FRAUD DETECTION IN R

# Dealing with imbalanced datasets

Bart Baesens
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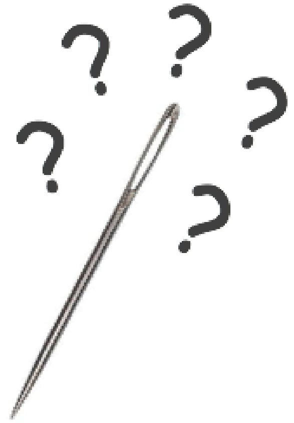
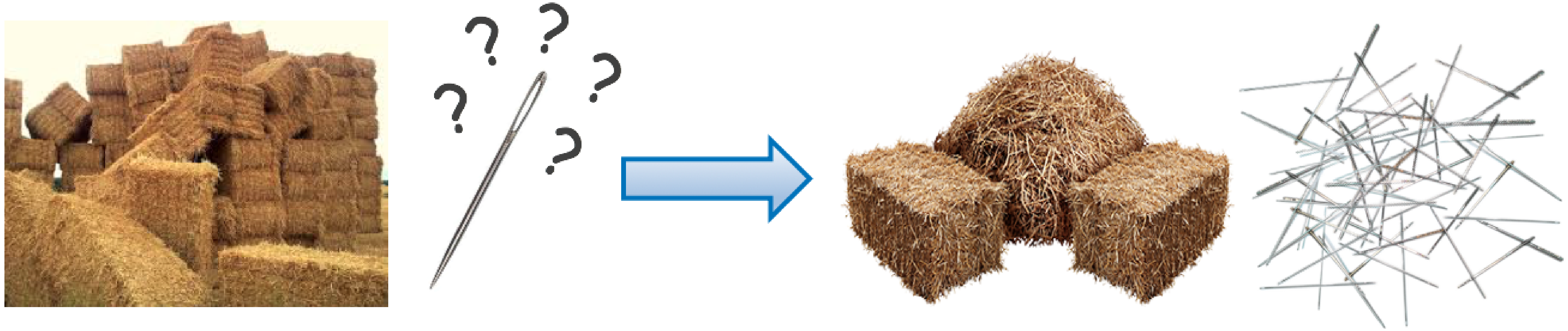
# Imbalanced data sets

- **Key challenge**: label events as fraud or not
  - Major challenge for classification methods & anomaly detection techniques
- Classifier tends to favour majority class (= no-fraud)
  - large classification error over the fraud cases
- Classifiers learn better from a *balanced* distribution

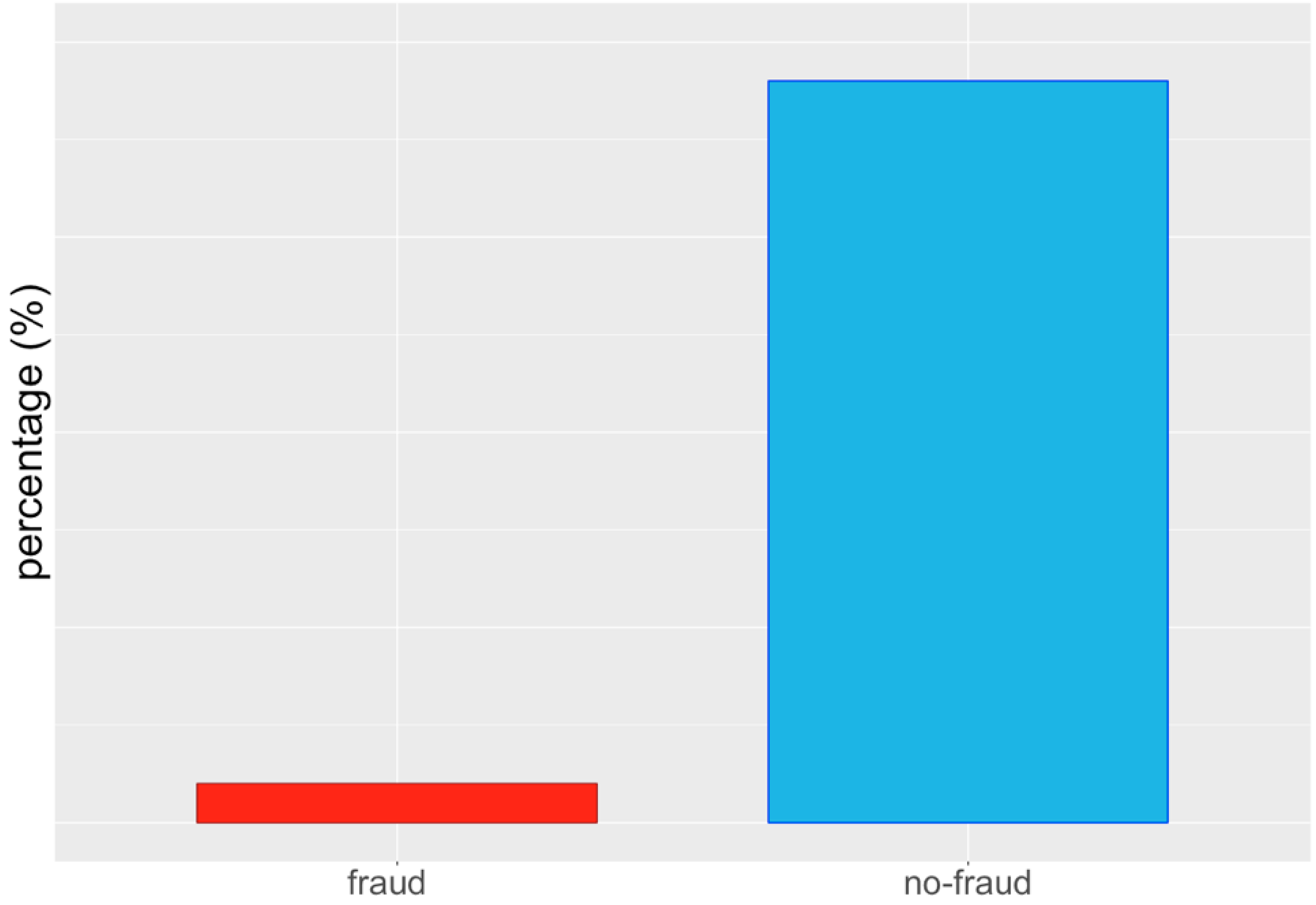


# Imbalanced data sets

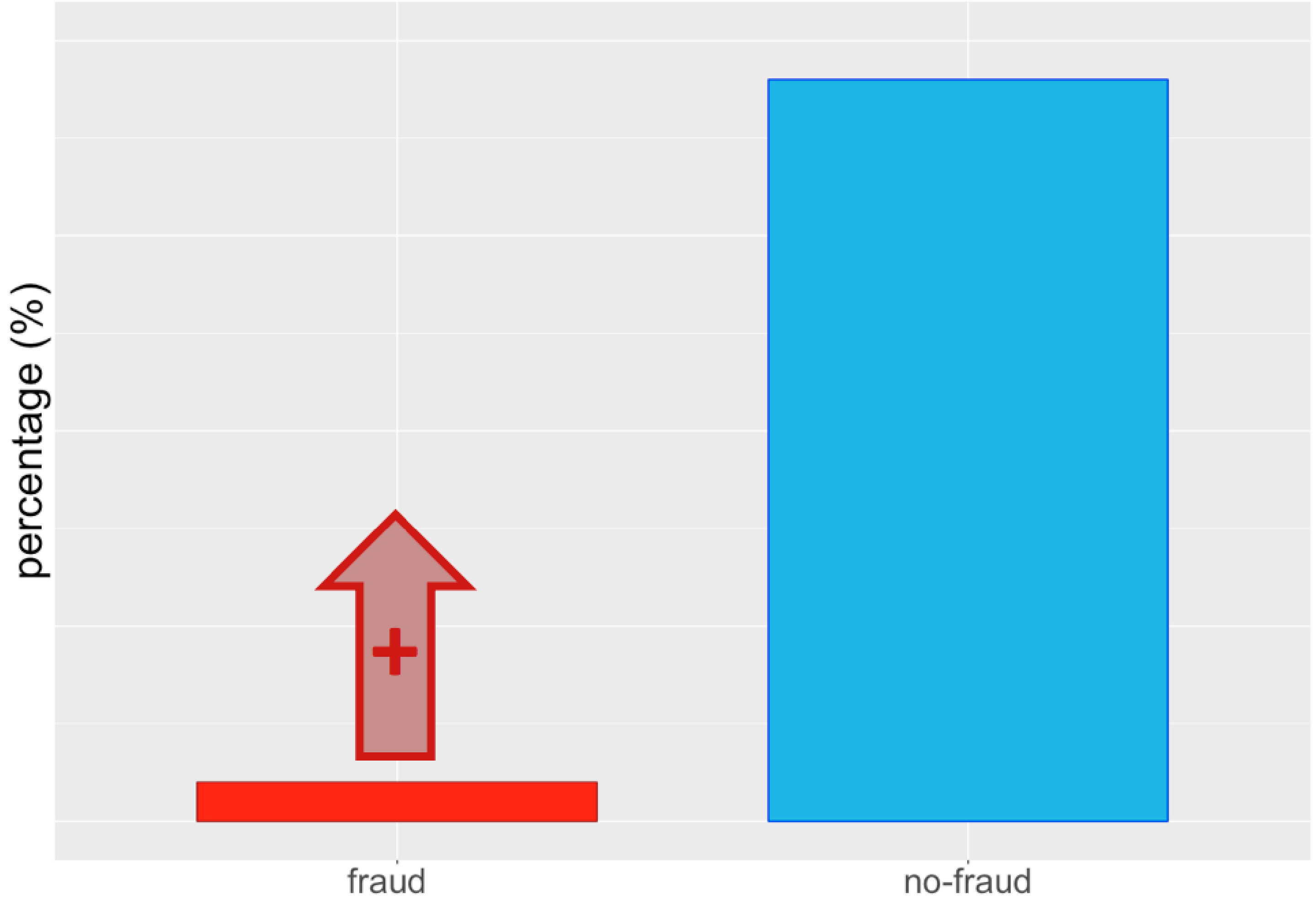
- **Key challenge** : label events as fraud or not
  - Major challenge for classification methods & anomaly detection techniques
- Classifier tends to favour majority class (= no-fraud)
  - large classification error over the fraud cases
- Classifiers learn better from a *balanced* distribution
- **Possible solution** : *change class distribution* with sampling methods



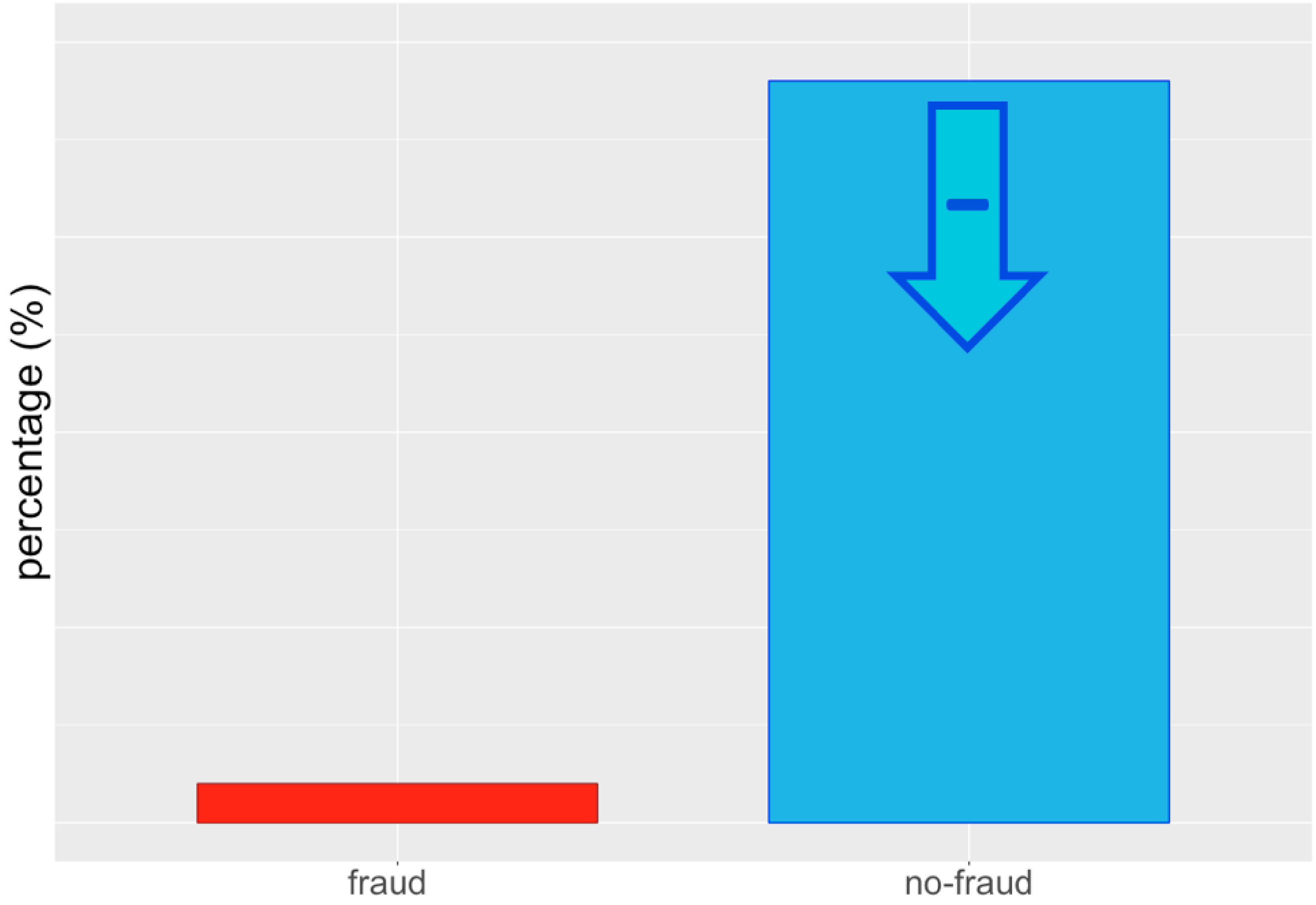
# Original imbalance



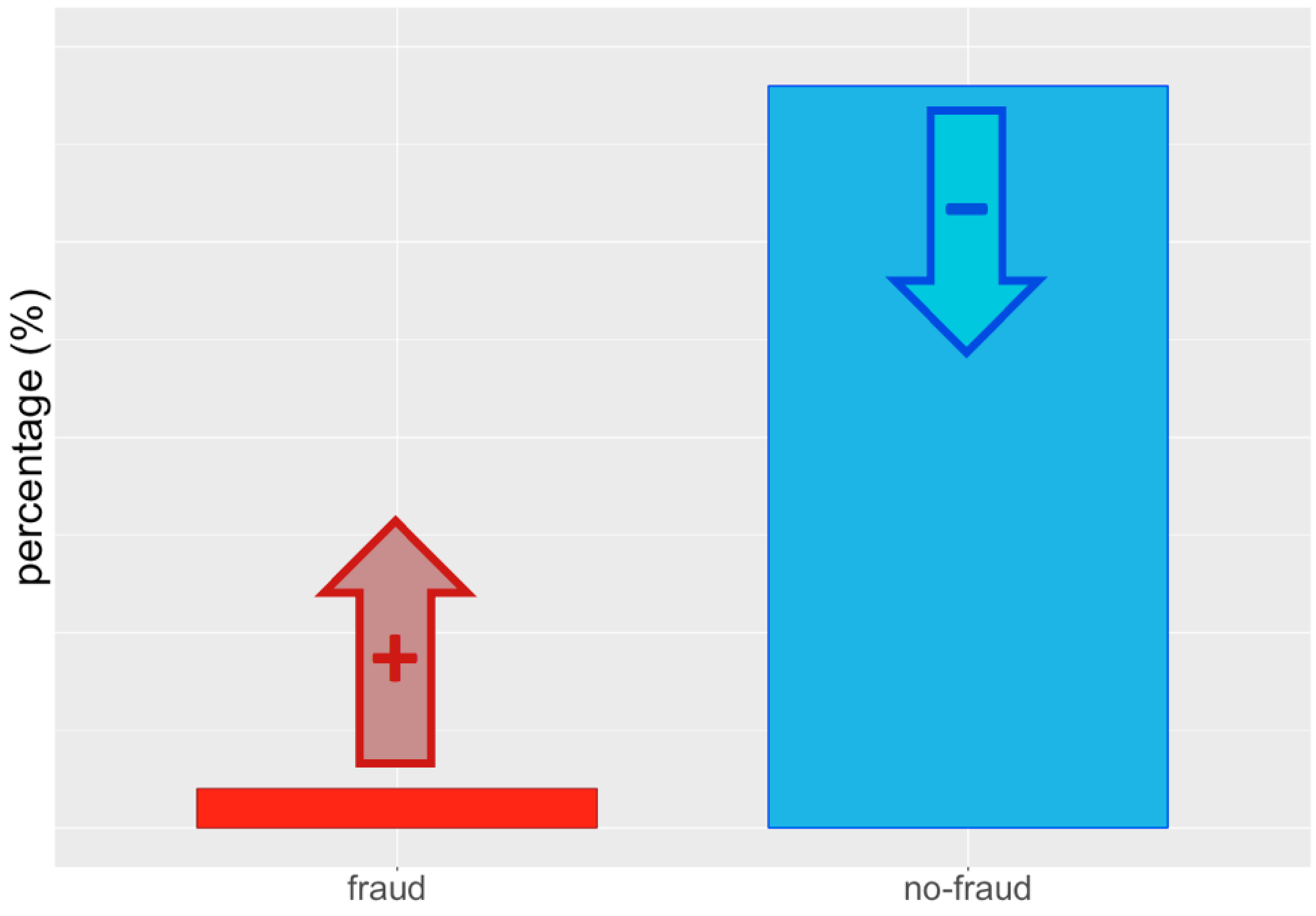
# Over-sampling minority class...



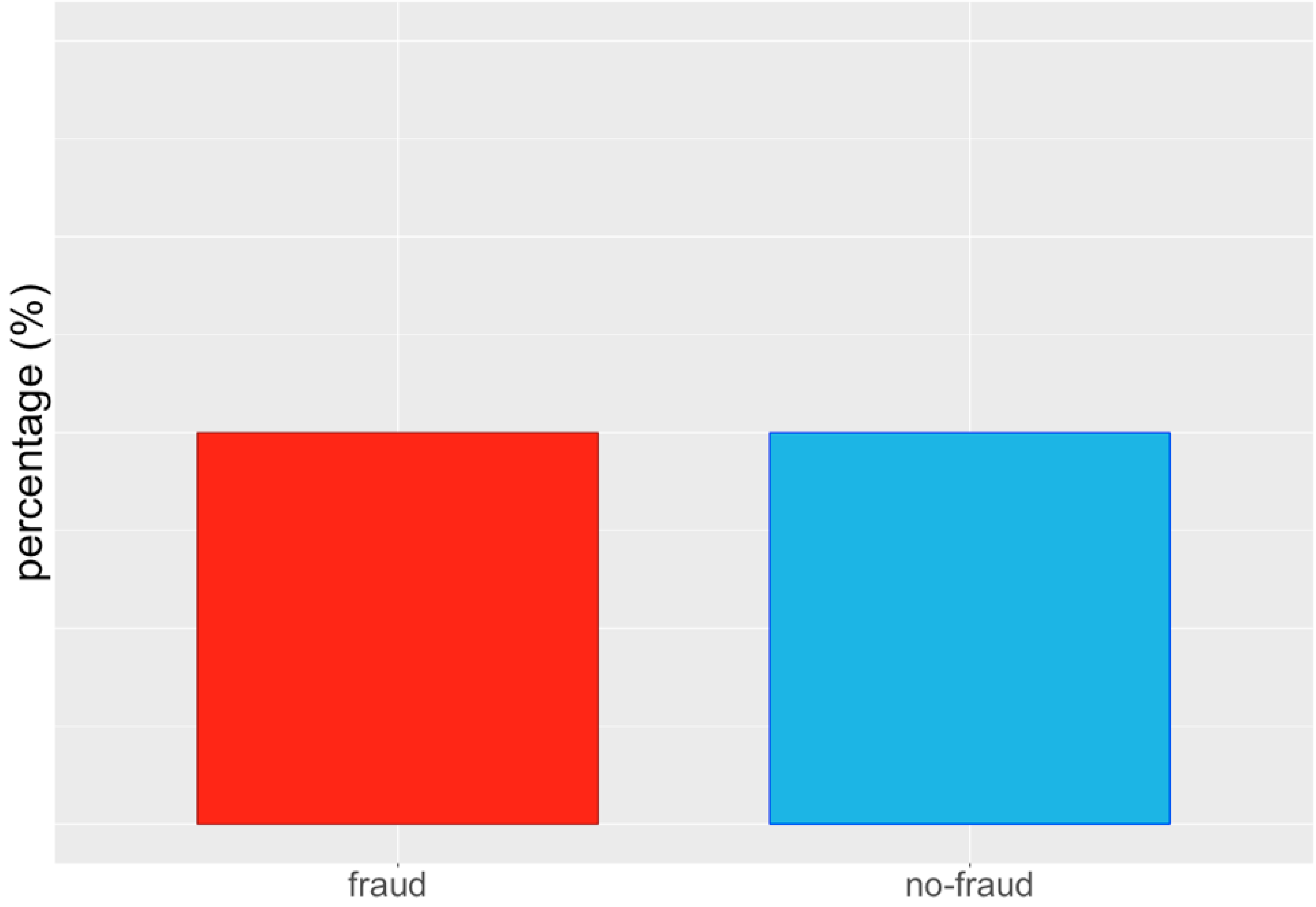
# ... or under-sampling majority class ...



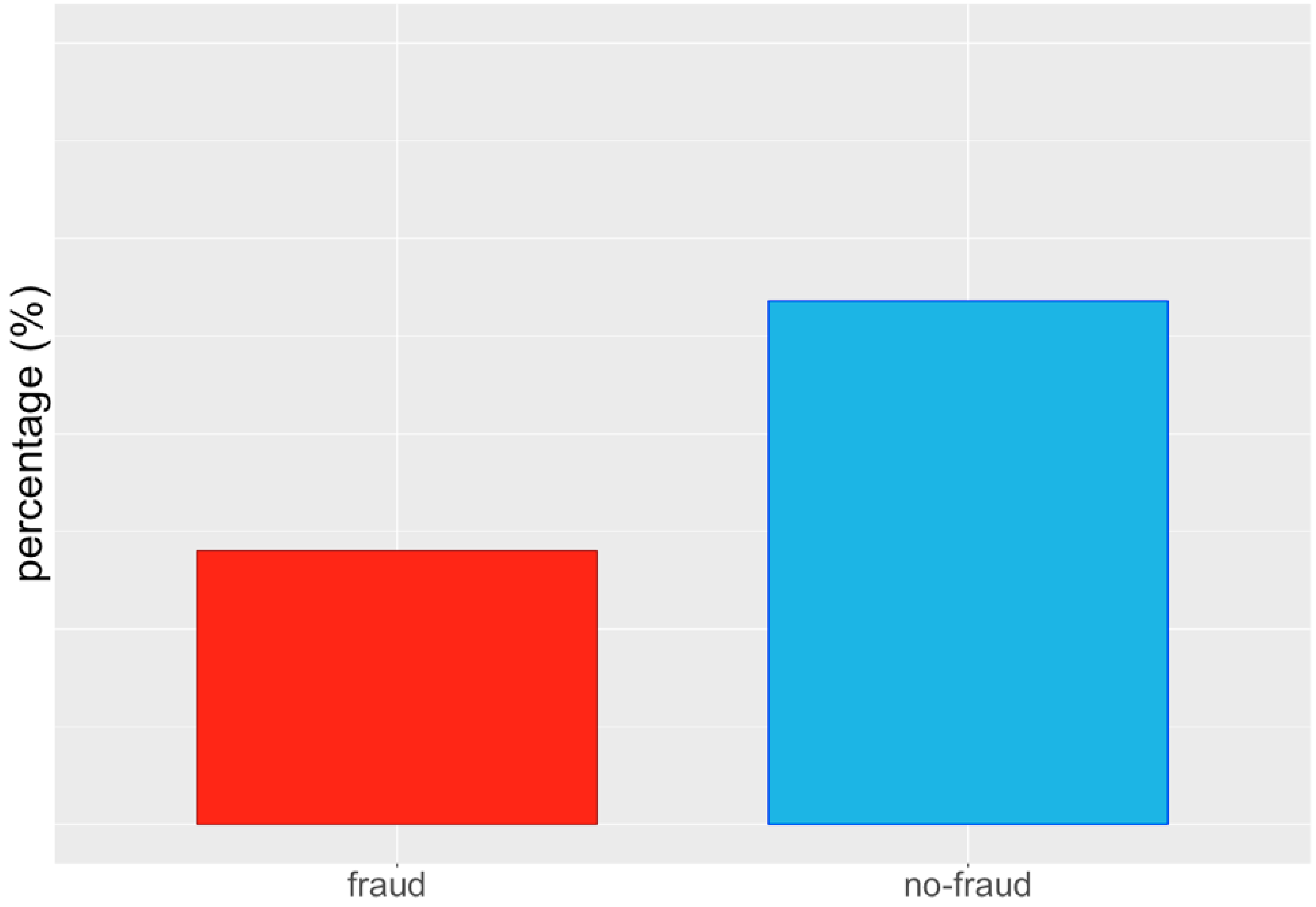
# ... or both!



# Result after sampling...



# ... or like this



# Random over-sampling (ROS)

**Original data**

| ID | Variables | Class |
|---|---|---|
| 1 | ... | Fraud |
| 2 | ... | No fraud |
| 3 | ... | No fraud |
| 4 | ... | Fraud |
| 5 | ... | No fraud |
| 6 | ... | No fraud |
| 7 | ... | No fraud |
| 8 | ... | No fraud |
| 9 | ... | Fraud |
| 10 | ... | No fraud |

# Random over-sampling (ROS)

**Original data**

| | ID | Variables | Class |
|---|---|---|---|
| Train | 1 | ··· | Fraud |
| | 2 | ··· | No fraud |
| | 3 | ··· | No fraud |
| | 4 | ··· | Fraud |
| | 5 | ··· | No fraud |
| | 6 | ··· | No fraud |
| Test | 7 | ··· | No fraud |
| | 8 | ··· | No fraud |
| | 9 | ··· | Fraud |
| | 10 | ··· | No fraud |

# Random over-sampling (ROS)

**Original data**

| | ID | Variables | Class |
|---|---|---|---|
| Train | 1 | ... | Fraud |
| | 2 | ... | No fraud |
| | 3 | ... | No fraud |
| | 4 | ... | Fraud |
| | 5 | ... | No fraud |
| | 6 | ... | No fraud |
| Test | 7 | ... | No fraud |
| | 8 | ... | No fraud |
| | 9 | ... | Fraud |
| | 10 | ... | No fraud |

# Random over-sampling (ROS)

**Original data**

| | ID | Variables | Class |
|---|---|---|---|
| Train | 1 | ··· | Fraud |
| | 2 | ··· | No fraud |
| | 3 | ··· | No fraud |
| | 4 | ··· | Fraud |
| | 5 | ··· | No fraud |
| | 6 | ··· | No fraud |
| Test | 7 | ··· | No fraud |
| | 8 | ··· | No fraud |
| | 9 | ··· | Fraud |
| | 10 | ··· | No fraud |

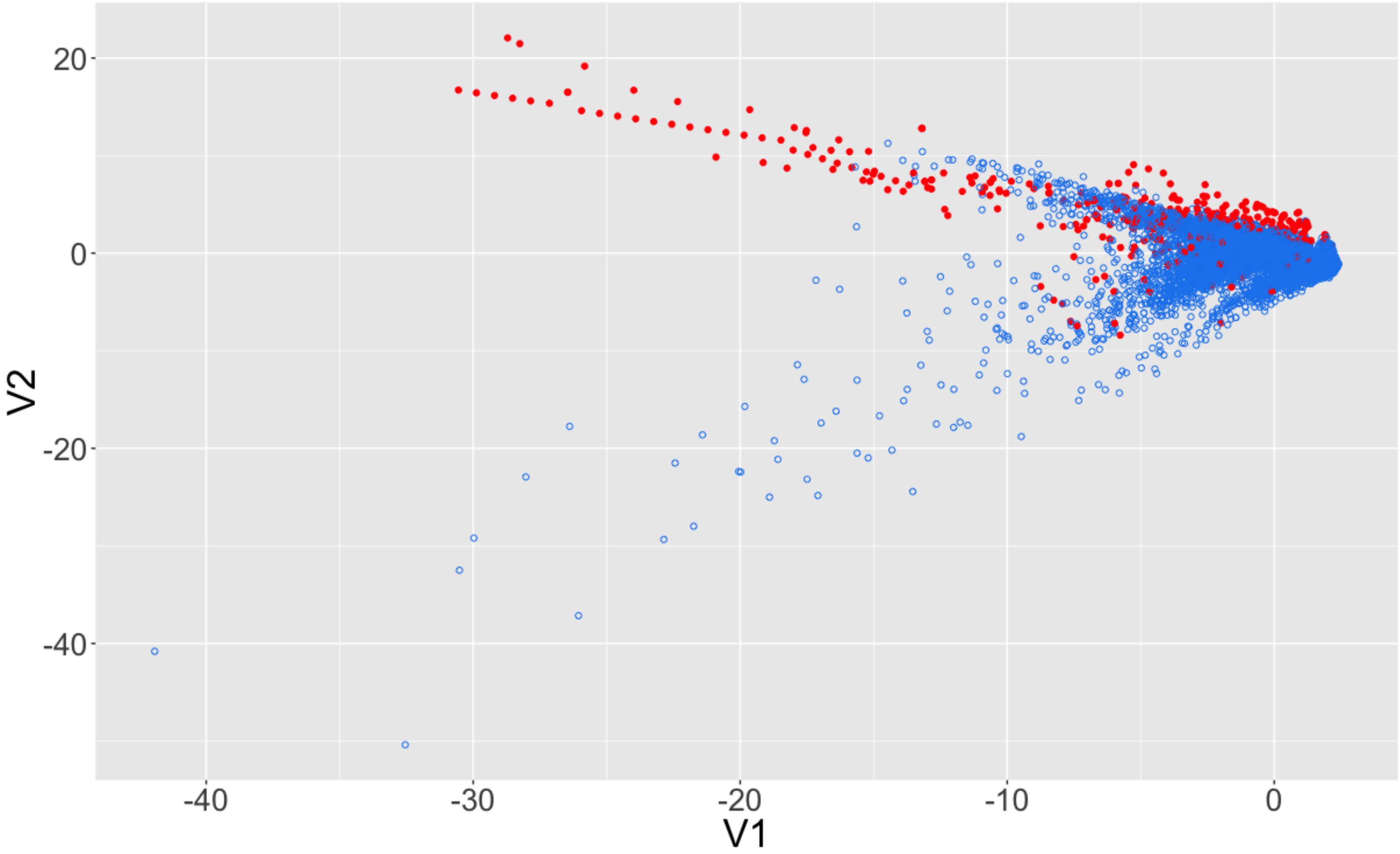
**Over-sampled data**

| | ID | Variables | Class |
|---|---|---|---|
| Train | 1 | ··· | Fraud |
| | 1 | ··· | Fraud |
| | 2 | ··· | No fraud |
| | 3 | ··· | No fraud |
| | 4 | ··· | Fraud |
| | 4 | ··· | Fraud |
| | 5 | ··· | No fraud |
| | 6 | ··· | No fraud |
| Test | 7 | ··· | No fraud |
| | 8 | ··· | No fraud |
| | 9 | ··· | Fraud |
| | 10 | ··· | No fraud |

# Random over-sampling in practice

- Credit Card Fraud Detection dataset on Kaggle
  - $\sim$ 300K anonymized credit card transfers labeled as fraudulent or genuine
- About the data...
  - Numerical (anonymized) variables: V1, V2, ... , V28
  - Time = seconds elapsed between each transfer and first transfer in dataset
  - Amount = transaction amount
  - Class = response variable: value 1 in case of fraud and 0 otherwise

# A look at (a subset of) the dataset



# Check the imbalance

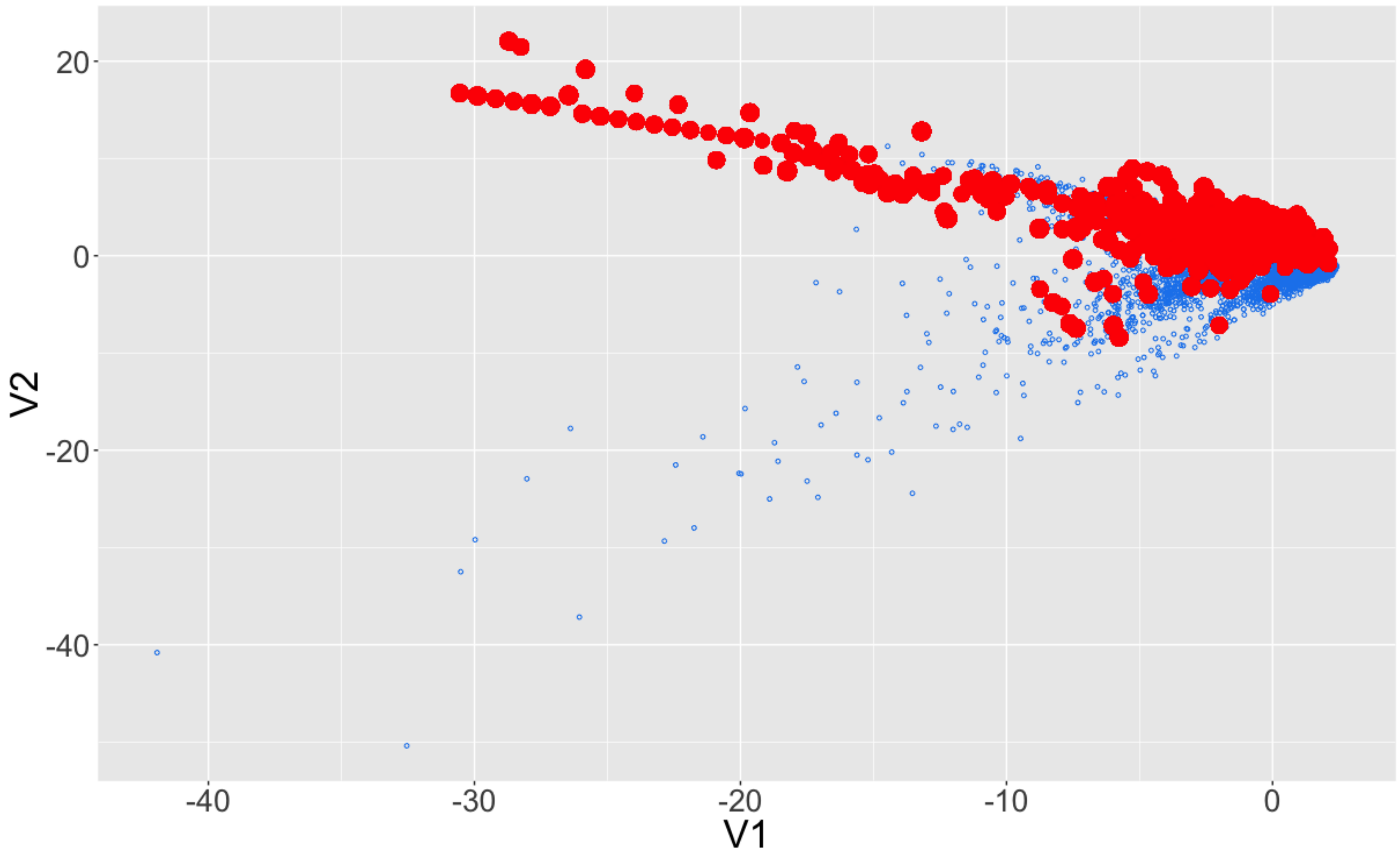
```
head(creditcard)

  Time        V1         V2   ...           V27         V28 Amount Class
1    0  1.1918571  0.2661507  ...  -0.0089830991  0.01472417   2.69     0
2   10  0.3849782  0.6161095  ...   0.0424724419 -0.05433739   9.99     0
3   12 -0.7524170  0.3454854  ...  -0.1809975001  0.12939406  15.99     0
4   17  0.9624961  0.3284610  ...   0.0163706433 -0.01460533  34.09     0
5   34  0.2016859  0.4974832  ...   0.1427572469  0.21923761   9.99     0
6   35  1.3863970 -0.7942095  ...   0.0005313319  0.01991062  30.90     0

table(creditcard$Class)

    0     1
24108   492

prop.table(table(creditcard$Class))

   0    1
0.98 0.02
```

# ovun.sample from ROSE package

- ROSE package: Random Over-Sampling Examples
- `ovun.sample()` for random over-sampling, under-sampling or combination!

```
n_legit <- 24108
new_frac_legit <- 0.50
new_n_total <- n_legit/new_frac_legit # = 21408/0.50 = 42816

library(ROSE)
oversampling_result <- ovun.sample(Class ~ .,
                                   data = creditcard,
                                   method = "over",
                                   N = new_n_total,
                                   seed = 2018)

oversampled_credit <- oversampling_result$data

table(oversampled_credit$Class)

    0     1
24108 24108
```

# A look at the over-sampled dataset



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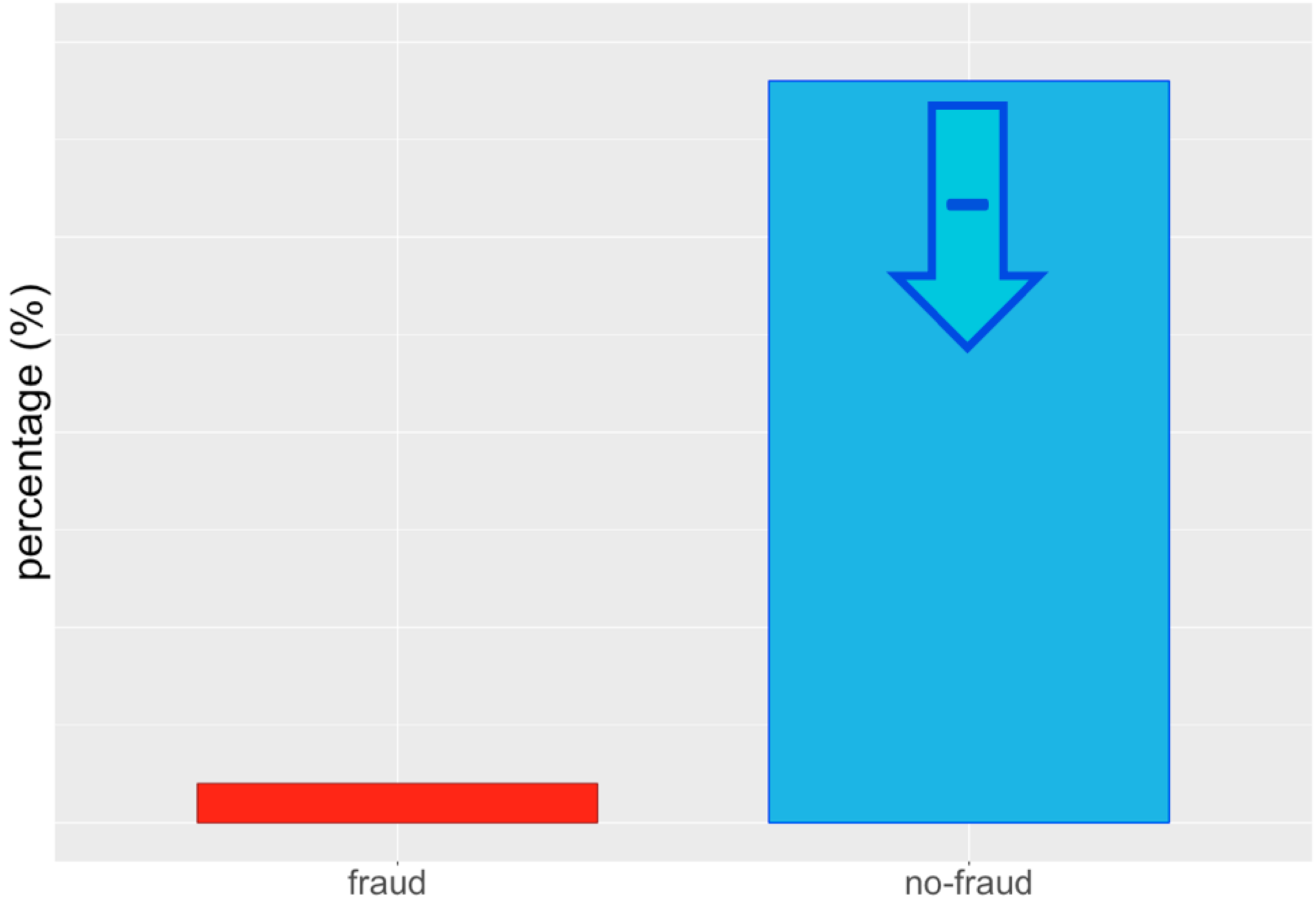
# Let's practice!

FRAUD DETECTION IN R

# Random under-sampling

Bart Baesens
Professor Data Science at KU Leuven

# Random under-sampling (RUS)



# Random under-sampling (RUS)

**Original data**

| | ID | Variables | Class |
|---|---|---|---|
| Train | 1 | ... | Fraud |
| | 2 | ... | No fraud |
| | 3 | ... | No fraud |
| | 4 | ... | Fraud |
| | 5 | ... | No fraud |
| | 6 | ... | No fraud |
| Test | 7 | ... | No fraud |
| | 8 | ... | No fraud |
| | 9 | ... | Fraud |
| | 10 | ... | No fraud |

# Random under-sampling (RUS)

**Original data**

| | ID | Variables | Class |
|---|---|---|---|
| Train | 1 | ··· | Fraud |
| | ~~2~~ | ~~···~~ | ~~No Fraud~~ |
| | 3 | ··· | No fraud |
| | 4 | ··· | Fraud |
| | ~~5~~ | ~~···~~ | ~~No Fraud~~ |
| | 6 | ··· | No fraud |
| Test | 7 | ··· | No fraud |
| | 8 | ··· | No fraud |
| | 9 | ··· | Fraud |
| | 10 | ··· | No fraud |

# Random under-sampling (RUS)

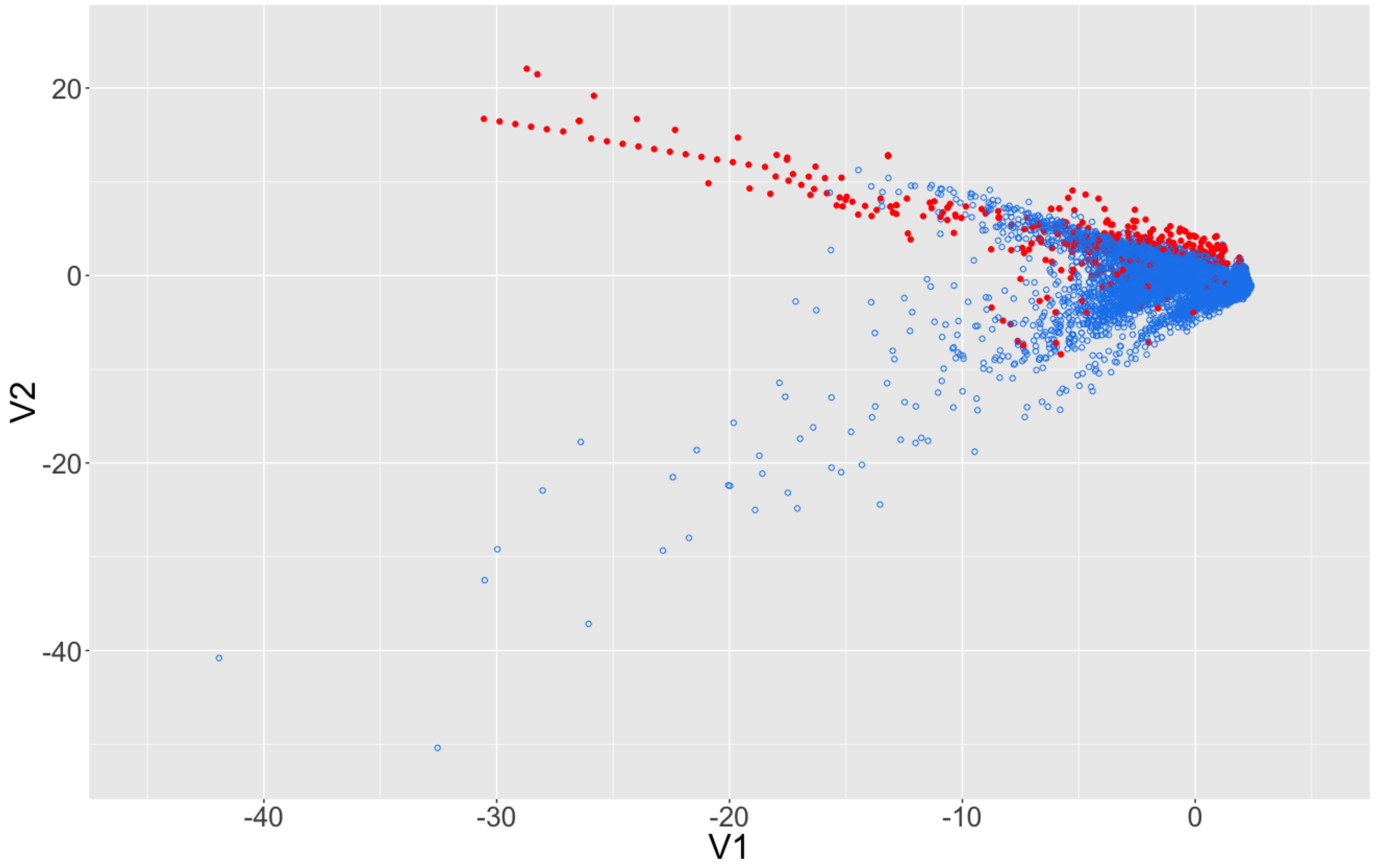
**Original data**

| | ID | Variables | Class |
|---|---|---|---|
| Train | 1 | ... | Fraud |
| | ~~2~~ | ~~...~~ | ~~No Fraud~~ |
| | 3 | ... | No fraud |
| | 4 | ... | Fraud |
| | ~~5~~ | ~~...~~ | ~~No Fraud~~ |
| | 6 | ... | No fraud |
| Test | 7 | ... | No fraud |
| | 8 | ... | No fraud |
| | 9 | ... | Fraud |
| | 10 | ... | No fraud |

**Under-sampled data**

| | ID | Variables | Class |
|---|---|---|---|
| Train | 1 | ... | Fraud |
| | 3 | ... | No fraud |
| | 4 | ... | Fraud |
| | 6 | ... | No fraud |
| Test | 7 | ... | No fraud |
| | 8 | ... | No fraud |
| | 9 | ... | Fraud |
| | 10 | ... | No fraud |

# A look at the imbalanced dataset

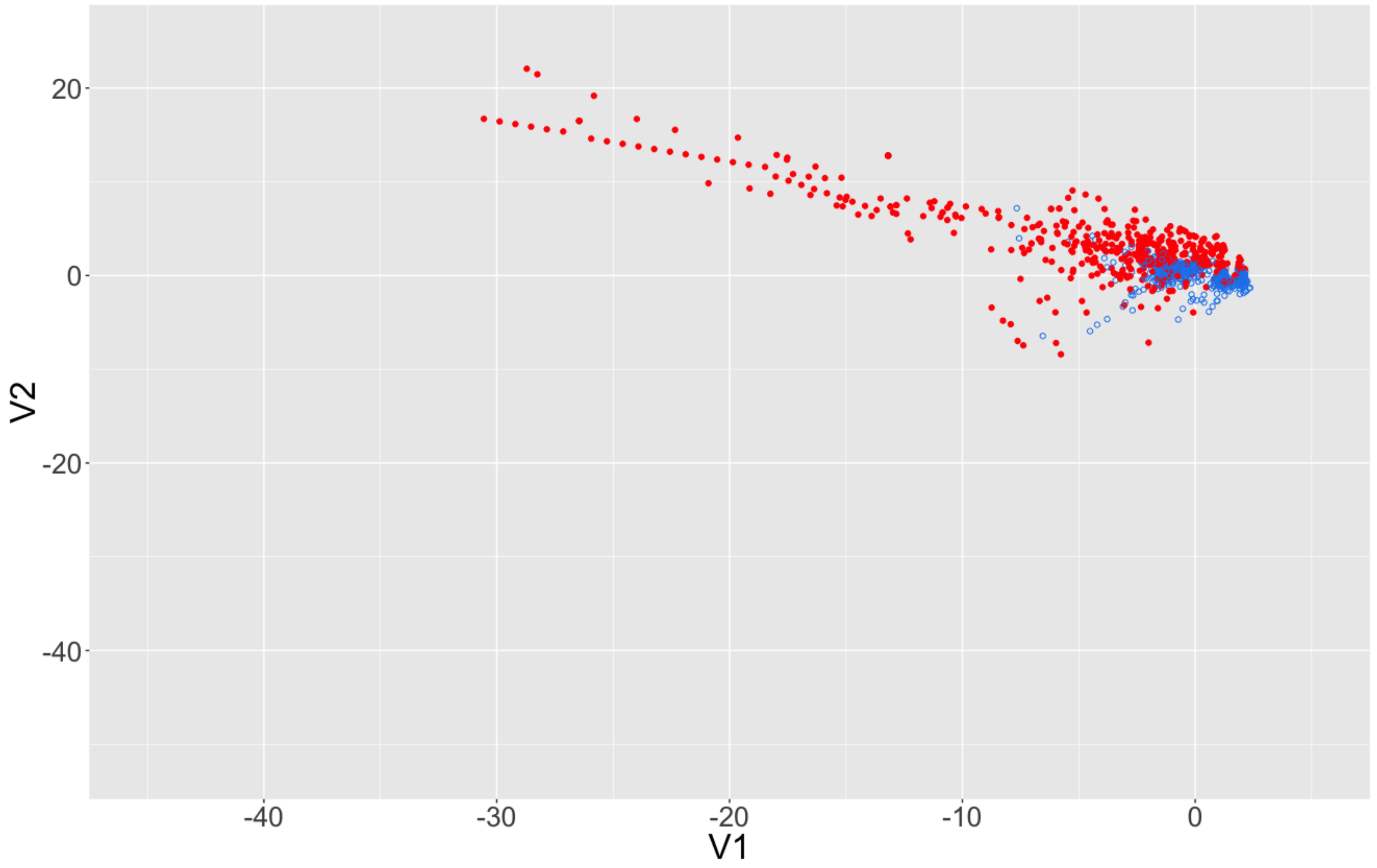


# Again ovun.sample

- `ovun.sample()` from ROSE package also for random under-sampling!

```
table(creditcard$Class)

    0     1
24108   492

n_fraud <- 492
new_frac_fraud <- 0.50
new_n_total <- n_fraud/new_frac_fraud # = 492/0.50 = 984

library(ROSE)
undersampling_result <- ovun.sample(Class ~ .,
                                    data = creditcard,
                                    method = "under",
                                    N = new_n_total,
                                    seed = 2018)

undersampled_credit <- undersampling_result$data

table(undersampled_credit$Class)

  0   1
492 492
```

# A look at the under-sampled dataset

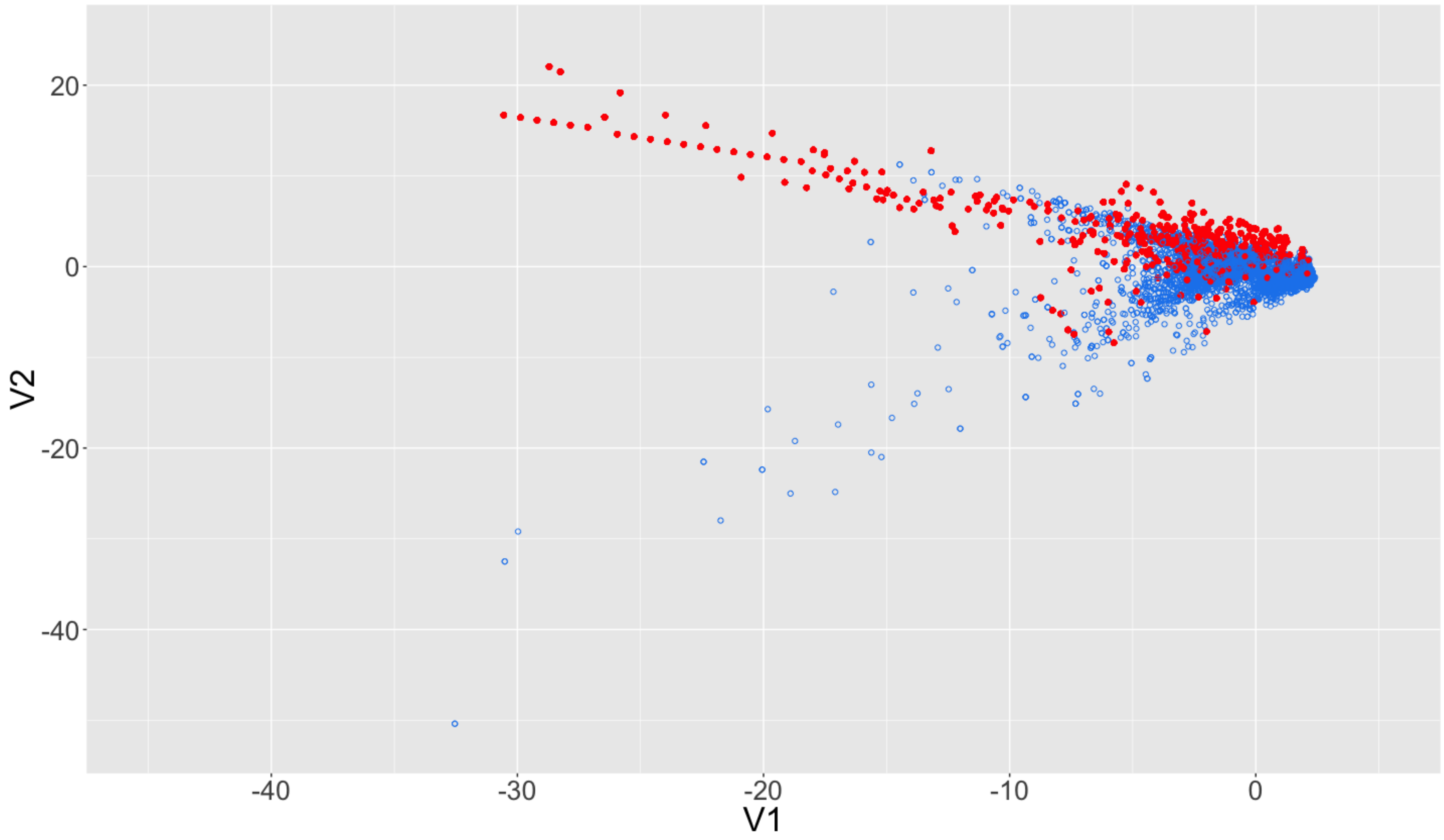


# Let's do both!

# Combination of over- & under-sampling

```
n_new <- nrow(creditcard) # = 24600
fraction_fraud_new <- 0.50

sampling_result <- ovun.sample(Class ~ .,
                               data = creditcard,
                               method = "both",
                               N = n_new,
                               p = fraction_fraud_new,
                               seed = 2018)

sampled_credit <- sampling_result$data

table(sampled_credit$Class)

    0     1
12398 12202

prop.table(table(sampled_credit$Class))

        0         1
0.5039837 0.4960163
```

# Result!



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# Let's practice!

FRAUD DETECTION IN R

# Synthetic Minority Over-sampling

Sebastiaan Höppner
PhD researcher in Data Science at KU Leuven

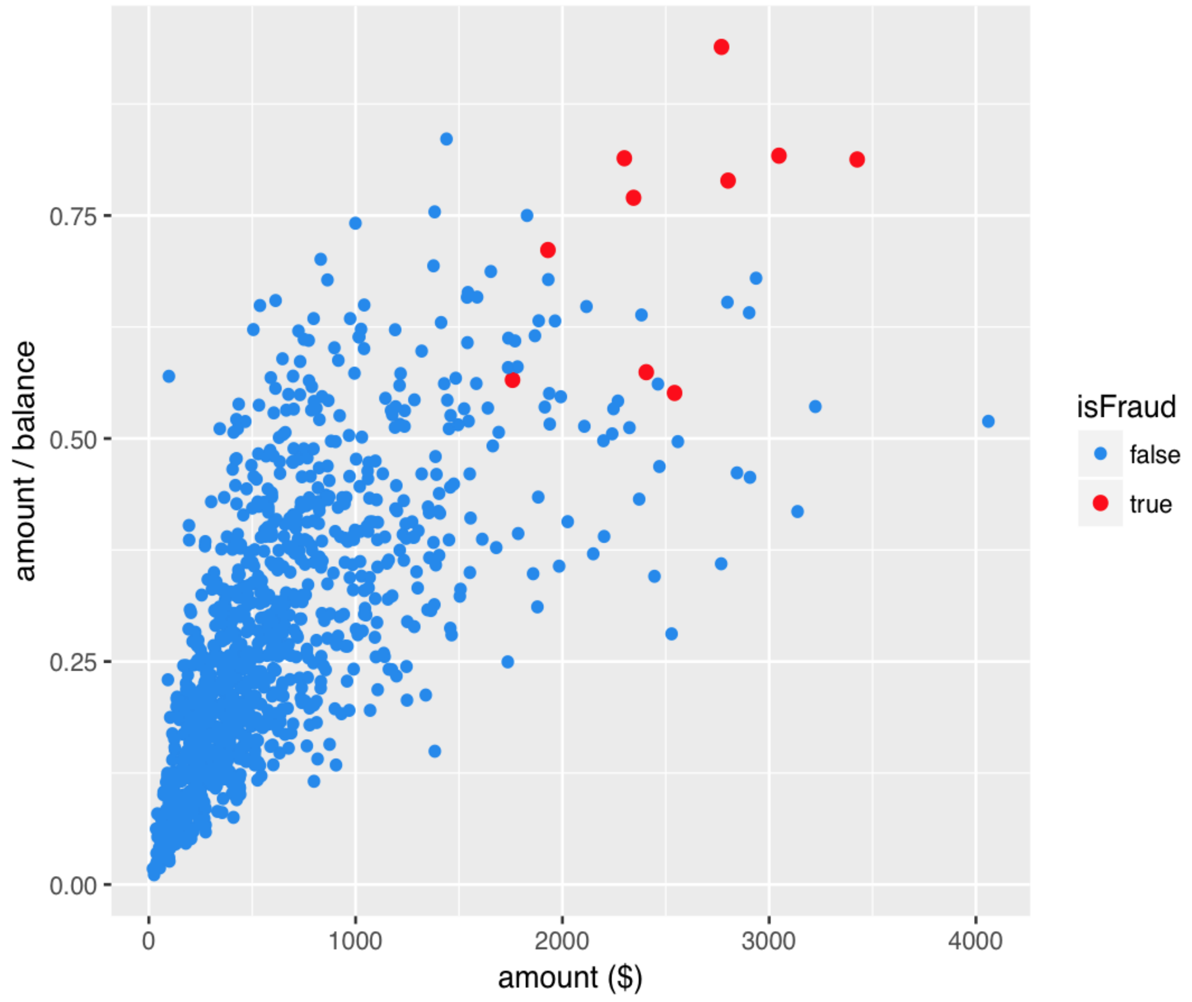
# Over-sampling with 'SMOTE'

- **SMOTE** : **S**ynthetic **M**inority **O**versampling **TE**chnique (Chawla et al., 2002)
- Over-sample minority class (i.e. fraud) by creating synthetic minority cases

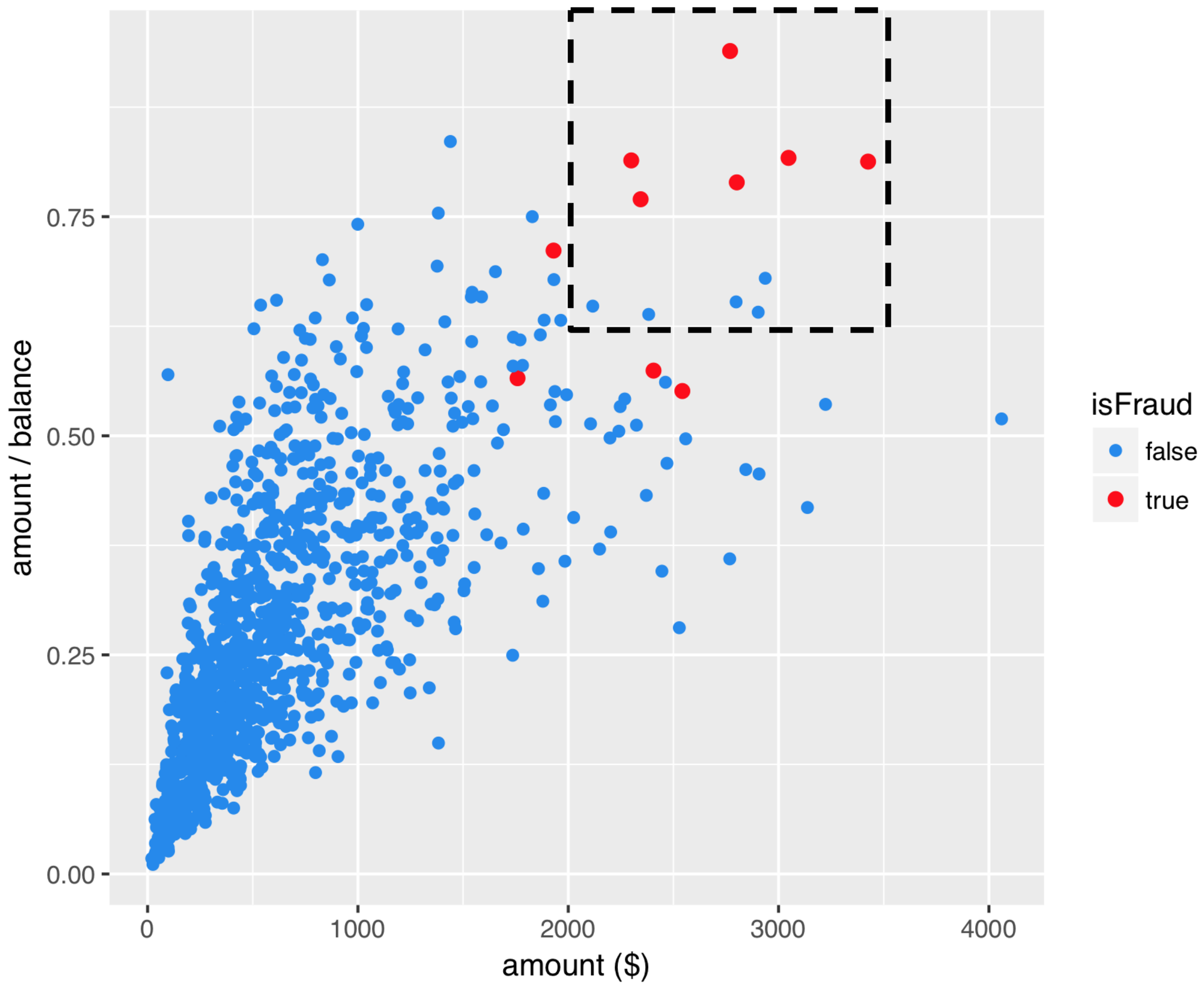
# Example: credit transfer data

```
dim(transfer_data)

[1] 1000    4

head(transfer_data)

  isFraud    amount   balance     ratio
1   false  528.6840 1529.4732 0.3456641
2   false  184.0193  836.3509 0.2200265
3   false 1885.8024 2984.0684 0.6319568
4   false  732.0286 1248.7217 0.5862224
5   false  694.0790 1464.3630 0.4739801
6   false 2461.9941 4387.8114 0.5610984

prop.table(table(transfer_data$isFraud))

 false  true
  0.99  0.01
```

# Look at the data (ratio vs amount)

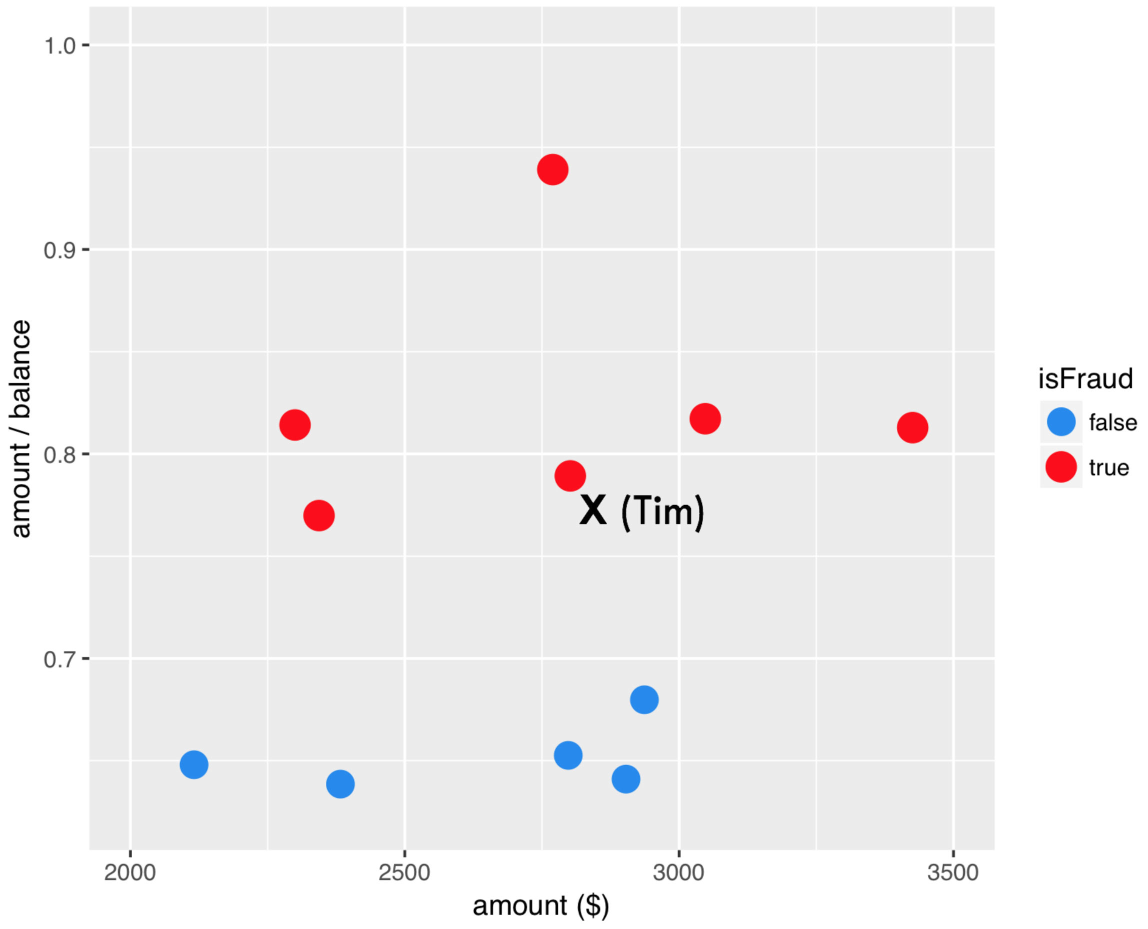


# Focus on fraud cases



# SMOTE

Let's select a fraud case **X** (Tim)

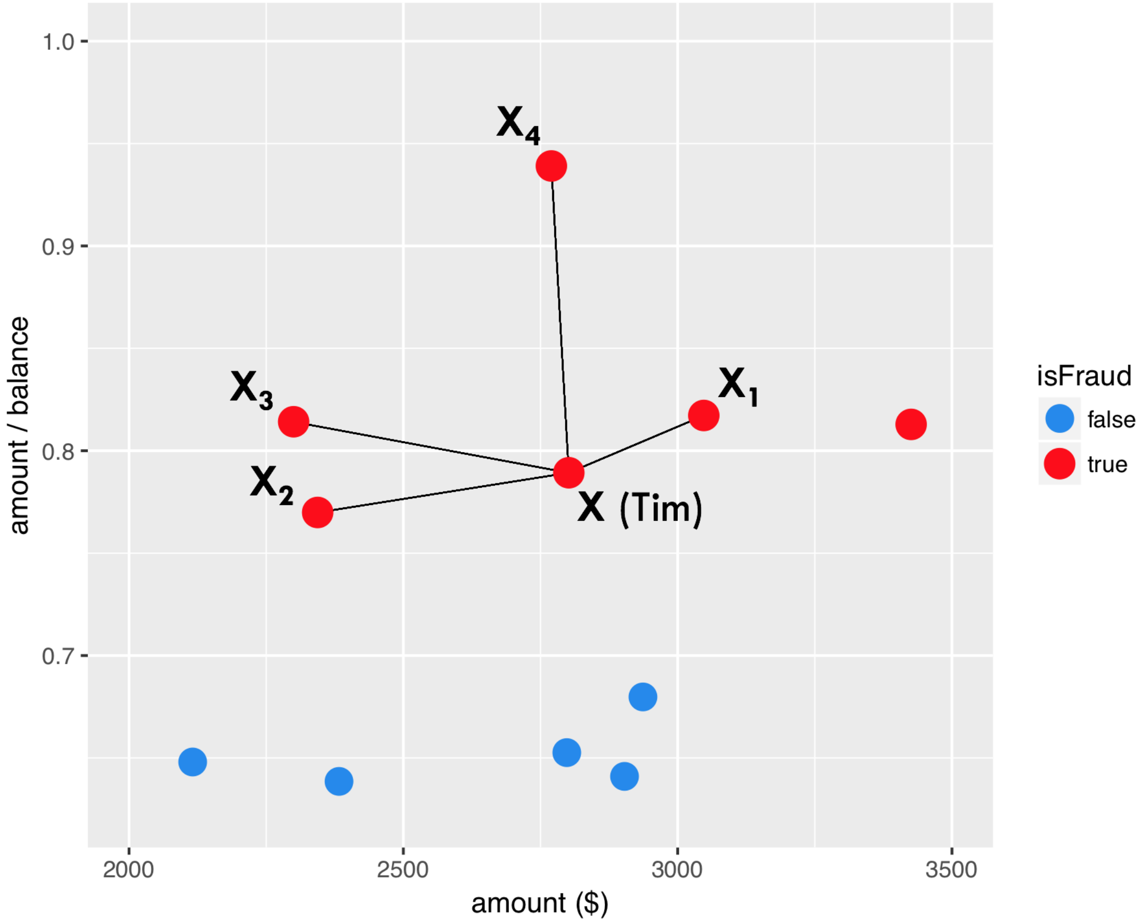


# SMOTE - step 1

**Step 1**

Find `K` nearest fraudulent neighbors of **X** (Tim)

e.g. `K = 4`

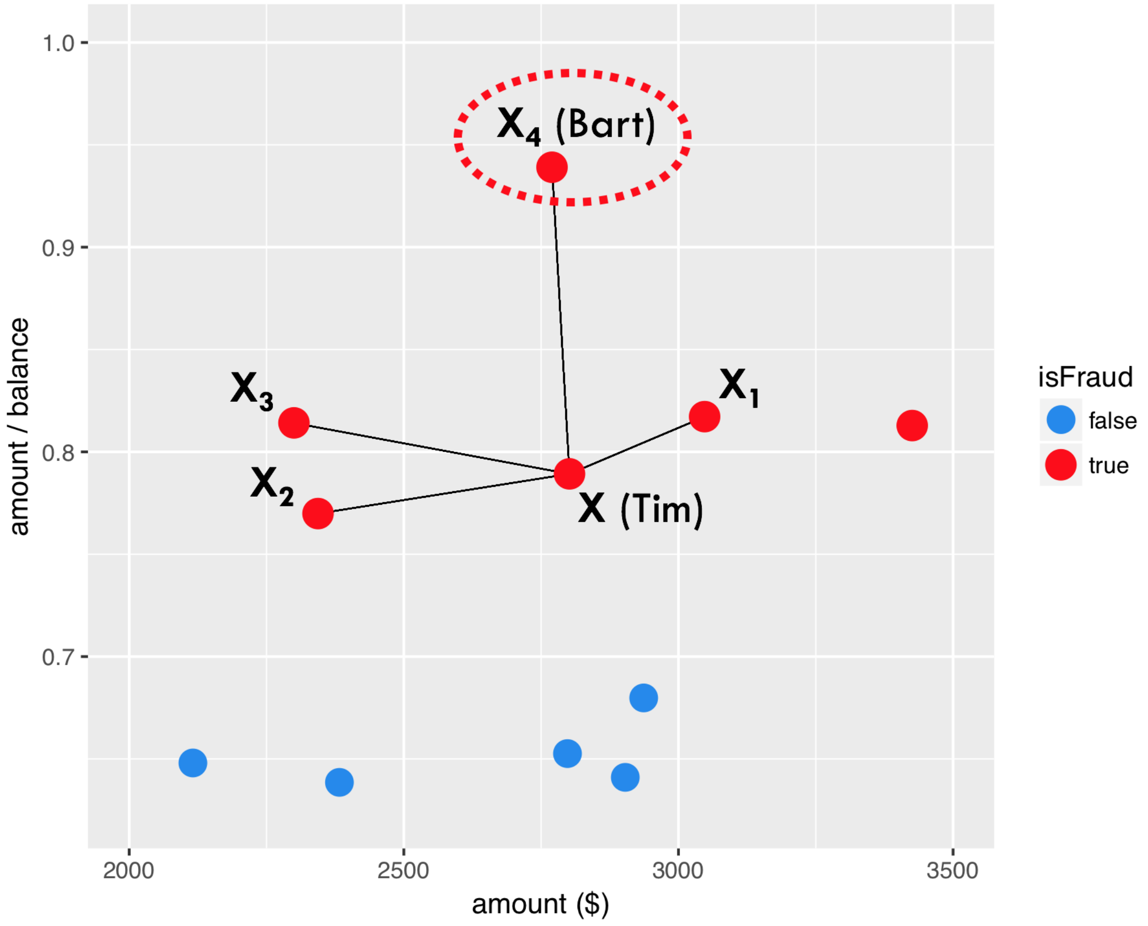


# SMOTE - step 2

**Step 2**

Randomly choose one of Tim's nearest neighbors

e.g. **X4** (Bart)



# SMOTE - step 3

**Step 3** : create synthetic sample

**X** (Tim)

| Amount | Ratio |
|---|---|
| 2800 | 0.79 |

$\mathbf{X_4}$ (Bart)

| Amount | Ratio |
|---|---|
| 2770 | 0.94 |

# SMOTE - step 3

**Step 3** : create synthetic sample

**X** (Tim)

| Amount | Ratio |
|---|---|
| 2800 | 0.79 |

**$X_4$** (Bart)

| Amount | Ratio |
|---|---|
| 2770 | 0.94 |

Choose random number
between 0 and 1, e.g. **0.6**

# SMOTE - step 3

**Step 3** : create synthetic sample

**X** (Tim)

| Amount | Ratio |
|---|---|
| 2800 | 0.79 |

$X_4$ (Bart)

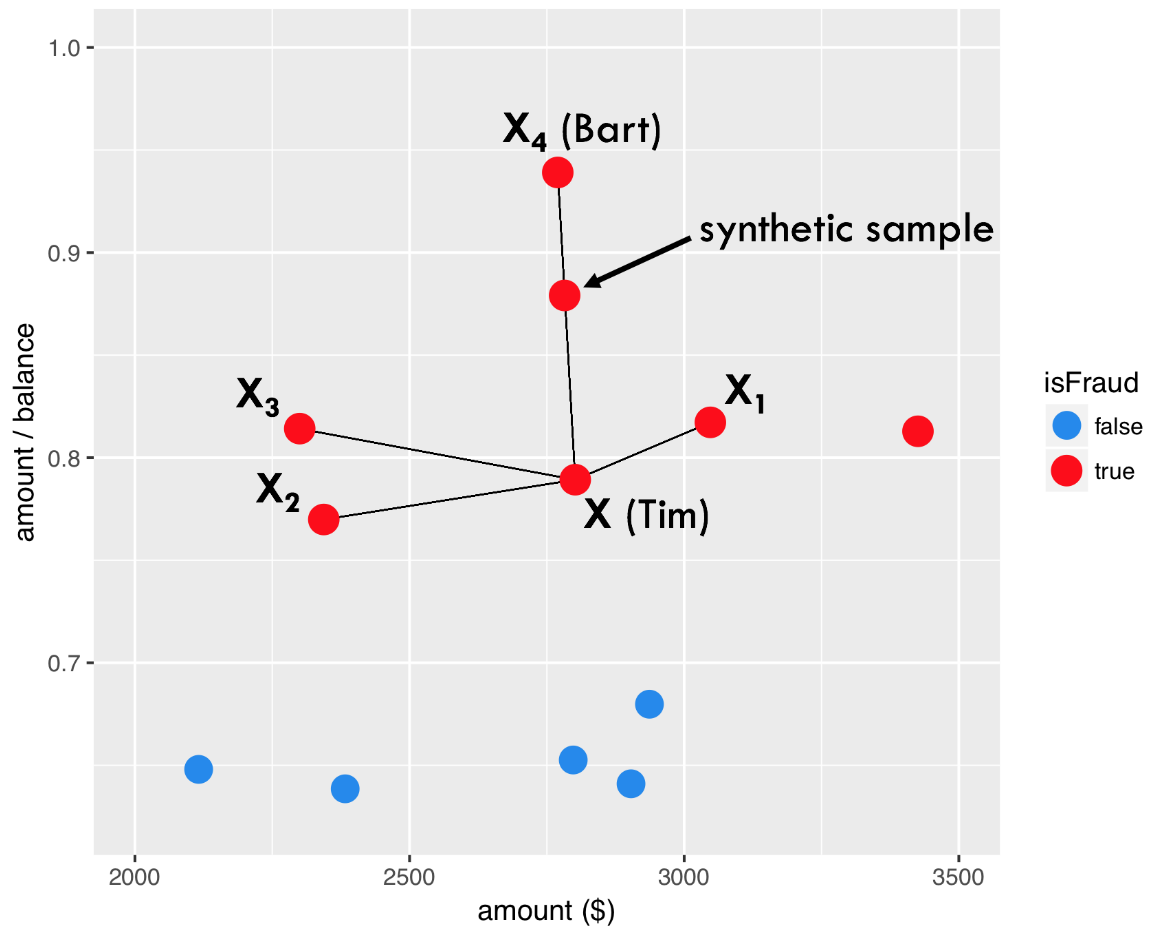
| Amount | Ratio |
|---|---|
| 2770 | 0.94 |

Choose random number between 0 and 1, e.g. 0.6

**Synthetic sample**

| Amount | Ratio |
|---|---|
| 2800 + 0.6 * (2770 - 2800) = **2782** | 0.79 + 0.6 * (0.94 – 0.79) = **0.88** |

# SMOTE - step 3

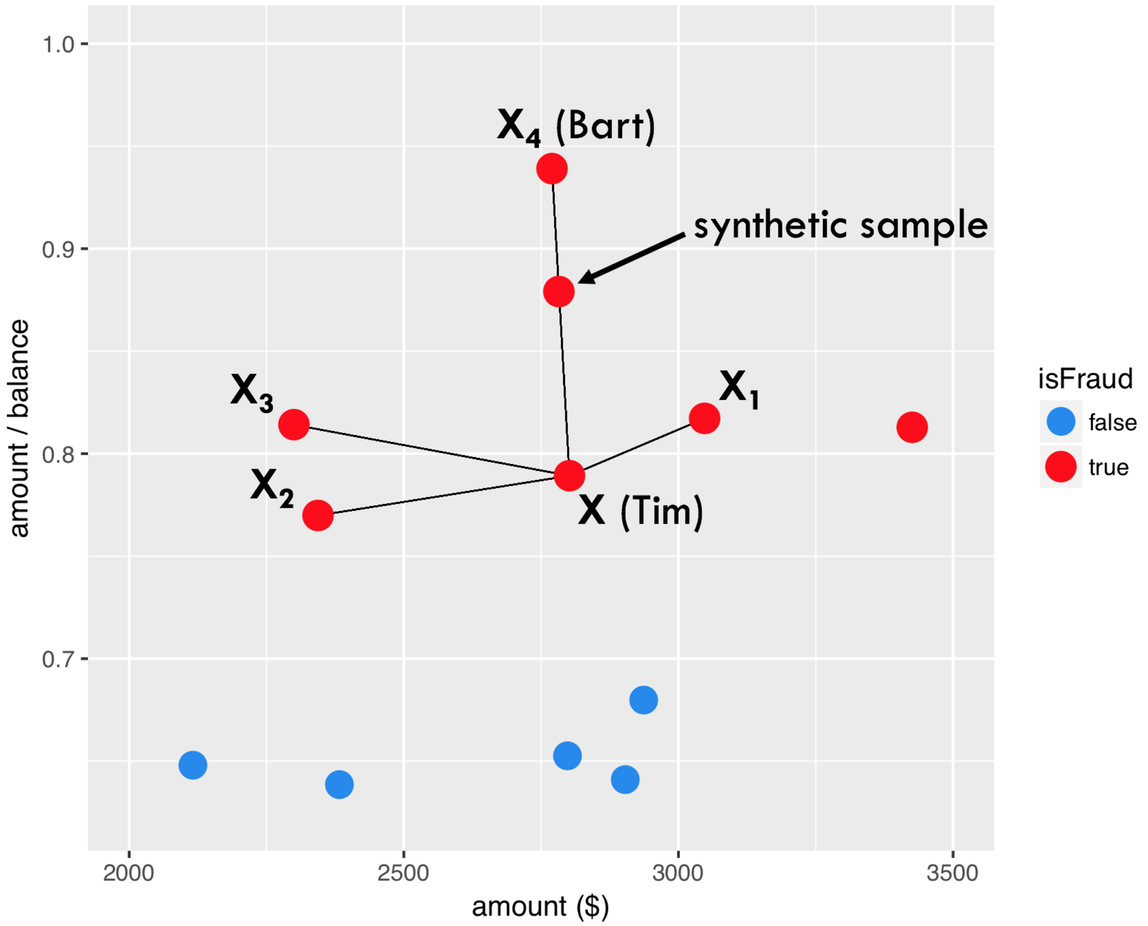

X4 (Bart)
synthetic sample
X3
X1
X2
X (Tim)
1.0
0.9
0.8
0.7
amount / balance
2000
2500
3000
3500
amount ($)
isFraud
false
true

# SMOTE - step 4

**Step 4**

Repeat steps 1-3 for each fraud case `dup_size` times

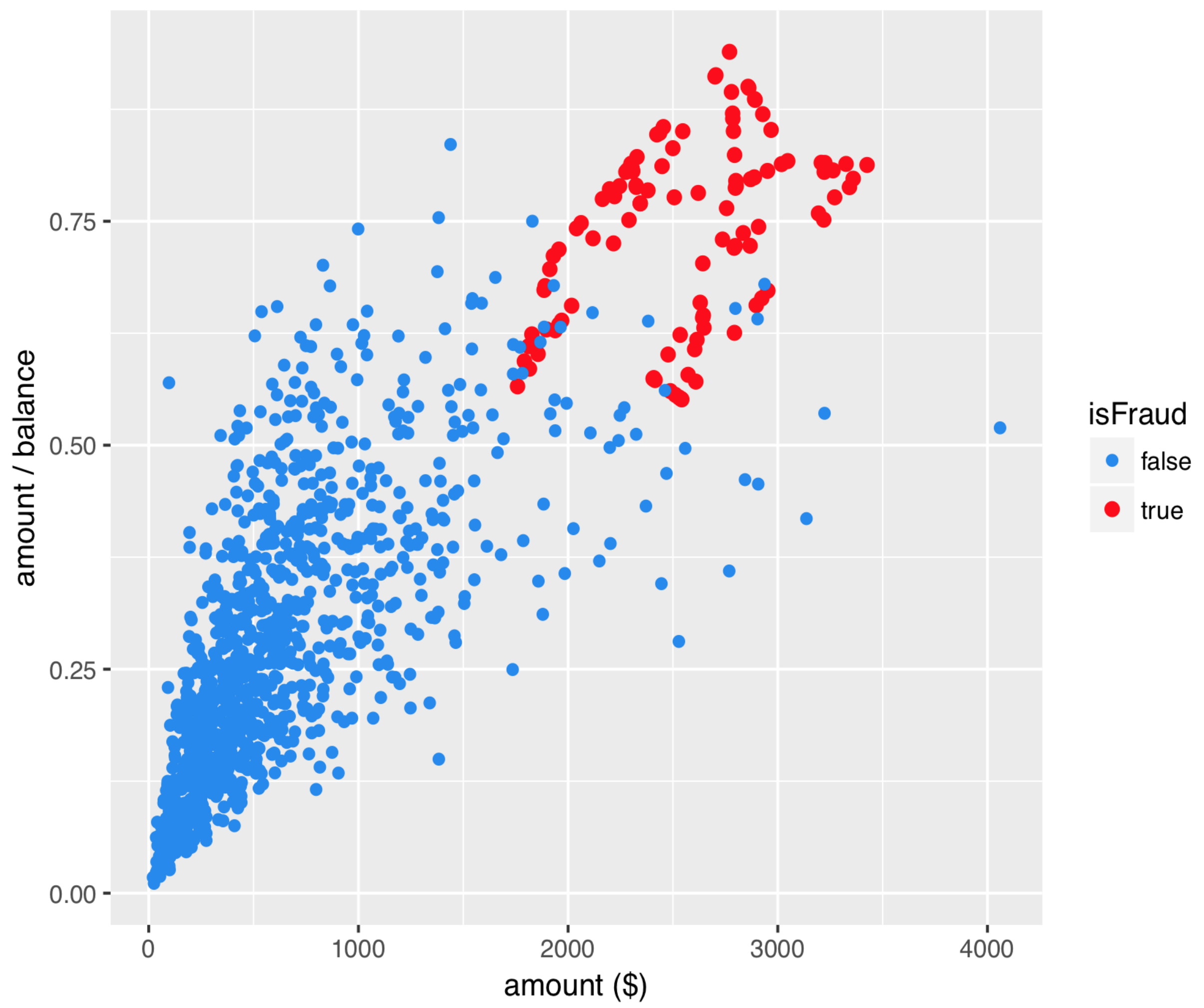
e.g. `dup_size = 10`



# SMOTE on transfer_data

```
> library(smotefamily)

> smote_output = SMOTE(X = transfer_data[, -1],
                       target = transfer_data$isFraud,
                       K = 4,
                       dup_size = 10)

> oversampled_data = smote_output$data

> table(oversampled_data$isFraud)

false  true
  990   110

> prop.table(table(oversampled_data$isFraud))

false  true
  0.9   0.1
```

# Synthetic fraud cases



FRAUD DETECTION IN R

# Let's practice!

FRAUD DETECTION IN R

# From dataset to detection model

Sebastiaan Höppner
PhD researcher in Data Science at KU Leuven

# Roadmap

- (1) Divide dataset in **training set** and **test set**
- (2) **Choose** a machine learning **model**
- (3) **Apply SMOTE** on training set to balance the class distribution
- (4) **Train model** on re-balanced training set
- (5) **Test performance** on (original) test set

# Divide dataset in training & set

- Split the dataset into a **training set** and a **test set** (e.g. 50/50, 75/25, ...)
- Make sure that both sets have identical class distribution (at first)
- Example: 50% training set and 50% test set

```
prop.table(table(train$Class))

   0    1
0.98 0.02

prop.table(table(test$Class))

   0    1
0.98 0.02
```

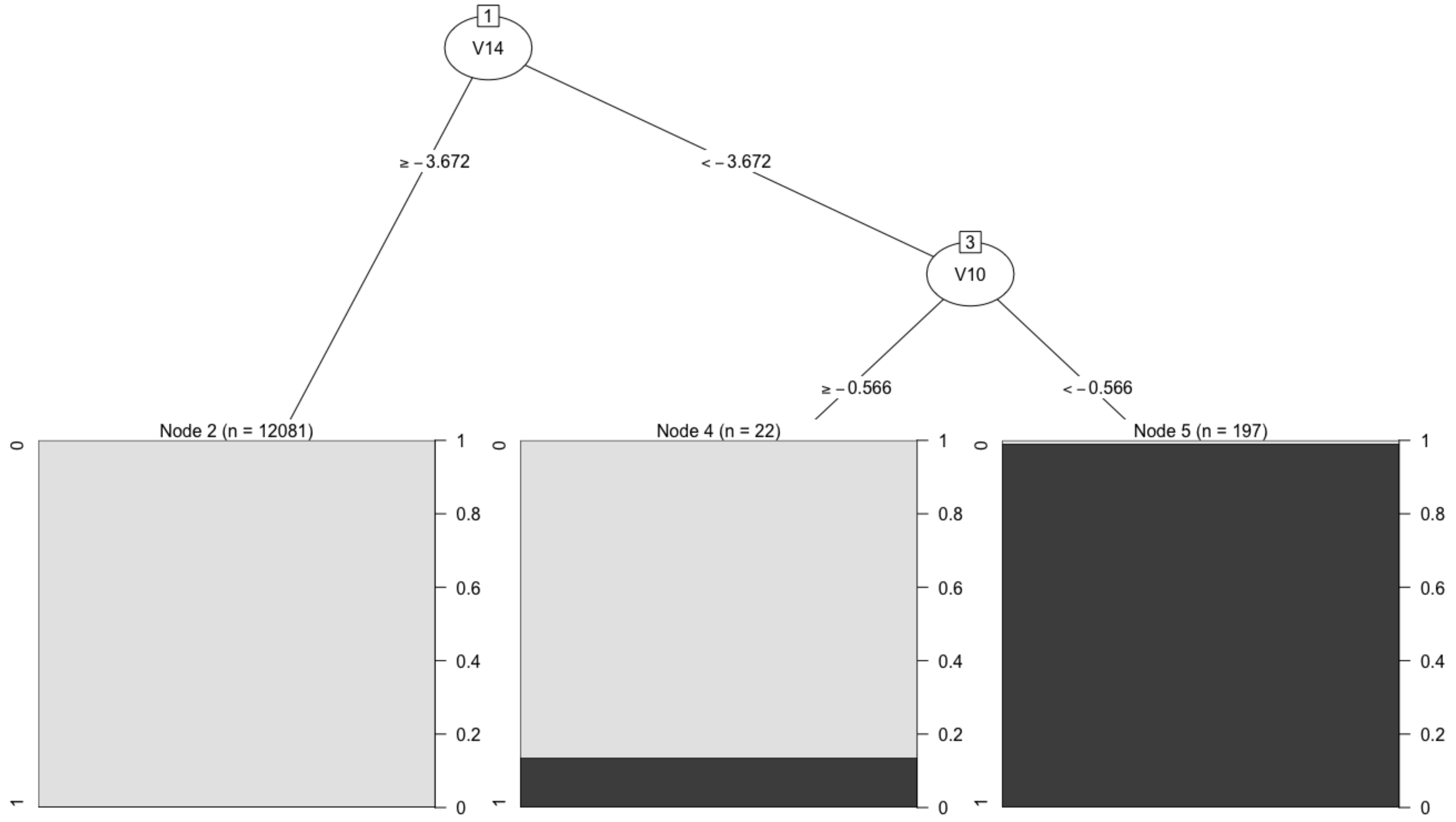
# Choose & train machine learning model

- Decision tree, artificial neural network, support vector machines, logistic regression, random forest, Naive Bayes, k-Nearest Neighbors, ...
- **Example:** Classification And Regression Tree (**CART**) algorithm
- Function `rpart` in `rpart` package

```
library(rpart)
model1 = rpart(Class ~ ., data = train)
```

# A simple classification tree model

```
library(partykit)
plot(as.party(model1))
```



# Test performance on test set

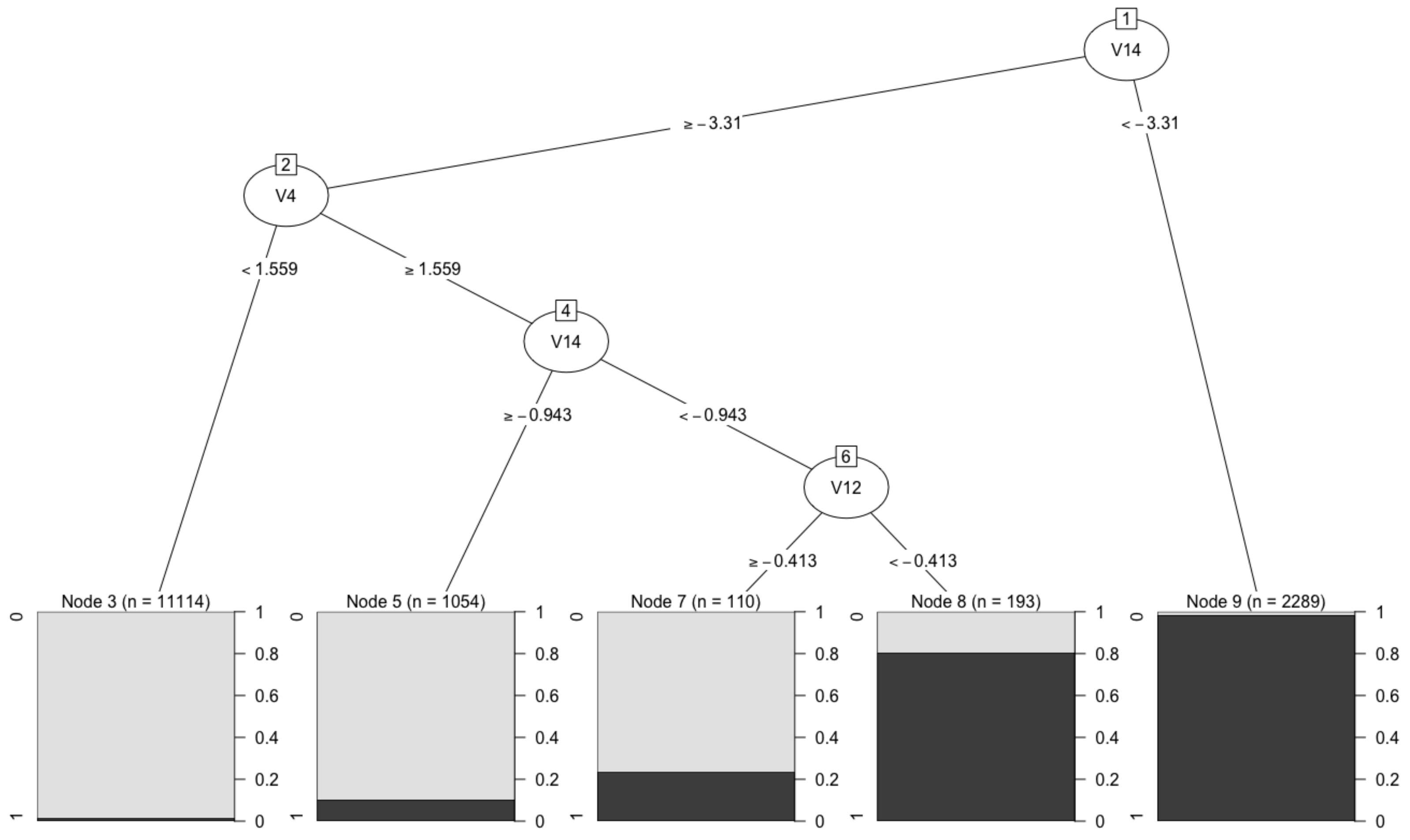
```
# Predict fraud probability
scores1 = predict(model1, newdata = test, type = "prob")[, 2]

# Predict class (fraud or not)
predicted_class1 = factor(ifelse(scores1 > 0.5, 1, 0))

# Confusion matrix & accuracy
library(caret)
CM1 = confusionMatrix(data = predicted_class1, reference = test$Class)

CM1

          Reference
Prediction     0     1
         0 12046    55
         1     8   191

Accuracy : 0.994878

# Area Under ROC Curve (AUC)
library(pROC)
auc(roc(response = test$Class, predictor = scores1))

Area under the curve: 0.8938
```

# Apply SMOTE on training set

```
library(smotefamily)
set.seed(123)

smote_result = SMOTE(X = train[, -17],
                     target = train$Class,
                     K = 5,
                     dup_size = 10)

train_oversampled = smote_result$data
colnames(train_oversampled)[17] = "Class"

table(train_oversampled$Class)

    0     1
12054  2706

prop.table(table(train_oversampled$Class))

        0         1
0.8166667 0.1833333
```

# Train model on re-balanced training set

```
library(rpart)

model2 = rpart(Class ~ ., data = train_oversampled)
```



# Test performance of new model on test set

```
# Predict fraud probability
scores2 = predict(model2, newdata = test, type = "prob")[, 2]

# Predict class (fraud or not)
predicted_class2 = factor(ifelse(scores2 > 0.5, 1, 0))

# Confusion matrix & accuracy
library(caret)
CM2 = confusionMatrix(data = predicted_class2, reference = test$Class)

CM2

          Reference
Prediction     0     1
         0 11967    34
         1    87   212

Accuracy : 0.9901626

# Area Under ROC Curve (AUC)
library(pROC)
auc(roc(response = test$Class, predictor = scores2))

Area under the curve: 0.9538
```

# Cost of deploying a detection model

- Take into account the different **costs of fraud detection** during the evaluation of an algorithm
- Costs are associated with both **misclassification errors** (false positives & false negatives) and **correct classifications** (true positives & true negatives)

# Cost matrix

| | Actual no-fraud $y_i = 0$ | Actual fraud $y_i = 1$ |
|---|---|---|
| Predicted no-fraud $c_i = 0$ | True negative (TN) $Cost_{TN_i} = 0$ | |
| Predicted fraud $c_i = 1$ | | |

- $y_i$ = true class of case $i$
- $c_i$ = predicted class for case $i$

# Cost matrix

| | Actual no-fraud $y_i = 0$ | Actual fraud $y_i = 1$ |
|---|---|---|
| Predicted no-fraud $c_i = 0$ | True negative (TN) $Cost_{TN_i} = 0$ | False negative (FN) $Cost_{FN_i} = Amount_i$ |
| Predicted fraud $c_i = 1$ | | |

- $y_i$ = true class of case $i$
- $c_i$ = predicted class for case $i$

# Cost matrix

| | Actual no-fraud $y_i = 0$ | Actual fraud $y_i = 1$ |
|---|---|---|
| Predicted no-fraud $c_i = 0$ | True negative (TN) $Cost_{TN_i} = 0$ | False negative (FN) $Cost_{FN_i} = Amount_i$ |
| Predicted fraud $c_i = 1$ | False positive (FP) $Cost_{FP_i} = C_a$ | |

- $C_a$ = cost for analyzing the case

# Cost matrix

| | Actual no-fraud $y_i = 0$ | Actual fraud $y_i = 1$ |
|---|---|---|
| Predicted no-fraud $c_i = 0$ | True negative (TN) $Cost_{TN_i} = 0$ | False negative (FN) $Cost_{FN_i} = Amount_i$ |
| Predicted fraud $c_i = 1$ | False positive (FP) $Cost_{FP_i} = C_a$ | True positive (TP) $Cost_{TP_i} = C_a$ |

- $C_a$ = cost for analyzing the case

# Cost measure for a detection model

- Take into account the actual costs of each case:

$$Cost(model) = \sum_{i=1}^{N} y_i(1 - c_i)Amount_i + c_i C_a$$

  - $y_i$ = true class of case $i$
  - $c_i$ = predicted class for case $i$

```
cost_model = function(predicted.classes, true.classes, amounts, fixedcost) {

    cost = sum(true.classes * (1 - predicted.classes) * amounts +
               predicted.classes * fixedcost)

    return(cost)
}
```

# True cost of fraud detection

```
# Total cost without using SMOTE:
cost_model(predicted_class1, test$Class, test$Amount, fixedcost = 10)
[1] 10061.8
# Total cost when using SMOTE:
cost_model(predicted_class2, test$Class, test$Amount, fixedcost = 10)
[1] 7431.93
```

- Losses decrease by 26%!

FRAUD DETECTION IN R

# Let's practice!