In [1]:
```
import os
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline
sns.set()

import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
os.getcwd()
```

Out[2]:
```
'C:\\Users\\bkolh\\OneDrive\\Desktop\\Priyanka\\2. Stats & ML\\July -23\\Lecture notes\\20-July-23 - Decision Tree\\21st July 2023'
```

In [3]:
```
credit_dt = pd.read_csv('German Credit Dataset.csv')
```

In [4]:
```
credit_dt.head()
```

Out[4]:

	checking_balance	months_loan_duration	credit_history	purpose	amount	savings_balance	employment_duration
0	< 0 DM	6	critical	furniture/appliances	1169	unknown	> 7 years
1	1 - 200 DM	48	good	furniture/appliances	5951	< 100 DM	1 - 4 years
2	unknown	12	critical	education	2096	< 100 DM	4 - 7 years
3	< 0 DM	42	good	furniture/appliances	7882	< 100 DM	4 - 7 years
4	< 0 DM	24	poor	car	4870	< 100 DM	1 - 4 years

- DM - Deutsche Mark(currency of West Germany)
- By analyzing this dataset we should be able to know if the person is a credit defaulter or not. The "default" is a dependent variable and others are independet variables

In [5]:
```
credit_dt.columns
```

Out[5]:
```
Index(['checking_balance', 'months_loan_duration', 'credit_history', 'purpose',
       'amount', 'savings_balance', 'employment_duration', 'percent_of_income',
       'years_at_residence', 'age', 'other_credit', 'housing',
       'existing_loans_count', 'job', 'dependents', 'phone', 'default'],
      dtype='object')
```

In [6]:
```
credit_dt.shape
```

Out[6]:
```
(1000, 17)
```

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 17 columns):
 #   Column                Non-Null Count  Dtype 
---  ------                --------------  ----- 
 0   checking_balance      1000 non-null   object
 1   months_loan_duration  1000 non-null   int64 
 2   credit_history        1000 non-null   object
 3   purpose               1000 non-null   object
 4   amount                1000 non-null   int64 
 5   savings_balance       1000 non-null   object
 6   employment_duration   1000 non-null   object
 7   percent_of_income     1000 non-null   int64 
 8   years_at_residence    1000 non-null   int64 
 9   age                   1000 non-null   int64 
 10  other_credit          1000 non-null   object
 11  housing               1000 non-null   object
 12  existing_loans_count  1000 non-null   int64 
 13  job                   1000 non-null   object
 14  dependents            1000 non-null   int64 
 15  phone                 1000 non-null   object
 16  default               1000 non-null   object
dtypes: int64(7), object(10)
memory usage: 132.9+ KB
```

Data Cleaning

In [8]:
```
credit_df = credit_dt.copy()
```

In [9]:
```
credit_df.head()
```

Out[9]:

	checking_balance	months_loan_duration	credit_history	purpose	amount	savings_balance	employment_duration
0	< 0 DM	6	critical	furniture/appliances	1169	unknown	> 7 years
1	1 - 200 DM	48	good	furniture/appliances	5951	< 100 DM	1 - 4 years
2	unknown	12	critical	education	2096	< 100 DM	4 - 7 years
3	< 0 DM	42	good	furniture/appliances	7882	< 100 DM	4 - 7 years
4	< 0 DM	24	poor	car	4870	< 100 DM	1 - 4 years

In [10]:
```
# checking_balance, savings_balance, employment_duration
```

In [11]:
```
credit_df['checking_balance']. value_counts().index
```

Out[11]:
```
Index(['unknown', '< 0 DM', '1 - 200 DM', '> 200 DM'], dtype='object')
```

In [12]:
```
data_correction = ['checking_balance','savings_balance','employment_duration']
def count_size():
    dict = {}
    for i in data_correction:
        x = credit_df[i].value_counts().index.size
        dict.update({i:x})
    return(dict)

# x = count_size()
# print(x, type(x))
```

In [13]:
```
for i in data_correction:
    x = count_size()
    if x[i]==4:
        credit_df[i]=np.where(credit_df[i]== credit_df[i].value_counts().index[0], 0,
                          np.where(credit_df[i]== credit_df[i].value_counts().index[1], 1,
                          np.where(credit_df[i]== credit_df[i].value_counts().index[2],2,3)) )
    elif x[i]==5:
        credit_df[i]=np.where(credit_df[i]== credit_df[i].value_counts().index[0], 0,
                          np.where(credit_df[i]== credit_df[i].value_counts().index[1], 1,
                          np.where(credit_df[i]== credit_df[i].value_counts().index[2],2,
                        np.where(credit_df[i]== credit_df[i].value_counts().index[3],3,4))) )
```

In [14]:
```
credit_df.head()
```

Out[14]:

	checking_balance	months_loan_duration	credit_history	purpose	amount	savings_balance	employment_duration
0	1	6	critical	furniture/appliances	1169	1	1
1	2	48	good	furniture/appliances	5951	0	0
2	0	12	critical	education	2096	0	2
3	1	42	good	furniture/appliances	7882	0	2
4	1	24	poor	car	4870	0	0

In [15]:
```
for i in data_correction:
    print("*******Original********\n")
    print('-----', i,'-----', '\n', credit_dt[i].value_counts(),'\n')
    print("*******Corrected********\n")
    print('-----', i,'-----', '\n',credit_df[i].value_counts(),'\n')
```

```
*******Original********

----- checking_balance -----
 unknown       394
< 0 DM         274
1 - 200 DM     269
> 200 DM        63
Name: checking_balance, dtype: int64

*******Corrected********

----- checking_balance -----
 0    394
1     274
2     269
3      63
Name: checking_balance, dtype: int64

*******Original********

----- savings_balance -----
 < 100 DM          603
unknown            183
100 - 500 DM       103
500 - 1000 DM       63
> 1000 DM           48
Name: savings_balance, dtype: int64

*******Corrected********

----- savings_balance -----
 0    603
1     183
2     103
3      63
4      48
Name: savings_balance, dtype: int64

*******Original********

----- employment_duration -----
 1 - 4 years    339
> 7 years       253
4 - 7 years     174
< 1 year        172
unemployed       62
Name: employment_duration, dtype: int64

*******Corrected********

----- employment_duration -----
 0    339
1     253
2     174
3     172
4      62
Name: employment_duration, dtype: int64
```

Looking at above data we can conclude that the data replacement is correctly done.

In [16]:
```
# purpose
```

In [17]:
```
credit_df['purpose'].value_counts()
```

Out[17]:
```
furniture/appliances    473
car                     337
business                 97
education                59
renovations              22
car0                     12
Name: purpose, dtype: int64
```

In [18]:
```
# Here we are replacing the "furniture/appliances" to "appliances"
```

In [19]:
```
credit_df['purpose'] = np.where(credit_df['purpose']=='furniture/appliances','appliances',credit_df['p
```

In [20]:
```
credit_df['purpose'].value_counts()
```

Out[20]:
```
appliances     473
car            337
business        97
education       59
renovations     22
car0            12
Name: purpose, dtype: int64
```

In [21]:
```
# Changes are reflecting.
```

In [22]:
```
print(list(credit_dt.select_dtypes(include = 'object')))
print(len(list(credit_dt.select_dtypes(include = 'object'))))
```

```
['checking_balance', 'credit_history', 'purpose', 'savings_balance', 'employment_duration', 'other_cr
edit', 'housing', 'job', 'phone', 'default']
10
```

In [23]:
```
print(list(credit_df.select_dtypes(include = 'object')))
print(len(list(credit_df.select_dtypes(include = 'object'))))
```

```
['credit_history', 'purpose', 'other_credit', 'housing', 'job', 'phone', 'default']
7
```

In [24]:
```
# before changes
credit_dt.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 17 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   checking_balance      1000 non-null   object
 1   months_loan_duration  1000 non-null   int64
 2   credit_history        1000 non-null   object
 3   purpose               1000 non-null   object
 4   amount                1000 non-null   int64
 5   savings_balance       1000 non-null   object
 6   employment_duration   1000 non-null   object
 7   percent_of_income     1000 non-null   int64
 8   years_at_residence    1000 non-null   int64
 9   age                   1000 non-null   int64
 10  other_credit          1000 non-null   object
 11  housing               1000 non-null   object
 12  existing_loans_count  1000 non-null   int64
 13  job                   1000 non-null   object
 14  dependents            1000 non-null   int64
 15  phone                 1000 non-null   object
 16  default               1000 non-null   object
dtypes: int64(7), object(10)
memory usage: 132.9+ KB
```

In [25]:
```
#after changes
credit_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 17 columns):
 #   Column                Non-Null Count  Dtype 
---  ------                --------------  ----- 
 0   checking_balance      1000 non-null   int32 
 1   months_loan_duration  1000 non-null   int64 
 2   credit_history        1000 non-null   object
 3   purpose               1000 non-null   object
 4   amount                1000 non-null   int64 
 5   savings_balance       1000 non-null   int32 
 6   employment_duration   1000 non-null   int32 
 7   percent_of_income     1000 non-null   int64 
 8   years_at_residence    1000 non-null   int64 
 9   age                   1000 non-null   int64 
 10  other_credit          1000 non-null   object
 11  housing               1000 non-null   object
 12  existing_loans_count  1000 non-null   int64 
 13  job                   1000 non-null   object
 14  dependents            1000 non-null   int64 
 15  phone                 1000 non-null   object
 16  default               1000 non-null   object
dtypes: int32(3), int64(7), object(7)
memory usage: 121.2+ KB
```

After the above changes in data actual numeric variables got converted into numeric from object such as variables 'checking_balance', 'savings_balance' and 'employment_duration'

In [26]:
```
credit_df.head()
```

Out[26]:

	checking_balance	months_loan_duration	credit_history	purpose	amount	savings_balance	employment_duration	percent
0	1	6	critical	appliances	1169	1	1	
1	2	48	good	appliances	5951	0	0	
2	0	12	critical	education	2096	0	2	
3	1	42	good	appliances	7882	0	2	
4	1	24	poor	car	4870	0	0	

Checking Missing values

In [27]:
```
credit_df.isna().sum()
```

Out[27]:
```
checking_balance        0
months_loan_duration    0
credit_history          0
purpose                 0
amount                  0
savings_balance         0
employment_duration     0
percent_of_income       0
years_at_residence      0
age                     0
other_credit            0
housing                 0
existing_loans_count    0
job                     0
dependents              0
phone                   0
default                 0
dtype: int64
```

No missing values are present.

Checking Duplicates

In [28]:
```
credit_df.duplicated().sum()
```

Out[28]: 0

In [29]:
```
credit_df[credit_df.duplicated()]
```

Out[29]:

checking_balance	months_loan_duration	credit_history	purpose	amount	savings_balance	employment_duration	percent_of

There are no duplicate values.

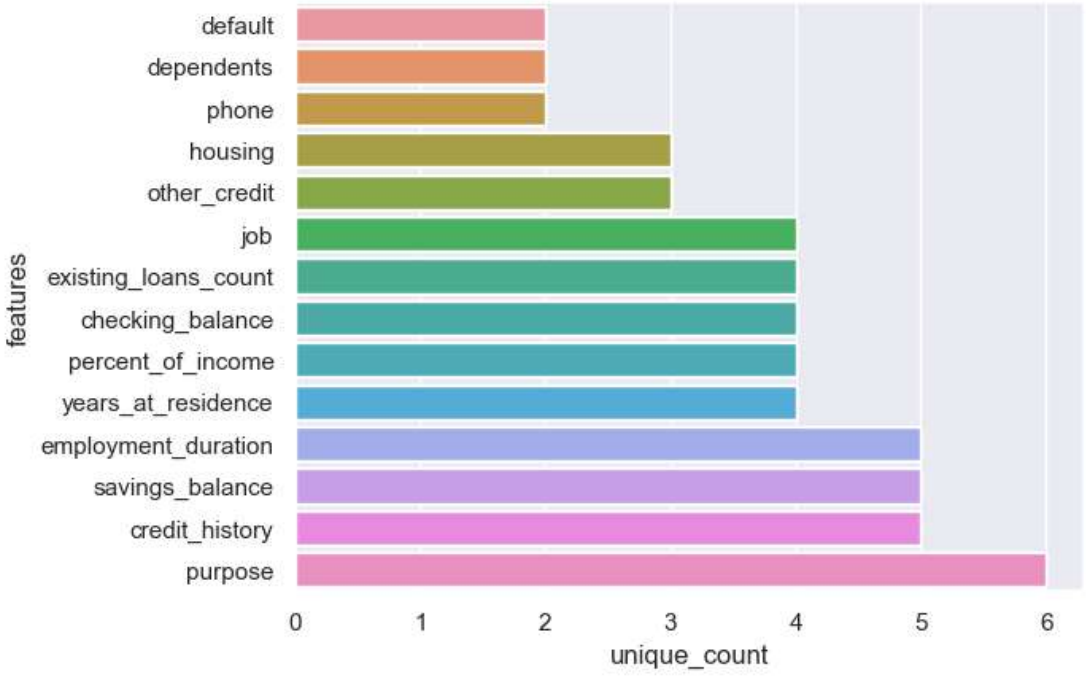
Unique Variables

In [30]:
```
dict={}
for i in credit_df.columns:
        x = len(credit_df[i].unique())
        dict[i]=x
        #print(f'{i}:\n{x}\n\n')
cnt = pd.DataFrame(dict.items(), columns = ['features','unique_count']).sort_values(by ='unique_count'
cnt
```

Out[30]:

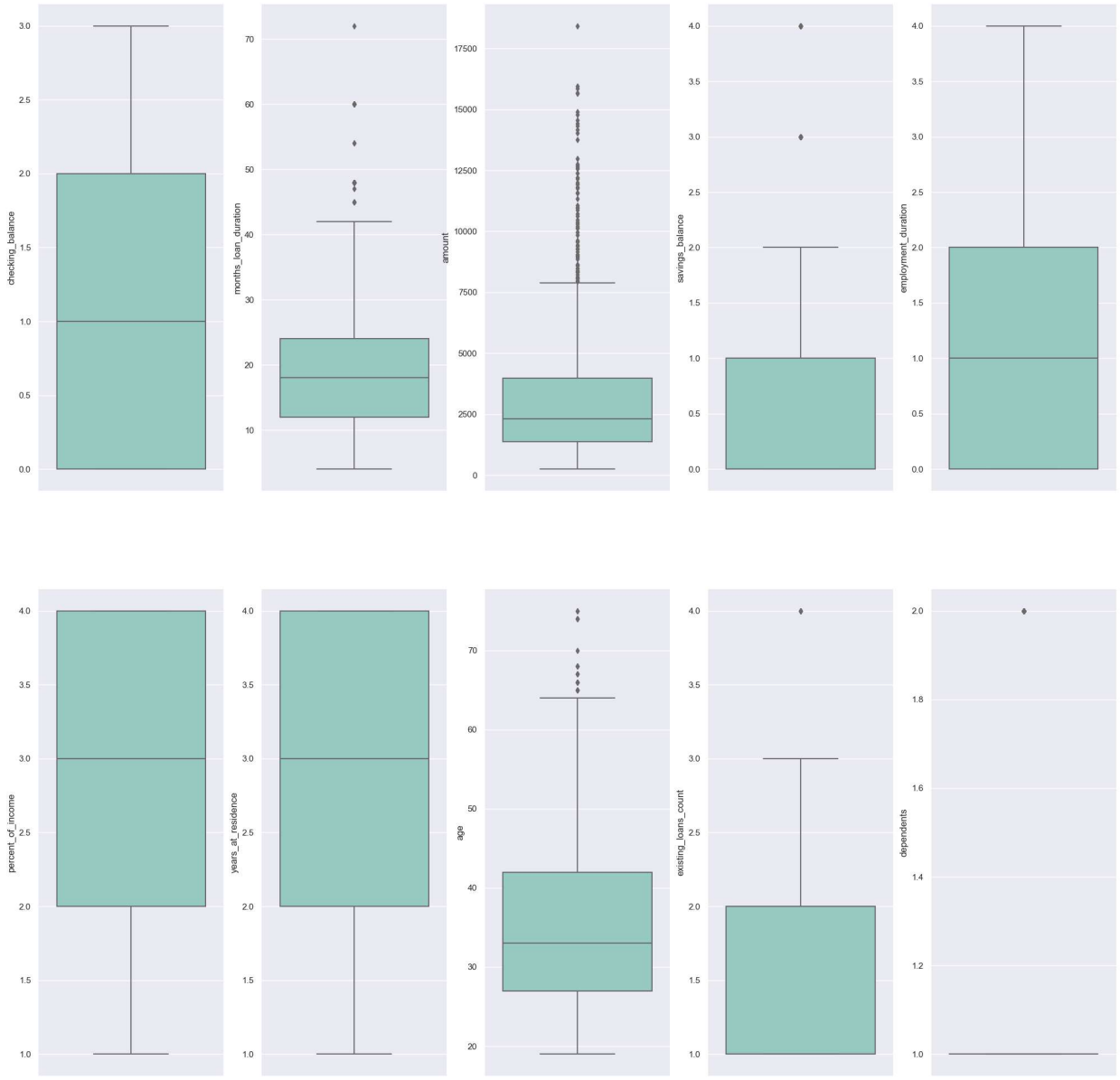
	features	unique_count
0	default	2
1	dependents	2
2	phone	2
3	housing	3
4	other_credit	3
5	job	4
6	existing_loans_count	4
7	checking_balance	4
8	percent_of_income	4
9	years_at_residence	4
10	employment_duration	5
11	savings_balance	5
12	credit_history	5
13	purpose	6
14	months_loan_duration	33
15	age	53
16	amount	921

In [31]:
```
for i in credit_df.columns:

    if i not in ['months_loan_duration','age','amount']:
        sns.barplot(y= cnt['features'][:14], x = cnt['unique_count'][:14])
        #plt.xticks(rotation = 90)
```



Checking Outliers

In [32]:
```
plt.figure(figsize = (25, 25), dpi = 100)

for x, col in enumerate(credit_df.select_dtypes(include = 'int').columns):
    plt.subplot(2,5,x + 1)
    sns.boxplot(y = credit_df[col], data=credit_df, palette = 'Set3')
```



In [33]:
```
credit_df.describe().loc[['min','max', '25%', '75%']].T
```

Out[33]:

	min	max	25%	75%
checking_balance	0.0	3.0	0.0	2.00
months_loan_duration	4.0	72.0	12.0	24.00
amount	250.0	18424.0	1365.5	3972.25
savings_balance	0.0	4.0	0.0	1.00
employment_duration	0.0	4.0	0.0	2.00
percent_of_income	1.0	4.0	2.0	4.00
years_at_residence	1.0	4.0	2.0	4.00
age	19.0	75.0	27.0	42.00
existing_loans_count	1.0	4.0	1.0	2.00
dependents	1.0	2.0	1.0	1.00

In [34]:
```
q1 = credit_df.quantile(0.25)
q3 = credit_df.quantile(0.75)
IQR = q3-q1

upper_limit = q3 + 1.5*IQR
lower_limit = q1 - 1.5*IQR
```

In [35]:
```
dict1 = {}
dict2 = {}
quant_list = []

dict1.update(upper_limit)
dict2.update(lower_limit)
quant_list.append(dict1)
quant_list.append(dict2)
```

In [36]:
```
limit = pd.DataFrame(quant_list).T
limit.columns = ['upper_limit', 'lower_limit']
limit
```

Out[36]:

	upper_limit	lower_limit
checking_balance	5.000	-3.000
months_loan_duration	42.000	-6.000
amount	7882.375	-2544.625
savings_balance	2.500	-1.500
employment_duration	5.000	-3.000
percent_of_income	7.000	-1.000
years_at_residence	7.000	-1.000
age	64.500	4.500
existing_loans_count	3.500	-0.500
dependents	1.000	1.000

In [37]:
```
#months_loan_duration, amount, age
#savings balance, existing_loans count, dependent
```

In [38]:
```
#count of values above the 75% percentile
for i in ['months_loan_duration','amount','age','savings_balance','existing_loans_count','dependents']
    print(i, ' - ', credit_df[credit_df[i] > credit_df.describe().loc['75%'][i]].shape[0])
```

```
months_loan_duration  -  230
amount  -  250
age  -  235
savings_balance  -  214
existing_loans_count  -  34
dependents  -  155
```

In [39]:
```
#count of values above the upper limit
for i in ['months_loan_duration','amount','age','savings_balance','existing_loans_count','dependents']
    print(i,' - ',credit_df[credit_df[i] > limit.loc[i][0]].shape[0])
```

```
months_loan_duration  -  70
amount  -  72
age  -  23
savings_balance  -  111
existing_loans_count  -  6
dependents  -  155
```

In [40]:
```
dict_values = {}

for i in ['months_loan_duration','amount','age','savings_balance','existing_loans_count','dependents']
    print(i, ':',credit_df[credit_df[i] > limit.loc[i][0]][i].values,'\n')
```

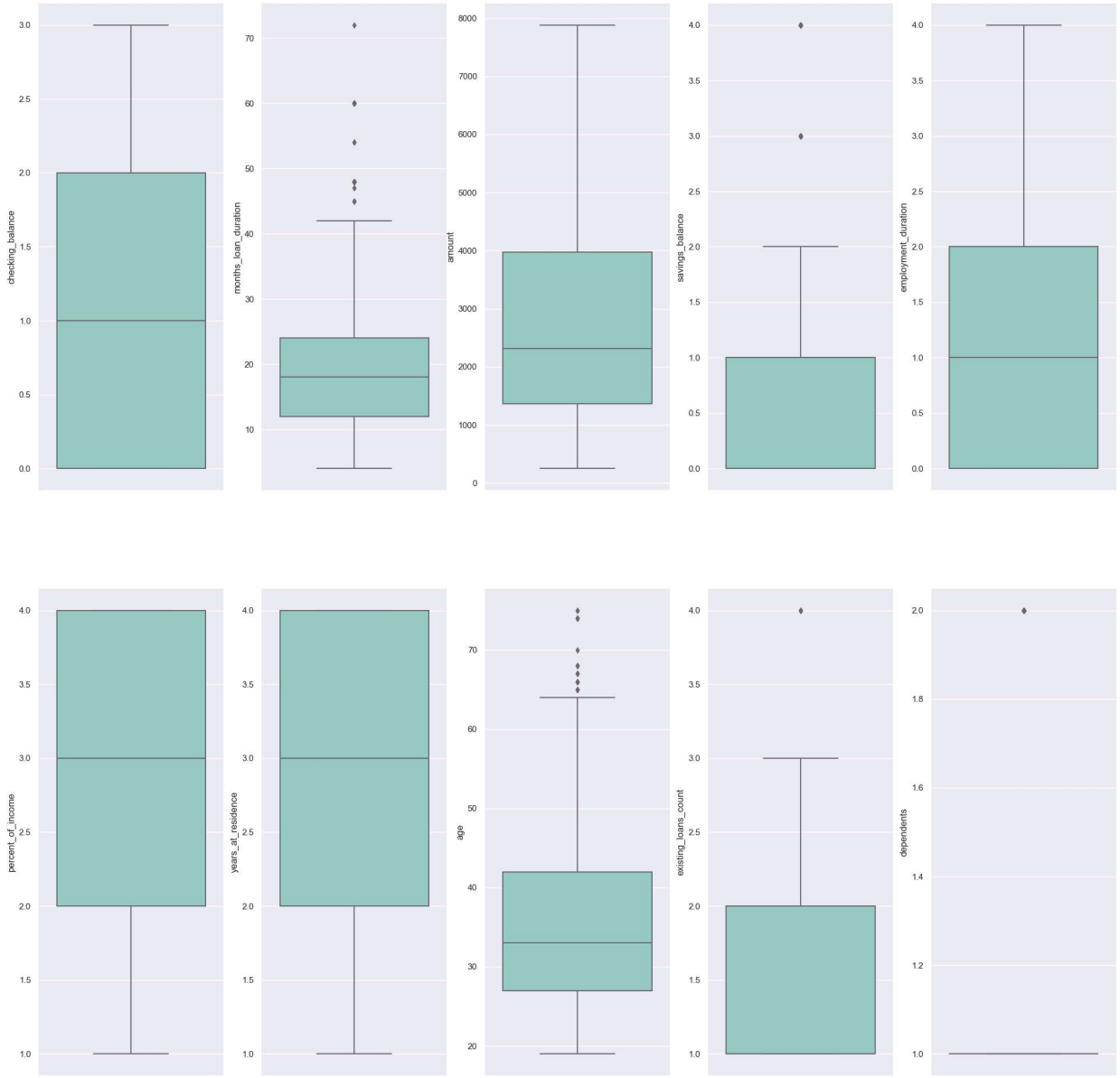
```
months_loan_duration : [48 48 60 45 48 48 48 54 54 48 48 60 48 48 45 48 48 60 48 48 47 48 48 48
 48 48 48 60 48 60 60 48 48 48 48 48 48 48 48 48 48 60 48 60 48 48 48 60
 72 60 48 48 60 48 48 48 48 48 48 45 48 48 48 48 60 48 60 48 45 45]

amount : [ 9055  8072 12579  9566 14421  8133  9436 12612 15945 11938  8487 10144
  8613  9572 10623 10961 14555  8978 12169 11998 10722  9398  9960 10127
 11590 13756 14782 14318 12976 11760  8648  8471 11328 11054  8318  9034
  8588  7966  8858 12389 12204  9157 15653  7980  8086 10222 10366  9857
 14027 11560 14179 12680  8065  9271  9283  9629 15857  8335 11816 10875
  9277 15672  8947 10477 18424 14896 12749 10297  8358 10974  8386  8229]

age : [67 66 66 70 65 74 68 66 75 74 65 75 67 74 65 66 74 66 67 65 68 65 68]

savings_balance : [3 4 3 3 4 4 3 3 3 3 4 3 4 3 3 3 3 4 3 4 4 4 3 3 3 4 3 4 4 3 4 4 3 3 4 3 4
 4 3 4 4 4 3 3 4 3 3 4 4 3 3 3 3 4 4 3 4 4 3 4 4 3 3 3 4 4 3 4 3 3 3 4 3 3
 4 3 3 3 3 4 3 4 3 4 4 3 4 3 4 4 4 3 3 3 3 4 4 3 3 4 4 4 3 3 3 3 3 4 3 3 3]

existing_loans_count : [4 4 4 4 4 4]

dependents : [2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
 2 2 2 2 2 2 2]
```

Handling Outliers

In [41]:
```
# outliers to be removed : amount, months loan duration > 50
```

In [42]:
```
#['months_loan_duration','amount','age','savings_balance','existing_loans_count','dependents']:
for i in ['amount']:
    credit_df[i].clip(upper = limit.loc[i][0] ,inplace=True)
```

In [43]:
```
plt.figure(figsize = (25, 25), dpi = 100)

for x, col in enumerate(credit_df.select_dtypes(include = ['int','float']).columns):
    plt.subplot(2,5,x + 1)
    sns.boxplot(y = credit_df[col], data=credit_df, palette = 'Set3')
```



In [44]:
```
#count of values above the upper limit
for i in ['months_loan_duration','amount','age','savings_balance','existing_loans_count','dependents']
    print(i,' - ',credit_df[credit_df[i] > limit.loc[i][0]].shape[0])
```

```
months_loan_duration  -  70
amount  -  0
age  -  23
savings_balance  -  111
existing_loans_count  -  6
dependents  -  155
```

Dropping Variable

In [45]:
```
#credit_df.drop(['phone'], axis =1, inplace = True)
```

Encoding

In [46]:
```
# lst = ['credit_history','purpose','other_credit','housing','job']
# for i in lst:
#     print('='*20,i,'='*20)`
#     print(credit_df[i].value_counts(),'\n')
```

In [47]:
```
credit_df1 = credit_df.copy()
```

In [48]:
```
credit_df1 = pd.get_dummies(credit_df1, columns=cnt['features'][:14], drop_first = True )
```

In [49]:
```
credit_df1.head()
```

Out[49]:

	months_loan_duration	amount	age	default_yes	dependents_2	phone_yes	housing_own	housing_rent	other_credit_none
0	6	1169.0	67	0	0	1	1	0	1
1	48	5951.0	22	1	0	0	1	0	1
2	12	2096.0	49	0	1	0	1	0	1
3	42	7882.0	45	0	1	0	0	0	1
4	24	4870.0	53	1	1	0	0	0	1

5 rows × 42 columns

In [50]:
```
credit_df1.columns
```

Out[50]:
```
Index(['months_loan_duration', 'amount', 'age', 'default_yes', 'dependents_2',
       'phone_yes', 'housing_own', 'housing_rent', 'other_credit_none',
       'other_credit_store', 'job_skilled', 'job_unemployed', 'job_unskilled',
       'existing_loans_count_2', 'existing_loans_count_3',
       'existing_loans_count_4', 'checking_balance_1', 'checking_balance_2',
       'checking_balance_3', 'percent_of_income_2', 'percent_of_income_3',
       'percent_of_income_4', 'years_at_residence_2', 'years_at_residence_3',
       'years_at_residence_4', 'employment_duration_1',
       'employment_duration_2', 'employment_duration_3',
       'employment_duration_4', 'savings_balance_1', 'savings_balance_2',
       'savings_balance_3', 'savings_balance_4', 'credit_history_good',
       'credit_history_perfect', 'credit_history_poor',
       'credit_history_very good', 'purpose_business', 'purpose_car',
       'purpose_car0', 'purpose_education', 'purpose_renovations'],
      dtype='object')
```

In [51]:
```
credit_df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 42 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   months_loan_duration      1000 non-null   int64
 1   amount                    1000 non-null   float64
 2   age                       1000 non-null   int64
 3   default_yes               1000 non-null   uint8
 4   dependents_2              1000 non-null   uint8
 5   phone_yes                 1000 non-null   uint8
 6   housing_own               1000 non-null   uint8
 7   housing_rent              1000 non-null   uint8
 8   other_credit_none         1000 non-null   uint8
 9   other_credit_store        1000 non-null   uint8
 10  job_skilled               1000 non-null   uint8
 11  job_unemployed            1000 non-null   uint8
 12  job_unskilled             1000 non-null   uint8
 13  existing_loans_count_2    1000 non-null   uint8
 14  existing_loans_count_3    1000 non-null   uint8
 15  existing_loans_count_4    1000 non-null   uint8
 16  checking_balance_1        1000 non-null   uint8
 17  checking_balance_2        1000 non-null   uint8
 18  checking_balance_3        1000 non-null   uint8
 19  percent_of_income_2       1000 non-null   uint8
 20  percent_of_income_3       1000 non-null   uint8
 21  percent_of_income_4       1000 non-null   uint8
 22  years_at_residence_2      1000 non-null   uint8
 23  years_at_residence_3      1000 non-null   uint8
 24  years_at_residence_4      1000 non-null   uint8
 25  employment_duration_1     1000 non-null   uint8
 26  employment_duration_2     1000 non-null   uint8
 27  employment_duration_3     1000 non-null   uint8
 28  employment_duration_4     1000 non-null   uint8
 29  savings_balance_1         1000 non-null   uint8
 30  savings_balance_2         1000 non-null   uint8
 31  savings_balance_3         1000 non-null   uint8
 32  savings_balance_4         1000 non-null   uint8
 33  credit_history_good       1000 non-null   uint8
 34  credit_history_perfect    1000 non-null   uint8
 35  credit_history_poor       1000 non-null   uint8
 36  credit_history_very good  1000 non-null   uint8
 37  purpose_business          1000 non-null   uint8
 38  purpose_car               1000 non-null   uint8
 39  purpose_car0              1000 non-null   uint8
 40  purpose_education         1000 non-null   uint8
 41  purpose_renovations       1000 non-null   uint8
dtypes: float64(1), int64(2), uint8(39)
memory usage: 61.6 KB
```

In [52]:
```
credit_df1 = credit_df1.rename(columns = {'default_yes':'default'})
```

In [53]:
```
credit_df1.head()
```

Out[53]:

	months_loan_duration	amount	age	default	dependents_2	phone_yes	housing_own	housing_rent	other_credit_none	oth
0	6	1169.0	67	0	0	1	1	0	1	
1	48	5951.0	22	1	0	0	1	0	1	
2	12	2096.0	49	0	1	0	1	0	1	
3	42	7882.0	45	0	1	0	0	0	1	
4	24	4870.0	53	1	1	0	0	0	1	

5 rows × 42 columns

In [54]:
```
credit_df1.drop(['phone_yes'], axis =1, inplace = True)
```

Seperate Indpendent And Dependent Variables

In [55]:
```
x = credit_df1.drop(['default'], axis=1)
y = credit_df1['default']
```

In [56]:
```
print(credit_df1.shape)
print(x.shape)
print(y.shape)
print(y.head())
```

```
(1000, 41)
(1000, 40)
(1000,)
0    0
1    1
2    0
3    0
4    1
Name: default, dtype: uint8
```

Feature Scaling

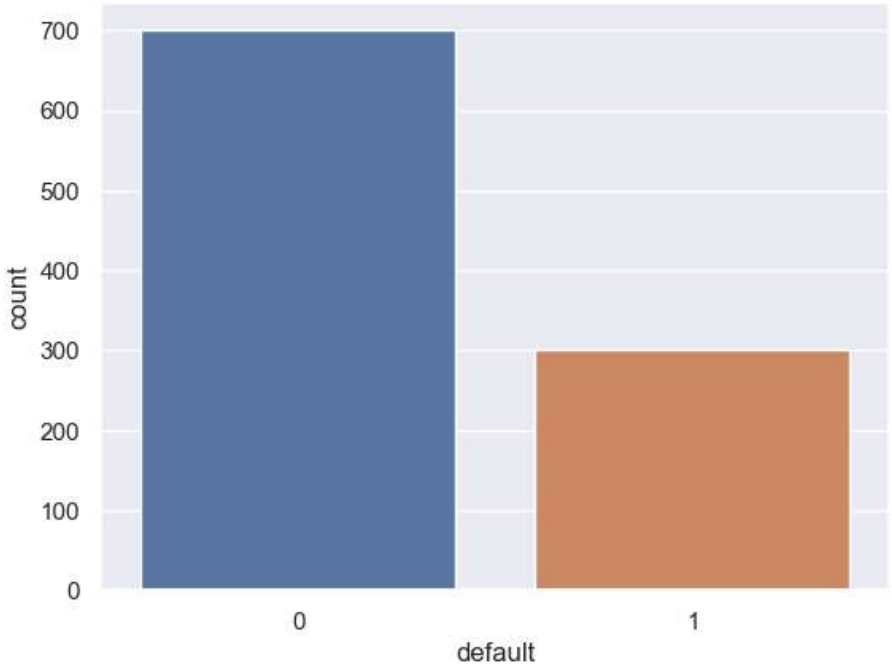
In [57]:
```
from sklearn.preprocessing import StandardScaler
fsc = StandardScaler()
sc_x = fsc.fit_transform(x)
sc_x
```

Out[57]:
```
array([[-1.23647786, -0.86096108,  2.76645648, ..., -0.11020775,
        -0.2503982 , -0.14998296],
       [ 2.24819436,  1.32654951, -1.19140394, ..., -0.11020775,
        -0.2503982 , -0.14998296],
       [-0.73866754, -0.43690789,  1.18331231, ..., -0.11020775,
         3.99363901, -0.14998296],
       ...,
       [-0.73866754, -1.02792916,  0.21583532, ..., -0.11020775,
        -0.2503982 , -0.14998296],
       [ 1.9992892 , -0.55172704, -1.10345149, ..., -0.11020775,
        -0.2503982 , -0.14998296],
       [ 1.9992892 ,  0.69756017, -0.75164167, ..., -0.11020775,
        -0.2503982 , -0.14998296]])
```

Imbalance Check

In [58]:
```
sns.countplot(data=credit_df, x = y)
print('No has the count : ', y.value_counts()[0])
print('Yes has the count : ',y.value_counts()[1])
plt.show()
```

```
No has the count :  700
Yes has the count :  300
```



This is the imbalance data. (300*2=600 < 700)

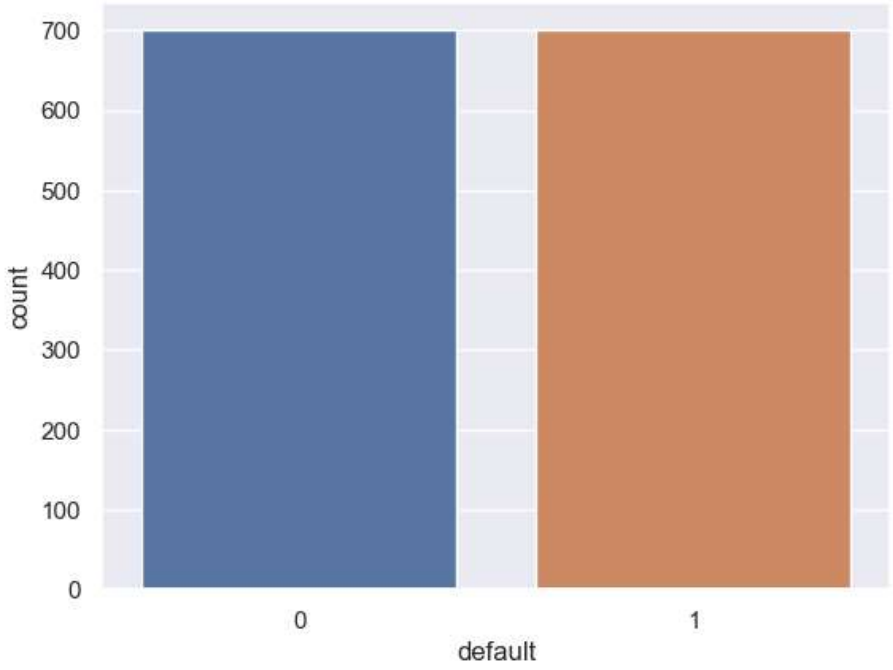
Handle Imbalance Data

In [59]:
```
# Oversampling method
import imblearn
```

In [60]:
```
from imblearn.over_sampling import RandomOverSampler
over = RandomOverSampler()
x_over, y_over = over.fit_resample(sc_x,y)
```

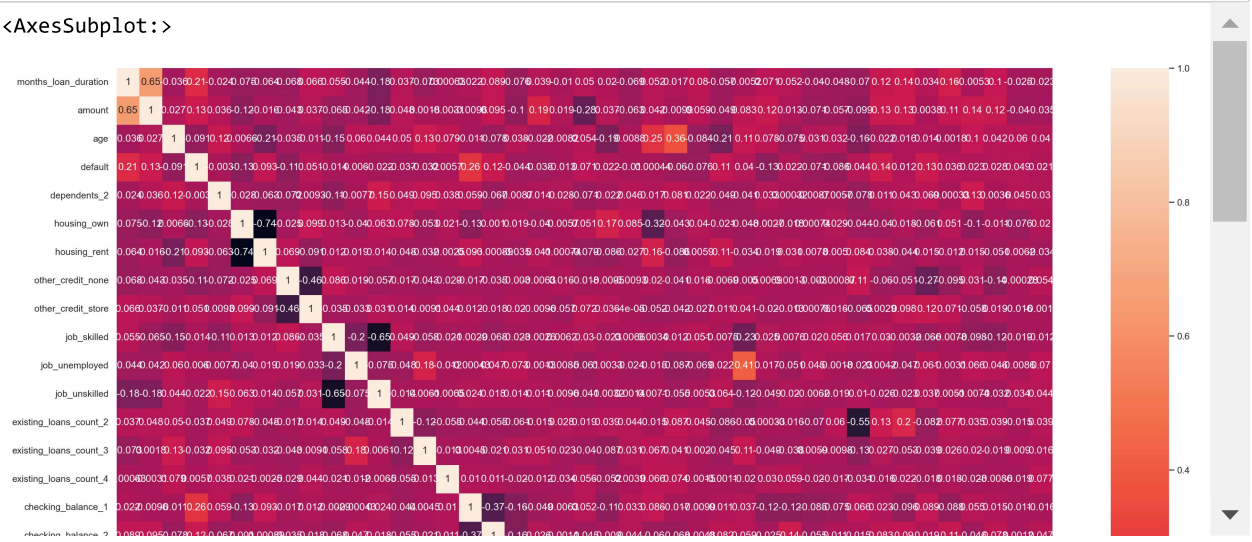
In [61]:
```
sns.countplot(data=credit_df, x = y_over)
print('No has the count : ', y_over.value_counts()[0])
print('Yes has the count : ',y_over.value_counts()[1])
plt.show()
```

```
No has the count :  700
Yes has the count :  700
```



In [62]:
```
plt.figure(figsize =(25,25), dpi = 200)
sns.heatmap(data = credit_df1.corr(), annot =True)
```

Out[62]: <AxesSubplot:>



In [63]:
```
# plt.figure(figsize=(50,50))
# sns.pairplot(data = credit_df1, hue = 'default')
```

Splitting Test And Train Dataset

In [64]:
```
from sklearn.model_selection import train_test_split
np.random.seed(10)
x_train, x_test, y_train, y_test = train_test_split(x_over, y_over, test_size = 0.25, random_state =50
print(x_train.shape, x_test.shape, y_train.shape, y_test.shape)
```

```
(1050, 40) (350, 40) (1050,) (350,)
```

Model Building

In [65]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix, roc_auc_score, ro
from sklearn.model_selection import cross_val_score
```

1. Logestic Regression

In [66]:
```
np.random.seed(10)
lr = LogisticRegression()
lr = lr.fit(x_train, y_train)
```

In [67]:
```
y_lr_predict_train = lr.predict(x_train)
y_lr_predict_test = lr.predict(x_test)
```

In [68]:
```
r = pd.DataFrame(y_test)
r.insert(1, 'predicted', y_lr_predict_test )
r
```

Out[68]:

	default	predicted
580	1	1
867	0	0
246	0	0
1378	1	1
287	0	1
...	...	...
1040	1	0
831	1	1
172	1	1
1255	1	0
1237	1	0

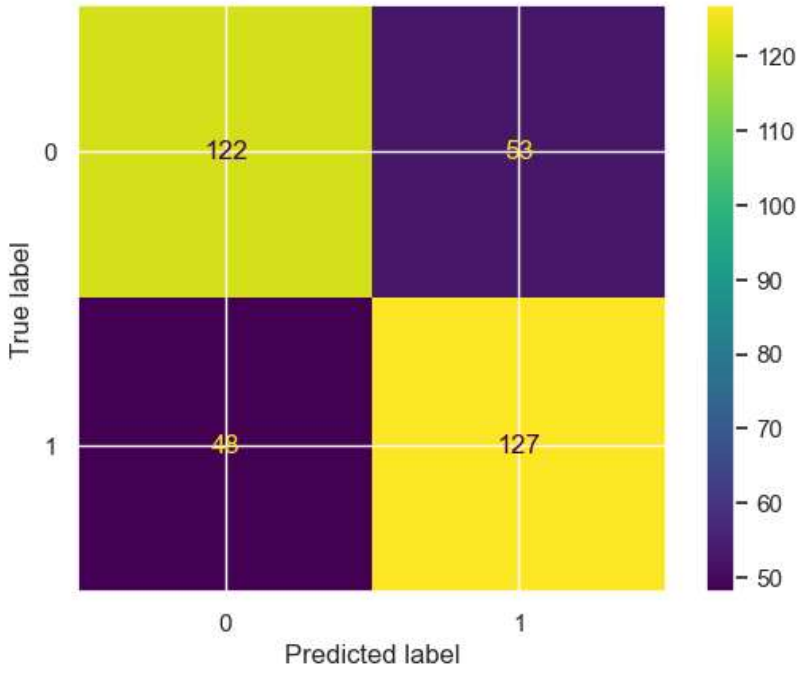
350 rows × 2 columns

Evaluate The Model

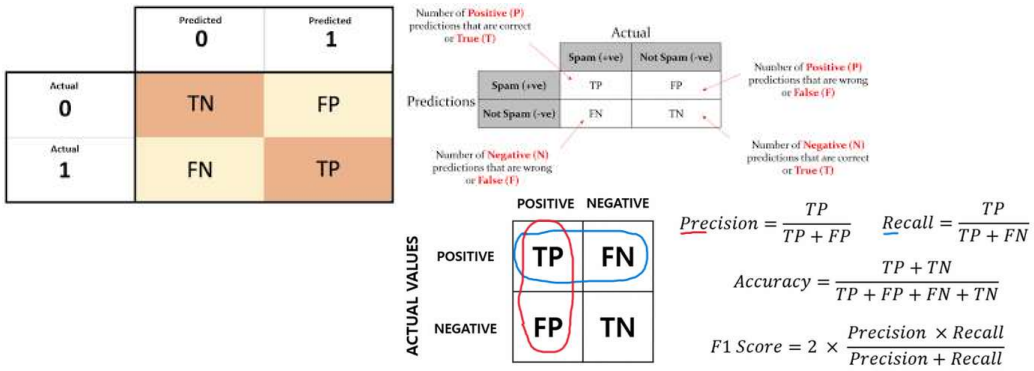
In [69]:
```
print('='*20,'Accuracy Score','='*20,'\n')
print("The Accuracy Score for train data is : ", accuracy_score(y_train,y_lr_predict_train ))
print("The Accuracy Score for test data is : ", accuracy_score(y_test,y_lr_predict_test ))

print('\n\n','='*20,'Classification Report','='*20,'\n')
print("The Classification Report for train data is :\n ", classification_report(y_train,y_lr_predict_t
print("The Classification Report for test data is :\n ", classification_report(y_test,y_lr_predict_tes

print('\n\n','='*20,'Confusion Matrix','='*20,'\n')
print("The Confusion Matrix for train data is :\n", confusion_matrix(y_train,y_lr_predict_train ))
print("The Confusion Matrix for test data is :\n", confusion_matrix(y_test,y_lr_predict_test ))
```

```
==================== Accuracy Score ====================

The Accuracy Score for train data is :  0.7304761904761905
The Accuracy Score for test data is :  0.7114285714285714


 ==================== Classification Report ====================

The Classification Report for train data is :
                precision    recall  f1-score   support

           0       0.74      0.71      0.72       525
           1       0.72      0.75      0.74       525

    accuracy                           0.73      1050
   macro avg       0.73      0.73      0.73      1050
weighted avg       0.73      0.73      0.73      1050

The Classification Report for test data is :
                precision    recall  f1-score   support

           0       0.72      0.70      0.71       175
           1       0.71      0.73      0.72       175

    accuracy                           0.71       350
   macro avg       0.71      0.71      0.71       350
weighted avg       0.71      0.71      0.71       350



 ==================== Confusion Matrix ====================

The Confusion Matrix for train data is :
 [[371 154]
 [129 396]]
The Confusion Matrix for test data is :
 [[122  53]
 [ 48 127]]
```

In [70]:
```
from sklearn.metrics import ConfusionMatrixDisplay

cm = confusion_matrix(y_test, y_lr_predict_test, labels = lr.classes_  )
display = ConfusionMatrixDisplay(confusion_matrix = cm, display_labels = lr.classes_)
display.plot()
plt.show()
```



Understanding Confusion Matrix



- Higher the recall/sensitivity, precision and F1-score better the result.

ROC/AUC

In [71]:
```
# roc_auc for test data
lr_roc_auc = roc_auc_score(y_test,y_lr_predict_test )
print("The roc_auc_score for logestic regression is : ", lr_roc_auc)
```

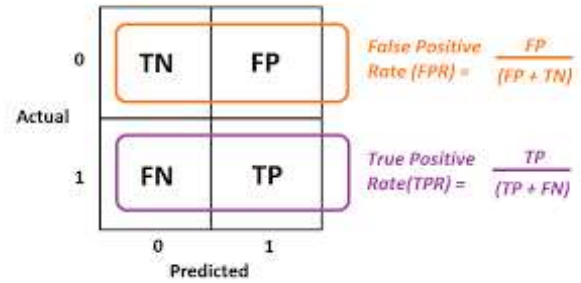
```
The roc_auc_score for logestic regression is :  0.7114285714285714
```

In [72]:
```
fpr, tpr, thresholds = roc_curve(y_test, y_lr_predict_test)
```

In [73]:
```
print("fpr : ", fpr)
print("tpr : ", tpr)
print("Thresholds : ", thresholds)
```

```
fpr :  [0.         0.30285714 1.        ]
tpr :  [0.         0.72571429 1.        ]
Thresholds :  [2 1 0]
```

True Positive Rate(TPR) & False Positive Rate(FPR)



- ROC: Receiver Operating Characteristics
- AUC: Area Under Curve

AUC stands for Area Under the Curve, and the AUC curve represents the area under the ROC curve. It measures the overall performance of the binary classification model. As both TPR and FPR range between 0 to 1, So, the area will always lie between 0 and 1, and A greater value of AUC denotes better model performance. Our main goal is to maximize this area in order to have the highest TPR and lowest FPR at the given threshold

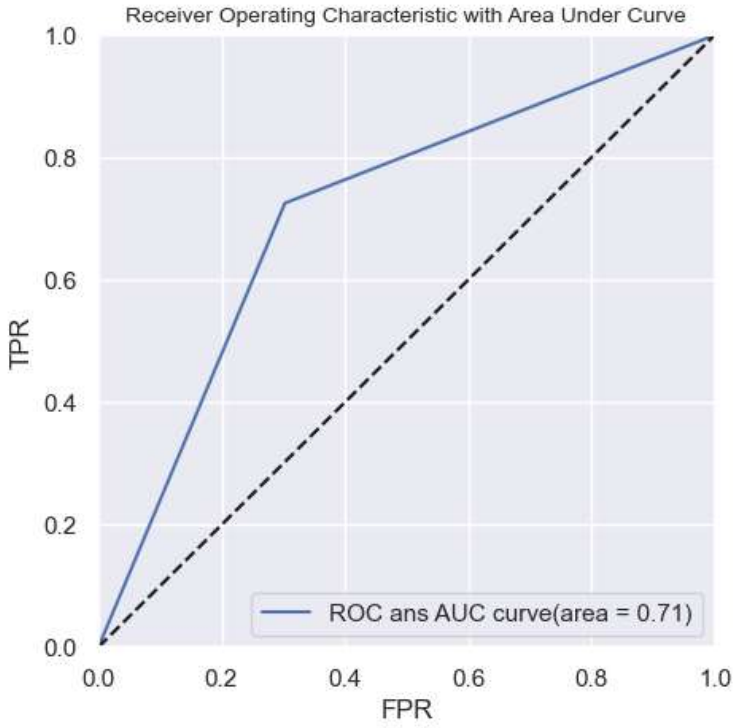
- AUC measures how well a model is able to distinguish between classes.

The classification threshold that returns the upper-left corner of the curve—minimizing the difference between TPR and FPR—is the optimal threshold.

Plotting the ROC-AUC curve

In [74]:
```
plt.figure(figsize = (5,5))
plt.plot(fpr, tpr, label = "ROC ans AUC curve(area = %0.2f)" %lr_roc_auc)
plt.plot([0,1],[0,1],'k--')
plt.xlim(0,1)
plt.ylim(0,1)
plt.xlabel('FPR')
plt.ylabel('TPR')
plt.title('Receiver Operating Characteristic with Area Under Curve', fontsize =10)
plt.legend(loc='lower right')
```

Out[74]: <matplotlib.legend.Legend at 0x1ea7e783be0>



Cross Validation

In [75]:
```
Training_CV = cross_val_score(lr, x_train, y_train, cv =10)
Testing_CV = cross_val_score(lr, x_test, y_test, cv= 10)
Avg_Training_CV = Training_CV.mean()
Avg_Testing_CV = Testing_CV.mean()

print(f"Training CV: {Training_CV}\n\nTesting CV: {Testing_CV}\n\nAvg_Training_CV: {Avg_Training_CV}\n
```

```
Training CV: [0.73333333 0.66666667 0.73333333 0.73333333 0.67619048 0.71428571
 0.66666667 0.66666667 0.74285714 0.71428571]

Testing CV: [0.82857143 0.65714286 0.62857143 0.71428571 0.71428571 0.54285714
 0.74285714 0.82857143 0.68571429 0.77142857]

Avg_Training_CV: 0.7047619047619047

Avg_Testing_CV: 0.7114285714285715
```

In [ ]: