Task: Determine the eligibility for granting a Home Loan

Objective of this notebook is:

1. To understand the patterns in the data.
2. How to Handle the categorical features.
3. How to deal with missing data.
4. Feature Engineering
5. Finding the most important features while taking the decision of granting a loan application.
6. Understanding the Normalization and standardisation of the data.

Importing Libraries

In [2]:
```
import numpy as np
import pandas as pd
from scipy import stats

import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import ttest_1samp,ttest_ind,chi2_contingency,shapiro
from statsmodels.graphics.gofplots import qqplot
from scipy.stats import kstest,norm
```

In [3]:
```
df = pd.read_csv('loan.csv')
df.head()
```

Out[3]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Property_Area	Loan_Status
0	LP001002	Male	No	0	Graduate	No	5849	0.0	NaN	360.0	1.0	Urban	Y
1	LP001003	Male	Yes	1	Graduate	No	4583	1508.0	128.0	360.0	1.0	Rural	N
2	LP001005	Male	Yes	0	Graduate	Yes	3000	0.0	66.0	360.0	1.0	Urban	Y
3	LP001006	Male	Yes	0	Not Graduate	No	2583	2358.0	120.0	360.0	1.0	Urban	Y
4	LP001008	Male	No	0	Graduate	No	6000	0.0	141.0	360.0	1.0	Urban	Y

Log Normal Distribution

In [4]:
```
data=pd.read_csv("waiting_time.csv")
data
```

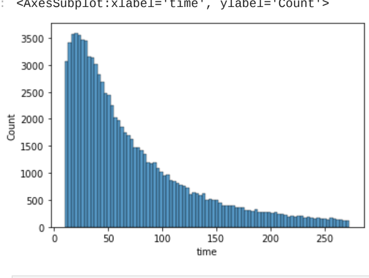
Out[4]:

	time
0	184.003075
1	36.721521
2	29.970417
3	75.640285
4	61.489439
...	...
90041	135.885984
90042	15.223970
90043	207.839528
90044	140.488418
90045	50.719544

90046 rows × 1 columns

In [5]:
```
sns.histplot(data["time"])
```

Out[5]: <AxesSubplot:xlabel='time', ylabel='Count'>



In [7]:
```
x1=10
x2=100
x3=1000
x4=10000
```

In [13]:
```
print("x1 :",x1,"| log(x1) : ", np.log(x1))
print("x2 :",x2,"| log(x2) : ", np.log(x2))
print("x3 :",x3,"| log(x3) : ", np.log(x3))
print("x4 :",x4,"| log(x4) : ", np.log(x4))
```

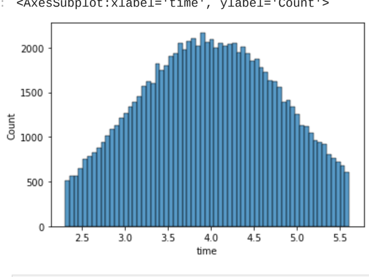
```
x1 : 10 | log(x1) :  2.302585092994046
x2 : 100 | log(x2) :  4.605170185988092
x3 : 1000 | log(x3) :  6.907755278982137
x4 : 10000 | log(x4) :  9.210340371976184
```

In [14]:
```
np.log(data["time"])
```

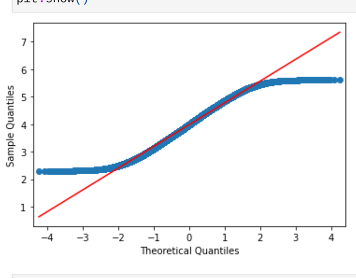
Out[14]:
```
0        5.214952
1        3.603363
2        3.400211
3        4.325989
4        4.118865
           ...   
90041    4.911816
90042    2.722871
90043    5.336766
90044    4.945125
90045    3.926311
Name: time, Length: 90046, dtype: float64
```

In [15]:
```
sns.histplot(np.log(data["time"]))
```

Out[15]: <AxesSubplot:xlabel='time', ylabel='Count'>



In [18]:
```
qqplot(np.log(data["time"]),line="s")
plt.show()
```



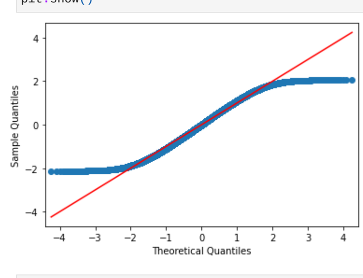
In [19]:
```
log_data=np.log(data["time"])
log_data
```

Out[19]:
```
0        5.214952
1        3.603363
2        3.400211
3        4.325989
4        4.118865
           ...   
90041    4.911816
90042    2.722871
90043    5.336766
90044    4.945125
90045    3.926311
Name: time, Length: 90046, dtype: float64
```

In [20]:
```
z_log_data=(log_data-log_data.mean())/log_data.std()
z_log_data
```

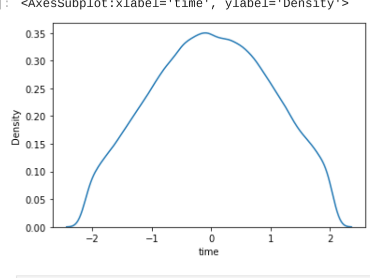
Out[20]:
```
0        1.554521
1       -0.484198
2       -0.741193
3        0.429950
4        0.167931
           ...   
90041    1.171043
90042   -1.598052
90043    1.708620
90044    1.213180
90045   -0.075657
Name: time, Length: 90046, dtype: float64
```

In [22]:
```
qqplot(z_log_data,line="s")
plt.show()
```



In [24]:
```
sns.kdeplot(z_log_data)
```

Out[24]: <AxesSubplot:xlabel='time', ylabel='Density'>



In [25]:
```
shapiro(z_log_data)
```

```
/Users/nikhilsanghi/opt/anaconda3/lib/python3.9/site-packages/scipy/stats/morestats.py:1760: UserWarning: p-value may not be accurate for N > 5000.
  warnings.warn("p-value may not be accurate for N > 5000.")
```

Out[25]: ShapiroResult(statistic=0.984922468662262, pvalue=0.0)

In [26]:
```
kstest(z_log_data,norm.cdf)
```

Out[26]: KstestResult(statistic=0.026341647509834476, pvalue=1.034110663995602e-54)

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

Basic Exploration

In [27]:
```
df.head()
```

Out[27]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Property_Area	Loan_Status
0	LP001002	Male	No	0	Graduate	No	5849	0.0	NaN	360.0	1.0	Urban	Y
1	LP001003	Male	Yes	1	Graduate	No	4583	1508.0	128.0	360.0	1.0	Rural	N
2	LP001005	Male	Yes	0	Graduate	Yes	3000	0.0	66.0	360.0	1.0	Urban	Y
3	LP001006	Male	Yes	0	Not Graduate	No	2583	2358.0	120.0	360.0	1.0	Urban	Y
4	LP001008	Male	No	0	Graduate	No	6000	0.0	141.0	360.0	1.0	Urban	Y

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 614 entries, 0 to 613
Data columns (total 13 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Loan_ID            614 non-null    object 
 1   Gender             601 non-null    object 
 2   Married            611 non-null    object 
 3   Dependents         599 non-null    object 
 4   Education          614 non-null    object 
 5   Self_Employed      582 non-null    object 
 6   ApplicantIncome    614 non-null    int64  
 7   CoapplicantIncome  614 non-null    float64
 8   LoanAmount         592 non-null    float64
 9   Loan_Amount_Term   600 non-null    float64
 10  Credit_History     564 non-null    float64
 11  Property_Area      614 non-null    object 
 12  Loan_Status        614 non-null    object 
dtypes: float64(4), int64(1), object(8)
memory usage: 62.5+ KB
```

In [29]:
```
df["Dependents"].value_counts()
```

Out[29]:
```
0     345
1     102
2     101
3+     51
Name: Dependents, dtype: int64
```

In [30]:
```
df.describe()
```

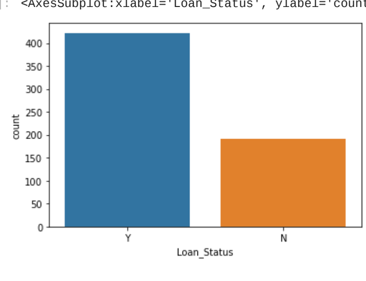
Out[30]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History
count	614.000000	614.000000	592.000000	600.00000	564.000000
mean	5403.459283	1621.245798	146.412162	342.00000	0.842199
std	6109.041673	2926.248369	85.587325	65.12041	0.364878
min	150.000000	0.000000	9.000000	12.00000	0.000000
25%	2877.500000	0.000000	100.000000	360.00000	1.000000
50%	3812.500000	1188.500000	128.000000	360.00000	1.000000
75%	5795.000000	2297.250000	168.000000	360.00000	1.000000
max	81000.000000	41667.000000	700.000000	480.00000	1.000000

In [31]:
```
sns.countplot(df["Loan_Status"])
```

```
/Users/nikhilsanghi/opt/anaconda3/lib/python3.9/site-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `dat
a`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[31]: <AxesSubplot:xlabel='Loan_Status', ylabel='count'>



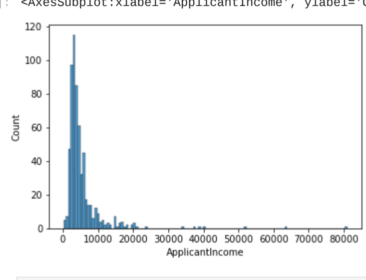
Univariate Analysis

In [32]:
```
"Applicant_Income"
```

Out[32]: 'Applicant_Income'

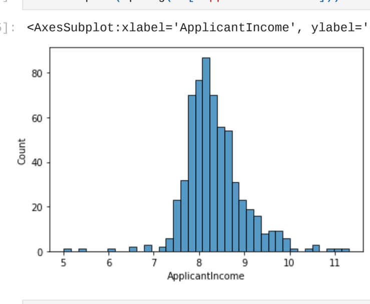
In [34]:
```
sns.histplot(df["ApplicantIncome"])
```

Out[34]: <AxesSubplot:xlabel='ApplicantIncome', ylabel='Count'>



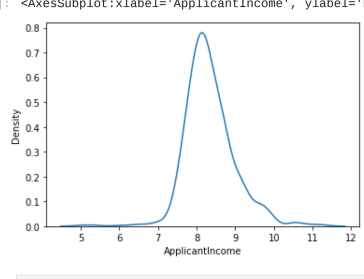
In [35]:
```
sns.histplot(np.log(df["ApplicantIncome"]))
```

Out[35]: <AxesSubplot:xlabel='ApplicantIncome', ylabel='Count'>

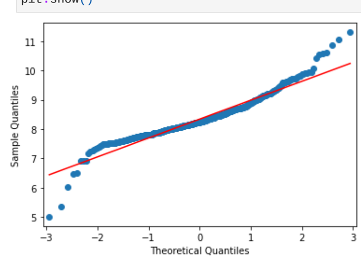


In [36]:
```
sns.kdeplot(np.log(df["ApplicantIncome"]))
```

Out[36]: <AxesSubplot:xlabel='ApplicantIncome', ylabel='Density'>



In [39]:
```
qqplot(np.log(df["ApplicantIncome"]),line="s")
plt.show()
```



Applicant Income is Important/ Good Predictor?

In [42]:
```
df.groupby("Loan_Status").mean()
```

Out[42]:

Loan_Status	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History
N	5446.078125	1877.807292	151.220994	344.064516	0.541899
Y	5384.068720	1504.516398	144.294404	341.072464	0.981818

In [ ]:

In [ ]:
```
# Ho : Acc = Rej
# Ha : Acc !=Rej
```

In [49]:
```
df_acc= df.loc[df["Loan_Status"]=="Y"]["ApplicantIncome"]
df_rej= df.loc[df["Loan_Status"]=="N"]["ApplicantIncome"]
```

In [50]:
```
df_acc.mean()
```

Out[50]: 5384.068720379147

In [52]:
```
df_rej.mean()
```

Out[52]: 5446.078125

In [53]:
```
ttest_ind(df_acc,df_rej,alternative="less")
```

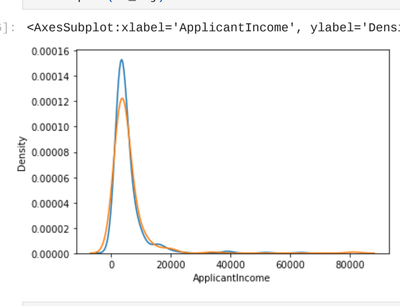
Out[53]: Ttest_indResult(statistic=-0.11650844828724542, pvalue=0.453643906065259)

In [55]:
```
ttest_ind(df_acc,df_rej,alternative="two-sided")
```

Out[55]: Ttest_indResult(statistic=-0.11650844828724542, pvalue=0.907287812130518)

In [56]:
```
sns.kdeplot(df_acc)
sns.kdeplot(df_rej)
```

Out[56]: <AxesSubplot:xlabel='ApplicantIncome', ylabel='Density'>



In [57]:
```
kstest(df_acc,df_rej)
```

Out[57]: KstestResult(statistic=0.04393759873617693, pvalue=0.9480203334325084)

In [59]:
```
bins=[0, 2500, 4000, 6000, 8000, 10000, 81000]
labels=['Low','Average','medium', 'h1', 'h2', 'Very high']
df["Income_bins"]=pd.cut(df["ApplicantIncome"],bins=bins,labels=labels)
df
```

Out[59]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Property_Area	Loan_Status	Income_bins
0	LP001002	Male	No	0	Graduate	No	5849	0.0	NaN	360.0	1.0	Urban	Y	medium
1	LP001003	Male	Yes	1	Graduate	No	4583	1508.0	128.0	360.0	1.0	Rural	N	medium
2	LP001005	Male	Yes	0	Graduate	Yes	3000	0.0	66.0	360.0	1.0	Urban	Y	Average
3	LP001006	Male	Yes	0	Not Graduate	No	2583	2358.0	120.0	360.0	1.0	Urban	Y	Average
4	LP001008	Male	No	0	Graduate	No	6000	0.0	141.0	360.0	1.0	Urban	Y	medium
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
609	LP002978	Female	No	0	Graduate	No	2900	0.0	71.0	360.0	1.0	Rural	Y	Average
610	LP002979	Male	Yes	3+	Graduate	No	4106	0.0	40.0	180.0	1.0	Rural	Y	medium
611	LP002983	Male	Yes	1	Graduate	No	8072	240.0	253.0	360.0	1.0	Urban	Y	h2
612	LP002984	Male	Yes	2	Graduate	No	7583	0.0	187.0	360.0	1.0	Urban	Y	h1
613	LP002990	Female	No	0	Graduate	Yes	4583	0.0	133.0	360.0	0.0	Semiurban	N	medium

614 rows × 14 columns

In [61]:
```
va1=pd.crosstab(df["Income_bins"],df["Loan_Status"])
va1
```

Out[61]:

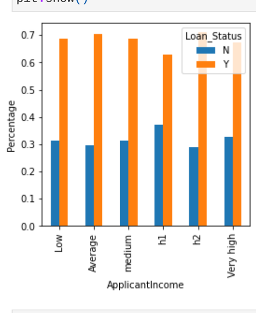
Income_bins \ Loan_Status	N	Y
Low	34	74
Average	67	159
medium	45	98
h1	20	34
h2	9	22
Very high	17	35

In [62]:
```
chi2_contingency(va1)
```

Out[62]:
```
(1.2390175474316056,
 0.941079844721327,
 5,
 array([[ 33.77198697,  74.22801303],
        [ 70.67100977, 155.32899023],
        [ 44.71661238,  98.28338762],
        [ 16.88599349,  37.11400651],
        [  9.69381107,  21.30618893],
        [ 16.26058632,  35.73941368]]))
```

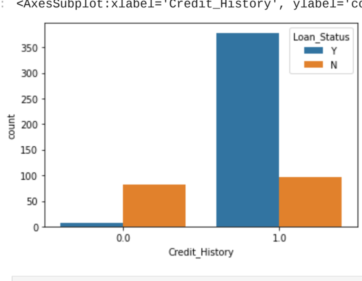
In [64]:
```
Income_bin = pd.crosstab(df["Income_bins"],df["Loan_Status"])

Income_bin.div(Income_bin.sum(axis=1),axis=0).plot(kind="bar",figsize=(4,4))
plt.xlabel("ApplicantIncome")
plt.ylabel("Percentage")
plt.show()
```



In [65]:
```
sns.countplot(x=df["Credit_History"],hue=df["Loan_Status"])
```

Out[65]: <AxesSubplot:xlabel='Credit_History', ylabel='count'>



In [66]:
```
va2=pd.crosstab(df["Credit_History"],df["Loan_Status"])
va2
```

Out[66]:

Credit_History \ Loan_Status	N	Y
0.0	82	7
1.0	97	378

In [67]:
```
chi2_contingency(va2)
```

Out[67]:
```
(174.63729658142535,
 7.184759548750746e-40,
 1,
 array([[ 28.2464539,  60.7535461],
        [150.7535461, 324.2464539]]))
```

In [ ]:

Univariate Analysis

In [ ]:

Binning the income

In [ ]:

In [ ]:

In [71]:
```
def check_ttest(x,y,alpha):
    _,p_value=ttest_ind(x,y)
    if p_value < alpha:
        print("Feature x is a good Predictor")
    else :
        print("Feature x is a bad Predictor")
```

In [72]:
```
check_ttest(df_acc,df_rej,0.05)
```

```
Feature x is a bad Predictor
```

In [ ]:
```
for i in cat_columns:
```

In [79]:
```
cat_cols_series=df.dtypes=="object"
cat_columns=list(cat_cols_series[cat_cols_series].index)
cat_columns
```

Out[79]:
```
['Loan_ID',
 'Gender',
 'Married',
 'Dependents',
 'Education',
 'Self_Employed',
 'Property_Area',
 'Loan_Status']
```

In [80]:
```
cat_columns.remove("Loan_ID")
```

In [86]:
```
# cat_columns.remove("Dependents")
# cat_columns.remove("Loan_Status")
```

In [106…
```
def check_chi2Contingency(x,y,alpha):
    va=pd.crosstab(x,y)
    _,p_value,_,_=chi2_contingency(va)
    if p_value < alpha:
        print(f"Feature {x.name} is a good Predictor for target variable Loan Status")
    else :
        print(f"Feature {x.name} is a bad Predictor for target variable Loan Status")
```

In [107…
```
cat_columns
```

Out[107]: ['Gender', 'Married', 'Education', 'Self_Employed', 'Property_Area']

In [108…
```
for col in cat_columns:
    check_chi2Contingency(df[col],df["Loan_Status"],0.05)
```

```
Feature Gender is a bad Predictor for target variable Loan Status
Feature Married is a good Predictor for target variable Loan Status
Feature Education is a good Predictor for target variable Loan Status
Feature Self_Employed is a bad Predictor for target variable Loan Status
Feature Property_Area is a good Predictor for target variable Loan Status
```

In [ ]:

In [ ]: