eda_cbm

June 6, 2024

1 Exploratory data analysis

For this notebook, I borrowed code from Sadegh Bolouki's Bank Account Fraud Detection: EDA and Model.

[ ]:
```
# Imports
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.colors
import seaborn as sns

# Define custom colors/cmaps/palettes for visualization purposes.
denim='#6F8FAF'
salmon='#FA8072'
slate_gray = '#404040'
cmap=matplotlib.colors.LinearSegmentedColormap.from_list("",[denim,salmon])
palette = 'colorblind'
sns.set_style('darkgrid')

from sklearn.model_selection import train_test_split
```

[ ]:
```
# Data loading
df = pd.read_csv('../data/Base.csv')

target = 'fraud_bool'

X = df.drop(target,axis=1)
y = df[target]
```

[ ]:
```
# Train/test split with stratified sampling

X_train, X_test, y_train, y_test = train_test_split(X, y, stratify=y,
↪test_size=0.2, random_state=42)

train = pd.concat([X_train, y_train], axis=1).copy()
train_copy = pd.concat([X_train, y_train], axis=1).copy()
```

[ ]:
```python
feature_descriptions = {
    'income' : "Annual income of the applicant (in decile form). Ranges between [0.1, 0.9].",
    'name_email_similarity' : "Metric of similarity between email and applicant’s name. Higher values represent higher similarity. Ranges between [0, 1].",
    'prev_address_months_count' : "Number of months in previous registered address of the applicant, i.e. the applicant’s previous residence, if applicable. Ranges between [-1, 380] months (-1 is a missing value).",
    'current_address_months_count' : "Months in currently registered address of the applicant. Ranges between [-1, 429] months (-1 is a missing value).",
    'customer_age' : "Applicant’s age in years, rounded to the decade. Ranges between [10, 90] years.",
    'days_since_request' : "Number of days passed since application was done. Ranges between [0, 79] days.",
    'intended_balcon_amount' : "Initial transferred amount for application. Ranges between [-16, 114] (negatives are missing values).",
    'payment_type': "Credit payment plan type. 5 possible (annonymized) values.",
    'zip_count_4w' : "Number of applications within same zip code in last 4 weeks. Ranges between [1, 6830].",
    'velocity_6h' : "Velocity of total applications made in last 6 hours i.e., average number of applications per hour in the last 6 hours. Ranges between [-175, 16818].",
    'velocity_24h' : "Velocity of total applications made in last 24 hours i.e., average number of applications per hour in the last 24 hours. Ranges between [1297, 9586].",
    'velocity_4w' : "Velocity of total applications made in last 4 weeks, i.e., average number of applications per hour in the last 4 weeks. Ranges between [2825, 7020].",
    'bank_branch_count_8w' : "Number of total applications in the selected bank branch in last 8 weeks. Ranges between [0, 2404].",
    'date_of_birth_distinct_emails_4w' : "Number of emails for applicants with same date of birth in last 4 weeks. Ranges between [0, 39].",
    'employment_status' : "Employment status of the applicant. 7 possible (annonymized) values.",
    'credit_risk_score' : "Internal score of application risk. Ranges between [-191, 389].",
    'email_is_free' : "Domain of application email (either free or paid).",
    'housing_status' : "Current residential status for applicant. 7 possible (annonymized) values.",
    'phone_home_valid' : "Validity of provided home phone.",
    'phone_mobile_valid' : "Validity of provided mobile phone.",
    'bank_months_count' : "How old is previous account (if held) in months. Ranges between [-1, 32] months (-1 is a missing value).",
```

```
    'has_other_cards' : "If applicant has other cards from the same banking␣
↪company.",
    'proposed_credit_limit' : "Applicant's proposed credit limit. Ranges␣
↪between [200, 2000].",
    'foreign_request' : "If origin country of request is different from bank's␣
↪country.",
    'source' : "Online source of application. Either browser (INTERNET) or app␣
↪(TELEAPP).",
    'session_length_in_minutes' : "Length of user session in banking website in␣
↪minutes. Ranges between [-1, 107] minutes (-1 is a missing value).",
    'device_os' : "Operative system of device that made request. Possible␣
↪values are: Windows, macOS, Linux, X11, or other.",
    'keep_alive_session' : "User option on session logout.",
    'device_distinct_emails_8w' : "Number of distinct emails in banking website␣
↪from the used device in last 8 weeks. Ranges between [-1, 2] emails (-1 is a␣
↪missing value).",
    'device_fraud_count' : "Number of fraudulent applications with used device.␣
↪Ranges between [0, 1].",
    'month' : "Month where the application was made. Ranges between [0, 7].",
    'fraud_bool' : "If the application is fraudulent or not."
}
```

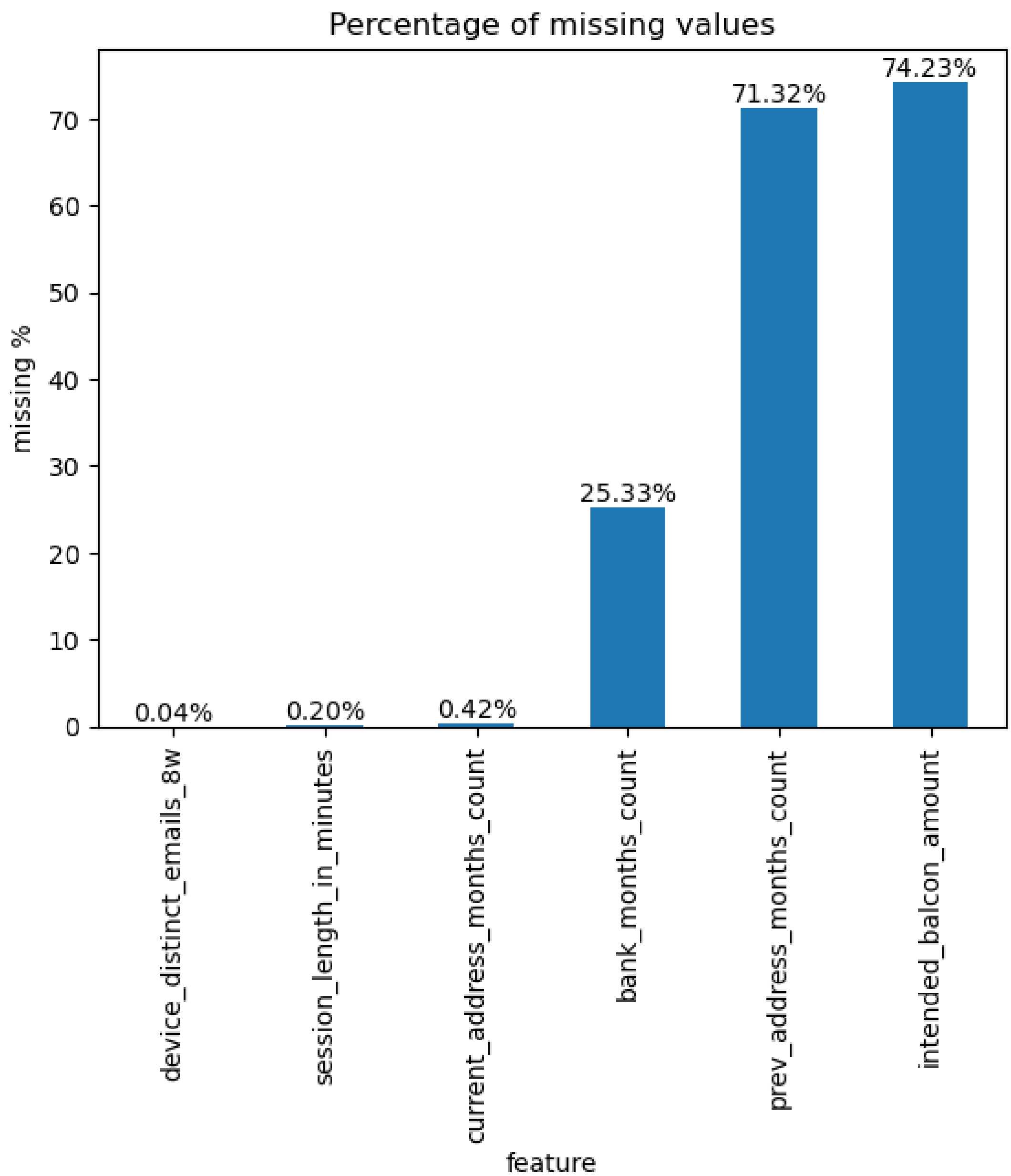
[ ]:
```
# Numerical (continuous/discrete) and categorical features

num_feats = X_train.select_dtypes(include='number').columns.tolist()

thresh = 25

cont_feats = [feat for feat in num_feats if df[feat].nunique() >= thresh]
disc_feats = [feat for feat in num_feats if df[feat].nunique() < thresh]

cat_feats = X_train.select_dtypes(exclude='number').columns.tolist()

print(f'Features: {X_train.shape[1]}\n\n\
Continuous: {len(cont_feats)}\n\
{cont_feats}\n\n\
Discrete: {len(disc_feats)}\n\
{disc_feats}\n\n\
Categorical: {len(cat_feats)}\n\
{cat_feats}')
```

```
Features: 31

Continuous: 14
['name_email_similarity', 'prev_address_months_count',
'current_address_months_count', 'days_since_request', 'intended_balcon_amount',
'zip_count_4w', 'velocity_6h', 'velocity_24h', 'velocity_4w',
```

```
'bank_branch_count_8w', 'date_of_birth_distinct_emails_4w', 'credit_risk_score',
'bank_months_count', 'session_length_in_minutes']

Discrete: 12
['income', 'customer_age', 'email_is_free', 'phone_home_valid',
'phone_mobile_valid', 'has_other_cards', 'proposed_credit_limit',
'foreign_request', 'keep_alive_session', 'device_distinct_emails_8w',
'device_fraud_count', 'month']

Categorical: 5
['payment_type', 'employment_status', 'housing_status', 'source', 'device_os']
```

[ ]:
```
# Missing values
# The datasheet details how the missing values are represented

cols_missing_neg1 = ['prev_address_months_count',
                     'current_address_months_count',
                     'bank_months_count',
                     'session_length_in_minutes',
                     'device_distinct_emails_8w']

X_train[cols_missing_neg1] = X_train[cols_missing_neg1].replace(-1,np.nan)

col_missing_neg = 'intended_balcon_amount'

X_train[col_missing_neg] = X_train[col_missing_neg]\
    .apply(lambda x: np.nan if x < 0 else x)

# Missing values by feature

null_X_train = X_train.isna().sum()/len(X_train)*100

fig = plt.figure(figsize=(6.4,4.8))
ax = null_X_train.loc[null_X_train>0].sort_values()\
    .plot(kind='bar',title='Percentage of missing values')

for p in ax.patches:
    ax.annotate(f'{p.get_height():.2f}%',
                (p.get_x() + p.get_width() / 2., p.get_height()),
                ha='center', va='bottom', xytext=(0,0), textcoords='offset␣
 ↪points')

ax.set_ylabel('missing %')
ax.set_xlabel('feature')

ax.xaxis.grid(False)
```

```
plt.show()
```



[ ]:
```
# Customized description and plots for any given feature

def summary(feat):

    if feat in cont_feats:
        cont_summary(feat)
        cont_plots(feat)
```

```
    elif feat in disc_feats:
        disc_summary(feat)
        disc_plots(feat)
    else:
        cat_summary(feat)
        cat_plots(feat)

    missing_flag_plot(feat)

    return

# Customized description for continuous features

def cont_summary(feat):

    # Create an empty summary
    columns = ['dtype', 'count', 'unique', 'top_value_counts', 'missing_count',
               'missing_percentage','mean', 'std', 'min', 'median', 'max',
               'corr_with_target']
    summary = pd.DataFrame(index=[feat],columns=columns,dtype=float)

    # Pull the feature column in question
    col = X_train[feat].copy()

    # Basic statistics using the original describe method
    summary.loc[feat,['count','mean', 'std', 'min', 'median', 'max']]\
        = col.describe(percentiles=[.5]).values.transpose()

    # Number of unique values
    summary.loc[feat,'unique'] = col.nunique()

    # Missing values count
    summary.loc[feat,'missing_count'] = col.isnull().sum()

    # Missing values percentage
    summary.loc[feat,'missing_percentage'] = col.isnull().sum()/len(col)*100

    # Correlation with target
    summary.loc[feat,'corr_with_target'] = col.corr(y_train)

    int_cols = ['count', 'unique', 'missing_count']
    summary[int_cols] = summary[int_cols].astype(int)
    summary = summary.round(2).astype(str)

    # Top 3 value_counts
    value_counts = X_train[feat].value_counts().head(3)
    value_counts.index = value_counts.index.astype(float).to_numpy().round(2)
```

```
    summary.loc[feat,'top_value_counts'] = str(value_counts.to_dict())

    # Data type
    summary.loc[feat,'dtype'] = col.dtypes

    return display(summary)

# Customized plots for continuous features

def cont_plots(feat,bins='auto'):

    n_cols = 3
    fig, axes = plt.subplots(1, n_cols, figsize=(6.4*n_cols, 4.8))

    # Histogram
    sns.histplot(data=X_train,
                 x=feat,
                 bins=bins,
                 ax=axes[0],
                 color=slate_gray)

    # Box plots with the target as hue
    sns.boxplot(data=X_train,
                x=feat,
                y=y_train,
                ax=axes[1],
                palette=palette,
                orient='h')

#     KDE plots with the target as hue
    sns.kdeplot(data=X_train,
                x=feat,
                hue=y_train,
                palette=palette,
                fill=True,
                common_norm=False,
                ax=axes[2])

    axes[0].title.set_text('Histogram')
    axes[1].title.set_text('Box Plots')
    axes[2].title.set_text('KDE Plots')

    fig.tight_layout()
    plt.show()
    return

# Customized description for discrete features
```

```python
def disc_summary(feat):

    # Create an empty summary
    columns = ['dtype', 'count', 'unique', 'missing_count',␣
 ↪'missing_percentage',
               'mean', 'std', 'min', 'median', 'max', 'cv', 'corr_with_target']
    summary = pd.DataFrame(index=[feat],columns=columns,dtype=float)

    # Pull the feature column in question
    col = X_train[feat].copy()

    # Basic statistics using the original describe method
    summary.loc[feat,['count','mean', 'std', 'min', 'median', 'max']]\
    = col.describe(percentiles=[.5]).values.transpose()

    # Number of unique values
    summary.loc[feat,'unique'] = col.nunique()

    # Coefficient of Variation (CV)
    summary.loc[feat,'cv'] = np.NaN if not col.mean() else col.std()/col.mean()

    # Missing values count
    summary.loc[feat,'missing_count'] = col.isnull().sum()

    # Missing values percentage
    summary.loc[feat,'missing_percentage'] = col.isnull().sum()/len(col)*100

    # Correlation with target
    summary.loc[feat,'corr_with_target'] = col.corr(y_train)

    int_cols = ['count','unique','missing_count']
    summary[int_cols] = summary[int_cols].astype(int)
    summary = summary.round(2).astype(str)

    # Data type
    summary.loc[feat,'dtype'] = col.dtypes


    return display(summary)

# Customized plots for discrete features

def disc_plots(feat):

    col = X_train[feat].copy()
```

```
    n_rows = 1
    n_cols = 2

    fig, axes = plt.subplots(n_rows, n_cols, figsize=(6.4 * n_cols, 4.8 *␣
 ↪n_rows))

    # Sort unique values
    unique_values = col.dropna().unique()
    unique_values.sort()

    # Value counts
    val_counts = col.dropna().value_counts()
    val_counts = val_counts.reindex(unique_values)
    val_counts_pct = val_counts/len(col)*100

    # Countplot
    sns.countplot(x=col, order=unique_values, palette=palette, ax=axes[0])
    axes[0].xaxis.grid(False)

    # Show count value if rare (less than 1%)
    lp_thresh = 1
    for i, p in enumerate(axes[0].patches):
        pct = val_counts_pct.iloc[i]
        axes[0].annotate(f'{pct:.2f}%',
                         (p.get_x() + p.get_width() / 2., p.get_height()),
                         ha='center', va='bottom', xytext=(0,0),
                         textcoords='offset points')
        if pct < lp_thresh:
            axes[0].annotate(val_counts.iloc[i],
                             (p.get_x() + p.get_width() / 2., p.get_height()),
                             ha='center', va='bottom', xytext=(0,10),
                             textcoords='offset points',color='red')

    # Barplot
    df = pd.concat([X_train,y_train],axis=1).groupby(feat)[target].mean()*100
    df = df.reindex(unique_values)  # Reindex to match the order
    sns.barplot(x=df.index, y=df.values, palette=palette, ax=axes[1])
    axes[1].set_ylabel('Fraud %')
    axes[1].xaxis.grid(False)

    fig.tight_layout()
    plt.show()

    return

# Customized description for categorical features
```

```python
def cat_summary(feat):

    # Create an empty summary
    columns = ['dtype', 'count', 'unique', 'missing_count',␣
↪'missing_percentage']
    summary = pd.DataFrame(index=[feat],columns=columns,dtype=float)

    # Pull the feature column in question
    col = X_train[feat].copy()

    # Count
    summary.loc[feat,'count'] = col.count()

    # Number of unique values
    summary.loc[feat,'unique'] = col.nunique()

    # Missing values count
    summary.loc[feat,'missing_count'] = col.isnull().sum()

    # Missing values percentage
    summary.loc[feat,'missing_percentage'] = col.isnull().sum()/len(col)*100

    int_cols = ['count', 'unique', 'missing_count']
    summary[int_cols] = summary[int_cols].astype(int)
    summary = summary.round(2).astype(str)

    # Data type
    summary.loc[feat,'dtype'] = col.dtypes

    return display(summary)

# Customized plots for categorical features

def cat_plots(feat):

    col = X_train[feat].copy()

    n_rows = 1
    n_cols = 2

    fig, axes = plt.subplots(n_rows, n_cols, figsize=(6.4 * n_cols, 4.8 *␣
↪n_rows))

    # Value counts
    val_counts = col.dropna().value_counts()

    # Unique values
```

```python
    unique_values = val_counts.index

    # Countplot with sorted order
    sns.countplot(x=col, order=unique_values, palette=palette, ax=axes[0])
    axes[0].xaxis.grid(False)

    val_counts_pct = val_counts/len(col)*100

    # Show count value if rare (less than 1%)
    lp_thresh = 1
    for i, p in enumerate(axes[0].patches):
        pct = val_counts_pct.iloc[i]
        axes[0].annotate(f'{pct:.2f}%',
                         (p.get_x() + p.get_width() / 2., p.get_height()),
                         ha='center', va='bottom', xytext=(0,0),
                         textcoords='offset points')
        if pct < lp_thresh:
            axes[0].annotate(val_counts.iloc[i],
                             (p.get_x() + p.get_width() / 2., p.get_height()),
                             ha='center', va='bottom', xytext=(0,10),
                             textcoords='offset points',color='red')

    # Barplot with the same order
    df = pd.concat([X_train,y_train],axis=1).groupby(feat)[target].mean()*100
    sns.barplot(x=df.index, y=df.values, order=unique_values, palette=palette,␣
↪ax=axes[1])
    axes[1].set_ylabel('Fraud %')
    axes[1].xaxis.grid(False)

    fig.tight_layout()
    plt.show()

    return

# Plot for the missing flag associated with a feature

def missing_flag_plot(feat):
    col = X_train[feat].isnull().astype(int)

    if not col.sum():
        return

    df = (pd.concat([col,y_train],axis=1).groupby(feat).mean()*100).
↪reset_index()
    cols = [f'MISSING_FLAG_{feat}', 'Fraud %']
    df.columns = cols
    fig = plt.figure(figsize=(6.4, 4.8))
```

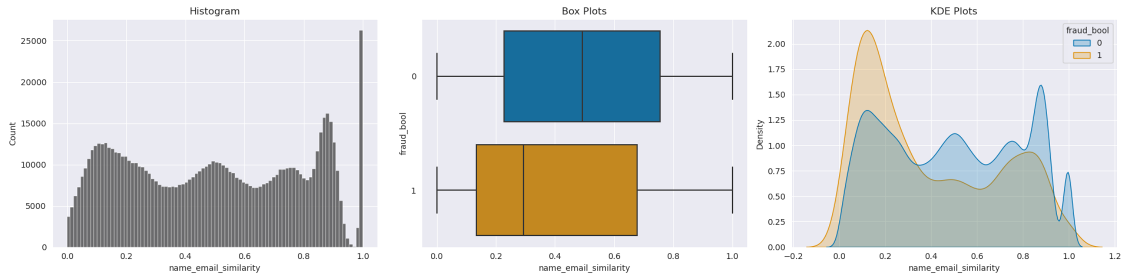
```
    ax = sns.barplot(data=df,x=cols[0], y=cols[1], palette=palette)

    fig.tight_layout()
    plt.show()

    return
```

1.1 Continuous features

Applying `summary` function to all continuous features:

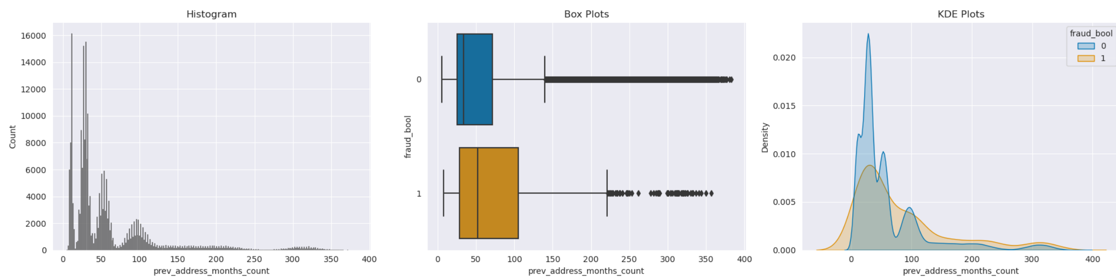
```
[ ]: for feat in cont_feats:
         print(f"\033[1m Feature:\033[0m '{feat}'\n")
         print(f'\033[1m Description:\033[0m {feature_descriptions[feat]}')
         summary(feat)
         print('-'*45,'\n')
```

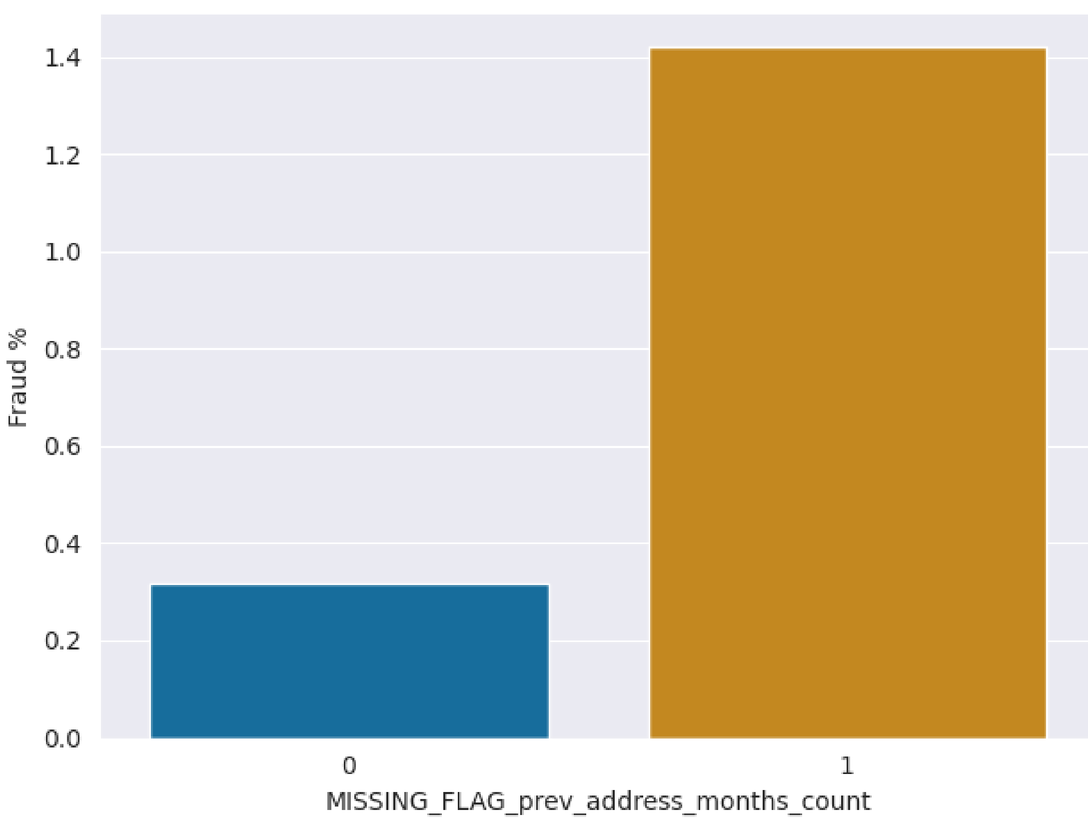
```
 Feature: 'name_email_similarity'

 Description: Metric of similarity between email and applicant's name.
Higher values represent higher similarity. Ranges between [0, 1].

                          dtype   count  unique            top_value_counts  \
name_email_similarity   float64  800000  799289  {0.23: 2, 0.26: 2, 0.78: 2}

                       missing_count missing_percentage  mean   std  min  \
name_email_similarity              0                0.0  0.49  0.29  0.0

                       median  max corr_with_target
name_email_similarity   0.49  1.0            -0.04
```




```
---------------------------------------------

 Feature: 'prev_address_months_count'

 Description: Number of months in previous registered address of the
applicant, i.e. the applicant's previous residence, if applicable. Ranges
between [-1, 380] months (-1 is a missing value).
```

```
                                dtype   count unique  \
prev_address_months_count  float64  229475    373

                                                      top_value_counts missing_count  \
prev_address_months_count  {11.0: 9204, 28.0: 8246, 29.0: 8079}        570525

                             missing_percentage   mean    std  min median    max  \
prev_address_months_count                 71.32  60.71  63.55  5.0   34.0  383.0

                             corr_with_target
prev_address_months_count              0.02
```

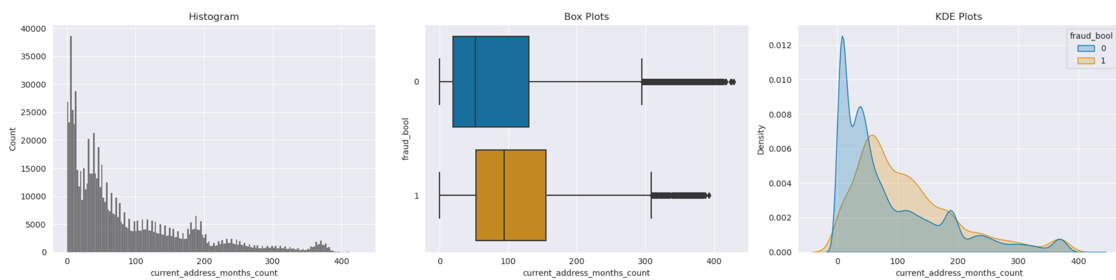


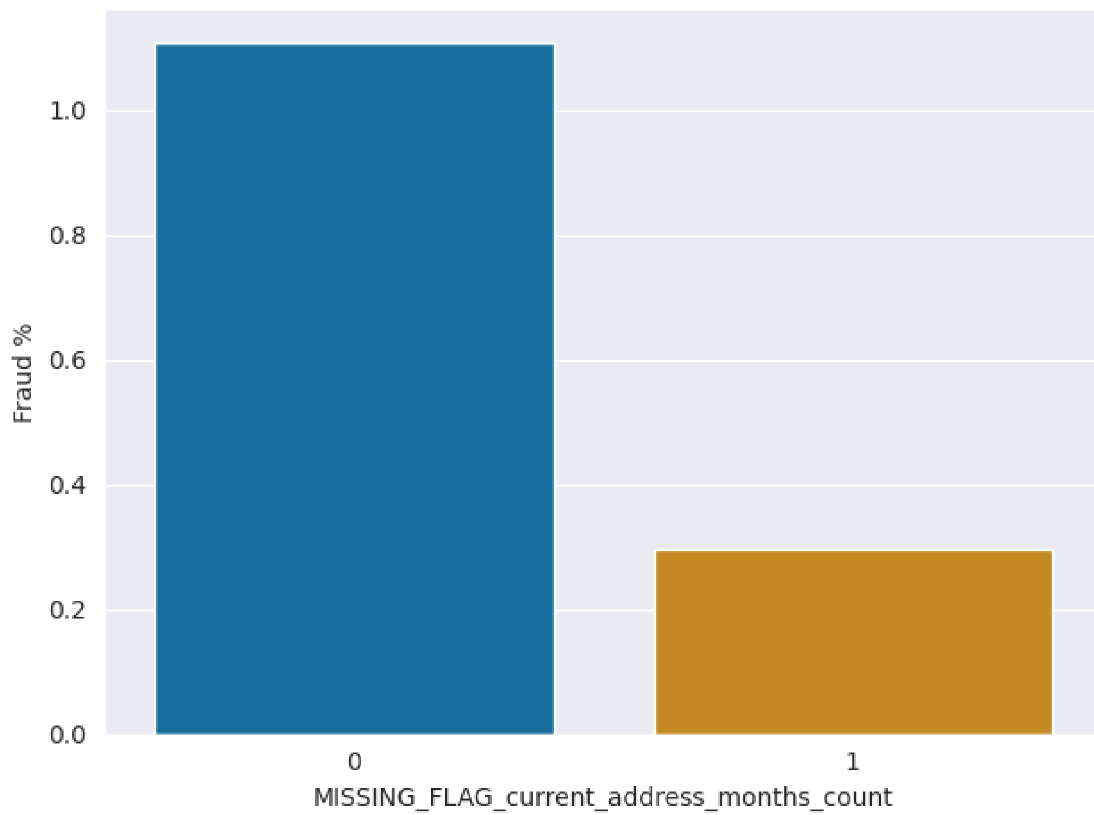


Feature: 'current_address_months_count'

Description: Months in currently registered address of the applicant. Ranges between [−1, 429] months (−1 is a missing value).

```
                                dtype    count unique  \
current_address_months_count  float64  796609    420

                                                   top_value_counts  \
current_address_months_count  {6.0: 13001, 7.0: 12952, 8.0: 12874}

                             missing_count missing_percentage   mean    std  \
current_address_months_count          3391               0.42  86.99  88.39

                              min median   max corr_with_target
current_address_months_count  0.0   53.0 428.0             0.03
```

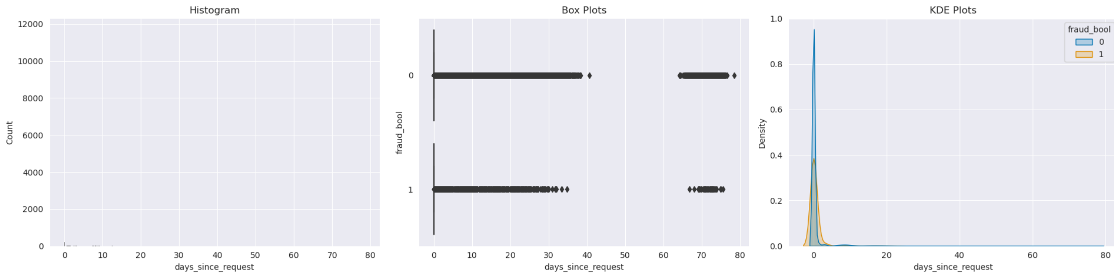




Feature: 'days_since_request'

Description: Number of days passed since application was done. Ranges between [0, 79] days.

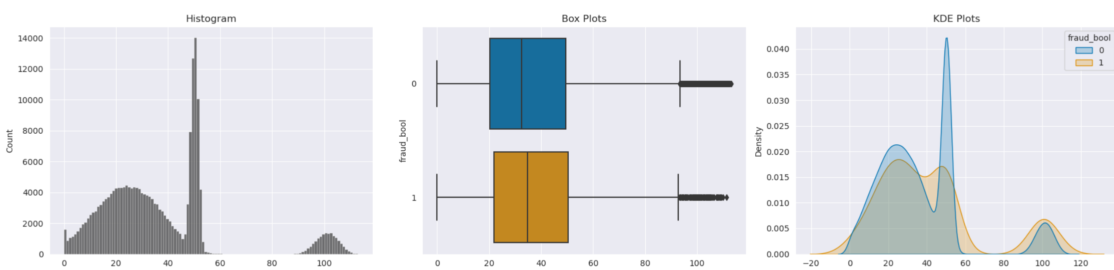
```
                      dtype   count  unique     top_value_counts missing_count  \
days_since_request  float64  800000  793121  {0.01: 3, 0.02: 3}             0

                   missing_percentage  mean   std  min median    max  \
days_since_request                0.0  1.02  5.38  0.0   0.02  78.46

                   corr_with_target
days_since_request              0.0
```

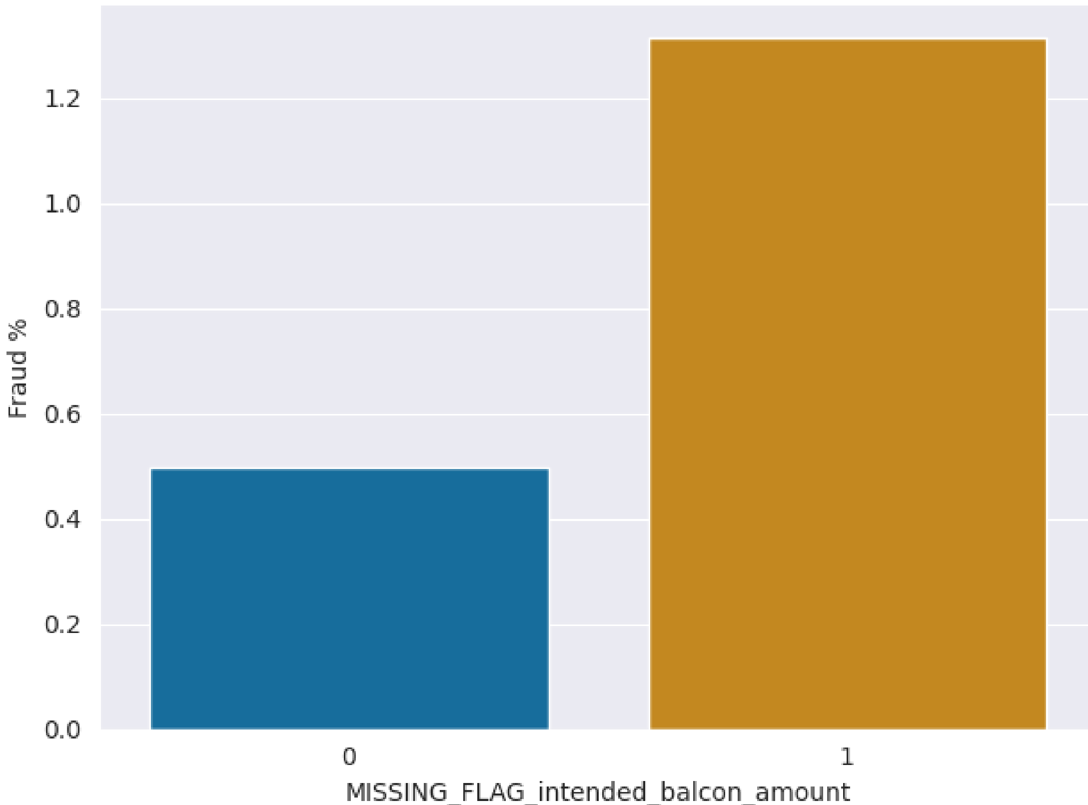


Feature: 'intended_balcon_amount'

Description: Initial transferred amount for application. Ranges between [−16, 114] (negatives are missing values).

```
                          dtype   count  unique  \
intended_balcon_amount  float64  206132  205910

                                              top_value_counts missing_count  \
intended_balcon_amount  {39.07: 2, 36.04: 2, 15.63: 2}        593868

                       missing_percentage   mean    std  min median     max  \
intended_balcon_amount              74.23  36.57  23.22  0.0  32.45  112.96

                       corr_with_target
intended_balcon_amount             0.01
```

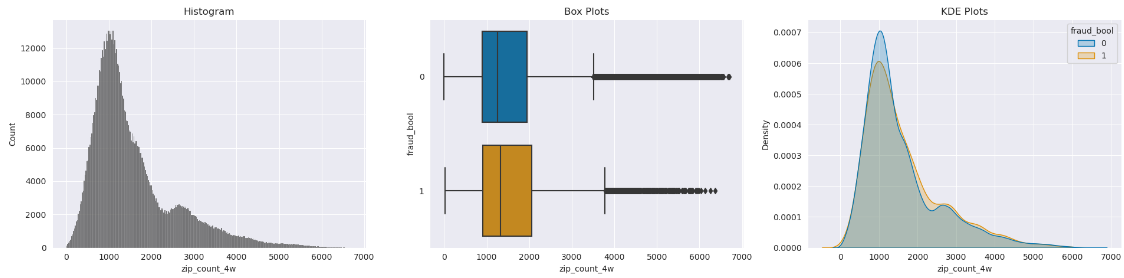




Feature: 'zip_count_4w'

Description: Number of applications within same zip code in last 4 weeks. Ranges between [1, 6830].

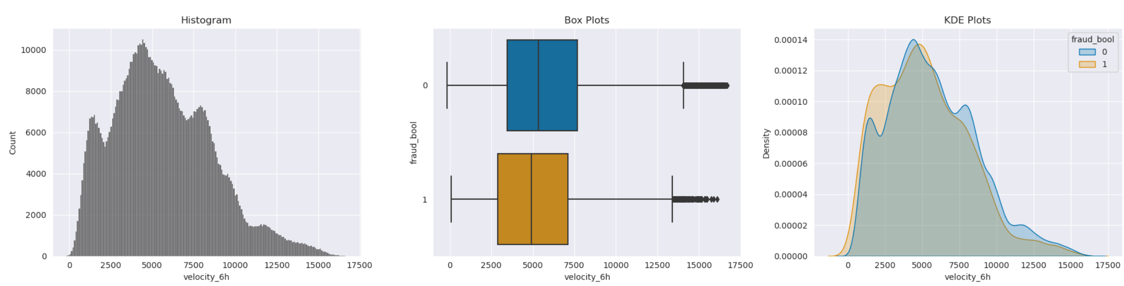
```
              dtype   count unique                        top_value_counts  \
zip_count_4w  int64  800000   6268  {1062.0: 645, 1020.0: 644, 941.0: 622}

             missing_count missing_percentage     mean      std  min  median  \
zip_count_4w             0                0.0  1572.77  1005.23  1.0  1263.0

                 max corr_with_target
zip_count_4w  6700.0             0.01
```



Feature: 'velocity_6h'

Description: Velocity of total applications made in last 6 hours i.e., average number of applications per hour in the last 6 hours. Ranges between [-175, 16818].

```
                 dtype   count  unique                     top_value_counts  \
velocity_6h    float64  800000  799150  {2985.72: 2, 5900.35: 2, 8769.6: 2}

            missing_count missing_percentage     mean      std    min  \
velocity_6h             0                0.0  5664.02  3009.68 -170.6

             median       max corr_with_target
velocity_6h  5316.3  16715.57            -0.02
```

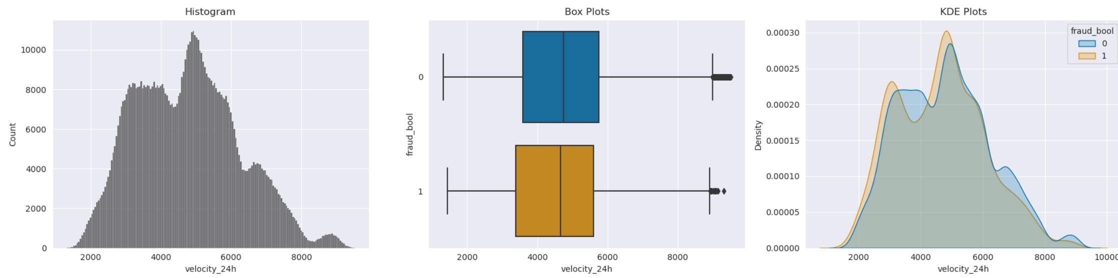


Feature: 'velocity_24h'

Description: Velocity of total applications made in last 24 hours i.e., average number of applications per hour in the last 24 hours. Ranges between [1297, 9586].

```
                 dtype   count  unique                     top_value_counts  \
velocity_24h   float64  800000  799310  {5082.33: 3, 4667.86: 3, 3906.42: 3}
```

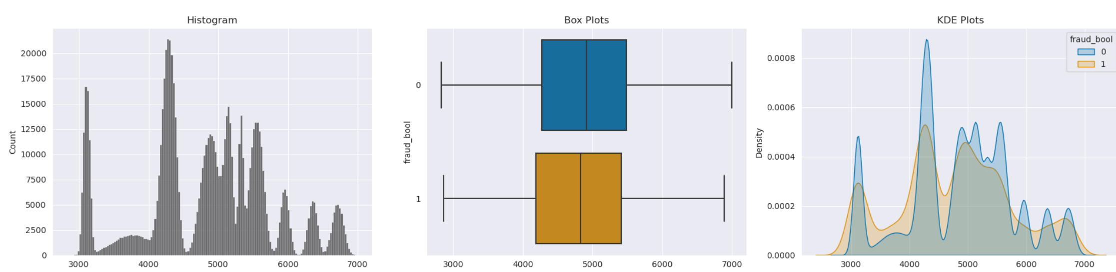
```
              missing_count missing_percentage     mean     std      min  \
velocity_24h              0                0.0  4770.23  1479.5  1320.28

               median     max corr_with_target
velocity_24h   4750.8  9506.9            -0.01
```



Feature: 'velocity_4w'

Description: Velocity of total applications made in last 4 weeks, i.e., average number of applications per hour in the last 4 weeks. Ranges between [2825, 7020].

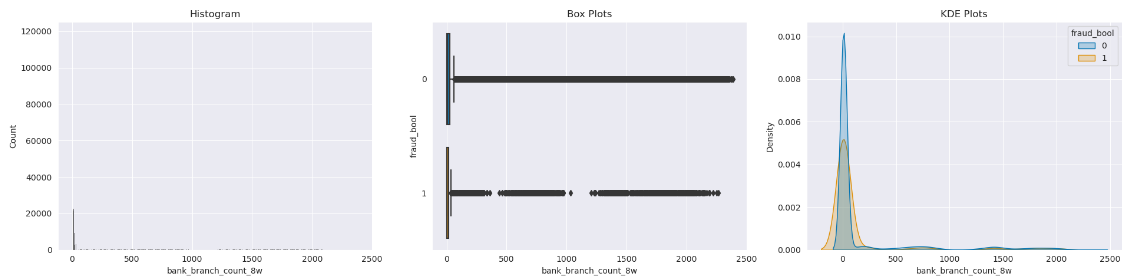
```
               dtype   count  unique                     top_value_counts  \
velocity_4w  float64  800000  798908  {5466.87: 3, 3137.5: 2, 4334.23: 2}

             missing_count missing_percentage    mean     std      min  \
velocity_4w              0                0.0  4856.0  919.62  2825.75

              median      max corr_with_target
velocity_4w  4913.54  6994.76            -0.01
```



Feature: 'bank_branch_count_8w'

Description: Number of total applications in the selected bank branch in last 8 weeks. Ranges between [0, 2404].

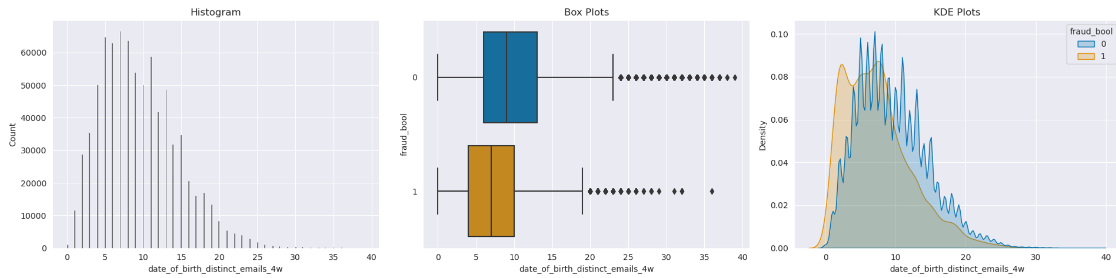
```
                     dtype   count unique  \
bank_branch_count_8w  int64  800000   2318

                                           top_value_counts missing_count  \
bank_branch_count_8w  {1.0: 119074, 0.0: 115535, 2.0: 46310}             0

                     missing_percentage   mean     std  min median     max  \
bank_branch_count_8w                0.0  184.3  459.48  0.0    9.0  2385.0

                     corr_with_target
bank_branch_count_8w            -0.01
```



Feature: 'date_of_birth_distinct_emails_4w'

Description: Number of emails for applicants with same date of birth in last 4 weeks. Ranges between [0, 39].

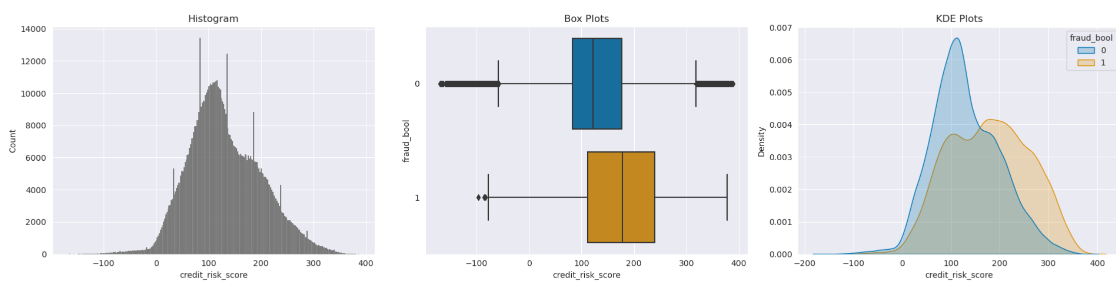
```
                                 dtype   count unique  \
date_of_birth_distinct_emails_4w  int64  800000     40

                                                        top_value_counts  \
date_of_birth_distinct_emails_4w  {7.0: 66534, 5.0: 64588, 8.0: 63581}

                                 missing_count missing_percentage mean   std  \
date_of_birth_distinct_emails_4w             0                0.0  9.5  5.04

                                 min median   max corr_with_target
date_of_birth_distinct_emails_4w  0.0    9.0  39.0            -0.04
```



Feature: 'credit_risk_score'

Description: Internal score of application risk. Ranges between [-191, 389].

```
                   dtype   count unique  \
credit_risk_score  int64  800000    550

                                          top_value_counts missing_count  \
credit_risk_score  {116.0: 5436, 115.0: 5417, 110.0: 5402}             0

                  missing_percentage   mean    std    min median    max  \
credit_risk_score                0.0 131.01  69.68 -170.0  122.0  389.0

                  corr_with_target
credit_risk_score             0.07
```

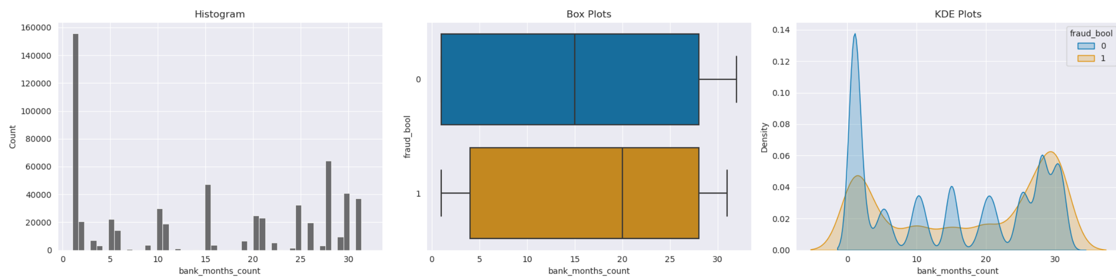


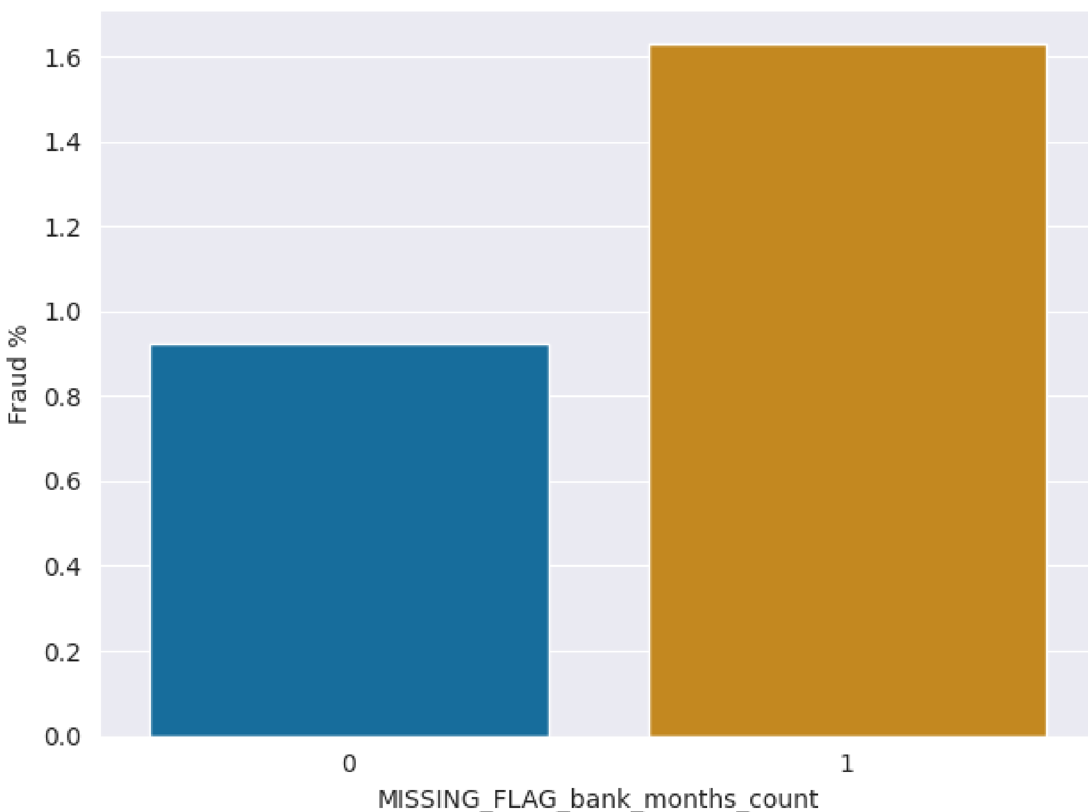
Feature: 'bank_months_count'

Description: How old is previous account (if held) in months. Ranges between [-1, 32] months (-1 is a missing value).

```
                     dtype   count unique  \
```

```
bank_months_count  float64  597396     32

                                           top_value_counts missing_count  \
bank_months_count  {1.0: 155878, 28.0: 64172, 15.0: 47326}         202604

                  missing_percentage   mean    std  min median   max  \
bank_months_count              25.33  14.87  11.53  1.0   15.0  32.0

                  corr_with_target
bank_months_count             0.02
```

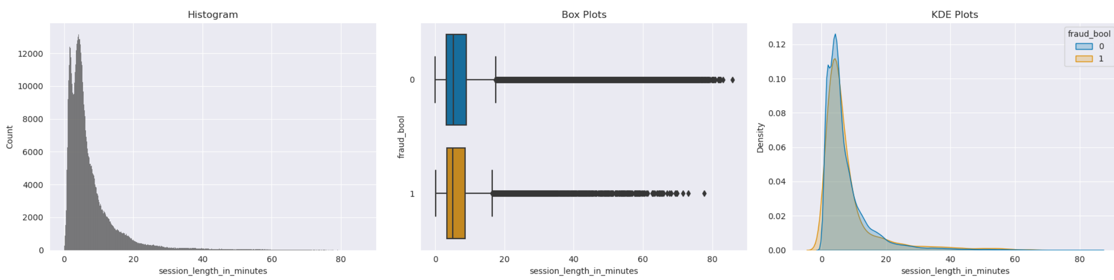


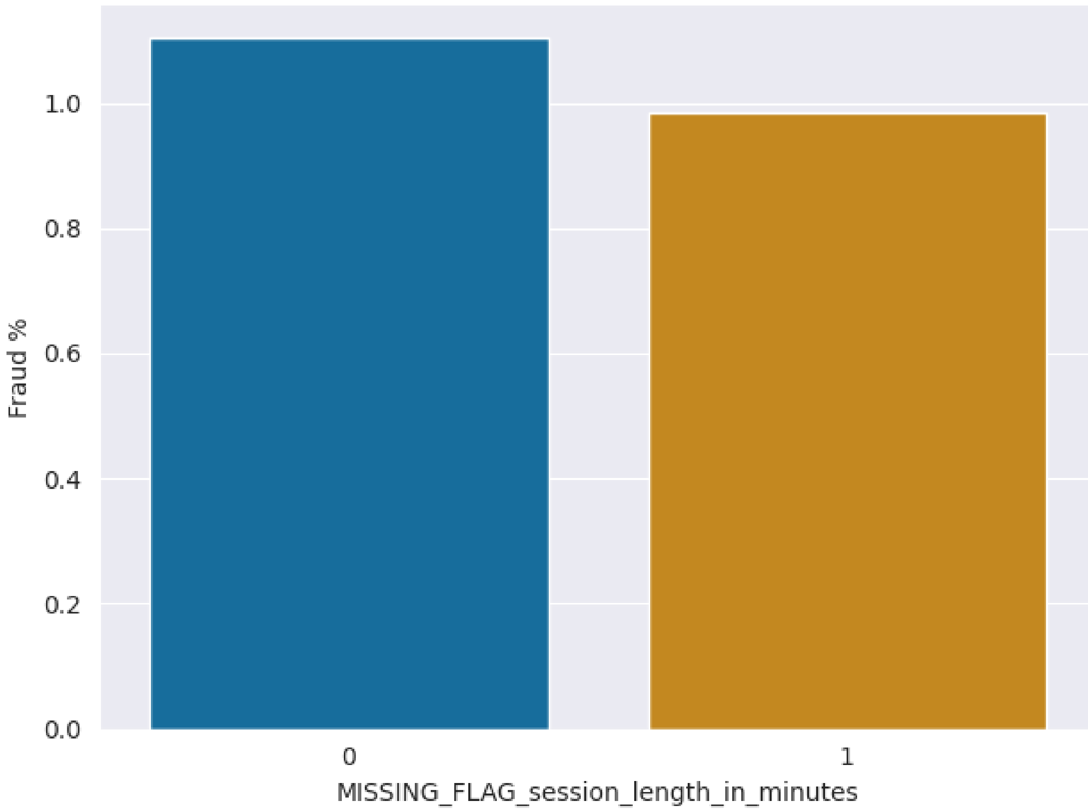


Feature: 'session_length_in_minutes'

Description: Length of user session in banking website in minutes.
Ranges between [-1, 107] minutes (-1 is a missing value).

```
                             dtype   count  unique  \
session_length_in_minutes  float64  798377  796390  


                                      top_value_counts missing_count  \
session_length_in_minutes  {4.74: 3, 4.19: 3, 4.64: 3}          1623   

                          missing_percentage  mean   std  min median   max  \
session_length_in_minutes                0.2  7.57  8.04  0.0   5.12  85.9   

                          corr_with_target  
session_length_in_minutes             0.01  
```



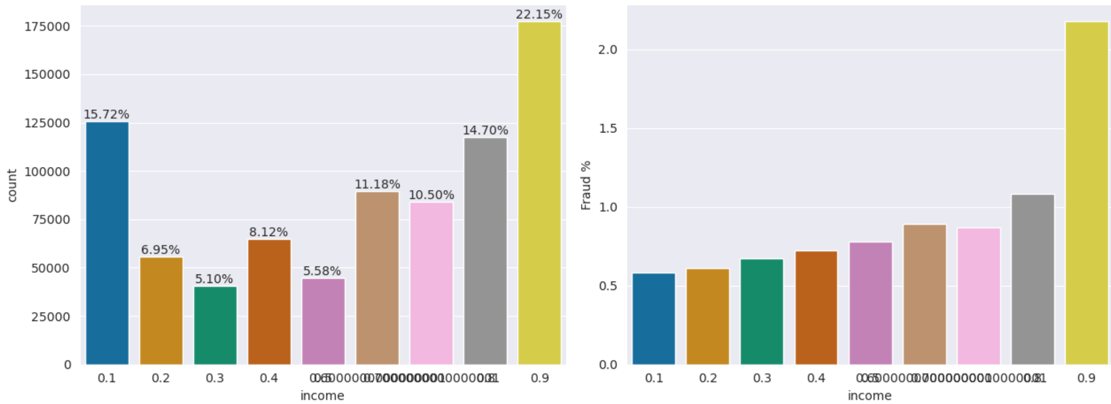


1.2 Discrete / Binary features

Applying `summary` function to all discrete / binary features:

```
[ ]: for feat in disc_feats:
         print(f"\033[1m Feature:\033[0m '{feat}'\n")
         print(f"\033[1m Description:\033[0m {feature_descriptions[feat]}")
         summary(feat)
         print('-'*45,'\n')
```

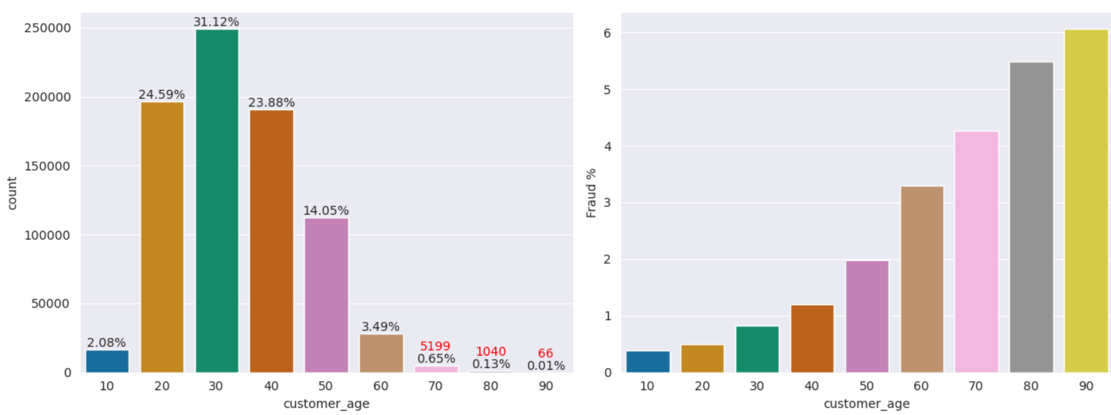
```
 Feature: 'income'

 Description: Annual income of the applicant (in decile form). Ranges
between [0.1, 0.9].
          dtype   count unique missing_count missing_percentage  mean   std  \
income  float64  800000      9             0                0.0  0.56  0.29

        min median  max    cv corr_with_target
income  0.1    0.6  0.9  0.52             0.05
```



Feature: 'customer_age'

Description: Applicant's age in years, rounded to the decade. Ranges between [10, 90] years.

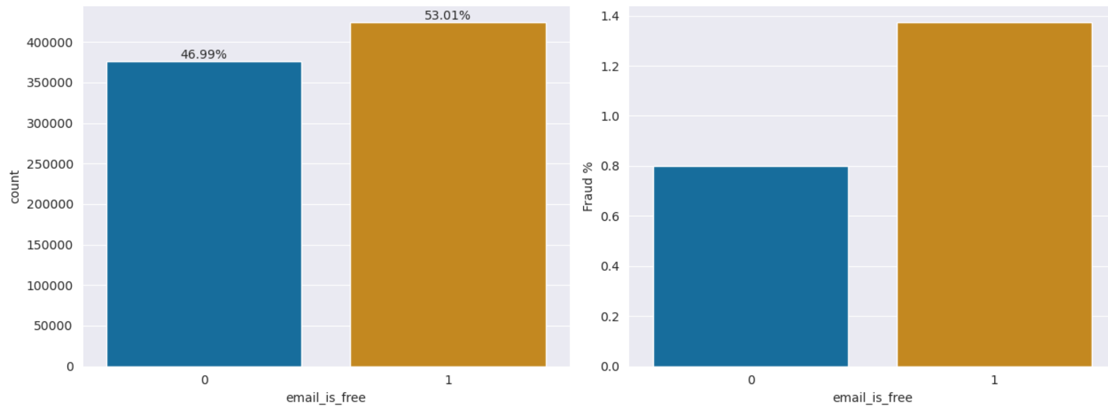
```
             dtype   count unique missing_count missing_percentage  mean  \
customer_age int64  800000      9             0                0.0  33.7

               std   min median   max    cv corr_with_target
customer_age 12.03  10.0   30.0  90.0  0.36             0.06
```



Feature: 'email_is_free'

Description: Domain of application email (either free or paid).

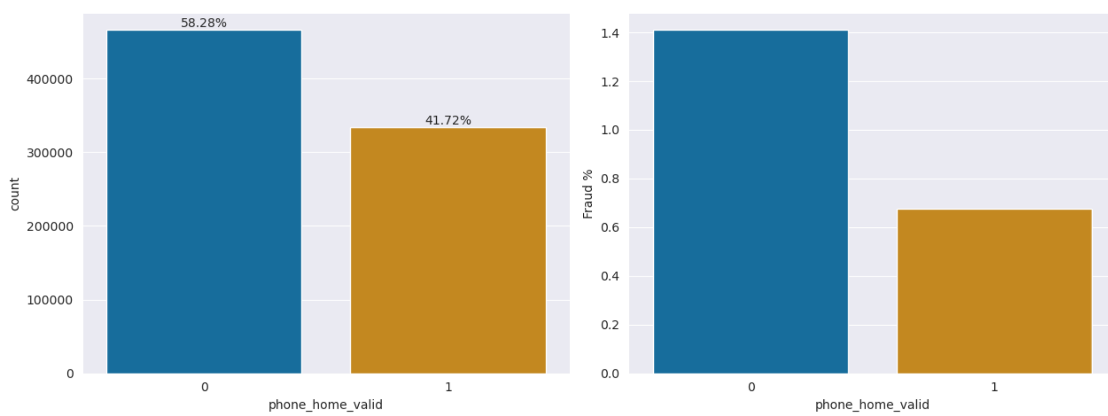
```
              dtype   count unique missing_count missing_percentage  mean  \
email_is_free  int64  800000      2             0                0.0  0.53

              std  min median  max    cv corr_with_target
email_is_free  0.5  0.0    1.0  1.0  0.94             0.03
```



Feature: 'phone_home_valid'

Description: Validity of provided home phone.

```
                 dtype   count unique missing_count missing_percentage  mean  \
phone_home_valid  int64  800000      2             0                0.0  0.42

                  std  min median  max    cv corr_with_target
phone_home_valid  0.49  0.0    0.0  1.0  1.18            -0.03
```

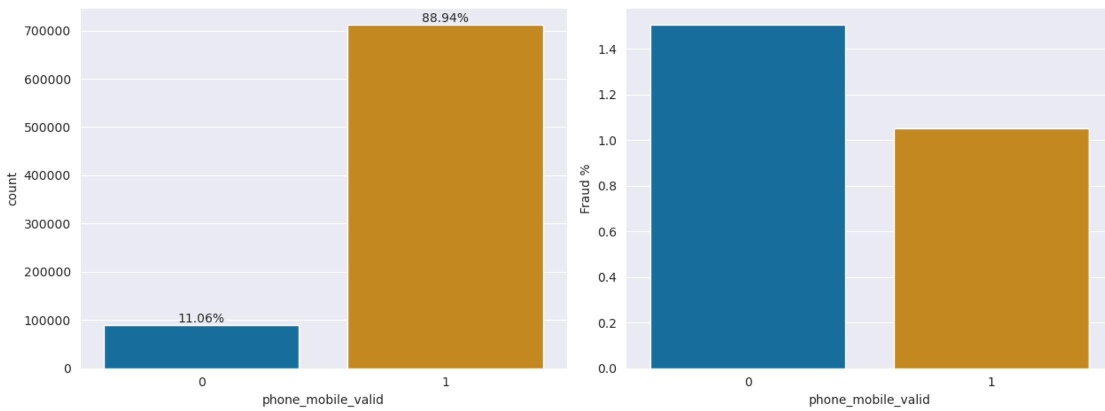


Feature: 'phone_mobile_valid'

Description: Validity of provided mobile phone.

	dtype	count	unique	missing_count	missing_percentage	\
phone_mobile_valid	int64	800000	2	0	0.0	

	mean	std	min	median	max	cv	corr_with_target
phone_mobile_valid	0.89	0.31	0.0	1.0	1.0	0.35	-0.01

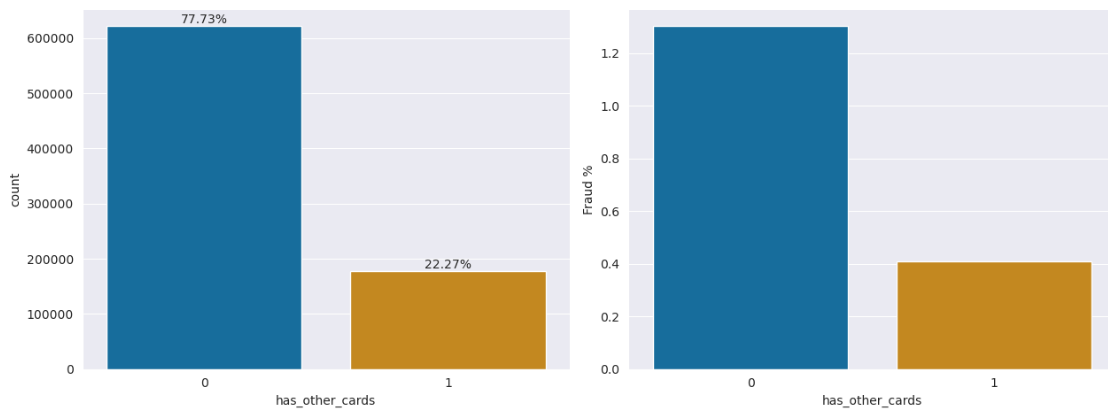


Feature: 'has_other_cards'

Description: If applicant has other cards from the same banking company.

	dtype	count	unique	missing_count	missing_percentage	mean	\
has_other_cards	int64	800000	2	0	0.0	0.22	

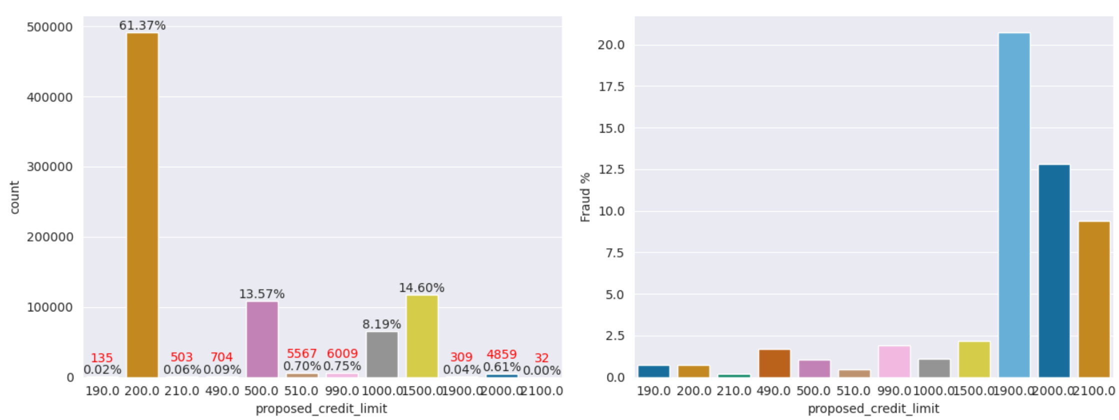
	std	min	median	max	cv	corr_with_target
has_other_cards	0.42	0.0	0.0	1.0	1.87	-0.04



Feature: 'proposed_credit_limit'

Description: Applicant's proposed credit limit. Ranges between [200, 2000].

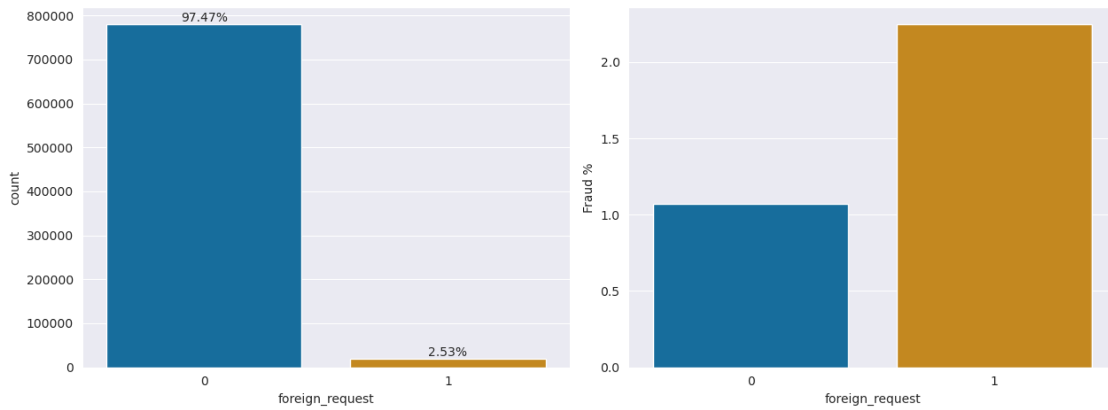
```
                        dtype   count unique missing_count  \
proposed_credit_limit  float64  800000     12             0

                      missing_percentage    mean     std   min median  \
proposed_credit_limit                0.0  516.09  487.74  190.0  200.0

                         max    cv corr_with_target
proposed_credit_limit  2100.0  0.95             0.07
```



Feature: 'foreign_request'

Description: If origin country of request is different from bank's country.

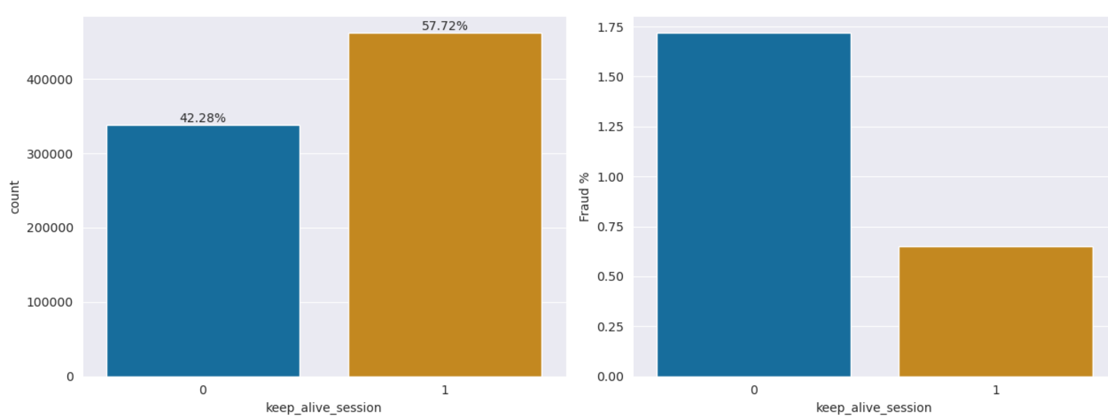
```
                 dtype   count unique missing_count missing_percentage  mean  \
foreign_request  int64  800000      2             0                0.0  0.03

                  std  min median  max    cv corr_with_target
foreign_request  0.16  0.0    0.0  1.0  6.21             0.02
```



Feature: 'keep_alive_session'

Description: User option on session logout.

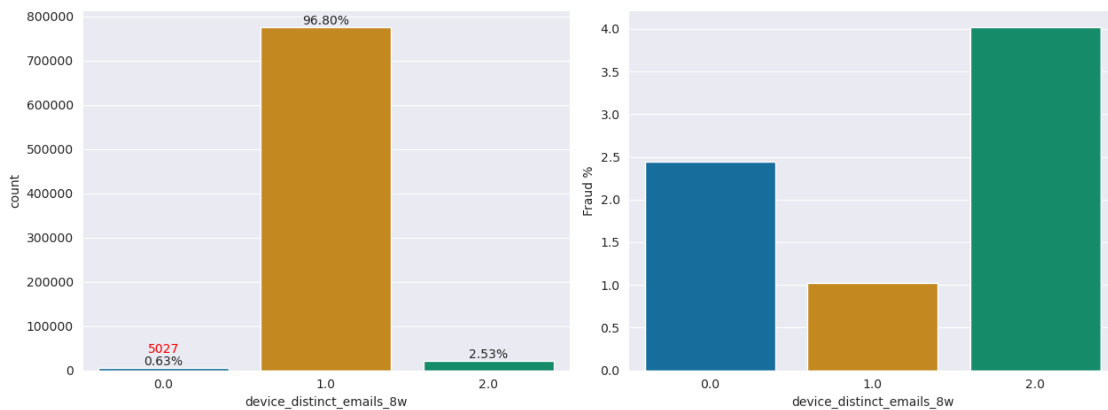
```
                    dtype   count unique missing_count missing_percentage  \
keep_alive_session  int64  800000      2             0                0.0

                    mean   std  min median  max    cv corr_with_target
keep_alive_session  0.58  0.49  0.0    1.0  1.0  0.86            -0.05
```

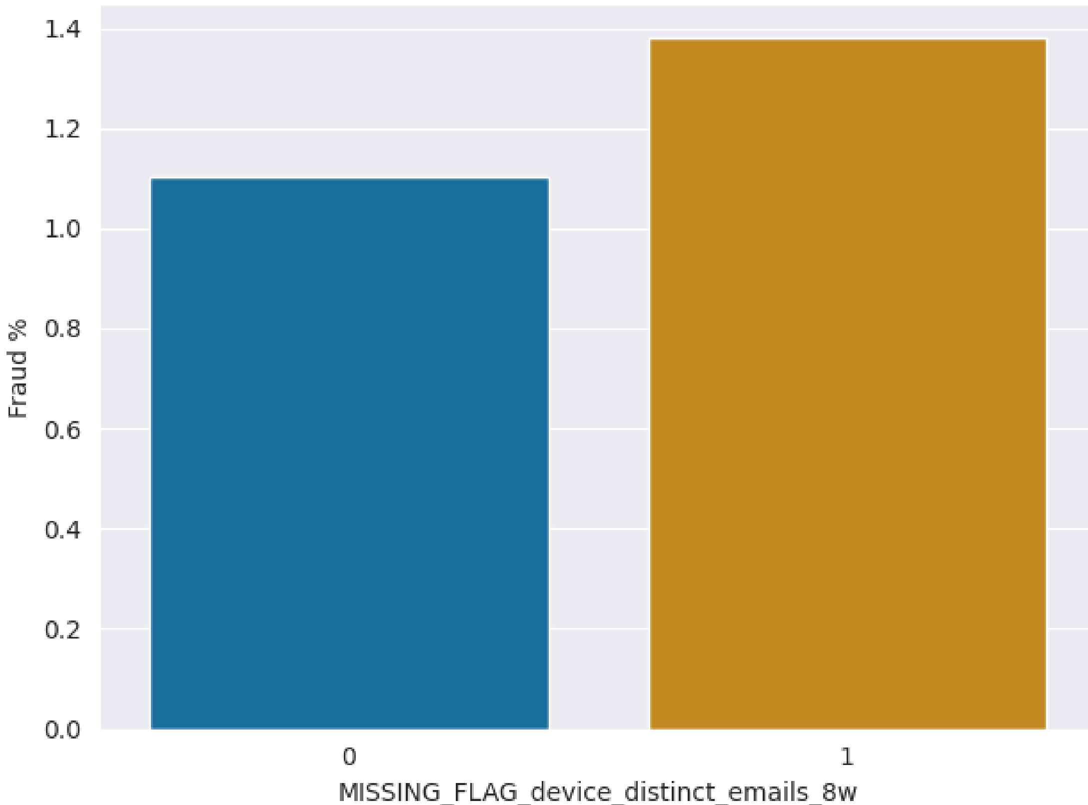


Feature: 'device_distinct_emails_8w'

Description: Number of distinct emails in banking website from the used device in last 8 weeks. Ranges between [-1, 2] emails (-1 is a missing value).

```
                              dtype   count unique missing_count  \
device_distinct_emails_8w   float64  799710      3           290

                           missing_percentage  mean   std  min median  max  \
device_distinct_emails_8w                0.04  1.02  0.18  0.0    1.0  2.0

                              cv corr_with_target
device_distinct_emails_8w   0.17             0.04
```

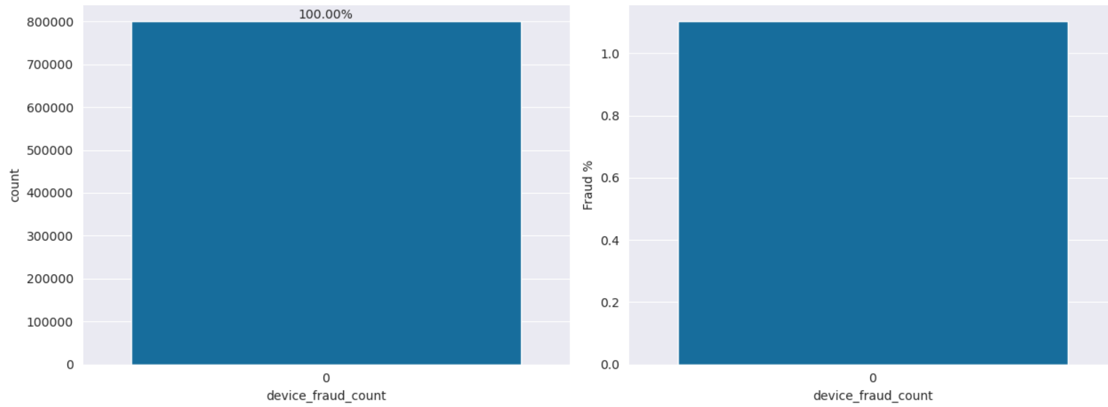




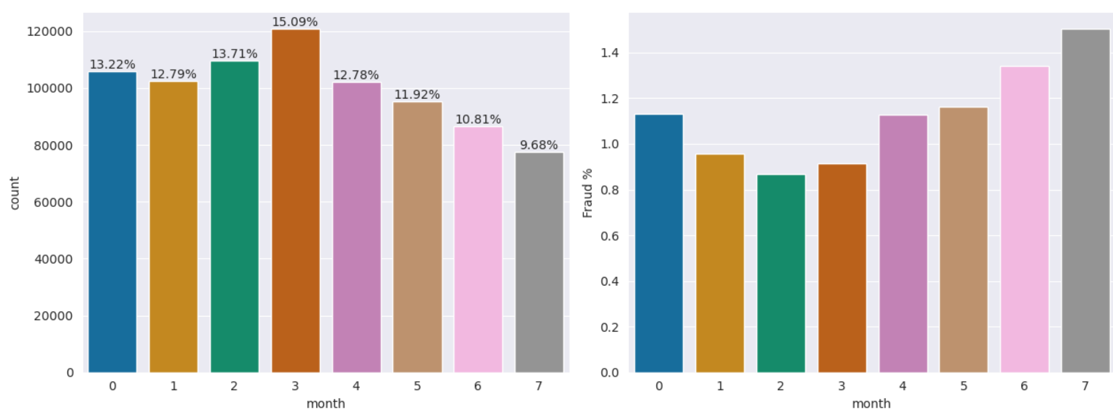
Feature: 'device_fraud_count'

Description: Number of fraudulent applications with used device. Ranges between [0, 1].

```
                    dtype   count unique missing_count missing_percentage  \
device_fraud_count  int64  800000      1             0                0.0

                   mean  std  min median  max   cv corr_with_target
device_fraud_count  0.0  0.0  0.0    0.0  0.0  nan              nan
```




```
---------------------------------------------

 Feature: 'month'

 Description: Month where the application was made. Ranges between [0,
7].
       dtype   count unique missing_count missing_percentage  mean   std  min  \
month  int64  800000      8             0                0.0  3.29  2.21  0.0

      median  max    cv corr_with_target
month    3.0  7.0  0.67             0.01
```



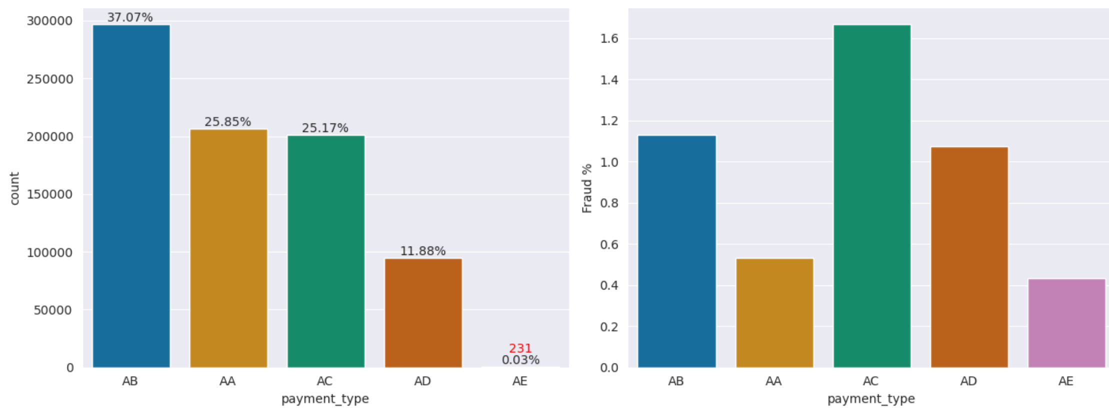

```
---------------------------------------------
```

1.3 Categorical features

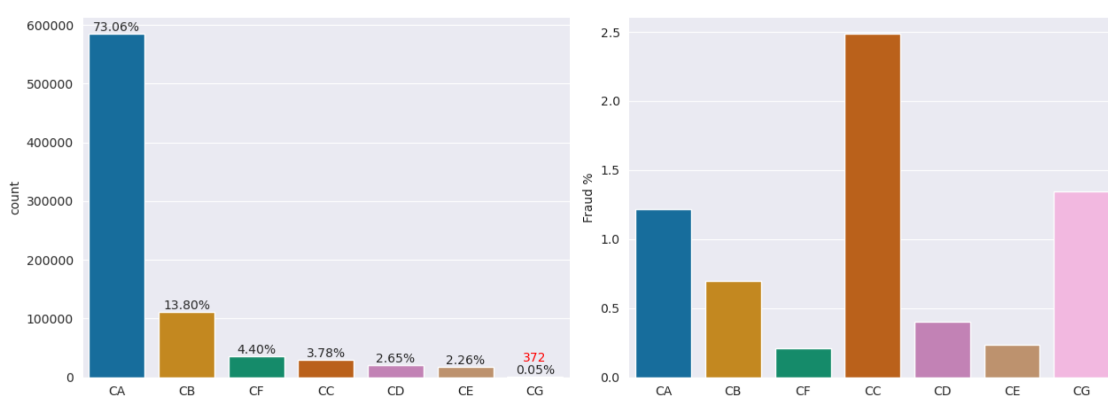
Applying `summary` function to all categorical features:

```
[ ]: for feat in cat_feats:
         print(f"\033[1m Feature:\033[0m '{feat}'\n")
         print(f'\033[1m Description:\033[0m {feature_descriptions[feat]}')
         summary(feat)
         print('-'*45,'\n')
```

```
 Feature: 'payment_type'

 Description: Credit payment plan type. 5 possible (annonymized) values.
                dtype   count unique missing_count missing_percentage
payment_type   object  800000      5             0                0.0
```



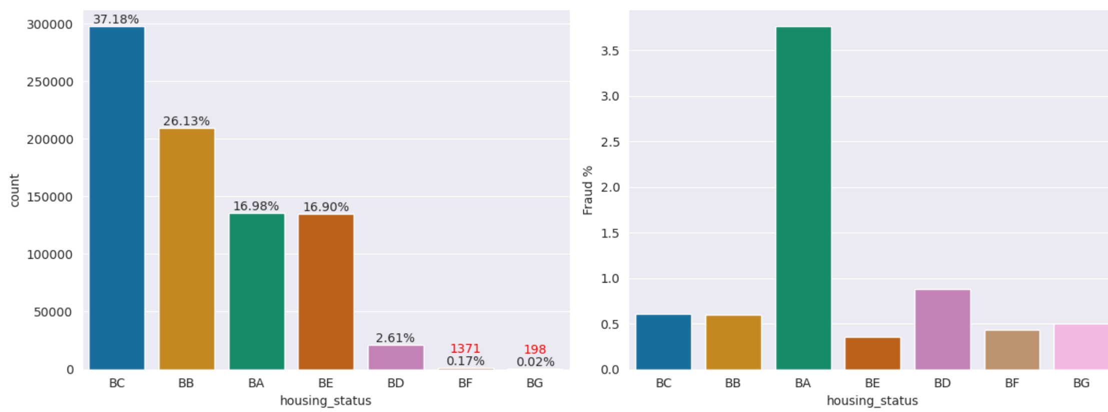

```
---------------------------------------------

 Feature: 'employment_status'

 Description: Employment status of the applicant. 7 possible
(annonymized) values.
                     dtype   count unique missing_count missing_percentage
employment_status   object  800000      7             0                0.0
```



Feature: 'housing_status'

Description: Current residential status for applicant. 7 possible (annonymized) values.

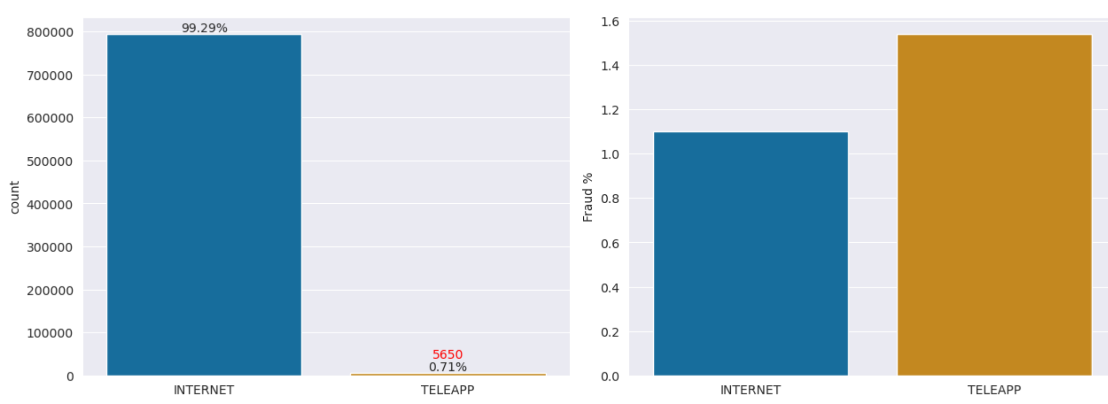
	dtype	count	unique	missing_count	missing_percentage
housing_status	object	800000	7	0	0.0



Feature: 'source'

Description: Online source of application. Either browser (INTERNET) or app (TELEAPP).

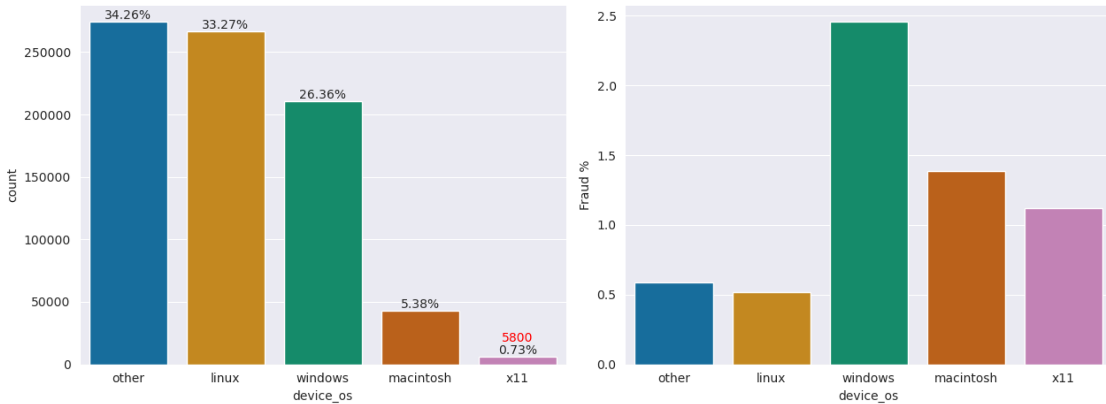
	dtype	count	unique	missing_count	missing_percentage
source	object	800000	2	0	0.0



Feature: 'device_os'

Description: Operative system of device that made request. Possible values are: Windows, macOS, Linux, X11, or other.

	dtype	count	unique	missing_count	missing_percentage
device_os	object	800000	5	0	0.0



1.4 Correlation coefficients

Correlation between each feature and the target (fraud or not):

[ ]:
```python
# Correlation coefficient between features and target

fig = plt.figure(figsize=(9.6,7.2))

corr_target = pd.DataFrame(pd.get_dummies(X_train.
 ↪drop('device_fraud_count',axis=1))
                              .corrwith(y_train)).reset_index()

corr_target.columns = ['feature','target_correlation']
corr_target = corr_target.sort_values(by='target_correlation')

ax = sns.
 ↪barplot(data=corr_target,x='feature',y='target_correlation',palette=palette)
ax.set_title('Feature correlations with target')
```

```
ax.set_xticklabels(ax.get_xticklabels(), rotation=90, ha="right")
ax.set_ylabel('Correlation with target')

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