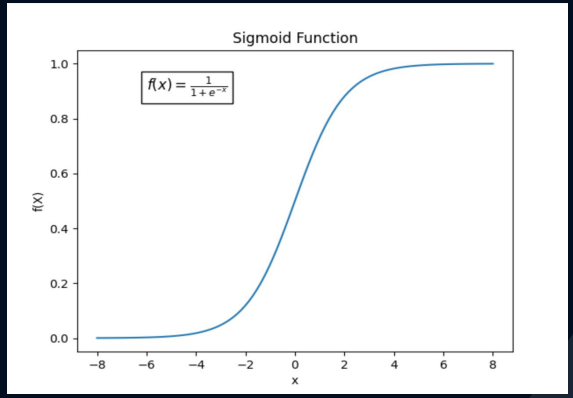
Linear Regression

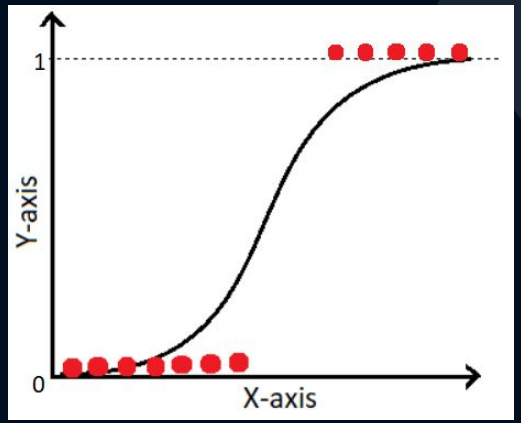
- Linear relation between input and output
- “Line of best fit”
- $y = w \cdot x + b$
- Can generalize to multiple variables
  - $y = w_1 \cdot x_1 + w_2 \cdot x_2 + \cdots + b$
- Easy to work with but only works well under certain conditions



Logistic Regression

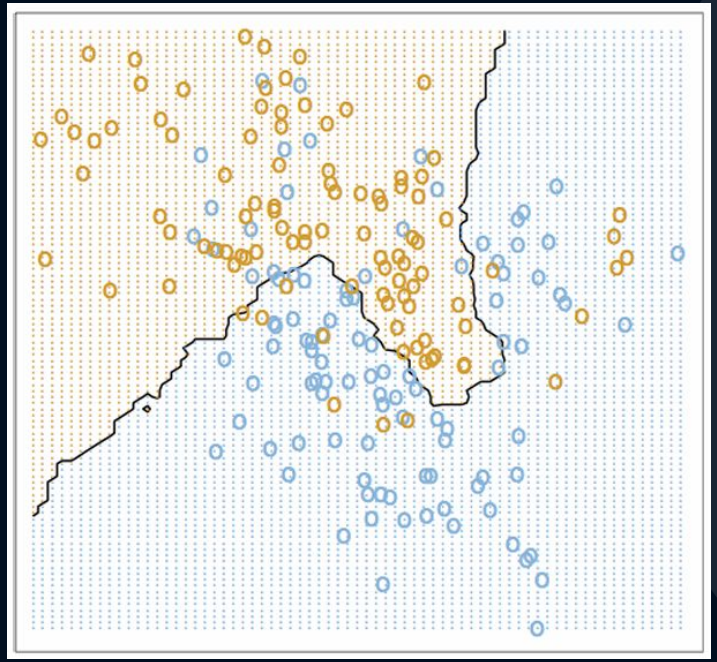
- Modifies linear regression for binary classification
- Sigmoid function $\sigma(x)$ transforms any real number onto interval (0,1).
- $y = \sigma(w \cdot x + b)$
- Interpreted as outputting a probability of belonging to a specified class





k-Nearest Neighbors (kNN)

- Classification or regression
- Decision using proximity
- For an input:
  - Find the *k* closest neighbors within dataset
  - Aggregate their labels to decide output
    - Majority vote for classification
    - Average for regression
- Very flexible and can represent complex patterns
- Struggles with higher dimensions



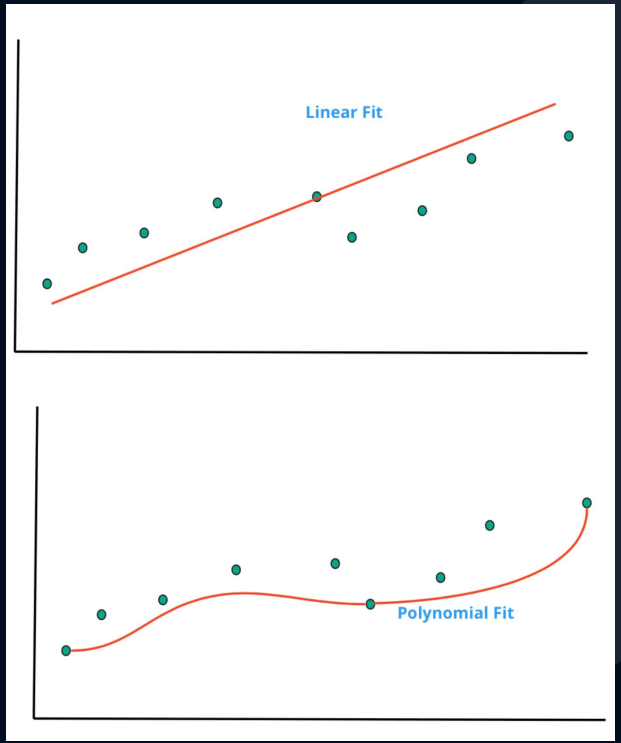
Questions?

Creating a Good Model

Creating a Good Model

What is a model?

- Template for an algorithm
- *Model class* or *hypothesis class* is the collection of all possible algorithms that follow that template
- Some models are defined by *parameters*
  - Ex: *w* and *b* in linear regression
  - Space of possible parameters ↔ model class
  - Choosing a model equates to choosing the parameters
- Other models are *non-parametric* (kNN)
- The larger the model class, the more *expressive* a model is



Creating a Good Model

Loss Functions

- Metric for seeing if model is good by measuring the error it makes on an example
- This equates to measuring some distance between predicted and true label
  - Linear Regression: squared distance
  - Logistic Regression: cross-entropy
  - kNN: 0/1 accuracy rate
- Loss function reports a penalty for a single input-output example - model is evaluates based on cumulative or average loss across whole set of examples

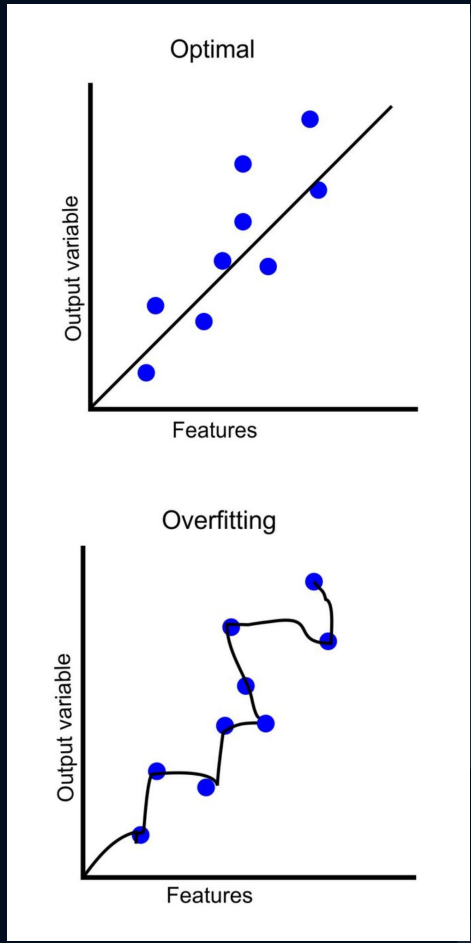
Creating a Good Model

Combine everything together!

- Consider all models within the hypothesis class and pick the one that has the best (lowest) loss across the entire dataset
- For parametric models, this is a minimization problem over the parameter space
    - “Training”
    - Sometimes near impossible to find the absolute best one so approximations are settled for
- Why don’t we simply just use the most expressive hypothesis class? More options means that the best options are going to have better results…
    - Ex: the space of polynomial functions can do more than everything linear functions can

Overfitting

- “Too good to be true”
- Model fits dataset extremely well but fails to capture underlying relationship (which is what we want)
- Memorization occurs, which prevents generalization
- Caused by overexpressive hypothesis class, aka too many parameters, relative to number of data points



Model Evaluation

- Split dataset into training and testing groups
  - Create model only using train set
  - Evaluate model based on loss across test set
- Goal is to detect overfitting and have a more realistic measure of a good model
- Perform the split randomly
  - Each data point has equal chance of showing up in either
  - Idea is to have the data be from the same distribution but still different
- Analogy: Practice exams vs Real exam
  - Test same capabilities using different questions
  - If real exam was exact copy of practice, then doing well doesn't say much about what was learned
- When we deploy model it may fail - we want to assess whether this would happen (ideally not)

Sources of Error

Bias

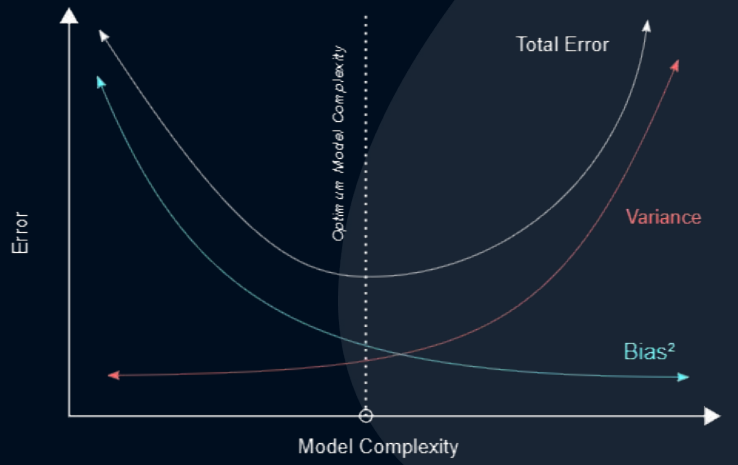
- error due to simplistic assumptions
- model class not expressive/flexible enough to represent data
- consistent error resulting from approach
- Characterized by high loss in both training and testing
- Ex: Linear Regression

Variance

- error from sensitivity to training data
- Model class is overly flexible, attempting to capture noise as a pattern
- Characterized by low loss in training but high loss in testing (aka overfitting)
- Ex: kNN

Bias-Variance Tradeoff

- There is an inherent tradeoff between bias and variance within model selection
- Many design decisions (aka hyperparameters) increase/decrease the model's complexity which could lead to too much bias or variance
- Some considerations to find the "sweet spot":
  - Validation sets
  - Regularization
  - Careful feature selection/pruning



Questions?

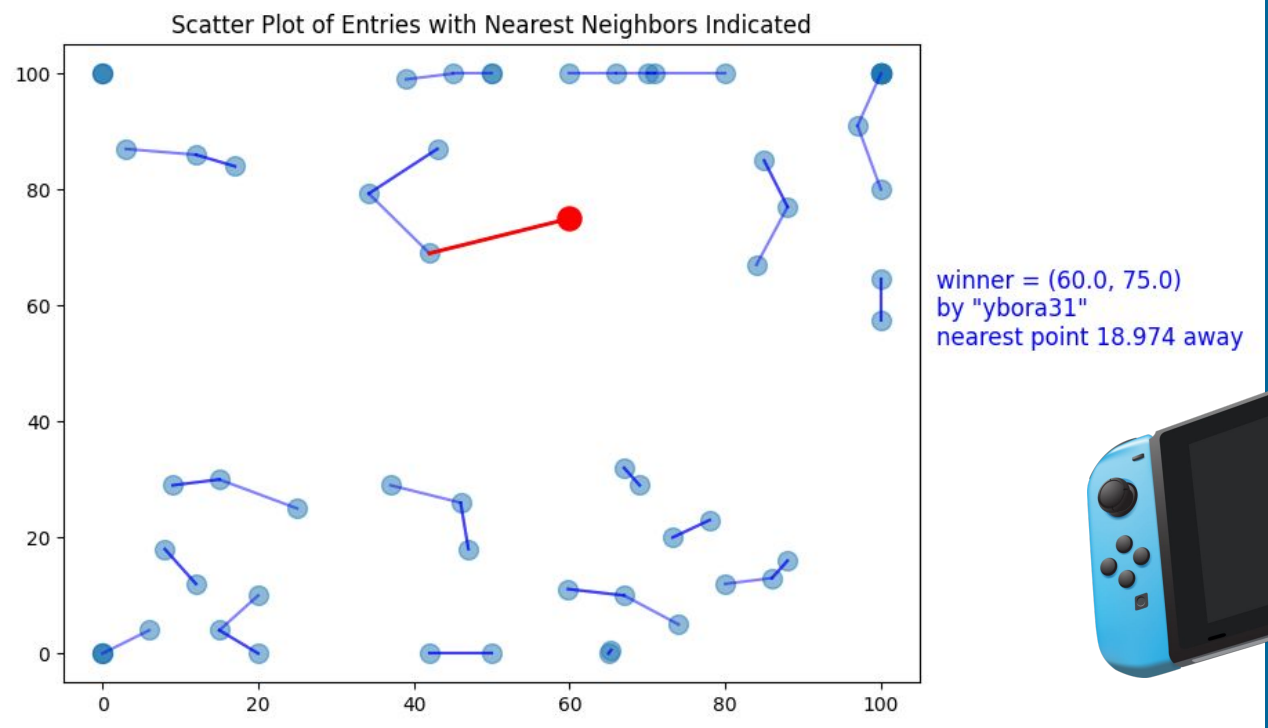
Lunch 😋

Leave any type of feedback at **pkr.bot/feedback**!

Live Coding: reference-5-2025

Survey Raffle: kerb “rlsalas”

Distance Game: kerb “ybora31”



Thanks for watching!

Slides/notes will be posted on **pkr.bot/resources**

Make sure to check **pkr.bot/piazza** for updates

Lecture recordings at **pkr.bot/panopto**

Leave feedback at **pkr.bot/feedback**!