final_project_team25

December 12, 2019

1 Final Project: -Display Advertising Challenge

Team 25: Michael Zeng, Param Viswanathan, Gopinath Duddi, Hailey Wu

2 Abstract

Prediction for click-through rate (CTR) is critical for target advertisement in order to drive purchase interests with the right content displayed. With more and more session or user specific cookies, data scientists now have more information to analyze on, but also need to take consideration of sensitive data. This report attempts to predict the CTR with multiple machine learning approaches based on the Criteo Labs' Kaggle Display Advertising Challenge dataset. Large effort involves data understanding, engineering and scalable processing. Using the best logistic regression model we trained, the lowest log loss reaches 0.50 on the test data.

3 Question Formulation

- The goal of this project is to predict the click-through rate on the advertising based on a variety of features collected.
- The empirical relationship between the observablem features and the efficiency of the advertisement distribution that this research is trying to establish will be extremely valuable to a lot of businesses.

As a billion dollar effort driven industry, target advertisement has long been the research focus to enhance the accuracy for the right content at the right time for the right group of viewers. Many machine learning models are built to understand the probability of a given user to click on a displayed advertisement, as called the prediction of click-through rate (CTR). With increasing footprint cookies on the Internet, marketing companies now have more user-specific information that can be fed into the models. Coming along with the benefit of user details, data scientists face new challenges. One concern is how to process efficiency With the massive data, under time and budget constraints, while the other is how to use the less comprehensible personal data under private information protection.

This study aims to use the user data provided by Criteo Labs' Kaggle Display Advertising Challenge to predict advertisement click-through rate. This two-class problem is approached with various machine learning models, mostly logistic regression and gradient boosted trees after trials. The work contains exploratory data analysis, feature engineering, feature selection, pipeline development and model tuning. Specifically, with unnamed integer and hashed categorical variables, the team puts main effort into interpreting and transforming the data that will reduce the log loss. With the massive data, the team takes a random 100,000 samples for model development, and runs the final model with parquet format, Spark dataframe type, and Spark MLLib on GCP engine (input the GCP engine information). With all attempts, the study tries to answer the question:

"Given a user and the page he or she is visiting, what is the probability that he will click on a given ad?"

The team considers the two real-life challenges for display advertisement while developing the model. The study uses log loss as the metric with limitation of the given background. With the prediction of CTR, companies can further look into the sale conversion rate and define a more specific metric to enhance the profit-driven model.

There are unique challenges to this problem: 1. The sheer size of the data makes it unsuitable for the typical tools people use for modeling, such as Pandas and SKlearn, which is why we choose to do it with Spark MLlib. 2. The complexity of the features space would normally require a lot of domain knowledge, yet here the data is presented anonymously. Therefore, the research presented in this notebook will be based on statistical observations and practices. 3. While researching into the problem, our team also keeps in mind the needs of real-time production. And that's why we have built Spark pipelines for the data, and depending on the business needs, we could efficiently deploy the code for updates/retrain of the model.

Yet, such unique problem setup also has certain benefits: 1. The data is not so imbalanced, which makes it suitable for a larger set of algorithms had it been imbalanced such as problem of predicting credit card default. 2. The lack of timestamps also frees us from considerations of time series property of our model and its predictions. 3. The problem itself allows bigger margin of error and is not so demanding on the intuitiveness of the model. Meaning the business wouldn't really grill us if we got one or two predictions wrong, nor are they likely to demand that we "open the box" for them and explain exactly what went into the prediction on any given case. This also opens up more freedom for us in terms of features engineering and model selection.

4 Download Data

4.1 Download the small dataset from Kaggle

The following cell is run in the conda environement that we used to submit jobs to clusters. You might need to install the kaggle module `kaggle` by `!pip install kaggle`, and go through the authentications and accept term of use.

[51]:
```
import os
# os.chdir('/Users/zengm71/Documents/Berkeley/W261/
↪f19-final-project-f19-team-25/')
!kaggle competitions download -c criteo-display-ad-challenge -p small_data/
```

```
Downloading criteo-display-ad-challenge.zip to small_data
 99%|                    | 47.0M/47.6M [00:02<00:00, 22.9MB/s]
```

```
100%|                    | 47.6M/47.6M [00:02<00:00, 21.9MB/s]
```

[54]:
```python
import zipfile
zipfile.ZipFile('small_data/criteo-display-ad-challenge.zip', 'r').\
        extractall('small_data/')
zipfile.ZipFile('small_data/random_submission.zip', 'r').\
        extractall('small_data/')

!rm small_data/criteo-display-ad-challenge.zip
!rm small_data/random_submission.zip
```

4.2 Download the full data set

[2]:
```
!curl -O https://s3-eu-west-1.amazonaws.com/
↪kaggle-display-advertising-challenge-dataset/dac.tar.gz
```

```
  % Total    % Received % Xferd  Average Speed   Time    Time     Time  Current
                                 Dload  Upload   Total   Spent    Left  Speed
100 4364M  100 4364M    0     0  21.2M      0  0:03:25  0:03:25 --:--:-- 21.5M
```

[3]:
```
!mkdir full_data
!tar -xvzf dac.tar.gz -C full_data/
!rm dac.tar.gz
```

```
tar: Ignoring unknown extended header keyword `SCHILY.dev'
tar: Ignoring unknown extended header keyword `SCHILY.ino'
tar: Ignoring unknown extended header keyword `SCHILY.nlink'
readme.txt
tar: Ignoring unknown extended header keyword `LIBARCHIVE.creationtime'
tar: Ignoring unknown extended header keyword `SCHILY.dev'
tar: Ignoring unknown extended header keyword `SCHILY.ino'
tar: Ignoring unknown extended header keyword `SCHILY.nlink'
test.txt
tar: Ignoring unknown extended header keyword `SCHILY.dev'
tar: Ignoring unknown extended header keyword `SCHILY.ino'
tar: Ignoring unknown extended header keyword `SCHILY.nlink'
train.txt
```

[1]:
```python
# imports
import re
import ast
import time
import numpy as np
import pandas as pd
import seaborn as sns
import networkx as nx
```

```
import matplotlib.pyplot as plt
import seaborn as sns
from pyspark.sql import Row
%matplotlib inline
```

[5]:
```
# set up spark
%reload_ext autoreload
%autoreload 2
# store path to notebook
PWD = !pwd
PWD = PWD[0]
# start Spark Session
from pyspark.sql import SparkSession
app_name = "final_project"
master = "local[*]"
spark = SparkSession\
        .builder\
        .appName(app_name)\
        .master(master)\
        .config('spark.executor.memory', '12g')\
        .getOrCreate()
# from pyspark import SparkContext
# SparkContext.setSystemProperty('spark.executor.memory', '15g')
sc = spark.sparkContext
spark
```

[5]:
```
<pyspark.sql.session.SparkSession at 0x7fd7570da240>
```

4.3 Read into dataframe

[10]:
```
# Read the text file in with RDD
# the categoricals can be read in as they are.
# Since the numerics are all integers, we add '0' to the end and devide by 10

df = sc.textFile('full_data/train.txt').\
        map(lambda l: l.split("\t")).\
        map(lambda p: Row(label=int(p[0]),
                            c01 = int(p[1] + '0') / 10, c02 = int(p[2] + '0') /␣
↪10, c03 = int(p[3] + '0') / 10, c04 = int(p[4] + '0') / 10, c05 = int(p[5] +␣
↪'0') / 10, c06 = int(p[6] + '0') / 10,
                            c07 = int(p[7] + '0') / 10, c08 = int(p[8] + '0') /␣
↪10, c09 = int(p[9] + '0') / 10, c10 = int(p[10] + '0') / 10, c11 = int(p[11]␣
↪+ '0') / 10, c12 = int(p[12] + '0') / 10,
                            c13 = int(p[13] + '0') / 10,
```

```
                                b01 = p[14], b02 = p[15], b03 = p[16], b04 = p[17],␣
↪b05 = p[18], b06 = p[19], b07 = p[20], b08 = p[21], b09 = p[22], b10 =␣
↪p[23], b11 = p[24], b12 = p[25], b13 = p[26],
                                b14 = p[27], b15 = p[28], b16 = p[29], b17 = p[30],␣
↪b18 = p[31], b19 = p[32], b20 = p[33], b21 = p[34], b22 = p[35], b23 =␣
↪p[36], b24 = p[37], b25 = p[38], b26 = p[39], ))

# Infer the schema, and register the DataFrame as a table.
schema_df = spark.createDataFrame(df)
schema_df.createOrReplaceTempView("df")
```

Print out just a few columns:

[11]:
```
schema_df.select('c01', 'c02', 'c03', 'b01', 'b02', 'b03', 'label').show()
```

```
+---+-----+-----+--------+--------+--------+-----+
|c01|  c02|  c03|     b01|     b02|     b03|label|
+---+-----+-----+--------+--------+--------+-----+
|1.0|  1.0|  5.0|68fd1e64|80e26c9b|fb936136|    0|
|2.0|  0.0| 44.0|68fd1e64|f0cf0024|6f67f7e5|    0|
|2.0|  0.0|  1.0|287e684f|0a519c5c|02cf9876|    0|
|0.0|893.0|  0.0|68fd1e64|2c16a946|a9a87e68|    0|
|3.0| -1.0|  0.0|8cf07265|ae46a29d|c81688bb|    0|
|0.0| -1.0|  0.0|05db9164|6c9c9cf3|2730ec9c|    0|
|0.0|  1.0|  2.0|439a44a4|ad4527a2|c02372d0|    0|
|1.0|  4.0|  2.0|68fd1e64|2c16a946|503b9dbc|    1|
|0.0| 44.0|  4.0|05db9164|d833535f|d032c263|    0|
|0.0| 35.0|  0.0|05db9164|510b40a5|d03e7c24|    0|
|0.0|  2.0|632.0|05db9164|0468d672|7ae80d0f|    0|
|0.0|  6.0|  6.0|05db9164|9b5fd12f|        |    0|
|0.0| -1.0|  0.0|241546e0|38a947a1|fa673455|    1|
|0.0|  2.0| 11.0|be589b51|287130e0|cd7a7a22|    1|
|0.0| 51.0| 84.0|5a9ed9b0|80e26c9b|97144401|    0|
|0.0|  2.0|  1.0|05db9164|bc6e3dc1|67799c69|    0|
|1.0|987.0|  0.0|68fd1e64|38d50e09|da603082|    1|
|0.0|  1.0|  0.0|8cf07265|7cd19acc|77f2f2e5|    0|
|0.0| 24.0|  4.0|05db9164|f0cf0024|08b45d8b|    0|
|7.0|102.0|  0.0|3c9d8785|b0660259|3a960356|    0|
+---+-----+-----+--------+--------+--------+-----+
only showing top 20 rows
```

The 3-bit hashed columns have different number of distinct values, so I will just leave the hash code as it is right now:

[12]:
```
schema_df.printSchema()
```

```
root
```

```
 |-- b01: string (nullable = true)
 |-- b02: string (nullable = true)
 |-- b03: string (nullable = true)
 |-- b04: string (nullable = true)
 |-- b05: string (nullable = true)
 |-- b06: string (nullable = true)
 |-- b07: string (nullable = true)
 |-- b08: string (nullable = true)
 |-- b09: string (nullable = true)
 |-- b10: string (nullable = true)
 |-- b11: string (nullable = true)
 |-- b12: string (nullable = true)
 |-- b13: string (nullable = true)
 |-- b14: string (nullable = true)
 |-- b15: string (nullable = true)
 |-- b16: string (nullable = true)
 |-- b17: string (nullable = true)
 |-- b18: string (nullable = true)
 |-- b19: string (nullable = true)
 |-- b20: string (nullable = true)
 |-- b21: string (nullable = true)
 |-- b22: string (nullable = true)
 |-- b23: string (nullable = true)
 |-- b24: string (nullable = true)
 |-- b25: string (nullable = true)
 |-- b26: string (nullable = true)
 |-- c01: double (nullable = true)
 |-- c02: double (nullable = true)
 |-- c03: double (nullable = true)
 |-- c04: double (nullable = true)
 |-- c05: double (nullable = true)
 |-- c06: double (nullable = true)
 |-- c07: double (nullable = true)
 |-- c08: double (nullable = true)
 |-- c09: double (nullable = true)
 |-- c10: double (nullable = true)
 |-- c11: double (nullable = true)
 |-- c12: double (nullable = true)
 |-- c13: double (nullable = true)
 |-- label: long (nullable = true)
```

[13]:
```
# the distribution of features are a bit imbalanced, but not extremely skewed
schema_df.groupBy('label').count().show()
```

```
+-----+--------+
|label|   count|
+-----+--------+
```

```
|    0|34095179|
|    1|11745438|
+-----+--------+
```

4.4 Write to parquet, because it makes everything a lot faster. Thanks James!

[ ]:
```python
schema_df.write.parquet("full_data/train.parquet")
```

[8]:
```python
parquet_df = spark.read.parquet("full_data/train.parquet")

# Parquet files can also be used to create a temporary view and then used in
 ↪SQL statements.
parquet_df.createOrReplaceTempView("parquet_df")
parquet_df.printSchema()
```

```
root
 |-- b01: string (nullable = true)
 |-- b02: string (nullable = true)
 |-- b03: string (nullable = true)
 |-- b04: string (nullable = true)
 |-- b05: string (nullable = true)
 |-- b06: string (nullable = true)
 |-- b07: string (nullable = true)
 |-- b08: string (nullable = true)
 |-- b09: string (nullable = true)
 |-- b10: string (nullable = true)
 |-- b11: string (nullable = true)
 |-- b12: string (nullable = true)
 |-- b13: string (nullable = true)
 |-- b14: string (nullable = true)
 |-- b15: string (nullable = true)
 |-- b16: string (nullable = true)
 |-- b17: string (nullable = true)
 |-- b18: string (nullable = true)
 |-- b19: string (nullable = true)
 |-- b20: string (nullable = true)
 |-- b21: string (nullable = true)
 |-- b22: string (nullable = true)
 |-- b23: string (nullable = true)
 |-- b24: string (nullable = true)
 |-- b25: string (nullable = true)
 |-- b26: string (nullable = true)
 |-- c01: double (nullable = true)
 |-- c02: double (nullable = true)
 |-- c03: double (nullable = true)
 |-- c04: double (nullable = true)
```

```
 |-- c05: double (nullable = true)
 |-- c06: double (nullable = true)
 |-- c07: double (nullable = true)
 |-- c08: double (nullable = true)
 |-- c09: double (nullable = true)
 |-- c10: double (nullable = true)
 |-- c11: double (nullable = true)
 |-- c12: double (nullable = true)
 |-- c13: double (nullable = true)
 |-- label: long (nullable = true)
```

4.5 Sample out a small dataframe for EDA

[9]:
```
# sample out 100k rows for the EDA and toy examples
sample_df = parquet_df.sample(fraction=100000/(34095179 + 11745438), seed=8888).
 ↪cache()
```

Turns out there is some floating value outflow in the sample, we got 100085 rows. But that should be OK for the purpose of some EDA and visualization.

[10]:
```
sample_df.count()
```

[10]:
```
100085
```

[11]:
```
sample_df.take(5)
```

[11]:
```
[Row(b01='5a9ed9b0', b02='80e26c9b', b03='51546964', b04='745c6c18',
b05='4cf72387', b06='', b07='1b2007fe', b08='0b153874', b09='a73ee510',
b10='f9065d00', b11='6c07e306', b12='179a11e3', b13='1cd94349', b14='b28479f6',
b15='4c1df281', b16='4bcf344c', b17='1e88c74f', b18='f54016b9', b19='21ddcdc9',
b20='5840adea', b21='2d1f75c0', b22='', b23='32c7478e', b24='b0fb6a50',
b25='e8b83407', b26='61556511', c01=0.0, c02=-1.0, c03=0.0, c04=0.0, c05=1475.0,
c06=0.0, c07=0.0, c08=22.0, c09=25.0, c10=0.0, c11=0.0, c12=0.0, c13=0.0,
label=0),
 Row(b01='05db9164', b02='68aede49', b03='dabd54b8', b04='c2268dde',
b05='25c83c98', b06='7e0ccccf', b07='5e64ce5f', b08='5b392875', b09='a73ee510',
b10='afd9b8fe', b11='8b94178b', b12='62231334', b13='025225f2', b14='b28479f6',
b15='5c595008', b16='9aa05cbb', b17='e5ba7672', b18='262c8681', b19='', b20='',
b21='a2bb9a62', b22='', b23='32c7478e', b24='2f4c59f7', b25='', b26='', c01=0.0,
c02=1.0, c03=1.0, c04=0.0, c05=1591.0, c06=0.0, c07=0.0, c08=4.0, c09=4.0,
c10=0.0, c11=0.0, c12=0.0, c13=0.0, label=0),
 Row(b01='05db9164', b02='59ab477c', b03='c48cd8f8', b04='24d89f30',
b05='25c83c98', b06='', b07='602c7597', b08='0b153874', b09='a73ee510',
b10='1d56e466', b11='159499d1', b12='f25a8037', b13='4ab361e1', b14='1adce6ef',
b15='38f1e55f', b16='9ca51d92', b17='1e88c74f', b18='74fc71da', b19='21ddcdc9',
b20='5840adea', b21='17b90ef0', b22='', b23='32c7478e', b24='da89b7d5',
```

```
b25='47907db5', b26='984e0db0', c01=0.0, c02=79.0, c03=4.0, c04=2.0, c05=9159.0,
c06=0.0, c07=0.0, c08=2.0, c09=62.0, c10=0.0, c11=0.0, c12=0.0, c13=2.0,
label=0),
 Row(b01='05db9164', b02='58e67aaf', b03='7a0e926f', b04='715dbf7b',
b05='25c83c98', b06='fbad5c96', b07='9f525672', b08='5b392875', b09='a73ee510',
b10='46a09953', b11='843d8639', b12='546509a2', b13='9cab1003', b14='1adce6ef',
b15='d002b6d9', b16='be3f514f', b17='e5ba7672', b18='c21c3e4c', b19='338f20de',
b20='b1252a9d', b21='f089c0a8', b22='', b23='bcdee96c', b24='bc8b14b9',
b25='9b3e8820', b26='cdd2b5b7', c01=1.0, c02=0.0, c03=216.0, c04=11.0,
c05=446.0, c06=49.0, c07=3.0, c08=22.0, c09=102.0, c10=1.0, c11=3.0, c12=0.0,
c13=28.0, label=0),
 Row(b01='8cf07265', b02='4e8d18ed', b03='dbe76869', b04='ed2916e0',
b05='25c83c98', b06='7e0ccccf', b07='09504918', b08='0b153874', b09='a73ee510',
b10='2b29a76b', b11='585f0af3', b12='f09e0613', b13='175d4f42', b14='07d13a8f',
b15='8d016df5', b16='f0bf03ac', b17='e5ba7672', b18='47e4d79e', b19='4764bf77',
b20='a458ea53', b21='cd5c4b8c', b22='', b23='3a171ecb', b24='1b2ee77b',
b25='c9f3bea7', b26='ab80f361', c01=0.0, c02=0.0, c03=27.0, c04=7.0, c05=5869.0,
c06=99.0, c07=5.0, c08=7.0, c09=31.0, c10=0.0, c11=1.0, c12=0.0, c13=7.0,
label=1)]
```

[13]:
```python
# write to csv to consume later
sample_df.repartition(1).write.csv(path='full_data/sample.csv', mode="append",␣
↪header="true")
```

[12]:
```python
# read to pandsa
sample_df_pd = sample_df.toPandas()
```

[13]:
```python
# create a copy for Breiman's method, since it will follow a very different␣
↪waterfall
sample_df_bm = sample_df
```

5 Algorithm explanation

In this section, we try to implement logistic regression using RDD with the sampled data (`sample_df`). To make the calculation easier, we picked the first numeric column `c01`, a categorical column `b09` with the least number of unique categories, and the top 100 rows to form a toy RDD dataset.

- Logistic Regression
  - Setup:

$$p(y=1) = \frac{1}{1+exp(-wX)}$$

  - Objective function:

$$L = \frac{1}{m}\sum_{i=1}^{m} y_i \cdot log(p(y_i=1)) + (1-y_i) \cdot log(1-p(y_i=1))$$

– Gradient:

$$J = \frac{1}{m}\sum_{i=1}^{m}(y_i - p(y_i = 1))x_i$$

[15]:
```
# head of sample_df_toy
sample_df_toy = sample_df.select("c01", "b09", "label").limit(100)
sample_df_toy.show(5)
```

```
+---+--------+-----+
|c01|     b09|label|
+---+--------+-----+
|0.0|a73ee510|    0|
|0.0|a73ee510|    0|
|0.0|a73ee510|    0|
|1.0|a73ee510|    0|
|0.0|a73ee510|    1|
+---+--------+-----+
only showing top 5 rows
```

[16]:
```
# distribution of labels, it is close to the full dataset
sample_df_toy.groupBy('label').count().show()
```

```
+-----+-----+
|label|count|
+-----+-----+
|    0|   73|
|    1|   27|
+-----+-----+
```

- Transform the continuous variable with log1p:

[17]:
```
# the original disttribution is skewed, but since it is non-negative, log1p is␣
↪a suitable transformation
sample_df_toy.select('c01').describe().toPandas().transpose()
```

[17]:

	0	1	2	3	4
summary	count	mean	stddev	min	max
c01	100	1.56	4.23148372860567	0.0	25.0

[18]:
```
# log1p transoformation, after which the scales are more compact.
from pyspark.sql.functions import when, log1p, col
sample_df_toy = sample_df_toy.withColumn('c01_t', log1p('c01'))
sample_df_toy.show(5)
sample_df_toy.select('c01_t').describe().toPandas().transpose()
```

```
+---+--------+-----+------------------+
```

```
|c01|     b09|label|            c01_t|
+---+--------+-----+-----------------+
|0.0|a73ee510|    0|              0.0|
|0.0|a73ee510|    0|              0.0|
|0.0|a73ee510|    0|              0.0|
|1.0|a73ee510|    0|0.6931471805599453|
|0.0|a73ee510|    1|              0.0|
+---+--------+-----+-----------------+
only showing top 5 rows
```

[18]:

	0	1	2	3	4
summary	count	mean	stddev	min	max
c01_t	100	0.429320903037294	0.8011288879342549	0.0	3.258096538021482

- Standardize the transformed c01:

[19]:

```
# we'd de-mean and devide by standard deviation
# after that the column is mean 0 with stdev 1
sample_df_toy = sample_df_toy.withColumn('c01_ts', (col('c01_t') - 0.
↪429320903037294)/0.8011288879342549)
sample_df_toy.show(5)
sample_df_toy.select('c01_ts').describe().toPandas().transpose()
```

```
+---+--------+-----+-----------------+------------------+
|c01|     b09|label|            c01_t|            c01_ts|
+---+--------+-----+-----------------+------------------+
|0.0|a73ee510|    0|              0.0|-0.535894922157053|
|0.0|a73ee510|    0|              0.0|-0.535894922157053|
|0.0|a73ee510|    0|              0.0|-0.535894922157053|
|1.0|a73ee510|    0|0.6931471805599453|0.3293181428058832|
|0.0|a73ee510|    1|              0.0|-0.535894922157053|
+---+--------+-----+-----------------+------------------+
only showing top 5 rows
```

[19]:

	0	1	2	3 \
summary	count	mean	stddev	min
c01_ts	100	7.549516567451065E-17	1.0	-0.535894922157053

	4
summary	max
c01_ts	3.5309869330493218

- One-hot Encode the categorical variable: here we only have two categories which makes it a lot easier.

[20]:
```
# there are two categories originally
sample_df_toy.groupBy('b09').count().show()
```

```
+--------+-----+
|     b09|count|
+--------+-----+
|a73ee510|   90|
|7cc72ec2|   10|
+--------+-----+
```

[21]:
```
# one-hot encoding
sample_df_toy = sample_df_toy.withColumn('b09_t1', when(col('b09') ==␣
↪'a73ee510', 1).otherwise(0))
sample_df_toy.show(10)
```

```
+---+--------+-----+------------------+------------------+------+
|c01|     b09|label|             c01_t|            c01_ts|b09_t1|
+---+--------+-----+------------------+------------------+------+
|0.0|a73ee510|    0|               0.0|-0.535894922157053|     1|
|0.0|a73ee510|    0|               0.0|-0.535894922157053|     1|
|0.0|a73ee510|    0|               0.0|-0.535894922157053|     1|
|1.0|a73ee510|    0|0.6931471805599453|0.3293181428058832|     1|
|0.0|a73ee510|    1|               0.0|-0.535894922157053|     1|
|3.0|a73ee510|    1|1.3862943611198906|1.1945312077688193|     1|
|0.0|a73ee510|    0|               0.0|-0.535894922157053|     1|
|0.0|a73ee510|    0|               0.0|-0.535894922157053|     1|
|0.0|a73ee510|    0|               0.0|-0.535894922157053|     1|
|0.0|7cc72ec2|    0|               0.0|-0.535894922157053|     0|
+---+--------+-----+------------------+------------------+------+
only showing top 10 rows
```

Now implement the gradient descend and logistic regression using RDD. The code largely leveraged the code for linear regression in HW4.

[22]:
```
# transform to RDD
sample_df_toy_rdd = sample_df_toy.select('c01_ts', 'b09_t1', 'label')\
                                 .rdd \
                                 .map(lambda x: ([x[0], x[1]], x[2]))
sample_df_toy_rdd.top(5)
```

[22]:
```
[([3.5309869330493218, 1], 1),
 ([3.264395497495463, 1], 0),
 ([3.0719786690064264, 1], 1),
 ([2.844397864544265, 1], 1),
 ([2.7582782993581283, 1], 1)]
```

[23]:

```
# the loss and GDUpdate are adapted from HW4

# part d - write function to compute loss (FILL IN MISSING CODE BELOW)
def Loss(dataRDD, W):
    """
    Compute mean squared error.
    Args:
        dataRDD - each record is a tuple of (features_array, y)
        W       - (array) model coefficients with bias at index 0
    """
    epsilon = 1e-16

    augmentedData = dataRDD.map(lambda x: (np.append([1.0], x[0]), x[1]))
    ################## YOUR CODE HERE ##################
    loss = augmentedData.map(lambda x: -x[1] * np.log(1/(1 + np.exp(- np.
 ↪dot(x[0], W))) + epsilon)
                                       -(1-x[1]) * np.log(1/(1 + np.exp(np.
 ↪dot(x[0], W))) + epsilon))\
                           .mean()
    ################## (END) YOUR CODE ##################
    return loss

def GDUpdate(dataRDD, W, learningRate = 0.2):
    """
    Perform one OLS gradient descent step/update.
    Args:
        dataRDD - records are tuples of (features_array, y)
        W       - (array) model coefficients with bias at index 0
    Returns:
        new_model - (array) updated coefficients, bias at index 0
    """
    # add a bias 'feature' of 1 at index 0
    augmentedData = dataRDD.map(lambda x: (np.append([1.0], x[0]), x[1])).
 ↪cache()

    ################## YOUR CODE HERE #################
    grad = augmentedData.map(lambda x: (1/(1 + np.exp(-np.dot(W, x[0]))) -␣
 ↪x[1]) * x[0]).mean() * 2
    new_model = W - grad * learningRate
    ################## (END) YOUR CODE #################

    return new_model
```

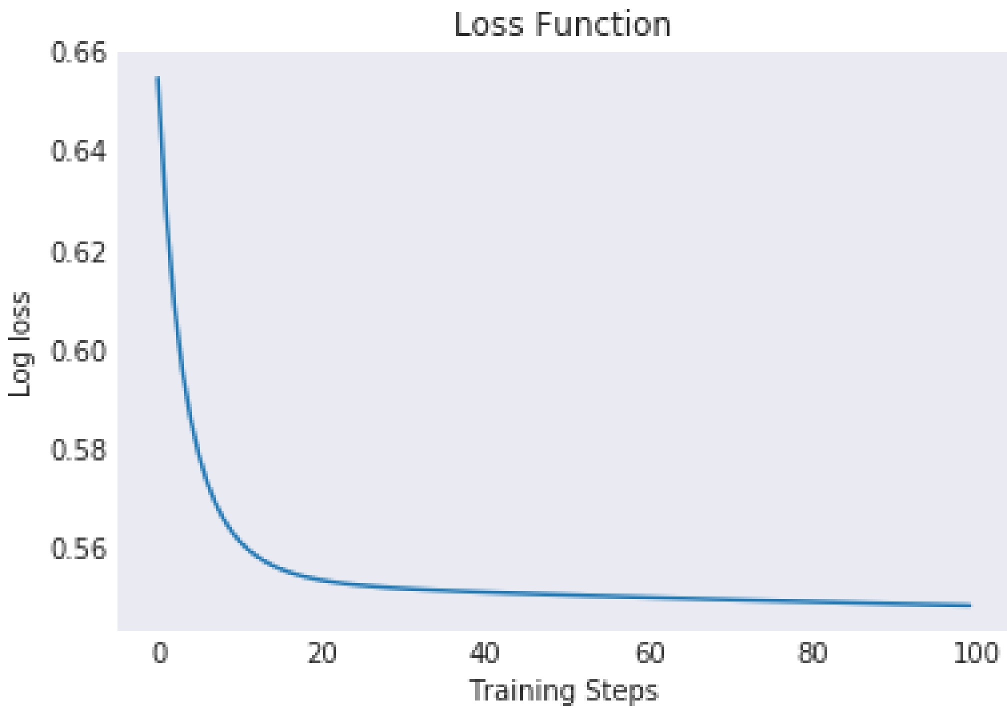
[24]:

```
# training process

nSteps = 100
# append 0s for intercept
```

```python
model = np.append([0], np.repeat(0, 2))
print(f"BASELINE:  Loss = {Loss(sample_df_toy_rdd,model)}")
print(f"BASELINE:  Model = {model}")
trace = []
print("showing the first 5 steps in print, the rest in chart")

for idx in range(nSteps):
    model = GDUpdate(sample_df_toy_rdd, model)
    loss = Loss(sample_df_toy_rdd, model)
    if (idx < 5):
        # show only the 5 steps
        print("----------")
        print(f"STEP: {idx+1}")
        print(f"Loss: {loss}")
        print(f"Model: {[round(w,3) for w in model]}")
    trace = np.append(trace, [loss])

g = sns.lineplot(x=range(nSteps), y=trace)
g.set_title('Loss Function')
g.set_xlabel('Training Steps')
g.set_ylabel('Log loss')

print(f'Final model: Model = {model}')

# Getting prediction
pred = sample_df_toy_rdd.map(lambda x: (np.append([1.0], x[0]), x[1]))\
                        .map(lambda x: 1 * (1/(1 + np.exp(- np.dot(model,␣
 ↪x[0]))) > 0.5))\
                        .collect()
```

```
BASELINE:  Loss = 0.6931471805599451
BASELINE:  Model = [0 0 0]
showing the first 5 steps in print, the rest in chart
----------
STEP: 1
Loss: 0.6547251711209194
Model: [-0.092, 0.05, -0.076]
----------
STEP: 2
Loss: 0.6280398732611083
Model: [-0.168, 0.096, -0.137]
----------
STEP: 3
Loss: 0.6092471394084692
Model: [-0.231, 0.138, -0.186]
----------
STEP: 4
```

```
Loss: 0.5957889561966307
Model: [-0.284, 0.176, -0.226]
----------
STEP: 5
Loss: 0.5859803799941462
Model: [-0.328, 0.211, -0.259]
Final model: Model = [-0.87190886  0.58637348 -0.15645926]
```



- Just to verify our results with a standard implementation from SKlearn:

[25]:
```python
# compare coef and f1-score
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import f1_score
sample_df_toy_pandas = sample_df_toy.select('c01_ts', 'b09_t1', 'label').
 ↪toPandas()
skl_model = LogisticRegression(fit_intercept=True)
skl_model.fit(sample_df_toy_pandas[['c01_ts', 'b09_t1']],␣
 ↪sample_df_toy_pandas['label'])
print(f'SKLearn logistic model weights: {np.append(skl_model.intercept_,␣
 ↪skl_model.coef_)}')
print(f'Self-implemented model weights: {model}')
skl_pred = skl_model.predict(sample_df_toy_pandas[['c01_ts', 'b09_t1']])
print(f'SKLearn logistic model f1-score: {round(f1_score(y_pred=skl_pred,␣
 ↪y_true=sample_df_toy_pandas.label), 3)}')
```

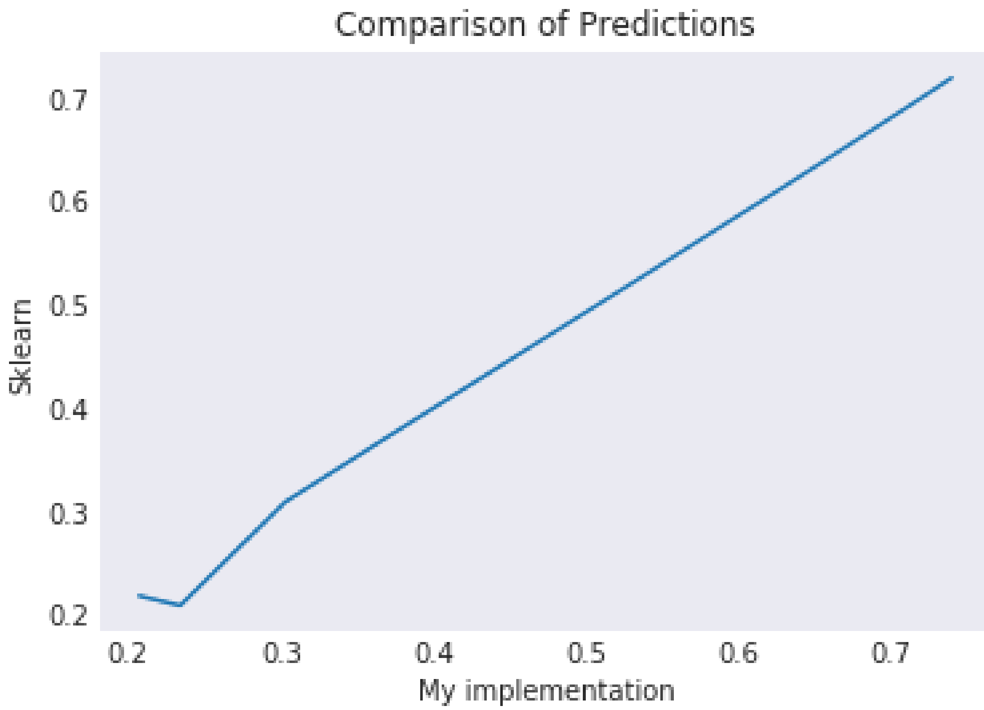
```
print(f'Self-implemented model f1-score: {round(f1_score(y_pred = pred, y_true␣
↪= sample_df_toy_pandas.label), 3)}')
```

```
SKLearn logistic model weights: [-1.03740904  0.5448784   0.05474129]
Self-implemented model weights: [-0.87190886  0.58637348 -0.15645926]
SKLearn logistic model f1-score: 0.333
Self-implemented model f1-score: 0.333
```

[26]:
```
# compare predictions
pred_prob = sample_df_toy_rdd.map(lambda x: (np.append([1.0], x[0]), x[1]))\
                    .map(lambda x: (1/(1 + np.exp(- np.dot(model, x[0])))))\
                    .collect()
g = sns.lineplot(x=pred_prob,
                 y=[x[1] for x in skl_model.
↪predict_proba(sample_df_toy_pandas[['c01_ts', 'b09_t1']])])
g.set_title('Comparison of Predictions')
g.set_xlabel('My implementation')
g.set_ylabel('Sklearn')
```

```
/opt/anaconda/lib/python3.6/site-packages/scipy/stats/stats.py:1713:
FutureWarning: Using a non-tuple sequence for multidimensional indexing is
deprecated; use `arr[tuple(seq)]` instead of `arr[seq]`. In the future this will
be interpreted as an array index, `arr[np.array(seq)]`, which will result either
in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

[26]: Text(0,0.5,'Sklearn')



- Observations:
  - the model coefficients are slightly off because we are only looking at numerical solutions for logistic regression, which also depends on initialization, learning rate, number of steps and a variety of parameters.
  - despite of that, the probability predictions are quite similar between the two implementations, which shows that our algorithm at least get most of the things correct;
  - the f1 score is exactly the same is quite coincidental given that we only have 100 data points in this toy training set.

6 EDA & Discussion of Challenges

- categorical features
- numerical features
- discussion of challenges

6.1 Categorical Features

- There are 26 categorical features in the data set, but each will have varying number of categories that is hashed.

[14]:
```
categorical_features = [t[0] for t in sample_df.dtypes if t[1] == 'string']
categorical_features
```

[14]:
```
['b01',
 'b02',
 'b03',
 'b04',
 'b05',
 'b06',
 'b07',
 'b08',
 'b09',
 'b10',
 'b11',
 'b12',
 'b13',
 'b14',
 'b15',
 'b16',
 'b17',
 'b18',
 'b19',
 'b20',
 'b21',
 'b22',
 'b23',
 'b24',
 'b25',
 'b26']
```

- The first things we want to explore with the categorical features is the number of unique categories in each one of them.

[15]:
```
features_summary = pd.DataFrame(columns=['name', '# unique', '# empty',
                                          '# count = 1', '# count < 10', '#␣
 ↪count < 100',
                                          '# count < 1000'])
for c in categorical_features:
    # number of categories
    nc = len(sample_df_pd.loc[:, c].unique())
    # number of empty strings
    ne = sum(sample_df_pd.loc[:, c] == '')
    # number of categories with only 1 counts
    n1 = sum(sample_df_pd.loc[:, c].value_counts() == 1)
    # number of categories with less than 10 occurances
    n10 = sum(sample_df_pd.loc[:, c].value_counts() < 10)
    # number of categories with less than 100 occurances
    n100 = sum(sample_df_pd.loc[:, c].value_counts() < 100)
    # number of categories with less than 1000 occurances, which is about 1%
    n1000 = sum(sample_df_pd.loc[:, c].value_counts() < 1000)
```

```
    features_summary.loc[-1] = [c, nc, ne, n1, n10, n100, n1000]
    features_summary.index = features_summary.index + 1
```

[16]:
```
features_summary
```

[16]:

	name	# unique	# empty	# count = 1	# count < 10	# count < 100	# count < 1000
25	b01	536	0	255	432	505	527
24	b02	518	0	30	140	381	499
23	b03	46692	3408	41673	45968	46621	46689
22	b04	25550	3408	19263	24565	25453	25543
21	b05	143	0	55	104	127	137
20	b06	12	12025	2	4	5	5
19	b07	8042	0	1985	6003	7901	8040
18	b08	235	0	87	173	214	228
17	b09	3	0	0	0	1	1
16	b10	12032	0	5848	10592	11948	12030
15	b11	3965	0	645	2303	3786	3960
14	b12	42896	3408	37748	42145	42819	42892
13	b13	2912	0	277	1441	2719	2905
12	b14	26	0	0	3	11	18
11	b15	5333	0	1741	3939	5133	5331
10	b16	35834	3408	30232	34981	35745	35830
9	b17	9	0	0	0	0	0
8	b18	2605	0	677	1717	2408	2595
7	b19	1295	43810	346	964	1254	1292
6	b20	4	43810	0	0	0	0
5	b21	39920	3408	34598	39144	39836	39916
4	b22	10	76163	0	1	4	7
3	b23	15	0	1	1	3	7
2	b24	12185	3408	7414	11240	12091	12172
1	b25	52	43810	6	16	30	42
0	b26	9291	43810	5637	8574	9235	9284

- A few observations from the analysis above:
  - columns `b03`, `b04`, `b12`, `b16`, `b21`, `b24` all have 3408 empty strings; columns `b19`, `b20`, `b25` and `b26` all have 43810 empty strings. And therefore, these columns might be related.
  - the distribution of categories are very skewed: for example, column `b04` has 25k unique categories, but 19K of them only have 1 occurances. Based on this observation, we could impute the categories with less than 1000 (which is 1% of the sample) count with some string, which will help reduce the number of unique categories.

After the imputation, the features summary goes as follows:

[17]:
```
categorical_features_select = []
features_summary = pd.DataFrame(columns=['name', '# unique before', '# unique␣
↪after',
                                         'larger_than_1pc'])
```

```
for c in categorical_features:
    # number of categories
    nc_bf = len(sample_df_pd.loc[:, c].unique())

    if c in ['b03', 'b03', 'b12', 'b16', 'b21', 'b24']:
        sample_df_pd.loc[sample_df_pd.loc[:, c] == '', c] = 'empty_1'
    elif c in ['b19', 'b20', 'b25', 'b26']:
        sample_df_pd.loc[sample_df_pd.loc[:, c] == '', c] = 'empty_2'
    else:
        sample_df_pd.loc[sample_df_pd.loc[:, c] == '', c] = 'empty_0'

    less_than_1000 = list(sample_df_pd.loc[:, c].value_counts()[sample_df_pd.
 ↪loc[:, c].value_counts() < 1000].index)
    sample_df_pd.loc[sample_df_pd.loc[:, c].isin(less_than_1000), c] =␣
 ↪'less_than_1pc'
    larger_than_1pc = [x for x in sample_df_pd.loc[:, c].unique() if x not in␣
 ↪['less_than_1pc']]
    nc_af = len(sample_df_pd.loc[:, c].unique())

    features_summary.loc[-1] = [c, nc_bf, nc_af, larger_than_1pc]
    features_summary.index = features_summary.index + 1
```

[18]:
```
features_summary
```

[18]:

	name	# unique before	# unique after	\
25	b01	536	10	
24	b02	518	20	
23	b03	46692	4	
22	b04	25550	8	
21	b05	143	7	
20	b06	12	8	
19	b07	8042	3	
18	b08	235	8	
17	b09	3	3	
16	b10	12032	3	
15	b11	3965	6	
14	b12	42896	5	
13	b13	2912	8	
12	b14	26	9	
11	b15	5333	3	
10	b16	35834	5	
9	b17	9	9	
8	b18	2605	11	
7	b19	1295	4	
6	b20	4	4	
5	b21	39920	5	
4	b22	10	4	

```
3    b23            15              9
2    b24         12185             14
1    b25            52             11
0    b26          9291              8

                                     larger_than_1pc
25  [5a9ed9b0, 05db9164, 8cf07265, 68fd1e64, 87552…
24  [80e26c9b, 58e67aaf, 38a947a1, 09e68b86, 28713…
23                      [empty_1, d032c263, 02cf9876]
22  [d16679b9, empty_0, c18be181, 85dd697c, f922ef…
21  [4cf72387, 25c83c98, 43b19349, 30903e74, 38487…
20  [empty_0, 7e0ccccf, fbad5c96, 6f6d9be8, fe6b92…
19                                [1c86e0eb, dc7659bd]
18  [0b153874, 5b392875, 1f89b562, 37e4aa92, 062b5…
17                                [a73ee510, 7cc72ec2]
16                                [3b08e48b, efea433b]
15  [8b94178b, 755e4a50, e51ddf94, 4d8549da, 7f8ff…
14            [empty_1, dfbb09fb, 8fe001f4, 6aaba33c]
13  [025225f2, 5978055e, 3516f6e6, 1aa94af3, 740c2…
12  [b28479f6, 1adce6ef, 07d13a8f, cfef1c29, 64c94…
11                                [d345b1a0, 2d0bb053]
10            [empty_1, 84898b2a, 36103458, b041b04a]
9   [1e88c74f, e5ba7672, d4bb7bd8, 776ce399, 2005a…
8   [c21c3e4c, 5aed7436, 891589e7, e88ffc9d, 5bb2e…
7                       [21ddcdc9, empty_2, 55dd3565]
6             [5840adea, empty_2, b1252a9d, a458ea53]
5             [empty_1, 0014c32a, e587c466, 723b4dfd]
4                       [empty_0, c9d4222a, ad3062eb]
3   [32c7478e, bcdee96c, 3a171ecb, 423fab69, 55dd3…
2   [aee52b6f, 3fdb382b, empty_1, ded4aac9, 3b183c…
1   [e8b83407, empty_2, 9b3e8820, 2bf691b1, ea9a24…
0   [empty_2, 984e0db0, 49d68486, aa5f0a15, c84c4a…
```

- For now, we select all the categorical variables for building the models. Based on the insights of the models we tested, we'd make further selections on the categorical features.

[19]:
```
categorical_features_select = categorical_features
```

[20]:
```
sample_df_pd.loc[:, 'b17'].unique()
```

[20]:
```
array(['1e88c74f', 'e5ba7672', 'd4bb7bd8', '776ce399', '2005abd1',
       '07c540c4', '27c07bd6', '3486227d', '8efede7f'], dtype=object)
```

6.2 Numerical Features

- first thing we did is to print out the sumamry of the numerical features: the average, the standard deviation, the minimum and maximum.

[21]:
```
numeric_features = [t[0] for t in sample_df.dtypes if t[1] == 'double']
sample_df.select(numeric_features).describe().toPandas().transpose()
```

[21]:

	0	1	2	3	4
summary	count	mean	stddev	min	max
c01	100085	1.9143927661487736	7.963545316430234	0.0	1262.0
c02	100085	104.71580156866663	385.10183633182993	-2.0	14091.0
c03	100085	22.30975670679922	440.1846081342075	0.0	65535.0
c04	100085	5.694329819653294	8.480746485453276	0.0	681.0
c05	100085	17772.16770744867	67149.887509406	0.0	2145045.0
c06	100085	89.60239796173252	280.98876472572186	0.0	19247.0
c07	100085	15.872578308437827	62.784068480288276	0.0	5014.0
c08	100085	12.46940100914223	21.491367038089617	0.0	4449.0
c09	100085	101.00950192336514	219.34656667004475	0.0	9094.0
c10	100085	0.3367237847829345	0.591824722218299	0.0	6.0
c11	100085	2.618744067542589	5.189745297992585	0.0	124.0
c12	100085	0.22399960033971125	2.336498615438213	0.0	207.0
c13	100085	6.445091672078733	17.562146641493655	0.0	3529.0

- Two observations from the summary above:
  - all of the numerical features are highly skewed
  - all of them are non-negative, except for the second one, which takes only 2 unique negative numbers

Based on the observations, we think log1p will be a suitable transformation for the numeric features.

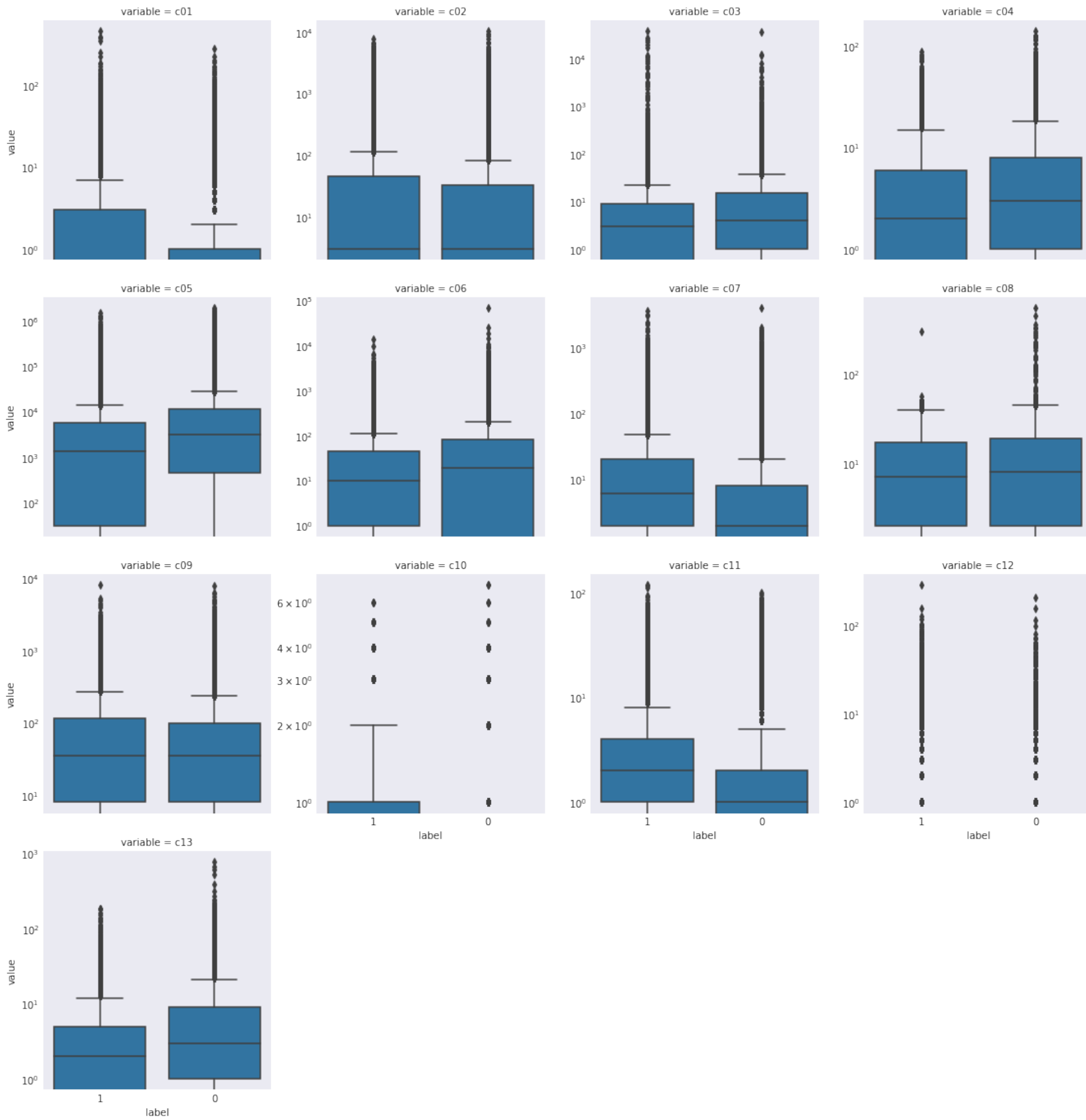
[22]:
```
sample_df_pd.loc[sample_df_pd.c02 < 0, 'c02'].unique()
```

[22]: array([-1., -2.])

- The second thing we looked at is the separation. The following plot shows the box plot of each variable by label, after transforming the y axis to log scale. What we see is that while the transformation brings the features to similar ranges, it is not quite clear any feature shows apparent separation between the two values of the label.

[47]:
```
# plot separation
sample_df_pd_melt = pd.melt(sample_df_pd.loc[:, numeric_features + ['label']],
                            id_vars='label', value_vars=numeric_features)
g = sns.FacetGrid(sample_df_pd_melt, col="variable", col_wrap=4, height=4,␣
 ↪sharex=True, sharey=False)
g.map(sns.boxplot, "label", "value", order = [1,0]).set(yscale = 'log')
```

[47]: <seaborn.axisgrid.FacetGrid at 0x7fd0ae21d850>



- The third thing we explored for the numerical features is the correlation: both with the labels to get a sense of relationship, and amongst themselves on the look out for multi-colinearity.

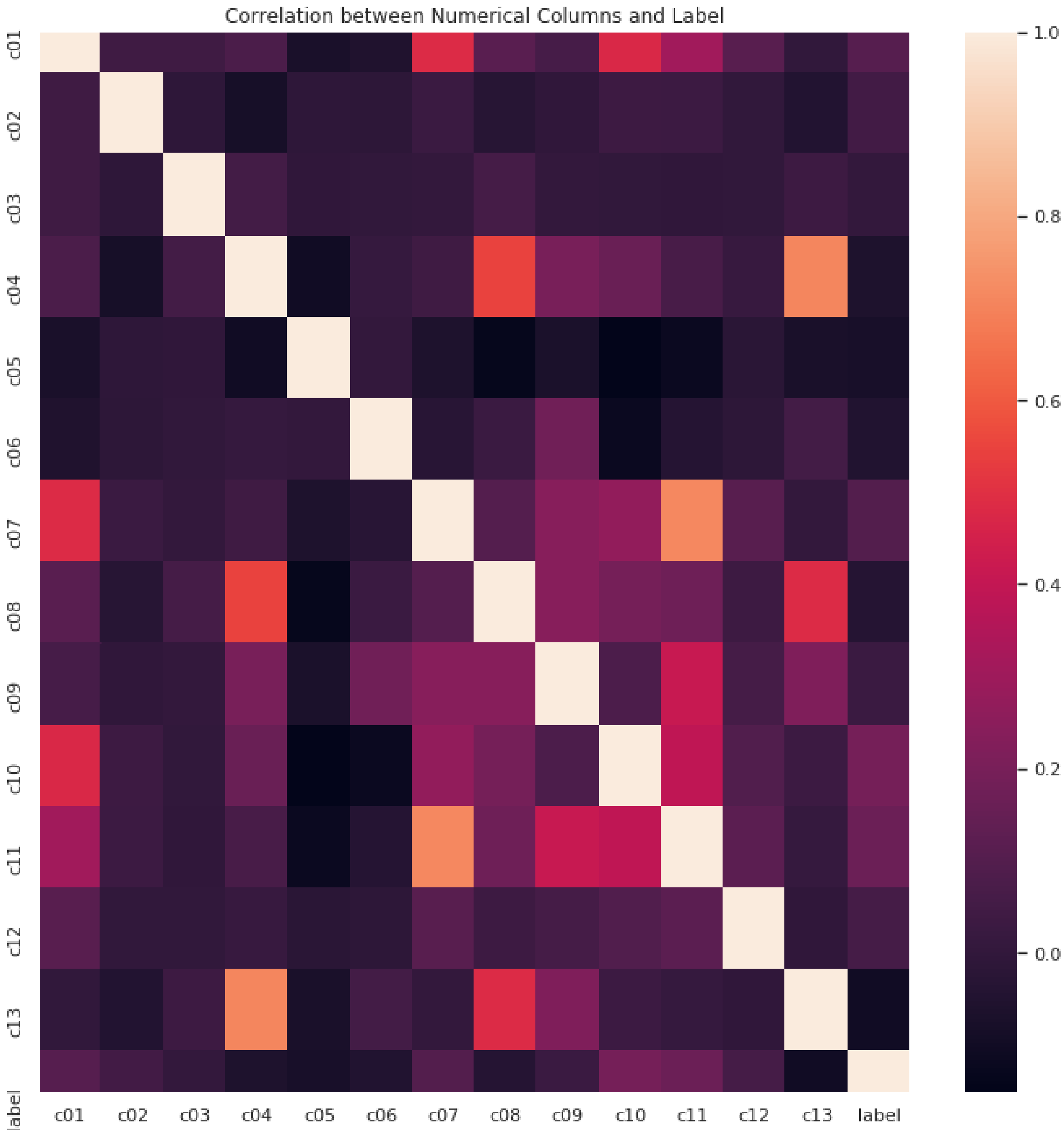
[48]:
```
corr = sample_df_pd.loc[:, numeric_features + ['label']].corr()
corr
```

[48]:
```
          c01       c02       c03       c04       c05       c06       c07  \
c01  1.000000  0.038640  0.041556  0.074903 -0.071644 -0.056218  0.486066
c02  0.038640  1.000000 -0.009548 -0.082262 -0.007676 -0.015031  0.025677
c03  0.041556 -0.009548  1.000000  0.053765 -0.004902  0.000612  0.005728
c04  0.074903 -0.082262  0.053765  1.000000 -0.097636  0.014181  0.037780
c05 -0.071644 -0.007676 -0.004902 -0.097636  1.000000  0.002441 -0.061365
```

```
c06   -0.056218 -0.015031  0.000612  0.014181  0.002441  1.000000 -0.027265
c07    0.486066  0.025677  0.005728  0.037780 -0.061365 -0.027265  1.000000
c08    0.116203 -0.032032  0.056393  0.549450 -0.134802  0.026852  0.101925
c09    0.064169 -0.003115  0.001875  0.199351 -0.069659  0.177932  0.242585
c10    0.478114  0.035070 -0.001286  0.159418 -0.151513 -0.118140  0.269622
c11    0.307638  0.032618 -0.005054  0.064560 -0.117859 -0.036526  0.715501
c12    0.112447 -0.002222 -0.002002  0.018145 -0.022218 -0.013711  0.113359
c13    0.000648 -0.043850  0.037314  0.709812 -0.070985  0.055231  0.002542
label  0.105860  0.047965  0.005701 -0.058050 -0.077539 -0.050264  0.098155

            c08       c09       c10       c11       c12       c13     label
c01    0.116203  0.064169  0.478114  0.307638  0.112447  0.000648  0.105860
c02   -0.032032 -0.003115  0.035070  0.032618 -0.002222 -0.043850  0.047965
c03    0.056393  0.001875 -0.001286 -0.005054 -0.002002  0.037314  0.005701
c04    0.549450  0.199351  0.159418  0.064560  0.018145  0.709812 -0.058050
c05   -0.134802 -0.069659 -0.151513 -0.117859 -0.022218 -0.070985 -0.077539
c06    0.026852  0.177932 -0.118140 -0.036526 -0.013711  0.055231 -0.050264
c07    0.101925  0.242585  0.269622  0.715501  0.113359  0.002542  0.098155
c08    1.000000  0.241435  0.192371  0.172562  0.035635  0.482819 -0.036956
c09    0.241435  1.000000  0.077957  0.412839  0.059862  0.220094  0.024588
c10    0.192371  0.077957  1.000000  0.391708  0.094954  0.030693  0.192421
c11    0.172562  0.412839  0.391708  1.000000  0.120696  0.014044  0.163560
c12    0.035635  0.059862  0.094954  0.120696  1.000000 -0.006465  0.057245
c13    0.482819  0.220094  0.030693  0.014044 -0.006465  1.000000 -0.099340
label -0.036956  0.024588  0.192421  0.163560  0.057245 -0.099340  1.000000
```

[49]:
```
# plot correlation
sns.set(rc={'figure.figsize':(12, 12)})
g = sns.heatmap(corr)
g.set_title('Correlation between Numerical Columns and Label')
```

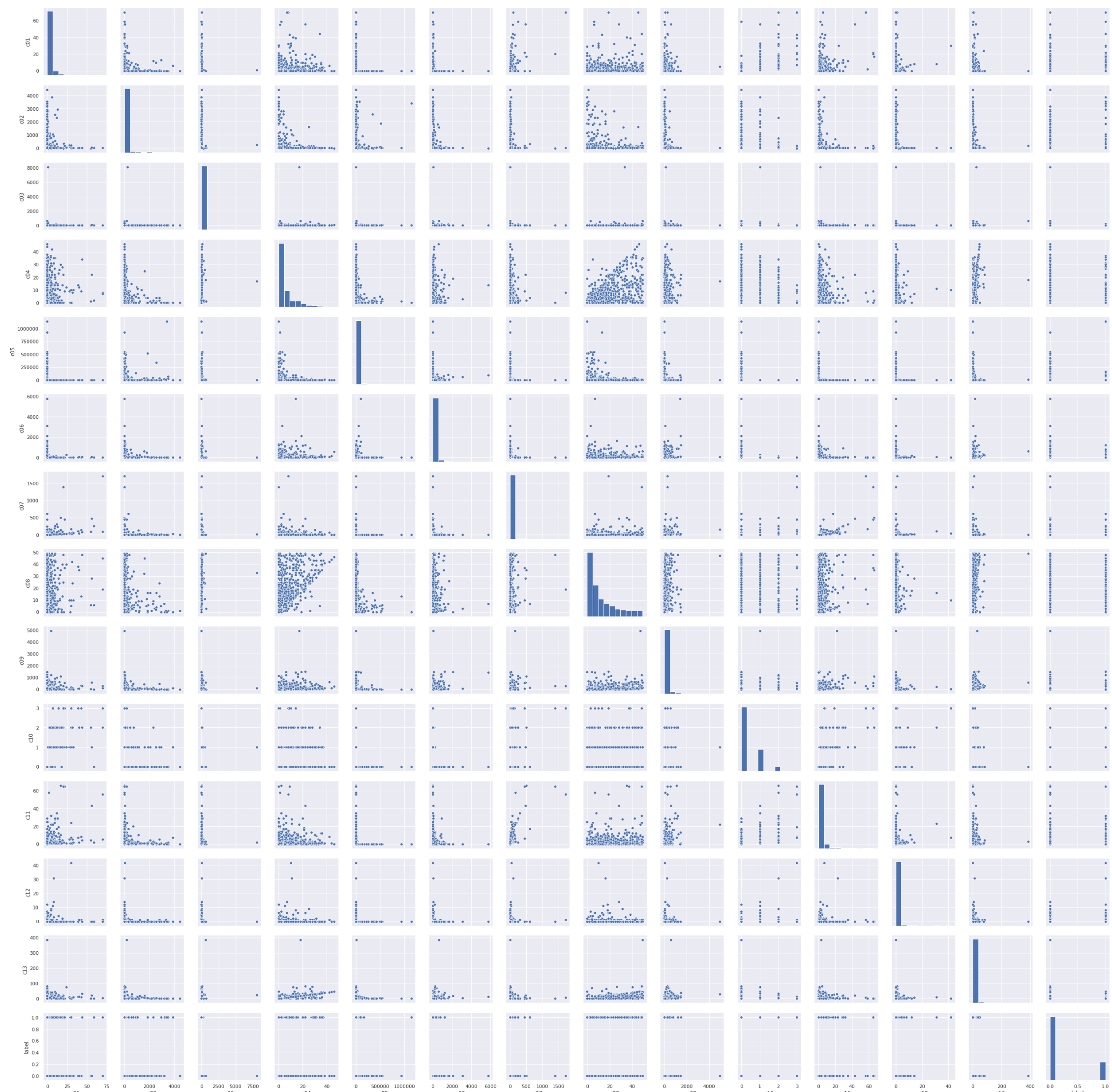
[49]:
```
Text(0.5, 1, 'Correlation between Numerical Columns and Label')
```



- And finally, we tried to use some scatter plot searching for obvious relationship, yet given the range of data we don't think we see anything too obvious.

[50]:
```
sns.pairplot(sample_df_pd.sample(n=1000, random_state=1).loc[:,␣
↪numeric_features + ['label']])
```

[50]: `<seaborn.axisgrid.PairGrid at 0x7fd09c7e3a50>`



6.3 Discussion of Challenges

There are unique challenges to this problem:

- The sheer size of the data makes it unsuitable for the typical tools people use for modeling, such as Pandas and SKlearn, which is why we choose to do it with Spark MLlib.
- The complexity of the features space would normally require a lot of domain knowledge, yet here the data is presented anonymously. Therefore, the research presented in this notebook will be based on statistical observations and practices.
- While researching into the problem, our team also keeps in mind the needs of real-time production. And that's why we have built Spark pipelines for the data, and depending on the business needs, we could efficiently deploy the code for updates/retrain of the model.

7 Build Toy Models for Sampled Data

We developed two separate pipelines based on how the categorical features are treated:

- Numericals + Categoricals

  This is the more typical pipeline people use, where the categoricals are one-hot encoded and numericals are scaled

- Breiman's method

  The categoricals are replaced with their respective average labels, and hence transformed into numericals.

This section is organized in the following logic:

- Evaluation metrics
- Numerical + Categorical
  1. Build pipeline + Train/Test split
  2. Decision Tree
  3. Logistic Regression
  4. Gradient Boosted Tree
- Breiman's Method
  1. Logistic Regression
  2. Gradient Boosted Tree

7.1 Evaluation Metrics

The are two major aspects of any classification algorithm:

- how accurate the prediction is
- how good the probability distributions are

Based on this, there are two metrics that we focus on in this study:

- f1-score: it is the harmonic mean of precision and recall, which presents a balanced view of how good the prediction is
  - Even though the event we are predicting is not extremely imbalanced like credit card default, f1-score still tells us more than simply the accuracy ratio.
  - For the f-1 score, we have built our custom function, since the one in Spark only seems to work for multi-class classfication.
- Log loss: this is the objective function in Logistic Regression, which is an good indicator of the distribution of the predicted probabilities.
  - There is no standard implementation of log loss in Spark MLlib, therefore we built our own, which takes input as `model.transform()`.

We believe the combination of the f1 score and log loss already will give us a 360-degree view of how the model is performing. The intricate trade-offs between the two are detailed in the later sessions.

In the code we also reported the AUC, because it is easy to implement.

[36]:
```
# custom functions

from pyspark.sql.types import FloatType
def log_loss_from_prediction(predictions):
    # predictions are what returns from model.transform
    # the data frame should have a column named probability, which is a tuple:
    # we need to extract the second item of the tuple and calculate log loss␣
↪with it
    # an exmaple of use:
    # predictions = lrModel.transform(test)
    # x = log_loss_from_prediction(predictions)
    epsilon = 1e-16
    split1_udf = udf(lambda value: value[1].item(), FloatType())
    predictions = predictions.select('*', split1_udf('probability').\
                                     alias('prob'))
    loss = predictions.select("*",
                              when(predictions.label == 1, 0. - log(predictions.
↪prob + epsilon)).\
                              otherwise(0. - log(1. - predictions.prob + epsilon)).
↪\
                              alias('log_loss')).\
                agg({'log_loss': 'avg'}).\
                take(1)
    return loss

def f1_score(predictions):
    # predictions are what returns from model.transform
    # an exmaple of use:
    # predictions = lrModel.transform(test)
    # x = f1_score(predictions)
    TN = predictions.filter('prediction = 0 AND label = prediction').count()
    TP = predictions.filter('prediction = 1 AND label = prediction').count()
    FN = predictions.filter('prediction = 0 AND label <> prediction').count()
    FP = predictions.filter('prediction = 1 AND label <> prediction').count()
    accuracy = (TN + TP) / (TN + TP + FN + FP)

    if (TP + FP > 0) and (TP + FN > 0):
        precision = TP / (TP + FP)
        recall = TP / (TP + FN)
        F =  2 * (precision*recall) / (precision + recall)
    else:
        F = 0
    return F

def eval(model, train, test, name):
```

```
    # this function evaluates the model, and returns a data frame

    print('Model:', name)
    predictions = model.transform(train)
    evaluator = BinaryClassificationEvaluator()
    train_roc = round(evaluator.evaluate(predictions), 6)
#     print('Train Area Under ROC', train_roc)
    ll_train = round(log_loss_from_prediction(predictions)[0][0], 6)
#     print('Train Area Log loss', ll_train)
    F_train = round(f1_score(predictions), 6)
#     print('Train F1-score', F_train)

    predictions = model.transform(test)
    test_roc = round(evaluator.evaluate(predictions), 6)
#     print('Test Area Under ROC', test_roc)
    ll_test = round(log_loss_from_prediction(predictions)[0][0], 6)
#     print('Test Area Log loss', ll_test)
    F_test = round(f1_score(predictions), 6)
#     print('Test F1-score', F_test)

    eval = pd.DataFrame({'Name': [name, name],
                         'Data': ['Train', 'Test'],
                         'ROC': [train_roc, test_roc],
                         'LogLoss': [ll_train, ll_test],
                         'F1-Score': [F_train, F_test]})
    print(eval)
    return(eval)
```

7.2 Categorical + Numerics

7.2.1 Build pipeline + Train/Test Split

- Categorical Features
  - We're imputing the empty categorical features with its own column name with "empty", otherwise the empty strings will throw error since column names can't be empty
  - For categories that represent less than 1 percent of the sample, we are encoding them with `_less_than_1pc` before the one-hot encoding. This drastically reduces the final feature space, as shown in the EDA

[ ]:
```
from pyspark.sql.functions import col, when, log, udf, log1p
def impute_blank(x):
    if x in ['b03', 'b03', 'b12', 'b16', 'b21', 'b24']:
        impute = 'empty_1'
    elif x in ['b19', 'b20', 'b25', 'b26']:
        impute = 'empty_2'
```

```
    else:
        impute = 'empty_0'

    return when(col(x) != "", col(x)).otherwise(impute)

def impute_1pc(x, less_than_1pc):
    return when(col(x).isin(list(larger_than_1pc)[0]), col(x)).
 ↪otherwise('less_than_1pc')

for c in categorical_features_select:
    # every categorical feature:
    # 1) replace empty string with 'empty'
    # 2) replace categories with less than 1pc with a string
    larger_than_1pc = features_summary.larger_than_1pc[features_summary.name ==␣
 ↪c]
    sample_df = sample_df.withColumn(c, impute_blank(c))\
                         .withColumn(c, impute_1pc(c, larger_than_1pc))
```

- Numerical Features For numerical columns, we are using `log1p` transformation, and then putting them through a standard scaler why each observation is de-meaned and devided by standard deviation.

[26]:
```
def log_transformation(x):
    return when(col(x) < 0, col(x)).otherwise(log1p(col(x)))

for n in numeric_features:
    # log1p on all numerical features
    # same for train and test
    sample_df = sample_df.withColumn(n, log_transformation(n))
```

- Pipeline
  - The categorical features are first indexed, and then one-hot encoded
  - the numerical features, given that they are already in the log space, are taken as they are
  - the scaler is applied to the feature space, with `selected_features` as the final features for modeling.
  - originally, we also had the chi-squared selector in the pipeline which filters the features by looking at their relationship with the label. Yet, the features coming out of the selector didn't go with models such as SVM or random forest. On the other hand, it also did not significantly improve the performance of models like logitic regression. As a result, we decided to leave it out.

After the pipeline, we have 202 features in total, which is a reasonable number given that we have about 50 million observations in the dataset.

[27]:
```
from pyspark.ml.feature import OneHotEncoderEstimator, StringIndexer,␣
 ↪VectorAssembler, StandardScaler, ChiSqSelector
```

```
stages = []
for categoricalCol in categorical_features_select:
    stringIndexer = StringIndexer(inputCol = categoricalCol,
                                  outputCol = categoricalCol + 'Index')
    encoder = OneHotEncoderEstimator(inputCols=[stringIndexer.getOutputCol()],
                                     outputCols=[categoricalCol + "classVec"],
                                     handleInvalid='keep', dropLast = True)
    stages += [stringIndexer, encoder]

assemblerInputs =  [c + "classVec" for c in categorical_features_select]␣
↪+numeric_features  #
assembler = VectorAssembler(inputCols=assemblerInputs, outputCol="features")
stages += [assembler]
scaler = StandardScaler(inputCol='features', outputCol='selected_features',
                        withStd=True, withMean=True)
stages += [scaler]
# selector = ChiSqSelector(numTopFeatures=50, featuresCol="scaled_features",
#                          outputCol="selected_features", labelCol="label")
# stages += [selector]
stages
```

[27]:
```
[StringIndexer_46ca8a85172d8ba9812f,
 OneHotEncoderEstimator_4500911a2fc36dec3417,
 StringIndexer_47519b23aa221672ad7e,
 OneHotEncoderEstimator_4cdd9364ebc0c1538c3a,
 StringIndexer_4329878e8ea34480bdf4,
 OneHotEncoderEstimator_4832a97729da07c95f8a,
 StringIndexer_43b0a58779495caf53f1,
 OneHotEncoderEstimator_415a8e12ad6472767e13,
 StringIndexer_42b28df24bd45fcdaf07,
 OneHotEncoderEstimator_4923a65b213c7029f467,
 StringIndexer_434c803722d1ac465cfb,
 OneHotEncoderEstimator_4382baaeed1245b125b5,
 StringIndexer_4e6ba3b1926a0bce6a76,
 OneHotEncoderEstimator_44c6b70c101ddd9d17e2,
 StringIndexer_43b2ba7ce42788b2ea80,
 OneHotEncoderEstimator_4da3bf817e58ddc13b39,
 StringIndexer_46609101f6b8288b0a46,
 OneHotEncoderEstimator_4d45a4b7dbe5d0c46284,
 StringIndexer_4c48831db347df56661c,
 OneHotEncoderEstimator_407298c45cfad87d39f5,
 StringIndexer_4cd093d43fba962a00fd,
 OneHotEncoderEstimator_4e85ad130751e81f1e26,
 StringIndexer_462ea1954d97073eae3c,
 OneHotEncoderEstimator_4fae8d566331d52750dc,
 StringIndexer_4dd180578fd0552fcc3f,
 OneHotEncoderEstimator_43d5b062f6b11ff5c699,
```

```
 StringIndexer_40a29464c56f524a2bea,
 OneHotEncoderEstimator_47dea4e012154b234887,
 StringIndexer_472fbc37593a5168bea6,
 OneHotEncoderEstimator_4f698e1b7f5a04b07583,
 StringIndexer_49a5864e0c89c7bb8f8c,
 OneHotEncoderEstimator_4e5c87a70c5a29838da8,
 StringIndexer_4fe4bc7e8b3ba66c77b8,
 OneHotEncoderEstimator_4fb7aeb828ec271ea822,
 StringIndexer_4b66a5bac81c2a5431d1,
 OneHotEncoderEstimator_4f62a6eaf3f4e0f66dda,
 StringIndexer_48d180879cad12fee17d,
 OneHotEncoderEstimator_48acaea22ed08f0b9aff,
 StringIndexer_4b7fb902b939564981f5,
 OneHotEncoderEstimator_4aeda8c5787ea0e28a40,
 StringIndexer_4a4a92b23e026fd53062,
 OneHotEncoderEstimator_4ce68d8b47046e0c218a,
 StringIndexer_4aa9a955fa0fb1a06a5e,
 OneHotEncoderEstimator_490aa11b827ad5ca6531,
 StringIndexer_468f9f081b7d26bd07fa,
 OneHotEncoderEstimator_4f2aa4b4356c00d42e86,
 StringIndexer_4b7abe7b0755a5077d9f,
 OneHotEncoderEstimator_47ff96062a3638ce23ed,
 StringIndexer_496fbe8b5a3c5c357580,
 OneHotEncoderEstimator_4da1b4c6780c36443696,
 StringIndexer_474e81bc0b64f8322c34,
 OneHotEncoderEstimator_4edc9418fccc3341f38a,
 VectorAssembler_427a8aff9ffd5609999e,
 StandardScaler_475095f5b1810c101f6d]
```

[28]:
```
from pyspark.ml import Pipeline
pipeline = Pipeline(stages = stages)
pipelineModel = pipeline.fit(sample_df)
sample_df_pipe = pipelineModel.transform(sample_df)
selectedCols = ['label', 'selected_features'] #+ cols
sample_df_pipe = sample_df_pipe.select(selectedCols)
sample_df_pipe.printSchema()
```

```
root
 |-- label: long (nullable = true)
 |-- selected_features: vector (nullable = true)
```

After the pipeline we have 202 features, which is equal to number of unique categories (189) plus the number of numeric features (13).

We didn't drop the last category of each column because the 1 hot encoded features are also put through the standard scaler, which frees us from the concerns of multi-colinearity.

[100]:
```
# number of features after pipeline
len(sample_df_pipe.select('selected_features').take(1)[0][0])
```

[100]: 202

[30]:
```
# total number of unique categories
features_summary['# unique after'].sum()
```

[30]: 189

[31]:
```
# sanity check
189 + 13
```

[31]: 202

Train/Test Split

- Given the metrics, we are splitting the sampled set with 100k observations further into training and testing set.
- The same procedure is done once again on the full training set, since the original test set didn't come with labels.

[101]:
```
train, test = sample_df_pipe.randomSplit([0.7, 0.3], seed = 2018)
print("Training Dataset Count: " + str(train.count()))
print("Test Dataset Count: " + str(test.count()))
```

```
Training Dataset Count: 70044
Test Dataset Count: 30041
```

7.2.2 Decision Tree Classifier

- Decision tree classifier with cross validation
- Feature importance and trimming
- Decision tree classifier with cross validation and sliced features

Decision Tree Classifier with Cross Validation For hyper-parameter tuning, the team sets the paramGrid to test various options in the cross validation of decision tree. * maxBins: The default setting is 32 bins, but the study also tries 16 bins to add penalization. We stop at 32 bins to avoid over-fitting. * maxDepth: The team tests 2, 4, 6, 8 depth and stops at 8 to avoid over-fitting. * impurity: The team uses both gini and entropy to understand information gain

[37]:
```
%%time
from pyspark.ml.classification import DecisionTreeClassifier
from pyspark.ml.tuning import ParamGridBuilder, CrossValidator
from pyspark.ml.evaluation import BinaryClassificationEvaluator
```

```python
dt = DecisionTreeClassifier(featuresCol = 'selected_features', labelCol =␣
↪'label',
                            maxDepth = 5, seed = 8888)
paramGrid = ParamGridBuilder()\
             .addGrid(dt.maxDepth, [2, 4, 6, 8])\
             .addGrid(dt.impurity, ['gini', 'entropy'])\
             .addGrid(dt.maxBins, [16, 32])\
             .build()
ev = BinaryClassificationEvaluator(metricName='areaUnderROC')
cv = CrossValidator(estimator=dt,
                    estimatorParamMaps=paramGrid,
                    evaluator=ev,
                    numFolds=3, seed = 8888)

cvModel = cv.fit(train)
dtModel = cvModel.bestModel
```

```
CPU times: user 1.65 s, sys: 770 ms, total: 2.42 s
Wall time: 2min 44s
```

[38]:

```python
bestBins = cvModel.bestModel._java_obj.getMaxBins()
bestDepth = cvModel.bestModel._java_obj.getMaxDepth()
bestImpurity = cvModel.bestModel._java_obj.getImpurity()
print('The best decision tree model has', bestDepth, 'layers,', bestBins,
      'bins and using', bestImpurity, 'as impurity measure.')
```

```
The best decision tree model has 6 layers, 32 bins and using entropy as impurity
measure.
```

[39]:

```python
eval_dt_cv = eval(cvModel, train, test, 'DT+CV')
```

```
Model: DT+CV
    Name   Data       ROC   LogLoss  F1-Score
0  DT+CV  Train  0.512806  0.512041  0.282334
1  DT+CV   Test  0.518036  0.529752  0.262007
```

The scores between train and test vary a bit, indicating that we might be over-fitting. It is a well-known disadvantage for Decision Tree, yet we started with this algorithm because we can easily calculate the feature importance based on gini index and use that for further features selection.

Feature Importance and Trimming

[40]:

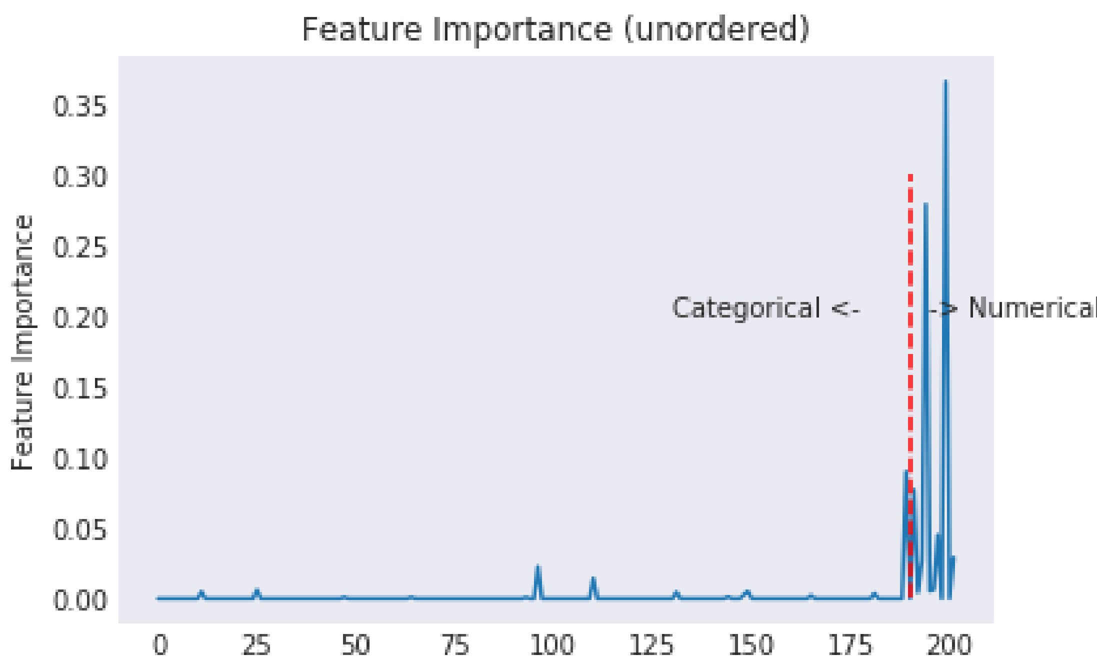
```python
featureImportance = list(cvModel.bestModel.featureImportances)
featureImportancePD = pd.DataFrame({'feature':␣
↪list(range(len(featureImportance))),
                                    'importance': featureImportance})
featureImportancePD.sort_values(by = 'importance', ascending=False).head(12)
```

[40]:

	feature	importance
199	199	0.366069
194	194	0.279176
189	189	0.089996
191	191	0.077002
197	197	0.044970
201	201	0.028960
193	193	0.027015
96	96	0.022601
110	110	0.014402
196	196	0.006306
25	25	0.006081
195	195	0.005327

[42]:

```
# plot out the feature importance
plt.plot(featureImportancePD.feature, featureImportancePD.importance)
plt.plot(np.repeat(202 - 13 + 1, 100), np.linspace(0, .3, 100),  'r', ls = '--')
plt.ylabel('Feature Importance')
plt.title('Feature Importance (unordered)')
plt.text(130, .2, 'Categorical <-')
plt.text(195, .2, '-> Numerical')
plt.show()
```



- There are 23 features (out of 202) that are shown to be “important”. If we were to further trim down the features space, wonder what that will do to the performance. The intuition there is that the less features we have, the more “regular” the loss surface will be and the less likely we are to overfit.

[43]:
```
features_lt0 = list(featureImportancePD[featureImportancePD.importance > 0.0].
 ↪feature)
len(features_lt0)
```

[43]: 23

[44]:
```
from pyspark.ml.feature import VectorSlicer
slicer = VectorSlicer(inputCol="selected_features",␣
 ↪outputCol="sliced_features", indices=features_lt0)
train_sliced = slicer.transform(train)
test_sliced = slicer.transform(test)
train_sliced.show(5)
```

```
+-----+--------------------+--------------------+
|label|   selected_features|     sliced_features|
+-----+--------------------+--------------------+
|    0|[-1.0016849885468...|[-0.3580504012046...|
|    0|[-1.0016849885468...|[-0.3580504012046...|
|    0|[-1.0016849885468...|[-0.3580504012046...|
|    0|[-1.0016849885468...|[-0.3580504012046...|
|    0|[-1.0016849885468...|[-0.3580504012046...|
+-----+--------------------+--------------------+
only showing top 5 rows
```

Decision Tree Classifier with Cross Validation and Sliced Features

[45]:
```
%%time
from pyspark.ml.classification import DecisionTreeClassifier
dt = DecisionTreeClassifier(featuresCol = 'sliced_features', labelCol = 'label',
                            maxDepth = 5, seed = 8888)
paramGrid = ParamGridBuilder()\
             .addGrid(dt.maxDepth, [2, 4, 6, 8, 10])\
             .addGrid(dt.impurity, ['gini', 'entropy'])\
             .addGrid(dt.maxBins, [16, 32])\
             .build()
ev = BinaryClassificationEvaluator(metricName='areaUnderROC')
cv = CrossValidator(estimator=dt,
                    estimatorParamMaps=paramGrid,
                    evaluator=ev,
                    numFolds=3, seed = 8888)

cvModel = cv.fit(train_sliced)
dtModel = cvModel.bestModel
```

```
CPU times: user 1.9 s, sys: 1 s, total: 2.9 s
Wall time: 2min 57s
```

[46]:
```
bestBins = cvModel.bestModel._java_obj.getMaxBins()
bestDepth = cvModel.bestModel._java_obj.getMaxDepth()
bestImpurity = cvModel.bestModel._java_obj.getImpurity()
print('The best decision tree model has', bestDepth, 'layers,', bestBins,
      'bins and using', bestImpurity, 'as impurity measure.')
```

```
The best decision tree model has 4 layers, 32 bins and using entropy as impurity
measure.
```

[47]:
```
eval_dt_sliced_cv = eval(cvModel, train_sliced, test_sliced, name = 'DT+CV+S')
```

```
Model: DT+CV+S
      Name   Data       ROC   LogLoss  F1-Score
0  DT+CV+S  Train  0.515661  0.522705  0.303729
1  DT+CV+S   Test  0.517672  0.529677  0.294018
```

The Decision Tree model will be a baseline model for us. Given the winning score log loss is .47 and this model is showing .53, it shows us that we are at least on the right track.

7.2.3 Logistic Regression

- Logistic regression with default parameters
- Logistic regression with parameter tuning
- Logistic regression with parameter tuning and sliced features

Logistic Regression with Default Parameters

[49]:
```
from pyspark.ml.classification import LogisticRegression
lr = LogisticRegression(featuresCol = 'selected_features', labelCol = 'label',
                        maxIter=10, regParam=0, elasticNetParam=0)
lrModel = lr.fit(train)
trainingSummary = lrModel.summary
```

[50]:
```
# optimize the threshold
fMeasure = trainingSummary.fMeasureByThreshold
maxFMeasure = fMeasure.groupBy().max('F-Measure').select('max(F-Measure)').
 ↪head()
bestThreshold = fMeasure.where(fMeasure['F-Measure'] ==␣
 ↪maxFMeasure['max(F-Measure)']) \
                        .select('threshold').head()['threshold']
lr.setThreshold(bestThreshold)
```

[50]:
```
LogisticRegression_49e5b431f0fb96b780d6
```

[51]:
```
eval_lr = eval(lrModel, train, test, 'LR')
```

```
Model: LR
  Name   Data       ROC   LogLoss  F1-Score
0   LR  Train  0.738119  0.498950  0.338664
1   LR   Test  0.730594  0.504101  0.335685
```

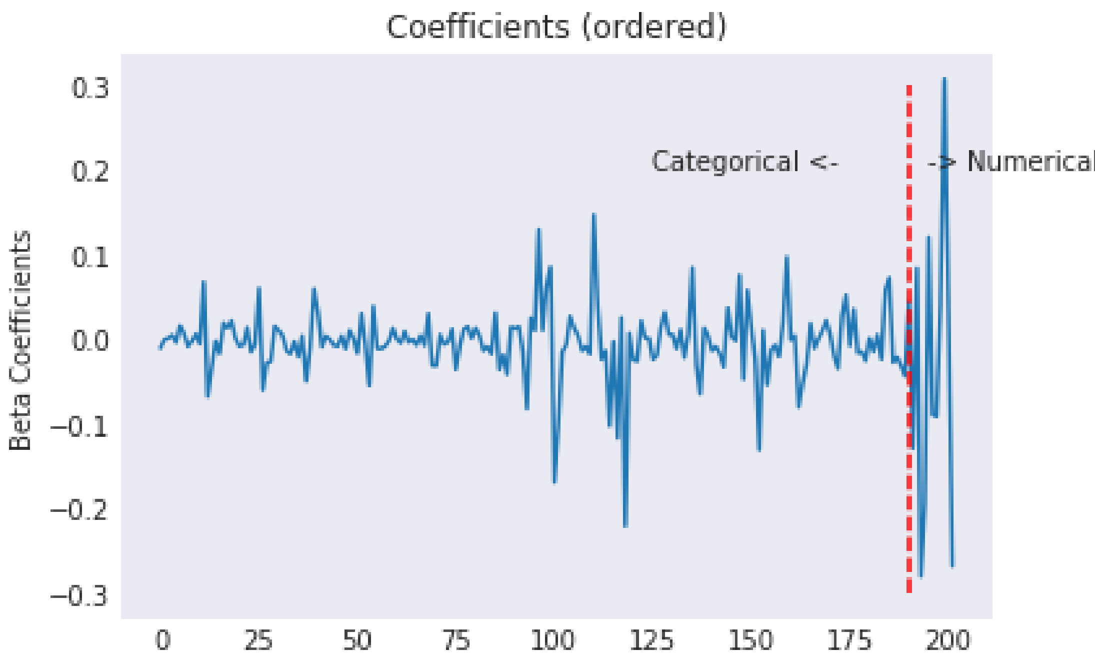
[52]:
```
# plot out training loss
g = sns.lineplot(x=range(1, len(trainingSummary.objectiveHistory) + 1),
                 y=trainingSummary.objectiveHistory)
g.set_title('Training Loss')
```

[52]: Text(0.5,1,'Training Loss')

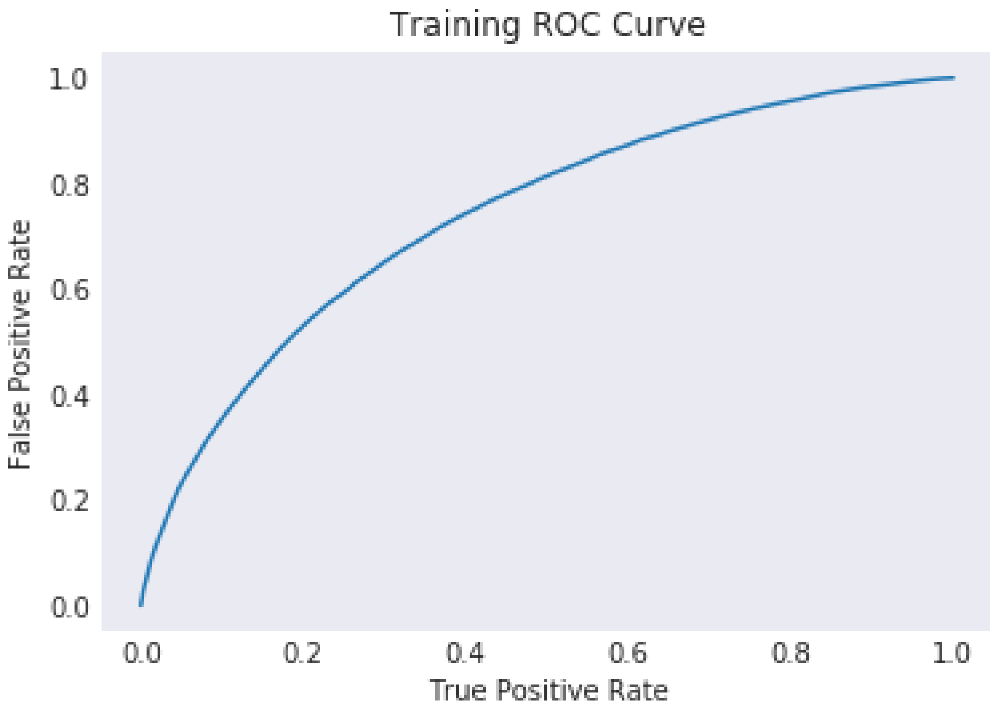
- There are 202 features in the logistic regression model (not including the intercept). Since the features are all normalized, the size of the coefficients should be a comparable scale. We see kind of a similar picture here as the feature importance chart shown from Decision Tree, yet categorical features seem to play a bigger role in this model.

[53]:
```
# plot out the coefs
beta = (lrModel.coefficients)
plt.plot(beta)
plt.plot(np.repeat(202-13+1, 100), np.linspace(-.3, 0.3, 100),  'r', ls = '--')
plt.ylabel('Beta Coefficients')
plt.title('Coefficients (ordered)')
```

```
plt.text(125, .2, 'Categorical <-')
plt.text(195, .2, '-> Numerical')
plt.show()
```



[54]:
```
# plot out the ROC curve
trainingSummary = lrModel.summary
roc = trainingSummary.roc.toPandas()
plt.plot(roc['FPR'],roc['TPR'])
plt.ylabel('False Positive Rate')
plt.xlabel('True Positive Rate')
plt.title('Training ROC Curve')
plt.show()
print('Training set areaUnderROC: ' + str(trainingSummary.areaUnderROC))
```




```
Training set areaUnderROC: 0.7380864336388292
```

Logistic Regression with Parameter Tuning Here I'm maining tuning the `elasticNetParam` and `regParam`, which corresponds α and λ in the following equation respectively

$$L + \lambda[(1-\alpha)\sum \beta^2 + \alpha \sum |\beta|]$$

- when `elasticNetParam` is 0, it is purely l2 penalty; when it is 1, it is purely l1 penalty. Otherwise it is the weight between the 2. The choice here are 0, 0.5 and 1.
- `regParam` is the sererity of the penalty, here we are incrementing it on log-scale. The sum of squared coefficients from the base model is .76, which is comparable to the loss. To add in regularization but not overwhelming the training, here the choices are 0.001, 0.002, 0.005 and 0.01.

[55]:
```
%%time
lr = LogisticRegression(featuresCol = 'selected_features', labelCol = 'label',
                        maxIter=10, regParam=0, elasticNetParam=0)

# Create 3-fold CrossValidator
evaluator = BinaryClassificationEvaluator()
paramGrid = ParamGridBuilder()\
    .addGrid(lr.elasticNetParam,[0.0, 0.5, 1.0])\
    .addGrid(lr.maxIter,[10, 50, 100])\
    .addGrid(lr.regParam,[0.001, 0.002, 0.005, 0.01]) \
```

```
    .build()
cv = CrossValidator(estimator = lr, estimatorParamMaps = paramGrid,
                    evaluator = evaluator, numFolds=3, seed = 8888)

# Run cross validations
cvModel = cv.fit(train)

best_alpha = cvModel.bestModel._java_obj.getElasticNetParam()
best_lambda = cvModel.bestModel._java_obj.getRegParam()
print('Best elasticNetParam is', best_alpha)
print('Best regParam is', best_lambda)
```

```
Best elasticNetParam is 0.5
Best regParam is 0.001
CPU times: user 5.7 s, sys: 2.95 s, total: 8.65 s
Wall time: 20min 5s
```

[56]:
```
eval_lr_cv = eval(cvModel, train, test, 'LR+CV')
```

```
Model: LR+CV
    Name   Data       ROC   LogLoss  F1-Score
0  LR+CV  Train  0.738823  0.498517  0.333954
1  LR+CV   Test  0.731641  0.503432  0.332678
```

Here the regularization helped collapsed the gap between the train and test log loss. On the other hand, the loss is not a lot larger compared to before the training, since the best `regParm` is 0.001.

Sliced features on Linear Regression

[57]:
```
%%time
lr = LogisticRegression(featuresCol = 'sliced_features', labelCol = 'label',
                        maxIter=10, regParam=0, elasticNetParam=0)
paramGrid = ParamGridBuilder()\
    .addGrid(lr.elasticNetParam,[0.0, 0.5, 1.0])\
    .addGrid(lr.maxIter,[10, 50, 100])\
    .addGrid(lr.regParam,[0.001, 0.002, 0.005, 0.01]) \
    .build()

# Create 5-fold CrossValidator
cv = CrossValidator(estimator = lr, estimatorParamMaps = paramGrid,
                    evaluator = evaluator, numFolds=3, seed = 8888)

# Run cross validations, use train_scliced here
cvModel = cv.fit(train_sliced)

best_alpha = cvModel.bestModel._java_obj.getElasticNetParam()
best_lambda = cvModel.bestModel._java_obj.getRegParam()
print('Best elasticNetParam is', best_alpha)
```

```
print('Best regParam is', best_lambda)
```

```
Best elasticNetParam is 0.5
Best regParam is 0.001
CPU times: user 4.65 s, sys: 2.65 s, total: 7.3 s
Wall time: 9min 44s
```

[58]:
```
eval_lr_cv_sliced = eval(cvModel, train_sliced, test_sliced, 'LR+CV+S')
```

```
Model: LR+CV+S
      Name   Data       ROC   LogLoss  F1-Score
0  LR+CV+S  Train  0.713115  0.514463  0.276960
1  LR+CV+S   Test  0.707870  0.517995  0.277437
```

The sliced features don't seem to improving the performance here. We think it is because when we reduce the features space from 202 to 23, the information loss outweighs the supposed gain in parsimony. We expect this to be more dramatic when applied to the full dataset.

7.2.4 Gradient Boosted Trees

Gradient boosted trees with default parameters

[59]:
```
from pyspark.ml.classification import GBTClassifier
gb = GBTClassifier(featuresCol = 'selected_features', labelCol = 'label',
                   maxIter = 20, seed = 8888)
gbModel = gb.fit(train)
eval_gbt = eval(gbModel, train, test, 'GBT')
```

```
Model: GBT
  Name   Data       ROC   LogLoss  F1-Score
0  GBT  Train  0.743022  0.497953  0.340222
1  GBT   Test  0.720755  0.511109  0.315513
```

Gradient boosted trees with parameter tuning The parameters we tuned here are: * maxDepth: the gradient boosted tree usually performs quite well with depth larger than 10, yet the it would also tend to overfit. Therefore the choices stopped at 10 * maxBins: the default is 32, we also tried 16 but didn't go higher. * maxIter: the GBT in spark runs very slow and consumes a lot of memory. We weren't able to go further than 20, given the choices on the other parameters.

[ ]:
```
%%time
# Create 3-fold CrossValidator
gb = GBTClassifier(featuresCol = 'selected_features', labelCol = 'label',
                   maxIter = 20, seed = 8888)
paramGrid = ParamGridBuilder()\
    .addGrid(gb.maxDepth,[4, 6, 8, 10])\
    .addGrid(gb.maxBins,[16, 32])\
    .addGrid(gb.maxIter,[10]) \
    .build()
```

```
evaluator = BinaryClassificationEvaluator()
cv = CrossValidator(estimator = gb, estimatorParamMaps = paramGrid,
                    evaluator = evaluator, numFolds=3)

# Run cross validations
cvModel = cv.fit(train)

best_maxDepth = cvModel.bestModel._java_obj.getMaxDepth()
best_maxBins = cvModel.bestModel._java_obj.getMaxBins()
best_maxIter = cvModel.bestModel._java_obj.getMaxIter()
```

[102]:
```
print('Best maxDepth is', best_maxDepth)
print('Best maxBins is', best_maxBins)
print('Best maxIter is', best_maxIter)
eval_gbt_cv = eval(cvModel, train, test, 'GBT+CV')
```

```
Best maxDepth is 6
Best maxBins is 32
Best maxIter is 10
Model: GBT+CV
     Name   Data       ROC   LogLoss  F1-Score
0  GBT+CV  Train  0.743550  0.498562  0.320988
1  GBT+CV   Test  0.716025  0.514783  0.291030
CPU times: user 4.15 s, sys: 4.04 s, total: 8.19 s
Wall time: 13min 41s
```

7.2.5 Summary for Categorical + Numerics

From the summary stats below, we recommend training both logistic regression and logistic regression for the full data set.

[106]:
```
eval_all = eval_dt_cv.append([eval_dt_sliced_cv, eval_lr, eval_lr_cv,
                              eval_lr_cv_sliced, eval_gbt, eval_gbt_cv])
eval_all
```

[106]:

	Name	Data	ROC	LogLoss	F1-Score
0	DT+CV	Train	0.512806	0.512041	0.282334
1	DT+CV	Test	0.518036	0.529752	0.262007
0	DT+CV+S	Train	0.515661	0.522705	0.303729
1	DT+CV+S	Test	0.517672	0.529677	0.294018
0	LR	Train	0.738119	0.498950	0.338664
1	LR	Test	0.730594	0.504101	0.335685
0	LR+CV	Train	0.738823	0.498517	0.333954
1	LR+CV	Test	0.731641	0.503432	0.332678
0	LR+CV+S	Train	0.713115	0.514463	0.276960
1	LR+CV+S	Test	0.707870	0.517995	0.277437
0	GBT	Train	0.743022	0.497953	0.340222

```
1       GBT   Test  0.720755  0.511109  0.315513
0    GBT+CV  Train  0.743550  0.498562  0.320988
1    GBT+CV   Test  0.716025  0.514783  0.291030
```

7.3 Breiman's Method

Here we are implementing Breiman's data transformation: replacing the categorical data with the average of labels. This allows us to convert categoricals to numerics, which reduces the features space. There are two versions of this method that we implemented:

1. Data transformation with imputed features:

   As discussed in the EDA, the categories are highly skewed. As a result, we propose to impute the categories that shows up less than 1 percent of the sample with string "less_than_1pc" before group by the categories and calculate the mean of each imputed category.

2. Data transformation without imputing features: using the raw categories as they are.

After implementing both versions, we see that the second version is grossly overfitting the data. Therefore we archived that version in the appendix, and highlight version 1 in this report in the following three sections:

- Data Transformation
- Logistic Regression
- Gradient Boosted Tree

7.3.1 Data Transformation

[63]:
```
# sample_df_bm = parquet_df.sample(fraction=100000/(34095179 + 11745438),␣
↪seed=8888).cache()
for c in categorical_features_select:
    # every categorical feature:
    # 1) replace empty string with name_na
    # 2) replace categories with less than 1pc with a string
    larger_than_1pc = features_summary.larger_than_1pc[features_summary.name ==␣
↪c]
    sample_df_bm = sample_df_bm.withColumn(c, impute_blank(c))\
                               .withColumn(c, impute_1pc(c, larger_than_1pc))
```

[64]:
```
train_bm, test_bm = sample_df_bm.randomSplit([0.7, 0.3], seed = 2018)
print("Training Dataset Count: " + str(train_bm.count()))
print("Test Dataset Count: " + str(test_bm.count()))
```

```
Training Dataset Count: 70044
Test Dataset Count: 30041
```

[65]:
```
!rm -rf full_data/temp/*
```

[66]:
```python
%%time
from pyspark.sql.functions import broadcast

for c in categorical_features:
    print(c)
    # get the categorical means
    means = train_bm.groupBy(c).agg({'label':'mean'})
    means = means.withColumnRenamed('avg(label)', c+'_bm')
    means = means.withColumnRenamed(c, 'r')

    # left join to train
    train_bm = train_bm.withColumnRenamed(c, 'l')
    train_bm.repartition('l')
    train_bm = train_bm.join(broadcast(means), train_bm.l == means.r, how =␣
↪'left').drop('l').drop('r')

    # left join to test
    test_bm = test_bm.withColumnRenamed(c, 'l')
    test_bm.repartition('l')
    test_bm = test_bm.join(broadcast(means), test_bm.l == means.r, how =␣
↪'left').drop('l').drop('r')

    # force it to repartition every 5 joins, otherwise the joining take FOREVER
    if c in ['b05', 'b10', 'b15', 'b20', 'b26']:
        print('repartition')
        train_bm.write.parquet("full_data/temp/trainbm.parquet" + c)
        test_bm.write.parquet("full_data/temp/testbm.parquet"+ c)
        train_bm = spark.read.parquet("full_data/temp/trainbm.parquet"+ c)
        test_bm = spark.read.parquet("full_data/temp/testbm.parquet"+ c)

test_bm = test_bm.na.fill(0)
```

```
b01
b02
b03
b04
b05
repartition
b06
b07
b08
b09
b10
repartition
b11
b12
b13
```

```
b14
b15
repartition
b16
b17
b18
b19
b20
repartition
b21
b22
b23
b24
b25
b26
repartition
CPU times: user 420 ms, sys: 340 ms, total: 760 ms
Wall time: 1min 25s
```

[67]:
```
# now the features are all non-negative and numeric, log1p is a suitable␣
↪transformation
train_bm.describe().toPandas().transpose()
```

[67]:
```
             0                    1                    2  \
summary  count                 mean               stddev
c01      70044    1.923319627662612    8.456498868306182
c02      70044   104.76753183713095    387.7734024368298
c03      70044    21.07773685112215    332.5048527295297
c04      70044    5.691750899434641    8.601616225368913
c05      70044   17690.220390040547    67387.39750468069
c06      70044    89.34445491405403    276.8271078976037
c07      70044   16.082505282393925    65.58877332646787
c08      70044    12.45959682485295   24.091326774205186
c09      70044   101.05192450459711    220.4359992919834
c10      70044  0.33547484438353037   0.5906897758068512
c11      70044    2.629575695277254    5.217911770389966
c12      70044  0.22258865855747817    2.378340929797678
c13      70044    6.423362457883616    19.41986720796582
label    70044    0.256710067957284  0.43682116838643975
b01_bm   70044  0.25671006795726564 0.003937842729848915
b02_bm   70044  0.25671006795729095  0.04602341711117553
b03_bm   70044   0.2567100679572486 0.020786524682880735
b04_bm   70044   0.2567100679572734 0.037807864835583425
b05_bm   70044   0.2567100679572858 0.003363670633409035
b06_bm   70044   0.2567100679573037  0.01908534648393859
b07_bm   70044   0.2567100679572611 0.019663820940577694
b08_bm   70044   0.2567100679572855 0.004418202069041978
```

b09_bm	70044	0.25671006795727525	0.04178667141482545
b10_bm	70044	0.25671006795727025	0.02420941092223398
b11_bm	70044	0.25671006795728246	0.028045345342703365
b12_bm	70044	0.2567100679572559	0.020787404732232506
b13_bm	70044	0.25671006795726475	0.02856184179741151
b14_bm	70044	0.25671006795730267	0.04771216747123047
b15_bm	70044	0.25671006795725015	0.001630855928479777
b16_bm	70044	0.2567100679572559	0.020787404732232506
b17_bm	70044	0.2567100679572807	0.07121082311452584
b18_bm	70044	0.2567100679572534	0.019043911182605
b19_bm	70044	0.25671006795728923	0.017861517687025753
b20_bm	70044	0.2567100679572931	0.020037572521667893
b21_bm	70044	0.2567100679572559	0.020787404732232506
b22_bm	70044	0.25671006795729595	0.01551106451058182
b23_bm	70044	0.2567100679572808	0.055284116140045664
b24_bm	70044	0.2567100679573013	0.04115832639189846
b25_bm	70044	0.25671006795729695	0.027913774730150095
b26_bm	70044	0.25671006795729323	0.03576759506439881

	3	4
summary	min	max
c01	0.0	1262.0
c02	-2.0	14091.0
c03	0.0	33086.0
c04	0.0	681.0
c05	0.0	2145045.0
c06	0.0	10456.0
c07	0.0	5014.0
c08	0.0	4449.0
c09	0.0	9094.0
c10	0.0	6.0
c11	0.0	124.0
c12	0.0	207.0
c13	0.0	3529.0
label	0	1
b01_bm	0.2520595461771932	0.26974536037980146
b02_bm	0.13656387665198239	0.4295051353874883
b03_bm	0.12195121951219512	0.28297161936560933
b04_bm	0.11828687967369136	0.42534595775673706
b05_bm	0.252518315018315	0.28160919540229884
b06_bm	0.09090909090909091	0.3393665158371041
b07_bm	0.2214765100671141	0.38755020080321284
b08_bm	0.24321997417133018	0.26766091051805335
b09_bm	0.0	0.2707033172947136
b10_bm	0.21291324319078733	0.27014510074884684
b11_bm	0.19141689373297002	0.39007400957771005
b12_bm	0.12195121951219512	0.28297161936560933

```
b13_bm    0.1933292155651637  0.39007400957771005
b14_bm   0.07206208425720621   0.3837684806542938
b15_bm   0.24832855778414517  0.26928471248246844
b16_bm   0.12195121951219512  0.28297161936560933
b17_bm   0.09821910415542363   0.3802117802779616
b18_bm   0.16366612111292964   0.3079736649597659
b19_bm   0.23342844146714634   0.3069511355815554
b20_bm   0.22707089266574798  0.27800059417706474
b21_bm   0.12195121951219512  0.28297161936560933
b22_bm   0.24946079258800802  0.29452341137123744
b23_bm   0.09523809523809523   0.3525247758376593
b24_bm   0.11799604482531312   0.4129141886151232
b25_bm   0.20749625187406298   0.3185354691075515
b26_bm   0.14383561643835616  0.42503639010189226
```

[68]:
```
test_bm.describe().toPandas().transpose()
```

[68]:
```
             0                    1                      2  \
summary  count                 mean                 stddev
c01      30041   1.8935787756732465      6.674306248068302
c02      30041   104.59518657834293      378.8059701897496
c03      30041   25.182350787257416      622.7022559003697
c04      30041    5.700342864751506      8.192138591520505
c05      30041    17963.23717585966       66593.5406237014
c06      30041     90.2038214440265     290.46445032769674
c07      30041   15.383109750008321      55.69667464855535
c08      30041   12.492260577211145     13.622089899931566
c09      30041   100.91058886188875     216.78878037004208
c10      30041  0.33963583103092443     0.5944622276306627
c11      30041    2.593488898505376       5.12346786694716
c12      30041  0.22728937119270332     2.2359344955429097
c13      30041    6.495755800406112     12.175609348672031
label    30041  0.25987816650577544    0.43857486011597396
b01_bm   30041   0.2567172277245689  0.0039401043898178l5
b02_bm   30041  0.25658403542653824    0.04647019381014678
b03_bm   30041   0.2566284909823078   0.020838605016081053
b04_bm   30041   0.2561095147770641    0.03831739205290418
b05_bm   30041   0.2566739100406926  0.0032660768899391l5
b06_bm   30041   0.2566206026917576   0.019026086684552704
b07_bm   30041  0.25659189978062313   0.019290732720599384
b08_bm   30041   0.2566948116540124   0.004368623363018956
b09_bm   30041   0.2567772372833837    0.04171442844285154
b10_bm   30041  0.25660841467771217   0.024272786549868853
b11_bm   30041  0.25657450452528646   0.027949447095643922
b12_bm   30041   0.2566287219441594   0.020839509388435873
b13_bm   30041   0.2565782040712956   0.028513318897482803
b14_bm   30041   0.2568573312617409   0.047600016953423786
```

b15_bm	30041	0.25671183848267615	0.0016214585415277717
b16_bm	30041	0.2566287219441594	0.020839509388435873
b17_bm	30041	0.25661307477626605	0.07105447059639196
b18_bm	30041	0.25673051886464787	0.018980249872092292
b19_bm	30041	0.2565874791964298	0.017839776737122646
b20_bm	30041	0.2567618269606064	0.02001649314324239
b21_bm	30041	0.2566287219441594	0.020839509388435873
b22_bm	30041	0.2567466635120095	0.01554648187896121
b23_bm	30041	0.2568467666664384	0.05478559721760852
b24_bm	30041	0.25645553316707687	0.04166701454183419
b25_bm	30041	0.2564506012537682	0.027958058431826034
b26_bm	30041	0.25674863020644934	0.03583068437654752

	3	4
summary	min	max
c01	0.0	320.0
c02	-2.0	9580.0
c03	0.0	65535.0
c04	0.0	118.0
c05	0.0	1680616.0
c06	0.0	19247.0
c07	0.0	2310.0
c08	0.0	346.0
c09	0.0	6697.0
c10	0.0	6.0
c11	0.0	116.0
c12	0.0	126.0
c13	0.0	675.0
label	0	1
b01_bm	0.2520595461771932	0.26974536037980146
b02_bm	0.13656387665198239	0.4295051353874883
b03_bm	0.12195121951219512	0.28297161936560933
b04_bm	0.11828687967369136	0.42534595775673706
b05_bm	0.252518315018315	0.28160919540229884
b06_bm	0.09090909090909091	0.3393665158371041
b07_bm	0.2214765100671141	0.38755020080321284
b08_bm	0.24321997417133018	0.26766091051805335
b09_bm	0.0	0.2707033172947136
b10_bm	0.21291324319078733	0.27014510074884684
b11_bm	0.19141689373297002	0.39007400957771005
b12_bm	0.12195121951219512	0.28297161936560933
b13_bm	0.1933292155651637	0.39007400957771005
b14_bm	0.07206208425720621	0.3837684806542938
b15_bm	0.24832855778414517	0.26928471248246844
b16_bm	0.12195121951219512	0.28297161936560933
b17_bm	0.09821910415542363	0.3802117802779616
b18_bm	0.16366612111292964	0.3079736649597659

```
b19_bm   0.23342844146714634   0.3069511355815554
b20_bm   0.22707089266574798  0.27800059417706474
b21_bm   0.12195121951219512  0.28297161936560933
b22_bm   0.24946079258800802  0.29452341137123744
b23_bm   0.09523809523809523   0.3525247758376593
b24_bm   0.11799604482531312   0.4129141886151232
b25_bm   0.20749625187406298   0.3185354691075515
b26_bm   0.14383561643835616  0.42503639010189226
```

[69]:
```
for n in numeric_features + [b + '_bm' for b in categorical_features]:
    # log1p on all numerical features
    # same for train and test
    train_bm = train_bm.withColumn(n, log_transformation(n))
    test_bm = test_bm.withColumn(n, log_transformation(n))
```

[70]:
```
# this pipeline will only contain the scaler and the assembler
stages = []
assemblerInputs =  [c + "_bm" for c in categorical_features_select]␣
 ↪+numeric_features  #
assembler = VectorAssembler(inputCols=assemblerInputs, outputCol="features")
stages += [assembler]
scaler = StandardScaler(inputCol='features', outputCol='selected_features',
                        withStd=True, withMean=True)
stages += [scaler]
stages
```

[70]:
```
[VectorAssembler_4293b738cea5d75e37ea, StandardScaler_4115a8344a757c8536aa]
```

[71]:
```
from pyspark.ml import Pipeline
pipeline = Pipeline(stages = stages)
pipelineModel = pipeline.fit(train_bm)
train = pipelineModel.transform(train_bm).select(['label', 'selected_features'])
train.printSchema()
test = pipelineModel.transform(test_bm).select(['label', 'selected_features'])
test.printSchema()
```

```
root
 |-- label: long (nullable = true)
 |-- selected_features: vector (nullable = true)

root
 |-- label: long (nullable = true)
 |-- selected_features: vector (nullable = true)
```

[72]:
```
# make sure there is no Nulls after the transformation
# there is not supposed to be any for train, but check it anyways
```

```python
from pyspark.sql.functions import isnan, when, count, col
train_bm.select([count(when(isnan(c) | col(c).isNull(), c)).alias(c) for c in␣
 ↪train_bm.columns]).collect()
```

[72]:
```
[Row(c01=0, c02=0, c03=0, c04=0, c05=0, c06=0, c07=0, c08=0, c09=0, c10=0,
c11=0, c12=0, c13=0, label=0, b01_bm=0, b02_bm=0, b03_bm=0, b04_bm=0, b05_bm=0,
b06_bm=0, b07_bm=0, b08_bm=0, b09_bm=0, b10_bm=0, b11_bm=0, b12_bm=0, b13_bm=0,
b14_bm=0, b15_bm=0, b16_bm=0, b17_bm=0, b18_bm=0, b19_bm=0, b20_bm=0, b21_bm=0,
b22_bm=0, b23_bm=0, b24_bm=0, b25_bm=0, b26_bm=0)]
```

[73]:
```python
# if a category showed up in train but not test, it will be null in the test␣
 ↪after the join
# since we already imputed the nulls with 0, here we shouldn't see any (and␣
 ↪didn't)
test_bm.select([count(when(isnan(c) | col(c).isNull(), c)).alias(c) for c in␣
 ↪test_bm.columns]).collect()
```

[73]:
```
[Row(c01=0, c02=0, c03=0, c04=0, c05=0, c06=0, c07=0, c08=0, c09=0, c10=0,
c11=0, c12=0, c13=0, label=0, b01_bm=0, b02_bm=0, b03_bm=0, b04_bm=0, b05_bm=0,
b06_bm=0, b07_bm=0, b08_bm=0, b09_bm=0, b10_bm=0, b11_bm=0, b12_bm=0, b13_bm=0,
b14_bm=0, b15_bm=0, b16_bm=0, b17_bm=0, b18_bm=0, b19_bm=0, b20_bm=0, b21_bm=0,
b22_bm=0, b23_bm=0, b24_bm=0, b25_bm=0, b26_bm=0)]
```

[74]:
```python
train.count()
```

[74]:
```
70044
```

[75]:
```python
test.count()
```

[75]:
```
30041
```

7.3.2 Logistic Regression with Breiman's method

[76]:
```python
from pyspark.ml.classification import LogisticRegression
lr = LogisticRegression(featuresCol = 'selected_features', labelCol = 'label',
                        maxIter=10, regParam=0, elasticNetParam=0)
lrModel = lr.fit(train)
trainingSummary = lrModel.summary
g = sns.lineplot(x=range(1, len(trainingSummary.objectiveHistory) + 1),
                 y=trainingSummary.objectiveHistory)
g.set_title('Training Loss')
```

[76]:
```
Text(0.5,1,'Training Loss')
```

[77]:
```
fMeasure = trainingSummary.fMeasureByThreshold
maxFMeasure = fMeasure.groupBy().max('F-Measure').select('max(F-Measure)').
 ↪head()
bestThreshold = fMeasure.where(fMeasure['F-Measure'] ==␣
 ↪maxFMeasure['max(F-Measure)']) \
                                .select('threshold').head()['threshold']
lr.setThreshold(bestThreshold)
predictions = lrModel.transform(test)
# predictions.show(10)
```

[78]:
```
eval_lr_bm = eval(lrModel, train, test, 'LR+BM')
```

```
Model: LR+BM
    Name   Data       ROC   LogLoss  F1-Score
0  LR+BM  Train  0.728219  0.504692  0.312716
1  LR+BM   Test  0.726216  0.508085  0.314968
```

We got similar (slightly higher) loss rate than the logistic regression in the other pipeline, which shows: 1. Breiman's method is an efficient way to deal with categorical variables, especially if the number of unique categories are so big that one-hot encoding it is not feasible. 2. The loss is still higher because Breiman's method all introduces information loss. Consider a feature with 100 observations divided 25 and 75: data will still show variations if one-hot encoded (0s and 1s), but they will be the same after Breiman's transformation.

7.3.3 Gradient Boosted Trees with Breiman's Method

[79]:
```
from pyspark.ml.classification import GBTClassifier
gb = GBTClassifier(featuresCol = 'selected_features', labelCol = 'label',
                   maxIter = 20, seed = 8888)
gbModel = gb.fit(train)
eval_gbt_bm = eval(gbModel, train, test, 'GBT+BM')
```

```
Model: GBT+BM
     Name   Data       ROC   LogLoss  F1-Score
0  GBT+BM  Train  0.744219  0.496481  0.327607
1  GBT+BM   Test  0.727692  0.508713  0.315204
```

7.3.4 Summary for Breiman's Method

GBT here showed similar results. Since the logistic regression will be more explainable, we chose to only run logistic regression when fitting the full data through Breiman's transformation in the next section.

[113]:
```
eval_all_BM = eval_lr_bm.append([eval_gbt_bm, eval_lr_bm_raw, eval_gbt_bm_raw])
eval_all_BM
```

[113]:

	Name	Data	ROC	LogLoss	F1-Score
0	LR+BM	Train	0.728219	0.504692	0.312716
1	LR+BM	Test	0.726216	0.508085	0.314968
0	GBT+BM	Train	0.744219	0.496481	0.327607
1	GBT+BM	Test	0.727692	0.508713	0.315204
0	LR+BM Raw	Train	0.962717	0.208049	0.812294
1	LR+BM Raw	Test	0.617494	0.902251	0.263471
0	GBT+BM Raw	Train	0.966866	0.219323	0.810052
1	GBT+BM Raw	Test	0.531103	0.727883	0.260219

8 Model with Full Data

- Categorical + Numerical
  - Logistic regression
  - Gradient boosted trees
- Breiman's Method
  - Logistic regression

This part is run in a jupyter notebook under environment GCP. We write to python files and submit it to the cluster for the calculation.

8.1 Categorical + Numerical

[5]:
```
%%writefile full_data_lr.py

#!/usr/bin/env python

####################################
# IMPORTS
####################################
import re
import ast
import time
import numpy as np
import pandas as pd
from pyspark.sql import Row

####################################
# SETUP SPARK
####################################
# start Spark Session
from pyspark.sql import SparkSession
app_name = "final_project"
# master = "local[*]"
spark = SparkSession\
        .builder\
        .appName(app_name)\
        .config('spark.executor.memory', '10g')\
        .getOrCreate()
# from pyspark import SparkContext
# SparkContext.setSystemProperty('spark.executor.memory', '15g')
sc = spark.sparkContext

####################################
# PIPE LINE
####################################
if False:
    # write data to parquet, only needed to be run once
    df = sc.textFile('gs://261_bucket_zengm71/full_data/train.txt').\
            map(lambda l: l.split("\t")).\
            map(lambda p: Row(label=int(p[0]),
                              c01 = int(p[1] + '0') / 10, c02 = int(p[2] + '0')␣
↪/ 10, c03 = int(p[3] + '0') / 10, c04 = int(p[4] + '0') / 10, c05 = int(p[5]␣
↪+ '0') / 10, c06 = int(p[6] + '0') / 10,
                              c07 = int(p[7] + '0') / 10, c08 = int(p[8] + '0')␣
↪/ 10, c09 = int(p[9] + '0') / 10, c10 = int(p[10] + '0') / 10, c11 =␣
↪int(p[11] + '0') / 10, c12 = int(p[12] + '0') / 10,
                              c13 = int(p[13] + '0') / 10,
```

```
                              b01 = p[14], b02 = p[15], b03 = p[16], b04 =␣
↪p[17], b05 = p[18], b06 = p[19], b07 = p[20], b08 = p[21], b09 = p[22], b10␣
↪= p[23], b11 = p[24], b12 = p[25], b13 = p[26],
                              b14 = p[27], b15 = p[28], b16 = p[29], b17 =␣
↪p[30], b18 = p[31], b19 = p[32], b20 = p[33], b21 = p[34], b22 = p[35], b23␣
↪= p[36], b24 = p[37], b25 = p[38], b26 = p[39], ))

    # Infer the schema, and register the DataFrame as a table.
    schema_df = spark.createDataFrame(df)
    schema_df.createOrReplaceTempView("df")
    schema_df.write.parquet("gs://261_bucket_zengm71/full_data/train.parquet")

if False:
    # fit the full dataset through the pipeline and write to parquet
    # only need to be run once as well, unless any changes to the pipeline
    ###################################
    # Get the categories
    ###################################
    parquet_df = spark.read.parquet("gs://261_bucket_zengm71/full_data/train.
↪parquet")

    # Parquet files can also be used to create a temporary view and then used␣
↪in SQL statements.
    parquet_df.createOrReplaceTempView("parquet_df")
    parquet_df.printSchema()

    sample_df = parquet_df.sample(fraction=100000/(34095179 + 11745438),␣
↪seed=8888).cache()
    print(sample_df.count())
    sample_df_pd = sample_df.toPandas()

    categorical_features = [t[0] for t in sample_df.dtypes if t[1] == 'string']
    features_summary = pd.DataFrame(columns=['name', '# unique', '# empty',
                                             '# count = 1', '# count < 10', '#␣
↪count < 100',
                                             '# count < 1000'])
    for c in categorical_features:
        # number of categories
        nc = len(sample_df_pd.loc[:, c].unique())
        # number of empty strings
        ne = sum(sample_df_pd.loc[:, c] == '')
        # number of categories with only 1 counts
        n1 = sum(sample_df_pd.loc[:, c].value_counts() == 1)
        # number of categories with less than 10 occurances
        n10 = sum(sample_df_pd.loc[:, c].value_counts() < 10)
        # number of categories with less than 100 occurances
```

```
        n100 = sum(sample_df_pd.loc[:, c].value_counts() < 100)
        # number of categories with less than 1000 occurances, which is about 1%
        n1000 = sum(sample_df_pd.loc[:, c].value_counts() < 1000)

        features_summary.loc[-1] = [c, nc, ne, n1, n10, n100, n1000]
        features_summary.index = features_summary.index + 1

    categorical_features_select = []
    features_summary = pd.DataFrame(columns=['name', '# unique before', '#␣
↪unique after',
                                             'larger_than_1pc'])
    for c in categorical_features:
        # number of categories
        nc_bf = len(sample_df_pd.loc[:, c].unique())

        if c in ['b03', 'b03', 'b12', 'b16', 'b21', 'b24']:
            sample_df_pd.loc[sample_df_pd.loc[:, c] == '', c] = 'empty_1'
        elif c in ['b19', 'b20', 'b25', 'b26']:
            sample_df_pd.loc[sample_df_pd.loc[:, c] == '', c] = 'empty_2'
        else:
            sample_df_pd.loc[sample_df_pd.loc[:, c] == '', c] = 'empty_0'

        less_than_1000 = list(sample_df_pd.loc[:, c].
↪value_counts()[sample_df_pd.loc[:, c].value_counts() < 1000].index)
        sample_df_pd.loc[sample_df_pd.loc[:, c].isin(less_than_1000), c] =␣
↪'less_than_1pc'
        larger_than_1pc = [x for x in sample_df_pd.loc[:, c].unique() if x not␣
↪in ['less_than_1pc']]
        nc_af = len(sample_df_pd.loc[:, c].unique())

        features_summary.loc[-1] = [c, nc_bf, nc_af, larger_than_1pc]
        features_summary.index = features_summary.index + 1
    categorical_features_select = categorical_features
    sample_df_pd.loc[:, 'b17'].unique()

    numeric_features = [t[0] for t in sample_df.dtypes if t[1] == 'double']

    ###################################
    # Preprocessing
    ###################################
    from pyspark.sql.functions import col, when, log, udf, log1p

    def impute_blank(x):
        if x in ['b03', 'b03', 'b12', 'b16', 'b21', 'b24']:
            impute = 'empty_1'
        elif x in ['b19', 'b20', 'b25', 'b26']:
            impute = 'empty_2'
```

```
        else:
            impute = 'empty_0'

        return when(col(x) != "", col(x)).otherwise(impute)


    def impute_1pc(x, larger_than_1pc):
        return when(col(x).isin(list(larger_than_1pc)[0]), col(x)).
↪otherwise('less_than_1pc')

    def log_transformation(x):
        return when(col(x) < 0, col(x)).otherwise(log1p(col(x)))

    from pyspark.ml.feature import OneHotEncoderEstimator, StringIndexer,␣
↪VectorAssembler, StandardScaler, ChiSqSelector
    stages = []
    for categoricalCol in categorical_features_select:
        stringIndexer = StringIndexer(inputCol = categoricalCol,
                                      outputCol = categoricalCol + 'Index')
        encoder = OneHotEncoderEstimator(inputCols=[stringIndexer.
↪getOutputCol()],
                                         outputCols=[categoricalCol +␣
↪"classVec"])
        stages += [stringIndexer, encoder]

    assemblerInputs = [c + "classVec" for c in categorical_features_select] +␣
↪numeric_features
    assembler = VectorAssembler(inputCols=assemblerInputs, outputCol="features")
    stages += [assembler]
    scaler = StandardScaler(inputCol='features', outputCol='selected_features',
                            withStd=True, withMean=True)
    stages += [scaler]
    # selector = ChiSqSelector(numTopFeatures=50, featuresCol="scaled_features",
    #                          outputCol="selected_features", labelCol="label")
    # stages += [selector]
    stages

    for c in categorical_features_select:
        larger_than_1pc = features_summary.larger_than_1pc[features_summary.
↪name == c]
        parquet_df = parquet_df.withColumn(c, impute_blank(c))\
                               .withColumn(c, impute_1pc(c, larger_than_1pc))

    for n in numeric_features:
        parquet_df = parquet_df.withColumn(n, log_transformation(n))
```

```
    print('fitting the pipeline')
    from pyspark.ml import Pipeline
    pipeline = Pipeline(stages = stages)
    pipelineModelFull = pipeline.fit(parquet_df)
    parquet_df_pipe = pipelineModelFull.transform(parquet_df)
    selectedCols = ['label', 'selected_features'] #+ cols
    parquet_df_pipe = parquet_df_pipe.select(selectedCols)
    parquet_df_pipe.printSchema()
    print(len(parquet_df_pipe.select('selected_features').take(1)[0][0]))
    print('writing to train.pipe.parquet')
    parquet_df_pipe.write.parquet("gs://261_bucket_zengm71/full_data/train.pipe.
↪parquet")

###################################
# TRAIN/TEST Split
###################################
from pyspark.sql.functions import col, when, log, udf, log1p
from pyspark.sql.types import FloatType
def log_loss_from_prediction(predictions):
    # predictions are what returns from model.transform
    # the data frame should have a column named probability, which is a tuple:
    # we need to extract the second item of the tuple and calculate log loss␣
↪with it
    epsilon = 1e-16
    split1_udf = udf(lambda value: value[1].item(), FloatType())
    predictions = predictions.select('*', split1_udf('probability').\
                                 alias('prob'))
    loss = predictions.select("*",
                          when(predictions.label == 1, 0. - log(predictions.
↪prob + epsilon)).\
                          otherwise(0. - log(1. - predictions.prob + epsilon)).
↪\
                          alias('log_loss')).\
                agg({'log_loss': 'avg'}).\
                take(1)
    return loss

def f1_score(predictions):
    # predictions are what returns from model.transform
    # an exmaple of use:
    # predictions = lrModel.transform(test)
    # x = f1_score(predictions)
    TN = predictions.filter('prediction = 0 AND label = prediction').count()
    TP = predictions.filter('prediction = 1 AND label = prediction').count()
    FN = predictions.filter('prediction = 0 AND label <> prediction').count()
    FP = predictions.filter('prediction = 1 AND label <> prediction').count()
    accuracy = (TN + TP) / (TN + TP + FN + FP)
```

```python
    precision = TP / (TP + FP)
    recall = TP / (TP + FN)
    F =  2 * (precision*recall) / (precision + recall)
    return F

parquet_df_pipe = spark.read.parquet("gs://261_bucket_zengm71/full_data/train.
 ↪pipe.parquet")
print(len(parquet_df_pipe.select('selected_features').take(1)[0][0]))
train, test = parquet_df_pipe.randomSplit([0.7, 0.3], seed = 2018)
print("====== Training Dataset Count: " + str(train.count()))
print("====== Test Dataset Count: " + str(test.count()))

###################################
# LOGISTIC REGRESSION
###################################
print("====== Logistic Regression ========================================")
from pyspark.ml.classification import LogisticRegression
from pyspark.ml.evaluation import BinaryClassificationEvaluator

lr = LogisticRegression(featuresCol = 'selected_features', labelCol = 'label',
                        maxIter=100, regParam=0.001, elasticNetParam=0.5)
lrModel = lr.fit(train)
trainingSummary = lrModel.summary

# Evaluate on Train
predictions = lrModel.transform(train)
evaluator = BinaryClassificationEvaluator()
f1 = f1_score(predictions)
print('====== Train Area Under ROC', evaluator.evaluate(predictions))
print('====== Train Log Loss: ', log_loss_from_prediction(predictions))
print('====== Train F1 Score: ', f1)

# Make Predictions
predictions = lrModel.transform(test)
evaluator = BinaryClassificationEvaluator()
f1 = f1_score(predictions)
print('====== Test Area Under ROC', evaluator.evaluate(predictions))
print('====== Test Log Loss: ', log_loss_from_prediction(predictions))
print('====== Test F1 Score: ', f1)


# ###################################
# # GBT
# ###################################
# print("====== Gradient Boosted Tress␣
 ↪========================================")
# from pyspark.ml.classification import GBTClassifier
```

```
# gb = GBTClassifier(featuresCol = 'selected_features', labelCol = 'label',
#                     maxIter = 100, seed = 8888)
# gbModel = gb.fit(train)

# # Evaluate on Train
# predictions = gbModel.transform(train)
# evaluator = BinaryClassificationEvaluator()
# f1 = f1_score(predictions)
# print('====== Train Area Under ROC', evaluator.evaluate(predictions))
# print('====== Train Log Loss: ', log_loss_from_prediction(predictions))
# print('====== Train F1 Score: ', f1)

# # Make Predictions
# predictions = gbModel.transform(test)
# f1 = f1_score(predictions)
# evaluator = BinaryClassificationEvaluator()
# print('====== Test Area Under ROC', evaluator.evaluate(predictions))
# print('====== Test Log Loss: ', log_loss_from_prediction(predictions))
# print('====== Test F1 Score: ', f1)

spark.stop()
```

```
Overwriting full_data_lr.py
```

[6]:
```
import time
start = time.time()
!python3 submit_job_to_cluster.py \
    --project_id=w261-256321 \
    --zone=us-west2-b \
    --cluster_name=final-project \
    --gcs_bucket=261_bucket_zengm71 \
    --key_file=$HOME/w261.json \
    --worker_nodes=15 \
    --create_new_cluster \
    --pyspark_file=full_data_lr.py
print(f'... completed job in {time.time() - start} seconds.')
```

```
Creating cluster…
Waiting for cluster creation…
Cluster created.
Uploading pyspark file to GCS
final-project - RUNNING
Submitted job ID f621583e-1c5a-4b0a-b417-670270e0315f
Waiting for job to finish…
Job finished.
Downloading output file
b'====== Training Dataset Count: 32089468'
```

```
b'====== Test Dataset Count: 13751149'
b'====== Logistic Regression ========================================'
b'====== Train Area Under ROC 0.7355051192582652'
b'====== Train Log Loss:  [Row(avg(log_loss)=0.4994656972474252)]'
b'====== Train F1 Score:  0.32399346059737827'
b'====== Test Area Under ROC 0.7353038324506003'
b'====== Test Log Loss:  [Row(avg(log_loss)=0.49963011166872723)]'
b'====== Test F1 Score:  0.32409527565021723'
Tearing down cluster
… completed job in 2049.138465166092 seconds.
```

[44]:

```
%%writefile full_data_gbt.py

#!/usr/bin/env python

###################################
# IMPORTS
###################################
import re
import ast
import time
import numpy as np
import pandas as pd
from pyspark.sql import Row

###################################
# SETUP SPARK
###################################
# start Spark Session
from pyspark.sql import SparkSession
app_name = "final_project"
# master = "local[*]"
spark = SparkSession\
        .builder\
        .appName(app_name)\
        .config('spark.executor.memory', '10g')\
        .getOrCreate()
# from pyspark import SparkContext
# SparkContext.setSystemProperty('spark.executor.memory', '15g')
sc = spark.sparkContext

###################################
# PIPE LINE
###################################
if False:
    # write data to parquet, only needed to be run once
    df = sc.textFile('gs://261_bucket_zengm71/full_data/train.txt').\
```

```
            map(lambda l: l.split("\t")).\
            map(lambda p: Row(label=int(p[0]),
                              c01 = int(p[1] + '0') / 10, c02 = int(p[2] + '0')␣
↪/ 10, c03 = int(p[3] + '0') / 10, c04 = int(p[4] + '0') / 10, c05 = int(p[5]␣
↪+ '0') / 10, c06 = int(p[6] + '0') / 10,
                              c07 = int(p[7] + '0') / 10, c08 = int(p[8] + '0')␣
↪/ 10, c09 = int(p[9] + '0') / 10, c10 = int(p[10] + '0') / 10, c11 =␣
↪int(p[11] + '0') / 10, c12 = int(p[12] + '0') / 10,
                              c13 = int(p[13] + '0') / 10,
                              b01 = p[14], b02 = p[15], b03 = p[16], b04 =␣
↪p[17], b05 = p[18], b06 = p[19], b07 = p[20], b08 = p[21], b09 = p[22], b10␣
↪= p[23], b11 = p[24], b12 = p[25], b13 = p[26],
                              b14 = p[27], b15 = p[28], b16 = p[29], b17 =␣
↪p[30], b18 = p[31], b19 = p[32], b20 = p[33], b21 = p[34], b22 = p[35], b23␣
↪= p[36], b24 = p[37], b25 = p[38], b26 = p[39], ))

    # Infer the schema, and register the DataFrame as a table.
    schema_df = spark.createDataFrame(df)
    schema_df.createOrReplaceTempView("df")
    schema_df.write.parquet("gs://261_bucket_zengm71/full_data/train.parquet")

if False:
    # fit the full dataset through the pipeline and write to parquet
    # only need to be run once as well, unless any changes to the pipeline
    ###################################
    # Get the categories
    ###################################
    parquet_df = spark.read.parquet("gs://261_bucket_zengm71/full_data/train.
↪parquet")

    # Parquet files can also be used to create a temporary view and then used␣
↪in SQL statements.
    parquet_df.createOrReplaceTempView("parquet_df")
    parquet_df.printSchema()

    sample_df = parquet_df.sample(fraction=100000/(34095179 + 11745438),␣
↪seed=8888).cache()
    print(sample_df.count())
    sample_df_pd = sample_df.toPandas()

    categorical_features = [t[0] for t in sample_df.dtypes if t[1] == 'string']
    features_summary = pd.DataFrame(columns=['name', '# unique', '# empty',
                                             '# count = 1', '# count < 10', '#␣
↪count < 100',
                                             '# count < 1000'])
    for c in categorical_features:
```

```
        # number of categories
        nc = len(sample_df_pd.loc[:, c].unique())
        # number of empty strings
        ne = sum(sample_df_pd.loc[:, c] == '')
        # number of categories with only 1 counts
        n1 = sum(sample_df_pd.loc[:, c].value_counts() == 1)
        # number of categories with less than 10 occurances
        n10 = sum(sample_df_pd.loc[:, c].value_counts() < 10)
        # number of categories with less than 100 occurances
        n100 = sum(sample_df_pd.loc[:, c].value_counts() < 100)
        # number of categories with less than 1000 occurances, which is about 1%
        n1000 = sum(sample_df_pd.loc[:, c].value_counts() < 1000)

        features_summary.loc[-1] = [c, nc, ne, n1, n10, n100, n1000]
        features_summary.index = features_summary.index + 1

    categorical_features_select = []
    features_summary = pd.DataFrame(columns=['name', '# unique before', '#␣
↪unique after',
                                             'larger_than_1pc'])
    for c in categorical_features:
        # number of categories
        nc_bf = len(sample_df_pd.loc[:, c].unique())

        if c in ['b03', 'b03', 'b12', 'b16', 'b21', 'b24']:
            sample_df_pd.loc[sample_df_pd.loc[:, c] == '', c] = 'empty_1'
        elif c in ['b19', 'b20', 'b25', 'b26']:
            sample_df_pd.loc[sample_df_pd.loc[:, c] == '', c] = 'empty_2'
        else:
            sample_df_pd.loc[sample_df_pd.loc[:, c] == '', c] = 'empty_0'

        less_than_1000 = list(sample_df_pd.loc[:, c].
↪value_counts()[sample_df_pd.loc[:, c].value_counts() < 1000].index)
        sample_df_pd.loc[sample_df_pd.loc[:, c].isin(less_than_1000), c] =␣
↪'less_than_1pc'
        larger_than_1pc = [x for x in sample_df_pd.loc[:, c].unique() if x not␣
↪in ['less_than_1pc']]
        nc_af = len(sample_df_pd.loc[:, c].unique())

        features_summary.loc[-1] = [c, nc_bf, nc_af, larger_than_1pc]
        features_summary.index = features_summary.index + 1
    categorical_features_select = categorical_features
    sample_df_pd.loc[:, 'b17'].unique()

    numeric_features = [t[0] for t in sample_df.dtypes if t[1] == 'double']

    ###################################
```

```
# Preprocessing
####################################
from pyspark.sql.functions import col, when, log, udf, log1p

def impute_blank(x):
    if x in ['b03', 'b03', 'b12', 'b16', 'b21', 'b24']:
        impute = 'empty_1'
    elif x in ['b19', 'b20', 'b25', 'b26']:
        impute = 'empty_2'
    else:
        impute = 'empty_0'

    return when(col(x) != "", col(x)).otherwise(impute)


def impute_1pc(x, larger_than_1pc):
    return when(col(x).isin(list(larger_than_1pc)[0]), col(x)).
↪otherwise('less_than_1pc')

def log_transformation(x):
    return when(col(x) < 0, col(x)).otherwise(log1p(col(x)))

from pyspark.ml.feature import OneHotEncoderEstimator, StringIndexer,␣
↪VectorAssembler, StandardScaler, ChiSqSelector
stages = []
for categoricalCol in categorical_features_select:
    stringIndexer = StringIndexer(inputCol = categoricalCol,
                                  outputCol = categoricalCol + 'Index')
    encoder = OneHotEncoderEstimator(inputCols=[stringIndexer.
↪getOutputCol()],
                                     outputCols=[categoricalCol +␣
↪"classVec"])
    stages += [stringIndexer, encoder]

assemblerInputs = [c + "classVec" for c in categorical_features_select] +␣
↪numeric_features
assembler = VectorAssembler(inputCols=assemblerInputs, outputCol="features")
stages += [assembler]
scaler = StandardScaler(inputCol='features', outputCol='selected_features',
                        withStd=True, withMean=True)
stages += [scaler]
# selector = ChiSqSelector(numTopFeatures=50, featuresCol="scaled_features",
#                          outputCol="selected_features", labelCol="label")
# stages += [selector]
stages

for c in categorical_features_select:
```

```
        larger_than_1pc = features_summary.larger_than_1pc[features_summary.
↪name == c]
        parquet_df = parquet_df.withColumn(c, impute_blank(c))\
                               .withColumn(c, impute_1pc(c, larger_than_1pc))

    for n in numeric_features:
        parquet_df = parquet_df.withColumn(n, log_transformation(n))

    print('fitting the pipeline')
    from pyspark.ml import Pipeline
    pipeline = Pipeline(stages = stages)
    pipelineModelFull = pipeline.fit(parquet_df)
    parquet_df_pipe = pipelineModelFull.transform(parquet_df)
    selectedCols = ['label', 'selected_features'] #+ cols
    parquet_df_pipe = parquet_df_pipe.select(selectedCols)
    parquet_df_pipe.printSchema()
    print(len(parquet_df_pipe.select('selected_features').take(1)[0][0]))
    print('writing to train.pipe.parquet')
    parquet_df_pipe.write.parquet("gs://261_bucket_zengm71/full_data/train.pipe.
↪parquet")

###################################
# TRAIN/TEST Split
###################################
from pyspark.sql.functions import col, when, log, udf, log1p
from pyspark.sql.types import FloatType

def log_loss_from_prediction(predictions):
    # predictions are what returns from model.transform
    # the data frame should have a column named probability, which is a tuple:
    # we need to extract the second item of the tuple and calculate log loss␣
↪with it
    epsilon = 1e-16
    split1_udf = udf(lambda value: value[1].item(), FloatType())
    predictions = predictions.select('*', split1_udf('probability').\
                                     alias('prob'))
    loss = predictions.select("*",
                              when(predictions.label == 1, 0. - log(predictions.
↪prob + epsilon)).\
                              otherwise(0. - log(1. - predictions.prob + epsilon)).
↪\
                              alias('log_loss')).\
                   agg({'log_loss': 'avg'}).\
                   take(1)
    return loss

def f1_score(predictions):
```

```
    # predictions are what returns from model.transform
    # an exmaple of use:
    # predictions = lrModel.transform(test)
    # x = f1_score(predictions)
    TN = predictions.filter('prediction = 0 AND label = prediction').count()
    TP = predictions.filter('prediction = 1 AND label = prediction').count()
    FN = predictions.filter('prediction = 0 AND label <> prediction').count()
    FP = predictions.filter('prediction = 1 AND label <> prediction').count()
    accuracy = (TN + TP) / (TN + TP + FN + FP)
    precision = TP / (TP + FP)
    recall = TP / (TP + FN)
    F =  2 * (precision*recall) / (precision + recall)
    return F

parquet_df_pipe = spark.read.parquet("gs://261_bucket_zengm71/full_data/train.
 ↪pipe.parquet")
print(len(parquet_df_pipe.select('selected_features').take(1)[0][0]))

train, test = parquet_df_pipe.randomSplit([0.7, 0.3], seed = 2018)
print("====== Training Dataset Count: " + str(train.count()))
print("====== Test Dataset Count: " + str(test.count()))

###################################
# LOGISTIC REGRESSION
###################################
# print("====== Logistic Regression ========================================")
# from pyspark.ml.classification import LogisticRegression
# from pyspark.ml.evaluation import BinaryClassificationEvaluator

# lr = LogisticRegression(featuresCol = 'selected_features', labelCol =␣
 ↪'label',
#                          maxIter=100, regParam=0.001, elasticNetParam=0.5)
# lrModel = lr.fit(train)
# trainingSummary = lrModel.summary

# # Evaluate on Train
# predictions = lrModel.transform(train)
# evaluator = BinaryClassificationEvaluator()
# f1 = f1_score(predictions)
# print('====== Train Area Under ROC', evaluator.evaluate(predictions))
# print('====== Train Log Loss: ', log_loss_from_prediction(predictions))
# print('====== Train F1 Score: ', f1)

# # Make Predictions
# predictions = lrModel.transform(test)
# evaluator = BinaryClassificationEvaluator()
# f1 = f1_score(predictions)
```

```
# print('====== Test Area Under ROC', evaluator.evaluate(predictions))
# print('====== Test Log Loss: ', log_loss_from_prediction(predictions))
# print('====== Test F1 Score: ', f1)


# ###################################
# # GBT
# ###################################
print("====== Gradient Boosted Tress ========================================")
from pyspark.ml.classification import GBTClassifier
from pyspark.ml.evaluation import BinaryClassificationEvaluator

gb = GBTClassifier(featuresCol = 'selected_features', labelCol = 'label',
                   maxIter = 50, seed = 8888)
gbModel = gb.fit(train)

# Evaluate on Train
predictions = gbModel.transform(train)
evaluator = BinaryClassificationEvaluator()
f1 = f1_score(predictions)
print('====== Train Area Under ROC', evaluator.evaluate(predictions))
print('====== Train Log Loss: ', log_loss_from_prediction(predictions))
print('====== Train F1 Score: ', f1)

# Make Predictions
predictions = gbModel.transform(test)
f1 = f1_score(predictions)
evaluator = BinaryClassificationEvaluator()
print('====== Test Area Under ROC', evaluator.evaluate(predictions))
print('====== Test Log Loss: ', log_loss_from_prediction(predictions))
print('====== Test F1 Score: ', f1)

spark.stop()
```

```
Overwriting full_data_gbt.py
```

[45]:

```
# GBT with 50 iterations
import time
start = time.time()
!python3 submit_job_to_cluster.py \
    --project_id=w261-256321 \
    --zone=us-west2-b \
    --cluster_name=final-project \
    --gcs_bucket=261_bucket_zengm71 \
    --key_file=$HOME/w261.json \
    --worker_nodes=23 \
    --create_new_cluster \
```

```
    --pyspark_file=full_data_gbt.py
print(f'... completed job in {time.time() - start} seconds.')
```

```
Creating cluster…
Waiting for cluster creation…
Cluster created.
Uploading pyspark file to GCS
final-project - RUNNING
Submitted job ID 6c9db092-6055-45e8-8a22-5c588f8c997f
Waiting for job to finish…
Job finished.
Downloading output file
b'====== Training Dataset Count: 32089468'
b'====== Test Dataset Count: 13751102'
b'====== Gradient Boosted Tress ========================================'
b'====== Train Area Under ROC 0.7399972672247248'
b'====== Train Log Loss:  [Row(avg(log_loss)=0.49682252147163386)]'
b'====== Train F1 Score:  0.3456295596321672'
b'====== Test Area Under ROC 0.7398007452800197'
b'====== Test Log Loss:  [Row(avg(log_loss)=0.4969489017311084)]'
b'====== Test F1 Score:  0.34557869909700195'
Tearing down cluster
… completed job in 3318.4152722358704 seconds.
```

8.2 Breiman's Method

[27]:
```
%%writefile full_data_bm.py

#!/usr/bin/env python

####################################
# IMPORTS
####################################
import re
import ast
import time
import numpy as np
import pandas as pd
from pyspark.sql import Row

####################################
# SETUP SPARK
####################################
# start Spark Session
from pyspark.sql import SparkSession
app_name = "final_project"
```

```
# master = "local[*]"
spark = SparkSession\
        .builder\
        .appName(app_name)\
        .config('spark.executor.memory', '10g')\
        .getOrCreate()
# from pyspark import SparkContext
# SparkContext.setSystemProperty('spark.executor.memory', '15g')
sc = spark.sparkContext

###################################
# TRAIN/TEST Split
###################################
from pyspark.sql.functions import col, when, log, udf, log1p
from pyspark.ml.feature import OneHotEncoderEstimator, StringIndexer,␣
 ↪VectorAssembler, StandardScaler, ChiSqSelector
from pyspark.sql.types import FloatType
def log_loss_from_prediction(predictions):
    # predictions are what returns from model.transform
    # the data frame should have a column named probability, which is a tuple:
    # we need to extract the second item of the tuple and calculate log loss␣
 ↪with it
    epsilon = 1e-16
    split1_udf = udf(lambda value: value[1].item(), FloatType())
    predictions = predictions.select('*', split1_udf('probability').\
                                     alias('prob'))
    loss = predictions.select("*",
                              when(predictions.label == 1, 0. - log(predictions.
 ↪prob + epsilon)).\
                              otherwise(0. - log(1. - predictions.prob + epsilon)).
 ↪\
                              alias('log_loss')).\
                agg({'log_loss': 'avg'}).\
                take(1)
    return loss

def f1_score(predictions):
    # predictions are what returns from model.transform
    # an exmaple of use:
    # predictions = lrModel.transform(test)
    # x = f1_score(predictions)
    TN = predictions.filter('prediction = 0 AND label = prediction').count()
    TP = predictions.filter('prediction = 1 AND label = prediction').count()
    FN = predictions.filter('prediction = 0 AND label <> prediction').count()
    FP = predictions.filter('prediction = 1 AND label <> prediction').count()
    accuracy = (TN + TP) / (TN + TP + FN + FP)
    precision = TP / (TP + FP)
```

```
    recall = TP / (TP + FN)
    F =  2 * (precision*recall) / (precision + recall)
    return F

def impute_blank(x):
        if x in ['b03', 'b03', 'b12', 'b16', 'b21', 'b24']:
            impute = 'empty_1'
        elif x in ['b19', 'b20', 'b25', 'b26']:
            impute = 'empty_2'
        else:
            impute = 'empty_0'

        return when(col(x) != "", col(x)).otherwise(impute)

def impute_1pc(x, larger_than_1pc):
    return when(col(x).isin(list(larger_than_1pc)[0]), col(x)).
 ↪otherwise('less_than_1pc')

def log_transformation(x):
    return when(col(x) < 0, col(x)).otherwise(log1p(col(x)))

parquet_df = spark.read.parquet("gs://261_bucket_zengm71/full_data/train.
 ↪parquet")
# parquet_df =  parquet_df.sample(fraction=100000/(34095179 + 11745438),␣
 ↪seed=8888).cache()

sample_df = parquet_df.sample(fraction=100000/(34095179 + 11745438), seed=8888).
 ↪cache()
print(sample_df.count())
sample_df_pd = sample_df.toPandas()

categorical_features = [t[0] for t in sample_df.dtypes if t[1] == 'string']
features_summary = pd.DataFrame(columns=['name', '# unique', '# empty',
                                         '# count = 1', '# count < 10', '#␣
 ↪count < 100',
                                         '# count < 1000'])
for c in categorical_features:
    # number of categories
    nc = len(sample_df_pd.loc[:, c].unique())
    # number of empty strings
    ne = sum(sample_df_pd.loc[:, c] == '')
    # number of categories with only 1 counts
    n1 = sum(sample_df_pd.loc[:, c].value_counts() == 1)
    # number of categories with less than 10 occurances
    n10 = sum(sample_df_pd.loc[:, c].value_counts() < 10)
    # number of categories with less than 100 occurances
    n100 = sum(sample_df_pd.loc[:, c].value_counts() < 100)
```

```
    # number of categories with less than 1000 occurances, which is about 1%
    n1000 = sum(sample_df_pd.loc[:, c].value_counts() < 1000)

    features_summary.loc[-1] = [c, nc, ne, n1, n10, n100, n1000]
    features_summary.index = features_summary.index + 1

categorical_features_select = []
features_summary = pd.DataFrame(columns=['name', '# unique before', '# unique␣
↪after',
                                          'larger_than_1pc'])
for c in categorical_features:
    # number of categories
    nc_bf = len(sample_df_pd.loc[:, c].unique())

    if c in ['b03', 'b03', 'b12', 'b16', 'b21', 'b24']:
        sample_df_pd.loc[sample_df_pd.loc[:, c] == '', c] = 'empty_1'
    elif c in ['b19', 'b20', 'b25', 'b26']:
        sample_df_pd.loc[sample_df_pd.loc[:, c] == '', c] = 'empty_2'
    else:
        sample_df_pd.loc[sample_df_pd.loc[:, c] == '', c] = 'empty_0'

    less_than_1000 = list(sample_df_pd.loc[:, c].value_counts()[sample_df_pd.
↪loc[:, c].value_counts() < 1000].index)
    sample_df_pd.loc[sample_df_pd.loc[:, c].isin(less_than_1000), c] =␣
↪'less_than_1pc'
    larger_than_1pc = [x for x in sample_df_pd.loc[:, c].unique() if x not in␣
↪['less_than_1pc']]
    nc_af = len(sample_df_pd.loc[:, c].unique())

    features_summary.loc[-1] = [c, nc_bf, nc_af, larger_than_1pc]
    features_summary.index = features_summary.index + 1

categorical_features = [t[0] for t in parquet_df.dtypes if t[1] == 'string']
numeric_features = [t[0] for t in parquet_df.dtypes if t[1] == 'double']

for c in categorical_features:
    # every categorical feature:
    # 1) replace empty string with name_na
    # 2) replace categories with less than 1pc with a string
    larger_than_1pc = features_summary.larger_than_1pc[features_summary.name ==␣
↪c]
    parquet_df = parquet_df.withColumn(c, impute_blank(c))\
                           .withColumn(c, impute_1pc(c, larger_than_1pc))

train_bm, test_bm = parquet_df.randomSplit([0.7, 0.3], seed = 2018)
print("Training Dataset Count: " + str(train_bm.count()))
print("Test Dataset Count: " + str(test_bm.count()))
```

```
####################################
# Breiman Transformation
####################################
print('starting Breiman Transformation')
from pyspark.sql.functions import broadcast

for c in categorical_features:
    print(c)
    means = train_bm.groupBy(c).agg({'label':'mean'})
    means = means.withColumnRenamed('avg(label)', c+'_bm')
    means = means.withColumnRenamed(c, 'r')

    train_bm = train_bm.withColumnRenamed(c, 'l')
    train_bm.repartition('l')
    train_bm = train_bm.join(broadcast(means), train_bm.l == means.r, how =␣
 ↪'left').drop('l').drop('r')

    test_bm = test_bm.withColumnRenamed(c, 'l')
    test_bm.repartition('l')
    test_bm = test_bm.join(broadcast(means), test_bm.l == means.r, how =␣
 ↪'left').drop('l').drop('r')

    if c in ['b05', 'b10', 'b15', 'b20', 'b26']:
        print('repartition')
        train_bm.write.parquet("full_data/temp/trainbm.parquet" + c)
        test_bm.write.parquet("full_data/temp/testbm.parquet"+ c)
        train_bm = spark.read.parquet("full_data/temp/trainbm.parquet"+ c)
        test_bm = spark.read.parquet("full_data/temp/testbm.parquet"+ c)

test_bm = test_bm.na.fill(0)
print('finished Breiman Transformation')
print(train_bm.describe().toPandas().transpose())

print('starting pipeline')
for n in numeric_features + [b + '_bm' for b in categorical_features]:
    # log1p on all numerical features
    # same for train and test
    train_bm = train_bm.withColumn(n, log_transformation(n))
    test_bm = test_bm.withColumn(n, log_transformation(n))
stages = []
assemblerInputs =  [c + "_bm" for c in categorical_features] +numeric_features ␣
 ↪#
assembler = VectorAssembler(inputCols=assemblerInputs, outputCol="features")
stages += [assembler]
scaler = StandardScaler(inputCol='features', outputCol='selected_features',
```

```
                        withStd=True, withMean=True)
stages += [scaler]
stages
from pyspark.ml import Pipeline
pipeline = Pipeline(stages = stages)
pipelineModel = pipeline.fit(train_bm)
train = pipelineModel.transform(train_bm).select(['label', 'selected_features'])
train.printSchema()
test = pipelineModel.transform(test_bm).select(['label', 'selected_features'])
test.printSchema()
from pyspark.sql.functions import isnan, when, count, col
train_bm.select([count(when(isnan(c) | col(c).isNull(), c)).alias(c) for c in␣
 ↪train_bm.columns]).collect()
test_bm.select([count(when(isnan(c) | col(c).isNull(), c)).alias(c) for c in␣
 ↪test_bm.columns]).collect()



print("====== Training Dataset Count: " + str(train.count()))
print("====== Training Dataset Features Count " + str(len(train.
 ↪select('selected_features').take(1)[0][0])))
print("====== Test Dataset Count: " + str(test.count()))
train.write.parquet("gs://261_bucket_zengm71/full_data/train.pipe.parquet.bm")
test.write.parquet("gs://261_bucket_zengm71/full_data/test.pipe.parquet.bm")


###################################
# LOGISTIC REGRESSION
###################################
print("====== Logistic Regression ========================================")
from pyspark.ml.classification import LogisticRegression
from pyspark.ml.evaluation import BinaryClassificationEvaluator

lr = LogisticRegression(featuresCol = 'selected_features', labelCol = 'label',
                        maxIter=100, regParam=0.001, elasticNetParam=0.5)
lrModel = lr.fit(train)
trainingSummary = lrModel.summary

# Evaluate on Train
predictions = lrModel.transform(train)
evaluator = BinaryClassificationEvaluator()
f1 = f1_score(predictions)
print('====== Train Area Under ROC', evaluator.evaluate(predictions))
print('====== Train Log Loss: ', log_loss_from_prediction(predictions))
print('====== Train F1 Score: ', f1)

# Make Predictions
```

```
predictions = lrModel.transform(test)
evaluator = BinaryClassificationEvaluator()
f1 = f1_score(predictions)
print('====== Test Area Under ROC', evaluator.evaluate(predictions))
print('====== Test Log Loss: ', log_loss_from_prediction(predictions))
print('====== Test F1 Score: ', f1)


# # ####################################
# # # GBT
# # ####################################
# print("====== Gradient Boosted Tress␣
 ↪==========================================")
# from pyspark.ml.classification import GBTClassifier
# gb = GBTClassifier(featuresCol = 'selected_features', labelCol = 'label',
#                     maxIter = 100, seed = 8888)
# gbModel = gb.fit(train)

# # Evaluate on Train
# predictions = gbModel.transform(train)
# evaluator = BinaryClassificationEvaluator()
# print('====== Train Area Under ROC', evaluator.evaluate(predictions))
# print('====== Train Log Loss: ', log_loss_from_prediction(predictions))

# # Make Predictions
# predictions = gbModel.transform(test)
# evaluator = BinaryClassificationEvaluator()
# print('====== Test Area Under ROC', evaluator.evaluate(predictions))
# print('====== Test Log Loss: ', log_loss_from_prediction(predictions))

spark.stop()
```

```
Overwriting full_data_bm.py
```

[29]:
```
import time
start = time.time()
!python3 submit_job_to_cluster.py \
    --project_id=w261-256321 \
    --zone=us-west2-b \
    --cluster_name=final-project-bm \
    --gcs_bucket=261_bucket_zengm71 \
    --key_file=$HOME/w261.json \
    --worker_nodes=23 \
    --create_new_cluster \
    --pyspark_file=full_data_bm.py
print(f'... completed job in {time.time() - start} seconds.')
```

```
Creating cluster…
Waiting for cluster creation…
Cluster created.
Uploading pyspark file to GCS
final-project-bm - RUNNING
Submitted job ID a815dd63-4089-48ca-bddd-8266b895e374
Waiting for job to finish…
Job finished.
Downloading output file
b'====== Training Dataset Count: 32090809'
b'====== Training Dataset Features Count 39'
b'====== Test Dataset Count: 13749808'
b'====== Logistic Regression ========================================'
b'====== Train Area Under ROC 0.7274902908194077'
b'====== Train Log Loss:  [Row(avg(log_loss)=0.5047032420511904)]'
b'====== Train F1 Score:  0.3063345442530332'
b'====== Test Area Under ROC 0.7272185613190802'
b'====== Test Log Loss:  [Row(avg(log_loss)=0.5046195075049039)]'
b'====== Test F1 Score:  0.30593882089018143'
Tearing down cluster
… completed job in 1510.3345432281494 seconds.
```

8.3 Summary Stats on Full Data

We got similar results as we do on the sampled data, which shows: 1. our implementation is scalable 2. GBT when trained with more iterations makes a big difference, but it takes a lot resources on the system.

Pipeline	Model	Train ROC	Train LogLoss	Test ROC	Test LogLoss
N+C	Logistic Regression	0.735505	0.499465	0.735304	0.499630
N+C	Gradient Boosted Trees	0.739997	0.496823	0.739801	0.496949
Breiman	Logistic Regression	0.727490	0.504703	0.727218	0.504619

9 Application of Course Concepts

- Decision Tree

As we learned in class, decision tree has quite flexible usage. It can return good prediction with a mixture of data types and minimum data cleansing. At the same time, it can be used for feature selection or as a classification model. In this study, the team uses the decision tree to find the feature importance, and picks inputs based on a threshold. Since the input data contains many one hot encoding categorical features, this feature selection reduces the input dimension. It helps making the model more parsimonious but it also introduces loss of information.

- Breiman's Theorem

With many categorical features, the team tries to use Breiman's theorem as an alternative to one hot encoding. The trials include replacing the values of the categorical features with the average values of the labels.

- Spark Pipeline

The team builds the feature engineering and model training steps in a MLLib pipeline, which not only helps to ease communication for process development among the team, but also increases the scalability of the model. We use the provided functions such as standard scaler, assembler, string indexer, one-hot encoder and vector slicer.

- Logistic Regression under Map Reduce paradigm

A toy example is presented where we implemented gradient descent with logistic regression as a proof-of-concept.

10 Next Steps

- The study only explores a few regularization and tuning opportunities on the 100,000 samples. The team doesn't see much enhancement from the result; therefore decides not to implement in the full dataset. However, there can be additional improvement with more focus on the hyper parameter tuning.
- Many research papers indicate advanced models, such as Field-Aware Factorization Machine (FFM), and a combination of decision tree and logistics regression that have shown to return better accuracy in the literature. Further study can test on implementing the scalable version of the advanced models in the Spark environment.

11 Reference

Code documentation:

- https://spark.apache.org/docs/latest/ml-guide.html

Notebooks:

- http://restanalytics.com/2019-03-11-Distributed-Machine-Learing-with-Spark-ML/
- https://docs.databricks.com/_static/notebooks/binary-classification.html

Papers & Articles: * https://medium.com/@jason9389/gini-impurity-and-entropy-16116e754b27 * https://arxiv.org/pdf/1711.01377.pdf * https://arxiv.org/pdf/1701.04099.pdf * https://research.fb.com/publications/practical-lessons-from-predicting-clicks-on-ads-at-facebook/ * https://www.dropbox.com/s/s4x7wp8gjsh021d/TISTRespPredAds-Chappelle-CTR-Prediction-2014Paper.pdf?dl+=0 * https://www.csie.ntu.edu.tw/r01922136/slides/ffm.pdf * https://www.dropbox.com/s/iozods194twg2pv/M * https://www.dropbox.com/s/2n8uekjwpaur3bj/Deep-Learning-for-Criteo-Documentation.pdf?dl=0 * https://www.csie.ntu.edu.tw/~r01922136/slides/kaggle-avazu.pdf

12 Appendix

Here we archived the work that we touched on but haven't drilled down due to limited time we have.

- Random forest classifier
- SVM
- Breiman's method with raw features

12.1 Random Forest Classifier

[230]:
```
from pyspark.ml.classification import RandomForestClassifier
rf = RandomForestClassifier(featuresCol = 'selected_features', labelCol =␣
 ↪'label',
                            numTrees = 10, seed = 8888)
rfModel = rf.fit(train)
```

[231]:
```
%%time
# Create 3-fold CrossValidator
gb = GBTClassifier(featuresCol = 'selected_features', labelCol = 'label',
                   maxIter = 20, seed = 8888)
paramGrid = ParamGridBuilder()\
    .addGrid(gb.maxDepth,[4, 6, 8, 10])\
    .addGrid(gb.maxBins,[16, 32])\
    .addGrid(gb.maxIter,[10]) \
    .build()
evaluator = BinaryClassificationEvaluator()
cv = CrossValidator(estimator = gb, estimatorParamMaps = paramGrid,
                    evaluator = evaluator, numFolds=3)
# Run cross validations
cvModel = cv.fit(train)predict_train=rfModel.transform(train)
F_train = f1_score(predict_train)
print("The area under ROC for train set after CV  is {}".format(evaluator.
 ↪evaluate(predict_train)))
print(log_loss_from_prediction(predict_train))
print('Train F1-score', round(F_train, 6))

predict_test=rfModel.transform(test)
F_train = f1_score(predict_test)
print("The area under ROC for train set after CV  is {}".format(evaluator.
 ↪evaluate(predict_train)))
print(log_loss_from_prediction(predict_test))
print('Test F1-score', round(F_test, 6))
```

```
The area under ROC for train set after CV  is 0.7131582369105327
[Row(avg(log_loss)=0.5246516146335557)]
Train F1-score 0.025323
```

```
The area under ROC for train set after CV  is 0.7131582369105323
[Row(avg(log_loss)=0.5267514684921555)]
Test F1-score 0.329445
```

	ROC	LogLoss	F-1 Score
Train	0.713158	0.524612	0.025323
Test	0.713158	0.526751	0.329445

12.2 SVM

[226]:
```
from pyspark.ml.classification import LinearSVC
svm = LinearSVC(featuresCol = 'selected_features', labelCol = 'label',
                 maxIter = 10, regParam = 0.1)
svmModel = svm.fit(train)
```

[230]:
```
# Evaluate on Train
predictions = svmModel.transform(train)
evaluator = BinaryClassificationEvaluator()
print('Train Area Under ROC', evaluator.evaluate(predictions))
# log_loss_from_prediction(predictions)
```

```
Train Area Under ROC 0.7108954779037794
```

[231]:
```
# Make Predictions
predictions = svmModel.transform(test)
evaluator = BinaryClassificationEvaluator()
print('Test Area Under ROC', evaluator.evaluate(predictions))
# log_loss_from_prediction(predictions)
```

```
Test Area Under ROC 0.7117912150639231
```

12.3 Breiman's method with raw features

12.3.1 Data Transformation

[80]:
```
# sample_df_bm = parquet_df.sample(fraction=100000/(34095179 + 11745438),␣
↪seed=8888).cache()
```

[81]:
```
train_bm, test_bm = sample_df_bm.randomSplit([0.7, 0.3], seed = 2018)
print("Training Dataset Count: " + str(train_bm.count()))
print("Test Dataset Count: " + str(test_bm.count()))
```

```
Training Dataset Count: 70044
Test Dataset Count: 30041
```

[82]:
```
!rm -rf full_data/temp/*
```

[83]:
```
%%time
from pyspark.sql.functions import broadcast

for c in categorical_features:
    print(c)
    means = train_bm.groupBy(c).agg({'label':'mean'})
    means = means.withColumnRenamed('avg(label)', c+'_bm')
    means = means.withColumnRenamed(c, 'r')

    train_bm = train_bm.withColumnRenamed(c, 'l')
    train_bm.repartition('l')
    train_bm = train_bm.join(broadcast(means), train_bm.l == means.r, how =␣
↪'left').drop('l').drop('r')

    test_bm = test_bm.withColumnRenamed(c, 'l')
    test_bm.repartition('l')
    test_bm = test_bm.join(broadcast(means), test_bm.l == means.r, how =␣
↪'left').drop('l').drop('r')

    if c in ['b05', 'b10', 'b15', 'b20', 'b26']:
        print('repartition')
        train_bm.write.parquet("full_data/temp/trainbm.parquet" + c)
        test_bm.write.parquet("full_data/temp/testbm.parquet"+ c)
        train_bm = spark.read.parquet("full_data/temp/trainbm.parquet"+ c)
        test_bm = spark.read.parquet("full_data/temp/testbm.parquet"+ c)

test_bm = test_bm.na.fill(0)
```

```
b01
b02
b03
b04
b05
repartition
b06
b07
b08
b09
b10
repartition
b11
b12
b13
b14
b15
```

```
repartition
b16
b17
b18
b19
b20
repartition
b21
b22
b23
b24
b25
b26
repartition
CPU times: user 520 ms, sys: 380 ms, total: 900 ms
Wall time: 1min 37s
```

[84]:
```
train_bm.describe().toPandas().transpose()
```

[84]:
```
                0                    1                    2  \
summary     count                 mean               stddev
c01         70044   1.9079150248415282    8.436324245731942
c02         70044   103.56326023642282   379.60798793041306
c03         70044    22.33397578664839    415.8105675132443
c04         70044    5.717192050710982    8.633066062412174
c05         70044    17544.489035463423    66795.23252293572
c06         70044     89.5373336759751    283.6069625449144
c07         70044    15.915681571583576    63.09961408977935
c08         70044    12.503826166409686    24.14854045820756
c09         70044   101.50942264862087   224.78697369124447
c10         70044   0.3356747187482154   0.5903102328127438
c11         70044     2.62286562731997   5.2069017520697445
c12         70044  0.23159728170864027   2.3508642383522154
c13         70044    6.486008794472046   19.697086932398644
label       70044    0.256952772542973  0.43695625764427837
b01_bm      70044   0.2569527725429834   0.0342809558984275
b02_bm      70044  0.25695277254297627  0.09065471879446911
b03_bm      70044   0.2569527725429733  0.32224916834846157
b04_bm      70044  0.25695277254297166   0.2523250477388642
b05_bm      70044   0.2569527725429715  0.015957176686511466
b06_bm      70044   0.2569527725429669  0.017719107640243502
b07_bm      70044   0.2569527725429721   0.17787102105953131
b08_bm      70044   0.2569527725429594   0.02344548686016638
b09_bm      70044  0.25695277254299104   0.0433795696739544
b10_bm      70044  0.25695277254297333   0.18462652981448346
b11_bm      70044  0.25695277254297316   0.14546306601236175
b12_bm      70044  0.25695277254297244   0.31136613982291117
```

b13_bm	70044	0.2569527725429744	0.13606744816029756
b14_bm	70044	0.25695277254295706	0.051980880857892806
b15_bm	70044	0.25695277254297244	0.15965142127271986
b16_bm	70044	0.25695277254297305	0.28900011315767266
b17_bm	70044	0.2569527725429928	0.07238047478217817
b18_bm	70044	0.25695277254297494	0.1314891645162688
b19_bm	70044	0.25695277254299415	0.06750245159172656
b20_bm	70044	0.25695277254298166	0.0222173502318156
b21_bm	70044	0.25695277254297283	0.3017667591935721
b22_bm	70044	0.2569527725429657	0.015212538285402977
b23_bm	70044	0.25695277254296606	0.05444575649614512
b24_bm	70044	0.256952772542978	0.18868858793335555
b25_bm	70044	0.25695277254298865	0.03605927474632768
b26_bm	70044	0.2569527725429843	0.16257856101235788

	3	4
summary	min	max
c01	0.0	1262.0
c02	-2.0	10090.0
c03	0.0	65535.0
c04	0.0	681.0
c05	0.0	2145045.0
c06	0.0	19247.0
c07	0.0	5014.0
c08	0.0	4449.0
c09	0.0	9094.0
c10	0.0	6.0
c11	0.0	124.0
c12	0.0	141.0
c13	0.0	3529.0
label	0	1
b01_bm	0.0	1.0
b02_bm	0.0	1.0
b03_bm	0.0	1.0
b04_bm	0.0	1.0
b05_bm	0.0	1.0
b06_bm	0.0	0.6
b07_bm	0.0	1.0
b08_bm	0.0	1.0
b09_bm	0.0	0.2713977539496225
b10_bm	0.0	1.0
b11_bm	0.0	1.0
b12_bm	0.0	1.0
b13_bm	0.0	1.0
b14_bm	0.0	0.6538461538461539
b15_bm	0.0	1.0
b16_bm	0.0	1.0

b17_bm	0.09116022099447514	0.381841596909208
b18_bm	0.0	1.0
b19_bm	0.0	1.0
b20_bm	0.22348252605763336	0.27598195132776093
b21_bm	0.0	1.0
b22_bm	0.1	0.5294117647058824
b23_bm	0.0	0.35101553166069294
b24_bm	0.0	1.0
b25_bm	0.0	1.0
b26_bm	0.0	1.0

[85]:
```
test_bm.describe().toPandas().transpose()
```

[85]:

	0	1	2 \
summary	count	mean	stddev
c01	30041	1.9294963549815252	6.733594932009489
c02	30041	107.40308245397956	397.61011372001377
c03	30041	22.253287174195265	492.35839142889506
c04	30041	5.641023933956926	8.11438859888294
c05	30041	18303.026363969242	67967.77610475718
c06	30041	89.7541027262741	274.7918675251339
c07	30041	15.772078159848208	62.04303208417861
c08	30041	12.389134849039646	13.383480254733904
c09	30041	99.84388003062482	206.10353749758744
c10	30041	0.33916980127159546	0.5953436411798926
c11	30041	2.6091341832828467	5.149594549150711
c12	30041	0.20628474418294998	2.3025969059581777
c13	30041	6.349688758696448	11.088356436147622
label	30041	0.25931227322659034	0.43826454564513434
b01_bm	30041	0.2561008845787955	0.03105377541244836
b02_bm	30041	0.25722245794736726	0.09219547106264007
b03_bm	30041	0.142627080728123	0.1975460336219721
b04_bm	30041	0.20376198164880197	0.20107260890468998
b05_bm	30041	0.25662903059642644	0.01567103188668346
b06_bm	30041	0.2571715587883923	0.018257241863840905
b07_bm	30041	0.2509356023168699	0.18111976393864018
b08_bm	30041	0.25663080311294295	0.024689916659215484
b09_bm	30041	0.25654784797945246	0.0438912012549035
b10_bm	30041	0.24012435668870516	0.1751846700888224
b11_bm	30041	0.2561402216942429	0.1489336334672037
b12_bm	30041	0.15247909312845206	0.1981393631249057
b13_bm	30041	0.25658654027942895	0.13894340773765793
b14_bm	30041	0.25755487809127614	0.051865576112615795
b15_bm	30041	0.2522560254500642	0.1608718247879636
b16_bm	30041	0.17217159152860287	0.20021006301428954
b17_bm	30041	0.2569549897079238	0.0716424855955467
b18_bm	30041	0.25526562803457614	0.13347012668085595

b19_bm	30041	0.2565807121896916	0.06827441964406074
b20_bm	30041	0.25675342142288354	0.022255561469988
b21_bm	30041	0.16139306155726085	0.1992047643939442
b22_bm	30041	0.25706455126601424	0.015495564459011867
b23_bm	30041	0.25769935468625155	0.05405132870483235
b24_bm	30041	0.23756234130774362	0.17224721319539224
b25_bm	30041	0.2573171026616034	0.036483620852172334
b26_bm	30041	0.24279252756045447	0.14942424980357352

	3	4
summary	min	max
c01	0.0	183.0
c02	-2.0	14091.0
c03	0.0	65535.0
c04	0.0	100.0
c05	0.0	2096160.0
c06	0.0	9621.0
c07	0.0	3131.0
c08	0.0	346.0
c09	0.0	6185.0
c10	0.0	5.0
c11	0.0	116.0
c12	0.0	207.0
c13	0.0	415.0
label	0	1
b01_bm	0.0	1.0
b02_bm	0.0	1.0
b03_bm	0.0	1.0
b04_bm	0.0	1.0
b05_bm	0.0	1.0
b06_bm	0.08333333333333333	0.6
b07_bm	0.0	1.0
b08_bm	0.0	1.0
b09_bm	0.0	0.2713977539496225
b10_bm	0.0	1.0
b11_bm	0.0	1.0
b12_bm	0.0	1.0
b13_bm	0.0	1.0
b14_bm	0.02564102564102564	0.6538461538461539
b15_bm	0.0	1.0
b16_bm	0.0	1.0
b17_bm	0.09116022099447514	0.381841596909208
b18_bm	0.0	1.0
b19_bm	0.0	1.0
b20_bm	0.22348252605763336	0.27598195132776093
b21_bm	0.0	1.0
b22_bm	0.0	0.5294117647058824

```
b23_bm    0.0977766548762001  0.35101553166069294
b24_bm                   0.0                  1.0
b25_bm                   0.0                  1.0
b26_bm                   0.0                  1.0
```

[86]:
```
for n in numeric_features + [b + '_bm' for b in categorical_features]:
    # log1p on all numerical features
    # same for train and test
    train_bm = train_bm.withColumn(n, log_transformation(n))
    test_bm = test_bm.withColumn(n, log_transformation(n))
```

[87]:
```
stages = []
assemblerInputs =  [c + "_bm" for c in categorical_features_select]␣
↪+numeric_features  #
assembler = VectorAssembler(inputCols=assemblerInputs, outputCol="features")
stages += [assembler]
scaler = StandardScaler(inputCol='features', outputCol='selected_features',
                        withStd=True, withMean=True)
stages += [scaler]
stages
```

[87]:
```
[VectorAssembler_46d3a370936ba087d39d, StandardScaler_49a6a8aefde55f78ee16]
```

[88]:
```
from pyspark.ml import Pipeline
pipeline = Pipeline(stages = stages)
pipelineModel = pipeline.fit(train_bm)
train = pipelineModel.transform(train_bm).select(['label', 'selected_features'])
train.printSchema()
test = pipelineModel.transform(test_bm).select(['label', 'selected_features'])
test.printSchema()
```

```
root
 |-- label: long (nullable = true)
 |-- selected_features: vector (nullable = true)

root
 |-- label: long (nullable = true)
 |-- selected_features: vector (nullable = true)
```

[89]:
```
from pyspark.sql.functions import isnan, when, count, col
train_bm.select([count(when(isnan(c) | col(c).isNull(), c)).alias(c) for c in␣
↪train_bm.columns]).collect()
```

[89]:
```
[Row(c01=0, c02=0, c03=0, c04=0, c05=0, c06=0, c07=0, c08=0, c09=0, c10=0,
c11=0, c12=0, c13=0, label=0, b01_bm=0, b02_bm=0, b03_bm=0, b04_bm=0, b05_bm=0,
b06_bm=0, b07_bm=0, b08_bm=0, b09_bm=0, b10_bm=0, b11_bm=0, b12_bm=0, b13_bm=0,
```

```
b14_bm=0, b15_bm=0, b16_bm=0, b17_bm=0, b18_bm=0, b19_bm=0, b20_bm=0, b21_bm=0,
b22_bm=0, b23_bm=0, b24_bm=0, b25_bm=0, b26_bm=0)]
```

[90]:
```
test_bm.select([count(when(isnan(c) | col(c).isNull(), c)).alias(c) for c in␣
↪test_bm.columns]).collect()
```

[90]:
```
[Row(c01=0, c02=0, c03=0, c04=0, c05=0, c06=0, c07=0, c08=0, c09=0, c10=0,
c11=0, c12=0, c13=0, label=0, b01_bm=0, b02_bm=0, b03_bm=0, b04_bm=0, b05_bm=0,
b06_bm=0, b07_bm=0, b08_bm=0, b09_bm=0, b10_bm=0, b11_bm=0, b12_bm=0, b13_bm=0,
b14_bm=0, b15_bm=0, b16_bm=0, b17_bm=0, b18_bm=0, b19_bm=0, b20_bm=0, b21_bm=0,
b22_bm=0, b23_bm=0, b24_bm=0, b25_bm=0, b26_bm=0)]
```

[91]:
```
train.count()
```

[91]:
```
70044
```

[92]:
```
test.count()
```

[92]:
```
30041
```

12.3.2 Logistic Regression

[93]:
```
from pyspark.ml.classification import LogisticRegression
lr = LogisticRegression(featuresCol = 'selected_features', labelCol = 'label',
                        maxIter=10, regParam=0, elasticNetParam=0)
lrModel = lr.fit(train)
trainingSummary = lrModel.summary
g = sns.lineplot(x=range(1, len(trainingSummary.objectiveHistory) + 1),
                 y=trainingSummary.objectiveHistory)
g.set_title('Training Loss')
```

[93]:
```
Text(0.5,1,'Training Loss')
```

[94]:
```
fMeasure = trainingSummary.fMeasureByThreshold
maxFMeasure = fMeasure.groupBy().max('F-Measure').select('max(F-Measure)').
 ↪head()
bestThreshold = fMeasure.where(fMeasure['F-Measure'] ==␣
 ↪maxFMeasure['max(F-Measure)']) \
                        .select('threshold').head()['threshold']
lr.setThreshold(bestThreshold)
predictions = lrModel.transform(test)
# predictions.show(10)
```

[96]:
```
eval_lr_bm_raw = eval(lrModel, train, test, 'LR+BM Raw')
```

```
Model: LR+BM Raw
        Name   Data       ROC   LogLoss  F1-Score
0  LR+BM Raw  Train  0.962717  0.208049  0.812294
1  LR+BM Raw   Test  0.617494  0.902251  0.263471
```

12.3.3 Gradient Boosted Trees

[97]:
```
from pyspark.ml.classification import GBTClassifier
gb = GBTClassifier(featuresCol = 'selected_features', labelCol = 'label',
                   maxIter = 20, seed = 8888)
gbModel = gb.fit(train)
eval_gbt_bm_raw = eval(gbModel, train, test, 'GBT+BM Raw')
```

Model: GBT+BM Raw

	Name	Data	ROC	LogLoss	F1-Score
0	GBT+BM Raw	Train	0.966866	0.219323	0.810052
1	GBT+BM Raw	Test	0.531103	0.727883	0.260219