

# Pokerbots 2025

Lecture 2: Probability and Statistics

## Sponsors



























# Register & Resume Drop: pkr.bot/register

# Giveaway!

# pkr.bot/people



Guess the number of people in class (measured by submissions).

Feel free to be precise with decimals.

Ties are broken by order of submission

Prize: Sony XM4 Headphones

# Announcements

#### Engine Updates

- Some bugs have been patched
- Keep letting us know about issues
- Latest version at pkr.bot/engine
- Important to always use most updated version of engine as it is what we use on the scrimmage server and in tournaments

#### Poker Social TODAY!

- Recitation block (26-168, 2-4PM)
  - Office hours will still run concurrently
- Great place to meet teammates!
- We will be giving a way a pair of Airpods Pro
- Also try pkr.bot/teammates

#### Week 1 Deadlines

- First pokerbot submission due Friday 1/10,
  11:59PM EST on scrimmage server
- Mini-tournament 1 will occur shortly after

#### Hackathon Next Week!

- Next Wednesday night (1/15)
- Show up and work on your pokerbot!
- Dinner provided, plan to go late into the night
- Snacks, fun, and games
- Prizes for challenges and those that stick around
- Location TBA

#### Outline of Today

- Probability Foundations
- Random Variables and Distributions
- Expected Value
- Law of Large Numbers

## Probability Foundations

#### What is Probability?

- We say "probability of [event] happening is x"
- x is usually a number from 0 to 1 or a percent
- But what does x's value mean?

#### Interpretations of Probability

#### Frequentist

- How often an event occurs over repeated trials
- Ex: When rolling a dice repeatedly, we notice 1/6th of rolls are a 2
- What about events that aren't repeated? Eg: 2024 election

#### Subjectivist (Bayesian)

- Degree of belief, or 'credence' of an event occurring from the perspective of an individual with a given set of information
- Different pieces of information 'update' the probability to be higher or lower depending on how much evidence they provide for the event
- However, this requires some assumptions for which default probability values to start with before any updates
- This is mostly a philosophical question within epistemology
- Regardless of interpretation, probability is used as a quantitative metric for modeling uncertainty in things we don't know

#### Motivation: Finite Possibilities with Equal Chance

- Wish to find/define probability of some event that occurs in some outcomes
- An intuitive definition:
  - Probability of event = (# favorable outcomes) / (# total outcomes)
- Ex: Randomly draw card from standard deck, probability of Spades
  - 13 cards with spades
  - o 52 cards total
  - $\circ 13/52 \rightarrow \frac{1}{4}$
- This reduces any question of probability into a counting problem
- What about outcomes with unequal chance?
- Or infinite outcomes? (e.g. continuous spectrum of possibilities)
- We need some general way to define their events and probabilities

#### Kolmogorov Axioms

Events are viewed as sets of outcomes, and every set is a subset of the largest set  $\Omega$ , which can be viewed as the 'universal' set encompassing all outcomes. We define a function P to give the probability of an outcome falling within an event set, satisfying the following axioms:

- 1.  $P(\Omega) = 1$
- 2.  $P(E) \ge 0$  for any event set E
- 3.  $P(A \cup B) = P(A) + P(B)$  for any disjoint (aka nonoverlapping) event sets A, B

#### Kolmogorov Axioms

These axioms can prove all other results which we'd expect to make sense:

- If  $A \subseteq B$ , then  $P(A) \le P(B)$
- P(empty set) = 0
- P(E) ≤ 1
- $P(\Omega E) = 1 P(E)$

As long as we can define a universal set  $\Omega$  and an idea of probability that follows the axioms, then we can use any of the results.

- Universe of possibilities representing opponent's bounty card
- P(bounty card is 2) = P(bounty card is 3) = ... = 1/13

## Questions?

#### Conditional Probability

"probability of A given B"  $P(A \mid B) = P(A \cap B) / P(B)$ 

Another way to write:  $P(A \cap B) = P(B) | P(A \mid B)$ 

The basis of inference aka updating beliefs based on information.

- Universe of possibilities representing opponent's bounty card and whether or not they go all in after a 2 turns over in the flop
- We know they always go all in if their bounty card is a 2, and go all in 1/24 of the time whenever their bounty card is not a 2.
- We want to find the conditional probability their bounty card is a 2 given that they just went all in after a 2 was revealed on the flop.
- P(All in| bounty is 2) = 1
- P(All in| other bounty) = 1/24
- Want to find P(bounty is 2 | All in)

• P(All in ∩ bounty is 2)

• P(All in  $\cap$  bounty is 2) = P(All in | bounty is 2) \* P(bounty is 2)

• P(All in  $\cap$  bounty is 2) = P(All in | bounty is 2) \* 1/13

• P(All in  $\cap$  bounty is 2) = 1 \* 1/13

• P(All in  $\cap$  bounty is 2) = 1/13

- P(All in  $\cap$  bounty is 2) = 1/13
- P(All in ∩ other bounty)

- P(All in  $\cap$  bounty is 2) = 1/13
- P(All in ∩ other bounty) = P(All in | other bounty) \* P(other bounty)

- P(All in  $\cap$  bounty is 2) = 1/13
- P(All in ∩ other bounty) = P(All in | other bounty) \* 12/13

- P(All in  $\cap$  bounty is 2) = 1/13
- P(All in ∩ other bounty) = 1/24 \* 12/13

- P(All in  $\cap$  bounty is 2) = 1/13
- $P(All in \cap other bounty) = 1/26$

- P(All in  $\cap$  bounty is 2) = 1/13
- P(All in  $\cap$  other bounty) = 1/26
- P(All in)

- P(All in  $\cap$  bounty is 2) = 1/13
- P(All in  $\cap$  other bounty) = 1/26
- $P(All in) = P(All in \cap bounty is 2) + P(All in \cap other bounty)$

- P(All in  $\cap$  bounty is 2) = 1/13
- $P(All in \cap other bounty) = 1/26$
- P(All in) = 1/13 + 1/26

- P(All in  $\cap$  bounty is 2) = 1/13
- P(All in  $\cap$  other bounty) = 1/26
- P(All in) = 3/26

- P(All in  $\cap$  bounty is 2) = 1/13
- P(All in  $\cap$  other bounty) = 1/26
- P(All in) = 3/26
- P(bounty is 2 | All in) = ?

- P(All in  $\cap$  bounty is 2) = 1/13
- P(All in  $\cap$  other bounty) = 1/26
- P(All in) = 3/26
- P(bounty is 2 | All in) = P(bounty is 2 ∩ All in) / P(All in)

- P(All in  $\cap$  bounty is 2) = 1/13
- P(All in  $\cap$  other bounty) = 1/26
- P(All in) = 3/26
- P(bounty is 2 | All in) = P(All in ∩ bounty is 2) / P(All in)

- P(All in  $\cap$  bounty is 2) = 1/13
- P(All in  $\cap$  other bounty) = 1/26
- P(All in) = 3/26
- P(bounty is 2 | All in) = P(All in  $\cap$  bounty is 2) / (3/26)

- P(All in  $\cap$  bounty is 2) = 1/13
- P(All in  $\cap$  other bounty) = 1/26
- P(All in) = 3/26
- P(bounty is 2 | All in) = (1/13) / (3/26)

- P(All in  $\cap$  bounty is 2) = 1/13
- P(All in  $\cap$  other bounty) = 1/26
- P(All in) = 3/26
- P(bounty is 2 | All in) = (2/26) / (3/26)

- P(All in  $\cap$  bounty is 2) = 1/13
- P(All in  $\cap$  other bounty) = 1/26
- P(All in) = 3/26
- P(bounty is 2 | All in) = 2/3

- P(bounty is 2) = 1/13
- P(bounty is 2 | All in) = 2/3
- Takeaway: probability of an event increases when you observe evidence that makes it more likely
- Conditional probabilities allow us to mathematically represent this effect, which is called Bayes' Theorem

# Questions?

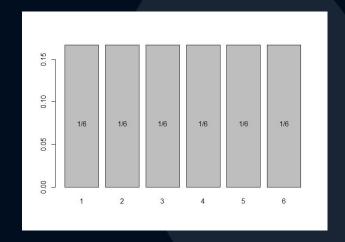
# Random Variables and Distributions

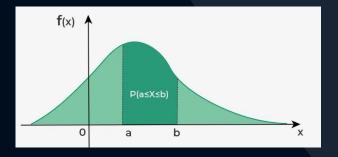
#### Random Variable

- A random variable is a quantity or event which takes on different values with different probabilities
  - o Ex: A drawn card that's face down and hasn't been turned over
- The set of possible values it can take on would represent the universal set of events for probabilities concerning this variable.
  - Ex: 52 total cards that our mystery card could have
- Any event concerning this variable corresponds to set possible values it takes on
  - Ex: "card is black" <--> set of 26 cards

#### Distributions

- Distributions are functions that are used to define probabilities for different events
- For discrete events, this is called a "probability mass function" (think bar graph)
- For continuous events, this is called a "probability density function" (think histogram)





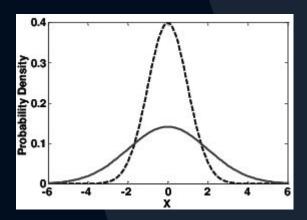
# Expected Value

### Expected Value

- The notion of expected value (EV) is used to summarize distributions on real numbers by some representative value
- In short, "expected value" is just another way to say "mean"
- Finite events with equal probability  $\rightarrow$  take the average
  - $\circ$  EV of dice roll: (1+2+3+4+5+6)/6 = 3.5
- What about events with different probabilities?
- Generalize to weighted average (weighted by probability)
  - X is a random variable with possible values in set S
- For continuous distributions, this generalizes to an integral calculation

#### **Variance**

- If expected value describes where random variable "usually" is, then variance measures how much the random variable may fluctuate
- This is done by finding the average squared distance from the mean:
  - $\circ$  Random variable X with E[X] =  $\mu$
  - $0 \longrightarrow Var[X] = E[(X \mu)^2]$
- Standard deviation is a similar measurement, which is simply the square root of variance



#### In short

- Expected Value is the average of a random variable and is often used as a "best guess" for the result
- Variance and standard deviation are used to measure how close this guess would generally be

# Law of Large Numbers

## Law of Large Numbers

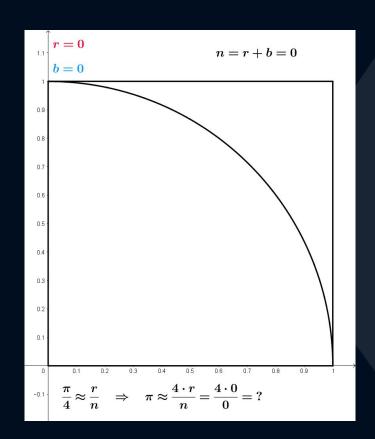
- X is a random variable with mean  $\mu$  with some distribution
- Independent samples  $X_1, X_2, ... X_n$  are drawn from the distribution.
- "Sample mean" X is the average of these samples.
- It can be shown that  $E[X] = \mu$  and Var[X] = Var[X]/n
- The law of large numbers states that this sample mean X is guaranteed to approach the actual mean  $\mu$  as n (the number of samples) approaches infinity

## Law of Large Numbers

- This gives us another intuitive way to think of the mean the average of infinite hypothetical trials
- The law of large numbers also conveys a powerful idea: with enough data points, you can accurately estimate properties of random processes, even if their underlying distributions are unknown
- With the ability of computation, certain quantities are now much easier to compute

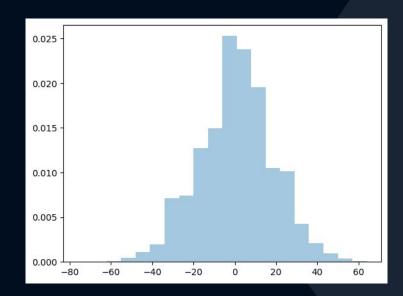
#### Monte Carlo Estimation

- Style of computational methods to calculate a result using repeated random sampling and averaging (aka a direct application of LLN)
- Ex: estimating area using geometric probability



#### Monte Carlo Estimation

- Another example is the way we run Pokerbots <u>matches!</u>
- Dividing the cumulative deltas by 1000 is a Monte Carlo estimate for the expected number of chips gained in a single round
- Therefore a good pokerbot should try to maximize the expected number of chips earned within a single hand



# Summary

## Summary

- Probability is a tool for describing uncertain situations
- In particular, Expected Value gives us a numerical estimate of an average scenario
- Law of Large Numbers and Monte Carlo use generated samples to make some calculations easy with computation
- If you'd like to learn how to use numerical/statistical packages to do some of these computations, come to recitation tomorrow!

# Lunch Time!

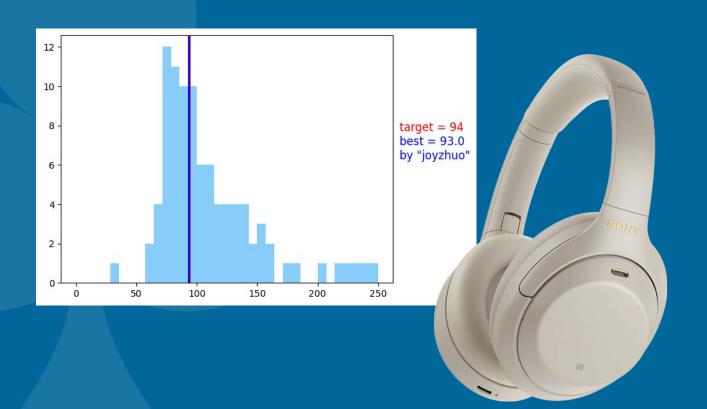
Leave any type of feedback at <a href="https://pkr.bot/feedback">pkr.bot/feedback</a>!





# Live Coding Session

# Estimation Game results



Answer: 94 '93' was guessed by 'joyzhuo' and 'kevinmz' in that order, 43 seconds apart

### Thanks for watching!

Slides 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!