Binary_class_replication

May 14, 2019

```
In [0]: import pandas as pd
```

```
In [0]: import numpy as np
```

```
In [3]: !pip install vaderSentiment
```

```
Collecting vaderSentiment
  Downloading https://files.pythonhosted.org/packages/86/9e/c53e1fc61aac5ee490a6ac5e21b1ac04e5
     || 133kB 3.6MB/s
Installing collected packages: vaderSentiment
Successfully installed vaderSentiment-3.2.1
```

```
In [0]: from sklearn.feature_extraction.text import CountVectorizer
        from sklearn.model_selection import train_test_split
        from sklearn.pipeline import make_pipeline
        from sklearn.linear_model import LogisticRegression
        from sklearn.model_selection import cross_val_score
        from sklearn.model_selection import GridSearchCV
        from sklearn.feature_extraction.text import TfidfVectorizer, TfidfTransformer
        import nltk
        import gensim
        from nltk.tokenize import sent_tokenize, word_tokenize
        from vaderSentiment.vaderSentiment import SentimentIntensityAnalyzer
        from scipy.sparse import hstack
        from sklearn.metrics import average_precision_score
        from sklearn.metrics import roc_auc_score
        from nltk import word_tokenize,sent_tokenize
        from gensim import corpora
        from sklearn.pipeline import Pipeline
        from sklearn.model_selection import cross_val_predict
        import matplotlib.pyplot as plt
```

0.1 Loading the data

Converting multi-class data to a binary class data. We want to know when a tweet is hate-speech or not, we merge the other two classes since offensive content isn't always hate speech. The report elaborates more upon the choice of classes.

```
In [0]: df_train = pd.read_csv("/content/labeled_data.csv")[["tweet","class"]]

        df_train.loc[df_train['class'] == 2, 'class'] = 1
```

```
In [6]: df_train.head()
```

Out[6]:

	tweet	class
0	!!! RT @mayasolovely: As a woman you shouldn't...	1
1	!!!!! RT @mleew17: boy dats cold...tyga dwn ba...	1
2	!!!!!!! RT @UrKindOfBrand Dawg!!!! RT @80sbaby...	1
3	!!!!!!!!! RT @C_G_Anderson: @viva_based she lo...	1
4	!!!!!!!!!!!!! RT @ShenikaRoberts: The shit you...	1

0.2 Taking equal data points of all classes

```
In [7]: X_train = df_train[df_train['class']==0]["tweet"]
        X__train = df_train[df_train['class']==1]["tweet"][:1000]
        X_train = X_train.append(X__train)
        y_train = df_train[df_train['class']==0]["class"]
        y_train = y_train.append(df_train[df_train['class']==1]["class"][:1000])

        len(X_train)
```

```
Out[7]: 2430
```

```
In [8]: len(y_train)
```

```
Out[8]: 2430
```

0.3 Baseline model

We choose a simple straight forward Count vector based regression model to establish a baseline

```
In [9]: pipe  =  make_pipeline(CountVectorizer(),LogisticRegression(solver="sag"))
        print("Cross val score on baseline model")
        pipe.fit(X_train,y_train)
        print(np.mean(cross_val_score(pipe,X_train,y_train,cv=5,scoring="roc_auc")))
```

```
Cross val score on baseline model


/usr/local/lib/python3.6/dist-packages/sklearn/linear_model/sag.py:334: ConvergenceWarning: The
  "the coef_ did not converge", ConvergenceWarning)
/usr/local/lib/python3.6/dist-packages/sklearn/linear_model/sag.py:334: ConvergenceWarning: The
  "the coef_ did not converge", ConvergenceWarning)
/usr/local/lib/python3.6/dist-packages/sklearn/linear_model/sag.py:334: ConvergenceWarning: The
  "the coef_ did not converge", ConvergenceWarning)
/usr/local/lib/python3.6/dist-packages/sklearn/linear_model/sag.py:334: ConvergenceWarning: The
  "the coef_ did not converge", ConvergenceWarning)
```

```
0.8547849650349649
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/linear_model/sag.py:334: ConvergenceWarning: The
  "the coef_ did not converge", ConvergenceWarning)
/usr/local/lib/python3.6/dist-packages/sklearn/linear_model/sag.py:334: ConvergenceWarning: The
  "the coef_ did not converge", ConvergenceWarning)
```

0.4 Re-implementing the paper

In this part, we follow the steps mentioned in the paper about how to replicate the paper.

1. Lowercase
2. Stem
3. bigram, unigram, trigram features, weighted by its tfidf
4. POS tag
5. FK Grade level
6. FK reading ease score
7. sentiment scores
8. binary indicators for: hashtags, mentions, retweets, urls
9. count indicatiors for :hashtags, mentions, retweets, urls
10. number of characters
11. numbers of words
12. number of syllables

```
In [10]: nltk.download("stopwords")
         from nltk.stem.porter import *
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.
```

```
In [0]: stopwords=stopwords = nltk.corpus.stopwords.words("english")

        other_exclusions = ["#ff", "ff", "rt","RT"]
        stopwords.extend(other_exclusions)

        stemmer = PorterStemmer()

        def preprocess(text_string):
```

```
            #Lowercase string
            text_string=text_string.lower()
            space_pattern = '\s+'
            giant_url_regex = ('http[s]?://(?:[a-zA-Z]|[0-9]|[$-_@.&+]|'
                '[!*\(\),]|(?:%[0-9a-fA-F][0-9a-fA-F]))+')
            mention_regex = '@[\w\-]+'
            hashtag_regex = '#[\w\-]+'
            parsed_text = re.sub(space_pattern, ' ', text_string)
            parsed_text = re.sub(giant_url_regex, 'URLHERE', parsed_text)
            parsed_text = re.sub(mention_regex, 'MENTIONHERE', parsed_text)
            parsed_text = re.sub(hashtag_regex, 'HASHTAGHERE', parsed_text)

            #Stem it
            tweet = " ".join(re.split("[^a-zA-Z]*", parsed_text)).strip()
            tokens = [stemmer.stem(t) for t in tweet.split()]
            return tokens


        def pos_tag_seq(tokens):
            tags = nltk.pos_tag(tokens)
            tag_list = [x[1] for x in tags]
            tag_str = " ".join(tag_list)
            return tag_str
```

```
In [0]: def join_sent(l):
          return " ".join(l)

In [0]: df_train=pd.DataFrame(X_train)

In [0]: df_train.columns=["tweet"]

In [15]: df_train.head()

Out[15]:                                                  tweet
         85   "@Blackman38Tide: @WhaleLookyHere @HowdyDowdy1...
         89   "@CB_Baby24: @white_thunduh alsarabsss" hes a ...
         110  "@DevilGrimz: @VigxRArts you're fucking gay, b...
         184  "@MarkRoundtreeJr: LMFAOOOO I HATE BLACK PEOPL...
         202  "@NoChillPaz: "At least I'm not a nigger" http...

In [16]: s_train=df_train['tweet'].apply(preprocess)

/usr/lib/python3.6/re.py:212: FutureWarning: split() requires a non-empty pattern match.
  return _compile(pattern, flags).split(string, maxsplit)


In [0]: s_tr=s_train.apply(join_sent)
```

```
In [18]: nltk.download('averaged_perceptron_tagger')
         t_tr=s_train.apply(pos_tag_seq)

[nltk_data] Downloading package averaged_perceptron_tagger to
[nltk_data]     /root/nltk_data...
[nltk_data]   Unzipping taggers/averaged_perceptron_tagger.zip.


In [0]: vectorizer = TfidfVectorizer(
            preprocessor=None,
            lowercase=False,
            ngram_range=(1, 3),
            use_idf=True,
            smooth_idf=False,
            norm=None,
            stop_words=stopwords,
            decode_error='replace',
            max_features=10000,
            min_df=5,
            max_df=0.75
            )

In [0]: pos_vectorizer = TfidfVectorizer(
            tokenizer=None,
            lowercase=False,
            preprocessor=None,
            ngram_range=(1, 3),
            stop_words=None,
            use_idf=False,
            smooth_idf=False,
            norm=None,
            decode_error='replace',
            max_features=5000,
            min_df=5,
            max_df=0.75,
            )

In [0]: tfidf_tr = vectorizer.fit_transform(s_tr).toarray()

        vocab = {v:i for i, v in enumerate(vectorizer.get_feature_names())}
        idf_vals = vectorizer.idf_
        idf_dict = {i:idf_vals[i] for i in vocab.values()}

In [0]: pos_tr = pos_vectorizer.fit_transform(t_tr).toarray()

        pos_vocab = {v:i for i, v in enumerate(pos_vectorizer.get_feature_names())}

In [0]: from vaderSentiment.vaderSentiment import SentimentIntensityAnalyzer as VS
        sentiment_analyzer = VS()
```

```
In [0]: def get_sentiment(text):
          sentiment = sentiment_analyzer.polarity_scores(text)
          return sentiment

        #   return sentiment["neg"], sentiment["pos"], sentiment["neu"]

In [0]: df_train["sent"]=df_train["tweet"].apply(get_sentiment)

In [26]: df_train.head()

Out[26]:                                                  tweet  \
         85   "@Blackman38Tide: @WhaleLookyHere @HowdyDowdy1...
         89   "@CB_Baby24: @white_thunduh alsarabsss" hes a ...
         110  "@DevilGrimz: @VigxRArts you're fucking gay, b...
         184  "@MarkRoundtreeJr: LMFAOOOO I HATE BLACK PEOPL...
         202  "@NoChillPaz: "At least I'm not a nigger" http...

                                                       sent
         85   {'neg': 0.0, 'neu': 1.0, 'pos': 0.0, 'compound...
         89   {'neg': 0.187, 'neu': 0.813, 'pos': 0.0, 'comp...
         110  {'neg': 0.0, 'neu': 1.0, 'pos': 0.0, 'compound...
         184  {'neg': 0.254, 'neu': 0.746, 'pos': 0.0, 'comp...
         202  {'neg': 0.232, 'neu': 0.488, 'pos': 0.28, 'com...

In [0]: foo_tr = lambda x: pd.Series([x["pos"],x["neg"],x["neu"]])
        rev_tr = df_train['sent'].apply(foo_tr)

In [0]: rev_tr.columns=["pos","neg","neu"]

In [29]: rev_tr.head()

Out[29]:       pos    neg    neu
         85   0.00  0.000  1.000
         89   0.00  0.187  0.813
         110  0.00  0.000  1.000
         184  0.00  0.254  0.746
         202  0.28  0.232  0.488
```

0.5 Binary count for URL https mentions etc

```
In [0]: def return_cont(parsed_text):
          return(parsed_text.count('urlher'),parsed_text.count('mentionher'),parsed_text.count

In [0]: df_train["counts"]=s_tr.apply(return_cont)

In [32]: df_train["counts"].head()

Out[32]: 85     (0, 3, 0)
         89     (0, 2, 0)
         110    (1, 2, 1)
```

```
184    (1, 1, 0)
202    (1, 1, 0)
Name: counts, dtype: object
```

```
In [0]: foo = lambda x: pd.Series([x[0],x[1],x[2]])
        mention_counts_tr = df_train['counts'].apply(foo)
```

```
In [34]: mention_counts_tr.head()
```

```
Out[34]:      0  1  2
         85   0  3  0
         89   0  2  0
         110  1  2  1
         184  1  1  0
         202  1  1  0
```

0.6 FKRA and Flesch and number of syllables etc

```
In [35]: !pip install textstat
         from textstat.textstat import *
```

```
Collecting textstat
  Downloading https://files.pythonhosted.org/packages/66/73/97bb64c89d6f2b24be6ad76007823e19b4
Collecting repoze.lru (from textstat)
  Downloading https://files.pythonhosted.org/packages/b0/30/6cc0c95f0b59ad4b3b9163bff7cdcf793c
Collecting pyphen (from textstat)
  Downloading https://files.pythonhosted.org/packages/15/82/08a3629dce8d1f3d91db843bb36d4d7db6
     || 3.0MB 5.0MB/s
Installing collected packages: repoze.lru, pyphen, textstat
Successfully installed pyphen-0.9.5 repoze.lru-0.7 textstat-0.5.6
```

```
In [0]: def get_other_features(text):
            space_pattern = '\s+'
            giant_url_regex = ('http[s]?://(?:[a-zA-Z]|[0-9]|[$-_@.&+]|'
                '[!*\(\),]|(?:%[0-9a-fA-F][0-9a-fA-F]))+')
            mention_regex = '@[\w\-]+'
            parsed_text = re.sub(space_pattern, ' ', text)
            parsed_text = re.sub(giant_url_regex, '', parsed_text)
            words = re.sub(mention_regex, '', parsed_text)

            syllables = textstat.syllable_count(words)
            num_chars = sum(len(w) for w in words)
            num_chars_total = len(text)
            num_terms = len(text.split())
            num_words = len(words.split())
            avg_syl = round(float((syllables+0.001))/float(num_words+0.001),4)
            num_unique_terms = len(set(words.split()))
```

```
            ###Modified FK grade, where avg words per sentence is just num words/1
            FKRA = round(float(0.39 * float(num_words)/1.0) + float(11.8 * avg_syl) - 15.59,1)
            ##Modified FRE score, where sentence fixed to 1
            FRE = round(206.835 - 1.015*(float(num_words)/1.0) - (84.6*float(avg_syl)),2)

            features = [FKRA, FRE,syllables, avg_syl, num_chars, num_terms, num_words,
                        num_unique_terms]
            return features


In [0]: other_feats_tr=df_train["tweet"].apply(get_other_features)

In [38]: other_feats_tr.head()

Out[38]: 85          [9.2, 34.62, 6, 1.9997, 18, 5, 3, 3]
         89        [6.8, 67.76, 18, 1.5, 59, 13, 12, 10]
         110    [9.1, 49.55, 19, 1.7272, 76, 13, 11, 11]
         184    [5.2, 84.46, 19, 1.2666, 78, 15, 15, 15]
         202        [2.3, 94.3, 11, 1.2222, 38, 9, 9, 9]
         Name: tweet, dtype: object

In [0]: other_features_names = ["FKRA", "FRE","num_syllables", "avg_syl_per_word", "num_chars"

In [0]: foo = lambda x: pd.Series(elem for elem in x)
        of_counts_tr = other_feats_tr.apply(foo)

In [41]: of_counts_tr.head()

Out[41]:        0      1     2       3     4     5     6     7
         85   9.2  34.62   6.0  1.9997  18.0   5.0   3.0   3.0
         89   6.8  67.76  18.0  1.5000  59.0  13.0  12.0  10.0
         110  9.1  49.55  19.0  1.7272  76.0  13.0  11.0  11.0
         184  5.2  84.46  19.0  1.2666  78.0  15.0  15.0  15.0
         202  2.3  94.30  11.0  1.2222  38.0   9.0   9.0   9.0

In [0]: of_counts_tr.columns=other_features_names

In [43]: of_counts_tr.head()

Out[43]:      FKRA    FRE  num_syllables  avg_syl_per_word  num_chars  num_terms  \
         85    9.2  34.62            6.0            1.9997       18.0        5.0
         89    6.8  67.76           18.0            1.5000       59.0       13.0
         110   9.1  49.55           19.0            1.7272       76.0       13.0
         184   5.2  84.46           19.0            1.2666       78.0       15.0
         202   2.3  94.30           11.0            1.2222       38.0        9.0

              num_words  num_unique_words
         85         3.0               3.0
```

```
89        12.0              10.0
110       11.0              11.0
184       15.0              15.0
202        9.0               9.0
```

In [44]:
```
#Removing unnecessary columns
df_train.drop([ "sent","counts"], axis=1)
```

Out[44]:

	tweet
85	"@Blackman38Tide: @WhaleLookyHere @HowdyDowdy1...
89	"@CB_Baby24: @white_thunduh alsarabsss" hes a ...
110	"@DevilGrimz: @VigxRArts you're fucking gay, b...
184	"@MarkRoundtreeJr: LMFAOOOO I HATE BLACK PEOPL...
202	"@NoChillPaz: "At least I'm not a nigger" http...
204	"@NotoriousBM95: @_WhitePonyJr_ Ariza is a sna...
219	"@RTNBA: Drakes new shoes that will be release...
260	"@TheoMaxximus: #GerrysHalloweenParty http://t...
312	"@ashlingwilde: @ItsNotAdam is bored supposed ...
315	"@bigbootybishopp: @white_thunduh lassen cc , ...
349	"@jayswaggkillah: Jackies a retard #blondeprob...
352	"@jgabsss: Stacey Dash won 💦 http://t...
437	"Don't worry about the nigga you see, worry ab...
459	"Hey go look at that video of the man that fou...
519	"Let's kill cracker babies!". WTF did I just h...
526	"My grandma used to call me a porch monkey all...
531	"Nah its You @NoMeek_JustMilz: 😂&#1285...
540	"Our people". Now is the time for the Aryan ra...
565	"These sour apple bitter bitches, I'm not fuck...
582	"We hate niggers, we hate faggots and we hate ...
583	"We're out here, and we're queer!"\n" 2, 4, 6,...
587	"Who the fuck you callin jiggaboo, nigga?!"
588	"Why people think gay marriage is okay is beyo...
603	"You ain't gunna do shit spear chucker"
614	"You ol trout mouth ass bitch" \nDEEEEAAAADD
625	"ayo i even kill handicapped and crippled bitc...
635	"fuck you you pussy ass hater go suck a dick a...
646	"on my way to fuck your bitch in the name of T...
647	"poor whitey" http://t.co/3UkKeyznz8
663	#AZmonsoon lot of rain, too bad it wasn't enou...
...	...
1027	😟 “@DubPeeWorld: So the new wave...
1028	😩 cunt
1029	😩 monkey mad
1030	😩😂 RT @willieBEAMINN: @_VinChi...
1031	😩😩😂 damn roaches got d...
1032	😩😩😂😭😭 ...
1033	😩😭 RT @Freegeezy17: My Co work...
1034	😩😭 RT @KingHov1313: Fox8 got d...

```
1035  &#128555;&#128555;&#128555;&#128555;&#128555;&...
1036                  &#128555;ugly bitches get no love
1037  &#128557; RT @KingHov1313: I be thinkin Errbod...
1038  &#128557; RT @That_Mclovin: &#8220;Yass bitch ...
1039  &#128557; RT @TrashAssTweets: When you wake up...
1040  &#128557; RT @red_daddy17: But wait if he got ...
1041  &#128557;&#128557; &#8220;@_____AL: Y'all be t...
1042  &#128557;&#128557; RT @KingHorseDick: Welp RT ...
1043  &#128557;&#128557; RT @KingHov1313: Niggaz get...
1044  &#128557;&#128557;&#128557; Foh RT @MizzCreme:...
1045  &#128557;&#128557;&#128557; RT @EsckmoTrent: I...
1046  &#128557;&#128557;&#128557; RT @VineForTheByrd...
1047  &#128557;&#128557;&#128557; RT @tryna_be_famou...
1048  &#128557;&#128557;&#128557;&#128530; RT @KingH...
1049  &#128557;&#128557;&#128557;&#128557;&#128557;&...
1050  &#128561;that bitch is from Moreno Valley...
1052  &#128563; RT @Pr3ttyN33: &#8220;@11wdNICK: I t...
1053  &#128563; RT @UBoyRock17: &#128557;&#128557;&#...
1054  &#128563; RT @ariluvsall: Niccas y'all need li...
1055  &#128563;&#128563;&#128563; RT @winterlove___:...
1056  &#128563;Oh this bitch Midy must be crazy http...
1057  &#128563;well damn.. RT @JackTheJokster: When ...

[2430 rows x 1 columns]
```

```
In [45]: #Confirming all dataframes have the same length
         for elem in [pd.DataFrame(tfidf_tr),pd.DataFrame(pos_tr),rev_tr,mention_counts_tr, of
           print(len(elem))
```

```
2430
2430
2430
2430
2430
```

```
In [0]: #Forming the final training dataset using the features
        x_train=np.concatenate([pd.DataFrame(tfidf_tr),pd.DataFrame(pos_tr),rev_tr,mention_cou
        x_train, x_test, y_train, y_test = train_test_split(x_train, y_train, test_size=0.2)
```

```
In [47]: print(len(x_train), len(y_train))
```

```
1944 1944
```

```
In [0]: from sklearn.feature_selection import SelectFromModel
        from sklearn.linear_model import LogisticRegression
        from sklearn.feature_selection import SelectFromModel
        from sklearn.metrics import classification_report
```

```
        from sklearn.svm import LinearSVC,SVC
        from sklearn.model_selection import StratifiedKFold, GridSearchCV
        from sklearn.pipeline import Pipeline
```

We run a grid search on SVC and LogisticRegression using various parameters.

```
In [50]: tuned_parameters = [{'kernel': ['rbf'], 'gamma': [1e-2,0.01, 10,100],
                              'C': [1, 10, 100, 1000]},
                             {'kernel': ['linear'], 'C': [0.1,0.01, 1, 10, 100]}]

         scores = ['precision', 'recall']

         for score in scores:
             print("# Tuning hyper-parameters for %s" % score)
             print()
             clf = GridSearchCV(SVC(), tuned_parameters, cv=5,
                                scoring='%s_macro' % score)
             clf.fit(x_train, y_train)

             print("Best parameters set found on development set:")
             print()
             print(clf.best_params_)
             print()
             print("Grid scores on development set:")
             print()
             means = clf.cv_results_['mean_test_score']
             stds = clf.cv_results_['std_test_score']
             for mean, std, params in zip(means, stds, clf.cv_results_['params']):
                 print("%0.3f (+/-%0.03f) for %r"
                       % (mean, std * 2, params))
             print()

             print("Detailed classification report:")
             print()
             print("The model is trained on the full development set.")
             print("The scores are computed on the full evaluation set.")
             print()
             y_true, y_pred = y_test, clf.predict(x_test)
             print(classification_report(y_true, y_pred))
             print()

# Tuning hyper-parameters for precision



/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1143: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1143: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1143: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1143: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1143: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1143: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1143: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1143: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1143: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1143: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1143: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1143: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1143: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1143: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1143: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1143: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1143: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
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  'precision', 'predicted', average, warn_for)
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1143: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1143: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1143: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1143: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1143: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1143: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1143: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1143: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1143: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1143: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1143: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1143: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1143: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1143: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1143: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1143: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1143: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1143: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1143: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1143: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1143: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1143: UndefinedMetricW
  'precision', 'predicted', average, warn_for)


Best parameters set found on development set:

{'C': 0.01, 'kernel': 'linear'}

Grid scores on development set:

0.664 (+/-0.103) for {'C': 1, 'gamma': 0.01, 'kernel': 'rbf'}
0.664 (+/-0.103) for {'C': 1, 'gamma': 0.01, 'kernel': 'rbf'}
0.294 (+/-0.001) for {'C': 1, 'gamma': 10, 'kernel': 'rbf'}
0.294 (+/-0.001) for {'C': 1, 'gamma': 100, 'kernel': 'rbf'}
0.672 (+/-0.101) for {'C': 10, 'gamma': 0.01, 'kernel': 'rbf'}
0.672 (+/-0.101) for {'C': 10, 'gamma': 0.01, 'kernel': 'rbf'}
0.294 (+/-0.001) for {'C': 10, 'gamma': 10, 'kernel': 'rbf'}
0.294 (+/-0.001) for {'C': 10, 'gamma': 100, 'kernel': 'rbf'}
0.672 (+/-0.101) for {'C': 100, 'gamma': 0.01, 'kernel': 'rbf'}
0.672 (+/-0.101) for {'C': 100, 'gamma': 0.01, 'kernel': 'rbf'}
0.294 (+/-0.001) for {'C': 100, 'gamma': 10, 'kernel': 'rbf'}
0.294 (+/-0.001) for {'C': 100, 'gamma': 100, 'kernel': 'rbf'}
```

```
0.672 (+/-0.101) for {'C': 1000, 'gamma': 0.01, 'kernel': 'rbf'}
0.672 (+/-0.101) for {'C': 1000, 'gamma': 0.01, 'kernel': 'rbf'}
0.294 (+/-0.001) for {'C': 1000, 'gamma': 10, 'kernel': 'rbf'}
0.294 (+/-0.001) for {'C': 1000, 'gamma': 100, 'kernel': 'rbf'}
0.783 (+/-0.032) for {'C': 0.1, 'kernel': 'linear'}
0.806 (+/-0.019) for {'C': 0.01, 'kernel': 'linear'}
0.751 (+/-0.052) for {'C': 1, 'kernel': 'linear'}
0.747 (+/-0.078) for {'C': 10, 'kernel': 'linear'}
0.747 (+/-0.078) for {'C': 100, 'kernel': 'linear'}

Detailed classification report:

The model is trained on the full development set.
The scores are computed on the full evaluation set.

              precision    recall  f1-score   support

           0       0.87      0.86      0.86       287
           1       0.80      0.81      0.81       199

   micro avg       0.84      0.84      0.84       486
   macro avg       0.83      0.84      0.83       486
weighted avg       0.84      0.84      0.84       486


# Tuning hyper-parameters for recall

Best parameters set found on development set:

{'C': 0.01, 'kernel': 'linear'}

Grid scores on development set:

0.543 (+/-0.028) for {'C': 1, 'gamma': 0.01, 'kernel': 'rbf'}
0.543 (+/-0.028) for {'C': 1, 'gamma': 0.01, 'kernel': 'rbf'}
0.500 (+/-0.000) for {'C': 1, 'gamma': 10, 'kernel': 'rbf'}
0.500 (+/-0.000) for {'C': 1, 'gamma': 100, 'kernel': 'rbf'}
0.563 (+/-0.033) for {'C': 10, 'gamma': 0.01, 'kernel': 'rbf'}
0.563 (+/-0.033) for {'C': 10, 'gamma': 0.01, 'kernel': 'rbf'}
0.500 (+/-0.000) for {'C': 10, 'gamma': 10, 'kernel': 'rbf'}
0.500 (+/-0.000) for {'C': 10, 'gamma': 100, 'kernel': 'rbf'}
0.563 (+/-0.033) for {'C': 100, 'gamma': 0.01, 'kernel': 'rbf'}
0.563 (+/-0.033) for {'C': 100, 'gamma': 0.01, 'kernel': 'rbf'}
0.500 (+/-0.000) for {'C': 100, 'gamma': 10, 'kernel': 'rbf'}
0.500 (+/-0.000) for {'C': 100, 'gamma': 100, 'kernel': 'rbf'}
0.563 (+/-0.033) for {'C': 1000, 'gamma': 0.01, 'kernel': 'rbf'}
0.563 (+/-0.033) for {'C': 1000, 'gamma': 0.01, 'kernel': 'rbf'}
0.500 (+/-0.000) for {'C': 1000, 'gamma': 10, 'kernel': 'rbf'}
```

```
0.500 (+/-0.000) for {'C': 1000, 'gamma': 100, 'kernel': 'rbf'}
0.781 (+/-0.032) for {'C': 0.1, 'kernel': 'linear'}
0.805 (+/-0.021) for {'C': 0.01, 'kernel': 'linear'}
0.749 (+/-0.052) for {'C': 1, 'kernel': 'linear'}
0.744 (+/-0.080) for {'C': 10, 'kernel': 'linear'}
0.744 (+/-0.080) for {'C': 100, 'kernel': 'linear'}

Detailed classification report:

The model is trained on the full development set.
The scores are computed on the full evaluation set.

              precision    recall  f1-score   support

           0       0.87      0.86      0.86       287
           1       0.80      0.81      0.81       199

   micro avg       0.84      0.84      0.84       486
   macro avg       0.83      0.84      0.83       486
weighted avg       0.84      0.84      0.84       486
```

```
In [0]: scores = ['precision', 'recall']
        penalty = ['l1', 'l2']

        logistic = LogisticRegression()

        # Create regularization hyperparameter space
        C = np.logspace(0, 4, 10)

        # Create hyperparameter options
        hyperparameters = dict(C=C, penalty=penalty)

        for score in scores:
            print("# Tuning hyper-parameters for %s" % score)
            print()
            clf = GridSearchCV(logistic, hyperparameters, cv=5,
                               scoring='%s_macro' % score)
            clf.fit(x_train, y_train)

            print("Best parameters set found on development set:")
            print()
            print(clf.best_params_)
            print()
            print("Grid scores on development set:")
            print()
```

```
means = clf.cv_results_['mean_test_score']
stds = clf.cv_results_['std_test_score']
for mean, std, params in zip(means, stds, clf.cv_results_['params']):
    print("%0.3f (+/-%0.03f) for %r"
          % (mean, std * 2, params))
print()

print("Detailed classification report:")
print()
print("The model is trained on the full development set.")
print("The scores are computed on the full evaluation set.")
print()
y_true, y_pred = y_test, clf.predict(x_test)
print(classification_report(y_true, y_pred))
print()
```

0.7 Chosing a model

From the given models, we choose using an SVC with the parameters 'C': 0.01, 'kernel': 'linear' This is because given the task of detecting hate speech requires that we maximize the amount of hate speech recognized from actual hate speech there exists. The cost of not recognizing hate speech is higher than the cost of recognizing false positives. Hence given a trade off, we chose to look for higher recall and hence settled on SVC model. The authors also did a similar thing.

```
In [0]: model=SVC(class_weight='balanced',C=0.01, kernel='linear',probability=True)
        model.fit(x_train,y_train)
        y_preds=model.predict(x_train)
        report = classification_report( y_preds, y_train )
```

0.8 Evaluating Model Performance

This section is divided into the following major parts : - In-sample predictive performance - Out-of-sample predictive performance - Effects of statistical significance on Predictive Power

Detailed explanations of the above parts follow.

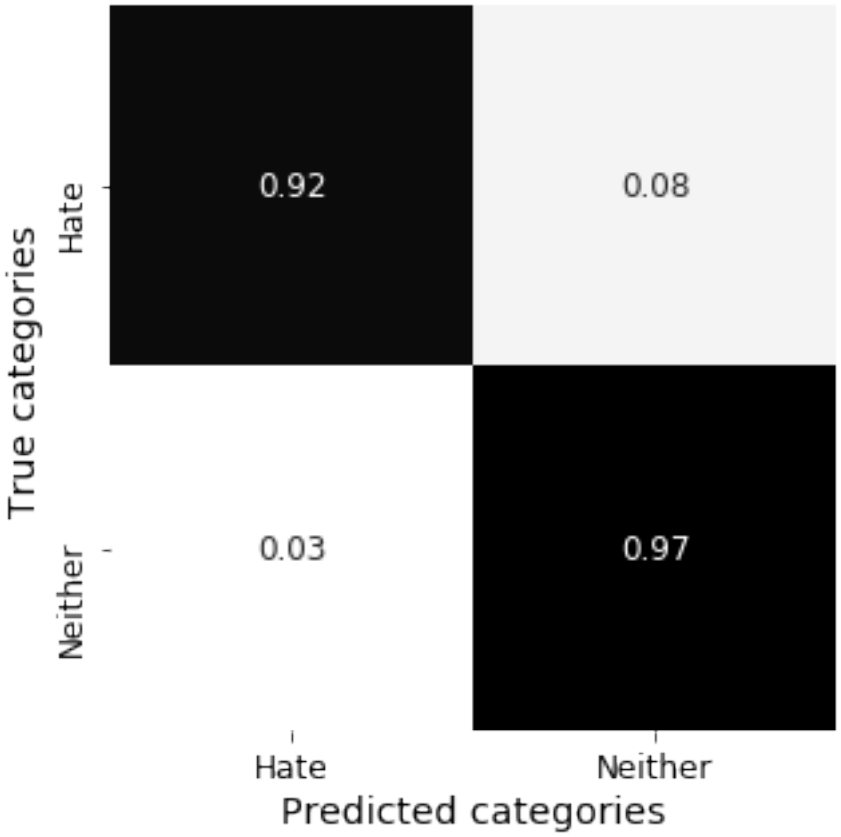
0.8.1 In-Sample Predictive Performance

We are interested in the training accuracy here, in other words the model is tested on data sampled from within the training set.

Logistic Regression is used here to obtain the best performing features using the "SelectFromModel" function and the Linear SVC model is trained and tested for performance.

```
In [52]: from sklearn.metrics import confusion_matrix
         import seaborn
         confusion_matrix = confusion_matrix(y_train,y_preds)
         matrix_proportions = np.zeros((2,2))
         for i in range(0,2):
             matrix_proportions[i,:] = confusion_matrix[i,:]/float(confusion_matrix[i,:].sum())
         names=['Hate','Neither']
```

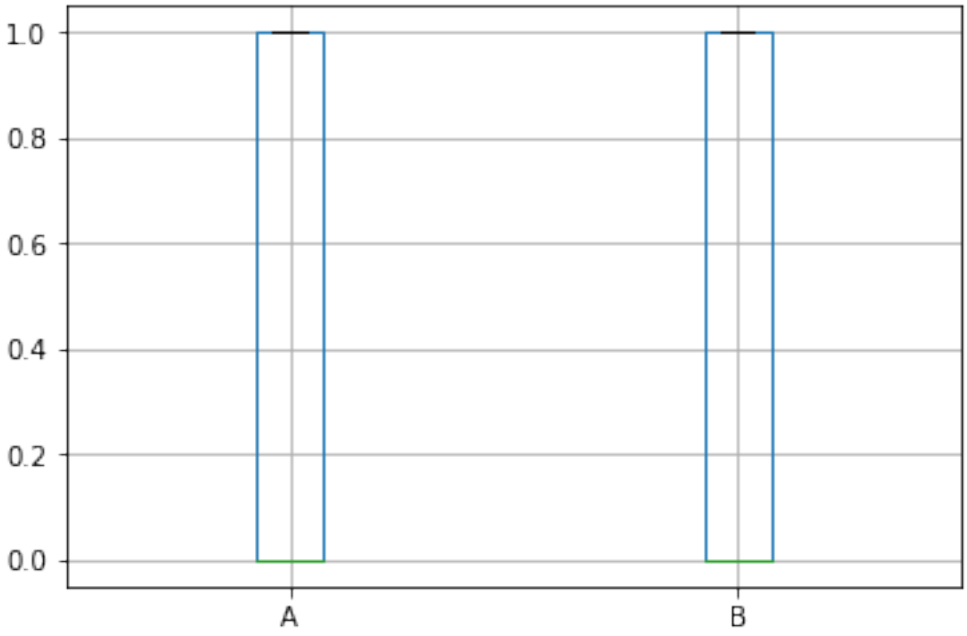
```
confusion_df = pd.DataFrame(matrix_proportions, index=names,columns=names)
plt.figure(figsize=(5,5))
seaborn.heatmap(confusion_df,annot=True,annot_kws={"size": 12},cmap='gist_gray_r',cba
plt.ylabel(r'True categories',fontsize=14)
plt.xlabel(r'Predicted categories',fontsize=14)
plt.tick_params(labelsize=12)
```

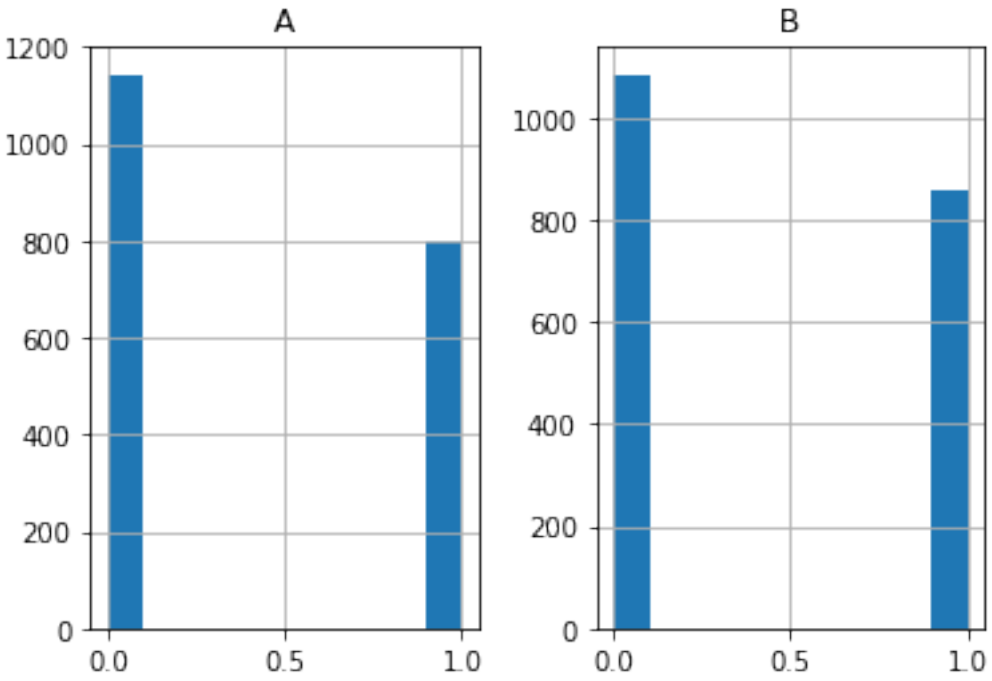


In [53]:
```
from pandas import read_csv
from matplotlib import pyplot
import pandas as pd
# load results file
results = pd.DataFrame()
results['A'] = y_train
results['B'] = y_preds
# descriptive stats
print(results.describe())
# box and whisker plot
results.boxplot()
pyplot.show()
# histogram
```

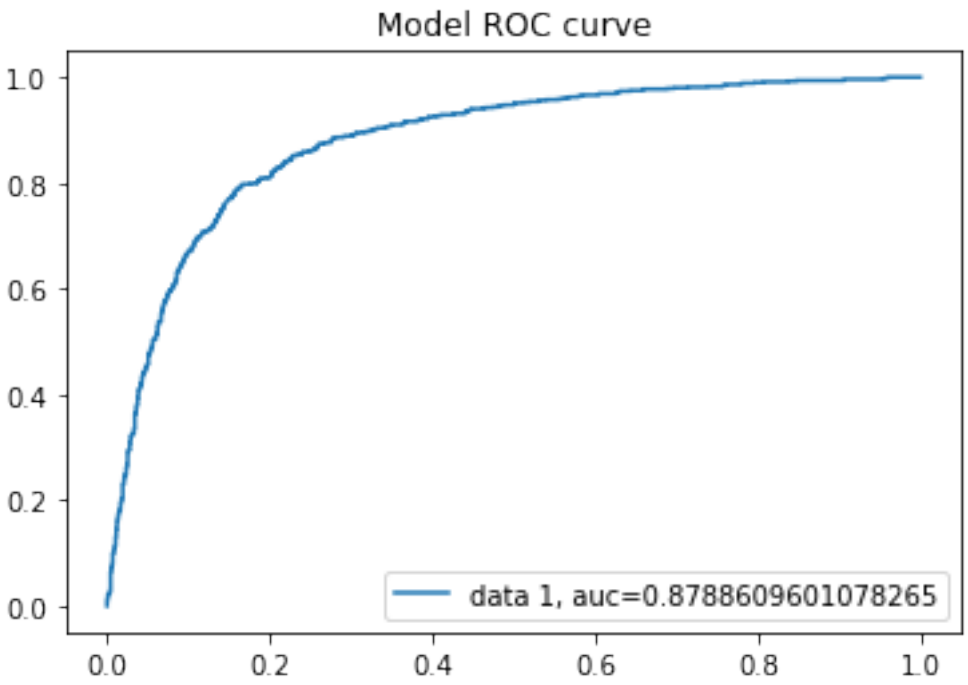
```
results.hist()
pyplot.show()
```

```
                A            B
count  1944.000000  1944.000000
mean      0.412037     0.441872
std       0.492328     0.496737
min       0.000000     0.000000
25%       0.000000     0.000000
50%       0.000000     0.000000
75%       1.000000     1.000000
max       1.000000     1.000000
```





In [54]:
```
clf = Pipeline(steps=[('classifier', SVC(class_weight='balanced',C=0.01, kernel='linea
clf.fit(x_train,y_train)

# {'C': 0.01, 'kernel': 'linear'}
proba = cross_val_predict(clf, x_train,y_train, cv=5, method='predict_proba')
from sklearn import metrics

fpr, tpr, _ = metrics.roc_curve(y_train,  proba[:,1])
auc = metrics.roc_auc_score(y_train, proba[:,1])
plt.plot(fpr,tpr,label="data 1, auc="+str(auc))
plt.legend(loc=4)
plt.title('Model ROC curve')
plt.show()
```



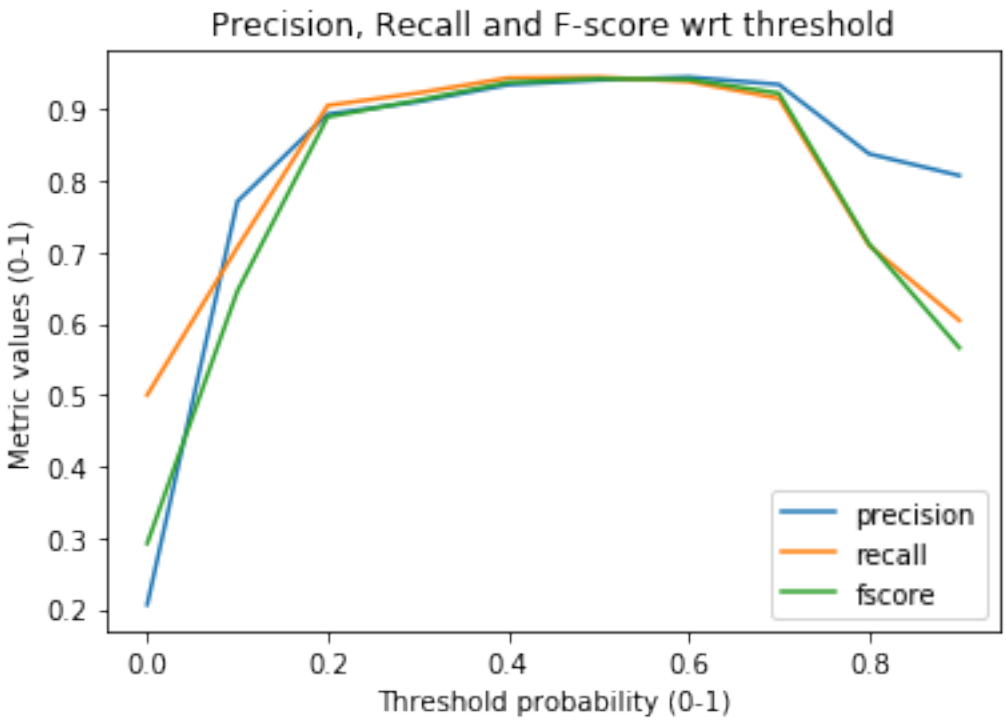
The ROC curve shows promising results, and an AUC of 0.87 was obtained. To give context, a model that randomly guessed the class (50-50 chance) would give a straight line ROC curve with an AUC of 0.5. The model performs significantly better.

We will now investigate the these metrics (precision, recall and f1-scores) at the various threshold values ranging from 0 to 1.

```
In [55]: from sklearn.metrics import precision_recall_fscore_support as score

         thresh_range = list(np.arange(0,1,0.1))
         p_list = list()
         r_list = list()
         f_list = list()
         for threshold in thresh_range:
             y_preds = np.where(model.predict_proba(x_train)[:,1] > threshold, 1, 0)
             precision,recall,fscore,support=score(y_train,y_preds,average='macro')
             p_list.append(precision)
             r_list.append(recall)
             f_list.append(fscore)
         plt.plot(thresh_range,p_list,label='precision')
         plt.plot(thresh_range,r_list,label='recall')
         plt.plot(thresh_range,f_list,label='fscore')
         plt.xlabel('Threshold probability (0-1)')
         plt.ylabel('Metric values (0-1)')
         plt.title('Precision, Recall and F-score wrt threshold')
         plt.legend()
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1143: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
```

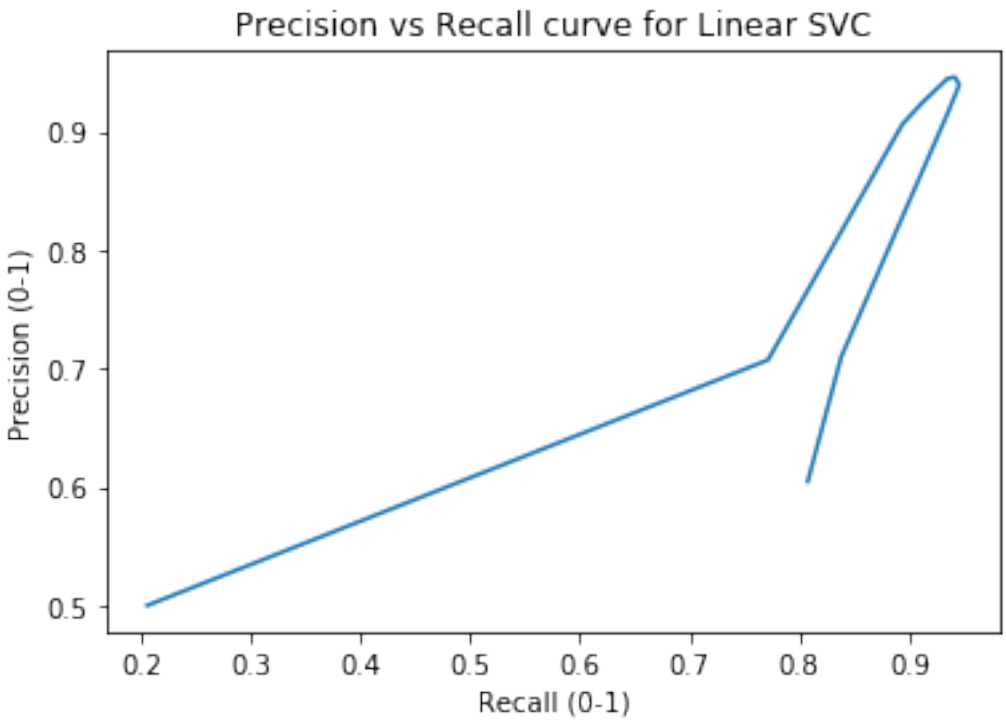
```
Out[55]: <matplotlib.legend.Legend at 0x7f79bdfb79e8>
```



The above curves demonstrate the best threshold values for our metrics. For this model we obtain an optimum threshold in the (0.4,0.6) range as seen from the above plot. The precision and recall tend to follow very similar trends. Would be interesting to see the precision vs recall curve.

```
In [56]: plt.plot(p_list,r_list)
         plt.title('Precision vs Recall curve for Linear SVC')
         plt.xlabel('Recall (0-1)')
         plt.ylabel('Precision (0-1)')
```

```
Out[56]: Text(0, 0.5, 'Precision (0-1)')
```



Interesting many-one, non-bijective curve. Both metrics peak at the same time, and at a little less than 1.

This concludes the In-sample performance evaluation. Now we will use a test dataset that isn't in-sample and see the difference in results.

0.8.2 Out-of-sample Predictive Performance

Here we use new unseen data to test our model. We expect a decline in performance, but this will also give us a peak into how generalizable the proposed Linear SVC model is.

```
In [0]: # model2 = SVC(kernel='linear',class_weight='balanced',C=0.01,probability=True).fit(x_
        # model2=SVC(class_weight='balanced',C=0.01, kernel='rbf',probability=True).fit(x_trai
        y_preds = model.predict(x_test)
        report = classification_report( y_test, y_preds )
```

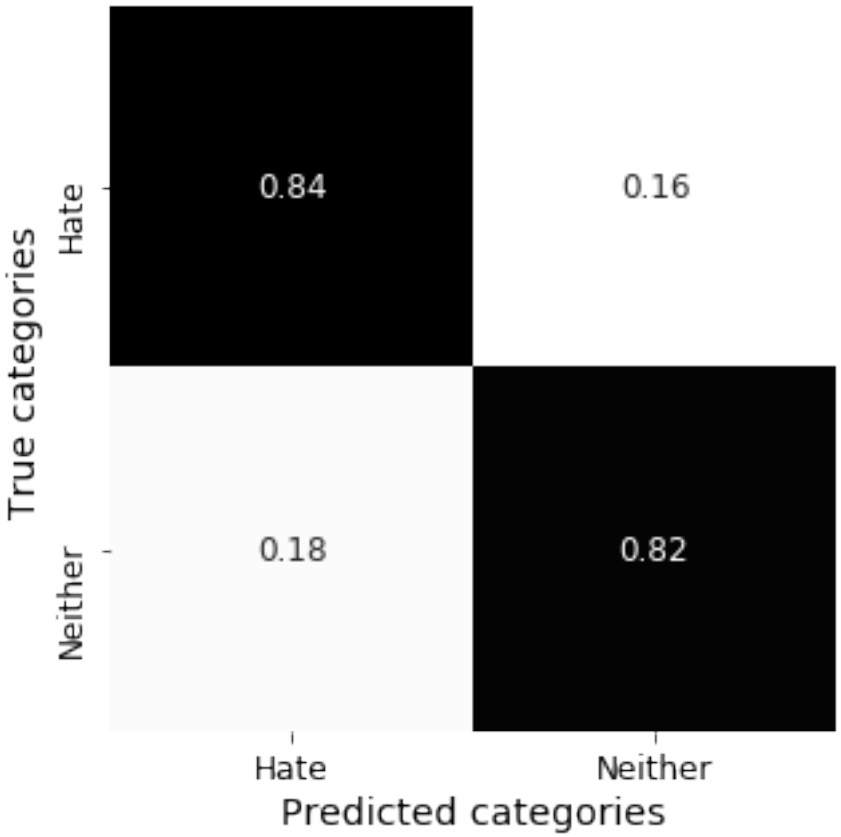
```
In [58]: print(report)
```

```
              precision    recall  f1-score   support

           0       0.87      0.84      0.85       287
           1       0.78      0.82      0.80       199

   micro avg       0.83      0.83      0.83       486
   macro avg       0.82      0.83      0.83       486
weighted avg       0.83      0.83      0.83       486
```

There is a 0.08 reduction across the weighted score of the three metrics. The values drop from 0.93 to 0.82. This was expected, and the ~10% reduction in the scores on unseen data shows that the model is generalizable and wasn't overfitting the training data.

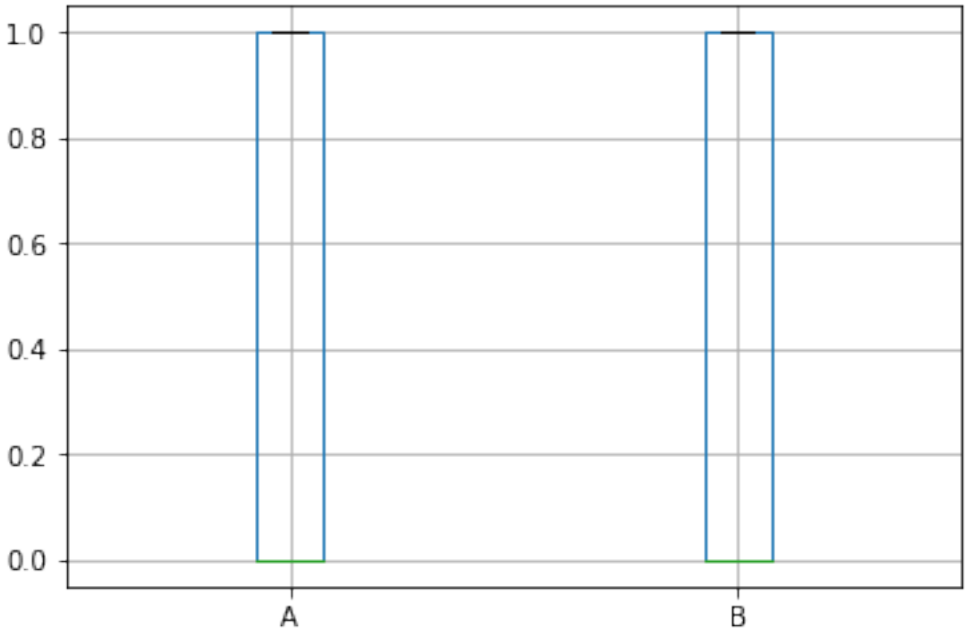
Let us now plot the roc curve for the out-sample case and compare it to our previous in-sample performance. One would expect a minor decline in AUC, which would be in line with the marginal performance metric decline we have seen above.

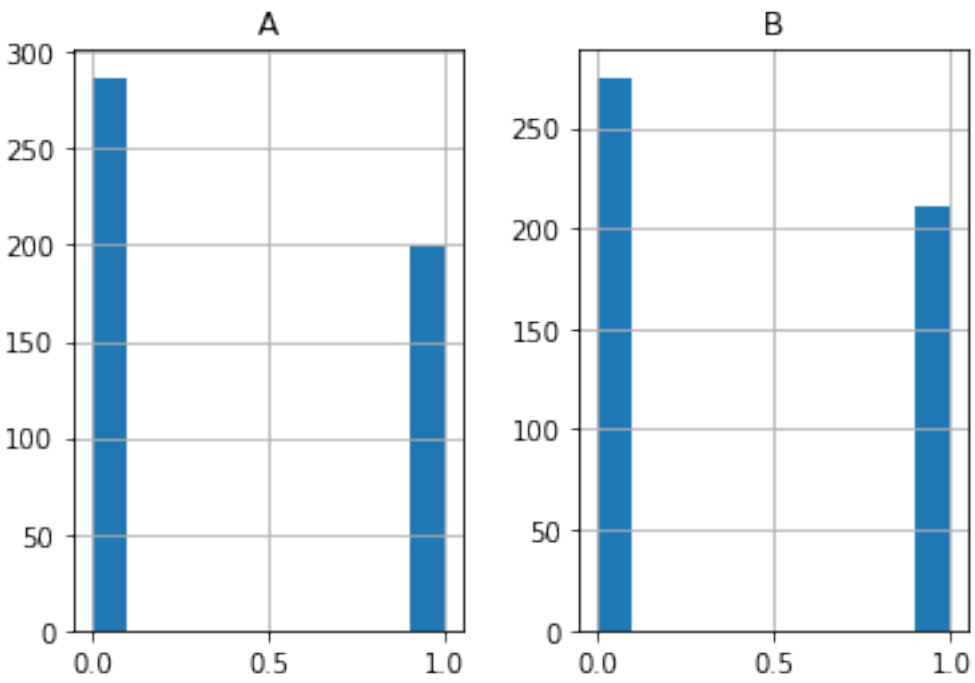
```
In [59]: from sklearn.metrics import confusion_matrix
         import seaborn
         confusion_matrix = confusion_matrix(y_test,y_preds)
         matrix_proportions = np.zeros((2,2))
         for i in range(0,2):
             matrix_proportions[i,:] = confusion_matrix[i,:]/float(confusion_matrix[i,:].sum())
         names=['Hate','Neither']
         confusion_df = pd.DataFrame(matrix_proportions, index=names,columns=names)
         plt.figure(figsize=(5,5))
         seaborn.heatmap(confusion_df,annot=True,annot_kws={"size": 12},cmap='gist_gray_r',cba
         plt.ylabel(r'True categories',fontsize=14)
         plt.xlabel(r'Predicted categories',fontsize=14)
         plt.tick_params(labelsize=12)
```



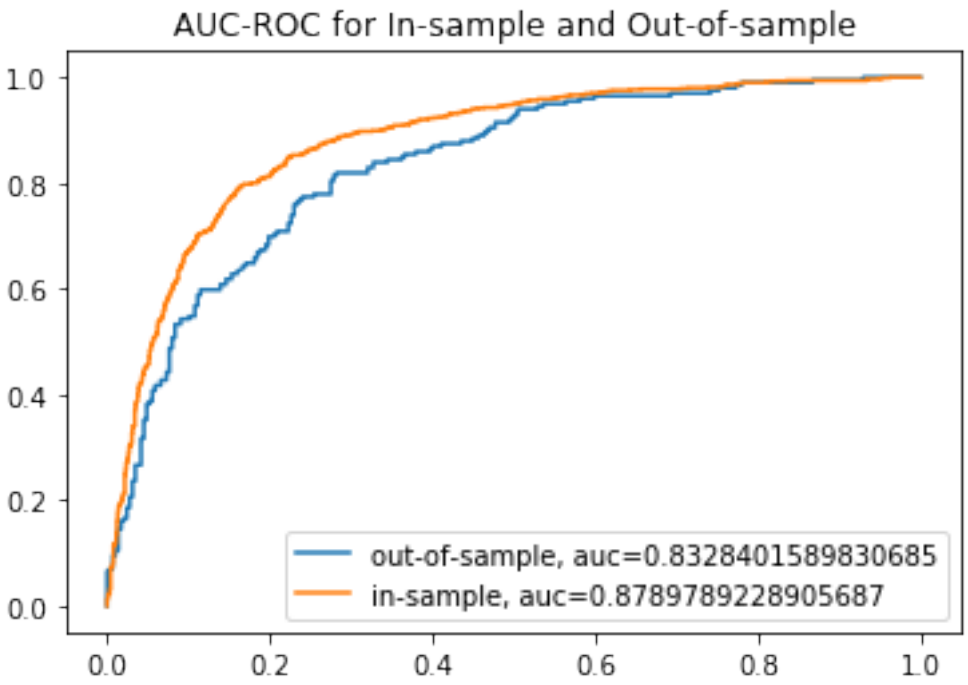
```
In [60]: from pandas import read_csv
         from matplotlib import pyplot
         import pandas as pd
         # load results file
         results = pd.DataFrame()
         results['A'] = y_test
         results['B'] = y_preds
         # descriptive stats
         print(results.describe())
         # box and whisker plot
         results.boxplot()
         pyplot.show()
         # histogram
         results.hist()
         pyplot.show()
```

```
                A           B
count  486.000000  486.000000
mean     0.409465    0.434156
std      0.492242    0.496156
min      0.000000    0.000000
25%      0.000000    0.000000
50%      0.000000    0.000000
75%      1.000000    1.000000
max      1.000000    1.000000
```





In [61]:
```
from sklearn.pipeline import Pipeline
from sklearn.model_selection import cross_val_predict
import matplotlib.pyplot as plt

clf = Pipeline(steps=[('classifier', SVC(class_weight='balanced',C=0.01, kernel='linea
clf.fit(x_train,y_train)

proba = cross_val_predict(clf, x_test,y_test, cv=5, method='predict_proba')
probb = cross_val_predict(clf, x_train,y_train, cv=5, method='predict_proba')
from sklearn import metrics

fpra, tpra, _ = metrics.roc_curve(y_test,  proba[:,1])
auca = metrics.roc_auc_score(y_test, proba[:,1])
fprb, tprb, _ = metrics.roc_curve(y_train,  probb[:,1])
aucb = metrics.roc_auc_score(y_train, probb[:,1])

plt.plot(fpra,tpra,label="out-of-sample, auc="+str(auca))
plt.plot(fprb,tprb,label="in-sample, auc="+str(aucb))

plt.legend(loc=4)
plt.title('AUC-ROC for In-sample and Out-of-sample')
plt.show()
```

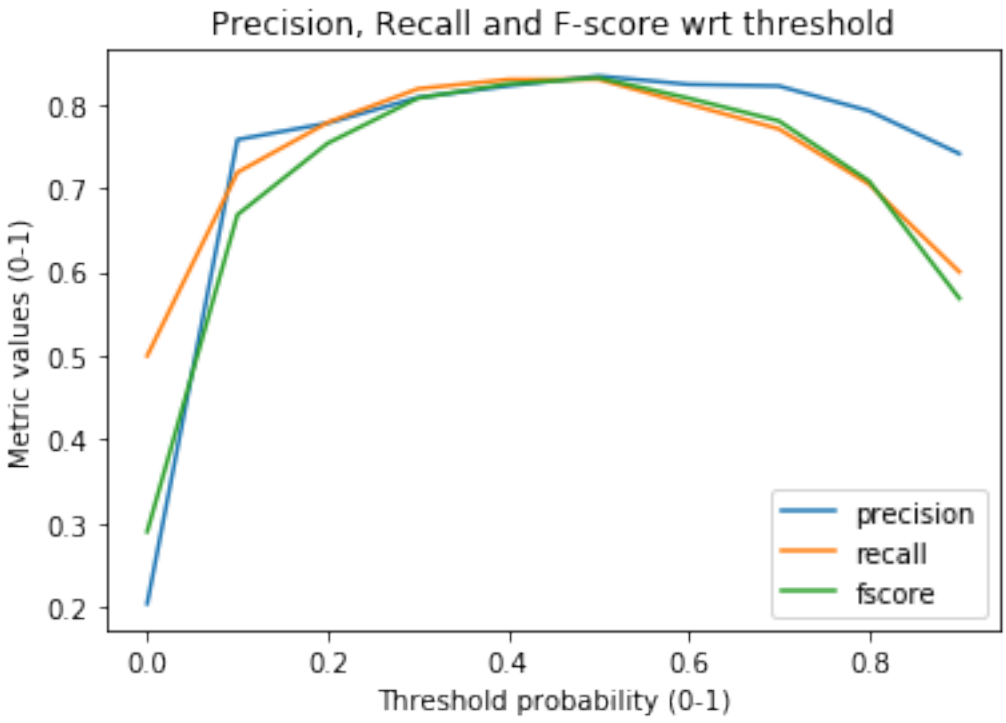


The AUC falls from 0.87 for in-sample to 0.82 for out-of-sample. The difference is clear from the ROC curves.

```
In [62]: from sklearn.metrics import precision_recall_fscore_support as score

         thresh_range = list(np.arange(0,1,0.1))
         p_list = list()
         r_list = list()
         f_list = list()
         for threshold in thresh_range:
             y_preds = np.where(model.predict_proba(x_test)[:,1] > threshold, 1, 0)
             precision,recall,fscore,support=score(y_test,y_preds,average='macro')
             p_list.append(precision)
             r_list.append(recall)
             f_list.append(fscore)
         plt.plot(thresh_range,p_list,label='precision')
         plt.plot(thresh_range,r_list,label='recall')
         plt.plot(thresh_range,f_list,label='fscore')

         plt.xlabel('Threshold probability (0-1)')
         plt.ylabel('Metric values (0-1)')
         plt.title('Precision, Recall and F-score wrt threshold')
         plt.legend()
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1143: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
```

```
Out[62]: <matplotlib.legend.Legend at 0x7f79b920f6d8>
```

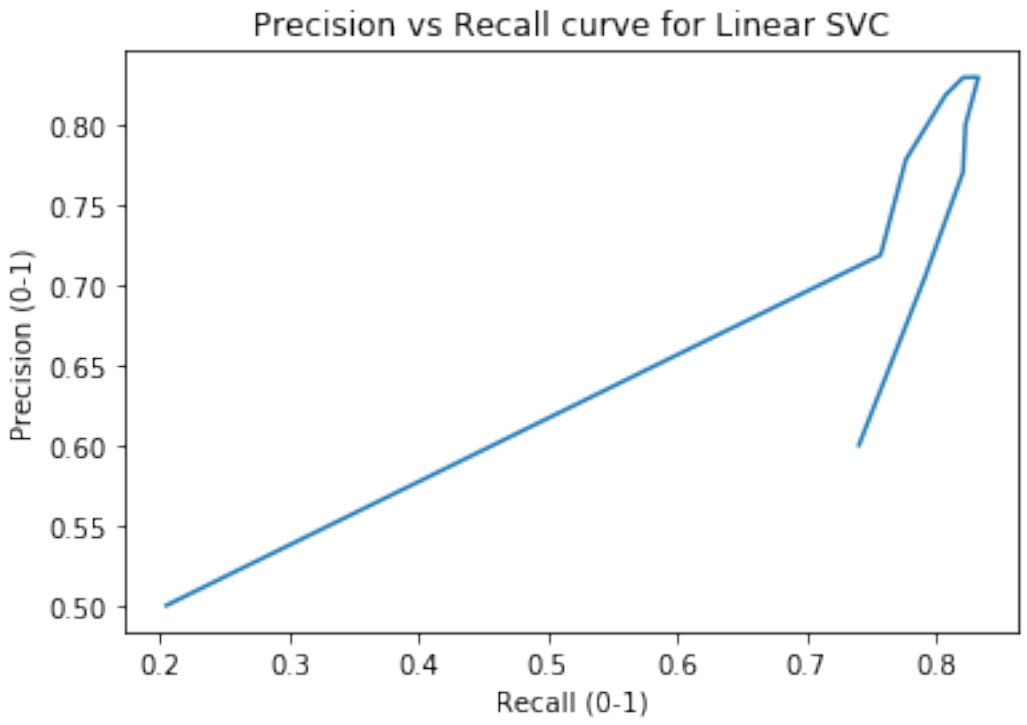


We see a similar plot as in-sample, though the maxima seems to have shifted to a lower threshold.

The precision and recall tend to follow very similar trends. Would be interesting to see the precision vs recall curve.

```
In [63]: plt.plot(p_list,r_list)
         plt.title('Precision vs Recall curve for Linear SVC')
         plt.xlabel('Recall (0-1)')
         plt.ylabel('Precision (0-1)')
```

```
Out[63]: Text(0, 0.5, 'Precision (0-1)')
```



As before, many-one, non-bijective curve. Both metrics peak at around the same time, with two marked differences from the corresponding in-sample plot. - The maximum observed for out-sample is of lower value than in-sample.

- While they do peak around the same time, the spread is more (i.e both don't peak at exactly the same time as was the case with in-sample, rather the peak shows a greater spread as seen above).

This concludes the out-of-sample performance evaluation. Now we will use a test dataset that isn't in-sample and see the difference in results.

0.8.3 Effects of Statistical Significance on Predictive Power

The following section investigates the effect of statistical significance of a variable on its prediction power. On second thought, 'Effect' might not be the appropriate term here, since that implies causation. Let us investigate the correlation of statistical significance of features with their predictive powers.

This is achieved by implementing a 'backward elimination' function, that assumes all features are significant and the eliminates those that are found to have p-values higher than 5% Level of significance.

An issue encountered was the painfully slow runtime, so we take a short-cut here. Let us select 500 features at random (of the 2303 total features). Empricial evidence during the course of this project suggests that we get back less than 10% of the features we created on this dataset.

We apply the backward elimination function to obtained a reduced feature set. The the model constructed on the 500 features, and another one constructed on the stat-significant feature subset obtained are evaluated.

```
In [0]: import statsmodels.formula.api as sm
        def backwardElimination(x, Y, sl,columns):
            numVars = len(x[0])
            for i in range(0, numVars):
                regressor_OLS = sm.OLS(Y, x).fit()
                maxVar = max(regressor_OLS.pvalues)
                if maxVar > sl:
                    for j in range(0, numVars - i):
                        if (regressor_OLS.pvalues[j].astype(float) == maxVar):
                            x = np.delete(x, j, 1)
                            columns = np.delete(columns, j)

            regressor_OLS.summary()
            return x,columns
        SL = 0.05
```

```
In [0]: from random import sample

        # Prints list of random items of given length
        tot_features = list(range(2033))
        subset = sample(tot_features,500)
        dm,col = backwardElimination(x_train[:,subset], y_train, SL,np.arange(500))
```

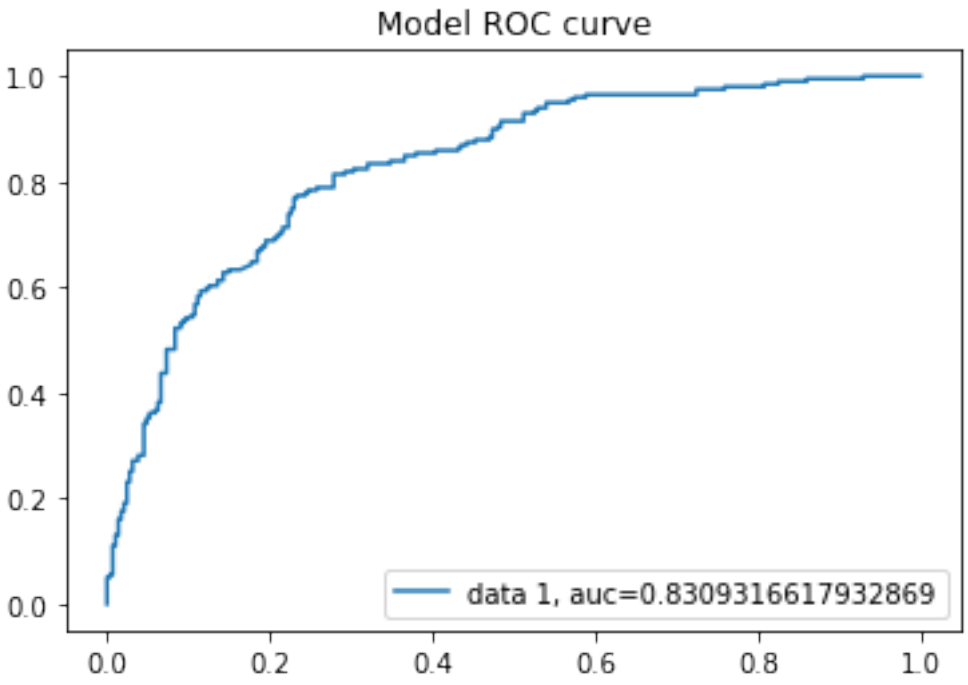
```
In [66]: print('The number of statistically significant features from the 500 : ',len(col))

The number of statistically significant features from the 500 :  81
```

```
In [0]: model = SVC(kernel='linear',class_weight='balanced',C=0.01,probability=True).fit(x_tra

        y_preds = model.predict(x_test)
        report = classification_report( y_test, y_preds )
```

```
In [68]: print(report)

              precision    recall  f1-score   support

           0       0.87      0.84      0.85       287
           1       0.78      0.82      0.80       199

   micro avg       0.83      0.83      0.83       486
   macro avg       0.82      0.83      0.83       486
weighted avg       0.83      0.83      0.83       486
```

```
In [69]: from sklearn.pipeline import Pipeline
         from sklearn.model_selection import cross_val_predict
         import matplotlib.pyplot as plt
```

```
clf = Pipeline(steps=[('classifier', SVC(class_weight='balanced',C=0.01, kernel='linea
clf.fit(x_train,y_train)

proba = cross_val_predict(clf, x_test,y_test, cv=5, method='predict_proba')
from sklearn import metrics

fpr, tpr, _ = metrics.roc_curve(y_test,  proba[::,1])
auc = metrics.roc_auc_score(y_test, proba[::,1])
plt.plot(fpr,tpr,label="data 1, auc="+str(auc))
plt.legend(loc=4)
plt.title('Model ROC curve')
plt.show()
```



The above analysis has been performed for the data with 500 randomly selected features.

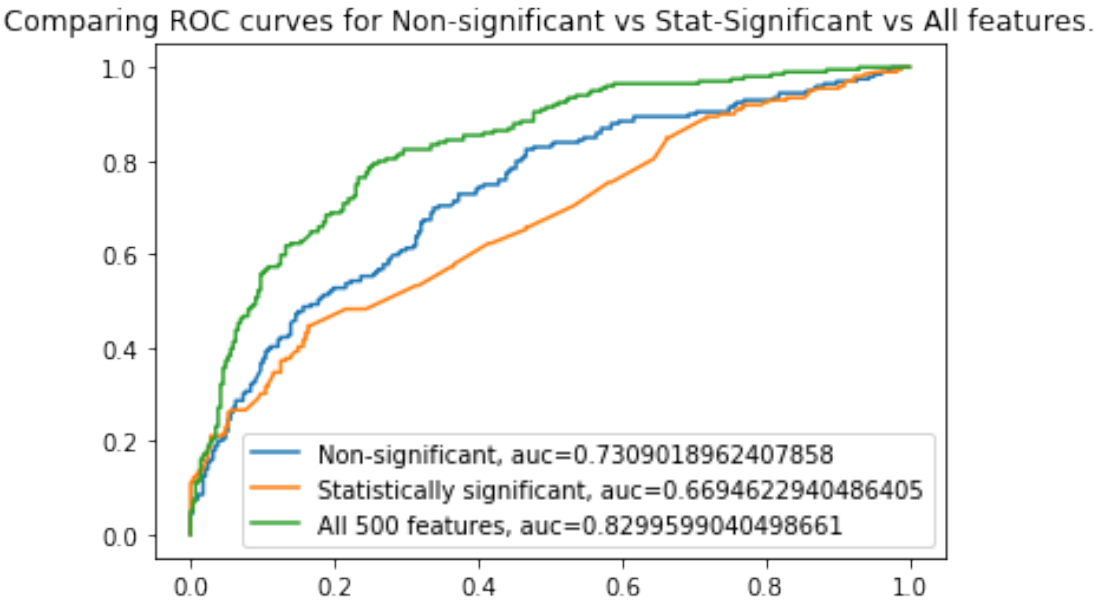
We can see that it gives us a reasonable 0.84 AUC value and the precision,recall and f1 are 0.82.

It would now be interesting to compare this to the results for a model that takes just the statistically significant features from these 500. We saw that 68 features qualified with p-values less than the 5% level of significance.

```
In [0]: model = SVC(kernel='linear',class_weight='balanced',C=0.01,probability=True).fit(x_tra

        y_preds = model.predict(x_test[:,col])
        report = classification_report( y_test, y_preds )

In [71]: print(report)
```

```
              precision    recall  f1-score   support

           0       0.67      0.87      0.76       287
           1       0.67      0.39      0.50       199

   micro avg       0.67      0.67      0.67       486
   macro avg       0.67      0.63      0.63       486
weighted avg       0.67      0.67      0.65       486
```

In [72]:
```
from sklearn.pipeline import Pipeline
from sklearn.model_selection import cross_val_predict
import matplotlib.pyplot as plt

clf1 = Pipeline(steps=[('classifier', SVC(class_weight='balanced',C=0.01, kernel='line
clf1.fit(x_train[:,~col],y_train)

clf2 = Pipeline(steps=[('classifier', SVC(class_weight='balanced',C=0.01, kernel='line
clf2.fit(x_train[:,col],y_train)

clf3 = Pipeline(steps=[('classifier', SVC(class_weight='balanced',C=0.01, kernel='line
clf3.fit(x_train,y_train)



proba = cross_val_predict(clf1, x_test[:,~col],y_test, cv=5, method='predict_proba')
probb = cross_val_predict(clf2, x_test[:,col],y_test, cv=5, method='predict_proba')
probc = cross_val_predict(clf3, x_test,y_test, cv=5, method='predict_proba')

from sklearn import metrics

fpra, tpra, _ = metrics.roc_curve(y_test,  proba[::,1])
auca = metrics.roc_auc_score(y_test, proba[::,1])

fprb, tprb, _ = metrics.roc_curve(y_test,  probb[::,1])
aucb = metrics.roc_auc_score(y_test, probb[::,1])

fprc, tprc, _ = metrics.roc_curve(y_test,  probc[::,1])
aucc = metrics.roc_auc_score(y_test, probc[::,1])

plt.plot(fpra,tpra,label="Non-significant, auc="+str(auca))
plt.plot(fprb,tprb,label="Statistically significant, auc="+str(aucb))
plt.plot(fprc,tprc,label="All 500 features, auc="+str(aucc))

plt.legend(loc=4)
plt.title('Comparing ROC curves for Non-significant vs Stat-Significant vs All feature
plt.show()
```



This is an interesting result, the performance for just the statistically significant features (68 in number) is 0.62, which is better than the 0.45 AUC result for the non-significant features (432 in number). Infact random guessing would give better results than the model trained on just the non-significant features.

The result taking all 500 features is the best performer by a margin. Model using the significant features alone is clearly overfitting.