

m.5.ASSIGNment → Spooky authorship identification via Apache Spark

Overview	Use Apache Spark and machine learning to determine sentence authorship labels.
Data	https://www.kaggle.com/competitions/spooky-author-identification/code



DETAILS

Dataset Description: The spooky author identification dataset contains text from works of fiction written by spooky authors of the public domain: Edgar Allan Poe, HP Lovecraft and Mary Shelley. The data was prepared by chunking larger texts into sentences using CoreNLP's MaxEnt sentence tokenizer resulting in an odd non-sentence here and there. Your objective is to accurately identify the author of the sentences in the test set.

- **id** - unique identifier for each sentence
- **text** - sentence written by one of the authors
- **author** - {EAP:Edgar Allan Poe}, {HPL:HP Lovecraft}; {MWS:Mary Wollstonecraft Shelley}

Objective: Accurately identify the author of the sentences in the test set.

Dataset:

- Training consists of passages with an author label.
- Test has sentences with no author labels.

Competition Evaluation: The submissions were evaluated based on multi-class logarithmic loss. The logarithmic loss assesses the uncertainty of the predicted probabilities, penalizing confident incorrect predictions. Lower log loss values indicated better performance.

Approach: NLP techniques + machine learning algorithms. Feature engineering like bag-of-words, TF-IDF, word embeddings/Word2Vec. Perform algorithmic work with logistic regression, support vector machines, neural networks, and as appropriate.

TASKS

Stage 0: Import Data

1. Create a code notebook called: code_6_of_10_data_mine_<your_name>.ipynb
2. Load data into Spark data objects and explore structure, size, and distribution of information.

Stage 1: Data Preparation - Exploratory data analysis and text mining pre-processing

3. Perform exploratory data analysis and create visualizations and tables as needed.
4. Text Preprocessing: perform tasks like tokenization and stopwords removal to clean text data.

- a. Tokenize - split the text into individual words aka tokens.
- b. Remove stop.words - frequently used pronouns and personal references.
 - i. Top ten include: I, you, he, she, it, we, they, me, him, her
- c. Lemmatization - convert words to their root (optional).
 - i. Lemmatization is a text normalization technique that reduces words to their base or dictionary form (lemma). Use to reduce inflected or derived words to their root form for better analysis and modeling outcomes.

```
from pyspark.ml.feature import StopWordsRemover, Tokenizer
from pyspark.ml.feature import CountVectorizer, IDF
from pyspark.ml.feature import Normalizer
from pyspark.ml import Pipeline

# Step 1: Tokenization
tokenizer = Tokenizer(inputCol="text", outputCol="tokens")
# Step 2: Stop word removal
stopwords_remover = StopWordsRemover(inputCol="tokens", outputCol="filtered_tokens")
'''
Step.1 replace "text" in Tokenizer(inputCol="text", outputCol="tokens")
with the actual column name from your CSV file that contains the text data.
'''
```

Stage 2: Feature Extraction

5. Perform TF-IDF to quantify word importance <[term.frequency.inverse.doc.frequency](#)>
6. Normalize is scaling or standardizing the numerical features to a standard range or distribution.
 - a. In text mining, normalization vectorizes features with methods like TF-IDF, a numerical measurement, to ensure a consistent scale.
 - b. It handles variations in the magnitude of feature values which impacts machine-learning algorithm performance. Normalize the features to ensure a similar scale and prevent features with larger values from dominating the analysis or modeling process.

```
# Step 3: TF-IDF calculation
vectorizer = CountVectorizer(inputCol="filtered_tokens", outputCol="vectorized_tokens")
idf = IDF(inputCol="vectorized_tokens", outputCol="tfidf")
# Step 4: Normalization
normalizer = Normalizer(inputCol="tfidf", outputCol="normalized_features")
# Step 5: Create pipeline for chaining the text mining transformers
pipeline = Pipeline(stages=[tokenizer, stopwords_remover, vectorizer, idf, normalizer])
# Step 6: Apply the pipeline to DataFrame
processed_data = pipeline.fit(your_dataframe).transform(your_dataframe)
'''
step.4 The processed_data object will contain the final processed features in the
"normalized_features" column. use for machine learning tasks.

Step.6 replace your_dataframe with the name of your DataFrame that holds the CSV data.
'''
```

Stage 3: Machine Learning

7. Perform train\test split.
8. Perform algorithmic analysis to assess and predict test labels.
 - a. Use as many algorithms as you need to get a good answer.
 - b. Supervised: logistic regression, random forest, support vector machines, etc.
 - c. Unsupervised: K-means, dimensionality reduction, PCA, etc.

Stage 4: Evaluation & Visualization

9. Choose a metric strategy to assess algorithmic performance like accuracy, precision, recall, or F1 score.
10. Visualize confusion matrix, correlations, and similar.
11. Identify important features contributing to classification.
12. Write a 2-3 sentence minimum of findings, learnings, and what you would do next.

```
from pyspark.ml import Pipeline
from pyspark.ml.feature import StopWordsRemover, Tokenizer, CountVectorizer, IDF
from pyspark.ml.classification import NaiveBayes
from pyspark.ml.evaluation import MulticlassClassificationEvaluator
```

1. Tokenizer to split split part of the pyspark.ml.feature module
2. StopWordsRemover in the pyspark.ml.feature module.
3. lemmatization - PySpark does not have a built-in lemmatization use User-Defined Functions UDF to create.
4. normalize like convert text to lowercase; remove special characters with PySpark user defined functions <UDF> or built-in string functions like lower() or regexp_replace().
5. tf.idf PySpark's CountVectorizer and IDF class compute tf.idf for text feature extraction.

Resources

- [algorithmic assessment reference table](#)
- [PySpark Code Dictionary](#)
- [pd.DataFrame vs. rdd.DataFrame](#)
- [Cheat Sheet for PySpark](#)
- [Additional PySpark Guide](#)
- [Cheat Sheet for LaTeX](#)
- [How to Assess Algorithm Fit](#)
- [Apache Spark Source Documentation](#)
- Feng, W. (2021). [Learning Apache Spark with Python](#). GitHub.

Additional Resources

- Feng, W., & Chen, M. (2017). [Learning Apache Spark](#). GitHub.
- Karau, H., Konwinski, A., Wendell, P., & Zaharia, M. (2015). *Learning Spark: Lightning-fast big data analysis*. O'Reilly Media, Inc.
- Kirillov, A. (2016). [Apache Spark: Core concepts, architecture and internals](#). Datastrophic.