VPS Customer churn prediction - Part 4

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Introduction

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

```r
library(tidyverse)
library(sparklyr)
#spark_install(version = "3.1")
sc <- spark_connect(master = "local")
connection_is_open(sc)
```

```
## [1] TRUE
```

```r
#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

## -- Column specification ---------------------------
## Delimiter: ","
## dbl (23): id, cpu_load_mean_m_3, disk_octets_read_mean_r

##
## i Use `spec()` to retrieve the full column specificatio
## i Specify the column types or set `show_col_types = FALS
```

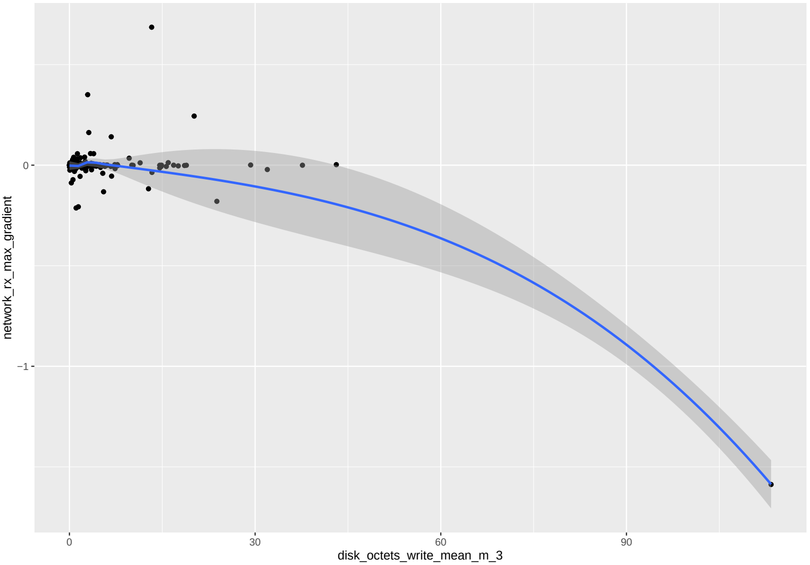
```
pro <- read_csv("./data/vps_test_data.txt")
```

```
## Rows: 95 Columns: 23

## -- Column specification ---------------------------
## Delimiter: ","
## dbl (22): id, cpu_load_mean_m_3, disk_octets_read_mean_r
## lgl  (1): is_churn
```

Plot some data from Spark

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

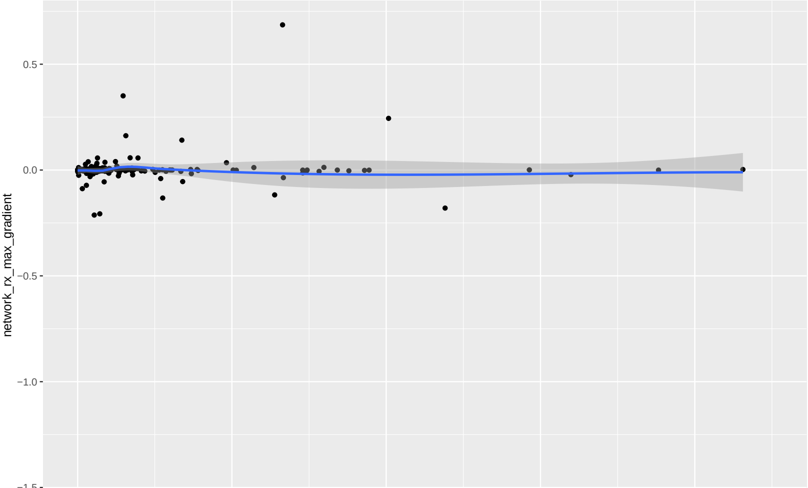


Plot some other data from Spark

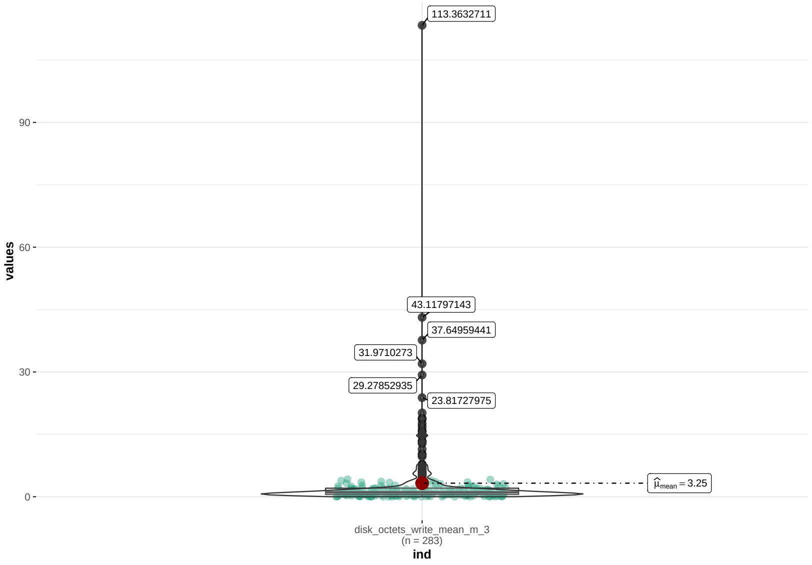
```
## `geom_smooth()` using method = 'loess' and formula 'y ~

## Warning: Removed 1 rows containing non-finite values (st

## Warning: Removed 1 rows containing missing values (geom_
```



Data with outliers



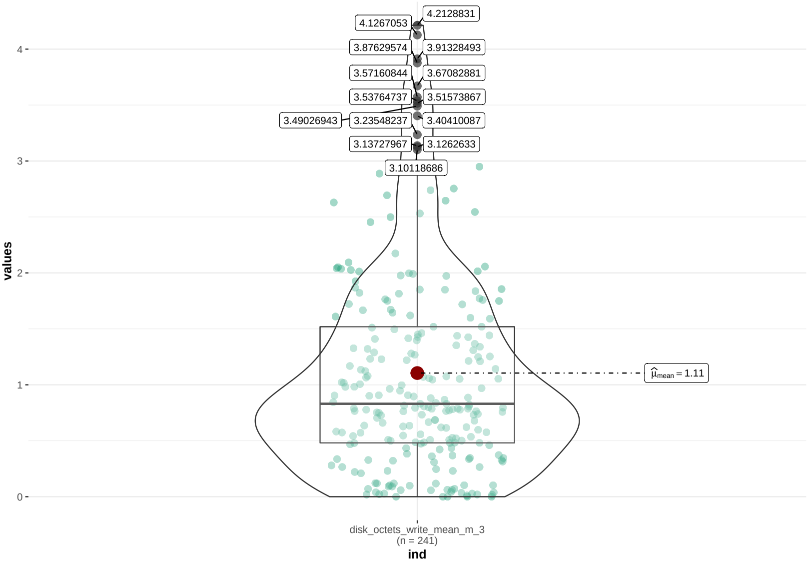
Outliers removal

```
var = 'disk_octets_write_mean_m_3'
tbl <- tbl(sc, 'vps') %>% select('id', all_of(var)) %>% co
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 <-  Q[2]+1.5*iqr # Upper Range
#low<- Q[1]-1.5*iqr # Lower Range
proper <- 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_ops_read_mean_m_3 disk_ops_write_mean_m_3 netwo
## 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
## 6            793.13655910               55.020000
```

Machine Learning

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   1
##   0 139   9
##   1  21 114
```

```
ml_evaluate(rf_model, vps_tbl)
```

```
## # A tibble: 1 x 1
##   Accuracy
##      <dbl>
## 1    0.894
```

Random forest, all vars, evaluation on test data

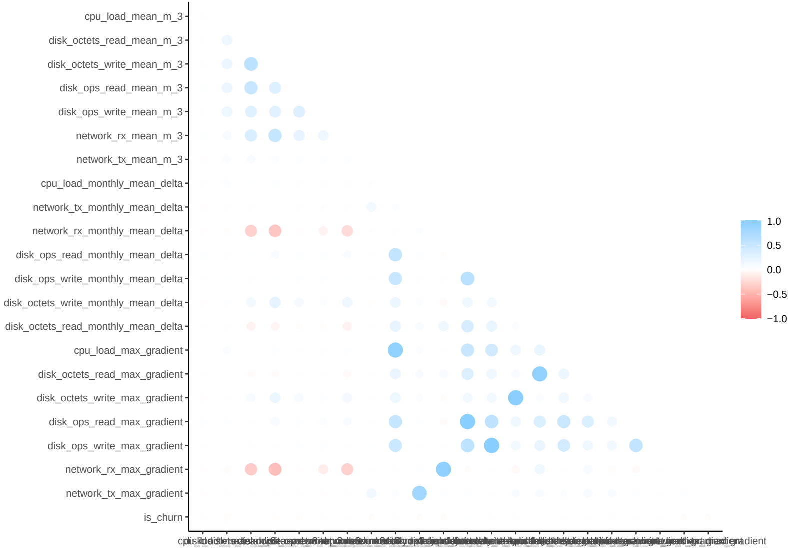
```
partitions <- tbl(sc, "vps") %>%
  sdf_random_split(training = 0.6, test = 0.4, seed = 888)
rf_model <- partitions$training %>%
  ml_random_forest(is_churn ~ ., type = "classification")
rf_predict <- ml_predict(rf_model, partitions$test) %>%
  ft_string_indexer("is_churn", "is_churn_idx") %>% collect
table(rf_predict$is_churn_idx, rf_predict$prediction)
```

```
##
##       0  1
##    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") %>% collect
table(rf_predict$is_churn_idx, rf_predict$prediction)
```

```
##
##       0  1
##    0 38 23
##    1 24 28
```

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

```
## # A tibble: 1 x 1
##   Accuracy
##      <dbl>
## 1    0.584
```

Python

PySpark

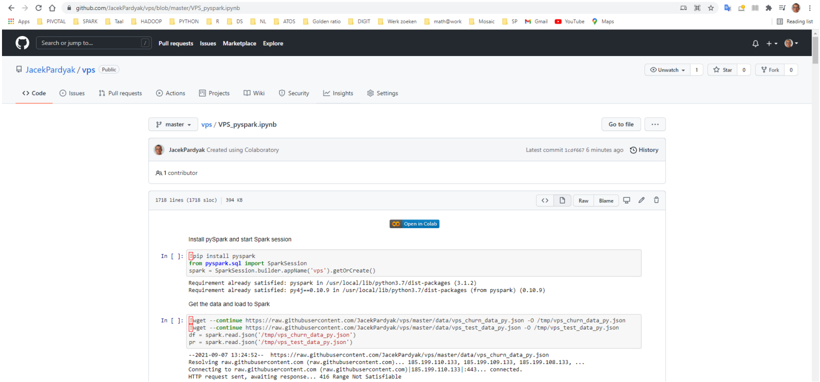


Figure 1: In this Colaboratory notebook you will find a step-by-step guide on how to use PySpark for the classification of VPS customers.

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

H2O

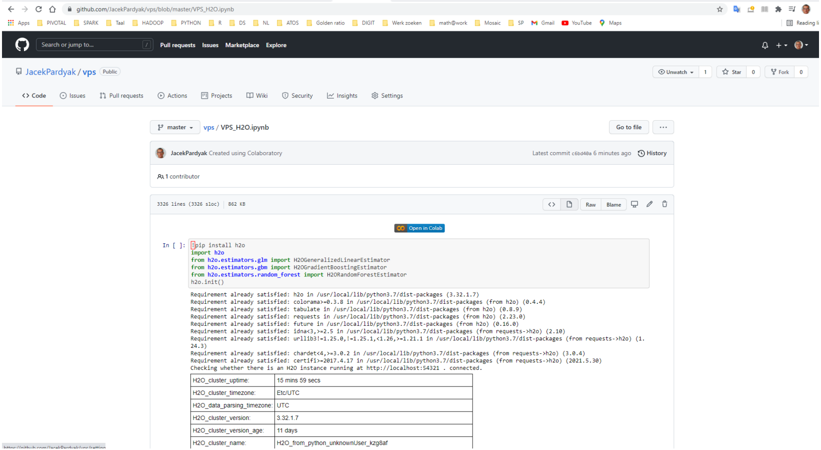


Figure 2: In this Colaboratory notebook you will find a step-by-step guide on how to use H2O for the classification of VPS customers.

https://github.com/JacekPardyak/vps/blob/master/VPS_H2O.ipynb

Further steps

Further steps

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