Models and Ensembling Methods + Interpretability with LIME

Import dependencies

In [1]:
```
import numpy
from gensim.models import word2vec
from gensim.models import KeyedVectors
import pandas
from nltk import WordPunctTokenizer
from sklearn.preprocessing import label_binarize
import sqlite3
from sklearn.multiclass import OneVsRestClassifier
from matplotlib import pyplot as plt
import seaborn as sns
from sklearn.metrics import precision_recall_curve
from sklearn.metrics import average_precision_score
from sklearn.metrics import f1_score
from sklearn.metrics import matthews_corrcoef
from sklearn.metrics import precision_recall_fscore_support
from sklearn import svm
from itertools import cycle
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import GaussianNB
from sklearn import tree
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_validate
from sklearn.metrics import precision_score, recall_score, roc_auc_score
from sklearn.metrics import multilabel_confusion_matrix, confusion_matrix
from sklearn.metrics import make_scorer
from sklearn.ensemble import StackingClassifier
from sklearn.ensemble import BaggingClassifier
from sklearn import tree
from sklearn.model_selection import GridSearchCV
from mlxtend.plotting import plot_learning_curves
import lime
import lime.lime_tabular
import lime.lime_text
```

Define Constants

In [2]:
```
W2V_FEATURE_SIZE = 300
N_CLASSES = 4
RANDOM_STATE = 123
N_FOLDS = 5
```

Read in the data

Load raw train and test data

Load in the data from the database

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

Check the if the data was loaded correctly

In [4]:
```
train_data_df
```

Out[4]:

	category	content_cleaned
0	3	wall street seeing green
1	3	private investment firm carlyle group reputati...
2	3	soaring crude prices plus economy outlook earn...
3	3	authorities halted oil main pipeline southern ...
4	3	tearaway world oil prices toppling records str...
...	...	...
119995	1	pakistani president pervez musharraf said stay...
119996	2	red sox general manager theo epstein acknowled...
119997	2	miami dolphins put courtship lsu coach nick sa...
119998	2	pittsburgh ny giants time line steelers record...
119999	2	vince carter traded toronto raptors new jersey...

120000 rows × 2 columns

In [5]:
```
test_data_df
```

Out[5]:

	category	content_cleaned
0	3	unions representing workers turner newall say ...
1	4	toronto canada rocketeers competing million an...
2	4	company founded chemistry researcher universit...
3	4	barely dawn mike fitzpatrick starts shift blur...
4	4	southern california agency went emissions bovi...
...	...	...
7595	1	ukrainian presidential candidate viktor yushch...
7596	2	supply attractive pitching options dwindling d...
7597	2	like roger clemens almost exactly eight years ...
7598	3	singapore doctors united states warned painkil...
7599	3	ebay plans buy apartment home rental service m...

7600 rows × 2 columns

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

In [6]:
```
x_train = train_data_df.content_cleaned
y_train = label_binarize(train_data_df.category, classes=range(1, N_CLASSES + 
1))

x_test = test_data_df.content_cleaned
y_test = label_binarize(test_data_df.category, classes=range(1, N_CLASSES + 1
))
```

Load word2vec data

Load word2vec feature arrays from .npz files

load dict of arrays

In [7]:
```
w2v_train_features_array_dict = numpy.load(
    './data/word2vec-train-features-120000-min5dim300.npz')
w2v_test_features_array_dict = numpy.load(
    './data/word2vec-test-features-120000-min5dim300.npz')
# extract the first array from train
data = w2v_train_features_array_dict['arr_0']
# print the array
print(data)
# extract the first array from test
data = w2v_test_features_array_dict['arr_0']
# print the array
print(data)
```

```
[[-0.43092448  0.50092196  0.08331972 ...  1.3914201   1.2953259
  -1.8574607 ]
 [-0.10783155 -0.35169265  0.90062636 ... -0.38979718  0.13664657
   0.5066641 ]
 [-1.0086536  -0.29255652 -0.7550053  ... -0.18521406  0.7896786
  -0.23576818]
 ...
 [-0.02566049  0.23409443 -0.8595321  ... -0.05427613 -0.89297265
  -0.09055152]
 [-0.6081659   0.42683512 -0.9105423  ... -0.06156884 -0.40654626
   0.07195716]
 [-1.0819023  -0.04211196 -0.16453283 ... -0.40625843 -0.13644677
  -0.0066904 ]]
[[-0.02657197 -1.0014614  -0.035705   ...  0.48677683  0.3947945
  -0.9894788 ]
 [-0.54866743 -1.3801866   0.66031504 ... -0.4012159   0.6803215
   0.92033225]
 [ 0.11171789  0.3781767  -0.26057357 ... -0.5006595   0.13674003
   0.10530389]
 ...
 [-0.46190766  0.7501185  -0.20256642 ... -0.32613838  0.09363924
   0.46578252]
 [-0.023529   -0.33200815 -0.63418424 ... -0.46149412  0.39634904
  -0.46027517]
 [-0.25388533 -0.6177681   0.9628809  ... -0.66557425 -0.1068292
  -0.64577085]]
```

Load word2vec model trained key vectors

In [8]:
```
w2v_model_train = KeyedVectors.load(
    './data/custom-trained-word2vec-120000-min5dim300.kv')
```

Get the word2vec data back into usable form

```
In [9]: wpt = WordPunctTokenizer()
tokenized_corpus_train = [wpt.tokenize(document) for document in x_train]
tokenized_corpus_test = [wpt.tokenize(document) for document in x_test]

def average_word_vectors(words, model, vocabulary, num_features):
    feature_vector = numpy.zeros((num_features,), dtype="float32")
    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, nu
m_features)
            for tokenized_sentence in corpus]
    return numpy.array(features)
```

Obtain document level embeddings

```
In [10]: w2v_feature_array_train = averaged_word_vectorizer(corpus=tokenized_corpus_tra
in,
    model=w2v_model_train, num_features=W2V_FEATURE_SIZE)
w2v_feature_array_test = averaged_word_vectorizer(corpus=tokenized_corpus_test
,
    model=w2v_model_train, num_features=W2V_FEATURE_SIZE)

x_train_w2v = pandas.DataFrame(w2v_feature_array_train)
x_test_w2v = pandas.DataFrame(w2v_feature_array_test)
```

Sample down for speed, for now. (use when testing)

x_train_w2v = x_train_w2v.sample(n = 3000, replace = False, random_state = RANDOM_STATE) y_train = train_data_df.category.sample(n = 3000, replace = False, random_state = RANDOM_STATE) y_train = label_binarize(y_train, classes=range(1, N_CLASSES + 1))

Build Models

SVM Model Building Function

In [11]:
```
def run_svm(x_train, y_train):
    classifier = OneVsRestClassifier(svm.LinearSVC(random_state=RANDOM_STATE))
    classifier.fit(x_train, y_train)
    return classifier
```

Logistic Regression Model Building Function

In [12]:
```
def run_logreg(x_train, y_train):
    classifier = OneVsRestClassifier(LogisticRegression(random_state=RANDOM_ST
ATE))
    classifier.fit(x_train, y_train)
    return classifier
```

Naive Bayes Function

In [13]:
```
def run_nb(x_train, y_train):
    classifier = OneVsRestClassifier(GaussianNB())
    classifier.fit(x_train, y_train)
    return classifier
```

Decision Trees Function

In [14]:
```
def run_dectree(x_train, y_train):
    classifier = OneVsRestClassifier(tree.DecisionTreeClassifier())
    classifier.fit(x_train, y_train)
    return classifier
```

Functions to calculate scores and to plot them

Calculate, then plot the Precision, Recall, Average Precision, F1

In [15]:
```
def prf1_calc(classifier, algo_name, n_classes, x_test, y_test):
    # Get the decision function from the classifier
    if algo_name == 'SVM':
        y_score = classifier.decision_function(x_test)
    else:
        y_score = classifier.predict_proba(x_test)
    y_pred = classifier.predict(x_test)

    # The average precision score in multi-label settings
    # For each class
    precision = dict()
    recall = dict()
    average_f1 = dict()
    average_precision = dict()
    mcc = 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])
        average_f1[i] = f1_score(y_test[:, i], y_pred[:, i])
        mcc[i] = matthews_corrcoef(y_test[:, i], y_pred[:, i])

    # A "micro-average": quantifying score on all classes jointly
    precision["micro"], recall["micro"], _ = precision_recall_curve(y_test.rav
el(),
        y_score.ravel())
    average_precision["micro"] = average_precision_score(y_test, y_score,
                                                         average="micro")
    average_f1['micro'] = f1_score(y_test, y_pred, average='micro')
    mcc['micro'] = sum(mcc.values())/4

    # Plot the data
    prf1_plot(precision, recall, average_precision, algo_name, n_classes)

    # Return all metrics
    results = pandas.DataFrame()

    for k in average_precision.keys():
        results.at[algo_name, f'P-R {k}'] = numpy.round(average_precision[k],
3)
        results.at[algo_name, f'F1 {k}'] = numpy.round(average_f1[k], 3)
        results.at[algo_name, f'MCC {k}'] = numpy.round(mcc[k], 3)

    return results

# Function to Plot Precision, Recall, F1
def prf1_plot(precision, recall, average_precision, algo_name, n_classes):
    print(algo_name)
    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, 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', 'tea
l'])

    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()
```

Run the Base Models

Run SVM Model

In [16]:
```
svm_model = run_svm(x_train_w2v, y_train)
```

Run Logistic Regression Model

In [17]:
```
logreg_model = run_logreg(x_train_w2v, y_train)
```

Run Naive Bayes Classifier

In [18]:
```
nb_model = run_nb(x_train_w2v, y_train)
```

Run Decision Trees Classifier

In [19]:
```
dectree_model = run_dectree(x_train_w2v, y_train)
```

Get the scores

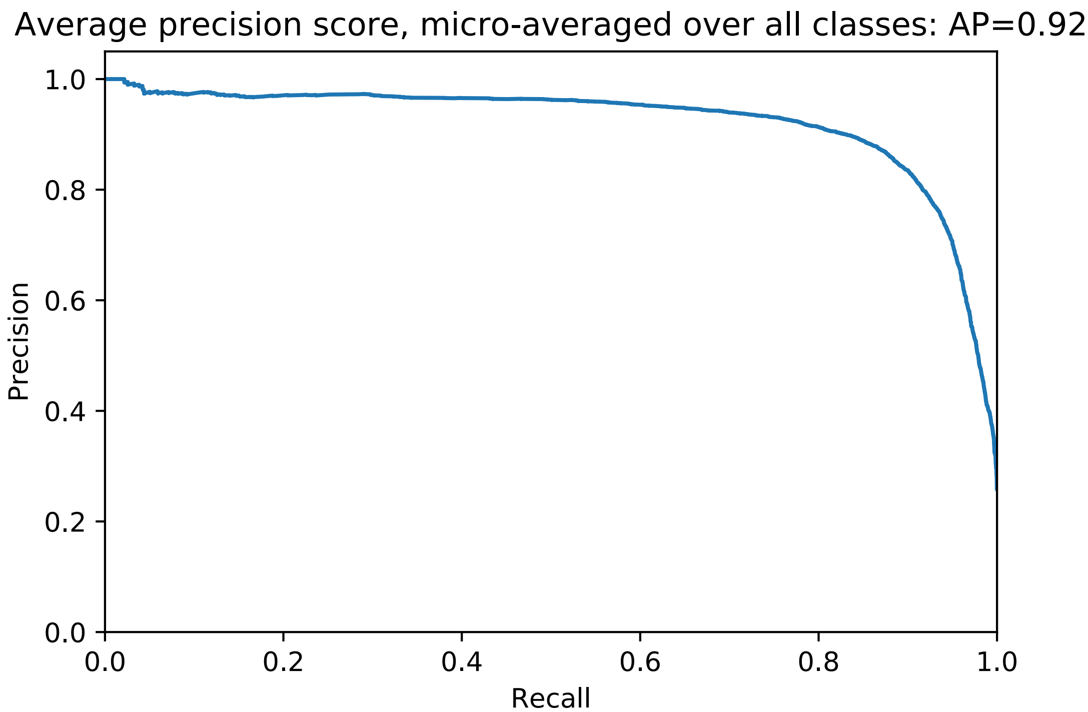
Initialize the dataframe to keep track of the scores

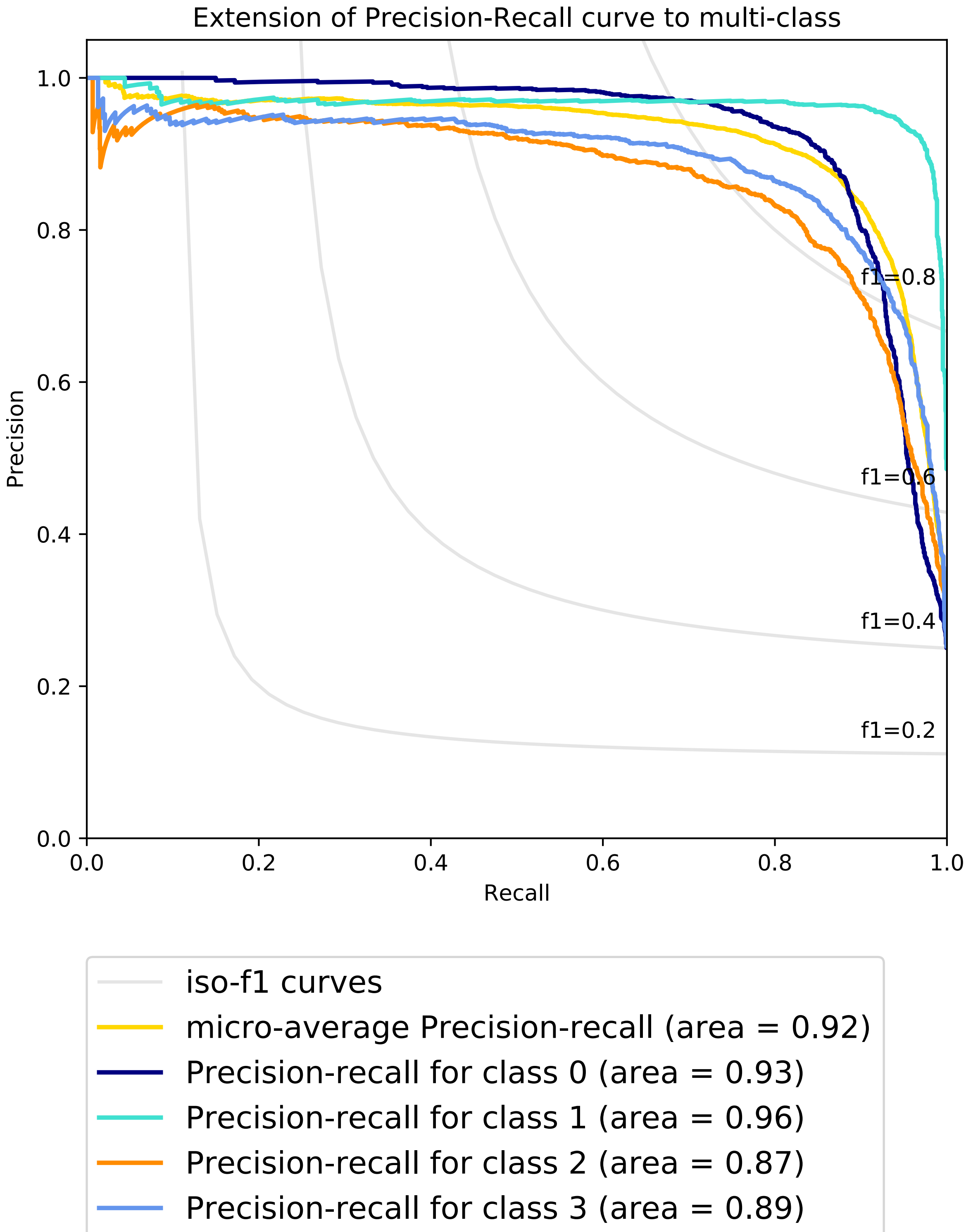
In [20]:
```
scores = pandas.DataFrame()
```

Precision, Recall, Avg. Precision for SVM

In [21]:
```
scores = scores.append(prf1_calc(svm_model, 'SVM', N_CLASSES, x_test_w2v, y_te
st))
```

```
SVM
Average precision score, micro-averaged over all classes: 0.92
```

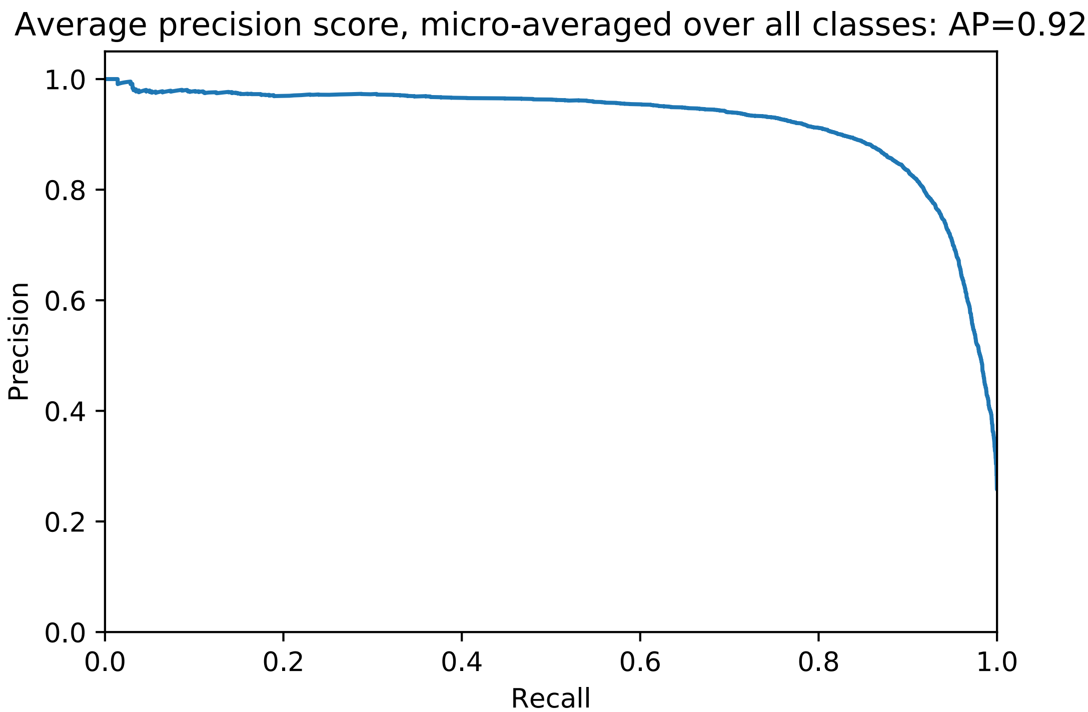


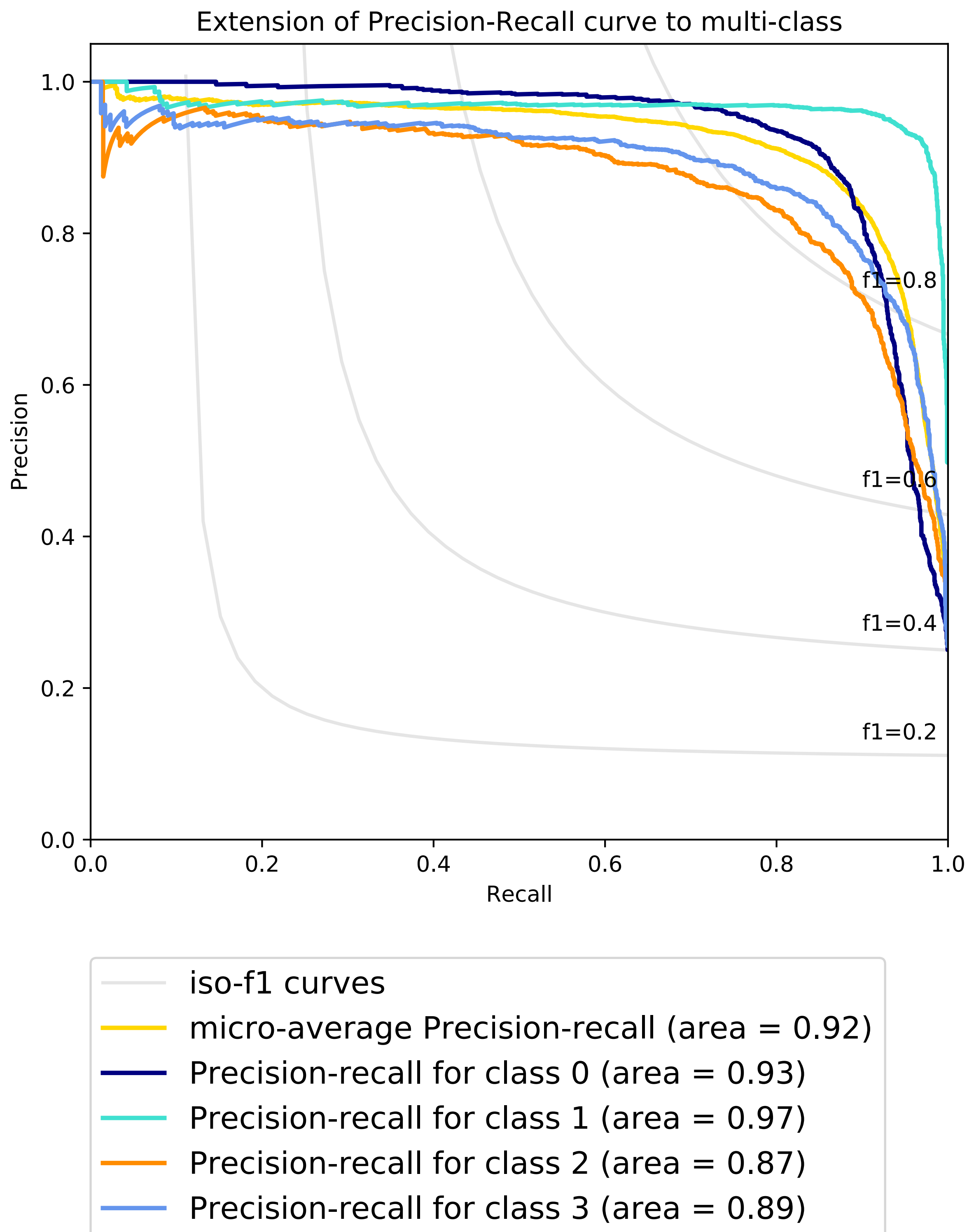


Precision, Recall, Avg. Precision for LOG REG

In [22]:
```
scores = scores.append(prf1_calc(logreg_model, 'LOGREG', N_CLASSES, x_test_w2v
, y_test))
```

```
LOGREG
Average precision score, micro-averaged over all classes: 0.92
```



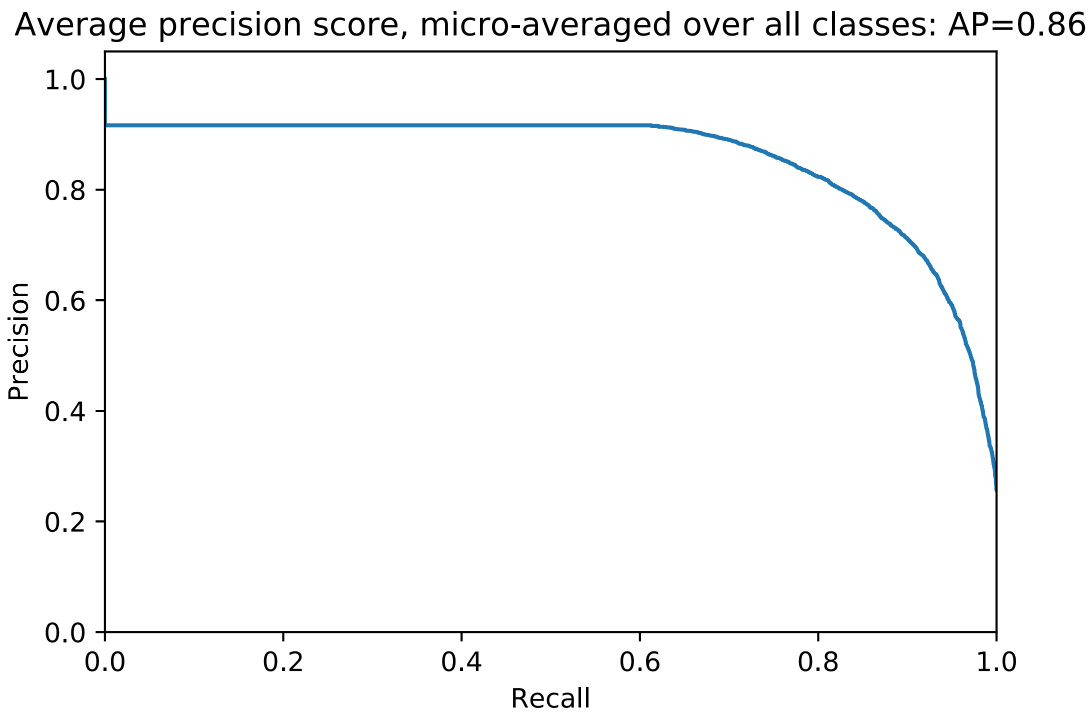


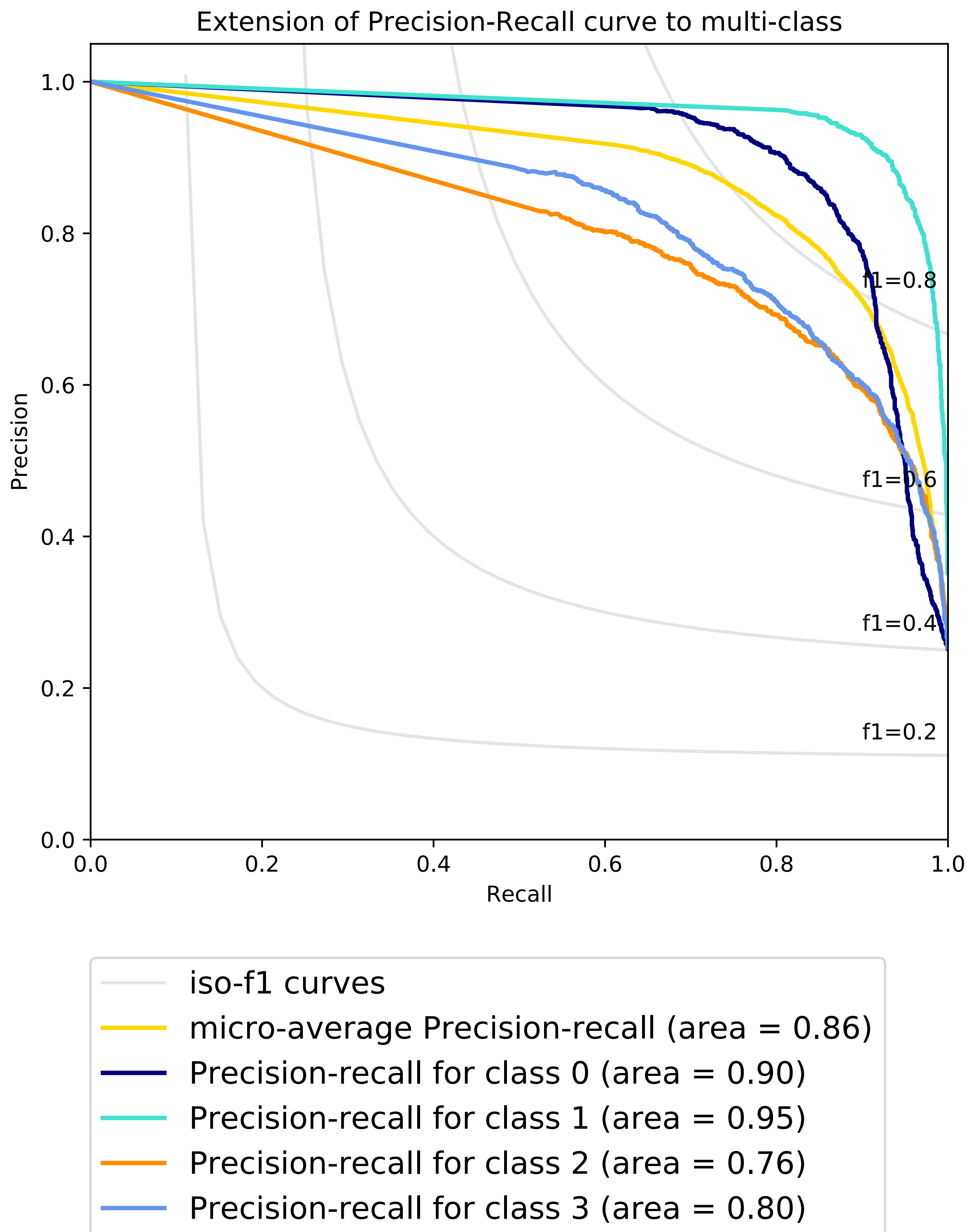
Precision, Recall, Avg. Precision for Naive Bayes

In [23]:

```
scores = scores.append(prf1_calc(nb_model, 'NB', N_CLASSES, x_test_w2v, y_test
))
```

```
NB
Average precision score, micro-averaged over all classes: 0.86
```

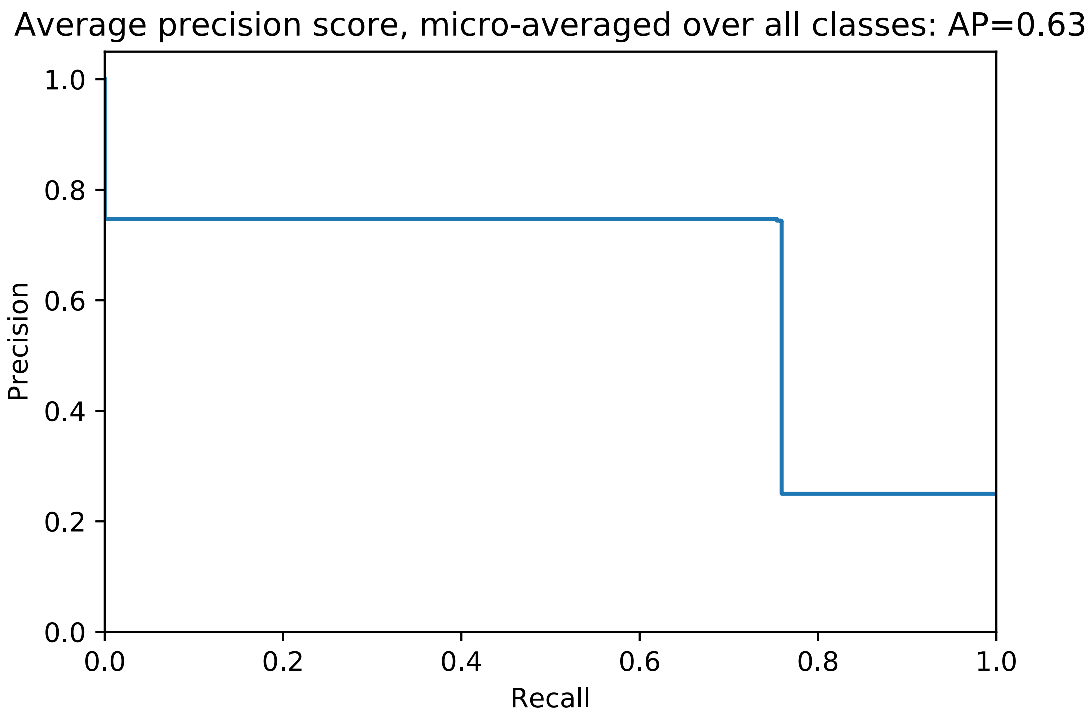


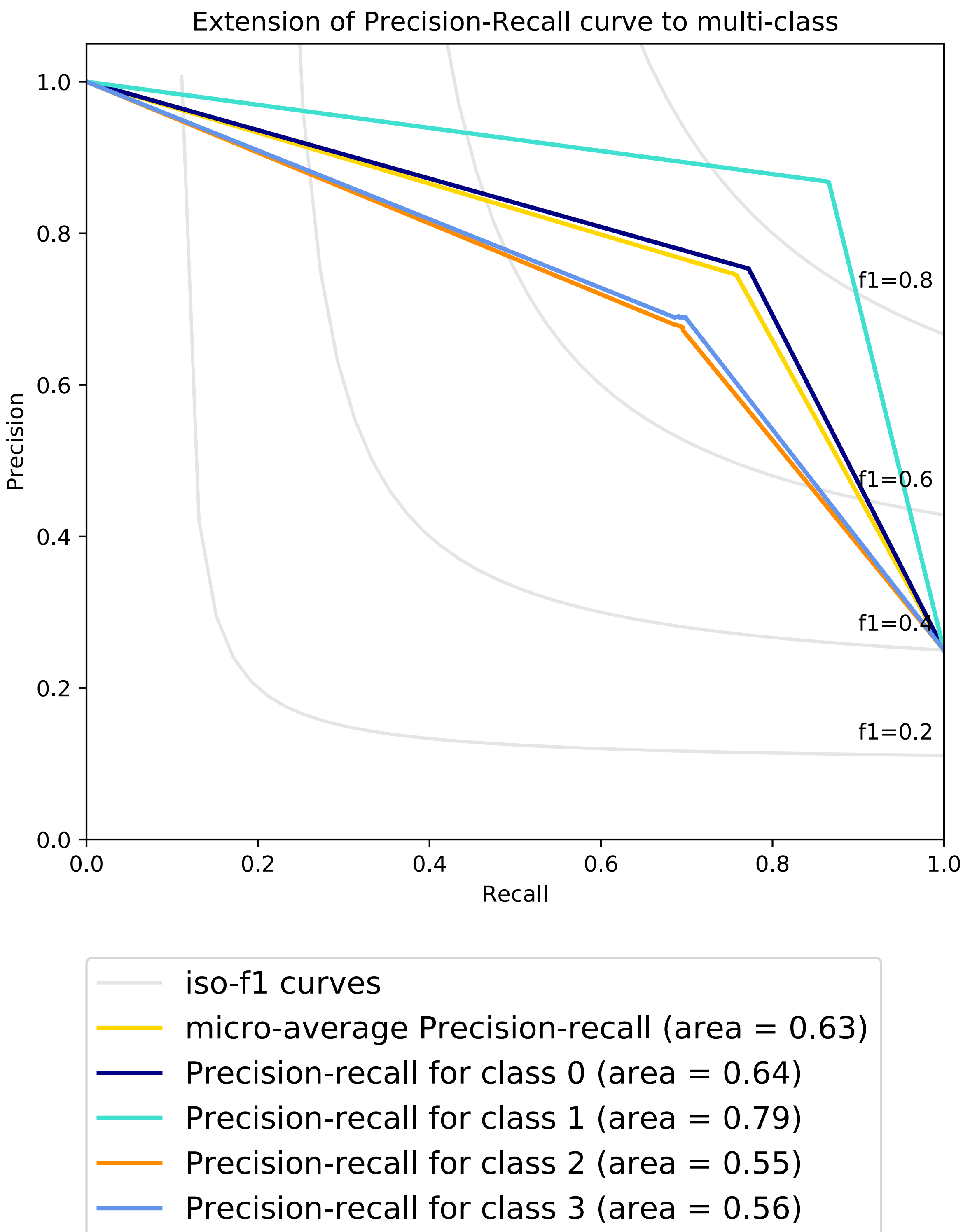


Precision, Recall, Avg. Precision for Decision Trees

In [24]:
```
scores = scores.append(prf1_calc(dectree_model, 'DT', N_CLASSES, x_test_w2v, y
_test))
```

```
DT
Average precision score, micro-averaged over all classes: 0.63
```





Look at Cross-Validation

Create model list to iterate through for cross validation

In [25]:
```
gnb = OneVsRestClassifier(GaussianNB())
sv = OneVsRestClassifier(svm.LinearSVC(random_state=RANDOM_STATE))
lreg = OneVsRestClassifier(LogisticRegression(random_state=RANDOM_STATE))
dtree = OneVsRestClassifier(tree.DecisionTreeClassifier())

model_list = [gnb, sv, lreg, dtree]
model_namelist = ['Gaussian Naive Bayes',
                  'SVM/Linear SVC',
                  'Logistic Regression',
                  'Decision Tree']
```

Make scoring metrics to pass cv function through

In [26]:
```
scoring = {'precision': make_scorer(precision_score, average='micro'),
           'recall': make_scorer(recall_score, average='micro'),
           'f1': make_scorer(f1_score, average='micro'),
           'roc_auc': make_scorer(roc_auc_score, average='micro'),
           # 'mcc': make_scorer(matthews_corrcoef) <- cannot support multi-lab
el
          }

cv_result_entries = []
i = 0
```

Loop cross validation through various models and generate results

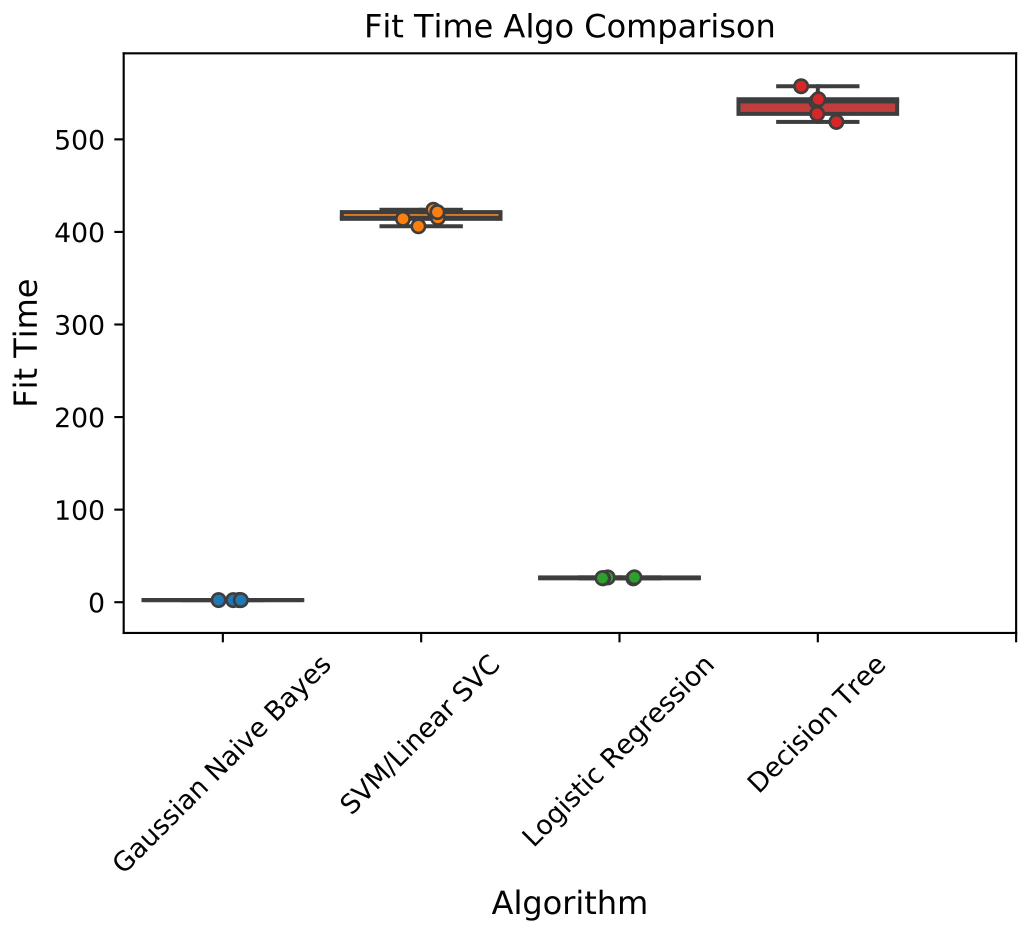
In [27]:
```
for mod in model_list:
    metrics = cross_validate(
        mod,
        x_train_w2v,
        y_train,
        cv=N_FOLDS,
        scoring = scoring,
        return_train_score=False,
        n_jobs=-1
    )
    for key in metrics.keys():
        for fold_index, score in enumerate(metrics[key]):
            cv_result_entries.append((model_namelist[i], fold_index, key, scor
e))
    i += 1
```

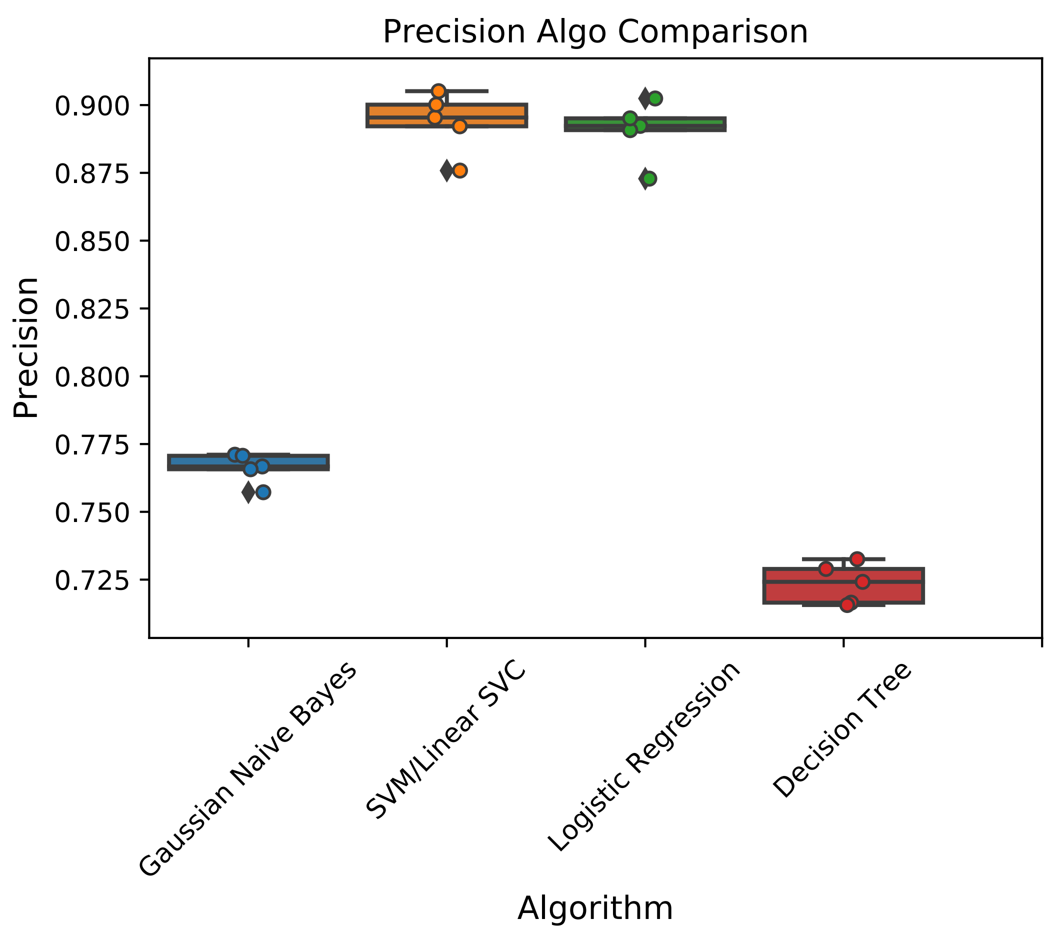
Save the cv results to a dataframe

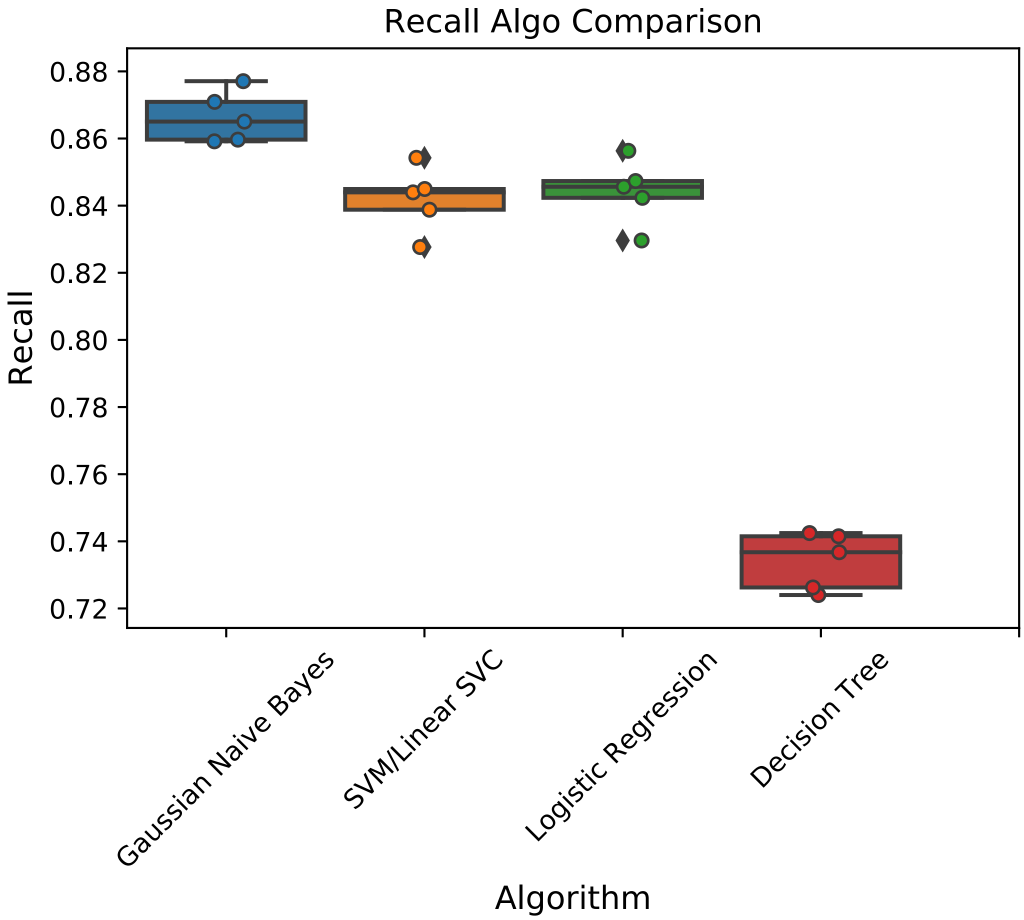
In [28]:
```
cv_results_df = pandas.DataFrame(cv_result_entries)
cv_results_df.columns = ['algo', 'cv fold', 'metric', 'value']
```

Plot cv results

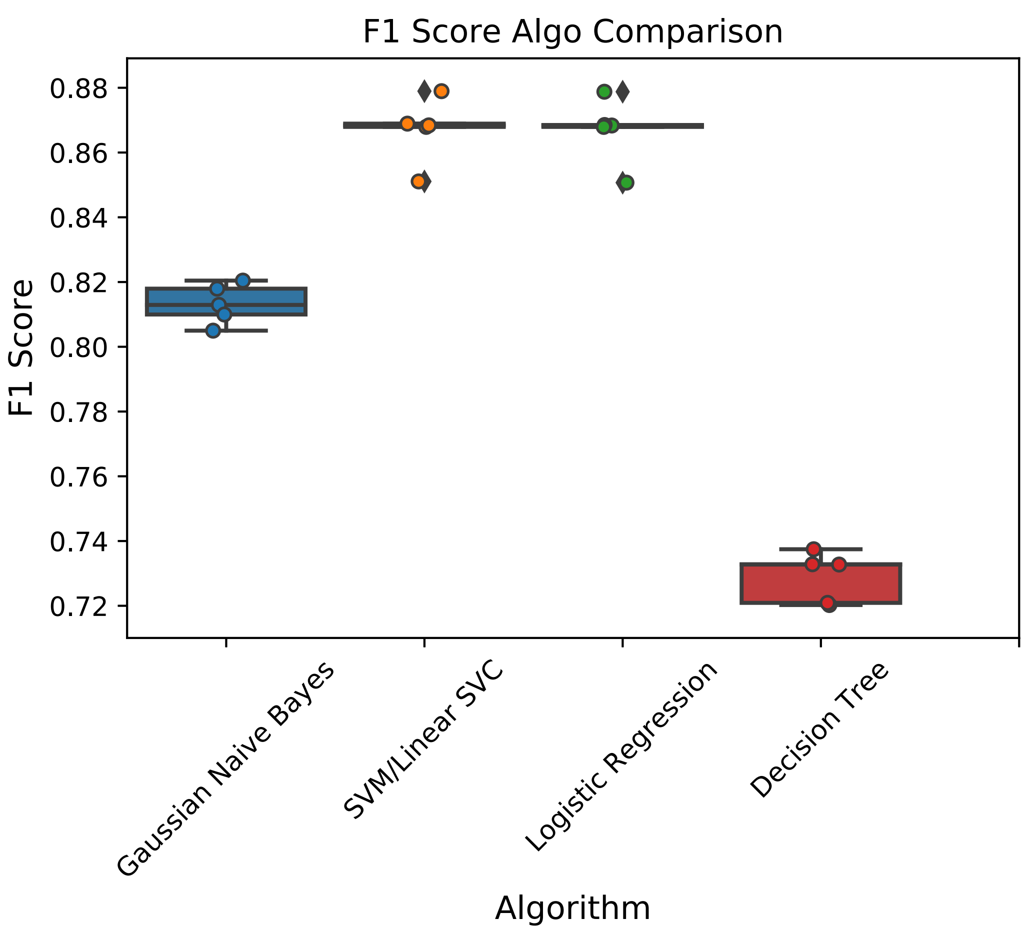
In [29]:
```
for metric_name, metric in zip(['fit_time',
                                'test_precision',
                                'test_recall',
                                'test_f1',
                                'test_roc_auc'],
                               ['Fit Time',
                                'Precision',
                                'Recall',
                                'F1 Score',
                                'ROC AUC']):
    sns.boxplot(x='algo', y='value', #hue='algo',
        data=cv_results_df[cv_results_df.metric.eq(f'{metric_name}')])
    sns.stripplot(x='algo', y = 'value',
        data = cv_results_df[cv_results_df.metric.eq(f'{metric_name}')],
        size = 5, linewidth = 1)
    plt.title(f'{metric} Algo Comparison', fontsize=12)
    plt.xlabel('Algorithm', fontsize=12)
    plt.ylabel(f'{metric}', fontsize=12)
    plt.xticks([0, 1, 2, 3, 4])
    plt.xticks(rotation=45)
    plt.show()
```


Fit Time Algo Comparison
Fit Time
500
400
300
200
100
0
Gaussian Naive Bayes
SVM/Linear SVC
Logistic Regression
Decision Tree
Algorithm

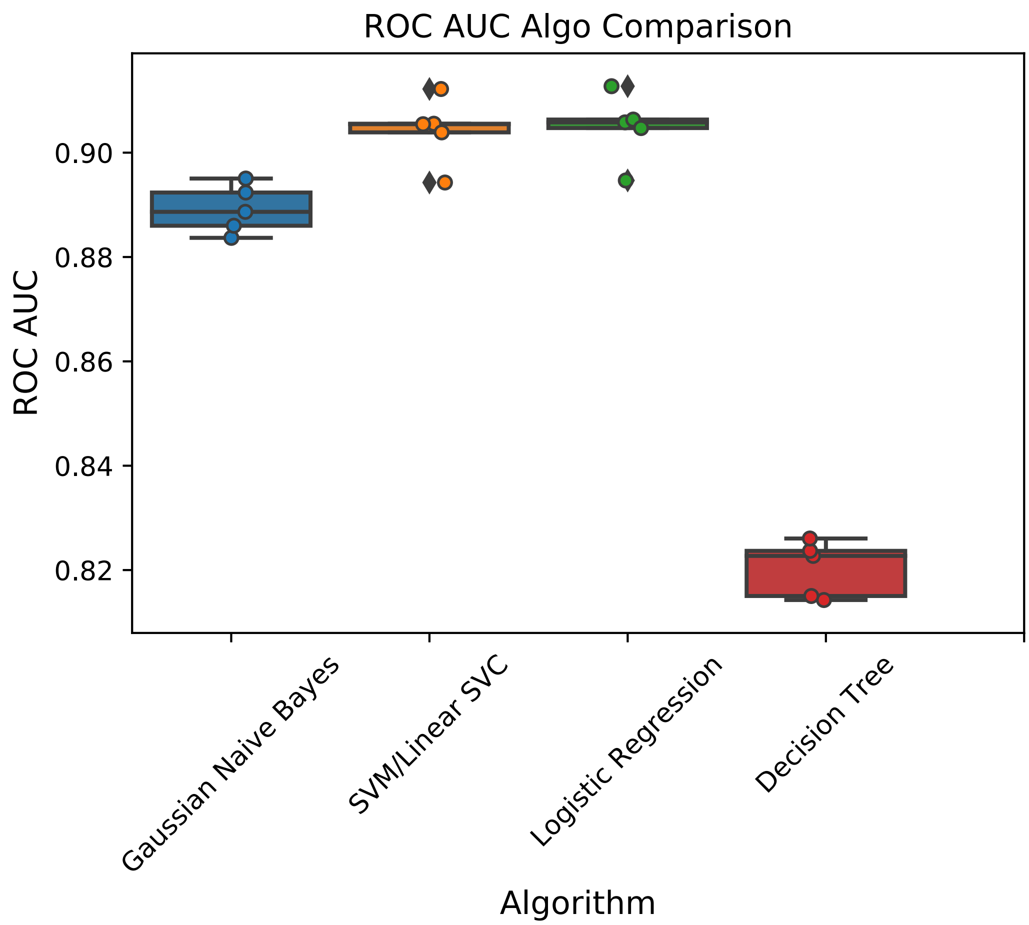

Precision Algo Comparison
Precision
0.900
0.875
0.850
0.825
0.800
0.775
0.750
0.725
Gaussian Naive Bayes
SVM/Linear SVC
Logistic Regression
Decision Tree
Algorithm



Recall Algo Comparison
Recall
0.88
0.86
0.84
0.82
0.80
0.78
0.76
0.74
0.72
Gaussian Naive Bayes
SVM/Linear SVC
Logistic Regression
Decision Tree
Algorithm



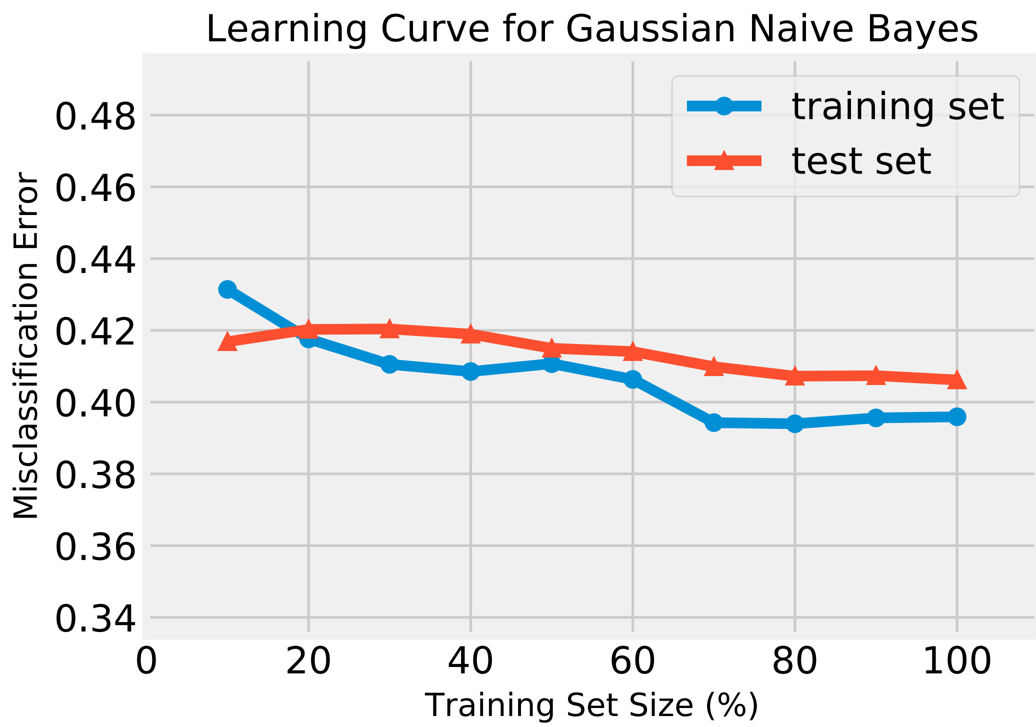
F1 Score Algo Comparison
F1 Score
0.88
0.86
0.84
0.82
0.80
0.78
0.76
0.74
0.72
Gaussian Naive Bayes
SVM/Linear SVC
Logistic Regression
Decision Tree
Algorithm

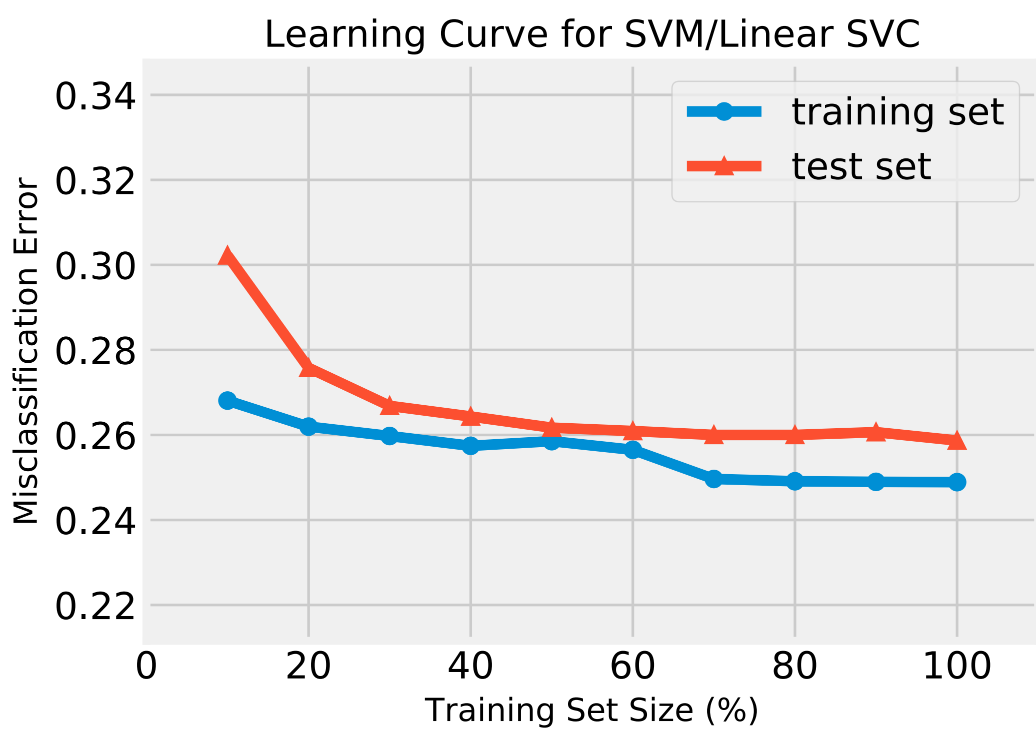


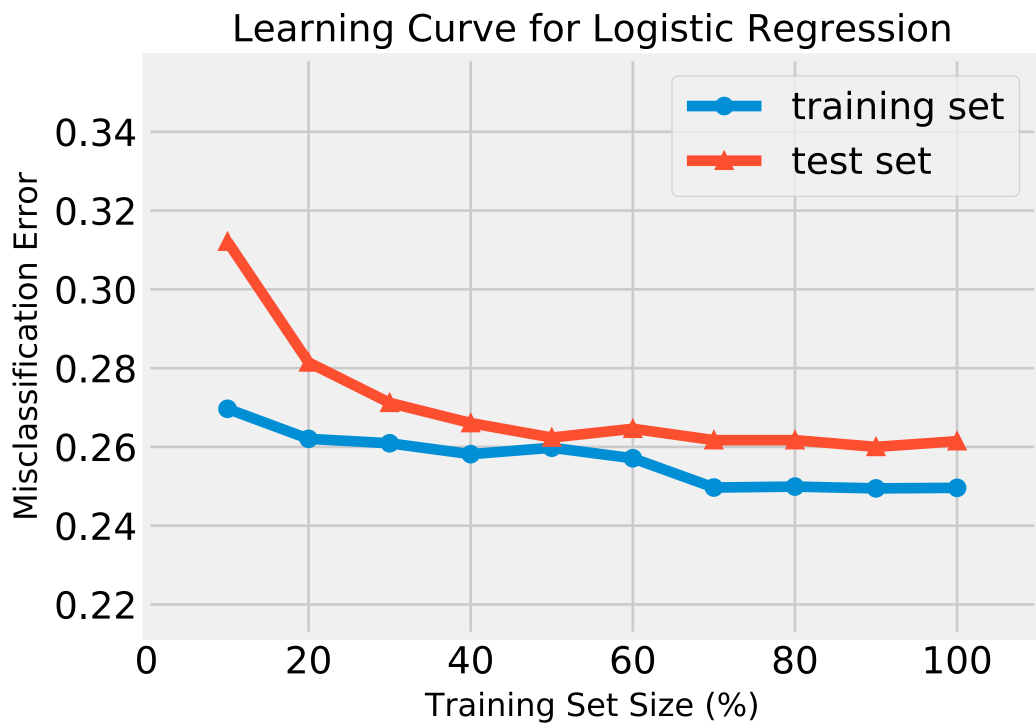
Misclassification Errors

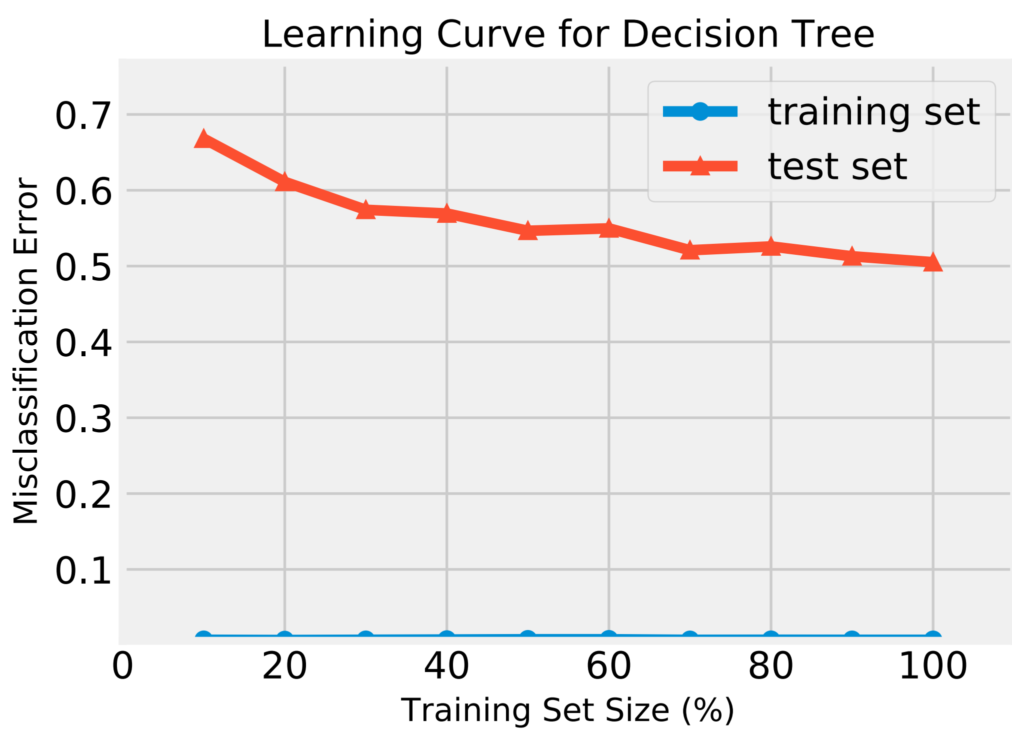
In [30]:

```
i=0
for model in model_list:
    plt.figure()
    plot_learning_curves(x_train_w2v, y_train, x_test_w2v, y_test, model)
    plt.title('Learning Curve for ' + model_namelist[i], fontsize=14)
    plt.xlabel('Training Set Size (%)', fontsize=12)
    plt.ylabel('Misclassification Error', fontsize=12)
    plt.show()
    i += 1
```


Learning Curve for Gaussian Naive Bayes
training set
test set
Misclassification Error
0.48
0.46
0.44
0.42
0.40
0.38
0.36
0.34
0
20
40
60
80
100
Training Set Size (%)


Learning Curve for SVM/Linear SVC
training set
test set
Misclassification Error
0.34
0.32
0.30
0.28
0.26
0.24
0.22
0
20
40
60
80
100
Training Set Size (%)



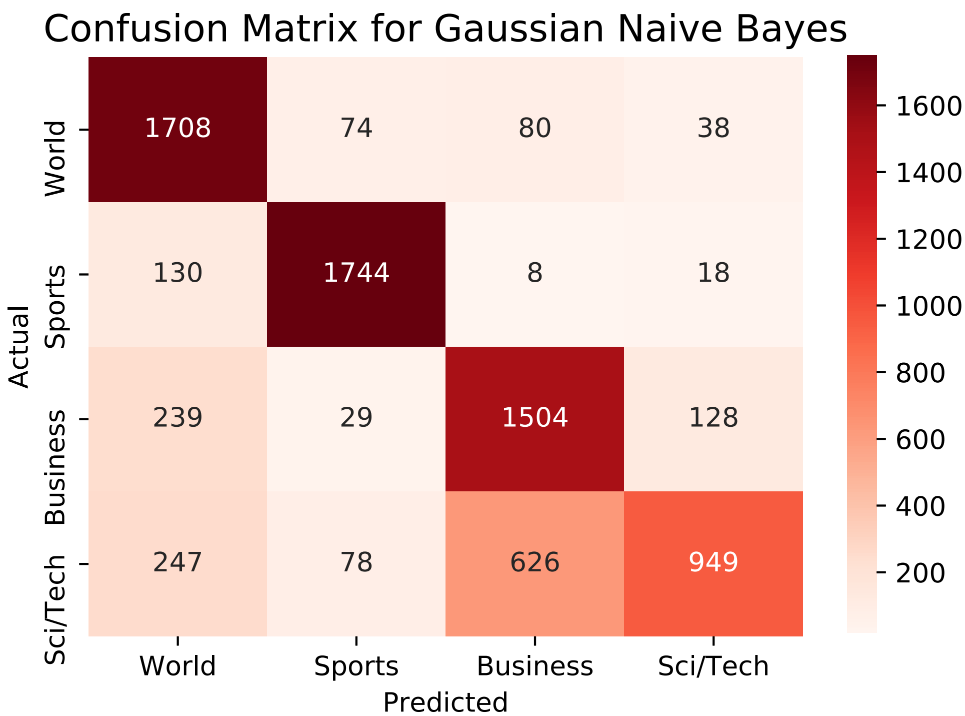


Get predictions

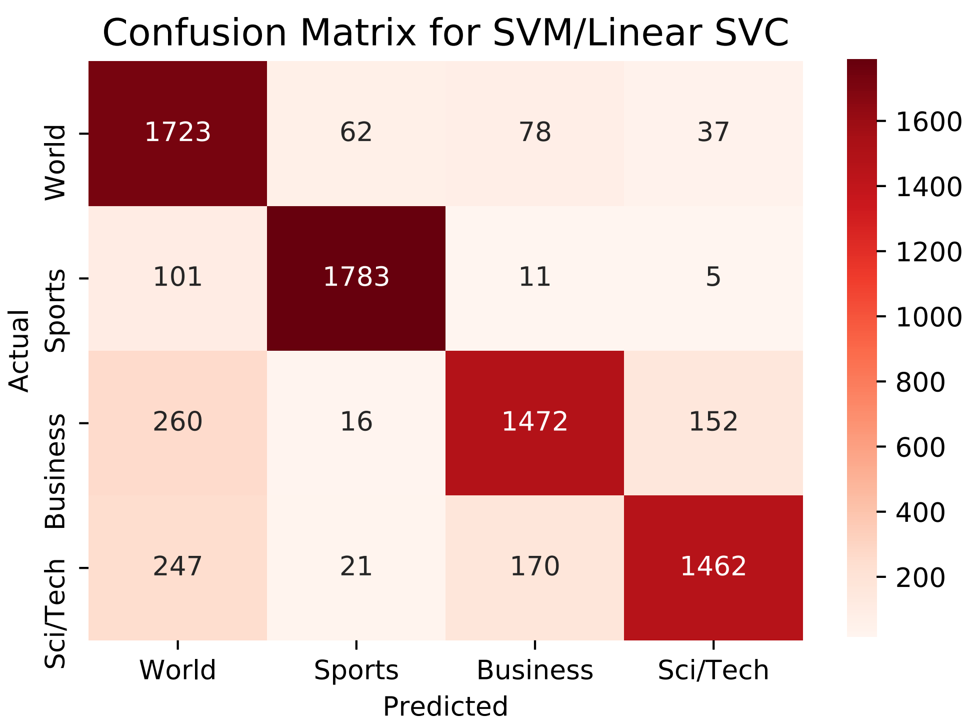
In [31]:
```
y_test_pred = []
for model in model_list:
    y_test_pred.append(model.predict(x_test_w2v))
```

Confusion Matrix

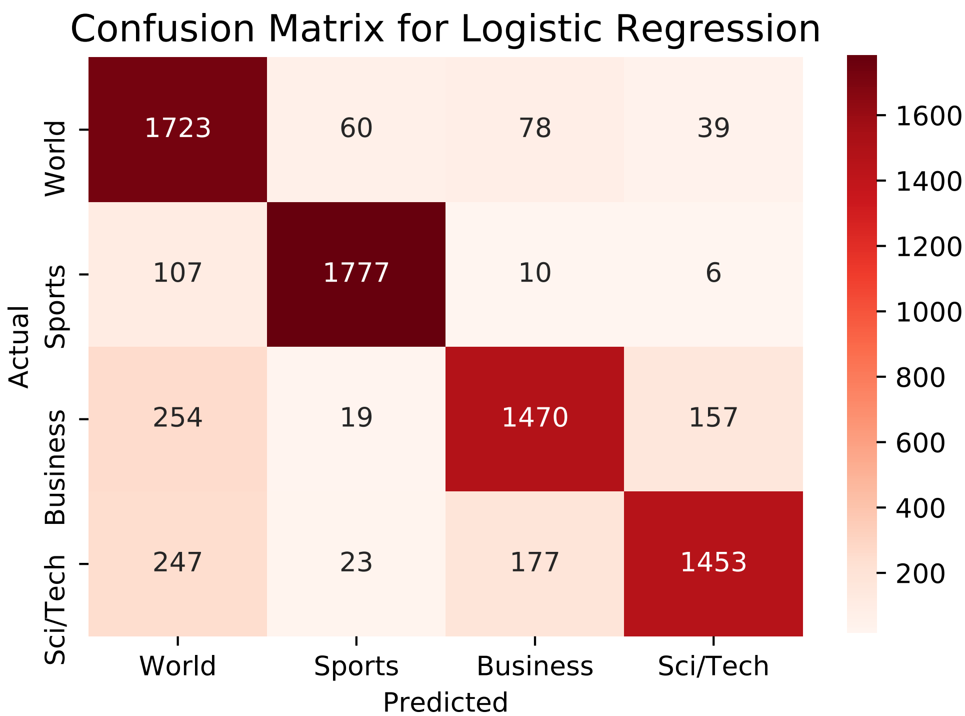
In [32]:
```
CLASSES = ['World', 'Sports', 'Business', 'Sci/Tech']
i=0
for _ in model_list:
    cm = confusion_matrix(numpy.argmax(y_test, axis=1),
                          numpy.argmax(y_test_pred[i], axis=1))
    cm_df = pandas.DataFrame(cm, index = CLASSES, columns = CLASSES)
    cm_df.index.name = 'Actual'
    cm_df.columns.name = 'Predicted'
    plt.title('Confusion Matrix for ' + model_namelist[i], fontsize=14)
    sns.heatmap(cm_df, annot=True, fmt='.6g', annot_kws={"size": 10}, cmap='Re
ds')
    plt.show()
    i += 1
```

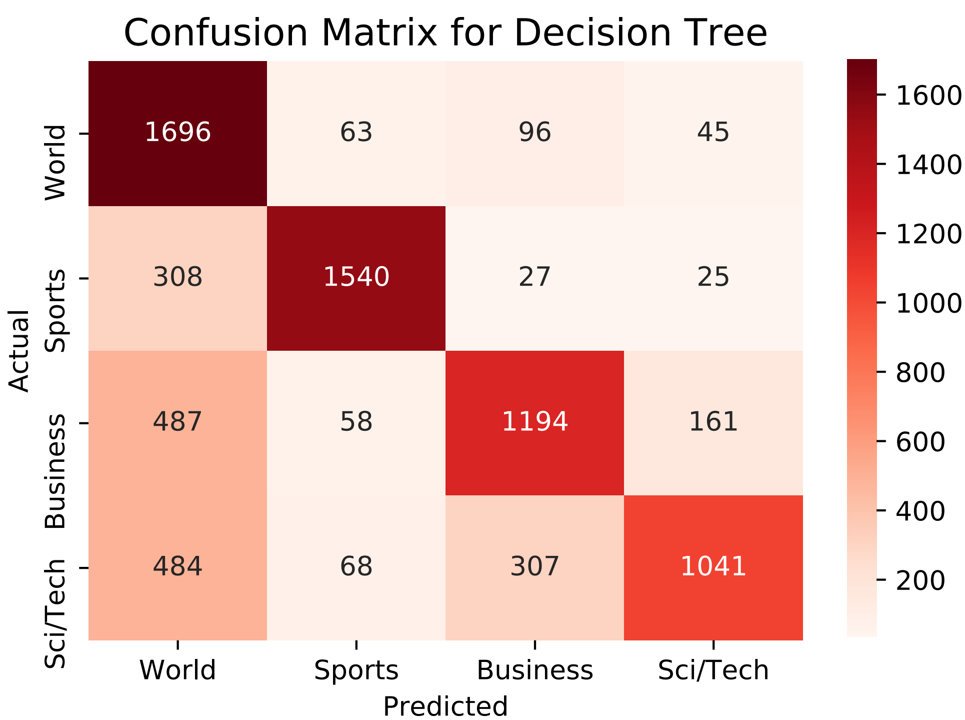


Confusion Matrix for Gaussian Naive Bayes
World
Sports
Business
Sci/Tech
Actual
1708
74
80
38
130
1744
8
18
239
29
1504
128
247
78
626
949
World
Sports
Business
Sci/Tech
Predicted
1600
1400
1200
1000
800
600
400
200



Confusion Matrix for SVM/Linear SVC
World
Sports
Business
Sci/Tech
Actual
1723
62
78
37
101
1783
11
5
260
16
1472
152
247
21
170
1462
World
Sports
Business
Sci/Tech
Predicted
1600
1400
1200
1000
800
600
400
200


Confusion Matrix for Logistic Regression
Actual
World
Sports
Business
Sci/Tech
1723
60
78
39
107
1777
10
6
254
19
1470
157
247
23
177
1453
World
Sports
Business
Sci/Tech
Predicted
1600
1400
1200
1000
800
600
400
200


Confusion Matrix for Decision Tree
Actual
World
Sports
Business
Sci/Tech
1696
63
96
45
308
1540
27
25
487
58
1194
161
484
68
307
1041
World
Sports
Business
Sci/Tech
Predicted
1600
1400
1200
1000
800
600
400
200

HYPER PARAMETER TUNING BY HYPEROPT (not working!!!)

from hyperopt import STATUS_OK N_FOLDS = 5

%%

Objective Function

def objective(params, n_folds = N_FOLDS): cv_results = cross_validate(OneVsRestClassifier(GaussianNB()), x_train_w2v, y_train, cv = n_folds, fit_params= params, scoring = {'f1': make_scorer(f1_score, average='micro')}, return_train_score=False, n_jobs=-1)

```
# Extract the best score
best_score = max(cv_results['test_f1'])
# Loss must be minimized
loss = 1 - best_score
# Dictionary with information for evaluation
return {'loss': loss, 'params': params, 'status': STATUS_OK}
```

Domain Space from hyperopt import hp space = {'estimator**var_smoothing': hp.uniform('estimator**var_smoothing', 1.e+00, 1.e-09)}

%%

Optimization Algorithm from hyperopt import tpe tpe_algo = tpe.suggest

%%

Results History from hyperopt import Trials bayes_trials = Trials()

%%

Run the optimization from hyperopt import fmin from hyperopt import rand MAX_EVALS = 500 params = space Optimize best = fmin(fn = objective, space = space, algo = tpe.suggest, max_evals = 100, trials = bayes_trials) print(best)

In [33]:
```
tempx = x_train_w2v
tempy = y_train
x_train_w2v = x_train_w2v.sample(n = 3000, replace = False, random_state = RAN
DOM_STATE)
y_train = train_data_df.category.sample(
    n = 3000, replace = False, random_state = RANDOM_STATE
)
y_train = label_binarize(y_train, classes=range(1, N_CLASSES + 1))
```

Hyper-parameter tuning with exhaustive Grid Search

Tune hyperparameters for Gaussian Naive-Bayes

In [34]:
```
params_gnb = {'estimator__var_smoothing': [1.e-09, 1.e-08, 1.e-07, 1.e-06, 1.e
-05,
                                           1.e-04, 1.e-03, 1.e-02, 1.e-01, 1.e
+00]
}
clf = GridSearchCV(estimator=gnb,
                   param_grid=params_gnb,
                   scoring='f1_micro',
                   n_jobs=-1,
                   cv=N_FOLDS,
                   return_train_score=True
                  )
clf_res = clf.fit(x_train_w2v, y_train)
print('Best Score: ', clf_res.best_score_)
print('Best Params: ', clf_res.best_params_)
```

```
Best Score:  0.801674851179991
Best Params:  {'estimator__var_smoothing': 0.001}
```

Tune hyperparameters for Logistic Regression

In [35]:
```
params_lreg = {
    "estimator__penalty": ['l1', 'l2'],
    "estimator__C": [0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000],
    #"estimator__class_weight":[{1:0.5, 0:0.5}, {1:0.4, 0:0.6},
    #                           {1:0.6, 0:0.4}, {1:0.7, 0:0.3}],
    "estimator__solver": ["newton-cg", "sag", "saga", "lbfgs"]
}
clf = GridSearchCV(estimator=lreg,
                   param_grid=params_lreg,
                   scoring='f1_micro',
                   n_jobs=-1,
                   cv=N_FOLDS,
                   return_train_score=True
                  )
clf_res = clf.fit(x_train_w2v, y_train)
print('Best score:', clf_res.best_score_)
print('Best Params:', clf_res.best_params_)
```

```
Best score: 0.8320745341017949
Best Params: {'estimator__C': 0.01, 'estimator__penalty': 'l2', 'estimator__s
olver': 'newton-cg'}
```

Tune hyperparameters for SVM (Linear SVC)

In [36]:
```
params_sv = {
    "estimator__penalty":['l1', 'l2'],
    "estimator__tol": [1.e-08, 1.e-07, 1.e-06, 1.e-05,
                      1.e-04, 1.e-03, 1.e-02, 1.e-01, 1.e+00],
    "estimator__loss":['hinge','squared_hinge'],
    "estimator__C": [0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000]
    #"estimator__class_weight":['None',{1:0.5, 0:0.5},
    #                           {1:0.4, 0:0.6}, {1:0.6, 0:0.4}, {1:0.7, 0:0.
3}],
}
clf = GridSearchCV(estimator=sv,
                   param_grid=params_sv,
                   scoring='f1_micro',
                   n_jobs=-1,
                   cv=N_FOLDS,
                   return_train_score=False
                  )
clf_res = clf.fit(x_train_w2v, y_train)
print('Best score:', clf_res.best_score_)
print('Best Params:', clf_res.best_params_)
```

```
Best score: 0.8440514791910111
Best Params: {'estimator__C': 0.001, 'estimator__loss': 'squared_hinge', 'est
imator__penalty': 'l2', 'estimator__tol': 1e-08}
```

Tune hyperparameters for Decision Trees

In [37]:
```
params_dtree = {
    "estimator__splitter":["best", "random"],
    "estimator__min_samples_split":range(1, 20, 1)
}
clf = GridSearchCV(estimator=dtree,
                   param_grid=params_dtree,
                   scoring='f1_micro',
                   n_jobs=-1,
                   cv=N_FOLDS,
                   return_train_score=False
                  )
clf_res = clf.fit(x_train_w2v, y_train)
print('Best score:', clf_res.best_score_)
print('Best Params:', clf_res.best_params_)
```

```
Best score: 0.6746835492233547
Best Params: {'estimator__min_samples_split': 9, 'estimator__splitter': 'bes
t'}
```

Conclusion:

Apparently the best params are pretty much the default ones. The algorithms are already pretty smart about the defaults or can calculate them. This tuning these hyper-parameters might actually cause overfitting.

Ensemble Methods

Stacking

In [39]:
```
estimators = [
              ('nb', GaussianNB()),
              ('svm', svm.LinearSVC())
             ]

sclf = OneVsRestClassifier(StackingClassifier(
    estimators=estimators, final_estimator=LogisticRegression())
)

metrics = cross_validate(
    sclf,
    x_train_w2v,
    y_train,
    cv=N_FOLDS,
    scoring = scoring,
    return_train_score=False,
    n_jobs=-1
)

res = []
for key in metrics.keys():
    for fold_index, score in enumerate(metrics[key]):
        res.append(('Stacking', fold_index, key, score))

res_df = pandas.DataFrame.from_dict(res)
res_df.columns = ['algo', 'cv fold', 'metric', 'value']
cv_results_inc_ens = pandas.concat([cv_results_df, res_df])
print(res_df)
```

```
algo  cv fold         metric        value
0   Stacking       0       fit_time  2086.022402
1   Stacking       1       fit_time  2133.732171
2   Stacking       2       fit_time  2122.568591
3   Stacking       3       fit_time  2172.070424
4   Stacking       4       fit_time  2157.726120
5   Stacking       0     score_time     1.544760
6   Stacking       1     score_time     1.320186
7   Stacking       2     score_time     1.514731
8   Stacking       3     score_time     1.128256
9   Stacking       4     score_time     1.213134
10  Stacking       0  test_precision     0.872012
11  Stacking       1  test_precision     0.893003
12  Stacking       2  test_precision     0.891541
13  Stacking       3  test_precision     0.902576
14  Stacking       4  test_precision     0.896064
15  Stacking       0    test_recall     0.831500
16  Stacking       1    test_recall     0.846083
17  Stacking       2    test_recall     0.848042
18  Stacking       3    test_recall     0.856958
19  Stacking       4    test_recall     0.841292
20  Stacking       0        test_f1     0.851274
21  Stacking       1        test_f1     0.868910
22  Stacking       2        test_f1     0.869248
23  Stacking       3        test_f1     0.879176
24  Stacking       4        test_f1     0.867814
25  Stacking       0   test_roc_auc     0.895410
26  Stacking       1   test_roc_auc     0.906146
27  Stacking       2   test_roc_auc     0.906826
28  Stacking       3   test_roc_auc     0.913063
29  Stacking       4   test_roc_auc     0.904382
```

Bagging

In [40]:
```python
sclf = OneVsRestClassifier(BaggingClassifier(
    base_estimator=LogisticRegression())
)

metrics = cross_validate(
    sclf,
    x_train_w2v,
    y_train,
    cv=N_FOLDS,
    scoring = scoring,
    return_train_score=False,
    n_jobs=-1
)

res = []
for key in metrics.keys():
    for fold_index, score in enumerate(metrics[key]):
        res.append(('Bagging', fold_index, key, score))

res_df = pandas.DataFrame.from_dict(res)
res_df.columns = ['algo', 'cv fold', 'metric', 'value']
cv_results_inc_ens = pandas.concat([cv_results_inc_ens, res_df])
print(res_df)
```

```
algo  cv fold         metric       value
0    Bagging        0       fit_time  293.037744
1    Bagging        1       fit_time  288.202163
2    Bagging        2       fit_time  289.632665
3    Bagging        3       fit_time  297.167599
4    Bagging        4       fit_time  298.388267
5    Bagging        0     score_time    4.499739
6    Bagging        1     score_time    4.891524
7    Bagging        2     score_time    4.782574
8    Bagging        3     score_time    3.733881
9    Bagging        4     score_time    3.392392
10   Bagging        0 test_precision    0.872692
11   Bagging        1 test_precision    0.891740
12   Bagging        2 test_precision    0.890813
13   Bagging        3 test_precision    0.902427
14   Bagging        4 test_precision    0.895352
15   Bagging        0    test_recall    0.829167
16   Bagging        1    test_recall    0.845667
17   Bagging        2    test_recall    0.846792
18   Bagging        3    test_recall    0.856667
19   Bagging        4    test_recall    0.842750
20   Bagging        0        test_f1    0.850373
21   Bagging        1        test_f1    0.868092
22   Bagging        2        test_f1    0.868245
23   Bagging        3        test_f1    0.878952
24   Bagging        4        test_f1    0.868255
25   Bagging        0   test_roc_auc    0.894424
26   Bagging        1   test_roc_auc    0.905722
27   Bagging        2   test_roc_auc    0.906097
28   Bagging        3   test_roc_auc    0.912896
29   Bagging        4   test_roc_auc    0.904958
```

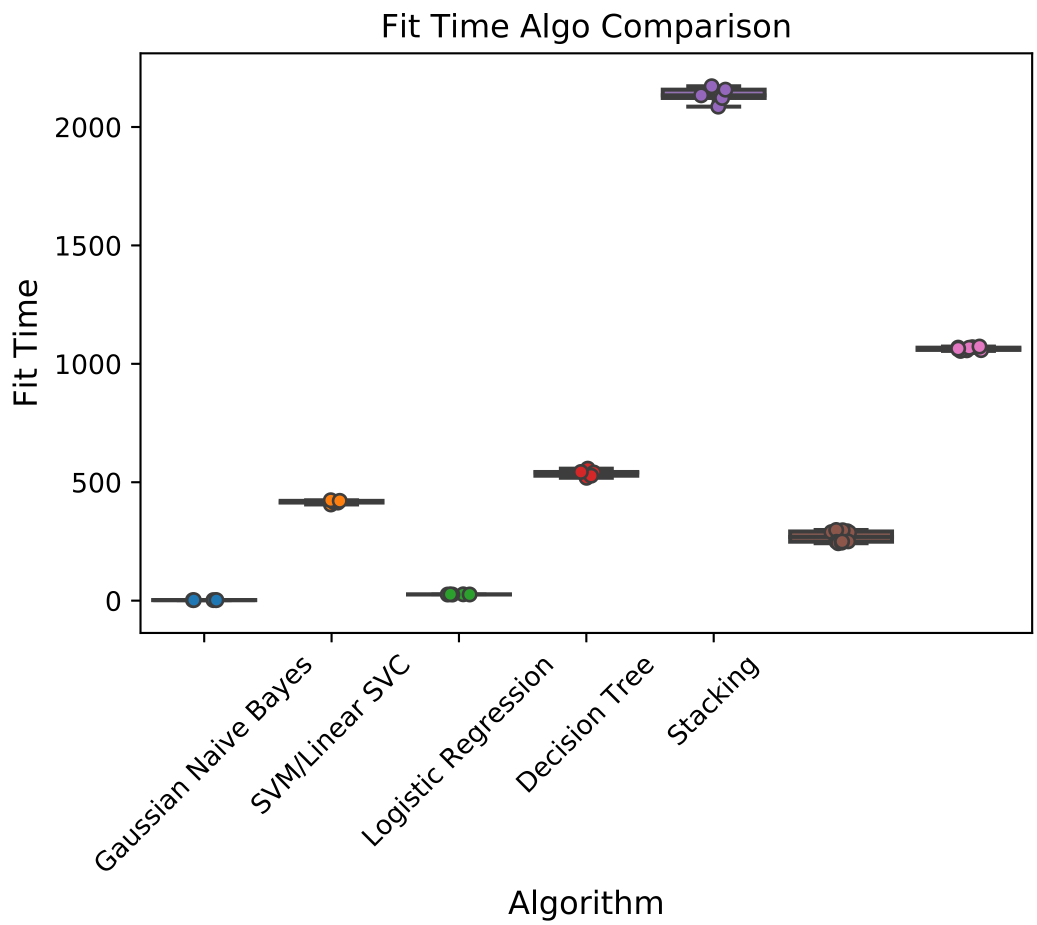
Boosting

In [41]:
```python
from sklearn.ensemble import AdaBoostClassifier
sclf = OneVsRestClassifier(AdaBoostClassifier(
    random_state=RANDOM_STATE)
)

metrics = cross_validate(
    sclf,
    x_train_w2v,
    y_train,
    cv=N_FOLDS,
    scoring = scoring,
    return_train_score=False,
    n_jobs=-1
)

res = []
for key in metrics.keys():
    for fold_index, score in enumerate(metrics[key]):
        res.append(('AdaBoost', fold_index, key, score))

res_df = pandas.DataFrame.from_dict(res)
res_df.columns = ['algo', 'cv fold', 'metric', 'value']
cv_results_inc_ens = pandas.concat([cv_results_inc_ens, res_df])
print(res_df)
```

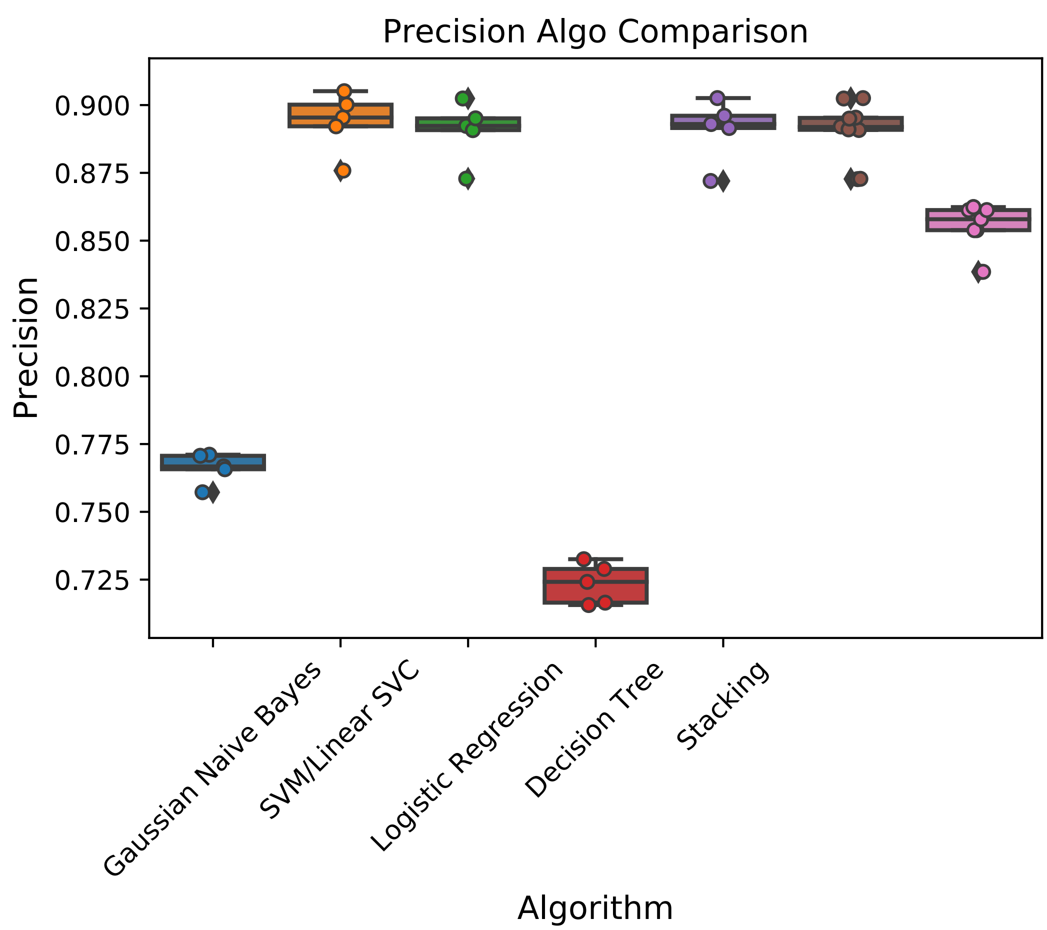
```
algo   cv fold         metric        value
0    AdaBoost        0        fit_time  1062.197975
1    AdaBoost        1        fit_time  1057.098244
2    AdaBoost        2        fit_time  1057.839918
3    AdaBoost        3        fit_time  1054.535914
4    AdaBoost        4        fit_time  1061.208005
5    AdaBoost        0      score_time     1.882781
6    AdaBoost        1      score_time     2.074911
7    AdaBoost        2      score_time     2.073910
8    AdaBoost        3      score_time     2.134933
9    AdaBoost        4      score_time     1.903810
10   AdaBoost        0  test_precision     0.838507
11   AdaBoost        1  test_precision     0.853863
12   AdaBoost        2  test_precision     0.857904
13   AdaBoost        3  test_precision     0.862374
14   AdaBoost        4  test_precision     0.861283
15   AdaBoost        0     test_recall     0.784458
16   AdaBoost        1     test_recall     0.807292
17   AdaBoost        2     test_recall     0.805500
18   AdaBoost        3     test_recall     0.811458
19   AdaBoost        4     test_recall     0.793708
20   AdaBoost        0         test_f1     0.810583
21   AdaBoost        1         test_f1     0.829924
22   AdaBoost        2         test_f1     0.830876
23   AdaBoost        3         test_f1     0.836142
24   AdaBoost        4         test_f1     0.826116
25   AdaBoost        0    test_roc_auc     0.867049
26   AdaBoost        1    test_roc_auc     0.880618
27   AdaBoost        2    test_roc_auc     0.880514
28   AdaBoost        3    test_roc_auc     0.884146
29   AdaBoost        4    test_roc_auc     0.875549
```

Plot cv results

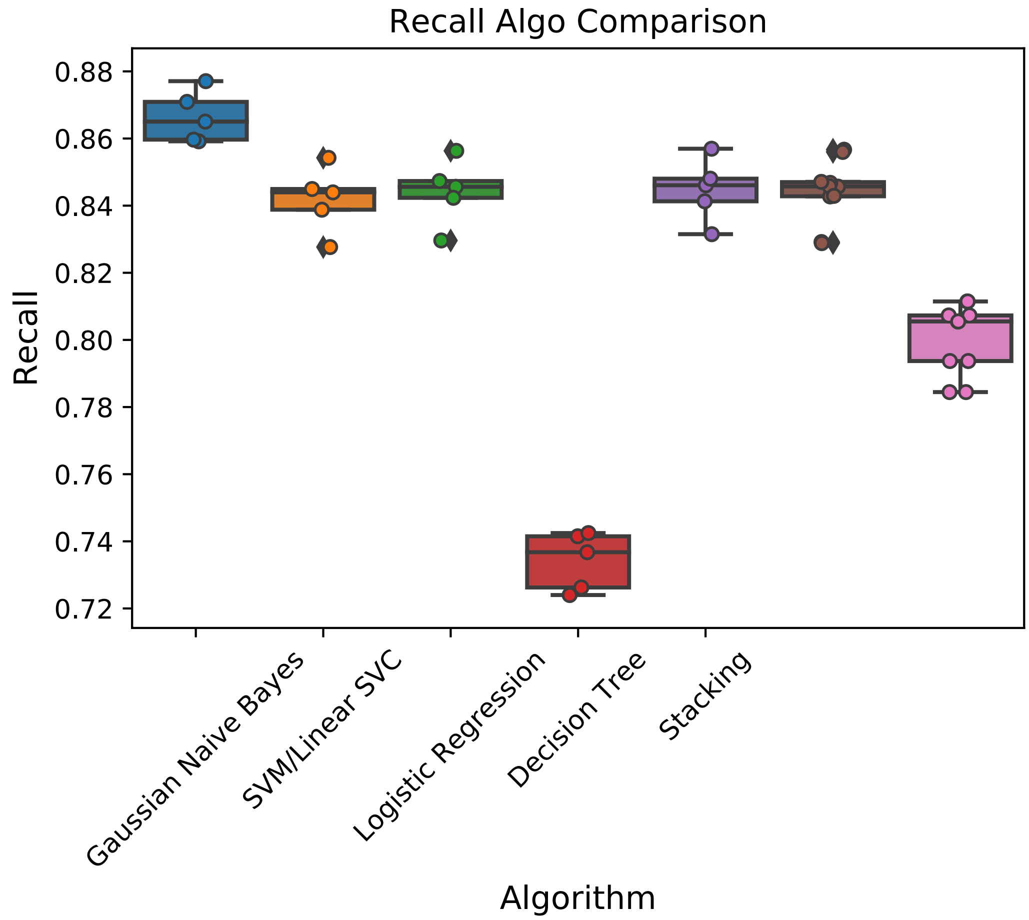
In [46]:
```
for metric_name, metric in zip(['fit_time',
                                'test_precision',
                                'test_recall',
                                'test_f1',
                                'test_roc_auc'],
                               ['Fit Time',
                                'Precision',
                                'Recall',
                                'F1 Score',
                                'ROC AUC']):
    sns.boxplot(x='algo', y='value', #hue='algo',
        data=cv_results_inc_ens[cv_results_inc_ens.metric.eq(f'{metric_name}'
)])
    sns.stripplot(x='algo', y = 'value',
        data = cv_results_inc_ens[cv_results_inc_ens.metric.eq(f'{metric_name}
')],
        size = 5, linewidth = 1)
    plt.title(f'{metric} Algo Comparison', fontsize=12)
    plt.xlabel('Algorithm', fontsize=12)
    plt.ylabel(f'{metric}', fontsize=12)
    plt.xticks([0, 1, 2, 3, 4])
    plt.xticks(rotation=45)
    plt.show()
```

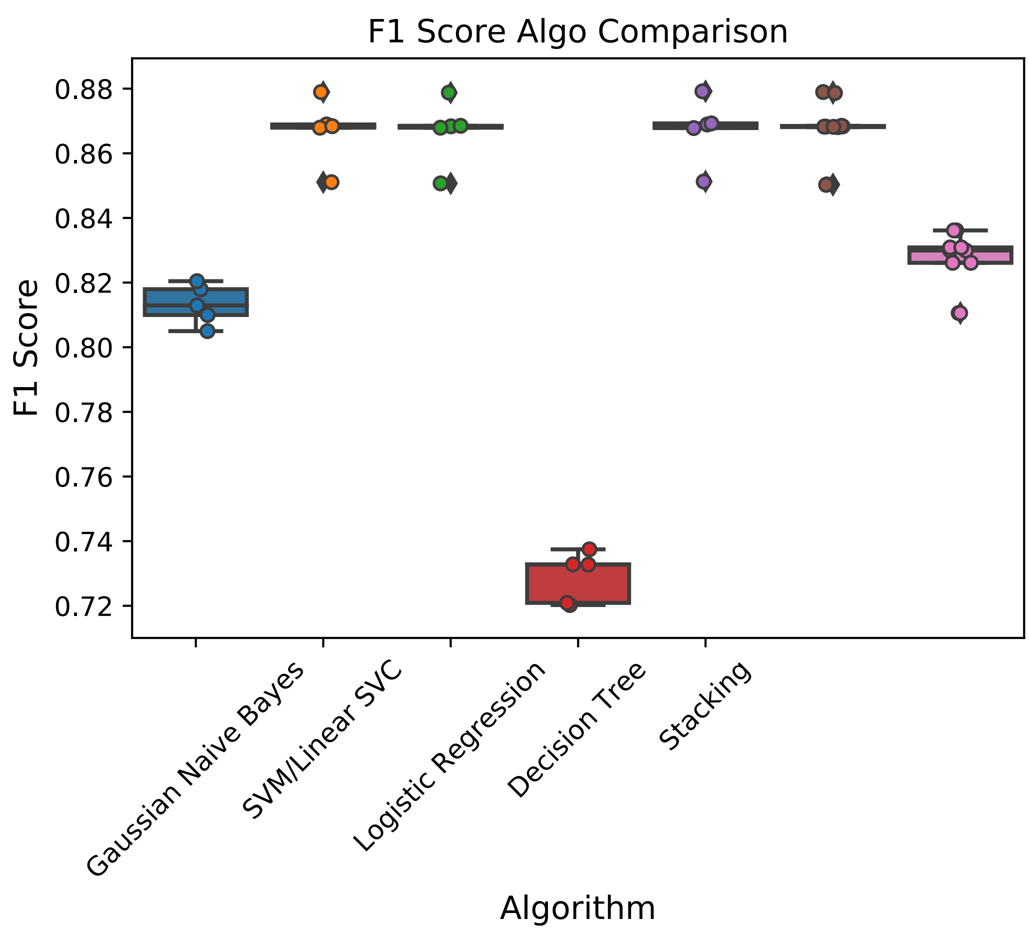


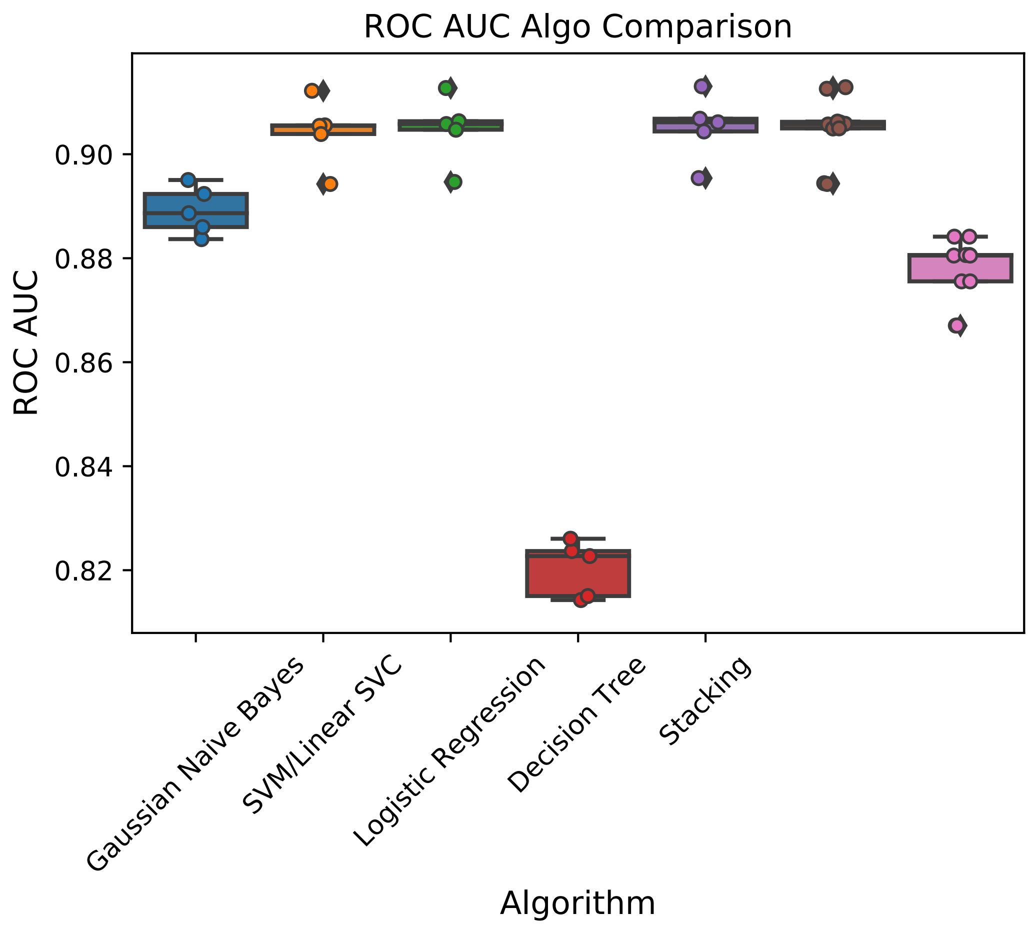
Fit Time Algo Comparison
Fit Time
2000
1500
1000
500
0
Gaussian Naive Bayes
SVM/Linear SVC
Logistic Regression
Decision Tree
Stacking
Algorithm



Precision Algo Comparison
Precision
0.900
0.875
0.850
0.825
0.800
0.775
0.750
0.725
Gaussian Naive Bayes
SVM/Linear SVC
Logistic Regression
Decision Tree
Stacking
Algorithm


Recall Algo Comparison
Recall
0.88
0.86
0.84
0.82
0.80
0.78
0.76
0.74
0.72
Gaussian Naive Bayes
SVM/Linear SVC
Logistic Regression
Decision Tree
Stacking
Algorithm


F1 Score Algo Comparison
F1 Score
0.88
0.86
0.84
0.82
0.80
0.78
0.76
0.74
0.72
Gaussian Naive Bayes
SVM/Linear SVC
Logistic Regression
Decision Tree
Stacking
Algorithm



Save our results

In [47]:
```
cv_results_inc_ens.to_csv('./data/cv-results-inc-ens.csv')
```

LIME for model interpretation

In [53]:
```
class_names=['World','Sports','Business','Tech/Sci']
```

Instantiate explainer

In [54]:
```
tab_explainer = lime.lime_tabular.LimeTabularExplainer(x_train_w2v.values,
    mode='classification', class_names=class_names)
```

Get explanations for: idx = Document

In [55]:
```
idx = 34
tab_exp_lreg = tab_explainer.explain_instance(x_test_w2v.values[idx], lreg.pre
dict_proba,
    num_features=10, top_labels=1)
print('Document id: %d' % idx)
print('Predicted class =',
    class_names[numpy.argmax(lreg.predict(numpy.array(x_test_w2v.values[idx]).
reshape(1, -1)))])
print('True class =', class_names[numpy.argmax(y_test[idx])])
```

```
Document id: 34
Predicted class = World
True class = World
```

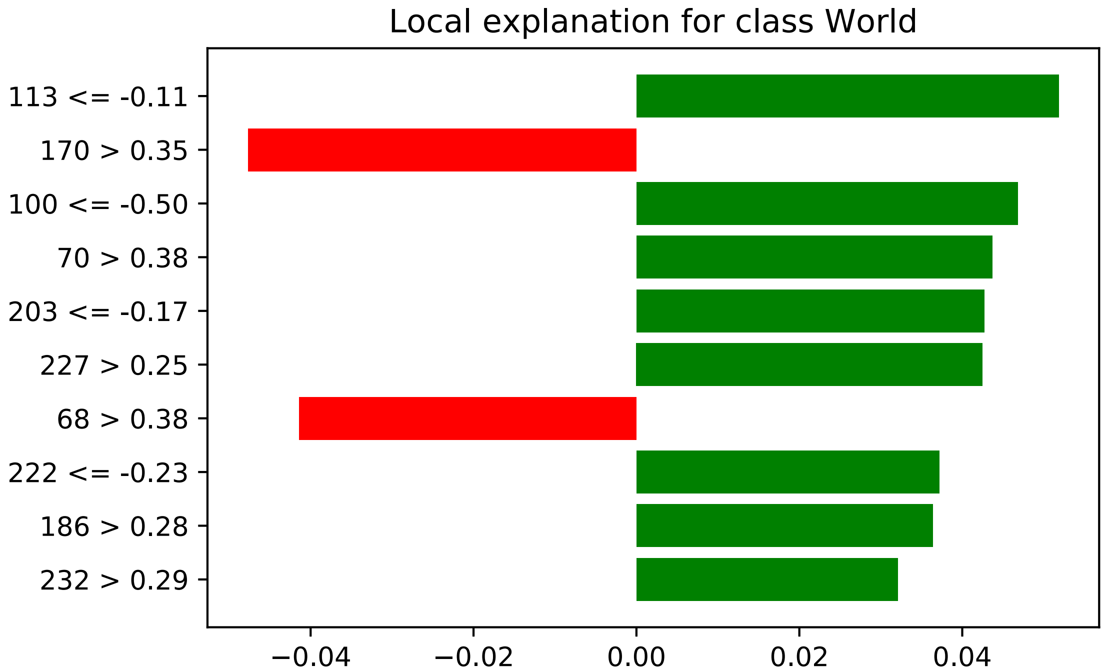
Get a text-only explanation

In [56]:
```
print ('\n'.join(map(str, tab_exp_lreg.as_list(label=numpy.argmax(y_test[idx
])))))
```

```
('113 <= -0.11', 0.05183064476272634)
('170 > 0.35', -0.04768800249242717)
('100 <= -0.50', 0.04679713796889845)
('70 > 0.38', 0.04368779818621363)
('203 <= -0.17', 0.04269222543391017)
('227 > 0.25', 0.04247870611665241)
('68 > 0.38', -0.041380166579130497)
('222 <= -0.23', 0.03715680647558889)
('186 > 0.28', 0.036387157957656235)
('232 > 0.29', 0.032059681278521886)
```

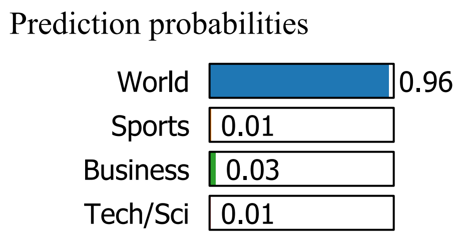
Get a graphical explanation of the predicted class

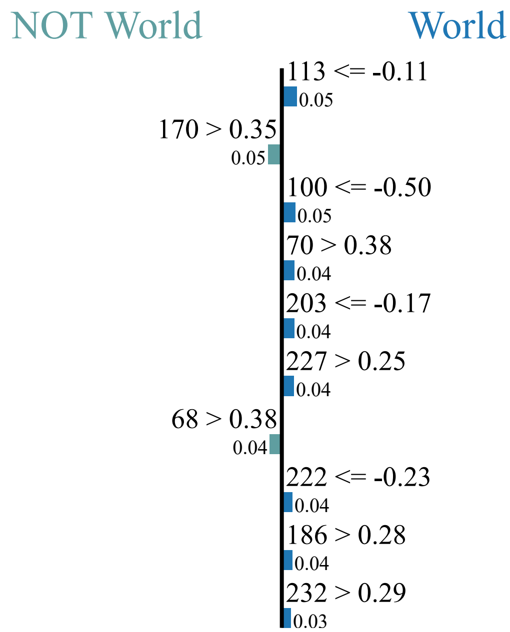
```
In [57]: fig = tab_exp_lreg.as_pyplot_figure(label=numpy.argmax(y_test[idx]))
```



Get a graphical explanation with class probabilities

In [58]:
```
tab_exp_lreg.show_in_notebook()
```





Feature	Value
113	-1.22
170	0.64
100	-0.55
70	1.06
203	-0.24
227	0.28
68	0.42
222	-0.29
186	0.42

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:

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