Loan Predication Data Analysis

In [66]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
```

In [67]:
```
import io
%cd "C:\Users\rakes\OneDrive\Desktop\D\dataset"
```

```
C:\Users\rakes\OneDrive\Desktop\D\dataset
```

In [68]:
```
loan_df=pd.read_csv("Loan prediction dataset.csv")
```

In [69]:
```
print(loan_df.shape)
```

```
(614, 13)
```

Data Preparation and Cleaning

In [70]:
```
loan_df.info
```

Out[70]:
```
<bound method DataFrame.info of       Loan_ID  Gender Married Dependents     Education Self_Employed  \
0    LP001002    Male      No          0      Graduate            No   
1    LP001003    Male     Yes          1      Graduate            No   
2    LP001005    Male     Yes          0      Graduate           Yes   
3    LP001006    Male     Yes          0  Not Graduate            No   
4    LP001008    Male      No          0      Graduate            No   
..        ...     ...     ...        ...           ...           ...   
609  LP002978  Female      No          0      Graduate            No   
610  LP002979    Male     Yes         3+      Graduate            No   
611  LP002983    Male     Yes          1      Graduate            No   
612  LP002984    Male     Yes          2      Graduate            No   
613  LP002990  Female      No          0      Graduate           Yes   

     ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term  \
0               5849                0.0         NaN             360.0   
1               4583             1508.0       128.0             360.0   
2               3000                0.0        66.0             360.0   
3               2583             2358.0       120.0             360.0   
4               6000                0.0       141.0             360.0   
..               ...                ...         ...               ...   
609             2900                0.0        71.0             360.0   
610             4106                0.0        40.0             180.0   
611             8072              240.0       253.0             360.0   
612             7583                0.0       187.0             360.0   
613             4583                0.0       133.0             360.0   

     Credit_History Property_Area Loan_Status  
0               1.0         Urban           Y  
1               1.0         Rural           N  
2               1.0         Urban           Y  
3               1.0         Urban           Y  
4               1.0         Urban           Y  
..              ...           ...         ...  
609             1.0         Rural           Y  
610             1.0         Rural           Y  
611             1.0         Urban           Y  
612             1.0         Urban           Y  
613             0.0     Semiurban           N  

[614 rows x 13 columns]>
```

In [71]:
```
loan_df.head()
```

Out[71]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	Coappl
0	LP001002	Male	No	0	Graduate	No	5849	
1	LP001003	Male	Yes	1	Graduate	No	4583	
2	LP001005	Male	Yes	0	Graduate	Yes	3000	
3	LP001006	Male	Yes	0	Not Graduate	No	2583	
4	LP001008	Male	No	0	Graduate	No	6000	

In [72]:
```
loan_df.describe()
```

Out[72]:

	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 [73]:
```
loan_df.columns
```

Out[73]:
```
Index(['Loan_ID', 'Gender', 'Married', 'Dependents', 'Education',
       'Self_Employed', 'ApplicantIncome', 'CoapplicantIncome', 'LoanAmount',
       'Loan_Amount_Term', 'Credit_History', 'Property_Area', 'Loan_Status'],
      dtype='object')
```

In [74]:
```
pd.set_option("display.max_rows",14)
loan_df.isnull().sum().sort_values(ascending=False)
```

Out[74]:
```
Credit_History       50
Self_Employed        32
LoanAmount           22
Dependents           15
Loan_Amount_Term     14
Gender               13
Married               3
Loan_ID               0
Education             0
ApplicantIncome       0
CoapplicantIncome     0
Property_Area         0
Loan_Status           0
dtype: int64
```

In [75]:
```
# split data into objectcols & numericols
objectcols=loan_df.select_dtypes(include=["object"])
numericcols=loan_df.select_dtypes(include=np.number)
```

In [76]:
```
print(objectcols.shape)
print(numericcols.shape)
```

```
(614, 8)
(614, 5)
```

In [77]:
```
loan_df['Loan_Status'].replace('N',0,inplace=True)
loan_df['Loan_Status'].replace('Y',1,inplace=True)
```

In [78]:
```
loan_df['Loan_Status'].value_counts()
```

Out[78]:
```
1    422
0    192
Name: Loan_Status, dtype: int64
```

In [79]:
```
loan_df.dtypes
```

Out[79]:
```
Loan_ID               object
Gender                object
Married               object
Dependents            object
Education             object
Self_Employed         object
ApplicantIncome        int64
CoapplicantIncome    float64
LoanAmount           float64
Loan_Amount_Term     float64
Credit_History       float64
Property_Area         object
Loan_Status            int64
dtype: object
```

In [80]:
```
loan_df.corr()
```

Out[80]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Cre
ApplicantIncome	1.000000	-0.116605	0.570909	-0.045306	
CoapplicantIncome	-0.116605	1.000000	0.188619	-0.059878	
LoanAmount	0.570909	0.188619	1.000000	0.039447	
Loan_Amount_Term	-0.045306	-0.059878	0.039447	1.000000	
Credit_History	-0.014715	-0.002056	-0.008433	0.001470	
Loan_Status	-0.004710	-0.059187	-0.037318	-0.021268	

Now let’s have a look if the data has missing values or not:

In [81]:
```
loan_df.isnull().sum()
```

Out[81]:
```
Loan_ID               0
Gender               13
Married               3
Dependents           15
Education             0
Self_Employed        32
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount           22
Loan_Amount_Term     14
Credit_History       50
Property_Area         0
Loan_Status           0
dtype: int64
```

The data has missing values in some of the categorical columns and some numerical columns.

Now Let's fill the missing values:

The mode represents the value that appears most often in the column and is an appropriate choice when dealing with categorical data.

The median is an appropriate measure to fill in missing values when dealing with skewed distributions or when outliers are present in the data

In [82]:
```
loan_df['Gender'].fillna(loan_df['Gender'].mode()[0],inplace=True)
loan_df['Married'].fillna(loan_df['Married'].mode()[0],inplace= True)
loan_df['Dependents'].fillna(loan_df['Dependents'].mode()[0],inplace= True)
loan_df['Self_Employed'].fillna(loan_df['Self_Employed'].mode()[0],inplace= Tr
loan_df['Credit_History'].fillna(loan_df['Credit_History'].mode()[0],inplace=T
loan_df['Loan_Amount_Term'].fillna(loan_df['Loan_Amount_Term'].mode()[0],inpla
loan_df['LoanAmount'].fillna(loan_df['LoanAmount'].median(),inplace=True)
```

In [83]:
```
loan_df.isna().sum()
```

Out[83]:
```
Loan_ID              0
Gender               0
Married              0
Dependents           0
Education            0
Self_Employed        0
ApplicantIncome      0
CoapplicantIncome    0
LoanAmount           0
Loan_Amount_Term     0
Credit_History       0
Property_Area        0
Loan_Status          0
dtype: int64
```

In [84]:
```
loan_df.head()
```

Out[84]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	Coappl
0	LP001002	Male	No	0	Graduate	No	5849	
1	LP001003	Male	Yes	1	Graduate	No	4583	
2	LP001005	Male	Yes	0	Graduate	Yes	3000	
3	LP001006	Male	Yes	0	Not Graduate	No	2583	
4	LP001008	Male	No	0	Graduate	No	6000	

Type *Markdown* and LaTeX: α^2

Convert categorical columns to numerical values

Type *Markdown* and LaTeX: α^2

In [85]:
```
loan_df.replace({'Married':{'No':0,'Yes':1},'Gender':{'Male':1,'Female':0},'Se
                 'Property_Area':{'Rural':0,'Urban':1,'Semiurban':2},
                 'Education':{'Graduate':1,'Not Graduate':0}},inplace=True)
```

In [86]:
```
loan_df.head()
```

Out[86]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	Coappl
0	LP001002	1	0	0	1	0	5849	
1	LP001003	1	1	1	1	0	4583	
2	LP001005	1	1	0	1	1	3000	
3	LP001006	1	1	0	0	0	2583	
4	LP001008	1	0	0	1	0	6000	

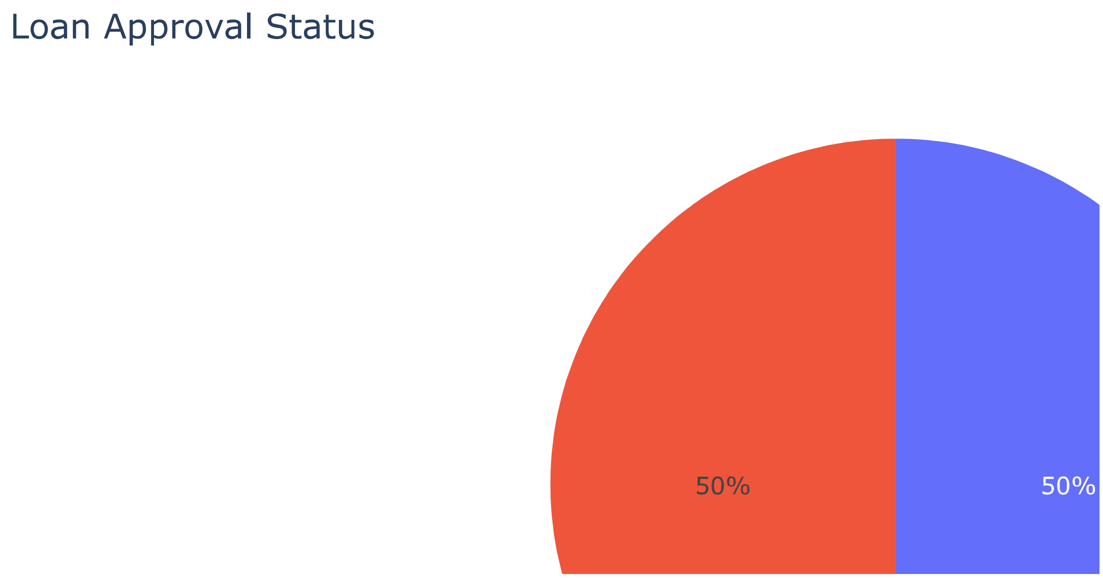
Type *Markdown* and LaTeX: α^2

Exploratory Data Analysis and Visualization

Type *Markdown* and LaTeX: α^2

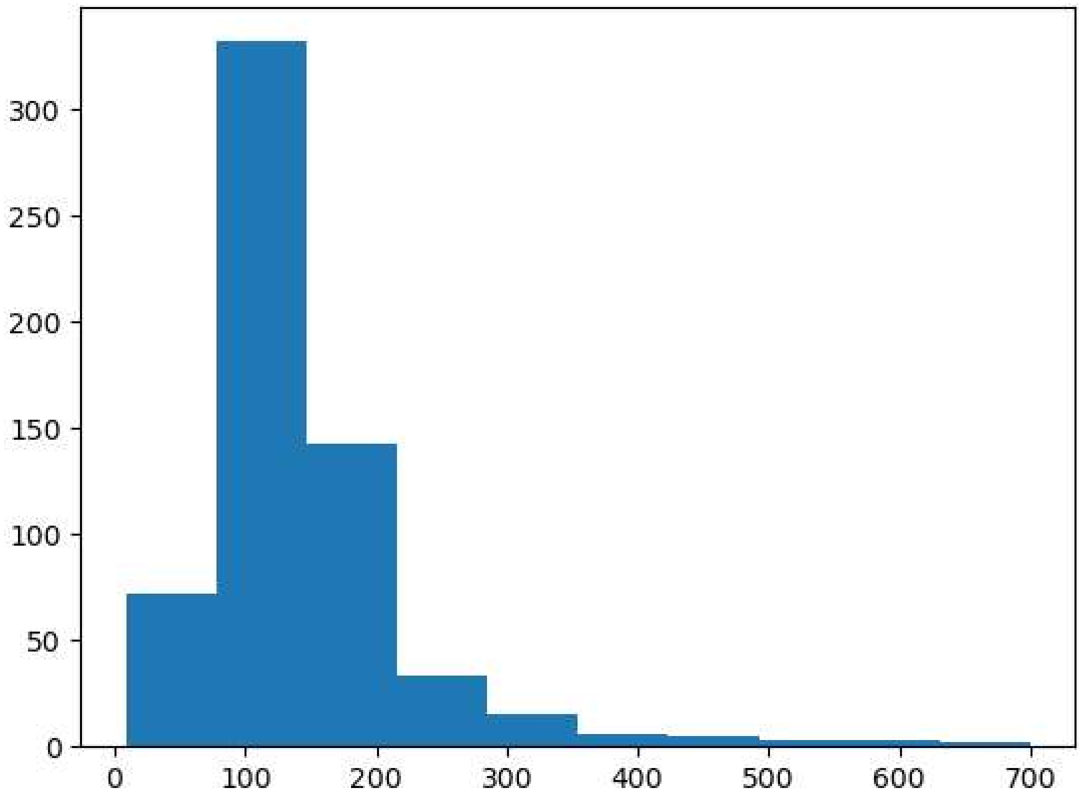
In [87]:
```
import plotly.express as px

loan_status_count = loan_df['Loan_Status'].value_counts()
fig_loan_status = px.pie(loan_status_count,
                         names=loan_status_count.index,
                         title='Loan Approval Status')
fig_loan_status.show()
```



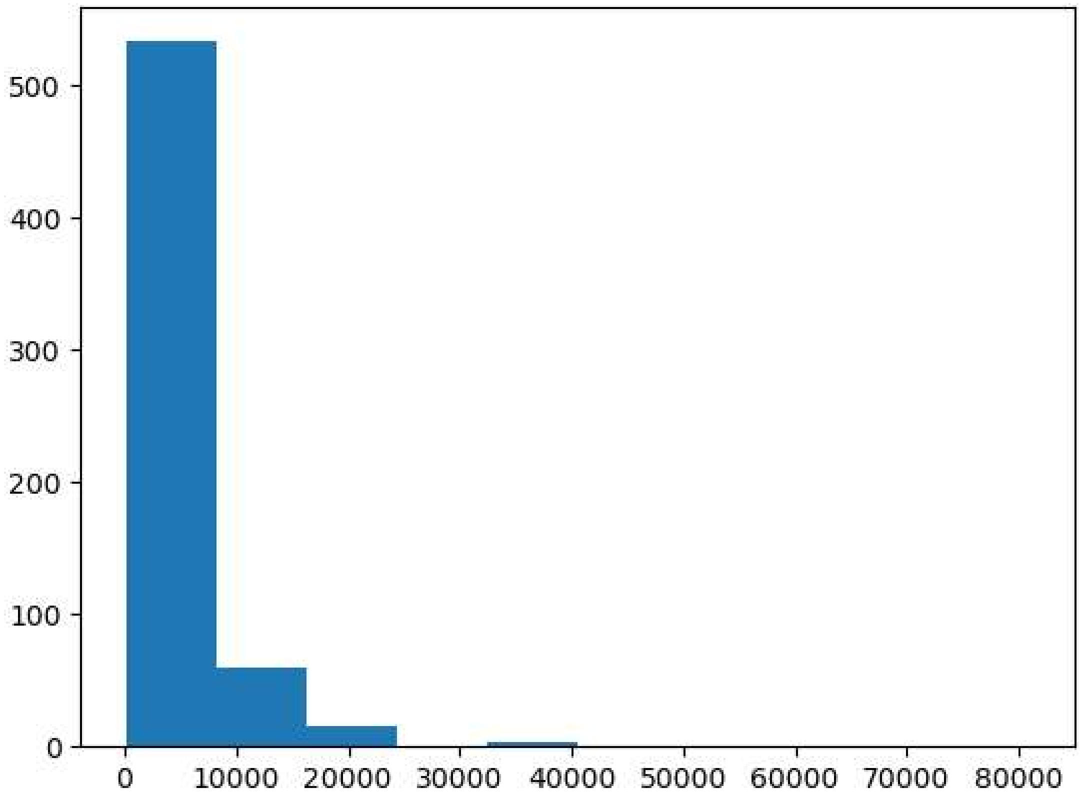
In [88]:
```
plt.hist(loan_df.LoanAmount)
```

Out[88]:
```
(array([ 72., 332., 143.,  33.,  15.,   6.,   5.,   3.,   3.,   2.]),
 array([  9. ,  78.1, 147.2, 216.3, 285.4, 354.5, 423.6, 492.7, 561.8,
        630.9, 700. ]),
 <BarContainer object of 10 artists>)
```



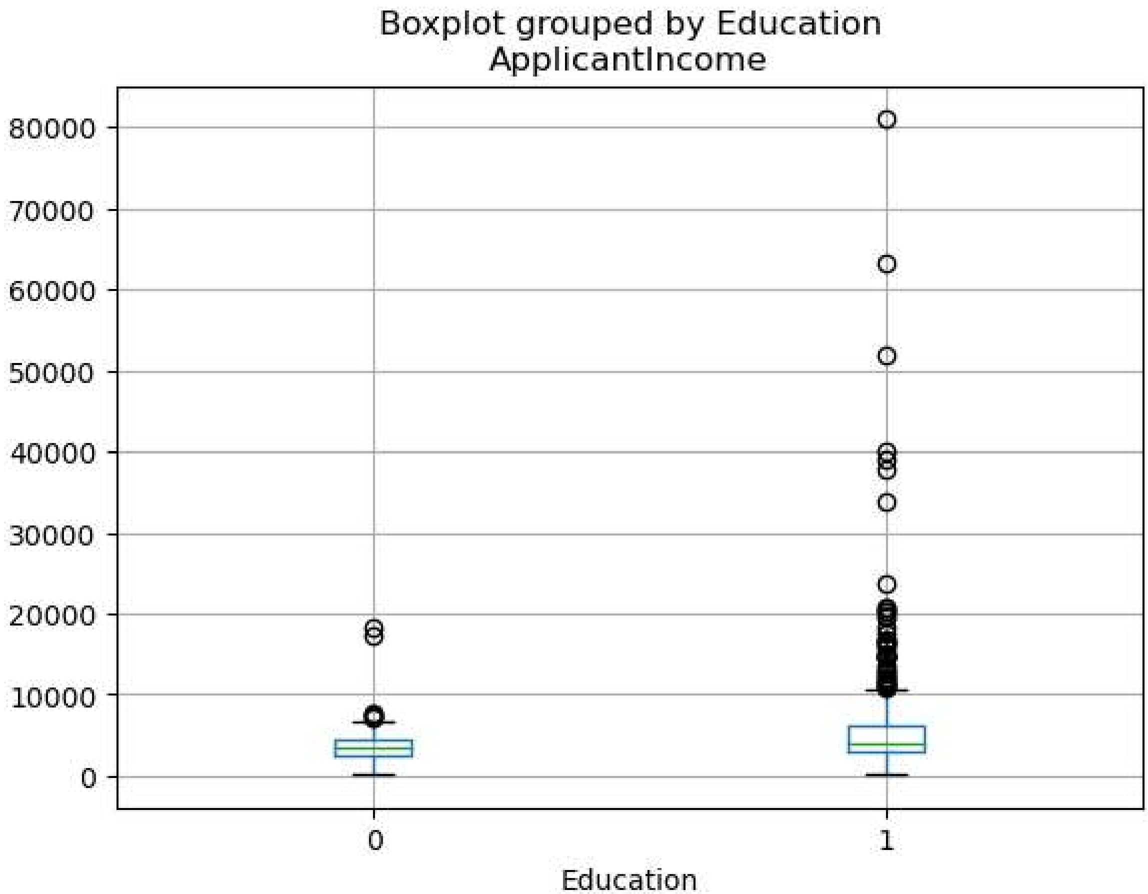
In [89]:
```
plt.hist(loan_df.ApplicantIncome)
```

Out[89]:
```
(array([533.,  59.,  15.,   0.,   4.,   0.,   1.,   1.,   0.,   1.]),
 array([  150.,  8235., 16320., 24405., 32490., 40575., 48660., 56745.,
        64830., 72915., 81000.]),
 <BarContainer object of 10 artists>)
```



In [90]:
```
loan_df.boxplot(column='ApplicantIncome', by = 'Education')
```

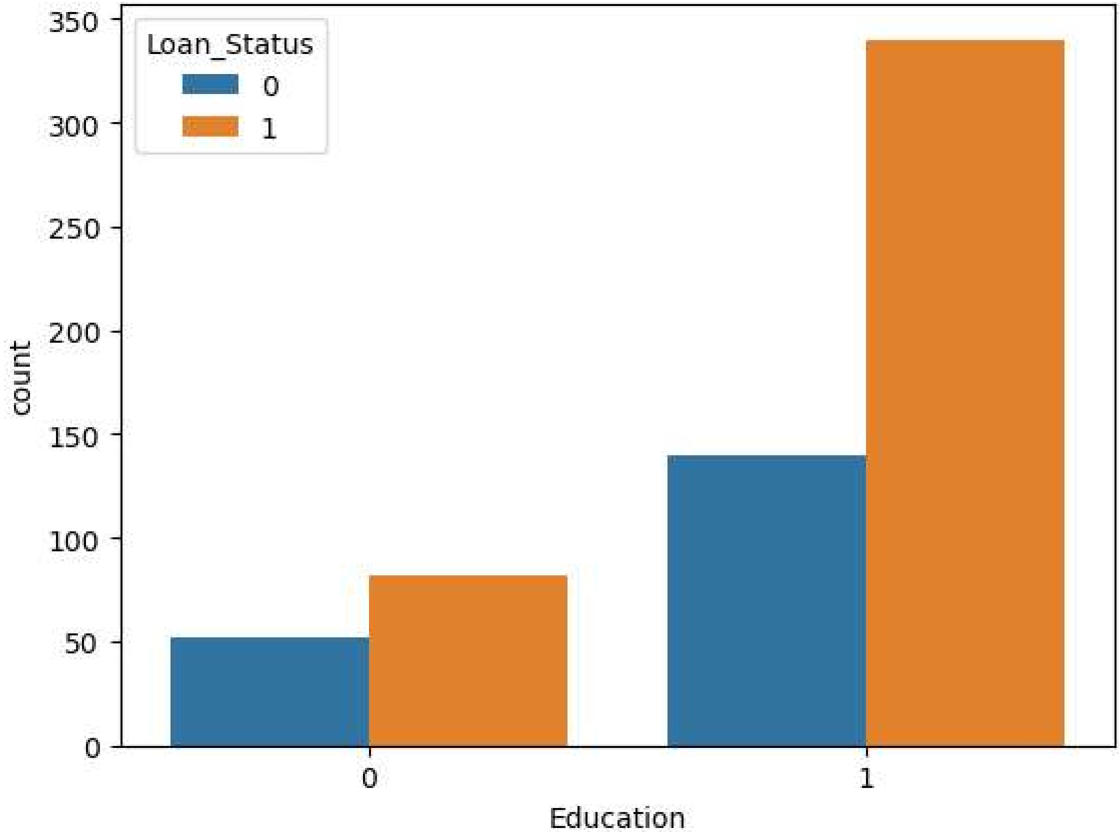
Out[90]:
```
<AxesSubplot: title={'center': 'ApplicantIncome'}, xlabel='Education'>
```



In [91]:
```
import seaborn as sns
```

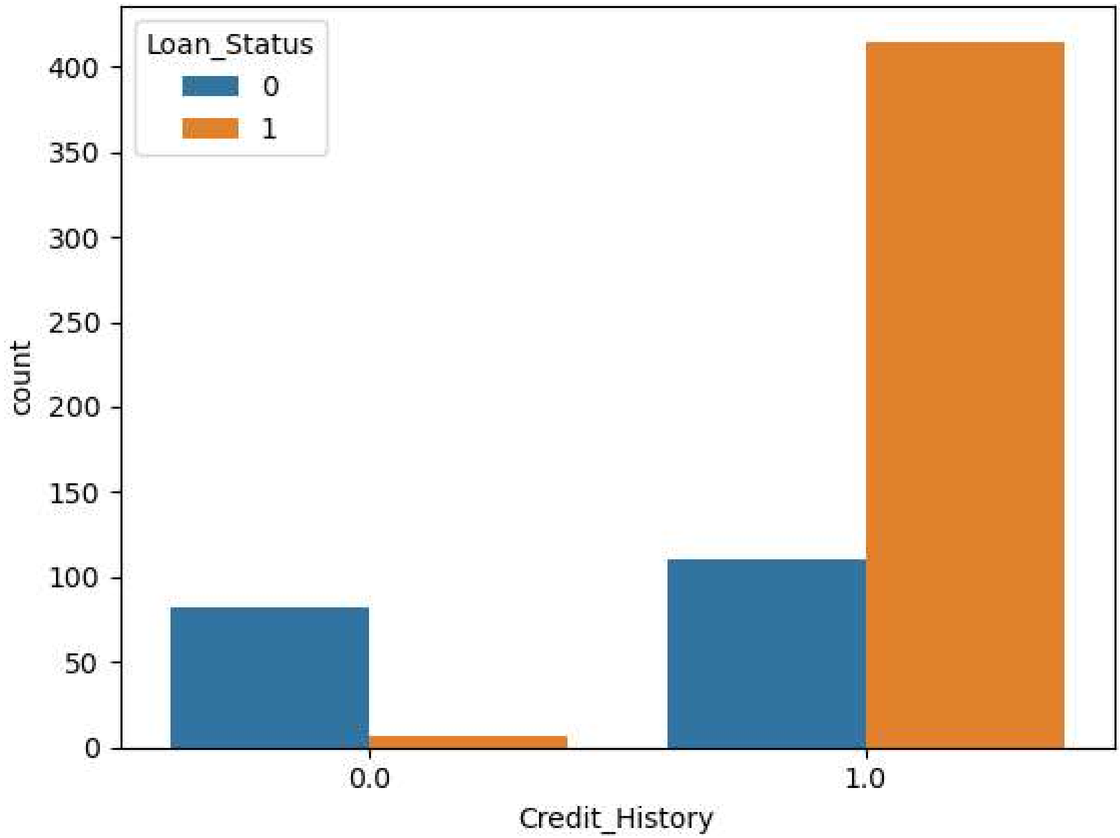
In [92]:
```
sns.countplot(x='Education',hue='Loan_Status',data=loan_df)
```

Out[92]: <AxesSubplot: xlabel='Education', ylabel='count'>



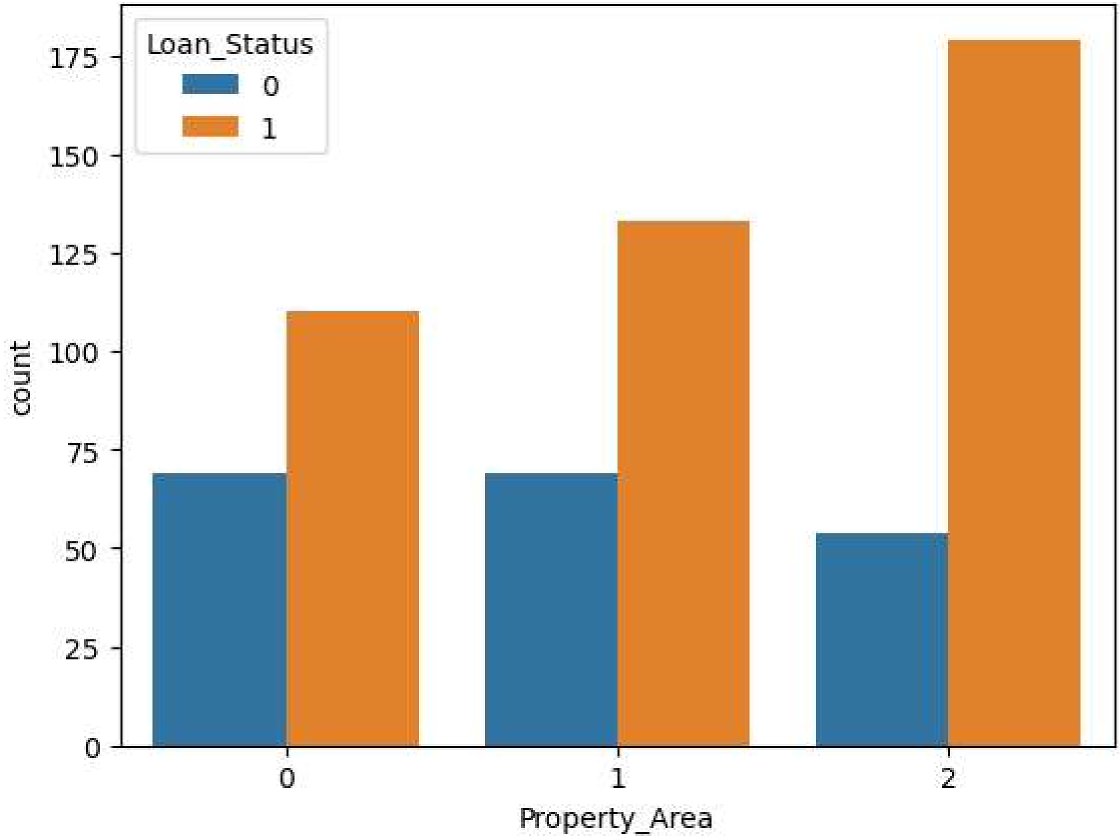
In [93]:
```
sns.countplot(x='Credit_History',hue='Loan_Status',data=loan_df)
```

Out[93]:
```
<AxesSubplot: xlabel='Credit_History', ylabel='count'>
```



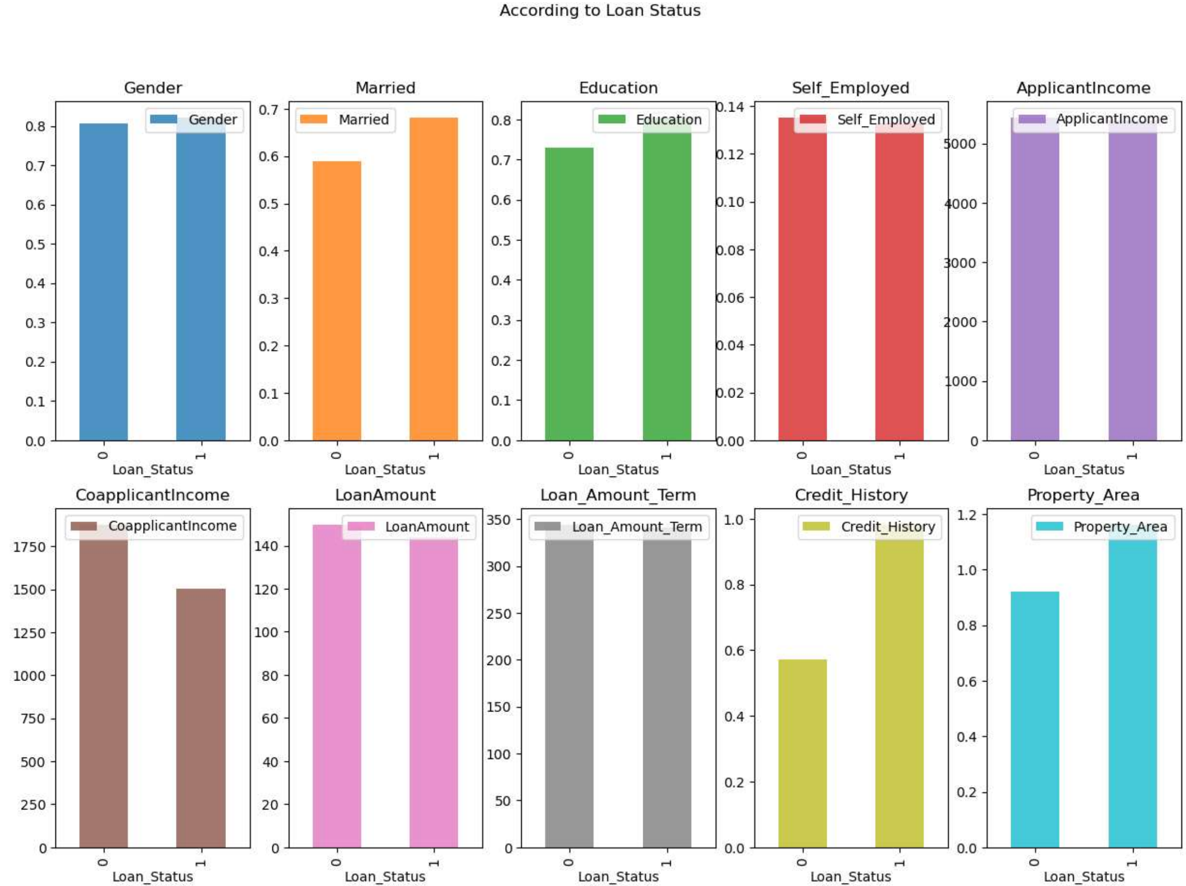
In [94]:
```
sns.countplot(x='Property_Area',hue='Loan_Status',data=loan_df)
```

Out[94]:
```
<AxesSubplot: xlabel='Property_Area', ylabel='count'>
```



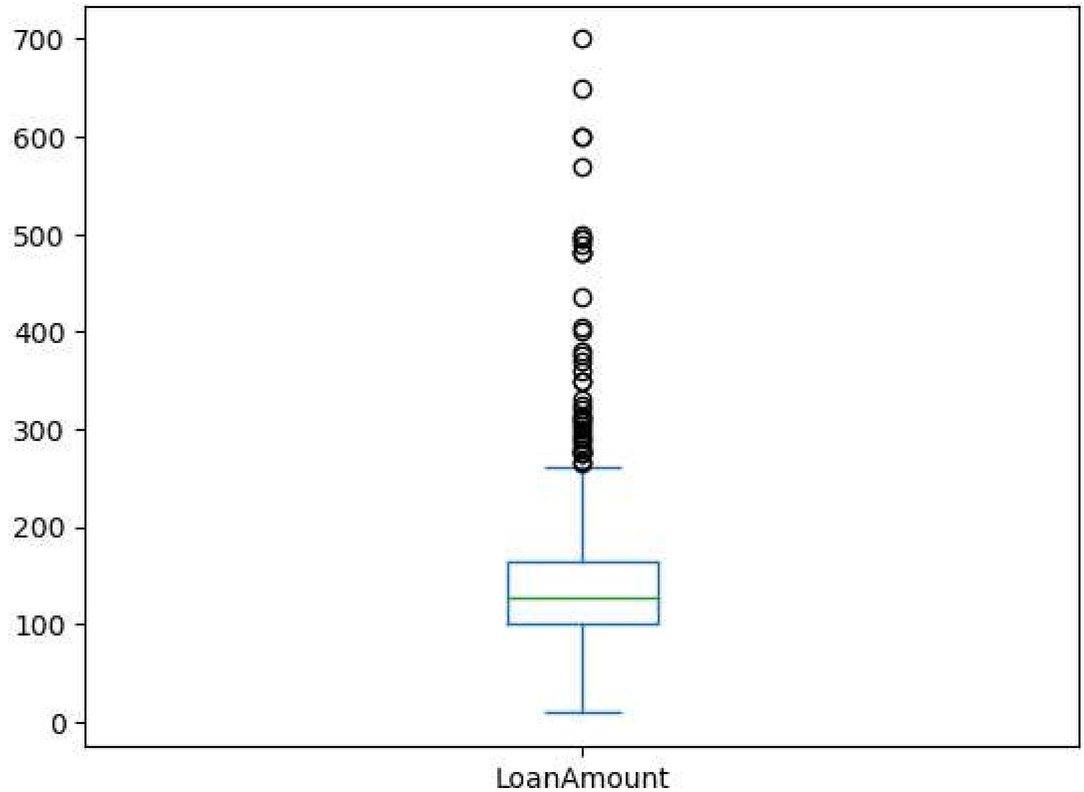
In [95]:
```
f=loan_df.groupby("Loan_Status").mean().plot(kind="bar",subplots=True,sharex=F
     sharey=False,figsize=(15,10),layout=(2,5),alpha=0.8,
     title="According to Loan Status")

plt.show()
```



In [96]:
```
loan_df.LoanAmount.plot(kind='box')
```

Out[96]: <AxesSubplot: >



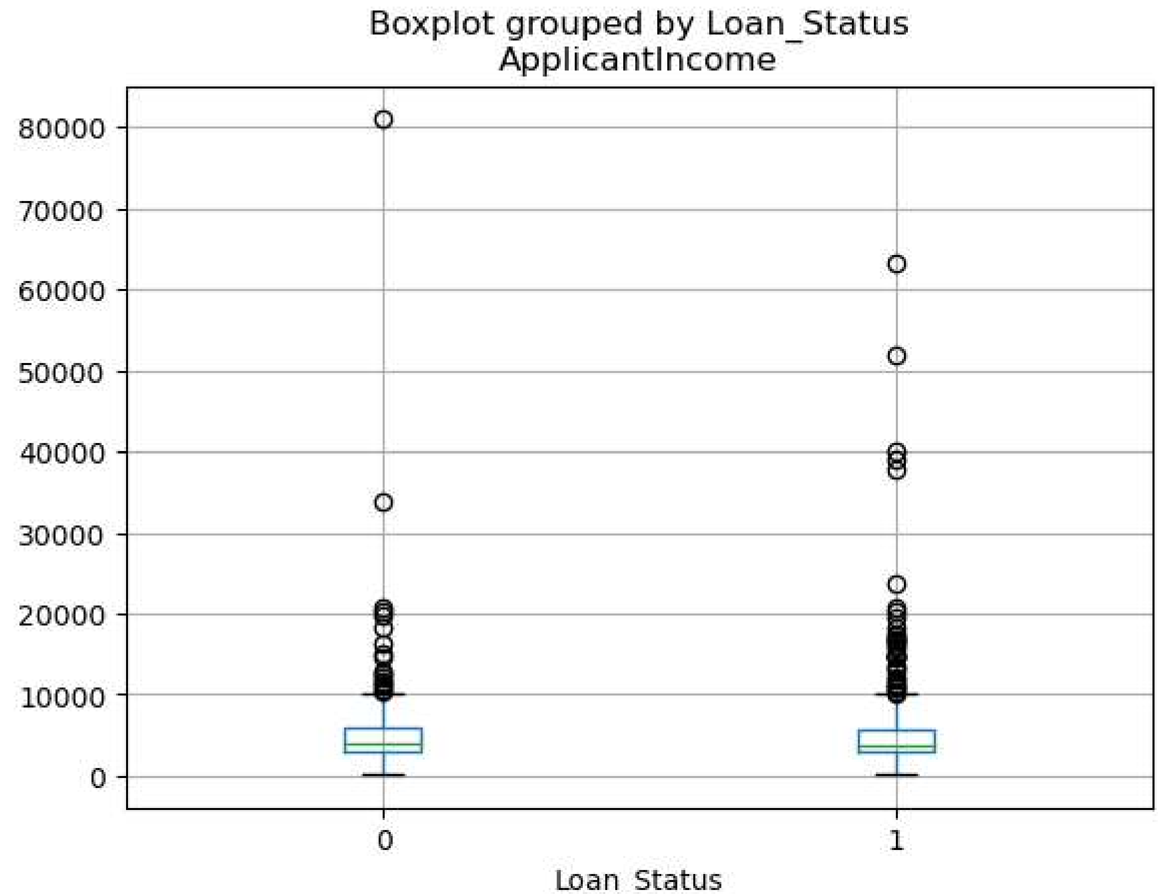
In [ ]:

Relationship between the income of the loan applicant and the loan status:

In [ ]:

In [97]:
```
loan_df.boxplot(column='ApplicantIncome', by = 'Loan_Status')
```

Out[97]: <AxesSubplot: title={'center': 'ApplicantIncome'}, xlabel='Loan_Status'>



The “ApplicantIncome” column contains outliers which need to be removed before moving further. Here’s how to remove the outliers:

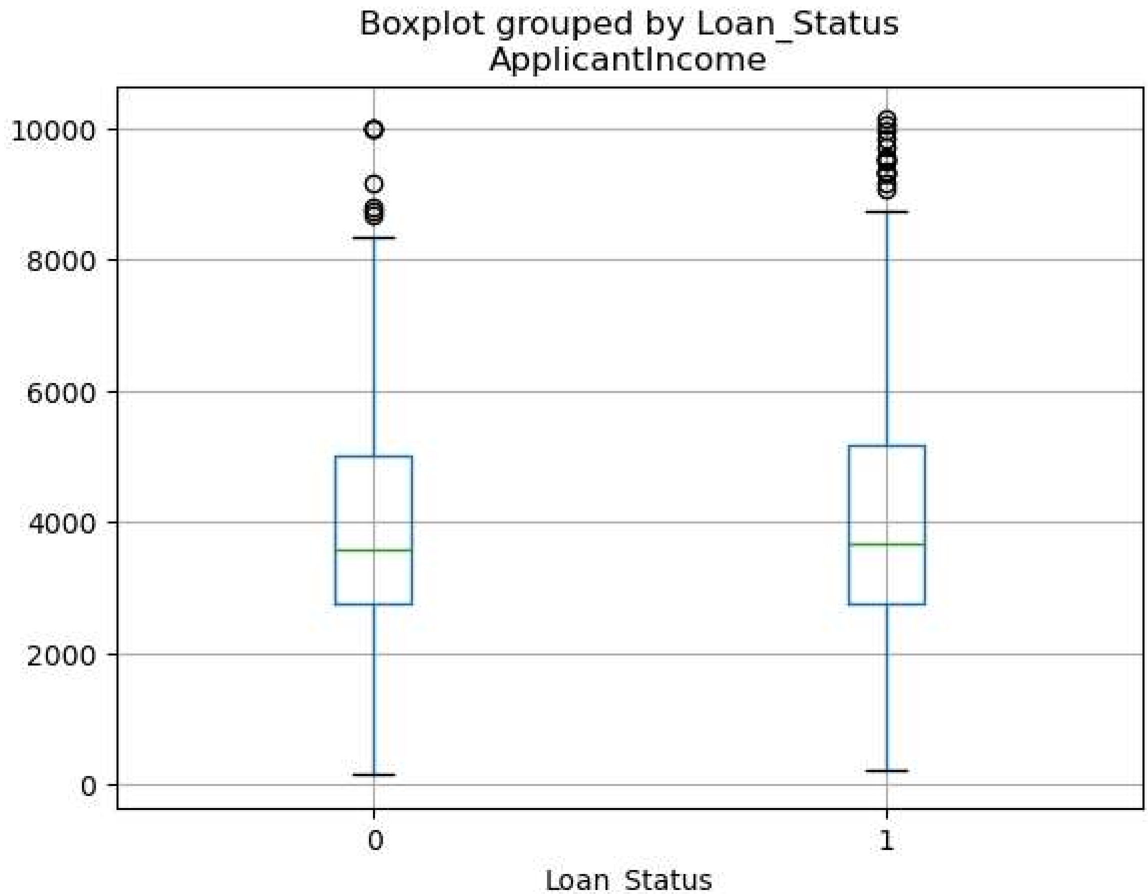
In [98]:
```
# Calculate the IQR
Q1 = loan_df['ApplicantIncome'].quantile(0.25)
Q3 = loan_df['ApplicantIncome'].quantile(0.75)
IQR = Q3 - Q1

# Define the lower and upper bounds for outliers
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

# Remove outliers
loan_df = loan_df[(loan_df['ApplicantIncome'] >= lower_bound) &
        (loan_df['ApplicantIncome'] <= upper_bound)]
```

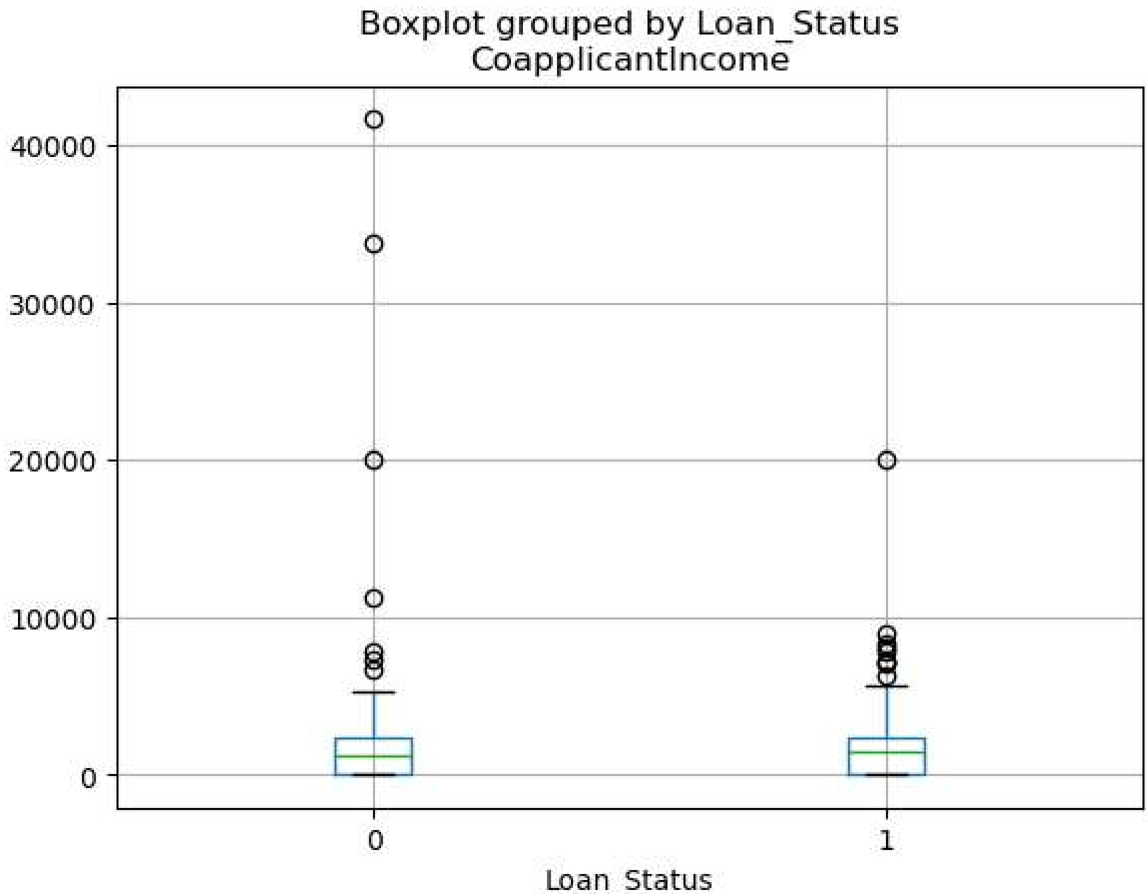
In [99]:
```
loan_df.boxplot(column='ApplicantIncome', by = 'Loan_Status')
```

Out[99]:
```
<AxesSubplot: title={'center': 'ApplicantIncome'}, xlabel='Loan_Status'>
```



In [100]:
```
loan_df.boxplot(column='CoapplicantIncome', by = 'Loan_Status')
```

Out[100]:
```
<AxesSubplot: title={'center': 'CoapplicantIncome'}, xlabel='Loan_Status'>
```



The income of the loan co-applicant also contains outliers. Let's remove the outliers from this column as well:

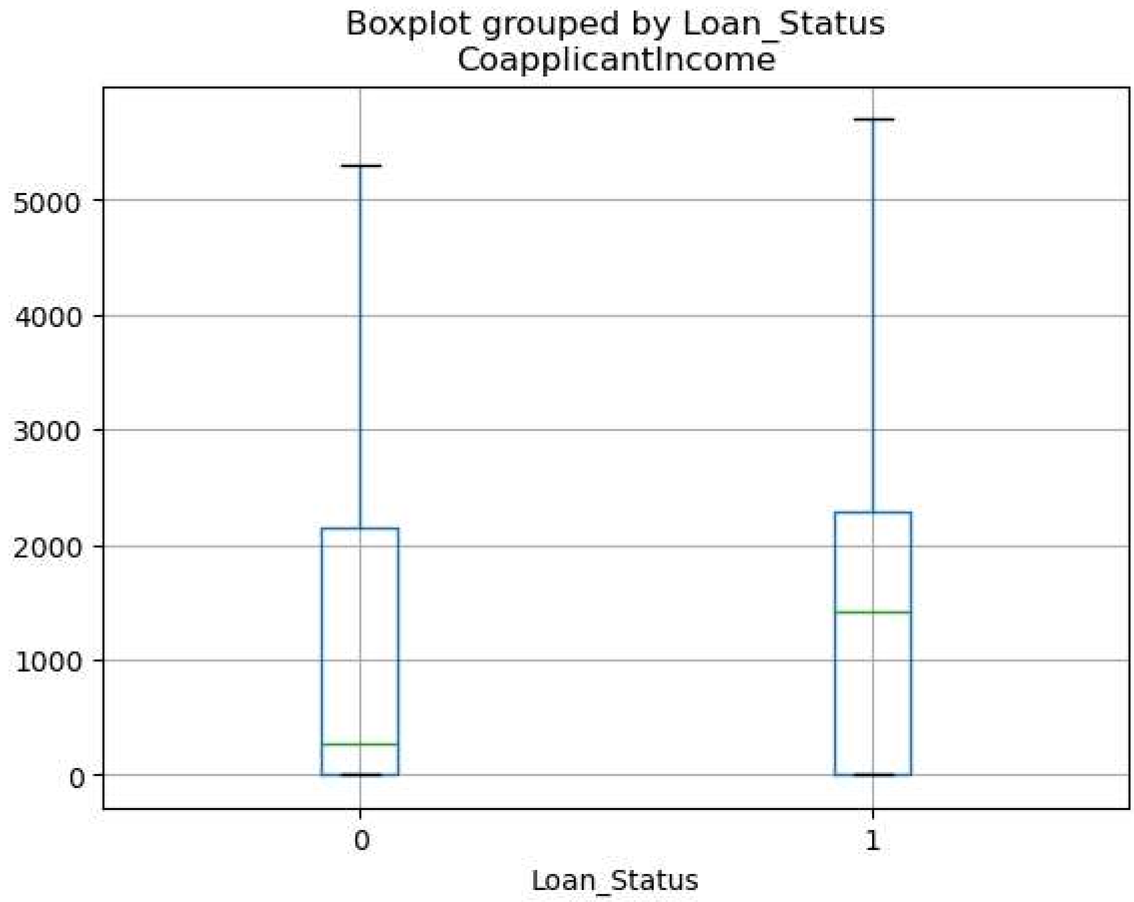
In [101]:
```
# Calculate the IQR
Q1 = loan_df['CoapplicantIncome'].quantile(0.25)
Q3 = loan_df['CoapplicantIncome'].quantile(0.75)
IQR = Q3 - Q1

# Define the lower and upper bounds for outliers
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

# Remove outliers
loan_df = loan_df[(loan_df['CoapplicantIncome'] >= lower_bound) &
        (loan_df['CoapplicantIncome'] <= upper_bound)]
```

In [102]:
```
loan_df.boxplot(column='CoapplicantIncome', by = 'Loan_Status')
```

Out[102]: <AxesSubplot: title={'center': 'CoapplicantIncome'}, xlabel='Loan_Status'>



split the data into training and test sets

In [103]:
```
X=loan_df.drop(columns=['Loan_ID','Loan_Status'],axis=1)
Y=loan_df['Loan_Status']
```

In [104]:
```
print(X)
print(Y)
```

```
     Gender  Married Dependents  Education  Self_Employed  ApplicantIncome  \
0         1        0          0          1              0             5849   
1         1        1          1          1              0             4583   
2         1        1          0          1              1             3000   
3         1        1          0          0              0             2583   
4         1        0          0          1              0             6000   
..      ...      ...        ...        ...            ...              ...   
609       0        0          0          1              0             2900   
610       1        1         3+          1              0             4106   
611       1        1          1          1              0             8072   
612       1        1          2          1              0             7583   
613       0        0          0          1              1             4583   

     CoapplicantIncome  LoanAmount  Loan_Amount_Term  Credit_History  \
0                  0.0       128.0             360.0             1.0   
1               1508.0       128.0             360.0             1.0   
2                  0.0        66.0             360.0             1.0   
3               2358.0       120.0             360.0             1.0   
4                  0.0       141.0             360.0             1.0   
..                 ...         ...               ...             ...   
609                0.0        71.0             360.0             1.0   
610                0.0        40.0             180.0             1.0   
611              240.0       253.0             360.0             1.0   
612                0.0       187.0             360.0             1.0   
613                0.0       133.0             360.0             0.0   

     Property_Area  
0                1  
1                0  
2                1  
3                1  
4                1  
..             ...  
609              0  
610              0  
611              1  
612              1  
613              2  

[548 rows x 11 columns]
0      1
1      0
2      1
3      1
4      1
      ..
609    1
610    1
611    1
612    1
613    0
Name: Loan_Status, Length: 548, dtype: int64
```

In [105]:
```
from sklearn.model_selection import train_test_split
```

In [106]:
```
X_train,X_test,Y_train,Y_test=train_test_split(X,Y,test_size=0.1,random_state=
```

In [107]:
```
print(X.shape,X_test.shape,Y.shape,X_test.shape)
```

```
(548, 11) (55, 11) (548,) (55, 11)
```

In [ ]:

In [108]:
```
loan_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 548 entries, 0 to 613
Data columns (total 13 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Loan_ID            548 non-null    object 
 1   Gender             548 non-null    int64  
 2   Married            548 non-null    int64  
 3   Dependents         548 non-null    object 
 4   Education          548 non-null    int64  
 5   Self_Employed      548 non-null    int64  
 6   ApplicantIncome    548 non-null    int64  
 7   CoapplicantIncome  548 non-null    float64
 8   LoanAmount         548 non-null    float64
 9   Loan_Amount_Term   548 non-null    float64
 10  Credit_History     548 non-null    float64
 11  Property_Area      548 non-null    int64  
 12  Loan_Status        548 non-null    int64  
dtypes: float64(4), int64(7), object(2)
memory usage: 59.9+ KB
```

In [109]:
```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
numerical_cols = ['ApplicantIncome', 'CoapplicantIncome', 'LoanAmount', 'Loan_
X_train[numerical_cols] = scaler.fit_transform(X_train[numerical_cols])
X_test[numerical_cols] = scaler.transform(X_test[numerical_cols])
```

In [110]:
```
from sklearn.preprocessing import LabelEncoder

# Create a label encoder
label_encoder = LabelEncoder()

# Apply label encoding to the 'Loan_Amount_Term' column (change this to your s
X_train['Loan_Amount_Term'] = label_encoder.fit_transform(X_train['Loan_Amount
X_test['Loan_Amount_Term'] = label_encoder.transform(X_test['Loan_Amount_Term'
```

In [111]:
```
#Dependent column values
loan_df['Dependents'].value_counts()
```

Out[111]:
```
0     328
2      91
1      87
3+     42
Name: Dependents, dtype: int64
```

In [112]:
```
loan_df=loan_df.replace(to_replace='3+',value=4)
```

In [113]:
```
loan_df['Dependents'].value_counts()
```

Out[113]:
```
0    328
2     91
1     87
4     42
Name: Dependents, dtype: int64
```

In [114]:
```
print(X)
print(Y)
```

```
     Gender  Married Dependents  Education  Self_Employed  ApplicantIncome  \
0         1        0          0          1              0             5849   
1         1        1          1          1              0             4583   
2         1        1          0          1              1             3000   
3         1        1          0          0              0             2583   
4         1        0          0          1              0             6000   
..      ...      ...        ...        ...            ...              ...   
609       0        0          0          1              0             2900   
610       1        1         3+          1              0             4106   
611       1        1          1          1              0             8072   
612       1        1          2          1              0             7583   
613       0        0          0          1              1             4583   

     CoapplicantIncome  LoanAmount  Loan_Amount_Term  Credit_History  \
0                  0.0       128.0             360.0             1.0   
1               1508.0       128.0             360.0             1.0   
2                  0.0        66.0             360.0             1.0   
3               2358.0       120.0             360.0             1.0   
4                  0.0       141.0             360.0             1.0   
..                 ...         ...               ...             ...   
609                0.0        71.0             360.0             1.0   
610                0.0        40.0             180.0             1.0   
611              240.0       253.0             360.0             1.0   
612                0.0       187.0             360.0             1.0   
613                0.0       133.0             360.0             0.0   

     Property_Area  
0                1  
1                0  
2                1  
3                1  
4                1  
..             ...  
609              0  
610              0  
611              1  
612              1  
613              2  

[548 rows x 11 columns]
0      1
1      0
2      1
3      1
4      1
      ..
609    1
610    1
611    1
612    1
613    0
Name: Loan_Status, Length: 548, dtype: int64
```

In [120]:
```
from sklearn.preprocessing import LabelEncoder

# Create a label encoder
label_encoder = LabelEncoder()

# Apply label encoding to the '3+' column in X_test (change this to your speci
X_train['Dependents'] = label_encoder.fit_transform(X_train['Dependents'])
```

In [121]:
```
from sklearn.preprocessing import LabelEncoder

# Create a label encoder
label_encoder = LabelEncoder()

# Apply label encoding to the '3+' column in X_test (change this to your speci
X_test['Dependents'] = label_encoder.fit_transform(X_test['Dependents'])
```

In [122]:
```
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import classification_report
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn import svm
from sklearn.svm import SVC
```

In [123]:
```
classifier = svm.SVC(kernel='linear')
```

In [124]:
```
classifier.fit(X_train,Y_train)
```

Out[124]:
```
SVC(kernel='linear')
```

In [125]:
```
X_train_prediction = classifier.predict(X_train)
training_data_accuracy = accuracy_score (X_train_prediction,Y_train)
```

In [126]:
```
print('Accuracy score on training data : ',training_data_accuracy)
```

```
Accuracy score on training data :  0.821501014198783
```

In [127]:
```
# accuracy score on test data
X_test_prediction = classifier.predict(X_test)
test_data_accuracy = accuracy_score (X_test_prediction,Y_test)
```

In [128]:
```
print('Accuracy score on test data:',test_data_accuracy)
```

```
Accuracy score on test data: 0.8
```

In [129]:
```
# Parameter grid for Logistic Regression
logistic_regression_param_grid = {
    'C': [0.1, 1, 10, 100],  # Adjust the values as needed
    'solver': ['liblinear', 'lbfgs'],
}

# Parameter grid for Decision Tree Classifier
decision_tree_param_grid = {
    'max_depth': [None, 10, 20, 30],  # Adjust the values as needed
    'min_samples_split': [2, 5, 10],
}

# Parameter grid for Random Forest Classifier
random_forest_param_grid = {
    'n_estimators': [100, 200, 300],  # Adjust the values as needed
    'max_depth': [None, 10, 20, 30],
}
```

In [130]:
```
# Create GridSearchCV instances for each classifier
logistic_regression_grid = GridSearchCV(LogisticRegression(), logistic_regress
decision_tree_grid = GridSearchCV(DecisionTreeClassifier(), decision_tree_para
random_forest_grid = GridSearchCV(RandomForestClassifier(), random_forest_para
```

In [131]:
```

# Fit the grid search on your data
logistic_regression_grid.fit(X_train, Y_train)
decision_tree_grid.fit(X_train, Y_train)
random_forest_grid.fit(X_train, Y_train)
```

Out[131]:
```
GridSearchCV(cv=5, estimator=RandomForestClassifier(),
             param_grid={'max_depth': [None, 10, 20, 30],
                         'n_estimators': [100, 200, 300]})
```

In [ ]:

In [132]:
```


# Access the best parameters and best score
best_logistic_regression_params = logistic_regression_grid.best_params_
best_decision_tree_params = decision_tree_grid.best_params_
best_random_forest_params = random_forest_grid.best_params_
best_logistic_regression_score = logistic_regression_grid.best_score_
best_decision_tree_score = decision_tree_grid.best_score_
best_random_forest_score = random_forest_grid.best_score_
```

In [133]:
```
print(best_logistic_regression_params)
print(best_decision_tree_params)
print(best_random_forest_params)
print(best_logistic_regression_score)
print(best_decision_tree_score)
print(best_random_forest_score)
```

```
{'C': 0.1, 'solver': 'liblinear'}
{'max_depth': 10, 'min_samples_split': 5}
{'max_depth': 10, 'n_estimators': 200}
0.8194599051741909
0.750587507730365
0.8133992991135848
```

In [134]:
```
print("Best parameters for Logistic Regression:", logistic_regression_grid.bes
print("Best parameters for Decision Tree:", decision_tree_grid.best_params_)
print("Best parameters for Random Forest:", random_forest_grid.best_params_)
```

```
Best parameters for Logistic Regression: {'C': 0.1, 'solver': 'liblinear'}
Best parameters for Decision Tree: {'max_depth': 10, 'min_samples_split': 5}
Best parameters for Random Forest: {'max_depth': 10, 'n_estimators': 200}
```

In [135]:
```
print("Best score for Logistic Regression:", logistic_regression_grid.best_sco
print("Best score for Decision Tree:", decision_tree_grid.best_score_)
print("Best score for Random Forest:", random_forest_grid.best_score_)
```

```
Best score for Logistic Regression: 0.8194599051741909
Best score for Decision Tree: 0.750587507730365
Best score for Random Forest: 0.8133992991135848
```

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The Best score for Logistic Regression: 0.8194599051741909

Loan approval prediction involves the analysis of various factors, such as the applicant's financial history, income, credit rating, employment status, and other relevant attributes. By leveraging historical loan data and applying machine learning algorithms, businesses can build models to determine loan approvals for new applicants.

In [ ]:
```
```