Yu-Gi-Oh! Data Report

**Dataset Overview:**

* **Total Entries**: 13,281
* **Total Columns**: 29 columns

**Background:**Yu-Gi-Oh! is a popular trading card game played in nearly every corner of the world. For my analysis, I chose to focus solely on the Trading Card Game (TCG), which is played globally, and exclude data from the Original Card Game (OCG), which is exclusively played in Asian territories. My background as a professional competitive player gives me insights into the game and its inner workings that a machine (or inexperienced observer) may not understand. Between topping 4 regional tournaments, countless locals, and qualifying for the World Championship in 2020, I have built quite a reputation for my game knowledge and skill within the community. I have played the game since I was an adolescent and have been involved in the competitive scene since I was twelve years old. My love and passion for the game has led me to create many tournament-topping decks, and even pioneered my own hybrid rogue decks that to this day still see competitive use. Not only do I feel that this background qualifies me to knowledgably speak on the subject, but it also is the reason for why I close this specific dataset for my project. This project is not only something that I found interesting, but something I learned from. I believe that in the future I will be using the Yu-Gi-Oh! API/Database in order to filter through competitively successful cards in order to perfect new decks, and refine old ones.

**Purpose:**The purpose of this project is to determine relationships, patterns, and perform an analysis on a dataset. More specifically, the [Yu-Gi-Oh! API](https://ygoprodeck.com/api-guide/), which can also be found on [Kaggle](https://www.kaggle.com/datasets/ioexception/yugioh-cards). Within this dataset, I intend to find relationships between different attributes of the cards and predict cards’ archetypes and levels based off certain metrics. My goal is to explore and determine any patterns that may arise from this exploratory analysis.

**What all makes a card?**

In Yu-Gi-Oh!, a card has many ‘pieces’ that all play a part in making each card an individual:

* Card Name
  + Name of the card, often includes an archetype of its ‘group’ of alike cards
* ATK/DEF
  + Represents the power of a card whenever placed in a vertical position (attack) or horizontal position (defense)
* Stars/Arrows/Scale
  + Represents the ‘level’ or ‘rank’ of the card in layman’s terms
* Text
  + Either used as flavor text, or to show a card has effects
* Type
  + ‘Race’ of the card
* Attribute
  + ‘Element’ of the card
* Card Type
  + Spell, Monster (Type), Trap

**Exploratory Analysis:**When first introducing myself to the dataset, there were a few things I wanted to try out. First, I wanted to determine the relationship between attack and defense values, level and attack values, along with level and defense values. Throughout all three analyses, I found a positive correlation in the data.

Comparing attack and defense values across the TCG (fig. 1), there is a noticeable upwards trend. As a monster’s attack grows, its defense usually follows. Although there is a defined ‘box’ that a lot of cards fall into (3000/3000 atk/def), that can be chalked up to the nature of the game’s mechanics. For one reason or another, 3000 seems to be the ‘hard cap’ for many monsters, with only excessively powerful outliers being able to break that power cap. There is a clearly defined ‘trend’ in the densest areas that shows a near 1:1 attack-to-defense ratio.

Comparing a card’s level to its attack values (fig. 2), a slight trend can be seen, with denser areas of the data showing a slight upwards trend, but with a lot of variance beyond level 6. Beyond level 10, the values shoot up, but also become more and more deviant from the ‘middle’ of the pack, with little actual relation between level and attack values.

Comparing a card’s level to its defensive value (fig. 3), across the board all ranges seem to be quite similar, with no real trend to be spotted. Near the higher levels (8+), any discernable similarities between the levels soon devolves into utter randomness, with very little correlation between a card’s level and its defensive values.

The discrepancies between the tail-ends of the plots can be explained by the fact that many high-power (and in turn, higher level) cards have powerful card effects. Rather than just a big number for offensive and defensive values, these cards rely on their effect on the game to deal damage to opponents.

A chart of a graph

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Fig. 1: ATK vs DEF Values Across The TCG

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Fig. 2: Level vs ATK Values Across The TCG

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Fig. 3: Level vs DEF Values Across The TCG

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Fig. 4: Distribution of Card Types (TCG)

**Breakdown of Card Types:**Across the dataset, there were 27 different values for card types. In Yu-Gi-Oh!, although there are many different sub-categories of cards, usually they are filtered into one of three categories: spells, traps, and monsters.

To filter down into these three most simple categories, I decided to take all cards with ‘spell’ and ‘trap’ in their type and put those two into their own respective groups. Before doing that, I declared all cards with ‘monster’ as any part of their type to be categorized as just ‘Monster’. Doing this made sure none of the sub-categories of monsters were displayed, and the piece of the pie chart was truly representative of the amount of monsters, spells, and traps present in the Trading Card Game.

The ratio for monsters makes sense from an inside perspective, as they are the most used cards, and most versatile. Many monsters have ‘effects’ (modifications to the normal rules of the game) that can be just as powerful, if not more powerful, than a spell or trap card. Nearly 65% of cards in the TCG are monster cards. Spells took up the second-most chunk of the pie, with roughly 20% of cards being spells. This makes sense, as trap cards in the current state of the game have not been utilized as much as they were in the past, and in turn, became obsolete and less common across newer products.

Trap cards, taking up a measly 15% of all cards, must be ‘set’ before activation, and in the modern state of the game have become “too slow” for many decks to properly utilize. This explains why they take up such a small portion of the pie.

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Fig. 5: Distribution of Monster Types (TCG)

**Breakdown of Monster Types:**

Removing spells and traps, there are 25 monster-exclusive types in Yu-Gi-Oh! Fortunately, many of them are hybrids between the ‘Big 8’, which are the most basic types of monster cards (without devolving into sub-categories or combinations). Monsters are divided into main and extra deck monsters. Main deck monster types include normal, effect, pendulum and ritual. Extra deck monster types include XYZ, fusion, synchro, and link monsters.

**Breakdown of Monster Types (Continued):**

In order to break down the monster types, I needed to create a filter. The filter searches for the uninterrupted string of each main monster types, and then classifies them as such, in this order:

1. Pendulum
2. XYZ
3. Synchro
4. Link
5. Fusion
6. Ritual
7. Effect
8. Normal

The cards were classified in this order because in order to be classified as a normal monster, it has to fail every other ‘test’ before becoming one. Most monsters in the game are effect monsters, as seen by the pie chart showing only a 6.7% representation of normal monsters. They are second-to-last on the list and represent cards with effects with NO other affiliations to other monster types. Effect monsters, as stated previously, in most instances can have abilities more powerful than those of spells or traps, which explains why there is such a high volume of effect-only monsters, and such a low volume of cards with no effects. The game has evolved into a state where if a card does not have an explicit effect, it is obsolete. Very rarely in the advanced format (current era of the game) will normal monsters be printed or released in new products, as they will more than likely never see competitive use.

**Card Type Conclusion:**

Throughout the Yu-Gi-Oh! TCG, there are many different types of monsters. By filtering them down to the game’s most basic system of organization (different colored cards are in different categories), we were able to reduce 27 different card types into 10, which made for a much clearer view of the true ratio of cards, instead of the 8 monster types being broken up into overlapping sub-categories.

A diagram of a box plot

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Fig. 6: Variability in ATK/DEF Values

**Atack/Defense Values:**

Comparing a boxplot of all ATK and DEF values in the TCG, a clear trend emerges. Attack values are generally higher than defense values across the board. This makes sense, as if monsters only sat and ‘defended’ all game, there would be little to no player interaction. Attack values being slightly higher than defense values (including a noticeably higher median) forces players to play more aggressively, and promotes a faster, more interactive game for both players. There are also a few outliers beyond the 4000 mark for ATK and DEF values, which can be summed up by a few exceedingly powerful cards from earlier days of the game (like Dystopia, The Despondent, who sits at 5000/5000 ATK/DEF). In the advanced format of the game, higher offensive and defensive statistics are a plus, but are not as important as the effects and impact the card will have on the game itself. The medians being so low is representative of that, as many cards recently won’t have much higher than 2500 ATK/DEF but will be loaded with powerful effects to compensate for the lack of ‘firepower’. In such an overly complex game like Yu-Gi-Oh!, the power level of a card is not solely reliant on the ATK/DEF values they present. Unfortunately, that makes determining whether a card is “good” or not difficult, as it is gauged by interactions with other cards and the rules of the game.

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Fig. 7: Card Attribute Ranges Across Types

**Attribute Ranges:**In Yu-Gi-Oh!, most cards in the game function on a ‘level’ system (represented by the stars on the card). Certain monsters, however, do not have levels. XYZ monsters have ranks, which are functionally identical to levels. Link monsters have link ratings from 1-6, and no level or DEF values. Pendulum monsters have a level, but also a ‘scale’ of 0-13 that represents the head or tail end of the levels of monsters they can bring out.

I compiled the XYZ ranks, the levels of all non-XYZ monsters, the ratings of all link monsters, and the scales of all pendulum monsters into a boxplot to show the ranges of such.

In Yu-Gi-Oh (minus 2 very specific outliers,) a card’s level/rank will always vary between 1 and 12. Link ratings will always vary between 1 and 6, and pendulum scale can only be between 0-13 (to capture the previously mentioned outliers).

The most common card level is 4, and that is shown across the board (minus link ratings, as it is a different metric). The level 4 being so common also influences pendulum scales, which pivot on summoning cards within a certain range (I.E. monsters level 4-8), and with 4 being the most common.

Link monsters range from link-1 to link-6, with the most common being link-2. This can be explained by most lower-link monsters being used to ‘build’ into higher-link monsters.

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Fig. 8: Correlation Heatmap

**Correlation Scores:**Across the board, pendulum scale is not directly related to any statistic. As seen earlier, attack and defense are fairly correlated with each other and level. Link monsters can never have a scale, a defense value, or a level. This is represented by the white ‘blanks’ inside of the correlation heatmap. There cannot be a correlation with a value that does not exist.

As shown by figures 1-3, there is definitely a noticeable correlation between the different card statistics, and the correlation scores represent that. Level and atk are very correlated, so is linkvalue and atk. Defense is also correlated with atk, but not as much as it is correlated with level. Level/link rating seem to be the most correlated with atk (and defense for non-links’) values.

**Why it’s important:**

Being able to discern other statistics from their relationship to others’ allows for us to predict other values of cards. Being able to recognize trends between different values helps visualize a relationship that may not be initially noticeable at a quick glance. If a better understanding of the game is achieved, it becomes much easier to play.

**Logistic Regression (Archetypes):**

To predict archetypes, I used a logistic regression machine learning model. I chose logistic regression because it is good for classification tasks. The goal was to predict a categorical output (archetype) from a card’s race, attribute, type, and name. There are many archetypes across Yu-Gi-Oh!, with many of them sharing only one or two similar qualities (besides a string of text in their name). This led to results being all over the place. The best combination of more than one or two X values was Race, Attribute, Type, and Name, which gave me 39.68% accuracy. This seems very low, but for a card game encompassing 13,000+ cards, all with differing relation to their ‘sets’, I found it to be the most accurate. Although it only may accurately describe roughly 40% of the data, that is a huge margin considering the fact that many cards do not even belong to an archetype.

**Challenges in Machine Learning:**There were multiple issues with the machine learning models that I ran into. Certain archetypes that are newer or smaller were very underrepresented, making it hard for the logistic regression model to work with. Another issue I ran into was extreme outliers, such as cards with 0 or 5000 attack/defense influencing the model more than they should. Throughout the model and figures, it can be determined that ATK has a stronger influence on level predictions than DEF does.

**Chi-Squared Test:**

I analyzed multiple variables with a chi-squared test. I analyzed multiple relationships: Type vs Race, Archetype vs Race, Archetype vs Attribute, and Archetype vs Type.

Contingency Tables were created for each pair of variables, comparing the observed counts vs expected counts, assuming no relationship between variables.

**Random Forest Classifier (Archetypes):**

I also tried to predict archetypes with another machine learning model, Random Forest Classifier. Random forest is good for regression tasks, and is useful for capturing complex non-linear relationships. I figured this would be worth a try as well, with more X values than I included in Logistic Regression. I chose Race, Attribute, Type, Name, Level, ATK and DEF values to try and predict archetype, with slightly better success. Using Random Forest, I was able to increase the accuracy of predictions to 43.12%. Although a minor increase, I was able to use more X values to improve accuracy, meanwhile the Logistic Regression model just got more confused as I added in more X values.

**Random Forest Classifier (Card Levels):**I also used Random Forest Classifier to predict card levels. The dataset has many non-linear relationships that have impact on each other. For example, higher ATK often is correlated with higher levels, but there are exceptions influenced by game and archetype mechanics. RFC is better at handling variance, so I chose to work with it. It performed well with 45.78% accuracy, which is solid considering the size of the sample (13,000+). However, the RFC showed 71.35% accuracy within one level, which demonstrates a high correlation between attack, defense, and the ability to determine a card’s level based on such. DEF has less influence due to many outliers in the TCG.

**Chi-Squared Results:**Chi-Squared Stat represents the magnitude of difference between observed and expected counts.

P-Value determines if difference is statistically significant (p < 0.05 is considered to be significant).

Degrees of Freedom reflect the number of values free that can vary. This helps show the shape and threshold for significance.

**Chi-Square Results (Continued):**

* Type vs. Race:
  + Chi2 Stat: 1792.995
  + p-value: 1.588e-157 (statistically significant)
  + Interpretation: Card type is strongly associated with race. For example, races like “Dragon” and “Warrior” are only represented in Monster cards, while Spells and Traps show minimal diversity.
* Archetype vs. Race:
  + Chi2 Stat: 72950.972
  + p-value: 0.000e+00 (statistically significant)
  + Interpretation: Archetypes are strongly linked to specific races. For instance, archetypes like “Blue-Eyes” or “Elemental HERO” are heavily tied to specific races (Dragon and Warrior, respectively).
* Archetype vs. Attribute:
  + Chi2 Stat: 17304.692
  + p-value: 0.000e+00 (statistically significant)
  + Interpretation: Attributes are associated with certain archetypes. Dark and Light dominate most archetypes, and are the most widespread, while others (Water, Fire) are more niche.
* Archetype vs. Type:
  + Chi2 Stat: 23099.207
  + p-value: 0.000e+00 (statistically significant)
  + Interpretation: Archetypes are associated with card types. For instance, archetypes like “Code Talker” are almost exclusively link Monsters, while others like “Spellbook” belong primarily to Spells.

**Pearson Correlation:**

Pearson Correlation is measured between -1 and 1. A negative score indicates a negative correlation, and a positive score indicates a positive correlation. A score of 0 shows no linear correlation. Below are the scores recorded:  
ATK/DEF: 0.478

Level/ATK: 0.707

Level/DEF: 0.569

**Spearman Correlations:**

A Spearman Correlation score is also measured from -1 to 1, just like a Pearson Correlation. It measures correlation without assuming linearity, suitable for data like this with extreme outliers. Below are the scores recorded:

ATK/DEF: 0.437

Level/ATK: 0.726

Level/DEF: 0.546

These results show very similar outcomes. There is a decent correlation between ATK/DEF values, demonstrating a fairly balanced card design. There is a very strong correlation between ATK and a card’s level, as there are certain ‘thresholds’ that only certain stars can pass, with less defined thresholds for DEF values (in relation to a card’s level). Statistically, all are related to one another.

**Kolmogorov-Smirnov (KS) Test:**

A KS test evaluates whether two distributions are significantly different. A D-statistic shows the largest distance between two Cumulative Distribution Functions (CDFs), and a small P value shows the distributions are significantly different from one another. KS Results:  
KS Test: ATK vs. DEF

D-Statistic: 0.128, p-value: 8.195e-54

The maximum difference between the CDFs are 12.8%, and the P-value is essentially 0, indicating that the differences between ATK and DEF distribution is statistically significant, meaning they do not follow the same distribution patterns. This highlights that by game design, offensive gameplay is more encouraged than defensive gameplay.

A graph of a distribution of scale

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Fig. 9: Distribution of TCG Pendulum Scales

**Distribution of Attributes:**

Across the board, there is a lot that can be seen from the distributions of numerical data. The most obvious trend is level 4 monsters being the most common. This can be explained by the fact that a level 4 monster is the highest level you can summon without a ‘sacrifice’. Pendulum scales are all over the place, with the most extreme values being the lowest frequencies. ATK and DEF across the board are very similar, with sharp peaks between 1000-2000 ATK/DEF, and a peak at 0, with less and less monsters being over 3000 ATK. Link-2 monsters are the most common, likely due to being essential to ‘build’ into higher level link monsters.

A graph of a number of bars

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Fig. 10: ATK Value Distribution Across TCGA graph of a distribution of numbers

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Fig. 11: DEF Value Distribution Across TCGA graph of a distribution of level

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Fig. 12: Distribution of Levels Across TCG

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Fig. 13: Link Value Distribution Across TCG

**Conclusion:**Yu-Gi-Oh! is an extremely complicated and competitive card game, with many underlying trends. Many things, such as ATK/DEF, level, attribute, and archetype usually have an influence on other attributes of a card. Many different archetypes in the game have one or more features in common, which can lead to relationships being drawn between. Throughout various tests, it was determined that there is a positive relationship between Level and statistical values (ATK/DEF), and a very strong relationship between cards within archetypes. Across all 13,000 plus cards that have been printed since the game’s release, many of the same patterns are still followed to this day. Although the game has changed a lot from what it originally was (in terms of complexity and the speed of the game), it will always be Yu-Gi-Oh!

Throughout 25 years of changes, and many product releases, the game has stayed true to its nature, and although much more difficult to understand, still primarily relies on the basics it was founded on: using alike cards to overpower an opponent’s alike cards. This basic foundation, no matter how complicated the game will become, will always hold true. This can be tested in numerous ways (as seen in this report). So long as people continue to build the most powerful decks they can, Yu-Gi-Oh!’s popularity, influence on other games, and most importantly it’s complexity, will not fade for as long as it exists.