A. Last Name: Kaushik.

B. Date: 14th Aug, 2017.

C. This solution is reflects a good mix of concepts of EDA, feature engineering, Model selection and parameter tuning to derive significant Out-of-Bag validation score.

D. Estimated AUC: 0.91

E. Paramter Tuning using Out-of-Bag validation resuts.

Importing Required Libraries

In [1]:
```
import pandas as pd
import numpy as np

import seaborn as sns

from sklearn import model_selection, preprocessing, ensemble
from sklearn import metrics

from sklearn.ensemble import RandomForestClassifier

from collections import OrderedDict
import warnings
warnings.filterwarnings("ignore")

import matplotlib.pyplot as plt

%matplotlib inline
```

Reading the data

In [2]:
```
train = pd.read_csv("train0.csv")
test = pd.read_csv("test0.csv")
```

In [3]:
```
#Glimpse of the dataset
train.head()
```

Out[3]:

	age	cost_of_ad	device_type	gender	in_initial_launch_location	income	n_drivers	n_vehicles	prior_ins_tenure	outcome
0	56	0.005737	iPhone	M	0	62717	2	1	4	0
1	50	0.004733	desktop	F	0	64328	2	3	2	0
2	54	0.004129	laptop	M	0	83439	1	3	7	0
3	16	0.005117	Android	F	0	30110	2	3	0	0
4	37	0.003635	desktop	M	0	76565	2	1	5	0

In [4]:
```
#Correcting the daat types

train['device_type'] = train['device_type'].astype('category')
train['gender'] = train['gender'].astype('category')

test['device_type'] = test['device_type'].astype('category')
test['gender'] = test['gender'].astype('category')
```

In [5]:
```
train.dtypes
```

Out[5]:
```
age                              int64
cost_of_ad                     float64
device_type                   category
gender                        category
in_initial_launch_location       int64
income                           int64
n_drivers                        int64
n_vehicles                       int64
prior_ins_tenure                 int64
outcome                          int64
dtype: object
```

EDA

In [6]:
```python
#Ouutcome Class Distribution in percentage

(train.outcome.value_counts()/len(train.outcome))*100
```

Out[6]:
```
0    90.18
1     9.82
Name: outcome, dtype: float64
```

Class Skew is high and Approaches like:

1. Undersampling.

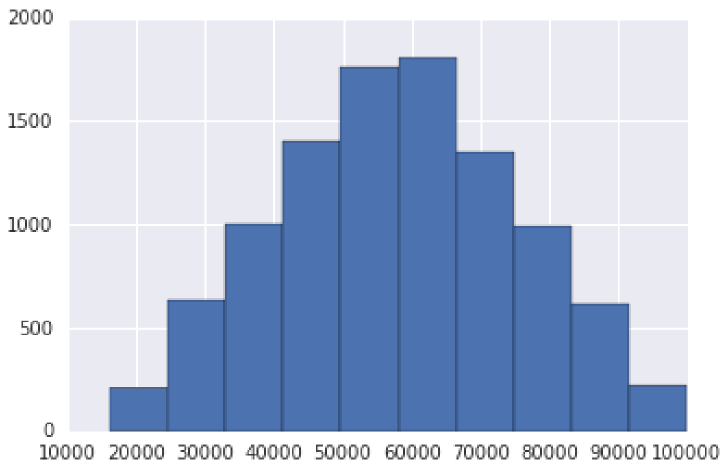
2. Oversampling.

3. Using Error Functions like F-Score, logloss for training.

Can be used. But since the evaluation metric in this test is auc, we'll use auc as well on the orignam dataset simulate the performance on test set through cross-validation

In [7]:
```python
train.income.hist()
```

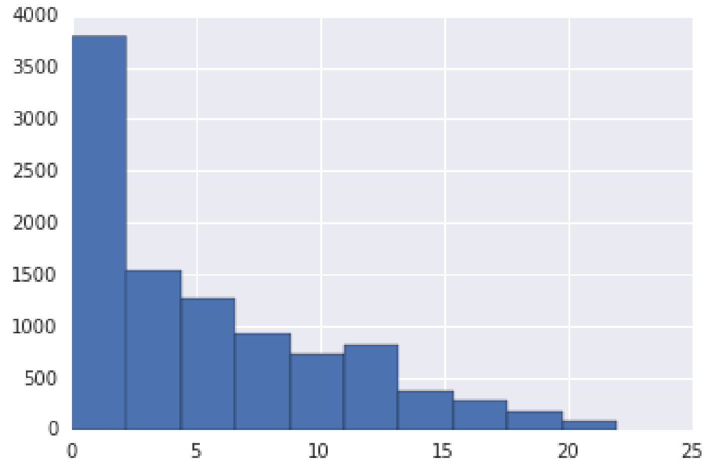
Out[7]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f9409ed43c8>
```



Generally the income distributions have long tails. This looks preety normally distributed. The data must have been treated beforehand.

In [8]:
```python
train.prior_ins_tenure.hist()
```

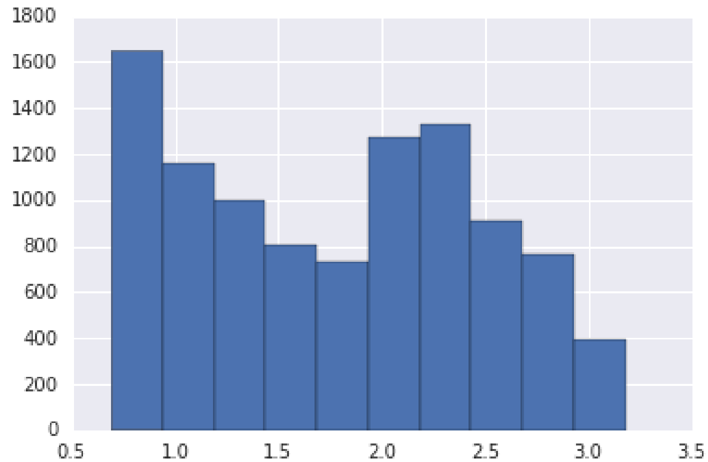
Out[8]: <matplotlib.axes._subplots.AxesSubplot at 0x7f9409df6cc0>



The distribution has heavy positive sckew. We can reduce the scew in this case by taking log(k+n) transformation.

In [9]:
```
np.log(2+train.prior_ins_tenure).hist()
```

Out[9]: <matplotlib.axes._subplots.AxesSubplot at 0x7f9438176630>



In [10]:
```
train.prior_ins_tenure = np.log(2+train.prior_ins_tenure)
test.prior_ins_tenure = np.log(2+test.prior_ins_tenure)
```

In [11]:
```
pd.crosstab(train.outcome, train.device_type, rownames=['Outcome'], colnames=['Device_Type'], margins=True)
```

Out[11]:

Device_Type	Android	desktop	iPhone	laptop	other	All
Outcome						
0	1719	1685	1803	1901	1910	9018
1	304	347	165	90	76	982
All	2023	2032	1968	1991	1986	10000

laptop and other devices have significantly lower ad click proportion compared to other platforms

In [12]:
```
pd.crosstab(train.outcome, train.gender, rownames=['Outcome'], colnames=['gender'], margins=True)
```

Out[12]:

gender	F	M	All
Outcome			
0	4677	4081	8758
1	293	680	973
All	4970	4761	9731

There are more number of females but males have more than double ad clicks than females.

In [13]:
```
pd.crosstab(train.outcome, train.in_initial_launch_location, rownames=['Outcome'], colnames=['in_initial_launch_location'], margins=True)
```

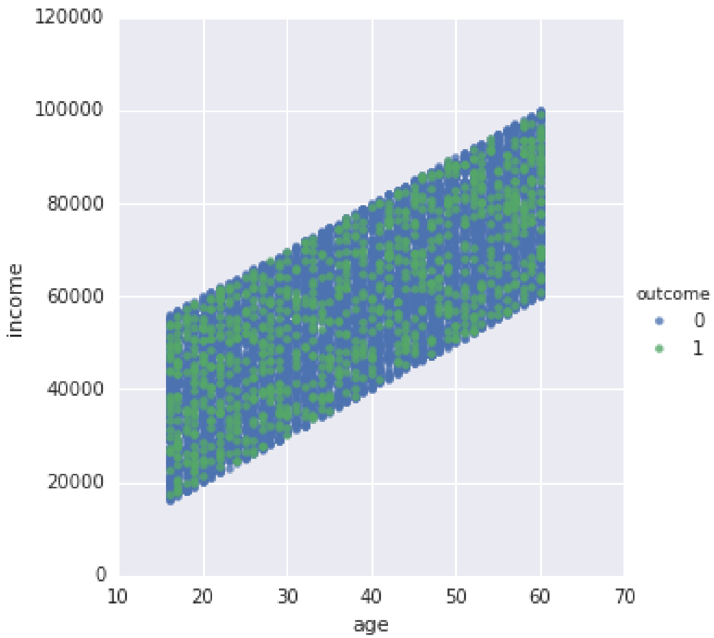
Out[13]:

in_initial_launch_location	0	1	All
Outcome			
0	4705	4313	9018
1	320	662	982
All	5025	4975	10000

Also, being in in initial launch location doubles the chances of clicking on an ad.

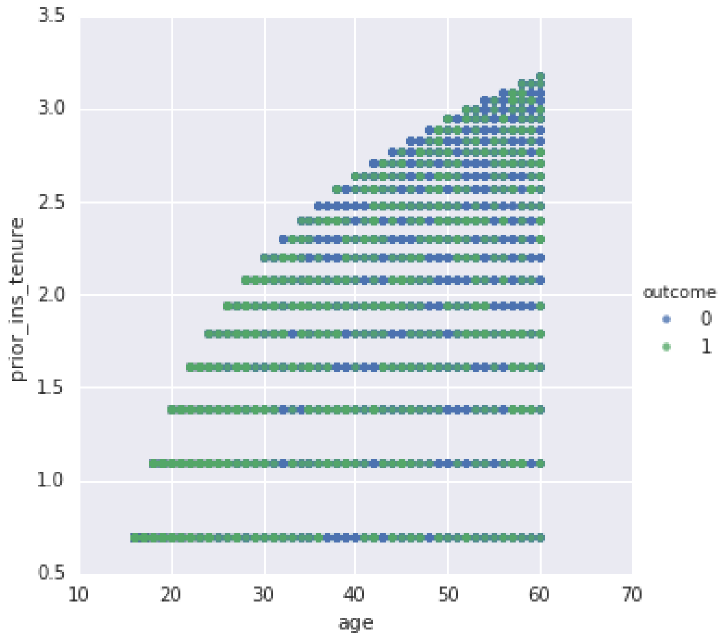
In [14]:
```
sns.lmplot(x='age', y='income', data=train,
           fit_reg=False, # No regression line
           hue='outcome')   # Color by evolution stage
```

Out[14]: <seaborn.axisgrid.FacetGrid at 0x7f9400542c18>



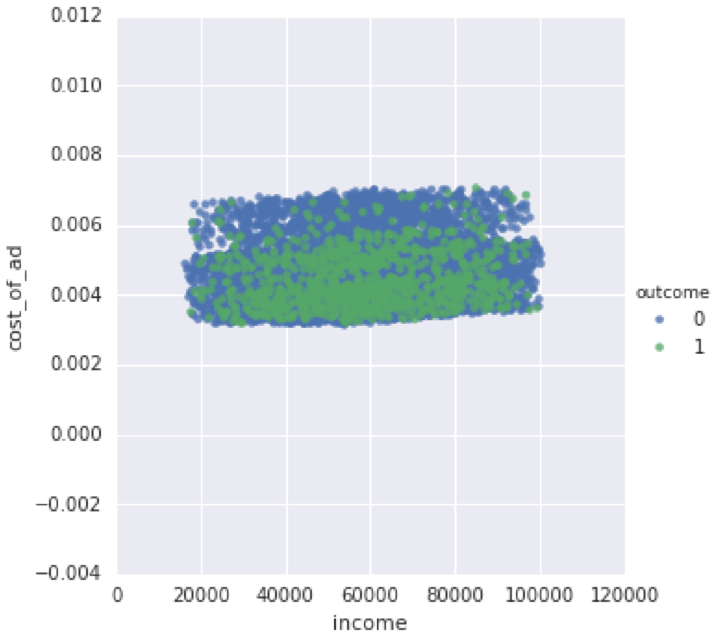
In [15]:
```
sns.lmplot(x='age', y='prior_ins_tenure', data=train,
           fit_reg=False,
           hue='outcome')
```

Out[15]: <seaborn.axisgrid.FacetGrid at 0x7f940042ff60>



In [16]:
```
sns.lmplot(x='income', y='cost_of_ad', data=train,
           fit_reg=False,
           hue='outcome')
```

Out[16]: <seaborn.axisgrid.FacetGrid at 0x7f94003b5160>



Observatios:

1. All these plots conforms our hypothisis that the data has been processed as it the plots look very indifferent.

2. By observing the color dimension, its clear that the outcome exhibits non-linear relationship with majority of the preictors. Therefore, tree based models are suited for this dataset. I'll use Random Forest model for this problem which leverages the bagging concept (growing multiple decesion trees with sample of features on bootstrap samples of the orignal data) to overcome the high variance issue observed in single decision trees.

Feature Engineering

Performing one hot encoding for device_type and gender features

In [17]:
```
oh = pd.get_dummies(train[['device_type', 'gender']])

train.drop(['device_type', 'gender'], axis=1, inplace=True)

train = pd.concat([train, oh], axis = 1)
```

In [18]:
```
oh2 = pd.get_dummies(test[['device_type', 'gender']])

test.drop(['device_type', 'gender'], axis=1, inplace=True)

test = pd.concat([test, oh2], axis = 1)
```

Creating a feature for income to age ratio

In [19]:
```
train['income_by_age'] = train.income/ train.age
test['income_by_age'] = test.income/ test.age
```

Creating a feature for no. of drivers per vehicle

In [20]:
```
train['drivers_per_vehicle'] = train.n_vehicles/train.n_drivers
test['drivers_per_vehicle'] = test.n_vehicles/test.n_drivers
```

Data Prepration

In [21]:
```
train_y = train.outcome

train.drop('outcome', axis=1, inplace=True)

train_X = train
```

In [22]:
```
test_X = test
```

In [23]:
```
print(train_X.shape)
print(train_y.shape)

print(test_X.shape)
```

```
(10000, 16)
(10000,)
(10000, 16)
```

Modelling

Findding the optimal paramteres on out of sample error.

In [24]:
```
RANDOM_STATE = 0

ensemble_clfs = [
    ("RandomForestClassifier, max_features='sqrt'",
        RandomForestClassifier(warm_start=False, oob_score=True,
                               max_features="sqrt",
                               random_state=RANDOM_STATE)),
    ("RandomForestClassifier, max_features='log2'",
        RandomForestClassifier(warm_start=False, max_features='log2',
                               oob_score=True,
                               random_state=RANDOM_STATE)),
    ("RandomForestClassifier, max_features=None",
        RandomForestClassifier(warm_start=False, max_features=None,
                               oob_score=True,
                               random_state=RANDOM_STATE))
]

# Map a classifier name to a list of (<n_estimators>, <error rate>) pairs.
error_rate = OrderedDict((label, []) for label, _ in ensemble_clfs)

# Range of `n_estimators` values to explore.
min_estimators = 10
max_estimators = 500

for label, clf in ensemble_clfs:
    for i in range(min_estimators, max_estimators, 50):
        clf.set_params(n_estimators=i)
        clf.fit(train_X, train_y)

        # Record the OOB error for each `n_estimators=i` setting.
        oob_error = 1 - clf.oob_score_
        error_rate[label].append((i, oob_error))

# Generate the "OOB error rate" vs. "n_estimators" plot.
for label, clf_err in error_rate.items():
    xs, ys = zip(*clf_err)
    plt.plot(xs, ys, label=label)

plt.xlim(min_estimators, max_estimators)
plt.xlabel("n_estimators")
plt.ylabel("OOB error rate")
plt.legend(loc="upper right")
plt.show()
```

Fitting the Random Forest model

In [25]:
```
model = RandomForestClassifier(n_estimators=300, criterion='gini', max_featur
es='log2',
                               bootstrap=True, oob_score=True, n_jobs=16,
                               random_state=RANDOM_STATE)


model.fit(train_X,train_y)
```

Out[25]:
```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
            max_depth=None, max_features='log2', 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=300, n_jobs=16,
            oob_score=True, random_state=0, verbose=0, warm_start=False)
```

Feature Importance

In [26]:
```
imp_df_rf = pd.DataFrame(
    {'Predictors': train_X.columns,
     'Importance': model.feature_importances_.tolist()
    })

imp_df_rf = imp_df_rf.sort(['Importance'], ascending=False)

imp_df_rf
```

Out[26]:

	Importance	Predictors
1	0.176602	cost_of_ad
3	0.166930	income
14	0.164967	income_by_age
0	0.132809	age
6	0.093298	prior_ins_tenure
15	0.051307	drivers_per_vehicle
2	0.046438	in_initial_launch_location
5	0.034792	n_vehicles
8	0.024634	device_type_desktop
7	0.021213	device_type_Android
13	0.019849	gender_M
10	0.017014	device_type_laptop
4	0.015992	n_drivers
11	0.014292	device_type_other
12	0.012280	gender_F
9	0.007584	device_type_iPhone

Expected Accuracy on test set

Let's check an estimate of the accuracy of our model on test set by looking at the model's out of bag accuracy.

In [27]:
```
model.oob_score_
```

Out[27]:
```
0.91020000000000001
```

Predicting for test

Predicting Labels

In [28]:
```
preds = model.predict(test_X)
```

In [29]:
```
pd.value_counts(pd.Series(preds))
```

Out[29]:
```
0    9615
1     385
dtype: int64
```

Predicting probabilities which can be used for leading propensity based advertising campaigns. Also, it can halp in evaluation like observing the aur-roc cure, etc

In [30]:
```
pred_prob = model.predict_proba(test_X)
```

Outputing First 5 preictions

In [31]:
```
preds[:5]
```

Out[31]:
```
array([0, 0, 0, 0, 0])
```

Outputing First 5 preiction probabilities | Of being 1 and 0 respectively

In [32]:
```
pred_prob[:5]
```

Out[32]:
```
array([[ 0.98666667,  0.01333333],
       [ 0.92666667,  0.07333333],
       [ 0.87333333,  0.12666667],
       [ 0.99333333,  0.00666667],
       [ 0.99      ,  0.01      ]])
```

In [ ]: