DataScienceFinalProject

May 12, 2024

[1]:
```
!pip install kaggle
!pip install autoviz
!pip install -U feature-engine
!pip install feature_engine
```

```
Requirement already satisfied: kaggle in /usr/local/lib/python3.10/dist-packages
(1.6.12)
Requirement already satisfied: six>=1.10 in /usr/local/lib/python3.10/dist-
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/usr/local/lib/python3.10/dist-packages (from
statsmodels>=0.11.1->feature_engine) (24.0)
Requirement already satisfied: six in /usr/local/lib/python3.10/dist-packages
(from patsy>=0.5.6->statsmodels>=0.11.1->feature_engine) (1.16.0)
```

1 Pre Mid-Term EDA

[2]:
```
from google.colab import drive
from scipy.stats import zscore, boxcox
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

```
import os

# Define the path to the folder you want to mount
drive_path = "/content/drive"
data_path = os.path.join(drive_path, "My Drive/dsa_project")

drive.mount(drive_path)
os.listdir(data_path)

TGT = "TARGET"
```

```
Mounted at /content/drive
```

Question 1: SK_ID_CURR Analysis:Get the count of unique values of SK_ID_CURR in file application_train.csv and compare this count to the number of rows in application_train.csv. Compare this with the total row count. Investigate if SK_ID_CURR serves as the table's primary key.?

Analysis:

Since the number of rows is same as number of unique values of SK_ID_CURR i.e. 307511, we can confirm that SK_ID_CURR is the primary id.

```
[3]: app_train = pd.read_csv(os.path.join(data_path, "application_train.csv"))
print(f"app_train.shape: {app_train.shape[0]} | len(app_train['SK_ID_CURR'].
 ↪unique()): {len(app_train['SK_ID_CURR'].unique())}")
```

```
app_train.shape: 307511 | len(app_train['SK_ID_CURR'].unique()): 307511
```

Question 2: TARGET Column Analysis: Identify and quantify the unique values within the TARGET column. Assess the dataset's balance by evaluating the proportions of each target value.

Analysis:

There is a clear imbalance in the Target Variables as evident by the percentage of each unique value.

```
[4]: print(app_train[TGT].value_counts())
print(app_train[TGT].value_counts(normalize=True))
```

```
TARGET
0    282686
1     24825
Name: count, dtype: int64
TARGET
0    0.919271
1    0.080729
Name: proportion, dtype: float64
```

```
[5]: all_num_cols = app_train.select_dtypes(include=['number']).columns.tolist()
```

There is an imbalance in the TARGET values with 0 being 91% of the data.

[6]:
```python
null_df = list()

for c in all_num_cols:
  _miss_count = len(app_train[app_train[c].isnull()])
  _miss_pct = round(_miss_count/len(app_train), 2) * 100

  null_df.append({"col": c, "miss": _miss_count, "miss_pct": _miss_pct})

null_df = pd.DataFrame(null_df).sort_values("miss").reset_index(drop=True)
null_df = null_df[null_df["col"].isin([c for c in null_df["col"].tolist() if␣
↪"FLAG" not in c.upper()])]
null_df.head(25)
```

[6]:

	col	miss	miss_pct
0	SK_ID_CURR	0	0.0
1	REG_CITY_NOT_WORK_CITY	0	0.0
22	REG_CITY_NOT_LIVE_CITY	0	0.0
23	LIVE_REGION_NOT_WORK_REGION	0	0.0
24	LIVE_CITY_NOT_WORK_CITY	0	0.0
25	REG_REGION_NOT_LIVE_REGION	0	0.0
26	AMT_CREDIT	0	0.0
27	REGION_POPULATION_RELATIVE	0	0.0
28	DAYS_BIRTH	0	0.0
29	DAYS_EMPLOYED	0	0.0
30	DAYS_REGISTRATION	0	0.0
31	DAYS_ID_PUBLISH	0	0.0
32	REG_REGION_NOT_WORK_REGION	0	0.0
35	AMT_INCOME_TOTAL	0	0.0
39	REGION_RATING_CLIENT	0	0.0
40	TARGET	0	0.0
41	REGION_RATING_CLIENT_W_CITY	0	0.0
42	HOUR_APPR_PROCESS_START	0	0.0
44	CNT_CHILDREN	0	0.0
45	DAYS_LAST_PHONE_CHANGE	1	0.0
46	CNT_FAM_MEMBERS	2	0.0
47	AMT_ANNUITY	12	0.0
48	AMT_GOODS_PRICE	278	0.0
49	EXT_SOURCE_2	660	0.0
50	DEF_60_CNT_SOCIAL_CIRCLE	1021	0.0

[7]:
```python
selected_num_col = list()
selected_num_col.append('TARGET')
selected_num_col.append("CNT_CHILDREN")
selected_num_col.append("AMT_INCOME_TOTAL")
selected_num_col.append("AMT_CREDIT")
```

```
selected_num_col.append("AMT_ANNUITY")
selected_num_col.append("REGION_POPULATION_RELATIVE")
selected_num_col.append("DAYS_BIRTH")
selected_num_col.append("DAYS_EMPLOYED")
selected_num_col.append("DAYS_REGISTRATION")
selected_num_col.append("DAYS_ID_PUBLISH")
selected_num_col.append("HOUR_APPR_PROCESS_START")

# Not sure if these columns should be considered numerical or categorical
# selected_num_col.append("REGION_RATING_CLIENT")
# selected_num_col.append("REG_REGION_NOT_WORK_REGION")

# Too many missing values
# selected_num_col.append('YEARS_BUILD_AVG')
# selected_num_col.append('DAYS_LAST_PHONE_CHANGE')
# selected_num_col.append('AMT_REQ_CREDIT_BUREAU_YEAR')
# selected_num_col.append('OWN_CAR_AGE')
# selected_num_col.append('AMT_GOODS_PRICE')

null_df[null_df["col"].isin(set(selected_num_col))]
```

[7]:

	col	miss	miss_pct
26	AMT_CREDIT	0	0.0
27	REGION_POPULATION_RELATIVE	0	0.0
28	DAYS_BIRTH	0	0.0
29	DAYS_EMPLOYED	0	0.0
30	DAYS_REGISTRATION	0	0.0
31	DAYS_ID_PUBLISH	0	0.0
35	AMT_INCOME_TOTAL	0	0.0
40	TARGET	0	0.0
42	HOUR_APPR_PROCESS_START	0	0.0
44	CNT_CHILDREN	0	0.0
47	AMT_ANNUITY	12	0.0

[8]:
```
app_train[selected_num_col].dtypes
```

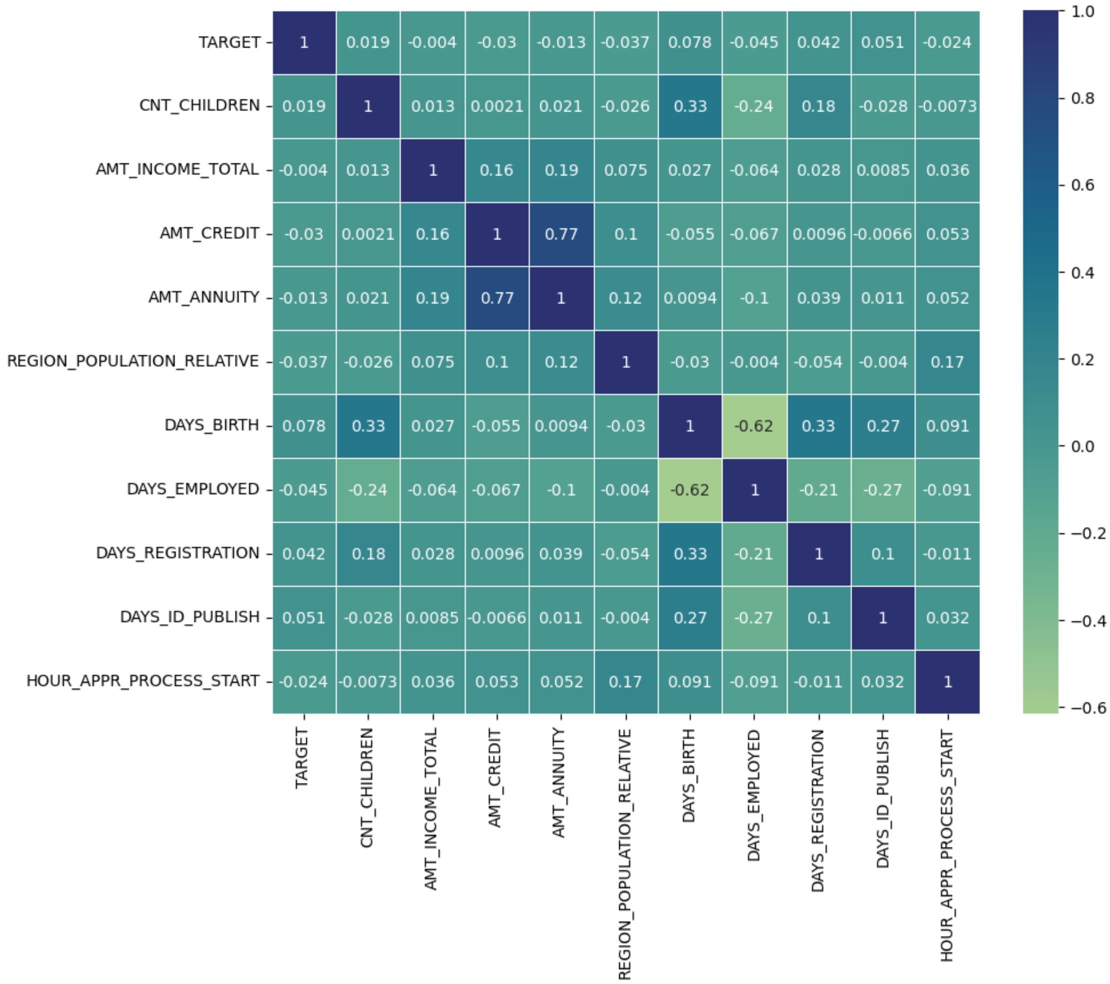
[8]:
```
TARGET                          int64
CNT_CHILDREN                    int64
AMT_INCOME_TOTAL              float64
AMT_CREDIT                    float64
AMT_ANNUITY                   float64
REGION_POPULATION_RELATIVE    float64
DAYS_BIRTH                      int64
DAYS_EMPLOYED                   int64
DAYS_REGISTRATION             float64
DAYS_ID_PUBLISH                 int64
HOUR_APPR_PROCESS_START         int64
```

```
dtype: object
```

Question 3: Correlation Analysis: Generate a Pearson correlation matrix and heatmap (for any 10 numeric variables of choice) on application_tain.csv. Write code to list the top 5 features correlated with the TARGET column.

[9]:
```python
corr = app_train[selected_num_col].corr()

plt.figure(figsize = (10,8))
sns.heatmap(corr, annot = True, cmap = 'crest', linewidth = 0.5)
```

[9]:
```
<Axes: >
```



[10]:
```python
corr_vars = corr[TGT].sort_values(ascending = False)
corr_vars = corr_vars.abs()
corr_vars = corr_vars.reset_index().rename(columns={"index": "vars"})
corr_vars = corr_vars[(corr_vars["vars"] != TGT)]
```

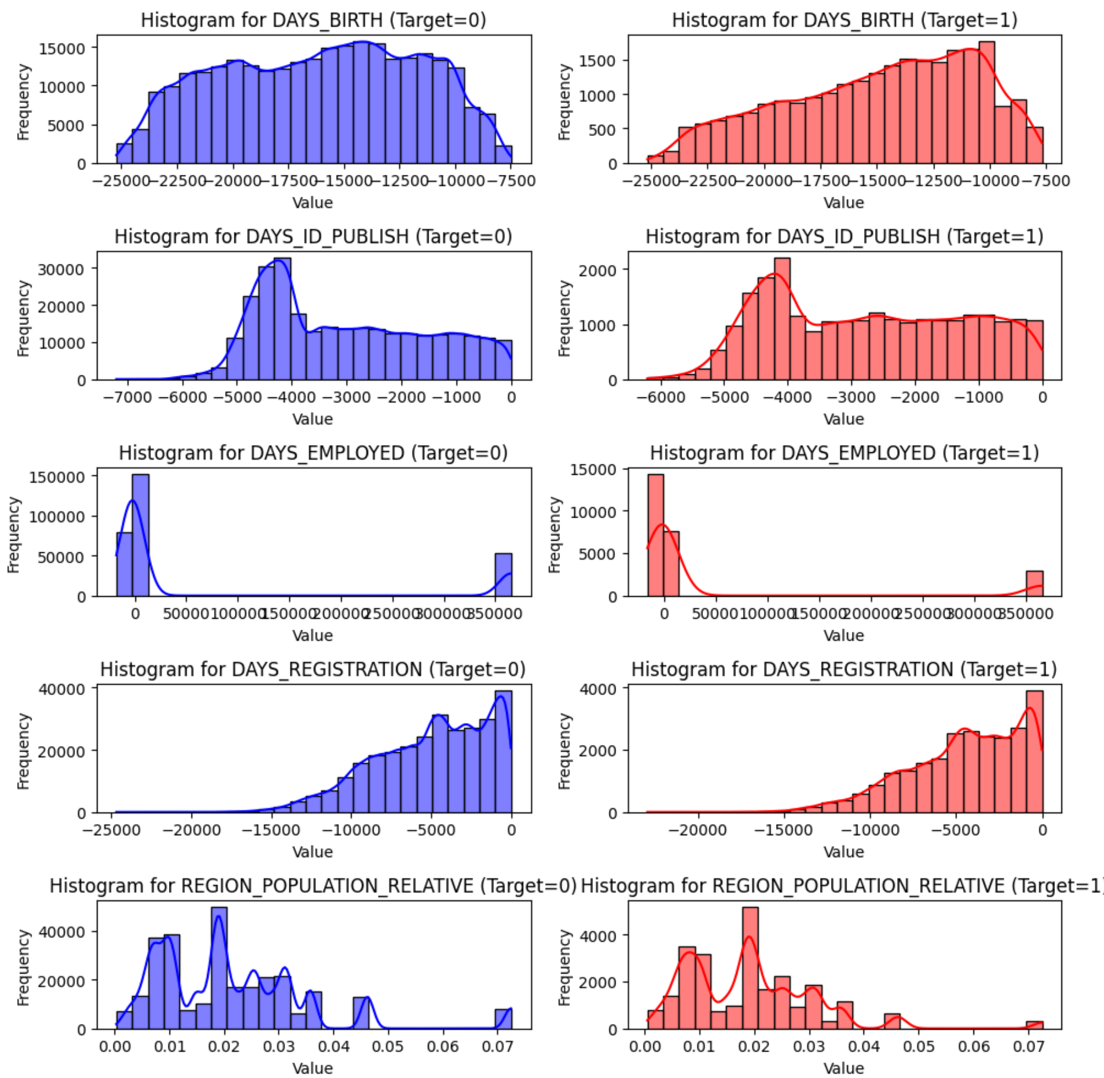
```
top5_corr_vars = corr_vars.sort_values(TGT, ascending=False).head(5)["vars"].
 ↪tolist()
corr_vars.sort_values(TGT, ascending=False).head(5)[["vars", "TARGET"]]
```

[10]:

	vars	TARGET
1	DAYS_BIRTH	0.078239
2	DAYS_ID_PUBLISH	0.051457
10	DAYS_EMPLOYED	0.044932
3	DAYS_REGISTRATION	0.041975
9	REGION_POPULATION_RELATIVE	0.037227

Question 4: Histogram: Generate histograms for any five numerical features in application_train.csv, and comment on whether they seem Gaussian, or have severe skews. Visualize the relationship between each of these numeric variables and the target variable.

[11]:
```
plt.figure(figsize = (10,10))

app_train0 = app_train[(app_train[TGT] == 0)]
app_train1 = app_train[(app_train[TGT] == 1)]

for i, _v in enumerate(top5_corr_vars):

    plt.subplot(len(top5_corr_vars), 2, 2*i+1)
    sns.histplot(x=app_train0[_v], bins=25, kde=True, color="blue")
    plt.title(f'Histogram for {_v} (Target=0)')
    plt.xlabel('Value')
    plt.ylabel('Frequency')

    plt.subplot(len(top5_corr_vars), 2, 2*i+2)
    sns.histplot(x=app_train1[_v], bins=25, kde=True, color="red")
    plt.title(f'Histogram for {_v} (Target=1)')
    plt.xlabel('Value')
    plt.ylabel('Frequency')

# Adjust layout to prevent overlapping titles
plt.tight_layout()

# Show the plots
plt.show()
```



[12]:
```python
plt.figure(figsize=(15, 5 * len(top5_corr_vars)))

for i, var in enumerate(top5_corr_vars):
    # Box plot
    plt.subplot(len(top5_corr_vars), 2, 2 * i + 1)
    sns.boxplot(x=app_train[TGT], y=app_train[var], hue=app_train[TGT],␣
 ↪palette={0: 'blue', 1: 'red'})
    plt.title(f'Box Plot for {var}')
    plt.xlabel('Target')
    plt.ylabel(var)

    # Violin plot
    plt.subplot(len(top5_corr_vars), 2, 2 * i + 2)
```

```python
    sns.violinplot(x=app_train[TGT], y=app_train[var], hue=app_train[TGT],␣
↪palette={0: 'blue', 1: 'red'})
    plt.title(f'Violin Plot for {var}')
    plt.xlabel('Target')
    plt.ylabel(var)

# Adjust layout to prevent overlapping titles
plt.tight_layout()

# Show the plots
plt.show()
```

```
/usr/local/lib/python3.10/dist-packages/seaborn/_base.py:949: FutureWarning:
When grouping with a length-1 list-like, you will need to pass a length-1 tuple
to get_group in a future version of pandas. Pass `(name,)` instead of `name` to
silence this warning.
  data_subset = grouped_data.get_group(pd_key)
/usr/local/lib/python3.10/dist-packages/seaborn/categorical.py:640:
FutureWarning: SeriesGroupBy.grouper is deprecated and will be removed in a
future version of pandas.
  positions = grouped.grouper.result_index.to_numpy(dtype=float)
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```

```
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/usr/local/lib/python3.10/dist-packages/seaborn/_base.py:949: FutureWarning:
When grouping with a length-1 list-like, you will need to pass a length-1 tuple
```
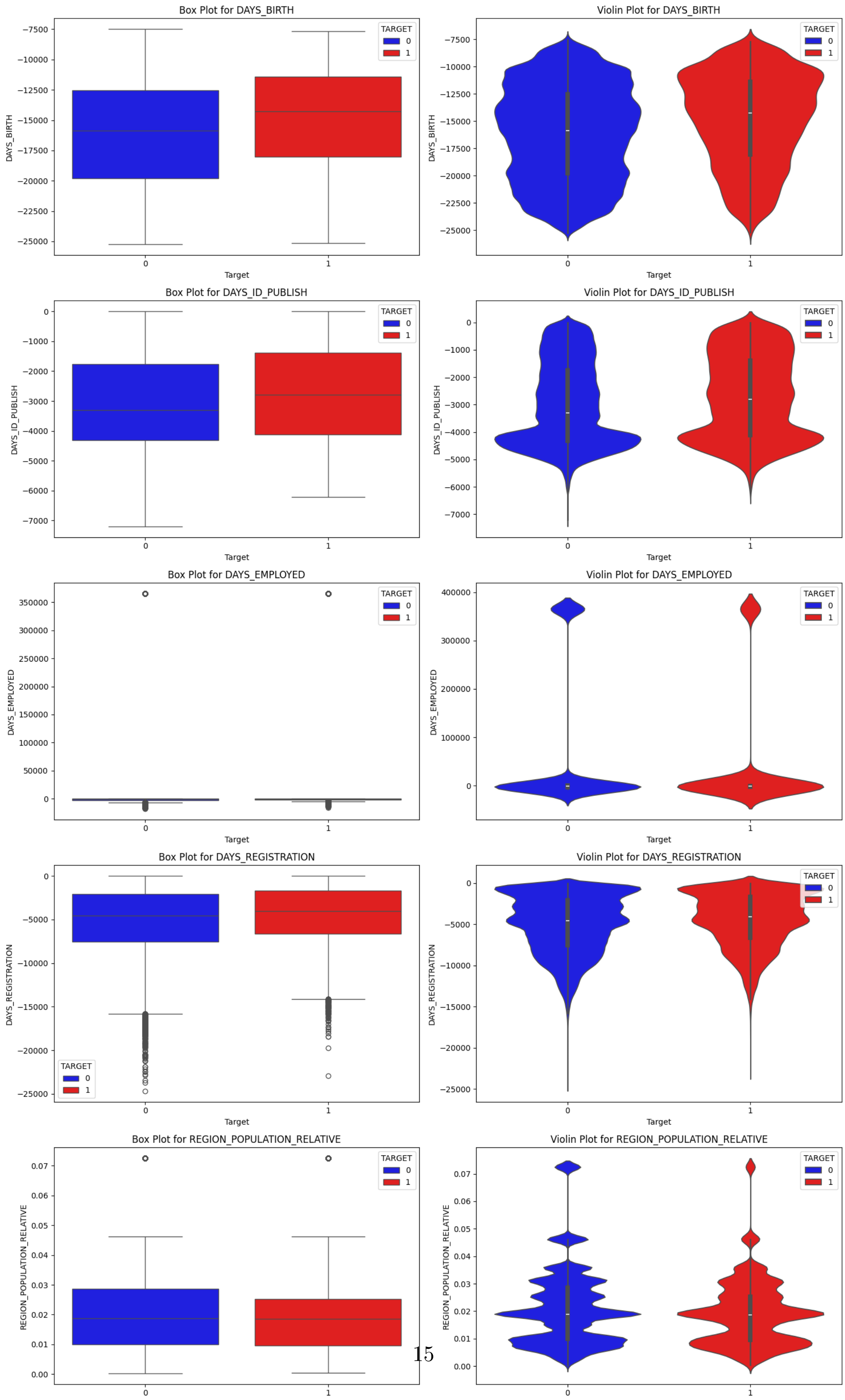

```
to get_group in a future version of pandas. Pass `(name,)` instead of `name` to
silence this warning.
  data_subset = grouped_data.get_group(pd_key)
/usr/local/lib/python3.10/dist-packages/seaborn/categorical.py:640:
FutureWarning: SeriesGroupBy.grouper is deprecated and will be removed in a
future version of pandas.
  positions = grouped.grouper.result_index.to_numpy(dtype=float)
```


Box Plot for DAYS_BIRTH
Violin Plot for DAYS_BIRTH
DAYS_BIRTH
Box Plot for DAYS_ID_PUBLISH
Violin Plot for DAYS_ID_PUBLISH
DAYS_ID_PUBLISH
Box Plot for DAYS_EMPLOYED
Violin Plot for DAYS_EMPLOYED
DAYS_EMPLOYED
Box Plot for DAYS_REGISTRATION
Violin Plot for DAYS_REGISTRATION
DAYS_REGISTRATION
Box Plot for REGION_POPULATION_RELATIVE
Violin Plot for REGION_POPULATION_RELATIVE
REGION_POPULATION_RELATIVE
Target
TARGET
0
1

[13]:
```
for c in top5_corr_vars:
  _miss_count = len(app_train[app_train[c].isnull()])
  print(f"Null values in {c}: {_miss_count}, {round(_miss_count/len(app_train),␣
↪2) * 100} %")
```

```
Null values in DAYS_BIRTH: 0, 0.0 %
Null values in DAYS_ID_PUBLISH: 0, 0.0 %
Null values in DAYS_EMPLOYED: 0, 0.0 %
Null values in DAYS_REGISTRATION: 0, 0.0 %
Null values in REGION_POPULATION_RELATIVE: 0, 0.0 %
```

[14]:
```
app_train["DAYS_EMPLOYED"].describe()
```

[14]:
```
count    307511.000000
mean      63815.045904
std      141275.766519
min      -17912.000000
25%       -2760.000000
50%       -1213.000000
75%        -289.000000
max      365243.000000
Name: DAYS_EMPLOYED, dtype: float64
```

Question 5: Outlier Analysis: Perform outlier analysis on the chosen variables.

[15]:
```
# Record count of rows where Z score of target column in higher than 2 and 3␣
↪separately
suff = "z_score"
z_score_cols = list()
outlier_df = list()

for c in top5_corr_vars:
  app_train[f"{c}_{suff}"] = zscore(app_train[c])
  over_2 = len(app_train[(app_train[f"{c}_{suff}"].abs() > 2)])
  over_3 = len(app_train[(app_train[f"{c}_{suff}"].abs() > 3)])
  outlier_df.append({"col": c, "over_2": over_2, "over_3": over_3})

outlier_df = pd.DataFrame(outlier_df)
outlier_df
```

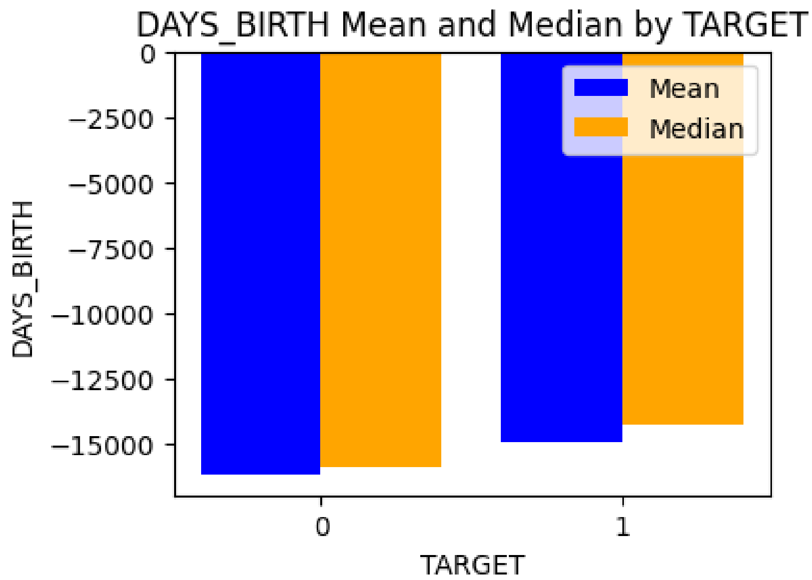
[15]:

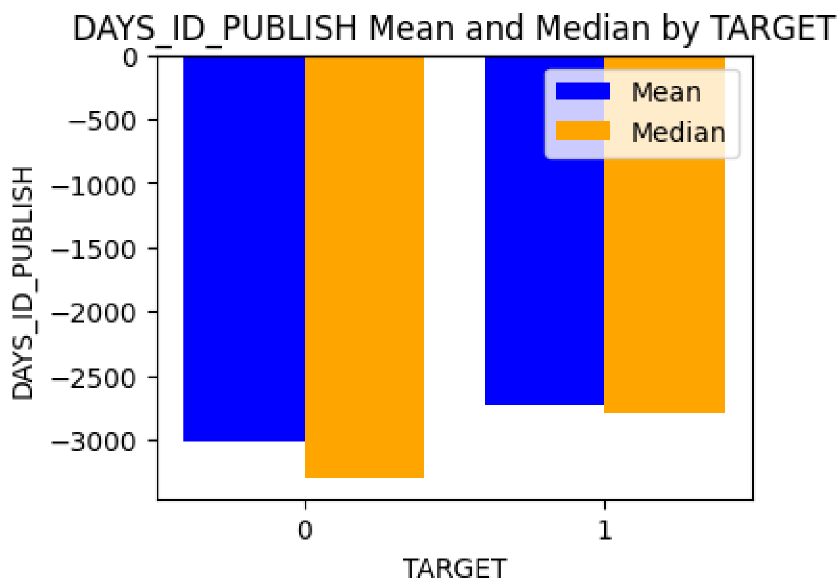
	col	over_2	over_3
0	DAYS_BIRTH	1210	0
1	DAYS_ID_PUBLISH	390	0
2	DAYS_EMPLOYED	55374	0
3	DAYS_REGISTRATION	11330	749

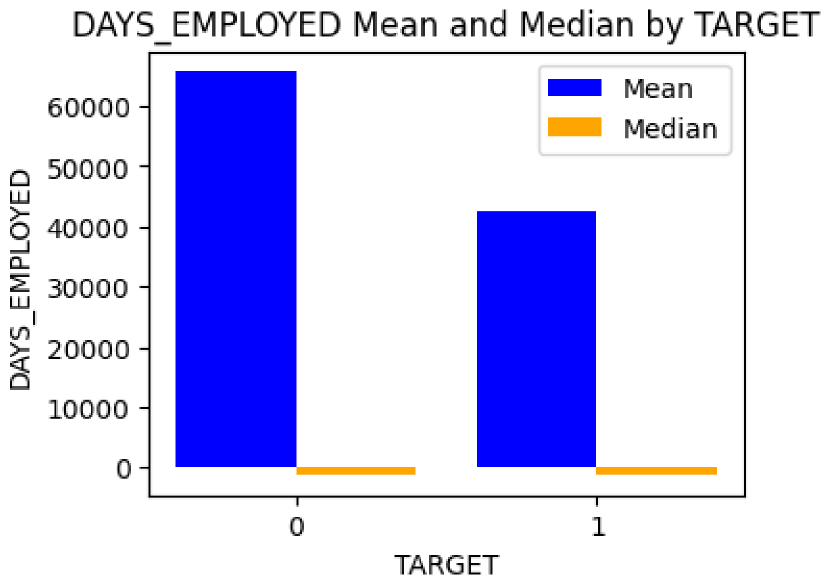
```
4  REGION_POPULATION_RELATIVE    8412    8412
```

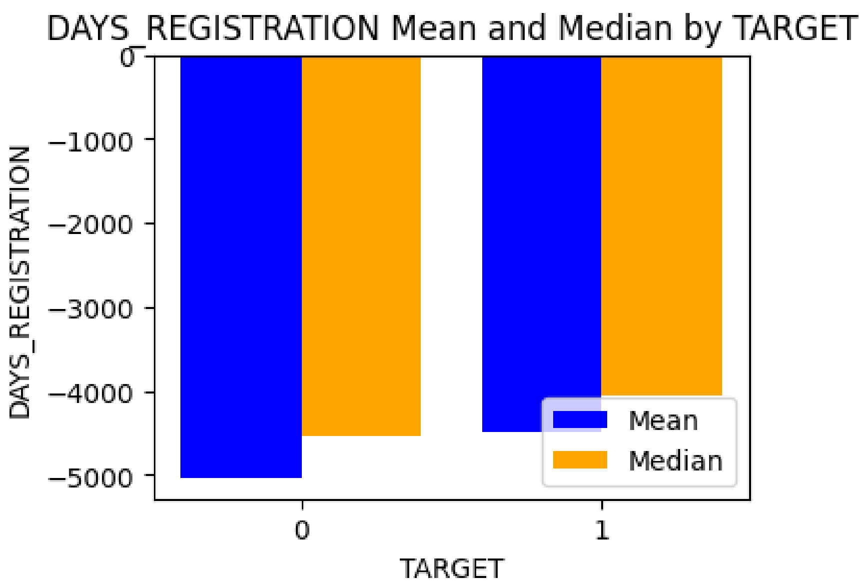
Question 6: Transformation of Nuemric Variables: If skewed, perform suitable transformations on these five numerical variables. Check the relationship of each of these numeric variables with the target variable using bar charts. Visualize the relationship between each of these numeric variables and the target variable. Perform outlier analysis on the transformed variables and report any differences before and after transformation.

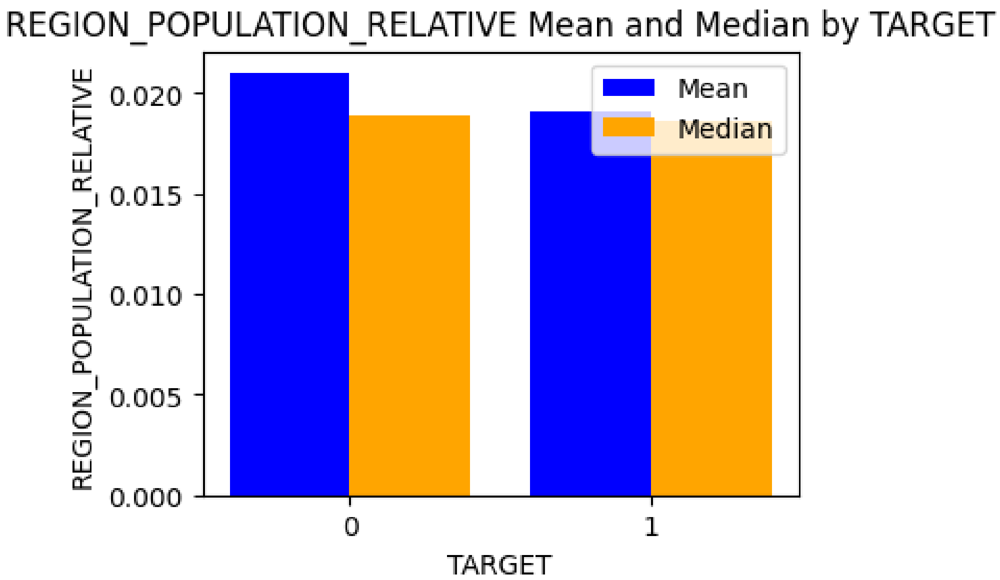
[16]:
```python
# Calculate the selected metrics for each numeric variable grouped by the␣
↪target variable
metrics = ['mean', 'median']
central_tend = {}
for metric in metrics:
    if metric == 'mean':
        t = app_train.groupby(TGT)[top5_corr_vars].mean()
    elif metric == 'median':
        t = app_train.groupby(TGT)[top5_corr_vars].median()
    elif metric == 'std':
        t = app_train.groupby(TGT)[top5_corr_vars].std()
    elif metric == 'count':
        t = app_train.groupby(TGT)[top5_corr_vars].count()
    central_tend[metric] = t

# Merge the DataFrames on 'TARGET' column
merged_df = pd.merge(central_tend["mean"],
                     central_tend["median"],\
                     left_index=True, right_index=True,
                     suffixes=('_mean', '_median'))

merged_df = merged_df.reset_index()

# Columns to plot
columns_to_plot = list(merged_df.columns)[1:]

# Plot bar graphs
for column in top5_corr_vars:
    plt.figure(figsize=(4, 3))
    plt.bar(merged_df['TARGET'], merged_df[column + '_mean'], label='Mean',␣
↪width=0.4, color='blue')
    plt.bar(merged_df['TARGET'] + 0.4, merged_df[column + '_median'],␣
↪label='Median', width=0.4, color='orange')
    plt.xlabel('TARGET')
    plt.ylabel(column)
    plt.title(f'{column} Mean and Median by TARGET')
    plt.xticks(merged_df['TARGET'] + 0.2, merged_df['TARGET'])
    plt.legend()
    plt.show()
```


DAYS_BIRTH Mean and Median by TARGET
0
−2500
−5000
−7500
−10000
−12500
−15000
DAYS_BIRTH
Mean
Median
0
1
TARGET


DAYS_ID_PUBLISH Mean and Median by TARGET
0
−500
−1000
−1500
−2000
−2500
−3000
DAYS_ID_PUBLISH
Mean
Median
0
1
TARGET


DAYS_EMPLOYED Mean and Median by TARGET
Mean
Median
60000
50000
40000
30000
20000
10000
0
DAYS_EMPLOYED
0
1
TARGET


DAYS_REGISTRATION Mean and Median by TARGET
0
−1000
−2000
−3000
−4000
−5000
DAYS_REGISTRATION
Mean
Median
0
1
TARGET



[17]:
```
import matplotlib.pyplot as plt
import seaborn as sns
unique_tgt_values = app_train[TGT].unique()
palette = {value: 'blue' if value == 0 else 'red' for value in␣
 ↪unique_tgt_values}
plt.figure(figsize=(5, 15))

for i, var in enumerate(top5_corr_vars):
    plt.subplot(len(top5_corr_vars), 1, i + 1)
    sns.stripplot(x=app_train[TGT], y=app_train[var], palette = {0:'blue', 1:
 ↪'red'}, jitter = True, hue=app_train[TGT], legend=False)
    plt.title(f'strip plot for {var}')
    plt.xlabel('Target')
    plt.ylabel(var)

# Adjust layout to prevent overlapping titles
plt.tight_layout()

# Show the plots
plt.show()
```

```
/usr/local/lib/python3.10/dist-packages/seaborn/_base.py:949: FutureWarning:
When grouping with a length-1 list-like, you will need to pass a length-1 tuple
to get_group in a future version of pandas. Pass `(name,)` instead of `name` to
silence this warning.
  data_subset = grouped_data.get_group(pd_key)
/usr/local/lib/python3.10/dist-packages/seaborn/_base.py:949: FutureWarning:
```

```
When grouping with a length-1 list-like, you will need to pass a length-1 tuple
to get_group in a future version of pandas. Pass `(name,)` instead of `name` to
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to get_group in a future version of pandas. Pass `(name,)` instead of `name` to
silence this warning.
  data_subset = grouped_data.get_group(pd_key)
```
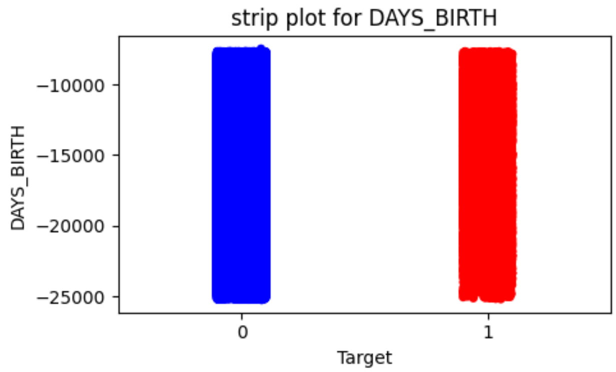
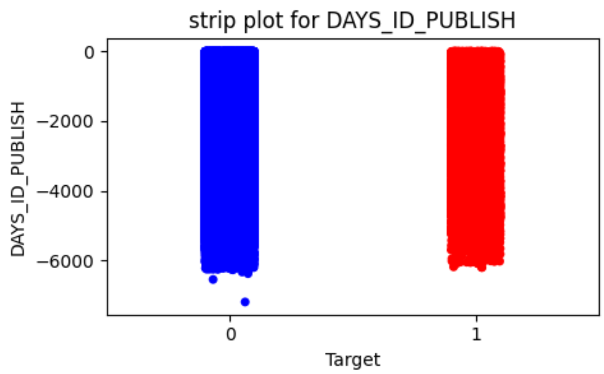
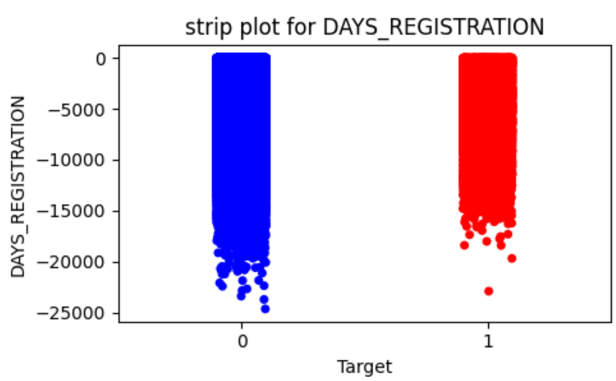
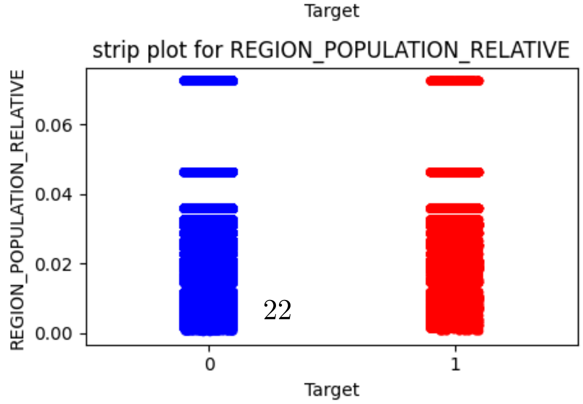


strip plot for DAYS_BIRTH
DAYS_BIRTH
−10000
−15000
−20000
−25000
0
1
Target


strip plot for DAYS_ID_PUBLISH
DAYS_ID_PUBLISH
0
−2000
−4000
−6000
0
1
Target


strip plot for DAYS_EMPLOYED
DAYS_EMPLOYED
300000
200000
100000
0
0
1
Target


strip plot for DAYS_REGISTRATION
DAYS_REGISTRATION
0
−5000
−10000
−15000
−20000
−25000
0
1
Target

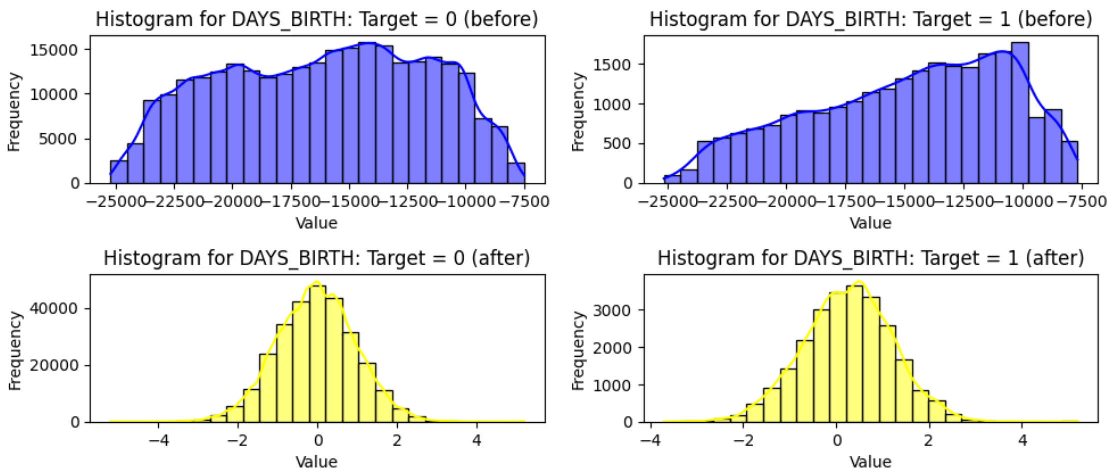

strip plot for REGION_POPULATION_RELATIVE
REGION_POPULATION_RELATIVE
0.06
0.04
0.02
0.00
0
1
Target

[18]:
```
from sklearn.preprocessing import QuantileTransformer

# Transformation for DAYS_REGISTRATION
# Increasing - Positively skewed
t_map = dict()
t_map["DAYS_ID_PUBLISH"] = "quantile"
t_map["DAYS_REGISTRATION"] = "quantile"
t_map["DAYS_BIRTH"] = "quantile"
t_map["DAYS_EMPLOYED"] = "quantile"
t_map["REGION_POPULATION_RELATIVE"] = "quantile"

offset_map = dict()
offset_map["DAYS_REGISTRATION"] = 50000
offset_map["DAYS_ID_PUBLISH"] = "min"
offset_map["DAYS_BIRTH"] = "min"
offset_map["DAYS_EMPLOYED"] = "min"

def transform_var(df, var, t_type):
  if t_type == "log":
    df[var] = df[var].apply(lambda x: np.log(x + 1))
  elif t_type == "sqrt":
    df[var] = df[var].apply(lambda x: np.sqrt(x + 1))
  elif t_type == "cube_root":
    df[var] = df[var].apply(lambda x: x**(1/3))
  elif t_type == "exp":
    df[var] = df[var].apply(lambda x: np.exp(x))
  elif t_type == "inv":
    df[var] = df[var].apply(lambda x: 1/x)
  elif t_type == "logit":
    df[var] = df[var].apply(lambda x: np.log(x/(1+x)))
  elif t_type == "boxcox":
    df[var], _ = boxcox(df[var])
  elif t_type == "quantile":
    df[var] = QuantileTransformer(output_distribution='normal').
↪fit_transform(np.array(df[var]).reshape(-1, 1))
  return df

def plot_histogram(df, col, col_i, all_cols, sp_i, sp_j, tgt_val, suffix,␣
↪color="blue"):
  plt.subplot(len(all_cols), sp_i, sp_j)
  sns.histplot(x=df[col], bins=25, kde=True, color=color)
  plt.title(f'Histogram for {col}: Target = {tgt_val} ({suffix})')
  plt.xlabel('Value')
  plt.ylabel('Frequency')
```

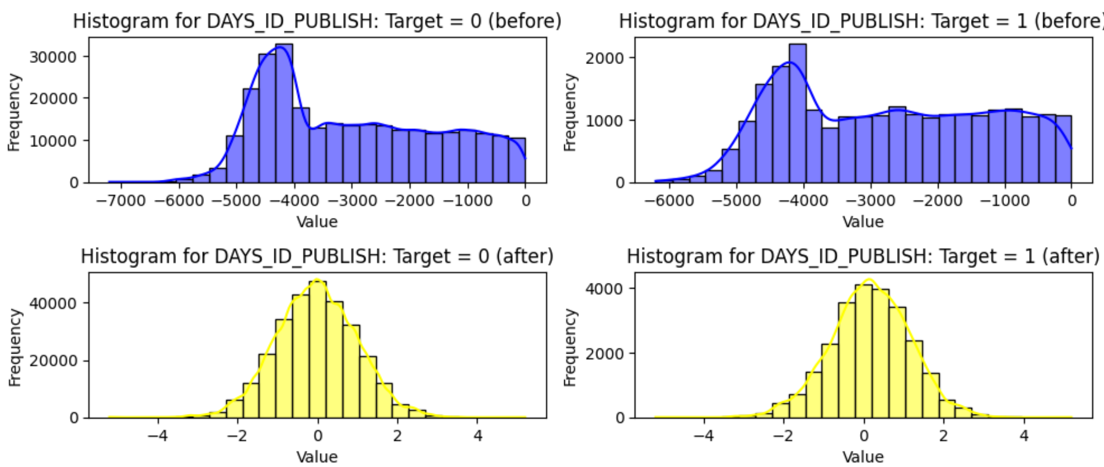
```python
def transform_var_and_plot(var, df, all_vars):

    i = 1
    plt.figure(figsize = (10,10))

    print(f"Plotting: {var}")

    if var in t_map:

      t_type = t_map[var]

      # ===============================
      # Plot before transformation
      # ===============================
      plot_histogram(df=df[(df[TGT] == 0)], col_i=i, col=var, suffix="before",
                     sp_i=2, sp_j=2*i+1, all_cols=all_vars, tgt_val="0")
      plot_histogram(df=app_train[(app_train[TGT] == 1)], col_i=i, col=var,
                     sp_i=2, sp_j=2*i+2, all_cols=all_vars, tgt_val="1",␣
 ↪suffix="before")

      # ===============================
      # Transform data
      # ===============================
      if var in offset_map:
        if str(offset_map[var]) == "min":
          df[var] = df[var] + abs(df[var].min())
        else:
          df[var] = df[var] + offset_map[var]

      df = transform_var(df=df, var=var, t_type=t_type)

      # Increment the value of i
      i += 1

    else:
      print(f"No Transformation required")

    # ===============================
    # Plot after transformation
    # ===============================
    plot_histogram(df=df[(df[TGT] == 0)], col_i=i, col=var,
                   sp_i=2, sp_j=2*i+1, all_cols=all_vars, tgt_val="0",
                   color="yellow", suffix="after")
    plot_histogram(df=df[(df[TGT] == 1)], col_i=i, col=var,
                   sp_i=2, sp_j=2*i+2, all_cols=all_vars, tgt_val="1",
```

```
                    color="yellow", suffix="after")

    # Increment the value of i
    i += 1

    # Adjust layout to prevent overlapping titles
    plt.tight_layout()

    # Show the plots
    plt.show()

for var in top5_corr_vars:
  transform_var_and_plot(var=var, all_vars=top5_corr_vars, df=app_train)
```

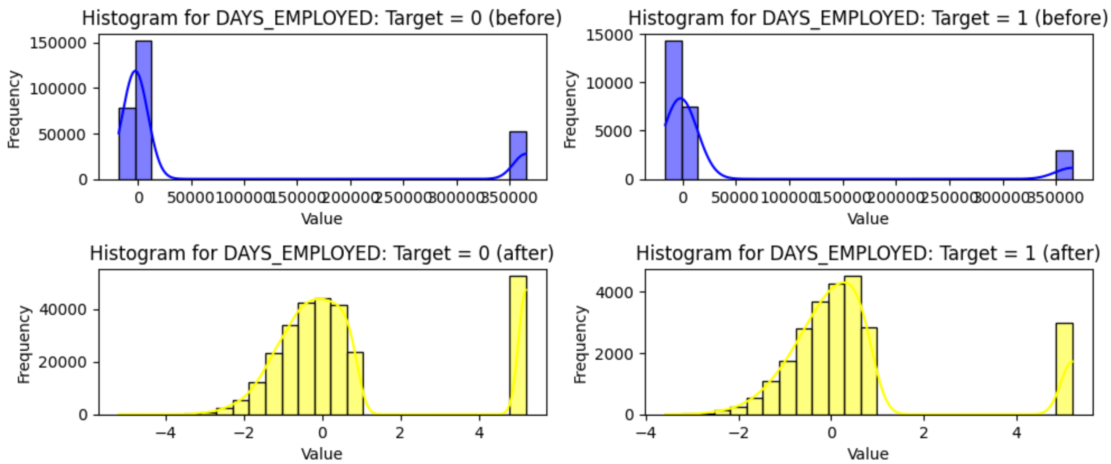
```
Plotting: DAYS_BIRTH
```



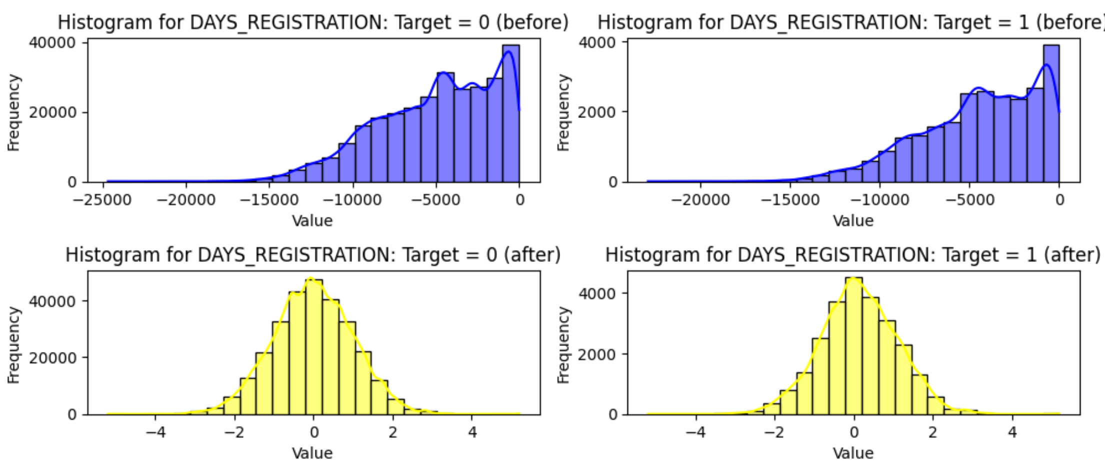

```
Plotting: DAYS_ID_PUBLISH
```



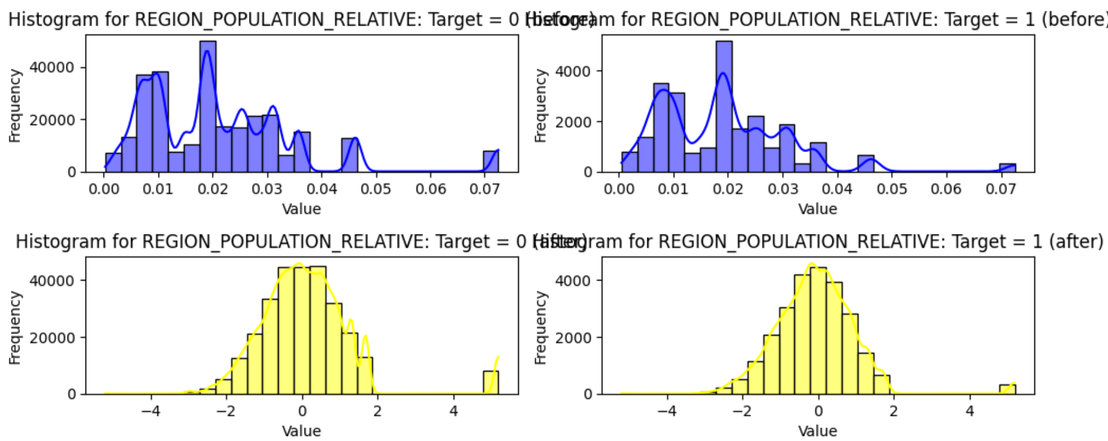
Plotting: DAYS_EMPLOYED



Plotting: DAYS_REGISTRATION



Plotting: REGION_POPULATION_RELATIVE



[19]:
```
# Running outlier analysis post transformation again
suff = "z_score"
z_score_cols = list()
outlier_df = list()

for c in top5_corr_vars:
  app_train[f"{c}_{suff}"] = zscore(app_train[c])
  over_2 = len(app_train[(app_train[f"{c}_{suff}"].abs() > 2)])
  over_3 = len(app_train[(app_train[f"{c}_{suff}"].abs() > 3)])
  outlier_df.append({"col": c, "over_2": over_2, "over_3": over_3})

outlier_df = pd.DataFrame(outlier_df)
outlier_df
```

[19]:

	col	over_2	over_3
0	DAYS_BIRTH	13791	903
1	DAYS_ID_PUBLISH	14070	1062
2	DAYS_EMPLOYED	55411	0
3	DAYS_REGISTRATION	13512	741
4	REGION_POPULATION_RELATIVE	9741	8453

[20]:
```
app_train.select_dtypes(include=['object']).columns
```

[20]:
```
Index(['NAME_CONTRACT_TYPE', 'CODE_GENDER', 'FLAG_OWN_CAR', 'FLAG_OWN_REALTY',
       'NAME_TYPE_SUITE', 'NAME_INCOME_TYPE', 'NAME_EDUCATION_TYPE',
       'NAME_FAMILY_STATUS', 'NAME_HOUSING_TYPE', 'OCCUPATION_TYPE',
       'WEEKDAY_APPR_PROCESS_START', 'ORGANIZATION_TYPE', 'FONDKAPREMONT_MODE',
       'HOUSETYPE_MODE', 'WALLSMATERIAL_MODE', 'EMERGENCYSTATE_MODE'],
      dtype='object')
```

Question 7: Categorical Features: Check cardinality and rare values of at least five categorical features. Discuss whether each of them is ordinal or nominal. Discuss the suitable methods for encoding each of them.

[21]:
```
cat_var = list()
cat_var.append("NAME_CONTRACT_TYPE")
cat_var.append("CODE_GENDER")
cat_var.append("ORGANIZATION_TYPE")
cat_var.append("WEEKDAY_APPR_PROCESS_START")
cat_var.append("EMERGENCYSTATE_MODE")

card = list()
card_pct = list()

for v in cat_var:
    u_count = len(app_train[v].unique())
    cat_pct = app_train[column].value_counts(normalize=True) * 100

    cat_pct = pd.DataFrame(app_train[v].value_counts(normalize=True) * 100)
    cat_pct = cat_pct.reset_index().rename(columns={"index": "val", v: "pct"})
    cat_pct["var"] = v

    card_pct.append(cat_pct)
    card.append({"var": v, "cardinality": u_count})

card = pd.DataFrame(card)
card_pct = pd.concat(card_pct, ignore_index=True).reset_index(drop=True)
card_pct.head()
```

[21]:

	pct	proportion	var
0	Cash loans	90.478715	NAME_CONTRACT_TYPE
1	Revolving loans	9.521285	NAME_CONTRACT_TYPE
2	F	65.834393	CODE_GENDER
3	M	34.164306	CODE_GENDER
4	XNA	0.001301	CODE_GENDER

[22]:
```
print(f"card.shape: {card.shape}")
card
```

```
card.shape: (5, 2)
```

[22]:

	var	cardinality
0	NAME_CONTRACT_TYPE	2
1	CODE_GENDER	3
2	ORGANIZATION_TYPE	58
3	WEEKDAY_APPR_PROCESS_START	7
4	EMERGENCYSTATE_MODE	3

[23]:
```python
# All values which have percentages less than 5
# Our threshold for categorization intorarity is 5 percent
rare_df = card[card["cardinality"] < 5]
rare_df.head()
```

[23]:

	var	cardinality
0	NAME_CONTRACT_TYPE	2
1	CODE_GENDER	3
4	EMERGENCYSTATE_MODE	3

Categorical Variables: 1. NAME_CONTRACT_TYPE: Nominal, One-Hot Encoding 2. CODE_GENDER: Nominal, One-Hot Encoding 3. ORGANIZATION_TYPE: Nominal, Target Encoding 4. WEEKDAY_APPR_PROCESS_START: Nominal, One-Hot Encoding 5. EMERGENCYSTATE_MODE: Nominal, Binary Encoding

Question 8: Feature Engineering: Utilize previous_application.csv to compute and integrate the count of previous applications per SK_ID_CURR into application_train.csv. Further, create at least five new features from additional files, justifying their selection and aggregation method.

[28]:
```python
prev_app = pd.read_csv(os.path.join(data_path, "previous_application.csv"))
bureau = pd.read_csv(os.path.join(data_path, "bureau.csv"))
bureau_bal = pd.read_csv(os.path.join(data_path, "bureau_balance.csv"))
cc_bal = pd.read_csv(os.path.join(data_path, "credit_card_balance.csv"))

# prev_app = pd.read_csv("previous_application.csv")
# bureau = pd.read_csv("bureau.csv")
# bureau_bal = pd.read_csv("bureau_balance.csv")
# cc_bal = pd.read_csv("credit_card_balance.csv")
```

[29]:
```python
# Integrate count of previous applications
app_train = app_train.merge(prev_app.groupby('SK_ID_CURR').size().
 ↪reset_index(name='PREV_APP_COUNT'), on='SK_ID_CURR', how='left')
```

[30]:
```python
# Feature 1: AVG_AMT_BALANCE
# Represents the average balance maintained by the client across all credit␣
 ↪cards. It's a direct indicator of the client's financial health and their␣
 ↪ability to maintain a balance.
# Aggregation Method: Calculate the mean of AMT_BALANCE for each SK_ID_CURR␣
 ↪across all records.
f1 = cc_bal.groupby('SK_ID_CURR')['AMT_BALANCE'].mean().
 ↪reset_index(name='AVG_AMT_BALANCE')

# Feature 2: MAX_AMT_CREDIT_LIMIT_ACTUAL
# Shows the maximum credit limit that has been granted to the client on any of␣
 ↪their credit cards, indicating the maximum level of trust a credit␣
 ↪institution has in them.
```

```
# Aggregation Method: Find the maximum of AMT_CREDIT_LIMIT_ACTUAL for each␣
↪SK_ID_CURR.
f2 = cc_bal.groupby('SK_ID_CURR')['AMT_CREDIT_LIMIT_ACTUAL'].max().
↪reset_index(name='MAX_AMT_CREDIT_LIMIT_ACTUAL')

# Feature 3: TOTAL_ACTIVE_CREDITS
# The total number of active credits as reported by the bureau can indicate the␣
↪current credit commitments of the client, providing insights into their debt␣
↪levels.
# Aggregation Method: Count the number of rows where CREDIT_ACTIVE equals␣
↪"Active" for each SK_ID_CURR.
f3 = bureau[bureau['CREDIT_ACTIVE'] == 'Active'].groupby('SK_ID_CURR').size().
↪reset_index(name='TOTAL_ACTIVE_CREDITS')

# Feature 4: AVG_DAYS_CREDIT
# Reflects the average number of days since each credit was reported to the␣
↪bureau, indicating the age of the client's credit history.
# Aggregation Method: Calculate the mean of DAYS_CREDIT (considering the␣
↪absolute value to reflect the age) for each SK_ID_CURR.
f4 = bureau.groupby('SK_ID_CURR')['DAYS_CREDIT'].mean().
↪reset_index(name='AVG_DAYS_CREDIT').abs()

# Feature 5: AVG_CREDIT_UTILIZATION
# Credit utilization ratio is a crucial factor in credit scoring models,␣
↪reflecting the amount of credit the client uses relative to their credit␣
↪limit. Lower utilization rates are generally seen as indicators of good␣
↪credit management and financial health, as they suggest the client is not␣
↪overly reliant on credit. This feature calculates the average credit␣
↪utilization ratio across all the client's credit card records.
# Calculate the credit utilization ratio for each record in cc_bal by dividing␣
↪AMT_BALANCE by AMT_CREDIT_LIMIT_ACTUAL (taking care to handle division by␣
↪zero).
# Compute the average of these ratios for each SK_ID_CURR to get their average␣
↪credit utilization.
cc_bal['CREDIT_UTILIZATION'] = cc_bal.apply(lambda x: x['AMT_BALANCE'] /␣
↪x['AMT_CREDIT_LIMIT_ACTUAL'] if x['AMT_CREDIT_LIMIT_ACTUAL'] > 0 else 0,␣
↪axis=1)
f5 = cc_bal.groupby('SK_ID_CURR')['CREDIT_UTILIZATION'].mean().
↪reset_index(name='AVG_CREDIT_UTILIZATION')
```

[31]:
```
# Merge all features
for f in [f1, f2, f3, f4, f5]:
  app_train = app_train.merge(f, on='SK_ID_CURR', how='left')
app_train.head()
```

[31]:
```
   SK_ID_CURR  TARGET NAME_CONTRACT_TYPE CODE_GENDER FLAG_OWN_CAR  \
0      100002       1         Cash loans           M            N
1      100003       0         Cash loans           F            N
2      100004       0    Revolving loans           M            Y
3      100006       0         Cash loans           F            N
4      100007       0         Cash loans           M            N

  FLAG_OWN_REALTY  CNT_CHILDREN  AMT_INCOME_TOTAL  AMT_CREDIT  AMT_ANNUITY  \
0               Y             0          202500.0    406597.5      24700.5
1               N             0          270000.0   1293502.5      35698.5
2               Y             0           67500.0    135000.0       6750.0
3               Y             0          135000.0    312682.5      29686.5
4               Y             0          121500.0    513000.0      21865.5

   …  DAYS_ID_PUBLISH_z_score DAYS_EMPLOYED_z_score  \
0  …                0.492319             -0.124706
1  …                1.760650             -0.295551
2  …                0.298792              0.033109
3  …                0.342485             -0.649687
4  …               -0.087390             -0.649470

  DAYS_REGISTRATION_z_score REGION_POPULATION_RELATIVE_z_score PREV_APP_COUNT  \
0                  0.217239                          -0.118721            1.0
1                  0.978618                          -1.582793            3.0
2                  0.065656                          -0.577713            1.0
3                 -1.260649                          -0.831600            9.0
4                  0.046744                           0.502601            6.0

  AVG_AMT_BALANCE  MAX_AMT_CREDIT_LIMIT_ACTUAL  TOTAL_ACTIVE_CREDITS  \
0             NaN                          NaN                   2.0
1             NaN                          NaN                   1.0
2             NaN                          NaN                   NaN
3             0.0                     270000.0                   NaN
4             NaN                          NaN                   NaN

   AVG_DAYS_CREDIT  AVG_CREDIT_UTILIZATION
0           874.00                     NaN
1          1400.75                     NaN
2           867.00                     NaN
3              NaN                     0.0
4          1149.00                     NaN

[5 rows x 133 columns]
```

Question 9: NaN Handling. Document your strategy for managing NaN values, providing rationale for your chosen approach.

```
[32]: # We will only consider numerical, categorical and new features for checking␣
       ↪null values and deciding the strategy
      # to handle null appropriately. Same strategies can be extended to handle␣
       ↪similar columns.

      num_vars = list()
      num_vars.append("DAYS_ID_PUBLISH")
      num_vars.append("DAYS_REGISTRATION")
      num_vars.append("DAYS_BIRTH")
      num_vars.append("DAYS_EMPLOYED")
      num_vars.append("REGION_POPULATION_RELATIVE")

      extra_features = list()
      extra_features.append("AVG_AMT_BALANCE")
      extra_features.append("MAX_AMT_CREDIT_LIMIT_ACTUAL")
      extra_features.append("TOTAL_ACTIVE_CREDITS")
      extra_features.append("AVG_DAYS_CREDIT")
      extra_features.append("AVG_CREDIT_UTILIZATION")

      all_req_cols = cat_var + num_vars + extra_features
      all_req_cols
```

```
[32]: ['NAME_CONTRACT_TYPE',
       'CODE_GENDER',
       'ORGANIZATION_TYPE',
       'WEEKDAY_APPR_PROCESS_START',
       'EMERGENCYSTATE_MODE',
       'DAYS_ID_PUBLISH',
       'DAYS_REGISTRATION',
       'DAYS_BIRTH',
       'DAYS_EMPLOYED',
       'REGION_POPULATION_RELATIVE',
       'AVG_AMT_BALANCE',
       'MAX_AMT_CREDIT_LIMIT_ACTUAL',
       'TOTAL_ACTIVE_CREDITS',
       'AVG_DAYS_CREDIT',
       'AVG_CREDIT_UTILIZATION']
```

```
[33]: # Percentage of Missing Values
      miss_df = app_train[all_req_cols].isnull().sum().sort_values(ascending=False)/
       ↪len(app_train)
      miss_df = miss_df[miss_df > 0]
      miss_df
```

```
[33]: AVG_AMT_BALANCE                0.717392
      MAX_AMT_CREDIT_LIMIT_ACTUAL    0.717392
      AVG_CREDIT_UTILIZATION         0.717392
```

```
EMERGENCYSTATE_MODE            0.473983
TOTAL_ACTIVE_CREDITS           0.293846
AVG_DAYS_CREDIT                0.143149
dtype: float64
```

[34]:
```python
# Checking unique values in columns to decide how to handle NULLS
# This is the only categorical column to be considered
app_train["EMERGENCYSTATE_MODE"].unique()
```

[34]:
```
array(['No', nan, 'Yes'], dtype=object)
```

[35]:
```python
# AVG_AMT_BALANCE
# MAX_AMT_CREDIT_LIMIT_ACTUAL
# AVG_DAYS_CREDIT
for c in ["AVG_AMT_BALANCE", "MAX_AMT_CREDIT_LIMIT_ACTUAL", "AVG_DAYS_CREDIT"]:
  num_rows = len(cc_bal[cc_bal["SK_ID_CURR"].isin(list(app_train[app_train[c].
 ↪isnull()]["SK_ID_CURR"]))])
  print(f"Number of rows {c}: {str(num_rows)}")
```

```
Number of rows AVG_AMT_BALANCE: 0
Number of rows MAX_AMT_CREDIT_LIMIT_ACTUAL: 0
Number of rows AVG_DAYS_CREDIT: 375463
```

[36]:
```python
# AVG_CREDIT_UTILIZATION
# TOTAL_ACTIVE_CREDITS
for c in ["AVG_CREDIT_UTILIZATION", "TOTAL_ACTIVE_CREDITS"]:
  num_rows = len(bureau[bureau["SK_ID_CURR"].isin(list(app_train[app_train[c].
 ↪isnull()]["SK_ID_CURR"]))])
  print(f"Number of rows {c}: {str(num_rows)}")
```

```
Number of rows AVG_CREDIT_UTILIZATION: 1014675
Number of rows TOTAL_ACTIVE_CREDITS: 119568
```

Handling Null Values

Categorical variables

- EMERGENCYSTATE_MODE: This is a categorical variable with only 2 unique values "Yes" and "No". For the rows with missing values, we can fill the column with an "Unknown" string.

Numerical variables

All the numerical fields are derived fields (type numerical) and the missing values are indicative of this data not being available (i.e. no history available for those customers). We can fill it with zeroes since it would indicate zero values for maintained by the client:

- AVG_CREDIT_UTILIZATION - Indicate 0 credit utilization.
- TOTAL_ACTIVE_CREDITS - Total active credits 0.
- AVG_AMT_BALANCE - 0 average amount balance.
- MAX_AMT_CREDIT_LIMIT_ACTUAL - 0 credit limit.

- AVG_DAYS_CREDIT - 0 days of credit.

NOTE: For all the numerical variables, we will also add a flag which will be indicative of whether the value is missing or not. In total we will need 5 flag columns, one for each of the above columns.

[ ]:
```
app_train.to_csv("app_train_modified.csv")
```

2 Post Mid-Term Modelling

2.1 Data Preparation and Pipeline setup

[37]:
```
from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import OneHotEncoder
from sklearn.preprocessing import OrdinalEncoder
from sklearn.preprocessing import KBinsDiscretizer
from sklearn.compose import ColumnTransformer

from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.impute import SimpleImputer
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import FunctionTransformer
from scipy.stats import zscore
from feature_engine.encoding import RareLabelEncoder # For encoding rare labels;
 ↪ we could have also used sklearn encoder with infrequent categories
from feature_engine.outliers import Winsorizer
from feature_engine.outliers import OutlierTrimmer
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import f1_score
```

[38]:
```
from sklearn.metrics import precision_score, recall_score, f1_score,␣
 ↪accuracy_score
from sklearn.metrics import confusion_matrix, classification_report
from sklearn.model_selection import GridSearchCV
```

[39]:
```
import pandas as pd
```

Dropping Columns with less than 50% Missing Values

[40]:
```
app_train_mod = app_train.copy()
```

[41]:
```
_null_count = app_train_mod.isnull().sum().sort_values(ascending = False)
_null_count = _null_count[_null_count <= (len(app_train_mod) * 0.20)]
print(f"len(_null_count): {len(_null_count)}")

app_train_mod = app_train_mod.reindex(columns = _null_count.index.tolist())
print(f"app_train_mod.shape (dropped columns with lots of nulls):␣
↪{app_train_mod.shape}")
print(f"app_train_mod.duplicated().sum(): {app_train_mod.duplicated().sum()}")
```

```
len(_null_count): 79
app_train_mod.shape (dropped columns with lots of nulls): (307511, 79)
app_train_mod.duplicated().sum(): 0
```

[42]:
```
from autoviz.AutoViz_Class import AutoViz_Class
AV = AutoViz_Class()
AV.AutoViz("", depVar= TGT,dfte = app_train_mod)
```

```
Imported v0.1.904. Please call AutoViz in this sequence:
    AV = AutoViz_Class()
    %matplotlib inline
    dfte = AV.AutoViz(filename, sep=',', depVar='', dfte=None, header=0,
verbose=1, lowess=False,
               chart_format='svg',max_rows_analyzed=150000,max_cols_analyzed=30,
save_plot_dir=None)
    Since nrows is smaller than dataset, loading random sample of 150000 rows
into pandas...
Shape of your Data Set loaded: (150000, 79)
################################################################################
#######
######################## C L A S S I F Y I N G  V A R I A B L E S
####################
################################################################################
#######
Classifying variables in data set...
    Number of Numeric Columns =  29
    Number of Integer-Categorical Columns =  4
    Number of String-Categorical Columns =  7
    Number of Factor-Categorical Columns =  0
    Number of String-Boolean Columns =  4
    Number of Numeric-Boolean Columns =  28
    Number of Discrete String Columns =  0
    Number of NLP String Columns =  0
    Number of Date Time Columns =  0
    Number of ID Columns =  1
    Number of Columns to Delete =  5
    78 Predictors classified...
        6 variable(s) removed since they were ID or low-information variables
```

```
        List of variables removed: ['SK_ID_CURR', 'FLAG_DOCUMENT_10',
'FLAG_DOCUMENT_4', 'FLAG_DOCUMENT_12', 'FLAG_DOCUMENT_2', 'FLAG_MOBIL']
Since Number of Rows in data 150000 exceeds maximum, randomly sampling 150000
rows for EDA…

################ Binary_Classification problem #####################
Number of variables = 72 exceeds limit, finding top 30 variables through XGBoost
    No categorical feature reduction done. All 43 Categorical vars selected
    Removing correlated variables from 29 numerics using SULO method

After removing highly correlated variables, following 20 numeric vars selected:
['EXT_SOURCE_3', 'AVG_DAYS_CREDIT', 'AMT_REQ_CREDIT_BUREAU_MON',
'PREV_APP_COUNT', 'EXT_SOURCE_2', 'DAYS_LAST_PHONE_CHANGE', 'AMT_INCOME_TOTAL',
'AMT_REQ_CREDIT_BUREAU_YEAR', 'AMT_REQ_CREDIT_BUREAU_QRT',
'AMT_REQ_CREDIT_BUREAU_DAY', 'AMT_REQ_CREDIT_BUREAU_WEEK', 'CNT_FAM_MEMBERS',
'AMT_ANNUITY', 'DAYS_EMPLOYED_z_score', 'DAYS_BIRTH',
'REGION_POPULATION_RELATIVE', 'DEF_30_CNT_SOCIAL_CIRCLE', 'DAYS_ID_PUBLISH',
'DAYS_REGISTRATION', 'OBS_30_CNT_SOCIAL_CIRCLE']
    Adding 43 categorical variables to reduced numeric variables  of 20
############## F E A T U R E   S E L E C T I O N  ####################
Current number of predictors = 63
    Finding Important Features using Boosted Trees algorithm…
        using 63 variables…
Finding top features using XGB is crashing. Continuing with all predictors…
    Since number of features selected is greater than max columns analyzed,
limiting to 30 variables
################################################################################
#######
######################## C L A S S I F Y I N G  V A R I A B L E S
####################
################################################################################
#######
Classifying variables in data set…
    30 Predictors classified…
    No variables removed since no ID or low-information variables found in data
    List of variables removed: []
   Total columns > 30, too numerous to print.
To fix these data quality issues in the dataset, import FixDQ from autoviz…
    All variables classified into correct types.

<pandas.io.formats.style.Styler at 0x7d7e73fc9cf0>

Total Number of Scatter Plots = 231
All Plots done
Time to run AutoViz = 124 seconds

 ###################### AUTO VISUALIZATION Completed ########################
```

[42]:
```
        EXT_SOURCE_3  AVG_DAYS_CREDIT  AMT_REQ_CREDIT_BUREAU_MON  \
253947           NaN       180.000000                        0.0
302190      0.715103      1269.000000                        0.0
270220      0.472253      1413.681818                        0.0
156194      0.780144      1253.333333                        0.0
189667           NaN              NaN                        NaN
…                  …                …                          …
138860      0.497469      1209.000000                        0.0
64389       0.810618      1823.285714                        2.0
6086        0.484851       347.666667                        0.0
217721      0.067794       608.666667                        0.0
298481      0.771362      1672.000000                        0.0

        PREV_APP_COUNT  EXT_SOURCE_2  DAYS_LAST_PHONE_CHANGE  \
253947             1.0      0.159322                    -8.0
302190             NaN      0.785922                  -643.0
270220             7.0      0.169953                 -1118.0
156194             5.0      0.646524                  -846.0
189667             NaN      0.784102                  -226.0
…                    …             …                       …
138860             2.0      0.784665                 -2535.0
64389              1.0      0.655614                  -507.0
6086               6.0      0.616141                  -826.0
217721             4.0      0.313795                  -694.0
298481             8.0      0.433269                  -194.0

        AMT_INCOME_TOTAL  AMT_REQ_CREDIT_BUREAU_YEAR  \
253947          112500.0                         0.0
302190          405000.0                         0.0
270220          202500.0                         3.0
156194          135000.0                         2.0
189667          315000.0                         NaN
…                      …                           …
138860          135000.0                         1.0
64389           135000.0                         1.0
6086             90000.0                         2.0
217721          126000.0                         1.0
298481          270000.0                         6.0

        AMT_REQ_CREDIT_BUREAU_QRT  AMT_REQ_CREDIT_BUREAU_DAY  \
253947                        0.0                        0.0
302190                        0.0                        0.0
270220                        0.0                        0.0
156194                        0.0                        0.0
189667                        NaN                        NaN
…                               …                          …
138860                        0.0                        0.0
```

```
64389              0.0                           0.0
6086               0.0                           0.0
217721             0.0                           0.0
298481             0.0                           0.0

        AMT_REQ_CREDIT_BUREAU_WEEK  CNT_FAM_MEMBERS  AMT_ANNUITY  \
253947             1.0                    2.0           21816.0
302190             0.0                    2.0           11250.0
270220             0.0                    2.0           18040.5
156194             0.0                    2.0           42385.5
189667             NaN                    2.0           24750.0
…                                …          …            …
138860             0.0                    2.0           21609.0
64389              0.0                    2.0           31653.0
6086               0.0                    1.0           20772.0
217721             0.0                    1.0           15331.5
298481             0.0                    2.0           49630.5

        DAYS_EMPLOYED_z_score  DAYS_BIRTH  REGION_POPULATION_RELATIVE  \
253947       -0.088011          1.226386          -0.163824
302190       -1.038353         -0.389249           1.684464
270220       -0.689922         -1.701739           0.134645
156194       -0.837413         -0.451297           1.318946
189667       -0.901045         -1.428183          -0.798769
…                         …         …                          …
138860       -0.377453         -0.045514           0.324254
64389         2.024377         -1.435355           5.199338
6086         -0.368728          0.703367          -1.674186
217721        0.105609          1.128438          -0.060256
298481       -0.202691         -0.816889          -0.993800

        DEF_30_CNT_SOCIAL_CIRCLE  DAYS_ID_PUBLISH  DAYS_REGISTRATION  \
253947             0.0                 1.373746         -0.089924
302190             0.0                 0.751890          1.088943
270220             0.0                -1.618226         -0.357069
156194             0.0                 0.900435          1.682452
189667             0.0                -5.199338          0.012071
…                             …               …                 …
138860             0.0                -0.947580          1.093425
64389              0.0                -0.344749          0.408149
6086               0.0                -0.810801          1.151862
217721             0.0                -0.026462          1.303989
298481             1.0                -0.145504         -0.413309

        OBS_30_CNT_SOCIAL_CIRCLE  AMT_REQ_CREDIT_BUREAU_HOUR NAME_TYPE_SUITE  \
253947             1.0                           0.0           Unaccompanied
302190             1.0                           0.0           Unaccompanied
```

```
270220               0.0                        0.0             Unaccompanied
156194               2.0                        0.0             Unaccompanied
189667               0.0                        NaN             Unaccompanied
…                          …                          …              …
138860               0.0                        0.0             Unaccompanied
64389                0.0                        0.0             Unaccompanied
6086                 6.0                        0.0             Unaccompanied
217721               0.0                        0.0             Unaccompanied
298481               1.0                        0.0             Unaccompanied

        FLAG_DOCUMENT_6  FLAG_DOCUMENT_7 NAME_CONTRACT_TYPE  FLAG_DOCUMENT_8  \
253947         0                0                 Cash loans          0
302190         0                0            Revolving loans          0
270220         0                0                 Cash loans          0
156194         0                0                 Cash loans          1
189667         0                0            Revolving loans          0
…                  …              …                 …              …
138860         0                0                 Cash loans          0
64389          1                0                 Cash loans          0
6086           0                0                 Cash loans          0
217721         0                0                 Cash loans          0
298481         0                0                 Cash loans          0

       CODE_GENDER  FLAG_DOCUMENT_9  FLAG_DOCUMENT_17  FLAG_DOCUMENT_20  \
253947       F             0                 0                 0
302190       M             0                 0                 0
270220       F             0                 0                 0
156194       M             0                 0                 0
189667       M             0                 0                 0
…            …              …               …                …
138860       M             0                 0                 0
64389        M             0                 0                 0
6086         F             0                 0                 0
217721       F             0                 0                 0
298481       F             0                 0                 0

        TARGET
253947     0
302190     1
270220     0
156194     1
189667     1
…         …
138860     1
64389      1
6086       1
217721     1
```

```
298481     1

[150000 rows x 31 columns]
```

[43]:
```
new_col = ["EXT_SOURCE_3", "AVG_DAYS_CREDIT", "AMT_REQ_CREDIT_BUREAU_YEAR",␣
 ↪"AMT_REQ_CREDIT_BUREAU_MON", "PREV_APP_COUNT", "EXT_SOURCE_2",␣
 ↪"DAYS_LAST_PHONE_CHANGE",
"HOUR_APPR_PROCESS_START", "AMT_INCOME_TOTAL", "AMT_REQ_CREDIT_BUREAU_WEEK",␣
 ↪"AMT_REQ_CREDIT_BUREAU_QRT", "AMT_REQ_CREDIT_BUREAU_DAY",␣
 ↪"AMT_REQ_CREDIT_BUREAU_HOUR",
"CNT_FAM_MEMBERS", "REGION_RATING_CLIENT_W_CITY", "AMT_ANNUITY",␣
 ↪"DAYS_EMPLOYED_z_score", "DAYS_BIRTH_z_score", "REGION_POPULATION_RELATIVE",␣
 ↪"OBS_60_CNT_SOCIAL_CIRCLE",
"DEF_30_CNT_SOCIAL_CIRCLE", "DAYS_ID_PUBLISH_z_score",␣
 ↪"DAYS_REGISTRATION_z_score", "NAME_TYPE_SUITE", "FLAG_DOCUMENT_11",␣
 ↪"FLAG_DOCUMENT_13", "FLAG_DOCUMENT_15",
"FLAG_DOCUMENT_3", "FLAG_DOCUMENT_16", "FLAG_DOCUMENT_17", "TARGET"]

app_train_selected_col = app_train_mod[new_col]
app_train_selected_col.shape
```

[43]:
```
(307511, 31)
```

[44]:
```
# Pipeline for Skewed numeric variables
skewed_num_pipe  = Pipeline(steps = [("imp", SimpleImputer(strategy= "median")),
                                     ("out",␣
 ↪Winsorizer(capping_method='quantiles', tail='both', fold=.01))]) # several␣
 ↪capping methods: gaussian; iqr; quantile. Fold paramater indicates how far␣
 ↪from the central position.

# Pipeline for normally distributed numeric variables
norm_num_pipe = Pipeline(steps = [("imp", SimpleImputer(strategy= "mean",␣
 ↪add_indicator= True))])


# Pipeline for variables that need discretization - We decide which ones to␣
 ↪discretize based on logic
disc_pipe = Pipeline(steps = [("imp", SimpleImputer(strategy= "median",␣
 ↪add_indicator= True)),
                              ("disc", KBinsDiscretizer(strategy=␣
 ↪"equal_width", encode = "ordinal"))])
```

[45]:
```
# Nominal categorical variables
nom_cat_pipe = Pipeline(steps = [("imp", SimpleImputer(strategy= "constant",␣
 ↪fill_value = "missing")),
                                 ("ohe", OneHotEncoder(sparse_output=False))])
```

```
# Ordinal Catgeorical variables
ord_cat_pipe = Pipeline(steps = [("imp", SimpleImputer(strategy=␣
↪"most_frequent", add_indicator = True)),
                                 ("ord", OrdinalEncoder( ))])

# Pipeline for Categorical variables with rare categories
rare_cat_pipe = Pipeline(steps = [("imp", SimpleImputer(strategy= "constant",␣
↪fill_value = "rare")),
                                  ("rare", RareLabelEncoder(tol=0.05,␣
↪n_categories=4)),
                                  ("ohe", OneHotEncoder(sparse_output=False))])
```

[46]:

```
# Nominal categorical variables from the dataset
nom_cat_vars = ["NAME_TYPE_SUITE"]

# Ordinal categorical variables from the dataset
ord_cat_vars = [] # There is none thus kept blank. If for a new dataset, you␣
↪find some relevant variables pass them here

# Categorical variables with rare categories
rare_cat_vars = []

# Numeric variables that require discretization
disc_num_vars = [] # None here

# Numeric variables that are normally distributed
norm_num_vars = ["EXT_SOURCE_3", "EXT_SOURCE_2", "FLAG_DOCUMENT_11",␣
↪"FLAG_DOCUMENT_13", "FLAG_DOCUMENT_15", "FLAG_DOCUMENT_3",
                 "FLAG_DOCUMENT_16", "FLAG_DOCUMENT_17",␣
↪"AMT_REQ_CREDIT_BUREAU_DAY", "AMT_REQ_CREDIT_BUREAU_HOUR"]

# Numeric variables that ahave skew in them
skewed_num_vars = ["AVG_DAYS_CREDIT", "AMT_REQ_CREDIT_BUREAU_YEAR",␣
↪"AMT_REQ_CREDIT_BUREAU_MON", "PREV_APP_COUNT", "DAYS_LAST_PHONE_CHANGE",
"HOUR_APPR_PROCESS_START", "AMT_INCOME_TOTAL", "AMT_REQ_CREDIT_BUREAU_WEEK",␣
↪"AMT_REQ_CREDIT_BUREAU_QRT",
"CNT_FAM_MEMBERS", "REGION_RATING_CLIENT_W_CITY", "AMT_ANNUITY",␣
↪"DAYS_EMPLOYED_z_score", "DAYS_BIRTH_z_score", "REGION_POPULATION_RELATIVE",␣
↪"OBS_60_CNT_SOCIAL_CIRCLE",
"DEF_30_CNT_SOCIAL_CIRCLE", "DAYS_ID_PUBLISH_z_score",␣
↪"DAYS_REGISTRATION_z_score"]
```

[ ]:

```
preprocessor = ColumnTransformer(transformers = [("nom", nom_cat_pipe,␣
↪nom_cat_vars),
```

```
                                                 ("ord", ord_cat_pipe,␣
 ↪ord_cat_vars),
                                                 ("rare", rare_cat_pipe,␣
 ↪rare_cat_vars),
                                                 ("norm", norm_num_pipe,␣
 ↪norm_num_vars),
                                                 ("skew", skewed_num_pipe,␣
 ↪skewed_num_vars),
                                                 ("disc", disc_pipe,␣
 ↪disc_num_vars),
                                                 ], remainder = "passthrough")


preprocessor.set_output(transform = "pandas")
```

[ ]:
```
ColumnTransformer(remainder='passthrough',
                  transformers=[('nom',
                                 Pipeline(steps=[('imp',
SimpleImputer(fill_value='missing',
strategy='constant')),
                                                 ('ohe',
OneHotEncoder(sparse_output=False))]),
                                 ['NAME_TYPE_SUITE']),
                                ('ord',
                                 Pipeline(steps=[('imp',
SimpleImputer(add_indicator=True,
strategy='most_frequent')),
                                                 ('ord', OrdinalEncoder())]),
                                 []),
                                ('rare',
                                 Pipeline(ste…
                                  'REGION_RATING_CLIENT_W_CITY', 'AMT_ANNUITY',
                                  'DAYS_EMPLOYED_z_score', 'DAYS_BIRTH_z_score',
                                  'REGION_POPULATION_RELATIVE',
                                  'OBS_60_CNT_SOCIAL_CIRCLE',
                                  'DEF_30_CNT_SOCIAL_CIRCLE',
                                  'DAYS_ID_PUBLISH_z_score',
                                  'DAYS_REGISTRATION_z_score']),
                                ('disc',
                                 Pipeline(steps=[('imp',
SimpleImputer(add_indicator=True,
strategy='median')),
                                                 ('disc',
KBinsDiscretizer(encode='ordinal',
strategy='equal_width'))]),
                                 [])])
```

[ ]:
```python
# Define target and features
target = 'TARGET'
features = app_train_selected_col.columns.drop(target)

# Split the data into train and test sets
X_train, X_test, y_train, y_test =␣
 ↪train_test_split(app_train_selected_col[features],␣
 ↪app_train_selected_col[target], test_size=0.2, random_state=42)
```

2.2 Random Forest

[ ]:
```python
import time
st = time.time()

modeling_pipeline_rf = Pipeline(steps = [("pre", preprocessor),  ("clf",␣
 ↪RandomForestClassifier())])
modeling_pipeline_rf.fit(X_train,y_train)
test_pred_rf = modeling_pipeline_rf.predict(X_test)

precision = precision_score(y_test, test_pred_rf)
recall = recall_score(y_test, test_pred_rf)
f1 = f1_score(y_test, test_pred_rf)
accuracy = accuracy_score(y_test, test_pred_rf)

print("Precision: {:.2f}%".format(precision * 100))
print("Recall: {:.2f}%".format(recall * 100))
print("F1 Score: {:.2f}%".format(f1 * 100))
print("Accuracy: {:.2f}%".format(accuracy * 100))

et = time.time()
print(f"Time taken: {et - st} seconds")
```

```
Precision: 59.52%
Recall: 0.51%
F1 Score: 1.00%
Accuracy: 91.97%
Time taken: 131.97388172149658 seconds
```

2.3 Logistics Regression

[ ]:
```python
import time
st = time.time()

modeling_pipeline_lr = Pipeline(steps = [("pre", preprocessor),  ("clf",␣
 ↪LogisticRegression(max_iter=15000, penalty='l2', solver='lbfgs', C=1.0,␣
 ↪tol=0.01))])
modeling_pipeline_lr.fit(X_train,y_train)
```

```
test_pred_lr = modeling_pipeline_lr.predict(X_test)

# Calculate metrics
precision = precision_score(y_test, test_pred_lr)
recall = recall_score(y_test, test_pred_lr)
f1 = f1_score(y_test, test_pred_lr)
accuracy = accuracy_score(y_test, test_pred_lr)

# Print metrics
print("Precision: {:.2f}%".format(precision * 100))
print("Recall: {:.2f}%".format(recall * 100))
print("F1 Score: {:.2f}%".format(f1 * 100))
print("Accuracy: {:.2f}%".format(accuracy * 100))

et = time.time()
print(f"Time taken: {et - st} seconds")
```

```
Precision: 62.50%
Recall: 0.20%
F1 Score: 0.40%
Accuracy: 91.96%
Time taken: 322.9417860507965 seconds
```

2.4 Gradient Boosting

[ ]:
```
import time
st = time.time()

modeling_pipeline_gb = Pipeline(steps = [("pre", preprocessor),  ("clf",␣
 ↪GradientBoostingClassifier())])
modeling_pipeline_gb.fit(X_train,y_train)
test_pred_gb = modeling_pipeline_gb.predict(X_test)

# Calculate metrics
precision = precision_score(y_test, test_pred_gb)
recall = recall_score(y_test, test_pred_gb)
f1 = f1_score(y_test, test_pred_gb)
accuracy = accuracy_score(y_test, test_pred_gb)

# Print metrics
print("Precision: {:.2f}%".format(precision * 100))
print("Recall: {:.2f}%".format(recall * 100))
print("F1 Score: {:.2f}%".format(f1 * 100))
print("Accuracy: {:.2f}%".format(accuracy * 100))

et = time.time()
print(f"Time taken: {et - st} seconds")
```

```
Precision: 52.00%
Recall: 0.79%
F1 Score: 1.55%
Accuracy: 91.96%
Time taken: 126.92177295684814 seconds
```

2.5 Grid Search CV

2.5.1 Logistics Regression CV

[ ]:
```
param_grid_lr = {
    'clf__C': [0.1, 1, 10]  # Regularization strength for Logistic Regression
}

lr_grid_search = GridSearchCV(modeling_pipeline_lr, param_grid_lr,␣
 ↪scoring='f1', cv=3, verbose=2)
lr_grid_search.fit(X_train, y_train)
```

```
Fitting 3 folds for each of 3 candidates, totalling 9 fits
[CV] END …clf__C=0.1; total time=  15.8s
[CV] END …clf__C=0.1; total time= 3.2min
[CV] END …clf__C=0.1; total time=   7.5s
[CV] END …clf__C=1; total time=   4.5s
[CV] END …clf__C=1; total time=   6.4s
[CV] END …clf__C=1; total time=   5.2s
[CV] END …clf__C=10; total time=   5.7s
[CV] END …clf__C=10; total time=   7.3s
[CV] END …clf__C=10; total time=   5.9s
```

[ ]:
```
GridSearchCV(cv=3,
             estimator=Pipeline(steps=[('pre',
ColumnTransformer(remainder='passthrough',
                                                          transformers=[('nom',
Pipeline(steps=[('imp',
          SimpleImputer(fill_value='missing',
                        strategy='constant')),
         ('ohe',
          OneHotEncoder(sparse_output=False))]),
['NAME_TYPE_SUITE']),
                                                                        ('ord',
Pipeline(steps=[('imp',
          SimpleImputer(add_indicator=True,
                        strategy='most_frequent')),…
'DEF_30_CNT_SOCIAL_CIRCLE',
'DAYS_ID_PUBLISH_z_score',
'DAYS_REGISTRATION_z_score']),
                                                                        ('disc',
Pipeline(steps=[('imp',
```

```
            SimpleImputer(add_indicator=True,
                          strategy='median')),
           ('disc',
            KBinsDiscretizer(encode='ordinal',
                             strategy='equal_width'))]),
                                                                  [])])),
                                     ('clf',
                                      LogisticRegression(max_iter=15000,
                                                         tol=0.01))]),
               param_grid={'clf__C': [0.1, 1, 10]}, scoring='f1', verbose=2)
```

[ ]:
```
best_params_lr = lr_grid_search.best_params_
best_score_lr = lr_grid_search.best_score_

print("Logistics Regression Model:")
print(f"Best parameters: {best_params_lr}")
print(f"Best cross-validation score: {round(best_score_lr, 2)}")

test_pred_lr = lr_grid_search.best_estimator_.predict(X_test)

# Calculate metrics
precision = precision_score(y_test, test_pred_lr)
recall = recall_score(y_test, test_pred_lr)
f1 = f1_score(y_test, test_pred_lr)
accuracy = accuracy_score(y_test, test_pred_lr)

# Print metrics
print("\n")
print("Printing results on Test Data")
print(f"Confusion Matrix: {confusion_matrix(y_test, test_pred_lr)}")
print("Precision: {:.2f}%".format(precision * 100))
print("Recall: {:.2f}%".format(recall * 100))
print("F1 Score: {:.2f}%".format(f1 * 100))
print("Accuracy: {:.2f}%".format(accuracy * 100))
```

```
Logistics Regression Model:
Best parameters: {'clf__C': 0.1}
Best cross-validation score: 0.0


Printing results on Test Data
Confusion Matrix: [[56554     0]
 [ 4949     0]]
Precision: 0.00%
Recall: 0.00%
F1 Score: 0.00%
Accuracy: 91.95%
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1509:
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", len(result))
```

2.5.2 Random Forest CV

[ ]:
```
param_grid_rf = {
    'clf__min_samples_split': [1, 5, 10], # Minimum number of samples required␣
 ↪to split an internal node
    'clf__min_samples_leaf': [2, 4], # Minimum number of samples required to be␣
 ↪at a leaf node
    'clf__criterion': ['gini']
    }

rf_grid_search = GridSearchCV(modeling_pipeline_rf, param_grid_rf,␣
 ↪scoring='f1', cv=3, verbose=2)
rf_grid_search.fit(X_train, y_train)
```

```
Fitting 3 folds for each of 6 candidates, totalling 18 fits
[CV] END clf__criterion=gini, clf__min_samples_leaf=2, clf__min_samples_split=1;
total time=   0.9s
[CV] END clf__criterion=gini, clf__min_samples_leaf=2, clf__min_samples_split=1;
total time=   0.9s
[CV] END clf__criterion=gini, clf__min_samples_leaf=2, clf__min_samples_split=1;
total time=   1.1s
[CV] END clf__criterion=gini, clf__min_samples_leaf=2, clf__min_samples_split=5;
total time= 1.4min
[CV] END clf__criterion=gini, clf__min_samples_leaf=2, clf__min_samples_split=5;
total time= 1.2min
[CV] END clf__criterion=gini, clf__min_samples_leaf=2, clf__min_samples_split=5;
total time= 1.1min
[CV] END clf__criterion=gini, clf__min_samples_leaf=2,
clf__min_samples_split=10; total time= 1.1min
[CV] END clf__criterion=gini, clf__min_samples_leaf=2,
clf__min_samples_split=10; total time= 1.1min
[CV] END clf__criterion=gini, clf__min_samples_leaf=2,
clf__min_samples_split=10; total time= 1.1min
[CV] END clf__criterion=gini, clf__min_samples_leaf=4, clf__min_samples_split=1;
total time=   1.1s
[CV] END clf__criterion=gini, clf__min_samples_leaf=4, clf__min_samples_split=1;
total time=   1.3s
[CV] END clf__criterion=gini, clf__min_samples_leaf=4, clf__min_samples_split=1;
total time=   1.3s
[CV] END clf__criterion=gini, clf__min_samples_leaf=4, clf__min_samples_split=5;
total time= 1.1min
[CV] END clf__criterion=gini, clf__min_samples_leaf=4, clf__min_samples_split=5;
total time= 1.1min
```

```
[CV] END clf__criterion=gini, clf__min_samples_leaf=4, clf__min_samples_split=5;
total time= 1.1min
[CV] END clf__criterion=gini, clf__min_samples_leaf=4,
clf__min_samples_split=10; total time= 1.0min
[CV] END clf__criterion=gini, clf__min_samples_leaf=4,
clf__min_samples_split=10; total time= 1.1min
[CV] END clf__criterion=gini, clf__min_samples_leaf=4,
clf__min_samples_split=10; total time= 1.1min
```

```
/usr/local/lib/python3.10/dist-
packages/sklearn/model_selection/_validation.py:547: FitFailedWarning:
6 fits failed out of a total of 18.
The score on these train-test partitions for these parameters will be set to
nan.
If these failures are not expected, you can try to debug them by setting
error_score='raise'.

Below are more details about the failures:
--------------------------------------------------------------------------------
6 fits failed with the following error:
Traceback (most recent call last):
  File "/usr/local/lib/python3.10/dist-
packages/sklearn/model_selection/_validation.py", line 895, in _fit_and_score
    estimator.fit(X_train, y_train, **fit_params)
  File "/usr/local/lib/python3.10/dist-packages/sklearn/base.py", line 1474, in
wrapper
    return fit_method(estimator, *args, **kwargs)
  File "/usr/local/lib/python3.10/dist-packages/sklearn/pipeline.py", line 475,
in fit
    self._final_estimator.fit(Xt, y, **last_step_params["fit"])
  File "/usr/local/lib/python3.10/dist-packages/sklearn/base.py", line 1467, in
wrapper
    estimator._validate_params()
  File "/usr/local/lib/python3.10/dist-packages/sklearn/base.py", line 666, in
_validate_params
    validate_parameter_constraints(
  File "/usr/local/lib/python3.10/dist-
packages/sklearn/utils/_param_validation.py", line 95, in
validate_parameter_constraints
    raise InvalidParameterError(
sklearn.utils._param_validation.InvalidParameterError: The 'min_samples_split'
parameter of RandomForestClassifier must be an int in the range [2, inf) or a
float in the range (0.0, 1.0]. Got 1 instead.

  warnings.warn(some_fits_failed_message, FitFailedWarning)
/usr/local/lib/python3.10/dist-packages/sklearn/model_selection/_search.py:1051:
UserWarning: One or more of the test scores are non-finite: [       nan
0.00590516 0.00510819        nan 0.0038125  0.0032087 ]
```

```
  warnings.warn(
```

[ ]:
```
GridSearchCV(cv=3,
             estimator=Pipeline(steps=[('pre',
ColumnTransformer(remainder='passthrough',
                                                          transformers=[('nom',
Pipeline(steps=[('imp',
          SimpleImputer(fill_value='missing',
                        strategy='constant')),
         ('ohe',
          OneHotEncoder(sparse_output=False))]),
['NAME_TYPE_SUITE']),
                                                                        ('ord',
Pipeline(steps=[('imp',
          SimpleImputer(add_indicator=True,
                        strategy='most_frequent')),…
'DAYS_REGISTRATION_z_score']),
                                                                        ('disc',
Pipeline(steps=[('imp',
          SimpleImputer(add_indicator=True,
                        strategy='median')),
         ('disc',
          KBinsDiscretizer(encode='ordinal',
                           strategy='equal_width'))]),
                                                                         [])])),
                                    ('clf', RandomForestClassifier())]),
             param_grid={'clf__criterion': ['gini'],
                         'clf__min_samples_leaf': [2, 4],
                         'clf__min_samples_split': [1, 5, 10]},
             scoring='f1', verbose=2)
```

[ ]:
```
best_params_rf = rf_grid_search.best_params_
best_score_rf = rf_grid_search.best_score_

print("Random Forest Model:")
print(f"Best parameters: {best_params_rf}")
print(f"Best cross-validation score: {round(best_score_rf, 2)}")

test_pred_rf = rf_grid_search.best_estimator_.predict(X_test)

# Calculate metrics
precision = precision_score(y_test, test_pred_rf)
recall = recall_score(y_test, test_pred_rf)
f1 = f1_score(y_test, test_pred_rf)
accuracy = accuracy_score(y_test, test_pred_rf)

# Print metrics
```

```
print("\n")
print("Printing results on Test Data")
print(f"Confusion Matrix: {confusion_matrix(y_test, test_pred_rf)}")
print("Precision: {:.2f}%".format(precision * 100))
print("Recall: {:.2f}%".format(recall * 100))
print("F1 Score: {:.2f}%".format(f1 * 100))
print("Accuracy: {:.2f}%".format(accuracy * 100))
```

```
Random Forest Model:
Best parameters: {'clf__criterion': 'gini', 'clf__min_samples_leaf': 2,
'clf__min_samples_split': 5}
Best cross-validation score: 0.01


Printing results on Test Data
Confusion Matrix: [[56547     7]
 [ 4936    13]]
Precision: 65.00%
Recall: 0.26%
F1 Score: 0.52%
Accuracy: 91.96%
```

2.5.3 Gradient Boosting CV

[ ]:
```
param_grid_gb = {
    'clf__learning_rate': [0.05, 0.1, 0.2], # Learning rate parameter for␣
 ↪GradientBoosting
    'clf__max_depth': [3, 5],  # Adjust depth for tree-based models, None for␣
 ↪no maximum depth
}

gb_grid_search = GridSearchCV(modeling_pipeline_gb, param_grid_gb,␣
 ↪scoring='f1', cv=3, verbose=2)
gb_grid_search.fit(X_train, y_train)
```

```
Fitting 3 folds for each of 6 candidates, totalling 18 fits
[CV] END …clf__learning_rate=0.05, clf__max_depth=3; total time= 1.9min
[CV] END …clf__learning_rate=0.05, clf__max_depth=3; total time= 1.6min
[CV] END …clf__learning_rate=0.05, clf__max_depth=3; total time= 1.4min
[CV] END …clf__learning_rate=0.05, clf__max_depth=5; total time= 2.4min
[CV] END …clf__learning_rate=0.05, clf__max_depth=5; total time= 2.4min
[CV] END …clf__learning_rate=0.05, clf__max_depth=5; total time= 2.3min
[CV] END …clf__learning_rate=0.1, clf__max_depth=3; total time= 1.3min
[CV] END …clf__learning_rate=0.1, clf__max_depth=3; total time= 1.4min
[CV] END …clf__learning_rate=0.1, clf__max_depth=3; total time= 1.4min
[CV] END …clf__learning_rate=0.1, clf__max_depth=5; total time= 2.3min
[CV] END …clf__learning_rate=0.1, clf__max_depth=5; total time= 2.3min
```

```
[CV] END …clf__learning_rate=0.1, clf__max_depth=5; total time= 2.3min
[CV] END …clf__learning_rate=0.2, clf__max_depth=3; total time= 1.3min
[CV] END …clf__learning_rate=0.2, clf__max_depth=3; total time= 1.4min
[CV] END …clf__learning_rate=0.2, clf__max_depth=3; total time= 1.3min
[CV] END …clf__learning_rate=0.2, clf__max_depth=5; total time= 2.2min
[CV] END …clf__learning_rate=0.2, clf__max_depth=5; total time= 2.2min
[CV] END …clf__learning_rate=0.2, clf__max_depth=5; total time= 2.2min
```

[ ]:
```
GridSearchCV(cv=3,
             estimator=Pipeline(steps=[('pre',
ColumnTransformer(remainder='passthrough',
                                                            transformers=[('nom',
Pipeline(steps=[('imp',
          SimpleImputer(fill_value='missing',
                        strategy='constant')),
         ('ohe',
          OneHotEncoder(sparse_output=False))]),
['NAME_TYPE_SUITE']),
                                                                          ('ord',
Pipeline(steps=[('imp',
          SimpleImputer(add_indicator=True,
                        strategy='most_frequent')),…
'DAYS_ID_PUBLISH_z_score',
'DAYS_REGISTRATION_z_score']),
                                                                          ('disc',
Pipeline(steps=[('imp',
          SimpleImputer(add_indicator=True,
                        strategy='median')),
         ('disc',
          KBinsDiscretizer(encode='ordinal',
                           strategy='equal_width'))]),
                                                                           [])])),
                                        ('clf', GradientBoostingClassifier())]),
             param_grid={'clf__learning_rate': [0.05, 0.1, 0.2],
                         'clf__max_depth': [3, 5]},
             scoring='f1', verbose=2)
```

[ ]:
```
best_params_gb = gb_grid_search.best_params_
best_score_gb = gb_grid_search.best_score_

print("Gradient Boosting Model:")
print(f"Best parameters: {best_params_gb}")
print("Best cross-validation score: {:.2f}%".format(round(best_score_gb, 4) *␣
 ↪100))

test_pred_gb = gb_grid_search.best_estimator_.predict(X_test)
```

```
# Calculate metrics
precision = precision_score(y_test, test_pred_gb)
recall = recall_score(y_test, test_pred_gb)
f1 = f1_score(y_test, test_pred_gb)
accuracy = accuracy_score(y_test, test_pred_gb)

# Print metrics
print("\n")
print("Printing results on Test Data")
print(f"Confusion Matrix: {confusion_matrix(y_test, test_pred_gb)}")
print("Precision: {:.2f}%".format(precision * 100))
print("Recall: {:.2f}%".format(recall * 100))
print("F1 Score: {:.2f}%".format(f1 * 100))
print("Accuracy: {:.2f}%".format(accuracy * 100))
```

```
Gradient Boosting Model:
Best parameters: {'clf__learning_rate': 0.2, 'clf__max_depth': 5}
Best cross-validation score: 3.59%


Printing results on Test Data
Confusion Matrix: [[56407   147]
 [ 4866    83]]
Precision: 36.09%
Recall: 1.68%
F1 Score: 3.21%
Accuracy: 91.85%
```

2.5.4 Saving the data and model in a pickle file

[ ]:
```
import pickle

best_model = gb_grid_search.best_estimator_
file_path = 'best_model.pkl'
with open(file_path, 'wb') as f:
    pickle.dump(best_model, f)

print("Best model saved as a pickle file successfully!")
```

```
Best model saved as a pickle file successfully!
```

[ ]:
```
X_test.to_csv("X_test.csv")
y_test.reset_index(drop=True).to_csv("y_test.csv")
pd.Series(test_pred_gb).to_csv("y_pred.csv")
```

[ ]:
```
!pip install nbconvert
```

```
Requirement already satisfied: nbconvert in /usr/local/lib/python3.10/dist-
```

```
packages (6.5.4)
Requirement already satisfied: lxml in /usr/local/lib/python3.10/dist-packages
(from nbconvert) (4.9.4)
Requirement already satisfied: beautifulsoup4 in /usr/local/lib/python3.10/dist-
packages (from nbconvert) (4.12.3)
Requirement already satisfied: bleach in /usr/local/lib/python3.10/dist-packages
(from nbconvert) (6.1.0)
Requirement already satisfied: defusedxml in /usr/local/lib/python3.10/dist-
packages (from nbconvert) (0.7.1)
Requirement already satisfied: entrypoints>=0.2.2 in
/usr/local/lib/python3.10/dist-packages (from nbconvert) (0.4)
Requirement already satisfied: jinja2>=3.0 in /usr/local/lib/python3.10/dist-
packages (from nbconvert) (3.1.4)
Requirement already satisfied: jupyter-core>=4.7 in
/usr/local/lib/python3.10/dist-packages (from nbconvert) (5.7.2)
Requirement already satisfied: jupyterlab-pygments in
/usr/local/lib/python3.10/dist-packages (from nbconvert) (0.3.0)
Requirement already satisfied: MarkupSafe>=2.0 in
/usr/local/lib/python3.10/dist-packages (from nbconvert) (2.1.5)
Requirement already satisfied: mistune<2,>=0.8.1 in
/usr/local/lib/python3.10/dist-packages (from nbconvert) (0.8.4)
Requirement already satisfied: nbclient>=0.5.0 in
/usr/local/lib/python3.10/dist-packages (from nbconvert) (0.10.0)
Requirement already satisfied: nbformat>=5.1 in /usr/local/lib/python3.10/dist-
packages (from nbconvert) (5.10.4)
Requirement already satisfied: packaging in /usr/local/lib/python3.10/dist-
packages (from nbconvert) (24.0)
Requirement already satisfied: pandocfilters>=1.4.1 in
/usr/local/lib/python3.10/dist-packages (from nbconvert) (1.5.1)
Requirement already satisfied: pygments>=2.4.1 in
/usr/local/lib/python3.10/dist-packages (from nbconvert) (2.16.1)
Requirement already satisfied: tinycss2 in /usr/local/lib/python3.10/dist-
packages (from nbconvert) (1.3.0)
Requirement already satisfied: traitlets>=5.0 in /usr/local/lib/python3.10/dist-
packages (from nbconvert) (5.7.1)
Requirement already satisfied: platformdirs>=2.5 in
/usr/local/lib/python3.10/dist-packages (from jupyter-core>=4.7->nbconvert)
(4.2.1)
Requirement already satisfied: jupyter-client>=6.1.12 in
/usr/local/lib/python3.10/dist-packages (from nbclient>=0.5.0->nbconvert)
(6.1.12)
Requirement already satisfied: fastjsonschema>=2.15 in
/usr/local/lib/python3.10/dist-packages (from nbformat>=5.1->nbconvert) (2.19.1)
Requirement already satisfied: jsonschema>=2.6 in
/usr/local/lib/python3.10/dist-packages (from nbformat>=5.1->nbconvert) (4.19.2)
Requirement already satisfied: soupsieve>1.2 in /usr/local/lib/python3.10/dist-
packages (from beautifulsoup4->nbconvert) (2.5)
Requirement already satisfied: six>=1.9.0 in /usr/local/lib/python3.10/dist-
```

```
packages (from bleach->nbconvert) (1.16.0)
Requirement already satisfied: webencodings in /usr/local/lib/python3.10/dist-
packages (from bleach->nbconvert) (0.5.1)
Requirement already satisfied: attrs>=22.2.0 in /usr/local/lib/python3.10/dist-
packages (from jsonschema>=2.6->nbformat>=5.1->nbconvert) (23.2.0)
Requirement already satisfied: jsonschema-specifications>=2023.03.6 in
/usr/local/lib/python3.10/dist-packages (from
jsonschema>=2.6->nbformat>=5.1->nbconvert) (2023.12.1)
Requirement already satisfied: referencing>=0.28.4 in
/usr/local/lib/python3.10/dist-packages (from
jsonschema>=2.6->nbformat>=5.1->nbconvert) (0.35.1)
Requirement already satisfied: rpds-py>=0.7.1 in /usr/local/lib/python3.10/dist-
packages (from jsonschema>=2.6->nbformat>=5.1->nbconvert) (0.18.1)
Requirement already satisfied: pyzmq>=13 in /usr/local/lib/python3.10/dist-
packages (from jupyter-client>=6.1.12->nbclient>=0.5.0->nbconvert) (24.0.1)
Requirement already satisfied: python-dateutil>=2.1 in
/usr/local/lib/python3.10/dist-packages (from jupyter-
client>=6.1.12->nbclient>=0.5.0->nbconvert) (2.8.2)
Requirement already satisfied: tornado>=4.1 in /usr/local/lib/python3.10/dist-
packages (from jupyter-client>=6.1.12->nbclient>=0.5.0->nbconvert) (6.3.3)
```

[ ]:

```python
from google.colab import files
from nbconvert import PDFExporter
from nbformat import read

# Load the notebook file
notebook_file = "DataScienceFinalProject.ipynb"
with open(notebook_file, 'r', encoding='utf-8') as f:
    notebook_content = read(f, as_version=4)

# Convert the notebook to PDF
pdf_exporter = PDFExporter()
(pdf_output, _) = pdf_exporter.from_notebook_node(notebook_content)

# Save the PDF output to a file
pdf_file = "DataScienceFinalProject.pdf"
with open(pdf_file, "wb") as f:
    f.write(pdf_output)

# Download the PDF file
files.download(pdf_file)
```

```
---------------------------------------------------------------------------
FileNotFoundError                         Traceback (most recent call last)
<ipython-input-65-a0fd668e4a0a> in <cell line: 7>()
      5 # Load the notebook file
      6 notebook_file = "DataScienceFinalProject.ipynb"
```

```
----> 7 with open(notebook_file, 'r', encoding='utf-8') as f:
      8     notebook_content = read(f, as_version=4)
      9

FileNotFoundError: [Errno 2] No such file or directory: 'DataScienceFinalProject.
↪ipynb'
```

```
[ ]: # from https://gist.github.com/jonathanagustin/b67b97ef12c53a8dec27b343dca4abba
# install can take a minute

import os
# @title Convert Notebook to PDF. Save Notebook to given directory
NOTEBOOKS_DIR = "/content/drive/MyDrive/dsa_project" # @param {type:"string"}
NOTEBOOK_NAME = "DataScienceFinalProject.ipynb" # @param {type:"string"}
#------------------------------------------------------------------------------#
from google.colab import drive
drive.mount("/content/drive/", force_remount=True)
NOTEBOOK_PATH = f"{NOTEBOOKS_DIR}/{NOTEBOOK_NAME}"
assert os.path.exists(NOTEBOOK_PATH), f"NOTEBOOK NOT FOUND: {NOTEBOOK_PATH}"
!apt install -y texlive-xetex texlive-fonts-recommended texlive-plain-generic >␣
↪/dev/null 2>&1
!jupyter nbconvert "$NOTEBOOK_PATH" --to pdf > /dev/null 2>&1
NOTEBOOK_PDF = NOTEBOOK_PATH.rsplit('.', 1)[0] + '.pdf'
assert os.path.exists(NOTEBOOK_PDF), f"ERROR MAKING PDF: {NOTEBOOK_PDF}"
print(f"PDF CREATED: {NOTEBOOK_PDF}")
```

```
Mounted at /content/drive/
```

```
---------------------------------------------------------------------------
AssertionError                            Traceback (most recent call last)
<ipython-input-62-0165186f7399> in <cell line: 12>()
     10 drive.mount("/content/drive/", force_remount=True)
     11 NOTEBOOK_PATH = f"{NOTEBOOKS_DIR}/{NOTEBOOK_NAME}"
---> 12 assert os.path.exists(NOTEBOOK_PATH), f"NOTEBOOK NOT FOUND:␣
↪{NOTEBOOK_PATH}"
     13 get_ipython().system('apt install -y texlive-xetex␣
↪texlive-fonts-recommended texlive-plain-generic > /dev/null 2>&1')
     14 get_ipython().system('jupyter nbconvert "$NOTEBOOK_PATH" --to pdf > /dev/
↪null 2>&1')

AssertionError: NOTEBOOK NOT FOUND: /content/drive/MyDrive/dsa_project/
↪ds_project_sshaurav.ipynb
```