In [1]:
```
# This Python 3 environment comes with many helpful analytics libraries installed
# It is defined by the kaggle/python Docker image: https://github.com/kaggle/docker-python
# For example, here's several helpful packages to load

import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)

# Input data files are available in the read-only "../input/" directory
# For example, running this (by clicking run or pressing Shift+Enter) will list all files under the input directory

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

# You can write up to 20GB to the current directory (/kaggle/working/) that gets preserved as output when you create a version usir
# You can also write temporary files to /kaggle/temp/, but they won't be saved outside of the current session
```

```
/kaggle/input/my-data/Customer Loyalty History.csv
/kaggle/input/my-data/Airline Loyalty Data Dictionary.csv
/kaggle/input/my-data/Customer Flight Activity.csv
```

Customer loyalty program data from Northern Lights Air (NLA) in Canada Analysis and Customer Lifetime Value(CLV) Prediction

In [2]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
import warnings
warnings.filterwarnings('ignore')
pd.set_option('display.max_columns', 50)
```

In [3]:
```
df_activity=pd.read_csv('/kaggle/input/my-data/Customer Flight Activity.csv')
df_loyality=pd.read_csv('/kaggle/input/my-data/Customer Loyalty History.csv')
```

In [4]:
```
df_activity.head(3)
```

Out[4]:

	Loyalty Number	Year	Month	Flights Booked	Flights with Companions	Total Flights	Distance	Points Accumulated	Points Redeemed	Dollar Cost Points Redeemed
0	100018	2017	1	3	0	3	1521	152.0	0	0
1	100102	2017	1	10	4	14	2030	203.0	0	0
2	100140	2017	1	6	0	6	1200	120.0	0	0

In [5]:
```
df_loyality.head(3)
```

Out[5]:

	Loyalty Number	Country	Province	City	Postal Code	Gender	Education	Salary	Marital Status	Loyalty Card	CLV	Enrollment Type	Enrollment Year	Enrollment Month	Cancellation Year	Canc
0	480934	Canada	Ontario	Toronto	M2Z 4K1	Female	Bachelor	83236.0	Married	Star	3839.14	Standard	2016	2	NaN	
1	549612	Canada	Alberta	Edmonton	T3G 6Y6	Male	College	NaN	Divorced	Star	3839.61	Standard	2016	3	NaN	
2	429460	Canada	British Columbia	Vancouver	V6E 3D9	Male	College	NaN	Single	Star	3839.75	Standard	2014	7	2018.0	

Merging all data

In [6]:
```
df=df_activity.merge(df_loyality,on='Loyalty Number')
```

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 405624 entries, 0 to 405623
Data columns (total 25 columns):
 #   Column                       Non-Null Count   Dtype  
---  ------                       --------------   -----  
 0   Loyalty Number               405624 non-null  int64  
 1   Year                         405624 non-null  int64  
 2   Month                        405624 non-null  int64  
 3   Flights Booked               405624 non-null  int64  
 4   Flights with Companions      405624 non-null  int64  
 5   Total Flights                405624 non-null  int64  
 6   Distance                     405624 non-null  int64  
 7   Points Accumulated           405624 non-null  float64
 8   Points Redeemed              405624 non-null  int64  
 9   Dollar Cost Points Redeemed  405624 non-null  int64  
 10  Country                      405624 non-null  object 
 11  Province                     405624 non-null  object 
 12  City                         405624 non-null  object 
 13  Postal Code                  405624 non-null  object 
 14  Gender                       405624 non-null  object 
 15  Education                    405624 non-null  object 
 16  Salary                       302952 non-null  float64
 17  Marital Status               405624 non-null  object 
 18  Loyalty Card                 405624 non-null  object 
 19  CLV                          405624 non-null  float64
 20  Enrollment Type              405624 non-null  object 
 21  Enrollment Year              405624 non-null  int64  
 22  Enrollment Month             405624 non-null  int64  
 23  Cancellation Year            50064 non-null   float64
 24  Cancellation Month           50064 non-null   float64
dtypes: float64(5), int64(11), object(9)
memory usage: 77.4+ MB
```

In [8]:
```
df.isna().sum()
```

Out[8]:
```
Loyalty Number                      0
Year                                0
Month                               0
Flights Booked                      0
Flights with Companions             0
Total Flights                       0
Distance                            0
Points Accumulated                  0
Points Redeemed                     0
Dollar Cost Points Redeemed         0
Country                             0
Province                            0
City                                0
Postal Code                         0
Gender                              0
Education                           0
Salary                         102672
Marital Status                      0
Loyalty Card                        0
CLV                                 0
Enrollment Type                     0
Enrollment Year                     0
Enrollment Month                    0
Cancellation Year              355560
Cancellation Month             355560
dtype: int64
```

Droping missing values in Cancellation Year& Cancellation& Month&Postal Code and Country because the missing values are more than 85% from all data

In [9]:
```
df=df.drop(['Cancellation Year','Cancellation Month','Postal Code','Country'],axis=1)
```

Completing missing values in Salary column by mean from simple imputer technique

In [10]:
```
from sklearn.impute import SimpleImputer

# Create an instance of SimpleImputer with the desired strategy
imputer = SimpleImputer(strategy='mean')

# Fit the imputer on the salary column and transform the missing values
df['Salary'] = imputer.fit_transform(df[['Salary']])
```

In [11]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 405624 entries, 0 to 405623
Data columns (total 21 columns):
 #   Column                     Non-Null Count   Dtype  
---  ------                     --------------   -----  
 0   Loyalty Number             405624 non-null  int64  
 1   Year                       405624 non-null  int64  
 2   Month                      405624 non-null  int64  
 3   Flights Booked             405624 non-null  int64  
 4   Flights with Companions    405624 non-null  int64  
 5   Total Flights              405624 non-null  int64  
 6   Distance                   405624 non-null  int64  
 7   Points Accumulated         405624 non-null  float64
 8   Points Redeemed            405624 non-null  int64  
 9   Dollar Cost Points Redeemed  405624 non-null  int64  
 10  Province                   405624 non-null  object 
 11  City                       405624 non-null  object 
 12  Gender                     405624 non-null  object 
 13  Education                  405624 non-null  object 
 14  Salary                     405624 non-null  float64
 15  Marital Status             405624 non-null  object 
 16  Loyalty Card               405624 non-null  object 
 17  CLV                        405624 non-null  float64
 18  Enrollment Type            405624 non-null  object 
 19  Enrollment Year            405624 non-null  int64  
 20  Enrollment Month           405624 non-null  int64  
dtypes: float64(3), int64(11), object(7)
memory usage: 65.0+ MB
```

In [12]:
```
df.head()
```

Out[12]:

	Loyalty Number	Year	Month	Flights Booked	Flights with Companions	Total Flights	Distance	Points Accumulated	Points Redeemed	Dollar Cost Points Redeemed	Province	City	Gender	Education	Salary	Marital Status
0	100018	2017	1	3	0	3	1521	152.0	0	0	Alberta	Edmonton	Female	Bachelor	92552.0	Married
1	100018	2017	2	2	2	4	1320	132.0	0	0	Alberta	Edmonton	Female	Bachelor	92552.0	Married
2	100018	2018	10	6	4	10	3110	311.0	385	31	Alberta	Edmonton	Female	Bachelor	92552.0	Married
3	100018	2017	4	4	0	4	924	92.0	0	0	Alberta	Edmonton	Female	Bachelor	92552.0	Married
4	100018	2017	5	0	0	0	0	0.0	0	0	Alberta	Edmonton	Female	Bachelor	92552.0	Married

Extracting top 10 customers having the highest average CLV

In [14]:
```
df.groupby('Loyalty Number')['CLV'].mean().sort_values(ascending=False).head(10)
```

Out[14]:
```
Loyalty Number
615459    83325.38
652627    83325.38
776187    74228.52
844145    74228.52
767366    73225.96
592003    73225.96
838263    67907.27
680886    67907.27
179870    66025.75
495253    66025.75
Name: CLV, dtype: float64
```

Extracting top 10 customers having the highest Total Flights number

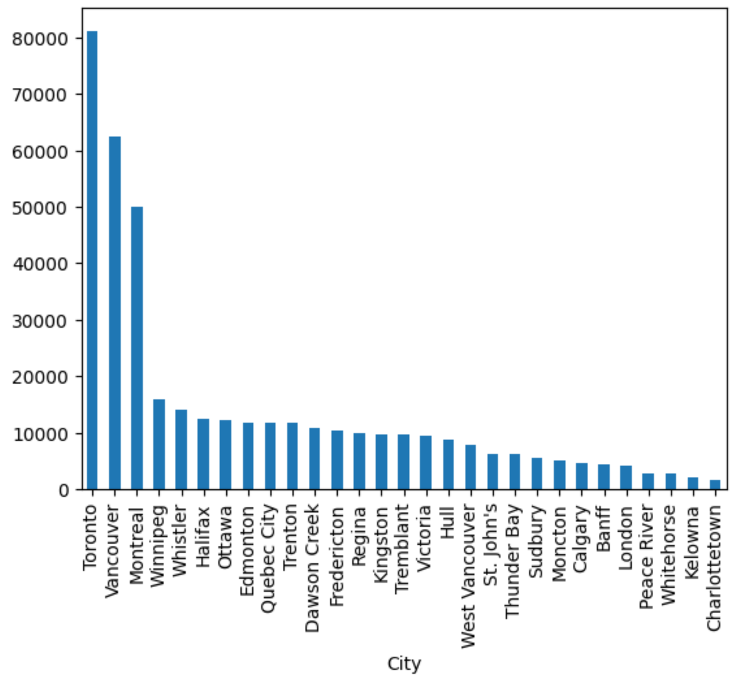
In [15]:
```
df.groupby('Loyalty Number')['Total Flights'].sum().sort_values(ascending=False).head(10)
```

Out[15]:
```
Loyalty Number
336882    448
775768    400
464187    399
255836    395
512296    392
736504    383
279419    379
215508    375
876062    372
615561    372
Name: Total Flights, dtype: int64
```

Exploratory Data Analysis(EDA)

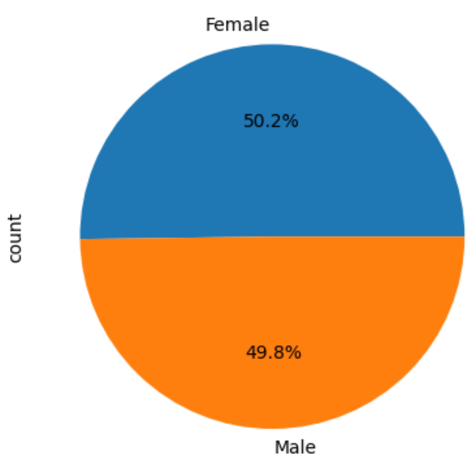
In [16]:
```
df['City'].value_counts().plot(kind='bar')
```

Out[16]: `<Axes: xlabel='City'>`

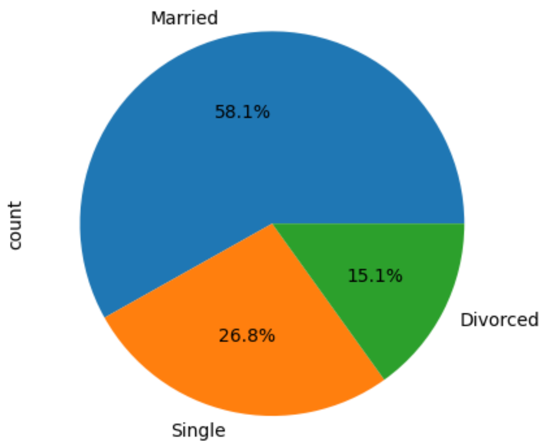


In [17]:
```
df['Gender'].value_counts().plot(kind='pie',autopct='%1.1f%%')
```

Out[17]: `<Axes: ylabel='count'>`

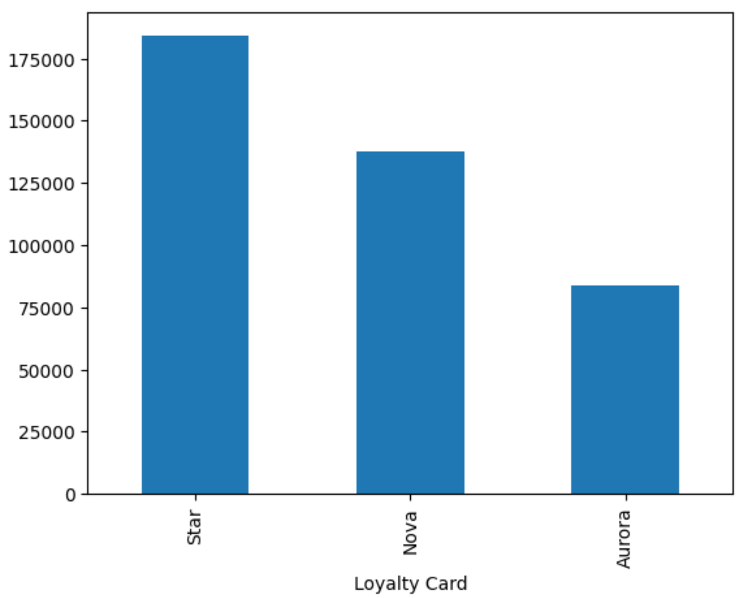


In [18]:
```
df['Marital Status'].value_counts().plot(kind='pie',autopct='%1.1f%%')
```
Out[18]: <Axes: ylabel='count'>



Most customers are from married people

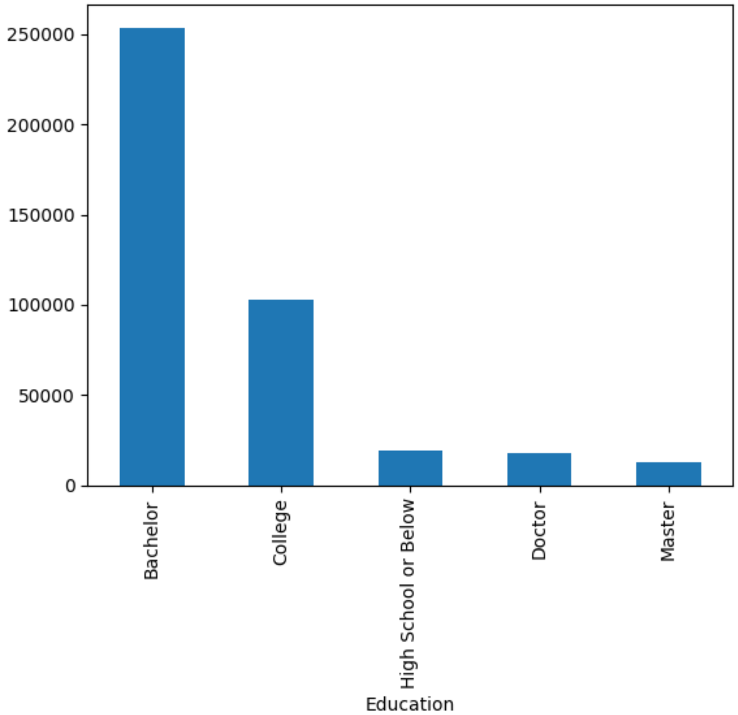
In [19]:
```
df['Loyalty Card'].value_counts().plot(kind='bar')
```
Out[19]: <Axes: xlabel='Loyalty Card'>



The highest selling loyality card is star and the lowest is aurora

In [20]:
```
df['Education'].value_counts().plot(kind='bar')
```

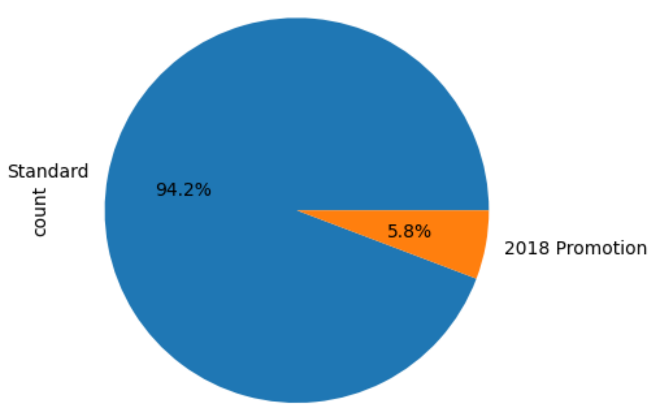
Out[20]: `<Axes: xlabel='Education'>`



The most customers are having Bachelor degree

In [21]:
```
df['Enrollment Type'].value_counts().plot(kind='pie',autopct='%1.1f%%')
```

Out[21]: `<Axes: ylabel='count'>`



In [22]:
```
df=df.drop('Loyalty Number',axis=1)
```

In [23]:
```
df['Enrollment Type'].value_counts()
```

Out[23]:
```
Enrollment Type
Standard          382200
2018 Promotion     23424
Name: count, dtype: int64
```

Converting Gender and Enrollment Type columns to numerical columns

In [24]:
```
df['Gender']=df['Gender'].replace({'Female':0,'Male':1})
df['Enrollment Type']=df['Enrollment Type'].replace({'Standard':0,'2018 Promotion':1})
```

Converting categorical features to numerical by LabelEncoder to can use them in prediction.

In [25]:
```
from sklearn.preprocessing import LabelEncoder
labelencoder=LabelEncoder()
df['Province']=labelencoder.fit_transform(df['Province'])
df['City']=labelencoder.fit_transform(df['City'])
df['Education']=labelencoder.fit_transform(df['Education'])
df['Marital Status']=labelencoder.fit_transform(df['Marital Status'])
df['Loyalty Card']=labelencoder.fit_transform(df['Loyalty Card'])
```

Extracting the correlations between all features and CLV column to determine the features that have the highest influence on CLV feature.

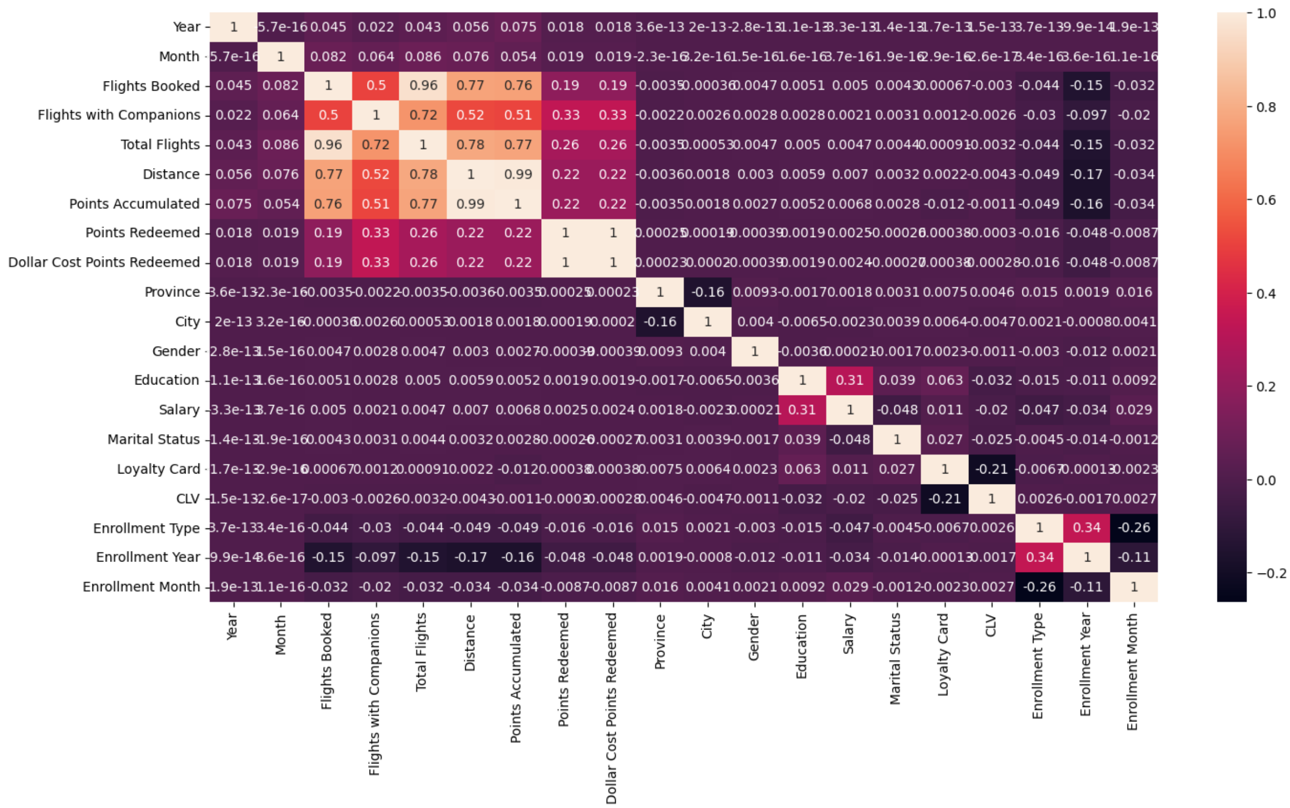
In [26]:
```
df.corr()
```

Out[26]:

	Year	Month	Flights Booked	Flights with Companions	Total Flights	Distance	Points Accumulated	Points Redeemed	Dollar Cost Points Redeemed	Province	City	G
Year	1.000000e+00	-5.737962e-16	0.044510	0.021615	0.042550	0.056140	0.075208	0.017633	0.017624	3.580244e-13	2.043782e-13	-2.83
Month	-5.737962e-16	1.000000e+00	0.082133	0.064492	0.086353	0.076345	0.054178	0.019408	0.019315	-2.307385e-16	3.152263e-16	1.4965
Flights Booked	4.451043e-02	8.213330e-02	1.000000	0.502500	0.961344	0.767457	0.760279	0.188232	0.188242	-3.461029e-03	-3.605528e-04	4.7096
Flights with Companions	2.161493e-02	6.449206e-02	0.502500	1.000000	0.721136	0.517979	0.511090	0.334325	0.334385	-2.193267e-03	2.562142e-03	2.8248
Total Flights	4.255050e-02	8.635348e-02	0.961344	0.721136	1.000000	0.779935	0.771989	0.257307	0.257334	-3.471862e-03	5.270724e-04	4.6735
Distance	5.614031e-02	7.634481e-02	0.767457	0.517979	0.779935	1.000000	0.994564	0.224261	0.224283	-3.625086e-03	1.791207e-03	3.0077
Points Accumulated	7.520848e-02	5.417842e-02	0.760279	0.511090	0.771989	0.994564	1.000000	0.223230	0.223264	-3.455821e-03	1.759084e-03	2.7329
Points Redeemed	1.763278e-02	1.940776e-02	0.188232	0.334325	0.257307	0.224261	0.223230	1.000000	0.999972	2.510058e-04	1.888936e-04	-3.86
Dollar Cost Points Redeemed	1.762408e-02	1.931472e-02	0.188242	0.334385	0.257334	0.224283	0.223264	0.999972	1.000000	2.325534e-04	1.974144e-04	-3.92
Province	3.580244e-13	-2.307385e-16	-0.003461	-0.002193	-0.003472	-0.003625	-0.003456	0.000251	0.000233	1.000000e+00	-1.558457e-01	9.2722
City	2.043782e-13	3.152263e-16	-0.000361	0.002562	0.000527	0.001791	0.001759	0.000189	0.000197	-1.558457e-01	1.000000e+00	4.0353
Gender	-2.834385e-13	1.496595e-16	0.004710	0.002825	0.004674	0.003008	0.002733	-0.000387	-0.000392	9.272205e-03	4.035342e-03	1.00000
Education	-1.086689e-13	1.626831e-16	0.005135	0.002838	0.005018	0.005853	0.005157	0.001889	0.001902	-1.741454e-03	-6.454917e-03	-3.62
Salary	-3.284742e-13	3.736994e-16	0.005010	0.002150	0.004699	0.006951	0.006802	0.002450	0.002445	1.843328e-03	-2.266529e-03	2.1481
Marital Status	-1.434437e-13	-1.916412e-16	0.004303	0.003115	0.004440	0.003229	0.002805	-0.000265	-0.000274	3.133414e-03	3.881080e-03	-1.66
Loyalty Card	-1.707973e-13	-2.915448e-16	0.000669	0.001160	0.000905	0.002201	-0.012249	0.000382	0.000379	7.527903e-03	6.350424e-03	2.2982
CLV	1.488269e-13	-2.556763e-17	-0.002964	-0.002583	-0.003197	-0.004252	-0.001075	-0.000304	-0.000277	4.567617e-03	-4.713820e-03	-1.10
Enrollment Type	3.697842e-13	3.445648e-16	-0.043759	-0.029551	-0.044476	-0.049261	-0.049275	-0.016238	-0.016254	1.521648e-02	2.096196e-03	-3.04
Enrollment Year	-9.927540e-14	3.564005e-16	-0.153455	-0.097012	-0.153861	-0.165263	-0.164645	-0.047867	-0.047915	1.909355e-03	-7.986071e-04	-1.23
Enrollment Month	1.890369e-13	1.100554e-16	-0.031528	-0.019644	-0.031520	-0.034416	-0.033893	-0.008689	-0.008692	1.589009e-02	4.096361e-03	2.0552

In [27]:
```
plt.figure(figsize=(16,8))
sns.heatmap(df.corr(),annot=True)
```

Out[27]: <Axes: >



In [28]:
```
df.head()
```

Out[28]:

	Year	Month	Flights Booked	Flights with Companions	Total Flights	Distance	Points Accumulated	Points Redeemed	Dollar Cost Points Redeemed	Province	City	Gender	Education	Salary	Marital Status	Loyalty Card	Cl
0	2017	1	3	0	3	1521	152.0	0	0	0	4	0	0	92552.0	1	0	791
1	2017	2	2	2	4	1320	132.0	0	0	0	4	0	0	92552.0	1	0	791
2	2018	10	6	4	10	3110	311.0	385	31	0	4	0	0	92552.0	1	0	791
3	2017	4	4	0	4	924	92.0	0	0	0	4	0	0	92552.0	1	0	791
4	2017	5	0	0	0	0	0.0	0	0	0	4	0	0	92552.0	1	0	791

In [29]:
```
X=df.drop('CLV',axis=1)
y=df.CLV
```

Splitting the data to train and test

In [30]:
```
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=.25,stratify=y,random_state=42)
```

Scaling all data by MinMaxScaler to increase the prediction accuracy

In [31]:
```
from sklearn.preprocessing import MinMaxScaler
scale=MinMaxScaler()
X_train_scaled=scale.fit_transform(X_train)
X_train_scaled
```

Out[31]:
```
array([[0.        , 0.        , 0.33333333, ..., 0.        , 0.66666667,
        1.        ],
       [0.        , 0.72727273, 0.38095238, ..., 0.        , 0.83333333,
        0.09090909],
       [1.        , 1.        , 0.28571429, ..., 0.        , 0.5       ,
        0.36363636],
       ...,
       [0.        , 0.90909091, 0.33333333, ..., 0.        , 0.83333333,
        0.27272727],
       [1.        , 1.        , 0.23809524, ..., 0.        , 0.5       ,
        1.        ],
       [1.        , 0.81818182, 0.        , ..., 0.        , 0.16666667,
        0.45454545]])
```

In [32]:
```
X_test_scaled=scale.transform(X_test)
X_test_scaled
```

Out[32]:
```
array([[1.        , 0.        , 0.        , ..., 1.        , 1.        ,
        0.27272727],
       [1.        , 0.09090909, 0.38095238, ..., 0.        , 0.        ,
        0.45454545],
       [1.        , 0.54545455, 0.23809524, ..., 0.        , 1.        ,
        0.        ],
       ...,
       [0.        , 0.72727273, 0.61904762, ..., 0.        , 0.66666667,
        1.        ],
       [0.        , 0.63636364, 0.        , ..., 0.        , 1.        ,
        0.54545455],
       [0.        , 1.        , 0.04761905, ..., 0.        , 0.16666667,
        0.27272727]])
```

In [33]:
```
from sklearn.metrics import mean_absolute_error, mean_squared_error
```

Using random forest regressor for CLV prediction

In [34]:
```
from sklearn.ensemble import RandomForestRegressor
RFR=RandomForestRegressor(n_estimators=300)
RFR.fit(X_train_scaled,y_train)
y_pred=RFR.predict(X_test_scaled)
print(mean_absolute_error(y_pred,y_test))
```

```
270.3215078472331
```

Using XGB Regressor for CLV prediction

In [35]:
```
from xgboost import XGBRegressor
XGB=XGBRegressor(n_estimators=1000,learning_rate=1,max_depth=13)
XGB.fit(X_train_scaled,y_train)
y_pred2=XGB.predict(X_test_scaled)
print(mean_absolute_error(y_pred2,y_test))
```

```
849.2057255379643
```

In [36]:
```
y_pred[:10]
```

Out[36]:
```
array([ 3115.7       ,  3530.23383333, 15943.436     ,  4621.43349167,
       11638.9       , 33806.78743333,  5674.93586667,  6288.7598    ,
        2916.64466667,  8622.84      ])
```

In [37]:
```
y_test.head(10)
```

Out[37]:
```
245412     3115.70
356677     3472.37
343052    16702.70
137897     4766.37
2895      11638.90
186527    34090.04
395808     5660.13
29135      6301.10
77628      2722.21
287876     8622.84
Name: CLV, dtype: float64
```

Comparing between actual and prediction CLV to determine the accuracy and

In [38]:
```
pred_df=pd.DataFrame(y_pred,index=X_test.index,columns=['prediction'])
# Merge the predicted values with the actual test data
merged_df = pd.concat([y_test,pred_df], axis=1)
merged_df=merged_df.rename(columns={'CLV':'Actual'})
merged_df
```

Out[38]:

	Actual	prediction
245412	3115.70	3115.700000
356677	3472.37	3530.233833
343052	16702.70	15943.436000
137897	4766.37	4621.433492
2895	11638.90	11638.900000
...	...	...
74002	3097.92	3130.740467
269131	3919.37	3919.370000
281504	3237.50	3290.053233
28471	8236.92	8236.920000
366563	17759.39	8745.155633

101406 rows × 2 columns

As we see the random forest regressor algorithm is the best one for CLV prediction