eXtreme Gradient Boosting as a Multiclass Classifier on Ontario Road Quality

Nyasha M, 30 Apr 2021

Background: This notebook used eXtreme Gradient Boosting (XGBoost) on the *Pavement condition for provincial highways* dataset from the government of Canada (available here: https://open.canada.ca/data/en/dataset/01dfc06c-6ef0-4fd0-a010-8ba20e3c9d10). The dataset contains the readings from an Automatic Road Analyzer (ARAN) that was used on various sections of road in Ontario (e.g., freeway, local road, arterial).

Each section of road pavement was automatically evaluated by the ARAN based on its distress (Distress Manifestation Index, DMI), wheel track rutting (in mm), and roughness (International Roughness Index, IRI). These indices were then combined into a Pavement Condition Index (PCI) for an overall rating of road pavement condition.

Objective: I wanted to determine what features might predict for good or bad quality roads in Ontario.

Methods: I changed the PCI scores into a multiclass feature, based upon the category that a particular PCI score fell into (see the table below). I then used an XGBoost Multiclass Classifier to predict what category different sections of road (e.g., freeway, local road, arterial) belonged to, based upon the features in the dataset. I also wanted to narrow down which features could be the best predictors of good/bad road quality (i.e., perform feature selection) and which could be ignored.

Category	PCI score
Good	85 - 100
Satisfactory	70 - 85
Fair	55 - 70
Poor	40 - 55
Very poor	25 - 40
Serious	10 - 25
Failed	0 - 10

Refer to the guide here for more information on the PCI and its categories: https://faapaveair.faa.gov/Help/PavementConditionIndexPCI.html.

Package Imports

In [1]:
```
import warnings;
warnings.filterwarnings('ignore');
```

In [2]:
```
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np
import seaborn as sns
import scipy as sc

# Model preprocessing
import sklearn.preprocessing as preprocess
from sklearn.model_selection import train_test_split
import itertools

# Modeling and model metrics
import xgboost
from xgboost import XGBClassifier, plot_tree
from sklearn.metrics import balanced_accuracy_score, classification_report, confusion_matrix, make_scor
er
from sklearn.model_selection import StratifiedKFold, RandomizedSearchCV, GridSearchCV
from sklearn.feature_selection import SelectFromModel
```

In [3]:
```
# Change plotting style.
#plt.style.use('default')
plt.style.use('bmh')
```

Data Exploration

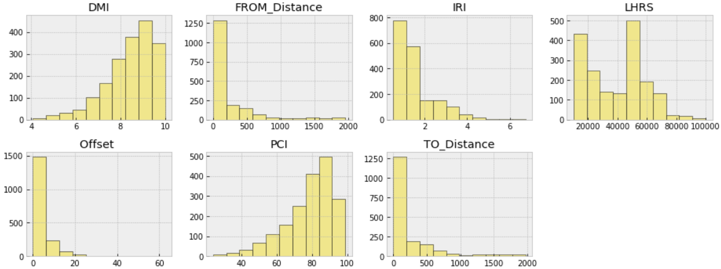
Note: Univariate plotting was not done on all variables.

In [253]:
```
df = pd.read_csv("open_data_submission_2017_pavement_final.csv")
df.head(3)
```

Out[253]:

	SectionID	Highway	DIR	LHRS	Offset	FROM_Distance	TO_Distance	PCI	DMI	IRI	Pave_Type	Pavement_Section_From	Pave
0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
1	NaN	QEW	E	10004.0	0.0	0.23	4.658	86.53	9.10	1.22	AC	FORT ERIE - GILMORE RD IC-5	
2	NaN	QEW	W	10004.0	0.0	0.23	4.658	84.26	8.74	1.09	AC	FORT ERIE - CENTRAL AV IC	(

In [5]:
```
df.loc[:,'LHRS':'IRI'].hist(figsize=(13,5), color='khaki', edgecolor='black', layout=(2,4)), plt.tight_layout()
plt.show()
```



Let's check if our outcome variable of interest--PCI--might have any missing values. Let's also explore how some of the categorical data looks like.

In [254]:
```
df.PCI.isna().value_counts() # only one missing value under the PCI column.
```

Out[254]:
```
False    1828
True        1
Name: PCI, dtype: int64
```

Now the categorical features:

In [278]:
```
print("Number of unique observations in Pavement_Section: ", len(df.Pavement_Section_From.unique()))
print("Number of unique observations in Highway: ", len(df['Highway '].unique()))

print(f"\nDIR, Pave_Type, and FUNC_CLASS: \n-----------------------------------",
      f"\n{df.DIR.value_counts()} \n\n{df.Pave_Type.value_counts()} \n\n{df.FUNC_CLASS.value_counts()}"
)
```

```
Number of unique observations in Pavement_Section:  1485
Number of unique observations in Highway:  243

DIR, Pave_Type, and FUNC_CLASS:
-----------------------------------
B    1175
W     187
E     186
N     140
S     140
Name: DIR, dtype: int64

AC     1422
ST      287
CO       85
PC       34
Name: Pave_Type, dtype: int64

ART    639
FWY    626
LOC    417
COL    146
Name: FUNC_CLASS, dtype: int64
```

In order to run XGBoost as a classifier, we need our outcome to be continuous. We were thinking of dividing PCI into categories based on the PCI score--what might be some plausible categories/divisions?

Note: I tested different cut-offs ahead of time and decided to group any PCI value that was equivalent to 'very poor' or worse together, due to the very small number of PCI scores that fell into the categories of 'failure', 'serious', or 'very poor' road conditions.

In [287]:
```
PCI_group_counts = [len(df.PCI[df.PCI<=40]), len(df.PCI[(df.PCI<=55) & (df.PCI>40)]), len(df.PCI[(df.PC
I<=70) & (df.PCI>55)]),
                       len(df.PCI[(df.PCI<=85) & (df.PCI>70)]), len(df.PCI[(df.PCI<=100) & (df.PCI>85
)])]
pd.DataFrame(data=[PCI_group_counts], columns=['< poor', 'poor', 'fair', 'satisfactory', 'good'], index
=['counts:'])
```

Out[287]:

	< poor	poor	fair	satisfactory	good
counts:	27	107	281	702	711

Data preprocessing

Let's first create a variable called `road_status` to categorize the pavement quality of each road, based on its PCI score.

We'll also remove some arbitrary features as well as features that have a massive number of unique identifiers. These would be useless/impractical to turn into value labels for our model. Finally, we'll then remove `PCI` given that its information would be stored (in the form of categories) in `road_status`.

In [301]:
```
df['road_status'] = np.nan
df.loc[df.PCI<=40, 'road_status'] = 'very poor'
df.loc[(df.PCI<=55) & (df.PCI>40), 'road_status'] = 'poor'
df.loc[(df.PCI<=70) & (df.PCI>55), 'road_status'] = 'fair'
df.loc[(df.PCI<=85) & (df.PCI>70), 'road_status'] = 'satisfactory'
df.loc[(df.PCI<=100) & (df.PCI>85), 'road_status'] = 'very good'

# 'SectionID' unlikely to be useful. 'Highway' has too many unique values for encoding (see above).
drop_col = ['SectionID', 'Pavement_Section_From', 'Pavement_Section_To', 'PCI', 'Highway ']
df.drop(drop_col, axis=1).head(3)
```

Out[301]:

	DIR	LHRS	Offset	FROM_Distance	TO_Distance	DMI	IRI	Pave_Type	FUNC_CLASS	road_status
0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
1	E	10004.0	0.0	0.23	4.658	9.10	1.22	AC	FWY	very good
2	W	10004.0	0.0	0.23	4.658	8.74	1.09	AC	FWY	satisfactory

Are there any missing values in the dataset and if so, where are they? Scikit-Learn's label encoder won't work with NaN, so we must remove these.

In [10]:
```
df[df.isna().any(axis=1)]
```

Out[10]:

	DIR	LHRS	Offset	FROM_Distance	TO_Distance	DMI	IRI	Pave_Type	FUNC_CLASS	road_status
0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

Remove NaN row and then run the label encoder.

In [11]:
```
df = df[df.isna().any(axis=1)==False]

le = preprocess.LabelEncoder()
df[['DIR', 'Pave_Type', 'FUNC_CLASS', 'road_status']] = df[[
    'DIR', 'Pave_Type', 'FUNC_CLASS', 'road_status']].apply(le.fit_transform)
```

Train-test Split

Let's select the 'x' and 'y' features to put into the model. 'y' is our outcome variable-- `road status` --which stores the categorized `PCI` scores.

In [13]:
```
# Create train and test splits of the data.
x, y = df.iloc[:,:-1], df.iloc[:,9]
seed = 100
test_size = 0.20

x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=test_size, random_state=seed)
eval_set = [(x_train, y_train), (x_test, y_test)]
```

Running an initial XGBoost Model

Let's run an initial model to see what the model suggests as predictors of poor/fair/good road pavement quality. We'll also set an early stopping round value to prevent overfitting.

In [242]:

```
params = {# Defaults
    'booster':'gbtree',
    'max_depth':6,
    'min_child_weight': 1,
    'eta':.3,
    'tree_method':'exact',

    # Type of model, number of classes in outcome variable
    'objective':'multi:softmax', 'num_class':5,

    # evaluation metrics for choosing the best model
    'eval_metric':['mlogloss', 'merror']}
```

In [243]:

```
stop_after = 40 # set number of early stopping rounds to prevent overfitting. Can adjust to test.
```

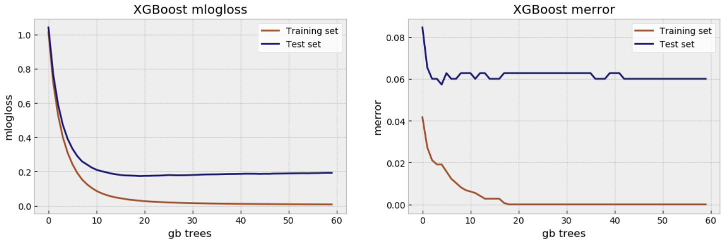
In [244]:

```
xgb_orig = XGBClassifier(n_estimators=1000, **params, use_label_encoder=False)
# Make equal to '_' to suppress output from .fit
_ = xgb_orig.fit(x_train, y_train, early_stopping_rounds=stop_after, eval_set=eval_set, eval_metric=["merror", "mlogloss"], verbose=False)
```

Extract the model's evaluation results from XGBoost. Plot the model's multiclass log loss and misclassification error.

In [245]:

```
train_results, test_results = xgb_orig.evals_result_['validation_0'], xgb_orig.evals_result_['validation_1']

plot_eval_metrics=['mlogloss', 'merror']

plt.style.use('bmh')
fig, axs = plt.subplots(1,2, figsize=(14,4))
for m in enumerate(plot_eval_metrics):
    axs[m[0]].plot(range(0,len(train_results[m[1]])), train_results[m[1]], color='sienna', label='Training set')
    axs[m[0]].plot(range(0,len(test_results[m[1]])), test_results[m[1]], color='midnightblue', label='Test set')

    axs[m[0]].set_title(f'XGBoost {m[1]}'),
    axs[m[0]].set_xlabel('gb trees'), axs[m[0]].set_ylabel(m[1])
    axs[m[0]].legend(facecolor='white')
plt.show()
```



In [240]:

```
y_pred = xgb_orig.predict(x_test) # predict on test dataset.

accuracy = balanced_accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy*100:.2f}% \n")

y_labs = le.inverse_transform(df['road_status'].unique())
print(classification_report(y_test, y_pred, target_names=y_labs, digits=2))
```

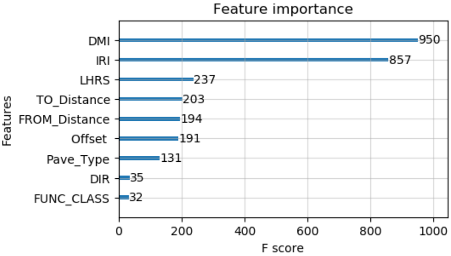
```
Accuracy: 89.14% 

              precision    recall  f1-score   support

   very good       0.87      0.93      0.90        56
satisfactory       0.89      0.89      0.89        18
        fair       0.94      0.92      0.93       146
```

```
        poor       0.96      0.96      0.96       142
   very poor       1.00      0.75      0.86         4

    accuracy                           0.94       366
   macro avg       0.93      0.89      0.91       366
weighted avg       0.94      0.94      0.94       366
```

Plotting the importance of the features, according to the model.

In [23]:

```
plt.style.use('default')
fig, ax= plt.subplots(figsize=(5,3))
xgboost.plot_importance(xgb_orig, ax=ax), ax.grid(alpha=.5)
plt.show()
```



We can see that the Average Distress Manifestation Index (DMI) and Average International Roughness Index (IRI) of the road were the best predictors of whether a road was in very poor, poor, fair, satisfactory, or very good condition in Ontario. This doesn't seem that surprising, actually, given that both make up the PCI score.

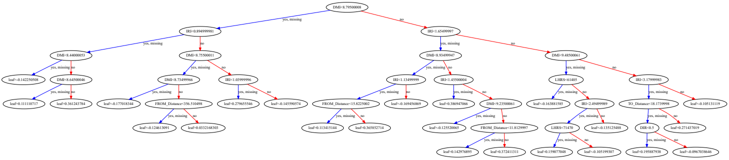
Feature	Description
DMI	Average Distress Manifestation Index (DMI) of the pavement surface
IRI	Average International Roughness Index (IRI; m/km) of the pavement surface
LHRS	Location reference based on Linear Highway Reference System Number
To_Distance	End chainage in kilometre (km) of the reporting interval
From_Distance	Start chainage in kilometre (km) of the reporting interval
Offset	Average International Roughness Index (IRI; m/km) of the pavement surface
Pave_Type	**One of the four pavement material types:** AC – Asphalt Concrete PC – Portland Cement Concrete COM – AC/PC Composite ST – Surface-treated
DIR	**Direction; travelling direction in which the pavement condition data was collected. Surveys are conducted in one direction only for undivided highways. Options:** E – East W – West N – North S - South
FUNC_CLASS	**Function Class; one of the four function classes of the roadway:** FWY – Freeway ART – Arterial Highway COL – Collector LOC – Local Road Text

Path that the model took:

In [24]:

```
xgboost.to_graphviz(xgb_orig, num_trees=8, format='png')
```

Out[24]:



XGBoost Parameter Tuning and Testing

Could our model have been improved by changing its parameters somehow? Let's test this with a list of various parameter alternatives we could have chosen. We will also use stratified k-folds sampling while running our cross-validated search to make sure that we are accounting for the imbalanced frequency of outcome classes in our dataset.

In [25]:

```
param_grid = {
    'eta': [0.1, 0.3, 0.5],
    'max_depth':[4, 5, 6],
    'min_child_weight': [1, 1.3, 1.6],
    'alpha':[0,1,2],
    'n_estimators':[500, 750, 1000]}

scorers = {'neg_log_loss_score': 'neg_log_loss', 'balanced_accuracy': make_scorer(balanced_accuracy_sco
re)}
param_num=len(param_grid)

model = XGBClassifier(objective='multi:softmax')
skf = StratifiedKFold(n_splits=5, shuffle = True, random_state = seed)
```

Below are two search methods that we could use to find the ideal parameters. **Warning: `GridSearchCV` is VERY slow!**.

In [235]:

```
# Try grid search--warning: SLOW!.
# gsearch = GridSearchCV(model, param_grid=param_grid, scoring=scorers, n_jobs=2,
#                        cv=skf.split(x_train,y_train), verbose=3,
#                                      refit='neg_log_loss_score', return_train_score=True)
#print(gsearch.fit(x, y))
```

In [241]:

```
random_search = RandomizedSearchCV(model, param_distributions=param_grid, n_iter=param_num, scoring=sco
rers,
                                   n_jobs=2, cv=skf.split(x_train,y_train), verbose=False, random_state
=seed,
                                   refit='neg_log_loss_score', return_train_score=True)
_ = random_search.fit(x, y)

print("\nThe best iteration of the model: \n\n", random_search.best_estimator_)
print("\n\nThe best parameter settings for the model: \n\n",random_search.best_params_)
```

```
[22:50:11] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.4.0/src/learner.cc:1095:
Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob' was
changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old beha
vior.

The best iteration of the model:

 XGBClassifier(alpha=0, base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, eta=0.5, gamma=0,
              gpu_id=-1, importance_type='gain', interaction_constraints='',
              learning_rate=0.5, max_delta_step=0, max_depth=5,
              min_child_weight=1, missing=nan, monotone_constraints='()',
              n_estimators=1000, n_jobs=8, num_parallel_tree=1,
              objective='multi:softprob', random_state=0, reg_alpha=0,
              reg_lambda=1, scale_pos_weight=None, subsample=1,
              tree_method='exact', validate_parameters=1, verbosity=None)


The best parameter settings for the model:

 {'n_estimators': 1000, 'min_child_weight': 1, 'max_depth': 5, 'eta': 0.5, 'alpha': 0}
```

Optimizing XGBoost and Re-running the Model on the Ontario Road Pavement Dataset

Now that we have some optimized parameters, let's try re-running our first XGBoost model but with these new parameters put in place.

In [239]:

```python
params_improved = {**params, **random_search.best_params_}

eval_set = [(x_train, y_train), (x_test, y_test)]

xgb_improved = XGBClassifier(**params_improved, use_label_encoder=False)
xgb_improved.fit(x_train, y_train, early_stopping_rounds=stop_after, eval_set=eval_set, eval_metric=["merror", "mlogloss"], verbose=False)
```

Out[239]:

```
XGBClassifier(alpha=0, base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, eta=0.5,
              eval_metric=['mlogloss', 'merror'], gamma=0, gpu_id=-1,
              importance_type='gain', interaction_constraints='',
              learning_rate=0.5, max_delta_step=0, max_depth=5,
              min_child_weight=1, missing=nan, monotone_constraints='()',
              n_estimators=1000, n_jobs=8, num_class=5, num_parallel_tree=1,
              objective='multi:softprob', random_state=0, reg_alpha=0,
              reg_lambda=1, scale_pos_weight=None, subsample=1,
              tree_method='exact', use_label_encoder=False, ...)
```

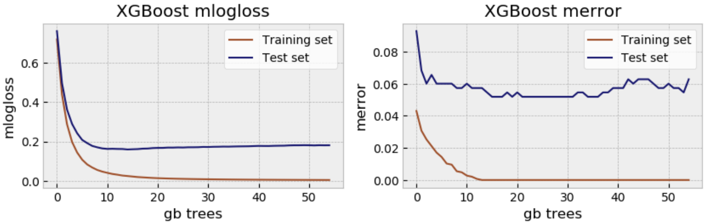
Let's extract the model's evaluation results.

In [33]:

```python
train_results, test_results = xgb_improved.evals_result_['validation_0'], xgb_improved.evals_result_['validation_1']
```

In [35]:

```python
plot_eval_metrics=['mlogloss', 'merror']

plt.style.use('bmh')
fig, axs = plt.subplots(1,2, figsize=(10,2.5))
for m in enumerate(plot_eval_metrics):
    axs[m[0]].plot(range(0,len(train_results[m[1]])), train_results[m[1]], color='sienna', label='Training set', linewidth=1.5)
    axs[m[0]].plot(range(0,len(test_results[m[1]])), test_results[m[1]], color='midnightblue',label='Test set', linewidth=1.5)

    axs[m[0]].set_title(f'XGBoost {m[1]}'),
    axs[m[0]].set_xlabel('gb trees'), axs[m[0]].set_ylabel(m[1])
    axs[m[0]].legend(facecolor='white')
plt.show()
```



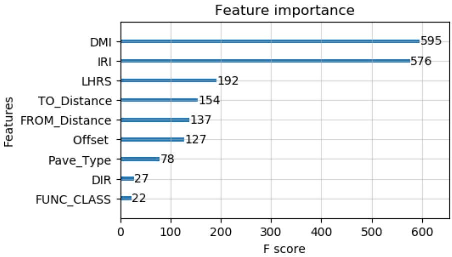
In [307]:

```python
y_pred = xgb_improved.predict(x_test) # predict on the test dataset.

accuracy = balanced_accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy*100:.2f}% \n")
print(classification_report(y_test, y_pred, target_names=y_labs, digits=2))
```

```
Accuracy: 89.77%

              precision    recall  f1-score   support

   very good       0.90      0.95      0.92        56
satisfactory       0.89      0.89      0.89        18
        fair       0.95      0.94      0.94       146
        poor       0.96      0.96      0.96       142
   very poor       1.00      0.75      0.86         4

    accuracy                           0.95       366
   macro avg       0.94      0.90      0.92       366
weighted avg       0.95      0.95      0.95       366
```

In [37]:

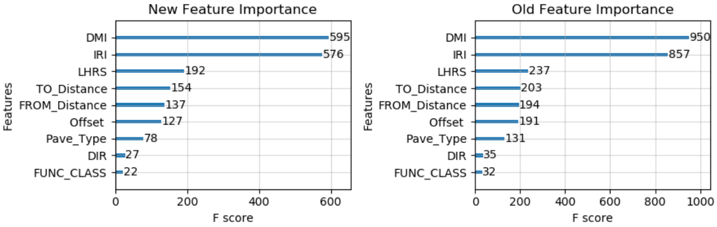
```python
plt.style.use('default')
fig, ax= plt.subplots(figsize=(5,3))
xgboost.plot_importance(xgb_improved, ax=ax, importance_type ='weight'), ax.grid(alpha=.5)
plt.show()
```



How do these results compare to the old model?

In [38]:

```python
fig, ax= plt.subplots(1,2, figsize=(9,3))
xgboost.plot_importance(xgb_improved, ax=ax[0]), ax[0].grid(alpha=.5), ax[0].set_title('New Feature Importance')
# Note: I went back to set the original xgboost model to n=1000 estimators as well to ensure comparability
xgboost.plot_importance(xgb_orig, ax=ax[1]), ax[1].grid(alpha=.5), ax[1].set_title('Old Feature Importance')
fig.tight_layout()
plt.show()
```



What about the new accuracy of our model, as well as some other metrics about its performance?

In [305]:

```python
y_pred_new = xgb_improved.predict(x_test)
y_pred_old = xgb_orig.predict(x_test)
```

In [306]:

```python
accuracy_new = balanced_accuracy_score(y_test, y_pred_new) # use balanced accuracy due to imbalanced frequency of classes
accuracy_old = balanced_accuracy_score(y_test, y_pred_old)

print(f"Balanced accuracy, new model: {accuracy_new*100:.2f}% \n")
print(classification_report(y_test, y_pred_new, target_names=y_labs, digits=2))

print(f"Balanced accuracy, old model: {accuracy_old*100:.2f}% \n")
print(classification_report(y_test, y_pred_old, target_names=y_labs, digits=2))
```

```
Balanced accuracy, new model: 89.77%

              precision    recall  f1-score   support

   very good       0.90      0.95      0.92        56
satisfactory       0.89      0.89      0.89        18
        fair       0.95      0.94      0.94       146
        poor       0.96      0.96      0.96       142
   very poor       1.00      0.75      0.86         4
```

```
    accuracy                           0.95       366
   macro avg       0.94      0.90      0.92       366
weighted avg       0.95      0.95      0.95       366

Balanced accuracy, old model: 89.14%

              precision    recall  f1-score   support

   very good       0.87      0.93      0.90        56
satisfactory       0.89      0.89      0.89        18
        fair       0.94      0.92      0.93       146
        poor       0.96      0.96      0.96       142
   very poor       1.00      0.75      0.86         4

    accuracy                           0.94       366
   macro avg       0.93      0.89      0.91       366
weighted avg       0.94      0.94      0.94       366
```

Feature Reduction: Selecting the Most Important Predictors of Road Pavement Quality

Let's now see if we could reduce our model into a more simplified version and select only those features that are important predictors of road pavement quality.

In [304]:

```
thresholds = np.sort(xgb_improved.feature_importances_) # sorted from least to most important.
select_accuracy = [np.nan]*len(thresholds)

for i, thresh in zip(range(len(thresholds)), thresholds):
    # select features using threshold
    selection = SelectFromModel(xgb_improved, threshold=thresh, prefit=True)
    select_x_train = selection.transform(x_train)

    # Returns boolean mask/array of the features (as names) that were removed out from the training set
 by SelectFromModel,
    # based on our threshold--recall that thresh passing over the features in order of least to greates
t importance.
    feature_idx = selection.get_support()
    # Find/select the colnames from the training set that were NOT removed according to thresh
    feature_name = x_train.columns[feature_idx]

    # Keep track of the features excluded from the training set
    reduced_x_train = pd.DataFrame(select_x_train, columns=feature_name)
    # Update eval set to allow for early stopping rounds to work
    select_eval_set = [(reduced_x_train, y_train), (x_test[x_test.columns & reduced_x_train.columns], y
_test)]
    selection_model = XGBClassifier(**params_improved, use_label_encoder=False)
    selection_model.fit(reduced_x_train, y_train, early_stopping_rounds=stop_after, eval_set=select_eva
l_set, verbose=False)

    # Evaluate model
    select_x_test = selection.transform(x_test)
    select_pred = selection_model.predict(select_x_test)
    select_accuracy[i] = balanced_accuracy_score(y_test, select_pred)
    print(f"Threshold: {thresh:.3f}, balanced accuracy: {select_accuracy[i]*100.0:.2f}%, Features left:
 {select_x_train.shape[1]}")
```

```
Threshold: 0.012, balanced accuracy: 89.91%, Features left: 9
Threshold: 0.015, balanced accuracy: 89.91%, Features left: 8
Threshold: 0.016, balanced accuracy: 88.94%, Features left: 7
Threshold: 0.018, balanced accuracy: 89.99%, Features left: 6
Threshold: 0.022, balanced accuracy: 88.80%, Features left: 5
Threshold: 0.023, balanced accuracy: 90.32%, Features left: 4
Threshold: 0.048, balanced accuracy: 88.80%, Features left: 3
Threshold: 0.212, balanced accuracy: 89.77%, Features left: 2
Threshold: 0.635, balanced accuracy: 63.33%, Features left: 1
```

Let's the extract feature names used during our testing process and sort them in ascending order of their feature importance. We'll use this to plot the changes in the balanced accuracy of our model from the progressive removal of features (in order of least to greatest importance).

In [171]:

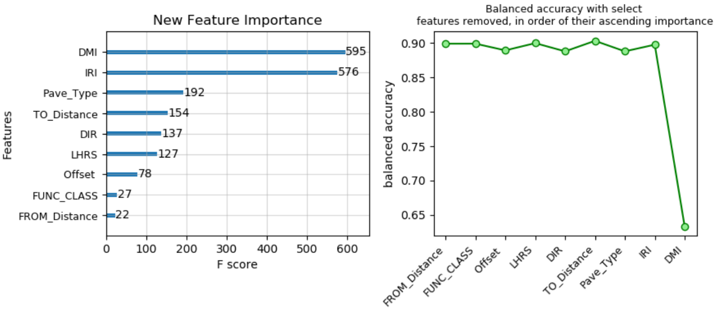
```
feature_dict = {}
for col, imp in zip(x_train.columns,xgb_improved.feature_importances_):
    feature_dict.update({col: imp})
feature_imp_named = pd.DataFrame(data=feature_dict, index=[0]).sort_values(by=0, axis=1)
feature_imp_named
```

Out[171]:

	FROM_Distance	FUNC_CLASS	Offset	LHRS	DIR	TO_Distance	Pave_Type	IRI	DMI
0	0.011615	0.015242	0.016105	0.01762	0.021802	0.023018	0.047511	0.212229	0.634858

In [317]:

```
plt.style.use('default')
fig, ax= plt.subplots(1,2, figsize=(9,4))
xgboost.plot_importance(xgb_improved, ax=ax[0]), ax[0].grid(alpha=.5), ax[0].set_title('New Feature Importance')
ax[0].set_yticklabels(labels=feature_imp_named.columns, fontsize=9)

ax[1].plot(range(len(thresholds)), select_accuracy, marker='o', markerfacecolor='lightgreen', color='green')
ax[1].set_xticks(range(len(thresholds)))
ax[1].set_xticklabels(feature_imp_named.columns, rotation=45, ha='right', fontsize=9),

ax[1].set_ylabel('balanced accuracy')
ax[1].set_title('Balanced accuracy with select \nfeatures removed, in order of their ascending importance', fontsize=9)

fig.tight_layout()
plt.show()
```



Conclusions:

The results of the feature importance plot, as well as from the balanced accuracy plot, suggest that `DMI` and `IRI` are the two most important features which predict for road pavement quality in Ontario.

In addition, `DMI` and `IRI` are some of the least redundant predictors of road pavement quality--meaning that many other features of the roads in Ontario (at least, from those features recorded in our dataset) could be ignored with little to no (or even an improved) accuracy in predicting our outcome.

Note: `DMI` and `IRI` were both likely strongly associated with our outcome *because* they are already constructs of our outcome--PCI--as mentioned in the introduction. Thus, our modeling was likely done on data that was already somewhat redundant. Our modeling and analysis plan could have been more meaningful, or less redundant, by *not* using features that are already constructs of our outcome.