Introduction

- We predicted the "conversion" evens by identifying critical features by combining the all of these 1000 features. With these critical features, we sampled the same number of position and negative instances in the training set, after that we used "decision tree" "random forest" "adaboost" "gradient boosting" etc. algorithms to predicte the "conversion" events from customers. The higest mean CV score for the training data set is from "random forest" which is 67.3, and the highest accuracy is 69.3% in the validation set with "random forest" algorithms.

Data Preparation

In [577]:

```
import pandas as pd
import ast

def load(file):

    df = pd.read_csv(file)

    # convert the column values from literal string to dictionary
    df['ltiFeatures'] = df['ltiFeatures'].apply(ast.literal_eval)
    df['stiFeatures'] = df['stiFeatures'].apply(ast.literal_eval)

    return df

# load all the data
training = load("valassis_dataset/training.csv")
validation = load("valassis_dataset/validation.csv")
interest_topics = pd.read_csv("valassis_dataset/interest_topics.csv")

# inspect the data
validation.head()
```

Out[577]:

	userID	inAudience	ltiFeatures	stiFeatures
0	0	True	{'89': 0.0027281240558934, '1264': 0.001862958...	{}
1	1	True	{'47': 0.0019292939671486482, '1187': 0.012261...	{}
2	2	True	{'45': 0.001961152113619305, '47': 0.001584126...	{}
3	3	True	{'1253': 0.006566573072362829, '1164': 0.00327...	{}
4	4	True	{'78': 0.013096540307802428, '1198': 0.0025546...	{}

In [8]:
```
interest_topics.head()
```

Out[8]:

	topic_id	topic_name
0	3	/Arts & Entertainment
1	5	/Computers & Electronics
2	7	/Finance
3	8	/Games
4	11	/Home & Garden

In [9]:
```
training.head()
```

Out[9]:

	userID	inAudience	ltiFeatures	stiFeatures
0	1	True	{'45': 0.020536141517834786, '47': 0.003117529...	{}
1	2	True	{'45': 0.001158253110658664, '592': 0.01546380...	{}
2	3	True	{'908': 0.002470851264264668, '590': 0.0021402...	{}
3	4	True	{'1187': 0.001127974558171163, '1780': 0.00117...	{}
4	5	True	{'907': 0.025339209040149392, '1187': 0.006020...	{'907': 0.10445132121076425, '908': 0.05651522...

Inspect the training dataset's inAudience value

In [10]:
```
training.groupby('inAudience').size()
```

Out[10]:
```
inAudience
False    94941
True      1465
dtype: int64
```

After inspecting the inAudience value of the training dataset,we found that the dataset is imbalanced, therefore, we decide to resample the data before applying our model

Feature Engineering

- We first extracted the main topic from the *topic_name* feature and created a **main_topic_mapping** dictionary structure to store the *main_topic* as the **key** and a list structure that holds different *topic_id* that belongs to the same main topic.
- Then we reasoned that it is possible for a user that has more detailed interests to be converted. By this we mean that if a user has interests in lots of subtopics then it is more possible that the user would be convereted. Therefore, we create a new feature that called *topic_name* to count the layers a topic have.

In [578]:
```
interest_topics['main_topic'] = interest_topics['topic_name'].str.split(
'/',expand = True)[1]
interest_topics['sub_topics'] = interest_topics['topic_name'].str.count(
'/')-1
interest_topics
```

Out[578]:

	topic_id	topic_name	main_topic	sub_topics
0	3	/Arts & Entertainment	Arts & Entertainment	0
1	5	/Computers & Electronics	Computers & Electronics	0
2	7	/Finance	Finance	0
3	8	/Games	Games	0
4	11	/Home & Garden	Home & Garden	0
5	12	/Business & Industrial	Business & Industrial	0
6	13	/Internet & Telecom	Internet & Telecom	0
7	14	/People & Society	People & Society	0
8	16	/News	News	0
9	18	/Shopping	Shopping	0
10	19	/Law & Government	Law & Government	0
11	20	/Sports	Sports	0
12	22	/Books & Literature	Books & Literature	0
13	23	/Arts & Entertainment/Performing Arts	Arts & Entertainment	1
14	24	/Arts & Entertainment/Visual Art & Design	Arts & Entertainment	1
15	25	/Business & Industrial/Advertising & Marketing	Business & Industrial	1
16	28	/Business & Industrial/Business Services/Offic...	Business & Industrial	2
17	29	/Real Estate	Real Estate	0
18	30	/Computers & Electronics/Computer Hardware	Computers & Electronics	1
19	31	/Computers & Electronics/Programming	Computers & Electronics	1
20	32	/Computers & Electronics/Software	Computers & Electronics	1
21	33	/Arts & Entertainment/Offbeat	Arts & Entertainment	1
22	34	/Arts & Entertainment/Movies	Arts & Entertainment	1
23	35	/Arts & Entertainment/Music & Audio	Arts & Entertainment	1
24	36	/Arts & Entertainment/TV & Video	Arts & Entertainment	1
25	37	/Finance/Banking	Finance	1
26	38	/Finance/Insurance	Finance	1
27	39	/Games/Card Games	Games	1
28	41	/Games/Computer & Video Games	Games	1
29	42	/Arts & Entertainment/Music & Audio/Jazz & Blu...	Arts & Entertainment	3
...	...	...	...	...
1381	1738	/People & Society/Family & Relationships/Famil...	People & Society	5

	topic_id	topic_name	main_topic	sub_topics
1382	1739	/Computers & Electronics/Software/Multimedia S...	Computers & Electronics	4
1383	1740	/Computers & Electronics/Software/Multimedia S...	Computers & Electronics	4
1384	1741	/People & Society/Family & Relationships/Famil...	People & Society	5
1385	1747	/Autos & Vehicles/Vehicle Parts & Services/Veh...	Autos & Vehicles	3
1386	1748	/Autos & Vehicles/Vehicle Parts & Services/Veh...	Autos & Vehicles	3
1387	1750	/Autos & Vehicles/Vehicle Parts & Services/Veh...	Autos & Vehicles	3
1388	1751	/Autos & Vehicles/Vehicle Parts & Services/Veh...	Autos & Vehicles	3
1389	1757	/Shopping/Photo & Video Services/Event & Studi...	Shopping	2
1390	1758	/Shopping/Photo & Video Services/Photo Printin...	Shopping	2
1391	1763	/Beauty & Fitness/Fitness/Fitness Equipment & ...	Beauty & Fitness	3
1392	1779	/Arts & Entertainment/Humor/Funny Pictures & V...	Arts & Entertainment	2
1393	1780	/Arts & Entertainment/TV & Video/Online Video/...	Arts & Entertainment	3
1394	1783	/Autos & Vehicles/Motor Vehicles (By Brand)/Ra...	Autos & Vehicles	2
1395	1784	/Autos & Vehicles/Motor Vehicles (By Brand)/Te...	Autos & Vehicles	2
1396	1785	/Computers & Electronics/Computer Hardware/Com...	Computers & Electronics	4
1397	1786	/Computers & Electronics/Consumer Electronics/...	Computers & Electronics	5
1398	1787	/Computers & Electronics/Consumer Electronics/...	Computers & Electronics	2
1399	1788	/Computers & Electronics/Consumer Electronics/...	Computers & Electronics	3
1400	1789	/Computers & Electronics/Consumer Electronics/...	Computers & Electronics	2
1401	1790	/Computers & Electronics/Consumer Electronics/...	Computers & Electronics	2
1402	1791	/Computers & Electronics/Consumer Electronics/...	Computers & Electronics	2
1403	1795	/Finance/Investing/Currencies & Foreign Exchan...	Finance	3
1404	1799	/Games/Computer & Video Games/Sandbox Games	Games	2
1405	1800	/Home & Garden/HVAC & Climate Control/Air Filt...	Home & Garden	2
1406	1801	/Jobs & Education/Education/Private Tutoring S...	Jobs & Education	2
1407	1802	/Computers & Electronics/Consumer Electronics/...	Computers & Electronics	4
1408	1804	/Sports/Sports Fan Gear & Apparel	Sports	1
1409	1820	/Finance/Credit & Lending/Loans/Vehicle Financ...	Finance	5
1410	1826	/Food & Drink/Cooking & Recipes/Desserts/Ice C...	Food & Drink	3

1411 rows × 4 columns

In [579]:
```
main_topic_mapping = {} # A dictionary structure key:main_topic values:
[topic_id]
topic_id_list = interest_topics['topic_id']
main_topics = interest_topics['main_topic']
for main_topic,tid in zip(main_topics,topic_id_list):
    if main_topic not in main_topic_mapping:
        main_topic_mapping[main_topic] = []
    else:
        main_topic_mapping[main_topic].append(str(tid))
sub_topics_mapping = interest_topics['sub_topics']
```

- After doing the feature engineering on the **interest_topics** dataset, we used two mappings that we extracted to aggregate the interest proportions for each user in the training dataset. One reasons for aggregating the interest proportions is to simplify the amounts of features, and another reason for aggregating the interest proportions is that we found some user would have interests in some sub topics that have the same main topic. Therefore, it is reasonale to aggregate the interest proportions.
- We then used the **sub_topics_mapping** to compute the total sub topics interested for each user.

In [580]:
```
def aggregateInterest(df,main_topic_mapping):
    features = ['ltiFeatures','stiFeatures']
    for feature in features:
        df_feature = df[feature]
        for main_topic in main_topic_mapping:
            aggInt = pd.DataFrame.from_records(df_feature,columns = np.a
rray(main_topic_mapping[main_topic]))
            aggInt.fillna(0)
            if feature == 'ltiFeatures':
                df[main_topic+'_l'] = aggInt.sum(axis=1)
            else:
                df[main_topic+'_s'] = aggInt.sum(axis=1)
    return df
def computeSubTopics(df,sub_topics_mapping):
    sub_topics = []
    for user in df['ltiFeatures']:
        tot = 0
        for interest in user:
            if int(interest) not in sub_topics_mapping:
                continue
            tot = tot + sub_topics_mapping[int(interest)]
        sub_topics.append(tot)
    df['sub_topics'] = np.array(sub_topics)
    return df
```

In [615]:
```
df_test = aggregateInterest(training,main_topic_mapping)
df_test = computeSubTopics(df,sub_topics_mapping)
df_test.head()
```

Out[615]:

	userID	inAudience	ltiFeatures	stiFeatures	Arts & Entertainment_I	Computer & Electronics_
0	1	True	{'45': 0.020536141517834786, '47': 0.003117529...	{}	0.017379	0.00130
1	2	True	{'45': 0.001158253110658664, '592': 0.01546380...	{}	0.087566	0.00000
2	3	True	{'908': 0.002470851264264668, '590': 0.0021402...	{}	0.182117	0.00000
3	4	True	{'1187': 0.001127974558171163, '1780': 0.00117...	{}	0.044449	0.00842
4	5	True	{'907': 0.025339209040149392, '1187': 0.006020...	{'907': 0.10445132121076425, '908': 0.05651522...	0.121597	0.01023

5 rows × 55 columns

In [616]:
```
df_val = aggregateInterest(validation,main_topic_mapping)
df_val = computeSubTopics(df_val,sub_topics_mapping)
df_val.head()
```

Out[616]:

	userID	inAudience	ltiFeatures	stiFeatures	Arts & Entertainment_I	Computers & Electronics_I	Financ
0	0	True	{'89': 0.0027281240558934, '1264': 0.001862958...	{}	0.272884	0.002753	0.00(
1	1	True	{'47': 0.0019292939671486482, '1187': 0.012261...	{}	0.381401	0.000000	0.00(
2	2	True	{'45': 0.001961152113619305, '47': 0.001584126...	{}	0.216383	0.015894	0.00(
3	3	True	{'1253': 0.006566573072362829, '1164': 0.00327...	{}	0.000000	0.000000	0.01ٍ
4	4	True	{'78': 0.013096540307802428, '1198': 0.0025546...	{}	0.025740	0.028871	0.00(

5 rows × 55 columns

Resampling Training Data

In [584]:
```
from sklearn.utils import resample
df_majority =df[df.inAudience == False]
df_minority =df[df.inAudience == True]
df_majority_downsampled = resample(df_majority, replace = False,
                                   n_samples = 1465)
df_downsampled = pd.concat([df_majority_downsampled,df_minority])
df_downsampled.inAudience.value_counts()
```

Out[584]:
```
True     1465
False    1465
Name: inAudience, dtype: int64
```

Resampling Validation Data

In [585]:
```
val_major = df_val[df_val.inAudience == False]
val_minor = df_val[df_val.inAudience == True]
val_major_resampled = resample(val_major,replace = False,n_samples = 620
)
val_downsampled = pd.concat([val_major_resampled,val_minor])
val_downsampled.inAudience.value_counts()
```

Out[585]:
```
True     620
False    620
Name: inAudience, dtype: int64
```

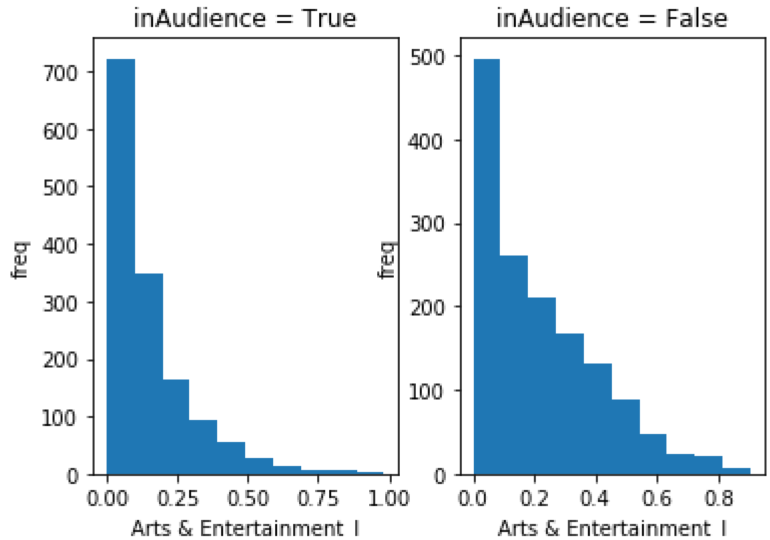
Plots

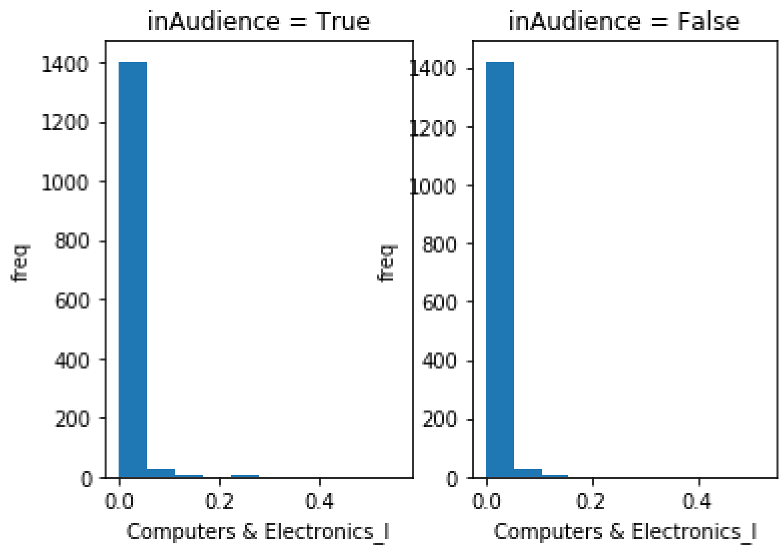
- In this section, we decided to use plots to select features that we think could have high significance on differentiating the classes. We mainly used box plots to see the distribution of each feature.

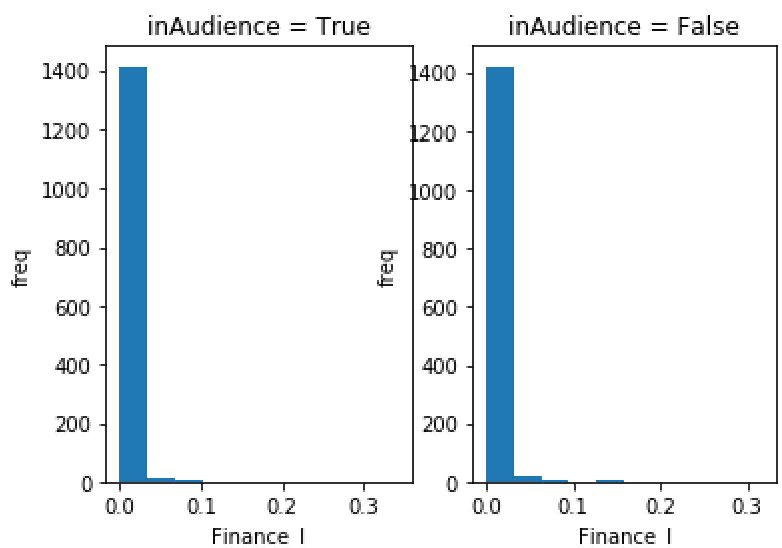
In [617]:
```
topic_features = []
for col in df_downsampled.columns[4:-1]:
    topic_features.append(col)
```

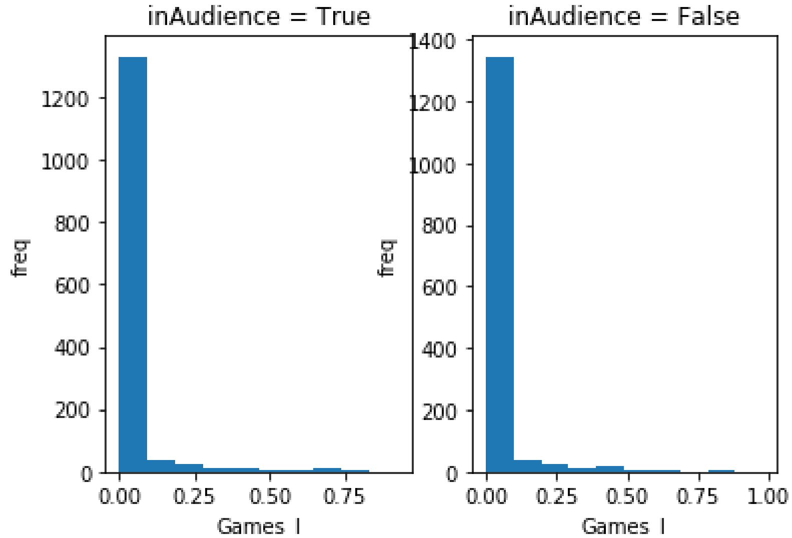
In [624]:
```
def plot(df,features):
    df_true = df[df.inAudience == True]
    df_false = df[df.inAudience == False]
    for feature in features:
        fig,axes = plt.subplots(1,2)
        axes[0].hist(df_true[feature])
        axes[0].set_xlabel(feature)
        axes[0].set_ylabel('freq')
        axes[0].set_title('inAudience = True')
        axes[1].hist(df_false[feature])
        axes[1].set_xlabel(feature)
        axes[1].set_ylabel('freq')
        axes[1].set_title('inAudience = False')
        plt.show()
```

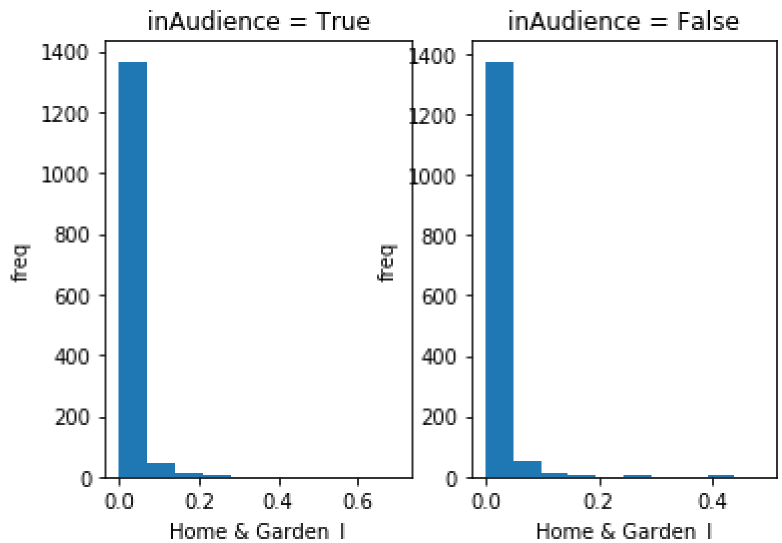
In [625]:
```
plot(df_downsampled,topic_features)
```

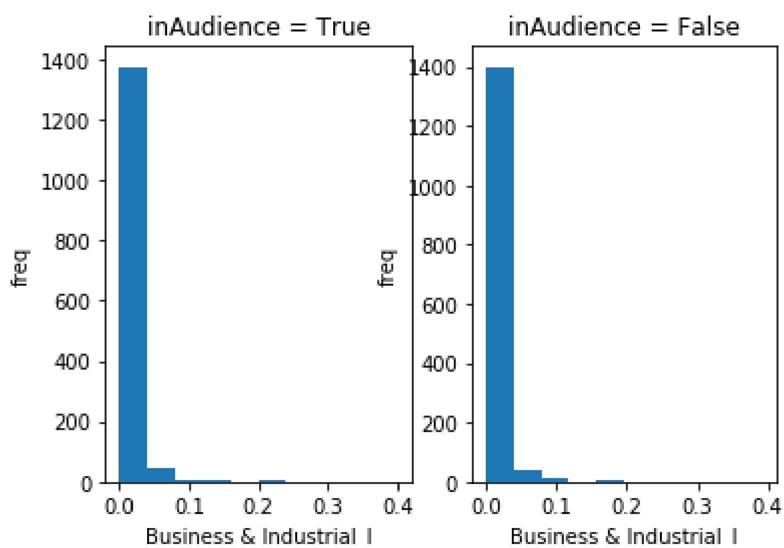

inAudience = True
inAudience = False
freq
Arts & Entertainment_I
0.00 0.25 0.50 0.75 1.00
0.0 0.2 0.4 0.6 0.8
0 100 200 300 400 500 600 700

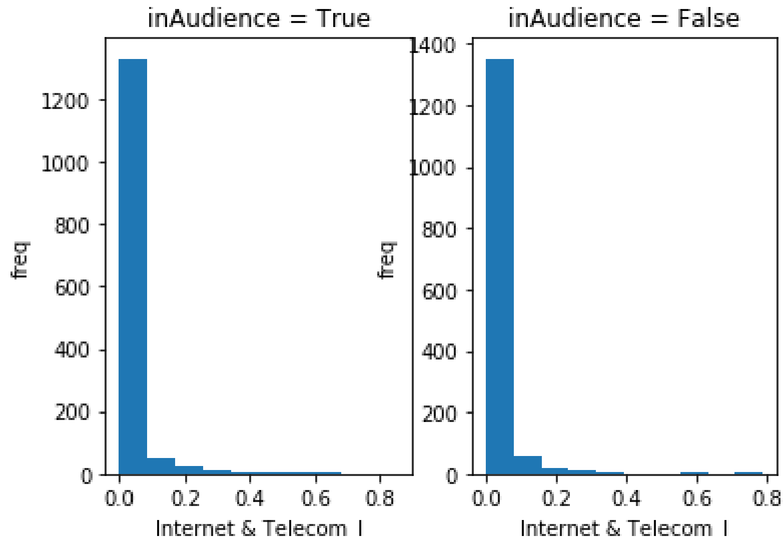

inAudience = True
inAudience = False
freq
Computers & Electronics_I
0.0 0.2 0.4
0 200 400 600 800 1000 1200 1400

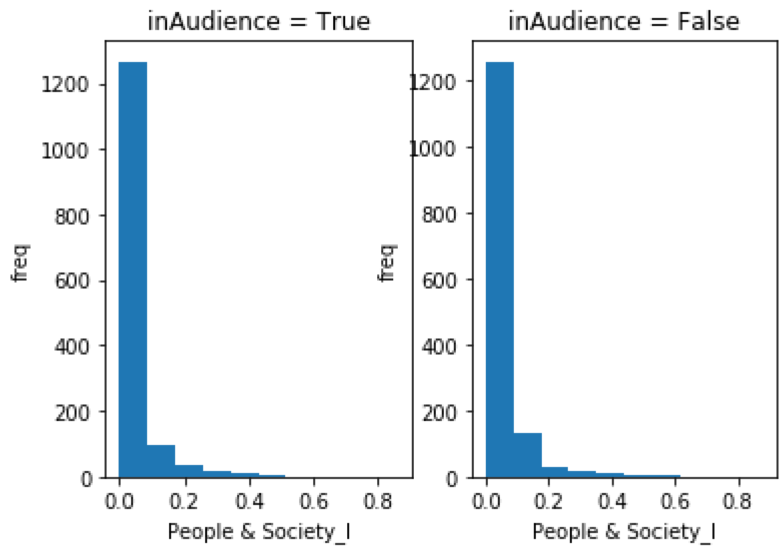

inAudience = True
inAudience = False
freq
Finance_I
0.0 0.1 0.2 0.3
0 200 400 600 800 1000 1200 1400

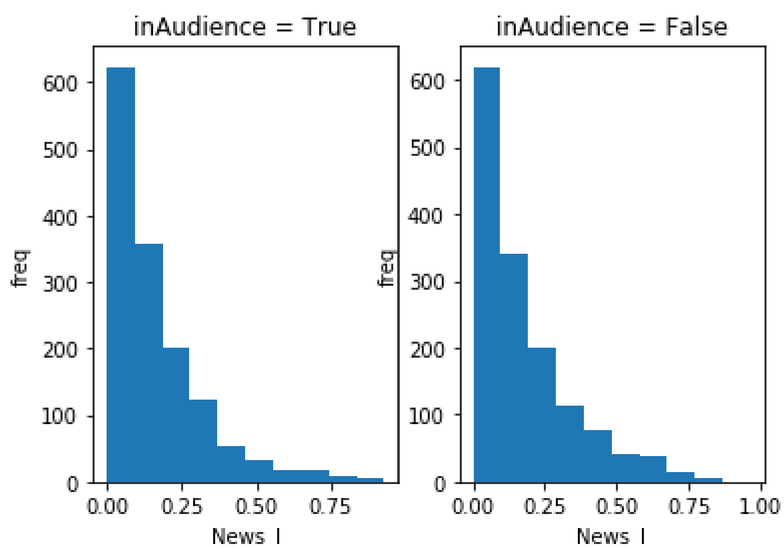

inAudience = True
inAudience = False
freq
0
200
400
600
800
1000
1200
1400
0.00
0.25
0.50
0.75
1.00
Games_l

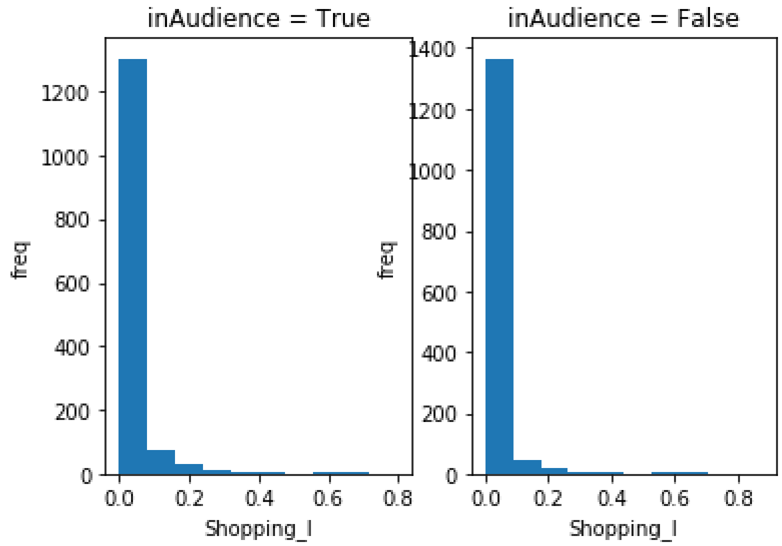

inAudience = True
inAudience = False
freq
0
200
400
600
800
1000
1200
1400
0.0
0.2
0.4
0.6
Home & Garden_l

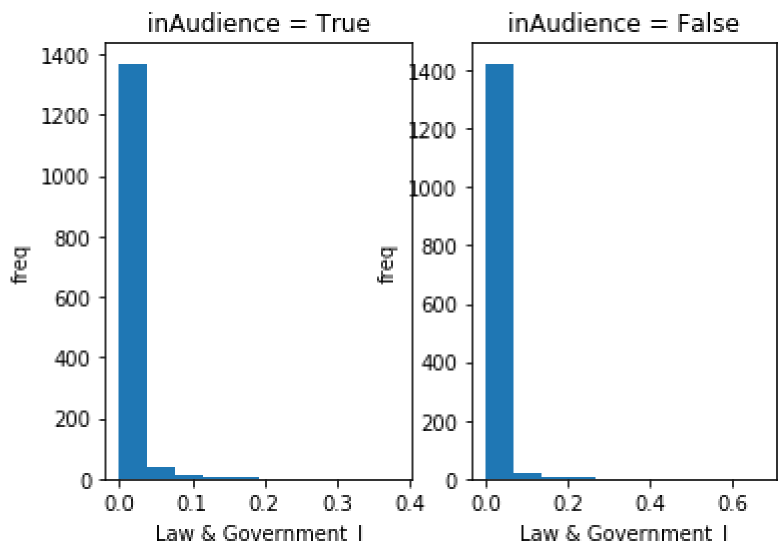

inAudience = True
inAudience = False
freq
0
200
400
600
800
1000
1200
1400
0.0
0.1
0.2
0.3
0.4
Business & Industrial_l

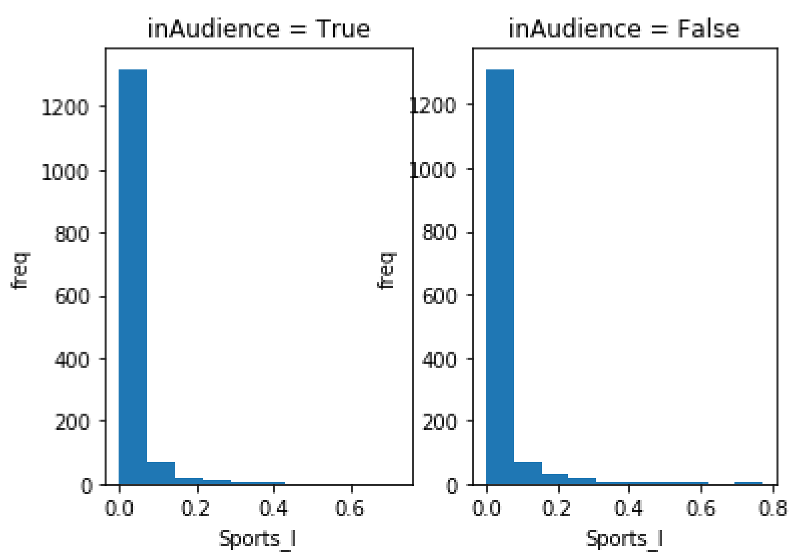

inAudience = True
inAudience = False
freq
Internet & Telecom_I
0.0 0.2 0.4 0.6 0.8
0 200 400 600 800 1000 1200 1400

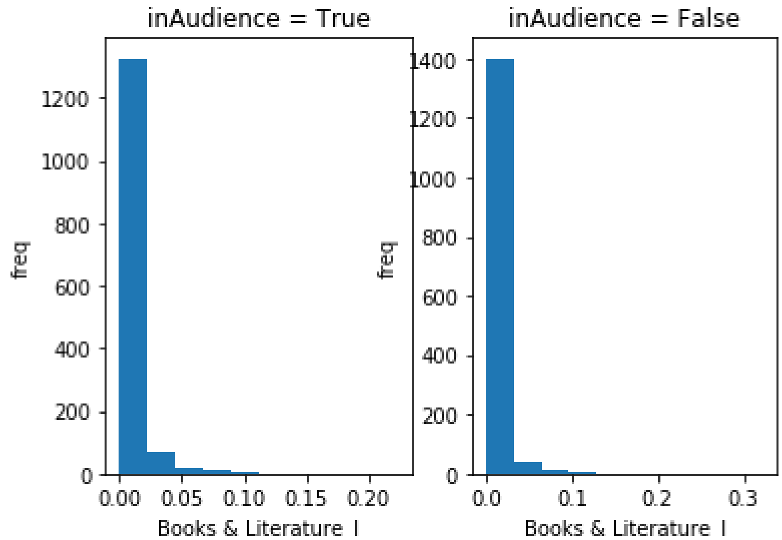

inAudience = True
inAudience = False
freq
People & Society_I
0.0 0.2 0.4 0.6 0.8
0 200 400 600 800 1000 1200

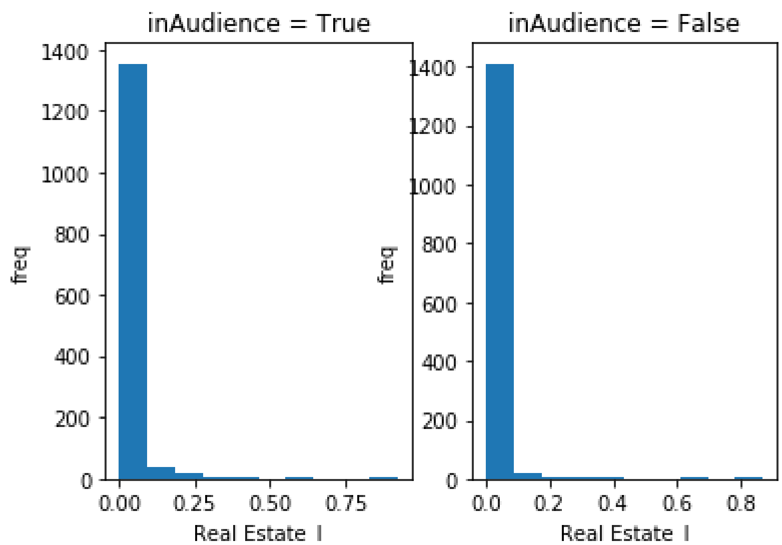

inAudience = True
inAudience = False
freq
News_I
0.00 0.25 0.50 0.75 1.00
0 100 200 300 400 500 600

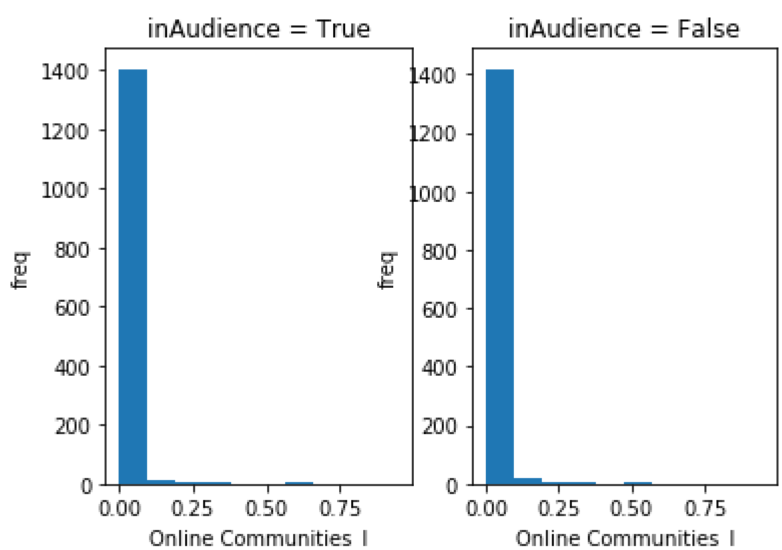

inAudience = True
inAudience = False
freq
Shopping_I
Shopping_I

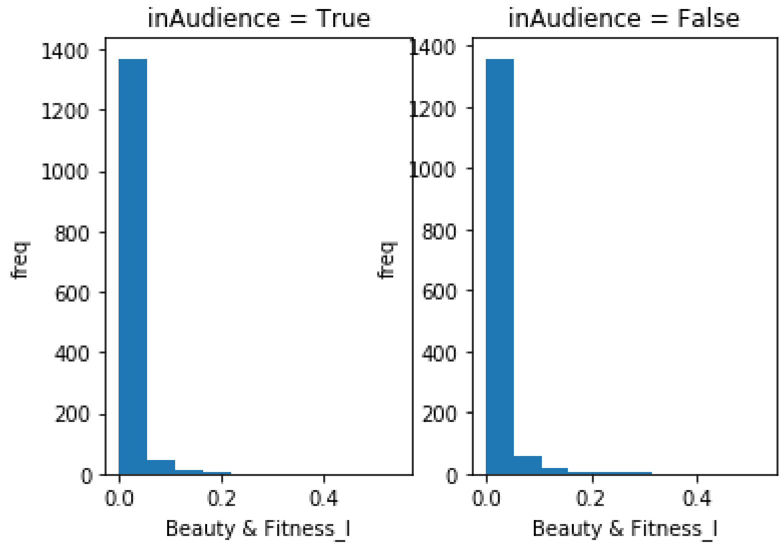

inAudience = True
inAudience = False
freq
Law & Government_I
Law & Government_I

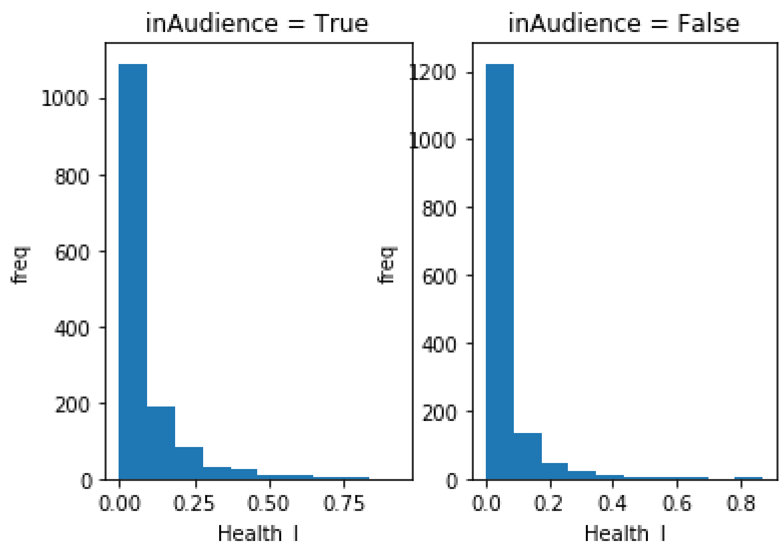

inAudience = True
inAudience = False
freq
Sports_I
Sports_I

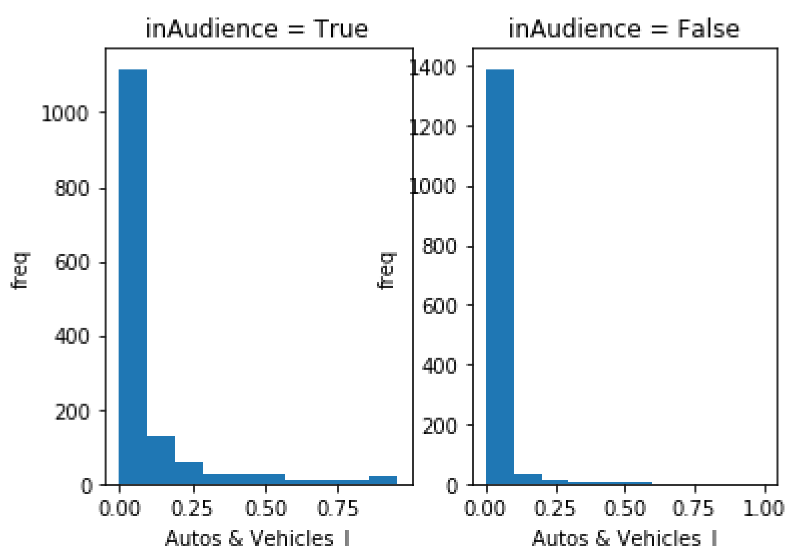

inAudience = True
inAudience = False
freq
Books & Literature_I

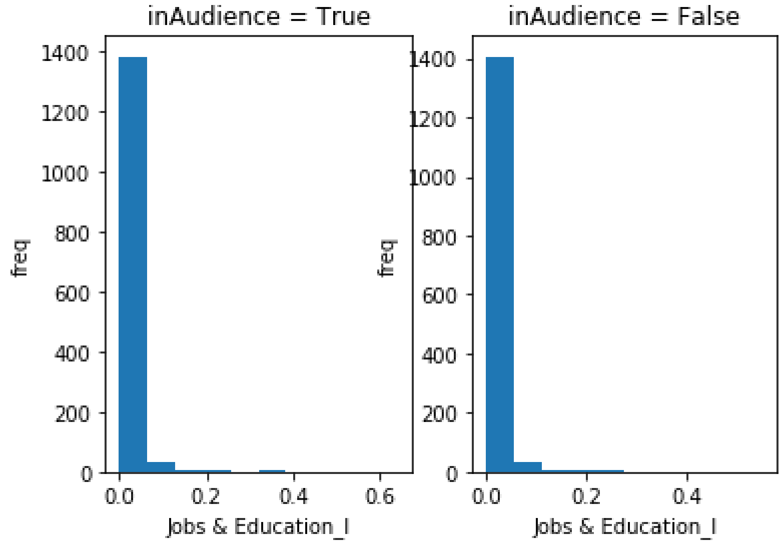

inAudience = True
inAudience = False
freq
Real Estate_I

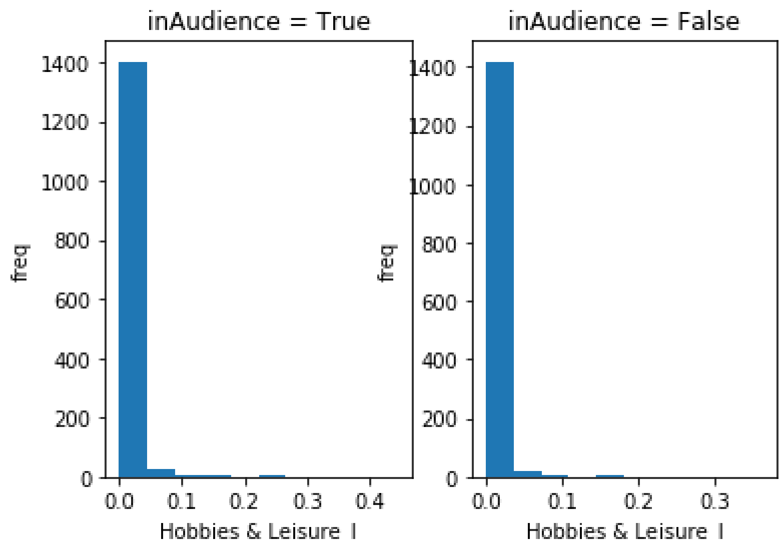

inAudience = True
inAudience = False
freq
Online Communities_I

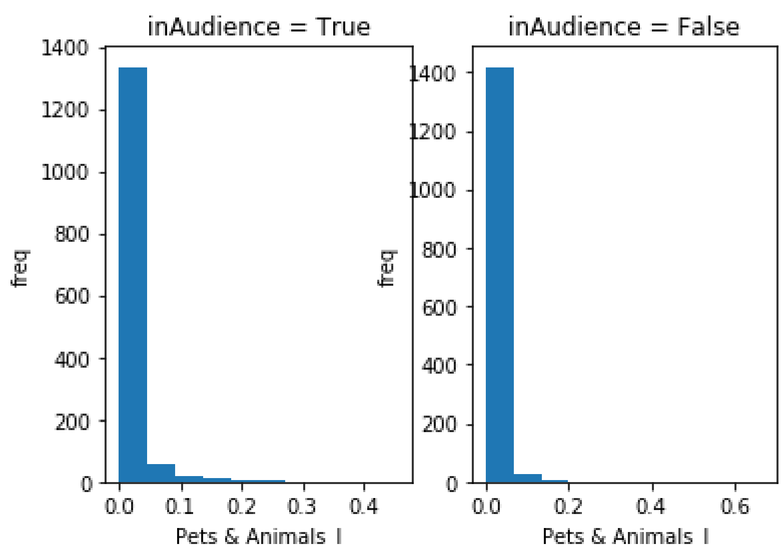

inAudience = True
inAudience = False
freq
Beauty & Fitness_I
0.0
0.2
0.4
0
200
400
600
800
1000
1200
1400

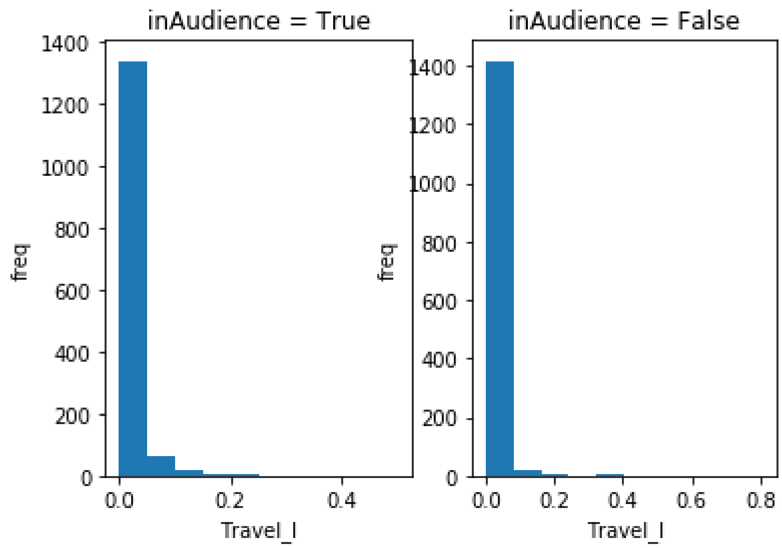

inAudience = True
inAudience = False
freq
Health_I
0.00
0.25
0.50
0.75
0.0
0.2
0.4
0.6
0.8
0
200
400
600
800
1000
1200

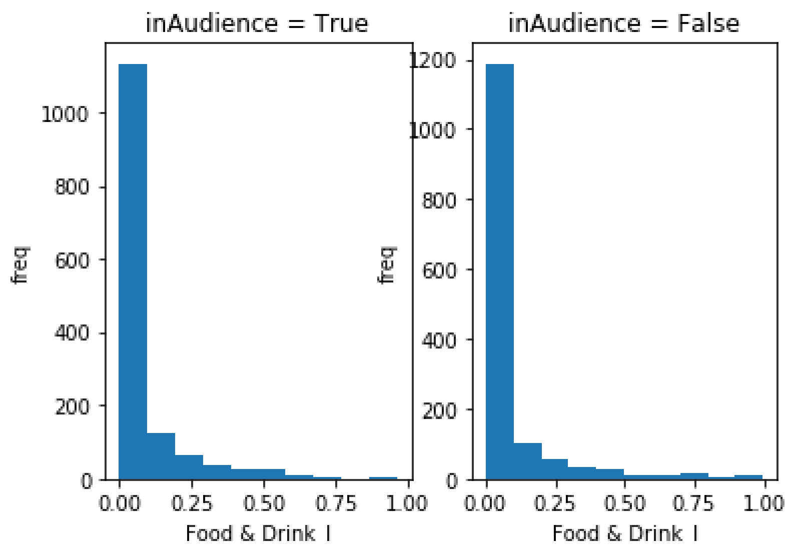

inAudience = True
inAudience = False
freq
Autos & Vehicles_I
0.00
0.25
0.50
0.75
1.00
0
200
400
600
800
1000
1200
1400

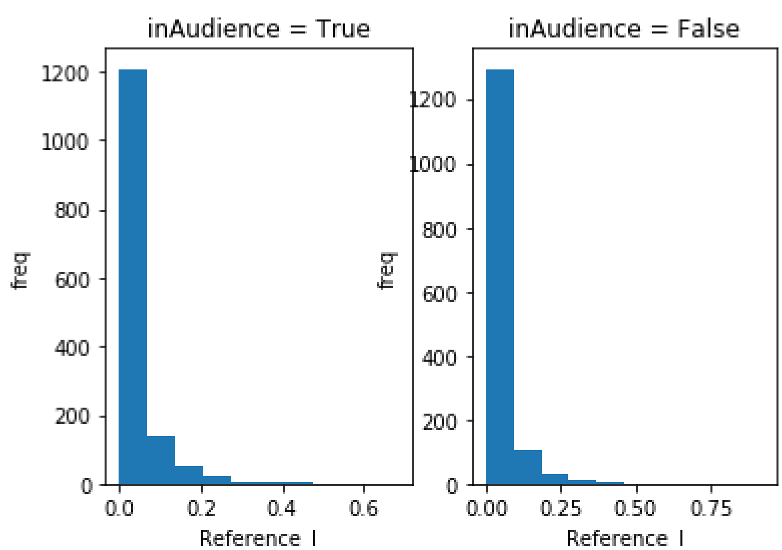

inAudience = True
inAudience = False
freq
Jobs & Education_l

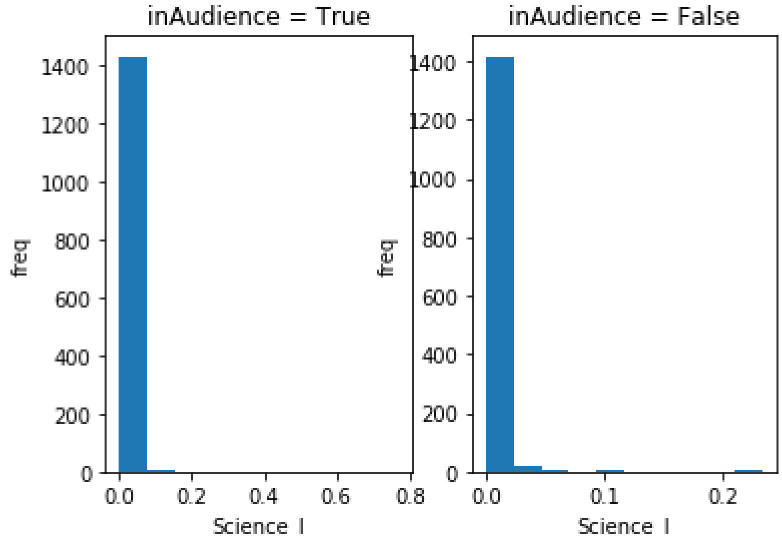

inAudience = True
inAudience = False
freq
Hobbies & Leisure_l

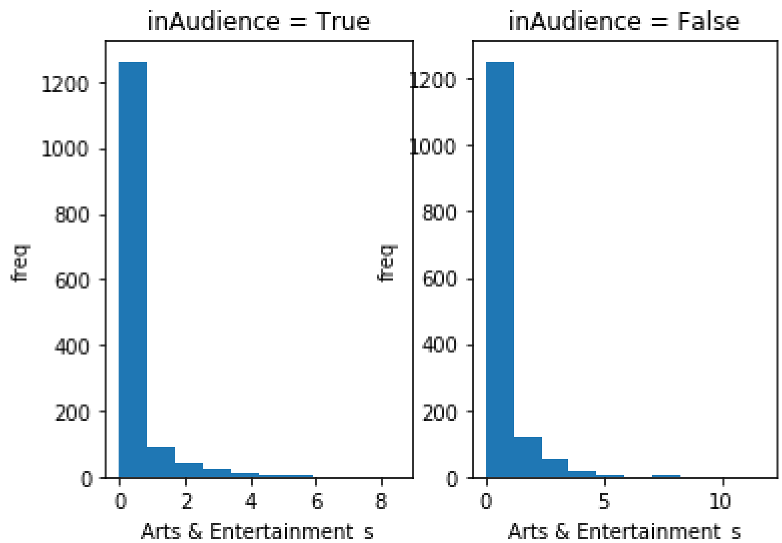

inAudience = True
inAudience = False
freq
Pets & Animals_l

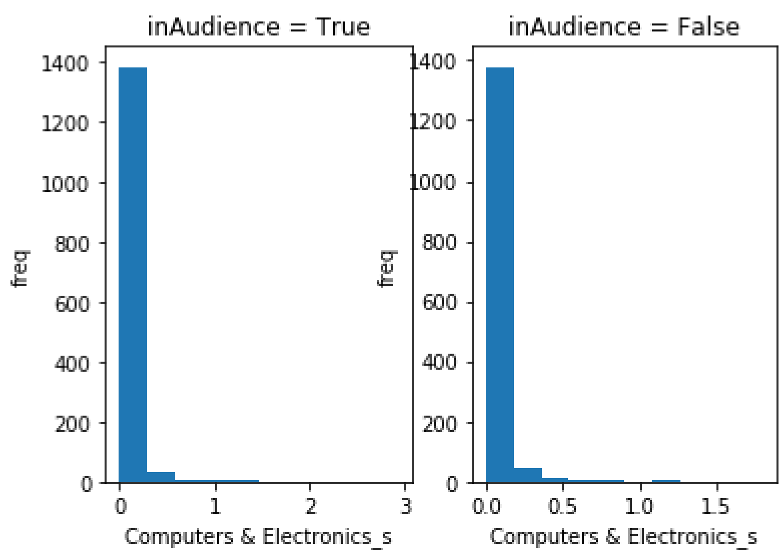

inAudience = True
inAudience = False
freq
Travel_I

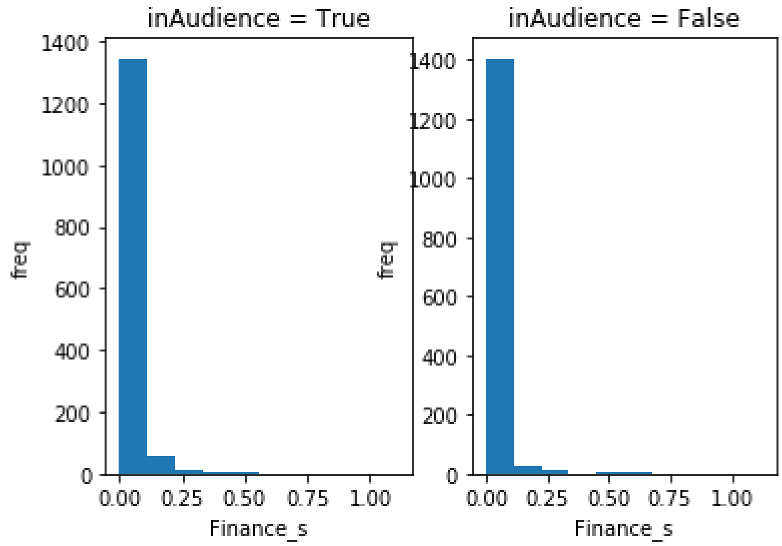

inAudience = True
inAudience = False
freq
Food & Drink_I

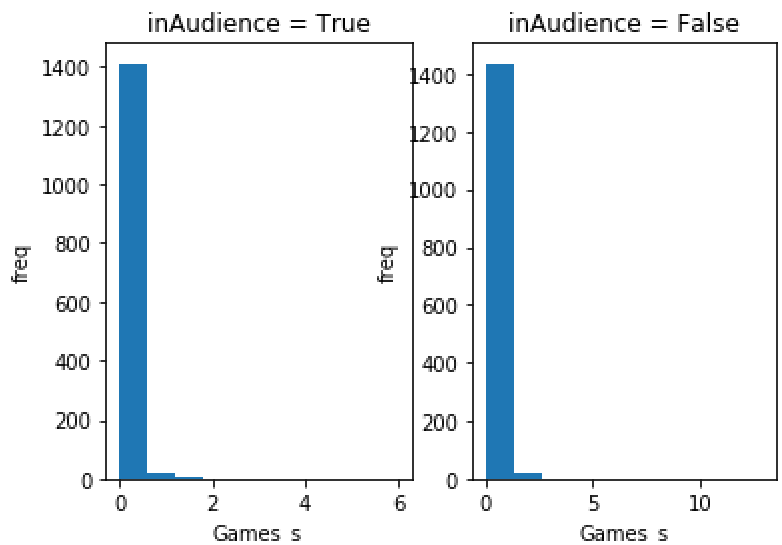

inAudience = True
inAudience = False
freq
Reference_I

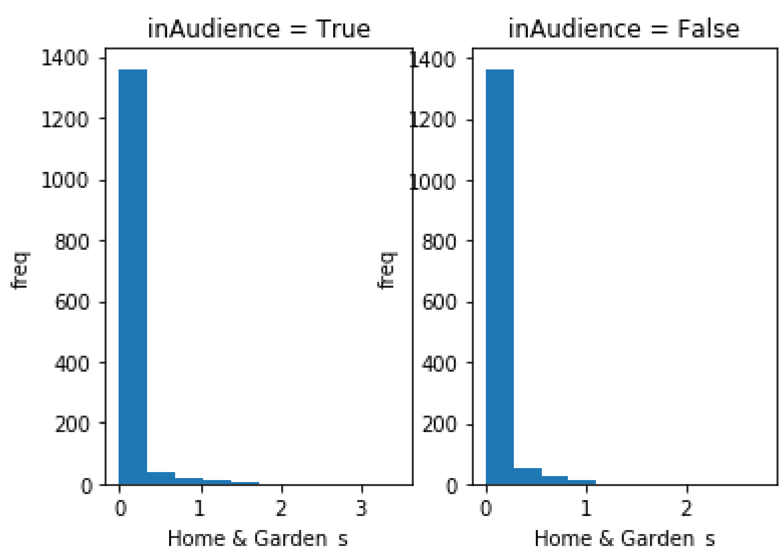

inAudience = True
inAudience = False
freq
Science_l
0.0
0.2
0.4
0.6
0.8
0.1
0
200
400
600
800
1000
1200
1400

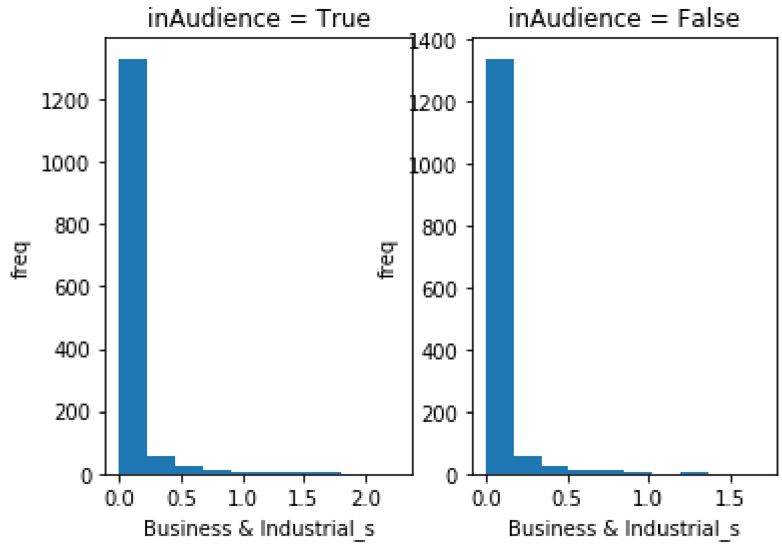

inAudience = True
inAudience = False
freq
Arts & Entertainment_s
0
2
4
6
8
5
10
200
400
600
800
1000
1200

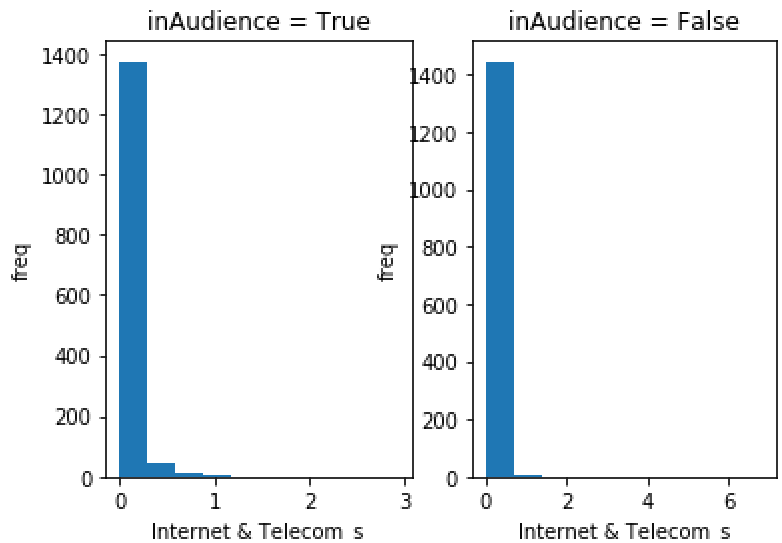

inAudience = True
inAudience = False
freq
Computers & Electronics_s
0
1
2
3
0.0
0.5
1.0
1.5
200
400
600
800
1000
1200
1400

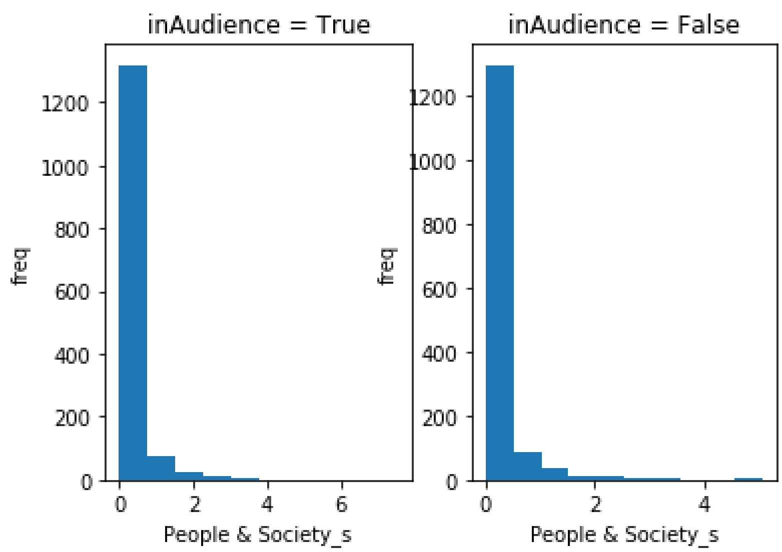

inAudience = True
inAudience = False
freq
Finance_s
0.00 0.25 0.50 0.75 1.00
0 200 400 600 800 1000 1200 1400

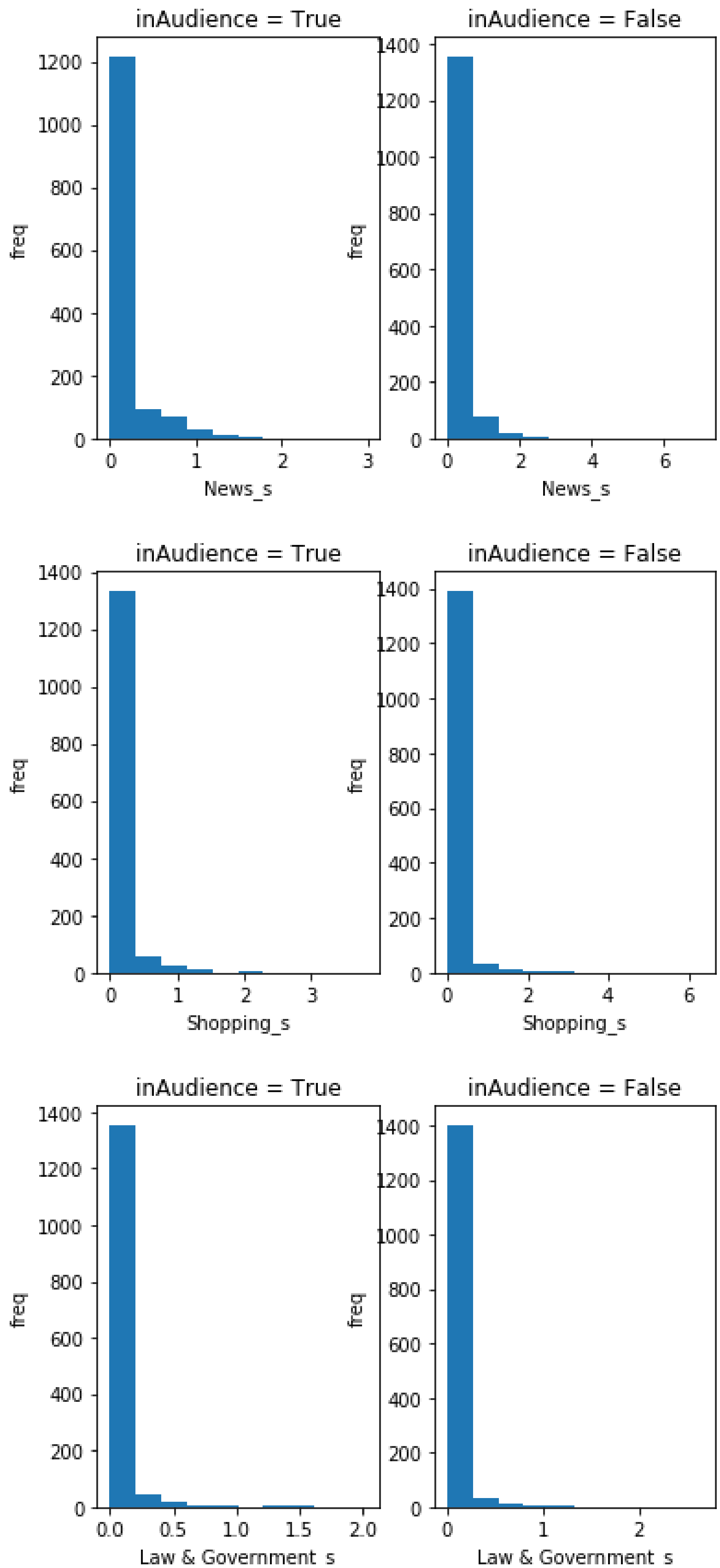

inAudience = True
inAudience = False
freq
Games_s
0 2 4 6
0 5 10
0 200 400 600 800 1000 1200 1400

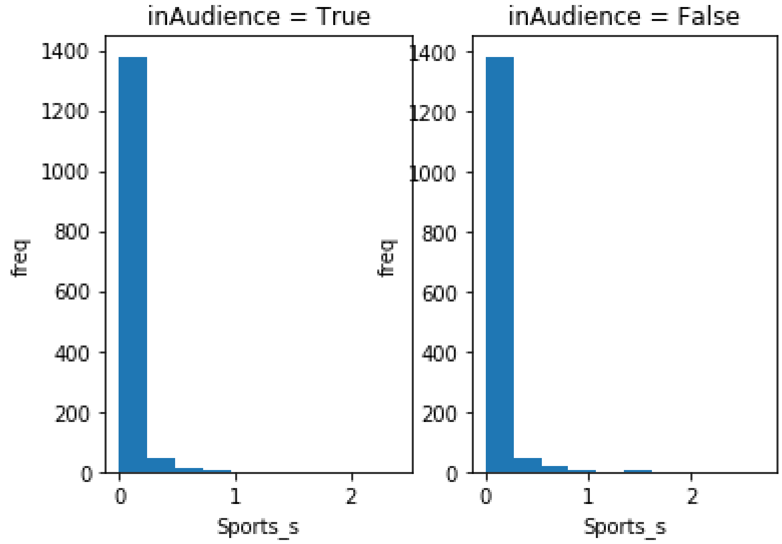

inAudience = True
inAudience = False
freq
Home & Garden_s
0 1 2 3
0 200 400 600 800 1000 1200 1400

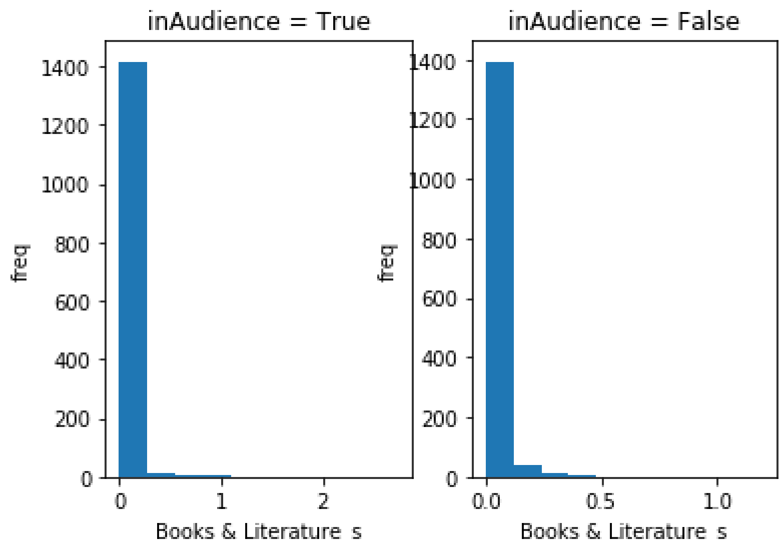

inAudience = True
inAudience = False
freq
Business & Industrial_s

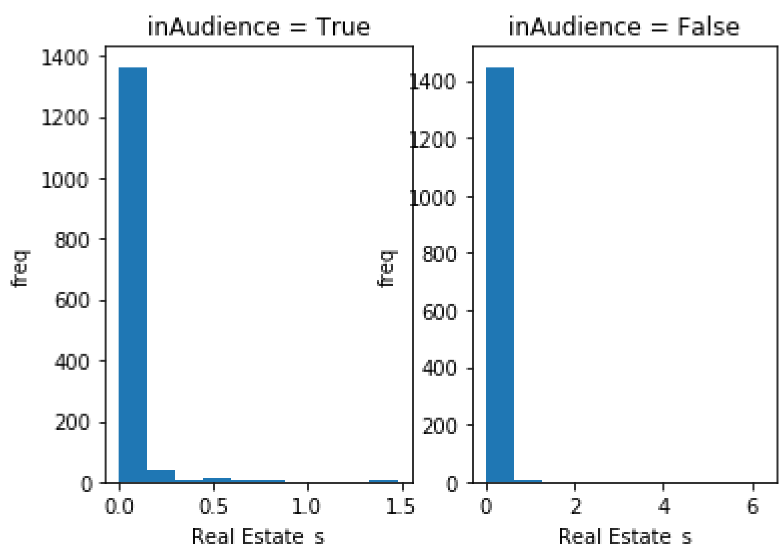

inAudience = True
inAudience = False
freq
Internet & Telecom_s

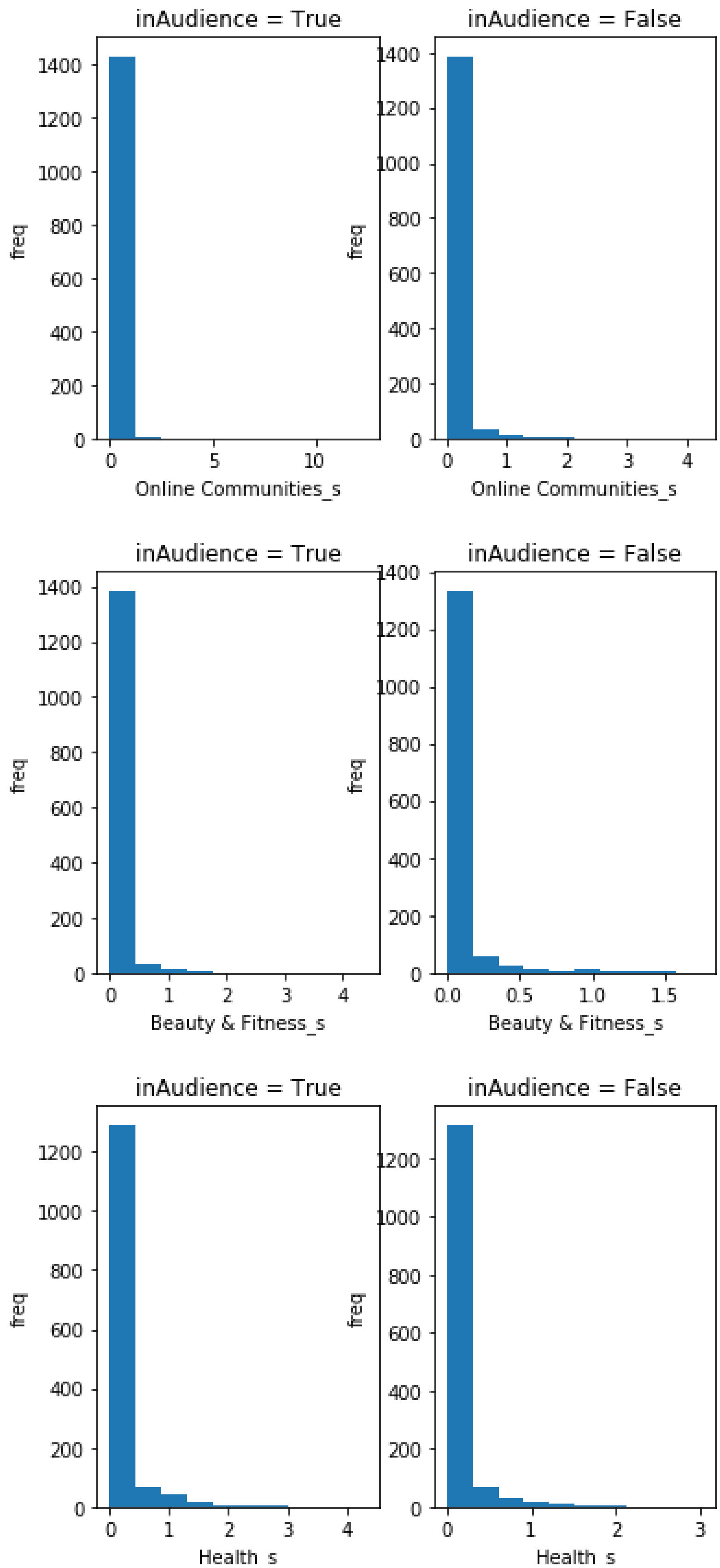

inAudience = True
inAudience = False
freq
People & Society_s

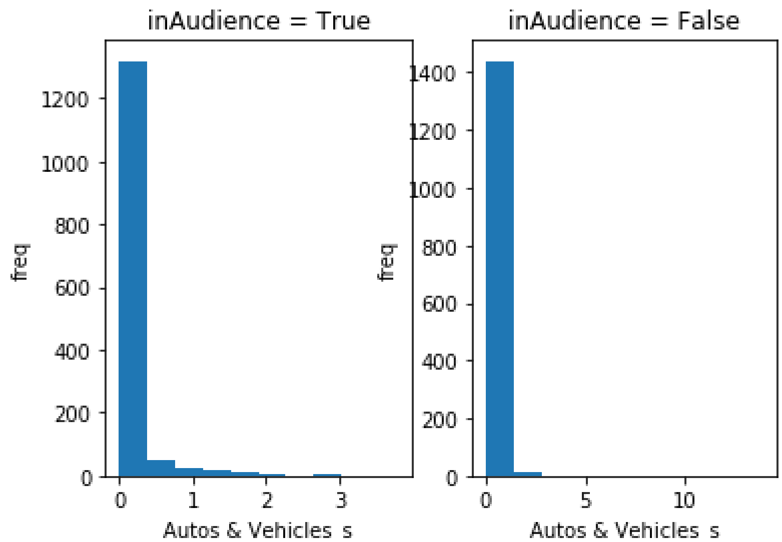

inAudience = True
inAudience = False
freq
News_s
inAudience = True
inAudience = False
freq
Shopping_s
inAudience = True
inAudience = False
freq
Law & Government_s

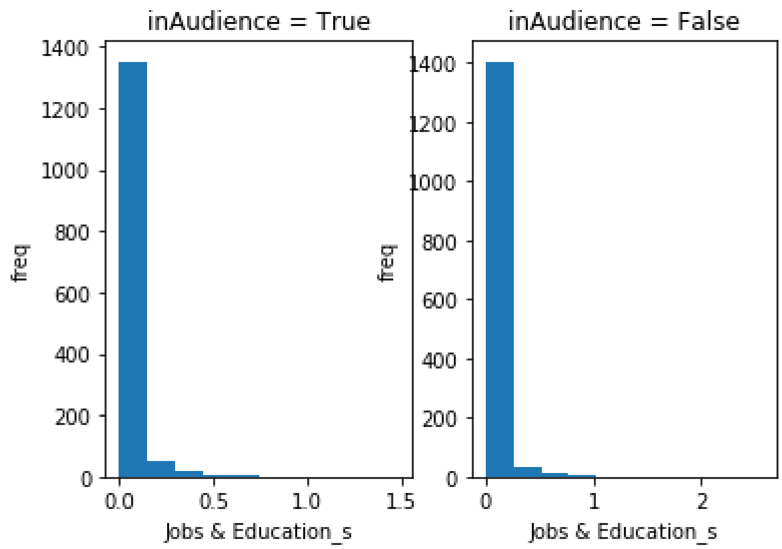

inAudience = True
inAudience = False
freq
freq
1400
1200
1000
800
600
400
200
0
0
1
2
Sports_s
Sports_s

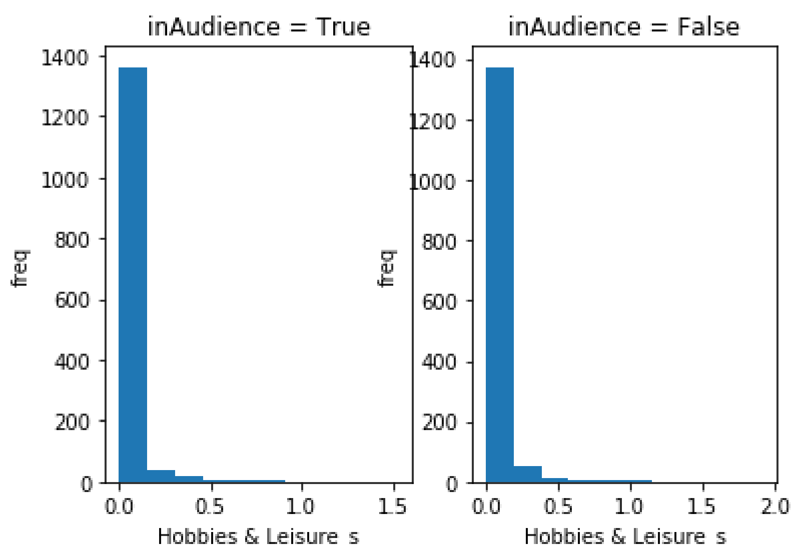

inAudience = True
inAudience = False
freq
freq
1400
1200
1000
800
600
400
200
0
0
1
2
0.0
0.5
1.0
Books & Literature_s
Books & Literature_s

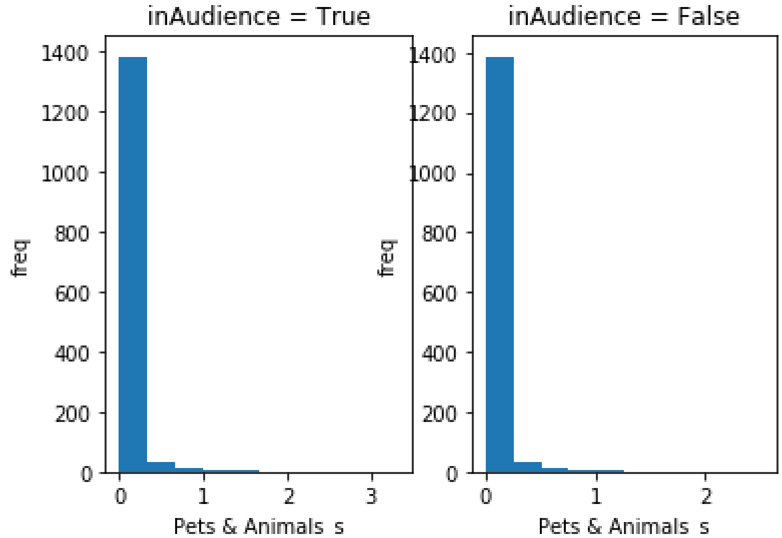

inAudience = True
inAudience = False
freq
freq
1400
1200
1000
800
600
400
200
0
0.0
0.5
1.0
1.5
0
2
4
6
Real Estate_s
Real Estate_s

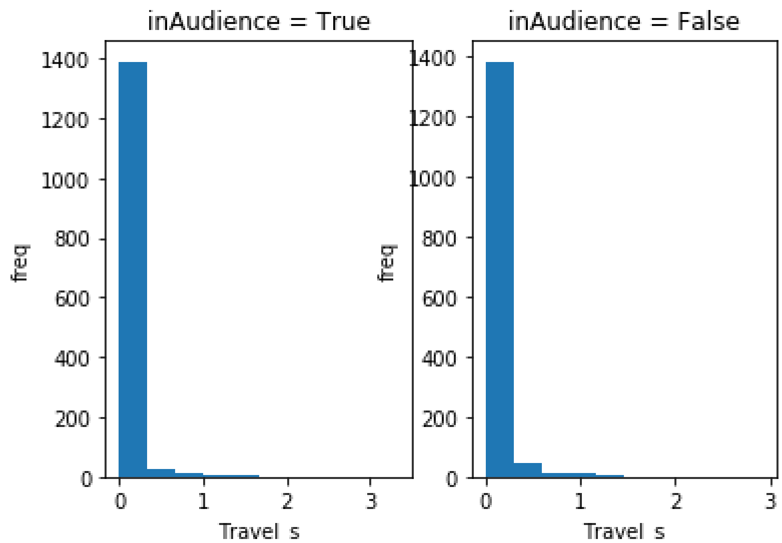

inAudience = True
inAudience = False
freq
Online Communities_s
inAudience = True
inAudience = False
freq
Beauty & Fitness_s
inAudience = True
inAudience = False
freq
Health_s

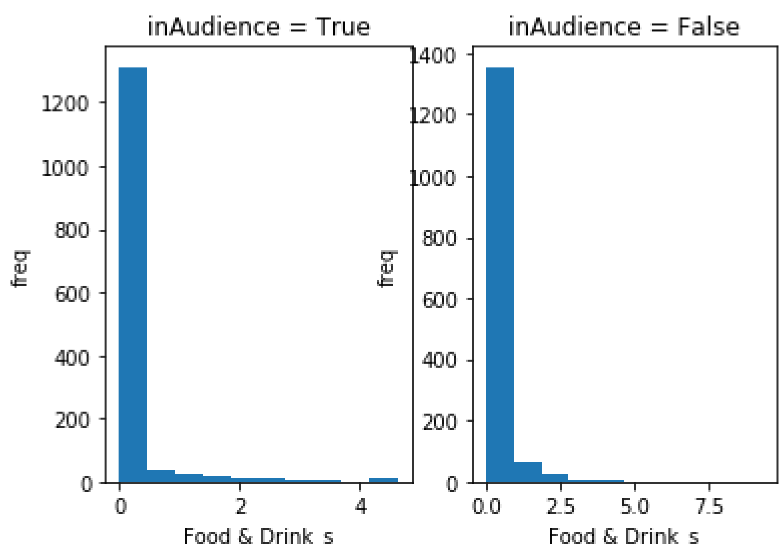

inAudience = True
inAudience = False
freq
0
200
400
600
800
1000
1200
1400
0
1
2
3
5
10
Autos & Vehicles_s
Autos & Vehicles_s

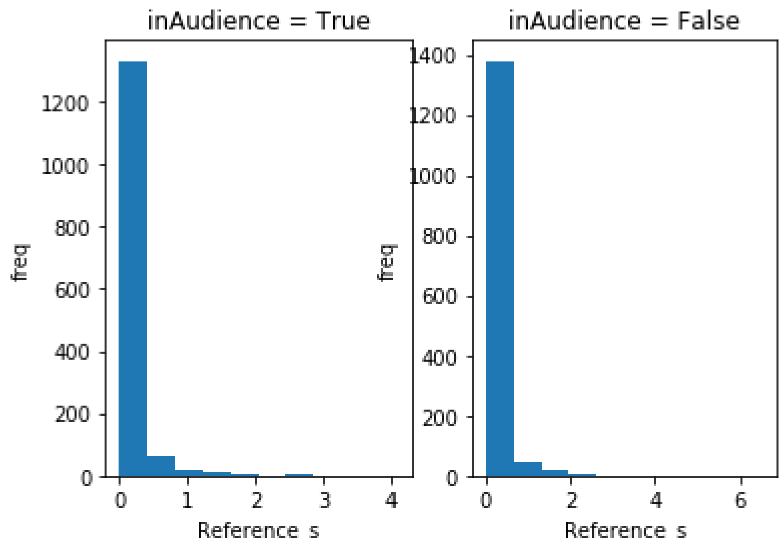

inAudience = True
inAudience = False
freq
0
200
400
600
800
1000
1200
1400
0.0
0.5
1.0
1.5
0
1
2
Jobs & Education_s
Jobs & Education_s

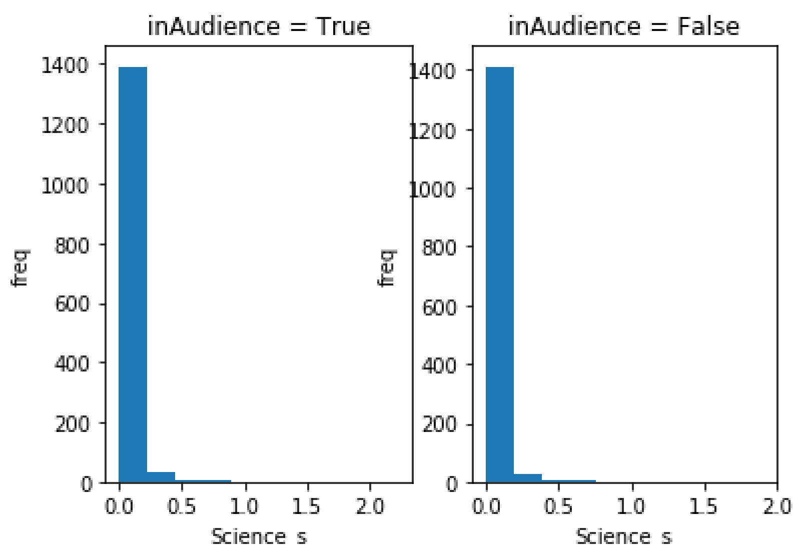

inAudience = True
inAudience = False
freq
0
200
400
600
800
1000
1200
1400
0.0
0.5
1.0
1.5
2.0
Hobbies & Leisure_s
Hobbies & Leisure_s


inAudience = True
inAudience = False
freq
0
200
400
600
800
1000
1200
1400
0
1
2
3
Pets & Animals_s


inAudience = True
inAudience = False
freq
0
200
400
600
800
1000
1200
1400
0
1
2
3
Travel_s

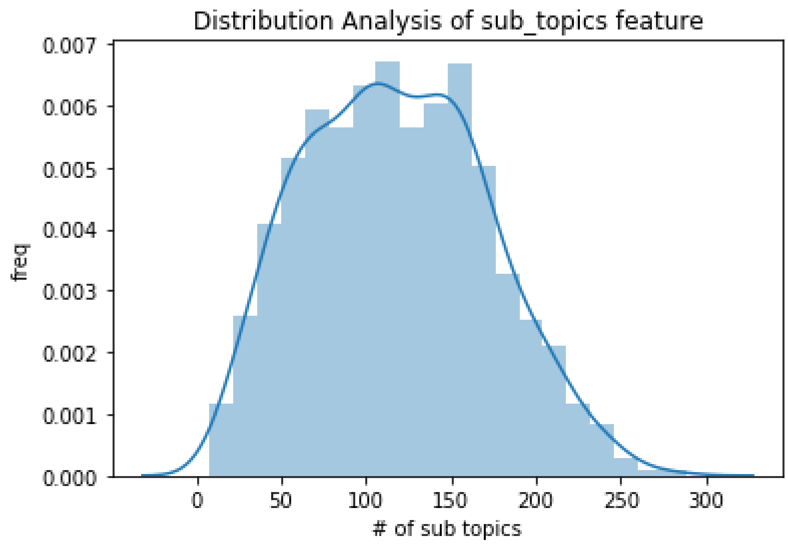

inAudience = True
inAudience = False
freq
0
200
400
600
800
1000
1200
1400
0
2
4
0.0
2.5
5.0
7.5
Food & Drink_s

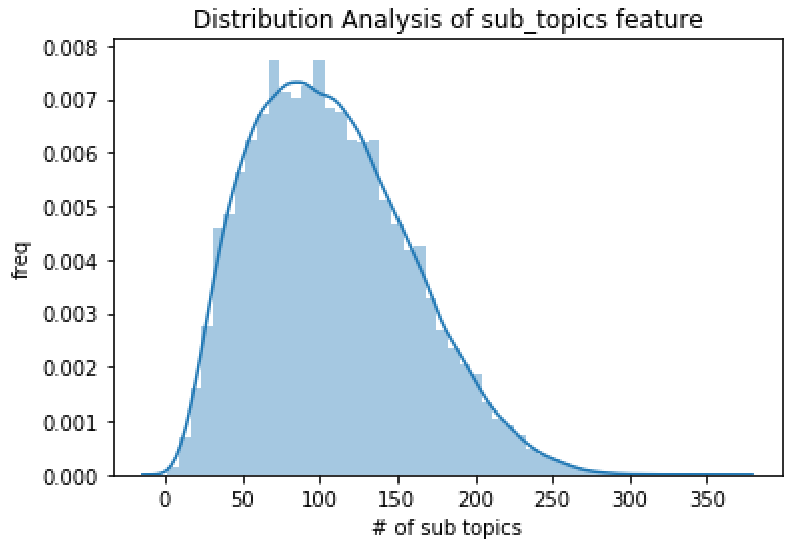




- Eventhough distributions of most features are left-skewed, we still could get some insights from these hitograms. For example, we see that for **Arts & Entertainment_l**, the distribution of converted customers is different from non-converted customers. Following this methodology, we selected following features [
'Arts & Entertainment_l','News_l','Shopping_l','Books & Literature_l','Health_l','Autos & Vel

In [614]:
```
sns.distplot(training['sub_topics'].loc[:1465])
plt.xlabel('# of sub topics')
plt.ylabel('freq')
plt.title('Distribution Analysis of sub_topics feature')
plt.show()
sns.distplot(training['sub_topics'].loc[1465:])
plt.xlabel('# of sub topics')
plt.ylabel('freq')
plt.title('Distribution Analysis of sub_topics feature')
plt.show()
```





- the distribution of **sub_topics** shows that indeed for some converted customers, they tend to be interested in more sub topics. Therefore, it confirmed our suspect and we decided to use this as one of our input features.

In [591]:
```
input_features = ['Arts & Entertainment_l','News_l','Health_l','Autos & 
 Vehicles_l','Finance_s','sub_topics']
```

In [592]:
```
X = df_downsampled[input_features]
y = df_downsampled['inAudience'].replace(y_mapping)
X_validate =val_downsampled[input_features]
y_validate = val_downsampled['inAudience'].replace(y_mapping)
```

Turkey's Method For Multiple outliers detection

- From the distribution analysis for each feature, we found that there are outliers for each feature, therefore, we use Turkey's Method to detect if an observation has multiple outliers in different features. And drop that observation from our dataset.
- The following code is an implementation of Turkey's Method from the interenet.

In [595]:
```
from collections import Counter


def detect_outliers(df, n, features):
    """
    Takes a dataframe df of features and returns a list of the indices
    corresponding to the observations containing more than n outliers ac
cording
    to the Tukey method.
    """
    outlier_indices = []

    # iterate over features(columns)
    for col in features:
        # 1st quartile (25%)
        Q1 = np.percentile(df[col], 25)
        # 3rd quartile (75%)
        Q3 = np.percentile(df[col], 75)
        # Interquartile range (IQR)
        IQR = Q3 - Q1

        # outlier step
        outlier_step = 1.5 * IQR

        # Determine a list of indices of outliers for feature col
        outlier_list_col = df[(df[col] < Q1 - outlier_step) | (df[col] >
Q3 + outlier_step )].index

        # append the found outlier indices for col to the list of outlie
r indices
        outlier_indices.extend(outlier_list_col)

    # select observations containing more than 2 outliers
    outlier_indices = Counter(outlier_indices)
    multiple_outliers = list(k for k, v in outlier_indices.items() if v
> n)

    return multiple_outliers

# detect outliers from list of features

#drop outliers in training
Outliers_to_drop = detect_outliers(df_downsampled, 2, input_features)
df_downsampled.drop(Outliers_to_drop,inplace=True)
```

Model Training and Validating

- In this section we trained different ML models, specifically **Decision Tree,Random Forest,AdaBoost,Gradient Boosting,XGBoost**, the first get the training accuracy, and then did a 5-fold cross-validation on the resampled validation set to determine the best model.
- We used GridCVSearch to search the best parameters for a given model

In [626]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import cross_val_score
from xgboost import XGBClassifier
import warnings
warnings.filterwarnings("ignore")
```

In [636]:
```
clf = DecisionTreeClassifier(random_state = 2019)
param = {'criterion':['gini','entropy'],
         'max_depth':[3,6,9],
         'min_samples_split':[2,3,5],
         'min_samples_leaf':[1,5,8],
         'max_features':['auto','sqrt','log2']
         }
grid = GridSearchCV(clf,param,scoring = 'accuracy')
grid = grid.fit(X,y)
clf = grid.best_estimator_
print('Model:')
print(clf)
clf.fit(X,y)
pred = clf.predict(X)
print('Accuracy Score on training dataset: ')
print(accuracy_score(y,pred))
print('-----')
print('5-fold Cross Validation Score:')
cross_val = cross_val_score(clf,X,y,cv = 5)
print(cross_val)
print('-----')
print('Mean CV score:')
print(np.mean(cross_val))
y_pred = clf.predict(X_validate)
print('-----')
print('Accuracy Score on Validation set:')
print(accuracy_score(y_validate,y_pred))
```

```
Model:
DecisionTreeClassifier(class_weight=None, criterion='entropy', max_dept
h=6,
                       max_features='log2', max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=No
ne,
                       min_samples_leaf=8, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort=False,
                       random_state=2019, splitter='best')
Accuracy Score on training dataset:
0.6996587030716723
-----
5-fold Cross Validation Score:
[0.66040956 0.62457338 0.62627986 0.65358362 0.65187713]
-----
Mean CV score:
0.643344709897611
-----
Accuracy Score on Validation set:
0.6661290322580645
```

In [637]:
```
clf  = RandomForestClassifier(random_state = 2019)
param = {'n_estimators':[4,6,9],
          'max_features':['log2','sqrt','auto'],
          'criterion':['entropy','gini'],
         'max_depth':[2,3,5,10],
         'min_samples_split':[2,3,5],
         'min_samples_leaf':[1,5,8]
         }
grid = GridSearchCV(clf,param,scoring = 'accuracy')
grid = grid.fit(X,y)
clf = grid.best_estimator_
print('Model:')
print(clf)
clf.fit(X,y)
pred = clf.predict(X)
print('Accuracy Score on training dataset: ')
print(accuracy_score(y,pred))
print('-----')
print('5-fold Cross Validation Score:')
cross_val = cross_val_score(clf,X,y,cv = 5)
print(cross_val)
print('-----')
print('Mean CV score:')
print(np.mean(cross_val))
y_pred = clf.predict(X_validate)
print('-----')
print('Accuracy Score on Validation set:')
print(accuracy_score(y_validate,y_pred))
```

```
Model:
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='en
tropy',
                       max_depth=2, max_features='log2', max_leaf_nodes
=None,
                       min_impurity_decrease=0.0, min_impurity_split=No
ne,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=9,
                       n_jobs=None, oob_score=False, random_state=2019,
                       verbose=0, warm_start=False)
Accuracy Score on training dataset:
0.6791808873720137
-----
5-fold Cross Validation Score:
[0.6774744  0.64334471 0.70307167 0.6774744  0.66723549]
-----
Mean CV score:
0.6737201365187714
-----
Accuracy Score on Validation set:
0.692741935483871
```

In [639]:
```
clf = AdaBoostClassifier(random_state = 2019)
param = {'n_estimators':[50,100,150,200,250],
        'learning_rate':[0.01,0.1,1],
        'algorithm':['SAMME','SAMME.R']
        }
grid = GridSearchCV(clf,param,scoring = 'accuracy')
grid = grid.fit(X,y)
clf = grid.best_estimator_
print('Model:')
print(clf)
clf.fit(X,y)
pred = clf.predict(X)
print('Accuracy Score on training dataset: ')
print(accuracy_score(y,pred))
print('-----')
print('5-fold Cross Validation Score:')
cross_val = cross_val_score(clf,X,y,cv = 5)
print(cross_val)
print('-----')
print('Mean CV score:')
print(np.mean(cross_val))
y_pred = clf.predict(X_validate)
print('-----')
print('Accuracy Score on Validation set:')
print(accuracy_score(y_validate,y_pred))
```

```
Model:
AdaBoostClassifier(algorithm='SAMME', base_estimator=None, learning_rat
e=0.1,
                   n_estimators=100, random_state=2019)
Accuracy Score on training dataset:
0.677815699658703
-----
5-fold Cross Validation Score:
[0.67406143 0.64505119 0.69283276 0.6774744  0.67064846]
-----
Mean CV score:
0.6720136518771331
-----
Accuracy Score on Validation set:
0.6814516129032258
```

In [640]:

```
clf = GradientBoostingClassifier(random_state = 2019)
param = {'n_estimators':[50,100,150],
         'min_samples_split':[2,3,4],
         'max_depth':[3,4,5],
         'max_features':['auto','sqrt','log2'],
         'min_samples_leaf':[1,5,8]}
grid = GridSearchCV(clf,param,scoring = 'accuracy')
grid = grid.fit(X,y)
clf = grid.best_estimator_
print('Model:')
print(clf)
clf.fit(X,y)
pred = clf.predict(X)
print('Accuracy Score on training dataset: ')
print(accuracy_score(y,pred))
print('-----')
print('5-fold Cross Validation Score:')
cross_val = cross_val_score(clf,X,y,cv = 5)
print(cross_val)
print('-----')
print('Mean CV score:')
print(np.mean(cross_val))
y_pred = clf.predict(X_validate)
print('-----')
print('Accuracy Score on Validation set:')
print(accuracy_score(y_validate,y_pred))
```

```
Model:
GradientBoostingClassifier(criterion='friedman_mse', init=None,
                           learning_rate=0.1, loss='deviance', max_dept
h=3,
                           max_features='sqrt', max_leaf_nodes=None,
                           min_impurity_decrease=0.0, min_impurity_spli
t=None,
                           min_samples_leaf=1, min_samples_split=2,
                           min_weight_fraction_leaf=0.0, n_estimators=5
0,
                           n_iter_no_change=None, presort='auto',
                           random_state=2019, subsample=1.0, tol=0.000
1,
                           validation_fraction=0.1, verbose=0,
                           warm_start=False)
Accuracy Score on training dataset:
0.7126279863481229
-----
5-fold Cross Validation Score:
[0.64846416 0.65699659 0.68771331 0.66382253 0.66552901]
-----
Mean CV score:
0.6645051194539249
-----
Accuracy Score on Validation set:
0.6806451612903226
```

In [641]:
```
clf = XGBClassifier()
param = {'eta':[0.1,0.3,0.5,1],
         'gamma':[0,3,6],
         'max_depth':[3,6,9,10,12],
         'subsample':[0.5,1]}
grid = GridSearchCV(clf,param,scoring = 'accuracy')
grid = grid.fit(X,y)
clf = grid.best_estimator_
print('Model:')
print(clf)
clf.fit(X,y)
pred = clf.predict(X)
print('Accuracy Score on training dataset: ')
print(accuracy_score(y,pred))
print('-----')
print('5-fold Cross Validation Score:')
cross_val = cross_val_score(clf,X,y,cv = 5)
print(cross_val)
print('-----')
print('Mean CV score:')
print(np.mean(cross_val))
y_pred = clf.predict(X_validate)
print('-----')
print('Accuracy Score on Validation set:')
print(accuracy_score(y_validate,y_pred))
```

```
Model:
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, eta=0.1, gamma=6,
              learning_rate=0.1, max_delta_step=0, max_depth=12,
              min_child_weight=1, missing=None, n_estimators=100, n_job
s=1,
              nthread=None, objective='binary:logistic', random_state=
0,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
              silent=None, subsample=1, verbosity=1)
Accuracy Score on training dataset:
0.7819112627986348
-----
5-fold Cross Validation Score:
[0.65017065 0.64846416 0.69795222 0.65017065 0.64675768]
-----
Mean CV score:
0.6587030716723549
-----
Accuracy Score on Validation set:
0.6774193548387096
```

Model Selection

- After the training and validating of our models, we see that **Random Forest** has the highest mean CV score, therefore, we choose **Random Forest** as our final model for this dataset.
- Eventhough we see that XGBoost gives a really high accuracy score on the training dataset, the average CV score is not that high, we conclude that XGBoost may overfitted on the training dataset

Conclusion

- Given the accuracy score on our models, we conclude that the features we selected are good in general. Therefore, when Valassis looking for rare converted customers from large dataset, we recommend to sepefically look at long term interest in **Arts & Entertainment, Autos & Vehicles** and short term interest in **Finance**
- Also, we strongly recommend Valassis to consider the number of sub topics a user would be interested in when predicting if a user would be converted

Reference

[1]: **Turkey's Method**: https://gist.github.com/joseph-allen/14d72af86689c99e1e225e5771ce1600 (https://gist.github.com/joseph-allen/14d72af86689c99e1e225e5771ce1600)

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