Predicting Winners in Clash Royale Using Logistic Regression and Random Forest Models

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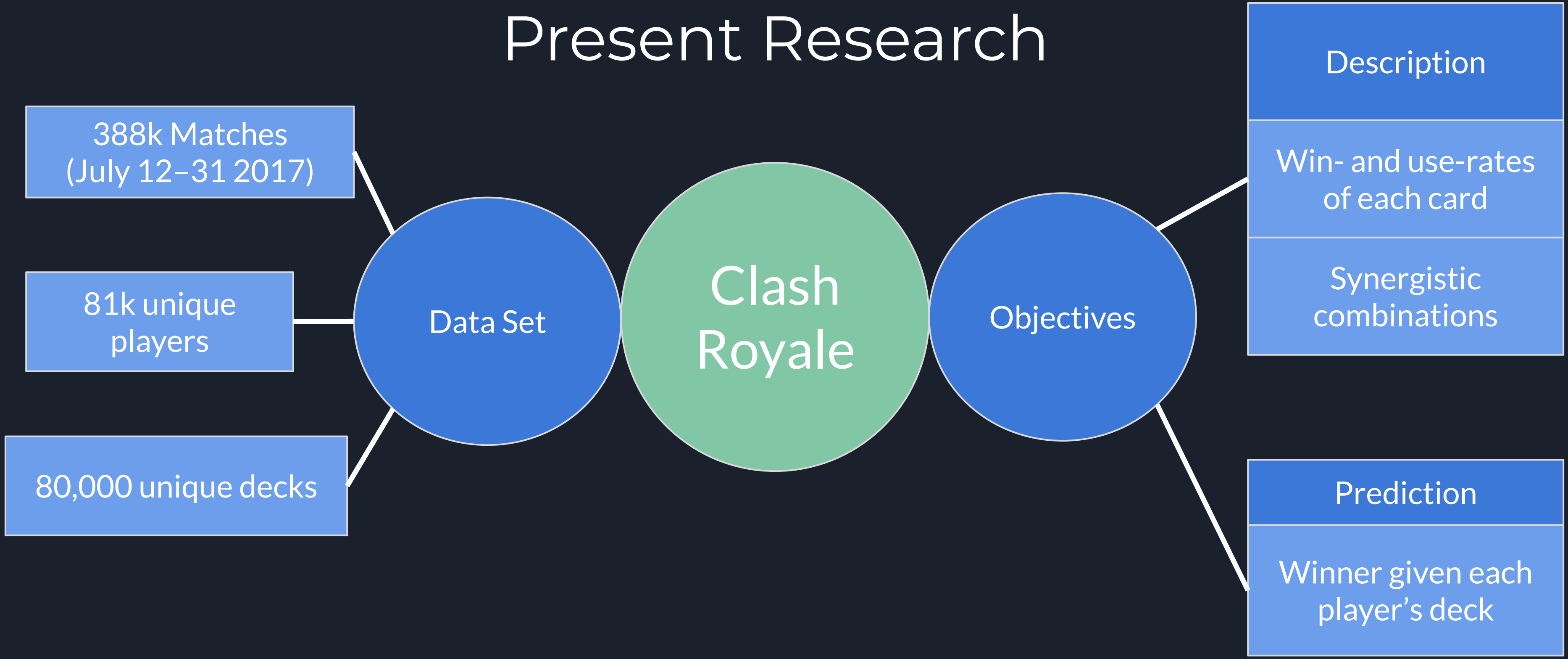
What is Clash Royale

- Real-time Multiplayer Strategy (1v1 or 2v2)
- Esport leagues and tournaments
- 8 card decks (troops, buildings and spells)
  - 380 trillion possible combos
- 12th highest-grossing mobile game of all time (>$2bn)

Present Research



Why

Developer insights

- Card and deck balancing
- Luck:skill ratio

Player performance insights

- Enable better decision making and learning strategies
- Optimal choice of deck

Skill development

- Strengths of different ML models
- Does expanding to more complex models give more info and accuracy?
- Data preprocessing pipelines

eSports casting and viewer experience

Player experience - motivation and enjoyment

Literature Review & Industry Relevance

Predicting Game Outcomes in Dota 2

- Features
  - Draft results
  - Heroes' win rates - 63%
  - Synergies and countering features - 73%
- Models used:
  - Naive Bayes classifier
  - Logistic Regression
  - Gradient Boosted Decision Trees
  - Factorization Machines
  - Random Forests
  - Support Vector Machines

Industry Applications

- **Clash Royale:** StatsRoyale
- **Hearthstone:** https://hsreplay.net
- **Magic The Gathering Arena:** mtga.untapped.gg

Related Papers	Models Investigated	Results
Dota 2 Win Prediction	Logistic Regression Random Forest	**Logistic Regression = T_73.2%, V_72.9%** Random Forest = T_99%, V_67% **Predictors:** Random = 50.1%, Heroes win rate = 63%, **Synergy & countering features = 73%**
Predicting Win-Rates of Hearthstone Decks	Ensemble model: 2x Logistic Regression & Deep Learning model	Winning model in AAIA'2018 data mining challenge
Predicting Winning Team and Probabilistic Ratings in "Dota 2" and "Counter-Strike"	Baseline: TrueSkill Logistic Regression Decision Trees	Wanted to compare their ML system with other rating systems and to improve the TrueSkill model used in these games. Highlighted improved predictions but wasn't clear to understand.
Predicting Win Rates for New Decks	Support Vector Regression Models (SVR)	Using active learning cycle approach to investigate production of new decks and predict their win rates

Description and Card Statistics

Data Pre-processing

- Removed non-ladder matches (~320k)
- Removed draws (~20k)
- One-hot encoded card decks

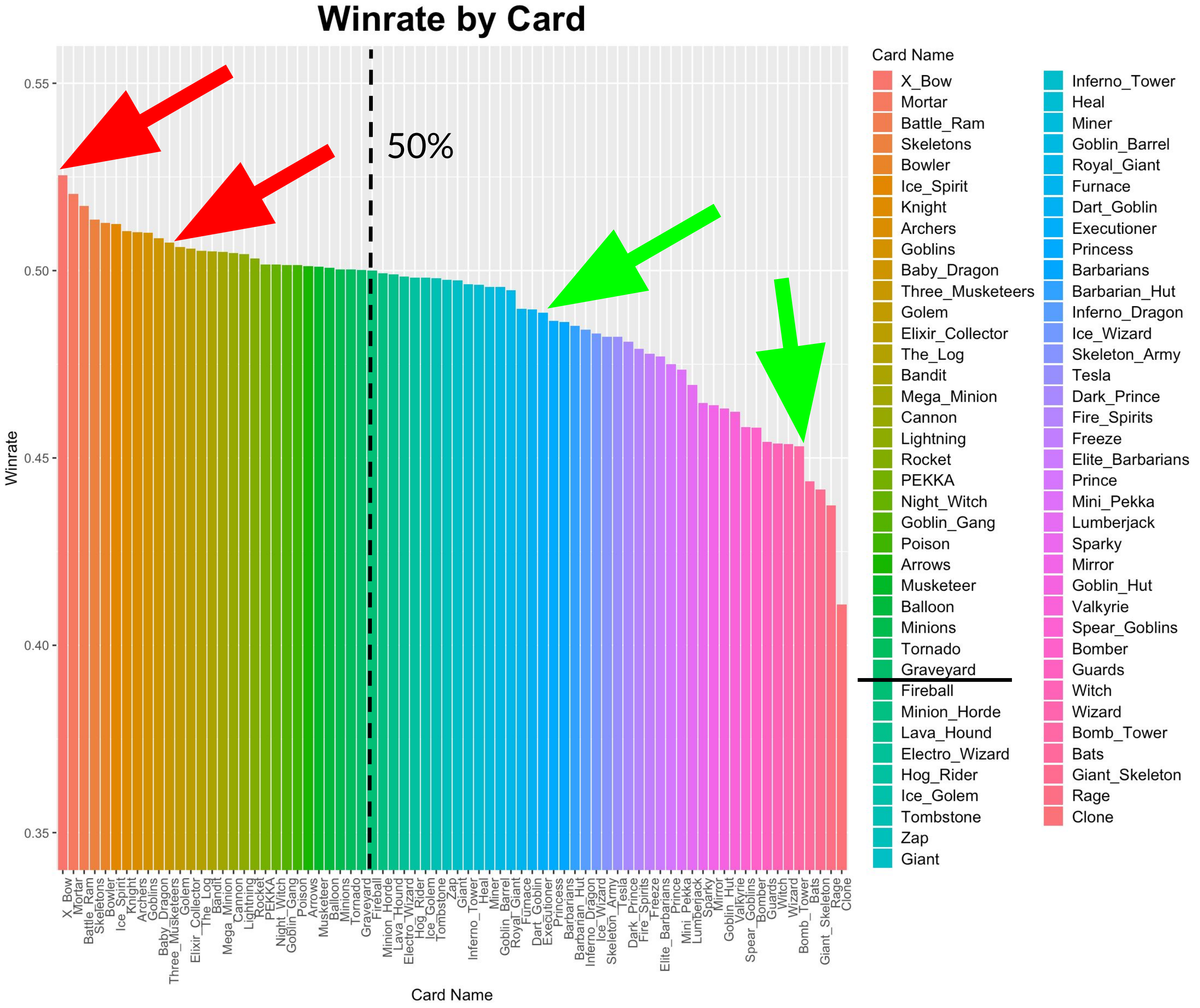
- ML Features
  - Trophies
    - Player 1 and 2
    - Difference
  - Cards
    - 8 cards out of 70
  - Card levels
    - 1–13

Best Combo:

X-Bow + Three Musketeers

84.2% winrate

32/38 matches



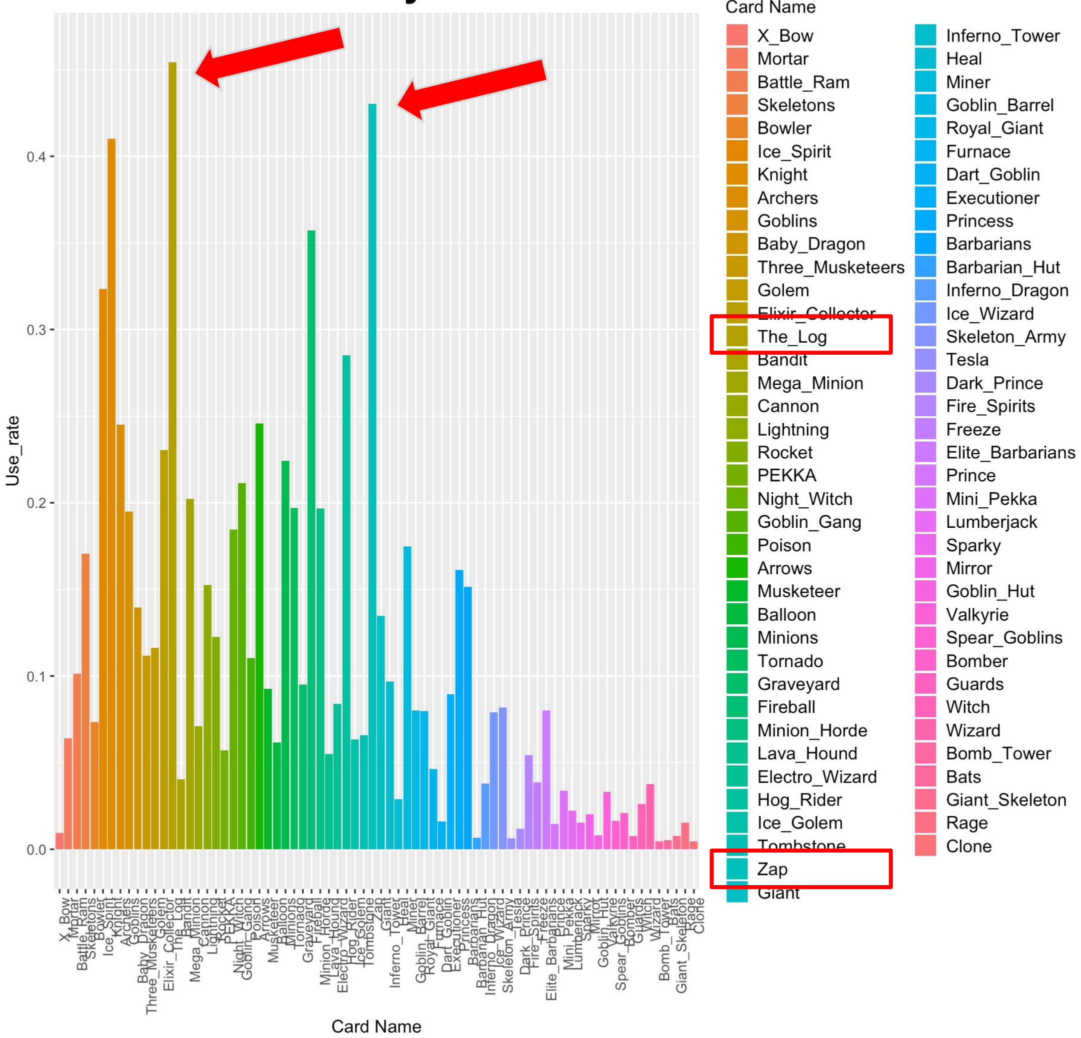
Worst Combo:

Dart Goblin and Bomb Tower

4% winrate

1/25 matches

Useserate by Card



Prediction

Selection Criteria for ML Methods

- Classification is a vehicle to understand the influence of a player's deck on their chances of winning
- Models should be interpretable
- and fit the limited resources of the module
  - Time
  - Computing power

- Logistic Regression
- Random Forest

ML Models

Logistic Regression

- With trophies/trophy discrepancy → 98.5% accuracy
- With cards only → 58%
- Cards + card levels
  - 58 %
- Only cards
  - 55.9 %
- Only card levels
  - 57.9 %
- Only trophy discrepancy
  - 98.59 %

Initial Interpretations

Good players do well even with bad cards

P2W argument weakened in some way - bad players do poorly even with good cards

Linear Models

Features	Logistic Regression	Random Forest
All (trophies, cards, and card levels)	98.59 %	57.65 %
No card levels	98.58 %	98.59 %
Only cards	55.91 %	55.91 %
Only card levels	57.9 %	55.91 %
Only difference in trophies (1 feature)	98.59 %	98.59 %

The Epiphany

- Near-perfect prediction depends on one single feature
  - The difference in trophies between the two players
- Unstandardised coefficient: `-0.09757535`
  - For every point in trophy difference a player's chance of winning drops by 10 %

- Trophies are reported post-match in the data set

Deeper Model 🤖

Multi-Layer Perceptron (Neural Network)

- 309 features
  - Cards and card levels
  - Card stats (avg. card levels and discrepancy, total deck elixir cost)
- 2 hidden layers (512 and 64 nodes)

- 272 epochs of weight optimisation (~45 minutes)
- 78 % accuracy

What does this mean?

- ✔️ Ability to recommend synergies and counters
- ✔️ Usefulness for balancing and metagame tracking
- ✔️ Prediction accuracy very strong
    - ‼️ But only with uninterpretable model

- ❓ Possibility to predict effectiveness of new decks

Limitations

- Deck of cards is only the starting point of a match
  - Strategy can only be modelled with detailed gameplay data
- No way of extracting pre match trophy count
- Our best model provides no insights for players

Future Work

- More complicated combinations of cards
- Web App
- Division of trophy ranges
- Deck clustering
- Infinite alternative ML models!

Live Demo 😱

Crown Championship Spring Finals (EU)
Playing for $15,000

Thank you!

Shoutout to my mom, she's the best