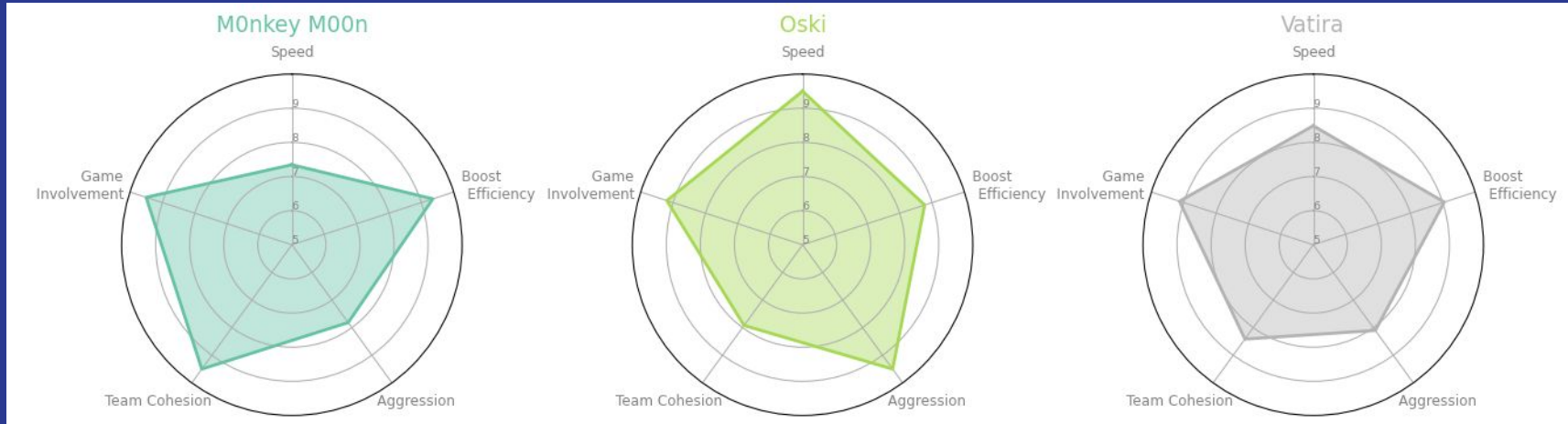


# Capstone - Rocket League

## Analysis and Modeling of play-styles and rank



# Agenda

- Problem Statement
- Introduction to Rocket League
- **Part 1: Playstyle Analysis and Prediction**
  - Pro Examples
  - Casual Examples
  - Modeling Results
- **Part 2: Rank Analysis and Prediction**
  - General trends
  - Modeling Results
- Application Demo
- Conclusions & Recommendations



# Problem Statement


- Very slow improvement rates at high ranks.
  - highly mechanics and precision required
- Professional players can be used as play-style case studies for developing players
  - Particularly at mid to high ranks

This project uses 3 pro players, selected as top-level examples of 3 distinct play-styles:

- MonkeyMoon
- Vatira
- Oski

An ExtraTrees classification model has been trained on replay data from professional tournaments for each of these players, and can be used to predict which play-style a player most closely fits from a submitted 3v3 replay ID and player ID.

Furthermore, a neural network regression model has been produced to estimate the rank of a player given the stats from a 3v3 replay ID and player ID



# Rocket League - A Summary



- 3v3 Player vs Player
- Using the car body to score in the opposition teams goal (Car Soccer)
- Team with most goals in a 5 minute game wins!

*Simple...*

# Rocket League - A Summary



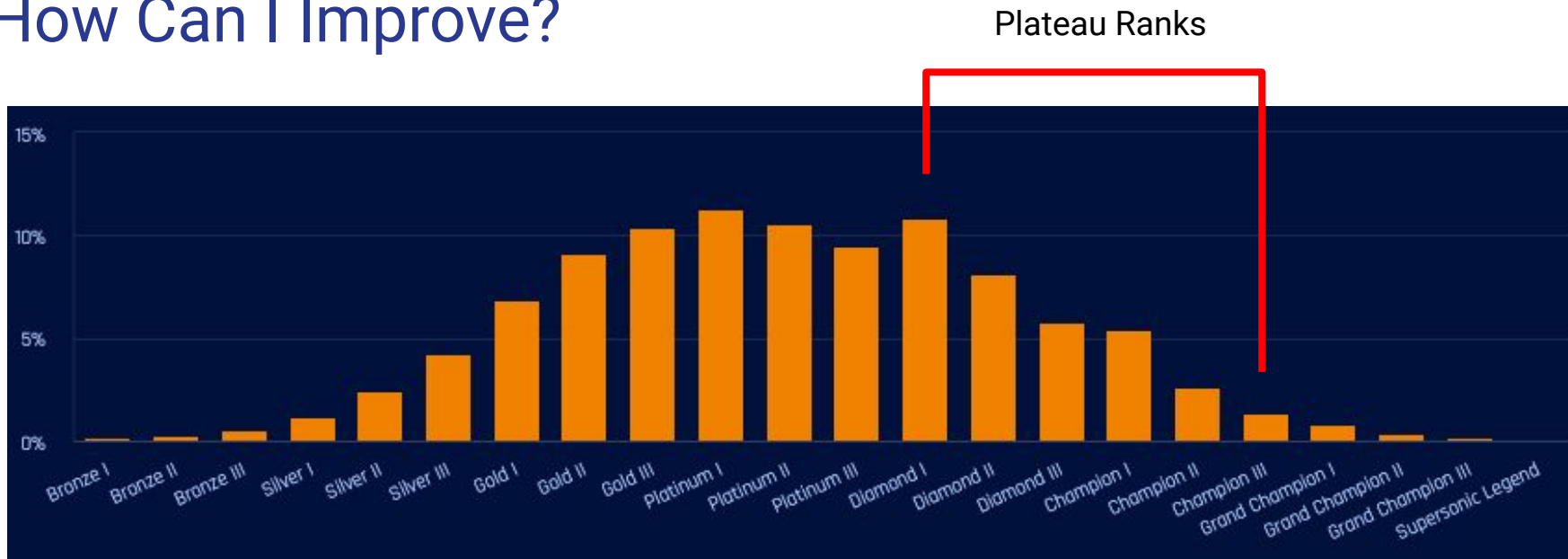
Shameless Plug :)

*...Maybe not...*

- Players can collect 'boost' off several spots on the ground
- This allows the cars to fly
- Car control becomes key to improvement



# How Can I Improve?



## Lower Ranks:

- Game Fundamentals:
  - Team Rotations
  - Muscle Memory

## Higher Ranks:

- Unclear:
  - Mechanics?
  - Speed?

# Part 1 - Identify Your Playstyle (or desired playstyle)

- Pro Players have proven that many playstyles can bring success
- 500 international tournament matches were collected for each player from *ballchasing.com*
- I have used three European top level players as exemplar playstyle models:

1 - **M0nkey M00n**



2 - **Oski**



3 - **Vatira**



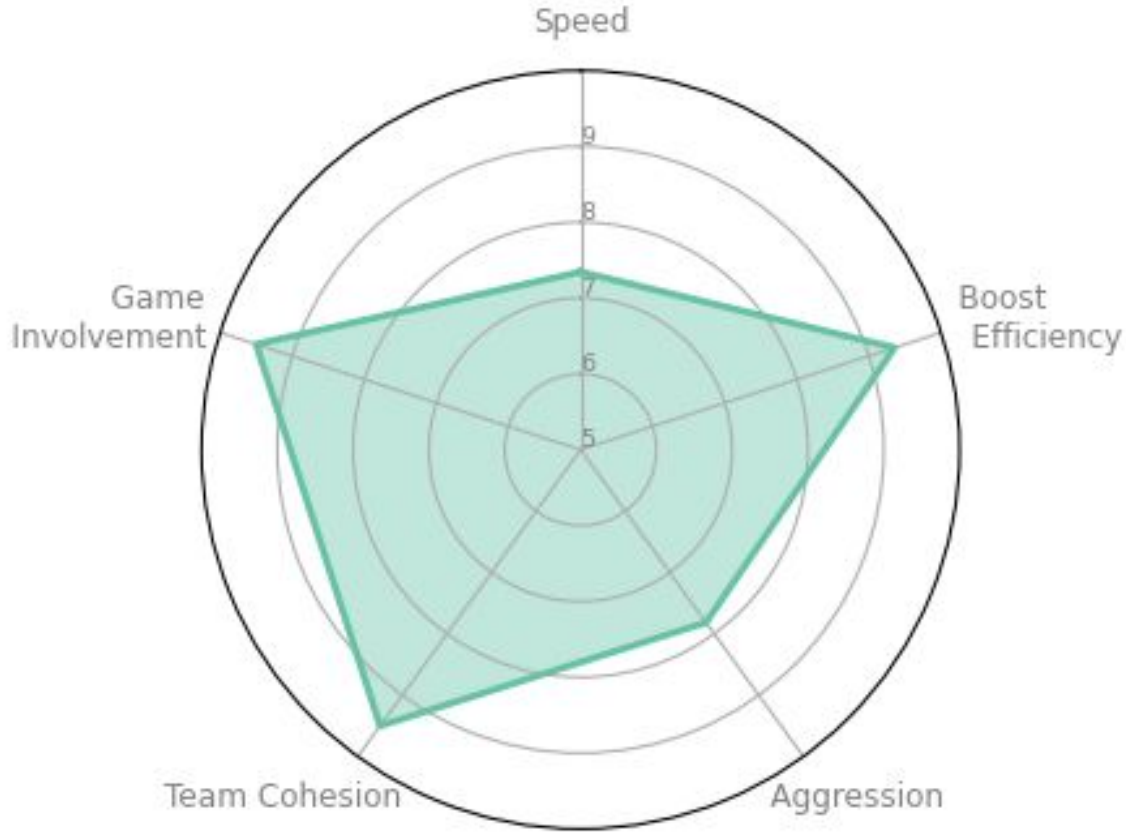
# M0nkey M00n - Team BDS

- **2022 World Champion**
- **2021 Fall Major Champion**
- **Season X 2nd Place**





## M0nkey M00n



## M0nkey M00n

- Highly Efficient with boost
  - Uses the minimum resources required
- Always available to receive a pass or intercept opponent
- Most defensive player on his team

# Oski - Team Liquid

- **2023 Winter Major Semi Finalist**
- **Regarded as one of the most mechanically talented players in Europe**



# Oski



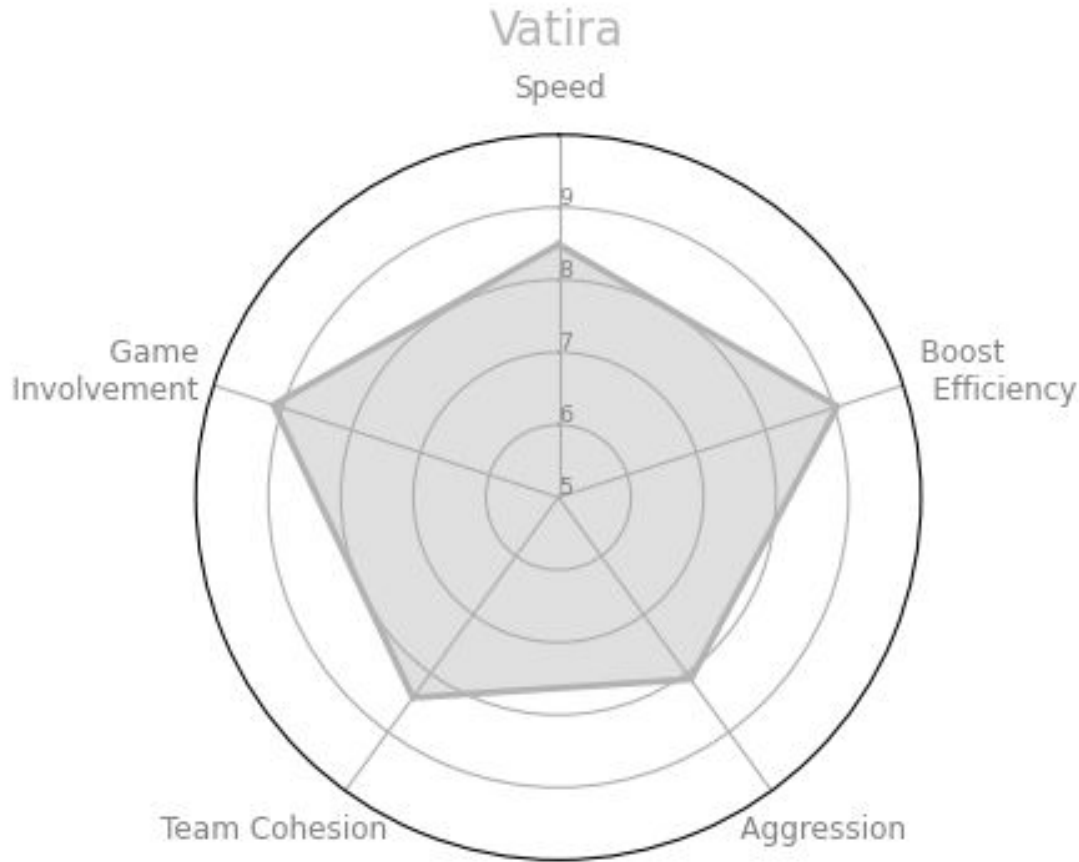
- Plays extremely aggressively
- Constantly looking to outplay opponents through mechanical skill
- Can leave team exposed, aims to create more chances than conceded

# Vatira - Karmine Corp

- 2 x Major Champion
- 2022 Winter Major Second Place
- Widely Regarded as the current best player in the world



# Vatira

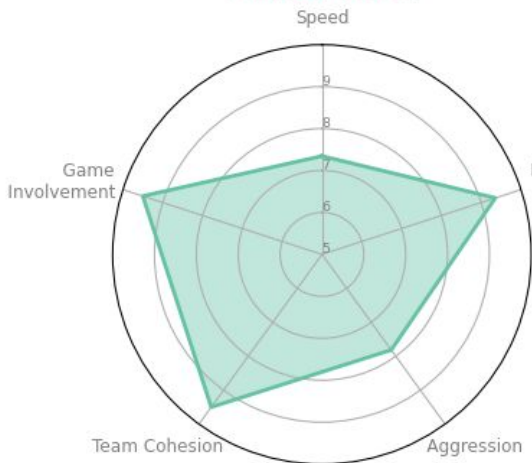


- Very Rounded Playstyle
- Capitalises on opportunities created through constant pressure and teamwork
- Generally plays as the most defensive player on the team, but able to create and score as well as any other player

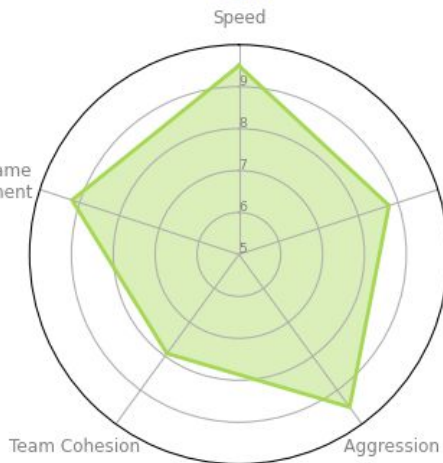
# Playstyle Modeling

- Playstyle were plotted using a designed algorithm
- Can Classification models replicate this?
- These can then be used to identify which play-style any player's gameplay is most alike

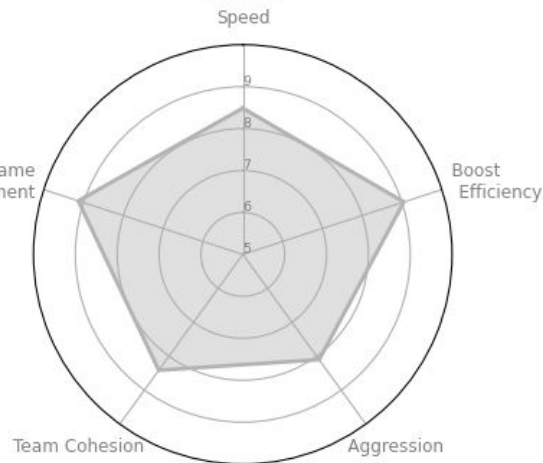
M0nkey M00n



Oski



Vatira





# Playstyle Modeling

- Null Model predicted the majority class - Vatira - with accuracy of 0.37
- Neural Network was by far the strongest predictor, with the lowest variance
- Gaussian Naive Bayes was not a suitable model, performing worse than the null model

	train_acc	test_acc	bal_acc
<b>knn</b>	1.000000	0.837500	0.831184
<b>et</b>	1.000000	0.879167	0.875863
<b>gnb</b>	0.339833	0.283333	0.342464
<b>stack</b>	1.000000	0.820833	0.817405
<b>neural_network</b>	0.968000	0.903000	NaN

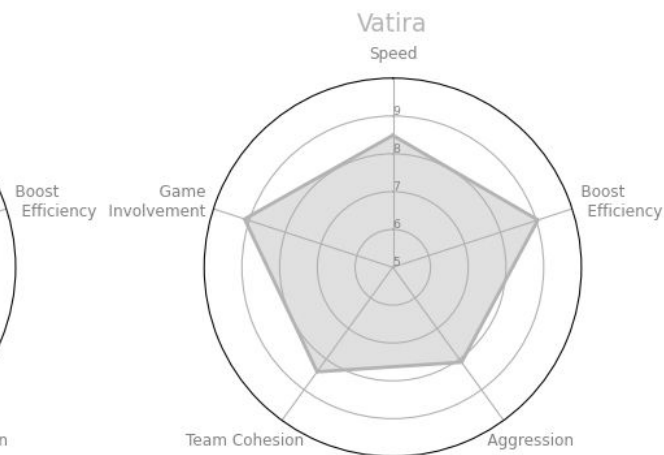
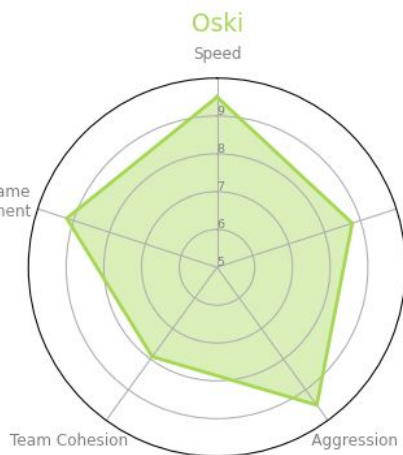
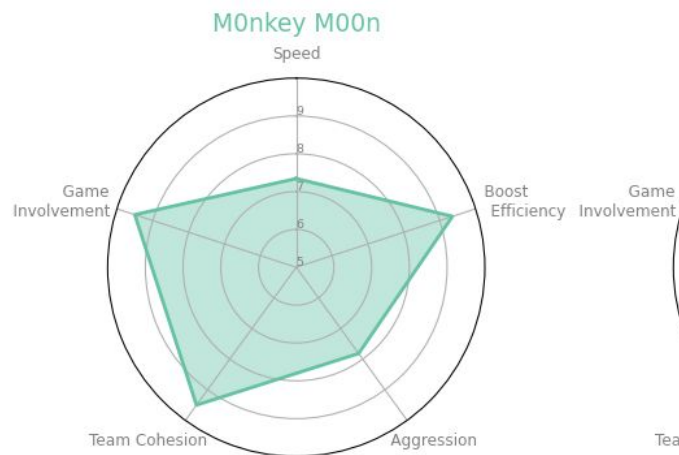
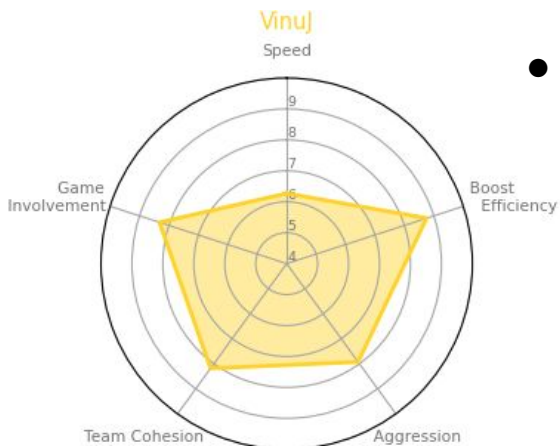
# Applying these Models to Casual Players

- Over 20-30 replays, Vinu's average predictions for each Playstyle:

**MonkeyMoon** - 0.483

**Oski** - 0.188

**Vatira** - 0.328



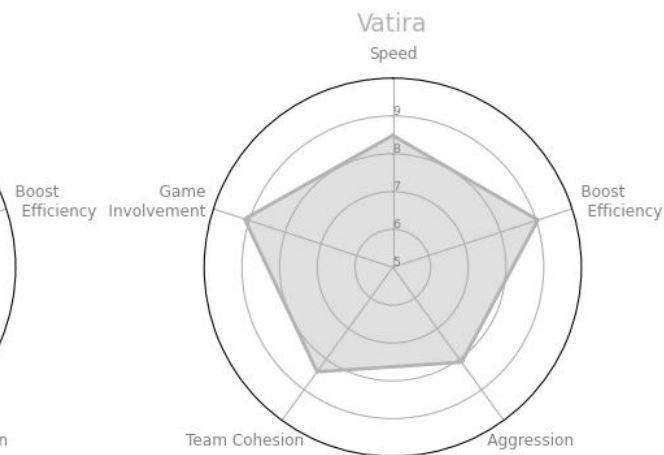
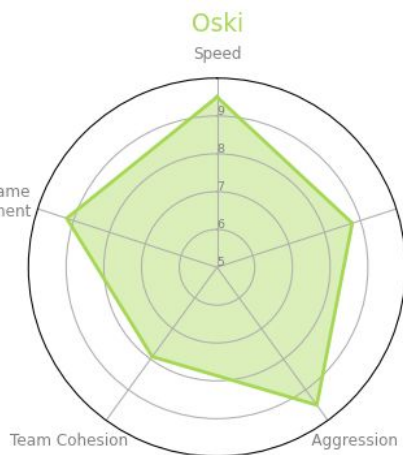
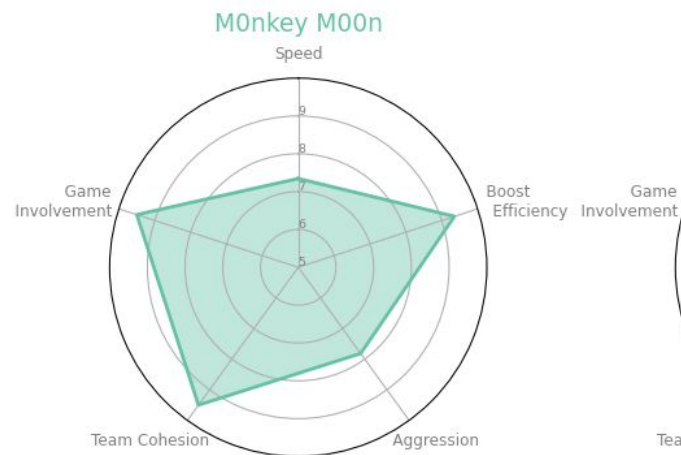
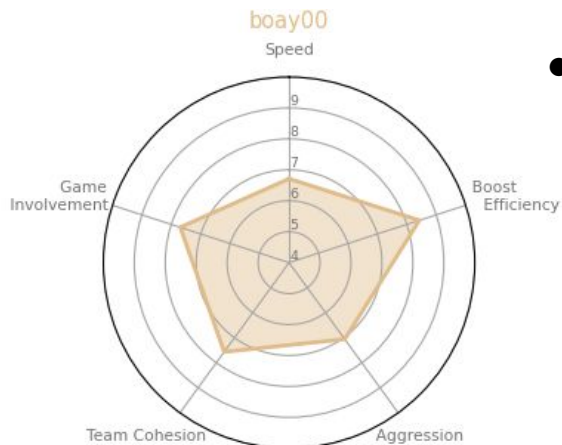
# Applying these Models to Casual Players

- Over 20 replays, boay00's average predictions for each Playstyle:

**MonkeyMoon** - 0.330

**Oski** - 0.197

**Vatira** - 0.473



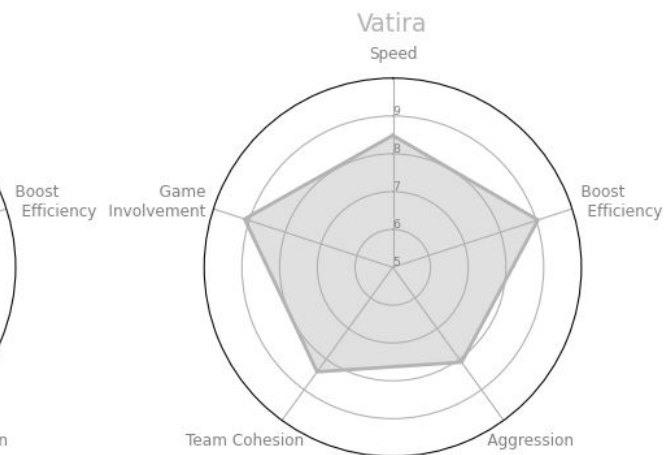
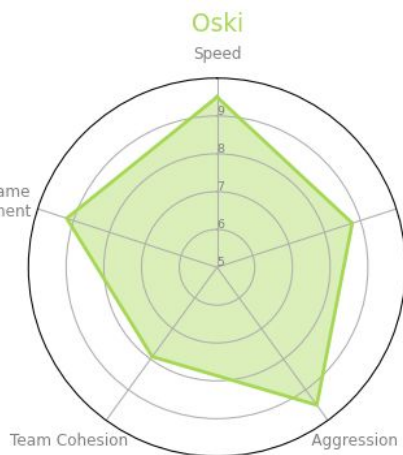
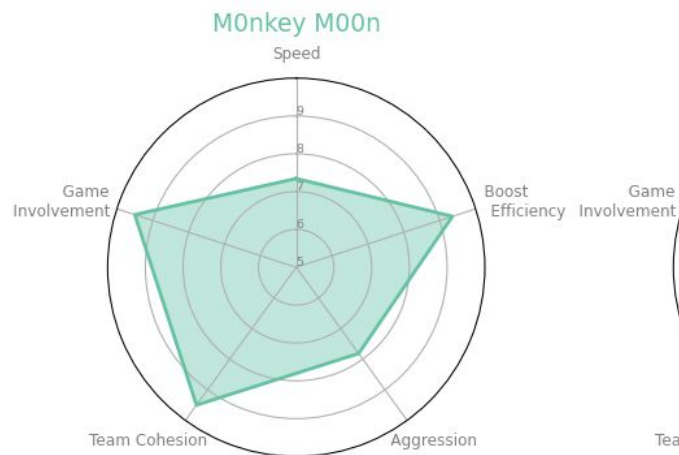
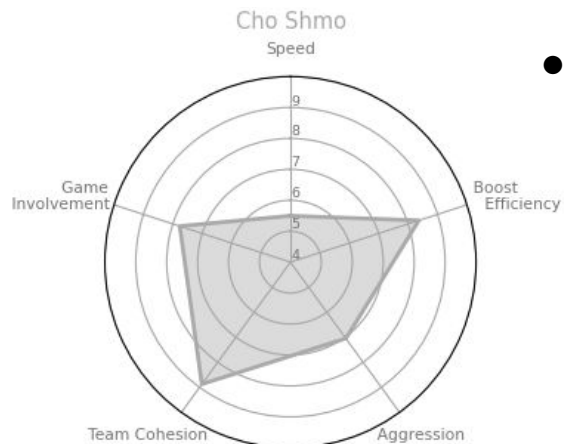
# Applying these Models to Casual Players

- Over 20 replays, Charles' average predictions for each Playstyle:

**MonkeyMoon** - 0.280

**Oski** - 0.261

**Vatira** - 0.458



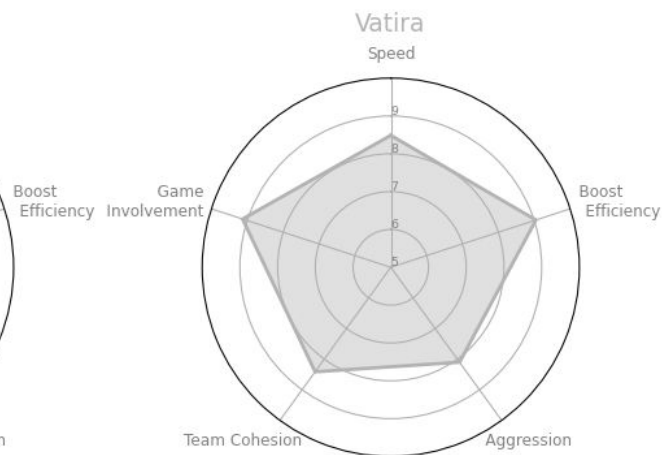
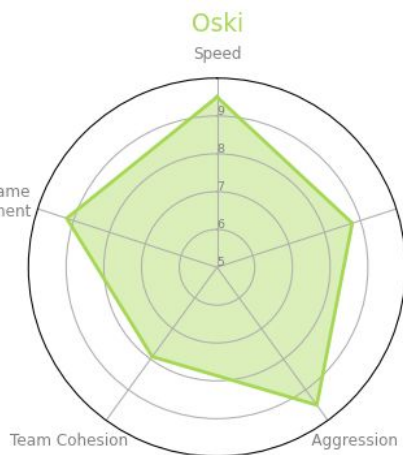
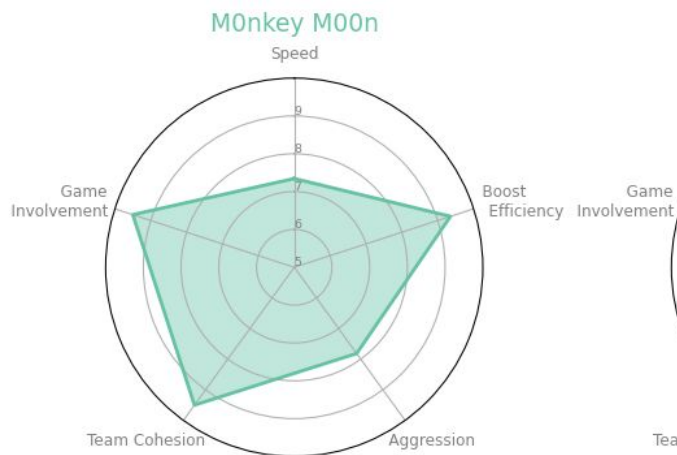
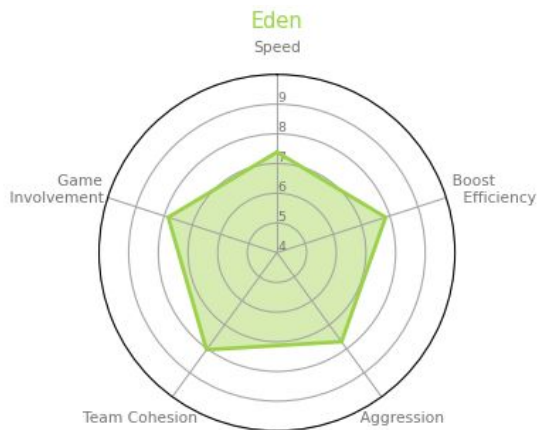
# Applying these Models to Casual Players

- Over 20 replays, Eden's average predictions for each Playstyle:

**MonkeyMoon** - 0.257

**Oski** - 0.275

**Vatira** - 0.468



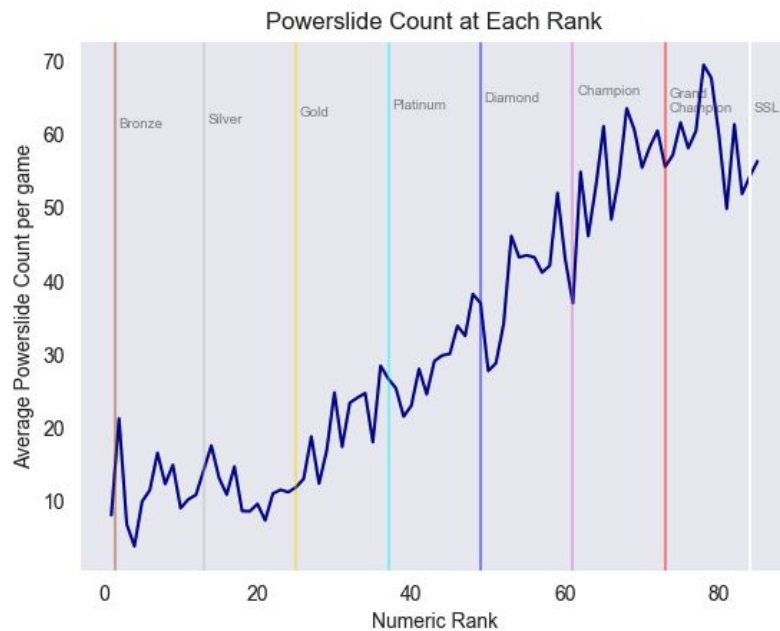
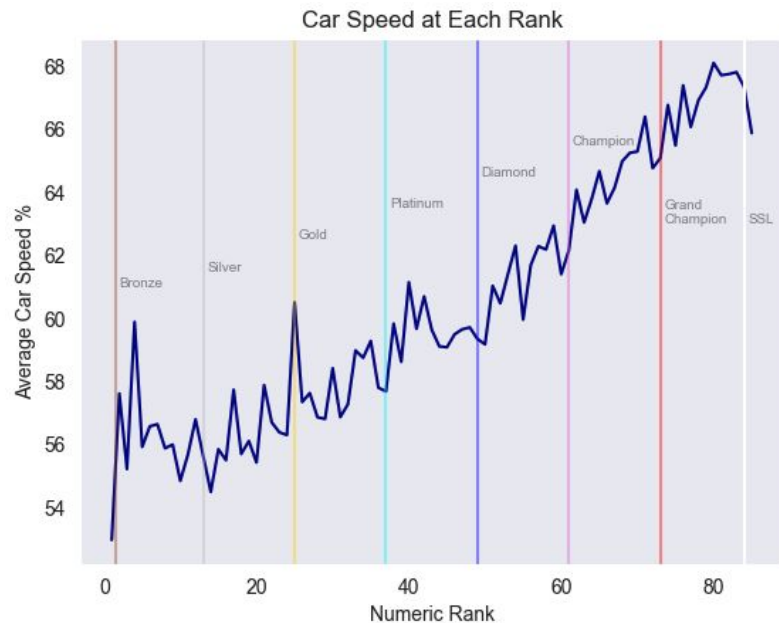
## Part 2 - Rank Predictions

- Many game statistics follow a linear trend as you move up the rank ladder
- Can a regression model predict what rank the gameplay has derived from?
- Can casual players use a rank prediction to determine their current level of skill by comparing this to their actual rank?
- Converted Entire rank ladder to numeric values, with 1 being the lowest rank and 85 being the highest

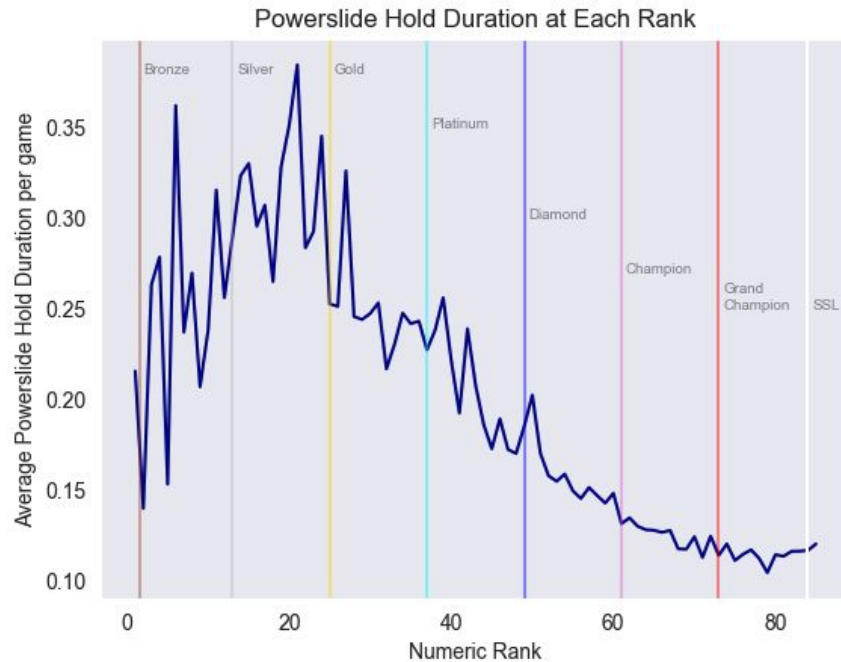
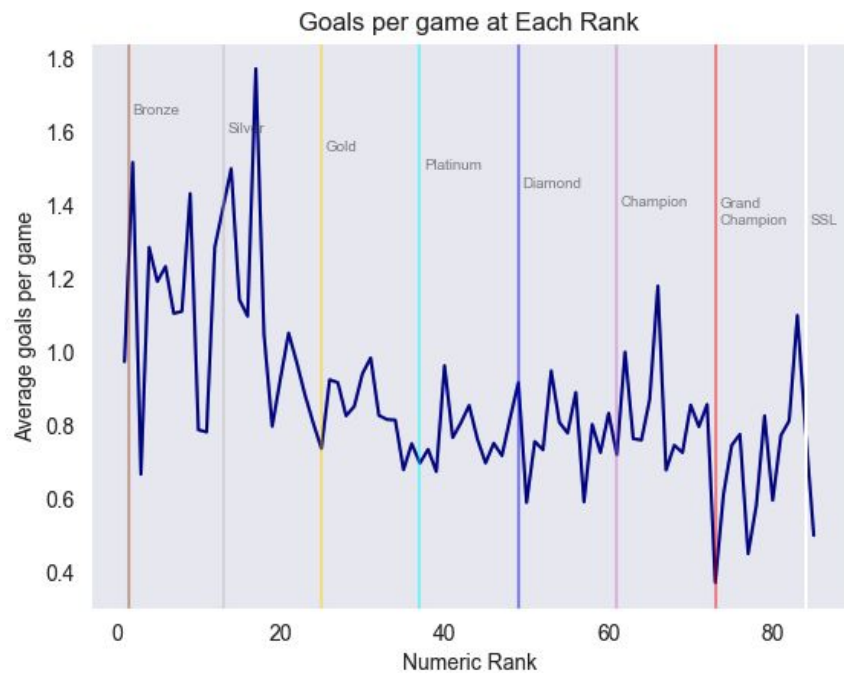




# Trends across ranks



# Trends across ranks



# Rank Models

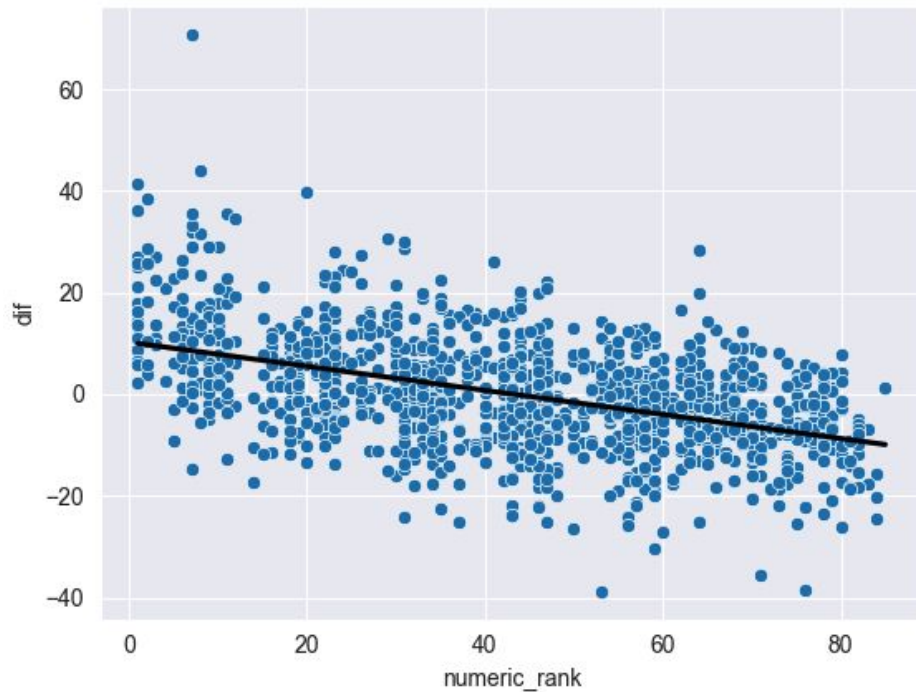
- Null Model  $R^2 < 0$
- Neural Network was the model with the lowest variance, whilst still having relatively high  $R^2$  scores and low rmse
- Gradient Boosting Regressor (GBRT) models produced very high training scores, and low rmse, but were generally high in variance

	train_r2	test_r2	MSE
<b>gradient boost</b>	0.825483	0.741011	10.939589
<b>gradient boost 2</b>	0.848500	0.757800	10.579077
<b>extra trees</b>	0.805168	0.710879	11.558469
<b>random forest</b>	0.809671	0.705284	11.669769
<b>k nearest</b>	0.757530	0.633170	13.019461
<b>gradient boost (overfit)</b>	0.947228	0.756691	10.603269
<b>neural_network</b>	0.790432	0.770315	10.908712

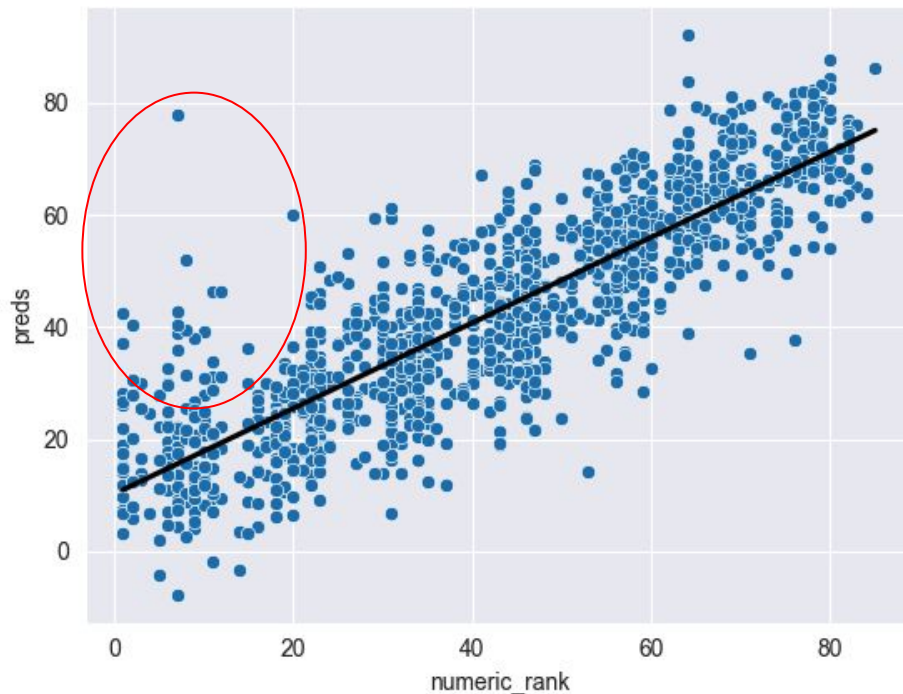
**\*\*GBRT models do not work in render\*\***

# Neural Network - Regression

Distribution of Errors Across Ranks

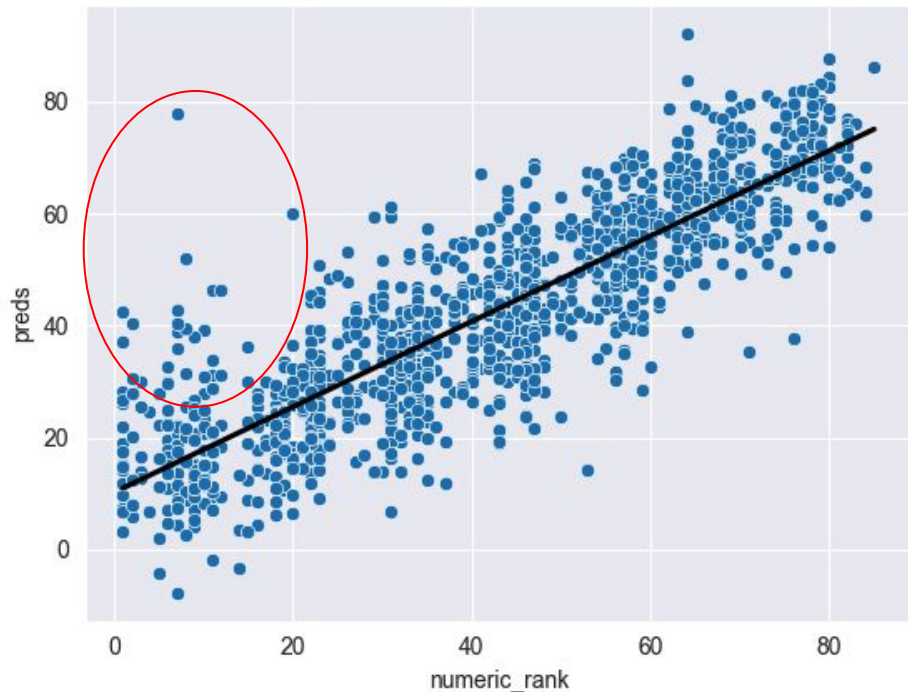


Actual Ranks vs Predicted Ranks



# Why is this happening?

- Players must have the plugin 'Bakkersmod' installed in order to upload replay files to Ballchasing.com
- This is something mostly used by more experienced players
- Therefore low rank players using bakkersmod are likely deliberately playing at rank below their skill level, resulting in high rank predictions



# Rocket League Playstyle Predictor Application

Link to the App:

<https://rocket-league-playstyle-predictor.onrender.com>





# Conclusions

- The Classification model was able to successfully distinguish between the three professional players' playstyles, and provided reasonable estimations for which of these was most suited to a given player
- The playstyle algorithm was somewhat effective in showcasing a players general attributes, however performs better with more than one game's worth of data
- The rank prediction model was unable to accurately place a players' games, however this was never the intention:
  - The model did show a linear increase in the prediction as rank increased, some error is inevitable and successfully highlights the differences in level at any given rank



# Recommendations

- Application
  - Process multiple games
    - Strain on the render server
    - Pressure on the host website's API
    - Would require user authentication and API token
  - Offer specific metric advice, as well as describing how these metrics are calculated
    - Visualise the sub-metrics for each attribute, and which need the most improvement
- Models
  - Classification model is still overfit
    - Further optimisation
  - Train rank prediction model on ranks above Platinum 3
    - Would remove the instances of players deliberately playing at ranks below their skill level and skewing the model



Thank You for Listening to me Talking about  
Car Football/Soccer for 20 Minutes!

I am happy to answer any questions

