VPS Customer churn prediction

JG Pardyak

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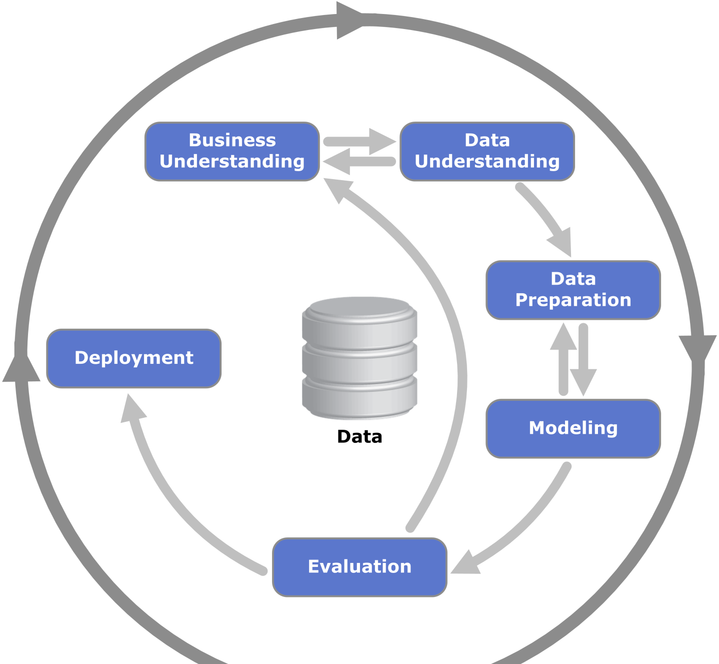
As an introduction

Figure 1: I did not expect that this interesting task would be intertwined with my long-awaited trip to Poland. So I start with Hello to everyone in front of the old locomotive in the city of Przeworsk. I tried my best to accomplish this task.

Presentantion outline



Business understanding

Company X sells a Virtual Private Server (VPS) as a service. The company wants to know which customers intend to leave VPS so they can devise an appropriate customer re-engagement strategy before it's too late.

Data understanding

```
library(tidyverse)
library(tidymodels)
vps <- read_csv("./data/vps_churn_data.txt") %>%
  mutate(is_churn = factor(ifelse(is_churn == 0,
                                  "No", "Yes")))

vps %>% dim()
```

```
## [1] 283  23
```

In this work we use *R* and *tidy-* libraries. All commands are visible to facilitate the verification of the presentation. We see that the dataset is composed of 283 observations described with 23 variables.

Data understanding cont.

The two classes (is_churn = Yes and is_churn = No) are almost equally distributed.

```
vps %>%
  count(is_churn) %>%
  mutate(prop = n/sum(n))
```

```
## # A tibble: 2 x 3
##   is_churn     n  prop
##   <fct>    <int> <dbl>
## 1 No         148 0.523
## 2 Yes        135 0.477
```

Data understanding cont.

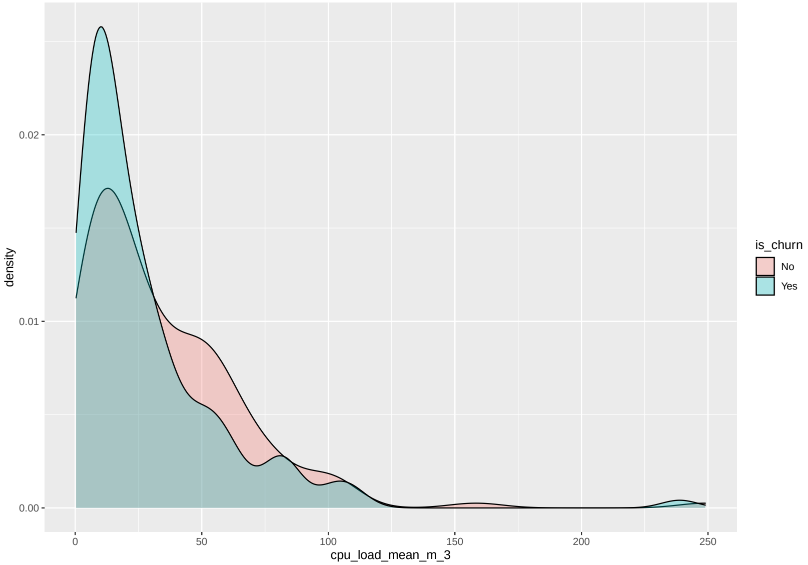
The dataset is complete - there are no missing values we have to deal with.

```
vps %>% is.na() %>% colSums() %>% head(6)
```

```
##                          id            cpu_load_mean_m_3
##                           0                            0
##  disk_octets_read_mean_m_3 disk_octets_write_mean_m_3
##                           0                            0
##     disk_ops_read_mean_m_3    disk_ops_write_mean_m_3
##                           0                            0
```

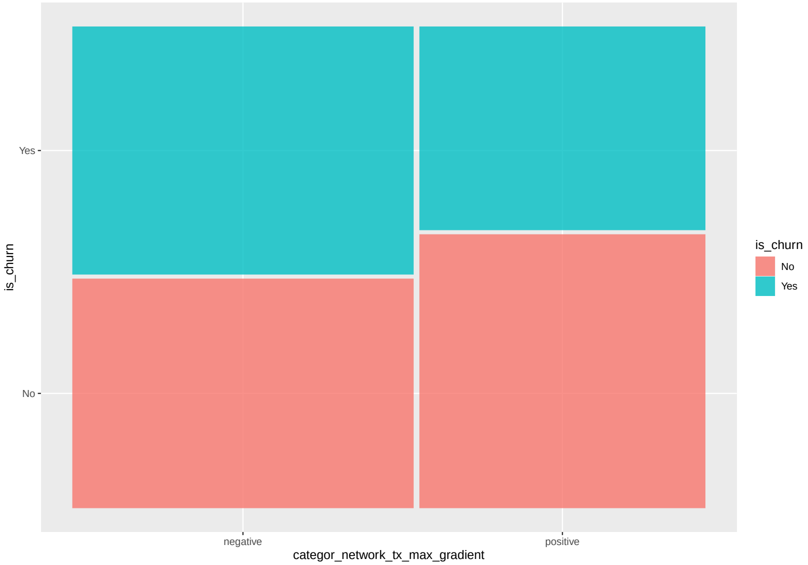
Data understanding cont.

We check whether first variable can serve as a “good” predictor.



Data understanding cont.

We check whether last variable can serve as a “good” predictor.



Data preparation

We split our data into training and test datasets.

```
set.seed(1234)
vps_split <- initial_split(vps, prop = 0.6,
                           strata = is_churn)
vps_split
```

```
## <Analysis/Assess/Total>
## <169/114/283>
```

Data preparation cont.

We check the observations used for training.

```
## Rows: 169
## Columns: 23
## $ id                                <dbl> 102, 104, 1
## $ cpu_load_mean_m_3                 <dbl> 248.935914,
## $ disk_octets_read_mean_m_3         <dbl> 19.3715277
## $ disk_octets_write_mean_m_3        <dbl> 31.9710273
## $ disk_ops_read_mean_m_3            <dbl> 213.160322
## $ disk_ops_write_mean_m_3           <dbl> 194.558279
## $ network_rx_mean_m_3               <dbl> 1.72831136,
## $ network_tx_mean_m_3               <dbl> 1.35480347,
## $ cpu_load_monthly_mean_delta       <dbl> 9.67491398,
## $ network_tx_monthly_mean_delta     <dbl> -0.1905986
## $ network_rx_monthly_mean_delta     <dbl> -0.3315117
## $ disk_ops_read_monthly_mean_delta  <dbl> -22.403232
## $ disk_ops_write_monthly_mean_delta <dbl> -26.080831
## $ disk_octets_write_monthly_mean_delta <dbl> -2.3433956
## $ disk_octets_read_monthly_mean_delta <dbl> -0.5359237
```

Data preparation cont.

We write recipe to prepare our data for training. Steps are described in comments.

```r
vps_recipe <- training(vps_split) %>% # on which data
  recipe(is_churn ~.) %>% # training formula
  step_rm(id) %>% # step remove id column
  # remove variables highly correlated with other vars
  step_corr(all_predictors()) %>%
  # make vars to be of mean zero
  step_center(all_predictors(), -all_outcomes()) %>%
  # make vars to be standard dev of 1
  step_scale(all_predictors(), -all_outcomes()) %>%
  prep() # execute transformations
```

Data preparation cont.

We use previously written recipe to prepare *training* data.

```r
vps_training <- juice(vps_recipe)
vps_training %>% select(1:10) %>% glimpse()
```

```
## Rows: 169
## Columns: 10
## $ cpu_load_mean_m_3                <dbl> 6.9540144, 1.7
## $ disk_octets_read_mean_m_3        <dbl> 0.7810093, 0.5
## $ disk_octets_write_mean_m_3       <dbl> 2.65330241, 1.
## $ disk_ops_read_mean_m_3           <dbl> 0.02212873, 0.
## $ disk_ops_write_mean_m_3          <dbl> 0.66829422, -0
## $ network_rx_mean_m_3              <dbl> -0.10276295, -
## $ network_tx_mean_m_3              <dbl> -0.190306768,
## $ network_tx_monthly_mean_delta    <dbl> -0.016170786,
## $ disk_ops_read_monthly_mean_delta <dbl> -0.1108472650
## $ disk_ops_write_monthly_mean_delta <dbl> -0.1447599445
```

Data preparation cont.

We use previously written recipe to prepare *test* data.

```
vps_testing <- vps_recipe %>%
  bake(testing(vps_split))
vps_testing %>% select(1:10) %>% glimpse()
```

```
## Rows: 114
## Columns: 10
## $ cpu_load_mean_m_3                <dbl> -0.608674397,
## $ disk_octets_read_mean_m_3        <dbl> 1.92677245, -0
## $ disk_octets_write_mean_m_3       <dbl> -0.36157310, -
## $ disk_ops_read_mean_m_3           <dbl> 0.328112376, -
## $ disk_ops_write_mean_m_3          <dbl> -0.29893573, -
## $ network_rx_mean_m_3              <dbl> -0.1932091, -0
## $ network_tx_mean_m_3              <dbl> -0.2665257913,
## $ network_tx_monthly_mean_delta    <dbl> 0.0849835086,
## $ disk_ops_read_monthly_mean_delta <dbl> 1.85174047, 0.
## $ disk_ops_write_monthly_mean_delta <dbl> 0.09257490, 0.
```

Modeling & Evaluation

Further we will interlace **Modeling** and **Evaluation** steps for selected algorithms. Previously defined *training* set is used to train models, the other *testing* for testing. Predicting power of each model is measured with *Accuracy* and *Area under curve* measures.

Modeling & Evaluation cont.

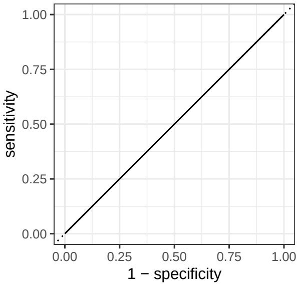
We start from *Null model* - assumption that no one will churn.

```
null_model <- null_model(mode = "classification") %>%
  set_engine("parsnip") %>%
  fit(is_churn ~ ., data = vps_training)
predict(null_model, vps_testing, type = "prob") %>%
  bind_cols(predict(null_model, vps_testing)) %>%
  bind_cols(select(vps_testing, is_churn)) %>%
  metrics(is_churn, .pred_No, estimate = .pred_class)
```

```
## # A tibble: 4 x 3
##   .metric     .estimator .estimate
##   <chr>       <chr>          <dbl>
## 1 accuracy    binary         0.526
## 2 kap         binary         0
## 3 mn_log_loss binary         0.692
## 4 roc_auc     binary         0.5
```

Modeling & Evaluation cont.

From now on our goal is to beat 0.526 in accuracy, 0.5 in AUC and bend the ROC curve up.



Modeling & Evaluation cont.

We will try to train `svm_poly()` - polynomial support vector machines model.

```
vps_svm <- svm_poly(mode = "classification") %>%
  set_engine("kernlab") %>%
  fit(is_churn ~ ., data = vps_training)
```

```
##  Setting default kernel parameters
```

Modeling & Evaluation cont.

The `svm_poly()` model is performing worse than `null_model()`.

```
predict(vps_svm, vps_testing, type = "prob") %>%
  bind_cols(predict(vps_svm, vps_testing)) %>%
  bind_cols(select(vps_testing, is_churn)) %>%
  metrics(is_churn, .pred_No, estimate = .pred_class)
```

```
## # A tibble: 4 x 3
##   .metric     .estimator .estimate
##   <chr>       <chr>          <dbl>
## 1 accuracy    binary        0.509
## 2 kap         binary        0.0414
## 3 mn_log_loss binary        0.693
## 4 roc_auc     binary        0.480
```

Modeling & Evaluation cont.

We will try to train `logistic_reg()` - generalized linear model for binary outcomes.

```
vps_lreg <- logistic_reg(mode = "classification",
                          engine = "glm") %>%
  fit(is_churn ~ ., data = vps_training)
```

Modeling & Evaluation cont.

The `logistic_reg()` model is performing worse in accuracy but better in AUC than `null_model()`.

```
predict(vps_lreg, vps_testing, type = "prob") %>%
  bind_cols(predict(vps_lreg, vps_testing)) %>%
  bind_cols(select(vps_testing, is_churn)) %>%
  metrics(is_churn, .pred_No, estimate = .pred_class)
```

```
## # A tibble: 4 x 3
##   .metric     .estimator .estimate
##   <chr>       <chr>          <dbl>
## 1 accuracy    binary        0.518
## 2 kap         binary        0.0509
## 3 mn_log_loss binary        0.807
## 4 roc_auc     binary        0.521
```

Modeling & Evaluation cont.

We will try to train `rand_forest()` - model that creates a large number of decision trees.

```
vps_rf <-  rand_forest(mode = "classification") %>%
  set_engine("randomForest") %>%
  fit(is_churn ~ ., data = vps_training)
```

Modeling & Evaluation cont.

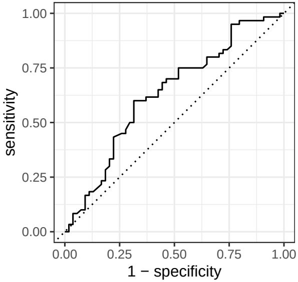
The `rand_forest()` model is performing better in accuracy and AUC than `null_model()`.

```
predict(vps_rf, vps_testing, type = "prob") %>%
  bind_cols(predict(vps_rf, vps_testing)) %>%
  bind_cols(select(vps_testing, is_churn)) %>%
  metrics(is_churn, .pred_No, estimate = .pred_class)
```

```
## # A tibble: 4 x 3
##   .metric     .estimator .estimate
##   <chr>       <chr>          <dbl>
## 1 accuracy    binary         0.596
## 2 kap         binary         0.191
## 3 mn_log_loss binary         0.671
## 4 roc_auc     binary         0.631
```

Modeling & Evaluation cont.

Accuracy, AUC and ROC curve has been bent up comparing to null model.



Deployment

The last model will be used to make predictions on production data. Output is available in https://github.com/JacekPardyak/vps repository.

```
production <- read_csv("./data/vps_test_data.txt")
vps_production <- vps_recipe %>%
  bake(production)

tmp <- predict(vps_rf, vps_production) %>%
  rename(is_churn = .pred_class) %>%
  mutate(is_churn = ifelse(is_churn == "Yes", 1, 0 ))

production %>% select(! one_of('is_churn')) %>%
  bind_cols(tmp) %>%
  write_csv("./data/vps_test_data_pred.txt")
```

Further steps

In other circumstances, I would go further with:

- feature engineering - combining and transforming further existing variables,
- tuning parameters of already tested algorithms used to train models,
- try another algorithms, such as: Boosted tree (XGBoost), K-nearest neighbor, Neural network with Keras
- demonstrate how to use **SparkR** (R on Spark)