

LLM Detection

Practical Data Science: 3rd Project

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1 Introduction

This report outlines results and conclusions drawn from the LLM detection project which can be found at <https://github.com/dimits-exe/practicaldatascience>. Implementation details, methodology and discussion can be found inside the relevant notebook and README file.

2 LLM Detection Results

Below we present graphs resulting from the LLM detection models presented in the original notebook.

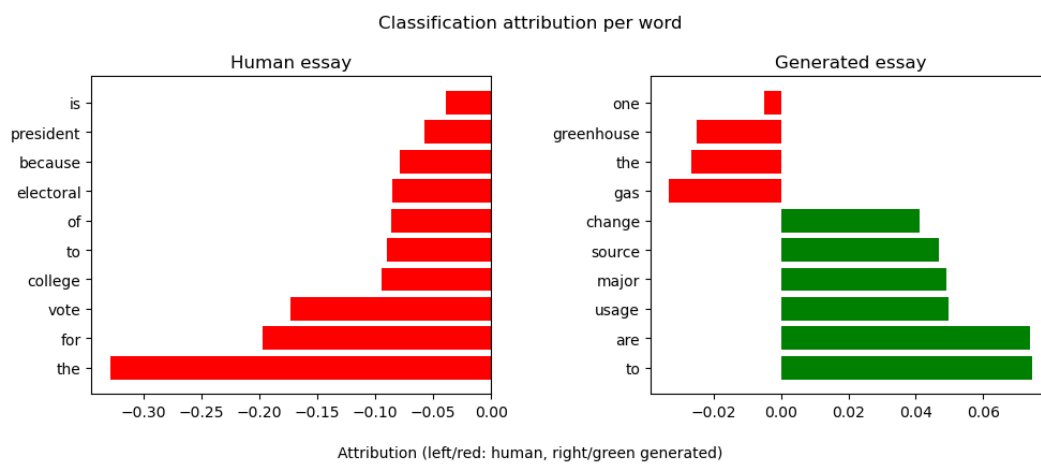


Figure 1: Classifier attribution (LIME) per word for correctly classified human and generated essays. Red (left) lines indicate the classifier leans towards the text being a human essay because of the word’s use, Green (right) lines indicate that it leans towards the text being LLM generated. The length of the lines indicates the certainty of the classifier towards the classification. Note that this graph does not necessarily represent probability values for each word.

Dataset size impact on LLM detection

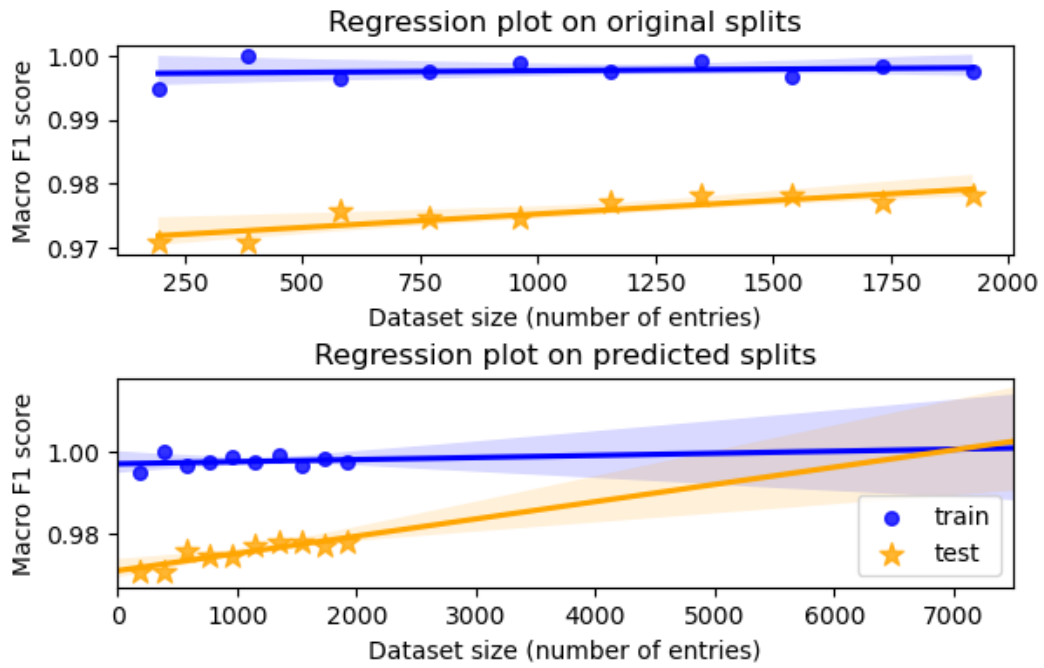


Figure 2: Impact of dataset size on LLM detection. The classifier used is the Random Forest Classifier with 15 simple decision trees. The green line indicates the expected classifier test score on unseen dataset sizes. This line follows the linear assumption which rarely applies to these kinds of problems. Shaded area represents the 95% Confidence Interval.

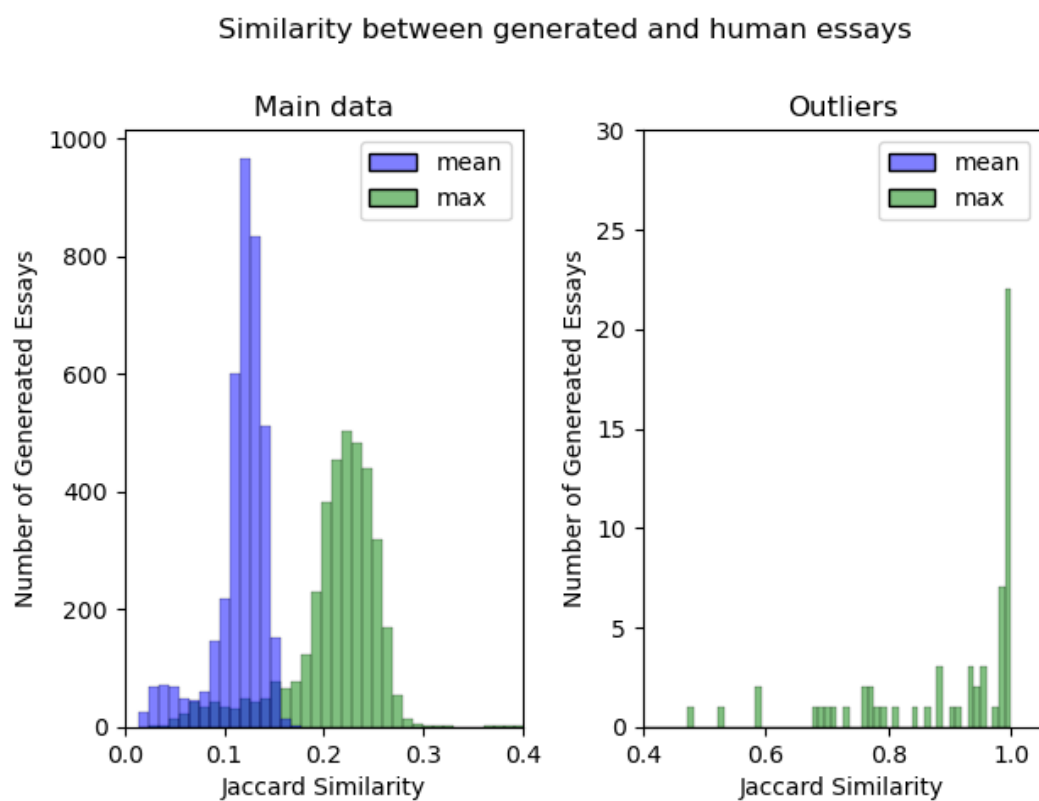


Figure 3: Mean and maximum Jaccard similarity between each generated essay compared to all human essays. This Figure demonstrates the very low similarity between the two kinds of essays in our dataset, largely explaining the exceptional performance of our classifiers.

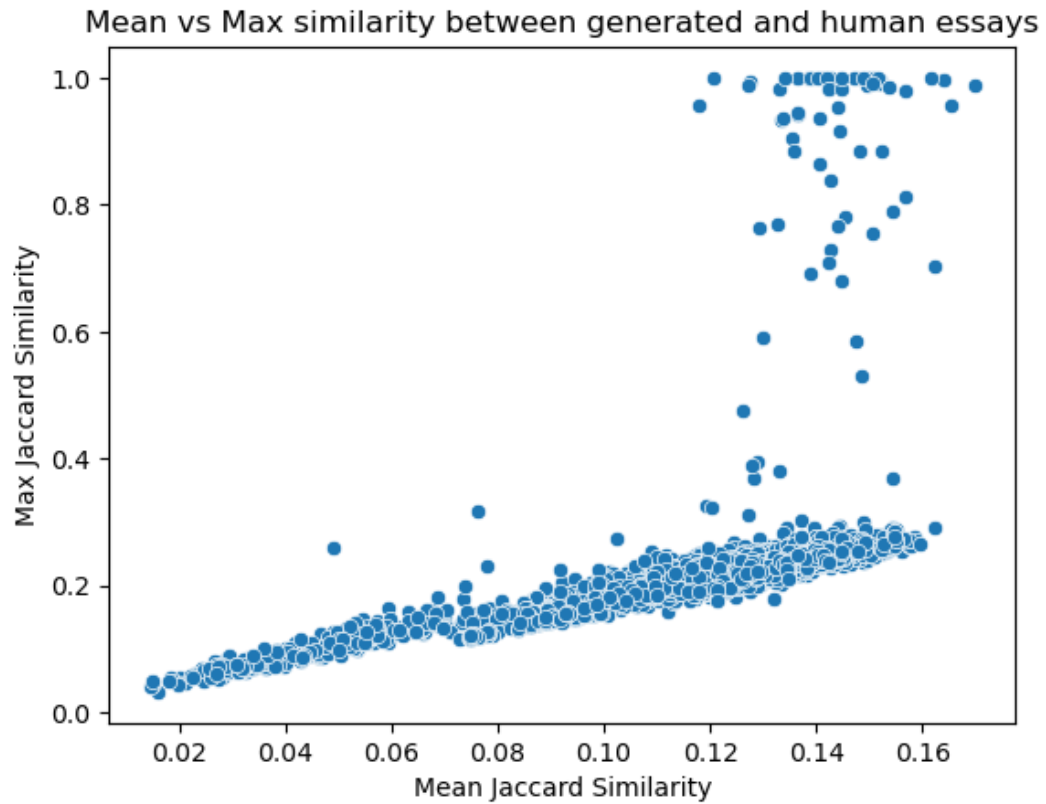


Figure 4: Relationship between mean and max similarity between each generated essay and all human essays. The relationship can be described as follows: From 0 to 0.12 mean similarity the relationship is clearly positive linear, while from 0.12 to 0.20 the relationship is still clearly positive and mostly linear but with significant outliers.

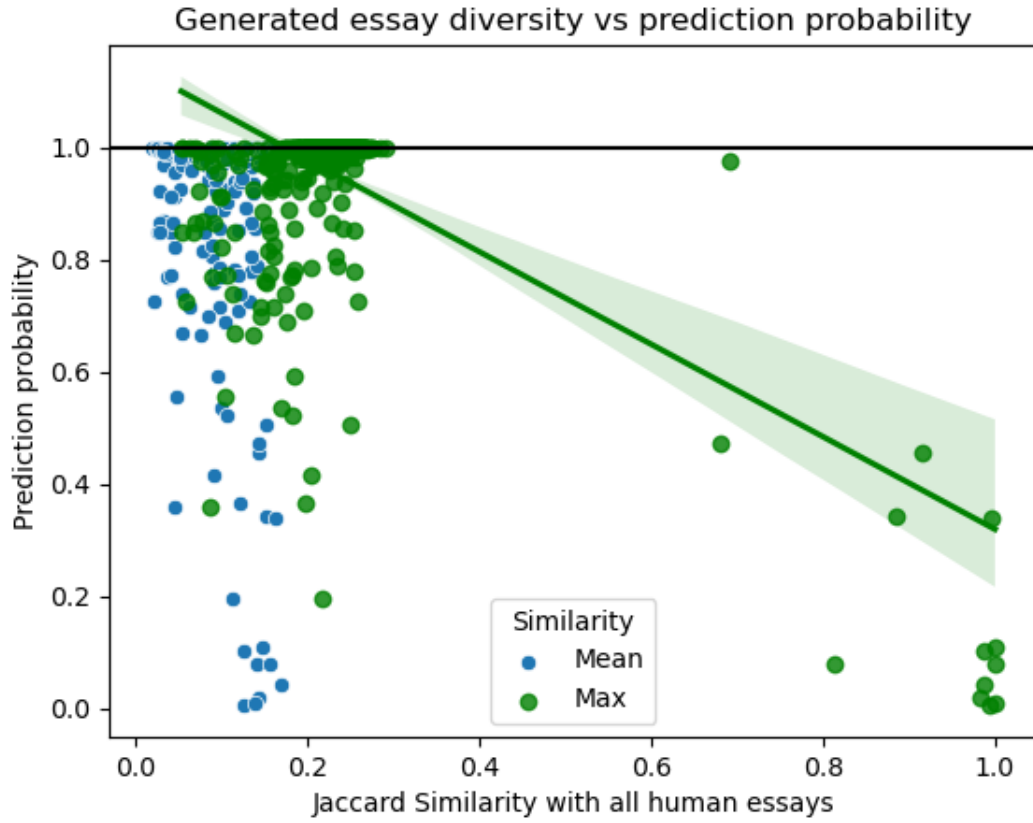


Figure 5: Relationship between essay similarity and prediction probability for that (generated) text. The distributions of mean and max similarity can also be seen in Figure 3. We notice a slight inverse trend between max similarity and prediction probability. When similarity becomes 1, or very close to 1, the classifier fails since the data point itself is mislabeled.

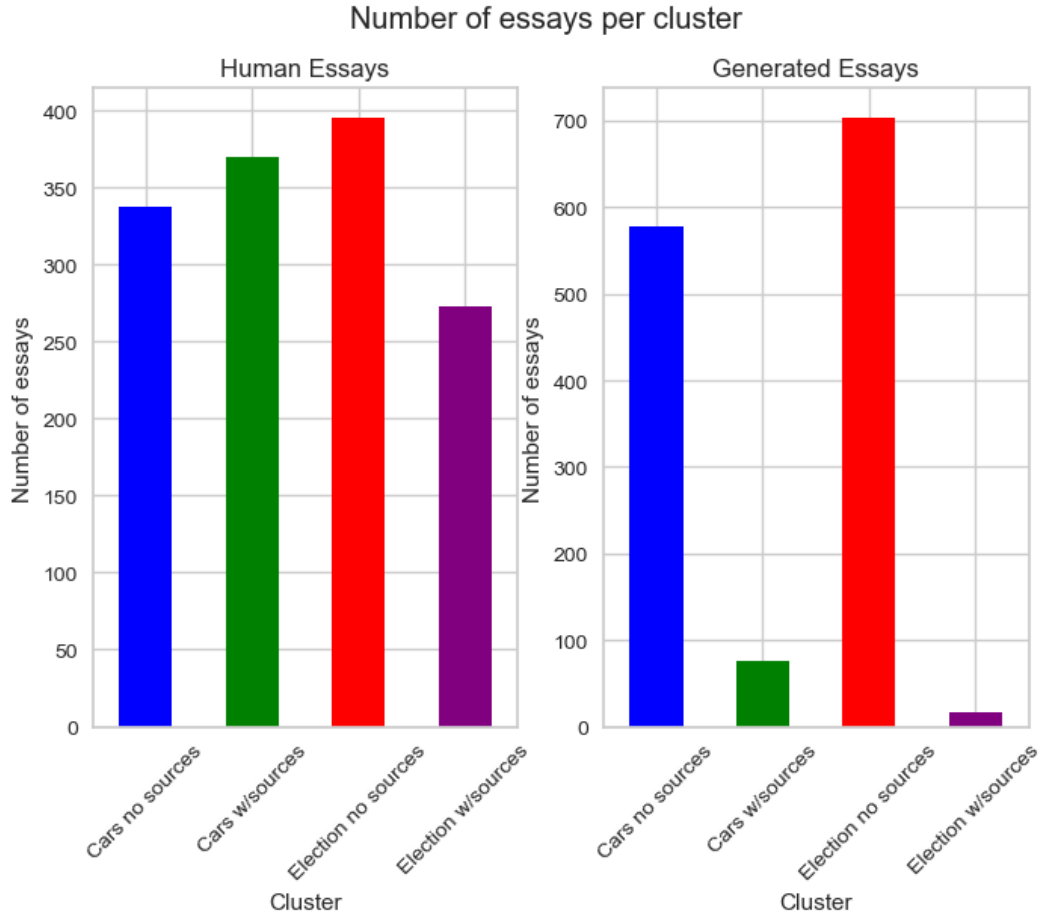


Figure 6: K-Means clustering of human and generated essays, labeled according to qualitative characteristics. Note that while the optimal dataset selected using similarity seems to be suffering from label imbalance, this may not actually influence the performance of our classifier. Furthermore, it could be attributed to significant differences between the two clustering models as our earlier clustering for generated texts clearly indicates the presence of two homogeneous and clearly separate clusters, and which do not seem to feature the natural sub-clusters of human texts. As such this imbalance is probably a product of the minimal variety encountered in generated texts.

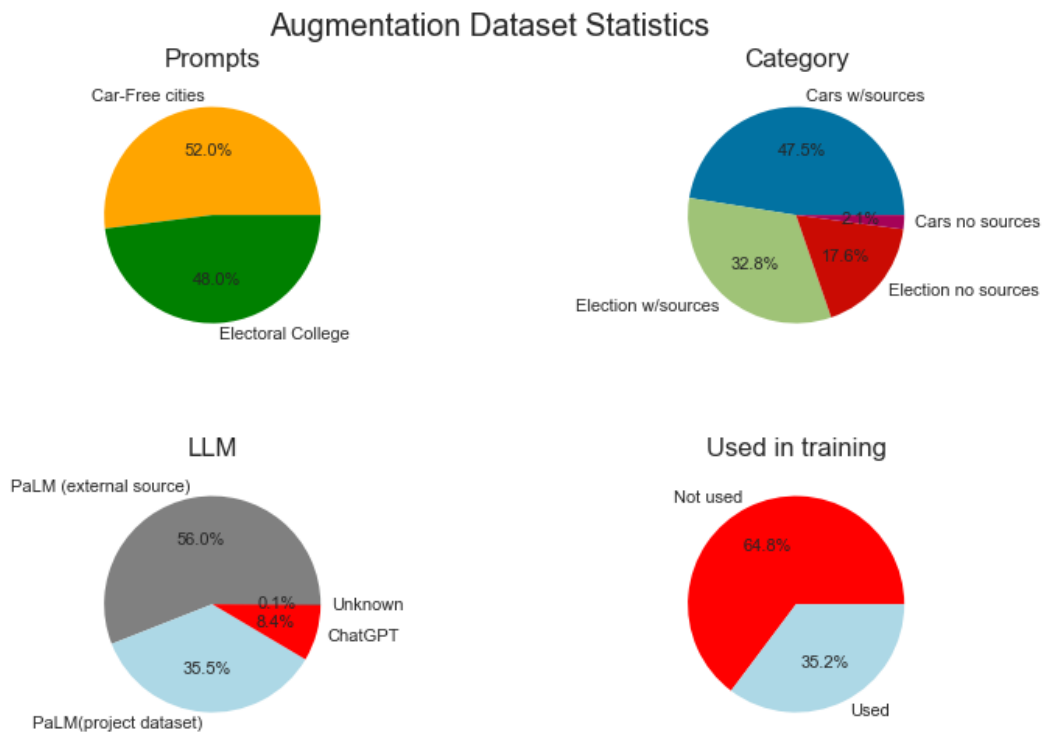


Figure 7: Statistics about the final, full augmented dataset comprising all the generated essays, even those not eventually used for the final model. The "Category" pie-plot displays the relative counts of clusterings as defined by the K-means algorithm with $K = 4$ trained on the human texts.