Grouping a Large Dataset of News Documents and predicting its' Classes



1. Frame problem at hand : Predict Classes of Large Dataset New Documents

- Unsupervised Learning -> Large Dataset News Documents -> features -> predict Classes
- Potential Stakeholders
 - Politicians ???
 - Companies??
- Potential Added Value via Project Implementation
 - Time saved on manual labor
 - Metric/s
 - Time
 - What happens if No Project Implementation
- Current Base Model to measure Potential Added Value??

1.1 Initial Evaluation of Potential Value of Project if Implemented

- Why should my data science team do this project instead of others?
 - Politics are significant in every nation -> Politicians will find said data product very useful in saving precious time
 - Metric to optimize for said project?
 - Most Valuable resource -> Time
- What is the outcome of this step?
 - Politicians able to save precious time

1.2 Determine current approach/ create Baseline Model

- Why do it?
 - Chosen ML model > Baseline Model → ADDED Potential Value?
 - ADDED Potential Value > Cost of Time investment?

Delving into the Data Science Process:

2. Collect the raw data needed for the problem

Regarding the chosen dataset:

- Contains:
 - 18828 Newsgroup documents(messages)
 - 20 different Newsgroups
 - Each message
 - File format
 - Text
- The chosen data set can be found: http://gwone.com/~jason/20Newsgroups/
- much appreciation for Ken Lang for the collection of the data & previous Kaggle contributors of analysis

3. Process & Explore the Data before In-Depth Analysis

Original Data

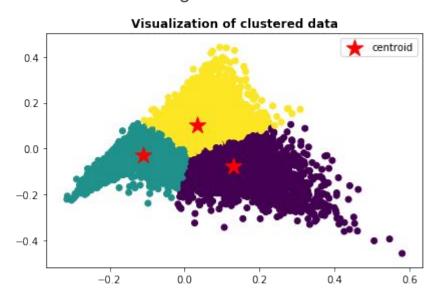
- List of 18828 News Documents
- List of 18828 pathnames of News Documents
- List of 20 Newsgroups each New Document belongs to

Clustering Dataset

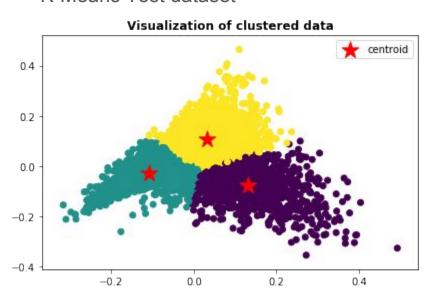
- 5000 features
- 18828 rows

K-Means Clustering

K-Means Training dataset



K-Means Test dataset



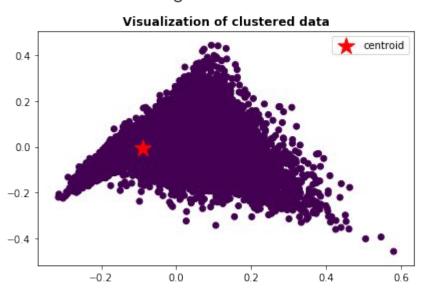
- Somewhat radially symmetrical isotropic true clusters
 - -> somewhat captures underlying patterns

K-Means Clustering Evaluation

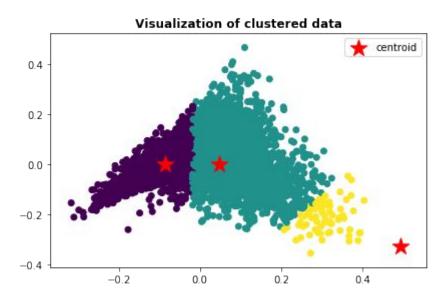
- ARI
 - 0.04 -
 - -> relation datapoint pairs ground truth & new solution -> close perfect randomness
- Similarity Silhoutte Coefficient
 - .007
 - .007
 - o .006
 - o .007
 - -> consistency coefficients of subsets
 - -> samples very close to neighboring clusters

Mean Shift Clustering

Mean Shift Training dataset



Mean Shift Test dataset



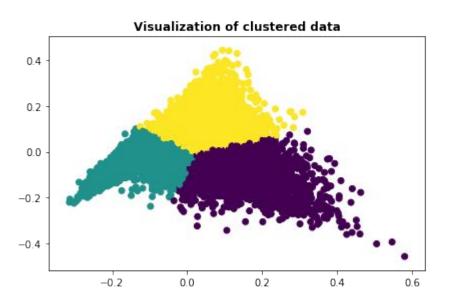
- Somewhat radially symmetric isotropic shape
 - -> Somewhat captures underlying data patterns

Mean Shift Clustering Evaluation

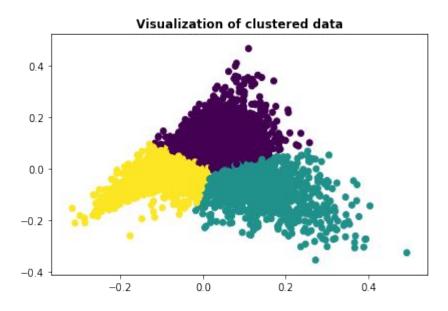
- ARI
 - .0004
 - -> relation datapoint pairs ground truth & new solution -> close perfect randomness
- Similarity Silhoutte Coefficient
 - o **-.06**
 - · -.05
 - o **-.06**
 - o **-.06**
 - Consistency of coefficients between subsets
 - Samples assigned to WRONG clusters

Spectral Clustering

Spectral Training dataset



Spectral Test dataset



- Somewhat radially symmetric isotropic shape
 - -> Somewhat captures underlying data patterns

Spectral Clustering Evaluation

- ARI
 - o .03
 - -> relation datapoint pairs ground truth & new solution -> close perfect randomness
- Similarity Silhoutte Coefficient
 - .007
 - .007
 - o .006
 - o .007
 - -> consistency coefficients of subsets
 - -> samples very close to neighboring clusters

Clustering Algorithms Evaluation

WORST in Capturing data patterns:

- MeanShift
 - Least true cluster shape
 - ARI
 - Ground truth vs new solution most close to perfect randomness
 - Similarity Silhoutte Coefficient
 - Negative
 - -> samples assigned to wrong clusters

BEST in Capturing data patterns:

- K-Means vs Spectral
 - K-Means
 - Slightly better ARI evaluation score

4. In-Depth Analysis

Classification -> Multi Classification

- 20 different classes
 - 3 Classes below in count
 - 1 Class significantly below
 - Class imbalanced
 - Multi Classification -> most common ML performance metrics:
 - Average accuracy
 - F1 score
 - Log- loss
 - Mathews Correlation Coefficient
 - Log-loss symmetric -> does not consider class imbalances
 - Average accuracy? No
 - Mathews very high performance but binary so -> F1 score micro

Training vs Test Accuracy F1- micro Score on ML models:

	Training data set Acc Score	Test data set Acc Score
Random Forest Classifier	.992	.691
Logistic Regression	.991	.812
Multinomial Naive Bayes	.858	.802

- RFC ml model overfitting immensely -> captures alot of noise
- LR ml model overfitting -> still captures noise
- MNB ml model not overfitting + not underfitting
- Decision Threshold = .5

5. Communicate Results of analysis (Potential Data Product)

Uncovered Insights for Proposal Implementation

- Multiclass Multinomial Naive Bayes best + solid ml model performer
 - Closest training and test F1- micro scores with training being tad bit higher-
 - -> .858 vs .802 not overfitting
 - Training F1 micro score decent
 - **858**
 - -> not underfitting
 - Initial Decision Threshold = .5
 - .802 > .5 -> positive + F1 score -> positive w uneven class
 - For even closer + higher training and test mean accuracy scores;
 - dimension reduction on 5000 features?
 - experimenting with NLP & Neural Network features
 - tuning parameters

Moving Forward:

- Aim to make data science project MOST CREDIBLE:
 - Need to implement couple ESSENTIAL CRUCIAL STEPS:
 - Determine current approach/ create baseline model
 - ML monitoring & feedback
 - ML model to Baseline model evaluation via A/B Testing

Link to Corresponding Jupyter Notebook:

https://github.com/pman117/Data Science Portfolio/blob/master/End to End Data Products/Grouping and Classifying Large Dataset News Documents/Grouping and Classifying Large Dataset News Documents.ipynb

Link to Corresponding folder containing entire project:

https://github.com/pman117/Data_Science_Portfolio/tree/master/End_to_End_Data_Product_s/Grouping_and_Classifying_Large_Dataset_News_Documents_