main

December 23, 2024

1 Summary

In this project, I worked with the Loan Approval Classification Dataset from Kaggle: https://www.kaggle.com/datasets/taweilo/loan-approval-classification-data/data. This project aims to build a classification model that would predict whether or not a person should be granted a loan, given the loan's details and that person's various characteristics: loan amount, interest rates, credit score, income, etc. To achieve that goal, I initially trained a random forest classifier. While this model achieved a high accuracy of 93% on the validation dataset, it does not perform very well on the positive instances. Therefore, I tried to improve the model twice using two different methods. However, none of these updated models significantly beated the first one in terms of accuracy, both on the whole validation dataset and on the positive instances. Therefore, I concluded by choosing the original model and use it to make predictions on the test dataset. The achieved accuracy is 92.94%.

2 Importing data

[1]:
```
import pandas as pd
csv_file_path = "./loan_data.csv"

df = pd.read_csv(csv_file_path)
df
```

[1]:
```
       person_age person_gender person_education  person_income  \
0            22.0        female           Master        71948.0
1            21.0        female      High School        12282.0
2            25.0        female      High School        12438.0
3            23.0        female         Bachelor        79753.0
4            24.0          male           Master        66135.0
…             …             …                …              …
44995        27.0          male        Associate        47971.0
44996        37.0        female        Associate        65800.0
44997        33.0          male        Associate        56942.0
44998        29.0          male         Bachelor        33164.0
44999        24.0          male      High School        51609.0

       person_emp_exp person_home_ownership  loan_amnt        loan_intent  \
0                   0                  RENT    35000.0           PERSONAL
```

```
1                   0                      OWN     1000.0          EDUCATION
2                   3                 MORTGAGE     5500.0            MEDICAL
3                   0                     RENT    35000.0            MEDICAL
4                   1                     RENT    35000.0            MEDICAL
…                 …                   …        …                …
44995               6                     RENT    15000.0            MEDICAL
44996              17                     RENT     9000.0    HOMEIMPROVEMENT
44997               7                     RENT     2771.0  DEBTCONSOLIDATION
44998               4                     RENT    12000.0          EDUCATION
44999               1                     RENT     6665.0  DEBTCONSOLIDATION

       loan_int_rate  loan_percent_income  cb_person_cred_hist_length  \
0              16.02                 0.49                         3.0
1              11.14                 0.08                         2.0
2              12.87                 0.44                         3.0
3              15.23                 0.44                         2.0
4              14.27                 0.53                         4.0
…                …                  …                          …
44995          15.66                 0.31                         3.0
44996          14.07                 0.14                        11.0
44997          10.02                 0.05                        10.0
44998          13.23                 0.36                         6.0
44999          17.05                 0.13                         3.0

       credit_score previous_loan_defaults_on_file  loan_status
0               561                             No            1
1               504                            Yes            0
2               635                             No            1
3               675                             No            1
4               586                             No            1
…               …                            …          …
44995           645                             No            1
44996           621                             No            1
44997           668                             No            1
44998           604                             No            1
44999           628                             No            1

[45000 rows x 14 columns]
```

3 Getting used to the data

3.1 Feature description

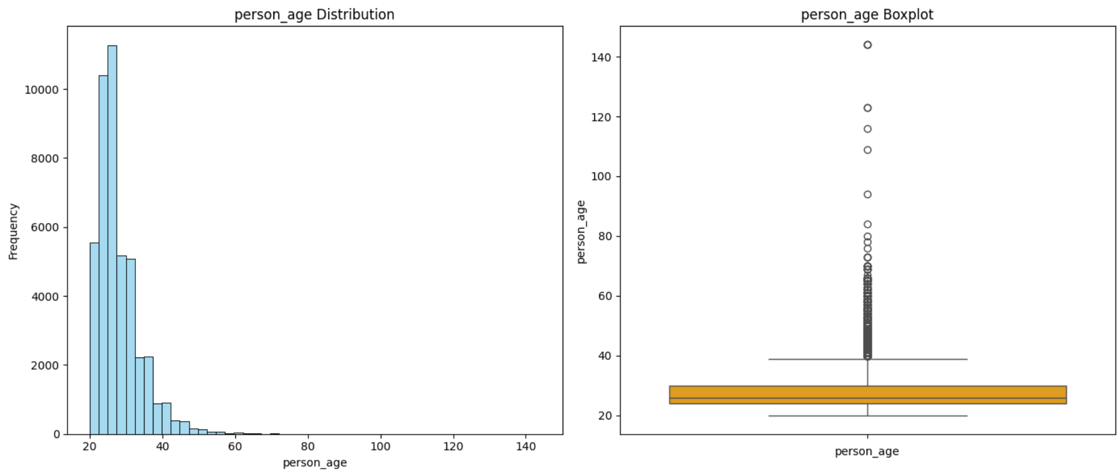
1. person_age: Age of the person
2. person_gender: Gender of the person
3. person_education: Highest education level
4. person_income: Annual income

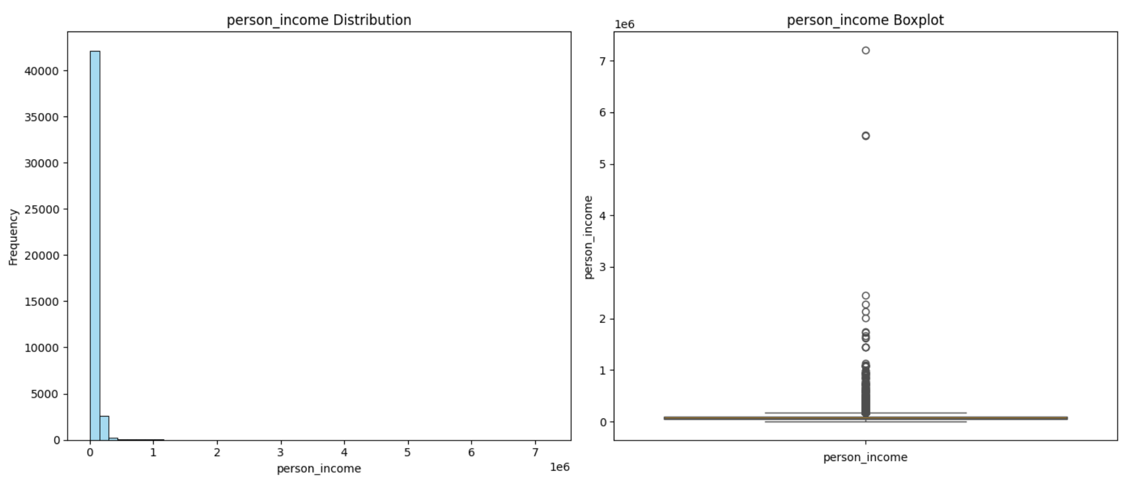
5. person_emp_exp: Years of employment experience
6. person_home_ownership: Home ownership status (e.g., rent, own, mortgage)
7. loan_amnt: Loan amount requested
8. loan_intent: Purpose of the loan
9. loan_int_rate: Loan interest rate
10. loan_percent_income: Loan amount as a percentage of annual income
11. cb_person_cred_hist_length: Length of credit history in years
12. credit_score: Credit score of the person
13. previous_loan_defaults_on_file: Indicator of previous loan defaults
14. loan_status (target variable): Loan approval status: 1 = approved; 0 = rejected

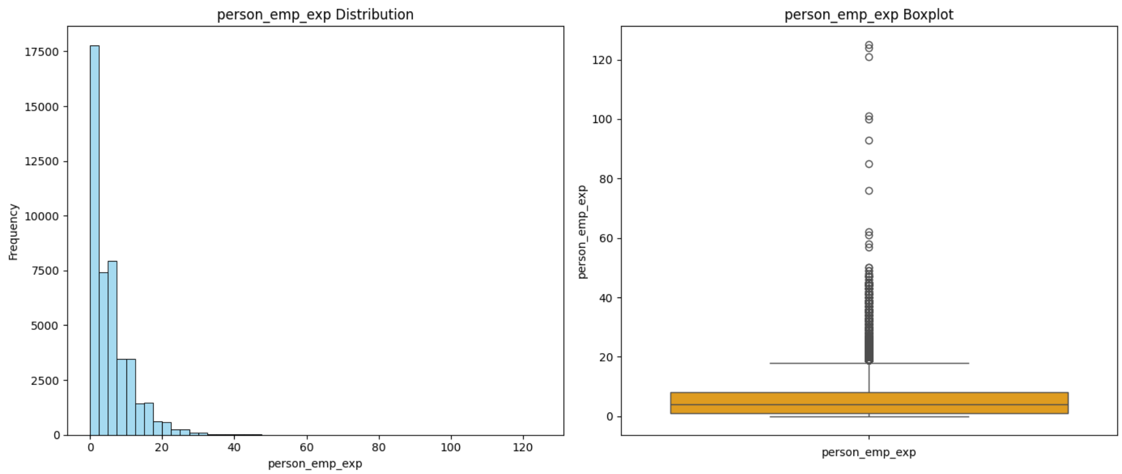
3.2 Visualizing numerical data

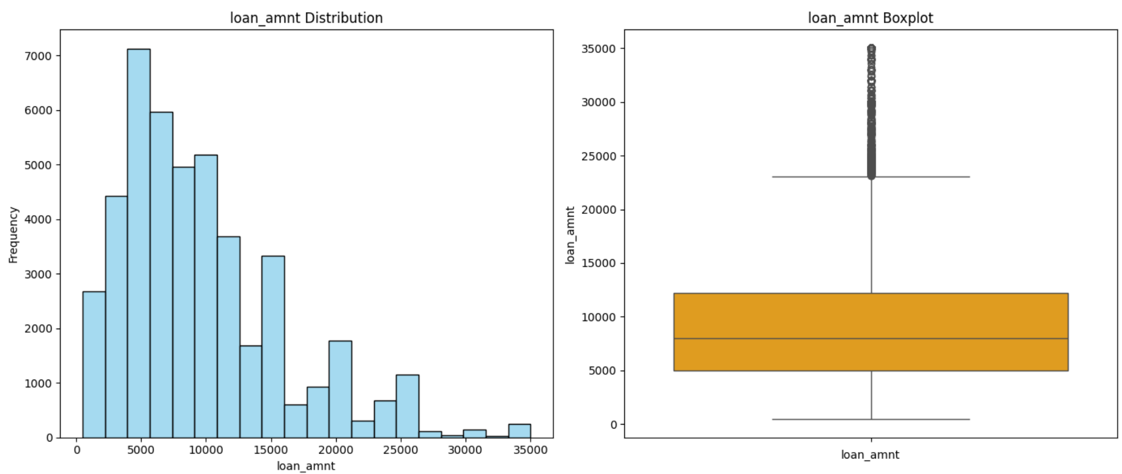
[2]:
```
# Helper function to draw a histogram and a boxplot showing the distribution of␣
↪each numerical feature
# Produced and edited from chatGPT prompt: Write Python function to draw a␣
↪graph summarizing the distribution
# of the columns with numerical data in the above DataFrame"
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

def plot_numerical_distributions(column, num_of_bins):
    """
    Plots the distribution and summary statistics of all numerical columns in␣
↪the DataFrame.
    Args:
        columns: pd.DataFrame.column, the DataFrame column containing numerical␣
↪values.
    """
    plt.figure(figsize=(14, 6))

    # Histogram
    plt.subplot(1, 2, 1)
    sns.histplot(column.dropna(), bins=num_of_bins, kde=False, color='skyblue')
    plt.title(f'{column.name} Distribution')
    plt.xlabel(column.name)
    plt.ylabel('Frequency')

    # Boxplot
    plt.subplot(1, 2, 2)
    sns.boxplot(column.dropna(), color='orange')
    plt.title(f'{column.name} Boxplot')
    plt.xlabel(column.name)

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

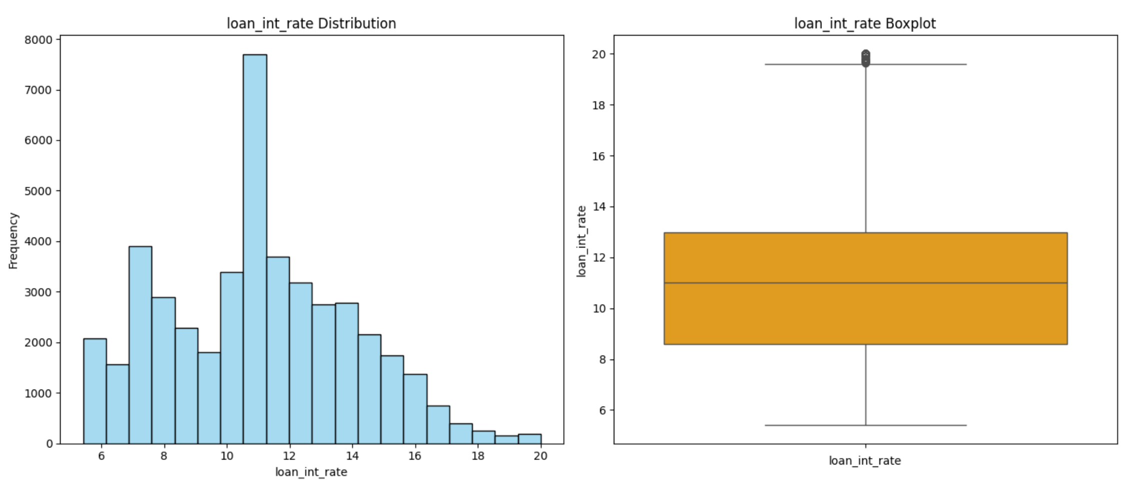
[3]:
```
plot_numerical_distributions(df['person_age'], 50)
plot_numerical_distributions(df['person_income'], 50)
plot_numerical_distributions(df['person_emp_exp'], 50)
plot_numerical_distributions(df['loan_amnt'], 20)
plot_numerical_distributions(df['loan_int_rate'], 20)
plot_numerical_distributions(df['loan_percent_income'], 20)
plot_numerical_distributions(df['cb_person_cred_hist_length'], 20)
plot_numerical_distributions(df['credit_score'], 20)
plot_numerical_distributions(df['loan_status'], 20)
```

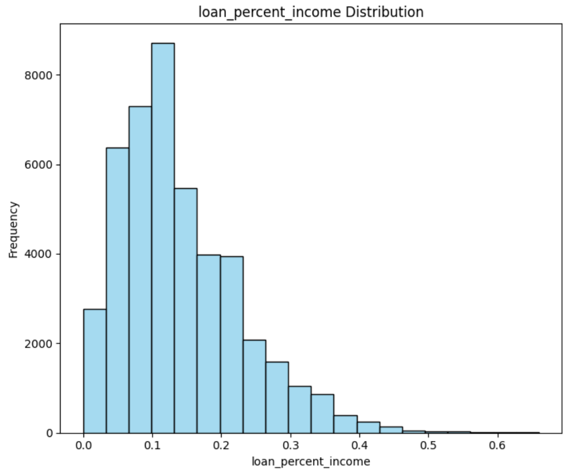


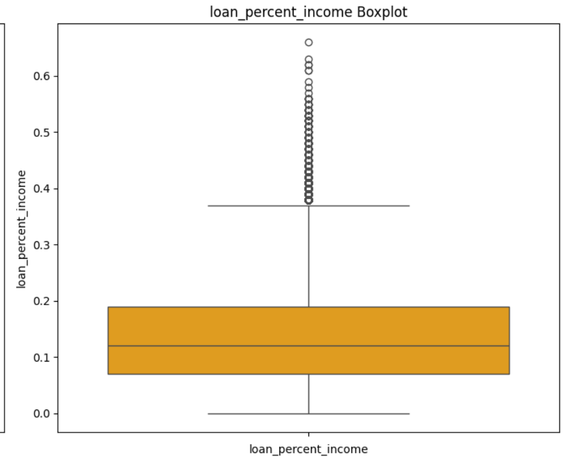


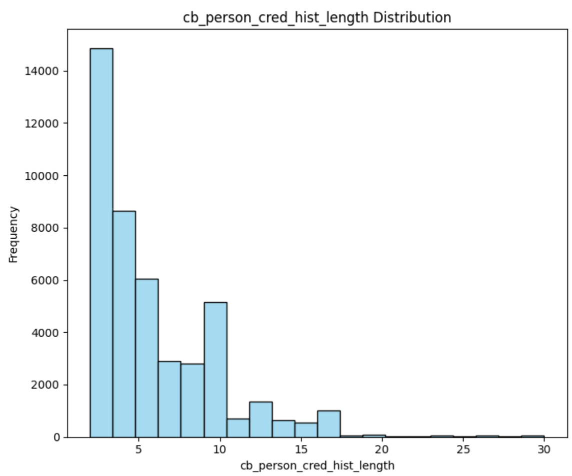

person_emp_exp Distribution
Frequency
person_emp_exp
person_emp_exp Boxplot
person_emp_exp
person_emp_exp

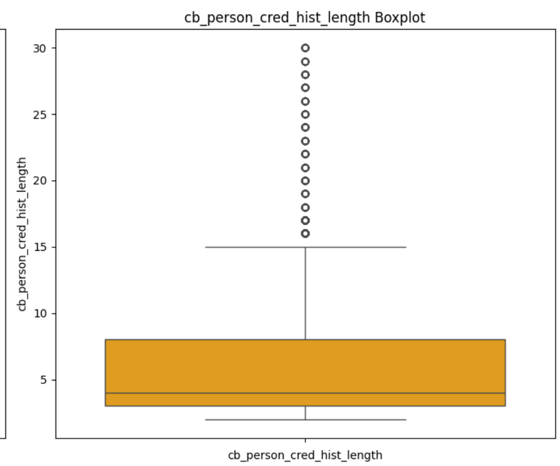

loan_amnt Distribution
Frequency
loan_amnt
loan_amnt Boxplot
loan_amnt
loan_amnt

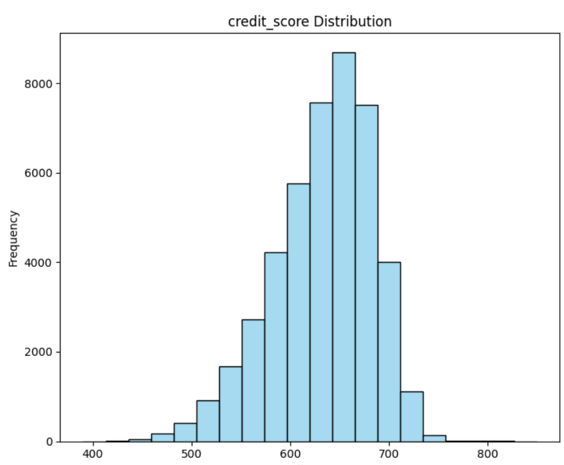

loan_int_rate Distribution
Frequency
loan_int_rate
loan_int_rate Boxplot
loan_int_rate
loan_int_rate

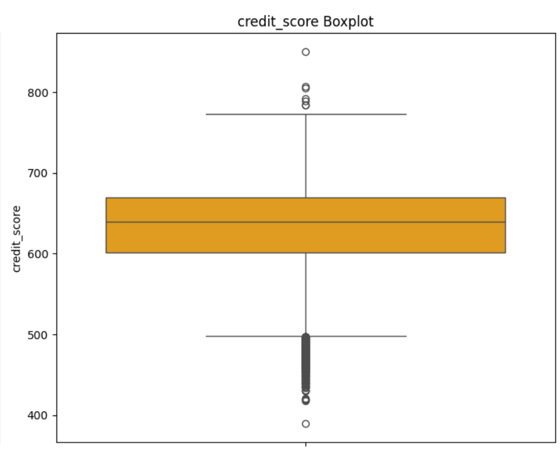

loan_percent_income Distribution
Frequency
0
2000
4000
6000
8000
0.0
0.1
0.2
0.3
0.4
0.5
0.6
loan_percent_income

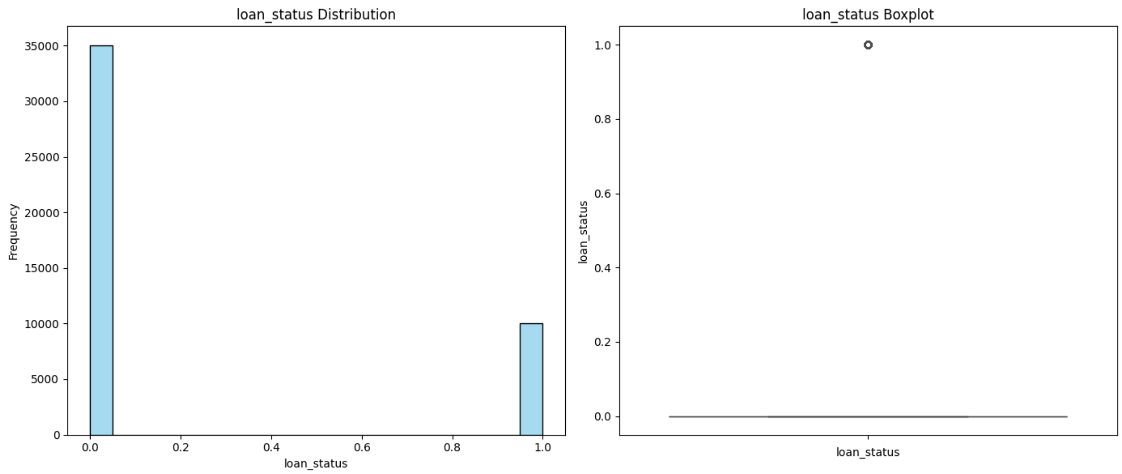

loan_percent_income Boxplot
loan_percent_income
0.0
0.1
0.2
0.3
0.4
0.5
0.6
loan_percent_income


cb_person_cred_hist_length Distribution
Frequency
0
2000
4000
6000
8000
10000
12000
14000
5
10
15
20
25
30
cb_person_cred_hist_length


cb_person_cred_hist_length Boxplot
cb_person_cred_hist_length
5
10
15
20
25
30
cb_person_cred_hist_length


credit_score Distribution
Frequency
0
2000
4000
6000
8000
400
500
600
700
800
credit_score


credit_score Boxplot
credit_score
400
500
600
700
800
credit_score

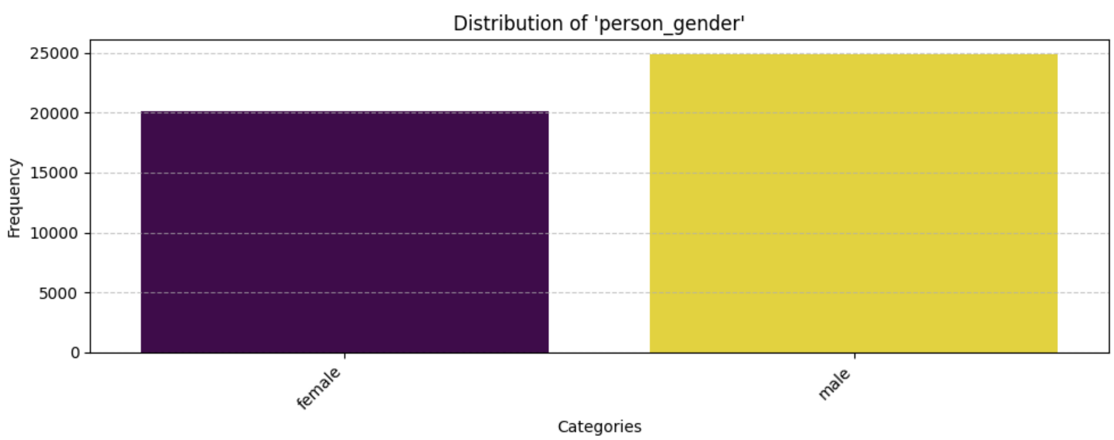


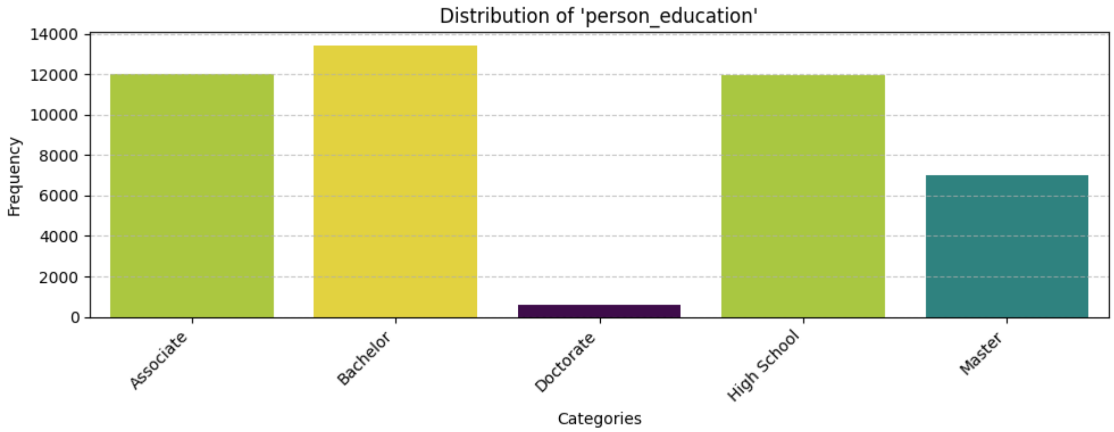
3.3 Visualizing categorical data

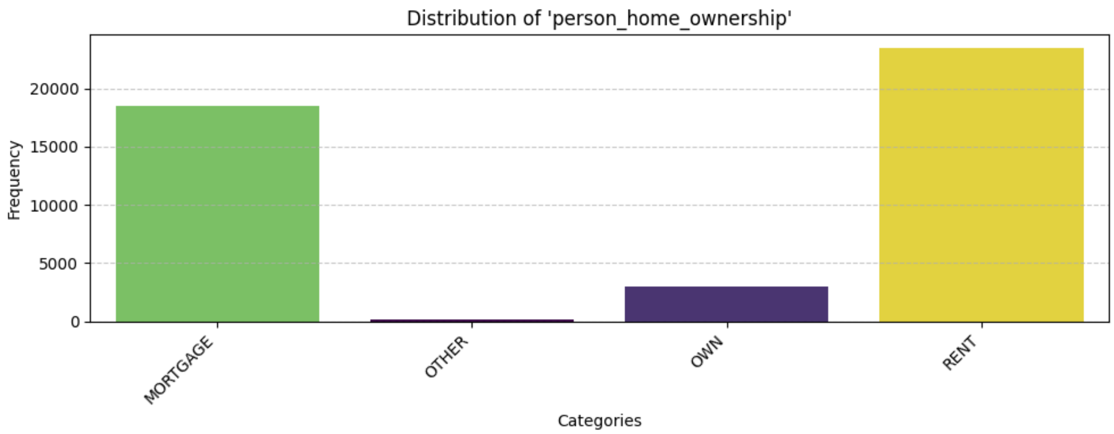
[4]:
```
# Helper function to draw a bar chart showing the distribution of each␣
↪categorical feature
# Produced and edited from chatGPT prompt: Write Python function to draw a␣
↪graph summarizing
# a column with categorical data in a DataFrame"
import seaborn as sns

def plot_categorical_column(df, column_name):
    """
    Plots a bar chart summarizing the distribution of a categorical column in␣
↪the DataFrame.

    Args:
        df: pd.DataFrame, the DataFrame containing the column.
        column_name: str, the name of the categorical column to be summarized.

    Returns:
        None
    """
    if column_name not in df.columns:
        print(f"Column '{column_name}' not found in the DataFrame.")
        return

    # Ensure the column is treated as categorical
    if not pd.api.types.is_categorical_dtype(df[column_name]):
        df[column_name] = df[column_name].astype('category')
```

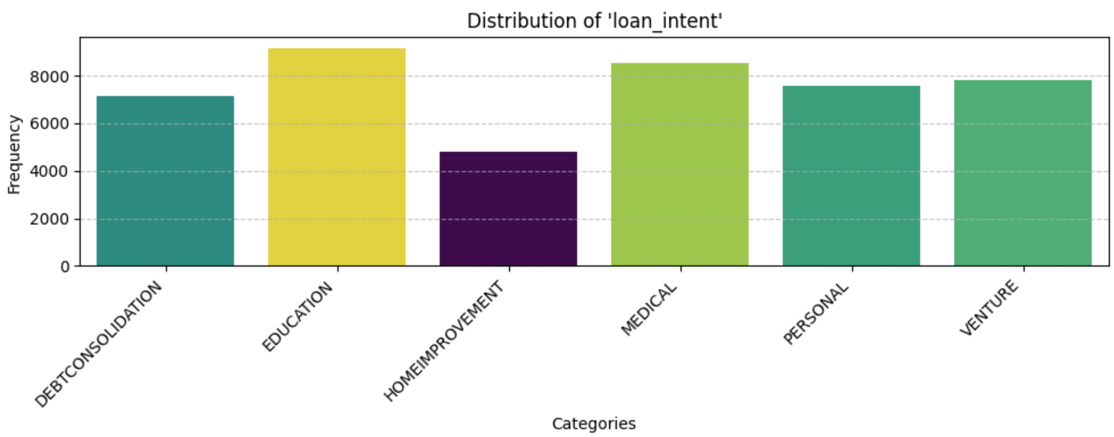
```
    # Count the occurrences of each category
    category_counts = df[column_name].value_counts()

    # Plot the distribution
    plt.figure(figsize=(10, 4))
    sns.barplot(x=category_counts.index, y=category_counts.values,␣
↪palette="viridis", hue=category_counts, legend=False)
    plt.title(f"Distribution of '{column_name}'")
    plt.xlabel("Categories")
    plt.ylabel("Frequency")
    plt.xticks(rotation=45, ha="right")
    plt.grid(axis='y', linestyle='--', alpha=0.7)
    plt.tight_layout()
    plt.show()
```

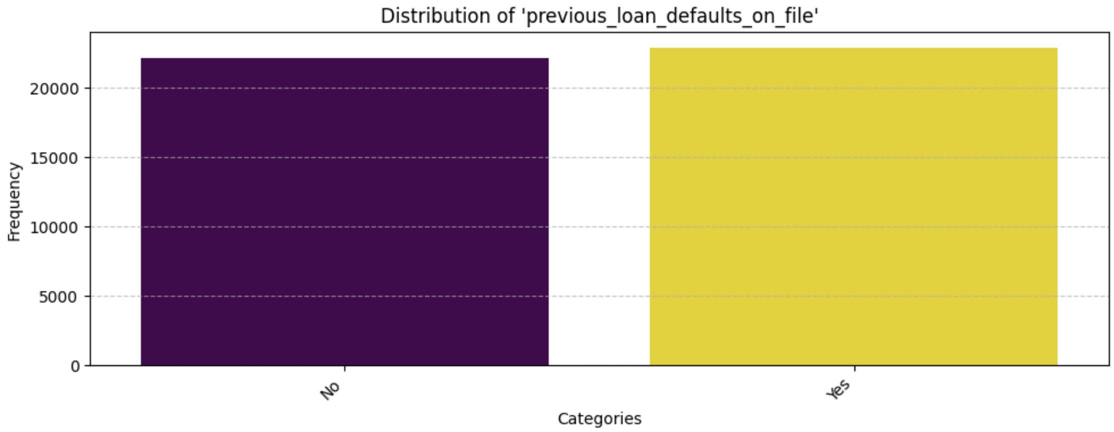
[5]:
```
plot_categorical_column(df, 'person_gender')
plot_categorical_column(df, 'person_education')
plot_categorical_column(df, 'person_home_ownership')
plot_categorical_column(df, 'loan_intent')
plot_categorical_column(df, 'previous_loan_defaults_on_file')
```




Distribution of 'person_education'
Frequency
0
2000
4000
6000
8000
10000
12000
14000
Associate
Bachelor
Doctorate
High School
Master
Categories


Distribution of 'person_home_ownership'
Frequency
0
5000
10000
15000
20000
MORTGAGE
OTHER
OWN
RENT
Categories


Distribution of 'loan_intent'
Frequency
0
2000
4000
6000
8000
DEBTCONSOLIDATION
EDUCATION
HOMEIMPROVEMENT
MEDICAL
PERSONAL
VENTURE
Categories



4 Cleaning data

4.1 Removing obvious data outliers

4.1.1 Removing those with age >= 100

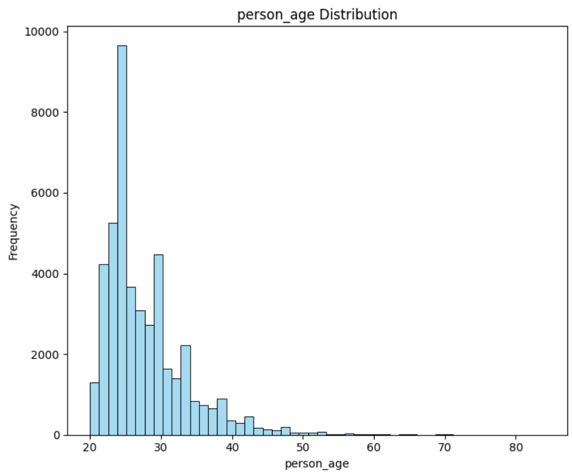
[6]:
```
drop_index = df[df['person_age'] >= 100].index
df.drop(drop_index , inplace=True)
```

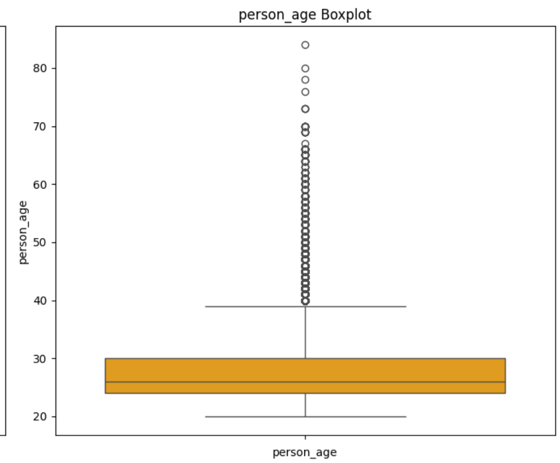
4.1.2 Removing those with employment experience >= 70

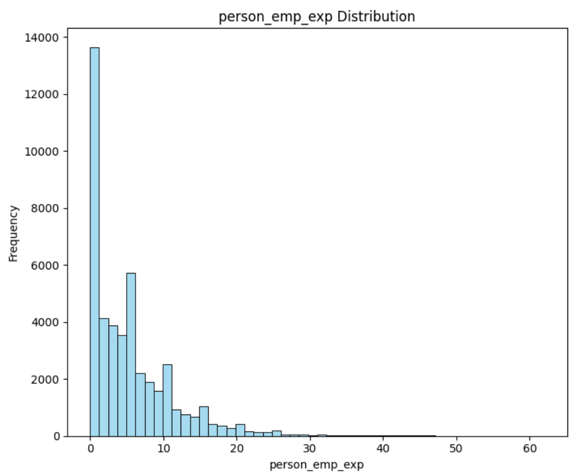
[7]:
```
drop_index = df[df['person_emp_exp'] >= 70].index
df.drop(drop_index , inplace=True)
```

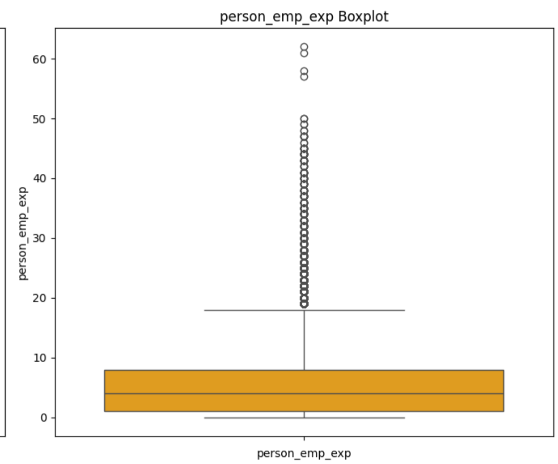
4.1.3 Viewing the changed distributions after cleaning the data

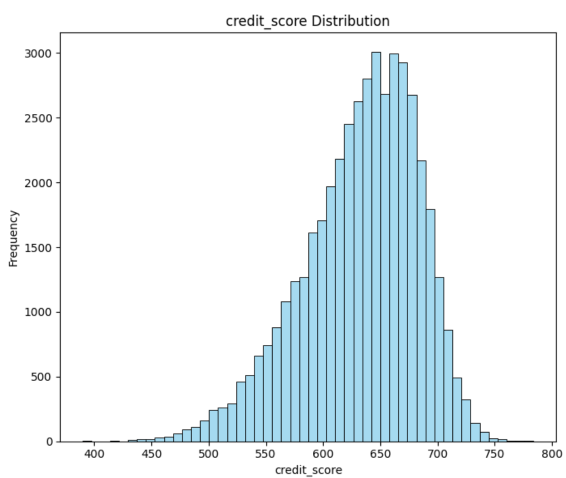
[8]:
```
plot_numerical_distributions(df['person_age'], 50)
plot_numerical_distributions(df['person_emp_exp'], 50)
plot_numerical_distributions(df['credit_score'], 50)
```

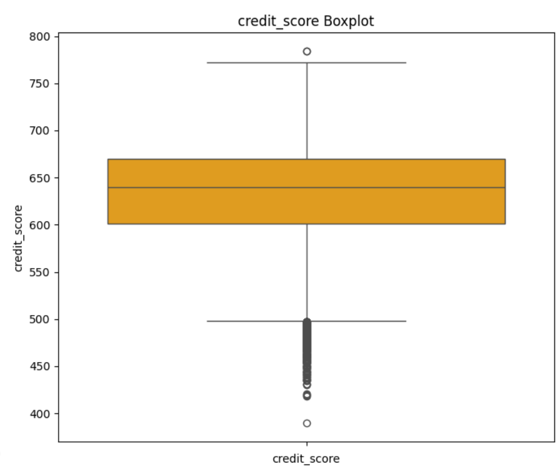

person_age Distribution
Frequency
person_age


person_age Boxplot
person_age
person_age


person_emp_exp Distribution
Frequency
person_emp_exp


person_emp_exp Boxplot
person_emp_exp
person_emp_exp


credit_score Distribution
Frequency
credit_score


credit_score Boxplot
credit_score
credit_score

4.2 Converting categorical data into dummies

[9]:
```python
df = pd.get_dummies(df, columns=None, drop_first=True)
df
```

[9]:
```
       person_age  person_income  person_emp_exp  loan_amnt  loan_int_rate  \
0            22.0        71948.0               0    35000.0          16.02
1            21.0        12282.0               0     1000.0          11.14
2            25.0        12438.0               3     5500.0          12.87
3            23.0        79753.0               0    35000.0          15.23
4            24.0        66135.0               1    35000.0          14.27
…               …              …               …         …              …
44995        27.0        47971.0               6    15000.0          15.66
44996        37.0        65800.0              17     9000.0          14.07
44997        33.0        56942.0               7     2771.0          10.02
44998        29.0        33164.0               4    12000.0          13.23
44999        24.0        51609.0               1     6665.0          17.05

       loan_percent_income  cb_person_cred_hist_length  credit_score  \
0                     0.49                         3.0           561
1                     0.08                         2.0           504
2                     0.44                         3.0           635
3                     0.44                         2.0           675
4                     0.53                         4.0           586
…                        …                           …             …
44995                 0.31                         3.0           645
44996                 0.14                        11.0           621
44997                 0.05                        10.0           668
44998                 0.36                         6.0           604
44999                 0.13                         3.0           628

       loan_status  person_gender_male  …  person_education_Master  \
0                1                   0  …                        1
1                0                   0  …                        0
2                1                   0  …                        0
3                1                   0  …                        0
4                1                   1  …                        1
…                …                   …  …                        …
44995            1                   1  …                        0
44996            1                   0  …                        0
44997            1                   1  …                        0
44998            1                   1  …                        0
44999            1                   1  …                        0

       person_home_ownership_OTHER  person_home_ownership_OWN  \
```

```
0                                 0                            0
1                                 0                            1
2                                 0                            0
3                                 0                            0
4                                 0                            0
…                              …                        …
44995                             0                            0
44996                             0                            0
44997                             0                            0
44998                             0                            0
44999                             0                            0

       person_home_ownership_RENT  loan_intent_EDUCATION  \
0                               1                      0
1                               0                      1
2                               0                      0
3                               1                      0
4                               1                      0
…                            …                    …
44995                           1                      0
44996                           1                      0
44997                           1                      0
44998                           1                      1
44999                           1                      0

       loan_intent_HOMEIMPROVEMENT  loan_intent_MEDICAL  loan_intent_PERSONAL  \
0                                0                    0                     1
1                                0                    0                     0
2                                0                    1                     0
3                                0                    1                     0
4                                0                    1                     0
…                             …                  …                   …
44995                            0                    1                     0
44996                            1                    0                     0
44997                            0                    0                     0
44998                            0                    0                     0
44999                            0                    0                     0

       loan_intent_VENTURE  previous_loan_defaults_on_file_Yes
0                        0                                   0
1                        0                                   1
2                        0                                   0
3                        0                                   0
4                        0                                   0
…                     …                                 …
44995                    0                                   0
44996                    0                                   0
```

```
44997                   0                             0
44998                   0                             0
44999                   0                             0

[44992 rows x 23 columns]
```

Out of k categorical levels in each category, we get an extra k-1 columns. For example, the "person_home_ownership" variable has 4 categories: "MORTGAGE, OTHER, OWN, RENT". 3 extra variables are created: "person_home_ownership_OTHER", "person_home_ownership_OWN", "person_home_ownership_RENT".

5 Creating datasets

5.1 Splitting features and labels

[10]:
```python
y = df['loan_status']
X = df[df.columns.drop('loan_status')]
```

5.2 Splitting the dataset into training, testing, and validating datasets

[11]:
```python
from sklearn.model_selection import train_test_split

train_test_X, validate_X, train_test_y, validate_y = train_test_split(X, y,
 ↪test_size=9000, random_state=10)
train_X, test_X, train_y, test_y = train_test_split(train_test_X, train_test_y,
 ↪test_size=9000, random_state=10)
```

The datasets' shape after splitting:

[12]:
```python
print(f"train_X: {train_X.shape}")
print(f"validate_X: {validate_X.shape}")
print(f"test_X: {test_X.shape}")
print(f"train_y: {train_y.shape}")
print(f"validate_y: {validate_y.shape}")
print(f"test_y: {test_y.shape}")
```

```
train_X: (26992, 22)
validate_X: (9000, 22)
test_X: (9000, 22)
train_y: (26992,)
validate_y: (9000,)
test_y: (9000,)
```

6 Training

6.1 Random Forest Classifier

6.1.1 Fitting

[13]:
```
from sklearn.ensemble import RandomForestClassifier

random_forest_classifier = RandomForestClassifier(n_estimators=500,
                                                   criterion='entropy',
                                                   n_jobs=-1,
                                                   random_state=40)
random_forest_classifier.fit(train_X, train_y)
```

[13]:
```
RandomForestClassifier(criterion='entropy', n_estimators=500, n_jobs=-1,
                       random_state=40)
```

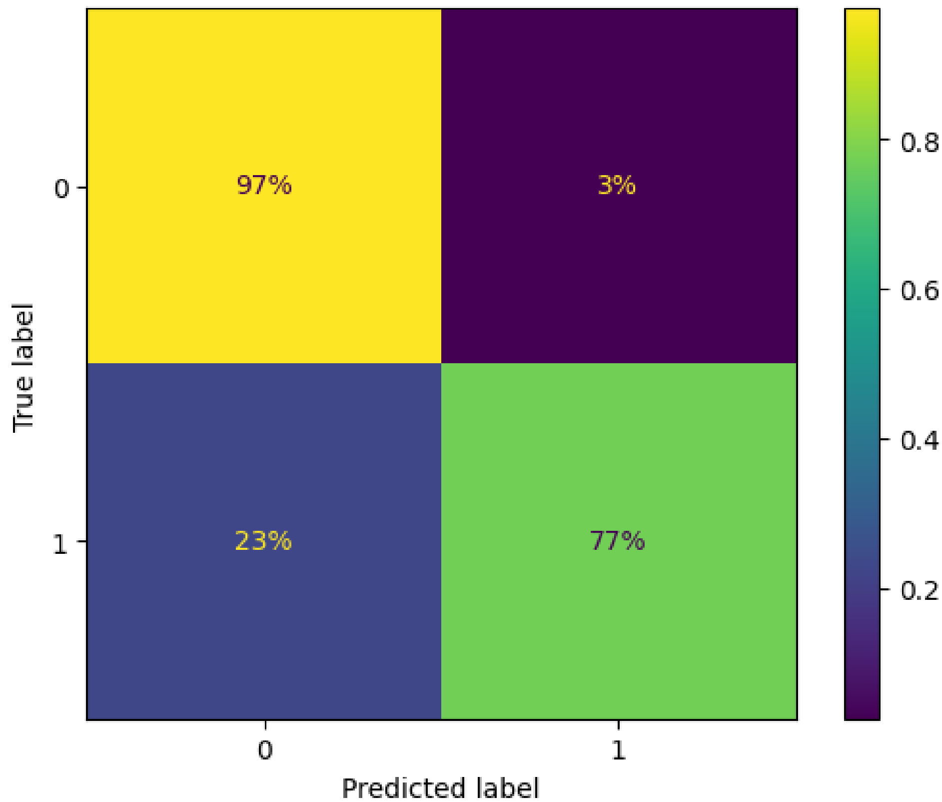
[14]:
```
# Saving the model
import joblib
joblib.dump(random_forest_classifier, "random_forest_classifier_v1.pkl")
```

[14]:
```
['random_forest_classifier_v1.pkl']
```

6.1.2 Evaluating

[15]:
```
from sklearn.metrics import ConfusionMatrixDisplay
print(f"The model's accuracy on the validation dataset is:␣
 ↪{round(random_forest_classifier.score(validate_X, validate_y), 4)}")
predicted_y = random_forest_classifier.predict(validate_X)
ConfusionMatrixDisplay.from_predictions(validate_y, predicted_y,␣
 ↪normalize="true", values_format=".0%")
plt.show()
```

```
The model's accuracy on the validation dataset is: 0.9303
```



We see that almost 1 in 4 positive instances is predicted as a negative one. We proceed to investigate the reason behind this issue.

6.1.3 View feature importances

[16]:
```
rfc_features_importances = pd.DataFrame({'Feature' : random_forest_classifier.
 ↪feature_names_in_,
                                          'Feature importance' :␣
 ↪random_forest_classifier.feature_importances_})

rfc_features_importances = rfc_features_importances.sort_values(by=['Feature␣
 ↪importance'], ascending=False).head(10)
rfc_features_importances
```

[16]:

	Feature	Feature importance
21	previous_loan_defaults_on_file_Yes	0.276974
5	loan_percent_income	0.140489
4	loan_int_rate	0.138041
1	person_income	0.112844
3	loan_amnt	0.059095
7	credit_score	0.053702

```
15          person_home_ownership_RENT           0.052389
0                           person_age           0.032056
2                       person_emp_exp           0.029754
6           cb_person_cred_hist_length           0.027219
```

The most important features are: 1. previous_loan_defaults_on_file: Indicator of previous loan defaults 2. loan_int_rate: Loan interest rate 3. loan_percent_income: Loan amount as a percentage of annual income 4. person_income: Annual income 5. loan_amnt: Loan amount requested 6. credit_score: Credit score of the person

6.1.4 Summary of false negatives

Collecting the TN, FP, FN, TP instances

[17]:
```python
# True negative
X_00 = validate_X[(validate_y == 0) & (predicted_y == 0)]

# False positive
X_01 = validate_X[(validate_y == 0) & (predicted_y == 1)]

# False negative
X_10 = validate_X[(validate_y == 1) & (predicted_y == 0)]

# True positive
X_11 = validate_X[(validate_y == 1) & (predicted_y == 1)]

# Viewing the false negative's dataframe
X_10
```

[17]:
```
       person_age  person_income  person_emp_exp  loan_amnt  loan_int_rate  \
2584         25.0        35864.0               1     3000.0           6.62
42638        23.0        39487.0               0     4882.0          14.25
44446        33.0        58656.0              14     6990.0          12.10
13613        23.0        85433.0               0    15000.0           8.90
27622        35.0       168855.0              11     8400.0          12.98
…             …            …                …         …               …
32274        38.0        36945.0              17     3000.0          13.85
42518        28.0        58368.0               3     8000.0          11.22
31018        46.0        65814.0              24    10000.0          11.71
43167        23.0       107265.0               0     8038.0          14.08
22185        28.0        57535.0               1     6000.0           8.88

       loan_percent_income  cb_person_cred_hist_length  credit_score  \
2584                  0.08                         2.0           600
42638                 0.12                         3.0           664
44446                 0.12                         5.0           654
13613                 0.18                         4.0           678
27622                 0.05                         9.0           657
```

```
…                  …                        …          …
32274               0.08                       14.0          695
42518               0.14                        6.0          647
31018               0.15                       15.0          698
43167               0.07                        4.0          619
22185               0.10                        6.0          671

       person_gender_male  person_education_Bachelor  …  \
2584                    0                          0  …
42638                   1                          0  …
44446                   1                          1  …
13613                   0                          0  …
27622                   1                          0  …
…                     …                        …  …
32274                   1                          0  …
42518                   0                          1  …
31018                   0                          1  …
43167                   0                          0  …
22185                   0                          0  …

       person_education_Master  person_home_ownership_OTHER  \
2584                         0                            0
42638                        0                            0
44446                        0                            0
13613                        0                            0
27622                        0                            0
…                          …                            …
32274                        0                            0
42518                        0                            0
31018                        0                            0
43167                        0                            0
22185                        0                            0

       person_home_ownership_OWN  person_home_ownership_RENT  \
2584                           0                           1
42638                          0                           1
44446                          0                           0
13613                          0                           0
27622                          0                           0
…                            …                           …
32274                          0                           1
42518                          0                           1
31018                          0                           1
43167                          0                           0
22185                          0                           0

       loan_intent_EDUCATION  loan_intent_HOMEIMPROVEMENT  \
```

```
2584                        0                           0
42638                       0                           0
44446                       0                           0
13613                       0                           0
27622                       0                           0
…                         …                           …
32274                       0                           0
42518                       1                           0
31018                       0                           0
43167                       0                           0
22185                       0                           1

       loan_intent_MEDICAL  loan_intent_PERSONAL  loan_intent_VENTURE  \
2584                     1                     0                    0
42638                    0                     0                    1
44446                    1                     0                    0
13613                    1                     0                    0
27622                    0                     1                    0
…                      …                     …                    …
32274                    1                     0                    0
42518                    0                     0                    0
31018                    0                     1                    0
43167                    0                     0                    0
22185                    0                     0                    0

       previous_loan_defaults_on_file_Yes
2584                                    0
42638                                   0
44446                                   0
13613                                   0
27622                                   0
…                                     …
32274                                   0
42518                                   0
31018                                   0
43167                                   0
22185                                   0

[452 rows x 22 columns]
```

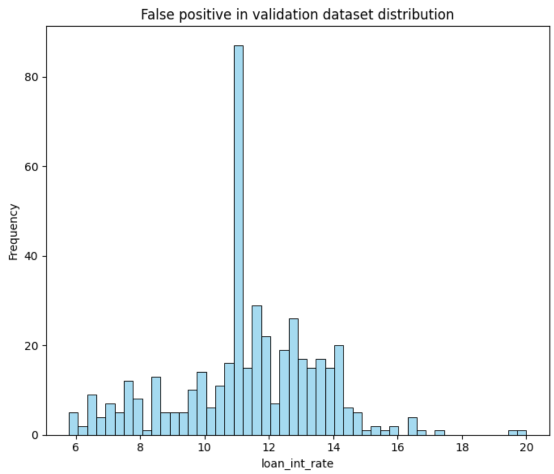
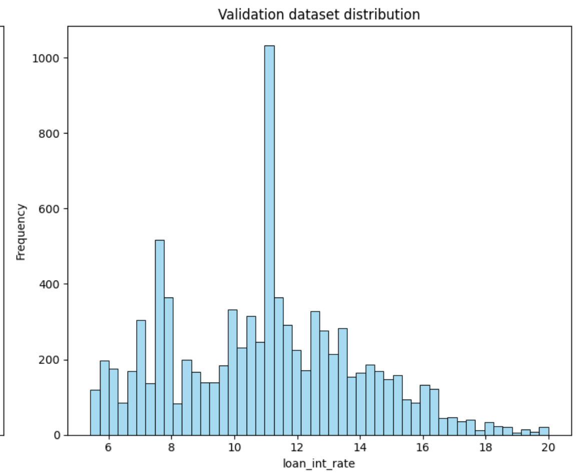
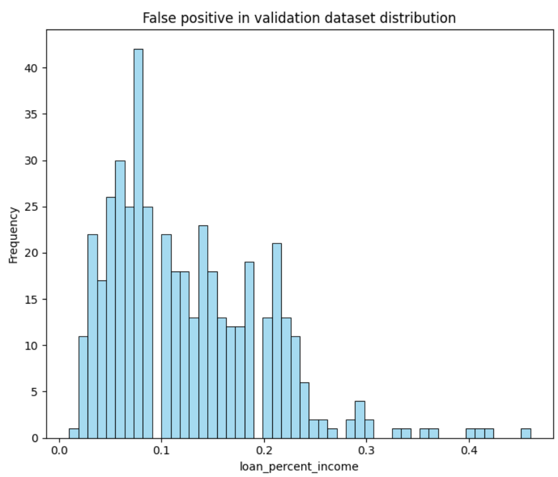
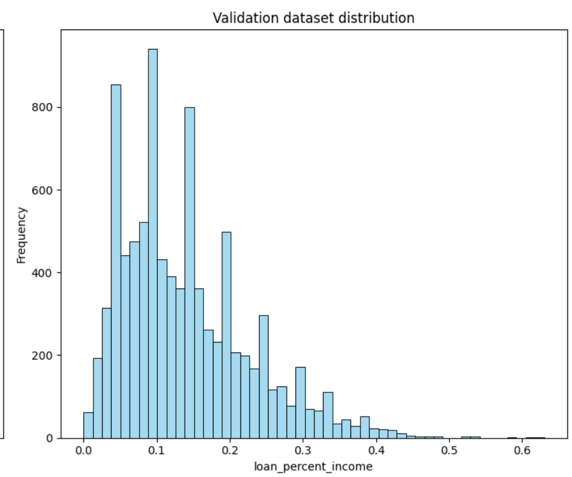
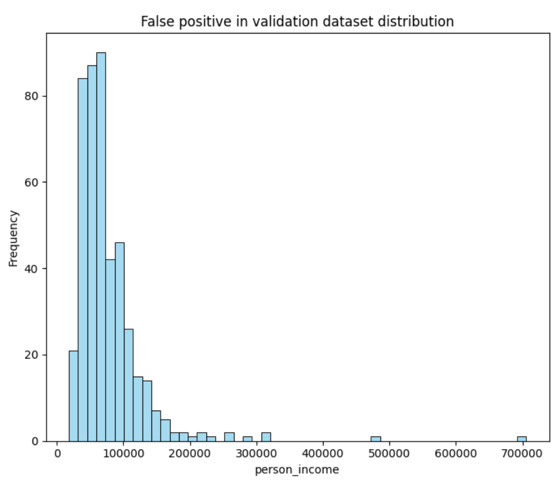
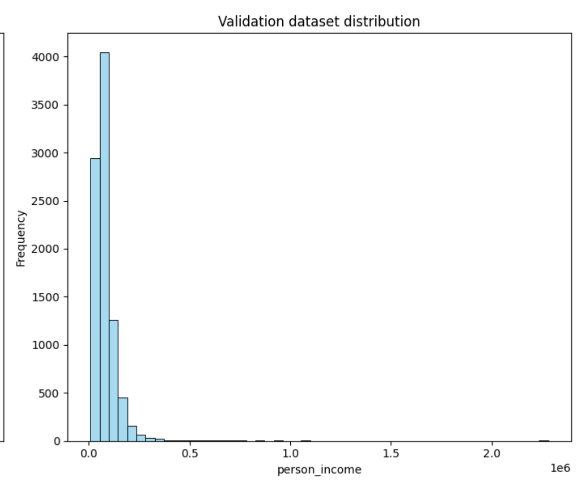
[18]:

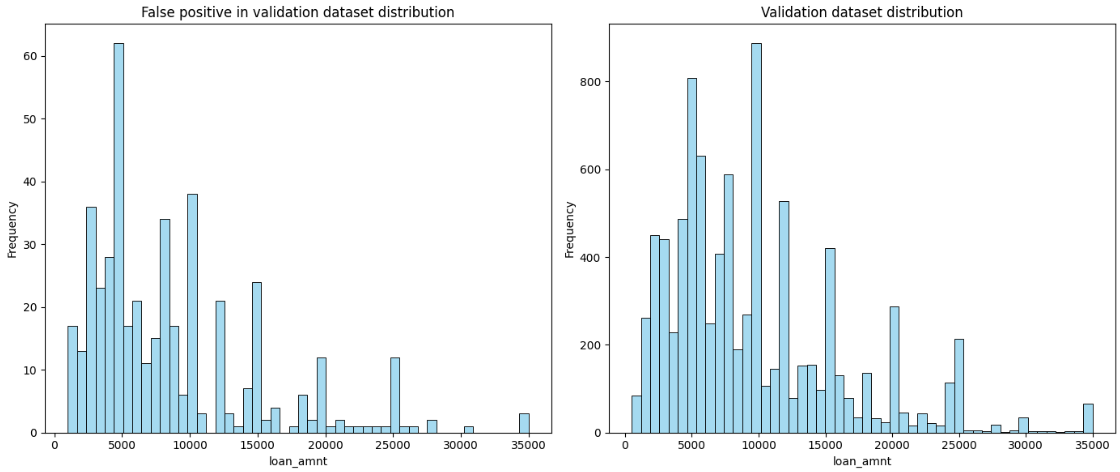
```
# Helper function to plot 2 histograms side-by-side
def plot_side_by_side_distributions(column1, column2):
    """
    Plots the distribution and summary statistics 2 DataFrame columns of␣
 ↪numerical data.
    Args:
```

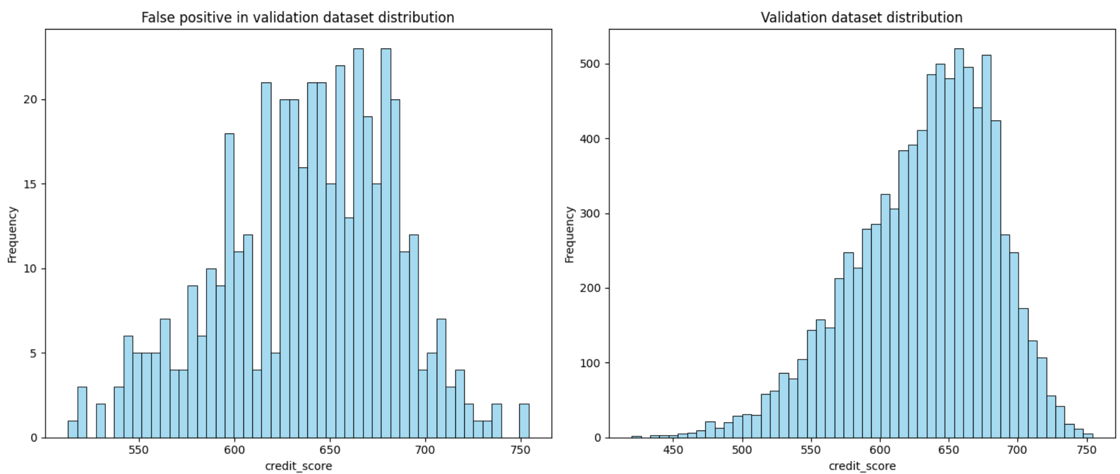
```
        column1, column2: pd.DataFrame.columns, the DataFrame column containing␣
↪numerical values.
    """
    plt.figure(figsize=(14, 6))

    # Histogram
    plt.subplot(1, 2, 1)
    sns.histplot(column1.dropna(), bins=50, kde=False, color='skyblue')
    plt.title("False positive in validation dataset distribution")
    plt.xlabel(column1.name)
    plt.ylabel('Frequency')

    # Histogram
    plt.subplot(1, 2, 2)
    sns.histplot(column2.dropna(), bins=50, kde=False, color='skyblue')
    plt.title("Validation dataset distribution")
    plt.xlabel(column1.name)
    plt.ylabel('Frequency')

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

[19]:

```
# Plotting 2 side-by-side historgrams, the left one shows the distribution of␣
↪the false negatives,
# while the right one shows the distribution of the validation dataset
plot_side_by_side_distributions(X_10['loan_int_rate'],␣
↪validate_X['loan_int_rate'])
plot_side_by_side_distributions(X_10['loan_percent_income'],␣
↪validate_X['loan_percent_income'])
plot_side_by_side_distributions(X_10['person_income'],␣
↪validate_X['person_income'])
plot_side_by_side_distributions(X_10['loan_amnt'], validate_X['loan_amnt'])
plot_side_by_side_distributions(X_10['credit_score'],␣
↪validate_X['credit_score'])
```


False positive in validation dataset distribution
Frequency
loan_int_rate

Validation dataset distribution
Frequency
loan_int_rate

False positive in validation dataset distribution
Frequency
loan_percent_income

Validation dataset distribution
Frequency
loan_percent_income

False positive in validation dataset distribution
Frequency
person_income

Validation dataset distribution
Frequency
person_income
1e6



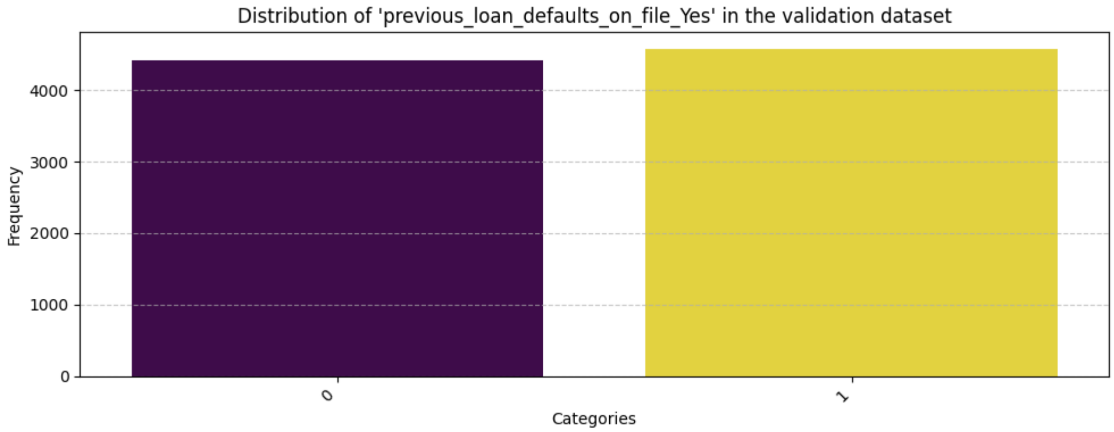


We see that the distribution of 5 numerical variables does not differ much from left to right. We conclude that no evidence indicating that the false positives concentrate proportionately in a numerical feature has been found.

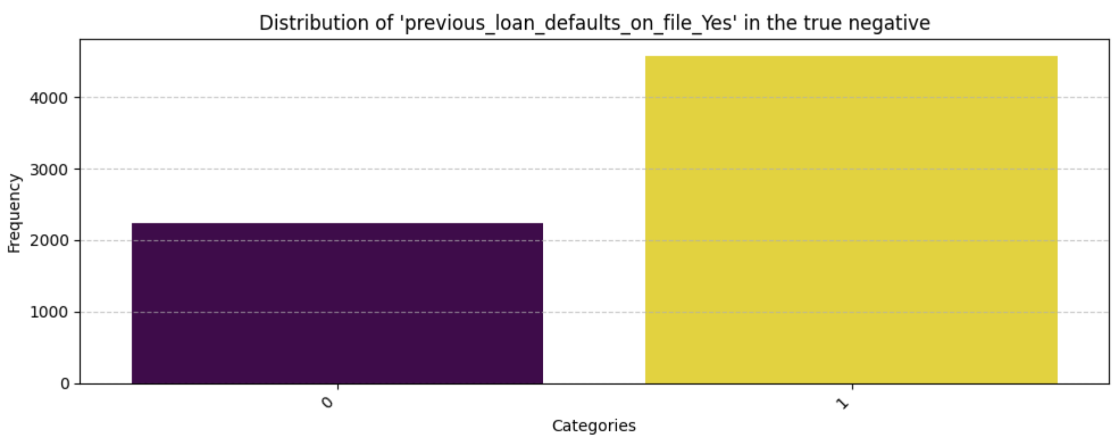
[20]:
```python
# Helper function to draw a bar chart showing the distribution of each categorical feature
# Produced and edited from chatGPT prompt: Write Python function to draw a graph summarizing a column with categorical data in a DataFrame"
import seaborn as sns

def plot_categorical_column_with_title_addition(df, column_name, title_addition):
    """
    Plots a bar chart summarizing the distribution of a categorical column in the DataFrame.
```

```
    Args:
        df: pd.DataFrame, the DataFrame containing the column.
        column_name: str, the name of the categorical column to be summarized.

    Returns:
        None
    """
    if column_name not in df.columns:
        print(f"Column '{column_name}' not found in the DataFrame.")
        return

    # Ensure the column is treated as categorical
    if not pd.api.types.is_categorical_dtype(df[column_name]):
        df[column_name] = df[column_name].astype('category')

    # Count the occurrences of each category
    category_counts = df[column_name].value_counts()

    # Plot the distribution
    plt.figure(figsize=(10, 4))
    sns.barplot(x=category_counts.index, y=category_counts.values,␣
 ↪palette="viridis", hue=category_counts, legend=False)
    plt.title(f"Distribution of '{column_name}' in the {title_addition}")
    plt.xlabel("Categories")
    plt.ylabel("Frequency")
    plt.xticks(rotation=45, ha="right")
    plt.grid(axis='y', linestyle='--', alpha=0.7)
    plt.tight_layout()
    plt.show()
```

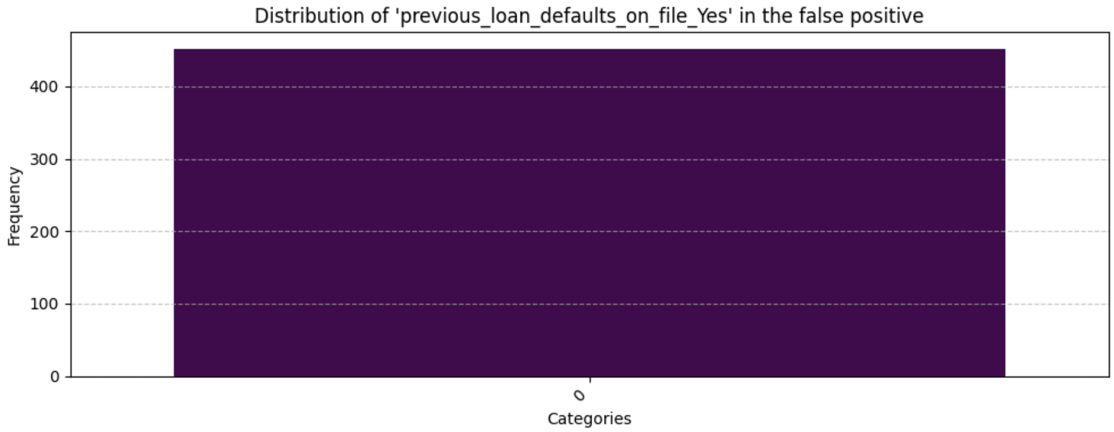
[21]:
```
plot_categorical_column_with_title_addition(validate_X,␣
 ↪'previous_loan_defaults_on_file_Yes', "validation dataset")
plot_categorical_column_with_title_addition(X_00,␣
 ↪'previous_loan_defaults_on_file_Yes', "true negative")
plot_categorical_column_with_title_addition(X_10,␣
 ↪'previous_loan_defaults_on_file_Yes', "false positive")
plot_categorical_column_with_title_addition(X_01,␣
 ↪'previous_loan_defaults_on_file_Yes', "false negative")
plot_categorical_column_with_title_addition(X_11,␣
 ↪'previous_loan_defaults_on_file_Yes', "true positive")
```



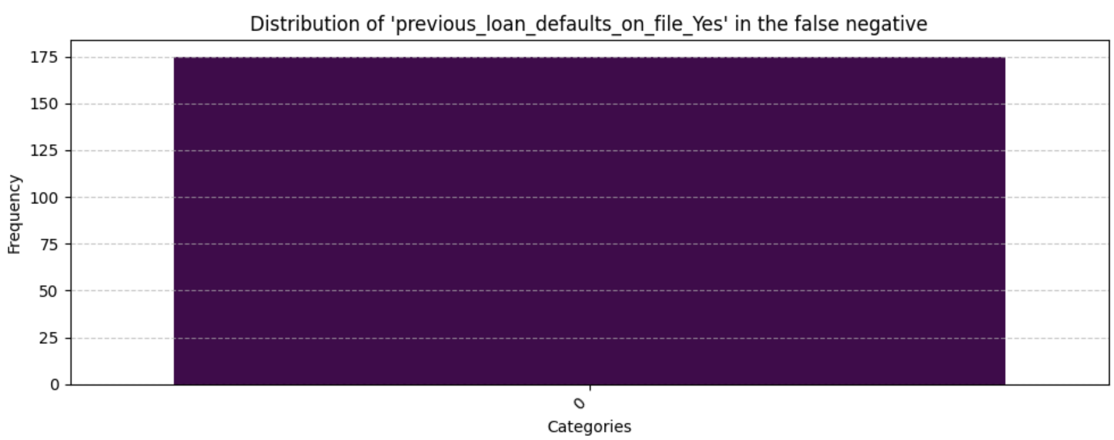

```
/var/folders/kh/5ycz460j13q1bq3hw3ytwplw0000gn/T/ipykernel_35804/1570375067.py:2
2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df[column_name] = df[column_name].astype('category')
```



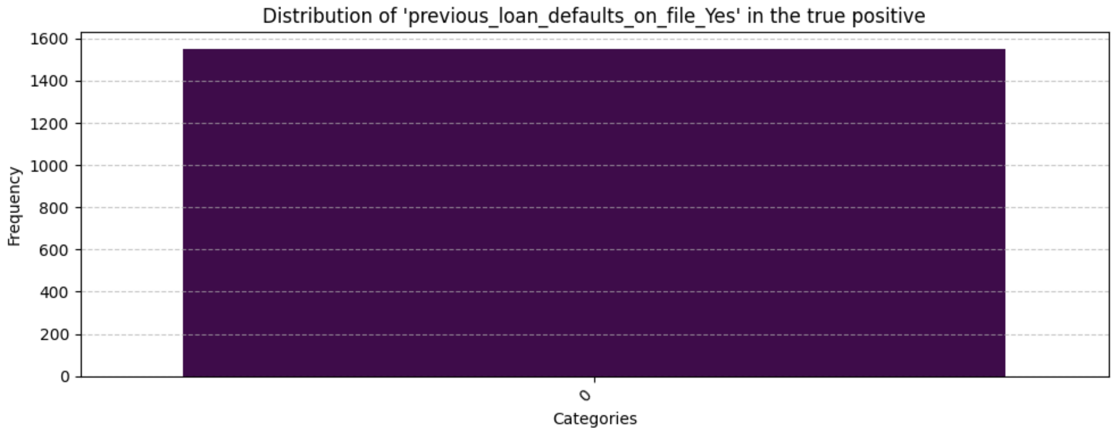

```
/var/folders/kh/5ycz460j13q1bq3hw3ytwplw0000gn/T/ipykernel_35804/1570375067.py:2
2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df[column_name] = df[column_name].astype('category')
```




```
/var/folders/kh/5ycz460j13q1bq3hw3ytwplw0000gn/T/ipykernel_35804/1570375067.py:2
2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df[column_name] = df[column_name].astype('category')
```




```
/var/folders/kh/5ycz460j13q1bq3hw3ytwplw0000gn/T/ipykernel_35804/1570375067.py:2
2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df[column_name] = df[column_name].astype('category')
```



All of the false positives have previous_loan_defaults_on_file_Yes = 0 i.e., previous_loan_defaults_on_file = "No" (the same happens for all of the True Positives and False Positives). Maybe the importance of previous_loan_defaults_on_file should be higher. We will examine that in section 6.3

6.2 Random Forest Classifier, Hyperparameter tuning version

6.2.1 Tuning the model

In the section below, I tried to search for the optimal combination of the number of estimators, the max depth, and the criterion function of the Random forest classifier

[22]:
```
from sklearn.model_selection import RandomizedSearchCV
from sklearn.ensemble import RandomForestClassifier

rfc = RandomForestClassifier(random_state=40)

param_distributions = dict(n_estimators=[100, 200, 300, 400, 500],
                           max_depth=[i for i in range(1, 100)],
                           criterion=['gini', 'entropy'])

rfc_searched = RandomizedSearchCV(
    rfc,
    param_distributions=param_distributions,
    n_iter=50,
    cv=3,
    verbose=2.5,
    scoring='accuracy', random_state=42)

rfc_searched.fit(train_X, train_y)
```

```
Fitting 3 folds for each of 50 candidates, totalling 150 fits
[CV 1/3] END criterion=gini, max_depth=43, n_estimators=400;, score=0.922 total
```

```
time=   7.2s
[CV 2/3] END criterion=gini, max_depth=43, n_estimators=400;, score=0.924 total
time=   6.9s
[CV 3/3] END criterion=gini, max_depth=43, n_estimators=400;, score=0.922 total
time=   6.8s
[CV 1/3] END criterion=gini, max_depth=67, n_estimators=200;, score=0.922 total
time=   3.5s
[CV 2/3] END criterion=gini, max_depth=67, n_estimators=200;, score=0.924 total
time=   3.6s
[CV 3/3] END criterion=gini, max_depth=67, n_estimators=200;, score=0.923 total
time=   3.5s
[CV 1/3] END criterion=entropy, max_depth=2, n_estimators=200;, score=0.804
total time=   1.4s
[CV 2/3] END criterion=entropy, max_depth=2, n_estimators=200;, score=0.810
total time=   1.1s
[CV 3/3] END criterion=entropy, max_depth=2, n_estimators=200;, score=0.806
total time=   1.1s
[CV 1/3] END criterion=gini, max_depth=62, n_estimators=500;, score=0.922 total
time=  11.3s
[CV 2/3] END criterion=gini, max_depth=62, n_estimators=500;, score=0.923 total
time=  13.2s
[CV 3/3] END criterion=gini, max_depth=62, n_estimators=500;, score=0.923 total
time=  10.2s
[CV 1/3] END criterion=gini, max_depth=18, n_estimators=400;, score=0.922 total
time=   7.1s
[CV 2/3] END criterion=gini, max_depth=18, n_estimators=400;, score=0.924 total
time=   8.2s
[CV 3/3] END criterion=gini, max_depth=18, n_estimators=400;, score=0.924 total
time=   7.2s
[CV 1/3] END criterion=entropy, max_depth=9, n_estimators=100;, score=0.917
total time=   1.2s
[CV 2/3] END criterion=entropy, max_depth=9, n_estimators=100;, score=0.921
total time=   1.3s
[CV 3/3] END criterion=entropy, max_depth=9, n_estimators=100;, score=0.921
total time=   1.4s
[CV 1/3] END criterion=gini, max_depth=57, n_estimators=100;, score=0.923 total
time=   1.7s
[CV 2/3] END criterion=gini, max_depth=57, n_estimators=100;, score=0.922 total
time=   1.7s
[CV 3/3] END criterion=gini, max_depth=57, n_estimators=100;, score=0.924 total
time=   1.7s
[CV 1/3] END criterion=gini, max_depth=22, n_estimators=300;, score=0.924 total
time=   5.1s
[CV 2/3] END criterion=gini, max_depth=22, n_estimators=300;, score=0.924 total
time=   8.6s
[CV 3/3] END criterion=gini, max_depth=22, n_estimators=300;, score=0.923 total
time=   7.8s
[CV 1/3] END criterion=gini, max_depth=12, n_estimators=500;, score=0.919 total
```

```
time=   7.6s
[CV 2/3] END criterion=gini, max_depth=12, n_estimators=500;, score=0.924 total
time=   7.9s
[CV 3/3] END criterion=gini, max_depth=12, n_estimators=500;, score=0.923 total
time=   8.9s
[CV 1/3] END criterion=entropy, max_depth=3, n_estimators=200;, score=0.863
total time=   1.7s
[CV 2/3] END criterion=entropy, max_depth=3, n_estimators=200;, score=0.859
total time=   1.7s
[CV 3/3] END criterion=entropy, max_depth=3, n_estimators=200;, score=0.857
total time=   1.9s
[CV 1/3] END criterion=gini, max_depth=72, n_estimators=500;, score=0.922 total
time=   9.4s
[CV 2/3] END criterion=gini, max_depth=72, n_estimators=500;, score=0.923 total
time=   8.8s
[CV 3/3] END criterion=gini, max_depth=72, n_estimators=500;, score=0.923 total
time=  10.0s
[CV 1/3] END criterion=gini, max_depth=90, n_estimators=100;, score=0.923 total
time=   2.0s
[CV 2/3] END criterion=gini, max_depth=90, n_estimators=100;, score=0.922 total
time=   2.0s
[CV 3/3] END criterion=gini, max_depth=90, n_estimators=100;, score=0.924 total
time=   1.9s
[CV 1/3] END criterion=gini, max_depth=15, n_estimators=100;, score=0.922 total
time=   1.6s
[CV 2/3] END criterion=gini, max_depth=15, n_estimators=100;, score=0.924 total
time=   1.6s
[CV 3/3] END criterion=gini, max_depth=15, n_estimators=100;, score=0.924 total
time=   1.6s
[CV 1/3] END criterion=gini, max_depth=20, n_estimators=200;, score=0.921 total
time=   3.5s
[CV 2/3] END criterion=gini, max_depth=20, n_estimators=200;, score=0.923 total
time=   3.4s
[CV 3/3] END criterion=gini, max_depth=20, n_estimators=200;, score=0.923 total
time=   3.5s
[CV 1/3] END criterion=entropy, max_depth=73, n_estimators=300;, score=0.923
total time=   5.8s
[CV 2/3] END criterion=entropy, max_depth=73, n_estimators=300;, score=0.922
total time=   7.1s
[CV 3/3] END criterion=entropy, max_depth=73, n_estimators=300;, score=0.924
total time=   6.2s
[CV 1/3] END criterion=entropy, max_depth=51, n_estimators=500;, score=0.924
total time=   9.4s
[CV 2/3] END criterion=entropy, max_depth=51, n_estimators=500;, score=0.922
total time=  10.0s
[CV 3/3] END criterion=entropy, max_depth=51, n_estimators=500;, score=0.924
total time=  11.4s
[CV 1/3] END criterion=entropy, max_depth=74, n_estimators=400;, score=0.923
```

```
total time=   9.4s
[CV 2/3] END criterion=entropy, max_depth=74, n_estimators=400;, score=0.922
total time=   8.4s
[CV 3/3] END criterion=entropy, max_depth=74, n_estimators=400;, score=0.923
total time=   7.8s
[CV 1/3] END criterion=entropy, max_depth=88, n_estimators=300;, score=0.923
total time=   6.2s
[CV 2/3] END criterion=entropy, max_depth=88, n_estimators=300;, score=0.922
total time=   6.0s
[CV 3/3] END criterion=entropy, max_depth=88, n_estimators=300;, score=0.924
total time=   5.9s
[CV 1/3] END criterion=gini, max_depth=16, n_estimators=200;, score=0.919 total
time=   3.7s
[CV 2/3] END criterion=gini, max_depth=16, n_estimators=200;, score=0.925 total
time=   3.3s
[CV 3/3] END criterion=gini, max_depth=16, n_estimators=200;, score=0.924 total
time=   3.7s
[CV 1/3] END criterion=entropy, max_depth=55, n_estimators=300;, score=0.923
total time=   7.3s
[CV 2/3] END criterion=entropy, max_depth=55, n_estimators=300;, score=0.922
total time=   7.3s
[CV 3/3] END criterion=entropy, max_depth=55, n_estimators=300;, score=0.924
total time=   6.4s
[CV 1/3] END criterion=gini, max_depth=40, n_estimators=400;, score=0.922 total
time=   7.0s
[CV 2/3] END criterion=gini, max_depth=40, n_estimators=400;, score=0.924 total
time=   6.8s
[CV 3/3] END criterion=gini, max_depth=40, n_estimators=400;, score=0.922 total
time=   7.1s
[CV 1/3] END criterion=entropy, max_depth=1, n_estimators=500;, score=0.777
total time=   2.5s
[CV 2/3] END criterion=entropy, max_depth=1, n_estimators=500;, score=0.777
total time=   2.9s
[CV 3/3] END criterion=entropy, max_depth=1, n_estimators=500;, score=0.777
total time=   2.7s
[CV 1/3] END criterion=entropy, max_depth=44, n_estimators=100;, score=0.923
total time=   1.9s
[CV 2/3] END criterion=entropy, max_depth=44, n_estimators=100;, score=0.924
total time=   1.9s
[CV 3/3] END criterion=entropy, max_depth=44, n_estimators=100;, score=0.923
total time=   2.0s
[CV 1/3] END criterion=entropy, max_depth=2, n_estimators=100;, score=0.813
total time=   0.7s
[CV 2/3] END criterion=entropy, max_depth=2, n_estimators=100;, score=0.813
total time=   0.7s
[CV 3/3] END criterion=entropy, max_depth=2, n_estimators=100;, score=0.819
total time=   0.7s
[CV 1/3] END criterion=entropy, max_depth=9, n_estimators=200;, score=0.918
```

```
total time=   3.4s
[CV 2/3] END criterion=entropy, max_depth=9, n_estimators=200;, score=0.922
total time=   2.6s
[CV 3/3] END criterion=entropy, max_depth=9, n_estimators=200;, score=0.922
total time=   2.9s
[CV 1/3] END criterion=entropy, max_depth=59, n_estimators=500;, score=0.924
total time=  11.4s
[CV 2/3] END criterion=entropy, max_depth=59, n_estimators=500;, score=0.922
total time=   9.9s
[CV 3/3] END criterion=entropy, max_depth=59, n_estimators=500;, score=0.924
total time=  12.5s
[CV 1/3] END criterion=entropy, max_depth=76, n_estimators=400;, score=0.923
total time=   7.6s
[CV 2/3] END criterion=entropy, max_depth=76, n_estimators=400;, score=0.922
total time=   7.7s
[CV 3/3] END criterion=entropy, max_depth=76, n_estimators=400;, score=0.923
total time=   7.8s
[CV 1/3] END criterion=entropy, max_depth=5, n_estimators=400;, score=0.908
total time=   3.8s
[CV 2/3] END criterion=entropy, max_depth=5, n_estimators=400;, score=0.910
total time=   4.4s
[CV 3/3] END criterion=entropy, max_depth=5, n_estimators=400;, score=0.905
total time=   4.6s
[CV 1/3] END criterion=gini, max_depth=92, n_estimators=300;, score=0.922 total
time=   8.0s
[CV 2/3] END criterion=gini, max_depth=92, n_estimators=300;, score=0.923 total
time=   5.8s
[CV 3/3] END criterion=gini, max_depth=92, n_estimators=300;, score=0.923 total
time=   5.9s
[CV 1/3] END criterion=entropy, max_depth=58, n_estimators=200;, score=0.923
total time=   4.7s
[CV 2/3] END criterion=entropy, max_depth=58, n_estimators=200;, score=0.923
total time=   4.8s
[CV 3/3] END criterion=entropy, max_depth=58, n_estimators=200;, score=0.924
total time=   4.0s
[CV 1/3] END criterion=entropy, max_depth=75, n_estimators=300;, score=0.923
total time=   5.7s
[CV 2/3] END criterion=entropy, max_depth=75, n_estimators=300;, score=0.922
total time=   5.9s
[CV 3/3] END criterion=entropy, max_depth=75, n_estimators=300;, score=0.924
total time=   6.4s
[CV 1/3] END criterion=entropy, max_depth=47, n_estimators=400;, score=0.923
total time=   8.5s
[CV 2/3] END criterion=entropy, max_depth=47, n_estimators=400;, score=0.922
total time=   9.0s
[CV 3/3] END criterion=entropy, max_depth=47, n_estimators=400;, score=0.923
total time=   8.2s
[CV 1/3] END criterion=entropy, max_depth=22, n_estimators=400;, score=0.923
```

```
total time=   7.6s
[CV 2/3] END criterion=entropy, max_depth=22, n_estimators=400;, score=0.924
total time=   7.9s
[CV 3/3] END criterion=entropy, max_depth=22, n_estimators=400;, score=0.923
total time=   8.1s
[CV 1/3] END criterion=entropy, max_depth=21, n_estimators=300;, score=0.922
total time=   6.0s
[CV 2/3] END criterion=entropy, max_depth=21, n_estimators=300;, score=0.923
total time=   6.1s
[CV 3/3] END criterion=entropy, max_depth=21, n_estimators=300;, score=0.923
total time=   5.7s
[CV 1/3] END criterion=entropy, max_depth=36, n_estimators=400;, score=0.923
total time=   7.5s
[CV 2/3] END criterion=entropy, max_depth=36, n_estimators=400;, score=0.922
total time=   7.7s
[CV 3/3] END criterion=entropy, max_depth=36, n_estimators=400;, score=0.924
total time=   7.9s
[CV 1/3] END criterion=entropy, max_depth=39, n_estimators=500;, score=0.924
total time=   9.6s
[CV 2/3] END criterion=entropy, max_depth=39, n_estimators=500;, score=0.922
total time=   9.8s
[CV 3/3] END criterion=entropy, max_depth=39, n_estimators=500;, score=0.924
total time=   9.8s
[CV 1/3] END criterion=gini, max_depth=77, n_estimators=300;, score=0.922 total
time=   5.3s
[CV 2/3] END criterion=gini, max_depth=77, n_estimators=300;, score=0.923 total
time=   5.6s
[CV 3/3] END criterion=gini, max_depth=77, n_estimators=300;, score=0.923 total
time=   8.0s
[CV 1/3] END criterion=entropy, max_depth=89, n_estimators=400;, score=0.923
total time=   8.4s
[CV 2/3] END criterion=entropy, max_depth=89, n_estimators=400;, score=0.922
total time=   7.6s
[CV 3/3] END criterion=entropy, max_depth=89, n_estimators=400;, score=0.923
total time=   7.8s
[CV 1/3] END criterion=entropy, max_depth=25, n_estimators=200;, score=0.923
total time=   4.0s
[CV 2/3] END criterion=entropy, max_depth=25, n_estimators=200;, score=0.923
total time=   3.9s
[CV 3/3] END criterion=entropy, max_depth=25, n_estimators=200;, score=0.924
total time=   3.9s
[CV 1/3] END criterion=entropy, max_depth=33, n_estimators=100;, score=0.923
total time=   1.9s
[CV 2/3] END criterion=entropy, max_depth=33, n_estimators=100;, score=0.923
total time=   1.9s
[CV 3/3] END criterion=entropy, max_depth=33, n_estimators=100;, score=0.923
total time=   1.9s
[CV 1/3] END criterion=entropy, max_depth=94, n_estimators=500;, score=0.924
```

```
total time=   9.6s
[CV 2/3] END criterion=entropy, max_depth=94, n_estimators=500;, score=0.922
total time=   9.5s
[CV 3/3] END criterion=entropy, max_depth=94, n_estimators=500;, score=0.924
total time=  10.4s
[CV 1/3] END criterion=gini, max_depth=5, n_estimators=400;, score=0.908 total
time=   3.7s
[CV 2/3] END criterion=gini, max_depth=5, n_estimators=400;, score=0.911 total
time=   3.6s
[CV 3/3] END criterion=gini, max_depth=5, n_estimators=400;, score=0.906 total
time=   3.6s
[CV 1/3] END criterion=gini, max_depth=7, n_estimators=100;, score=0.914 total
time=   1.0s
[CV 2/3] END criterion=gini, max_depth=7, n_estimators=100;, score=0.920 total
time=   1.1s
[CV 3/3] END criterion=gini, max_depth=7, n_estimators=100;, score=0.919 total
time=   1.1s
[CV 1/3] END criterion=entropy, max_depth=48, n_estimators=100;, score=0.923
total time=   1.9s
[CV 2/3] END criterion=entropy, max_depth=48, n_estimators=100;, score=0.924
total time=   1.9s
[CV 3/3] END criterion=entropy, max_depth=48, n_estimators=100;, score=0.923
total time=   1.9s
[CV 1/3] END criterion=gini, max_depth=3, n_estimators=100;, score=0.873 total
time=   0.7s
[CV 2/3] END criterion=gini, max_depth=3, n_estimators=100;, score=0.871 total
time=   0.7s
[CV 3/3] END criterion=gini, max_depth=3, n_estimators=100;, score=0.867 total
time=   0.6s
[CV 1/3] END criterion=gini, max_depth=35, n_estimators=500;, score=0.922 total
time=   8.6s
[CV 2/3] END criterion=gini, max_depth=35, n_estimators=500;, score=0.923 total
time=   8.8s
[CV 3/3] END criterion=gini, max_depth=35, n_estimators=500;, score=0.923 total
time=  10.8s
[CV 1/3] END criterion=entropy, max_depth=6, n_estimators=300;, score=0.911
total time=   3.2s
[CV 2/3] END criterion=entropy, max_depth=6, n_estimators=300;, score=0.916
total time=   3.4s
[CV 3/3] END criterion=entropy, max_depth=6, n_estimators=300;, score=0.914
total time=   4.0s
[CV 1/3] END criterion=entropy, max_depth=30, n_estimators=400;, score=0.923
total time=   8.1s
[CV 2/3] END criterion=entropy, max_depth=30, n_estimators=400;, score=0.924
total time=   8.4s
[CV 3/3] END criterion=entropy, max_depth=30, n_estimators=400;, score=0.924
total time=   7.7s
[CV 1/3] END criterion=entropy, max_depth=46, n_estimators=200;, score=0.923
```

```
total time=   4.0s
[CV 2/3] END criterion=entropy, max_depth=46, n_estimators=200;, score=0.923
total time=   4.1s
[CV 3/3] END criterion=entropy, max_depth=46, n_estimators=200;, score=0.924
total time=   3.8s
[CV 1/3] END criterion=gini, max_depth=64, n_estimators=400;, score=0.922 total
time=   6.9s
[CV 2/3] END criterion=gini, max_depth=64, n_estimators=400;, score=0.924 total
time=   7.3s
[CV 3/3] END criterion=gini, max_depth=64, n_estimators=400;, score=0.922 total
time=   7.9s
```

[22]:
```
RandomizedSearchCV(cv=3, estimator=RandomForestClassifier(random_state=40),
                   n_iter=50,
                   param_distributions={'criterion': ['gini', 'entropy'],
                                        'max_depth': [1, 2, 3, 4, 5, 6, 7, 8, 9,
                                                      10, 11, 12, 13, 14, 15,
                                                      16, 17, 18, 19, 20, 21,
                                                      22, 23, 24, 25, 26, 27,
                                                      28, 29, 30, …],
                                        'n_estimators': [100, 200, 300, 400,
                                                         500]},
                   random_state=42, scoring='accuracy', verbose=2.5)
```

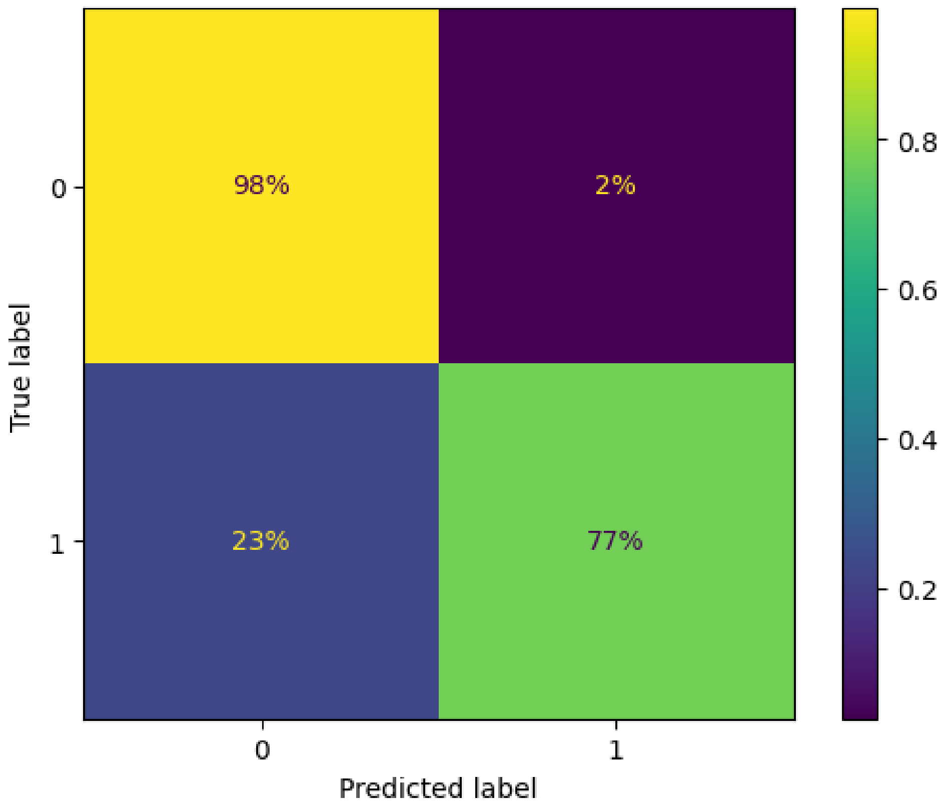
[23]:
```
joblib.dump(rfc_searched, "random_forest_classifier_tuned.pkl")
```

[23]:
```
['random_forest_classifier_tuned.pkl']
```

6.2.2 Evaluating the tuned Random Forest Classifier

[24]:
```
print(f"The model's accuracy on the validation dataset is: {round(rfc_searched.
 ↪score(validate_X, validate_y), 4)}")
predicted_y = rfc_searched.predict(validate_X)
ConfusionMatrixDisplay.from_predictions(validate_y, predicted_y,␣
 ↪normalize="true", values_format=".0%")
plt.show()
```

```
The model's accuracy on the validation dataset is: 0.9301
```



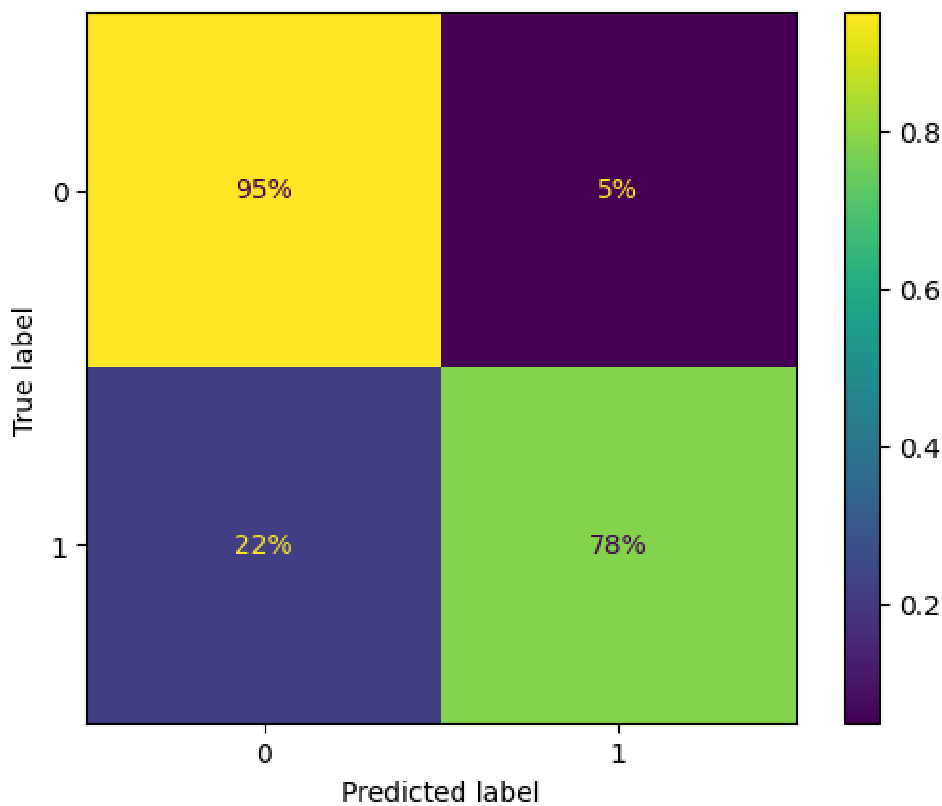
After doing random hyperparameter search, we arrive at a model whose's accuracy on the validation set does not differ much from that of the original model (0.9301 compared to 0.9303)

6.3 Random Forest Classifier, but with only 6 important parameters involved

[27]:
```
new_y = df['loan_status']
new_X = df[["previous_loan_defaults_on_file_Yes", "loan_int_rate",␣
↪"loan_percent_income", "person_income", "loan_amnt", "credit_score"]]

new_train_test_X, new_validate_X, new_train_test_y, new_validate_y =␣
↪train_test_split(new_X, new_y, test_size=9000, random_state=10)
new_train_X, new_test_X, new_train_y, new_test_y =␣
↪train_test_split(new_train_test_X, new_train_test_y, test_size=9000,␣
↪random_state=10)

random_forest_classifier_v3 = RandomForestClassifier(n_estimators=500,
                                                    criterion='entropy',
                                                    n_jobs=-1,
                                                    random_state=40)
random_forest_classifier_v3.fit(new_train_X, new_train_y)
```

```
joblib.dump(random_forest_classifier_v3, "random_forest_classifier_v3.pkl")

print(f"The model's accuracy on the validation dataset is:␣
 ↪{round(random_forest_classifier_v3.score(new_validate_X, new_validate_y),␣
 ↪4)}")
new_predicted_y = random_forest_classifier_v3.predict(new_validate_X)
ConfusionMatrixDisplay.from_predictions(new_validate_y, new_predicted_y,␣
 ↪normalize="true", values_format=".0%")
plt.show()

rfc_v3_features_importances = pd.DataFrame({'feature' :␣
 ↪random_forest_classifier_v3.feature_names_in_,
                                            'Feature Importances' :␣
 ↪random_forest_classifier_v3.feature_importances_})
rfc_v3_features_importances = rfc_v3_features_importances.
 ↪sort_values(by=['Feature Importances'], ascending=False).head(10)
rfc_v3_features_importances
```

```
The model's accuracy on the validation dataset is: 0.9139
```



[27]:

	feature	Feature Importances
0	previous_loan_defaults_on_file_Yes	0.314016
1	loan_int_rate	0.183111
3	person_income	0.168589
2	loan_percent_income	0.154359
5	credit_score	0.099608
4	loan_amnt	0.080317

Unfortunately, limiting the model to only 6 most important features does not solve the problem that many positive instances are incorrectly predicted.

7 Testing the model on the test set

We choose the model with the best performance i.e. the initial random_forest_classifier

[30]:
```
from sklearn.metrics import ConfusionMatrixDisplay
print(f"The model's accuracy on the test dataset is:␣
↪{round(random_forest_classifier.score(test_X, test_y), 4)}")
random_forest_classifier_prediction = random_forest_classifier.predict(test_X)
ConfusionMatrixDisplay.from_predictions(test_y,␣
↪random_forest_classifier_prediction, normalize="true", values_format=".0%")
plt.show()
```

```
The model's accuracy on the test dataset is: 0.9294
```