Snapchat Political Ads

- **See the main project notebook for instructions to be sure you satisfy the rubric!**
- See Project 03 for information on the dataset.
- A few example prediction questions to pursue are listed below. However, don't limit yourself to them!
  - Predict the reach (number of views) of an ad.
  - Predict how much was spent on an ad.
  - Predict the target group of an ad. (For example, predict the target gender.)
  - Predict the (type of) organization/advertiser behind an ad.

Be careful to justify what information you would know at the "time of prediction" and train your model using only those features.

Summary of Findings

Introduction

```
In dataframe ads, we have one column names "Impression" which represents "Number o
f times the Ad has been viewed by Snapchatters". To some degree, this value can sh
ow how much benefits this ads can bring to its company. In this project, I am gonn
a train a linear regression model to predict the 'Impression' values
```

- Prediction Problem: Predict the reach (number of views) of an ad.
- Problem Type: Regression problem,
- Models Choosing: Linear Regression model for predicting.
- Target Variable: Values in "Impression" column in ads dataframe
- Evaluation metrics: RMSE (rooted mean square error) for evaluating the accuracy and R2 score for evaluating how good our model fit to data

Baseline Model

- Model description For a baseline model, I am gonna use 1 quantitative data - Spend, and five catagorical data (nominal data) - Gender, RegionID, AgeBracket, Language, Segments. For baseline model, I will do nothing on the quantitative data and one hot every catagorical data (after replce all nan values with 'all'). Intuitively, all four parameters should somehow related to values in "Impression" and that is why I chose them for trainning baseline model.
  - X1: values in column "spend", which represents "Amount (In USD) spent by the advertiser over the campaign (up to the current date)". The values will keep as what they are. There will be no features engineering on it for now. It is a quantitative data.
  - X2: values in column "Gender", since nan values mean all genders here, we will first repalce nan with all and then one hot.
  - X3: values in column "RegionID", same with 'Gender'.
  - X4: values in column "AgeBracket", same with 'Gender'.
  - X5: values in column "Segments", same with 'Gender'
  - X6: values in column 'Language', same with'Gender'.
  - Y: values in 'Impressions"
  - test, train ration: 3:7
- Model Performance
  - For trainning sets, rmse is 2.028559e+06, and r2_score is 0.795591.

- For test sets, rmse is 2.010769e+06 and r2_score is 0.448908.
- rmses are quite high
- r2_score of trainning set are quite good, especially for a baseline model. However, what we care about is r2score for test sets. The baseline model did not really good on test sets, with r2scroe of only 0.407115. Our model may overfitted on the trainning set and when it predicts values on test sets, it did pretty bad

Final Model

- Model description We will add a new data - Duration, which is calculated by EndDate - StartDate (for null values in EndDate, I repalce them with 12/04/2019. The results will be numbers representing how many days the ad is on Snapchat. For both Duration and Spend, I will do no features. Also, I add three features to catogricals data. For data Gender, Segments, RegionID, since the number of Nan values (replaced by "ALL") is too big that we will transform data to 0/1 (is all or not). For data Language, we will replace nan with all, keep en and replace all others with 'others' and then one hot. For data AgeBracket, we will replace nan with all and keep 18+ and 18-30 and then one hot. For the regressor model, we will still use linear regression but we will adt pvc and gready search for a best fitted model.
  - X1: values in column 'Spend', no features applied
  - X2: values in column 'EndDate' and 'StartDate', get how many days between two dates, replace nan values in 'EndDate' with 12/04/2019
  - X3: values in column 'AgeBracket', keep 'All', '18+' and '18-30', replace all others with 'others' and then one-hot.
  - X4: values in column 'Segments', replace 'ALl' with 1 and others with 0
  - X5: values in column 'Gender', same with X4
  - X6: values in column 'RegionID', same with X4
  - X7: values in column 'Language', keep 'All' and 'en', repalce all others with 'others' and then one-hot
  - Y: values in column 'Impressions'
  - test, train ration: 3:7
- Model Performence
  - For trainning sets, rmse is 2.466698e+06, and r2_score is 0.713277.
  - For test sets, rmse is 1.355102e+06 and r2_score is 0.615836.
  - For both rmse, there is not a clear improvement than baseline model
  - However, for test sets, there is a huge improvement from 0.45 to 0.61
- Model Analysis
  - The model performence is not good enough, so we plot the data and found out that original data do not have a strong linear relationship and other relationships. As a result, we can not get a highly usefull data trained from such a data set.

Fairness Evaluation

First, we fould out that there is a huge difference in rmse (between predicts of x_test and y_test) in three different catogories in column 'Gender'. This may means that our model have a unfair prediction toward a specific values in column "Gender".

- Then we first ran a permutation test to see whether our model will predicts a better result when 'Gender' is 'MALE';
  - Null Hypothesis: there is no difference between rmse in ['diff'] when Gender is MALE and total_rmse
  - Alternative Hypothesis: rmse in ['diff'] when Gender is MALE is lower than total_rmse, which means that our better predicts a better result when Gender is MALE
  - Test stats: difference between rooted mean square of column['diff'] when Gender is ‘MALE’ and total_rmse
  - Significant Level: 0.95

    - outcome p_value: 0.01 < 0.025
    - we have enough evidence to say null hypothesis is wrong.
- Then we ran a permutation test to see whether our model will predicts a worse result when 'Gender' is 'All';
    - Null Hypothesis: there is no difference between rmse in ['diff'] when Gender is All and NOTAll
    - Alternative Hypothesis: rmse in ['diff'] when Gender is ALL is higher than rmse in ['diff] when Gender is NOTAll.
    - Test stats: absolute difference between rooted mean square of column['diff'] when Gender is ‘ALL’ and NOTAll
    - Significant Level: 0.95
    - outcome p_value: 0.00 < 0.025
    - we have enough evidence to say null hypothesis is wrong.

Two permurtation test shows that our model do have a unfairness on 'Gender' input. More specifically, it will predicts a better result if input Gender is not 'All'

Code

In [786]:

```
import matplotlib.pyplot as plt
import numpy as np
import os
import pandas as pd
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from dateutil.rrule import rrule, DAILY
from sklearn.metrics import mean_squared_error
from sklearn.metrics import r2_score
import datetime
import math
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import FunctionTransformer
from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.model_selection import GridSearchCV
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler
%matplotlib inline
%config InlineBackend.figure_format = 'retina'  # Higher resolution figures
ads_2018 = pd.read_csv('data/2018.csv') #import data
ads_2019 = pd.read_csv('data/2019.csv') #import data
ads_2018 = ads_2018.assign(Year=2018) # assign a column represent the year before concate
ads_2019 = ads_2019.assign(Year=2019)
ads = pd.concat([ads_2018, ads_2019], axis=0) # concate two dataframe
```

In [658]:

```
ads.head()
```

Out[658]:

ADID	CreativeUrl	Spend	Impressions	StartDate	EndDate	Organ
f2c25ae9b6bb9e...	https://www.snap.com/political-ads/asset/69afd...	165	49446	2018/11/01 22:42:22Z	2018/11/06 23:00:00Z	
6d5aab0e8d0f51...	https://www.snap.com/political-ads/asset/0885d...	17	23805	2018/11/15 15:52:06Z	2018/11/24 15:50:38Z	
589ca710d51925...	https://www.snap.com/political-ads/asset/a36b7...	60	12883	2018/09/28 23:10:14Z	2018/10/10 02:00:00Z	Chor
94e2fadede0478...	https://www.snap.com/political-ads/asset/46819...	2492	377236	2018/10/27 19:23:19Z	2018/11/06 23:00:00Z	Co
ɔ856df916df5bdc...	https://www.snap.com/political-ads/asset/ee833...	5795	467760	2018/10/25 04:00:00Z	2018/11/06 23:00:00Z	Co

Baseline Model

Model Training

In [977]:

```
X = ads.loc[:, ['Spend', 'Gender', 'Language', 'RegionID', "Segments", 'AgeBracket']] # get
X = X.fillna('All')
y = ads.Impressions # get y
x_train, x_test, y_train, y_test = train_test_split(X, y, test_size=0.3) # get test and tra
```

In [978]:

```
# cat
cat_feat = ['Language', 'Gender', 'RegionID', 'Segments', 'AgeBracket']
cat_transformer = Pipeline([
    ('one-hot', OneHotEncoder())
])

spend_feat = ['Spend']
spend_transformer = Pipeline([
    ('same', FunctionTransformer(lambda x: x))
])
# preprocessing pipeline (put them together)
preproc = ColumnTransformer([
    ('cat', cat_transformer, cat_feat),
    ('spend', spend_transformer, spend_feat)
])

plb = Pipeline([('preprocessor', preproc), ('regressor', LinearRegression())])
```

In [979]:

```
plb.fit(X, y)
```

```
C:\Users\xinrui zhan\Anaconda3\lib\site-packages\sklearn\preprocessing\_func
tion_transformer.py:97: FutureWarning: The default validate=True will be rep
laced by validate=False in 0.22.
  "validate=False in 0.22.", FutureWarning)
C:\Users\xinrui zhan\Anaconda3\lib\site-packages\sklearn\preprocessing\_func
tion_transformer.py:97: FutureWarning: The default validate=True will be rep
laced by validate=False in 0.22.
  "validate=False in 0.22.", FutureWarning)
```

Out[979]:

```
Pipeline(memory=None,
         steps=[('preprocessor',
                 ColumnTransformer(n_jobs=None, remainder='drop',
                                   sparse_threshold=0.3,
                                   transformer_weights=None,
                                   transformers=[('cat',
                                                  Pipeline(memory=None,
                                                           steps=[('one-ho
t',
                                                                   OneHotEnc
oder(categorical_features=None,

categories=None,

drop=None,

dtype=<class 'numpy.float64'>,

handle_unknown='error',

n_values=None,

sparse=True))],
                                                           verbos...
                                                           steps=[('same',
                                                                   FunctionT
ransformer(accept_sparse=False,

check_inverse=True,

func=<function <lambda> at 0x000002093B057488>,

inv_kw_args=None,

inverse_func=None,

kw_args=None,

pass_y='deprecated',

validate=None))],
                                                           verbose=False),
                                                  ['Spend'])],
                                   verbose=False)),
                ('regressor',
                 LinearRegression(copy_X=True, fit_intercept=True, n_jobs=No
```

```
ne,
                                  normalize=False))],
         verbose=False)
```

Performence

In [980]:

```
# get the predict values of trainning sets and calculate rmse and r2 score of trainning set
base_predict_train = plb.predict(x_train)
base_rmse_train = math.sqrt(mean_squared_error(base_predict_train, y_train))
base_r2_train = plb.score(x_train, y_train)
print("baseline model rmse_train: ", base_rmse_train)
print("baseline model r2_train: ", base_r2_train)
```

```
baseline model rmse_train:  2028559.1175926698
baseline model r2_train:  0.7955913044571379

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tion_transformer.py:97: FutureWarning: The default validate=True will be rep
laced by validate=False in 0.22.
  "validate=False in 0.22.", FutureWarning)
C:\Users\xinrui zhan\Anaconda3\lib\site-packages\sklearn\preprocessing\_func
tion_transformer.py:97: FutureWarning: The default validate=True will be rep
laced by validate=False in 0.22.
  "validate=False in 0.22.", FutureWarning)
```

In [981]:

```
# get the predict values of test sets and calculate rmse and r2 score of test sets
base_predict_test = plb.predict(x_test)
base_rmse_test = math.sqrt(mean_squared_error(base_predict_test, y_test))
base_r2_test = plb.score(x_test, y_test)
print("baseline model rmse_test: ", base_rmse_test)
print("baseline model r2_test: ", base_r2_test)
```

```
baseline model rmse_test:  2010769.3499899418
baseline model r2_test:  0.44890792360942205

C:\Users\xinrui zhan\Anaconda3\lib\site-packages\sklearn\preprocessing\_func
tion_transformer.py:97: FutureWarning: The default validate=True will be rep
laced by validate=False in 0.22.
  "validate=False in 0.22.", FutureWarning)
C:\Users\xinrui zhan\Anaconda3\lib\site-packages\sklearn\preprocessing\_func
tion_transformer.py:97: FutureWarning: The default validate=True will be rep
laced by validate=False in 0.22.
  "validate=False in 0.22.", FutureWarning)
```

In [982]:

```
stats_baseline = pd.DataFrame([[base_rmse_train, base_r2_train], [base_rmse_test, base_r2_t
stats_baseline
```

Out[982]:

	rmse	r2
trainning sets	2.028559e+06	0.795591
test sets	2.010769e+06	0.448908

As we can see, the rmse for both trainning sets and test sets are quite high (but we still do not know whether it is good or bad yet); The r2 score for both sets actually are quite good for a baseline model.

In [810]:

```
pd.DataFrame(base_predict_test).describe()
```

Out[810]:

	0
count	9.960000e+02
mean	5.672722e+05
std	2.125240e+06
min	-5.588122e+06
25%	6.066061e+04
50%	1.780759e+05
75%	4.611449e+05
max	3.795103e+07

Final Model

Analysis

In [918]:

```
X = ads.loc[:, ['Language', 'Spend', 'RegionID', 'Gender', "AgeBracket", 'StartDate', 'EndD
X = clean(X) # calculate duration and repalce nan values
y = ads['Impressions'] # get the y
x_train, x_test, y_train, y_test = train_test_split(X, y, test_size=0.3)
```

In [919]:

```
x_train['Gender'].value_counts()
# huge difference between both and female/male, so transform gender column to 'both/single
```

Out[919]:

```
All       2102
FEMALE     167
MALE        53
Name: Gender, dtype: int64
```

In [920]:

```
x_train['Language'].value_counts()[:10]
# replace nan to all, en to en, and all others to other. Then use one-hot.
```

Out[920]:

```
All      1672
en        404
fr         71
nb         44
nl         32
da         26
en,es      20
de         17
es         11
ar          7
Name: Language, dtype: int64
```

In [921]:

```
x_train['RegionID'].value_counts()[:10]
# same method with gender since the number of all is huge.
```

Out[921]:

```
All           1619
Minnesota      212
Florida         43
Virginia        41
Colorado        40
Arizona         20
Iowa            20
Texas           15
Queensland      11
California      11
Name: RegionID, dtype: int64
```

In [922]:

```
x_train['AgeBracket'].value_counts()[:10]
# keep 18+, all, and 18-30, replace all others with 'others' and then one hot
```

Out[922]:

```
18+      760
18-30    238
All      215
18-34    167
17+       81
18-24     74
25+       60
18-29     60
21+       57
18-25     54
Name: AgeBracket, dtype: int64
```

In [923]:

```
x_train['Segments'].value_counts()[:10]
# since only two, replace with 1/0 (all or provided by advertiser)
```

Out[923]:

```
Provided by Advertiser    1540
All                        782
Name: Segments, dtype: int64
```

Helper functions

In [924]:

```
def cal_days(df):
    # calculating how many months
    df[['StartDate', 'EndDate']] = df[['StartDate', 'EndDate']].apply(pd.to_datetime) # tra
    today = datetime.datetime(2019, 12, 5, tzinfo=datetime.timezone.utc)
    df['EndDate'] = df['EndDate'].fillna(today) # replace the nan with today(12/4/2019)
    func = lambda x: len([dt for dt in rrule(DAILY, dtstart=x['StartDate'], until=x['EndDat
    duaration = df.apply(func, axis=1) # calculate how many days
    return duaration
```

In [925]:

```
def clean(df):
    df = (
        df
        .assign(Duration=cal_days(df))
        .drop(columns=['StartDate', 'EndDate'])
        .fillna('All')
    )
    return df
```

In [926]:

```
def trans_01(df):
    return pd.DataFrame(df.iloc[:, 0].apply(lambda x: 1 if x == 'All' else 0))
```

In [927]:

```
def trans_language(df):
    df = df.iloc[:,0]
    df = df.apply(lambda x: 'others' if x != 'All' and x != 'en' else x)
    return pd.DataFrame(df)
```

In [928]:

```
def trans_age(df):
    df = df.iloc[:,0]
    df = df.apply(lambda x: 'others' if x != 'All' and x != '18+' and x != '18-30' else x)
    return pd.DataFrame(df)
```

Model Training

In [948]:

```
# transform spend to spend per day
money_feat = ['Spend']
money_transformer = Pipeline(steps=[
    ('money_p_d', FunctionTransformer(lambda x: x, validate=True))
])

duration_feat = ['Duration']
duration_transformer = Pipeline(steps=[
    ('duration', FunctionTransformer(lambda x: x, validate=True)),
    ('pca', PCA(svd_solver='full'))
])

# Gender
gender_feat = ['Gender']
gender_transformer = Pipeline(steps=[
    ('01', FunctionTransformer(trans_01, validate=False)),
    ('pca', PCA(svd_solver='full'))
])

# region
region_feat = ['RegionID']
region_transformer = Pipeline(steps=[
    ('01', FunctionTransformer(trans_01, validate=False)),
    ('pca', PCA(svd_solver='full'))
])

# language
language_feat = ['Language']
language_transformer = Pipeline(steps=[
    ('language', FunctionTransformer(trans_language, validate=False)),
    ('one-hot', OneHotEncoder(sparse=False)),
    ('pca', PCA(svd_solver='full'))
])

# AgeBracket
age_feat = ['AgeBracket']
age_transformer = Pipeline(steps=[
    ('age', FunctionTransformer(trans_age, validate=False)),
    ('one-hot', OneHotEncoder(sparse=False)),
    ('pca', PCA(svd_solver='full'))
])

# Segments
seg_feat = ['Segments']
seg_transformer = Pipeline(steps=[
    ('01', FunctionTransformer(trans_01, validate=False)),
    ('pca', PCA(svd_solver='full'))
])

# preprocessing pipeline (put them together)
preproc = ColumnTransformer(transformers=[
    ('money', money_transformer, money_feat),
    ('Duration', duration_transformer, duration_feat),
    ('gender', gender_transformer, gender_feat),
    ('region', region_transformer, region_feat),
    ('language', language_transformer, language_feat),
    ('seg', seg_transformer, seg_feat),
    ('Age', age_transformer, age_feat)
])
```

```
plf = Pipeline(steps=[('prep', preproc), ('regressor', LinearRegression())])
```

In [949]:

```
plf.get_params().keys()
```

Out[949]:

```
dict_keys(['memory', 'steps', 'verbose', 'prep', 'regressor', 'prep__n_job
s', 'prep__remainder', 'prep__sparse_threshold', 'prep__transformer_weight
s', 'prep__transformers', 'prep__verbose', 'prep__money', 'prep__Duration',
'prep__gender', 'prep__region', 'prep__language', 'prep__seg', 'prep__Age',
'prep__money__memory', 'prep__money__steps', 'prep__money__verbose', 'prep__
money__money_p_d', 'prep__money__money_p_d__accept_sparse', 'prep__money__mo
ney_p_d__check_inverse', 'prep__money__money_p_d__func', 'prep__money__money
_p_d__inv_kw_args', 'prep__money__money_p_d__inverse_func', 'prep__money__mo
ney_p_d__kw_args', 'prep__money__money_p_d__pass_y', 'prep__money__money_p_d
__validate', 'prep__Duration__memory', 'prep__Duration__steps', 'prep__Durat
ion__verbose', 'prep__Duration__duration', 'prep__Duration__pca', 'prep__Dur
ation__duration__accept_sparse', 'prep__Duration__duration__check_inverse',
'prep__Duration__duration__func', 'prep__Duration__duration__inv_kw_args',
'prep__Duration__duration__inverse_func', 'prep__Duration__duration__kw_arg
s', 'prep__Duration__duration__pass_y', 'prep__Duration__duration__validat
e', 'prep__Duration__pca__copy', 'prep__Duration__pca__iterated_power', 'pre
p__Duration__pca__n_components', 'prep__Duration__pca__random_state', 'prep_
_Duration__pca__svd_solver', 'prep__Duration__pca__tol', 'prep__Duration__pc
a__whiten', 'prep__gender__memory', 'prep__gender__steps', 'prep__gender__ve
rbose', 'prep__gender__01', 'prep__gender__pca', 'prep__gender__01__accept_s
parse', 'prep__gender__01__check_inverse', 'prep__gender__01__func', 'prep__
gender__01__inv_kw_args', 'prep__gender__01__inverse_func', 'prep__gender__0
1__kw_args', 'prep__gender__01__pass_y', 'prep__gender__01__validate', 'prep
__gender__pca__copy', 'prep__gender__pca__iterated_power', 'prep__gender__pc
a__n_components', 'prep__gender__pca__random_state', 'prep__gender__pca__svd
_solver', 'prep__gender__pca__tol', 'prep__gender__pca__whiten', 'prep__regi
on__memory', 'prep__region__steps', 'prep__region__verbose', 'prep__region__
01', 'prep__region__pca', 'prep__region__01__accept_sparse', 'prep__region__
01__check_inverse', 'prep__region__01__func', 'prep__region__01__inv_kw_arg
s', 'prep__region__01__inverse_func', 'prep__region__01__kw_args', 'prep__re
gion__01__pass_y', 'prep__region__01__validate', 'prep__region__pca__copy',
'prep__region__pca__iterated_power', 'prep__region__pca__n_components', 'pre
p__region__pca__random_state', 'prep__region__pca__svd_solver', 'prep__regio
n__pca__tol', 'prep__region__pca__whiten', 'prep__language__memory', 'prep__
language__steps', 'prep__language__verbose', 'prep__language__language', 'pr
ep__language__one-hot', 'prep__language__pca', 'prep__language__language__ac
cept_sparse', 'prep__language__language__check_inverse', 'prep__language__la
nguage__func', 'prep__language__language__inv_kw_args', 'prep__language__lan
guage__inverse_func', 'prep__language__language__kw_args', 'prep__language__
language__pass_y', 'prep__language__language__validate', 'prep__language__on
e-hot__categorical_features', 'prep__language__one-hot__categories', 'prep__
language__one-hot__drop', 'prep__language__one-hot__dtype', 'prep__language_
_one-hot__handle_unknown', 'prep__language__one-hot__n_values', 'prep__langu
age__one-hot__sparse', 'prep__language__pca__copy', 'prep__language__pca__it
erated_power', 'prep__language__pca__n_components', 'prep__language__pca__ra
ndom_state', 'prep__language__pca__svd_solver', 'prep__language__pca__tol',
'prep__language__pca__whiten', 'prep__seg__memory', 'prep__seg__steps', 'pre
p__seg__verbose', 'prep__seg__01', 'prep__seg__pca', 'prep__seg__01__accept_
sparse', 'prep__seg__01__check_inverse', 'prep__seg__01__func', 'prep__seg__
01__inv_kw_args', 'prep__seg__01__inverse_func', 'prep__seg__01__kw_args',
'prep__seg__01__pass_y', 'prep__seg__01__validate', 'prep__seg__pca__copy',
'prep__seg__pca__iterated_power', 'prep__seg__pca__n_components', 'prep__seg
__pca__random_state', 'prep__seg__pca__svd_solver', 'prep__seg__pca__tol',
'prep__seg__pca__whiten', 'prep__Age__memory', 'prep__Age__steps', 'prep__Ag
e__verbose', 'prep__Age__age', 'prep__Age__one-hot', 'prep__Age__pca', 'prep
```

```
__Age__age__accept_sparse', 'prep__Age__age__check_inverse', 'prep__Age__age
__func', 'prep__Age__age__inv_kw_args', 'prep__Age__age__inverse_func', 'pre
p__Age__age__kw_args', 'prep__Age__age__pass_y', 'prep__Age__age__validate',
'prep__Age__one-hot__categorical_features', 'prep__Age__one-hot__categorie
s', 'prep__Age__one-hot__drop', 'prep__Age__one-hot__dtype', 'prep__Age__one
-hot__handle_unknown', 'prep__Age__one-hot__n_values', 'prep__Age__one-hot__
sparse', 'prep__Age__pca__copy', 'prep__Age__pca__iterated_power', 'prep__Ag
e__pca__n_components', 'prep__Age__pca__random_state', 'prep__Age__pca__svd_
solver', 'prep__Age__pca__tol', 'prep__Age__pca__whiten', 'regressor__copy_
X', 'regressor__fit_intercept', 'regressor__n_jobs', 'regressor__normaliz
e'])
```

In [950]:

```
# fit model
ohtpara = [None, 0.90, 0.99, 0.8]
onezero = [None, 0.5, 1]
params = {'prep__language__pca__n_components':ohtpara,
          'prep__Age__pca__n_components':ohtpara,
          'prep__Duration__pca__n_components':onezero,
          'prep__seg__pca__n_components':onezero,
          'prep__gender__pca__n_components':onezero,
          'prep__region__pca__n_components':onezero}
grids = GridSearchCV(plf, param_grid=params, cv=5, iid=False)
grids.fit(x_train, y_train)
```

Out[950]:

```
GridSearchCV(cv=5, error_score='raise-deprecating',
             estimator=Pipeline(memory=None,
                                steps=[('prep',
                                        ColumnTransformer(n_jobs=None,
                                                          remainder='drop',
                                                          sparse_threshold=
0.3,
                                                          transformer_weight
s=None,
                                                          transformers=[('mo
ney',
                                                                         Pip
eline(memory=None,

steps=[('money_p_d',

FunctionTransformer(accept_sparse=False,

check_inverse=True,

func=<function <lambda> at 0x000002093B8A...
             param_grid={'prep__Age__pca__n_components': [None, 0.9, 0.99,
0.8],
                         'prep__Duration__pca__n_components': [None, 0.5,
1],
                         'prep__gender__pca__n_components': [None, 0.5, 1],
                         'prep__language__pca__n_components': [None, 0.9, 0.
99,
                                                               0.8],
                         'prep__region__pca__n_components': [None, 0.5, 1],
                         'prep__seg__pca__n_components': [None, 0.5, 1]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring=None, verbose=0)
```

In [953]:

```
grids.best_params_
```

Out[953]:

```
{'prep__Age__pca__n_components': 0.8,
 'prep__Duration__pca__n_components': None,
 'prep__gender__pca__n_components': None,
 'prep__language__pca__n_components': None,
 'prep__region__pca__n_components': None,
 'prep__seg__pca__n_components': None}
```

In [951]:

```
# get the predict values of trainning sets and calculate rmse and r2 score of trainning set
final_predict_train = grids.predict(x_train)
final_rmse_train = math.sqrt(mean_squared_error(final_predict_train, y_train))
final_r2_train = grids.score(x_train, y_train)
print("final model rmse_train: ", final_rmse_train)
print("final model r2_train: ", final_r2_train)
```

```
final model rmse_train:  2466698.010610956
final model r2_train:  0.7132773197014166
```

In [952]:

```
# get the predict values of test sets and calculate rmse and r2 score of test sets
final_predict_test = grids.predict(x_test)
final_rmse_test = math.sqrt(mean_squared_error(final_predict_test, y_test))
final_r2_test = grids.score(x_test, y_test)
print("final model rmse_test: ", final_rmse_test)
print("final model r2_test: ", final_r2_test)
```

```
final model rmse_test:  1355101.7457937612
final model r2_test:  0.6158357853569362
```

In [985]:

```
stats_final = pd.DataFrame([[final_rmse_train, final_r2_train], [final_rmse_test, final_r2_
stats_final
```

Out[985]:

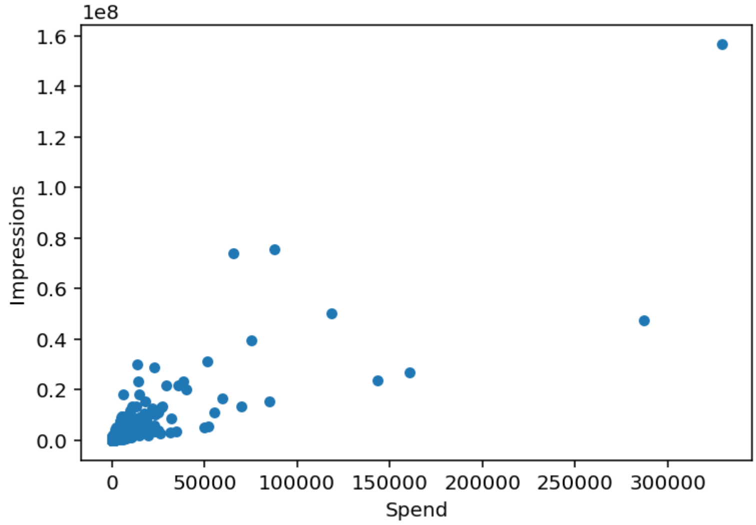
	rmse	r2
trainning sets	2.466698e+06	0.713277
test sets	1.355102e+06	0.615836

In [940]:

```
ads[['Spend', 'Impressions']].plot(x='Spend', y='Impressions', kind='Scatter') # a few outl
```

Out[940]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2093bbdf710>
```

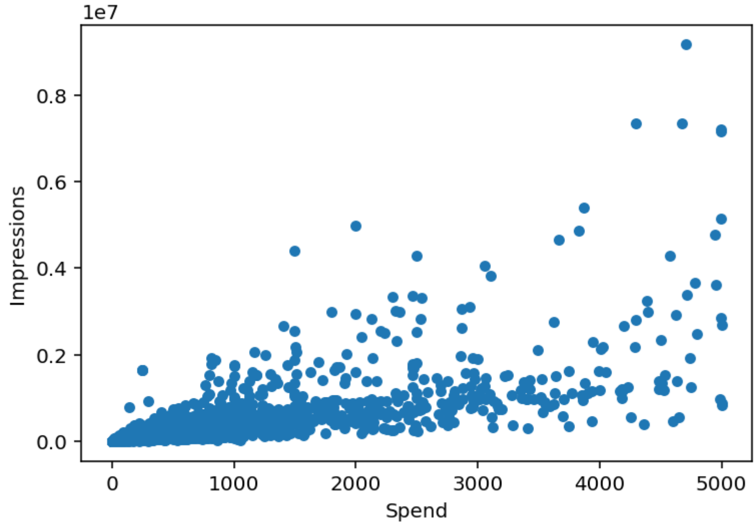


In [941]:

```
ads.loc[ads['Spend'] <= 5000][['Spend', 'Impressions']].plot(x='Spend', y='Impressions', ki
```

Out[941]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2093b02b908>
```

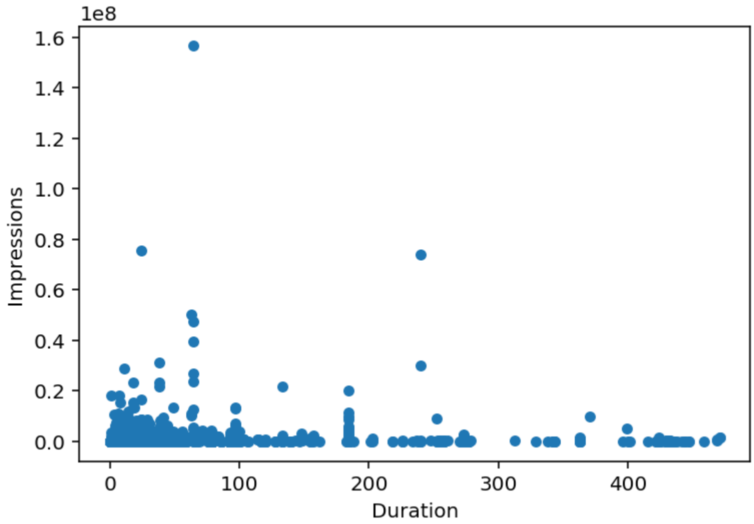


In [946]:

```
full = X.assign(Impressions=y)
full[['Duration', 'Impressions']].plot(x='Duration', y='Impressions', kind='Scatter')
```

Out[946]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2093bb864a8>
```



Fairness Evaluation

In [1070]:

```
# Fairness will be investigated in predict values of x_test.
fair = (
    x_test
    .assign(predicts=final_predict_test)
    .assign(real=y_test)
    .reset_index(drop=True)
)
```

In [1071]:

```
fair.head() # values 'ALL' means nan in orignial dataset. it will have no effect on our Fai
```

Out[1071]:

	Language	Spend	RegionID	Gender	AgeBracket	Segments	Duration	predicts	
0	All	252	All	FEMALE	18+	Provided by Advertiser	15	220551.171258	71
1	All	119	Wien	All	35++	Provided by Advertiser	21	100693.379105	73
2	en	314	All	All	20-	All	66	239700.253395	169
3	All	19	Minnesota	All	18-30	Provided by Advertiser	77	25521.459368	6
4	en	1	All	All	All	Provided by Advertiser	50	28075.053181	

In [1072]:

```
# assign differen column |predicts - real|
fair = fair.assign(diff=abs(fair['predicts'] - fair['real']))
fair.head()
```

Out[1072]:

	Language	Spend	RegionID	Gender	AgeBracket	Segments	Duration	predicts	
0	All	252	All	FEMALE	18+	Provided by Advertiser	15	220551.171258	71
1	All	119	Wien	All	35++	Provided by Advertiser	21	100693.379105	73
2	en	314	All	All	20-	All	66	239700.253395	169
3	All	19	Minnesota	All	18-30	Provided by Advertiser	77	25521.459368	6
4	en	1	All	All	All	Provided by Advertiser	50	28075.053181	

In [1073]:

```
# total rmse
total_rmse = final_rmse_test
total_rmse
```

Out[1073]:

```
1355101.7457937612
```

In [1074]:

```
# lets see how each gender's performence
grps = fair.groupby('Gender')['diff'].apply(lambda x: math.sqrt((x**2).sum()))
grps
```

Out[1074]:

```
Gender
All       1.465952e+07
FEMALE    1.610217e+06
MALE      6.761784e+05
Name: diff, dtype: float64
```

we see there is a huge difference between 'MALE' and total_rmse, lets run a permutation test to see whether these is a unfair prediction toward 'MALE'. More specifically, models did better on data whose Gender value is MALE

- Null Hypothesis: there is no difference between rmse in ['diff'] when Gender is MALE and total_rmse
- Alternative Hypothesis: rmse in ['diff'] when Gender is MALE is lower than total_rmse, which means that our better predicts a better result when Gender is MALE
- Test stats: difference between rooted mean square of column['diff'] when Gender is 'MALE' and total_rmse
- Significant Level: 0.95

In [1075]:

```
g = fair[['Gender', 'diff']]
obs = total_rmse - grps['MALE']
obs
```

Out[1075]:

```
678923.3085604407
```

In [1079]:

```
stats = []
for i in range(100):
    spl = pd.DataFrame()
    spl = (
        spl
        .assign(samp_gender=(g['Gender'].sample(frac=1, replace=False).reset_index(drop=Tru
        .assign(samp_diff=g['diff'])
        .groupby('samp_gender')['samp_diff'].apply(lambda x: math.sqrt((x**2).sum()))
    )
    stats.append(total_rmse - spl['MALE'])
```

In [1081]:

```
p_value = (stats > obs).sum()/len(stats)
p_value
```

Out[1081]:

```
0.01
```

Since 0.01 < 0.025, we have enough evidence to say null hypothesis is wrong. In other words, we may can say that our model did a better job on columns whose Gender is MALE. However, remeber that we combined "MALE" and "FEMALE' into one category "NOT All" when trainning our model. As a result, if our model did a better job on "MALE", it should did a better job on "FEMALE" too. In other words, our model should predicts a high rmse results when "Gender" is 'ALL'

so lets run a permutation test to see whether our model have a bias on column whose Gender is 'ALL'.

In [1053]:

```
#
test_all = fair[['Gender', 'diff']]
test_all.loc[:,'Gender'] = test_all['Gender'].replace({'MALE': 'NOTAll', 'FEMALE': 'NOTAll'
test_all.head()
```

Out[1053]:

	Gender	diff
0	NOTAll	148812.171258
1	All	27461.379105
2	All	70694.253395
3	All	19281.459368
4	All	27379.053181

- Null Hypothesis: there is no difference between rmse in ['diff'] when Gender is All and NOTAll
- Alternative Hypothesis: rmse in ['diff'] when Gender is ALL is higher than rmse in ['diff] when Gender is NOTAll.
- Test stats: absolute difference between rooted mean square of column['diff'] when Gender is ‘ALL’ and NOTAll
- Significant Level: 0.95

In [1056]:

```
grps = test_all.groupby('Gender')['diff'].apply(lambda x: math.sqrt((x**2).sum()))
grps
```

Out[1056]:

```
Gender
All       1.465952e+07
NOTAll    1.746430e+06
Name: diff, dtype: float64
```

In [1065]:

```
obs = grps[0] - grps[1]
obs
```

Out[1065]:

12913085.629401743

In [1066]:

```
stats = []
for i in range(100):
    spl = pd.DataFrame()
    spl = (
        spl
        .assign(samp_gender=(test_all['Gender'].sample(frac=1, replace=False).reset_index(d
        .assign(samp_diff=test_all['diff'])
        .groupby('samp_gender')['samp_diff'].apply(lambda x: math.sqrt((x**2).sum()))
    )
    stats.append(spl[0] - spl[1])
```

In [1067]:

```
p_value = (stats > obs).sum()/len(stats)
p_value
```

Out[1067]:

0.0

since 0,0 is less than 0.025, we have enough evidences to say that rmse in ['diff'] when Gender is All is higher than rmse in ['diff'] when Gender is 'MALE" or "FEMALE"; In other words, we may can say our model has a bias toward input whose Gender is "ALL".

In [ ]:

```

```