# R (ADP)

2023-05-18

# Table of contents

# Preface

This is a Quarto book.

To learn more about Quarto books visit https://quarto.org/docs/books.

```
1 + 1
```

```
[1] 2
```

# 1 Introduction

This is a book created from markdown and executable code.

See Knuth (1984) for additional discussion of literate programming.

```
kmeans_spec <- linear_reg()
show_engines("linear_reg")
```

```
# A tibble: 7 x 2
  engine mode
  <chr>  <chr>
1 lm     regression
2 glm    regression
3 glmnet regression
4 stan   regression
5 spark  regression
6 keras  regression
7 brulee regression
```

#### 1.0.0.1

```
yardstick::metric_set()
```

# Part I

# ADP :

R ADP

# 2 27 ADP

# 1.

## 1.1. (EDA) .

.

```
pacman::p_load(tidyverse, tidymodels, data.table, gt,
               skimr, ggcorrplot, themis, solitude)
```

.

```
db_1a <- fread("test/27/data/problem1.csv")
```

(EDA) `skim` .

```
db_1a %>% skim()
```

Table 2.1: Data summary

| | |
|---|---|
| Name | Piped data |
| Number of rows | 1193 |
| Number of columns | 20 |
| Key | NULL |
| _____ | |
| Column type frequency: | |
| numeric | 20 |
| _____ | |
| Group variables | None |

**Variable type: numeric**

| skim_variable | n_missing | complete_rate | mean | sd | p0 | p25 | p50 | p75 | p100 | hist |
|---|---|---|---|---|---|---|---|---|---|---|
| Time | 0 | 1 | 91514.49 | 47896.08 | 60.00 | 50265.00 | 81797.00 | 136995.00 | 172676.00 | |

| skim_variable | n_missing | complete_rate | mean | sd | p0 | p25 | p50 | p75 | p100 | hist |
|---|---|---|---|---|---|---|---|---|---|---|
| V1 | 0 | 1 | -0.76 | 3.62 | -30.55 | -1.30 | -0.30 | 1.25 | 2.32 | |
| V2 | 0 | 1 | 0.54 | 2.66 | -33.64 | -0.44 | 0.23 | 1.11 | 19.17 | |
| V3 | 0 | 1 | -1.15 | 3.91 | -31.10 | -1.61 | -0.23 | 0.81 | 3.32 | |
| V4 | 0 | 1 | 0.78 | 2.35 | -4.29 | -0.61 | 0.33 | 1.34 | 12.11 | |
| V5 | 0 | 1 | -0.41 | 2.70 | -22.11 | -0.84 | -0.07 | 0.68 | 15.28 | |
| V6 | 0 | 1 | -0.28 | 1.51 | -10.89 | -1.02 | -0.38 | 0.30 | 6.27 | |
| V7 | 0 | 1 | -0.85 | 3.40 | -37.06 | -0.81 | -0.08 | 0.46 | 8.12 | |
| V8 | 0 | 1 | 0.15 | 2.47 | -37.35 | -0.22 | 0.07 | 0.45 | 20.01 | |
| V9 | 0 | 1 | -0.45 | 1.66 | -11.13 | -1.04 | -0.21 | 0.45 | 5.92 | |
| V10 | 0 | 1 | -0.90 | 2.90 | -23.23 | -0.88 | -0.23 | 0.29 | 7.14 | |
| V11 | 0 | 1 | 0.66 | 1.96 | -2.65 | -0.60 | 0.28 | 1.21 | 11.67 | |
| V12 | 0 | 1 | -1.01 | 3.00 | -17.23 | -0.97 | -0.01 | 0.51 | 3.11 | |
| V13 | 0 | 1 | 0.01 | 1.01 | -2.80 | -0.69 | 0.02 | 0.70 | 3.07 | |
| V14 | 0 | 1 | -1.17 | 3.23 | -18.49 | -0.95 | -0.10 | 0.42 | 3.89 | |
| V15 | 0 | 1 | 0.02 | 0.91 | -4.50 | -0.55 | 0.05 | 0.66 | 2.87 | |
| V16 | 0 | 1 | -0.63 | 2.27 | -14.13 | -0.70 | -0.06 | 0.46 | 3.14 | |
| V17 | 0 | 1 | -1.07 | 3.81 | -25.16 | -0.68 | -0.15 | 0.37 | 6.74 | |
| Amount | 0 | 1 | 88.89 | 220.14 | 0.00 | 3.54 | 20.99 | 77.49 | 3335.73 | |
| Class | 0 | 1 | 0.17 | 0.37 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 | |

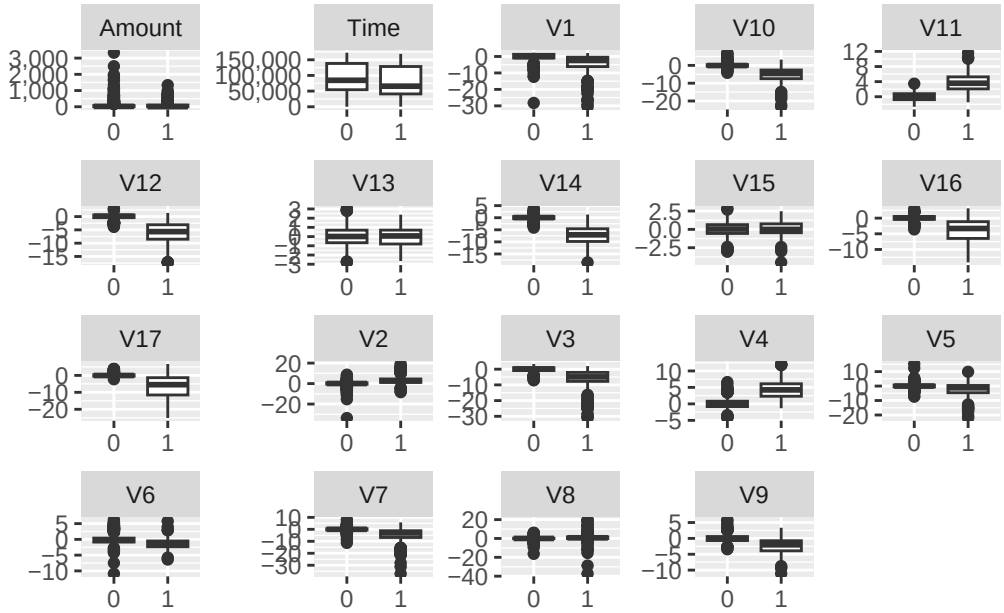
:

- 
- (numeric) , Class (factor)

- Class 1 16.7%

.

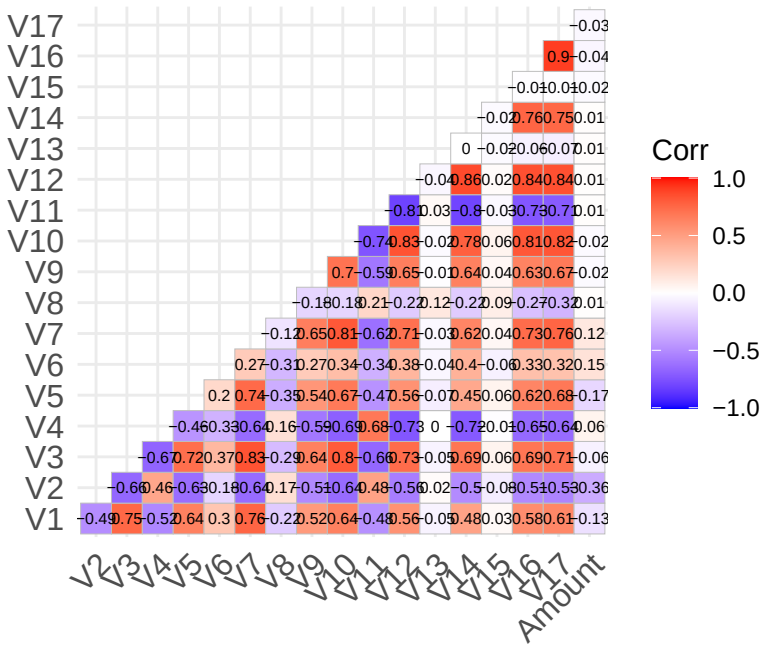
```
db_1a %>%
  # id
  mutate(id = row_number()) %>%
  # Wide-to-long
  pivot_longer(cols = !c(id, Class)) %>%
  ggplot(aes(x = as.factor(Class), y = value)) +
  geom_boxplot() +
  facet_wrap(name ~ ., scales = "free") +
  labs(x = "", y = "") +
  scale_y_continuous(labels = comma)
```




## 1.2.

.

```
db_1a %>% select(-c("Time", "Class")) %>%
  cor() %>% ggcorrplot(type = "lower", lab = TRUE, lab_size = 2)
```




V1-V3, V14-V17 0.75 . .

# 2.

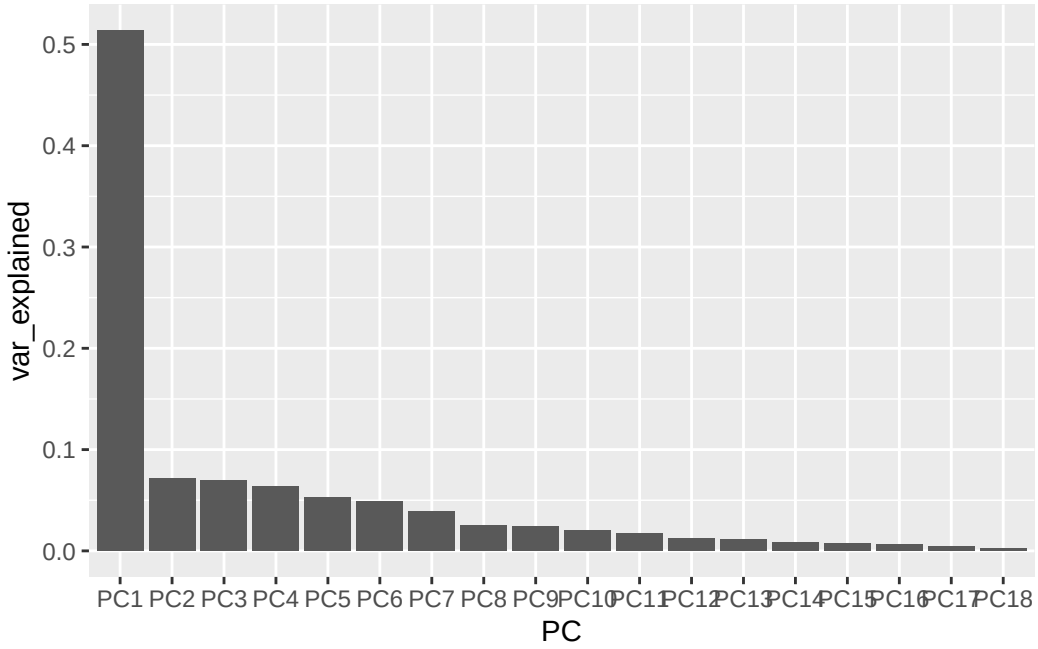
## 2.1. 2 .

PCA , MDS , t-SNE . ,
. , . t-SEN
.

**PCA** .

PCA scree .

```
db_1b <- db_1a %>% select(-c("Time", "Class"))

# PCA   recipe
rec <- recipe(~., data = db_1b) %>%
  step_center(all_predictors()) %>%
  step_scale(all_predictors()) %>%
  step_pca(all_predictors())

# recipe   ( )
prep_rec <- prep(rec)

# Scree
sdev <- prep_rec$steps[[3]]$res$sdev
percent_variation <- sdev^2 / sum(sdev^2)
data.frame(PC=paste0("PC",1:length(sdev)),
                     var_explained=percent_variation,
                     stringsAsFactors = FALSE) %>%
  mutate(PC = fct_inorder(PC)) %>%
  ggplot(aes(x=PC,y=var_explained))+geom_col()
```

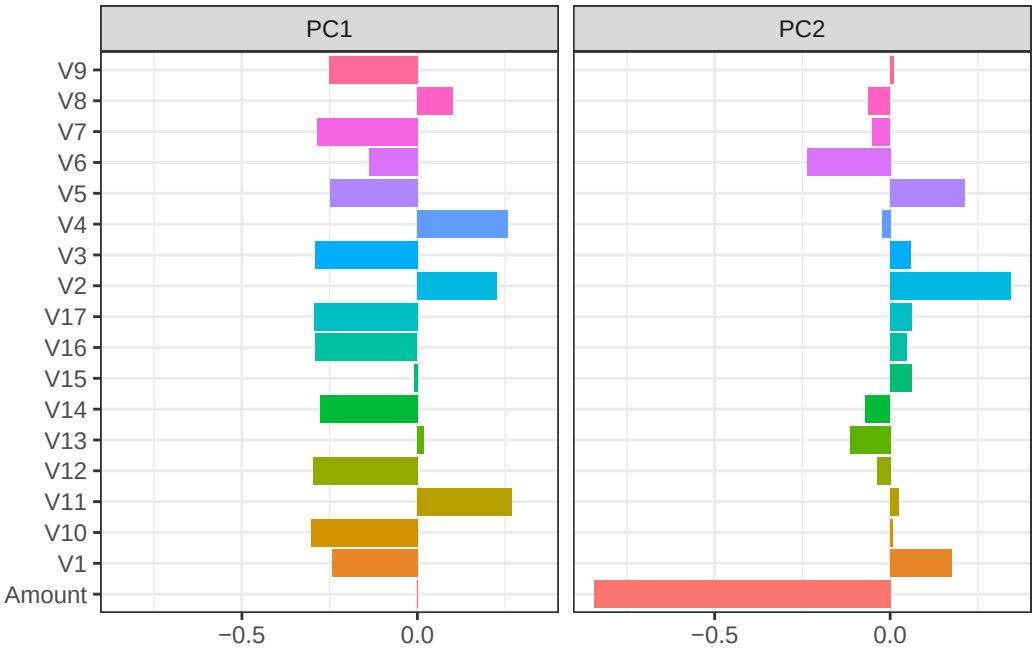



2 1 . 2 .

2 PCA .

```
db_1b <- db_1a %>% select(-c("Time", "Class"))
# PCA   recipe
rec <- recipe(~., data = db_1b) %>%
  step_center(all_predictors()) %>%
  step_scale(all_predictors()) %>%
  step_pca(all_predictors(), num_comp = 2) #    2

prep_rec <- prep(rec)

tidy_rec <- tidy(prep_rec, number = 3)

tidy_rec %>%
  filter(component %in% paste0("PC", 1:2)) %>%
  mutate(component = fct_inorder(component)) %>%
  ggplot(aes(value, terms, fill = terms)) +
  geom_col(show.legend = FALSE) +
  facet_wrap(~component, nrow = 1) +
  labs(y = NULL, x = NULL) +
```

```
theme_bw()
```


PC1
PC2
V9
V8
V7
V6
V5
V4
V3
V2
V17
V16
V15
V14
V13
V12
V11
V10
V1
Amount
−0.5
0.0
−0.5
0.0

# 3.

## 3.1. .

.

- :  ,
- :

.

- :  ,
- :

. Class  20 ,  .

```
table(db_1a$Class)
```

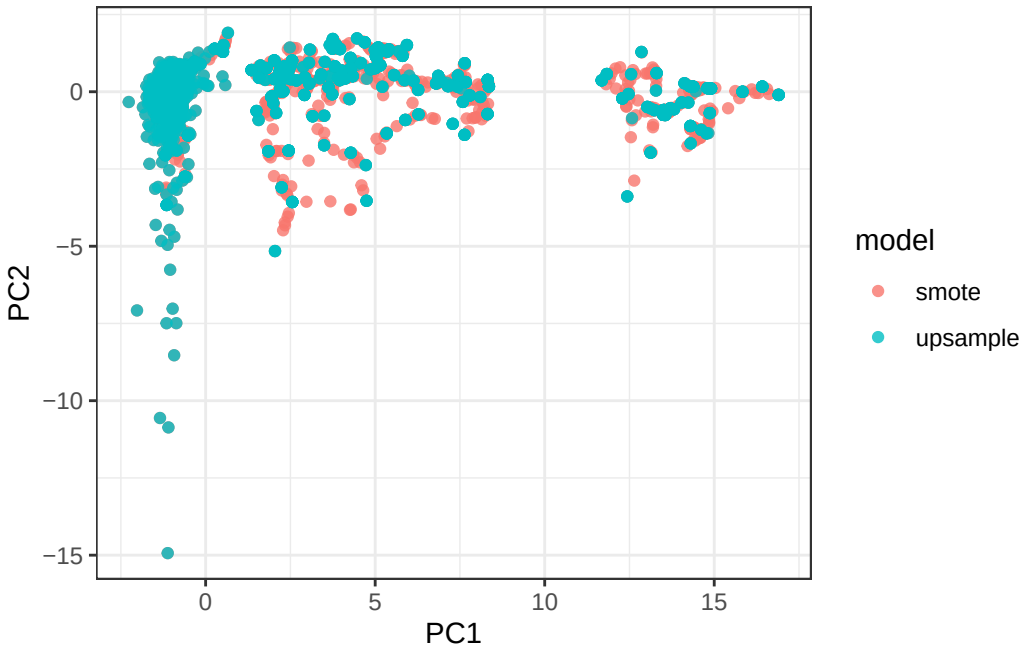
```
  0   1
993 200
```

## 3.2.  2  .

, 1) SMOTE  2) upsampling  .

```
db_1c <- db_1a[, -c("Time")]

# Recipe
rec <- recipe(Class ~ ., data = db_1c) %>%
  step_mutate(Class = as.factor(Class)) %>%
  step_center(all_predictors(),  -all_outcomes()) %>%
  step_scale(all_predictors(),  -all_outcomes()) %>%
  step_pca(all_predictors(),  -all_outcomes(), num_comp = 2) #    2
```

```r
#
model_spec <- decision_tree() %>%
  set_engine("rpart") %>%
  set_mode("classification")

# SMOTE
rec_smote <- rec %>% step_smote(Class) %>% prep(db_1c) %>% bake(new_data = NULL)
rec_upsample <- rec %>% step_upsample(Class) %>% prep(db_1c) %>% bake(new_data = NULL)

bind_rows(rec_smote %>% mutate(model = "smote"),
          rec_upsample %>% mutate(model = "upsample")) %>%
  ggplot(aes(x = PC1, y = PC2, color = model)) +
  geom_point(alpha = 0.8) +
  theme_bw()
```



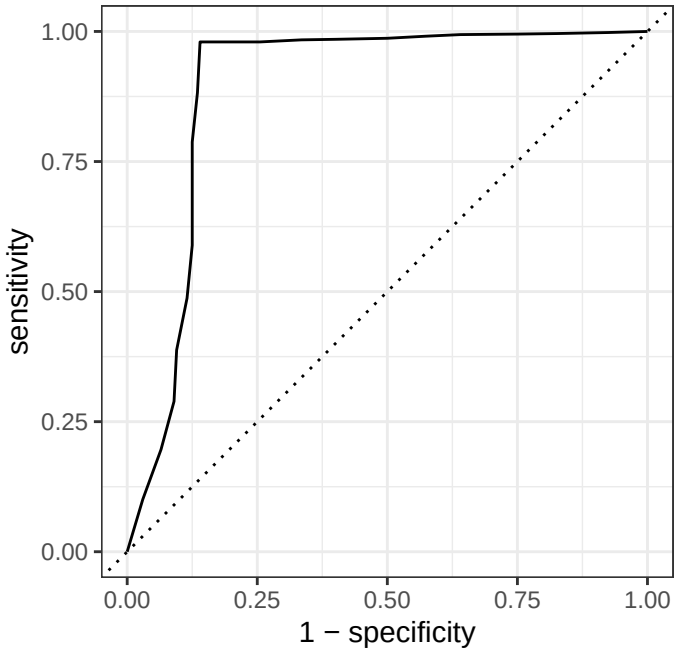

, upsample SMOTE .

## 3.3. ,

```
set.seed(2023)

db_1c <- db_1a[, -c("Time")]

# Recipe
rec <- recipe(Class ~ ., data = db_1c) %>%
  step_mutate(Class = as.factor(Class)) %>%
  step_center(all_predictors(),  -all_outcomes()) %>%
  step_scale(all_predictors(),  -all_outcomes()) %>%
  step_pca(all_predictors(),  -all_outcomes(), num_comp = 2) #    2

#
model_spec <- decision_tree() %>%
  set_engine("rpart") %>%
  set_mode("classification")

# SMOTE
rec_smote <- rec %>% step_smote(Class) %>% prep(db_1c)
wk_smote <- workflow() %>% add_recipe(rec_smote) %>% add_model(model_spec)

cv <- vfold_cv(db_1c)

result_smote <- fit_resamples(
  wk_smote,
  resamples = cv,
  control = control_resamples(save_pred = TRUE))

predictions <- result_smote %>%
  collect_predictions()

collect_metrics(result_smote)
```

```
# A tibble: 2 x 6
  .metric  .estimator  mean     n std_err .config
  <chr>    <chr>      <dbl> <int>   <dbl> <chr>
1 accuracy binary     0.960    10 0.00671 Preprocessor1_Model1
2 roc_auc  binary     0.922    10 0.0185  Preprocessor1_Model1
```

```
predictions %>%
  yardstick::roc_curve(Class, .pred_0) %>% autoplot()
```




, 95.9%, AUC 92.1% .

# 4.

## 2.1 4.1. 2 .

- Isolation Forest: , . ,
  - :
  - :
- Autoencoder: , . , Autoencoder , ,
  . .
  - :
  - :

## 2.2 4.2. 3

```
db_1c <- db_1a[, -c("Time")]

# Recipe
rec <- recipe(Class ~ ., data = db_1c) %>%
  step_mutate(Class = as.factor(Class)) %>%
  step_center(all_predictors(),  -all_outcomes()) %>%
  step_scale(all_predictors(),  -all_outcomes()) %>%
  step_pca(all_predictors(),  -all_outcomes(), num_comp = 2) #    2

# SMOTE
rec_smote <- rec %>% step_smote(Class) %>% prep(db_1c)



wk_smote <- workflow() %>% add_recipe(rec_smote) %>% add_model(model_spec)

data_preprocessed <- juice(rec_smote)
```

```
model <- isolationForest$new()
model$fit(data_preprocessed[, -which(names(data_preprocessed) == "Class")])
```

```
INFO  [17:59:25.393] dataset has duplicated rows
INFO  [17:59:25.411] Building Isolation Forest ...
INFO  [17:59:25.434] done
INFO  [17:59:25.435] Computing depth of terminal nodes ...
INFO  [17:59:25.614] done
INFO  [17:59:25.653] Completed growing isolation forest
```

```
scores <- model$predict(data_preprocessed[, -which(names(data_preprocessed) == "Class")])
data_preprocessed$anomaly_score <- scores

quantile(data_preprocessed$anomaly_score$anomaly_score)
```

```
      0%       25%       50%       75%      100%
0.5820092 0.5827973 0.5847722 0.5955529 0.7654805
```

```
#
threshold <- 0.6
data_preprocessed$anomaly <- ifelse(data_preprocessed$anomaly_score > threshold, 1, 0)

# SMOTE
ttt <- as.data.table(data_preprocessed$anomaly)

data_preprocessed$anomaly <- as.factor(ttt$anomaly_score)
table(data_preprocessed$Class, data_preprocessed$anomaly)
```

```
    0   1
0 929  64
1 649 344
```

```
tttt <- data_preprocessed %>%
  conf_mat(truth = Class, estimate = anomaly)


class_metrics <- metric_set(accuracy, sens, spec)
```

```r
data_preprocessed |>
  class_metrics(truth = Class, estimate = anomaly)
```

```
# A tibble: 3 x 3
  .metric  .estimator .estimate
  <chr>    <chr>          <dbl>
1 accuracy binary         0.641
2 sens     binary         0.936
3 spec     binary         0.346
```

- https://amaruak00.github.io/2022/12/17/adp27th.html
- https://www.datamanim.com/dataset/ADPpb/00/27.html
- https://www.kaggle.com/code/johyunkang/adp-27/notebook

# 3 Summary

In summary, this book has no content whatsoever.

```
1 + 1
```

```
[1] 2
```

# References

Knuth, Donald E. 1984. “Literate Programming.” *Comput. J.* 27 (2): 97–111. https://doi.org/10.1093/comjnl/27.2.97.