In [ ]:
```
# notebook submitted as solution to problemset 4 for the course Building a Robot Judge at ETHZ in spring 2019
```

In [42]:
```
%matplotlib notebook
```

In [2]:
```
import pickle

# to load from saved pickle:
pkl_file = open("./p2_df_1k.20190418_1538.pkl", 'rb')
df = pickle.load(pkl_file)

# df3 has 1 label (rev/nonrev) and 1000 trigrams with last gram = a noun, could potentially be used to do class
ification
pkl3_file = open("./p2_df3_1k.20190418_1538.pkl", 'rb')
df3 = pickle.load(pkl3_file)

import numpy as np
import csv

import pandas as pd
import os
from datetime import datetime
import matplotlib.pyplot as plt
from txt_utils import *
```

In [3]:
```
df3.head()
```

Out[3]:

	rev	v_unit_state	#_district_court	#_suprem_court	#_#_court	#_unit_state	judgment_district_court	#_et_seq	state_district_court	grant_sur
X3N6DO	0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
X3CEDR	0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
X3BD9F	0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
X3IJOI	0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
X3LJCS	0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	

5 rows × 1001 columns

In [4]:
```
df3["state_district_court"].describe()
```

Out[4]:
```
count    1000.000000
mean        0.232000
std         0.585251
min         0.000000
25%         0.000000
50%         0.000000
75%         0.000000
max         6.000000
Name: state_district_court, dtype: float64
```

In [5]:
```
df3["v_unit_state"].describe()
```

Out[5]:
```
count    1000.000000
mean        1.066000
std         3.126887
min         0.000000
25%         0.000000
50%         0.000000
75%         1.000000
max        37.000000
Name: v_unit_state, dtype: float64
```

In [8]:
```
dff_fname = open("./p4_df_1k.20190613_005107.pkl", 'rb') # see separate jupyter notebook for generating this pi
ckle
dff = pickle.load(dff_fname)
```

In [9]:
```
dff.head()
```

Out[9]:

caseid	case_reversed	judge_id	year	x_republican	log_cites	doc	jahr	nlets	nsents	nwords	nnouns	nverbs	nadjes
X53OBB	0	1641.0	1989.0	1.0	2.639057	PIERCE , Circuit Judge: The Government of Ind...	1989	15514.0	108.0	2641.0	864.0	387.0	89.0
X3UGPI	0	1421.0	1981.0	1.0	2.772589	MESKILL , Circuit Judge: This is an appeal fr...	1981	18260.0	112.0	2979.0	951.0	395.0	214.0
X46BHQ	0	367.0	1988.0	0.0	4.043051	CLARK , Circuit Judge: In another chapter of ...	1988	54172.0	439.0	9210.0	2938.0	1247.0	538.0
X46C0P	0	751.0	1989.0	1.0	2.772589	D.H.\nGINSBURG , Circuit Judge: This appeal a...	1989	28840.0	179.0	4811.0	1527.0	655.0	277.0
XABC47	1	2035.0	1979.0	0.0	2.397895	TANG , Circuit Judge.\nStandard Oil Company o...	1979	16334.0	141.0	2787.0	887.0	394.0	153.0

In [10]:
```
len(dff)
```

Out[10]: 1000

In [11]:
```
dff["log_cites"].describe()
```

Out[11]:
```
count    1000.000000
mean        2.118470
std         0.928693
min         0.693147
25%         1.386294
50%         2.079442
75%         2.833213
max         4.927254
Name: log_cites, dtype: float64
```

In [12]:
```
dff["x_republican"].describe()
```

Out[12]:
```
count    1000.000000
mean        0.494000
std         0.500214
min         0.000000
25%         0.000000
50%         0.000000
75%         1.000000
max         1.000000
Name: x_republican, dtype: float64
```

In [13]:
```
X = dff.loc[: , ["log_cites", "judge_id","jahr", "x_republican", "nsents", "nwords", "nlets", "nnouns", "nverbs
", "nadjes"]]

#for inde in dff.index:
#    log_cites = np.ceil(np.exp(dff.loc[inde, "log_cites"]) - 1)
#    dff.at[inde, "citeCounts"] = log_cites
Y = dff["case_reversed"]
```

In [14]:
```
len(X)
```

Out[14]:
```
1000
```

In [15]:
```
Y.head(15)
```

Out[15]:
```
caseid
X53OBB    0
X3UGPI    0
X46BHQ    0
X46C0P    0
XABC47    1
X3SSDU    1
XAFG1C    1
XABG48    1
X3I632    1
X3UPA9    1
X47RS2    0
X3TJ7T    1
X31UV5    1
X3PO3D    0
XACCQ4    1
Name: case_reversed, dtype: int64
```

In [16]:
```
X.head()
```

Out[16]:

	log_cites	judge_id	jahr	x_republican	nsents	nwords	nlets	nnouns	nverbs	nadjes
caseid										
X53OBB	2.639057	1641.0	1989	1.0	108.0	2641.0	15514.0	864.0	387.0	89.0
X3UGPI	2.772589	1421.0	1981	1.0	112.0	2979.0	18260.0	951.0	395.0	214.0
X46BHQ	4.043051	367.0	1988	0.0	439.0	9210.0	54172.0	2938.0	1247.0	538.0
X46C0P	2.772589	751.0	1989	1.0	179.0	4811.0	28840.0	1527.0	655.0	277.0
XABC47	2.397895	2035.0	1979	0.0	141.0	2787.0	16334.0	887.0	394.0	153.0

In [17]:
```
X["jahr"] = X["jahr"].astype(int)
```

In [18]:
```
X.dtypes
```

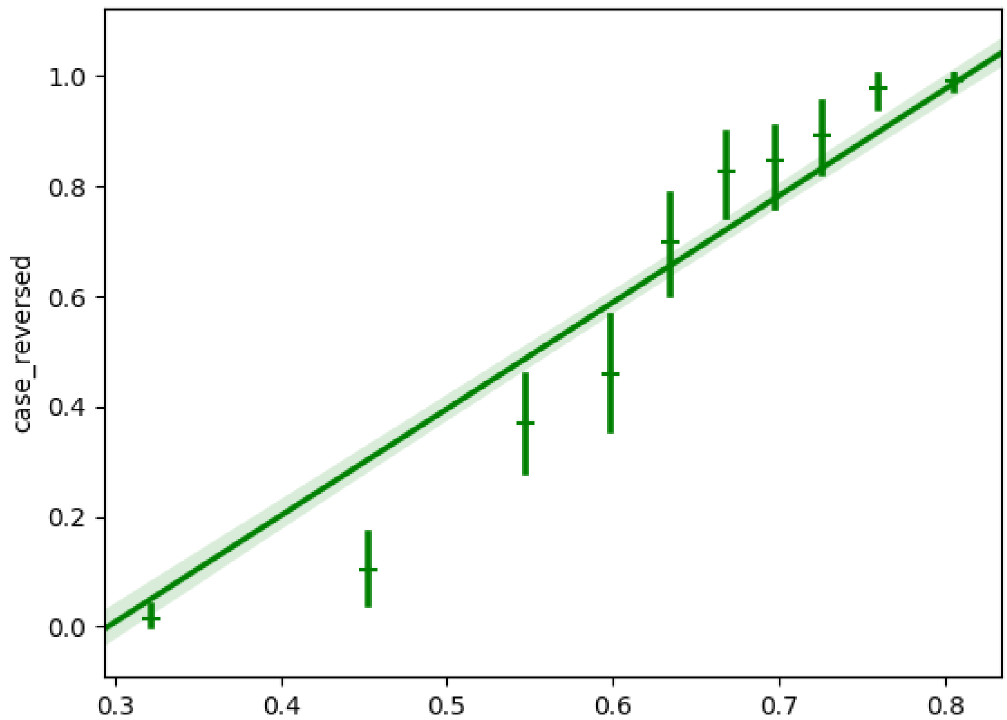
Out[18]:
```
log_cites       float64
judge_id        float64
jahr              int64
x_republican    float64
nsents          float64
nwords          float64
nlets           float64
nnouns          float64
nverbs          float64
nadjes          float64
dtype: object
```

In [19]:
```
from sklearn.ensemble import GradientBoostingClassifier
gbclf = GradientBoostingClassifier()
gbclf.fit(X, Y)
```

Out[19]:
```
GradientBoostingClassifier(criterion='friedman_mse', init=None,
              learning_rate=0.1, loss='deviance', max_depth=3,
              max_features=None, max_leaf_nodes=None,
              min_impurity_decrease=0.0, min_impurity_split=None,
              min_samples_leaf=1, min_samples_split=2,
              min_weight_fraction_leaf=0.0, n_estimators=100,
              n_iter_no_change=None, presort='auto', random_state=None,
              subsample=1.0, tol=0.0001, validation_fraction=0.1,
              verbose=0, warm_start=False)
```

In [20]:
```
ypred = gbclf.predict_proba(X)[:,1]
```

In [21]:
```
import seaborn as sns
plot = sns.regplot(ypred, Y, color = 'g', marker = '+', x_bins = 10)
plt.show()
```



Permutation importances with ELI5

In [22]:
```
import eli5
from sklearn.metrics import mean_squared_error, make_scorer
from eli5.sklearn import PermutationImportance
perm = PermutationImportance(gbclf, random_state=1).fit(X,Y)
eli5.show_weights(perm, feature_names = list(X.columns))
```

Out[22]:

Weight	Feature
0.1218 ± 0.0093	nverbs
0.1014 ± 0.0241	jahr
0.0914 ± 0.0146	log_cites
0.0660 ± 0.0156	nadjes
0.0554 ± 0.0057	judge_id
0.0324 ± 0.0098	nnouns
0.0248 ± 0.0095	nlets
0.0192 ± 0.0118	nsents
0.0140 ± 0.0107	nwords
0.0030 ± 0.0025	x_republican

In [23]:
```
from sklearn.model_selection import train_test_split
X_train, X_test,  Y_train, Y_test = train_test_split(X, Y, test_size = 0.3, random_state = 1234)
```

Feature Importance

In [24]:
```
# see savvastsortjoglou.com/interpretable-machine-learning-nfl-combine.html
from sklearn.preprocessing import Imputer
from sklearn.model_selection import  cross_val_score
from sklearn.pipeline import Pipeline
from sklearn.metrics import make_scorer
from sklearn.ensemble import RandomForestRegressor

from skll.metrics import spearman

from skopt import BayesSearchCV
from skopt.space import Real, Categorical, Integer

import warnings
```

In [25]:

```
RANDOM_STATE=1234
N_JOBS=8
# the modeling pipeline
pipe = Pipeline([("imputer", Imputer()),
                 ("estimator", RandomForestRegressor(random_state=RANDOM_STATE))])
```

```
/home/xhta/anaconda3/lib/python3.5/site-packages/sklearn/utils/deprecation.py:58: DeprecationWarning: Class I
mputer is deprecated; Imputer was deprecated in version 0.20 and will be removed in 0.22. Import impute.Simpl
eImputer from sklearn instead.
  warnings.warn(msg, category=DeprecationWarning)
```

In [26]:

```
spearman_scorer = make_scorer(spearman)
# the hyperparamters to search over, including different imputation strategies
rf_param_space = {
    'imputer__strategy': Categorical(['mean', 'median', 'most_frequent']),
    'estimator__max_features': Integer(1, 5),   # was Integer(1, 8),
    'estimator__n_estimators': Integer(50, 60),    # was Integer(50, 500)
    'estimator__min_samples_split': Integer(70, 85),  # was Integer(2, 200)
}
# create our search object
search = BayesSearchCV(pipe,
                      rf_param_space,
                      cv=10,
                      n_jobs=N_JOBS,
                      verbose=0,
                      error_score=-9999,
                      scoring=spearman_scorer,
                      random_state=RANDOM_STATE,
                      return_train_score=True,
                      n_iter=75)
```

In [27]:

```
# attention, search can take some time
import time
start_time = time.time()
with warnings.catch_warnings():
    warnings.filterwarnings('ignore')
    search.fit(X_train, Y_train)
print (time.time() - start_time)
```

```
314.9102966785431
```

In [29]:
```
search.best_params_
```

Out[29]:
```
{'estimator__max_features': 2,
 'estimator__min_samples_split': 77,
 'estimator__n_estimators': 50,
 'imputer__strategy': 'median'}
```

In [30]:
```
# CV score
search.best_score_
```

Out[30]:
```
0.11712952086074066
```

In [31]:
```
# CV standard deviation
search.cv_results_['std_test_score'][search.best_index_]
```

Out[31]:
```
0.09807688772016362
```

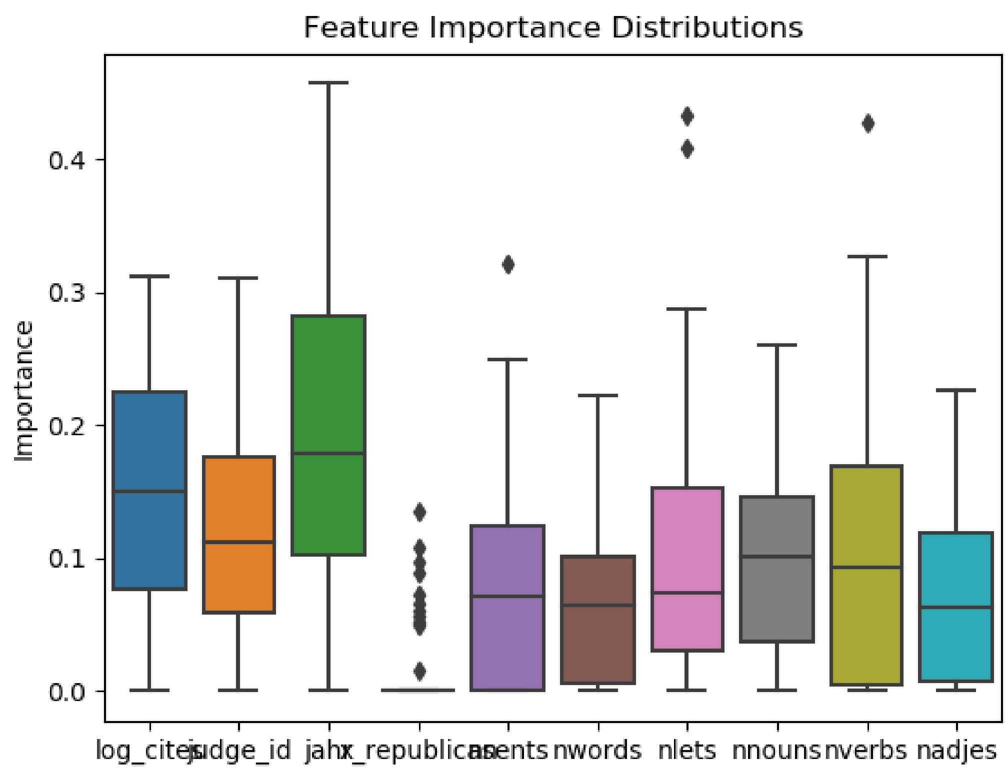
In [32]:
```
estimator = search.best_estimator_.named_steps['estimator']
imputer = search.best_estimator_.named_steps['imputer']

estimator.feature_importances_
```

Out[32]:
```
array([0.14137685, 0.11828633, 0.1958735 , 0.01701467, 0.07693439,
       0.07352204, 0.09844742, 0.09854429, 0.10300105, 0.07699945])
```

In [33]:
```
# get the feature importances from each tree and then visualize the
# distributions as boxplots
all_feat_imp_df = pd.DataFrame(data=[tree.feature_importances_ for tree in
                                     estimator],
                               columns=list(X.columns))

(sns.boxplot(data=all_feat_imp_df)
        .set(title='Feature Importance Distributions',
             ylabel='Importance'))
plt.show()
```



In [33]:
```
# see https://nbviewer.jupyter.org/github/dipanjanS/data_science_for_all/blob/master/tds_model_interpretation_x
ai/Human_interpretable%20Machine%Learning%20-%20DS.ipynb#
```

In [34]:
```
%%time
import xgboost as xgb
xgc = xgb.XGBClassifier(n_estimators=500, max_depth=5, best_score=0.5, objective='binary:logistic', random_stat
e=1234)
```

```
CPU times: user 450 µs, sys: 0 ns, total: 450 µs
Wall time: 5.2 ms
```

In [35]:
```
xgc.fit(X_train, Y_train)
```

Out[35]:
```
XGBClassifier(base_score=0.5, best_score=0.5, booster='gbtree',
       colsample_bylevel=1, colsample_bynode=1, colsample_bytree=1,
       gamma=0, learning_rate=0.1, max_delta_step=0, max_depth=5,
       min_child_weight=1, missing=None, n_estimators=500, n_jobs=1,
       nthread=None, objective='binary:logistic', random_state=1234,
       reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
       silent=None, subsample=1, verbosity=1)
```

In [36]:
```
X_train.dtypes
```

Out[36]:
```
log_cites       float64
judge_id        float64
jahr              int64
x_republican    float64
nsents          float64
nwords          float64
nlets           float64
nnouns          float64
nverbs          float64
nadjes          float64
dtype: object
```

In [37]:
```
pred = xgc.predict(X_test)
```

In [38]:
```
pred[0:10]
```

Out[38]:
```
array([1, 1, 1, 1, 1, 0, 1, 1, 1, 0])
```

In [39]:
```
Y_test[0:10]
```

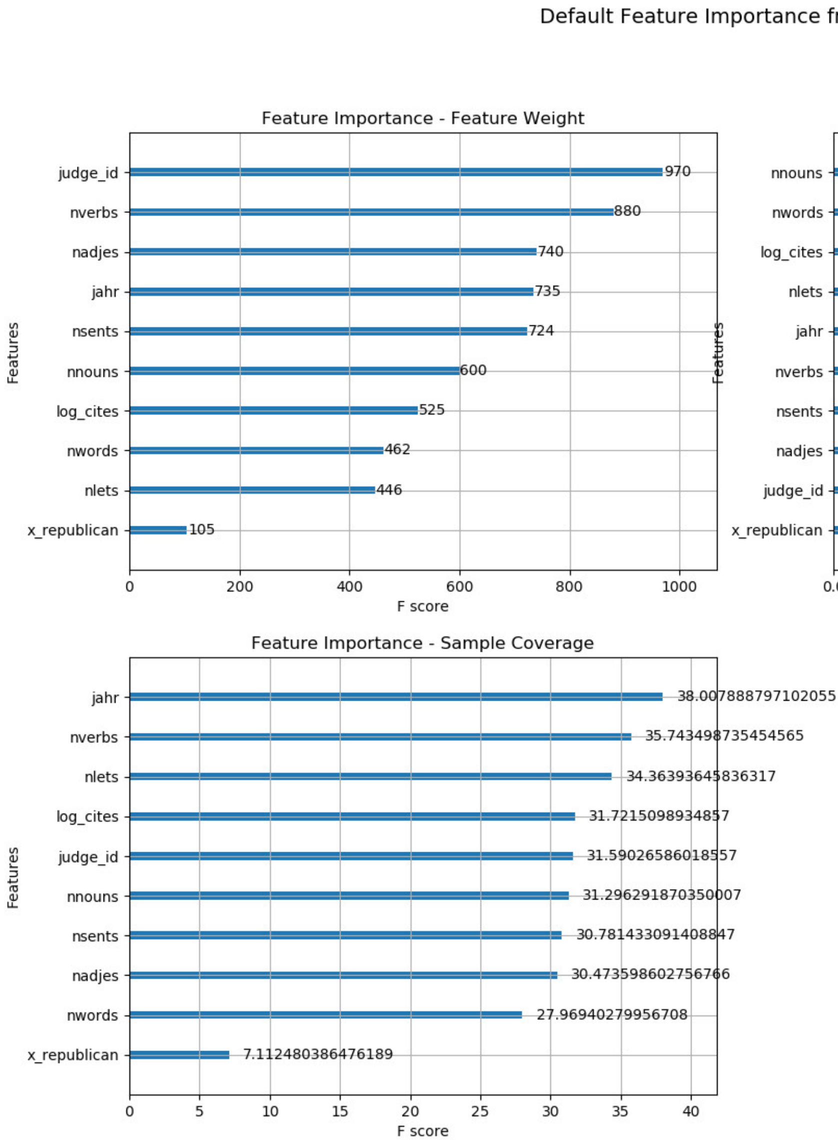
Out[39]:
```
caseid
X369VS        1
X40G3F        1
X1B6SUE003    0
X3P7L9        1
X46H9S        0
X3AE83        0
X2O2SC        0
X41U1F        1
X3J6BO        0
X12DAOQ003    0
Name: case_reversed, dtype: int64
```

In [43]:
```
fig = plt.figure(figsize  = (16,12))
title = fig.suptitle("Default Feature Importance from XGBoost", fontsize=14)

ax1 = fig.add_subplot(2,2,1)
xgb.plot_importance(xgc, importance_type = 'weight', ax = ax1)
t = ax1.set_title("Feature Importance - Feature Weight")

ax2 = fig.add_subplot(2,2,2)
xgb.plot_importance(xgc, importance_type = 'gain', ax = ax2)
t = ax2.set_title("Feature Importance - Split Mean Gain")

ax3 = fig.add_subplot(2,2,3)
xgb.plot_importance(xgc, importance_type = 'cover', ax = ax3)
t = ax3.set_title("Feature Importance - Sample Coverage")
```


Default Feature Importance from XGBoost
Feature Importance - Feature Weight
judge_id 970
nverbs 880
nadjes 740
jahr 735
nsents 724
nnouns 600
log_cites 525
nwords 462
nlets 446
x_republican 105
Features
F score
Feature Importance - Split Mean Gain
nnouns
nwords
log_cites
nlets
jahr
nverbs
nsents
nadjes
judge_id
x_republican
Features
F score
Feature Importance - Sample Coverage
jahr 38.007888797102055
nverbs 35.743498735454565
nlets 34.36393645836317
log_cites 31.7215098934857
judge_id 31.590265860 18557
nnouns 31.296291870350007
nsents 30.7814330914088 47
nadjes 30.473598602756766
nwords 27.96940279956708
x_republican 7.112480386476189
Features
F score

feature importances with ELI5

In [44]:
```
eli5.show_weights(xgc.get_booster())
```

Out[44]:

Weight	Feature
0.1204	nnouns
0.1110	nwords
0.1099	log_cites
0.1062	nlets
0.1005	jahr
0.1003	nverbs
0.0968	nsents
0.0963	nadjes
0.0903	judge_id
0.0682	x_republican

Global interpretation with Skater

In [45]:
```
from skater.core.explanations import Interpretation
from skater.model import InMemoryModel
```

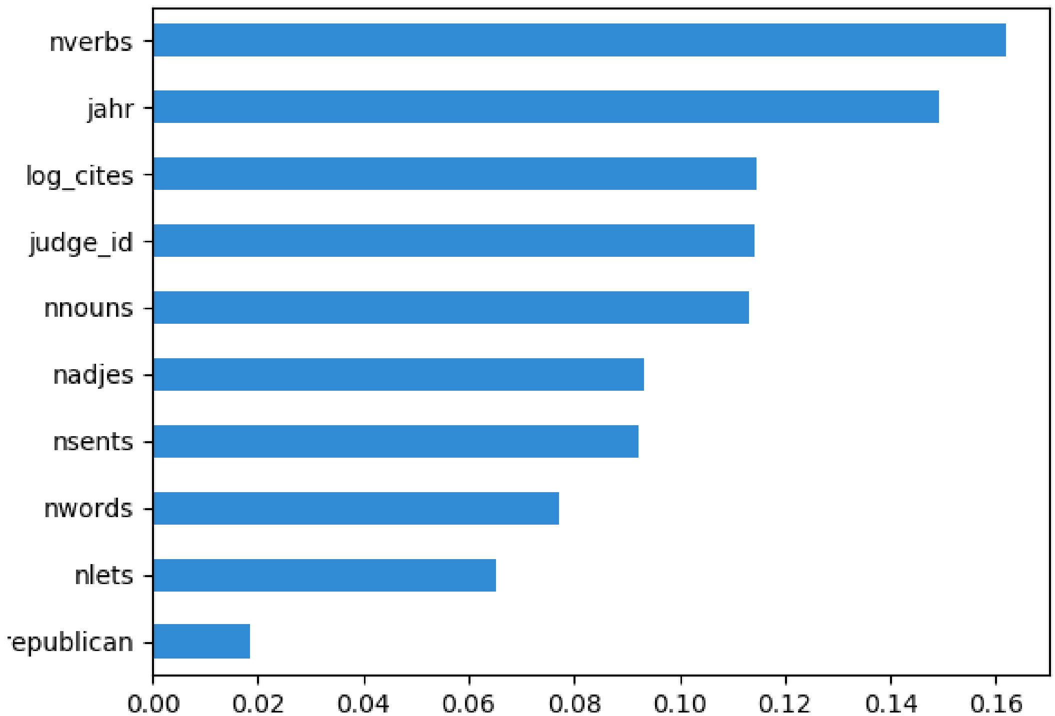
In [46]:
```
#Create an interpretation object
```

In [47]:
```
interpreter = Interpretation(training_data=X_test, training_labels=Y_test, feature_names=list(X.columns))
im_model = InMemoryModel(xgc.predict_proba, examples=X_train, target_names=['not reverted', 'reverted'])
```

In [48]:
```
plots = interpreter.feature_importance.plot_feature_importance(im_model, ascending=True, n_samples=1000)
```

```
2019-06-13 02:07:09,470 - skater.core.explanations - WARNING - Progress bars slow down runs by 10-20%. For sl
ightly
faster runs, do progress_bar=False

[10/10] features  Time elapsed: 3 seconds
```



Local interpretation with Skater LIME

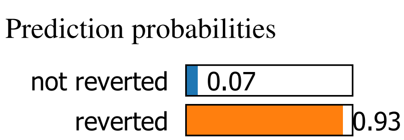
In [49]:
```
xgc_np = xgb.XGBClassifier(n_estimators=500, map_depth=5, base_score=0.5, objective = 'binary:logistic', random
_state=1234)
xgc_np.fit(X_train.values, Y_train)
```

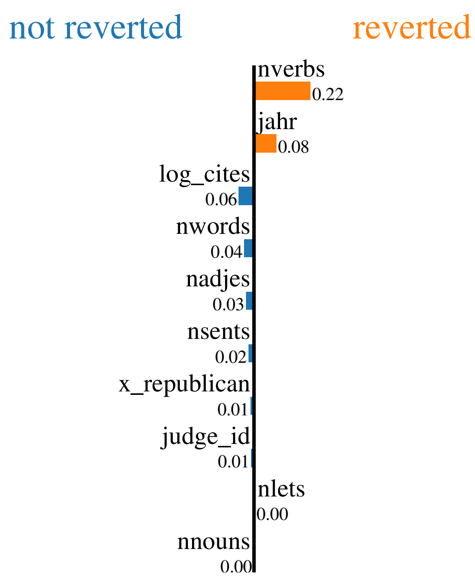
Out[49]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0, learning_rate=0.1,
              map_depth=5, max_delta_step=0, max_depth=3, min_child_weight=1,
              missing=None, n_estimators=500, n_jobs=1, nthread=None,
              objective='binary:logistic', random_state=1234, reg_alpha=0,
              reg_lambda=1, scale_pos_weight=1, seed=None, silent=None,
              subsample=1, verbosity=1)
```

In [50]:
```
from skater.core.local_interpretation.lime.lime_tabular import LimeTabularExplainer
exp = LimeTabularExplainer(X_test, feature_names= list(X.columns), discretize_continuous = False, class_names=[
'not reverted', 'reverted'])
```

In [51]:
```
print('Actual Label:', Y_test[0])
print('Predicted Label:', pred[0])
exp.explain_instance(X_train.loc[0], xgc_np.predict_proba).show_in_notebook()
```

```
Actual Label: 1
Predicted Label: 1
```





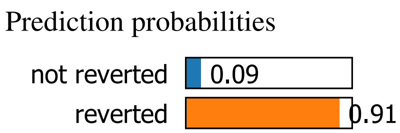
Feature	Value
nverbs	241.00
jahr	1950.00
log_cites	1.79
nwords	1690.00
nadjes	64.00
nsents	62.00
x_republican	1.00
judge_id	1814.00
nlets	9426.00
nnouns	520.00

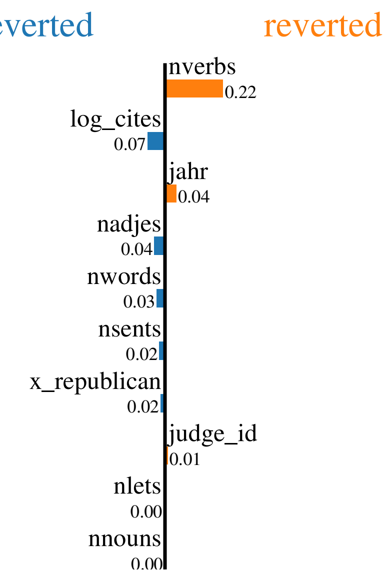
In [52]:
```
pred[0:10]
```

Out[52]:
```
array([1, 1, 1, 1, 1, 0, 1, 1, 1, 0])
```

In [53]:
```
print('Actual Label:', Y_test[2])
print('Predicted Label:', pred[2])
exp.explain_instance(X_train.loc[2], xgc_np.predict_proba).show_in_notebook()
```

```
Actual Label: 0
Predicted Label: 1
```





Feature	Value
nverbs	96.00
log_cites	1.79
jahr	1996.00
nadjes	24.00
nwords	665.00
nsents	53.00
x_republican	1.00
judge_id	644.00
nlets	3666.00
nnouns	208.00

In [54]:
```
#using Tree surrogate
surrogate_explainer = interpreter.tree_surrogate(oracle=im_model, seed=1234)
```

In [55]:
```
surrogate_explainer.fit(X_train, Y_train)
```

```
2019-06-13 02:07:46,191 - skater.core.global_interpretation.tree_surrogate - INFO - post pruning applied ...
2019-06-13 02:07:46,223 - skater.core.global_interpretation.tree_surrogate - INFO - Scorer used cross-entropy
2019-06-13 02:07:46,231 - skater.core.global_interpretation.tree_surrogate - INFO - original score using base
model 9.992007221626413e-16
2019-06-13 02:07:47,031 - skater.core.global_interpretation.tree_surrogate - INFO - Summary: childrens of the
following nodes are removed [2, 3, 11]
2019-06-13 02:07:47,041 - skater.core.global_interpretation.tree_surrogate - INFO - Done generating predictio
n using the surrogate, shape (700, 2)
2019-06-13 02:07:47,050 - skater.core.global_interpretation.tree_surrogate - INFO - Done scoring, surrogate s
core 0.009; oracle score 0.062
2019-06-13 02:07:47,061 - skater.core.global_interpretation.tree_surrogate - WARNING - impurity score: 0.053
of the surrogate model is higher than the impurity threshold: 0.01. The higher the impurity score, lower is t
he fidelity/faithfulness of the surrogate model
```

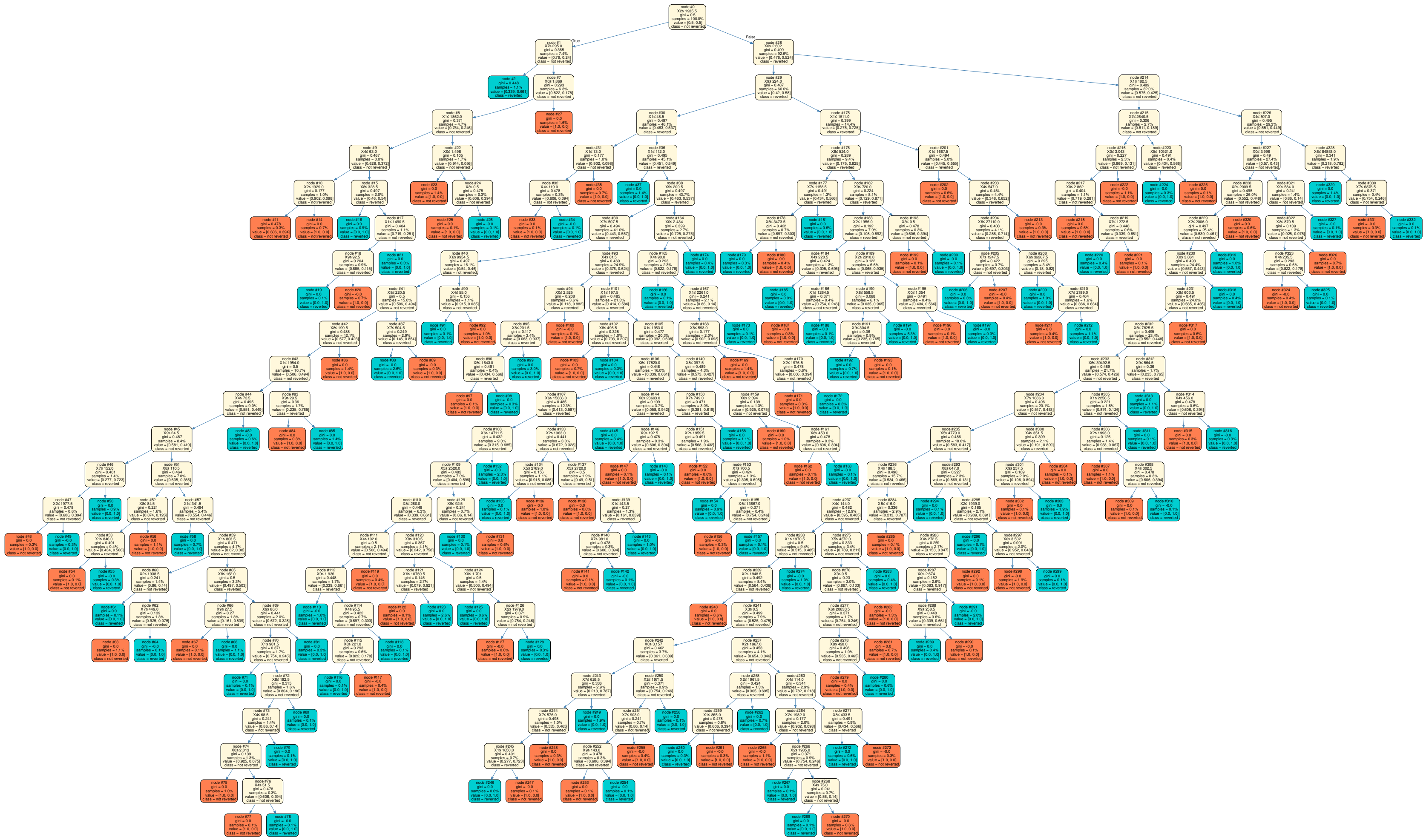
Out[55]:
```
0.053
```

In [56]:

```
from skater.util.dataops import show_in_notebook
from graphviz import Source
from IPython.display import SVG

graph = Source (surrogate_explainer.plot_global_decisions(colors=['coral', 'darkturquoise'], file_name='p4a.png
' ).to_string())
svg_data = graph.pipe(format='svg')
with open ('dtree.svg', 'wb') as f:
    f.write(svg_data)
SVG(svg_data)
```

Out[56]:



Global Surrogate

In [57]:
```
# use X_train and xgc's prediction to train a LogisticClassifier
from sklearn.linear_model import LogisticRegression
gsur_log = LogisticRegression(C=1e5)
```

In [58]:
```
# get  y^ = output of xgc if fed with X_train
yhat = xgc.predict(X_train)
```

In [59]:
```
gsur_log.fit(X_train.values, yhat)
```

Out[59]:
```
LogisticRegression(C=100000.0, class_weight=None, dual=False,
          fit_intercept=True, intercept_scaling=1, max_iter=100,
          multi_class='warn', n_jobs=None, penalty='l2', random_state=None,
          solver='warn', tol=0.0001, verbose=0, warm_start=False)
```

In [60]:
```
yhathat = gsur_log.predict(X_test)
```

In [61]:
```
len(yhathat)
```

Out[61]:
```
300
```

In [62]:
```
yhathat[0:10]
```

Out[62]:
```
array([1, 1, 1, 1, 1, 1, 1, 1, 1, 1])
```

In [63]:
```
pred[0:10]
```

Out[63]:
```
array([1, 1, 1, 1, 1, 0, 1, 1, 1, 0])
```

In [64]:
```
from sklearn.metrics import confusion_matrix
confusion_matrix(yhathat, pred)
```

Out[64]:
```
array([[  9,   4],
       [ 92, 195]])
```

In [65]:
```
(195+9)/300
```

Out[65]:
```
0.68
```

TextExplainer

In [66]:
```
import pickle
pkl_file = open("/home/xhta/Robot/problemsets/prob4/p4_df_1k.20190613_005107.pkl", "rb")
p4_df = pickle.load(pkl_file)
```

In [67]:
```
p4_df.head()
```

Out[67]:

caseid	case_reversed	judge_id	year	x_republican	log_cites	doc	jahr	nlets	nsents	nwords	nnouns	nverbs	nadjes
X53OBB	0	1641.0	1989.0	1.0	2.639057	PIERCE , Circuit Judge: The Government of Ind...	1989	15514.0	108.0	2641.0	864.0	387.0	89.0
X3UGPI	0	1421.0	1981.0	1.0	2.772589	MESKILL , Circuit Judge: This is an appeal fr...	1981	18260.0	112.0	2979.0	951.0	395.0	214.0
X46BHQ	0	367.0	1988.0	0.0	4.043051	CLARK , Circuit Judge: In another chapter of ...	1988	54172.0	439.0	9210.0	2938.0	1247.0	538.0
X46C0P	0	751.0	1989.0	1.0	2.772589	D.H.\nGINSBURG , Circuit Judge: This appeal a...	1989	28840.0	179.0	4811.0	1527.0	655.0	277.0
XABC47	1	2035.0	1979.0	0.0	2.397895	TANG , Circuit Judge.\nStandard Oil Company o...	1979	16334.0	141.0	2787.0	887.0	394.0	153.0

In [68]:
```
p4_df.shape
```

Out[68]: (1000, 13)

In [69]:
```
p4_df = p4_df.dropna()
```

In [70]:
```
#Xt = p4_df.loc[:, "judge_id":"nadjes"]
#Yt = p4_df.loc[:, "case_reversed"]
Xt = p4_df.loc[:, ["judge_id", "log_cites", "doc", "jahr", "nlets", "nsents", "nwords", "nnouns", "nverbs", "na
djes"]]
Yt = p4_df.loc[:, "x_republican"]
```

In [71]:
```
Xt_train, Xt_test,  Yt_train, Yt_test = train_test_split(Xt, Yt, test_size = 0.3, random_state = 1234)
```

In [72]:
```
Xt_train.shape, Yt_train.shape
```
Out[72]:
```
((700, 10), (700,))
```

In [73]:
```
Xt_train.head()
```
Out[73]:

	judge_id	log_cites	doc	jahr	nlets	nsents	nwords	nnouns	nverbs	nadjes
caseid										
X3CQCM	1814.0	1.791759	SANBORN , Circuit Judge.\nThis action, which ...	1950	9426.0	62.0	1690.0	520.0	241.0	64.0
X40SFF	1990.0	1.098612	STEPHENS , Circuit Judge.\nAnne Johnson is ap...	1947	6692.0	55.0	1169.0	338.0	184.0	66.0
X3ILN5	644.0	1.791759	FERNANDEZ , Circuit Judge: Robert Elmer Hyde ...	1996	3666.0	53.0	665.0	208.0	96.0	24.0
X3PAGN	1112.0	0.693147	CORNELIA G. KENNEDY , Circuit Judge.\nOhio re...	1981	45083.0	329.0	7570.0	2261.0	990.0	579.0
X6CQBP	1598.0	3.610918	B.D.\nPARKER, Jr., Circuit Judge.\nThis case,...	2003	84348.0	705.0	14270.0	4660.0	1733.0	941.0

In [74]:
```
Yt_train.head()
```
Out[74]:
```
caseid
X3CQCM    1.0
X40SFF    0.0
X3ILN5    1.0
X3PAGN    0.0
X6CQBP    1.0
Name: x_republican, dtype: float64
```

In [75]:
```
Yt_test[0:5]
```
Out[75]:
```
caseid
X369VS        1.0
X40G3F        0.0
X1B6SUE003    0.0
X3P7L9        1.0
X46H9S        1.0
Name: x_republican, dtype: float64
```

In [76]:
```
# source : github TeamHG-Memex  TextExplainer.ipynb
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.svm import SVC
from sklearn.decomposition import TruncatedSVD
from sklearn.pipeline import Pipeline, make_pipeline

vec = TfidfVectorizer(min_df = 1, max_df = 4, stop_words = 'english', ngram_range = (1,3))
svd = TruncatedSVD(n_components=11, n_iter = 5, random_state=1234)
lsa = make_pipeline(vec, svd)

svcclf = SVC(C=100, gamma = 1e-2, probability=True)
pipe = make_pipeline(lsa, svcclf)
pipe.fit(Xt_train["doc"].values.tolist(), Yt_train.values.tolist())
pipe.score(Xt_test["doc"].values.tolist(), Yt_test.values.tolist())
```

Out[76]:
```
0.5133333333333333
```

In [322]:
```
type(Xt_train)
```

Out[322]:
```
pandas.core.frame.DataFrame
```

In [77]:
```
type(Xt_train["doc"])
```

Out[77]:
```
pandas.core.series.Series
```

In [78]:
```
type(Yt_train)
```

Out[78]:
```
pandas.core.series.Series
```

In [79]:
```
Yt_test[0:5]
```

Out[79]:
```
caseid
X369VS        1.0
X40G3F        0.0
X1B6SUE003    0.0
X3P7L9        1.0
X46H9S        1.0
Name: x_republican, dtype: float64
```

In [ ]:

In [80]:
```
type(Xt_train["doc"].values.tolist())
```

Out[80]:
```
list
```

In [81]:

```
def print_prediction(doc):
    y_pred = pipe.predict_proba([doc])[0]
    for target, prob in zip(['democrat', 'republican'], y_pred):
        print("{:.3f} {}".format(prob, target))

doclist=Xt_test["doc"].values.tolist()
doc = doclist[0]
print_prediction(doc)
```

```
0.467 democrat
0.533 republican
```

In [84]:
```
import eli5
from eli5.lime import TextExplainer

te = TextExplainer(random_state=1234)
te.fit(doc, pipe.predict_proba)
te.show_prediction(target_names=['democrat', 'republican'])
```

Out[84]: **y=republican** (probability **1.000**, score **98.413**) top features

Contribution?	Feature
+98.366	Highlighted in text (sum)
+0.047	<BIAS>

coffey , circuit judge. the defendants-appellees, carle clinic association, p.c. ("carle"), health alliance medical plans, inc. ("hamp"), and carle health insurance management co., inc., operate a pre-paid health insurance plan which provides medical and hospital services. the plaintiff-appellant, cynthia herdrich ("herdrich"), was covered under a plan subscription through her husband's employer, state farm insurance company, an illinois corporation. in march of 1992, herdrich's appendix ruptured as the result of alleged improper medical treatment while she was in the care of dr. lori pegram ("pegram"), a physician who practiced under the plan. 1 on october 21, 1992, herdrich filed a two-count complaint, alleging medical negligence against the health plan operators. herdrich later added counts iii and iv, alleging state law fraud. the defendants, in response, contended that the employee retirement income security act of 1974 ("erisa"), 29 u.s.c. 1001 et seq. , preempted counts iii and iv, and successfully removed the case to federal court. they subsequently filed a motion for summary judgment as to counts iii and iv. the trial judge granted the summary judgment motion on count iv only, and gave herdrich leave to amend count iii. in accordance with the court's instructions, herdrich amended count iii to allege that the defendants had breached their fiduciary duty to plan participants, in violation of erisa. the defendants moved to dismiss the amended count iii for failure to state a claim upon which relief could be granted. the court agreed and granted the motion. the remaining two medical negligence counts (i and ii) went to trial before a jury. herdrich prevailed on both of them. thereafter, she filed a notice of appeal as to the trial court's dismissal of her amended count iii. we reverse and remand this case to the district court (on count iii) for a trial. i. background this appeal arises out of a complaint filed by herdrich in the circuit court of mclean county, illinois, on october 21, 1992, against lori pegram, m.d. and carle clinic association. counts i and ii of the plaintiff's complaint were based upon a theory of professional medical negligence. specifically, herdrich alleged that she suffered a ruptured appendix and, in turn, contracted peritonitis due to pegram's negligence in failing to provide her with timely and adequate medical care. on february 18, 1994, herdrich was granted leave to amend the complaint. in her amended complaint, she added two counts (iii and iv) of state law fraud against carle and health alliance medical plans, inc. 2 the defendants removed the case to federal court, asserting that the two new counts were preempted by erisa, and thereafter filed a motion for summary judgment as to counts iii and iv only. the court granted summary judgment against herdrich on count iv "to the extent [she] relies on 502(a)(3)(b) [of erisa] as a basis for monetary relief, as opposed to equitable relief," and that provision does not provide for extra-contractual damages. while the trial judge denied the defendants' summary judgment motion as to count iii, he did conclude erisa preempted that count, and granted herdrich "leave to submit an amended count iii which clearly sets forth her basis for proceeding under erisa, including the applicable civil enforcement provision." on september 1, 1995, herdrich filed her amended count iii in accordance with the court's instructions. in it, she averred that the defendants breached their fiduciary duty to plan beneficiaries by depriving them of proper medical care and retaining the savings resulting therefrom for themselves. 3 the defendants thereafter moved, pursuant to rule 12 of the federal rules of civil procedure, to dismiss herdrich's amended count iii for failure to state a claim upon which relief could be granted. by agreement, the case--including the defendants' motion to dismiss--was assigned to a magistrate judge, who recommended that the amended count iii be dismissed because, in his opinion, "[t]he plaintiff fail[ed] to identify how any of the defendants is involved as a fiduciary to the plan." he did, however, recommend that the court afford herdrich "one last opportunity" to re-plead her claim under erisa. herdrich promptly filed a rule 72 objection to the magistrate's recommendation. less than two weeks later, on april 15, 1996, the district court denied that objection and adopted the magistrate's recommendation as to count iii. in so doing, it gave herdrich 21 days from the entry of the order to re-plead her claim. herdrich chose not to re-plead and stood on count iii as amended. the remaining counts, i and ii, went to trial in early december 1996, and the jury returned a verdict in herdrich's favor on both counts, awarding her $35,000 in compensatory damages. she then appealed the district court's earlier dismissal of her amended count iii. ii. issues on appeal, herdrich contends that the district court erred in dismissing the amended count iii of her complaint for failing to sufficiently state a claim for breach of a fiduciary duty under erisa. the defendants contend that we lack jurisdiction to hear this case due to herdrich's failure to file a timely notice

metrrics_

shows the quality of the surrogate model. 'score' indicates the accuracy weighted by the cosine distance between generated sample and the original document. The higher the better 'mean_KL_divergence' : mean over all target classes. KL show how well probabilities are approximated: 0.0 means a perfect match

In [90]:
```
te.metrics_
```

Out[90]:
```
{'mean_KL_divergence': 0.17909169690334967, 'score': 0.11217143196344301}
```

In [89]:
```
te.fit(Xt_train["doc"].values.tolist()[1], pipe.predict_proba)
te.show_prediction(target_names=['democrat','republican'])  # column x_republican = 0 for democrat and = 1 for republican
```

Out[89]: **y=democrat** (probability **0.810**, score **-1.449**) top features

Contribution?	Feature
+1.546	Highlighted in text (sum)
-0.097	<BIAS>

stephens , circuit judge. anne johnson is appealing from the judgment after she was tried, convicted and sentenced (count 1) for purchasing "approximately 85 grains of opium prepared for smoking, which was not then in nor from the original stamped package", 26 u.s.c.a. int.rev.code, 2553(a), (count 11) of having "knowingly received and concealed 85 grains of opium prepared for smoking, which had theretofore been imported and brought into the united states of america contrary to law *", 21 u.s.c.a. 174, (count 3) of purchasing "approximately 41 grains of yen shee, partially smoked opium prepared for smoking, which was not then in nor from the original stamped package", 26 u.s.c.a. int.rev.code, 2553(a), (count 4) of having "knowingly received and concealed 41 grains of yen shee, partially smoked opium prepared for smoking, which had theretofore been imported into the united states of america contrary to law *", 21 u.s.c.a. 174. appellant claims reversible error because the conviction would have no substantial support without evidence secured through an illegal search and seizure (fourth amendment of united states constitution) and because of misconduct of counsel for the government. there is substantial evidence to support the following factual situation: officer belland, with long experience on a narcotic detail, was informed that smoking of opium was in progress in a certain hotel. at the time of receiving such information, the officer was engaged in the arrest of a person, and upon completion of that duty, he proceeded to investigate the information given him. he arrived at the hotel shortly before 9:00 p. m., taking three other officers with him, and with two of the officers, went to the second floor, where he detected a strong odor of burning opium. the officers traced the odor to room number one, and there smelled strong current of opium fumes coming from the cracks in the panels and from the cracks around the loosely fitting door. officer belland rapped, stated his name and requested admittance. there were sounds of some one scurrying around within the room for several minutes, after which the officer was admitted by appellant. upon inquiry as to the opium fumes, she denied their presence, whereupon she was placed under arrest and a search for evidence of smoking opium was set in progress. a rather complete opium smoking outfit with opium was found under bed covers, the pipe still being quite warm. yen shee was discovered in a suit case. the search was not unreasonable or illegal provided the circumstances just briefly related were sufficient to constitute probable cause for the arrest. kwong how v. united states , 9 cir., 71 f.2d 71 ; garske v. united states , 8 cir., 1 f.2d 620 ; carroll v. united states , 267 u.s. 132 , 45 s.ct. 280 , 69 l.ed. 543 , 39 a.l.r. 790; stacey v. emery , 97 u.s. 642 , 24 l.ed. 1035 ; mccarthy v. de armit , 99 pa. 63 ; green v. united states , 8 cir., 289 f. 236 ; pong ying v. united states , 3 cir., 66 f.2d 67 . the following cases are cited as authority for the conclusion that mere smell of burning opium is not sufficient to constitute probable cause. taylor v. united states , 286 u.s. 1 , 52 s.ct. 466 , 76 l.ed. 951 ; united states v. lee , 2 cir., 83 f.2d 195 ; united states v. kind , 2 cir., 87 f.2d 315 ; united states v. kaplan , 2 cir., 98 f.2d 869 . of course, there is nothing in the statutory law to the effect that the sense of smell alone is not sufficient to constitute probable cause, and, therefore, any such holding in a given case is premised upon the facts of the given case. we venture to say that the smell of opium fumes may in some circumstances be second only to the well-known maxim that "seeing is believing." in this case we find three experienced officers being directed to the door of appellant's room by the sense of smell and there experiencing the current of the fumes coming from the cracks of an ill-fitting and loose-paneled door. before admission, there ensues some minutes of scurrying within; when admitted, appellant is found to be alone. no one has left the room because all exits have been under observation. all of this follows the informer's "tip". the whole action on behalf of the officers has been prompt and delay for the purpose of securing warrant for arrest and search in the circumstances probably would have been fatal to the detection of the suspected crimes. we hold the arrest to have been made under probable cause, and the search and seizure to have been reasonable and legal. we come now to the conduct of the prosecuting officer. it goes merely with the saying that public prosecutors in the performance of their duties must present their cases and their argument with care and vigor. too much nicety would destroy the true effect of a point under presentation. it is not unusual, however, for a defense counsel to "bait" the prosecuting attorney and reasonable counter strokes may be justified even though the prosecutor is the people's attorney and should strive only for justice. the bar, however, should never be degraded to that of a pasquino by one of its officers, least of all by a government counsel in a criminal case. the deputy district

In [87]:
```
te.metrics_
```
Out[87]:
```
{'mean_KL_divergence': 0.1660828903609619, 'score': 0.1067110836233576}
```

In [97]:
```
te.fit(Xt_train["doc"].values.tolist()[7], pipe.predict_proba)
te.metrics_
```
Out[97]:
```
{'mean_KL_divergence': 0.13647336446015787, 'score': 0.338589334084546}
```

In [ ]:
```

```

In [ ]:
```
# using min_df = 2  instead of 1  and ngram_range = (2,3)  and gamma = 1e-4 instead of 1e-2 in SVCClassifier:
```

In [98]:
```
# source : github TeamHG-Memex  TextExplainer.ipynb
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.svm import SVC
from sklearn.decomposition import TruncatedSVD
from sklearn.pipeline import Pipeline, make_pipeline

vec = TfidfVectorizer(min_df = 2, max_df = 4, stop_words = 'english', ngram_range = (2,3))
svd = TruncatedSVD(n_components=11, n_iter = 5, random_state=1234)
lsa = make_pipeline(vec, svd)

svcclf = SVC(C=100, gamma = 1e-4, probability=True)
pipe = make_pipeline(lsa, svcclf)
pipe.fit(Xt_train["doc"].values.tolist(), Yt_train.values.tolist())
pipe.score(Xt_test["doc"].values.tolist(), Yt_test.values.tolist())
```
Out[98]:
```
0.5133333333333333
```

In [99]:
```
te = TextExplainer(random_state=1234)
te.fit(doc, pipe.predict_proba)
te.show_prediction(target_names=['democrat', 'republican'])
te.metrics_
```
Out[99]:
```
{'mean_KL_divergence': 3.9849186347704486, 'score': 0.7893171128892489}
```

In [100]:
```
te = TextExplainer(random_state=1234)
te.fit(Xt_train["doc"].values.tolist()[0], pipe.predict_proba)
te.show_prediction(target_names=['democrat', 'republican'])
te.metrics_
```
Out[100]:
```
{'mean_KL_divergence': 1.2364966024527837, 'score': 0.058939661735066595}
```

In [101]:
```
te = TextExplainer(random_state=1234)
te.fit(Xt_train["doc"].values.tolist()[1], pipe.predict_proba)
te.show_prediction(target_names=['democrat', 'republican'])
te.metrics_
```

Out[101]: {'mean_KL_divergence': 0.057575538892662245, 'score': 0.3686694379535143}

In [102]:
```
te = TextExplainer(random_state=1234)
te.fit(Xt_train["doc"].values.tolist()[2], pipe.predict_proba)
te.show_prediction(target_names=['democrat', 'republican'])
te.metrics_
```

Out[102]: {'mean_KL_divergence': 0.027043167920026315, 'score': 0.8025921018252219}

In [103]:
```
te = TextExplainer(random_state=1234)
te.fit(Xt_train["doc"].values.tolist()[4], pipe.predict_proba)
te.show_prediction(target_names=['democrat', 'republican'])
te.metrics_
```

Out[103]: {'mean_KL_divergence': 8.761650710238545, 'score': 0.9664562083867334}

better metrics should be achievable by applying a GridSearchCV to look for best parameters for the TfIdfvectorizer and the SVD Classifier