WHAT WILL ASH DO?: POKÉMON BATTLE PREDICTOR

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1 INTRODUCTION

Pokémon is a popular media franchise, with the core concept driven by Pokémon trainers who catch and train Pokémon, and battle other Pokémon and trainers to become the Champion. Each Pokémon has various qualities, such as its type, abilities and stats such as attack, defense, etc. So, Pokémon battles are strategic in nature, and trainers take all these factors into account before choosing their best Pokémon to battle the opponent. In this project, we aim to use datasets of Pokémon descriptors and battle match-ups to predict the best Pokémon for a trainer to play given the opponent Pokémon, using Spark and Tensorflow.

2 PROBLEM STATEMENT

The data used are the Complete Pokémon Dataset (Romero, 2021) and Pokémon- Weedle's Cave (Hackathon, 2017) datasets. The first has a detailed list of Pokémon along with descriptions and information on each of their unique abilities. The second dataset has two files: one with the battle pairings and the battle winner, and one with a list of Pokémon and their descriptors.

Exploratory data analysis (EDA) will be performed on the datasets using Spark to get some insight into the relationship between the features and the battle outcomes. Based on this analysis, the final feature set to be used can be determined. Lastly, we plan to deploy classification machine learning algorithms on these features using packages like Scikit-learn and Tensorflow to predict the likely winner of a battle given two Pokémon.

After putting our models to the test, we intend to expand it to include in-battle scenarios. In these cases, we will advise a trainer facing an opponent with a set of six Pokémon on what Pokémon to use to win. In order to know the outcome of a battle if we have already predicted it for that particular Pokémon combination, we would also save the predicted values in a database. This would reduce the number of predictions needed to choose the optimal Pokémon to utilize in a match.

The machine learning models will be evaluated on metrics such as accuracy, precision, recall and F1-score. The scalability of the system will be evaluated by varying the number of threads and measuring the corresponding latency.

3 TECHNICAL APPROACH

By this milestone, we have completed pre-processing and combining the datasets, and have conducted a detailed EDA.

For these components, we utilized PySpark and Jupyter Notebooks.

The datasets were loaded into Spark DataFrames. The two datasets with descriptive features of each Pokémon were combined using the Spark transformation join. Irrelevant features such as names of Pokémon in other languages were dropped. An inner join with the 'combats' dataset was performed so as to generate a DataFrame with each row containing the details of both Pokémon involved in a battle, and the winner of the battle. The Winner feature was encoded with 1 representing the winner being the first Pokémon, and 0 indicating that the second Pokémon was the winner. The newly created data frame was written into a csv file for EDA, and the columns relevant for training the classification models were retained and written into a corresponding csv file.

For the EDA task, Spark DataFrames and the Pandas API on PySpark were used. The average of stats like Attack and Defense was calculated type-wise. The win-percentage of each type of Pokémon was plotted, to obtain the best and worst performing Pokémon. The win percentage of each type of Pokémon in battles against each other type was also visualized. Some of the key plots have been listed in the next section. These provided valuable insights into the datasets, telling us which features play a role in determining the winner of a battle, and will help us with feature selection prior to training our classification models.

4 PRELIMINARY RESULTS

A selection of the visualizations obtained from the EDA have been listed. These provide key insight for the upcoming modules of the project - feature selection and model training.

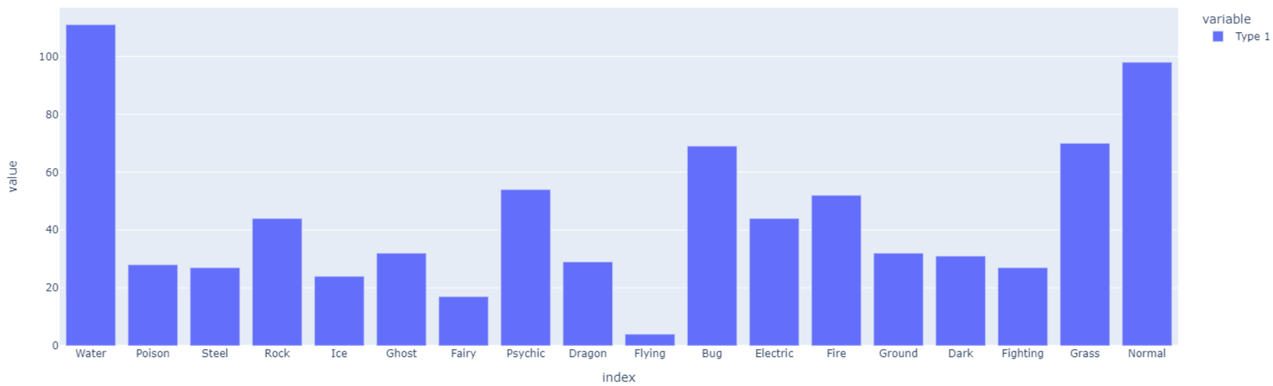

Figure 1. A plot showing the number of Pokémon of each type in the dataset

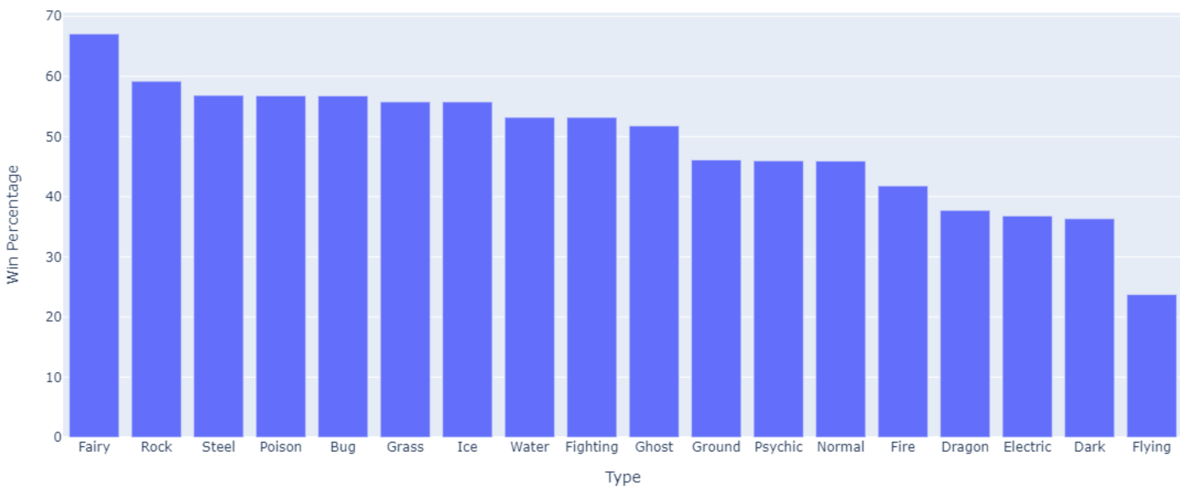

Figure 2. The win-percentage of each type of Pokémon

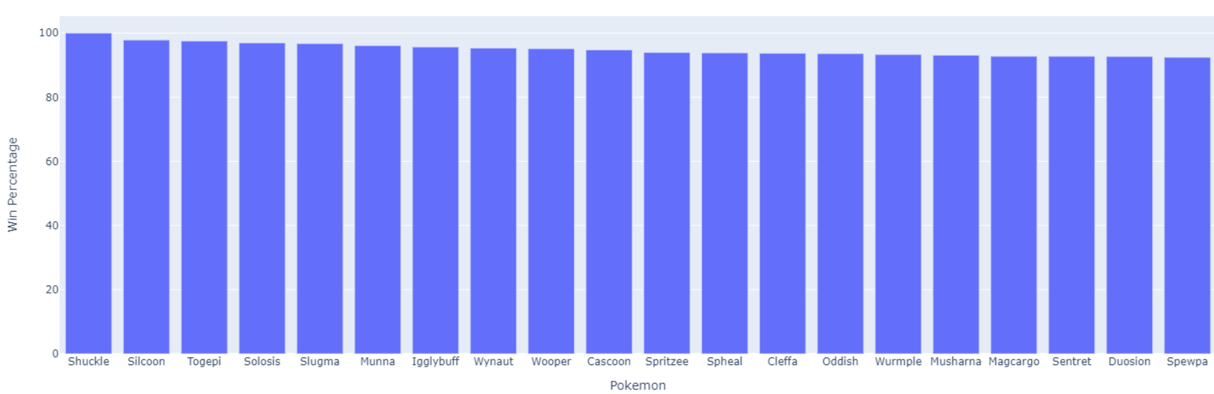

Figure 3. The Top 20 Pokémon with highest win percentages

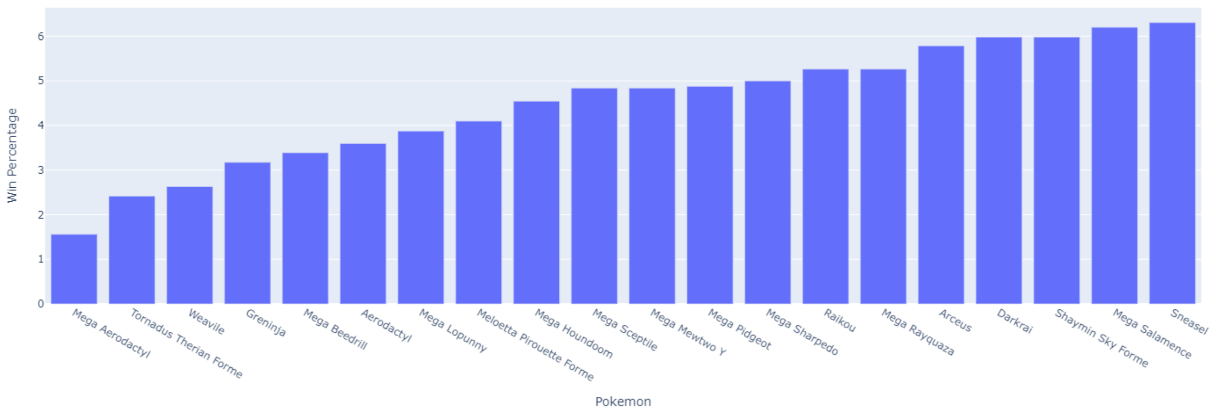

Figure 4. The Bottom 20 Pokémon with lowest win percentages

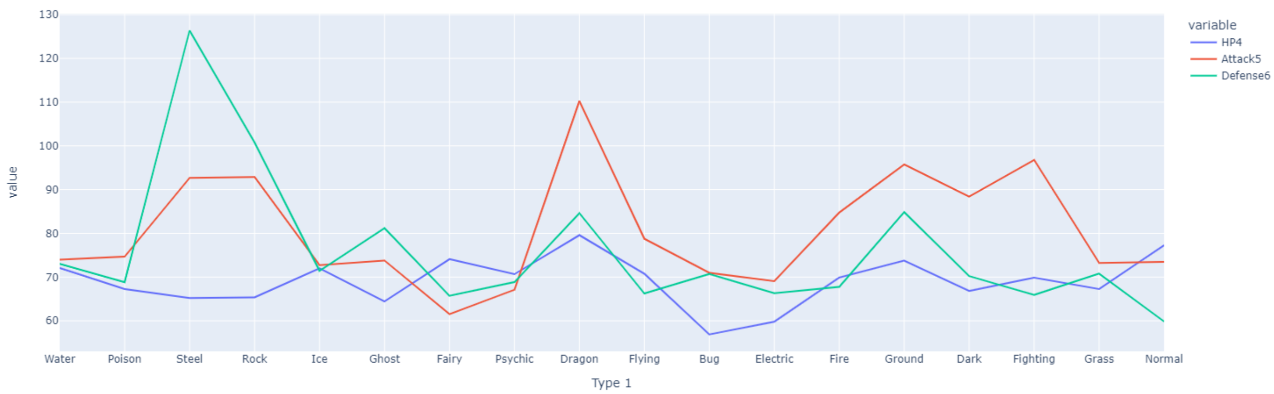

Figure 5. Plot of the HP, Attack and Defense stats by type

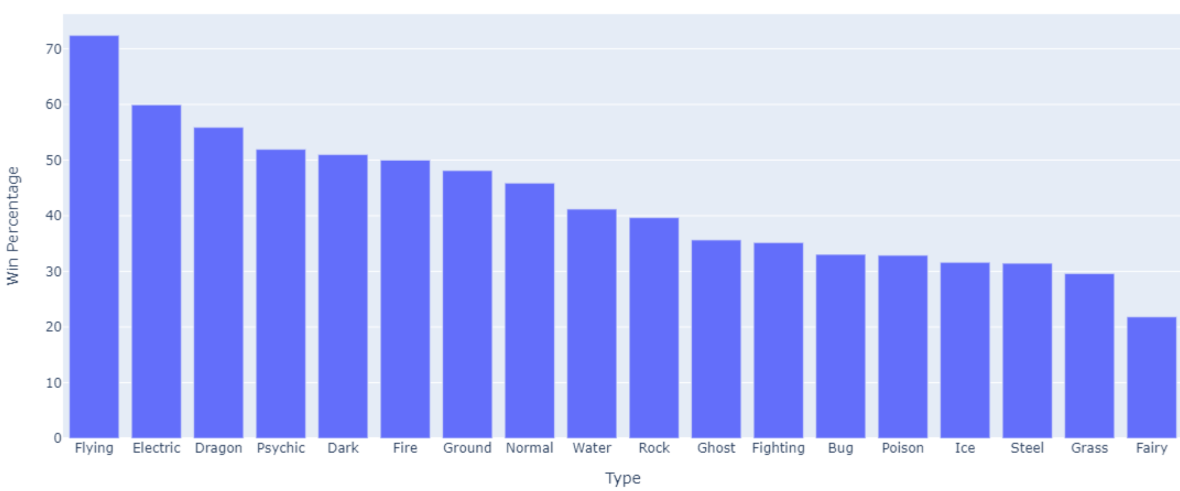

Figure 6. Win percentage of Fire Type Pokémon against other types

We now have a better understanding of the trends and patterns that our final model should exhibit. For example, the win percentage of Fire Type Pokémon against Water Type Pokémon is quite low. So, we expect this factor to come into play when we predict the outcome for a battle between a Fire and Water Pokémon.

REFERENCES

Hackathon, T. Pokemon- weedle's cave, 2017. https://www.kaggle.com/datasets/terminus7/pokemon-challenge.

Romero, M. T. Complete pokemon dataset (updated 16.04.21), 2021. https://www.kaggle.com/datasets/mariotormo/complete-pokemon-dataset-updated-090420.