Fall 2018

Jupyter: Intro to Data Science - Lecture 10 Fitting and Evaluating Classification Models

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Data Dive Week 10: Fitting and Evaluating Classification Models

Today we revisit our Kiva data to review model performance and tradeoffs between different classification methods. We'll use logistic regression, decision trees, random forests, and gradient boosting machines to predict whether loan requests posted on Kiva.org (kiva.org) recevie funding. We'll be using `scikit-learn` for all of the models in today's exercise.

Kiva is an international nonprofit, founded in 2005 and based in San Francisco, with a mission to connect people through lending to alleviate poverty. Kiva seeks to celebrate and support people looking to create a better future for themselves, their families and their communities.

By lending as little as $25 on Kiva, anyone can help a borrower start or grow a business, go to school, access clean energy or realize their potential. For some, it's a matter of survival, for others it's the fuel for a life-long ambition.

Today's Modeling Objective

Our focus today will be determining whether microfinance projects on the site Kiva.org (kiva.org) receive funding or not using a host of features made available by Kiva, along with some features we'll design ourselves.

Today's data is a subsample of projects in Kenya, one of Kiva's most active countries for lending. We'll be working with 18,000 observations, 12,000 of which were funded.

Documentation on the data is available on Kiva's website (http://build.kiva.org/docs/data/basic_types).

In [1]:
```
%matplotlib inline

import pandas as pd
import numpy as np
import warnings
import matplotlib.pyplot as plt
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassi
from sklearn.metrics import accuracy_score, recall_score, precision_score,
from sklearn.metrics import roc_curve, roc_auc_score
from sklearn.model_selection import KFold, train_test_split

warnings.filterwarnings("ignore")
random_state = 20181112
```

In [2]:
```
df = pd.read_csv('https://grantmlong.com/data/kiva_kenya_sample.csv')
print(df.shape)
print(list(df))
df.head()
```

```
(18000, 25)
['LOAN_ID', 'DESCRIPTION', 'FUNDED_AMOUNT', 'LOAN_AMOUNT', 'STATUS', 'ACT
IVITY_NAME', 'SECTOR_NAME', 'LOAN_USE', 'TOWN_NAME', 'CURRENCY', 'PARTNER
_ID', 'POSTED_TIME', 'PLANNED_EXPIRATION_TIME', 'DISBURSE_TIME', 'RAISED_
TIME', 'LENDER_TERM', 'NUM_LENDERS_TOTAL', 'NUM_JOURNAL_ENTRIES', 'NUM_BU
LK_ENTRIES', 'TAGS', 'BORROWER_NAMES', 'BORROWER_GENDERS', 'BORROWER_PICT
URED', 'REPAYMENT_INTERVAL', 'DISTRIBUTION_MODEL']
```

Out[2]:

	LOAN_ID	DESCRIPTION	FUNDED_AMOUNT	LOAN_AMOUNT	STATUS	ACTIVITY_NAME	SECTO
0	854452	Janepher, pictured above, is a group leader an...	725.0	1000.0	expired	Agriculture	A
1	868233	John is a married man. He has two children. He...	825.0	1100.0	expired	Grocery Store	
2	1429009	Margaret is a single mother and lives with her...	275.0	500.0	expired	Farming	A
3	1077128	Agriphine is a proud mother of angelic-looking...	225.0	1000.0	expired	Farming	A
4	825980	Bernard is 32 years. He is married to Caroline...	275.0	500.0	expired	Butcher Shop	

5 rows × 25 columns

Tidying Up Our Data

There are a couple of different things we'll want to off the bat:

1. Create a target variable
2. Generate a more usable version of the `POSTED_TIME` column.
3. Generate a variable with the amount of planned time before expiration for each project.
4. Generate boolean variables for each of the following categorical columns:
    - `SECTOR_NAME`
    - `ACTIVITY_NAME`
    - `REPAYMENT_INTERVAL`
5. Create boolean variables for a handful of other free text and categorical columns, including:

- BORROWER_PICTURED
- BORROWER_GENDERS
- DISTRIBUTION_MODEL

In [3]:
```
df.STATUS.value_counts()
```

Out[3]:
```
funded     12000
expired     6000
Name: STATUS, dtype: int64
```

In [4]:
```
df['success'] = (df.STATUS=='funded')*1
```

In [5]:
```
df.POSTED_TIME.head()
```

Out[5]:
```
0    2015-03-12 12:14:55.000 +0000
1    2015-04-10 10:47:35.000 +0000
2    2017-12-06 10:12:14.000 +0000
3    2016-05-27 13:05:40.000 +0000
4    2015-01-09 09:10:57.000 +0000
Name: POSTED_TIME, dtype: object
```

In [6]:
```
df['posted_year'] = pd.to_datetime(df.POSTED_TIME).dt.year
df['posted_duration'] = (pd.to_datetime(df.PLANNED_EXPIRATION_TIME)
                              - pd.to_datetime(df.POSTED_TIME)
                             ).dt.days
```

In [7]:
```
sector_names = ['sector_' + name.lower() for name in df.SECTOR_NAME.unique(
for name in df.SECTOR_NAME.unique():
    df['sector_' + name.lower()] = (df.SECTOR_NAME==name)*1

activity_names = ['activity_' + name.lower() for name in df.ACTIVITY_NAME.u
for name in df.ACTIVITY_NAME.unique():
    df['activity_' + name.lower()] = (df.ACTIVITY_NAME==name)*1

repayment_types = ['repayment_' + interval.lower() for interval in df.REPAY
for interval in df.REPAYMENT_INTERVAL.unique():
    df['repayment_' + interval.lower()] = (df.REPAYMENT_INTERVAL==interval)
```

In [8]:
```
other_names = ['has_borrower_pic', 'has_female_borrower', 'direct_distribut

df['has_borrower_pic'] = df.BORROWER_PICTURED.str.contains('true')*1
df['has_borrower_pic'] = df['has_borrower_pic'].fillna(0)

df['has_female_borrower'] = df.BORROWER_GENDERS.str.contains('female')*1
df['has_female_borrower'] = df['has_female_borrower'].fillna(0)

df['direct_distribution'] = (df.DISTRIBUTION_MODEL=='direct')*1

df['currency_usd'] = (df.CURRENCY=='USD')*1
```

In [ ]:

In [ ]:

Data Handling

In [9]:

```
features = (['posted_year', 'posted_duration', 'LOAN_AMOUNT', 'LENDER_TERM'
            + repayment_types + sector_names + activity_names
            + other_names
           )

model_df = df[(features + ['success'])].dropna().reset_index()

train_df, holdout_df, y_train, y_holdout = train_test_split(
    model_df[features],
    model_df['success'], test_size=0.1,
    random_state=random_state)



train_df['success'] = y_train
holdout_df['success'] = y_holdout

train_df.reset_index(inplace=True)
holdout_df.reset_index(inplace=True)

print(train_df.shape[0], train_df.success.mean())
print(holdout_df.shape[0], holdout_df.success.mean())
```

```
14297 0.621668881583549
1589 0.6280679672750157
```

In [ ]:

Model Training

Let's take a quick look at all of our classification model options using cross validation. For the tree based models, we'll use the hyperparameter `max_depth=6` as a naive attempt at voiding overfitting before we dig deeper.

Let's fit and score the model, this time using cross validation:

In [10]:

```
k_fold = KFold(n_splits=5, random_state=random_state)
```

In [11]:
```
def get_cv_results(classifier):

    results = []
    for train, test in k_fold.split(train_df):
        classifier.fit(train_df.loc[train, features], train_df.loc[train, '
        y_predicted = classifier.predict(train_df.loc[test, features])
        accuracy = accuracy_score(train_df.loc[test, 'success'], y_predicte
        results.append(accuracy)

    return np.mean(results), np.std(results)
```

First, let's look at the cv performance of Logistic Regression

In [12]:
```
logreg = LogisticRegression(
    random_state=random_state,
    solver='lbfgs'
)

get_cv_results(logreg)
```

Out[12]:
```
(0.7644260915719467, 0.010979146454348028)
```

Next, let's take a naive attempt to beat Logistic Regression using a Tree

In [13]:
```
dtree = DecisionTreeClassifier(
    random_state=random_state,
    max_depth=6
)

get_cv_results(dtree)
```

Out[13]:
```
(0.8217106573035219, 0.0024906435410496208)
```

Looks like a non-linear method gives us a big boost. Let's try a Random Forest.

In [14]:
```
rforest = RandomForestClassifier(
    random_state=random_state,
    max_depth=6,
    n_estimators=100
)

get_cv_results(rforest)
```

Out[14]:
```
(0.8154853890425768, 0.0032988376919777453)
```

Finally, let's take a naive approach to Gradient Boosting.

In [15]:
```python
gbm = GradientBoostingClassifier(
    random_state=random_state,
    max_depth=6,
    n_estimators=100
)

get_cv_results(gbm)
```

Out[15]:
```
(0.8613691764688618, 0.003947793716135799)
```

In [ ]:

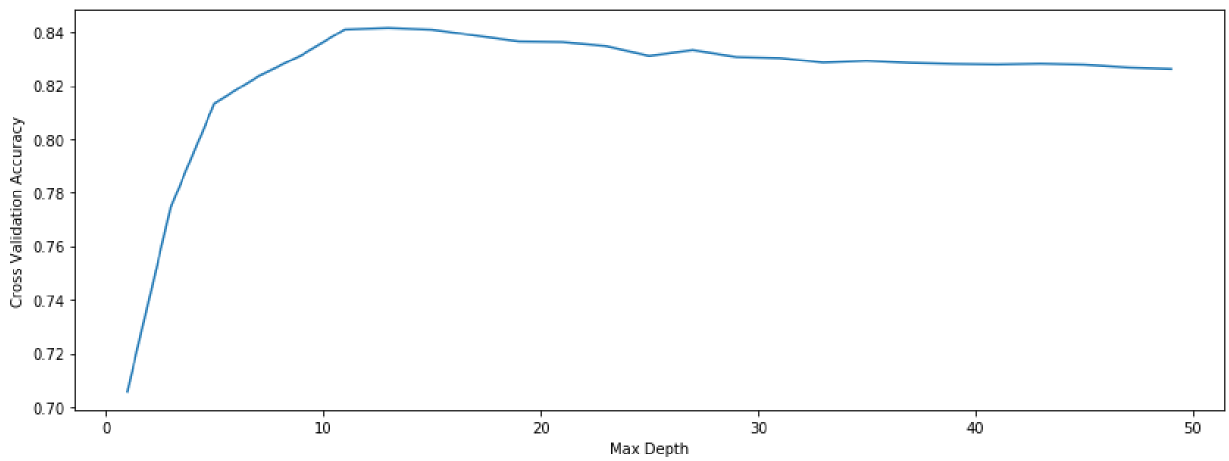
Learning Curves, Revisited

Now that we're working with a more complex data set, we should be able to build more robust learning curves than we had experience with when we were using the

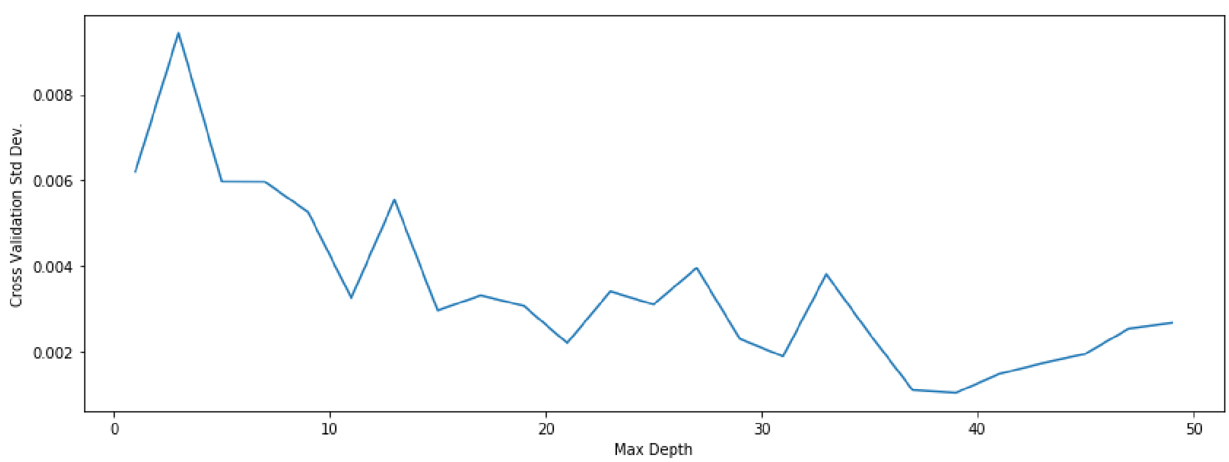
In [16]:
```python
hp_values = range(1,50, 2)
all_mu = []
all_sigma = []

for m in hp_values:

    dtree=DecisionTreeClassifier(
        criterion='entropy',
        random_state=random_state,
        max_depth=m,
    )

    mu, sigma = get_cv_results(dtree)
    all_mu.append(mu)
    all_sigma.append(sigma)

    print(m, mu, sigma)
```

```
1 0.7057419215971157 0.006197712587708798
3 0.7747080621372332 0.009441268420865052
5 0.8133173367381132 0.005966408795355334
7 0.8233893214166038 0.005961895906191497
9 0.8313628169661749 0.005254125604413617
11 0.8410155147405934 0.0032442400799333236
13 0.8415746373248997 0.005544680690834588
15 0.8409455602110377 0.0029511699042006935
17 0.8387077245943984 0.003306029540725475
19 0.8364695710026243 0.003056774265880661
21 0.8362592671406942 0.0021894358037878414
23 0.8347902953988999 0.0033983751530999467
25 0.8311532468930161 0.0030919273854788116
27 0.8333216905514911 0.003947312027337628
29 0.8307337398523128 0.0022859692370877506
31 0.8303139637557265 0.0018769514022197087
33 0.828634932748259 0.003799783904552117
35 0.8292645724335126 0.0024081721767429177
37 0.8284953905835334 0.0010897286961143453
39 0.828075981381333 0.001024310882906459 4
41 0.8278657753579054 0.0014648761806115424
43 0.8281455200972514 0.0017175627267847198
45 0.8277957474494725 0.001936419524087309
47 0.8267466251831415 0.002524934415322217
49 0.8261870867851979 0.002659735726027208
```

In [17]:
```
plt.figure(figsize=(14, 5))
plt.plot(hp_values, all_mu)
plt.ylabel('Cross Validation Accuracy')
plt.xlabel('Max Depth')
```
Out[17]:
```
Text(0.5, 0, 'Max Depth')
```



In [18]:
```
plt.figure(figsize=(14, 5))
plt.plot(hp_values, all_sigma)
plt.ylabel('Cross Validation Std Dev.')
plt.xlabel('Max Depth')
```
Out[18]:
```
Text(0.5, 0, 'Max Depth')
```



In [ ]:
```

```

Evaluating Model Performance

We can use ROC curves to look at how our models perform across a variety of threshholds against our holdout data.

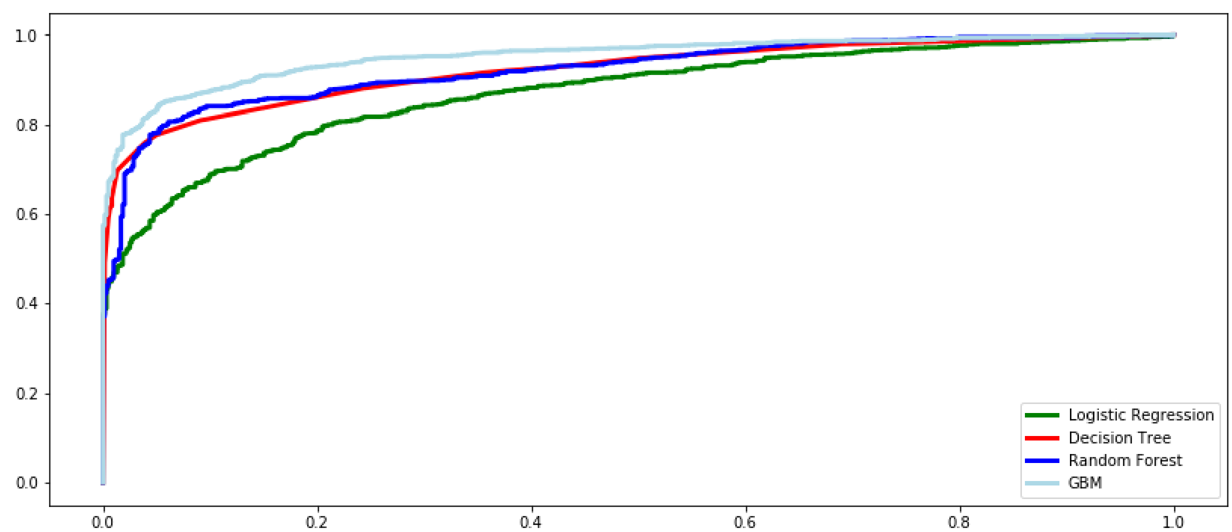
In [19]:

```
def plot_roc(classifier, label, color):

    classifier.fit(train_df[features], train_df['success'])
    y_prob = classifier.predict_proba(holdout_df[features])

    fpr, tpr, thresh = roc_curve(holdout_df['success'], y_prob[:,1])
    plt.plot(fpr, tpr,
             label=label,
             color=color, linewidth=3)

    auc = roc_auc_score(holdout_df['success'], y_prob[:,1])

    print('AUC: %0.3f (%s)' % (auc, label))
```

In [20]:
```python
f1 = plt.figure(figsize=(14,6))

logreg = LogisticRegression(
    random_state=random_state,
    solver='lbfgs'
)
plot_roc(logreg, 'Logistic Regression', 'green')

dtree = DecisionTreeClassifier(
    random_state=random_state,
    max_depth=6
)
plot_roc(dtree, 'Decision Tree', 'red')

rforest = RandomForestClassifier(
    random_state=random_state,
    max_depth=6,
    n_estimators=100
)
plot_roc(rforest, 'Random Forest', 'blue')

gbm = GradientBoostingClassifier(
    random_state=random_state,
    max_depth=6,
    n_estimators=100
)
plot_roc(gbm, 'GBM', 'lightblue')

plt.legend(loc='lower right')
```

```
AUC: 0.871 (Logistic Regression)
AUC: 0.921 (Decision Tree)
AUC: 0.923 (Random Forest)
AUC: 0.953 (GBM)
```

Out[20]: <matplotlib.legend.Legend at 0x1a1f40ea90>



In [ ]:

In [ ]: