04a_Modeling_Final

April 14, 2023

1 ADS-508-01-SP23 Team 8: Final Project

2 Train model

Much of the code is modified from `Fregly, C., & Barth, A. (2021). Data science on AWS: Implementing end-to-end, continuous AI and machine learning pipelines. O'Reilly.`

2.1 Install missing dependencies

PyAthena is a Python DB API 2.0 (PEP 249) compliant client for Amazon Athena.

[37]:
```
!pip install --disable-pip-version-check -q PyAthena==2.1.0
!pip install --disable-pip-version-check -q sagemaker-experiments==0.1.26
!pip install missingno
!pip install xgboost
!pip install torch==1.8.1
#!pip install torchvision
```

```
WARNING: Running pip as the 'root' user can result in broken permissions
and conflicting behaviour with the system package manager. It is recommended to
use a virtual environment instead: https://pip.pypa.io/warnings/venv
WARNING: Running pip as the 'root' user can result in broken
permissions and conflicting behaviour with the system package manager. It is
recommended to use a virtual environment instead:
https://pip.pypa.io/warnings/venv
Requirement already satisfied: missingno in /opt/conda/lib/python3.7/site-
packages (0.5.2)
Requirement already satisfied: matplotlib in /opt/conda/lib/python3.7/site-
packages (from missingno) (3.1.3)
Requirement already satisfied: scipy in /opt/conda/lib/python3.7/site-packages
(from missingno) (1.4.1)
Requirement already satisfied: numpy in /opt/conda/lib/python3.7/site-packages
(from missingno) (1.21.6)
Requirement already satisfied: seaborn in /opt/conda/lib/python3.7/site-packages
(from missingno) (0.10.0)
```

```
Requirement already satisfied: python-dateutil>=2.1 in
/opt/conda/lib/python3.7/site-packages (from matplotlib->missingno) (2.8.2)
Requirement already satisfied: kiwisolver>=1.0.1 in
/opt/conda/lib/python3.7/site-packages (from matplotlib->missingno) (1.1.0)
Requirement already satisfied: cycler>=0.10 in /opt/conda/lib/python3.7/site-
packages (from matplotlib->missingno) (0.10.0)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in
/opt/conda/lib/python3.7/site-packages (from matplotlib->missingno) (2.4.6)
Requirement already satisfied: pandas>=0.22.0 in /opt/conda/lib/python3.7/site-
packages (from seaborn->missingno) (1.3.5)
Requirement already satisfied: six in /opt/conda/lib/python3.7/site-packages
(from cycler>=0.10->matplotlib->missingno) (1.14.0)
Requirement already satisfied: setuptools in /opt/conda/lib/python3.7/site-
packages (from kiwisolver>=1.0.1->matplotlib->missingno) (59.3.0)
Requirement already satisfied: pytz>=2017.3 in /opt/conda/lib/python3.7/site-
packages (from pandas>=0.22.0->seaborn->missingno) (2019.3)
WARNING: Running pip as the 'root' user can result in broken permissions
and conflicting behaviour with the system package manager. It is recommended to
use a virtual environment instead: https://pip.pypa.io/warnings/venv
Requirement already satisfied: xgboost in /opt/conda/lib/python3.7/site-
packages (1.6.2)
Requirement already satisfied: scipy in /opt/conda/lib/python3.7/site-packages
(from xgboost) (1.4.1)
Requirement already satisfied: numpy in /opt/conda/lib/python3.7/site-packages
(from xgboost) (1.21.6)
WARNING: Running pip as the 'root' user can result in broken permissions
and conflicting behaviour with the system package manager. It is recommended to
use a virtual environment instead: https://pip.pypa.io/warnings/venv
Collecting torch==1.8.1
  Downloading torch-1.8.1-cp37-cp37m-manylinux1_x86_64.whl (804.1 MB)
                           804.1/804.1
MB 1.0 MB/s eta 0:00:0000:0100:01
Requirement already satisfied: numpy in /opt/conda/lib/python3.7/site-
packages (from torch==1.8.1) (1.21.6)
Requirement already satisfied: typing-extensions in
/opt/conda/lib/python3.7/site-packages (from torch==1.8.1) (4.5.0)
Installing collected packages: torch
Successfully installed torch-1.8.1
WARNING: Running pip as the 'root' user can result in broken permissions
and conflicting behaviour with the system package manager. It is recommended to
use a virtual environment instead: https://pip.pypa.io/warnings/venv
```

2.2 Globally import libraries

[36]:
```
import boto3
from botocore.client import ClientError
import pandas as pd
import numpy as np
from pyathena import connect
from IPython.core.display import display, HTML
import missingno as msno
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import make_pipeline, Pipeline
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.model_selection import train_test_split, cross_val_score,␣
 ↪GridSearchCV
from sklearn.ensemble import RandomForestRegressor
from sagemaker.tuner import HyperparameterTuner
from sklearn.linear_model import LinearRegression
from sklearn.neural_network import MLPRegressor
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.impute import SimpleImputer
from sklearn.metrics import r2_score, mean_squared_error
from sklearn.linear_model import Lasso
import datetime as dt
import time
import sagemaker
from smexperiments.experiment import Experiment
from smexperiments.trial import Trial
import joblib
import os
```

```
---------------------------------------------------------------------------
ModuleNotFoundError                       Traceback (most recent call last)
<ipython-input-36-5a961501dccc> in <module>
      3 import pandas as pd
      4 import numpy as np
----> 5 import torch
      6 from pyathena import connect
      7 from IPython.core.display import display, HTML

ModuleNotFoundError: No module named 'torch'
```

2.3 Instantiate AWS SageMaker and S3 sessions

[4]:
```
session = boto3.session.Session()
sess = sagemaker.Session()
role = sagemaker.get_execution_role()
region = session.region_name
sagemaker_session = sagemaker.Session()
def_bucket = sagemaker_session.default_bucket()
bucket = 't8-test-final'

s3 = boto3.Session().client(service_name="s3",
                            region_name=region)

sm = boto3.Session().client(service_name="sagemaker",
                            region_name=region)

np.random.seed(1)
```

[5]:
```
setup_s3_bucket_passed = False
ingest_create_athena_db_passed = False
ingest_create_athena_table_tsv_passed = False
```

[6]:
```
print(f"Default bucket: {def_bucket}")
print(f"Public T8 bucket: {bucket}")
```

```
Default bucket: sagemaker-us-east-1-122149314005
Public T8 bucket: t8-test-final
```

2.4 Verify S3 Bucket Creation

[7]:
```
%%bash

aws s3 ls s3://${bucket}/
```

```
2023-03-18 20:53:08 aws-athena-query-results-122149314005-us-east-1
2023-03-05 21:53:59 sagemaker-studio-122149314005-sw16ud198bb
2023-03-05 21:59:02 sagemaker-us-east-1-122149314005
2023-03-19 21:18:45 t8-mc-access
2023-03-23 20:28:25 t8-test-final
```

[8]:
```
response = None

try:
    response = s3.head_bucket(Bucket=bucket)
    print(response)
    setup_s3_bucket_passed = True
except ClientError as e:
    print(f"[ERROR] Cannot find bucket {bucket} in {response} due to {e}.")
```

```
{'ResponseMetadata': {'RequestId': 'ZERW41J0A920GJKT', 'HostId':
'vhG9zTYVva1TPUdeUaFpzfCwVnWsg5Bxs98GWURjnvuv9KcU46GC78IYlE+i1EcaoHaFT1NO0Xs=',
'HTTPStatusCode': 200, 'HTTPHeaders': {'x-amz-id-2':
'vhG9zTYVva1TPUdeUaFpzfCwVnWsg5Bxs98GWURjnvuv9KcU46GC78IYlE+i1EcaoHaFT1NO0Xs=',
'x-amz-request-id': 'ZERW41J0A920GJKT', 'date': 'Tue, 04 Apr 2023 04:05:28 GMT',
'x-amz-bucket-region': 'us-east-1', 'x-amz-access-point-alias': 'false',
'content-type': 'application/xml', 'server': 'AmazonS3'}, 'RetryAttempts': 0}}
```

[9]:
```
%store setup_s3_bucket_passed
```

```
Stored 'setup_s3_bucket_passed' (bool)
```

2.5 Pass in ABT from CSV

[10]:
```
s3_abt_csv_path = f"s3://{def_bucket}/team_8_data/abt/abt_encoded_df01.csv"
abt_encoded_df01 = pd.read_csv(s3_abt_csv_path)
```

[11]:
```
y01 = ['childpoverty']
abt_encoded_y01_vc01 = abt_encoded_df01[y01].to_numpy()
print(abt_encoded_y01_vc01.shape)
display(abt_encoded_y01_vc01[0:11])
abt_encoded_x01_df01 = abt_encoded_df01.drop(y01, axis=1)
print(abt_encoded_x01_df01.shape)
display(abt_encoded_x01_df01.head(11))
```

```
(31605, 1)
```

```
array([[20.7],
       [23.6],
       [35.9],
       [31.5],
       [67.7],
       [68.3],
       [ 0. ],
       [62.4],
       [64.9],
       [63.1],
       [ 6.5]])
```

```
(31605, 49)
```

	borough_bronx	borough_brooklyn	borough_manhattan	borough_queens	\
0	1.0	0.0	0.0	0.0	
1	1.0	0.0	0.0	0.0	
2	1.0	0.0	0.0	0.0	
3	1.0	0.0	0.0	0.0	
4	1.0	0.0	0.0	0.0	
5	1.0	0.0	0.0	0.0	
6	1.0	0.0	0.0	0.0	
7	1.0	0.0	0.0	0.0	

```
8             1.0               0.0                0.0             0.0
9             1.0               0.0                0.0             0.0
10            1.0               0.0                0.0             0.0

    borough_staten island  relative_data_year_-4  relative_data_year_-3  \
0                     0.0                    1.0                    0.0
1                     0.0                    1.0                    0.0
2                     0.0                    1.0                    0.0
3                     0.0                    1.0                    0.0
4                     0.0                    1.0                    0.0
5                     0.0                    1.0                    0.0
6                     0.0                    1.0                    0.0
7                     0.0                    1.0                    0.0
8                     0.0                    1.0                    0.0
9                     0.0                    1.0                    0.0
10                    0.0                    1.0                    0.0

    relative_data_year_-2  relative_data_year_-1  relative_data_year_0  …  \
0                     0.0                    0.0                   0.0  …
1                     0.0                    0.0                   0.0  …
2                     0.0                    0.0                   0.0  …
3                     0.0                    0.0                   0.0  …
4                     0.0                    0.0                   0.0  …
5                     0.0                    0.0                   0.0  …
6                     0.0                    0.0                   0.0  …
7                     0.0                    0.0                   0.0  …
8                     0.0                    0.0                   0.0  …
9                     0.0                    0.0                   0.0  …
10                    0.0                    0.0                   0.0  …

    walk  othertransp  workathome  meancommute  employed  privatework  \
0    2.9          0.0         0.0         43.0    2308.0         80.8
1    1.4          0.5         2.1         45.0    2675.0         71.7
2    8.6          1.6         1.7         38.8    2120.0         75.0
3    3.0          2.4         6.2         45.4    1083.0         76.8
4    4.3          1.0         0.0         46.0    2508.0         71.0
5   14.0          1.5         4.1         42.7    1191.0         74.2
6    0.0          0.0         0.0          NaN     113.0         62.8
7   17.7          1.8         2.7         35.5    1691.0         85.1
8   18.0          0.0         1.6         42.8    1102.0         86.9
9    7.1          0.7         0.5         44.0    1559.0         75.0
10   2.0          0.6         2.7         47.3    2394.0         61.9

    publicwork  selfemployed  familywork  unemployment
0         16.2           2.9         0.0           7.7
1         25.3           2.5         0.6           9.5
2         21.3           3.8         0.0           8.7
3         15.5           7.7         0.0          19.2
```

4	21.3	7.7	0.0	17.2
5	16.1	9.7	0.0	18.9
6	37.2	0.0	0.0	0.0
7	8.3	6.1	0.5	9.4
8	8.5	4.5	0.0	15.2
9	14.0	11.0	0.0	10.6
10	37.4	0.6	0.0	12.8

[11 rows x 49 columns]

[12]:
```
abt_encoded_x01_df02 = abt_encoded_x01_df01.fillna(abt_encoded_x01_df01.
 ↪median())

data_types = abt_encoded_x01_df02.dtypes
data_types = pd.DataFrame(data_types)
data_types = data_types.assign(Null_Values =
                               abt_encoded_x01_df02.isnull().sum())
data_types.reset_index(inplace = True)
data_types.rename(columns={0:'Data Type',
                           'index': 'Column/Variable',
                           'Null_Values': "# of Nulls"})
```

[12]:

	Column/Variable	Data Type	# of Nulls
0	borough_bronx	float64	0
1	borough_brooklyn	float64	0
2	borough_manhattan	float64	0
3	borough_queens	float64	0
4	borough_staten island	float64	0
5	relative_data_year_-4	float64	0
6	relative_data_year_-3	float64	0
7	relative_data_year_-2	float64	0
8	relative_data_year_-1	float64	0
9	relative_data_year_0	float64	0
10	complaint_type_FELONY	float64	0
11	complaint_type_MISDEMEANOR	float64	0
12	complaint_type_VIOLATION	float64	0
13	annual_evictions_x_borough	float64	0
14	annual_complaint_counts	float64	0
15	annual_grad_n	float64	0
16	annual_dropped_out_n	float64	0
17	totalpop	float64	0
18	men	float64	0
19	women	float64	0
20	hispanic	float64	0
21	white	float64	0
22	black	float64	0
23	native	float64	0

```
24                      asian   float64           0
25                    citizen   float64           0
26                     income   float64           0
27                  incomeerr   float64           0
28               incomepercap   float64           0
29          incomepercaperr   float64           0
30                    poverty   float64           0
31               professional   float64           0
32                    service   float64           0
33                     office   float64           0
34               construction   float64           0
35                 production   float64           0
36                      drive   float64           0
37                    carpool   float64           0
38                    transit   float64           0
39                       walk   float64           0
40                 othertransp   float64           0
41                  workathome   float64           0
42                 meancommute   float64           0
43                    employed   float64           0
44                 privatework   float64           0
45                  publicwork   float64           0
46                selfemployed   float64           0
47                  familywork   float64           0
48                unemployment   float64           0
```

[13]:
```
abt_encoded_x01_df02['boroughs'] = abt_encoded_x01_df02['borough_bronx'].
 ↪astype(int).astype(str) + abt_encoded_x01_df02['borough_brooklyn'].
 ↪astype(int).astype(str) + abt_encoded_x01_df02['borough_manhattan'].
 ↪astype(int).astype(str) + abt_encoded_x01_df02['borough_queens'].astype(int).
 ↪astype(str) + abt_encoded_x01_df02['borough_staten island'].astype(int).
 ↪astype(str)
display(abt_encoded_x01_df02.head(5))

scaler = StandardScaler()
abt_encoded_x01_df02_scaled = scaler.fit_transform(abt_encoded_x01_df02.
 ↪drop(['boroughs', 'poverty'], axis=1))

train_x01, test_x01, train_y01, test_y01 =␣
 ↪train_test_split(abt_encoded_x01_df02_scaled,
                                                                  ␣
 ↪abt_encoded_y01_vc01,
                                                                   test_size=.2,
                                                                  ␣
 ↪stratify=abt_encoded_x01_df02[['boroughs']],
                                                                   shuffle=True,
                                                                   random_state=1699)
```

```
train_x01 = pd.DataFrame(train_x01, columns=abt_encoded_x01_df02.
 ↪drop(['boroughs', 'poverty'], axis=1).columns)
test_x01 = pd.DataFrame(test_x01, columns=abt_encoded_x01_df02.
 ↪drop(['boroughs', 'poverty'], axis=1).columns)

train_y01 = train_y01.ravel()
test_y01 = test_y01.ravel()


print(f'{train_x01.shape}')
print(f'{train_y01.shape}')
print(f'\n{test_x01.shape}')
print(f'{test_y01.shape}')
```

```
   borough_bronx  borough_brooklyn  borough_manhattan  borough_queens  \
0            1.0               0.0                0.0             0.0
1            1.0               0.0                0.0             0.0
2            1.0               0.0                0.0             0.0
3            1.0               0.0                0.0             0.0
4            1.0               0.0                0.0             0.0

   borough_staten island  relative_data_year_-4  relative_data_year_-3  \
0                    0.0                    1.0                    0.0
1                    0.0                    1.0                    0.0
2                    0.0                    1.0                    0.0
3                    0.0                    1.0                    0.0
4                    0.0                    1.0                    0.0

   relative_data_year_-2  relative_data_year_-1  relative_data_year_0  …  \
0                    0.0                    0.0                   0.0  …
1                    0.0                    0.0                   0.0  …
2                    0.0                    0.0                   0.0  …
3                    0.0                    0.0                   0.0  …
4                    0.0                    0.0                   0.0  …

   othertransp  workathome  meancommute  employed  privatework  publicwork  \
0          0.0         0.0         43.0    2308.0         80.8        16.2
1          0.5         2.1         45.0    2675.0         71.7        25.3
2          1.6         1.7         38.8    2120.0         75.0        21.3
3          2.4         6.2         45.4    1083.0         76.8        15.5
4          1.0         0.0         46.0    2508.0         71.0        21.3

   selfemployed  familywork  unemployment  boroughs
0           2.9         0.0           7.7     10000
1           2.5         0.6           9.5     10000
2           3.8         0.0           8.7     10000
```

```
3           7.7         0.0          19.2     10000
4           7.7         0.0          17.2     10000

[5 rows x 50 columns]
```

```
(25284, 48)
(25284,)

(6321, 48)
(6321,)
```

Untuned Linear Regression Model

[14]:
```
# create an un-tuned linear regression model
lin_reg = LinearRegression()

# fit the model to the training set
lin_reg.fit(train_x01, train_y01)

# make predictions on the validation set
lin_reg_pred = lin_reg.predict(test_x01)
```

[15]:
```
# calculate the model performance metrics
lin_reg_mse = mean_squared_error(test_y01, lin_reg_pred)
lin_reg_rmse = lin_reg_mse ** 0.5
lin_reg_r2 = r2_score(test_y01, lin_reg_pred)

# print the performance metrics
print(f"Un-tuned Linear Regression Model: RMSE = {lin_reg_rmse:.3f}, R-squared␣
 ↪= {lin_reg_r2:.3f}")
```

```
Un-tuned Linear Regression Model: RMSE = 11.331, R-squared = 0.648
```

Random Forest

[40]:
```
# Define the hyperparameters to tune
param_dist = {
    'n_estimators': randint(50, 200),
    'max_depth': randint(3, 10),
    'min_samples_split': uniform(0.01, 0.19),
    'min_samples_leaf': uniform(0.01, 0.19),
    'max_features': ['auto', 'sqrt']
}

# Create the Random Forest Regressor model
rf = RandomForestRegressor(random_state=42)

# Perform a randomized search to find the best hyperparameters
random_search = RandomizedSearchCV(estimator=rf,␣
 ↪param_distributions=param_dist, cv=5, n_iter=10, n_jobs=-1)
```

```
random_search.fit(train_x01, train_y01)

# Print the best hyperparameters found
print("Best hyperparameters: ", random_search.best_params_)
```

```
Best hyperparameters:  {'max_depth': 5, 'max_features': 'auto',
'min_samples_leaf': 0.05482542923388117, 'min_samples_split':
0.12414899564785374, 'n_estimators': 153}
```

[41]:
```
# Make predictions on the train and test data
rf_train_preds = random_search.predict(train_x01)
rf_test_preds = random_search.predict(test_x01)
```

[45]:
```
# Evaluate the performance of the model using mean squared error
train_rf_mse = mean_squared_error(train_y01, rf_train_preds)
train_rf_rmse = train_rf_mse ** 0.5
train_rf_r2 = r2_score(train_y01, rf_train_preds)
print(f"XGBoost train model performance: RMSE = {train_rf_rmse:.3f}, R-squared␣
 ↪= {train_rf_r2:.3f}")

# Evaluate the performance of the model using mean squared error
test_rf_mse = mean_squared_error(test_y01, rf_test_preds)
test_rf_rmse = test_rf_mse ** 0.5
test_rf_r2 = r2_score(test_y01, rf_test_preds)
print(f"XGBoost test model performance: RMSE = {test_rf_rmse:.3f}, R-squared =␣
 ↪{test_rf_r2:.3f}")
```

```
XGBoost train model performance: RMSE = 11.276, R-squared = 0.644
XGBoost test model performance: RMSE = 11.301, R-squared = 0.650
```

XGBoost

[16]:
```
# Set the hyperparameters for the Gradient Boosting Regressor model
params = {
    'max_depth': 5,
    'learning_rate': 0.1,
    'loss': 'ls'
}

# Train the Gradient Boosting Regressor model
model = GradientBoostingRegressor(**params)
model.fit(train_x01, train_y01)

# Make predictions on the train data
xgb_y__train_pred = model.predict(train_x01)

# Make predictions on the test data
xgb_y_pred = model.predict(test_x01)
```

[18]:
```
# Evaluate the performance of the model using mean squared error
train_xgb_mse = mean_squared_error(train_y01, xgb_y__train_pred)
train_xgb_rmse = train_xgb_mse ** 0.5
train_xgb_r2 = r2_score(train_y01, xgb_y__train_pred)
print(f"XGBoost train model performance: RMSE = {train_xgb_rmse:.3f}, R-squared␣
 ↪= {train_xgb_r2:.3f}")

# Evaluate the performance of the model using mean squared error
test_xgb_mse = mean_squared_error(test_y01, xgb_y_pred)
test_xgb_rmse = test_xgb_mse ** 0.5
test_xgb_r2 = r2_score(test_y01, xgb_y_pred)
print(f"XGBoost test model performance: RMSE = {test_xgb_rmse:.3f}, R-squared =␣
 ↪{test_xgb_r2:.3f}")
```

```
XGBoost train model performance: RMSE = 5.204, R-squared = 0.924
XGBoost test model performance: RMSE = 5.327, R-squared = 0.922
```

Tuned XGBoost

[19]:
```
from sklearn.model_selection import RandomizedSearchCV
from scipy.stats import randint, uniform

# Define the hyperparameters to tune
param_dist = {
    'max_depth': randint(3, 10),
    'learning_rate': uniform(0.05, 0.5),
    'loss': ['ls', 'lad', 'huber']
}

# Create the Gradient Boosting Regressor model
gbm = GradientBoostingRegressor()

# Perform a randomized search to find the best hyperparameters
random_search = RandomizedSearchCV(estimator=gbm,␣
 ↪param_distributions=param_dist, cv=3, n_iter=10, n_jobs=-1)
random_search.fit(train_x01, train_y01)

# Print the best hyperparameters found
print("Best hyperparameters: ", random_search.best_params_)
```

```
Best hyperparameters:  {'learning_rate': 0.4911814805544623, 'loss': 'ls',
'max_depth': 8}
```

[20]:
```
# Train the model with the best hyperparameters found
xgb_tune_model = GradientBoostingRegressor(**random_search.best_params_)
xgb_tune_model.fit(train_x01, train_y01)
```

[20]:
```
GradientBoostingRegressor(alpha=0.9, ccp_alpha=0.0, criterion='friedman_mse',
                          init=None, learning_rate=0.4911814805544623,
```

```
                                   loss='ls', max_depth=8, 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='deprecated', random_state=None,
                                   subsample=1.0, tol=0.0001, validation_fraction=0.1,
                                   verbose=0, warm_start=False)
```

[21]:
```
# Make predictions on the train data
xgb_tune_ytrain_pred = xgb_tune_model.predict(train_x01)

# Evaluate the performance of the model using mean squared error
xgb_tune_ytrain_mse = mean_squared_error(train_y01, xgb_tune_ytrain_pred)
xgb_tune_ytrain_rmse = xgb_tune_ytrain_mse ** 0.5
xgb_tune_ytrain_r2 = r2_score(train_y01, xgb_tune_ytrain_pred)
print(f"XGBoost model train performance: RMSE = {xgb_tune_ytrain_rmse:.3f},␣
 ↪R-squared = {xgb_tune_ytrain_r2:.3f}")

# Make predictions on the test data
xgb_tune_ytest_pred = xgb_tune_model.predict(test_x01)

# Evaluate the performance of the model using mean squared error
xgb_tune_ytest_mse = mean_squared_error(test_y01, xgb_tune_ytest_pred)
xgb_tune_ytest_rmse = xgb_tune_ytest_mse ** 0.5
xgb_tune_ytest_r2 = r2_score(test_y01, xgb_tune_ytest_pred)
print(f"XGBoost model test performance: RMSE = {xgb_tune_ytest_rmse:.3f},␣
 ↪R-squared = {xgb_tune_ytest_r2:.3f}")
```

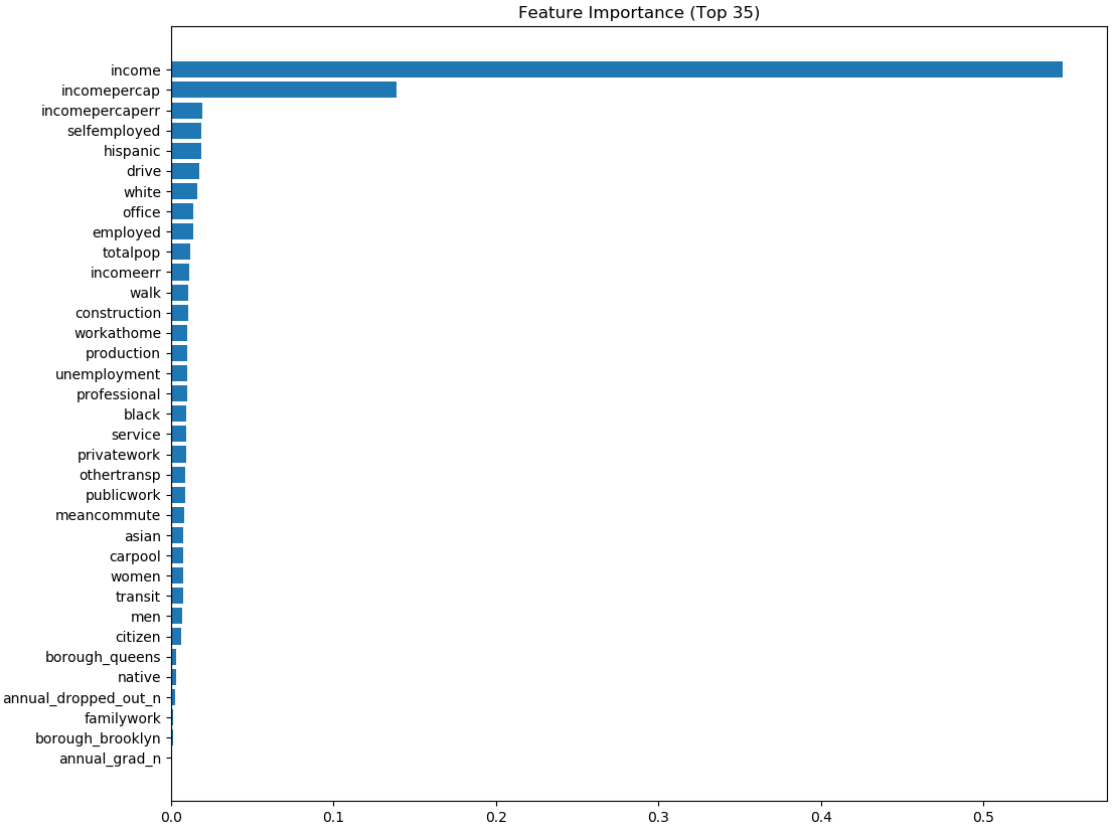
```
XGBoost model train performance: RMSE = 0.002, R-squared = 1.000
XGBoost model test performance: RMSE = 0.002, R-squared = 1.000
```

[22]:
```
# r2 of 1 is a bit... suspicious.
```

[23]:
```
'''Citations:
https://www.rasgoml.com/feature-engineering-tutorials/
 ↪how-to-generate-feature-importance-plots-from-scikit-learn;
OpenAI. (2021). ChatGPT [Computer software]. https://openai.com/'''
import matplotlib.pyplot as plt

feature_importance = xgb_tune_model.feature_importances_
feature_idx = np.argsort(feature_importance)
fig = plt.figure(figsize=(12, 10))
plt.barh(range(-1, -36, -1),
         feature_importance[feature_idx][-35:][::-1],
         align='center')
```

```
plt.yticks(range(-1, -36, -1), np.array(train_x01.columns)[feature_idx][-35:][::
 ↪-1])
plt.title('Feature Importance (Top 35)')
plt.show()
```



Weighted Ensemble of XGBoost - Reccomended by AutoML App

[24]:
```
# Train multiple Gradient Boosting Regressor models with different␣
 ↪hyperparameters
models = []
models.append(('model1', GradientBoostingRegressor(max_depth=2, learning_rate=0.
 ↪2, loss='ls')))
models.append(('model2', GradientBoostingRegressor(max_depth=3, learning_rate=0.
 ↪1, loss='ls')))
models.append(('model3', GradientBoostingRegressor(max_depth=4, learning_rate=0.
 ↪05, loss='ls')))
models.append(('model4', GradientBoostingRegressor(max_depth=5, learning_rate=0.
 ↪01, loss='ls')))
models.append(('model5', GradientBoostingRegressor(max_depth=6, learning_rate=0.
 ↪01, loss='ls')))
```

```
# Train the models and make predictions on the train data
predictions = []
weights = [0.2, 0.2, 0.2, 0.2, 0.2]
for name, model in models:
    model.fit(train_x01, train_y01)
    wr_y_pred = model.predict(train_x01)
    predictions.append(wr_y_pred)

# Combine the predictions with the weights to get the final prediction
wr_final_train_pred = np.average(predictions, axis=0, weights=weights)
```

[25]:
```
# Train the models and make predictions on the test data
predictions = []
weights = [0.2, 0.2, 0.2, 0.2, 0.2]
for name, model in models:
    model.fit(train_x01, train_y01)
    wr_y_pred = model.predict(test_x01)
    predictions.append(wr_y_pred)

# Combine the predictions with the weights to get the final prediction
wr_final_test_pred = np.average(predictions, axis=0, weights=weights)
```

[26]:
```
# Evaluate the performance of the model using root mean squared error
wr_train_mse = mean_squared_error(train_y01, wr_final_train_pred)
wr_train_rmse = wr_train_mse ** 0.5
wr_train_r2 = r2_score(train_y01, wr_final_train_pred)
print(f"Weighted Ensemble model train performance: RMSE = {wr_train_rmse:.3f},␣
 ↪R-squared = {wr_train_r2:.3f}")

# Evaluate the performance of the model using root mean squared error
wr_test_mse = mean_squared_error(test_y01, wr_final_test_pred)
wr_test_rmse = wr_test_mse ** 0.5
wr_test_r2 = r2_score(test_y01, wr_final_test_pred)
print(f"Weighted Ensemble model test performance: RMSE = {wr_test_rmse:.3f},␣
 ↪R-squared = {wr_test_r2:.3f}")
```

```
Weighted Ensemble model train performance: RMSE = 8.954, R-squared = 0.776
Weighted Ensemble model test performance: RMSE = 9.050, R-squared = 0.776
```

PyTorch Neural Network

[38]:
```
import torch
import torch.nn as nn
import torch.optim as optim

# Convert Pandas dataframes to numpy arrays
np_train_x01 = train_x01.to_numpy()
np_train_y01 = train_y01
```

```
np_test_x01 = test_x01.to_numpy()
np_test_y01 = test_y01

# Define PyTorch neural network model
class Net(nn.Module):
    def __init__(self):
        super(Net, self).__init__()
        self.fc1 = nn.Linear(np_train_x01.shape[1], 10)
        self.fc2 = nn.Linear(10, 7)
        self.fc3 = nn.Linear(7, 5)
        self.fc4 = nn.Linear(5, 1)

    def forward(self, x):
        x = nn.functional.relu(self.fc1(x))
        x = nn.functional.relu(self.fc2(x))
        x = nn.functional.relu(self.fc3(x))
        x = self.fc4(x)
        return x

# Instantiate model, loss function, and optimizer
model = Net()
criterion = nn.MSELoss()
optimizer = optim.Adam(model.parameters(), lr=0.01)

# Train model for data
for epoch in range(300):
    inputs = torch.Tensor(np_train_x01)
    targets = torch.Tensor(np_train_y01).view(-1, 1)
    optimizer.zero_grad()
    outputs = model(inputs)
    loss = criterion(outputs, targets)
    loss.backward()
    optimizer.step()
```

[39]:
```
# Evaluate model performance
inputs = torch.Tensor(np_test_x01)
targets = torch.Tensor(np_test_y01).view(-1, 1)
outputs = model(inputs)
Py_y_pred = outputs.detach().numpy().reshape(-1,)
Py_rmse = np.sqrt(mean_squared_error(np_test_y01, Py_y_pred))
Py_r2 = r2_score(np_test_y01, Py_y_pred)

print(f"PyTorch neural network model performance: RMSE = {Py_rmse:.3f},␣
 ↪R-squared = {Py_r2:.3f}")
```

```
PyTorch neural network model performance: RMSE = 10.353, R-squared = 0.707
```

2.6 Release Resources

[ ]:
```
%%html

<p><b>Shutting down your kernel for this notebook to release resources.</b></p>
<button class="sm-command-button" data-commandlinker-command="kernelmenu:
 ↪shutdown" style="display:none;">Shutdown Kernel</button>

<script>
try {
    els = document.getElementsByClassName("sm-command-button");
    els[0].click();
}
catch(err) {
    // NoOp
}
</script>
```

[ ]:
```
%%javascript

try {
    Jupyter.notebook.save_checkpoint();
    Jupyter.notebook.session.delete();
}
catch(err) {
    // NoOp
}
```