Assessing Product Recommendation Likelihood

May 11, 2018

1 The dataset consists of Women's fashion online shop reviews, consisting of a title, a review text, and whether the review author would recommend the product. The goal is to determine whether a reviewer will recommend a product or not based on review title and review. Such a classifier can help find out what is good or bad about certain products or to highlight more relevant reviews (like a very critical and a very positive one) about certain products.

```
In [1]: import numpy as np
        import scipy.io as sc
        import pandas as pd
        from sklearn.linear_model import LogisticRegression
        from sklearn.model_selection import GridSearchCV
        from sklearn.model_selection import train_test_split
        from sklearn.pipeline import make_pipeline
        import matplotlib.pyplot as plt
        from sklearn.preprocessing import Normalizer
        from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer
        %matplotlib inline
```

1.1 1. Data loading and pre-processing

```
In [2]: trainDat = pd.read_csv("data_train.csv")
        testDat = pd.read_csv("data_test.csv")
```

```
In [3]: print(trainDat.shape)
        print(testDat.shape)
```

```
(17614, 3)
(5872, 3)
```

```
In [4]: trainDat.head(n=10)
```

```
Out[4]:                          Title  \
        0        Beautiful unique dress
```

```
1         Had high hopes but...
2     Buttons -buttons so cute!
3              Love this dress
4         Perfect summer pants!
5                    Too bulky
6                      Love it
7  Beautiful drape, very deep v
8                          NaN
9       Awkward length in front

                                              Review  Recommended
0  Wore this to my sons wedding. found it last mi...            1
1  Gals, if you absolutely must have this top wai...            0
2  I hardly believe i have not reviewed htis yet...            1
3  This dress is so cute and comfortable. i'm nor...            1
4  The linen- cotton blend breathes so well for a...            1
5  I like the quality of material of this top but...            0
6  Great top. i got the size 4 but i ordered a 6 ...            1
7  I bought this yesterday and love it. it drapes...            1
8  The design of the pant hangs nicely and fit,well,            1
9  It seems like most people love this tee, so yo...            0
```

In [5]:
```
trainDat.columns
```

Out[5]:
```
Index(['Title', 'Review', 'Recommended'], dtype='object')
```

In [6]:
```
#Dropping any rows with missing information (with respect to any of the three columns)
trainDatNew = trainDat.dropna(axis=0,how='any')
trainDatNew.shape
```

Out[6]:
```
(14762, 3)
```

In [7]:
```
text_train_title = trainDatNew['Title'].tolist()
text_train_review = trainDatNew['Review'].tolist()
```

In [8]:
```
text_train_title[:5]
```

Out[8]:
```
['Beautiful unique dress',
 'Had high hopes but...',
 'Buttons -buttons so cute!',
 'Love this dress',
 'Perfect summer pants!']
```

In [9]:
```
text_train_review[:5]
```

Out[9]:
```
['Wore this to my sons wedding. found it last minute when i had changed my mind about a
 "Gals, if you absolutely must have this top wait for it to go on sale (don't worry, if
 'I hardly believe i have not reviewed htis yet... so i tried it on in the sotre and wa
 "This dress is so cute and comfortable. i'm normally a 0 or 2 and the xs is plenty roo
 "The linen- cotton blend breathes so well for a hot summer day! the design on the wais
```

In [10]:
```
typesList = []
for a,b in zip(text_train_title,text_train_review):
    typePair = (type(a),type(b))
    typesList.append(typePair)
typesList[:5]
```

Out[10]:
```
[(str, str), (str, str), (str, str), (str, str), (str, str)]
```

In [11]:
```
text_train_title_review = [a+" "+b for a,b in
                           zip(text_train_title,text_train_review)]
text_train_title_review[:5]
```

Out[11]:
```
['Beautiful unique dress Wore this to my sons wedding. found it last minute when i had
 "Had high hopes but... Gals, if you absolutely must have this top wait for it to go o
 'Buttons -buttons so cute! I hardly believe i have not reviewed htis yet... so i trie
 "Love this dress This dress is so cute and comfortable. i'm normally a 0 or 2 and the
 "Perfect summer pants! The linen- cotton blend breathes so well for a hot summer day
```

In [12]:
```
y_train = trainDatNew['Recommended']
trainDatNew = trainDatNew.drop(columns=['Recommended'])
```

In [13]:
```
#check if any value missing in training labels
print(y_train.isnull().values.any())
print(len(y_train))
```

```
False
14762
```

In [14]:
```
testDatNew = testDat.dropna(axis=0,how='any')
testDatNew.shape
```

Out[14]:
```
(4913, 3)
```

In [15]:
```
testDatNew.columns
```

Out[15]:
```
Index(['Title', 'Review', 'Recommended'], dtype='object')
```

In [16]:
```
y_test = testDatNew['Recommended']
testDatNew = testDatNew.drop(columns=['Recommended'])
text_test_title = testDatNew['Title'].tolist()
text_test_review = testDatNew['Review'].tolist()
```

In [17]:
```
print(len(y_test))
```

```
4913
```

In [18]:
```
text_test_title_review = [a+" "+b for a,b in
                          zip(text_test_title,text_test_review)]
text_test_title_review[:5]
```

```
Out[18]: ['Perfect pair!! This pair of age stevie capris is everything that i could want in a p
          "Talk about creature comforts! This is a beautifully designed jacket that everyone wi
          'So comfotable I ordered this dress in 0p since i am 5ft. it fits great its not too s
          'Love this cozy sweater Cozy and nice quality. great fit and runs true to size. could
          "Don't miss this top This is a great top and worth the money. nice flow to it, soft m
```

1.2 2. Basic Model Building and Evaluation

1.2.1 Model building without GridSearchCV

Evaluation Using `Title` field only

```
In [19]: vect1 = CountVectorizer()
         X_train_title = vect1.fit_transform(text_train_title)
         X_val_title = vect1.transform(text_test_title)
         print(len(vect1.get_feature_names()))
```

```
3219
```

```
In [20]: X_train_title

Out[20]: <14762x3219 sparse matrix of type '<class 'numpy.int64'>'
                 with 47745 stored elements in Compressed Sparse Row format>
```

```
In [21]: feature_names_title = vect1.get_feature_names()
         print(feature_names_title[:10])
         print(feature_names_title[1000:1010])
         print(feature_names_title[::500])
```

```
['00', '10', '100', '12', '14', '150', '16', '16s', '1950', '1960s']
['farm', 'farrah', 'fashion', 'fashionable', 'fast', 'fat', 'fatal', 'fav', 'fave', 'favorite']
['00', 'chests', 'farm', 'kick', 'petites', 'slit', 'use']
```

```
In [22]: from sklearn.linear_model import LogisticRegressionCV
         lr1 = LogisticRegressionCV(scoring='roc_auc').fit(X_train_title, y_train)

In [23]: lr1.C_

Out[23]: array([2.7825594])

In [24]: lr1.score(X_val_title, y_test)

Out[24]: 0.8827600244249949

In [25]: def plot_important_features(coef, feature_names, top_n=20,
                                     ax=None, rotation=60):
             if ax is None:
                 ax = plt.gca()
             inds = np.argsort(coef)
```

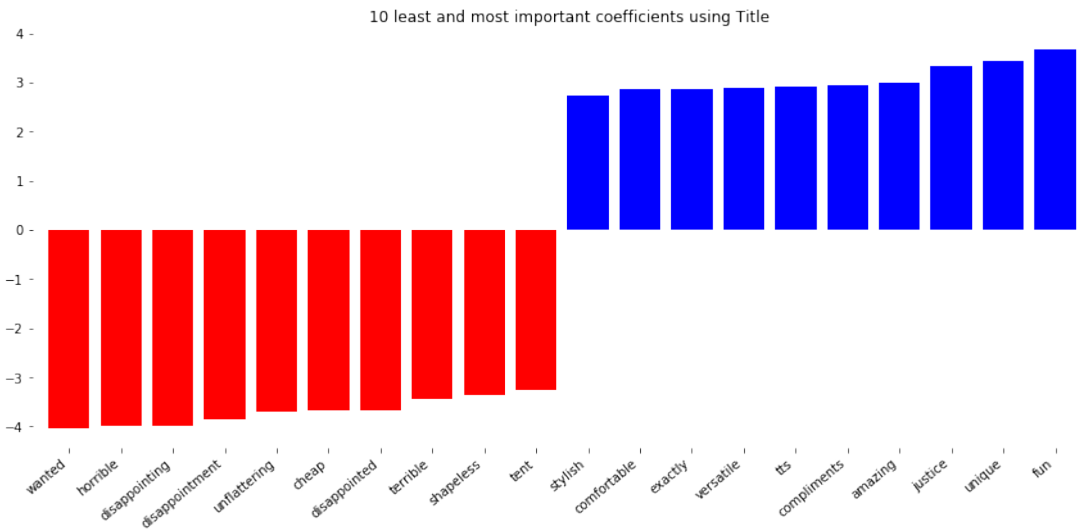
```
            low = inds[:top_n]
            high = inds[-top_n:]
            important = np.hstack([low, high])
            myrange = range(len(important))
            colors = ['red'] * top_n + ['blue'] * top_n

            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 [26]: %%time
         from sklearn.model_selection import cross_val_score
         bow_pipe_title = make_pipeline(CountVectorizer(),
                                        LogisticRegressionCV(scoring='roc_auc'))
         print(cross_val_score(bow_pipe_title, text_train_title,
                               y_train, cv=5, scoring='roc_auc'))
```

```
[0.91901162 0.9244011  0.91295734 0.92318662 0.92155286]
CPU times: user 12.2 s, sys: 119 ms, total: 12.3 s
Wall time: 12.8 s
```

```
In [27]: bow_pipe_title.fit(text_train_title,y_train)

         lr_title = bow_pipe_title.named_steps['logisticregressioncv']
         feature_names_title = np.array(bow_pipe_title
                                        .named_steps['countvectorizer']
                                        .get_feature_names())
         #n_classes_title = len(lr_title.classes_)
```

```
In [28]: plt.figure(figsize=(15, 6))
         plot_important_features(lr_title.coef_.ravel(),
                                 np.array(feature_names_title),
                                 top_n=10, rotation=40)
         ax = plt.gca()
         plt.title("10 least and most important coefficients using Title")
         plt.show()
```




```
In [29]: cv_title = bow_pipe_title.named_steps['countvectorizer']
         X_train_title = cv_title.transform(text_train_title)
         X_val_title = cv_title.transform(text_test_title)
         lr_title.score(X_val_title, y_test)
```

```
Out[29]: 0.8827600244249949
```

```
In [30]: print(X_train_title.shape)
         print(len(feature_names_title))
```

```
(14762, 3219)
3219
```

Evaluation using `Review` field only

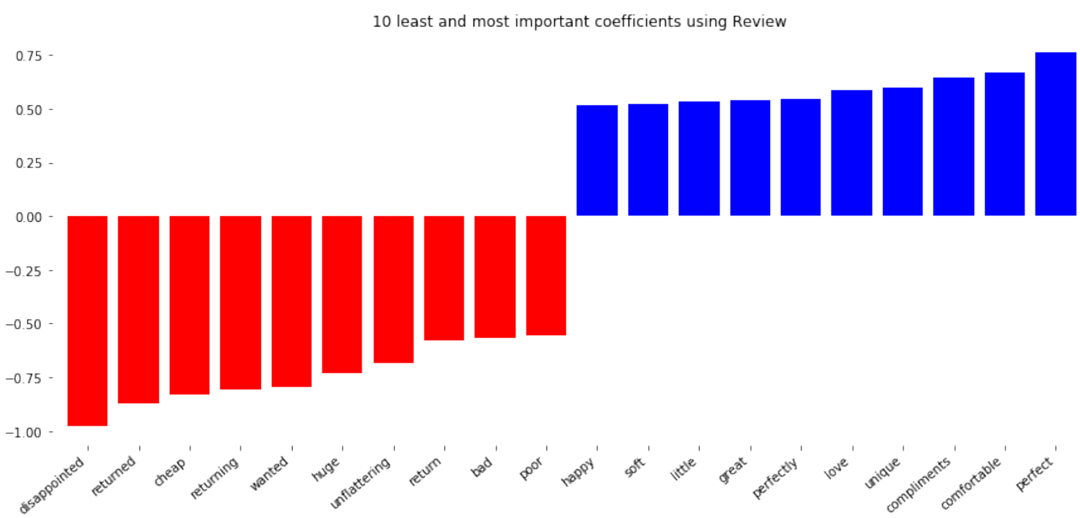
```
In [31]: %%time
         bow_pipe_review = make_pipeline(CountVectorizer(),
                                         LogisticRegressionCV(scoring='roc_auc'))
         print(cross_val_score(bow_pipe_review, text_train_review,
                               y_train, cv=5, scoring='roc_auc'))
```

```
[0.92095963 0.9270255  0.9173906  0.92501866 0.92596217]
CPU times: user 1min 11s, sys: 1.33 s, total: 1min 12s
Wall time: 39.9 s
```

```
In [32]: bow_pipe_review.fit(text_train_review,y_train)

         lr_review = bow_pipe_review.named_steps['logisticregressioncv']
```

```
feature_names_review = np.array(bow_pipe_review
                                .named_steps['countvectorizer']
                                .get_feature_names())
```

In [33]:
```
plt.figure(figsize=(15, 6))
plot_important_features(lr_review.coef_.ravel(),
                        np.array(feature_names_review),
                        top_n=10, rotation=40)
ax = plt.gca()
plt.title("10 least and most important coefficients using Review")
plt.show()
```



In [34]:
```
cv_review = bow_pipe_review.named_steps['countvectorizer']
X_train_review = cv_review.transform(text_train_review)
X_val_review = cv_review.transform(text_test_review)
lr_review.score(X_val_review, y_test)
```

Out[34]: 0.8843883574190922

In [35]:
```
print(X_train_review.shape)
print(len(feature_names_review))
```

```
(14762, 12041)
12041
```

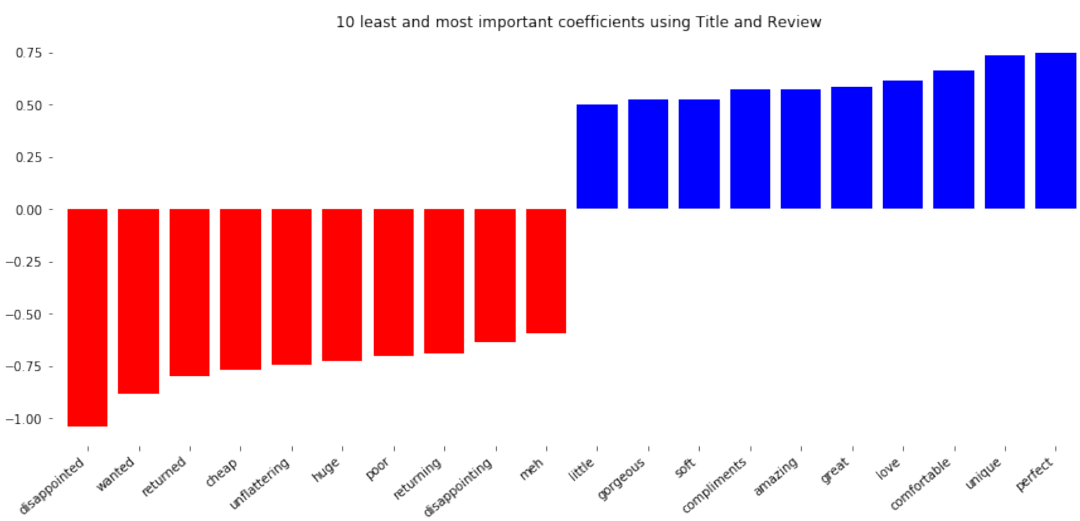
Evaluation using `Title` and `Review` fields

In [36]:
```
%%time
bow_pipe_title_review = make_pipeline(CountVectorizer(),
                                      LogisticRegressionCV(scoring='roc_auc'))
cross_val_score(bow_pipe_title_review, text_train_title_review,
                y_train, cv=5, scoring='roc_auc')
```

```
CPU times: user 1min 19s, sys: 1.82 s, total: 1min 21s
Wall time: 46.4 s
```

```
In [37]: bow_pipe_title_review.fit(text_train_title_review,y_train)

         lr_title_review = bow_pipe_title_review.named_steps['logisticregressioncv']
         feature_names_title_review = np.array(bow_pipe_title_review
                                              .named_steps['countvectorizer']
                                              .get_feature_names())
```

```
In [38]: plt.figure(figsize=(15, 6))
         plot_important_features(lr_title_review.coef_.ravel(),
                                 np.array(feature_names_title_review),
                                 top_n=10, rotation=40)
         ax = plt.gca()
         plt.title("10 least and most important coefficients using Title and Review")
         plt.show()
```




```
In [39]: cv_title_review = bow_pipe_title_review.named_steps['countvectorizer']
         X_train_title_review = cv_title_review.transform(text_train_title_review)
         X_val_title_review = cv_title_review.transform(text_test_title_review)
         lr_title_review.score(X_val_title_review, y_test)

Out[39]: 0.8963973132505597
```

```
In [40]: print(X_train_title_review.shape)
         print(len(feature_names_title_review))

(14762, 12515)
12515
```

Vectorizing `Title` and `Review` individually and concatenating the vector representations

```
In [41]: from scipy.sparse import hstack

         feature_names_title_new = [feat+"_t" for feat in feature_names_title]
         print(feature_names_title_new[:10])

         feature_names_review_new = [feat+"_r" for feat in feature_names_review]
         print(feature_names_review_new[:10])
```

```
['00_t', '10_t', '100_t', '12_t', '14_t', '150_t', '16_t', '16s_t', '1950_t', '1960s_t']
['00_r', '00p_r', '03_r', '03dd_r', '04_r', '06_r', '0dd_r', '0in_r', '0p_r', '0petite_r']
```

```
In [42]: print(X_train_title.shape)
         print(X_train_review.shape)
         X_train_title_review_concat = hstack([X_train_title,X_train_review])
         print(X_train_title_review_concat.shape)
```

```
(14762, 3219)
(14762, 12041)
(14762, 15260)
```

```
In [43]: %%time
         print(cross_val_score(LogisticRegressionCV(), X_train_title_review_concat,
                               y_train, cv=5, scoring='roc_auc'))
```

```
[0.9454991  0.94365854 0.93439082 0.94418817 0.94631581]
CPU times: user 1min 15s, sys: 1.36 s, total: 1min 16s
Wall time: 39.3 s
```

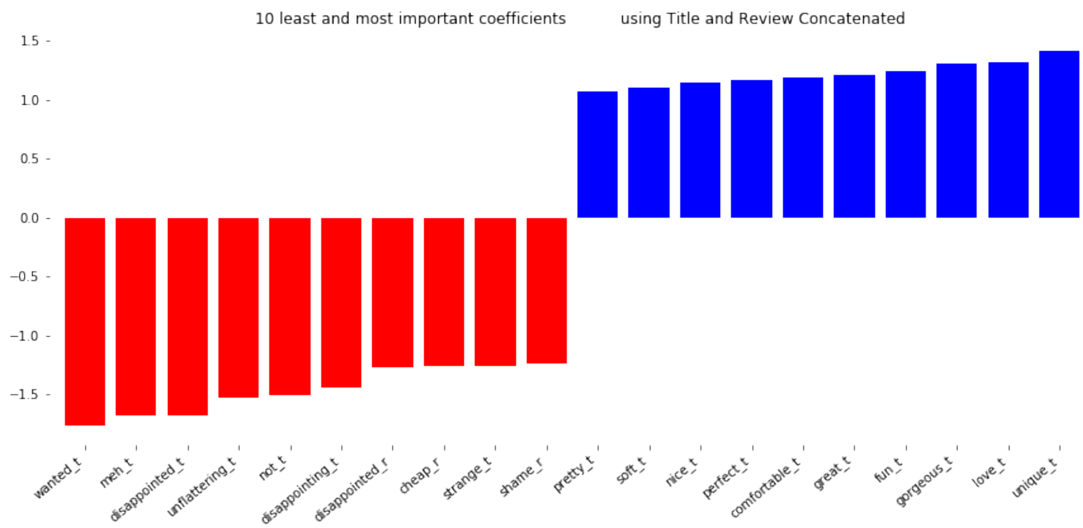
```
In [45]: feature_names_title_review_concat = feature_names_title_new + \
                                             feature_names_review_new
         print(len(feature_names_title_review_concat))
```

```
15260
```

```
In [46]: lr_title_review_concat = LogisticRegressionCV(scoring='roc_auc')
         lr_title_review_concat.fit(X_train_title_review_concat,y_train)
```

```
Out[46]: LogisticRegressionCV(Cs=10, class_weight=None, cv=None, dual=False,
                    fit_intercept=True, intercept_scaling=1.0, max_iter=100,
                    multi_class='ovr', n_jobs=1, penalty='l2', random_state=None,
                    refit=True, scoring='roc_auc', solver='lbfgs', tol=0.0001,
                    verbose=0)
```

```
In [47]: plt.figure(figsize=(15, 6))
         plot_important_features(lr_title_review_concat.coef_.ravel(),
                                 np.array(feature_names_title_review_concat),
                                 top_n=10, rotation=40)
         ax = plt.gca()
         plt.title("10 least and most important coefficients \
                   using Title and Review Concatenated")
         plt.show()
```




```
In [48]: print(X_val_title.shape)
         print(X_val_review.shape)
         X_val_title_review_concat = hstack([X_val_title,X_val_review])
         print(X_val_title_review_concat.shape)
```

```
(4913, 3219)
(4913, 12041)
(4913, 15260)
```

```
In [49]: lr_title_review_concat.score(X_val_title_review_concat,y_test)
```

```
Out[49]: 0.9037248117239975
```

1.2.2 With GridSearchCV

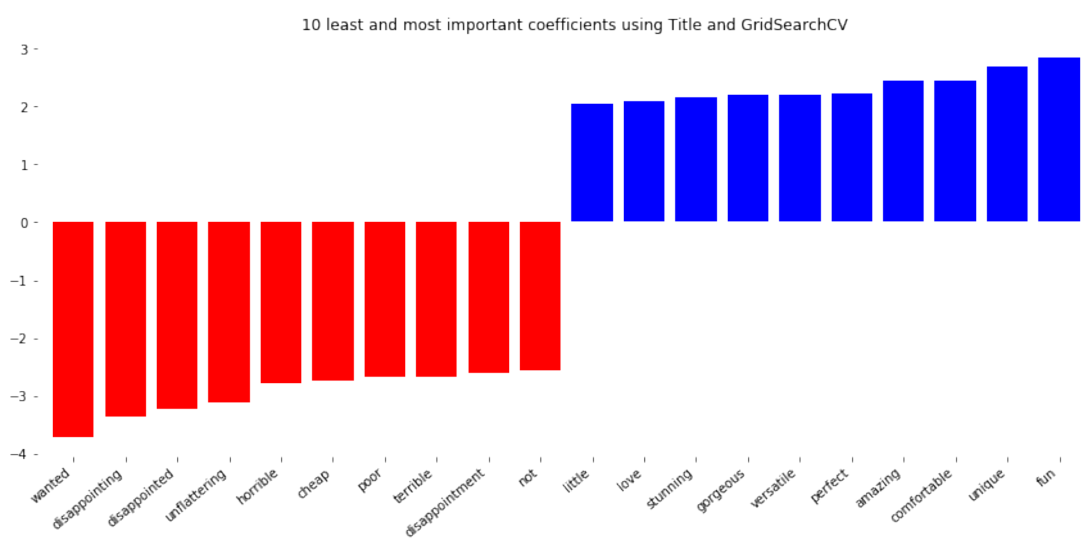
Evaluating using `Title` field only

```
In [50]: from sklearn.linear_model import LogisticRegression
```

In [53]:
```
%%time
param_grid_lr = {"logisticregression__C": [100, 10, 1, 0.1, 0.001]}
grid_title = GridSearchCV(make_pipeline(CountVectorizer(),
                                        LogisticRegression()),
                          param_grid=param_grid_lr, cv=5,
                          scoring="roc_auc")
grid_title.fit(text_train_title,y_train)

print(grid_title.best_score_)
print(grid_title.best_params_)

lr_title_grid = grid_title.best_estimator_.named_steps['logisticregression']
feature_names_title_grid = np.array(grid_title
                                    .best_estimator_
                                    .named_steps['countvectorizer']
                                    .get_feature_names())
```

```
0.9204469952584714
{'logisticregression__C': 1}
CPU times: user 5.12 s, sys: 60.5 ms, total: 5.18 s
Wall time: 5.22 s
```

In [54]:
```
plt.figure(figsize=(15, 6))
plot_important_features(lr_title_grid.coef_.ravel(),
                        np.array(feature_names_title_grid),
                        top_n=10, rotation=40)
ax = plt.gca()
plt.title("10 least and most important coefficients \
using Title and GridSearchCV")
plt.show()
```



In [55]:
```
print(grid_title.score(text_test_title,y_test))
```

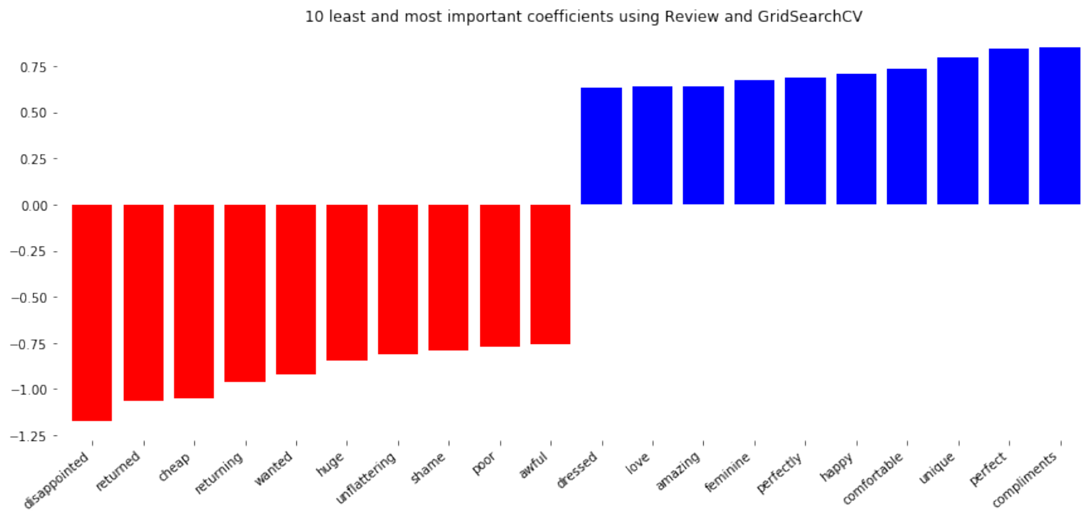
```
0.9214984071094153
```

Evaluating using `Review` field only

In [57]:
```
%%time
grid_review = GridSearchCV(make_pipeline(CountVectorizer(),
                                         LogisticRegression()),
                           param_grid=param_grid_lr, cv=5,
                           scoring="roc_auc")
grid_review.fit(text_train_review,y_train)

print(grid_review.best_score_)
print(grid_review.best_params_)

lr_review_grid = grid_review.best_estimator_.named_steps['logisticregression']
feature_names_review_grid = np.array(grid_review
                                     .best_estimator_
                                     .named_steps['countvectorizer']
                                     .get_feature_names())
```

```
0.9237641674362176
{'logisticregression__C': 0.1}
CPU times: user 1min 17s, sys: 1.75 s, total: 1min 19s
Wall time: 57.8 s
```

In [58]:
```
plt.figure(figsize=(15, 6))
plot_important_features(lr_review_grid.coef_.ravel(),
                        np.array(feature_names_review_grid),
                        top_n=10, rotation=40)
ax = plt.gca()
plt.title("10 least and most important coefficients using \
Review and GridSearchCV")
plt.show()
```




```
In [59]: print(grid_review.score(text_test_review,y_test))
```

```
0.9221417324054474
```

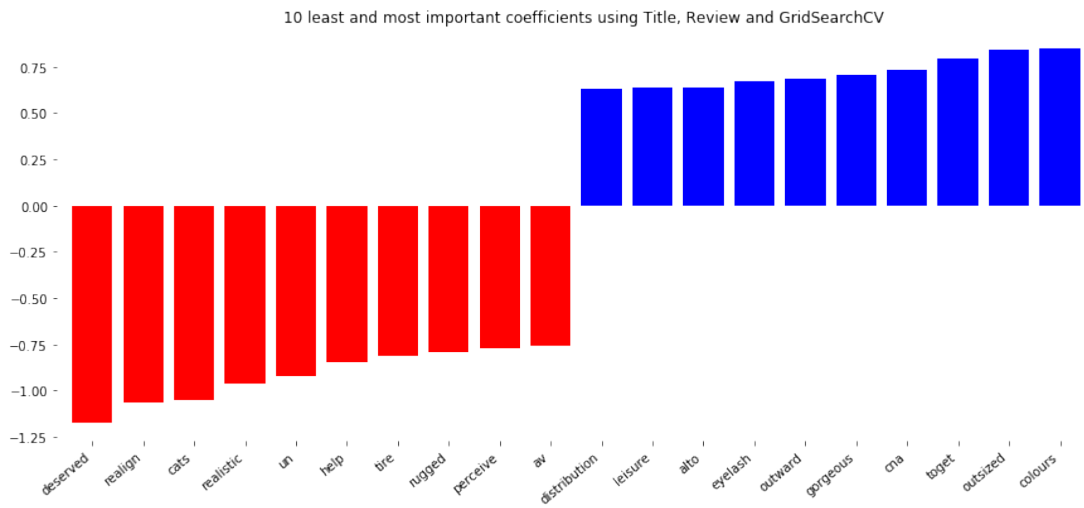
Evaluating using `Title` and `Review`

```
In [60]: %%time
         grid_title_review = GridSearchCV(make_pipeline(CountVectorizer(),
                                                        LogisticRegression()),
                                          param_grid=param_grid_lr, cv=5,
                                          scoring="roc_auc")
         grid_title_review.fit(text_train_title_review,y_train)

         print(grid_title_review.best_score_)
         print(grid_title_review.best_params_)

         lr_title_review_grid = grid_title_review.best_estimator_.named_steps['logisticregress
         feature_names_title_review_grid = np.array(grid_title_review
                                                    .best_estimator_
                                                    .named_steps['countvectorizer']
                                                    .get_feature_names())
```

```
0.9424097253719665
{'logisticregression__C': 0.1}
CPU times: user 1min 14s, sys: 1.69 s, total: 1min 16s
Wall time: 56.7 s
```

```
In [61]: plt.figure(figsize=(15, 6))
         plot_important_features(lr_review_grid.coef_.ravel(),
```

```
                              np.array(feature_names_title_review_grid),
                              top_n=10, rotation=40)
ax = plt.gca()
plt.title("10 least and most important coefficients \
using Title, Review and GridSearchCV")
plt.show()
```




```
In [62]: print(grid_title_review.score(text_test_title_review,y_test))
```

```
0.9388955774186873
```

Vectorizing `Title` and `Review` individually and concatenating the vector representations

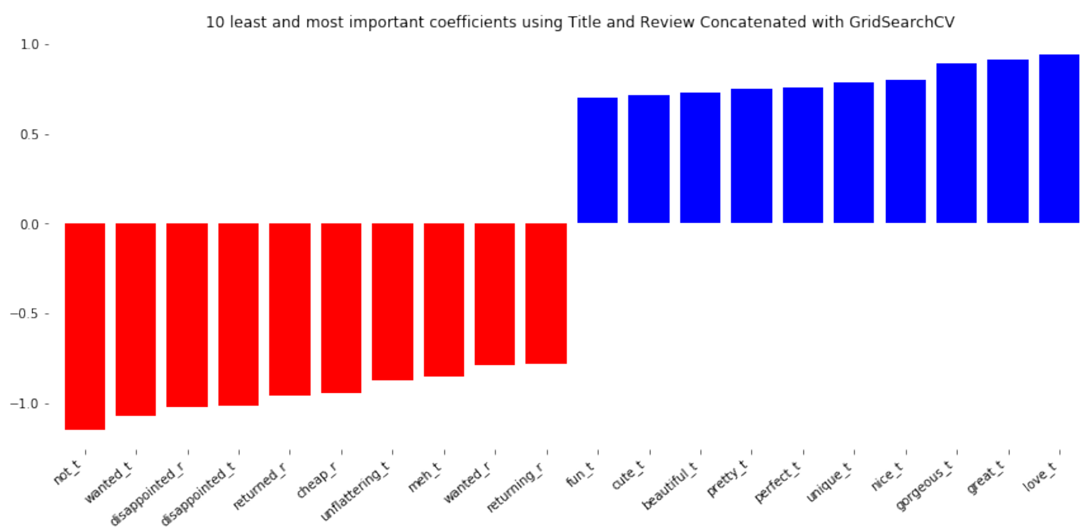
```
In [63]: cv_title_grid = grid_title.best_estimator_.named_steps['countvectorizer']
         cv_review_grid = grid_review.best_estimator_.named_steps['countvectorizer']
         X_train_title_grid = cv_title_grid.transform(text_train_title)
         X_train_review_grid = cv_review_grid.transform(text_train_review)
         X_train_title_review_concat_grid = hstack([X_train_title_grid,
                                                    X_train_review_grid])

         X_val_title_grid = cv_title_grid.transform(text_test_title)
         X_val_review_grid = cv_review_grid.transform(text_test_review)
         X_val_title_review_concat_grid = hstack([X_val_title_grid,
                                                  X_val_review_grid])
```

```
In [67]: feature_names_title_grid_new = [feat+"_t" for
                                         feat in feature_names_title_grid]
         feature_names_review_grid_new = [feat+"_r" for
                                          feat in feature_names_review_grid]
         feature_names_title_review_concat_grid = feature_names_title_grid_new + \
                                                  feature_names_review_grid_new
```

```
In [68]: %%time
         param_grid_lr_new = {"C": [100, 10, 1, 0.1, 0.001]}
         grid_title_review_concat = GridSearchCV(LogisticRegression(),
                                                 param_grid=param_grid_lr_new,
                                                 cv=5, scoring="roc_auc")
         grid_title_review_concat.fit(X_train_title_review_concat_grid,y_train)

         lr_title_review_grid_concat = grid_title_review_concat.best_estimator_
         print(grid_title_review_concat.best_score_)
         print(grid_title_review_concat.best_params_)
```

```
0.9436040159028604
{'C': 0.1}
CPU times: user 35 s, sys: 966 ms, total: 35.9 s
Wall time: 20.7 s
```

```
In [69]: plt.figure(figsize=(15, 6))
         plot_important_features(lr_title_review_grid_concat.coef_.ravel(),
                                 np.array(feature_names_title_review_concat_grid),
                                 top_n=10, rotation=40)
         ax = plt.gca()
         plt.title("10 least and most important coefficients using \
         Title and Review Concatenated with GridSearchCV")
         plt.show()
```




```
In [70]: print(grid_title_review_concat.score(X_val_title_review_concat_grid,
                                              y_test))
```

```
0.9431201401345355
```

The 4th setting which is vectorizing title and reviews individually and concatenating them works the best marginally. The best regularization parameter (C) for this setting is 0.1.

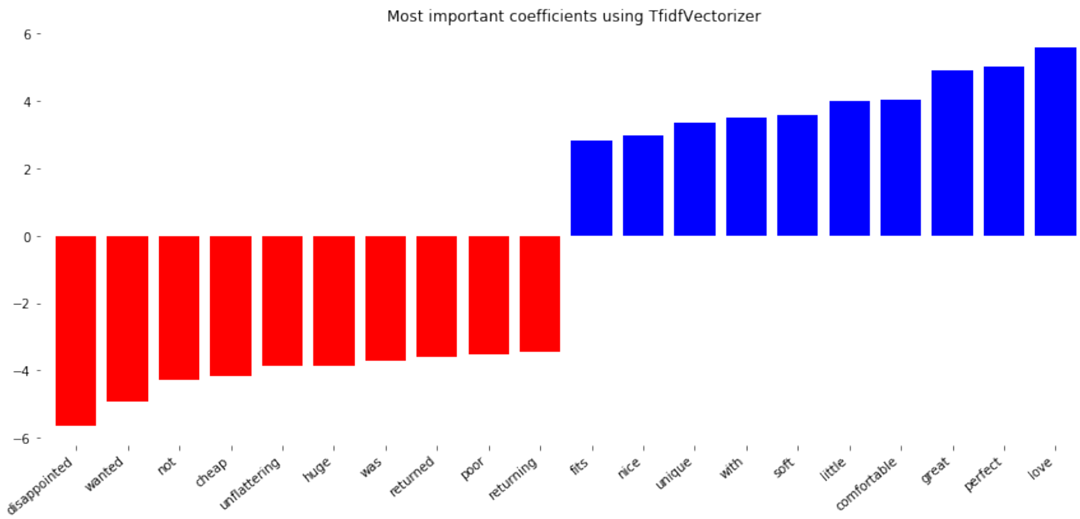
1.3 3. Feature Tuning

Using `TfidfVectorizer` to check its impact on model score and importance coefficients

```
In [72]: %%time
         param_grid_lr = {"logisticregression__C": [100, 10, 1, 0.1, 0.001]}
         grid_tfidf = GridSearchCV(make_pipeline(TfidfVectorizer(),
                                                 LogisticRegression()),
                                   param_grid=param_grid_lr, cv=5,
                                   scoring="roc_auc")
         grid_tfidf.fit(text_train_title_review,y_train)

         print(grid_tfidf.best_score_)
         print(grid_tfidf.best_params_)

         lr_tfidf = grid_tfidf.best_estimator_.named_steps['logisticregression']
         feature_names_tfidf = np.array(grid_tfidf.best_estimator_
                                        .named_steps['tfidfvectorizer']
                                        .get_feature_names())
```

```
0.9498551621199149
{'logisticregression__C': 1}
CPU times: user 48 s, sys: 1.23 s, total: 49.2 s
Wall time: 42.5 s
```

```
In [73]: plt.figure(figsize=(15, 6))
         plot_important_features(lr_tfidf.coef_.ravel(),
                                 np.array(feature_names_tfidf),
                                 top_n=10, rotation=40)
         ax = plt.gca()
         plt.title("Most important coefficients using TfidfVectorizer")
         plt.show()
```




```
In [74]: print(grid_tfidf.score(text_test_title_review,y_test))
```

```
0.9454635538445706
```

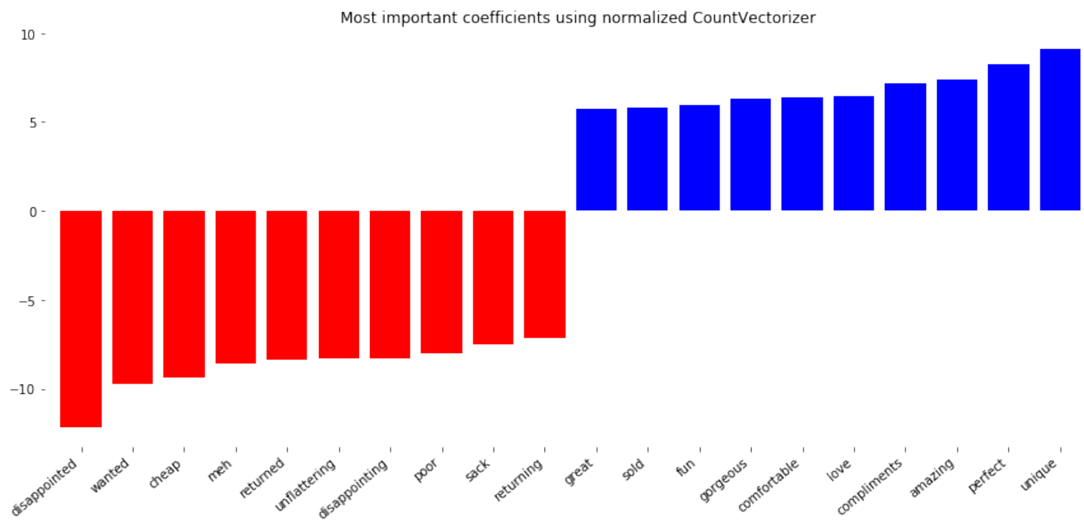
Using the TfidfVectorizer increases the test score to 0.945. Some of the important coefficients remain the same but the majority are changed.

Using a `CountVectorizer` with `Normalizer` to check impact on model performance

```
In [77]: grid_countvect_normalized = GridSearchCV(make_pipeline(CountVectorizer(),
                                                                 Normalizer(),
                                                                 LogisticRegression()),
                                                   param_grid=param_grid_lr, cv=5,
                                                   scoring="roc_auc")
         grid_countvect_normalized.fit(text_train_title_review,
                                       y_train)

         print(grid_countvect_normalized.best_score_)
         print(grid_countvect_normalized.best_params_)

         lr_countvect_normalized = grid_countvect_normalized\
         .best_estimator_\
         .named_steps['logisticregression']
         feature_names_countvect_normalized = np.array(grid_countvect_normalized
                                                      .best_estimator_
                                                      .named_steps['countvectorizer']
                                                      .get_feature_names())
```

```
0.9476031785092168
{'logisticregression__C': 10}
```

In [78]:
```
plt.figure(figsize=(15, 6))
plot_important_features(lr_countvect_normalized.coef_.ravel(),
                        np.array(feature_names_countvect_normalized),
                        top_n=10, rotation=40)
ax = plt.gca()
plt.title("Most important coefficients using \
normalized CountVectorizer")
plt.show()
```



In [79]:
```
print(grid_countvect_normalized.score(text_test_title_review,
                                      y_test))
```

```
0.9441320876438387
```

Using a Normalizer with CountVectorizer gives a worse performance than using a TfidfVectorizer but the performance improves compared to just using the CountVectorizer without the Normalizer.

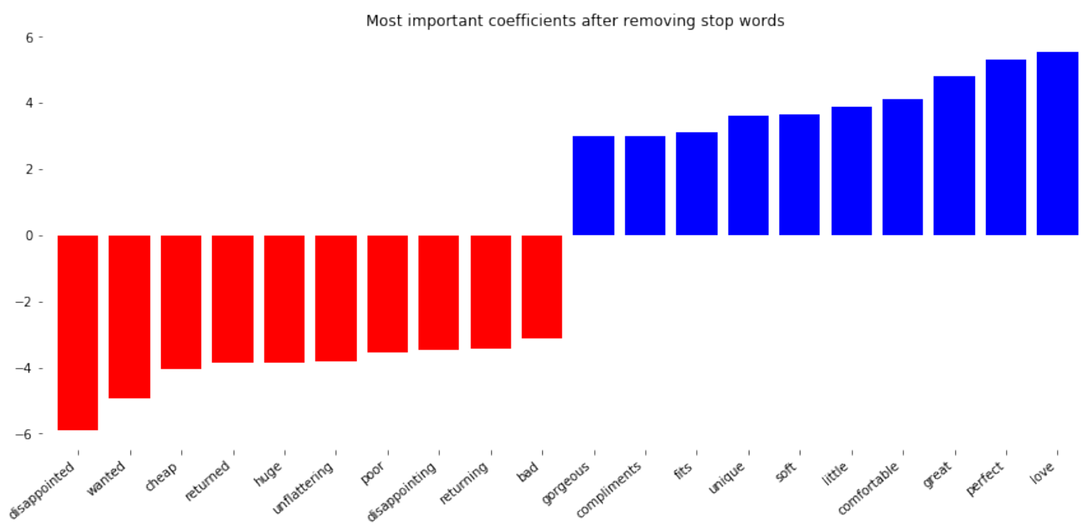
Removing `Stop Words` and checking impact on number of features and model performance

In [81]:
```
%%time
grid_tfidf_stop = GridSearchCV(make_pipeline(TfidfVectorizer(stop_words =
                                                             'english'),
                                             LogisticRegression()),
                               param_grid=param_grid_lr, cv=5,
                               scoring="roc_auc")
grid_tfidf_stop.fit(text_train_title_review,y_train)

print(grid_tfidf_stop.best_score_)
```

```
print(grid_tfidf_stop.best_params_)

lr_tfidf_stop = grid_tfidf_stop.best_estimator_.named_steps['logisticregression']
feature_names_tfidf_stop = np.array(grid_tfidf_stop
                                    .best_estimator_
                                    .named_steps['tfidfvectorizer']
                                    .get_feature_names())
```

```
0.9434995623247132
{'logisticregression__C': 1}
CPU times: user 40.4 s, sys: 805 ms, total: 41.2 s
Wall time: 35.9 s
```

In [82]:
```
plt.figure(figsize=(15, 6))
plot_important_features(lr_tfidf_stop.coef_.ravel(),
                        np.array(feature_names_tfidf_stop),
                        top_n=10, rotation=40)
ax = plt.gca()
plt.title("Most important coefficients after removing stop words")
plt.show()
```



In [83]:
```
print(grid_tfidf_stop.score(text_test_title_review,y_test))
```

```
0.9397407112735047
```

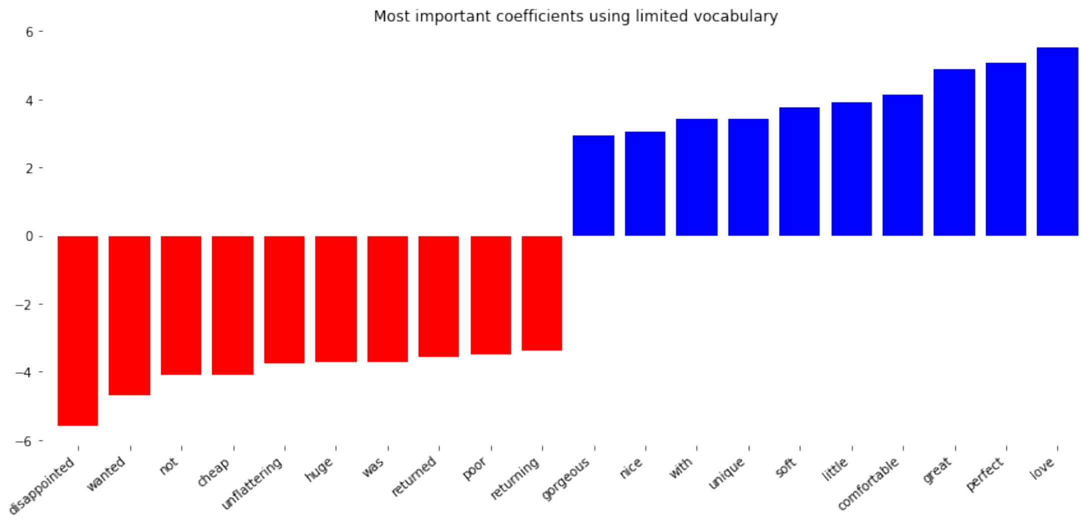
Standard english words as stop words don't help with the performance of the model. This is because stop words, by definition, are the most common words in english language and they will very likely be present across most documents. Since TfidfVectorizer is being used, the stop words will have less importance and hence removing them shouldn't affect the performance of the model too much. Another reason is that the total number of stop words are insignicant compared to total number of tokens.

Limiting Vocabulary using `min_df` or `max_df`

```
In [85]: %%time
         param_grid_lr_vocab = {"logisticregression__C": [100, 10, 1, 0.1, 0.001],
                                 "tfidfvectorizer__min_df": [0.00001, 0.0001, 0.001],
                                 "tfidfvectorizer__max_df": [0.5, 0.6, 0.7],
                               }

         #using pipeline memory option to decrease grid-search run-time
         grid_tfidf_vocab = GridSearchCV(make_pipeline(TfidfVectorizer(),
                                                       LogisticRegression(),
                                                       memory = 'cache_folder'),
                                         param_grid=param_grid_lr_vocab, cv=5,
                                         scoring="roc_auc", n_jobs = -1)
         grid_tfidf_vocab.fit(text_train_title_review,y_train)

         print(grid_tfidf_vocab.best_score_)
         print(grid_tfidf_vocab.best_params_)

         lr_tfidf_vocab = grid_tfidf_vocab.best_estimator_.named_steps['logisticregression']
         feature_names_tfidf_vocab = np.array(grid_tfidf_vocab
                                              .best_estimator_
                                              .named_steps['tfidfvectorizer']
                                              .get_feature_names())
```

```
0.9503769994060268
{'logisticregression__C': 1, 'tfidfvectorizer__max_df': 0.6, 'tfidfvectorizer__min_df': 0.0001
CPU times: user 4.26 s, sys: 2.15 s, total: 6.41 s
Wall time: 2min 45s
```

```
In [86]: plt.figure(figsize=(15, 6))
         plot_important_features(lr_tfidf_vocab.coef_.ravel(),
                                 np.array(feature_names_tfidf_vocab),
                                 top_n=10, rotation=40)
         ax = plt.gca()
         plt.title("Most important coefficients using limited vocabulary")
         plt.show()
```




```
In [87]: print(grid_tfidf_vocab.score(text_test_title_review,y_test))
```

```
0.9460682879220274
```

```
In [88]: print(len(feature_names_tfidf), len(feature_names_tfidf_vocab))
```

```
12515 7176
```

The number of features are decreased from 12515 to 7176 after using min_df = 0.0001 and max_df = 0.6 with the tfidf vectorizer. The score was improved by a significant amount after limiting vocabulary.

1.4 4. Using n-grams and assesing impact

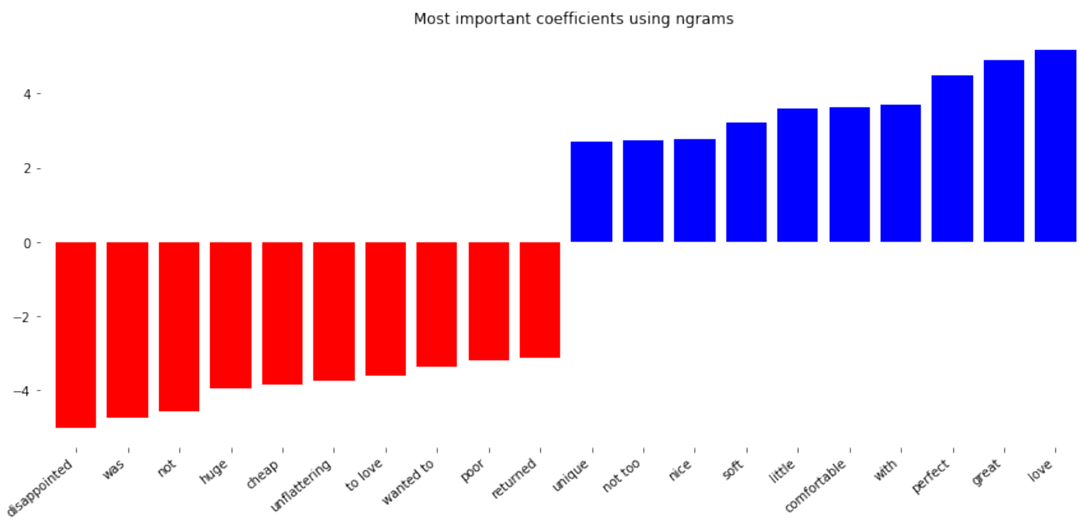
Using current best model, changing from unigrams to n-grams of varying length

```
In [89]: %%time
         param_grid_lr_ngrams = {"tfidfvectorizer__ngram_range": [(1,2),
                                                                   (1,3),
                                                                   (2,3)]}


         grid_tfidf_ngrams = GridSearchCV(make_pipeline(TfidfVectorizer(max_df = 0.6,
                                                                          min_df = 0.0001),
                                                         LogisticRegression(C = 1),
                                                         memory = 'cache_folder'),
                                           param_grid=param_grid_lr_ngrams, cv=5,
                                           scoring="roc_auc", n_jobs = -1)
         grid_tfidf_ngrams.fit(text_train_title_review,y_train)
```

```
print(grid_tfidf_ngrams.best_score_)
print(grid_tfidf_ngrams.best_params_)

lr_tfidf_ngrams = grid_tfidf_ngrams.best_estimator_.\
named_steps['logisticregression']
feature_names_tfidf_ngrams = np.array(grid_tfidf_ngrams.
                                      best_estimator_.
                                      named_steps['tfidfvectorizer'].
                                      get_feature_names())
```

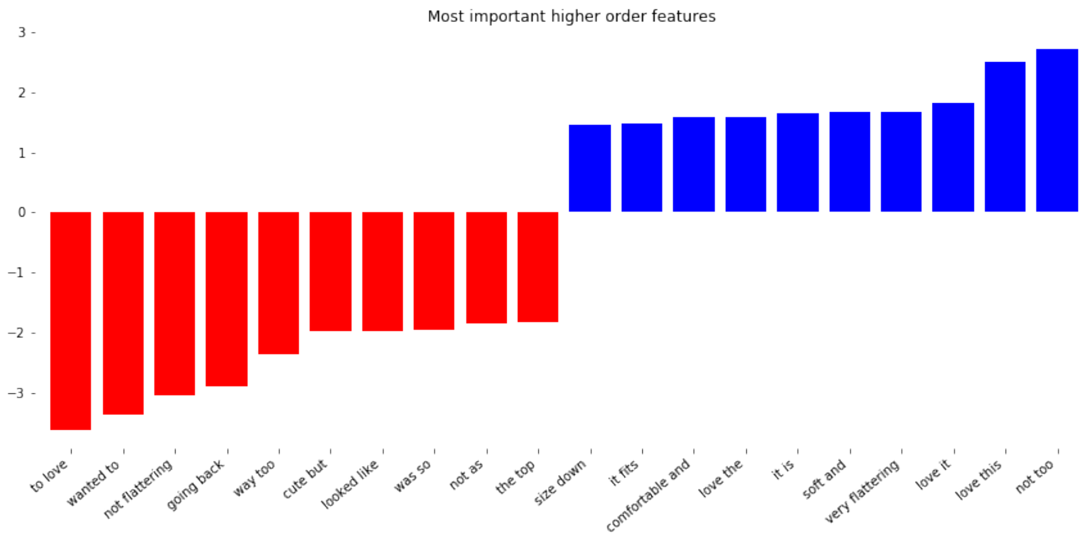
```
0.9534868951199252
{'tfidfvectorizer__ngram_range': (1, 2)}
CPU times: user 6.76 s, sys: 510 ms, total: 7.27 s
Wall time: 1min 35s
```

In [90]:
```
plt.figure(figsize=(15, 6))
plot_important_features(lr_tfidf_ngrams.coef_.ravel(),
                        np.array(feature_names_tfidf_ngrams),
                        top_n=10, rotation=40)
ax = plt.gca()
plt.title("Most important coefficients using ngrams")
plt.show()
```



In [91]:
```
features = pd.Series(feature_names_tfidf_ngrams)

plt.figure(figsize=(15, 6))
plot_important_features(np.array(pd.Series(lr_tfidf_ngrams
                                           .coef_.ravel())[features\
```

```
                                                      .str
                                                      .contains(' ')]),
                         np.array(features[features.str.contains(' ')]),
                         top_n=10, rotation=40)
ax = plt.gca()
plt.title("Most important higher order features")
plt.show()
```




```
In [92]: print(grid_tfidf_ngrams.score(text_test_title_review,y_test))
```

```
0.9518813149895486
```

The best performance is given my ngram_range = (1,2) with a test score of 0.952.

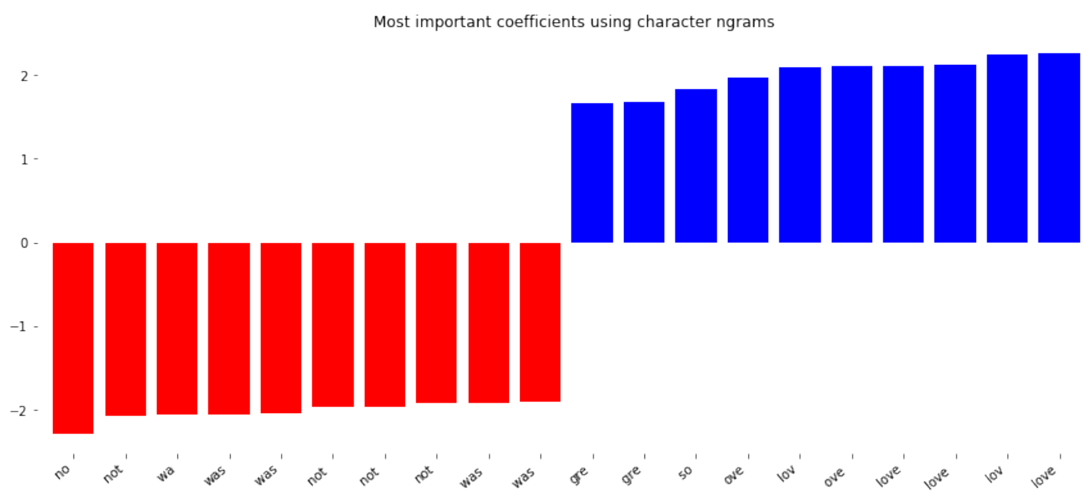
Using character n-grams and assesing impact

```
In [93]: %%time
         param_grid_lr_ngrams = {"tfidfvectorizer__ngram_range": [(2,5),
                                                                  (3,4),
                                                                  (3,5)]}


         grid_tfidf_ngrams_char = GridSearchCV(make_pipeline(TfidfVectorizer(max_df = 0.6,
                                                                              min_df = 0.0001,
                                                                              analyzer = 'char_
                                                             LogisticRegression(C = 1),
                                                             memory = 'cache_folder'),
                                                param_grid=param_grid_lr_ngrams,
```

```
                                            cv=5,scoring="roc_auc", n_jobs = -1)

        grid_tfidf_ngrams_char.fit(text_train_title_review,y_train)

        print(grid_tfidf_ngrams_char.best_score_)
        print(grid_tfidf_ngrams_char.best_params_)

        lr_tfidf_ngrams_char = grid_tfidf_ngrams_char.best_estimator_\
        .named_steps['logisticregression']
        feature_names_tfidf_ngrams_char = np.array(grid_tfidf_ngrams_char
                                                   .best_estimator_
                                                   .named_steps['tfidfvectorizer']
                                                   .get_feature_names())
```

```
0.9495127385389969
{'tfidfvectorizer__ngram_range': (3, 5)}
CPU times: user 15 s, sys: 991 ms, total: 16 s
Wall time: 3min 9s
```

```
In [94]: plt.figure(figsize=(15, 6))
         plot_important_features(lr_tfidf_ngrams_char.coef_.ravel(),
                                 np.array(feature_names_tfidf_ngrams_char),
                                 top_n=10, rotation=40)
         ax = plt.gca()
         plt.title("Most important coefficients using character ngrams")
         plt.show()
```




```
In [95]: print(grid_tfidf_ngrams_char.score(text_test_title_review,y_test))
```

```
0.9449816477316109
```

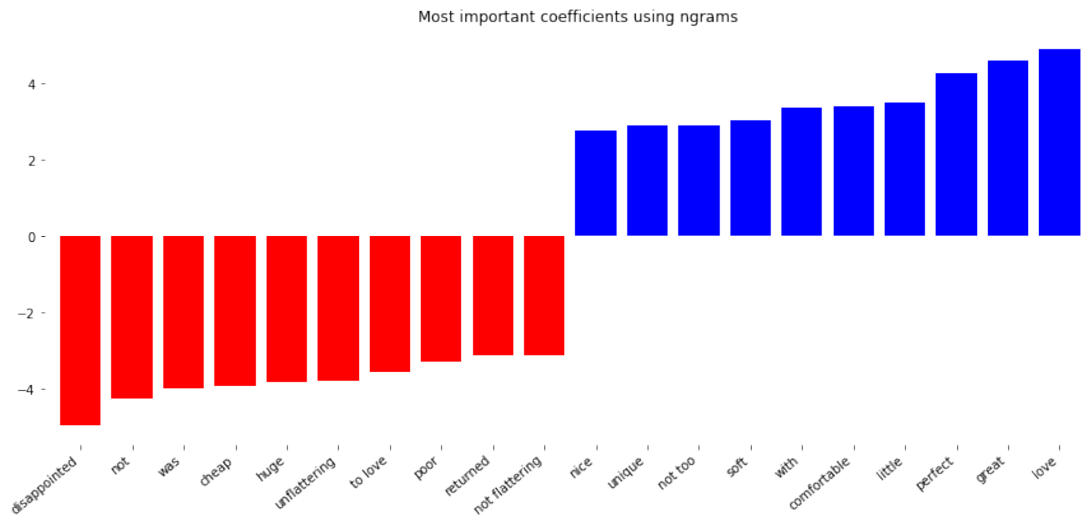
Even after using character n-grams, it is observed that most important features are usually whole words and they are similar to the features in word n-gram. `char_wb` is the analyzer used so as to respect the word boundaries of the character windows.

Investigating impact of `stop words` and `min-df` on word `n-grams`

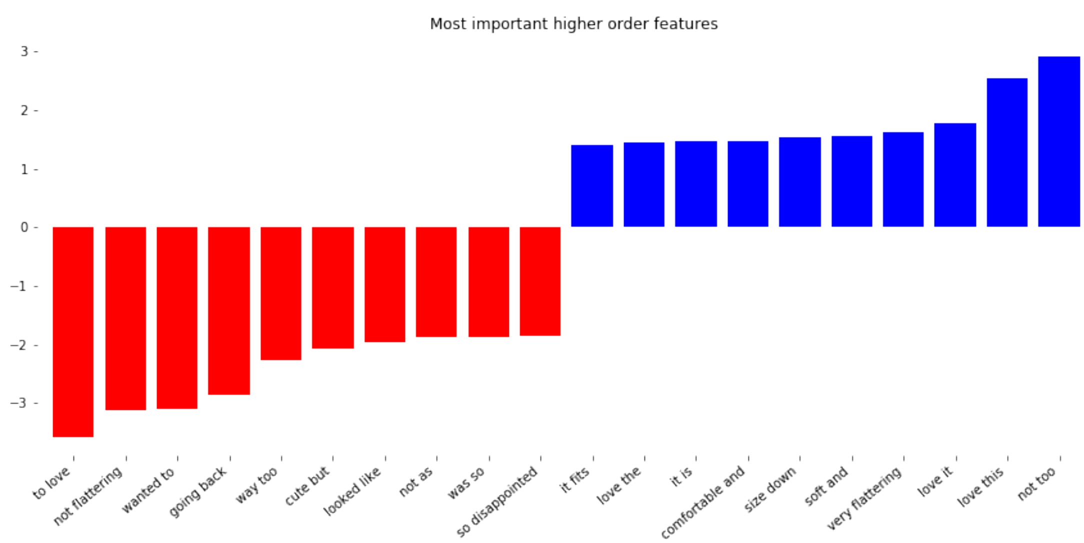
```
In [98]: param_grid_lr_ngrams = {"tfidfvectorizer__min_df": [0.00001,
                                                          0.0001,
                                                          0.001,
                                                          0.1],
                                "tfidfvectorizer__stop_words": ['english',
                                                                None]}

         grid_tfidf_ngrams = GridSearchCV(make_pipeline(TfidfVectorizer(max_df = 0.6,
                                                                      ngram_range = (1,2)),
                                                       LogisticRegression(C = 1),
                                                       memory = 'cache_folder'),
                                         param_grid=param_grid_lr_ngrams, cv=5,
                                          scoring="roc_auc", n_jobs = -1)
         grid_tfidf_ngrams.fit(text_train_title_review,y_train)

         print(grid_tfidf_ngrams.best_score_)
         print(grid_tfidf_ngrams.best_params_)

         lr_tfidf_ngrams = grid_tfidf_ngrams.best_estimator_\
         .named_steps['logisticregression']
         feature_names_tfidf_ngrams = np.array(grid_tfidf_ngrams
                                               .best_estimator_
                                               .named_steps['tfidfvectorizer']
                                               .get_feature_names())
```

```
0.9539853060627546
{'tfidfvectorizer__min_df': 0.001, 'tfidfvectorizer__stop_words': None}
```

```
In [99]: plt.figure(figsize=(15, 6))
         plot_important_features(lr_tfidf_ngrams.coef_.ravel(),
                                 np.array(feature_names_tfidf_ngrams),
                                 top_n=10, rotation=40)
         ax = plt.gca()
         plt.title("Most important coefficients using ngrams")
         plt.show()
```




```
In [100]: features = pd.Series(feature_names_tfidf_ngrams)

          plt.figure(figsize=(15, 6))
          plot_important_features(np.array(pd.Series(lr_tfidf_ngrams.coef_.ravel())[features.st
                                  np.array(features[features.str.contains(' ')]),
                                  top_n=10, rotation=40)
          ax = plt.gca()
          plt.title("Most important higher order features")
          plt.show()
```




```
In [101]: print(grid_tfidf_ngrams.score(text_test_title_review,y_test))
```

```
0.9523242149245934
```

```
In [102]: len(features)
```

```
Out[102]: 10220
```

Removing stop words gives a slightly worse performance than keeping them. And the min_df = 0.001 gives the best score. The test score improved from 0.9518 to 0.9523. The total number of features are reduced from 12515 to 10220 after applying these transformations.

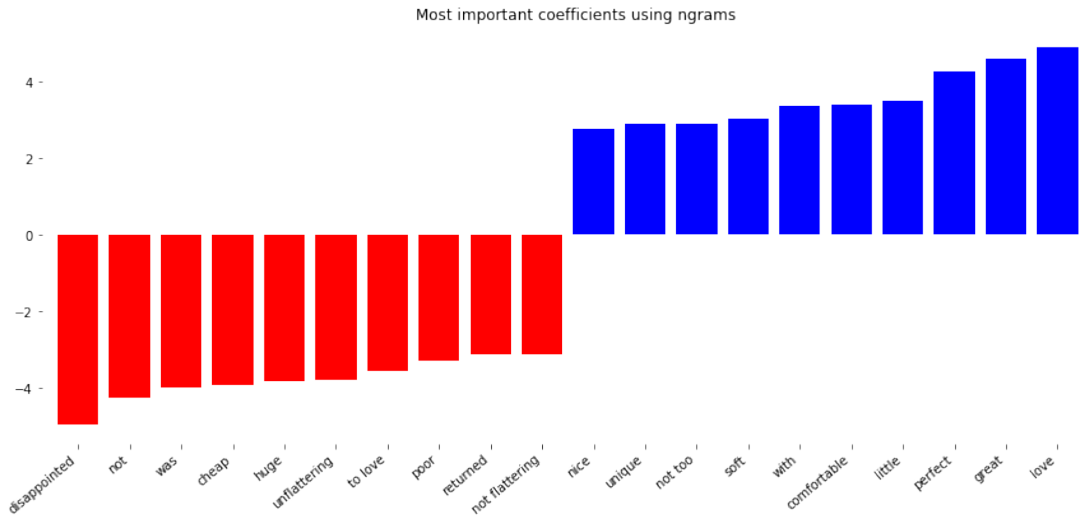
1.5 5. Comparing L1 and L2 penalty on best model from previous step

```
In [104]: param_grid_lr_ngrams = {"logisticregression__penalty": ['l1',
                                                                   'l2'],
                                 "logisticregression__C": [0.001,
                                                           0.01,
                                                           0.1,
                                                           1,
                                                           10,
                                                           100]}


          grid_tfidf_final = GridSearchCV(make_pipeline(TfidfVectorizer(max_df = 0.6,
                                                                     min_df = 0.001,
                                                                     ngram_range = (1,2)),
                                                       LogisticRegression(),
                                                      memory = 'cache_folder'),
                                          param_grid=param_grid_lr_ngrams,
                                          cv=5,scoring="roc_auc", n_jobs = -1)
          grid_tfidf_final.fit(text_train_title_review,y_train)

          print(grid_tfidf_final.best_score_)
          print(grid_tfidf_final.best_params_)

          lr_tfidf_final = grid_tfidf_final.best_estimator_\
          .named_steps['logisticregression']
          feature_names_tfidf_final = np.array(grid_tfidf_final
                                               .best_estimator_
                                               .named_steps['tfidfvectorizer']
                                               .get_feature_names())
```

```
0.9539853060627546
{'logisticregression__C': 1, 'logisticregression__penalty': 'l2'}
```

```
In [105]: plt.figure(figsize=(15, 6))
          plot_important_features(lr_tfidf_final.coef_.ravel(),
                                  np.array(feature_names_tfidf_final),
                                  top_n=10, rotation=40)
```

```python
ax = plt.gca()
plt.title("Most important coefficients using ngrams")
plt.show()
```




```python
In [106]: print(grid_tfidf_final.score(text_test_title_review,y_test))
```

```
0.9523242149245934
```

l2 penalty is better than l1 penalty for this model. Different regularization parameters are tried and it is found that `C`=0.1 is the best performing regularization parameter.

Other features that can be tried are: - Length of text - Number of *out-of-vocabulary* words - Using *sentiment* words - Presence and *frequency* of all *upper-case* words - Taking punctuation into account with character n-grams