A2A_template

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1 FIT5202 Assignment 2A : Building Models to Predict Loan Default

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Please add code/markdown cells as you need.

2 Part 1: Data Loading, Transformation and Exploration

2.1 1.1 Data Loading

In this section, you need to load the given datasets into PySpark DataFrames and use DataFrame functions to process the data, usage of Spark SQL is discouraged. You are allowed to use third-party libraries to format the output. For plotting, different visualisation packages can be used, please ensure that you have included instructions to install the additional packages and the installation will be successful in the provided docker container(in case your marker needs to clear the notebook and rerun it).

2.1.1 1.1.1 Data Loading

Write the code to create a SparkSession. For creating the SparkSession, you need to use a SparkConf object to configure the Spark app with a proper application name, to ensure the maximum partition size does not exceed 20MB, and to run locally with 4 CPU cores on your machine. (2%)

[38]:
```python
# Import libraries needed from pyspark
from pyspark import SparkConf
from pyspark import SparkContext
from pyspark.sql import SparkSession

# Create Spark Configuration Object
master = "local[4]"
app_name = "FIT5202 Assignment 2A"
spark_conf = SparkConf().setMaster(master).setAppName(app_name)\
                        .set("spark.sql.files.maxPartitionBytes", "20M")\
```

```
                        .set("spark.driver.memory", "8g")

# Create SparkSession
spark = SparkSession.builder.config(conf = spark_conf).getOrCreate()
sc = spark.sparkContext
sc.setLogLevel('ERROR')
```

1.1.2 Write code to define the schemas for previous_application and application_data, following the data types suggested in the metadata file. (3%)

[39]:
```
from pyspark.sql import functions as F
from pyspark.sql.types import StructType, StructField, IntegerType, StringType,␣
↪FloatType, LongType

pre_app_schema = StructType([
    StructField("id_app", IntegerType()),
    StructField("contract_type", IntegerType()),
    StructField("amt_annuity", FloatType()),
    StructField("amt_application", FloatType()),
    StructField("amt_credit", FloatType()),
    StructField("amt_down_payment", FloatType()),
    StructField("amt_goods_price", FloatType()),
    StructField("hour_appr_process_start", IntegerType()),
    StructField("rate_down_payment", FloatType()),
    StructField("rate_interest_primary", FloatType()),
    StructField("rate_interest_privileged", FloatType()),
    StructField("name_cash_loan_purpose", StringType()),
    StructField("name_contract_status", StringType()),
    StructField("days_decision", IntegerType()),
    StructField("name_payment_type", StringType()),
    StructField("code_reject_reason", StringType()),
    StructField("name_type_suite", StringType()),
    StructField("name_client_type", StringType()),
    StructField("name_goods_category", StringType()),
    StructField("name_portfolio", StringType()),
    StructField("name_product_type", StringType()),
    StructField("channel_type", StringType()),
    StructField("sellerplace_area", IntegerType()),
    StructField("name_seller_industry", StringType()),
    StructField("cnt_payment", FloatType()),
    StructField("name_yield_group", StringType()),
    StructField("product_combination", StringType()),
    StructField("days_first_drawing", FloatType()),
    StructField("days_first_due", FloatType()),
    StructField("days_last_due_1st_version", FloatType()),
    StructField("days_last_due", FloatType()),
    StructField("days_termination", FloatType()),
```

```python
    StructField("nflag_insured_on_approval", FloatType()),
    StructField("id", LongType())
])

app_schema = StructType([
    StructField("id_app", IntegerType()),
    StructField("target", IntegerType()),
    StructField("contract_type", IntegerType()),
    StructField("gender", StringType()),
    StructField("own_car", StringType()),
    StructField("own_property", StringType()),
    StructField("num_of_children", IntegerType()),
    StructField("income_total", FloatType()),
    StructField("amt_credit", FloatType()),
    StructField("amt_annuity", FloatType()),
    StructField("amt_goods_price", FloatType()),
    StructField("income_type", IntegerType()),
    StructField("education_type", IntegerType()),
    StructField("family_status", IntegerType()),
    StructField("housing_type", IntegerType()),
    StructField("region_population_relative", FloatType()),
    StructField("days_birth", IntegerType()),
    StructField("days_employed", IntegerType()),
    StructField("own_car_age", FloatType()),
    StructField("flag_mobile", IntegerType()),
    StructField("flag_emp_phone", IntegerType()),
    StructField("flag_work_phone", IntegerType()),
    StructField("flag_cont_mobile", IntegerType()),
    StructField("flag_phone", IntegerType()),
    StructField("flag_email", IntegerType()),
    StructField("occupation_type", IntegerType()),
    StructField("cnt_fam_members", FloatType()),
    StructField("weekday_appr_process_start", StringType()),
    StructField("hour_appr_process_start", IntegerType()),
    StructField("organization_type", IntegerType()),
    StructField("credit_score_1", FloatType()),
    StructField("credit_score_2", FloatType()),
    StructField("credit_score_3", FloatType()),
    StructField("days_last_phone_change", FloatType()),
    StructField("amt_credit_req_last_hour", FloatType()),
    StructField("amt_credit_req_last_day", FloatType()),
    StructField("amt_credit_req_last_week", FloatType()),
    StructField("amt_credit_req_last_month", FloatType()),
    StructField("amt_credit_req_last_quarter", FloatType()),
    StructField("amt_credit_req_last_year", FloatType())
])
```

1.1.3 Using your schemas from step 2, write code to load all CSV files into separate data frames(note: value_dict and loan_default are simple and don't need schemas). Print the schemas of all data frames. (2%)

[40]:
```
# Load CSV files
pre_app_df = spark.read.schema(pre_app_schema).csv('previous_application.csv',␣
 ↪header = True)
app_df = spark.read.schema(app_schema).csv('application_data.csv', header =␣
 ↪True)
value_df = spark.read.csv('value_dict.csv', header = True, inferSchema = True)
loan_df = spark.read.csv('loan_default.csv', header = True, inferSchema = True)

print('Previous Application Schema:')
pre_app_df.printSchema()

print('Application Data Schema:')
app_df.printSchema()

print('Value Dict Schema:')
value_df.printSchema()

print('Loan Default Schema:')
loan_df.printSchema()
```

```
Previous Application Schema:
root
 |-- id_app: integer (nullable = true)
 |-- contract_type: integer (nullable = true)
 |-- amt_annuity: float (nullable = true)
 |-- amt_application: float (nullable = true)
 |-- amt_credit: float (nullable = true)
 |-- amt_down_payment: float (nullable = true)
 |-- amt_goods_price: float (nullable = true)
 |-- hour_appr_process_start: integer (nullable = true)
 |-- rate_down_payment: float (nullable = true)
 |-- rate_interest_primary: float (nullable = true)
 |-- rate_interest_privileged: float (nullable = true)
 |-- name_cash_loan_purpose: string (nullable = true)
 |-- name_contract_status: string (nullable = true)
 |-- days_decision: integer (nullable = true)
 |-- name_payment_type: string (nullable = true)
 |-- code_reject_reason: string (nullable = true)
 |-- name_type_suite: string (nullable = true)
 |-- name_client_type: string (nullable = true)
 |-- name_goods_category: string (nullable = true)
 |-- name_portfolio: string (nullable = true)
 |-- name_product_type: string (nullable = true)
 |-- channel_type: string (nullable = true)
```

```
 |-- sellerplace_area: integer (nullable = true)
 |-- name_seller_industry: string (nullable = true)
 |-- cnt_payment: float (nullable = true)
 |-- name_yield_group: string (nullable = true)
 |-- product_combination: string (nullable = true)
 |-- days_first_drawing: float (nullable = true)
 |-- days_first_due: float (nullable = true)
 |-- days_last_due_1st_version: float (nullable = true)
 |-- days_last_due: float (nullable = true)
 |-- days_termination: float (nullable = true)
 |-- nflag_insured_on_approval: float (nullable = true)
 |-- id: long (nullable = true)

Application Data Schema:
root
 |-- id_app: integer (nullable = true)
 |-- target: integer (nullable = true)
 |-- contract_type: integer (nullable = true)
 |-- gender: string (nullable = true)
 |-- own_car: string (nullable = true)
 |-- own_property: string (nullable = true)
 |-- num_of_children: integer (nullable = true)
 |-- income_total: float (nullable = true)
 |-- amt_credit: float (nullable = true)
 |-- amt_annuity: float (nullable = true)
 |-- amt_goods_price: float (nullable = true)
 |-- income_type: integer (nullable = true)
 |-- education_type: integer (nullable = true)
 |-- family_status: integer (nullable = true)
 |-- housing_type: integer (nullable = true)
 |-- region_population_relative: float (nullable = true)
 |-- days_birth: integer (nullable = true)
 |-- days_employed: integer (nullable = true)
 |-- own_car_age: float (nullable = true)
 |-- flag_mobile: integer (nullable = true)
 |-- flag_emp_phone: integer (nullable = true)
 |-- flag_work_phone: integer (nullable = true)
 |-- flag_cont_mobile: integer (nullable = true)
 |-- flag_phone: integer (nullable = true)
 |-- flag_email: integer (nullable = true)
 |-- occupation_type: integer (nullable = true)
 |-- cnt_fam_members: float (nullable = true)
 |-- weekday_appr_process_start: string (nullable = true)
 |-- hour_appr_process_start: integer (nullable = true)
 |-- organization_type: integer (nullable = true)
 |-- credit_score_1: float (nullable = true)
 |-- credit_score_2: float (nullable = true)
 |-- credit_score_3: float (nullable = true)
```

```
 |-- days_last_phone_change: float (nullable = true)
 |-- amt_credit_req_last_hour: float (nullable = true)
 |-- amt_credit_req_last_day: float (nullable = true)
 |-- amt_credit_req_last_week: float (nullable = true)
 |-- amt_credit_req_last_month: float (nullable = true)
 |-- amt_credit_req_last_quarter: float (nullable = true)
 |-- amt_credit_req_last_year: float (nullable = true)

Value Dict Schema:
root
 |-- id: integer (nullable = true)
 |-- category: string (nullable = true)
 |-- key: string (nullable = true)
 |-- value: integer (nullable = true)

Loan Default Schema:
root
 |-- id_app: integer (nullable = true)
 |-- is_default: boolean (nullable = true)
```

2.1.2 1.2 Data Transformation and Create Features

In this step, we're going to perform data transformation and create some new features using existing information. (note: you are allowed to use your own code from assignment 1 for some transformation.)
Perform the following tasks on the application_data data frame:

1.2.1 Create a new column called loan_to_income_ratio(loan to income ratio) defined as amt_credit/income_total.

[41]:
```
app_df = app_df.withColumn('loan_to_income_ratio', F.col('amt_credit') / F.
  ↪col('income_total'))
app_df.select('id_app','amt_credit','income_total', 'loan_to_income_ratio').
  ↪show(10)
```

```
+------+----------+------------+--------------------+
|id_app|amt_credit|income_total|loan_to_income_ratio|
+------+----------+------------+--------------------+
|118100|  667237.5|    247500.0|   2.695909090909091|
|110133| 1374480.0|    112500.0|             12.2176|
|110215|  545040.0|    166500.0|  3.2735135135135134|
|194051|  900000.0|    112500.0|                 8.0|
|110368| 1237684.5|    261000.0|   4.742086206896552|
|110498|  179865.0|    157500.0|               1.142|
|110561| 1256400.0|    157500.0|   7.977142857142857|
|110836|  454500.0|    126000.0|   3.607142857142857|
|110985|  454500.0|     76500.0|  5.9411764705882355|
|109621|  513531.0|     67500.0|   7.607866666666666|
```

```
+------+----------+------------+--------------------+
only showing top 10 rows
```

1.2.2. Perform age bucketing and create a new string column called age_bucket and set the value below:
age < 25: Y
25 <= age <35: E
35 <= age <45: M
45 <= age < 55: L
55 <= age < 65: N
Age >= 65: R

[42]:
```
import math
from datetime import datetime, timedelta
from pyspark.sql.functions import udf
from pyspark.sql.types import DateType

def age_calculate(days_birth):
    age = math.floor(days_birth/-365)
    return age

def classify_age(age):
    if age < 25:
        return 'Y'
    elif 25 <= age < 35:
        return 'E'
    elif 35 <= age < 45:
        return 'M'
    elif 45 <= age < 55:
        return 'L'
    elif 55 <= age < 65:
        return 'N'
    elif age >= 65:
        return 'R'

# Register the functions as UDFs
age_calculate_udf = udf(age_calculate, IntegerType())
classify_age_udf = udf(classify_age, StringType())

# Calculate applicants' age and create 'age_bucket' column
app_df = app_df.withColumn("age_bucket", classify_age_udf(age_calculate_udf(F.
 ↪col('days_birth'))))
app_df.select('id_app', 'age_bucket').show(10)
```

```
+------+----------+
|id_app|age_bucket|
+------+----------+
```

```
|118100|         E|
|110133|         E|
|110215|         L|
|194051|         L|
|110368|         N|
|110498|         N|
|110561|         E|
|110836|         M|
|110985|         L|
|109621|         E|
+------+----------+
only showing top 10 rows
```

1.2.3 Create a new string column named credit_worthiness. It takes the average value of credit_score_1,2,3 (note: replace null value with 0.5, not 0). If the average >= 0.7, set credit_worthiness to "high"; 0.4 <= average <= 0.7 set to "medium", < 0.4 set to "low".

[43]:
```python
def set_credit_worthiness(avg_score):
    if avg_score >= 0.7:
        return 'high'
    elif 0.4 <= avg_score < 0.7:
        return 'medium'
    elif avg_score < 0.4:
        return 'low'

# replace null value with 0.5
columns = ['credit_score_1', 'credit_score_2', 'credit_score_3']
for col in columns:
    app_df = app_df.withColumn(col, F.coalesce(col, F.lit(0.5)))

# Register the function as UDF
set_credit_worthiness_udf = udf(set_credit_worthiness, StringType())

# Create 'credit_worthiness' column
app_df = app_df.withColumn('credit_worthiness', set_credit_worthiness_udf((F.
 ↪col('credit_score_1') + F.col('credit_score_2') + F.col('credit_score_3')) /␣
 ↪3))
app_df.select('id_app', 'credit_score_1', 'credit_score_2', 'credit_score_3',␣
 ↪'credit_worthiness').show(10)
```

```
+------+-------------------+-------------------+-------------------+-----------
-----+
|id_app|     credit_score_1|     credit_score_2|
credit_score_3|credit_worthiness|
+------+-------------------+-------------------+-------------------+-----------
-----+
|118100| 0.6099422574043274| 0.5884348154067993|                0.5|
```

```
medium|
|110133| 0.7081763744354248| 0.6865754127502441|                 0.5|
medium|
|110215|0.49497994780540466| 0.5847758650779724|0.47225335240364075|
medium|
|194051|                0.5| 0.5962075591087341| 0.6195276975631714|
medium|
|110368|                0.5|   0.64156574010849| 0.3996756076812744|
medium|
|110498|                0.5|0.14626194536685944| 0.5064842104911804|
low|
|110561|0.13320907950401306| 0.5543783903121948|                 0.5|
low|
|110836|                0.5| 0.7807371616363525| 0.5797274112701416|
medium|
|110985|                0.5|0.19403037428855896|                 0.5|
low|
|109621|0.42454174160957336|0.17806705832481384| 0.5989262461662292|
medium|
+------+-------------------+-------------------+-------------------+------------
-----+
only showing top 10 rows
```

1.2.4 Create 4 columns: num_of_prev_app(number of previous applications), num_of_approved_app (number of approved applications), total_credit (sum of credit of all approved previous applications), total_credit_to_income_ratio (total credit/income). (note: you need to join previous applications to fill in the values.)

[44]:
```python
pre_app_df_renamed = pre_app_df.withColumnRenamed('id_app', 'id_app_1')\
                               .withColumnRenamed('amt_credit', 'amt_credit_1')

# join application_data with previous_application
joined_df = app_df.join(pre_app_df_renamed, app_df.id_app == pre_app_df_renamed.
 ↪id_app_1, how = 'left_outer')

# Create 'num_of_prev_app' column
joined_df_count_pre = joined_df.groupby('id_app').agg(F.count('id').
 ↪alias('num_of_prev_app'))

# Rename column to avoid duplicate column name
joined_df_count_pre = joined_df_count_pre.withColumnRenamed('id_app',␣
 ↪'id_app_2')

app_df_1 = app_df.join(joined_df_count_pre, app_df.id_app ==␣
 ↪joined_df_count_pre.id_app_2, how = 'left_outer')\
                    .drop('id_app_2')
```

[45]:
```
# Create 'num_of_approved_app' column
joined_df_count_approved = joined_df.filter(F.col('name_contract_status') ==␣
↪'Approved').groupby('id_app')\
                                    .agg(F.count('id').
↪alias('num_of_approved_app'))

# Rename column to avoid duplicate column name
joined_df_count_approved = joined_df_count_approved.withColumnRenamed('id_app',␣
↪'id_app_2')

app_df_2 = app_df_1.join(joined_df_count_approved, app_df_1.id_app ==␣
↪joined_df_count_approved.id_app_2, how = 'left_outer')\
                    .drop('id_app_2')

# Replace null value with 0
app_df_2 = app_df_2.withColumn('num_of_approved_app', F.when(F.
↪col('num_of_approved_app').isNull(), 0).otherwise(F.
↪col('num_of_approved_app')))
```

[46]:
```
# Create 'total_credit' column
joined_df_total = joined_df.filter(F.col('name_contract_status') == 'Approved').
↪groupBy('id_app')\
                            .agg(F.sum('amt_credit_1').alias('total_credit'))

# Rename column to avoid duplicate column name
joined_df_total = joined_df_total.withColumnRenamed('id_app', 'id_app_2')

app_df_3 = app_df_2.join(joined_df_total, app_df_2.id_app == joined_df_total.
↪id_app_2, how = 'left_outer')\
                    .drop('id_app_2')

# Replace null value with 0
app_df_3 = app_df_3.withColumn('total_credit', F.when(F.col('total_credit').
↪isNull(), 0).otherwise(F.col('total_credit')))
```

[47]:
```
# Create 'total_credit_to_income_ratio' column
app_df_4 = app_df_3.withColumn('total_credit_to_income_ratio', F.
↪col('total_credit')/F.col('income_total'))
app_df_4.select('id_app', 'num_of_prev_app', 'num_of_approved_app',␣
↪'total_credit', 'total_credit_to_income_ratio')\
        .show(10)
```

```
+------+---------------+-------------------+------------+----------------------
-----+
|id_app|num_of_prev_app|num_of_approved_app|total_credit|total_credit_to_income_
ratio|
+------+---------------+-------------------+------------+----------------------
```

```
-----+
|100003|              3|                   3|   1452573.0|
5.3799|
|100007|              6|                   6|    999832.5|
8.229074074074074|
|100008|              5|                   4|    813838.5|
8.220590909090909|
|100016|              4|                   4|    424885.5|
6.2946|
|100020|              2|                   2|     83412.0|
0.7723333333333333|
|100024|              0|                   0|         0.0|
0.0|
|100025|              8|                   7|  2363406.25|
11.671141975308641|
|100035|             22|                   8|   1624342.5|
5.553307692307692|
|100039|              4|                   3|   1535143.5|
4.2642875|
|100050|              3|                   2|    333598.5|
3.088875|
+------+---------------+-------------------+------------+----------------------
-----+
only showing top 10 rows
```

1.2.5 Replace education_type, occupation_type, income_type and family_status with matching strings from value_dict (hint: consider reusing code from your A1).

[48]:
```python
from pyspark.sql.functions import when

def replace_value(df, column, value_df):
    df = df.join(value_df, F.col(column) == value_df.value, how = 'left_outer')
    df = df.withColumn(column, F.col('key'))
    df = df.drop('value').drop('key')
    return df

# Replace education_type
value_df_edu = value_df.filter(F.col('category') == 'education_type').
 ↪select('value', 'key')
app_df_edu = replace_value(app_df_4, 'education_type', value_df_edu)

# Replace occupation_type
value_df_occ = value_df.filter(F.col('category') == 'occupation_type').
 ↪select('value', 'key')
app_df_occ = replace_value(app_df_edu, 'occupation_type', value_df_occ)

# Replace income_type
```

```
value_df_in = value_df.filter(F.col('category') == 'income_type').
↪select('value', 'key')
app_df_in = replace_value(app_df_occ, 'income_type', value_df_in)

# Replace family_status
value_df_fam = value_df.filter(F.col('category') == 'family_status').
↪select('value', 'key')
app_df_fam = replace_value(app_df_in, 'family_status', value_df_fam)

app_df_fam.select('id_app', 'education_type', 'occupation_type', 'income_type',␣
↪'family_status').show(10)
```

```
+------+--------------------+---------------+--------------------+--------------
------+
|id_app|      education_type|occupation_type|         income_type|
family_status|
+------+--------------------+---------------+--------------------+--------------
------+
|118100|    Higher education|       Laborers|             Working|
Married|
|110133|Secondary / secon…|    Sales staff|Commercial associate|
Married|
|110215|Secondary / secon…|     Core staff|             Working|Single / not
married|
|194051|Secondary / secon…| Security staff|             Working|      Civil
marriage|
|110368|    Higher education|        (Empty)|           Pensioner|
Married|
|110498|Secondary / secon…|        (Empty)|           Pensioner|
Married|
|110561|    Higher education|    Accountants|Commercial associate|Single / not
married|
|110836|Secondary / secon…|        (Empty)|Commercial associate|
Married|
|110985|    Higher education|     Core staff|Commercial associate|      Civil
marriage|
|109621|Secondary / secon…|    Accountants|             Working|
Married|
+------+--------------------+---------------+--------------------+--------------
------+
only showing top 10 rows
```

1.2.6 Join the loan_default data frame and add is_default to application data. We'll use this column as the label.

[49]:
```
# Rename column to avoid duplicate column name
loan_df = loan_df.withColumnRenamed('id_app', 'id_app_1')
```

```
joined_loan = app_df_fam.join(loan_df, app_df_fam.id_app == loan_df.id_app_1,␣
↪how = 'left_outer').drop('id_app_1')
```

Print 10 records from the application_data data frame.

[50]:
```
import pandas as pd

# Use pandas to display dataframe
app_df = joined_loan
pandas_df = app_df.toPandas()
pd.set_option('display.max_columns', None)
pd.set_option('display.width', 100)
print(pandas_df.head(10))
```

```
   id_app  target  contract_type gender own_car own_property  num_of_children
income_total  \
0  100003       0              2      F       N            N                0
270000.0
1  100007       0              2      M       N            Y                0
121500.0
2  100008       0              2      M       N            Y                0
99000.0
3  100016       0              2      F       N            Y                0
67500.0
4  100020       0              2      M       N            N                0
108000.0
5  100024       0              1      M       Y            Y                0
135000.0
6  100025       0              2      F       Y            Y                1
202500.0
7  100035       0              2      F       N            Y                0
292500.0
8  100039       0              2      M       Y            N                1
360000.0
9  100050       0              2      F       N            Y                0
108000.0

   amt_credit  amt_annuity  amt_goods_price           income_type
education_type  \
0   1293502.5      35698.5        1129500.0         State servant
Higher education
1    513000.0      21865.5         513000.0               Working  Secondary /
secondary special
2    490495.5      27517.5         454500.0         State servant  Secondary /
secondary special
3     80865.0       5881.5          67500.0               Working  Secondary /
secondary special
4    509602.5      26149.5         387000.0               Working  Secondary /
```

```
secondary special
5    427500.0      21375.0         427500.0               Working  Secondary /
secondary special
6   1132573.5      37561.5         927000.0  Commercial associate  Secondary /
secondary special
7    665892.0      24592.5         477000.0  Commercial associate  Secondary /
secondary special
8    733315.5      39069.0         679500.0  Commercial associate  Secondary /
secondary special
9    746280.0      42970.5         675000.0             Pensioner
Higher education

          family_status  housing_type  region_population_relative  days_birth
days_employed  \
0               Married             6                    0.003541      -16765
-1188
1  Single / not married             6                    0.028663      -19932
-3038
2               Married             6                    0.035792      -16941
-1588
3               Married             6                    0.031329      -13439
-2717
4               Married             6                    0.018634      -12931
-1317
5               Married             6                    0.015221      -18252
-4286
6               Married             6                    0.025164      -14815
-1652
7        Civil marriage             6                    0.025164      -15280
-2668
8               Married             6                    0.015221      -11694
-2060
9  Single / not married             6                    0.010966      -23548
365243

   own_car_age  flag_mobile  flag_emp_phone  flag_work_phone  flag_cont_mobile
flag_phone  \
0          NaN            1               1                0                 1
1
1          NaN            1               1                0                 1
0
2          NaN            1               1                1                 1
1
3          NaN            1               1                1                 1
1
4          NaN            1               1                0                 1
0
5          7.0            1               1                0                 1
```

```
0
6        14.0            1                1                0                  1
0
7         NaN            1                1                0                  1
0
8         3.0            1                1                0                  1
0
9         NaN            1                0                0                  1
0

   flag_email occupation_type  cnt_fam_members weekday_appr_process_start  \
0           0      Core staff              2.0                     MONDAY
1           0      Core staff              1.0                   THURSDAY
2           0        Laborers              2.0                  WEDNESDAY
3           0        Laborers              2.0                     FRIDAY
4           0         Drivers              2.0                   THURSDAY
5           0        Laborers              2.0                     FRIDAY
6           0     Sales staff              3.0                     MONDAY
7           1         (Empty)              2.0                  WEDNESDAY
8           0         Drivers              3.0                   THURSDAY
9           0         (Empty)              1.0                  WEDNESDAY

   hour_appr_process_start  organization_type  credit_score_1  credit_score_2
credit_score_3  \
0                       11                 30        0.311267        0.622246
0.500000
1                       11                  4        0.500000        0.322738
0.500000
2                       16                  9        0.500000        0.354225
0.621226
3                       10                  1        0.464831        0.715042
0.176653
4                       12                 28        0.500000        0.236378
0.062103
5                       13                 50        0.565655        0.113375
0.500000
6                        9                 42        0.437709        0.233767
0.542445
7                       13                 36        0.500000        0.479987
0.410103
8                       10                 50        0.500000        0.321745
0.411849
9                        9                 31        0.500000        0.766138
0.684828

   days_last_phone_change  amt_credit_req_last_hour  amt_credit_req_last_day  \
0                  -828.0                       0.0                      0.0
1                 -1106.0                       0.0                      0.0
```

```
2             -2536.0                        0.0                        0.0
3             -2370.0                        0.0                        0.0
4                -3.0                        0.0                        0.0
5              -296.0                        NaN                        NaN
6                 0.0                        0.0                        0.0
7             -1634.0                        0.0                        0.0
8              -697.0                        0.0                        0.0
9              -491.0                        0.0                        0.0

   amt_credit_req_last_week  amt_credit_req_last_month
amt_credit_req_last_quarter  \
0                       0.0                        0.0
0.0
1                       0.0                        0.0
0.0
2                       0.0                        0.0
1.0
3                       0.0                        1.0
0.0
4                       0.0                        0.0
1.0
5                       NaN                        NaN
NaN
6                       0.0                        0.0
1.0
7                       0.0                        1.0
0.0
8                       0.0                        0.0
1.0
9                       0.0                        0.0
0.0

   amt_credit_req_last_year  loan_to_income_ratio age_bucket credit_worthiness
num_of_prev_app  \
0                       0.0              4.790750          L            medium
3
1                       0.0              4.222222          L            medium
6
2                       1.0              4.954500          L            medium
5
3                       0.0              1.198000          M            medium
4
4                       0.0              4.718542          M               low
2
5                       NaN              3.166667          L               low
0
6                       4.0              5.592956          M            medium
8
```

```
7                        5.0              2.276554           M            medium
22
8                        1.0              2.036987           E            medium
4
9                        3.0              6.910000           N            medium
3

   num_of_approved_app  total_credit  total_credit_to_income_ratio  is_default
0                    3    1452573.00                      5.379900       False
1                    6     999832.50                      8.229074       False
2                    4     813838.50                      8.220591       False
3                    4     424885.50                      6.294600       False
4                    2      83412.00                      0.772333       False
5                    0          0.00                      0.000000       False
6                    7    2363406.25                     11.671142       False
7                    8    1624342.50                      5.553308       False
8                    3    1535143.50                      4.264288       False
9                    2     333598.50                      3.088875       False
```

2.1.3 1.3 Exploring the Data

1.3.1 With the transformed data frame from 1.2, write code to show the basic statistics (3%) (pandas is allowed for this task):
a) For each numeric column, show count, mean, stddev, min, max, 25 percentile, 50 percentile, and 75 percentile;
b) For each non-numeric column, display the top 5 based on counts in descending order;
c) For each boolean column, display the value and count(i.e., two rows in total).

[51]:
```
# replace contract_type with string values
value_df_con = value_df.filter(F.col('category') == 'contract_type').
 ↪select('value', 'key')
app_df_con = replace_value(app_df, 'contract_type', value_df_con)

# replace housing_type with string values
value_df_housing = value_df.filter(F.col('category') == 'housing_type').
 ↪select('value', 'key')
app_df_housing = replace_value(app_df_con, 'housing_type', value_df_housing)

# replace organization_type with string values
value_df_or = value_df.filter(F.col('category') == 'organization_type').
 ↪select('value', 'key')
app_df_or = replace_value(app_df_housing, 'organization_type', value_df_or)

app_df = app_df_or

numeric_column = ['target', 'num_of_children', 'income_total', 'amt_credit',␣
 ↪'amt_annuity', 'amt_goods_price',
```

```
                 'region_population_relative', 'days_birth', 'days_employed',␣
↪'own_car_age', 'cnt_fam_members',
                 'hour_appr_process_start', 'credit_score_1', 'credit_score_2',␣
↪'credit_score_3', 'days_last_phone_change',
                 'amt_credit_req_last_hour', 'amt_credit_req_last_day',␣
↪'amt_credit_req_last_week', 'amt_credit_req_last_month',
                 'amt_credit_req_last_quarter', 'amt_credit_req_last_year',␣
↪'loan_to_income_ratio', 'num_of_prev_app', 'num_of_approved_app',
                 'total_credit', 'total_credit_to_income_ratio']
nonnumeric_column = ['contract_type', 'gender', 'income_type',␣
↪'education_type', 'family_status', 'housing_type',
                   'occupation_type', 'weekday_appr_process_start',␣
↪'organization_type', 'age_bucket', 'credit_worthiness']
boolean_column = ['own_car', 'own_property', 'flag_mobile', 'flag_emp_phone',␣
↪'flag_work_phone', 'flag_cont_mobile',
                 'flag_phone', 'flag_email', 'is_default']
```

a) For each numeric column, show count, mean, stddev, min, max, 25 percentile, 50 percentile, and 75 percentile;

[52]:
```
import pandas as pd

for col in numeric_column:
    numeric_df = app_df.select(col)
    numeric_pd_df = numeric_df.toPandas()
    with pd.option_context('display.float_format', '{:.6f}'.format):
        print(f"Statistics for column {col}:")
        print(numeric_pd_df.describe() )
        print("\n" + "-" * 30 + "\n")
```

```
Statistics for column target:
             target
count 172591.000000
mean       0.081464
std        0.273548
min        0.000000
25%        0.000000
50%        0.000000
75%        0.000000
max        1.000000

------------------------------

Statistics for column num_of_children:
       num_of_children
count    172591.000000
mean          0.419228
```

```
std          0.724401
min          0.000000
25%          0.000000
50%          0.000000
75%          1.000000
max         19.000000
```

```
Statistics for column income_total:
          income_total
count    172591.000000
mean     168919.906250
std      299292.031250
min       25650.000000
25%      112500.000000
50%      144000.000000
75%      202500.000000
max   117000000.000000
```

```
Statistics for column amt_credit:
          amt_credit
count  172591.000000
mean   599010.312500
std    402946.343750
min     45000.000000
25%    270000.000000
50%    512446.500000
75%    808650.000000
max   4050000.000000
```

```
Statistics for column amt_annuity:
        amt_annuity
count 172583.000000
mean   27115.226562
std    14580.680664
min     1980.000000
25%    16506.000000
50%    24894.000000
75%    34596.000000
max   258025.500000
```

```
Statistics for column amt_goods_price:
       amt_goods_price
count    172449.000000
mean     538425.187500
std      370185.125000
min       45000.000000
25%      238500.000000
50%      450000.000000
75%      679500.000000
max     4050000.000000

------------------------------

Statistics for column region_population_relative:
       region_population_relative
count               172591.000000
mean                     0.020880
std                      0.013841
min                      0.000533
25%                      0.010006
50%                      0.018850
75%                      0.028663
max                      0.072508

------------------------------

Statistics for column days_birth:
         days_birth
count 172591.000000
mean  -16026.153084
std     4367.826105
min   -25201.000000
25%   -19672.000000
50%   -15728.000000
75%   -12395.500000
max    -7673.000000

------------------------------

Statistics for column days_employed:
       days_employed
count  172591.000000
mean    63626.667868
std    141115.249490
min    -17531.000000
25%     -2757.000000
50%     -1215.000000
75%      -289.000000
```

```
max    365243.000000

------------------------------

Statistics for column own_car_age:
       own_car_age
count 58703.000000
mean     12.039402
std      11.937061
min       0.000000
25%       5.000000
50%       9.000000
75%      15.000000
max      69.000000

------------------------------

Statistics for column cnt_fam_members:
       cnt_fam_members
count    172590.000000
mean          2.156614
std           0.912762
min           1.000000
25%           2.000000
50%           2.000000
75%           3.000000
max          20.000000

------------------------------

Statistics for column hour_appr_process_start:
       hour_appr_process_start
count            172591.000000
mean                 12.062338
std                   3.265509
min                   0.000000
25%                  10.000000
50%                  12.000000
75%                  14.000000
max                  23.000000

------------------------------

Statistics for column credit_score_1:
       credit_score_1
count   172591.000000
mean         0.500757
std          0.139774
```

```
min          0.014568
25%          0.500000
50%          0.500000
75%          0.500000
max          0.951624

------------------------------

Statistics for column credit_score_2:
       credit_score_2
count   172591.000000
mean         0.513977
std          0.191304
min          0.000000
25%          0.391532
50%          0.565430
75%          0.663754
max          0.855000

------------------------------

Statistics for column credit_score_3:
       credit_score_3
count   172591.000000
mean         0.508452
std          0.174561
min          0.000527
25%          0.417100
50%          0.500000
75%          0.634706
max          0.896010

------------------------------

Statistics for column days_last_phone_change:
       days_last_phone_change
count           172590.000000
mean              -961.946533
std                826.945496
min              -4185.000000
25%              -1569.000000
50%               -756.000000
75%               -272.000000
max                  0.000000

------------------------------

Statistics for column amt_credit_req_last_hour:
```

```
       amt_credit_req_last_hour
count             149402.000000
mean                   0.006526
std                    0.085924
min                    0.000000
25%                    0.000000
50%                    0.000000
75%                    0.000000
max                    4.000000

------------------------------

Statistics for column amt_credit_req_last_day:
       amt_credit_req_last_day
count            149402.000000
mean                  0.007169
std                   0.113801
min                   0.000000
25%                   0.000000
50%                   0.000000
75%                   0.000000
max                   9.000000

------------------------------

Statistics for column amt_credit_req_last_week:
       amt_credit_req_last_week
count             149402.000000
mean                   0.033955
std                    0.203978
min                    0.000000
25%                    0.000000
50%                    0.000000
75%                    0.000000
max                    8.000000

------------------------------

Statistics for column amt_credit_req_last_month:
       amt_credit_req_last_month
count              149402.000000
mean                    0.266255
std                     0.914857
min                     0.000000
25%                     0.000000
50%                     0.000000
75%                     0.000000
max                    24.000000
```

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

Statistics for column amt_credit_req_last_quarter:
       amt_credit_req_last_quarter
count                149402.000000
mean                      0.264019
std                       0.610364
min                       0.000000
25%                       0.000000
50%                       0.000000
75%                       0.000000
max                       8.000000

------------------------------

Statistics for column amt_credit_req_last_year:
       amt_credit_req_last_year
count             149402.000000
mean                   1.890985
std                    1.863520
min                    0.000000
25%                    0.000000
50%                    1.000000
75%                    3.000000
max                   25.000000

------------------------------

Statistics for column loan_to_income_ratio:
       loan_to_income_ratio
count         172591.000000
mean               3.960632
std                2.697759
min                0.004808
25%                2.018667
50%                3.269067
75%                5.171429
max               84.736842

------------------------------

Statistics for column num_of_prev_app:
       num_of_prev_app
count    172591.000000
mean          4.579659
std           4.163129
min           0.000000
```

```
25%           2.000000
50%           3.000000
75%           6.000000
max          73.000000

------------------------------

Statistics for column num_of_approved_app:
       num_of_approved_app
count        172591.000000
mean              2.875781
std               2.178800
min               0.000000
25%               1.000000
50%               2.000000
75%               4.000000
max              24.000000

------------------------------

Statistics for column total_credit:
         total_credit
count   172591.000000
mean    579670.400685
std     757286.921769
min          0.000000
25%     107716.500000
50%     284107.500000
75%     753993.000000
max   10370380.500000

------------------------------

Statistics for column total_credit_to_income_ratio:
       total_credit_to_income_ratio
count                 172591.000000
mean                       3.811772
std                        4.971278
min                        0.000000
25%                        0.742500
50%                        2.002667
75%                        5.009034
max                      104.130571

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

b) For each non-numeric column, display the top 5 based on counts in descending order;

[53]:
```
for col in nonnumeric_column:
    count_df = app_df.groupBy(col).count().orderBy(F.desc("count"))
    print(f"Top 5 most common values for column {col}:")
    count_df.show(5, truncate = False)
```

```
Top 5 most common values for column contract_type:
+---------------+------+
|contract_type  |count |
+---------------+------+
|Revolving loans|156155|
|XNA            |16436 |
+---------------+------+

Top 5 most common values for column gender:
+------+------+
|gender|count |
+------+------+
|F     |113467|
|M     |59121 |
|XNA   |3     |
+------+------+

Top 5 most common values for column income_type:
+--------------------+-----+
|income_type         |count|
+--------------------+-----+
|Working             |89283|
|Commercial associate|40237|
|Pensioner           |30983|
|State servant       |12057|
|Unemployed          |13   |
+--------------------+-----+
only showing top 5 rows

Top 5 most common values for column education_type:
+-----------------------------+------+
|education_type               |count |
+-----------------------------+------+
|Secondary / secondary special|122629|
|Higher education             |42044 |
|Incomplete higher            |5720  |
|Lower secondary              |2108  |
|Academic degree              |90    |
+-----------------------------+------+

Top 5 most common values for column family_status:
+--------------------+-------+
```

```
|family_status       |count |
+--------------------+------+
|Married             |110626|
|Single / not married|25327 |
|Civil marriage      |16639 |
|Separated           |11004 |
|Widow               |8994  |
+--------------------+------+
only showing top 5 rows

Top 5 most common values for column housing_type:
+-------------------+------+
|housing_type       |count |
+-------------------+------+
|House / apartment  |153176|
|With parents       |8300  |
|Municipal apartment|6319  |
|Rented apartment   |2685  |
|Office apartment   |1488  |
+-------------------+------+
only showing top 5 rows

Top 5 most common values for column occupation_type:
+---------------+-----+
|occupation_type|count|
+---------------+-----+
|(Empty)        |54225|
|Laborers       |31108|
|Sales staff    |17808|
|Core staff     |15490|
|Managers       |11993|
+---------------+-----+
only showing top 5 rows

Top 5 most common values for column weekday_appr_process_start:
+--------------------------+-----+
|weekday_appr_process_start|count|
+--------------------------+-----+
|TUESDAY                   |30140|
|WEDNESDAY                 |29158|
|MONDAY                    |28531|
|THURSDAY                  |28460|
|FRIDAY                    |28282|
+--------------------------+-----+
only showing top 5 rows

Top 5 most common values for column organization_type:
+----------------------+-----+
```

```
|organization_type     |count|
+----------------------+-----+
|Business Entity Type 3|38394|
|XNA                   |30989|
|Self-employed         |21404|
|Other                 |9323 |
|Medicine              |6298 |
+----------------------+-----+
only showing top 5 rows

Top 5 most common values for column age_bucket:
+----------+-----+
|age_bucket|count|
+----------+-----+
|M         |47282|
|E         |40733|
|L         |39218|
|N         |33957|
|Y         |6833 |
+----------+-----+
only showing top 5 rows

Top 5 most common values for column credit_worthiness:
+-----------------+------+
|credit_worthiness|count |
+-----------------+------+
|medium           |140188|
|low              |28238 |
|high             |4165  |
+-----------------+------+
```

c) For each boolean column, display the value and count(i.e., two rows in total).

[54]:
```
for col in boolean_column:
    count_df = app_df.groupBy(col).count()

    print(f"Value and count for boolean column {col}:")
    count_df.show()
```

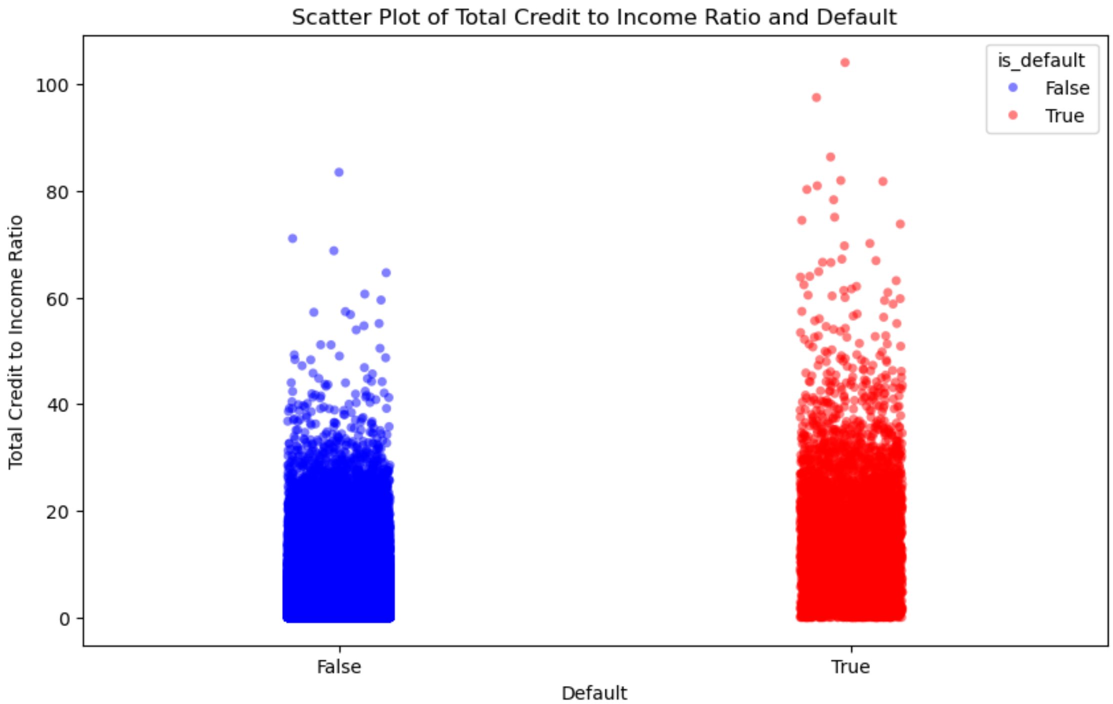
```
Value and count for boolean column own_car:
+-------+------+
|own_car| count|
+-------+------+
|      Y| 58704|
|      N|113887|
+-------+------+
```

```
Value and count for boolean column own_property:
+------------+------+
|own_property| count|
+------------+------+
|           Y|119580|
|           N| 53011|
+------------+------+

Value and count for boolean column flag_mobile:
+-----------+------+
|flag_mobile| count|
+-----------+------+
|          1|172590|
|          0|     1|
+-----------+------+

Value and count for boolean column flag_emp_phone:
+--------------+------+
|flag_emp_phone| count|
+--------------+------+
|             1|141593|
|             0| 30998|
+--------------+------+

Value and count for boolean column flag_work_phone:
+---------------+------+
|flag_work_phone| count|
+---------------+------+
|              1| 34441|
|              0|138150|
+---------------+------+

Value and count for boolean column flag_cont_mobile:
+----------------+------+
|flag_cont_mobile| count|
+----------------+------+
|               1|172250|
|               0|   341|
+----------------+------+

Value and count for boolean column flag_phone:
+----------+------+
|flag_phone| count|
+----------+------+
|         1| 48413|
|         0|124178|
+----------+------+
```

```
Value and count for boolean column flag_email:
+----------+------+
|flag_email| count|
+----------+------+
|         1|  9804|
|         0|162787|
+----------+------+

Value and count for boolean column is_default:
+----------+------+
|is_default| count|
+----------+------+
|      true|  5162|
|     false|167429|
+----------+------+
```

1.3.2 Explore the data frame and write code to present two plots worthy of presentation to MoLoCo, describe your plots and discuss the findings from the plots. (8%)
- One plot must be related to the default. (e.g. what attribute/attributes are correlated to default, what kind of application/applicant has a higher probability of default, etc.)
- Feel free to choose any for the other plot.
- Hint: you can use the basic plots (e.g., histograms, line charts, scatter plots) for the relationship between a column and the label; or more advanced plots like correlation plots. If the data is too large for the plotting, consider using sampling before plotting.
- 150 words max for each plot's description and discussion
- Feel free to use any plotting libraries: matplotlib, seabon, plotly, etc.

[55]:
```
import matplotlib.pyplot as plt
import seaborn as sns

# Select columns
selected_cols = ['total_credit_to_income_ratio', 'is_default']
correlation_data = app_df.select(selected_cols).toPandas()

# Plot the scatter plot
plt.figure(figsize = (10, 6))
sns.stripplot(x = 'is_default', y = 'total_credit_to_income_ratio', hue =␣
↪'is_default', data = correlation_data,
              palette = {True: 'red', False: 'blue'}, jitter = True, alpha = 0.
↪5)
plt.title("Scatter Plot of Total Credit to Income Ratio and Default")
plt.xlabel("Default")
plt.ylabel("Total Credit to Income Ratio")
plt.xticks([0, 1], ['False', 'True'])
plt.show()
```



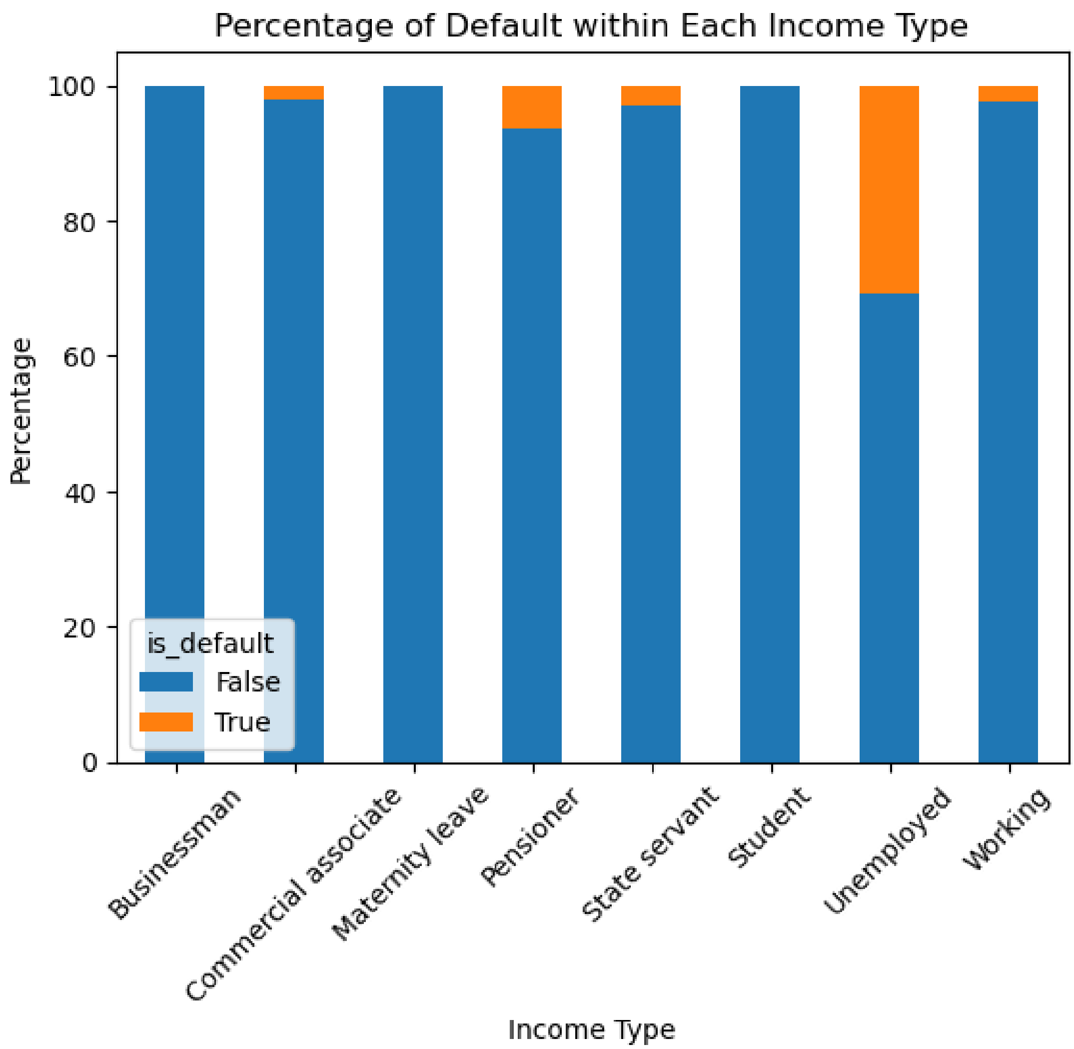
The scatter plot illustrates the correlation between two attributes, namely “total_credit_to_income_ratio” and “is_default,” within the application dataframe. The x-axis shows the default status (True or False), while the y-axis represents the ratio. Each data point on the plot corresponds to the information of an applicant.

Upon examining the graph, it is evident that the distribution of true and false points below the ratio of 30 is fairly similar. However, as the ratio surpasses 30, the concentration of true points significantly increases, which indicates a higher likelihood of the default value being true with a higher ratio of total credit to income.

[56]:
```
selected_df = app_df.select('income_type', 'is_default')

# Count the number of true within each income type
count_df = selected_df.groupBy('income_type', 'is_default').count()

# Count the total number of applications in each income type
total_count_df = count_df.groupBy('income_type').agg(F.sum('count').
 ↪alias('total_count'))

# Join the count_df with total_count_df
result_df = count_df.join(total_count_df, 'income_type')

# Calculate the percentage
result_df = result_df.withColumn('percentage', F.col('count') / F.
 ↪col('total_count') * 100).sort('percentage', ascending = False)
```

```
# Plot a bar chart
pandas_result_df = result_df.toPandas()
plt.figure(figsize = (12, 8))
pandas_result_df.groupby(['income_type', 'is_default']).mean()['percentage'].
↪unstack().plot(kind = 'bar',
                                                                              ␣
↪            stacked = True)
plt.title("Percentage of Default within Each Income Type")
plt.xlabel("Income Type")
plt.ylabel("Percentage")
plt.xticks(rotation=45)
plt.show()
```

```
<Figure size 1200x800 with 0 Axes>
```



The bar chart demonstrates the percentage distribution of default value (True and False) within each income type. Each bar is stacked to visually represent the proportion of true and false defaults corresponding to a particular income type.

From this chart, it is obvious that the "Unemployed" income type has a higher percentage of true defaults, followed by the "Pensioner" income type. These two types are generally associated with economic instability, which suggest a higher likelihood of true defaults. The chart highlights the connection between income types and default values.

2.2 Part 2. Feature extraction and ML training

In this section, you are only allowed to use PySpark DataFrame functions and ML packages for data preparation, model building, and evaluation. Other ML packages, such as scikit-learn, would receive zero marks. Excessive usage of Spark SQL is discouraged. ### 2.1 Discuss the feature selection and prepare the feature columns

2.1.1 Based on the data exploration from 1.2 and considering the use case, discuss the importance of those features. (For example, which features may be useless and should be removed, which feature has a great impact on the label column, which should be transformed) Which features you are planning to use? Discuss the reasons for selecting them and how you create/transform them - 300 words max for the discussion - Feel free to add/remove features based on your exploration

To prepare the dataset for machine learning, I start by removing the "id_app" column, which serves as an identifier, and the "target" column, as it is not in use. For the label column, I convert boolean values to integers, assigning 1 for True and 0 for False.

For numerical attributes, Pearson Correlation is adopted to evaluate their relationship with the label (see the below result). The attributes with correlation value within the range are selected: value >= 0.1 and value <= 0.1. The chosen numerical attributes include days_birth, days_employed, flag_emp_phone, days_last_phone_change, amt_credit_request_last_year, loan_to_income_ratio, num_of_prev_app, num_of_approved_app, total_credit, total_credit_to_income_ratio.

Among these numerical attributes, "total_credit" and "total_credit_to_income_ratio" are especially significant as the correlation value is 0.8 and 1.0. Additionally, "days_birth" is replaced by "age_bucket"; "days_employed" will be transformed into "work_year" with the same logic as the transformation for "days_birth" and "days_last_phone_change" will be transformed into "changephone_year".

For categorical attributes, gender, own_car, own_property, income_type, education_type, family_status, housing_type, occapation_type, age_bucket, credit_worthiness are selected because these attributes are particularly relevant to the prediction of defaults.

In summary, all the chosen attributes for machine learning models include 'gender', 'own_car', 'own_property', 'income_type', 'education_type', 'family_status', 'housing_type', 'flag_emp_phone', 'occupation_type','amt_credit_req_last_year', 'age_bucket', 'loan_to_income_ratio', 'credit_worthiness', 'total_credit', 'total_credit_to_income_ratio', 'work_year', 'num_of_prev_app','num_of_approved_app', 'changephone_year','is_default'.

*** Correlation Results ***

[57]:

```python
from pyspark.ml.feature import VectorAssembler
from pyspark.ml.stat import Correlation
from pyspark.sql.functions import when

numeric_cols = ['target', 'num_of_children', 'income_total', 'amt_credit',␣
 ↪'amt_annuity', 'amt_goods_price',
                 'region_population_relative', 'days_birth', 'days_employed',␣
 ↪'own_car_age', 'cnt_fam_members',
                'flag_mobile', 'flag_emp_phone', 'flag_work_phone',␣
 ↪'flag_cont_mobile', 'flag_phone', 'flag_email',
                 'hour_appr_process_start', 'credit_score_1', 'credit_score_2',␣
 ↪'credit_score_3', 'days_last_phone_change',
                 'amt_credit_req_last_hour', 'amt_credit_req_last_day',␣
 ↪'amt_credit_req_last_week', 'amt_credit_req_last_month',
                 'amt_credit_req_last_quarter', 'amt_credit_req_last_year',␣
 ↪'loan_to_income_ratio', 'num_of_prev_app',
                 'num_of_approved_app', 'total_credit',␣
 ↪'total_credit_to_income_ratio', 'is_default']

df_cor = app_df[numeric_cols]
df_cor = df_cor.withColumn('is_default', when(df_cor['is_default'] == True, 1).
 ↪otherwise(0))

# Fill null with 0
df_cor = df_cor.fillna(0)

df_cor = df_cor.withColumnRenamed('is_default', 'label')

assembler = VectorAssembler(inputCols=numeric_cols[:-1], outputCol="features",␣
 ↪handleInvalid = "keep")
assembled_data = assembler.transform(df_cor)

# Compute the correlation values
correlation_matrix = Correlation.corr(assembled_data, "features").head()

# Extract the correlation valus from the result
corr_matrix = correlation_matrix[0].toArray()

# Display the correlation results
for i in range(len(numeric_cols) - 1):
    print(f"Correlation between {numeric_cols[i]} and label:␣
 ↪{corr_matrix[i][-1]}")
```

```
Correlation between target and label: -0.01807841206407206
Correlation between num_of_children and label: -0.06383746065375039
Correlation between income_total and label: -0.04315781273848933
Correlation between amt_credit and label: -0.016667599302042514
```

```
Correlation between amt_annuity and label: -0.0449886824671642
Correlation between amt_goods_price and label: -0.016365599697350606
Correlation between region_population_relative and label: -0.008317297127011706
Correlation between days_birth and label: -0.19979663076787507
Correlation between days_employed and label: 0.13463261021111117
Correlation between own_car_age and label: -0.041415374885985096
Correlation between cnt_fam_members and label: -0.009309780553431297
Correlation between flag_mobile and label: 0.0018456625868547827
Correlation between flag_emp_phone and label: -0.13574535619977138
Correlation between flag_work_phone and label: -0.060848602031071036
Correlation between flag_cont_mobile and label: 0.019493989694038417
Correlation between flag_phone and label: 0.012991871189041167
Correlation between flag_email and label: 0.03563108241674096
Correlation between hour_appr_process_start and label: -0.05320213213513396
Correlation between credit_score_1 and label: 0.08221394543153275
Correlation between credit_score_2 and label: 0.004425984096463248
Correlation between credit_score_3 and label: 0.042802982447522606
Correlation between days_last_phone_change and label: -0.1687381131740679
Correlation between amt_credit_req_last_hour and label: -0.001632924064716796
Correlation between amt_credit_req_last_day and label: -0.005321906185296472
Correlation between amt_credit_req_last_week and label: 0.011131679402898473
Correlation between amt_credit_req_last_month and label: 0.024631736639039135
Correlation between amt_credit_req_last_quarter and label: 0.07819611769209611
Correlation between amt_credit_req_last_year and label: 0.38104174588608897
Correlation between loan_to_income_ratio and label: 0.10612514744898638
Correlation between num_of_prev_app and label: 0.531440264746293
Correlation between num_of_approved_app and label: 0.6404988148337947
Correlation between total_credit and label: 0.8324735875685986
Correlation between total_credit_to_income_ratio and label: 1.0
```

2.1.2 Write code to create/transform the columns based on your discussion above.

[58]:
```python
# Transform "days_employed" into "work_year"

def workyear_calculate(days_employed):
    workyear = days_employed/-365
    return workyear

def classify_workyear(workyear):
    if 0 < workyear < 1:
        return '< 1'
    elif 1 <= workyear <= 10:
        return '1-10'
    elif 10 < workyear <= 20:
        return '11-20'
    elif 20 < workyear <= 30:
        return '21-30'
    elif 30 < workyear <= 40:
```

```
        return '31-40'
    elif 40 < workyear <= 50:
        return '41-50'
    elif 50 < workyear <= 60:
        return '51-60'
    elif workyear < 0 or workyear == 0:
        return '0'


# Register the functions as UDFs
workyear_calculate_udf = udf(workyear_calculate, IntegerType())
classify_workyear_udf = udf(classify_workyear, StringType())

# Calculate work year and create 'work_year' column
app_df = app_df.withColumn("work_year",␣
 ↪classify_workyear_udf(workyear_calculate_udf(F.col('days_employed'))))
app_df.select('id_app', 'work_year').show(10)
```

```
+-------+---------+
|id_app|work_year|
+-------+---------+
|118100|     1-10|
|110133|     1-10|
|110215|     1-10|
|194051|    11-20|
|110368|        0|
|110498|        0|
|110561|      < 1|
|110836|    11-20|
|110985|     1-10|
|109621|     1-10|
+------+---------+
only showing top 10 rows
```

[59]:

```
# Transform "days_last_phone_change" into "changephone_year"

def changephone_calculate(days_last_phone_change):
    if days_last_phone_change is not None:
        changeyear = days_last_phone_change / -365
        return changeyear
    else:
        return 0

def classify_changephone(changeyear):
    if 0 < changeyear < 1:
        return '< 1'
```

```
    elif 1 <= changeyear <= 5:
        return '1-5'
    elif 5 < changeyear <= 10:
        return '6-10'
    elif 10 < changeyear <= 15:
        return '11-15'
    elif 15 < changeyear <= 20:
        return '16-20'
    else:
        return '0'

# Register the functions as UDFs
changephone_calculate_udf = udf(changephone_calculate, IntegerType())
classify_changephone_udf = udf(classify_changephone, StringType())

# Calculate the change phone year and create 'changephone_year' column
app_df = app_df.withColumn("changephone_year",␣
 ↪classify_changephone_udf(changephone_calculate_udf(F.
 ↪col('days_last_phone_change'))))
app_df.select('id_app', 'changephone_year').show(10)
```

```
+------+----------------+
|id_app|changephone_year|
+------+----------------+
|118100|             1-5|
|110133|               0|
|110215|             1-5|
|194051|             1-5|
|110368|             1-5|
|110498|               0|
|110561|             1-5|
|110836|             1-5|
|110985|             1-5|
|109621|               0|
+------+----------------+
only showing top 10 rows
```

[60]:
```
# Fill null with 0 for "amt_credit_req_last_year"
app_df = app_df.fillna(0, subset=['amt_credit_req_last_year'])
app_df.select("id_app", "amt_credit_req_last_year").show(10)
```

```
+------+------------------------+
|id_app|amt_credit_req_last_year|
+------+------------------------+
|118100|                     0.0|
|110133|                     0.0|
```

```
|110215|                     3.0|
|194051|                     1.0|
|110368|                     0.0|
|110498|                     4.0|
|110561|                     0.0|
|110836|                     1.0|
|110985|                     0.0|
|109621|                     2.0|
+------+------------------------+
only showing top 10 rows
```

[61]:
```python
from pyspark.sql.functions import isnan, when, count, col

cols = ['gender', 'own_car', 'own_property', 'income_type', 'education_type',␣
↪'family_status', 'housing_type',
        'flag_emp_phone', 'occupation_type','amt_credit_req_last_year',␣
↪'age_bucket', 'loan_to_income_ratio',
        'credit_worthiness', 'total_credit', 'total_credit_to_income_ratio',␣
↪'work_year', 'num_of_prev_app',
        'num_of_approved_app', 'changephone_year','is_default']


df = app_df[cols]

# Change the default value to 1 (True) and 0 (False)
df = df.withColumn('is_default', when(df['is_default'] == True, 1).otherwise(0))

# Change "is_default" to "label"
df = df.withColumnRenamed('is_default', 'label')

# Check for missing data, drop the rows for missing data.
df = df.na.drop()
```

2.2.1 2.2 Preparing Spark ML Transformers/Estimators for features, labels, and models

2.2.1 Write code to create Transformers/Estimators for transforming/assembling the columns you selected above in 2.1, and create ML model Estimators for Random Forest (RF) and Gradient-boosted tree (GBT) model.
Please DO NOT fit/transform the data yet

[62]:
```python
# Seperate numerical and non-numerical columns
categoryInputCols = ['gender','own_car', 'own_property', 'income_type',␣
↪'education_type','family_status',
                     'housing_type','occupation_type', 'age_bucket',␣
↪'credit_worthiness', 'work_year',
```

```
                     'changephone_year']


numericInputCols = ['flag_emp_phone',␣
 ↪'amt_credit_req_last_year','num_of_prev_app','num_of_approved_app',
                    'loan_to_income_ratio',␣
 ↪'total_credit','total_credit_to_income_ratio','label']
```

[63]:
```
from pyspark.ml.feature import StringIndexer, OneHotEncoder, VectorAssembler
from pyspark.ml import Pipeline
from pyspark.ml.classification import RandomForestClassifier, GBTClassifier

# String Indexer
# Define the output columns
outputCols=[f'{x}_index' for x in categoryInputCols]

# Initialise StringIndexer
indexer = StringIndexer(inputCols = categoryInputCols, outputCols = outputCols,␣
 ↪handleInvalid = 'keep')

# One Hot Encoder
# Define input columns and outpu columns for OHE
inputCols_OHE = outputCols
outputCols_OHE = [f'{x}_vec' for x in categoryInputCols]

# Initialise OneHotEncoder
encoder = OneHotEncoder(inputCols = inputCols_OHE, outputCols = outputCols_OHE)

# Vector Assembler
# Define input columns and output columns (plus numerical columns)
#inputCols = outputCols_OHE
assemblerInputs = outputCols_OHE + [x for x in numericInputCols if x != 'label']

# Initialise VectorAssembler
assembler = VectorAssembler(inputCols = assemblerInputs, outputCol = 'features')

# Create ML model Estimators for RF and GBT
rf = RandomForestClassifier(labelCol = 'label', featuresCol = 'features',␣
 ↪numTrees = 10)
gbt = GBTClassifier(labelCol = 'label', featuresCol = 'features')
```

2.2.2 Write code to include the above Transformers/Estimators into two pipelines(RF and GBT). **Please DO NOT fit/transform the data yet**

[64]:
```
rf_pipeline = Pipeline(stages = [indexer, encoder, assembler, rf])
gbt_pipeline = Pipeline(stages = [indexer, encoder, assembler, gbt])
```

2.2.2 2.3 Prepare, Train and Evaluate models

2.3.1 Write code to split the data for training and testing purposes. (Note: if the dataset is too large for your machine to train, sampling/sub-sampling is allowed.)

[65]:
```
train, test = df.randomSplit([0.8, 0.2], seed = 2020)

print('Number of records in training set: ', train.count())
print('Number of records in testing set: ', test.count())
```

```
Number of records in training set:  138017
Number of records in testing set:  34574
```

2.3.2 Write code to use the corresponding ML Pipelines to train the models on the training data. And then use the trained models to predict the testing data from 2.3.

[66]:
```
# Train the RF model
rf_model = rf_pipeline.fit(train)

# Train the GBT model
gbt_model = gbt_pipeline.fit(train)

# Make predictions on the testing data with models
rf_predictions = rf_model.transform(test)
gbt_predictions = gbt_model.transform(test)

# Display the predictions
rf_predictions.select('features','label','prediction','probability').show()
gbt_predictions.select('features','label','prediction','probability').show()
```

```
+--------------------+-----+----------+--------------------+
|            features|label|prediction|         probability|
+--------------------+-----+----------+--------------------+
|(78,[0,3,6,8,16,2…|    0|       0.0|[0.97855845553545…|
|(78,[0,3,6,8,16,2…|    0|       0.0|[0.96922887206139…|
|(78,[0,3,6,8,16,2…|    0|       0.0|[0.97855845553545…|
|(78,[0,3,6,8,16,2…|    0|       0.0|[0.97394204921974…|
|(78,[0,3,6,8,16,2…|    0|       0.0|[0.97394204921974…|
|(78,[0,3,6,8,16,2…|    0|       0.0|[0.97855845553545…|
|(78,[0,3,6,8,16,2…|    0|       0.0|[0.97855845553545…|
|(78,[0,3,6,8,16,2…|    0|       0.0|[0.94721835458229…|
|(78,[0,3,6,8,16,2…|    1|       0.0|[0.97855845553545…|
|(78,[0,3,6,8,16,2…|    0|       0.0|[0.97764762114476…|
|(78,[0,3,6,8,16,2…|    0|       0.0|[0.97855845553545…|
|(78,[0,3,6,8,16,2…|    0|       0.0|[0.97855845553545…|
|(78,[0,3,6,8,16,2…|    0|       0.0|[0.97855845553545…|
|(78,[0,3,6,8,16,2…|    1|       0.0|[0.97764762114476…|
|(78,[0,3,6,8,16,2…|    0|       0.0|[0.96922887206139…|
|(78,[0,3,6,8,16,2…|    0|       0.0|[0.97394204921974…|
```

```
|(78,[0,3,6,8,16,2…|    0|       0.0|[0.97394204921974…|
|(78,[0,3,6,8,16,2…|    0|       0.0|[0.97764762114476…|
|(78,[0,3,6,8,16,2…|    0|       0.0|[0.97855845553545…|
|(78,[0,3,6,8,16,2…|    0|       0.0|[0.97855845553545…|
+--------------------+-----+----------+--------------------+
only showing top 20 rows

+--------------------+-----+----------+--------------------+
|            features|label|prediction|         probability|
+--------------------+-----+----------+--------------------+
|(78,[0,3,6,8,16,2…|    0|       0.0|[0.95523188876905…|
|(78,[0,3,6,8,16,2…|    0|       0.0|[0.95170786590695…|
|(78,[0,3,6,8,16,2…|    0|       0.0|[0.82622211645018…|
|(78,[0,3,6,8,16,2…|    0|       0.0|[0.95523188876905…|
|(78,[0,3,6,8,16,2…|    0|       0.0|[0.93906611989137…|
|(78,[0,3,6,8,16,2…|    0|       0.0|[0.95523188876905…|
|(78,[0,3,6,8,16,2…|    0|       0.0|[0.95523188876905…|
|(78,[0,3,6,8,16,2…|    0|       0.0|[0.95170786590695…|
|(78,[0,3,6,8,16,2…|    1|       0.0|[0.93565741347025…|
|(78,[0,3,6,8,16,2…|    0|       0.0|[0.95442435522548…|
|(78,[0,3,6,8,16,2…|    0|       0.0|[0.95523188876905…|
|(78,[0,3,6,8,16,2…|    0|       0.0|[0.95170786590695…|
|(78,[0,3,6,8,16,2…|    0|       0.0|[0.95523188876905…|
|(78,[0,3,6,8,16,2…|    1|       0.0|[0.93618372148223…|
|(78,[0,3,6,8,16,2…|    0|       0.0|[0.95442435522548…|
|(78,[0,3,6,8,16,2…|    0|       0.0|[0.95170786590695…|
|(78,[0,3,6,8,16,2…|    0|       0.0|[0.95170786590695…|
|(78,[0,3,6,8,16,2…|    0|       0.0|[0.95523188876905…|
|(78,[0,3,6,8,16,2…|    0|       0.0|[0.95523188876905…|
|(78,[0,3,6,8,16,2…|    0|       0.0|[0.94695663802877…|
+--------------------+-----+----------+--------------------+
only showing top 20 rows
```

2.4.2 For both models(RF and GBT) and testing data, write code to display the count of TP/TN/FP/FN. Compute the AUC, accuracy, recall, and precision for the above-threshold/below-threshold label from each model testing result using pyspark MLlib/ML APIs. 1. Draw an ROC plot. 2. Discuss which one is the better model and use metrics to support your claim (no word limit, please keep it concise)

*** The count of TP/TN/FP/FN ***

[67]:
```
# Calculate TP/TN/FP/FN

def count_prediction(predictions):
    TP = predictions.filter(F.col('prediction') == 1.0).filter(F.col('label')␣
 ↪== 1).count()
```

```
    TN = predictions.filter(F.col('prediction') == 0.0).filter(F.col('label')␣
↪== 0).count()
    FN = predictions.filter(F.col('prediction') == 0.0).filter(F.col('label')␣
↪== 1).count()
    FP = predictions.filter(F.col('prediction') == 1.0).filter(F.col('label')␣
↪== 0).count()

    return f'TP: {TP}, TN: {TN}, FN: {FN}, FP: {FP}'

print('Random Forest: ')
print(count_prediction(rf_predictions))

print('\nGradient_Boosted Tree: ')
print(count_prediction(gbt_predictions))
```

```
Random Forest:
TP: 0, TN: 33523, FN: 1051, FP: 0

Gradient_Boosted Tree:
TP: 148, TN: 33416, FN: 903, FP: 107
```

*** The AUC, accuracy, recall, and precision for the above-threshold/below-threshold labe ***

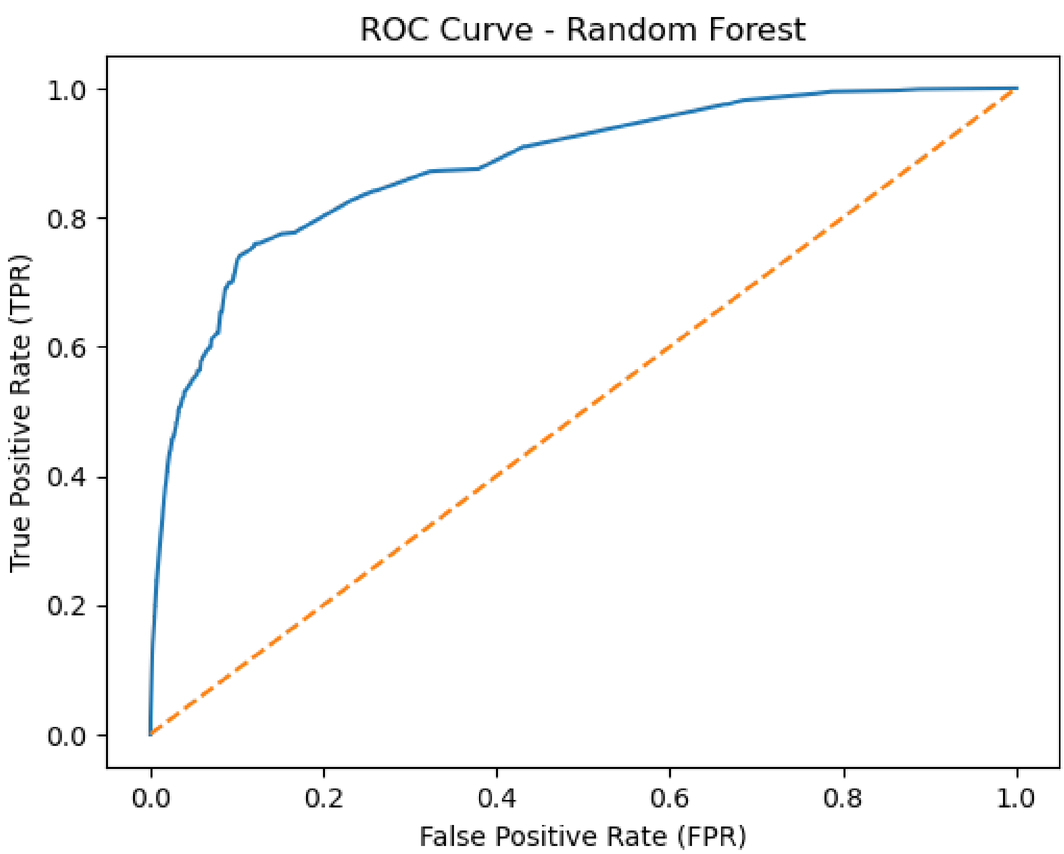
[68]:
```
from pyspark.ml.evaluation import BinaryClassificationEvaluator
import matplotlib.pyplot as plt

# Compute accuracy, precision, recall
def compute_metrics(predictions):
    TP = predictions.filter(F.col('prediction') == 1.0).filter(F.col('label')␣
↪== 1).count()
    TN = predictions.filter(F.col('prediction') == 0.0).filter(F.col('label')␣
↪== 0).count()
    FN = predictions.filter(F.col('prediction') == 0.0).filter(F.col('label')␣
↪== 1).count()
    FP = predictions.filter(F.col('prediction') == 1.0).filter(F.col('label')␣
↪== 0).count()

    accuracy = 'NA'
    precision = 'NA'
    recall = 'NA'

    if TN + TP + FN + FP != 0:
        accuracy = (TN + TP) / (TN + TP + FN + FP)

    if TP + FP != 0:
        precision = TP / (TP + FP)
```

```python
    if TP + FN != 0:
        recall = TP / (TP + FN)

    print(f'Accuracy: {accuracy}')
    print(f'Precision: {precision}')
    print(f'Recall: {recall}')


# Compute above/below threshold values and AUC
def calculate_metrics(predictions):
    evaluator = BinaryClassificationEvaluator(labelCol='label',␣
 ↪metricName='areaUnderROC')
    auc = evaluator.evaluate(predictions)

    # Default threshold = 0.5
    print('Metrics for above-threshold label:')
    compute_metrics(predictions.filter(F.col('prediction') == 1.0))

    print('\nMetrics for below-threshold label:')
    compute_metrics(predictions.filter(F.col('prediction') == 0.0))

    print(f'\nAUC: {auc}')

# Calculate metrics for Random Forest predictions
print('=== Random Forest Metrics ===')
calculate_metrics(rf_predictions)

# Calculate metrics for Gradient-Boosted Tree predictions
print('\n=== Gradient-Boosted Tree Metrics ===')
calculate_metrics(gbt_predictions)
```

```
=== Random Forest Metrics ===
Metrics for above-threshold label:
Accuracy: NA
Precision: NA
Recall: NA

Metrics for below-threshold label:
Accuracy: 0.9696014346040377
Precision: NA
Recall: 0.0

AUC: 0.8862498170377253

=== Gradient-Boosted Tree Metrics ===
Metrics for above-threshold label:
Accuracy: 0.5803921568627451
```

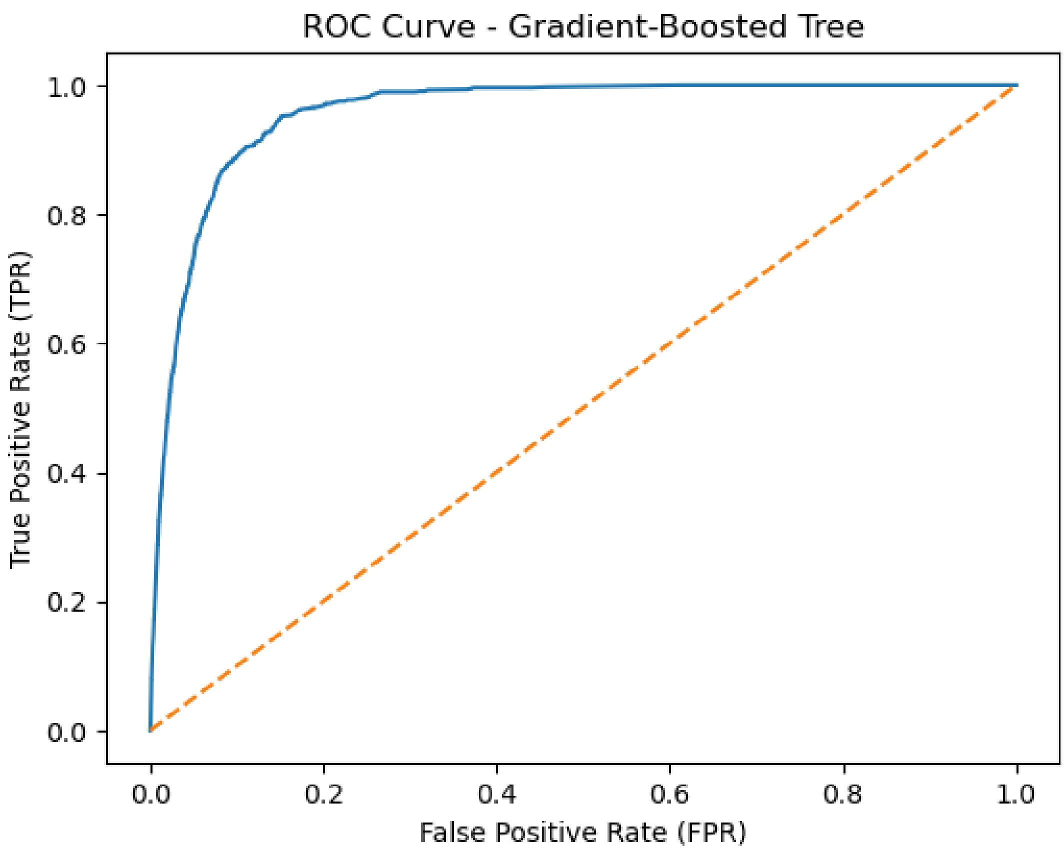
```
Precision: 0.5803921568627451
Recall: 1.0

Metrics for below-threshold label:
Accuracy: 0.9736880445234418
Precision: NA
Recall: 0.0

AUC: 0.9572122160586568
```

[69]:
```
# Plot Random Forest ROC curve
trainingSummary = rf_model.stages[-1].summary
roc = trainingSummary.roc.toPandas()
plt.plot(roc['FPR'], roc['TPR'])
plt.plot([0, 1], [0, 1],linestyle='--')
plt.ylabel('True Positive Rate (TPR)')
plt.xlabel('False Positive Rate (FPR)')
plt.title('ROC Curve - Random Forest')
plt.show()
```



[70]:
```python
# GBT plotting reference: https://stackoverflow.com/questions/52847408/
↪pyspark-extract-roc-curve
from pyspark.mllib.evaluation import BinaryClassificationMetrics

class CurveMetrics(BinaryClassificationMetrics):
    def __init__(self, *args):
        super(CurveMetrics, self).__init__(*args)

    def _to_list(self, rdd):
        return [(float(row._1()), float(row._2())) for row in rdd.collect()]

    def plot_curve(self, method):
        rdd = getattr(self._java_model, method)().toJavaRDD()
        return self._to_list(rdd)

# Extract 'label' and 'probability' from dataframe
preds = gbt_predictions.select('label', 'probability').rdd.map(lambda row:␣
↪(float(row['probability'][1]), float(row['label'])))
roc_curve = CurveMetrics(preds).plot_curve('roc')

# Plot ROC Curve
plt.figure()
x_vals, y_vals = zip(*roc_curve)
plt.plot(x_vals, y_vals)
plt.plot([0, 1], [0, 1], linestyle='--')
plt.title('ROC Curve - Gradient-Boosted Tree')
plt.xlabel('False Positive Rate (FPR)')
plt.ylabel('True Positive Rate (TPR)')
plt.show()
```

```
/opt/conda/lib/python3.10/site-packages/pyspark/sql/context.py:158:
FutureWarning: Deprecated in 3.0.0. Use SparkSession.builder.getOrCreate()
instead.
  warnings.warn(
```



2.4.3 Save the better model, we will need this for Part B of assignment 2. (note: You may need to go through a few training loops, adjust features, use more data and other techniques to create a better-performing model.)

[71]:
```
# Save GBT model
gbt_model.save('default_gbt_prediction_model')
```

2.2.3 Part 3. Applicant Segmentation and Knowledge sharing with K-Mean

Please see the specification for this task and add code/markdown cells. 1. Utilize K-Mean clustering/hyperparameter tuning you have learned in this unit and try to find the optimal K value and train the model. 2. Based on your trained model parameters, make recommendations on how to segment the applicants. Write a paragraph with 300 words maximum.

1. Utilize K-Mean clustering/hyperparameter tuning you have learned in this unit and try to find the optimal K value and train the model.

[72]:
```
from pyspark.ml.feature import StandardScaler
from pyspark.ml.feature import VectorAssembler
from pyspark.ml.clustering import KMeans
from pyspark.ml.evaluation import ClusteringEvaluator
```

```
from pyspark.sql.functions import count, isnan, col, when

df_new = spark.read.csv('application_data.csv', header = True, inferSchema =␣
↪True)

# Prepare the datagrame for K-means clustering
df_new = df_new.withColumn('gender', when(df_new['gender'] == 'M', 1).
↪when(df_new['gender'] == 'F', 2).otherwise(3))\
            .withColumn('age', age_calculate_udf(F.col('days_birth')))\
            .withColumn('loan_to_income_ratio', F.col('amt_credit') / F.
↪col('income_total'))\
            .select('id_app','gender', 'income_type', 'education_type',␣
↪'family_status', 'age', 'loan_to_income_ratio')

df_2 = df_new.drop('id_app')
df_2 = df_2.na.drop()

df_2_cols = df_2.columns
df_2_assembler = VectorAssembler(inputCols = df_2_cols, outputCol = 'features')
df_2_scaler = StandardScaler(inputCol = 'features', outputCol =␣
↪'scaledFeatures')
df_2_pipeline = Pipeline(stages = [df_2_assembler, df_2_scaler])

df_2_model = df_2_pipeline.fit(df_2)
scaled_data = df_2_model.transform(df_2)

# Find the best K value
evaluator = ClusteringEvaluator()
silhouette_arr=[]
for k in range(2,10):
    k_means= KMeans(featuresCol = 'scaledFeatures', k = k)
    model = k_means.fit(scaled_data)
    predictions = model.transform(scaled_data)
    silhouette = evaluator.evaluate(predictions)
    silhouette_arr.append(silhouette)
    print('No of clusters:',k,'Silhouette Score:',silhouette)
```

```
No of clusters: 2 Silhouette Score: 0.22575217847308604
No of clusters: 3 Silhouette Score: 0.04049325756989309
No of clusters: 4 Silhouette Score: 0.14268557204023644
No of clusters: 5 Silhouette Score: -0.016519195519834832
No of clusters: 6 Silhouette Score: -0.033622285806179375
No of clusters: 7 Silhouette Score: -0.18200395445180764
No of clusters: 8 Silhouette Score: -0.23547361633161948
No of clusters: 9 Silhouette Score: -0.18981257273379365
```

2. Based on your trained model parameters, make recommendations on how to segment the

applicants. Write a paragraph with 300 words maximum.

The optimal clustering model suggests that the K value is 2, which mean that it is better to divide the applicants into two distinct clusters. To improve the accuracy of default likelihood, specific attributes have been chosen for segmentation. The selected attributes include "gender," "income_type," "education_type," "family_status," and "loan_to_income_ratio. Through an analysis of the relationship between these attributes and defaults (see below), it is recommended to create a cluster composed of individuals with lower or secondary education, widowed family status, pensioner or unemployed income types, an age above 45, and a higher loan-to-income ratio. This cluster is expected to have a higher likelihood of defaults based on previous data. On the contrary, the second cluster contains the applicants who do not possess these characteristics.

*** The relationship between attributes and defaults ***

[73]:
```
df_ch = df_new.join(loan_df, df_new.id_app == loan_df.id_app_1, how = 'inner')
df_ch = df_ch.drop('id_app', 'id_app_1')

def calculate_ratio(column):
    selected_df = df_ch.select(column, 'is_default')

    # Count the number of true within each income type
    count_df = selected_df.groupBy(column, 'is_default').count()

    # Count the total number of applications in each income type
    total_count_df = count_df.groupBy(column).agg(F.sum('count').
 ↪alias('total_count'))

    # Join the count_df with total_count_df
    result_df = count_df.join(total_count_df, column)

    # Calculate the percentage
    result_df = result_df.withColumn('percentage', F.col('count') / F.
 ↪col('total_count') * 100).sort('percentage', ascending = False)

    # Show the resulting DataFrame
    result_df = result_df.filter(F.col('is_default') == True).
 ↪sort('percentage', ascending = False).show()

new_column = df_ch.columns

for col in new_column:
    calculate_ratio(col)
```

```
+------+----------+-----+-----------+------------------+
|gender|is_default|count|total_count|        percentage|
+------+----------+-----+-----------+------------------+
|     2|      true| 4441|     113467|3.9139132963769203|
|     1|      true|  721|      59121| 1.219532822516534|
+------+----------+-----+-----------+------------------+
```

income_type	is_default	count	total_count	percentage
7	true	4	13	30.76923076923077
5	true	1945	30983	6.277636123035213
1	true	368	12057	3.0521688645600067
2	true	2030	89283	2.2736691195412337
8	true	815	40237	2.025498918905485

education_type	is_default	count	total_count	percentage
3	true	76	2108	3.6053130929791273
1	true	4156	122629	3.3890841481215697
4	true	850	42044	2.0216915612215773
2	true	79	5720	1.381118881118881
5	true	1	90	1.1111111111111112

family_status	is_default	count	total_count	percentage
5	true	566	8994	6.293084278407828
4	true	418	11004	3.7986186841148677
3	true	3769	110626	3.406974852204726
2	true	205	16639	1.2320451950237394
6	true	204	25327	0.8054645240257433

age	is_default	count	total_count	percentage
64	true	246	2885	8.526863084922011
62	true	234	3094	7.563025210084033
63	true	210	2951	7.11623178583531
61	true	210	3060	6.862745098039216
65	true	115	1734	6.6320645905420985
60	true	228	3438	6.631762652705062
59	true	220	3727	5.902870941776228
58	true	191	3509	5.443146195497293
57	true	200	3791	5.275652862041678
66	true	57	1179	4.8346055979643765
56	true	169	3801	4.446198368850303
55	true	159	3701	4.29613617941097
54	true	158	4193	3.7681850703553543
53	true	149	4114	3.6217792902284884

```
| 51|      true|  128|       3640|3.5164835164835164|
| 52|      true|  135|       3860|3.4974093264248705|
| 48|      true|  128|       3919| 3.266139321255422|
| 46|      true|  125|       4120| 3.033980582524272|
| 50|      true|  110|       3664| 3.002183406113537|
| 44|      true|  130|       4359|2.9823353980270704|
+---+----------+-----+-----------+------------------+
only showing top 20 rows

+--------------------+----------+-----+-----------+----------+
|loan_to_income_ratio|is_default|count|total_count|percentage|
+--------------------+----------+-----+-----------+----------+
|  12.788055555555555|      true|    1|          1|     100.0|
|             2.98475|      true|    1|          1|     100.0|
|  6.5088888888888885|      true|    1|          1|     100.0|
|                9.55|      true|    1|          1|     100.0|
|  13.266666666666667|      true|    1|          1|     100.0|
|  11.320754716981131|      true|    1|          1|     100.0|
|   9.801846153846153|      true|    1|          1|     100.0|
|             19.4684|      true|    1|          1|     100.0|
|            4.714325|      true|    1|          1|     100.0|
|  17.416363636363638|      true|    1|          1|     100.0|
|              24.214|      true|    1|          1|     100.0|
|  12.261133333333333|      true|    1|          1|     100.0|
|   6.173913043478261|      true|    1|          1|     100.0|
|   10.20904347826087|      true|    1|          1|     100.0|
|   8.715571428571428|      true|    1|          1|     100.0|
|   18.16863157894737|      true|    1|          1|     100.0|
|   27.77777777777778|      true|    2|          2|     100.0|
|   5.667461538461539|      true|    1|          1|     100.0|
|               16.75|      true|    1|          1|     100.0|
|  12.978066666666667|      true|    1|          1|     100.0|
+--------------------+----------+-----+-----------+----------+
only showing top 20 rows

+----------+-----+-----------+----------+
|is_default|count|total_count|percentage|
+----------+-----+-----------+----------+
|      true| 5162|       5162|     100.0|
+----------+-----+-----------+----------+
```

2.2.4 Part 4: Data Ethics, Privacy, and Security

Please see the specification for this task and add markdown cells(word limit: 500).

a. Define the concepts of data ethics, privacy, and security within the big data domain.

```
Data ethics refers to the ethical responsibilities associated with the collection, protection,
```

Data privacy is centered on the management and governance of personal data. This involves the c
As for data security, it is concerned with safeguarding data from malicious attacks and prevent

b. Explain the significance of these issues in today's data-driven world. Data Ethics: Analyze how data ethics can influence big data processing; Examine real-world examples of how data ethics has been handled, both positively and negatively. Analyze the balance between technological advancements and ethical responsibilities

In the realm of big data processing, it is believed that ethical considerations includes inform
One of the key principles is to obtain informed consent, which emphasises on the importance of
The balance between technological advancements and ethical responsibilities is essential to ens

c. Summarize the key findings of your analysis and include a list of references (see the next section).

Data ethics plays a vital role in today's society particularly due to the widespread use of Big

2.3 References:

Please add your references below:

Cote, C. (2021, March 16). 5 Principles of Data Ethics for Business. Harvard Business School Online. https://online.hbs.edu/blog/post/data-ethics

Data Ethics Unveiled: Principles & Frameworks Explored. (n.d.). Atlan.com. https://atlan.com/data-ethics-101/#:~:text=Data%20ethics%20refers%20to%20the

Jain, P., Gyanchandani, M., & Khare, N. (2016). Big data privacy: a technological perspective and review. Journal of Big Data, 3(1). https://doi.org/10.1186/s40537-016-0059-y

Herschel, R., & Miori, V. M. (2017). Ethics & Big Data. Technology in Society, 49(0160-791X), 31–36. https://doi.org/10.1016/j.techsoc.2017.03.003

Legal - Apple Privacy Policy - Apple. (n.d.). Apple Legal. https://www.apple.com/legal/privacy/en-ww/#:~:text=Apple%20uses%20personal%20data%20to

Wong, J. C. (2019, March 18). The Cambridge Analytica Scandal Changed the World – but It Didn't Change Facebook. The Guardian. https://www.theguardian.com/technology/2019/mar/17/the-cambridge-analytica-scandal-changed-the-world-but-it-didnt-change-facebook