Data Analytics and Machine Learning - Lars Lochstoer

Problem Set 6

1. Run the codes from the lecture to preprocess the data and create the text files corresponding to each date in the news headline data. That is, remove numbers, make all lower case, remove stopwords, stemming, etc. Use PlaintextCorpusReader to load the corpus. Now, each document corresponds to a different date in the dataset.

In [1]:
```
# Ignore warnings
import warnings
warnings.filterwarnings("ignore")

# Import packages
import os
import re
import nltk
import pandas            as pd
import numpy             as np
import matplotlib.pyplot as plt
import statsmodels.api   as sm
import seaborn           as sns
import sklearn.metrics   as metrics
import pysentiment2      as ps
import scikitplot        as skplt



from sklearn.metrics  import mean_squared_error as mse
from collections      import Counter
from nltk.stem        import WordNetLemmatizer
from nltk             import ngrams
from wordcloud        import WordCloud
from nltk.tokenize    import word_tokenize
from nltk.stem.porter import PorterStemmer
from nltk.corpus      import stopwords, PlaintextCorpusReader
from sklearn.linear_model     import LogisticRegressionCV,LogisticRegression
from sklearn import preprocessing





#nltk.download('punkt')
#nltk.download('stopwords')
### Set correct path to data directory
os.chdir("")
```

In [2]:
```
data = pd.read_csv('business_insider_text_data2.csv')

# Merge all headlines from the same dates.
data = data.groupby('Date')['Headline'].apply(lambda x: "%s" % ', '.join(x))
data = pd.DataFrame(data)
```

```python
vix_data = pd.read_csv('vix_data.csv')
vix_data.index=vix_data.Date
vix_data = vix_data[['label']]

### Preprocess the headlines using create_df function from the code snippets
def create_df(dataset):
    stop_words = set(stopwords.words('english'))
    lm         = ps.LM()
#    dataset    = dataset.drop(columns=['Date', 'Label'])
    dataset.replace("[^a-zA-Z]", " ", regex=True, inplace=True)

    for col in dataset.columns:
        dataset[col] = dataset[col].str.lower()
        dataset[col] = dataset[col].str.replace('b ','')
    headlines  = []
    head_clean = []
    sentscore  = []
    porter = PorterStemmer()

    for row in range(len(dataset.index)):
        document = ' '.join(str(x) for x in dataset.iloc[row, 0:25])
        headlines.append(document)
        tokens  =  word_tokenize(document)
        stemmed = [porter.stem(word) for word in tokens]
        words   = [w for w in stemmed if not w in stop_words]
        head_clean.append(' '.join(word for word in words))
        tokens  = lm.tokenize(' '.join(word for word in words))
        sentscore.append(lm.get_score(tokens)['Polarity'])
    df               = pd.DataFrame(headlines, columns=['All'])
    df['processed'] = head_clean
    df['score']      = sentscore
    # data is the dataset after filling NaNs defined out of the function scope
#    df['label'] = data.Label
    df['date']  = data.index

    entire_processed_text = ' '.join(doc for doc in head_clean)
    return df[['date','All','processed','score']], entire_processed_text

df_full, entire_text = create_df(data)

# Set the directory to where you want to save the text files for the corpora
os.chdir("")

### Now that we have the pre-processed dataframe with the headlines,
###save each row as an individual text file.
for ind in range(len(df_full)):
    file_id = df_full.date[ind]
    with open('file_'+file_id+'.txt','w') as fout:
        fout.write(df_full.processed[ind])
        fout.close()

# Create a corpus using PlaintextCorpusReader
newcorpus = PlaintextCorpusReader('', '.*')
```

1. As in the lecture note, create a DocumentTermMatrix, call it dtm. Run the line “dtm.iloc[5:10, 201:210].” Notice that the matrix is quite sparse (a lot of zeros).

In [4]:
```python
# Create a document-term-matrix using dtm_from_corpus
def dtm_from_corpus(xCorpus):
```

```
    '''
    '''
    fd_list = []
    for x in range(0, len(xCorpus.fileids())):
        fd_list.append(nltk.FreqDist(xCorpus.words(xCorpus.fileids()[x])))
    dtm = pd.DataFrame(fd_list, index = xCorpus.fileids()[0:])
    dtm.fillna(0,inplace = True)
    return dtm

dtm       = dtm_from_corpus(newcorpus)
dtm.index = data.index

print(dtm.iloc[5:10, 801:810])
```

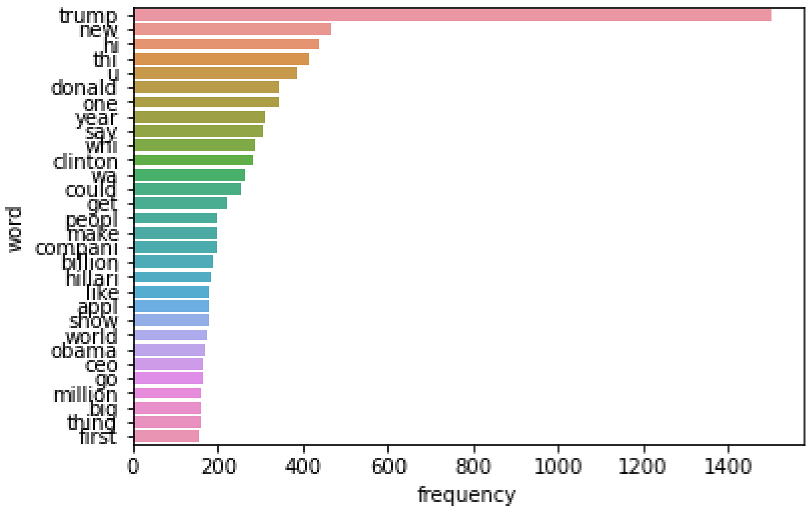
```
            cnn  jake  tapper  confront  secretari  hold  soldier  stealth  \
Date
2016-01-06  0.0   0.0     0.0       0.0        0.0   0.0      0.0      0.0
2016-01-07  0.0   0.0     0.0       0.0        0.0   0.0      0.0      0.0
2016-01-08  0.0   0.0     0.0       0.0        0.0   0.0      0.0      0.0
2016-01-09  0.0   0.0     0.0       0.0        0.0   0.0      0.0      0.0
2016-01-10  0.0   0.0     0.0       0.0        0.0   0.0      0.0      0.0

            beat
Date
2016-01-06   0.0
2016-01-07   0.0
2016-01-08   0.0
2016-01-09   0.0
2016-01-10   0.0
```

1. As in the lecture note, create a frequency matrix as the column sums of the DTM. Show in a bar plot the frequency of words that occur more than 25 times.

In [5]:

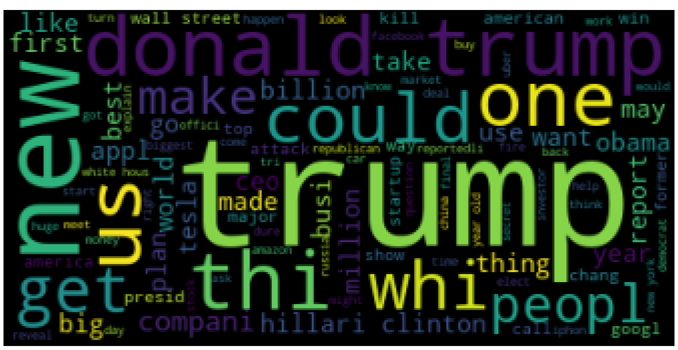
```
s_words = stopwords.words('english')
additional_stopwords = ['u','ha']
s_words.extend(additional_stopwords)
def word_frequency(sentence,stopwords):
    # joins all the sentenses
    # creates tokens, creates lower class, removes numbers and lemmatizes the words
    new_tokens = word_tokenize(sentence)
    new_tokens = [t.lower() for t in new_tokens]
    new_tokens = [t for t in new_tokens if t not in s_words]
    new_tokens = [t for t in new_tokens if t.isalpha()]
    lemmatizer = WordNetLemmatizer()
    new_tokens = [lemmatizer.lemmatize(t) for t in new_tokens]
    counted    = Counter(new_tokens)
    word_freq  = pd.DataFrame(counted.items(),columns=['word','frequency']).
                            sort_values(by='frequency',ascending=False)
    return word_freq

freq_doc = word_frequency(entire_text,s_words)
freq_doc = freq_doc[freq_doc.frequency >=150]
ax1 = plt.figure()
sns.barplot(x='frequency',y='word',data=freq_doc.head(100))
```

Out[5]: <AxesSubplot:xlabel='frequency', ylabel='word'>



1. Create a wordcloud of the 20 most frequent words. Based on this (and 3.), how would you characterize the typical headline in terms of the news subject? Are there words that, intuitively, can matter for the stock market returns that day?

In [6]:
```
wc = WordCloud(max_words=100,stopwords={'say','ha','wa','u','hi'}).
                                                     generate_from_text(entire_text)

plt.imshow(wc)
plt.axis('off')
plt.show()
```



We see words like `Trump`, `Clinton`, `ceo`, `wall street`. These headlines are very oriented around the 2016 U.S. election, and these words can matter a lot for the stock market.

1. Create the endogenous variable “y_data = df_full['label']” and the exogenous matrix “x_data = dtm.” You will try to construct an index based on the words in dtm that predicts the direction of stock returns.

In [7]:
```
x_data        = dtm[dtm.index.isin(vix_data.index)]
y_data        = vix_data[vix_data.index.isin(dtm.index)]
```

1. Split the data into a training dataset, based on data up to and including 2016-12-31. The remaining data should be used for actual out-of-sample testing.

In [8]:
```
split_index   = '2016-12-31'
x_train       = x_data.loc[:split_index,:]
```

```
x_test       = x_data.loc[split_index:,:]
y_train      = y_data.loc[:split_index]
y_test       = y_data.loc[split_index:]
```

1. We will first let the logistic regression create the word-based index. That is, try to fit a regular logistic regression using y_data and x_data and the training dataset. Explain why this doesn't work.

Consider how the logit coefficients are estimated:

$$\log\left(\frac{p}{1-p}\right) = \beta X + \varepsilon$$

Notice the dimensions of our matrices:

In [9]:
```
print(np.shape(x_data))
```

```
(347, 6929)
```

$X'X$ is not full rank and $\hat{\beta} = (X'X)^{-1} X'Y$ can therefore not be computed.

1. Next, run a logistic regression with an elastic net constraint (let l1_ratio= 0.5) using cross-validation and the training dataset. Why does the regression routine work now (i.e., why does it give an answer (a coefficient vector; no meltdown))?

The dataset is large and the cross-validation is computationally intensive. We use a two-fold cross-validation to find the penalizing parameter that gives the best out-of-sample fit of the model. Some of the penalizing parameters gives unstable results.

In [10]:
```
# Define alphas for iterative fitting of regularized model
alphas = np.logspace(-2, 0.5, 10)

# Grid search over MSE for the best lambda
dev_lambda  = np.empty((2,len(alphas)))
dev_lambda2 = np.empty((2,len(alphas)))

x_data_for_cv       = x_train
x_data_for_cv.index = range(len(x_train))
y_data_for_cv       = y_train
y_data_for_cv.index = range(len(x_train))

for ind1,(start,end) in enumerate(zip(np.arange(198,219,20),np.arange(218,239,20))):

    X    = x_data_for_cv.drop(range(start,end))
    y    = y_data_for_cv.drop(range(start,end))

    out_of_sample_X  = x_data_for_cv.loc[range(start,end)]
    out_of_sample_y  = y_data_for_cv.loc[range(start,end)]



    # We can either manually compute the out of sample prediction of the model
    # or we can use the inbuilt method 'predict'
    for ind2, alph in enumerate(alphas):
        glm_binom = sm.GLM(  y  ,sm.add_constant( X ),family=sm.families.Binomial())
        glm_binom = glm_binom.fit_regularized(method = "elastic_net",
                                              L1_wt  = 0.5,
```

```
                                        alpha  = alph)
        dev_lambda[ind1,ind2] = 2*metrics.log_loss(out_of_sample_y, glm_binom.predict
                                                  (sm.add_constant(out_of_sample_X)),
                                                  normalize=True)
```

To see why the penalized regression works, consider the ridge regression:

$$\hat{\beta}_{ridge} = \left(X'X + \lambda I_N\right) X'Y,$$

where I_N is the identity matrix. $(X'X + \lambda I_N)$ is invertible and estimates can be computed.

1. Using best_alpha (the penalizing term chosen by the cross validation), what (if any) are the words chosen and their associated coefficients? Comment on your results.

In [13]:
```
best_alpha_elnet = alphas[np.min(np.mean(dev_lambda,axis=0))==\
                                                  np.mean(dev_lambda,axis=0)][0]
glm_binom = sm.GLM(  y_train  ,sm.add_constant( x_train ),family=sm.families.Binomial()
glm_binom = glm_binom.fit_regularized(method = "elastic_net",
                                              L1_wt  = 0.5,
                                              alpha  = best_alpha_elnet)
print(glm_binom.params[glm_binom.params>0])
print(glm_binom.params[glm_binom.params<0])
```

```
Series([], dtype: float64)
Series([], dtype: float64)
```

It sets all estimates to zero. We can try to manually adjust the alpha parameter to see if it picks up anything

In [14]:
```
test_alpha=0.035
glm_binom = sm.GLM(  y_train  ,sm.add_constant( x_train ),family=sm.families.Binomial()
glm_binom = glm_binom.fit_regularized(method = "elastic_net",
                                              L1_wt  = 0.5,
                                              alpha  = test_alpha)
print(glm_binom.params[glm_binom.params>0])
print(glm_binom.params[glm_binom.params<0])
```

```
new         0.051182
need        0.165414
old         0.104525
chang       0.027809
us          0.113005
war         0.045940
ceo         0.051630
week        0.110955
talk        0.056567
wrong       0.218070
start       0.028988
campaign    0.051952
ted         0.132214
back        0.067584
law         0.044984
cook        0.101217
hit         0.054191
use         0.043262
iphon       0.141772
could       0.033009
point       0.029068
presid      0.153551
lose        0.049874
dtype: float64
```

```
world         -0.167805
ha            -0.040072
earn          -0.170473
attack        -0.013553
type          -0.016168
million       -0.117352
made          -0.008611
go            -0.087230
kill          -0.007912
donald        -0.214627
bill          -0.076497
greatest      -0.110907
microsoft     -0.122382
wall          -0.030307
die           -0.013580
republican    -0.114853
dtype: float64
```

We see that the model starts to pick up some words. However, these terms does not help to improve the fit of the model. Additionally, the signs of all of the coefficients do not necessarily make sense.

1. Now, create instead a pre-defined sentiment word list:

sent_words =

["trump","invest","growth","grow","high","strong","lead","good","risk","debt","oil","loss", "war","rate",

"hous","weak"]

dtm_sentiment = dtm[sent_words]

Run the elastic net with “x_data_pre=dtm_sentiment” using cross-validation and the training sample. Create a bar plot with the words on the x-axis and the coefficients on the y-axis. Comment on differences and similarities to the case in 9. Again, get the coefficients using cross-validation.

In [84]:
```
sent_words    = ["trump","invest","grow","high","strong","lead","good","risk","debt"
                 ,"oil","loss","war","rate","hous","weak"]
dtm_sentiment = x_data[sent_words]
x_test        = dtm_sentiment.loc[split_index:,:]
y_test        = y_data.loc[split_index:]


x_data_for_cv = x_data_for_cv[sent_words]

# Define alphas for iterative fitting of regularized model
alphas = np.logspace(-4, 1, 200)
dev_lambda = np.empty((2,len(alphas)))
dev_lambda2 = np.empty((2,len(alphas)))
for ind1,(start,end) in enumerate(zip(np.arange(198,219,20),np.arange(218,239,20))):

    X     = x_data_for_cv.drop(range(start,end))
    y     = y_data_for_cv.drop(range(start,end))

    out_of_sample_X  = x_data_for_cv.loc[range(start,end)]
    out_of_sample_y  = y_data_for_cv.loc[range(start,end)]


    for ind2, alph in enumerate(alphas):
```

```
        glm_binom = sm.GLM(  y  ,sm.add_constant( X ),family=sm.families.Binomial())
        glm_binom = glm_binom.fit_regularized(method = "elastic_net",
                                          L1_wt  = 0.5,
                                          alpha  = alph)
        dev_lambda[ind1,ind2] = -2*np.sum(np.dot(out_of_sample_y.values.ravel(),
        np.log(glm_binom.predict(sm.add_constant(out_of_sample_X))))
                            +np.dot((1-out_of_sample_y.values.ravel()),
        np.log(1-glm_binom.predict(sm.add_constant(out_of_sample_X)))))


best_alpha_elnet = alphas[np.min(np.mean(dev_lambda,axis=0))==\
                                                 np.mean(dev_lambda,axis=0)][0]
glm_binom_elnet = sm.GLM(  y_data_for_cv  ,sm.add_constant( x_data_for_cv ),
                                            family=sm.families.Binomial())
glm_binom_elnet = glm_binom_elnet.fit_regularized(method = "elastic_net",
                                              L1_wt  = 0.5,
                                              alpha  = best_alpha_elnet)


print(glm_binom_elnet.params)
```

```
const     0.0
trump     0.0
invest    0.0
grow      0.0
high      0.0
strong    0.0
lead      0.0
good      0.0
risk      0.0
debt      0.0
oil       0.0
loss      0.0
war       0.0
rate      0.0
hous      0.0
weak      0.0
dtype: float64
```

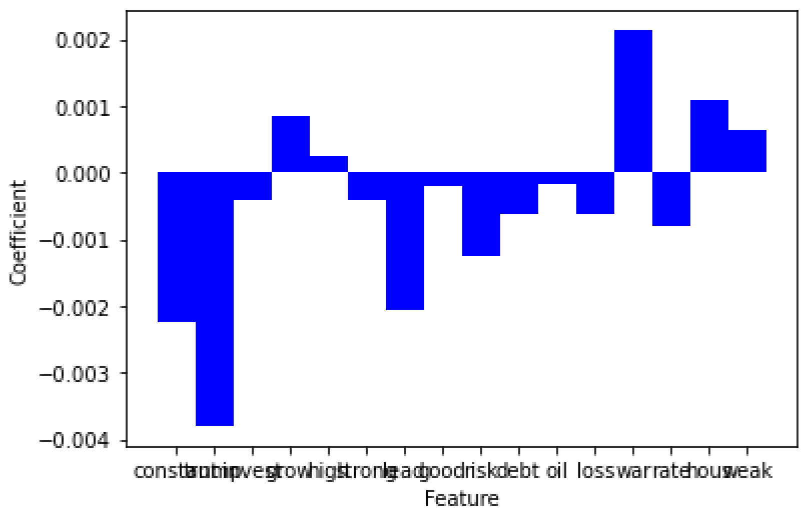
Unsurprisingly, elastic net still shrinks all coefficients to zero. Looking at a ridge regression could be more informative in that case.

In [80]:

```
# Grid search over Log-Loss for the best Lambda
dev_lambda  = np.empty((2,len(alphas)))


for ind1,(start,end) in enumerate(zip(np.arange(198,219,20),np.arange(218,239,20))):

    X    = x_data_for_cv.drop(range(start,end))
    y    = y_data_for_cv.drop(range(start,end))

    out_of_sample_X  = x_data_for_cv.loc[range(start,end)]
    out_of_sample_y  = y_data_for_cv.loc[range(start,end)]

    for ind2, alph in enumerate(alphas):
        glm_binom = sm.GLM(  y  ,sm.add_constant( X ),family=sm.families.Binomial())
        glm_binom = glm_binom.fit_regularized(L1_wt  = 0,alpha  = alph)

        dev_lambda[ind1,ind2] = -2*np.sum(np.dot(out_of_sample_y.values.ravel(),
                    np.log(glm_binom.predict(sm.add_constant(out_of_sample_X))))
                    +np.dot((1-out_of_sample_y.values.ravel()),
                    np.log(1-glm_binom.predict(sm.add_constant(out_of_sample_X)))))
```

```
best_alpha_ridge = alphas[np.min(np.mean(dev_lambda,axis=0))==\
                                                    np.mean(dev_lambda,axis=0)][0]
glm_binom_ridge = sm.GLM(  y_data_for_cv  ,sm.add_constant( x_data_for_cv ),
                                                   family=sm.families.Binomial())
glm_binom_ridge = glm_binom_ridge.fit_regularized(L1_wt  = 0,alpha  = best_alpha_ridge)

fig = plt.figure()
ax  = plt.subplot(111)
l   = ['constant']
l.extend(list(x_data_for_cv.columns))
ax.bar(l, glm_binom_ridge.params, width=1, color='b')
ax.set_ylabel('Coefficient')
ax.set_xlabel('Feature')
```

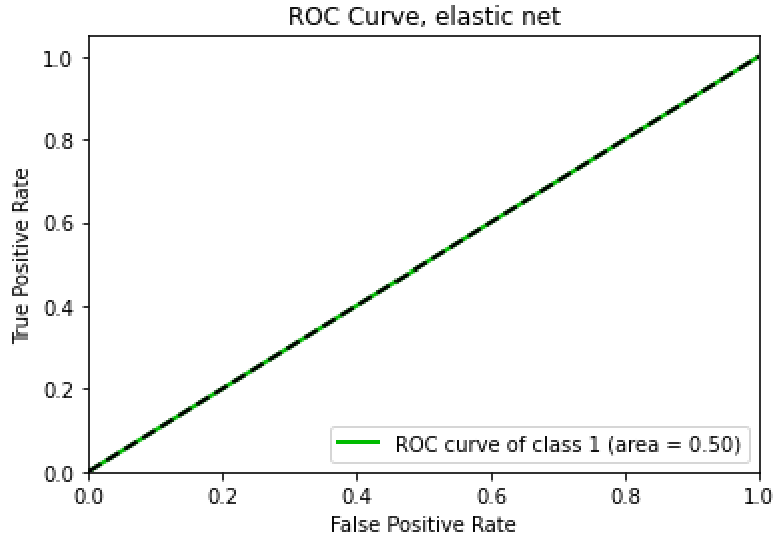
Out[80]: Text(0.5, 0, 'Feature')

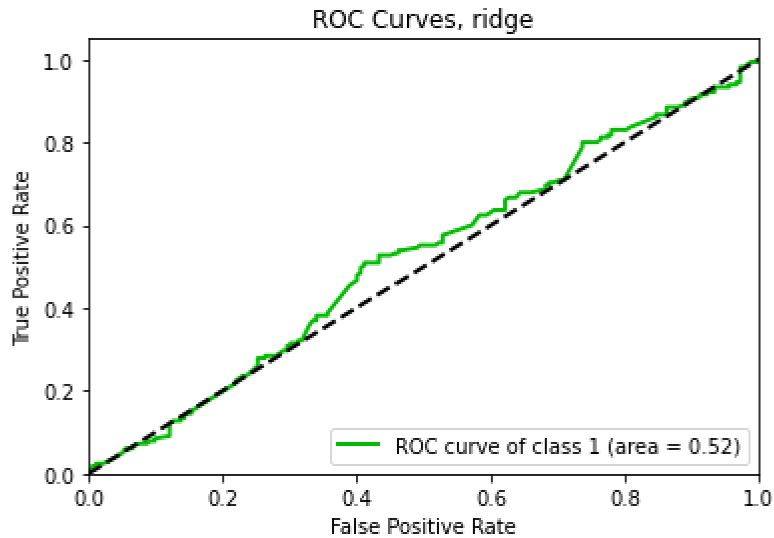


We see that `lead`, `war`, `trump`, and `risk` seem to be some of the most important features.

1. Create the ROC curves for the sentiment model in 10, using cross-validation to get coefficient vector. Is it better than random? You likely want to use the predict function to get the model predictions.

In [81]:
```
elnet_z = np.ones(347)-glm_binom_elnet.predict(sm.add_constant( dtm_sentiment ))
elnet   = pd.concat([elnet_z,glm_binom_elnet.predict(sm.add_constant( dtm_sentiment ))],
                    axis=1)

ax = skplt.metrics.plot_roc(y_data,elnet,#,
                   title='ROC Curve, elastic net',
                   plot_micro=False, plot_macro=False,classes_to_plot=1,
                   ax=None, figsize=None, cmap='nipy_spectral',
                   title_fontsize="large", text_fontsize="medium")


ridge_z = np.ones(347)-glm_binom_ridge.predict(sm.add_constant( dtm_sentiment ))
ridge   = pd.concat([ridge_z,glm_binom_ridge.predict(sm.add_constant( dtm_sentiment ))],
                    axis=1)

ax = skplt.metrics.plot_roc(y_data,ridge,
                   title='ROC Curves, ridge',
                   plot_micro=False, plot_macro=False,classes_to_plot=1,
                   ax=None, figsize=None, cmap='nipy_spectral',
                   title_fontsize="large", text_fontsize="medium")
```





1. Now, using the test sample and the model in 10, what is the proportion of days the model would have made the right prediction in this new sample? Is it better than random (50/50)?

In [88]:
```
# Elastic net
glm_binom_elnet = sm.GLM(  y_train  ,sm.add_constant( x_data_for_cv ),family=sm.familie
glm_binom_elnet = glm_binom_elnet.fit_regularized(method = "elastic_net",
                                                   L1_wt  = 0.5,
                                                   alpha  = best_alpha_elnet)
elnet_test=
pd.concat([pd.DataFrame((glm_binom_elnet.predict(sm.add_constant( x_test ))>=0.5)*1,
                                   columns=['test']),y_test],axis=1)
print('Elastic net: ' + str((elnet_test['test'] == elnet_test['label'])
                                                     .sum()/len(elnet_test)))


# Ridge
glm_binom_ridge = sm.GLM(  y_train  ,sm.add_constant( x_data_for_cv ),
                         family=sm.families.Binomial())
glm_binom_ridge = glm_binom_ridge.fit_regularized(L1_wt  = 0,alpha  = best_alpha_ridge)

ridge_test =
pd.concat([pd.DataFrame((glm_binom_ridge.predict(sm.add_constant( x_test ))>=0.5)*1,
                                     columns=['test']),y_test],axis=1)
```

```
print('Ridge: ' + str((ridge_test['test'] == ridge_test['label'])
                                                  .sum()/len(ridge_test)))
```

```
Elastic net: 0.47706422018348627
Ridge: 0.5229357798165137
```

The elastic net is worse than 50/50, the ridge is slightly better.

In [ ]:

In [ ]:

In [ ]: