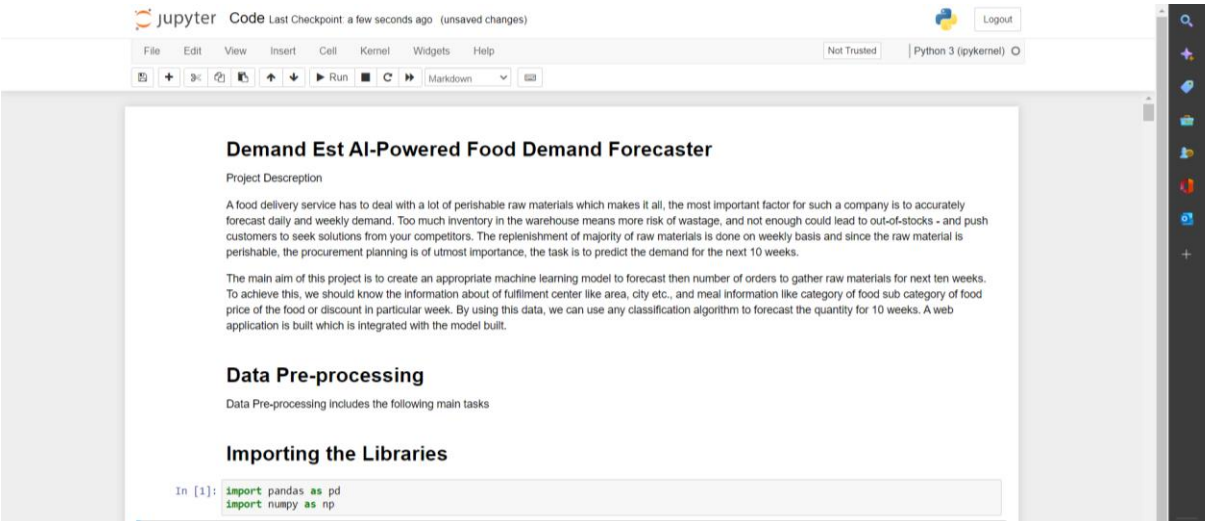
DATA PRE-PROCESSING

Importing the libraries



Demand Est AI-Powered Food Demand Forecaster

Project Descreption

A food delivery service has to deal with a lot of perishable raw materials which makes it all, the most important factor for such a company is to accurately forecast daily and weekly demand. Too much inventory in the warehouse means more risk of wastage, and not enough could lead to out-of-stocks - and push customers to seek solutions from your competitors. The replenishment of majority of raw materials is done on weekly basis and since the raw material is perishable, the procurement planning is of utmost importance, the task is to predict the demand for the next 10 weeks.

The main aim of this project is to create an appropriate machine learning model to forecast then number of orders to gather raw materials for next ten weeks. To achieve this, we should know the information about of fulfilment center like area, city etc., and meal information like category of food sub category of food price of the food or discount in particular week. By using this data, we can use any classification algorithm to forecast the quantity for 10 weeks. A web application is built which is integrated with the model built.

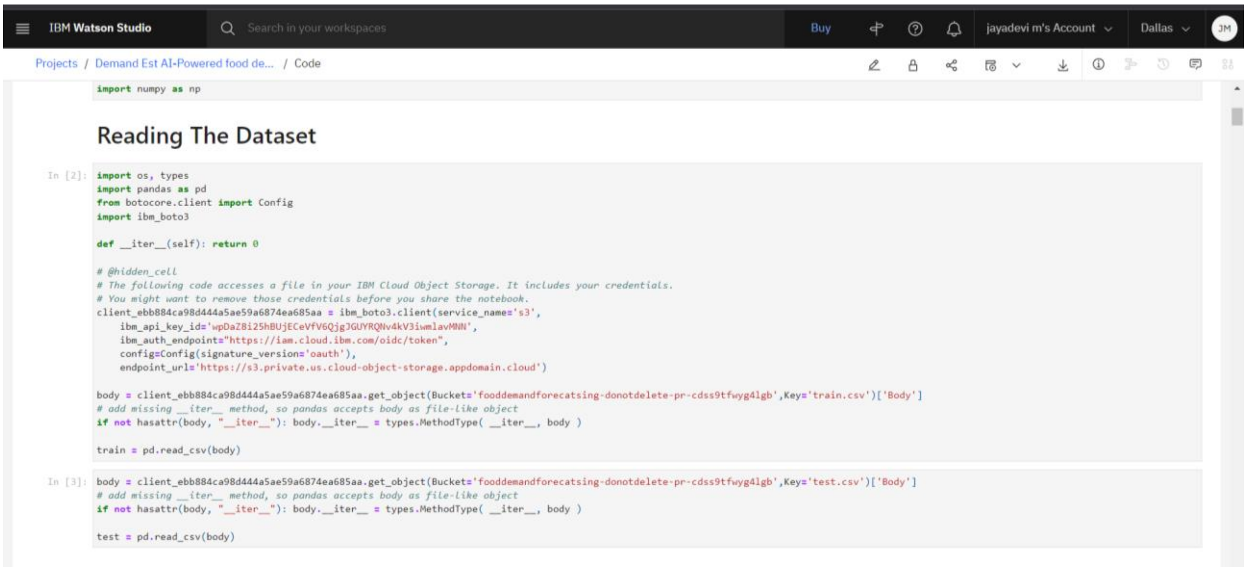
Data Pre-processing

Data Pre-processing includes the following main tasks

Importing the Libraries

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

Reading the dataset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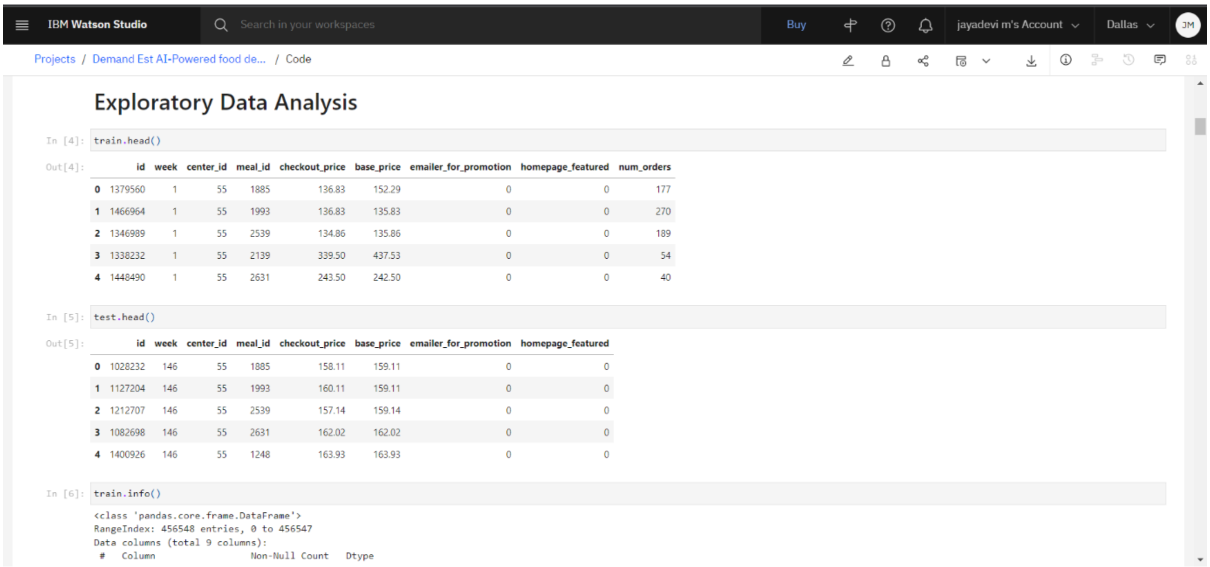
```
import numpy as np
```

Reading The Dataset

In [2]:
```
import os, types
import pandas as pd
from botocore.client import Config
import ibm_boto3

def __iter__(self): return 0

# @hidden_cell
# The following code accesses a file in your IBM Cloud Object Storage. It includes your credentials.
# You might want to remove those credentials before you share the notebook.
client_ebb884ca98d444a5ae59a6874ea685aa = ibm_boto3.client(service_name='s3',
    ibm_api_key_id='wpDaZ8i25hBUjECeVfV6QjgJGUYRQNv4kV3iwmlavMNN',
    ibm_auth_endpoint="https://iam.cloud.ibm.com/oidc/token",
    config=Config(signature_version='oauth'),
    endpoint_url='https://s3.private.us.cloud-object-storage.appdomain.cloud')

body = client_ebb884ca98d444a5ae59a6874ea685aa.get_object(Bucket='fooddemandforecatsing-donotdelete-pr-cdss9tfwyg4lgb',Key='train.csv')['Body']
# add missing __iter__ method, so pandas accepts body as file-like object
if not hasattr(body, "__iter__"): body.__iter__ = types.MethodType( __iter__, body )

train = pd.read_csv(body)
```

In [3]:
```
body = client_ebb884ca98d444a5ae59a6874ea685aa.get_object(Bucket='fooddemandforecatsing-donotdelete-pr-cdss9tfwyg4lgb',Key='test.csv')['Body']
# add missing __iter__ method, so pandas accepts body as file-like object
if not hasattr(body, "__iter__"): body.__iter__ = types.MethodType( __iter__, body )

test = pd.read_csv(body)
```

Exploratory Data analysis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Exploratory Data Analysis

In [4]:
```
train.head()
```

Out[4]:

	id	week	center_id	meal_id	checkout_price	base_price	emailer_for_promotion	homepage_featured	num_orders
0	1379560	1	55	1885	136.83	152.29	0	0	177
1	1466964	1	55	1993	136.83	135.83	0	0	270
2	1346989	1	55	2539	134.86	135.86	0	0	189
3	1338232	1	55	2139	339.50	437.53	0	0	54
4	1448490	1	55	2631	243.50	242.50	0	0	40

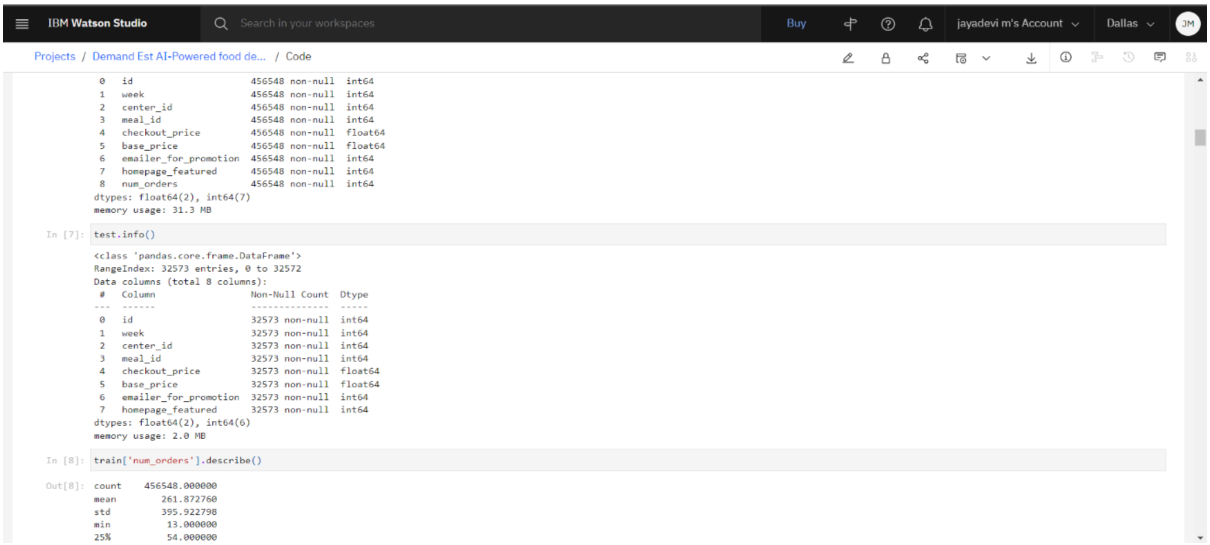
In [5]:
```
test.head()
```

Out[5]:

	id	week	center_id	meal_id	checkout_price	base_price	emailer_for_promotion	homepage_featured
0	1028232	146	55	1885	158.11	159.11	0	0
1	1127204	146	55	1993	160.11	159.11	0	0
2	1212707	146	55	2539	157.14	159.14	0	0
3	1082698	146	55	2631	162.02	162.02	0	0
4	1400926	146	55	1248	163.93	163.93	0	0

In [6]:
```
train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 456548 entries, 0 to 456547
Data columns (total 9 columns):
 #   Column                 Non-Null Count   Dtype
```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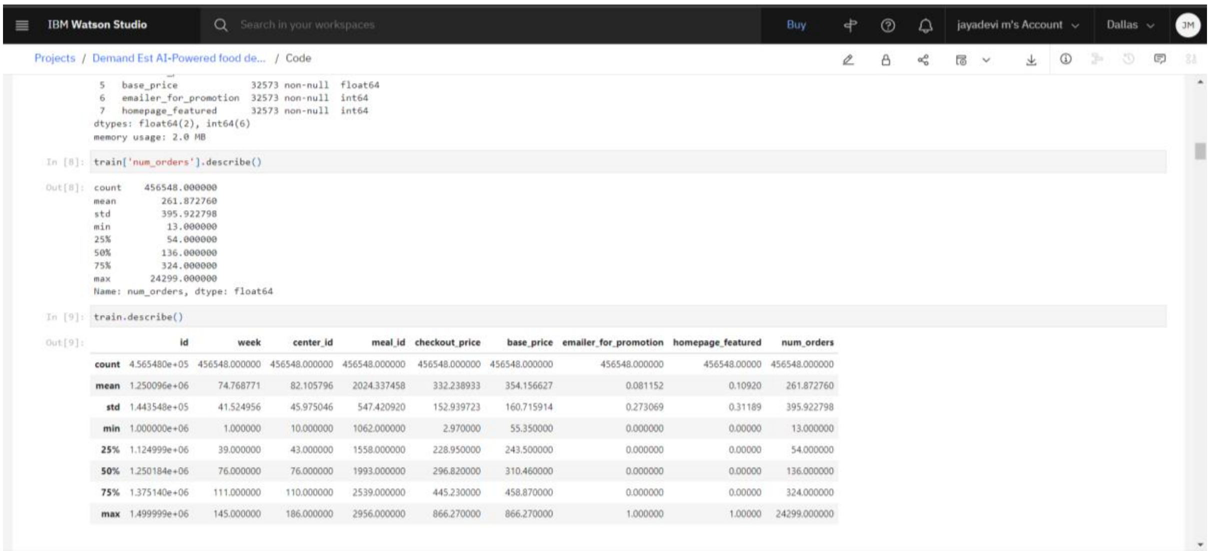
```
 0   id                     456548 non-null  int64
 1   week                   456548 non-null  int64
 2   center_id              456548 non-null  int64
 3   meal_id                456548 non-null  int64
 4   checkout_price         456548 non-null  float64
 5   base_price             456548 non-null  float64
 6   emailer_for_promotion  456548 non-null  int64
 7   homepage_featured      456548 non-null  int64
 8   num_orders             456548 non-null  int64
dtypes: float64(2), int64(7)
memory usage: 31.3 MB
```

In [7]:
```
test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32573 entries, 0 to 32572
Data columns (total 8 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   id                     32573 non-null  int64
 1   week                   32573 non-null  int64
 2   center_id              32573 non-null  int64
 3   meal_id                32573 non-null  int64
 4   checkout_price         32573 non-null  float64
 5   base_price             32573 non-null  float64
 6   emailer_for_promotion  32573 non-null  int64
 7   homepage_featured      32573 non-null  int64
dtypes: float64(2), int64(6)
memory usage: 2.0 MB
```

In [8]:
```
train['num_orders'].describe()
```

Out[8]:
```
count    456548.000000
mean        261.872760
std         395.922798
min          13.000000
25%          54.000000
```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```
 5   base_price             32573 non-null  float64
 6   emailer_for_promotion  32573 non-null  int64
 7   homepage_featured      32573 non-null  int64
dtypes: float64(2), int64(6)
memory usage: 2.0 MB
```

In [8]:
```
train['num_orders'].describe()
```

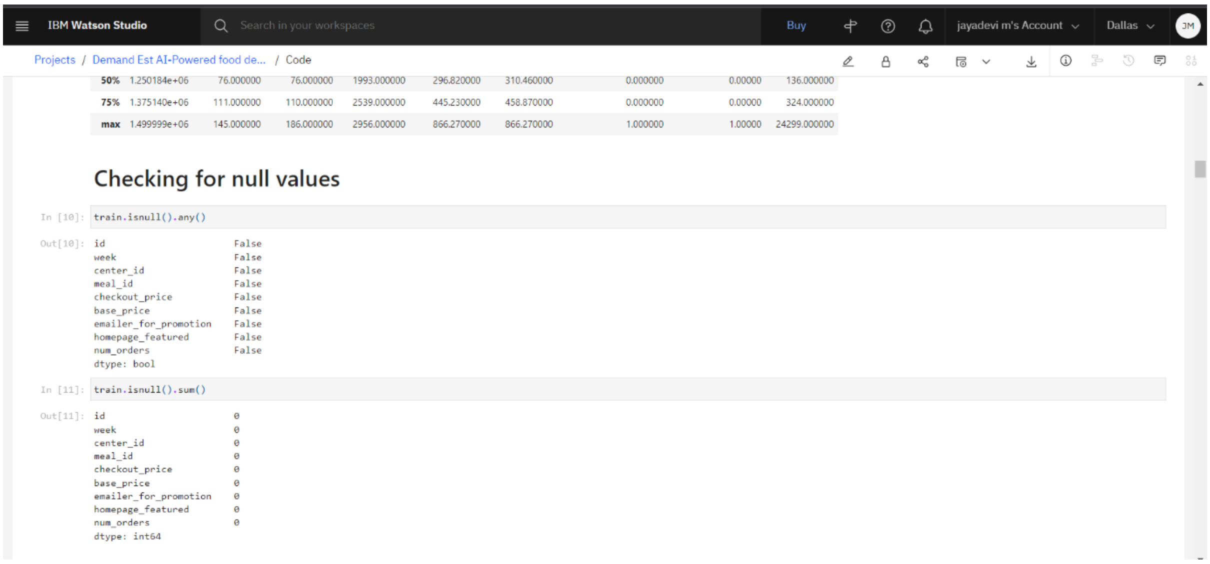
Out[8]:
```
count    456548.000000
mean        261.872760
std         395.922798
min          13.000000
25%          54.000000
50%         136.000000
75%         324.000000
max       24299.000000
Name: num_orders, dtype: float64
```

In [9]:
```
train.describe()
```

Out[9]:

	id	week	center_id	meal_id	checkout_price	base_price	emailer_for_promotion	homepage_featured	num_orders
count	4.565480e+05	456548.000000	456548.000000	456548.000000	456548.000000	456548.000000	456548.000000	456548.00000	456548.000000
mean	1.250096e+06	74.768771	82.105796	2024.337458	332.238933	354.156627	0.081152	0.10920	261.872760
std	1.443548e+05	41.524956	45.975046	547.420920	152.939723	160.715914	0.273069	0.31189	395.922798
min	1.000000e+06	1.000000	10.000000	1062.000000	2.970000	55.350000	0.000000	0.00000	13.000000
25%	1.124999e+06	39.000000	43.000000	1558.000000	228.950000	243.500000	0.000000	0.00000	54.000000
50%	1.250184e+06	76.000000	76.000000	1993.000000	296.820000	310.460000	0.000000	0.00000	136.000000
75%	1.375140e+06	111.000000	110.000000	2539.000000	445.230000	458.870000	0.000000	0.00000	324.000000
max	1.499999e+06	145.000000	186.000000	2956.000000	866.270000	866.270000	1.000000	1.00000	24299.000000

Checking for null values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50%	1.250184e+06	76.000000	76.000000	1993.000000	296.820000	310.460000	0.000000	0.00000	136.000000
75%	1.375140e+06	111.000000	110.000000	2539.000000	445.230000	458.870000	0.000000	0.00000	324.000000
max	1.499999e+06	145.000000	186.000000	2956.000000	866.270000	866.270000	1.000000	1.00000	24299.000000

Checking for null values

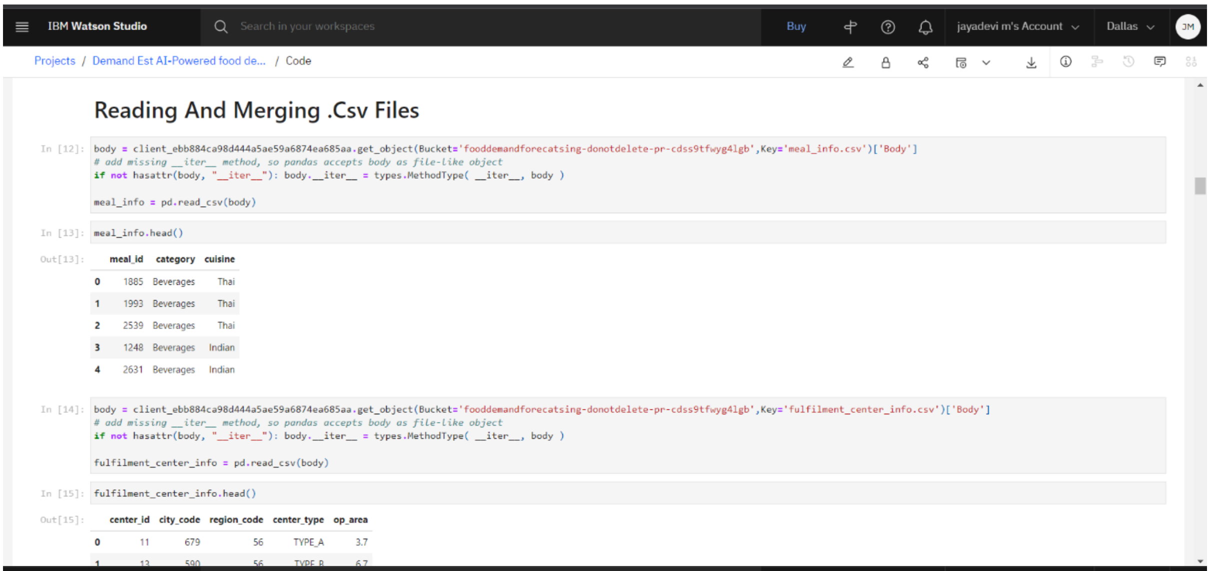
```
In [10]: train.isnull().any()
```

```
Out[10]: id                       False
         week                     False
         center_id                False
         meal_id                  False
         checkout_price           False
         base_price               False
         emailer_for_promotion    False
         homepage_featured        False
         num_orders               False
         dtype: bool
```

```
In [11]: train.isnull().sum()
```

```
Out[11]: id                       0
         week                     0
         center_id                0
         meal_id                  0
         checkout_price           0
         base_price               0
         emailer_for_promotion    0
         homepage_featured        0
         num_orders               0
         dtype: int64
```

Reading and merging .csv files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Reading And Merging .Csv Files

```
In [12]: body = client_ebb884ca98d444a5ae59a6874ea685aa.get_object(Bucket='fooddemandforecatsing-donotdelete-pr-cdss9tfwyg4lgb',Key='meal_info.csv')['Body']
         # add missing __iter__ method, so pandas accepts body as file-like object
         if not hasattr(body, "__iter__"): body.__iter__ = types.MethodType( __iter__, body )

         meal_info = pd.read_csv(body)
```

```
In [13]: meal_info.head()
```

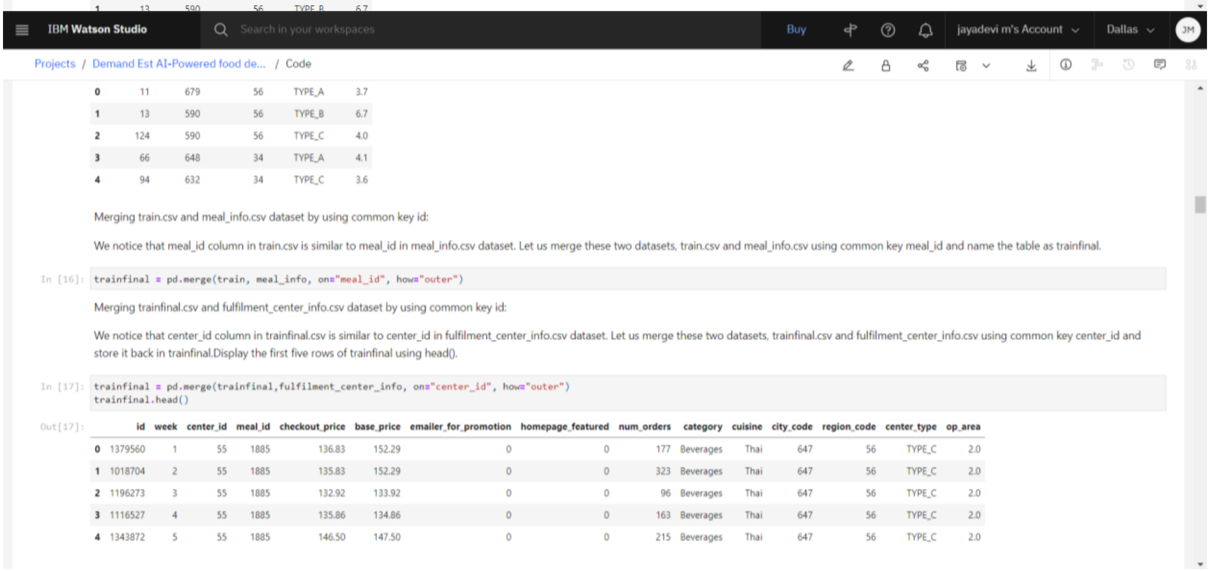
Out[13]:

	meal_id	category	cuisine
0	1885	Beverages	Thai
1	1993	Beverages	Thai
2	2539	Beverages	Thai
3	1248	Beverages	Indian
4	2631	Beverages	Indian

```
In [14]: body = client_ebb884ca98d444a5ae59a6874ea685aa.get_object(Bucket='fooddemandforecatsing-donotdelete-pr-cdss9tfwyg4lgb',Key='fulfilment_center_info.csv')['Body']
         # add missing __iter__ method, so pandas accepts body as file-like object
         if not hasattr(body, "__iter__"): body.__iter__ = types.MethodType( __iter__, body )

         fulfilment_center_info = pd.read_csv(body)
```

```
In [15]: fulfilment_center_info.head()
```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Out[15]:

	center_id	city_code	region_code	center_type	op_area
0	11	679	56	TYPE_A	3.7
1	13	590	56	TYPE_B	6.7
2	124	590	56	TYPE_C	4.0
3	66	648	34	TYPE_A	4.1
4	94	632	34	TYPE_C	3.6

Merging train.csv and meal_info.csv dataset by using common key id:

We notice that meal_id column in train.csv is similar to meal_id in meal_info.csv dataset. Let us merge these two datasets, train.csv and meal_info.csv using common key meal_id and name the table as trainfinal.

```
In [16]: trainfinal = pd.merge(train, meal_info, on="meal_id", how="outer")
```

Merging trainfinal.csv and fulfilment_center_info.csv dataset by using common key id:

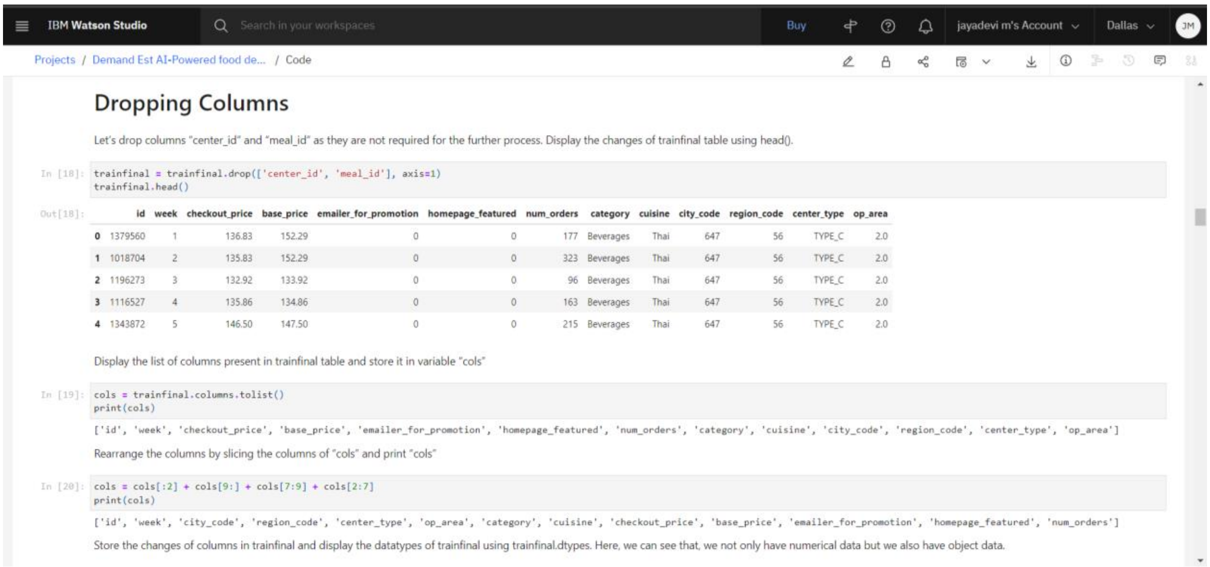
We notice that center_id column in trainfinal.csv is similar to center_id in fulfilment_center_info.csv dataset. Let us merge these two datasets, trainfinal.csv and fulfilment_center_info.csv using common key center_id and store it back in trainfinal.Display the first five rows of trainfinal using head().

```
In [17]: trainfinal = pd.merge(trainfinal,fulfilment_center_info, on="center_id", how="outer")
         trainfinal.head()
```

Out[17]:

	id	week	center_id	meal_id	checkout_price	base_price	emailer_for_promotion	homepage_featured	num_orders	category	cuisine	city_code	region_code	center_type	op_area
0	1379560	1	55	1885	136.83	152.29	0	0	177	Beverages	Thai	647	56	TYPE_C	2.0
1	1018704	2	55	1885	135.83	152.29	0	0	323	Beverages	Thai	647	56	TYPE_C	2.0
2	1196273	3	55	1885	132.92	133.92	0	0	96	Beverages	Thai	647	56	TYPE_C	2.0
3	1116527	4	55	1885	135.86	134.86	0	0	163	Beverages	Thai	647	56	TYPE_C	2.0
4	1343872	5	55	1885	146.50	147.50	0	0	215	Beverages	Thai	647	56	TYPE_C	2.0

Dropping Columns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Dropping Columns

Let's drop columns "center_id" and "meal_id" as they are not required for the further process. Display the changes of trainfinal table using head().

```
In [18]: trainfinal = trainfinal.drop(['center_id', 'meal_id'], axis=1)
         trainfinal.head()
```

Out[18]:

	id	week	checkout_price	base_price	emailer_for_promotion	homepage_featured	num_orders	category	cuisine	city_code	region_code	center_type	op_area
0	1379560	1	136.83	152.29	0	0	177	Beverages	Thai	647	56	TYPE_C	2.0
1	1018704	2	135.83	152.29	0	0	323	Beverages	Thai	647	56	TYPE_C	2.0
2	1196273	3	132.92	133.92	0	0	96	Beverages	Thai	647	56	TYPE_C	2.0
3	1116527	4	135.86	134.86	0	0	163	Beverages	Thai	647	56	TYPE_C	2.0
4	1343872	5	146.50	147.50	0	0	215	Beverages	Thai	647	56	TYPE_C	2.0

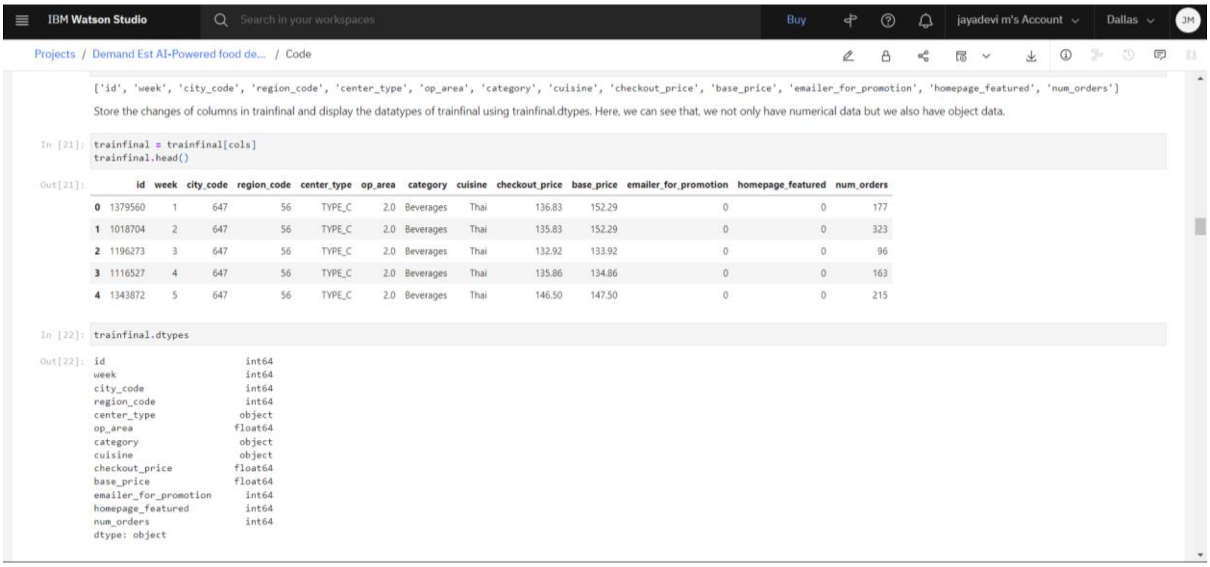
Display the list of columns present in trainfinal table and store it in variable "cols"

```
In [19]: cols = trainfinal.columns.tolist()
         print(cols)

         ['id', 'week', 'checkout_price', 'base_price', 'emailer_for_promotion', 'homepage_featured', 'num_orders', 'category', 'cuisine', 'city_code', 'region_code', 'center_type', 'op_area']
```

Rearrange the columns by slicing the columns of "cols" and print "cols"

```
In [20]: cols = cols[:2] + cols[9:] + cols[7:9] + cols[2:7]
         print(cols)

         ['id', 'week', 'city_code', 'region_code', 'center_type', 'op_area', 'category', 'cuisine', 'checkout_price', 'base_price', 'emailer_for_promotion', 'homepage_featured', 'num_orders']
```

Store the changes of columns in trainfinal and display the datatypes of trainfinal using trainfinal.dtypes. Here, we can see that, we not only have numerical data but we also have object data.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```
['id', 'week', 'city_code', 'region_code', 'center_type', 'op_area', 'category', 'cuisine', 'checkout_price', 'base_price', 'emailer_for_promotion', 'homepage_featured', 'num_orders']
```

Store the changes of columns in trainfinal and display the datatypes of trainfinal using trainfinal.dtypes. Here, we can see that, we not only have numerical data but we also have object data.

```
In [21]: trainfinal = trainfinal[cols]
         trainfinal.head()
```

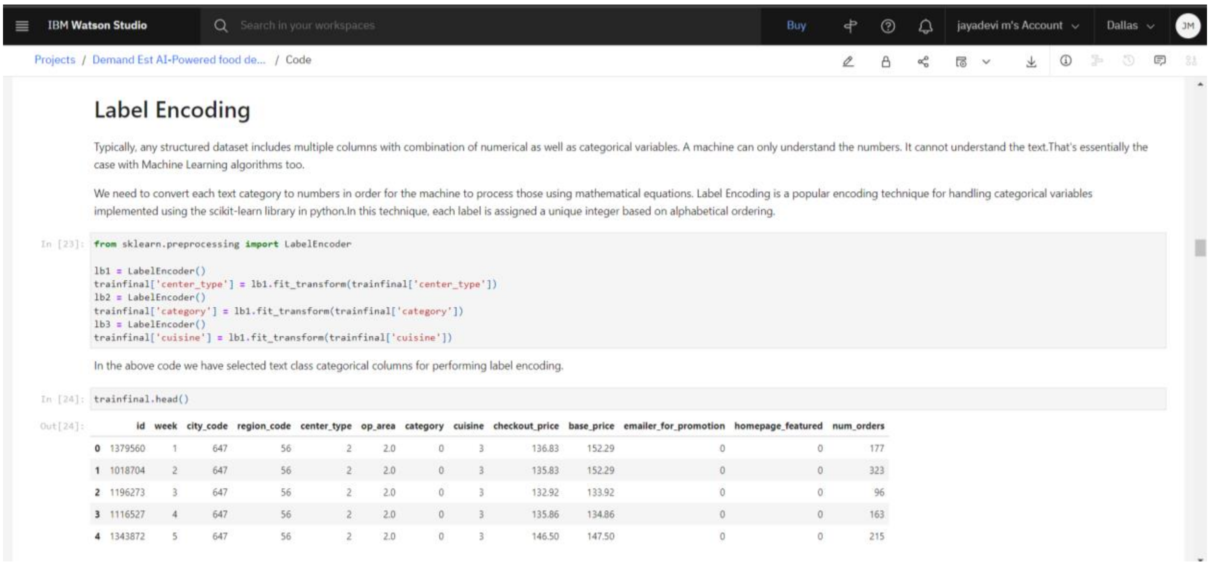
Out[21]:

	id	week	city_code	region_code	center_type	op_area	category	cuisine	checkout_price	base_price	emailer_for_promotion	homepage_featured	num_orders
0	1379560	1	647	56	TYPE_C	2.0	Beverages	Thai	136.83	152.29	0	0	177
1	1018704	2	647	56	TYPE_C	2.0	Beverages	Thai	135.83	152.29	0	0	323
2	1196273	3	647	56	TYPE_C	2.0	Beverages	Thai	132.92	133.92	0	0	96
3	1116527	4	647	56	TYPE_C	2.0	Beverages	Thai	135.86	134.86	0	0	163
4	1343872	5	647	56	TYPE_C	2.0	Beverages	Thai	146.50	147.50	0	0	215

```
In [22]: trainfinal.dtypes

Out[22]: id                         int64
         week                       int64
         city_code                  int64
         region_code                int64
         center_type               object
         op_area                  float64
         category                  object
         cuisine                   object
         checkout_price           float64
         base_price               float64
         emailer_for_promotion      int64
         homepage_featured          int64
         num_orders                 int64
         dtype: object
```

Label encoding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Label Encoding

Typically, any structured dataset includes multiple columns with combination of numerical as well as categorical variables. A machine can only understand the numbers. It cannot understand the text.That's essentially the case with Machine Learning algorithms too.

We need to convert each text category to numbers in order for the machine to process those using mathematical equations. Label Encoding is a popular encoding technique for handling categorical variables implemented using the scikit-learn library in python.In this technique, each label is assigned a unique integer based on alphabetical ordering.

```
In [23]: from sklearn.preprocessing import LabelEncoder

         lb1 = LabelEncoder()
         trainfinal['center_type'] = lb1.fit_transform(trainfinal['center_type'])
         lb2 = LabelEncoder()
         trainfinal['category'] = lb1.fit_transform(trainfinal['category'])
         lb3 = LabelEncoder()
         trainfinal['cuisine'] = lb1.fit_transform(trainfinal['cuisine'])
```

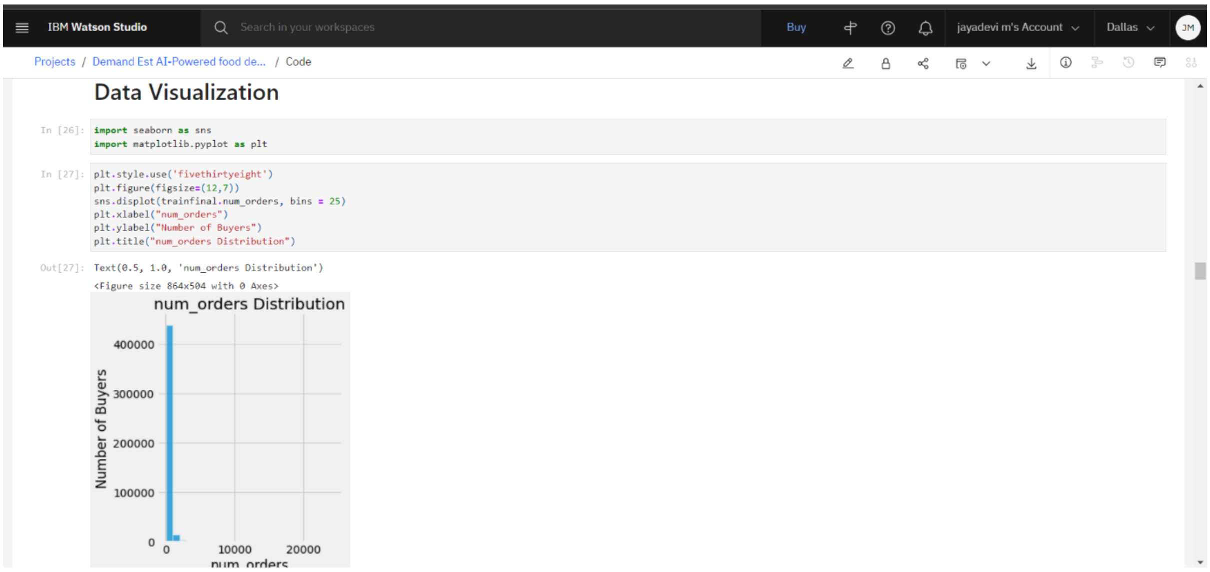
In the above code we have selected text class categorical columns for performing label encoding.

```
In [24]: trainfinal.head()
```

Out[24]:

	id	week	city_code	region_code	center_type	op_area	category	cuisine	checkout_price	base_price	emailer_for_promotion	homepage_featured	num_orders
0	1379560	1	647	56	2	2.0	0	3	136.83	152.29	0	0	177
1	1018704	2	647	56	2	2.0	0	3	135.83	152.29	0	0	323
2	1196273	3	647	56	2	2.0	0	3	132.92	133.92	0	0	96
3	1116527	4	647	56	2	2.0	0	3	135.86	134.86	0	0	163
4	1343872	5	647	56	2	2.0	0	3	146.50	147.50	0	0	215

Data visualization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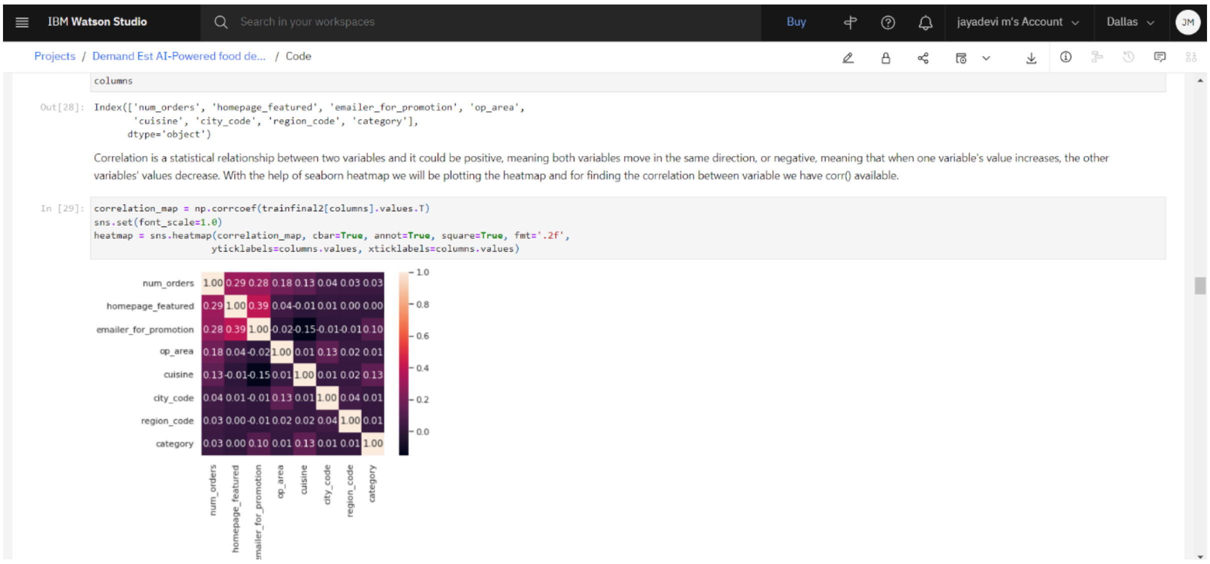
Data Visualization

```
In [26]: import seaborn as sns
         import matplotlib.pyplot as plt
```

```
In [27]: plt.style.use('fivethirtyeight')
         plt.figure(figsize=(12,7))
         sns.displot(trainfinal.num_orders, bins = 25)
         plt.xlabel("num_orders")
         plt.ylabel("Number of Buyers")
         plt.title("num_orders Distribution")
```

```
Out[27]: Text(0.5, 1.0, 'num_orders Distribution')
         <Figure size 864x504 with 0 Axes>
```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```
columns
```

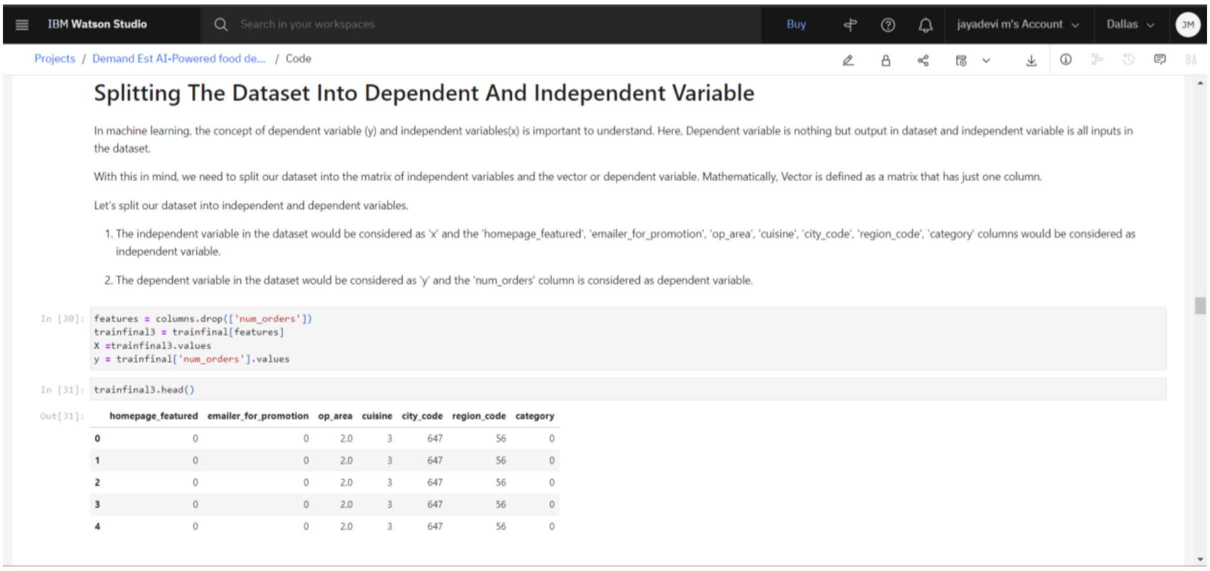
```
Out[28]: Index(['num_orders', 'homepage_featured', 'emailer_for_promotion', 'op_area',
                'cuisine', 'city_code', 'region_code', 'category'],
               dtype='object')
```

Correlation is a statistical relationship between two variables and it could be positive, meaning both variables move in the same direction, or negative, meaning that when one variable's value increases, the other variables' values decrease. With the help of seaborn heatmap we will be plotting the heatmap and for finding the correlation between variable we have corr() available.

```
In [29]: correlation_map = np.corrcoef(trainfinal2[columns].values.T)
         sns.set(font_scale=1.0)
         heatmap = sns.heatmap(correlation_map, cbar=True, annot=True, square=True, fmt='.2f',
                               yticklabels=columns.values, xticklabels=columns.values)
```

num_orders 1.00 0.29 0.28 0.18 0.13 0.04 0.03 0.03
homepage_featured 0.29 1.00 0.39 0.04 -0.01 0.01 0.00 0.00
emailer_for_promotion 0.28 0.39 1.00 -0.02 -0.15 -0.01 -0.01 0.10
op_area 0.18 0.04 -0.02 1.00 0.01 0.13 0.02 0.01
cuisine 0.13 -0.01 -0.15 0.01 1.00 0.01 0.02 0.13
city_code 0.04 0.01 -0.01 0.13 0.01 1.00 0.04 0.01
region_code 0.03 0.00 -0.01 0.02 0.02 0.04 1.00 0.01
category 0.03 0.00 0.10 0.01 0.13 0.01 0.01 1.00
num_orders
homepage_featured
emailer_for_promotion
op_area
cuisine
city_code
region_code
category
1.0
0.8
0.6
0.4
0.2
0.0

Splitting the dataset into dependent and independent variable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Splitting The Dataset Into Dependent And Independent Variable

In machine learning, the concept of dependent variable (y) and independent variables(x) is important to understand. Here, Dependent variable is nothing but output in dataset and independent variable is all inputs in the dataset.

With this in mind, we need to split our dataset into the matrix of independent variables and the vector or dependent variable. Mathematically, Vector is defined as a matrix that has just one column.

Let's split our dataset into independent and dependent variables.

1. The independent variable in the dataset would be considered as 'x' and the 'homepage_featured', 'emailer_for_promotion', 'op_area', 'cuisine', 'city_code', 'region_code', 'category' columns would be considered as independent variable.
2. The dependent variable in the dataset would be considered as 'y' and the 'num_orders' column is considered as dependent variable.

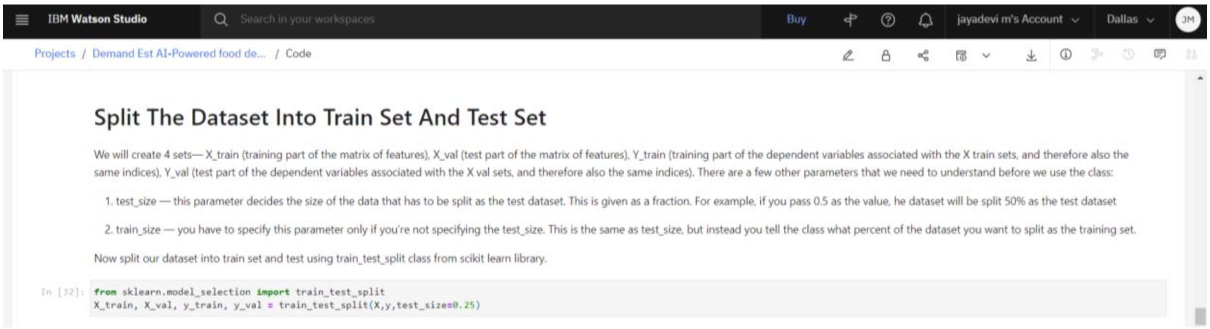
```
In [30]: features = columns.drop(['num_orders'])
         trainfinal3 = trainfinal[features]
         X =trainfinal3.values
         y = trainfinal['num_orders'].values
```

```
In [31]: trainfinal3.head()
```

Out[31]:

	homepage_featured	emailer_for_promotion	op_area	cuisine	city_code	region_code	category
0	0	0	2.0	3	647	56	0
1	0	0	2.0	3	647	56	0
2	0	0	2.0	3	647	56	0
3	0	0	2.0	3	647	56	0
4	0	0	2.0	3	647	56	0

Split the dataset into train set and test set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Split The Dataset Into Train Set And Test Set

We will create 4 sets— X_train (training part of the matrix of features), X_val (test part of the matrix of features), Y_train (training part of the dependent variables associated with the X train sets, and therefore also the same indices), Y_val (test part of the dependent variables associated with the X val sets, and therefore also the same indices). There are a few other parameters that we need to understand before we use the class:

1. test_size — this parameter decides the size of the data that has to be split as the test dataset. This is given as a fraction. For example, if you pass 0.5 as the value, he dataset will be split 50% as the test dataset
2. train_size — you have to specify this parameter only if you're not specifying the test_size. This is the same as test_size, but instead you tell the class what percent of the dataset you want to split as the training set.

Now split our dataset into train set and test using train_test_split class from scikit learn library.

```
In [32]: from sklearn.model_selection import train_test_split
         X_train, X_val, y_train, y_val = train_test_split(X,y,test_size=0.25)
```