Snapchat Ads Regressional Analysis

Summary of Findings

Introduction

- Prediction Problem: **Regression problem to predict Impressions**.
- Features that will be used to predict Impressions would be: 'Currency Code', 'Spend', 'Impressions', 'StartDate','EndDate', 'Gender', 'AgeBracket', 'CountryCode', 'Interests', and 'Language'
- The objective of the project is to increase accuracy measured by the R^2 score of the model.
- Since it is not a classification problem, we can ignore the Sensitivity and Specificity aspects of the model.

Baseline Model

- Features
  - Quantitative: Spend
  - Ordinal: *None*
  - Nominal: CurrencyCode, CountryCode
- Notice how there are no ordinal features, for the baseline model.
- A lot of the initial features are taken away as they need to be engineered in order to be useful.
- Nominal Features will be one-hot encoded.
- **The R^2 score of the baseline model floats around 0.3 and 0.6 for the most part.**
- I think that the score value looks promising. It looks like most of the regression is done based on Spend, which makes sense since higher spending on the ad correlates directly with impressions observed.
- However, I think that the model can be improved by engineering additional features.

Final Model

- Engineered Features:
  - MultiLabelBinarizer for OHE of Interests and Language: targeted interests of ads might play a role on the impressions it gets. Perhaps certain interests are taken more seriously for some viewers.
  - Duration derived from StartDate and EndDate. There should be a direct correlation between duration of the ads airtime and its impressions.
- Findings:
  - GridSearch on best parameter for categorical features PCA n_components (Currency Code, CountryCode, Interests, Language)
  - Discovered that all the categorical features are advised to be taken out.
  - Essentially back to baseline model but added imputation strategy for quantitative columns
  - Slight imporvement in R^2 score, better accuracy.

Fairness Evaluation

- Compared the accuracy of the model for year 2019 and 2020.
- It seems to be doing better for the year 2019 than 2020 by quite a margin.
- The mean R^2 value for the 2020 model is negative.
- One reason to explain this is probably the fact that 2020 is still the current year so there is not sufficient data to model it.
- Whereas 2019 data make up for most of the main dataset which created the model so it results in a higher accuracy.

accuracy.

Code

Data Cleaning

In [3]:

```
import matplotlib.pyplot as plt
import numpy as np
import os
import pandas as pd
import seaborn as sns
%matplotlib inline
%config InlineBackend.figure_format = 'retina'  # Higher resolution figures
```

In [4]:

```
ads_19 = pd.read_csv('data/political_ads_19.csv')
ads_20 = pd.read_csv('data/political_ads_20.csv')
```

Concatenate the two different DataFrames from two different years.

In [6]:

```
data = pd.concat([ads_19, ads_20], ignore_index=True)
data.head()
```

Out[6]:

	ADID	CreativeUrl	Currency Code
0	a18429b490a54c3fe6e9c726f9dc7279ea4d2d51285fc1...	https://www.snap.com/political-ads/asset/94e84...	GBP
1	4f322a3bfda8c0defb40b5880d5c1a1e92955059b201cd...	https://www.snap.com/political-ads/asset/fb0dd...	EUR
2	2f1481be8088238a3c653748920ff56f46061e6d0df74e...	https://www.snap.com/political-ads/asset/7d646...	EUR
3	1579898f558416cbb3d7fe840d537cabeabf0e1d4432bf...	https://www.snap.com/political-ads/asset/1ad06...	GBP
4	90dd24346e85cf696f5ac1573d7176989b844b380bba3c...	https://www.snap.com/political-ads/asset/52f99...	USD

5 rows × 34 columns

Convert StartDate and EndDate to datetime

In [8]:

```
# equals 1 means all values of 'StartDate' and 'EndDate' ends with 'Z'
[np.mean(data['StartDate'].apply(lambda x: str(x)[-1])=='Z'), \
 np.mean(data['StartDate'].apply(lambda x: str(x)[-1])=='Z')]
```

Out[8]:

```
[1.0, 1.0]
```

The tailing 'Z' stands for Zulu Time, or GMT/UTC

In [9]:

```
data['StartDate'] = pd.to_datetime(data['StartDate'])
data['EndDate'] = pd.to_datetime(data['EndDate'])
data.head()
```

Out[9]:

	ADID	CreativeUrl	Currency Code
0	a18429b490a54c3fe6e9c726f9dc7279ea4d2d51285fc1...	https://www.snap.com/political-ads/asset/94e84...	GBP
1	4f322a3bfda8c0defb40b5880d5c1a1e92955059b201cd...	https://www.snap.com/political-ads/asset/fb0dd...	EUR
2	2f1481be8088238a3c653748920ff56f46061e6d0df74e...	https://www.snap.com/political-ads/asset/7d646...	EUR
3	1579898f558416cbb3d7fe840d537cabeabf0e1d4432bf...	https://www.snap.com/political-ads/asset/1ad06...	GBP
4	90dd24346e85cf696f5ac1573d7176989b844b380bba3c...	https://www.snap.com/political-ads/asset/52f99...	USD

5 rows × 34 columns

In [15]:

```
# get columns (possible features)
data.columns
```

Out[15]:

```
Index(['ADID', 'CreativeUrl', 'Currency Code', 'Spend', 'Impressions',
       'StartDate', 'EndDate', 'OrganizationName', 'BillingAddress',
       'CandidateBallotInformation', 'PayingAdvertiserName', 'Gender',
       'AgeBracket', 'CountryCode', 'Regions (Included)', 'Regions (Ex
cluded)',
       'Electoral Districts (Included)', 'Electoral Districts (Exclude
d)',
       'Radius Targeting (Included)', 'Radius Targeting (Excluded)',
       'Metros (Included)', 'Metros (Excluded)', 'Postal Codes (Includ
ed)',
       'Postal Codes (Excluded)', 'Location Categories (Included)',
       'Location Categories (Excluded)', 'Interests', 'OsType', 'Segme
nts',
       'Language', 'AdvancedDemographics', 'Targeting Connection Typ
e',
       'Targeting Carrier (ISP)', 'CreativeProperties'],
      dtype='object')
```

In [16]:

```
# get first row for sample entry
data.iloc[0,:]
```

...

In [17]:

```
# get proportion that is NaN and dtype of each column
for col in data.columns:
    print(col, data[col].isna().mean(), data[col].dtype)
```

```
ADID 0.0 object
CreativeUrl 0.0 object
Currency Code 0.0 object
Spend 0.0 int64
Impressions 0.0 int64
StartDate 0.0 datetime64[ns, UTC]
EndDate 0.22954128440366972 datetime64[ns, UTC]
OrganizationName 0.0 object
BillingAddress 0.0 object
CandidateBallotInformation 0.7770642201834862 object
PayingAdvertiserName 0.0 object
Gender 0.9233027522935779 object
AgeBracket 0.07834862385321101 object
CountryCode 0.0 object
Regions (Included) 0.7080733944954128 object
Regions (Excluded) 0.9710091743119266 object
Electoral Districts (Included) 0.9880733944954129 object
Electoral Districts (Excluded) 1.0 float64
Radius Targeting (Included) 0.9412844036697248 object
Radius Targeting (Excluded) 0.998165137614679 object
Metros (Included) 0.9609174311926606 object
Metros (Excluded) 0.996697247706422 object
Postal Codes (Included) 0.8434862385321101 object
Postal Codes (Excluded) 0.9737614678899082 object
Location Categories (Included) 0.9979816513761468 object
Location Categories (Excluded) 1.0 float64
Interests 0.7638532110091744 object
OsType 0.9972477064220183 object
Segments 0.33908256880733945 object
Language 0.7335779816513761 object
AdvancedDemographics 0.9680733944954129 object
Targeting Connection Type 0.9961467889908256 object
Targeting Carrier (ISP) 1.0 float64
CreativeProperties 0.14605504587155962 object
```

Picking potential columns to be used as features for baseline model. Some columns cannot be used since it is mostly NaN or irrelevant with modeling (e.g. OrganizationName or BillingAddress).

In [45]:

```
feasible_feat_columns = ['Currency Code', 'Spend', 'Impressions', 'StartDate',
                         'EndDate', 'Gender', 'AgeBracket',
                         'CountryCode','Interests', 'Language']
```

In [47]:

```
data_filt = data[feasible_feat_columns]
data_filt.head()
```

Out[47]:

	Currency Code	Spend	Impressions	StartDate	EndDate	Gender	AgeBracket	Country(
0	GBP	8	4167	2019-11-26 00:00:06+00:00	2019-11-26 23:00:00+00:00	NaN	18-40	u king
1	EUR	505	646878	2019-10-02 16:49:19+00:00	2019-10-23 21:59:26+00:00	NaN	17+	fr
2	EUR	186	179036	2019-08-12 08:30:41+00:00	2019-08-25 21:32:12+00:00	FEMALE	14-19	den
3	GBP	4624	2909454	2019-05-21 11:51:56+00:00	2019-05-23 15:58:14+00:00	NaN	18+	u king
4	USD	1687	570706	2019-07-02 22:52:36+00:00	2019-07-31 22:52:36+00:00	NaN	18+	united s

Above is the DataFrame containing the baseline model features and the given Impressions.

Baseline Model

In [146]:

```
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import FunctionTransformer
from sklearn.preprocessing import OneHotEncoder
from sklearn.preprocessing import MultiLabelBinarizer

from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.model_selection import train_test_split
from sklearn.impute import SimpleImputer
from sklearn.decomposition import PCA
```

Configuring Pipeline and applying OHE to categorical columns.

In [412]:

```
cats = Pipeline([
    ('ohe', OneHotEncoder(sparse=False, handle_unknown='ignore'))
])
catcols = ['Currency Code', 'CountryCode']

nums = FunctionTransformer(lambda x:x)
numcols = ['Spend']

ct = ColumnTransformer([('cat', cats, catcols), ('num', nums, numcols)])

baseline_pl = Pipeline([('feats', ct), ('lr', LinearRegression())])
```

Initializing X and y columns and splitting train and test data. Training on train data, then test on test data.

In [413]:

```
X = data_filt.drop(['Impressions'], axis=1)
y = data_filt.Impressions

X_train, X_test, y_train, y_test = train_test_split(X, y)

baseline_pl.fit(X_train, y_train)

r2 = baseline_pl.score(X_test, y_test)
print("R^2: %s" % r2)

preds = baseline_pl.predict(X_test)
rmse = np.sqrt(np.mean((preds - y_test)**2))
print("RMSE: %s" % rmse)
```

```
R^2: 0.6728413730990455
RMSE: 1867746.8356924905
```

The R^2 score above looks promising b ut it looks like it can be improved with additional engineered features. Below is the process repeated 100 times to see the distribution of the fit score over 100 trials.

In [414]:

```
out = []
for _ in range(100):
    X_tr, X_ts, y_tr, y_ts = train_test_split(X, y)
    baseline_pl.fit(X_tr, y_tr)
    out.append(baseline_pl.score(X_ts, y_ts))
mean_r2 = np.mean(out)
print("Mean R^2 across 100 reps: %s" % mean_r2)
```

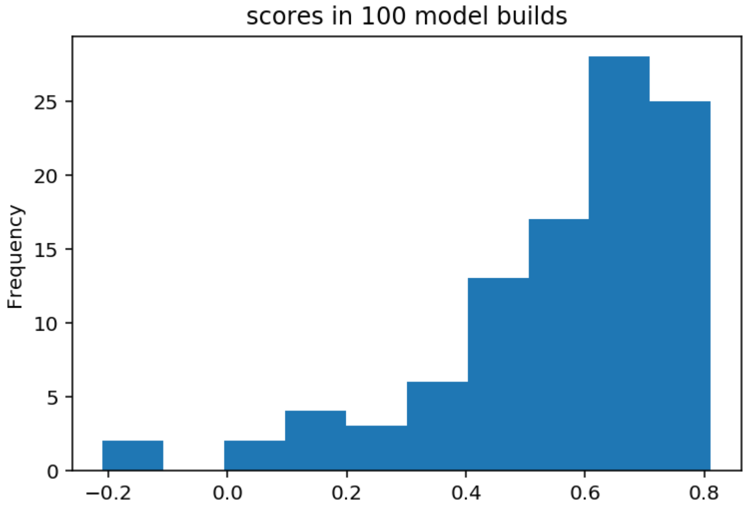
```
Mean R^2 across 100 reps: 0.5615195530471999
```

In [415]:

```
pd.Series(out).plot(kind='hist', title='scores in 100 model builds')
```

Out[415]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1a1dd49290>
```



Final Model

Below is a function to use the StartDate and EndDate features to generate a **Duration** feature of how long (in hours) the ad is up.

In [416]:

```
def get_duration_hours(df):
    duration = df['EndDate'] - df['StartDate']
    hours = duration.apply(lambda x: x.seconds//3600)
    return pd.DataFrame(hours)
```

Below is a function to use the Interests feature to set it up for the MultiLabelBinarizer by splitting interests on comma and performing a one-hot encoding later on.

In [417]:

```
def split_array(df): # of one column
    colname = df.columns[0]
    col = df[colname]
    ret = col.apply(lambda x: x.split(',') if pd.isnull(x)==False else [])
    return np.array(ret)
```

The class below is a custom transformer class I made because I encountered some error with implementing JultiLabelBinarizer directly to the pipeline. To be more specific, the fit_transform method requires 3 arguments, but only two are passed. Hence, this class fixes the issue by passing an empty argument everytime fit_transform is called on the Pipeline/ColumnTransformer.

In [418]:

```
from sklearn.base import TransformerMixin
class MyMultiLabelBinarizer(TransformerMixin):
    def __init__(self, *args, **kwargs):
        self.encoder = MultiLabelBinarizer(*args, **kwargs)
    def fit(self, x, y=0):
        self.encoder.fit(x)
        return self
    def transform(self, x, y=0):
        return self.encoder.transform(x)
```

First Trial Model

In [419]:

```
# Interests and Language
split = FunctionTransformer(split_array)
mlb_pl = Pipeline([
    ('split', split),
    ('mlb', MyLabelBinarizer()),
    ('pca', PCA(svd_solver='full'))  # later do gridsearch
])
mlbcols = ['Interests', 'Language']


# Currency Code and CountryCode
simple_cats = Pipeline([
    ('imp', SimpleImputer(strategy='constant', fill_value='NULL')),
    ('ohe', OneHotEncoder(sparse=False, handle_unknown='ignore')),
    ('pca', PCA(svd_solver='full'))  # later do gridsearch
])
simple_catcols = ['Currency Code', 'CountryCode']


# StartDate and EndDate
duration = FunctionTransformer(get_duration_hours)
duration_pl = Pipeline([
    ('get_hours', duration),
    ('imp', SimpleImputer(strategy='mean'))
])
durationcols = ['StartDate', 'EndDate']


# Spend
nums = FunctionTransformer(lambda x:x)
numcols = ['Spend']

ct = ColumnTransformer([('mlb_cat', mlb_pl, mlbcols),
                        ('simple_cat', simple_cats, simple_catcols),
                        ('duration', duration_pl, durationcols),
                        ('num', nums, numcols)
                       ])

trial_pl1 = Pipeline([('feats', ct), ('lr', LinearRegression())])
```

We will split the data set (75%, 25%) for train and test datasets.

In [420]:

```
X = data_filt.drop(['Impressions'], axis=1)
y = data_filt.Impressions

X_train, X_test, y_train, y_test = train_test_split(X, y)
```

GridSearch on n_components for simple_cat_pca

In [421]:

```
trial_pl1.get_params().keys()
```

Out[421]:

```
dict_keys(['memory', 'steps', 'verbose', 'feats', 'lr', 'feats__n_job
s', 'feats__remainder', 'feats__sparse_threshold', 'feats__transformer
_weights', 'feats__transformers', 'feats__verbose', 'feats__mlb_cat',
'feats__simple_cat', 'feats__duration', 'feats__num', 'feats__mlb_cat_
_memory', 'feats__mlb_cat__steps', 'feats__mlb_cat__verbose', 'feats__
mlb_cat__split', 'feats__mlb_cat__mlb', 'feats__mlb_cat__pca', 'feats_
_mlb_cat__split__accept_sparse', 'feats__mlb_cat__split__check_invers
e', 'feats__mlb_cat__split__func', 'feats__mlb_cat__split__inv_kw_arg
s', 'feats__mlb_cat__split__inverse_func', 'feats__mlb_cat__split__kw_
args', 'feats__mlb_cat__split__validate', 'feats__mlb_cat__pca__copy',
'feats__mlb_cat__pca__iterated_power', 'feats__mlb_cat__pca__n_compone
nts', 'feats__mlb_cat__pca__random_state', 'feats__mlb_cat__pca__svd_s
olver', 'feats__mlb_cat__pca__tol', 'feats__mlb_cat__pca__whiten', 'fe
ats__simple_cat__memory', 'feats__simple_cat__steps', 'feats__simple_c
at__verbose', 'feats__simple_cat__imp', 'feats__simple_cat__ohe', 'fea
ts__simple_cat__pca', 'feats__simple_cat__imp__add_indicator', 'feats_
_simple_cat__imp__copy', 'feats__simple_cat__imp__fill_value', 'feats_
_simple_cat__imp__missing_values', 'feats__simple_cat__imp__strategy',
'feats__simple_cat__imp__verbose', 'feats__simple_cat__ohe__categorie
s', 'feats__simple_cat__ohe__drop', 'feats__simple_cat__ohe__dtype',
'feats__simple_cat__ohe__handle_unknown', 'feats__simple_cat__ohe__spa
rse', 'feats__simple_cat__pca__copy', 'feats__simple_cat__pca__iterate
d_power', 'feats__simple_cat__pca__n_components', 'feats__simple_cat__
pca__random_state', 'feats__simple_cat__pca__svd_solver', 'feats__simp
le_cat__pca__tol', 'feats__simple_cat__pca__whiten', 'feats__duration_
_memory', 'feats__duration__steps', 'feats__duration__verbose', 'feats
__duration__get_hours', 'feats__duration__imp', 'feats__duration__get_
hours__accept_sparse', 'feats__duration__get_hours__check_inverse', 'f
eats__duration__get_hours__func', 'feats__duration__get_hours__inv_kw_
args', 'feats__duration__get_hours__inverse_func', 'feats__duration__g
et_hours__kw_args', 'feats__duration__get_hours__validate', 'feats__du
ration__imp__add_indicator', 'feats__duration__imp__copy', 'feats__dur
ation__imp__fill_value', 'feats__duration__imp__missing_values', 'feat
s__duration__imp__strategy', 'feats__duration__imp__verbose', 'feats__
num__accept_sparse', 'feats__num__check_inverse', 'feats__num__func',
'feats__num__inv_kw_args', 'feats__num__inverse_func', 'feats__num__kw
_args', 'feats__num__validate', 'lr__copy_X', 'lr__fit_intercept', 'lr
__n_jobs', 'lr__normalize'])
```

In [422]:

```
from sklearn.model_selection import GridSearchCV

params = {'feats__simple_cat__pca__n_components':[0.70, 0.75, 0.80, 0.85, 0.90, 0.99

# train using cross validation
grids1 = GridSearchCV(trial_pl1, param_grid=params, cv=5, iid = False)
```

In [423]:

```
grids1.fit(X_train, y_train)
```

```
/Users/jonathant/anaconda3/lib/python3.7/site-packages/sklearn/preproc
essing/_label.py:987: UserWarning: unknown class(es) ['Frequent Intern
ational Travelers', 'Gift Shoppers', 'Holiday Online Buyers - Appare
l', 'Holiday Online Shoppers', 'Home Movie Viewers (Science Fiction)',
'nln_8059'] will be ignored
  .format(sorted(unknown, key=str))
/Users/jonathant/anaconda3/lib/python3.7/site-packages/sklearn/preproc
essing/_label.py:987: UserWarning: unknown class(es) ['Apparel Store B
uyers - Charlotte Russe', 'Apparel Store Buyers - Express', 'Apparel S
tore Buyers - Guess', 'Apparel Store Buyers - H & M', 'Apparel Store B
uyers - Michael Kors', 'Apparel Store Buyers - TJ Maxx', 'Apparel Stor
e Buyers - Victorias Secret', 'Beauty and Fragrance Shoppers', "Wome
n's Apparel Shoppers"] will be ignored
  .format(sorted(unknown, key=str))
/Users/jonathant/anaconda3/lib/python3.7/site-packages/sklearn/preproc
essing/_label.py:987: UserWarning: unknown class(es) ['Baby & Toddler
- Baby Food Buyers', 'Baby & Toddler - Baby Formula Buyers', 'Baby & T
oddler - Baby HBC Buyers', 'Baby & Toddler - Baby HBC Buyers - Huggies
Brands', 'Baby & Toddler - Disposable Diaper & Training Pant Buyers',
```

In [424]:

```
grids1.best_params_
```

Out[424]:

```
{'feats__simple_cat__pca__n_components': None}
```

This is interesting since the GridSearch tells us that the regression model will be better of if we drop the simple_cat features (Currency Code and CountryCode). So we will do so.

Second trial model

In [425]:

```
# Interests and Language
split = FunctionTransformer(split_array)
mlb_pl = Pipeline([
    ('split', split),
    ('mlb', MyLabelBinarizer()),
    ('pca', PCA(svd_solver='full'))  # later do gridsearch
])
mlbcols = ['Interests', 'Language']


# Currency Code and CountryCode
simple_cats = Pipeline([
    ('imp', SimpleImputer(strategy='constant', fill_value='NULL')),
    ('ohe', OneHotEncoder(sparse=False, handle_unknown='ignore')),
    ('pca', PCA(svd_solver='full', n_components=None))
])
simple_catcols = ['Currency Code', 'CountryCode']


# StartDate and EndDate
duration = FunctionTransformer(get_duration_hours)
duration_pl = Pipeline([
    ('get_hours', duration),
    ('imp', SimpleImputer(strategy='mean'))
])
durationcols = ['StartDate', 'EndDate']


# Spend
nums = FunctionTransformer(lambda x:x)
numcols = ['Spend']

ct = ColumnTransformer([('mlb_cat', mlb_pl, mlbcols),
                        ('simple_cat', simple_cats, simple_catcols),
                        ('duration', duration_pl, durationcols),
                        ('num', nums, numcols)
                       ])

trial_pl2 = Pipeline([('feats', ct), ('lr', LinearRegression())])
```

GridSearch on n_components of mlb_cat_pca

In [426]:

```
trial_pl2.get_params().keys()
```

Out[426]:

```
dict_keys(['memory', 'steps', 'verbose', 'feats', 'lr', 'feats__n_job
s', 'feats__remainder', 'feats__sparse_threshold', 'feats__transformer
_weights', 'feats__transformers', 'feats__verbose', 'feats__mlb_cat',
'feats__simple_cat', 'feats__duration', 'feats__num', 'feats__mlb_cat_
_memory', 'feats__mlb_cat__steps', 'feats__mlb_cat__verbose', 'feats__
mlb_cat__split', 'feats__mlb_cat__mlb', 'feats__mlb_cat__pca', 'feats_
_mlb_cat__split__accept_sparse', 'feats__mlb_cat__split__check_invers
e', 'feats__mlb_cat__split__func', 'feats__mlb_cat__split__inv_kw_arg
s', 'feats__mlb_cat__split__inverse_func', 'feats__mlb_cat__split__kw_
args', 'feats__mlb_cat__split__validate', 'feats__mlb_cat__pca__copy',
'feats__mlb_cat__pca__iterated_power', 'feats__mlb_cat__pca__n_compone
nts', 'feats__mlb_cat__pca__random_state', 'feats__mlb_cat__pca__svd_s
olver', 'feats__mlb_cat__pca__tol', 'feats__mlb_cat__pca__whiten', 'fe
ats__simple_cat__memory', 'feats__simple_cat__steps', 'feats__simple_c
at__verbose', 'feats__simple_cat__imp', 'feats__simple_cat__ohe', 'fea
ts__simple_cat__pca', 'feats__simple_cat__imp__add_indicator', 'feats_
_simple_cat__imp__copy', 'feats__simple_cat__imp__fill_value', 'feats_
_simple_cat__imp__missing_values', 'feats__simple_cat__imp__strategy',
'feats__simple_cat__imp__verbose', 'feats__simple_cat__ohe__categorie
s', 'feats__simple_cat__ohe__drop', 'feats__simple_cat__ohe__dtype',
'feats__simple_cat__ohe__handle_unknown', 'feats__simple_cat__ohe__spa
rse', 'feats__simple_cat__pca__copy', 'feats__simple_cat__pca__iterate
d_power', 'feats__simple_cat__pca__n_components', 'feats__simple_cat__
pca__random_state', 'feats__simple_cat__pca__svd_solver', 'feats__simp
le_cat__pca__tol', 'feats__simple_cat__pca__whiten', 'feats__duration_
_memory', 'feats__duration__steps', 'feats__duration__verbose', 'feats
__duration__get_hours', 'feats__duration__imp', 'feats__duration__get_
hours__accept_sparse', 'feats__duration__get_hours__check_inverse', 'f
eats__duration__get_hours__func', 'feats__duration__get_hours__inv_kw_
args', 'feats__duration__get_hours__inverse_func', 'feats__duration__g
et_hours__kw_args', 'feats__duration__get_hours__validate', 'feats__du
ration__imp__add_indicator', 'feats__duration__imp__copy', 'feats__dur
ation__imp__fill_value', 'feats__duration__imp__missing_values', 'feat
s__duration__imp__strategy', 'feats__duration__imp__verbose', 'feats__
num__accept_sparse', 'feats__num__check_inverse', 'feats__num__func',
'feats__num__inv_kw_args', 'feats__num__inverse_func', 'feats__num__kw
_args', 'feats__num__validate', 'lr__copy_X', 'lr__fit_intercept', 'lr
__n_jobs', 'lr__normalize'])
```

In [427]:

```
params = {'feats__mlb_cat__pca__n_components':[0.70, 0.75, 0.80, 0.85, 0.90, 0.99, N

# train using cross validation
grids2 = GridSearchCV(trial_pl2, param_grid=params, cv=5, iid = False)
```

In [428]:

```
grids2.fit(X_train, y_train)
```

```
/Users/jonathant/anaconda3/lib/python3.7/site-packages/sklearn/preproc
essing/_label.py:987: UserWarning: unknown class(es) ['Frequent Intern
ational Travelers', 'Gift Shoppers', 'Holiday Online Buyers - Appare
l', 'Holiday Online Shoppers', 'Home Movie Viewers (Science Fiction)',
'nln_8059'] will be ignored
  .format(sorted(unknown, key=str)))
/Users/jonathant/anaconda3/lib/python3.7/site-packages/sklearn/preproc
essing/_label.py:987: UserWarning: unknown class(es) ['Apparel Store B
uyers - Charlotte Russe', 'Apparel Store Buyers - Express', 'Apparel S
tore Buyers - Guess', 'Apparel Store Buyers - H & M', 'Apparel Store B
uyers - Michael Kors', 'Apparel Store Buyers - TJ Maxx', 'Apparel Stor
e Buyers - Victorias Secret', 'Beauty and Fragrance Shoppers', "Wome
n's Apparel Shoppers"] will be ignored
  .format(sorted(unknown, key=str)))
/Users/jonathant/anaconda3/lib/python3.7/site-packages/sklearn/preproc
essing/_label.py:987: UserWarning: unknown class(es) ['Baby & Toddler
- Baby Food Buyers', 'Baby & Toddler - Baby Formula Buyers', 'Baby & T
oddler - Baby HBC Buyers', 'Baby & Toddler - Baby HBC Buyers - Huggies
Brands', 'Baby & Toddler - Disposable Diaper & Training Pant Buyers',
```

In [429]:

```
grids2.best_params_
```

Out[429]:

```
{'feats__mlb_cat__pca__n_components': 0.75}
```

With the Interests and Language features, we are also advised to take it out.

In [430]:

```
# Interests and Language
split = FunctionTransformer(split_array)
mlb_pl = Pipeline([
    ('split', split),
    ('mlb', MyLabelBinarizer()),
    ('pca', PCA(svd_solver='full', n_components=None))
])
mlbcols = ['Interests', 'Language']


# Currency Code and CountryCode
simple_cats = Pipeline([
    ('imp', SimpleImputer(strategy='constant', fill_value='NULL')),
    ('ohe', OneHotEncoder(sparse=False, handle_unknown='ignore')),
    ('pca', PCA(svd_solver='full', n_components=None))
])
simple_catcols = ['Currency Code', 'CountryCode']


# StartDate and EndDate
duration = FunctionTransformer(get_duration_hours)
duration_pl = Pipeline([
    ('get_hours', duration),
    ('imp', SimpleImputer(strategy='median'))
])
durationcols = ['StartDate', 'EndDate']


# Spend
nums = FunctionTransformer(lambda x:x)
numcols = ['Spend']

ct = ColumnTransformer([('mlb_cat', mlb_pl, mlbcols),
                        ('simple_cat', simple_cats, simple_catcols),
                        ('duration', duration_pl, durationcols),
                        ('num', nums, numcols)
                       ])

final_pl = Pipeline([('feats', ct), ('lr', LinearRegression())])
```

We will now train the model and predict.

In [434]:

```
X = data_filt.drop(['Impressions'], axis=1)
y = data_filt.Impressions

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=.25)

final_pl.fit(X_train, y_train)

r2 = final_pl.score(X_test, y_test)
print("R^2: %s" % r2)

final_preds = final_pl.predict(X_test)
rmse = np.sqrt(np.mean((final_preds - y_test)**2))
print("RMSE: %s" % rmse)
```

```
R^2: 0.6937881160154702
RMSE: 4357424.355017208

/Users/jonathant/anaconda3/lib/python3.7/site-packages/sklearn/preproc
essing/_label.py:987: UserWarning: unknown class(es) ['Apparel Store B
uyers - Charlotte Russe', 'Apparel Store Buyers - Express', 'Apparel S
tore Buyers - Guess', 'Apparel Store Buyers - H & M', 'Apparel Store B
uyers - Michael Kors', 'Apparel Store Buyers - TJ Maxx', 'Apparel Stor
e Buyers - Victorias Secret', 'Beauty and Fragrance Shoppers', 'Drama
Genre Fans', 'Home Movie Viewers (Science Fiction)', 'Indie & Alternat
ive Music Fans', 'Mexican Food Shoppers', 'Rock Music Fans', 'Soul & R
&B Fans', 'TV Viewers (Educational)', "Women's Apparel Shoppers"] will
be ignored
  .format(sorted(unknown, key=str)))
```


```
/Users/jonathant/anaconda3/lib/python3.7/site-packages/sklearn/preproc
essing/_label.py:987: UserWarning: unknown class(es) ['Apparel Store B
uyers - Charlotte Russe', 'Apparel Store Buyers - Express', 'Apparel S
tore Buyers - Guess', 'Apparel Store Buyers - H & M', 'Apparel Store B
uyers - Michael Kors', 'Apparel Store Buyers - TJ Maxx', 'Apparel Stor
e Buyers - Victorias Secret', 'Beauty and Fragrance Shoppers', 'Drama
Genre Fans', 'Home Movie Viewers (Science Fiction)', 'Indie & Alternat
ive Music Fans', 'Mexican Food Shoppers', 'Rock Music Fans', 'Soul & R
&B Fans', 'TV Viewers (Educational)', "Women's Apparel Shoppers"] will
be ignored
  .format(sorted(unknown, key=str)))
```

In [432]:

```
out = []
for _ in range(100):
    X_tr, X_ts, y_tr, y_ts = train_test_split(X, y)
    final_pl.fit(X_tr, y_tr)
    out.append(final_pl.score(X_ts, y_ts))
mean_r2 = np.mean(out)
print("Mean R^2 across 100 reps: %s" % mean_r2)
```

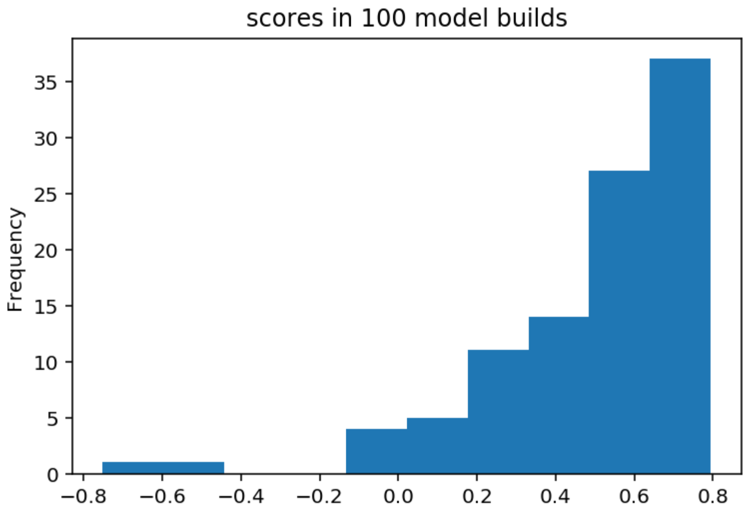
```
/Users/jonathant/anaconda3/lib/python3.7/site-packages/sklearn/preproc
essing/_label.py:987: UserWarning: unknown class(es) ["Men's Apparel S
hoppers", 'Sporting Goods Buyers - Bass Pro Shop', 'Sporting Goods Buy
ers - Cabelas', 'TV Light Viewers'] will be ignored
  .format(sorted(unknown, key=str)))
/Users/jonathant/anaconda3/lib/python3.7/site-packages/sklearn/preproc
essing/_label.py:987: UserWarning: unknown class(es) ['Apparel Buyer
s', 'Baby & Toddler - Baby Food Buyers', 'Baby & Toddler - Baby Formul
a Buyers', 'Baby & Toddler - Baby HBC Buyers', 'Baby & Toddler - Baby
HBC Buyers - Huggies Brands', 'Baby & Toddler - Disposable Diaper & Tr
aining Pant Buyers', 'Baby & Toddler - Disposable Diaper & Training Pa
nt Buyers - Huggies Brands', 'Baby & Toddler - Disposable Diaper & Tra
ining Pant Buyers - Pampers Brands', 'Baby Product Buyers', 'Baby Stor
e Buyers', 'Baby Store Buyers - Buy Buy Baby', 'Baby Store Buyers - Ca
rters', 'Baby Store Buyers - Diapers.com', 'Black Friday & Cyber Monda
y Shoppers', 'Black Friday Buyers', 'Black Friday Buyers - Apparel',
'Black Friday Online Buyers - Amazon', "Children's Product Buyers", "C
hildren's Product Shoppers", 'Deal & Value Shoppers', 'Discount Buyer
s', 'Discount Store Shoppers', 'Food Buyers', 'Home Movie Viewers (Sci
```

In [433]:

```
pd.Series(out).plot(kind='hist', title='scores in 100 model builds')
```

Out[433]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1a1ef818d0>
```



We see here that there has been a bit of an increase in accuracy from the baseline model to the final model going from 0.56 to 0.69.

Fairness Evaluation

I will evaluate how fair the model is for regression on ads data in 2019 and 2020.

In [439]:

```
filt19 = data_filt['StartDate'].apply(lambda x: x.year==2019)
data_19 = data_filt[filt19.values]

filt20 = data_filt['StartDate'].apply(lambda x: x.year==2020)
data_20 = data_filt[filt20.values]
```

On 2019

In [447]:

```
X19 = data_19.drop(['Impressions'], axis=1)
y19 = data_19.Impressions

X_train, X_test, y_train, y_test = train_test_split(X19, y19, test_size=.25)

final_pl.fit(X_train, y_train)

print(2019)
r2 = final_pl.score(X_test, y_test)
print("R^2: %s" % r2)

final_preds = final_pl.predict(X_test)
rmse = np.sqrt(np.mean((final_preds - y_test)**2))
print("RMSE: %s" % rmse)
```

```
2019
R^2: 0.7297120416759013
RMSE: 4437666.785179717

/Users/jonathant/anaconda3/lib/python3.7/site-packages/sklearn/preproc
essing/_label.py:987: UserWarning: unknown class(es) ['Country Music F
ans'] will be ignored
  .format(sorted(unknown, key=str)))
/Users/jonathant/anaconda3/lib/python3.7/site-packages/sklearn/preproc
essing/_label.py:987: UserWarning: unknown class(es) ['Country Music F
ans'] will be ignored
  .format(sorted(unknown, key=str)))
```

In [448]:

```
out = []
for _ in range(100):
    X_tr, X_ts, y_tr, y_ts = train_test_split(X19, y19)
    final_pl.fit(X_tr, y_tr)
    out.append(final_pl.score(X_ts, y_ts))
mean_r2 = np.mean(out)
print("Mean R^2 across 100 reps: %s" % mean_r2)
```

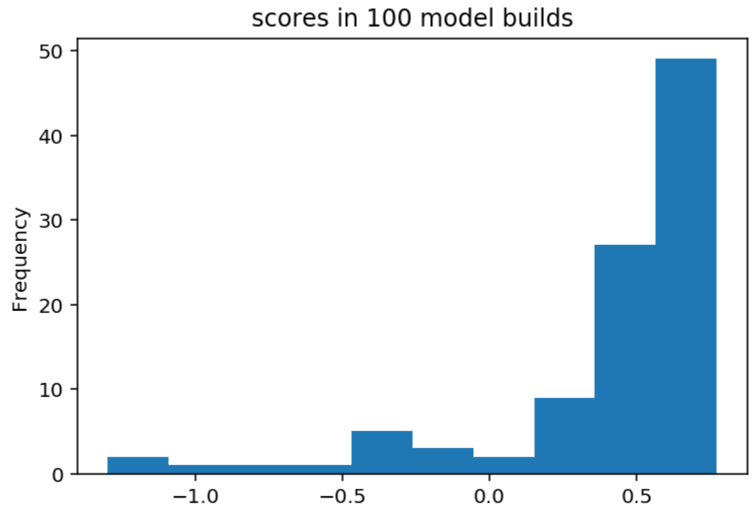
```
/Users/jonathant/anaconda3/lib/python3.7/site-packages/sklearn/preproc
essing/_label.py:987: UserWarning: unknown class(es) ['Hybrid & Altern
ative Vehicle Shoppers', 'TV Viewers (Comedy)'] will be ignored
  .format(sorted(unknown, key=str)))
/Users/jonathant/anaconda3/lib/python3.7/site-packages/sklearn/preproc
essing/_label.py:987: UserWarning: unknown class(es) ['Dining Establis
hment Visitors', 'Grocery Shoppers', 'Home & Garden Shoppers', 'Retail
Store Visitors', 'Seasonal Shoppers', 'TV Light Viewers'] will be igno
red
  .format(sorted(unknown, key=str)))
/Users/jonathant/anaconda3/lib/python3.7/site-packages/sklearn/preproc
essing/_label.py:987: UserWarning: unknown class(es) ['TV Light Viewer
s', 'TV Viewers (Educational)', 'nln_8059'] will be ignored
  .format(sorted(unknown, key=str)))
/Users/jonathant/anaconda3/lib/python3.7/site-packages/sklearn/preproc
essing/_label.py:987: UserWarning: unknown class(es) ['Electronics Buy
ers - Apple Store', 'Last 12 Months Buyers - Apple', 'TV Viewers (Come
dy)'] will be ignored
  .format(sorted(unknown, key=str)))
```

In [449]:

```
pd.Series(out).plot(kind='hist', title='scores in 100 model builds')
```

Out[449]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1a1fb2f8d0>
```



On 2020

In [450]:

```python
X20 = data_20.drop(['Impressions'], axis=1)
y20 = data_20.Impressions

X_train, X_test, y_train, y_test = train_test_split(X20, y20, test_size=.25)

final_pl.fit(X_train, y_train)

print(2020)
r2 = final_pl.score(X_test, y_test)
print("R^2: %s" % r2)

final_preds = final_pl.predict(X_test)
rmse = np.sqrt(np.mean((final_preds - y_test)**2))
print("RMSE: %s" % rmse)
```

```
2020
R^2: 0.4533685046606899
RMSE: 2626097.322470323
```

In [451]:

```python
out = []
for _ in range(100):
    X_tr, X_ts, y_tr, y_ts = train_test_split(X20, y20)
    final_pl.fit(X_tr, y_tr)
    out.append(final_pl.score(X_ts, y_ts))
mean_r2 = np.mean(out)
print("Mean R^2 across 100 reps: %s" % mean_r2)
```

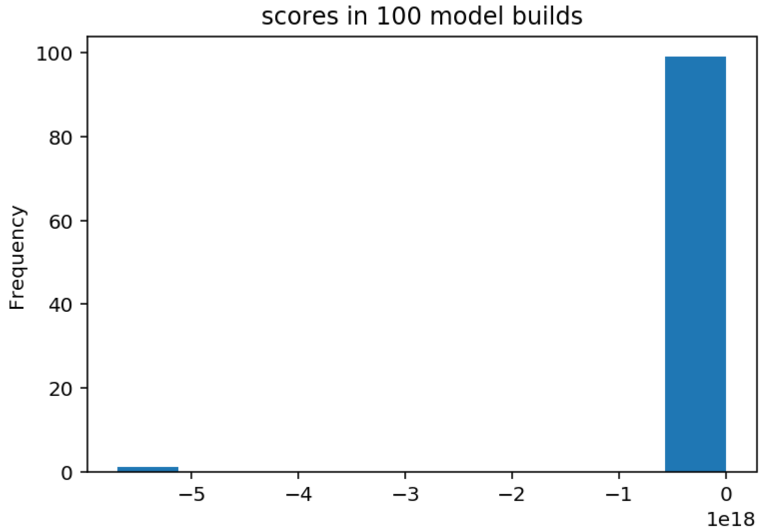
```
/Users/jonathant/anaconda3/lib/python3.7/site-packages/sklearn/preproc
essing/_label.py:987: UserWarning: unknown class(es) ['Big Box Store B
uyers - Walmart', 'Black Friday & Cyber Monday Shoppers', 'Last 12 Mon
ths Buyers - Walmart', 'Mexican Food Shoppers', 'Pet Owners', 'Post-Ho
liday Bargain Shoppers', 'Soul & R&B Fans', 'TV Network Viewers (FX)',
'Vegans & Organic Foodies'] will be ignored
  .format(sorted(unknown, key=str)))
/Users/jonathant/anaconda3/lib/python3.7/site-packages/sklearn/preproc
essing/_label.py:987: UserWarning: unknown class(es) ['Baby & Toddler
- Baby Food Buyers', 'Baby & Toddler - Baby Formula Buyers', 'Baby & T
oddler - Baby HBC Buyers', 'Baby & Toddler - Baby HBC Buyers - Huggies
Brands', 'Baby & Toddler - Disposable Diaper & Training Pant Buyers',
'Baby & Toddler - Disposable Diaper & Training Pant Buyers - Huggies B
rands', 'Baby & Toddler - Disposable Diaper & Training Pant Buyers - P
ampers Brands', 'Baby Product Buyers', 'Baby Store Buyers', 'Baby Stor
e Buyers - Buy Buy Baby', 'Baby Store Buyers - Carters', 'Baby Store B
uyers - Diapers.com', "Children's Product Buyers", "Children's Product
Shoppers", 'Food Buyers', 'Last 12 Months Buyers - Buybuy Baby', "Me
n's Apparel Shoppers", 'Mexican Food Shoppers', 'Pet Owners', 'Recent
```

In [452]:

```
pd.Series(out).plot(kind='hist', title='scores in 100 model builds')
```

Out[452]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1a20f37d90>
```



One interesting observation here is the difference in how the model predicted impressions for data on 2019 and 2020. It seems to be doing better for the year 2019 than 2020 by quite a margin. The mean R^2 value for the 2020 model is negative. One reason to explain this is probably the fact that 2020 is still the current year so there is not sufficient data to model it. Whereas 2019 data make up for most of the main dataset which created the model so it results in a higher accuracy.

In [ ]:

```

```