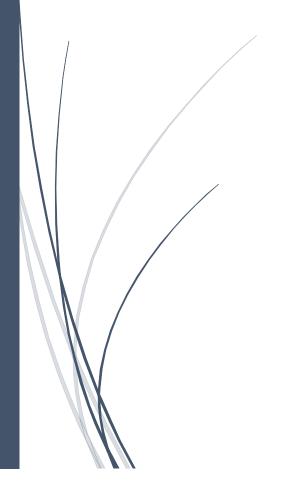
# 7/31/2018

# Data Management, Warehousing Analytics CSCI 5408

Assignment 6: Analyzing data patterns and different classification methods



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# 1. Task Description

In the objective of this project was to implement different machine learning algorithms on a single data set so that the performance of each algorithm can be compared to that of the other. This project uses the language dataset from DSL 2014 workshop to train machine learning models to predict the language a sentence has been written in based on the occurrences or absence of certain words. The data set consists of two .txt files one for the testing data and the other for the training data.[1]

The process of achieving the predictions from these machine learning algorithms involves a number of steps. The data set has to downloaded and imported into the Anaconda Jupiter notebook. Followed by the process of feature extraction, feature selection and model training. These processes are encapsulated in a pipeline so that the training dataset can be rationalized and passed through the already trained model. The resulting prediction is then compared to the actual results to calculate the accuracy of the model. [2], [3]

The accuracy of a model varies based on multiple parameters such as the algorithm used and how well it is suited to the data as well as the features selected. [4] The variation of model accuracy has been shown based on the change in these parameters. A number of visualization techniques have been used to represent this data. In order to perform these predictions, visualizations and analysis a number of resources have been used. These resources include Python libraries like the sklearn, numpy, pandas and matplotlib. [5][6]–[8][9] The Anaconda Jupiter notebook provides a user friendly development environment for easy execution and debugging. [10]

# 2. Procedures Followed

# 2.1 Parsing dataset into a Dataframe

The dataset consists of sentences and the language this sentence belongs to. This data is not in a suitable format for training a classifier.

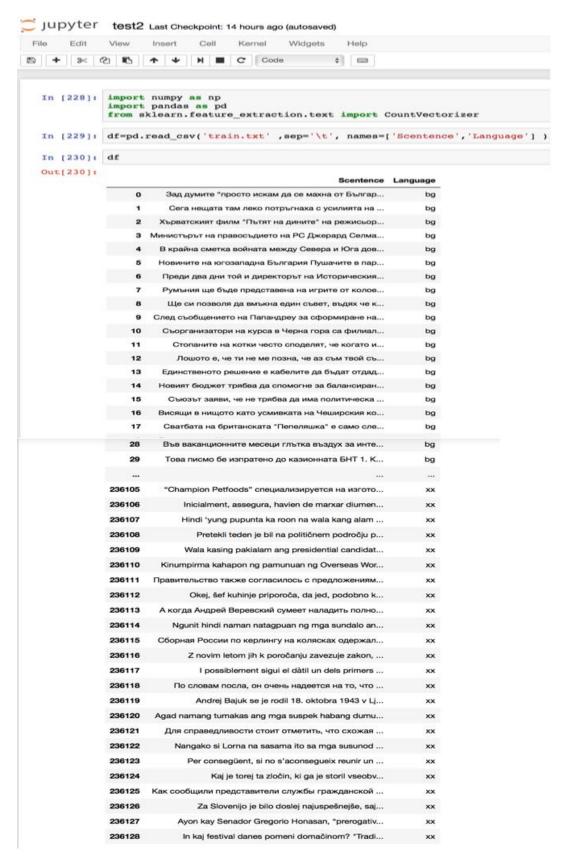


Figure 1: The training dataset imported into a pandas Dataframe

#### 2.2 Feature Extraction

The CountVectorizer() function has to be used to extract the features from the dataset.[11] Features are parameters that vary from one record to another effecting the resulting classification of the record. In this case the frequency of occurrence of each word in a given sentence are the features extracted and the language a sentence belongs to is the label used for classification.

```
In [398]: x traincv=cv.fit transform(df x)
In [399]: x=x traincv.toarray()
In [400]: from sklearn.feature_extraction.text import TfidfTransformer
          tf transformer = TfidfTransformer(use idf=False).fit(x)
In [401]: X_train_tf = tf_transformer.transform(x)
In [402]: X train tf.shape
Out[402]: (2600, 35996)
In [403]: a=X_train_tf.toarray()
In [404]: a
Out[404]: array([[0.14142136, 0.14142136, 0.
                            1,
                            , 0.
                                                                       , 0.
                 .01
                                                     , ..., 0.
                  0 -
                 .0]
                            , 0.
                                         , 0.
                             . 0.
                 .01
                  0.
                             , 0.
                 .0]
                                         , 0.
                                                                       , 0.
                 [0.
```

Figure 2: The training dataset imported into a pandas Dataframe

# 2.3 Sampling

This dataset is quite large consisting of 2000 records per language. Since this dataset has thirteen languages this means there are 26,0000 records in total.[1] In order to generate plots that show a clear separation of points, based on the language class the point belongs to, a smaller sample of points has been taken for plotting the graphs. The sample function from the pandas library has been used to select an equal number of points from each of the thirteen language classes.[5] These points from each of the thirteen languages have been chosen in random order. We wanted to select 200 points from each language this is achieved by setting the n parameter of the sample function to the total number of records to be returned and leaving all the other parameters at the default setting. When all parameters except the n value are given the default setting the function chooses an equal weightage of

points for each of the classes.[5] In our case we need 200 records for each of the 13 values giving a total of 2600 returned records. Therefor the value of the n parameter must be set to 2600 to select 200 points from each language.

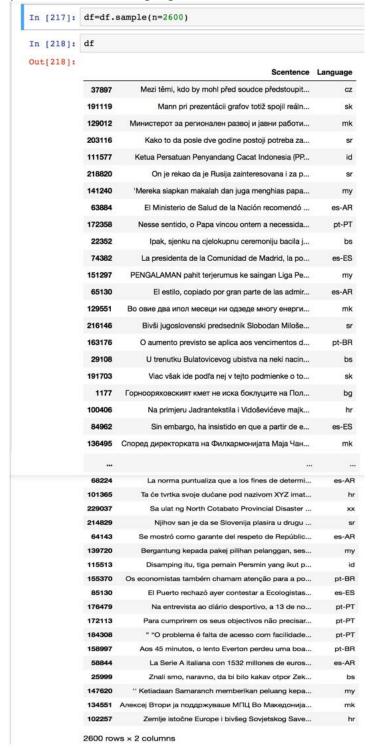


Figure 3: running query after extraction

# 2.4 Feature Selection

We have used chi square to select the features since the desired number of features can be selected with best scores using the chi square statistics. The training dataset is divided to data and target. Using SelectKBest function, we select best features. The best features are displayed using fit\_transform function.

```
In [421]: from sklearn.feature selection import SelectKBest, chi2
          from sklearn.datasets import load_iris
          iris = load_iris()
          x_train, y_train = iris.data, iris.target# Select 3 top features
          selection = SelectKBest(chi2, k=3)
In [422]: selection.fit transform(x train, y train)
Out[422]: array([[5.1, 1.4, 0.2],
                 [4.9, 1.4, 0.2],
                 [4.7, 1.3, 0.2],
                  [4.6, 1.5, 0.2],
                  [5., 1.4, 0.2],
                  [5.4, 1.7, 0.4],
                  [4.6, 1.4, 0.3],
                 [5., 1.5, 0.2],
                  [4.4, 1.4, 0.2],
                  [4.9, 1.5, 0.1],
                  [5.4, 1.5, 0.2],
                  [4.8, 1.6, 0.2],
                  [4.8, 1.4, 0.1],
                  [4.3, 1.1, 0.1],
                  [5.8, 1.2, 0.2],
                  [5.7, 1.5, 0.4],
                  [5.4, 1.3, 0.4],
                 [5.1, 1.4, 0.3],
                 [5.7, 1.7, 0.3],
```

Figure 4: The three best features

```
In [299]:
           y train=df["Language"]
           y train
           #ay= y_train.toarray
Out[299]: 92107
                          hr
           215429
                          sr
           196971
                          sk
           118461
                          id
           57203
                      es-AR
           168426
                      pt-PT
           28027
                          bs
           212969
                          sr
           147004
                         my
           91292
                          hr
           154313
                      pt-BR
           156602
                      pt-BR
           128438
                         mk
           217649
                          sr
           138243
                         my
           53555
                      es-AR
           65562
                      es-AR
           26386
                         bs
           67565
                      es-AR
           109688
                          id
           216743
                          sr
           118508
                          id
           16463
                         bg
           186554
                          sk
           144376
                         my
           146992
                         my
           217614
                          sr
           138633
                         my
           79182
                      es-ES
           119142
                          id
           35282
                          cz
```

Figure 5. Language column is taken as training dataset

The whole dataset is divided into training and testing data. Training data is fitted into df\_x and df\_y. The testing data is fitted into dft. The number of columns, 2600 is randomly selected from the dataset as training and testing. The training dataset is utilized to train the pipeline model and testing data is used to predict accuracy and confusion matrix of the model. Detailed process is described below. The test data is splitted into two dataframes, one dataframe consisting Sentence column, other column consisting Language dataset.

```
In [124]: dft=pd.read csv('C:/Users/bhavy/Downloads/DSL-Task-master/DSL-Task-master/data/DSLCC-v2.0/test/test.txt', sep='\t', names=['Scenter']
In [125]: dft=df.sample(n=2600)
In [126]: dft
Out[126]:
               99074
                              Puniti će se mađarska i norveška blagajna na š.
              155974
                                                                               pt-BR
                                 Já a Copa do Brasil, prioridade tricolor no pr.
              128712
                          (Од лево) палестинскиот лекар со бугарско држа.
              182574
                               Porém, esta série inexplicável de erros, sempr.
                                                                               pt-PT
               59875
                            A sólo unas semanas del Salón de Ginebra 2011,...
                                                                               es-AR
              123999
                          Милошевиќ умре на 11 март, ден пред денот на к..
                                                                                  mk
                                                                               pt-PT
              170636
                            Francisco Rodrigues Santos, da Associação de E.,
               66511
                                Y en sintonía con los instrumentos contracícli.
                                                                               es-AR
               10735
                         По случая с лекарите в Горна Оряховица Цветано...
                                                                                  bg
              191349
                              Keď budú existovať dve strany v istom zmysle
                                                                                  sk
               11348
                         Румъния е на последно място в ЕС по размер на ..
                                                                                  ba
              173279
                             Esta ronda de audicões decorre depois do Presi.
                                                                               pt-PT
               58923
                                Racanelli pidió la libertad de ambos, pero le ..
```

Figure 6: Test data

pt-BR

Salvador, 01 de março de 2011 Repercussão de s...

165737

```
2600 rows × 2 columns
In [127]: dft_x=dft["Scentence"]
          dft_y = dft["Language"]
In [128]: dft x
Out[128]: 99074
                    Puniti će se mađarska i norveška blagajna na š...
          155974
                    Já a Copa do Brasil, prioridade tricolor no pr...
          128712
                    (Од лево) палестинскиот лекар со бугарско држа...
                    Porém, esta série inexplicável de erros, sempr...
          182574
          59875
                    A sólo unas semanas del Salón de Ginebra 2011,...
          123999
                    Милошевиќ умре на 11 март, ден пред денот на к...
          170636
                    Francisco Rodrigues Santos, da Associação de E...
          66511
                    Y en sintonía con los instrumentos contracícli...
          10735
                    По случая с лекарите в Горна Оряховица Цветано...
          191349
                    Keď budú existovať dve strany, v istom zmysle ...
          11348
                    Румъния е на последно място в ЕС по размер на ...
          173279
                    Esta ronda de audições decorre depois do Presi...
          58923
                    Racanelli pidió la libertad de ambos, pero le ...
          165737
                    Salvador, 01 de março de 2011 Repercussão de s...
          149757
                    Beliau berkata lebih mudah untuk mengawal golo...
          112616
                    Puncaknya, JC bertugas menggelar kongres pada ...
          92963
                    Dok smo punili krmeno skladište vodom, naš str...
                    Banka však nebije na poplach a argumentuje, že...
          196758
                    Iz suhoparne formulacije referendumskega vpraš...
          228974
          45634
                    Je neuvěřitelné jak si všichni lidi přejí aby ...
                    Terlepas dari siapa yang menyebarkan, yang jel...
          105098
          137007
                    Но, само еден ден по потпишувањето на меморанд...
          164622
                    Unidade Modular do Beira Rio retoma atendiment...
          114109
                    Puluhan tenaga bakti Pemadam Kebakaran Krueng ...
          11564
                    Уругвайците обаче не само участват, но и отива...
          32776
                    Programi za pripremnost u slučaju vanrednih st...
          10151
                    Според съобщение на Ройтерс, Лимай е заявил по...
          188490
                    Roky trvajúce rokovania na expertnej úrovni o ...
```

Figure 7: Displaying one set of Dataframe

In [129]:	dft y	
111 [153]:	urt_y	
Out[129]:	99074	hr
	155974	pt-BR
	128712	mk
	182574	pt-PT
	59875	es-AR
	123999	mk
	170636	pt-PT
	66511	es-AR
	10735	bg
	191349	sk
	11348	bg
	173279	pt-PT
	58923	es-AR
	165737	pt-BR
	149757	my
	112616	id
	92963	hr
	196758	sk
	228974	XX
	45634	CZ
	105098	id
	137007	mk
	164622	pt-BR
	114109	id
	11564	bg
	32776	bs
	10151	bg
	188490	sk
	98662	hr
	139203	my
	0.0043	
	96013	hr
	125873	mk

Figure 8: Displaying Language dataframe

# 2.5 Pipelining

The pipeline is consisted of vectorizer, classifier and feature selection. The features are counted by vectorizer and selected and reduced by Dimensionality reduction algorithm and the classifier is applied on the selected features.

```
In [130]: from sklearn.pipeline import FeatureUnion
          from sklearn.pipeline import Pipeline
          from sklearn.decomposition import TruncatedSVD
          from sklearn.linear model import LogisticRegression
          ##pipeline = Pipeline([('clf', LinearSVC(random state=0))])
          ##pipeline.fit(x_train)
          lrp = Pipeline([
              ('vect', CountVectorizer()),
              ('svd', TruncatedSVD(n_components=10)),
              ##('tfid',TfidfTransformer()),
                                 ('lr',LogisticRegression())
                                 1)
In [131]: lrp.steps
Out[131]: [('vect', CountVectorizer(analyzer='word', binary=False, decode error='strict',
                    dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
                    lowercase=True, max_df=1.0, max_features=None, min_df=1,
                    ngram range=(1, 1), preprocessor=None, stop words=None,
                    strip_accents=None, token_pattern='(?u)\\b\\w\\w+\\b',
                    tokenizer=None, vocabulary=None)),
           ('svd', TruncatedSVD(algorithm='randomized', n_components=10, n_iter=5,
                   random state=None, tol=0.0)),
```

Figure 9: Example of a Pipeline model

LogisticRegression(C=1.0, class weight=None, dual=False, fit intercept=True,

intercept\_scaling=1, max\_iter=100, multi\_class='ovr', n\_jobs=1,
penalty='l2', random\_state=None, solver='liblinear', tol=0.0001,

# 2.6 Training, Testing and Evaluating accuracy of the model

The pipeline model is then trained on the training dataset df\_x and df\_y and is predicted on the testing data that is different to training data.

verbose=0, warm\_start=False))]

```
In [132]: model = lrp.fit(df_x,df_y)
In [133]: model.predict(dft_x)
Out[133]: array(['cz', 'pt-BR', 'mk', ..., 'sk', 'pt-PT', 'es-ES'], dtype=object)
```

Figure 10: Pipeline model result

# 3. Classification Algorithm

('lr',

# 3.1 Scatter plot of training data

Output:

Code:

```
In [414]: import matplotlib.pyplot as plt
In [420]: N = 50
x = np.random.rand(N)
y = np.random.rand(N)
colors = np.random.rand(N)
area = (30 * np.random.rand(N))**2 # 0 to 15 point radii

plt.scatter(x_train[:,0], y_train, c=x_train[:,1], s=area, alpha=0.5)
plt.show()
```

Figure 11: Code to scatter plot training data

The above shows the Scatter plot code on how x\_train[:,0] is plotted against y\_train where the x\_train[:,1] are depicted as colors. The plt.show() displays the graph that is shown below. From the graph it is seen that second column of the training data is displayed in color and the first column of the data is depicted in x-axis.

# Visualization:

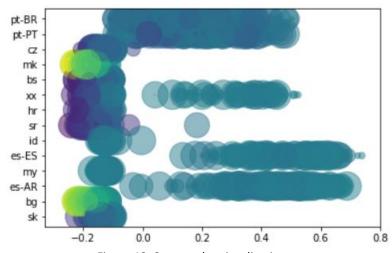


Figure 12: Scatter plot visualization

# 3.2 Linear SVM

# **Pipeline Code:**

Linear Supervised Model classifier is used to classify the features. Each feature is varied with the value. The pipeline is consisted of CountVectorizer, TruncatedSVD and

LinearSVC. The model is fitted with training data and predicted with testing data. The output is displayed in one dimensional array.

```
In [137]: from sklearn.pipeline import FeatureUnion
          from sklearn.pipeline import Pipeline
          from sklearn.decomposition import TruncatedSVD
          from sklearn.svm import LinearSVC
          ##pipeline = Pipeline([('clf', LinearSVC(random state=0))])
          ##pipeline.fit(x train)
          lsvc = Pipeline([
              ('vect', CountVectorizer()),
               ('svd', TruncatedSVD(n_components=10)),
              ##('tfid',TfidfTransformer()),
                                 ('lr',LinearSVC())
                                 1)
In [138]: lsvc.steps
Out[138]: [('vect', CountVectorizer(analyzer='word', binary=False, decode error='strict',
                    dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
                    lowercase=True, max_df=1.0, max_features=None, min_df=1,
                    ngram_range=(1, 1), preprocessor=None, stop_words=None,
                    strip accents=None, token pattern='(?u)\\b\\w\\w+\\b',
                    tokenizer=None, vocabulary=None)),
           ('svd', TruncatedSVD(algorithm='randomized', n components=10, n iter=5,
                   random state=None, tol=0.0)),
           ('lr', LinearSVC(C=1.0, class weight=None, dual=True, fit intercept=True,
                  intercept scaling=1, loss='squared hinge', max iter=1000,
                 multi class='ovr', penalty='l2', random state=None, tol=0.0001,
                 verbose=0))]
In [139]: model1 = lsvc.fit(df x, df y)
In [140]: model1.predict(dft x)
Out[140]: array(['cz', 'pt-BR', 'mk', ..., 'xx', 'pt-BR', 'es-ES'], dtype=object)
                     Figure 13: Pipeline model prediction for Linear SVM
```

#### **Accuracy:**

The accuracy score when Linear SVC is implemented in pipeline model results in 0.57

```
In [141]: accuracy_score(dft_y,lsvc.predict(dft_x), normalize=True, sample_weight=None) #svc
Out[141]: 0.5746153846153846
```

Figure 14: Pipeline model accuracy for Linear SVM

```
In [142]: cm1=confusion_matrix(dft_y,lsvc.predict(dft_x))
    fg = plt.figure()
    axi = fg.add_subplot(111)
    cx = axi.matshow(cm1)
    plt.title('Linear SVC')
    fg.colorbar(cx)
    #ax.set_xticklabels([''] + labels)
    #ax.set_yticklabels([''] + labels)
    #plt.xlabel('Predicted')
    #plt.ylabel('True')
    plt.show()
```

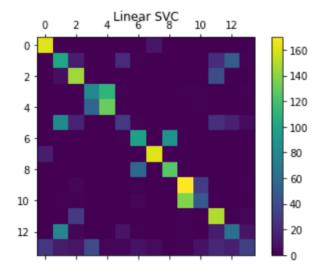


Figure 15: Pipeline model confusion matrix for Linear SVM

# 3.3 Logistic Regression

# **Pipeline Code:**

Logistic Regression classifier is used to classify the features. Each feature is plotted with ita value to form a line. The pipeline is consisted of CountVectorizer, TruncatedSVD and Logistic Regression. The model is fitted with training data and predicted with testing data. The output is displayed in one dimensional array.

```
In [130]: from sklearn.pipeline import FeatureUnion
          from sklearn.pipeline import Pipeline
          from sklearn.decomposition import TruncatedSVD
          from sklearn.linear_model import LogisticRegression
           ##pipeline = Pipeline([('clf', LinearSVC(random_state=0))])
          ##pipeline.fit(x train)
          lrp = Pipeline([
              ('vect', CountVectorizer()),
              ('svd', TruncatedSVD(n components=10)),
              ##('tfid',TfidfTransformer()),
                                 ('lr',LogisticRegression())
                                 1)
In [131]: lrp.steps
Out[131]: [('vect', CountVectorizer(analyzer='word', binary=False, decode_error='strict',
                    dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
                    lowercase=True, max df=1.0, max features=None, min df=1,
                    ngram_range=(1, 1), preprocessor=None, stop_words=None,
                    strip accents=None, token pattern='(?u)\\b\\w\\w+\\b',
                    tokenizer=None, vocabulary=None)),
           ('svd', TruncatedSVD(algorithm='randomized', n components=10, n iter=5,
                   random state=None, tol=0.0)),
           ('lr',
            LogisticRegression(C=1.0, class weight=None, dual=False, fit intercept=True,
                      intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
                      penalty='l2', random state=None, solver='liblinear', tol=0.0001,
                      verbose=0, warm start=False))]
```

Figure 16: The training dataset imported into a pandas Dataframe

#### Accuracy:

The accuracy of the Logistic Regression pipeline model is 0.56

```
In [134]: from sklearn.metrics import accuracy_score
In [135]: accuracy_score(dft_y,lrp.predict(dft_x), normalize=True, sample_weight=None) #logistic
Out[135]: 0.5676923076923077
```

Figure 18: Accuracy for Logistic Regression pipeline model

# **Output: Confusion matrix**

```
In [136]: from sklearn.metrics import confusion_matrix
    cm=confusion_matrix(dft_y,lrp.predict(dft_x)) #logistic
    fg = plt.figure()
    axi = fg.add_subplot(111)
    cx = axi.matshow(cm)
    plt.title('Logistic Regression')
    fg.colorbar(cx)
    #ax.set_xticklabels([''] + labels)
    #ax.set_yticklabels([''] + labels)
    #plt.xlabel('Predicted')
    #plt.ylabel('True')
    plt.show()
```

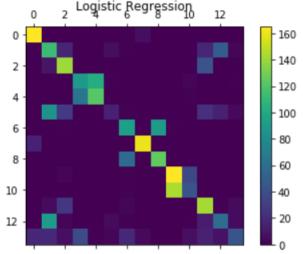


Figure 19: Confusion matrix for Logistic Regression pipeline model

# 3.4 Decision Tree

# **Pipeline Code:**

Here, the decision Tree classifier is used to classify the features. The pipeline is consisted of CountVectorizer, TruncatedSVD and Decision Tree. The model is fitted with training data and predicted with testing data. The output is displayed in one dimensional array.

```
In [155]: from sklearn.tree import DecisionTreeClassifier
           dtc= Pipeline([
               ('vect', CountVectorizer()),
               ('svd', TruncatedSVD(n_components=10)),
               ##('tfid',TfidfTransformer()),
                                 ('dtc', DecisionTreeClassifier())
In [156]: dtc.steps
Out[156]: [('vect', CountVectorizer(analyzer='word', binary=False, decode error='strict',
                     dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
                     lowercase=True, max df=1.0, max features=None, min df=1,
                     ngram range=(1, 1), preprocessor=None, stop words=None,
                     strip_accents=None, token_pattern='(?u)\\b\\w\\w+\\b',
                     tokenizer=None, vocabulary=None)),
            ('svd', TruncatedSVD(algorithm='randomized', n components=10, n iter=5,
                    random state=None, tol=0.0)),
            ('dtc',
             DecisionTreeClassifier(class weight=None, criterion='gini', max depth=None,
                         max features=None, max leaf nodes=None,
                         min impurity decrease=0.0, min impurity split=None,
                         min samples leaf=1, min samples split=2,
                         min weight fraction leaf=0.0, presort=False, random state=None,
                         splitter='best'))]
                       Figure 20: Decision Tree classifier pipeline model
In [157]: model4 = dtc.fit(df x, df y)
In [158]: model4.predict(dft x)
Out[158]: array(['hr', 'pt-BR', 'mk', ..., 'hr', 'pt-PT', 'es-ES'], dtype=object)
                   Figure 21: Decision Tree classifier pipeline model prediction
Accuracy:
 The accuracy of Decision Tree classifier is 1.0
```

```
In [159]: accuracy score(dft y,dtc.predict(dft x), normalize=True, sample weight=None)
Out[159]: 1.0
```

Figure 22: Decision Tree classifier pipeline model accuracy

# **Confusion Matrix:**

```
In [160]: cm4=confusion_matrix(dft_y,dtc.predict(dft_x))
    fg = plt.figure()
    axi = fg.add_subplot(111)
    cx = axi.matshow(cm4)
    plt.title('Decision Tree Classifier')
    fg.colorbar(cx)
    #ax.set_xticklabels([''] + labels)
    #ax.set_yticklabels([''] + labels)
    #plt.xlabel('Predicted')
    #plt.ylabel('True')
    plt.show()
```

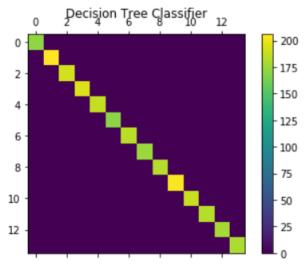


Figure 23: Decision Tree classifier pipeline model confusion matrix

# 3.5 Naïve Bayes

# **Pipeline Code:**

Two pipelines named mnb and bnb are created where in mnb consists of CountVectorizer, SelectKBest and MultinomialNB classifier as shown in the below code. Bnb is created based on CountVectorizer, TruncatedSVD and Burnoulli NB. The model is predicted with the test data for both mnb and bnb.

```
In [143]: from sklearn.pipeline import FeatureUnion
           from sklearn.pipeline import Pipeline
           from sklearn.decomposition import TruncatedSVD
           from sklearn.naive bayes import MultinomialNB
           ##pipeline = Pipeline([('clf', LinearSVC(random state=0))])
           ##pipeline.fit(x train)
           mnb = Pipeline([
               ('vect', CountVectorizer()),
               ('svd', SelectKBest()),
               ##('tfid', TfidfTransformer()),
                                 ('mnb', MultinomialNB())
In [144]: mnb.steps
Out[144]: [('vect', CountVectorizer(analyzer='word', binary=False, decode_error='strict',
                     dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
                     lowercase=True, max df=1.0, max features=None, min df=1,
                     ngram_range=(1, 1), preprocessor=None, stop_words=None,
                     strip accents=None, token_pattern='(?u)\\b\\w\\w+\\b',
                     tokenizer=None, vocabulary=None)),
            ('svd',
            SelectKBest(k=10, score func=<function f classif at 0x0000001E1082B81E0>)),
            ('mnb', MultinomialNB(alpha=1.0, class prior=None, fit prior=True))]
                       Figure 24: Multinomial Naïve Bayes pipeline model
In [145]: model2 = mnb.fit(df x, df y)
In [146]: model2.predict(dft x)
Out[146]: array(['bs', 'pt-BR', 'bs', ..., 'bs', 'pt-BR', 'es-ES'], dtype='<U5')
                  Figure 25: Multinomial Naïve Bayes pipeline model prediction
Accuracy:
```

The accuracy for the Multinomial Naïve Bayes is 0.26

```
In [147]: accuracy_score(dft_y,mnb.predict(dft_x), normalize=True, sample_weight=None) #mnb
Out[147]: 0.2684615384615385
```

Figure 26: Multinomial Naïve Bayes pipeline model accuracy

```
In [148]: cm2=confusion_matrix(dft_y,mnb.predict(dft_x))
    fg = plt.figure()
    axi = fg.add_subplot(111)
    cx = axi.matshow(cm2)
    plt.title('Mutlinomial MNB')
    fg.colorbar(cx)
    #ax.set_xticklabels([''] + labels)
    #ax.set_yticklabels([''] + labels)
    #plt.xlabel('Predicted')
    #plt.ylabel('True')
    plt.show()
```

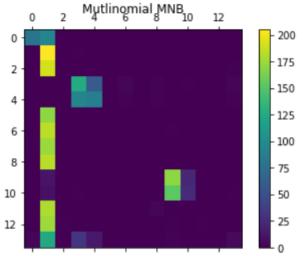


Figure 27: Multinomial Naïve Bayes pipeline model confusion matrix

# 3.6 Naïve Bayes – BNB

Pipeline:

Below shows the code for Bernoulli Naïve Bayes classifier that is fitted into pipeline.

```
In [149]: from sklearn.pipeline import FeatureUnion
          from sklearn.pipeline import Pipeline
          from sklearn.decomposition import TruncatedSVD
          from sklearn.naive bayes import BernoulliNB
           ##pipeline = Pipeline([('clf', LinearSVC(random_state=0))])
          ##pipeline.fit(x train)
          bnb= Pipeline([
               ('vect', CountVectorizer()),
               ('svd', TruncatedSVD(n_components=10)),
              ##('tfid',TfidfTransformer()),
                                 ('mnb',BernoulliNB())
                                 1) #bnb
In [150]: bnb.steps
Out[150]: [('vect', CountVectorizer(analyzer='word', binary=False, decode_error='strict',
                    dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
                    lowercase=True, max df=1.0, max features=None, min df=1,
                    ngram range=(1, 1), preprocessor=None, stop words=None,
                    strip accents=None, token pattern='(?u)\\b\\w\\w+\\b',
                    tokenizer=None, vocabulary=None)),
           ('svd', TruncatedSVD(algorithm='randomized', n components=10, n iter=5,
                   random state=None, tol=0.0)),
           ('mnb',
            BernoulliNB(alpha=1.0, binarize=0.0, class prior=None, fit prior=True))]
                        Figure 28: Bernoulli Naïve Bayes pipeline model
In [151]: model3 = bnb.fit(df x, df y)
In [152]: model3.predict(dft x)
Out[152]: array(['cz', 'pt-BR', 'bg', ..., 'sk', 'pt-BR', 'es-ES'], dtype='<U5')
                    Figure 29: Bernoulli Naïve Bayes pipeline model prediction
In [153]: accuracy score(dft y,bnb.predict(dft x), normalize=True, sample weight=None) #bnb
Out[153]: 0.4765384615384615
                    Figure 30: Bernoulli Naïve Bayes pipeline model accuracy
```

```
In [154]: cm3=confusion_matrix(dft_y,bnb.predict(dft_x))
    fg = plt.figure()
    axi = fg.add_subplot(111)
    cx = axi.matshow(cm3)
    plt.title('Burnoulli NB')
    fg.colorbar(cx)
    #ax.set_xticklabels([''] + labels)
    #ax.set_yticklabels([''] + labels)
    #plt.xlabel('Predicted')
    #plt.ylabel('True')
    plt.show()
```

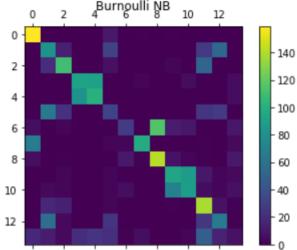


Figure 31: Bernoulli Naïve Bayes pipeline model confusion matrix

# 3.7 Comparison of accuracy

Classifier	Accuracy
Linear SVC	0.57
Logistic Regression	0.56
Decision Tree Classifier	1.0
Multinomial Naïve Bayes	0.26
Bernoulli Naïve Bayes	0.47

Table 1: Accuracy Comparision table

Based on the classifiers' accuracy, we can say that Decision Tree classifier gives the best accurate results compared to other classifiers. The Linear SVC and Logistic Regression give almost close accurate results after Decision Tree Classifier.

# 3.8 Impact of feature selection

The features that are selected and extracted from the given text contains noisy data that makes harder to plot the values. The noisy data can be viewed in the array when the Sentence text is mapped to an array.

# 4. Code Submission

The code has been submitted on both brightspace and on Github. The Github link has been given below.

https://github.com/SograMemon/DataWarehouse-A2.git

# 5. References

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