FRAUD DETECTION IN R

Introduction & Motivation

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What is fraud?

- Fraud is an uncommon, well-considered, imperceptibly concealed, time-evolving and often carefully organized crime which appears in many types and forms.

Impact of fraud

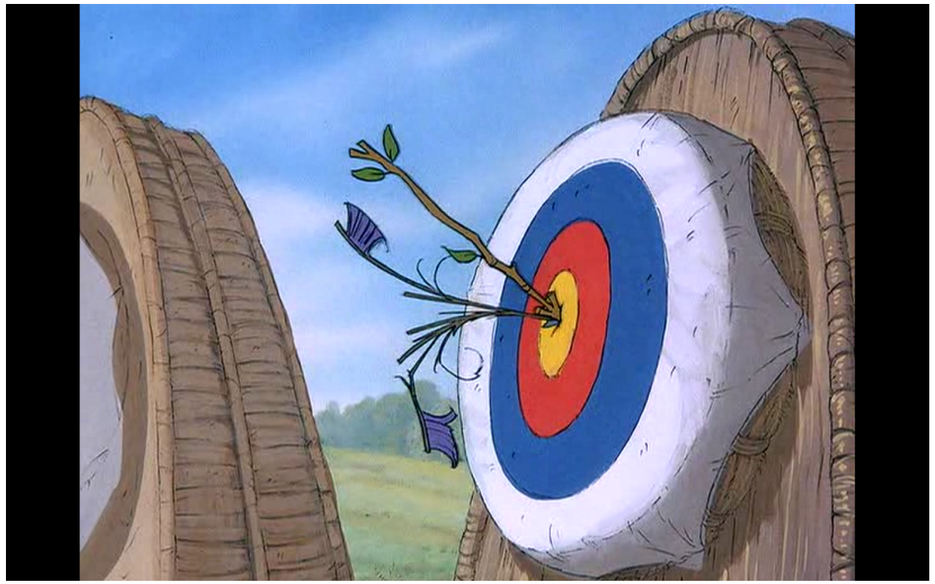
- Fraud is very rare, but cost of not detecting fraud can be huge!
- Examples:
  - Organizations lose **5% of their yearly revenues** to fraud
  - Money lost by businesses to fraud > $3.5 trillion each year
  - **Credit card** companies lose approximately **7 cents per $100** of transactions due to fraud
  - Fraud takes up **5-10% of the claim amounts** paid for **non-life insurance**

Types of fraud

- Anti-money laundering
- Check fraud
- (Credit) card fraud
- Click fraud
- Customs fraud
- Counterfeit
- Identity theft
- Insurance fraud
- Mortgage fraud
- Non-delivery fraud
- Online fraud
- Product warranty fraud
- Tax evasion
- Telecommunication fraud
- Theft of inventory
- Threat
- Ticket fraud
- Transit faud
- Wire fraud
- Workers compensation fraud

Key characteristics of successful fraud analytics models

- Statistical accuracy



Key characteristics of successful fraud analytics models

- Statistical accuracy
- Interpretability

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Key characteristics of successful fraud analytics models

- Statistical accuracy
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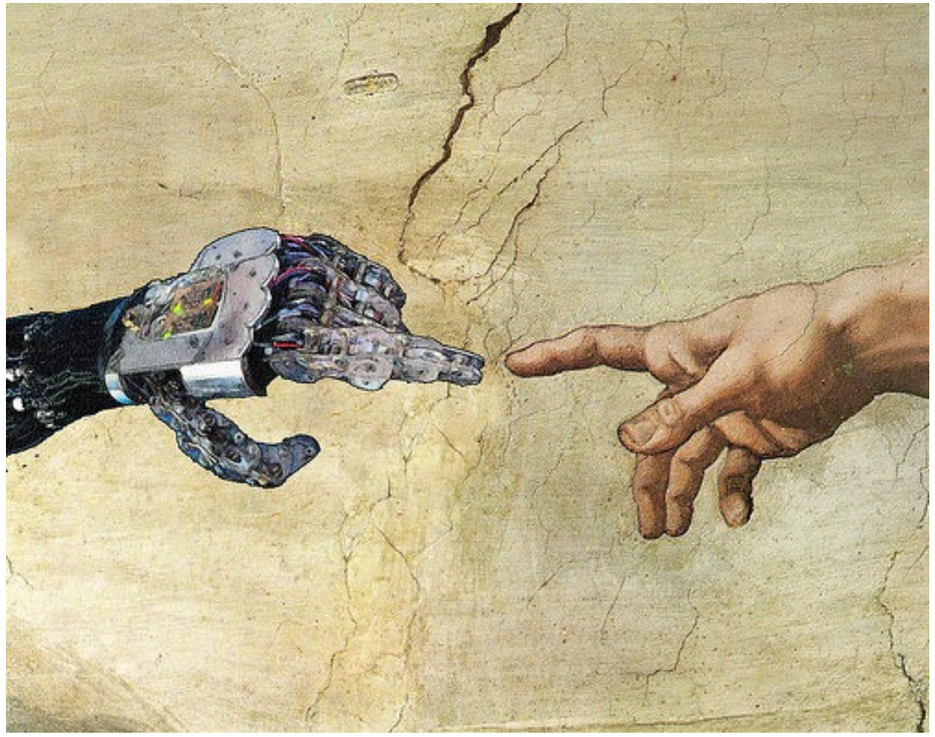
- Economical impact

Key characteristics of successful fraud analytics models

- Statistical accuracy
- Interpretability
- Regulatory compliance
- Economical cost
- Complement expert based approaches with data-driven techniques



Challenges of fraud detection model

- Imbalance
  - e.g. in credit card fraud < 0.5% frauds typically

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  - e.g. in credit card fraud < 8 seconds decision time

Challenges of fraud detection model

- Imbalance
  - e.g. in credit card fraud < 0.5% frauds typically
- Operational efficiency
  - e.g. in credit card fraud < 8 seconds decision time
- Avoid harassing good customers

Imbalanced data

- After a major storm, an insurance company received many claims
  - Fraudulent claims are labeled with 1 and legitimate claims with 0
- The percentage of fraud cases in the data can be determined by using the functions `table()` and `prop.table()`
- `prop.table(table())` to determine percentage of fraud

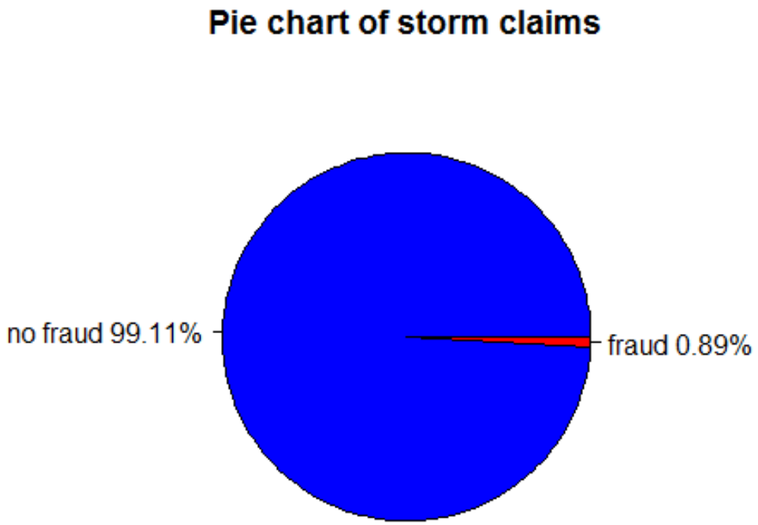
```
> prop.table(table(fraud_label))

     0      1
0.9911 0.0089
```

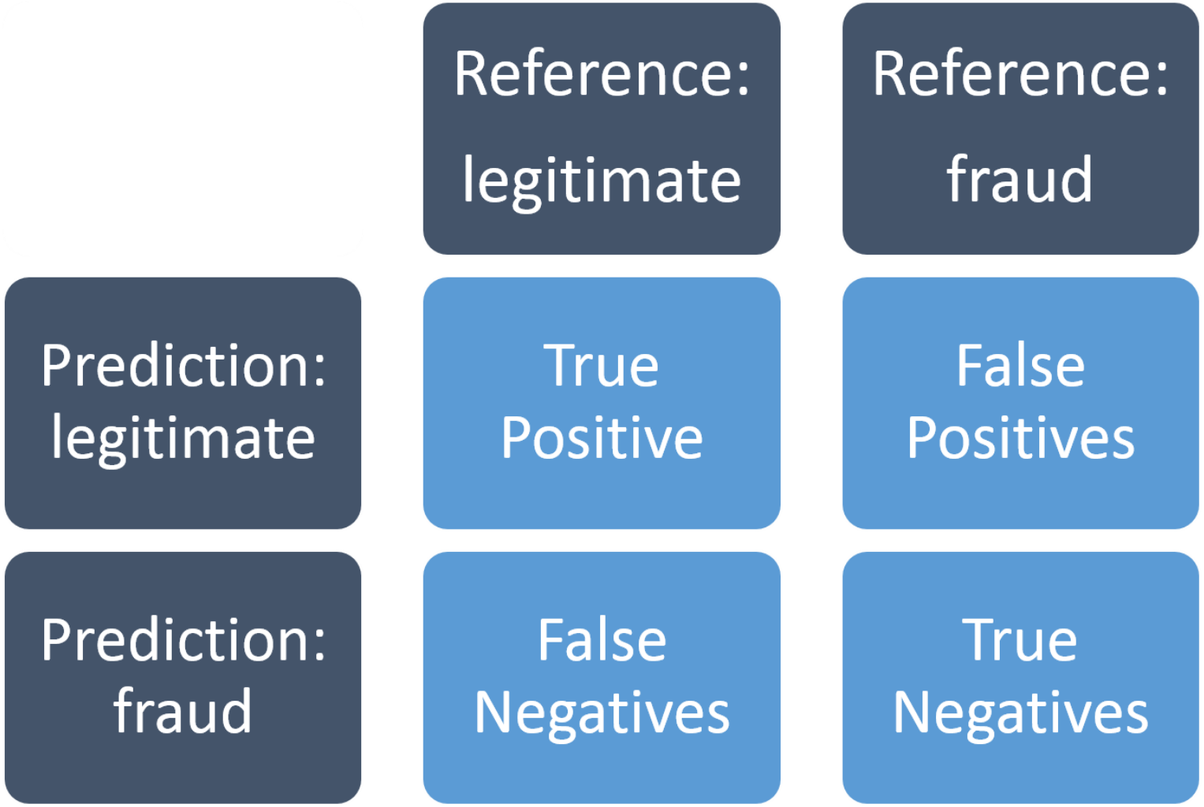
Imbalanced data

- Visualize imbalance with pie chart

```
> labels <- c("no fraud", "fraud")
> labels <- paste(labels, round(100*prop.table(table(fraud_label)), 2))
> labels <- paste0(labels, "%")
> pie(table(fraud_label), labels, col = c("blue", "red"),
      main = "Pie chart of storm claims")
```



Evaluation of supervised method: confusion matrix



Confusion matrix: claims example

- Suppose no detection model is used, so all claims are considered as legitimate:

```
> predictions <- rep.int(0, nrow(claims))
> predictions <- factor(predictions, levels = c("no fraud", "fraud"))
```

- Function confusionMatrix() from package caret:

```
> library(caret)
> confusionMatrix(data = predictions, reference = fraud_label)

 Confusion Matrix and Statistics

             Reference
 Prediction    0   1
            0 614  14
            1   0   0

 Accuracy : 0.9777
```

Total cost of not detecting fraud: claims example

- Total cost of fraud defined as the sum of fraudulent amounts

- Total cost if no fraud is detected:

```
> total_cost <- sum(claim_amount[fraud_label == "fraud"])
> print(total_cost)

[1] 2301508
```

FRAUD DETECTION IN R

Let's practice!

FRAUD DETECTION IN R

Time features

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Analyzing time

- Certain events are expected to occur at similar moments in time
- Example: customer making transactions at similar hours
- Aim: capture information about the time aspect by meaningful features
- Dealing with time can be tricky
  - 00:00 = 24:00
  - no natural ordering: 23:00 $<$, $>$ 01:00?

Mean of timestamps

- Do not use arithmetic mean to compute an average timestamp!
  - Example: transaction made at 01:00, 02:00, 21:00 and 22:00
  - arithmetic mean is 11:30, but no transfer was made close to that time!

```
> data(timestamps)
> head(timestamps)

[1] "20:27:28" "21:08:41" "01:30:16" "00:57:04" "23:12:14" "22:54:16"
```

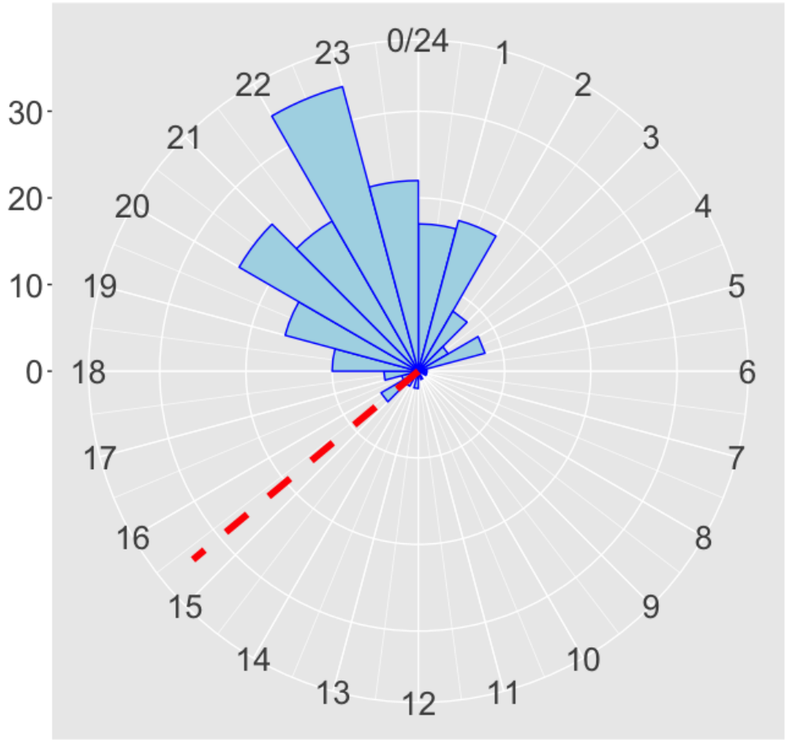
- Convert digital timestamps to decimal format in hours

```
> library(lubridate)
> ts <- as.numeric(hms(timestamps)) / 3600

> head(ts)

[1] 20.4577778 21.1447222  1.5044444  0.9511111 23.2038889 22.9044444
```

Circular histogram

```
> library(ggplot2)

> clock <- ggplot(data.frame(ts), aes(x = ts)) +
  geom_histogram(breaks = seq(0, 24), colour = "blue", fill = "lightblue") +
  coord_polar()

> arithmetic_mean <- mean(ts)

> clock + geom_vline(xintercept = arithmetic_mean,
                     linetype = 2, color = "red", size = 2)
```

Circular histogram with arithmetic mean



von Mises distribution

- Model time as a periodic variable using the von Mises probability distribution (Correa Bahnsen et al., 2016)
- Periodic normal distribution = normal distribution wrapped around a circle
- von Mises distribution of a set of timestamps $D = \{t_1, t_2, \ldots, t_n\}$

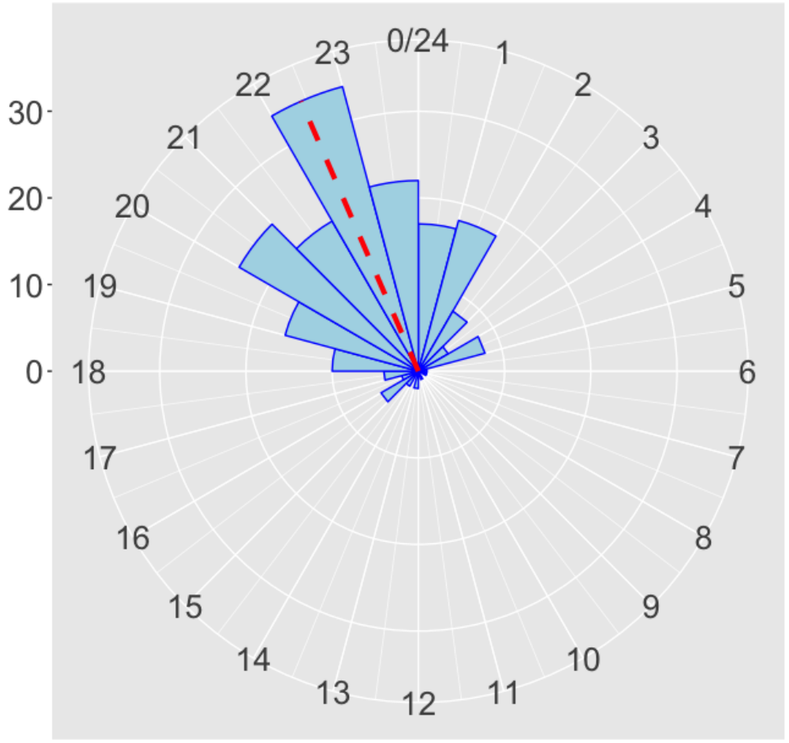
$$D \sim vonMises\left(\mu, \kappa\right)$$

- μ: periodic mean, measure of location, distribution is clustered around μ
- $1/\kappa$: periodic variance; κ is a measure of concentration

Estimating parameters μ and κ

```
# Convert the decimal timestamps to class "circular"
> library(circular)
> ts <- circular(ts, units = "hours", template = "clock24")

> head(ts)

Circular Data:
[1] 20.457889 21.144607  1.504422  0.950982 23.203917  4.904397

> estimates <- mle.vonmises(ts)
> p_mean <- estimates$mu %% 24
> concentration <- estimates$kappa
```

Circular histogram with periodic mean



Confidence interval

- Extract new features: confidence interval for the time of a transaction
- $S = \{x_i^{time} | i = 1, \ldots, n\}$: set of transactions made by the same customer

(1) Estimate $\mu(S)$ and $\kappa(S)$ based on S:

```
> estimates <- mle.vonmises(ts)
> p_mean <- estimates$mu %% 24
> concentration <- estimates$kappa
```

(2) Calculate the density (= likelihood) of the timestamps for the estimated von Mises distribution:

```
> densities <- dvonmises(ts, mu = p_mean, kappa = concentration)
```

Feature extraction

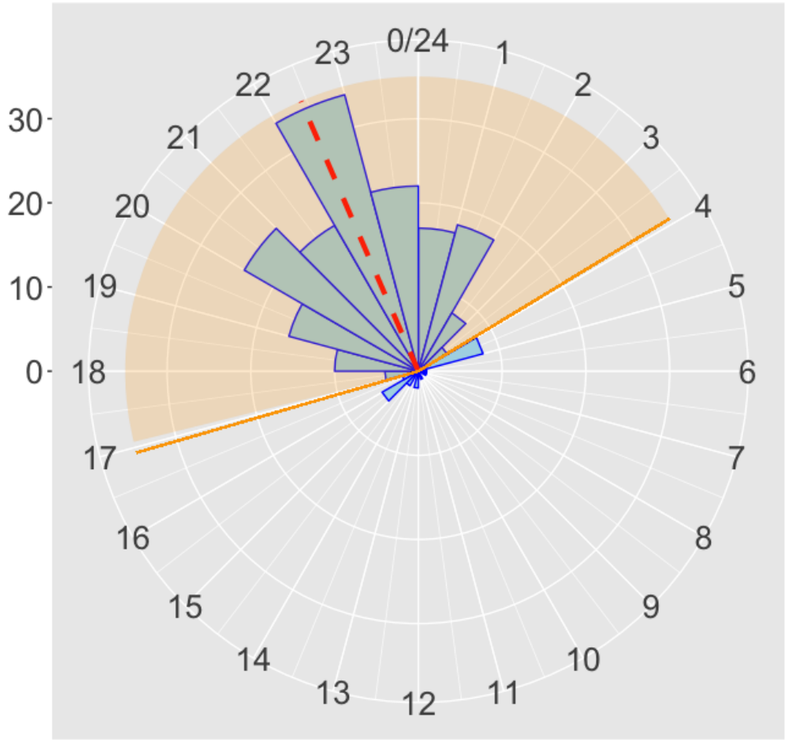
- Binary feature if a new transaction time is within the confidence interval (CI) with probability α (e.g. 0.90, 0.95)
- Timestamp is within 90% CI if its density is larger than the cutoff value:

```
> alpha <- 0.90

> quantile <- qvonmises((1 - alpha)/2,
                        mu = p_mean, kappa = concentration) %% 24

> cutoff <- dvonmises(quantile,
                      mu = p_mean, kappa = concentration)
```

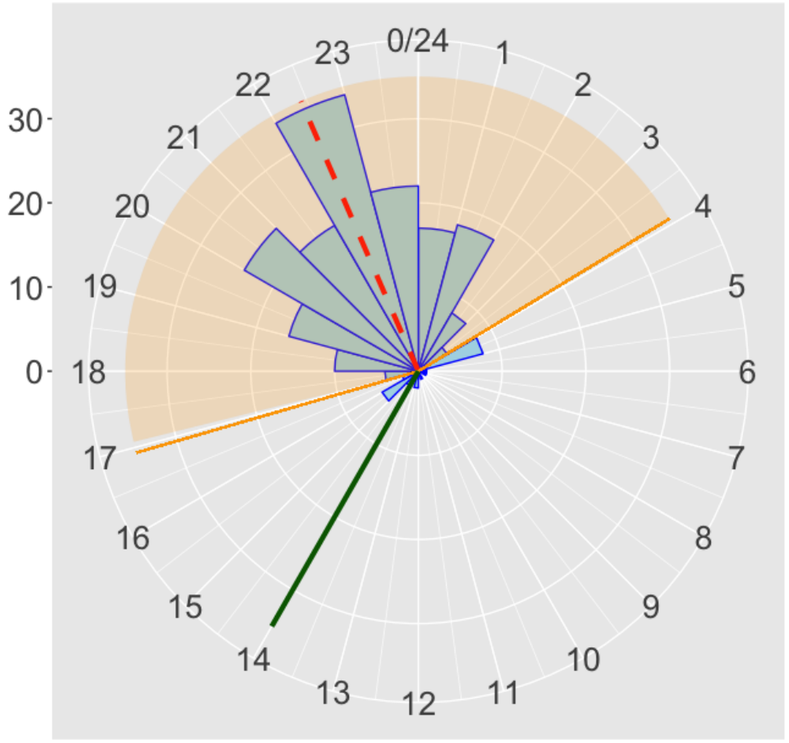
- Binary time feature: `TRUE` if timestamp lies inside CI, `FALSE` otherwise

```
> time_feature <- densities >= cutoff
```

Confidence interval



Confidence interval



Example

Time	Arithmetic mean	Periodic mean	Confidence interval	Periodic feature
18:25	-	-	-	-
20:27	-	-	-	-
20:53	19:26	19:26	17:45 – 21:07	TRUE
00:45	19:55	19:56	18:09 – 21:42	FALSE
19:12	15:08	21:02	17:13 – 00:51	TRUE
23:39	15:56	20:37	17:00 – 00:14	TRUE
06:05	17:14	21:10	17:21 – 00:59	FALSE

Confidence interval with moving time window

```
> print(ts)
[1] 18.42 20.45 20.88  0.75 19.20 23.65  6.08

> time_feature = c(NA, NA)
> for (i in 3:length(ts)) {
    # Previous timestamps
    ts_history <- ts[1:(i-1)]

    # Estimate mu and kappa on historic timestamps
    estimates <- mle.vonmises(ts_history)
    p_mean <- estimates$mu %% 24
    concentration <- estimates$kappa

    # Estimate density of current timestamp
    dens_i <- dvonmises(ts[i], mu = p_mean, kappa = concentration)

    # Check if density is larger than cutoff with confidence level 90%
    alpha <- 0.90
    quantile <- qvonmises((1-alpha)/2, mu=p_mean, kappa=concentration) %% 24
    cutoff <- dvonmises(quantile, mu = p_mean, kappa = concentration)
    time_feature[i] <- dens_i >= cutoff
}

> print(time_feature)
[1]    NA    NA  TRUE FALSE  TRUE  TRUE FALSE
```

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Frequency features

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Need for additional features

Transfers made by Alice & Bob:

```
> trans %>% select(fraud_flag, orig_account_id,
                   benef_country, authentication_cd, channel_cd, amount)

   fraud_flag account_name benef_country authentication_cd channel_cd amount
1           0          Bob         ISO03               AU02       CH07    549
2           0        Alice         ISO03               AU03       CH04     37
3           0          Bob         ISO03               AU04       CH07     25
4           0          Bob         ISO03               AU02       CH06     25
5           0        Alice         ISO03               AU01       CH07     13
6           0          Bob         ISO03               AU02       CH06    785
7           0        Alice         ISO03               AU03       CH04     49
8           0          Bob         ISO03               AU02       CH07     35
...       ...          ...          ...                ...        ...    ...
36          0        Alice         ISO03               AU05       CH04    126
37          0          Bob         ISO03               AU02       CH06     22
38          0        Alice         ISO03               AU03       CH04     41
39          1          Bob         ISO03               AU03       CH05   3779
40          1        Alice         ISO03               AU04       CH05   1531
```

Alice's & Bob's profile

Authentication methods used by Alice:

```
                  fraud_flag
authentication_cd 0 1
             AU01 6 0
             AU02 0 0
             AU03 7 0
             AU04 0 1
             AU05 9 0
```

Alice's & Bob's profile

Authentication methods used by Alice:

```
                  fraud_flag
authentication_cd 0 1
             AU01 6 0
             AU02 0 0
             AU03 7 0
             AU04 0 1
             AU05 9 0
```

Authentication methods used by Bob:

```
                  fraud_flag
authentication_cd 0 1
             AU01 1 0
             AU02 8 0
             AU03 0 1
             AU04 7 0
             AU05 0 0
```

Frequency feature for one account

Arrange the data according to time

```
> library(dplyr)
> trans <- trans %>% arrange(timestamp)
```

Frequency feature for one account

Arrange the data according to time

```
> library(dplyr)
> trans <- trans %>% arrange(timestamp)
```

Alice's data:

```
> trans_Alice <- trans %>% filter(account_name == "Alice")
```

Frequency feature for one account

Arrange the data according to time

```
> library(dplyr)
> trans <- trans %>% arrange(timestamp)
```

Alice's data:

```
> trans_Alice <- trans %>% filter(account_name == "Alice")
```

Alice her first transaction:

```
steps authentication_cd freq_auth
                  AU03         0
```

Frequency feature for one account (step 1)

Step 1: create function `frequency_fun`

Function counts the number of **previous** transfers with the same authentication method as the current one:

```
> frequency_fun <- function(steps, auth_method) {
      n <- length(steps)
      frequency <- sum(auth_method[1:n] == auth_method[n + 1])
      return(frequency)
  }
```

```
steps authentication_cd freq_auth
                  AU03         0
    1             AU03         1
```

Frequency feature for one account (step 1)

Step 1: create function `frequency_fun`

Function counts the number of **previous** transfers with the same authentication method as the current one:

```
> frequency_fun <- function(steps, auth_method) {
      n <- length(steps)
      frequency <- sum(auth_method[1:n] == auth_method[n + 1])
      return(frequency)
  }
```

```
steps authentication_cd freq_auth
                  AU03         0
    1             AU03         1
    2             AU03         2
```

Frequency feature for one account (step 1)

Step 1: create function `frequency_fun`

Function counts the number of **previous** transfers with the same authentication method as the current one:

```
> frequency_fun <- function(steps, auth_method) {
      n <- length(steps)
      frequency <- sum(auth_method[1:n] == auth_method[n + 1])
      return(frequency)
  }
```

```
steps authentication_cd freq_auth
                   AU03         0
    1              AU03         1
    2              AU03         2
    3              AU01         0
```

Frequency feature for one account (step 1)

Step 1: create function `frequency_fun`

Function counts the number of **previous** transfers with the same authentication method as the current one:

```
> frequency_fun <- function(steps, auth_method) {
      n <- length(steps)
      frequency <- sum(auth_method[1:n] == auth_method[n + 1])
      return(frequency)
  }
```

```
steps authentication_cd freq_auth
                   AU03         0
    1              AU03         1
    2              AU03         2
    3              AU01         0
    4              AU01         1
```

Frequency feature for one account (step 2)

Step 2: use `rollapply` from the package `zoo`

```
> library(zoo)
> freq_auth <- rollapply(trans_Alice$transfer_id,
                         width = list(-1:-length(trans_Alice$transfer_id)),
                         partial = TRUE,
                         FUN = frequency_fun,
                         trans_Alice$authentication_cd)
```

Frequency feature for one account (step 2 & 3)

Step 2: use `rollapply` from the package `zoo`

```
> library(zoo)
> freq_auth <- rollapply(trans_Alice$transfer_id,
                         width = list(-1:-length(trans_Alice$transfer_id)),
                         partial = TRUE,
                         FUN = frequency_fun,
                         trans_Alice$authentication_cd)
```

Step 3: frequency feature starts with a zero

```
> freq_auth <- c(0, freq_auth)
```

Result!

	authentication_cd	freq_auth	fraud_flag
1	AU03	0	0
2	AU03	1	0
3	AU03	2	0
4	AU01	0	0
5	AU01	1	0
6	AU05	0	0
7	AU05	1	0
8	AU05	2	0
9	AU01	2	0
10	AU05	3	0
11	AU05	4	0
12	AU05	5	0
13	AU03	3	0
14	AU05	6	0
15	AU01	3	0
16	AU05	7	0
17	AU03	4	0
18	AU01	4	0
19	AU01	5	0
20	AU03	5	0
21	AU05	8	0
22	AU03	6	0
23	AU04	0	1

For multiple accounts

Step 1: group the data by `account_name`:

```
> trans %>% group_by(account_name)
```

Step 2: use `group_by()` and `mutate()` from `dplyr` package

```
> trans <- trans %>% group_by(account_name) %>%
   mutate(freq_auth = c(0,
                        rollapplyr(transfer_id,
                                   width = list(-1:-length(transfer_id)),
                                   partial = TRUE,
                                   FUN = count_fun, authentication_cd)
                        )
          )
```

Result for multiple accounts

	account_name	authentication_cd	freq_auth	fraud_flag
1	Bob	AU02	0	0
2	Alice	AU03	0	0
3	Bob	AU04	0	0
4	Bob	AU02	1	0
5	Alice	AU01	0	0
6	Bob	AU02	2	0
7	Alice	AU03	1	0
8	Bob	AU02	3	0
9	Alice	AU01	1	0
10	Bob	AU04	1	0
11	Bob	AU02	4	0
12	Alice	AU01	2	0
13	Alice	AU05	0	0
14	Alice	AU05	1	0
15	Alice	AU05	2	0
16	Bob	AU02	5	0
17	Bob	AU04	2	0
18	Bob	AU02	6	0
...	...	...	...	...
37	Bob	AU02	7	0
38	Alice	AU03	5	0
39	Bob	AU03	0	1
40	Alice	AU04	0	1

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Recency features

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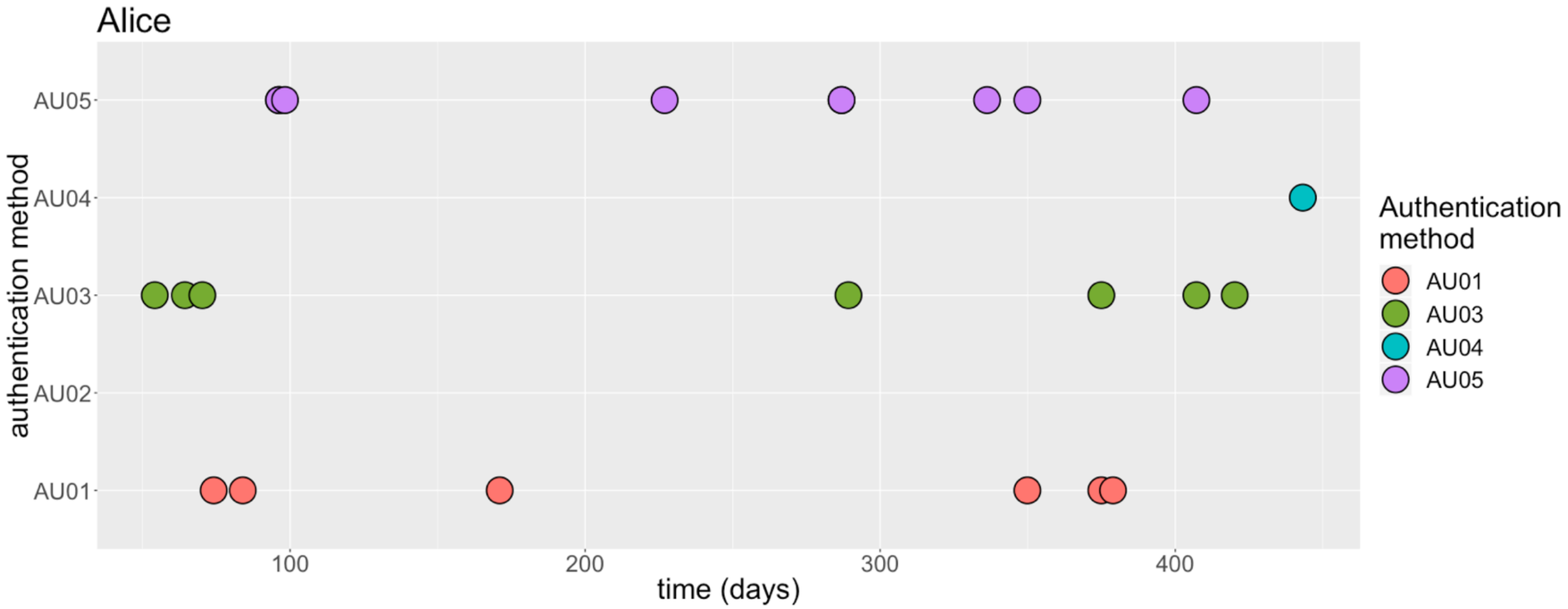
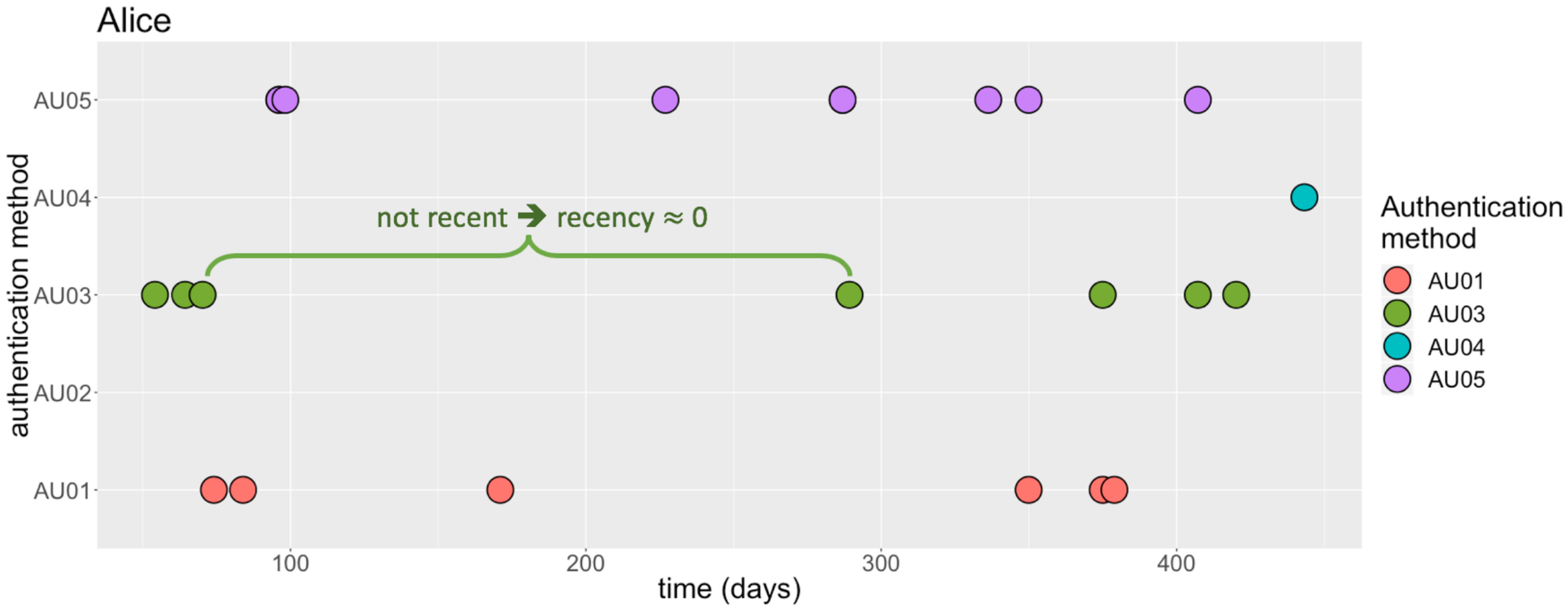
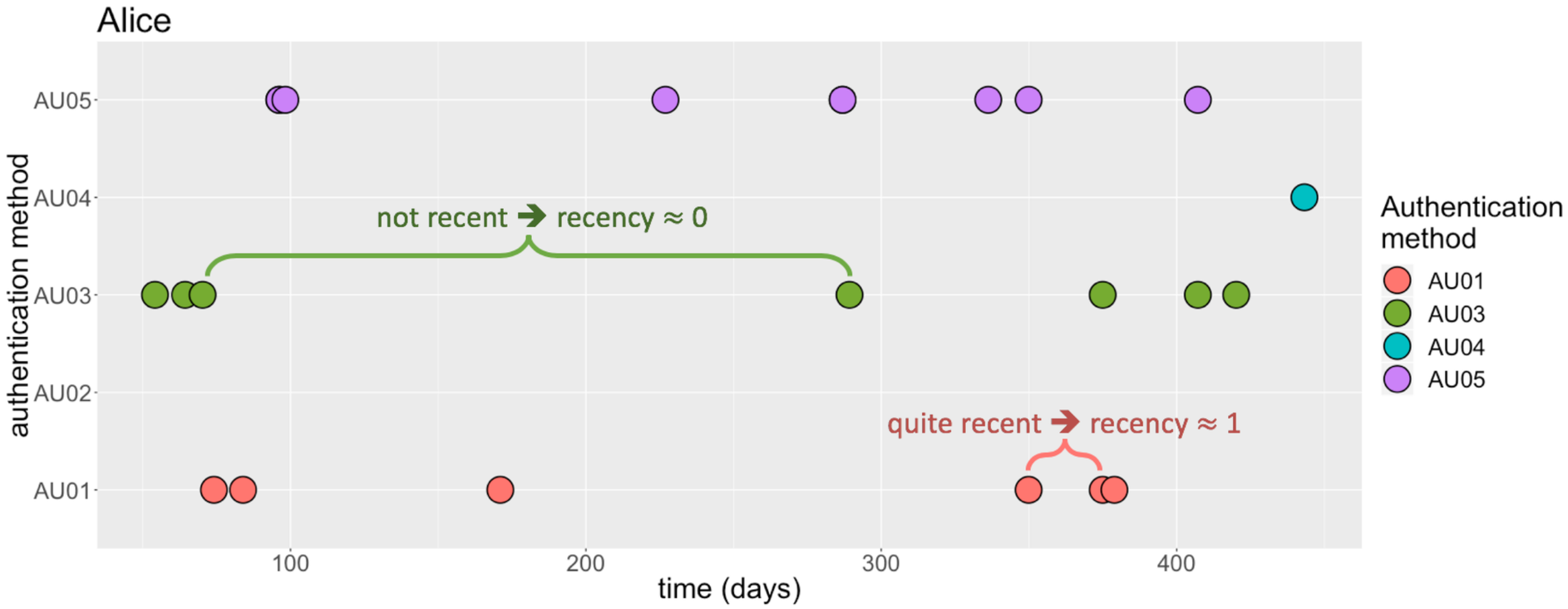
Authentication method vs time



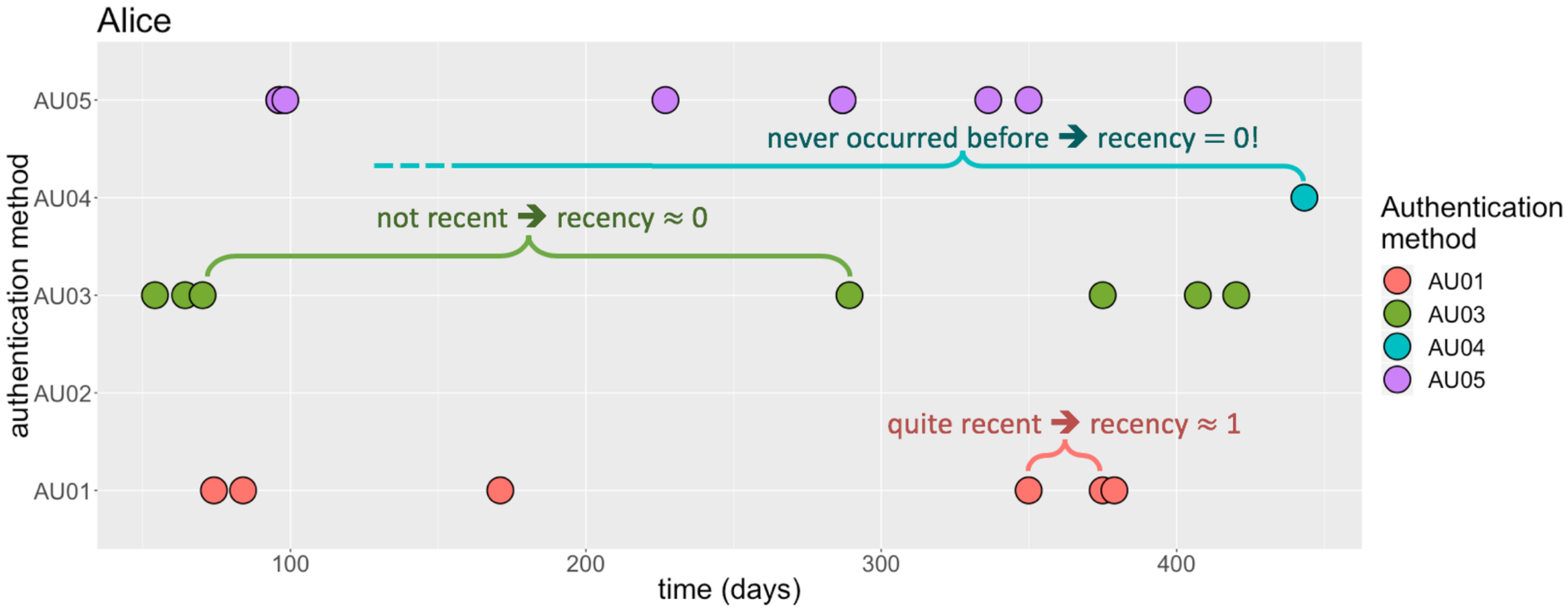
Large time interval



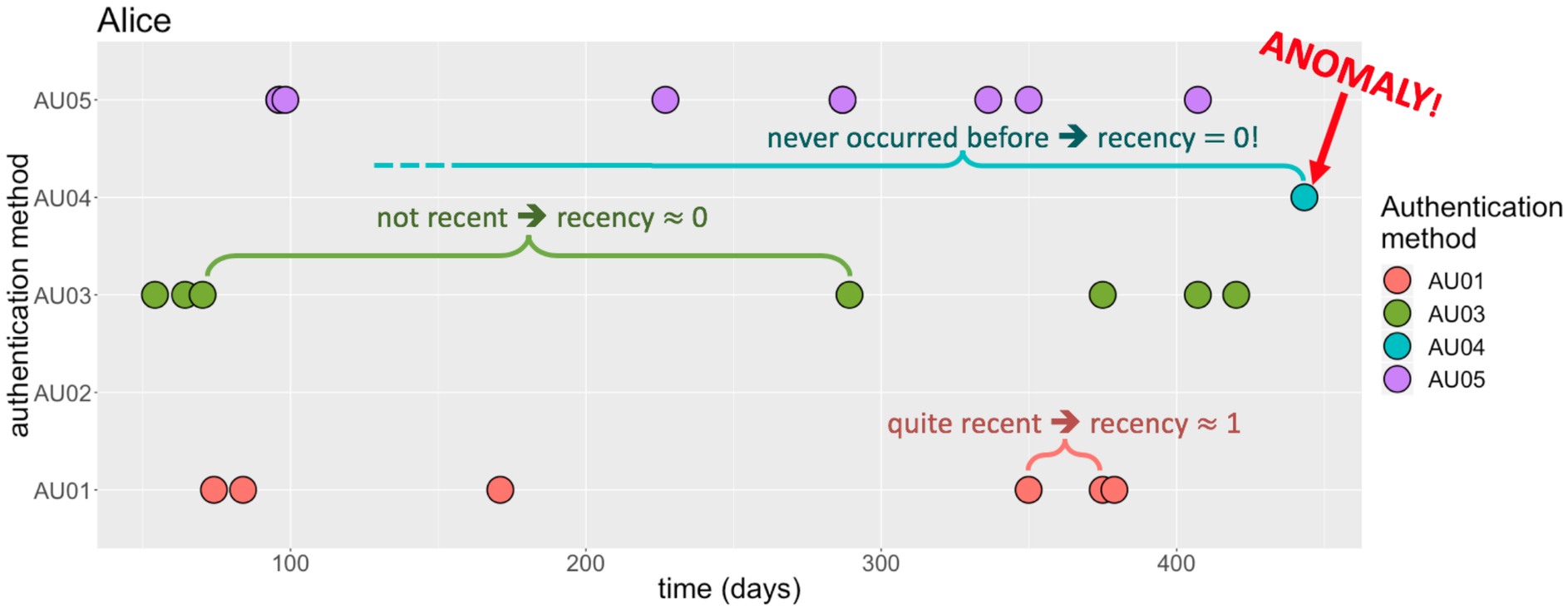
Small time interval



Zero recency



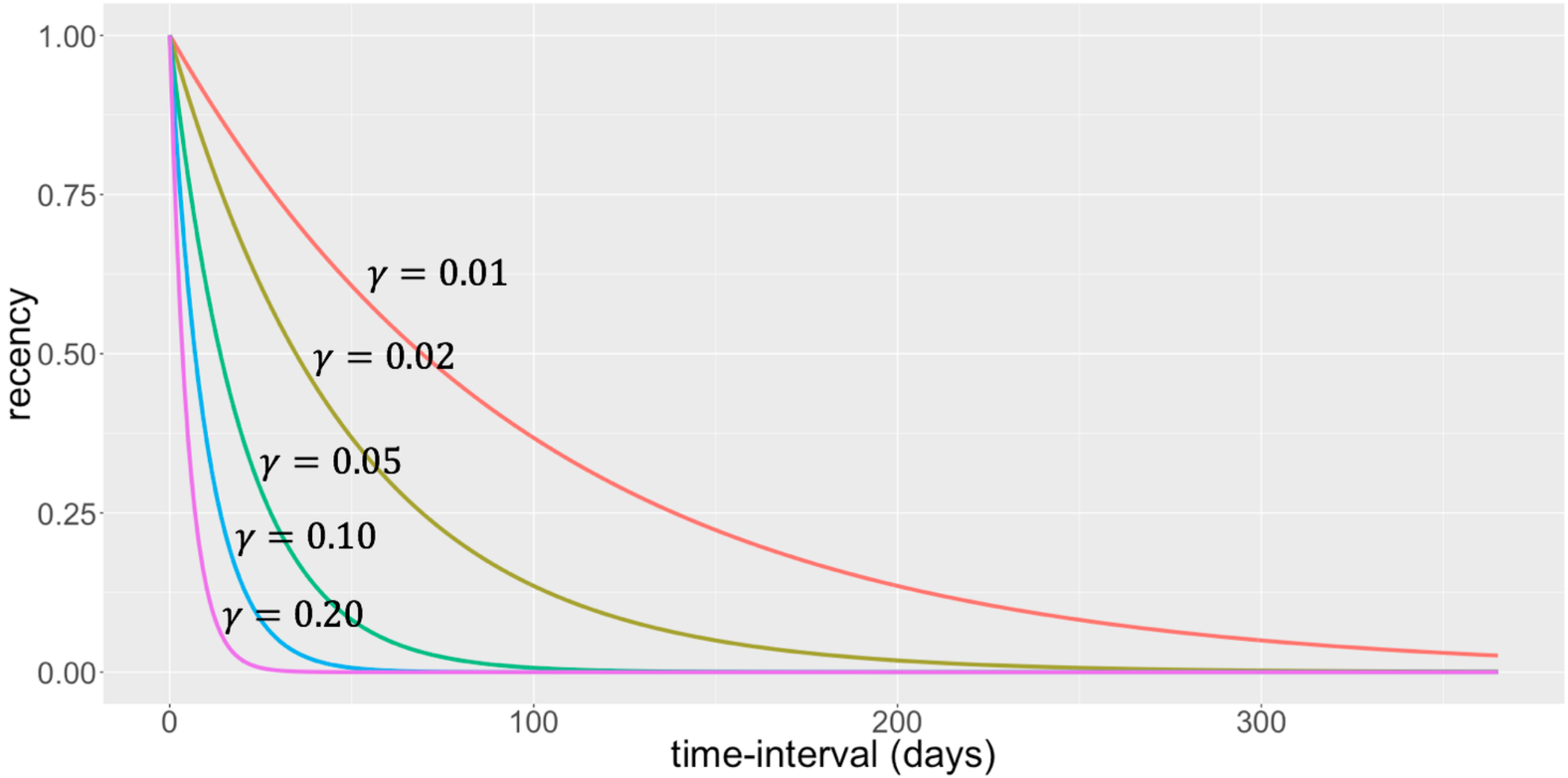
Anomalous behavior



Definition

- $recency = exp(-\gamma \cdot t) = e^{-\gamma t}$
  - t = time-interval between two consecutive events of the same type
  - γ = tuning parameter, typically close to 0 (e.g. 0.01, 0.02, 0.05)
  - $0 \leq recency \leq 1$

Recency vs time



How to choose parameter γ?

- (1) choose when recency is small (e.g. 0.01) after certain amount (t) of time
- (2) calculate $\gamma = -log(recency)/t$
- **Example**: set γ such that recency = 0.01 after t = 180 days

```
> gamma <- -log(0.01)/180
> gamma

[1] 0.02558428
```

Recency feature in R (step 1)

```
recency_fun <- function(t, gamma, auth_cd, freq_auth) {

  n_t <- length(t)

  if (freq_auth[n_t] == 0) {
    recency <- 0 # recency = 0 when frequency = 0

  } else {
    time_diff <- t[1] - max(t[2:n_t][auth_cd[(n_t-1):1] == auth_cd[n_t]])
    # time-interval = current timestamp
    #                 - timestamp of previous transfer with same auth_cd

    recency <- exp(-gamma * time_diff)
  }
  return(recency)

}
```

Recency feature in R (step 2)

(1) Choose value for γ

```
> gamma <- -log(0.01)/180 # = 0.0256
```

(2) Use `rollapply()`, `group_by()`, and `mutate()`

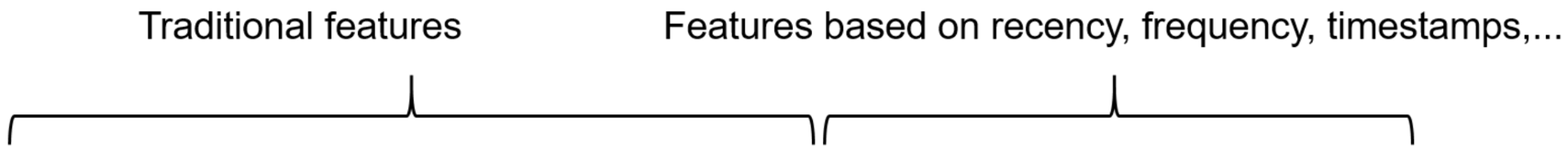
```
> library(dplyr) # needed for group_by() and mutate()
> library(zoo) # needed for rollapply()

> trans <- trans %>% group_by(account_name) %>%
    mutate(rec_auth = rollapply(timestamp,
                                width = list(0:-length(transfer_id)),
                                partial = TRUE,
                                FUN = recency_fun,
                                gamma, authentication_cd, freq_auth))
```

Result!

	account_name	timestamp	authentication_cd	rec_auth	fraud_flag
1	Bob	44.25	AU02	0.000	0
2	Alice	54.12	AU03	0.000	0
3	Bob	57.45	AU04	0.000	0
4	Bob	64.29	AU02	0.599	0
5	Alice	64.29	AU03	0.771	0
6	Bob	64.29	AU02	1.000	0
7	Alice	70.25	AU03	0.859	0
8	Bob	70.25	AU02	0.859	0
9	Alice	74.08	AU01	0.000	0
10	Bob	74.08	AU04	0.653	0
11	Bob	74.08	AU02	0.907	0
12	Alice	83.93	AU01	0.777	0
13	Alice	96.21	AU05	0.000	0
14	Alice	96.21	AU05	1.000	0
15	Alice	98.25	AU05	0.949	0
16	Bob	109.27	AU02	0.406	0
17	Bob	123.89	AU04	0.280	0
18	Bob	155.95	AU02	0.303	0
...	...	...	...	...	...
37	Bob	407.17	AU02	0.002	0
38	Alice	420.17	AU03	0.717	0
39	Bob	441.34	AU03	0.000	1
40	Alice	443.24	AU04	0.000	1

Features based on time, frequency and recency



	Country Beneficiary	Age Beneficiary	Payment channel	...	Amount	Freq_auth	Rec_auth	...	Time_feat	Fraud
1	Belgium	42	Mobile		102	3	0.02		0	No
2	Greece	35	ATM		125	1	0.59		0	No
3	Germany	27	Web		1067	0	0.86		1	No
...										
n	Belgium	56	Mobile		1039	2	0.12		0	No

FRAUD DETECTION IN R

Let's practice!