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Data Analyst

Case

cloudwalk

Exploratory Analysis

Answer the question: how to identify which transactions, given a payload, are fraudulent?

Infrastructure

GitHub

python™

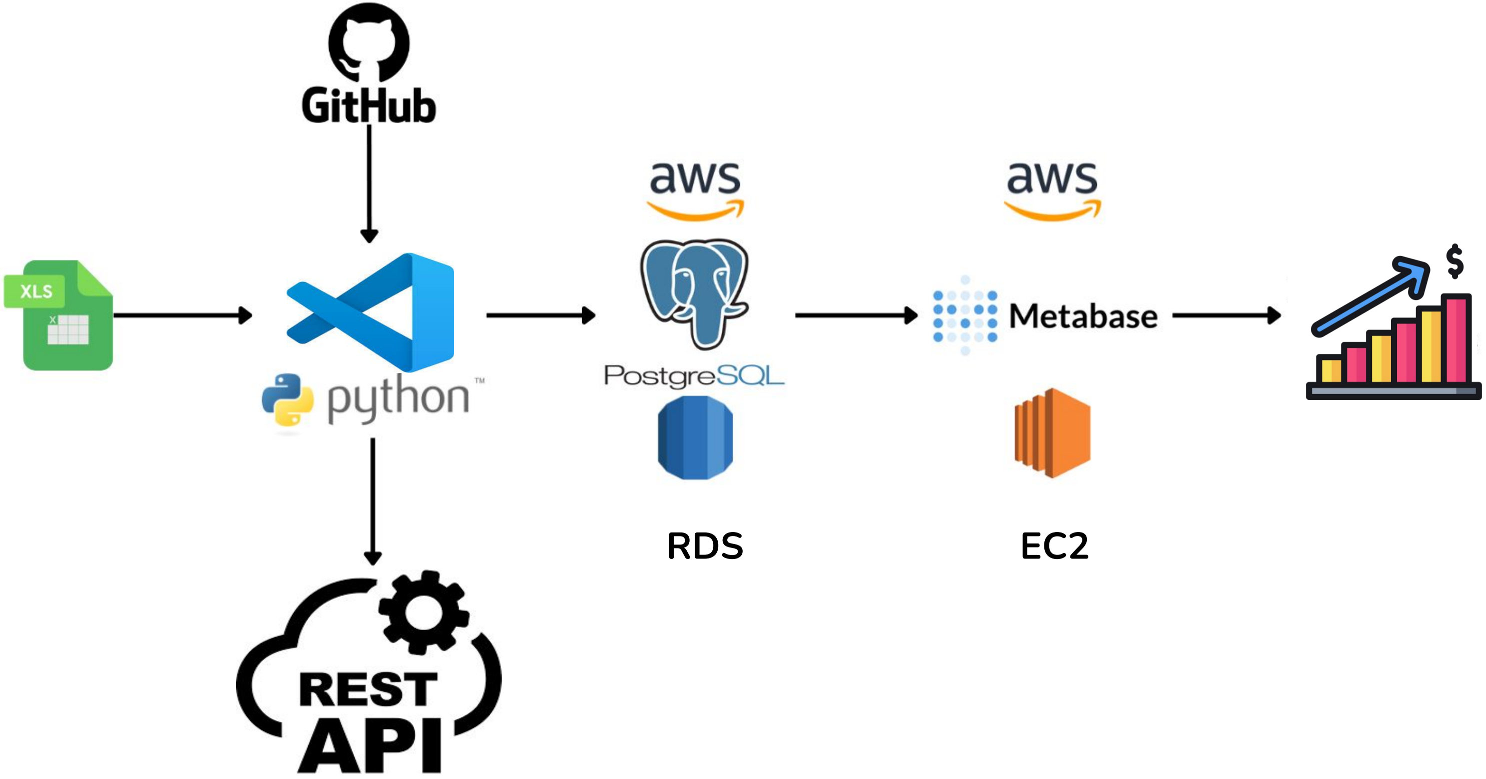
PostgreSQL

Metabase

Code versioning

Data cleaning, exploratory analysis, and API development

Infrastructure



01

Descriptive Analysis

Understanding the data

Understanding the data

With Chargeback - Details	Without Chargeback - Details
12%	88%
% of transactions with chargeback	% of transactions without chargeback

Understanding the data

With Chargeback - Details	Without Chargeback - Details
R$1,454	R$672
AVG value of transactions with chargeback	AVG value of transactions without chargeback

Understanding the data

With Chargeback - Details	Without Chargeback - Details
2.56	1.09
AVG number of transactions per user with chargeback	AVG number of transactions per user without chargeback

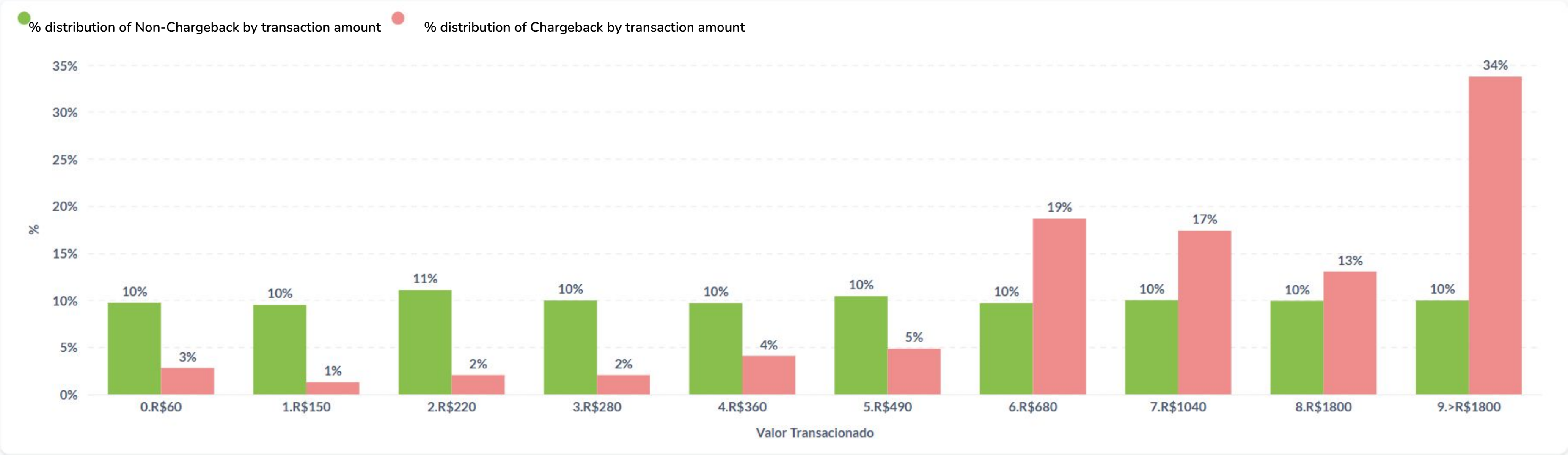
Understanding the data

Transactions without chargeback

💡Only 10% of the transactions are over R$1800

Transactions with chargeback

💡34% of the transactions are over R$1800
💡82% are over R$680



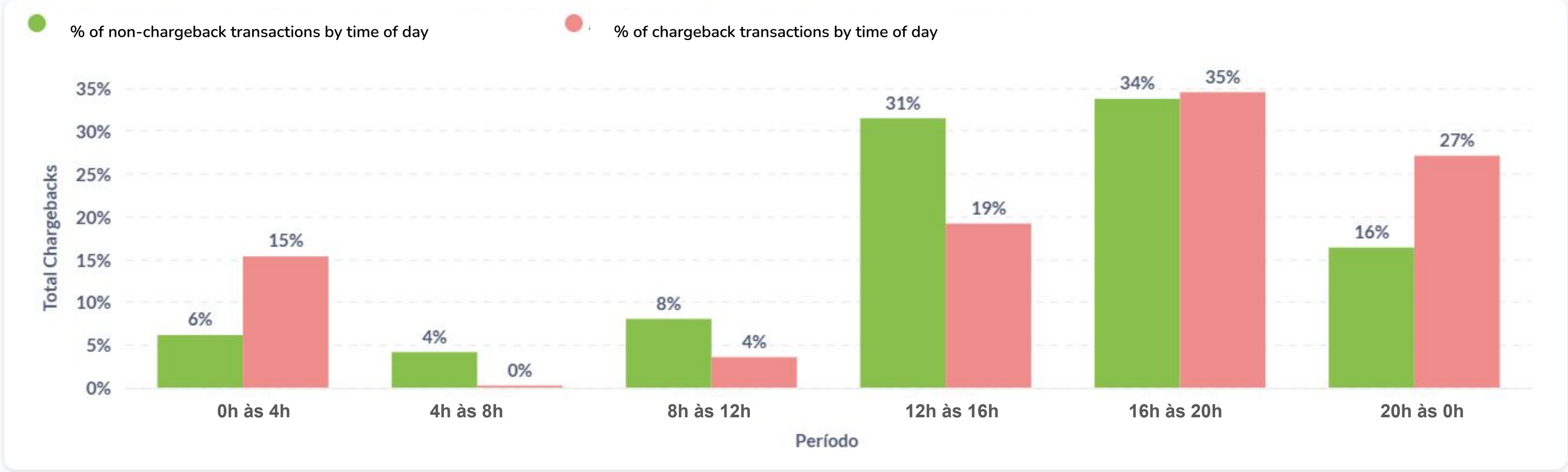
Understanding the data

Transactions without chargeback

💡22% of transactions occur between 8 PM and 4 AM

Transactions with chargeback

💡42% of transactions occur between 8 PM and 4 AM



How to measure the predictive power of these metrics?

02

Correlations and Patterns

Connecting everything

Information Value - IV

- **Which columns in a dataset have predictive power or influence over the value of a variable?**

Information Value

Methodology

1. Split the variable into clusters
2. Calculate the number of users with cbk in each cluster
3. Calculate what % of the total the previous number represents
4. Calculate the probability of the event occurring in the cluster
5. Apply the formula:
   iv = (% cbk - % não-cbk)*ln(% cbk / % não-cbk)

Information Value

Anti-fraud requirements

1. Reject the transaction if the user is attempting too many consecutive transactions.
2. Reject transactions above a certain amount within a given time period.
3. Reject the transaction if a user has had a previous chargeback.

IV Questions

1. Is there any relationship between a user who has previously had a chargeback and the likelihood of a future chargeback?
2. What about cards?
3. And the merchant?
4. Which value ranges are more likely to result in a chargeback?
5. Which times of day are more likely to result in a chargeback?

Information Value

Probability of the user having a chargeback

Análise IV - Usuário já teve cbk?

qnt_cbk_anteriores	has_cbk	no_cbk	total_geral	%_has_cbk	%_no_cbk	probabilidade_de_cbk	information_value
0	72	2,551	2,623	50%	99.65%	2.74%	0.34
1	28	3	31	19.44%	0.12%	90.32%	0.99
2-3	30	4	34	20.83%	0.16%	88.24%	1.01
>4	14	2	16	9.72%	0.08%	87.5%	0.47
total	144	2,560	2,704	100%	100%	268.8%	2.81

Information Value

Probability of the credit card having a chargeback

Análise IV - Cartão já teve cbk?

qnt_fraudes_anteriores	has_cbk	no_cbk	total_geral	%_has_cbk	%_no_cbk	probabilidade_de_cbk	information_value
0	203	2,651	2,854	74.63%	99.92%	7.11%	0.074
1	40	1	41	14.71%	0.04%	97.56%	0.88
>=2	29	1	30	10.66%	0.04%	96.67%	0.6
total	272	2,653	2,925	100%	100%	201.34%	1.55

💡For credit cards, the probability is even higher — 97.56% — despite the IV being lower.

💡That's because cards are often used by different users or in varying contexts, whereas users tend to show consistent and predictable behavior over time.

Information Value

Probability of the merchant having a chargeback

Análise IV - Comerciante já teve cbk?

qnt_fraudes_anteriores	has_cbk	no_cbk	total_geral	%_has_cbk	%_no_cbk	probabilidade_de_cbk	information_value
0	43	1,638	1,681	42.57%	98.97%	2.56%	0.48
1	18	9	27	17.82%	0.54%	66.67%	0.6
2-3	16	4	20	15.84%	0.24%	80%	0.65
>4	24	4	28	23.76%	0.24%	85.71%	1.08
total	101	1,655	1,756	100%	100%	234.94%	2.81

💡In the case of merchants, we have 66.67% for those who had only one.

💡There's only a significant increase in the 2–3 range, since the first event might have been just an isolated case.

Information Value

Transaction amount

Análise IV - Valor transacionado

valor_por_transacao	has_cbk	no_cbk	total_geral	%_has_cbk	%_no_cbk	probabilidade_de_cbk	information_value
0.R$60	11	273	284	2.81%	9.72%	3.87%	0.086
1.R$150	5	267	272	1.28%	9.51%	1.84%	0.17
2.R$220	8	311	319	2.05%	11.08%	2.51%	0.15
3.R$280	8	280	288	2.05%	9.97%	2.78%	0.13
4.R$360	16	272	288	4.09%	9.69%	5.56%	0.048
5.R$490	19	293	312	4.86%	10.43%	6.09%	0.043
6.R$680	73	272	345	18.67%	9.69%	21.16%	0.059
7.R$1040	68	281	349	17.39%	10.01%	19.48%	0.041
8.R$1800	51	279	330	13.04%	9.94%	15.45%	0.0085
9.>R$1800	132	280	412	33.76%	9.97%	32.04%	0.29
total	391	2,808	3,199	100%	100%	110.78%	1.02

💡Here we can confirm what the graphs were already showing us: above R$1800, the probability of a chargeback increases significantly.

Information Value

Transaction Time

Análise IV - Hora da transação

categoria	has_cbk	no_cbk	total_geral	%_has_cbk	%_no_cbk	probabilidade_de_cbk	information_value
0. até 4h	60	282	342	15.35%	10.04%	17.54%	0.022
1. até 8h	1	8	9	0.26%	0.28%	11.11%	0.000031
2. até 12h	14	226	240	3.58%	8.05%	5.83%	0.036
3. até 16h	75	884	959	19.18%	31.48%	7.82%	0.061
4. até 20h	135	948	1,083	34.53%	33.76%	12.47%	0.00017
9.> 20h	106	460	566	27.11%	16.38%	18.73%	0.054
total	391	2,808	3,199	100%	100%	73.5%	0.17

💡Here we see that 18.73% of transactions after 8 PM may result in a chargeback.

How to determine the relevance of the Information Value?

Information Value

Information Value - IV

IV	Poder Preditivo
<0,02	Inútil
0,02 - 0,1	Fraco
0,1 - 0,3	Médio
0,3 - 0,5	Forte
> 0,5	Muito forte

Tabela 1- fonte: **https://bit.ly/iv-fonte**

Fórmula: (% cbk - % não-cbk)*ln(% cbk/%não-cbk)

Information Value

In order, the factors most strongly correlated with transaction chargebacks, according to the IV analysis:

IV	Poder Preditivo	Factor
2,81	Too Strong	User has had a chargeback before
2,81	Too Strong	Merchant's had a chargeback before
1,55	Too Strong	Credit card has had a chargeback before
1,02	Too Strong	Transaction amount
0,17	Medium	Transaction time

💡These will be the variables used to build the rules for approving or rejecting a transaction.

03

Anti-Fraud System

Predicting the future

Modeling

What are the main variables that influence the probability of a chargeback?

Em termos de probabilidade de chargeback, as principais variáveis e intervalos são:

- Usuário já teve pelo menos 1 chargeback: **90,32%**
- Cartão já teve pelo menos 1 chargeback: **97,56%**
- Comerciante já teve pelo menos 1 chargeback: **66,67%**
- Valor transacionado > R$ 1800: **32,04%**
- Horário da transação entre 20h e 4h: **18%**

Modeling

Rule Based

How to identify which transactions, given a payload, are fraudulent?

Risk Factors:

- Users, merchants, and cards with a history of chargebacks
- High transaction amounts
- Time of transaction

Modeling

Rule Based

Rules used

- Deny transactions from users, merchants, or cards with a history of chargebacks.
- Deny transactions over R$1800 made between 8 PM and 4 AM.
- Deny transactions from devices that made more than 3 transactions within 1 hour, and whose total value exceeds R$2500.
- Transactions that do not meet the criteria above are approved.

Modeling

Rule Based

- Step 1: Create the transactions_log table

```sql
CREATE TABLE transactions_log (
    transaction_id BIGINT PRIMARY KEY,
    user_id BIGINT,
    merchant_id BIGINT,
    card_number VARCHAR(16),
    transaction_date TIMESTAMP,
    transaction_amount DOUBLE PRECISION,
    device_id BIGINT,
    recommendation VARCHAR(20),
    rule_applied VARCHAR(50),
    has_chargeback BOOLEAN
);
```

- Step 2: Copy data from the transactions table to transactions_log

```sql
INSERT INTO transactions_log (
    transaction_id, user_id, merchant_id, card_number,
    transaction_date, transaction_amount, device_id,
    has_chargeback, recommendation, rule_applied
)
SELECT
    transaction_id, user_id, merchant_id, card_number,
    transaction_date, transaction_amount, device_id,
    has_cbk AS has_chargeback,
    CASE
        WHEN has_cbk = TRUE THEN 'deny'
        ELSE 'approve'
    END AS recommendation,
    'historical_chargeback' AS rule_applied
FROM transactions;
```

Modelagem

Rule Based

- **How It Works**

```python
# Defina os parâmetros da transação
transaction_data = {
    "transaction_id": 2342357,
    "merchant_id": 56107,
    "user_id": 2708,
    "card_number": "434505******9116",
    "transaction_date": "2019-11-30T23:16:32.812632",
    "transaction_amount": 100,
    "device_id": 285475
}
```

```json
{
  "transaction_id" : 2342357,
  "recommendation" : "approve"
}
```

Model Accuracy

API Evaluation

- The accuracy of the API is evaluated by comparing the actual chargeback status of the transactions (has_cbk) with the API's recommendation (recommendation).

92.25%

API Evaluation

```sql
SELECT
  SUM(
    CASE
      WHEN (
        has_cbk = FALSE
        AND Recommendation = 'approve'
      )
      OR (
        has_cbk = TRUE
        AND Recommendation = 'deny'
      ) THEN 1
    END
  ) * 1.00 / COUNT(*) AS acuracia_api
FROM
  transactions_api_results
```

Model Accuracy

How to evaluate model accuracy?

1. Test the model using the chargeback base itself
2. Cross-Validation with Machine Learning

04

Recommendations and Prevention Strategies

Reducing Chargeback

Next steps

1. Collect more information, such as:
2. Geographic location
3. Suspicious websites and browsers

Thank you!

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