Logistic Regression on Amazon Reviews Dataset

June 16, 2018

```
In [1]: import sqlite3
        import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
        import plotly.plotly as py
        import plotly.graph_objs as go
        from sklearn.cross_validation import train_test_split
        from sklearn.neighbors import KNeighborsClassifier
        from sklearn.metrics import accuracy_score
        from sklearn.cross_validation import cross_val_score
        from collections import Counter
        from sklearn.metrics import accuracy_score
        from sklearn import cross_validation
        from sklearn.feature_extraction.text import TfidfTransformer
        from sklearn.feature_extraction.text import TfidfVectorizer
        from sklearn.feature_extraction.text import CountVectorizer
        from sklearn.metrics import confusion_matrix
        from sklearn import metrics
        from sklearn.metrics import roc_curve, auc
        from nltk.stem.porter import PorterStemmer
        from sklearn.decomposition import TruncatedSVD
        from sklearn.model_selection import TimeSeriesSplit
        from sklearn.model_selection import GridSearchCV
        from sklearn.linear_model import LogisticRegression
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/cross_validation.py:41: DeprecationWarning:

This module was deprecated in version 0.18 in favor of the model_selection module into which a
```

1 Loading and Sampling the dataset(100k data-points)

```
In [0]: final = pd.read_csv("final.csv")


        final_data = final.sample(n = 100000)
```

```
        final_data = final_data.drop(["Text"], axis = 1)
        final_data = final_data.drop(final_data.columns[0], axis = 1)
```

```
In [0]: labels = final_data.Score
        final_data = final_data.sort_values("Time")
        final_data.shape
```

```
Out[0]: (100000, 10)
```

2 Train/Test Split

```
In [0]: n = final_data.shape[0]
        train_size = 0.7

        train_set = final_data.iloc[:int(n*train_size)]
        test_set =final_data.iloc[int(n*train_size):]

        X_train = train_set.CleanedText
        y_train = train_set.Score

        X_test = test_set.CleanedText
        y_test= test_set.Score
```

```
In [0]: ## tokenizing the training data to find frequency of words
        t = []
        for line in X_train:
            l = nltk.word_tokenize(line)
            for w in l:
                t.append(w)
```

```
In [0]: word_features = nltk.FreqDist(t)
        print (len(word_features))
```

```
36299
```

3 Feature Selection

```
In [0]: #The most frequent 5000 features as the featureset

        topwords = [fpair[0] for fpair in list(word_features.most_common(5000))]
        print (word_features.most_common(25))
```

```
[("'", 69999), ('like', 30800), ('tast', 30378), ('flavor', 24481), ('good', 23182), ('one', 2
```

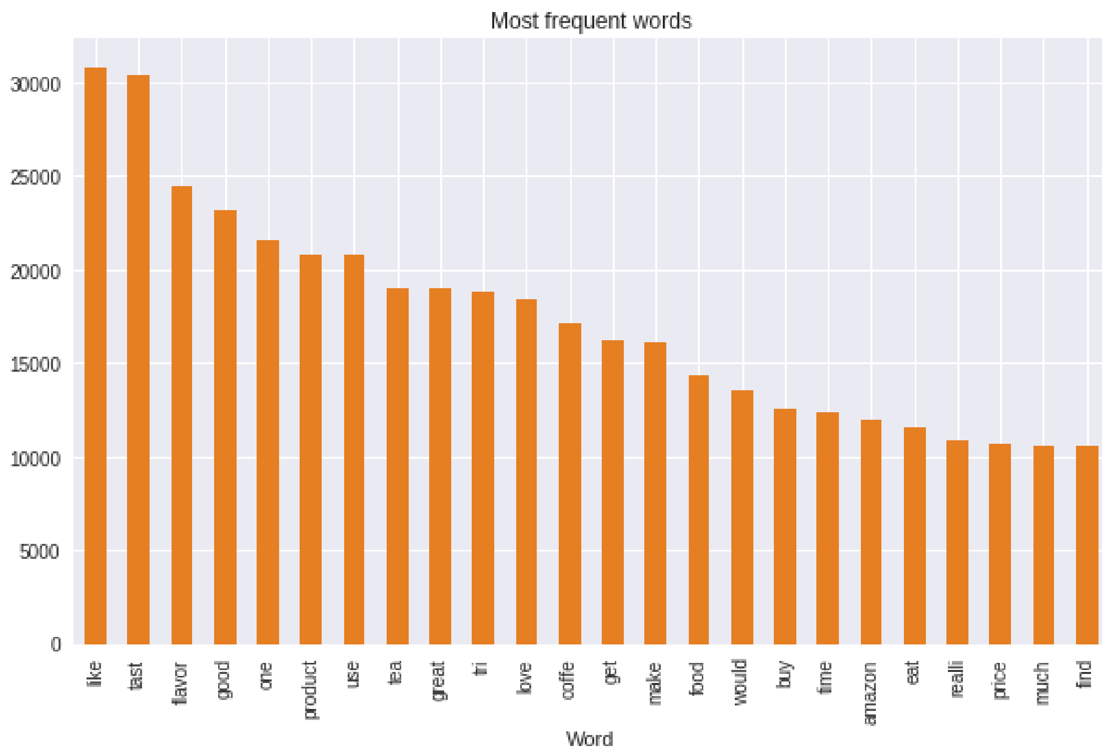
```
In [0]: word_plot = pd.DataFrame(word_features.most_common(25),columns=['Word','Count'])
```

```
In [0]: print(word_plot)
```

```
       Word  Count
1      like  30800
2      tast  30378
3    flavor  24481
4      good  23182
5       one  21533
6   product  20781
7       use  20744
8       tea  19030
9     great  19021
10      tri  18764
11     love  18374
12    coffe  17075
13      get  16219
14     make  16114
15     food  14288
16    would  13576
17      buy  12549
18     time  12343
19   amazon  11952
20      eat  11543
21   realli  10904
22    price  10670
23     much  10596
24     find  10563
```

```
In [0]: word_plot.plot(kind='bar',x=word_plot['Word'],legend=False,title='Most frequent words'
```

```
Out[0]: <matplotlib.axes._subplots.AxesSubplot at 0x7fccc3566c50>
```



3.1 We can observe from the above plot that the most important words are:

- **like**
- **taste**
- **flavour**

4 Bag of words Vectorization

```
In [0]: count_vect = CountVectorizer() #in scikit-learn
        X_train1 = count_vect.fit_transform(X_train)
        X_test1 = count_vect.transform(X_test)
```

```
In [0]: #Standardization
        from sklearn.preprocessing import StandardScaler
        sc= StandardScaler(with_mean=False)
        X_train1 = sc.fit_transform(X_train1)
        X_test1 = sc.transform(X_test1)
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/utils/validation.py:475: DataConversionWarning:

Data with input dtype int64 was converted to float64 by StandardScaler.
```

5 GridSearch Cross-Validation

```
In [0]: my_cv = [(train,test) for train, test in TimeSeriesSplit(n_splits=10).split(X_train1)]

        param_grid  = {'C': [0.001, 0.01, 0.1, 1, 10]}

        grid = GridSearchCV(LogisticRegression(), param_grid, cv=my_cv)
        grid.fit(X_train1, y_train)

Out[0]: GridSearchCV(cv=[(array([    0,     1, ..., 6368, 6369]), array([ 6370,  6371, ..., 1273
               error_score='raise',
               estimator=LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercep
                  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),
               fit_params=None, iid=True, n_jobs=1,
               param_grid={'C': [0.001, 0.01, 0.1, 1, 10]},
               pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
               scoring=None, verbose=0)

In [0]: print("Best cross-validation score: {:.3f}".format(grid.best_score_))
        print("Best parameters: ", grid.best_params_)

Best cross-validation score: 0.899
Best parameters:  {'C': 0.001}
```

6 RandomizedSearch Cross-Validation

```
In [0]: from sklearn.model_selection import RandomizedSearchCV
        from scipy import stats


        my_cv = [(train,test) for train, test in TimeSeriesSplit(n_splits=10).split(X_train1)]

        param_grid  = {"C": stats.uniform(0.001, 10)}


        grid =  RandomizedSearchCV(LogisticRegression(), param_grid, cv=my_cv, n_iter = 10)
        grid.fit(X_train1, y_train)

Out[0]: RandomizedSearchCV(cv=[(array([    0,     1, ..., 6368, 6369]), array([ 6370,  6371, ...
                  error_score='raise',
                  estimator=LogisticRegression(C=1.0, class_weight=None, dual=False, fit_interc
                  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),
                  fit_params=None, iid=True, n_iter=10, n_jobs=1,
```

```
                  param_distributions={'C': <scipy.stats._distn_infrastructure.rv_frozen objec
                  pre_dispatch='2*n_jobs', random_state=None, refit=True,
                  return_train_score='warn', scoring=None, verbose=0)
```

```
In [0]: print("Best cross-validation score: {:.3f}".format(grid.best_score_))
        print("Best parameters: ", grid.best_params_)
```

```
Best cross-validation score: 0.869
Best parameters:  {'C': 0.6203520096925298}
```

7 Applying Logistic Regression

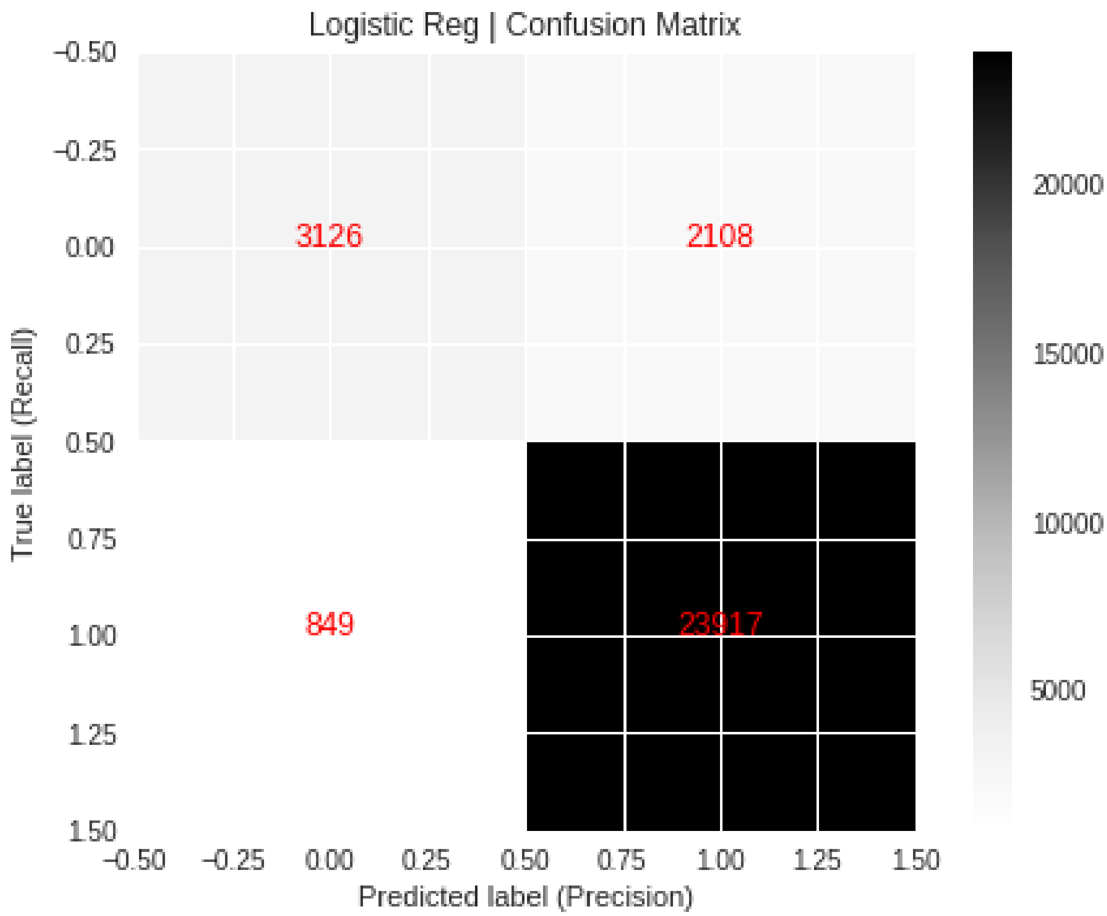
```
In [0]: logreg = LogisticRegression(C = 0.001).fit(X_train1, y_train)


        print("Training set score: {:.3f}".format(logreg.score(X_train1, y_train)))
        print("Test set score: {:.3f}".format(logreg.score(X_test1, y_test)))
```

```
Training set score: 0.970
Test set score: 0.901
```

8 Generating a Confusion matrix

```
In [0]: y_pred = logreg.predict(X_test1)

        log_cfm = confusion_matrix(y_test, y_pred)
```

```
In [0]: import itertools

        plt.imshow(log_cfm, interpolation='nearest')

        for i, j in itertools.product(range(log_cfm.shape[0]), range(log_cfm.shape[1])):
            plt.text(j, i, log_cfm[i, j],
                     horizontalalignment="center",
                     color="red")

        plt.ylabel('True label (Recall)')
        plt.xlabel('Predicted label (Precision)')
        plt.title('Logistic Reg | Confusion Matrix')
        plt.colorbar();
```



9 Comparing 'L1' and 'L2' regularization techniques

```
In [0]: for i, C in enumerate((0.001, 0.01, 0.1, 1)):
            # turn down tolerance for short training time
            clf_l1_LR = LogisticRegression(C=C, penalty='l1', tol=0.01)
            clf_l2_LR = LogisticRegression(C=C, penalty='l2', tol=0.01)
            clf_l1_LR.fit(X_train1, y_train)
            clf_l2_LR.fit(X_train1, y_train)

            coef_l1_LR = clf_l1_LR.coef_.ravel()
            coef_l2_LR = clf_l2_LR.coef_.ravel()

            # coef_l1_LR contains zeros due to the
            # L1 sparsity inducing norm

            sparsity_l1_LR = np.mean(coef_l1_LR == 0) * 100
            sparsity_l2_LR = np.mean(coef_l2_LR == 0) * 100
```

```
            print("C=%.3f" % C)
            print("Sparsity with L1 penalty: %.3f%%" % sparsity_l1_LR)
            print("score with L1 penalty: %.4f" % clf_l1_LR.score(X_train1, y_train))
            print("Sparsity with L2 penalty: %.3f%%" % sparsity_l2_LR)
            print("score with L2 penalty: %.4f" % clf_l2_LR.score(X_train1, y_train))
```

```
C=0.001
Sparsity with L1 penalty: 99.759%
score with L1 penalty: 0.8743
Sparsity with L2 penalty: 0.000%
score with L2 penalty: 0.9695
C=0.010
Sparsity with L1 penalty: 88.691%
score with L1 penalty: 0.9404
Sparsity with L2 penalty: 0.000%
score with L2 penalty: 0.9805
C=0.100
Sparsity with L1 penalty: 65.301%
score with L1 penalty: 0.9767
Sparsity with L2 penalty: 0.000%
score with L2 penalty: 0.9856
C=1.000
Sparsity with L1 penalty: 52.631%
score with L1 penalty: 0.9848
Sparsity with L2 penalty: 0.000%
score with L2 penalty: 0.9872
```

	Hyper-parameter	Sparsity	Score
L1-regularizer	0.001	99.7 %	0 .87
L2-regularizer	0.001	0 %	0.96
---	---	---	---
L1-regularizer	0.01	88.6%	0 .94
L2-regularizer	0.01	0 %	0.98
---	---	---	---
L1-regularizer	0.1	65.3%	0.97
L2-regularizer	0.1	0 %	0.98
---	---	---	---
L1-regularizer	1.0	52.6%	0.98
L2-regularizer	1.0	0 %	0.98

10 TF-idf Vectorization

```
In [0]: #TF-IDF
        tf_idf_vect = TfidfVectorizer(ngram_range=(1,2))
```

```
X_train2 = tf_idf_vect.fit_transform(X_train)
X_test2 = tf_idf_vect.transform(X_test)
```

```
In [0]: #Standardization
        from sklearn.preprocessing import StandardScaler
        sc= StandardScaler(with_mean=False)
        X_train2 = sc.fit_transform(X_train2)
        X_test2 = sc.transform(X_test2)
```

11 Applying GridSearch CV

```
In [0]: my_cv = [(train,test) for train, test in TimeSeriesSplit(n_splits=10).split(X_train2)]

        param_grid  = {'C': [0.001, 0.01, 0.1, 1, 10]}

        grid = GridSearchCV(LogisticRegression(), param_grid, cv=my_cv)
        grid.fit(X_train2, y_train)
```

```
Out[0]: GridSearchCV(cv=[(array([    0,     1, ..., 6368, 6369]), array([ 6370,  6371, ..., 1273
               error_score='raise',
               estimator=LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercep
                  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),
               fit_params=None, iid=True, n_jobs=1,
               param_grid={'C': [0.001, 0.01, 0.1, 1, 10]},
               pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
               scoring=None, verbose=0)
```

```
In [0]: print("Best cross-validation score: {:.3f}".format(grid.best_score_))
        print("Best parameters: ", grid.best_params_)
```

```
Best cross-validation score: 0.857
Best parameters:  {'C': 10}
```

12 Applying RandomizedSearch CV

```
In [0]: from sklearn.model_selection import RandomizedSearchCV
        from scipy import stats


        my_cv = [(train,test) for train, test in TimeSeriesSplit(n_splits=10).split(X_train2)]

        param_grid  = {"C": stats.uniform(0.001, 10)}


        grid =  RandomizedSearchCV(LogisticRegression(), param_grid, cv=my_cv, n_iter = 10)
        grid.fit(X_train2, y_train)
```

```
Out[0]: RandomizedSearchCV(cv=[(array([   0,    1, ..., 6368, 6369]), array([ 6370,  6371, ...
                   error_score='raise',
                   estimator=LogisticRegression(C=1.0, class_weight=None, dual=False, fit_interc
                   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),
                   fit_params=None, iid=True, n_iter=1, n_jobs=1,
                   param_distributions={'C': <scipy.stats._distn_infrastructure.rv_frozen objec
                   pre_dispatch='2*n_jobs', random_state=None, refit=True,
                   return_train_score='warn', scoring=None, verbose=0)
```

```
In [0]: print("Best cross-validation score: {:.3f}".format(grid.best_score_))
        print("Best parameters: ", grid.best_params_)
```

```
Best cross-validation score: 0.857
Best parameters:  {'C': 1.9773164474979121}
```

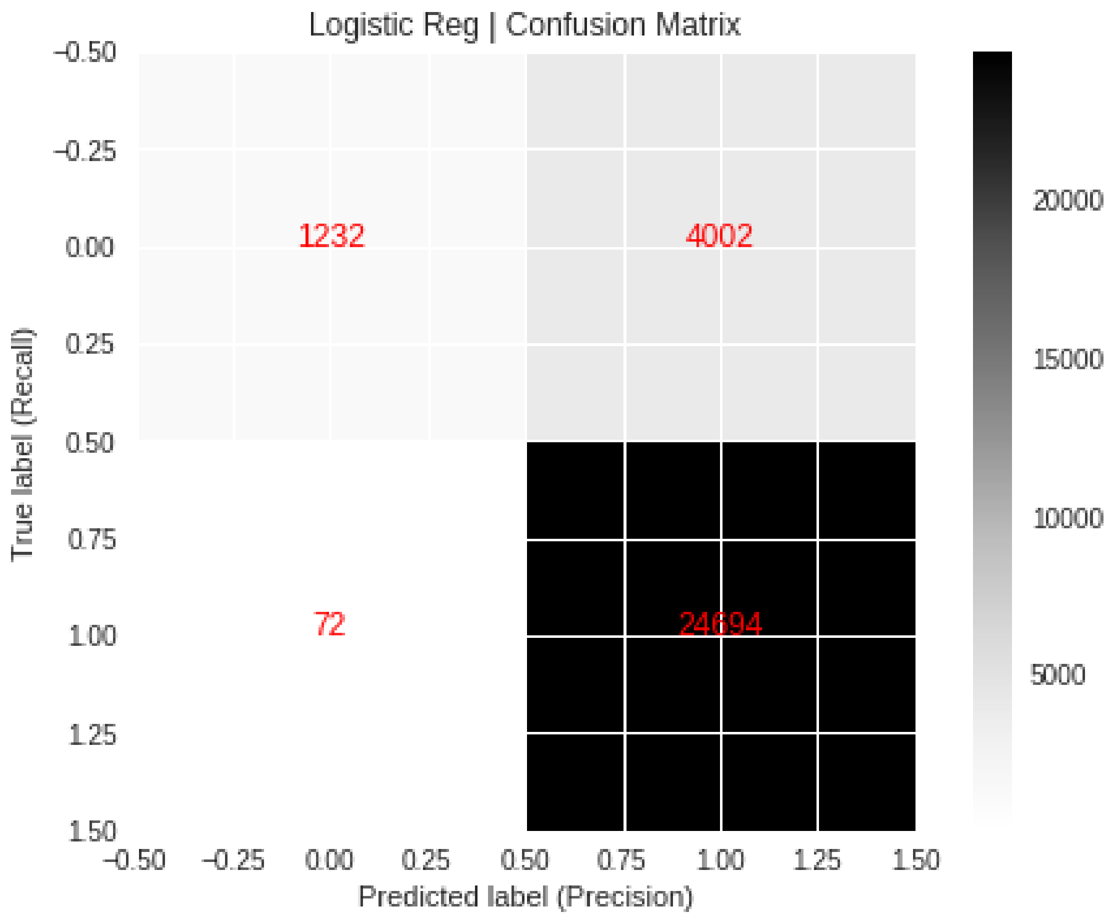
```
In [0]: logreg = LogisticRegression(C = 10.0).fit(X_train2, y_train)


        print("Training set score: {:.3f}".format(logreg.score(X_train2, y_train)))
        print("Test set score: {:.3f}".format(logreg.score(X_test2, y_test)))
```

```
Training set score: 1.000
Test set score: 0.864
```

13 Generating Confusion matrix

```
In [0]: y_pred = logreg.predict(X_test2)

        log_cfm = confusion_matrix(y_test, y_pred)
```

```
In [0]: import itertools

        plt.imshow(log_cfm, interpolation='nearest')

        for i, j in itertools.product(range(log_cfm.shape[0]), range(log_cfm.shape[1])):
            plt.text(j, i, log_cfm[i, j],
                     horizontalalignment="center",
                     color="red")

        plt.ylabel('True label (Recall)')
        plt.xlabel('Predicted label (Precision)')
        plt.title('Logistic Reg | Confusion Matrix')
        plt.colorbar();
```




```
In [0]: for i, C in enumerate((0.001, 0.01, 0.1, 1)):
            # turn down tolerance for short training time
            clf_l1_LR = LogisticRegression(C=C, penalty='l1', tol=0.01)
            clf_l2_LR = LogisticRegression(C=C, penalty='l2', tol=0.01)
            clf_l1_LR.fit(X_train2, y_train)
            clf_l2_LR.fit(X_train2, y_train)

            coef_l1_LR = clf_l1_LR.coef_.ravel()
            coef_l2_LR = clf_l2_LR.coef_.ravel()

            # coef_l1_LR contains zeros due to the
            # L1 sparsity inducing norm

            sparsity_l1_LR = np.mean(coef_l1_LR == 0) * 100
            sparsity_l2_LR = np.mean(coef_l2_LR == 0) * 100

            print("C=%.3f" % C)
            print("Sparsity with L1 penalty: %.3f%%" % sparsity_l1_LR)
```

```
    print("score with L1 penalty: %.4f" % clf_l1_LR.score(X_train2, y_train))
    print("Sparsity with L2 penalty: %.3f%%" % sparsity_l2_LR)
    print("score with L2 penalty: %.4f" % clf_l2_LR.score(X_train2, y_train))
```

```
C=0.001
Sparsity with L1 penalty: 99.992%
score with L1 penalty: 0.8777
Sparsity with L2 penalty: 0.000%
score with L2 penalty: 1.0000
C=0.010
Sparsity with L1 penalty: 97.911%
score with L1 penalty: 0.9996
Sparsity with L2 penalty: 0.000%
score with L2 penalty: 1.0000
C=0.100
Sparsity with L1 penalty: 94.378%
score with L1 penalty: 1.0000
Sparsity with L2 penalty: 0.000%
score with L2 penalty: 1.0000
C=1.000
Sparsity with L1 penalty: 85.909%
score with L1 penalty: 1.0000
Sparsity with L2 penalty: 0.000%
score with L2 penalty: 1.0000
```

	Hyper-parameter	Sparsity	Score
L1-regularizer	0.001	99.9 %	0.87
L2-regularizer	0.001	0 %	1.0
---	---	---	---
L1-regularizer	0.01	97.9%	0.99
L2-regularizer	0.01	0 %	1.0
---	---	---	---
L1-regularizer	0.1	94.3%	1.0
L2-regularizer	0.1	0 %	1.0
---	---	---	---
L1-regularizer	1.0	85.9%	1.0
L2-regularizer	1.0	0 %	1.0

14 Word2Vec Vectorization

```
In [5]: import nltk
        nltk.download('stopwords')
        import re
        # Tutorial about Python regular expressions: https://pymotw.com/2/re/
        import string
```

```
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from nltk.stem.wordnet import WordNetLemmatizer

stop = set(stopwords.words('english')) #set of stopwords
sno = nltk.stem.SnowballStemmer('english') #initialising the snowball stemmer

def cleanhtml(sentence): #function to clean the word of any html-tags
    cleanr = re.compile('<.*?>')
    cleantext = re.sub(cleanr, ' ', sentence)
    return cleantext
def cleanpunc(sentence): #function to clean the word of any punctuation or special cha
    cleaned = re.sub(r'[?|!|\'|"|#]',r'',sentence)
    cleaned = re.sub(r'[.|,|)|(|\|/]',r' ',cleaned)
    return  cleaned
print(stop)
print('************************************')
print(sno.stem('tasty'))
```

```
[nltk_data] Downloading package stopwords to /content/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
{"that'll", 'his', 've', 'we', 'how', 'about', 'some', 'didn', 'an', 'for', 'y', 'down', "coul
************************************
tasti
```

14.1 *Training Word2Vec model using own text corpus*

In [0]:
```
import gensim
i=0
train_sent=[]
for sent in X_train:
    filtered_sentence=[]
    sent=cleanhtml(sent)
    for w in sent.split():
        for cleaned_words in cleanpunc(w).split():
            if(cleaned_words.isalpha()):
                filtered_sentence.append(cleaned_words.lower())
            else:
                continue
    train_sent.append(filtered_sentence)
```

In [0]:
```
test_sent=[]
for sent in X_test:
    filtered_sentence=[]
    sent=cleanhtml(sent)
    for w in sent.split():
```

```
            for cleaned_words in cleanpunc(w).split():
                if(cleaned_words.isalpha()):
                    filtered_sentence.append(cleaned_words.lower())
                else:
                    continue
        test_sent.append(filtered_sentence)
```

In [0]:
```
from gensim.models import Word2Vec
from gensim.models import KeyedVectors

w2v_model=gensim.models.Word2Vec(train_sent,min_count=5,size=50, workers=4)
```

15 Applying Average Word2vec

In [0]:
```
#AVG-W2V
sent_vectors = []; # the avg-w2v for each sentence/review is stored in this list
for sent in train_sent: # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length
    cnt_words =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        try:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
        except:
            pass
    sent_vec /= cnt_words
    sent_vectors.append(sent_vec)
print(len(sent_vectors))
print(len(sent_vectors[0]))
```

```
70000
50
```

In [0]:
```
#AVG-W2V
sent_vectors2 = []; # the avg-w2v for each sentence/review is stored in this list
for sent in test_sent: # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length
    cnt_words =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        try:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
        except:
            pass
    sent_vec /= cnt_words
```

```
            sent_vectors2.append(sent_vec)
        print(len(sent_vectors2))
        print(len(sent_vectors2[0]))
```

```
30000
50
```

```
In [0]: #Standardization
        from sklearn.preprocessing import StandardScaler
        sc= StandardScaler(with_mean=False)
        X_train3 = sc.fit_transform(sent_vectors)
        X_test3 = sc.transform(sent_vectors2)
```

16 Applying GridSearch CV

```
In [0]: my_cv = [(train,test) for train, test in TimeSeriesSplit(n_splits=10).split(X_train3)]

        param_grid  = {'C': [0.001, 0.01, 0.1, 1, 10]}

        grid = GridSearchCV(LogisticRegression(), param_grid, cv=my_cv)
        grid.fit(X_train3, y_train)
```

```
Out[0]: GridSearchCV(cv=[(array([   0,    1, ..., 6368, 6369]), array([ 6370,  6371, ..., 1273
               error_score='raise',
               estimator=LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercep
                  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),
               fit_params=None, iid=True, n_jobs=1,
               param_grid={'C': [0.001, 0.01, 0.1, 1, 10]},
               pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
               scoring=None, verbose=0)
```

```
In [0]: print("Best cross-validation score: {:.3f}".format(grid.best_score_))
        print("Best parameters: ", grid.best_params_)
```

```
Best cross-validation score: 0.887
Best parameters:  {'C': 0.1}
```

17 Applying Randomized CV

```
In [0]: from sklearn.model_selection import RandomizedSearchCV
        from scipy import stats


        my_cv = [(train,test) for train, test in TimeSeriesSplit(n_splits=10).split(X_train3)]
```

```
param_grid  = {"C": stats.uniform(0.001, 10)}


grid =  RandomizedSearchCV(LogisticRegression(), param_grid, cv=my_cv, n_iter = 10)
grid.fit(X_train3, y_train)
```

```
Out[0]: RandomizedSearchCV(cv=[(array([   0,    1, ..., 6368, 6369]), array([ 6370,  6371, ...
                  error_score='raise',
                  estimator=LogisticRegression(C=1.0, class_weight=None, dual=False, fit_interc
                  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),
                  fit_params=None, iid=True, n_iter=1, n_jobs=1,
                  param_distributions={'C': <scipy.stats._distn_infrastructure.rv_frozen object
                  pre_dispatch='2*n_jobs', random_state=None, refit=True,
                  return_train_score='warn', scoring=None, verbose=0)
```

```
In [0]: print("Best cross-validation score: {:.3f}".format(grid.best_score_))
        print("Best parameters: ", grid.best_params_)
```

```
Best cross-validation score: 0.887
Best parameters:  {'C': 5.16712437106295}
```

```
In [0]: logreg = LogisticRegression(C = 0.1).fit(X_train3, y_train)


        print("Training set score: {:.3f}".format(logreg.score(X_train3, y_train)))
        print("Test set score: {:.3f}".format(logreg.score(X_test3, y_test)))
```

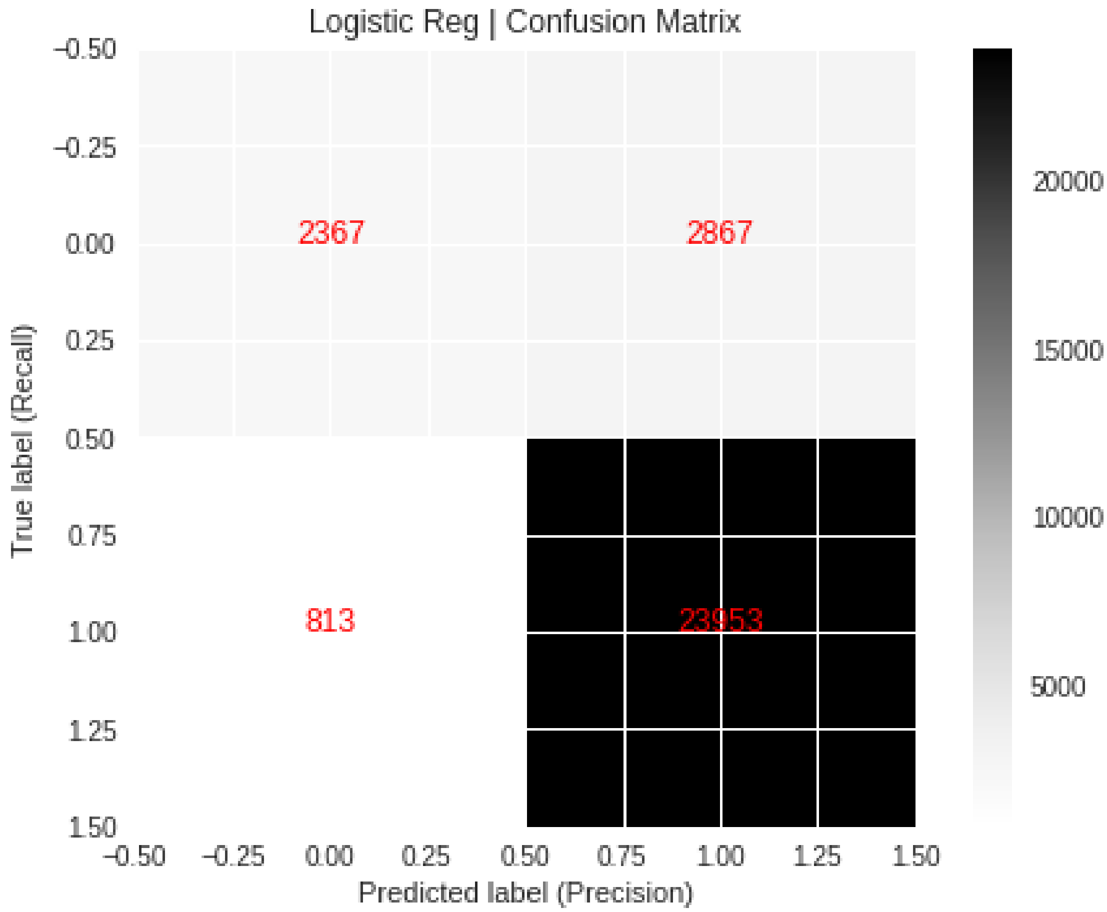
```
Training set score: 0.891
Test set score: 0.877
```

18 Generating Confusion matrix

```
In [0]: y_pred = logreg.predict(X_test3)

        log_cfm = confusion_matrix(y_test, y_pred)
```

```
In [0]: import itertools

        plt.imshow(log_cfm, interpolation='nearest')

        for i, j in itertools.product(range(log_cfm.shape[0]), range(log_cfm.shape[1])):
            plt.text(j, i, log_cfm[i, j],
                     horizontalalignment="center",
```

```
                    color="red")

plt.ylabel('True label (Recall)')
plt.xlabel('Predicted label (Precision)')
plt.title('Logistic Reg | Confusion Matrix')
plt.colorbar();
```




```
In [0]: for i, C in enumerate((0.001, 0.01, 0.1, 1)):
            # turn down tolerance for short training time
            clf_l1_LR = LogisticRegression(C=C, penalty='l1', tol=0.01)
            clf_l2_LR = LogisticRegression(C=C, penalty='l2', tol=0.01)
            clf_l1_LR.fit(X_train3, y_train)
            clf_l2_LR.fit(X_train3, y_train)

            coef_l1_LR = clf_l1_LR.coef_.ravel()
            coef_l2_LR = clf_l2_LR.coef_.ravel()

            # coef_l1_LR contains zeros due to the
```

```python
    # L1 sparsity inducing norm

    sparsity_l1_LR = np.mean(coef_l1_LR == 0) * 100
    sparsity_l2_LR = np.mean(coef_l2_LR == 0) * 100

    print("C=%.3f" % C)
    print("Sparsity with L1 penalty: %.3f%%" % sparsity_l1_LR)
    print("score with L1 penalty: %.4f" % clf_l1_LR.score(X_train3, y_train))
    print("Sparsity with L2 penalty: %.3f%%" % sparsity_l2_LR)
    print("score with L2 penalty: %.4f" % clf_l2_LR.score(X_train3, y_train))
```

```
C=0.001
Sparsity with L1 penalty: 60.000%
score with L1 penalty: 0.8749
Sparsity with L2 penalty: 0.000%
score with L2 penalty: 0.8885
C=0.010
Sparsity with L1 penalty: 14.000%
score with L1 penalty: 0.8900
Sparsity with L2 penalty: 0.000%
score with L2 penalty: 0.8911
C=0.100
Sparsity with L1 penalty: 0.000%
score with L1 penalty: 0.8910
Sparsity with L2 penalty: 0.000%
score with L2 penalty: 0.8913
C=1.000
Sparsity with L1 penalty: 0.000%
score with L1 penalty: 0.8909
Sparsity with L2 penalty: 0.000%
score with L2 penalty: 0.8913
```

	Hyper-parameter	Sparsity	Score
L1-regularizer	0.001	60 %	0 .87
L2-regularizer	0.001	0 %	0.88
---	---	---	---
L1-regularizer	0.01	14 %	0.89
L2-regularizer	0.01	0 %	0.89
---	---	---	---
L1-regularizer	0.1	0 %	0.89
L2-regularizer	0.1	0 %	0.89
---	---	---	---
L1-regularizer	1.0	0%	0.89
L2-regularizer	1.0	0 %	0.89

19 Word2Vec Tf-idf Vectorization

```
In [0]: #TF-IDF

        tf_idf_vect = TfidfVectorizer()
        final_tf_idf = tf_idf_vect.fit_transform(X_train)
        tfidf_feat = tf_idf_vect.get_feature_names()
         # tfidf words/col-names
        # final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val = tfidf

        train_vectors = []; # the tfidf-w2v for each sentence/review is stored in this list
        row=0;
        for sent in train_sent: # for each review/sentence
            sent_vec = np.zeros(50) # as word vectors are of zero length
            weight_sum = 0; # num of words with a valid vector in the sentence/review
            for word in sent: # for each word in a review/sentence
                try:
                    vec = w2v_model.wv[word]
                    # obtain the tf_idf of a word in a sentence/review
                    tfidf = final_tf_idf[row, tfidf_feat.index(word)]
                    sent_vec += (vec * tfidf)
                    weight_sum += tfidf


                except:
                    pass

            sent_vec /= weight_sum
            #print(np.isnan(np.sum(sent_vec)))

            train_vectors.append(sent_vec)
            row += 1
```

```
In [0]: #TF-IDF

        tf_idf_vect = TfidfVectorizer()
        final_tf_idf = tf_idf_vect.fit_transform(X_test)
        tfidf_feat = tf_idf_vect.get_feature_names()
         # tfidf words/col-names
        # final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val = tfidf

        test_vectors = []; # the tfidf-w2v for each sentence/review is stored in this list
        row=0;
        for sent in test_sent: # for each review/sentence
            sent_vec = np.zeros(50) # as word vectors are of zero length
            weight_sum = 0; # num of words with a valid vector in the sentence/review
            for word in sent: # for each word in a review/sentence
                try:
```

```
                vec = w2v_model2.wv[word]
                # obtain the tf_idf of a word in a sentence/review
                tfidf = final_tf_idf[row, tfidf_feat.index(word)]
                sent_vec += (vec * tfidf)
                weight_sum += tfidf


            except:
                pass

        sent_vec /= weight_sum
        #print(np.isnan(np.sum(sent_vec)))

        test_vectors.append(sent_vec)
        row += 1
```

In [0]:
```
#Standardization
from sklearn.preprocessing import StandardScaler
sc= StandardScaler(with_mean=False)
X_train4 = sc.fit_transform(train_vectors)
X_test4 = sc.transform(test_vectors)
```

20 Applying GridSearch CV

In [16]:
```
my_cv = [(train,test) for train, test in TimeSeriesSplit(n_splits=10).split(X_train4)]

param_grid  = {'C': [0.001, 0.01, 0.1, 1, 10]}

grid = GridSearchCV(LogisticRegression(), param_grid, cv=my_cv)
grid.fit(X_train4, y_train)
```

Out[16]:
```
GridSearchCV(cv=[(array([   0,    1, ...,  638,  639]), array([ 640,  641, ..., 1274, 127
       error_score='raise',
       estimator=LogisticRegression(C=1.0, class_weight=None, dual=False, fit_interce
          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),
       fit_params=None, iid=True, n_jobs=1,
       param_grid={'C': [0.001, 0.01, 0.1, 1, 10]},
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
       scoring=None, verbose=0)
```

In [17]:
```
print("Best cross-validation score: {:.3f}".format(grid.best_score_))
print("Best parameters: ", grid.best_params_)
```

```
Best cross-validation score: 0.850
Best parameters:  {'C': 10}
```

21 Applying RandomizedSearch CV

In [18]:
```
from sklearn.model_selection import RandomizedSearchCV
from scipy import stats


my_cv = [(train,test) for train, test in TimeSeriesSplit(n_splits=10).split(X_train4)]

param_grid  = {"C": stats.uniform(0.001, 10)}


grid =  RandomizedSearchCV(LogisticRegression(), param_grid, cv=my_cv, n_iter = 10)
grid.fit(X_train4, y_train)
```

Out[18]:
```
RandomizedSearchCV(cv=[(array([   0,    1, ..., 638, 639]), array([ 640,  641, ..., 1274
          error_score='raise',
          estimator=LogisticRegression(C=1.0, class_weight=None, dual=False, fit_inte
          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),
          fit_params=None, iid=True, n_iter=1, n_jobs=1,
          param_distributions={'C': <scipy.stats._distn_infrastructure.rv_frozen obje
          pre_dispatch='2*n_jobs', random_state=None, refit=True,
          return_train_score='warn', scoring=None, verbose=0)
```

In [19]:
```
print("Best cross-validation score: {:.3f}".format(grid.best_score_))
print("Best parameters: ", grid.best_params_)
```

```
Best cross-validation score: 0.850
Best parameters:  {'C': 9.080485889967418}
```

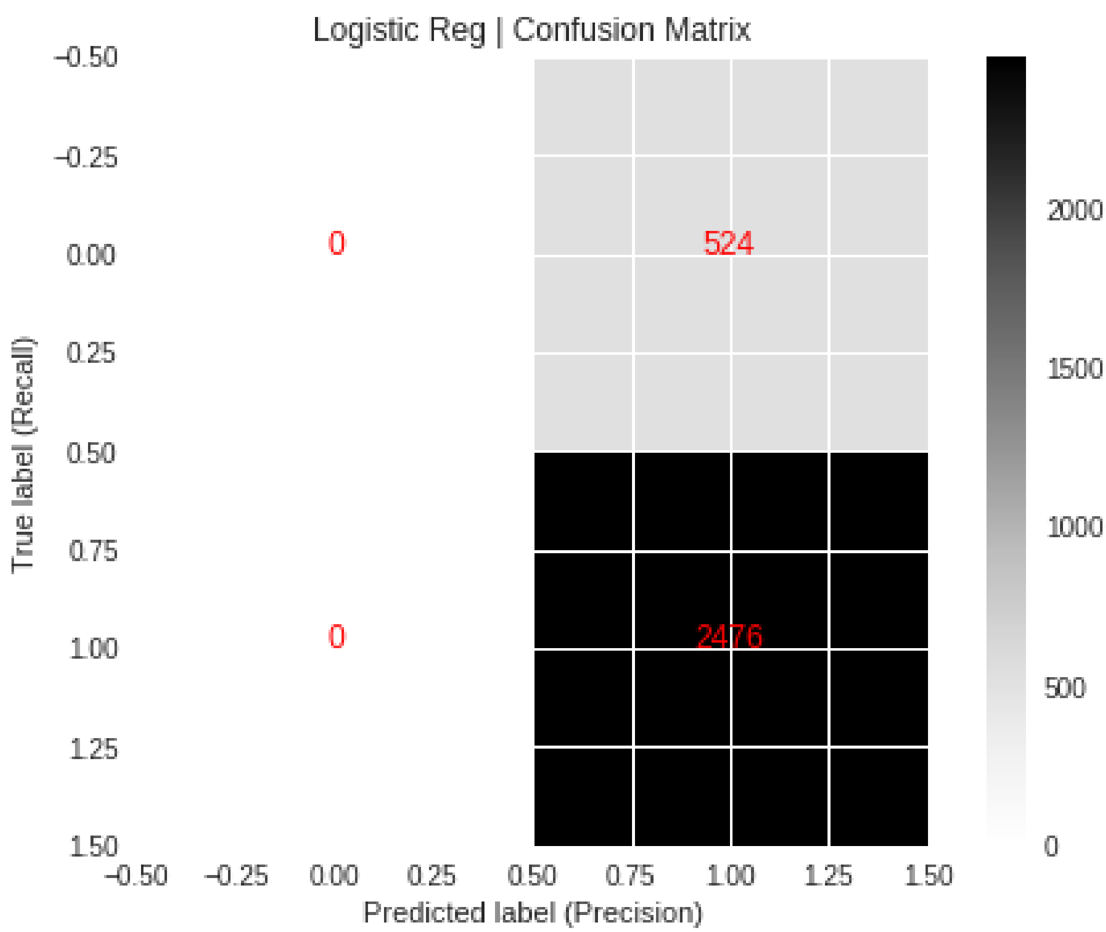
In [20]:
```
logreg = LogisticRegression(C = 10).fit(X_train4, y_train)


print("Training set score: {:.3f}".format(logreg.score(X_train4, y_train)))
print("Test set score: {:.3f}".format(logreg.score(X_test4, y_test)))
```

```
Training set score: 0.858
Test set score: 0.825
```

22 Generating Confusion matrix

In [0]:
```
y_pred = logreg.predict(X_test4)

log_cfm = confusion_matrix(y_test, y_pred)
```

In [22]:
```
import itertools

plt.imshow(log_cfm, interpolation='nearest')

for i, j in itertools.product(range(log_cfm.shape[0]), range(log_cfm.shape[1])):
    plt.text(j, i, log_cfm[i, j],
             horizontalalignment="center",
             color="red")

plt.ylabel('True label (Recall)')
plt.xlabel('Predicted label (Precision)')
plt.title('Logistic Reg | Confusion Matrix')
plt.colorbar();
```



In [23]:
```
for i, C in enumerate((0.001, 0.01, 0.1, 1,10.0)):
    # turn down tolerance for short training time
    clf_l1_LR = LogisticRegression(C=C, penalty='l1', tol=0.01)
    clf_l2_LR = LogisticRegression(C=C, penalty='l2', tol=0.01)
```

```
            clf_l1_LR.fit(X_train4, y_train)
            clf_l2_LR.fit(X_train4, y_train)

            coef_l1_LR = clf_l1_LR.coef_.ravel()
            coef_l2_LR = clf_l2_LR.coef_.ravel()

            # coef_l1_LR contains zeros due to the
            # L1 sparsity inducing norm

            sparsity_l1_LR = np.mean(coef_l1_LR == 0) * 100
            sparsity_l2_LR = np.mean(coef_l2_LR == 0) * 100

            print("C=%.3f" % C)
            print("Sparsity with L1 penalty: %.3f%%" % sparsity_l1_LR)
            print("score with L1 penalty: %.4f" % clf_l1_LR.score(X_train4, y_train))
            print("Sparsity with L2 penalty: %.3f%%" % sparsity_l2_LR)
            print("score with L2 penalty: %.4f" % clf_l2_LR.score(X_train4, y_train))
```

```
C=0.001
Sparsity with L1 penalty: 90.000%
score with L1 penalty: 0.8514
Sparsity with L2 penalty: 0.000%
score with L2 penalty: 0.8516
C=0.010
Sparsity with L1 penalty: 80.000%
score with L1 penalty: 0.8514
Sparsity with L2 penalty: 0.000%
score with L2 penalty: 0.8514
C=0.100
Sparsity with L1 penalty: 28.000%
score with L1 penalty: 0.8519
Sparsity with L2 penalty: 0.000%
score with L2 penalty: 0.8520
C=1.000
Sparsity with L1 penalty: 0.000%
score with L1 penalty: 0.8516
Sparsity with L2 penalty: 0.000%
score with L2 penalty: 0.8531
C=10.000
Sparsity with L1 penalty: 0.000%
score with L1 penalty: 0.8521
Sparsity with L2 penalty: 0.000%
score with L2 penalty: 0.8577
```

	Hyper-parameter	Sparsity	Score
L1-regularizer	0.001	90%	0 .85

	Hyper-parameter	Sparsity	Score
L2-regularizer	0.001	0 %	0.85
---	---	---	---
L1-regularizer	0.01	80%	0 .85
L2-regularizer	0.01	0 %	0.85
---	---	---	---
L1-regularizer	0.1	28 %	0.85
L2-regularizer	0.1	0 %	0.85
---	---	---	---
L1-regularizer	1.0	0%	0.85
L2-regularizer	1.0	0 %	0.85
---	---	---	---
L1-regularizer	10.0	0%	0.85
L2-regularizer	10.0	0%	0.85

23 Conclusion

23.1 The most important words are:

-

23.2 tast

-

23.3 like

-

23.4 product

23.5 Bag of Words:

-

23.5.1 GridSearch CV

- Best Parameter C = 0.001
- CV Score = 0.854
-

	Hyper-parameter	Sparsity	Score
L1-regularizer	0.001	99.7 %	0 .87
L2-regularizer	0.001	0 %	0.96
---	---	---	---
L1-regularizer	0.01	88.6%	0 .94
L2-regularizer	0.01	0 %	0.98
---	---	---	---
L1-regularizer	0.1	65.3%	0.97
L2-regularizer	0.1	0 %	0.98
---	---	---	---
L1-regularizer	1.0	52.6%	0.98
L2-regularizer	1.0	0 %	0.98

23.5.2 RandomizedSearch CV

- Best Parameter C = 0.54
- CV Score = 0.796
-

23.6 Test set score = 0.90

-

23.7 Train set score = 0.97

23.8 Tf-IDF:

-

	Hyper-parameter	Sparsity	Score
L1-regularizer	0.001	99.9 %	0.87
L2-regularizer	0.001	0 %	1.0
---	---	---	---
L1-regularizer	0.01	97.9%	0.99
L2-regularizer	0.01	0 %	1.0
---	---	---	---
L1-regularizer	0.1	94.3%	1.0
L2-regularizer	0.1	0 %	1.0
---	---	---	---
L1-regularizer	1.0	85.9%	1.0
L2-regularizer	1.0	0 %	1.0

23.8.1 GridSearch CV

- Best Parameter C = 0.001
- CV Score = 0.824
-

23.8.2 RandomizedSearch CV

- Best Parameter C = 1.79
- CV Score = 0.823
-

23.9 Test set score = 0.86

-

23.10 Train set score = 1.0

23.11 Average Word2vec:

-

23.11.1 GridSearch CV

- Best Parameter C = 0.001
- CV Score = 0.832
-

	Hyper-parameter	Sparsity	Score
L1-regularizer	0.001	60 %	0 .87
L2-regularizer	0.001	0 %	0.88
---	---	---	---
L1-regularizer	0.01	14 %	0.89
L2-regularizer	0.01	0 %	0.89
---	---	---	---
L1-regularizer	0.1	0 %	0.89
L2-regularizer	0.1	0 %	0.89
---	---	---	---
L1-regularizer	1.0	0%	0.89
L2-regularizer	1.0	0 %	0.89

23.11.2 RandomizedSearch CV

- Best Parameter C = 4.27
- CV Score = 0.831
-

23.12 Test set score = 0.87

-

23.13 Train set score = 0.89

23.14 Word2vec-tfidf:

-

23.14.1 GridSearch CV

- Best Parameter C = 10.0
- CV Score = 0.738
-

	Hyper-parameter	Sparsity	Score
L1-regularizer	0.001	90%	0 .85
L2-regularizer	0.001	0 %	0.85
---	---	---	---
L1-regularizer	0.01	80%	0 .85
L2-regularizer	0.01	0 %	0.85
---	---	---	---
L1-regularizer	0.1	28 %	0.85
L2-regularizer	0.1	0 %	0.85
---	---	---	---
L1-regularizer	1.0	0%	0.85
L2-regularizer	1.0	0 %	0.85
---	---	---	---
L1-regularizer	10.0	0%	0.85
L2-regularizer	10.0	0%	0.85

23.14.2 RandomizedSearch CV

- Best Parameter C = 8.42
- CV Score = 0.737
-

23.15 Test set score = 0.82

-

23.16 Train set score = 0.85