DSA 210: Introduction to Data Science Spring 2025 - 2026

Clash Royale Meta Analysis: Card Usage and Performance in High Level Play

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Motivation

Understanding the current meta is crucial for competitive Clash Royale players who must decide which decks to play in order to succeed.By analyzing current usage and win rates, can provide insights. For instance, if a card is extremely common but has only average win rates, it might indicate that players use it for its utility or synergy rather than raw power. Conversely, a card with a high win rate but low usage might be a noticeable utility that could gain popularity in future metas. These insights help players understand whether following the crowd is justified or if there are opportunities to exploit less popular but effective cards. Finally, this project's findings could guide competitive players in making informed deck building decisions and also reflect on how well the game's balance aligns with player behavior.

Datasets & Data Enrichment

Using two primary data sources: RoyaleAPI and the official Clash Royale API. RoyaleAPI is a community driven analytics site that shows global Clash Royale statistics. In particular, obtained summaries of card UsagePct (percent of decks using the card) and WinPct (percent win rate when the card is played) for each card in four play brackets: All Ranked, Ladder, Top 1000, and Top 200. This 7 day window dataset covers. Also, accessed raw usage and win counts from the API data shown in *Figure 1.* to cross check totals. In total, data for ~160 cards per bracket were collected.

Data cleaning and enrichment steps included converting text to consistent card names, filtering out any cards with no data, and dropping cards with extremely low usage to reduce noise (cards with usage <1%). A rating metric from the data and computed UsageNumber and WinNumber shows by scaling the percentage values). This allowed us to treat usage and wins as counts for statistical tests. Brackets were encoded as categorical variables for modeling. All datasets were merged into a unified table of card stats by bracket.

1	CardName	Bracket	UsagePct	WinPct	Rating
2	Tower Princess	Top 200	93.0	48.0	49
3	Barbarian Barrel	Top 200	45.0	49.0	48
4	Skeletons	Top 200	32.0	49.0	47
5	Fireball	Top 200	31.0	48.0	45
6	Royal Ghost	Top 200	28.0	49.0	46
7	Electro Spirit	Top 200	26.0	48.0	44
8	Vines	Top 200	21.0	49.0	52
9	Minions	Top 200	17.0	49.0	49
10	Baby Dragon	Top 200	17.0	50.0	52
11	The Log	Top 200	15.0	47.0	42
12	Lightning	Top 200	15.0	48.0	46

Figure 1. Extracted card data with UsagePct and WinPct.

Data Collection & Preparation

The data collection process involved extracting data from the RoyaleAPI endpoints for each bracket and saving results as CSV. The consistency of usage percentages was verified. Percentages were converted into count by assuming a nominal total deck sample or by using the *UsageNumber* field from the decks dataset. For example, if a card had 45% usage and *UsageNumber*=50,000 in the *Ranked* bracket, set an approximate total decks = 50,000/0.45≈111,111.Computed estimated wins and losses by applying WinPct to the usage count. This allowed chi-square tests using integer counts rather than percentages. Also created new features. All data as shown in *Figure 2* were done in Python/pandas, and the final cleaned dataset contained 648 card bracket records after filtering.

1	Bracket	DeckName	Card1	Card2	Card3	Card4	Card5	Card6	Card7	Card8	WinPct	UsagePCT	Rating	UsageNumber	WinNumber	LoseNumber
2	Ultimate Champion	GolemEvoBBD	Baby Dragon	Valkyrie	Golem	Mini P.E.K.K.A	Battle Healer	Vines	Zappies	Elixir Collector	52.3	2	52	41,408	21,995	19,355
3	Ultimate Champion	EvoRHogs	Royal Hogs	Royal Ghost	Lightning	Ice Wizard	Goblin Hut	Skeletons	Electro Spirit	Barbarian Barrel	51.7	2.2	51	49,940	25,761	24,029
4	Ultimate Champion	GolemEvoBBDV2	Baby Dragon	Valkyrie	Golem	Mini P.E.K.K.A	Minions	Vines	Zappies	Barbarian Barrel	52.7	1	55	31,939	16,830	15,061
5	Ultimate Champion	WBEvoGhost	Skeleton Barrel	Royal Ghost	Wall Breakers	Dart Goblin	Vines	Bomb Tower	Barbarian Barrel	Rascals	52.4	1.2	54	37,306	19,565	17,723
6	Ultimate Champion	EvoRGFishboy	Royal Giant	Royal Ghost	Hunter	Fisherman	Fireball	Skeletons	Electro Spirit	Barbarian Barrel	50.9	3.7	51	114,242	58,190	55,959
7	Ultimate Champion	Lavaloon	Baby Dragon	Valkyrie	Lava Hound	Balloon	Fireball	Mega Minion	Vines	Tombstone	50.9	1.5	51	45,452	23,140	22,221
8	Ultimate Champion	X-bowCycle	Archers	Tesla	X-Bow	Knight	Fireball	Skeletons	Electro Spirit	Log	50.2	1.3	49	40,946	20,569	20,323
9	Ultimate Champion	EvoCannonHog2.6	Cannon	Skeletons	Hog Rider	Musketeer	Fireball	Ice Golem	Ice Spirit	Log	50.2	1	49	31,243	15,687	15,500
10	Ultimate Champion	EvoMuskLoon	Musketeer	Skeletons	Balloon	Miner	Ice Golem	Barbarian Barrel	Giant Snowball	Bomb Tower	49.8	1.5	48	46,877	23,353	23,481
11	Ultimate Champion	HogMM2.6	Firecracker	Cannon	Mighty Miner	Hog Rider	Earthquake	Skeletons	Electro Spirit	Barbarian Barrel	49	1.8	46	54,096	26,523	26,523
12	Ranked	WBEvoGhost	Skeleton Barrel	Royal Ghost	Wall Breakers	Dart Goblin	Vines	Bomb Tower	Barbarian Barrel	Rascals	54.3	0.7	59	68,903	37,384	31,500
13	Ranked	Lavaloon	Baby Dragon	Valkyrie	Lava Hound	Balloon	Fireball	Mega Minion	Vines	Tombstone	52.4	0.6	55	60,328	31,594	28,643
14	Ranked	EvoRHogs	Royal Hogs	Royal Ghost	Lightning	Ice Wizard	Goblin Hut	Skeletons	Electro Spirit	Barbarian Barrel	52.2	0.8	55	79,160	41,311	37,696
15	Ranked	EvoMuskLoon	Musketeer	Skeletons	Balloon	Miner	Ice Golem	Barbarian Barrel	Giant Snowball	Bomb Tower	51.8	0.9	53	86,738	44,938	41,756
16	Ranked	EvoRGFishboy	Royal Giant	Royal Ghost	Hunter	Fisherman	Fireball	Skeletons	Electro Spirit	Barbarian Barrel	51.7	1.8	53	177,835	91,877	85,864

Figure 2. Extracted Deck data.

Exploratory Data Analysis

Figure 5 summarizes card usage and win rate statistics by bracket. Average usage percentages are similar (~5–6%) across brackets, but win rates trend slightly lower in higher brackets. For instance, the Top 200 bracket had a mean win rate of 46.7%, versus 50.4% in the Ladder bracket. Median usage is 3% or 4% in all brackets, indicating most cards are rarely used, while a few cards have extremely high usage. The standard deviation of win rate is larger in Top 200 (7.19) than in All Ranked (1.80), reflecting greater variability at the highest skill level.

Also examined the relationship between usage and win rate. *Figure 3* shows a scatter plot of usage percentage vs. win percentage for all cards across brackets. The points are widely dispersed with no clear linear trend: some highly used cards have low win rates, and some rarely used cards have high win rates.

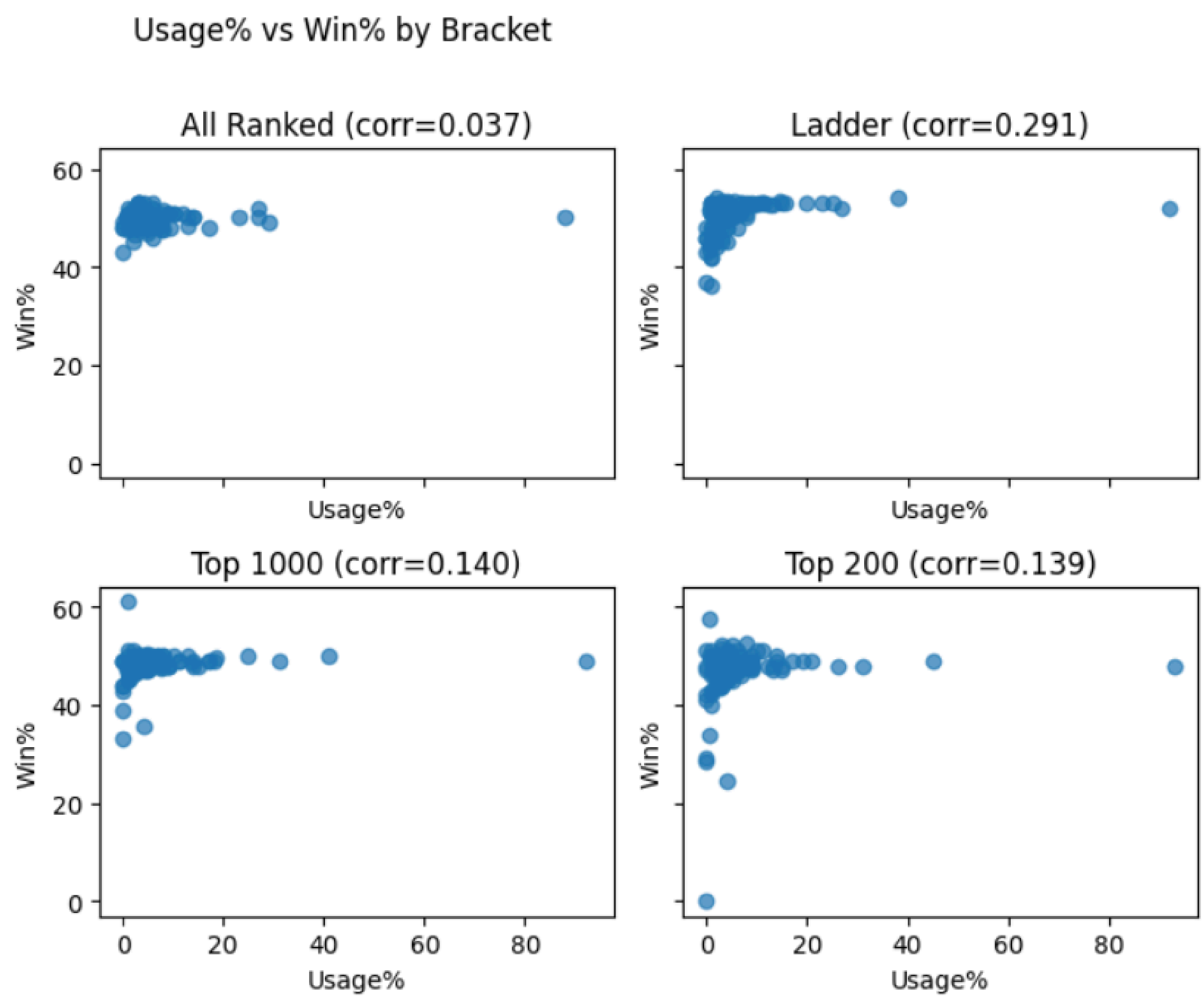
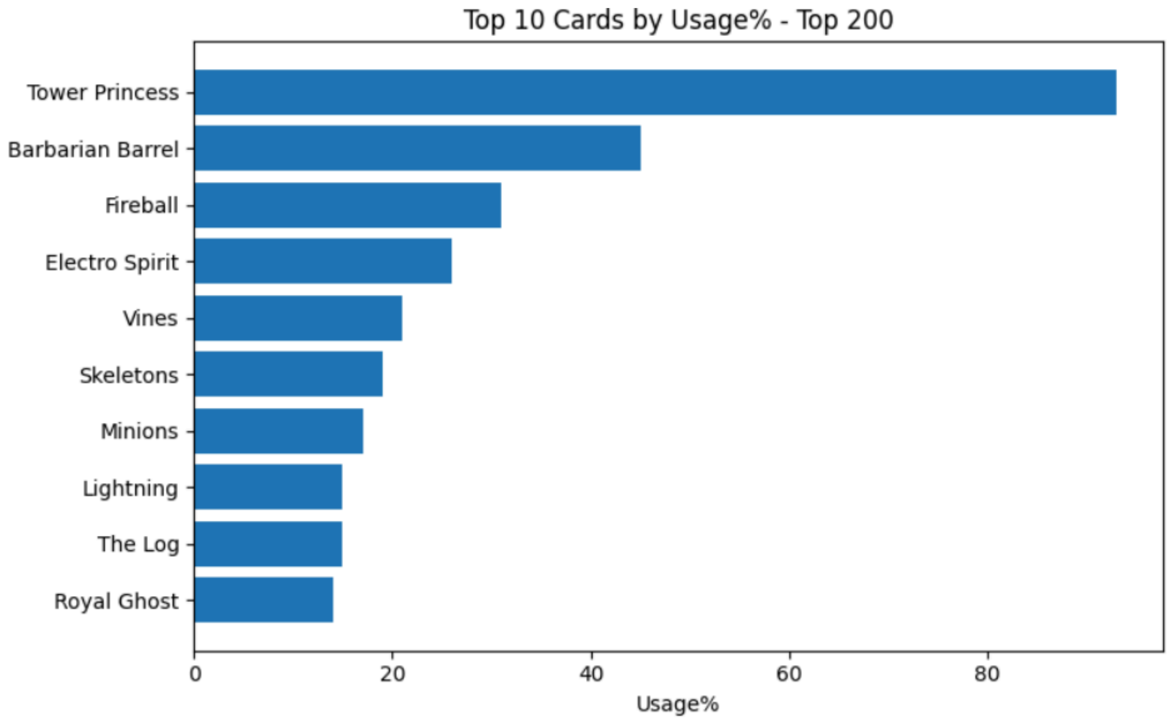


Figure 3. Usage vs Win rate by Bracket.

Comparing brackets, *Tower Princess* stands out: it was the top used card in the Top 200 (93% usage) and Ladder (92%) brackets. Other consistently high usage cards include The Log, Fireball, and Skeletons, each appearing in the top-five usage list of multiple brackets.



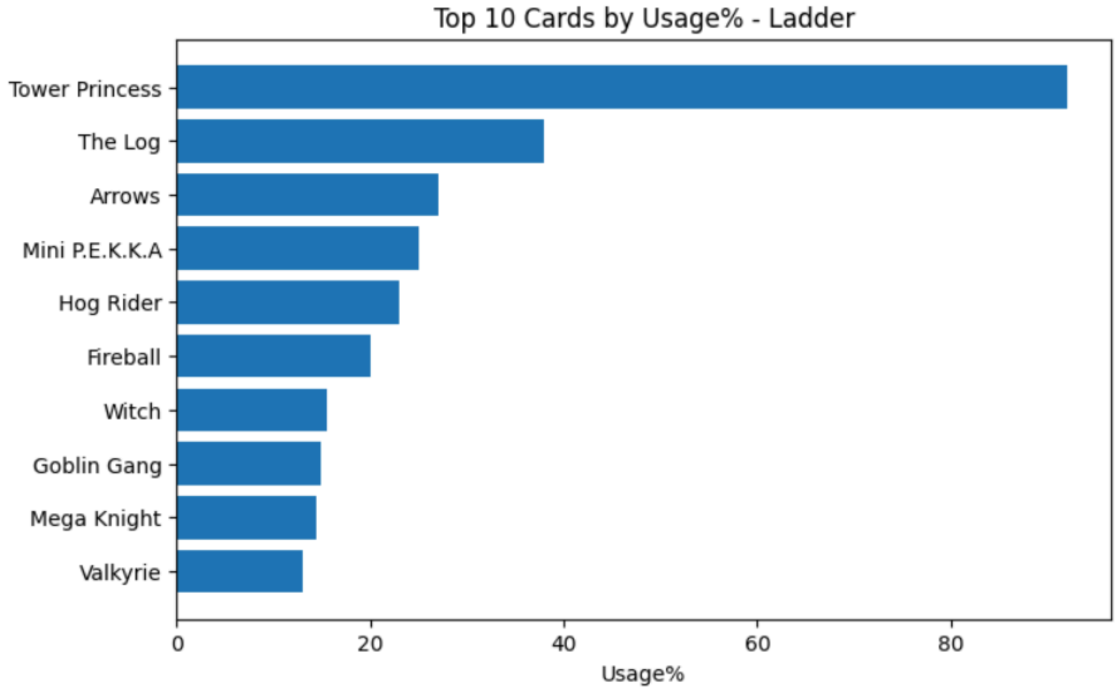


Figure 4. Top 10 Cards Usage rate Ladder and Top 200.

However, even the most used cards had win rates near 48–54%, similar to the overall average, indicating a balanced meta shown in *Figure 5*. Overall, usage varies widely between brackets and between cards, while win rates cluster around 50%. The EDA suggests that bracket context changes which cards are popular, but does not drastically skew win probabilities.

```
Top 10 by UsagePct in Top 200:
            CardName  UsagePct  WinPct
460   Tower Princess      93.0    48.0
27  Barbarian Barrel      45.0    49.0
138          Fireball     31.0    48.0
110   Electro Spirit      26.0    48.0
468             Vines     21.0    49.0
420         Skeletons     19.0    49.0
314           Minions     17.0    49.0
274         Lightning     15.0    48.0
444           The Log     15.0    47.0
386       Royal Ghost     14.0    49.0

Top 10 by UsagePct in Top 1000:
            CardName  UsagePct  WinPct
459   Tower Princess      92.0    49.0
26  Barbarian Barrel      41.0    50.0
137          Fireball     31.0    49.0
109   Electro Spirit      25.0    50.0
419         Skeletons     18.5    49.5
443           The Log     18.0    49.0
313           Minions     17.0    49.0
467             Vines     17.0    49.0
10             Arrows     15.0    48.0
305     Mini P.E.K.K.A    14.0    49.0

Top 10 by UsagePct in Top Ladder:
          CardName  UsagePct  WinPct
458 Tower Princess      92.0    52.0
442        The Log      38.0    54.0
9           Arrows      27.0    52.0
304 Mini P.E.K.K.A      25.0    53.0
236      Hog Rider      23.0    53.0
136       Fireball      20.0    53.0
478          Witch      15.5    53.0
192    Goblin Gang      15.0    53.0
288    Mega Knight      14.5    53.5
462       Valkyrie      13.0    52.5

Top 10 by UsagePct in All Ranked:
            CardName  UsagePct  WinPct
457   Tower Princess      88.0    50.0
441          The Log      29.0    49.0
8             Arrows      27.0    50.0
24  Barbarian Barrel      27.0    52.0
135         Fireball      23.0    50.0
235        Hog Rider      17.0    48.0
303   Mini P.E.K.K.A      14.0    50.0
191      Goblin Gang      14.0    50.0
107   Electro Spirit      13.0    50.0
417        Skeletons      13.0    48.5
```

Figure 5. Top 10 Cards Usage rate and Win rate all across brackets.

Hypothesis Testing

Hypothesis testing formulated on two hypotheses and tested them with chi-square tests (α=0.05):

- **Hypothesis 1 (Usage Differences):** "Card usage distribution differs significantly across brackets." and binned each card's usage percentage into categorical levels (quartiles) and performed a chi-square test of independence on Bracket vs. Usage Category. The contingency table (count of cards in each usage quartile by bracket) yielded χ^2=425,039 with $p \approx 0.01364$ shown in *Figure 3*. Since $p<0.05$, reject the null hypothesis and conclude card usage does differ significantly by bracket. In other words, the mix of high, medium, and low usage cards is not uniform between Top 200, Top 1000, Ladder, and All Ranked.

```
Chi-square statistic: 425.039
p-value: 0.01364
Degrees of freedom: 363
```

Figure 3. Chi-square test statistics.

- **Hypothesis 2 (Win Rate Differences):** "Card win rate distribution differs significantly across brackets." similarly binned win percentages and performed a chi-square test on Bracket vs. Win Category. However, because this involves multiple comparisons and applied a Bonferroni correction. For $m=4$ brackets, the adjusted $\alpha'=0.05/4 \approx 0.000442$ shown in *Figure 4*. All bracket pairs had $p>0.0125$ after correction, so fail to reject the null hypothesis under the stricter criterion. Thus, after correcting for multiple tests, there is no significant difference in win rate distribution across brackets.

```
Number of cards tested: 113
Bonferroni alpha per test: 0.000442
Cards with significant bracket differences in win rate:
```

Figure 4. Bonferroni test statistics.

The chi-square test results are summarized above (showing χ^2, dof, and p-values). Note the application of Bonferroni α=0.000442 for H2.

Feature Engineering

To prepare for modeling:

- **One-hot encoding** of the bracket field (creating binary indicator variables for each bracket).

- **UsagePct binning:** For classification of popularity, binned *UsagePct* into categorical levels (Low, Medium, High) using quantile ranges.

- **Derived target (Popularity):** Defined a card's *Popularity* label (Low/Medium/High) based on its usage percentile.

- **Numeric transformations:** Retained UsagePct, WinPct, and Rating as numeric predictors. No further scaling was needed given similar numeric ranges.

These transformations yielded a design matrix suitable for regression and classification. Dummy variables for brackets and a popularity target label were the key engineered features.

Machine Learning Modeling

Performed two prediction tasks using Python:

Regression Task (WinPct): Predict each card's win rate using its usage, rating, and bracket. Trained a Linear Regression model and a Gradient Boosting Regressor on 80% of the data, evaluating on a 20% hold out set. compares the models by Root Mean Squared Error (RMSE) and R^2:

```
Linear Regression: RMSE = 4.361, R^2 = 0.488
```

Figure 5. Linear Regression.

```
Gradient Boosting Regressor: RMSE = 1.891, R^2 = 0.904
```

Figure 6. Gradient Boosting Regressor.

Classification Task (Popularity): Classified cards into Low, Medium, or High popularity based on UsagePct (as defined above). Predictors were UsagePct, WinPct, Rating, and bracket dummies. Compared a multinomial Logistic Regression and a Random Forest classifier. Both models achieved perfect accuracy on the test set. the metrics, which are all 1.0. The Random Forest's confusion matrix is the identity matrix shown in *Figure 7* . This perfect performance is expected because Popularity was directly derived from UsagePct, a feature included in the model.

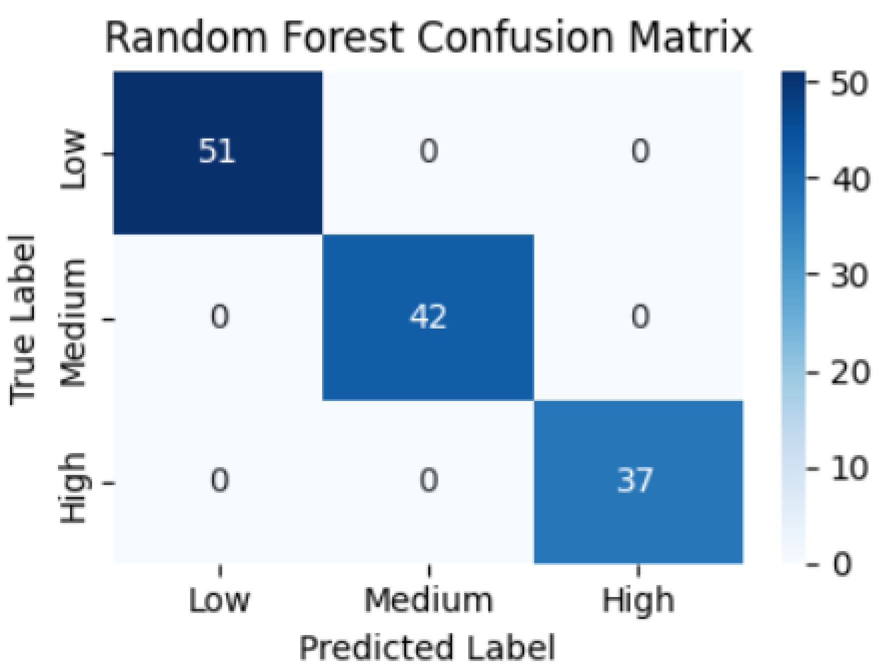


Figure 7. The Random Forest's confusion matrix.

Key Findings

- **Usage by Bracket:** Card usage rates do vary significantly across brackets (H1 rejected). High tier play has a different distribution of popular cards compared to ladder and broad ranked play. For example, some cards reach very high usage in Top 200 that are less common elsewhere.

- **Win Rates by Bracket:** There is no strong evidence of different win rate distributions across brackets once multiple comparison correction is applied (H2 not supported after Bonferroni). All brackets exhibit mean win rates near 50%.

- **Regression Modeling:** The Gradient Boosting Regressor predicted *WinPct* much better than linear regression (higher R^2). This suggests nonlinear interactions influence win rate.

- **Classification Modeling:** The Random Forest perfectly predicted popularity bins. This outcome is trivial since *Popularity* was derived from *UsagePct*, and *UsagePct* was included as a feature. In practice, a simpler threshold rule would suffice.

Limitations & Future Work

This analysis has limitations. First, using percentage data instead of full game logs, so all counts are approximate. Without true sample sizes for each card, statistical tests may lack sensitivity. In particular, chi-square tests on binned percentages are not fully robust. Accessing the raw battle data would improve test validity. Second, the 7 day time interval may not capture longer term trends or newer balance changes. Extending the time window or using rolling averages could smooth noise. Third, popularity target was artificially based on usage percentile; real popularity could be defined more continuously.

Future work could make more features, such as card rarity or interactions. Automating regular data extractions via the Clash Royale API or RoyaleAPI's endpoints would allow ongoing meta tracking. More complex models or cross validation over time could also be explored. Finally, integrating deck composition data (beyond single cards) might yield deeper strategic insights.

Technology Stack

- **Language & Libraries:** Python (pandas, NumPy) for data analysis and modeling.
- **Visualization:** Matplotlib and Seaborn for plots.
- **Statistics:** SciPy for chi-square tests.
- **Data Sources:** RoyaleAPI and official Clash Royale API.
- **Environment:** Jupyter notebooks for analysis and VS Code for development.

Project Timeline

- **Week 1 and 2:** Data collection from RoyaleAPI and ClashRoyale API, initial cleaning and exploratory analysis.
- **Week 3 and 4:** Detailed EDA and statistical hypothesis testing.
- **Week 5:** Feature engineering and model development (regression and classification).
- **Week 6:** Model evaluation, interpretation of results.
- **Week 7:** Writing report, creating tables and figures, and revisions.