TsnePlotOnCreditCard

February 16, 2018

0.1 Kaggle Data Set - Credit Card Fraud

0.1.1 The datasets contains transactions made by credit cards in September 2013 by european cardholders.

0.2 Dataset Information:

```
* Number of Instances: 284,807
* Number of Attributes: 31 (including the class attribute)
* Attribute Information:
* Features V1, V2, ... V28 are the principal components obtained with PCA.
* The only features which have not been transformed with PCA are 'Time' and 'Amount'.
* Feature 'Time' contains the seconds elapsed between each transaction and the first
  transaction in the   dataset.
```

0.2.1 Class (class attribute):

```
* Feature 'Class' is the response variable and it takes value 1 in case of fraud and 0
  otherwise.
  1 = Fraud Transaction
  0 = Normal Transaction
```

0.2.2 All the remaining details regarding the data set can be found in the below link.

0.2.3 CreditCardFraud

```
In [5]: import pandas as pd
        import seaborn as sn
        import matplotlib.pyplot as plt
        import numpy as np
        from sklearn.metrics.pairwise import cosine_similarity

        %matplotlib inline
```

```
In [6]: #download the data set from
        #https://www.kaggle.com/dalpozz/creditcardfraud/data
        # load the data set
        data=pd.read_csv("creditcard.csv")
```

```
In [7]: data.shape
```

Out[7]: (284807, 31)

In [8]:
```
data.head()
```

Out[8]:
```
   Time        V1        V2        V3        V4        V5        V6        V7  \
0   0.0 -1.359807 -0.072781  2.536347  1.378155 -0.338321  0.462388  0.239599
1   0.0  1.191857  0.266151  0.166480  0.448154  0.060018 -0.082361 -0.078803
2   1.0 -1.358354 -1.340163  1.773209  0.379780 -0.503198  1.800499  0.791461
3   1.0 -0.966272 -0.185226  1.792993 -0.863291 -0.010309  1.247203  0.237609
4   2.0 -1.158233  0.877737  1.548718  0.403034 -0.407193  0.095921  0.592941

         V8        V9  ...         V21       V22       V23       V24  \
0  0.098698  0.363787  ...   -0.018307  0.277838 -0.110474  0.066928
1  0.085102 -0.255425  ...   -0.225775 -0.638672  0.101288 -0.339846
2  0.247676 -1.514654  ...    0.247998  0.771679  0.909412 -0.689281
3  0.377436 -1.387024  ...   -0.108300  0.005274 -0.190321 -1.175575
4 -0.270533  0.817739  ...   -0.009431  0.798278 -0.137458  0.141267

        V25       V26       V27       V28  Amount  Class
0  0.128539 -0.189115  0.133558 -0.021053  149.62      0
1  0.167170  0.125895 -0.008983  0.014724    2.69      0
2 -0.327642 -0.139097 -0.055353 -0.059752  378.66      0
3  0.647376 -0.221929  0.062723  0.061458  123.50      0
4 -0.206010  0.502292  0.219422  0.215153   69.99      0

[5 rows x 31 columns]
```

0.3 UnderSampling the DataSet to apply t-SNE

0.3.1 Approach:

0.3.2 UnderSampling the data to nearly imbalanced and balanced datasets seperately to apply tsne.

0.3.3 1) Applied t-SNE to Nearly Balanced DataSet by UnderSampling under different parameters of t-SNE.

In [9]:
```
# underSampleRatio -> fraud/normal
def UnderSampleData(data,underSampleRatio):

    # Number of data points in the minority class
    fraudrecords = len(data[data.Class == 1])
    fraudindices = np.array(data[data.Class == 1].index)
    # Picking the indices of the normal classes
    normalindices = data[data.Class == 0].index

    samples=(fraudrecords)/underSampleRatio

    randomnormalindices = np.random.choice(normalindices, int(samples), replace = Fals
    randomnormalindices = np.array(randomnormalindices)
```

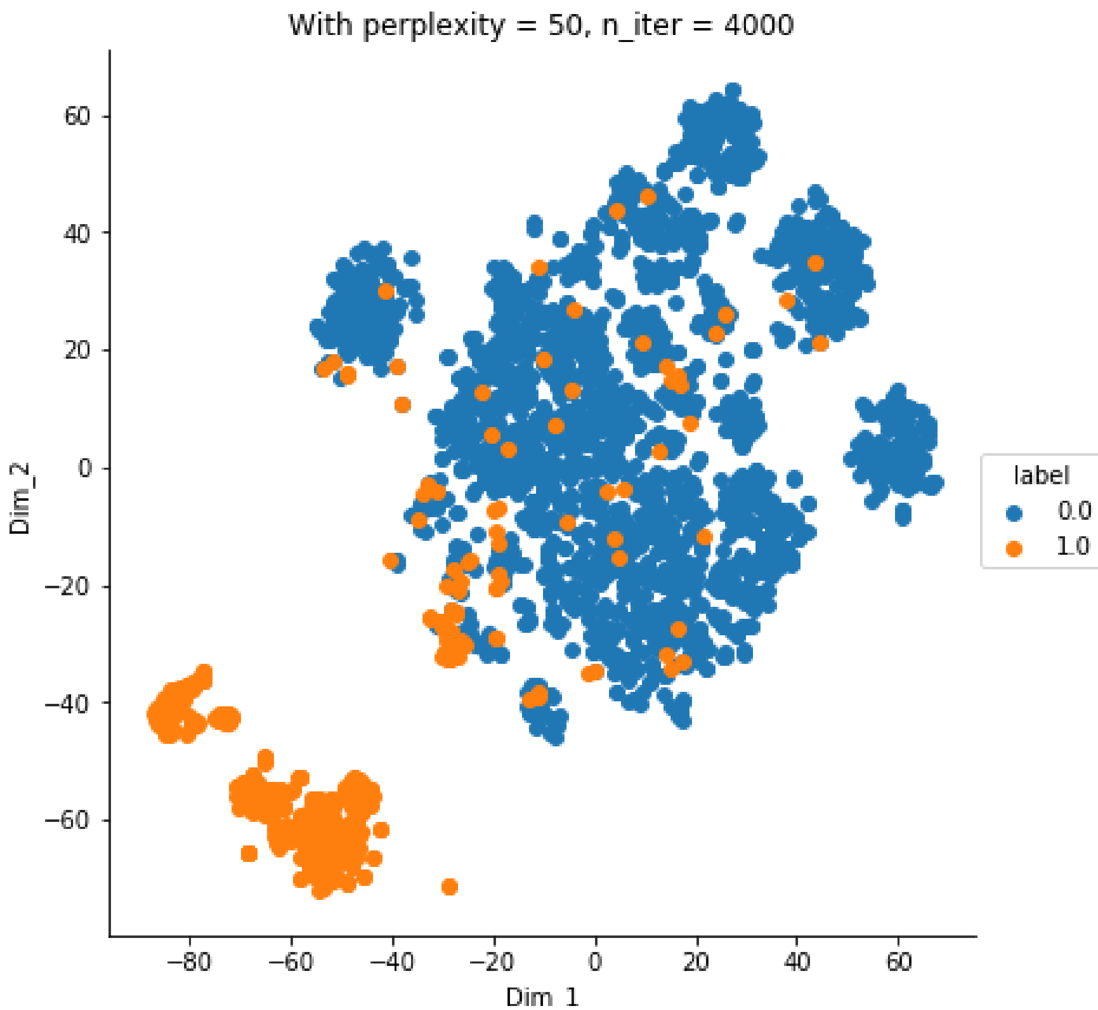
```
    # Appending the 2 indices
    undersampleindices = np.concatenate([fraudindices,randomnormalindices])

    # Under sample dataset
    undersampledata = data.iloc[undersampleindices,:]
    return undersampledata
```

```
In [10]: def standardize(X):
             # Data-preprocessing: Standardizing the data
             from sklearn.preprocessing import StandardScaler
             standardized_data = StandardScaler().fit_transform(X)
             ## stddata - data which is standardized
             stddata = pd.DataFrame(standardized_data, columns = X.columns)
             return stddata
```

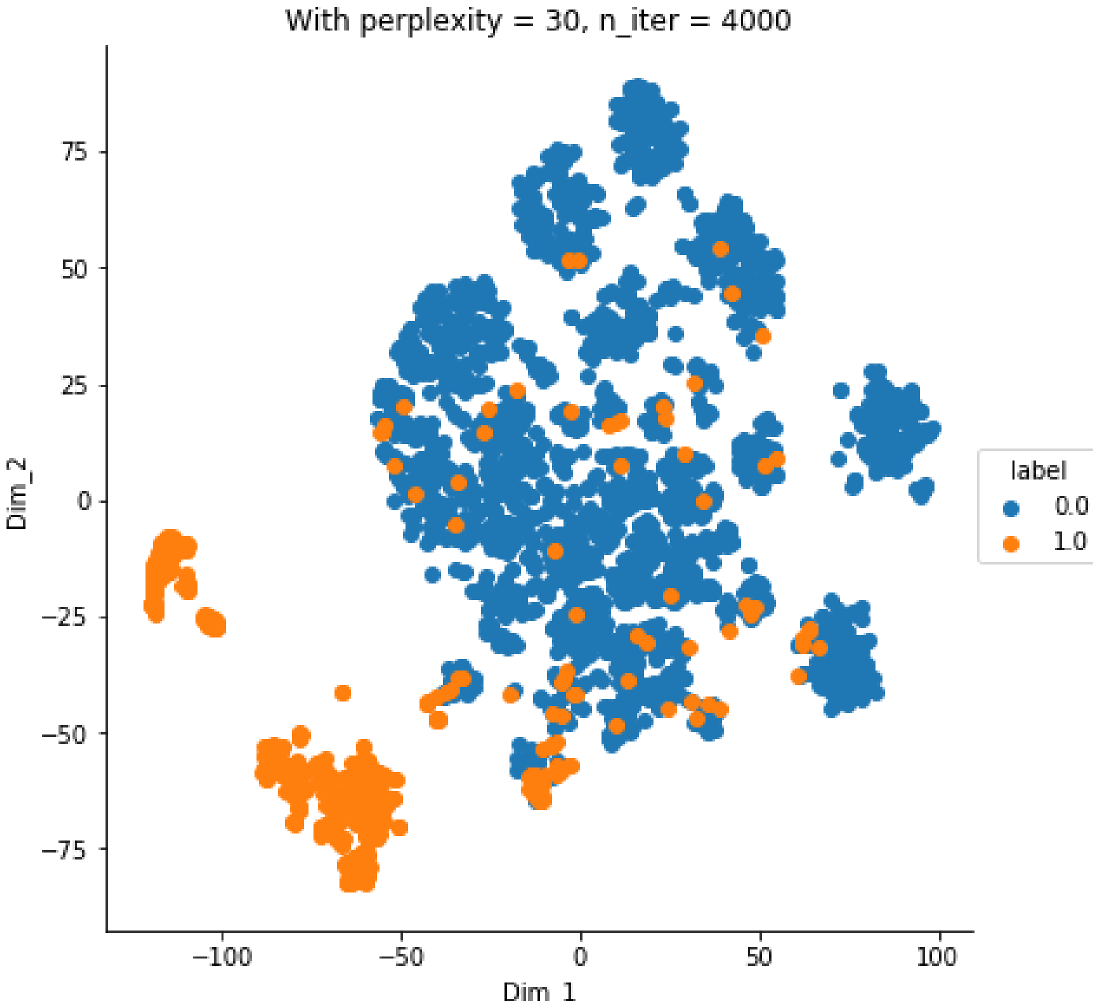
```
In [11]: def TSNEModel(perplexity,iterations,sampledata):
             from sklearn.manifold import TSNE
             model = TSNE(n_components=2, random_state=0,perplexity=perplexity,n_iter=iteratio
             # save the labels into a variable y.
             y = sampledata['Class']
             # Drop the label feature,store the  data in X.
             X = sampledata.drop("Class",axis=1)
             # creating a new data frame which help us in ploting the result data
             tsne_data = model.fit_transform(X)
             tsne_data = np.vstack((tsne_data.T, y)).T
             tsne_df = pd.DataFrame(data=tsne_data, columns=("Dim_1", "Dim_2", "label"))
             # Ploting the result of tsne
             sn.FacetGrid(tsne_df, hue="label", size=6).map(plt.scatter, 'Dim_1', 'Dim_2').add_
             str="With perplexity = {0}, n_iter = {1}".format(perplexity, iterations)
             plt.title(str)
             plt.show()
```

```
In [12]: # Standardize the dataSet
         # save the labels into a variable y.
         y = data['Class']
         # Drop the label feature, standardize the data and store the  data in X.
         X = standardize(data.drop("Class",axis=1))
         stddata = pd.concat([X, y], axis=1)
```

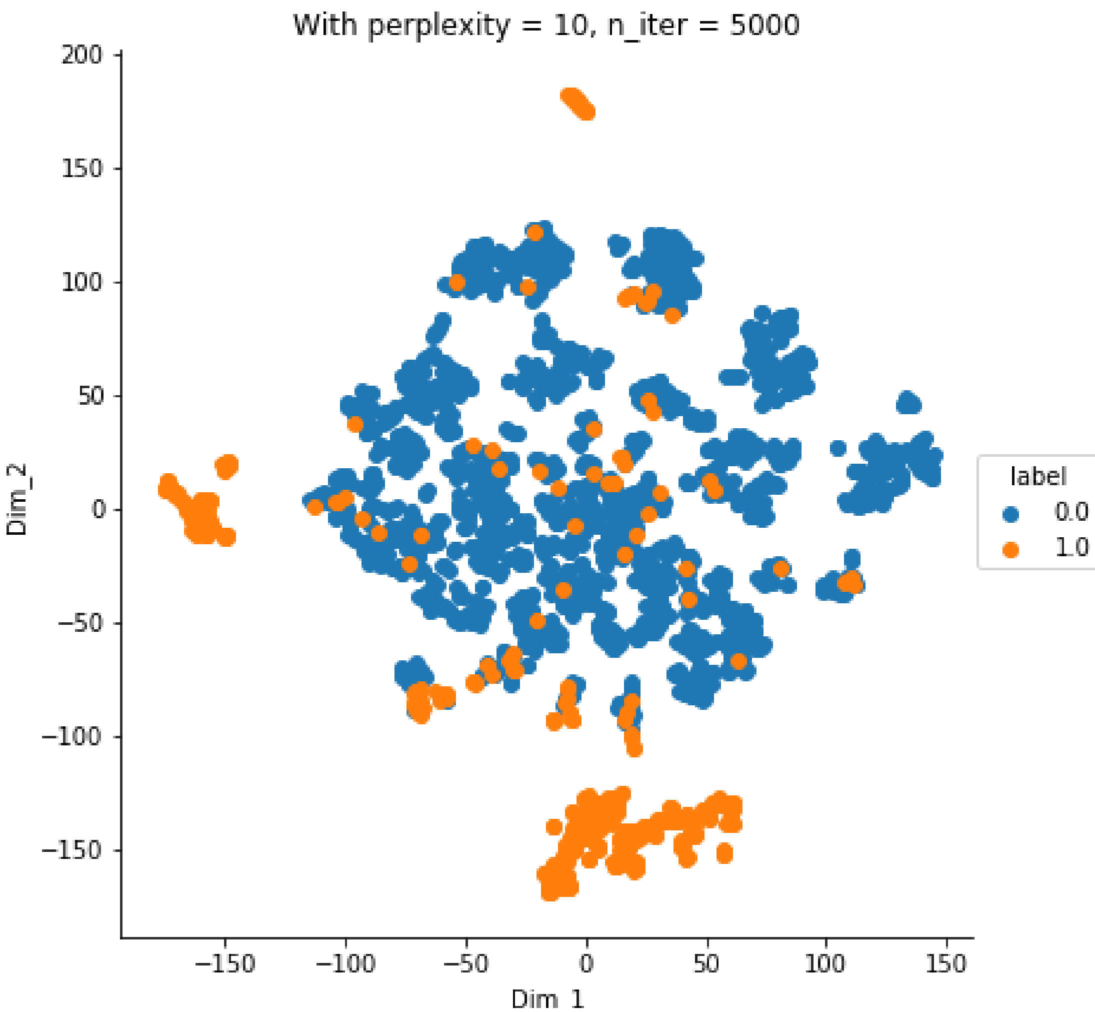
```
In [20]: ImbalanceSample=UnderSampleData(stddata,0.2)  ## sample the unbalanced dataset in to 
         TSNEModel(50,4000,ImbalanceSample)
```




```
In [14]: TSNEModel(30,4000,ImbalanceSample)
```




```
In [19]: TSNEModel(10,5000,ImbalanceSample)
```

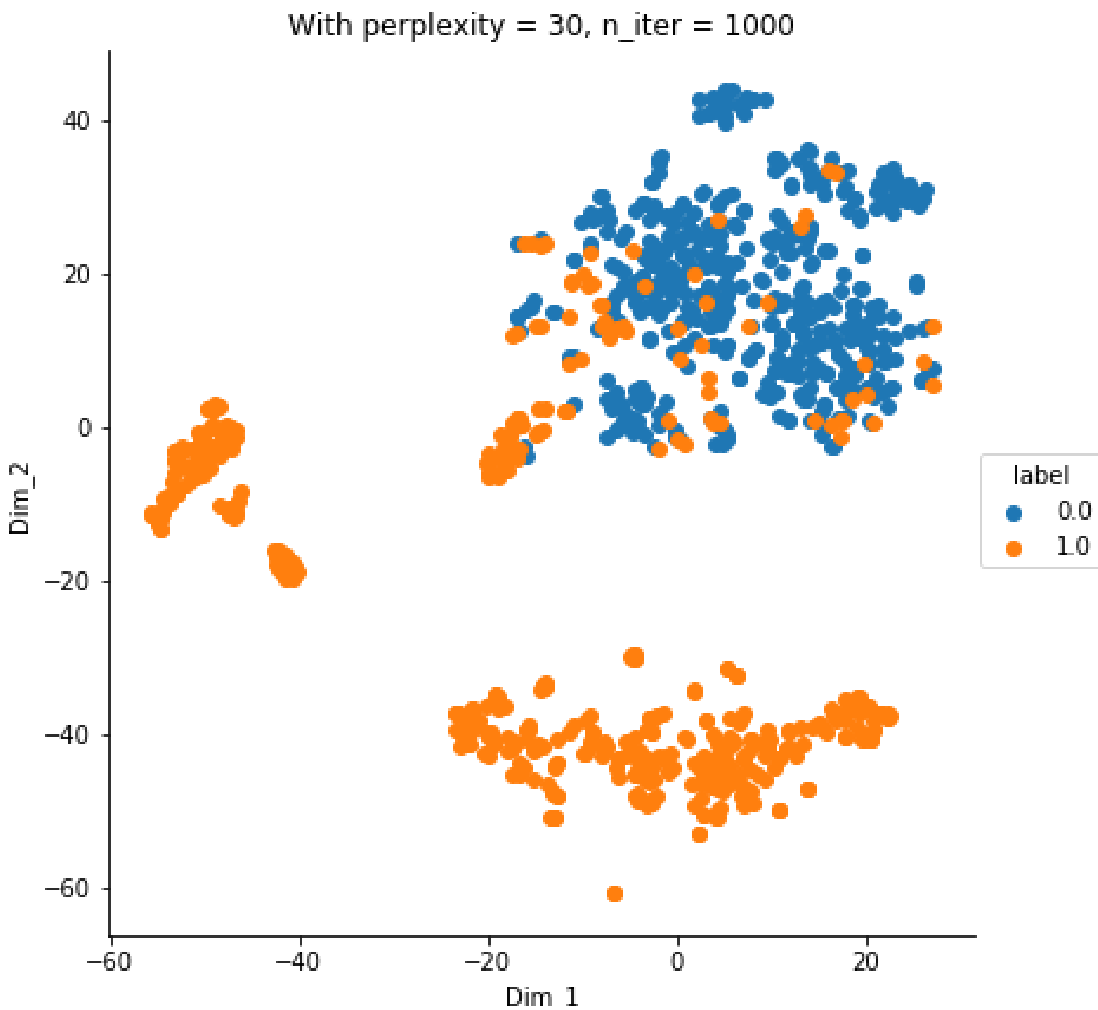


From the t-SNE plots, it seems fraud transactions are seperated from normal transactions more or less.

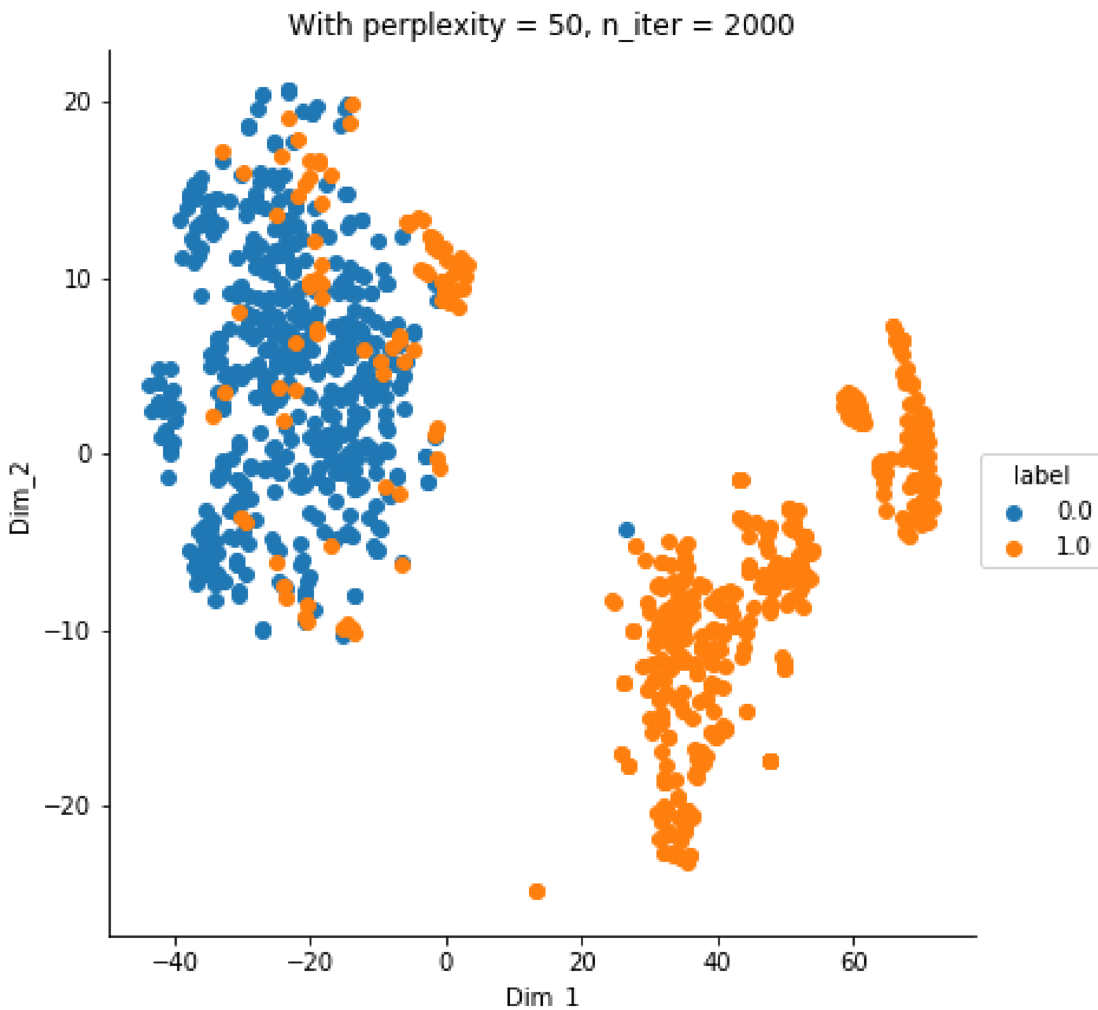
0.3.4 2) Applied t-SNE to perfectly Balanced Dataset by varying different parameters of t-SNE.

```
In [15]: balanceSample=UnderSampleData(stddata,1)  ## sample the unbalanced dataset in to perf
```

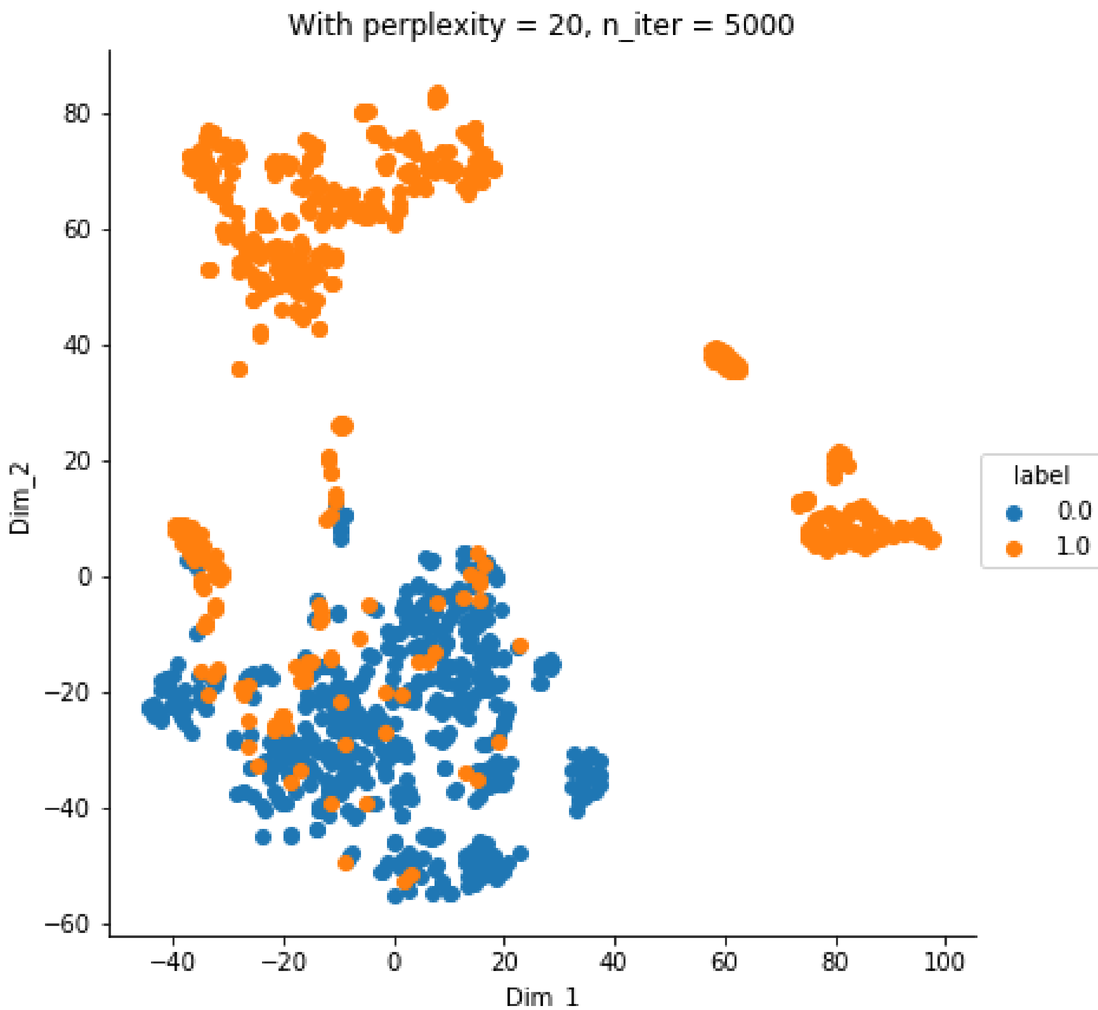
```
In [16]: TSNEModel(30,1000,balanceSample)
```




```
In [17]: TSNEModel(50,4000,balanceSample)
```




```
In [18]: TSNEModel(20,5000,balanceSample)
```


With perplexity = 20, n_iter = 5000
Dim_2
80
60
40
20
0
−20
−40
−60
−40
−20
0
20
40
60
80
100
Dim_1
label
0.0
1.0