Winning March Madness Pools with Bracket Networks

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Problem: Optimizing March Madness Brackets in Small to Medium Sized Pools

Motivation

- ~40 million Americans create brackets for the college March Madness basketball tournament
- Professor Tauhid Zaman presented an approach to the problem of maximizing his chances of winning the ESPN nationwide competition by optimizing a portfolio of 1,000 brackets at the 2019 MIT Sloan Sports Analytics Conference

Problem Statement

- We focus on the problem of building an "optimal bracket" in pools
- The optimal bracket is defined as the bracket that maximizes your probability of winning a pool with N participants. Specifically, we recommend the "optimal bracket" for a player to enter in a pool of size N

Datasets

- FiveThirtyEight's pre-tournament predictions for the 2019 March Madness tournament
  - Predicts how likely it is for each team to win the Round of 64, Round of 32, Sweet 16, Elite 8, Final 4, and the Championship
  - Results in a matrix of size 64x6, because there are 64 teams and 6 rounds in the tournament, and each entry in the matrix represents FiveThirtyEight's prediction of how likely it is that the corresponding team will win that respective round
  - Used FiveThirtyEight's predictions as the ground truth for our analysis, meaning that we sampled what actually happened from their probability estimates

			CHANCE OF REACHING ROUND					
TEAM	REGION	POWER RATING	1ST	2ND	SWEET 16	ELITE EIGHT	FINAL FOUR	CHAMP.
Villanova 1	East	94.9	✓	99%	86%	67%	50%	29%
Virginia 1	South	93.1	✓	98%	83%	61%	41%	26%
Duke 2	Midwest	92.8	✓	96%	81%	47%	29%	16%
Kansas 1	Midwest	90.9	✓	95%	76%	62%	32%	15%
Michigan St. 3	Midwest	91.7	✓	92%	75%	49%	24%	12%
Cincinnati 3	South	91.1	✓	93%	78%	53%	25%	15%
Purdue 2	East	91.1	✓	98%	73%	50%	20%	10%
UNC 2	West	90.8	✓	96%	79%	46%	25%	12%
Gonzaga 4	West	89.5	✓	92%	70%	43%	24%	10%
Xavier 1	West	88.8	✓	98%	70%	34%	17%	7%

- ESPN's Who Picked Whom for 2019 March Madness tournament
  - Millions of people enter brackets for ESPN's nationwide competition, and ESPN aggregates how the players in the competition made their selections
  - ESPN publishes a 64x6 matrix, where every entry represents the percentage of nationwide participants who selected that team to win that respective round
  - Used ESPN's Who Picked Whom as the basis on which we sampled possible brackets that our opponents in our office pool might create

Who Picked Whom

This page shows you how the rest of the Tournament Challenge players have made their selections. Below is a list of the respective round.

Tournament Challenge

R64	R32	S16	E8
1 Duke - 97.5%	1 Duke - 94.0%	1 Duke - 86.3%	1 Duke - 68.7%
1 North Carolina - 97.1%	1 North Carolina - 92.2%	1 North Carolina - 77.5%	1 North Carolina - 56.2%
1 Gonzaga - 96.9%	1 Virginia - 89.6%	1 Virginia - 74.6%	1 Virginia - 42.6%
1 Virginia - 96.6%	1 Gonzaga - 83.9%	2 Michigan State - 66.1%	1 Gonzaga - 42.4%
2 Kentucky - 96.3%	2 Kentucky - 83.7%	1 Gonzaga - 64.3%	2 Tennessee - 32.0%
2 Michigan State - 95.8%	2 Michigan State - 82.8%	2 Kentucky - 62.1%	2 Michigan - 26.3%
2 Tennessee - 95.6%	2 Tennessee - 81.1%	2 Tennessee - 58.1%	2 Kentucky - 22.3%
2 Michigan - 95.5%	2 Michigan - 77.3%	2 Michigan - 54.7%	2 Michigan State - 18.6%

Representing a Bracket as a Deep Network

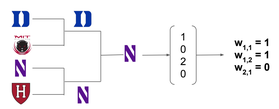
Definitions and Notation

- Realization = an instance generated from FiveThirtyEight's data representing what actually happened, meaning who actually beat whom in the tournament and to which round each team went
- $w_{i,j}$ = optimal weights to be learned by deep network, which will later be transformed into the optimal bracket
- $z_{i,j}$ = output of linear transformation in the hidden layers
- S = steep sigmoid function
- r_{round} = reward at each round
  - $r_1 = 1$, $r_2 = 2$, $r_3 = 4$, $r_4 = 8$, $r_5 = 16$, $r_6 = 32$
- z_{pool} = output after taking the max of all the other pool participant's bracket scores
- y = the output of the objective function, which is stated as follows:

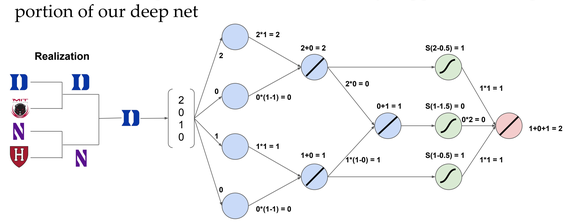
$$\text{Objective: } \max_{w} \frac{1}{n} \sum_{r \in 1..n} y_r$$

Example: Bracket with 4 Teams and 2 Rounds

- Jonah's bracket predictions are as follows:



- After generating a realization of what actually happened, we can see how Jonah's bracket predictions perform and the score of his bracket. This is representative of what actually happens in the top portion of our deep net



Building an Optimal Bracket

- Randomly initialized weights to values between 0.4 and 0.6
- Used SGD to optimize weights while also randomly changing the weights throughout the optimization process, so as to explore other solutions
  - The factor by which we explore decreases over time

Results

vs. pools sampled from "Who Picked Whom"

vs. pools sampled from ground truth (FiveThirtyEight)

# competitors	1	15	50	100	500
Unoptimized P(win)	.5	.0625	.0196	.0099	.002
P(win) vs who picked whom	.731	.174	.088	.047	.018
P(win) vs smart competition	.768	.14	.047	.017	.00425
Expected Return vs. who picked whom	173%	361%	540%	570%	1000%
Expected Return vs smart competition	177%	310%	335%	270%	313%

Key Insights

- Brackets can be effectively optimized with the use of a network framework and SGD
- Brackets optimized via this framework perform very strongly and present potential for high returns
- Even if one does not optimize their bracket through any sort of computation, there are qualitative insights that our optimal brackets provide; some are obvious but others are not. For instance:
  - The more people that you are competing against, the more upsets that you should predict (expected)
  - For pools with N<200, one does not need to pick many upsets to differentiate (it seems people commonly over estimate the number that they need)
  - Stay away from picking first round upsets (unless you are playing against at least 200 others)! This is rarely done.
  - The smarter that you think your opponents are, the more upsets that one should pick