Lab 7

Jiarong Ye

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import packages

```
In [156]: import datascience as ds
          from datascience import *
          import numpy as np
          from graphviz import Source
          import pandas as pd
          import re, string
          import nltk
          from functools import reduce
          import seaborn as sns
          from sklearn.feature_extraction.text import CountVectorizer
          from sklearn.tree import DecisionTreeClassifier
          from sklearn import tree
          from sklearn.metrics import confusion_matrix, precision_score, recall_score, f1_score, accurac
          import matplotlib.pyplot as plt
          from sklearn.model_selection import train_test_split, cross_val_score, StratifiedKFold

          %matplotlib inline
```

tweets data loaded into Jupyter Notebook as Table object

```
In [140]: df = ds.Table.read_table('relevant_tagged.csv', sep=',')
```

StratifiedKFold Model Building

```
In [141]: X = list(df['text'])
          y = list(df['sentiment'])
```

```
In [127]: def custom_split(train_index, test_index):
              trainingset = df.take(train_index)
              testingset = df.take(test_index)

              X_train= list(trainingset['text'])
              y_train= list(trainingset['sentiment'])
              X_test= list(testingset['text'])
              y_test= list(testingset['sentiment'])

              return X_train, X_test, y_train, y_test
```

```
In [128]: def word_vectorizer(X_train, X_test):
              vect = CountVectorizer(
                   analyzer="word", ngram_range=([1,2]), tokenizer=nltk.word_tokenize,
                  preprocessor=None, stop_words='english', max_features=3000)
              X_train_vect = vect.fit_transform(X_train)
              X_test_vect = vect.transform(X_test)
              return X_train_vect, X_test_vect, vect.get_feature_names()
```

```
In [193]: def classifier(X_train, y_train, X_test, fold, feature_names, max_depth, min_samples_leaf):
              clf = DecisionTreeClassifier(criterion = 'entropy',
                                          random_state = 100,
                                          max_depth = max_depth,
                                          min_samples_leaf = min_samples_leaf)


              clf.fit(X_train, y_train)
              try:
                  dot_data = tree.export_graphviz(clf, out_file=None,
                                              feature_names=feature_names)
                  graph = Source(dot_data)
                  graph.render('SentientClassifier-Fold_{}_depth{}_leaf_{}'.format(fold, max_depth,
                   min_samples_leaf))
              except Exception as e:
                  print(e)
              predicted_y_test = clf.predict(X_test)
              return predicted_y_test
```

```
In [194]: def eval_results(predicted_y_test, y_test):
              precision_s = precision_score(y_test, predicted_y_test, average='weighted')
              recall_s = recall_score(y_test, predicted_y_test, average='weighted')
              f1_s = f1_score(y_test, predicted_y_test, average='weighted')
              cm = confusion_matrix(y_test, predicted_y_test)
              return precision_s, recall_s, f1_s, cm
```

```
In [220]: def plot_results(res, idx):
              metrics_df = pd.DataFrame(
                  {'precision': res[idx].precision_score,
                  'recall':res[idx].recall_score,
                  'f1':res[idx].f1_score}
                  )
              metrics_df.index = np.arange(1,6)
              metrics_df.plot(linewidth=2)
              plt.show()
```

1) Stratified k-fold cross validation results for each combination of max_depth and min_samples_leaf you chose

```
In [237]: def k_fold_evaluate(X, y, n_splits, max_depth_tests, min_samples_leaf_tests):

              classes = ['neutral', 'positive', 'negative']
              skf = StratifiedKFold(n_splits=n_splits, random_state=1, shuffle= True)
```

```
    res = []
    res_total = []

    for depth in max_depth_tests:
        for leaf in min_samples_leaf_tests:
            fold = 1
            for train_index, test_index in skf.split(X, y):

                X_train, X_test, y_train, y_test = custom_split(train_index, test_index)

                X_train_vect, X_test_vect, feature_names = word_vectorizer(X_train, X_test)

                # print('max_depth = {}'.format(depth))
                # print('min_samples_leaf = {}\n'.format(leaf))
                predicted_y_test = classifier(X_train=X_train_vect, y_train=y_train,
                                              X_test=X_test_vect, fold=fold,
                                              feature_names=feature_names,
                                              max_depth=depth,
                                              min_samples_leaf=leaf)
                precision_s, recall_s, f1_s, cm = eval_results(predicted_y_test, y_test)

                res.append(['fold{}'.format(fold), depth, leaf, f1_s, precision_s, recall_s])
                fold += 1

    res_df = pd.DataFrame(res, columns=['fold', 'max_depth', 'min_samples_leaf',
    'f1_score', 'precision_score', 'recall_score'])

    for s in ['f1_score', 'precision_score', 'recall_score']:
        max_score = np.array(res_df.groupby(by='fold')
        .apply(lambda x: x[s].values.argmax()).values)
        res_total.append(pd.DataFrame([res_df[res_df.fold=='fold{}'.format(i)]
         .iloc[max_score[i-1], :] for i in range(1,6)]))

    return res_total
```

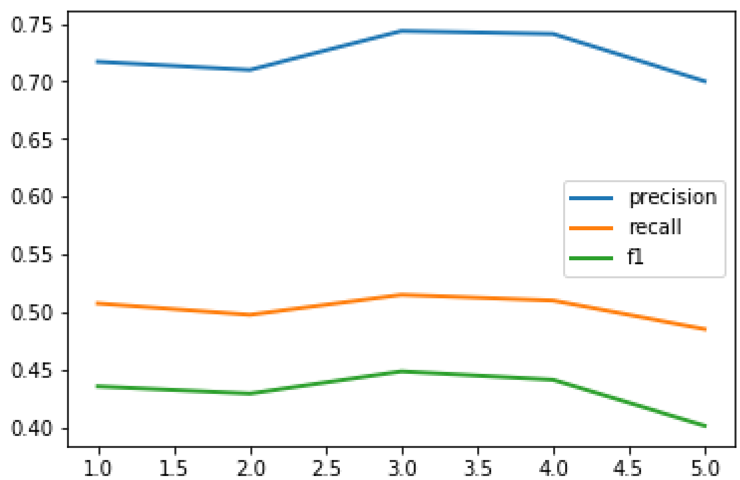
```
In [238]: max_depth_tests = np.arange(5, 15, 1)
          min_samples_leaf_tests = np.arange(1, 5, 1)
          res_total = k_fold_evaluate(X, y, n_splits=5, max_depth_tests=max_depth_tests,
           min_samples_leaf_tests=min_samples_leaf_tests)
```

when reach max f1 score in each fold:

```
In [239]: res_total[0]
```

	fold	max_depth	min_samples_leaf	f1_score	precision_score	recall_score
155	fold1	12	4	0.435166	0.717057	0.507389
161	fold2	13	1	0.428888	0.709975	0.497537
182	fold3	14	1	0.448121	0.743648	0.514851
183	fold4	14	1	0.440867	0.741167	0.509901
164	fold5	13	1	0.401043	0.700211	0.485149

```
In [240]: plot_results(res_total, idx=0)
```

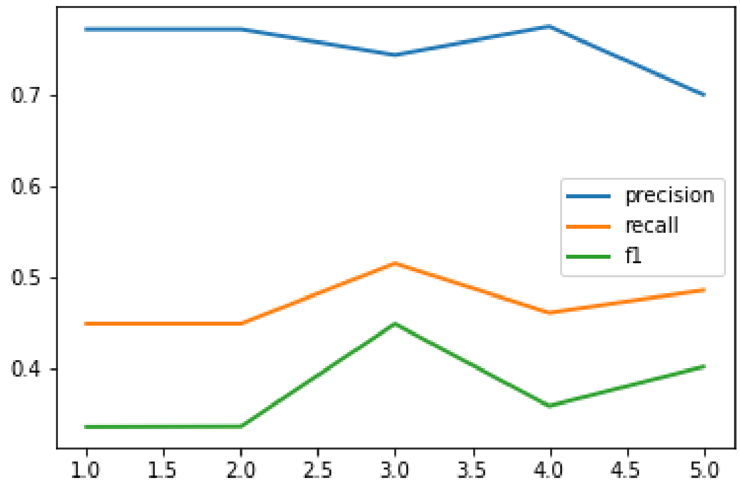


when reach max precision score in each fold:

```
In [241]: res_total[1]
```

	fold	max_depth	min_samples_leaf	f1_score	precision_score	recall_score
20	fold1	6	1	0.334993	0.771800	0.448276
1	fold2	5	1	0.335450	0.771800	0.448276
182	fold3	14	1	0.448121	0.743648	0.514851
23	fold4	6	1	0.358025	0.774925	0.460396
164	fold5	13	1	0.401043	0.700211	0.485149

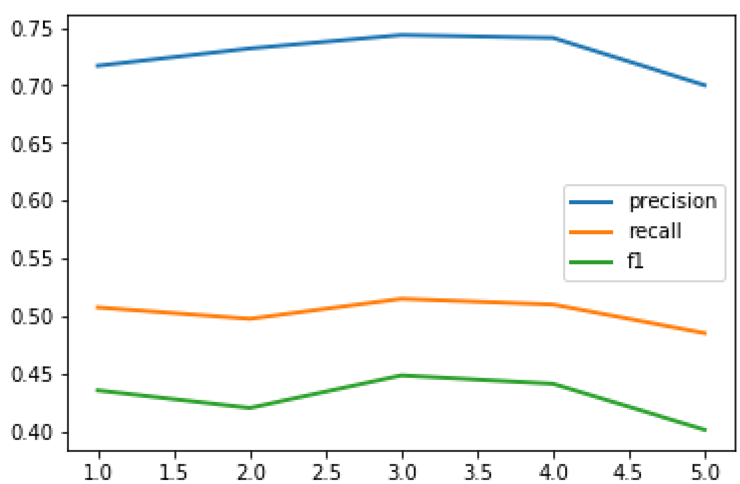
```
In [242]: plot_results(res_total, idx=1)
```



when reach max recall score in each fold:

```
In [243]: res_total[2]
```

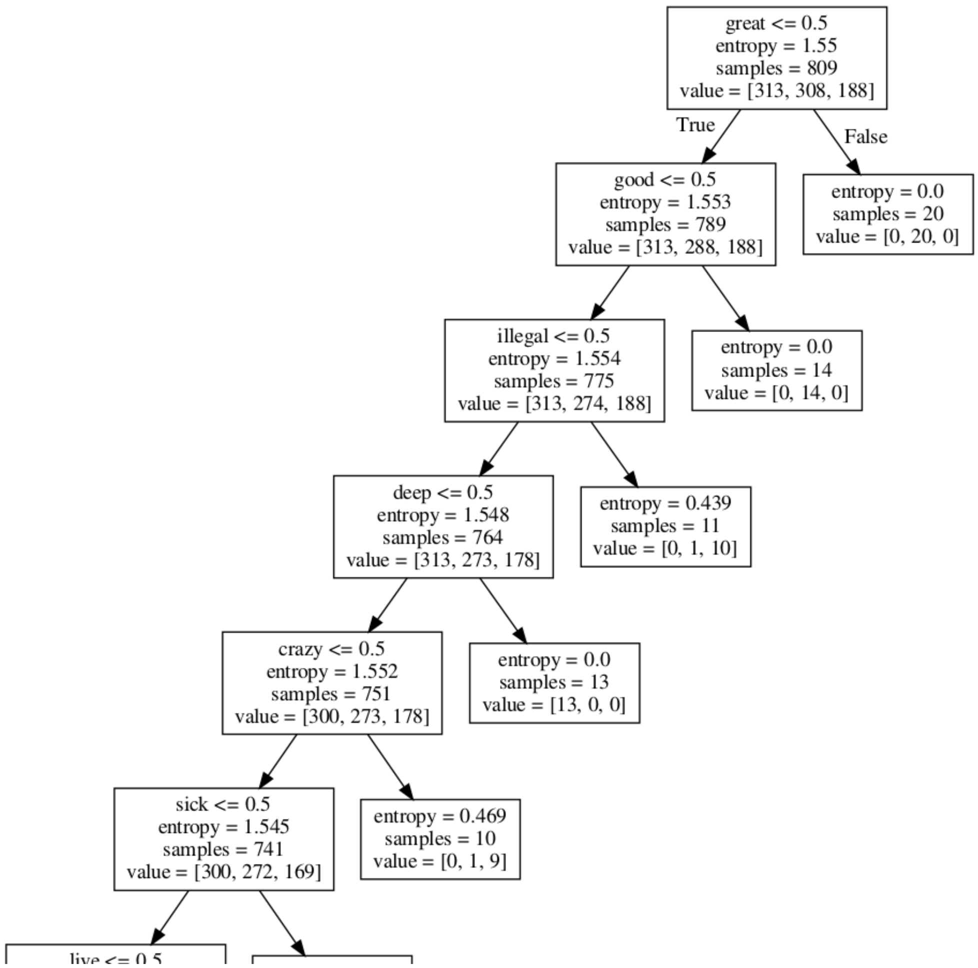
	fold	max_depth	min_samples_leaf	f1_score	precision_score	recall_score
155	fold1	12	4	0.435166	0.717057	0.507389
151	fold2	12	3	0.419940	0.732016	0.497537
182	fold3	14	1	0.448121	0.743648	0.514851
183	fold4	14	1	0.440867	0.741167	0.509901
164	fold5	13	1	0.401043	0.700211	0.485149



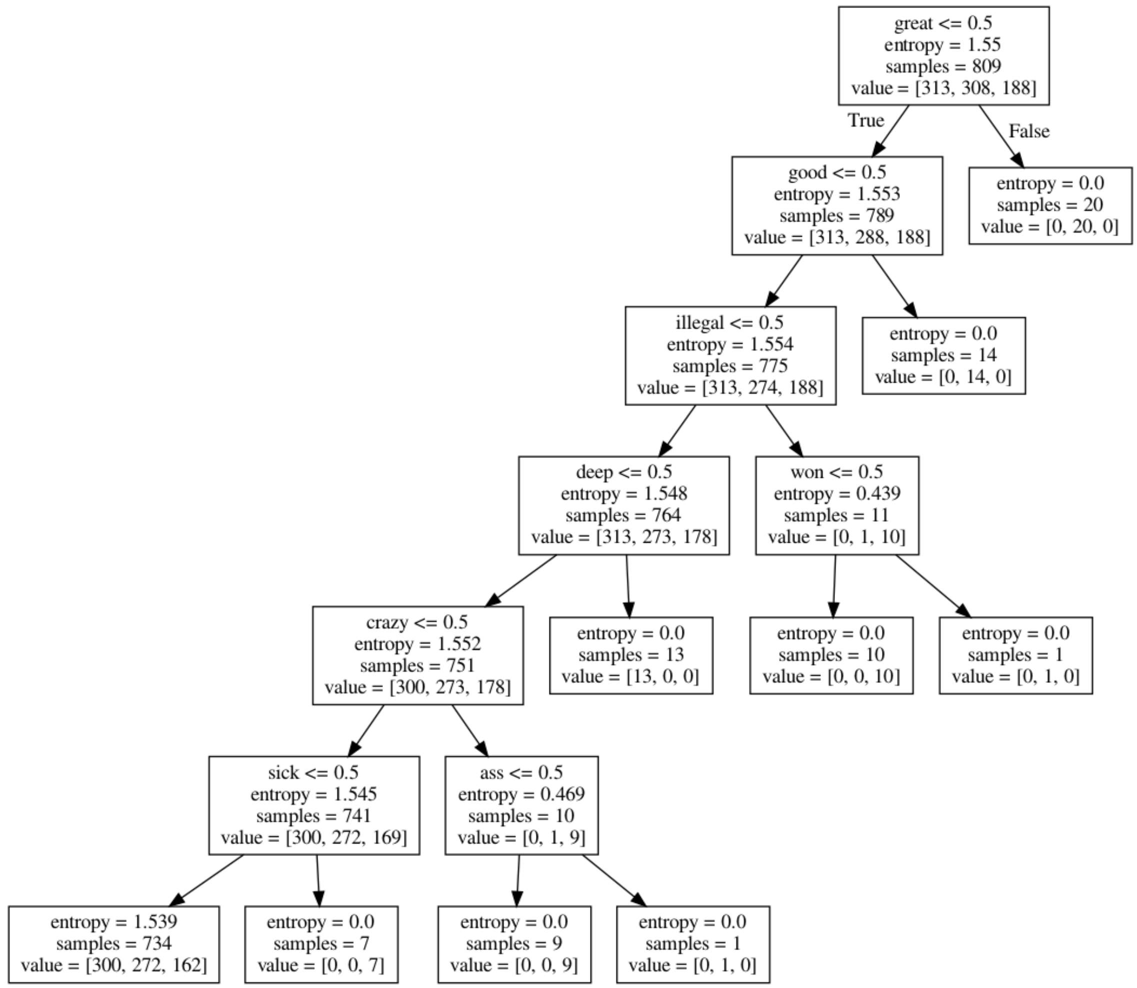
2) discuss common features across the trees generated for each k-fold cross validation (include visualization of exemplar trees)

Here we display the tree in randomly chosen folds that reaches the highest f1, precision and recall scores:

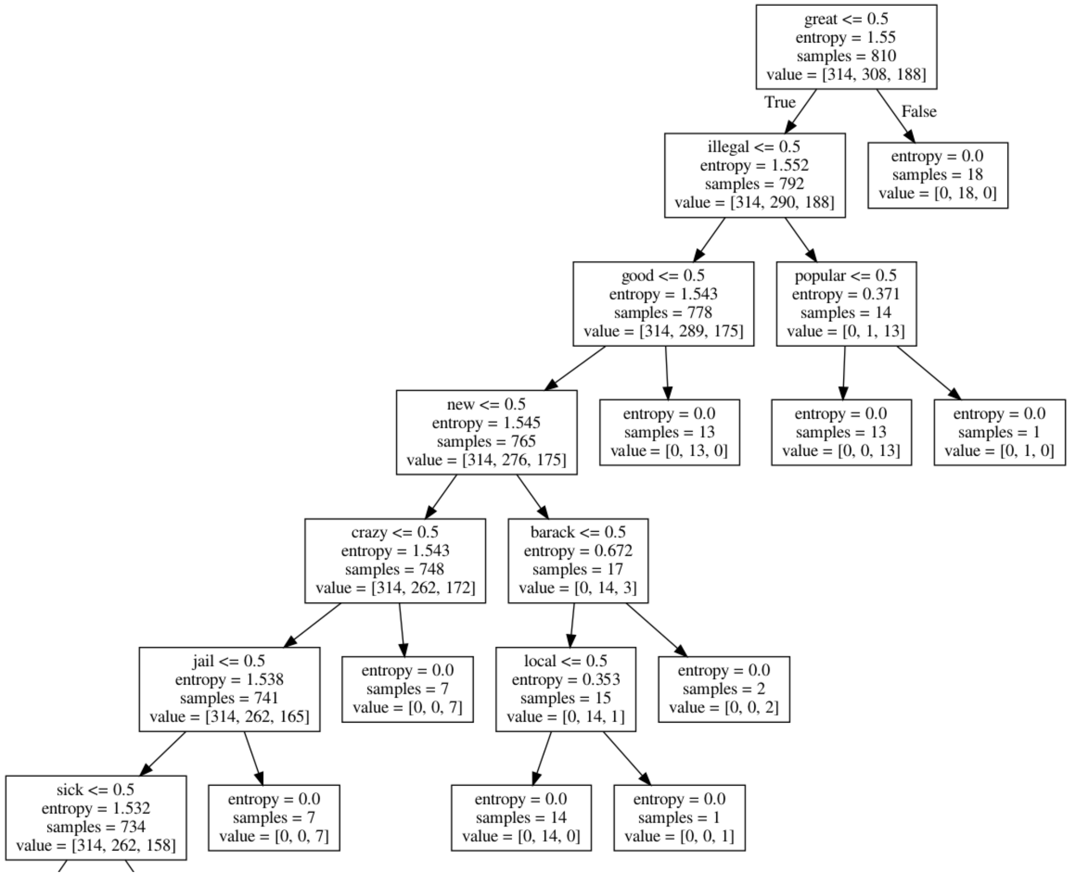
- Fold 1: max_depth = 12, min_samples_leaf = 4



- Fold 1: max_depth = 6, min_samples_leaf = 1



- Fold 5: max_depth = 13, min_samples_leaf = 1



- Decision Trees of different combination of max_depth and min_samples_leaf and different folds share some similar features, for instance:
  - $great \leq 5$ is the root node of all the sampled trees here
  - $illegal \leq 0.5, good \leq 0.5$ also appears in all sampled trees
  - $crazy \leq 0.5, deep \leq 0.5$ appears in not all but also more than 1 tree

3) discuss the results (e.g., the best combination of max_depth and min_samples_leaf)

To summarize, when

$maxDepth \in [1, 15], minSamplesLeaf \in [1, 5]$

$$maxDepth = 14$$

$$minSamplesLeaf = 1$$

or

$$maxDepth = 13$$

$$minSamplesLeaf = 1$$

are probably the optimal choices since in the 5 fold cross validation, these combination reach: -

- 14, 1
  - the highest f1 score in fold3 and fold4
  - the highest precision score in fold3
  - the highest recall score in fold3 and fold4
- 13, 1
  - the highest f1 score in fold2 and fold5
  - the highest precision score in fold5
  - the highest recall score in fold5