

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

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

```
In [2]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
```

```
In [3]: test_loan_data = pd.read_csv('data.csv')
train_loan_data = pd.read_csv('data.csv')
```

```
In [4]: train_loan_data.shape
```

```
Out[4]: (367, 12)
```

```
In [5]: train_loan_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 367 entries, 0 to 366
Data columns (total 12 columns):
 #   Column                Non-Null Count  Dtype
---  -
 0   Loan_ID               367 non-null   object
 1   Gender                356 non-null   object
 2   Married               367 non-null   object
 3   Dependents            357 non-null   object
 4   Education             367 non-null   object
 5   Self_Employed         344 non-null   object
 6   ApplicantIncome       367 non-null   int64
 7   CoapplicantIncome     367 non-null   int64
 8   LoanAmount            362 non-null   float64
 9   Loan_Amount_Term      361 non-null   float64
10   Credit_History        338 non-null   float64
11   Property_Area         367 non-null   object
dtypes: float64(3), int64(2), object(7)
memory usage: 34.5+ KB
```

```
In [6]: train_loan_data.dtypes
```

```
Out[6]: Loan_ID                object
Gender                object
Married              object
Dependents           object
Education            object
Self_Employed        object
ApplicantIncome      int64
CoapplicantIncome     int64
LoanAmount           float64
Loan_Amount_Term     float64
Credit_History       float64
Property_Area        object
dtype: object
```

```
In [7]: train_loan_data.columns

Out[7]: Index(['Loan_ID', 'Gender', 'Married', 'Dependents', 'Education',
        'Self_Employed', 'ApplicantIncome', 'CoapplicantIncome', 'LoanAmount',
        'Loan_Amount_Term', 'Credit_History', 'Property_Area'],
        dtype='object')

In [8]: test_loan_data.columns

Out[8]: Index(['Loan_ID', 'Gender', 'Married', 'Dependents', 'Education',
        'Self_Employed', 'ApplicantIncome', 'CoapplicantIncome', 'LoanAmount',
        'Loan_Amount_Term', 'Credit_History', 'Property_Area'],
        dtype='object')

In [9]: train_loan_data.head(5)
```

Out[9]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount
0	LP001015	Male	Yes	0	Graduate	No	5720	0	1200
1	LP001022	Male	Yes	1	Graduate	No	3076	1500	1200
2	LP001031	Male	Yes	2	Graduate	No	5000	1800	1200
3	LP001035	Male	Yes	2	Graduate	No	2340	2546	1200
4	LP001051	Male	No	0	Not Graduate	No	3276	0	1200

```
In [10]: train_loan_data.tail(5)

Out[10]:
```

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount
362	LP002971	Male	Yes	3+	Not Graduate	Yes	4009	1777	1200
363	LP002975	Male	Yes	0	Graduate	No	4158	709	1200
364	LP002980	Male	No	0	Graduate	No	3250	1993	1200
365	LP002986	Male	Yes	0	Graduate	No	5000	2393	1200
366	LP002989	Male	No	0	Graduate	Yes	9200	0	1200

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

Out[11]: Loan_ID      0
        Gender      11
        Married      0
        Dependents  10
        Education      0
        Self_Employed 23
        ApplicantIncome      0
        CoapplicantIncome      0
        LoanAmount      5
        Loan_Amount_Term      6
        Credit_History      29
        Property_Area      0
        dtype: int64
```

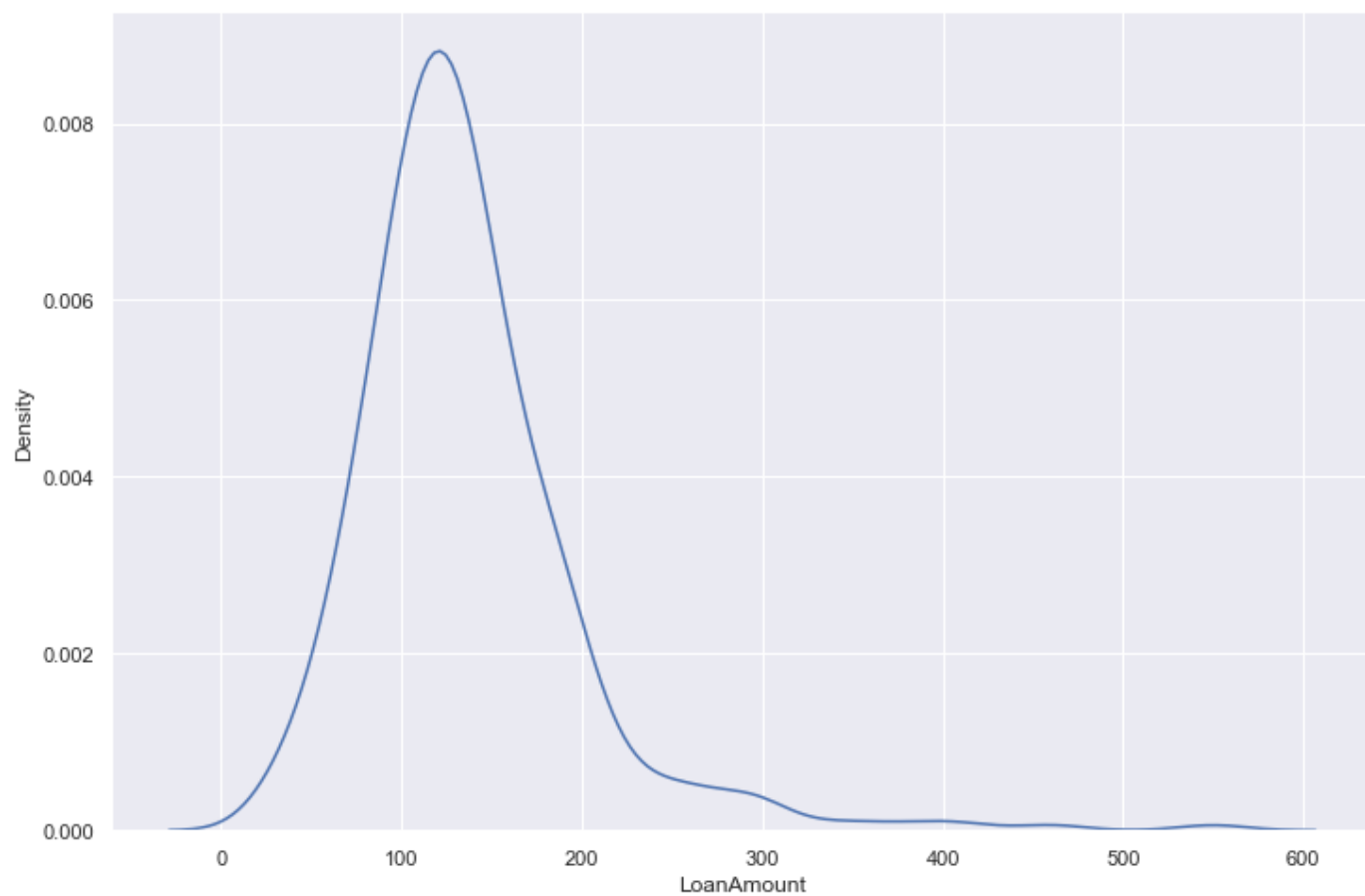
```
In [12]: x_data = train_loan_data.drop('LoanAmount', axis='columns')

In [13]: y_data = train_loan_data['LoanAmount']

In [14]: plt.figure(figsize=(12,8))
```

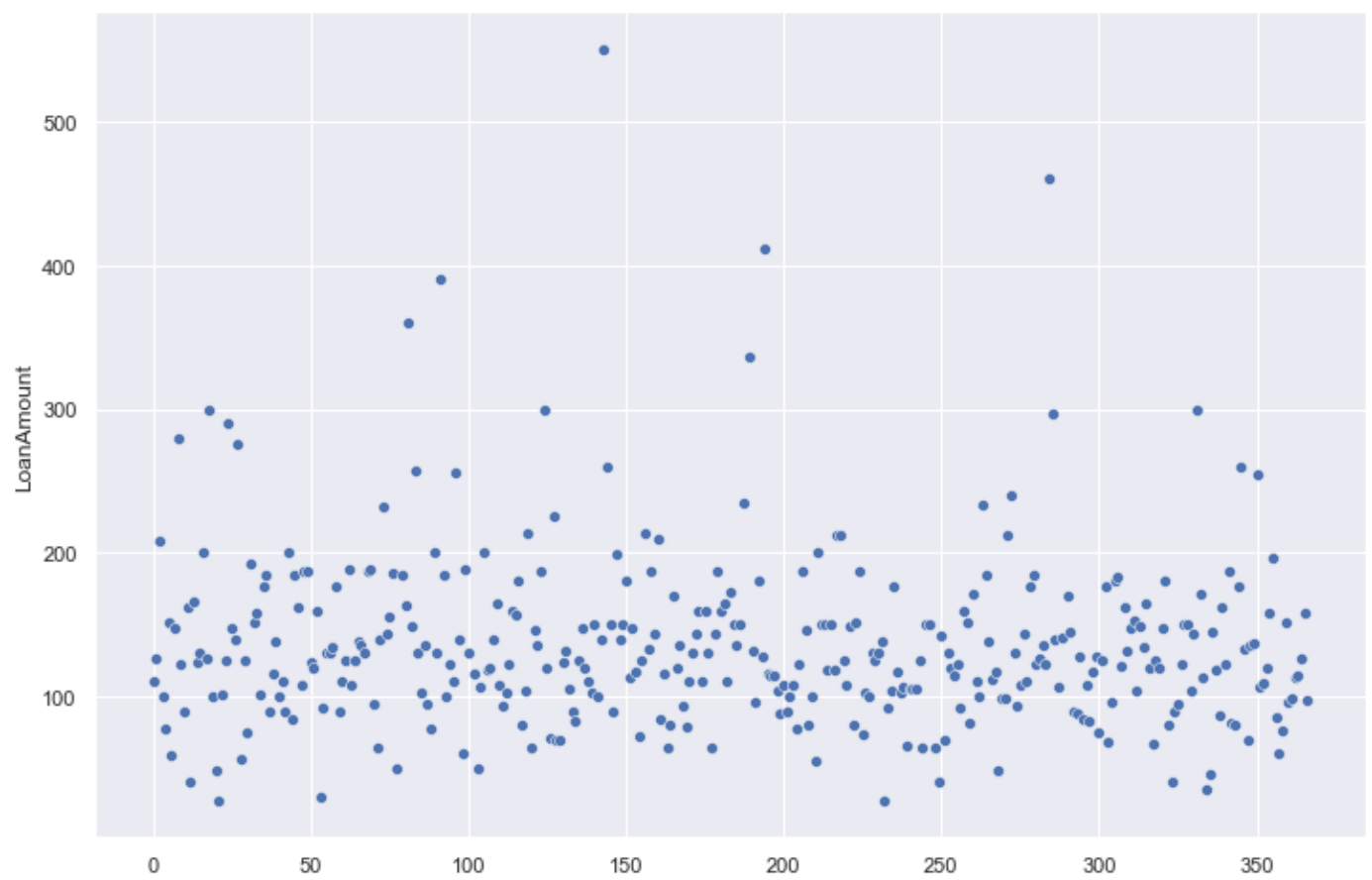
```
sns.set(style='darkgrid')  
sns.kdeplot(y_data)
```

Out[14]: <AxesSubplot:xlabel='LoanAmount', ylabel='Density'>



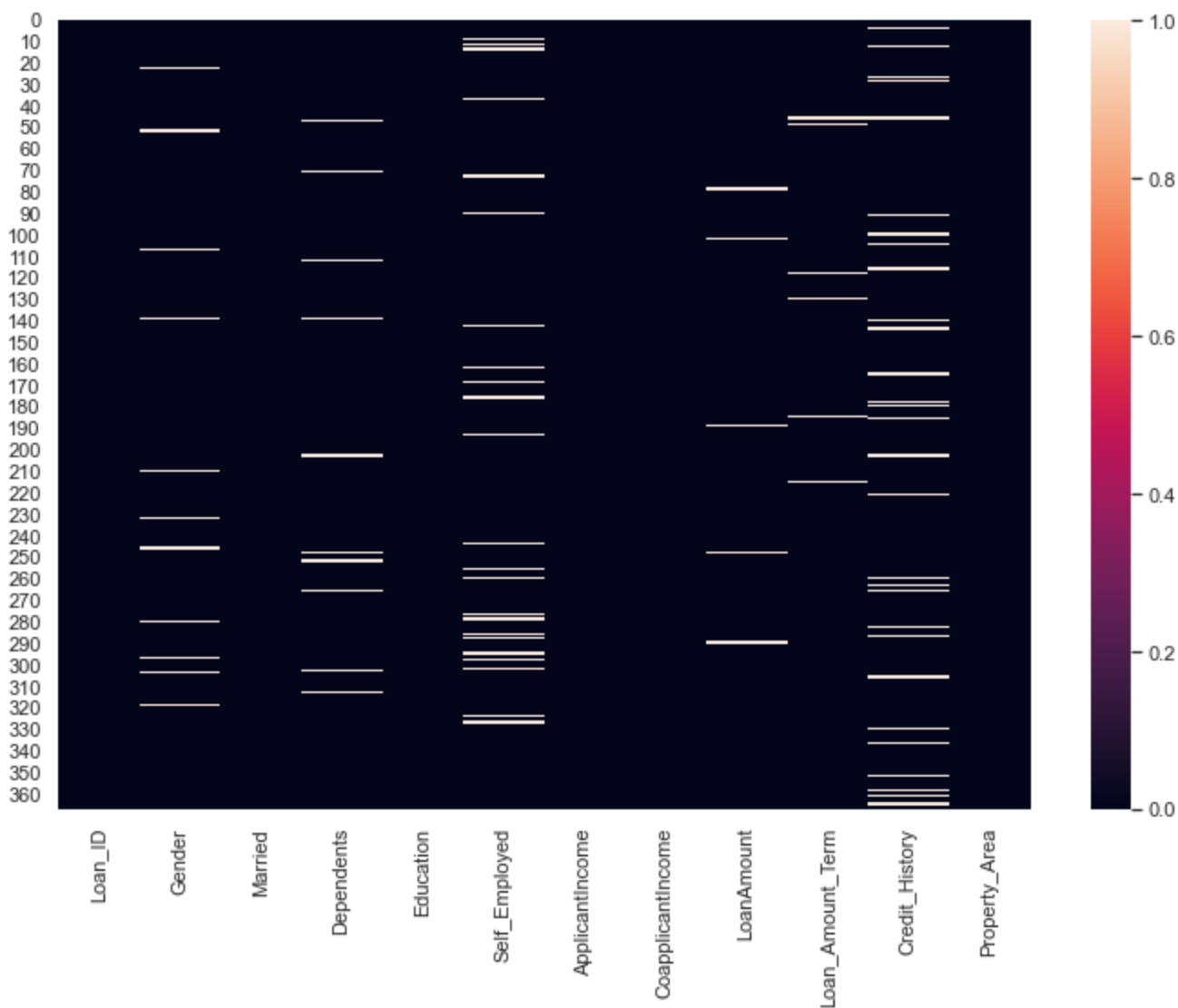
In [15]: `plt.figure(figsize=(12,8))`
`sns.scatterplot(data=y_data)`

Out[15]: <AxesSubplot:ylabel='LoanAmount'>

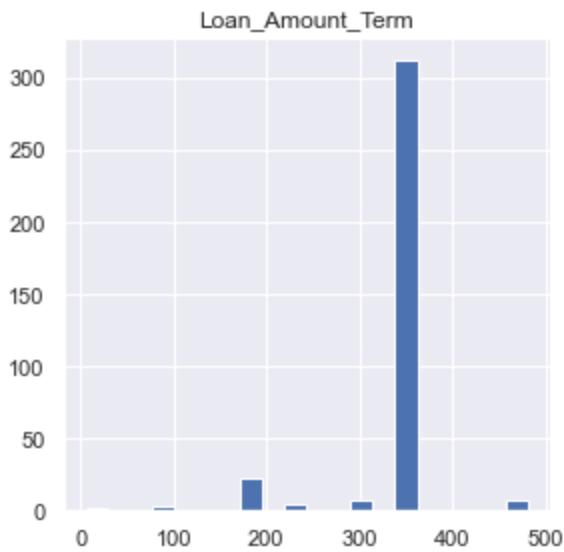
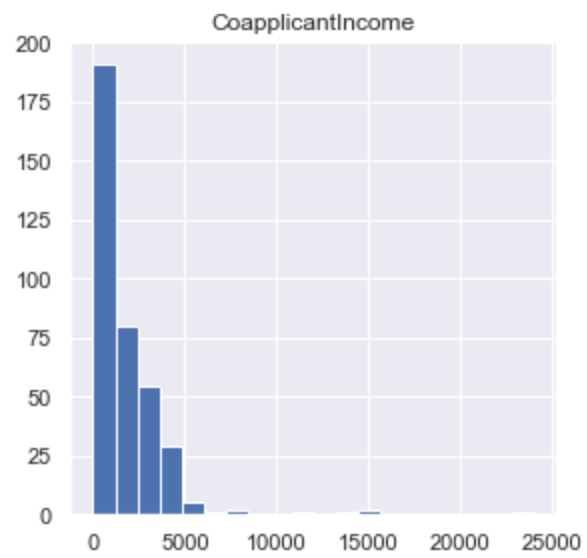
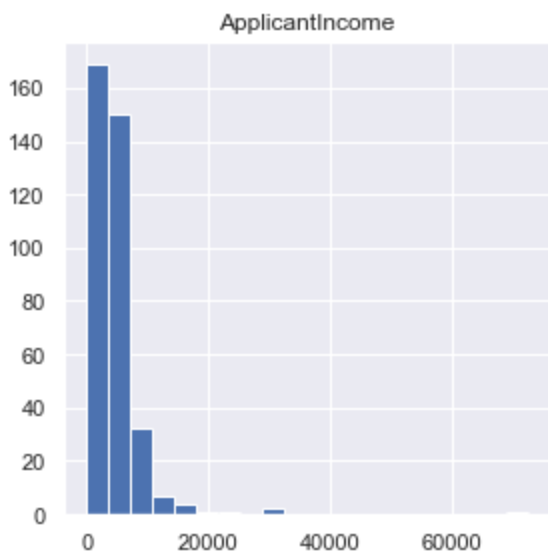


```
In [16]: plt.figure(figsize=(12,8))  
sns.heatmap(train_loan_data.isnull())
```

```
Out[16]: <AxesSubplot:>
```

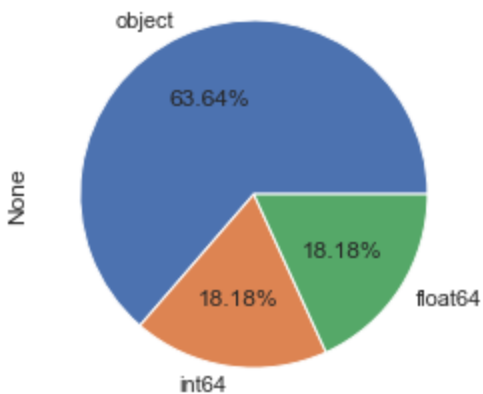


```
In [17]: x_data.hist(figsize = (10, 10), bins = 20, legend = False)
plt.show()
```



```
In [18]: x_data.dtypes.value_counts().plot.pie(autopct='%0.2f%%')
```

```
Out[18]: <AxesSubplot:ylabel='None'>
```



```
In [19]: obj_col = x_data.select_dtypes(include='object').columns
int_col = x_data.select_dtypes(include='int').columns
flt_col = x_data.select_dtypes(include='float').columns
```

```
In [20]: le = LabelEncoder()
```

```
In [21]: for obj in obj_col:
```

```
x_data[obj] = le.fit_transform(x_data[obj].astype(str))
```

```
In [22]: for nt in int_col:
         x_data[nt] = le.fit_transform(x_data[nt].astype(int))
```

```
In [23]: for flt in flt_col:
         x_data[flt] = le.fit_transform(x_data[flt].astype(float))
```

```
In [24]: x_data
```

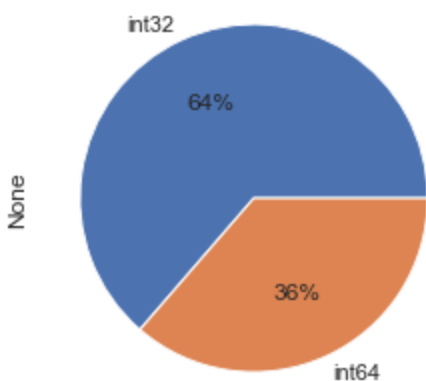
```
Out[24]:
```

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	Loan_Amount
0	0	1	1	0	0	0	251	0	12000
1	1	1	1	1	0	0	102	43	10000
2	2	1	1	2	0	0	230	67	12000
3	3	1	1	2	0	0	43	110	10000
4	4	1	0	0	1	0	120	0	10000
...
362	362	1	1	3	1	1	177	65	10000
363	363	1	1	0	0	0	186	12	10000
364	364	1	0	0	0	0	117	75	10000
365	365	1	1	0	0	0	230	101	10000
366	366	1	0	0	0	1	292	0	10000

367 rows × 11 columns

```
In [25]: x_data.dtypes.value_counts().plot.pie(autopct='%2.0f%%')
```

```
Out[25]: <AxesSubplot:ylabel='None'>
```

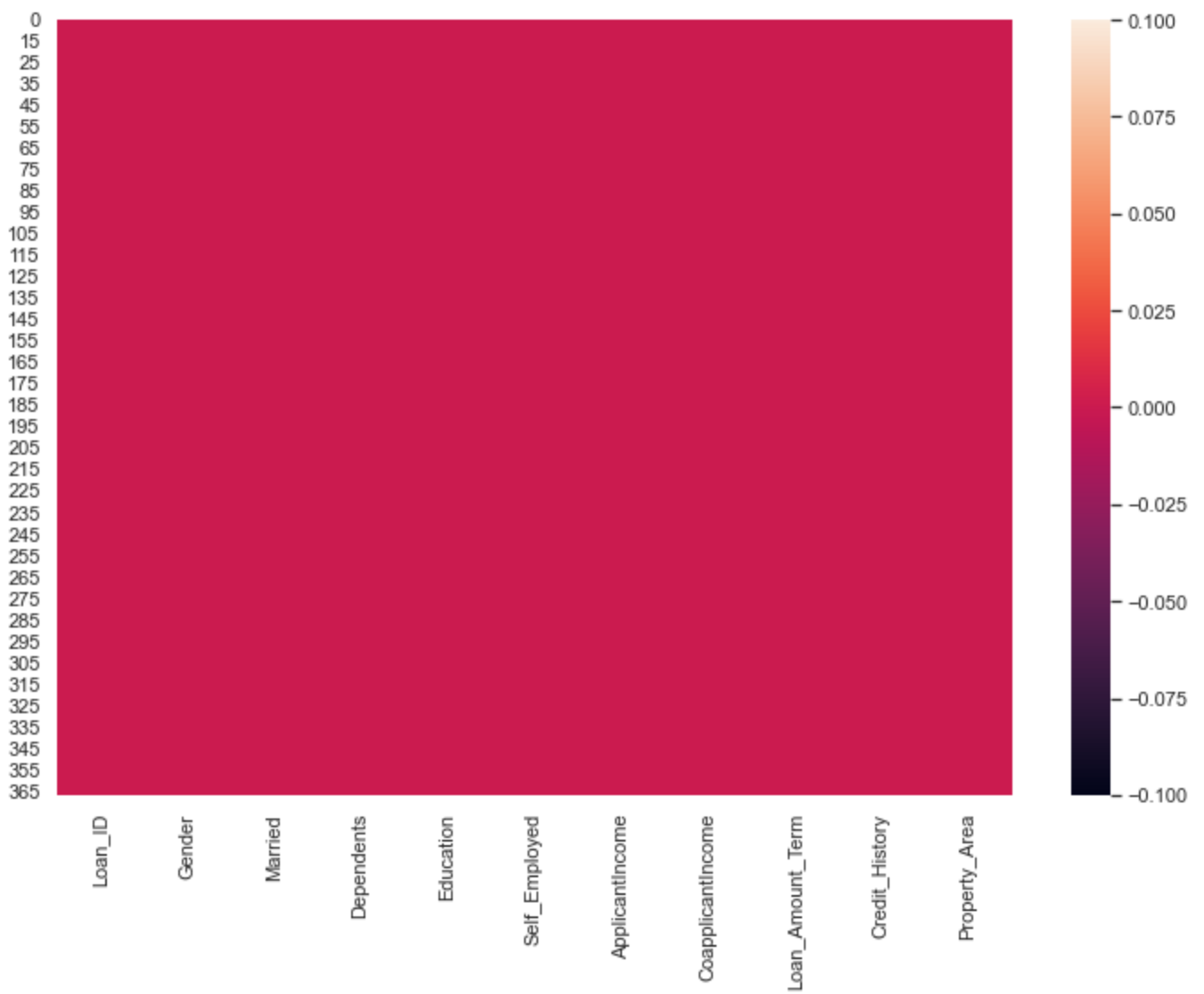


```
In [26]: x_data = x_data.dropna()
         y_data = y_data.dropna()
```

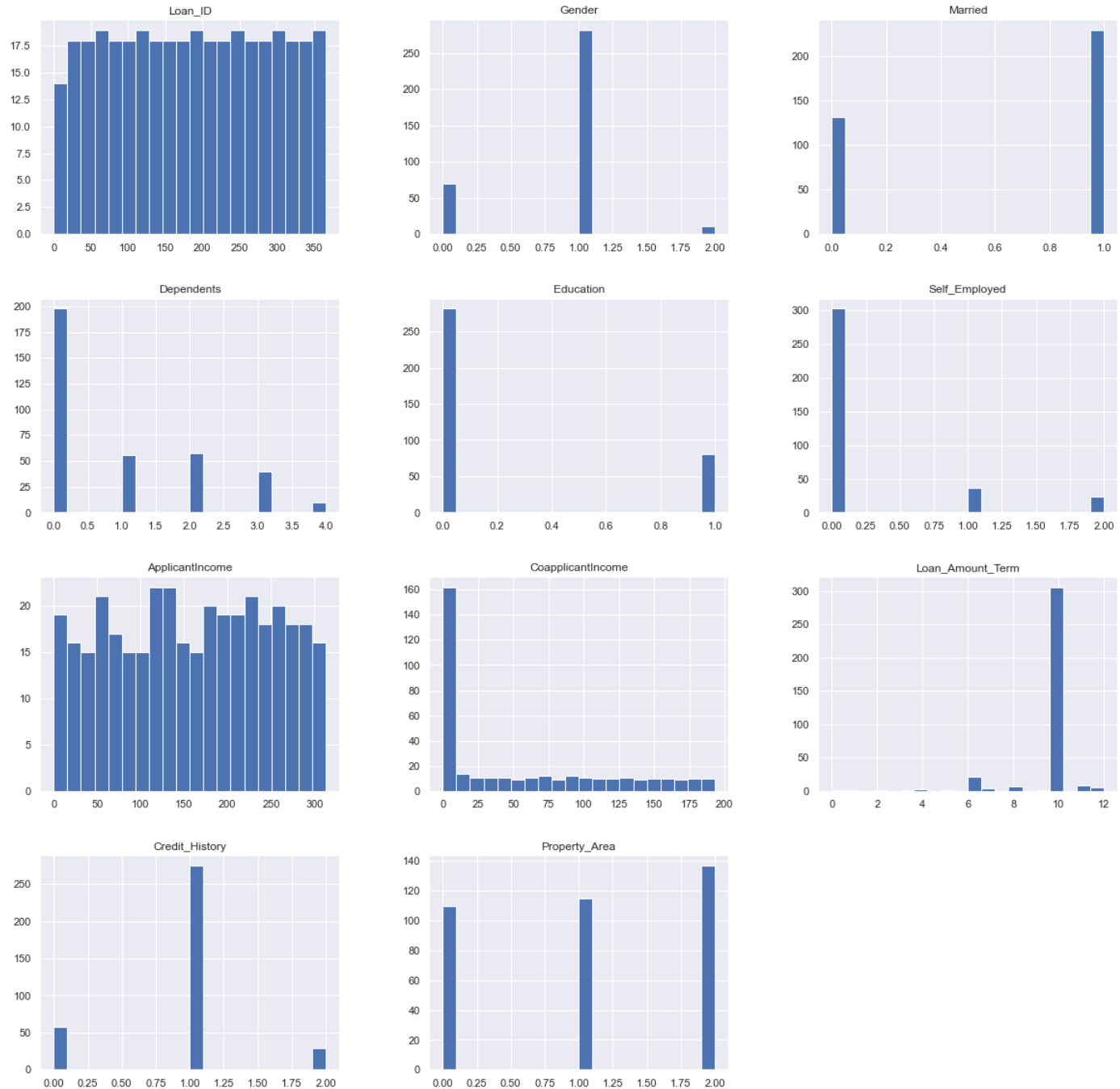
```
In [27]: x_data = x_data.drop([5,6,1,4,7])
```

```
In [28]: plt.figure(figsize=(12,8))
         sns.heatmap(x_data.isnull())
```

```
Out[28]: <AxesSubplot:>
```



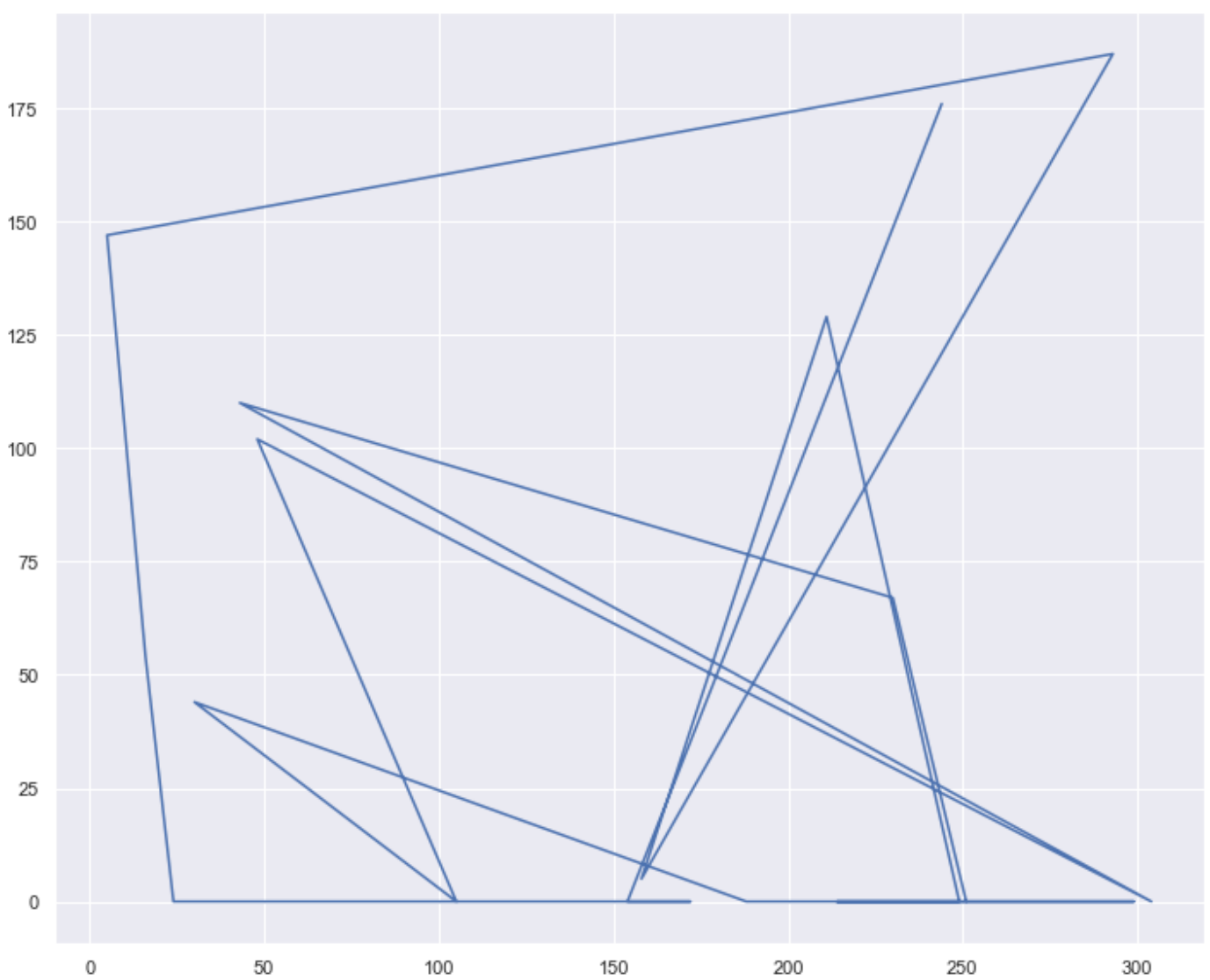
```
In [29]: x_data.hist(figsize = (20, 20), bins = 20, legend = False)
plt.show()
```

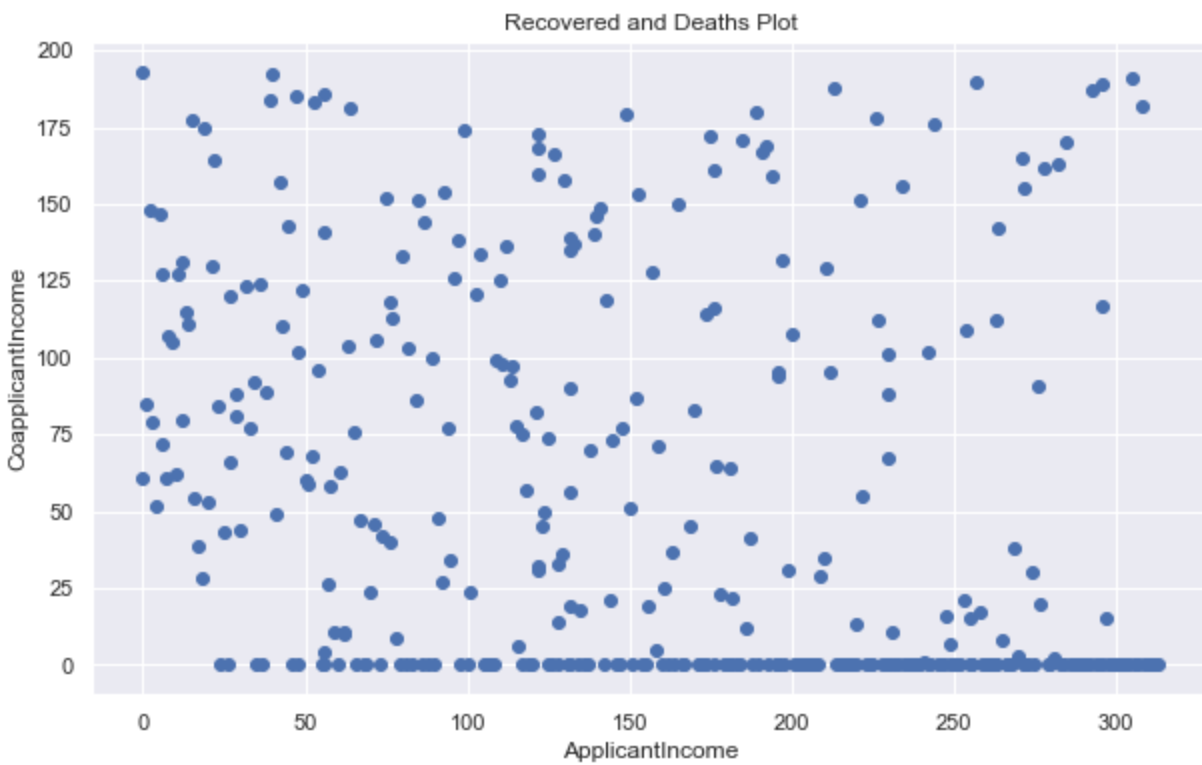
```
In [30]: x_data.columns
```

```
Out[30]: Index(['Loan_ID', 'Gender', 'Married', 'Dependents', 'Education',
        'Self_Employed', 'ApplicantIncome', 'CoapplicantIncome',
        'Loan_Amount_Term', 'Credit_History', 'Property_Area'],
        dtype='object')
```

```
In [31]: plt.figure(figsize=(12,10))
plt.plot(x_data['ApplicantIncome'][0:20], x_data['CoapplicantIncome'][0:20])
plt.show()
```



```
In [32]: plt.figure(figsize=(10, 6))
plt.plot(x_data['ApplicantIncome'], x_data['CoapplicantIncome'], 'o')
plt.title("Recovered and Deaths Plot")
plt.xlabel("ApplicantIncome")
plt.ylabel("CoapplicantIncome")
plt.show()
```



```
In [33]: x_train, x_test, y_train, y_test = train_test_split(x_data, y_data, test_size=0.1)
```

```
In [34]: rmr = RandomForestRegressor()
```

```
In [35]: x_test
```

```
Out[35]:
```

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	Loan_Amount
178	178	1	1	2	0	0	235	0	12000
126	126	1	0	0	0	0	263	0	8000
25	25	1	0	0	0	0	0	193	12000
262	262	1	0	0	0	0	128	14	12000
12	12	1	0	3	0	0	188	0	12000
203	203	0	1	0	0	0	109	99	12000
111	111	1	1	4	0	0	180	0	12000
293	293	0	1	0	0	0	33	77	12000
106	106	2	0	0	0	0	7	61	12000
261	261	1	1	0	0	0	91	48	12000
133	133	0	0	1	0	0	142	0	12000
154	154	1	1	2	0	0	225	0	12000
365	365	1	1	0	0	0	230	101	12000
280	280	1	0	0	0	0	29	81	12000
157	157	1	1	0	0	0	196	94	12000
128	128	1	0	0	0	0	100	0	12000
10	10	1	0	0	1	0	105	0	12000
277	277	0	0	0	0	0	252	0	12000

135	135	1	1	0	0	0	193	0
328	328	1	1	3	0	1	269	38
62	62	0	0	2	0	0	228	0
80	80	1	1	3	0	0	161	25
243	243	1	1	0	0	2	58	58
116	116	0	0	0	1	0	0	61
345	345	1	1	3	0	0	283	0
282	282	0	0	0	0	0	246	0
190	190	0	1	1	0	0	196	0
232	232	1	1	0	0	0	4	52
29	29	1	0	0	0	0	89	100
117	117	1	1	1	0	0	6	127
225	225	0	0	0	0	0	60	0
184	184	1	1	3	0	0	297	15
242	242	1	1	0	0	0	135	18
21	21	0	0	3	1	0	24	0
359	359	1	0	0	0	0	176	116
89	89	0	0	0	0	2	232	0
255	255	1	0	0	0	2	79	0

In [36]:

rmr.fit(x_train, y_train)

Out[36]: RandomForestRegressor()

In [37]:

rmr.predict(x_test)

Out[37]: array([123.97, 152.11, 195.43, 124.46, 99.38, 109.8 , 125.94, 101.39,
140.74, 137.7 , 138.75, 155.12, 122.57, 112.94, 130.84, 154.76,
201.32, 144.5 , 140.06, 174.09, 147.28, 129.55, 118.39, 152.9 ,
226. , 134.81, 169.18, 84.73, 115.06, 119.62, 115.18, 142.26,
103.32, 163.09, 124. , 170.28, 100.74])

In [38]:

test_loan_data

Out[38]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	L
0	LP001015	Male	Yes	0	Graduate	No	5720	0	
1	LP001022	Male	Yes	1	Graduate	No	3076	1500	
2	LP001031	Male	Yes	2	Graduate	No	5000	1800	
3	LP001035	Male	Yes	2	Graduate	No	2340	2546	
4	LP001051	Male	No	0	Not Graduate	No	3276	0	
...
362	LP002971	Male	Yes	3+	Not Graduate	Yes	4009	1777	

363	LP002975	Male	Yes	0	Graduate	No	4158	709
364	LP002980	Male	No	0	Graduate	No	3250	1993
365	LP002986	Male	Yes	0	Graduate	No	5000	2393
366	LP002989	Male	No	0	Graduate	Yes	9200	0

367 rows × 12 columns

In []: