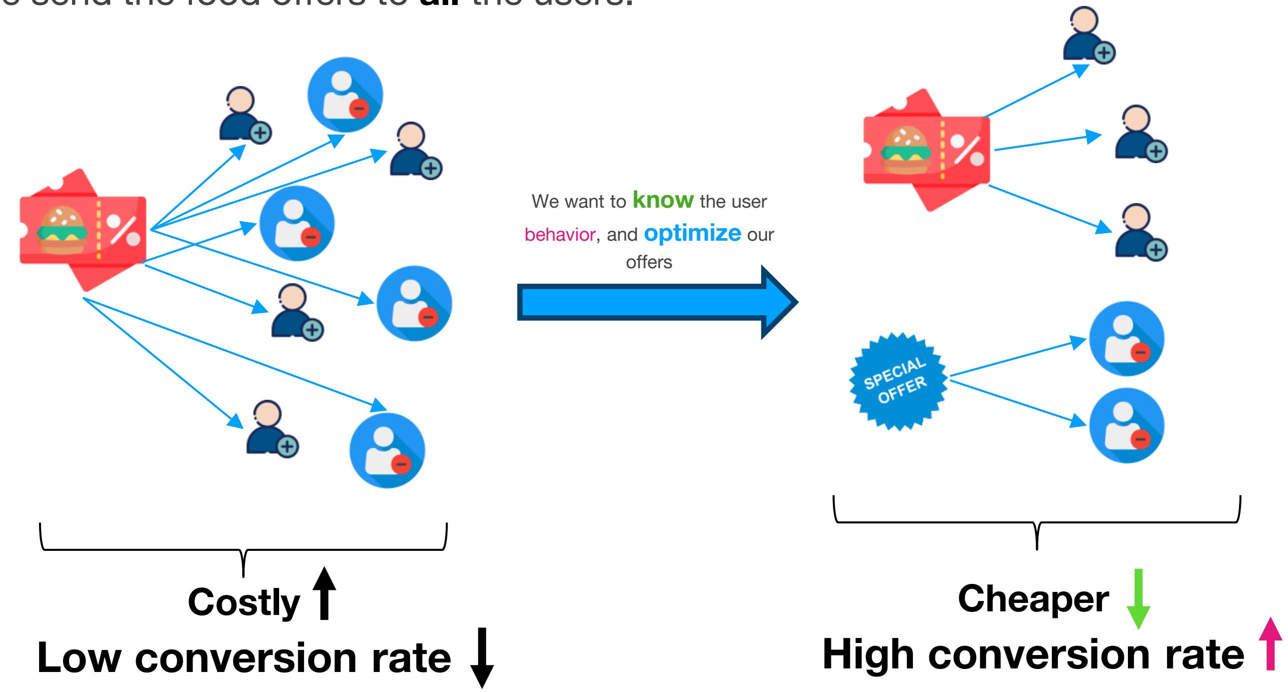
# iFood

## Marketing offer optimization

# Problem

Currently, we send the food offers to **all** the users.



# Before

**EDA Data:**

**50.6k** offers → **41.5k** used

**82%** conversion rate

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**Evaluation Data:**

**12.6k** offers → **10.3k** used

**81%** conversion rate

# Now: targeted users

Evaluation Data: ~~12.6k~~ 7.4k offers → 6.8k used

92% conversion rate

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Marketing cost: **R$522.00 saved**

# Ifood has 50MM users

Marketing campaign

1MM users

**414,678** saved marketing messages (SMS or E-mail)

414,678 x R$0.1 + 414,678 x R$0.004 = **R$43,126.0**

saved

# Now: targeted offers

Evaluation Data: **12.6k**

**92%** conversion rate

Projection

**Randomly selected offers**

**67.1%**

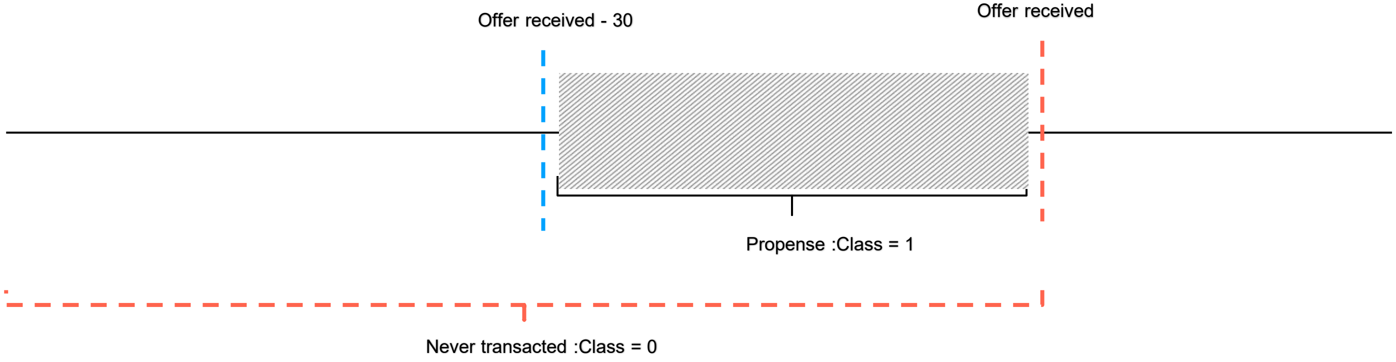
# Exploratory Data Analysis

# Probably the Data were Generated Sintetically

- Some data are inconsistente or wierd. There are offers that are completed with time_since_test_start = 0
- Ages of 120 Years
- Credit card with mean limit value of 60,000

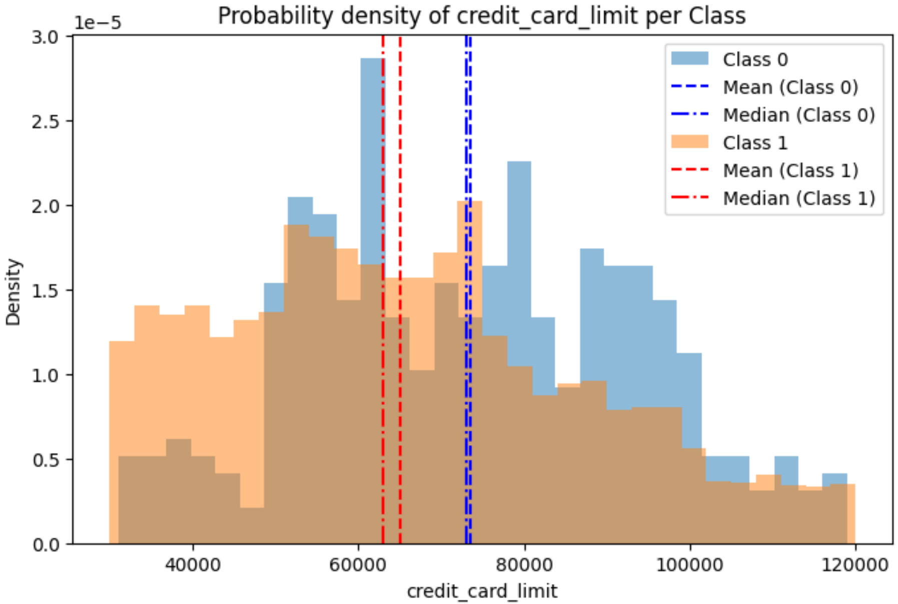
# User profile – without offer

“Propense” user definition



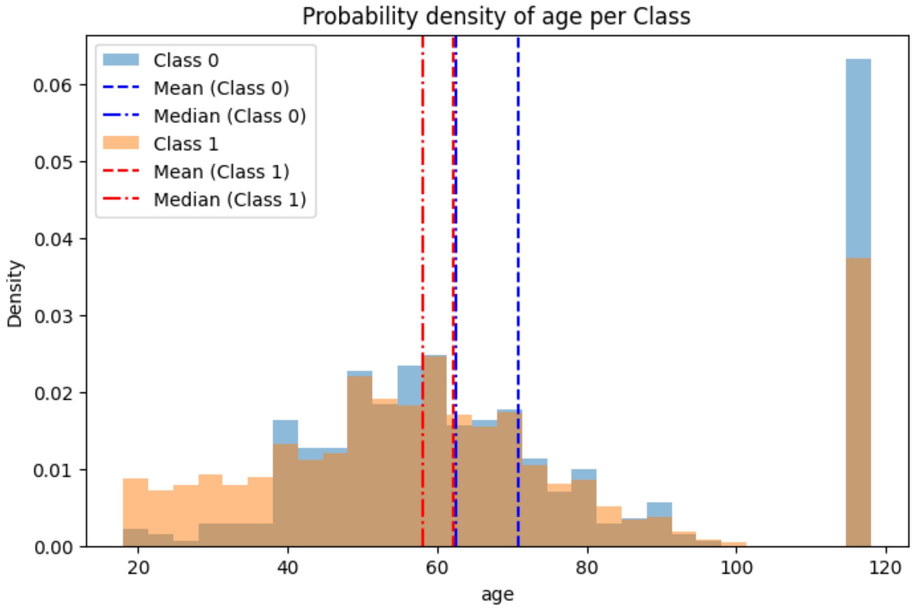
# User profile – without offer

Credit Limit and Conversion: mid class uses the application more frequently



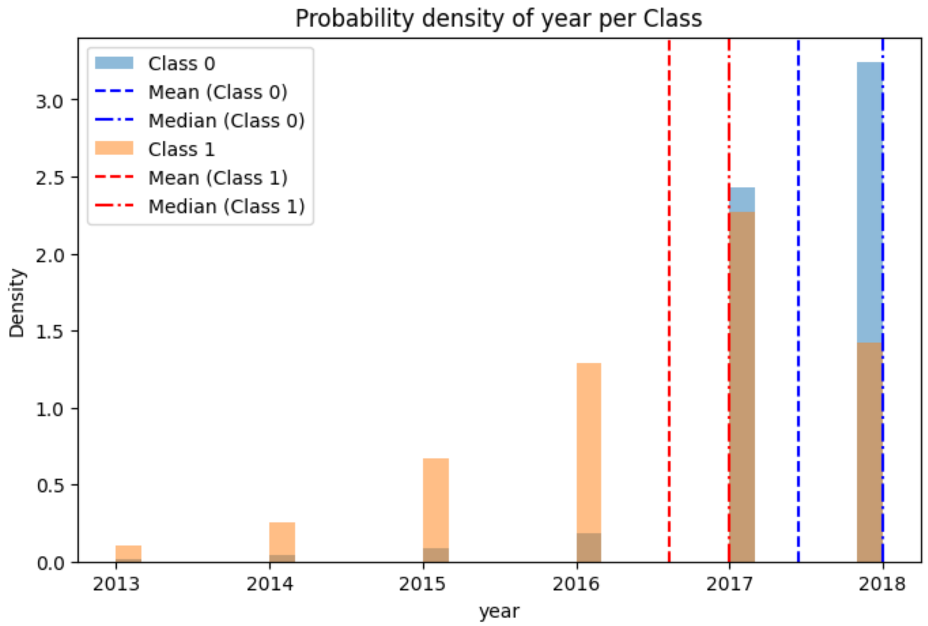
# User profile – without offer

Age and Conversion: youngers transact more



# User profile – without offer

Time of using the application: newer users transact less oftren than older ones

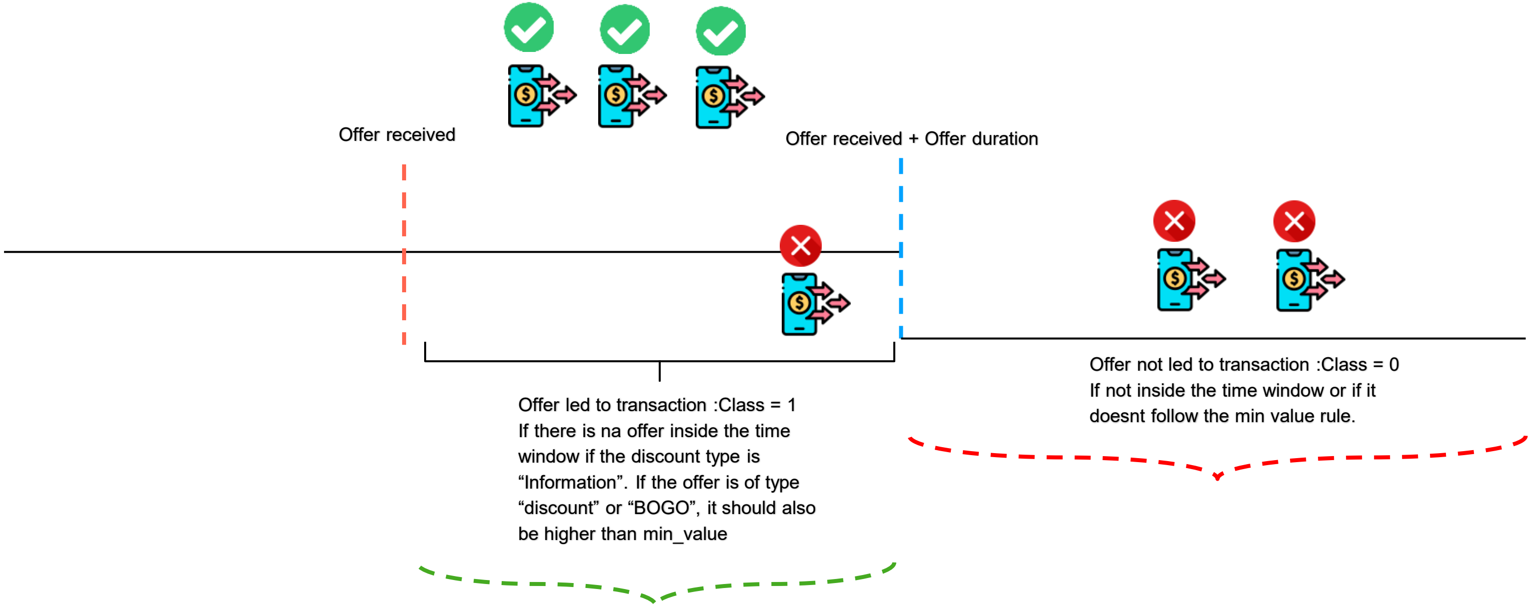


# User profile – without offer

Gender: plays no rule

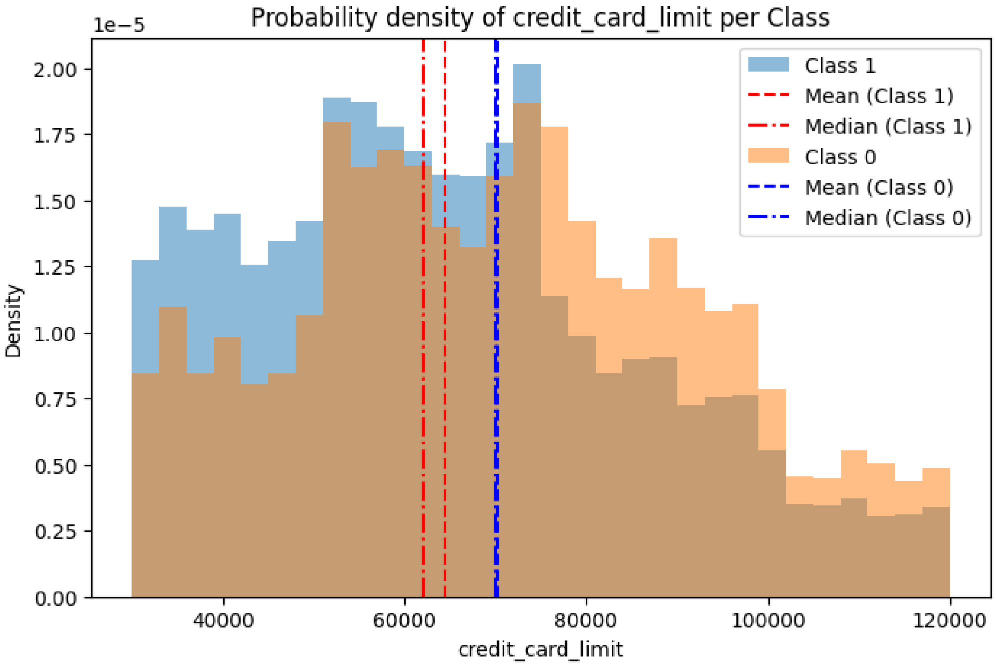
# User profile – without offer

"Propense" after receiving an offer



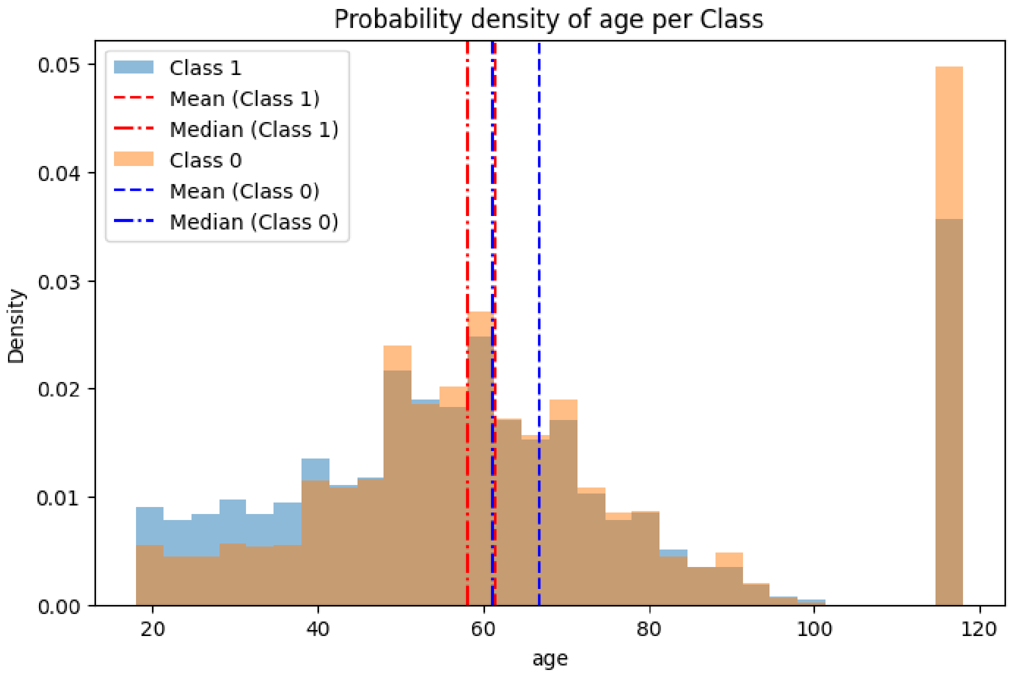
# User profile – offer received

Credit Limit and Conversion: mid class uses offers more frequently



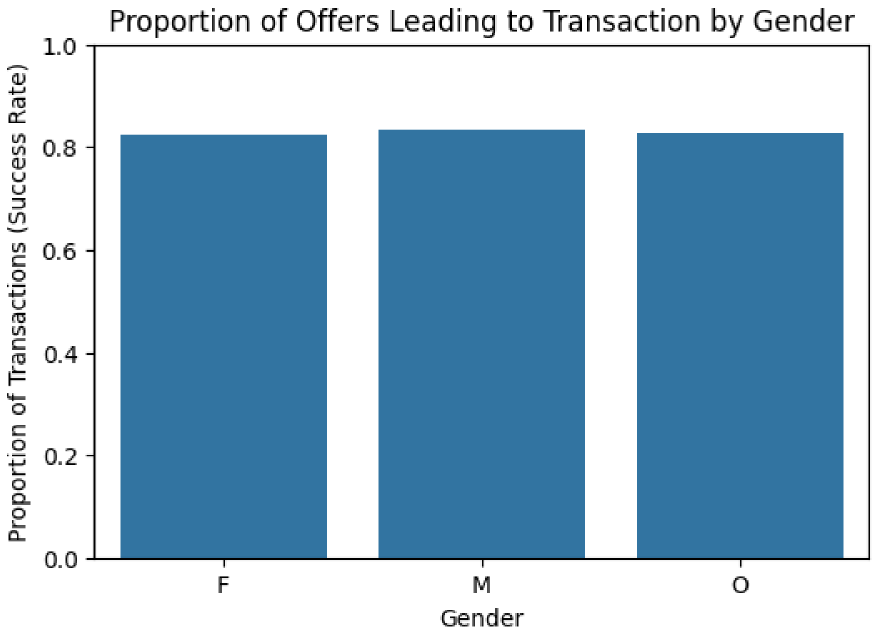
# User profile – offer received

Age and Conversion: youngers accept offers better



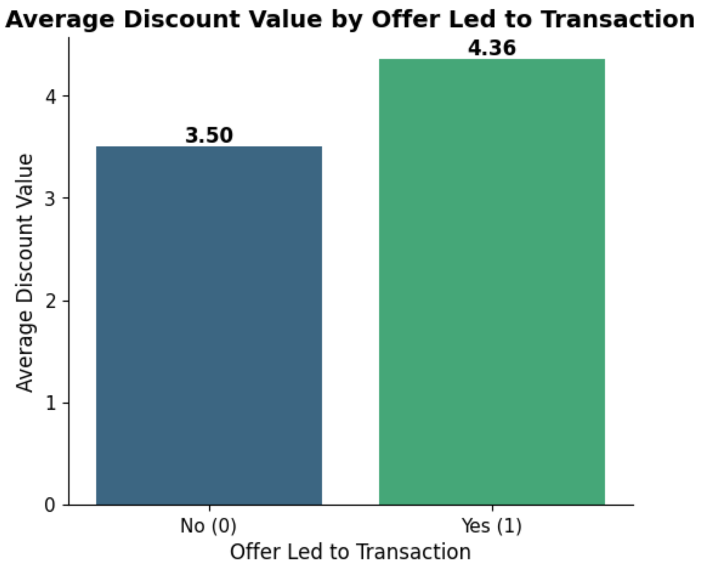
# User profile – offer received

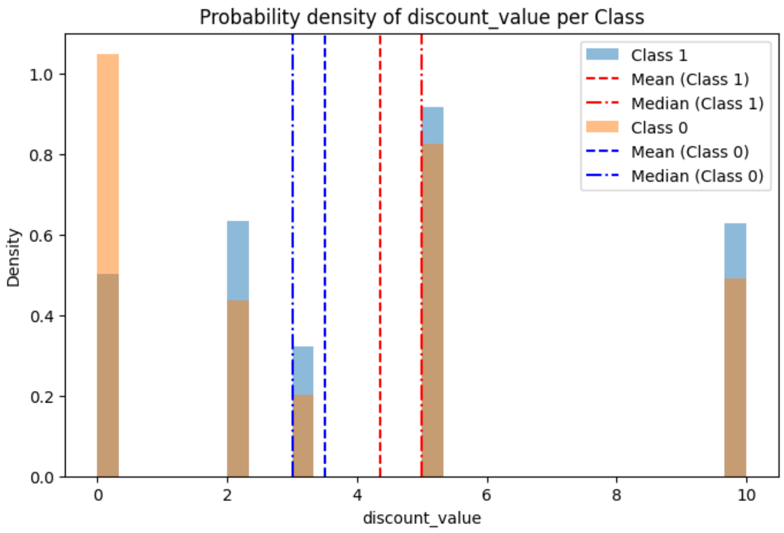
Gender: again no rule at all



# Offer characteristics

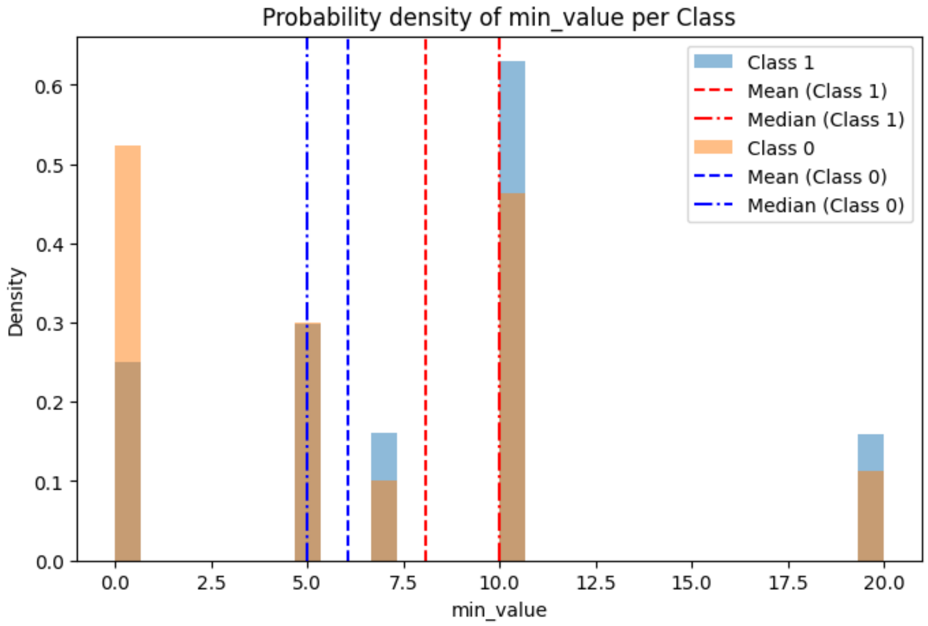
Discount value: offers with higher discount value are more likely led to transaction



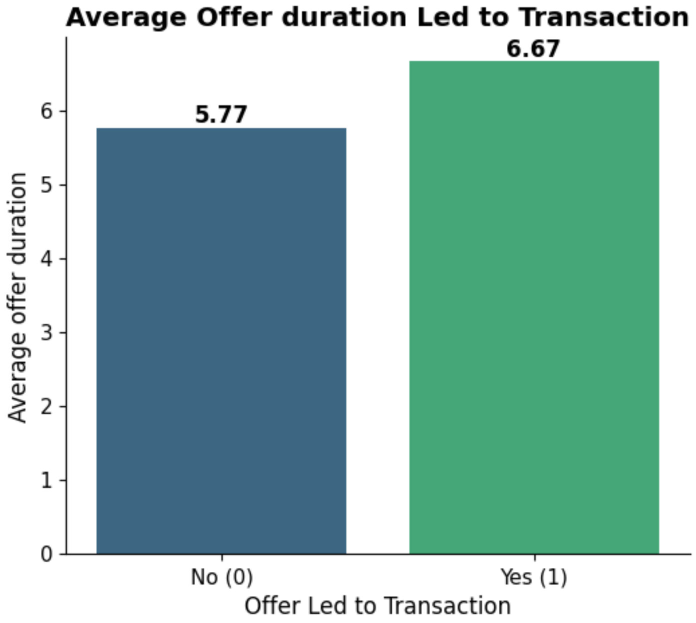
# Offer characteristics

Min value: offers with higher min value result more often to a transaction



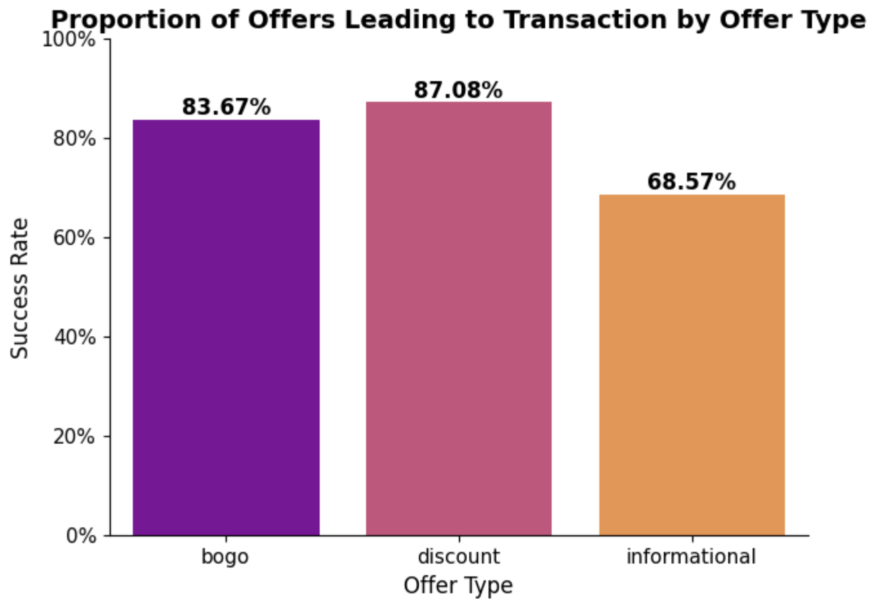
# Offer characteristics

Offers duration: longer offers are more likely led to transaction



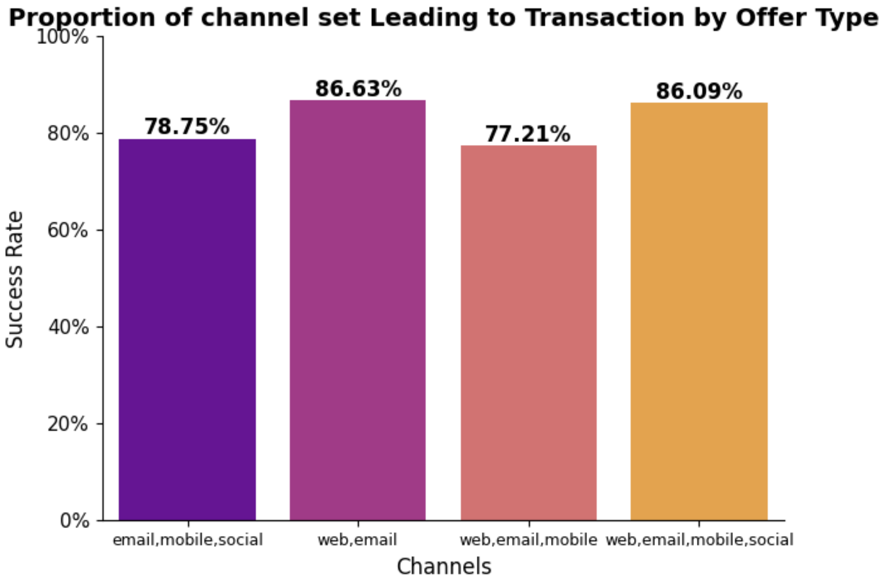
# Offer characteristics

Offers type: BOGO and Discount lead to transaction more likely



# Offer characteristics

Offers channels: web and e-mail results in a higher transaction rate, mobile offers (SMS pushes) are not accepted so well



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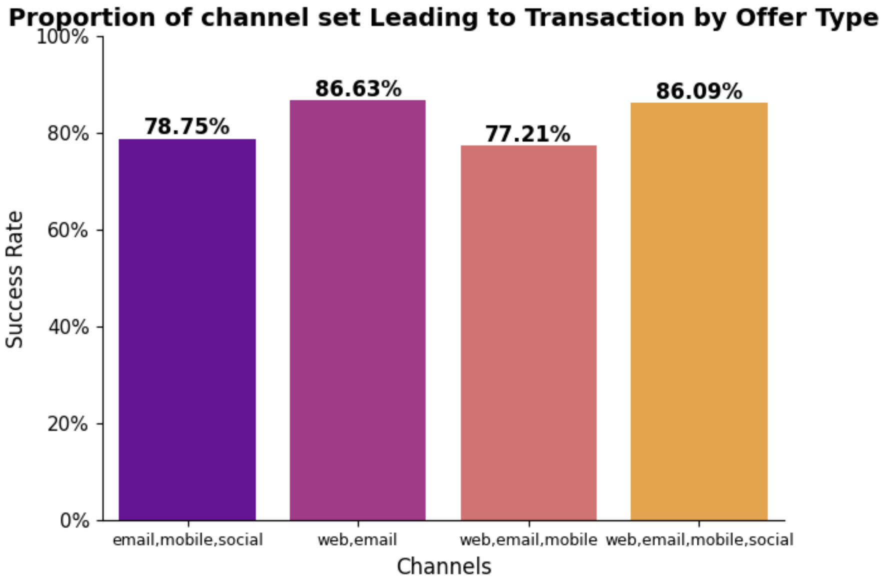

# Recommendations to Marketing Team

# Choosing the user

- Do not send offer to everyone
- Target your user
- Define Marketing Goal
    - Goal: new transaction -> Send offers with high value and long duration for users who never transacted
    - Goal: more transactions -> Send offers to those with a high probability of transaction

# Choosing offer type

## For each user:

1 - Find the probability of the transaction by changing the offer type

- P(transaction | offer type = ‘BOGO’)
- P(transaction | offer type = ‘Discount’)
- P(transaction | offer type = ‘Information’)

2 - Choose offer type which resulted in a higher transaction probability

# Causality

## Some users transact anyway

- Use the uplift model. Send the offers for those users who:

**Probability of transacting with offer – Probability of transacting without offer >= some predefined threshold**

# Obrigad!

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