## Competitive Machine Learning

Workshop — March 24, 2022

## Competing with Data Science

- ▶ I want to call your attention to and/or provide insight into how methods/techniques you learn in your various DATA modules can be immediately used in a variety of online competitions
- ▶ Some of this will definitely come with disclaimers!
- ▶ I will break this into a couple parts
  - 1. Kaggle: introduce, provide some guidance and advice
  - 2. Daily Fantasy Sports: introduce, provide guidance, walkthrough an example

## Kaggle — What is it?

- Kaggle.com is an online data science competition hosting platform
- Beyond competitions, it also serves as an excellent repository for interesting data sets.



- ▶ Disclaimer: I have not competed in any kaggle competitions, though I have sourced many data sets from there
- My advice therefore will be a mix of my general modelling experiences (consulting, research, etc), combined with other sources on how kaggle competitions operate.

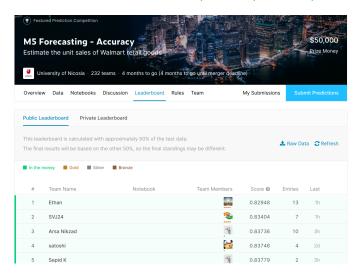
#### Comments on "Evaluation"

- ► This is one of the most important pieces of information to consider for the competition
- ► Competitions can be scored in several manners, and the choice of scoring can determine what your modeling concerns are.
- ► For example, scoring on minimizing squared error vs minimizing absolute error.
- ► The former would suggest avoiding any really large errors, the latter would suggest avoiding making lots of medium errors...

	Mod1	Mod2	Truth
	0	9	10
	50	20	40
	90	101	100
Sum Sq Error	300	402	
Sum Abs Error	30	22	

### Kaggle — Competitions

Leaderboards! Note that these are split into public vs private...



# Primer: Training vs Testing

- ➤ Supervised ML methods are fitted (or trained) on observed data with a known response variable the training data.
- ➤ The fitted model is then used to predict for some held out data (not used during fitting) to check how well the model predicts in a realistic scenario the testing data.
- ► This is to help avoid the plague of overfitting.
- ► Kaggle further splits testing sets in order to provide feedback (public leaderboard) on a subset of the testing data, while witholding the results on the remainder of the test set (private leaderboard) until the competition closes

# Something to be aware of

- ▶ Interestingly, this setup leads to a different kind of overfitting than we are often worried about we should be cognizant of the potential of overfitting on the subset of the test set!
- While you can't explicitly train your supervised model on the test set used for that leaderboard, you are provided feedback on it through the evaluation index.
- And naturally, you are trying to climb that leaderboard...so you will try to make modelling choices that predict better on the public test set...which may not always predict better on the private test set!
- One way to guard against this is to ensure that you see improvement on both your training data (through cross-validation) in tandem with improvement on the leaderboard
  but it's not foolproof.

#### General Advice

- ► Evaluation is always (at least that I've seen) on a prediction metric of one form or another.
- ► This essentially means we can ignore one of our core modelling tradeoffs: inference vs prediction!
- As such, the most common winning methodologies usually fall into one of the following (relatively large) bins
  - ► Deep neural nets
  - ► Ensemble techniques (often boosted models)

#### General Advice

- "Wait, if we basically know what methodologies will win, where does the competition take place?"
- ► The main game of most Kaggle competitions is finding (externally to the data) or generating (internally from the data) useful variables on which to fit the winning method.
- ► This is often referred to as 'feature engineering'.
- There are usually notebooks dedicated to this on most competitions. I would encourage you to browse these from old and current competitions to get a feel for it.

#### General Advice

- Often good feature engineering comes down to reasonable domain knowledge.
- ➤ AKA, it often helps to have at least some knowledge/understanding of the phenomena that you are trying to model.
- Admittedly, this is more important in a general modelling/consulting context, as it helps you to find simple models that perform 'well-enough' (again, inference vs prediction tradeoff).
- Now, we will get some practice feature engineering...but outside of Kaggle, in the world of daily fantasy sports.

#### DFS — What is it?

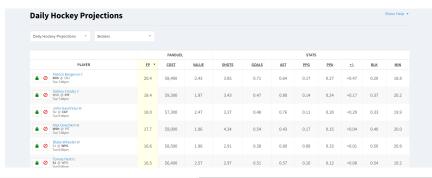
- Daily Fantasy Sports have exploded as a massive industry in the past decade.
- Draftkings and Fanduel are the two biggest platforms.
- ▶ Disclaimer: Legality of DFS in Canada is a gray area they claim to be games of skill, others claim it is functionally equivalent to gambling. The truth is likely somewhere in between, but the variability in results is high enough that even with a significant predictive advantage (which you won't necessarily know you have), you can lose a substantial amount of money in the short-to-medium term.
- ► HUGE Personal Disclaimer: My discussion here should not be taken as encouragement for you to partake. I have played off-and-on for approx 6 years, with a TOTAL investment of around \$50 (I really only compete in super low-stakes events).

- Okay, so disclaimers out of the way...how does it work?
- ► That depends on the sport, competition, and website...and it's not worth our time to cover all the specifics.
- ▶ In general, you are given a certain amount of units (a salary cap) that you can use to pick players for the games that day, and better players will cost more to select.
- ► The players will accrue points based on good performance in their respective sport (hockey example: shots, goals, assists, blocked shots, etc) — rarer positive events are generally worth more (goals > shots, etc).

- So competing in DFS (in any sport) comes down to two basic tasks
  - 1. Predicting the performance of all players specifically their total amount of fantasy points that day
  - 2. Selecting a team that is under budget that maximizes the sum of those predicted points
- ► Task 1 is a machine learning task, with a whole lot of necessity for external information and feature engineering
- ► Task 2 is a constrained optimization task. It can be formatted as a (binary) linear programming problem.

## DFS — Our goals

- Since it's more fun (and potentially more advantageous) we will approach Task 1 from scratch
- ▶ It's worth noting however that there are several websites out there that provide their own predictions (usually using some undescribed model).



- ► I have built algorithms for most sports, though of varying complexity. Some I just source other website predictions (like on previous slide).
- Later on in my DFS journey, I focussed entirely on golf.
- ▶ I've played golf once in the past 7 years.
- ▶ I don't enjoy watching golf on TV.
- ► So why golf???

## DFS — Why golf?

- Golf competitions last 4 days. This has two positives from my standpoint:
  - ► I can field a team for 10 cents, and potentially get back 4 days of model-watching 'excitement'.
  - ▶ 4 days expands the essential 'sample size' of the competition...this reduces variability (though there is still a crazy amount of it). For example, it's very hard to predict if Connor McDavid will score a goal tonight...it's marginally easier to predict if Rory McIlroy will finish in the top 20 for an entire tournament.
- ▶ DFS Golf scoring, on the face of it, is complicated (score on each hole counts, various bonuses for birdies-in-a-row, bogey-free rounds, etc)...BUT extremely correlated with the end rank of the tournament, especially near the top of the leaderboard.
  - This means I can try to predict one response variable (tournament rank) as an effective proxy for the complicated scoring system.
  - Note: many other sports do not have this simplicity. Connor McDavid's fantasy points are more weakly correlated with whether, say, Edmonton wins their upcoming game.

## DFS — Towards a Workshop

- Let's move towards getting our hands dirty.
- Reminder: I am not endorsing DFS in any way, shape, or form. I am also not endorsing any particular website for DFS. I am using draftkings because I am most familiar with their data setup.
- ► AND SADLY...PGA wised up to how easily accessible their raw data was over the past year, so I can't show you that raw source anymore.

### DFS — Final comments

- ▶ The biggest advantages in DFS come from late-breaking news...
- ➤ Suppose Connor McDavid is announced to be sitting out 10 minutes before faceoff since he's a strong player, a high percentage of teams (say 20-30%) are likely to have him.
- ► If it's late-breaking enough, this will tank a large portion of the competition
- Conversely, suppose McDavid will be playing, and a recent AHL call-up appears to be skating on his line during warm-ups — that player is likely low-cost with big potential upside in terms of fantasy points.
- ► This type of information is exceedingly valuable though exceedingly time consuming to be on top of.

#### DFS — Final comments

- ▶ In DFS, you're competing against other players.
- ▶ Because of high variability in daily performance, and heavy reward for the top of the leaderboard (in larger competitions), it's worth noting that selecting players that nobody else has is one of the core tenets of 'winning big'
- ► This leads to a bit of a paradox...if everyone is predicting well, everyone will field similar teams, in which case you have higher expected winnings if you select a player predicted to do poorly who happens to do well that night.
- ➤ This type of reasoning can drive you crazy...but you can gain some insight by properly investigating the variability in your predictions (think prediction intervals rather than point estimates).

#### MAIN TAKEAWAY

- ► If you're interested in Data Science, there are many fun sandboxes out there for you to hone your skills.
- Pursue your non-DS interests using DS! As a statistician, I have zero background in things like web scraping, but I come from a sports-oriented family, and have always participated in fantasy sports.
- ► From playing around with building models for fantasy sports in my spare time, I've learned countless tricks and techniques that have improved my coding skills.
- ➤ These things almost always translate, in some shape or form, into improvements in my core research (finding interesting data sets, improving my open source software, identifying research opportunities, etc...)