

Pokerbots 2025

Lecture 9: Decision Trees

Sponsors



























Announcements

Last Night's Lightning Tournament #2

1.	Pineappl	e	\$400
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- 2. Encore 1/2 Regs \$300
- 3. heyo394 \$225
- 4. pink fluffy sheep \$175
- 5. DKE juniors \$150

Week 3 Bot Deadline!

- Third pokerbot due Tomorrow 1/24, 11:59PM EST
- Submission on scrimmage server
- Mini-tournament 3 will occur shortly after

Next Week...

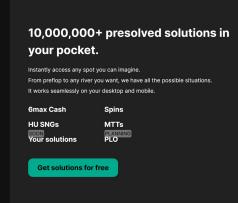
Monday 1/27

Guest Lecture: GTO Wizard

- Current state of the art Poker Solver and Study tool
- Developed by team of top AI researchers and engineers
- Core team will be presenting their journey and research
- RSVP at pkr.bot/gto









Tuesday 1/28

Team Strategy Reports due 11:59PM EST

- No Lecture
- 3-5 pages, double spaced, ≥1 member must submit
- Assignment details and submission on Canvas: pkr.bot/canvas
- Description also available in syllabus: pkr.bot/syllabus

Wednesday 1/29

Guest Lecture: Dr. Noam Brown

- Won Pokerbots and co-created Deep CFR while PhD at CMU
- Created Libratus and Pluribus, the world's first superhuman poker Als
- Research scientist currently at OpenAI, previously worked at Meta AI
- Leading role in developing OpenAI's latest GPT o1 and o3 LLMs







Wednesday 1/29 (cont.)

Poker Social After!

- During office hours block
- Come play with Noam!



Wednesday 1/29 (cont.)

Final Bot Submission due 11:59PM EST

- Upload and select bot as active on scrimmage server
- Both report and bot needed to pass this class!
- Bot will compete in last and final Pokerbots tournament
- Non-secret prize amounts listed on syllabus

Final Tournament Prizes				
First place	\$10,000			
Second place	\$6,500			
Third place	\$3,500			
Fourth place	\$2,000			
Fifth place	\$1,000			
First place in language (Python, Java, or C++)	\$500 x 3			
Second place in language (Python, Java, or C++)	\$250 x 3			
Third place in language (Python, Java, or C++)	\$125 x 3			
Best freshman-majority (>51%) team	\$2,000			

Friday 1/31

Pokerbots Final Event 4:30-7PM in Kresge Auditorium

- Presentation of Awards
- Closing Ceremony
- Sponsor Event and Puzzle Hunt
- Lots of free merch and raffle prizes!
- Dinner provided

All in all...

1/24 Tomorrow Week 3 Bot Due

1/27 Monday GTO Wizard Talk

1/28 Tuesday Final Report Due

1/29 Wednesday Noam Brown Talk

Social Event

Final Bot Due

1/31 Friday Final Event

Giveaways!

Connection Game: pkr.bot/connect

- List the kerbs of up to 3 other classmates in your submission
- Two people are connected if they list each other (strings must match exactly)
- A connected component is a group of people who are all directly or indirectly connected
- **Four winners** are randomly drawn from the largest connected component(s)!

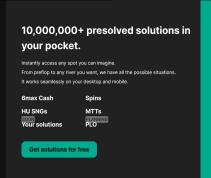
Prize: One year's worth of GTO Wizard Full Subscription <u>each</u>







Feel free to get up and travel!
But be back to your seat in 4 min





RSVP for GTO Wizard: pkr.bot/gto

- Indicate whether you plan to attend next Monday's talk
- Winner selected at random
- Prize: Sony XM4



Decision Trees

From last lecture...

Model training steps on a large representation (tabular CFR) causes issues

→ Use compressed approximation method like a neural network to store model, Making training require less steps and inference (or evaluation) less costly

Why we use neural networks:

- Expressive
- Flexible over different data types
- Does well with large amounts of data

What other approximation methods could we use?

What are some processes we'd like to be able to express?

From pot odds bot:

```
if RaiseAction in legal actions:
    if random.random() < 0.5:
        if strength > 2*pot odds:
            raise amount = int(min raise + 0.1 * (max raise - min raise))
            return RaiseAction(raise amount)
        return RaiseAction(min raise)
if CheckAction in legal_actions: # check-call
    return CheckAction()
if random.random() < 0.25:</pre>
    return FoldAction()
return CallAction()
```

What are some processes we'd like to be able to express?

We'd like:

- Qualitative selection of variables to condition a decision on
 - Pot odds
 - Legal actions
 - Hole strength
 - Randomly generated values
- Quantitative tuning of how to decide based on that variable
 - Pot odds threshold
 - Ratio of p:pot odds
 - Threshold for random values

Can neural networks do this?

Well, yes...

- Nonlinear activations like ReLU and Sigmoid can capture qualitative regions of similar behavior ('step functions')
- Linear layers can learn weights for specific thresholds needed
- So for a large enough neural network, all the if statements and thresholds could be encoded as linear transformations and nonlinear activations

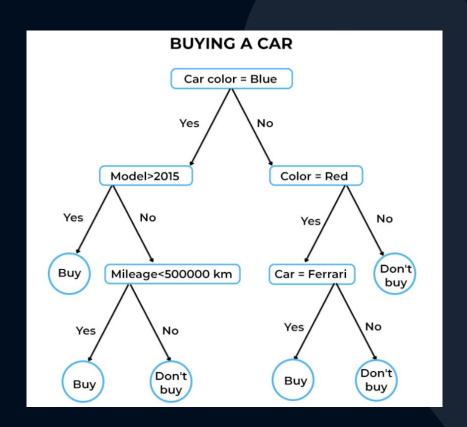
But this seems like overkill if we desire to capture a simple relationship...

Decision Trees

 Definition: A tree-like model used to make decisions by splitting data based on feature values.

Structure:

- Nodes: Represent a feature to split on.
- Edges: Represent decision outcomes.
- Leaves: Represent the final prediction (class or value).
- Example: Classifying if we'd like to buy a car based on various characteristics



How Decision Trees are Trained

- Start with some tree (initially root node), that sends the dataset into a number of leaves with a label on each leaf
- Performance of the tree is related to how many dataset examples are sent to a leaf with a good prediction. We'd like to consider how we can add additional splits at each leaf to improve this performance.
- Split data on a feature that maximizes information gain or reduces impurity (e.g., Gini index, entropy).
- Repeat recursively until a stopping condition is met (e.g., maximum depth, minimum samples per leaf).
- Predict based on majority class (classification) or average value (regression).

Feature Selection

Incredibly important in decision trees

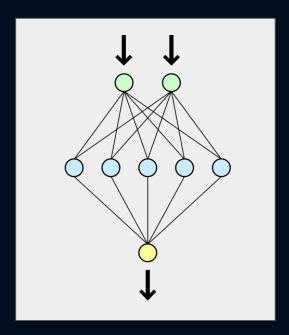
- If we want a quality of data to play a factor in our output, we need to construct it as a feature.
- Ex: We want to raise if p > c * pot_odds, for a learned constant c.
 - This condition is not immediately representable in terms of features over/under a constant
 - We have to *transform* existing features to make it easier for the decision tree to pick up on this condition.
 - New feature: p/pot_odds
 - Raise if this new feature is greater than a learned constant c

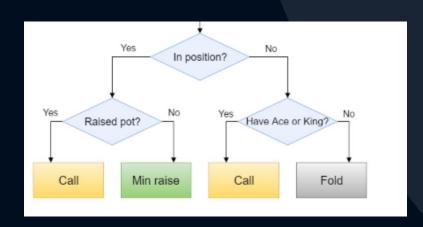
Disadvantages to NNs

- Have to construct features
- Prone to overfitting or variance if not enough examples
 - Creating a leaf for each data point is too much fitting
 - A single data point can greatly sway behavior
- Meanwhile neural nets create their own features and do well at smoothly reacting to each data point via gradient descent.

Advantages

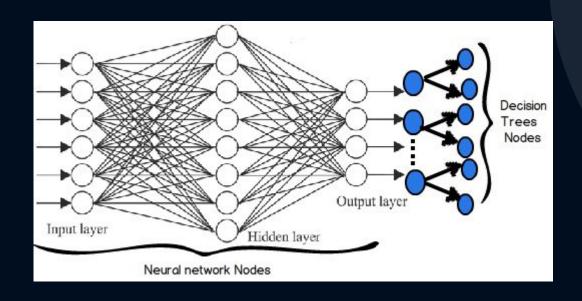
Interpretable!





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What about both?

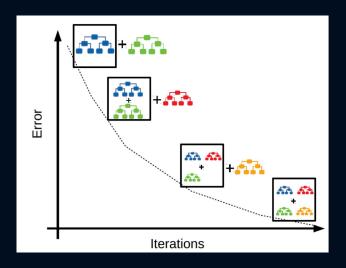


Boosting

Another way to resolve disadvantages

- An ensemble technique that builds multiple weak learners (e.g., decision trees) iteratively, where each new tree corrects errors of the previous one.
- Key Idea: Combine many weak models to form a strong one.
- Loss Minimization:
- Fit each tree to minimize the residual error of the previous trees.

Boosting



- Result: smooths out variance while being able to make more complex decisions
- General result that can be used to improve additive models



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



reference-9-2025

Giveaway Winners

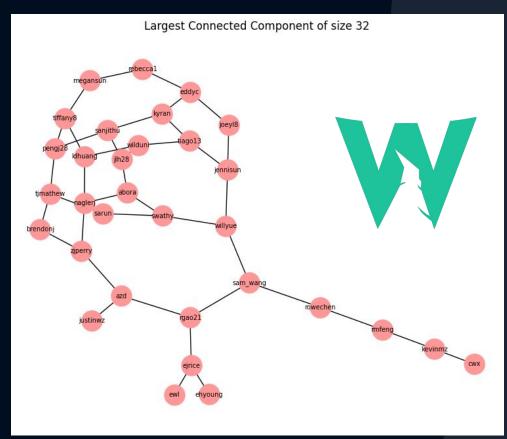
GTO RSVP Raffle: kerb "cleve195"



Connection Game: kerbs ['kyran', 'ehyoung', 'abora', 'tiago13']

N=48 total entries 44 successful connections 15 failed connections

```
{'jorgevas', 'jiange12', 'eposondu'}
{'mandoj', 'mattzhou'}
{'emilyc', 'rlsalas'}
{'merey'}
{'kjiang77'}
{'ljkeller'}
{'gsjau'}
{'decoudav'}
{'tjwshu'}
{'akshaya7'}
{'bocchi'}
{'pky'}
```



Closing Remarks...

Thanks for coming!

Slides will be posted on pkr.bot/resources

Repo will be pushed to pkr.bot/github

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

Lecture recordings at pkr.bot/panopto

Leave feedback at pkr.bot/feedback!