Valorant Esports Analysis

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Problem Identification

- **Problem Identification / Statement:** The project aims to quantitatively analyze and predict team and player performances in the Valorant Champions Tour 2023, with the goal of improving win rates. Success will be measured by achieving a predictive accuracy of at least 75% in match outcome predictions and identifying possible team compositions to ensure success of both professional and casual players.
    - **Context:** Esports, particularly competitive games like Valorant, are rich in data and ripe for analytical exploration. Teams and players are constantly looking for insights to gain a competitive edge. The esports industry, including sponsors and team managers, can leverage these insights for decision-making and strategy development.
    - **Data Source:** The data contains around 6000 rows with around 20 columns. The provided dataset with match IDs, game IDs, team names, scores, player IDs, player names, agents, and various performance metrics like ACS, kills, deaths, assists, etc.

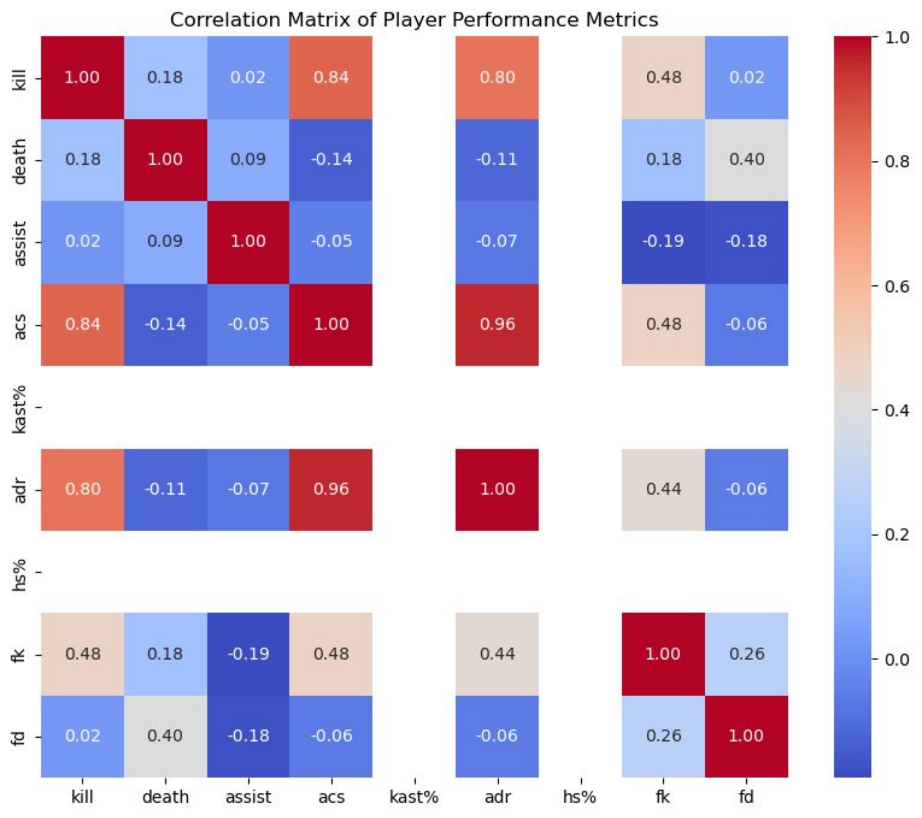
Background Info

Valorant is a team-based shooter game where players assume the role of agents, each with unique abilities. Matches are played on various maps, requiring strategy and skill. Agents contribute to their team's success through kills, assists, and strategic play. Performance is often measured by metrics like KDA (Kills, Deaths, Assists) and ACS (Average Combat Score). Competitive matches typically follow a best-of-three format, with the winning team needing to secure victories in two out of three games to win the match. This setup tests teams' adaptability and strategy across different game environments.

Data Wrangling

- There were no missing values which makes the data more readable to our code.
- Additionally, outliers are encouraged since it highlights excellent team work which is predicated on the agents they play.
- Feature Engineering will be highlighted with the analysis of the models.

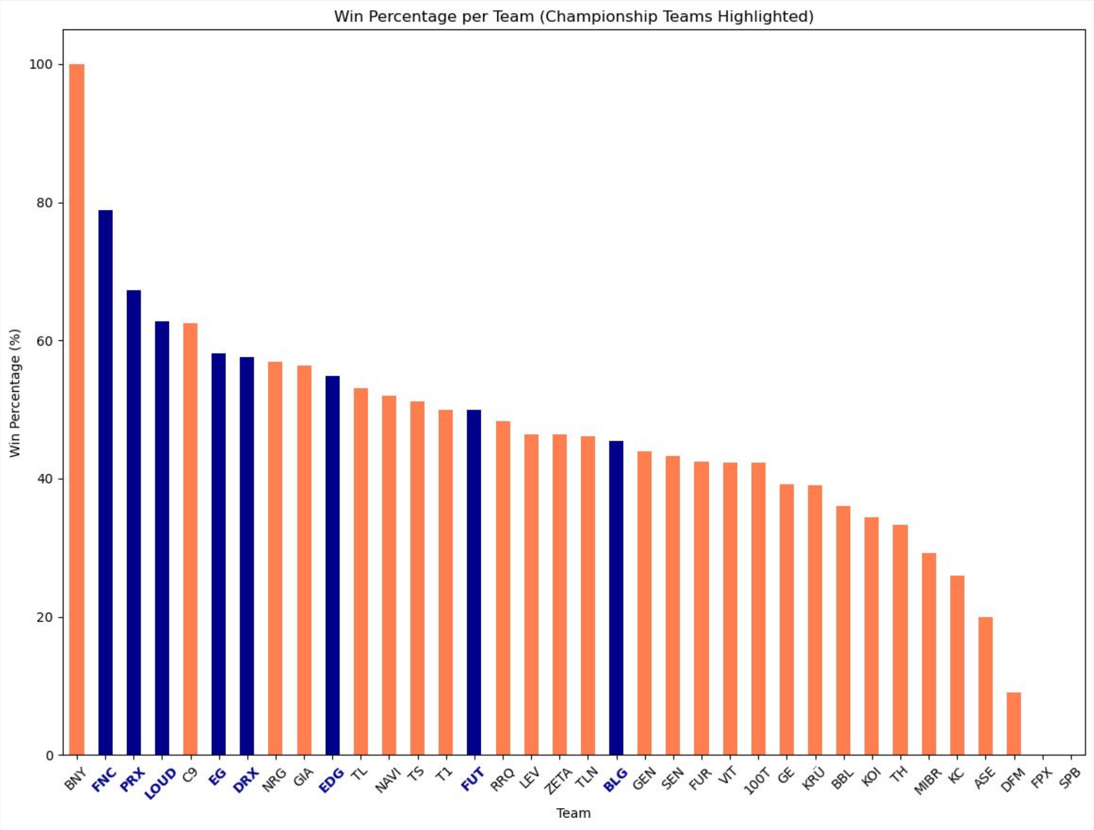
Exploratory Data Analysis: Correlation Plot



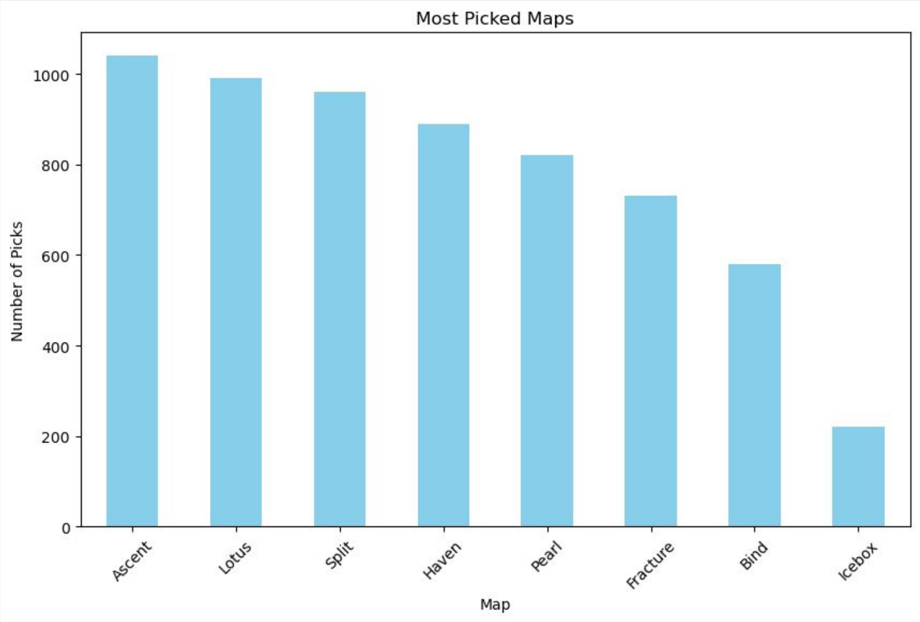
Feature Analysis

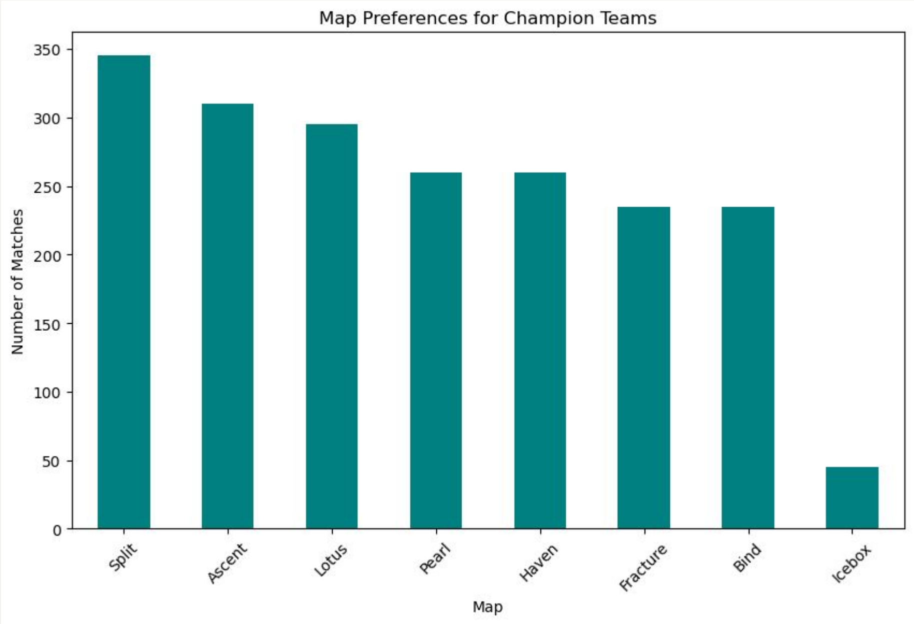
- The correlation matrix indicates that ACS, ADR (average damage per round) and # kills would all be good features to use for our prediction, since the correlation between them is strong and higher values of these statistics indicate good player performance, these are likely reliable features.
- Later during the modeling section there is some analysis into which features are the most important.

Exploratory Data Analysis: Win Percentages for Teams



Exploratory Data Analysis: Most Picked Maps

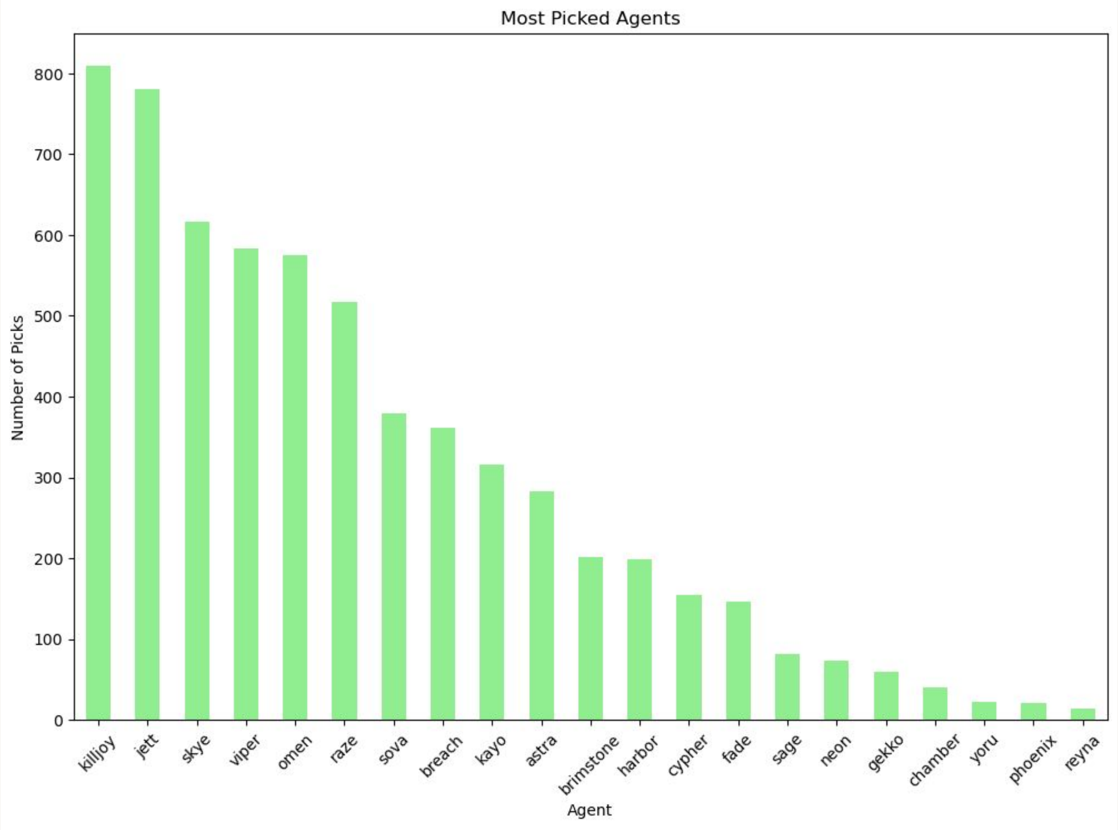




All teams vs Championship Teams

- This first plot indicates that the map ‘Ascent’ was chosen almost 800 times over ‘Icebox’, this means the cluster for the most chosen map would have more data to use over others.
- The reason why the champion teams needed to be plotted is to show how little data they give us and why it should not be used for the modeling. Their instance of Icebox has less than 50 picks.

Exploratory Data Analysis: Most Picked Agents



Most Picked Agents Analysis

The problem with this plot is that same agents like Reyna, Phoenix, or Yoru have very low pick rates, meaning the data surrounding their use would be quite unreliable. But they probably will not be shown frequently in our cluster and not with a high yield.

Modeling: Traditional Modeling

Goals: High predictive accuracy and Feature importance

This is a **binary classification problem**, Since the target variable is being encoded as 1 for a 'team win' and 0 otherwise, this is a binary classification problem where the model will predict two distinct classes (win or loss)

Traditional Modeling: Preprocessing

- Data Cleaning: Non-numeric characters are removed from numerical columns, ensuring the data is in the correct format for modeling.
- Feature Encoding: Categorical features are encoded using OneHotEncoder to convert them into numerical values without imposing ordinality/
- Data Scaling: The StandardScaler is applied to numerical features to standardize them, which is particularly beneficial for models that are sensitive to the scale of the data, such as logistic regression.
- Missing Value Handling: SimpleImputer is used to fill missing values, preserving the integrity of the dataset for training.

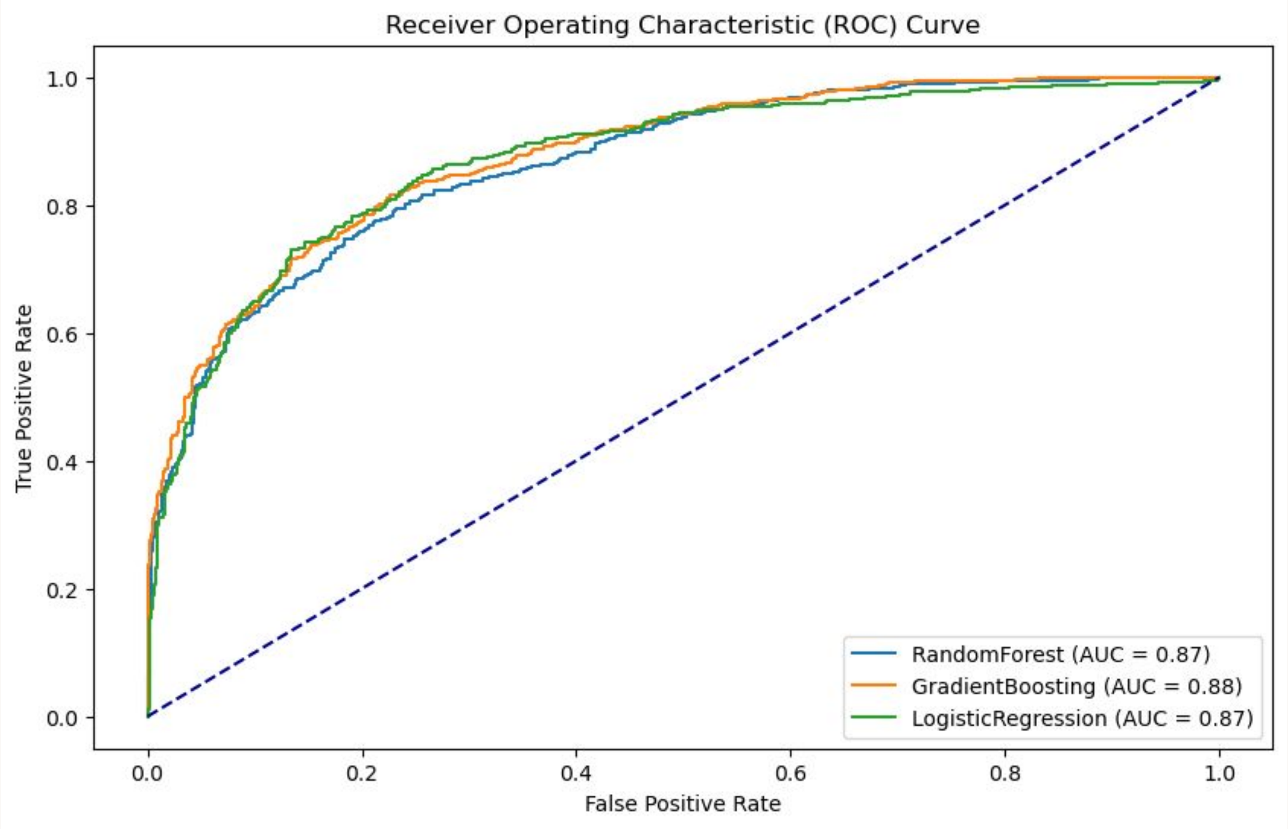
Traditional Modeling: Models Used

- **Random Forests --** less likely to overfit, it can handle a large number of features which is good for testing feature importance, and its nonlinear which is good for complex non-linear interactions, like video games.
- **Gradient Boosting Classier** -- supposedly high accuracy since it corrects errors and gradient boosting makes good use of hyperparameters.
- **Logistic Regression** -- good baselines model for binary classification, verify ast and simple, if high accuracy then the data is not complex.

Traditional Modeling: Evaluation Metrics

- **Accuracy**: All three models show similar accuracy (around 0.79), indicating that approximately 79% of predictions are correct. This suggests that the models have a good overall rate of correct predictions for this dataset.
- **Precision**: The precision is also at 0.79 for LogisticRegression, which means that when the model predicts a team will win, it is correct about 79% of the time. This is valuable in scenarios where the cost of false positives (predicting a win when it's a loss) is high.
- **Recall**: With a recall of 0.79, the models are able to capture 79% of the actual wins. This is important in scenarios where missing out on true wins (false negatives) is costly.
- **ROC AUC:** The GradientBoosting model has the highest ROC AUC of 0.88, indicating a very good ability to distinguish between the winning and losing classes. ROC AUC is a robust metric as it evaluates model performance across all classification thresholds.

Traditional Models: AUC-ROC curve



Traditional Modeling: Feature Importance

- The feature importances from the RandomForest and GradientBoosting models give us insight into what factors are most predictive of a win in Valorant. Notably, 'death' is the most significant feature for both models, suggesting that the frequency of player deaths is a strong indicator of the match outcome.
- Other important features like 'kill', 'assist', 'acs', and 'adr' are also indicative of a player's contribution to the team's success, the three features mentioned earlier play a heavy role.

Modeling: Deep Learning

Data Preprocessing:

- Preprocessing steps include cleaning numerical features, handling missing values, scaling numerical features for normalization, and encoding categorical features.
- The preprocessing method returns scaled and encoded feature arrays ready for model input, along with a binary-encoded target variable array derived from a 'win_lose' column.

Goal: TRY to uncover differences between Deep Learning Rates and traditional model rates.

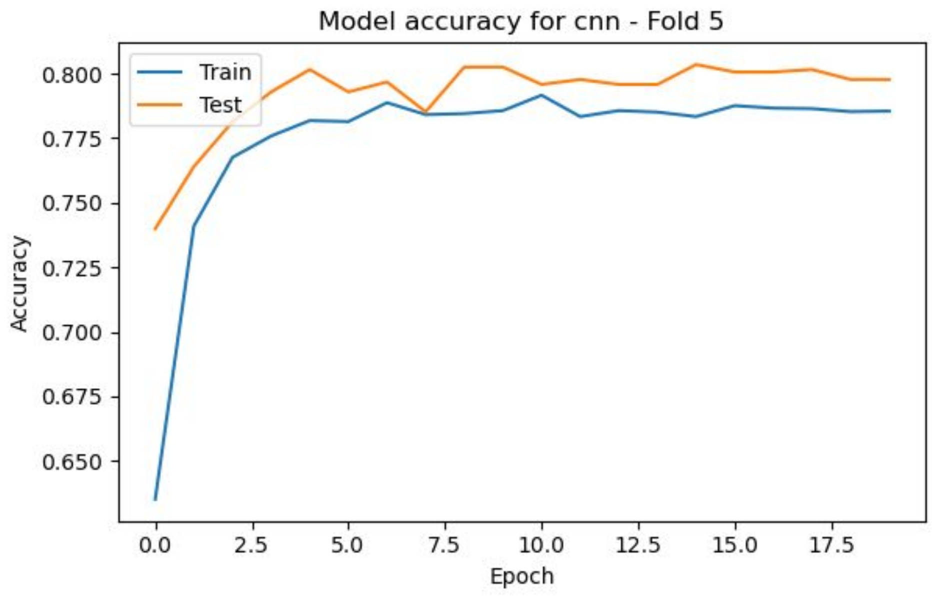
Deep Learning: Models

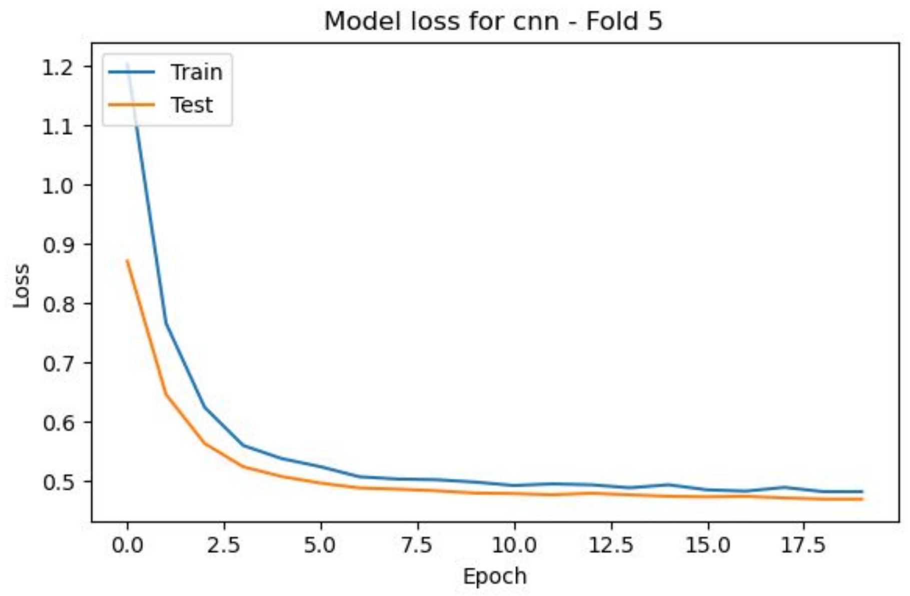
- Multi-Layer Perceptron (MLP): A basic dense neural network suitable for tabular data.
- Long Short-Term Memory (LSTM): A type of recurrent neural network (RNN) optimized for learning order dependence in sequence prediction problems.
- Simple RNN: A more straightforward RNN architecture for learning sequential patterns.
- Convolutional Neural Network (CNN): Primarily known for image processing but adapted here for time-series data.

Deep Learning: Training

- Cross Validation
- Binary Cross-Entropy Loss Function: good for binary classification problems.
- Early stopping is employed to prevent overfitting

Deep Learning: Evaluation Metrics

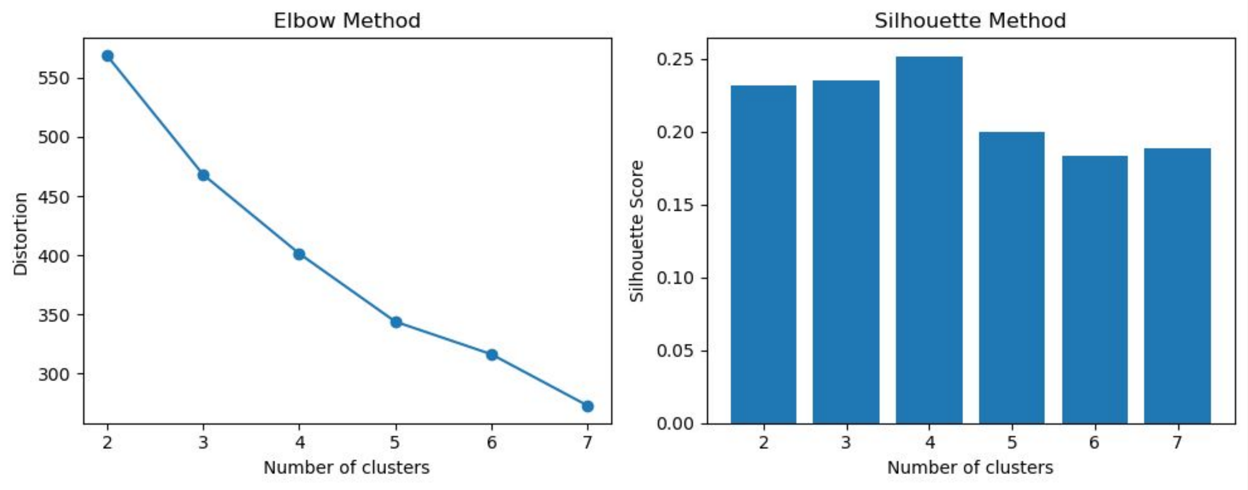




Recommendation Systems

- **Non-clustering calculation:** A method called agent_performance calculates the average performance metrics for agents on each map, displaying the top-performing agents. This could help teams understand which agents are typically most effective on any given map if you wanted to play them individually.
- **K-Means Clustering**: The cluster_teams method applies KMeans clustering to group similar team compositions together. A 3D visualization of the clusters is provided, using PCA for dimensionality reduction.

K-Means Clustering: # of Clusters



of Clusters Analysis

- The elbow method looks for a point of distortion where decreases happen slowly, this seems to be at cluster 3 or 4.
- The Silhouette Method measures how similar an object is to its own cluster compared to others. Cluster 2, 3, and 4 show a higher silhouette score, but there is a sharp decline after.
- **Three clusters** ended up being used because the elbow in the plot is a little more pronounced and the silhouette score difference was next to marginal.

K-Means Clustering Results

Cluster Results:

Using one map 'Ascent' as an example

Cluster 0:		Cluster 1:		Cluster 2:	
kayo	0.994737	cluster	1.00	cluster	2.000000
omen	0.989474	viper	1.00	omen	0.928571
jett	0.989474	harbor	1.00	killjoy	0.857143
sova	0.889474	reyna	1.00	jett	0.785714
killjoy	0.836842	raze	1.00	skye	0.642857
fade	0.094737	skye	0.75	viper	0.642857
cypher	0.078947	kayo	0.25	fade	0.285714
viper	0.052632	phoenix	0.00	breach	0.285714
sage	0.031579	sova	0.00	phoenix	0.142857
raze	0.015789	sage	0.00	cypher	0.071429
astra	0.010526	astra	0.00	harbor	0.071429
gekko	0.010526	breach	0.00	kayo	0.071429
skye	0.005263	killjoy	0.00	raze	0.071429
phoenix	0.000000	jett	0.00	sova	0.071429
reyna	0.000000	gekko	0.00	astra	0.071429
breach	0.000000	fade	0.00	gekko	0.000000
harbor	0.000000	cypher	0.00	reyna	0.000000
		omen	0.00	sage	0.000000

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How Can This Be Used

Agent Recommendations: Based on the prevalent compositions within a cluster, a recommendation system can suggest agents to players that complement the existing picks. For example, if a team has selected agents that are commonly found in Cluster 0 but hasn't chosen Kayo, the system might recommend picking Kayo to align with successful team strategies.\

Strategic Insights: For new or less experienced players, the system can provide insights on which agents are often picked together, helping them understand synergistic relationships and popular strategies within the game.

Future Improvements

- **Personalized Suggestions**
- **Algorithm Enhancements**
- **Model Testing**