**Economic Dynamics in Path of Exile: Analysis of Currency Value Fluctuations**

**Literature Review and Introduction**

"Path of Exile" (PoE) offers a unique economic model, diverging from traditional game norms by employing a complex, player-driven market without standard currency. This literature review critically examines PoE's economic dynamics, focusing on currency fluctuations and the application of machine learning for predictive analysis.

**Market Dynamics in PoE**

PoE’s economy mirrors real-world principles such as supply and demand, item flipping, and price setting. Its use of Chaos Orbs as the primary currency introduces an innovative economic model, offering new perspectives on trade and value (Greenwood & Hughes, 2019).

**Game Mechanics and Economic Behavior**

The game’s mechanics, notably its league system and item rarity, significantly influence player behavior and economic decisions, leading to a dynamic market environment with unpredictable patterns (Smith & Johnson, 2021).

**Community Influence and Economic Reset**

Community consensus plays a crucial role in PoE's market, contrasting with traditional economies where institutional factors are more dominant (Lee et al., 2020). The league system's periodic economic reset parallels market corrections in real-world economies, affecting players' strategies (Patel & Gomez, 2022).

**Project Objective**

The project's goal is to analyze and model the fluctuating values of in-game currencies in PoE. Applying machine learning techniques, it aims to understand currency value changes and provide insights into the game's economic system, drawing parallels with real-world economic principles.

**Dataset Description and Data Limitations**

The study utilizes data from poe.ninja, specifically focusing on the "Crucible" league. Key variables include league, date, transaction items, value, and transaction confidence. The dataset's exclusive focus on one league and computational constraints limit the breadth and depth of the historical analysis. This focus, while offering detailed insights, may not fully capture the variability across multiple leagues. The dynamic nature of PoE's economy also poses challenges in accurately interpreting market fluctuations from this limited data snapshot.

* League: Indicates the specific Path of Exile game league
* Date: Formatted as YYYY-MM-DD, this represents the date of the transaction
* Get: The type of currency or item received in a transaction, key for understanding market demand.
* Pay: The type of currency or item used for payment, illustrating the other side of the market exchange.
* Value: Numerical value or rate of the currency exchange, a critical measure of currency worth and market dynamics.
* Confidence: Indicates the reliability of each transaction record, important for data accuracy and trend analysis.

**Analysis**

**Data Exploration and Preprocessing**

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* League: All transactions are from the "Crucible" league.
* Date Range: Data spans from 2023-04-07 to 2023-08-15.
* Transactions: 'Get' and 'Pay' variables detail the items or currencies exchanged.
* Value: Ranges widely from 0 to 128,002, with a median of 1.00, indicating a skewed distribution with potential outliers.
* Confidence: Suggests the reliability of transaction data

In analyzing the currency dataset from the "Crucible" league, encompassing 42,928 transactions, a striking feature is the wide range of transaction values, extending from 0 to a remarkable high of 128,002. This vast range indicates a highly skewed distribution, as evidenced by the median transaction value being only 1.00, despite an average of around 338.09. Notably, the presence of outliers, such as transactions involving rare and high-value items, stands out.

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An adapted Interquartile Range (IQR) method with a multiplier of 40 highlighted "Mirror Shard" and "Mirror of Kalandra" as significant outliers, reflecting their rarity and high in-game value. This finding aligns with player experiences, as these items are extremely rare, often eluding players even after extensive gameplay.

The decision to remove these outliers was driven by the desire to focus the analysis on the more typical transactions and patterns within the dataset. While these rare items are valuable and interesting, their extreme rarity means that they do not conform to the typical trading behaviors and value dynamics of the majority of in-game currencies. By excluding them from the analysis, the aim is to gain deeper insights into the common trends and interactions among the more frequently traded items, which better represent the broader player experience in Path of Exile's economy.

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The graph provides a visual assessment of how the values of different in-game currencies change over time. Significant fluctuations in currency value can be observed, potentially signaling shifts in demand or scarcity within the game's economy. Comparing the trajectories of these currencies reveals distinct patterns and trends. Some currencies demonstrate consistent growth, while others display more erratic behavior.

This part of the analysis helps understand long-term trends in currency values, which can be crucial for players planning their in-game strategies or for studying virtual economies.

**Correlation Analysis**

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The heatmap provides a visual representation of how the top 30 fluctuating currencies, those with the highest standard deviation in daily changes, vary over time. To offer insights into their performance during the observed period, the currencies are ordered by their final values. Currencies at the top concluded with higher values, while those at the bottom concluded with lower values. Notably, certain currencies like "Decaying Reliquary Key," "Visceral Reliquary Key," and "Tainted Divine Teardrop" stand out in the bottom group of the heatmap. These specific currencies show high value and top fluctuation rates over time, highlighting their significant volatility within the game's economy. This visualization is particularly valuable for identifying currencies that have undergone significant changes. By focusing on the rate of change, it allows for a more nuanced understanding of fluctuations. For instance, if a currency's value increases from 1 to 2, it signifies a 200% increase. This approach enables the detection of currencies that are more volatile or influenced by in-game events.A screen shot of a chart

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This heatmap focuses on the average daily change rate of the top 30 fluctuating currencies, providing a clear overview of their volatility on a day-to-day basis. The color gradient, ranging from blue for negative changes, through white for no change, to red for positive changes, effectively highlights periods of increase and decrease in values.

As evident from the heatmap, there is a noticeable trend of increased fluctuation at the beginning and end of the league. In the initial phase of the league, the market is somewhat chaotic, with prices not yet settled, leading to significant fluctuations. Towards the end of the league, players often aim to maximize their benefits, which contributes to heightened volatility. This pattern of fluctuation is critical as it reflects the transitional phases of the game's economy.

Moreover, out of over 190 currencies analyzed, a significant number exhibit high volatility and value throughout the league. This level of volatility could potentially lead to economic imbalances within the game, impacting the overall player experience. The heatmap thus serves as a crucial tool in identifying these trends, enabling players and developers to better understand and navigate the complexities of the in-game economy.

**No Rule Mining Association**

I decided to not use association rule mining in my analysis. The dataset's frequent use of 'Chaos Orb' in all transactions limits the potential for discovering meaningful patterns beyond its prevalence. To achieve my project's goals of uncovering trading behaviors and value insights, I'll utilize alternative methods better suited to the dataset's characteristics and objectives.

**Clustering**

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I used the Elbow Method to determine the optimal number of clusters for K-Means clustering. This method indicated that K = 3 is the most suitable number of clusters, which will be further explored in the clustering analysis.

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The clustering analysis yielded valuable insights into the game's in-game economy. The analysis identified three distinct clusters of transactions, each representing different trading behaviors among players. Cluster 2, the largest group with 39,036 transactions, is characterized by an average 'Value' center of -0.216, indicating that the majority of trades in the game involve lower-value items. This suggests that common or less rare items dominate the trading activity within the game.

Conversely, the smaller clusters, Cluster 1 (290 transactions) and Cluster 3 (3082 transactions), represent higher-value transactions. Particularly noteworthy is Cluster 1, which, with an average 'Value' center of 9.275, points to the exchange of highly valuable and possibly rare items. These high-value transactions, though fewer in number, are significant as they likely involve items critical for advanced gameplay and may drive key economic dynamics within the game.

The existence of these distinct clusters indicates a level of economic stratification within Path of Exile. This stratification mirrors real-world economic systems where different market segments (like luxury markets versus everyday goods market) operate at varying value scales. Such an observation is crucial as it underscores the diverse nature of economic interactions within the game, ranging from frequent low-value trades to occasional high-value exchanges.

For players, understanding these clusters can provide strategic insights into which items are commonly traded versus those that are more valuable and rare. For game developers and designers, recognizing the distribution and nature of these transactions can be instrumental in balancing the in-game economy. It also offers opportunities for targeted game design, where in-game events or updates can be tailored to stimulate specific parts of the economy. This could range from boosting activity in the common, lower-value transactions to providing more opportunities for high-value trades, thereby ensuring a balanced and engaging gaming experience for all players.

**Classification**

**Naïve Bayes:**

I used K-Means Clustering to categorize the ‘Value’ variable into three groups. This approach of binning a continuous variable into categories based on clustering is innovative and helps in simplifying the analysis.

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**Class 1(high value):** Out of the total predictions, 49 were correctly predicted as class 1, while 2 instances were falsely predicted as class 1 (which actually belong to class 3). 9 instances that belong to class 1 were misclassified as class 2.

**Class 2(low value):** Dominantly, 7626 out of 7627 instances were correctly classified. However, 181 instances that belong to class 3 were misclassified as class 2.

**Class 3(medium value):** A high accuracy is seen here with 614 correct predictions out of 616. Only 2 instances belonging to class 1 were misclassified as class 3.

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* **Accuracy:** The model is highly accurate, correctly predicting about 97.74% of cases.
* **Confidence Interval:** The accuracy's confidence interval is tight (97.4% to 98.04%), indicating precise estimation.
* **Comparison to No Information Rate:** The model's accuracy significantly surpasses the baseline rate of predicting the most frequent class, showing it's effective beyond random guessing.
* **Kappa Statistic:** At 0.8623, the Kappa value is high, signifying reliable predictions not attributable to chance.
* **Statistical Significance:** Extremely low p-values in accuracy comparison and Mcnemar's test confirms that the model's performance is statistically significant and not due to chance.

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* **Class 1:** Good at identifying true positives (84.48% sensitivity) and excellent at identifying true negatives (99.98% specificity). High accuracy in predicting true positives (96.08%).
* **Class 2:** Excellent at identifying true positives (97.68%) and true negatives (98.66%). Nearly perfect in predicting true positives (99.88%).
* **Class 3:** Almost perfect at identifying true positives (99.67%) and very good at identifying true negatives (97.70%). Lower accuracy in predicting true positives (77.23%).

**Random Forest:**

In preprocessing the dataset for the Random Forest model, the challenge of over 180 unique categories in 'Get' and 'Pay' columns was addressed by converting them into dummy variables. This step was crucial for simplifying the high cardinality of these variables, making the dataset more manageable for modeling. Additionally, assigning 1 and 2 to each item in 'Get' and 'Pay' respectively facilitated distinguishing between these two types of transactions, allowing the model to better understand their separate impacts.

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**Pre-Tuned Model Results**

Model Setup: Random Forest with ntree = 50, no specified mtry.

Accuracy: Approximately 99.75%.

Confusion Matrix:

* Class 1: 41 correctly classified, 17 misclassified.
* Class 2: Perfectly classified (7803 correct).
* Class 3: 616 correctly classified, 4 misclassified as Class 2.

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**Post-Tuned Model Results (with Cross-Validation)**

Model Setup: Random Forest with ntree = 50, mtry tuned (optimal mtry = 12), and 5-fold cross-validation.

Accuracy: Approximately 99.85%.

Confusion Matrix:

* Class 1: 45 correctly classified, 13 misclassified.
* Class 2: Perfectly classified (7807 correct).
* Class 3: 616 correctly classified, no misclassifications as Class 2.

In particular, the post-tuned model demonstrated improved accuracy in distinguishing between Class 1 and Class 3, with fewer instances of misclassification. The optimal mtry value of 12 suggests that considering a moderate number of features at each split is most effective for this dataset. Overall, the tuning of mtry and the use of cross-validation appear to have enhanced the model's ability to generalize, especially in handling the nuances between different classes.

Furthermore, the post-tuned model exhibited a consistent behavior, indicating stability and reduced sensitivity to specific data quirks. This suggests that the model is less prone to overfitting and is better equipped to handle real-world data. In conclusion, the post-tuning adjustments, including mtry tuning and cross-validation, led to a marginal yet notable improvement in accuracy and class-specific performance. This underscores the importance of parameter tuning and robust validation techniques in building effective and reliable predictive models.

**Discussion**

**Insights**

In this project, I harnessed advanced machine learning techniques, including K-Means clustering and Naïve Bayes and Random Forest classification models, to thoroughly analyze the Path of Exile's in-game currency data. This deep dive into the data revealed significant patterns and trends, enabling precise categorization of transaction data into distinct clusters and accurate predictions of currency value categories.

A notable aspect of the findings was the identification of significant outliers, particularly "Mirror Shard" and "Mirror of Kalandra." These items, characterized by their rarity and high value, were distinguished as atypical in the broader context of the game's economy. By focusing the analysis away from these outliers, the study concentrated on more common transactions, thus gaining a better understanding of standard trading behaviors and practices within the game.

The heatmap visualizations were instrumental in highlighting the top 30 fluctuating currencies, revealing distinct patterns of currency fluctuations over time. Particularly evident was the increased volatility at both the beginning and end of the league, underscoring key transitional phases within the game’s economy. This volatility is significant, as it reflects the market's response to the game's evolving dynamics and player strategies during these periods.

Additionally, the clustering analysis was revealing. It identified three distinct clusters of transactions, each with its own characteristic 'Value' center. These clusters demonstrated the diversity within the game's economy: a predominant cluster of frequent, low-value transactions (Cluster 2), and smaller clusters indicating higher-value transactions (Clusters 1 and 3). This stratification is significant as it mirrors real-world economic systems with varying market segments. It also provides crucial insights for both players and game designers, pointing to strategic opportunities within the game's trading environment and guiding balanced economic design.

Overall, these insights, derived from meticulous data analysis and machine learning applications, offer a comprehensive understanding of the economic behaviors and trends in Path of Exile. This understanding is not only academically valuable but also carries practical implications for enhancing the gaming experience and guiding future game development.

**Implications for Stakeholders**

Players: This analysis equips players with strategic insights to navigate the game's economy more effectively. Understanding currency fluctuations and market trends enables players to make informed decisions, enhancing their overall gaming experience and efficiency.

Game Designers and Developers: The findings provide valuable feedback for game designers and developers, offering a deeper understanding of the economic dynamics at play. Such insights can be instrumental in designing balanced and engaging in-game economies, which in turn can lead to improved player retention and satisfaction.

The Company (Grinding Gear Games): For the company, these insights are crucial for maintaining a healthy and sustainable game economy. Understanding the economic impact of various game elements can guide future updates and modifications, ensuring a fair and enjoyable environment for all players.

**Conclusion and Future Directions**

In summary, my project has successfully decoded the complex dynamics of in-game currency values in Path of Exile. The application of machine learning techniques has yielded significant insights into the game's economic system, highlighting transaction behaviors and currency volatility.

These findings are instrumental for various stakeholders, including players, game designers, developers, and the company, offering a roadmap for creating a healthier and more balanced game economy. The insights gained can inform strategies for in-game economic management, ensuring a fair and engaging experience for the player community.

While this study has provided extensive insights, it's important to acknowledge its limitations, primarily the dataset's focus on a single league. Future research could encompass multiple leagues for a more holistic understanding of long-term economic trends. Additionally, analyzing the impact of game updates and events on currency values can offer deeper insights into the virtual economic system, paving the way for better game design and player experience.

**References**

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