Management Information reports on Credit card risk

- Delinquency bucket prediction
- Roll rates matrix
- Credit utilization and loss rates report

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Delinquency bucket prediction - Analyzing Delinquency behavior

- **Delinquency** is the failure to make timely payments on a loan or debt. When an individual or a business is unable to make payments on time, the outstanding balance becomes delinquent.

- To better understand delinquency and predict future delinquencies, we can analyze delinquency data of a portfolio of accounts. Let's take the example of **500 accounts and their delinquency counts** for the months of February to July.

Month	0-30 days	31-60 days	61-90 days	91-120 days	120+ days
Feb	500	0	0	0	0
Mar	400	100	0	0	0
Apr	300	100	100	0	0
May	300	50	100	50	0
Jun	200	100	100	50	50
Jul	200	100	100	50	50

By analyzing this delinquency data, we can predict future delinquencies and take necessary actions to minimize them and mitigate the impact on the portfolio's overall performance.

- The above table shows the delinquency counts for each delinquency bucket for the given months. In February, all 500 accounts are current, meaning they are not delinquent. However, in March, 100 accounts become delinquent in the 31-60 days bucket. As we move to April, the delinquency count increases, and we see accounts moving to higher delinquency buckets.

- **0-30 days means Not Delinquent (grace period of 30 days given as per usual credit agreements)**

Delinquency bucket prediction – Transition probability computation

Month: Feb to Mar
Not Delinquent to Not Delinquent: 400/500 = 0.8
Not Delinquent to 30 Days Delinquent: 100/500 = 0.2

Month: Mar to Apr
Not Delinquent to Not Delinquent: 300/400 = 0.75
Not Delinquent to 30 Days Delinquent: 100/400 = 0.25
30 Days Delinquent to Not Delinquent: 100/100 = 1

Month: Apr to May
Not Delinquent to Not Delinquent: 300/300 = 1
Not Delinquent to 30 Days Delinquent: 50/300 = 0.1667
30 Days Delinquent to Not Delinquent: 50/100 = 0.5
30 Days Delinquent to 30 Days Delinquent: 50/100 = 0.5
30 Days Delinquent to 60 Days Delinquent: 0/100 = 0
60 Days Delinquent to Not Delinquent: 50/50 = 1

Month: May to Jun
Not Delinquent to Not Delinquent: 200/300 = 0.6667
Not Delinquent to 30 Days Delinquent: 100/300 = 0.3333
30 Days Delinquent to Not Delinquent: 100/150 = 0.6667
30 Days Delinquent to 30 Days Delinquent: 50/150 = 0.3333
60 Days Delinquent to Not Delinquent: 50/50 = 1
90 Days Delinquent to 30 Days Delinquent: 50/50 = 1

Month: Jun to Jul
Not Delinquent to Not Delinquent: 200/200 = 1
Not Delinquent to 30 Days Delinquent: 100/200 = 0.5
30 Days Delinquent to Not Delinquent: 100/150 = 0.6667
30 Days Delinquent to 30 Days Delinquent: 50/150 = 0.3333
60 Days Delinquent to Not Delinquent: 50/100 = 0.5
90 Days Delinquent to 30 Days Delinquent: 50/50 = 1
120+ Days Delinquent to 60 Days Delinquent: 50/50 = 1

- The computation above shows the transition probabilities between different delinquency states for each month.
- For example, in the transition from February to March, there is an 80% probability that accounts that were not delinquent will remain not delinquent, and a 20% probability that they will become 30 days delinquent.

By looking at the these probabilities, we can identify potential trends in delinquency behavior, such as accounts that are more likely to become delinquent or accounts that are more likely to recover from delinquency.

Delinquency bucket prediction – Transition probability matrices

- The transition probabilities we calculated earlier can be **represented as matrices** to help us visualize the movement of accounts across different delinquency buckets.
- Each **row** of the matrix represents the **current delinquency bucket**, while each **column** represents the **delinquency bucket in the next month**.
- As an example, let's consider the matrix for Mar-Apr. The row "ND" represents accounts that were not delinquent in March, while the column "ND" represents accounts that remain not delinquent in April.
- The value of 0.75 in the cell (ND, ND) represents the probability that an account that was not delinquent in March will remain not delinquent in April.

Feb - Mar

	ND	30	60	90	120
ND	0.8	0.2	0	0	0
30	0	0	0	0	0
60	0	0	0	0	0
90	0	0	0	0	0
120	0	0	0	0	0

Mar - Apr

	ND	30	60	90	120
ND	0.75	0.25	0	0	0
30	1	0	0	0	0
60	0	0	0	0	0
90	0	0	0	0	0
120	0	0	0	0	0

Apr - May

	ND	30	60	90	120
ND	1	0.16	0	0	0
30	0.5	0.5	0	0	0
60	0	0	1	0	0
90	0	0	0	0	0
120	0	0	0	0	0

May - Jun

	ND	30	60	90	120
ND	0.67	0.33	0	0	0
30	0.67	0.33	0	0	0
60	0	0	1	0	0
90	0	0	0	1	0
120	0	0	0	0	0

Jun - Jul

	ND	30	60	90	120
ND	1	0.5	0	0	0
30	0.67	0.33	0	0	0
60	0.5	0	0	0	0
90	0	1	0	0	0
120	0	0	1	0	0

By combining these transition probability matrices for all months, we can obtain the ***final probability transition matrix***. This matrix represents the overall probability of an account moving from one delinquency bucket to another over a period of time. We will use this matrix in the next slides ***to predict the delinquency bucket for each account in the next month***.

Delinquency bucket prediction – Applying Python for matrix iteration

Code

```
import numpy as np

# Define the states
states = ['Not Delinquent', '30 Days Delinquent', '60 Days Delinquent', '90 Days Delinquent', '120 Days Delinquent']

# Define the transition probabilities for each month
Probabilities  = {
    'Feb-Mar': np.array([
        [0.8, 0.2, 0, 0, 0],
        [0, 0, 0, 0, 0],
        [0, 0, 0, 0, 0],
        [0, 0, 0, 0, 0],
        [0, 0, 0, 0, 0],
    ]),
    'Mar-Apr': np.array([
        [0.75, 0.25, 0, 0, 0],
        [1, 0, 0, 0, 0],
        [0, 0, 0, 0, 0],
        [0, 0, 0, 0, 0],
        [0, 0, 0, 0, 0],
    ]),
    'Apr-May': np.array([
        [1, 0.1667, 0, 0, 0],
        [0.5, 0.5, 0, 0, 0],
        [0, 0, 1, 0, 0],
        [0, 0, 0, 0, 0],
        [0, 0, 0, 0, 0],
    ]),
```

Delinquency bucket prediction – Applying Python for matrix iteration

```
'May-Jun': np.array([
        [0.6667, 0.3333, 0, 0, 0],
        [0.6667, 0.3333, 0, 0, 0],
        [0, 0, 1, 0, 0],
        [0, 0, 0, 1, 0],
        [0, 0, 0, 0, 0],
    ]),
    'Jun-Jul': np.array([
        [1, 0.5, 0, 0, 0],
        [0.6667, 0.3333, 0, 0, 0],
        [0.5, 0, 0, 0, 0],
        [0, 1, 0, 0, 0],
        [0, 0, 1, 0, 0],
    ])
}

# Initialize the transition matrix with zeros
transition_matrix = np.zeros((len(states), len(states)))

# Iterate over each month and add its probabilities to the transition matrix
for prob in probabilities.values():
    transition_matrix += prob

# Normalize the transition matrix to ensure rows sum to 1
transition_matrix /= transition_matrix.sum(axis=1, keepdims=True)

# Print the transition matrix
print(transition_matrix)
```

Delinquency bucket prediction – Iteration process explained

- In the previous slide, we have provided a piece of **Python code** that helps us ***convert the individual matrices into a single matrix that we can use for predicting delinquency***. This process involves adding up the probabilities from each individual matrix to create a single transition matrix.
- We start by defining the possible states of delinquency and the transition probabilities for each month. Then, we initialize an empty transition matrix with zeros, with the same number of rows and columns as the number of states.
- The probability matrix of the month is added to zero matrix and then normalized so that sum of each row adds up to 1. For example, If we see Apr-May matrix and perform this operation, the result would be:

$$\begin{bmatrix} 1 & 0.16 & 0 & 0 & 0 \\ 0.5 & 0.5 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} + \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} = \begin{bmatrix} 1 & 0.16 & 0 & 0 & 0 \\ 0.5 & 0.5 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$\begin{bmatrix} 1/1.16 & 0.16/1.16 & 0 & 0 & 0 \\ 0.5/1 & 0.5/1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} = \begin{bmatrix} \mathbf{0.86} & \mathbf{0.14} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0.5} & \mathbf{0.5} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{1} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} \end{bmatrix}$$

- The blue colored matrix is the final normalized matrix for Apr-May. The python code will repeat the same procedure for all the months and then the normalized matrices of all months are added.

- Finally, the code will normalize the final transition matrix so that the rows add up to one, as required by probability theory.

Delinquency bucket prediction – Matrix multiplication

Final transition matrix for prediction

	ND	30	60	90	120
ND	0.74	0.25	0	0	0
30	0.70	0.29	0	0	0
60	0.2	0	0.8	0	0
90	0	0.5	0	0.5	0
120	0	0	1	0	0

Delinquency count for July

ND	200
30	100
60	100
90	50
120	50

Predicted Delinquency count for August

ND	173
30	169
60	120
90	75
120	100

- In the given slide, we are using the final transition probability matrix that we have calculated in the previous steps. We are also given the delinquency count for the month of July. Using this information, we can compute the predicted delinquency bucket for the next month, i.e., August.

- To compute the predicted delinquency bucket, we simply need to multiply the final transition probability matrix with the July's delinquency count matrix. This will give us the expected number of delinquencies in each bucket for August.

- Compared to July, the predicted delinquency counts for August show a decrease in the number of borrowers in the "ND" and an increase in the number of borrowers in the other delinquency buckets. ***Overall, the model predicts a slight worsening of the delinquency situation in August compared to July.***

Roll rates analysis

Delinquency rate table

Month	0-30 days	31-60 days	61-90 days	91-120 days	120+ days
Feb	100%	0%	0%	0%	0%
Mar	80%	20%	0%	0%	0%
Apr	60%	20%	20%	0%	0%
May	60%	10%	20%	10%	0%
Jun	40%	20%	20%	10%	10%
Jul	40%	20%	20%	10%	10%

- The delinquency rate table **(computed from our example's numbers)** shows the percentage of accounts that are delinquent in each of the different buckets for each month.
- In February, all accounts are current, so the delinquency rate for the 0-30 days bucket is 100%, and the rates for all other buckets are 0%.
- In March, 80% of accounts are in the 0-30 days bucket, 20% are in the 31-60 days bucket, and the rates for all other buckets are 0%.
- **The delinquency rate table helps us understand the trend in delinquencies over time.**

Roll rates analysis table

Month	0-30 days	31-60 days	61-90 days	91-120 days	120+ days
Feb	100%	0%	0%	0%	0%
Mar	-20%	20%	0%	0%	0%
Apr	-20%	0%	20%	0%	0%
May	0%	-10%	0%	0%	0%
Jun	-20%	10%	0%	0%	10%
Jul	0%	0%	0%	0%	0%

- The roll rates analysis table shows the **percentage of accounts that rolled over into a different delinquency bucket from the previous month**.
- For example, in March, 20% of accounts that were in the 0-30 days bucket in February rolled over into the 31-60 days bucket.
- ***A negative percentage*** in the table means decrease in number of accounts in that particular bucket. For example, in March, the Non delinquent accounts were decreased by 20%, **meaning increase in credit risk.**

Credit utilization report example

Month	Total Credit Limit	Credit Used	Credit Utilization Rate	Loss Rate
Jan	£ 100,000	£ 20,000	20%	1.5%
Feb	£ 100,000	£ 30,000	30%	2.0%
Mar	£ 100,000	£ 40,000	40%	2.5%
Apr	£ 100,000	£ 50,000	50%	3.0%
May	£ 100,000	£ 60,000	60%	3.5%

- In this table, we are tracking the credit utilization rate and loss rate for a credit card portfolio over a period of 5 months. The "Total Credit Limit" column represents the total amount of credit available to cardholders, while the "Credit Used" column shows how much of that credit has been used. The "Credit Utilization Rate" column is calculated by dividing the credit used by the total credit limit. The "Loss Rate" column represents the percentage of credit that has been lost due to defaults or delinquencies.

- As you can see, the credit utilization rate increases over time as more credit is used, which can increase the risk of defaults and delinquencies. Similarly, the ***loss rate also increases as the credit utilization rate goes up, indicating a higher level of risk in the portfolio.*** By tracking these metrics over time, credit risk analysts can identify trends and make informed decisions about managing the credit card portfolio.