single_class_Base_paper_replication

May 13, 2019

```
In [1]: import pandas as pd

In [2]: import numpy as np

In [3]: !pip install vaderSentiment

Requirement already satisfied: vaderSentiment in /Users/ankitpeshin/anaconda2/envs/aml/lib/pytl

In [80]: 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

In [81]: df_train = pd.read_csv("../data/labeled_data.csv")[["tweet","class"]]

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

In [82]: df_train.head()

Out[82]:                                                   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
```

```
In [83]: 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[83]: 2430
```

```
In [84]: len(y_train)
```

```
Out[84]: 2430
```

0.1 Baseline model

```
In [20]: 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


/Users/ankitpeshin/anaconda2/envs/aml/lib/python3.6/site-packages/sklearn/linear_model/sag.py:3
  "the coef_ did not converge", ConvergenceWarning)
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  "the coef_ did not converge", ConvergenceWarning)


0.8548793706293706


/Users/ankitpeshin/anaconda2/envs/aml/lib/python3.6/site-packages/sklearn/linear_model/sag.py:3
  "the coef_ did not converge", ConvergenceWarning)
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  "the coef_ did not converge", ConvergenceWarning)
```

0.2 Re-implementing 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 indicators for :hashtags, mentions, retweets, urls
10. number of characters
11. numbers of words
12. number of syllables

```
In [21]: nltk.download("stopwords")
         from nltk.stem.porter import *
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     /Users/ankitpeshin/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
```

```
In [22]: 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 [23]: def join_sent(l):
             return " ".join(l)

In [24]: df_train=pd.DataFrame(X_train)

In [25]: df_train.columns=["tweet"]

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...

In [27]: s_train=df_train['tweet'].apply(preprocess)

/Users/ankitpeshin/anaconda2/envs/aml/lib/python3.6/re.py:212: FutureWarning: split() requires
  return _compile(pattern, flags).split(string, maxsplit)


In [28]: s_tr=s_train.apply(join_sent)

In [29]: nltk.download('averaged_perceptron_tagger')
         t_tr=s_train.apply(pos_tag_seq)

[nltk_data] Downloading package averaged_perceptron_tagger to
[nltk_data]     /Users/ankitpeshin/nltk_data...
[nltk_data]   Package averaged_perceptron_tagger is already up-to-
[nltk_data]       date!
```

In [30]:
```
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 [31]:
```
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 [32]:
```
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 [33]:
```
pos_tr = pos_vectorizer.fit_transform(t_tr).toarray()

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

In [34]:
```
from vaderSentiment.vaderSentiment import SentimentIntensityAnalyzer as VS
sentiment_analyzer = VS()
```

In [35]:
```
def get_sentiment(text):
  sentiment = sentiment_analyzer.polarity_scores(text)
  return sentiment

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

In [36]:
```
df_train["sent"]=df_train["tweet"].apply(get_sentiment)
```

```
In [37]: df_train.head()

Out[37]:                                                  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 [38]: foo_tr = lambda x: pd.Series([x["pos"],x["neg"],x["neu"]])
         rev_tr = df_train['sent'].apply(foo_tr)

In [39]: rev_tr.columns=["pos","neg","neu"]

In [40]: rev_tr.head()

Out[40]:       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
```

0.3 Binary count for URL https mentions etc

```
In [41]: def return_cont(parsed_text):
           return(parsed_text.count('urlher'),parsed_text.count('mentionher'),parsed_text.coun

In [42]: df_train["counts"]=s_tr.apply(return_cont)

In [43]: df_train["counts"].head()

Out[43]: 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 [44]: foo = lambda x: pd.Series([x[0],x[1],x[2]])
         mention_counts_tr = df_train['counts'].apply(foo)

In [45]: mention_counts_tr.head()
```

```
Out[45]:      0  1  2
         85   0  3  0
         89   0  2  0
         110  1  2  1
         184  1  1  0
         202  1  1  0
```

0.4 FKRA and Flesch and number of syllables etc

```
In [46]: !pip install textstat
         from textstat.textstat import *
```

```
Requirement already satisfied: textstat in /Users/ankitpeshin/anaconda2/envs/aml/lib/python3.6/
Requirement already satisfied: pyphen in /Users/ankitpeshin/anaconda2/envs/aml/lib/python3.6/si
Requirement already satisfied: repoze.lru in /Users/ankitpeshin/anaconda2/envs/aml/lib/python3
```

```
In [47]: 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 [48]: other_feats_tr=df_train["tweet"].apply(get_other_features)
```

```
In [49]: other_feats_tr.head()
```

```
Out[49]: 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 [50]: other_features_names = ["FKRA", "FRE","num_syllables", "avg_syl_per_word", "num_chars"
```

```
In [51]: foo = lambda x: pd.Series(elem for elem in x)
         of_counts_tr = other_feats_tr.apply(foo)
```

```
In [52]: of_counts_tr.head()
```

```
Out[52]:        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 [53]: of_counts_tr.columns=other_features_names
```

```
In [54]: of_counts_tr.head()
```

```
Out[54]:      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 [55]: df_train.drop([ "sent","counts"], axis=1)
```

```
Out[55]:                                                    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 &#128166; 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: &#128514;&#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  &#128543; &#8220;@DubPeeWorld: So the new wave...
1028                                    &#128553; cunt
1029                              &#128553; monkey mad
1030  &#128553;&#128514; RT @willieBEAMINN: @_VinChi...
1031  &#128553;&#128553;&#128514; damn roaches got d...
1032  &#128553;&#128553;&#128514;&#128557;&#128557; ...
1033  &#128553;&#128557; RT @Freegeezy17: My Co work...
1034  &#128553;&#128557; 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 [56]:
```python
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 [85]:
```python
# x_train=np.column_stack([tfidf,pos,rev,mention_counts, other_feats])
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 [86]:
```python
print(len(x_train))
```

```
1944
```

In [87]:
```python
print(len(y_train))
```

```
1944
```

In [60]:
```python
param_grid = {"logisticregression__C": [100,10,1,0.1,0.01],}
grid = GridSearchCV(make_pipeline(LogisticRegression(solver="sag"),memory="cache_folde
```

In [61]:
```python
grid.fit(x_train, y_train)
```

```
/Users/ankitpeshin/anaconda2/envs/aml/lib/python3.6/site-packages/sklearn/linear_model/sag.py:3
  "the coef_ did not converge", ConvergenceWarning)
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/Users/ankitpeshin/anaconda2/envs/aml/lib/python3.6/site-packages/sklearn/linear_model/sag.py:3
  "the coef_ did not converge", ConvergenceWarning)
/Users/ankitpeshin/anaconda2/envs/aml/lib/python3.6/site-packages/sklearn/linear_model/sag.py:3
  "the coef_ did not converge", ConvergenceWarning)
/Users/ankitpeshin/anaconda2/envs/aml/lib/python3.6/site-packages/sklearn/linear_model/sag.py:3
  "the coef_ did not converge", ConvergenceWarning)
/Users/ankitpeshin/anaconda2/envs/aml/lib/python3.6/site-packages/sklearn/linear_model/sag.py:3
  "the coef_ did not converge", ConvergenceWarning)
/Users/ankitpeshin/anaconda2/envs/aml/lib/python3.6/site-packages/sklearn/linear_model/sag.py:3
  "the coef_ did not converge", ConvergenceWarning)
/Users/ankitpeshin/anaconda2/envs/aml/lib/python3.6/site-packages/sklearn/linear_model/sag.py:3
  "the coef_ did not converge", ConvergenceWarning)
/Users/ankitpeshin/anaconda2/envs/aml/lib/python3.6/site-packages/sklearn/linear_model/sag.py:3
  "the coef_ did not converge", ConvergenceWarning)
/Users/ankitpeshin/anaconda2/envs/aml/lib/python3.6/site-packages/sklearn/linear_model/sag.py:3
  "the coef_ did not converge", ConvergenceWarning)
/Users/ankitpeshin/anaconda2/envs/aml/lib/python3.6/site-packages/sklearn/linear_model/sag.py:3
  "the coef_ did not converge", ConvergenceWarning)
/Users/ankitpeshin/anaconda2/envs/aml/lib/python3.6/site-packages/sklearn/linear_model/sag.py:3
  "the coef_ did not converge", ConvergenceWarning)
/Users/ankitpeshin/anaconda2/envs/aml/lib/python3.6/site-packages/sklearn/linear_model/sag.py:3
  "the coef_ did not converge", ConvergenceWarning)
```

```
Out[61]: GridSearchCV(cv=5, error_score='raise-deprecating',
                estimator=Pipeline(memory='cache_folder',
              steps=[('logisticregression', LogisticRegression(C=1.0, class_weight=None, dual=F
```

```
                   intercept_scaling=1, max_iter=100, multi_class='warn',
                   n_jobs=None, penalty='l2', random_state=None, solver='sag',
                   tol=0.0001, verbose=0, warm_start=False))]),
                fit_params=None, iid='warn', n_jobs=None,
                param_grid={'logisticregression__C': [100, 10, 1, 0.1, 0.01]},
                pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
                scoring='roc_auc', verbose=0)
```

In [62]: grid.best_score_

Out[62]: 0.8872078043089882

In [63]: grid.cv_results_

```
/Users/ankitpeshin/anaconda2/envs/aml/lib/python3.6/site-packages/sklearn/utils/deprecation.py
  warnings.warn(*warn_args, **warn_kwargs)
/Users/ankitpeshin/anaconda2/envs/aml/lib/python3.6/site-packages/sklearn/utils/deprecation.py
  warnings.warn(*warn_args, **warn_kwargs)
/Users/ankitpeshin/anaconda2/envs/aml/lib/python3.6/site-packages/sklearn/utils/deprecation.py
  warnings.warn(*warn_args, **warn_kwargs)
/Users/ankitpeshin/anaconda2/envs/aml/lib/python3.6/site-packages/sklearn/utils/deprecation.py
  warnings.warn(*warn_args, **warn_kwargs)
/Users/ankitpeshin/anaconda2/envs/aml/lib/python3.6/site-packages/sklearn/utils/deprecation.py
  warnings.warn(*warn_args, **warn_kwargs)
/Users/ankitpeshin/anaconda2/envs/aml/lib/python3.6/site-packages/sklearn/utils/deprecation.py
  warnings.warn(*warn_args, **warn_kwargs)
/Users/ankitpeshin/anaconda2/envs/aml/lib/python3.6/site-packages/sklearn/utils/deprecation.py
  warnings.warn(*warn_args, **warn_kwargs)
```

```
Out[63]: {'mean_fit_time': array([3.09123259, 2.62944183, 2.77978692, 2.51133776, 2.80759144])
          'std_fit_time': array([0.52430068, 0.15701865, 0.72007294, 0.23866098, 0.14979511]),
          'mean_score_time': array([0.00305047, 0.00243516, 0.00221386, 0.00235043, 0.00231457
          'std_score_time': array([0.00134944, 0.00027968, 0.00018668, 0.0001367 , 0.00030969]
          'param_logisticregression__C': masked_array(data=[100, 10, 1, 0.1, 0.01],
                       mask=[False, False, False, False, False],
                 fill_value='?',
                      dtype=object),
          'params': [{'logisticregression__C': 100},
           {'logisticregression__C': 10},
           {'logisticregression__C': 1},
           {'logisticregression__C': 0.1},
           {'logisticregression__C': 0.01}],
          'split0_test_score': array([0.87919628, 0.87900569, 0.87892401, 0.87889678, 0.878678
          'split1_test_score': array([0.91019962, 0.91017227, 0.91011758, 0.91006289, 0.906371
          'split2_test_score': array([0.87703035, 0.87722177, 0.8773038 , 0.87713973, 0.875690
          'split3_test_score': array([0.88428729, 0.88450743, 0.88478261, 0.88425977, 0.883214
          'split4_test_score': array([0.88478261, 0.88503027, 0.8849202 , 0.88464502, 0.882113
          'mean_test_score': array([0.8870978 , 0.88718577, 0.8872078 , 0.88699929, 0.88521291
```

```
'std_test_score': array([0.01192672, 0.01189032, 0.01185911, 0.01190242, 0.010909  ]
'rank_test_score': array([3, 2, 1, 4, 5], dtype=int32),
'split0_train_score': array([0.95577596, 0.9557931 , 0.95576567, 0.95541078, 0.95160
'split1_train_score': array([0.94880924, 0.94886405, 0.94883151, 0.94828177, 0.94395
'split2_train_score': array([0.95730022, 0.95732591, 0.95730364, 0.95679158, 0.95268
'split3_train_score': array([0.95311498, 0.95292347, 0.9530483 , 0.95267212, 0.94861
'split4_train_score': array([0.96164559, 0.96170544, 0.9615943 , 0.96132926, 0.95625
'mean_train_score': array([0.9553292 , 0.95532239, 0.95530868, 0.9548971 , 0.9506231
'std_train_score': array([0.00427537, 0.00429986, 0.00426054, 0.00433449, 0.00413288
```

```
In [64]: grid.best_params_
```

```
Out[64]: {'logisticregression__C': 1}
```

0.5 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.

```
In [65]: 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
```

0.5.1 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 [106]: select = SelectFromModel(LogisticRegression(class_weight='balanced',penalty="l1",C=1
          X_ = select.fit_transform(x_train,y_train)
          model = SVC(class_weight='balanced',C=0.01, kernel='linear',probability=True).fit(X_
```

```
/Users/ankitpeshin/anaconda2/envs/aml/lib/python3.6/site-packages/sklearn/linear_model/logisti
  FutureWarning)
```

```
In [107]: y_preds = model.predict(X_)
```

```
In [108]: report = classification_report( y_preds, y_train )
```

```
In [109]: print(report)
```

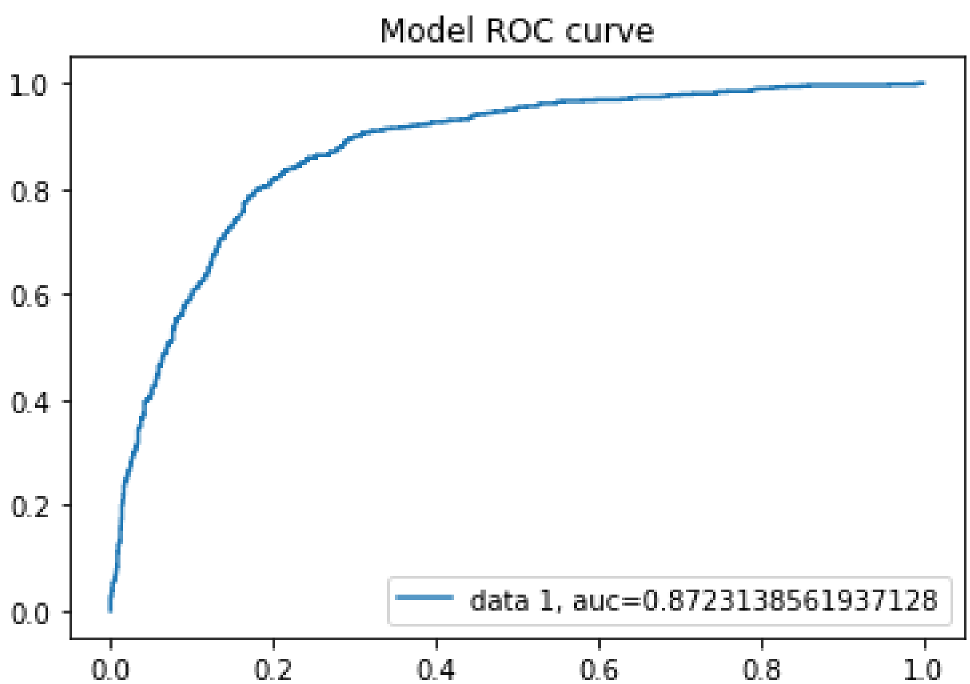
```
              precision    recall  f1-score   support

           0       0.91      0.97      0.94      1074
```

```
           1       0.96      0.88      0.92       870

   micro avg       0.93      0.93      0.93      1944
   macro avg       0.93      0.92      0.93      1944
weighted avg       0.93      0.93      0.93      1944
```

We achieve a pretty decent precision of 0.93 (weighted average). The model was trained on balanced classes so there isn't much variation in the class 0 and class 1 values.

Similarly a recall of 0.93 and an f1-score of 0.93 was obtained when weighted by class. We will now plot the ROC curve and calculate the AUC.

```
In [92]: 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_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()
```



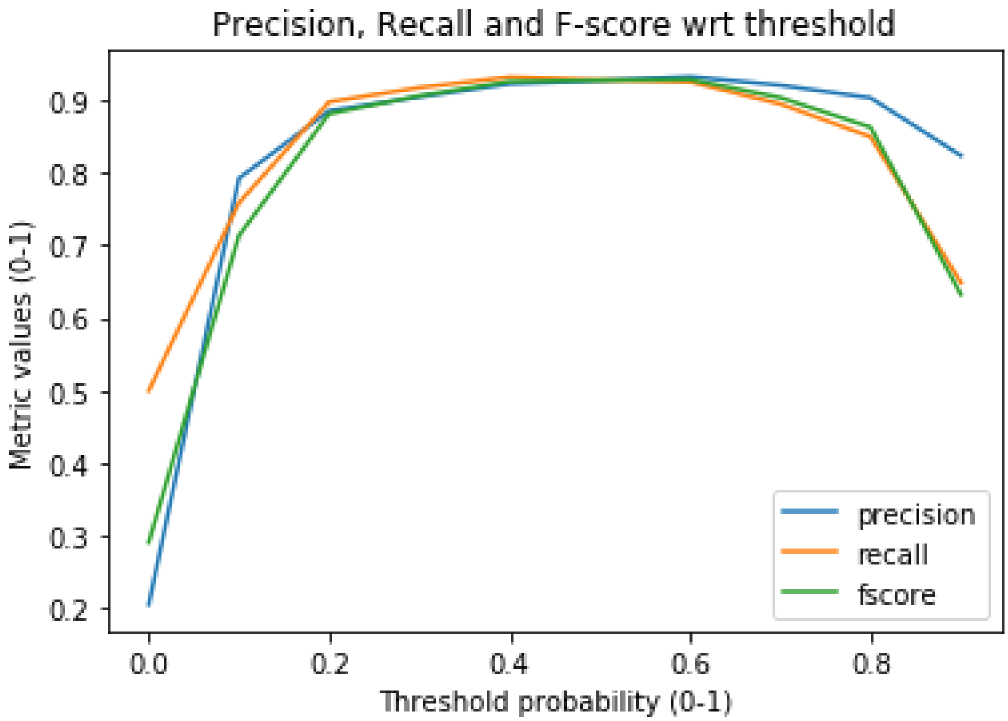
The ROC curve shows promising results, and an AUC of 0.87 was obtained. To give context, a model that randomly guessed the class (50-50 chance) would give a straight line ROC curve with an AUC of 0.5. The model performs significantly better.

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

```
In [115]: 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_)[:,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()
```

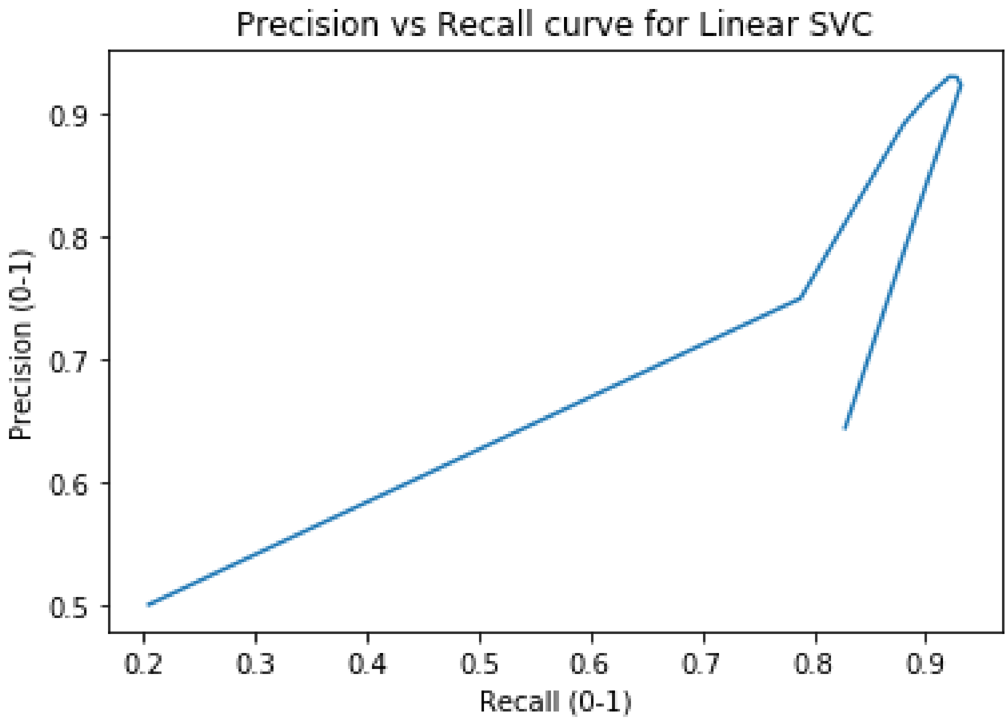
```
/Users/ankitpeshin/anaconda2/envs/aml/lib/python3.6/site-packages/sklearn/metrics/classificatio
  'precision', 'predicted', average, warn_for)
```

```
Out[115]: <matplotlib.legend.Legend at 0x128850588>
```



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 [94]: 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[94]: 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.

0.5.2 Out-of-sample Predictive Performance

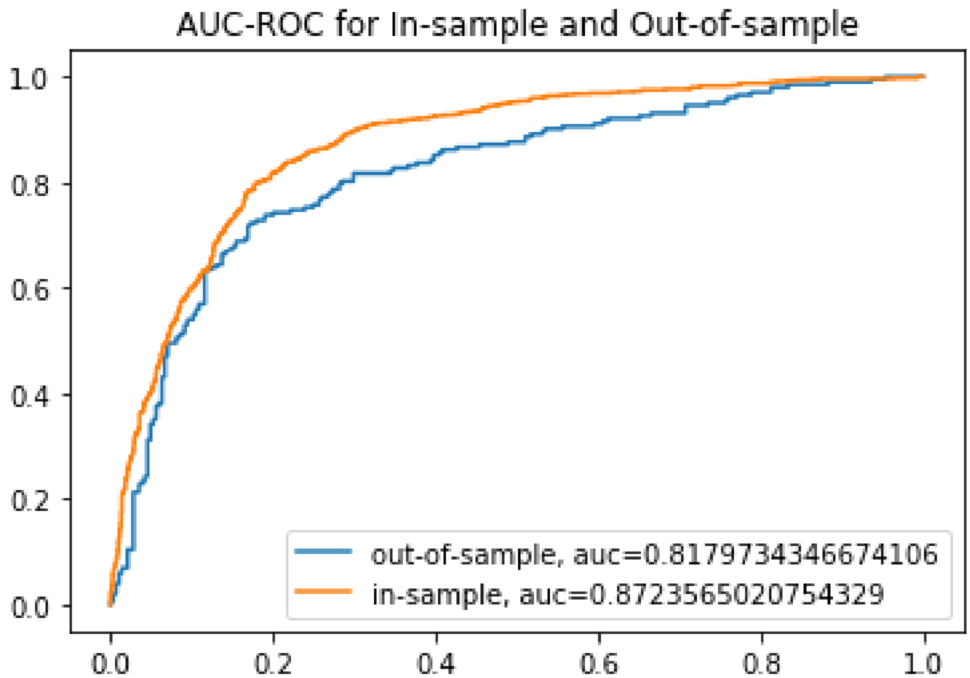
Here we use new unseen data to test our model. We expect a decline in performance, but this will also give us a peak into how generalizable the proposed Linear SVC model is.

```
In [116]: model = SVC(kernel='linear',class_weight='balanced',C=0.01,probability=True).fit(x_t

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

In [117]: print(report)

              precision    recall  f1-score   support

           0       0.85      0.84      0.85       284
           1       0.78      0.79      0.79       202

   micro avg       0.82      0.82      0.82       486
   macro avg       0.82      0.82      0.82       486
weighted avg       0.82      0.82      0.82       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 [102]: 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='line
          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()
```

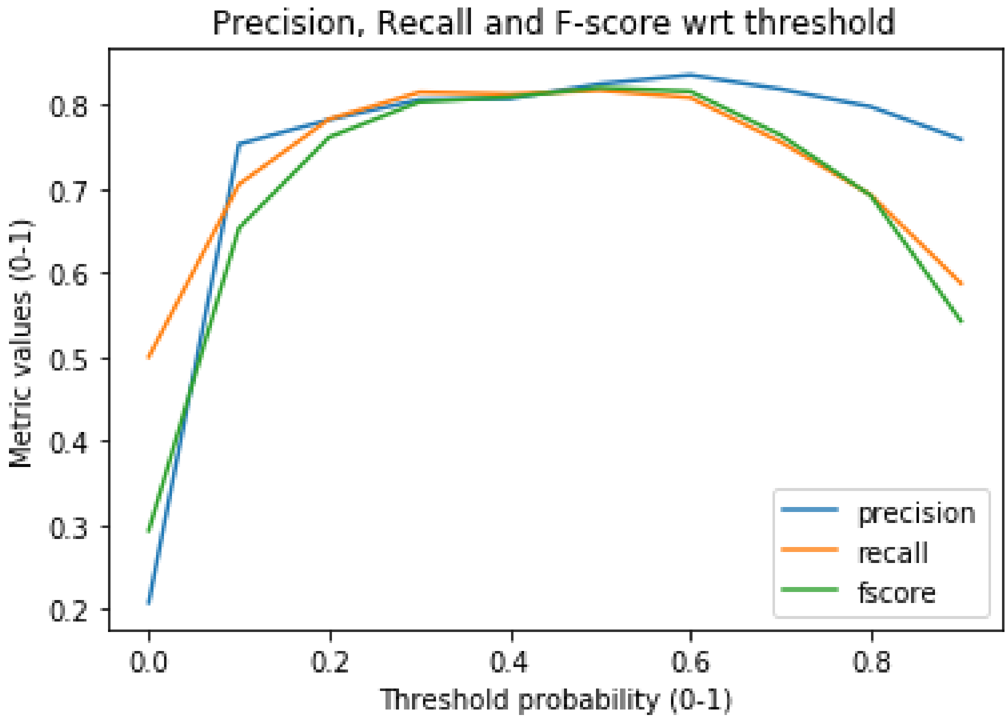


The AUC falls from 0.87 for in-sample to 0.82 for out-of-sample. The difference is clear from the ROC curves.

```
In [118]: 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()
```

```
/Users/ankitpeshin/anaconda2/envs/aml/lib/python3.6/site-packages/sklearn/metrics/classificati
  'precision', 'predicted', average, warn_for)
```

Out[118]: <matplotlib.legend.Legend at 0x12897cef0>

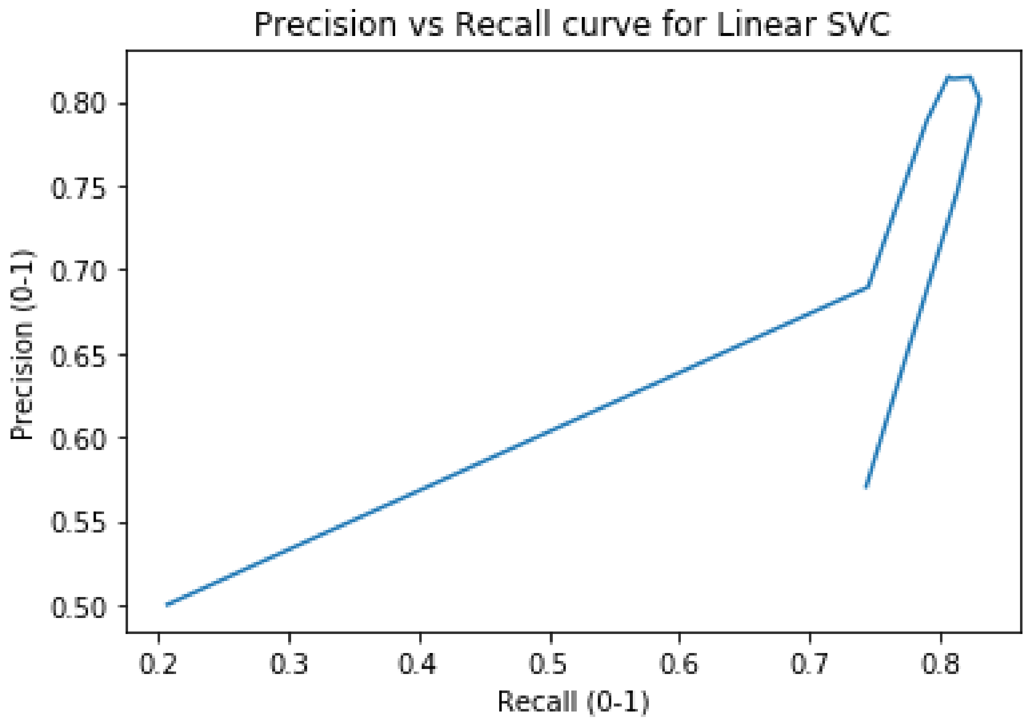


We see a similar plot as in-sample, though the maxima seems to have shifted to a lower threshold.

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

In [104]:
```
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[104]: 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.

0.5.3 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 [119]:
```
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 [120]:
```
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 [123]:
```
print('The number of statistically significant features from the 500 : ',len(col))
```

```
The number of statistically significant features from the 500 :  68
```

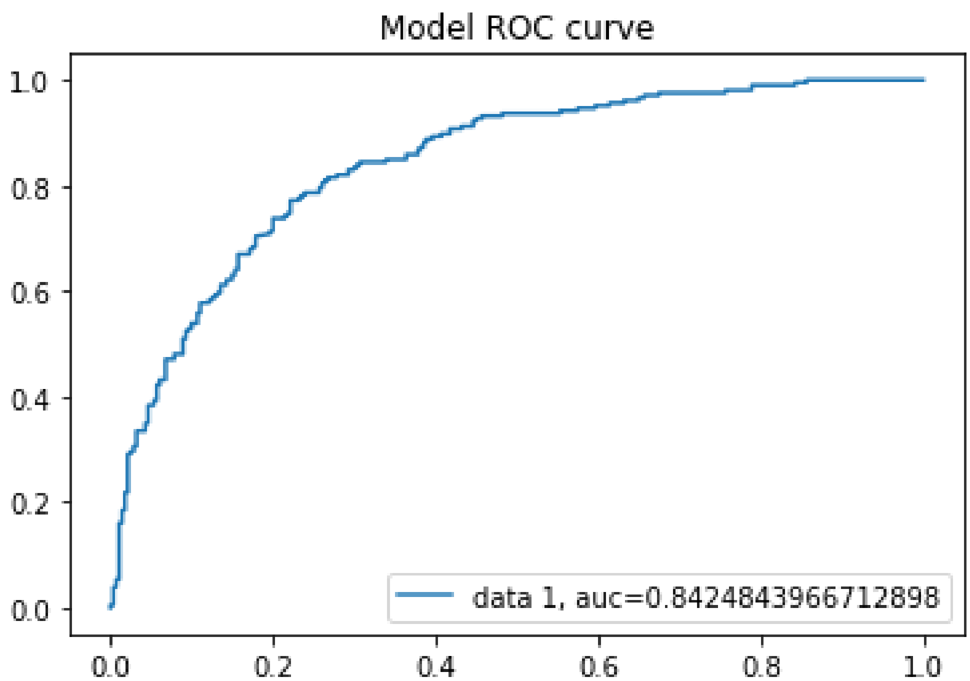
In [692]:
```
model = SVC(kernel='linear',class_weight='balanced',C=0.01,probability=True).fit(x_t

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

In [693]:
```
print(report)
```

```
              precision    recall  f1-score   support

           0       0.86      0.81      0.84       280
           1       0.76      0.83      0.79       206

   micro avg       0.82      0.82      0.82       486
   macro avg       0.81      0.82      0.81       486
weighted avg       0.82      0.82      0.82       486
```

In [696]:
```
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='line
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.

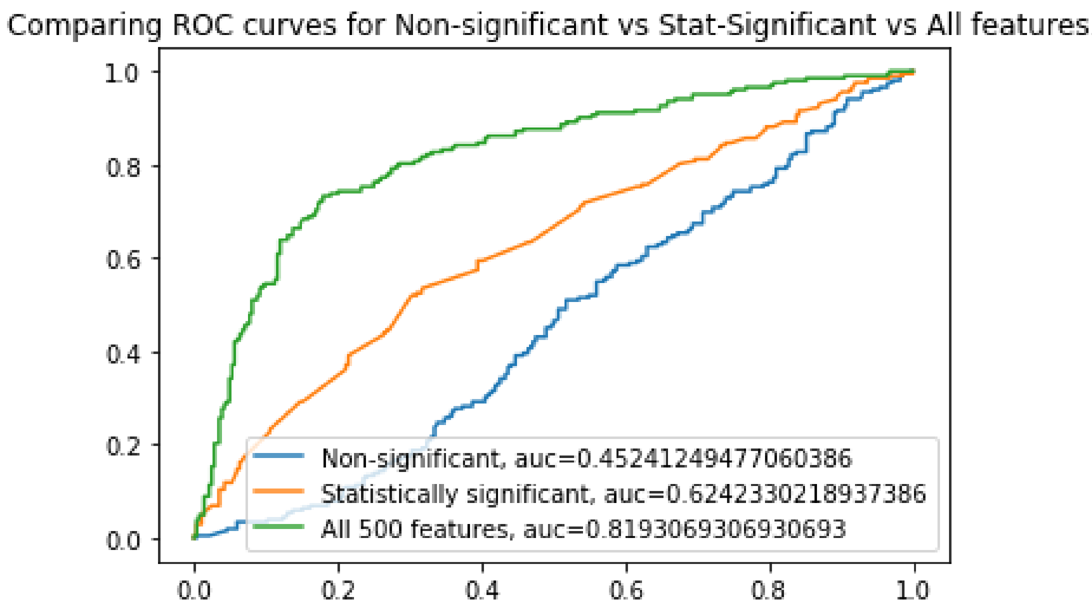
We can see that it gives us a reasonable 0.84 AUC value and the precision,recall and f1 are 0.82.

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 [124]: model = SVC(kernel='linear',class_weight='balanced',C=0.01,probability=True).fit(x_t

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

In [125]: print(report)
```

```
              precision    recall  f1-score   support

           0       0.69      0.68      0.68       284
           1       0.56      0.58      0.57       202

   micro avg       0.64      0.64      0.64       486
   macro avg       0.63      0.63      0.63       486
weighted avg       0.64      0.64      0.64       486
```

```
In [131]: 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='li
          clf1.fit(x_train[:,~col],y_train)

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

          clf3 = Pipeline(steps=[('classifier', SVC(class_weight='balanced',C=0.01, kernel='li
          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 featu
          plt.show()
```



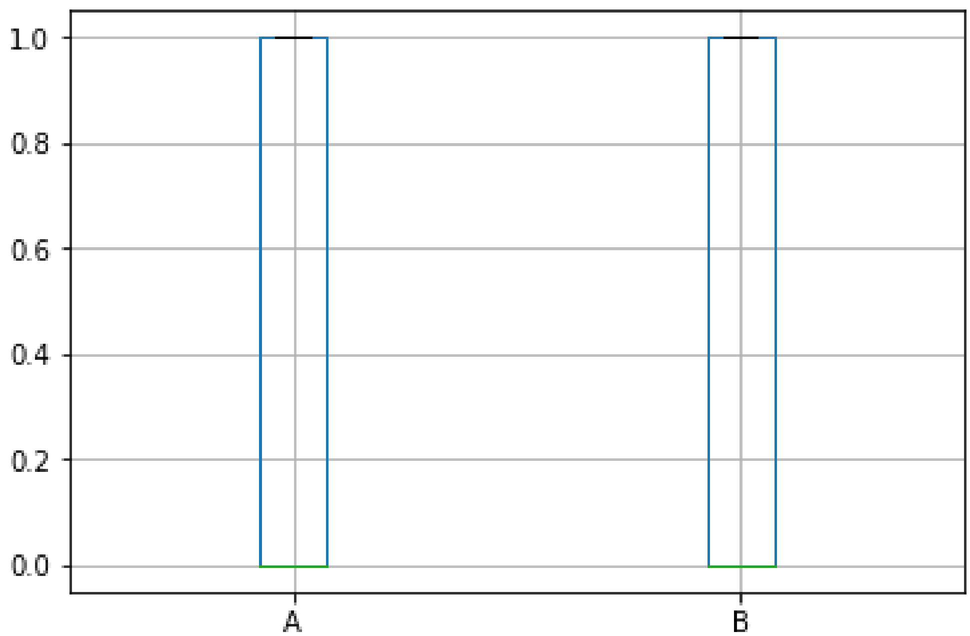
This is an interesting result, the performance for just the statistically significant features (68 in number) is 0.62, which is better than the 0.45 AUC result for the non-significant features (432 in number). Infact random guessing would give better results than the model trained on just the non-significant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

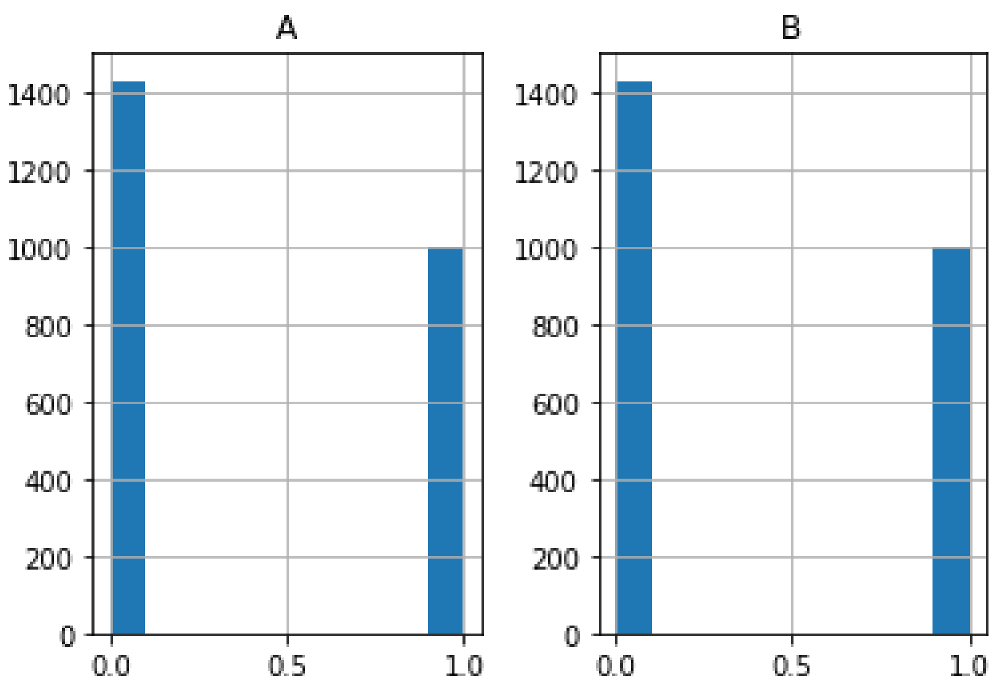
The result taking all 500 features is the best performer by a margin. Model using the significant features alone is clearly overfitting.

```
In [152]: from pandas import read_csv
          from matplotlib import pyplot
          import pandas as pd
          # load results file
          results = pd.DataFrame()
          results['A'] = y
          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  2430.000000  2430.000000
mean      0.411523     0.411934
std       0.492211     0.492285
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 [155]:
```
from scipy.stats import ttest_ind
value, pvalue = ttest_ind(y, y_preds, equal_var=True)
print(value, pvalue)
if pvalue > 0.05:
        print('Samples are likely drawn from the same distributions (fail to reject H
else:
        print('Samples are likely drawn from different distributions (reject H0)')
```

```
-0.029140578637050166 0.9767536694548906
Samples are likely drawn from the same distributions (fail to reject H0)
```