Machine Learning Engineer Nanodegree

Capstone Project

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I. Definition

Project Overview

- Within the business strategy of the Starbucks company, we focus on the permeability of its offers for a limited group. The datasets provide us with information on both the demographic characteristics of consumers and their receptivity to different types of offers.

- Within the supervised models of Machine learning, these types of problems refer to Classification issues. It consists of a predictive model that infers a target class from a data set

- This model is highly applied in all kinds of disciplines.
    - Email spam detector
    - Conversion prediction
    - Movie review classification
    - MRI images classification
    - Fraud detection
    - e-commerce, customer sentiment analysis…

- We refer to an example that describes a case study of opinion polarity classification:
    - https://www.researchgate.net/publication/328306943_A_Comparison_of_Machine_Learning_Algorithms_in_Opinion_Polarity_Classification_of_Customer_Reviews

- The data is contained in three files:

    - **portfolio.json -** containing offer ids and meta data about each offer (duration, type, etc.)
        - *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)

- **profile.json** - demographic data for each customer
    - *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

- **transcript.json** - records for transactions, offers received, offers viewed, and offers completed
    - *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 the record

Problem Statement

- Using the information provided in the datasets, we intend to infer which way a specific client will respond to a certain type of offer.
    - On one hand, We are able to establish a demographic segmentation based on the different categorical fields such as age, gender, income
    - On the other, we can link these demographic segments to the type of offer and their associated receptivity
- The desired objective through this model is to identify the position of the different demographic segments in relation to the offers promoted by the company. And in this way, provide analytical instruments for the future develop a mechanism to optimize the impact of promotional strategies to each of the different clusters.

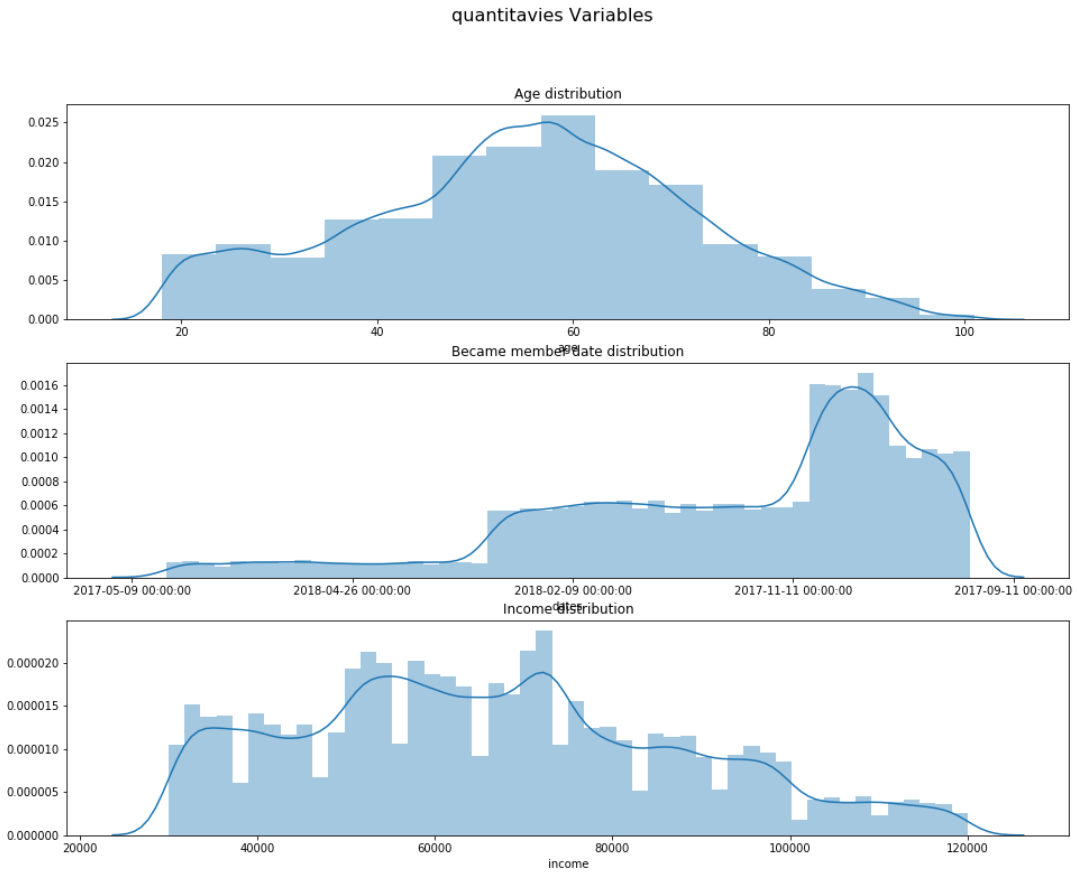
Metrics

- The metrics not only depend on the type of problem we want to solve but also on the distribution of the target class. In this case, the metrics involved are those associated with a Balanced Classification Problem.
    - Accuracy
    - Precision
    - Recall
    - F-Measure

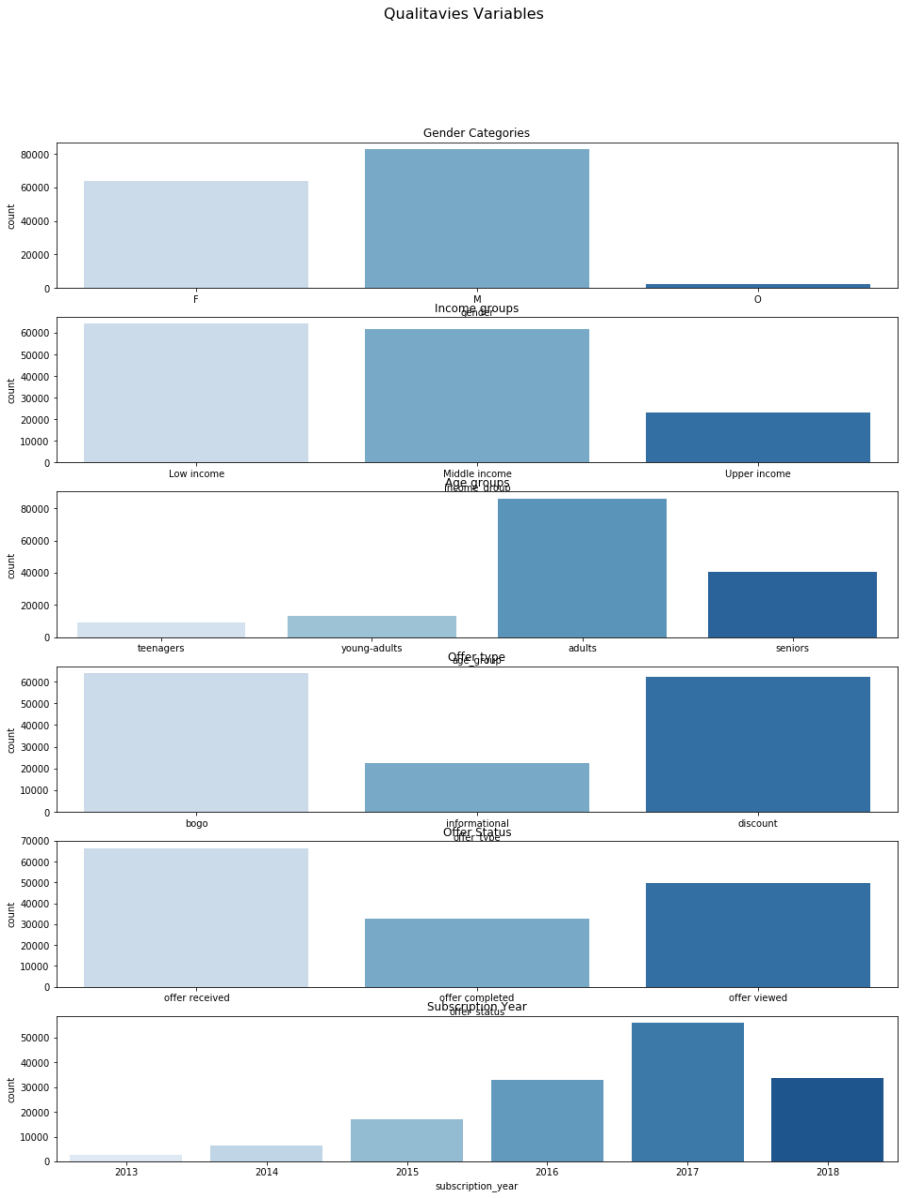
II. Analysis

Data Exploration

- In a first approximation, we focus on obtaining the distributions of the numerical variables:
    - age tends towards a symmetrical distribution with its center around 60 years and with a large sigma
    - the distribution of subscription dates is right skewed, it has its peak at the end of 2018
    - Income is distributed multimodally



- secondly, and to build a general perspective of the features, we analyze the categorical variables:
    - Men with 80,000 interventions are represented 20% more than women. around 2000 cases do not have a defined gender
    - The age group that will consent to the greatest number of cases is that of adults with more than the friendship of the participants. for population segmentation analyzes this bias should be considered
    - with respect to income, upper income has 50% fewer interventions than the other 2
    - the type of offer is divided unevenly: 40 BOGO 40 discount 20 informational
    - the conversion ratio seems less than 50% but we are going to develop it and segment it throughout this notebook
    - There has definitely been a growth in the number of subscribers to starbucks between 2013 and 2018, peaking in 2017

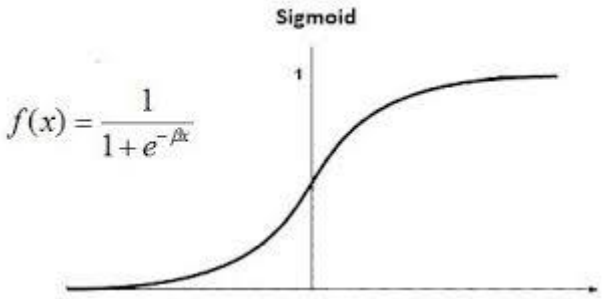


Algorithms and Techniques

- The objective will be to build a machine learning model that allows identifying, based on the different demographic segments, the result of the offers offered to customers.
- To model the predictions about this problem we required supervised Machine learning algorithms. we will use classification algorithms

Logistic regression:

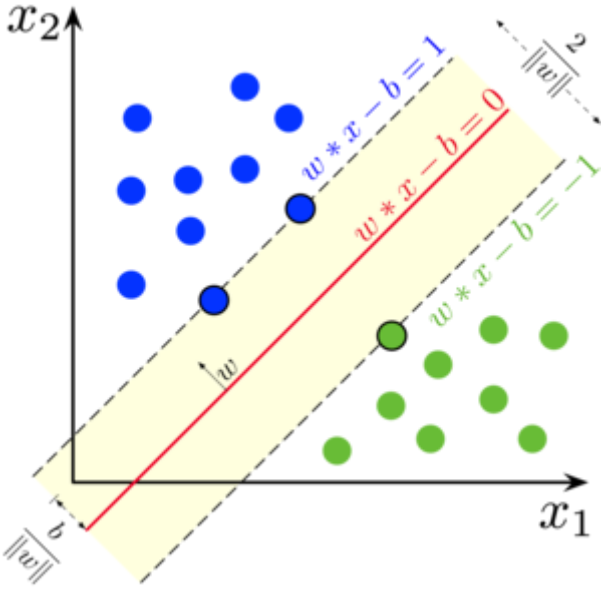
- Logistic regression is a traditional statistical technique, this model was used in the biological sciences in the early twentieth century. It was then adapted by many social science applications.



- It has become a very popular tool for building machine learning models
- Although logistic regression indicates the probability of success or failure of an event, it is normally used as a classification model
- Logistic regression allows to infer probabilities and classify new samples using numerical and categorical characteristics
- Logistic regression to calculate how the line fits the data applies the "maximum likelihood"

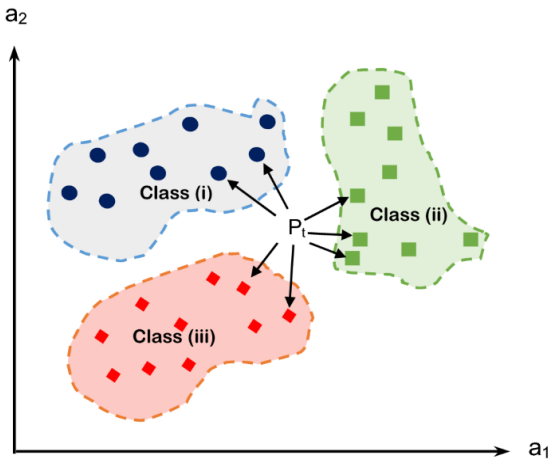
Support Vector Machine

- This Machine learning algorithm provides high accuracy with lower computational power.
- Although it can be used for both regression tasks and classification,
- Its objective is to find the hyperplane that specifically defines the different data points in a n_ dimensional space defined by the number of features.
- The optimal separation of 2 classes rests on maximizing the distance between the points of both classes. There are an infinite number of hyperplanes that can be selected. however, maximizing margins generates more robust rankings
-



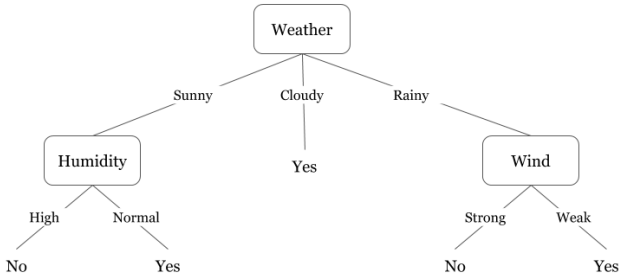
K-Nearest Neighbors

- KNN is a simple machine learning algorithm. It rests on the idea that the greater the similarity between points, the smaller their distance, that is, similar things should be found at a smaller distance.
- In this sense, the algorithm calculates the distance between each of the points and based on their proximity it is capable of assigning a label. the fact that the calculation between 2 points is the basis of the algorithm gives us great versatility to adapt the model to our needs such as Euclidean, Manhattan or Minkowski
- Selecting the correct K for our data set, we must run the model a certain number of times until we find the result with the least amount of errors. For this reason it is not necessary to build a model or develop hyper parameter tuning
- However, when faced with large volumes of data, this model becomes inefficient and requires large computational costs.



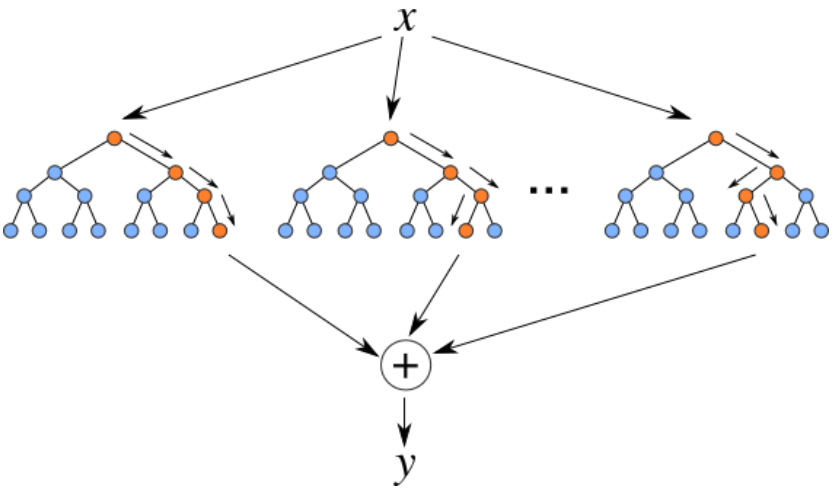
Decision Tree

- It is a supervised learning model that is based on asking questions to classify the samples. It consists of predicting the value of the target field from a series of decision rules that are inferred from the rest of the features.
- Its tree morphology contains a graph where the nodes represent the classification points, the tree questions, and the edges their respective answers.
- By nature the decision tree generation process is recursive. consists in:
    - define the root, the attribute that separates the data with less impurity (to measure it we use the GINI coefficient)
    - go through the rest of the nodes, until reaching the final answer
    - repat the process by rearranging the nodes



random forest

- Random Forest is a set of combined decision trees. Each tree is provided with different data, that is, none of the trees sees the complete training set. in this way, when combining the results, the errors compensate each other and we obtain a more robust prediction



Benchmark

- As a baseline solution to compare the results of the final model against. we will use the results of a simplistic model:
    - Logistic Regression model

III. Methodology

Data Preprocessing

- Data Cleaning
  - portfolio dataframe:
    - Rename id column name to offert_id and set as index
    - Hot-encoding the offer_type column
    - Hot-encoding the channels column
  - profile dataframe:
    - Drop age values == 118
    - Drop NaN values for income and gender columns
    - Dateformat became_member_on
    - Binary values for gender column
  - transcript dataframe:
    - unstack amount and offer id columns
    - set time unit in days

- Master table consolidation

	gender	age	income	subscription_year	offer_id	time	amount	reward	difficulty	duration	email	mobile	social	web	offer_type
1	1	55.0	112000.0	2017	1	22	0.0	5.0	5	7	1	1	0	1	1
3	1	75.0	100000.0	2017	1	0	0.0	0.0	5	7	1	1	0	1	1
4	1	75.0	100000.0	2017	1	5	0.0	5.0	5	7	1	1	0	1	1
6	2	68.0	70000.0	2018	1	17	0.0	0.0	5	7	1	1	0	1	1
7	2	68.0	70000.0	2018	1	21	0.0	5.0	5	7	1	1	0	1	1

- Exploratory Data Analysis
  - Univariable exploration
  - Bivariable exploration
  - Segmentation demographics and offer status summary table

- Machine learning preprocessing
  - Based on the different categorical fields, how the different demographic segmentations respond to each one of the types of offers present in the exercise, we can build a Machine learning model that indicates how a certain demographic profile would respond to the different types of offers
  - To validate the impact that Starbucks promotions have, we are going to exclude received offers from the study, in this way we will only take into account the offers seen over the completed ones.
  - Map the categorical fields
    - offer_Status
    - offer_type
    - gender

```
# Build dictionary mappings for Categorical fields
status_map = {'offer completed':1, 'offer viewed':2}
type_map = {'bogo':1, 'informational':2, 'discount':3}
gender_map = {'F':1, 'M':2, 'O':3}
offers_id = df_master['offer_id'].unique().tolist()
```

```
offer_id_map = {value:index for index, value in enumerate(offers_id,
start=1)}

# map Offer status with numeric values
df_master['offer_status'] = df_master['offer_status'].map(status_map)
# map Offer type with numeric values
df_master['offer_type'] = df_master['offer_type'].map(type_map)
# map gender with numeric values
df_master['gender'] = df_master['gender'].map(gender_map)
# map offer_id with numeric values
df_master['offer_id'] = df_master['offer_id'].map(offer_id_map)

# Rename 'reward_x' column to 'reward'
df_master.rename(columns ={'reward_x':'reward'}, inplace = True)
```

- Standardize numerical values with MinMaxScaler from scikit learn

	gender	age	income	subscription_year	offer_id	time	amount	reward	difficulty	duration	email	mobile	social	web	offer_type
1	1	0.445783	0.911111	0.8	1	0.758621	0.0	0.5	0.25	0.571429	1	1	0	1	1
3	1	0.686747	0.777778	0.8	1	0.000000	0.0	0.0	0.25	0.571429	1	1	0	1	1
4	1	0.686747	0.777778	0.8	1	0.172414	0.0	0.5	0.25	0.571429	1	1	0	1	1
6	2	0.602410	0.444444	1.0	1	0.586207	0.0	0.0	0.25	0.571429	1	1	0	1	1
7	2	0.602410	0.444444	1.0	1	0.724138	0.0	0.5	0.25	0.571429	1	1	0	1	1

Implementation

- Regarding data cleaning, we have concatenated the unpack of a dictionary contained in a field using a .iteritems within a tuple comprehension to then generate the columns associated with the key-value pair

```
# unpack value column
df_transcript = pd.concat([df_transcript, pd.DataFrame((d for idx, d in
df_transcript['value'].iteritems()))], axis=1).fillna(0)
# integrate offer id & offer_id
df_transcript['offer_id'] = np.where(df_transcript['offer id'] == 0,
df_transcript['offer_id'], df_transcript['offer id'])
# drop unnecessary columns
df_transcript.drop(columns=['offer id', 'value'], inplace=True)
```

- To carry out the visualization we have built some functions as well

```
def barchar(df, cat_var, order_list=None, rot=None, hue=None):

    plt.figure(figsize=(16,9))
    base_color = sns.color_palette()[0]
    sns.countplot(data= df, x=cat_var, hue=hue, color=base_color,
order=order_list)

    #add annotations
```

```
    n_values = df.shape[0]
    cat_count = df[cat_var].value_counts()
    locs, labels = plt.xticks()
    plt.title(f'{cat_var}', fontsize=20)
    plt.xticks(rotation=rot);
```

- In addition, to generate interactive filtering tables we have incorporated the ***ipywidgets*** package that allows you to interactively view different levels of filtering at the same time. We use this tool to build the summary table of the segmented demographics

```
GENDER_ALL = ['F', 'M', 'O']
AGE_GROUP_ALL = ['adults', 'seniors', 'teenagers', 'young-adults']
INCOME_GROUP_ALL = ['Low income', 'Middle income', 'Upper income']
OFFER_TYPE_ALL = ['bogo', 'discount', 'informational']


filtered_output = widgets.Output()

multisel_gender = widgets.SelectMultiple(
                        options=GENDER_ALL,
                        value=GENDER_ALL,
                        #rows=10,
                        description='Gender',
                        disabled=False)

multisel_age_group = widgets.SelectMultiple(
                        options=AGE_GROUP_ALL,
                        value=AGE_GROUP_ALL,
                        description='Age group',
                        disabled=False)

multisel_income_group = widgets.SelectMultiple(
                        options=INCOME_GROUP_ALL,
                        value=INCOME_GROUP_ALL,
                        description='Income',
                        disabled=False)

multisel_offer_type = widgets.SelectMultiple(
                        options=OFFER_TYPE_ALL,
                        value=OFFER_TYPE_ALL,
                        description='Offer type',
                        disabled=False)

def common_filtering(gender, age_group=None, income_group=None,
offer_type=None):
```

```
    global master_filtred
    filtered_output.clear_output()
    if (gender == GENDER_ALL) & (age_group == AGE_GROUP_ALL) &
(income_group == INCOME_GROUP_ALL) & (offer_type ==OFFER_TYPE_ALL):
        master_filtered = master_pivoted

    elif (gender == GENDER_ALL):
        master_filtered =
master_pivoted.loc[(master_pivoted.index.get_level_values('gender').isin
(gender))]

    elif (gender == GENDER_ALL) & (age_group == AGE_GROUP_ALL):
        master_filtered =
master_pivoted.loc[(master_pivoted.index.get_level_values('gender').isin
(gender)) &

(master_pivoted.index.get_level_values('age_group').isin(age_group))]

    elif (gender == GENDER_ALL) & (age_group == AGE_GROUP_ALL) &
(income_group == INCOME_GROUP_ALL):
        master_filtered =
master_pivoted.loc[(master_pivoted.index.get_level_values('gender').isin
(gender)) &

(master_pivoted.index.get_level_values('age_group').isin(age_group)) &

(master_pivoted.index.get_level_values('income_group').isin(income_group
))]

    else:
        master_filtered =
master_pivoted.loc[(master_pivoted.index.get_level_values('gender').isin
(gender)) &

(master_pivoted.index.get_level_values('age_group').isin(age_group)) &

(master_pivoted.index.get_level_values('income_group').isin(income_group
)) &

(master_pivoted.index.get_level_values('offer_type').isin(offer_type))]
    with filtered_output:
        display(master_filtered)

def filter_multisel_gender(change):
    common_filtering(change.new, multisel_age_group.value,
multisel_income_group.value, multisel_offer_type.value)
```

```
def filter_multisel_age_group(change):
    common_filtering(multisel_gender.value, change.new,
multisel_income_group.value, multisel_offer_type.value)

def filter_multisel_income_group(change):
    common_filtering(multisel_gender.value, multisel_age_group.value,
change.new, multisel_offer_type.value)

def filter_multisel_offer_type(change):
    common_filtering(multisel_gender.value, multisel_age_group.value,
multisel_income_group.value, change.new)

multisel_gender.observe(filter_multisel_gender, names='value')
multisel_age_group.observe(filter_multisel_age_group, names='value')
multisel_income_group.observe(filter_multisel_income_group,
names='value')
multisel_offer_type.observe(filter_multisel_offer_type, names='value')


display(multisel_gender)
display(multisel_age_group)
display(multisel_income_group)
display(multisel_offer_type)
```

- Finally we have built 2 functions plus one to train and predict the model and another to evaluate its results

```
def model_train_and_predict(model, X_train=X_train, y_train=y_train):
    # fit the model
    model.fit(X_train, y_train)
    # predict the vañues
    y_pred = model.predict(X_test)

    return y_pred

def model_evaluate(y_true, y_pred):
    #calculate accuracy
    accuracy = accuracy_score(y_true, y_pred)
    print('Accuracy: %.3f' % accuracy)
    # calculate prediction
    precision = precision_score(y_true, y_pred)
    print('Precision: %.3f' % precision)
    # calculate recall
    recall = recall_score(y_true, y_pred)
```

```
    print('Recall: %.3f' % recall)
    # calculate score
    score = f1_score(y_true, y_pred)
    print('F-Measure: %.3f' % score)
```

Refinement

- In a first iteration, for each one of the studied models, the default parameter settings were used

	Decision Tree	**Random Forest**	**Logistic Regression**	**Support Vector Machine**	**Naive Bayes**	**K-Nearest Neighbors**
Accuracy	56.2	57.4	66.5	66.5	66.3	55.6
Precision	56.2	57.4	66.5	66.5	66.3	55.6
Recall	56.2	57.4	66.5	66.5	66.3	55.6
F-Measure	56.2	57.4	66.5	66.5	66.3	55.6

- By the evaluation metrics it looks like we could apply some refinement to the models, WE choose to work on:
    - Decision Tree
    - Random Forest
    - Logistic Regression

- In the first place we will use the gridsearch to do Cross validations on the different sets of parameters. We introduce this functionality within a function:

```
def model_refinement_and_predict(model, X_train, y_train, grid_values, cv=6):
    grid_clf = GridSearchCV(model, param_grid = grid_values,scoring = 'f1_macro', cv=cv)
    grid_clf.fit(X_train, y_train)
    y_pred = grid_clf.predict(X_test)
    return y_pred
```

- Hyper parameter tuning
    - Decision tree:
        - 'max_depth':[8,12,15],
        - 'min_samples_leaf':[4,6,8],
        - 'criterion':["gini", "entropy"]
    - Random forest:
        - 'max_depth':[8,12,15],
        - 'min_samples_leaf':[4,6,8],

        - 'criterion':["gini", "entropy"]
    - Logistic Regression:
        - 'C':[0.001,.009,0.01,.09,1,5,10,25]

IV. Results

Model Evaluation and Validation

- After applying the refinement, we obtain metrics with a higher accuracy, they have validated the better suited models.

	Decision Tree	**Random Forest**	**Logistic Regression**
Accuracy	79.7	72.8	80.2
Precision	79.7	72.8	80.2
Recall	79.7	72.8	80.2
F-Measure	79.7	72.8	80.2

- The results obtained leave us satisfied in terms of the accuracy for the refined models. However, in the future, we consider it interesting to implement a previous PCA to focus the study on the most significant features.

Justification

- In relation to the proposed benchmark, we have achieved a considerable improvement in the evaluation metrics over the test datasets. Compared to 66 initial points, we increased the accuracy of the models to a maximum of 80.that is more than 15 points in some cases.

V. Conclusion

Free-Form Visualization

- Summary table: demographic segmentation of offer status

  We decided to build an interactive dataframe using ipywidgets to have a better understanding of the behaviors that different consumer groups have. For this, we are first going to group the dataframe by the categorical fields that identify demographic groups:

  - gender
  - age
  - income

  and by the fields that describe the characteristics of the established offers:

  - offer type

- offer status

gender	age_group	income_group	offer_status / offer_type	offer completed	offer received	offer viewed	offer conversion
F	teenagers	Low income	bogo	191.0	357.0	295.0	53.50
			discount	225.0	341.0	213.0	65.98
			informational	NaN	189.0	125.0	NaN
		Middle income	bogo	104.0	144.0	119.0	72.22
			discount	100.0	149.0	89.0	67.11
			informational	NaN	61.0	37.0	NaN
	young-adults	Low income	bogo	345.0	546.0	446.0	63.19
			discount	334.0	511.0	319.0	65.36
			informational	NaN	293.0	178.0	NaN
		Middle income	bogo	147.0	222.0	178.0	66.22
			discount	137.0	209.0	130.0	65.55
			informational	NaN	103.0	70.0	NaN
	adults	Low income	bogo	1238.0	2027.0	1724.0	61.08
			discount	1373.0	2074.0	1433.0	66.20
			informational	NaN	1018.0	757.0	NaN
		Middle income	bogo	2009.0	2782.0	2366.0	72.21
			discount	2195.0	2879.0	2191.0	76.24
			informational	NaN	1427.0	1069.0	NaN
		Upper income	bogo	1096.0	1412.0	1129.0	77.62
			discount	1094.0	1379.0	966.0	79.33
			informational	NaN	729.0	488.0	NaN

Reflection

- In the first instance we concentrate on structuring the data sets, understanding the information that they do not provide and doing the pertinent data wrangling necessary to continue with the EDA. These intermediate transformations added to the analysis and their respective visualizations gave us a more acute perspective of the characteristics of the datasets and their possibilities. In summary, we decided to implement an interactive table that would describe the convertibility ratio between the different types of offer for each of the demographic segments. This descriptive analysis gave us a very complete picture regarding the diversity of results found. Finally, we convert the datasets into a master table which we use to build the machine learning models.
- The fact of being able to be working and analyzing business data in a study environment is highly valuable and makes the final project very attractive. Here the skills developed throughout the course should be applied as a means to provide a solution to a specific client. It was a very complete training for me and I had a lot of fun reflecting on the insights that could be extracted from this data

Improvement

- Develop more the model refinement, continue with a deep workflow over the hyperparameter tuning
- Deploy it to a cloud environment and prepare it to have CD/CI integration with the client's database platform.
- On the other hand, using the Xgboost model may be a good possibility also due to its robust predictions and its easy implementation as well.
- Test other ML algorithms like neural networks to make classifications.