$$DataScienceAssignment - FullTime$$

Credit Risk Prediciton

Life cycle of Machine learning Project

- Understanding the Problem Statement
- Data Collection
- Data Cleaning
- Exploratory data analysis
- Data Pre-Processing
- Model Training
- Choose best model

1) Problem statement.

- A person's creditworthiness is often associated (conversely) with the likelihood they may default on loans.
- In the proposed model, credit risk prediction is performed on the given dataset. The model predicts the chances an applicant to be considered at high risk.
    - 0 = Low credit risk i.e high chance of paying back the loan amount
    - 1 = High credit risk i.e low chance of paying back the loan amount

Dataset

The dataset has two files:

1. `applicant.csv` : This file contains personal data about the (primary) applicant

    - Unique ID: `applicant_id` (string)
    - Other fields:
        - Primary_applicant_age_in_years (numeric)
        - Gender (string)
        - Marital_status (string)
        - Number_of_dependents (numeric)
        - Housing (string)
        - Years_at_current_residence (numeric)
        - Employment_status (string)
        - Has_been_employed_for_at_least (string)
        - Has_been_employed_for_at_most (string)
        - Telephone (string)
        - Foreign_worker (numeric)
        - Savings_account_balance (string)

- Balance_in_existing_bank_account_(lower_limit_of_bucket) (string)
- Balance_in_existing_bank_account_(upper_limit_of_bucket) (string)

2. `loan.csv` : This file contains data more specific to the loan application

   - Target: `high_risk_application` (numeric)
   - Other fields:
     - applicant_id (string)
     - Months_loan_taken_for (numeric)
     - Purpose (string)
     - Principal_loan_amount (numeric)
     - EMI_rate_in_percentage_of_disposable_income (numeric)
     - Property (string)
     - Has_coapplicant (numeric)
     - Has_guarantor (numeric)
     - Other_EMI_plans (string)
     - Number_of_existing_loans_at_this_bank (numeric)
     - Loan_history (string)

2) Import Data

Importing Pandas, Numpy, Matplotlib, Seaborn and Warings Library.

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sb
import plotly.express as px

import matplotlib.pyplot as plt
%matplotlib inline

from scipy.stats import chi2_contingency

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

Import the CSV Data as Pandas DataFrame

In [2]:
```python
data_1 = pd.read_csv('data/applicant.csv')
data_1.head()     # Show Top 5 Records
```

Out[2]:

	applicant_id	Primary_applicant_age_in_years	Gender	Marital_status	Number_of_dependents	Hou
0	1469590	67	male	single	1	
1	1203873	22	female	divorced/separated/married	1	
2	1432761	49	male	single	2	
3	1207582	45	male	single	2	for
4	1674436	53	male	single	2	for

In [3]:
```python
data_2 = pd.read_csv('data/loan.csv')
data_2.head()
```

Out[3]:

	loan_application_id	applicant_id	Months_loan_taken_for	Purpose	Principal_loan_amount	EMI_rate_in_perc
0	d68d975e-edad-11ea-8761-1d6f9c1ff461	1469590	6	electronic equipment	1169000	
1	d68d989e-edad-11ea-b1d5-2bcf65006448	1203873	48	electronic equipment	5951000	
2	d68d995c-edad-11ea-814a-1b6716782575	1432761	12	education	2096000	
3	d68d99fc-edad-11ea-8841-17e8848060ae	1207582	42	FF&E	7882000	
4	d68d9a92-edad-11ea-9f3d-1f8682db006a	1674436	24	new vehicle	4870000	

Shape of the dataset

In [4]:
```python
print('data_1 shape: {} \ndata_2 shape: {}'.format(data_1.shape, data_2.shape))
```

```
data_1 shape: (1000, 15)
data_2 shape: (1000, 13)
```

Merge dataset with common feature - applicant_id

In [5]:
```
df = pd.merge(data_1, data_2, on='applicant_id', how='outer')
pd.set_option('display.max_columns', None) # to display all columns
df.head()
```

Out[5]:

	applicant_id	Primary_applicant_age_in_years	Gender	Marital_status	Number_of_dependents	Hous
0	1469590	67	male	single	1	
1	1203873	22	female	divorced/separated/married	1	
2	1432761	49	male	single	2	
3	1207582	45	male	single	2	for
4	1674436	53	male	single	2	for

In [6]:
```
print('df shape: {}'.format(df.shape))
```

```
df shape: (1000, 27)
```

Save merged dataset to csv file.

In [7]:
```
df.to_csv('data/merged_data.csv')
```

In [8]:
```
df.high_risk_applicant.value_counts()
```

Out[8]:
```
0    700
1    300
Name: high_risk_applicant, dtype: int64
```

- More number of applicants, have low credit risk.

Summary of the dataset

In [9]:
```
# Display summary statistics for a dataframe
df.describe()
```

Out[9]:

	applicant_id	Primary_applicant_age_in_years	Number_of_dependents	Years_at_current_residence	Forei
count	1.000000e+03	1000.000000	1000.000000	1000.000000	10
mean	1.514763e+06	35.546000	1.155000	2.845000	
std	2.286764e+05	11.375469	0.362086	1.103718	
min	1.105364e+06	19.000000	1.000000	1.000000	
25%	1.321398e+06	27.000000	1.000000	2.000000	
50%	1.529114e+06	33.000000	1.000000	3.000000	
75%	1.707752e+06	42.000000	1.000000	4.000000	
max	1.903505e+06	75.000000	2.000000	4.000000	

Statistical Inferences

- Min `age` is 19 & Max is 75.
- Median `age` of applicant is 35 years and median `Months_loan_taken_for` is 20.
- 25% of the applicant is aged below 27.
- Another 25% is aged above 42 and remaining in between these ages.
- Max of `Number_of_dependents` is 2.
- Max `Principal_loan_amount` is 1.842400e+07 (1.84 Cr.) & Min is 2.500000e+05 (2.5 Lakh).
- Mean/Average `Principal_loan_amount` is 3.271258e+06 (32.7 Lakh).

Check Datatypes in the dataset

In [10]:
```
# Check Null and Dtypes
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1000 entries, 0 to 999
Data columns (total 27 columns):
 #   Column                                                Non-Null Count  Dtype 
---  ------                                                --------------  ----- 
 0   applicant_id                                          1000 non-null   int64 
 1   Primary_applicant_age_in_years                        1000 non-null   int64 
 2   Gender                                                1000 non-null   object
 3   Marital_status                                        1000 non-null   object
 4   Number_of_dependents                                  1000 non-null   int64 
 5   Housing                                               1000 non-null   object
 6   Years_at_current_residence                            1000 non-null   int64 
 7   Employment_status                                     1000 non-null   object
 8   Has_been_employed_for_at_least                        938 non-null    object
 9   Has_been_employed_for_at_most                         747 non-null    object
 10  Telephone                                             404 non-null    object
 11  Foreign_worker                                        1000 non-null   int64 
 12  Savings_account_balance                               817 non-null    object
 13  Balance_in_existing_bank_account_(lower_limit_of_bucket)  332 non-null    object
 14  Balance_in_existing_bank_account_(upper_limit_of_bucket)  543 non-null    object
 15  loan_application_id                                   1000 non-null   object
 16  Months_loan_taken_for                                 1000 non-null   int64 
 17  Purpose                                               988 non-null    object
 18  Principal_loan_amount                                 1000 non-null   int64 
 19  EMI_rate_in_percentage_of_disposable_income           1000 non-null   int64 
 20  Property                                              846 non-null    object
 21  Has_coapplicant                                       1000 non-null   int64 
 22  Has_guarantor                                         1000 non-null   int64 
 23  Other_EMI_plans                                       186 non-null    object
 24  Number_of_existing_loans_at_this_bank                 1000 non-null   int64 
 25  Loan_history                                          1000 non-null   object
 26  high_risk_applicant                                   1000 non-null   int64 
dtypes: int64(12), object(15)
memory usage: 218.8+ KB
```

3. EXPLORING DATA

In [11]:
```
# define numerical & categorical columns
numeric_features = [feature for feature in df.columns if df[feature].dtype != 'O']
categorical_features = [feature for feature in df.columns if df[feature].dtype == 'O']

# print columns
print('We have {} numerical features : \n{}'.format(len(numeric_features), numeric_features
print('\nWe have {} categorical features : \n{}'.format(len(categorical_features), categor
```

```
We have 12 numerical features :
['applicant_id', 'Primary_applicant_age_in_years', 'Number_of_dependents', 'Years_at_curr
ent_residence', 'Foreign_worker', 'Months_loan_taken_for', 'Principal_loan_amount', 'EMI_
rate_in_percentage_of_disposable_income', 'Has_coapplicant', 'Has_guarantor', 'Number_of_
existing_loans_at_this_bank', 'high_risk_applicant']

We have 15 categorical features :
['Gender', 'Marital_status', 'Housing', 'Employment_status', 'Has_been_employed_for_at_le
ast', 'Has_been_employed_for_at_most', 'Telephone', 'Savings_account_balance', 'Balance_i
n_existing_bank_account_(lower_limit_of_bucket)', 'Balance_in_existing_bank_account_(uppe
r_limit_of_bucket)', 'loan_application_id', 'Purpose', 'Property', 'Other_EMI_plans', 'Lo
an_history']
```

Proportion of count data on categorical columns

In [12]:
```python
for col in categorical_features:
    print(df[col].value_counts(normalize=True) * 100)
    print('--'*50)
```

```
male      69.0
female    31.0
Name: Gender, dtype: float64
-----------------------------------------------------------------------------------------
-----------
single                         54.8
divorced/separated/married    31.0
married/widowed                 9.2
divorced/separated              5.0
Name: Marital_status, dtype: float64
-----------------------------------------------------------------------------------------
-----------
own         71.3
rent        17.9
for free    10.8
Name: Housing, dtype: float64
-----------------------------------------------------------------------------------------
-----------
skilled employee / official                                                   63.0
unskilled - resident                                                          20.0
management / self-employed / highly qualified employee / officer    14.8
unemployed / unskilled - non-resident                                          2.2
Name: Employment_status, dtype: float64
-----------------------------------------------------------------------------------------
-----------
1 year     36.140725
7 years    26.972281
4 years    18.550107
0 year     18.336887
Name: Has_been_employed_for_at_least, dtype: float64
-----------------------------------------------------------------------------------------
-----------
4 years    45.381526
7 years    23.293173
1 year     23.025435
0 year      8.299866
Name: Has_been_employed_for_at_most, dtype: float64
-----------------------------------------------------------------------------------------
-----------
Registered under the applicant's name    100.0
Name: Telephone, dtype: float64
-----------------------------------------------------------------------------------------
-----------
Low          73.806610
Medium       12.607099
High          7.711138
Very high     5.875153
Name: Savings_account_balance, dtype: float64
-----------------------------------------------------------------------------------------
-----------
0        81.024096
2 lac    18.975904
Name: Balance_in_existing_bank_account_(lower_limit_of_bucket), dtype: float64
-----------------------------------------------------------------------------------------
-----------
0        50.460405
```

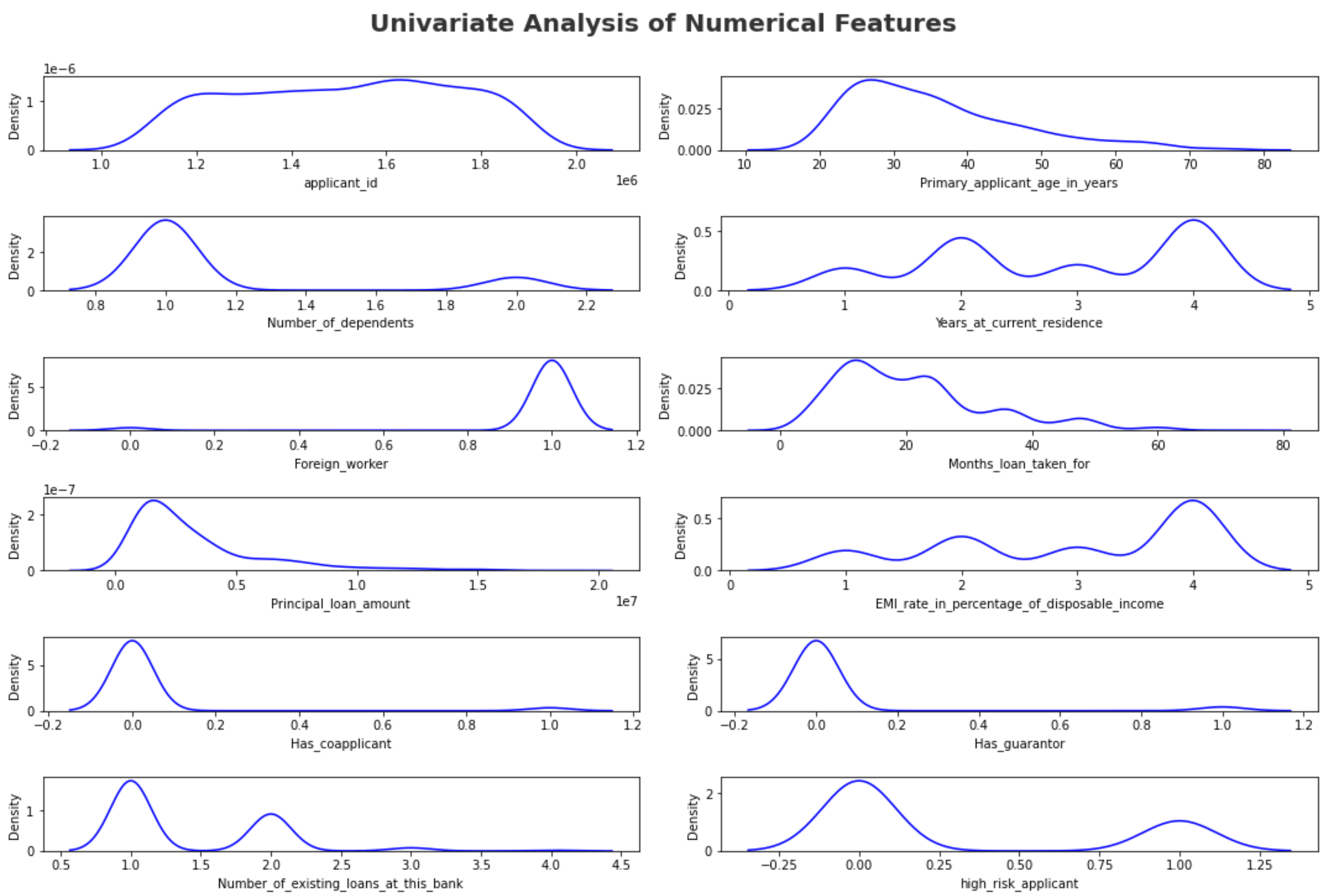
```
2 lac    49.539595
Name: Balance_in_existing_bank_account_(upper_limit_of_bucket), dtype: float64
------------------------------------------------------------------------------------------
-----------
d68d975e-edad-11ea-8761-1d6f9c1ff461    0.1
d68f0dd2-edad-11ea-8785-076f1a6b0e1d    0.1
d68f06d4-edad-11ea-8933-08c4e91e1cae    0.1
d68f0760-edad-11ea-9800-185713046169    0.1
d68f07ec-edad-11ea-b6db-3496b8dbd5c8    0.1
                                       ...
d68e4d0c-edad-11ea-ae79-3a47e5e3c803    0.1
d68e4d98-edad-11ea-acca-3ea777d761b0    0.1
d68e4e24-edad-11ea-9c36-4de81fb02fb0    0.1
d68e4ea6-edad-11ea-9dd8-15c117e65378    0.1
d68fbdae-edad-11ea-a2ea-1c661d77d225    0.1
Name: loan_application_id, Length: 1000, dtype: float64
------------------------------------------------------------------------------------------
-----------
electronic equipment    28.340081
new vehicle             23.684211
FF&E                    18.319838
used vehicle            10.425101
business                 9.817814
education                5.060729
repair costs             2.226721
domestic appliances      1.214575
career development       0.910931
Name: Purpose, dtype: float64
------------------------------------------------------------------------------------------
-----------
car or other                                            39.243499
real estate                                             33.333333
building society savings agreement/life insurance    27.423168
Name: Property, dtype: float64
------------------------------------------------------------------------------------------
-----------
bank      74.731183
stores    25.268817
Name: Other_EMI_plans, dtype: float64
------------------------------------------------------------------------------------------
-----------
existing loans paid back duly till now     53.0
critical/pending loans at other banks      29.3
delay in paying off loans in the past       8.8
all loans at this bank paid back duly       4.9
no loans taken/all loans paid back duly     4.0
Name: Loan_history, dtype: float64
------------------------------------------------------------------------------------------
-----------
```

Univariate Analysis

- The term univariate analysis refers to the analysis of one variable prefix “uni” means “one.” The purpose of univariate analysis is to understand the distribution of values for a single variable.

Numerical Features

In [13]:
```python
plt.figure(figsize=(15, 10))
plt.suptitle('Univariate Analysis of Numerical Features', fontsize=20, fontweight='bold', a

for i in range(0, len(numeric_features)):
    plt.subplot(6, 2, i+1)
    sb.kdeplot(x=df[numeric_features[i]], color='blue')
    plt.xlabel(numeric_features[i])
    plt.tight_layout()

# save plot
# plt.savefig('./images/Univariate_Num.png')
```



Report

1. `applicant_id` is a primary key which have no importance.

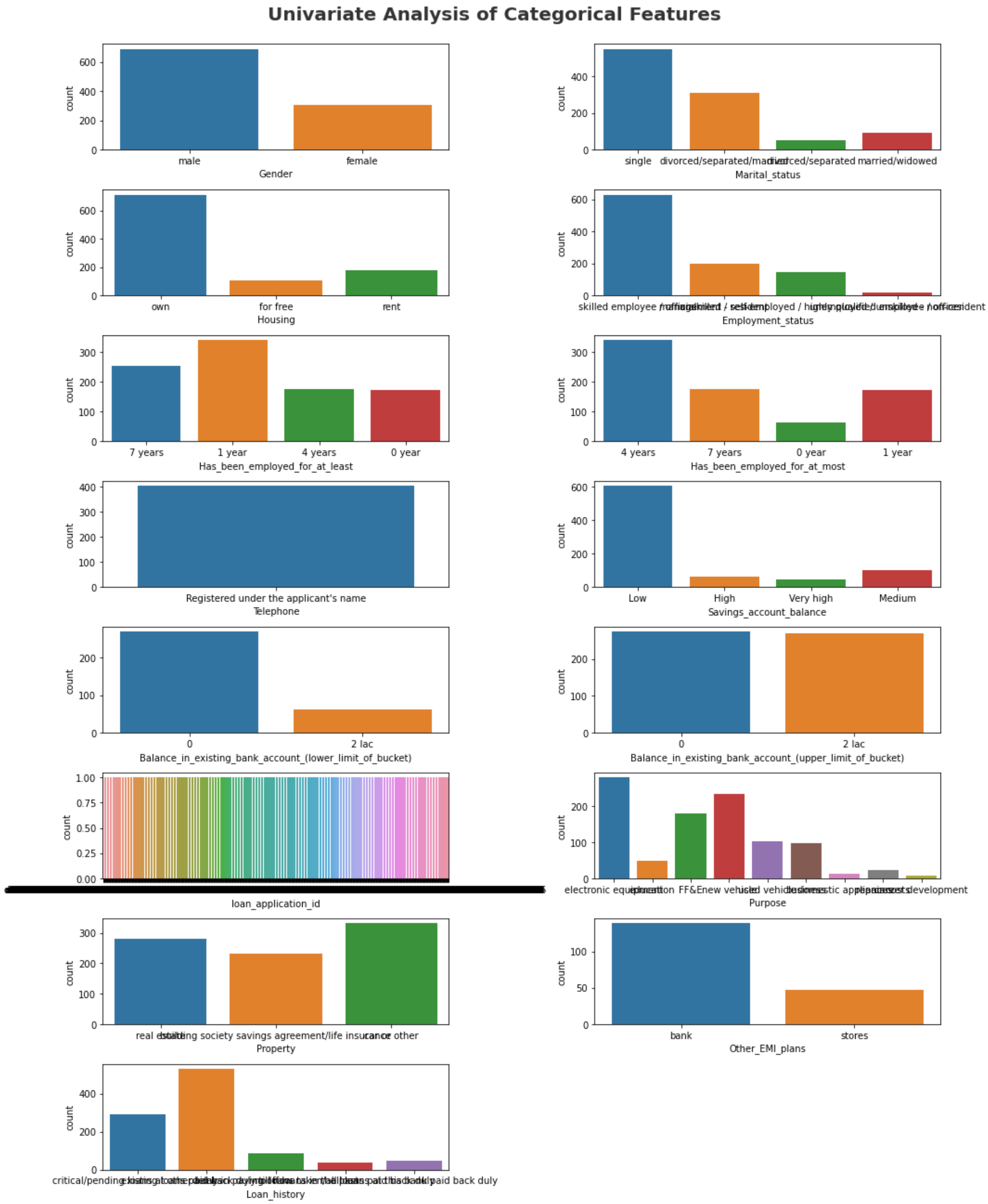
2. Below are the only continuous features -
    - `Primary_applicant_age_in_years`
    - `Months_loan_taken_for`
    - `Principal_loan_amount`

3. Below are the categorical features but they are encoded -
    - `Number_of_dependents`
    - `Years_at_current_residence`
    - `Foreign_worker`
    - `EMI_rate_in_percentage_of_disposable_income`
    - `Has_coapplicant`
    - `Has_guarantor`
    - `Number_of_existing_loans_at_this_bank`

- `high_risk_applicant`

Categorical Features

In [14]:
```
# categorical columns
plt.figure(figsize=(15, 18))
plt.suptitle('Univariate Analysis of Categorical Features', fontsize=20, fontweight='bold'

# Adjusting space between/among subplots
plt.subplots_adjust(hspace=0.2)

for i in range(0, len(categorical_features)):
    plt.subplot(8, 2, i+1)
    sb.countplot(x=df[categorical_features[i]])
    plt.xlabel(categorical_features[i])
    plt.tight_layout()

# save plot
# plt.savefig('./images/Univariate_Cat.png')
```



- `loan_application_id` have no importance.
- Most of the loan applicants are male (as per `Gender`) and single (as per the `Marital_status`), they own house (as per `Housing`).
- Most of the loan applicants are skilled employee / official (as per `Employment_status`).
- Most of the loan applicants taking loan for purchasing electronic equipment & new vehicle (as per `Purpose`).

Multivariate Analysis

- Multivariate analysis is the analysis of more than one variable.

In [15]:
```
discrete_features = [feature for feature in numeric_features if (len(df[feature].unique())<

continuous_features = [feature for feature in numeric_features if len(df[feature].unique()]

encoded_categorical = [feature for feature in numeric_features if len(df[feature].unique()]

print('We have {} discrete features : {}'.format(len(discrete_features), discrete_features]
print('\nWe have {} continuous_features : {}'.format(len(continuous_features), continuous_f
print('\nWe have {} encoded_categorical : {}'.format(len(encoded_categorical), encoded_cate
```

```
We have 0 discrete features : []

We have 4 continuous_features : ['applicant_id', 'Primary_applicant_age_in_years', 'Month
s_loan_taken_for', 'Principal_loan_amount']

We have 8 encoded_categorical : ['Number_of_dependents', 'Years_at_current_residence', 'F
oreign_worker', 'EMI_rate_in_percentage_of_disposable_income', 'Has_coapplicant', 'Has_gu
arantor', 'Number_of_existing_loans_at_this_bank', 'high_risk_applicant']
```

- There are no discrete numerical features

In [16]:
```
categorical_features = categorical_features + encoded_categorical
print(categorical_features)
```

```
['Gender', 'Marital_status', 'Housing', 'Employment_status', 'Has_been_employed_for_at_le
ast', 'Has_been_employed_for_at_most', 'Telephone', 'Savings_account_balance', 'Balance_i
n_existing_bank_account_(lower_limit_of_bucket)', 'Balance_in_existing_bank_account_(uppe
r_limit_of_bucket)', 'loan_application_id', 'Purpose', 'Property', 'Other_EMI_plans', 'Lo
an_history', 'Number_of_dependents', 'Years_at_current_residence', 'Foreign_worker', 'EMI
_rate_in_percentage_of_disposable_income', 'Has_coapplicant', 'Has_guarantor', 'Number_of
_existing_loans_at_this_bank', 'high_risk_applicant']
```

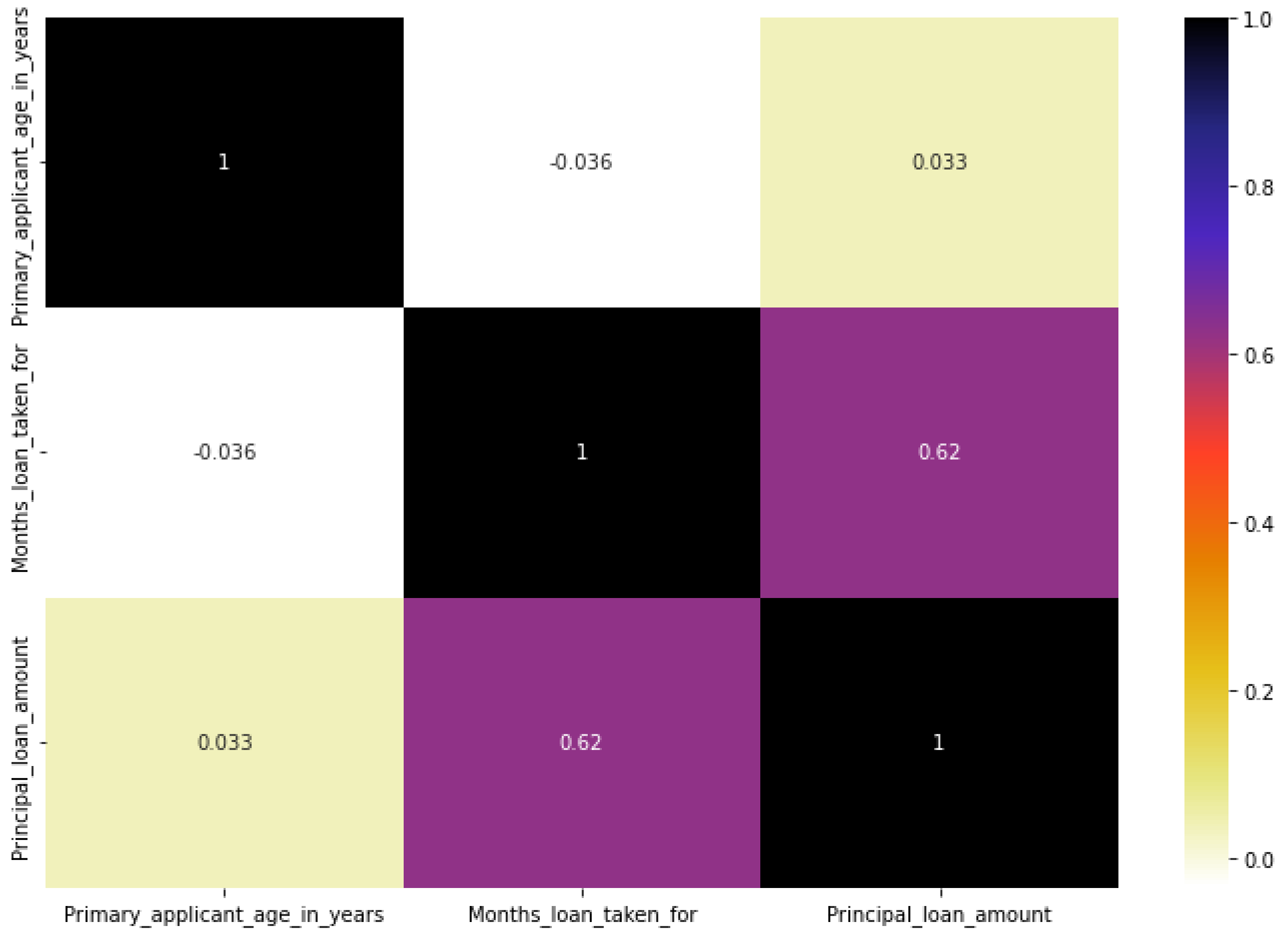
Check Multicollinearity in Numerical features

In [17]:
```
df[(list(df[continuous_features])[1:])].corr()
```

Out[17]:

	Primary_applicant_age_in_years	Months_loan_taken_for	Principal_loan_amount
Primary_applicant_age_in_years	1.000000	-0.036136	0.032716
Months_loan_taken_for	-0.036136	1.000000	0.624984
Principal_loan_amount	0.032716	0.624984	1.000000

In [18]:
```
plt.figure(figsize = (12, 8))
cont_features = continuous_features.copy()
cont_features.remove('applicant_id')
sb.heatmap(df[cont_features].corr(), cmap="CMRmap_r", annot=True)
plt.show()
```



Insight

- `Months_loan_taken_for` & `Principal_loan_amount` are slightly positively correlated, for the same the reason may be that highter the loan principle amount have higher loan tenure. We can not remove one of these feature as it may lead to loss vital imformation.
- For other features, there is no multicollinearity present in the dataset since their is no correlation between the features.

Check Multicollinearity for Categorical features

- **A chi-squared test (also chi-square or χ2 test) is a statistical hypothesis test that is valid to**

perform when the test statistic is chi-squared distributed under the null hypothesis, specifically Pearson's chi-squared test

- A chi-square statistic is one way to show a relationship between two categorical variables.
- Here we test correlation of Categorical columns with Target column i.e `high_risk_applicant` .

Null Hypothesis (H_0): The Feature is independent of target column (No-Correlation)

Alternative Hypothesis (H_1): The Feature and Target column are not independent (Correlated)

In [19]:
```python
# from scipy.stats import chi2_contingency
chi2_test = []

try:
    for feature in categorical_features:
        if chi2_contingency(pd.crosstab(df['high_risk_applicant'], df[feature]))[1] < 0.05
            chi2_test.append('Reject Null Hypothesis')
        else:
            chi2_test.append('Fail to Reject Null Hypothesis')
except Exception as e:
    print('Error: ', str(e))

result = pd.DataFrame(data=[categorical_features, chi2_test]).T
result.columns = ['Column', 'Hypothesis Result']
result
```

Out[19]:

	Column	Hypothesis Result
0	Gender	Reject Null Hypothesis
1	Marital_status	Reject Null Hypothesis
2	Housing	Reject Null Hypothesis
3	Employment_status	Fail to Reject Null Hypothesis
4	Has_been_employed_for_at_least	Reject Null Hypothesis
5	Has_been_employed_for_at_most	Reject Null Hypothesis
6	Telephone	Fail to Reject Null Hypothesis
7	Savings_account_balance	Reject Null Hypothesis
8	Balance_in_existing_bank_account_(lower_limit_...	Reject Null Hypothesis
9	Balance_in_existing_bank_account_(upper_limit_...	Reject Null Hypothesis
10	loan_application_id	Fail to Reject Null Hypothesis
11	Purpose	Reject Null Hypothesis
12	Property	Reject Null Hypothesis
13	Other_EMI_plans	Fail to Reject Null Hypothesis
14	Loan_history	Reject Null Hypothesis
15	Number_of_dependents	Fail to Reject Null Hypothesis
16	Years_at_current_residence	Fail to Reject Null Hypothesis
17	Foreign_worker	Reject Null Hypothesis
18	EMI_rate_in_percentage_of_disposable_income	Fail to Reject Null Hypothesis
19	Has_coapplicant	Fail to Reject Null Hypothesis
20	Has_guarantor	Fail to Reject Null Hypothesis
21	Number_of_existing_loans_at_this_bank	Fail to Reject Null Hypothesis
22	high_risk_applicant	Reject Null Hypothesis

Report

- From the above, we can observe that below feautes are independent to the target columnn (Not-Correlated with target).
  - Employment_status

- Telephone
- loan_application_id
- Other_EMI_plans
- Number_of_dependents
- Years_at_current_residence
- EMI_rate_in_percentage_of_disposable_income
- Has_coapplicant
- Has_guarantor
- Number_of_existing_loans_at_this_bank

Checking Null Values

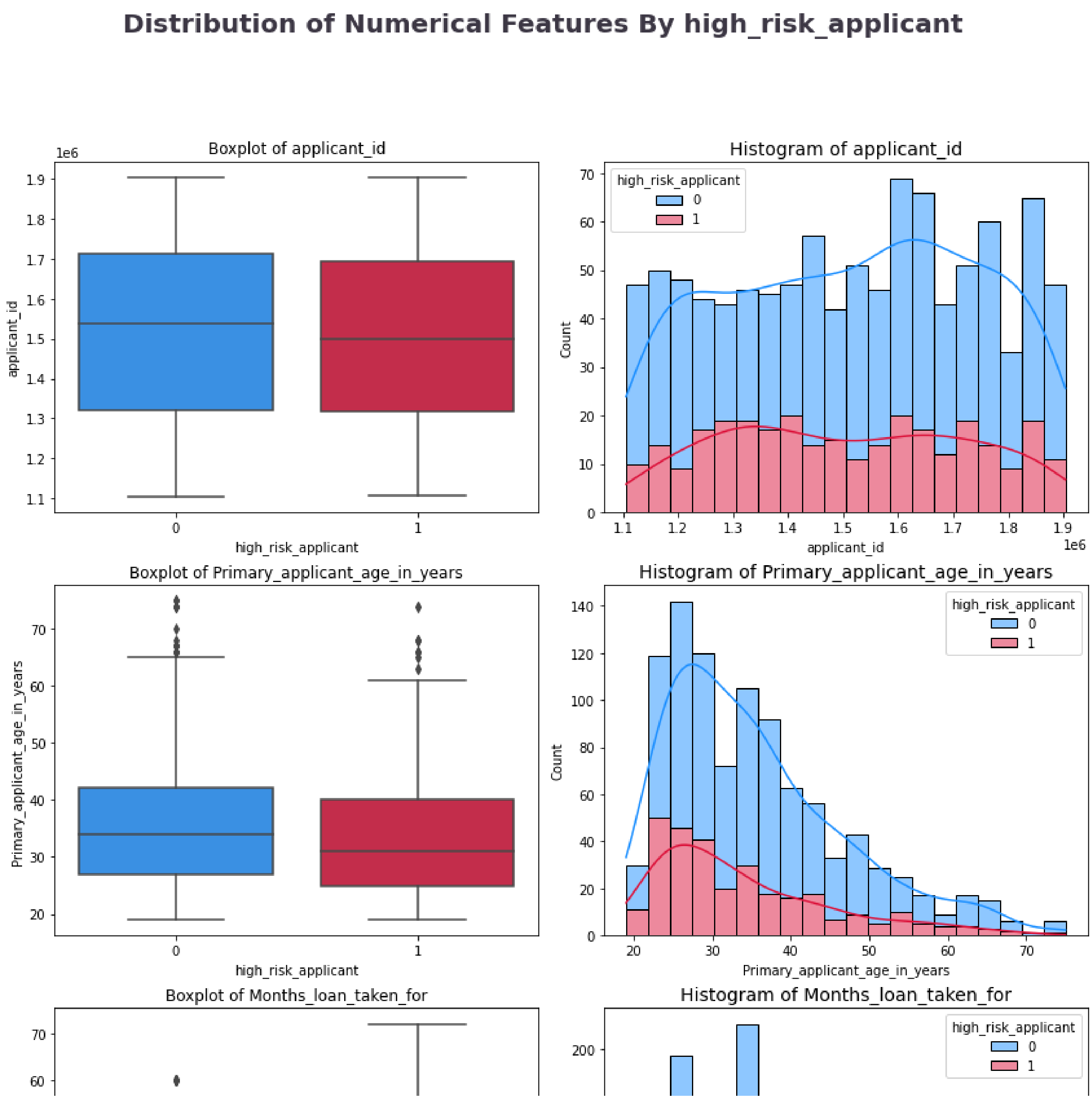
In [20]:
```
df.isnull().sum().sort_values(ascending=True)
```

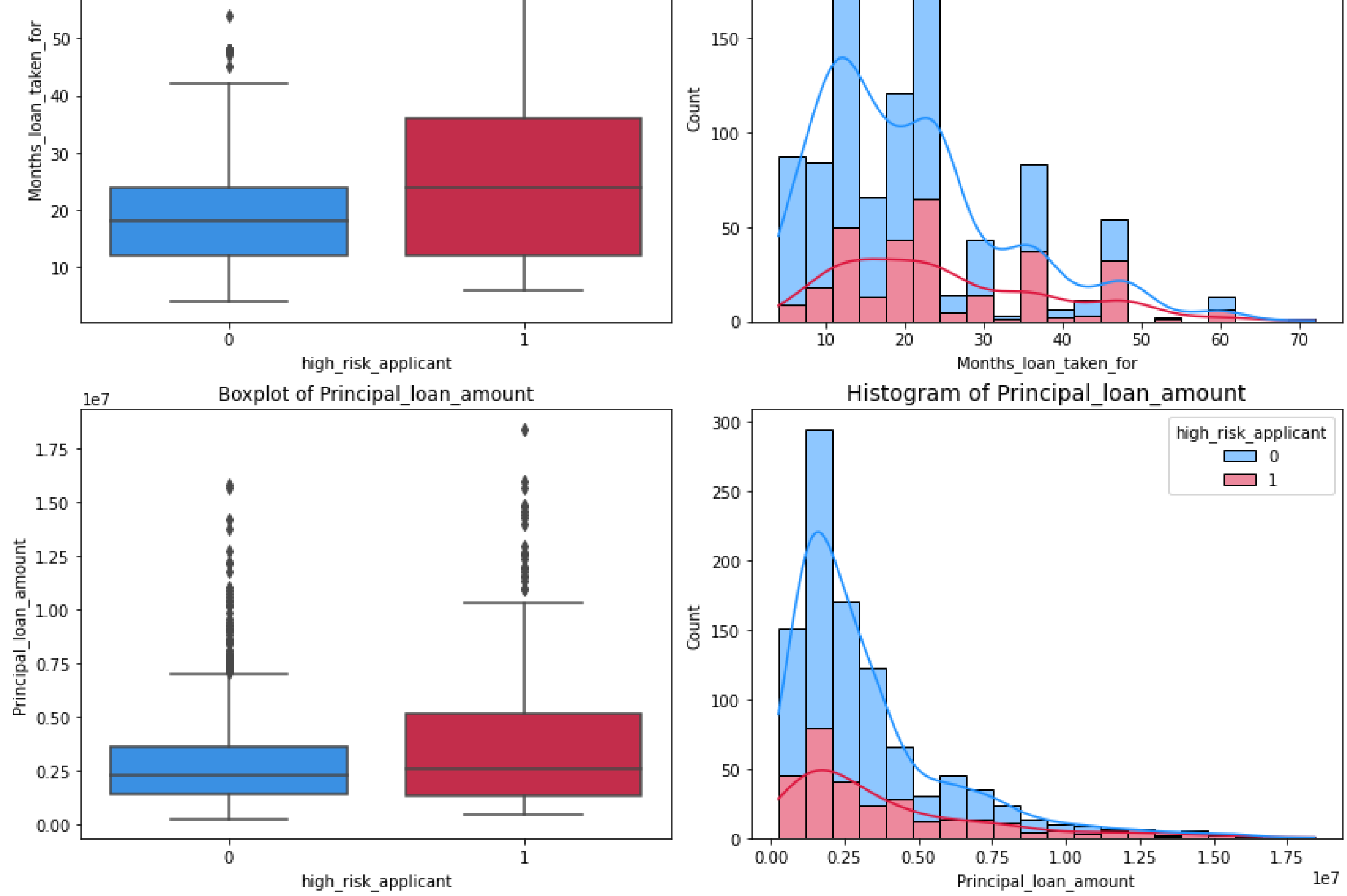
Out[20]:
```
applicant_id                                        0
Number_of_existing_loans_at_this_bank               0
Has_guarantor                                       0
Has_coapplicant                                     0
EMI_rate_in_percentage_of_disposable_income         0
Principal_loan_amount                               0
Months_loan_taken_for                               0
loan_application_id                                 0
Loan_history                                        0
Foreign_worker                                      0
high_risk_applicant                                 0
Employment_status                                   0
Years_at_current_residence                          0
Housing                                             0
Number_of_dependents                                0
Marital_status                                      0
Gender                                              0
Primary_applicant_age_in_years                      0
Purpose                                            12
Has_been_employed_for_at_least                     62
Property                                          154
Savings_account_balance                           183
Has_been_employed_for_at_most                     253
Balance_in_existing_bank_account_(upper_limit_of_bucket)     457
Telephone                                         596
Balance_in_existing_bank_account_(lower_limit_of_bucket)     668
Other_EMI_plans                                   814
dtype: int64
```

In [21]:
```
# df.isnull().mean().sort_values(ascending=True)
```

We have missing values in which we have to deal with

In [22]:
```python
clr1 = ['#1E90FF', '#DC143C']
fig, ax = plt.subplots(4, 2, figsize=(12,20))
fig.suptitle('Distribution of Numerical Features By high_risk_applicant',
             color='#3C3744', fontsize=20, fontweight='bold', ha='center')
plt.subplots_adjust(hspace=0.2)  # Adjusting space between/among subplots

try:
    for i, col in enumerate(continuous_features):
        sb.boxplot(data=df, x='high_risk_applicant', y=col,  palette=clr1, ax=ax[i,0])
        ax[i,0].set_title(f'Boxplot of {col}', fontsize=12)
        sb.histplot(data=df, x=col, hue='high_risk_applicant', bins=20,
                    kde=True, multiple='stack', palette=clr1, ax=ax[i,1])
        ax[i,1].set_title(f'Histogram of {col}', fontsize=14)
except Exception as e:
    print('Error: ', str(e))

fig.tight_layout()
fig.subplots_adjust(top=0.90)
# plt.savefig('images/multivariate_num.png')
```





Report

- In the `applicant_id` column has unique value for each row, it can be ignored as a feature.
- Minimum `age` group people have seems to have low credit risk.
- Higher the `Months_loan_taken_for` higher will be the chance of credit risk.
- Higher the `Principal_loan_amount` have some credit risk.

Initial Analysis Report

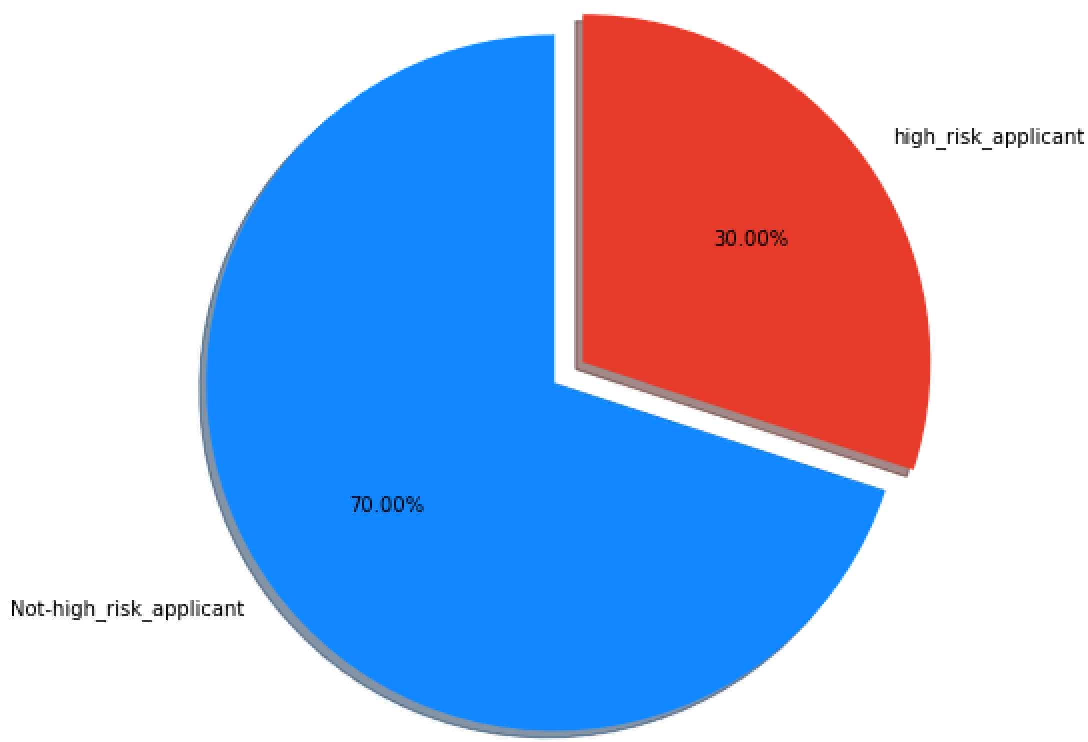
- **The `high_risk_applicant` column is the target to predict.**
- **The `applicant_id` & `loan_application_id` column can be dropped because each row has unique values.**
- **There are missing values present in below features -**
  - `Purpose` 12
  - `Has_been_employed_for_at_least` 62
  - `Property` 154
  - `Savings_account_balance` 183
  - `Has_been_employed_for_at_most` 253
  - `Balance_in_existing_bank_account_(upper_limit_of_bucket)` 457
  - `Telephone` 596
  - `Balance_in_existing_bank_account_(lower_limit_of_bucket)` 668
  - `Other_EMI_plans` 814
- **`Telephone` column isn't a useful, also not correlated with `high_risk_applicant` (Target Column), hence this can be dropped.**
- **`Other_EMI_plans` column have more than 80% of missing value, hence this can be dropped.**

4. Visualization

4.1 Visualize the Target Feature

In [23]:
```
df1 = df.copy()
df1['high_risk_applicant'] = np.where((df.high_risk_applicant == 1),'high_risk_applicant',
```

In [24]:
```
percentage = df1.high_risk_applicant.value_counts(normalize=True)*100
label = ["Not-high_risk_applicant", "high_risk_applicant"]

# Plot PieChart with Ploty library
fig, ax = plt.subplots(figsize =(15, 8))
explode = (0, 0.1)
colors = ['#1188ff', '#e63a2a']
ax.pie(percentage, labels = label, startangle = 90, autopct='%1.2f%%',
       explode=explode, shadow=True, colors=colors)
plt.show()
```



- From the chart it is clear that the Target Variable is Imbalanced

What is imbalanced data?

Imbalanced data are types of data where the target class has an uneven distribution of observations, i.e Here number of Not-high_risk_applicant has more count than the number of high_risk_applicant of the dataset.

4.2 Do Men or Women have more chance of high_risk_applicant?

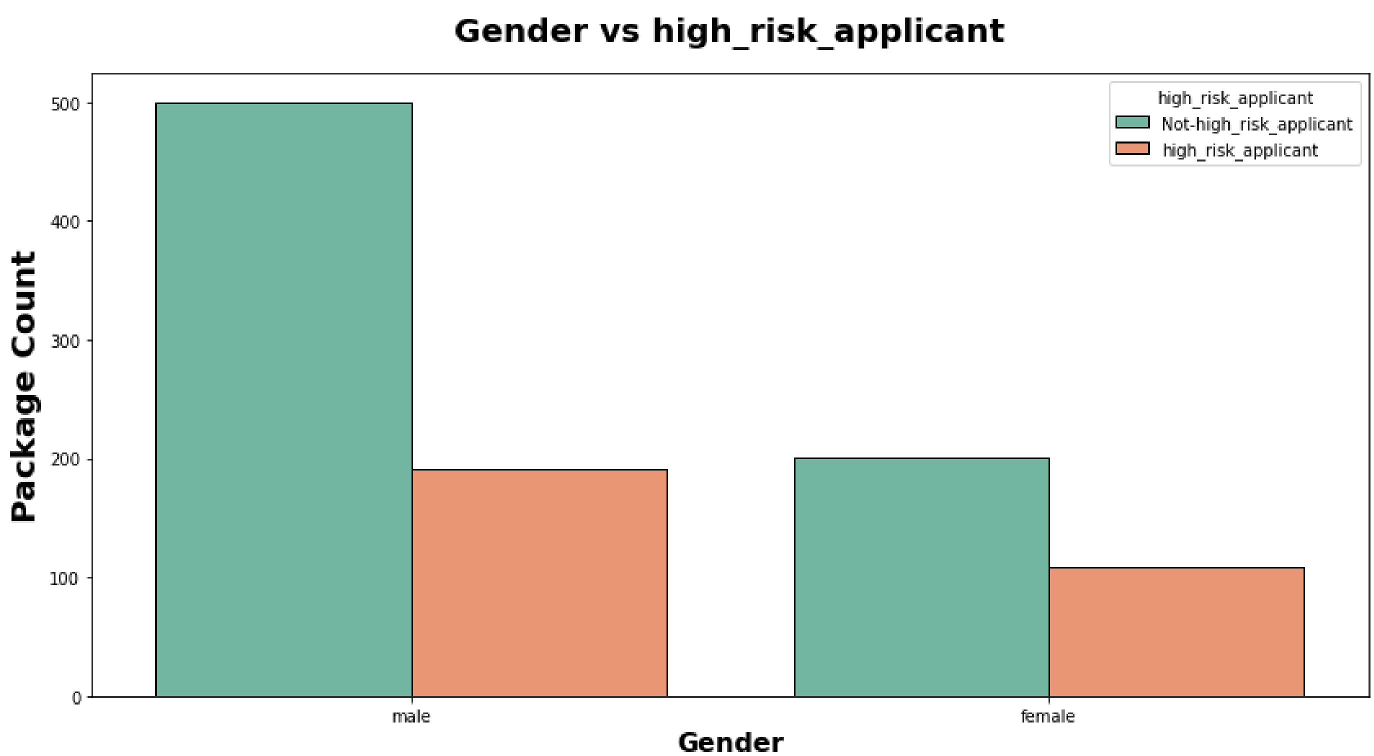
```
In [25]: df1.columns
```

```
Out[25]: Index(['applicant_id', 'Primary_applicant_age_in_years', 'Gender',
       'Marital_status', 'Number_of_dependents', 'Housing',
       'Years_at_current_residence', 'Employment_status',
       'Has_been_employed_for_at_least', 'Has_been_employed_for_at_most',
       'Telephone', 'Foreign_worker', 'Savings_account_balance',
       'Balance_in_existing_bank_account_(lower_limit_of_bucket)',
       'Balance_in_existing_bank_account_(upper_limit_of_bucket)',
       'loan_application_id', 'Months_loan_taken_for', 'Purpose',
       'Principal_loan_amount', 'EMI_rate_in_percentage_of_disposable_income',
       'Property', 'Has_coapplicant', 'Has_guarantor', 'Other_EMI_plans',
       'Number_of_existing_loans_at_this_bank', 'Loan_history',
       'high_risk_applicant'],
      dtype='object')
```

```
In [26]: df1[df1.high_risk_applicant == 'high_risk_applicant'].Gender.value_counts(normalize=True)
```

```
Out[26]: male      0.636667
female    0.363333
Name: Gender, dtype: float64
```

```
In [27]: plt.subplots(figsize=(14,7))
sb.countplot(x="Gender", hue="high_risk_applicant", data=df1, ec = "black", palette="Set2")
plt.title("Gender vs high_risk_applicant", weight="bold",fontsize=20, pad=20)
plt.ylabel("Package Count", weight="bold", fontsize=20)
plt.xlabel("Gender", weight="bold", fontsize=16)
plt.show()
```



insights

- As per the chart there is no much difference between the high_risk_applicant of male and female.
- This Feature has no impact on the Target Variable.

- **Our Insights from Chi2 test is that `Gender` column is not correlated with target column. Which is justified by above chart**

4.3 Are young people more creditworthy?

AGE Category Split

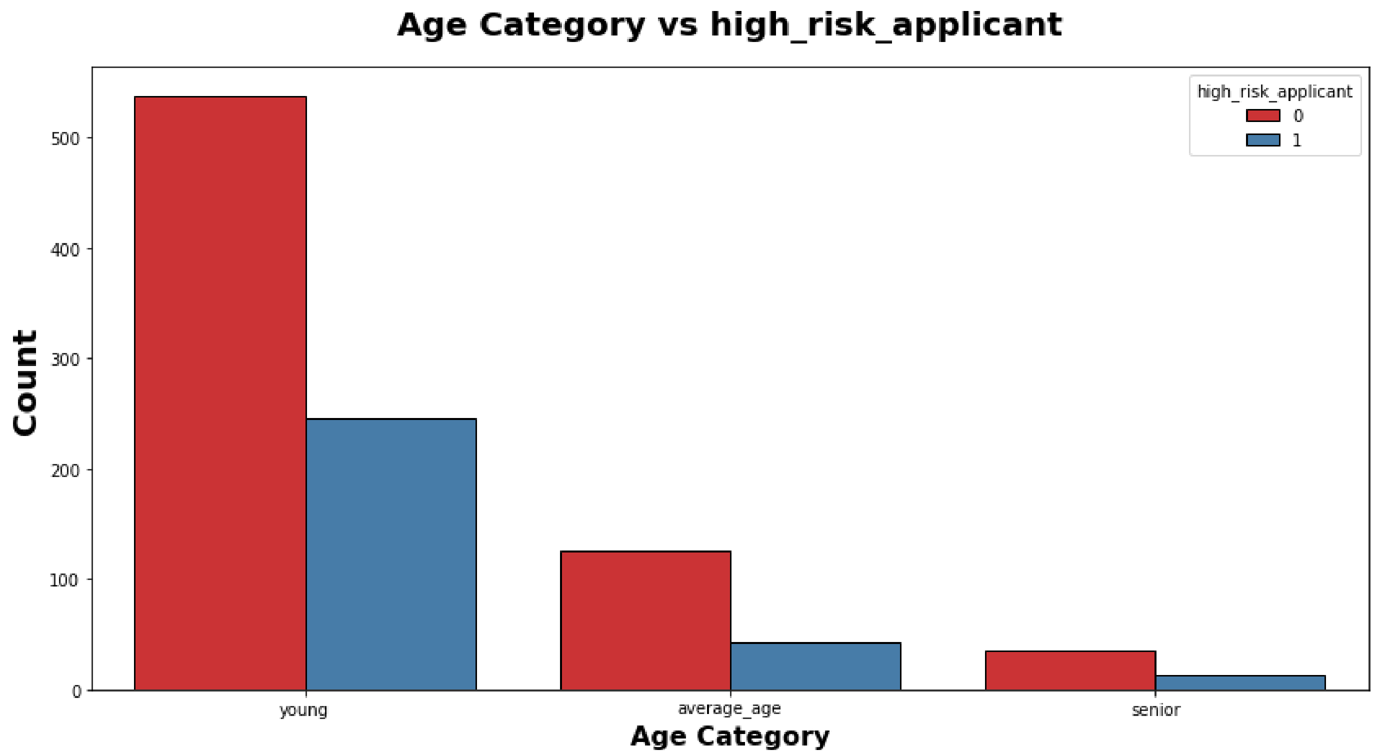
- There is min age is 19 & max is 75.
- Deviding Age into three category as below -
  - young: 19 to 44.
  - average_age: 45 to 60.
  - senior: 60 to 75.

In [28]:
```
bins = [19, 44, 60, 75]
labels = ['young', 'average_age', 'senior']
df2 = df.copy()
df2['age_cat'] = pd.cut(df['Primary_applicant_age_in_years'], bins=bins, labels=labels, rig
age_group = df2.groupby(['age_cat', 'high_risk_applicant'])['applicant_id'].count().reset_i
age_group
```

Out[28]:

	age_cat	high_risk_applicant	count
0	young	0	537
1	young	1	245
2	average_age	0	125
3	average_age	1	42
4	senior	0	36
5	senior	1	13

In [29]:
```
plt.subplots(figsize=(14, 7))
sb.countplot(x="age_cat", hue="high_risk_applicant", data=df2, ec="black", palette="Set1")
plt.title("Age Category vs high_risk_applicant", weight="bold",fontsize=20, pad=20)
plt.ylabel("Count", weight="bold", fontsize=20)
plt.xlabel("Age Category", weight="bold", fontsize=16)
plt.show()
```



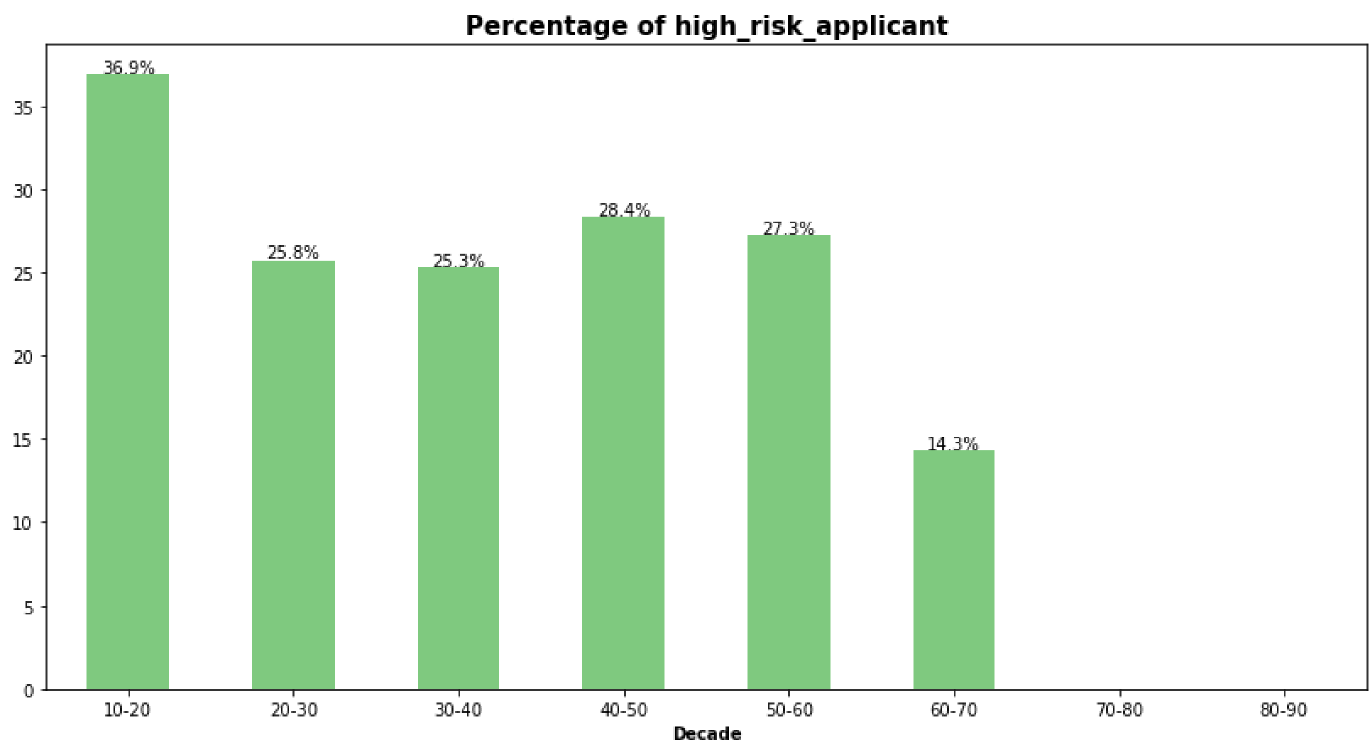
Report:

- `young` age applicant have least chance of the high_risk_applicant i.e. young people seems more creditworthy.
- As per the Chart `senior` age Group has the more chance of heart high_risk_applicant followed by `average_age`.

Percentage of high_risk_applicant applicants with age

In [30]:
```
df2 = df.copy()
bins = [19, 29, 39, 49, 59, 69, 79, 89, 99]
labels = ['10-20', '20-30','30-40','40-50','50-60','60-70','70-80','80-90']
df2['age_group'] = pd.cut(df['Primary_applicant_age_in_years'], bins=bins, labels=labels)

import matplotlib.ticker as mtick

plt.figure(figsize=[14,7])

(100*df2[df2["high_risk_applicant"].isin([1])]['age_group'].value_counts()/df2['age_group']
    kind='bar',stacked=True , colormap='Accent')
plt.title("Percentage of high_risk_applicant" , fontsize = 15, fontweight ='bold')
order1 = (100*df2[df2["high_risk_applicant"].isin([1])]['age_group'].value_counts()/df2['ag

for n in range(order1.shape[0]):
    count = order1[n]
    strt='{:0.1f}%'.format(count)
    plt.text(n, count+0.1, strt, ha='center')

plt.xlabel('Decade', fontweight ='bold')
plt.xticks(rotation=0)
plt.show()
```

```
posx and posy should be finite values
posx and posy should be finite values
posx and posy should be finite values
posx and posy should be finite values
```

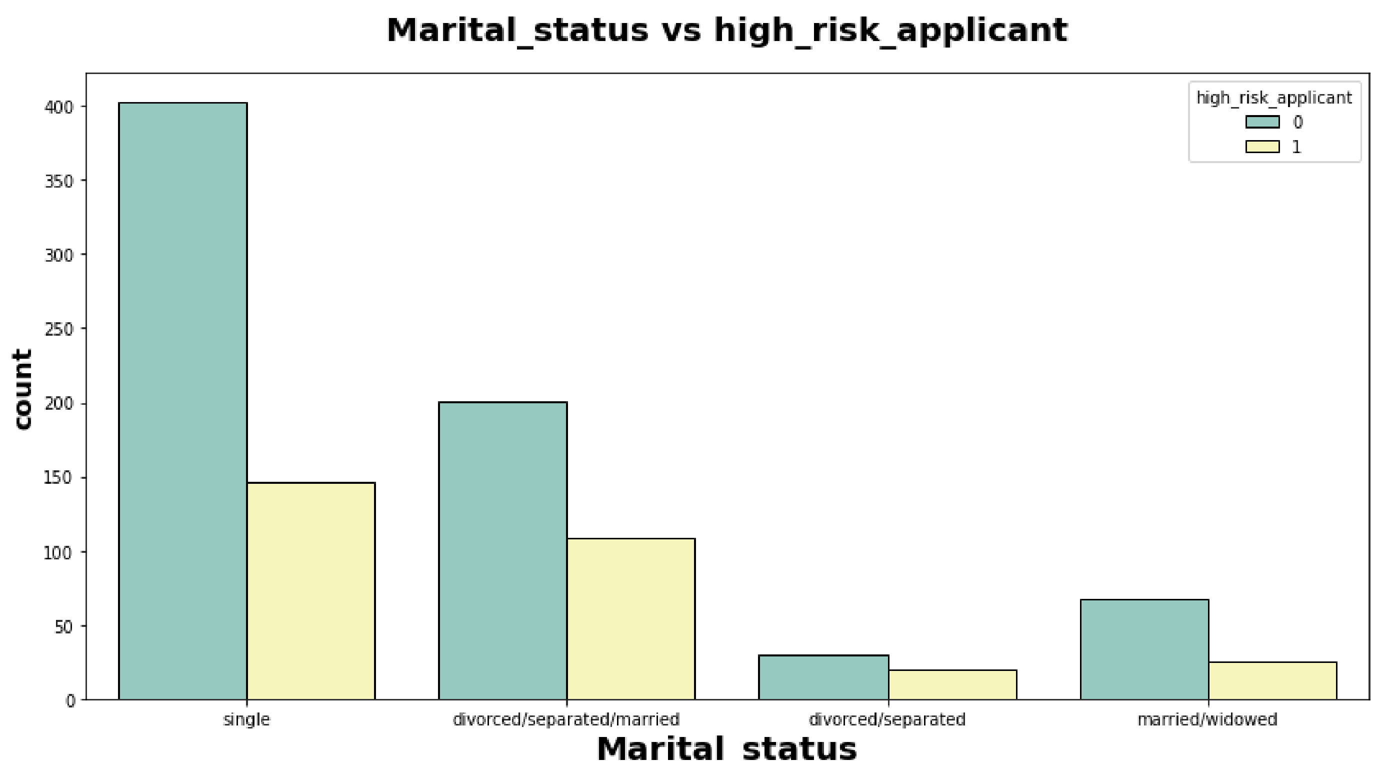


Report

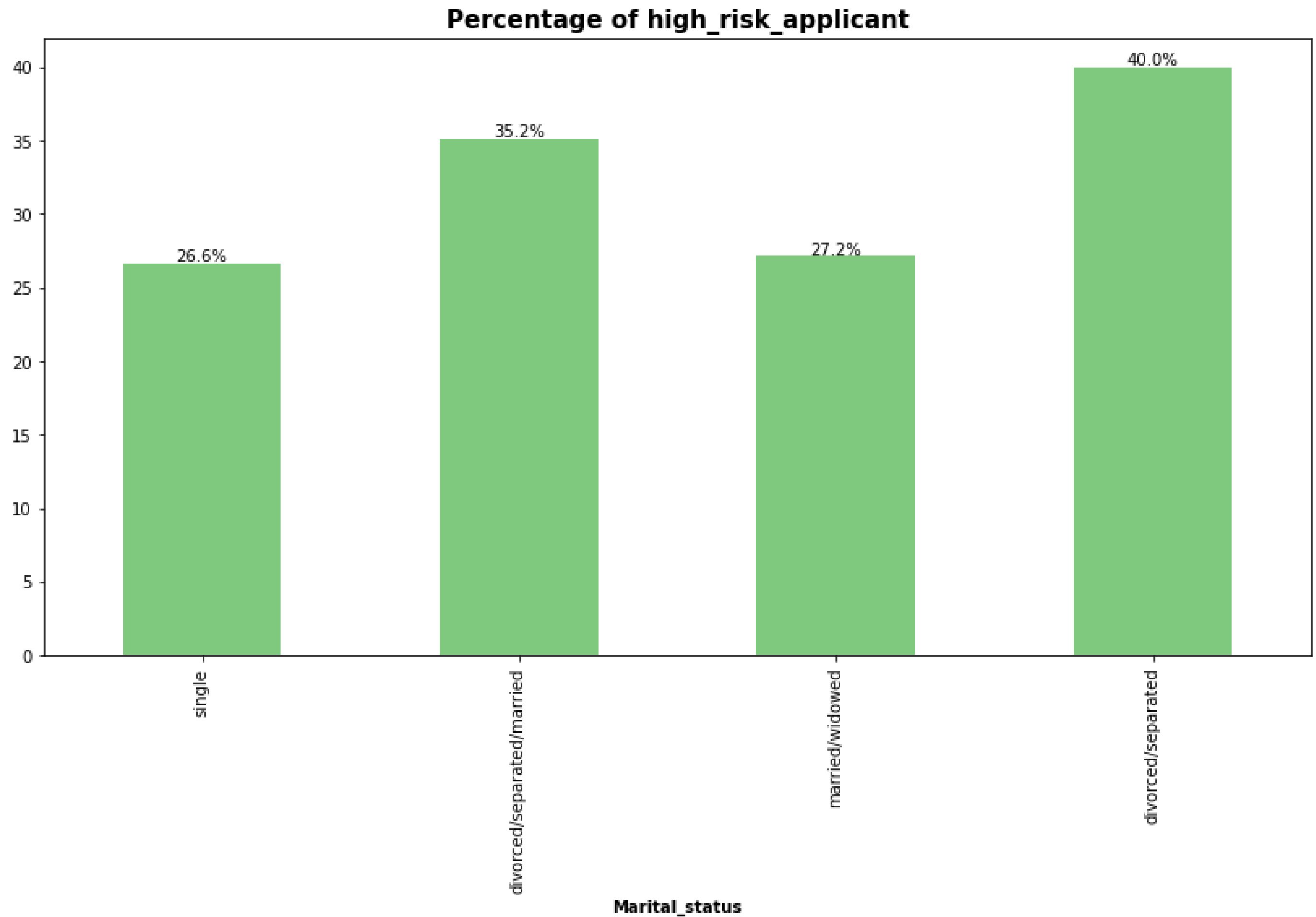
- Surprisingly, it is showing as the age increases there is lower percentage of chance of high_risk_applicant, it doesn't make sense. Not supporting previous statement.

4.4 Does marriage have any effect on the high_risk_applicant

In [31]:
```
plt.subplots(figsize=(14,7))
sb.countplot(x="Marital_status", hue='high_risk_applicant', data=df, ec="black", palette="S
plt.title("Marital_status vs high_risk_applicant", weight="bold", fontsize=20, pad=20)
plt.xlabel("Marital_status", weight="bold", fontsize=20)
plt.ylabel("count", weight="bold", fontsize=16)
plt.show()
```



In [32]:
```
plt.subplots(figsize=(14,7))

(100*df2[df2["high_risk_applicant"].isin([1])]['Marital_status'].value_counts()/df2['Marit
    kind='bar',stacked=True , colormap='Accent')
plt.title("Percentage of high_risk_applicant" , fontsize = 15, fontweight ='bold'  )
order1 = (100*df2[df2["high_risk_applicant"].isin([1])]['Marital_status'].value_counts()/d

for n in range(order1.shape[0]):
    count = order1[n]
    strt='{:0.1f}%'.format(count)
    plt.text(n,count+0.1,strt,ha='center')

plt.xlabel('Marital_status' , fontweight ='bold')
plt.show()
```



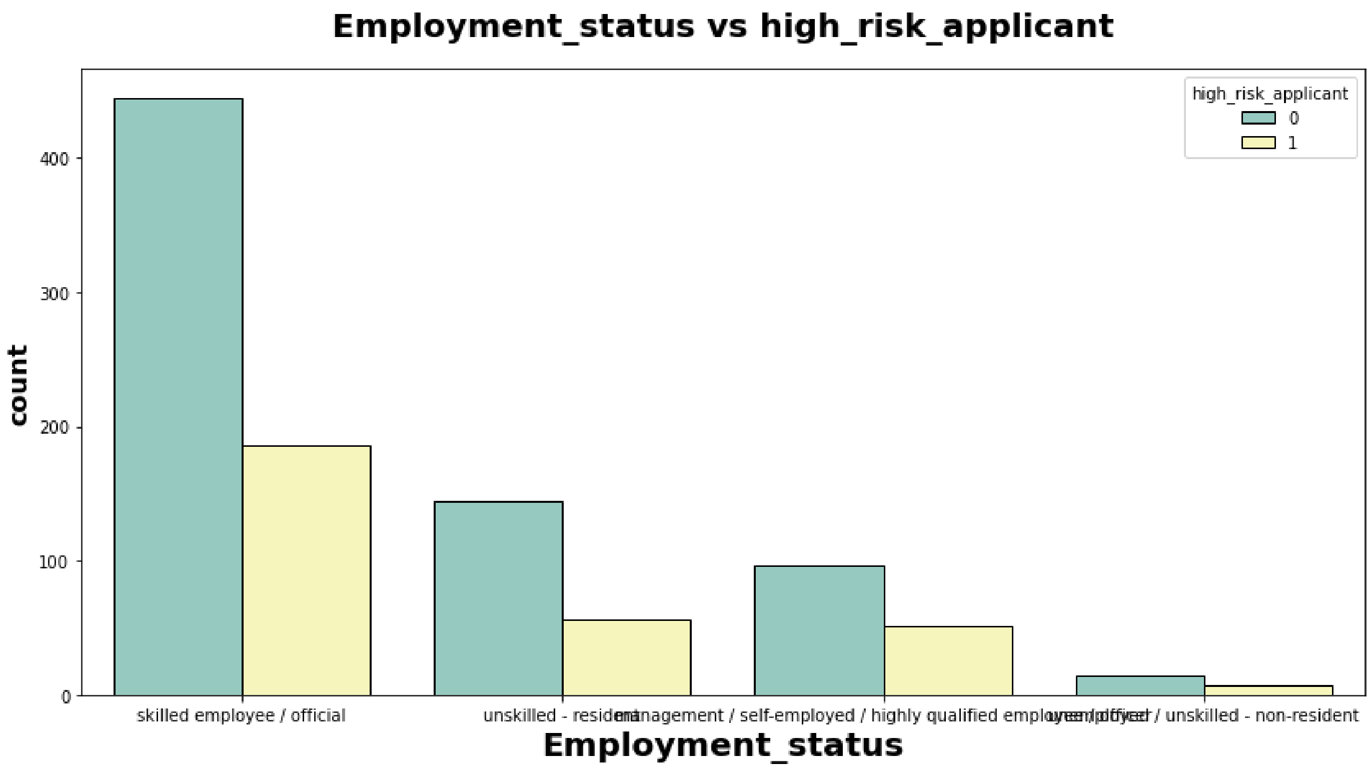
Insights

- `divorced/separated` applicants have high chance of high_risk_applicant.

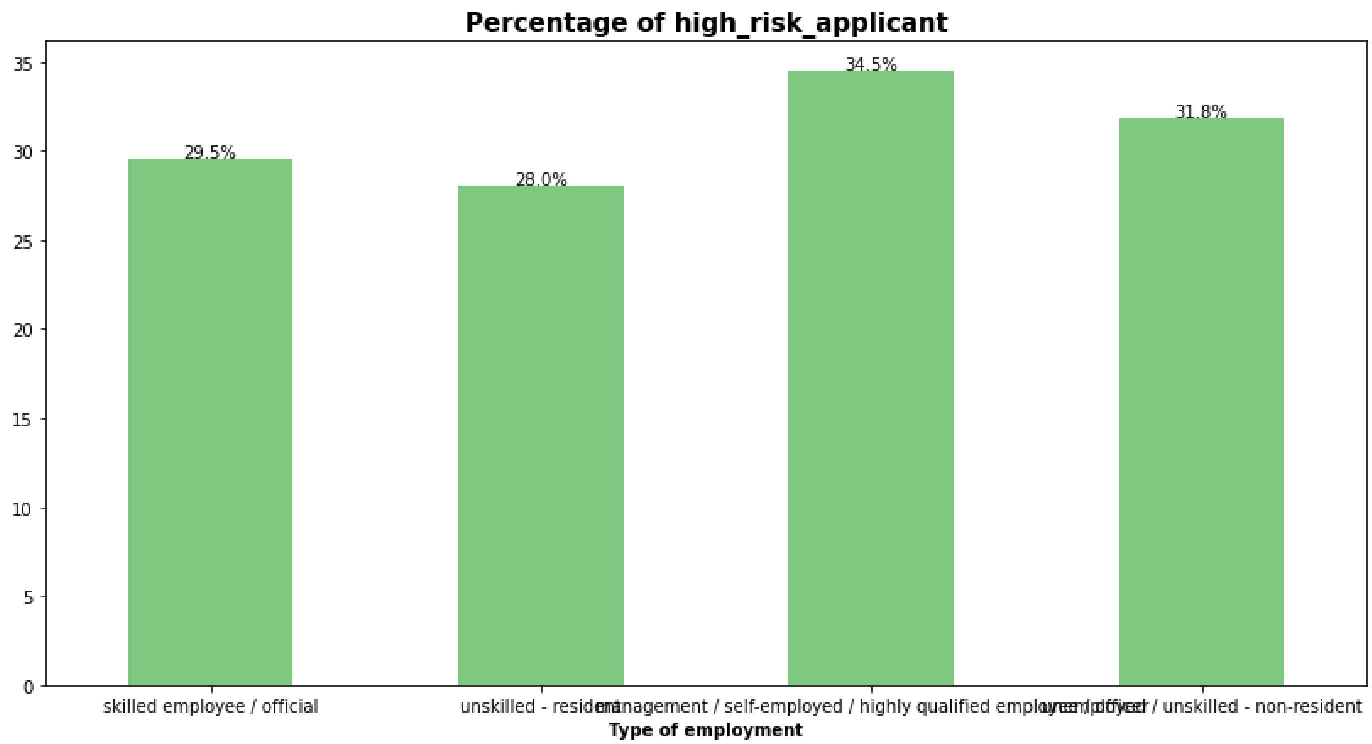
- However also it seems that regardless of the Marital_status, applicants have high percentage of credit risk.

4.5 Employment_status vs high_risk_applicant

In [33]:
```
plt.subplots(figsize=(14,7))
sb.countplot(x="Employment_status", hue='high_risk_applicant', data=df, ec="black", palette
plt.title("Employment_status vs high_risk_applicant", weight="bold",fontsize=20, pad=20)
plt.xlabel("Employment_status", weight="bold", fontsize=20)
plt.ylabel("count", weight="bold", fontsize=16)
plt.show()
```



In [34]:
```
plt.subplots(figsize=(14,7))

(100*df2[df2["high_risk_applicant"].isin([1])]['Employment_status'].value_counts()/df2['Emp
    kind='bar',stacked=True , colormap='Accent' )
plt.title("Percentage of high_risk_applicant" , fontsize = 15, fontweight ='bold'  )
order1 = (100*df2[df2["high_risk_applicant"].isin([1])]['Employment_status'].value_counts()

for n in range(order1.shape[0]):
    count = order1[n]
    strt='{:0.1f}%'.format(count)
    plt.text(n, count+0.1, strt, ha='center')

plt.xlabel('Type of employment', fontweight='bold')
plt.xticks(rotation=0)
plt.show()
```

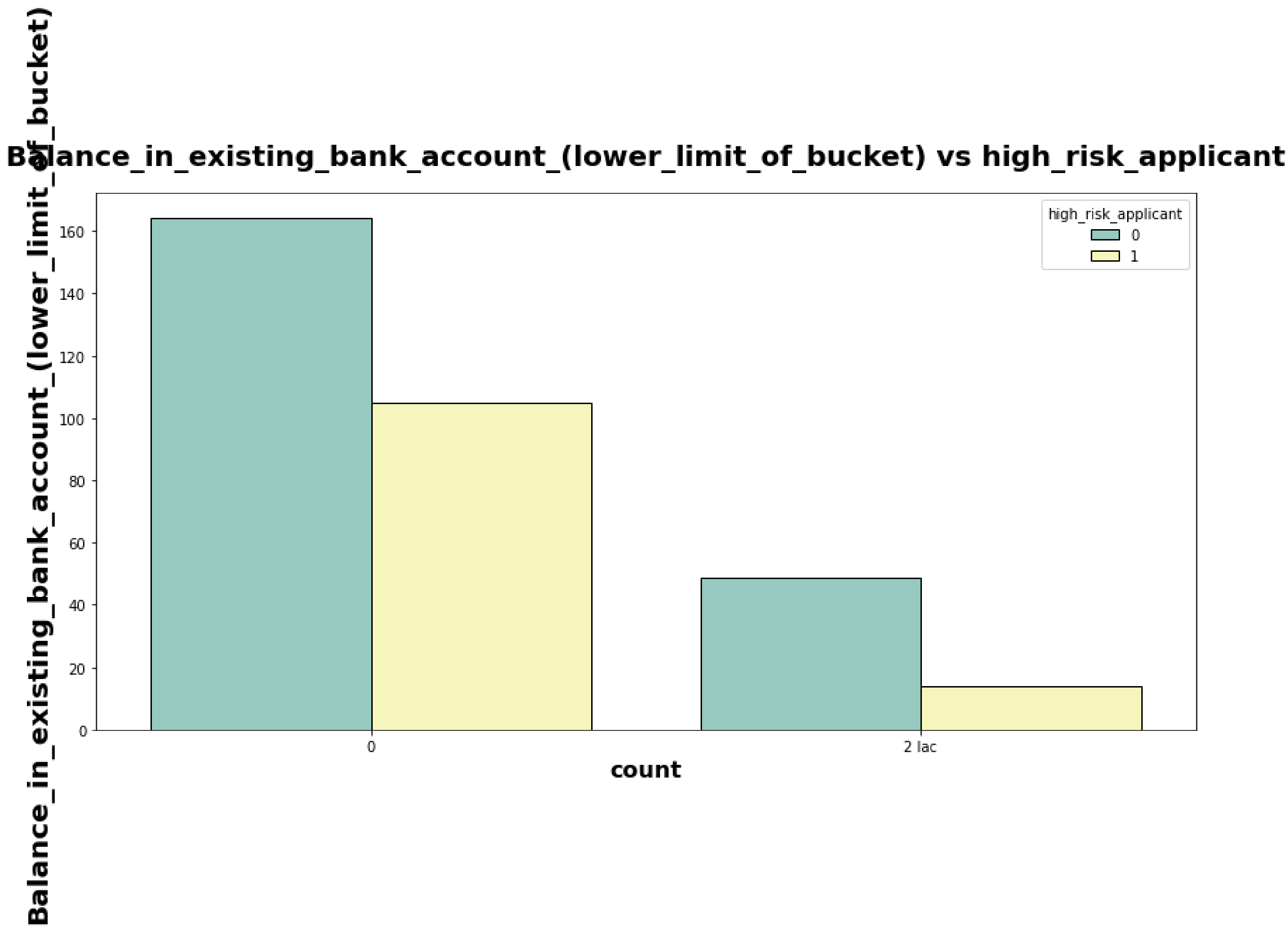


Insights

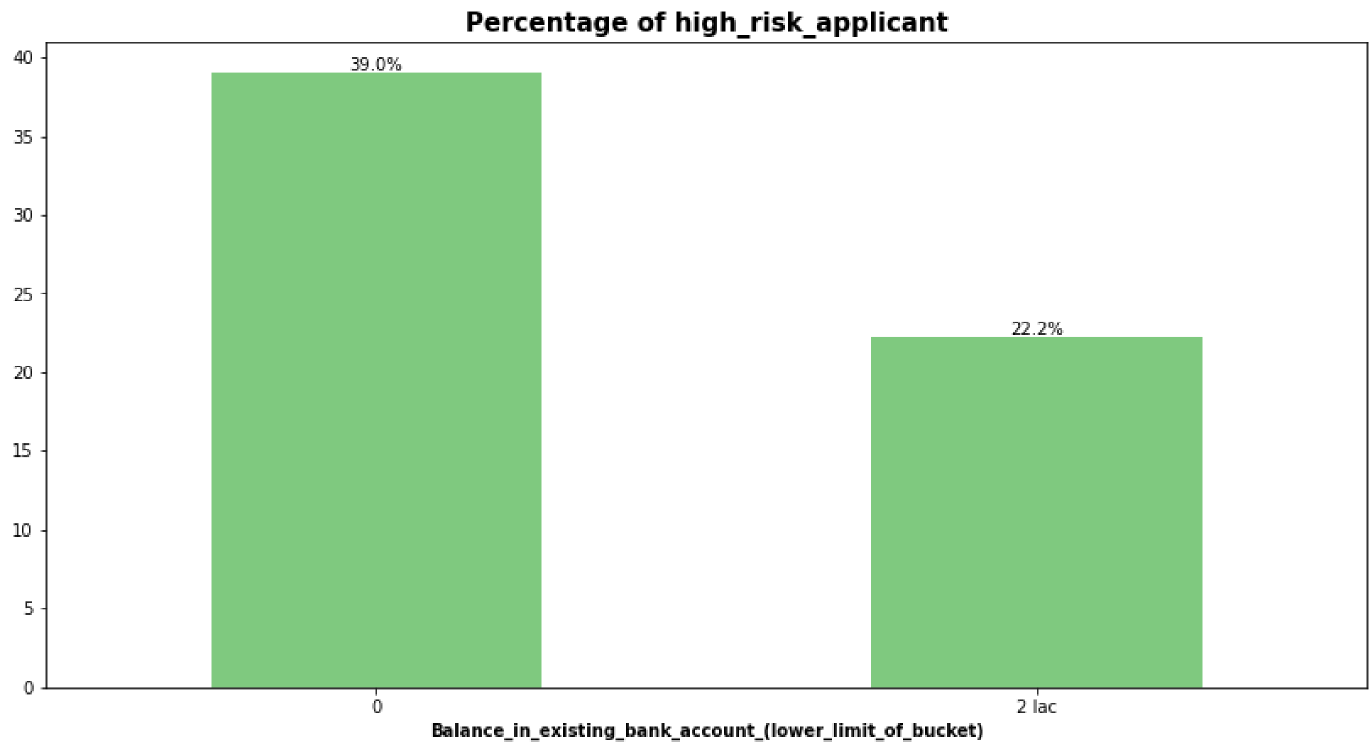
- `management / self-employed / highly qualified employee / officer` applicants have high chance of high_risk_applicant.
- However also it seems that regardless of the Employment_status, applicants have high percentage of credit risk.

4.6 Balance_in_existing_bank_account_(lower_limit_of_bucket) vs high_risk_applicant

In [35]:
```
plt.subplots(figsize=(14,7))
sb.countplot(x="Balance_in_existing_bank_account_(lower_limit_of_bucket)", hue='high_risk_a
plt.title("Balance_in_existing_bank_account_(lower_limit_of_bucket) vs high_risk_applicant'
plt.ylabel("Balance_in_existing_bank_account_(lower_limit_of_bucket)", weight="bold", fonts
plt.xlabel("count", weight="bold", fontsize=16)
plt.show()
```



In [36]:
```
plt.subplots(figsize=(14,7))

(100*df2[df2["high_risk_applicant"].isin([1])]['Balance_in_existing_bank_account_(lower_lir
plt.title("Percentage of high_risk_applicant" , fontsize = 15, fontweight ='bold'   )
order1 = (100*df2[df2["high_risk_applicant"].isin([1])]['Balance_in_existing_bank_account_(

for n in range(order1.shape[0]):
    count = order1[n]
    strt='{:0.1f}%'.format(count)
    plt.text(n,count+0.1,strt,ha='center')

plt.xlabel('Balance_in_existing_bank_account_(lower_limit_of_bucket)', fontweight ='bold')
plt.xticks(rotation=0)
plt.show()
```

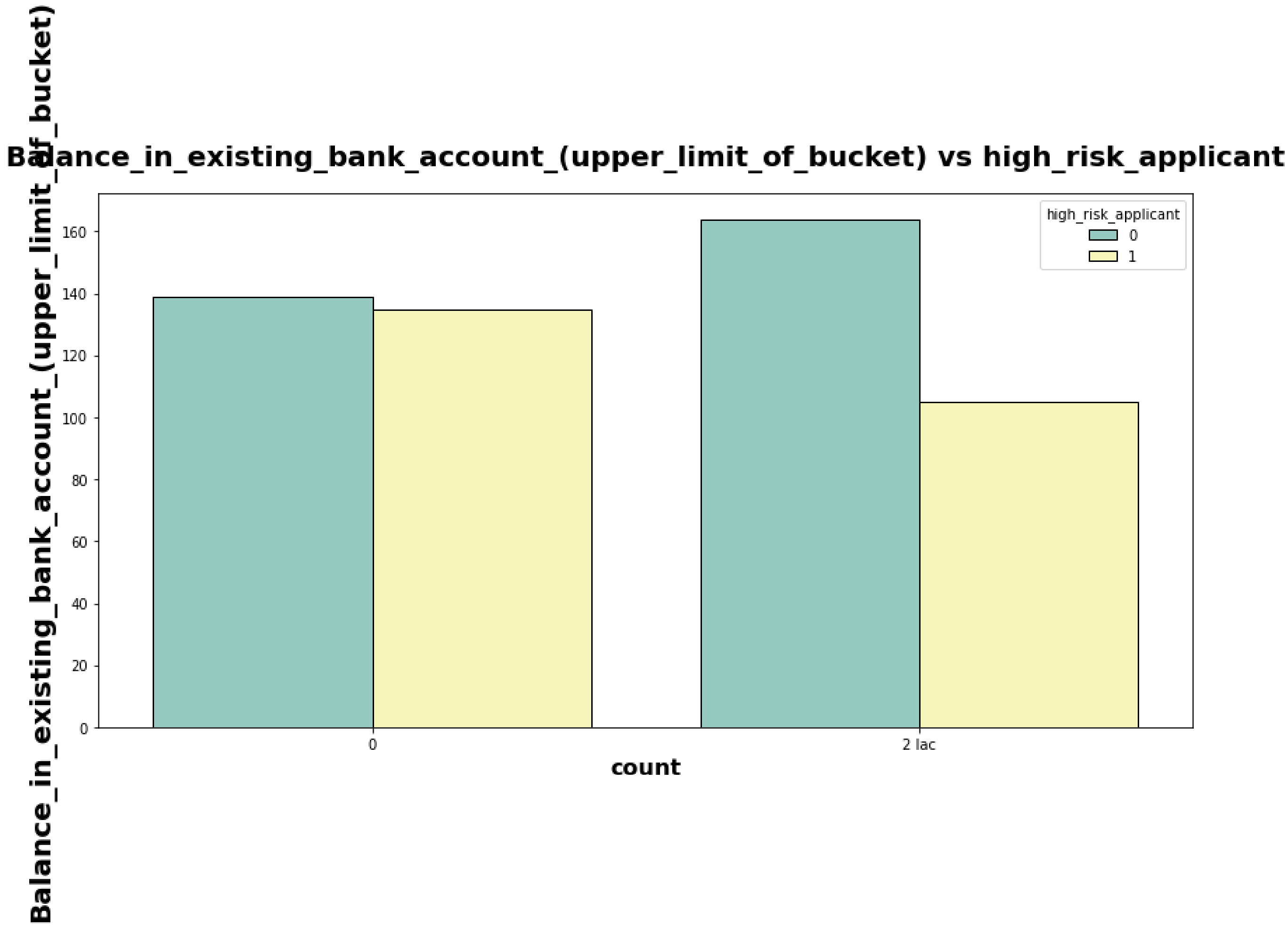


Insights

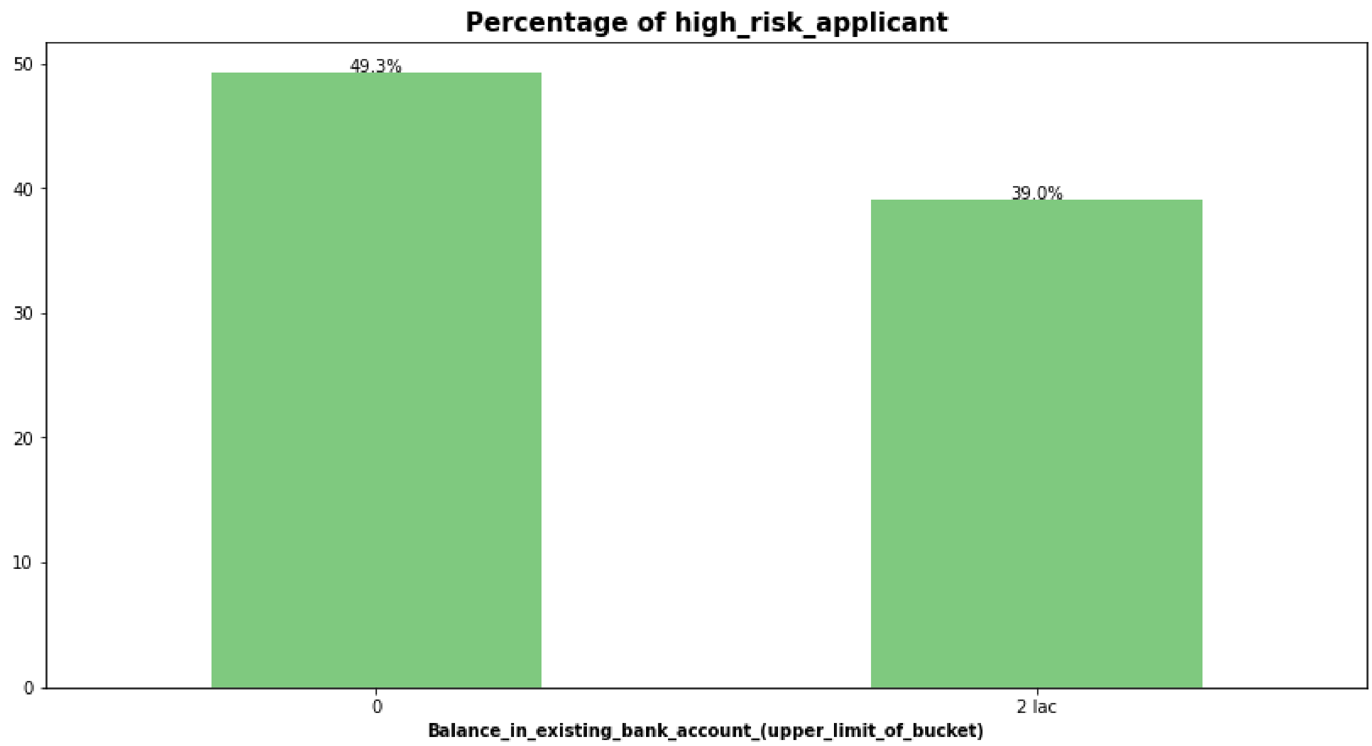
- With lower limit `0` applicants have high chance of high_risk_applicant, however we cannot be reliable on this feature as there is 66.8 % missing values in this feature.

4.7 Balance_in_existing_bank_account_(upper_limit_of_bucket) vs high_risk_applicant

In [37]:
```
plt.subplots(figsize=(14,7))
sb.countplot(x="Balance_in_existing_bank_account_(upper_limit_of_bucket)", hue='high_risk_a
plt.title("Balance_in_existing_bank_account_(upper_limit_of_bucket) vs high_risk_applicant"
plt.ylabel("Balance_in_existing_bank_account_(upper_limit_of_bucket)", weight="bold", fonts
plt.xlabel("count", weight="bold", fontsize=16)
plt.show()
```



In [38]:
```
plt.subplots(figsize=(14,7))

(100*df2[df2["high_risk_applicant"].isin([1])]['Balance_in_existing_bank_account_(upper_lir
plt.title("Percentage of high_risk_applicant" , fontsize = 15, fontweight ='bold'   )
order1 = (100*df2[df2["high_risk_applicant"].isin([1])]['Balance_in_existing_bank_account_(

for n in range(order1.shape[0]):
    count = order1[n]
    strt='{:0.1f}%'.format(count)
    plt.text(n,count+0.1,strt,ha='center')

plt.xlabel('Balance_in_existing_bank_account_(upper_limit_of_bucket)', fontweight ='bold')
plt.xticks(rotation=0)
plt.show()
```

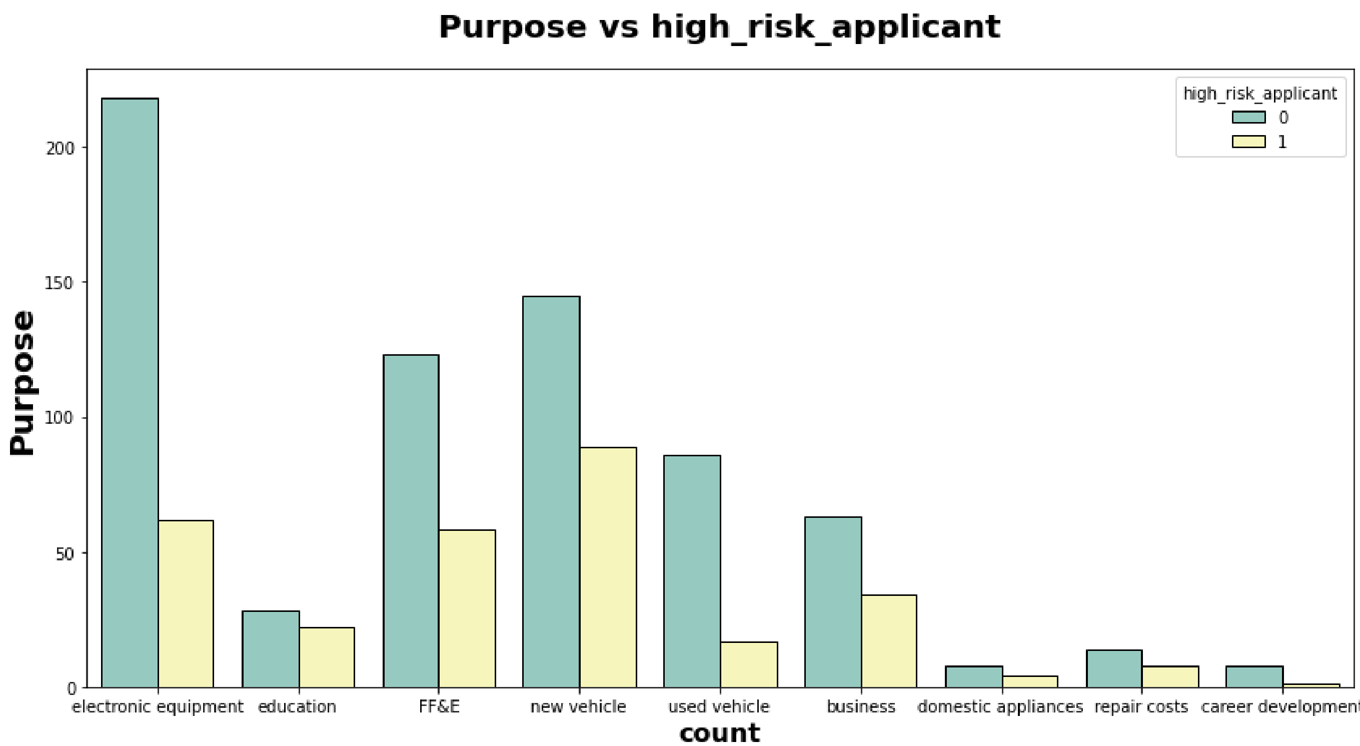


- With upper limit `0` applicants have high chance of high_risk_applicant, however we cannot be reliable on this feature as there is 45.7 % missing values in this feature.

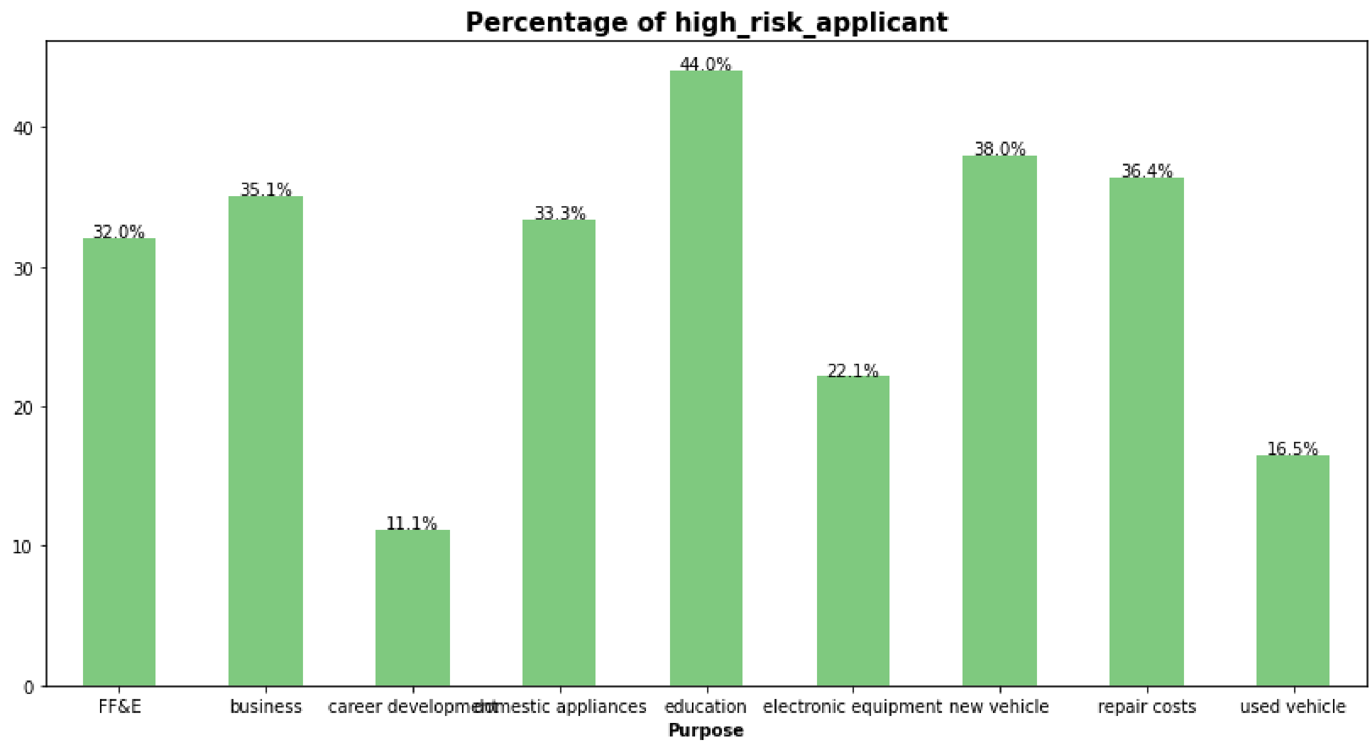
4.8 Purpose vs high_risk_applicant

In [39]:

```
plt.subplots(figsize=(14,7))
sb.countplot(x="Purpose", hue='high_risk_applicant', data=df2, ec="black", palette="Set3")
plt.title("Purpose vs high_risk_applicant", weight="bold",fontsize=20, pad=20)
plt.ylabel("Purpose", weight="bold", fontsize=20)
plt.xlabel("count", weight="bold", fontsize=16)
plt.show()
```



In [40]:
```
plt.subplots(figsize=(14,7))

(100*df2[df2["high_risk_applicant"].isin([1])]['Purpose'].value_counts()/df2['Purpose'].val
plt.title("Percentage of high_risk_applicant" , fontsize = 15, fontweight ='bold'  )
order1 = (100*df2[df2["high_risk_applicant"].isin([1])]['Purpose'].value_counts()/df2['Purp

for n in range(order1.shape[0]):
    count = order1[n]
    strt='{:0.1f}%'.format(count)
    plt.text(n,count+0.1,strt,ha='center')

plt.xlabel('Purpose', fontweight ='bold')
plt.xticks(rotation=0)
plt.show()
```

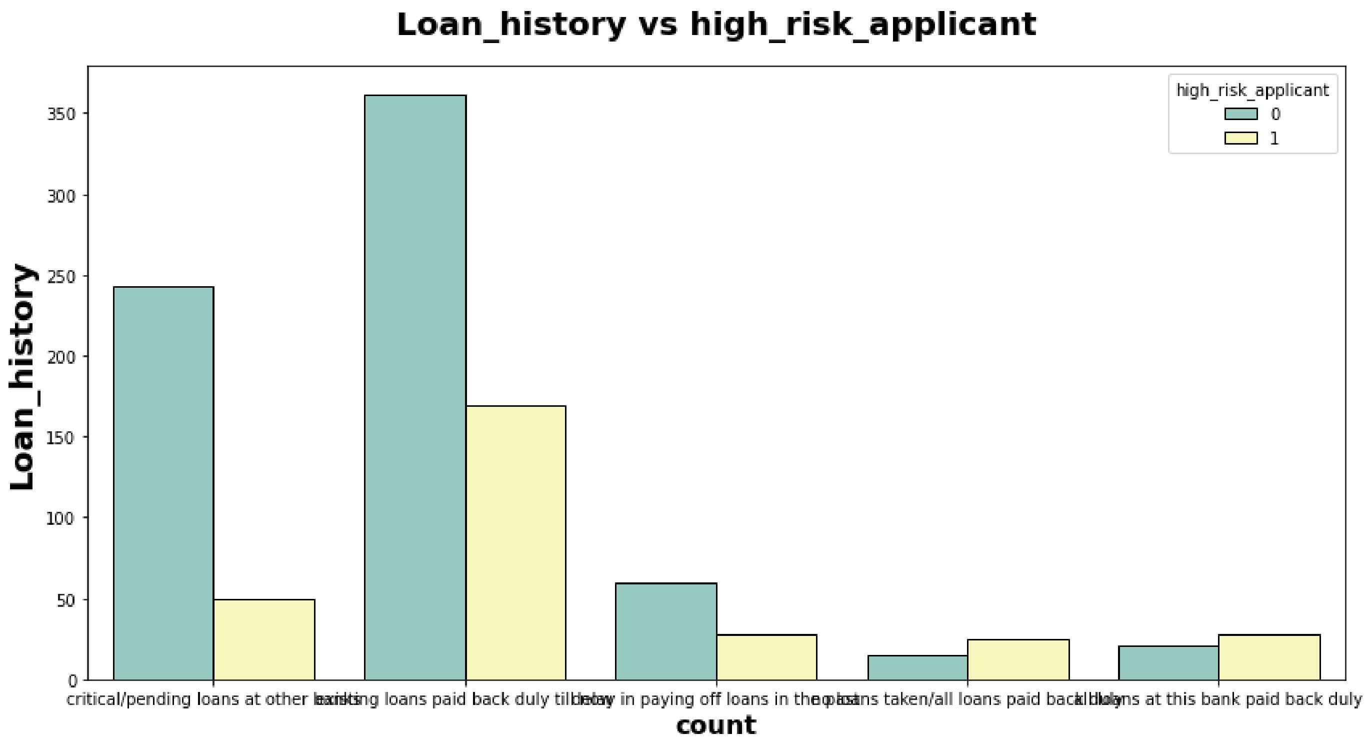


Insights

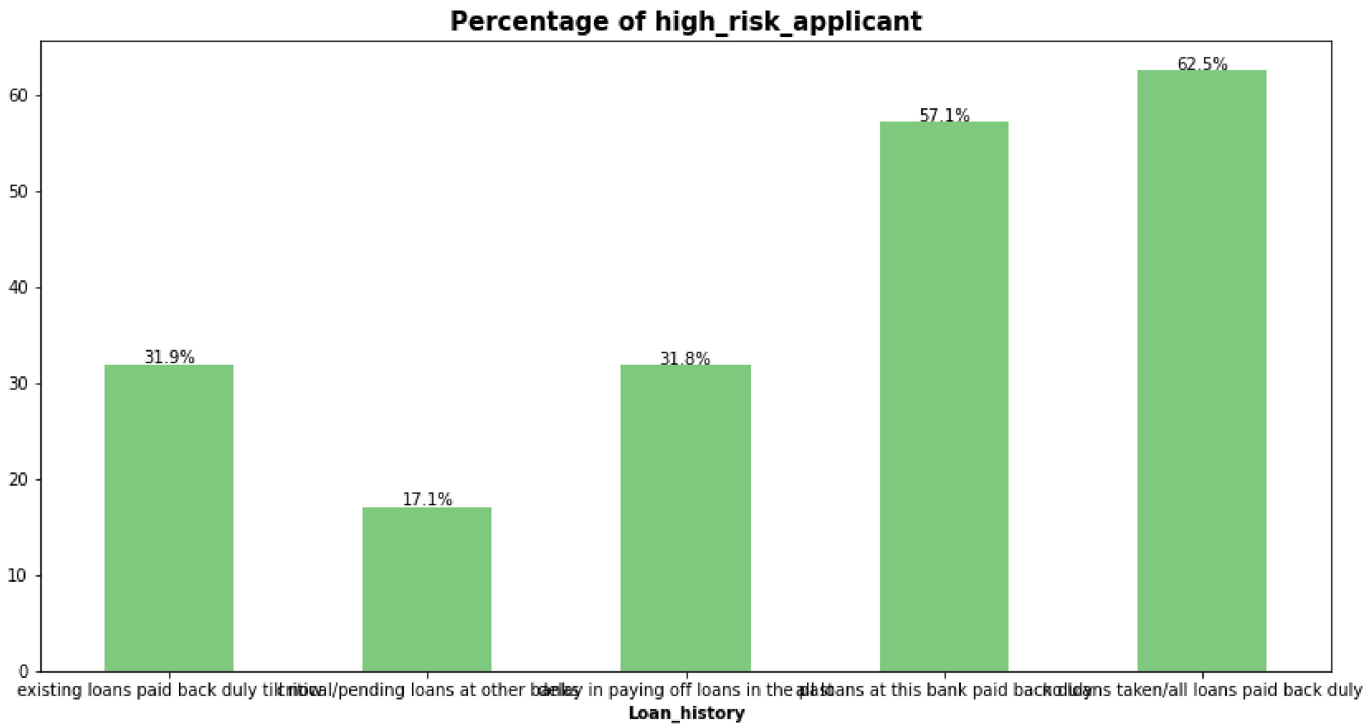
- Purpose for `education` applicants have high chance of high_risk_applicant, followed by `new vehicle` .
- `career development` applicants have lowest chance of high_risk_applicant, may be got better oportunities after completing the course.

4.9 Loan_history vs high_risk_applicant

In [41]:
```
plt.subplots(figsize=(14,7))
sb.countplot(x="Loan_history", hue='high_risk_applicant', data=df2, ec="black", palette="Se
plt.title("Loan_history vs high_risk_applicant", weight="bold",fontsize=20, pad=20)
plt.ylabel("Loan_history", weight="bold", fontsize=20)
plt.xlabel("count", weight="bold", fontsize=16)
plt.show()
```



In [42]:
```
plt.subplots(figsize=(14,7))

(100*df2[df2["high_risk_applicant"].isin([1])]['Loan_history'].value_counts()/df2['Loan_his
plt.title("Percentage of high_risk_applicant" , fontsize = 15, fontweight ='bold'  )
order1 = (100*df2[df2["high_risk_applicant"].isin([1])]['Loan_history'].value_counts()/df2[

for n in range(order1.shape[0]):
    count = order1[n]
    strt='{:0.1f}%'.format(count)
    plt.text(n,count+0.1,strt,ha='center')

plt.xlabel('Loan_history', fontweight ='bold')
plt.xticks(rotation=0)
plt.show()
```

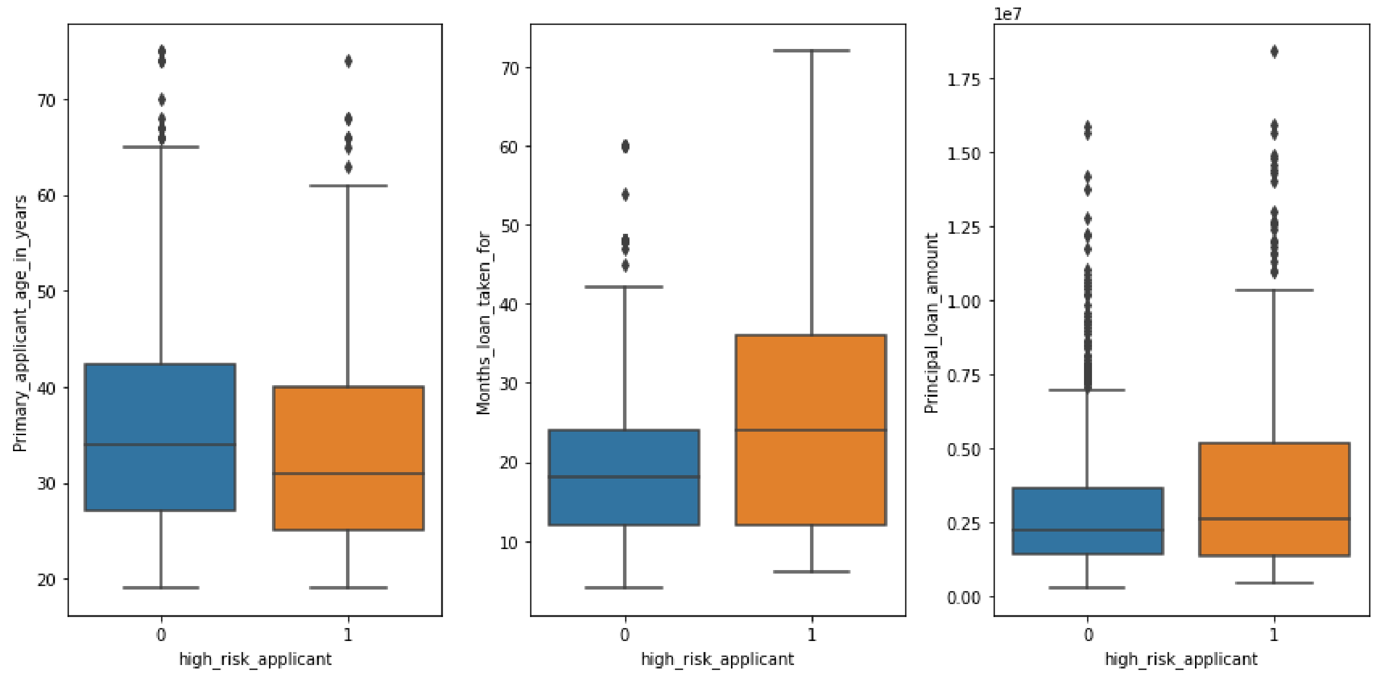


Insights

- Loan_history for `no loans taken/all loans paid back duly` applicants have high chance of high_risk_applicant, however it doesn't make any sense.

Checking outliers for continuous features

In [43]:
```
column_list = ['Primary_applicant_age_in_years', 'Months_loan_taken_for', 'Principal_loan_a

fig, ax = plt.subplots(1, 3, figsize=(12,6))

for i, col in enumerate(column_list):
    sb.boxplot(data=df, x='high_risk_applicant', y=col, ax=ax[i])

plt.tight_layout()
plt.show()
```



Final Report

- The `high_risk_applicant` column is the target to predict.
- The target variable here is imbalanced, Handling imbalanced data is required.
- There are outliers in the `'Primary_applicant_age_in_years`, `Months_loan_taken_for`, `Principal_loan_amount` columns.
- `applicant_id` & `loan_application_id` columns have no importance, we can drop these.
- `Telephone` column isn't a useful, also not correlated with `high_risk_applicant` (Target Column), hence this can be dropped.
- `Other_EMI_plans` column have more than 80% of missing value, hence this can be dropped.
- Null values present, should be handled.

In [44]:
```
####################-------------Feature Engineering and Model Training in TASK-2 noteboo
```