Starbucks Capstone Project Report

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Udacity – Machine Learning Engineer Nanodegree

Definition

Project Overview

Starbucks is a largest and passionate vendor of coffee and other beverages, headquartered in Seattle, Washington. The corporation is ranked 125 in the list of 2021 Fortune 500 companies. They have a mobile application where registered users can use it to order coffee for pickup while mobile, pay in-store directly using the app, and collect rewards points. This app also offers promotions for bonus points to these users.

The promotional offer can be merely an advertisement for a drink or an actual offer such as a discount or BOGO (buy one get one free). This project is focused on tailoring the promotional offers for customers based on their responses to the previous offers and find out which of them are most likely to respond to an offer.

To Analyze the simulated data about the Starbucks user's behavior & predict offer effectiveness.

Not every customer responds the same way to these offers. Some customers are very active with the offers while many do not respond at all. To analyze customer interactions and keep recommending great offers to interested users, we need to exhaustively analyze the simulated data that mimics customer behavior on the Starbucks rewards mobile app.

Problem Statement

The project will aim towards maximizing the profits for starbucks by using Machine Learning model to predict to best determine which kind of offer to send to each user based on their response to the previously sent offers.

To Analyze the simulated data about the Starbucks user's behavior & predict offer effectiveness.

I'll also build a machine learning model that will predict the response of a customer to an offer. This prediction will eventually improve the conversion rate of the offers and in turn increase the profitability.

The data set is provided in form of three JSON files:

- portfolio.json - containing offer ids and meta data about each offer (duration, type, etc.)
- profile.json - demographic data for each customer
- transcript.json - records for transactions, offers received, offers viewed, and offers completed

The following steps will be taken to build our model.

- Data Collection: Gather all the relevant data
- Data Wrangling, Data Preprocessing: Clean and transform the data as needed for modeling
- Build a Model: Train a classifier which will predict customers response
- Evaluate: checking accuracy and metrics for data sanity

Metrics

A Model metric is needed to access the quality of the approach and and determine which model to consider for its best results. For this problem, considered the F1 score as the model metric to assess the quality of the approach and determine which model gives the best results. It can be interpreted as the weighted average of the precision and recall. The traditional or balanced F-score (F1 score) is the harmonic mean of precision and recall, where an F1 score reaches its best value at 1 and worst at 0.

Analysis

Data Exploration and Visualization

Here is the schema and explanation of each variable in the files:

portfolio.json

- id (string) - offer id
- offer_type (string) - type of offer ie BOGO, discount, informational
- difficulty (int) - minimum required spend to complete an offer
- reward (int) - reward given for completing an offer
- duration (int) - time for offer to be open, in days
- channels (list of strings)

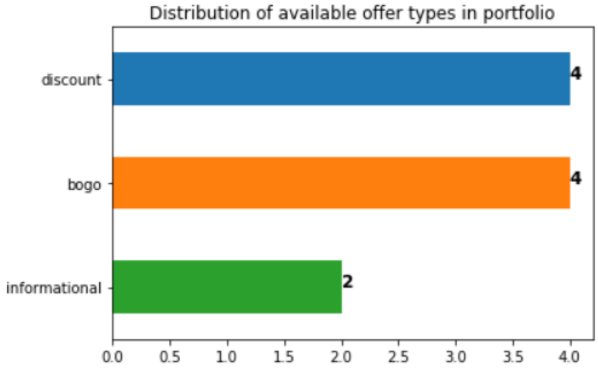
In [2]:
```
#Access the portfolio data
portfolio.head(10)
```

Out[2]:

	channels	difficulty	duration	id	offer_type	reward
0	[email, mobile, social]	10	7	ae264e3637204a6fb9bb56bc8210ddfd	bogo	10
1	[web, email, mobile, social]	10	5	4d5c57ea9a6940dd891ad53e9dbe8da0	bogo	10
2	[web, email, mobile]	0	4	3f207df678b143eea3cee63160fa8bed	informational	0
3	[web, email, mobile]	5	7	9b98b8c7a33c4b65b9aebfe6a799e6d9	bogo	5
4	[web, email]	20	10	0b1e1539f2cc45b7b9fa7c272da2e1d7	discount	5
5	[web, email, mobile, social]	7	7	2298d6c36e964ae4a3e7e9706d1fb8c2	discount	3
6	[web, email, mobile, social]	10	10	fafdcd668e3743c1bb461111dcafc2a4	discount	2
7	[email, mobile, social]	0	3	5a8bc65990b245e5a138643cd4eb9837	informational	0
8	[web, email, mobile, social]	5	5	f19421c1d4aa40978ebb69ca19b0e20d	bogo	5
9	[web, email, mobile]	10	7	2906b810c7d4411798c6938adc9daaa5	discount	2

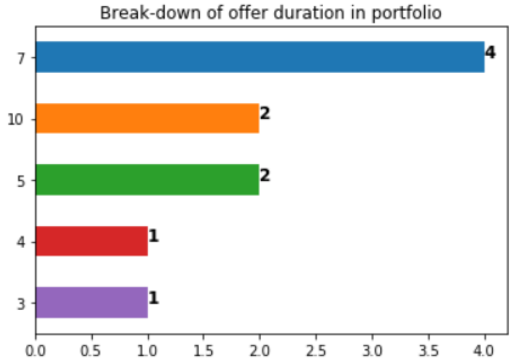
```
[7]: horizontal_bar_plot(portfolio, 'offer_type', "Distribution of available offer types in portfolio")
```

<matplotlib.figure.Figure at 0x7f16c4af5a58>




```
In [8]: horizontal_bar_plot(portfolio, 'duration', "Break-down of offer duration in portfolio")
```

<matplotlib.figure.Figure at 0x7f16c5cc74a8>



profile.json

- age (int) - age of the customer
- became_member_on (int) - date when customer created an app account
- gender (str) - gender of the customer (note some entries contain 'O' for other rather than M or F)
- id (str) - customer id
- income (float) - customer's income

```
In [9]: #Exploring the profile
profile.head()
```

Out[9]:

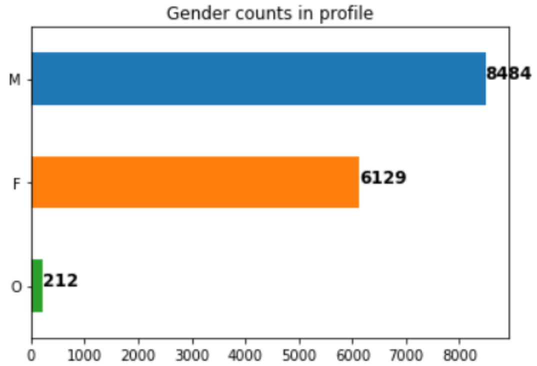
	age	became_member_on	gender	id	income
0	118	20170212	None	68be06ca386d4c31939f3a4f0e3dd783	NaN
1	55	20170715	F	0610b486422d4921ae7d2bf64640c50b	112000.0
2	118	20180712	None	38fe809add3b4fcf9315a9694bb96ff5	NaN
3	75	20170509	F	78afa995795e4d85b5d9ceeca43f5fef	100000.0
4	118	20170804	None	a03223e636434f42ac4c3df47e8bac43	NaN

```
In [10]: print("profile: Rows = {0}, Columns = {1}".format(str(profile.shape[0]), str(profile.shape[1])))
```

profile: Rows = 17000, Columns = 5

In [13]:
```
#checking is null values in profile data
profile.isnull().sum()
```
Out[13]:
```
age                    0
became_member_on       0
gender              2175
id                     0
income              2175
dtype: int64
```

In [15]:
```
horizontal_bar_plot(profile, 'gender', "Gender counts in profile")
```
```
<matplotlib.figure.Figure at 0x7f16c5c27a20>
```



transcript.json

- event (str) - record description (ie transaction, offer received, offer viewed, etc.)
- person (str) - customer id
- time (int) - time in hours since start of test. The data begins at time t=0
- value - (dict of strings) - either an offer id or transaction amount depending on

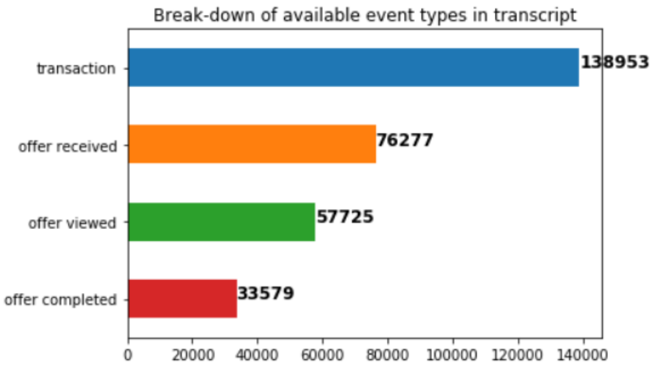
In [16]:
```
#Explore transcript data
transcript.head(10)
```
Out[16]:

	event	person	time	value
0	offer received	78afa995795e4d85b5d9ceeca43f5fef	0	{'offer id': '9b98b8c7a33c4b65b9aebfe6a799e6d9'}
1	offer received	a03223e636434f42ac4c3df47e8bac43	0	{'offer id': '0b1e1539f2cc45b7b9fa7c272da2e1d7'}
2	offer received	e2127556f4f64592b11af22de27a7932	0	{'offer id': '2906b810c7d4411798c6938adc9daaa5'}
3	offer received	8ec6ce2a7e7949b1bf142def7d0e0586	0	{'offer id': 'fafdcd668e3743c1bb461111dcafc2a4'}
4	offer received	68617ca6246f4fbc85e91a2a49552598	0	{'offer id': '4d5c57ea9a6940dd891ad53e9dbe8da0'}
5	offer received	389bc3fa690240e798340f5a15918d5c	0	{'offer id': 'f19421c1d4aa40978ebb69ca19b0e20d'}
6	offer received	c4863c7985cf408faee930f111475da3	0	{'offer id': '2298d6c36e964ae4a3e7e9706d1fb8c2'}
7	offer received	2eeac8d8feae4a8cad5a6af0499a211d	0	{'offer id': '3f207df678b143eea3cee63160fa8bed'}
8	offer received	aa4862eba776480b8bb9c68455b8c2e1	0	{'offer id': '0b1e1539f2cc45b7b9fa7c272da2e1d7'}
9	offer received	31dda685af34476cad5bc968bdb01c53	0	{'offer id': '0b1e1539f2cc45b7b9fa7c272da2e1d7'}

In [17]:
```
print("transcript: Rows = {0}, Columns = {1}".format(str(transcript.shape[0]), str(transcript.shape[1])))
```
```
transcript: Rows = 306534, Columns = 4
```

In [20]:
```
horizontal_bar_plot(transcript, 'event', "Break-down of available event types in transcript")
```

```
<matplotlib.figure.Figure at 0x7f16c5bd50b8>
```



Data Preprocessing:

This will involve removing or processing any missing values and cleaning the datasets to analyse the data better.

Cleaning portfolio:

- ✓ Duration: converted to hours
- ✓ Channels : splitted and encoded to different columns – web, email, mobile, social
- ✓ Id: renamed to offer_id
- ✓ Dropped columns channels and offer_type
- ✓ One hot encoding applied and columns added as offer_bogo, offer_discount, offer_informational

In [23]:
```
cleaned_portfolio
```

Out[23]:

	difficulty	duration	offer_id	reward	web	email	mobile	social	offer_bogo	offer_discount	offer_informational
0	10	168	ae264e3637204a6fb9bb56bc8210ddfd	10	0	1	1	1	1	0	0
1	10	120	4d5c57ea9a6940dd891ad53e9dbe8da0	10	1	1	1	1	1	0	0
2	0	96	3f207df678b143eea3cee63160fa8bed	0	1	1	1	0	0	0	1
3	5	168	9b98b8c7a33c4b65b9aebfe6a799e6d9	5	1	1	1	0	1	0	0
4	20	240	0b1e1539f2cc45b7b9fa7c272da2e1d7	5	1	1	0	0	0	1	0
5	7	168	2298d6c36e964ae4a3e7e9706d1fb8c2	3	1	1	1	1	0	1	0
6	10	240	fafdcd668e3743c1bb461111dcafc2a4	2	1	1	1	1	0	1	0

Cleaning Profile:

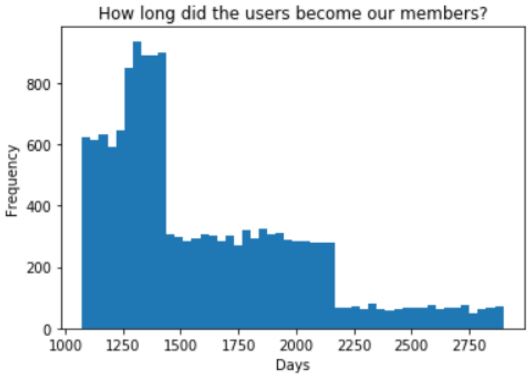
- ✓ Id , income : renamed to customer_id, customer_income
- ✓ Dropped all missing values
- ✓ Dropped age column and added new column for Age_group for range of ages

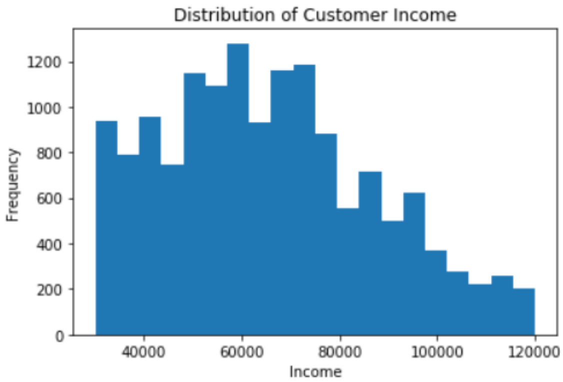
```
In [26]: cleaned_profile
```

Out[26]:

	became_member_on	gender	customer_id	customer_income	memberdays	Age_group
1	20170715	F	0610b486422d4921ae7d2bf64640c50b	112000.0	1450	46-60
3	20170509	F	78afa995795e4d85b5d9ceeca43f5fef	100000.0	1517	61-80
5	20180426	M	e2127556f4f64592b11af22de27a7932	70000.0	1165	61-80
8	20180209	M	389bc3fa690240e798340f5a15918d5c	53000.0	1241	61-80
12	20171111	M	2eeac8d8feae4a8cad5a6af0499a211d	51000.0	1331	46-60
13	20170911	F	aa4862eba776480b8bb9c68455b8c2e1	57000.0	1392	61-80
14	20140213	M	e12aeaf2d47d42479ea1c4ac3d8286c6	46000.0	2698	20-45
15	20160211	F	31dda685af34476cad5bc968bdb01c53	71000.0	1970	61-80
16	20141113	M	62cf5e10845442329191fc246e7bcea3	52000.0	2425	46-60

```
In [29]: display_customer_profile()
```





Cleaning Transcript:

- ✓ New columns : offer_id, money_gained, money_spent
- ✓ Person: renamed to customer_id
- ✓ Extracted the offer_id from the value column
- ✓ Replaced null with fillna

```
In [32]: cleaned_transcript
```

Out[32]:

	event	customer_id	time	value	offer_id	money_gained
0	offer received	78afa995795e4d85b5d9ceeca43f5fef	0	{'offer id': '9b98b8c7a33c4b65b9aebfe6a799e6d9'}	9b98b8c7a33c4b65b9aebfe6a799e6d9	0.0
1	offer received	a03223e636434f42ac4c3df47e8bac43	0	{'offer id': '0b1e1539f2cc45b7b9fa7c272da2e1d7'}	0b1e1539f2cc45b7b9fa7c272da2e1d7	0.0
2	offer received	e2127556f4f64592b11af22de27a7932	0	{'offer id': '2906b810c7d4411798c6938adc9daaa5'}	2906b810c7d4411798c6938adc9daaa5	0.0
3	offer received	8ec6ce2a7e7949b1bf142def7d0e0586	0	{'offer id': 'fafdcd668e3743c1bb461111dcafc2a4'}	fafdcd668e3743c1bb461111dcafc2a4	0.0
4	offer received	68617ca6246f4fbc85e91a2a49552598	0	{'offer id': '4d5c57ea9a6940dd891ad53e9dbe8da0'}	4d5c57ea9a6940dd891ad53e9dbe8da0	0.0
5	offer	[illegible]	[illegible]	{'offer id':	[illegible]	[illegible]

Data Merging:

At this stage, preparing the final dataframe by merging the cleaned data sets and cleaning the final data.

```
In [36]: merged_df.head()
```

Out[36]:

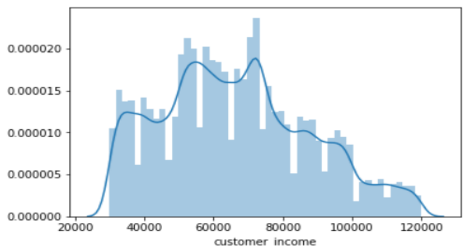
	difficulty	duration	offer_id	reward	web	email	mobile	social	offer_bogo	offer_discount	...	customer_id
0	10	168	ae264e3637204a6fb9bb56bc8210ddfd	10	0	1	1	1	1	0	...	4b0da7e80e5945209a1fdddfe813c
1	10	168	ae264e3637204a6fb9bb56bc8210ddfd	10	0	1	1	1	1	0	...	4b0da7e80e5945209a1fdddfe813c
2	10	168	ae264e3637204a6fb9bb56bc8210ddfd	10	0	1	1	1	1	0	...	4b0da7e80e5945209a1fdddfe813c
3	10	168	ae264e3637204a6fb9bb56bc8210ddfd	10	0	1	1	1	1	0	...	4b0da7e80e5945209a1fdddfe813c
4	10	168	ae264e3637204a6fb9bb56bc8210ddfd	10	0	1	1	1	1	0	...	4b0da7e80e5945209a1fdddfe813c

5 rows × 22 columns

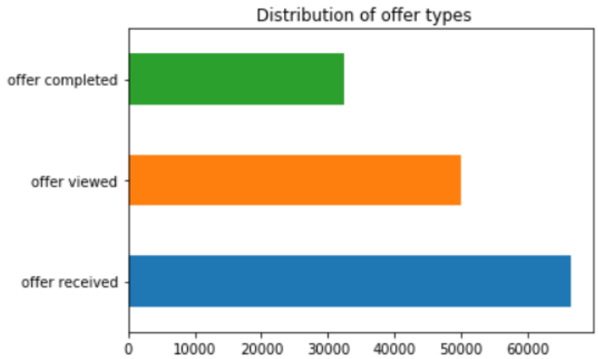
Data Visualization:

This will provide us a deep knowledge in the distribution of data based on various factors.

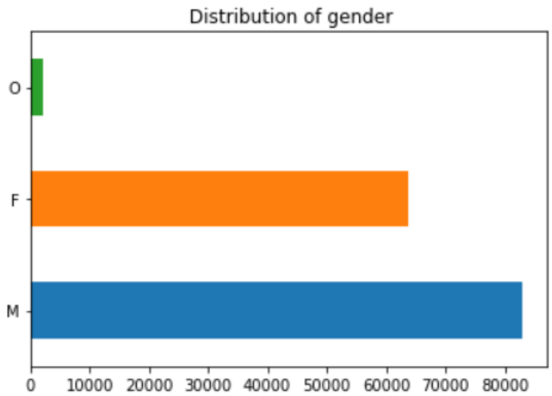
```
In [37]: sns.distplot(merged_df['customer_income'], bins=50, hist_kws={'alpha': 0.4});
```



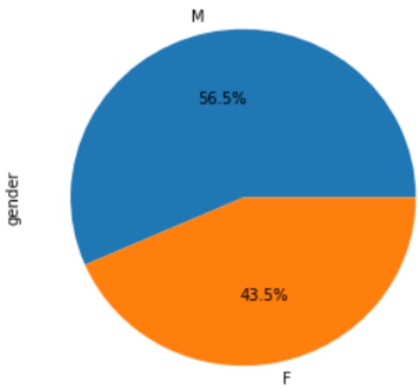
```
In [38]: merged_df['event'].value_counts().plot.barh(title=' Distribution of offer types')
Out[38]: <matplotlib.axes._subplots.AxesSubplot at 0x7f16c59ebd68>
```




```
In [39]: merged_df['gender'].value_counts().plot.barh(title=' Distribution of gender')
Out[39]: <matplotlib.axes._subplots.AxesSubplot at 0x7f16c5a6ecf8>
```

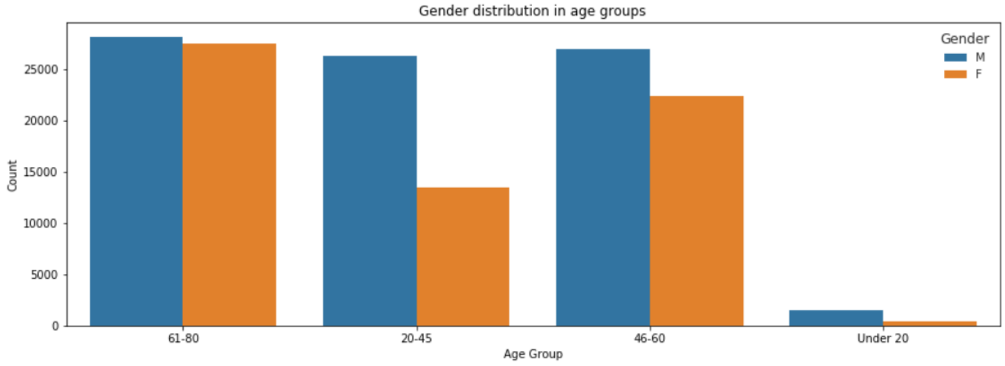



```
In [42]: plot_gender.gender.value_counts().plot(kind='pie' , figsize=(5, 5), autopct='%1.1f%%')
Out[42]: <matplotlib.axes._subplots.AxesSubplot at 0x7f16c5c68dd8>
```



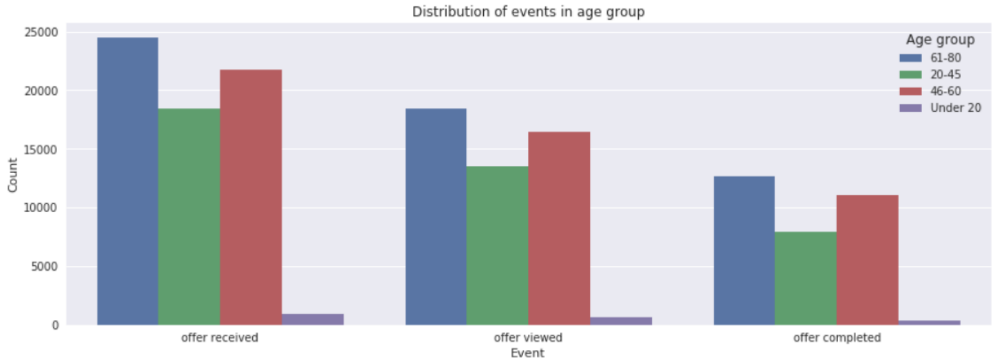
In [43]:
```python
#plotting Gender distribution
plt.figure(figsize=(15, 5))
sns.countplot(x= "Age_group", hue= "gender", data=plot_gender)
sns.set(style="darkgrid")
plt.title('Gender distribution in age groups')
plt.ylabel('Count')
plt.xlabel('Age Group')
plt.legend(title='Gender')
```

Out[43]: <matplotlib.legend.Legend at 0x7f16c5bf3240>



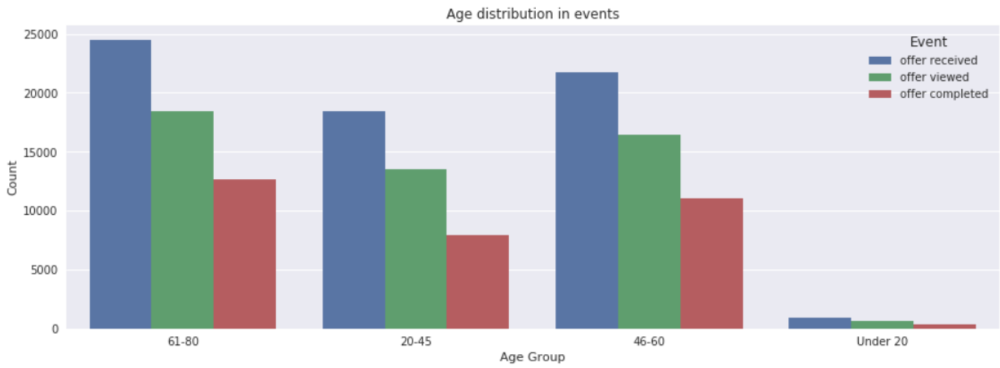
In [44]:
```python
#Plotting evnts distribution in age group
plt.figure(figsize=(15, 5))
sns.countplot(x= "event", hue= "Age_group", data=plot_gender)
sns.set(style="darkgrid")
plt.title('Distribution of events in age group')
plt.ylabel('Count')
plt.xlabel('Event')
plt.legend(title='Age group')
```

Out[44]: <matplotlib.legend.Legend at 0x7f16c5c30c50>



In [45]:
```python
plt.figure(figsize=(15, 5))
sns.countplot(x= "Age_group", hue= "event", data=plot_gender)
sns.set(style="darkgrid")
plt.title('Age distribution in events')
plt.ylabel('Count')
plt.xlabel('Age Group')
plt.legend(title='Event')
```

Out[45]: <matplotlib.legend.Legend at 0x7f16c5c303c8>



Cleaning Merged Data:

- ✓ Encode categorial data such as gender, offer type, age groups
- ✓ Encode event into numerical values – Offer received:1, offer viewed:2, offer completed:3
- ✓ Encode offer id and customer id
- ✓ Drop column became_member on and split into month and year
- ✓ Scale and normalize the numerical data

In [69]:
```
cleaned_final_data.head(10)
```

Out[69]:

	difficulty	duration	offer_id	reward	web	email	mobile	social	offer_bogo	offer_discount	...	memberdays	gender_F	gender_M	gender_O	Age_group_ 45
0	0.5	0.571429	0	1.0	0	1	1	1	1	0	...	1394	0	1	0	0
1	0.5	0.571429	0	1.0	0	1	1	1	1	0	...	1394	0	1	0	0
2	0.5	0.571429	0	1.0	0	1	1	1	1	0	...	1394	0	1	0	0
3	0.5	0.571429	0	1.0	0	1	1	1	1	0	...	1394	0	1	0	0
4	0.5	0.571429	0	1.0	0	1	1	1	1	0	...	1394	0	1	0	0
5	0.0	0.142857	1	0.0	1	1	1	0	0	0	...	1394	0	1	0	0
6	0.0	0.142857	1	0.0	1	1	1	0	0	0	...	1394	0	1	0	0
7	1.0	1.000000	2	0.5	1	1	0	0	0	1	...	1394	0	1	0	0
8	1.0	1.000000	2	0.5	1	1	0	0	0	1	...	1394	0	1	0	0
9	1.0	1.000000	2	0.5	1	1	0	0	0	1	...	1394	0	1	0	0

10 rows × 27 columns

Split Train and test data:

After cleaning the final data , data is split (both features and their labels) into training and test sets, taking 60% of data for training and 40% for testing.

Benchmark Model

A quick and fairly accurate model can be considered as a benchmark. I will use the KNeighborsClassifier to build the benchmark, as it is simple, a fast and considered standard method for binary classification machine learning problems and evaluate the model result using F1 score as the evaluation metric.

Since the KNN algorithm requires no training before making predictions, new data can be added seamlessly which will not impact the accuracy of the algorithm.

[84]:
```
benchmark
```

[84]:

	Benchmark Model	train F1 score	test F1 score
0	KNeighborsClassifier	53.101934	32.209939

Methodology

Implementing Models:

At this stage, we will build a Machine Learning model based on the above understanding of the data sets. Since it falls under the supervised binary classification problem, we can try any of the models like RandomForestClassifier, DecisionTreeClassifier etc and determine the accuracy

The Models we are implementing should meet the benchmark F1 score.

We plan to implement two machine learning models, RandomForestClassifier and DecisionTreeClassifier. Both the models are based on tress, the difference is that a decision tree is built on an entire dataset, using all the features/variables of interest, whereas a random forest randomly selects observations/rows and specific features/variables to build multiple decision trees from and then averages the results.

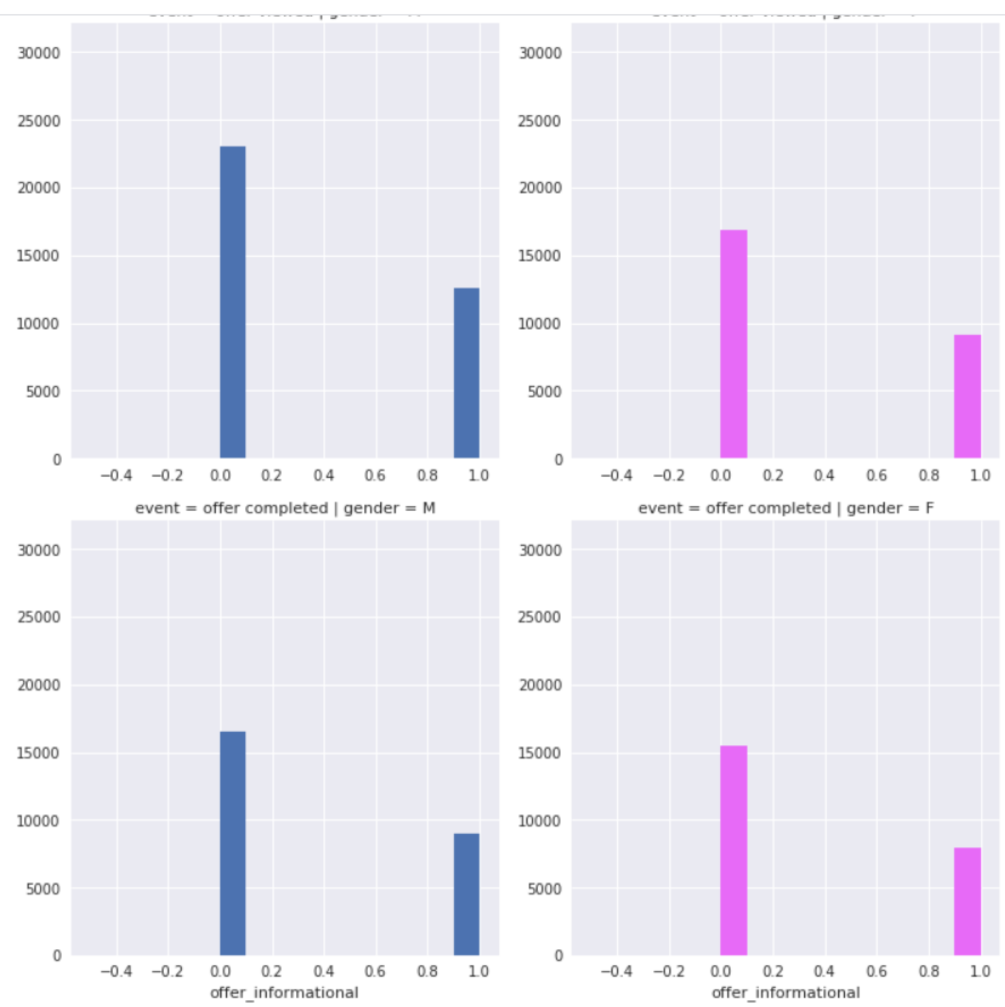
Results & Conclusions

Analysis

```
In [117]: #EDA to determine which offers to be sent to which customers

          d = {'color': ['C0', "#e76af7"]}
          g = sns.FacetGrid(plot_gender, row='event', col='gender', hue_kws=d, hue='gender', size=5)
          g.map(plt.hist, 'offer_bogo')
          g.map(plt.hist, 'offer_discount')
          g.map(plt.hist, 'offer_informational')

Out[117]: <seaborn.axisgrid.FacetGrid at 0x7f16beeacb00>
```



On seeing the data analysis, Bogo offers are most peffered by both male and female customers. Also, there is less number of customers who actually complete the offer as compared to the ones who just view & ignore it. Males generally ignore offers more & offers are nearly equally completed by males & females. The ratio of males to females in each offer type is nearly the same, with male customers being more. We can look more at the figures & information in the Exploratory Data Analysis section more to best determine which kind of offers to send to the customers.

Evaluation

The validation set (test data set) is used to evaluate the model. All the models are better than the benchmark. The AdaBoostClassifier and DecisionTreeClassifier model performs good as its validate F1 score is 92.72.10, F1 score is 85.56, which is much higher than the benchmark. The RandomForestClassifier scores good as well, compared to the benchmark, with a test F1 score of 68.48. Our problem to solve is not that sensitive which requires a very high F1 score, so these scores are sufficient and our model did not overfit the training data.

```
In [119]: comparison
```

Out[119]:

	Model	train F1 score	test F1 score
0	KNeighborsClassifier (Benchmark)	53.101934	32.209939
1	RandomForestClassifier	94.496153	68.483922
2	DecisionTreeClassifier	95.704669	85.561641
3	AdaBoostClassifier	92.670497	92.725379
4	GaussianNB	63.658255	63.248883

```
In [ ]:
```

Improvements

The scores that we achieved are relatively good for our classification problem. We can still improve the RandomForestClassifier by refining the hyperparameters using Grid Search with Cross Validation and the DecisionTreeClassifier with K- Fold Cross Validation for hyperparameter tuning.

Also we can work on implementing and deploying into a web app which would be helpful in the business area as this prediction will eventually improve the conversion rate of the offers and in turn increase the profitability.