

# DEFAULT RISK PREDICTION — HOME CREDIT

## 1. Objective

Desenvolver um modelo preditivo que estime a probabilidade de inadimplência de clientes (variável TARGET) usando dados demográficos, financeiros, histórico de crédito e comportamento passado. O objetivo prático é permitir que a instituição tome decisões de crédito mais seguras: ajustar limites, aprovar ou recusar solicitações e priorizar ações de cobrança preventivas, reduzindo perdas e melhorando rentabilidade.

Considerando a complexidade e o alto desbalanceamento do conjunto de dados do Home Credit Default Risk, o modelo foi ajustado para equilibrar precisão e capacidade de detecção (recall), priorizando a identificação de clientes com maior risco de inadimplência. O foco é apoiar decisões de crédito mais seguras e proativas, minimizando o risco de perdas e fortalecendo a gestão do portfólio financeiro.

## 2. Executive Summary

The project aimed to **develop a predictive default risk model** to support safer and more profitable credit decisions, using the *Home Credit Default Risk* dataset, characterized by **high complexity, more than 800 variables, and strong class imbalance** (approximately **8% defaulters**).

Even in the presence of variables with **low individual correlation** with default risk, the application of statistical and *machine learning* techniques made it possible to **combine multiple weak signals into a robust and interpretable model**, capable of consistently estimating the probability of default.

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### 1. Business Challenge

The central need was to **reduce financial losses from default** without compromising the experience and conversion of good customers. The main challenges were:

- Identifying **high-risk customers in advance**;
- Reducing the impact of **false negatives** (defaulters not detected);
- Controlling the volume of **false positives** and their operational costs;
- Ensuring **scalability** in an environment with hundreds of variables.

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### 2. Developed Solution

A **binary classification model** was built and trained using a wide set of demographic, socioeconomic, behavioral, and credit history variables, totaling **more than 800 features**.

The model was calibrated with an **optimal threshold of 0.191 (based on F1-score ≈ 0.344)**, prioritizing the **capture of defaulters** without excessive loss of good customers, making it suitable for **risk screening and prevention stages**.

Main patterns identified:

- Employment stability and consistent financial history reduce risk;
- High volume of credit inquiries and recent financial decisions increase risk;
- Recent behavioral changes are strong indicators of instability;
- The **combination of multiple variables** proved essential for predictive performance.

### 3. Performance and Results

Metric	Result
Recall (Defaulters)	<b>38%</b>
Precision (Defaulters)	<b>31%</b>
AUC-ROC	<b>0.80</b>
MCC	<b>0.28</b>
Overall Accuracy	<b>88%</b>

The model demonstrated **good discriminatory power**, especially considering the strong class imbalance and high dimensionality of the data.

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### 4. Financial Impact

Based on realistic simulations (46,127 customers, average loss of **R\$ 5,000** per defaulter and an average preventive action cost of **R\$ 500**), the estimated impact was:

Scenario	Estimated Net Profit
<b>Without model</b>	<b>R\$ 23.78 million</b>
<b>With model (th = 0.191)</b>	<b>R\$ 30.17 million</b>

**Estimated incremental gain:** approximately **R\$ 6.39 million**.

This result shows that the model generates **direct financial value**, even after considering losses from false positives and operational costs.

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### 5. Conclusion

The model achieved its primary objective: **reducing default risk and increasing portfolio profitability** in a measurable way.

The project demonstrated that, even in a scenario of **high complexity, more than 800 variables, and strong class imbalance**, it is possible to build solutions that are:

- Robust,
- Interpretable,
- Scalable,
- Financially advantageous.

In summary, the work reinforces that **data science applied to credit risk management** not only improves technical metrics but also **generates real and sustainable business impact**.

## 3. About the Data

The data used in this analysis refer to the financial, demographic, and behavioral history of customers from the **Home Credit Default Risk** dataset, which contains detailed information on thousands of individuals with different socioeconomic profiles.

Currently, credit decision-making depends on multiple factors, such as loan history, repayment capacity, property characteristics, employment status, and social behavior patterns. This complexity and variability make manual decisions inconsistent, justifying the application of Data Science and Machine Learning techniques to support default risk assessment and proactive customer portfolio management.

## 4. Getting Started

### 4.1 Importing Libraries

```
In [1]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import chi2_contingency
from sklearn.preprocessing import RobustScaler, StandardScaler, MinMaxScaler, OneHotEncoder
from sklearn.model_selection import train_test_split
import xgboost as xgb
from sklearn.metrics import recall_score, precision_score, f1_score, roc_auc_score, average_precision_score
from skopt import BayesSearchCV
from skopt.space import Real, Integer, Categorical
import lightgbm as lgb
from imblearn.ensemble import BalancedRandomForestClassifier
from catboost import CatBoostClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.base import clone
from sklearn.ensemble import AdaBoostClassifier, HistGradientBoostingClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
import shap
from sklearn.preprocessing import PolynomialFeatures
```

### 4.2 Style Import

```
In [2]: plt.style.use('..../styles/personalestilo.mplstyle')
```

```
Bad key axes.color_cycle in file ..../styles/personalestilo.mplstyle, line 9 ('axes.color_cycle:
df691b, 5cb85c, 5bc0de, f0ad4e, d9534f, 4e5d6c')
You probably need to get an updated matplotlibrc file from
https://github.com/matplotlib/matplotlib/blob/v3.10.6/lib/matplotlib/mpl-data/matplotlibrc
or from the matplotlib source distribution
```

### 4.3 Additional Functions

```
In [2]: def snake_case(lst):
    def convert(s):
        s = s.replace(' ', '_')
        new_s = ""
        for i, c in enumerate(s):
            if c.isupper():
                if i > 0 and (s[i-1].islower() or (i+1 < len(s) and s[i+1].islower())):
                    new_s += "_"
                new_s += c.lower()
            else:
                new_s += c
        return new_s
    return [convert(s) for s in lst]

def agg_numeric(df, key, prefix):
    df_num = df.select_dtypes(include=[np.number])

    df_num[key] = df[key]

    agg = df_num.groupby(key).agg(['mean', 'max', 'min', 'count'])

    agg.columns = [prefix + "_" + col[0].join(col[1]) for col in agg.columns]

    return agg
```

```

def plot_numeric_block(df_block, bins=30, color='orange', rows=3, figsize=(18, 12)):
    plt.figure(figsize=figsize)
    cols = df_block.columns
    n_cols = int(np.ceil(len(cols) / rows))
    for i, col in enumerate(cols, 1):
        plt.subplot(rows, n_cols, i)
        sns.histplot(df_block[col], kde=True, color=color, bins=bins)
        plt.title(col)
        plt.xlabel(col)
        plt.ylabel('Frequência')
    plt.tight_layout()
    plt.show()

def plot_target_by_categorical(df, cat_col, target_col='target', suptitle=None):
    categorias = df[cat_col].unique()
    categorias = [str(c) for c in categorias]
    n_categorias = len(categorias)
    n_linhas = (n_categorias // 3) + (1 if n_categorias % 3 != 0 else 0)
    n_linhas = max(n_linhas, 1)
    ncols = 3 if n_categorias > 1 else 1

    fig, axes = plt.subplots(n_linhas, ncols, figsize=(7 * ncols, 5 * n_linhas))
    axes = np.array(axes).reshape(-1)

    palette_target = {'0': "orange", '1': "red"}

    for ax in axes[n_categorias:]:
        ax.axis('off')

    for i, categoria in enumerate(categorias):
        data_plot = df[df[cat_col] == categoria].copy()
        data_plot['target_str'] = data_plot[target_col].astype(str)
        sns.countplot(
            data=data_plot,
            x='target_str',
            hue='target_str',
            palette=palette_target,
            order=['0', '1'],
            ax=axes[i],
            legend=False
        )
        axes[i].set_title(f'{cat_col}: {categoria}')
        axes[i].set_xlabel(target_col)
        axes[i].set_ylabel('Frequência')
        axes[i].set_xticks([0, 1])
        axes[i].set_xticklabels(['Não Inadimplente (0)', 'Inadimplente (1)'])

    if suptitle is None:
        suptitle = f'Frequência de {target_col} por categoria de {cat_col}'
    plt.suptitle(suptitle)
    plt.tight_layout(rect=[0, 0, 1, 0.95])
    plt.show()

def find_best_threshold(y_true, y_proba, metric="f1"):
    thresholds = np.linspace(0, 1, 200)

    best_t = 0.5
    best_score = -1

    for t in thresholds:
        y_pred = (y_proba >= t).astype(int)

        if metric == "f1":
            score = f1_score(y_true, y_pred)
        elif metric == "mcc":
            score = matthews_corrcoef(y_true, y_pred)
        elif metric == "recall":
            score = recall_score(y_true, y_pred)

```

```

        elif metric == "precision":
            score = precision_score(y_true, y_pred)
        elif metric == "f2":
            score = fbeta_score(y_true, y_pred, beta=2)
        elif metric == "f05":
            score = fbeta_score(y_true, y_pred, beta=0.5)
        else:
            raise ValueError("Métrica inválida.")

        if score > best_score:
            best_score = score
            best_t = t

    return best_t, best_score


def get_fold(X, idx):
    return X.iloc[idx] if hasattr(X, "iloc") else X[idx]

def get_model_clone(name, model):
    if "cat" in name:
        return CatBoostClassifier(**model.get_params())
    elif "xgb" in name:
        return xgb.XGBClassifier(**model.get_params())
    elif "lgbm" in name:
        return lgb.LGBMClassifier(**model.get_params())
    else:
        return clone(model)


def plot_binaria_target(
    df,
    var_binaria,
    target='target',
    label_0='Não Possui',
    label_1='Possui',
    suptitle=None
):
    flags = [0, 1]
    palette_target = {'0': "orange", '1': "red"}

    fig, axes = plt.subplots(1, 2, figsize=(14, 6), sharey=False)
    for i, flag in enumerate(flags):
        data_plot = df[df[var_binaria] == flag].copy()
        data_plot['target_str'] = data_plot[target].astype(str)
        sns.countplot(
            data=data_plot,
            x='target_str',
            hue='target_str',
            palette=palette_target,
            order=['0', '1'],
            ax=axes[i],
            legend=False
        )
        label = label_0 if flag == 0 else label_1
        axes[i].set_title(f"{label}")
        axes[i].set_xlabel('Resposta')
        axes[i].set_ylabel('Frequência')
        axes[i].set_xticks([0, 1])
        axes[i].set_xticklabels(['Não Inadimplente (0)', 'Inadimplente (1)'])

    if suptitle is None:
        suptitle = f'Frequência de {target} por {var_binaria}'
    plt.suptitle(suptitle)
    plt.tight_layout(rect=[0, 0, 1, 0.95])
    plt.show()

```

```

def plot_num_var_by_target(
    df,
    num_var,
    target_var='target',
    title_0=None,
    title_1=None,
    label_x=None,
    color_0='blue',
    color_1='orange',
    figsize=(10, 8),
    discrete=False
):
    fig, axes = plt.subplots(2, 1, figsize=figsize, sharey=False)

    sns.histplot(
        data=df[df[target_var] == 0],
        x=num_var,
        color=color_0,
        ax=axes[0],
        discrete=discrete
    )
    axes[0].set_title(title_0 or f'Distribuição de {num_var} (Sem Inadimplência)')
    axes[0].set_ylabel('Frequência')
    axes[0].set_xlabel(label_x or num_var)

    sns.histplot(
        data=df[df[target_var] == 1],
        x=num_var,
        color=color_1,
        ax=axes[1],
        discrete=discrete
    )
    axes[1].set_title(title_1 or f'Distribuição de {num_var} (Inadimplentes)')
    axes[1].set_ylabel('Frequência')
    axes[1].set_xlabel(label_x or num_var)

    plt.tight_layout()
    plt.show()

def calcular_cramers_v(df, col1, col2):
    contingency_table = pd.crosstab(df[col1], df[col2])
    chi2_stat, p, dof, expected = chi2_contingency(contingency_table)
    n = contingency_table.sum().sum()
    min_dim = min(contingency_table.shape) - 1
    cramers_v = np.sqrt(chi2_stat / (n * min_dim)) if min_dim > 0 else np.nan
    print(f"V de Cramer entre {col1} e {col2}: {cramers_v:.4f}")

def avaliar_metricas(modelo, X_val, y_val, X_test, y_test):
    def obter_prob(modelo, X):
        if hasattr(modelo, "predict_proba"):
            probas = modelo.predict_proba(X)
            return probas[:, 1]
        elif hasattr(modelo, "predict"):
            if isinstance(X, (pd.DataFrame, pd.Series, np.ndarray)):
                dmatrix = xgb.DMatrix(X)
            else:
                dmatrix = X
            probas = modelo.predict(dmatrix)
            return probas
        else:
            raise ValueError("O modelo precisa implementar predict_proba ou ser booster do xgbc")

    y_val_prob = obter_prob(modelo, X_val)
    y_test_prob = obter_prob(modelo, X_test)

    y_val_pred = (y_val_prob >= 0.5).astype(int)
    y_test_pred = (y_test_prob >= 0.5).astype(int)

```

```

metrics = {
    'recall': [
        recall_score(y_val, y_val_pred),
        recall_score(y_test, y_test_pred)
    ],
    'precision': [
        precision_score(y_val, y_val_pred),
        precision_score(y_test, y_test_pred)
    ],
    'f1_score': [
        f1_score(y_val, y_val_pred),
        f1_score(y_test, y_test_pred)
    ],
    'auc_roc': [
        roc_auc_score(y_val, y_val_prob),
        roc_auc_score(y_test, y_test_prob)
    ],
    'auc_pr': [
        average_precision_score(y_val, y_val_prob),
        average_precision_score(y_test, y_test_prob)
    ]
}
df_metrics = pd.DataFrame(metrics, index=['validacao', 'teste']).T
return df_metrics

def income_stability(row):
    low_income_types = ['Unemployed', 'Student', 'Maternity leave', 'Pensioner']
    high_income_types = ['State servant', 'Businessman', 'Civil servant']
    stable_occupations = [
        'Accountants', 'Core staff', 'HR staff', 'High skill tech staff', 'Managers', 'Medicine',
        'Private service staff', 'Secretaries', 'Officials', 'IT staff'
    ]
    unstable_occupations = [
        'Laborers', 'Low-skill Laborers', 'Cleaning staff', 'Waiters/barmen staff', 'Security s
    ]
    inc_type = str(row['name_income_type'])
    occ_type = str(row['occupation_type'])
    days_employed = abs(row['days_employed']) if not pd.isnull(row['days_employed']) else 0

    if (inc_type in low_income_types) or (occ_type in unstable_occupations) or (days_employed <
        return 0
    elif (inc_type in high_income_types) or (occ_type in stable_occupations and days_employed >
        return 2
    else:
        return 1

```

## 4.4 Loading the Data

```
In [4]: app_train = pd.read_csv('../data/application_train.csv')
app_test = pd.read_csv('../data/application_test.csv')
```

```
In [5]: bureau = pd.read_csv('../data/bureau.csv')
bureau.name = "bureau"

bureau_balance = pd.read_csv('../data/bureau_balance.csv')
bureau_balance.name = "bb"

prev = pd.read_csv('../data/previous_application.csv')
prev.name = "prev"

pos = pd.read_csv('../data/POS_CASH_balance.csv')
pos.name = "pos"

cc = pd.read_csv('../data/credit_card_balance.csv')
cc.name = "cc"
```

```

inst = pd.read_csv('../data/installments_payments.csv')
inst.name = "inst"

In [6]: bb_agg = agg_numeric(bureau_balance, 'SK_ID_BUREAU', 'bb')
bureau = bureau.merge(bb_agg, on='SK_ID_BUREAU', how='left')

bureau_agg = agg_numeric(bureau, 'SK_ID_CURR', 'bur')

prev_agg = agg_numeric(prev, 'SK_ID_CURR', 'prev')

pos_agg = agg_numeric(pos, 'SK_ID_PREV', 'pos')

prev_pos = prev[['SK_ID_CURR', 'SK_ID_PREV']].merge(pos_agg, on='SK_ID_PREV', how='left')
pos_final = agg_numeric(prev_pos, 'SK_ID_CURR', 'posf')

cc_agg = agg_numeric(cc, 'SK_ID_PREV', 'cc')

prev_cc = prev[['SK_ID_CURR', 'SK_ID_PREV']].merge(cc_agg, on='SK_ID_PREV', how='left')
cc_final = agg_numeric(prev_cc, 'SK_ID_CURR', 'ccf')

inst_agg = agg_numeric(inst, 'SK_ID_PREV', 'inst')

prev_inst = prev[['SK_ID_CURR', 'SK_ID_PREV']].merge(inst_agg, on='SK_ID_PREV', how='left')
inst_final = agg_numeric(prev_inst, 'SK_ID_CURR', 'instf')

df = app_train.copy()
df_test = app_test.copy()

for auxiliary in [bureau_agg, prev_agg, pos_final, cc_final, inst_final]:
    df = df.merge(auxiliary, on='SK_ID_CURR', how='left')
    df_test = df_test.merge(auxiliary, on='SK_ID_CURR', how='left')

```

```

In [31]: pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', None)

```

```

In [8]: df.to_csv('../data/train.csv', index=False)
df_test.to_csv('../data/test.csv', index=False)

```

## 5. Data Description

```

In [ ]: df1 = df.copy()

```

### 5.1 Renaming Columns

```

In [4]: cols_old = list(df1.columns)

cols_old = list(df1.columns)

cols_new = snake_case(cols_old)

df1.columns = cols_new

```

```

In [5]: for idx, (col, dtype) in enumerate(df1.dtypes.items(), 1):
    print(f'{idx} - {col}: {dtype}')

```

```
1 - sk_id_curr: int64
2 - target: int64
3 - name_contract_type: object
4 - code_gender: object
5 - flag_own_car: object
6 - flag_own_realty: object
7 - cnt_children: int64
8 - amt_income_total: float64
9 - amt_credit: float64
10 - amt_annuity: float64
11 - amt_goods_price: float64
12 - name_type_suite: object
13 - name_income_type: object
14 - name_education_type: object
15 - name_family_status: object
16 - name_housing_type: object
17 - region_population_relative: float64
18 - days_birth: int64
19 - days_employed: int64
20 - days_registration: float64
21 - days_id_publish: int64
22 - own_car_age: float64
23 - flag_mobil: int64
24 - flag_emp_phone: int64
25 - flag_work_phone: int64
26 - flag_cont_mobile: int64
27 - flag_phone: int64
28 - flag_email: int64
29 - occupation_type: object
30 - cnt_fam_members: float64
31 - region_rating_client: int64
32 - region_rating_client_w_city: int64
33 - weekday_appr_process_start: object
34 - hour_appr_process_start: int64
35 - reg_region_not_live_region: int64
36 - reg_region_not_work_region: int64
37 - live_region_not_work_region: int64
38 - reg_city_not_live_city: int64
39 - reg_city_not_work_city: int64
40 - live_city_not_work_city: int64
41 - organization_type: object
42 - ext_source_1: float64
43 - ext_source_2: float64
44 - ext_source_3: float64
45 - apartments_avg: float64
46 - basementarea_avg: float64
47 - years_beginexpluatation_avg: float64
48 - years_build_avg: float64
49 - commonarea_avg: float64
50 - elevators_avg: float64
51 - entrances_avg: float64
52 - floorsmax_avg: float64
53 - floorsmin_avg: float64
54 - landarea_avg: float64
55 - livingapartments_avg: float64
56 - livingarea_avg: float64
57 - nonlivingapartments_avg: float64
58 - nonlivingarea_avg: float64
59 - apartments_mode: float64
60 - basementarea_mode: float64
61 - years_beginexpluatation_mode: float64
62 - years_build_mode: float64
63 - commonarea_mode: float64
64 - elevators_mode: float64
65 - entrances_mode: float64
66 - floorsmax_mode: float64
67 - floorsmin_mode: float64
68 - landarea_mode: float64
69 - livingapartments_mode: float64
```

```
70 - livingarea_mode: float64
71 - nonlivingapartments_mode: float64
72 - nonlivingarea_mode: float64
73 - apartments_medi: float64
74 - basementarea_medi: float64
75 - years_beginexpluatation_medi: float64
76 - years_build_medi: float64
77 - commonarea_medi: float64
78 - elevators_medi: float64
79 - entrances_medi: float64
80 - floorsmax_medi: float64
81 - floorsmin_medi: float64
82 - landarea_medi: float64
83 - livingapartments_medi: float64
84 - livingarea_medi: float64
85 - nonlivingapartments_medi: float64
86 - nonlivingarea_medi: float64
87 - fondkapremont_mode: object
88 - housetype_mode: object
89 - totalarea_mode: float64
90 - wallsmaterial_mode: object
91 - emergencystate_mode: object
92 - obs_30_cnt_social_circle: float64
93 - def_30_cnt_social_circle: float64
94 - obs_60_cnt_social_circle: float64
95 - def_60_cnt_social_circle: float64
96 - days_last_phone_change: float64
97 - flag_document_2: int64
98 - flag_document_3: int64
99 - flag_document_4: int64
100 - flag_document_5: int64
101 - flag_document_6: int64
102 - flag_document_7: int64
103 - flag_document_8: int64
104 - flag_document_9: int64
105 - flag_document_10: int64
106 - flag_document_11: int64
107 - flag_document_12: int64
108 - flag_document_13: int64
109 - flag_document_14: int64
110 - flag_document_15: int64
111 - flag_document_16: int64
112 - flag_document_17: int64
113 - flag_document_18: int64
114 - flag_document_19: int64
115 - flag_document_20: int64
116 - flag_document_21: int64
117 - amt_req_credit_bureau_hour: float64
118 - amt_req_credit_bureau_day: float64
119 - amt_req_credit_bureau_week: float64
120 - amt_req_credit_bureau_mon: float64
121 - amt_req_credit_bureau_qrt: float64
122 - amt_req_credit_bureau_year: float64
123 - bur_sk_id_bureau_mean: float64
124 - bur_sk_id_bureau_max: float64
125 - bur_sk_id_bureau_min: float64
126 - bur_sk_id_bureau_count: float64
127 - bur_days_credit_mean: float64
128 - bur_days_credit_max: float64
129 - bur_days_credit_min: float64
130 - bur_days_credit_count: float64
131 - bur_credit_day_overdue_mean: float64
132 - bur_credit_day_overdue_max: float64
133 - bur_credit_day_overdue_min: float64
134 - bur_credit_day_overdue_count: float64
135 - bur_days_credit_enddate_mean: float64
136 - bur_days_credit_enddate_max: float64
137 - bur_days_credit_enddate_min: float64
138 - bur_days_credit_enddate_count: float64
```

```
139 - bur_days_enddate_fact_mean: float64
140 - bur_days_enddate_fact_max: float64
141 - bur_days_enddate_fact_min: float64
142 - bur_days_enddate_fact_count: float64
143 - bur_amt_credit_max_overdue_mean: float64
144 - bur_amt_credit_max_overdue_max: float64
145 - bur_amt_credit_max_overdue_min: float64
146 - bur_amt_credit_max_overdue_count: float64
147 - bur_cnt_credit_prolong_mean: float64
148 - bur_cnt_credit_prolong_max: float64
149 - bur_cnt_credit_prolong_min: float64
150 - bur_cnt_credit_prolong_count: float64
151 - bur_amt_credit_sum_mean: float64
152 - bur_amt_credit_sum_max: float64
153 - bur_amt_credit_sum_min: float64
154 - bur_amt_credit_sum_count: float64
155 - bur_amt_credit_sum_debt_mean: float64
156 - bur_amt_credit_sum_debt_max: float64
157 - bur_amt_credit_sum_debt_min: float64
158 - bur_amt_credit_sum_debt_count: float64
159 - bur_amt_credit_sum_limit_mean: float64
160 - bur_amt_credit_sum_limit_max: float64
161 - bur_amt_credit_sum_limit_min: float64
162 - bur_amt_credit_sum_limit_count: float64
163 - bur_amt_credit_sum_overdue_mean: float64
164 - bur_amt_credit_sum_overdue_max: float64
165 - bur_amt_credit_sum_overdue_min: float64
166 - bur_amt_credit_sum_overdue_count: float64
167 - bur_days_credit_update_mean: float64
168 - bur_days_credit_update_max: float64
169 - bur_days_credit_update_min: float64
170 - bur_days_credit_update_count: float64
171 - bur_amt_annuity_mean: float64
172 - bur_amt_annuity_max: float64
173 - bur_amt_annuity_min: float64
174 - bur_amt_annuity_count: float64
175 - bur_bb_months_balance_mean_mean: float64
176 - bur_bb_months_balance_mean_max: float64
177 - bur_bb_months_balance_mean_min: float64
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179 - bur_bb_months_balance_max_mean: float64
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182 - bur_bb_months_balance_max_count: float64
183 - bur_bb_months_balance_min_mean: float64
184 - bur_bb_months_balance_min_max: float64
185 - bur_bb_months_balance_min_min: float64
186 - bur_bb_months_balance_min_count: float64
187 - bur_bb_months_balance_count_mean: float64
188 - bur_bb_months_balance_count_max: float64
189 - bur_bb_months_balance_count_min: float64
190 - bur_bb_months_balance_count_count: float64
191 - prev_sk_id_prev_mean: float64
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194 - prev_sk_id_prev_count: float64
195 - prev_amt_annuity_mean: float64
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203 - prev_amt_credit_mean: float64
204 - prev_amt_credit_max: float64
205 - prev_amt_credit_min: float64
206 - prev_amt_credit_count: float64
207 - prev_amt_down_payment_mean: float64
```

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208 - prev_amt_down_payment_max: float64
209 - prev_amt_down_payment_min: float64
210 - prev_amt_down_payment_count: float64
211 - prev_amt_goods_price_mean: float64
212 - prev_amt_goods_price_max: float64
213 - prev_amt_goods_price_min: float64
214 - prev_amt_goods_price_count: float64
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216 - prev_hour_appr_process_start_max: float64
217 - prev_hour_appr_process_start_min: float64
218 - prev_hour_appr_process_start_count: float64
219 - prev_nflag_last_appl_in_day_mean: float64
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221 - prev_nflag_last_appl_in_day_min: float64
222 - prev_nflag_last_appl_in_day_count: float64
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270 - prev_nflag_insured_on_approval_count: float64
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273 - posf_sk_id_prev_min: float64
274 - posf_sk_id_prev_count: float64
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276 - posf_pos_sk_id_curr_mean_max: float64
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297 - posf\_pos\_months\_balance\_max\_min: float64  
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350 - posf\_pos\_sk\_dpd\_min\_count: float64  
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397 - ccf\_cc\_months\_balance\_max\_min: float64  
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405 - ccf\_cc\_months\_balance\_count\_min: float64  
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412 - ccf\_cc\_amt\_balance\_max\_max: float64  
413 - ccf\_cc\_amt\_balance\_max\_min: float64  
414 - ccf\_cc\_amt\_balance\_max\_count: float64

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422 - ccf_cc_amt_balance_count_count: float64
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429 - ccf_cc_amt_credit_limit_actual_max_min: float64
430 - ccf_cc_amt_credit_limit_actual_max_count: float64
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433 - ccf_cc_amt_credit_limit_actual_min_min: float64
434 - ccf_cc_amt_credit_limit_actual_min_count: float64
435 - ccf_cc_amt_credit_limit_actual_count_mean: float64
436 - ccf_cc_amt_credit_limit_actual_count_max: float64
437 - ccf_cc_amt_credit_limit_actual_count_min: float64
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445 - ccf_cc_amt_drawings_atm_current_max_min: float64
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449 - ccf_cc_amt_drawings_atm_current_min_min: float64
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451 - ccf_cc_amt_drawings_atm_current_count_mean: float64
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465 - ccf_cc_amt_drawings_current_min_min: float64
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477 - ccf_cc_amt_drawings_other_current_max_min: float64
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481 - ccf_cc_amt_drawings_other_current_min_min: float64
482 - ccf_cc_amt_drawings_other_current_min_count: float64
483 - ccf_cc_amt_drawings_other_current_count_mean: float64
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544 - ccf\_cc\_payment\_total\_current\_min\_max: float64  
545 - ccf\_cc\_payment\_total\_current\_min\_min: float64  
546 - ccf\_cc\_payment\_total\_current\_min\_count: float64  
547 - ccf\_cc\_payment\_total\_current\_count\_mean: float64  
548 - ccf\_cc\_payment\_total\_current\_count\_max: float64  
549 - ccf\_cc\_payment\_total\_current\_count\_min: float64  
550 - ccf\_cc\_payment\_total\_current\_count\_count: float64  
551 - ccf\_cc\_receivable\_principal\_mean\_mean: float64  
552 - ccf\_cc\_receivable\_principal\_mean\_max: float64

553 - ccf\_cc\_amt\_receivable\_principal\_mean\_min: float64  
554 - ccf\_cc\_amt\_receivable\_principal\_mean\_count: float64  
555 - ccf\_cc\_amt\_receivable\_principal\_max\_mean: float64  
556 - ccf\_cc\_amt\_receivable\_principal\_max\_max: float64  
557 - ccf\_cc\_amt\_receivable\_principal\_max\_min: float64  
558 - ccf\_cc\_amt\_receivable\_principal\_max\_count: float64  
559 - ccf\_cc\_amt\_receivable\_principal\_min\_mean: float64  
560 - ccf\_cc\_amt\_receivable\_principal\_min\_max: float64  
561 - ccf\_cc\_amt\_receivable\_principal\_min\_min: float64  
562 - ccf\_cc\_amt\_receivable\_principal\_min\_count: float64  
563 - ccf\_cc\_amt\_receivable\_principal\_count\_mean: float64  
564 - ccf\_cc\_amt\_receivable\_principal\_count\_max: float64  
565 - ccf\_cc\_amt\_receivable\_principal\_count\_min: float64  
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567 - ccf\_cc\_amt\_recivable\_mean\_mean: float64  
568 - ccf\_cc\_amt\_recivable\_mean\_max: float64  
569 - ccf\_cc\_amt\_recivable\_mean\_min: float64  
570 - ccf\_cc\_amt\_recivable\_mean\_count: float64  
571 - ccf\_cc\_amt\_recivable\_max\_mean: float64  
572 - ccf\_cc\_amt\_recivable\_max\_max: float64  
573 - ccf\_cc\_amt\_recivable\_max\_min: float64  
574 - ccf\_cc\_amt\_recivable\_max\_count: float64  
575 - ccf\_cc\_amt\_recivable\_min\_mean: float64  
576 - ccf\_cc\_amt\_recivable\_min\_max: float64  
577 - ccf\_cc\_amt\_recivable\_min\_min: float64  
578 - ccf\_cc\_amt\_recivable\_min\_count: float64  
579 - ccf\_cc\_amt\_recivable\_count\_mean: float64  
580 - ccf\_cc\_amt\_recivable\_count\_max: float64  
581 - ccf\_cc\_amt\_recivable\_count\_min: float64  
582 - ccf\_cc\_amt\_recivable\_count\_count: float64  
583 - ccf\_cc\_amt\_total\_receivable\_mean\_mean: float64  
584 - ccf\_cc\_amt\_total\_receivable\_mean\_max: float64  
585 - ccf\_cc\_amt\_total\_receivable\_mean\_min: float64  
586 - ccf\_cc\_amt\_total\_receivable\_mean\_count: float64  
587 - ccf\_cc\_amt\_total\_receivable\_max\_mean: float64  
588 - ccf\_cc\_amt\_total\_receivable\_max\_max: float64  
589 - ccf\_cc\_amt\_total\_receivable\_max\_min: float64  
590 - ccf\_cc\_amt\_total\_receivable\_max\_count: float64  
591 - ccf\_cc\_amt\_total\_receivable\_min\_mean: float64  
592 - ccf\_cc\_amt\_total\_receivable\_min\_max: float64  
593 - ccf\_cc\_amt\_total\_receivable\_min\_min: float64  
594 - ccf\_cc\_amt\_total\_receivable\_min\_count: float64  
595 - ccf\_cc\_amt\_total\_receivable\_count\_mean: float64  
596 - ccf\_cc\_amt\_total\_receivable\_count\_max: float64  
597 - ccf\_cc\_amt\_total\_receivable\_count\_min: float64  
598 - ccf\_cc\_amt\_total\_receivable\_count\_count: float64  
599 - ccf\_cc\_cnt\_drawings\_atm\_current\_mean\_mean: float64  
600 - ccf\_cc\_cnt\_drawings\_atm\_current\_mean\_max: float64  
601 - ccf\_cc\_cnt\_drawings\_atm\_current\_mean\_min: float64  
602 - ccf\_cc\_cnt\_drawings\_atm\_current\_mean\_count: float64  
603 - ccf\_cc\_cnt\_drawings\_atm\_current\_max\_mean: float64  
604 - ccf\_cc\_cnt\_drawings\_atm\_current\_max\_max: float64  
605 - ccf\_cc\_cnt\_drawings\_atm\_current\_max\_min: float64  
606 - ccf\_cc\_cnt\_drawings\_atm\_current\_max\_count: float64  
607 - ccf\_cc\_cnt\_drawings\_atm\_current\_min\_mean: float64  
608 - ccf\_cc\_cnt\_drawings\_atm\_current\_min\_max: float64  
609 - ccf\_cc\_cnt\_drawings\_atm\_current\_min\_min: float64  
610 - ccf\_cc\_cnt\_drawings\_atm\_current\_min\_count: float64  
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612 - ccf\_cc\_cnt\_drawings\_atm\_current\_count\_max: float64  
613 - ccf\_cc\_cnt\_drawings\_atm\_current\_count\_min: float64  
614 - ccf\_cc\_cnt\_drawings\_atm\_current\_count\_count: float64  
615 - ccf\_cc\_cnt\_drawings\_current\_mean\_mean: float64  
616 - ccf\_cc\_cnt\_drawings\_current\_mean\_max: float64  
617 - ccf\_cc\_cnt\_drawings\_current\_mean\_min: float64  
618 - ccf\_cc\_cnt\_drawings\_current\_mean\_count: float64  
619 - ccf\_cc\_cnt\_drawings\_current\_max\_mean: float64  
620 - ccf\_cc\_cnt\_drawings\_current\_max\_max: float64  
621 - ccf\_cc\_cnt\_drawings\_current\_max\_min: float64

622 - ccf\_cc\_cnt\_drawings\_current\_max\_count: float64  
623 - ccf\_cc\_cnt\_drawings\_current\_min\_mean: float64  
624 - ccf\_cc\_cnt\_drawings\_current\_min\_max: float64  
625 - ccf\_cc\_cnt\_drawings\_current\_min\_min: float64  
626 - ccf\_cc\_cnt\_drawings\_current\_min\_count: float64  
627 - ccf\_cc\_cnt\_drawings\_current\_count\_mean: float64  
628 - ccf\_cc\_cnt\_drawings\_current\_count\_max: float64  
629 - ccf\_cc\_cnt\_drawings\_current\_count\_min: float64  
630 - ccf\_cc\_cnt\_drawings\_current\_count\_count: float64  
631 - ccf\_cc\_cnt\_drawings\_other\_current\_mean\_mean: float64  
632 - ccf\_cc\_cnt\_drawings\_other\_current\_mean\_max: float64  
633 - ccf\_cc\_cnt\_drawings\_other\_current\_mean\_min: float64  
634 - ccf\_cc\_cnt\_drawings\_other\_current\_mean\_count: float64  
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636 - ccf\_cc\_cnt\_drawings\_other\_current\_max\_max: float64  
637 - ccf\_cc\_cnt\_drawings\_other\_current\_max\_min: float64  
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639 - ccf\_cc\_cnt\_drawings\_other\_current\_min\_mean: float64  
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643 - ccf\_cc\_cnt\_drawings\_other\_current\_count\_mean: float64  
644 - ccf\_cc\_cnt\_drawings\_other\_current\_count\_max: float64  
645 - ccf\_cc\_cnt\_drawings\_other\_current\_count\_min: float64  
646 - ccf\_cc\_cnt\_drawings\_other\_current\_count\_count: float64  
647 - ccf\_cc\_cnt\_drawings\_pos\_current\_mean\_mean: float64  
648 - ccf\_cc\_cnt\_drawings\_pos\_current\_mean\_max: float64  
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654 - ccf\_cc\_cnt\_drawings\_pos\_current\_max\_count: float64  
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659 - ccf\_cc\_cnt\_drawings\_pos\_current\_count\_mean: float64  
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663 - ccf\_cc\_cnt\_instalment\_mature\_cum\_mean\_mean: float64  
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668 - ccf\_cc\_cnt\_instalment\_mature\_cum\_max\_max: float64  
669 - ccf\_cc\_cnt\_instalment\_mature\_cum\_max\_min: float64  
670 - ccf\_cc\_cnt\_instalment\_mature\_cum\_max\_count: float64  
671 - ccf\_cc\_cnt\_instalment\_mature\_cum\_min\_mean: float64  
672 - ccf\_cc\_cnt\_instalment\_mature\_cum\_min\_max: float64  
673 - ccf\_cc\_cnt\_instalment\_mature\_cum\_min\_min: float64  
674 - ccf\_cc\_cnt\_instalment\_mature\_cum\_min\_count: float64  
675 - ccf\_cc\_cnt\_instalment\_mature\_cum\_count\_mean: float64  
676 - ccf\_cc\_cnt\_instalment\_mature\_cum\_count\_max: float64  
677 - ccf\_cc\_cnt\_instalment\_mature\_cum\_count\_min: float64  
678 - ccf\_cc\_cnt\_instalment\_mature\_cum\_count\_count: float64  
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680 - ccf\_cc\_sk\_dpd\_mean\_max: float64  
681 - ccf\_cc\_sk\_dpd\_mean\_min: float64  
682 - ccf\_cc\_sk\_dpd\_mean\_count: float64  
683 - ccf\_cc\_sk\_dpd\_max\_mean: float64  
684 - ccf\_cc\_sk\_dpd\_max\_max: float64  
685 - ccf\_cc\_sk\_dpd\_max\_min: float64  
686 - ccf\_cc\_sk\_dpd\_max\_count: float64  
687 - ccf\_cc\_sk\_dpd\_min\_mean: float64  
688 - ccf\_cc\_sk\_dpd\_min\_max: float64  
689 - ccf\_cc\_sk\_dpd\_min\_min: float64  
690 - ccf\_cc\_sk\_dpd\_min\_count: float64

691 - ccf\_cc\_sk\_dpd\_count\_mean: float64  
692 - ccf\_cc\_sk\_dpd\_count\_max: float64  
693 - ccf\_cc\_sk\_dpd\_count\_min: float64  
694 - ccf\_cc\_sk\_dpd\_count\_count: float64  
695 - ccf\_cc\_sk\_dpd\_def\_mean\_mean: float64  
696 - ccf\_cc\_sk\_dpd\_def\_mean\_max: float64  
697 - ccf\_cc\_sk\_dpd\_def\_mean\_min: float64  
698 - ccf\_cc\_sk\_dpd\_def\_mean\_count: float64  
699 - ccf\_cc\_sk\_dpd\_def\_max\_mean: float64  
700 - ccf\_cc\_sk\_dpd\_def\_max\_max: float64  
701 - ccf\_cc\_sk\_dpd\_def\_max\_min: float64  
702 - ccf\_cc\_sk\_dpd\_def\_max\_count: float64  
703 - ccf\_cc\_sk\_dpd\_def\_min\_mean: float64  
704 - ccf\_cc\_sk\_dpd\_def\_min\_max: float64  
705 - ccf\_cc\_sk\_dpd\_def\_min\_min: float64  
706 - ccf\_cc\_sk\_dpd\_def\_min\_count: float64  
707 - ccf\_cc\_sk\_dpd\_def\_count\_mean: float64  
708 - ccf\_cc\_sk\_dpd\_def\_count\_max: float64  
709 - ccf\_cc\_sk\_dpd\_def\_count\_min: float64  
710 - ccf\_cc\_sk\_dpd\_def\_count\_count: float64  
711 - instf\_sk\_id\_prev\_mean: float64  
712 - instf\_sk\_id\_prev\_max: float64  
713 - instf\_sk\_id\_prev\_min: float64  
714 - instf\_sk\_id\_prev\_count: float64  
715 - instf\_inst\_sk\_id\_curr\_mean\_mean: float64  
716 - instf\_inst\_sk\_id\_curr\_mean\_max: float64  
717 - instf\_inst\_sk\_id\_curr\_mean\_min: float64  
718 - instf\_inst\_sk\_id\_curr\_mean\_count: float64  
719 - instf\_inst\_sk\_id\_curr\_max\_mean: float64  
720 - instf\_inst\_sk\_id\_curr\_max\_max: float64  
721 - instf\_inst\_sk\_id\_curr\_max\_min: float64  
722 - instf\_inst\_sk\_id\_curr\_max\_count: float64  
723 - instf\_inst\_sk\_id\_curr\_min\_mean: float64  
724 - instf\_inst\_sk\_id\_curr\_min\_max: float64  
725 - instf\_inst\_sk\_id\_curr\_min\_min: float64  
726 - instf\_inst\_sk\_id\_curr\_min\_count: float64  
727 - instf\_inst\_sk\_id\_curr\_count\_mean: float64  
728 - instf\_inst\_sk\_id\_curr\_count\_max: float64  
729 - instf\_inst\_sk\_id\_curr\_count\_min: float64  
730 - instf\_inst\_sk\_id\_curr\_count\_count: float64  
731 - instf\_inst\_num\_instalment\_version\_mean\_mean: float64  
732 - instf\_inst\_num\_instalment\_version\_mean\_max: float64  
733 - instf\_inst\_num\_instalment\_version\_mean\_min: float64  
734 - instf\_inst\_num\_instalment\_version\_mean\_count: float64  
735 - instf\_inst\_num\_instalment\_version\_max\_mean: float64  
736 - instf\_inst\_num\_instalment\_version\_max\_max: float64  
737 - instf\_inst\_num\_instalment\_version\_max\_min: float64  
738 - instf\_inst\_num\_instalment\_version\_max\_count: float64  
739 - instf\_inst\_num\_instalment\_version\_min\_mean: float64  
740 - instf\_inst\_num\_instalment\_version\_min\_max: float64  
741 - instf\_inst\_num\_instalment\_version\_min\_min: float64  
742 - instf\_inst\_num\_instalment\_version\_min\_count: float64  
743 - instf\_inst\_num\_instalment\_version\_count\_mean: float64  
744 - instf\_inst\_num\_instalment\_version\_count\_max: float64  
745 - instf\_inst\_num\_instalment\_version\_count\_min: float64  
746 - instf\_inst\_num\_instalment\_version\_count\_count: float64  
747 - instf\_inst\_num\_instalment\_number\_mean\_mean: float64  
748 - instf\_inst\_num\_instalment\_number\_mean\_max: float64  
749 - instf\_inst\_num\_instalment\_number\_mean\_min: float64  
750 - instf\_inst\_num\_instalment\_number\_mean\_count: float64  
751 - instf\_inst\_num\_instalment\_number\_max\_mean: float64  
752 - instf\_inst\_num\_instalment\_number\_max\_max: float64  
753 - instf\_inst\_num\_instalment\_number\_max\_min: float64  
754 - instf\_inst\_num\_instalment\_number\_max\_count: float64  
755 - instf\_inst\_num\_instalment\_number\_min\_mean: float64  
756 - instf\_inst\_num\_instalment\_number\_min\_max: float64  
757 - instf\_inst\_num\_instalment\_number\_min\_min: float64  
758 - instf\_inst\_num\_instalment\_number\_min\_count: float64  
759 - instf\_inst\_num\_instalment\_number\_count\_mean: float64

```
760 - instf_inst_num_instalment_number_count_max: float64
761 - instf_inst_num_instalment_number_count_min: float64
762 - instf_inst_num_instalment_number_count_count: float64
763 - instf_inst_days_instalment_mean_mean: float64
764 - instf_inst_days_instalment_mean_max: float64
765 - instf_inst_days_instalment_mean_min: float64
766 - instf_inst_days_instalment_mean_count: float64
767 - instf_inst_days_instalment_max_mean: float64
768 - instf_inst_days_instalment_max_max: float64
769 - instf_inst_days_instalment_max_min: float64
770 - instf_inst_days_instalment_max_count: float64
771 - instf_inst_days_instalment_min_mean: float64
772 - instf_inst_days_instalment_min_max: float64
773 - instf_inst_days_instalment_min_min: float64
774 - instf_inst_days_instalment_min_count: float64
775 - instf_inst_days_instalment_count_mean: float64
776 - instf_inst_days_instalment_count_max: float64
777 - instf_inst_days_instalment_count_min: float64
778 - instf_inst_days_instalment_count_count: float64
779 - instf_inst_days_entry_payment_mean_mean: float64
780 - instf_inst_days_entry_payment_mean_max: float64
781 - instf_inst_days_entry_payment_mean_min: float64
782 - instf_inst_days_entry_payment_mean_count: float64
783 - instf_inst_days_entry_payment_max_mean: float64
784 - instf_inst_days_entry_payment_max_max: float64
785 - instf_inst_days_entry_payment_max_min: float64
786 - instf_inst_days_entry_payment_max_count: float64
787 - instf_inst_days_entry_payment_min_mean: float64
788 - instf_inst_days_entry_payment_min_max: float64
789 - instf_inst_days_entry_payment_min_min: float64
790 - instf_inst_days_entry_payment_min_count: float64
791 - instf_inst_days_entry_payment_count_mean: float64
792 - instf_inst_days_entry_payment_count_max: float64
793 - instf_inst_days_entry_payment_count_min: float64
794 - instf_inst_days_entry_payment_count_count: float64
795 - instf_inst_amt_instalment_mean_mean: float64
796 - instf_inst_amt_instalment_mean_max: float64
797 - instf_inst_amt_instalment_mean_min: float64
798 - instf_inst_amt_instalment_mean_count: float64
799 - instf_inst_amt_instalment_max_mean: float64
800 - instf_inst_amt_instalment_max_max: float64
801 - instf_inst_amt_instalment_max_min: float64
802 - instf_inst_amt_instalment_max_count: float64
803 - instf_inst_amt_instalment_min_mean: float64
804 - instf_inst_amt_instalment_min_max: float64
805 - instf_inst_amt_instalment_min_min: float64
806 - instf_inst_amt_instalment_min_count: float64
807 - instf_inst_amt_instalment_count_mean: float64
808 - instf_inst_amt_instalment_count_max: float64
809 - instf_inst_amt_instalment_count_min: float64
810 - instf_inst_amt_instalment_count_count: float64
811 - instf_inst_amt_payment_mean_mean: float64
812 - instf_inst_amt_payment_mean_max: float64
813 - instf_inst_amt_payment_mean_min: float64
814 - instf_inst_amt_payment_mean_count: float64
815 - instf_inst_amt_payment_max_mean: float64
816 - instf_inst_amt_payment_max_max: float64
817 - instf_inst_amt_payment_max_min: float64
818 - instf_inst_amt_payment_max_count: float64
819 - instf_inst_amt_payment_min_mean: float64
820 - instf_inst_amt_payment_min_max: float64
821 - instf_inst_amt_payment_min_min: float64
822 - instf_inst_amt_payment_min_count: float64
823 - instf_inst_amt_payment_count_mean: float64
824 - instf_inst_amt_payment_count_max: float64
825 - instf_inst_amt_payment_count_min: float64
826 - instf_inst_amt_payment_count_count: float64
```

```
In [6]: df1 = df1.drop(columns=['sk_id_curr'])
```

## 5.2 Data Dimensions

```
In [7]: print('Número de linhas:', df1.shape[0])
print('Número de colunas:', df1.shape[1])
```

```
Número de linhas: 307511
Número de colunas: 825
```

## 5.3 Data Types

```
In [8]: for idx, (col, dtype) in enumerate(df1.dtypes.items(), 1):
    print(f'{idx} - {col}: {dtype}')
```

```
1 - target: int64
2 - name_contract_type: object
3 - code_gender: object
4 - flag_own_car: object
5 - flag_own_realty: object
6 - cnt_children: int64
7 - amt_income_total: float64
8 - amt_credit: float64
9 - amt_annuity: float64
10 - amt_goods_price: float64
11 - name_type_suite: object
12 - name_income_type: object
13 - name_education_type: object
14 - name_family_status: object
15 - name_housing_type: object
16 - region_population_relative: float64
17 - days_birth: int64
18 - days_employed: int64
19 - days_registration: float64
20 - days_id_publish: int64
21 - own_car_age: float64
22 - flag_mobil: int64
23 - flag_emp_phone: int64
24 - flag_work_phone: int64
25 - flag_cont_mobile: int64
26 - flag_phone: int64
27 - flag_email: int64
28 - occupation_type: object
29 - cnt_fam_members: float64
30 - region_rating_client: int64
31 - region_rating_client_w_city: int64
32 - weekday_appr_process_start: object
33 - hour_appr_process_start: int64
34 - reg_region_not_live_region: int64
35 - reg_region_not_work_region: int64
36 - live_region_not_work_region: int64
37 - reg_city_not_live_city: int64
38 - reg_city_not_work_city: int64
39 - live_city_not_work_city: int64
40 - organization_type: object
41 - ext_source_1: float64
42 - ext_source_2: float64
43 - ext_source_3: float64
44 - apartments_avg: float64
45 - basementarea_avg: float64
46 - years_beginexpluatation_avg: float64
47 - years_build_avg: float64
48 - commonarea_avg: float64
49 - elevators_avg: float64
50 - entrances_avg: float64
51 - floorsmax_avg: float64
52 - floorsmin_avg: float64
53 - landarea_avg: float64
54 - livingapartments_avg: float64
55 - livingarea_avg: float64
56 - nonlivingapartments_avg: float64
57 - nonlivingarea_avg: float64
58 - apartments_mode: float64
59 - basementarea_mode: float64
60 - years_beginexpluatation_mode: float64
61 - years_build_mode: float64
62 - commonarea_mode: float64
63 - elevators_mode: float64
64 - entrances_mode: float64
65 - floorsmax_mode: float64
66 - floorsmin_mode: float64
67 - landarea_mode: float64
68 - livingapartments_mode: float64
69 - livingarea_mode: float64
```

70 - nonlivingapartments\_mode: float64  
71 - nonlivingarea\_mode: float64  
72 - apartments\_medi: float64  
73 - basementarea\_medi: float64  
74 - years\_beginexpluatation\_medi: float64  
75 - years\_build\_medi: float64  
76 - commonarea\_medi: float64  
77 - elevators\_medi: float64  
78 - entrances\_medi: float64  
79 - floorsmax\_medi: float64  
80 - floorsmin\_medi: float64  
81 - landarea\_medi: float64  
82 - livingapartments\_medi: float64  
83 - livingarea\_medi: float64  
84 - nonlivingapartments\_medi: float64  
85 - nonlivingarea\_medi: float64  
86 - fondkapremont\_mode: object  
87 - housetype\_mode: object  
88 - totalarea\_mode: float64  
89 - wallsmaterial\_mode: object  
90 - emergencystate\_mode: object  
91 - obs\_30\_cnt\_social\_circle: float64  
92 - def\_30\_cnt\_social\_circle: float64  
93 - obs\_60\_cnt\_social\_circle: float64  
94 - def\_60\_cnt\_social\_circle: float64  
95 - days\_last\_phone\_change: float64  
96 - flag\_document\_2: int64  
97 - flag\_document\_3: int64  
98 - flag\_document\_4: int64  
99 - flag\_document\_5: int64  
100 - flag\_document\_6: int64  
101 - flag\_document\_7: int64  
102 - flag\_document\_8: int64  
103 - flag\_document\_9: int64  
104 - flag\_document\_10: int64  
105 - flag\_document\_11: int64  
106 - flag\_document\_12: int64  
107 - flag\_document\_13: int64  
108 - flag\_document\_14: int64  
109 - flag\_document\_15: int64  
110 - flag\_document\_16: int64  
111 - flag\_document\_17: int64  
112 - flag\_document\_18: int64  
113 - flag\_document\_19: int64  
114 - flag\_document\_20: int64  
115 - flag\_document\_21: int64  
116 - amt\_req\_credit\_bureau\_hour: float64  
117 - amt\_req\_credit\_bureau\_day: float64  
118 - amt\_req\_credit\_bureau\_week: float64  
119 - amt\_req\_credit\_bureau\_mon: float64  
120 - amt\_req\_credit\_bureau\_qrt: float64  
121 - amt\_req\_credit\_bureau\_year: float64  
122 - bur\_sk\_id\_bureau\_mean: float64  
123 - bur\_sk\_id\_bureau\_max: float64  
124 - bur\_sk\_id\_bureau\_min: float64  
125 - bur\_sk\_id\_bureau\_count: float64  
126 - bur\_days\_credit\_mean: float64  
127 - bur\_days\_credit\_max: float64  
128 - bur\_days\_credit\_min: float64  
129 - bur\_days\_credit\_count: float64  
130 - bur\_credit\_day\_overdue\_mean: float64  
131 - bur\_credit\_day\_overdue\_max: float64  
132 - bur\_credit\_day\_overdue\_min: float64  
133 - bur\_credit\_day\_overdue\_count: float64  
134 - bur\_days\_credit\_enddate\_mean: float64  
135 - bur\_days\_credit\_enddate\_max: float64  
136 - bur\_days\_credit\_enddate\_min: float64  
137 - bur\_days\_credit\_enddate\_count: float64  
138 - bur\_days\_enddate\_fact\_mean: float64

139 - bur\_days\_enddate\_fact\_max: float64  
140 - bur\_days\_enddate\_fact\_min: float64  
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142 - bur\_amt\_credit\_max\_overdue\_mean: float64  
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145 - bur\_amt\_credit\_max\_overdue\_count: float64  
146 - bur\_cnt\_credit\_prolong\_mean: float64  
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156 - bur\_amt\_credit\_sum\_debt\_min: float64  
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159 - bur\_amt\_credit\_sum\_limit\_max: float64  
160 - bur\_amt\_credit\_sum\_limit\_min: float64  
161 - bur\_amt\_credit\_sum\_limit\_count: float64  
162 - bur\_amt\_credit\_sum\_overdue\_mean: float64  
163 - bur\_amt\_credit\_sum\_overdue\_max: float64  
164 - bur\_amt\_credit\_sum\_overdue\_min: float64  
165 - bur\_amt\_credit\_sum\_overdue\_count: float64  
166 - bur\_days\_credit\_update\_mean: float64  
167 - bur\_days\_credit\_update\_max: float64  
168 - bur\_days\_credit\_update\_min: float64  
169 - bur\_days\_credit\_update\_count: float64  
170 - bur\_amt\_annuity\_mean: float64  
171 - bur\_amt\_annuity\_max: float64  
172 - bur\_amt\_annuity\_min: float64  
173 - bur\_amt\_annuity\_count: float64  
174 - bur\_bb\_months\_balance\_mean\_mean: float64  
175 - bur\_bb\_months\_balance\_mean\_max: float64  
176 - bur\_bb\_months\_balance\_mean\_min: float64  
177 - bur\_bb\_months\_balance\_mean\_count: float64  
178 - bur\_bb\_months\_balance\_max\_mean: float64  
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180 - bur\_bb\_months\_balance\_max\_min: float64  
181 - bur\_bb\_months\_balance\_max\_count: float64  
182 - bur\_bb\_months\_balance\_min\_mean: float64  
183 - bur\_bb\_months\_balance\_min\_max: float64  
184 - bur\_bb\_months\_balance\_min\_min: float64  
185 - bur\_bb\_months\_balance\_min\_count: float64  
186 - bur\_bb\_months\_balance\_count\_mean: float64  
187 - bur\_bb\_months\_balance\_count\_max: float64  
188 - bur\_bb\_months\_balance\_count\_min: float64  
189 - bur\_bb\_months\_balance\_count\_count: float64  
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191 - prev\_sk\_id\_prev\_max: float64  
192 - prev\_sk\_id\_prev\_min: float64  
193 - prev\_sk\_id\_prev\_count: float64  
194 - prev\_amt\_annuity\_mean: float64  
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196 - prev\_amt\_annuity\_min: float64  
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202 - prev\_amt\_credit\_mean: float64  
203 - prev\_amt\_credit\_max: float64  
204 - prev\_amt\_credit\_min: float64  
205 - prev\_amt\_credit\_count: float64  
206 - prev\_amt\_down\_payment\_mean: float64  
207 - prev\_amt\_down\_payment\_max: float64

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208 - prev_amt_down_payment_min: float64
209 - prev_amt_down_payment_count: float64
210 - prev_amt_goods_price_mean: float64
211 - prev_amt_goods_price_max: float64
212 - prev_amt_goods_price_min: float64
213 - prev_amt_goods_price_count: float64
214 - prev_hour_appr_process_start_mean: float64
215 - prev_hour_appr_process_start_max: float64
216 - prev_hour_appr_process_start_min: float64
217 - prev_hour_appr_process_start_count: float64
218 - prev_nflag_last_appl_in_day_mean: float64
219 - prev_nflag_last_appl_in_day_max: float64
220 - prev_nflag_last_appl_in_day_min: float64
221 - prev_nflag_last_appl_in_day_count: float64
222 - prev_rate_down_payment_mean: float64
223 - prev_rate_down_payment_max: float64
224 - prev_rate_down_payment_min: float64
225 - prev_rate_down_payment_count: float64
226 - prev_rate_interest_primary_mean: float64
227 - prev_rate_interest_primary_max: float64
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229 - prev_rate_interest_primary_count: float64
230 - prev_rate_interest_privileged_mean: float64
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233 - prev_rate_interest_privileged_count: float64
234 - prev_days_decision_mean: float64
235 - prev_days_decision_max: float64
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237 - prev_days_decision_count: float64
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240 - prev_sellerplace_area_min: float64
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245 - prev_cnt_payment_count: float64
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252 - prev_days_first_due_min: float64
253 - prev_days_first_due_count: float64
254 - prev_days_last_due_1st_version_mean: float64
255 - prev_days_last_due_1st_version_max: float64
256 - prev_days_last_due_1st_version_min: float64
257 - prev_days_last_due_1st_version_count: float64
258 - prev_days_last_due_mean: float64
259 - prev_days_last_due_max: float64
260 - prev_days_last_due_min: float64
261 - prev_days_last_due_count: float64
262 - prev_days_termination_mean: float64
263 - prev_days_termination_max: float64
264 - prev_days_termination_min: float64
265 - prev_days_termination_count: float64
266 - prev_nflag_insured_on_approval_mean: float64
267 - prev_nflag_insured_on_approval_max: float64
268 - prev_nflag_insured_on_approval_min: float64
269 - prev_nflag_insured_on_approval_count: float64
270 - posf_sk_id_prev_mean: float64
271 - posf_sk_id_prev_max: float64
272 - posf_sk_id_prev_min: float64
273 - posf_sk_id_prev_count: float64
274 - posf_pos_sk_id_curr_mean_mean: float64
275 - posf_pos_sk_id_curr_mean_max: float64
276 - posf_pos_sk_id_curr_mean_min: float64
```

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279 - posf_pos_sk_id_curr_max_max: float64
280 - posf_pos_sk_id_curr_max_min: float64
281 - posf_pos_sk_id_curr_max_count: float64
282 - posf_pos_sk_id_curr_min_mean: float64
283 - posf_pos_sk_id_curr_min_max: float64
284 - posf_pos_sk_id_curr_min_min: float64
285 - posf_pos_sk_id_curr_min_count: float64
286 - posf_pos_sk_id_curr_count_mean: float64
287 - posf_pos_sk_id_curr_count_max: float64
288 - posf_pos_sk_id_curr_count_min: float64
289 - posf_pos_sk_id_curr_count_count: float64
290 - posf_pos_months_balance_mean_mean: float64
291 - posf_pos_months_balance_mean_max: float64
292 - posf_pos_months_balance_mean_min: float64
293 - posf_pos_months_balance_mean_count: float64
294 - posf_pos_months_balance_max_mean: float64
295 - posf_pos_months_balance_max_max: float64
296 - posf_pos_months_balance_max_min: float64
297 - posf_pos_months_balance_max_count: float64
298 - posf_pos_months_balance_min_mean: float64
299 - posf_pos_months_balance_min_max: float64
300 - posf_pos_months_balance_min_min: float64
301 - posf_pos_months_balance_min_count: float64
302 - posf_pos_months_balance_count_mean: float64
303 - posf_pos_months_balance_count_max: float64
304 - posf_pos_months_balance_count_min: float64
305 - posf_pos_months_balance_count_count: float64
306 - posf_pos_cnt_instalment_mean_mean: float64
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308 - posf_pos_cnt_instalment_mean_min: float64
309 - posf_pos_cnt_instalment_mean_count: float64
310 - posf_pos_cnt_instalment_max_mean: float64
311 - posf_pos_cnt_instalment_max_max: float64
312 - posf_pos_cnt_instalment_max_min: float64
313 - posf_pos_cnt_instalment_max_count: float64
314 - posf_pos_cnt_instalment_min_mean: float64
315 - posf_pos_cnt_instalment_min_max: float64
316 - posf_pos_cnt_instalment_min_min: float64
317 - posf_pos_cnt_instalment_min_count: float64
318 - posf_pos_cnt_instalment_count_mean: float64
319 - posf_pos_cnt_instalment_count_max: float64
320 - posf_pos_cnt_instalment_count_min: float64
321 - posf_pos_cnt_instalment_count_count: float64
322 - posf_pos_cnt_instalment_future_mean_mean: float64
323 - posf_pos_cnt_instalment_future_mean_max: float64
324 - posf_pos_cnt_instalment_future_mean_min: float64
325 - posf_pos_cnt_instalment_future_mean_count: float64
326 - posf_pos_cnt_instalment_future_max_mean: float64
327 - posf_pos_cnt_instalment_future_max_max: float64
328 - posf_pos_cnt_instalment_future_max_min: float64
329 - posf_pos_cnt_instalment_future_max_count: float64
330 - posf_pos_cnt_instalment_future_min_mean: float64
331 - posf_pos_cnt_instalment_future_min_max: float64
332 - posf_pos_cnt_instalment_future_min_min: float64
333 - posf_pos_cnt_instalment_future_min_count: float64
334 - posf_pos_cnt_instalment_future_count_mean: float64
335 - posf_pos_cnt_instalment_future_count_max: float64
336 - posf_pos_cnt_instalment_future_count_min: float64
337 - posf_pos_cnt_instalment_future_count_count: float64
338 - posf_pos_sk_dpd_mean_mean: float64
339 - posf_pos_sk_dpd_mean_max: float64
340 - posf_pos_sk_dpd_mean_min: float64
341 - posf_pos_sk_dpd_mean_count: float64
342 - posf_pos_sk_dpd_max_mean: float64
343 - posf_pos_sk_dpd_max_max: float64
344 - posf_pos_sk_dpd_max_min: float64
345 - posf_pos_sk_dpd_max_count: float64
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347 - posf\_pos\_sk\_dpd\_min\_max: float64  
348 - posf\_pos\_sk\_dpd\_min\_min: float64  
349 - posf\_pos\_sk\_dpd\_min\_count: float64  
350 - posf\_pos\_sk\_dpd\_count\_mean: float64  
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352 - posf\_pos\_sk\_dpd\_count\_min: float64  
353 - posf\_pos\_sk\_dpd\_count\_count: float64  
354 - posf\_pos\_sk\_dpd\_def\_mean\_mean: float64  
355 - posf\_pos\_sk\_dpd\_def\_mean\_max: float64  
356 - posf\_pos\_sk\_dpd\_def\_mean\_min: float64  
357 - posf\_pos\_sk\_dpd\_def\_mean\_count: float64  
358 - posf\_pos\_sk\_dpd\_def\_max\_mean: float64  
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360 - posf\_pos\_sk\_dpd\_def\_max\_min: float64  
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364 - posf\_pos\_sk\_dpd\_def\_min\_min: float64  
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367 - posf\_pos\_sk\_dpd\_def\_count\_max: float64  
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371 - ccf\_sk\_id\_prev\_max: float64  
372 - ccf\_sk\_id\_prev\_min: float64  
373 - ccf\_sk\_id\_prev\_count: float64  
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379 - ccf\_cc\_sk\_id\_curr\_max\_max: float64  
380 - ccf\_cc\_sk\_id\_curr\_max\_min: float64  
381 - ccf\_cc\_sk\_id\_curr\_max\_count: float64  
382 - ccf\_cc\_sk\_id\_curr\_min\_mean: float64  
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384 - ccf\_cc\_sk\_id\_curr\_min\_min: float64  
385 - ccf\_cc\_sk\_id\_curr\_min\_count: float64  
386 - ccf\_cc\_sk\_id\_curr\_count\_mean: float64  
387 - ccf\_cc\_sk\_id\_curr\_count\_max: float64  
388 - ccf\_cc\_sk\_id\_curr\_count\_min: float64  
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392 - ccf\_cc\_months\_balance\_mean\_min: float64  
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395 - ccf\_cc\_months\_balance\_max\_max: float64  
396 - ccf\_cc\_months\_balance\_max\_min: float64  
397 - ccf\_cc\_months\_balance\_max\_count: float64  
398 - ccf\_cc\_months\_balance\_min\_mean: float64  
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400 - ccf\_cc\_months\_balance\_min\_min: float64  
401 - ccf\_cc\_months\_balance\_min\_count: float64  
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408 - ccf\_cc\_amt\_balance\_mean\_min: float64  
409 - ccf\_cc\_amt\_balance\_mean\_count: float64  
410 - ccf\_cc\_amt\_balance\_max\_mean: float64  
411 - ccf\_cc\_amt\_balance\_max\_max: float64  
412 - ccf\_cc\_amt\_balance\_max\_min: float64  
413 - ccf\_cc\_amt\_balance\_max\_count: float64  
414 - ccf\_cc\_amt\_balance\_min\_mean: float64

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416 - ccf_cc_amt_balance_min_min: float64
417 - ccf_cc_amt_balance_min_count: float64
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419 - ccf_cc_amt_balance_count_max: float64
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428 - ccf_cc_amt_credit_limit_actual_max_min: float64
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430 - ccf_cc_amt_credit_limit_actual_min_mean: float64
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432 - ccf_cc_amt_credit_limit_actual_min_min: float64
433 - ccf_cc_amt_credit_limit_actual_min_count: float64
434 - ccf_cc_amt_credit_limit_actual_count_mean: float64
435 - ccf_cc_amt_credit_limit_actual_count_max: float64
436 - ccf_cc_amt_credit_limit_actual_count_min: float64
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438 - ccf_cc_amt_drawings_atm_current_mean_mean: float64
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440 - ccf_cc_amt_drawings_atm_current_mean_min: float64
441 - ccf_cc_amt_drawings_atm_current_mean_count: float64
442 - ccf_cc_amt_drawings_atm_current_max_mean: float64
443 - ccf_cc_amt_drawings_atm_current_max_max: float64
444 - ccf_cc_amt_drawings_atm_current_max_min: float64
445 - ccf_cc_amt_drawings_atm_current_max_count: float64
446 - ccf_cc_amt_drawings_atm_current_min_mean: float64
447 - ccf_cc_amt_drawings_atm_current_min_max: float64
448 - ccf_cc_amt_drawings_atm_current_min_min: float64
449 - ccf_cc_amt_drawings_atm_current_min_count: float64
450 - ccf_cc_amt_drawings_atm_current_count_mean: float64
451 - ccf_cc_amt_drawings_atm_current_count_max: float64
452 - ccf_cc_amt_drawings_atm_current_count_min: float64
453 - ccf_cc_amt_drawings_atm_current_count_count: float64
454 - ccf_cc_amt_drawings_current_mean_mean: float64
455 - ccf_cc_amt_drawings_current_mean_max: float64
456 - ccf_cc_amt_drawings_current_mean_min: float64
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460 - ccf_cc_amt_drawings_current_max_min: float64
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465 - ccf_cc_amt_drawings_current_min_count: float64
466 - ccf_cc_amt_drawings_current_count_mean: float64
467 - ccf_cc_amt_drawings_current_count_max: float64
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469 - ccf_cc_amt_drawings_current_count_count: float64
470 - ccf_cc_amt_drawings_other_current_mean_mean: float64
471 - ccf_cc_amt_drawings_other_current_mean_max: float64
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474 - ccf_cc_amt_drawings_other_current_max_mean: float64
475 - ccf_cc_amt_drawings_other_current_max_max: float64
476 - ccf_cc_amt_drawings_other_current_max_min: float64
477 - ccf_cc_amt_drawings_other_current_max_count: float64
478 - ccf_cc_amt_drawings_other_current_min_mean: float64
479 - ccf_cc_amt_drawings_other_current_min_max: float64
480 - ccf_cc_amt_drawings_other_current_min_min: float64
481 - ccf_cc_amt_drawings_other_current_min_count: float64
482 - ccf_cc_amt_drawings_other_current_count_mean: float64
483 - ccf_cc_amt_drawings_other_current_count_max: float64
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484 - ccf\_cc\_amt\_drawings\_other\_current\_count\_min: float64  
485 - ccf\_cc\_amt\_drawings\_other\_current\_count\_count: float64  
486 - ccf\_cc\_amt\_drawings\_pos\_current\_mean\_mean: float64  
487 - ccf\_cc\_amt\_drawings\_pos\_current\_mean\_max: float64  
488 - ccf\_cc\_amt\_drawings\_pos\_current\_mean\_min: float64  
489 - ccf\_cc\_amt\_drawings\_pos\_current\_mean\_count: float64  
490 - ccf\_cc\_amt\_drawings\_pos\_current\_max\_mean: float64  
491 - ccf\_cc\_amt\_drawings\_pos\_current\_max\_max: float64  
492 - ccf\_cc\_amt\_drawings\_pos\_current\_max\_min: float64  
493 - ccf\_cc\_amt\_drawings\_pos\_current\_max\_count: float64  
494 - ccf\_cc\_amt\_drawings\_pos\_current\_min\_mean: float64  
495 - ccf\_cc\_amt\_drawings\_pos\_current\_min\_max: float64  
496 - ccf\_cc\_amt\_drawings\_pos\_current\_min\_min: float64  
497 - ccf\_cc\_amt\_drawings\_pos\_current\_min\_count: float64  
498 - ccf\_cc\_amt\_drawings\_pos\_current\_count\_mean: float64  
499 - ccf\_cc\_amt\_drawings\_pos\_current\_count\_max: float64  
500 - ccf\_cc\_amt\_drawings\_pos\_current\_count\_min: float64  
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504 - ccf\_cc\_inst\_min\_regularity\_mean\_min: float64  
505 - ccf\_cc\_inst\_min\_regularity\_mean\_count: float64  
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509 - ccf\_cc\_inst\_min\_regularity\_max\_count: float64  
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512 - ccf\_cc\_inst\_min\_regularity\_min\_min: float64  
513 - ccf\_cc\_inst\_min\_regularity\_min\_count: float64  
514 - ccf\_cc\_inst\_min\_regularity\_count\_mean: float64  
515 - ccf\_cc\_inst\_min\_regularity\_count\_max: float64  
516 - ccf\_cc\_inst\_min\_regularity\_count\_min: float64  
517 - ccf\_cc\_inst\_min\_regularity\_count\_count: float64  
518 - ccf\_cc\_amt\_payment\_current\_mean\_mean: float64  
519 - ccf\_cc\_amt\_payment\_current\_mean\_max: float64  
520 - ccf\_cc\_amt\_payment\_current\_mean\_min: float64  
521 - ccf\_cc\_amt\_payment\_current\_mean\_count: float64  
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523 - ccf\_cc\_amt\_payment\_current\_max\_max: float64  
524 - ccf\_cc\_amt\_payment\_current\_max\_min: float64  
525 - ccf\_cc\_amt\_payment\_current\_max\_count: float64  
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527 - ccf\_cc\_amt\_payment\_current\_min\_max: float64  
528 - ccf\_cc\_amt\_payment\_current\_min\_min: float64  
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530 - ccf\_cc\_amt\_payment\_current\_count\_mean: float64  
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536 - ccf\_cc\_amt\_payment\_total\_current\_mean\_min: float64  
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538 - ccf\_cc\_amt\_payment\_total\_current\_max\_mean: float64  
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540 - ccf\_cc\_amt\_payment\_total\_current\_max\_min: float64  
541 - ccf\_cc\_amt\_payment\_total\_current\_max\_count: float64  
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544 - ccf\_cc\_amt\_payment\_total\_current\_min\_min: float64  
545 - ccf\_cc\_amt\_payment\_total\_current\_min\_count: float64  
546 - ccf\_cc\_amt\_payment\_total\_current\_count\_mean: float64  
547 - ccf\_cc\_amt\_payment\_total\_current\_count\_max: float64  
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552 - ccf\_cc\_amt\_receivable\_principal\_mean\_min: float64

553 - ccf\_cc\_amt\_receivable\_principal\_mean\_count: float64  
554 - ccf\_cc\_amt\_receivable\_principal\_max\_mean: float64  
555 - ccf\_cc\_amt\_receivable\_principal\_max\_max: float64  
556 - ccf\_cc\_amt\_receivable\_principal\_max\_min: float64  
557 - ccf\_cc\_amt\_receivable\_principal\_max\_count: float64  
558 - ccf\_cc\_amt\_receivable\_principal\_min\_mean: float64  
559 - ccf\_cc\_amt\_receivable\_principal\_min\_max: float64  
560 - ccf\_cc\_amt\_receivable\_principal\_min\_min: float64  
561 - ccf\_cc\_amt\_receivable\_principal\_min\_count: float64  
562 - ccf\_cc\_amt\_receivable\_principal\_count\_mean: float64  
563 - ccf\_cc\_amt\_receivable\_principal\_count\_max: float64  
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572 - ccf\_cc\_amt\_recivable\_max\_min: float64  
573 - ccf\_cc\_amt\_recivable\_max\_count: float64  
574 - ccf\_cc\_amt\_recivable\_min\_mean: float64  
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576 - ccf\_cc\_amt\_recivable\_min\_min: float64  
577 - ccf\_cc\_amt\_recivable\_min\_count: float64  
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580 - ccf\_cc\_amt\_recivable\_count\_min: float64  
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583 - ccf\_cc\_amt\_total\_receivable\_mean\_max: float64  
584 - ccf\_cc\_amt\_total\_receivable\_mean\_min: float64  
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587 - ccf\_cc\_amt\_total\_receivable\_max\_max: float64  
588 - ccf\_cc\_amt\_total\_receivable\_max\_min: float64  
589 - ccf\_cc\_amt\_total\_receivable\_max\_count: float64  
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591 - ccf\_cc\_amt\_total\_receivable\_min\_max: float64  
592 - ccf\_cc\_amt\_total\_receivable\_min\_min: float64  
593 - ccf\_cc\_amt\_total\_receivable\_min\_count: float64  
594 - ccf\_cc\_amt\_total\_receivable\_count\_mean: float64  
595 - ccf\_cc\_amt\_total\_receivable\_count\_max: float64  
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602 - ccf\_cc\_cnt\_drawings\_atm\_current\_max\_mean: float64  
603 - ccf\_cc\_cnt\_drawings\_atm\_current\_max\_max: float64  
604 - ccf\_cc\_cnt\_drawings\_atm\_current\_max\_min: float64  
605 - ccf\_cc\_cnt\_drawings\_atm\_current\_max\_count: float64  
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611 - ccf\_cc\_cnt\_drawings\_atm\_current\_count\_max: float64  
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659 - ccf\_cc\_cnt\_drawings\_pos\_current\_count\_max: float64  
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674 - ccf\_cc\_cnt\_instalment\_mature\_cum\_count\_mean: float64  
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676 - ccf\_cc\_cnt\_instalment\_mature\_cum\_count\_min: float64  
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687 - ccf\_cc\_sk\_dpd\_min\_max: float64  
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689 - ccf\_cc\_sk\_dpd\_min\_count: float64  
690 - ccf\_cc\_sk\_dpd\_count\_mean: float64

691 - ccf\_cc\_sk\_dpd\_count\_max: float64  
692 - ccf\_cc\_sk\_dpd\_count\_min: float64  
693 - ccf\_cc\_sk\_dpd\_count\_count: float64  
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695 - ccf\_cc\_sk\_dpd\_def\_mean\_max: float64  
696 - ccf\_cc\_sk\_dpd\_def\_mean\_min: float64  
697 - ccf\_cc\_sk\_dpd\_def\_mean\_count: float64  
698 - ccf\_cc\_sk\_dpd\_def\_max\_mean: float64  
699 - ccf\_cc\_sk\_dpd\_def\_max\_max: float64  
700 - ccf\_cc\_sk\_dpd\_def\_max\_min: float64  
701 - ccf\_cc\_sk\_dpd\_def\_max\_count: float64  
702 - ccf\_cc\_sk\_dpd\_def\_min\_mean: float64  
703 - ccf\_cc\_sk\_dpd\_def\_min\_max: float64  
704 - ccf\_cc\_sk\_dpd\_def\_min\_min: float64  
705 - ccf\_cc\_sk\_dpd\_def\_min\_count: float64  
706 - ccf\_cc\_sk\_dpd\_def\_count\_mean: float64  
707 - ccf\_cc\_sk\_dpd\_def\_count\_max: float64  
708 - ccf\_cc\_sk\_dpd\_def\_count\_min: float64  
709 - ccf\_cc\_sk\_dpd\_def\_count\_count: float64  
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711 - instf\_sk\_id\_prev\_max: float64  
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713 - instf\_sk\_id\_prev\_count: float64  
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715 - instf\_inst\_sk\_id\_curr\_mean\_max: float64  
716 - instf\_inst\_sk\_id\_curr\_mean\_min: float64  
717 - instf\_inst\_sk\_id\_curr\_mean\_count: float64  
718 - instf\_inst\_sk\_id\_curr\_max\_mean: float64  
719 - instf\_inst\_sk\_id\_curr\_max\_max: float64  
720 - instf\_inst\_sk\_id\_curr\_max\_min: float64  
721 - instf\_inst\_sk\_id\_curr\_max\_count: float64  
722 - instf\_inst\_sk\_id\_curr\_min\_mean: float64  
723 - instf\_inst\_sk\_id\_curr\_min\_max: float64  
724 - instf\_inst\_sk\_id\_curr\_min\_min: float64  
725 - instf\_inst\_sk\_id\_curr\_min\_count: float64  
726 - instf\_inst\_sk\_id\_curr\_count\_mean: float64  
727 - instf\_inst\_sk\_id\_curr\_count\_max: float64  
728 - instf\_inst\_sk\_id\_curr\_count\_min: float64  
729 - instf\_inst\_sk\_id\_curr\_count\_count: float64  
730 - instf\_inst\_num\_instalment\_version\_mean\_mean: float64  
731 - instf\_inst\_num\_instalment\_version\_mean\_max: float64  
732 - instf\_inst\_num\_instalment\_version\_mean\_min: float64  
733 - instf\_inst\_num\_instalment\_version\_mean\_count: float64  
734 - instf\_inst\_num\_instalment\_version\_max\_mean: float64  
735 - instf\_inst\_num\_instalment\_version\_max\_max: float64  
736 - instf\_inst\_num\_instalment\_version\_max\_min: float64  
737 - instf\_inst\_num\_instalment\_version\_max\_count: float64  
738 - instf\_inst\_num\_instalment\_version\_min\_mean: float64  
739 - instf\_inst\_num\_instalment\_version\_min\_max: float64  
740 - instf\_inst\_num\_instalment\_version\_min\_min: float64  
741 - instf\_inst\_num\_instalment\_version\_min\_count: float64  
742 - instf\_inst\_num\_instalment\_version\_count\_mean: float64  
743 - instf\_inst\_num\_instalment\_version\_count\_max: float64  
744 - instf\_inst\_num\_instalment\_version\_count\_min: float64  
745 - instf\_inst\_num\_instalment\_version\_count\_count: float64  
746 - instf\_inst\_num\_instalment\_number\_mean\_mean: float64  
747 - instf\_inst\_num\_instalment\_number\_mean\_max: float64  
748 - instf\_inst\_num\_instalment\_number\_mean\_min: float64  
749 - instf\_inst\_num\_instalment\_number\_mean\_count: float64  
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752 - instf\_inst\_num\_instalment\_number\_max\_min: float64  
753 - instf\_inst\_num\_instalment\_number\_max\_count: float64  
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755 - instf\_inst\_num\_instalment\_number\_min\_max: float64  
756 - instf\_inst\_num\_instalment\_number\_min\_min: float64  
757 - instf\_inst\_num\_instalment\_number\_min\_count: float64  
758 - instf\_inst\_num\_instalment\_number\_count\_mean: float64  
759 - instf\_inst\_num\_instalment\_number\_count\_max: float64

```
760 - instf_inst_num_instalment_number_count_min: float64
761 - instf_inst_num_instalment_number_count_count: float64
762 - instf_inst_days_instalment_mean_mean: float64
763 - instf_inst_days_instalment_mean_max: float64
764 - instf_inst_days_instalment_mean_min: float64
765 - instf_inst_days_instalment_mean_count: float64
766 - instf_inst_days_instalment_max_mean: float64
767 - instf_inst_days_instalment_max_max: float64
768 - instf_inst_days_instalment_max_min: float64
769 - instf_inst_days_instalment_max_count: float64
770 - instf_inst_days_instalment_min_mean: float64
771 - instf_inst_days_instalment_min_max: float64
772 - instf_inst_days_instalment_min_min: float64
773 - instf_inst_days_instalment_min_count: float64
774 - instf_inst_days_instalment_count_mean: float64
775 - instf_inst_days_instalment_count_max: float64
776 - instf_inst_days_instalment_count_min: float64
777 - instf_inst_days_instalment_count_count: float64
778 - instf_inst_days_entry_payment_mean_mean: float64
779 - instf_inst_days_entry_payment_mean_max: float64
780 - instf_inst_days_entry_payment_mean_min: float64
781 - instf_inst_days_entry_payment_mean_count: float64
782 - instf_inst_days_entry_payment_max_mean: float64
783 - instf_inst_days_entry_payment_max_max: float64
784 - instf_inst_days_entry_payment_max_min: float64
785 - instf_inst_days_entry_payment_max_count: float64
786 - instf_inst_days_entry_payment_min_mean: float64
787 - instf_inst_days_entry_payment_min_max: float64
788 - instf_inst_days_entry_payment_min_min: float64
789 - instf_inst_days_entry_payment_min_count: float64
790 - instf_inst_days_entry_payment_count_mean: float64
791 - instf_inst_days_entry_payment_count_max: float64
792 - instf_inst_days_entry_payment_count_min: float64
793 - instf_inst_days_entry_payment_count_count: float64
794 - instf_inst_amt_instalment_mean_mean: float64
795 - instf_inst_amt_instalment_mean_max: float64
796 - instf_inst_amt_instalment_mean_min: float64
797 - instf_inst_amt_instalment_mean_count: float64
798 - instf_inst_amt_instalment_max_mean: float64
799 - instf_inst_amt_instalment_max_max: float64
800 - instf_inst_amt_instalment_max_min: float64
801 - instf_inst_amt_instalment_max_count: float64
802 - instf_inst_amt_instalment_min_mean: float64
803 - instf_inst_amt_instalment_min_max: float64
804 - instf_inst_amt_instalment_min_min: float64
805 - instf_inst_amt_instalment_min_count: float64
806 - instf_inst_amt_instalment_count_mean: float64
807 - instf_inst_amt_instalment_count_max: float64
808 - instf_inst_amt_instalment_count_min: float64
809 - instf_inst_amt_instalment_count_count: float64
810 - instf_inst_amt_payment_mean_mean: float64
811 - instf_inst_amt_payment_mean_max: float64
812 - instf_inst_amt_payment_mean_min: float64
813 - instf_inst_amt_payment_mean_count: float64
814 - instf_inst_amt_payment_max_mean: float64
815 - instf_inst_amt_payment_max_max: float64
816 - instf_inst_amt_payment_max_min: float64
817 - instf_inst_amt_payment_max_count: float64
818 - instf_inst_amt_payment_min_mean: float64
819 - instf_inst_amt_payment_min_max: float64
820 - instf_inst_amt_payment_min_min: float64
821 - instf_inst_amt_payment_min_count: float64
822 - instf_inst_amt_payment_count_mean: float64
823 - instf_inst_amt_payment_count_max: float64
824 - instf_inst_amt_payment_count_min: float64
825 - instf_inst_amt_payment_count_count: float64
```

### 5.3.1 Modifying Data Types

```
In [9]: df1['flag_own_car'] = df1['flag_own_car'].map({'N': 0, 'Y': 1})
df1['flag_own_realty'] = df1['flag_own_realty'].map({'N': 0, 'Y': 1})
df1['emergencystate_mode'] = df1['emergencystate_mode'].map({'No': 0, 'Yes': 1})

weekday_map = {
    'MONDAY': 1,
    'TUESDAY': 2,
    'WEDNESDAY': 3,
    'THURSDAY': 4,
    'FRIDAY': 5,
    'SATURDAY': 6,
    'SUNDAY': 7
}

df1['weekday_appr_process_start'] = df1['weekday_appr_process_start'].map(weekday_map)
```

## 5.4 Checking and Filling NaN Values

```
In [10]: df1 = df1.replace('XNA', pd.NA)

print(df1.isna().sum().to_string())
```

target	0
name_contract_type	0
code_gender	4
flag_own_car	0
flag_own_realty	0
cnt_children	0
amt_income_total	0
amt_credit	0
amt_annuity	12
amt_goods_price	278
name_type_suite	1292
name_income_type	0
name_education_type	0
name_family_status	0
name_housing_type	0
region_population_relative	0
days_birth	0
days_employed	0
days_registration	0
days_id_publish	0
own_car_age	202929
flag_mobil	0
flag_emp_phone	0
flag_work_phone	0
flag_cont_mobile	0
flag_phone	0
flag_email	0
occupation_type	96391
cnt_fam_members	2
region_rating_client	0
region_rating_client_w_city	0
weekday_appr_process_start	0
hour_appr_process_start	0
reg_region_not_live_region	0
reg_region_not_work_region	0
live_region_not_work_region	0
reg_city_not_live_city	0
reg_city_not_work_city	0
live_city_not_work_city	0
organization_type	55374
ext_source_1	173378
ext_source_2	660
ext_source_3	60965
apartments_avg	156061
basementarea_avg	179943
years_beginexpluatation_avg	150007
years_build_avg	204488
commonarea_avg	214865
elevators_avg	163891
entrances_avg	154828
floorsmax_avg	153020
floorsmin_avg	208642
landarea_avg	182590
livingapartments_avg	210199
livingarea_avg	154350
nonlivingapartments_avg	213514
nonlivingarea_avg	169682
apartments_mode	156061
basementarea_mode	179943
years_beginexpluatation_mode	150007
years_build_mode	204488
commonarea_mode	214865
elevators_mode	163891
entrances_mode	154828
floorsmax_mode	153020
floorsmin_mode	208642
landarea_mode	182590
livingapartments_mode	210199
livingarea_mode	154350

nonlivingapartments_mode	213514
nonlivingarea_mode	169682
apartments_medi	156061
basementarea_medi	179943
years_beginexploitation_medi	150007
years_build_medi	204488
commonarea_medi	214865
elevators_medi	163891
entrances_medi	154828
floorsmax_medi	153020
floorsmin_medi	208642
landarea_medi	182590
livingapartments_medi	210199
livingarea_medi	154350
nonlivingapartments_medi	213514
nonlivingarea_medi	169682
fondkapremont_mode	210295
housetype_mode	154297
totalarea_mode	148431
wallsmaterial_mode	156341
emergencystate_mode	145755
obs_30_cnt_social_circle	1021
def_30_cnt_social_circle	1021
obs_60_cnt_social_circle	1021
def_60_cnt_social_circle	1021
days_last_phone_change	1
flag_document_2	0
flag_document_3	0
flag_document_4	0
flag_document_5	0
flag_document_6	0
flag_document_7	0
flag_document_8	0
flag_document_9	0
flag_document_10	0
flag_document_11	0
flag_document_12	0
flag_document_13	0
flag_document_14	0
flag_document_15	0
flag_document_16	0
flag_document_17	0
flag_document_18	0
flag_document_19	0
flag_document_20	0
flag_document_21	0
amt_req_credit_bureau_hour	41519
amt_req_credit_bureau_day	41519
amt_req_credit_bureau_week	41519
amt_req_credit_bureau_mon	41519
amt_req_credit_bureau_qrt	41519
amt_req_credit_bureau_year	41519
bur_sk_id_bureau_mean	44020
bur_sk_id_bureau_max	44020
bur_sk_id_bureau_min	44020
bur_sk_id_bureau_count	44020
bur_days_credit_mean	44020
bur_days_credit_max	44020
bur_days_credit_min	44020
bur_days_credit_count	44020
bur_credit_day_overdue_mean	44020
bur_credit_day_overdue_max	44020
bur_credit_day_overdue_min	44020
bur_credit_day_overdue_count	44020
bur_days_credit_enddate_mean	46269
bur_days_credit_enddate_max	46269
bur_days_credit_enddate_min	46269
bur_days_credit_enddate_count	44020
bur_days_enddate_fact_mean	77156

bur_days_enddate_fact_max	77156
bur_days_enddate_fact_min	77156
bur_days_enddate_fact_count	44020
bur_amt_credit_max_overdue_mean	123625
bur_amt_credit_max_overdue_max	123625
bur_amt_credit_max_overdue_min	123625
bur_amt_credit_max_overdue_count	44020
bur_cnt_credit_prolong_mean	44020
bur_cnt_credit_prolong_max	44020
bur_cnt_credit_prolong_min	44020
bur_cnt_credit_prolong_count	44020
bur_amt_credit_sum_mean	44021
bur_amt_credit_sum_max	44021
bur_amt_credit_sum_min	44021
bur_amt_credit_sum_count	44020
bur_amt_credit_sum_debt_mean	51380
bur_amt_credit_sum_debt_max	51380
bur_amt_credit_sum_debt_min	51380
bur_amt_credit_sum_debt_count	44020
bur_amt_credit_sum_limit_mean	65069
bur_amt_credit_sum_limit_max	65069
bur_amt_credit_sum_limit_min	65069
bur_amt_credit_sum_limit_count	44020
bur_amt_credit_sum_overdue_mean	44020
bur_amt_credit_sum_overdue_max	44020
bur_amt_credit_sum_overdue_min	44020
bur_amt_credit_sum_overdue_count	44020
bur_days_credit_update_mean	44020
bur_days_credit_update_max	44020
bur_days_credit_update_min	44020
bur_days_credit_update_count	44020
bur_amt_annuity_mean	227502
bur_amt_annuity_max	227502
bur_amt_annuity_min	227502
bur_amt_annuity_count	44020
bur_bb_months_balance_mean_mean	215280
bur_bb_months_balance_mean_max	215280
bur_bb_months_balance_mean_min	215280
bur_bb_months_balance_mean_count	44020
bur_bb_months_balance_max_mean	215280
bur_bb_months_balance_max_max	215280
bur_bb_months_balance_max_min	215280
bur_bb_months_balance_max_count	44020
bur_bb_months_balance_min_mean	215280
bur_bb_months_balance_min_max	215280
bur_bb_months_balance_min_min	215280
bur_bb_months_balance_min_count	44020
bur_bb_months_balance_count_mean	215280
bur_bb_months_balance_count_max	215280
bur_bb_months_balance_count_min	215280
bur_bb_months_balance_count_count	44020
prev_sk_id_prev_mean	16454
prev_sk_id_prev_max	16454
prev_sk_id_prev_min	16454
prev_sk_id_prev_count	16454
prev_amt_annuity_mean	16871
prev_amt_annuity_max	16871
prev_amt_annuity_min	16871
prev_amt_annuity_count	16454
prev_amt_application_mean	16454
prev_amt_application_max	16454
prev_amt_application_min	16454
prev_amt_application_count	16454
prev_amt_credit_mean	16454
prev_amt_credit_max	16454
prev_amt_credit_min	16454
prev_amt_credit_count	16454
prev_amt_down_payment_mean	33906
prev_amt_down_payment_max	33906

prev_amt_down_payment_min	33906
prev_amt_down_payment_count	16454
prev_amt_goods_price_mean	17429
prev_amt_goods_price_max	17429
prev_amt_goods_price_min	17429
prev_amt_goods_price_count	16454
prev_hour_appr_process_start_mean	16454
prev_hour_appr_process_start_max	16454
prev_hour_appr_process_start_min	16454
prev_hour_appr_process_start_count	16454
prev_nflag_last_appl_in_day_mean	16454
prev_nflag_last_appl_in_day_max	16454
prev_nflag_last_appl_in_day_min	16454
prev_nflag_last_appl_in_day_count	16454
prev_rate_down_payment_mean	33906
prev_rate_down_payment_max	33906
prev_rate_down_payment_min	33906
prev_rate_down_payment_count	16454
prev_rate_interest_primary_mean	302902
prev_rate_interest_primary_max	302902
prev_rate_interest_primary_min	302902
prev_rate_interest_primary_count	16454
prev_rate_interest_privileged_mean	302902
prev_rate_interest_privileged_max	302902
prev_rate_interest_privileged_min	302902
prev_rate_interest_privileged_count	16454
prev_days_decision_mean	16454
prev_days_decision_max	16454
prev_days_decision_min	16454
prev_days_decision_count	16454
prev_sellerplace_area_mean	16454
prev_sellerplace_area_max	16454
prev_sellerplace_area_min	16454
prev_sellerplace_area_count	16454
prev_cnt_payment_mean	16869
prev_cnt_payment_max	16869
prev_cnt_payment_min	16869
prev_cnt_payment_count	16454
prev_days_first_drawing_mean	17751
prev_days_first_drawing_max	17751
prev_days_first_drawing_min	17751
prev_days_first_drawing_count	16454
prev_days_first_due_mean	17751
prev_days_first_due_max	17751
prev_days_first_due_min	17751
prev_days_first_due_count	16454
prev_days_last_due_1st_version_mean	17751
prev_days_last_due_1st_version_max	17751
prev_days_last_due_1st_version_min	17751
prev_days_last_due_1st_version_count	16454
prev_days_last_due_mean	17751
prev_days_last_due_max	17751
prev_days_last_due_min	17751
prev_days_last_due_count	16454
prev_days_termination_mean	17751
prev_days_termination_max	17751
prev_days_termination_min	17751
prev_days_termination_count	16454
prev_nflag_insured_on_approval_mean	17751
prev_nflag_insured_on_approval_max	17751
prev_nflag_insured_on_approval_min	17751
prev_nflag_insured_on_approval_count	16454
posf_sk_id_prev_mean	16454
posf_sk_id_prev_max	16454
posf_sk_id_prev_min	16454
posf_sk_id_prev_count	16454
posf_pos_sk_id_curr_mean_mean	20544
posf_pos_sk_id_curr_mean_max	20544
posf_pos_sk_id_curr_mean_min	20544

posf_pos_sk_id_curr_mean_count	16454
posf_pos_sk_id_curr_max_mean	20544
posf_pos_sk_id_curr_max_max	20544
posf_pos_sk_id_curr_max_min	20544
posf_pos_sk_id_curr_max_count	16454
posf_pos_sk_id_curr_min_mean	20544
posf_pos_sk_id_curr_min_max	20544
posf_pos_sk_id_curr_min_min	20544
posf_pos_sk_id_curr_min_count	16454
posf_pos_sk_id_curr_count_mean	20544
posf_pos_sk_id_curr_count_max	20544
posf_pos_sk_id_curr_count_min	20544
posf_pos_sk_id_curr_count_count	16454
posf_pos_months_balance_mean_mean	20544
posf_pos_months_balance_mean_max	20544
posf_pos_months_balance_mean_min	20544
posf_pos_months_balance_mean_count	16454
posf_pos_months_balance_max_mean	20544
posf_pos_months_balance_max_max	20544
posf_pos_months_balance_max_min	20544
posf_pos_months_balance_max_count	16454
posf_pos_months_balance_min_mean	20544
posf_pos_months_balance_min_max	20544
posf_pos_months_balance_min_min	20544
posf_pos_months_balance_min_count	16454
posf_pos_months_balance_count_mean	20544
posf_pos_months_balance_count_max	20544
posf_pos_months_balance_count_min	20544
posf_pos_months_balance_count_count	16454
posf_pos_cnt_instalment_mean_mean	20576
posf_pos_cnt_instalment_mean_max	20576
posf_pos_cnt_instalment_mean_min	20576
posf_pos_cnt_instalment_mean_count	16454
posf_pos_cnt_instalment_max_mean	20576
posf_pos_cnt_instalment_max_max	20576
posf_pos_cnt_instalment_max_min	20576
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posf_pos_cnt_instalment_min_mean	20576
posf_pos_cnt_instalment_min_max	20576
posf_pos_cnt_instalment_min_min	20576
posf_pos_cnt_instalment_min_count	16454
posf_pos_cnt_instalment_count_mean	20544
posf_pos_cnt_instalment_count_max	20544
posf_pos_cnt_instalment_count_min	20544
posf_pos_cnt_instalment_count_count	16454
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posf_pos_cnt_instalment_future_mean_max	20576
posf_pos_cnt_instalment_future_mean_min	20576
posf_pos_cnt_instalment_future_mean_count	16454
posf_pos_cnt_instalment_future_max_mean	20576
posf_pos_cnt_instalment_future_max_max	20576
posf_pos_cnt_instalment_future_max_min	20576
posf_pos_cnt_instalment_future_max_count	16454
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posf_pos_cnt_instalment_future_min_max	20576
posf_pos_cnt_instalment_future_min_min	20576
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posf_pos_cnt_instalment_future_count_count	16454
posf_pos_sk_dpd_mean_mean	20544
posf_pos_sk_dpd_mean_max	20544
posf_pos_sk_dpd_mean_min	20544
posf_pos_sk_dpd_mean_count	16454
posf_pos_sk_dpd_max_mean	20544
posf_pos_sk_dpd_max_max	20544
posf_pos_sk_dpd_max_min	20544
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posf_pos_sk_dpd_min_max	20544
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posf_pos_sk_dpd_def_mean_max	20544
posf_pos_sk_dpd_def_mean_min	20544
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posf_pos_sk_dpd_def_max_min	20544
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posf_pos_sk_dpd_def_min_count	16454
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posf_pos_sk_dpd_def_count_count	16454
ccf_sk_id_prev_mean	16454
ccf_sk_id_prev_max	16454
ccf_sk_id_prev_min	16454
ccf_sk_id_prev_count	16454
ccf_cc_sk_id_curr_mean_mean	229577
ccf_cc_sk_id_curr_mean_max	229577
ccf_cc_sk_id_curr_mean_min	229577
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ccf_cc_sk_id_curr_max_max	229577
ccf_cc_sk_id_curr_max_min	229577
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ccf_cc_sk_id_curr_min_max	229577
ccf_cc_sk_id_curr_min_min	229577
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ccf_cc_months_balance_max_min	229577
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ccf_cc_months_balance_count_mean	229577
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ccf_cc_amt_balance_mean_mean	229577
ccf_cc_amt_balance_mean_max	229577
ccf_cc_amt_balance_mean_min	229577
ccf_cc_amt_balance_mean_count	16454
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ccf_cc_amt_balance_min_mean	229577

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ccf_cc_amt_balance_min_min	229577
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ccf_cc_amt_credit_limit_actual_mean_mean	229577
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ccf_cc_amt_credit_limit_actual_max_max	229577
ccf_cc_amt_credit_limit_actual_max_min	229577
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ccf_cc_amt_credit_limit_actual_min_min	229577
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ccf_cc_amt_credit_limit_actual_count_count	16454
ccf_cc_amt_drawings_atm_current_mean_mean	254581
ccf_cc_amt_drawings_atm_current_mean_max	254581
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ccf_cc_amt_drawings_current_count_min	229577
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ccf_cc_amt_drawings_other_current_mean_mean	254581
ccf_cc_amt_drawings_other_current_mean_max	254581
ccf_cc_amt_drawings_other_current_mean_min	254581
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ccf_cc_amt_drawings_other_current_max_mean	254581
ccf_cc_amt_drawings_other_current_max_max	254581
ccf_cc_amt_drawings_other_current_max_min	254581
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ccf_cc_amt_drawings_other_current_min_mean	254581
ccf_cc_amt_drawings_other_current_min_max	254581
ccf_cc_amt_drawings_other_current_min_min	254581
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ccf_cc_amt_drawings_other_current_mean_mean	229577
ccf_cc_amt_drawings_other_current_mean_max	229577

ccf_cc_amt_drawings_other_current_count_min	229577
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ccf_cc_amt_drawings_pos_current_mean_mean	254581
ccf_cc_amt_drawings_pos_current_mean_max	254581
ccf_cc_amt_drawings_pos_current_mean_min	254581
ccf_cc_amt_drawings_pos_current_mean_count	16454
ccf_cc_amt_drawings_pos_current_max_mean	254581
ccf_cc_amt_drawings_pos_current_max_max	254581
ccf_cc_amt_drawings_pos_current_max_min	254581
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ccf_cc_amt_drawings_pos_current_min_max	254581
ccf_cc_amt_drawings_pos_current_min_min	254581
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ccf_cc_amt_drawings_pos_current_count_max	229577
ccf_cc_amt_drawings_pos_current_count_min	229577
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ccf_cc_amt_inst_min_regularity_mean_mean	229577
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ccf_cc_amt_inst_min_regularity_mean_min	229577
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ccf_cc_amt_inst_min_regularity_max_max	229577
ccf_cc_amt_inst_min_regularity_max_min	229577
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ccf_cc_amt_inst_min_regularity_min_max	229577
ccf_cc_amt_inst_min_regularity_min_min	229577
ccf_cc_amt_inst_min_regularity_min_count	16454
ccf_cc_amt_inst_min_regularity_count_mean	229577
ccf_cc_amt_inst_min_regularity_count_max	229577
ccf_cc_amt_inst_min_regularity_count_min	229577
ccf_cc_amt_inst_min_regularity_count_count	16454
ccf_cc_amt_payment_current_mean_mean	254669
ccf_cc_amt_payment_current_mean_max	254669
ccf_cc_amt_payment_current_mean_min	254669
ccf_cc_amt_payment_current_mean_count	16454
ccf_cc_amt_payment_current_max_mean	254669
ccf_cc_amt_payment_current_max_max	254669
ccf_cc_amt_payment_current_max_min	254669
ccf_cc_amt_payment_current_max_count	16454
ccf_cc_amt_payment_current_min_mean	254669
ccf_cc_amt_payment_current_min_max	254669
ccf_cc_amt_payment_current_min_min	254669
ccf_cc_amt_payment_current_min_count	16454
ccf_cc_amt_payment_current_count_mean	229577
ccf_cc_amt_payment_current_count_max	229577
ccf_cc_amt_payment_current_count_min	229577
ccf_cc_amt_payment_current_count_count	16454
ccf_cc_amt_payment_total_current_mean_mean	229577
ccf_cc_amt_payment_total_current_mean_max	229577
ccf_cc_amt_payment_total_current_mean_min	229577
ccf_cc_amt_payment_total_current_mean_count	16454
ccf_cc_amt_payment_total_current_max_mean	229577
ccf_cc_amt_payment_total_current_max_max	229577
ccf_cc_amt_payment_total_current_max_min	229577
ccf_cc_amt_payment_total_current_max_count	16454
ccf_cc_amt_payment_total_current_min_mean	229577
ccf_cc_amt_payment_total_current_min_max	229577
ccf_cc_amt_payment_total_current_min_min	229577
ccf_cc_amt_payment_total_current_min_count	16454
ccf_cc_amt_payment_total_current_mean_mean	229577
ccf_cc_amt_payment_total_current_mean_max	229577
ccf_cc_amt_payment_total_current_mean_min	229577
ccf_cc_amt_payment_total_current_count_mean	16454
ccf_cc_amt_payment_total_current_count_max	229577
ccf_cc_amt_payment_total_current_count_min	229577
ccf_cc_amt_payment_total_current_count_count	16454
ccf_cc_amt_receivable_principal_mean_mean	229577
ccf_cc_amt_receivable_principal_mean_max	229577
ccf_cc_amt_receivable_principal_mean_min	229577

ccf_cc_amt_receivable_principal_mean_count	16454
ccf_cc_amt_receivable_principal_max_mean	229577
ccf_cc_amt_receivable_principal_max_max	229577
ccf_cc_amt_receivable_principal_max_min	229577
ccf_cc_amt_receivable_principal_max_count	16454
ccf_cc_amt_receivable_principal_min_mean	229577
ccf_cc_amt_receivable_principal_min_max	229577
ccf_cc_amt_receivable_principal_min_min	229577
ccf_cc_amt_receivable_principal_min_count	16454
ccf_cc_amt_receivable_principal_count_mean	229577
ccf_cc_amt_receivable_principal_count_max	229577
ccf_cc_amt_receivable_principal_count_min	229577
ccf_cc_amt_receivable_principal_count_count	16454
ccf_cc_amt_recivable_mean_mean	229577
ccf_cc_amt_recivable_mean_max	229577
ccf_cc_amt_recivable_mean_min	229577
ccf_cc_amt_recivable_mean_count	16454
ccf_cc_amt_recivable_max_mean	229577
ccf_cc_amt_recivable_max_max	229577
ccf_cc_amt_recivable_max_min	229577
ccf_cc_amt_recivable_max_count	16454
ccf_cc_amt_recivable_min_mean	229577
ccf_cc_amt_recivable_min_max	229577
ccf_cc_amt_recivable_min_min	229577
ccf_cc_amt_recivable_min_count	16454
ccf_cc_amt_recivable_count_mean	229577
ccf_cc_amt_recivable_count_max	229577
ccf_cc_amt_recivable_count_min	229577
ccf_cc_amt_recivable_count_count	16454
ccf_cc_amt_total_receivable_mean_mean	229577
ccf_cc_amt_total_receivable_mean_max	229577
ccf_cc_amt_total_receivable_mean_min	229577
ccf_cc_amt_total_receivable_mean_count	16454
ccf_cc_amt_total_receivable_max_mean	229577
ccf_cc_amt_total_receivable_max_max	229577
ccf_cc_amt_total_receivable_max_min	229577
ccf_cc_amt_total_receivable_max_count	16454
ccf_cc_amt_total_receivable_min_mean	229577
ccf_cc_amt_total_receivable_min_max	229577
ccf_cc_amt_total_receivable_min_min	229577
ccf_cc_amt_total_receivable_min_count	16454
ccf_cc_amt_total_receivable_count_mean	229577
ccf_cc_amt_total_receivable_count_max	229577
ccf_cc_amt_total_receivable_count_min	229577
ccf_cc_amt_total_receivable_count_count	16454
ccf_cc_cnt_drawings_atm_current_mean_mean	254581
ccf_cc_cnt_drawings_atm_current_mean_max	254581
ccf_cc_cnt_drawings_atm_current_mean_min	254581
ccf_cc_cnt_drawings_atm_current_mean_count	16454
ccf_cc_cnt_drawings_atm_current_max_mean	254581
ccf_cc_cnt_drawings_atm_current_max_max	254581
ccf_cc_cnt_drawings_atm_current_max_min	254581
ccf_cc_cnt_drawings_atm_current_max_count	16454
ccf_cc_cnt_drawings_atm_current_min_mean	254581
ccf_cc_cnt_drawings_atm_current_min_max	254581
ccf_cc_cnt_drawings_atm_current_min_min	254581
ccf_cc_cnt_drawings_atm_current_min_count	16454
ccf_cc_cnt_drawings_atm_current_count_mean	229577
ccf_cc_cnt_drawings_atm_current_count_max	229577
ccf_cc_cnt_drawings_atm_current_count_min	229577
ccf_cc_cnt_drawings_atm_current_count_count	16454
ccf_cc_cnt_drawings_current_mean_mean	229577
ccf_cc_cnt_drawings_current_mean_max	229577
ccf_cc_cnt_drawings_current_mean_min	229577
ccf_cc_cnt_drawings_current_mean_count	16454
ccf_cc_cnt_drawings_current_max_mean	229577
ccf_cc_cnt_drawings_current_max_max	229577
ccf_cc_cnt_drawings_current_max_min	229577
ccf_cc_cnt_drawings_current_max_count	16454

ccf_cc_cnt_drawings_current_min_mean	229577
ccf_cc_cnt_drawings_current_min_max	229577
ccf_cc_cnt_drawings_current_min_min	229577
ccf_cc_cnt_drawings_current_min_count	16454
ccf_cc_cnt_drawings_current_count_mean	229577
ccf_cc_cnt_drawings_current_count_max	229577
ccf_cc_cnt_drawings_current_count_min	229577
ccf_cc_cnt_drawings_current_count_count	16454
ccf_cc_cnt_drawings_other_current_mean_mean	254581
ccf_cc_cnt_drawings_other_current_mean_max	254581
ccf_cc_cnt_drawings_other_current_mean_min	254581
ccf_cc_cnt_drawings_other_current_mean_count	16454
ccf_cc_cnt_drawings_other_current_max_mean	254581
ccf_cc_cnt_drawings_other_current_max_max	254581
ccf_cc_cnt_drawings_other_current_max_min	254581
ccf_cc_cnt_drawings_other_current_max_count	16454
ccf_cc_cnt_drawings_other_current_min_mean	254581
ccf_cc_cnt_drawings_other_current_min_max	254581
ccf_cc_cnt_drawings_other_current_min_min	254581
ccf_cc_cnt_drawings_other_current_min_count	16454
ccf_cc_cnt_drawings_other_current_count_mean	229577
ccf_cc_cnt_drawings_other_current_count_max	229577
ccf_cc_cnt_drawings_other_current_count_min	229577
ccf_cc_cnt_drawings_other_current_count_count	16454
ccf_cc_cnt_drawings_pos_current_mean_mean	254581
ccf_cc_cnt_drawings_pos_current_mean_max	254581
ccf_cc_cnt_drawings_pos_current_mean_min	254581
ccf_cc_cnt_drawings_pos_current_mean_count	16454
ccf_cc_cnt_drawings_pos_current_max_mean	254581
ccf_cc_cnt_drawings_pos_current_max_max	254581
ccf_cc_cnt_drawings_pos_current_max_min	254581
ccf_cc_cnt_drawings_pos_current_max_count	16454
ccf_cc_cnt_drawings_pos_current_min_mean	254581
ccf_cc_cnt_drawings_pos_current_min_max	254581
ccf_cc_cnt_drawings_pos_current_min_min	254581
ccf_cc_cnt_drawings_pos_current_min_count	16454
ccf_cc_cnt_drawings_pos_current_count_mean	229577
ccf_cc_cnt_drawings_pos_current_count_max	229577
ccf_cc_cnt_drawings_pos_current_count_min	229577
ccf_cc_cnt_drawings_pos_current_count_count	16454
ccf_cc_instalment_mature_cum_mean_mean	229577
ccf_cc_instalment_mature_cum_mean_max	229577
ccf_cc_instalment_mature_cum_mean_min	229577
ccf_cc_instalment_mature_cum_mean_count	16454
ccf_cc_instalment_mature_cum_max_mean	229577
ccf_cc_instalment_mature_cum_max_max	229577
ccf_cc_instalment_mature_cum_max_min	229577
ccf_cc_instalment_mature_cum_max_count	16454
ccf_cc_instalment_mature_cum_min_mean	229577
ccf_cc_instalment_mature_cum_min_max	229577
ccf_cc_instalment_mature_cum_min_min	229577
ccf_cc_instalment_mature_cum_min_count	16454
ccf_cc_instalment_mature_cum_count_mean	229577
ccf_cc_instalment_mature_cum_count_max	229577
ccf_cc_instalment_mature_cum_count_min	229577
ccf_cc_instalment_mature_cum_count_count	16454
ccf_cc_sk_dpd_mean_mean	229577
ccf_cc_sk_dpd_mean_max	229577
ccf_cc_sk_dpd_mean_min	229577
ccf_cc_sk_dpd_mean_count	16454
ccf_cc_sk_dpd_max_mean	229577
ccf_cc_sk_dpd_max_max	229577
ccf_cc_sk_dpd_max_min	229577
ccf_cc_sk_dpd_max_count	16454
ccf_cc_sk_dpd_min_mean	229577
ccf_cc_sk_dpd_min_max	229577
ccf_cc_sk_dpd_min_min	229577
ccf_cc_sk_dpd_min_count	16454
ccf_cc_sk_dpd_count_mean	229577

ccf_cc_sk_dpd_count_max	229577
ccf_cc_sk_dpd_count_min	229577
ccf_cc_sk_dpd_count_count	16454
ccf_cc_sk_dpd_def_mean_mean	229577
ccf_cc_sk_dpd_def_mean_max	229577
ccf_cc_sk_dpd_def_mean_min	229577
ccf_cc_sk_dpd_def_mean_count	16454
ccf_cc_sk_dpd_def_max_mean	229577
ccf_cc_sk_dpd_def_max_max	229577
ccf_cc_sk_dpd_def_max_min	229577
ccf_cc_sk_dpd_def_max_count	16454
ccf_cc_sk_dpd_def_min_mean	229577
ccf_cc_sk_dpd_def_min_max	229577
ccf_cc_sk_dpd_def_min_min	229577
ccf_cc_sk_dpd_def_min_count	16454
ccf_cc_sk_dpd_def_count_mean	229577
ccf_cc_sk_dpd_def_count_max	229577
ccf_cc_sk_dpd_def_count_min	229577
ccf_cc_sk_dpd_def_count_count	16454
instf_sk_id_prev_mean	16454
instf_sk_id_prev_max	16454
instf_sk_id_prev_min	16454
instf_sk_id_prev_count	16454
instf_inst_sk_id_curr_mean_mean	18105
instf_inst_sk_id_curr_mean_max	18105
instf_inst_sk_id_curr_mean_min	18105
instf_inst_sk_id_curr_mean_count	16454
instf_inst_sk_id_curr_max_mean	18105
instf_inst_sk_id_curr_max_max	18105
instf_inst_sk_id_curr_max_min	18105
instf_inst_sk_id_curr_max_count	16454
instf_inst_sk_id_curr_min_mean	18105
instf_inst_sk_id_curr_min_max	18105
instf_inst_sk_id_curr_min_min	18105
instf_inst_sk_id_curr_min_count	16454
instf_inst_sk_id_curr_count_mean	18105
instf_inst_sk_id_curr_count_max	18105
instf_inst_sk_id_curr_count_min	18105
instf_inst_sk_id_curr_count_count	16454
instf_inst_num_instalment_version_mean_mean	18105
instf_inst_num_instalment_version_mean_max	18105
instf_inst_num_instalment_version_mean_min	18105
instf_inst_num_instalment_version_mean_count	16454
instf_inst_num_instalment_version_max_mean	18105
instf_inst_num_instalment_version_max_max	18105
instf_inst_num_instalment_version_max_min	18105
instf_inst_num_instalment_version_max_count	16454
instf_inst_num_instalment_version_min_mean	18105
instf_inst_num_instalment_version_min_max	18105
instf_inst_num_instalment_version_min_min	18105
instf_inst_num_instalment_version_min_count	16454
instf_inst_num_instalment_version_count_mean	18105
instf_inst_num_instalment_version_count_max	18105
instf_inst_num_instalment_version_count_min	18105
instf_inst_num_instalment_version_count_count	16454
instf_inst_num_instalment_number_mean_mean	18105
instf_inst_num_instalment_number_mean_max	18105
instf_inst_num_instalment_number_mean_min	18105
instf_inst_num_instalment_number_mean_count	16454
instf_inst_num_instalment_number_max_mean	18105
instf_inst_num_instalment_number_max_max	18105
instf_inst_num_instalment_number_max_min	18105
instf_inst_num_instalment_number_max_count	16454
instf_inst_num_instalment_number_min_mean	18105
instf_inst_num_instalment_number_min_max	18105
instf_inst_num_instalment_number_min_min	18105
instf_inst_num_instalment_number_min_count	16454
instf_inst_num_instalment_number_count_mean	18105
instf_inst_num_instalment_number_count_max	18105

instf_inst_num_instalment_number_count_min	18105
instf_inst_num_instalment_number_count_count	16454
instf_inst_days_instalment_mean_mean	18105
instf_inst_days_instalment_mean_max	18105
instf_inst_days_instalment_mean_min	18105
instf_inst_days_instalment_mean_count	16454
instf_inst_days_instalment_max_mean	18105
instf_inst_days_instalment_max_max	18105
instf_inst_days_instalment_max_min	18105
instf_inst_days_instalment_max_count	16454
instf_inst_days_instalment_min_mean	18105
instf_inst_days_instalment_min_max	18105
instf_inst_days_instalment_min_min	18105
instf_inst_days_instalment_min_count	16454
instf_inst_days_instalment_count_mean	18105
instf_inst_days_instalment_count_max	18105
instf_inst_days_instalment_count_min	18105
instf_inst_days_instalment_count_count	16454
instf_inst_days_entry_payment_mean_mean	18113
instf_inst_days_entry_payment_mean_max	18113
instf_inst_days_entry_payment_mean_min	18113
instf_inst_days_entry_payment_mean_count	16454
instf_inst_days_entry_payment_max_mean	18113
instf_inst_days_entry_payment_max_max	18113
instf_inst_days_entry_payment_max_min	18113
instf_inst_days_entry_payment_max_count	16454
instf_inst_days_entry_payment_min_mean	18113
instf_inst_days_entry_payment_min_max	18113
instf_inst_days_entry_payment_min_min	18113
instf_inst_days_entry_payment_min_count	16454
instf_inst_days_entry_payment_count_mean	18105
instf_inst_days_entry_payment_count_max	18105
instf_inst_days_entry_payment_count_min	18105
instf_inst_days_entry_payment_count_count	16454
instf_inst_amt_instalment_mean_mean	18105
instf_inst_amt_instalment_mean_max	18105
instf_inst_amt_instalment_mean_min	18105
instf_inst_amt_instalment_mean_count	16454
instf_inst_amt_instalment_max_mean	18105
instf_inst_amt_instalment_max_max	18105
instf_inst_amt_instalment_max_min	18105
instf_inst_amt_instalment_max_count	16454
instf_inst_amt_instalment_min_mean	18105
instf_inst_amt_instalment_min_max	18105
instf_inst_amt_instalment_min_min	18105
instf_inst_amt_instalment_min_count	16454
instf_inst_amt_instalment_count_mean	18105
instf_inst_amt_instalment_count_max	18105
instf_inst_amt_instalment_count_min	18105
instf_inst_amt_instalment_count_count	16454
instf_inst_amt_payment_mean_mean	18113
instf_inst_amt_payment_mean_max	18113
instf_inst_amt_payment_mean_min	18113
instf_inst_amt_payment_mean_count	16454
instf_inst_amt_payment_max_mean	18113
instf_inst_amt_payment_max_max	18113
instf_inst_amt_payment_max_min	18113
instf_inst_amt_payment_max_count	16454
instf_inst_amt_payment_min_mean	18113
instf_inst_amt_payment_min_max	18113
instf_inst_amt_payment_min_min	18113
instf_inst_amt_payment_min_count	16454
instf_inst_amt_payment_count_mean	18105
instf_inst_amt_payment_count_max	18105
instf_inst_amt_payment_count_min	18105
instf_inst_amt_payment_count_count	16454

#### 5.4.1 Filling Missing Values

```
In [11]: aux_missing_cols = {}

aux_missing_cols['is_building'] = df1.filter(like='commonarea_').notna().any(axis=1).z
aux_missing_cols['is_building_missing'] = (~df1.filter(like='commonarea_').notna().any(axis=1))
aux_missing_cols['has_basement'] = df1['basementarea_avg'].notna().astype(int)
aux_missing_cols['basementarea_missing'] = df1['basementarea_avg'].isna().astype(int)
aux_missing_cols['has_noliving'] = df1['nonlivingarea_avg'].notna().astype(int)
aux_missing_cols['nonlivingarea_missing'] = df1['nonlivingarea_avg'].isna().astype(int)
aux_missing_cols['is_employed'] = (~df1['days_employed'].isna()).astype(int)

aux_missing_cols['livingarea_missing'] = df1['livingarea_avg'].isna().astype(int)
aux_missing_cols['apartments_missing'] = df1['apartments_avg'].isna().astype(int)
aux_missing_cols['floorsmax_missing'] = df1['floorsmax_avg'].isna().astype(int)
aux_missing_cols['years_build_missing'] = df1['years_build_avg'].isna().astype(int)
aux_missing_cols['commonarea_missing'] = df1['commonarea_avg'].isna().astype(int)

aux_missing_cols['emergencystate_missing'] = df1['emergencystate_mode'].isna().astype(int)
df1['emergencystate_mode'] = df1['emergencystate_mode'].fillna(0)
for col in ['elevators_avg', 'elevators_mode', 'elevators_medi']:
    aux_missing_cols[col + "_missing"] = df1[col].isna().astype(int)
    df1[col] = df1[col].fillna(0)

cols_moda = [
    'housetype_mode', 'wallsmaterial_mode', 'occupation_type', 'organization_type'
]
for col in cols_moda:
    aux_missing_cols[col + '_missing'] = df1[col].isna().astype(int)

df1['housetype_mode'] = df1['housetype_mode'].fillna('Unknown')
df1['wallsmaterial_mode'] = df1['wallsmaterial_mode'].fillna('Unknown')
df1['occupation_type'] = df1['occupation_type'].fillna('Other')
df1['organization_type'] = df1['organization_type'].fillna('Unknown')

drop_columns = {
    'fondkapremont_mode', 'landarea_mode', 'landarea_medi',
    'livingarea_mode', 'livingarea_medi',
    'entrances_avg', 'entrances_mode', 'entrances_medi',
    'floorsmax_mode', 'floorsmax_medi',
    'apartments_mode', 'apartments_medi', 'years_build_mode', 'years_build_medi'
}

do_not_drop = {
    'livingarea_avg', 'apartments_avg', 'floorsmax_avg', 'years_build_avg',
    'basementarea_avg', 'nonlivingarea_avg', 'livingapartments_missing',
    'own_car_age', 'years_beginexpluatation_avg', 'commonarea_avg', 'nonlivingapartments_avg',
}

prefixes = (
    'nonlivingapartments_', 'livingapartments_', 'floorsmin_', 'commonarea_', 'basementarea_',
    'nonlivingarea_', 'years_beginexpluatation_'
)

cols_to_drop = [
    col for col in df1.columns
    if ((col.startswith(prefixes) and col not in do_not_drop) or col in drop_columns)
]

df1 = df1.drop(columns=cols_to_drop)
```

```
In [12]: aux_missing_cols['name_type_suite_missing'] = df1['name_type_suite'].isna().astype(int)
mode_suite = df1["name_type_suite"].mode()[0]
df1["name_type_suite"] = df1["name_type_suite"].fillna(mode_suite)

aux_missing_cols['code_gender_missing'] = df1['code_gender'].isna().astype(int)
mode_gender = df1["code_gender"].mode()[0]
df1["code_gender"] = df1["code_gender"].fillna(mode_gender)
```

```
cols_nan_remanescentes = df1.columns[df1.isnull().any()]
df_mediana = pd.DataFrame(columns=['coluna', 'mediana'])
medianas = []
for col_nome in cols_nan_remanescentes:
    aux_missing_cols[col_nome + '_missing'] = df1[col_nome].isna().astype(int)
    mediana = df1[col_nome].median()
    medianas.append({'coluna': col_nome, 'mediana': mediana})
    df1[col_nome] = df1[col_nome].fillna(mediana)
df_mediana = pd.DataFrame(medianas)
```

```
In [13]: df1 = pd.concat([df1, pd.DataFrame(aux_missing_cols, index=df1.index)], axis=1)
df1 = df1.copy()
```

#### 5.4.2 Checking Missing Values After Modifications

```
In [14]: print(df1.isna().sum().to_string())
```

target	0
name_contract_type	0
code_gender	0
flag_own_car	0
flag_own_realty	0
cnt_children	0
amt_income_total	0
amt_credit	0
amt_annuity	0
amt_goods_price	0
name_type_suite	0
name_income_type	0
name_education_type	0
name_family_status	0
name_housing_type	0
region_population_relative	0
days_birth	0
days_employed	0
days_registration	0
days_id_publish	0
own_car_age	0
flag_mobil	0
flag_emp_phone	0
flag_work_phone	0
flag_cont_mobile	0
flag_phone	0
flag_email	0
occupation_type	0
cnt_fam_members	0
region_rating_client	0
region_rating_client_w_city	0
weekday_appr_process_start	0
hour_appr_process_start	0
reg_region_not_live_region	0
reg_region_not_work_region	0
live_region_not_work_region	0
reg_city_not_live_city	0
reg_city_not_work_city	0
live_city_not_work_city	0
organization_type	0
ext_source_1	0
ext_source_2	0
ext_source_3	0
apartments_avg	0
basementarea_avg	0
years_beginexpluatation_avg	0
years_build_avg	0
commonarea_avg	0
elevators_avg	0
floorsmax_avg	0
landarea_avg	0
livingapartments_avg	0
livingarea_avg	0
nonlivingapartments_avg	0
nonlivingarea_avg	0
elevators_mode	0
elevators_medi	0
housetype_mode	0
totalarea_mode	0
wallsmaterial_mode	0
emergencystate_mode	0
obs_30_cnt_social_circle	0
def_30_cnt_social_circle	0
obs_60_cnt_social_circle	0
def_60_cnt_social_circle	0
days_last_phone_change	0
flag_document_2	0
flag_document_3	0
flag_document_4	0

flag_document_5	0
flag_document_6	0
flag_document_7	0
flag_document_8	0
flag_document_9	0
flag_document_10	0
flag_document_11	0
flag_document_12	0
flag_document_13	0
flag_document_14	0
flag_document_15	0
flag_document_16	0
flag_document_17	0
flag_document_18	0
flag_document_19	0
flag_document_20	0
flag_document_21	0
amt_req_credit_bureau_hour	0
amt_req_credit_bureau_day	0
amt_req_credit_bureau_week	0
amt_req_credit_bureau_mon	0
amt_req_credit_bureau_qrt	0
amt_req_credit_bureau_year	0
bur_sk_id_bureau_mean	0
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bur_sk_id_bureau_min	0
bur_sk_id_bureau_count	0
bur_days_credit_mean	0
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bur_days_credit_min	0
bur_days_credit_count	0
bur_credit_day_overdue_mean	0
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bur_credit_day_overdue_count	0
bur_days_credit_enddate_mean	0
bur_days_credit_enddate_max	0
bur_days_credit_enddate_min	0
bur_days_credit_enddate_count	0
bur_days_enddate_fact_mean	0
bur_days_enddate_fact_max	0
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bur_days_enddate_fact_count	0
bur_amt_credit_max_overdue_mean	0
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bur_cnt_credit_prolong_mean	0
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bur_amt_credit_sum_debt_mean	0
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bur_amt_credit_sum_overdue_mean	0
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bur_days_credit_update_mean	0
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bur_amt_annuity_mean	0
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prev_amt_goods_price_mean	0
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prev_hour_appr_process_start_mean	0
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prev_nflag_last_appl_in_day_mean	0
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prev_days_decision_mean	0
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prev_cnt_payment_mean	0
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elevators_medi_missing	0
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wallsmaterial_mode_missing	0
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ccf_cc_cnt_drawings_other_current_mean_count_missing	0
ccf_cc_cnt_drawings_other_current_max_mean_missing	0
ccf_cc_cnt_drawings_other_current_max_max_missing	0
ccf_cc_cnt_drawings_other_current_max_min_missing	0
ccf_cc_cnt_drawings_other_current_max_count_missing	0
ccf_cc_cnt_drawings_other_current_min_mean_missing	0
ccf_cc_cnt_drawings_other_current_min_max_missing	0
ccf_cc_cnt_drawings_other_current_min_min_missing	0
ccf_cc_cnt_drawings_other_current_min_count_missing	0
ccf_cc_cnt_drawings_other_current_count_mean_missing	0
ccf_cc_cnt_drawings_other_current_count_max_missing	0
ccf_cc_cnt_drawings_other_current_count_min_missing	0
ccf_cc_cnt_drawings_other_current_count_count_missing	0
ccf_cc_cnt_drawings_pos_current_mean_mean_missing	0
ccf_cc_cnt_drawings_pos_current_mean_max_missing	0
ccf_cc_cnt_drawings_pos_current_mean_min_missing	0
ccf_cc_cnt_drawings_pos_current_mean_count_missing	0
ccf_cc_cnt_drawings_pos_current_max_mean_missing	0
ccf_cc_cnt_drawings_pos_current_max_max_missing	0
ccf_cc_cnt_drawings_pos_current_max_min_missing	0
ccf_cc_cnt_drawings_pos_current_max_count_missing	0

ccf_cc_cnt_drawings_pos_current_min_mean_missing	0
ccf_cc_cnt_drawings_pos_current_min_max_missing	0
ccf_cc_cnt_drawings_pos_current_min_min_missing	0
ccf_cc_cnt_drawings_pos_current_min_count_missing	0
ccf_cc_cnt_drawings_pos_current_count_mean_missing	0
ccf_cc_cnt_drawings_pos_current_count_max_missing	0
ccf_cc_cnt_drawings_pos_current_count_min_missing	0
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ccf_cc_cnt_instalment_mature_cum_mean_min_missing	0
ccf_cc_cnt_instalment_mature_cum_mean_count_missing	0
ccf_cc_cnt_instalment_mature_cum_max_mean_missing	0
ccf_cc_cnt_instalment_mature_cum_max_max_missing	0
ccf_cc_cnt_instalment_mature_cum_max_min_missing	0
ccf_cc_cnt_instalment_mature_cum_max_count_missing	0
ccf_cc_cnt_instalment_mature_cum_min_mean_missing	0
ccf_cc_cnt_instalment_mature_cum_min_max_missing	0
ccf_cc_cnt_instalment_mature_cum_min_min_missing	0
ccf_cc_cnt_instalment_mature_cum_min_count_missing	0
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ccf_cc_sk_dpd_mean_min_missing	0
ccf_cc_sk_dpd_mean_count_missing	0
ccf_cc_sk_dpd_max_mean_missing	0
ccf_cc_sk_dpd_max_max_missing	0
ccf_cc_sk_dpd_max_min_missing	0
ccf_cc_sk_dpd_max_count_missing	0
ccf_cc_sk_dpd_min_mean_missing	0
ccf_cc_sk_dpd_min_max_missing	0
ccf_cc_sk_dpd_min_min_missing	0
ccf_cc_sk_dpd_min_count_missing	0
ccf_cc_sk_dpd_count_mean_missing	0
ccf_cc_sk_dpd_count_max_missing	0
ccf_cc_sk_dpd_count_min_missing	0
ccf_cc_sk_dpd_count_count_missing	0
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ccf_cc_sk_dpd_def_mean_max_missing	0
ccf_cc_sk_dpd_def_mean_min_missing	0
ccf_cc_sk_dpd_def_mean_count_missing	0
ccf_cc_sk_dpd_def_max_mean_missing	0
ccf_cc_sk_dpd_def_max_max_missing	0
ccf_cc_sk_dpd_def_max_min_missing	0
ccf_cc_sk_dpd_def_max_count_missing	0
ccf_cc_sk_dpd_def_min_mean_missing	0
ccf_cc_sk_dpd_def_min_max_missing	0
ccf_cc_sk_dpd_def_min_min_missing	0
ccf_cc_sk_dpd_def_min_count_missing	0
ccf_cc_sk_dpd_def_count_mean_missing	0
ccf_cc_sk_dpd_def_count_max_missing	0
ccf_cc_sk_dpd_def_count_min_missing	0
ccf_cc_sk_dpd_def_count_count_missing	0
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instf_sk_id_prev_max_missing	0
instf_sk_id_prev_min_missing	0
instf_sk_id_prev_count_missing	0
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instf_inst_sk_id_curr_mean_min_missing	0
instf_inst_sk_id_curr_mean_count_missing	0
instf_inst_sk_id_curr_max_mean_missing	0
instf_inst_sk_id_curr_max_max_missing	0
instf_inst_sk_id_curr_max_min_missing	0
instf_inst_sk_id_curr_max_count_missing	0
instf_inst_sk_id_curr_min_mean_missing	0

instf_inst_sk_id_curr_min_max_missing	0
instf_inst_sk_id_curr_min_min_missing	0
instf_inst_sk_id_curr_min_count_missing	0
instf_inst_sk_id_curr_count_mean_missing	0
instf_inst_sk_id_curr_count_max_missing	0
instf_inst_sk_id_curr_count_min_missing	0
instf_inst_sk_id_curr_count_count_missing	0
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instf_inst_num_instalment_version_mean_max_missing	0
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instf_inst_num_instalment_version_max_mean_missing	0
instf_inst_num_instalment_version_max_max_missing	0
instf_inst_num_instalment_version_max_min_missing	0
instf_inst_num_instalment_version_max_count_missing	0
instf_inst_num_instalment_version_min_mean_missing	0
instf_inst_num_instalment_version_min_max_missing	0
instf_inst_num_instalment_version_min_min_missing	0
instf_inst_num_instalment_version_min_count_missing	0
instf_inst_num_instalment_version_mean_count_missing	0
instf_inst_num_instalment_version_count_max_missing	0
instf_inst_num_instalment_version_count_min_missing	0
instf_inst_num_instalment_version_count_count_missing	0
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instf_inst_num_instalment_number_mean_max_missing	0
instf_inst_num_instalment_number_mean_min_missing	0
instf_inst_num_instalment_number_mean_count_missing	0
instf_inst_num_instalment_number_max_mean_missing	0
instf_inst_num_instalment_number_max_max_missing	0
instf_inst_num_instalment_number_max_min_missing	0
instf_inst_num_instalment_number_max_count_missing	0
instf_inst_num_instalment_number_min_mean_missing	0
instf_inst_num_instalment_number_min_max_missing	0
instf_inst_num_instalment_number_min_min_missing	0
instf_inst_num_instalment_number_min_count_missing	0
instf_inst_num_instalment_number_count_mean_missing	0
instf_inst_num_instalment_number_count_max_missing	0
instf_inst_num_instalment_number_count_min_missing	0
instf_inst_num_instalment_number_count_count_missing	0
instf_inst_days_instalment_mean_mean_missing	0
instf_inst_days_instalment_mean_max_missing	0
instf_inst_days_instalment_mean_min_missing	0
instf_inst_days_instalment_mean_count_missing	0
instf_inst_days_instalment_max_mean_missing	0
instf_inst_days_instalment_max_max_missing	0
instf_inst_days_instalment_max_min_missing	0
instf_inst_days_instalment_max_count_missing	0
instf_inst_days_instalment_min_mean_missing	0
instf_inst_days_instalment_min_max_missing	0
instf_inst_days_instalment_min_min_missing	0
instf_inst_days_instalment_min_count_missing	0
instf_inst_days_instalment_count_mean_missing	0
instf_inst_days_instalment_count_max_missing	0
instf_inst_days_instalment_count_min_missing	0
instf_inst_days_instalment_count_count_missing	0
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instf_inst_days_entry_payment_mean_max_missing	0
instf_inst_days_entry_payment_mean_min_missing	0
instf_inst_days_entry_payment_mean_count_missing	0
instf_inst_days_entry_payment_max_mean_missing	0
instf_inst_days_entry_payment_max_max_missing	0
instf_inst_days_entry_payment_max_min_missing	0
instf_inst_days_entry_payment_max_count_missing	0
instf_inst_days_entry_payment_min_mean_missing	0
instf_inst_days_entry_payment_min_max_missing	0
instf_inst_days_entry_payment_min_min_missing	0
instf_inst_days_entry_payment_min_count_missing	0
instf_inst_days_entry_payment_count_mean_missing	0
instf_inst_days_entry_payment_count_max_missing	0

instf_inst_days_entry_payment_count_min_missing	0
instf_inst_days_entry_payment_count_count_missing	0
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instf_inst_amt_instalment_mean_max_missing	0
instf_inst_amt_instalment_mean_min_missing	0
instf_inst_amt_instalment_mean_count_missing	0
instf_inst_amt_instalment_max_mean_missing	0
instf_inst_amt_instalment_max_max_missing	0
instf_inst_amt_instalment_max_min_missing	0
instf_inst_amt_instalment_max_count_missing	0
instf_inst_amt_instalment_min_mean_missing	0
instf_inst_amt_instalment_min_max_missing	0
instf_inst_amt_instalment_min_min_missing	0
instf_inst_amt_instalment_min_count_missing	0
instf_inst_amt_instalment_count_mean_missing	0
instf_inst_amt_instalment_count_max_missing	0
instf_inst_amt_instalment_count_min_missing	0
instf_inst_amt_instalment_count_count_missing	0
instf_inst_amt_payment_mean_mean_missing	0
instf_inst_amt_payment_mean_max_missing	0
instf_inst_amt_payment_mean_min_missing	0
instf_inst_amt_payment_mean_count_missing	0
instf_inst_amt_payment_max_mean_missing	0
instf_inst_amt_payment_max_max_missing	0
instf_inst_amt_payment_max_min_missing	0
instf_inst_amt_payment_max_count_missing	0
instf_inst_amt_payment_min_mean_missing	0
instf_inst_amt_payment_min_max_missing	0
instf_inst_amt_payment_min_min_missing	0
instf_inst_amt_payment_min_count_missing	0
instf_inst_amt_payment_count_mean_missing	0
instf_inst_amt_payment_count_max_missing	0
instf_inst_amt_payment_count_min_missing	0
instf_inst_amt_payment_count_count_missing	0

## 6. Feature Engineering

```
In [ ]: df2 = df1.copy()
```

### 6.1 List of Hypotheses

Block 1 - (1 a 20)

**H1** — Contract type influences the probability of default.

It is expected that customers with Revolving loans present higher risk, as these are short-term credits with higher interest rates.

**H2** — Gender is associated with default risk.

Differences in financial behavior between men and women may be reflected in payment rates.

**H3** — Customers who own a car have a lower probability of default.

Vehicle ownership may indicate greater financial stability.

**H4** — Owning a home reduces the chance of default.

Ownership of a fixed asset may reflect financial security and a stronger credit history.

**H5** — The number of children influences default risk.

Larger families tend to have higher fixed expenses, which may increase the probability of late payments.

**H6** — Higher total income is associated with lower default risk.

Customers with greater financial capacity have more margin to honor their debts.

**H7** — Higher credit amounts are related to higher default risk.

Larger loans may overload the budget, especially for lower-income customers.

**H8** — Higher monthly installments increase the chance of default.

High payments may compromise the customer's cash flow.

**H9** — The value of goods purchased influences default risk.

High-value purchases may indicate higher indebtedness and greater financial risk.

**H10** — The type of accompaniment when applying for credit is associated with default risk.

Customers who apply alone (Unaccompanied) may have different financial behavior than couples or families.

## Block 2 - (21 a 40)

**H21** — Having a work phone registered reduces the risk of default.

A validated employment link may indicate professional stability and more reliable income.

**H22** — Customers with a work phone provided are less likely to default.

This information tends to be provided by formally employed workers, reflecting better economic stability.

**H23** — Having a registered mobile phone is associated with lower default risk.

It indicates greater ease of communication and follow-up by the lender.

**H24** — Having a landline phone registered reduces default risk.

It may be associated with fixed residences and greater social stability.

**H25** — Customers with a registered email tend to present lower default risk.

It indicates a higher level of formalization, digital access, and ease of communication for collections or notifications.

**H26** — Occupation type influences default risk.

Self-employed and temporary workers tend to have more unstable income, increasing risk compared to formally employed or public servants.

**H27** — The number of family members is positively related to default risk.

Larger families imply higher fixed expenses and lower financial margin for payments.

**H28** — Customers from regions with lower ratings have a higher probability of default.

Regional ratings may reflect socioeconomic conditions and access to credit in the area.

**H29** — The customer's city rating influences default risk.

Urban regions with worse economic indicators may concentrate customers with higher financial risk.

**H30** — The day of the week when the credit application is made influences the probability of default.

Applications made on weekdays (especially early in the week) may come from more organized profiles than those made on weekends.

**H31** — The time of credit application is associated with default.

Requests made at atypical hours (late night, early morning) may be linked to impulsive behavior or higher risk.

**H32** — Living in a region different from the registered one increases default risk.

It indicates recent mobility or registration inconsistencies, factors linked to lower reliability.

**H33** — Working in a region different from the registered one is associated with higher risk.

It may represent long commutes or job instability.

**H34** — Living and working in different regions may increase the probability of default.

Commuting may indicate additional costs and less available time, affecting financial stability.

**H35** — Living in a city different from the registered one increases the chance of default.

Differences between official and actual addresses may signal registration inconsistencies or residential instability.

**H36** — Working in a city different from the registered one increases default risk.

It indicates possible long commutes or informal employment.

**H37** — Living in a different city than the workplace influences default risk.

Long commutes can represent higher costs and lower professional stability.

**H38** — The type of employing organization is associated with default risk.

Public employees and workers in large companies tend to present lower risk compared to self-employed or small company workers.

**H39** — External score 2 is inversely related to default.

The higher the ext\_source\_2 value, the lower the default risk, as it indicates a better external credit assessment.

**H40** — External score 3 is inversely related to default.

High values reflect greater trustworthiness and lower credit risk according to external sources.

Block 3 - (41 a 72)

**H41** — The average number of elevators in a building is inversely related to the probability of default.

Properties with more elevators usually belong to higher-standard buildings, indicating better socioeconomic conditions and lower credit risk.

**H42** — Housing type influences default risk.

Customers living in owned houses or apartments tend to have lower default rates than those living in rented or third-party housing, reflecting greater asset stability.

**H43** — The main wall material of the property is associated with default risk.

More durable or higher-quality materials (such as stone or brick) tend to indicate higher-standard

properties and better financial conditions.

**H44** — A higher number of observations or defaulters in the 30-day social circle increases the customer's probability of default.

Individuals inserted in social groups with higher default incidence may share similar risk profiles or economic vulnerability.

**H45** — Default in the 60-day social circle is positively associated with individual default risk.

The financial behavior of close contacts over longer periods tends to reflect social influence and similar economic conditions.

**H46** — The time since the last phone change is related to default probability.

Customers who frequently change their phone number may present greater instability or contact difficulties, increasing credit risk.

**H47** — The number of submitted documents is inversely associated with default.

Submitting more documents indicates greater transparency and compliance, while fewer documents may signal fraud risk or lower reliability.

## Block 4 - (73 a 90)

**H48** — Credit inquiry history and credit amounts influence the probability of default.

These variables represent both the frequency of credit bureau inquiries and the average and total amounts of contracted credit. Customers who perform many bureau checks or hold large amounts of active credit tend to show higher financial exposure and, consequently, higher default risk.

**H49** — Property characteristics and employment status influence repayment capacity.

Variables related to property structure and employment situation help estimate the customer's economic and social stability.

## 6.2 Feature Derivation

```
In [6]: df2['days_employed_anom'] = df2["days_employed"] == 365243
df2['days_birth'] = df2['days_birth'].abs()
df2['days_employed'] = df2['days_employed'].abs()
df2['days_id_publish'] = df2['days_id_publish'].abs()
df2['days_registration'] = df2['days_registration'].abs()
df2['age_years'] = df2['days_birth'] / 365
df2['employment_years'] = df2['days_employed'] / 365
df2['id_publish_years'] = df2['days_id_publish'] / 365

df2['annuity_burden_ratio'] = df2['amt_annuity'] / (df2['bur_amt_credit_sum_mean'] + 1e-6)
df2['phone_change_rate'] = df2['days_last_phone_change'] / (df2['days_birth'] + 1e-6)
df2['id_change_rate'] = df2['days_id_publish'] / (df2['days_birth'] + 1e-6)
df2['ext_source_weighted_mean'] = (
    0.5 * df2['ext_source_2'] + 0.3 * df2['ext_source_3'] + 0.2 * df2['ext_source_1']
)
df2['ext_source_max'] = df2[['ext_source_1', 'ext_source_2', 'ext_source_3']].max(axis=1)
df2['amt_application_credit_diff'] = df2['prev_amt_application_mean'] - df2['bur_amt_credit_sum']
df2['amt_application_goods_diff'] = df2['prev_amt_application_mean'] - df2['amt_goods_price']

flag_document_cols = [col for col in df2.columns if col.startswith('flag_document_')]
df2['num_flag_document'] = df2[flag_document_cols].sum(axis=1)
df2['credit_to_income_ratio'] = df2['bur_amt_credit_sum_mean'] / (df2['amt_income_total'] + 1e-5)
df2['annuity_to_income_ratio'] = df2['amt_annuity'] / (df2['amt_income_total'] + 1e-5)
```

```

df2['payment_rate'] = df2['amt_annuity'] / (df2['bur_amt_credit_sum_mean'] + 1e-5)
df2['goods_to_credit_ratio'] = df2['bur_amt_credit_sum_mean'] / (df2['amt_goods_price'] + 1e-5)
df2['credit_efficiency'] = df2['bur_amt_credit_sum_mean'] / (df2['prev_amt_application_mean'] + 1e-5)
df2['employment_life_ratio'] = df2['days_employed'] / (df2['days_birth'])
df2['bureau_request_intensity'] = (
    df2['amt_req_credit_bureau_day'] +
    df2['amt_req_credit_bureau_week'] +
    df2['amt_req_credit_bureau_mon'] +
    df2['amt_req_credit_bureau_qrt']
)

ext_sources = ['ext_source_1', 'ext_source_2', 'ext_source_3']
df2['ext_source_mean'] = df2[ext_sources].mean(axis=1)
df2['ext_source_range'] = df2[ext_sources].max(axis=1) - df2[ext_sources].min(axis=1)
df2['ext_source_std'] = df2[ext_sources].std(axis=1)
df2['ext_source_agreement'] = 1 / (df2['ext_source_std'] + 1e-5)

df2['decision_credit_diff'] = df2['prev_days_decision_mean'] / (df2['bur_amt_credit_sum_mean'] + 1e-5)
df2['bureau_to_credit_ratio'] = df2['bureau_request_intensity'] / (df2['bur_amt_credit_sum_mean'] + 1e-5)

df2['credit_per_employment_year'] = df2['bur_amt_credit_sum_mean'] / (df2['employment_years'] + 1e-6)
df2['annuity_per_employment_year'] = df2['amt_annuity'] / (df2['employment_years'] + 1e-6)

df2['income_per_employed'] = df2['amt_income_total'] / ((df2['days_employed']+ 1e-5))
df2['income_per_birth'] = df2['amt_income_total'] / (df2['days_birth'])
df2['own_car_age_birth_ratio'] = df2['own_car_age'] / (df2['days_birth'])
df2['own_car_age_employed_ratio'] = df2['own_car_age'] / ((df2['days_employed']+ 1e-5))
df2['days_since_last_employment_until_application'] = df2['days_employed'] - df2['days_birth']

poly_vars = [
    'days_birth',
    'payment_rate',
    'ext_source_mean',
]
X_poly = df2[poly_vars].fillna(0).copy()
poly = PolynomialFeatures(degree=3, include_bias=False)
X_poly_trans = poly.fit_transform(X_poly)
poly_feature_names = poly.get_feature_names_out(poly_vars)
df_poly = pd.DataFrame(X_poly_trans, columns=poly_feature_names, index=df2.index)
df_poly = df_poly.drop(columns=poly_vars, errors='ignore')
df2 = pd.concat([df2, df_poly], axis=1)

df2['employment_stability'] = df2['employment_years'] / (df2['age_years'] + 1e-6)
df2['id_document_age_ratio'] = df2['id_publish_years'] / (df2['age_years'] + 1e-6)
df2['phone_change_frequency'] = 1 / (df2['days_last_phone_change'] + 1e-6)

df2['recent_instability'] = df2['phone_change_rate'] + df2['id_change_rate']
df2['bureau_overdue_ratio'] = df2['bur_amt_credit_max_overdue_max'] / (df2['bur_amt_credit_sum_mean'] + 1e-5)
df2['credit_risk_signal'] = df2['credit_to_income_ratio'] * ((df2['ext_source_1'] + df2['ext_source_3']) / 2)
df2['annuity_per_age'] = df2['amt_annuity'] / (df2['own_car_age'] + 1e-6)
df2['overdue_flag'] = (df2['bur_amt_credit_max_overdue_max'] > 0).astype(int)
df2['entry_vs_due_ratio'] = df2['instf_inst_days_entry_payment_mean_mean'] / (df2['prev_days_fi'])
df2['ext_source_interaction'] = df2['ext_source_1'] * df2['ext_source_3']
df2['pos_balance_range'] = df2['posf_pos_months_balance_max_max'] - df2['bur_bb_months_balance_max']
df2['area_quality'] = df2['totalarea_mode'] / (df2['region_population_relative'] + 1e-6)

```

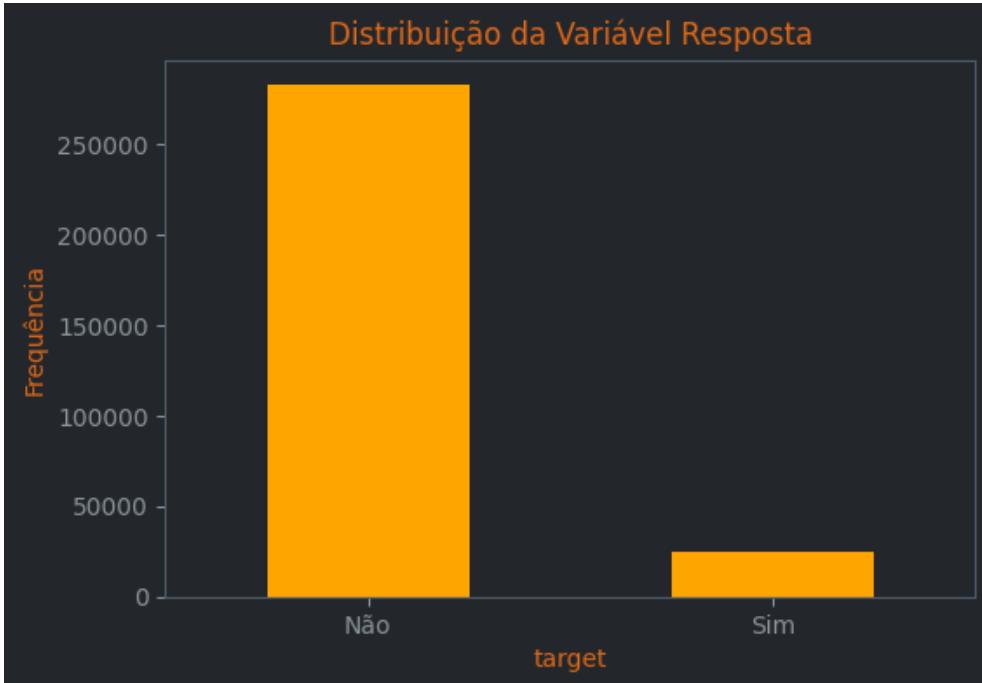
## 7. Exploratory Data Analysis

In [ ]: df3 = df2.copy()

### 7.1 Univariate Analysis

### 7.1.1 Target Variable

```
In [57]: plt.figure(figsize=(6,4))
df3['target'].value_counts().plot(kind='bar', color='orange')
plt.title('Distribuição da Variável Resposta')
plt.xlabel('target')
plt.ylabel('Frequência')
plt.xticks([0,1], ['Não', 'Sim'], rotation=0)
plt.show()
```



### 7.1.2 Numerical Variables

```
In [ ]: df_numeric = df3.select_dtypes(include=['number']).drop(columns=['target'])

df_numeric_1 = df_numeric.iloc[:, 0:15]    # colunas 0 a 14 (15 colunas)
df_numeric_2 = df_numeric.iloc[:, 15:30]   # colunas 15 a 29 (15 colunas)
df_numeric_3 = df_numeric.iloc[:, 30:45]   # colunas 30 a 44 (15 colunas)
df_numeric_4 = df_numeric.iloc[:, 45:60]   # colunas 45 a 59 (15 colunas)
df_numeric_5 = df_numeric.iloc[:, 60:75]   # colunas 60 a 74 (15 colunas)
```

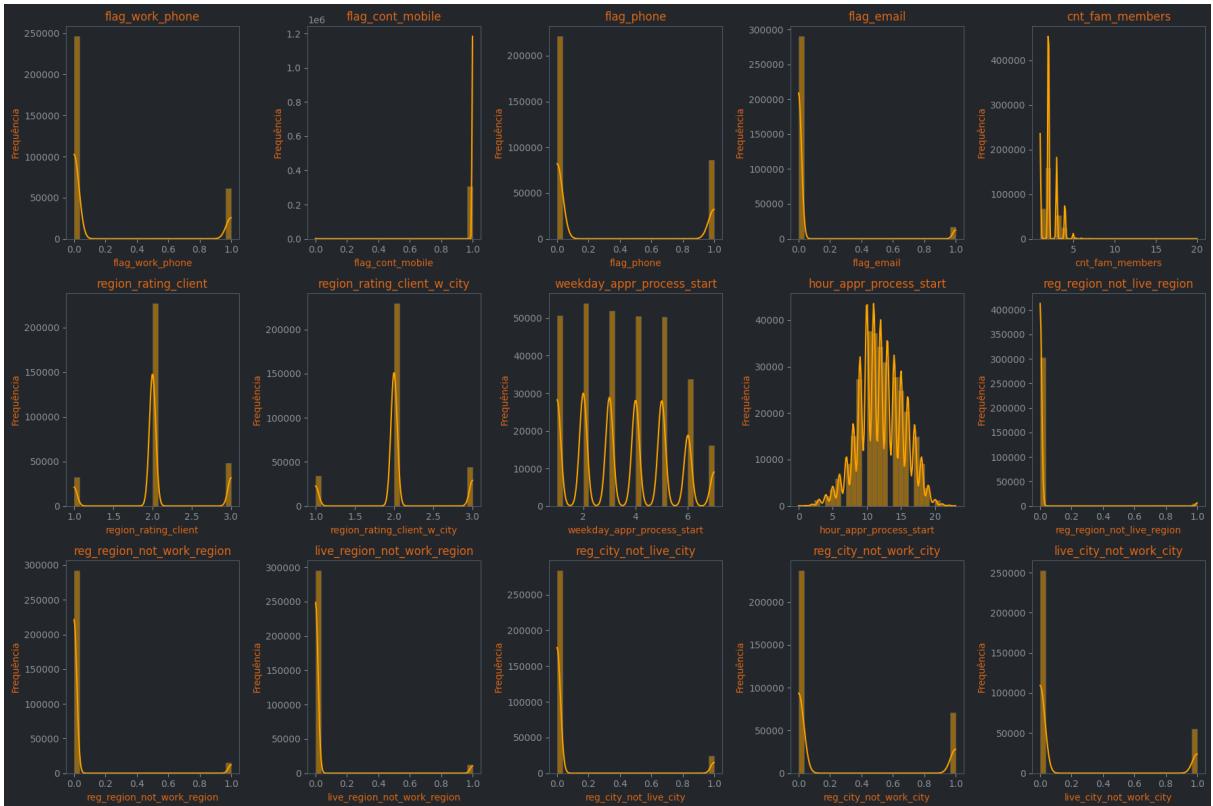
Block 1 - (1 a 15)

```
In [59]: plot_numeric_block(df_numeric_1)
```



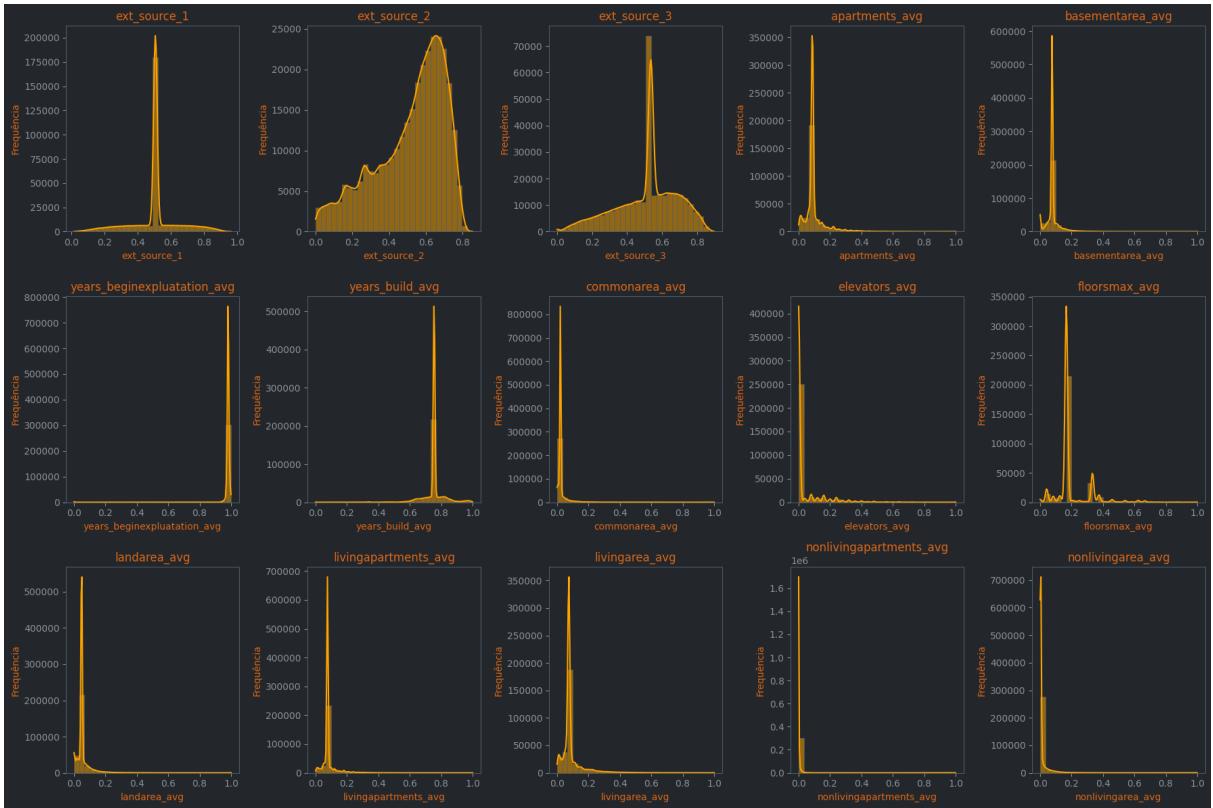
Block 2 - (16 a 30)

In [60]: `plot_numeric_block(df_numeric_2)`



Block 3 - (31 a 45)

In [61]: `plot_numeric_block(df_numeric_3)`



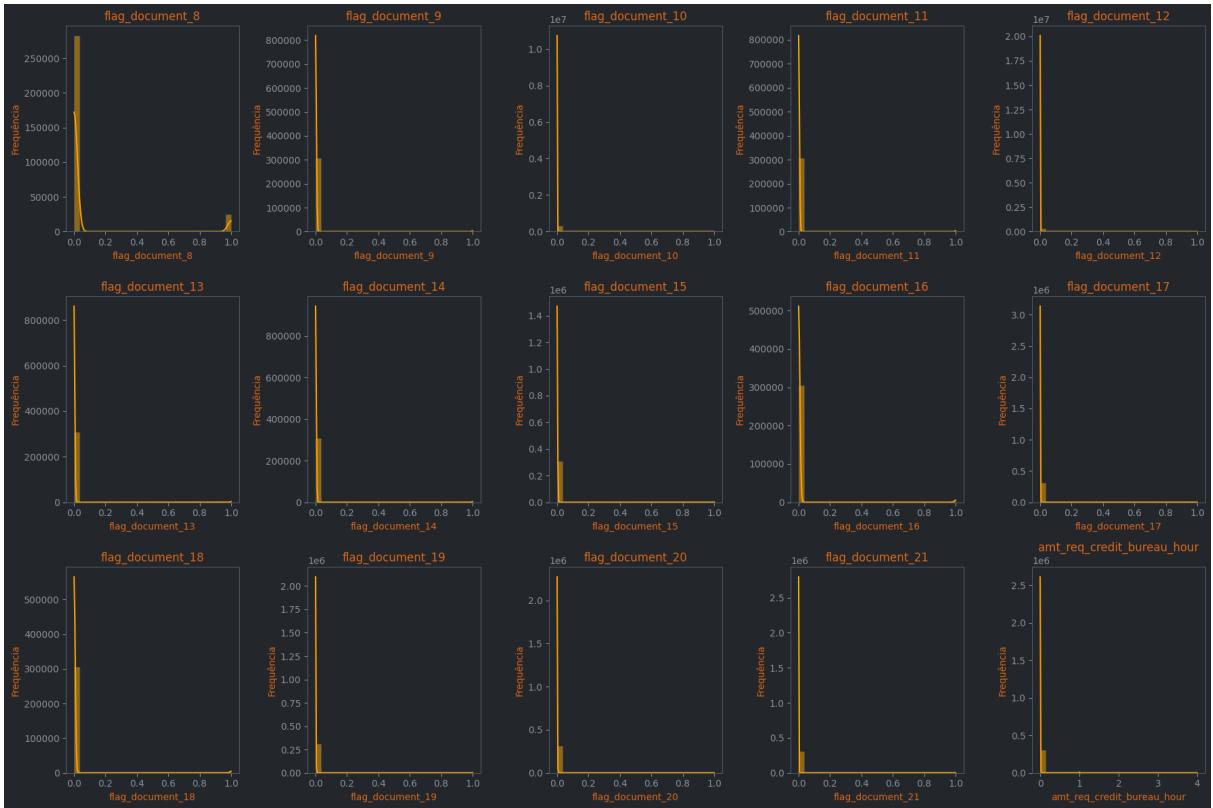
Block 4 - (46 a 60)

```
In [62]: plot_numeric_block(df_numeric_4)
```



Block 5 - (61 a 75)

```
In [63]: plot_numeric_block(df_numeric_5)
```



### 7.1.3 Categorical Variables

```
In [66]: df_categorical = df3.select_dtypes(include=['object', 'category'])

cat_cols = df_categorical.columns.tolist()

df_categorical_1 = df_categorical[cat_cols[:4]]
df_categorical_2 = df_categorical[cat_cols[4:8]]
df_categorical_3 = df_categorical[cat_cols[8:13]]
```

Block 1 - (1 a 4)

```
In [67]: fig, axs = plt.subplots(2, 2, figsize=(16, 12))

categorical_columns = df_categorical_1.columns.tolist()
colors_list = [
    ['royalblue', 'orange', 'seagreen', 'crimson'],
    ['red', 'mediumseagreen', 'steelblue', 'gold'],
    ['firebrick', 'rebeccapurple', 'teal', 'magenta'],
    ['slateblue', 'orange', 'forestgreen', 'orchid']
]

for idx, col in enumerate(categorical_columns):
    row = idx // 2
    col_pos = idx % 2

    count_vals = df_categorical_1[col].value_counts()
    ordered_categories = count_vals.index.tolist()

    sns.countplot(
        x=col,
        data=df_categorical_1,
        ax=axs[row, col_pos],
        order=ordered_categories,
        color=None
    )
    colors = colors_list[idx] if idx < len(colors_list) else None
    for i, bar in enumerate(axs[row, col_pos].patches):
        bar.set_color(colors[i])
```

```

        if colors and i < len(colors):
            bar.set_color(colors[i])

        axs[row, col_pos].set_title(f'Countplot de {col}')
        axs[row, col_pos].set_xlabel(col)
        axs[row, col_pos].set_ylabel('Frequência')

plt.tight_layout()
plt.show()

```



### Block 2 - (5 a 8)

```

In [68]: categorical_columns = df_categorical_2.columns.tolist()

fig, axs = plt.subplots(len(categorical_columns), 1, figsize=(12, 24))
colors_list = [
    ['royalblue', 'orange', 'seagreen', 'crimson'],
    ['red', 'mediumseagreen', 'steelblue', 'gold'],
    ['firebrick', 'rebeccapurple', 'teal', 'magenta'],
    ['slateblue', 'orange', 'forestgreen', 'orchid'],
]

if len(categorical_columns) == 1:
    axs = [axs]

for idx, col in enumerate(categorical_columns):
    ax = axs[idx]

    freq_order = df_categorical_2[col].value_counts().index.tolist()

    sns.countplot(
        x=col,
        data=df_categorical_2,
        ax=ax,
        order=freq_order,
        color=None
    )

```

```
colors = colors_list[idx] if idx < len(colors_list) else None
for i, bar in enumerate(ax.patches):
    if colors and i < len(colors):
        bar.set_color(colors[i])

ax.set_title(f'Countplot de {col}')
ax.set_xlabel(col)
ax.set_ylabel('Frequência')

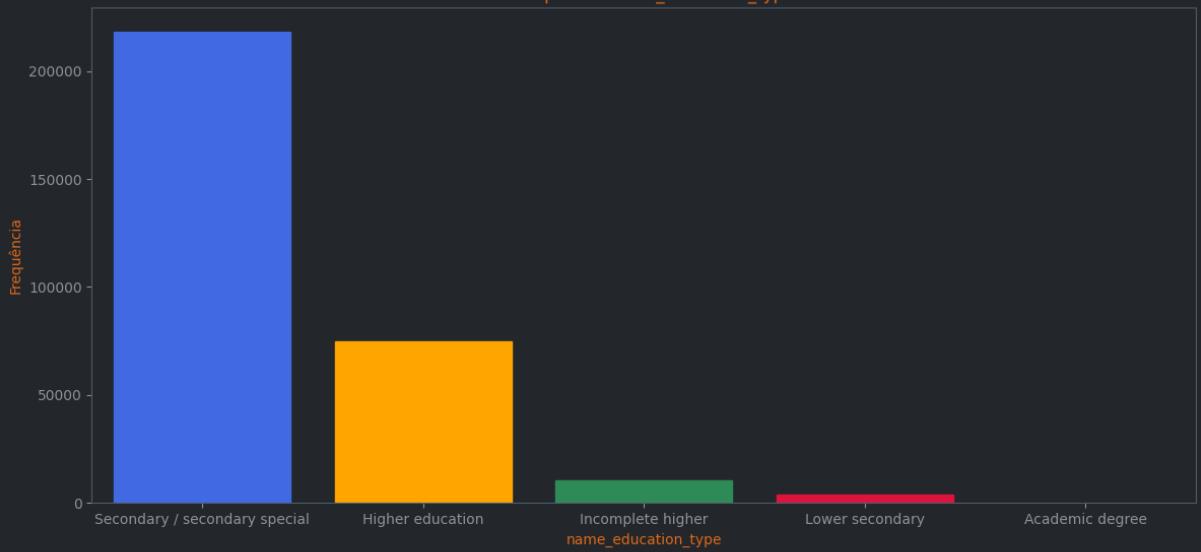
if col.upper() == "OCCUPATION_TYPE":
    ax.set_xticklabels(ax.get_xticklabels(), rotation=45, ha='right', fontsize=11)
    ax.margins(y=0.18)

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

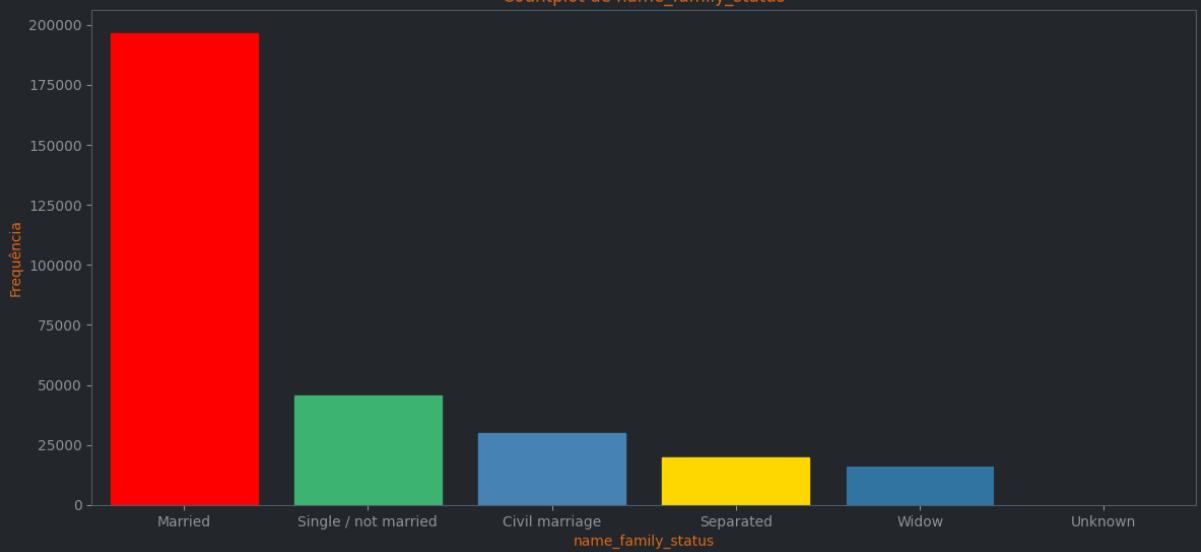
C:\Users\Patryck\AppData\Local\Temp\ipykernel\_12620\382229923.py:37: UserWarning: set\_ticklabel  
s() should only be used with a fixed number of ticks, i.e. after set\_ticks() or using a FixedLo  
cator.

```
    ax.set_xticklabels(ax.get_xticklabels(), rotation=45, ha='right', fontsize=11)
```

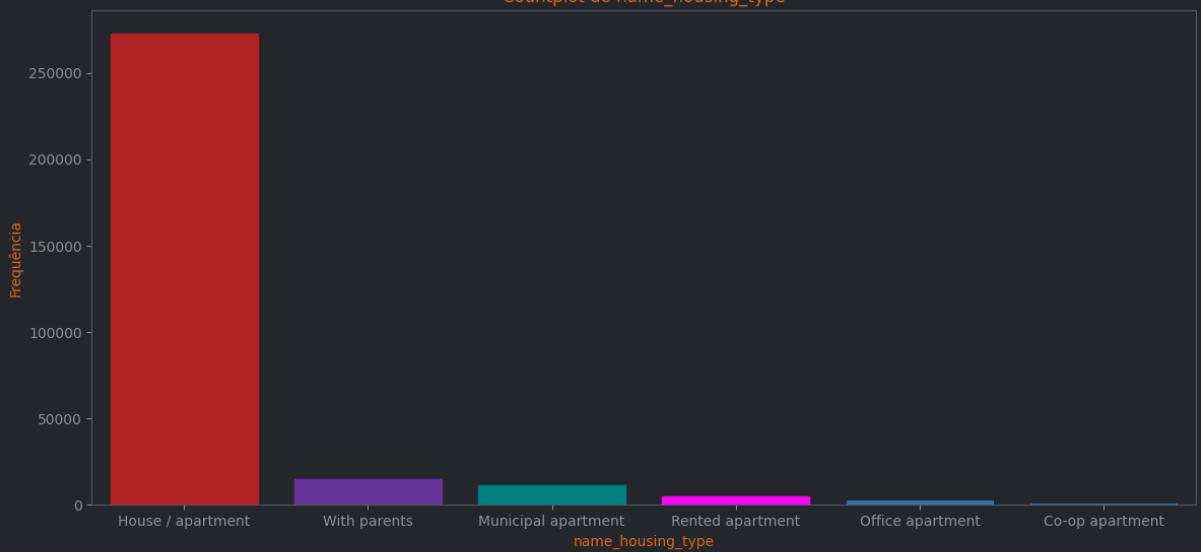
Countplot de name\_education\_type



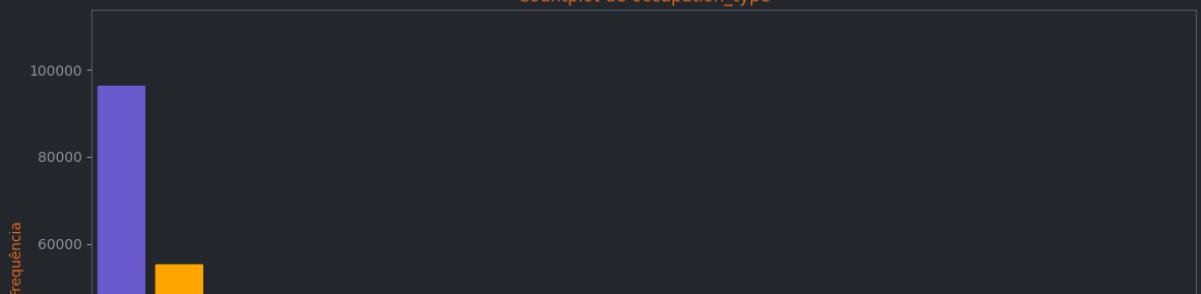
Countplot de name\_family\_status

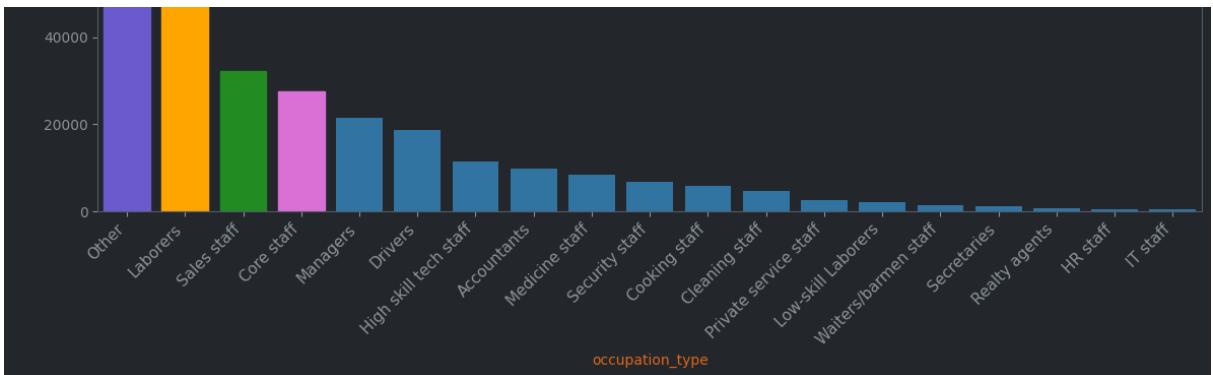


Countplot de name\_housing\_type



Countplot de occupation\_type





Block 3 - (8 a 13)

```
In [69]: categorical_columns = df_categorical_3.columns.tolist()

fig, axs = plt.subplots(5, 1, figsize=(12, 28))

colors_list = [
    ['royalblue', 'orange', 'seagreen', 'crimson'],
    ['red', 'mediumseagreen', 'steelblue', 'gold'],
    ['firebrick', 'rebeccapurple', 'teal', 'magenta'],
    ['slateblue', 'orange', 'forestgreen', 'orchid'],
    ['goldenrod', 'orchid', 'dodgerblue', 'firebrick'],
]

for idx, col in enumerate(categorical_columns):
    ax = axs[idx]

    order = df_categorical_3[col].value_counts().index.tolist()

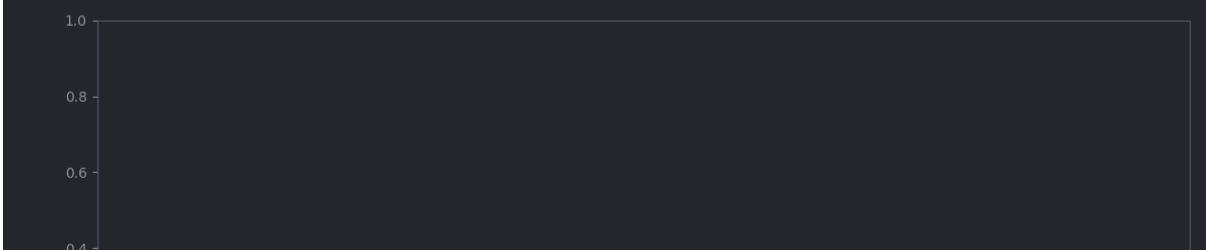
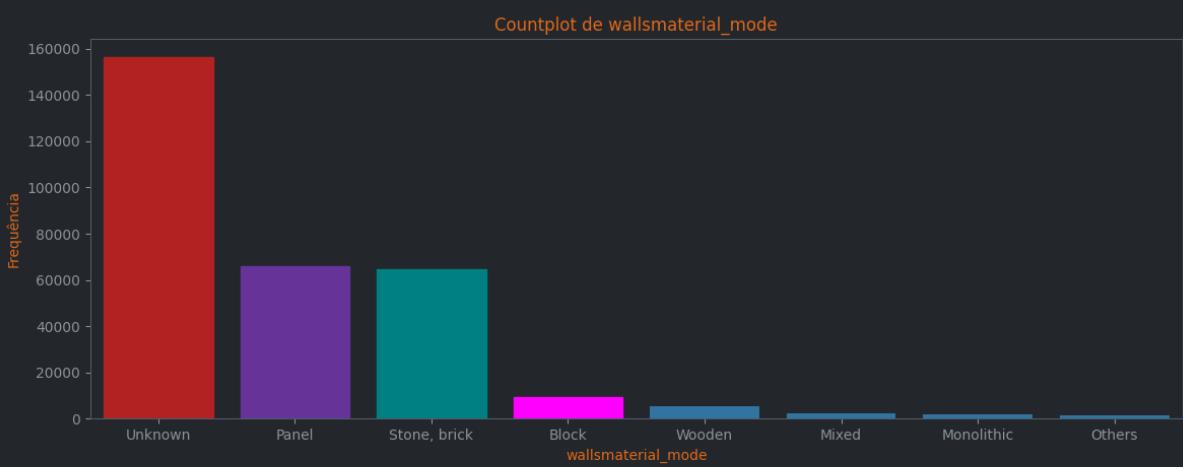
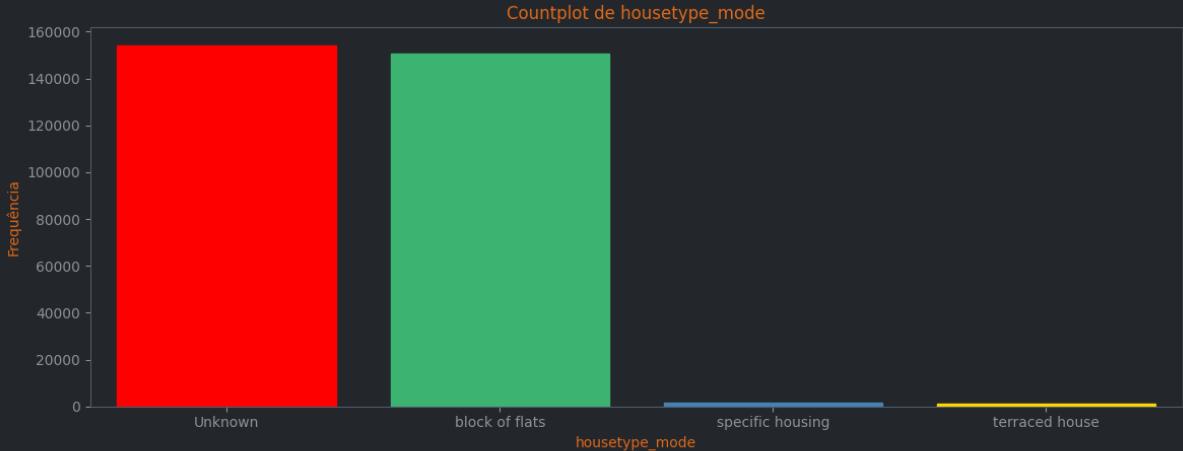
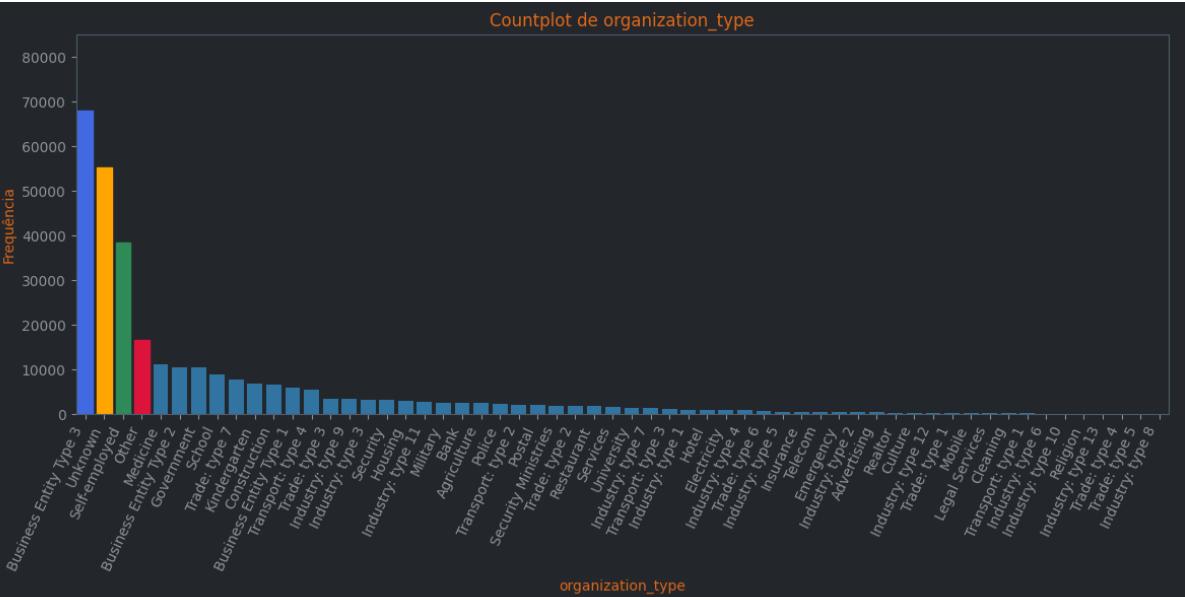
    sns.countplot(
        x=col,
        data=df_categorical_3,
        ax=ax,
        order=order,
        color=None
    )
    colors = colors_list[idx] if idx < len(colors_list) else None
    for i, bar in enumerate(ax.patches):
        if colors and i < len(colors):
            bar.set_color(colors[i])

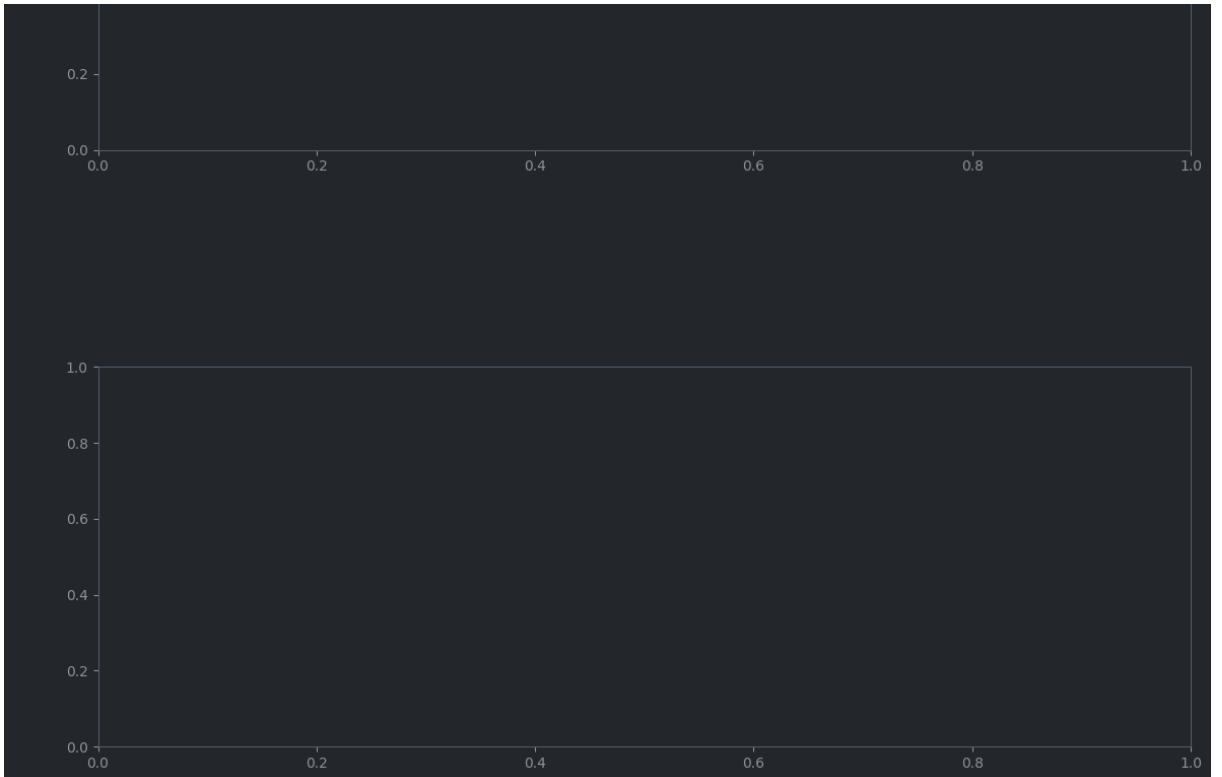
    ax.set_title(f'Countplot de {col}')
    ax.set_xlabel(col)
    ax.set_ylabel('Frequênciac')

    if col.upper() == "ORGANIZATION_TYPE":
        ax.set_xticklabels(
            ax.get_xticklabels(),
            rotation=65,
            ha='right',
            fontsize=10
        )
    ax.margins(y=0.25)
    plt.subplots_adjust(bottom=0.38, top=0.96)

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

C:\Users\Patryck\AppData\Local\Temp\ipykernel\_12620\372829898.py:35: UserWarning: set\_ticklabel  
s() should only be used with a fixed number of ticks, i.e. after set\_ticks() or using a FixedLo  
cator.  
ax.set\_xticklabels(



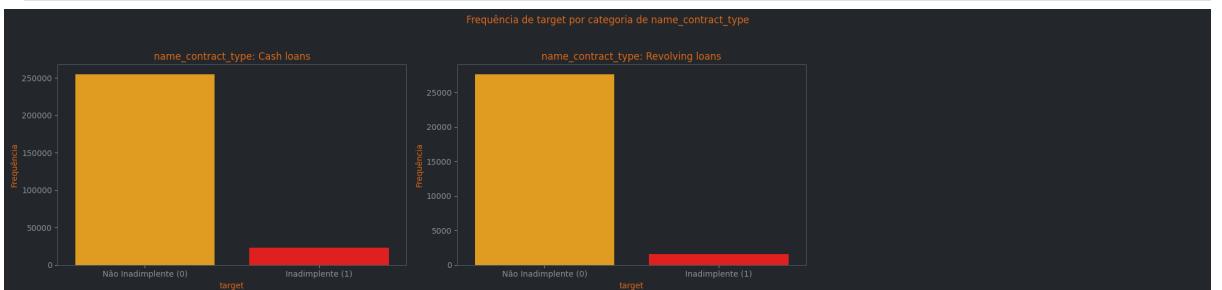


## 7.2 Bivariate Analysis

### Block 1 Hypothesis

H1 — Contract type influences the probability of default. FALSE

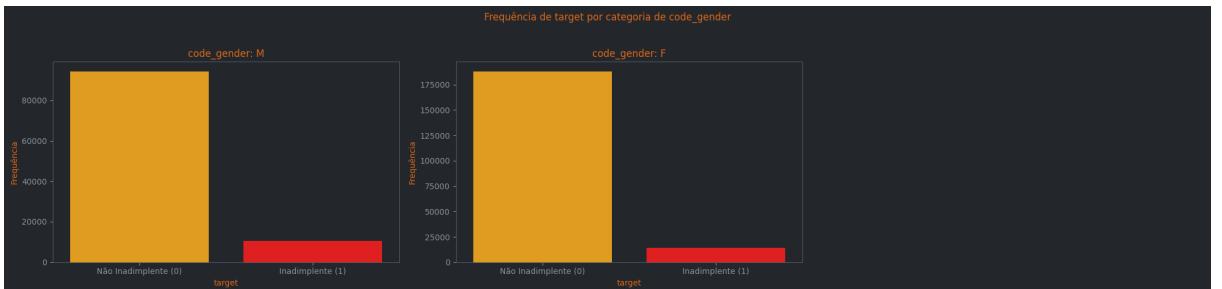
```
In [70]: plot_target_by_categorical(df3, cat_col='name_contract_type', target_col='target')
calcular_cramers_v(df3, 'name_contract_type', 'target')
```



V de Cramer entre name\_contract\_type e target: 0.0309

H2 — Gender is associated with default risk. FALSE

```
In [71]: plot_target_by_categorical(df3, cat_col='code_gender', target_col='target')
calcular_cramers_v(df3, 'code_gender', 'target')
```

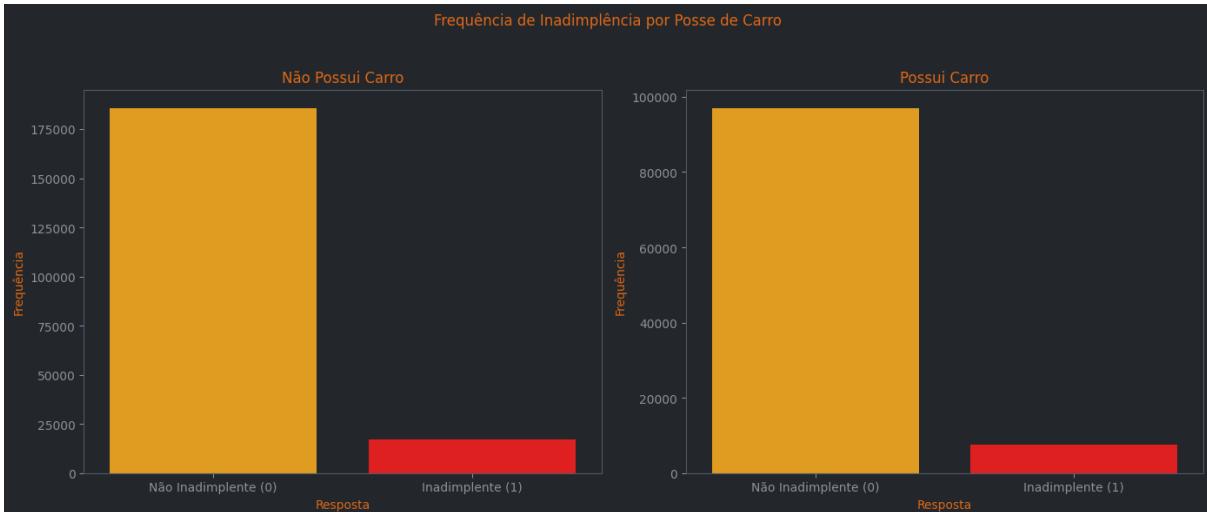


V de Cramer entre code\_gender e target: 0.0547

H3 — Customers who own a car have a lower probability of default. FALSE

```
In [72]: plot_binaria_target(
    df3,
    var_binaria='flag_own_car',
    label_0='Não Possui Carro',
    label_1='Possui Carro',
    suptitle='Frequência de Inadimplência por Posse de Carro'
)

calcular_cramers_v(df3, 'flag_own_car', 'target')
```

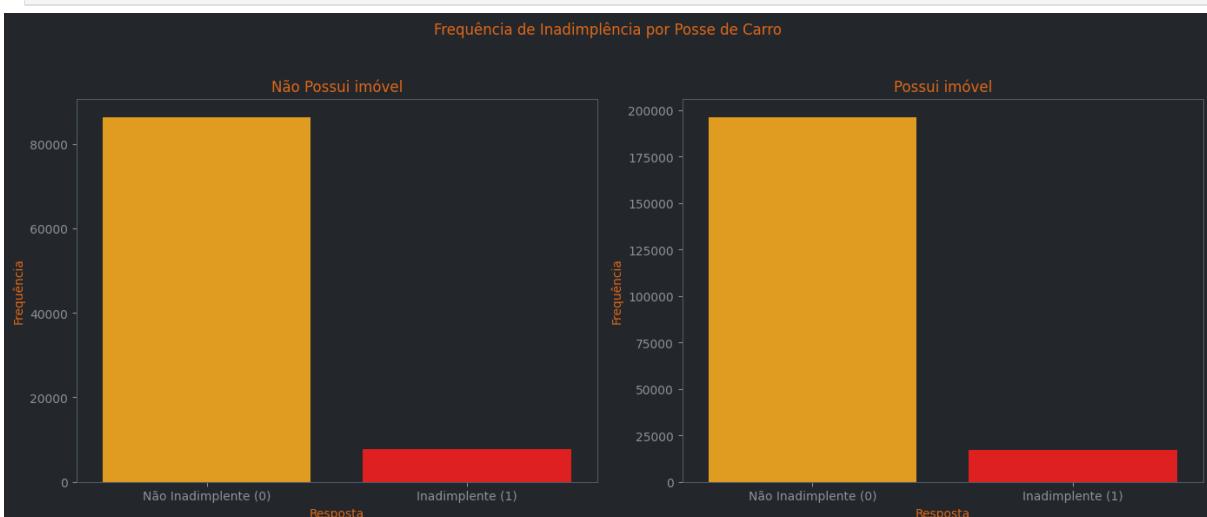


V de Cramer entre flag\_own\_car e target: 0.0218

H4 — Owning a home reduces the chance of default. FALSE

```
In [73]: plot_binaria_target(
    df3,
    var_binaria='flag_own_realty',
    label_0='Não Possui imóvel',
    label_1='Possui imóvel',
    suptitle='Frequência de Inadimplência por Posse de Carro'
)

calcular_cramers_v(df3, 'flag_own_realty', 'target')
```



V de Cramer entre flag\_own\_realty e target: 0.0061

H5 — The number of children influences default risk. FALSE

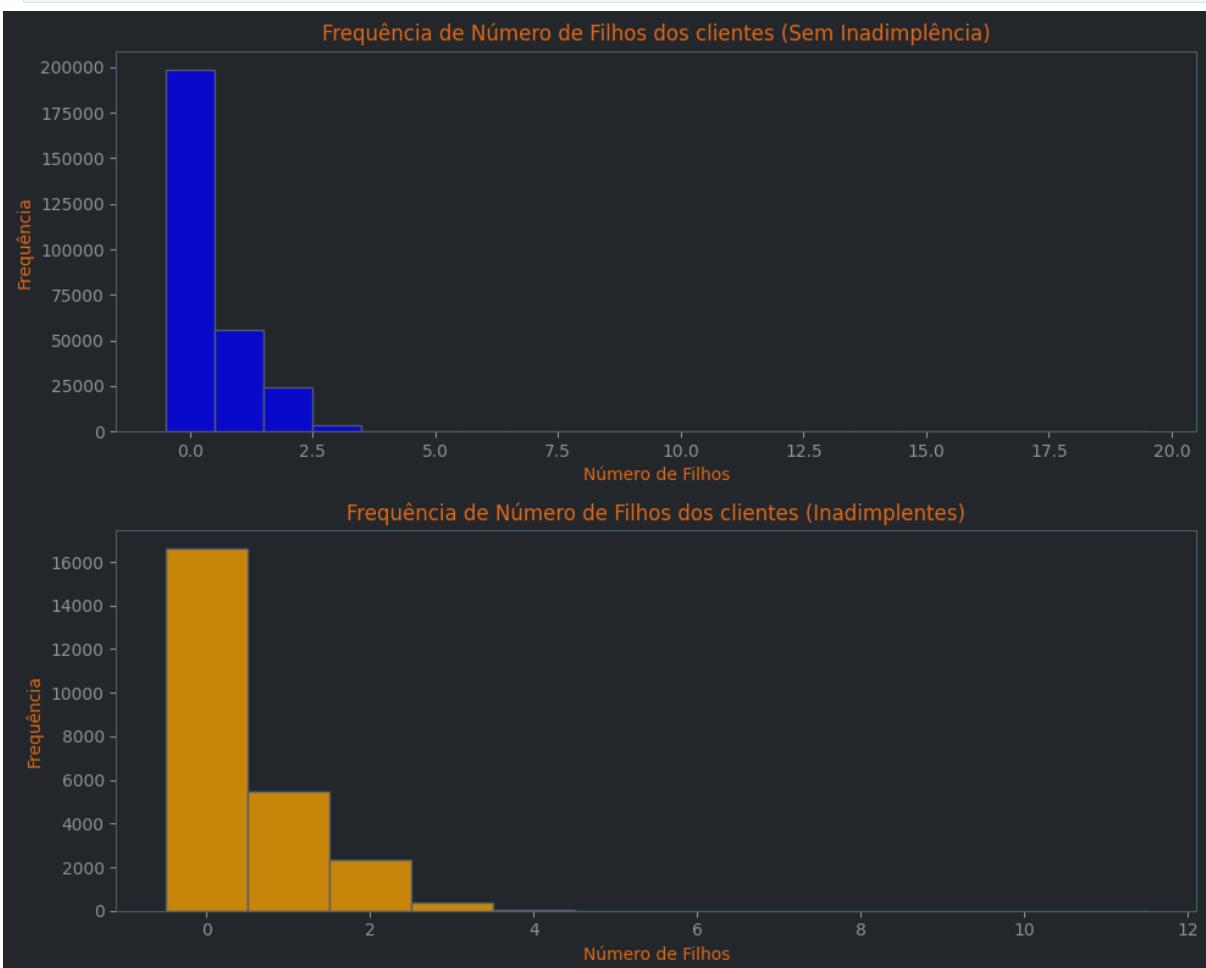
```
In [74]: plot_num_var_by_target(
    df3,
    num_var='cnt_children',
    title_0='Frequência de Número de Filhos dos clientes (Sem Inadimplência)',
    title_1='Frequência de Número de Filhos dos clientes (Inadimplentes)',
    label_x='Número de Filhos',
```

```

        discrete=True
    )

pearson_corr = df3['cnt_children'].corr(df3['target'], method='pearson')
print(f"Correlação de Pearson entre cnt_children e target: {pearson_corr:.4f}")

```



Correlação de Pearson entre cnt\_children e target: 0.0192

H6 — Higher total income is associated with lower default risk. TRUE

```

In [ ]: plot_num_var_by_target(
    df3,
    num_var='amt_income_total',
    title_0='Distribuição da Renda Total (amt_income_total) dos clientes (Sem Inadimplência)',
    title_1='Distribuição da Renda Total (amt_income_total) dos clientes (Inadimplentes)',
    label_x='Renda Total',
    discrete=True
)

pearson_corr = df3['amt_income_total'].corr(df3['target'], method='pearson')
print(f"Correlação de Pearson entre amt_income_total e target: {pearson_corr:.4f}")

```

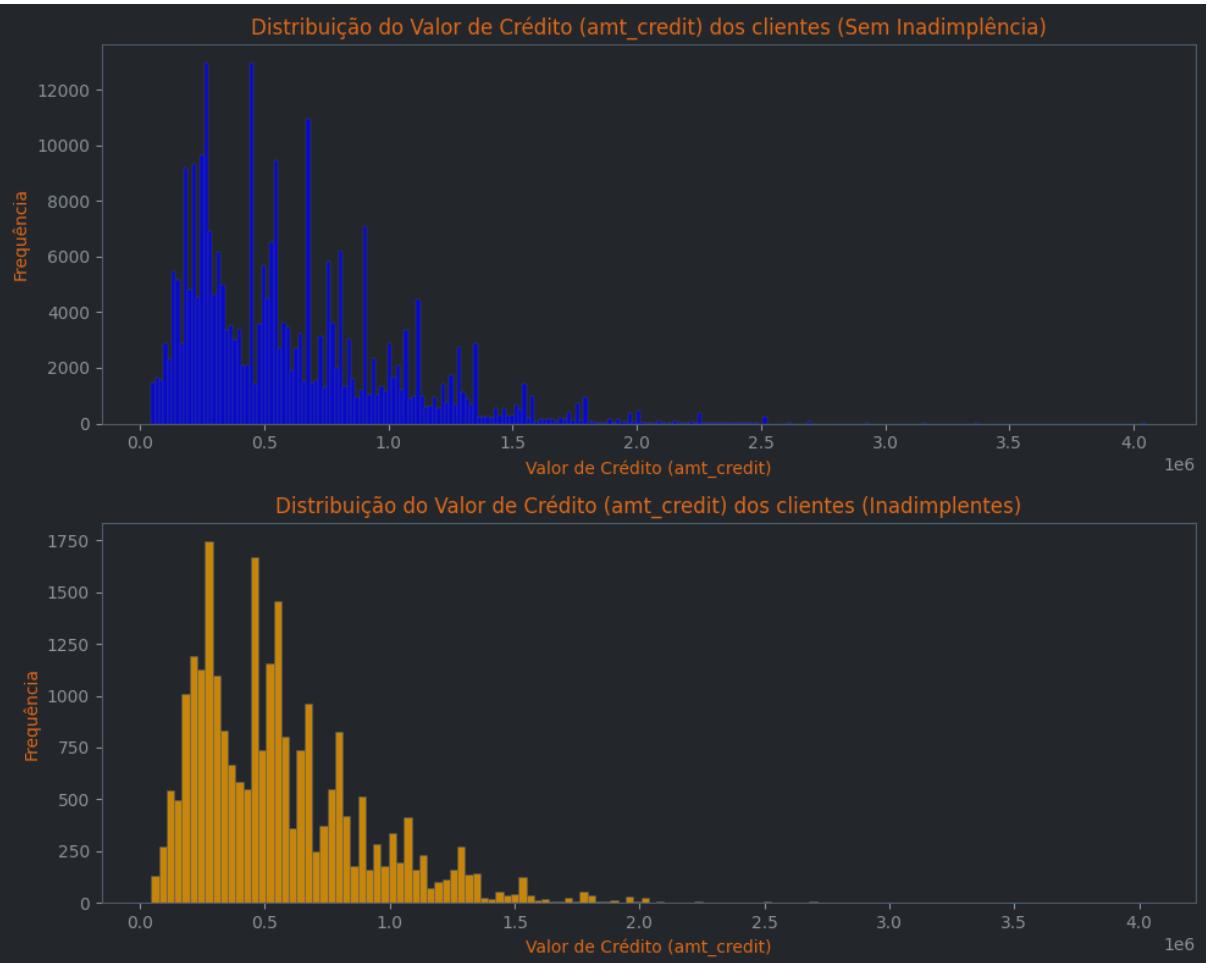
H7 — Higher credit amounts are related to higher default risk. FALSE

```

In [ ]: plot_num_var_by_target(
    df3,
    num_var='amt_credit',
    title_0='Distribuição do Valor de Crédito (amt_credit) dos clientes (Sem Inadimplência)',
    title_1='Distribuição do Valor de Crédito (amt_credit) dos clientes (Inadimplentes)',
    label_x='Valor de Crédito',
    discrete=True
)

pearson_corr = df3['amt_credit'].corr(df3['target'], method='pearson')
print(f"Correlação de Pearson entre amt_credit e target: {pearson_corr:.4f}")

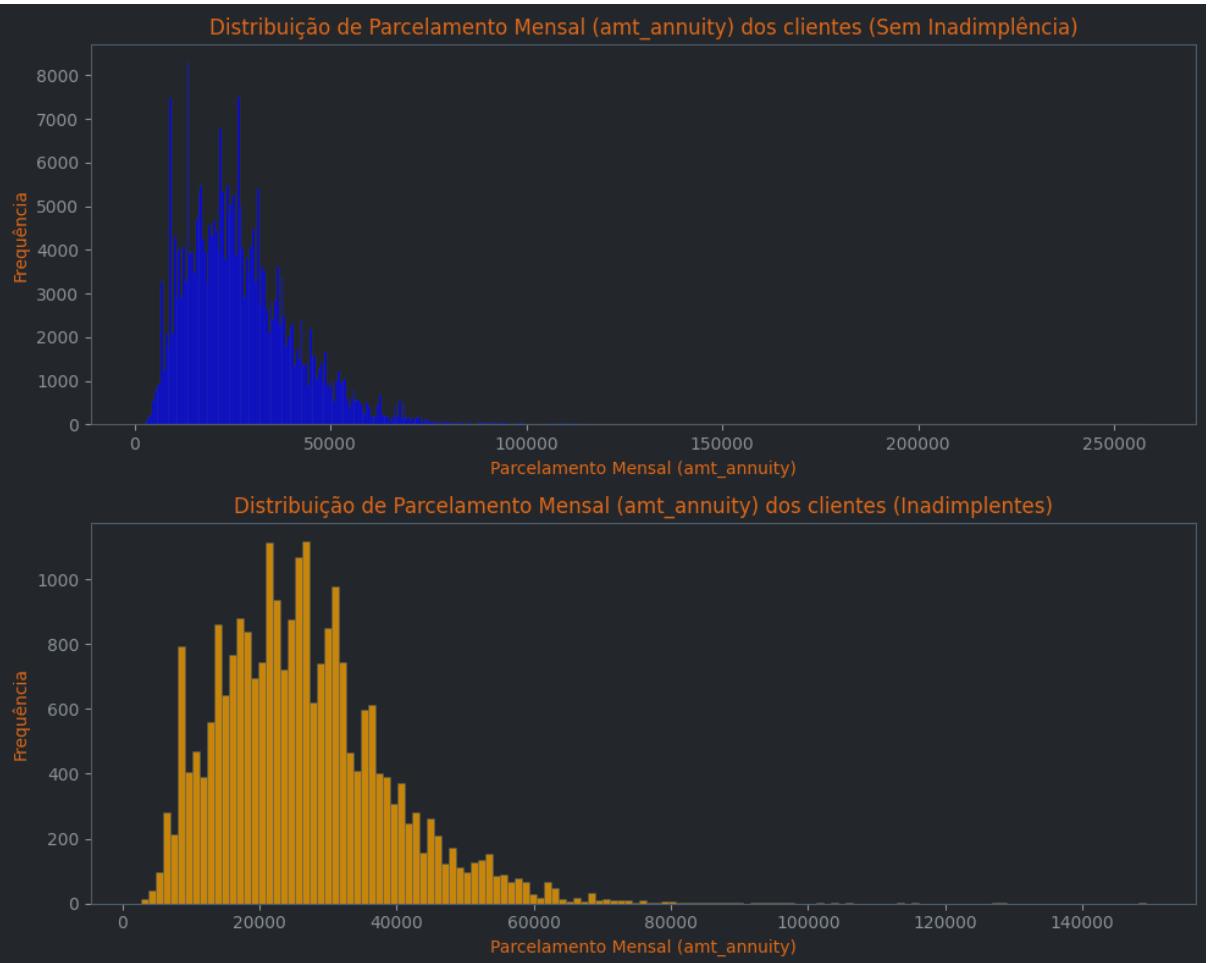
```



Correlação de Pearson entre amt\_credit e target: -0.0304

H8 — Higher monthly installments increase the chance of default. FALSE

```
In [ ]: plot_num_var_by_target(
    df3,
    num_var='amt_annuity',
    title_0='Distribuição de Parcelamento Mensal (amt_annuity) dos clientes (Sem Inadimplência)',
    title_1='Distribuição de Parcelamento Mensal (amt_annuity) dos clientes (Inadimplentes)',
    label_x='Parcelamento Mensal',
    discrete=True
)
pearson_corr = df3['amt_annuity'].corr(df3['target'], method='pearson')
print(f"Correlação de Pearson entre amt_annuity e target: {pearson_corr:.4f}")
```

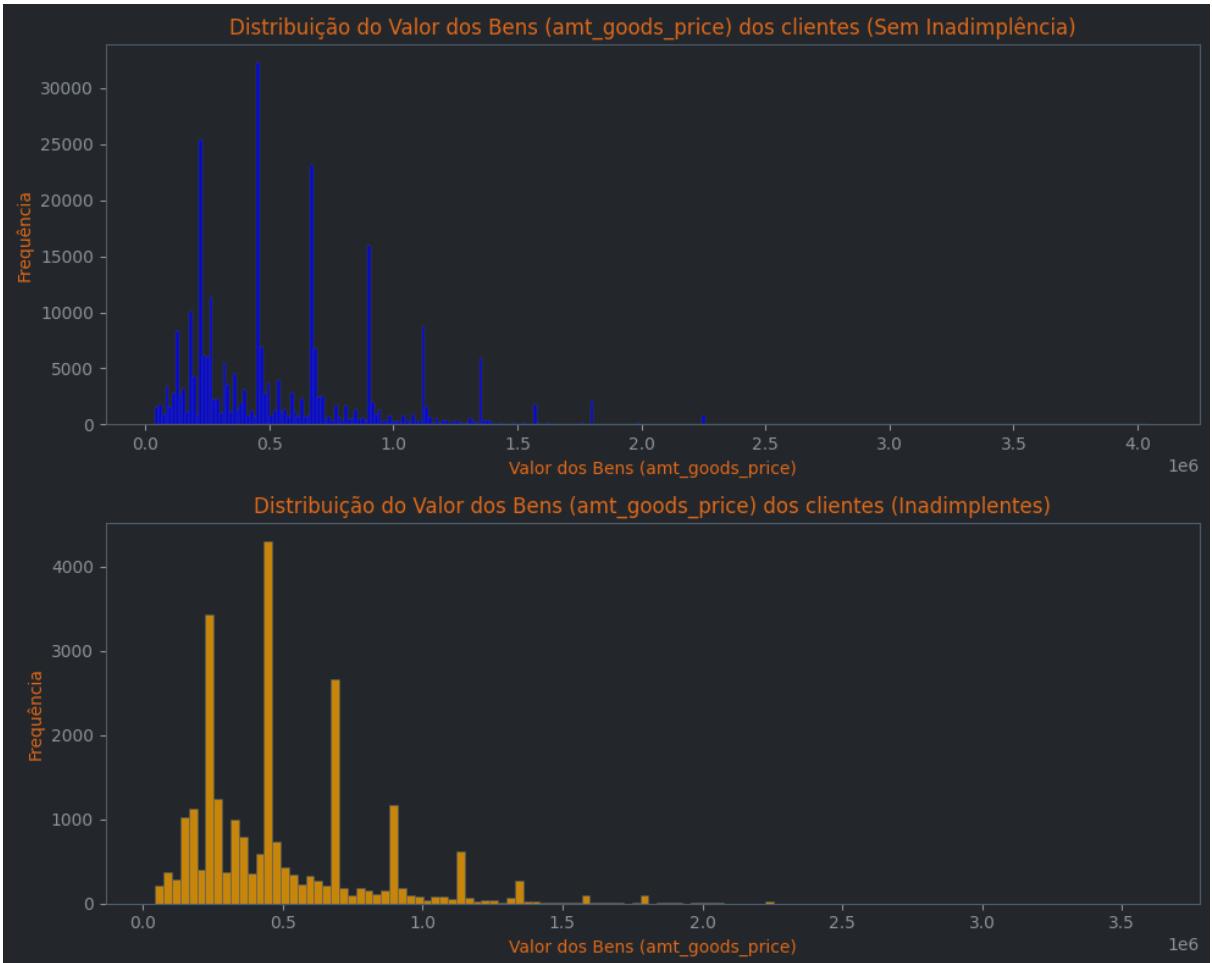


Correlação de Pearson entre amt\_annuity e target: -0.0128

H9 — The value of goods purchased influences default risk. FALSE

```
In [ ]: plot_num_var_by_target(
    df3,
    num_var='amt_goods_price',
    title_0='Distribuição do Valor dos Bens (amt_goods_price) dos clientes (Sem Inadimplência)',
    title_1='Distribuição do Valor dos Bens (amt_goods_price) dos clientes (Inadimplentes)',
    label_x='Valor dos Bens',
    discrete=True
)

pearson_corr = df3['amt_goods_price'].corr(df3['target'], method='pearson')
print(f"Correlação de Pearson entre amt_goods_price e target: {pearson_corr:.4f}")
```



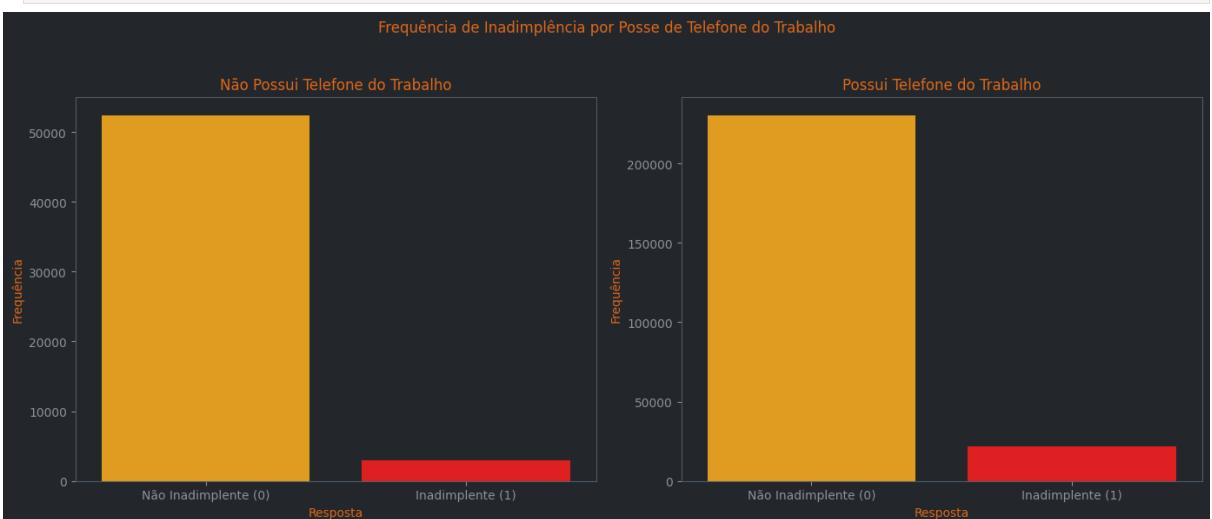
Correlação de Pearson entre amt\_goods\_price e target: -0.0396

## Block 2 Hypothesis

H21 — Having a work phone registered reduces the risk of default. TRUE

```
In [ ]: plot_binaria_target(
    df3,
    var_binaria='flag_emp_phone',
    label_0='Não Possui Telefone do Trabalho',
    label_1='Possui Telefone do Trabalho',
    suptitle='Frequência de Inadimplência por Posse de Telefone do Trabalho'
)

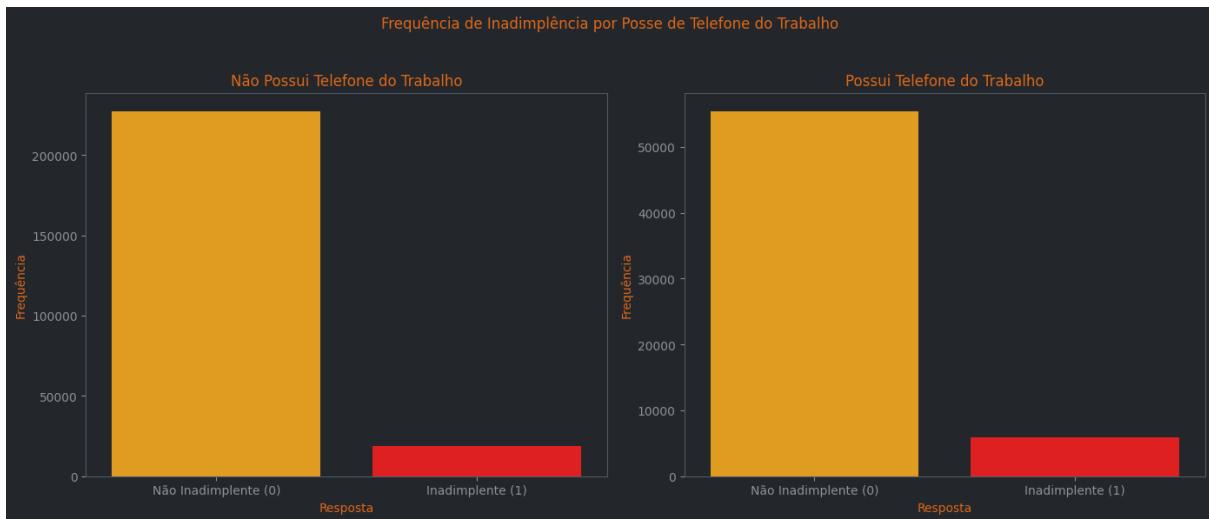
calcular_cramers_v(df3, 'flag_emp_phone', 'target')
```



V de Cramer entre flag\_emp\_phone e target: 0.0460

H22 — Customers with a work phone provided are less likely to default. TRUE

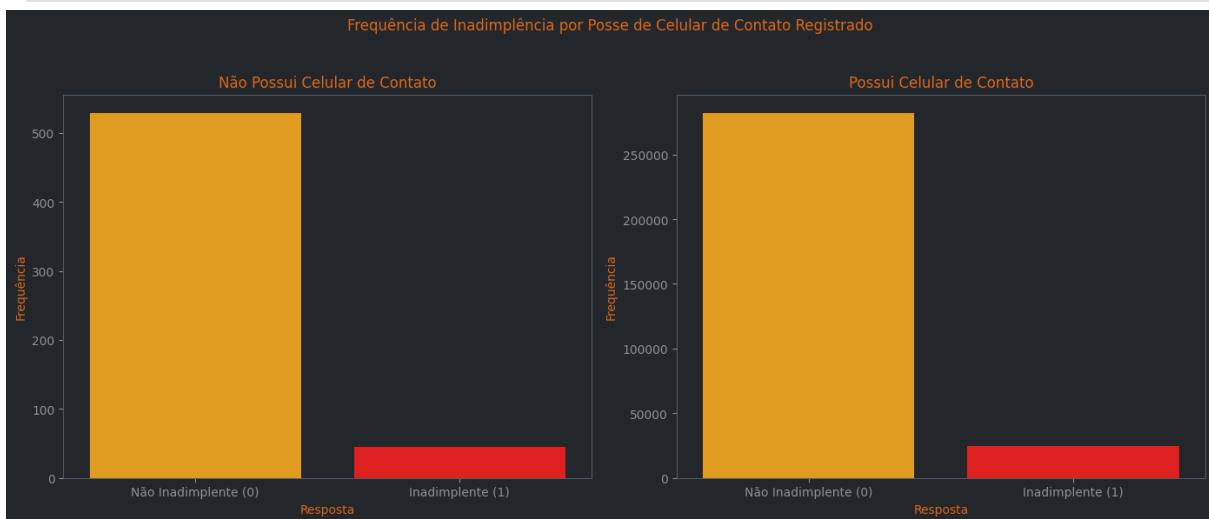
```
In [ ]: plot_binaria_target(  
    df3,  
    var_binaria='flag_work_phone',  
    label_0='Não Possui Telefone do Trabalho',  
    label_1='Possui Telefone do Trabalho',  
    suptitle='Frequência de Inadimplência por Posse de Telefone do Trabalho'  
)  
  
calcular_cramers_v(df3, 'flag_work_phone', 'target')
```



V de Cramer entre flag\_work\_phone e target: 0.0285

H23 — Having a registered mobile phone is associated with lower default risk. FALSE

```
In [ ]: plot_binaria_target(  
    df3,  
    var_binaria='flag_cont_mobile',  
    label_0='Não Possui Celular de Contato',  
    label_1='Possui Celular de Contato',  
    suptitle='Frequência de Inadimplência por Posse de Celular de Contato Registrado'  
)  
  
calcular_cramers_v(df3, 'flag_cont_mobile', 'target')
```



V de Cramer entre flag\_cont\_mobile e target: 0.0002

H24 — Having a landline phone registered reduces default risk. TRUE

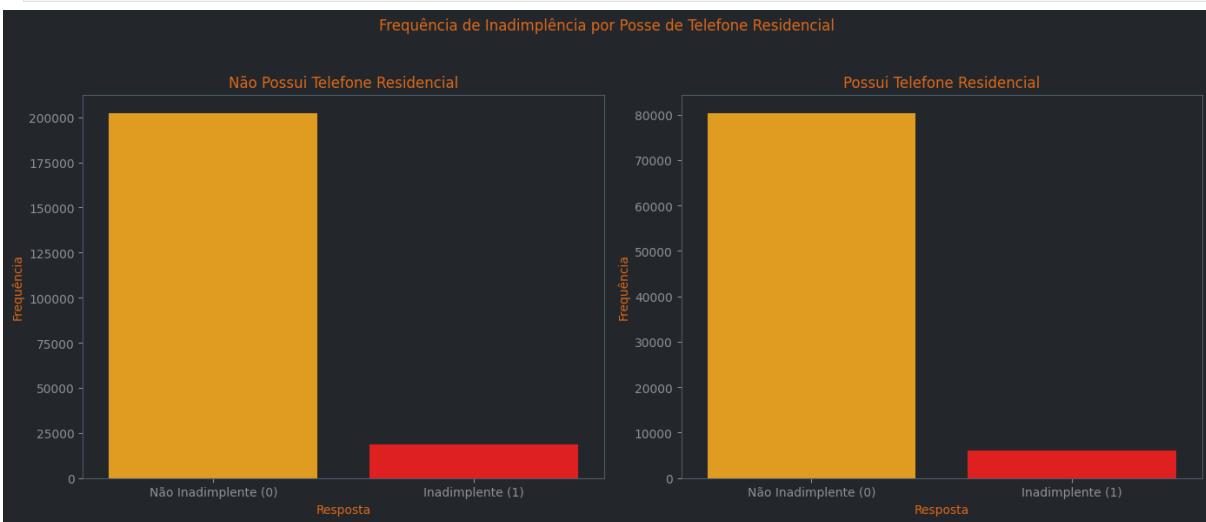
```
In [ ]: plot_binaria_target(  
    df3,  
    var_binaria='flag_phone',  
    label_0='Não Possui Telefone Residencial',
```

```

        label_1='Possui Telefone Residencial',
        suptitle='Frequência de Inadimplência por Posse de Telefone Residencial'
    )

calcular_cramers_v(df3, 'flag_phone', 'target')

```



V de Cramer entre flag\_phone e target: 0.0238

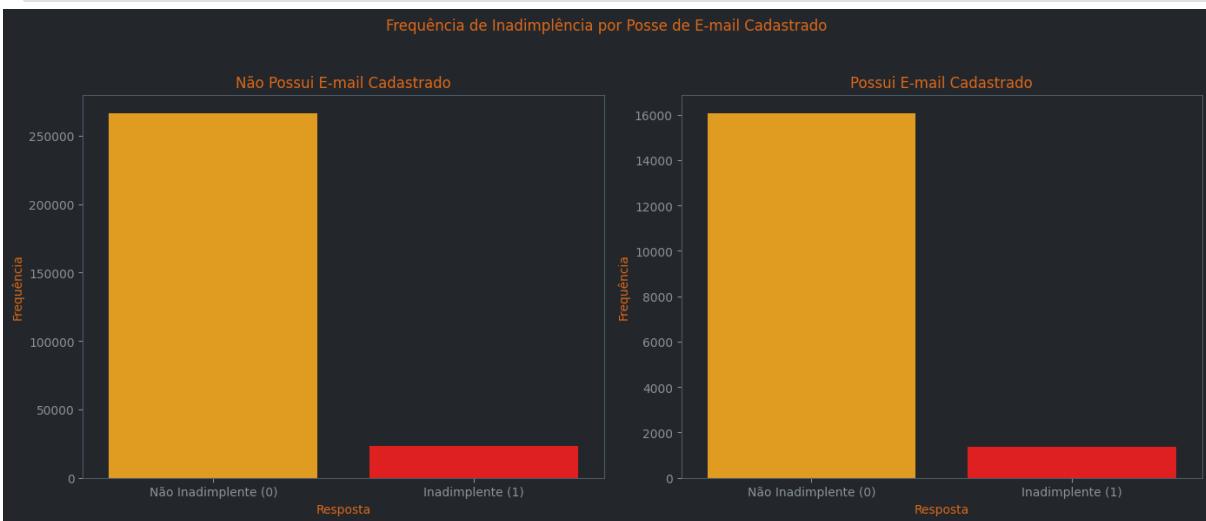
H25 — Customers with a registered email tend to present lower default risk. FALSE

```

In [ ]: plot_binaria_target(
    df3,
    var_binaria='flag_email',
    label_0='Não Possui E-mail Cadastrado',
    label_1='Possui E-mail Cadastrado',
    suptitle='Frequência de Inadimplência por Posse de E-mail Cadastrado'
)

calcular_cramers_v(df3, 'flag_email', 'target')

```



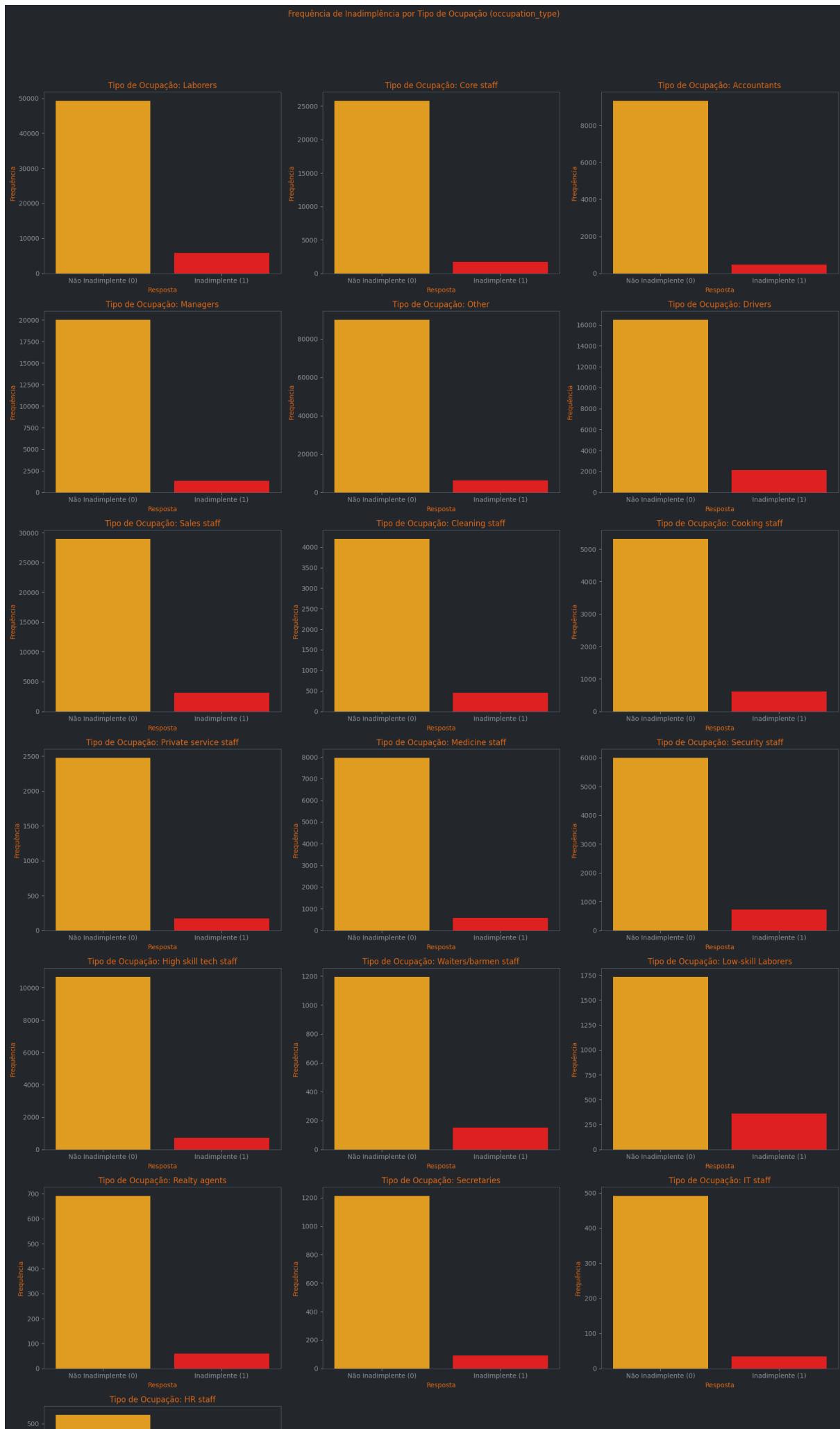
V de Cramer entre flag\_email e target: 0.0017

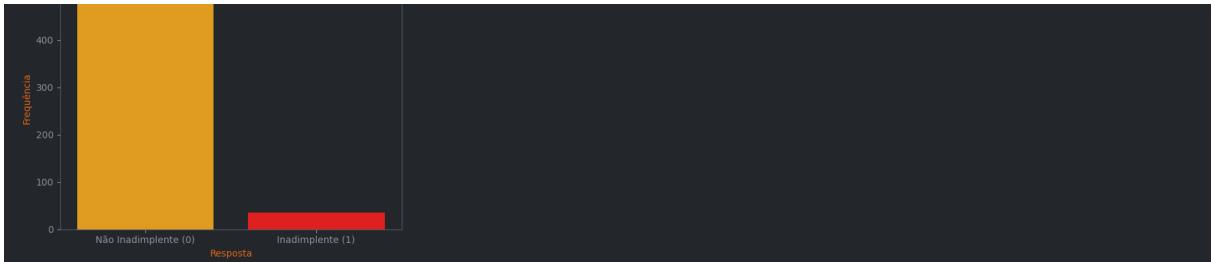
H26 — Occupation type influences default risk. TRUE

```

In [ ]: plot_target_by_categorical(df3, cat_col='occupation_type', target_col='target')
calcular_cramers_v(df3, 'occupation_type', 'target')

```





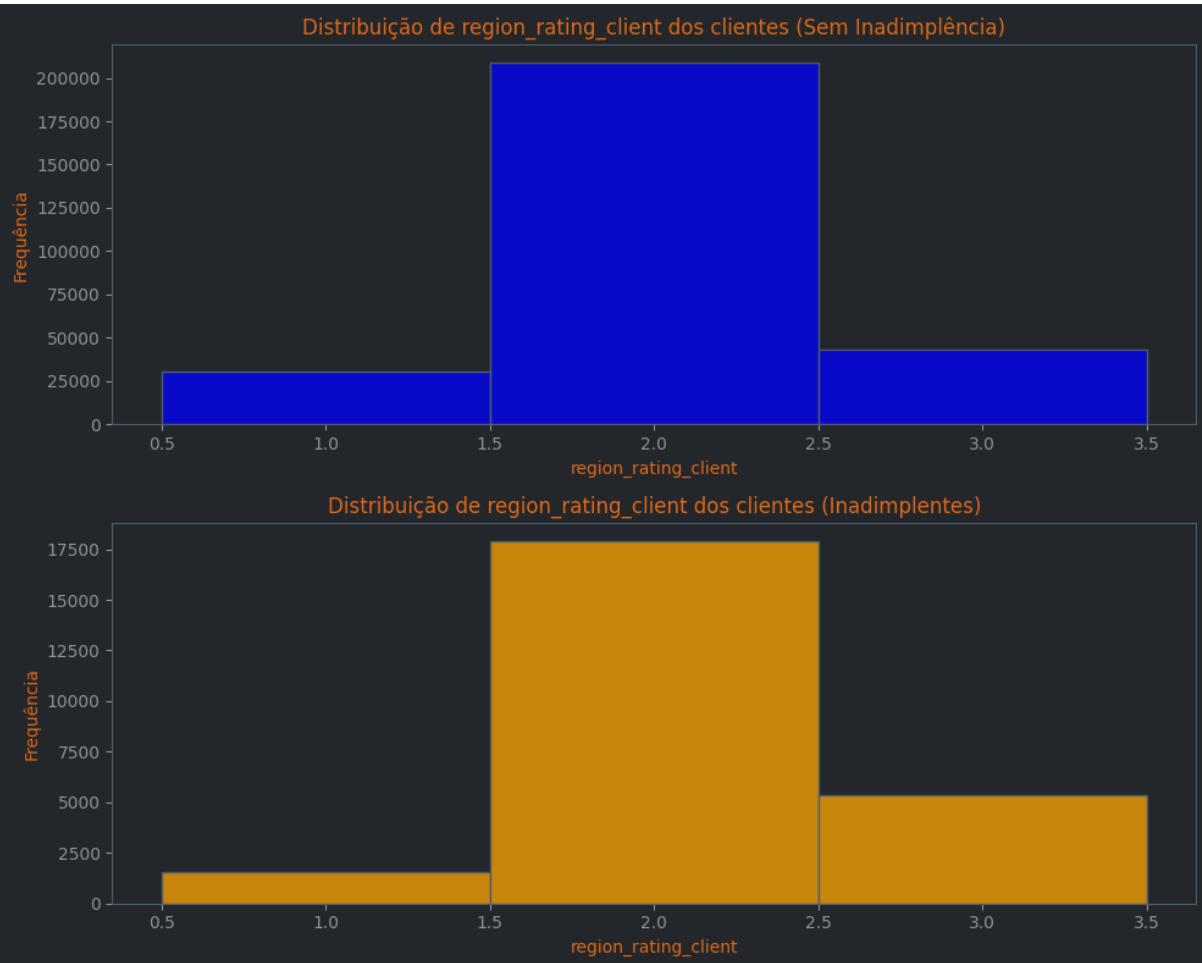
V de Cramer entre occupation\_type e target: 0.0801

H27 — The number of family members is positively related to default risk. FALSE

```
In [ ]: plot_num_var_by_target(
    df3,
    num_var='cnt_fam_members',
    title_0='Distribuição de cnt_fam_members dos clientes (Sem Inadimplência)',
    title_1='Distribuição de cnt_fam_members dos clientes (Inadimplentes)',
    label_x='cnt_fam_members',
    discrete=True
)
pearson_corr = df3['cnt_fam_members'].corr(df3['target'], method='pearson')
print(f"Correlação de Pearson entre cnt_fam_members e target: {pearson_corr:.4f}")
```

H28 — Customers from regions with lower ratings have a higher probability of default. TRUE

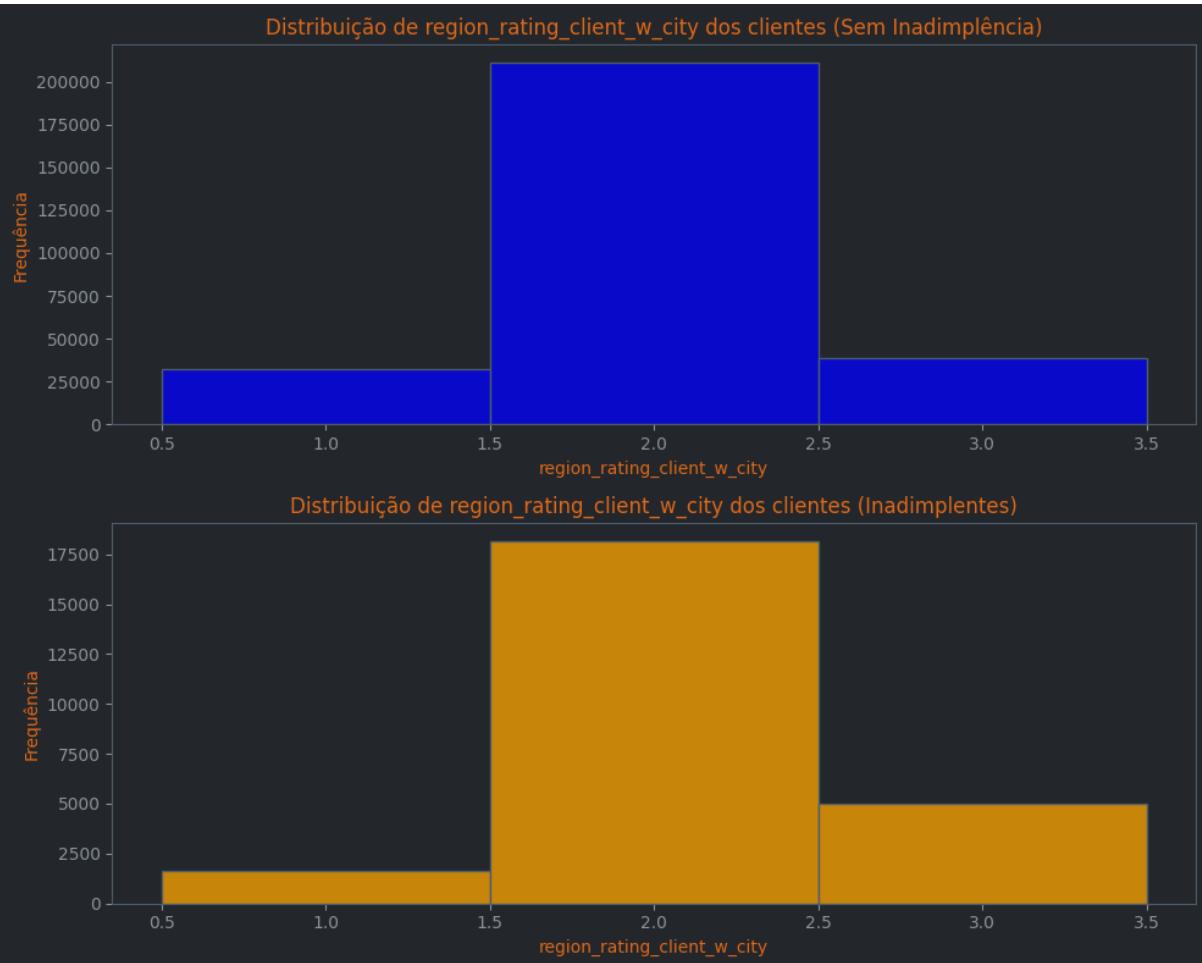
```
In [ ]: plot_num_var_by_target(
    df3,
    num_var='region_rating_client',
    title_0='Distribuição de region_rating_client dos clientes (Sem Inadimplência)',
    title_1='Distribuição de region_rating_client dos clientes (Inadimplentes)',
    label_x='region_rating_client',
    discrete=True
)
# Correlação de region_rating_client com a target
pearson_corr = df3['region_rating_client'].corr(df3['target'], method='pearson')
print(f"Correlação de Pearson entre region_rating_client e target: {pearson_corr:.4f}")
```



Correlação de Pearson entre region\_rating\_client e target: 0.0589

H29 — The customer's city rating influences default risk. TRUE

```
In [ ]: plot_num_var_by_target(
    df3,
    num_var='region_rating_client_w_city',
    title_0='Distribuição de region_rating_client_w_city dos clientes (Sem Inadimplência)',
    title_1='Distribuição de region_rating_client_w_city dos clientes (Inadimplentes)',
    label_x='region_rating_client_w_city',
    discrete=True
)
# Correlação de region_rating_client_w_city com a target
pearson_corr = df3['region_rating_client_w_city'].corr(df3['target'], method='pearson')
print(f"Correlação de Pearson entre region_rating_client_w_city e target: {pearson_corr:.4f}")
```

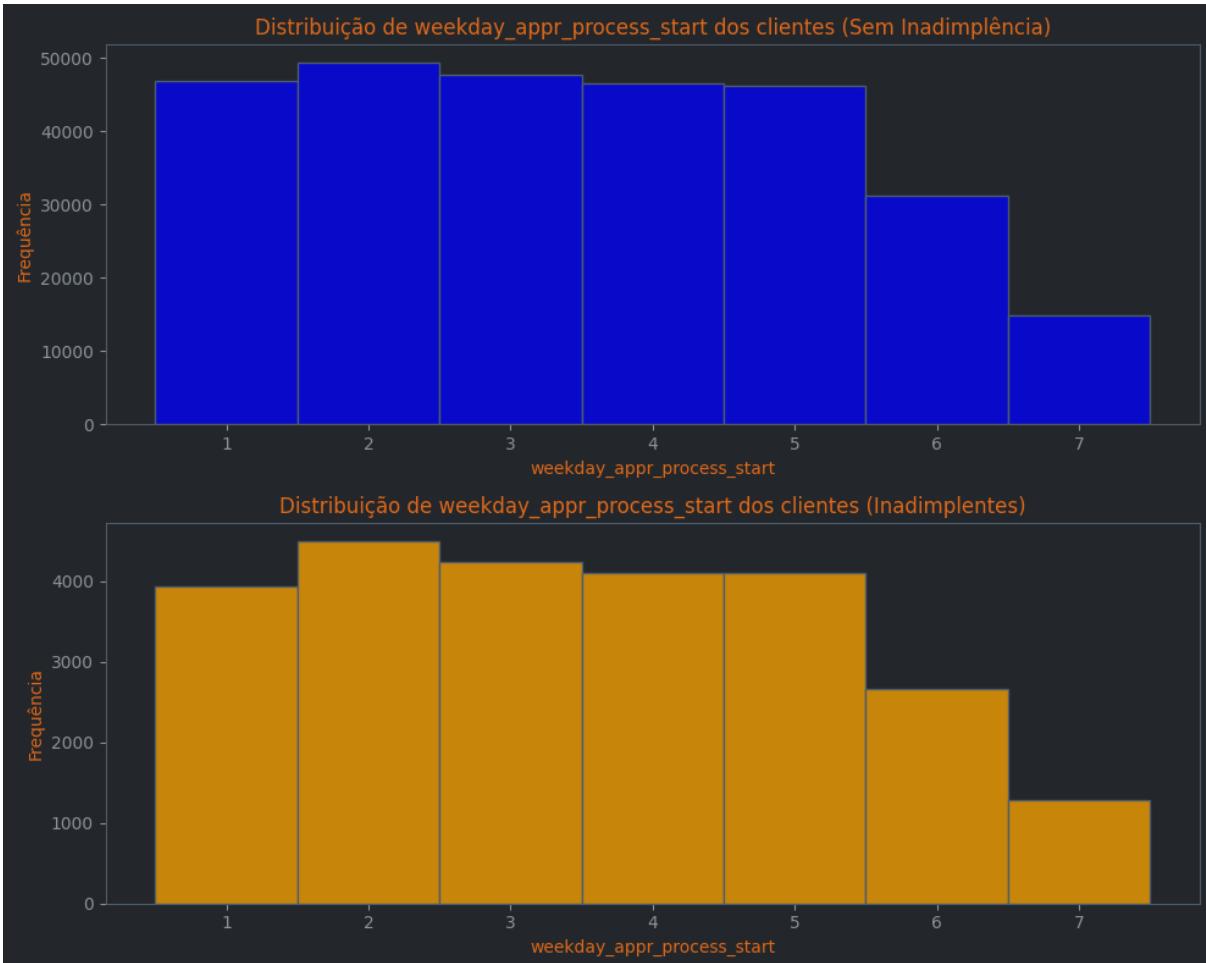


Correlação de Pearson entre region\_rating\_client\_w\_city e target: 0.0609

H30 — The day of the week when the credit application is made influences the probability of default.  
FALSE

```
In [ ]: plot_num_var_by_target(
    df3,
    num_var='weekday_appr_process_start',
    title_0='Distribuição de weekday_appr_process_start dos clientes (Sem Inadimplência)',
    title_1='Distribuição de weekday_appr_process_start dos clientes (Inadimplentes)',
    label_x='weekday_appr_process_start',
    discrete=True
)

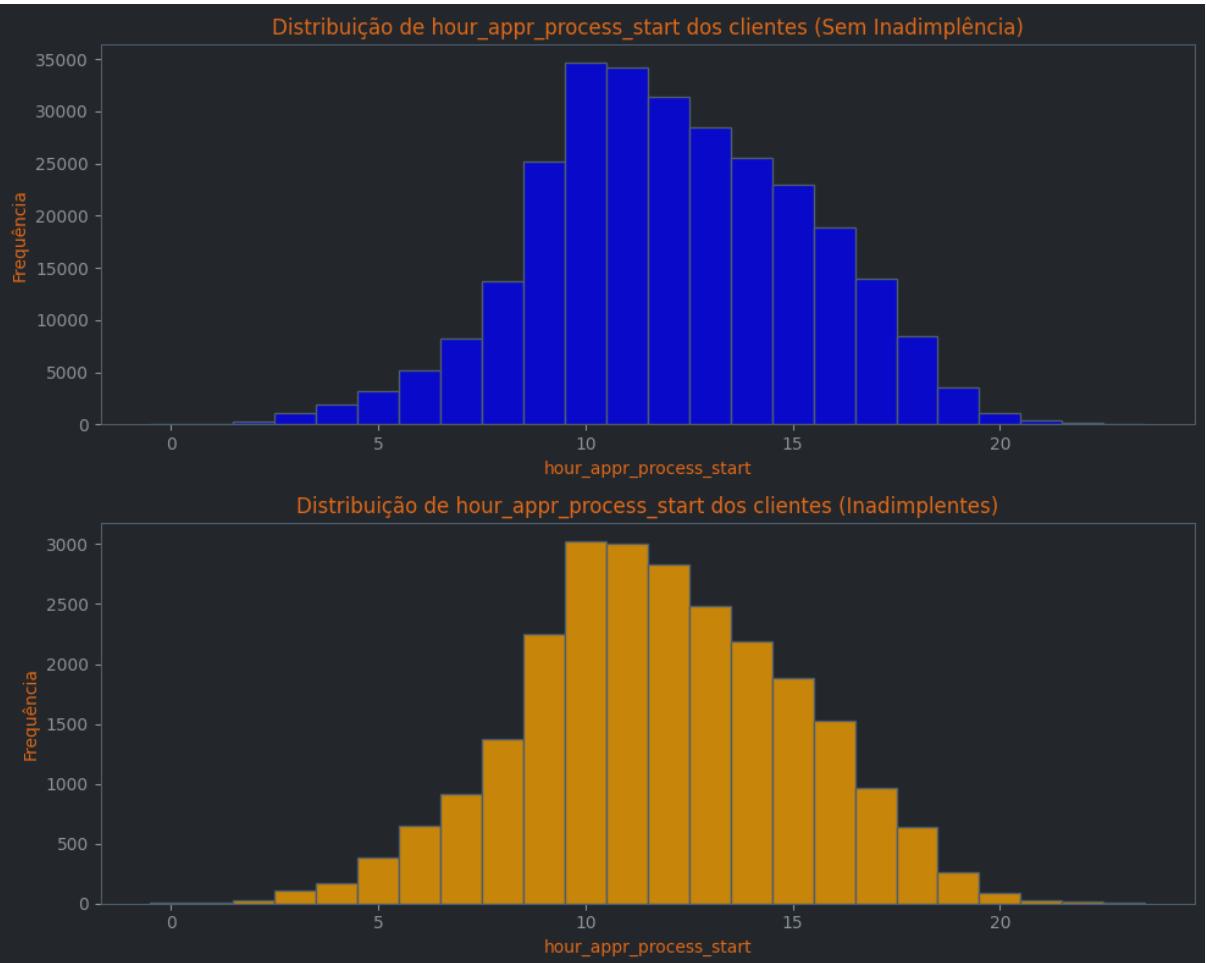
pearson_corr = df3['weekday_appr_process_start'].corr(df3['target'], method='pearson')
print(f"Correlação de Pearson entre weekday_appr_process_start e target: {pearson_corr:.4f}")
```



Correlação de Pearson entre weekday\_appr\_process\_start e target: -0.0002

H31 — The time of credit application is associated with default. FALSE

```
In [ ]: plot_num_var_by_target(
    df3,
    num_var='hour_appr_process_start',
    title_0='Distribuição de hour_appr_process_start dos clientes (Sem Inadimplência)',
    title_1='Distribuição de hour_appr_process_start dos clientes (Inadimplentes)',
    label_x='hour_appr_process_start',
    discrete=True
)
pearson_corr = df3['hour_appr_process_start'].corr(df3['target'], method='pearson')
print(f"Correlação de Pearson entre hour_appr_process_start e target: {pearson_corr:.4f}")
```



Correlação de Pearson entre hour\_appr\_process\_start e target: -0.0242

H32 — Living in a region different from the registered one increases default risk. FALSE

```
In [ ]: reg_region_flags = [0, 1]

palette_target = {'0': "orange", '1': "red"}

fig, axes = plt.subplots(1, 2, figsize=(14, 6), sharey=False)

for i, flag in enumerate(reg_region_flags):
    data_plot = df3[df3['reg_region_not_live_region'] == flag].copy()
    data_plot['target_str'] = data_plot['target'].astype(str)
    sns.countplot(
        data=data_plot,
        x='target_str',
        hue='target_str',
        palette=palette_target,
        order=['0', '1'],
        ax=axes[i],
        legend=False
    )
    reg_region_label = "Mesma Região" if flag == 0 else "Regiões Diferentes"
    axes[i].set_title(f"Residência e Registro: {reg_region_label}")
    axes[i].set_xlabel('Resposta')
    axes[i].set_ylabel('Frequência')
    axes[i].set_xticks([0, 1])
    axes[i].set_xticklabels(['Não Inadimplente (0)', 'Inadimplente (1)'])

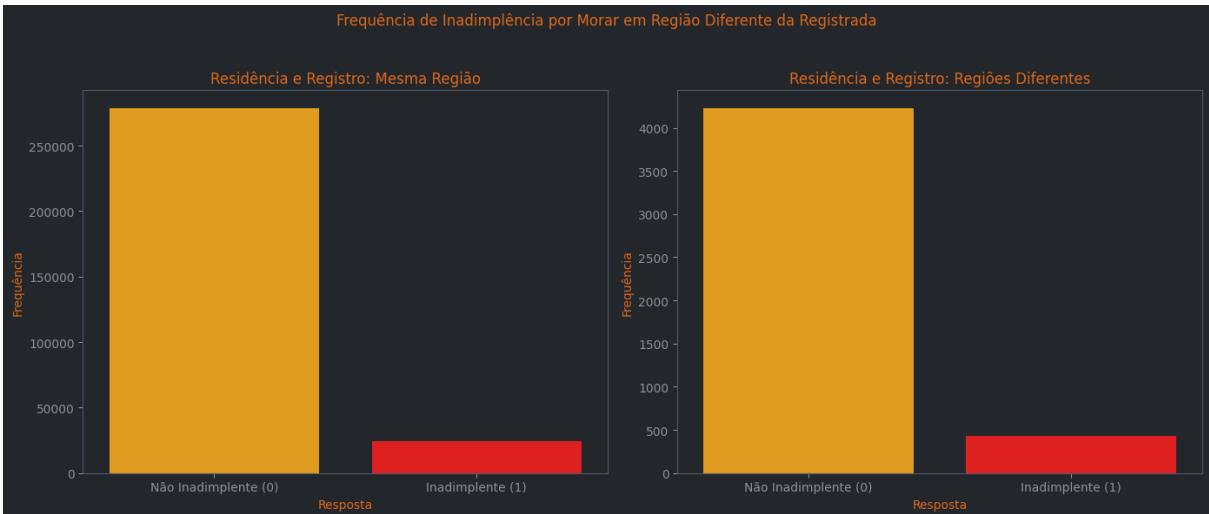
plt.suptitle('Frequência de Inadimplência por Morar em Região Diferente da Registrada')
plt.tight_layout(rect=[0, 0, 1, 0.95])
plt.show()

plot_num_var_by_target(
    df3,
    num_var='reg_region_not_live_region',
```

```

        title_0='Distribuição do Valor de Crédito (amt_credit) dos clientes (Sem Inadimplência)',
        title_1='Distribuição do Valor de Crédito (amt_credit) dos clientes (Inadimplentes)',
        label_x='reg_region_not_live_region',
        discrete=True
    )
calcular_cramers_v(df3, 'reg_region_not_live_region', 'target')

```



V de Cramer entre reg\_region\_not\_live\_region e target: 0.0055

H33 — Working in a region different from the registered one is associated with higher risk. FALSE

```

In [ ]: plot_binaria_target(
    df3,
    var_binaria='reg_region_not_work_region',
    label_0='Mesma Região',
    label_1='Regiões Diferentes',
    suptitle='Frequência de Inadimplência por Morar em Região Diferente da Região de Trabalho'
)

calcular_cramers_v(df3, 'reg_region_not_work_region', 'target')

```

H34 — Living and working in different regions may increase the probability of default. FALSE

```

In [ ]: live_region_not_work_flags = [0, 1]

palette_target = {'0': "orange", '1': "red"}

fig, axes = plt.subplots(1, 2, figsize=(14, 6), sharey=False)

for i, flag in enumerate(live_region_not_work_flags):

    data_plot = df3[df3['live_region_not_work_region'] == flag].copy()
    data_plot['target_str'] = data_plot['target'].astype(str)
    sns.countplot(
        data=data_plot,
        x='target_str',
        hue='target_str',
        palette=palette_target,
        order=['0', '1'],
        ax=axes[i],
        legend=False
    )

    live_region_work_str = "Mesma Cidade" if flag == 0 else "Cidades Diferentes"
    axes[i].set_title(f"Cidade de Residência e Trabalho: {live_region_work_str}")
    axes[i].set_xlabel('Resposta')
    axes[i].set_ylabel('Frequência')
    axes[i].set_xticks([0, 1])
    axes[i].set_xticklabels(['Não Inadimplente (0)', 'Inadimplente (1)'])

plt.suptitle('Frequência de Inadimplência por Morar em Cidade Diferente da Cidade de Trabalho')

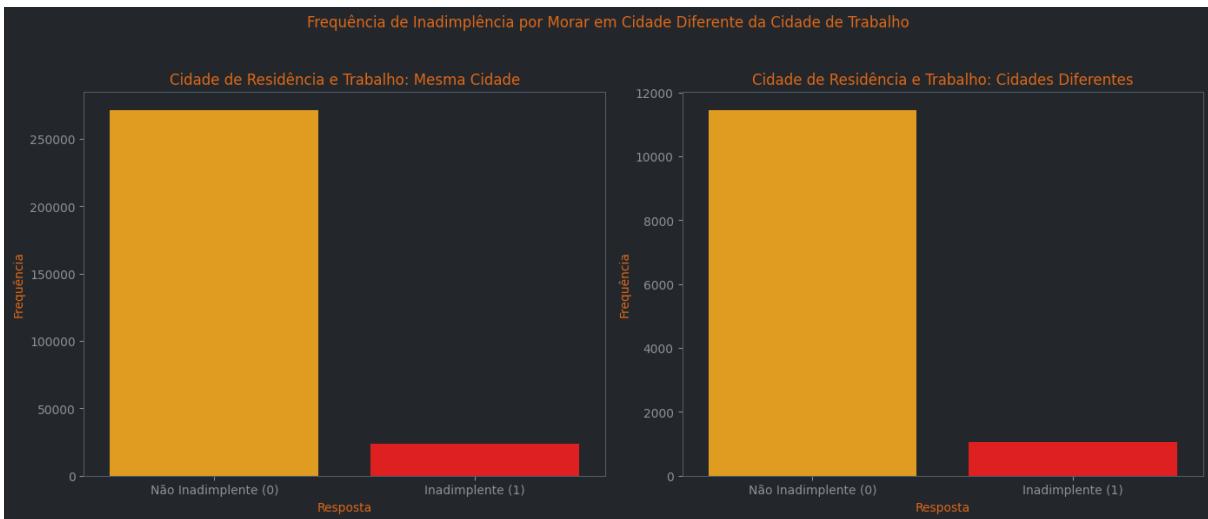
```

```

plt.tight_layout(rect=[0, 0, 1, 0.95])
plt.show()

plot_binaria_target(
    df3,
    var_binaria='live_region_not_work_region',
    label_0='Mesma Cidade',
    label_1='Cidades Diferentes',
    suptitle='Frequência de Inadimplência por Morar em Cidade Diferente da Cidade de Trabalho'
)
calcular_cramers_v(df3, 'live_region_not_work_region', 'target')

```



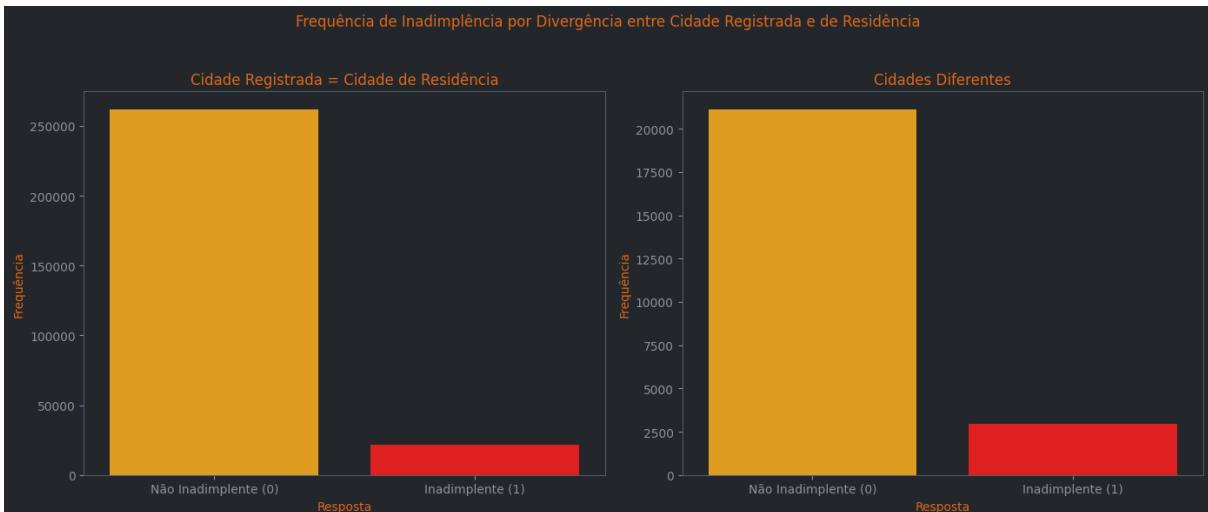
V de Cramer entre live\_region\_not\_work\_region e target: 0.0028

H35 — Living in a city different from the registered one increases the chance of default. TRUE

```

In [ ]: plot_binaria_target(
    df3,
    var_binaria='reg_city_not_live_city',
    label_0='Cidade Registrada = Cidade de Residência',
    label_1='Cidades Diferentes',
    suptitle='Frequência de Inadimplência por Divergência entre Cidade Registrada e de Residência'
)
calcular_cramers_v(df3, 'reg_city_not_live_city', 'target')

```



V de Cramer entre reg\_city\_not\_live\_city e target: 0.0444

H36 — Working in a city different from the registered one increases default risk. TRUE

```

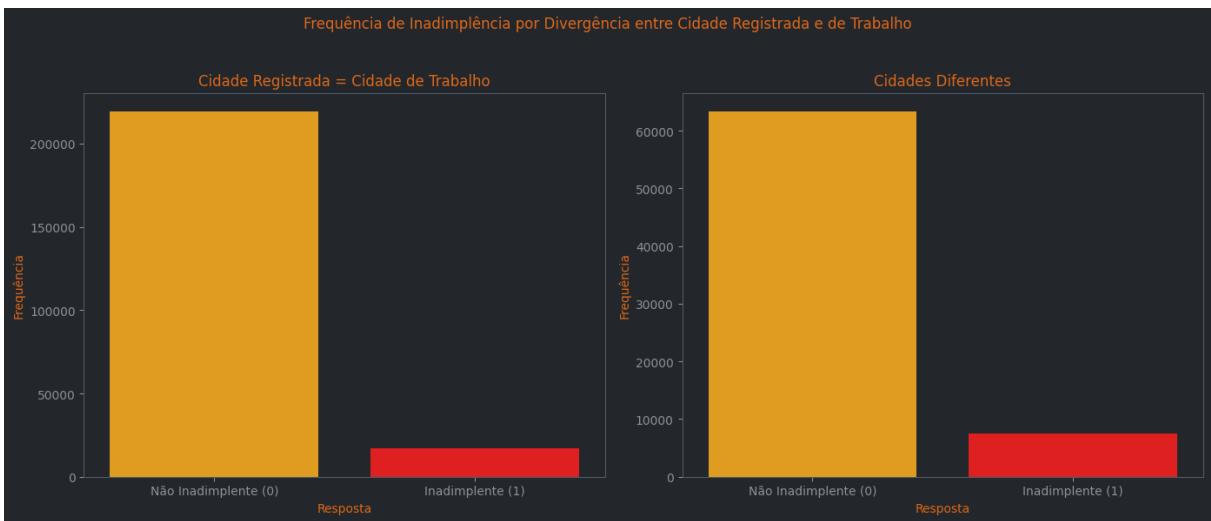
In [ ]: plot_binaria_target(
    df3,
    var_binaria='reg_city_not_work_city',
    label_0='Cidade Registrada = Cidade de Trabalho',
    label_1='Cidades Diferentes',
    suptitle='Frequência de Inadimplência por Divergência entre Cidade Registrada e de Trabalho'
)
calcular_cramers_v(df3, 'reg_city_not_work_city', 'target')

```

```

    suptitle='Frequência de Inadimplência por Divergência entre Cidade Registrada e de Trabalho')
)
calcular_cramers_v(df3, 'reg_city_not_work_city', 'target')

```



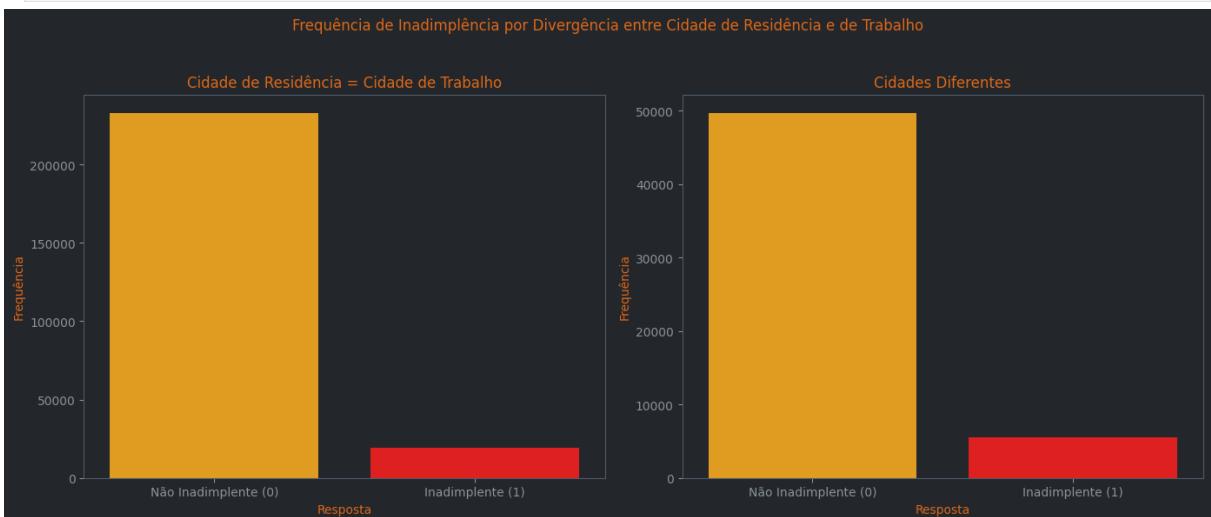
V de Cramer entre reg\_city\_not\_work\_city e target: 0.0510

H37 — Living in a different city than the workplace influences default risk. TRUE

```

In [ ]: plot_binaria_target(
    df3,
    var_binaria='live_city_not_work_city',
    label_0='Cidade de Residência = Cidade de Trabalho',
    label_1='Cidades Diferentes',
    suptitle='Frequência de Inadimplência por Divergência entre Cidade de Residência e de Trabalho')
)
calcular_cramers_v(df3, 'live_city_not_work_city', 'target')

```



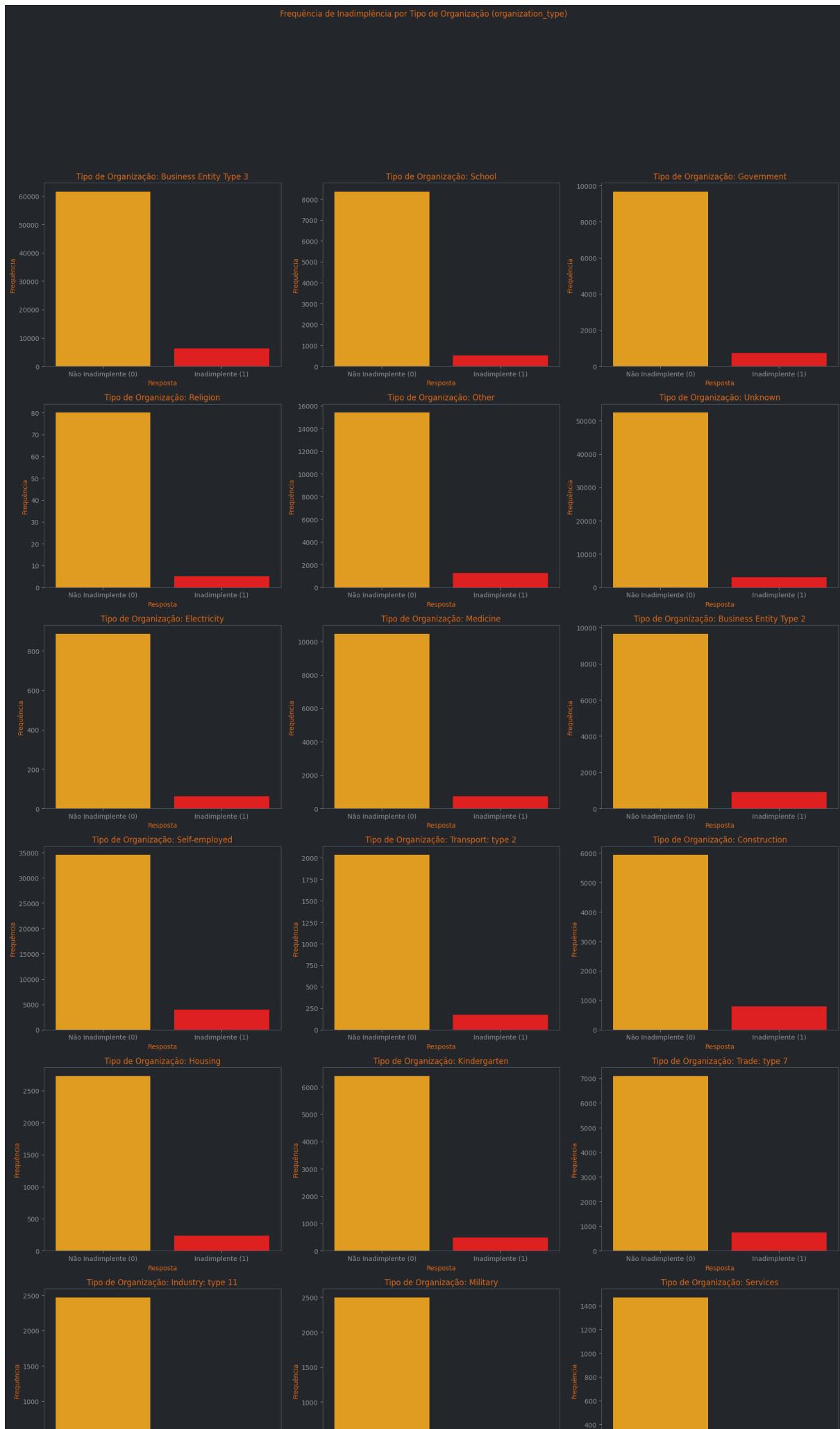
V de Cramer entre live\_city\_not\_work\_city e target: 0.0325

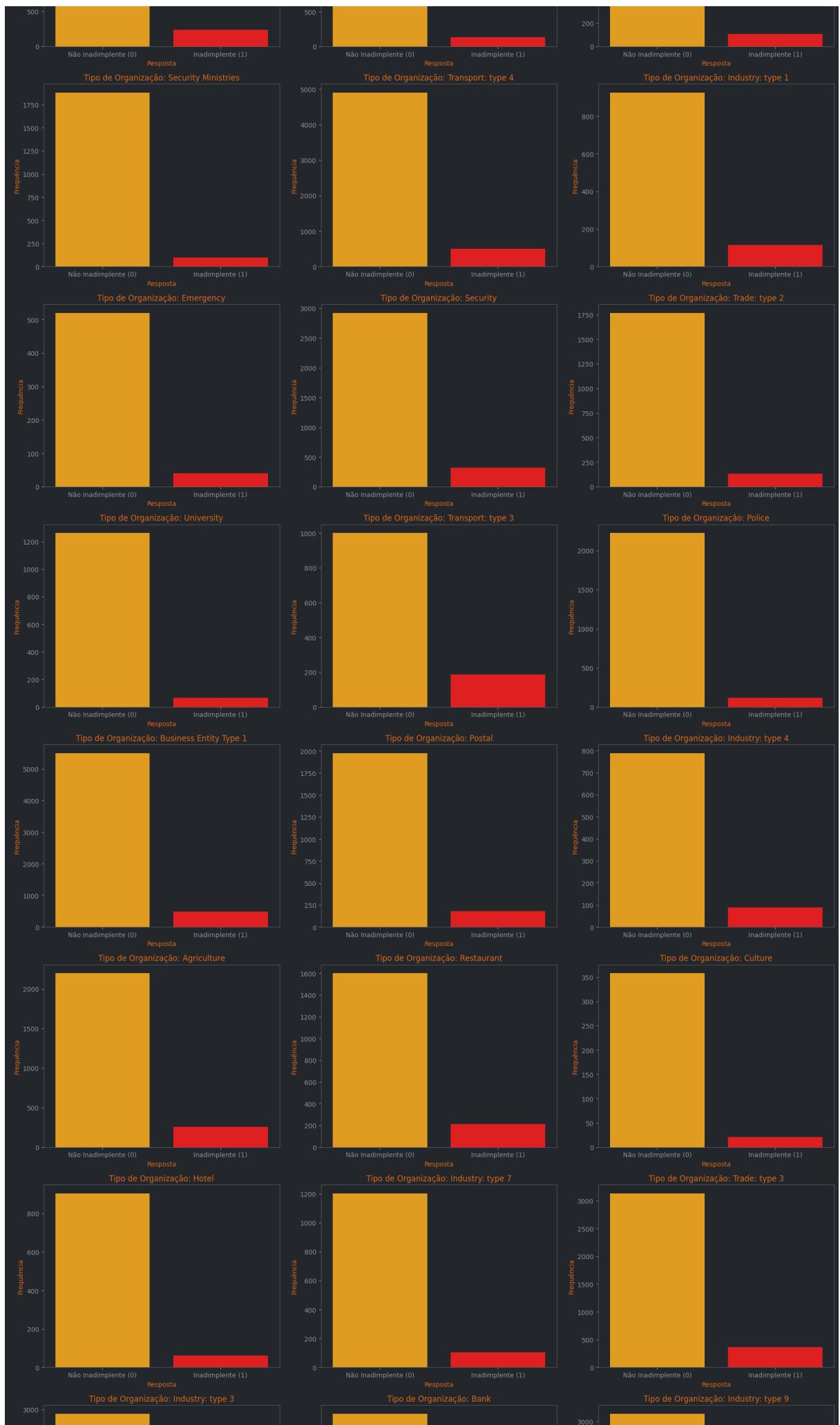
H38 — The type of employing organization is associated with default risk. TRUE

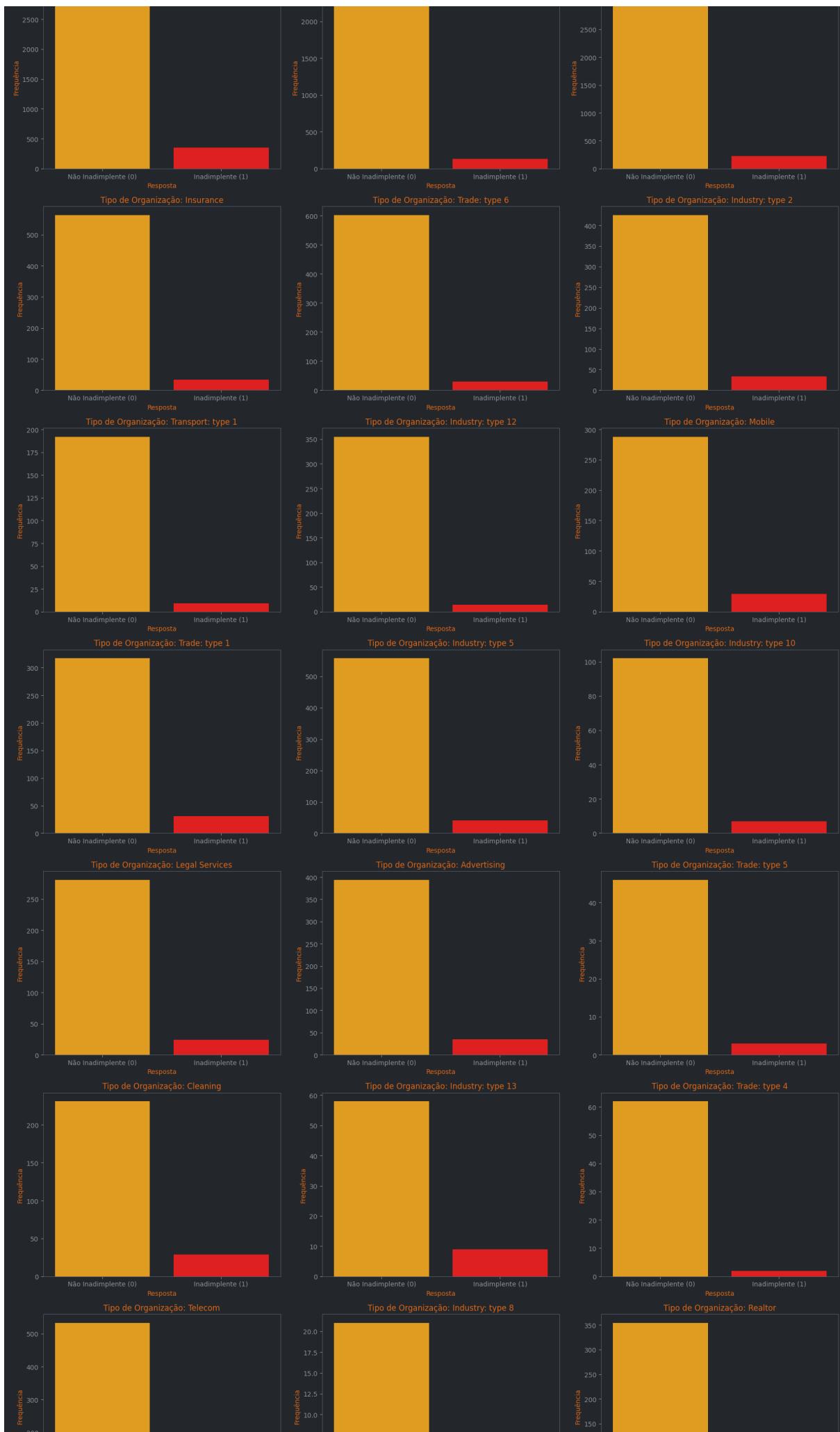
```

In [ ]: plot_target_by_categorical(df3, cat_col='organization_type', target_col='target')
calcular_cramers_v(df3, 'organization_type', 'target')

```





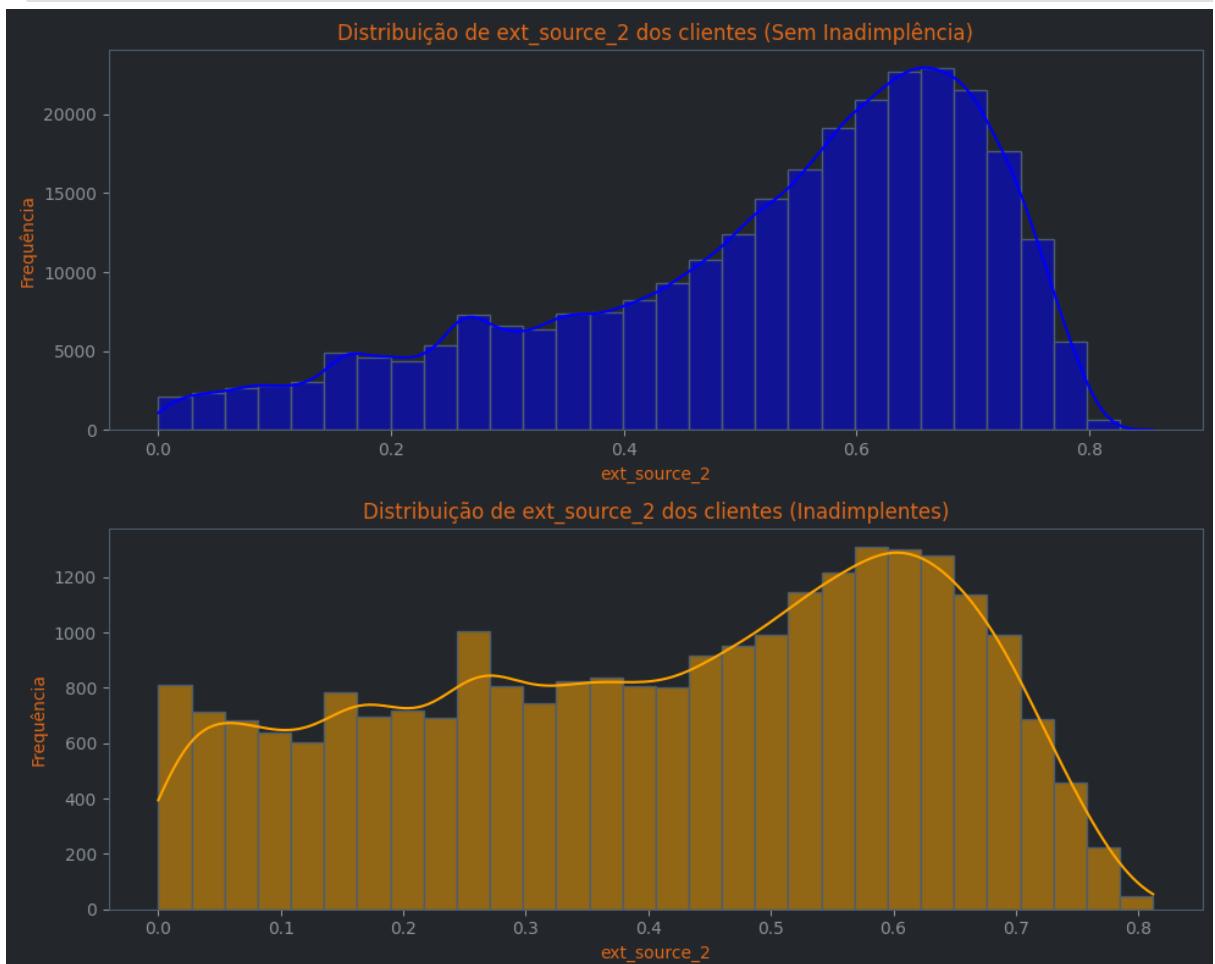




$V$  de Cramer entre organization\_type e target: 0.0723

H39 — External score 2 is inversely related to default. TRUE

```
In [ ]: plot_num_var_by_target(
    df3,
    num_var='ext_source_2',
    title_0='Distribuição de ext_source_2 dos clientes (Sem Inadimplência)',
    title_1='Distribuição de ext_source_2 dos clientes (Inadimplentes)',
    label_x='Distribuição de ext_source_2 dos clientes (Inadimplentes)',
    discrete=True
)
pearson_corr = df3['ext_source_2'].corr(df3['target'], method='pearson')
print(f"Correlação de Pearson entre ext_source_2 e target: {pearson_corr:.4f}")
```



Correlação de Pearson entre ext\_source\_2 e target: -0.1603

H40 — External score 3 is inversely related to default. TRUE

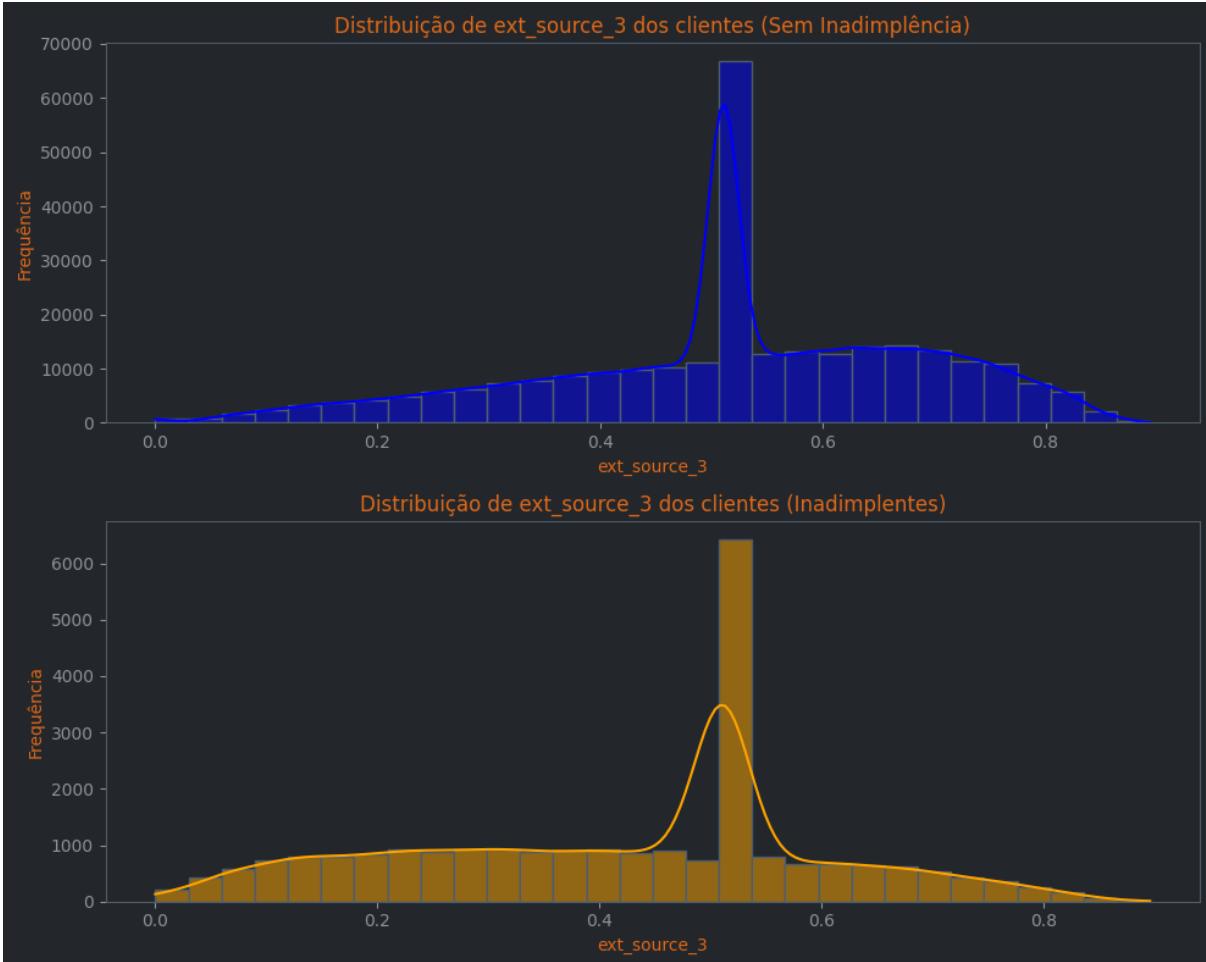
```
In [ ]: plot_num_var_by_target(
    df3,
```

```

        num_var='ext_source_2',
        title_0='Distribuição de ext_source_3 dos clientes (Sem Inadimplência)',
        title_1='Distribuição de ext_source_3 dos clientes (Inadimplentes)',
        label_x='Distribuição de ext_source_3 dos clientes (Inadimplentes)',
        discrete=True
    )

pearson_corr = df3['ext_source_3'].corr(df3['target'], method='pearson')
print(f"Correlação de Pearson entre ext_source_3 e target: {pearson_corr:.4f}")

```



Correlação de Pearson entre ext\_source\_3 e target: -0.1574

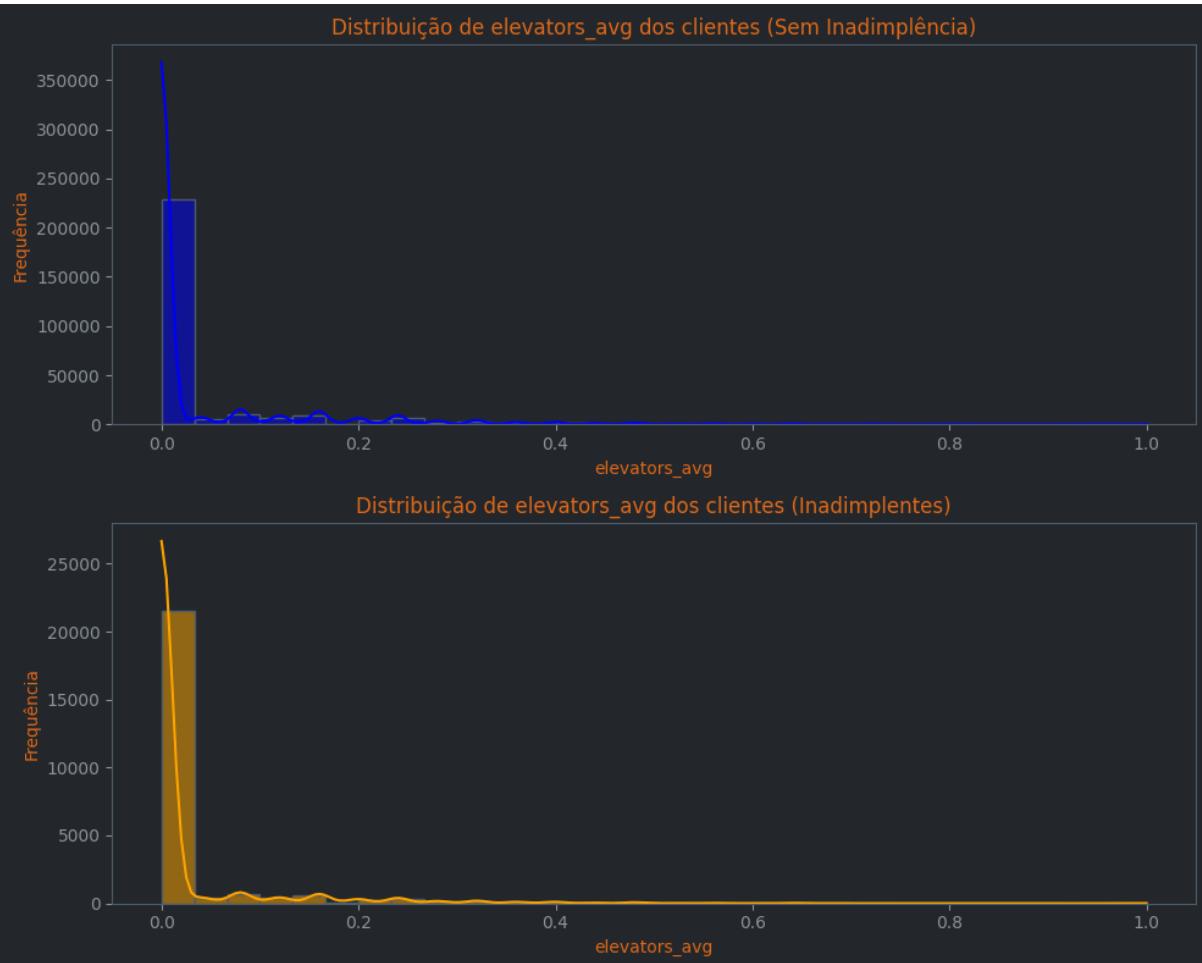
### Block 3 Hypothesis

H41 — The average number of elevators in a building is inversely related to the probability of default.  
TRUE

```

In [ ]: plot_num_var_by_target(
    df3,
    num_var='elevators_avg',
    title_0='Distribuição de elevators_avg dos clientes (Sem Inadimplência)',
    title_1='Distribuição de elevators_avg dos clientes (Inadimplentes)',
    label_x='elevators_avg',
    discrete=True
)
# Correlação de elevators_avg com a target
pearson_corr = df3['elevators_avg'].corr(df3['target'], method='pearson')
print(f"Correlação de Pearson entre elevators_avg e target: {pearson_corr:.4f}")

```



Correlação de Pearson entre elevators\_avg e target: -0.0359

H42 — Housing type influences default risk. TRUE

```
In [ ]: plot_target_by_categorical(df3, cat_col='housetype_mode', target_col='target')

calcular_cramers_v(df3, 'housetype_mode', 'target')
```



V de Cramer entre housetype\_mode e target: 0.0407

H43 — The main wall material of the property is associated with default risk. TRUE

```
In [ ]: plot_target_by_categorical(df3, cat_col='wallsmaterial_mode', target_col='target')
```

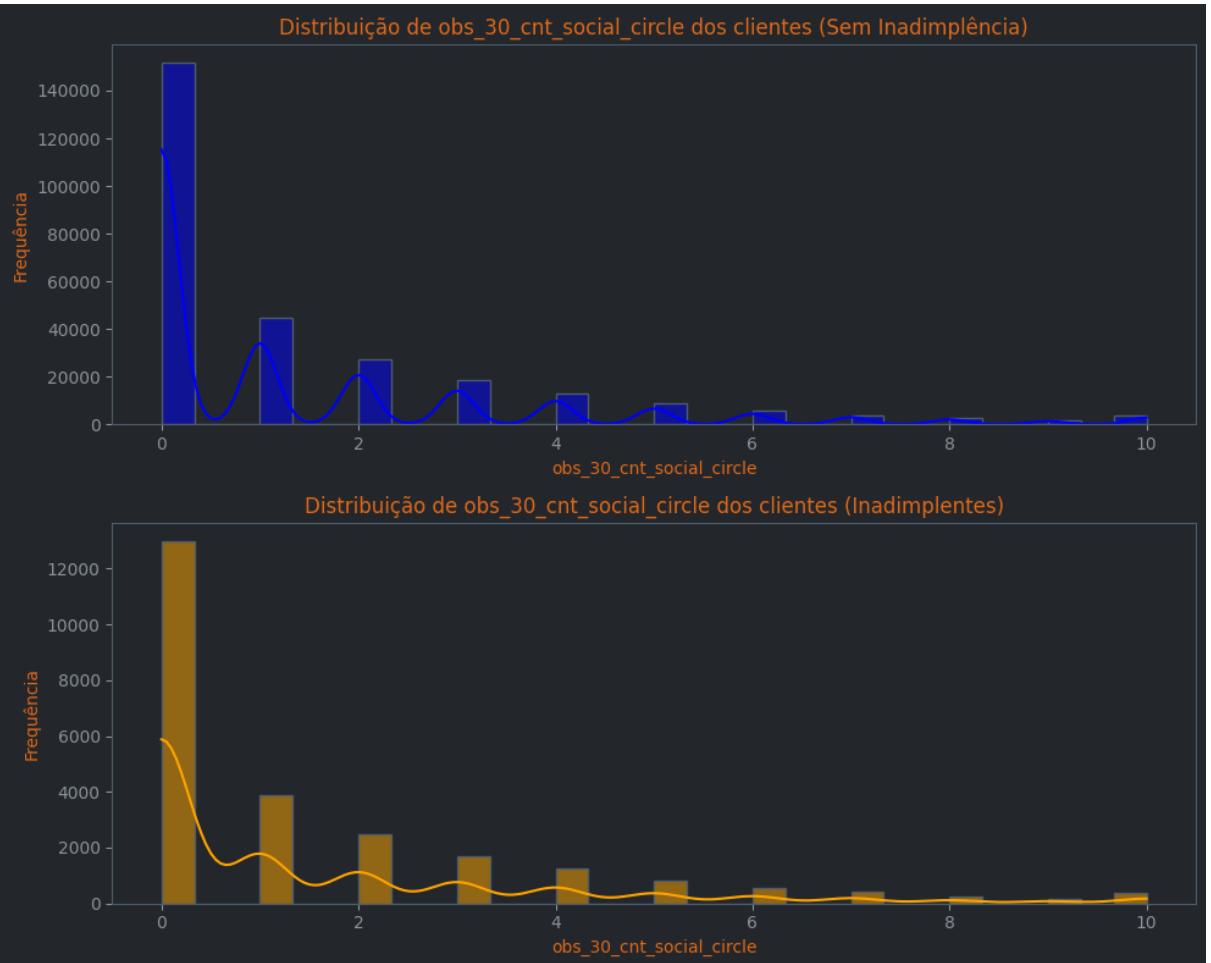
```
calcular_cramers_v(df3, 'wallsmaterial_mode', 'target')
```



V de Cramer entre wallsmaterial\_mode e target: 0.0441

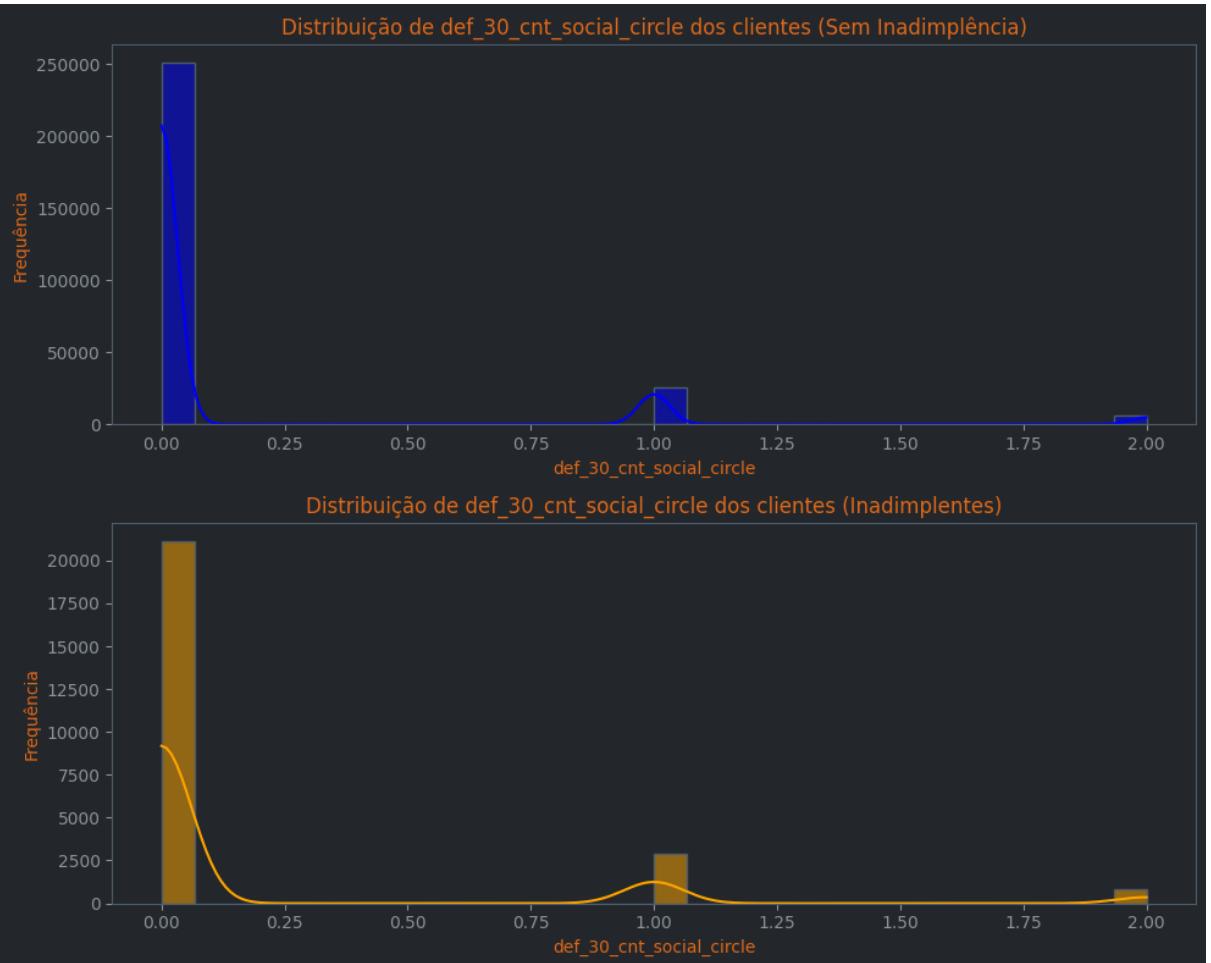
H44 — A higher number of observations or defaulters in the 30-day social circle increases the customer's probability of default. TRUE

```
In [ ]: plot_num_var_by_target(  
    df3,  
    num_var='obs_30_cnt_social_circle',  
    title_0='Distribuição de obs_30_cnt_social_circle dos clientes (Sem Inadimplência)',  
    title_1='Distribuição de obs_30_cnt_social_circle dos clientes (Inadimplentes)',  
    label_x='obs_30_cnt_social_circle',  
    discrete=True  
)  
# Correlação de obs_30_cnt_social_circle com a target  
pearson_corr = df3['obs_30_cnt_social_circle'].corr(df3['target'], method='pearson')  
print(f"Correlação de Pearson entre obs_30_cnt_social_circle e target: {pearson_corr:.4f}")
```



Correlação de Pearson entre obs\_30\_cnt\_social\_circle e target: 0.0104

```
In [ ]: plot_num_var_by_target(
    df3,
    num_var='def_30_cnt_social_circle',
    title_0='Distribuição de def_30_cnt_social_circle dos clientes (Sem Inadimplência)',
    title_1='Distribuição de def_30_cnt_social_circle dos clientes (Inadimplentes)',
    label_x='def_30_cnt_social_circle',
    discrete=True
)
# Correlação de def_30_cnt_social_circle com a target
pearson_corr = df3['def_30_cnt_social_circle'].corr(df3['target'], method='pearson')
print(f"Correlação de Pearson entre def_30_cnt_social_circle e target: {pearson_corr:.4f}")
```

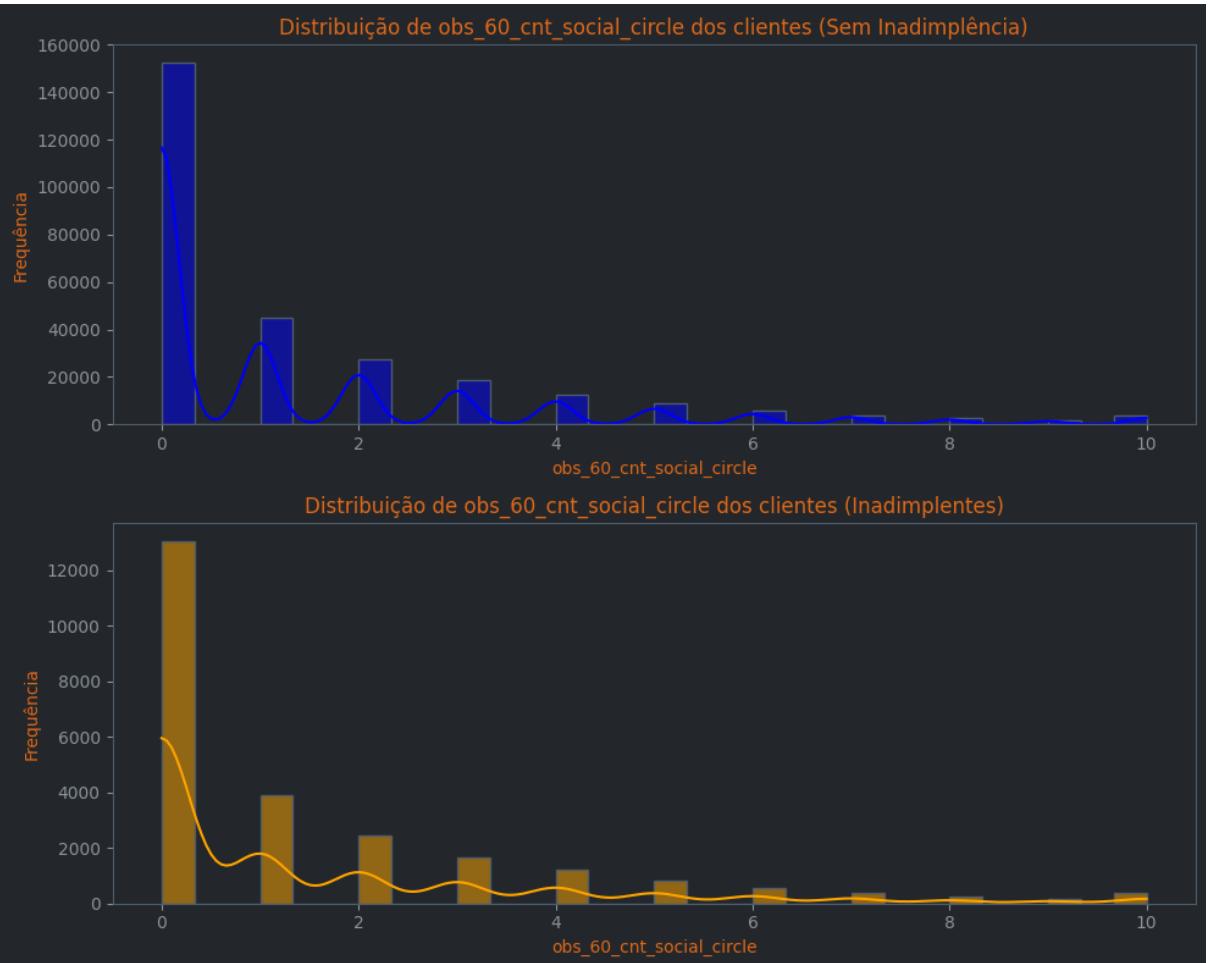


Correlação de Pearson entre def\_30\_cnt\_social\_circle e target: 0.0331

H45 — Default in the 60-day social circle is positively associated with individual default risk. TRUE

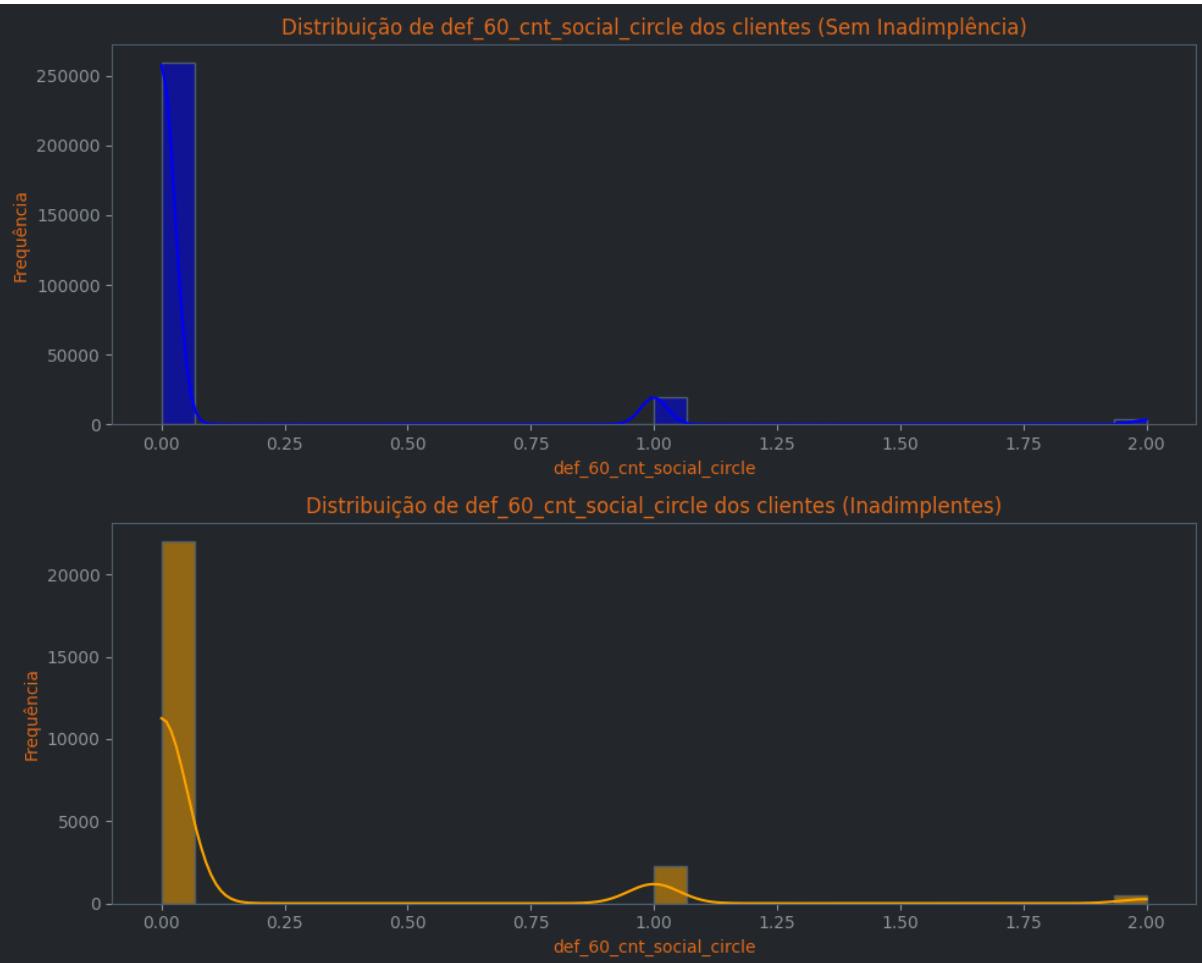
```
In [ ]: plot_num_var_by_target(
    df3,
    num_var='obs_60_cnt_social_circle',
    title_0='Distribuição de obs_60_cnt_social_circle dos clientes (Sem Inadimplência)',
    title_1='Distribuição de obs_60_cnt_social_circle dos clientes (Inadimplentes)',
    label_x='obs_60_cnt_social_circle',
    discrete=True
)

# Correlação de obs_60_cnt_social_circle com a target
pearson_corr = df3['obs_60_cnt_social_circle'].corr(df3['target'], method='pearson')
print(f"Correlação de Pearson entre obs_60_cnt_social_circle e target: {pearson_corr:.4f}")
```



Correlação de Pearson entre obs\_60\_cnt\_social\_circle e target: 0.0103

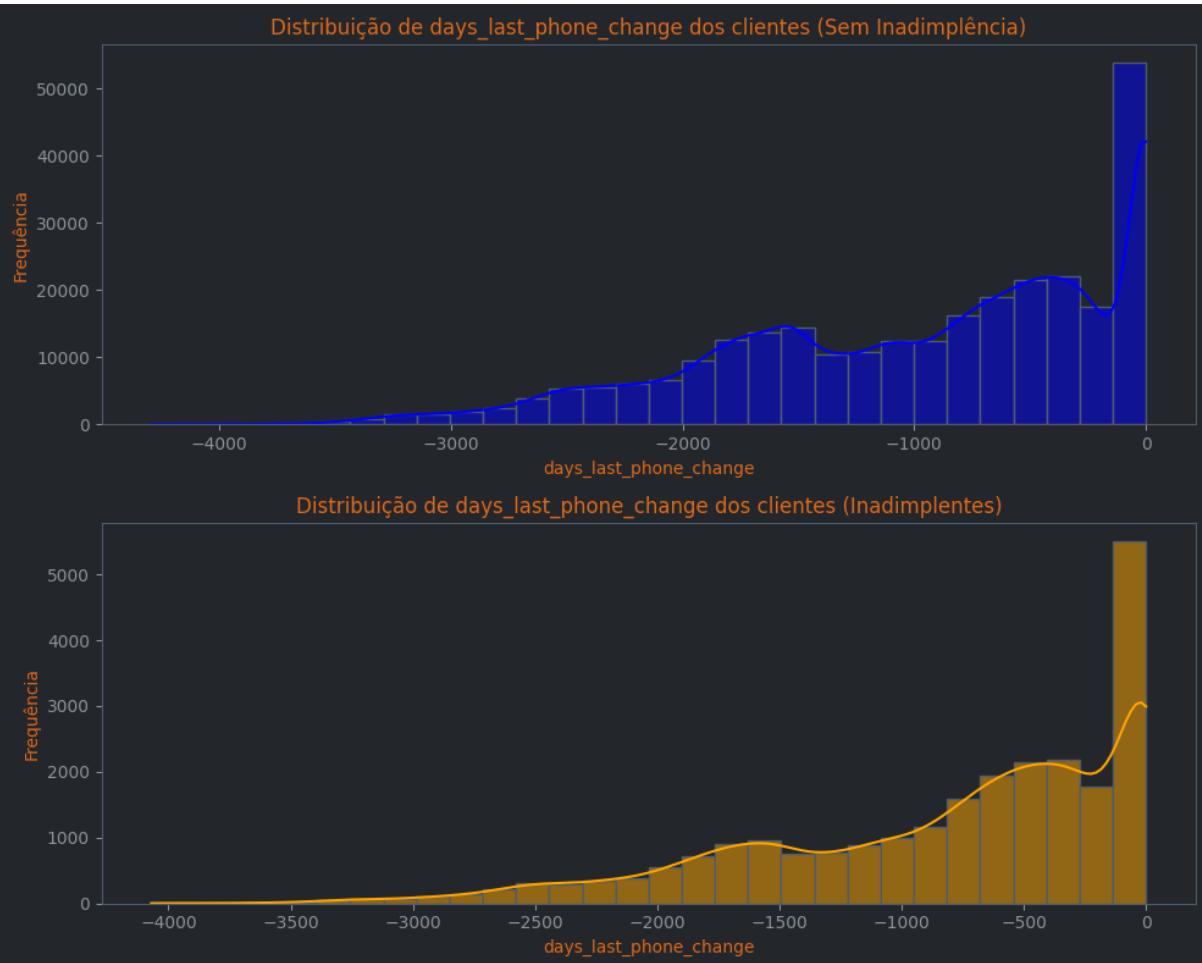
```
In [ ]: plot_num_var_by_target(
    df3,
    num_var='def_60_cnt_social_circle',
    title_0='Distribuição de def_60_cnt_social_circle dos clientes (Sem Inadimplência)',
    title_1='Distribuição de def_60_cnt_social_circle dos clientes (Inadimplentes)',
    label_x='def_60_cnt_social_circle',
    discrete=True
)
# Correlação de def_60_cnt_social_circle com a target
pearson_corr = df3['def_60_cnt_social_circle'].corr(df3['target'], method='pearson')
print(f"Correlação de Pearson entre def_60_cnt_social_circle e target: {pearson_corr:.4f}")
```



Correlação de Pearson entre def\_60\_cnt\_social\_circle e target: 0.0318

H46 — The time since the last phone change is related to default probability. FALSE

```
In [ ]: plot_num_var_by_target(
    df3,
    num_var='days_last_phone_change',
    title_0='Distribuição de days_last_phone_change dos clientes (Sem Inadimplência)',
    title_1='Distribuição de days_last_phone_change dos clientes (Inadimplentes)',
    label_x='days_last_phone_change',
    discrete=True
)
# Correlação de days_Last_phone_change com a target
pearson_corr = df3['days_last_phone_change'].corr(df3['target'], method='pearson')
print(f"Correlação de Pearson entre days_last_phone_change e target: {pearson_corr:.4f}")
```

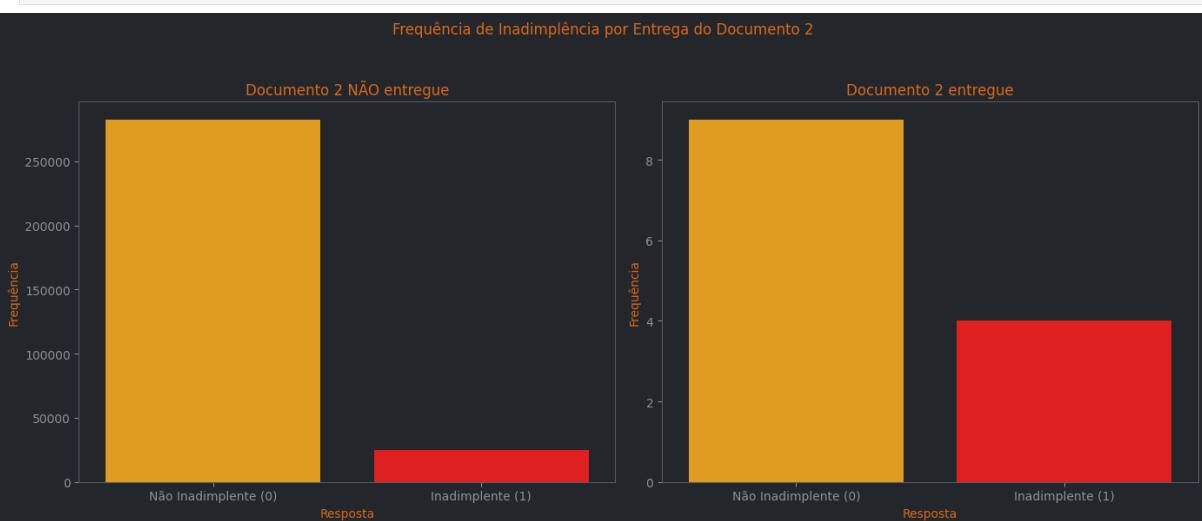


Correlação de Pearson entre days\_last\_phone\_change e target: 0.0552

H47 — The number of submitted documents is inversely associated with default. FALSE

flag\_document\_2

```
In [ ]: plot_binaria_target(
    df3,
    var_binaria='flag_document_2',
    label_0='Documento 2 NÃO entregue',
    label_1='Documento 2 entregue',
    suptitle='Frequência de Inadimplência por Entrega do Documento 2'
)
calcular_cramers_v(df3, 'flag_document_2', 'target')
```

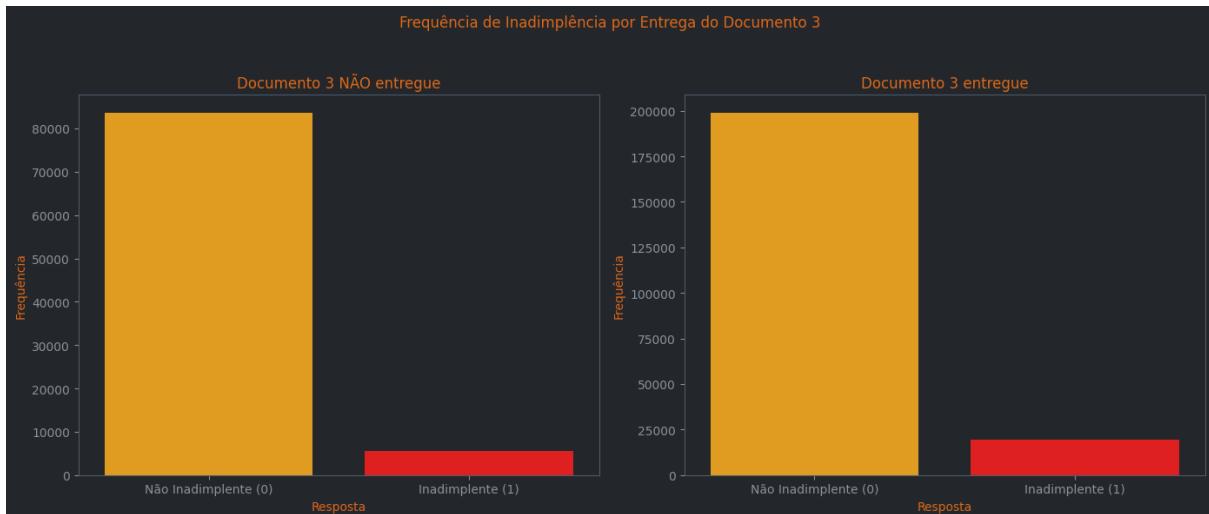


V de Cramer entre flag\_document\_2 e target: 0.0045

flag\_document\_3

```
In [ ]: plot_binaria_target(
    df3,
    var_binaria='flag_document_3',
    label_0='Documento 3 NÃO entregue',
    label_1='Documento 3 entregue',
    suptitle='Frequência de Inadimplência por Entrega do Documento 3'
)

calcular_cramers_v(df3, 'flag_document_3', 'target')
```

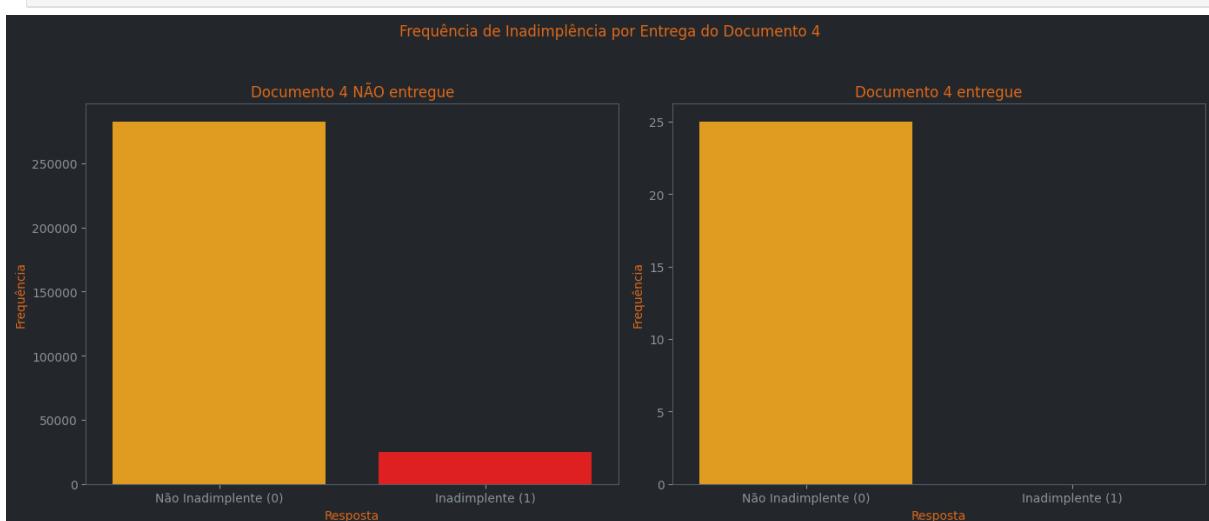


V de Cramer entre flag\_document\_3 e target: 0.0443

flag\_document\_4

```
In [ ]: plot_binaria_target(
    df3,
    var_binaria='flag_document_4',
    label_0='Documento 4 NÃO entregue',
    label_1='Documento 4 entregue',
    suptitle='Frequência de Inadimplência por Entrega do Documento 4'
)

calcular_cramers_v(df3, 'flag_document_4', 'target')
```

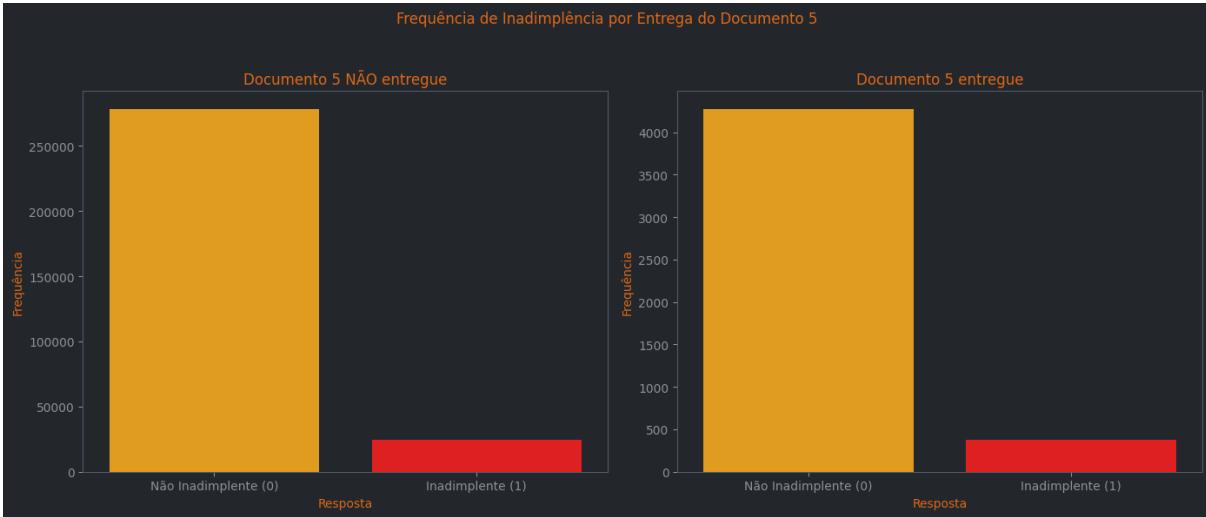


V de Cramer entre flag\_document\_4 e target: 0.0020

flag\_document\_5

```
In [ ]: plot_binaria_target(
    df3,
    var_binaria='flag_document_5',
    label_0='Documento 5 NÃO entregue',
    label_1='Documento 5 entregue',
    suptitle='Frequência de Inadimplência por Entrega do Documento 5'
)
```

```
calcular_cramers_v(df3, 'flag_document_5', 'target')
```

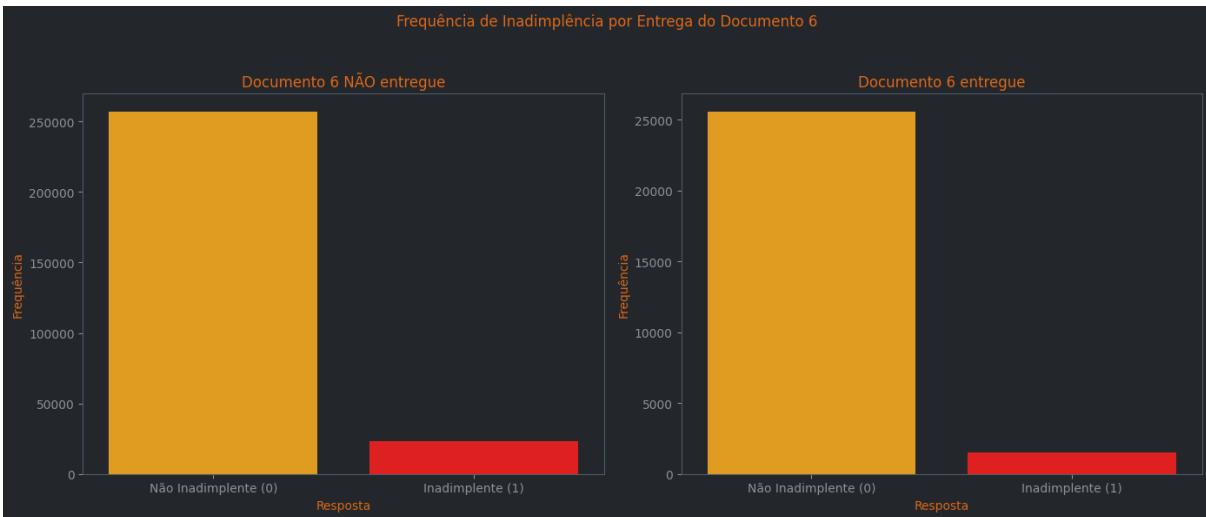


V de Cramer entre flag\_document\_5 e target: 0.0003

flag\_document\_6

```
In [ ]: plot_binaria_target(  
        df3,  
        var_binaria='flag_document_6',  
        label_0='Documento 6 NÃO entregue',  
        label_1='Documento 6 entregue',  
        suptitle='Frequência de Inadimplência por Entrega do Documento 6'  
)
```

```
calcular_cramers_v(df3, 'flag_document_6', 'target')
```



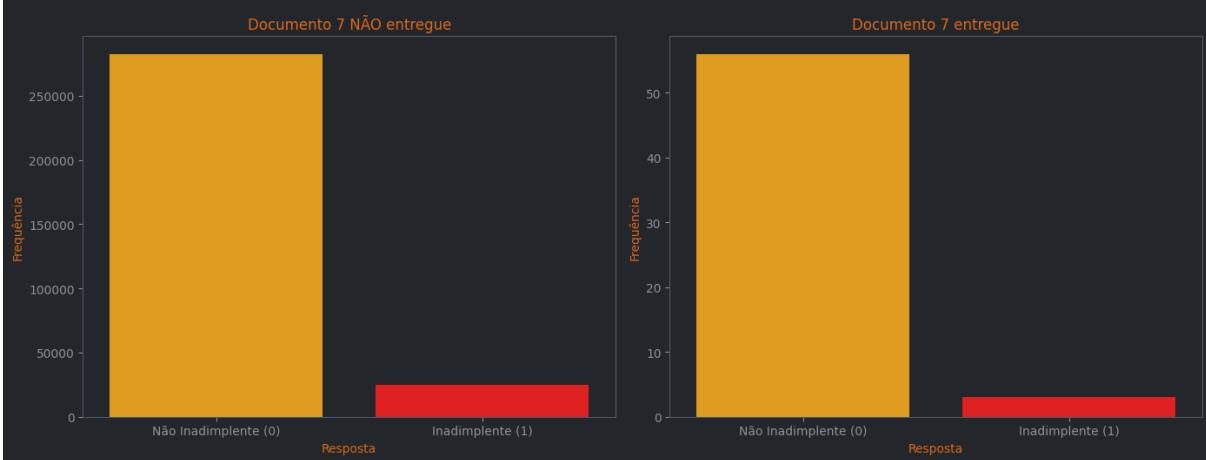
V de Cramer entre flag\_document\_6 e target: 0.0286

flag\_document\_7

```
In [ ]: plot_binaria_target(  
        df3,  
        var_binaria='flag_document_7',  
        label_0='Documento 7 NÃO entregue',  
        label_1='Documento 7 entregue',  
        suptitle='Frequência de Inadimplência por Entrega do Documento 7'  
)
```

```
calcular_cramers_v(df3, 'flag_document_7', 'target')
```

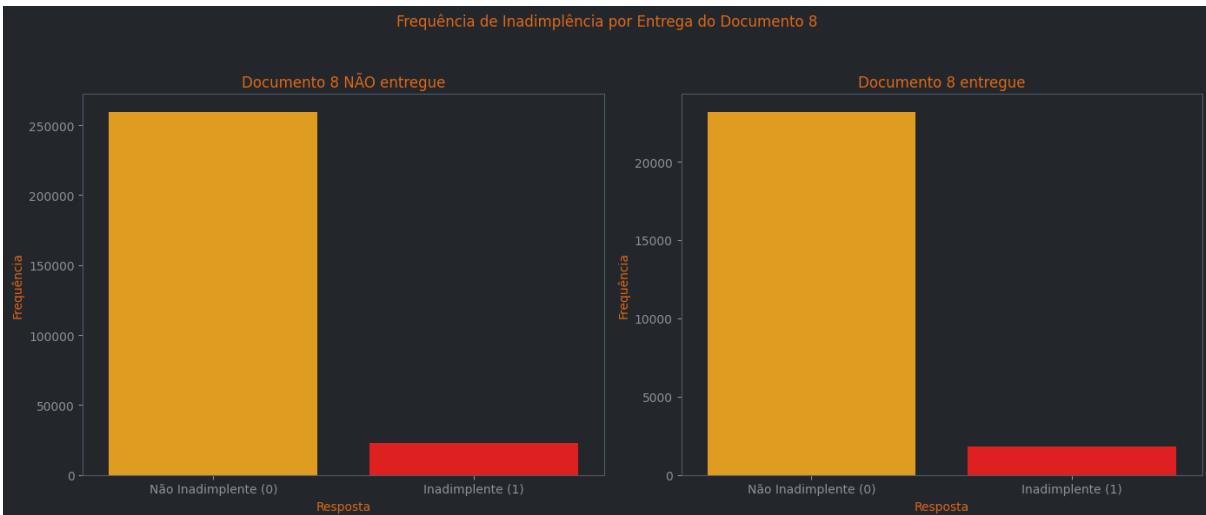
Frequência de Inadimplência por Entrega do Documento 7



V de Cramer entre flag\_document\_7 e target: 0.0011

flag\_document\_8

```
In [ ]: plot_binaria_target(  
        df3,  
        var_binaria='flag_document_8',  
        label_0='Documento 8 NÃO entregue',  
        label_1='Documento 8 entregue',  
        suptitle='Frequência de Inadimplência por Entrega do Documento 8'  
)  
  
calcular_cramers_v(df3, 'flag_document_8', 'target')
```

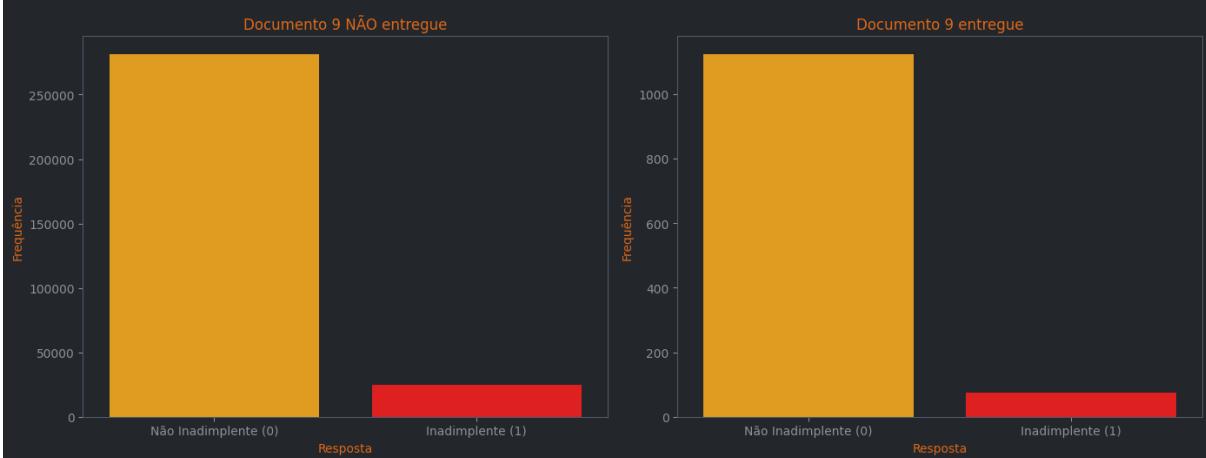


V de Cramer entre flag\_document\_8 e target: 0.0080

flag\_document\_9

```
In [ ]: plot_binaria_target(  
        df3,  
        var_binaria='flag_document_9',  
        label_0='Documento 9 NÃO entregue',  
        label_1='Documento 9 entregue',  
        suptitle='Frequência de Inadimplência por Entrega do Documento 9'  
)  
  
calcular_cramers_v(df3, 'flag_document_9', 'target')
```

Frequência de Inadimplência por Entrega do Documento 9

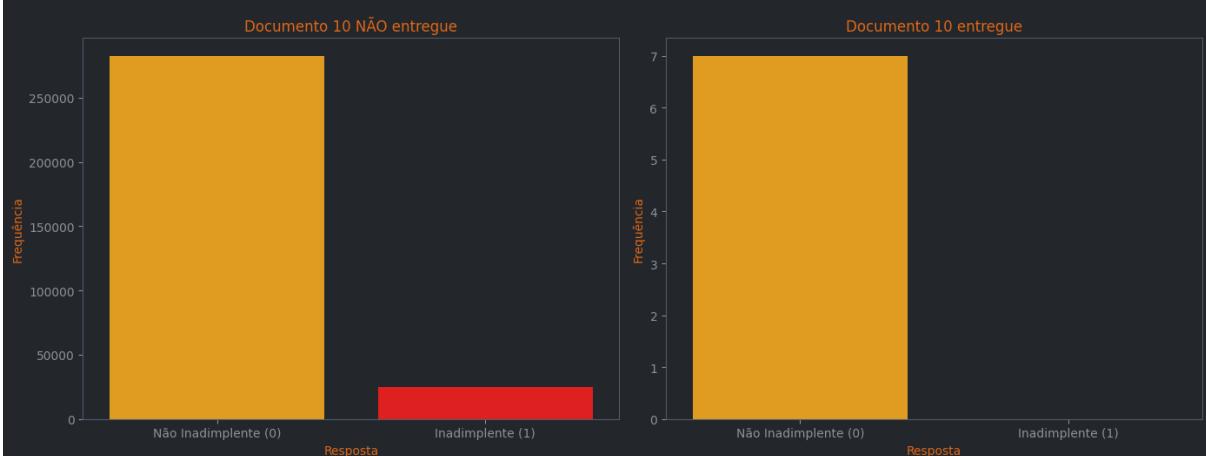


V de Cramer entre flag\_document\_9 e target: 0.0043

flag\_document\_10

```
In [ ]: plot_binaria_target(  
        df3,  
        var_binaria='flag_document_10',  
        label_0='Documento 10 NÃO entregue',  
        label_1='Documento 10 entregue',  
        suptitle='Frequência de Inadimplência por Entrega do Documento 10'  
)  
  
calcular_cramers_v(df3, 'flag_document_10', 'target')
```

Frequência de Inadimplência por Entrega do Documento 10

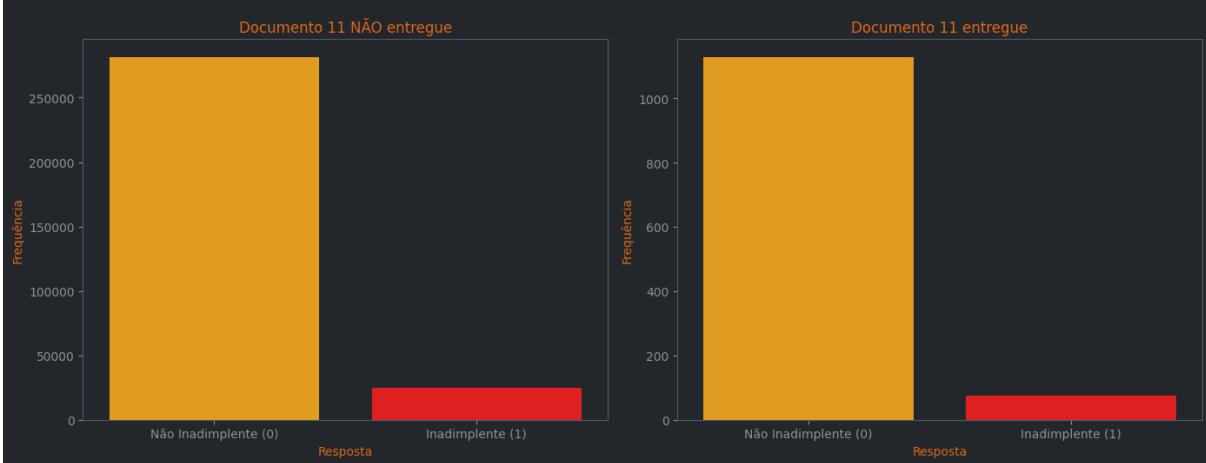


V de Cramer entre flag\_document\_10 e target: 0.0002

flag\_document\_11

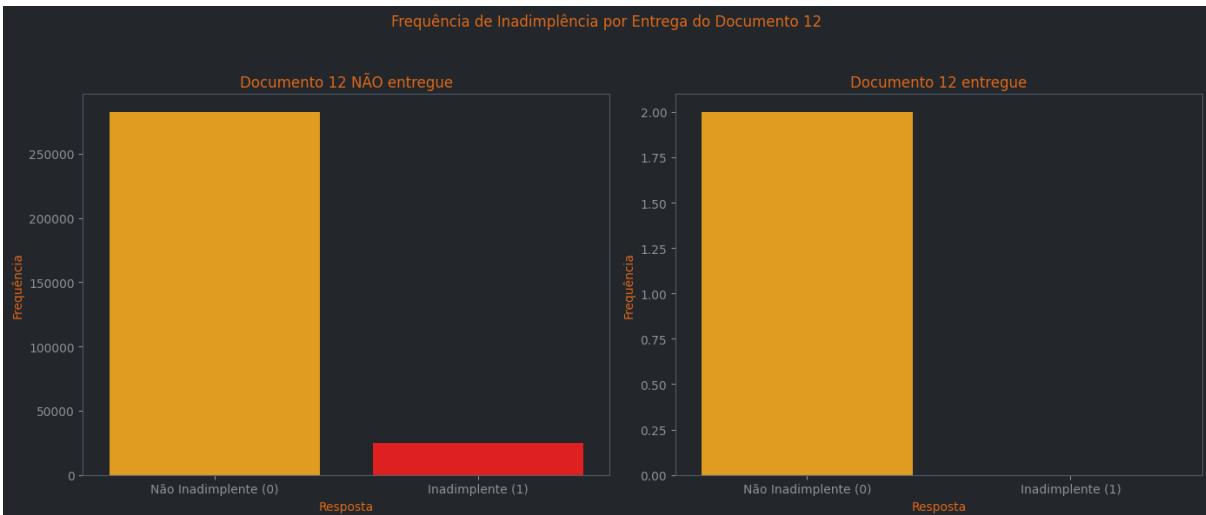
```
In [ ]: plot_binaria_target(  
        df3,  
        var_binaria='flag_document_11',  
        label_0='Documento 11 NÃO entregue',  
        label_1='Documento 11 entregue',  
        suptitle='Frequência de Inadimplência por Entrega do Documento 11'  
)  
  
calcular_cramers_v(df3, 'flag_document_11', 'target')
```

Frequência de Inadimplência por Entrega do Documento 11



flag\_document\_12

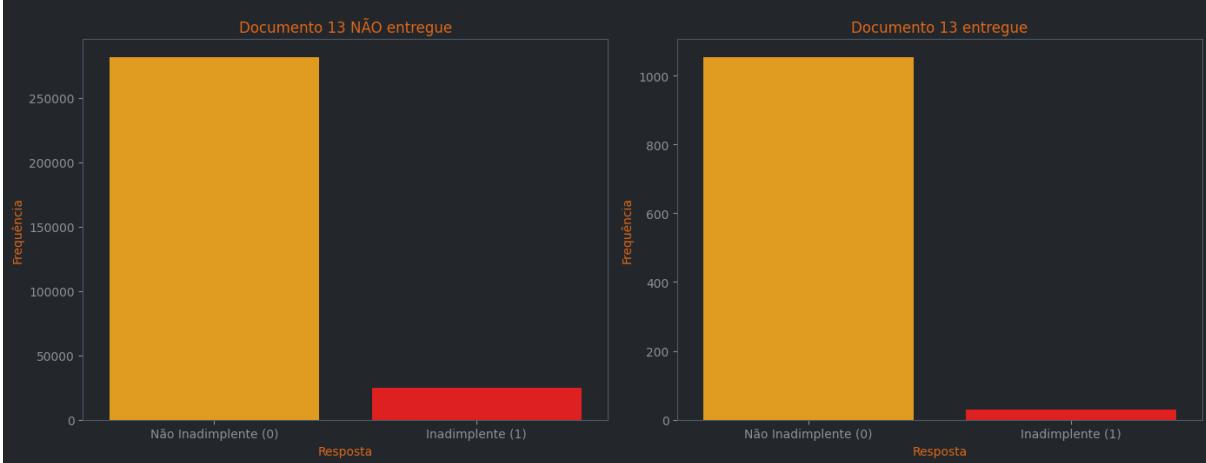
```
In [ ]: plot_binaria_target(  
        df3,  
        var_binaria='flag_document_12',  
        label_0='Documento 12 NÃO entregue',  
        label_1='Documento 12 entregue',  
        suptitle='Frequência de Inadimplência por Entrega do Documento 12'  
)  
  
calcular_cramers_v(df3, 'flag_document_12', 'target')
```



flag\_document\_13

```
In [ ]: plot_binaria_target(  
        df3,  
        var_binaria='flag_document_13',  
        label_0='Documento 13 NÃO entregue',  
        label_1='Documento 13 entregue',  
        suptitle='Frequência de Inadimplência por Entrega do Documento 13'  
)  
  
calcular_cramers_v(df3, 'flag_document_13', 'target')
```

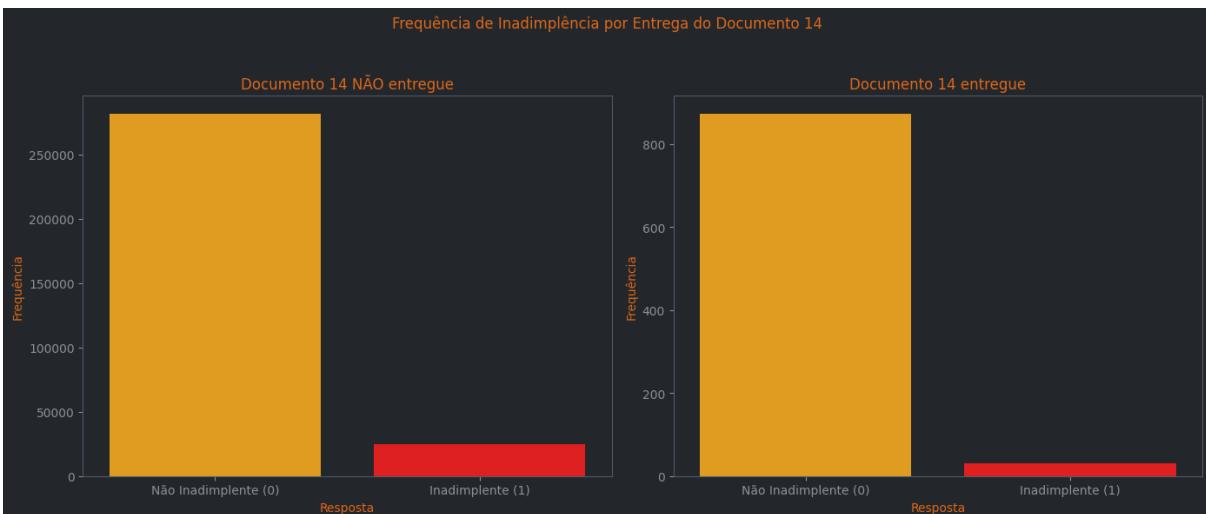
Frequência de Inadimplência por Entrega do Documento 13



V de Cramer entre flag\_document\_13 e target: 0.0115

flag\_document\_14

```
In [ ]: plot_binaria_target(  
        df3,  
        var_binaria='flag_document_14',  
        label_0='Documento 14 NÃO entregue',  
        label_1='Documento 14 entregue',  
        suptitle='Frequência de Inadimplência por Entrega do Documento 14'  
)  
calcular_cramers_v(df3, 'flag_document_14', 'target')
```

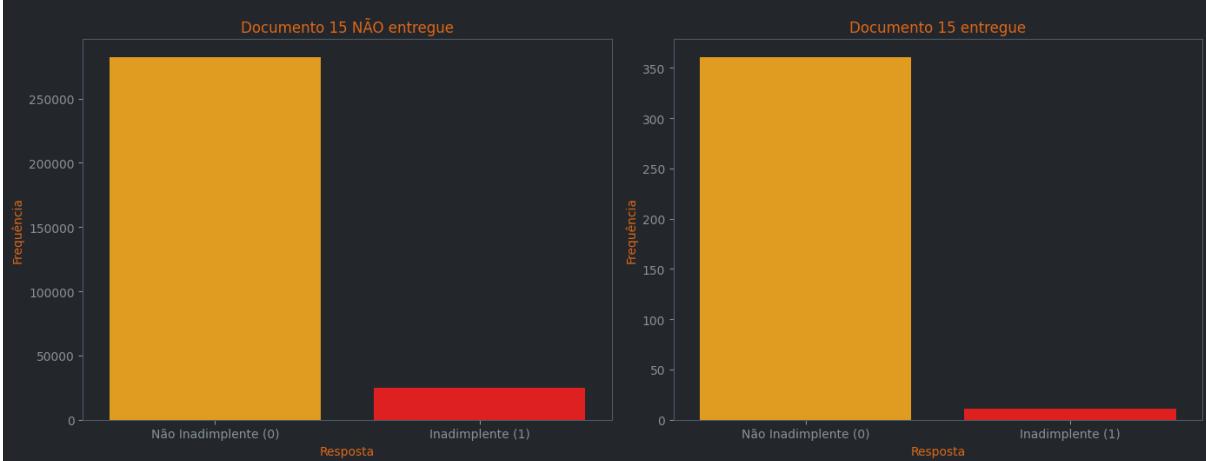


V de Cramer entre flag\_document\_14 e target: 0.0094

flag\_document\_15

```
In [ ]: plot_binaria_target(  
        df3,  
        var_binaria='flag_document_15',  
        label_0='Documento 15 NÃO entregue',  
        label_1='Documento 15 entregue',  
        suptitle='Frequência de Inadimplência por Entrega do Documento 15'  
)  
calcular_cramers_v(df3, 'flag_document_15', 'target')
```

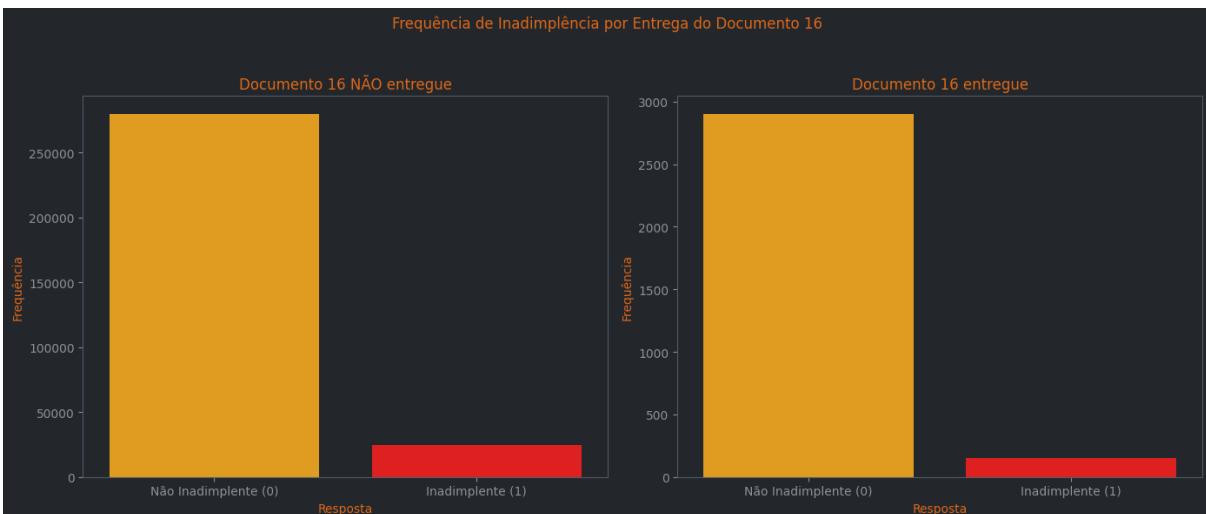
Frequência de Inadimplência por Entrega do Documento 15



V de Cramer entre flag\_document\_15 e target: 0.0064

flag\_document\_16

```
In [ ]: plot_binaria_target(  
        df3,  
        var_binaria='flag_document_16',  
        label_0='Documento 16 NÃO entregue',  
        label_1='Documento 16 entregue',  
        suptitle='Frequência de Inadimplência por Entrega do Documento 16'  
)  
  
calcular_cramers_v(df3, 'flag_document_16', 'target')
```

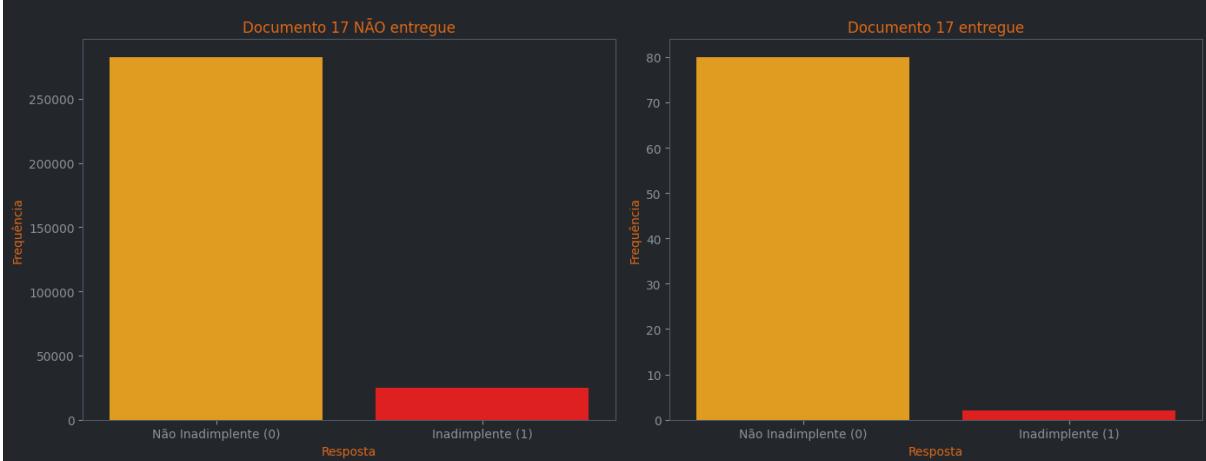


V de Cramer entre flag\_document\_16 e target: 0.0116

flag\_document\_17

```
In [ ]: plot_binaria_target(  
        df3,  
        var_binaria='flag_document_17',  
        label_0='Documento 17 NÃO entregue',  
        label_1='Documento 17 entregue',  
        suptitle='Frequência de Inadimplência por Entrega do Documento 17'  
)  
  
calcular_cramers_v(df3, 'flag_document_17', 'target')
```

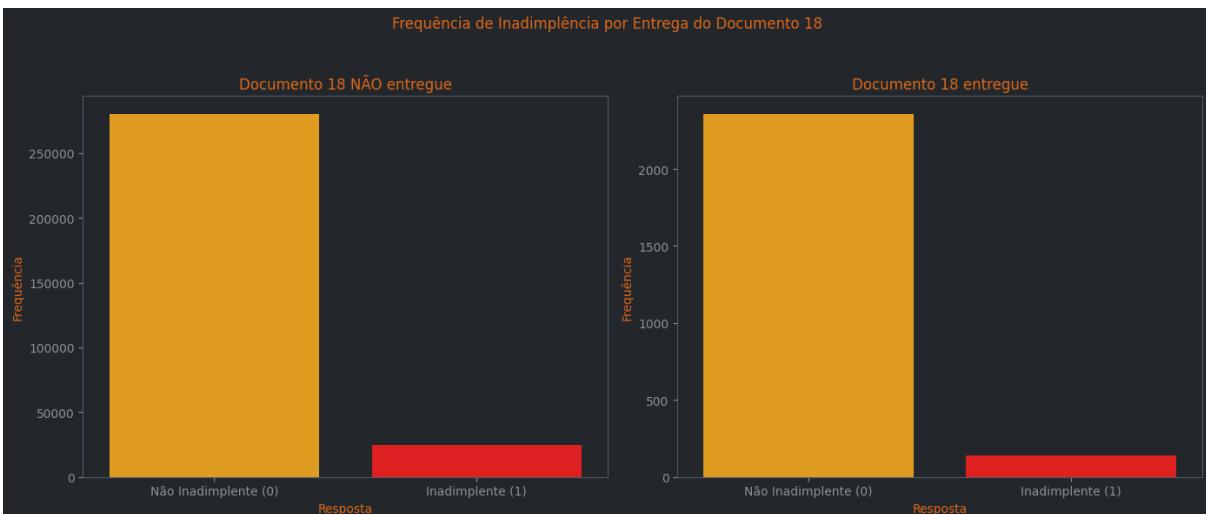
Frequência de Inadimplência por Entrega do Documento 17



V de Cramer entre flag\_document\_17 e target: 0.0030

flag\_document\_18

```
In [ ]: plot_binaria_target(  
        df3,  
        var_binaria='flag_document_18',  
        label_0='Documento 18 NÃO entregue',  
        label_1='Documento 18 entregue',  
        suptitle='Frequência de Inadimplência por Entrega do Documento 18'  
)  
  
calcular_cramers_v(df3, 'flag_document_18', 'target')
```

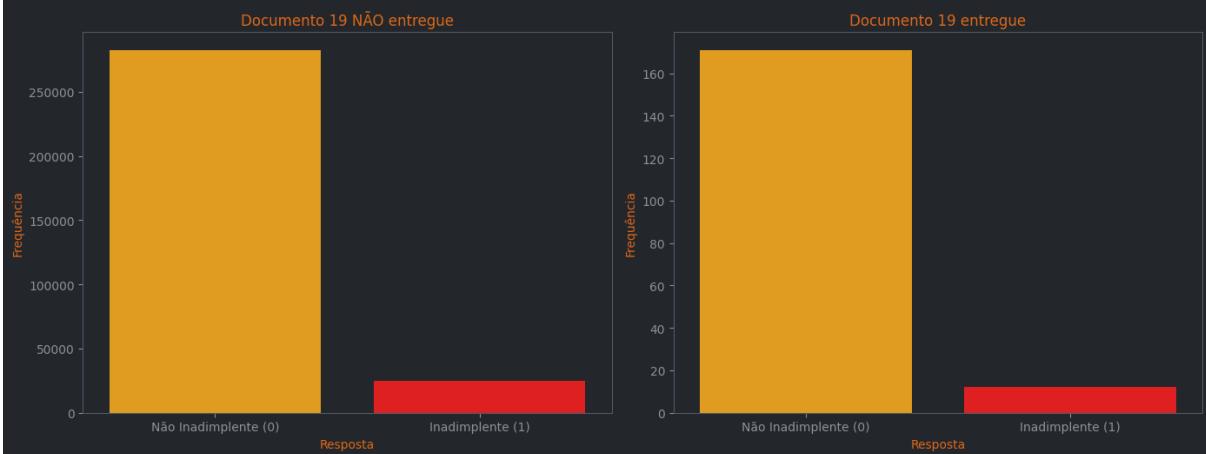


V de Cramer entre flag\_document\_18 e target: 0.0079

flag\_document\_19

```
In [ ]: plot_binaria_target(  
        df3,  
        var_binaria='flag_document_19',  
        label_0='Documento 19 NÃO entregue',  
        label_1='Documento 19 entregue',  
        suptitle='Frequência de Inadimplência por Entrega do Documento 19'  
)  
  
calcular_cramers_v(df3, 'flag_document_19', 'target')
```

#### Frequência de Inadimplência por Entrega do Documento 19



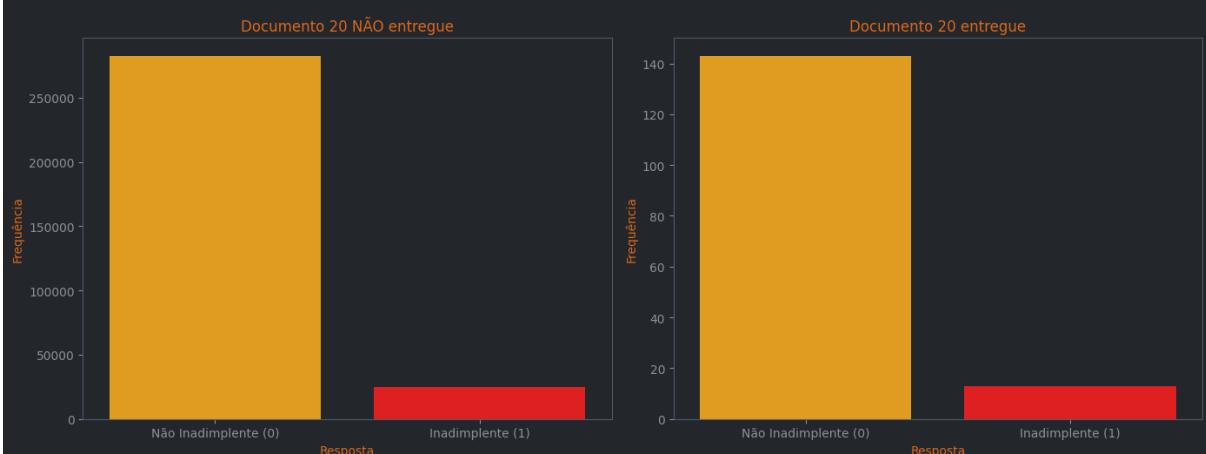
V de Cramer entre flag\_document\_19 e target: 0.0011

flag\_document\_20

```
In [ ]: plot_binaria_target(
    df3,
    var_binaria='flag_document_20',
    label_0='Documento 20 NÃO entregue',
    label_1='Documento 20 entregue',
    suptitle='Frequência de Inadimplência por Entrega do Documento 20'
)

calcular_cramers_v(df3, 'flag_document_20', 'target')
```

#### Frequência de Inadimplência por Entrega do Documento 20

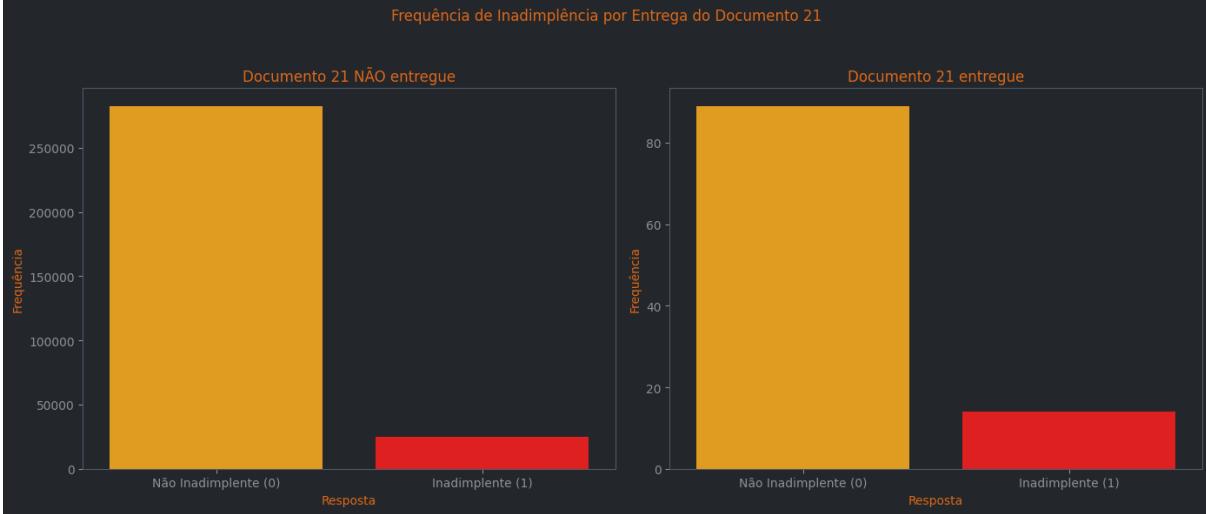


V de Cramer entre flag\_document\_20 e target: 0.0000

flag\_document\_21

```
In [ ]: plot_binaria_target(
    df3,
    var_binaria='flag_document_21',
    label_0='Documento 21 NÃO entregue',
    label_1='Documento 21 entregue',
    suptitle='Frequência de Inadimplência por Entrega do Documento 21'
)

calcular_cramers_v(df3, 'flag_document_21', 'target')
```



V de Cramer entre flag\_document\_21 e target: 0.0034

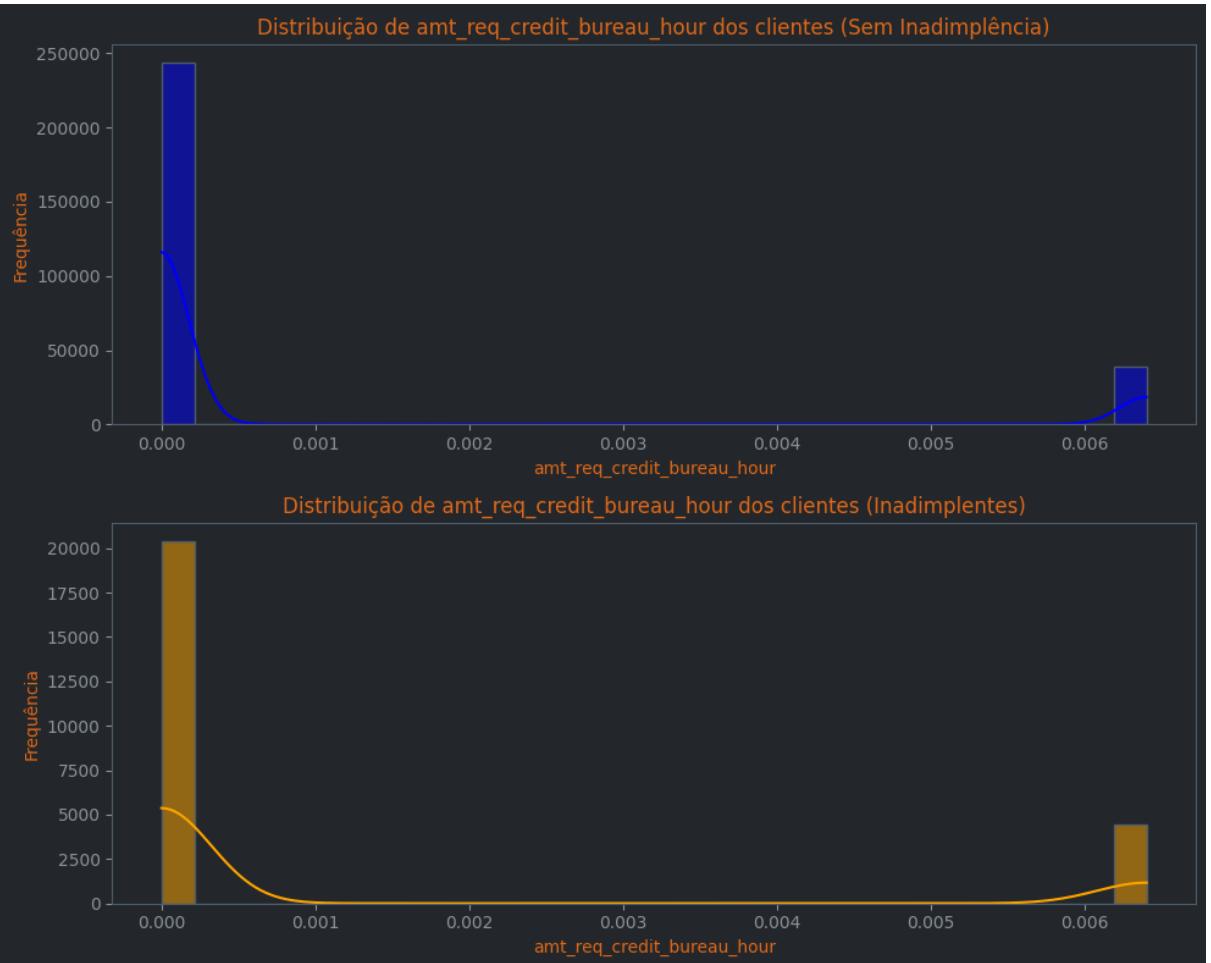
#### Block 4 Hypothesis

H48 — Credit inquiry history and credit amounts influence the probability of default. TRUE

amt\_req\_credit\_bureau\_hour

```
In [ ]: plot_num_var_by_target(
    df3,
    num_var='amt_req_credit_bureau_hour',
    title_0='Distribuição de amt_req_credit_bureau_hour dos clientes (Sem Inadimplência)',
    title_1='Distribuição de amt_req_credit_bureau_hour dos clientes (Inadimplentes)',
    label_x='amt_req_credit_bureau_hour',
    discrete=True
)

# Correlação de amt_req_credit_bureau_hour com a target
pearson_corr = df3['amt_req_credit_bureau_hour'].corr(df3['target'], method='pearson')
print(f"Correlação de Pearson entre amt_req_credit_bureau_hour e target: {pearson_corr:.4f}")
```



Correlação de Pearson entre amt\_req\_credit\_bureau\_hour e target: 0.0323

amt\_req\_credit\_bureau\_day

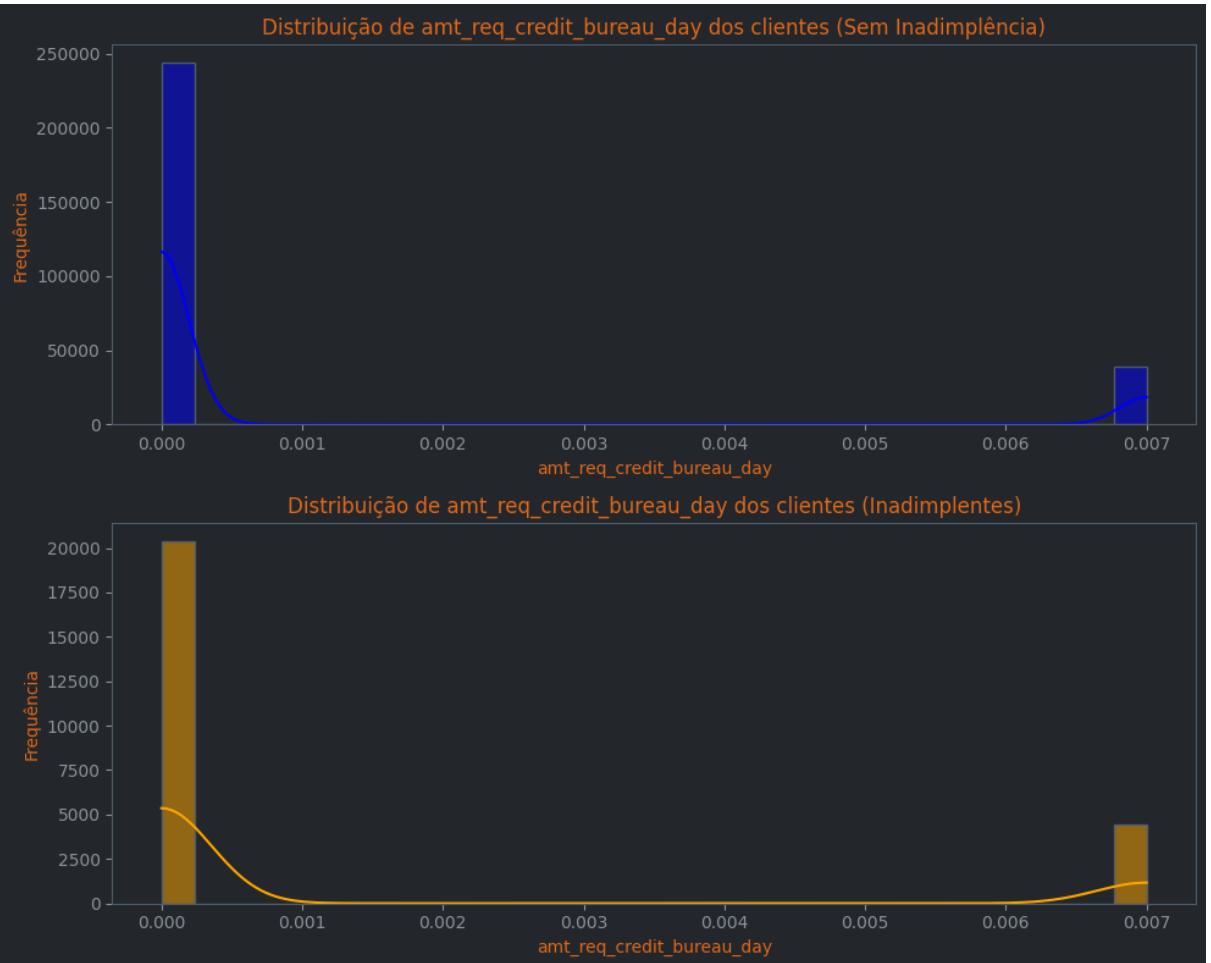
```
In [ ]: fig, axes = plt.subplots(2, 1, figsize=(10, 8), sharey=False)

sns.histplot(
    data=df3[df3['target'] == 0],
    x='amt_req_credit_bureau_day',
    color='blue',
    ax=axes[0],
    kde=True,
    bins=30
)
axes[0].set_title('Distribuição de amt_req_credit_bureau_day dos clientes (Sem Inadimplência)')
axes[0].set_ylabel('Frequência')
axes[0].set_xlabel('amt_req_credit_bureau_day')

sns.histplot(
    data=df3[df3['target'] == 1],
    x='amt_req_credit_bureau_day',
    color='orange',
    ax=axes[1],
    kde=True,
    bins=30
)
axes[1].set_title('Distribuição de amt_req_credit_bureau_day dos clientes (Inadimplentes)')
axes[1].set_ylabel('Frequência')
axes[1].set_xlabel('amt_req_credit_bureau_day')

plt.tight_layout()
plt.show()

pearson_corr = df3['amt_req_credit_bureau_day'].corr(df3['target'], method='pearson')
print(f"Correlação de Pearson entre amt_req_credit_bureau_day e target: {pearson_corr:.4f}")
```



Correlação de Pearson entre amt\_req\_credit\_bureau\_day e target: 0.0331

amt\_req\_credit\_bureau\_week

```
In [ ]: fig, axes = plt.subplots(2, 1, figsize=(10, 8), sharey=False)

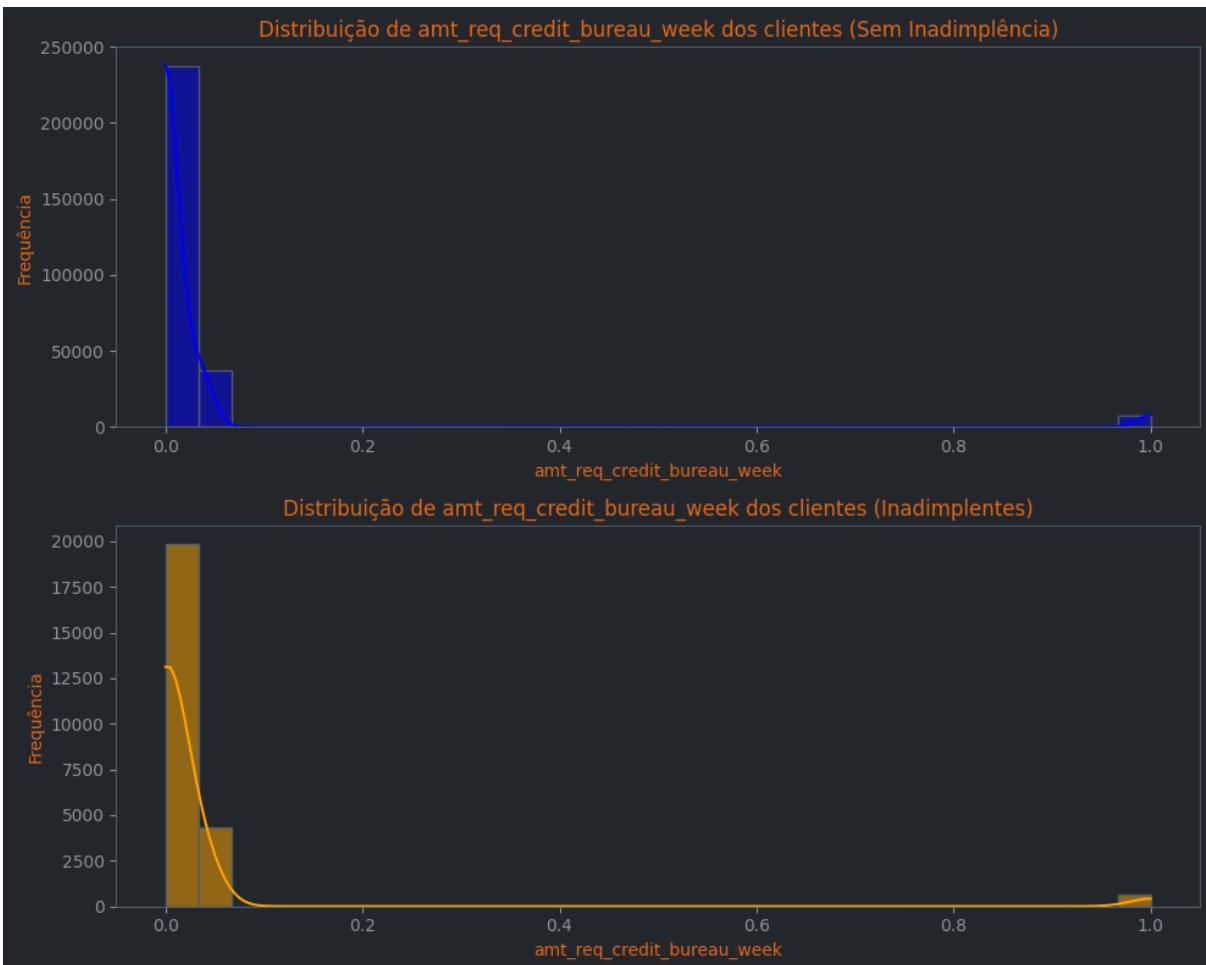
sns.histplot(
    data=df3[df3['target'] == 0],
    x='amt_req_credit_bureau_week',
    color='blue',
    ax=axes[0],
    kde=True,
    bins=30
)
axes[0].set_title('Distribuição de amt_req_credit_bureau_week dos clientes (Sem Inadimplência)')
axes[0].set_ylabel('Frequência')
axes[0].set_xlabel('amt_req_credit_bureau_week')

sns.histplot(
    data=df3[df3['target'] == 1],
    x='amt_req_credit_bureau_week',
    color='orange',
    ax=axes[1],
    kde=True,
    bins=30
)
axes[1].set_title('Distribuição de amt_req_credit_bureau_week dos clientes (Inadimplentes)')
axes[1].set_ylabel('Frequência')
axes[1].set_xlabel('amt_req_credit_bureau_week')

plt.tight_layout()
plt.show()

pearson_corr = df3['amt_req_credit_bureau_week'].corr(df3['target'], method='pearson')
```

```
print(f"Correlação de Pearson entre amt_req_credit_bureau_week e target: {pearson_corr:.4f}")
```



Correlação de Pearson entre amt\_req\_credit\_bureau\_week e target: 0.0008

amt\_req\_credit\_bureau\_mon

```
In [ ]: fig, axes = plt.subplots(2, 1, figsize=(10, 8), sharey=False)

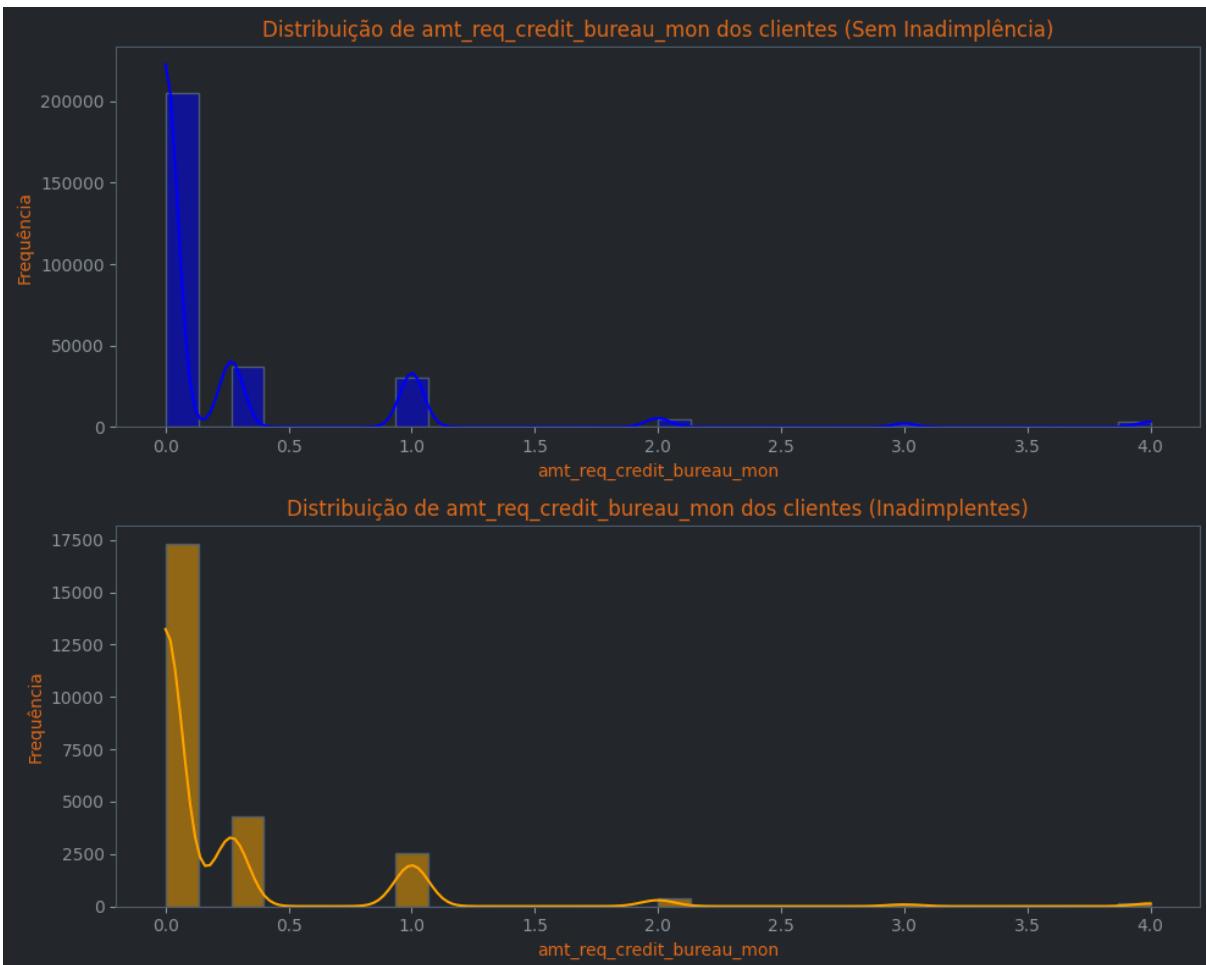
sns.histplot(
    data=df3[df3['target'] == 0],
    x='amt_req_credit_bureau_mon',
    color='blue',
    ax=axes[0],
    kde=True,
    bins=30
)
axes[0].set_title('Distribuição de amt_req_credit_bureau_mon dos clientes (Sem Inadimplência)')
axes[0].set_ylabel('Frequência')
axes[0].set_xlabel('amt_req_credit_bureau_mon')

sns.histplot(
    data=df3[df3['target'] == 1],
    x='amt_req_credit_bureau_mon',
    color='orange',
    ax=axes[1],
    kde=True,
    bins=30
)
axes[1].set_title('Distribuição de amt_req_credit_bureau_mon dos clientes (Inadimplentes)')
axes[1].set_ylabel('Frequência')
axes[1].set_xlabel('amt_req_credit_bureau_mon')

plt.tight_layout()
plt.show()

pearson_corr = df3['amt_req_credit_bureau_mon'].corr(df3['target'], method='pearson')
```

```
print(f"Correlação de Pearson entre amt_req_credit_bureau_mon e target: {pearson_corr:.4f}")
```



Correlação de Pearson entre amt\_req\_credit\_bureau\_mon e target: -0.0099

amt\_req\_credit\_bureau\_qrt

```
In [ ]: fig, axes = plt.subplots(2, 1, figsize=(10, 8), sharey=False)

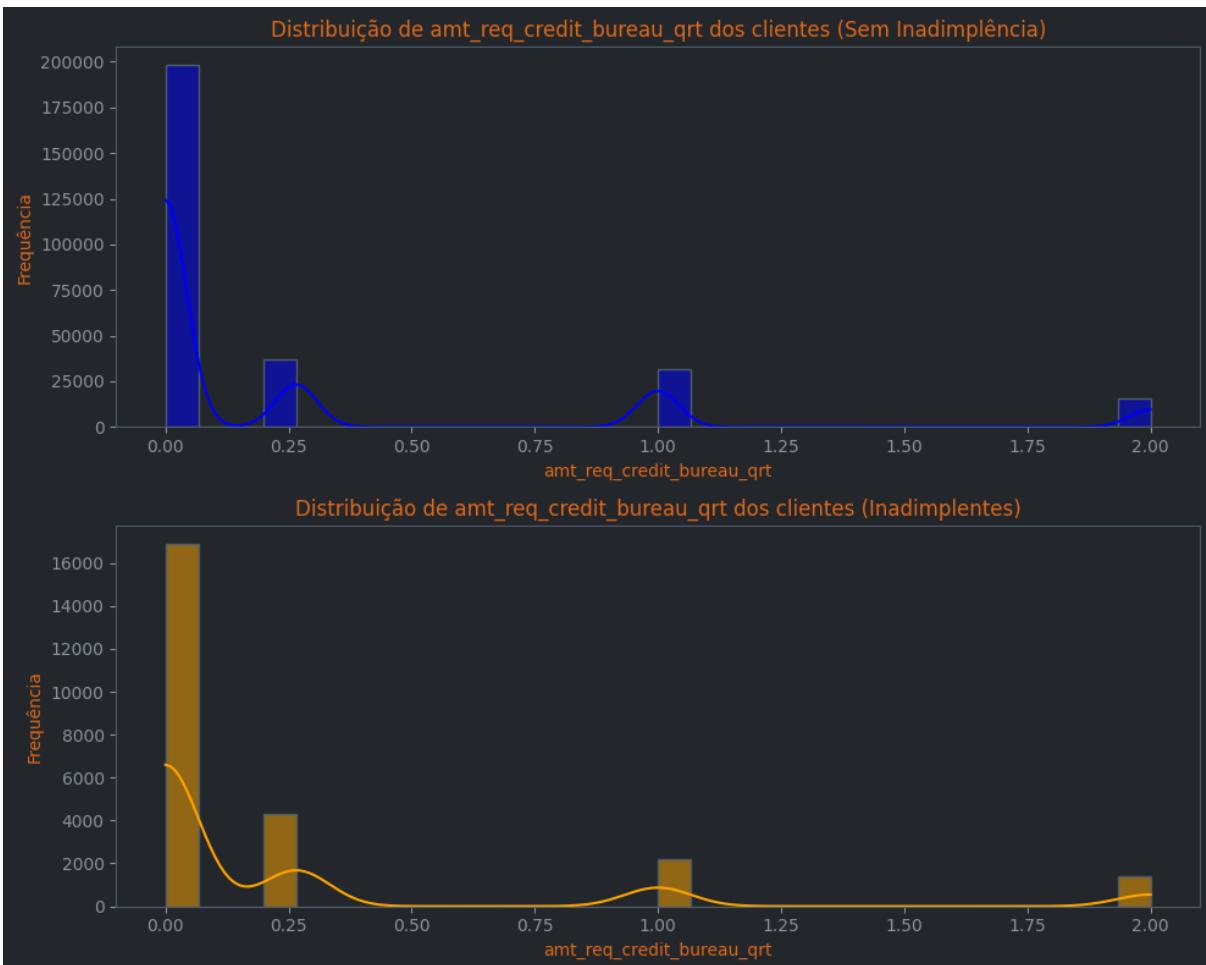
sns.histplot(
    data=df3[df3['target'] == 0],
    x='amt_req_credit_bureau_qrt',
    color='blue',
    ax=axes[0],
    kde=True,
    bins=30
)
axes[0].set_title('Distribuição de amt_req_credit_bureau_qrt dos clientes (Sem Inadimplência)')
axes[0].set_ylabel('Frequência')
axes[0].set_xlabel('amt_req_credit_bureau_qrt')

sns.histplot(
    data=df3[df3['target'] == 1],
    x='amt_req_credit_bureau_qrt',
    color='orange',
    ax=axes[1],
    kde=True,
    bins=30
)
axes[1].set_title('Distribuição de amt_req_credit_bureau_qrt dos clientes (Inadimplentes)')
axes[1].set_ylabel('Frequência')
axes[1].set_xlabel('amt_req_credit_bureau_qrt')

plt.tight_layout()
plt.show()

pearson_corr = df3['amt_req_credit_bureau_qrt'].corr(df3['target'], method='pearson')
```

```
print(f"Correlação de Pearson entre amt_req_credit_bureau_qrt e target: {pearson_corr:.4f}")
```



Correlação de Pearson entre amt\_req\_credit\_bureau\_qrt e target: -0.0035

amt\_req\_credit\_bureau\_year

```
In [ ]: fig, axes = plt.subplots(2, 1, figsize=(10, 8), sharey=False)

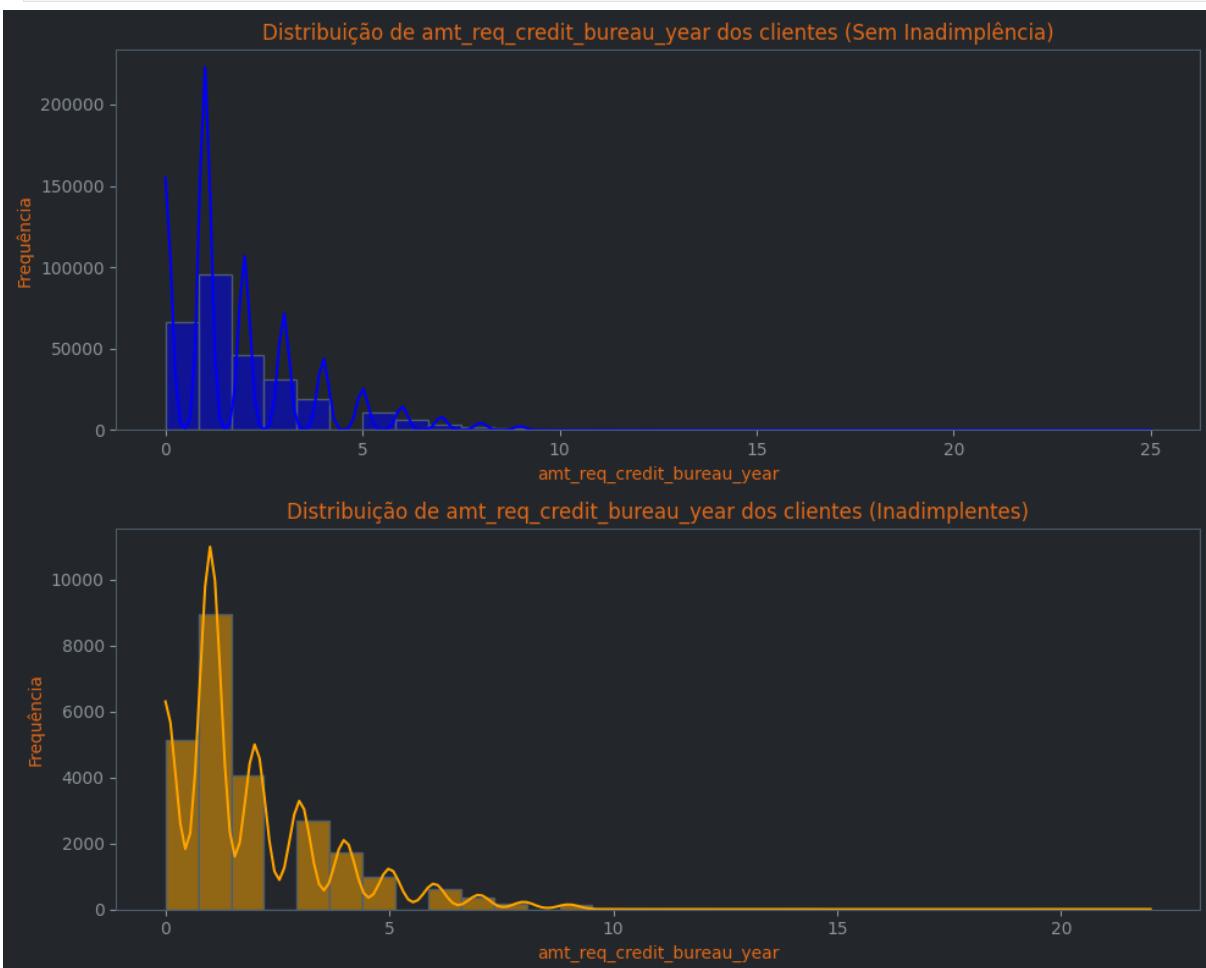
sns.histplot(
    data=df3[df3['target'] == 0],
    x='amt_req_credit_bureau_year',
    color='blue',
    ax=axes[0],
    kde=True,
    bins=30
)
axes[0].set_title('Distribuição de amt_req_credit_bureau_year dos clientes (Sem Inadimplência)')
axes[0].set_ylabel('Frequência')
axes[0].set_xlabel('amt_req_credit_bureau_year')

sns.histplot(
    data=df3[df3['target'] == 1],
    x='amt_req_credit_bureau_year',
    color='orange',
    ax=axes[1],
    kde=True,
    bins=30
)
axes[1].set_title('Distribuição de amt_req_credit_bureau_year dos clientes (Inadimplentes)')
axes[1].set_ylabel('Frequência')
axes[1].set_xlabel('amt_req_credit_bureau_year')

plt.tight_layout()
plt.show()

pearson_corr = df3['amt_req_credit_bureau_year'].corr(df3['target'], method='pearson')
```

```
print(f"Correlação de Pearson entre amt_req_credit_bureau_year e target: {pearson_corr:.4f}")
```



Correlação de Pearson entre amt\_req\_credit\_bureau\_year e target: 0.0122

amt\_credit\_sum\_mean

```
In [ ]: fig, axes = plt.subplots(2, 1, figsize=(10, 8), sharey=False)

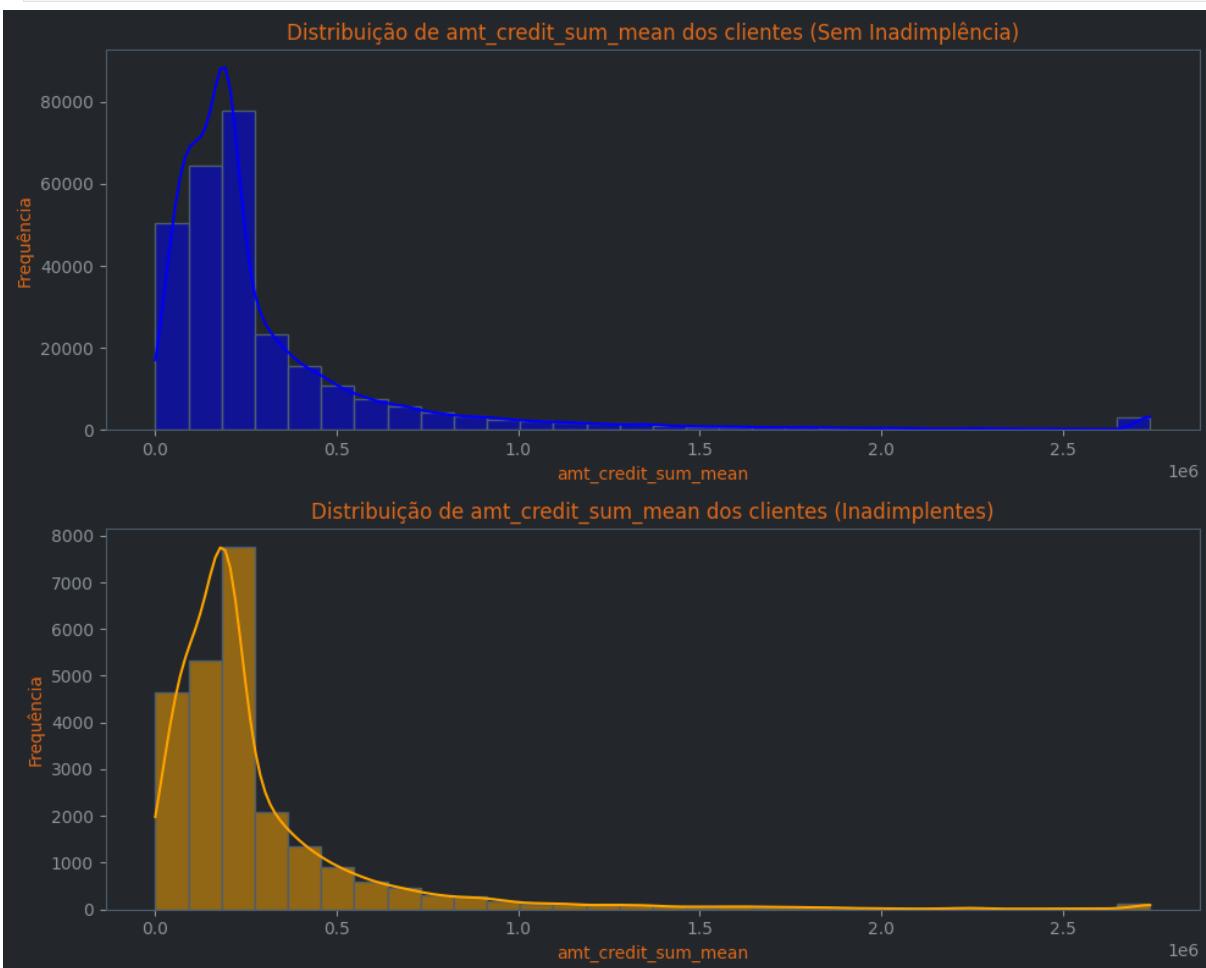
sns.histplot(
    data=df3[df3['target'] == 0],
    x='amt_credit_sum_mean',
    color='blue',
    ax=axes[0],
    kde=True,
    bins=30
)
axes[0].set_title('Distribuição de amt_credit_sum_mean dos clientes (Sem Inadimplência)')
axes[0].set_ylabel('Frequência')
axes[0].set_xlabel('amt_credit_sum_mean')

sns.histplot(
    data=df3[df3['target'] == 1],
    x='amt_credit_sum_mean',
    color='orange',
    ax=axes[1],
    kde=True,
    bins=30
)
axes[1].set_title('Distribuição de amt_credit_sum_mean dos clientes (Inadimplentes)')
axes[1].set_ylabel('Frequência')
axes[1].set_xlabel('amt_credit_sum_mean')

plt.tight_layout()
plt.show()

pearson_corr = df3['amt_credit_sum_mean'].corr(df3['target'], method='pearson')
```

```
print(f"Correlação de Pearson entre amt_credit_sum_mean e target: {pearson_corr:.4f}")
```



Correlação de Pearson entre amt\_credit\_sum\_mean e target: -0.0289

amt\_credit\_sum\_sum

```
In [ ]: fig, axes = plt.subplots(2, 1, figsize=(10, 8), sharey=False)

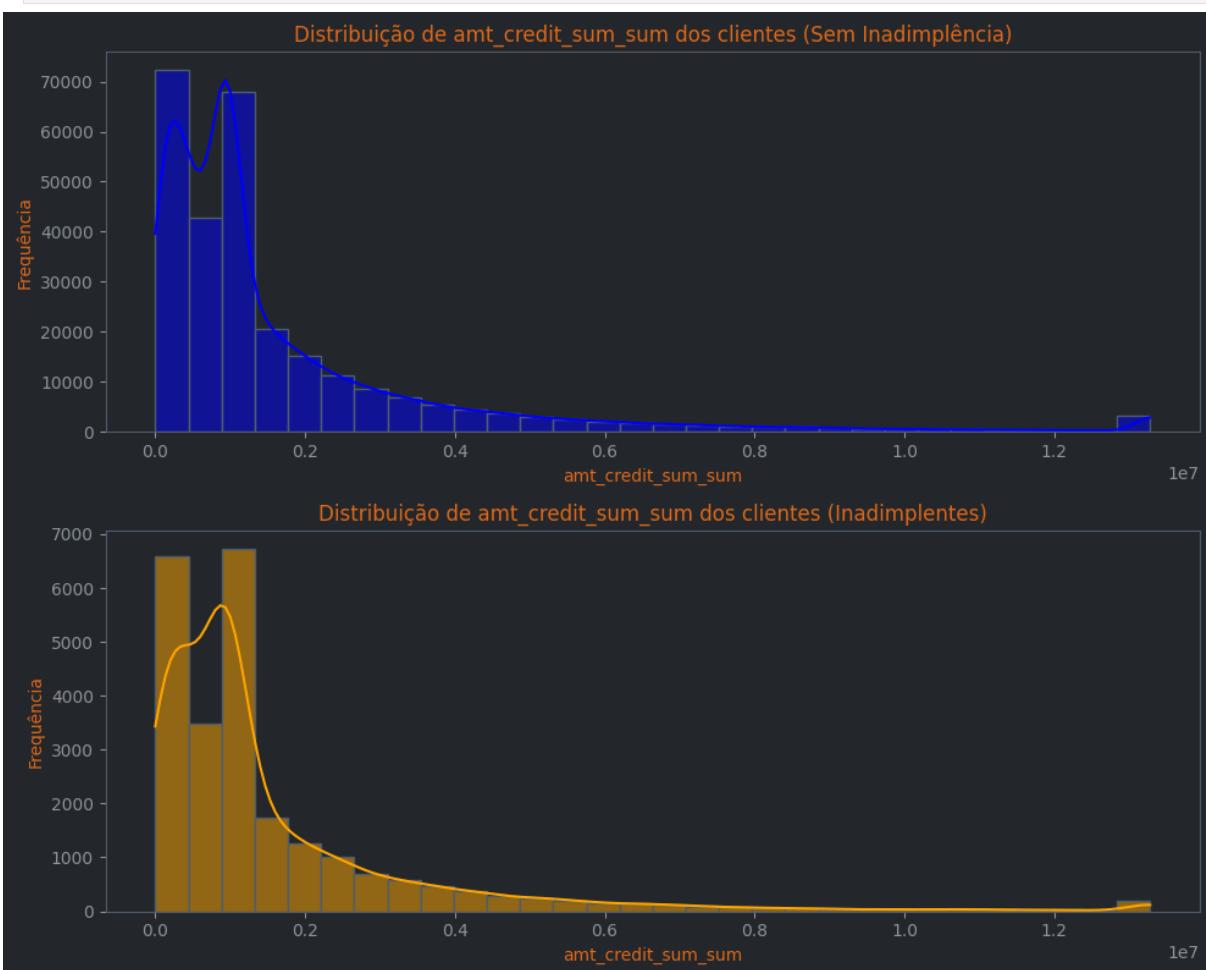
sns.histplot(
    data=df3[df3['target'] == 0],
    x='amt_credit_sum_sum',
    color='blue',
    ax=axes[0],
    kde=True,
    bins=30
)
axes[0].set_title('Distribuição de amt_credit_sum_sum dos clientes (Sem Inadimplência)')
axes[0].set_ylabel('Frequência')
axes[0].set_xlabel('amt_credit_sum_sum')

sns.histplot(
    data=df3[df3['target'] == 1],
    x='amt_credit_sum_sum',
    color='orange',
    ax=axes[1],
    kde=True,
    bins=30
)
axes[1].set_title('Distribuição de amt_credit_sum_sum dos clientes (Inadimplentes)')
axes[1].set_ylabel('Frequência')
axes[1].set_xlabel('amt_credit_sum_sum')

plt.tight_layout()
plt.show()

pearson_corr = df3['amt_credit_sum_sum'].corr(df3['target'], method='pearson')
```

```
print(f"Correlação de Pearson entre amt_credit_sum_sum e target: {pearson_corr:.4f}")
```



Correlação de Pearson entre amt\_credit\_sum\_sum e target: -0.0198

credit\_active\_nunique

```
In [ ]: fig, axes = plt.subplots(2, 1, figsize=(10, 8), sharey=False)

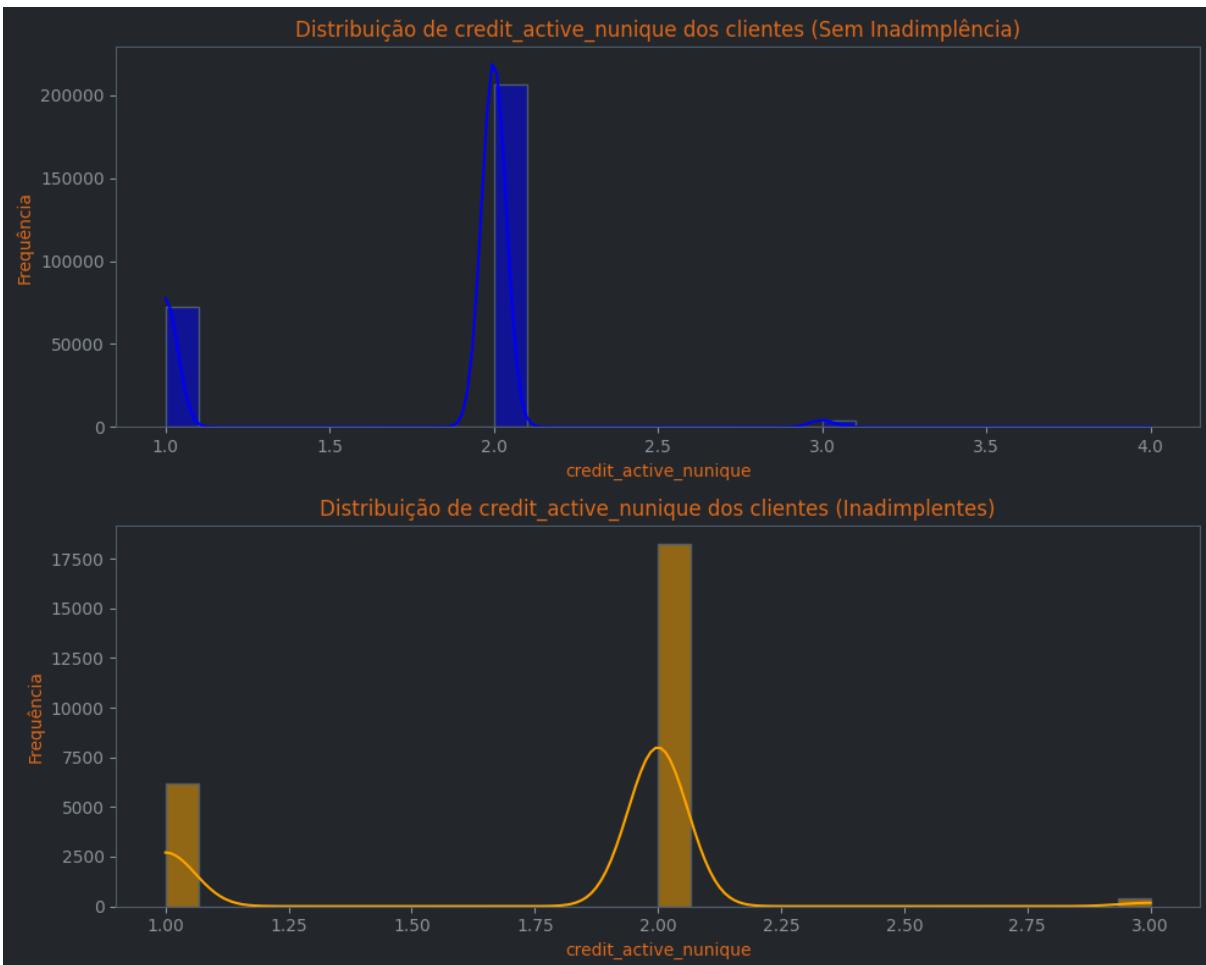
sns.histplot(
    data=df3[df3['target'] == 0],
    x='credit_active_nunique',
    color='blue',
    ax=axes[0],
    kde=True,
    bins=30
)
axes[0].set_title('Distribuição de credit_active_nunique dos clientes (Sem Inadimplência)')
axes[0].set_ylabel('Frequência')
axes[0].set_xlabel('credit_active_nunique')

sns.histplot(
    data=df3[df3['target'] == 1],
    x='credit_active_nunique',
    color='orange',
    ax=axes[1],
    kde=True,
    bins=30
)
axes[1].set_title('Distribuição de credit_active_nunique dos clientes (Inadimplentes)')
axes[1].set_ylabel('Frequência')
axes[1].set_xlabel('credit_active_nunique')

plt.tight_layout()
plt.show()

pearson_corr = df3['credit_active_nunique'].corr(df3['target'], method='pearson')
```

```
print(f"Correlação de Pearson entre credit_active_nunique e target: {pearson_corr:.4f}")
```



Correlação de Pearson entre credit\_active\_nunique e target: 0.0060

amt\_credit\_mean

```
In [ ]: fig, axes = plt.subplots(2, 1, figsize=(10, 8), sharey=False)

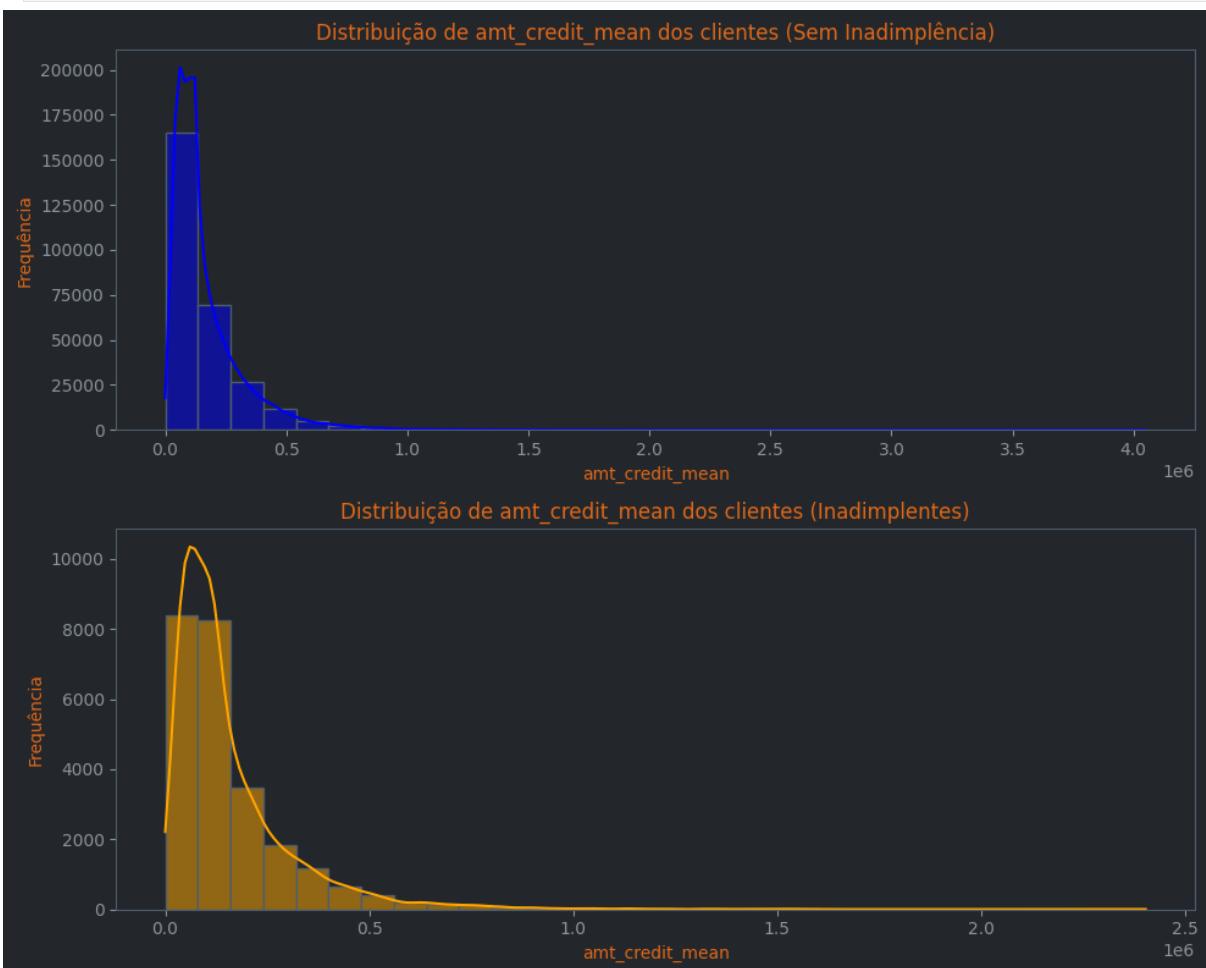
sns.histplot(
    data=df3[df3['target'] == 0],
    x='amt_credit_mean',
    color='blue',
    ax=axes[0],
    kde=True,
    bins=30
)
axes[0].set_title('Distribuição de amt_credit_mean dos clientes (Sem Inadimplência)')
axes[0].set_ylabel('Frequência')
axes[0].set_xlabel('amt_credit_mean')

sns.histplot(
    data=df3[df3['target'] == 1],
    x='amt_credit_mean',
    color='orange',
    ax=axes[1],
    kde=True,
    bins=30
)
axes[1].set_title('Distribuição de amt_credit_mean dos clientes (Inadimplentes)')
axes[1].set_ylabel('Frequência')
axes[1].set_xlabel('amt_credit_mean')

plt.tight_layout()
plt.show()

pearson_corr = df3['amt_credit_mean'].corr(df3['target'], method='pearson')
```

```
print(f"Correlação de Pearson entre amt_credit_mean e target: {pearson_corr:.4f}")
```



Correlação de Pearson entre amt\_credit\_mean e target: -0.0144

amt\_credit\_sum

```
In [ ]: fig, axes = plt.subplots(2, 1, figsize=(10, 8), sharey=False)

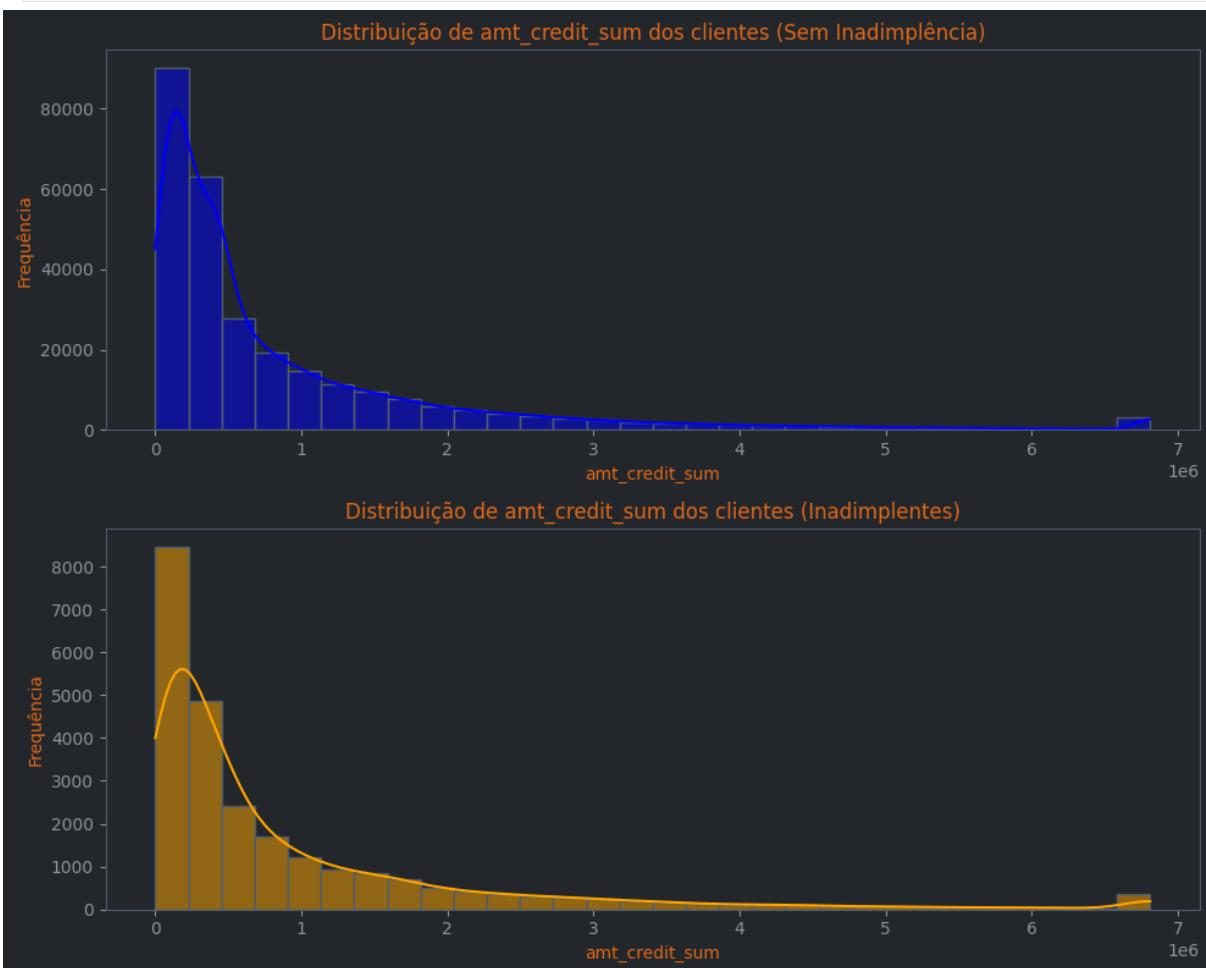
sns.histplot(
    data=df3[df3['target'] == 0],
    x='amt_credit_sum',
    color='blue',
    ax=axes[0],
    kde=True,
    bins=30
)
axes[0].set_title('Distribuição de amt_credit_sum dos clientes (Sem Inadimplência)')
axes[0].set_ylabel('Frequência')
axes[0].set_xlabel('amt_credit_sum')

sns.histplot(
    data=df3[df3['target'] == 1],
    x='amt_credit_sum',
    color='orange',
    ax=axes[1],
    kde=True,
    bins=30
)
axes[1].set_title('Distribuição de amt_credit_sum dos clientes (Inadimplentes)')
axes[1].set_ylabel('Frequência')
axes[1].set_xlabel('amt_credit_sum')

plt.tight_layout()
plt.show()

pearson_corr = df3['amt_credit_sum'].corr(df3['target'], method='pearson')
```

```
print(f"Correlação de Pearson entre amt_credit_sum e target: {pearson_corr:.4f}")
```



Correlação de Pearson entre amt\_credit\_sum e target: 0.0076

amt\_credit\_max

```
In [ ]: fig, axes = plt.subplots(2, 1, figsize=(10, 8), sharey=False)

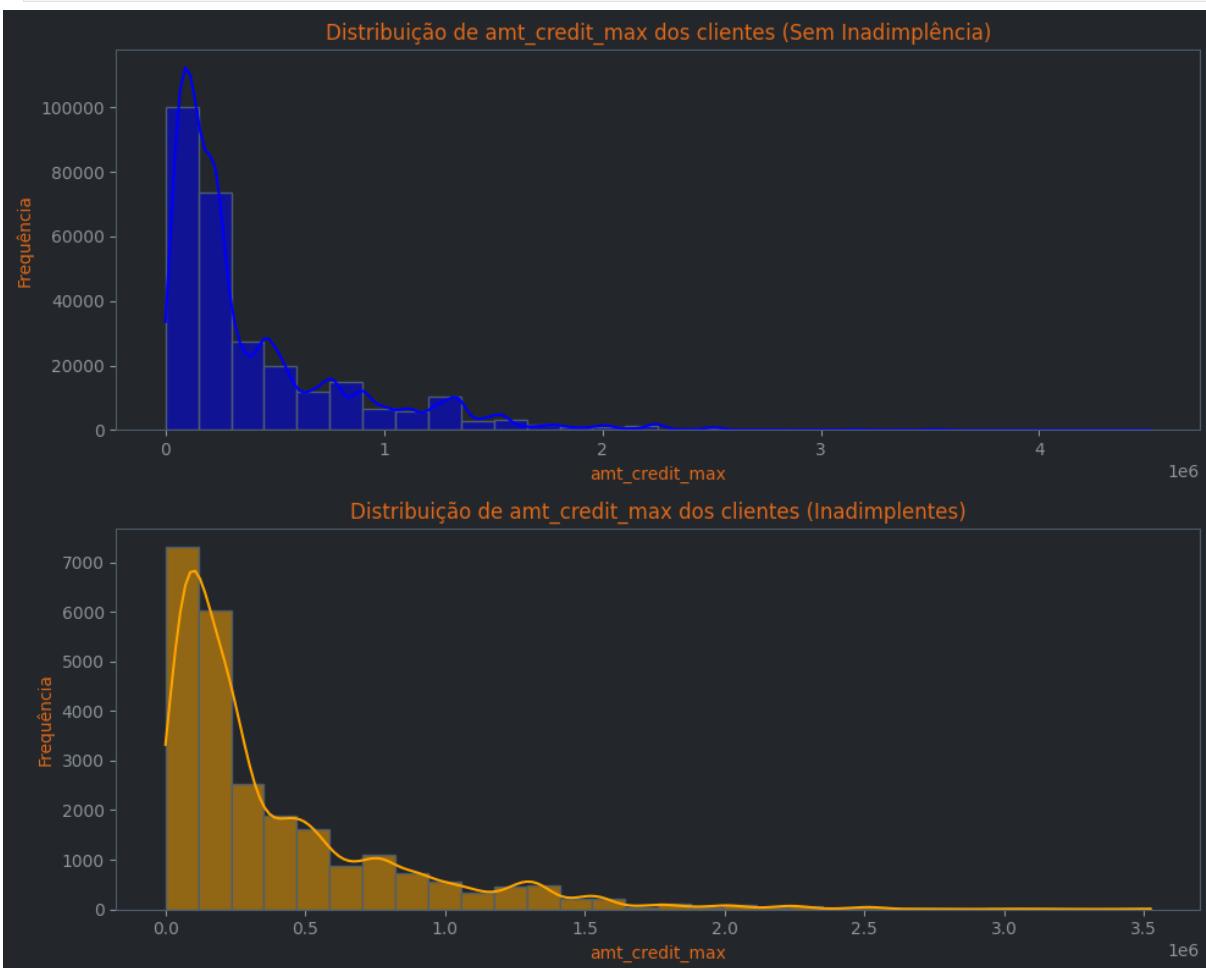
sns.histplot(
    data=df3[df3['target'] == 0],
    x='amt_credit_max',
    color='blue',
    ax=axes[0],
    kde=True,
    bins=30
)
axes[0].set_title('Distribuição de amt_credit_max dos clientes (Sem Inadimplência)')
axes[0].set_ylabel('Frequência')
axes[0].set_xlabel('amt_credit_max')

sns.histplot(
    data=df3[df3['target'] == 1],
    x='amt_credit_max',
    color='orange',
    ax=axes[1],
    kde=True,
    bins=30
)
axes[1].set_title('Distribuição de amt_credit_max dos clientes (Inadimplentes)')
axes[1].set_ylabel('Frequência')
axes[1].set_xlabel('amt_credit_max')

plt.tight_layout()
plt.show()

pearson_corr = df3['amt_credit_max'].corr(df3['target'], method='pearson')
```

```
print(f"Correlação de Pearson entre amt_credit_max e target: {pearson_corr:.4f}")
```



Correlação de Pearson entre amt\_credit\_max e target: -0.0065

amt\_application\_mean

```
In [ ]: fig, axes = plt.subplots(2, 1, figsize=(10, 8), sharey=False)

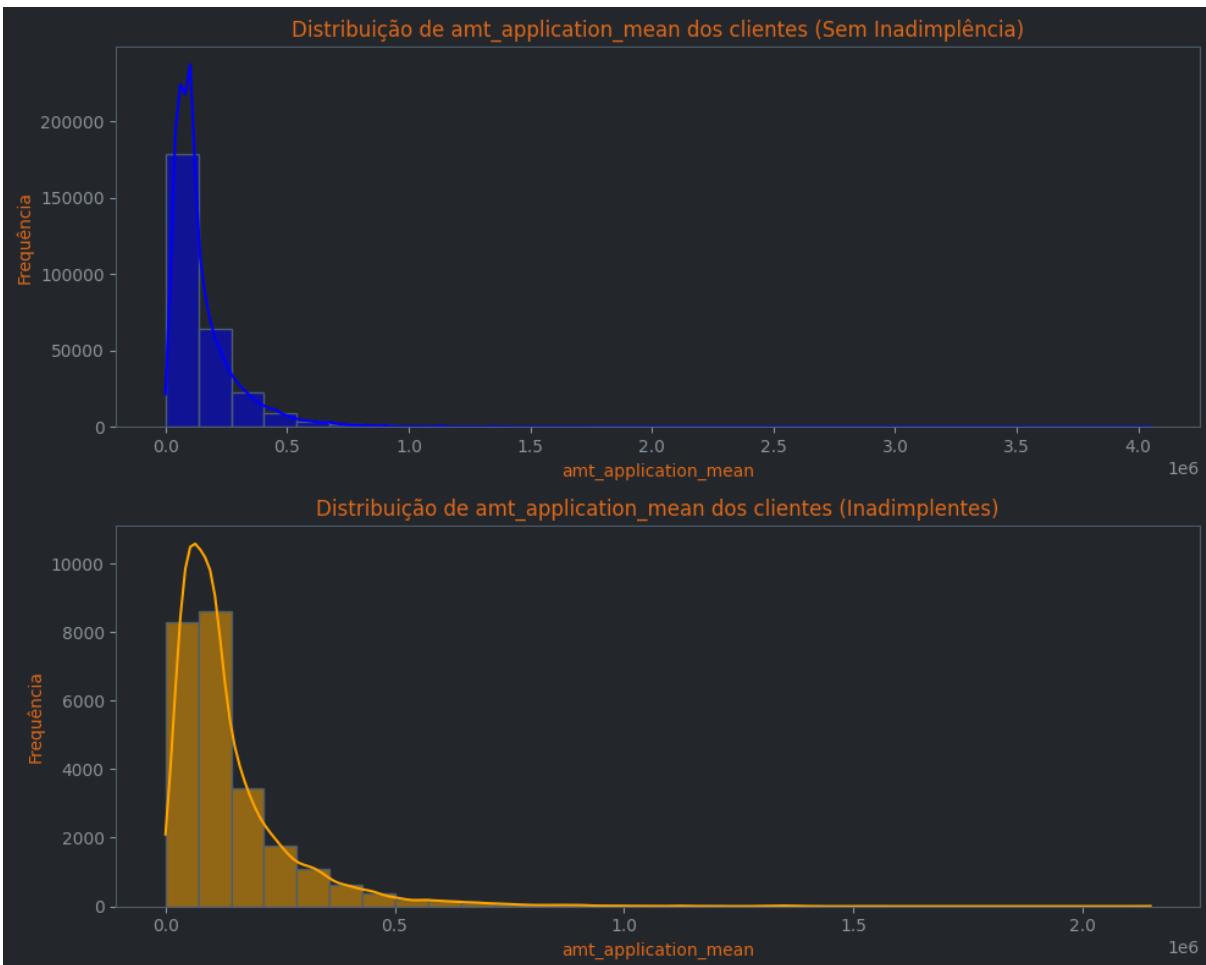
sns.histplot(
    data=df3[df3['target'] == 0],
    x='amt_application_mean',
    color='blue',
    ax=axes[0],
    kde=True,
    bins=30
)
axes[0].set_title('Distribuição de amt_application_mean dos clientes (Sem Inadimplência)')
axes[0].set_ylabel('Frequência')
axes[0].set_xlabel('amt_application_mean')

sns.histplot(
    data=df3[df3['target'] == 1],
    x='amt_application_mean',
    color='orange',
    ax=axes[1],
    kde=True,
    bins=30
)
axes[1].set_title('Distribuição de amt_application_mean dos clientes (Inadimplentes)')
axes[1].set_ylabel('Frequência')
axes[1].set_xlabel('amt_application_mean')

plt.tight_layout()
plt.show()

pearson_corr = df3['amt_application_mean'].corr(df3['target'], method='pearson')
```

```
print(f"Correlação de Pearson entre amt_application_mean e target: {pearson_corr:.4f}")
```



Correlação de Pearson entre amt\_application\_mean e target: -0.0200

days\_decision\_mean

```
In [ ]: fig, axes = plt.subplots(2, 1, figsize=(10, 8), sharey=False)

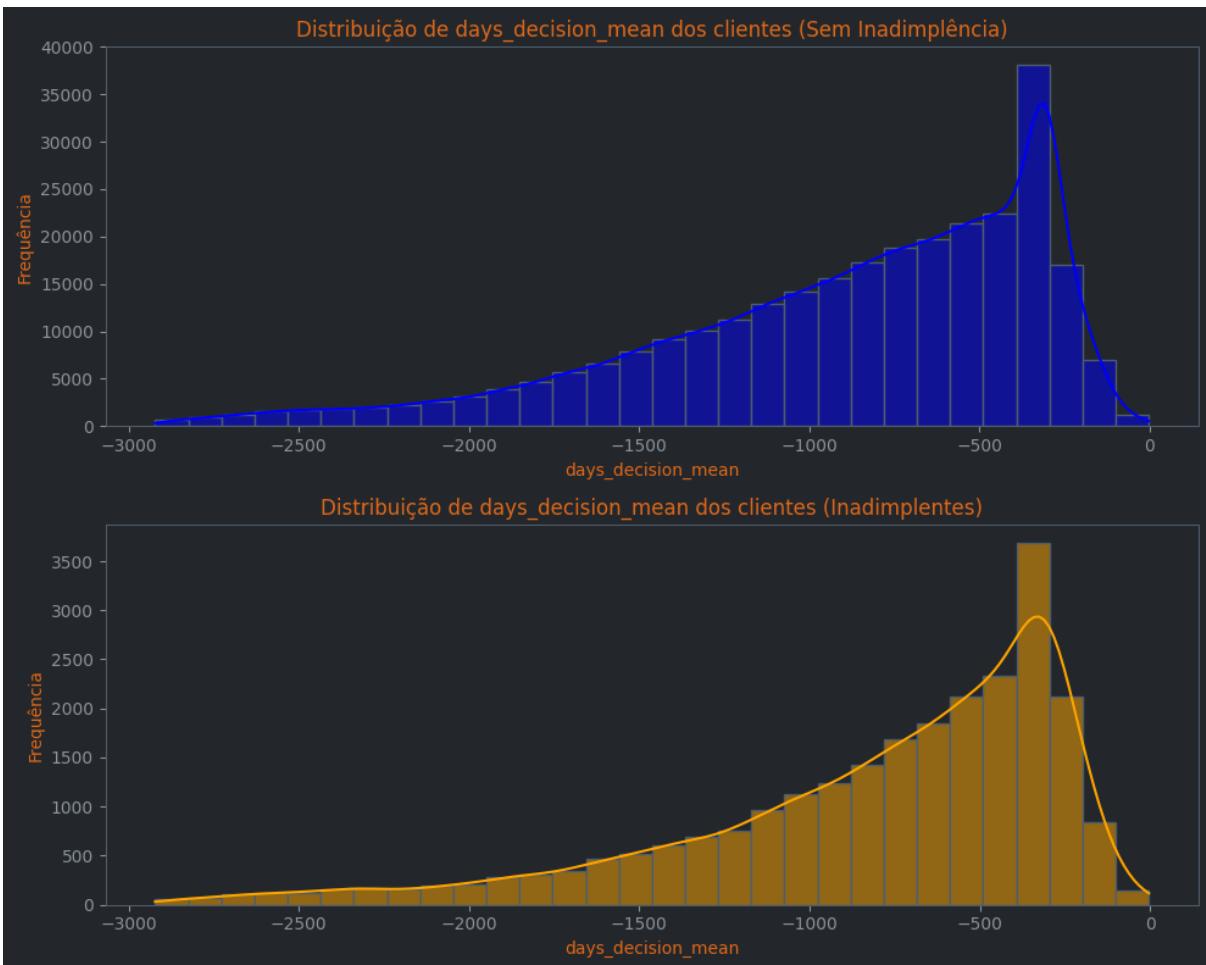
sns.histplot(
    data=df3[df3['target'] == 0],
    x='days_decision_mean',
    color='blue',
    ax=axes[0],
    kde=True,
    bins=30
)
axes[0].set_title('Distribuição de days_decision_mean dos clientes (Sem Inadimplência)')
axes[0].set_ylabel('Frequência')
axes[0].set_xlabel('days_decision_mean')

sns.histplot(
    data=df3[df3['target'] == 1],
    x='days_decision_mean',
    color='orange',
    ax=axes[1],
    kde=True,
    bins=30
)
axes[1].set_title('Distribuição de days_decision_mean dos clientes (Inadimplentes)')
axes[1].set_ylabel('Frequência')
axes[1].set_xlabel('days_decision_mean')

plt.tight_layout()
plt.show()

pearson_corr = df3['days_decision_mean'].corr(df3['target'], method='pearson')
```

```
print(f"Correlação de Pearson entre days_decision_mean e target: {pearson_corr:.4f}")
```

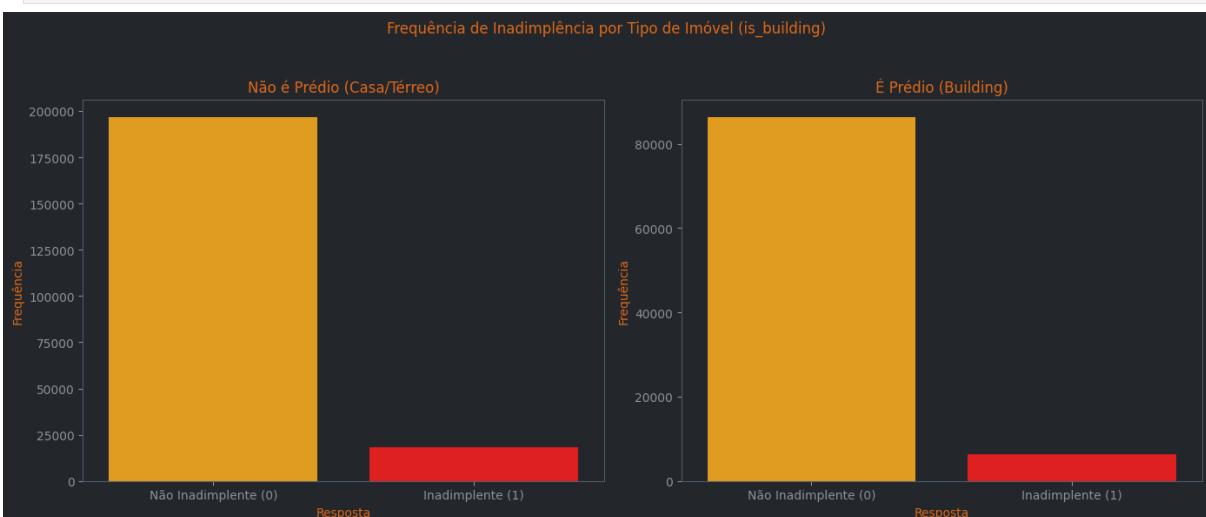


Correlação de Pearson entre days\_decision\_mean e target: 0.0402

H49 — Property characteristics and employment status influence repayment capacity. TRUE

is\_building

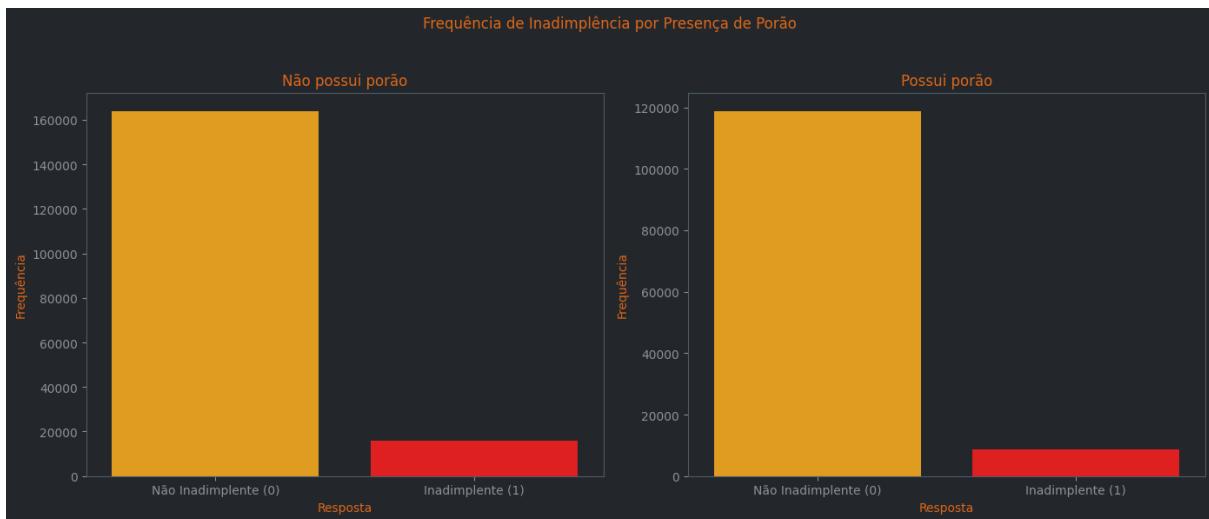
```
In [ ]: plot_binaria_target(  
    df3,  
    var_binaria='is_building',  
    label_0='Não é Prédio',  
    label_1='É Prédio',  
    suptitle='Frequência de Inadimplência por tipo do Imóvel'  
)  
  
calcular_cramers_v(df3, 'is_building', 'target')
```



V de Cramer entre is\_building e target: 0.0280

has\_basement

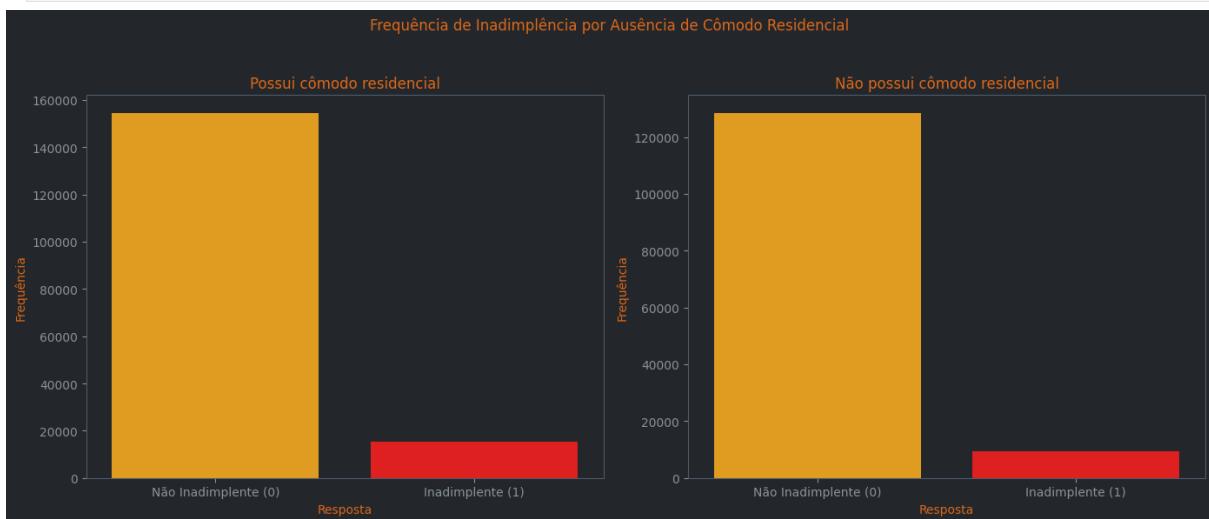
```
In [ ]: plot_binaria_target(  
        df3,  
        var_binaria='has_basement',  
        label_0='Não possui porão',  
        label_1='Possui porão',  
        suptitle='Frequência de Inadimplência por Presença de Porão'  
)  
  
calcular_cramers_v(df3, 'has_basement', 'target')
```



V de Cramer entre has\_basement e target: 0.0366

has\_noliving

```
In [ ]: plot_binaria_target(  
        df3,  
        var_binaria='has_noliving',  
        label_0='Possui cômodo residencial',  
        label_1='Não possui cômodo residencial',  
        suptitle='Frequência de Inadimplência por Ausência de Cômodo Residencial'  
)  
  
calcular_cramers_v(df3, 'has_noliving', 'target')
```



V de Cramer entre has\_noliving e target: 0.0392

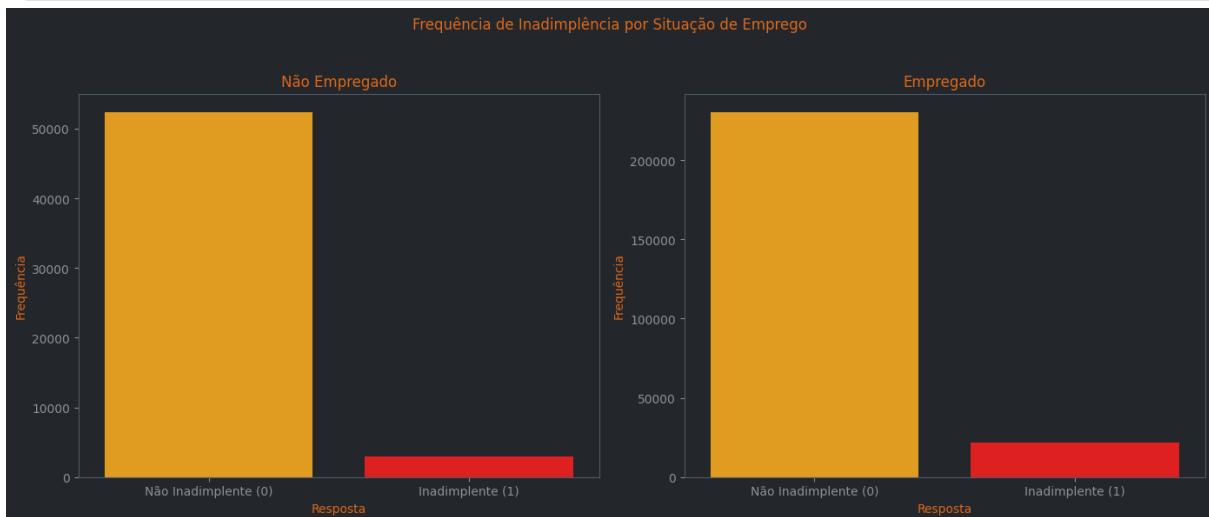
is\_employed

```
In [ ]: plot_binaria_target(  
        df3,  
        var_binaria='is_building',  
        label_0='Não Empregado',
```

```

        label_1='Empregado',
        suptitle='Frequência de Inadimplência por Situação de Emprego'
    )
calcular_cramers_v(df3, 'is_employed', 'target')

```



V de Cramer entre is\_employed e target: 0.0460

## 8. Data Preparation

```
In [ ]: df4 = df3.copy()
```

### 8.1 Scaling

#### 8.1.1 Log Transform

```
In [8]: log_transform_cols = [
    'decision_credit_diff',
    'annuity_burden_ratio',
    'credit_efficiency',
]

for col in log_transform_cols:
    df4[col + '_log'] = np.log1p(df4[col])
    df4.drop(columns=col, inplace=True)
```

```
c:\Users\Patryck\AppData\Local\Programs\Python\Python311\Lib\site-packages\pandas\core\arraylike.py:399: RuntimeWarning: invalid value encountered in log1p
    result = getattr(ufunc, method)(*inputs, **kwargs)
```

#### 8.1.2 Robust Scaler

```
In [9]: cols_to_scale = [
    'phone_change_frequency',
    'amt_income_total',
    'amt_credit',
    'num_flag_document',
    'amt_annuity',
    'amt_goods_price',
    'apartments_avg',
    'floorsmax_avg',
    'livingarea_avg',
    'years_build_avg',
    'phone_change_rate',
    'elevators_avg',
    'elevators_mode',
    'elevators_medi',
    'own_car_age',
    'obs_30_cnt_social_circle',
```

```

'def_30_cnt_social_circle',
'obs_60_cnt_social_circle',
'def_60_cnt_social_circle',
'amt_req_credit_bureau_hour',
'amt_req_credit_bureau_day',
'amt_req_credit_bureau_week',
'amt_req_credit_bureau_mon',
'amt_req_credit_bureau_qrt',
'amt_req_credit_bureau_year',
'goods_to_credit_ratio',
'basementarea_avg',
'livingapartments_avg',
'landarea_avg',
'nonlivingapartments_avg',
'commonarea_avg',
'years_beginexpluatation_avg',
'nonlivingarea_avg',
'days_employed',
'payment_rate',
'payment_rate^2',
'payment_rate ext_source_mean',
'days_birth^2 payment_rate',
'days_birth payment_rate^2',
'payment_rate^3',
'payment_rate^2 ext_source_mean',
'payment_rate ext_source_mean^2',
]
]

robust_scaler = RobustScaler()
df4[cols_to_scale] = robust_scaler.fit_transform(df4[cols_to_scale])

```

### 8.1.3 Standard Scaler

```

In [10]: cols_to_standard_scale = [
    'days_registration',
    'days_since_last_employment_until_application',
    'income_per_employed',
    'days_id_publish',
    'days_last_phone_change',
    'recent_instability',
    'employment_stability',
    'employment_life_ratio',
    'cnt_fam_members',
    'goods_to_credit_ratio',
    'days_birth',
    'days_birth^2',
    'days_birth payment_rate',
    'days_birth ext_source_mean',
    'ext_source_mean^2',
    'days_birth^3',
    'days_birth^2 ext_source_mean',
    'days_birth payment_rate ext_source_mean',
    'days_birth ext_source_mean^2',
    'ext_source_mean^3'
]

standard_scaler = StandardScaler()
df4[cols_to_standard_scale] = standard_scaler.fit_transform(df4[cols_to_standard_scale])

```

### 8.1.4 MinMaxScaler

```

In [11]: cols_to_minmax_scale = [
    'cnt_children',
    'region_population_relative',
    'bureau_to_credit_ratio',
    'bureau_request_intensity',

```

```

        'annuity_to_income_ratio',
        'id_document_age_ratio',
    ]
minmax_scaler = MinMaxScaler()

df4[cols_to_minmax_scale] = minmax_scaler.fit_transform(df4[cols_to_minmax_scale])

```

## 8.1.5 Scaling Final

```
In [12]: binary_cols = [col for col in df4.columns if sorted(df4[col].dropna().unique()) in [[0, 1], [1, 0]]]

lists_to_exclude = set(
    cols_to_standard_scale +
    cols_to_scale +
    cols_to_minmax_scale +
    binary_cols +
    [col for col in df4.columns if df4[col].dtype == 'object'] +
    ['target']
)

other_columns = [col for col in df4.columns if (col not in lists_to_exclude) and (col not in binary_cols)]

scaler = StandardScaler()
df4[other_columns] = scaler.fit_transform(df4[other_columns])

```

## 8.2 Encoding

### 8.2.1 BinaryEncoding

```
In [4]: df4['name_contract_type'] = (df4['name_contract_type'] != 'Cash loans').astype(int)
df4['code_gender'] = df4['code_gender'].map({'F': 0, 'M': 1})
```

### 8.2.2 OneHotEncoding

```
In [5]: encoder_suite = OneHotEncoder(drop='first', sparse_output=False)
encoded_suite = encoder_suite.fit_transform(df4[['name_type_suite']])
col_names_suite = [f"nts_{cat}" for cat in encoder_suite.categories_[0][1:]]
encoded_df_suite = pd.DataFrame(encoded_suite, columns=col_names_suite, index=df4.index)
df4 = pd.concat([df4.drop(columns=['name_type_suite']), encoded_df_suite], axis=1)

encoder_fam = OneHotEncoder(drop='first', sparse_output=False)
encoded_fam = encoder_fam.fit_transform(df4[['name_family_status']])
col_names_fam = [f"nfs_{cat}" for cat in encoder_fam.categories_[0][1:]]
encoded_df_fam = pd.DataFrame(encoded_fam, columns=col_names_fam, index=df4.index)
df4 = pd.concat([df4.drop(columns=['name_family_status']), encoded_df_fam], axis=1)

encoder_housing = OneHotEncoder(drop='first', sparse_output=False)
encoded_housing = encoder_housing.fit_transform(df4[['name_housing_type']])
col_names_housing = [f"nht_{cat}" for cat in encoder_housing.categories_[0][1:]]
encoded_df_housing = pd.DataFrame(encoded_housing, columns=col_names_housing, index=df4.index)
df4 = pd.concat([df4.drop(columns=['name_housing_type']), encoded_df_housing], axis=1)

encoder_housetype_mode = OneHotEncoder(drop='first', sparse_output=False)
encoded_housetype_mode = encoder_housetype_mode.fit_transform(df4[['housetype_mode']])
col_names_housetype_mode = [f"htm_{cat}" for cat in encoder_housetype_mode.categories_[0][1:]]
encoded_df_housetype_mode = pd.DataFrame(encoded_housetype_mode, columns=col_names_housetype_mode, index=df4.index)
df4 = pd.concat([df4.drop(columns=['housetype_mode']), encoded_df_housetype_mode], axis=1)

encoder_walls = OneHotEncoder(drop='first', sparse_output=False)
encoded_walls = encoder_walls.fit_transform(df4[['wallsmaterial_mode']])
col_names_walls = [f"wm_{cat}" for cat in encoder_walls.categories_[0][1:]]
encoded_df_walls = pd.DataFrame(encoded_walls, columns=col_names_walls, index=df4.index)
df4 = pd.concat([df4.drop(columns=['wallsmaterial_mode']), encoded_df_walls], axis=1)
```

### 8.2.3 TargetEncoding

```
In [6]: target_mean_income = df4.groupby('name_income_type')['target'].mean()
df4['name_income_type_te'] = df4['name_income_type'].map(target_mean_income)
df4.drop('name_income_type', axis=1, inplace=True)

target_mean_occupation = df4.groupby('occupation_type')['target'].mean()
df4['occupation_type_te'] = df4['occupation_type'].map(target_mean_occupation)
df4.drop('occupation_type', axis=1, inplace=True)

target_mean_organization = df4.groupby('organization_type')['target'].mean()
df4['organization_type_te'] = df4['organization_type'].map(target_mean_organization)
df4.drop('organization_type', axis=1, inplace=True)

target_mean_region_rating_client = df4.groupby('region_rating_client')['target'].mean()
df4['region_rating_client_te'] = df4['region_rating_client'].map(target_mean_region_rating_client)
df4.drop('region_rating_client', axis=1, inplace=True)

target_mean_region_rating_client_w_city = df4.groupby('region_rating_client_w_city')['target'].mean()
df4['region_rating_client_w_city_te'] = df4['region_rating_client_w_city'].map(target_mean_region_rating_client_w_city)
df4.drop('region_rating_client_w_city', axis=1, inplace=True)
```

### 8.2.4 OrdinalEncoding

```
In [7]: education_order = [
    'Lower secondary',
    'Secondary / secondary special',
    'Incomplete higher',
    'Higher education',
    'Academic degree'
]
df4['name_education_type'] = pd.Categorical(
    df4['name_education_type'],
    categories=education_order,
    ordered=True
).codes
```

## 9. Feature Selection

```
In [ ]: df5 = df3.copy()

In [4]: df5.columns = [col.replace('/', '_').replace(',', '_').replace(' ', '') for col in df5.columns]
```

### 9.1 Features Importance

```
In [5]: X = df5.drop(['target'], axis=1)
y = df5['target']

target = df5['target']
num_neg = (target == 0).sum()
num_pos = (target == 1).sum()
scale_pos_weight = num_neg / num_pos

xgbm_model = xgb.XGBClassifier(
    n_estimators=300,
    random_state=42,
    n_jobs=-1,
    scale_pos_weight=scale_pos_weight,
    eval_metric='logloss'
)
xgbm_model.fit(X, y)

lgbm_model = lgb.LGBMClassifier(
```

```

        n_estimators=300,
        random_state=42,
        n_jobs=1,
        scale_pos_weight=scale_pos_weight
    )
lgbm_model.fit(X, y)

cat_model = CatBoostClassifier(
    iterations=300,
    random_state=42,
    verbose=0,
    scale_pos_weight=scale_pos_weight
)
cat_model.fit(X, y)
shap_sample = X.sample(n=min(1000, len(X)), random_state=42)

explainer_xgb = shap.TreeExplainer(xgbm_model)
shap_values_xgb = explainer_xgb.shap_values(shap_sample)
mean_abs_shap_xgb = np.abs(shap_values_xgb).mean(axis=0)

feat_importance_xgb = pd.DataFrame({
    'Feature': X.columns,
    'SHAP_XGB': mean_abs_shap_xgb
})

explainer_lgb = shap.TreeExplainer(lgbm_model)
shap_values_lgb = explainer_lgb.shap_values(shap_sample)
if isinstance(shap_values_lgb, list):
    shap_values_lgb = shap_values_lgb[1]

mean_abs_shap_lgb = np.abs(shap_values_lgb).mean(axis=0)
feat_importance_lgb = pd.DataFrame({
    'Feature': X.columns,
    'SHAP_LGBM': mean_abs_shap_lgb
})

explainer_cat = shap.TreeExplainer(cat_model)
shap_values_cat = explainer_cat.shap_values(shap_sample)
if isinstance(shap_values_cat, (list, tuple)):
    shap_values_cat = shap_values_cat[1]

mean_abs_shap_cat = np.abs(shap_values_cat).mean(axis=0)
feat_importance_cat = pd.DataFrame({
    'Feature': X.columns,
    'SHAP_CAT': mean_abs_shap_cat
})

feat_importance_df = (
    feat_importance_xgb
        .merge(feat_importance_lgb, on='Feature')
        .merge(feat_importance_cat, on='Feature')
)

feat_importance_df['SHAP_XGB_NORM'] = feat_importance_df['SHAP_XGB'] / feat_importance_df['SHAP_XGB'].sum()
feat_importance_df['SHAP_LGBM_NORM'] = feat_importance_df['SHAP_LGBM'] / feat_importance_df['SHAP_LGBM'].sum()
feat_importance_df['SHAP_CAT_NORM'] = feat_importance_df['SHAP_CAT'] / feat_importance_df['SHAP_CAT'].sum()

feat_importance_df['SHAP_MEAN_NORM'] = feat_importance_df[
    ['SHAP_XGB_NORM', 'SHAP_LGBM_NORM', 'SHAP_CAT_NORM']
].mean(axis=1)

feat_importance_df = feat_importance_df.sort_values(by='SHAP_MEAN_NORM', ascending=False).reset_index()

```

```
[LightGBM] [Info] Number of positive: 24825, number of negative: 282686
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 5.431486
seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 119911
[LightGBM] [Info] Number of data points in the train set: 307511, number of used features: 1603
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.080729 -> initscore=-2.432486
[LightGBM] [Info] Start training from score -2.432486
c:\Users\Patryck\AppData\Local\Programs\Python\Python311\Lib\site-packages\shap\explainers\_tre
e.py:587: UserWarning: LightGBM binary classifier with TreeExplainer shap values output has cha
nged to a list of ndarray
    warnings.warn(

```

```
In [6]: feat_importance_df.head(50)
```

Out[6]:

	Feature	SHAP_XGB	SHAP_LGBM	SHAP_CAT	SHAP_XGB_NORM	SI
0	ext_source_mean	0.479819	0.136462	0.098005	0.053773	
1	ext_source_mean^3	0.000000	0.234489	0.196949	0.000000	
2	amt_goods_price	0.180001	0.119373	0.168450	0.020172	
3	amt_credit	0.188181	0.099917	0.149596	0.021089	
4	ext_source_mean^2	0.000000	0.128990	0.256225	0.000000	
5	code_gender	0.131131	0.120886	0.131836	0.014696	
6	name_education_type	0.093606	0.084137	0.100661	0.010490	
7	instf_inst_amt_payment_min_mean	0.112430	0.082894	0.070336	0.012600	
8	amt_annuity	0.100947	0.068007	0.084914	0.011313	
9	nfs_Married	0.080827	0.077176	0.077103	0.009058	
10	organization_type_te	0.082617	0.071622	0.078300	0.009259	
11	bur_amt_credit_sum_debt_mean	0.078518	0.064338	0.091906	0.008799	
12	ext_source_1_missing	0.085076	0.064582	0.085060	0.009534	
13	ext_source_weighted_mean	0.069700	0.057586	0.080541	0.007811	
14	instf_inst_amt_payment_min_min	0.071058	0.061853	0.058185	0.007963	
15	occupation_type_te	0.058921	0.054293	0.069931	0.006603	
16	bur_days_credit_enddate_max	0.072368	0.052928	0.056696	0.008110	
17	posf_pos_cnt_instalment_future_mean_mean	0.061260	0.042279	0.080664	0.006865	
18	employment_life_ratio	0.032763	0.033041	0.115123	0.003672	
19	prev_cnt_payment_max	0.038009	0.047791	0.069048	0.004260	
20	bur_days_enddate_fact_max	0.061550	0.043459	0.054840	0.006898	
21	flag_own_car	0.072230	0.059843	0.018257	0.008095	
22	posf_pos_months_balance_max_max	0.061593	0.043903	0.047087	0.006903	
23	num_flag_document	0.056485	0.046360	0.039938	0.006330	
24	bur_days_credit_max	0.056292	0.039222	0.049257	0.006309	
25	annuity_per_employment_year	0.041860	0.040980	0.057281	0.004691	
26	annuity_to_income_ratio	0.055552	0.032860	0.047513	0.006226	
27	instf_inst_days_entry_payment_max_max	0.064776	0.025673	0.046376	0.007259	
28	ext_source_3	0.041073	0.029021	0.058268	0.004603	
29	instf_inst_amt_payment_min_max	0.032871	0.028211	0.066105	0.003684	
30	own_car_age_employed_ratio	0.048990	0.038457	0.030191	0.005490	
31	days_birthext_source_mean^2	0.068693	0.034609	0.017099	0.007698	
32	prev_cnt_payment_mean	0.064248	0.032823	0.017195	0.007200	
33	region_population_relative	0.045858	0.024654	0.043919	0.005139	
34	bur_amt_credit_sum_min	0.046560	0.024092	0.044253	0.005218	
35	amt_application_goods_diff	0.048215	0.025340	0.039803	0.005403	
36	days_id_publish	0.047277	0.039052	0.014773	0.005298	

	Feature	SHAP_XGB	SHAP_LGBM	SHAP_CAT	SHAP_XGB_NORM	SI
37	prev_amt_down_payment_max	0.042961	0.034000	0.024261	0.004815	
38	ext_source_2	0.046125	0.021802	0.040196	0.005169	
39	days_birth	0.049212	0.021245	0.037912	0.005515	
40	instf_inst_days_instalment_max_max	0.050373	0.019795	0.039331	0.005645	
41	flag_document_3	0.035472	0.021595	0.047636	0.003975	
42	posf_pos_cnt_instalment_future_min_mean	0.039702	0.033119	0.024424	0.004449	
43	bur_amt_credit_max_overdue_max	0.053756	0.027124	0.020737	0.006024	
44	phone_change_rate	0.076217	0.014552	0.022423	0.008542	
45	income_per_employed	0.041240	0.009397	0.057745	0.004622	
46	posf_pos_cnt_instalment_future_min_max	0.024989	0.025092	0.044489	0.002800	
47	region_rating_client_w_city_te	0.033190	0.025745	0.035299	0.003720	
48	days_birth^2ext_source_mean	0.038953	0.016967	0.044518	0.004365	
49	days_registration	0.043024	0.019410	0.033100	0.004822	

```
In [7]: print(f"Número de colunas iniciais em X: {df5.shape[1]}")

feat_importance_df_ordenado = feat_importance_df.sort_values(by='SHAP_LGBM_NORM', ascending=False)

cumsum = feat_importance_df_ordenado['SHAP_LGBM_NORM'].cumsum()
n_feat_95 = (cumsum <= 0.95).sum() + 1

selected_features_95 = feat_importance_df_ordenado.loc[:n_feat_95-1, 'Feature'].tolist()

print(f"Quantidade de features para explicar 95% do fenômeno: {len(selected_features_95)}")
print(selected_features_95)

X = df5[selected_features_95]
```

Número de colunas iniciais em X: 1628

Quantidade de features para explicar 95% do fenômeno: 256

```
['ext_source_mean^3', 'ext_source_mean', 'ext_source_mean^2', 'code_gender', 'amt_goods_price', 'amt_credit', 'name_education_type', 'instf_inst_amt_payment_min_mean', 'nfs_Married', 'organization_type_te', 'amt_annuity', 'ext_source_1_missing', 'bur_amt_credit_sum_debt_mean', 'instf_inst_amt_payment_min_min', 'flag_own_car', 'ext_source_weighted_mean', 'occupation_type_te', 'bur_days_credit_enddate_max', 'prev_cnt_payment_max', 'num_flag_document', 'posf_pos_months_balance_max_max', 'bur_days_enddate_fact_max', 'posf_pos_cnt_instalment_future_mean_mean', 'annuity_per_employment_year', 'bur_days_credit_max', 'days_id_publish', 'own_car_age_employed_ratio', 'days_birthext_source_mean^2', 'prev_amt_down_payment_max', 'posf_pos_cnt_instalment_future_min_mean', 'employment_life_ratio', 'annuity_to_income_ratio', 'prev_cnt_payment_mean', 'ext_source_3', 'instf_inst_amt_payment_min_max', 'posf_pos_cnt_instalment_future_mean_max', 'bur_amt_credit_max_overdue_max', 'region_rating_client_w_city_te', 'instf_inst_days_entry_payment_max_max', 'amt_application_goods_diff', 'posf_pos_cnt_instalment_future_min_max', 'region_population_relative', 'bur_amt_credit_sum_min', 'own_car_age', 'ccf_cc_cnt_drawings_atm_current_mean_max', 'ext_source_2', 'flag_document_3', 'def_30_cnt_social_circle', 'amt_req_credit_bureau_qrt', 'days_birth', 'posf_pos_sk_id_curr_mean_count', 'weekday_appr_process_start', 'bur_days_enddate_fact_count', 'instf_inst_days_instalment_max_max', 'bur_days_credit_mean', 'days_registration', 'posf_pos_sk_dpd_def_max_mean', 'prev_rate_down_payment_max', 'ext_source_interaction', 'prev_sellerplace_area_mean', 'bur_amt_credit_sum_limit_count', 'days_last_phone_change', 'ext_source_1', 'days_birth^2ext_source_mean', 'prev_cnt_payment_min', 'bur_amt_credit_sum_max', 'instf_inst_days_entry_payment_count_mean', 'instf_inst_num_instalment_version_mean_mean', 'bur_amt_credit_sun_limit_mean', 'posf_pos_months_balance_mean_max', 'own_car_age_birth_ratio', 'flag_work_phone', 'days_since_last_employment_until_application', 'days_birth^2', 'phone_change_rate', 'days_birthpayment_rate', 'bureau_overdue_ratio', 'posf_pos_cnt_instalment_count_max', 'instf_inst_num_instalment_version_mean_max', 'days_birthext_source_mean', 'ext_source_max', 'reg_city_not_live_city', 'bur_amt_credit_max_overdue_mean', 'posf_pos_sk_dpd_def_mean_max', 'bur_sk_id_bureau_mean_missing', 'def_60_cnt_social_circle', 'instf_inst_num_instalment_number_max_max', 'bur_days_credit_update_max', 'instf_inst_amt_payment_mean_max', 'prev_days_first_drawing_count', 'prev_amt_annuity_mean', 'bur_days_credit_update_mean', 'prev_nflag_insured_on_approval_mean', 'prev_amt_annuity_min', 'name_contract_type', 'decision_credit_diff_log', 'pos_balance_range', 'bur_amt_credit_sum_limit_mean_missing', 'years_beginexpluatation_avg', 'area_quality', 'id_document_ag_ratio', 'goods_to_credit_ratio', 'prev_sellerplace_area_max', 'instf_inst_amt_instalment_min_min', 'ccf_cc_cnt_drawings_atm_current_mean_mean', 'wm_Panel', 'prev_amt_goods_price_mean', 'phone_change_frequency', 'prev_days_last_due_1st_version_max', 'prev_sk_id_prev_max', 'ccf_cc_amt_credit_limit_actual_mean_mean', 'name_income_type_te', 'hour_appr_process_start', 'posf_pos_cnt_instalment_mean_count', 'income_per_employed', 'prev_days_decision_mean', 'income_per_birth', 'posf_pos_cnt_instalment_count_mean', 'bur_amt_credit_sum_debt_max', 'ccf_cc_amt_balance_max_max', 'bur_days_credit_min', 'prev_amt_down_payment_mean', 'id_change_rate', 'instf_inst_num_instalment_version_max_max', 'credit_per_employment_year', 'posf_pos_sk_id_curr_count_max', 'instf_inst_amt_payment_mean_min', 'prev_days_last_due_mean', 'prev_sk_id_prev_count', 'prev_days_decision_max', 'prev_days_decision_min', 'entry_vs_due_ratio', 'bur_days_credit_enddate_mean', 'days_employed', 'ccf_cc_amt_payment_current_mean_mean', 'bur_sk_id_bureau_mean', 'prev_hour_appr_process_start_mean', 'prev_rate_down_payment_mean', 'prev_rate_down_payment_min', 'prev_days_first_due_min', 'flag_phone', 'credit_risk_signal', 'ccf_cc_cnt_drawings_atm_current_mean_min', 'posf_pos_sk_id_curr_count_mean', 'instf_inst_amt_instalment_max_max', 'annuity_per_age', 'bur_days_credit_update_min', 'instf_inst_amt_payment_max_mean', 'credit_efficiency_log', 'posf_pos_sk_id_curr_mean_mean', 'ccf_cc_cnt_drawings_current_max_max', 'prev_sk_id_prev_mean', 'apartments_avg', 'ccf_cc_cnt_drawings_current_mean_max', 'employment_years', 'bur_sk_id_bureau_min', 'prev_hour_appr_process_start_min', 'bur_bb_months_balance_mean_count', 'bureau_to_credit_ratio', 'days_birth^3', 'payment_rate', 'posf_pos_cnt_instalment_count_min', 'instf_inst_amt_instalment_min_max', 'landarea_avg', 'bur_days_credit_enddate_min', 'posf_pos_cnt_instalment_future_max_mean', 'posf_pos_sk_id_curr_count_min', 'bur_amt_credit_sum_limit_max', 'prev_hour_appr_process_start_max', 'bur_days_enddate_fact_min', 'days_birth^2payment_rate', 'posf_pos_cnt_instalment_max_mean', 'instf_inst_days_instalment_max_min', 'bur_amt_credit_sum_mean', 'posf_pos_cnt_instalment_future_count_mean', 'livingarea_avg', 'bur_amt_credit_max_overdue_mean_missing', 'instf_inst_amt_payment_max_max', 'recent_instability', 'floorsmax_avg', 'amt_income_total', 'instf_inst_num_instalment_number_max_mean', 'instf_inst_days_entry_payment_min_mean', 'credit_to_income_ratio', 'bur_sk_id_bureau_max', 'posf_pos_cnt_instalment_min_mean', 'instf_inst_days_instalment_min_min', 'ccf_cc_months_balance_mean_min', 'instf_inst_sk_id_curr_mean_mean', 'prev_amt_goods_price_min', 'posf_pos_months_balance_min_min', 'posf_pos_cnt_instalment_mean_mean', 'posf_pos_cnt_instalment_mean_min', 'years_build_avg', 'posf_pos_months_balance_min_mean', 'instf_inst_sk_id_curr_mean_count', 'ccf_cc_amt_balance_mean_mean', 'instf_inst_days_instalment_min_max', 'prev_days_last_due_1st_version_mean', 'days_birthpayment_rateext_source_mean', 'ccf_cc_amt_receivable_principal_mean_min', 'instf_inst_num_instalment_version_max_mean', 'ext_source_agreement', 'prev_sellerplace_area_min', 'bur_days_enddate_fact_mean', 'payment_rateext_source_mean^2', 'instf_inst_sk_id_curr_count_mean', 'prev_amt_application_mean', 'instf_inst_amt_instalment_min_mean', 'bur_bb_months_balance_count_mean', 'ccf_cc_amt_receivable_principal_mean_mean', 'prev_amt_application_max', 'instf_inst_days_entry_payment_mean_max', 'prev_amt_credit_min', 'prev_amt_a
```

```

nnuity_max', 'prev_amt_annuity_count', 'ext_source_range', 'commonarea_avg', 'bur_bb_months_balance_count_max',
'prev_amt_goods_price_max', 'prev_amt_credit_max', 'amt_application_credit_diff',
'posf_pos_cnt_instalment_min_min', 'annuity_burden_ratio_log', 'ccf_cc_amt_payment_total_current_mean_max',
'ext_source_std', 'bur_bb_months_balance_max_mean', 'prev_days_last_due_1st_version_min',
'ext_source_3_missing', 'ccf_cc_amt_receivable_principal_mean_max', 'bur_amt_credit_sum_debt_min',
'instf_inst_num_instalment_number_mean_min', 'instf_inst_amt_payment_mean_mean',
'prev_amt_application_min', 'ccf_cc_amt_balance_min_mean', 'ccf_cc_amt_balance_mean_max',
'instf_inst_days_instalment_mean_max', 'instf_inst_amt_instalment_max_min', 'days_birthpayment_rate^2',
'totalarea_mode', 'nonlivingarea_avg', 'ccf_cc_amt_credit_limit_actual_min_min',
'prev_sk_id_prev_min', 'bur_amt_credit_sum_debt_count', 'ccf_cc_amt_balance_mean_min',
'prev_days_termination_min', 'nht_Municipalapartment', 'posf_pos_sk_dpd_def_mean_mean',
'bur_sk_id_bureau_count', 'ccf_cc_cnt_drawings_current_mean_min', 'bureau_request_intensity',
'payment_rate^2ext_source_mean', 'ccf_cc_cnt_drawings_current_max_mean', 'prev_days_termination_mean',
'instf_inst_amt_instalment_max_mean', 'livingapartments_avg']

```

## 10. Machine Learning

```

In [9]: X_train, X_temp, y_train, y_temp = train_test_split(
    X, y, test_size=0.3, random_state=0, stratify=y
)

X_val, X_test, y_val, y_test = train_test_split(
    X_temp, y_temp, test_size=0.5, random_state=0, stratify=y_temp
)

```

### 10.1 Logistic Regression

```

In [9]: neg, pos = np.bincount(y_train)
scale_pos_weight = neg / pos

logreg = LogisticRegression(
    max_iter=2000,
    class_weight='balanced'
)

In [10]: logreg.fit(X_train, y_train)

df_metricas = avaliar_metricas(logreg, X_val, y_val, X_test, y_test)
display(df_metricas)

```

	validacao	teste
<b>recall</b>	0.997315	0.998120
<b>precision</b>	0.080792	0.080845
<b>f1_score</b>	0.149475	0.149574
<b>auc_roc</b>	0.500389	0.500746
<b>auc_pr</b>	0.080792	0.080845

### 10.2 Random Forest

```

In [ ]: rf_clf = BalancedRandomForestClassifier(
    n_estimators=1000,
    random_state=42,
    n_jobs=-1
)

In [ ]: rf_clf.fit(X_train, y_train)

df_metricas = avaliar_metricas(rf_clf, X_val, y_val, X_test, y_test)
display(df_metricas)

```

	<b>validacao</b>	<b>teste</b>
<b>recall</b>	0.504834	0.516917
<b>precision</b>	0.215893	0.219950
<b>f1_score</b>	0.302445	0.308592
<b>auc_roc</b>	0.757899	0.768832
<b>auc_pr</b>	0.230295	0.240063

## 10.3 XGBoost

```
In [10]: num_neg = (y_train == 0).sum()
num_pos = (y_train == 1).sum()
scale_pos_weight = num_neg / num_pos

xgb_clf = xgb.XGBClassifier(
    n_estimators=1000,
    random_state=42,
    scale_pos_weight=scale_pos_weight,
)

In [11]: xgb_clf.fit(X_train, y_train)

df_metricas = avaliar_metricas(xgb_clf, X_val, y_val, X_test, y_test)
display(df_metricas)
```

	<b>validacao</b>	<b>teste</b>
<b>recall</b>	0.209184	0.204082
<b>precision</b>	0.304654	0.292871
<b>f1_score</b>	0.248050	0.240544
<b>auc_roc</b>	0.729740	0.723740
<b>auc_pr</b>	0.217711	0.214192

## 10.4 LightGBM

```
In [12]: num_neg = (y_train == 0).sum()
num_pos = (y_train == 1).sum()
scale_pos_weight = num_neg / num_pos

lgbm_clf = lgb.LGBMClassifier(
    n_estimators=1000,
    random_state=42,
    scale_pos_weight=scale_pos_weight,
    verbose=-1
)

In [13]: lgbm_clf.fit(X_train, y_train)

df_metricas = avaliar_metricas(lgbm_clf, X_val, y_val, X_test, y_test)
display(df_metricas)
```

	<b>validacao</b>	<b>teste</b>
<b>recall</b>	0.488722	0.485768
<b>precision</b>	0.232024	0.230387
<b>f1_score</b>	0.314661	0.312543
<b>auc_roc</b>	0.764907	0.763319
<b>auc_pr</b>	0.252291	0.250929

## 10.5 CatBoost

```
In [14]: num_neg = (y_train == 0).sum()
num_pos = (y_train == 1).sum()
scale_pos_weight = num_neg / num_pos

cat_clf = CatBoostClassifier(
    iterations=1000,
    random_state=42,
    verbose=0,
    scale_pos_weight=scale_pos_weight,
)
```

```
In [15]: cat_clf.fit(X_train, y_train)

df_metricas = avaliar_metricas(cat_clf, X_val, y_val, X_test, y_test)
display(df_metricas)
```

	<b>validacao</b>	<b>teste</b>
<b>recall</b>	0.601504	0.594522
<b>precision</b>	0.208391	0.207265
<b>f1_score</b>	0.309542	0.307372
<b>auc_roc</b>	0.774728	0.776648
<b>auc_pr</b>	0.271922	0.267967

## 10.6 ADABoosting

```
In [ ]: adaboost_clf = AdaBoostClassifier(
    estimator=DecisionTreeClassifier(
        max_depth=1,
        class_weight={0: 1.0, 1: scale_pos_weight}
    ),
    n_estimators=1000,
    random_state=42
)
```

```
In [ ]: adaboost_clf.fit(X_train, y_train)

df_metricas = avaliar_metricas(adaboost_clf, X_val, y_val, X_test, y_test)
display(df_metricas)
```

	<b>validacao</b>	<b>teste</b>
<b>recall</b>	0.656284	0.675081
<b>precision</b>	0.143900	0.147026
<b>f1_score</b>	0.236044	0.241464
<b>auc_roc</b>	0.656692	0.665560
<b>auc_pr</b>	0.122189	0.125486

## 10.7 HistBoosting

```
In [ ]: histboost_clf = HistGradientBoostingClassifier(
    max_iter=200,
    learning_rate=0.1,
    max_depth=None,
    random_state=42,
    class_weight='balanced'
)

In [ ]: histboost_clf.fit(X_train, y_train)

df_metricas = avaliar_metricas(histboost_clf, X_val, y_val, X_test, y_test)
display(df_metricas)
```

	<b>validacao</b>	<b>teste</b>
<b>recall</b>	0.665951	0.693609
<b>precision</b>	0.182299	0.188595
<b>f1_score</b>	0.286242	0.296556
<b>auc_roc</b>	0.774241	0.783426
<b>auc_pr</b>	0.254090	0.272599

## 10.8 Nayves Bayes

```
In [ ]: nb_clf = GaussianNB()
nb_clf.fit(X_train, y_train)

df_metricas = avaliar_metricas(nb_clf, X_val, y_val, X_test, y_test)
display(df_metricas)
```

c:\Users\Patryck\AppData\Local\Programs\Python\Python311\Lib\site-packages\sklearn\metrics\\_classification.py:1731: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 due to no predicted samples. Use `zero\_division` parameter to control this behavior.  
 \_warn\_prf(average, modifier, f"{{metric.capitalize()}} is", result.shape[0])  
c:\Users\Patryck\AppData\Local\Programs\Python\Python311\Lib\site-packages\sklearn\metrics\\_classification.py:1731: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 due to no predicted samples. Use `zero\_division` parameter to control this behavior.  
 \_warn\_prf(average, modifier, f"{{metric.capitalize()}} is", result.shape[0])

	validacao	teste
<b>recall</b>	0.000000	0.000000
<b>precision</b>	0.000000	0.000000
<b>f1_score</b>	0.000000	0.000000
<b>auc_roc</b>	0.500378	0.500664
<b>auc_pr</b>	0.080792	0.080839

## 11. HyperTuning

### 11.1 BayesSearch

```
In [ ]: X_full = pd.concat([X_train, X_val]).reset_index(drop=True)
y_full = pd.concat([y_train, y_val]).reset_index(drop=True)

search_spaces = {
    'n_estimators': Integer(2000, 6000),
    'learning_rate': Real(0.0005, 0.1, prior='log-uniform'),
    'max_depth': Integer(3, 12),
    'min_child_weight': Integer(1, 30),
    'gamma': Real(0, 5.0),
    'reg_alpha': Real(1e-8, 50, prior='log-uniform'),
    'reg_lambda': Real(1e-6, 300, prior='log-uniform'),
    'subsample': Real(0.5, 1.0),
    'colsample_bytree': Real(0.4, 1.0),
    'colsample_bylevel': Real(0.3, 1.0),
    'colsample_bynode': Real(0.3, 1.0),
    'booster': Categorical(['gbtree']),
    'tree_method': Categorical(['hist', 'exact']),
    'grow_policy': Categorical(['depthwise', 'lossguide']),
    'scale_pos_weight': Integer(1, 40),
    'max_delta_step': Integer(0, 10),
}

model = xgb.XGBClassifier(
    random_state=42,
    eval_metric='auc',
    tree_method='hist'
)

bayes = BayesSearchCV(
    estimator=model,
    search_spaces=search_spaces,
    scoring='roc_auc',
    n_iter=120,
    cv=3,
    n_jobs=-1,
```

```

        verbose=3,
        random_state=42,
        refit=True,
        optimizer_kwargs={'acq_func': 'EI'}
    )

bayes.fit(
    X_full,
    y_full,
    callback=None,
    **{
        "eval_set": [(X_val, y_val)],
        "early_stopping_rounds": 50,
        "verbose": False
    }
)

print("\n👉 Melhor score (roc_auc):", bayes.best_score_)
print("🔧 Melhores parâmetros encontrados:\n")
for p, v in bayes.best_params_.items():
    print(f"  {p}: {v}")

```

## 12. Training the Final Model

```

In [10]: xgb_params = {
    'booster': 'gbtree',
    'n_estimators': 5116,
    'learning_rate': 0.006466,
    'max_depth': 6,
    'subsample': 0.83743,
    'colsample_bytree': 0.921139,
    'colsample_bylevel': 0.674959,
    'gamma': 2.165815,
    'min_child_weight': 12,
    'reg_alpha': 0.000102,
    'reg_lambda': 17.3739,
    'scale_pos_weight': 1,
    'random_state': 42,
}

X_trainval = np.concatenate([X_train, X_val])
y_trainval = np.concatenate([y_train, y_val])

xgb_final = xgb.XGBClassifier(**xgb_params)
xgb_final.fit(X_trainval, y_trainval)

y_pred_proba = xgb_final.predict_proba(X_test)[:, 1]
y_pred = xgb_final.predict(X_test)

print("Classification Report (TESTE):")
print(classification_report(y_test, y_pred))

print("Matriz de Confusão (TESTE):")
print(confusion_matrix(y_test, y_pred))

print("\nAUC-ROC:", roc_auc_score(y_test, y_pred_proba))
print("AUC-PR:", average_precision_score(y_test, y_pred_proba))
print("Recall:", recall_score(y_test, y_pred))
print("Precision:", precision_score(y_test, y_pred))
print("F1 Score:", f1_score(y_test, y_pred))

```

```

Classification Report (TESTE):
      precision    recall  f1-score   support

          0       0.92     1.00      0.96     42403
          1       0.57     0.04      0.08      3724

   accuracy                           0.92     46127
macro avg       0.75     0.52      0.52     46127
weighted avg    0.89     0.92      0.89     46127

```

Matriz de Confusão (TESTE):

```

[[42290  113]
 [ 3574  150]]

```

AUC-ROC: 0.795399200495334

AUC-PR: 0.2904329200889078

Recall: 0.040279269602577876

Precision: 0.5703422053231939

F1 Score: 0.07524454477050414

```

In [11]: best_threshold, best_f1 = find_best_threshold(y_test, y_pred_proba, metric="f1")
y_pred_best = (y_pred_proba >= best_threshold).astype(int)

print(f"Melhor threshold para F1: {best_threshold:.4f} (F1: {best_f1:.4f})\n")

print("Classification Report (TESTE):")
print(classification_report(y_test, y_pred_best))

print("Matriz de Confusão (TESTE):")
print(confusion_matrix(y_test, y_pred_best))

print("\nAUC-ROC:", roc_auc_score(y_test, y_pred_proba))
print("AUC-PR:", average_precision_score(y_test, y_pred_proba))
print("Recall:", recall_score(y_test, y_pred_best))
print("Precision:", precision_score(y_test, y_pred_best))
print("F1 Score:", f1_score(y_test, y_pred_best))

```

Melhor threshold para F1: 0.1910 (F1: 0.3437)

```

Classification Report (TESTE):
      precision    recall  f1-score   support

          0       0.94     0.93      0.94     42403
          1       0.31     0.38      0.34      3724

   accuracy                           0.88     46127
macro avg       0.63     0.65      0.64     46127
weighted avg    0.89     0.88      0.89     46127

```

Matriz de Confusão (TESTE):

```

[[39255  3148]
 [ 2298  1426]]

```

AUC-ROC: 0.795399200495334

AUC-PR: 0.2904329200889078

Recall: 0.382921589688507

Precision: 0.31176213379973766

F1 Score: 0.34369727645215714

## 12.1 Training with All Data

```

In [13]: xgb_params = {
    'booster': 'gbtree',
    'n_estimators': 5116,
    'learning_rate': 0.006466,
    'max_depth': 6,
    'subsample': 0.83743,
    'colsample_bytree': 0.921139,
}

```

```
'colsample_bytree': 0.674959,
'gamma': 2.165815,
'min_child_weight': 12,
'reg_alpha': 0.000102,
'reg_lambda': 17.3739,
'scale_pos_weight': 1,
'random_state': 42,
}

xgb_final = xgb.XGBClassifier(**xgb_params)

xgb_final.fit(X, y)
```

Out[13]:

XGBClassifier		
► Parameters		
objective	'binary:logistic'	
base_score	None	
booster	'gbtree'	
callbacks	None	
colsample_bylevel	0.674959	
colsample_bynode	None	
colsample_bytree	0.921139	
device	None	
early_stopping_rounds	None	
enable_categorical	False	
eval_metric	None	
feature_types	None	
feature_weights	None	
gamma	2.165815	
grow_policy	None	
importance_type	None	
interaction_constraints	None	
learning_rate	0.006466	
max_bin	None	
max_cat_threshold	None	
max_cat_to_onehot	None	
max_delta_step	None	
max_depth	6	
max_leaves	None	
min_child_weight	12	
missing	nan	
monotone_constraints	None	
multi_strategy	None	
n_estimators	5116	
n_jobs	None	
num_parallel_tree	None	
random_state	42	
reg_alpha	0.000102	
reg_lambda	17.3739	
sampling_method	None	
scale_pos_weight	1	

	subsample	0.83743
	tree_method	None
	validate_parameters	None
	verbosity	None

## 13. Error Interpretation and Translation

```
In [12]: best_threshold, best_f1 = find_best_threshold(y_test, y_pred_proba, metric="f1")
y_pred_best = (y_pred_proba >= best_threshold).astype(int)

print(f"Melhor threshold para F1: {best_threshold:.4f} (F1: {best_f1:.4f})")

print("\nClassification Report:")
print(classification_report(y_test, y_pred_best))

print("Matriz de Confusão:")
print(confusion_matrix(y_test, y_pred_best))

print("\nAUC-ROC:", roc_auc_score(y_test, y_pred_proba))
print("AUC-PR :", average_precision_score(y_test, y_pred_proba))
print("MCC   :", matthews_corrcoef(y_test, y_pred_best))
```

Melhor threshold para F1: 0.1910 (F1: 0.3437)

Classification Report:				
	precision	recall	f1-score	support
0	0.94	0.93	0.94	42403
1	0.31	0.38	0.34	3724
accuracy			0.88	46127
macro avg	0.63	0.65	0.64	46127
weighted avg	0.89	0.88	0.89	46127

Matriz de Confusão:

```
[[39255 3148]
 [ 2298 1426]]
```

AUC-ROC: 0.795399200495334  
AUC-PR : 0.2904329200889078  
MCC : 0.28136141644784807

### Model Results Summary

The optimal decision threshold was **0.1910**, with an **F1-score of 0.3437** for the defaulter class.

The model shows:

- **Overall accuracy of 88%**, indicating strong global performance.
- **Recall of 38% for defaulters**, meaning the model is able to identify a relevant portion of high-risk customers.
- **Precision of 31% for the defaulter class**, still impacted by data imbalance.
- **AUC-ROC of 0.795**, showing good ability to separate good and bad payers.
- **MCC of 0.28**, indicating a reasonable correlation between predictions and actual values.

### Business Impact

With the threshold set at **0.19**, the model:

- **Anticipates a significant portion of defaulters.**

- Reduces the risk of granting credit to bad payers.
- Generates some **false positives** (good customers flagged as risky), but keeps financial risk more controlled.

### Practical Recommendation

Use a threshold close to **0.19** as an **initial risk screening filter**, prioritizing loss prevention. For final credit decisions, a more conservative criterion is recommended to balance approval rates and profitability.

## 13.1 Financial Interpretation of the Error

### Assumptions

- Total customers: **46,127**
- Good payers: **42,403**
- Defaulters: **3,724**

Financial assumptions:

- Profit per good payer: **R\$ 1,000**
- Loss per defaulter: **R\$ 5,000**
- Cost per false positive: **R\$ 500**
- A false positive **does not generate profit**

### Model Threshold

- **Optimal threshold (F1): 0.1910**
- **F1-score: 0.3437**
- **AUC-ROC: 0.795**
- **MCC: 0.281**

### Confusion Matrix (0.1910)

	Predicted 0	Predicted 1
Actual 0 (Good payer)	39,255	3,148
Actual 1 (Defaulter)	2,298	1,426

### Summary:

- **TP:** 1,426
- **FN:** 2,298
- **FP:** 3,148
- **TN:** 39,255

### Financial Impact

1) **TP (defaulters avoided)** Gain:  $1,426 \times 5,000 = \text{R\$ } 7,130,000$

2) **FN (undetected defaulters)** Loss:  $2,298 \times 5,000 = -\text{R\$ } 11,490,000$

3) **FP (good customers wrongly blocked)** Loss:  $3,148 \times (1,000 + 500) = -\text{R\$ } 4,722,000$

4) **TN (good customers correctly approved)** Gain:  $39,255 \times 1,000 = \text{R\$ } 39,255,000$

## Net Profit with the Model

```
Profit = 7,130,000  
-11,490,000  
- 4,722,000  
+39,255,000
```

Net profit = R\$ 30,173,000

---

## Scenario Without the Model

- Loss from defaulters:  $3,724 \times 5,000 = -R\$ 18,620,000$
- Profit from good payers:  $42,403 \times 1,000 = R\$ 42,403,000$

**Net profit without model = R\$ 23,783,000**

---

## Incremental Gain from the Model

$30,173,000 - 23,783,000 = R\$ 6,390,000$

---

## Final Result

With **threshold = 0.1910**, the model generates approximately:

**R\$ 6.39 million in additional profit** compared to the scenario without the model.

## 14. Testing in a Real Production Environment

```
In [16]: df_test = pd.read_csv('../data/test.csv')
```

### 14.1 Missing Values

```
In [17]: cols_old = list(df_test.columns)  
  
cols_old = list(df_test.columns)  
  
cols_new = snake_case(cols_old)  
  
df_test.columns = cols_new  
  
df_test_final = df_test[['sk_id_curr']].copy()  
  
df_test = df_test.drop(columns=["sk_id_curr"])  
  
df_test['flag_own_car'] = df_test['flag_own_car'].map({'N': 0, 'Y': 1})  
df_test['flag_own_realty'] = df_test['flag_own_realty'].map({'N': 0, 'Y': 1})  
df_test['emergencystate_mode'] = df_test['emergencystate_mode'].map({'No': 0, 'Yes': 1})  
  
weekday_map = {  
    'MONDAY': 1,  
    'TUESDAY': 2,  
    'WEDNESDAY': 3,  
    'THURSDAY': 4,  
    'FRIDAY': 5,  
    'SATURDAY': 6,  
    'SUNDAY': 7  
}
```

```

df_test['weekday_appr_process_start'] = df_test['weekday_appr_process_start'].map(weekday_map)

df_test = df_test.replace('XNA', pd.NA)

aux_missing_cols = {}

aux_missing_cols['is_building'] = df_test.filter(like='commonarea_').notna().any(axis=1)
aux_missing_cols['is_building_missing'] = (~df_test.filter(like='commonarea_').notna().any(axis=1))
aux_missing_cols['has_basement'] = df_test['basementarea_avg'].notna().astype(int)
aux_missing_cols['basementarea_missing'] = df_test['basementarea_avg'].isna().astype(int)
aux_missing_cols['has_noliving'] = df_test['nonlivingarea_avg'].notna().astype(int)
aux_missing_cols['nonlivingarea_missing'] = df_test['nonlivingarea_avg'].isna().astype(int)
aux_missing_cols['is_employed'] = (~df_test['days_employed'].isna()).astype(int)

aux_missing_cols['livingarea_missing'] = df_test['livingarea_avg'].isna().astype(int)
aux_missing_cols['apartments_missing'] = df_test['apartments_avg'].isna().astype(int)
aux_missing_cols['floorsmax_missing'] = df_test['floorsmax_avg'].isna().astype(int)
aux_missing_cols['years_build_missing'] = df_test['years_build_avg'].isna().astype(int)
aux_missing_cols['commonarea_missing'] = df_test['commonarea_avg'].isna().astype(int)

aux_missing_cols['emergencystate_missing'] = df_test['emergencystate_mode'].isna().astype(int)
df_test['emergencystate_mode'] = df_test['emergencystate_mode'].fillna(0)
for col in ['elevators_avg', 'elevators_mode', 'elevators_medi']:
    aux_missing_cols[col + '_missing'] = df_test[col].isna().astype(int)
    df_test[col] = df_test[col].fillna(0)

cols_moda = [
    'housetype_mode', 'wallsmaterial_mode', 'occupation_type', 'organization_type'
]
for col in cols_moda:
    aux_missing_cols[col + '_missing'] = df_test[col].isna().astype(int)

df_test['housetype_mode'] = df_test['housetype_mode'].fillna('Unknown')
df_test['wallsmaterial_mode'] = df_test['wallsmaterial_mode'].fillna('Unknown')
df_test['occupation_type'] = df_test['occupation_type'].fillna('Other')
df_test['organization_type'] = df_test['organization_type'].fillna('Unknown')

drop_columns = {
    'fondkapremont_mode', 'landarea_mode', 'landarea_medi',
    'livingarea_mode', 'livingarea_medi',
    'entrances_avg', 'entrances_mode', 'entrances_medi',
    'floorsmax_mode', 'floorsmax_medi',
    'apartments_mode', 'apartments_medi', 'years_build_mode', 'years_build_medi'
}

do_not_drop = {
    'livingarea_avg', 'apartments_avg', 'floorsmax_avg', 'years_build_avg',
    'basementarea_avg', 'nonlivingarea_avg', 'livingapartments_missing',
    'own_car_age', 'years_beginexpluatation_avg', 'commonarea_avg', 'nonlivingapartments_avg',
}

prefixes = (
    'nonlivingapartments_', 'livingapartments_', 'floorsmin_', 'commonarea_', 'basementarea_',
    'nonlivingarea_', 'years_beginexpluatation_'
)

cols_to_drop = [
    col for col in df_test.columns
    if ((col.startswith(prefixes) and col not in do_not_drop) or col in drop_columns)
]

df_test = df_test.drop(columns=cols_to_drop)

```

In [18]: aux\_missing\_cols['name\_type\_suite\_missing'] = df\_test['name\_type\_suite'].isna().astype(int)  
df\_test["name\_type\_suite"] = df\_test["name\_type\_suite"].fillna(mode\_suite)

```

aux_missing_cols['code_gender_missing'] = df_test['code_gender'].isna().astype(int)
df_test["code_gender"] = df_test["code_gender"].fillna(mode_gender)

cols_nan_remanescentes = df_test.columns[df_test.isnull().any()]
for col_nome in cols_nan_remanescentes:
    aux_missing_cols[col_nome + '_missing'] = df_test[col_nome].isna().astype(int)
    mediana = df_mediana.loc[df_mediana['coluna'] == col_nome, 'mediana'].values
    if len(mediana) > 0:
        mediana_value = mediana[0]
        df_test[col_nome] = df_test[col_nome].fillna(mediana_value)
    else:
        df_test[col_nome] = df_test[col_nome].fillna(0)

```

```
In [19]: df_test = pd.concat([df_test, pd.DataFrame(aux_missing_cols, index=df_test.index)], axis=1)
df_test = df_test.copy()
```

## 14.2 Feature Engineering

```
In [ ]: df_test2 = df_test.copy()
```

```

In [9]: df_test2['days_employed_anom'] = df_test2["days_employed"] == 365243
df_test2['days_birth'] = df_test2['days_birth'].abs()
df_test2['days_employed'] = df_test2['days_employed'].abs()
df_test2['days_id_publish'] = df_test2['days_id_publish'].abs()
df_test2['days_registration'] = df_test2['days_registration'].abs()
df_test2['age_years'] = df_test2['days_birth'] / 365
df_test2['employment_years'] = df_test2['days_employed'] / 365
df_test2['id_publish_years'] = df_test2['days_id_publish'] / 365

df_test2['annuity_burden_ratio'] = df_test2['amt_annuity'] / (df_test2['bur_amt_credit_sum_mean'])
df_test2['phone_change_rate'] = df_test2['days_last_phone_change'] / (df_test2['days_birth'] +
df_test2['id_change_rate'] = df_test2['days_id_publish'] / (df_test2['days_birth'] + 1e-6)
df_test2['ext_source_weighted_mean'] = (
    0.5 * df_test2['ext_source_2'] + 0.3 * df_test2['ext_source_3'] + 0.2 * df_test2['ext_source_1']
)
df_test2['ext_source_max'] = df_test2[['ext_source_1', 'ext_source_2', 'ext_source_3']].max(axis=1)
df_test2['amt_application_credit_diff'] = df_test2['prev_amt_application_mean'] - df_test2['bur_amt_credit_mean']
df_test2['amt_application_goods_diff'] = df_test2['prev_amt_application_mean'] - df_test2['amt_goods_mean']

flag_document_cols = [col for col in df_test2.columns if col.startswith('flag_document_')]
df_test2['num_flag_document'] = df_test2[flag_document_cols].sum(axis=1)
df_test2['credit_to_income_ratio'] = df_test2['bur_amt_credit_sum_mean'] / (df_test2['amt_income_total'] +
df_test2['annuity_to_income_ratio'] = df_test2['amt_annuity'] / (df_test2['amt_income_total'] +
df_test2['payment_rate'] = df_test2['amt_annuity'] / (df_test2['bur_amt_credit_sum_mean'] + 1e-6)
df_test2['goods_to_credit_ratio'] = df_test2['bur_amt_credit_sum_mean'] / (df_test2['amt_goods_mean'] +
df_test2['credit_efficiency'] = df_test2['bur_amt_credit_sum_mean'] / (df_test2['prev_amt_application_mean'] +
df_test2['employment_life_ratio'] = df_test2['days_employed'] / (df_test2['days_birth'])
df_test2['bureau_request_intensity'] = (
    df_test2['amt_req_credit_bureau_day'] +
    df_test2['amt_req_credit_bureau_week'] +
    df_test2['amt_req_credit_bureau_mon'] +
    df_test2['amt_req_credit_bureau_qrt']
)
ext_sources = ['ext_source_1', 'ext_source_2', 'ext_source_3']
df_test2['ext_source_mean'] = df_test2[ext_sources].mean(axis=1)
df_test2['ext_source_range'] = df_test2[ext_sources].max(axis=1) - df_test2[ext_sources].min(axis=1)
df_test2['ext_source_std'] = df_test2[ext_sources].std(axis=1)
df_test2['ext_source_agreement'] = 1 / (df_test2['ext_source_std'] + 1e-5)

df_test2['decision_credit_diff'] = df_test2['prev_days_decision_mean'] / (df_test2['bur_amt_credit_mean'] +
df_test2['bureau_to_credit_ratio'] = df_test2['bureau_request_intensity'] / (df_test2['bur_amt_credit_mean'] +
df_test2['credit_per_employment_year'] = df_test2['bur_amt_credit_sum_mean'] / (df_test2['employment_years'] +

```

```

df_test2['annuity_per_employment_year'] = df_test2['amt_annuity'] / (df_test2['employment_years'] + 1)
df_test2['income_per_employed'] = df_test2['amt_income_total'] / ((df_test2['days_employed']+1) * df_test2['days_employed'])
df_test2['income_per_birth'] = df_test2['amt_income_total'] / (df_test2['days_birth'])
df_test2['own_car_age_birth_ratio'] = df_test2['own_car_age'] / (df_test2['days_birth'])
df_test2['own_car_age_employed_ratio'] = df_test2['own_car_age'] / ((df_test2['days_employed']+1) * df_test2['days_employed'])
df_test2['days_since_last_employment_until_application'] = df_test2['days_employed'] - df_test2['days_birth']

poly_vars = [
    'days_birth',
    'payment_rate',
    'ext_source_mean',
]
X_poly = df_test2[poly_vars].fillna(0).copy()

X_poly_trans = poly.transform(X_poly)
poly_feature_names = poly.get_feature_names_out(poly_vars)
df_poly = pd.DataFrame(X_poly_trans, columns=poly_feature_names, index=df_test2.index)
df_poly = df_poly.drop(columns=poly_vars, errors='ignore')
df_test2 = pd.concat([df_test2, df_poly], axis=1)

df_test2['employment_stability'] = df_test2['employment_years'] / (df_test2['age_years'] + 1e-6)
df_test2['id_document_age_ratio'] = df_test2['id_publish_years'] / (df_test2['age_years'] + 1e-6)
df_test2['phone_change_frequency'] = 1 / (df_test2['days_last_phone_change'] + 1e-6)

df_test2['recent_instability'] = df_test2['phone_change_rate'] + df_test2['id_change_rate']
df_test2['bureau_overdue_ratio'] = df_test2['bur_amt_credit_max_overdue_max'] / (df_test2['bur_bb'] + 1)
df_test2['credit_risk_signal'] = df_test2['credit_to_income_ratio'] * ((df_test2['ext_source_1'] + 1) / (df_test2['ext_source_1'] + 1e-6))
df_test2['annuity_per_age'] = df_test2['amt_annuity'] / (df_test2['own_car_age'] + 1e-6)
df_test2["overdue_flag"] = (df_test2["bur_amt_credit_max_overdue_max"] > 0).astype(int)
df_test2["entry_vs_due_ratio"] = df_test2["instf_inst_days_entry_payment_mean_mean"] / (df_test2['days_employed'] + 1)
df_test2["ext_source_interaction"] = df_test2["ext_source_1"] * df_test2["ext_source_3"]
df_test2["pos_balance_range"] = df_test2["posf_pos_months_balance_max_max"] - df_test2["bur_bb"]
df_test2["area_quality"] = df_test2["totalarea_mode"] / (df_test2["region_population_relative"] + 1)

```

## 14.3 Scaling and Encoding

```
In [ ]: df_test3 = df_test2.copy()
```

```
In [14]: log_transform_cols = [
    'decision_credit_diff',
    'annuity_burden_ratio',
    'credit_efficiency',
]

for col in log_transform_cols:

    df_test3[col + '_log'] = np.log1p(df_test3[col])
    df_test3.drop(columns=col, inplace=True)
```

c:\Users\Patryck\AppData\Local\Programs\Python\Python311\Lib\site-packages\pandas\core\arraylike.py:399: RuntimeWarning: invalid value encountered in log1p  
 result = getattr(ufunc, method)(\*inputs, \*\*kwargs)

```
In [15]: cols_to_scale = [
    'phone_change_frequency',
    'amt_income_total',
    'amt_credit',
    'num_flag_document',
    'amt_annuity',
    'amt_goods_price',
    'apartments_avg',
    'floorsmax_avg',
    'livingarea_avg',
```

```

'years_build_avg',
'phone_change_rate',
'elevators_avg',
'elevators_mode',
'elevators_medi',
'own_car_age',
'obs_30_cnt_social_circle',
'def_30_cnt_social_circle',
'obs_60_cnt_social_circle',
'def_60_cnt_social_circle',
'amt_req_credit_bureau_hour',
'amt_req_credit_bureau_day',
'amt_req_credit_bureau_week',
'amt_req_credit_bureau_mon',
'amt_req_credit_bureau_qrt',
'amt_req_credit_bureau_year',
'goods_to_credit_ratio',
'basementarea_avg',
'livingapartments_avg',
'landarea_avg',
'nonlivingapartments_avg',
'commonarea_avg',
'years_beginexpluatation_avg',
'nonlivingarea_avg',
'days_employed',
'payment_rate',
'payment_rate^2',
'payment_rate ext_source_mean',
'days_birth^2 payment_rate',
'days_birth payment_rate^2',
'payment_rate^3',
'payment_rate^2 ext_source_mean',
'payment_rate ext_source_mean^2',
]
]

df_test3[cols_to_scale] = robust_scaler.transform(df_test3[cols_to_scale])

```

```

In [16]: cols_to_standard_scale = [
    'days_registration',
    'days_since_last_employment_until_application',
    'income_per_employed',
    'days_id_publish',
    'days_last_phone_change',
    'recent_instability',
    'employment_stability',
    'employment_life_ratio',
    'cnt_fam_members',
    'goods_to_credit_ratio',
    'days_birth',
    'days_birth^2',
    'days_birth payment_rate',
    'days_birth ext_source_mean',
    'ext_source_mean^2',
    'days_birth^3',
    'days_birth^2 ext_source_mean',
    'days_birth payment_rate ext_source_mean',
    'days_birth ext_source_mean^2',
    'ext_source_mean^3'
]

```

```

df_test3[cols_to_standard_scale] = standard_scaler.transform(df_test3[cols_to_standard_scale])

```

```

In [17]: cols_to_minmax_scale = [
    'cnt_children',
    'region_population_relative',
    'bureau_to_credit_ratio',
    'bureau_request_intensity',
]

```

```

        'annuity_to_income_ratio',
        'id_document_age_ratio',
    ]

df_test3[cols_to_minmax_scale] = minmax_scaler.transform(df_test3[cols_to_minmax_scale])

In [20]: binary_cols = [col for col in df_test3.columns if sorted(df_test3[col].dropna().unique()) in [
lists_to_exclude = set(
    cols_to_standard_scale +
    cols_to_scale +
    cols_to_minmax_scale +
    binary_cols +
    [col for col in df_test3.columns if df_test3[col].dtype == 'object'] +
    ['target']
)

other_columns = [col for col in df_test3.columns if (col not in lists_to_exclude) and (col not in binary_cols)]
df_test3[other_columns] = scaler.transform(df_test3[other_columns])

In [10]: df_test3['name_contract_type'] = (df_test3['name_contract_type'] != 'Cash loans').astype(int)
df_test3['code_gender'] = df_test3['code_gender'].map({'F': 0, 'M': 1})

encoded_suite_test = encoder_suite.transform(df_test3[['name_type_suite']])
col_names_suite = [f"nts_{cat}" for cat in encoder_suite.categories_[0][1:]]
encoded_df_suite_test = pd.DataFrame(encoded_suite_test, columns=col_names_suite, index=df_test3.index)
df_test3 = pd.concat([df_test3.drop(columns=['name_type_suite']), encoded_df_suite_test], axis=1)

encoded_fam_test = encoder_fam.transform(df_test3[['name_family_status']])
col_names_fam = [f"nfs_{cat}" for cat in encoder_fam.categories_[0][1:]]
encoded_df_fam_test = pd.DataFrame(encoded_fam_test, columns=col_names_fam, index=df_test3.index)
df_test3 = pd.concat([df_test3.drop(columns=['name_family_status']), encoded_df_fam_test], axis=1)

encoded_housing_test = encoder_housing.transform(df_test3[['name_housing_type']])
col_names_housing = [f"nht_{cat}" for cat in encoder_housing.categories_[0][1:]]
encoded_df_housing_test = pd.DataFrame(encoded_housing_test, columns=col_names_housing, index=df_test3.index)
df_test3 = pd.concat([df_test3.drop(columns=['name_housing_type']), encoded_df_housing_test], axis=1)

encoded_housetype_mode_test = encoder_housetype_mode.transform(df_test3[['housetype_mode']])
col_names_housetype_mode = [f"htm_{cat}" for cat in encoder_housetype_mode.categories_[0][1:]]
encoded_df_housetype_mode_test = pd.DataFrame(encoded_housetype_mode_test, columns=col_names_housetype_mode, index=df_test3.index)
df_test3 = pd.concat([df_test3.drop(columns=['housetype_mode']), encoded_df_housetype_mode_test], axis=1)

encoded_walls_test = encoder_walls.transform(df_test3[['wallsmaterial_mode']])
col_names_walls = [f"wm_{cat}" for cat in encoder_walls.categories_[0][1:]]
encoded_df_walls_test = pd.DataFrame(encoded_walls_test, columns=col_names_walls, index=df_test3.index)
df_test3 = pd.concat([df_test3.drop(columns=['wallsmaterial_mode']), encoded_df_walls_test], axis=1)

In [11]: df_test3['name_income_type_te'] = df_test3['name_income_type'].map(target_mean_income)
df_test3.drop('name_income_type', axis=1, inplace=True)

df_test3['occupation_type_te'] = df_test3['occupation_type'].map(target_mean_occupation)
df_test3.drop('occupation_type', axis=1, inplace=True)

df_test3['organization_type_te'] = df_test3['organization_type'].map(target_mean_organization)
df_test3.drop('organization_type', axis=1, inplace=True)

df_test3['region_rating_client_te'] = df_test3['region_rating_client'].map(target_mean_region_r
df_test3.drop('region_rating_client', axis=1, inplace=True)

df_test3['region_rating_client_w_city_te'] = df_test3['region_rating_client_w_city'].map(target_mean_
df_test3.drop('region_rating_client_w_city', axis=1, inplace=True)

In [12]: education_order = [
    'Lower secondary',
    'Secondary / secondary special',
    'Incomplete higher',

```

```

        'Higher education',
        'Academic degree'
    ]
df_test3['name_education_type'] = pd.Categorical(
    df_test3['name_education_type'],
    categories=education_order,
    ordered=True
).codes

```

## 14.4 Selecting Features

```

In [ ]: df_test4 = df_test3.copy()

In [15]: df_test4.columns = [col.replace('/', '_').replace(',', '_').replace(' ', '') for col in df_test]

In [16]: X_test_final = df_test4[X.columns].copy()

In [18]: df_test_final = pd.read_csv("../data/test.csv")[['SK_ID_CURR']].copy()

In [19]: df_test_final['TARGET'] = xgb_final.predict_proba(X_test_final)[:, 1]

In [ ]: df_test_final.to_csv('../data/test_final.csv', index=False)

```

Auc final : 0.78421

## 15. Conclusion

### Project Conclusion

The development of the predictive model to estimate the **probability of customer default** demonstrated, in a practical way, the level of **real-world complexity of large-scale credit risk problems**. Working with a dataset containing **more than 800 variables**, strong **class imbalance**, and weak signals in individual variables, the project required a deeply analytical, careful, and business value–driven approach.

The high number of variables introduced additional challenges, such as **multicollinearity, informational noise, and risk of overfitting**, requiring strong discipline in **feature selection, regularization, and cross-validation**. Even so, the combination of feature engineering, ensemble techniques, and probabilistic calibration made it possible to extract relevant patterns from a highly complex and heterogeneous dataset.

### Strategic Value of the Model

The model demonstrated a real capacity to:

- Consistently differentiate **higher- and lower-risk profiles**;
- Anticipate default behavior with **measurable financial impact**;
- Support decisions based on **calibrated probabilities**, rather than purely heuristic rules.

The chosen threshold proved to be appropriate for the institution's strategic objective: **reducing losses without compromising commercial efficiency**.

The financial simulation confirmed that the use of the model generates **incremental profit**, even after considering the operational costs of preventive actions and the impact of false positives. This demonstrates that the project not only improves statistical metrics but also **delivers real financial results**.

### Analytical and Technical Maturity

Beyond the practical results, the project consolidated a relevant level of **technical maturity**, including:

- Handling a dataset with **more than 800 variables** and different data types;
- Balancing **model interpretability and performance**;
- Integrating technical metrics (AUC, F1, MCC) with **business metrics** (profit, losses avoided, and operational cost).

The project reinforces that credit risk models are not built merely to "predict", but to **support strategic decisions with direct impact on portfolio profitability and sustainability**.

---

### **Closing Remarks**

The final result is a **robust, scalable, and business-aligned model**, capable of operating in scenarios with a large number of variables, strong class imbalance, and weak signals.

More than a technical exercise, the project highlights the role of **data science as a central tool for risk management, operational efficiency, and competitive advantage in the financial sector**.

In summary, the work demonstrates that, even in complex and noisy environments, the combination of **data engineering, statistical modeling, and business strategy generates concrete and measurable value**.