VPS Customer churn prediction - Part 2

JG Pardyak

03-9-2021

Introduction

Apache Spark

Machine Learning

PySpark

Further steps



Motivation

This is the continuation of the presentations:

- https://github.com/JacekPardyak/vps/blob/master/vps-part-1.pdf ,
- https://github.com/JacekPardyak/vps/blob/master/vps-part-2.pdf ,
- https://github.com/JacekPardyak/vps/blob/master/vps-part-3.pdf.

In this presentation we:

demonstrate how to use sparklyr R interface for Apache Spark

Apache Spark

Setting up Spark connection

```
library(tidyverse)
library(sparklyr)
#spark install(version = "3.1")
sc <- spark_connect(master = "local")</pre>
connection_is_open(sc)
## [1] TRUE
#spark_disconnect(sc)
## [1] '3.1.1'
```

Copy local data frames to a remote src vps <- read_csv("./data/vps_churn_data.txt")

Rows: 283 Columns: 23

Delimiter: "."

Delimiter: "."

lgl (1): is_churn

dbl (22): id, cpu_load_mean_m_3, disk_octets_read_mean_r

-- Column specification ------

dbl (23): id, cpu_load_mean_m_3, disk_octets_read_mean_r

Plot some data from Spark

`geom_smooth()` using method = 'loess' and formula 'y ~ network_rx_max_gradient

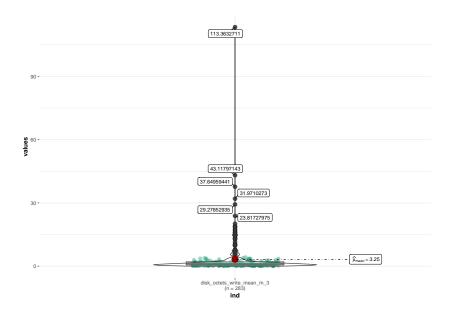
disk octets write mean m 3

Plot some other data from Spark

`geom_smooth()` using method = 'loess' and formula 'y ~
Warning: Removed 1 rows containing non-finite values (s-



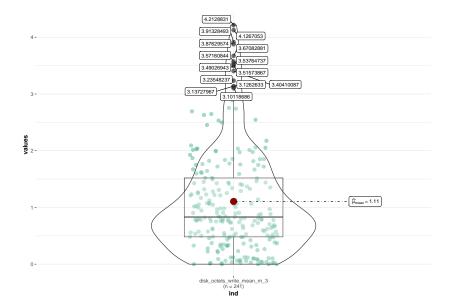
Data with outliers



Outliers removal

```
var = 'disk_octets_write_mean_m_3'
tbl <- tbl(sc, 'vps') %>% select('id', all of(var)) %>% col
summary(tbl)
##
   id
                   disk octets write mean m 3
## Min. :100.0 Min. : 0.0000
## 1st Qu.:170.5 1st Qu.: 0.5245
## Median :241.0 Median : 1.0526
## Mean :241.0 Mean : 3.2483
## 3rd Qu.:311.5 3rd Qu.: 2.0462
## Max. :382.0 Max. :113.3633
Q <- tbl %>% select(!! sym(var)) %>% pull() %>% quantile(p
iqr <- tbl %>% select(!! sym(var)) %>% pull() %>% IQR()
\#up \leftarrow Q[2]+1.5*igr \# Upper Range
#low < - Q[1] - 1.5 * igr # Lower Range
proper \leftarrow tbl %>% filter((!! sym(var) > (Q[1] - 1.5*iqr) &
```

Data without outliers



Using SQL

_				
##		id	cpu_load_mean_m_3	disk_octets_read_mean_m_3 disk
##	1	100	13.379892	38.82583205
##	2	101	16.902043	0.00328473
##	3	102	248.935914	19.37152776
##	4	103	14.054194	0.10182502
##	5	104	85.793333	15.49345957
##	6	105	39.394301	11.36519674
##	7	106	1.288280	0.00176921
##	8	107	79.788387	27.30295340
##	9	108	68.253118	18.10863666
##	10	109	8.866774	1.17613777
##		disk	c_ops_read_mean_m_3	disk_ops_write_mean_m_3 network
##	1		336.69720430	6.770323
##	2		0.08150538	2.793979
##	3		213.16032260	194.558280
##	4		2.18870968	9.634839
##	5		280.23193550	9.595376

55.020000

793.13655910



Random forest, all vars, training & evaluation on all data

```
rf model <- vps tbl %>%
  ml_random_forest(is_churn ~ ., type = "classification")
rf predict <- ml predict(rf model, vps tbl) %>%
  ft_string_indexer("is_churn", "is_churn_idx") %>% collect
table(rf_predict$is_churn_idx, rf_predict$prediction)
##
##
## 0 139 9
## 1 21 114
ml evaluate(rf model, vps tbl)
## # A tibble: 1 x 1
```

##

##

1 0.894

Accuracy

<dbl>

Random forest, all vars, evaluation on test data partitions <- tbl(sc, "vps") %>% sdf_random_split(training = 0.6, test = 0.4, seed = 888) rf_model <- partitions\$training %>%

ml random forest(is_churn ~ ., type = "classification") rf_predict <- ml_predict(rf_model, partitions\$test) %>% ft string indexer("is churn", "is churn idx") %>% collection table(rf predict\$is churn idx, rf predict\$prediction)

```
##
##
## 0 39 22
```

1 28 24

```
ml_evaluate(rf_model, partitions$test)
```

```
## # A tibble: 1 x 1
```

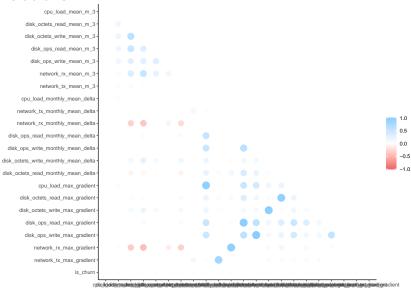
##

Accuracy

<dbl>

1 0.554

Correlations



[1] NA ## [1] 0.02383503

```
Random forest, chosen vars, evaluation on test data
   partitions <- tbl(sc, "vps") %>%
    sdf_random_split(training = 0.6, test = 0.4, seed = 888)
   rf_model <- partitions$training %>%
     ml_random_forest(formula, type = "classification")
   rf_predict <- ml_predict(rf_model, partitions$test) %>%
     ft string indexer("is churn", "is churn idx") %>% collection
   table(rf predict$is churn idx, rf predict$prediction)
   ##
   ##
   ## 0 38 23
   ## 1 24 28
```

ml evaluate(rf_model, partitions\$test)

A tibble: 1 x 1

Accuracy

<dbl> ## 1 0.584



PySpark

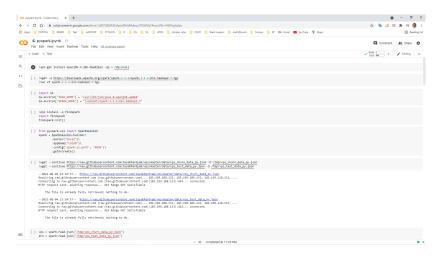


Figure 1: In this Colaboratory notebook you will find a step-by-step guide on how to use PySpark for the classification of VPS customers with Random Forest Classifier

https://github.com/JacekPardyak/vps/blob/master/pyspark.ipynb



Further steps

discuss with domain experts: outliers detected, crossing variables for feature engineering