TEXT CLASSIFICATION

In this assignment, you will

1. Download text (the IMDB reviews dataset).
2. Process it; vectorize it.
3. Perform parameter selection (for logistic regression) using cross validation on the train split.
4. Train a model using the best parameter setting.
5. Report the top positive and negative features and discuss your findings.
6. Evaluate the model on the test split. Report performance metrics.
7. Choose a few random test documents.
8. Print the top positive and negative words in those documents.
9. Discuss your findings.

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In [1]:
```
!cd  /opt/anaconda3/envs/venv_581
# !pip install matplotlib
# !pip install nltk
# !pip install pandas
# !pip install scikit-learn
# !pip install seaborn
# !pip install tqdm
import copy
from   IPython.display import display_html
import matplotlib.pyplot as plt
import nltk
from   nltk import corpus, WordNetLemmatizer
from   nltk.corpus import stopwords
nltk.download(['stopwords','wordnet','omw-1.4'], quiet=True)

import numpy as np
import os
import pandas as pd
from   pandas import DataFrame as df
import random
import re
import seaborn as sns
import sklearn
from   sklearn.feature_extraction.text import TfidfVectorizer, CountVectorizer
from   sklearn.linear_model import LogisticRegression
from   sklearn.model_selection import GridSearchCV, learning_curve

import tqdm
from   tqdm import tqdm
```

Dataset

The IMDB review dataset is available via different platforms. We will work with the "raw" text version of it.

Download the dataset from https://ai.stanford.edu/~amaas/data/sentiment/.

Unzip it; put it into a folder called `aclImdb` (case senstive). The `aclImdb` folder should be in the same folder as this notebook. The folder structure should look like this:

```
aclImdb
-> train
---> neg
---> pos
-> test
```

```
---> neg
---> pos
```

You can ignore the other folders.

The files in the `train` folder are train documents and the `test` are, well, the test documents. The documents in `neg` are negative documents and the documents in `pos` are the positive documents.

Load the documents and their labels.

In [2]:
```
dir_ = '/Users/janedowner/Desktop/CS 581/CS 581 - Assignment 4'
os.chdir(dir_)

train = {'File #':[], 'Document': [],'Label':[]}
test  = {'File #':[], 'Document': [],'Label':[]}

def build_dict(dictionary,folder_extension, label):
    folder = os.listdir(dir_ + folder_extension)
    for file in folder:
        with open(dir_ + folder_extension + file) as f:
            dictionary['File #']  .append(file[:-4])
            dictionary['Document'].append(''.join(f.readlines()))
            dictionary['Label']   .append(label)

build_dict(train,'/aclImdb/train/pos/',1)
build_dict(train,'/aclImdb/train/neg/',0)
build_dict(test, '/aclImdb/test/pos/', 1)
build_dict(test, '/aclImdb/test/neg/', 0)

train_df = pd.DataFrame(train).sample(frac=1).reset_index(drop=True)
test_df  = pd.DataFrame(test) .sample(frac=1).reset_index(drop=True)
```

In [3]:
```
def compose(functions, input_):
    while len(functions) > 0:
        inner_most = functions[-1]
        input_     = inner_most(input_)
        functions  = functions[:-1]
    output = input_
    return output

sw       = stopwords.words('english')
lower    = lambda doc: ''.join([w.lower() for w in doc])
no_hyph  = lambda doc: re.sub(r'-',' ',doc)
no_punct = lambda doc: ''.join([w for w in doc if w.isalpha() or w == ' '])
tok      = lambda doc: doc.split()
no_sw    = lambda doc: [w for w in doc if w not in sw]
lemm     = lambda doc: [WordNetLemmatizer().lemmatize(w) for w in doc]

prep_row = lambda df,row: ' '.join(compose([lemm,
                                            no_sw,
                                            tok,
                                            no_punct,
                                            no_hyph,
                                            lower],df.iloc[row,1]))

train_df_preprocessed = train_df.copy()
test_df_preprocessed  = test_df .copy()
for row in tqdm(range(len(train_df))):
    train_df_preprocessed.iloc[row,1] = prep_row(train_df_preprocessed,row)
    test_df_preprocessed .iloc[row,1] = prep_row(test_df_preprocessed,row)

train_df_preprocessed.to_csv('train_df - preprocessed', index=False)
test_df_preprocessed .to_csv('test_df - preprocessed',  index=False)
```

```
100%|██████████████████████████████████| 25000/25000 [00:50<00:00, 495.02it/s]
```

Vectorization

You must use the scikit-learn package for vectorization and for the classifier: https://scikit-learn.org/stable/index.html

You have freedom regarding the vectorizer: https://scikit-learn.org/stable/modules/classes.html#module-sklearn.feature_extraction.text You can use the `CountVectorizer` or the `TfidfVectorizer` with parameters of your choice.

In [4]:
```
train_df_preprocessed = pd.read_csv(filepath_or_buffer='train_df - preprocessed',
                                    index_col         = False)
test_df_preprocessed  = pd.read_csv(filepath_or_buffer='test_df - preprocessed',
                                    index_col         = False)
X_train               = train_df_preprocessed.iloc[:,1]
X_test                = test_df_preprocessed .iloc[:,1]
y_train               = train_df_preprocessed.iloc[:,2]
y_test                = test_df_preprocessed .iloc[:,2]

TFIDF                 = TfidfVectorizer()

X_all                 = pd.concat([X_train,X_test],keys=['X_train','X_test'])
BOW_all               = TFIDF.fit_transform(X_all)
train_indices         = range(len(X_train))
test_indices          = range(len(X_train),len(X_train)+len(X_test))
BOW_train             = BOW_all[train_indices,:]
BOW_test              = BOW_all[test_indices, :]
BOW_train_norm        = sklearn.preprocessing.normalize(BOW_train,
                                                        norm='l2',
                                                        return_norm=False)
BOW_test_norm         = sklearn.preprocessing.normalize(BOW_test,
                                                        norm='l2',
                                                        return_norm=False)
```

Parameter Selection

For the classifier, you must use `LogisticRegression` : https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LogisticRegression.html

Use 10-fold cross validation using various parameter settings for `C` . Please use `penalty='l2'` . You can use any solver; the results should not change drastically based on the solver; I do not recommend spending a lot of time on trying different solvers.

I recommend using https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.GridSearchCV.html. Report the grid search results using a table.

In [5]:
```
param_grid = {'penalty': ['l2'],
              'C':       [1.0,5.0,10.0],
              'tol':     [0.0001,0.01,0.1],
              'solver':  ['liblinear']}

LR_model = LogisticRegression()
grid_clf = GridSearchCV(estimator=LR_model,
                        cv=10,
                        param_grid=param_grid,
                        refit=True,
                        return_train_score=True)

grid_clf.fit(BOW_train_norm,y_train)

best_params = df(grid_clf.cv_results_)[['mean_fit_time',
                                        'params',
                                        'mean_train_score']]

best_params.to_csv(dir_ + '/aclImdb/best_params')
pd.set_option("display.max_colwidth",100)
display(best_params)
```

	mean_fit_time	params	mean_train_score
0	1.386041	{'C': 1.0, 'penalty': 'l2', 'solver': 'liblinear', 'tol': 0.0001}	0.936093
1	0.863272	{'C': 1.0, 'penalty': 'l2', 'solver': 'liblinear', 'tol': 0.01}	0.936187
2	0.648403	{'C': 1.0, 'penalty': 'l2', 'solver': 'liblinear', 'tol': 0.1}	0.934929

	mean_fit_time	params	mean_train_score
3	2.127197	{'C': 5.0, 'penalty': 'l2', 'solver': 'liblinear', 'tol': 0.0001}	0.978658
4	1.508836	{'C': 5.0, 'penalty': 'l2', 'solver': 'liblinear', 'tol': 0.01}	0.978609
5	5.683586	{'C': 5.0, 'penalty': 'l2', 'solver': 'liblinear', 'tol': 0.1}	0.978449
6	2.564791	{'C': 10.0, 'penalty': 'l2', 'solver': 'liblinear', 'tol': 0.0001}	0.991320
7	1.754672	{'C': 10.0, 'penalty': 'l2', 'solver': 'liblinear', 'tol': 0.01}	0.991262
8	1.430334	{'C': 10.0, 'penalty': 'l2', 'solver': 'liblinear', 'tol': 0.1}	0.991609

The following parameters maximize mean training score, while resulting in lower mean fit time than parameters with comparable scores:

```
C: 10.0
penalty: l2
solver: liblinear
tol: 0.1
```

Refit

Fit a logistic regression on the full training data using the best parameter settings above.

In [6]:
```
LR_model = LogisticRegression(C=10.0,
                              penalty='l2',
                              solver='liblinear',
                              tol=0.1)
LR_model.fit(BOW_train_norm,y_train)
```

Out[6]:
```
LogisticRegression(C=10.0, solver='liblinear', tol=0.1)
```

Top Model Features

Present a table of top 20 positive features (the feature names and their coefficients) and another table of top 20 negative features, with respect to the logistic regression weights.

In [7]:
```
coefs       = LR_model.coef_[0]
###
idxs_pos20  = np.argpartition(coefs, -20)[-20:]
idxs_neg20  = np.argpartition(coefs,  20)[: 20]
###
feats_pos20 = TFIDF.get_feature_names_out()[idxs_pos20]
feats_neg20 = TFIDF.get_feature_names_out()[idxs_neg20]
###
coefs_pos20 = coefs[idxs_pos20]
coefs_neg20 = coefs[idxs_neg20]

fts_df  = lambda fts,cfs,cols: df({cols[0]:fts,cols[1]:cfs})
sort_df = lambda df,cols,asc: df.sort_values(by=cols[1],
                                             ascending=asc).reset_index(drop=1)

cols_=['Feature','Coefficient']
featsDF_pos = sort_df(fts_df(feats_pos20,coefs_pos20,cols_),cols_,0)
featsDF_neg = sort_df(fts_df(feats_neg20,coefs_neg20,cols_),cols_,1)

dfL_ = featsDF_pos.style.set_table_attributes("style='display:inline'")
dfL_ = dfL_.set_caption('Top 20 Positive Features')
dfR_ = featsDF_neg.style.set_table_attributes("style='display:inline'")
dfR_ = dfR_.set_caption('Top 20 Negative Features')

space = "\xa0" * 10
display_html(dfL_._repr_html_() + space + dfR_._repr_html_(), raw=True)
```

Top 20 Positive Features

	Feature	Coefficient
0	excellent	10.713445
1	great	9.763227
2	perfect	8.997792
3	favorite	8.383455
4	highly	7.663079
5	wonderful	7.643704
6	best	7.557310
7	superb	7.362319
8	amazing	7.125742
9	refreshing	7.075560
10	today	6.847153
11	wonderfully	6.773022
12	loved	6.679158
13	enjoyed	6.569295
14	enjoyable	6.506980
15	funniest	6.469119
16	rare	6.271659
17	well	6.231693
18	perfectly	6.196527
19	entertaining	6.190200

Top 20 Negative Features

	Feature	Coefficient
0	worst	-16.055477
1	waste	-12.417070
2	awful	-12.340263
3	disappointment	-9.723372
4	poorly	-9.694385
5	poor	-9.339205
6	boring	-9.331024
7	worse	-9.091707
8	bad	-8.689208
9	unfortunately	-8.582801
10	fails	-8.393731
11	horrible	-8.286555
12	disappointing	-8.124976
13	annoying	-7.906527
14	nothing	-7.785515
15	dull	-7.738423
16	save	-7.734250
17	mess	-7.214230
18	weak	-7.185120
19	supposed	-7.181713

Evaluation

Print a classification report on the train and another classification report on the test. Discuss your findings.

In [8]:

```
y_pred_train = LR_model.predict(BOW_train_norm)
y_pred_test  = LR_model.predict(BOW_test_norm)

train_report = sklearn.metrics.classification_report(y_train,
                                                     y_pred_train,
                                                     digits=2,
                                                     zero_division='warn')

test_report  = sklearn.metrics.classification_report(y_test,
                                                     y_pred_test,
                                                     digits=2,
                                                     zero_division='warn')

print('Classification Report -- training data:\n{}'.format(train_report))
print('Classification Report -- testing data:\n{}' .format(test_report))
```

```
Classification Report -- training data:
              precision    recall  f1-score   support

           0       0.99      0.99      0.99     12500
           1       0.99      0.99      0.99     12500

    accuracy                           0.99     25000
   macro avg       0.99      0.99      0.99     25000
weighted avg       0.99      0.99      0.99     25000

Classification Report -- testing data:
              precision    recall  f1-score   support

           0       0.86      0.88      0.87     12500
           1       0.88      0.86      0.87     12500
```

```
    accuracy                           0.87     25000
   macro avg       0.87      0.87      0.87     25000
weighted avg       0.87      0.87      0.87     25000
```

The classifier performs better on the training data than on the testing data. This makes sense to a degree, because the classifier has complete information about the training data, but not the testing data. However, it might be an indicator of overfitting, or some other issue. I will discuss this more later.

High accuracy by itself doesn't mean very much without these other scores to back it up, especially when there is class imbalance. However, within each classification report, these scores are similar to eachother and to accuracy. Moreover, there are an equal number of positive and negative samples anyway. Given this scenario, it is appropriate to consider the accuracy scores.

Top Features In Each Document

Pick a few (at least 3) documents at random. For each document:

1. Print the document.
2. Print its label.
3. Present a a table of top 10 positive features (in that document), their weights, and their weights*feature values.
4. Present a a table of top 10 negative features (in that document), their weights, and their weights*feature values.

Note: if your vectorizer is binary, you weigths and weights*feature should be the same.

In [9]:
```
'''
I wasn't sure whether the question was asking to choose documents
from the training or testing data (or both). These docuents come
from the testing data.
'''
keys_    = lambda dict_: list(dict_.keys())
vals_    = lambda dict_: list(dict_.values())
items_   = lambda dict_: list(dict_.items())
list_zip = lambda L1,L2: list(zip(L1,L2))

random_indices  = random.sample(range(len(test_df_preprocessed)),5)
random_data     = test_df_preprocessed.iloc[random_indices,:].reset_index(drop=True)
random_docs_raw = test_df.iloc[random_indices,1].tolist()
random_BOW      = BOW_test_norm.toarray()[random_indices,:]


weights_list_pos, weights_list_neg = [],[]
values_list_pos,  values_list_neg  = [],[]
all_feats = TFIDF.get_feature_names_out().tolist()
for i in range(len(random_data)):
    lab = random_data.iloc[i,2]
    feats_idx   = [idx for idx in range(len(random_BOW[i])) if random_BOW[i][idx] != 0]
    feats       = [all_feats[idx] for idx in feats_idx]
    feats_coefs = [coefs[idx] for idx in feats_idx]
    feats_vals  = [random_BOW[i][idx] for idx in feats_idx]

    items = sorted(list_zip(feats,
                            feats_coefs),
                   key=lambda item: item[1],
                   reverse=True)

    pos_items, neg_items = items[:10], items[-10:]
    pos_feats, neg_feats = keys_(dict(items))[:10], keys_(dict(items))[-10:]

    weights_pos = {k:v for (k,v) in pos_items}
    weights_neg = {k:v for (k,v) in neg_items}

    values     = {k:v for (k,v) in list_zip(feats, feats_vals)}
    values_pos = {k:v for (k,v) in items_(values) if k in pos_feats}
    values_neg = {k:v for (k,v) in items_(values) if k in neg_feats}
    weights_list_pos.append(weights_pos)
    weights_list_neg.append(weights_neg)
```

```
    values_list_pos .append(values_pos)
    values_list_neg .append(values_neg)


w_x_v = lambda weights,values,i: [w*v for (w,v) in zip(vals_(weights[i]),
                                                       vals_(values[i]))]

for i in range(5):
    sub_file = 'pos' if random_data.Label[i]==1 else 'neg'
    print('~/test/{}/{}:\n'.format(sub_file, random_data.iloc[i,:]["File #"]))
    print(random_docs_raw[i])
    df_pos = df({'Feature':      keys_(weights_list_pos[i]),
                 'Weight':       vals_(weights_list_pos[i]),
                 'Weight*Value': w_x_v(weights_list_pos, values_list_pos,i)})

    df_neg = df({'Feature':      keys_(weights_list_neg[i]),
                 'Weight':       vals_(weights_list_neg[i]),
                 'Weight*Value': w_x_v(weights_list_neg, values_list_neg, i)})

    dfL_ = df_pos.style.set_table_attributes("style='display:inline'")
    dfL_ = dfL_.set_caption('Top 10 Positive Features')
    dfR_ = df_neg.style.set_table_attributes("style='display:inline'")
    dfR_ = dfR_.set_caption('Top 10 Negative Features')
    space = "\xa0" * 10
    display_html(dfL_._repr_html_() + space + dfR_._repr_html_(), raw=True)

    true_label = random_data.Label[i]
    pred_label = y_pred_test[random_indices[i]]
    sums_pos = round(sum(df_pos['Weight*Value']),3)
    sums_neg = round(sum(df_neg['Weight*Value']),3)

    print('True label:      {}'.format('POSITIVE' if true_label==1 else 'NEGATIVE'))
    print('Predicted label: {}'.format('POSITIVE' if pred_label==1 else 'NEGATIVE'))
    print('Sum(weights*values) of the features above: {}'.format(sums_pos+sums_neg))
    print('\n\n')
```

~/test/neg/1053_4:

Most Lorne Michaels films seem to fail because they're essentially just extended versions of skits that barely managed to make people laugh in five-minute segments. "Tommy Boy" is a character right from "SNL" - a big fat lovable (in their opinion) goof who doesn't know anything.

David Spade gets the T hankless Overwhelmed Everyman role. He's paired with the Annoying Overweight Slob and they endure Misera ble Misfortunes as they travel cross country to Save Daddy's Business.

The plot, for starter s, is really faulty. The whole premise - daddy dies and rich stupid son has to save the family biz - can be traced back to just about any movie you want. Like any SNL style film it is reduced to a simple motiv ation - empty, shallow; just a reason to see a fat guy and a thin guy be "funny" together.

Th e movie's biggest "influence" is the 1987 comedy classic "Planes, Trains & Automobiles." That movie is g reat because the plot isn't stale and recycled. It's basic, yeah - a guy traveling home for Thanksgiving gets stuck with a slob. But it's real, dammit. It makes all the difference. The characters are real, the situations are far more real. "Tommy Boy" is pure slapstick and its ridiculous situations undermine the characters - we feel nothing for them, and we don't care about what's happening on-screen. "PTA" walked the careful line between outrageous and utterly believable and relate-able - "Tommy Boy" is simply absur d, with jokes like a simple deer-in-the-headlights turning into a crash turning into a struggle with a d ead deer that really isn't dead, then awakens and wrecks their car.

The whole wrecked car thi ng is stolen completely from "PTA" and it's eerie how much stuff in this film actually does resemble the Steve Martin/John Candy movie.

Farley is simply way too obnoxious to find likable - I've neve r enjoyed watching him in any movies and this hasn't changed my mind. Spade's given very little to do, s erving as the movie's most thankless character.

Dan Aykroyd is wasted as the Evil Baddie who plans to destroy Daddy's Business. The ending is a joke, and not in a "har-har funny" way. More like a "oh god are they serious?!" way.

Some people dig it, that's cool. But I just can't get into i t, nor do I appreciate all the stuff it "borrows" from - not just counting "PT&A" - without any credit w hatsoever.

Top 10 Positive Features

	Feature	Weight	Weight*Value
0	great	9.763227	0.502943
1	enjoyed	6.569295	0.317609
2	simple	4.777892	0.183258
3	classic	4.413306	0.200593
4	believable	3.629697	0.239013
5	see	3.420720	0.146622
6	eerie	3.394600	0.084096
7	cool	3.276795	0.108443
8	right	3.195455	0.069656
9	appreciate	3.113110	0.278466

Top 10 Negative Features

	Feature	Weight	Weight*Value
0	reason	-4.353591	-0.200074
1	premise	-4.409692	-0.145055
2	obnoxious	-4.478247	-0.140025
3	minute	-4.661077	-0.295803
4	stupid	-5.002793	-0.208933
5	oh	-6.482083	-0.311900
6	ridiculous	-6.619695	-0.230438
7	save	-7.734250	-0.353583
8	nothing	-7.785515	-0.671300
9	annoying	-7.906527	-0.322341

```
True label:       NEGATIVE
Predicted label: NEGATIVE
Sum(weights*values) of the features above: -0.7480000000000002
```

```
~/test/pos/5695_10:

BLACK WATER is a thriller that manages to completely transcend it's limitations (it's an indie flick) by
continually subverting expectations to emerge as an intense experience.<br /><br />In the tradition of a
ll good animal centered thrillers ie Jaws, The Edge, the original Cat People, the directors know that re
straint and what isn't shown are the best ways to pack a punch. The performances are real and gripping,
the crocdodile is extremely well done, indeed if the Black Water website is to be believed that's becaus
e they used real crocs and the swamp location is fabulous.<br /><br />If you are after a B-grade gore fe
st croc romp forget Black Water but if you want a clever, suspenseful ride that will have you fearing th
e water and wondering what the hell would I do if i was up that tree then it's a must see.
```

Top 10 Positive Features

	Feature	Weight	Weight*Value
0	best	7.557310	0.392156
1	well	6.231693	0.619490
2	ride	4.105707	0.158641
3	manages	3.944566	0.473768
4	good	3.640288	0.383272
5	see	3.420720	0.324552
6	intense	3.283365	0.326474
7	suspenseful	2.972616	0.122031
8	edge	2.969616	0.343430
9	gripping	2.525904	0.109914

Top 10 Negative Features

	Feature	Weight	Weight*Value
0	extremely	-1.199460	-0.193260
1	pack	-1.442617	-0.082710
2	expectation	-1.465372	-0.147315
3	croc	-2.105913	-0.175638
4	fest	-2.936020	-0.360388
5	original	-3.143663	-0.309872
6	director	-3.672592	-0.246021
7	tree	-3.748019	-0.436294
8	grade	-4.248211	-0.479329
9	would	-4.775723	-0.199995

```
True label:       POSITIVE
Predicted label: POSITIVE
Sum(weights*values) of the features above: 0.6230000000000002
```

```
~/test/neg/4057_4:

It is amazing what you can see if you wake at 2 am and turn on the telly. I didn't know they showed film
s like this. I immediately thought of Roger Corman, who reused locations for movies or used other films
locations for his own movies.<br /><br />The makes of this film could just move the camera angles and ad
d some time and they would have an XXX film.<br /><br />There was no story, just minimum dialog that led
to stripping and sex. I bet there wasn't 100 words in the whole film, but there sure was a lot of very l
arge busts and hot lesbian action. There was male/female action too, but it was only about 25% of the mo
vie.<br /><br />Another interesting thing came to mind in watching this film that may interest those who
are buying hi def DVDs. Sony refused to license Betamax to adult film makers and adult films came out on
VHS. You can guess what happened to beta max as the adult film industry makes millions of videos. Sony h
as again refused to license Blu-ray to the adult film industry and they have just signed a deal with Tos
hiba. You can guess which high def system will disappear.
```

Top 10 Positive Features

	Feature	Weight	Weight*Value
0	amazing	7.125742	0.763909
1	deal	3.728409	0.249815
2	vhs	3.435878	0.238287
3	see	3.420720	0.195213
4	lot	3.414416	0.261379
5	time	2.902021	0.134016
6	dvd	2.794541	0.145733
7	may	2.696600	0.090954
8	action	2.247620	0.069648
9	hot	2.138861	0.191611

Top 10 Negative Features

	Feature	Weight	Weight*Value
0	refused	-1.711916	-0.067931
1	whole	-1.908479	-0.091060
2	wasnt	-1.937090	-0.251772
3	interest	-2.524149	-0.172861
4	interesting	-2.540809	-0.134080
5	maker	-2.547517	-0.197115
6	didnt	-3.185201	-0.693183
7	guess	-3.495973	-0.200657
8	could	-4.133775	-0.216800
9	would	-4.775723	-0.164321

```
True label:      NEGATIVE
Predicted label: POSITIVE
Sum(weights*values) of the features above: 0.15100000000000025
```

```
~/test/neg/10609_1:

So, it's Friday night and you want to go watch a movie...all you want is something entertaining, not too
artsy, or anything that might require a long night of philosophical discussions. So, you pay $10 to watc
h the Mod Squad. The trailer to this movie should have tipped me off, but come on...it's three of Hollyw
ood's most beautiful people--eye candy. But that's about it...a string of moving Prada ads. And what did
Hollywood producers forget? A plot. Why are these kids running around the streets after some unknown ene
my? Where are they? But, don't worry, after a while, you'll just stop caring. I was on the verge of walk
ing out of this movie, because I thought sitting in my room and staring at the wall might have been more
productive (and free), but by that time, it was over (90 minutes--it's only saving grace). So, still wil
ling to waste $10? Go, get yourself a nice hot meal.
```

Top 10 Positive Features

	Feature	Weight	Weight*Value
0	entertaining	6.190200	0.493475
1	still	4.758718	0.410372
2	moving	4.569449	0.369561
3	beautiful	3.993864	0.413424
4	nice	3.657173	0.355705
5	time	2.902021	0.235905
6	trailer	2.349717	0.140948
7	hot	2.138861	0.089623
8	watch	2.084473	0.237044
9	eye	2.043611	0.224313

Top 10 Negative Features

	Feature	Weight	Weight*Value
0	three	-2.058881	-0.265896
1	artsy	-2.087848	-0.150211
2	dont	-2.324019	-0.355207
3	ad	-2.589474	-0.133684
4	plot	-2.614430	-0.380012
5	anything	-2.805804	-0.193110
6	saving	-3.117509	-0.175779
7	might	-3.118415	-0.374683
8	minute	-4.661077	-0.366092
9	waste	-12.417070	-1.067251

```
True label:      NEGATIVE
Predicted label: NEGATIVE
Sum(weights*values) of the features above: -0.492
```

```
~/test/pos/11517_8:

Lights of New York was the first all-talking feature film. There had been, of course, The Jazz Singer, r
eleased in Oct. 1927 as the first feature film incorporating synchronized dialog. However, this film rel
eased in July 1928 is virtually unremembered for its place in film history. It had started out as a shor
t, but gradually more was tacked on until - clocking in at 58 minutes - it accidentally became the first
all-talking feature film. It opened to a grind house run and to Warner Bros. surprise, made over a milli
on dollars. That was good money back in 1928.<br /><br />The plot is quite simple. Two country barbers n
aively buy into a barber shop on Broadway that fronts as a speak-easy for "The Hawk", a gangster. When t
hey learn the truth they can't afford to get out, because the younger barber, Eddie, has all of his moth
er's money tied up in the place. Kitty is the younger barber's girlfriend, and gangster Hawk (Wheeler Oa
kman) has an eye for turning in his older girlfriend (Gladys Brockwell) for a newer model - chorus girl
Kitty(Helene Costello). A cop is killed while trying to stop the Hawk's men from unloading a shipment of
```

```
bootleg liquor, and the Hawk sees it as an opportunity to frame Eddie, thus getting Kitty for himself.<b
r /><br />This early talkie is loads of fun for the enthusiast of these pioneering works. Sure, the plot
is elementary and the dialog stilted, but there is something you don't see much of in early talkies - ba
ckground musical scoring. Vitaphone had originally been used for this very purpose, and here they are st
ill using it for musical accompaniment along with the dialog. And there are singing and dancing numbers!
The scenes in Hawk's nightclub are used as an opportunity to show off what films could never do before -
musical numbers. There is even a wild-eyed emcee with some heavy makeup left over from the silent era th
at is a hoot to watch.<br /><br />Vitaphone could not go outdoors at this point due to the static camera
booths, so the scene in the park between the two lovers Eddie and Kitty is simulated - and cheaply. The
greenery looks like something out of an Ed Wood movie or perhaps a high school production of "Our Town".
<br /><br />Gladys Brockwell, as the Hawk's castoff girlfriend, delivers her lines with punch. She's a r
eal trooper considering what lines she has to deliver. To the Hawk - "So you think you can have any chic
ken you want and throw me back in the deck!". Huh? mixed metaphors anyone? And then there are her final
lines "I've lived, and I've loved, and I've lost!" Did someone get paid to write this dialog? Brockwell
was making a good success of her talkie career after scoring some triumphs in silent films (the evil sis
ter in "Seventh Heaven"), when a fatal car accident cut her career short.<br /><br />Then there is Eugen
e Palette - the older of the two barbers in our story. His frog voice, natural delivery of lines, and cu
ddly appearance gave him a long career as a character actor usually appearing as a put-upon family man/b
usinessman with a gruff exterior and heart of gold. In fact, Mr. Palette is the only member of this cast
who still has a notable career in films just three years after this movie is released.<br /><br />Finall
y there is the question of "where is that microphone hidden?" Microphones were still stationary at this
point, and it's fun to figure out where they've hidden it. There is one famous scene, though, where ever
ybody can pretty much figure it out. Hawk is in his office talking to his two henchman - who seem to com
prehend as slowly as they talk - about "taking Eddie for a ride". If you watch this scene you'd swear th
e phone on the desk is a character in this film. It's front and center during the whole conversation. Th
e microphone is likely planted in the phone.<br /><br />There is something heroic about these pioneers f
lying blind in the face of the new technology of sound. You have silent actors who are accustomed to usi
ng pantomime for expression, vaudevillians who know how to play to a live audience but don't know how to
make the same impression on a Vitaphone camera booth, and you have dialog writers either trying to write
conversation as compactly as they did title cards or filling up films with endless chatter. <br /><br />
Check this one out. It is not boring, moves fast, and is loads of fun if you know what to look for. And
no, I don't expect this one to ever be out on Blu-Ray, but I hope that the folks at Warner Brothers add
it to the Warner Archive soon so everyone can see it.
```

Top 10 Positive Features

	Feature	Weight	Weight*Value
0	loved	6.679158	0.198570
1	fun	6.112624	0.418368
2	simple	4.777892	0.123752
3	still	4.758718	0.126260
4	kitty	4.327683	0.630010
5	ride	4.105707	0.107286
6	easy	3.953185	0.131746
7	good	3.640288	0.150261
8	see	3.420720	0.096567
9	heart	3.348762	0.181797

Top 10 Negative Features

	Feature	Weight	Weight*Value
0	look	-3.129556	-0.078664
1	stilted	-3.151003	-0.102012
2	even	-3.604726	-0.135608
3	money	-3.697884	-0.050945
4	endless	-3.789859	-0.132014
5	paid	-3.955850	-0.082135
6	could	-4.133775	-0.195642
7	someone	-4.401279	-0.153093
8	minute	-4.661077	-0.108213
9	boring	-9.331024	-0.404422

```
True label:      POSITIVE
Predicted label: POSITIVE
Sum(weights*values) of the features above: 0.722
```

Final Discussion

Discuss your findings.

1.

Do you think your model is accurate, based on classification metrics?

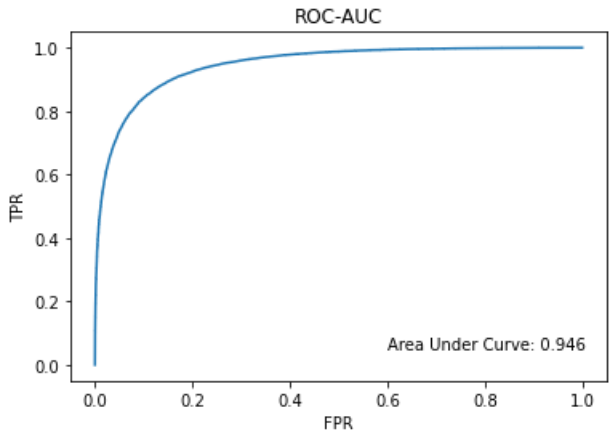
When considered simultaneously, precision, recall and F1 can give a more holistic representation of model performance than just an accuracy score alone. As we saw above, they are all between 0.86 and 0.88, which is decent, but not perfect. Another way to represent the model performance is with the ROC

(receiver operator characteristic) -- which shows the tradeoff between false positive rates and true positive rates -- and AUC (area under the ROC curve).

In [10]:

```
y_pred_prob = LR_model.predict_proba(BOW_test_norm)
y_          = y_test.tolist()
y_          = np.asarray([[0,1] if y == 1 else [1,0] for y in y_])
fpr, tpr, _ = sklearn.metrics.roc_curve(y_.ravel(), y_pred_prob.ravel())
auc         = round(sklearn.metrics.auc(fpr,tpr),3)

plt.plot(fpr,tpr)
plt.title('ROC-AUC')
plt.xlabel('FPR')
plt.ylabel('TPR')
plt.annotate("Area Under Curve: {}".format(auc),xy=[0.6,0.05])
plt.show()
```



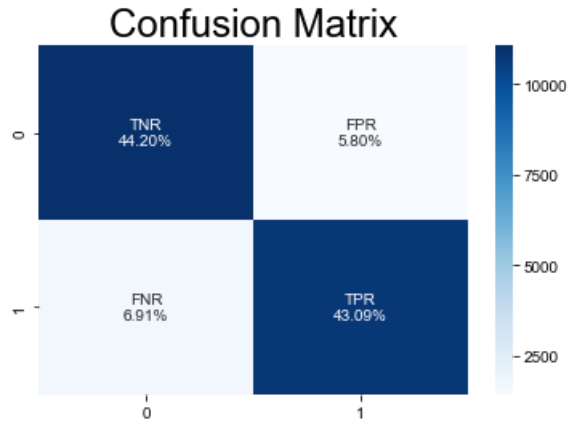
A perfect classifier will have an area under the curve value of 1. Here, it's 0.946, which is pretty good. Moreover, the fact that the curve is pulled toward the upper left-hand corner means that at certain threshold levels, the model can achieve high true positive rates without much of an increase in false positive rates. This is what we want.

The confusion matrix can also provide us with information about model accuracy:

In [11]:

```
cm     = sklearn.metrics.confusion_matrix(y_test,y_pred_test)
grps   = ['TNR','FPR','FNR','TPR']
pcts   = ["{0:.2%}".format(val) for val in cm.flatten()/np.sum(cm)]
labels = np.asarray(["{}\n{}".format(g,p) for (g,p) in zip(grps,pcts)]).reshape(2,2)

sns.heatmap(cm,annot=labels,fmt='',cmap=sns.color_palette("Blues",as_cmap=True))
sns.set(font_scale = 2)
plt.title('Confusion Matrix')
plt.show()
```



The confusion matrix shows that false negatives and false positive occur at rates of 6.91% and 5.80%. In other words, the model guesses incorrectly 6.91+5.80=12.71% of the time. This is acceptable, but could be better.

All of the above classification metrics suggest that the model is acceptably accurate.

2.

Do you think your model is smart? Answer this question solely based on the classification accuracy.

The model accuracy is 0.87, which is decent. Based on this number alone, the model seems relatively smart, or at the very least, does its job. However, as I've explained above, accuracy by itself doesn't provide a holistic view of model performance.

3.

Do you think your model is smart? Answer this question solely based on top features in each document.

Some of the top features in each document make sense, and others do not. In my opinion, the top features of these individual documents provide the strongest evidence that the model is *not* smart.

For example, there is no apparent reason why these words should be associated with positive labels:

```
eerie
kitty
ride
see
```

... Or why these words should be associated with negative labels:

```
artsy
croc
grade
three
tree
```

It's worth noting that the top features of the training data in its entirety made much more sense. With more data, the strongest trends emerge. With just five documents, however -- as in this case -- it makes more sense that unexpected words might appear on the 'top features' lists. Overarching training data trends are not necessarily reflected in individual documents.

4.

General Discussion.

Generally, the model performed better than I expected. However, I'm curious about the gap between the training and testing data -- why is this occurring? To investigate, let's look at the trends in training error and validation error as they relate to the size of the training data.

In [12]:

```
def error_scores(X, y, C=10, pen ='l2', slvr ='liblinear', tol=0.1):
    LR = LogisticRegression(C=C, penalty=pen, solver=slvr, tol=tol)
    LR.fit(X,y)

    size, scores_trn, scores_val = learning_curve(estimator=LR,
                                                  X=X,
                                                  y=y,
                                                  cv=10,
                                                  scoring="accuracy")
    errors_trn = 1-np.mean(scores_trn, axis=1)
    errors_val = 1-np.mean(scores_val, axis=1)
    output_df  = pd.DataFrame({"Training Size"   : size,
                               "Training Error"  : errors_trn,
                               "Validation Error": errors_val})
    return output_df

all_scores = error_scores(BOW_train_norm,y_train)
```

```
scores_val = all_scores['Validation Error']
scores_trn = all_scores['Training Error']
size       = all_scores['Training Size']

sns.set(font_scale = 1)
sns.set_style("whitegrid", {'axes.grid' : False})

plt.plot(size, scores_val, label='Validation Error')
plt.plot(size, scores_trn, label='Training Error')

plt.title ("Validation and Training Error")
plt.xlabel('Training Data Size')
plt.ylabel('Error Rate')
plt.legend()
plt.show()
```

The plot above shows that validation error -- which represents the model's potential to perform on unseen data -- continually decreases as the size of the training data increases. Meanwhile, the training error is consistently very low. This combination of high variance and low bias indicates overfitting. Given the downward trend of the validation error with increasing training size, the ability of the model to generalize to unseen data could likely be improved with additional data. This overfitting is why there is a difference between the training and testing scores. Moreover, the training and testing data we are given are equal in size. Train/test splits typically result in much more training data than testing data -- i.e., something like an 80/20 split, rather than 50/50. So it seems like we could afford to take some of the current testing data and include it in the training process, because we probably don't need as much data for testing, and the model could benefit from more training examples.

For me, the biggest takeaway from this assignment is that we need multiple ways to measure the model's success, because a single score doesn't capture all of the relevant information.