# Spooky Authors Identification


Edgar Allan Poe


HP Lovecraft


Mary Shelley

# Introduction

- Kaggle Data Science Competition
- Small extracts from horror stories written by three authors: Edgar Allan Poe (EAP), Mary Shelley (MWS) , and HP Lovecraft (HPL)
- Data:
  - One Training set (TR0): 19,579 extracts whose authors are known
  - One Test set (TS0): 8,392 extracts whose author must be identified

**Goal: For each extract, give probability to the potential authors (among the three mentioned above) to determine which one is the most likely to be its author**

# Outline

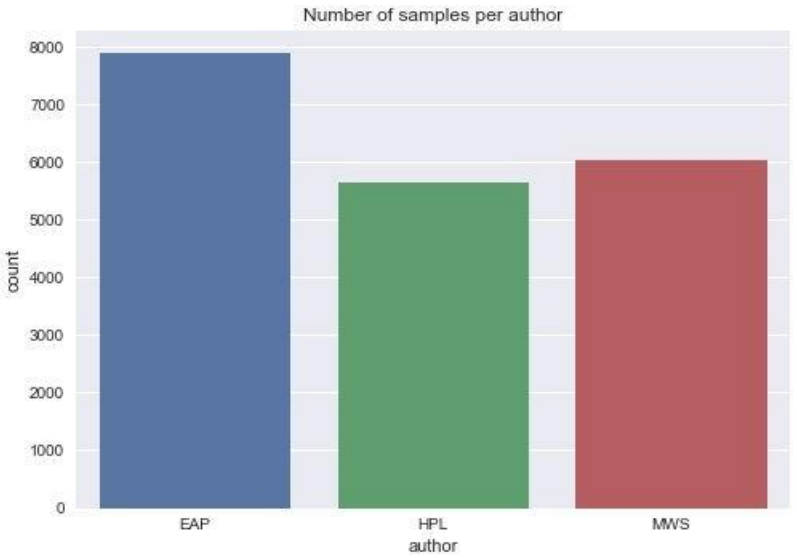
I. About the dataset
II. Our strategy
III. Features and highlights
IV. Results

# About the dataset

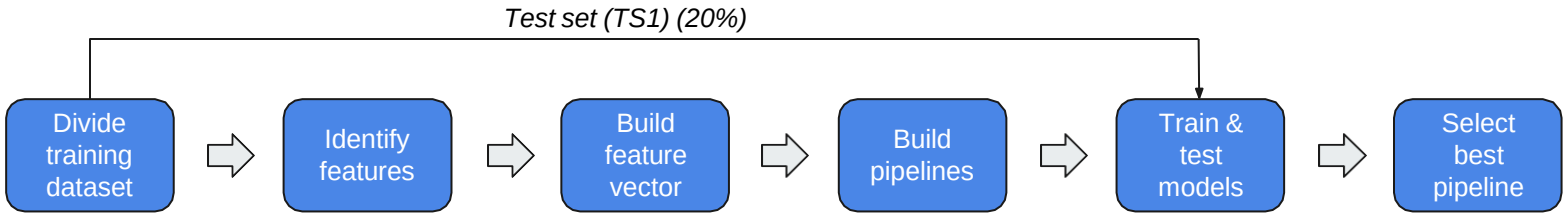
- ID - a unique identifier for each sentence
- Text - some text written by one of the authors
- Author - author of the sentence (EAP/HPL/MWS)

Sample extract:

| ID | Text | Author |
|---|---|---|
| id02499 | "Verney," said he, "my first act when I become King of England, will be to unite with the Greeks, take Constantinople, and subdue all Asia. | MWS |
| id04092 | "Upon honor," said I. "Nose and all?" she asked. | EAP |



# Our Strategy - *Structure*




Split training dataset (TR0) 80% / 20% into training set (TR1) and test set (TS1)

Identify interesting features of the TR1 set

Populate the dataframe containing values for each feature

Build combinations of selectors, models, and size reduction*

Train and test models on the TR1 set and test top 10 on the TS1 set all using logloss criteria for evaluation**

Use best pipeline to train over the entire training set (TR1 +TS1) and use to predict on final test set (TS0)

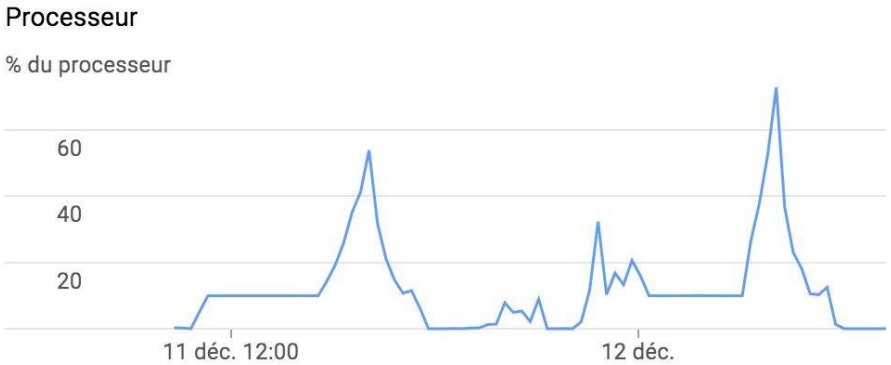
*Reducing the number of features to the most useful ones (avoid over-fitting)
**Kaggle uses logloss model for evaluating model performance

$$logloss = -\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{M} y_{ij}\log(p_{ij})$$

# Our Strategy - *Computation on the Cloud*

Use of a Google Cloud instance (with 10 vCPU)

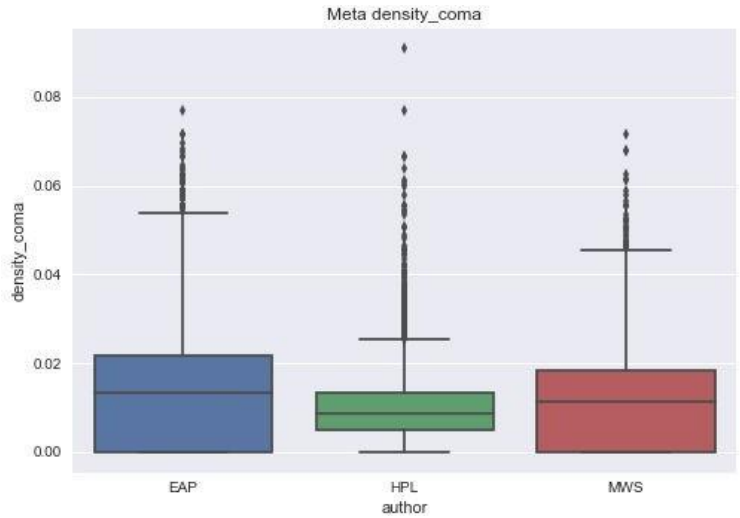
- Quicker: Parallelisation using up to 7 processors
- Less risk of system error: Use of GNU Screen (safely kill the SSH connection)
- Doesn’t burn down our laptops



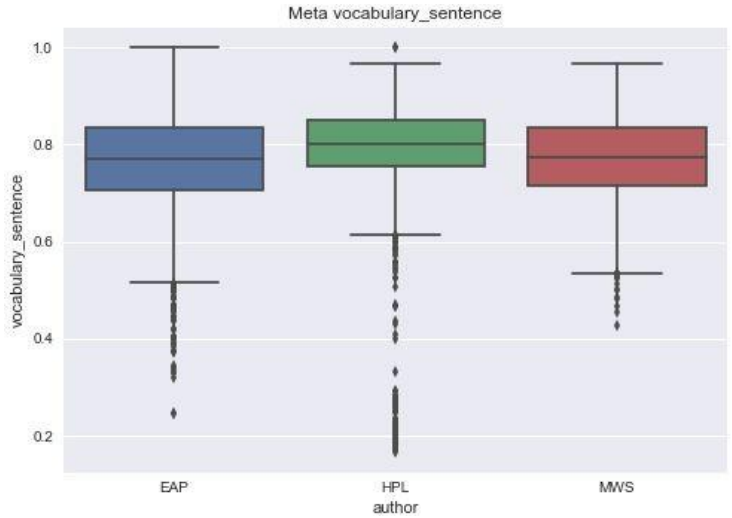
# Features and Highlights - *(1/4)*

| Meta Features | Text Features |
|---|---|
| 1. Sentence length (characters & words)<br>2. Word length<br>3. Punctuation density<br>4. Percentage of unique words<br>5. Stopword count<br>6. Noun/adjective/verb density<br>7. Adjective to noun ratio<br>8. Emphases on words or phrases<br>9. Dialogue density<br>10. Feminine to masculine words ratio<br>11. Use of foreign languages | 1. POS tag of first/last word of a sentence<br>2. Emotions (NRC data), positive/negative<br>3. TF-IDF (words n-grams): degree to which an author uses a word more than the two other authors<br>4. TF-IDF (characters n-grams)<br>5. TF-IDF (POS tags n-grams) |

# Features and Highlights - *(2/4)*

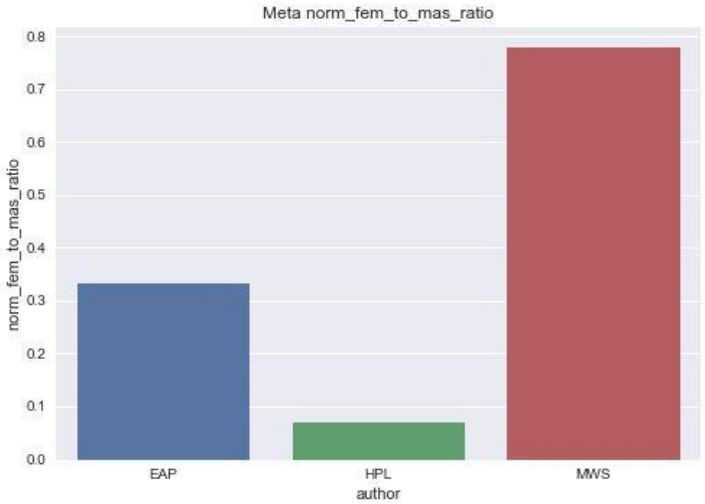



Comma density

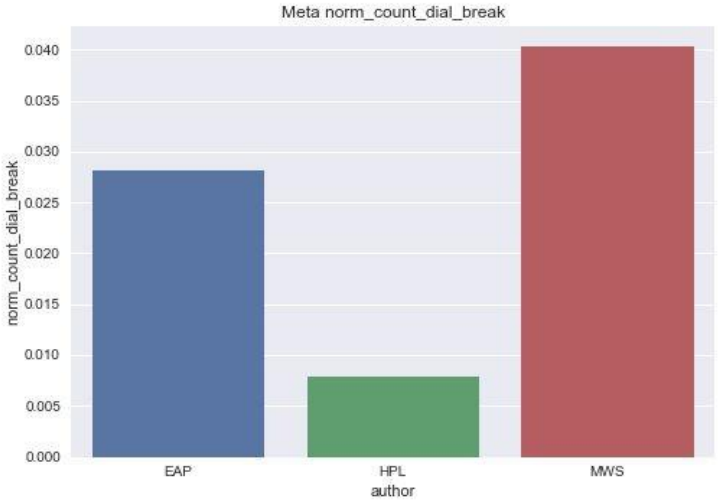



Vocabulary Variation

# Features and Highlights - *(3/4)*



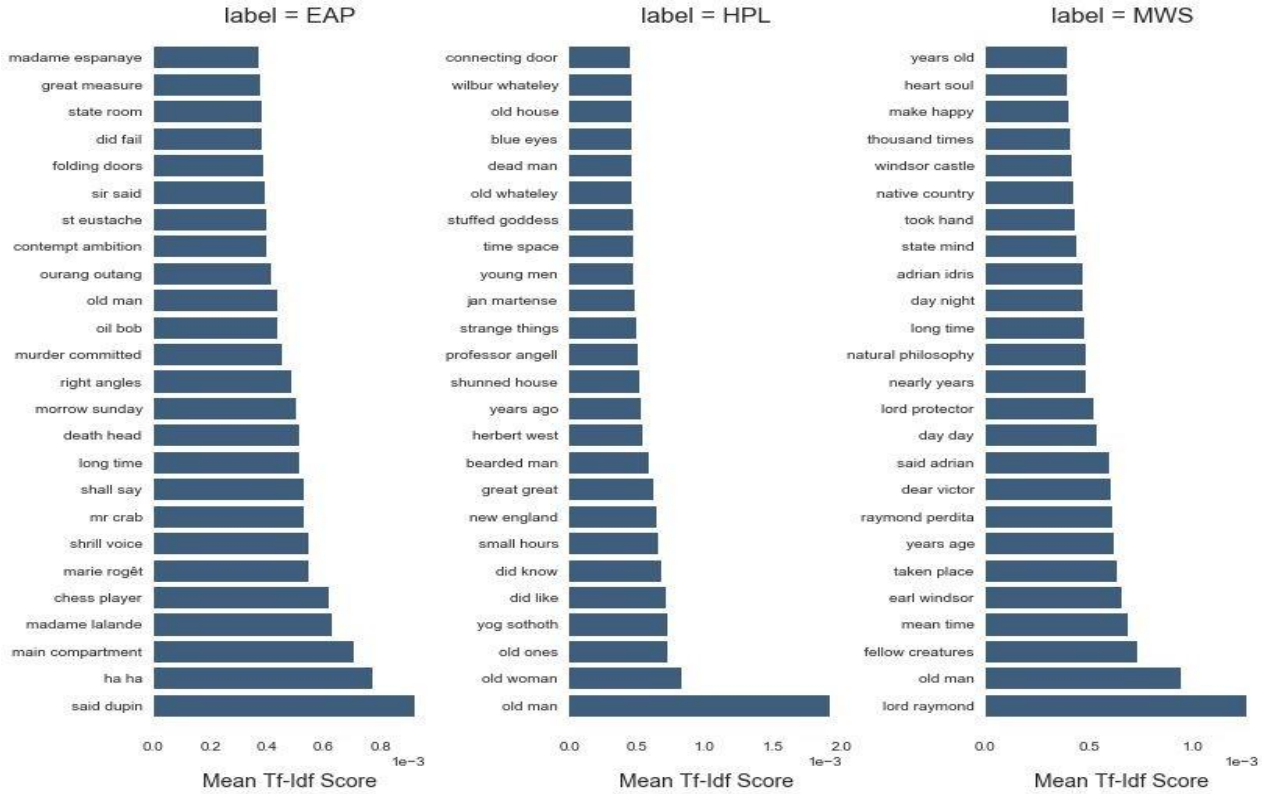

Feminine to Masculine Word Ratio




Use of Dialogue Breaks

# Features and Highlights - *(4/4)*

TF-IDF Bigrams



# Pipeline Combinations

**Feature Count**

- Exactly 10
- Exactly 20
- One-fourth
- Half

X

**Feature Selector**

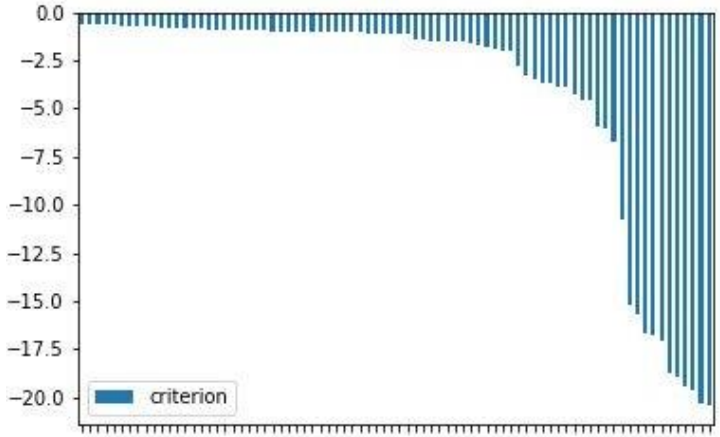
- Univariate Feature Selection
- Recursive Feature Elimination
- Principal Components Analysis

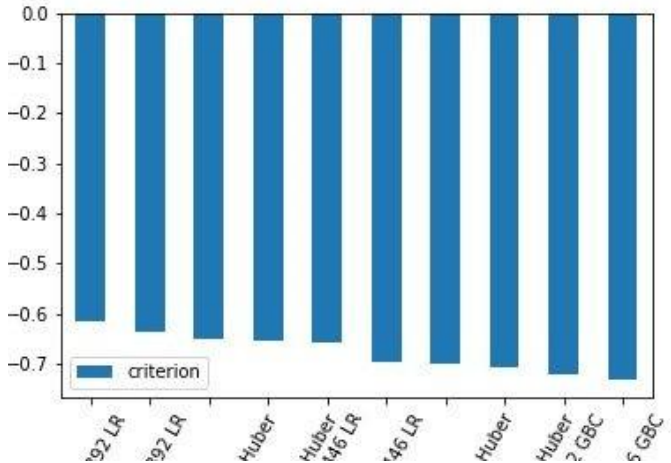
X

**Predictive Model**

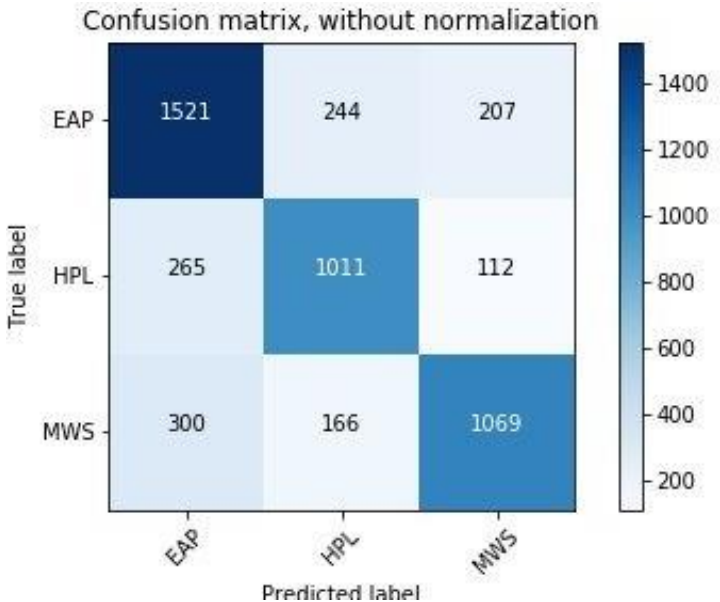
- Logistic Regression
- K-Neighbors Classifier
- Decision Tree Classifier
- Gaussian NB
- Gradient Boosting Classifier
- Ada Boost Classifier
- Extra Trees Classifier
- Random Forest Classifier
- Calibrated Bernoulli NB
- Calibrated Huber

# Results: Pipe Selection



# Results: On TS1




- **Logloss = 0.64**
  **for Half (892) - PCA - Logistic Regression**

| | EAP | HPL | MWS | Formula |
|---|---|---|---|---|
| **Sensitivity** | 0.77 | 0.73 | 0.70 | tp/(tp +fn) |
| **Specificity** | 0.81 | 0.88 | 0.91 | tn/(tn+fp) |
| **Precision** | 0.73 | 0.71 | 0.77 | tp/(tp+fp) |
| **f-score** | 0.75 | 0.72 | 0.73 | 2*prec*sens / (prec+sens) |
| **Accuracy** | 0.79 | 0.84 | 0.84 | (tp+tn)/total |

# Conclusion / Improvements

Gradient descent for coefficients of the selected pipeline

Adding features

Ensembling

Voting system

Deep Learning / Neural Networks

# Questions ?