Bag of Words Meets Bags of Popcorn

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1 Bag of Words Meets Bags of Popcorn

Data Set: The labeled data set consists of 50,000 IMDB movie reviews, specially selected for sentiment analysis. The sentiment of reviews is binary, meaning the IMDB rating < 5 results in a sentiment score of 0, and rating >=7 have a sentiment score of 1. No individual movie has more than 30 reviews. The 25,000 review labeled training set does not include any of the same movies as the 25,000 review test set. In addition, there are another 50,000 IMDB reviews provided without any rating labels.

File descriptions: labeledTrainData - The labeled training set. The file is tab-delimited and has a header row followed by 25,000 rows containing an id, sentiment, and text for each review.

Data fields: id - Unique ID of each review sentiment - Sentiment of the review; 1 for positive reviews and 0 for negative reviews review - Text of the review

```
In [2]: from bs4 import BeautifulSoup
        from ggplot import *
        import numpy as np
        import nltk
        from nltk.corpus import stopwords
        from nltk.stem.snowball import SnowballStemmer
        import pandas as pd
        import re
        from sklearn.feature_extraction.text import TfidfVectorizer
        from sklearn.model_selection import train_test_split
        from sklearn.metrics import hamming_loss
        from sklearn.metrics import confusion_matrix
        from sklearn import metrics
        from sklearn import metrics, cross_validation
        from sklearn.model_selection import cross_val_predict
        from sklearn.metrics import roc_curve
        from sklearn import svm
        from sklearn.feature_extraction.text import CountVectorizer
        from sklearn.ensemble import RandomForestClassifier
        from sklearn.neighbors import KNeighborsClassifier
        from sklearn.linear_model import LogisticRegression
```

```
In [3]: data = pd.read_csv("labeledTrainData.tsv",
                          header = 0,
                          delimiter = "\t",
                          quoting = 3)
```

```
In [4]: print(data.shape)
```

```
(25000, 3)
```

```
In [5]: print(data.columns.values)
```

```
['id' 'sentiment' 'review']
```

```
In [6]: print(data["review"][0])
```

```
"With all this stuff going down at the moment with MJ i've started listening to his music, .."
```

2 Data Cleaning and Text preprocessing

1. BeautifulSoup Package – Removing HTML Markup

2. Regular Expression – To remove punctuation and numbers

3. Converting reviews to lowercase and split them into individual words

4. Stopwords list from NLTK– Removing words like "a", "the", "and", "is" etc

5. NLTK porter stemmer – It allows us to treat "message", "messages", "messaging" as a single word

```
In [7]: # Testing the beautifulsoup package with the first review
        first_review = BeautifulSoup(data["review"][0], "html.parser")

        # Printing the original strings
        print(data["review"][0])

        # Printing the review after removing html markups using beautiful soup package
        print(first_review.get_text())
```

```
"With all this stuff going down at the moment with MJ i've started listening to his music, .."
```

```
In [8]: # Keeping only the Alphabets and removing .,! etc using regular expression
        alphabets_only = re.sub("[^a-zA-Z]", " ", first_review.get_text())
        print(alphabets_only)
```

```
With all this stuff going down at the moment with MJ i ve started listening to his music
```

```
In [9]: # Converting all values to lower case and splitting them
        lowercase = alphabets_only.lower()
        words = lowercase.split()
        print(words)
```

```
['with', 'all', 'this', 'stuff', 'going', 'down', 'at', 'the', 'moment', 'with', 'mj', ...]
```

```
In [10]: nltk_words = [words for sent in nltk.sent_tokenize(lowercase) for word in nltk.word_tok
```

```
In [11]: print(stopwords.words("english"))
```

```
['i', 'me', 'my', 'myself', 'we', 'our', 'ours', 'ourselves', 'you', 'your', ...]
```

```
In [12]: # Removing all the stopwords from the list of words.
         filtered_words = [w for w in words if not w in stopwords.words("english")]
         print(filtered_words)
```

```
['stuff', 'going', 'moment', 'mj', 'started', 'listening', 'music', 'watching', 'odd', ...]
```

```
In [13]: # Stemming is a process which treats strings like message, messages, messaging as a sin
         # Using SnowballStemmer to do the process here
         stemmer = SnowballStemmer("english")

         stem_words = [stemmer.stem(w) for w in filtered_words]
         print(stem_words)
```

```
['stuff', 'go', 'moment', 'mj', 'start', 'listen', 'music', 'watch', 'odd', 'documentari', ...]
```

2.0.1 Putting it all together

```
In [14]: stemmer = SnowballStemmer("english")

         stopwords_ = set(stopwords.words("english"))

         # All the process is combined in this function convert_reviews_to_words
         def convert_reviews_to_words(review):
             review_text = BeautifulSoup(review, "html.parser").get_text()
             alphabets_only = re.sub("[^a-zA-Z]", " ", review_text)
             words = alphabets_only.lower().split()
             meaningful_words = [w for w in words if not w in stopwords_]
             stemmed_words = [stemmer.stem(w) for w in meaningful_words]
             print(stemmed_words)
             return(" ".join(stemmed_words))
```

In [3]:
```
no_of_reviews = data["review"].size
cleaned_data_reviews = []

# Calling the convert_reviews_to_words function for every review in the dataset
# Appending those values to cleaned_data_reviews list
print("Cleaning and parsing the movie reviews from data....")
for i in range(0, no_of_reviews):
    if((i+1)%1000 == 0):
        #print("Review %d of %d complete" % (i+1, no_of_reviews))
    cleaned_data_reviews.append(convert_reviews_to_words(data["review"][i]))

print("Cleaning and Parsing complete.")
```

In [16]:
```
print(cleaned_data_reviews[:][0:20])
```

```
['stuff go moment mj start listen music watch odd documentari watch wiz ..]
```

3 Bag of Words

3.0.1 Bag of words model:

Takes all the words from a sentence and then models them by counting how many times each word appears.

Example: Sentence 1: "The cat sat on the hat" Sentence 2: "The dog ate the cat and the hat"
Vocabularies from both the sentences: [the, cat, sat, on, hat, dog, ate, and]
Feature vector for both the sentences: Sentence 1: [2,1,1,1,1,0,0,0] Sentence 2: [3,1,0,0,1,1,1,1]
In the IMDB data there are many too many reviews and we get large vocabularies from it. So in order to reduce the number of feature vector we set the maximum features to be 1000. Those are thousand most frequent words.

Using feature_extraction moodule from scikit-learning to create bag of words bag of words features.

In [17]:
```
print("Starting Bag of Words...")

# The CountVectorizer function does the bag of words process
# Since the data cleaning and the text processing was done separately in the previous s
# assigning tokenizer, preprocessor, and stopwords as None
# max_feature = number of features to be taken into account.
# It takes into account the top first 1000 frequent words
vectorizer = CountVectorizer(analyzer="word",
                             tokenizer=None,
                             preprocessor=None,
                             stop_words=None,
                             max_features=1000)

data_features = vectorizer.fit_transform(cleaned_data_reviews)
data_features = data_features.toarray()
```

```
Starting Bag of Words...
```

The data now has 25000 rows and 1000 features.

```
In [18]: print(data_features.shape)
```

```
(25000, 1000)
```

We can now take a look at the vocabularies that we get after initiating the Bag of Words model.

```
In [19]: # Printing the features
         vocabulary = vectorizer.get_feature_names()
         print(vocabulary)
```

```
['abil', 'abl', 'absolut', 'accent', 'accept', 'achiev', '...]
```

```
In [20]: print(data_features)
```

```
[[0 0 0 ..., 0 0 0]
 [0 0 0 ..., 0 0 0]
 [0 0 0 ..., 0 0 0]
 ...,
 [0 0 0 ..., 0 0 0]
 [0 0 0 ..., 0 0 0]
 [0 0 0 ..., 0 0 0]]
```

```
In [4]: # Frequency of each word in the feature vector
        dist = np.sum(data_features, axis=0)
        for tag, count in zip(vocabulary, dist):
            print(tag, count)
```

4 Classification

Predicting the sentiment of each reviews using the models such as:

1. Random Forest
2. Logistic Regression
3. Support Vector Machine (SVM)

5 Random Forest

```
In [23]: # Splitting the data into training and test with the ratio of 80:20
         xtrain, xtest, ytrain, ytest = train_test_split(data_features,
                                                         data["sentiment"].values,
```

```
                                                          test_size = 0.2)
        print("Training the random forest...")

        # Training the data using random forest model
        forest = RandomForestClassifier(n_estimators = 100)
        forest_model = forest.fit(xtrain, ytrain)
```

```
Training the random forest...
```

```
In [24]: # Predicting the model
         ypred = forest_model.predict(xtest)

         print(1-hamming_loss(ypred, ytest))
```

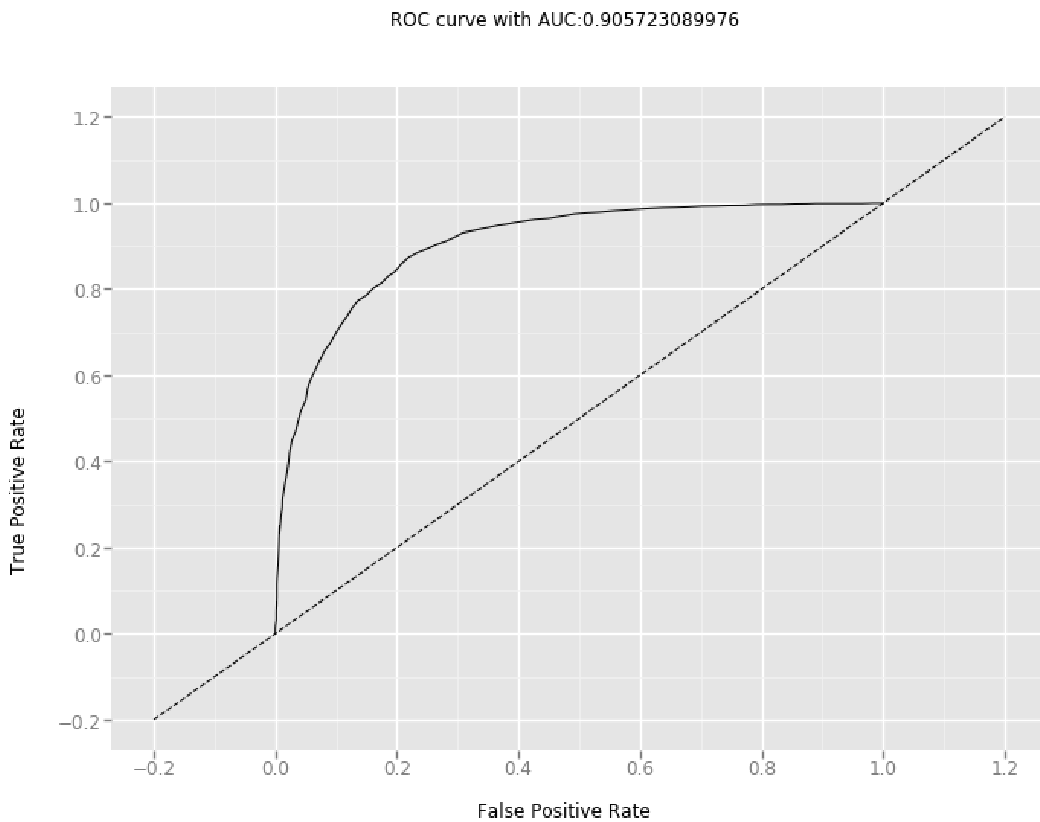
```
0.8196
```

```
In [25]: # Confusion matrix for train data
         conf_matrix = confusion_matrix(ytest, ypred)
         conf_matrix
```

```
Out[25]: array([[2018,  427],
                [ 475, 2080]], dtype=int64)
```

```
In [30]: # AUC score and ROC curve for train data
         predict_ = forest.predict_proba(xtest)[:, 1]
         fpr, tpr, _ = metrics.roc_curve(ytest, predict_)

         auc = metrics.roc_auc_score(ytest, predict_)
         print("AUC:" + str(auc))

         df = pd.DataFrame(dict(fpr=fpr, tpr=tpr))
         ggplot(df, aes(x='fpr', y="tpr")) +
             geom_line() +
             geom_abline(linetype='dashed') +
             ggtitle("ROC curve with AUC:%s" % str(auc)) +
             xlab("False Positive Rate") +
             ylab("True Positive Rate")
```

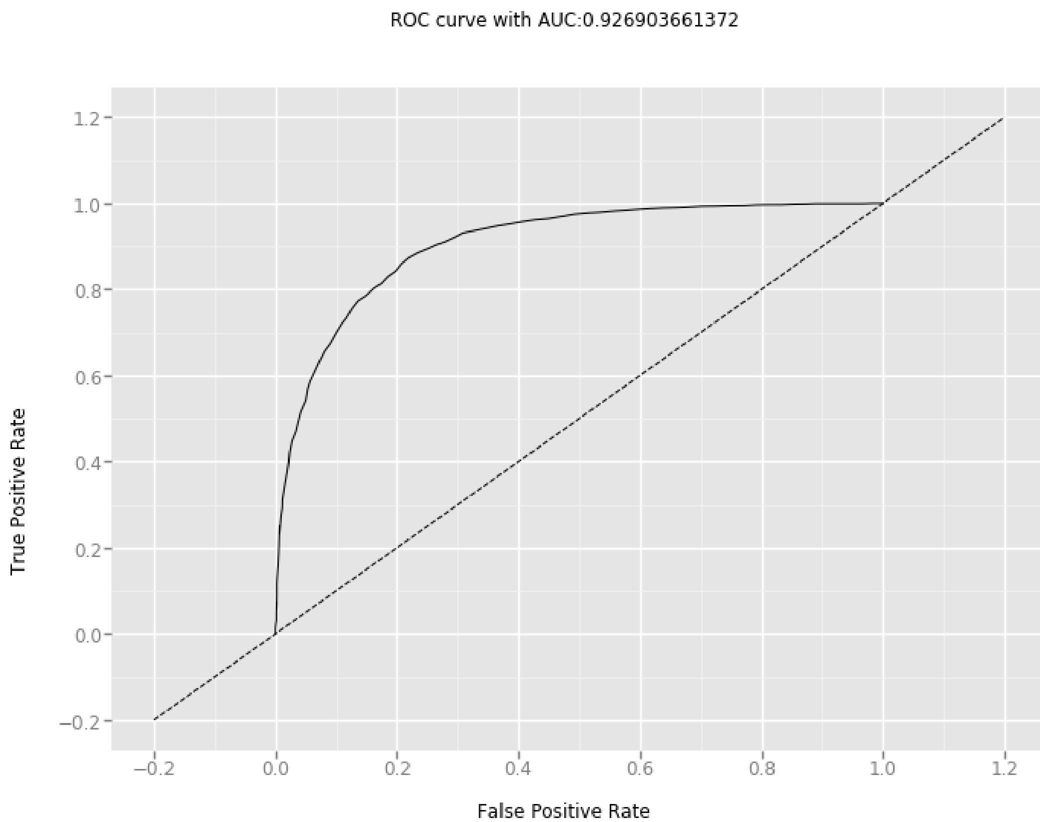
```
AUC:0.905723089976
```




```
Out[30]: <ggplot: (174732687294)>

In [31]: # Model Prediction with 10 cross validation
         predicted = cross_validation.cross_val_predict(forest, xtest, ytest, cv=10)
         print(metrics.accuracy_score(ytest, predicted))

0.82964

In [33]: # Confusion matrix
         conf_matrix = confusion_matrix(data["sentiment"].values, predicted)
         conf_matrix

Out[33]: array([[10352,  2148],
                [ 2111, 10389]], dtype=int64)

In [2]: #predict_1 = predicted.predict(data_features)[:, 1000]
        #fpr, tpr, _ = metrics.roc_curve(data["sentiment"].values, predict_1)

        #auc = metrics.roc_auc_score(data["sentiment"].values, predict_1)
        #print("AUC:" + str(auc))

        #df = pd.DataFrame(dict(fpr=fpr, tpr=tpr))
        #ggplot(df, aes(x='fpr', y="tpr")) + geom_line() + geom_abline(linetype='dashed') + ggti
```

6 Logistic Regression

```
In [38]: logreg = LogisticRegression()
         logreg_model = logreg.fit(xtrain, ytrain)

In [39]: ypred1 = logreg_model.predict(xtest)

In [40]: conf_matrix2 = confusion_matrix(ytest, ypred1)
         conf_matrix2

Out[40]: array([[2065,  380],
                [ 355, 2200]], dtype=int64)

In [41]: print(1-hamming_loss(ypred1, ytest))

0.853


In [43]: preds = logreg.predict_proba(xtest)[:, 1]
         fpr2, tpr2, _ = metrics.roc_curve(ytest, preds)

         auc1 = metrics.roc_auc_score(ytest, preds)
         print("AUC:" + str(auc1))

         df2 = pd.DataFrame(dict(fpr=fpr2, tpr=tpr2))
         ggplot(df, aes(x='fpr', y="tpr")) +
             geom_line() +
             geom_abline(linetype='dashed') +
             ggtitle("ROC curve with AUC:%s" % str(auc1)) +
             xlab("False Positive Rate") +
             ylab("True Positive Rate")

AUC:0.926903661372
```




```
Out[43]: <ggplot: (174735586838)>
```

```
In [44]: print(metrics.roc_auc_score(ytest, preds))
```

```
0.926903661372
```

```
In [45]: predicted2 = cross_validation.cross_val_predict(LogisticRegression(),
                                                          data_features,
                                                          data["sentiment"].values,
                                                          cv=10)
         print(metrics.accuracy_score(data["sentiment"].values, predicted2))
```

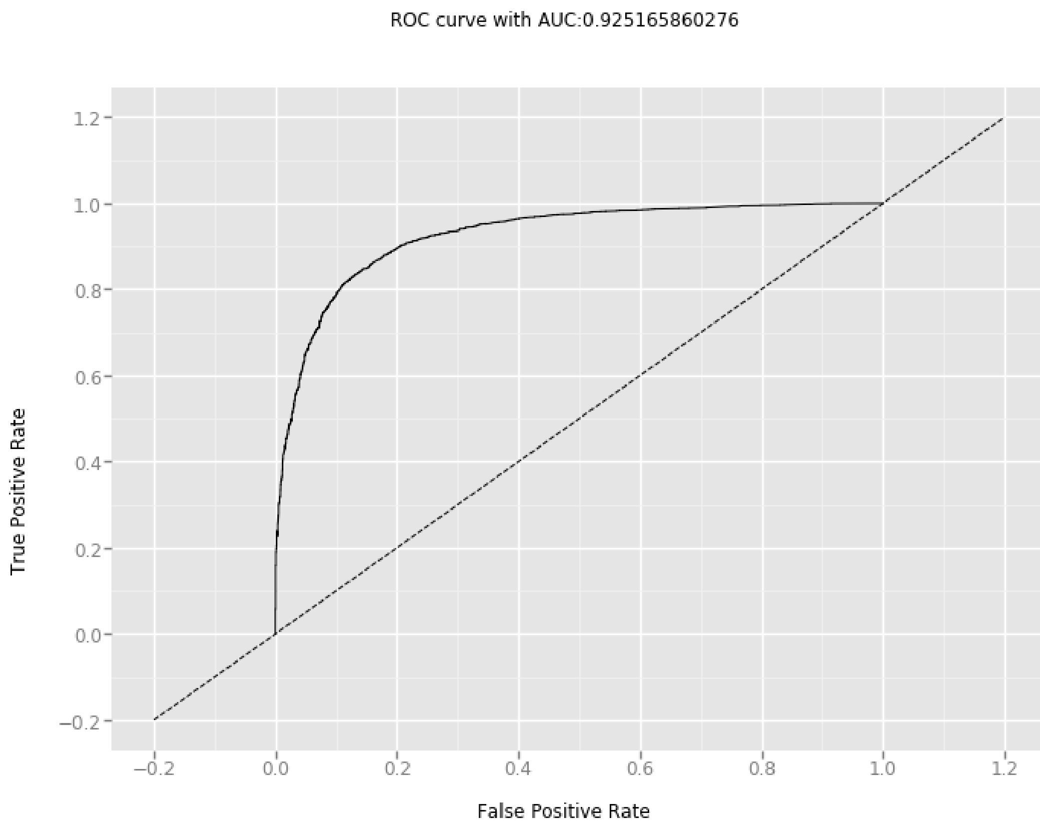
```
0.85632
```

```
In [ ]: conf_matrix = confusion_matrix(data["sentiment"].values, predicted2)
        conf_matrix
```

7 SVM

```
In [54]: svm_ = svm.SVC(kernel = "linear", C = 1, probability = True)
```

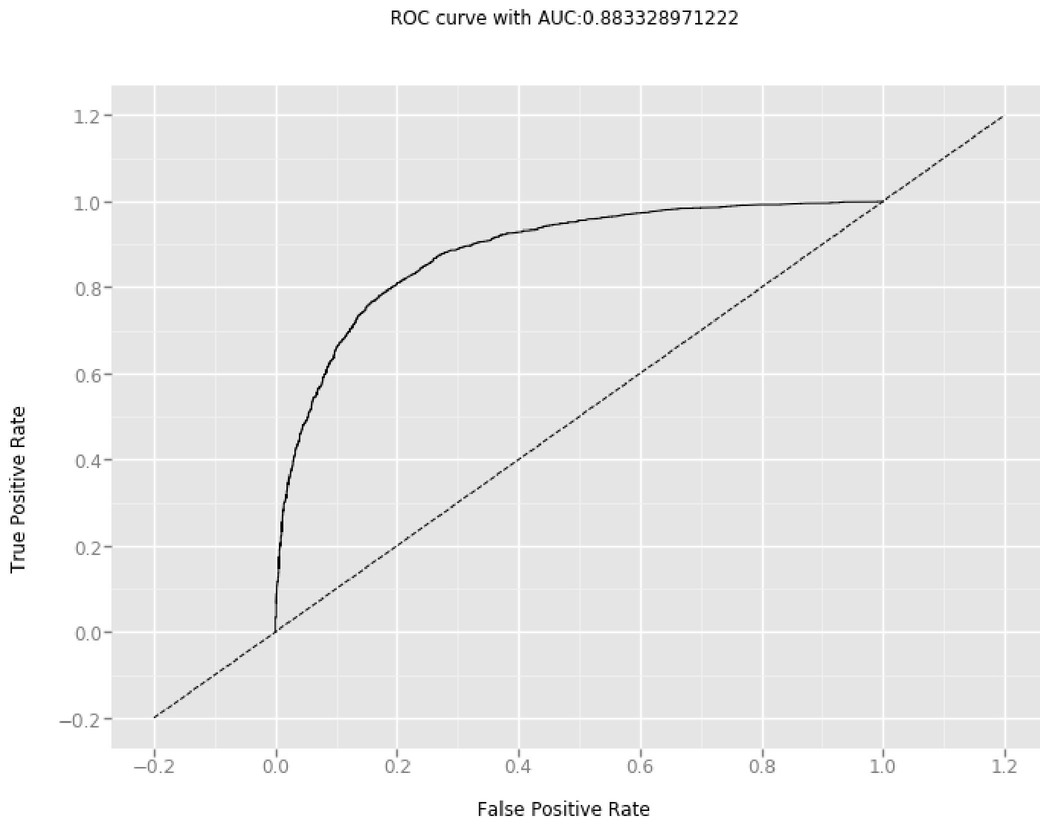
```
In [55]: svm_model = svm_.fit(xtrain, ytrain)
         svm_.score(xtrain, ytrain)

Out[55]: 0.88439999999999996

In [56]: ypred2 = svm_model.predict(xtest)

In [49]: conf_matrix2 = confusion_matrix(ytest, ypred2)
         conf_matrix2

Out[49]: array([[2052,  393],
                [ 352, 2203]], dtype=int64)

In [50]: print(1-hamming_loss(ypred2, ytest))

0.851


In [57]: preds3 = svm_.predict_proba(xtest)[:, 1]
         fpr3, tpr3, _ = metrics.roc_curve(ytest, preds3)

         auc3 = metrics.roc_auc_score(ytest, preds3)
         print("AUC:" + str(auc3))

         df3 = pd.DataFrame(dict(fpr=fpr3, tpr=tpr3))
         ggplot(df3, aes(x='fpr', y="tpr")) +
             geom_line() + geom_abline(linetype='dashed') +
             ggtitle("ROC curve with AUC:%s" % str(auc3)) +
             xlab("False Positive Rate") +
             ylab("True Positive Rate")

AUC:0.925165860276
```




```
Out[57]: <ggplot: (174724739220)>

In [60]: predicted3 = cross_val_predict(svm_, xtest, ytest, cv=10, method='predict_proba')
         scores = predicted3[:,1]
         fpr, tpr, thresholds = roc_curve(ytest, scores)

In [59]: conf_matrix = confusion_matrix(ytest, scores)
         print(conf_matrix)
         #scores.size
         print(metrics.accuracy_score(ytest, predicted3))

[[1943  502]
 [ 480 2075]]
0.8036


In [61]: auc_cm2 = metrics.roc_auc_score(ytest, scores)
         print("AUC:" + str(auc_cm2))

         df = pd.DataFrame(dict(fpr=fpr, tpr=tpr))
         ggplot(df, aes(x='fpr', y="tpr")) +
             geom_line() +
```

```
    geom_abline(linetype='dashed') +
    ggtitle("ROC curve with AUC:%s" % str(auc_cm2)) +
    xlab("False Positive Rate") +
    ylab("True Positive Rate")
```

```
AUC:0.883328971222
```




```
Out[61]: <ggplot: (-9223371862117908904)>
```

7.1 Conclusion:

Among the three classification models, Logistic Regression predicts much better without cross validation having AUC score 0.9285 and Random Forest predicts better with 10 cross validation whose AUC score is 0.8953.