In [1]:
```
# To add a new cell, type '# %%'
# To add a new markdown cell, type '# %% [markdown]'
# %% [markdown]
# # Feature Engineering, Baseline Model and Feature Selection
```

Import necessary dependencies

In [2]:
```
import pandas
from matplotlib import pyplot as plt
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.feature_extraction.text import CountVectorizer
import numpy
from sklearn.feature_selection import chi2
from PIL import Image
from collections import Counter
import re
import sqlite3
from sklearn import decomposition, ensemble
import nltk
from keras.preprocessing import text
from keras.utils import np_utils
from keras.preprocessing import sequence
import pydot
import seaborn as sns
from sklearn.metrics import precision_recall_curve # The average precision score in multi-label settings
from sklearn.metrics import average_precision_score
from sklearn import svm # Support Vector Machine
from sklearn.preprocessing import label_binarize # Split category encoding eg. y=[1,2,3] into y1=[0,1], y2=[0,1], y3=
[0,1]
from sklearn.model_selection import train_test_split # Built-in train test splitter
from sklearn.multiclass import OneVsRestClassifier # We use OneVsRestClassifier for multi-label prediction
from itertools import cycle
from sklearn.feature_selection import SelectPercentile, f_classif
```

```
Using TensorFlow backend.
```

Load in the data from the database

In [3]:
```
dbconn = sqlite3.connect('./data/cleanedtraintest_v2.db')
train_data_df = pandas.read_sql_query('SELECT * FROM train_data', dbconn)
test_data_df = pandas.read_sql_query('SELECT * FROM test_data', dbconn)
dbconn.commit()
dbconn.close()
```

Check the if the data was loaded correctly

In [4]:
```
train_data_df.head()
```

Out[4]:

	index	category	headline	content	headline_cleaned	content_cleaned	content_nosources
0	0	3	Wall St. Bears Claw Back Into the Black (Reuters)	Reuters - Short-sellers, Wall Street's dwindli...	wall bears claw back black	wall street seeing green	Short-sellers, Wall Street's dwindling\band ...
1	1	3	Carlyle Looks Toward Commercial Aerospace (Reu...	Reuters - Private investment firm Carlyle Grou...	carlyle looks toward commercial aerospace	private investment firm carlyle group reputati...	Private investment firm Carlyle Group,\which...
2	2	3	Oil and Economy Cloud Stocks' Outlook (Reuters)	Reuters - Soaring crude prices plus worries\ab...	oil economy cloud stocks outlook	soaring crude prices plus economy outlook earn...	Soaring crude prices plus worries\about the ...
3	3	3	Iraq Halts Oil Exports from Main Southern Pipe...	Reuters - Authorities have halted oil export\f...	iraq halts oil exports main southern pipeline	authorities halted oil main pipeline southern ...	Authorities have halted oil export\flows fro...
4	4	3	Oil prices soar to all-time record, posing new...	AFP - Tearaway world oil prices, toppling reco...	oil prices soar record posing new menace us ec...	tearaway world oil prices toppling records str...	Tearaway world oil prices, toppling records ...

In [5]:
```
train_data_df.drop('index', axis=1, inplace=True)
train_data_df.head()
```

Out[5]:

	category	headline	content	headline_cleaned	content_cleaned	content_nosources
0	3	Wall St. Bears Claw Back Into the Black (Reuters)	Reuters - Short-sellers, Wall Street's dwindli...	wall bears claw back black	wall street seeing green	Short-sellers, Wall Street's dwindling\band ...
1	3	Carlyle Looks Toward Commercial Aerospace (Reu...	Reuters - Private investment firm Carlyle Grou...	carlyle looks toward commercial aerospace	private investment firm carlyle group reputati...	Private investment firm Carlyle Group,\which...
2	3	Oil and Economy Cloud Stocks' Outlook (Reuters)	Reuters - Soaring crude prices plus worries\ab...	oil economy cloud stocks outlook	soaring crude prices plus economy outlook earn...	Soaring crude prices plus worries\about the ...
3	3	Iraq Halts Oil Exports from Main Southern Pipe...	Reuters - Authorities have halted oil export\f...	iraq halts oil exports main southern pipeline	authorities halted oil main pipeline southern ...	Authorities have halted oil export\flows fro...
4	3	Oil prices soar to all-time record, posing new...	AFP - Tearaway world oil prices, toppling reco...	oil prices soar record posing new menace us ec...	tearaway world oil prices toppling records str...	Tearaway world oil prices, toppling records ...

In [6]:
```
test_data_df.head()
```

Out[6]:

	index	category	headline	content	headline_cleaned	content_cleaned	content_nosources
0	0	3	Fears for T N pension after talks	Unions representing workers at Turner Newall...	fears n pension talks	unions representing workers turner newall say ...	Unions representing workers at Turner Newall...
1	1	4	The Race is On: Second Private Team Sets Launc...	SPACE.com - TORONTO, Canada -- A second\team o...	race second private team sets launch date huma...	toronto canada rocketeers competing million an...	TORONTO, Canada -- A second\team of rocketee...
2	2	4	Ky. Company Wins Grant to Study Peptides (AP)	AP - A company founded by a chemistry research...	company wins grant study peptides	company founded chemistry researcher universit...	A company founded by a chemistry researcher ...
3	3	4	Prediction Unit Helps Forecast Wildfires (AP)	AP - It's barely dawn when Mike Fitzpatrick st...	prediction unit helps forecast wildfires	barely dawn mike fitzpatrick starts shift blur...	It's barely dawn when Mike Fitzpatrick start...
4	4	4	Calif. Aims to Limit Farm-Related Smog (AP)	AP - Southern California's smog-fighting agenc...	calif aims limit smog	southern california agency went emissions bovi...	Southern California's smog-fighting agency w...

In [7]:
```
test_data_df.drop('index', axis=1, inplace=True)
test_data_df.head()
```

Out[7]:

	category	headline	content	headline_cleaned	content_cleaned	content_nosources
0	3	Fears for T N pension after talks	Unions representing workers at Turner Newall...	fears n pension talks	unions representing workers turner newall say ...	Unions representing workers at Turner Newall...
1	4	The Race is On: Second Private Team Sets Launc...	SPACE.com - TORONTO, Canada -- A second\team o...	race second private team sets launch date huma...	toronto canada rocketeers competing million an...	TORONTO, Canada -- A second\team of rocketee...
2	4	Ky. Company Wins Grant to Study Peptides (AP)	AP - A company founded by a chemistry research...	company wins grant study peptides	company founded chemistry researcher universit...	A company founded by a chemistry researcher ...
3	4	Prediction Unit Helps Forecast Wildfires (AP)	AP - It's barely dawn when Mike Fitzpatrick st...	prediction unit helps forecast wildfires	barely dawn mike fitzpatrick starts shift blur...	It's barely dawn when Mike Fitzpatrick start...
4	4	Calif. Aims to Limit Farm-Related Smog (AP)	AP - Southern California's smog-fighting agenc...	calif aims limit smog	southern california agency went emissions bovi...	Southern California's smog-fighting agency w...

Sample 4000 rows

In [8]:
```
train_data_sample = train_data_df.sample(n = 4000, replace = False, random_state = 123)
train_data_sample.head()
```

Out[8]:

	category	headline	content	headline_cleaned	content_cleaned	content_nosources
30870	2	NHL on Ice, Maybe for Whole 2004-05 Season (AP)	AP - No shots, no saves, no goals. The Nationa...	nhl ice maybe whole season	shots saves goals national hockey league locke...	No shots, no saves, no goals. The National H...
7738	2	Rowers to be punished for criticism of teammate	ROWER Sally Robbins #39;s teammates are expect...	rowers punished criticism teammate	rower sally robbins teammates expected face di...	ROWER Sally Robbins #39;s teammates are expect...
25351	2	Changing Directions	Over at USA Today -- Slogan: "All the News Tha...	changing directions	slogan news fit print four paragraphs less got...	Over at - Slogan: "All the News That's Fit to...
74309	4	Cassini snapshots murky moon Titan	The Cassini probe got the first close-up photo...	cassini snapshots murky moon titan	cassini probe got first photos saturn murky mo...	The Cassini probe got the first close-up photo...
88347	1	Farewell Yasser Arafat	GAZA CITY, 12 November 2004 - The world will b...	farewell yasser arafat	gaza city world bid farewell abu ammar yasser ...	GAZA CITY, - The world will bid farewell to Ab...

In [9]:
```
test_data_sample = test_data_df.sample(n = 4000, replace = False, random_state = 123)
test_data_sample.head()
```

Out[9]:

	category	headline	content	headline_cleaned	content_cleaned	content_nosources
646	1	Panama pardons Castro 'plotters'	Four men accused of planning to kill Cuba's Fi...	panama pardons castro	four men accused planning kill cuba fidel cast...	Four men accused of planning to kill Cuba's Fi...
2616	4	Elephant DNA Could Help Stem Ivory Trade (AP)	AP - Analyzing the DNA of elephants may help t...	elephant dna could help stem ivory trade	analyzing dna elephants may help trace origins...	Analyzing the DNA of elephants may help trac...
2300	1	Job-Loss Panic Rises in Western Europe (AP)	AP - Stephane Zervos first suspected his job w...	panic rises western europe	stephane zervos first suspected job threatened...	Stephane Zervos first suspected his job was ...
4764	1	Remark on Homosexuality Delays Seating of Euro...	The European Union #39;s normally yawn-inducin...	remark homosexuality delays seating european p...	european union normally institutions raised ey...	The European Union #39;s normally yawn-inducin...
3617	3	Linux: Paris weighs a shift to open-source camp	PARIS The open-source computer system known as...	linux paris weighs shift camp	paris computer system known linux tough battle...	PARIS The open-source computer system known as...

Train & Test data where x is the predictor features, y is the predicted feature

In [10]:
```
n_classes = 4

x_train = train_data_sample.content_cleaned
y_train = label_binarize(train_data_sample.category, classes=[1, 2, 3, 4])

x_test = test_data_sample.content_cleaned
y_test = label_binarize(test_data_sample.category, classes=[1, 2, 3, 4])
```

Let's make a Bag of Words

In [11]:
```
# Use countvectorizer to get a vector of words
cv = CountVectorizer(min_df = 2, lowercase = True,
                     token_pattern=r'\b[A-Za-z]{2,}\b', ngram_range = (1, 1))
x_train_cv = cv.fit_transform(x_train)
x_test_cv = cv.transform(x_test)

selector = SelectPercentile(f_classif, percentile=10)
selector.fit(x_train_cv, train_data_sample.category)
x_train_cv_10p = selector.transform(x_train_cv).toarray()
x_test_cv_10p = selector.transform(x_test_cv).toarray()

# get all unique words in the corpus
bow_vocab = cv.get_feature_names()

columns = numpy.asarray(bow_vocab)
support = numpy.asarray(selector.get_support())
bow_vocab_10p = columns[support]

x_train_cv = x_train_cv.toarray()
x_test_cv = x_test_cv.toarray()

# produce a dataframe including the feature names
x_train_bagofwords = pandas.DataFrame(x_train_cv, columns=bow_vocab)
x_test_bagofwords = pandas.DataFrame(x_test_cv, columns=bow_vocab)
x_train_bagofwords_10p = pandas.DataFrame(x_train_cv_10p, columns=bow_vocab_10p)
x_test_bagofwords_10p = pandas.DataFrame(x_test_cv_10p, columns=bow_vocab_10p)
x_train_bagofwords.head()
```

Out[11]:

	aaron	ab	abandon	abandoned	abandons	abbas	abc	abducted	abduction	abductions	...	zaragoza	zdnet	zealand	zee	zero	zimbabwe
0	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0

5 rows × 6873 columns

In [12]:
```
x_test_bagofwords_10p.head()
```

Out[12]:

	abducted	abu	access	according	accounting	accused	administration	adrian	afghan	afghanistan	...	writes	xp	yahoo	yankees	yards	ya
0	0	0	0	0	0	1	0	0	0	0	...	0	0	0	0	0	
1	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	
2	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	
3	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	
4	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	

5 rows × 687 columns

We have bag of words already, let's make a Bag of N-Grams

In [13]:
```
# Use countvectorizer to get a vector of ngrams
cv = CountVectorizer(min_df = 2, lowercase = True,
                     token_pattern=r'\b[A-Za-z]{2,}\b', ngram_range = (2, 3))
x_train_cv = cv.fit_transform(x_train)
x_test_cv = cv.transform(x_test)

# get all unique words in the corpus
ngram_vocab = cv.get_feature_names()

selector = SelectPercentile(f_classif, percentile=10)
selector.fit(x_train_cv, train_data_sample.category)
x_train_cv_10p = selector.transform(x_train_cv).toarray()
x_test_cv_10p = selector.transform(x_test_cv).toarray()

columns = numpy.asarray(ngram_vocab)
support = numpy.asarray(selector.get_support())
ngram_vocab_10p = columns[support]

x_train_cv = x_train_cv.toarray()
x_test_cv = x_test_cv.toarray()

# produce a dataframe including the feature names
x_train_bagofngrams = pandas.DataFrame(x_train_cv, columns=ngram_vocab)
x_test_bagofngrams = pandas.DataFrame(x_test_cv, columns=ngram_vocab)
x_train_bagofngrams_10p = pandas.DataFrame(x_train_cv_10p, columns=ngram_vocab_10p)
x_test_bagofngrams_10p = pandas.DataFrame(x_test_cv_10p, columns=ngram_vocab_10p)
x_train_bagofngrams.head()
```

Out[13]:

	ab billion	abducted militants	abductions foreigners	abductions foreigners iraq	aboard international	aboard international space	abu ghraib	abu ghraib prison	abu musab	ac milan	...	yukos said	yukos said would	zdnet survey	zdnet survey professionals	z b
0	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	
1	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	
2	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	
3	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	
4	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	

5 rows × 5929 columns

In [14]:
```
# Use countvectorizer to get a vector of chars
cv = CountVectorizer(analyzer='char', min_df = 2, ngram_range = (2, 3),
                     token_pattern=r'\b[A-Za-z]{2,}\b')
x_train_cv = cv.fit_transform(x_train)
x_test_cv = cv.transform(x_test)

# get all unique words in the corpus
cv_char_vocab = cv.get_feature_names()

selector = SelectPercentile(f_classif, percentile=10)
selector.fit(x_train_cv, train_data_sample.category)
x_train_cv_10p = selector.transform(x_train_cv).toarray()
x_test_cv_10p = selector.transform(x_test_cv).toarray()

columns = numpy.asarray(cv_char_vocab)
support = numpy.asarray(selector.get_support())
cv_char_vocab_10p = columns[support]

x_train_cv = x_train_cv.toarray()
x_test_cv = x_test_cv.toarray()

# produce a dataframe including the feature names
x_train_cv_char = pandas.DataFrame(x_train_cv, columns = cv_char_vocab)
x_test_cv_char = pandas.DataFrame(x_test_cv, columns=cv_char_vocab)
x_train_cv_char_10p = pandas.DataFrame(x_train_cv_10p, columns = cv_char_vocab_10p)
x_test_cv_char_10p = pandas.DataFrame(x_test_cv_10p, columns=cv_char_vocab_10p)
x_train_cv_char.head()
```

Out[14]:

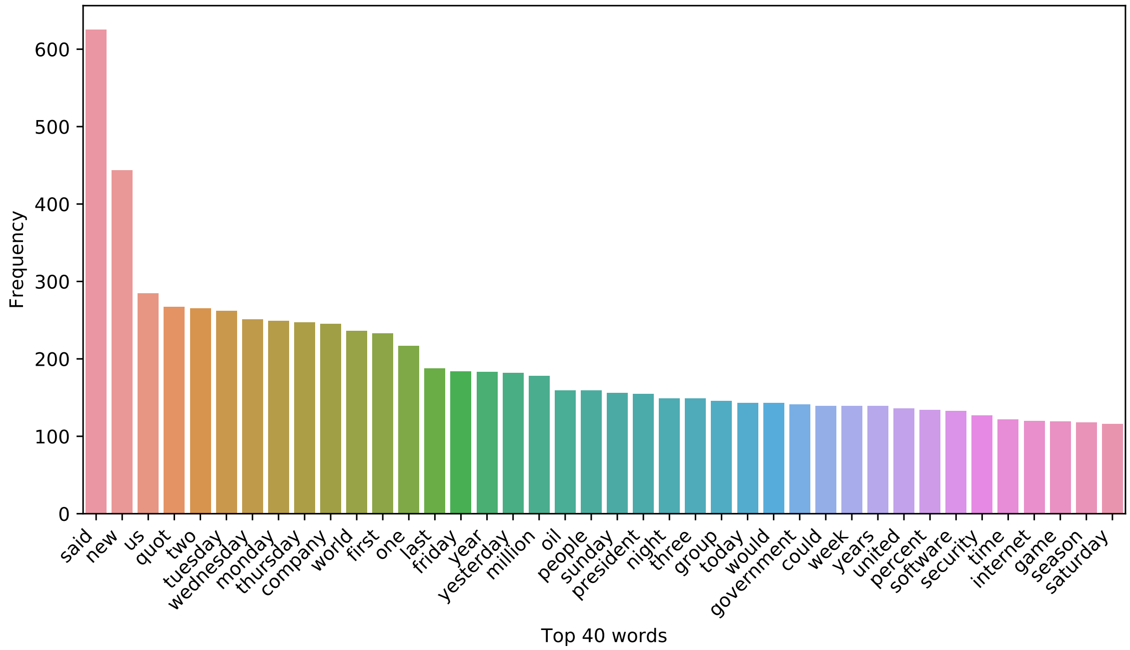
	a	aa	ab	ac	ad	ae	af	ag	ah	ai	...	zur	zv	zvo	zy	zy	zz	zz	zza	zzi	zzl
0	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
1	1	0	0	1	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
2	1	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	...	0	0	0	1	1	0	0	0	0	0
4	4	0	1	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0

5 rows × 5834 columns

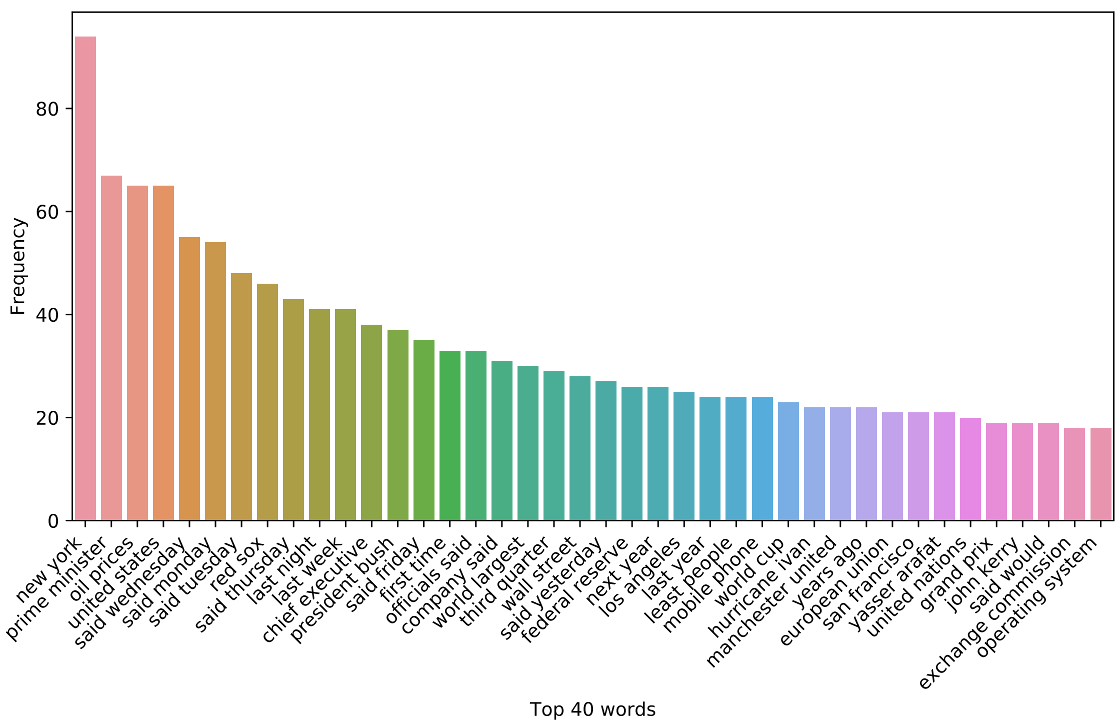
Let's explore the data we got through plots and tables

In [15]:
```
def words_barchart(df, df_label):
    word_count_dict = {}
    for word in df_label:
        word_count_dict[word] = int(sum(df.loc[:, word]))

    counter = Counter(word_count_dict)

    freq_df = pandas.DataFrame.from_records(counter.most_common(40),
                                            columns=['Top 40 words', 'Frequency'])

    plt.figure(figsize=(10,5))
    chart = sns.barplot(
        data=freq_df,
        x='Top 40 words',
        y='Frequency'
    )

    chart.set_xticklabels(
        chart.get_xticklabels(),
        rotation=45,
        horizontalalignment='right',
        fontweight='light'
    )
```

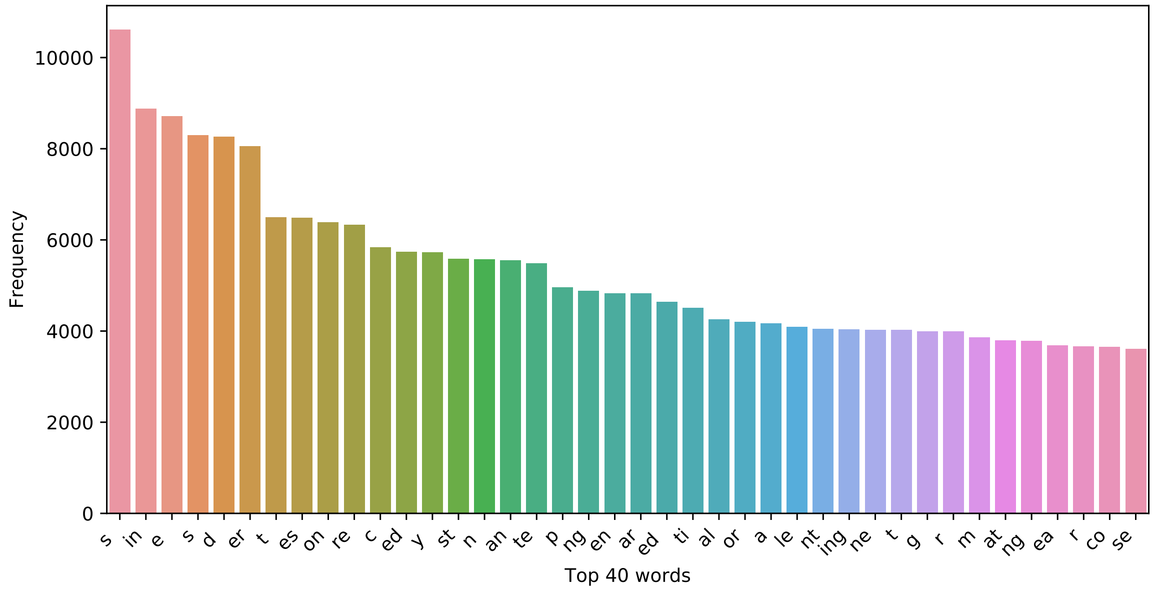
In [16]:
```
words_barchart(x_train_bagofwords, bow_vocab)
```



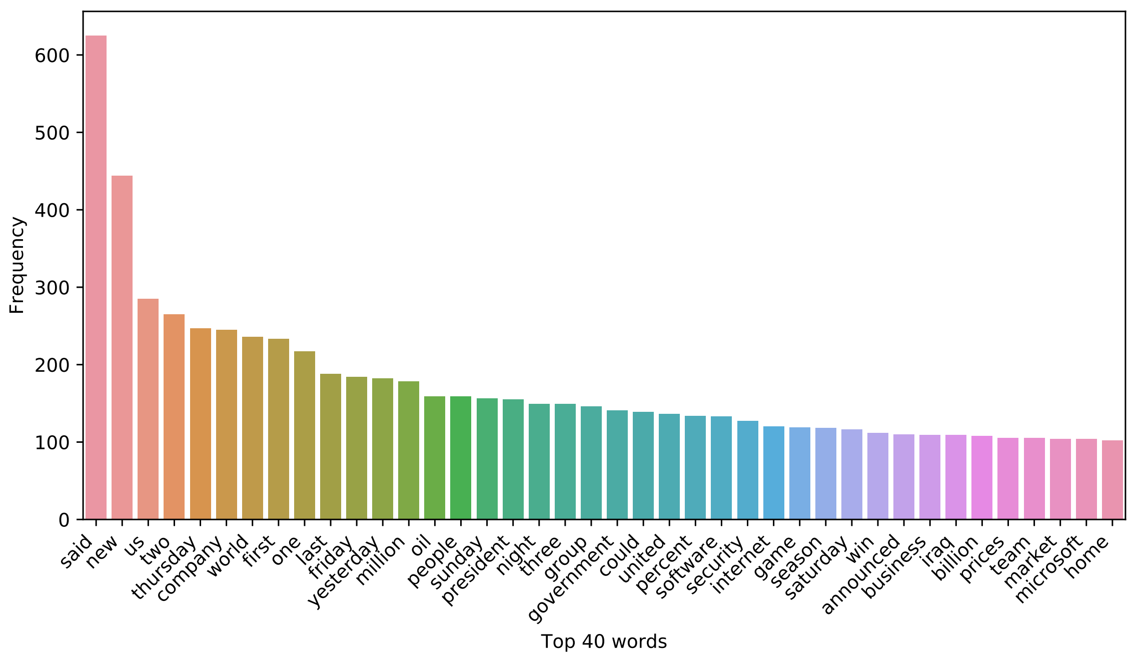
In [17]:
```
words_barchart(x_train_bagofngrams, ngram_vocab)
```



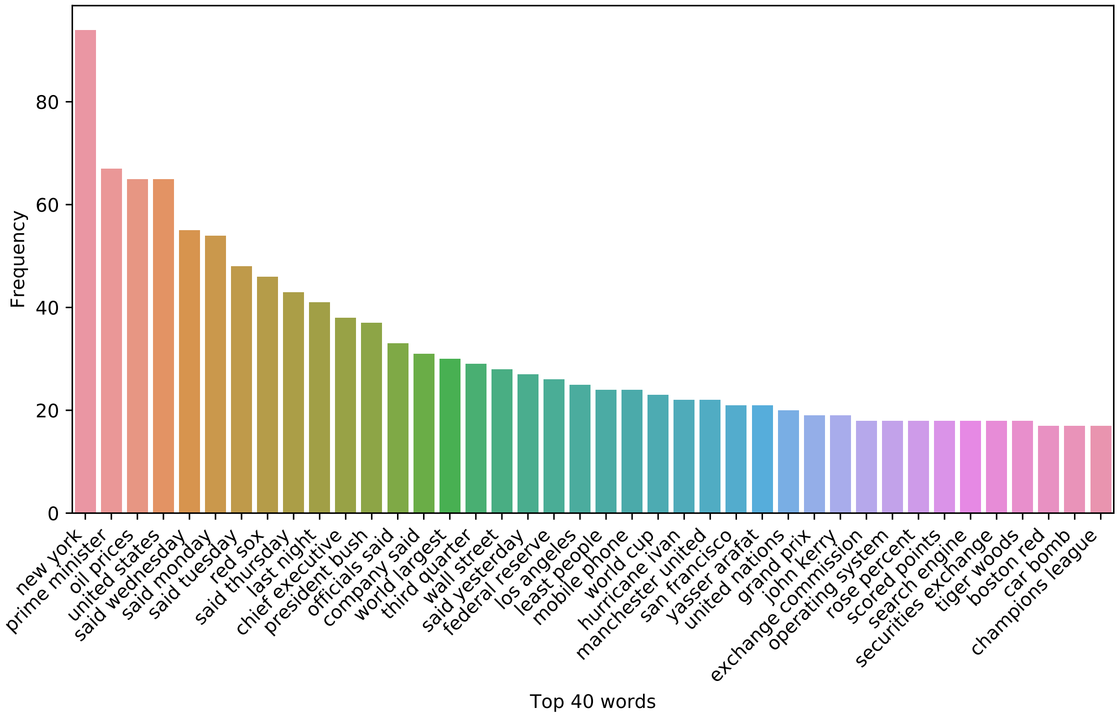
In [18]:
```
words_barchart(x_train_cv_char, cv_char_vocab)
```



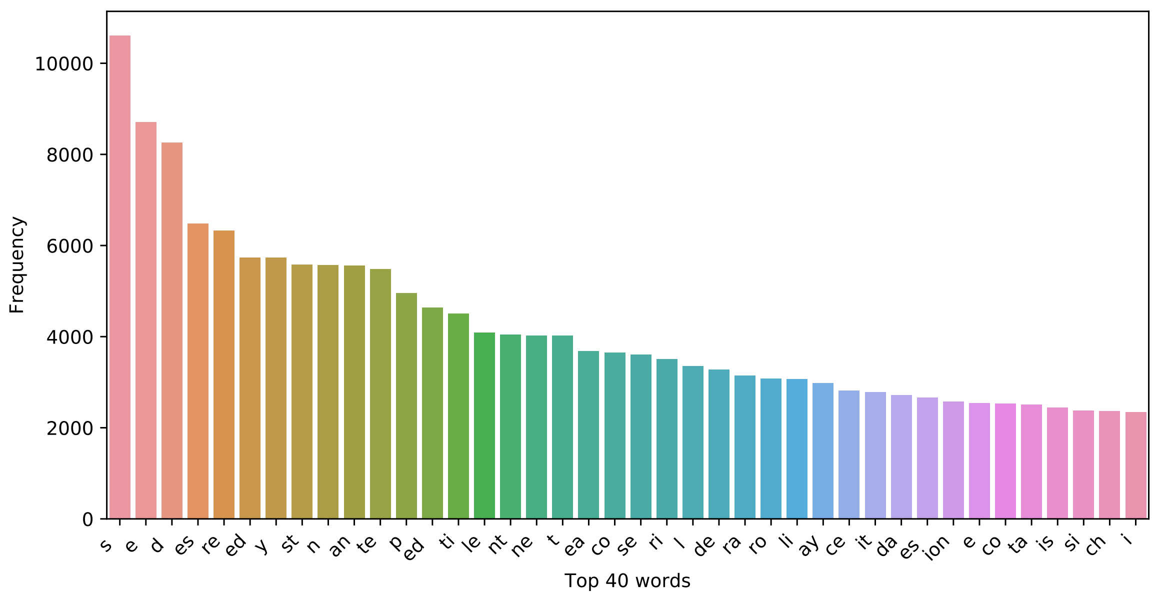
In [19]:
```
words_barchart(x_train_bagofwords_10p, bow_vocab_10p)
```



In [20]:
```
words_barchart(x_train_bagofngrams_10p, ngram_vocab_10p)
```



In [21]:
```
words_barchart(x_train_cv_char_10p, cv_char_vocab_10p)
```



TF/IDF

Unigram TF/IDF

In [22]:
```
# Use TF/IDF vectorizer to get a vector of unigrams
tfidf_vect = TfidfVectorizer(sublinear_tf = True, min_df = 2, ngram_range = (1, 1),
                             use_idf = True, token_pattern=r'\b[A-Za-z]{2,}\b')
x_train_tfidf_unigram = tfidf_vect.fit_transform(x_train).toarray()
x_test_tfidf_unigram = tfidf_vect.transform(x_test).toarray()

# get all unique words in the corpus
vocab = tfidf_vect.get_feature_names()

# produce a dataframe including the feature names
x_train_tfidf_unigram = pandas.DataFrame(numpy.round(x_train_tfidf_unigram, 2), columns = vocab)
x_test_tfidf_unigram = pandas.DataFrame(numpy.round(x_test_tfidf_unigram, 2), columns = vocab)
x_train_tfidf_unigram.head()
```

Out[22]:

	aaron	ab	abandon	abandoned	abandons	abbas	abc	abducted	abduction	abductions	...	zaragoza	zdnet	zealand	zee	zero	zimbabwe
0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0
1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0
2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0
4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0

5 rows × 6873 columns

N-Gram TF/IDF

Use TF/IDF vectorizer to get a vector of n-grams

In [23]:
```
tfidf_vect = TfidfVectorizer(sublinear_tf = True, min_df = 2, ngram_range = (2, 3),
                             use_idf = True, token_pattern=r'\b[A-Za-z]{2,}\b')
x_train_tfidf_ngram = tfidf_vect.fit_transform(x_train).toarray()
x_test_tfidf_ngram = tfidf_vect.transform(x_test).toarray()
# get all unique words in the corpus
vocab = tfidf_vect.get_feature_names()

# produce a dataframe including the feature names
x_train_tfidf_ngram = pandas.DataFrame(numpy.round(x_train_tfidf_ngram, 2), columns = vocab)
x_test_tfidf_ngram = pandas.DataFrame(numpy.round(x_test_tfidf_ngram, 2), columns = vocab)
x_train_tfidf_ngram.head()
```

Out[23]:

	ab billion	abducted militants	abductions foreigners	abductions foreigners iraq	aboard international	aboard international space	abu ghraib	abu ghraib prison	abu musab	ac milan	...	yukos said	yukos said would	zdnet survey	zdnet survey professionals	z b
0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	
1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	
2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	
4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	

5 rows × 5929 columns

Character TF/IDF

Use TF/IDF vectorizer to get a vector of chars

In [24]:
```
tfidf_vect = TfidfVectorizer(analyzer = 'char', sublinear_tf = True, min_df = 2,
                             ngram_range = (2, 3), use_idf = True,
                             token_pattern=r'\b[A-Za-z]{2,}\b')
x_train_tfidf_char = tfidf_vect.fit_transform(x_train).toarray()
x_test_tfidf_char = tfidf_vect.transform(x_test).toarray()

# get all unique words in the corpus
char_vocab = tfidf_vect.get_feature_names()

# produce a dataframe including the feature names
x_train_tfidf_char = pandas.DataFrame(numpy.round(x_train_tfidf_char, 2), columns = char_vocab)
x_test_tfidf_char = pandas.DataFrame(numpy.round(x_test_tfidf_char, 2), columns = char_vocab)
x_train_tfidf_char.head()
```

Out[24]:

	a	aa	ab	ac	ad	ae	af	ag	ah	ai	...	zur	zv	zvo	zy	zy	zz	zz	zza	zzi	zzl
0	0.00	0.0	0.00	0.00	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.00	0.00	0.0	0.0	0.0	0.0	0.0
1	0.03	0.0	0.00	0.07	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.00	0.00	0.0	0.0	0.0	0.0	0.0
2	0.03	0.0	0.00	0.00	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.00	0.00	0.0	0.0	0.0	0.0	0.0
3	0.00	0.0	0.00	0.00	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.13	0.14	0.0	0.0	0.0	0.0	0.0
4	0.06	0.0	0.07	0.00	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.00	0.00	0.0	0.0	0.0	0.0	0.0

5 rows × 5834 columns

Using gensim to build Word2Vec

In [25]:
```
from gensim.models import word2vec

# tokenize sentences in corpus
wpt = nltk.WordPunctTokenizer()
tokenized_corpus_train = [wpt.tokenize(document) for document in x_train]
tokenized_corpus_test = [wpt.tokenize(document) for document in x_test]

# Set values for various parameters
feature_size = 4000    # Word vector dimensionality
window_context = 20          # Context window size
workers = 12
min_word_count = 5   # Minimum word count
sample = 1e-3   # Downsample setting for frequent words

w2v_model_train = word2vec.Word2Vec(tokenized_corpus_train, size=feature_size,
                          window=window_context, min_count=min_word_count,
                          sample=sample, iter=50)
w2v_model_test = word2vec.Word2Vec(tokenized_corpus_test, size=feature_size,
                          window=window_context, min_count=min_word_count,
                          sample=sample, iter=50)
```

Functions to get document level embeddings

The idea is to distill a word vector of 'n' features into a single point and use that at a document level

In [27]:
```
def average_word_vectors(words, model, vocabulary, num_features):

 feature_vector = numpy.zeros((num_features,),dtype="float64")
 nwords = 0.

 for word in words:
    if word in vocabulary:
      nwords = nwords + 1.
      feature_vector = numpy.add(feature_vector, model[word])

 if nwords:
    feature_vector = numpy.divide(feature_vector, nwords)

 return feature_vector


def averaged_word_vectorizer(corpus, model, num_features):
 vocabulary = set(model.wv.index2word)
 features = [average_word_vectors(tokenized_sentence, model, vocabulary, num_features)
            for tokenized_sentence in corpus]
 return numpy.array(features)
```

Obtain document level embeddings

In [28]:
```
w2v_feature_array_train = averaged_word_vectorizer(corpus=tokenized_corpus_train, model=w2v_model_train,
                                            num_features=feature_size)
w2v_feature_array_test = averaged_word_vectorizer(corpus=tokenized_corpus_test, model=w2v_model_test,
                                            num_features=feature_size)
x_train_w2v = pandas.DataFrame(w2v_feature_array_train)
x_test_w2v = pandas.DataFrame(w2v_feature_array_test)
```

In [29]:
```
x_train_w2v.head()
```

Out[29]:

	0	1	2	3	4	5	6	7	8	9	...	3990	3991	3992
0	-0.047792	-0.010078	-0.047501	0.065156	0.040363	0.053578	-0.078255	-0.072195	-0.048381	0.004039	...	0.018117	0.001505	0.024522
1	-0.027499	-0.007007	-0.011028	0.007280	0.062373	-0.033475	-0.064167	-0.063685	-0.071467	-0.020646	...	-0.004596	0.036393	-0.014121
2	-0.033255	-0.047467	-0.039281	0.084740	0.031803	-0.025014	-0.062031	-0.059123	-0.036834	-0.017421	...	0.015355	-0.048778	0.069986
3	0.037945	0.031579	-0.041542	-0.051591	0.080797	-0.051425	0.027580	-0.023383	0.061208	-0.056261	...	0.007027	0.010646	-0.012574
4	0.064920	0.018165	-0.029505	0.007345	0.056818	-0.126387	-0.068517	-0.032791	-0.055429	0.016335	...	-0.033108	-0.024404	0.020513

5 rows × 4000 columns

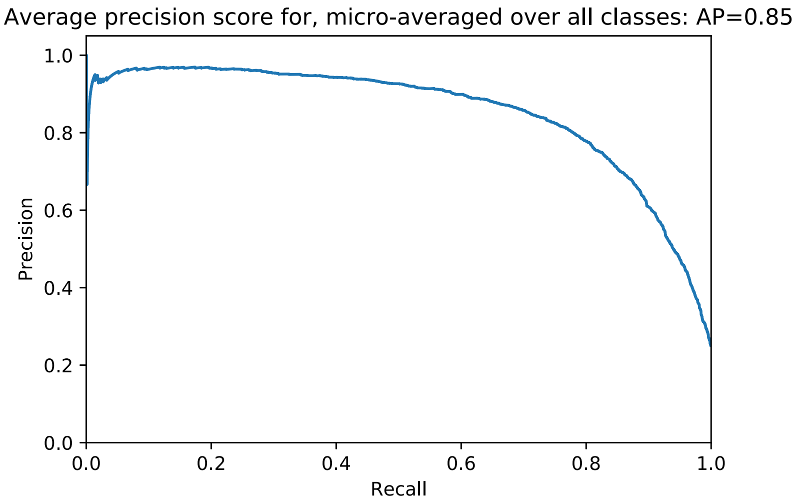
Perform SVM as a baseline model and evaluate it.

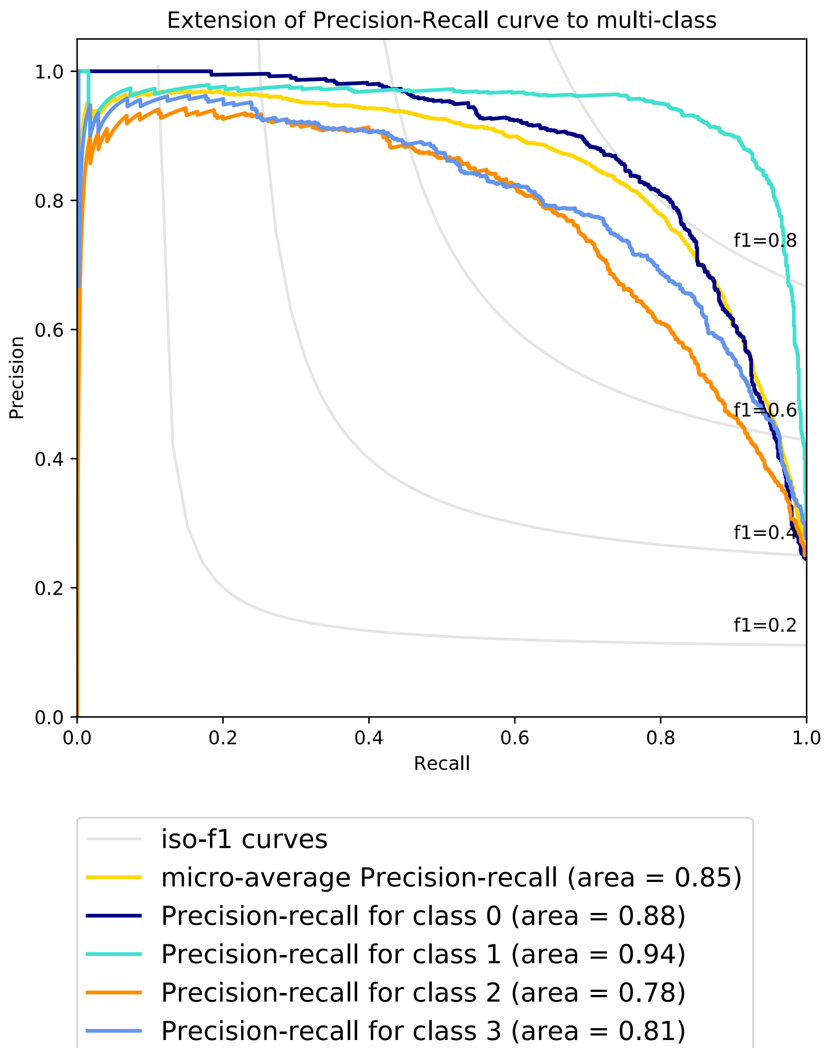
In [30]:
```
# SVM classifier and plot superfunction
def run_svm(x_train, y_train, x_test, emb):
    str(emb)
    classifier = OneVsRestClassifier(svm.LinearSVC(random_state=1))
    classifier.fit(x_train, y_train)
    y_score = classifier.decision_function(x_test)


    # The average precision score in multi-label settings
    # For each class
    precision = dict()
    recall = dict()
    average_precision = dict()
    for i in range(n_classes):
        precision[i], recall[i], _ = precision_recall_curve(y_test[:, i],
                                                            y_score[:, i])
        average_precision[i] = average_precision_score(y_test[:, i], y_score[:, i])

    # A "micro-average": quantifying score on all classes jointly
    precision["micro"], recall["micro"], _ = precision_recall_curve(y_test.ravel(),
        y_score.ravel())
    average_precision["micro"] = average_precision_score(y_test, y_score,
                                                         average="micro")
    print(emb)
    print('Average precision score, micro-averaged over all classes: {0:0.2f}'
        .format(average_precision["micro"]))

    # Plot the micro-averaged Precision-Recall curve
    plt.figure()
    plt.step(recall['micro'], precision['micro'], where='post')

    plt.xlabel('Recall')
    plt.ylabel('Precision')
    plt.ylim([0.0, 1.05])
    plt.xlim([0.0, 1.0])
    plt.title(
        'Average precision score for, micro-averaged over all classes: AP={0:0.2f}'
        .format(average_precision["micro"]))

    # Plot Precision-Recall curve for each class and iso-f1 curves
    # setup plot details
    colors = cycle(['navy', 'turquoise', 'darkorange', 'cornflowerblue', 'teal'])

    plt.figure(figsize=(7, 8))
    f_scores = numpy.linspace(0.2, 0.8, num=4)
    lines = []
    labels = []
    for f_score in f_scores:
        x = numpy.linspace(0.01, 1)
        y = f_score * x / (2 * x - f_score)
        l, = plt.plot(x[y >= 0], y[y >= 0], color='gray', alpha=0.2)
        plt.annotate('f1={0:0.1f}'.format(f_score), xy=(0.9, y[45] + 0.02))

    lines.append(l)
    labels.append('iso-f1 curves')
    l, = plt.plot(recall["micro"], precision["micro"], color='gold', lw=2)
    lines.append(l)
    labels.append('micro-average Precision-recall (area = {0:0.2f})'
                  ''.format(average_precision["micro"]))

    for i, color in zip(range(n_classes), colors):
        l, = plt.plot(recall[i], precision[i], color=color, lw=2)
        lines.append(l)
        labels.append('Precision-recall for class {0} (area = {1:0.2f})'
                      ''.format(i, average_precision[i]))

    fig = plt.gcf()
    fig.subplots_adjust(bottom=0.25)
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('Recall')
    plt.ylabel('Precision')
    plt.title('Extension of Precision-Recall curve to multi-class')
    plt.legend(lines, labels, loc=(0, -.5), prop=dict(size=14))

    plt.show()
```

SVM for Bag of Words

In [31]:
```
run_svm(x_train_bagofwords, y_train, x_test_bagofwords, 'Bag of Words')
```

```
Bag of Words
Average precision score, micro-averaged over all classes: 0.85
```

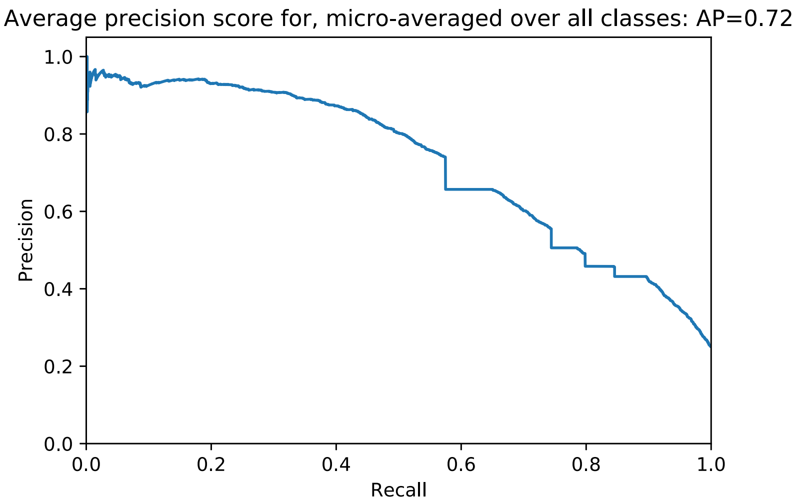


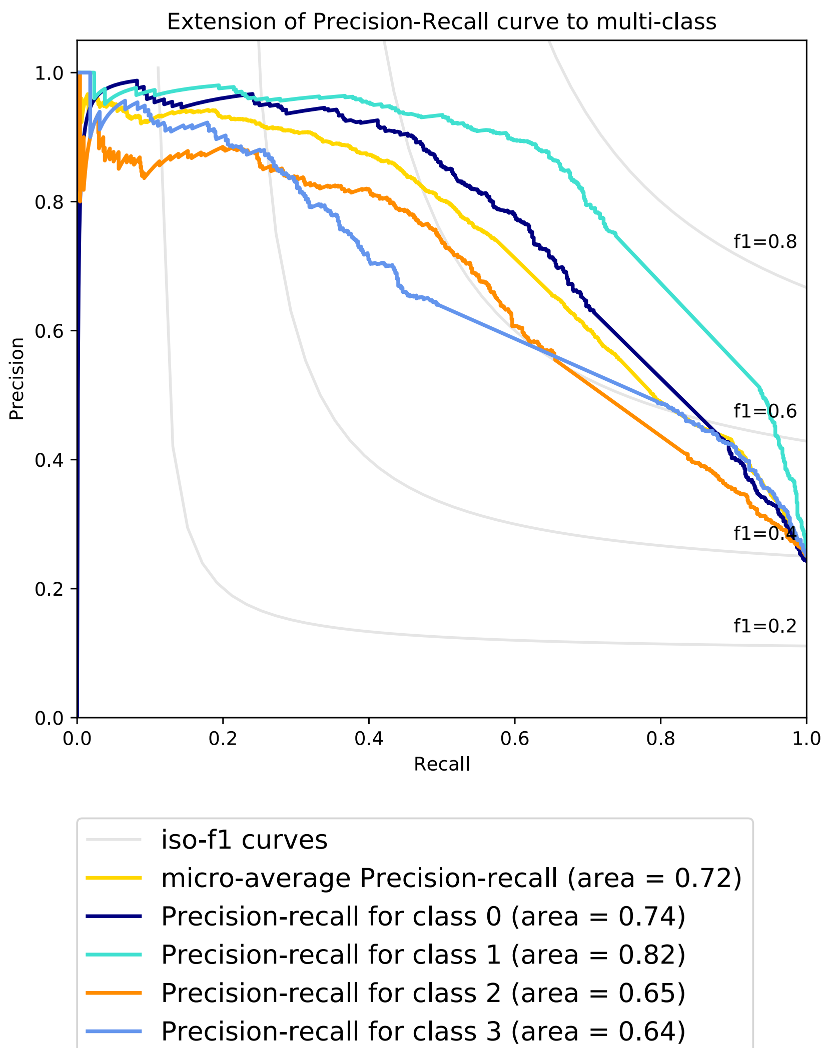


SVM for Bag of N-grams

In [32]:
```
run_svm(x_train_bagofngrams, y_train, x_test_bagofngrams, 'Bag of N-Grams')
```

```
Bag of N-Grams
Average precision score, micro-averaged over all classes: 0.72
```

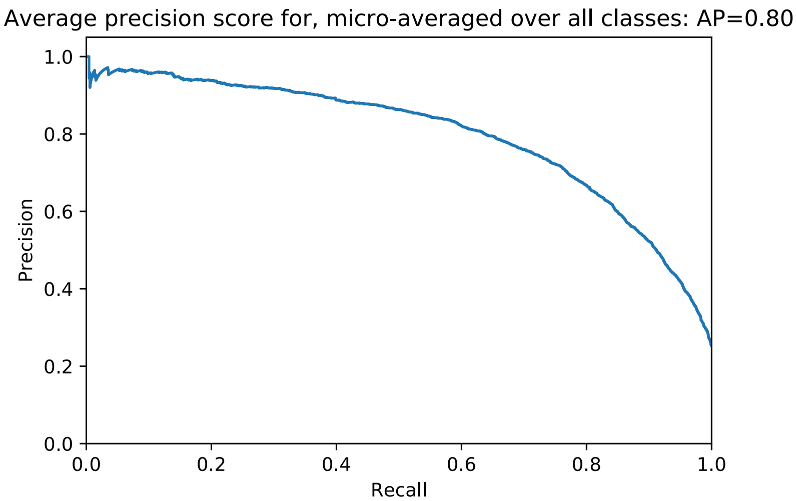


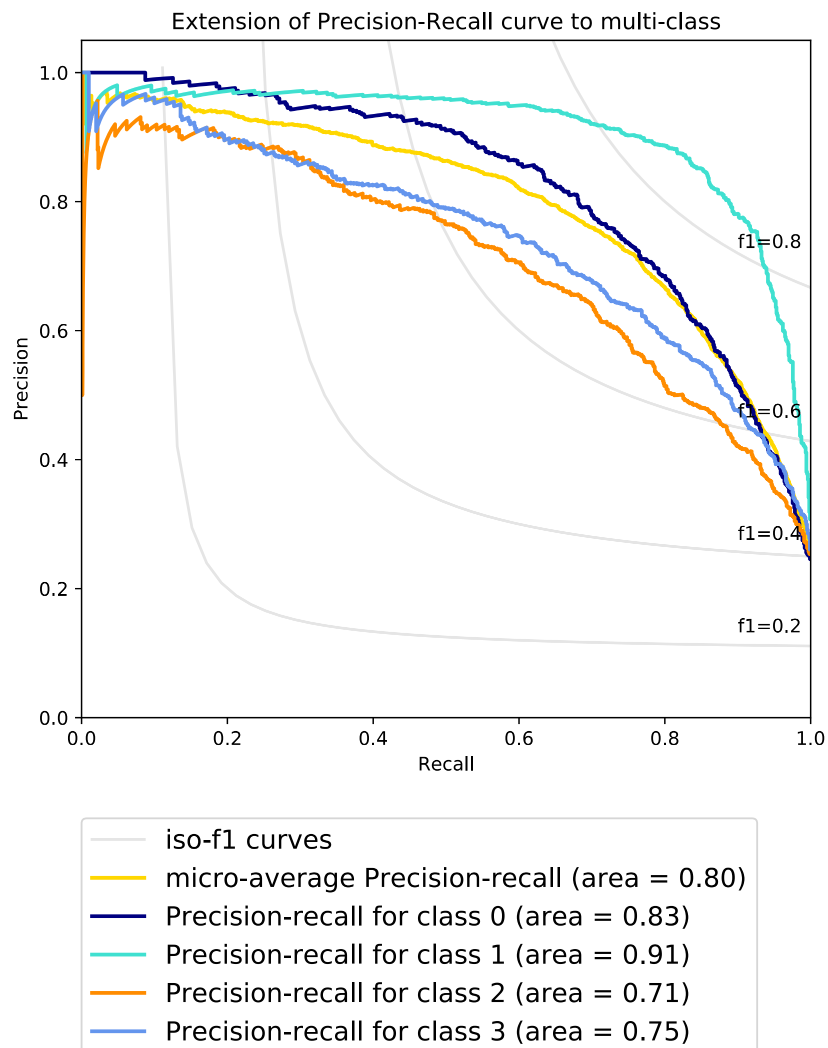


SVM for Bag of Chars

In [33]:
```
run_svm(x_train_cv_char, y_train, x_test_cv_char, 'Bag of Chars')
```

```
Bag of Chars
Average precision score, micro-averaged over all classes: 0.80
```

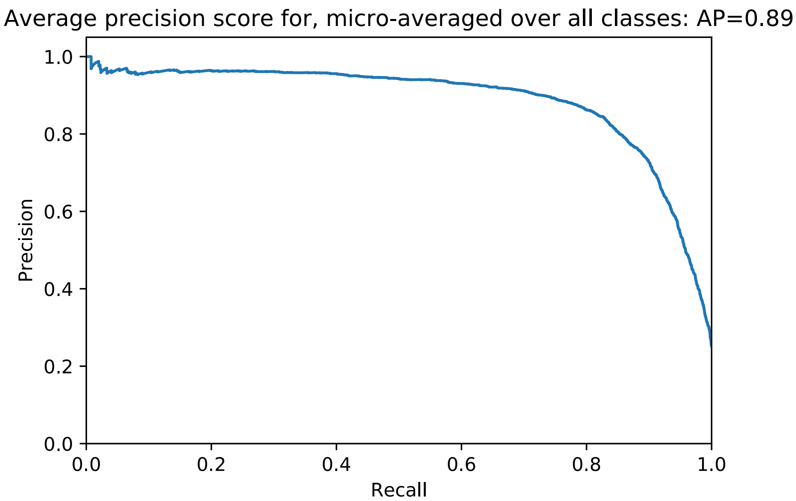


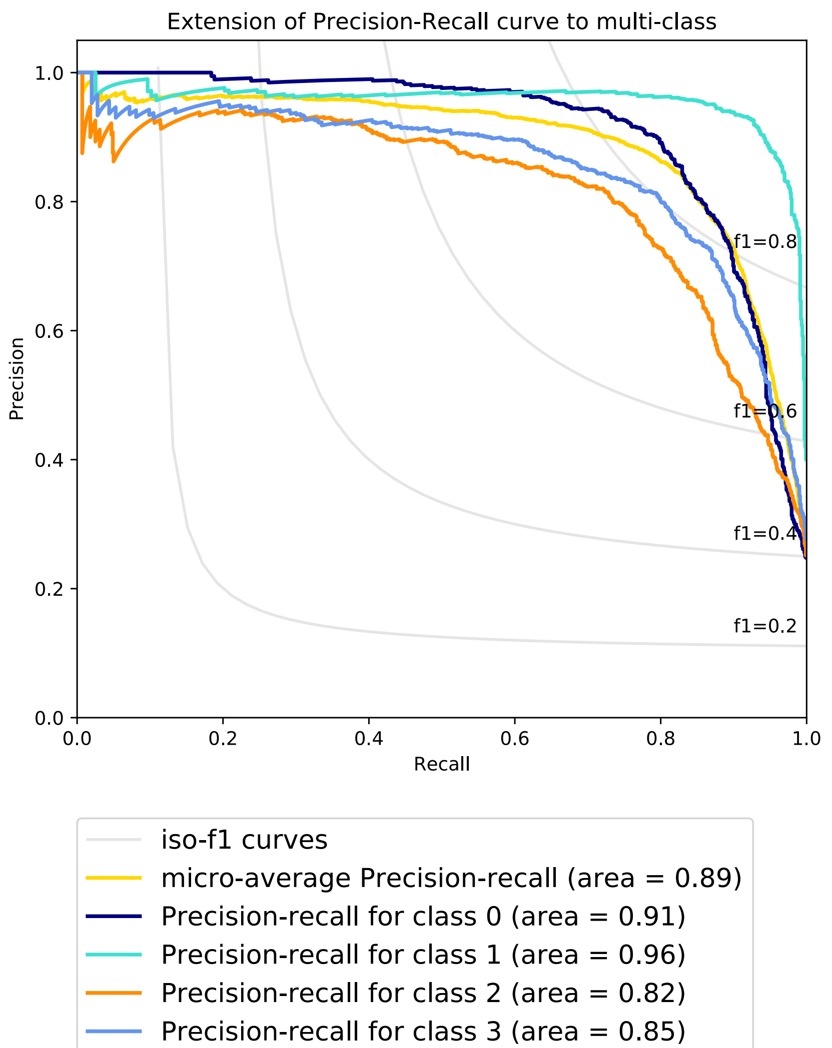


SVM for TF/IDF Unigram

In [34]:
```
run_svm(x_train_tfidf_unigram, y_train, x_test_tfidf_unigram, 'TF/IDF Unigram')
```

```
TF/IDF Unigram
Average precision score, micro-averaged over all classes: 0.89
```

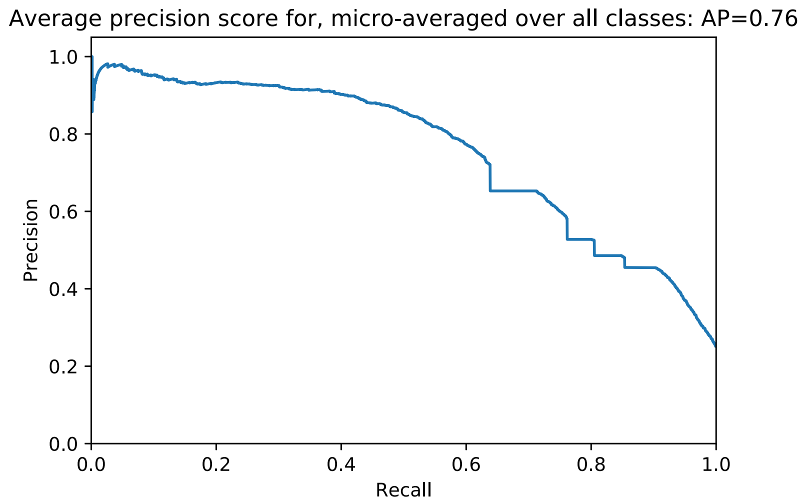


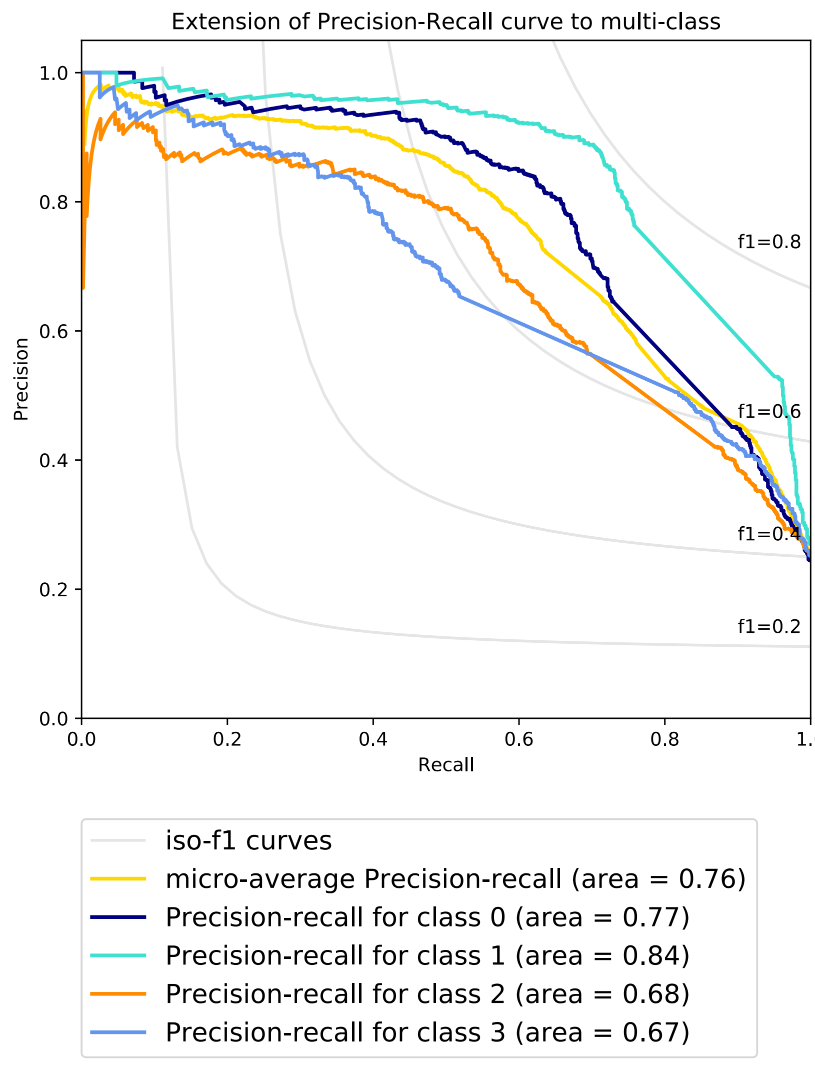


SVM for TF/IDF N-grams

In [35]:
```
run_svm(x_train_tfidf_ngram, y_train, x_test_tfidf_ngram, 'TF/IDF N-Grams')
```

```
TF/IDF N-Grams
Average precision score, micro-averaged over all classes: 0.76
```

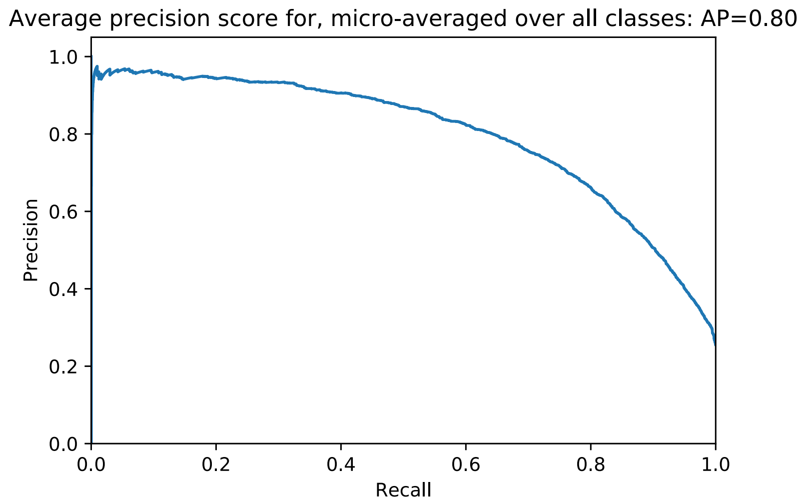


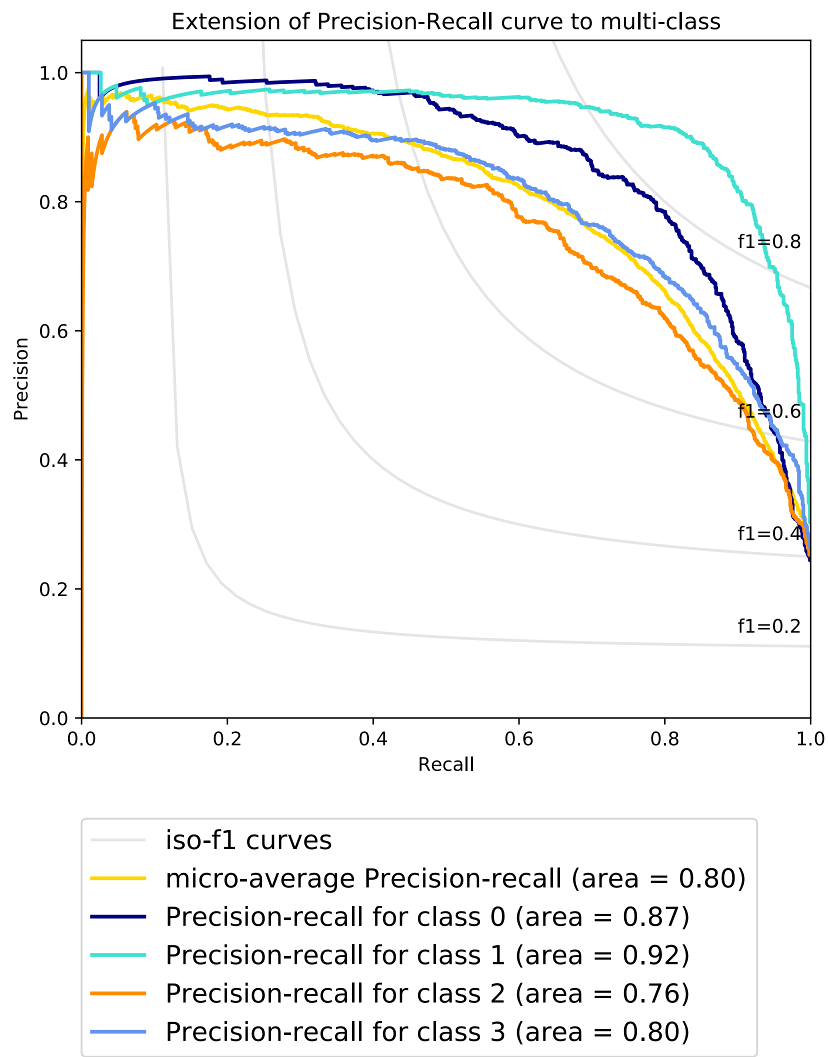


SVM for TF/IDF Chars

In [36]:
```
run_svm(x_train_tfidf_char, y_train, x_test_cv_char, 'TF/IDF Chars')
```

```
TF/IDF Chars
Average precision score, micro-averaged over all classes: 0.80
```

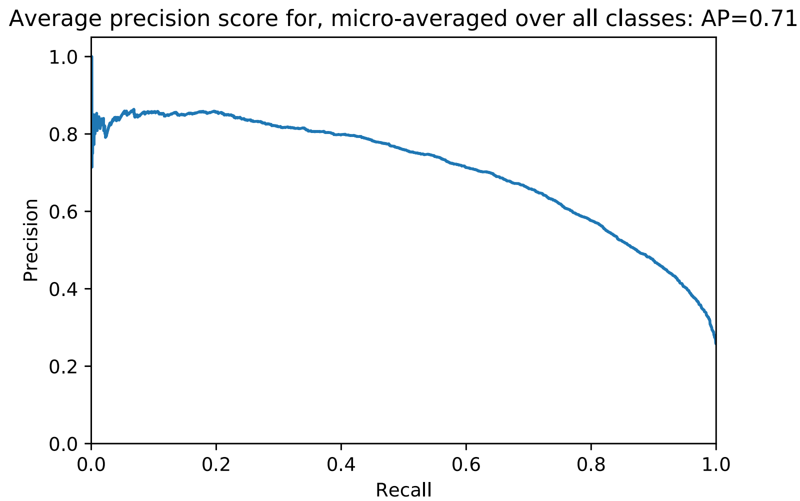


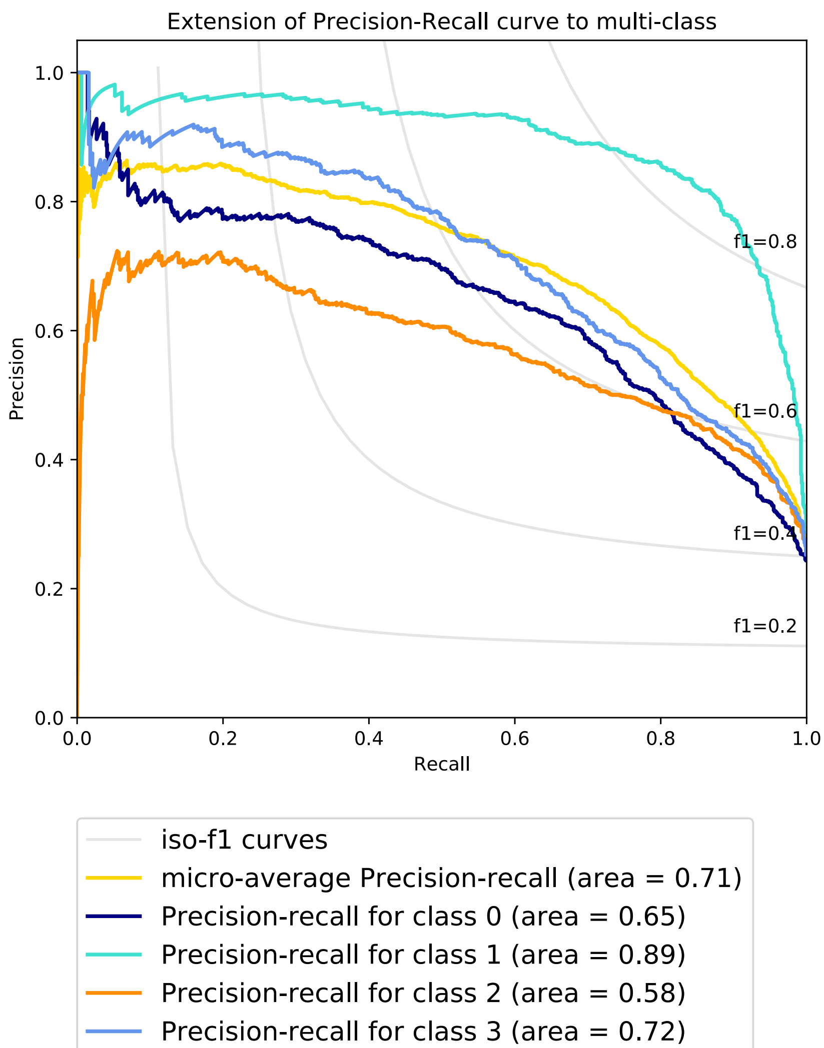


SVM for Word2Vec

In [37]:
```
run_svm(x_train_w2v, y_train, x_test_w2v, 'Word2Vec')
```

```
Word2Vec
Average precision score, micro-averaged over all classes: 0.71
```



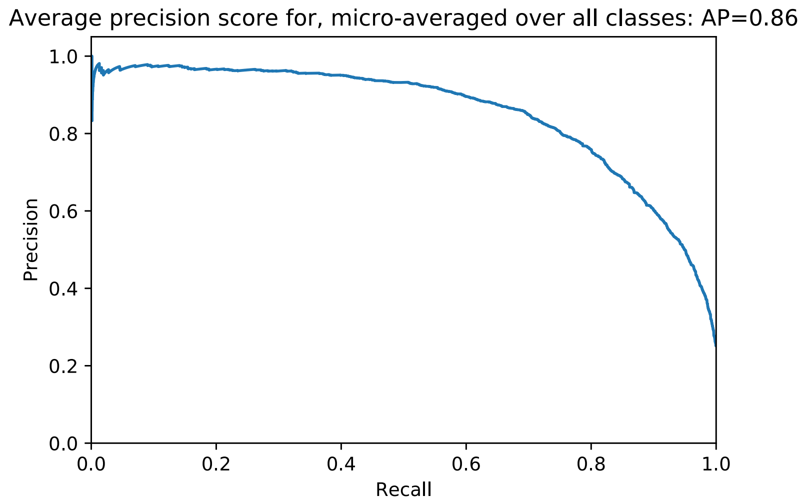


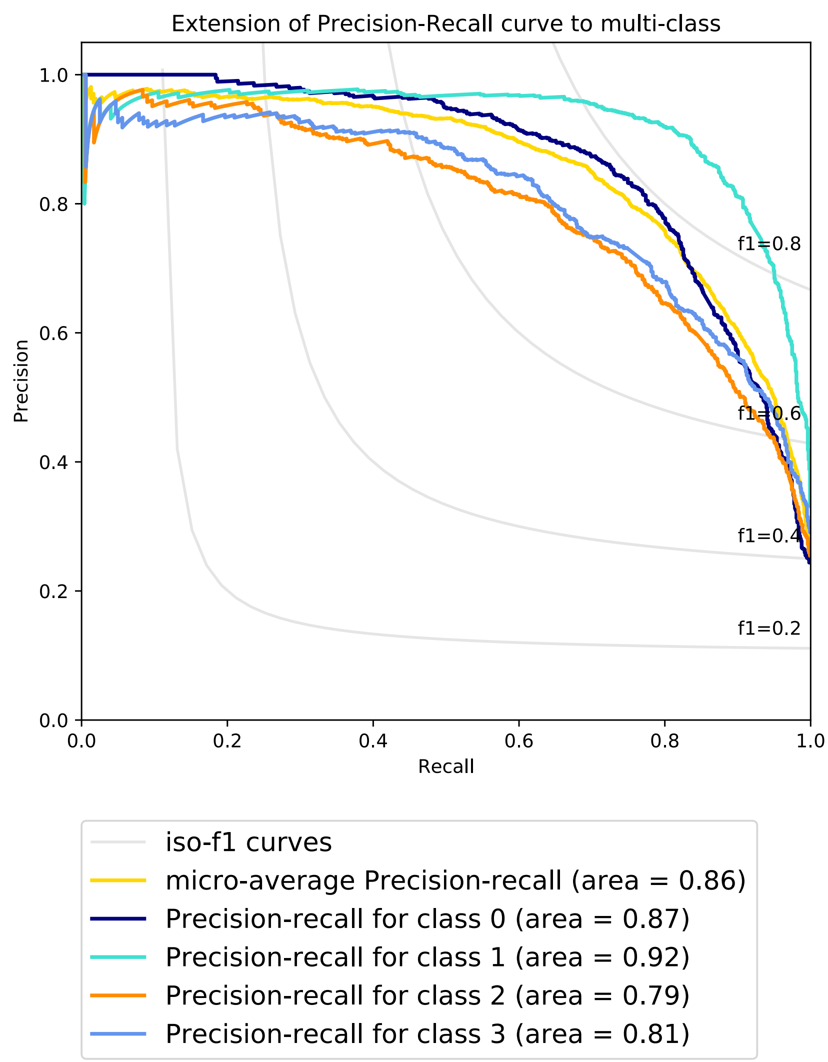
Let's explore also the SVM performance on 90th percentile feature selection

SVM for Bag of Words 90th percentile

In [38]:
```
run_svm(x_train_bagofwords_10p, y_train, x_test_bagofwords_10p, 'Bag of Words - 90th percentile')
```

```
Bag of Words - 90th percentile
Average precision score, micro-averaged over all classes: 0.86
```

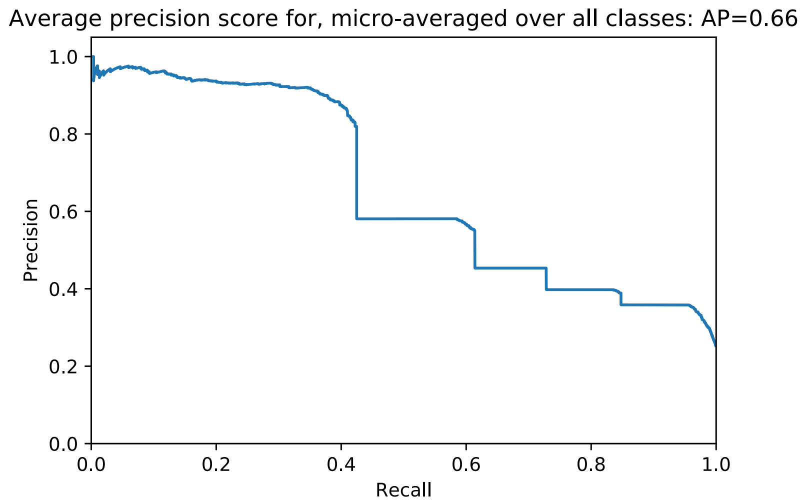


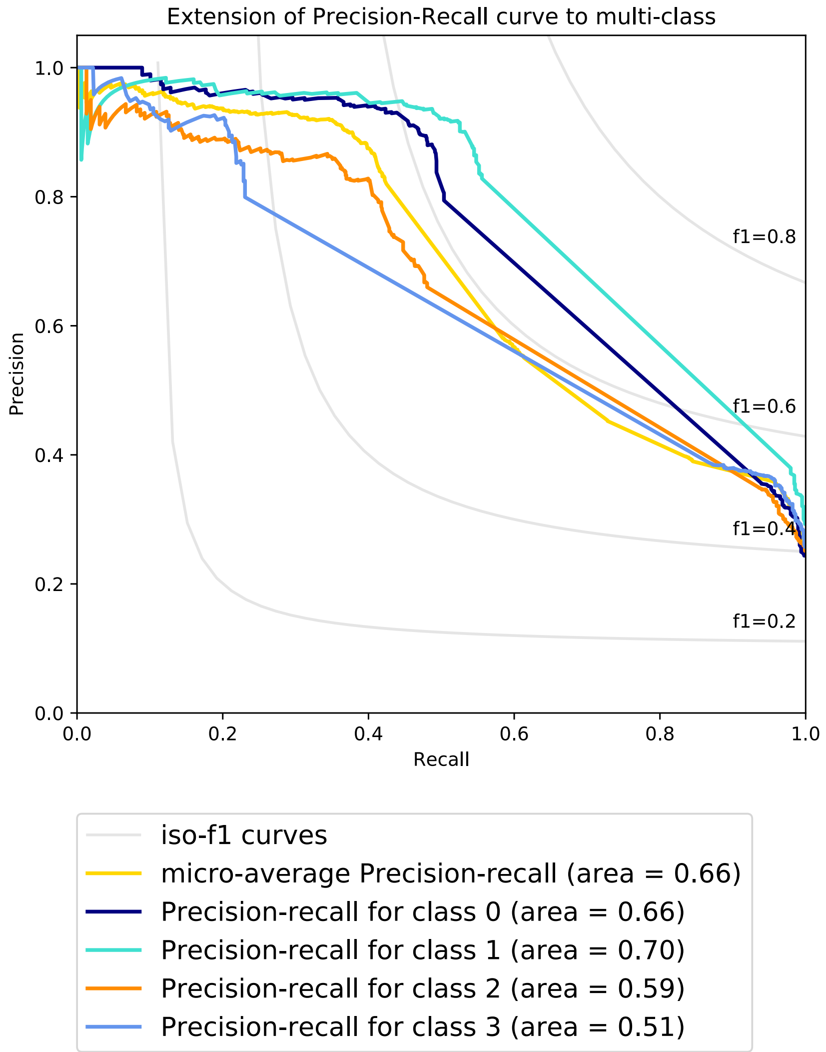


SVM for Bag of N-grams 90th percentile

In [39]:
```
run_svm(x_train_bagofngrams_10p, y_train, x_test_bagofngrams_10p, 'Bag of N-Grams - 90th percentile')
```

```
Bag of N-Grams - 90th percentile
Average precision score, micro-averaged over all classes: 0.66
```

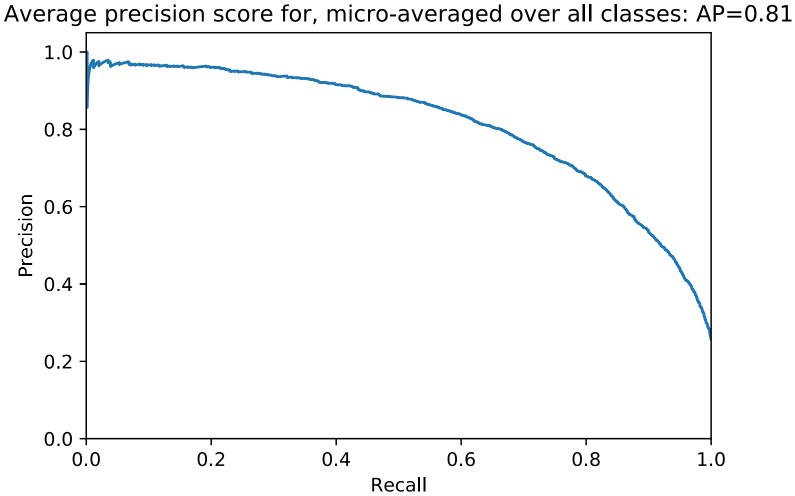


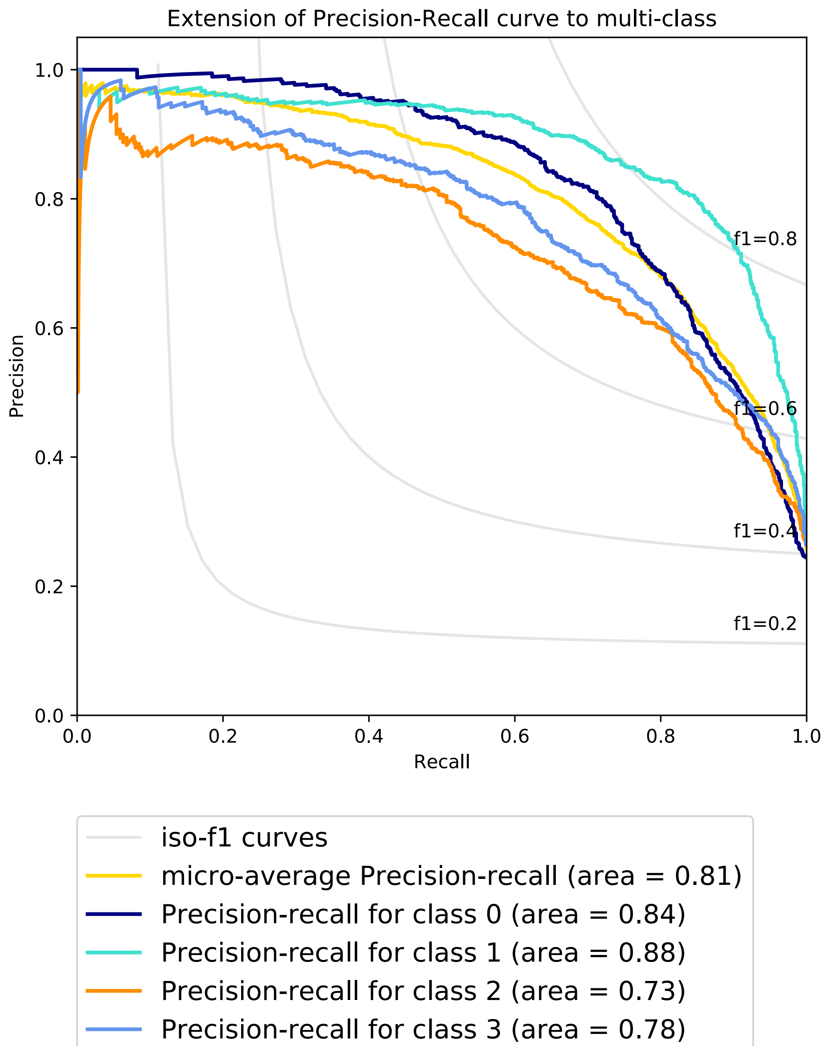


SVM for Bag of Chars 90th percentile

In [40]:
```
run_svm(x_train_cv_char_10p, y_train, x_test_cv_char_10p, 'Bag of Chars - 90th percentile')
```

```
Bag of Chars - 90th percentile
Average precision score, micro-averaged over all classes: 0.81
```





References - Code sample sources disclaimer:

Code for this project is either directly from (with some modification), or inspired by, but not limited to the following sources:

- Kelly Epley Naive Bayes: https://towardsdatascience.com/naive-bayes-document-classification-in-python-e33ff50f937e (https://towardsdatascience.com/naive-bayes-document-classification-in-python-e33ff50f937e)
- MLWhiz's excellent blogs about text classification and NLP: https://mlwhiz.com/blog/2018/12/17/text_classification/ (https://mlwhiz.com/blog/2018/12/17/text_classification/) https://mlwhiz.com/blog/2019/01/17/deeplearning_nlp_preprocess/ (https://mlwhiz.com/blog/2019/01/17/deeplearning_nlp_preprocess/) https://mlwhiz.com/blog/2019/02/08/deeplearning_nlp_conventional_methods/ (https://mlwhiz.com/blog/2019/02/08/deeplearning_nlp_conventional_methods/) https://www.kaggle.com/mlwhiz/conventional-methods-for-quora-classification/ (https://www.kaggle.com/mlwhiz/conventional-methods-for-quora-classification/)
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- datanizing GmbH: https://medium.com/@datanizing/modern-text-mining-with-python-part-1-of-5-introduction-cleaning-and-linguistics-647f9ec85b6a (https://medium.com/@datanizing/modern-text-mining-with-python-part-1-of-5-introduction-cleaning-and-linguistics-647f9ec85b6a)
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- Jason Brownlee's Feature Selection For Machine Learning in Python https://machinelearningmastery.com/feature-selection-machine-learning-python/ (https://machinelearningmastery.com/feature-selection-machine-learning-python/)
- Susan Li's Multi-class text classification with Scikit-learn: https://towardsdatascience.com/multi-class-text-classification-with-scikit-learn-12f1e60e0a9f (https://towardsdatascience.com/multi-class-text-classification-with-scikit-learn-12f1e60e0a9f)
- Vadim Smolyakov Ensemble Learning to Improve Machine Learning Results: https://blog.statsbot.co/ensemble-learning-d1dcd548e936 (https://blog.statsbot.co/ensemble-learning-d1dcd548e936)
- Udacity course video on Youtube UD120: https://www.youtube.com/watch?v=GdsLRKjjKLw (https://www.youtube.com/watch?v=GdsLRKjjKLw)