Sentiment Analysis Movie Review

For this analysis we'll be using a dataset of 50,000 movie reviews taken from IMDb. The data was compiled by Andrew Maas and can be found here: IMDb Reviews. The data is split evenly with 25k reviews intended for training and 25k for testing your classifier. Moreover, each set has 12.5k positive and 12.5k negative reviews. IMDb lets users rate movies on a scale from 1 to 10. To label these reviews the curator of the data labeled anything with ≤ 4 stars as negative and anything with ≥ 7 stars as positive. Reviews with 5 or 6 stars were left out.

The dataset is available at http://ai.stanford.edu/~amaas/data/sentiment/.

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

In [49]:
```
# load_files module loads text files with categories as subfolder names.
# The folder names are used as supervised signal label names.
# The individual file names are not important.
from sklearn.datasets import load_files
import numpy as np
from sklearn.feature_extraction.text import CountVectorizer
import os
import random
np.set_printoptions(precision=3, suppress=True)
import pandas as pd
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import scale, StandardScaler

import matplotlib.pyplot as plt
%matplotlib inline
#plt.rcParams["figure.dpi"] = 300
plt.rcParams["savefig.dpi"] = 300
plt.rcParams["savefig.bbox"] = "tight"
```

You may not always find the dataset available for you to download from Sklearn, Keras type of platforms. Most of the times, you will have to find the dataset yourself and read it to your work space from some file. Below, you will find how you can read the IMDB text files from a folder where files are arranged by the label names.

In [7]:
```
def load_imdb_sentiment_analysis_dataset(data_path, seed=123):
    """Loads the IMDb movie reviews sentiment analysis dataset.

    # Arguments
        data_path: string, path to the data directory.
```

```
        seed: int, seed for randomizer.

    # Returns
        A tuple of training and validation data.
        Number of training samples: 25000
        Number of test samples: 25000
        Number of categories: 2 (0 - negative, 1 - positive)

    # References
        Mass et al., http://www.aclweb.org/anthology/P11-1015

        Download and uncompress archive from:
        http://ai.stanford.edu/~amaas/data/sentiment/aclImdb_v1.tar.gz
    """
    imdb_data_path = os.path.join(data_path, 'aclImdb')

    # Load the training data
    train_texts = []
    train_labels = []
    for category in ['pos', 'neg']:
        train_path = os.path.join(imdb_data_path, 'train', category)
        for fname in sorted(os.listdir(train_path)):
            if fname.endswith('.txt'):
                with open(os.path.join(train_path, fname)) as f:
                    z=f.read()
                    train_texts.append(str(z))
                train_labels.append(0 if category == 'neg' else 1)

    # Load the validation data.
    test_texts = []
    test_labels = []
    for category in ['pos', 'neg']:
        test_path = os.path.join(imdb_data_path, 'test', category)
        for fname in sorted(os.listdir(test_path)):
            if fname.endswith('.txt'):
                with open(os.path.join(test_path, fname)) as f:
                    z=f.read()
                    test_texts.append(str(z))
                test_labels.append(0 if category == 'neg' else 1)

    # Shuffle the training data and labels.
    random.seed(seed)
    random.shuffle(train_texts)
    random.seed(seed)
    random.shuffle(train_labels)

    return (train_texts, np.array(train_labels),
            test_texts, np.array(test_labels))
```

Load the train dataset

- Load the dataset and divide data into trainval and test datasets.
- Print the type of the trainval dataset
- Print the length of the trainval dataset
- Print the first document in your trainval dataset

In [8]:
```
#reviews_train = load_files("aclImdb/train")
#text_train, y_train = reviews_train.data, reviews_train.target
text_trainval, y_trainval, text_test, y_test = load_imdb_sentiment_analysis_d
print("type of text train: {}".format(type(text_trainval)))
print("length of text_train: {}".format(len(text_trainval)))
print("text_train[1]:\n{}".format(text_trainval[1]))
```

```
type of text train: <class 'list'>
length of text_train: 25000
text_train[1]:
The long list of "big" names in this flick (including the ubiquitous John Mill
s) didn't bowl me over to the extent that I couldn't judge the film on its act
ual merits. It is FULL of stereotypes, caricatures, and standard, set scenes,
from the humble air-ace hero to the loud-mouthed yank flyer. The music track w
as such that at one point, about an hour before the end, I thought the film wa
s over: loud, rising crescendo, grand flourish and finish then silence, but th
en the movie continued! I found no real storyline, haphazard writing, but smar
tly-pressed uniforms and the pretty Jean Simmons (pre-nose job) with a rousing
little ditty. I cannot say that this picture has any of the ingredients which
make a film great. I found it maudlin, mawkish and minor.
```

- Print the type of your labels 'y'
- Print the lnegth of your labels
- Print the first three labels

In [9]:
```
print("type of y train: {}\n".format(type(y_trainval)))
print("length of y train: {}\n".format(len(y_trainval)))
print("y_train[0]:{}".format(y_trainval[0]))
print("y_train[1]:{}".format(y_trainval[1]))
print("y_train[2]:{}".format(y_trainval[2]))
```

```
type of y train: <class 'numpy.ndarray'>

length of y train: 25000

y_train[0]:0
y_train[1]:0
y_train[2]:1
```

In [31]:
```
a=(text_train[1])
print(a)
a[0]
a.replace("<br />", " ")
```

```
The long list of "big" names in this flick (including the ubiquitous John Mill
s) didn't bowl me over to the extent that I couldn't judge the film on its act
ual merits. It is FULL of stereotypes, caricatures, and standard, set scenes,
from the humble air-ace hero to the loud-mouthed yank flyer. The music track w
as such that at one point, about an hour before the end, I thought the film wa
s over: loud, rising crescendo, grand flourish and finish then silence, but th
en the movie continued! I found no real storyline, haphazard writing, but smar
tly-pressed uniforms and the pretty Jean Simmons (pre-nose job) with a rousing
little ditty. I cannot say that this picture has any of the ingredients which
make a film great. I found it maudlin, mawkish and minor.
```

Out[31]:
```
'The long list of "big" names in this flick (including the ubiquitous John Mil
ls) didn\'t bowl me over to the extent that I couldn\'t judge the film on its
actual merits. It is FULL of stereotypes, caricatures, and standard, set scene
s, from the humble air-ace hero to the loud-mouthed yank flyer. The music trac
k was such that at one point, about an hour before the end, I thought the film
was over: loud, rising crescendo, grand flourish and finish then silence, but
then the movie continued! I found no real storyline, haphazard writing, but sm
artly-pressed uniforms and the pretty Jean Simmons (pre-nose job) with a rousi
ng little ditty. I cannot say that this picture has any of the ingredients whi
ch make a film great. I found it maudlin, mawkish and minor.'
```

- If you go over the reviews in the directory structure, you will notice that many of the reviews contain some html line breaks.
- Let's clean this. text_trainval is a list containing type bytes(bytes represents a binary encoding of the string data in Python 3.
- after cleaning your dataset, divide your trainval dataset into train and validation datasets

In [11]:
```
text_trainval = [doc.replace("<br />", " ") for doc in text_trainval]
print("\nSamples per class (training): {}\n".format(np.bincount(y_trainval)))
```

```
Samples per class (training): [12500 12500]
```

In [34]:
```
len(np.unique(text_train))
```

Out[34]:
```
24904
```

In [35]:
```
len(np.unique(y_train))
```

Out[35]:
```
2
```

In [36]:
```
print("text_train[1]:\n{}".format(text_train[1]))
```

```
text_train[1]:
The long list of "big" names in this flick (including the ubiquitous John Mill
s) didn't bowl me over to the extent that I couldn't judge the film on its act
ual merits. It is FULL of stereotypes, caricatures, and standard, set scenes,
from the humble air-ace hero to the loud-mouthed yank flyer. The music track w
as such that at one point, about an hour before the end, I thought the film wa
s over: loud, rising crescendo, grand flourish and finish then silence, but th
en the movie continued! I found no real storyline, haphazard writing, but smar
tly-pressed uniforms and the pretty Jean Simmons (pre-nose job) with a rousing
little ditty. I cannot say that this picture has any of the ingredients which
make a film great. I found it maudlin, mawkish and minor.
```

In [37]:

```
print("y_train[1]:\n{}".format(y_train[1]))
```

```
y_train[1]:
0
```

In [22]:

```
text_train, text_val, y_train, y_val = train_test_split(text_trainval, y_trai
```

Load the test dataset

- This is for the purpose of demonstrating that we can load the same dataset using Sklearn available function

In [14]:

```
reviews_test = load_files("aclImdb/test/")
text_test, y_test = reviews_test.data, reviews_test.target
print("Number of documents in test data: {}".format(len(text_test)))
print("Samples per class (test): {}".format(np.bincount(y_test)))
text_test = [doc.replace(b"<br />", b" ") for doc in text_test]
```

```
Number of documents in test data: 25002
Samples per class (test): [12501 12501]
```

Bag of Words

We need to convert the string representation of the corpus into a numeric representation that we can apply our machine learning algorithms to. We discard most of the structure of the input text, and only count how oftern each word appears in each text in the corpus. This is the mental image of a "bag of words" for a corpus of docs. It consists of three steps:

- Tokenization, (CountVectorizer)
- Vocabulary Building, (fitting the CountVectorizer builds the vocabulary)(vocabulary_)
- Encoding (in the form of SciPy sparse matrix)(boW is created via transform) (one vector of word counts for each document in the corpus)(for each word in the document, we have a count of how often it appears in each document)

CountVectorizer

- eliminates single letter words like "a"
- tokenizes using a regular expression "\b\w\w+\b".
- converts all to lowercase letters.

In [15]:
```
# Fitting of the CountVectorizer consists of tokenization of the training dat
# and building the vocabulary
# Transforming the CountVectorizer creates the bag-of-words representation
# of the train data.
# the bow is stored in a SciPy sparse matrix that only stores the nonzero
# entries.
# to look at the actual content of the sparse matrix, convert it to dense
# array using numpy.toarray() method
vect = CountVectorizer()
# X_train is in the form of bow (after calling transform, bow is created)
X_train = vect.fit_transform(text_train)
print("X_train:\n{}".format(repr(X_train)))
X_val = vect.transform(text_val)
```

```
X_train:
<18750x66605 sparse matrix of type '<class 'numpy.int64'>'
	with 2564934 stored elements in Compressed Sparse Row format>
```

In [17]:
```
print(text_test[11451].decode())
```

```
What can be said of this independent effort beyond the fact that it was shot w
ith television cameras, and whether that was by conceit or budget constraints
doesn't make the watching of this variation on a theme by Romero any easier. I
was constantly reminded that I was watching somebody's school project, at best
derivative, at worst cheap.  Writer/director Georg Koszulinski (who also appea
rs in the film) does some interesting things with stock footage, but that says
more about his editing style than his directing style, which consists of in-yo
ur-face close-ups with TV cameras which made me think I was watching public-ac
cess television instead of an actual, honest-to-goodness film.  The story copi
es and pastes bits and pieces from various sources, including the aforemention
ed Romero's DEAD trilogy, THE ROAD WARRIOR (dig that stock footage of a "futur
e" that looks like the past) and THE BLAIR WITCH PROJECT.  What results is an
hour-and-nothing's worth of zombies tracking down and eating humans. (Okay, th
e "humans" in this case are clones, but that doesn't change anything. It's the
same menu.)  The year is 2031, and the first strand of people who were cloned
nineteen years before have started to malfunction, particularly in the dietary
area. Of course, when clones go bad, the first thing they have a taste for is
human flesh (or, in this case, cloned human flesh). It's not safe to be indoor
s, it's not safe to be outdoors. It's just a matter of time before the flesh-e
ating ghouls devour our heroes. Have you seen this before?   I don't mind peop
le ripping off Romero, if it's done well, but no new territory is covered in t
his film. It's NIGHT OF THE LIVING DEAD meets THE BLAIR WITCH PROJECT, shot wi
th television cameras. What is particularly disappointing is that the DVD cove
r makes it look like it was shot, at the very least, with 8mm film. This would
n't have been a problem with me if the story had not been equally cheap. The f
ilm offers a bleak vision of the future in which technology has evolved to the
point where human cloning is possible. Must we continue to clone our favourite
movies?
```

- Print the length of the vocabulary vector

In [19]:
```
print(len(vect.vocabulary_))
#vect.vocabulary_
#vocabulary_ includes a map of feature terms to indices.
#get_feature_names array mapping from feature integer indices to feature
#name.
```

```
66605
```

- Get the feature names from the 'vect' object
- Print the type of the feature names
- Print the first 20 feature names
- Print every other 2000th feature name

In [20]:
```
feature_names = vect.get_feature_names()
print(type(feature_names))
print("Number of features: {}".format(len(feature_names)))
print("First 20 features:\n{}".format(feature_names[:20]))
print("Features 20010 to 20030:\n{}".format(feature_names[20010:20030]))
print("Every 2000th feature:\n{}".format(feature_names[::2000]))
```

```
<class 'list'>
Number of features: 66605
First 20 features:
['00', '000', '0000000000001', '00001', '000s', '001', '003830', '006', '007',
'0079', '0080', '0083', '0093638', '00am', '00pm', '00s', '01', '01pm', '02',
'020410']
Features 20010 to 20030:
['eschews', 'escort', 'escorted', 'escorting', 'escorts', 'escpecially', 'escr
ow', 'esculator', 'ese', 'eser', 'esha', 'eshaan', 'eshley', 'eskimo', 'eskimo
s', 'esl', 'esmond', 'esophagus', 'esoteric', 'esoterically']
Every 2000th feature:
['00', 'ahahahahahhahahahahahahahahahahhahahahahahahah', 'ashwar', 'beloved', 'b
ribe', 'celery', 'comforted', 'crossings', 'deter', 'droplet', 'escargot', 'fi
ngertips', 'gaspard', 'gunner', 'homepage', 'inherently', 'kabinett', 'lederho
sen', 'majority', 'mikuni', 'nasha', 'organise', 'perversely', 'primrose', 're
boots', 'robson', 'scuppered', 'skimpier', 'starbase', 'synanomess', 'toothpic
ks', 'unforgiven', 'wager', 'yearbook']
```

If you notice, the first features are all numbers that appeared somewhere in the reviews. Also, some words appear multiple times both in singular and plural forms.

Logistic Regression with cross validation

- Build a Logistic Regression model
- Train the model with cross validation of 5 folds
- Print the mean accuracy score of the corss validation

In [23]:

```python
from sklearn.model_selection import cross_val_score
from sklearn.linear_model import LogisticRegression
scores = cross_val_score(LogisticRegression(), X_train, y_train, cv=5)
print("Mean cross-validation accuracy: {:.2f}".format(np.mean(scores)))
```

```
Mean cross-validation accuracy: 0.88
```

- Get the score on the validation dataset after retaraaiing the model on the train dataset

In [25]:

```python
from sklearn.linear_model import LogisticRegression
lr = LogisticRegression(max_iter=2000).fit(X_train, y_train)
print(lr.score(X_train, y_train))
print(lr.score(X_val, y_val))
```

```
0.9994133333333334
0.87424
```

Hypertuning C with a GridSearch

- You can tune upir model up by exploring for the best `C` parameter value in your logistic regression model
- Use `GridSearchCV` from Scikitlearn

In [27]:
```
from sklearn.model_selection import GridSearchCV
param_grid = {'C': [0.001, 0.01, 0.1, 1, 10]}
# countvectorizer (text_train)
# pipeline (CountVectorizer, LogisticRegression )
grid = GridSearchCV(LogisticRegression(), param_grid, cv=5)
grid.fit(X_train, y_train)
print("Best cross-validation score: {:.2f}".format(grid.best_score_))
print("Best parameters: ", grid.best_params_)
```

```
Best cross-validation score: 0.88
Best parameters:  {'C': 0.1}
```

In [28]:
```
X_test = vect.transform(text_test)
print("{:.2f}".format(grid.score(X_test, y_test)))
```

```
0.88
```

min_df

- Let's modify the CountVectorizer so that it uses tokens that appear in at least five documents. This will get rid of the silly numbers in the feature set.
- Make the grid search again and print the best score

In [31]:
```
vect = CountVectorizer(min_df=5).fit(text_train)
X_train = vect.transform(text_train)
print("X_train with min_df: {}".format(repr(X_train)))
```

```
X_train with min_df: <18750x23692 sparse matrix of type '<class 'numpy.int64'>
'
	with 2494812 stored elements in Compressed Sparse Row format>
```

In [32]:
```
feature_names = vect.get_feature_names()
print("num of features :{}".format(len(feature_names)))
print("First 50 features:\n{}".format(feature_names[:50]))
print("Features 20010 to 20030:\n{}".format(feature_names[20010:20030]))
print("Every 700th feature:\n{}".format(feature_names[::700]))
```

```
num of features :23692
First 50 features:
['00', '000', '007', '00s', '01', '02', '03', '05', '06', '07', '08', '09', '1
0', '100', '1000', '101', '102', '103', '105', '108', '10th', '11', '110', '11
2', '117', '11th', '12', '120', '12th', '13', '13th', '14', '140', '14th', '15
', '150', '15th', '16', '160', '16mm', '16s', '16th', '17', '17th', '18', '180
', '1800', '1800s', '1840', '1860']
Features 20010 to 20030:
['stand', 'standard', 'standards', 'standing', 'standout', 'standouts', 'stand
point', 'stands', 'standup', 'stanford', 'stank', 'stanley', 'stanton', 'stanw
yck', 'staple', 'stapleton', 'star', 'starbuck', 'stardom', 'stardust']
Every 700th feature:
['00', 'agnes', 'ashton', 'behold', 'bressart', 'cellar', 'colored', 'coups',
'deformed', 'diver', 'elves', 'exuberant', 'forehead', 'god', 'headless', 'il'
, 'invent', 'kristen', 'lovable', 'melt', 'muslims', 'omar', 'penance', 'preac
hes', 'railway', 'residents', 'salute', 'shepherd', 'solve', 'stretched', 'tea
ring', 'trapper', 'unwilling', 'welcomed']
```

In [33]:

```
grid = GridSearchCV(LogisticRegression(), param_grid, cv=5)
grid.fit(X_train, y_train)
print("Best cross-validation score: {:.2f}".format(grid.best_score_))
```

```
Best cross-validation score: 0.88
```

Although accuracy did not improve, the number of features are less. The cross validation score did not improve but it speeds up to deal with fewer features.

Stopwords

Getting rid of uninformative words that are too frequent and language specific. Scikit-learn has a built-in list of English stopwords

In [34]:

```
from sklearn.feature_extraction.text import ENGLISH_STOP_WORDS
print("Number of stop words: {}".format(len(ENGLISH_STOP_WORDS)))
print("Every 10th stopword:\n{}".format(list(ENGLISH_STOP_WORDS)[::10]))
```

```
Number of stop words: 318
Every 10th stopword:
['whoever', 'becomes', 'well', 'three', 'thin', 'very', 'un', 'whether', 'how'
, 'among', 'moreover', 'not', 'neither', 'further', 'herself', 'before', 'with
out', 'enough', 'back', 'become', 'mine', 'through', 'sometime', 'fill', 'besi
des', 're', 'next', 'seemed', 'anyway', 'seem', 'put', 'eg']
```

In [35]:

```
# Specifying stop_words="english" uses the built-in list.
# We could also augment it and pass our own.
vect = CountVectorizer(min_df=5, stop_words="english").fit(text_train)
X_train = vect.transform(text_train)
print("X_train with stop words:\n{}".format(repr(X_train)))
```

```
X_train with stop words:
<18750x23390 sparse matrix of type '<class 'numpy.int64'>'
	with 1594124 stored elements in Compressed Sparse Row format>
```

In [36]:
```
grid = GridSearchCV(LogisticRegression(), param_grid, cv=5)
grid.fit(X_train, y_train)
print("Best cross-validation score: {:.2f}".format(grid.best_score_))
print("Best parameters: ", grid.best_params_)
```

```
Best cross-validation score: 0.88
Best parameters:  {'C': 0.1}
```

- Fixed sets of stopwords are not very likely to increase the performance. Let's try another approach.
- Removing stopwords might not always be a good idea especially in sentiment analysis. By removing the stop word, a negative string could turn out to be positive and vice versa.

max_df

- max_df also eliminates frequently used words.

In [37]:
```
vect = CountVectorizer(min_df=5, max_df=55).fit(text_train)
X_train = vect.transform(text_train)
print("X_train with stop words:\n{}".format(repr(X_train)))
```

```
X_train with stop words:
<18750x18903 sparse matrix of type '<class 'numpy.int64'>'
	with 302276 stored elements in Compressed Sparse Row format>
```

In [38]:
```
grid = GridSearchCV(LogisticRegression(), param_grid, cv=5)
grid.fit(X_train, y_train)
print("Best cross-validation score: {:.2f}".format(grid.best_score_))
```

```
Best cross-validation score: 0.76
```

Rescaling with tf-idf

Until now, we dropped features that are deemed unimportant. Another approach is to rescale features. The intuition is to give high weight to any term that appears often IN A PARTICULAR DOC, but NOT in many documents in the corpus. term-frequency, inverse document frequency. The lower the IDF value of a word, the less unique it is to any particular document.

go over tfidf at web site: https://kavita-ganesan.com/tfidftransformer-tfidfvectorizer-usage-differences/

- Create a pipeline of tfidf vectorizer and a logistic regression estimator
- use the pipe object in your gridsearch with a cross validation with 5-folds

In [39]:
```
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.pipeline import make_pipeline
pipe = make_pipeline(TfidfVectorizer(min_df=5, norm=None),
                         LogisticRegression())
param_grid = {'logisticregression__C': [0.001, 0.01, 0.1, 1, 10]}
grid = GridSearchCV(pipe, param_grid, cv=5)
grid.fit(text_train, y_train)
print("Best cross-validation score: {:.2f}".format(grid.best_score_))
```

```
Best cross-validation score: 0.89
```

In [40]:
```
grid.best_estimator_
```

Out[40]:
```
Pipeline(steps=[('tfidfvectorizer', TfidfVectorizer(min_df=5, norm=None)),
                ('logisticregression', LogisticRegression(C=0.001))])
```

If you like, you can 3xtract your vectorizer from the pipeline and transform your train or test dataset

- extract tfidfvectorizer from the pipeline
- transform the training dataset
- find max values for each of the features over the dataset
- print the lowest 20 tfidf features
- print the highest 20 tfidf features

In [41]:
```
#Extract tfidfvectorizer from the pipeline
vectorizer = grid.best_estimator_.named_steps["tfidfvectorizer"]
print(type(vectorizer))
#transform the training dataset
X_train = vectorizer.transform(text_train)
#find max values for each of the features over the dataset
max_value = X_train.max(axis=0).toarray().ravel()
sorted_by_tfidf = max_value.argsort()
    # get feature names
feature_names = np.array(vectorizer.get_feature_names())
print("Features with lowest tfidf:\n{}".format(
feature_names[sorted_by_tfidf[:20]]))
print("Features with highest tfidf: \n{}".format(
feature_names[sorted_by_tfidf[-20:]]))
```

```
<class 'sklearn.feature_extraction.text.TfidfVectorizer'>
Features with lowest tfidf:
['costs' 'amateurish' 'everywhere' 'prepared' 'poignant' 'uncomfortable'
 'concerns' 'instantly' 'importantly' 'regardless' 'disagree' 'bucks'
 'exaggerated' 'lacked' 'handful' 'occurred' 'areas' 'currently'
 'altogether' 'logical']
Features with highest tfidf:
['superman' 'gypo' 'keaton' 'europa' 'cal' 'blob' 'paulie' 'roy'
 'hackenstein' 'dillinger' 'vargas' 'jesse' 'basket' 'the' 'victor'
 'victoria' 'zizek' 'rob' 'timon' 'titanic']
```

Lowest tfidf features are common accross the documents Highest tfidf features identify specific movies.

Work on idf score

- Similarly, we can find the word that have low idf. You can see that they are mosly stopwords.
- And some are domain specific words like watch, movie, etc.
- Notice that some words like good, great, bad are also among most frequent according to tfidf.

In [42]:
```
sorted_by_idf = np.argsort(vectorizer.idf_)
print("Features with lowest idf:\n{}".format(
feature_names[sorted_by_idf[:100]]))
```

```
Features with lowest idf:
['the' 'and' 'of' 'to' 'this' 'is' 'it' 'in' 'that' 'but' 'for' 'with'
 'as' 'was' 'on' 'movie' 'not' 'have' 'one' 'be' 'are' 'film' 'you' 'all'
 'at' 'an' 'by' 'like' 'from' 'so' 'who' 'they' 'there' 'if' 'his' 'out'
 'just' 'about' 'he' 'or' 'has' 'what' 'some' 'can' 'good' 'when' 'more'
 'time' 'up' 'very' 'even' 'only' 'no' 'would' 'my' 'see' 'really' 'story'
 'which' 'had' 'well' 'me' 'than' 'much' 'their' 'get' 'been' 'were'
 'other' 'do' 'don' 'also' 'most' 'made' 'first' 'her' 'great' 'into'
 'how' 'will' 'because' 'make' 'people' 'way' 'could' 'bad' 'we' 'after'
 'any' 'too' 'then' 'them' 'watch' 'she' 'think' 'acting' 'movies' 'seen'
 'its' 'many']
```

When you look at the lowest idf words, some words are stop words. Interestingly, great, good are also in the list.

Investigating Model Coefficients

To understand what our model learned, we are going to investigate the model coefficients by looking at the most and least important coeefficients. We will extract the last model that we trained.

- If you like, you can install a module `mglearn` to print the plots. use `! pip install mglearn`

In [43]:
```
#! pip install mglearn
```

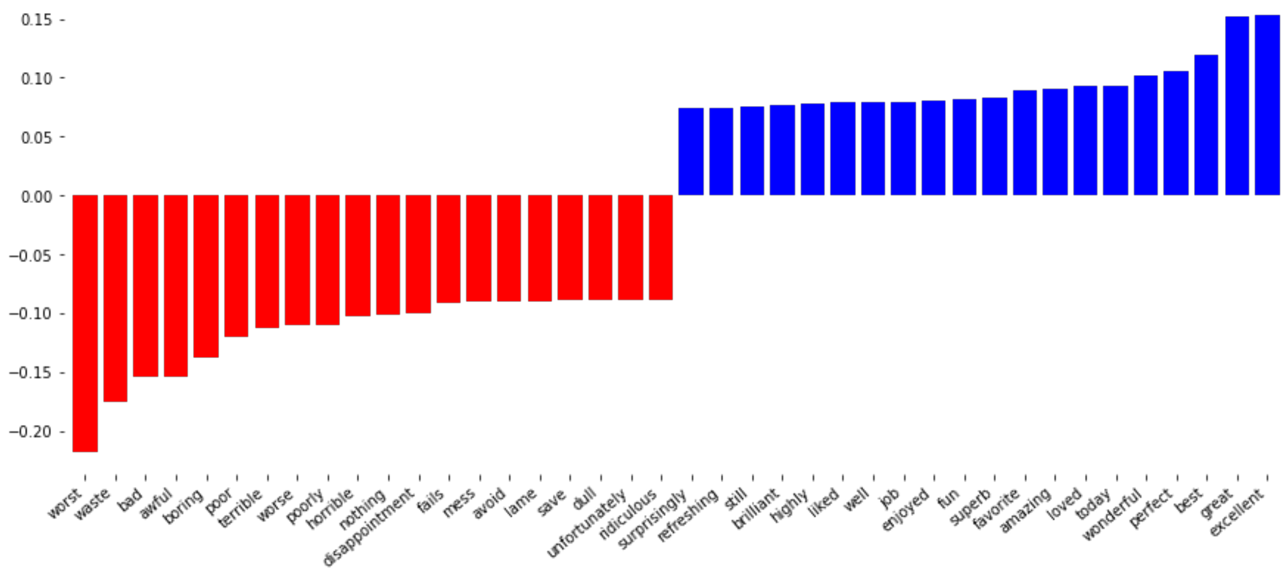
In [44]:
```
#import mglearn
#mglearn.tools.visualize_coefficients(
#        grid.best_estimator_.named_steps["logisticregression"].coef_,
#        feature_names, n_top_features=25)
```

I provide a function to plot important features.

In [47]:
```
def plot_important_features(coef, feature_names, top_n=20, ax=None, rotation=
    if ax is None:
        ax = plt.gca()
    inds = np.argsort(coef)
    low = inds[:top_n]
    high = inds[-top_n:]
    important = np.hstack([low, high])
    myrange = range(len(important))
    colors = ['red'] * top_n + ['blue'] * top_n

    ax.bar(myrange, coef[important], color=colors)
    ax.set_xticks(myrange)
    ax.set_xticklabels(feature_names[important], rotation=rotation, ha="right
    ax.set_xlim(-.7, 2 * top_n)
    ax.set_frame_on(False)
```

In [50]:
```
plt.figure(figsize=(15, 6))
plot_important_features(grid.best_estimator_.named_steps\
["logisticregression"].coef_.ravel(), np.array(feature_names), \
top_n=20, rotation=40)
ax = plt.gca()
```



Bag-of-words

- disadvantage: word order is completely discarded. "It is bad, not good at all" is the same as "It is good, not bad at all." # n_grams
- pairs of tokens are bigrams
  - unigrams - only one
- `n_gram_range` parameter of `CountVectorizer` and `TfidfVectorizer` is a tuple -> (min, max)
- Adding longer sequences—up to 5-grams—might help too, but this will lead to an explosion of the number of features and might lead to overfitting, as there will be many very specific features.

In [53]:
```
malory = ["Do you want ants?",
          "Because that’s how you get ants."]
```

In [54]:
```
cv = CountVectorizer(ngram_range=(1, 1)).fit(malory)
print("Vocabulary size: {}".format(len(cv.vocabulary_)))
print("Vocabulary:\n{}".format(cv.get_feature_names()))
```

```
Vocabulary size: 8
Vocabulary:
['ants', 'because', 'do', 'get', 'how', 'that', 'want', 'you']
```

In [55]:
```
cv = CountVectorizer(ngram_range=(2, 2)).fit(malory)
print("Vocabulary size: {}".format(len(cv.vocabulary_)))
print("Vocabulary:\n{}".format(cv.get_feature_names()))
```

```
Vocabulary size: 8
Vocabulary:
['because that', 'do you', 'get ants', 'how you', 'that how', 'want ants', 'yo
u get', 'you want']
```

In [56]:
```
cv = CountVectorizer(ngram_range=(1, 2)).fit(malory)
print("Vocabulary size: {}".format(len(cv.vocabulary_)))
print("Vocabulary:\n{}".format(cv.get_feature_names()))
```

```
Vocabulary size: 16
Vocabulary:
['ants', 'because', 'because that', 'do', 'do you', 'get', 'get ants', 'how',
'how you', 'that', 'that how', 'want', 'want ants', 'you', 'you get', 'you wan
t']
```

In [57]:
```
for ngram_range in [(1, 1), (1, 2), (1, 3), (1, 4)]:

    cv = CountVectorizer(ngram_range=ngram_range, min_df=4).fit(text_train)
    print("Vocabulary size {} (min_df=4): {}".\
          format(ngram_range, len(cv.vocabulary_)))
```

```
Vocabulary size (1, 1) (min_df=4): 26907
Vocabulary size (1, 2) (min_df=4): 153673
Vocabulary size (1, 3) (min_df=4): 248752
Vocabulary size (1, 4) (min_df=4): 280226
```

In [58]:
```
cv = CountVectorizer(ngram_range=(1, 4)).fit(text_train)
print("Vocabulary size 1-4gram: {}".format(len(cv.vocabulary_)))
```

```
Vocabulary size 1-4gram: 7773845
```

In [59]:
```
cv = CountVectorizer(ngram_range=(1, 2), min_df=4).fit(text_train)
print("Vocabulary size (1, 2), min_df=4: {}".format(len(cv.vocabulary_)))
cv = CountVectorizer(ngram_range=(1, 2), min_df=4, \
                     stop_words="english").fit(text_train)
print("Vocabulary size (1, 2), stopwords, min_df=4: {}".\
      format(len(cv.vocabulary_)))
```

```
Vocabulary size (1, 2), min_df=4: 153673
Vocabulary size (1, 2), stopwords, min_df=4: 78373
```

In [60]:
```
cv4 = CountVectorizer(ngram_range=(4, 4), min_df=4).fit(text_train)
cv4sw = CountVectorizer(ngram_range=(4, 4), min_df=4,\
                        stop_words="english").fit(text_train)
print(len(cv4.get_feature_names()))
print(len(cv4sw.get_feature_names()))
```

```
31474
372
```

In [61]:
```
print(cv4.get_feature_names()[::1000])
```

```
['10 for this movie', 'and even then you', 'anyone familiar with the', 'bad bu
t this is', 'but the ending is', 'devil knows you re', 'faithful to the book',
'for what it really', 'has the feel of', 'if they had been', 'in the movie can
', 'is not love song', 'it is far from', 'just one of the', 'material to work
with', 'my big fat greek', 'of the actors have', 'on so many levels', 'perform
ance in this film', 'seem like they re', 'take it too seriously', 'the action
scenes are', 'the film succeeds in', 'the movie would have', 'the time and pla
ce', 'thirds of the way', 'this movie when it', 'to go see this', 'took me by
surprise', 'was trying to make', 'which is why the', 'you can tell they']
```

In [62]:
```
print(cv4sw.get_feature_names()[::10])
```

```
['10 year old boy', 'academy award best picture', 'alison parker cristina rain
es', 'bad acting bad special', 'best movies ve seen', 'burt reynolds dom delui
se', 'church jesus christ day', 'dauphine university paris pantheon', 'doc sav
age man bronze', 'don say didn warn', 'douglas fairbanks william hart', 'fast
times ridgemont high', 'film worst film seen', 'gave great supporting role', '
harris arden patrick wilson', 'jacques coulardeau university paris', 'john roo
ney paul newman', 'la maman et la', 'like texas chainsaw massacre', 'low budge
t horror flick', 'makes movie worth watching', 'morning sunday night monday',
'movie great story great', 'movie ve seen years', 'mystery science theater 300
0', 'palm springs international film', 'pierce brosnan greg kinnear', 'product
ion design spectacular costumes', 'really looking forward seeing', 'robert sta
ck dorothy malone', 'saw movie years ago', 'sky captain world tomorrow', 'stor
y doesn make sense', 'total waste time money', 've seen long time', 'walter ma
tthau george burns', 'won golden globe best', 'wrong place wrong time']
```

In [63]:
```
bla = cv4sw.transform(text_train)
```

In [64]:
```
print(np.array(cv4sw.get_feature_names())\
      [np.argsort(np.array(bla.sum(axis=0)).\
                  ravel())[::-1][:50]])
```

```
['worst movie ve seen' 'worst movies ve seen' '40 year old virgin'
 'mystery science theater 3000' 've seen long time' 'don waste time money'
 'worst film ve seen' 'best movies ve seen' 'worst films ve seen'
 'don waste time watching' 'jean claude van damme'
 'really wanted like movie' 'lose friends alienate people'
 'don think ve seen' 'toronto international film festival'
 'just doesn make sense' 'let face music dance' 've seen ve seen'
 'bad bad bad bad' 'fred astaire ginger rogers' 'vote seven title brazil'
 'trey parker matt stone' 'just didn make sense'
 'santa claus conquers martians' 'rock roll high school'
 'don say didn warn' 'crouching tiger hidden dragon' 'best movie ve seen'
 'mystery science theatre 3000' 'maman et la putain' 'la maman et la'
 'low budget horror films' 'don make mistake did'
 'night evelyn came grave' 'according dvd sleeve synopsis'
 'peter cushing christopher lee' 'movies ve seen long'
 'won academy award best' 'left cutting room floor'
 'movie complete waste time' 've seen better acting'
 'really wanted like film' 'story doesn make sense' 'low budget sci fi'
 'saw movie years ago' 'low budget horror movies'
 'saturday night friday night' 'james van der beek'
 'looking forward seeing movie' 'robert blake scott wilson']
```

In [65]:
```
pd.Series("".join(cv4sw.get_feature_names()).\
          split()).value_counts()[:10]
```

Out[65]:
```
ve       32
seen     30
movie    17
bad      16
good     13
waste    12
time     12
worst    11
make     11
best     10
dtype: int64
```

In [71]:
```
pd.Series(str(cv4sw.get_feature_names()).\
          split()).value_counts()[:10]
```

Out[71]:
```
ve         32
seen       30
seen',     24
'movie     21
movie      17
bad        16
movie',    16
'don       13
good       13
waste      12
dtype: int64
```

In [72]:
```
vect3 = CountVectorizer(ngram_range=(1, 3), min_df=4)
X_train3 = vect3.fit_transform(text_train)
```

In [73]:
```
lr3 = LogisticRegression().fit(X_train3, y_train)
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
<ipython-input-73-dd55f1a29f73> in <module>
----> 1 lr3 = LogisticRegressionCV().fit(X_train3, y_train)

NameError: name 'LogisticRegressionCV' is not defined
```

In [ ]:
```
lr3.C_
```

In [ ]:
```
X_val3 = vect3.transform(text_val)
lr3.score(X_val3, y_val)
```

In [ ]:
```
plt.figure(figsize=(15, 4))
plot_important_features(lr3.coef_.ravel(),\
    np.array(vect3.get_feature_names()), top_n=40, rotation=70)
plt.title("Stopwords included (1-3 gram)")
plt.savefig("images/stopwords_1.png")
```

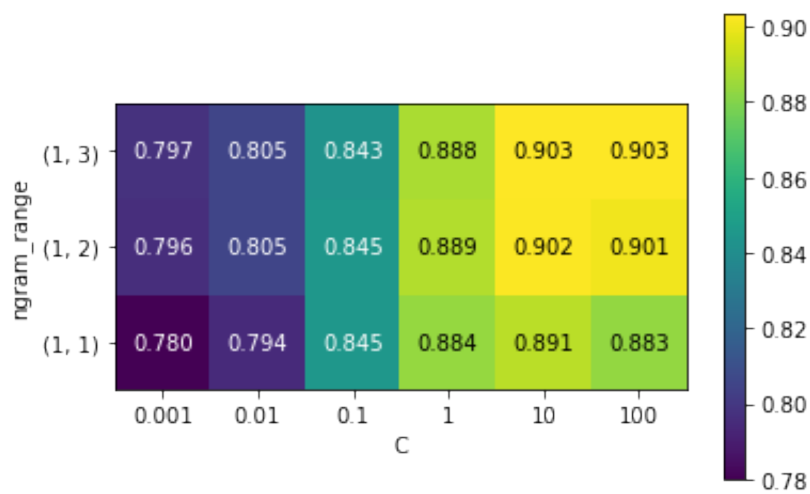
Let’s try out the TfidfVectorizer on the IMDb movie review data and find the best setting of n-gram range using a grid search: (n_gram_range is a tuple consisting of min and max number of words in a token) Single words capture a lot of info. Upto 5 is considerable but increasing the max increases the features

In [74]:
```
pipe = make_pipeline(TfidfVectorizer(min_df=5), LogisticRegression())
param_grid = {"logisticregression__C": [0.001, 0.01, 0.1, 1, 10, 100],
              "tfidfvectorizer__ngram_range": [(1, 1), (1, 2), (1, 3)]}
grid = GridSearchCV(pipe, param_grid, cv=5)
grid.fit(text_train, y_train)
print("Best cross-validation score: {:.2f}".format(grid.best_score_))
print("Best parameters:\n{}".format(grid.best_params_))
```

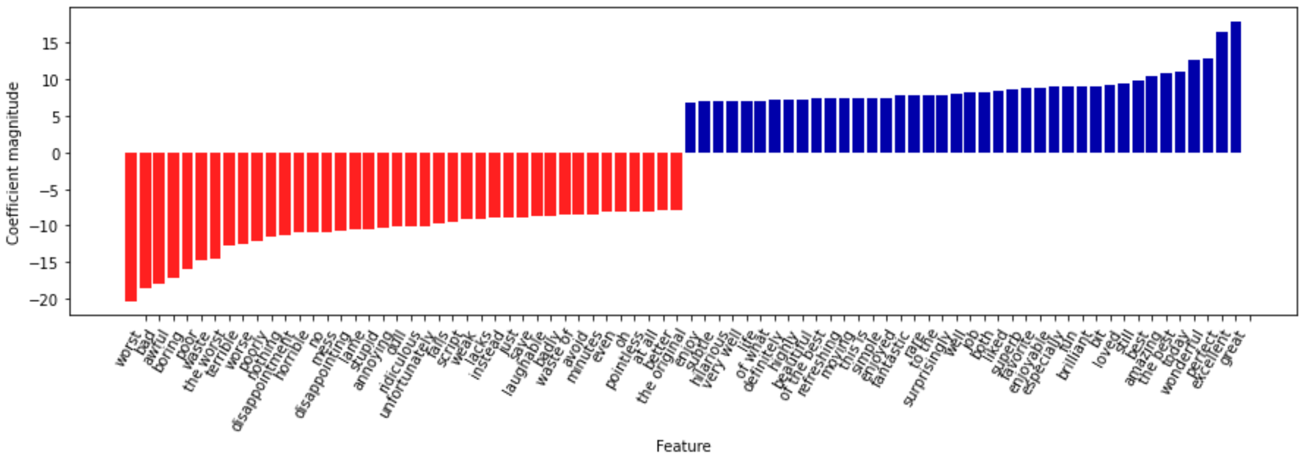
```
Best cross-validation score: 0.90
Best parameters:
{'logisticregression__C': 100, 'tfidfvectorizer__ngram_range': (1, 3)}
```

Performance increase a bit more by adding bigram and trigram features. Let's visualise the cross-validation accuracy as a function of the ngram_range and C parameter as a heatmap.

In [76]:
```
from matplotlib import pyplot as plt
import mglearn
# extract scores from grid_search
scores = grid.cv_results_['mean_test_score'].reshape(-1, 3).T # visualize hea
heatmap = mglearn.tools.heatmap(
        scores, xlabel="C", ylabel="ngram_range", cmap="viridis", fmt="%.3f",
        xticklabels=param_grid['logisticregression__C'],
        yticklabels=param_grid['tfidfvectorizer__ngram_range'])
plt.colorbar(heatmap);
```



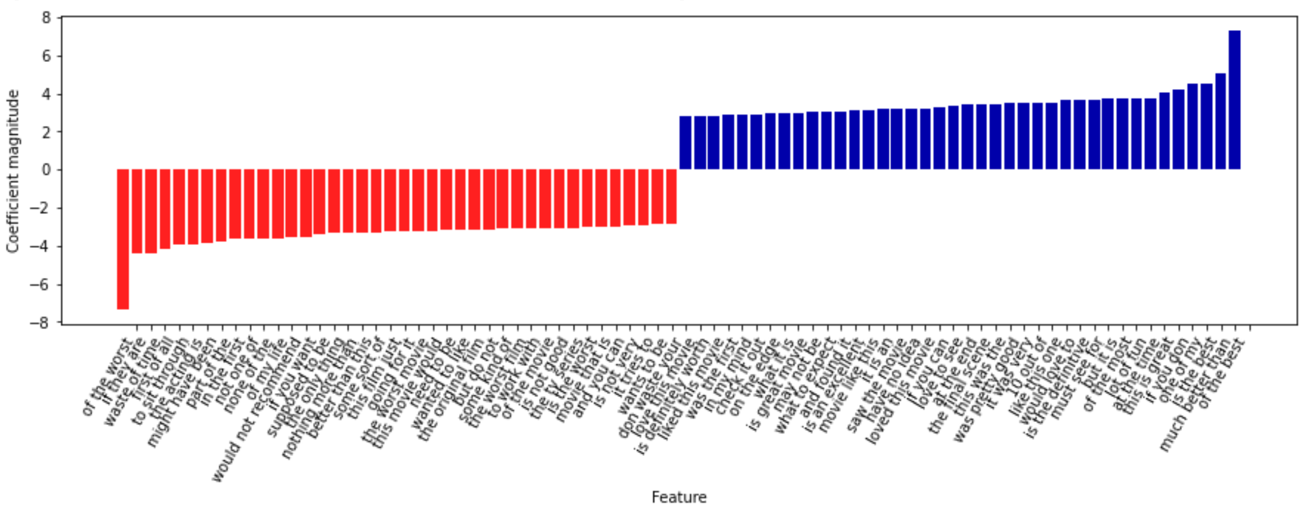
In [77]:
```python
# extract feature names and coefficients
vect = grid.best_estimator_.named_steps['tfidfvectorizer']
feature_names = np.array(vect.get_feature_names())
coef = grid.best_estimator_.named_steps\
['logisticregression'].coef_\
mglearn.tools.visualize_coefficients
(coef, feature_names, n_top_features=40)
```



Next, let's visualise only trigrams

In [78]:
```python
 # find 3-gram features
mask = np.array([len(feature.split(" ")) for feature in feature_names]) == 3
print(mask)
# visualize only 3-gram features
mglearn.tools.visualize_coefficients\
(coef.ravel()[mask],feature_names[mask], n_top_features=40)
```

```
[False False False ... False False False]
```



Tokenization, Stemming, Lemmatization

- Stemming : dropping common suffixes
- Lemmatization : a known dictionary is applied to get the root of the word (was, were -> be) Both methods are known as normalization of the text data
- Spelling correction is also another way of normalization
- scikit-learn does NOT implement text normalization

In [79]:
```
#python -m spacy download en
```

https://docs.python.org/3/howto/regex.html#regex-howto

In [80]:
```
import spacy
import nltk

# load spacy's English-language models
en_nlp = spacy.load('en')

# instantiate nltk's Porter stemmer
stemmer = nltk.stem.PorterStemmer()

# define function to compare lemmatization in spacy with stemming in nltk
def compare_normalization(doc):
    # tokenize document in spacy
    doc_spacy = en_nlp(doc)
    # print lemmas found by spacy
    print("Lemmatization:")
    print([token.lemma_ for token in doc_spacy])
    # print tokens found by Porter stemmer
    print("Stemming:")
    print([stemmer.stem(token.norm_.lower()) for token in doc_spacy])
```

In [81]:
```
compare_normalization(u"Our meeting today was worse than yesterday, "
                       "I'm scared of meeting the clients tomorrow.")
```

```
Lemmatization:
['-PRON-', 'meeting', 'today', 'be', 'bad', 'than', 'yesterday', ',', '-PRON-'
, 'be', 'scared', 'of', 'meet', 'the', 'client', 'tomorrow', '.']
Stemming:
['our', 'meet', 'today', 'wa', 'wors', 'than', 'yesterday', ',', 'i', 'am', 's
care', 'of', 'meet', 'the', 'client', 'tomorrow', '.']
```

(?...) This is an extension notation (a '?' following a '(' is not meaningful otherwise). The first character after the '?' determines what the meaning and further syntax of the construct is. Extensions usually do not create a new group; (?P...) is the only exception to this rule. Following are the currently supported extensions. (?iLmsux) (One or more letters from the set 'i', 'L', 'm', 's', 'u', 'x'.) The group matches the empty string; the letters set the corresponding flags: re.I (ignore case), re.L (locale dependent), re.M (multi-line), re.S (dot matches all), re.U (Unicode dependent), and re.X (verbose), for the entire regular expression. (The flags are described in Module Contents.) This is useful if you wish to include the flags as part of the regular expression, instead of passing a flag argument to the re.compile() function.

Note that the (?x) flag changes how the expression is parsed. It should be used first in the expression string, or after one or more whitespace characters. If there are non-whitespace characters before the flag, the results are undefined.

In [82]:

```
# Technicality: we want to use the regexp-based tokenizer
# that is used by CountVectorizer and only use the lemmatization
# from spacy. To this end, we replace en_nlp.tokenizer (the spacy tokenizer)
# with the regexp-based tokenization.
import re
import spacy

# regexp used in CountVectorizer
# (?u) means unicode dependent
# esc sequence is repeated twice for the python interpreter to recognize
# \b is for word boundaries
# \w\w+ is for two or more words
regexp = re.compile('(?u)\\b\\w\\w+\\b')

# load spacy language model and save old tokenizer
en_nlp = spacy.load('en')
old_tokenizer = en_nlp.tokenizer
# replace the tokenizer with the preceding regexp
en_nlp.tokenizer = lambda string: old_tokenizer.tokens_from_list(
        regexp.findall(string))

# create a custom tokenizer using the spacy document processing pipeline
# (now using our own tokenizer)
def custom_tokenizer(document):
    #doc_spacy = en_nlp(document, entity=False, parse=False)
    doc_spacy = en_nlp(document)
    return [token.lemma_ for token in doc_spacy]

# define a count vectorizer with the custom tokenizer
lemma_vect = CountVectorizer(tokenizer=\
                             custom_tokenizer, min_df=5)
```

Let's transform the data and inspect the vocabulary size:

In [83]:
```
# transform text_train using CountVectorizer with lemmatization
X_train_lemma = lemma_vect.fit_transform(text_train)
print("X_train_lemma.shape: {}".format(X_train_lemma.shape))
# standard CountVectorizer for reference
vect = CountVectorizer(min_df=5).fit(text_train)
X_train = vect.transform(text_train)
print("X_train.shape: {}".format(X_train.shape))
```

```
X_train_lemma.shape: (18750, 19047)
X_train.shape: (18750, 23692)
```

Lemmatization reduced the number of features to 21571. Lemmatization can be seen as a kind of regularization, as it conflates certain features. Therefore, we expect lemmatization to improve performance most when the dataset is small.

During data splitting operations, train_test_split represents random sampling while StratifiedShuffleSplit represents Stratified Sampling. This is a sampling technique that is best used when a statistical population can easily be broken down into distinctive sub-groups. Then samples are taken from each sub-groups based on the ratio of the sub groups size to the total population. On the other hand, Random sampling is ideal when there is not much information about a population or when the data is diverse and not easily grouped.

In [84]:
```
# build a grid search using only 1% of the data as the training set
from sklearn.model_selection import StratifiedShuffleSplit

param_grid = {'C': [0.001, 0.01, 0.1, 1, 10]}
cv = StratifiedShuffleSplit(n_splits=5, test_size=0.99,
                                train_size=0.01, random_state=0)
grid = GridSearchCV(LogisticRegression(), param_grid, cv=cv)
# perform grid search with standard CountVectorizer
grid.fit(X_train, y_train)
print("Best cross-validation score "
"(standard CountVectorizer): {:.3f}".format(grid.best_score_))
# perform grid search with lemmatization
grid.fit(X_train_lemma, y_train)
print("Best cross-validation score "
      "(lemmatization): {:.3f}".format(grid.best_score_))
```

```
Best cross-validation score (standard CountVectorizer): 0.685
Best cross-validation score (lemmatization): 0.694
```

In this case, lemmatization provided a modest improvement in performance.

Latent Dirichlet Allocation

In [ ]:
```
vect = CountVectorizer(max_features=10000, max_df=.15)
X = vect.fit_transform(text_train)
from sklearn.decomposition import LatentDirichletAllocation
lda = LatentDirichletAllocation(n_components=10, learning_method="batch",
        max_iter=25, random_state=0)
# We build the model and transform the data in one step
# Computing transform takes some time,
# and we can save time by doing both at once
document_topics = lda.fit_transform(X)
```

In [ ]:
```
lda.components_.shape
```

In [ ]:
```
# For each topic (a row in the components_), sort the features (ascending) #
sorting = np.argsort(lda.components_, axis=1)[:, ::-1]
# Get the feature names from the vectorizer
feature_names = np.array(vect.get_feature_names())
# Print out the 10 topics:
mglearn.tools.print_topics(topics=range(10),\
feature_names=feature_names,\
sorting= sorting, topics_per_chunk=5, n_words=10)
```

Next, we will learn another model, this time with 100 topics. Using more topics makes the analysis much harder, but makes it more likely that topics can specialize to interesting subsets of the data:

In [ ]:
```
lda100 = LatentDirichletAllocation(n_components=100,\
learning_method="batch",max_iter=25, random_state=0)
document_topics100 = lda100.fit_transform(X)
```

Instead of looking at all the topics, let us look at some of them.

In [ ]:
```
topics = np.array([7, 16, 24, 25, 28, 36, 37, 45, 51, 53, 54, 63, 89, 97])
sorting = np.argsort(lda100.components_, axis=1)[:, ::-1]
feature_names = np.array(vect.get_feature_names())
mglearn.tools.print_topics(topics=topics,\
feature_names=feature_names,sorting=sorting,\
    topics_per_chunk=7, n_words=20)
```

Let’s check which kinds of reviews are assigned to this topic:

In [ ]:
```
# sort by weight of "music" topic 45
music = np.argsort(document_topics100[:, 45])[::-1]
# print the five documents where the topic is most important
for i in music[:10]:
    # pshow first two sentences
    print(b".".join(text_train[i].split(b".")[:2]) + b".\n")
```

In [ ]:
```
fig, ax = plt.subplots(1, 2, figsize=(10, 10))
topic_names = ["{:>2} ".format(i) + " ".join(words)
for i, words in enumerate(\
feature_names[sorting[:, :2]])] # two column bar chart:
for col in [0, 1]:
    start=col*50
    end=(col+1)*50
    ax[col].barh(np.arange(50), \
    np.sum(document_topics100, axis=0)[start:end])
    ax[col].set_yticks(np.arange(50))
    ax[col].set_yticklabels(topic_names[start:end], ha="left", va="top")
    ax[col].invert_yaxis()
    ax[col].set_xlim(0, 2000)
    yax = ax[col].get_yaxis()
    yax.set_tick_params(pad=130)
plt.tight_layout()
```

SpaCy tutorial

https://nlpforhackers.io/complete-guide-to-spacy/

In [ ]:
```
import spacy
nlp = spacy.load('en')
doc = nlp('Hello     World!')
for token in doc:
    print('"' + token.text + '"', token.idx)
```

NLTK vs spaCY

Notice the index preserving tokenization in action. Rather than only keeping the words, spaCy keeps the spaces too. This is helpful for situations when you need to replace words in the original text or add some annotations. With NLTK tokenization, there’s no way to know exactly where a tokenized word is in the original raw text. spaCy preserves this “link” between the word and its place in the raw text.

Nltk was for research purposes. Nltk supports various languages, spaCy supports 7 languages with NER. Nltk is a string processing library. spaCy uses OO. In sentence tokenization, nltk outperforms spaCy. in word tokenization and POS-tagging spaCy performs better,

spaCy has support for word vectors. nltk does not.

In [ ]:
```
nlp = spacy.load('en_core_web_lg')
print(nlp.vocab['banana'].vector)
```

In [ ]:
```
import en_core_web_sm
nlp = en_core_web_sm.load()
```

In [ ]:
```
from sklearn.feature_extraction.text import CountVectorizer
corpus = [
     'This is the first document.',
     'This document is the second document.',
     'And this is the third one.',
     'Is this the first document?',
 ]
vectorizer = CountVectorizer()
X = vectorizer.fit_transform(corpus)
print(vectorizer.get_feature_names())
print(vectorizer.vocabulary_)
```

In [ ]: