

Introduction and data structure

CREDIT RISK MODELING IN R



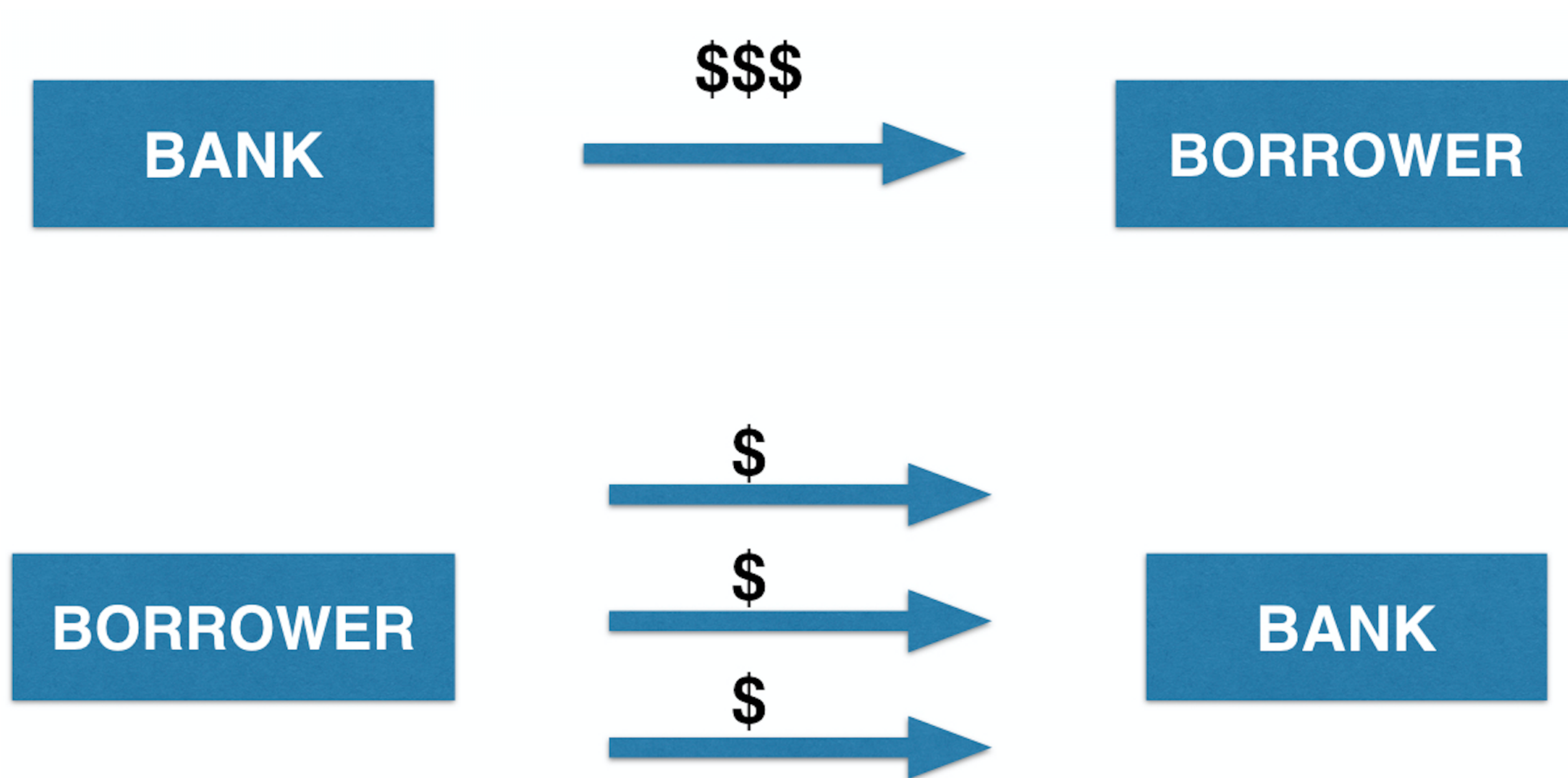
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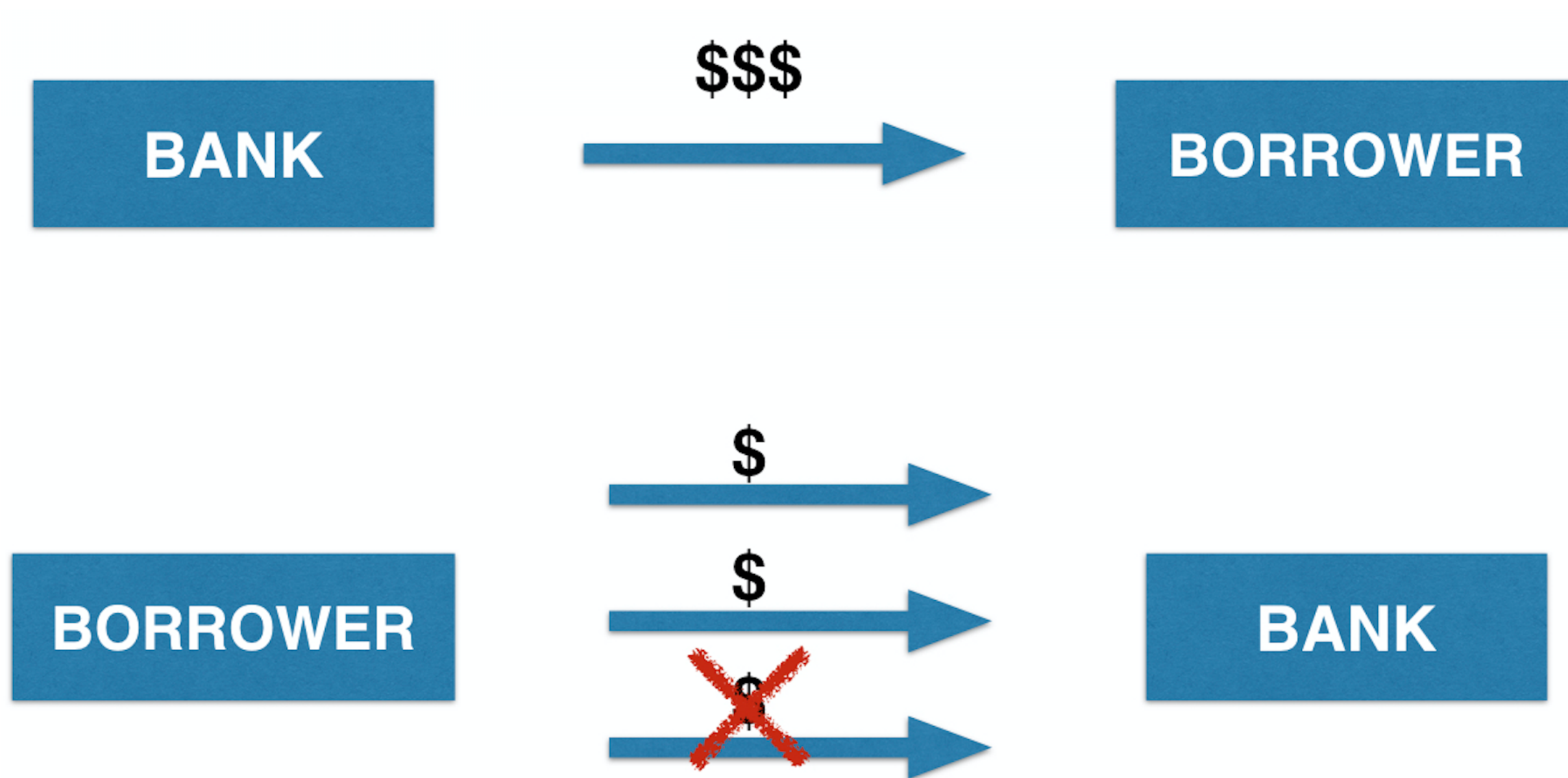
What is loan default?



What is loan default?



What is loan default?



Components of expected loss (EL)

- Probability of default (PD)
- Exposure at default (EAD)
- Loss given default (LGD)

$$EL = PD \times EAD \times LGD$$

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$$EL = PD \times EAD \times LGD$$

Information used by banks

- Application information:
 - Income
 - Marital status
 - ...
- Behavioral information
 - Current account balance
 - Payment arrears in account history
 - ...


```
head(loan_data, 10)
```

	loan_status	loan_amnt	int_rate	grade	emp_length	home_ownership	annual_inc	age
1	0	5000	10.65	B	10	RENT	24000	33
2	0	2400	NA	C	25	RENT	12252	31
3	0	10000	13.49	C	13	RENT	49200	24
4	0	5000	NA	A	3	RENT	36000	39
5	0	3000	NA	E	9	RENT	48000	24
6	0	12000	12.69	B	11	OWN	75000	28
7	1	9000	13.49	C	0	RENT	30000	22
8	0	3000	9.91	B	3	RENT	15000	22
9	1	10000	10.65	B	3	RENT	100000	28
10	0	1000	16.29	D	0	RENT	28000	22


```
library(gmodels)
CrossTable(loan_data$home_ownership)
```

Cell Contents

```
|-----|
|              N |
|      N / Table Total |
|-----|
```

Total Observations in Table: 29092

MORTGAGE	OTHER	OWN	RENT
12002	97	2301	14692
0.413	0.003	0.079	0.505

```
CrossTable(loan_data$home_ownership, loan_data$loan_status, prop.r = TRUE,  
           prop.c = FALSE, prop.t = FALSE, prop.chisq = FALSE)
```

	loan_data\$loan_status		
loan_data\$home_ownership	0	1	Row Total
MORTGAGE	10821	1181	12002
	0.902	0.098	0.413
OTHER	80	17	97
	0.825	0.175	0.003
OWN	2049	252	2301
	0.890	0.110	0.079
RENT	12915	1777	14692
	0.879	0.121	0.505
Column Total	25865	3227	29092

Let's practice!
CREDIT RISK MODELING IN R

Histograms and outliers

CREDIT RISK MODELING IN R

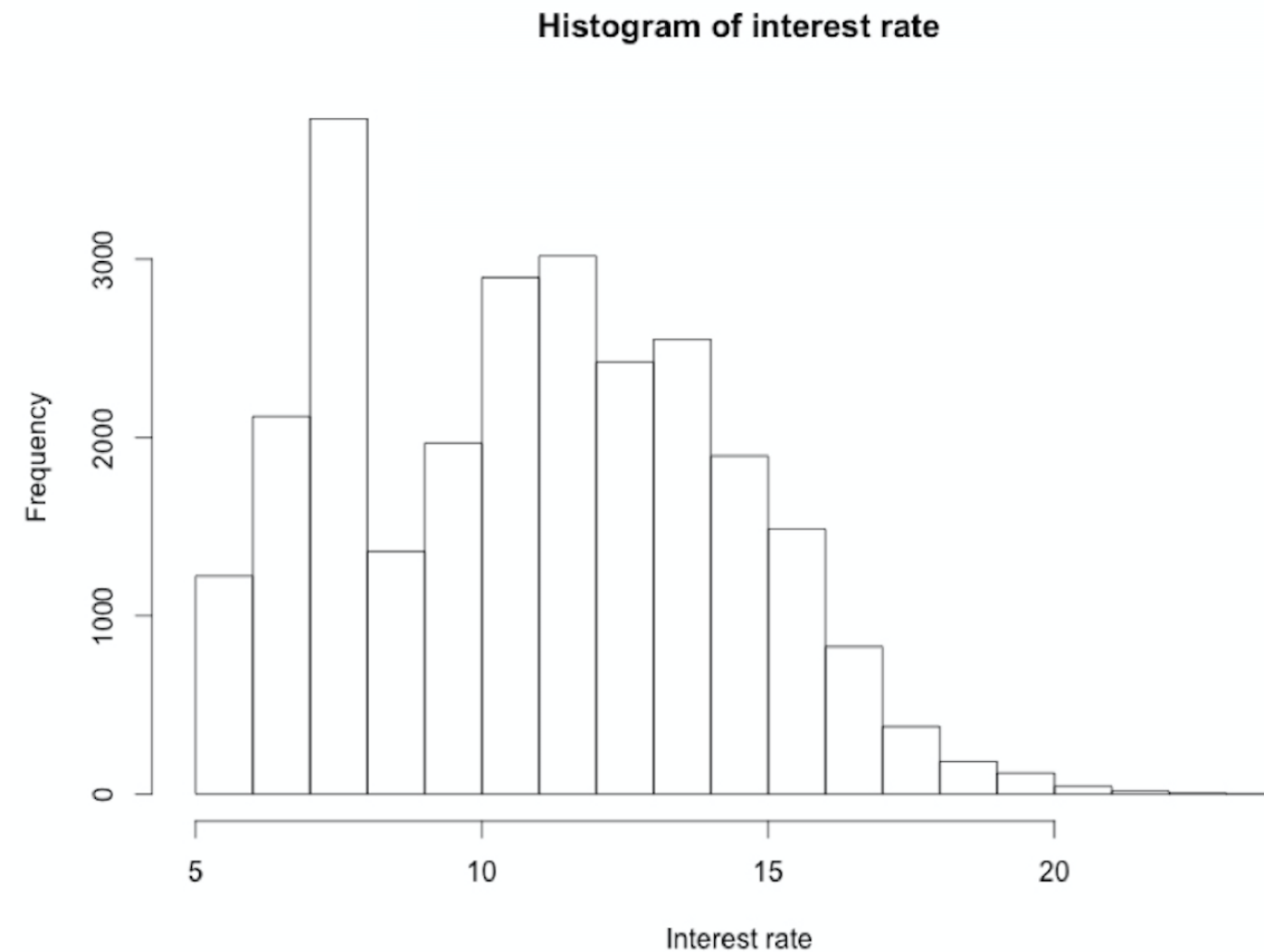


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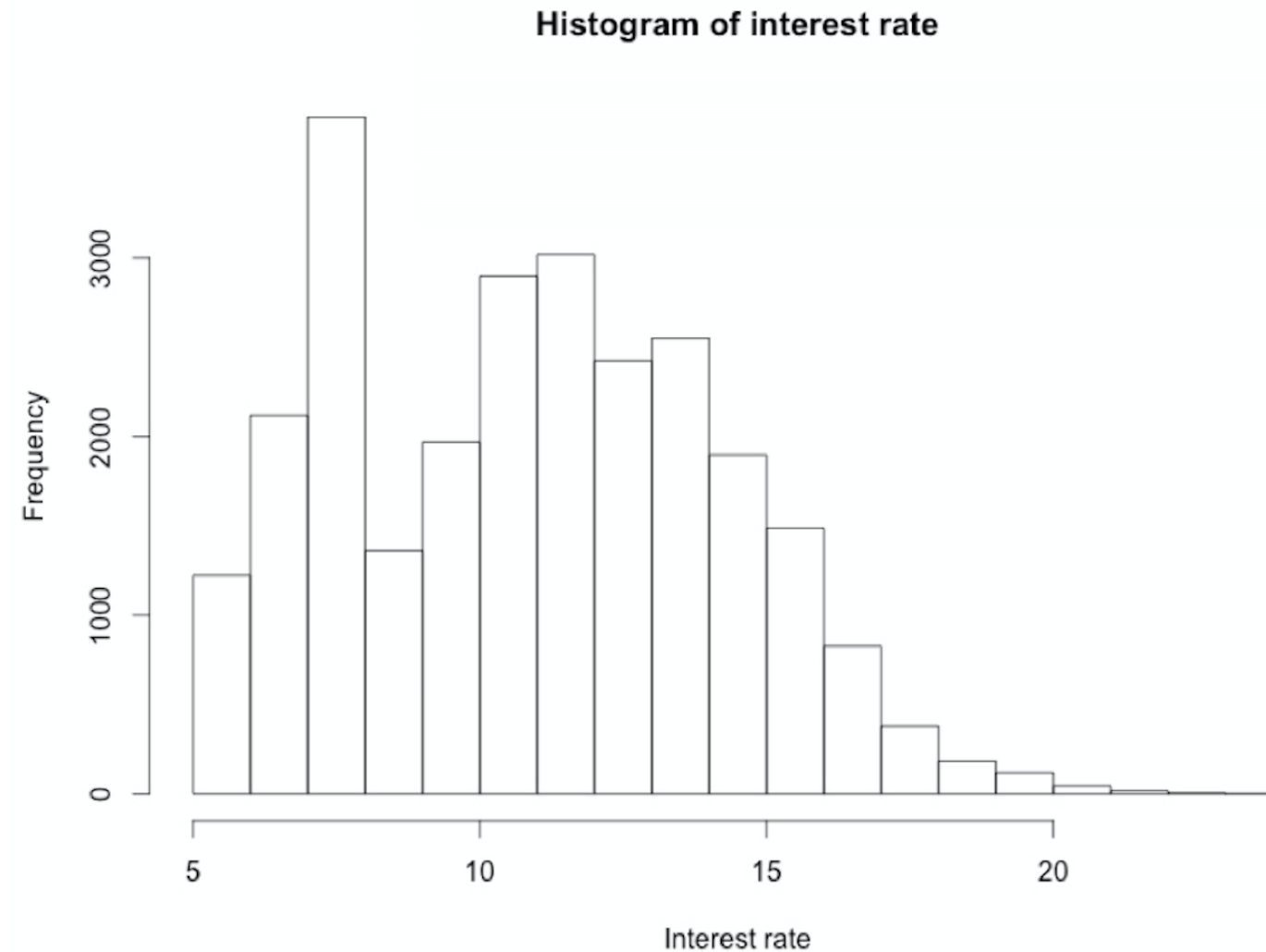
Using function hist()

```
hist(loop_data$int_rate)
```



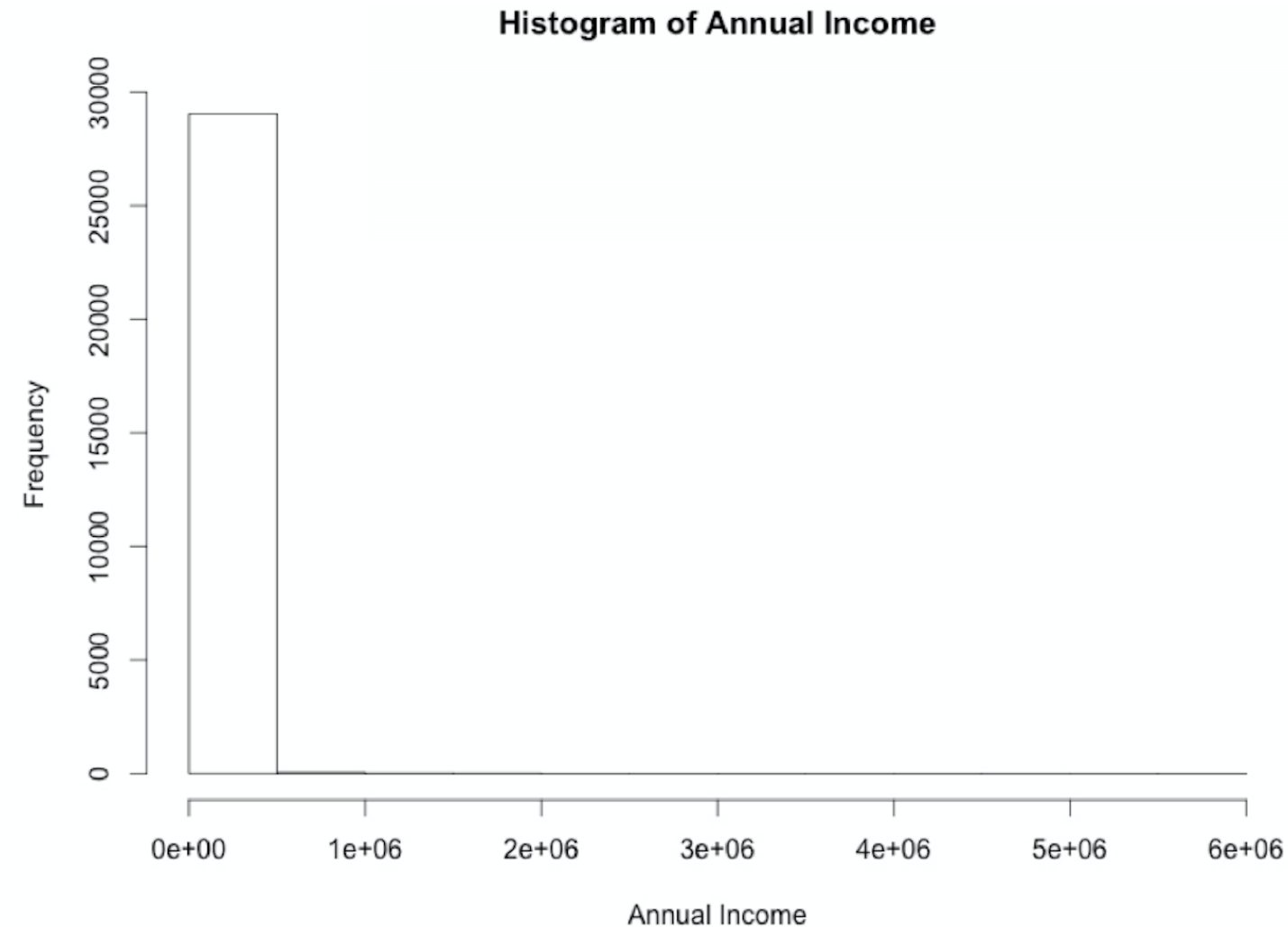
Using function hist()

```
hist(loop_data$int_rate, main = "Histogram of interest rate", xlab = "Interest rate")
```



Using function `hist()` on `annual_inc`

```
hist(loan_data$annual_inc, xlab = "Annual Income", main = "Histogram of Annual Income")
```



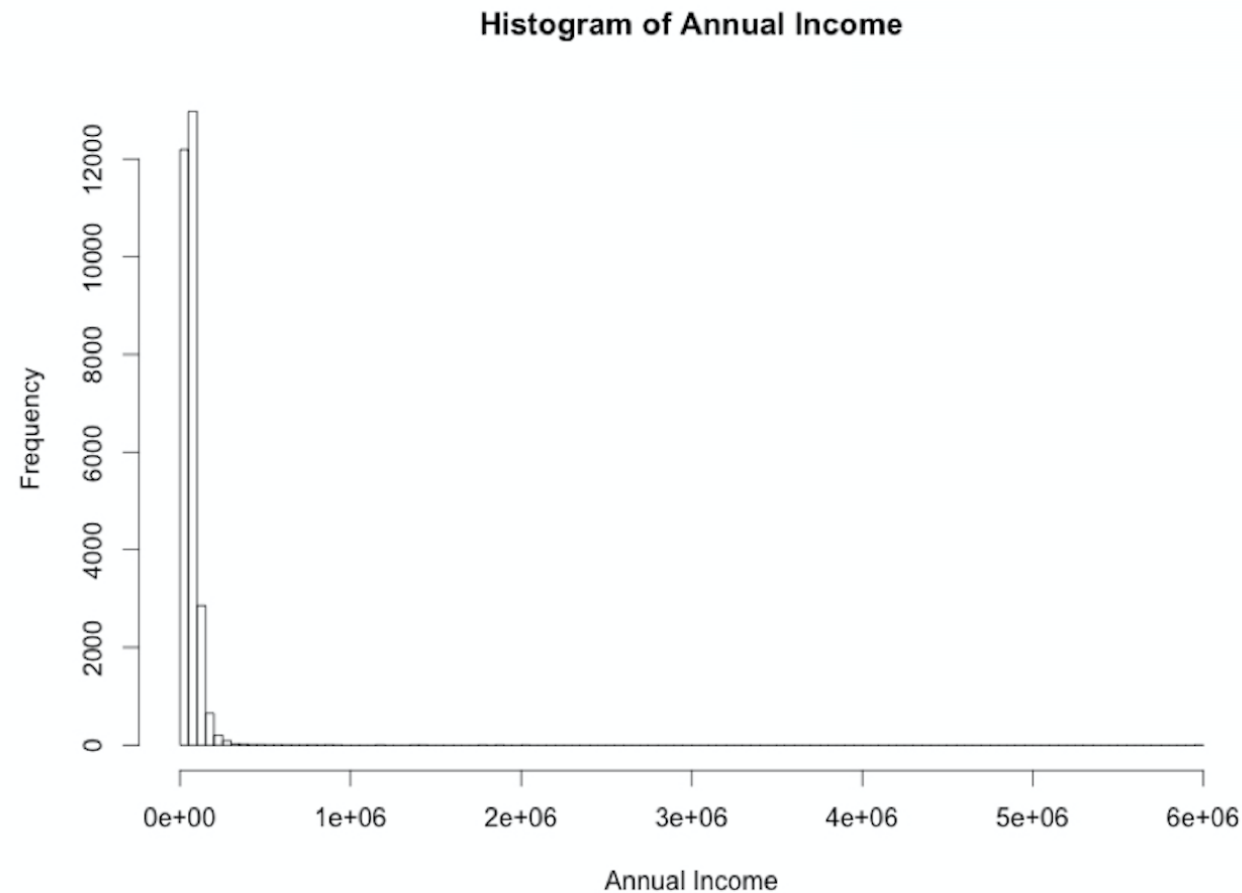
Using function hist() on annual_inc

```
hist_income <- hist(loan_data$annual_inc,  
                    xlab = "Annual Income",  
                    main = "Histogram of Annual Income")  
  
hist_income$breaks
```

```
0  500000 1000000 1500000 2000000 2500000 3000000 3500000 4000000 4500000 ...
```

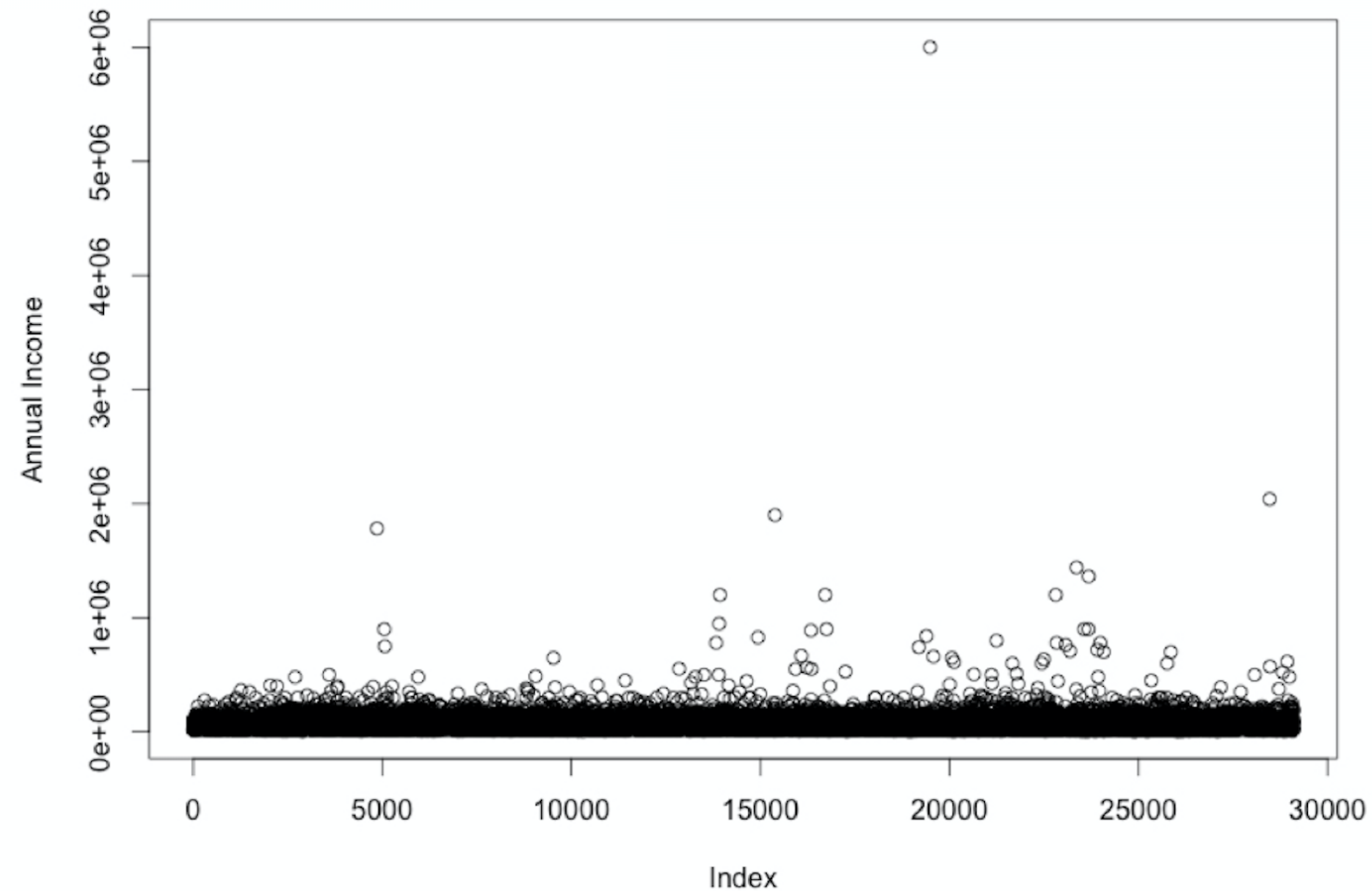

The breaks-argument

```
n_breaks <- sqrt(nrow(loan_data)) # n_breaks = 170.5638
hist_income_n <- hist(loan_data$annual_inc, breaks = n_breaks,
                      xlab = "Annual Income", main = "Histogram of Annual Income")
```



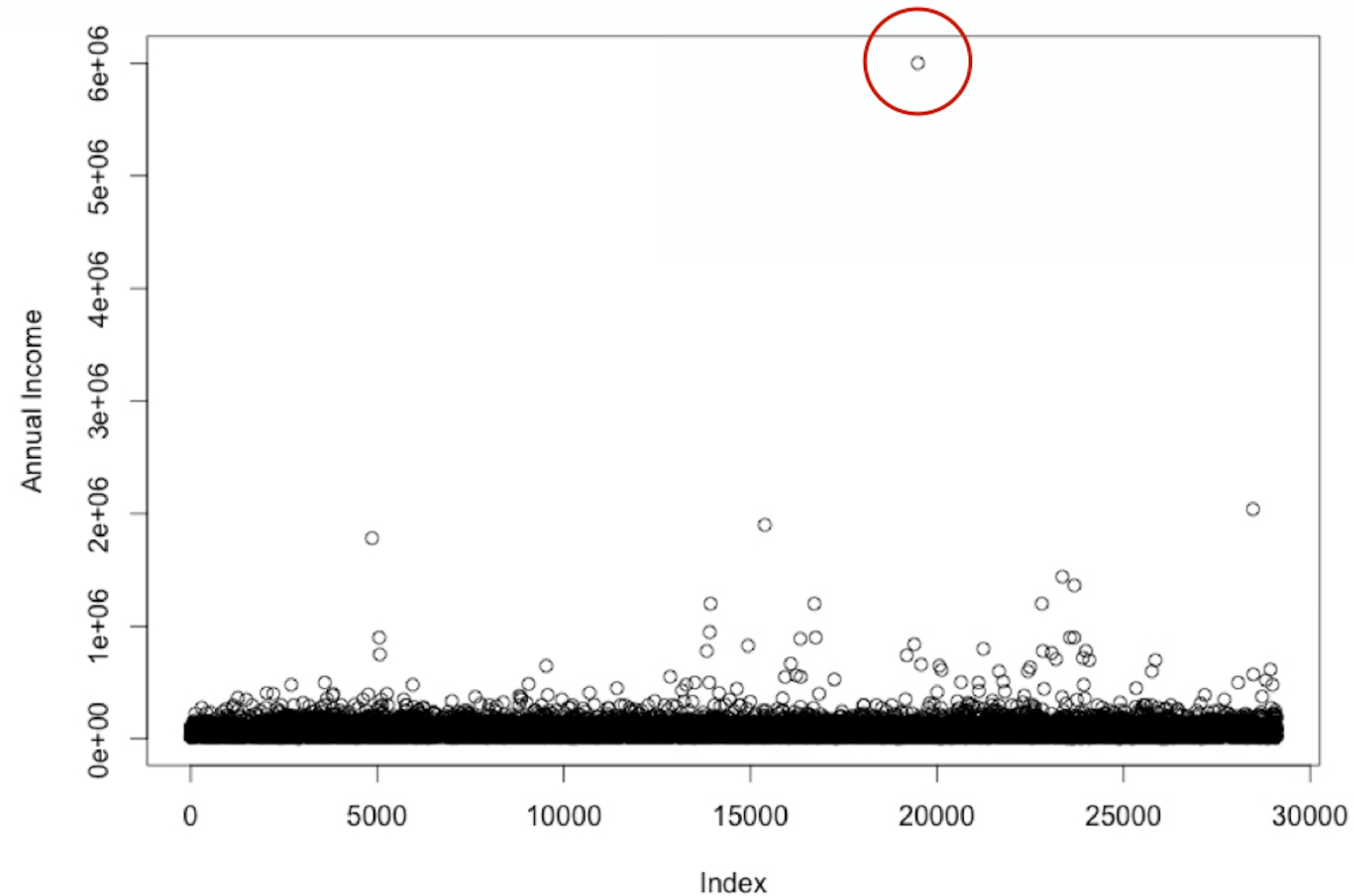
annual_inc

```
plot(loan_data$annual_inc, ylab = "Annual Income")
```



annual_inc

```
plot(loan_data$annual_inc, ylab = "Annual Income")
```



Outliers

- When is a value an outlier?
 - Expert judgment
 - Rule of thumb, e.g.,
 - $Q1 - 1.5 * IQR$
 - $Q3 + 1.5 * IQR$
 - Mostly: combination of both

Expert judgment

"Annual salaries > \$3 million are outliers"

```
# Find outlier
index_outlier_expert <- which(loan_data$annual_inc > 3000000)

# Remove outlier from dataset
loan_data_expert <- loan_data[-index_outlier_expert, ]
```

Rule of thumb

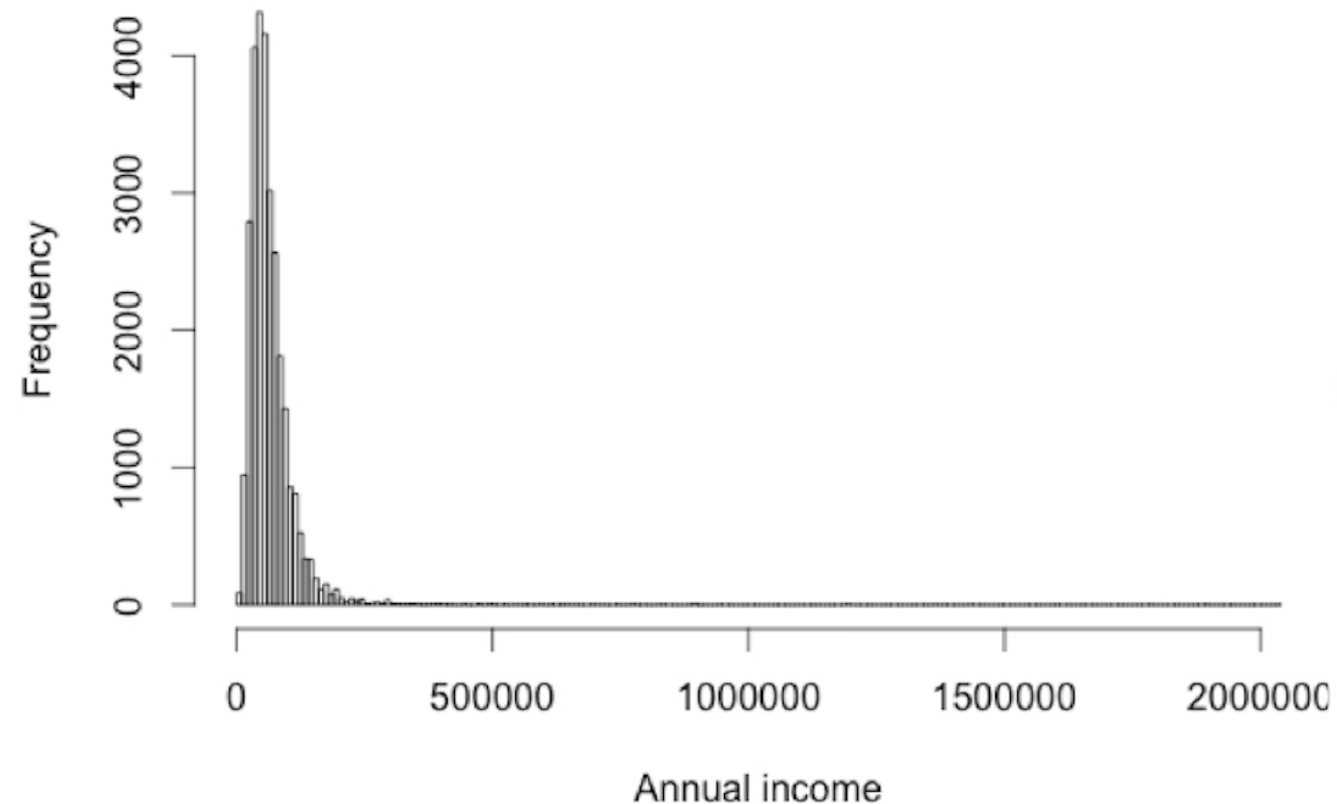
Outlier if bigger than $Q3 + 1.5 * IQR$

```
# Calculate Q3 + 1.5 * IQR
outlier_cutoff <- quantile(loan_data$annual_inc, 0.75) + 1.5 * IQR(loan_data$annual_inc)
# Identify outliers
index_outlier_ROT <- which(loan_data$annual_inc > outlier_cutoff)
# Remove outliers
loan_data_ROT <- loan_data[-index_outlier_ROT, ]
```

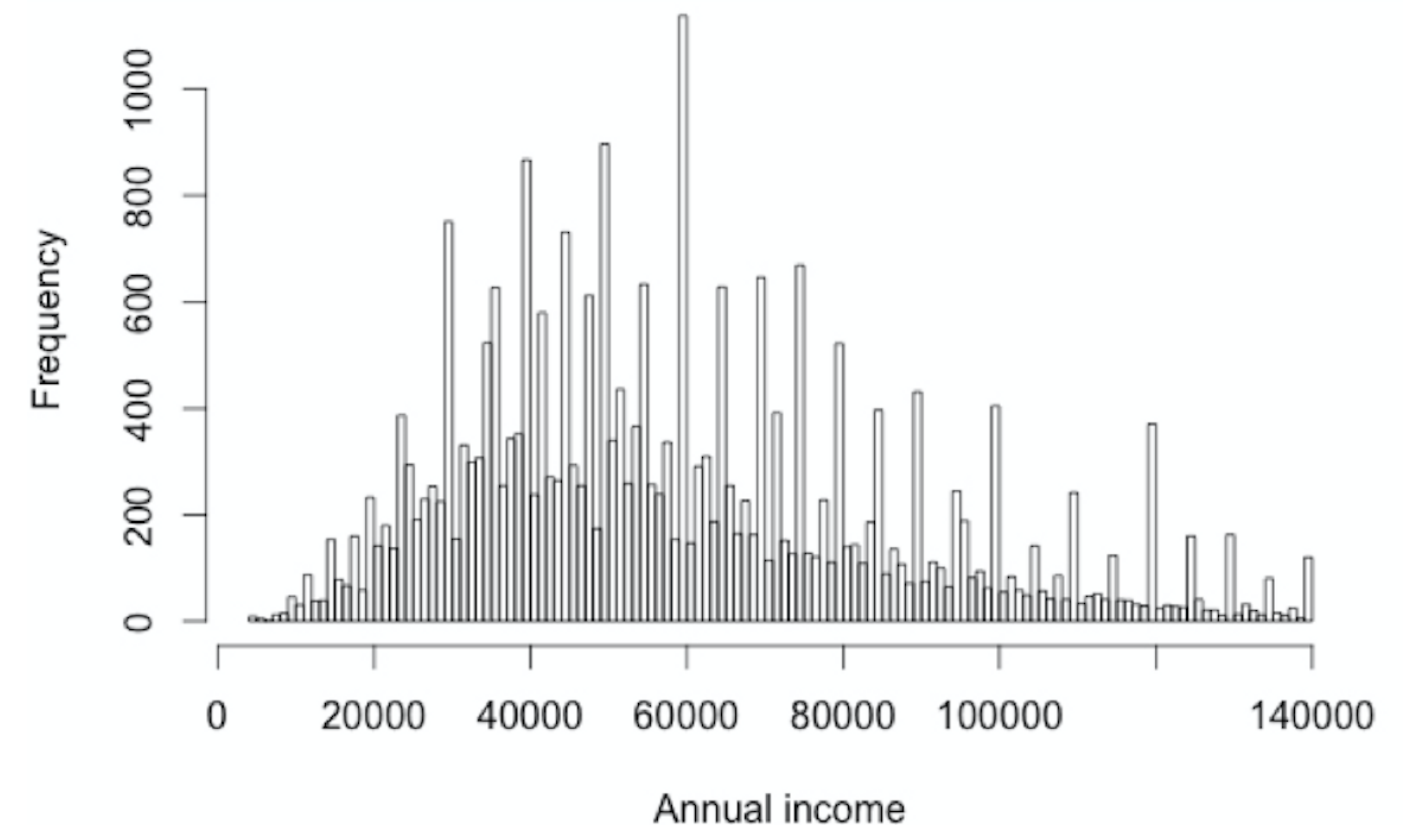
```
hist(loan_data_expert$annual_inc,  
     sqrt(nrow(loan_data_expert)),  
     xlab = "Annual income")
```

```
hist(loan_data_ROT$annual_inc,  
     sqrt(nrow(loan_data_ROT)),  
     xlab = "Annual income")
```

expert judgement

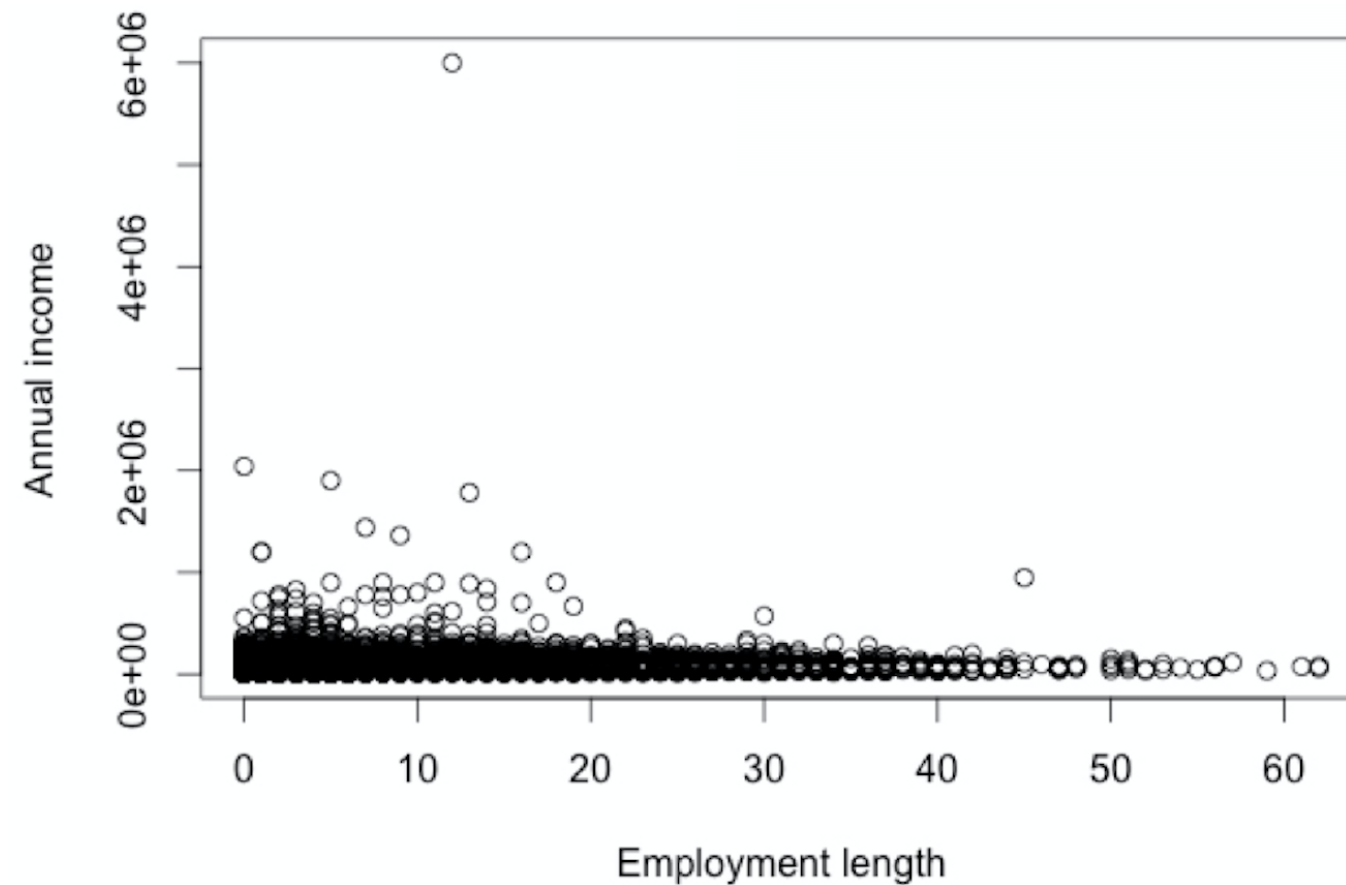


rule of thumb



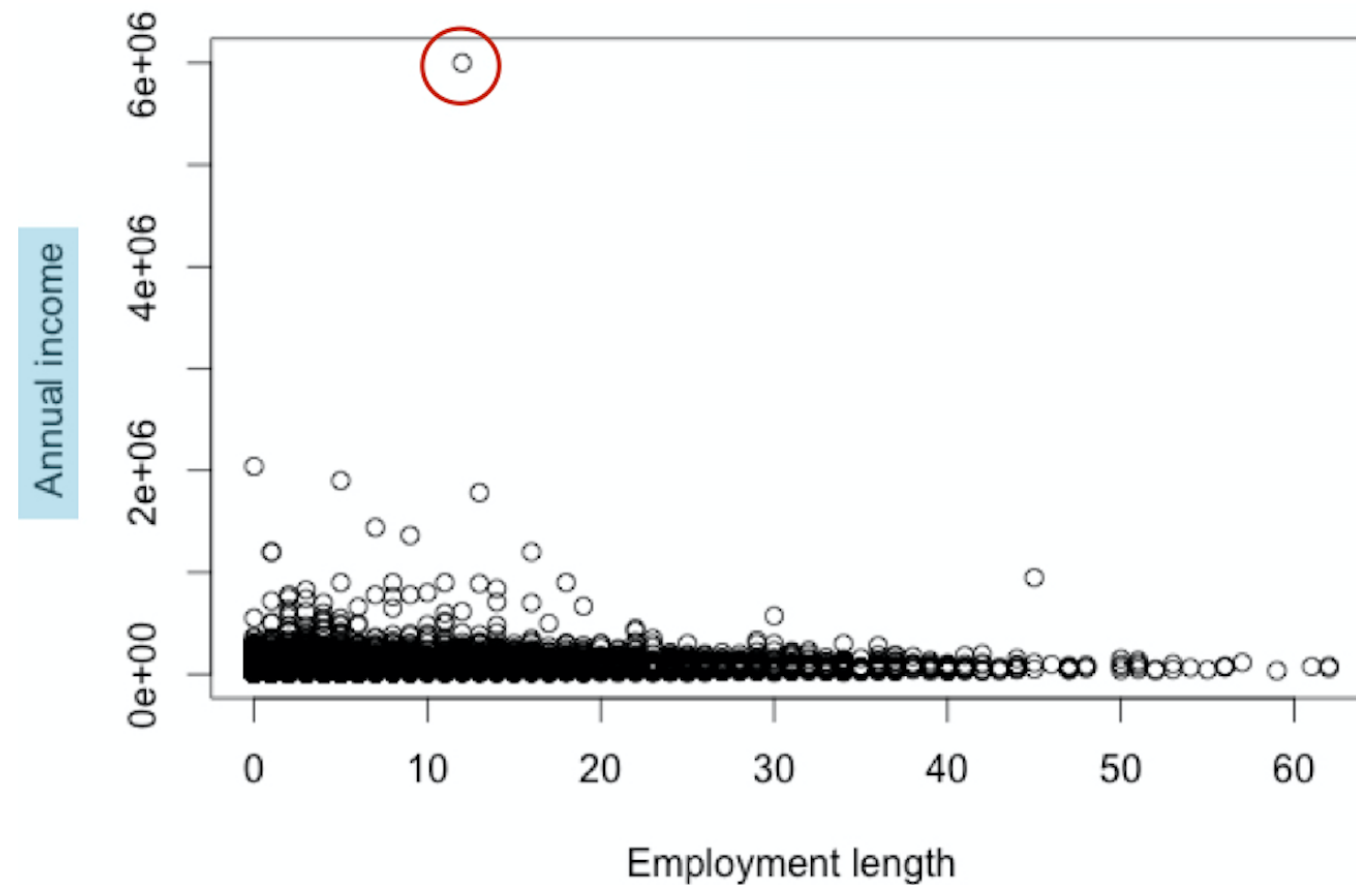
Bivariate plot

```
plot(loan_data$emp_length, loan_data$annual_inc,  
     xlab= "Employment length", ylab= "Annual income")
```



Bivariate plot

```
plot(loan_data$emp_length, loan_data$annual_inc,  
     xlab= "Employment length", ylab= "Annual income")
```



Let's practice!
CREDIT RISK MODELING IN R

Missing data and coarse classification

CREDIT RISK MODELING IN R



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Outlier deleted

loan_status	loan_amnt	int_rate	grade	emp_length	home_ownership	annual_inc	age
0	5000	12.73	C	12	MORTGAGE	6000000	144

Missing inputs

loan_status		loan_amnt	int_rate	grade	emp_length	home_ownership	annual_inc	age
...	...	...	...	...	...	...	...	...
125	0	6000	14.27	C	14	MORTGAGE	94800	23
126	1	2500	7.51	A	NA	OWN	12000	21
127	0	13500	9.91	B	2	MORTGAGE	36000	30
128	0	25000	12.42	B	2	RENT	225000	30
129	0	10000	NA	C	2	RENT	45900	65
130	0	2500	13.49	C	4	RENT	27200	26
...	...	...	...	...	...	...	...	...
2108	0	8000	7.90	A	8	RENT	64000	24
2109	0	12000	8.90	A	0	RENT	38400	26
2110	0	4000	NA	A	7	RENT	48000	30
2111	0	7000	9.91	B	20	MORTGAGE	130000	30
2112	0	7600	6.03	A	41	MORTGAGE	70920	28

Missing inputs

```
summary(loan_data$emp_length)
```

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	NA's
0.000	2.000	4.000	6.145	8.000	62.000	809

Missing inputs: strategies

- Delete row/column
- Replace
- Keep

Delete rows

```
index_NA <- which(is.na(loan_data$emp_length))
loan_data_no_NA <- loan_data[-c(index_NA), ]
```

	loan_status	loan_amnt	int_rate	grade	emp_length	home_ownership	annual_inc	age
...	...	...	...	...	...	...	...	...
125	0	6000	14.27	C	14	MORTGAGE	94800	23
126	1	2500	7.51	A	NA	OWN	12000	21
127	0	13500	9.91	B	2	MORTGAGE	36000	30
128	0	25000	12.42	B	2	RENT	225000	30
129	0	10000	NA	C	2	RENT	45900	65
130	0	2500	13.49	C	4	RENT	27200	26
...	...	...	...	...	...	...	...	...
2112	0	7600	6.03	A	41	MORTGAGE	70920	28
2113	0	10000	11.71	B	5	RENT	48132	22
2114	0	8000	6.62	A	17	OWN	42000	24
2115	0	4475	NA	B	NA	OWN	15000	23
2116	0	5750	8.90	A	3	RENT	17000	21
...	...	...	...	...	...	...	...	...

Delete column

```
loan_data_delete_employ <- loan_data
loan_data_delete_employ$emp_length <- NULL
```

loan_status	loan_amnt	int_rate	grade	home_ownership	annual_inc	age	
...	...	...	...	...	...	...	
125	0	6000	14.27	C	MORTGAGE	94800	23
126	1	2500	7.51	A	OWN	12000	21
127	0	13500	9.91	B	MORTGAGE	36000	30
128	0	25000	12.42	B	RENT	225000	30
129	0	10000	NA	C	RENT	45900	65
130	0	2500	13.49	C	RENT	27200	26
...	...	...	...	...	...	...	
2112	0	7600	6.03	A	MORTGAGE	70920	28
2113	0	10000	11.71	B	RENT	48132	22
2114	0	8000	6.62	A	OWN	42000	24
2115	0	4475	NA	B	OWN	15000	23
2116	0	5750	8.90	A	RENT	17000	21
...	...	...	...	...	...	...	

Replace: median imputation

```
index_NA <- which(is.na(loan_data$emp_length))
loan_data_replace <- loan_data
loan_data_replace$emp_length[index_NA] <- median(loan_data$emp_length, na.rm = TRUE)
```

```
loan_status loan_amnt int_rate grade emp_length home_ownership annual_inc age
...      ...      ...      ...      ...      ...      ...      ...
125        0        6000    14.27    C         14      MORTGAGE    94800    23
126        1        2500     7.51    A         NA         OWN     12000    21
127        0       13500     9.91    B          2      MORTGAGE    36000    30
128        0       25000    12.42    B          2         RENT   225000    30
129        0       10000      NA     C          2         RENT    45900    65
130        0        2500    13.49    C          4         RENT    27200    26
...      ...      ...      ...      ...      ...      ...      ...
2112       0        7600     6.03    A         41      MORTGAGE    70920    28
2113       0       10000    11.71    B          5         RENT    48132    22
2114       0        8000     6.62    A         17         OWN     42000    24
2115       0        4475      NA     B         NA         OWN     15000    23
2116       0        5750     8.90    A          3         RENT     17000    21
...      ...      ...      ...      ...      ...      ...      ...
```

Replace: median imputation

```
index_NA <- which(is.na(loan_data$emp_length))
loan_data_replace <- loan_data
loan_data_replace$emp_length[index_NA] <- median(loan_data$emp_length, na.rm = TRUE)
```

```
loan_status loan_amnt int_rate grade emp_length home_ownership annual_inc age
...      ...      ...      ...      ...      ...      ...      ...
125      0      6000    14.27    C      14      MORTGAGE    94800    23
126      1      2500     7.51    A       4      OWN      12000    21
127      0     13500     9.91    B       2      MORTGAGE    36000    30
128      0     25000    12.42    B       2      RENT     225000    30
129      0     10000      NA     C       2      RENT     45900    65
130      0      2500    13.49    C       4      RENT     27200    26
...      ...      ...      ...      ...      ...      ...      ...
2112     0      7600     6.03    A      41      MORTGAGE    70920    28
2113     0     10000    11.71    B       5      RENT     48132    22
2114     0      8000     6.62    A      17      OWN      42000    24
2115     0      4475      NA     B       4      OWN      15000    23
2116     0      5750     8.90    A       3      RENT     17000    21
...      ...      ...      ...      ...      ...      ...      ...
```

Keep

- Keep `NA`
- *Problem:* will cause row deletions for many models
- *Solution:* coarse classification, put variable in "bins"
 - New variable `emp_cat`
 - Range: 0-62 years → make bins of +/- 15 years
 - Categories: "0-15", "15-30", "30-45", "45+", "missing"

Keep: coarse classification

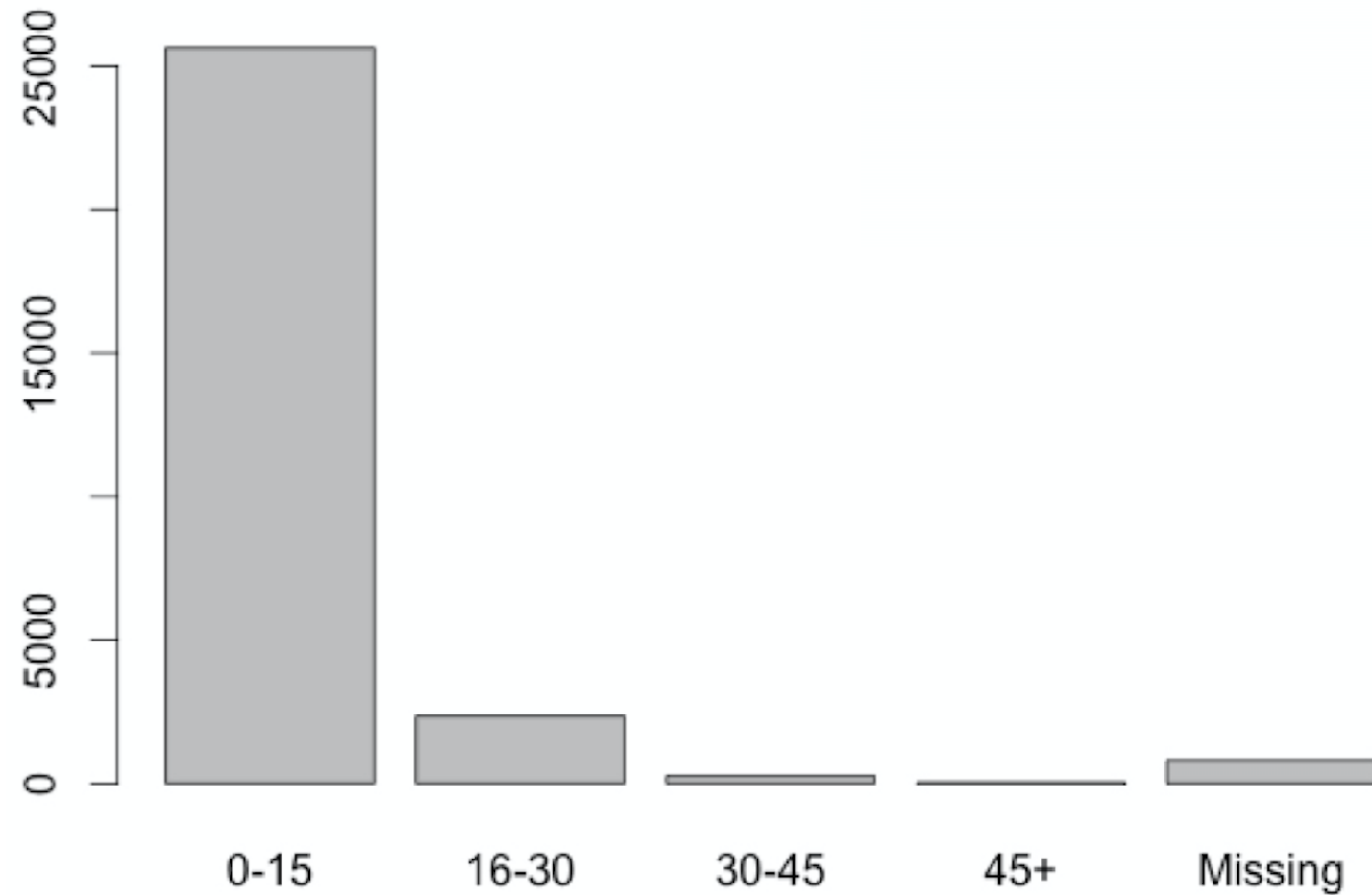
```
loan_status  loan_amnt  int_rate  grade  emp_length  home_ownership  annual_inc  age
...          ...      ...      ...      ...          ...          ...      ...
125          0        6000    14.27    C          14        MORTGAGE    94800    23
126          1        2500     7.51    A          NA          OWN        12000    21
127          0       13500     9.91    B           2        MORTGAGE    36000    30
128          0       25000    12.42    B           2         RENT     225000    30
129          0       10000     NA      C           2         RENT     45900    65
130          0        2500    13.49    C           4         RENT     27200    26
...          ...      ...      ...      ...          ...          ...      ...
2112         0        7600     6.03    A          41        MORTGAGE    70920    28
2113         0       10000    11.71    B           5         RENT     48132    22
2114         0        8000     6.62    A          17         OWN     42000    24
2115         0        4475     NA      B          NA         OWN     15000    23
2116         0        5750     8.90    A           3         RENT     17000    21
...          ...      ...      ...      ...          ...          ...      ...
```

Keep: coarse classification

```
loan_status  loan_amnt  int_rate  grade    emp_cat  home_ownership  annual_inc  age
...          ...      ...      ...      ...      ...          ...      ...
125          0        6000    14.27    C        0-15        MORTGAGE    94800    23
126          1        2500     7.51    A      Missing          OWN    12000    21
127          0       13500     9.91    B        0-15        MORTGAGE    36000    30
128          0       25000    12.42    B        0-15          RENT   225000    30
129          0       10000     NA      C        0-15          RENT    45900    65
130          0        2500    13.49    C        0-15          RENT    27200    26
...          ...      ...      ...      ...      ...          ...      ...
2112         0        7600     6.03    A       30-45        MORTGAGE    70920    28
2113         0       10000    11.71    B        0-15          RENT    48132    22
2114         0        8000     6.62    A       15-30          OWN    42000    24
2115         0        4475     NA      B      Missing          OWN    15000    23
2116         0        5750     8.90    A        0-15          RENT    17000    21
...          ...      ...      ...      ...      ...          ...      ...
```

Bin frequencies

```
plot(loan_data$emp_cat)
```



```
emp_cat
```

```
...
```

```
0-15
```

```
Missing
```

```
0-15
```

```
0-15
```

```
0-15
```

```
0-15
```

```
...
```

```
30-45
```

```
0-15
```

```
15-30
```

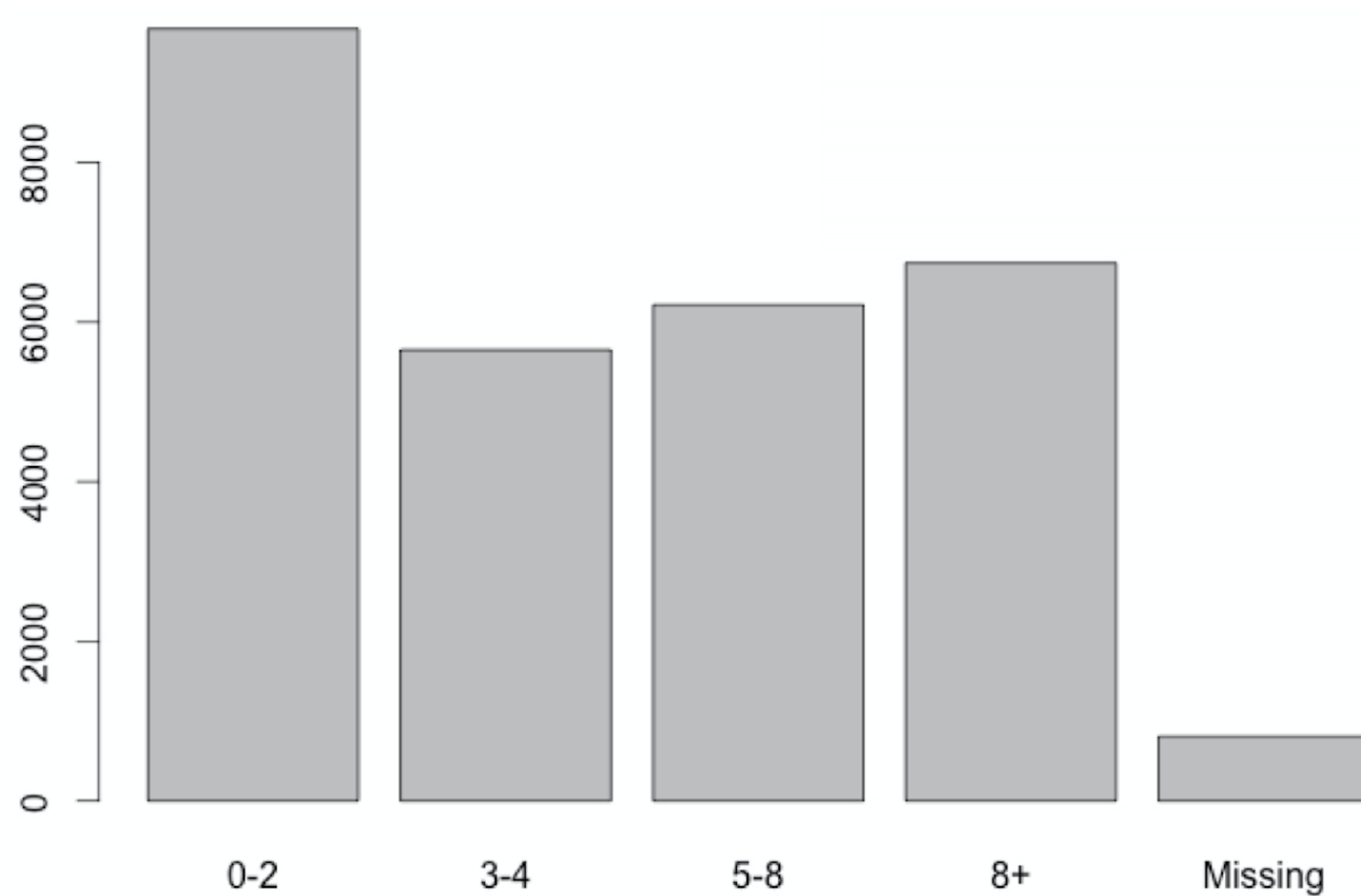
```
Missing
```

```
0-15
```

```
...
```


Bin frequencies

```
plot(loan_data$emp_cat)
```



```
emp_cat
```

```
...
```

```
8+
```

```
Missing
```

```
0-2
```

```
0-2
```

```
0-2
```

```
3-4
```

```
...
```

```
8+
```

```
5-8
```

```
8+
```

```
Missing
```

```
3-4
```

```
...
```


Final remarks

- Treat outliers as `NA`s

Final remarks

- Treat outliers as `NA`s

	CONTINUOUS	CATEGORICAL
DELETE	Delete rows (observations with <code>NA</code> s) Delete column (entire variable)	Delete rows (observations with <code>NA</code> s) Delete column (entire variable)
REPLACE	Replace using median	Replace using most frequent category
KEEP	Keep as <code>NA</code> (not always possible) Keep using coarse classification	<code>NA</code> category

Let's practice!
CREDIT RISK MODELING IN R

Data splitting and confusion matrices

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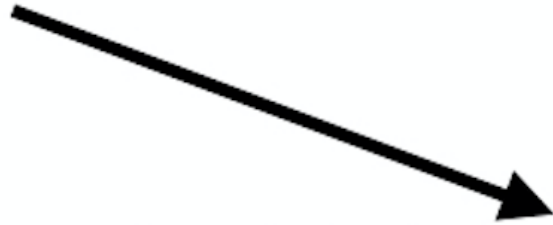


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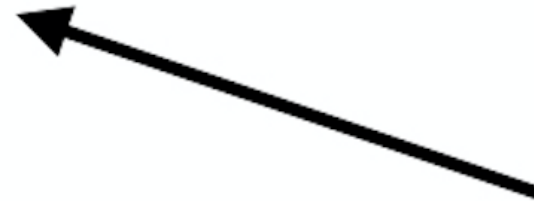
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Start analysis

Run the model

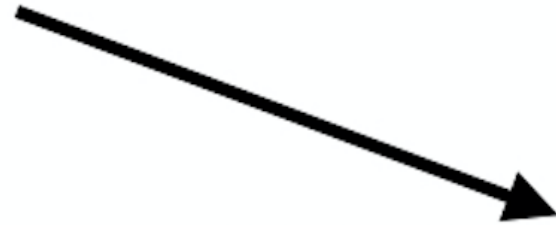


evaluate the result



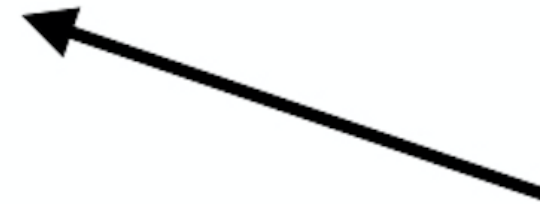
Training and test set

Run the model



training set

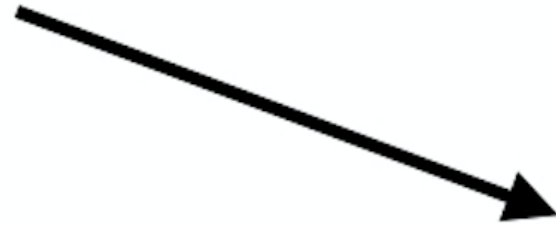
test set



evaluate the result

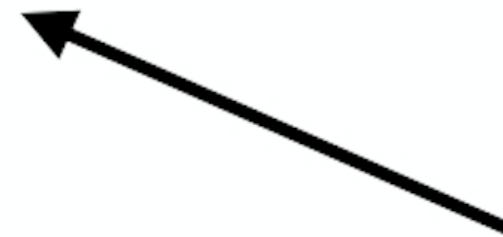
Training and test set

Run the model



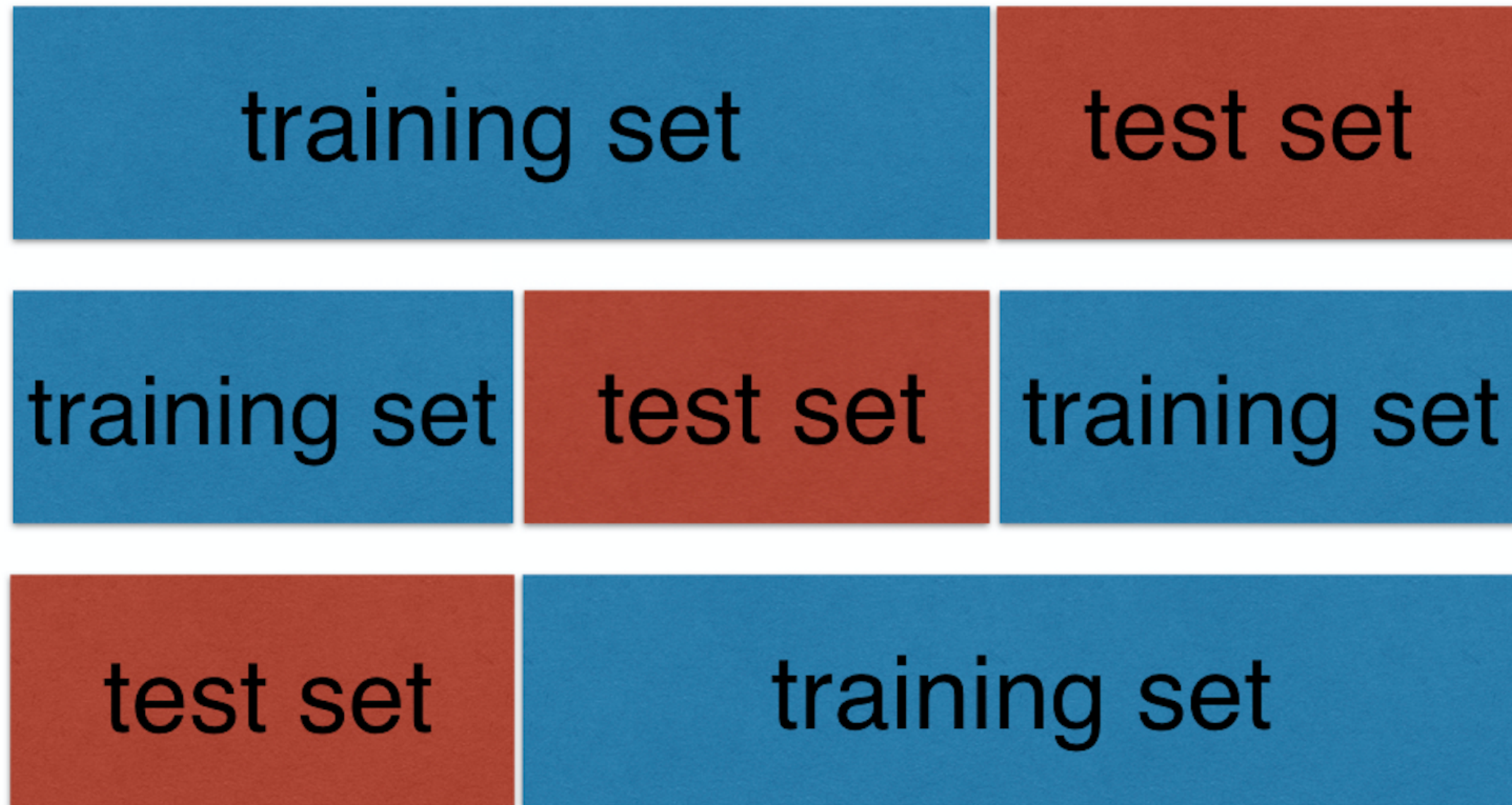
training set

test set



evaluate the result

Cross-validation



Evaluate a model

```
test_set$loan_status  model_prediction
...
[8066,]              1                1
[8067,]              0                0
[8068,]              0                0
[8069,]              0                0
[8070,]              0                0
[8071,]              0                1
[8072,]              1                0
[8073,]              1                1
[8074,]              0                0
[8075,]              0                0
[8076,]              0                0
[8077,]              1                1
[8078,]              0                0
...
```

Evaluate a model

test_set\$loan_status	model_prediction
...	...
[8066,]	1
[8067,]	0
[8068,]	0
[8069,]	0
[8070,]	0
[8071,]	1
[8072,]	0
[8073,]	1
[8074,]	0
[8075,]	0
[8076,]	0
[8077,]	1
[8078,]	0
[8079,]	1

Actual loan status v. Model prediction

	No default (0)	Default (1)
No default (0)	8	2
Default (1)	1	3

Evaluate a model

```
test_set$loan_status  model_prediction
...                  ...
[8066,]              1              1
[8067,]              0              0
[8068,]              0              0
[8069,]              0              0
[8070,]              0              0
[8071,]              0              1
[8072,]              1              0
[8073,]              1              1
[8074,]              0              0
[8075,]              0              0
[8076,]              0              0
[8077,]              1              1
[8078,]              0              0
[8079,]              0              1
```

Actual loan status v. Model prediction

	No default (0)	Default (1)
No default (0)	TN	FP
Default (1)	FN	TP

Some measures...

- *Accuracy*

$$\frac{(8 + 3)}{14} = 78.57\%$$

- *Sensitivity*

$$\frac{3}{(1 + 3)} = 75\%$$

- *Specificity*

$$\frac{8}{(8 + 2)} = 80\%$$

Actual loan status v. Model prediction

	No default (0)	Default (1)
No default (0)	8	2
Default (1)	1	3

Let's practice!
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