Determining the Most Efficient Weapon Combinations Against *The Legend of Zelda: Breath of the Wild* Beasts through Supervised Machine Learning

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The large scale of *The Legend of Zelda: Breath of the Wild* often presents an issue for new and old players alike who enter into the game, namely, the large number of beasts, or enemies, that can potentially be encountered and the limited weapon inventory slots initially provided. For players unwilling to devote large amounts of time to expanding their inventory, a process that can be arduous and difficult, they are left with the ability to only carry eight melee weapons with them at a time. This can lead to difficult decisions for the player as weapons within the game are built with different durability statistics and strengths and must be chosen carefully. With limited inventory space, players are prone to hoarding, quickly filling up their weapon cache and are left with weapons they are unsure when to use. The model discussed in this white paper addresses this issue by analyzing beast data with melee weapon statistics to determine the best weapon combinations to carry when encountering these beasts through a supervised machine learning model.

The data for this project was pulled from *The Legend of Zelda: Breath of the Wild, the Complete Official Guide: Expanded Edition* and further enriched with data from avid *Zelda* player and Reddit user, RogueT3ch. The data pulled from the official guidebook consisted of Melee Weapon Durability, Strength, Subclass, and Wield Grip. Additionally, the guidebook provided data on beast Health Points (HP) and Rank (Difficulty). Data pulled from Reddit user RogueT3ch, consisted of calculated Attack per Second (APS) for each Subclass of weapon. The data was sorted into two Microsoft Excel Sheets, one sheet representing Weapon data and the other Beast Data. A combined Microsoft Excel Sheet was created with combined Weapon and Beast data, however this dataset pertained specifically to weapon statistics and the win-loss calculation for each beast encounter corresponding to each weapon. The win-loss calculation was a new feature engineered by taking the Weapon Durability multiplied by it's Strength and comparing that to the overall Health of the Monster. This feature was called the Beast-Weapon Outcome (BW Outcome) and is the feature relating weapon statistics to beast statistics. Using this new feature, 8,450 data points were able to be generated to build and train the model for this project.

Three target variables were examined for this model: the Weapon ID, the Weapon Subclass, and the Beast-Weapon Outcome Variable. Initial examination of the dataset indicated that there were not enough features for a model to properly distinguish between the large number of weapons, as within subclasses, weapons were very similar with regard to durability and strength statistics. This assumption proved true when a model with this target variable could not achieve above a 4% accuracy score. The next target variable examined was the Weapon Subclass variable. This target variable, while not providing a direct recommendation of weapon, would still provide a weapon subclass and therefore meet the intent of this project. Finally, the third and final target variable examined for this model was the BW Outcome variable. This variable was ultimately decided against due to a lack of additional data such as elemental strengths, weaknesses, speed, and range of attack. Ultimately, the target variable chosen for this project was the Weapon Subclass variable, providing users with one of three weapon types that they would need to carry in their inventory.

In preparing the data, several beasts and weapons were removed from the dataset. All 7 bosses were removed from the dataset as these beasts must be specifically targeted and sought out prior to engaging in battle. Additionally, these beasts have no listed rank by which to compare to other monsters and their level of dangerousness changes based on when the player chooses to fight them (Beatty & Pargney, 2017). This variability in rank cannot be adequately accounted for in the model as significant player specific data would need to be acquired. Of the 127 weapons able to be used in game, 119 were chosen to remain in the dataset. Six weapons were removed from the dataset as these weapons must be specially acquired through out of game means through Amiibo purchases. This project focuses on weapons that can be encountered naturally through gameplay. Two additional weapons were removed for separate reasons: the Korok Leaf and the Master Sword. The Korok Leaf was removed as it cannot be considered a true weapon due to its inability to cause damage to enemies. The Master Sword was removed from the dataset due to its infinite durability. This sword was identified as an outlier during Exploratory Data Analysis (EDA) and removed so as not to skew the model toward its subclass, Light.

In building the model, a 70/30 split was chosen to segment out the data into Training and Testing data. This split offered an increase of 1.3% accuracy when compared to the model created with an 80/20 split. The maximum depth chosen for this model was 3. An examination of the Validation Curve for this model showed that the Training Score Line and the Cross Validation Score are close together at 3. After this point, the model begins to overfit at a maximum depth of 4.

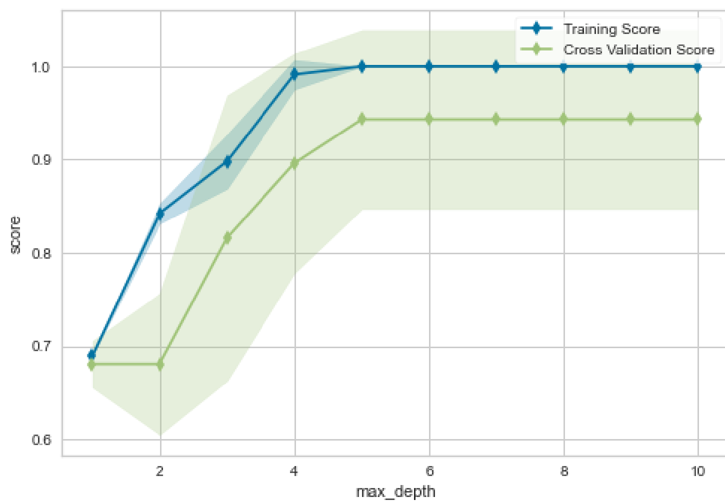

Figure 1: Validation Curve for Decision Tree Classifier

The final version of the Decision Tree model produced an accuracy of 88.72% when determining what Subclass of weapon should be used against various beasts in gameplay. The model was highly accurate for the Light Subclass, with Precision, Recall, and F1-Scores of 1.0. The model performed slightly lower for the Heavy and Pole-Arm Subclasses, with F1-Scores of 0.81 and 0.83, respectively. The model's performance for each of these subclasses can most likely be attributed to the number of data points available. The Light Subclass had 3,053 samples, Heavy had 2,769 samples, and Pole-Arm had 2,627 samples. Taking a 70/30 split leaves the training set with 2,159 Light samples, 1955 Heavy Samples, and 1800 Pole-Arm samples.

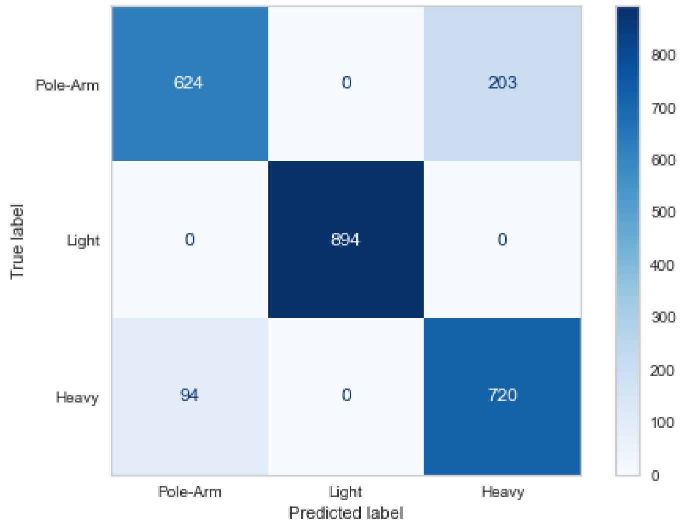

Figure 2: Confusion Matrix for Decision Tree Classifier

In Figure 3, it can be observed that the largest density of Light weapons was clustered around Mid-Durability / Mid-Strength. This produced a higher number of weapons with a D*S score capable of tackling a larger variety of beasts. Heavy weapons are very scattered in their distribution of durability in relation to strength while Pole-Arm weapons tended to have less strength overall.

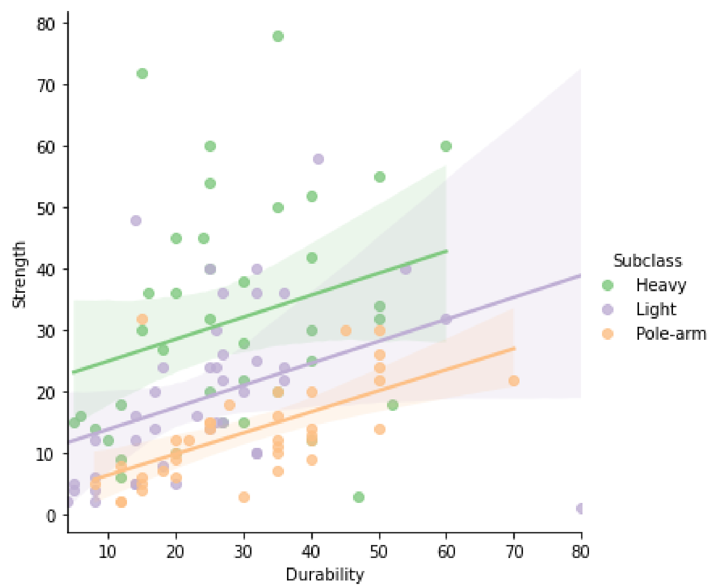

Figure 3: Scatterplot of Weapon Subclass by Strength vs. Durability

Challenges in building this model were related to establishing a common feature that would connect the Beast data to the Weapon data. When attempting to establish connections between the two datasets, player data and encounters would have been beneficial. Player data would have provided a wide spread of unique encounters for various weapons with various beasts. Ideally, this player data would have included encounters from novice to advanced players to account for a wide spread experience. Lacking this data, new features had to be engineered in order to establish a connection. The sole feature utilized to connect the data was the BW Outcome variable. Challenges were experienced when attempting to establish further connections based on Beast Rank and Weapon Speed. While the official guidebook for the game provides Beast rank, it can be hard to determine how this rank affects beast encounters in detail as the rank is simply defined as “a general evaluation of each creature’s overall dangerousness” (Beatty & Pargney, 2017). Beast rank is not always absolute as the game levels up throughout based on how many beasts the player has encountered versus defeated in their journey. This project is limited by this lack of unique player data and the model produced operates under the assumption that all beasts begin at their standard rank versus their leveled-up rank.

This project sought to predict what weapons were best suited for various beast encounters in *The Legend of Zelda: Breath of the Wild.* While unique weapons cannot be predicted due to lack of available features, the best subclass of melee weapon can be determined through data not reliant to unique player data. While presented with a larger number of weapons of the Light Subclass, this model predicted that the Light Subclass would be the best suitable weapon for a larger variety of beasts within the game. Analysis of the dataset itself showed that Light weapons were more versatile with regard to Durability and Strength. To create a stronger model, efforts could be made to gather player specific data and incorporate that data within this model. This model could also be improved by building out a more solid connection between Beast and Weapon data.

In addition to being used by players in the game to determine what type of weapon to carry, this model could potentially be used by game developers to increase or decrease difficulty of play. *Zelda* is a very adaptable game, relying on user experiences to modify each journey. If a user were to stick to a specific type of weapon, this model could be adapted to produce more enemies either vulnerable or not to that weapon subclass depending on the difficultly level selected by the user. To implement this into gameplay, however, user data would still need to be collected. The model would then rely solely on that user's data, leading to some ethical implications such as data gathering of an non-consenting or unaware player. This could be addressed by alerting the player of data gathering and giving the player the option to turn off this style of play.

Appendix A: Supporting Documentation

Beatty, L., & Pargney, V. (Eds.). (2017). *The Legend of Zelda: Breath of the Wild: The Complete Official Guide: Expanded Edition*. Piggyback Interactive Limited.

Nintendo Co., Ltd. (2017). The Legend of Zelda: Breath of the Wild. Redmond, WA.

[RogueT3ch]. (2017). *Did the math for the DPS for the top 7 weapons of each melee type* [Online forum post]. Reddit. https://www.reddit.com/r/Breath_of_the_Wild/comments/61wa9x/did_the_math_for_the_dps_for_the_top_7_weapons_of/

Appendix B: Additional Questions

1. Are there any potential biases within your dataset?
2. How would incorporating user data affect the model?
3. How much user data would you need to create an accurate assessment based on player experience?
4. How would players be able to use this model while playing the game?
5. What was the basis for your decision in choosing a Decision Tree model over a Random Forest model?
6. Do you believe a Random Forest model would be better suited to this problem-set?
7. There is only one feature relating Beast Data to Monster data, do you believe this hurts the model and provides an inaccurate prediction?
8. Would this model be useful to advanced players who have expanded their inventory beyond the initial 8 inventory slots?
9. Do you believe how you evaluated the model performance is valid?
10. How do you plan to develop the model further?