1. DataLinkEDA

April 30, 2023

1 Exploratory Data Analysis

1. Set up and import data
2. Univariate analysis - view how the features are distributed
3. Bivariate analysis - view how/if the distribution changes based on whether the class of the credit is good or bad
4. Data Pre-processing and Feature Engineering

1.1 1. Set up and import data

Importing libraries and set up

[1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from sklearn.preprocessing import LabelEncoder, StandardScaler
from scipy.stats import chi2_contingency


sns.set_theme(style="whitegrid")
pd.set_option('display.max_columns', None)
```

Importing Data

[2]:
```
df = pd.read_csv("credit_traindata.csv")
df.head(5)
```

[2]:
```
  checking_status  duration                    credit_history  \
0              <0         6  critical/other existing credit
1        0<=X<200        48                     existing paid
2     no checking        12  critical/other existing credit
3              <0        42                     existing paid
4              <0        24                delayed previously

               purpose  credit_amount    savings_status employment  \
0             radio/tv           1169  no known savings        >=7
1             radio/tv           5951              <100     1<=X<4
2            education           2096              <100     4<=X<7
```

```
3  furniture/equipment           7882              <100     4<=X<7
4               new car           4870              <100     1<=X<4

   installment_commitment     personal_status other_parties  residence_since  \
0                       4         male single          none                4
1                       2  female div/dep/mar          none                2
2                       2         male single          none                3
3                       2         male single     guarantor                4
4                       3         male single          none                4

  property_magnitude  age other_payment_plans   housing  existing_credits  \
0        real estate   67                none       own                 2
1        real estate   22                none       own                 1
2        real estate   49                none       own                 1
3     life insurance   45                none  for free                 1
4  no known property   53                none  for free                 2

                  job  num_dependents own_telephone foreign_worker class
0             skilled               1           yes            yes  good
1             skilled               1          none            yes   bad
2  unskilled resident               2          none            yes  good
3             skilled               2          none            yes  good
4             skilled               2          none            yes   bad
```

Check for any missing data:

[3]:
```
print(df.isnull().sum())
```

```
checking_status           0
duration                  0
credit_history            0
purpose                   0
credit_amount             0
savings_status            0
employment                0
installment_commitment    0
personal_status           0
other_parties             0
residence_since           0
property_magnitude        0
age                       0
other_payment_plans       0
housing                   0
existing_credits          0
job                       0
num_dependents            0
own_telephone             0
foreign_worker            0
```

```
class                          0
dtype: int64
```

There is no missing data. Some more information about the dataset:

[4]:
```
print(df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 798 entries, 0 to 797
Data columns (total 21 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   checking_status         798 non-null    object
 1   duration                798 non-null    int64
 2   credit_history          798 non-null    object
 3   purpose                 798 non-null    object
 4   credit_amount           798 non-null    int64
 5   savings_status          798 non-null    object
 6   employment              798 non-null    object
 7   installment_commitment  798 non-null    int64
 8   personal_status         798 non-null    object
 9   other_parties           798 non-null    object
 10  residence_since         798 non-null    int64
 11  property_magnitude      798 non-null    object
 12  age                     798 non-null    int64
 13  other_payment_plans     798 non-null    object
 14  housing                 798 non-null    object
 15  existing_credits        798 non-null    int64
 16  job                     798 non-null    object
 17  num_dependents          798 non-null    int64
 18  own_telephone           798 non-null    object
 19  foreign_worker          798 non-null    object
 20  class                   798 non-null    object
dtypes: int64(7), object(14)
memory usage: 131.0+ KB
None
```

Detail on the breakdown of the categorical variables:

[5]:
```
cat_cols = [col for col in df.columns if df[col].dtypes == 'O']

for col in cat_cols:
    print(df[col].value_counts(), "\n\n")
```

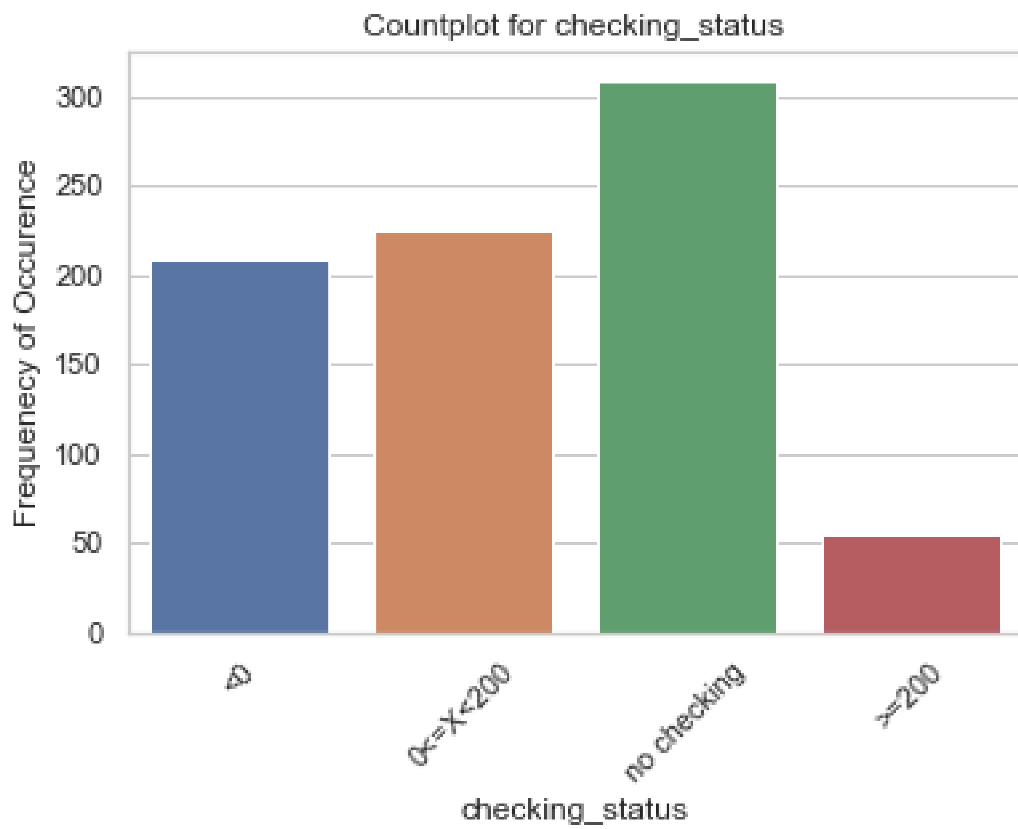
```
no checking    309
0<=X<200       225
<0             209
>=200           55
Name: checking_status, dtype: int64
```

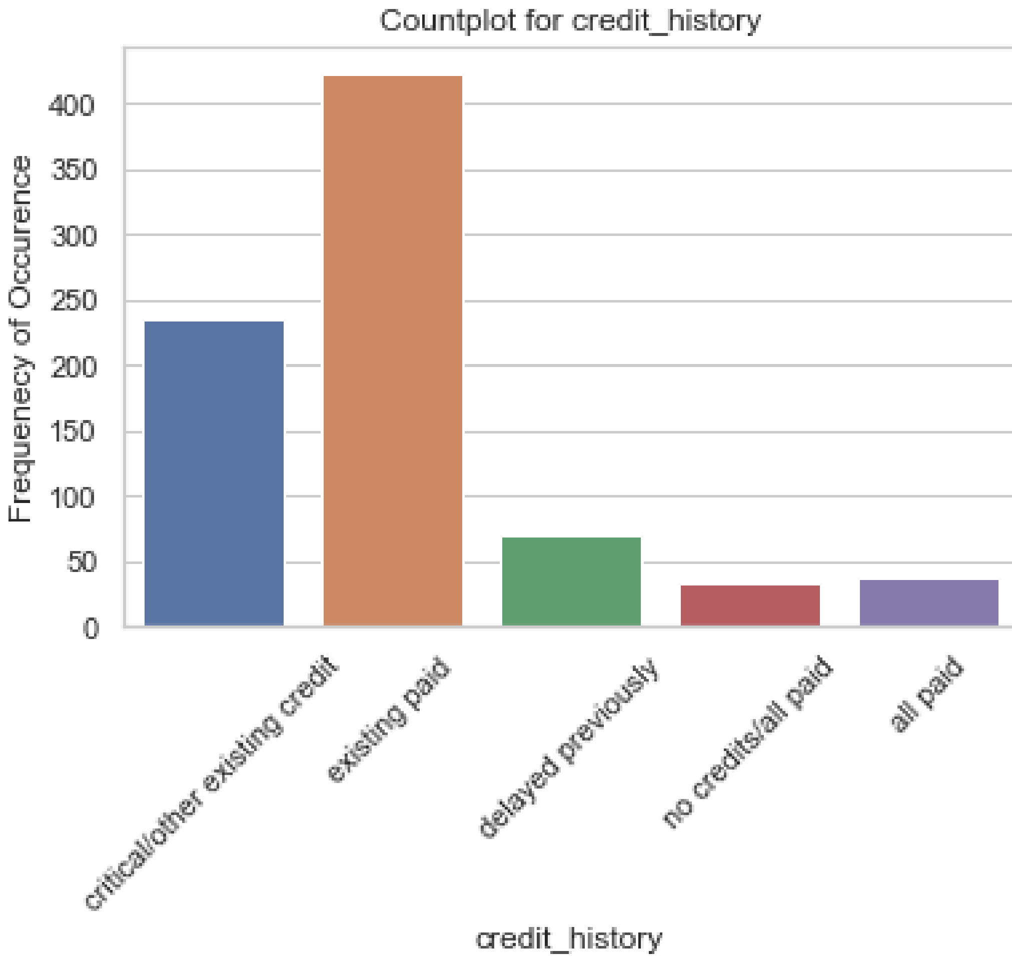
```
existing paid                    423
critical/other existing credit   235
delayed previously                70
all paid                          37
no credits/all paid               33
Name: credit_history, dtype: int64


radio/tv               223
new car                182
furniture/equipment    144
used car                81
business                77
education               45
repairs                 19
other                   10
domestic appliance       9
retraining               8
Name: purpose, dtype: int64


<100                476
no known savings    140
100<=X<500           89
500<=X<1000          51
>=1000               42
Name: savings_status, dtype: int64


1<=X<4        275
>=7           202
4<=X<7        141
<1            132
unemployed     48
Name: employment, dtype: int64


male single           436
female div/dep/mar    255
male mar/wid           69
male div/sep           38
Name: personal_status, dtype: int64


none            726
guarantor        42
```

```
co applicant     30
Name: other_parties, dtype: int64


car                  265
real estate          228
life insurance       177
no known property    128
Name: property_magnitude, dtype: int64


none      651
bank      112
stores     35
Name: other_payment_plans, dtype: int64


own         568
rent        140
for free     90
Name: housing, dtype: int64


skilled                      502
unskilled resident           161
high qualif/self emp/mgmt    119
unemp/unskilled non res       16
Name: job, dtype: int64


none    480
yes     318
Name: own_telephone, dtype: int64


yes    771
no      27
Name: foreign_worker, dtype: int64


good    559
bad     239
Name: class, dtype: int64
```

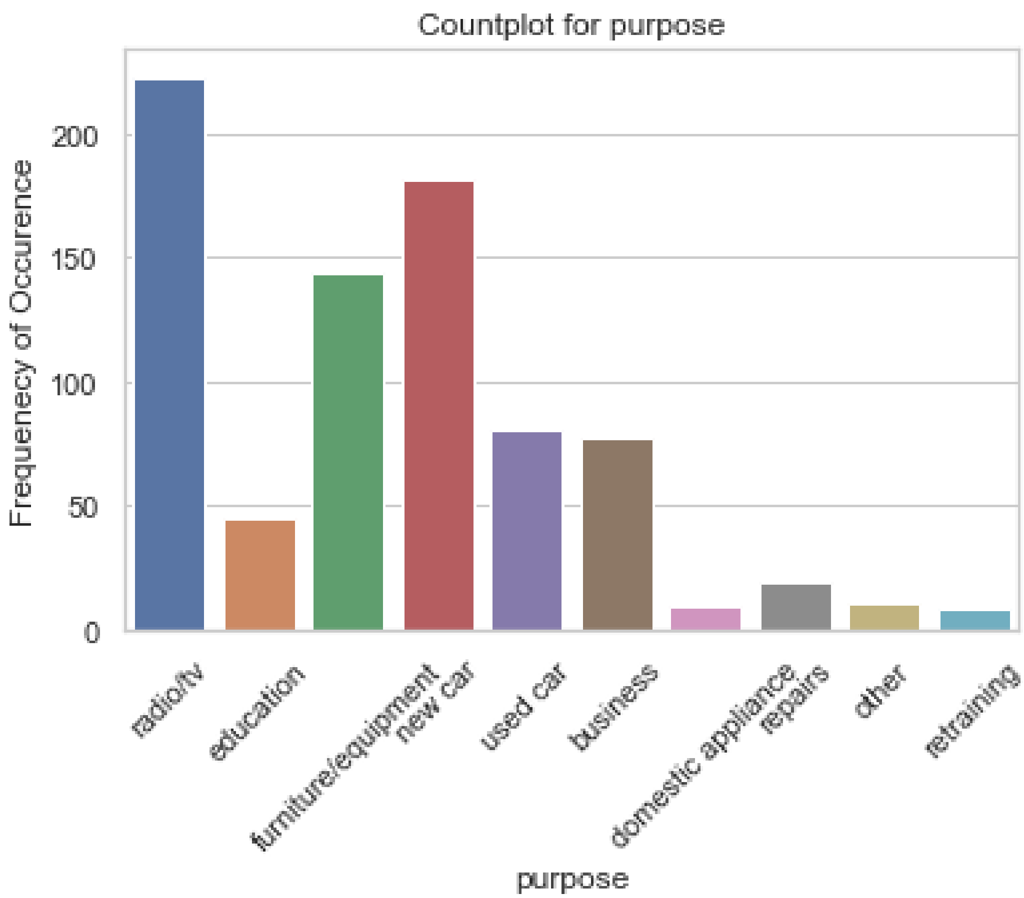
1.2 2. Univariate Analysis

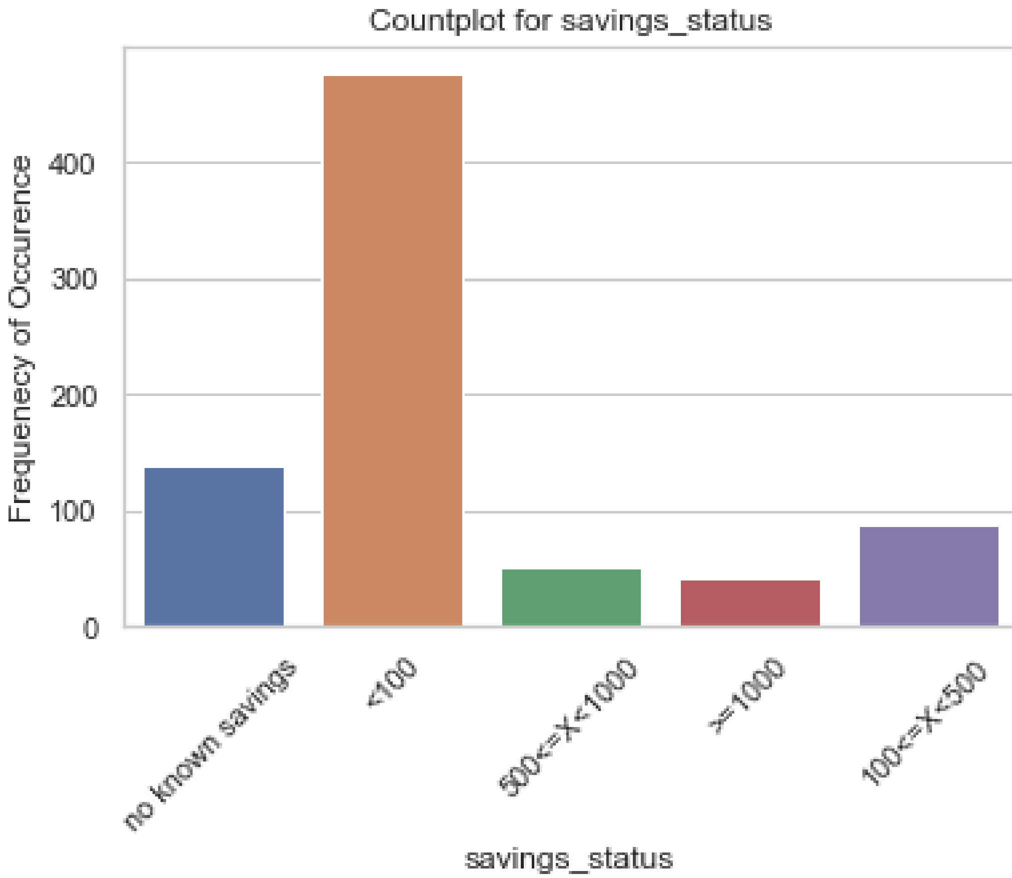
[6]:
```
for col in df.select_dtypes(include='object'):
    sns.countplot(x=col, data=df)
    plt.xlabel(f"{col}")
    plt.ylabel("Frequenecy of Occurence")
    plt.title(f"Countplot for {col}")
    plt.xticks(rotation=45)
    plt.show()
```

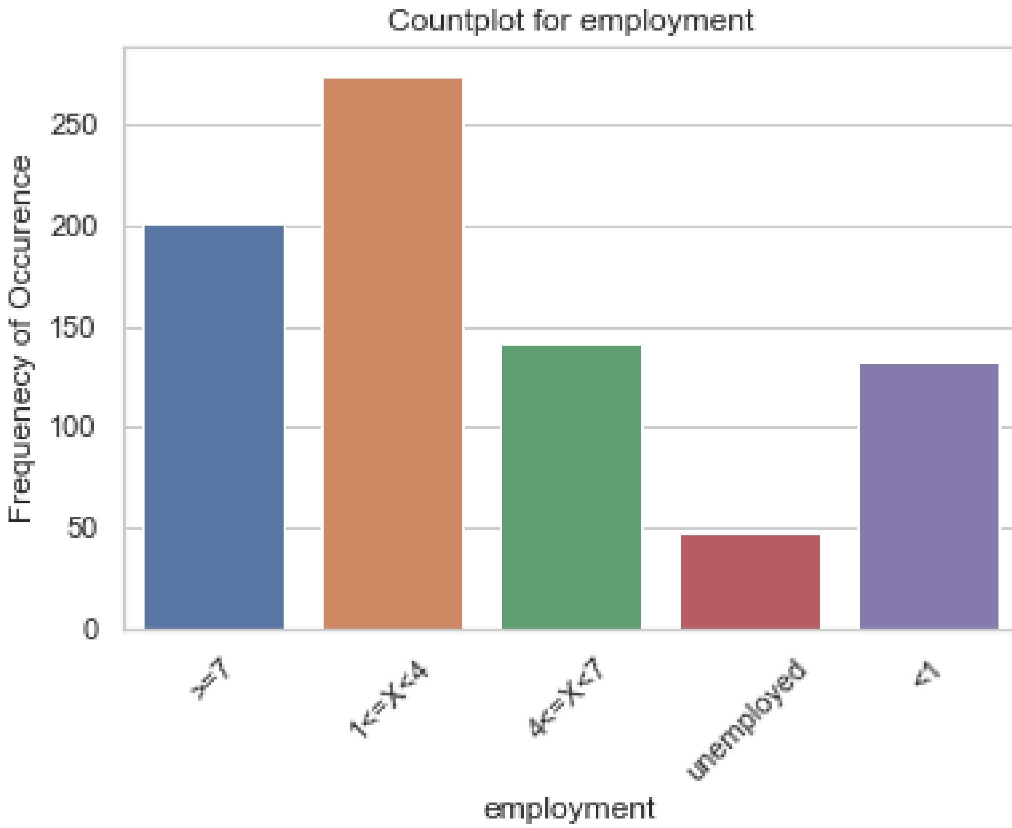




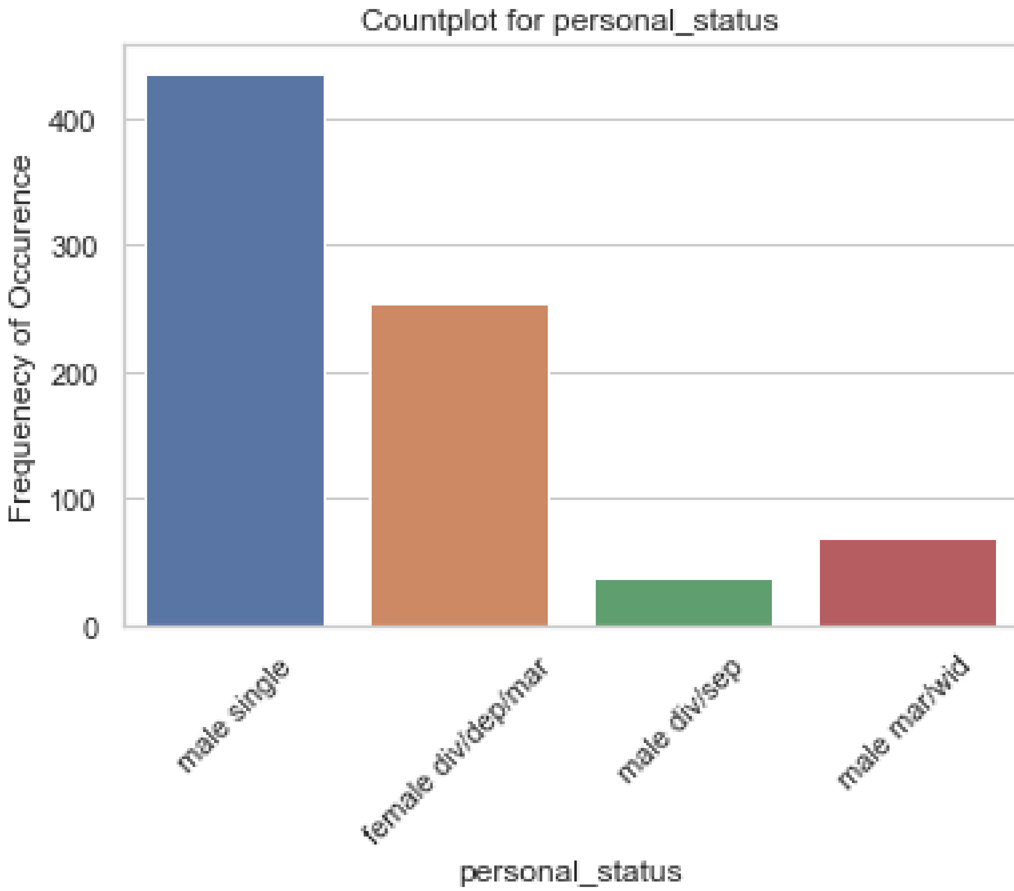
Countplot for credit_history
Frequenecy of Occurence
400
350
300
250
200
150
100
50
0
critical/other existing credit
existing paid
delayed previously
no credits/all paid
all paid
credit_history

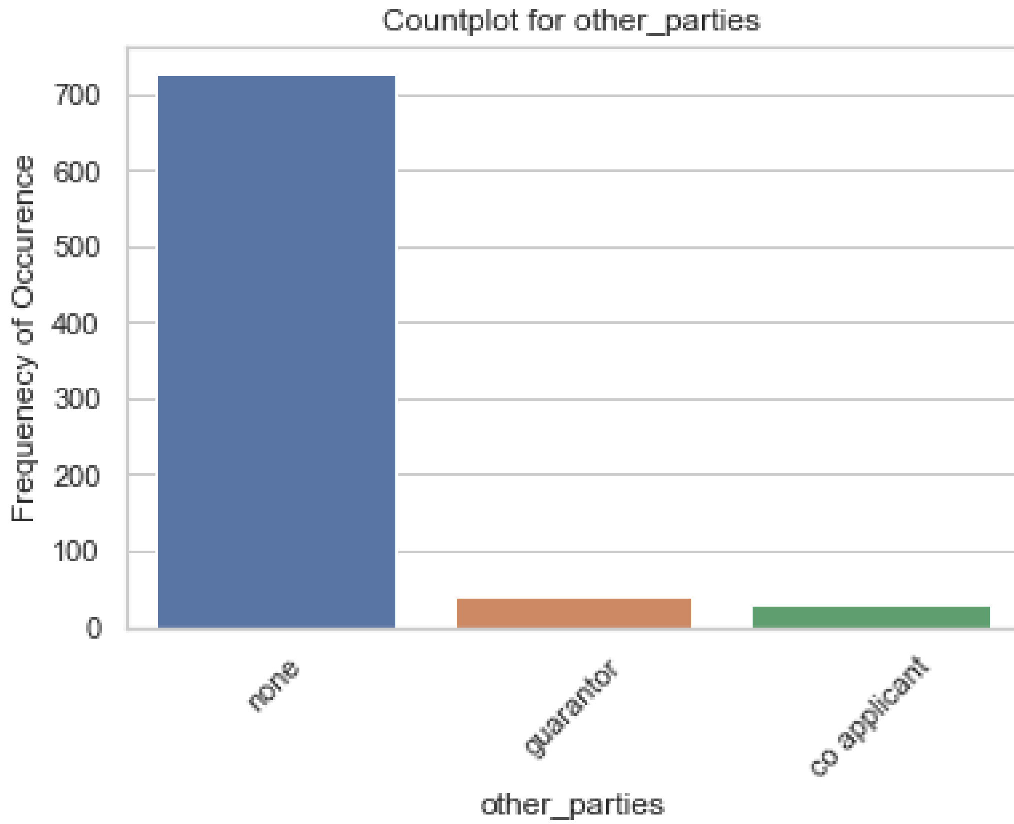

Countplot for purpose
Frequenecy of Occurence
0
50
100
150
200
radio/tv
education
furniture/equipment
new car
used car
business
domestic appliance
repairs
other
retraining
purpose

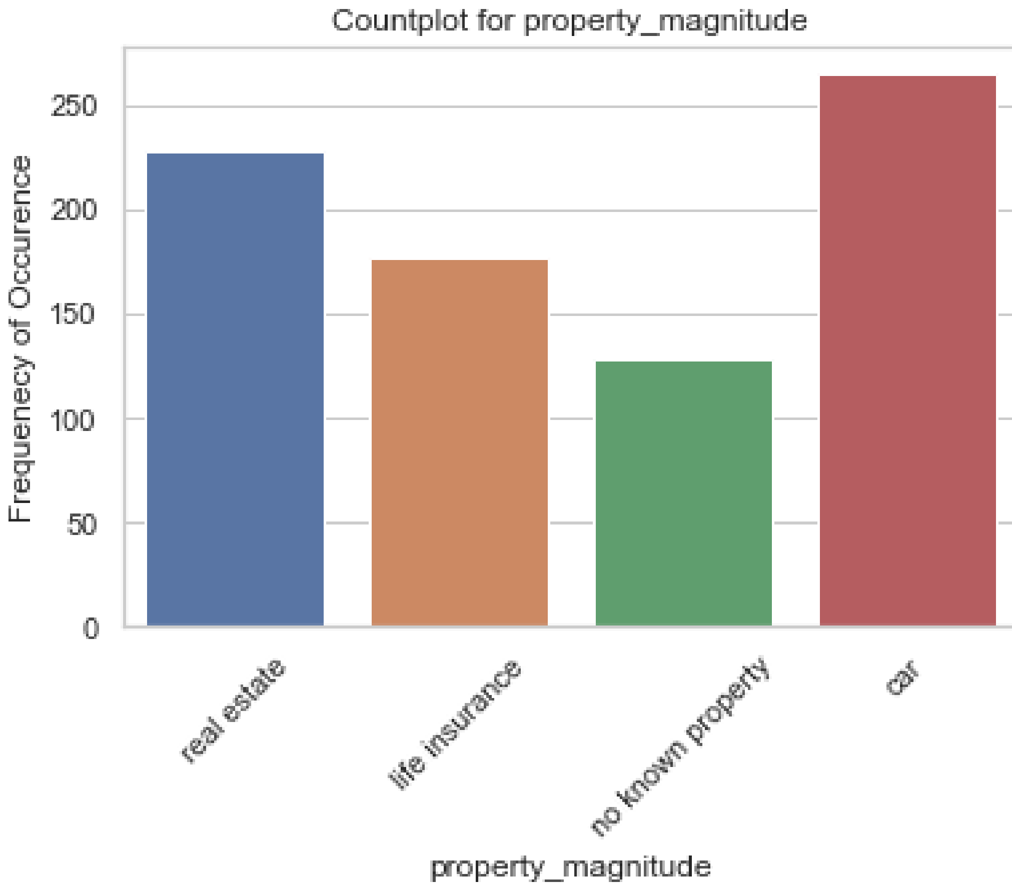

Countplot for savings_status
Frequenecy of Occurence
400
300
200
100
0
no known savings
<100
500<=X<1000
>=1000
100<=X<500
savings_status



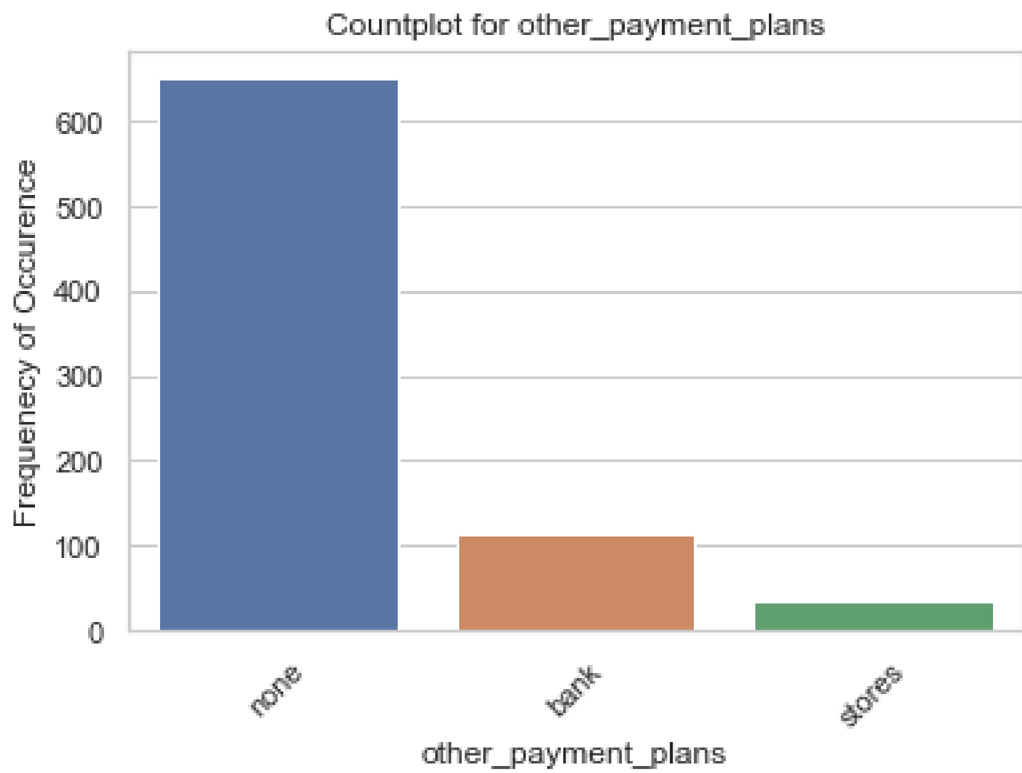
Countplot for employment
Frequenecy of Occurence
250
200
150
100
50
0
>=7
1<=X<4
4<=X<7
unemployed
<1
employment

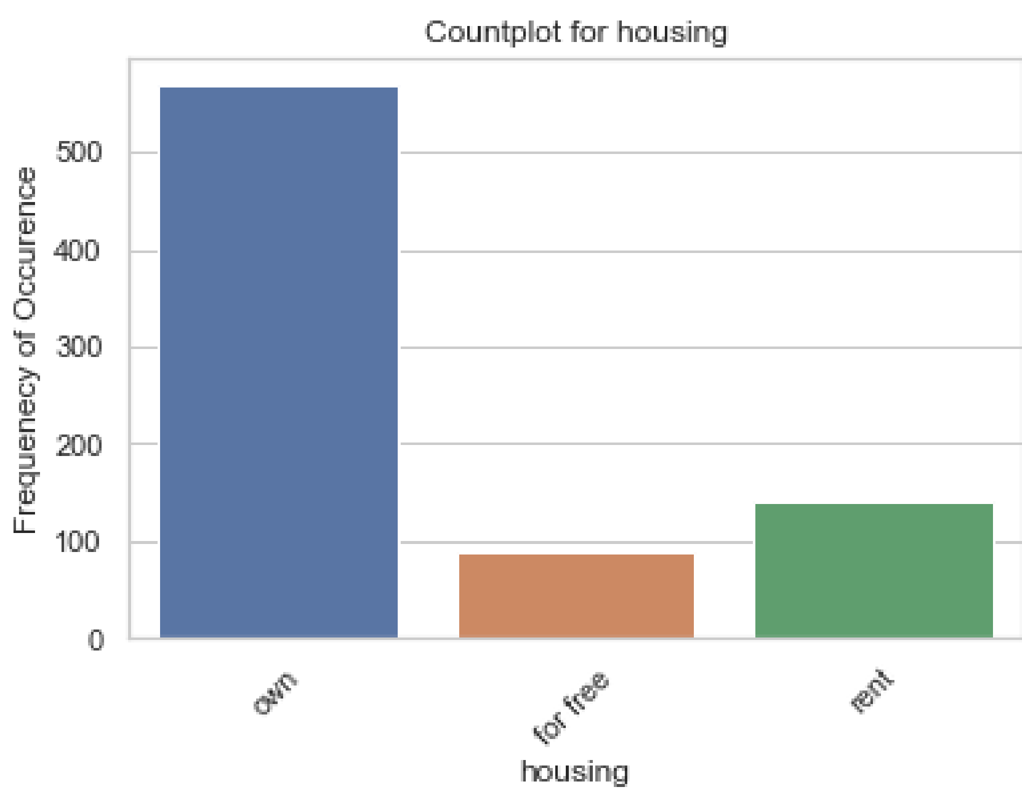

Countplot for personal_status
Frequenecy of Occurence
400
300
200
100
0
male single
female div/dep/mar
male div/sep
male mar/wid
personal_status

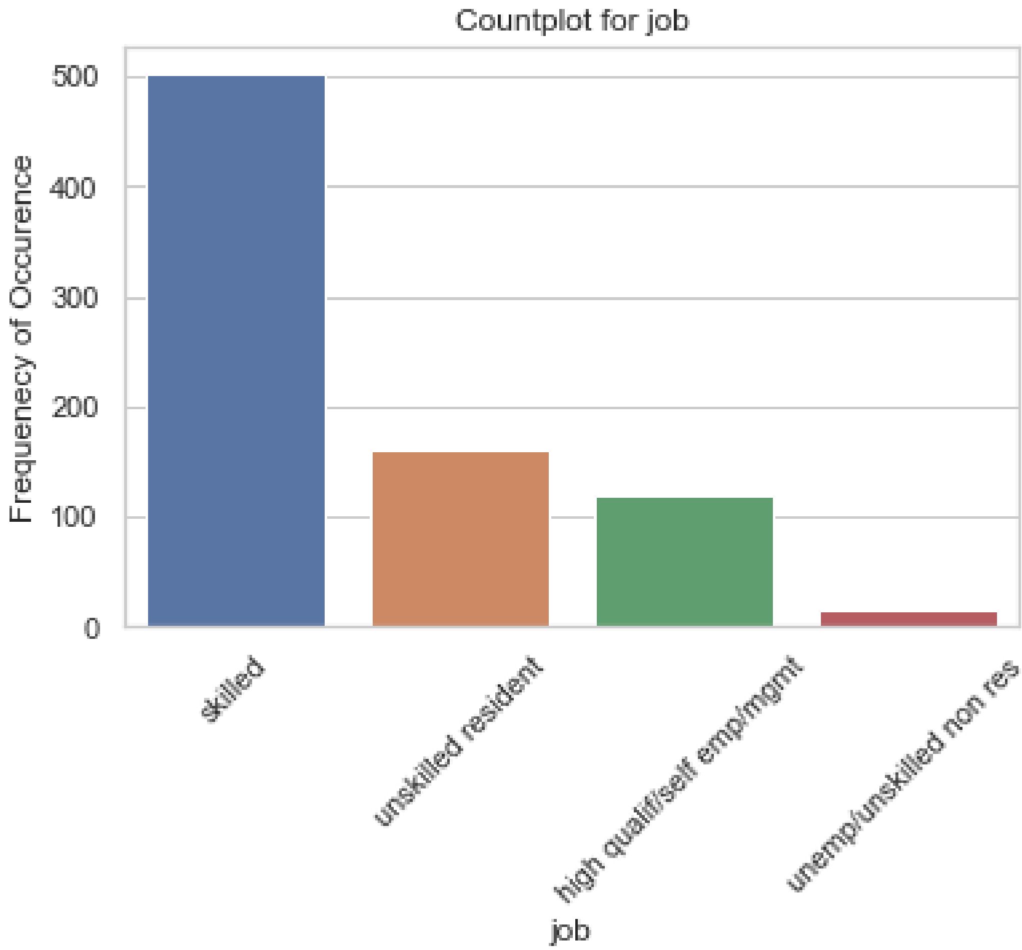

Countplot for other_parties
Frequenecy of Occurence
0
100
200
300
400
500
600
700
none
guarantor
co applicant
other_parties

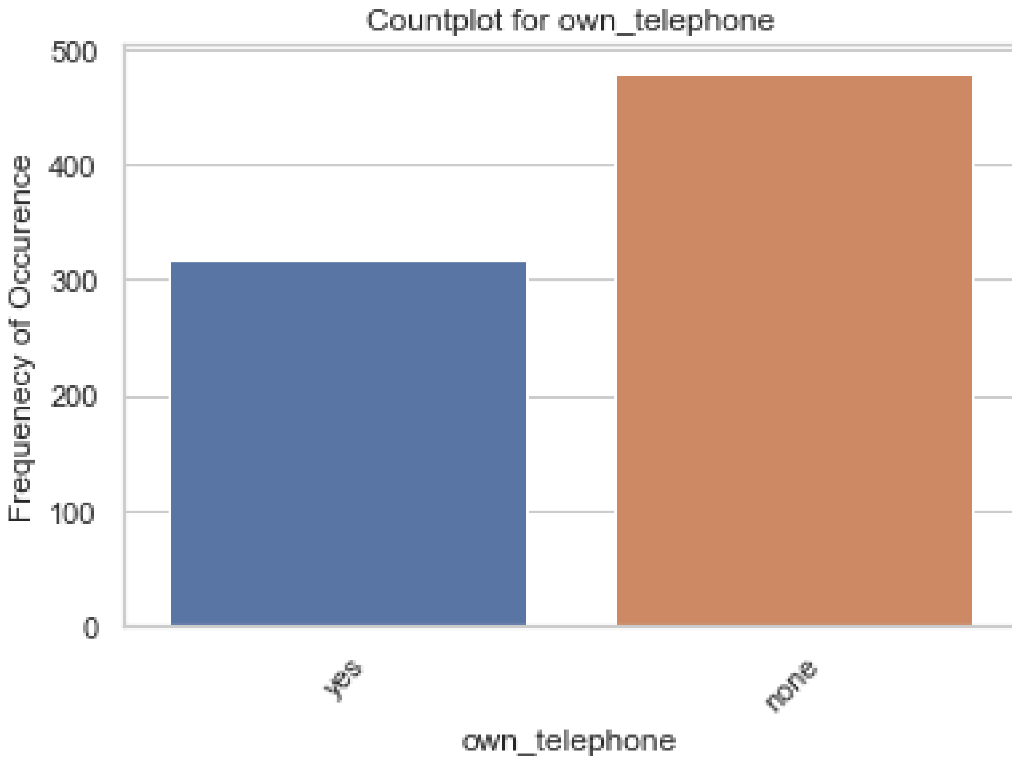


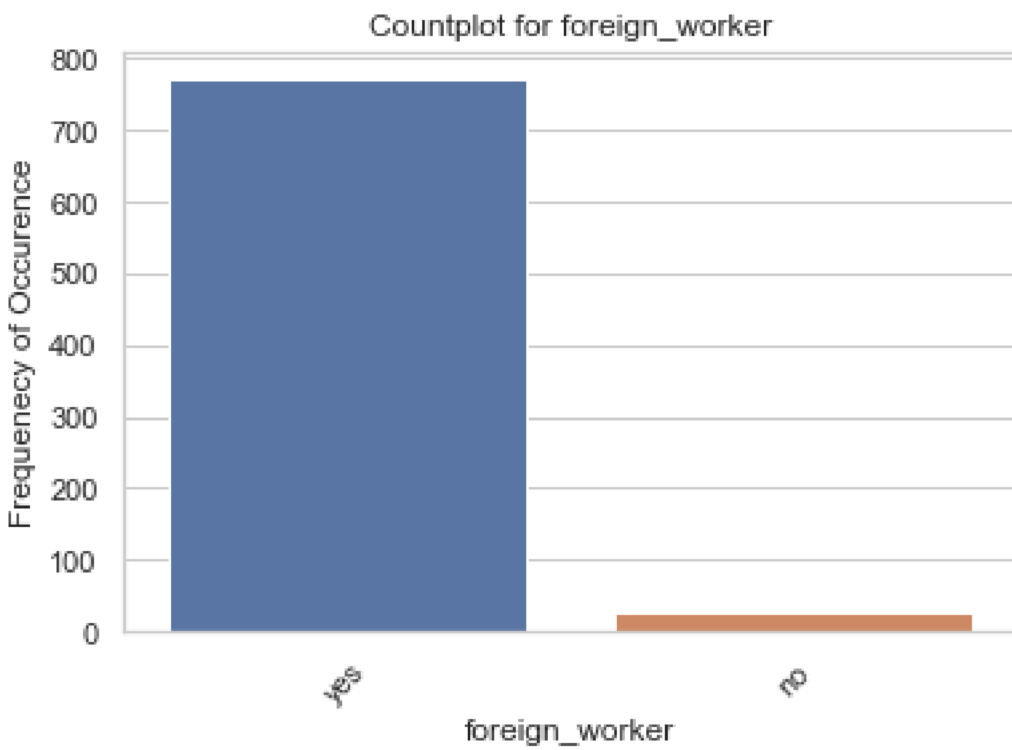
Countplot for property_magnitude
Freque necy of Occurence
0
50
100
150
200
250
real estate
life insurance
no known property
car
property_magnitude

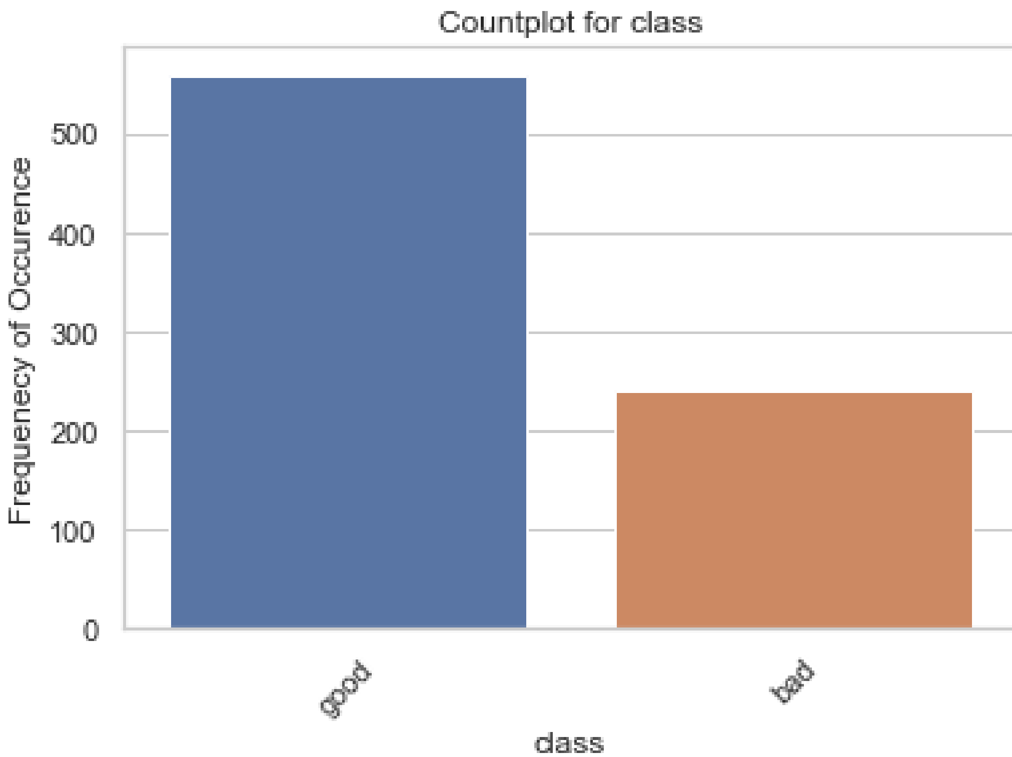

Countplot for other_payment_plans
Frequenecy of Occurence
0
100
200
300
400
500
600
none
bank
stores
other_payment_plans


Countplot for housing
Frequenecy of Occurence
0
100
200
300
400
500
own
for free
rent
housing


Countplot for job
Frequenecy of Occurence
500
400
300
200
100
0
skilled
unskilled resident
high qualif/self emp/mgmt
unemp/unskilled non res
job

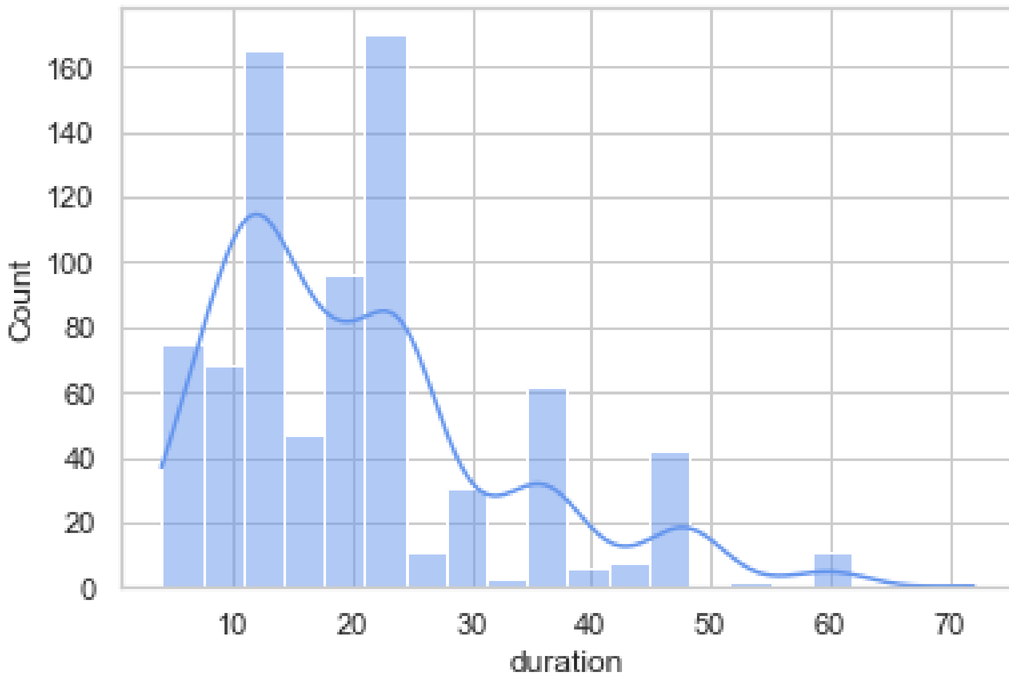

Countplot for own_telephone
Frequenecy of Occurence
500
400
300
200
100
0
yes
none
own_telephone

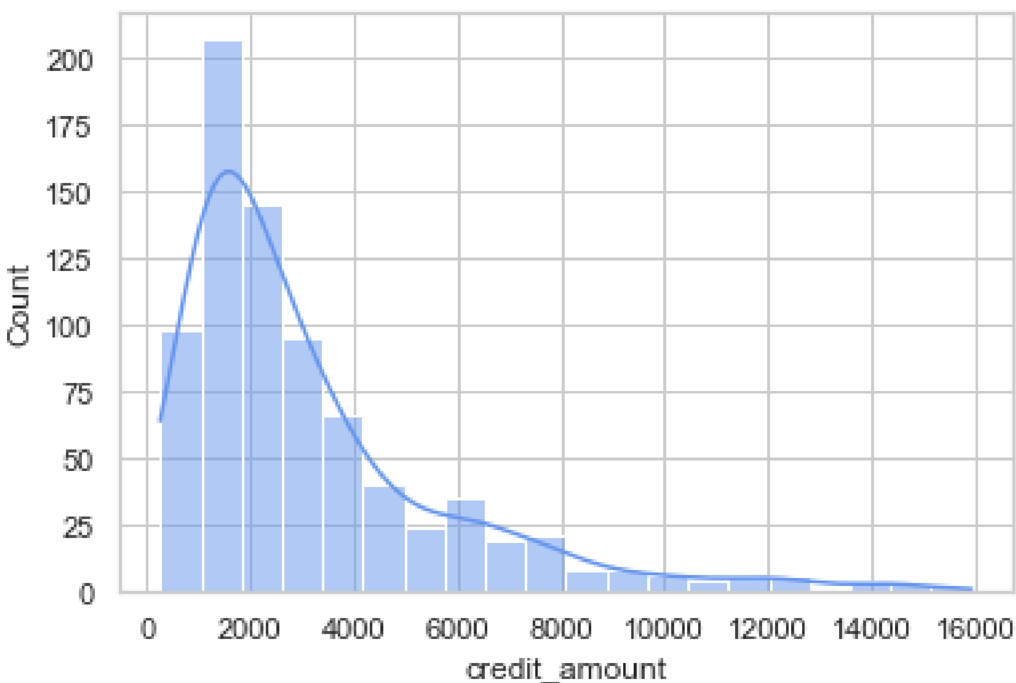

Countplot for foreign_worker
Frequenecy of Occurence
800
700
600
500
400
300
200
100
0
yes
no
foreign_worker

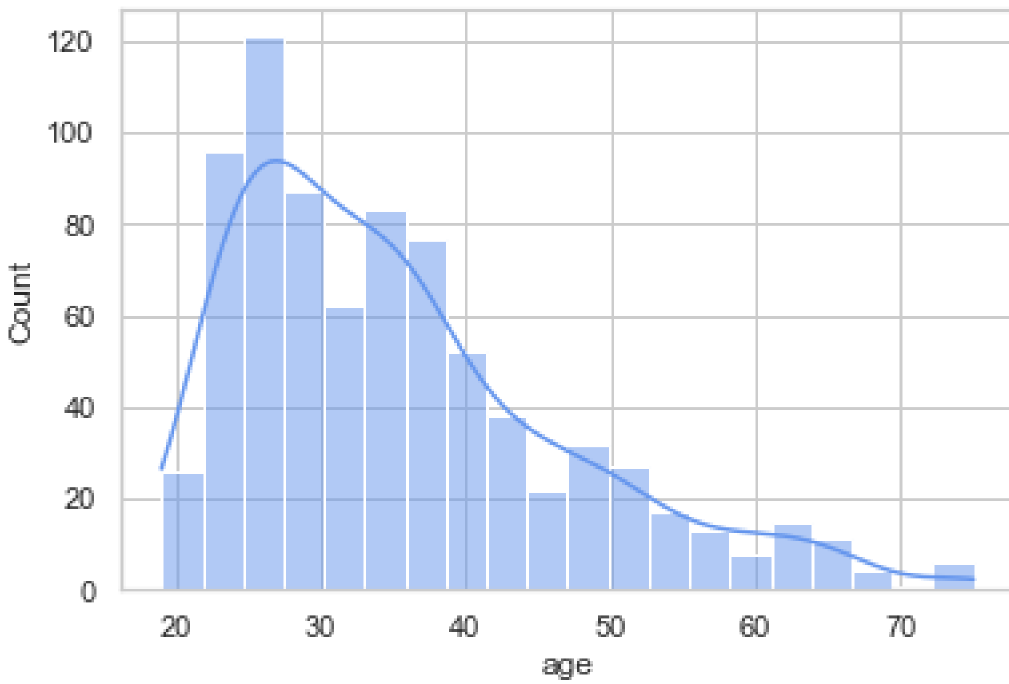


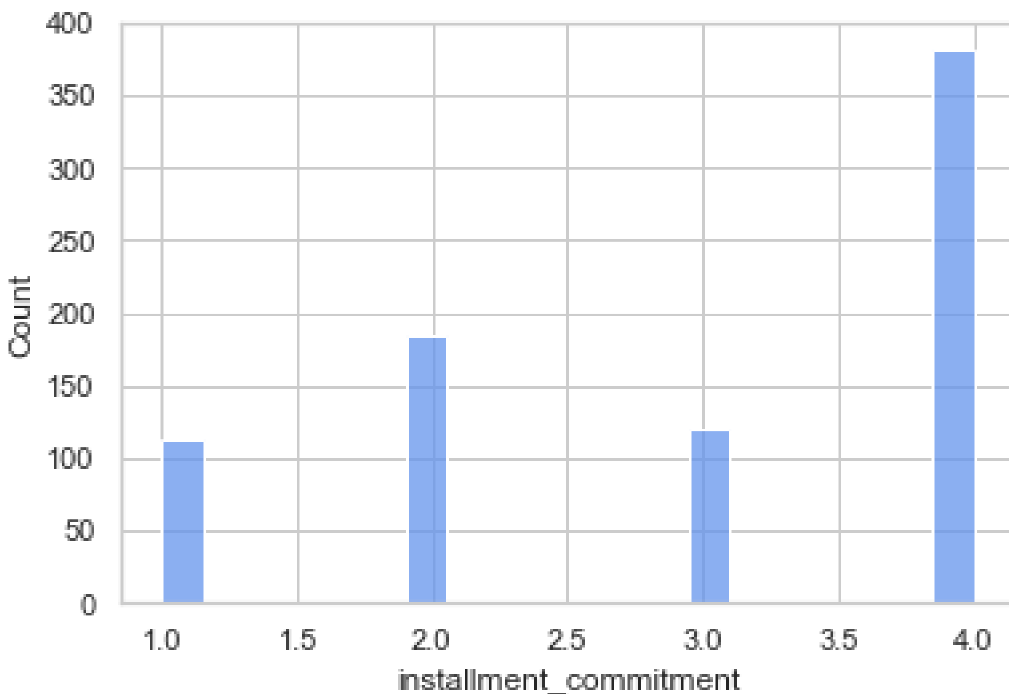
Some histograms of the numerical features:

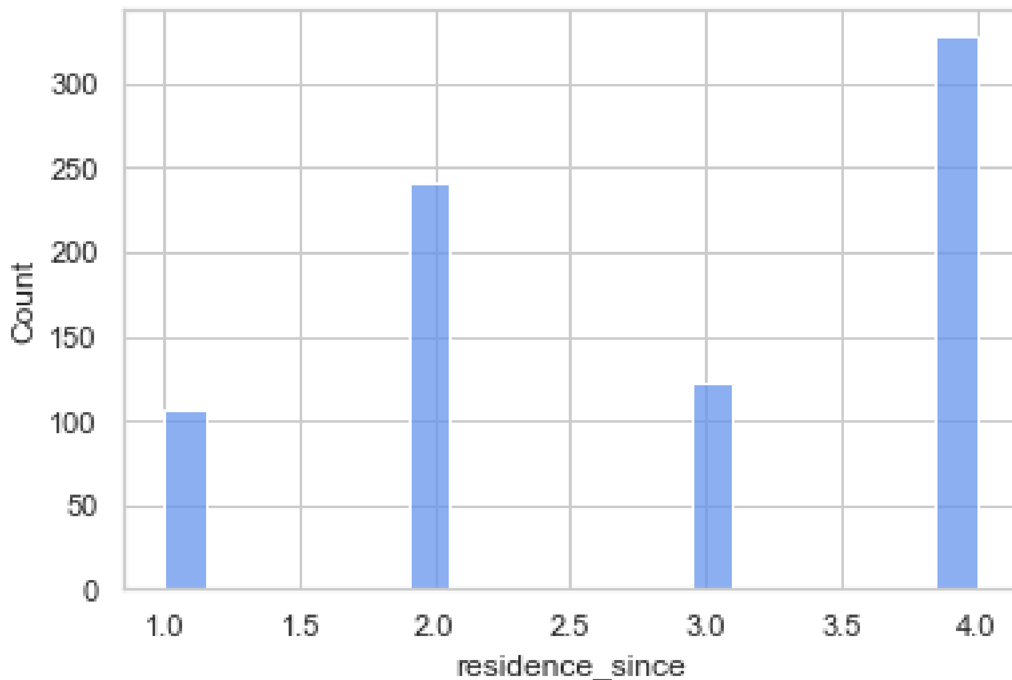
[7]:
```
num_cols = ['duration', 'credit_amount', 'age', 'installment_commitment',␣
↪'residence_since', 'existing_credits']

for col in num_cols:
    kde = False
    if col in ['duration', 'credit_amount', 'age']:
        kde = True
    sns.histplot(x=col,data=df,bins=20, color='cornflowerblue',kde=kde)
    plt.show()
```

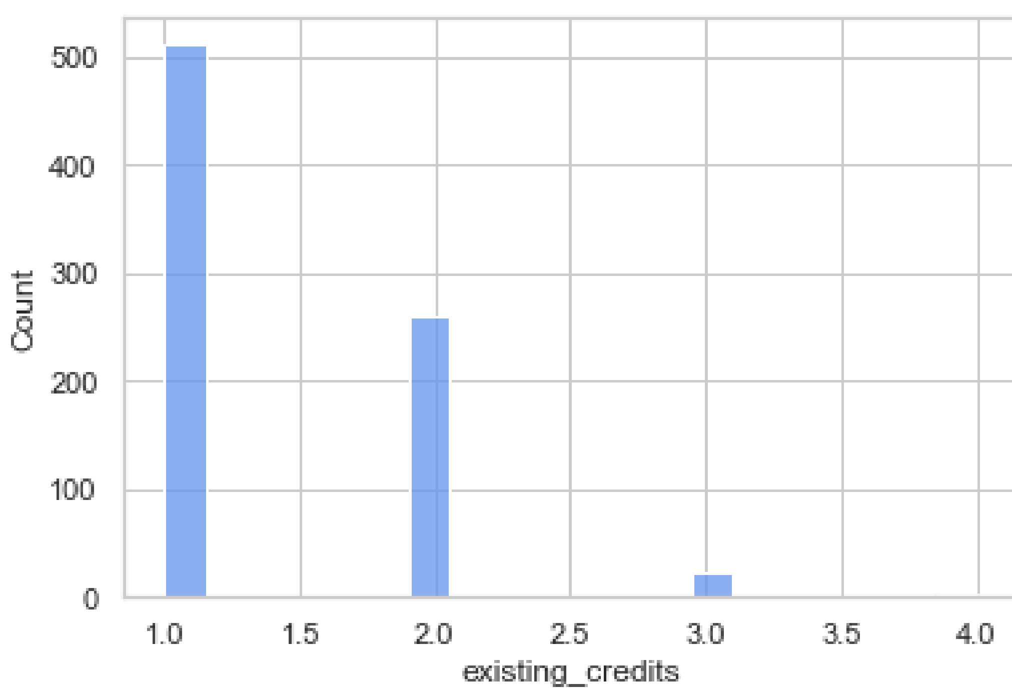

Count
0
20
40
60
80
100
120
140
160
10
20
30
40
50
60
70
duration


Count
0
25
50
75
100
125
150
175
200
0
2000
4000
6000
8000
10000
12000
14000
16000
credit_amount


120
100
80
60
40
20
0
Count
20
30
40
50
60
70
age


400
350
300
250
200
150
100
50
0
Count
1.0
1.5
2.0
2.5
3.0
3.5
4.0
installment_commitment



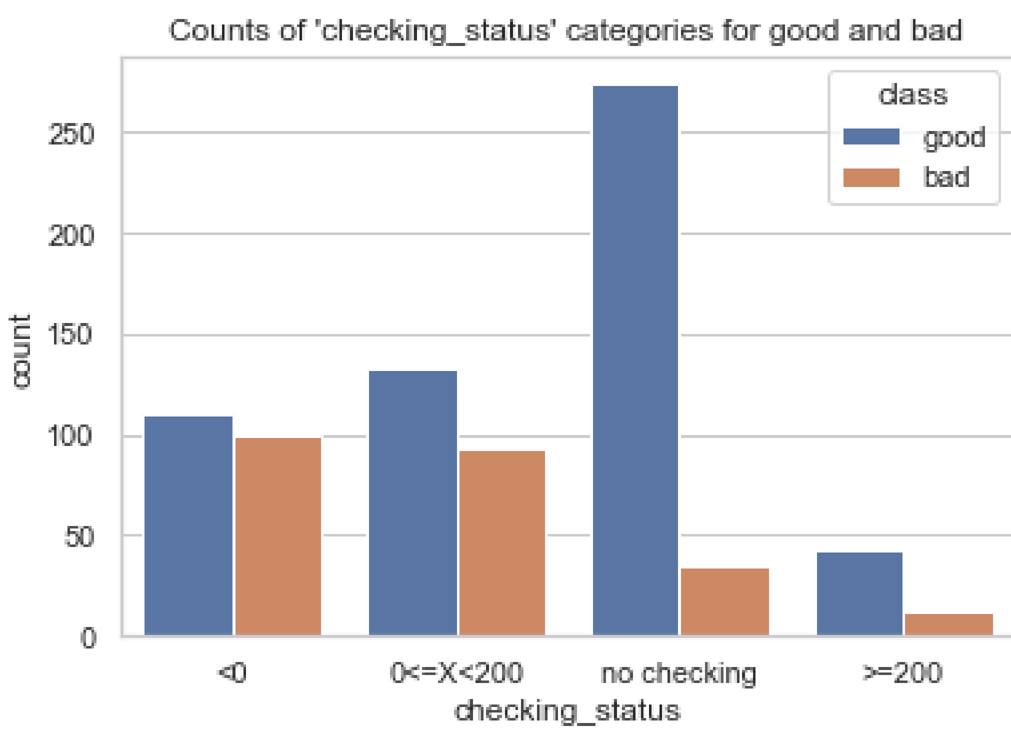


The continuous numerical distributions are all positively skewed.

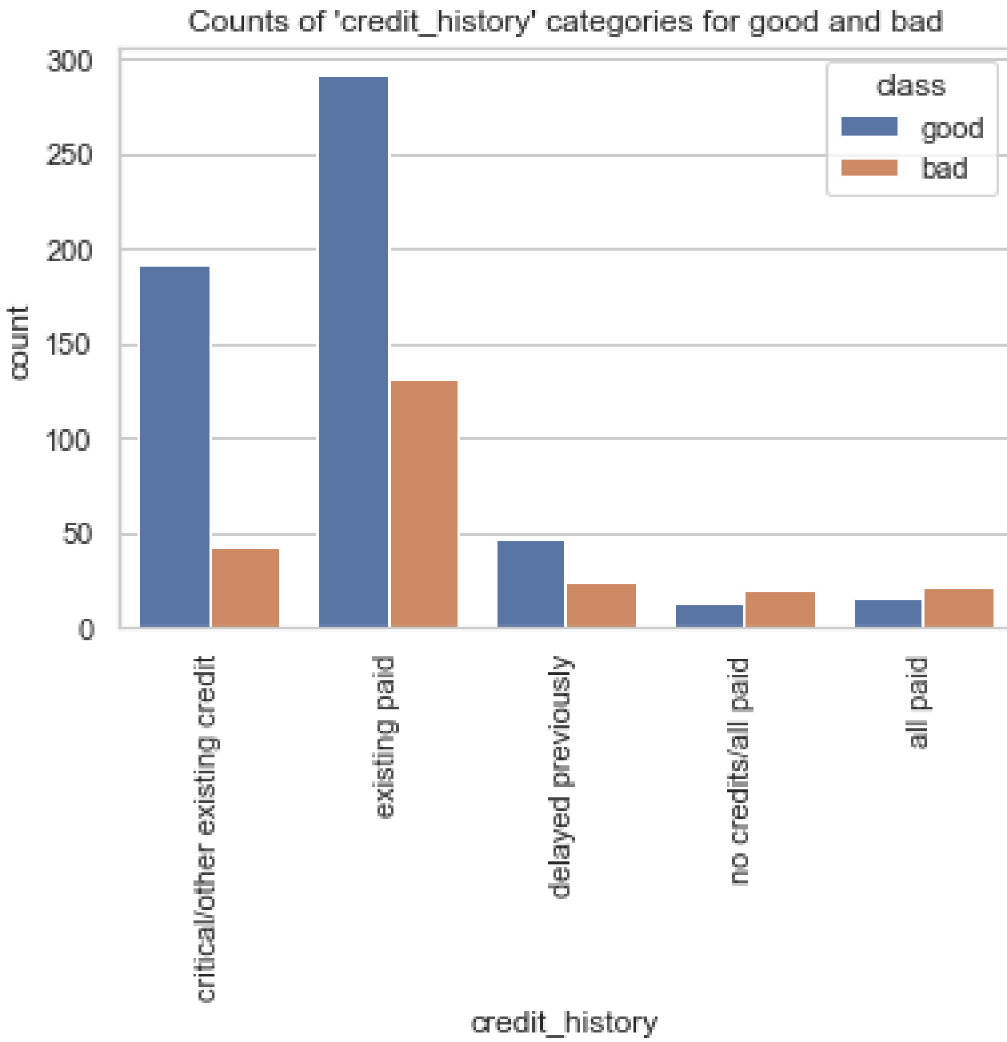
1.3 3. Bivariate Analysis

Let's see how different the distribution of the numerical features are for the two different classes of good and bad:

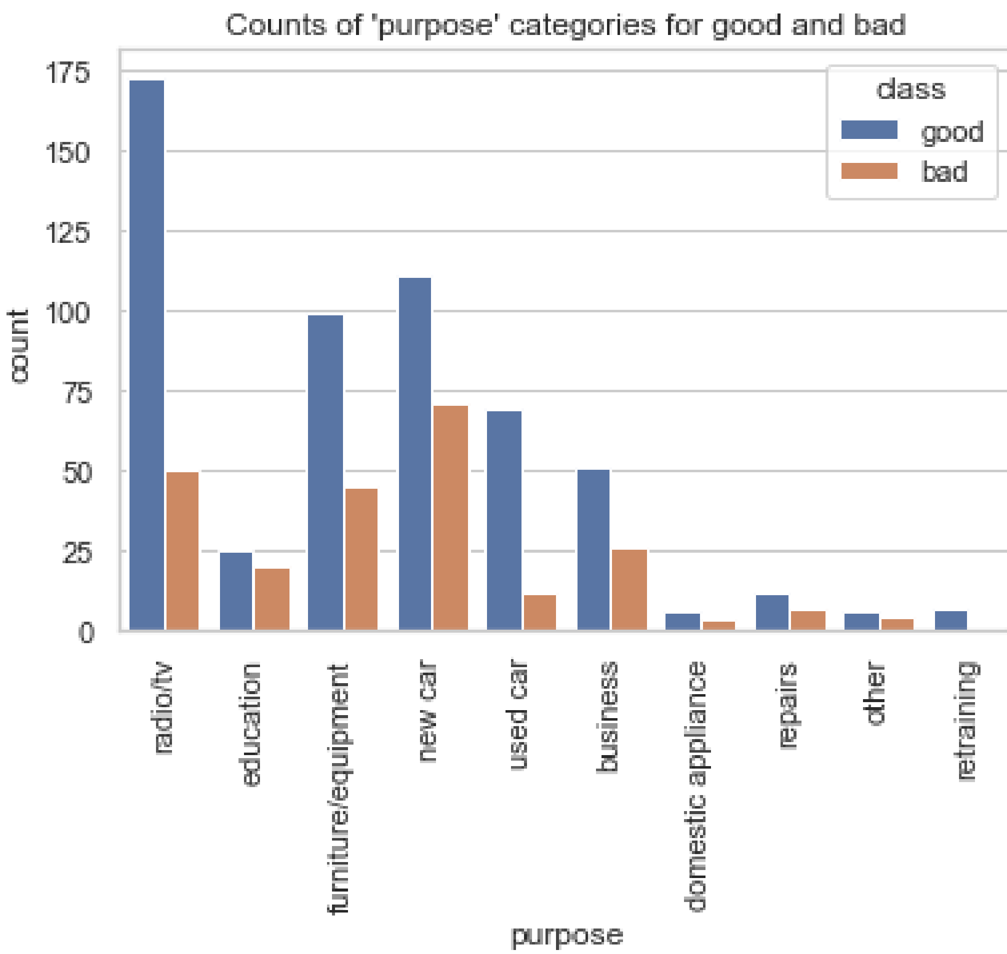
[8]:
```
for col in df.select_dtypes(include='object'):
#     plt.figure(figsize=(15,5))
    plot = sns.countplot(x = col, data=df, hue = 'class')
    if col in ["purpose", "credit_history", "job"]:
            plt.xticks(rotation=90)
    plt.title(f"Counts of '{col}' categories for good and bad")
    plt.show()
    for category in df[col].unique():
        x = len(df[(df[col]==category) & (df['class']=='bad')]) /␣
 ↪len(df[df[col]==category]) * 100
        x = round(x, 2)
        print(f"Percentage of {category} classified as bad: {x}%")
    print("\n")
# g = sns.countplot(x="Purpose", data=df_credit,
#                 palette="hls", hue = "Risk")
```



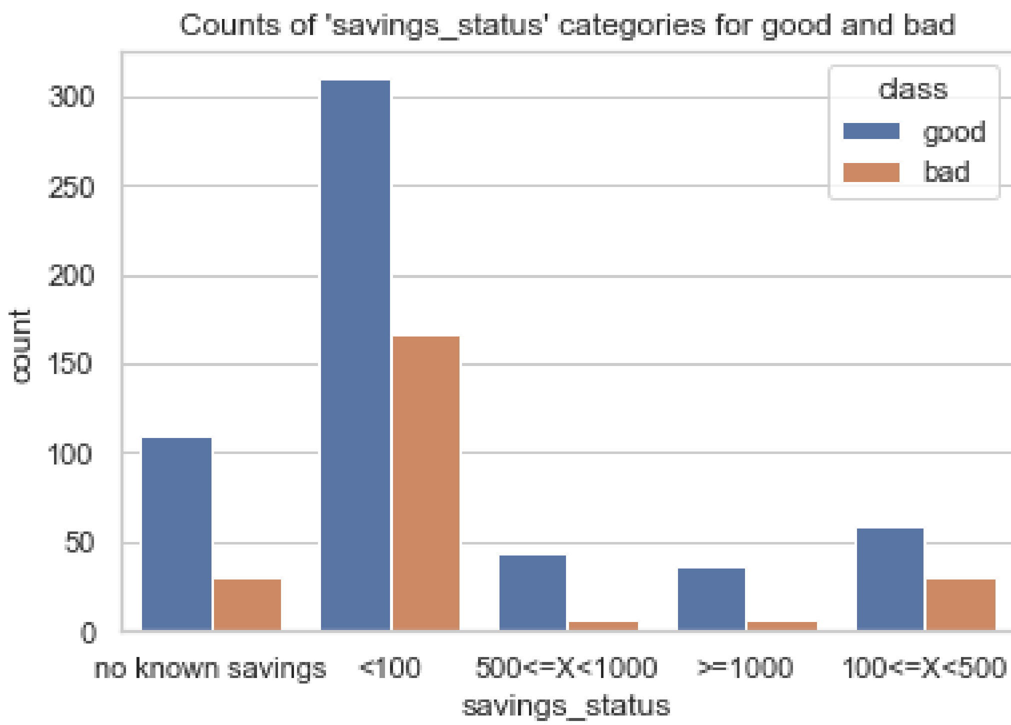

```
Percentage of <0 classified as bad: 47.37%
Percentage of 0<=X<200 classified as bad: 41.33%
Percentage of no checking classified as bad: 11.33%
Percentage of >=200 classified as bad: 21.82%
```



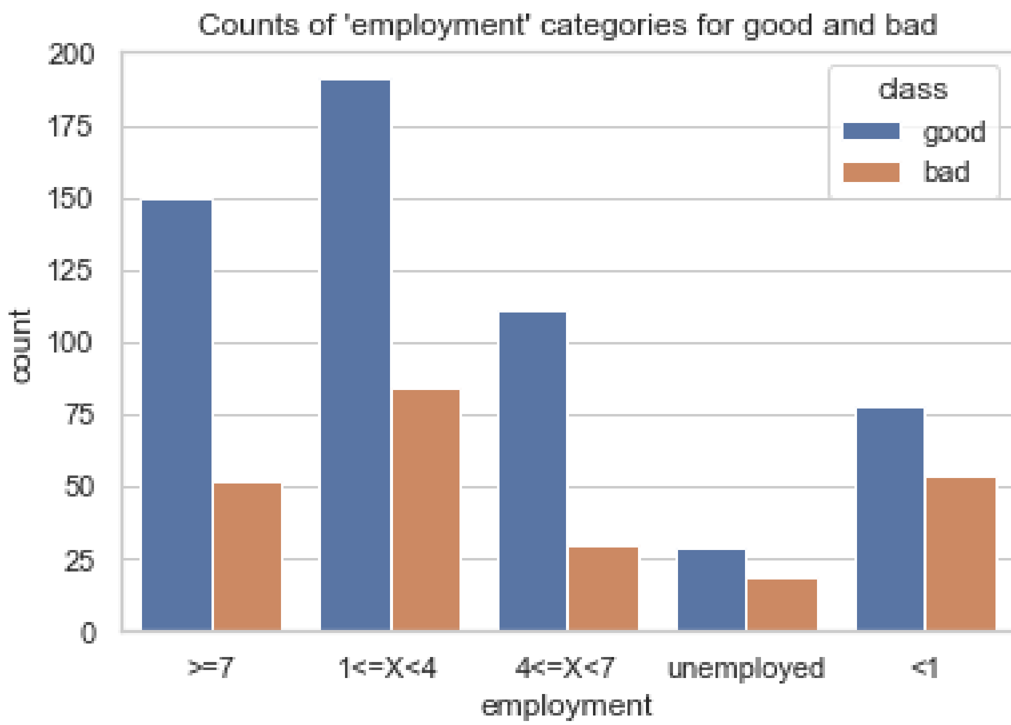

```
Percentage of critical/other existing credit classified as bad: 18.3%
Percentage of existing paid classified as bad: 30.97%
Percentage of delayed previously classified as bad: 34.29%
Percentage of no credits/all paid classified as bad: 60.61%
Percentage of all paid classified as bad: 56.76%
```



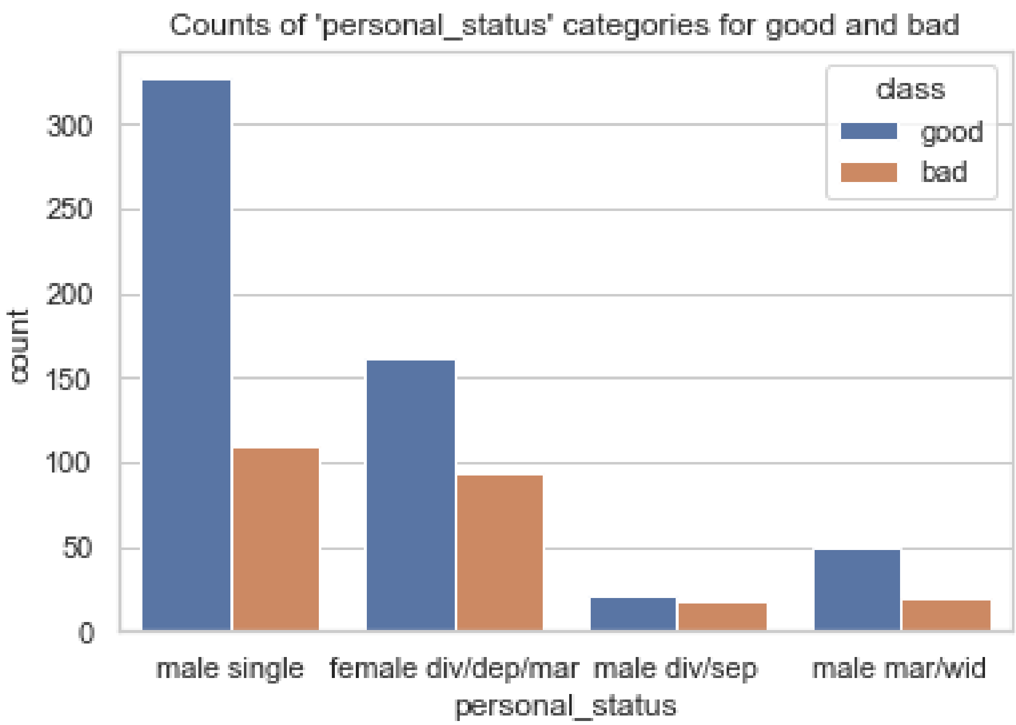

```
Percentage of radio/tv classified as bad: 22.42%
Percentage of education classified as bad: 44.44%
Percentage of furniture/equipment classified as bad: 31.25%
Percentage of new car classified as bad: 39.01%
Percentage of used car classified as bad: 14.81%
Percentage of business classified as bad: 33.77%
Percentage of domestic appliance classified as bad: 33.33%
Percentage of repairs classified as bad: 36.84%
Percentage of other classified as bad: 40.0%
Percentage of retraining classified as bad: 12.5%
```



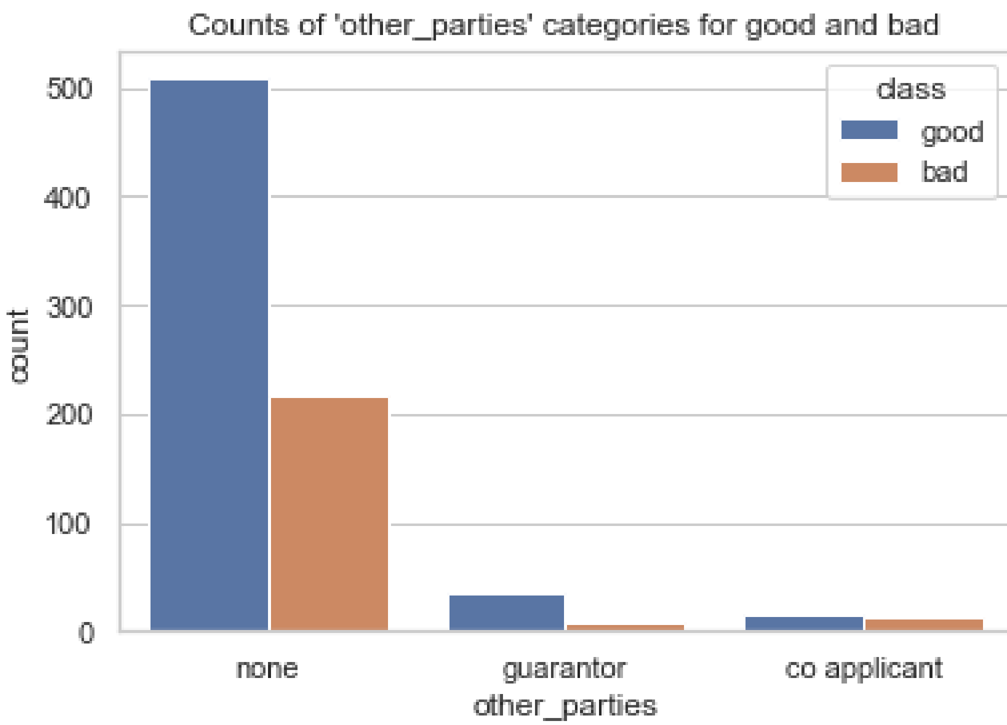

```
Percentage of no known savings classified as bad: 21.43%
Percentage of <100 classified as bad: 34.87%
Percentage of 500<=X<1000 classified as bad: 13.73%
Percentage of >=1000 classified as bad: 14.29%
Percentage of 100<=X<500 classified as bad: 33.71%
```



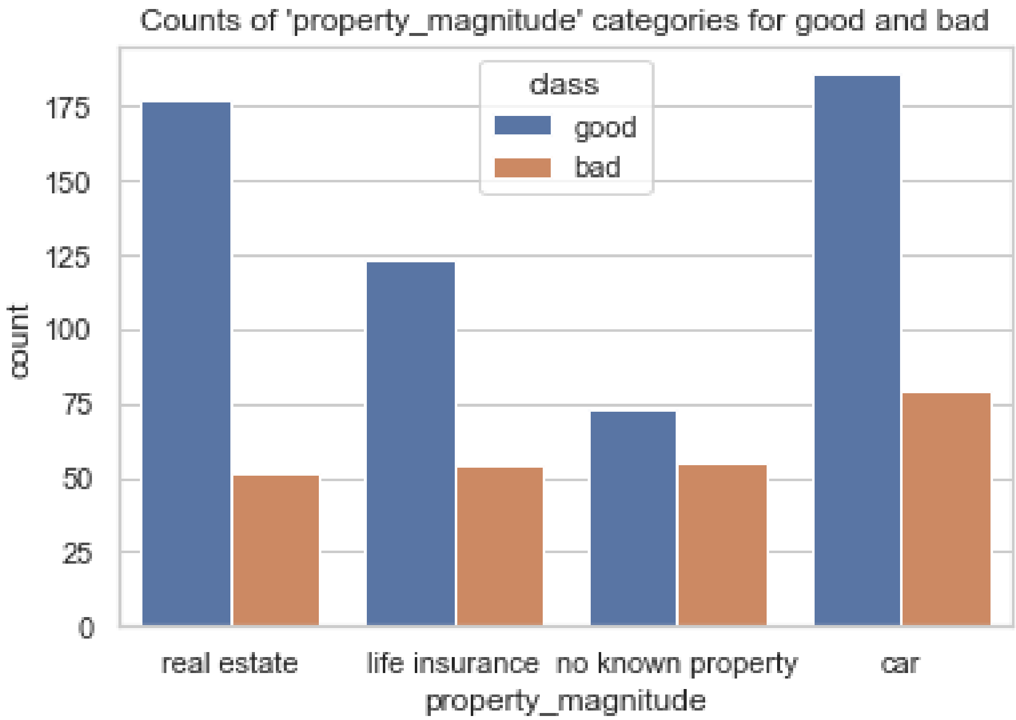

```
Percentage of >=7 classified as bad: 25.74%
Percentage of 1<=X<4 classified as bad: 30.55%
Percentage of 4<=X<7 classified as bad: 21.28%
Percentage of unemployed classified as bad: 39.58%
Percentage of <1 classified as bad: 40.91%
```



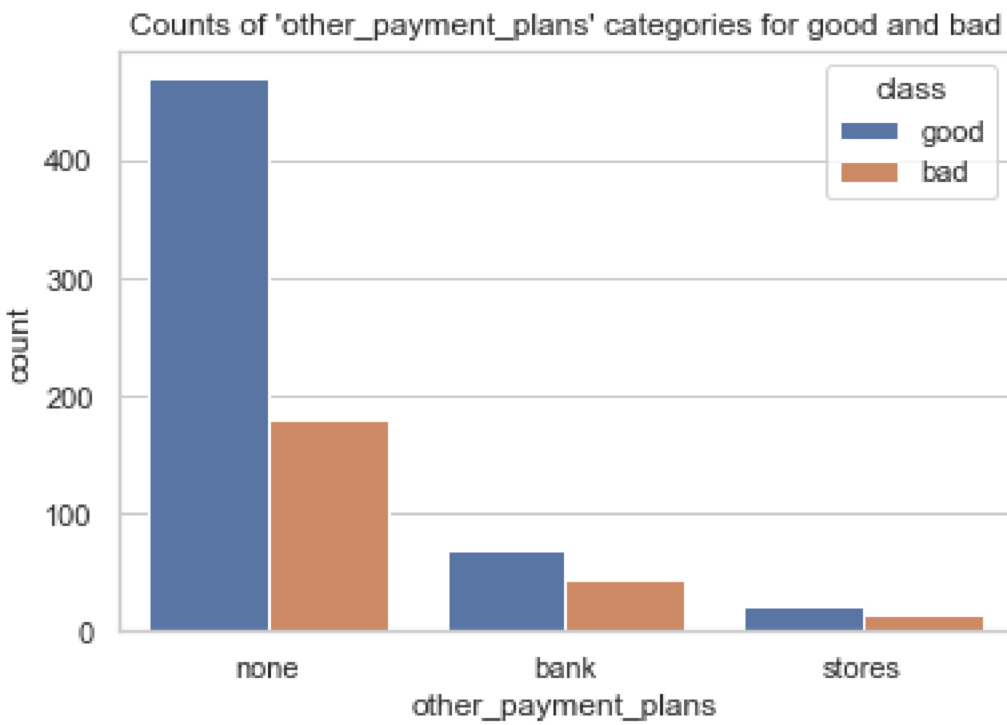

```
Percentage of male single classified as bad: 25.0%
Percentage of female div/dep/mar classified as bad: 36.47%
Percentage of male div/sep classified as bad: 44.74%
Percentage of male mar/wid classified as bad: 28.99%
```



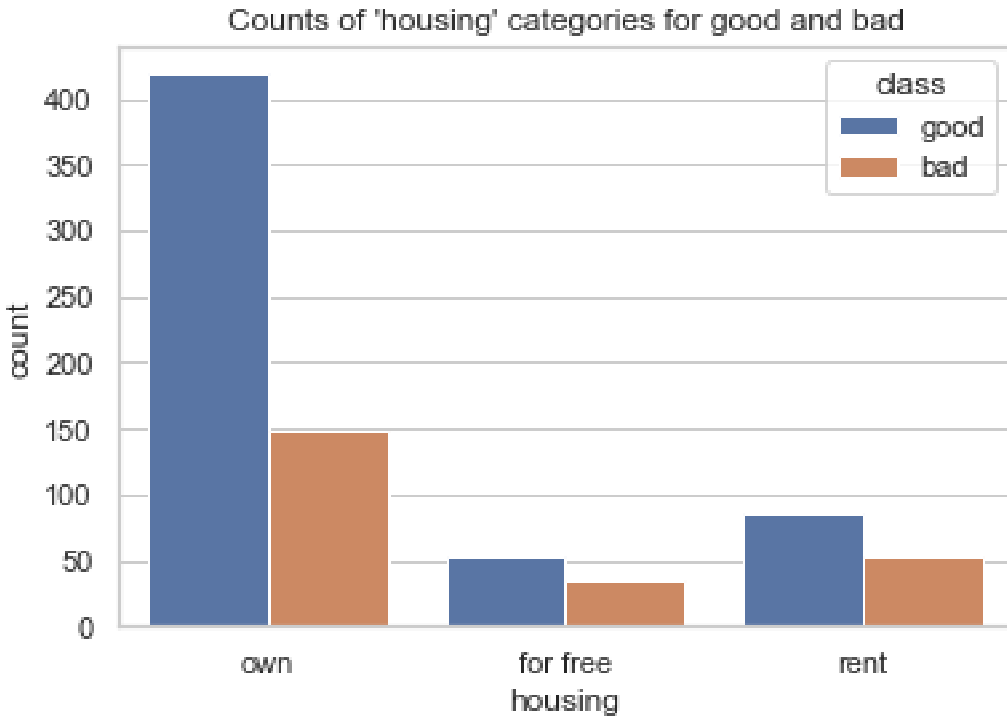

```
Percentage of none classified as bad: 29.89%
Percentage of guarantor classified as bad: 19.05%
Percentage of co applicant classified as bad: 46.67%
```



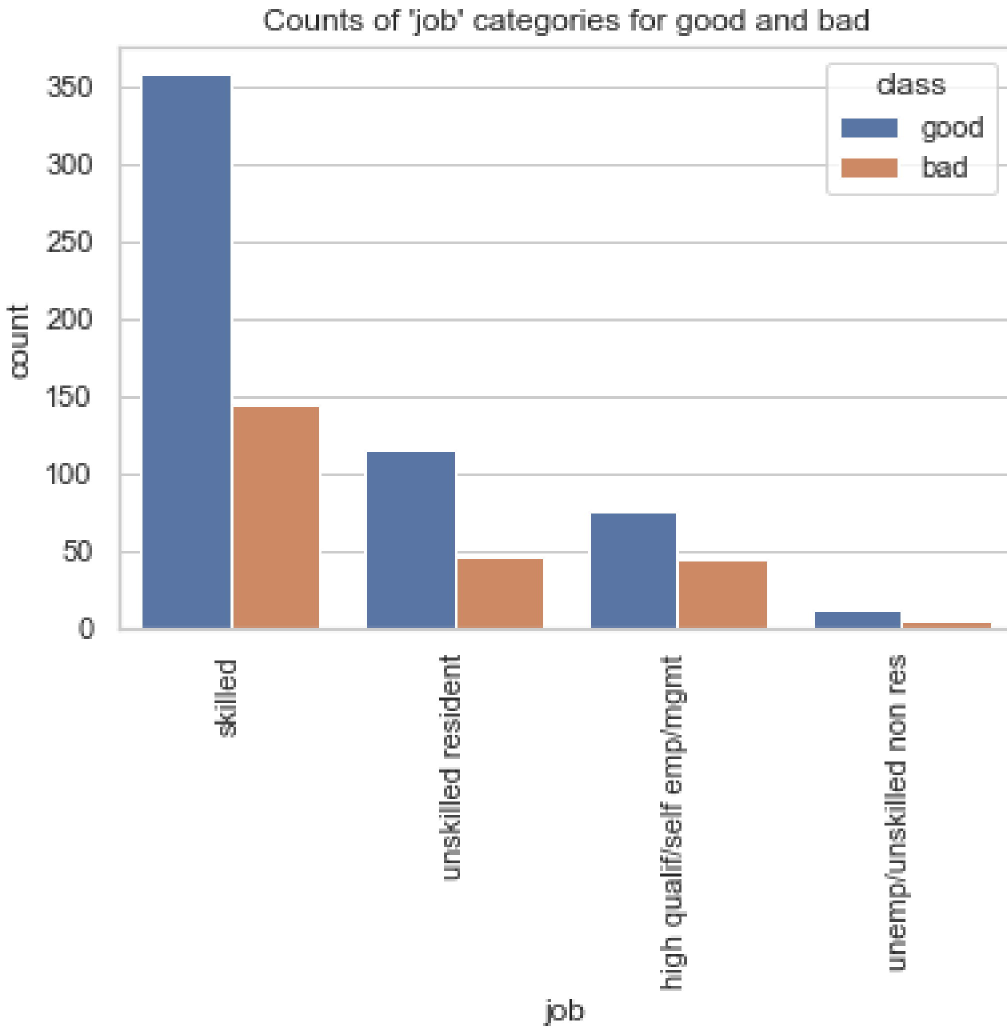

```
Percentage of real estate classified as bad: 22.37%
Percentage of life insurance classified as bad: 30.51%
Percentage of no known property classified as bad: 42.97%
Percentage of car classified as bad: 29.81%
```



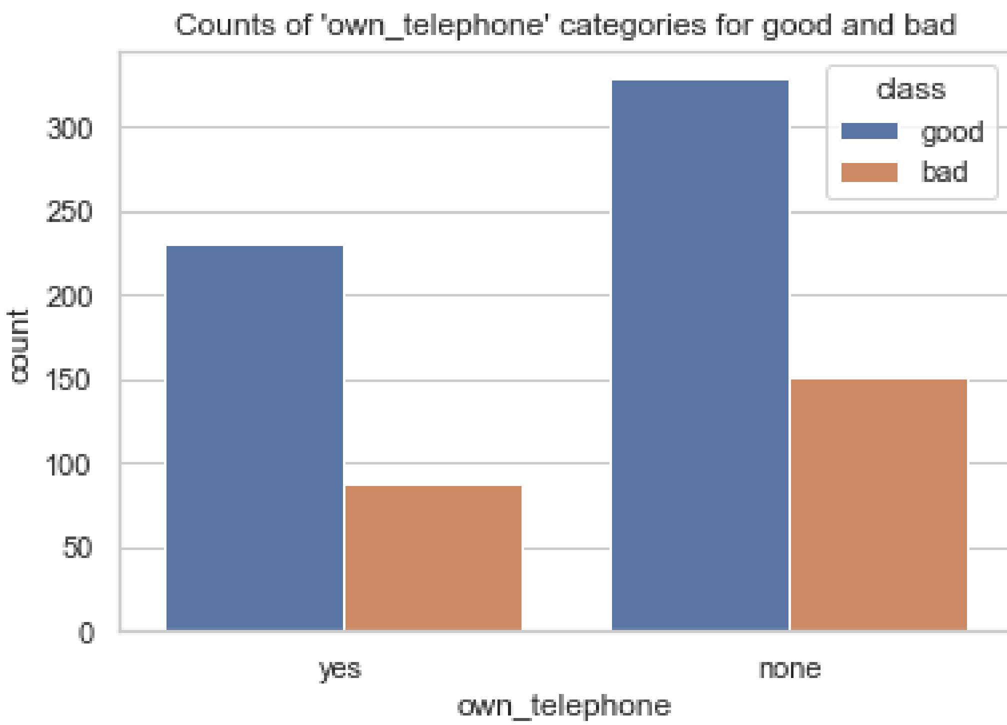

```
Percentage of none classified as bad: 27.8%
Percentage of bank classified as bad: 38.39%
Percentage of stores classified as bad: 42.86%
```



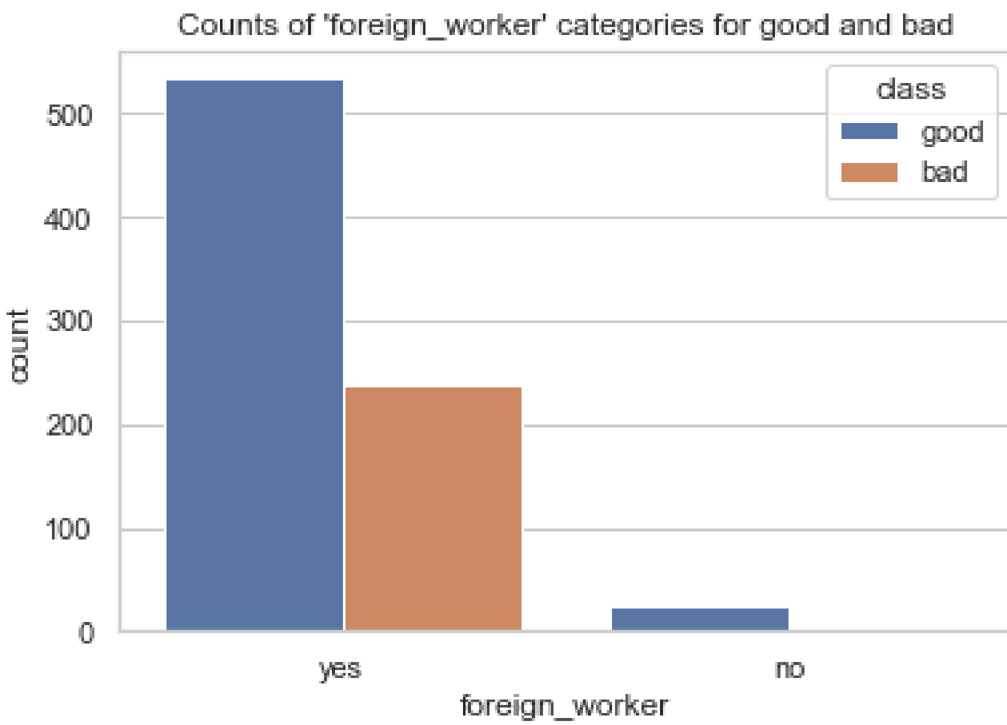

```
Percentage of own classified as bad: 26.23%
Percentage of for free classified as bad: 40.0%
Percentage of rent classified as bad: 38.57%
```



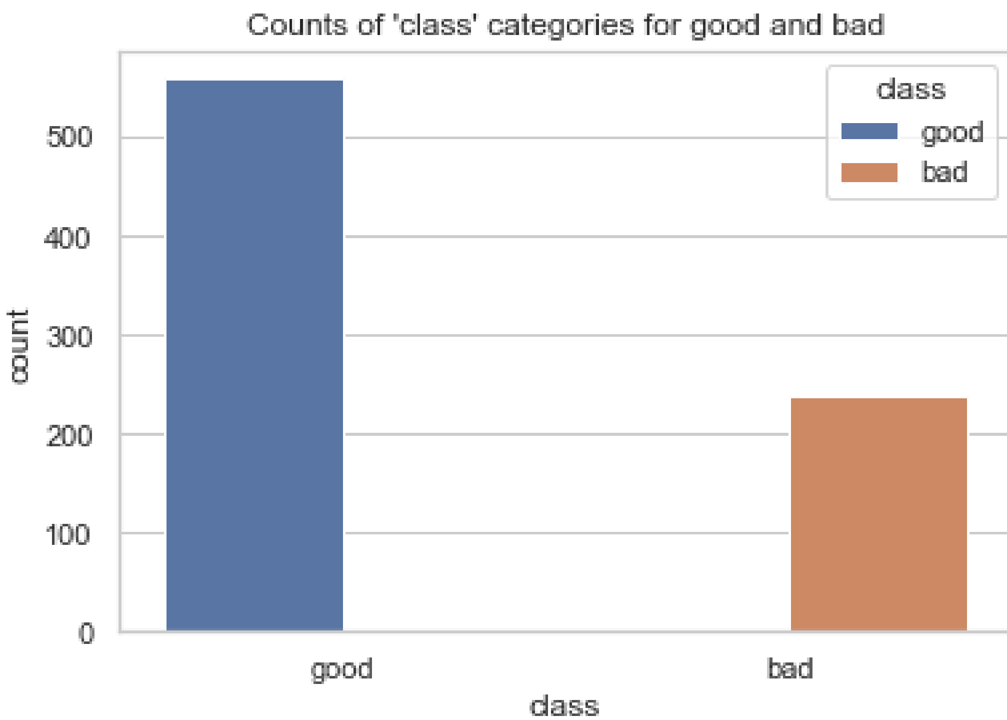

```
Percentage of skilled classified as bad: 28.69%
Percentage of unskilled resident classified as bad: 28.57%
Percentage of high qualif/self emp/mgmt classified as bad: 36.97%
Percentage of unemp/unskilled non res classified as bad: 31.25%
```




```
Percentage of yes classified as bad: 27.67%
Percentage of none classified as bad: 31.46%
```



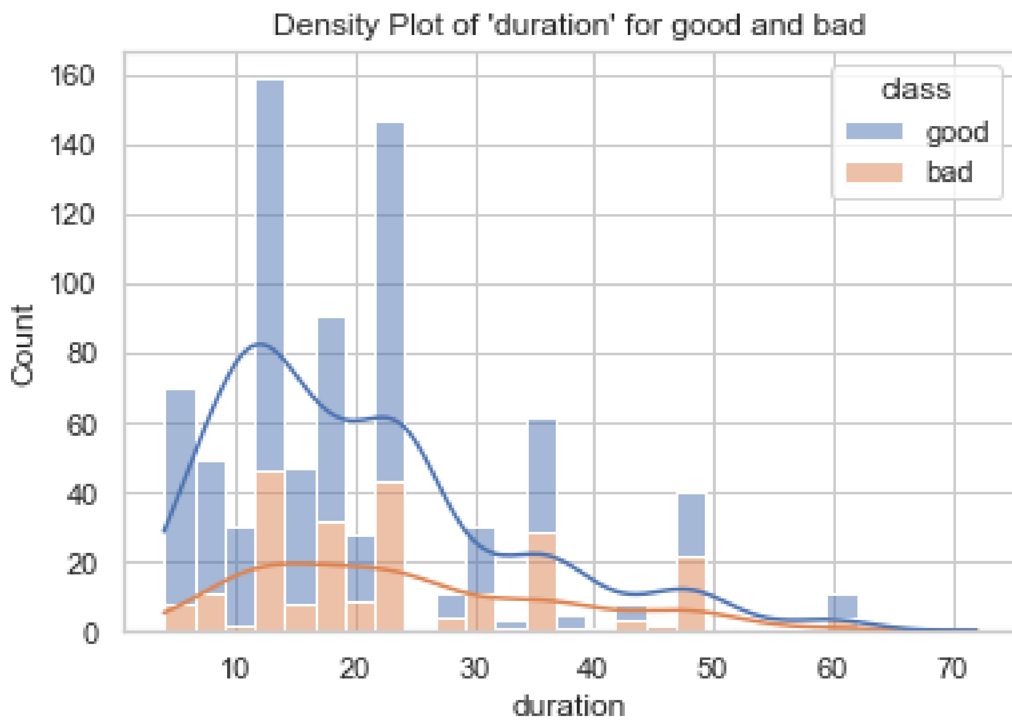

```
Percentage of yes classified as bad: 30.74%
Percentage of no classified as bad: 7.41%
```

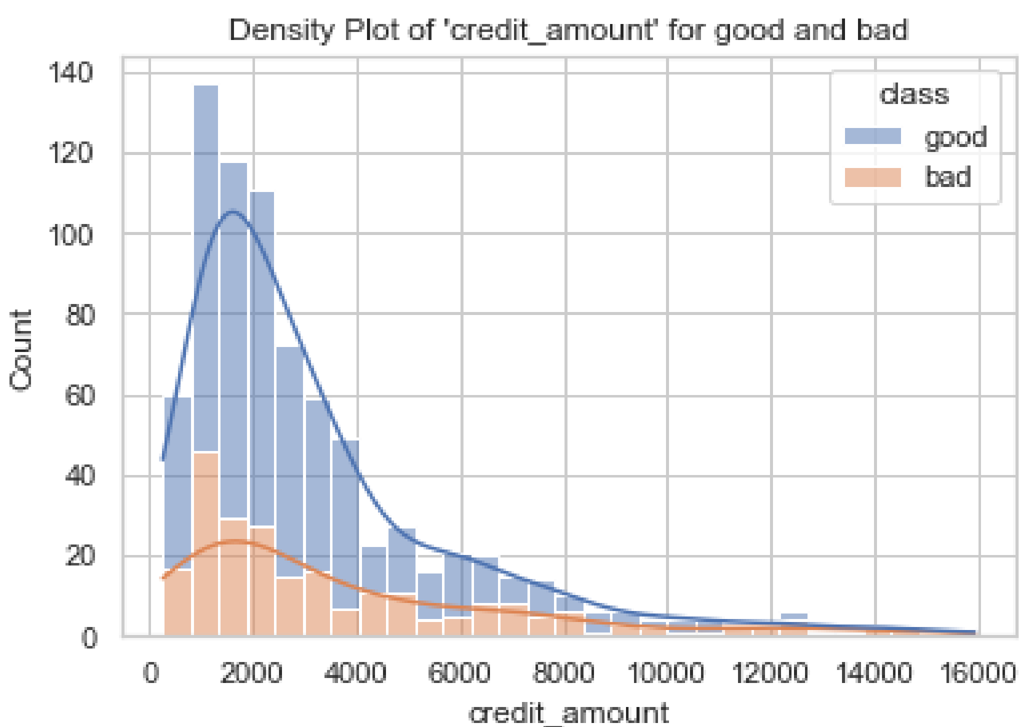


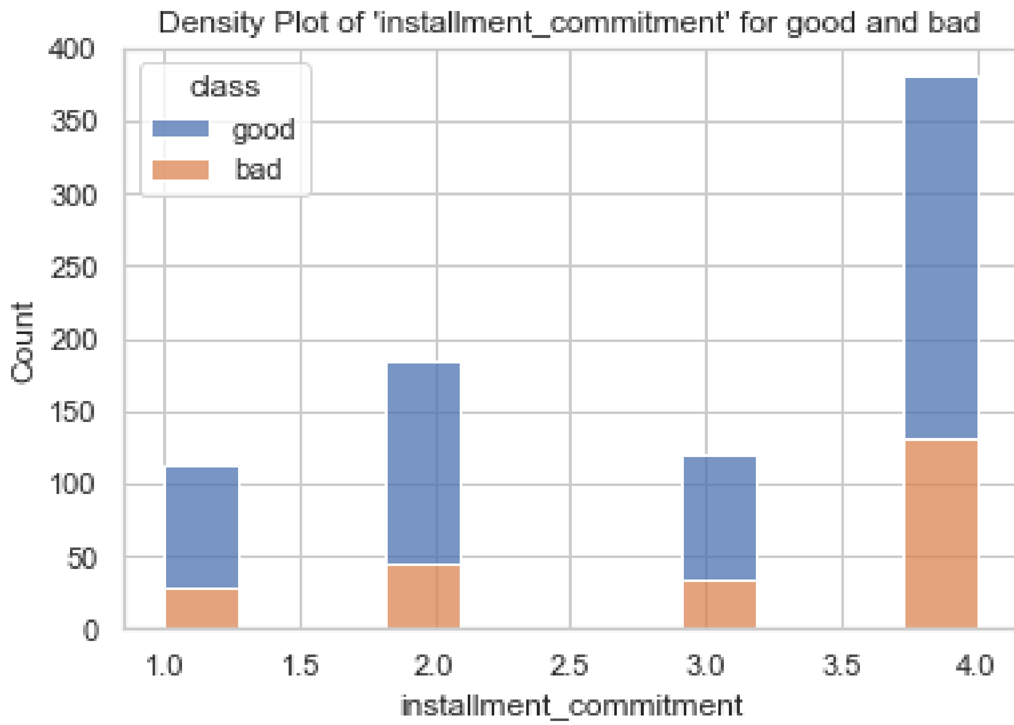

```
Percentage of good classified as bad: 0.0%
Percentage of bad classified as bad: 100.0%
```

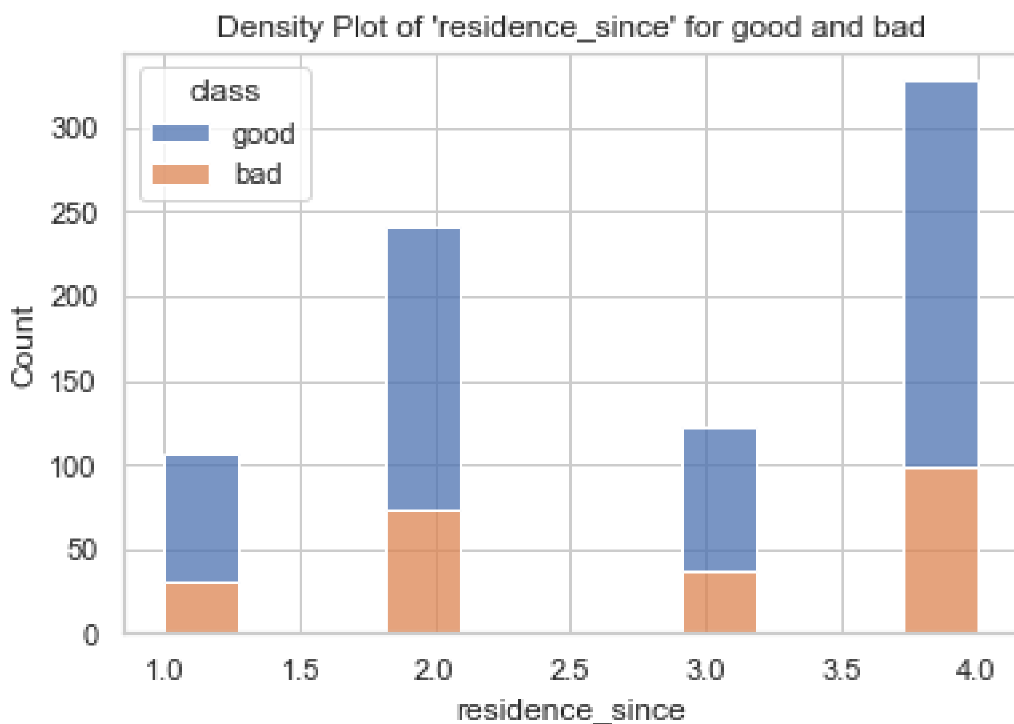
Numerical Features:

[9]:
```
num_cols = ['duration', 'credit_amount', 'installment_commitment',␣
↪'residence_since', 'age', 'existing_credits']

for col in num_cols:
#     good = df[df[col] == 'good']
#     bad = df[df[col] == 'bad']
    kde = False
    if col in ['duration', 'credit_amount', 'age']:
        kde = True
    sns.histplot(data = df, x = col, hue='class', kde=kde, multiple="stack")
    plt.title(f"Density Plot of '{col}' for good and bad")
    plt.show()
```

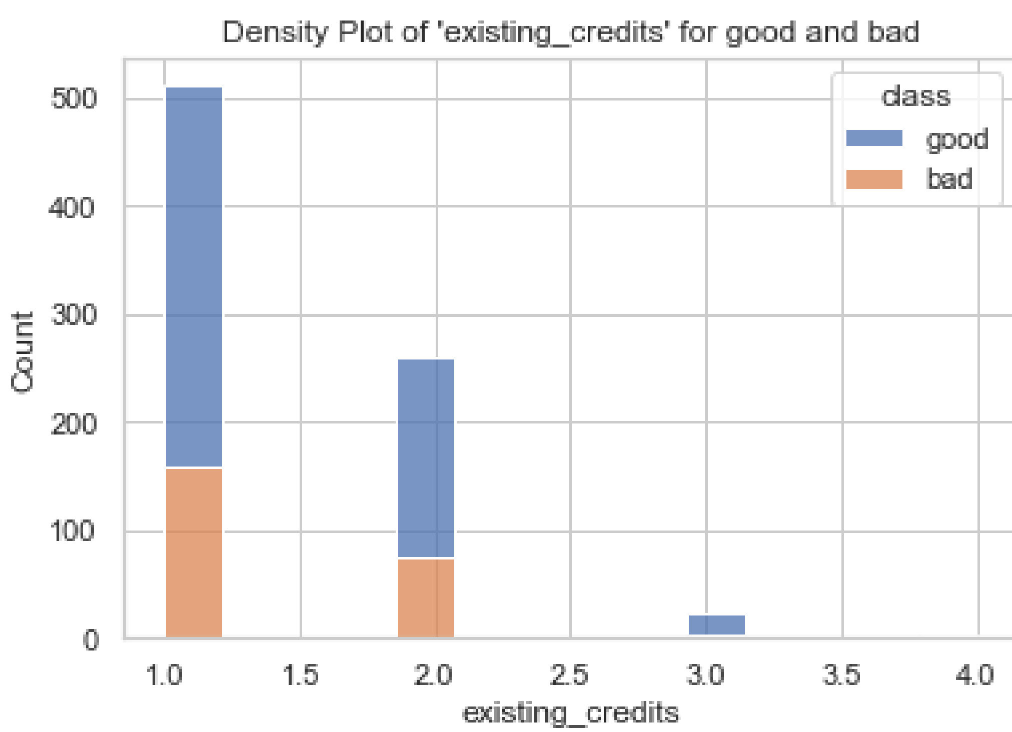

Density Plot of 'duration' for good and bad
class
good
bad
Count
duration
0
20
40
60
80
100
120
140
160
10
20
30
40
50
60
70


Density Plot of 'credit_amount' for good and bad
class
good
bad
Count
credit_amount
0
20
40
60
80
100
120
140
0
2000
4000
6000
8000
10000
12000
14000
16000


Density Plot of 'installment_commitment' for good and bad
class
good
bad
Count
0
50
100
150
200
250
300
350
400
1.0
1.5
2.0
2.5
3.0
3.5
4.0
installment_commitment


Density Plot of 'residence_since' for good and bad
class
good
bad
Count
0
50
100
150
200
250
300
1.0
1.5
2.0
2.5
3.0
3.5
4.0
residence_since

Density Plot of 'age' for good and bad
class
good
bad
Count
age
0
20
40
60
80
100
120
20
30
40
50
60
70



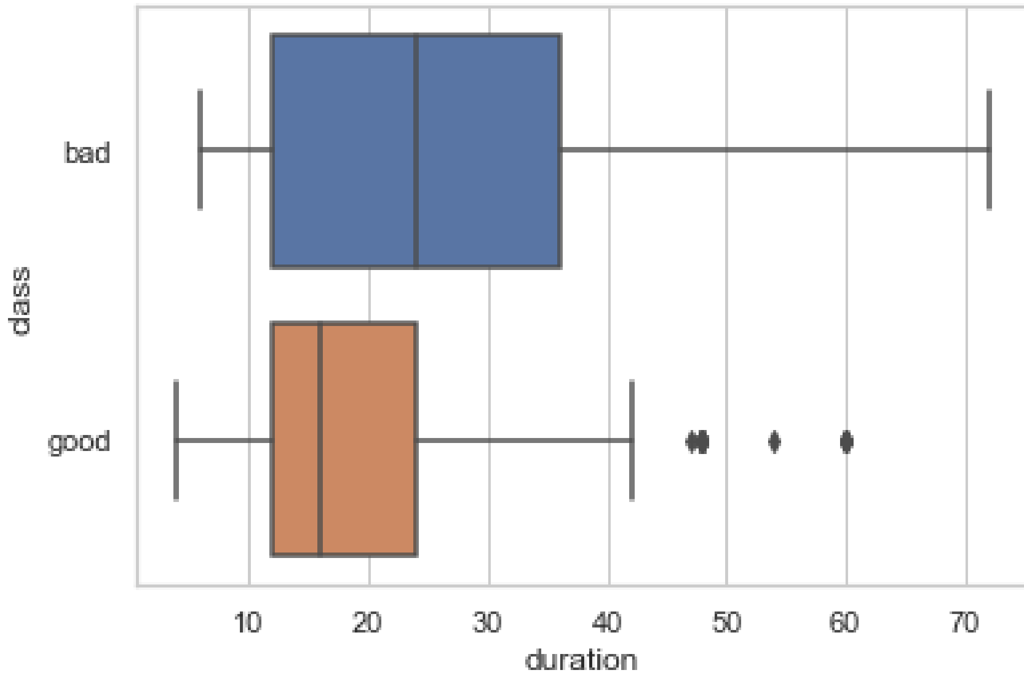
Density Plot of 'existing_credits' for good and bad
class
good
bad
Count
existing_credits
0
100
200
300
400
500
1.0
1.5
2.0
2.5
3.0
3.5
4.0

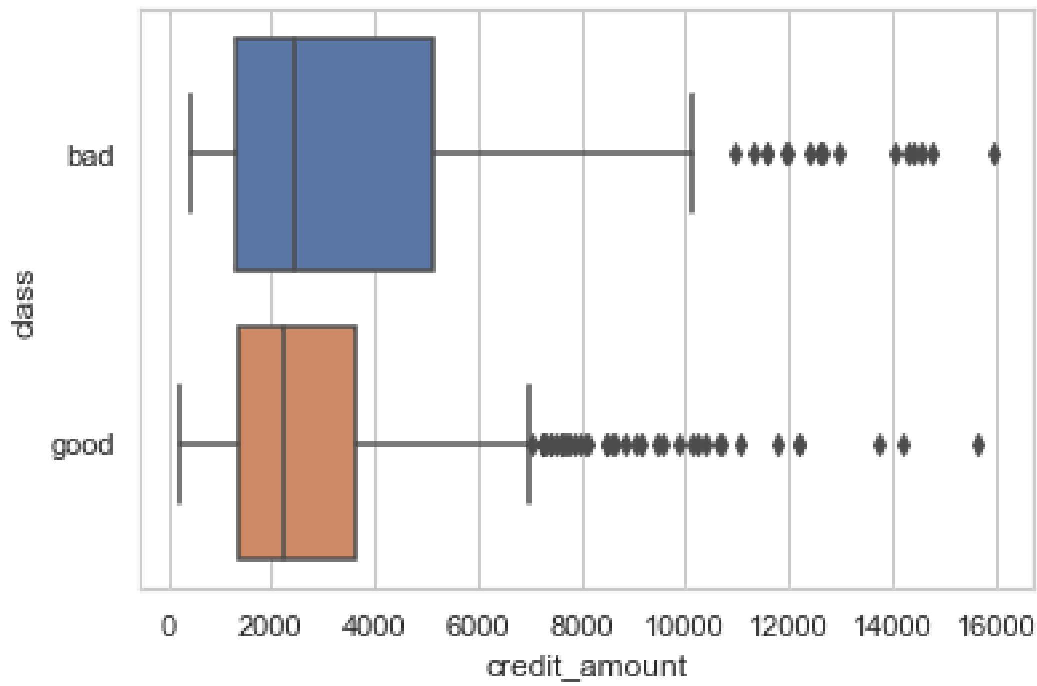
1.4 4. Data Pre-processing and Feature Engineering

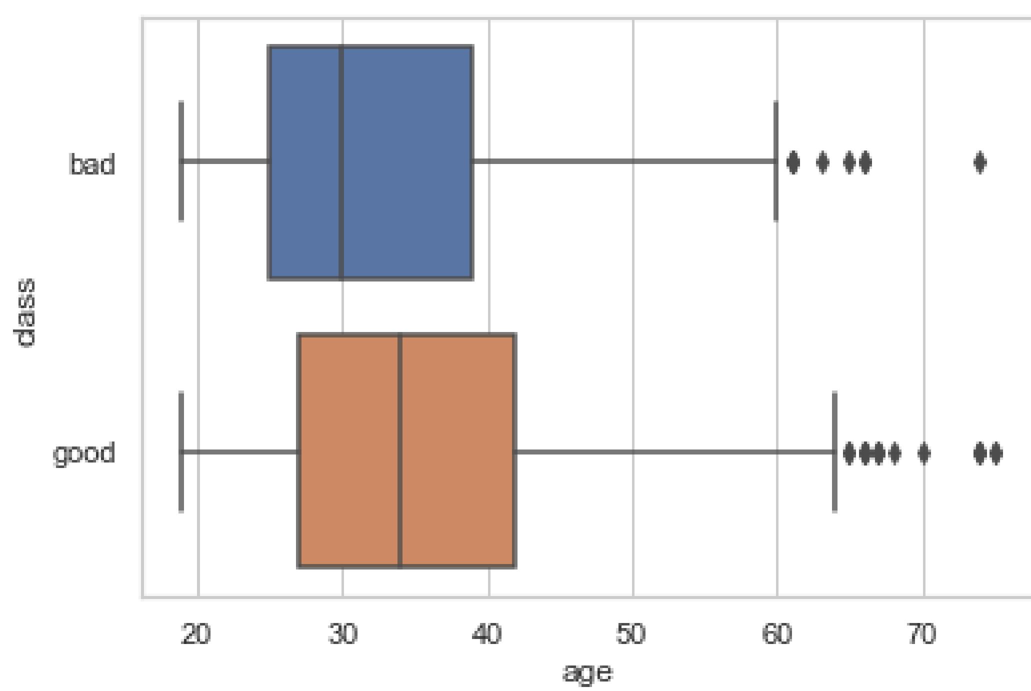
Outlier Analysis:

Next, let's create some box plots for the continuous numerical features to explore their distribution:

[10]:
```
num_cols = ['duration', 'credit_amount', 'age']
for col in num_cols:
    sns.boxplot(y = df['class'].astype('category'), x = col, data=df)
    plt.show()
```







We can see that these variables have some outliers which lie outside the range where the majority of the rest of the data is. We can place upper and lower thresholds of 1.5x the interquartile range to handle these outliers.

[11]:
```
def get_upper_lower_thresholds(df, col):
    q1 = df[col].quantile(0.25)
    q3 = df[col].quantile(0.75)
    iqr = q3 - q1
    up_limit = q3 + 1.5 * iqr
    low_limit = q1 - 1.5 * iqr
    return low_limit, up_limit


def outliers_check(df, num_cols):
    has_outliers = []
    for col in num_cols:
        low_limit, up_limit = get_upper_lower_thresholds(df, col)
        if df[(df[col] > up_limit) | (df[col] < low_limit)].any(axis=None):
            number_of_outliers = df[(df[col] > up_limit) | (df[col] <␣
↪low_limit)].shape[0]
            print(f"'{col}' number of outliers outside 1.5x the inter-quartile␣
↪range: {number_of_outliers}")
            has_outliers.append(col)
    return has_outliers


outliers_check(df, num_cols)
```

```
'duration' number of outliers outside 1.5x the inter-quartile range: 56
'credit_amount' number of outliers outside 1.5x the inter-quartile range: 56
'age' number of outliers outside 1.5x the inter-quartile range: 29
```

[11]: ['duration', 'credit_amount', 'age']

[12]:
```
def replace_outliers_with_limits(df, col):
    low_limit, up_limit = get_upper_lower_thresholds(df, col)
    df.loc[(df[col] < low_limit), col] = low_limit
    df.loc[(df[col] > up_limit), col] = up_limit

for col in ['duration', 'credit_amount', 'age']:
    replace_outliers_with_limits(df, col)

outliers_check(df, num_cols)
```

[12]: []

Feature Encoding

[13]:

```python
for col in ["credit_history", "purpose", "savings_status", "personal_status",␣
↪"other_parties", "other_payment_plans", "employment", "property_magnitude",␣
↪"own_telephone", "foreign_worker", "job", "housing", 'checking_status']:
    le = LabelEncoder()
    le.fit(df[col])
    df[col] = le.transform(df[col])

df['class'] = df['class'].replace({'bad': 0, 'good': 1})
```

[14]:
```python
df
```

[14]:
```
     checking_status  duration  credit_history  purpose  credit_amount  \
0                  1         6               1        6       1169.000
1                  0        42               3        6       5951.000
2                  3        12               1        2       2096.000
3                  1        42               3        3       7770.125
4                  1        24               2        4       4870.000
..               …       …              …      …            …
793                2        24               3        3       2892.000
794                3        24               3        3       3062.000
795                3         9               3        3       2301.000
796                1        18               3        9       7511.000
797                3        12               1        3       1258.000

     savings_status  employment  installment_commitment  personal_status  \
0                 4           3                       4                3
1                 2           0                       2                0
2                 2           1                       2                3
3                 2           1                       2                3
4                 2           0                       3                3
..              …         …                     …              …
793               2           3                       3                1
794               1           3                       4                3
795               0           2                       2                0
796               4           3                       1                3
797               2           2                       2                0

     other_parties  residence_since  property_magnitude  age  \
0                2                4                   3   62
1                2                2                   3   22
2                2                3                   3   49
3                1                4                   1   45
4                2                4                   2   53
..             …              …                 …  …
793              2                4                   2   51
794              2                3                   2   32
795              2                4                   1   22
```

```
796                 2                 4                   1   51
797                 2                 4                   1   22

     other_payment_plans  housing  existing_credits  job  num_dependents  \
0                      1        1                 2    1               1
1                      1        1                 1    1               1
2                      1        1                 1    3               2
3                      1        0                 1    1               2
4                      1        0                 2    1               2
..                   …      …               …  …             …
793                    1        0                 1    1               1
794                    1        2                 1    1               1
795                    1        2                 1    1               1
796                    1        0                 1    1               2
797                    1        2                 2    3               1

     own_telephone  foreign_worker  class
0                1               1      1
1                0               1      0
2                0               1      1
3                0               1      1
4                0               1      0
..             …             …    …
793              0               1      1
794              1               1      1
795              0               1      1
796              1               1      0
797              0               1      1

[798 rows x 21 columns]
```

Standardising our continuous numerical variables **duration**, **credit_amount**, **age**:

[15]:
```
for col in ['duration', 'credit_amount', 'age']:
    std_scaler = StandardScaler()
    df[col] = std_scaler.fit_transform(df[col].values.reshape(-1,1))
```

[16]:
```
df
```

[16]:
```
     checking_status  duration  credit_history  purpose  credit_amount  \
0                  1 -1.320416               1        6      -0.851865
1                  0  2.065544               3        6       1.385029
2                  3 -0.756089               1        2      -0.418239
3                  1  2.065544               3        3       2.235967
4                  1  0.372564               2        4       0.879365
..               …       …             …      …            …
793                2  0.372564               3        3      -0.045891
```

```
794                3  0.372564             3        3       0.033630
795                3 -1.038253             3        3      -0.322345
796                1 -0.191763             3        9       2.114756
797                3 -0.756089             1        3      -0.810233

     savings_status  employment  installment_commitment  personal_status  \
0                 4           3                       4                3
1                 2           0                       2                0
2                 2           1                       2                3
3                 2           1                       2                3
4                 2           0                       3                3
..              …         …                       …                …
793               2           3                       3                1
794               1           3                       4                3
795               0           2                       2                0
796               4           3                       1                3
797               2           2                       2                0

     other_parties  residence_since  property_magnitude       age  \
0                2                4                   3  2.445612
1                2                2                   3 -1.204794
2                2                3                   3  1.259230
3                1                4                   1  0.894190
4                2                4                   2  1.624271
..             …                …                   …       …
793              2                4                   2  1.441751
794              2                3                   2 -0.292193
795              2                4                   1 -1.204794
796              2                4                   1  1.441751
797              2                4                   1 -1.204794

     other_payment_plans  housing  existing_credits  job  num_dependents  \
0                      1        1                 2    1               1
1                      1        1                 1    1               1
2                      1        1                 1    3               2
3                      1        0                 1    1               2
4                      1        0                 2    1               2
..                   …      …                 …  …             …
793                    1        0                 1    1               1
794                    1        2                 1    1               1
795                    1        2                 1    1               1
796                    1        0                 1    1               2
797                    1        2                 2    3               1

     own_telephone  foreign_worker  class
0                1               1      1
1                0               1      0
```

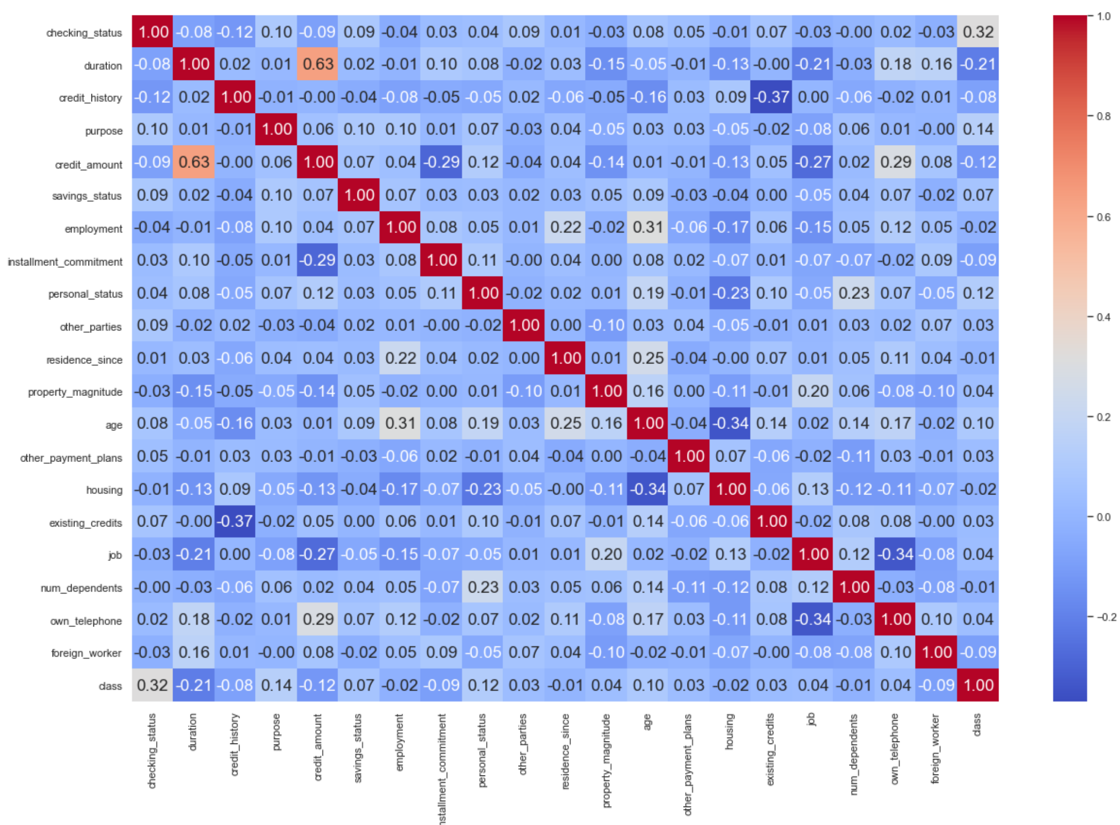
```
2                0            1      1
3                0            1      1
4                0            1      0
..             ...          ...    ...
793              0            1      1
794              1            1      1
795              0            1      1
796              1            1      0
797              0            1      1

[798 rows x 21 columns]
```

Feature Selection

Correlation Heatmap:

[17]:
```
plt.figure(figsize=(20,13))
sns.heatmap(df.corr(), cmap='coolwarm', annot=True, fmt=".2f",
            annot_kws={'size':17},
            cbar=True)
```

[17]: <AxesSubplot:>



For the categorical variables, we can use a chi-squared test to determine whether or not they have a meaningful correlation to the 'class' target. We will only select categorical features with meaningful correlation to use in our model.

[18]:
```
def corr_to_target(col):
    contingency_table = pd.crosstab(df['class'], df[col])
    chi2, p_value, dof, expected_freq = chi2_contingency(contingency_table)
    if(p_value>0.05):
        print(f"No significant correlation between the target (class) and␣
↪{col}\n")
    else:
        print(f"Significant correlation between the target (class) and {col}")
        print("p-value:", p_value)
        print('\n')
```

[19]:
```
for col in cat_cols:
    if col == "class":
        pass
    else:
        corr_to_target(col)
```

```
Significant correlation between the target (class) and checking_status
p-value: 7.082562999210413e-21


Significant correlation between the target (class) and credit_history
p-value: 8.147367095552182e-09


Significant correlation between the target (class) and purpose
p-value: 0.0005835908539298064


Significant correlation between the target (class) and savings_status
p-value: 0.00017817404026571038


Significant correlation between the target (class) and employment
p-value: 0.0024313071818130045


Significant correlation between the target (class) and personal_status
p-value: 0.0025828821993882974


Significant correlation between the target (class) and other_parties
p-value: 0.04124015180854718
```

```
Significant correlation between the target (class) and property_magnitude
p-value: 0.0008475938166062993


Significant correlation between the target (class) and other_payment_plans
p-value: 0.018184189919915755


Significant correlation between the target (class) and housing
p-value: 0.001477691202038189


No significant correlation between the target (class) and job

No significant correlation between the target (class) and own_telephone

Significant correlation between the target (class) and foreign_worker
p-value: 0.016942049655713313
```

Based on the above, let's drop the **job** and **own_telephone** features:

[20]:
```
df.drop(labels=['job', 'own_telephone'], axis=1, inplace=True)
df
```

[20]:
```
     checking_status  duration  credit_history  purpose  credit_amount  \
0                  1 -1.320416               1        6      -0.851865
1                  0  2.065544               3        6       1.385029
2                  3 -0.756089               1        2      -0.418239
3                  1  2.065544               3        3       2.235967
4                  1  0.372564               2        4       0.879365
..               …         …             …        …            …
793                2  0.372564               3        3      -0.045891
794                3  0.372564               3        3       0.033630
795                3 -1.038253               3        3      -0.322345
796                1 -0.191763               3        9       2.114756
797                3 -0.756089               1        3      -0.810233

     savings_status  employment  installment_commitment  personal_status  \
0                 4           3                       4                3
1                 2           0                       2                0
2                 2           1                       2                3
3                 2           1                       2                3
4                 2           0                       3                3
..              …         …                     …              …
793               2           3                       3                1
```

```
794               1           3                     4               3
795               0           2                     2               0
796               4           3                     1               3
797               2           2                     2               0

     other_parties  residence_since  property_magnitude       age  \
0                2                4                   3  2.445612
1                2                2                   3 -1.204794
2                2                3                   3  1.259230
3                1                4                   1  0.894190
4                2                4                   2  1.624271
..             …                …                   …       …
793              2                4                   2  1.441751
794              2                3                   2 -0.292193
795              2                4                   1 -1.204794
796              2                4                   1  1.441751
797              2                4                   1 -1.204794

     other_payment_plans  housing  existing_credits  num_dependents  \
0                      1        1                 2               1
1                      1        1                 1               1
2                      1        1                 1               2
3                      1        0                 1               2
4                      1        0                 2               2
..                   …      …                 …             …
793                    1        0                 1               1
794                    1        2                 1               1
795                    1        2                 1               1
796                    1        0                 1               2
797                    1        2                 2               1

     foreign_worker  class
0                 1      1
1                 1      0
2                 1      1
3                 1      1
4                 1      0
..              …    …
793               1      1
794               1      1
795               1      1
796               1      0
797               1      1

[798 rows x 19 columns]
```

Now that we can export our processed data set to use in the Prediction notebook:

[21]:
```
df.to_csv('credit_data_processed.csv', index=False)
```