

# FLOPKART, LLC

**CHURN ANALYSIS,  
CUSTOMER LIFETIME  
VALUE, REVENUE  
PREDICTION**

TEAM 5

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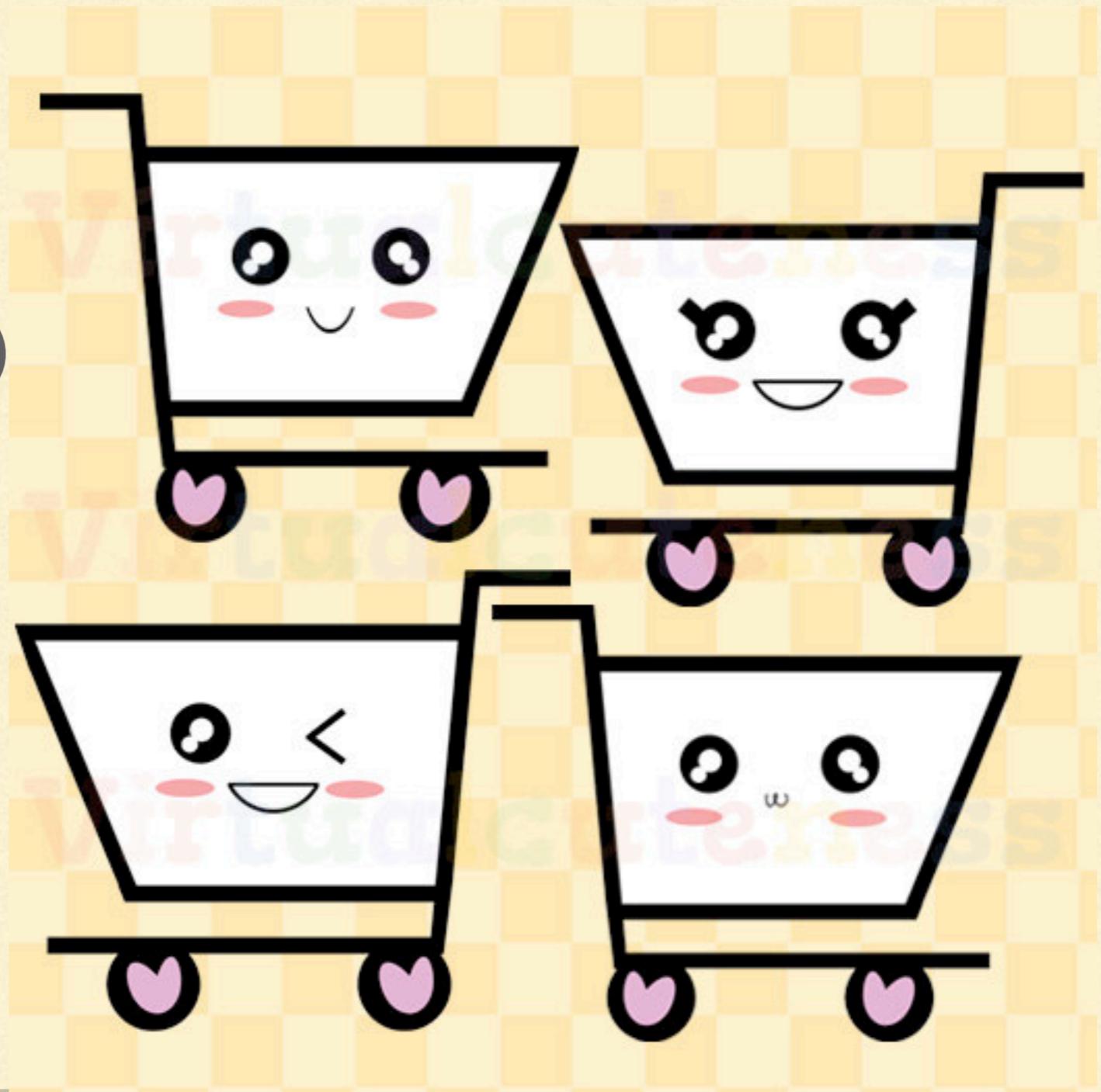
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# COMPANY BACKGROUND

**FLOPKART :)**



# THE CHALLENGE

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- FlopKart is an e-commerce company
  - Leader in space, but spending aggressively and ultimately not profitable
  - Facing increasing competition due to developing economy
  - Want to spend money smarter
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# ACQUISITION VS. RETENTION

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- Retaining is much cheaper than acquiring
  - Good: spend more money on high value customers
  - Bad: waste money on customers that have churned or are going to churn soon
- Problem: churn is not clearly defined in e-commerce
  - Cannot be predicted using supervised learning
  - Answer: RFM/CLV

# MODEL DESCRIPTION

## Traditional RFM Model

Recency

Frequency

Monetary

# RFM MODEL

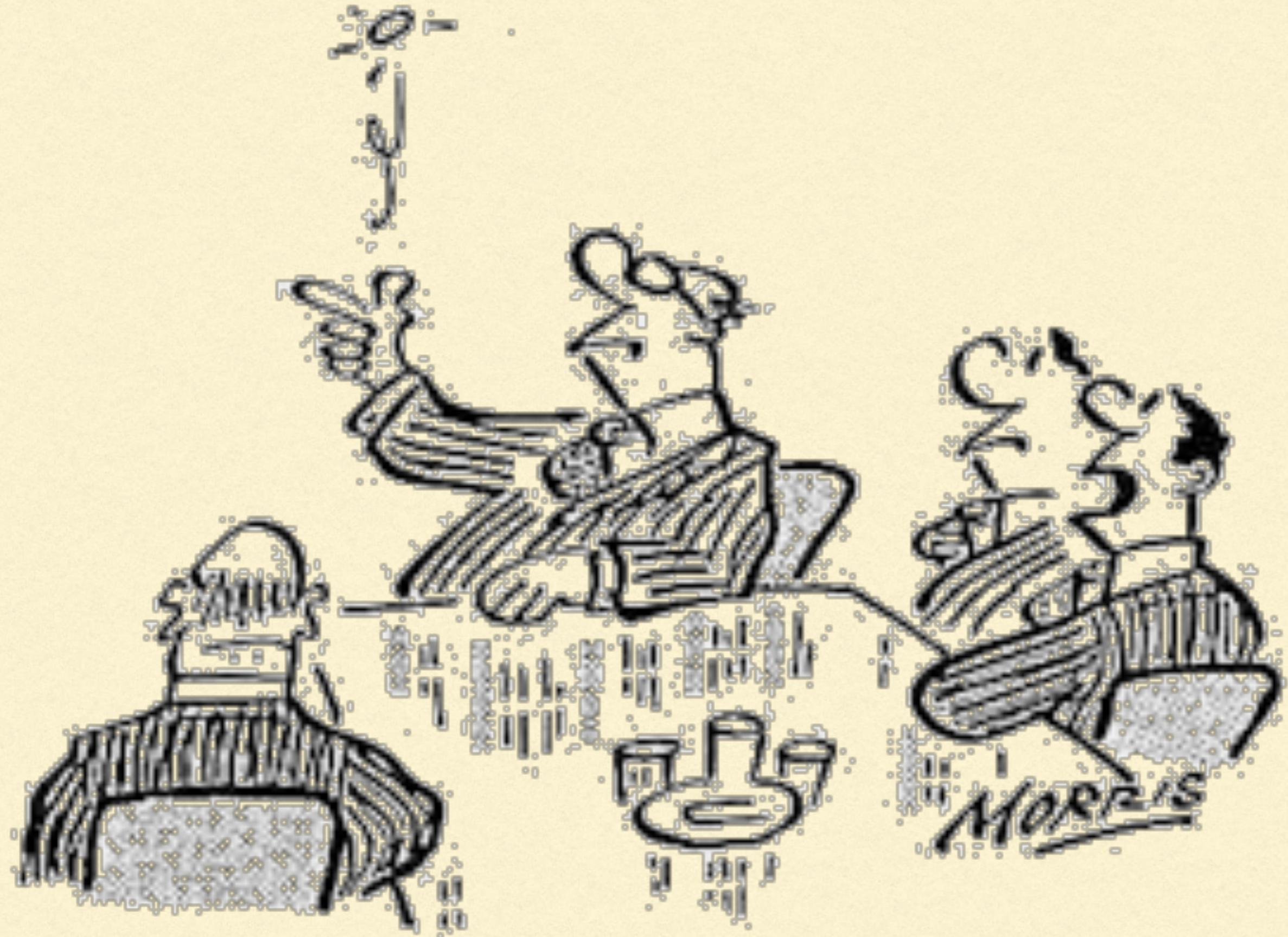
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- All users assigned a “tuple” score
  - Recency - number of years since last purchase
  - Frequency - number of purchases to date
  - Monetary - total amount spent in each year
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# CUSTOMER SEGMENTATION

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- RFM tuples make up an infinite state space
- Segmentation is necessary
  - e.g. “platinum, gold, silver”
- State space becomes discrete and finite
- A cut-off point for recency is defined as “churn”
  - Probability of returning is very low



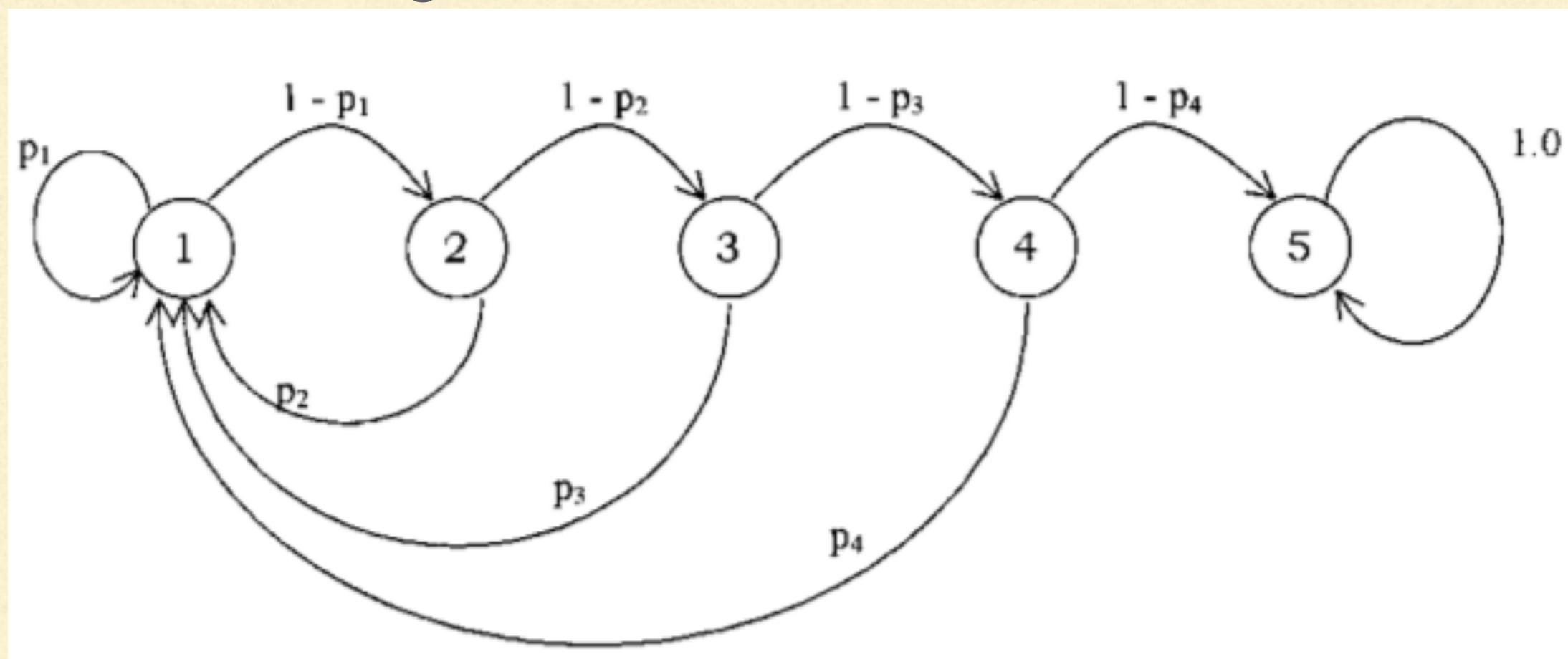
# MARKOV MODEL

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- Customers transition to different states depending on purchase behavior
- From historical data, transition probabilities may be calculated
  - $P(i, j)$  = probability of transitioning from state i to state j over some time period
- Build matrix P of transition probabilities
  - P is of size nxn where n is number of possible states
- Once a customer is churned, they are considered churned forever
  - Absorbing state: they can only transition back into current state

# MARKOV MODEL: ILLUSTRATION

- Markov transitions for recency
- 5 is absorbing state



# MARKOV MODEL: PREDICTIONS

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- Predict future state of customer base using Markov model
- State vector  $V_p(t)$  is defined at time-step  $t$ 
  - $V_p$  is of size  $n$ ;  $n$  is number of states
  - $V_p[i]$  gives proportion of customers in state  $i$
- $V_p(t+1) = V_p(t)P$

# CUSTOMER LIFETIME VALUE

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- Given a customer starting at some RFM state, CLV gives their value to the company over an infinite time frame
- Why is it valuable?
  - Some customers may not have churned yet, but have negative CLV
  - Should not expend marketing budget on these customers

# CLV: REWARD VECTOR

- First step in CLV is to define reward vector  $R$ 
  - $R[i]$  gives the value of a customer in state  $i$
  - $R = NC - M$ 
    - $NC$  = net contribution (money spent that year)
    - $M$  = cost spent on marketing
- Only customers with recency 0 have non-zero  $NC$ 
  - Unchurned customers with  $\text{recency} \geq 1$  have negative reward
  - Churned customers have no marketing cost and therefore zero reward

$$\mathbf{R} = \begin{bmatrix} NC - M \\ -M \\ -M \\ -M \\ 0 \end{bmatrix}$$

# CLV: CALCULATION

- Value vector over some time frame T:

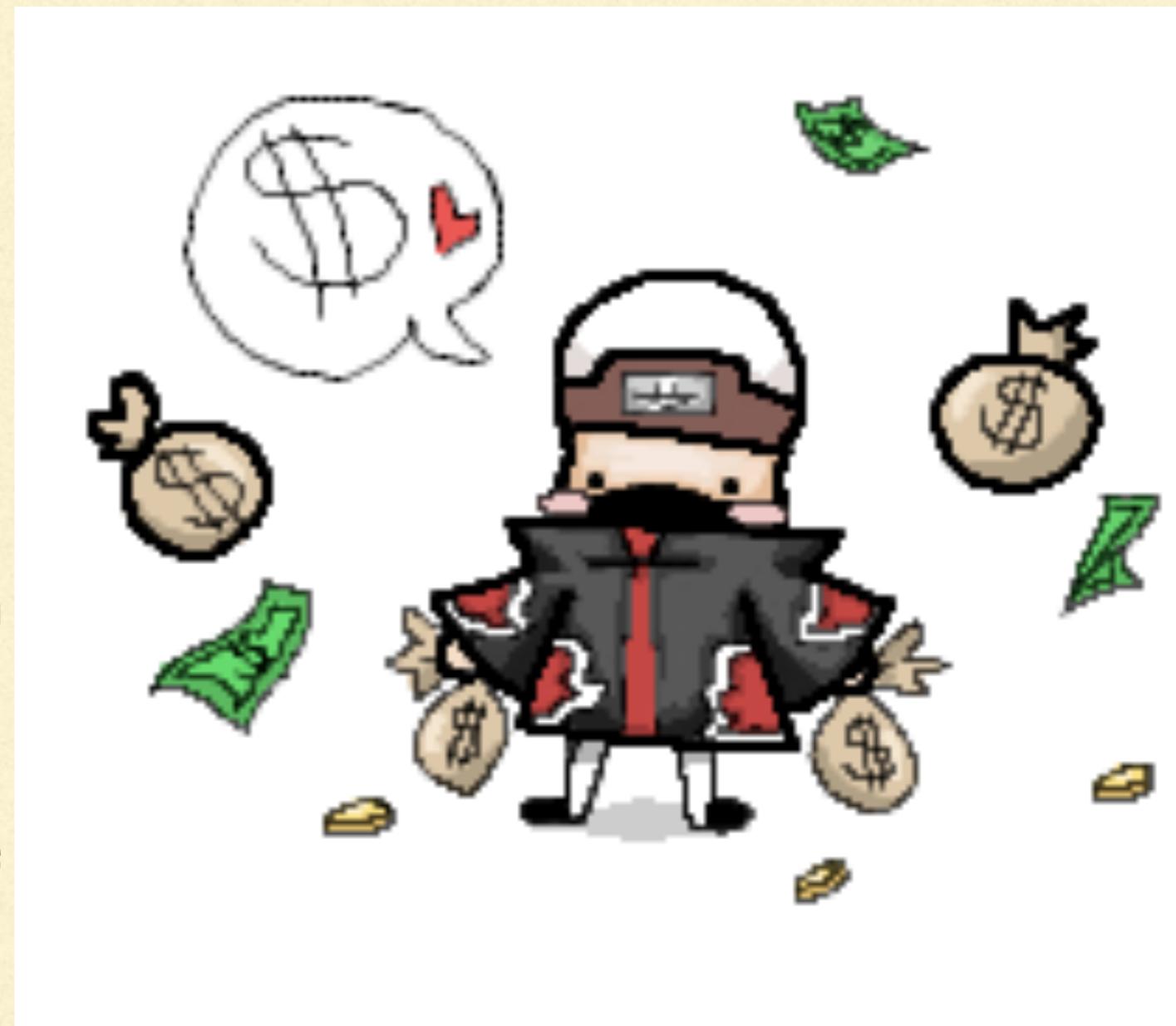
$$\mathbf{V}^T = \sum_{t=0}^T [(1 + d)^{-1} \mathbf{P}]^t \mathbf{R}$$

- CLV extends time frame to infinity:

$$\begin{aligned}\mathbf{V} &\equiv \lim_{T \rightarrow \infty} \mathbf{V}^T \\ &= \{\mathbf{I} - (1 + d)^{-1} \mathbf{P}\}^{-1} \mathbf{R}\end{aligned}$$

# ***CLV: POLICY ADJUSTMENT***

- Standard policy is to stop marketing to customers who have churned
- Customers with negative CLV haven't churned yet, but are a net negative to the company over the long term
- Policy is then adjusted to also stop marketing to these customers



# CASE SPECIFICS: FLOPKART



# DATA

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- Entirety of FlopKart's transactional data
  - 44966 records
  - Format: `cust_id, purchase_amt, date_purchase`
  - Data from 2005 to 2015
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# EDA: PURCHASE AMOUNTS

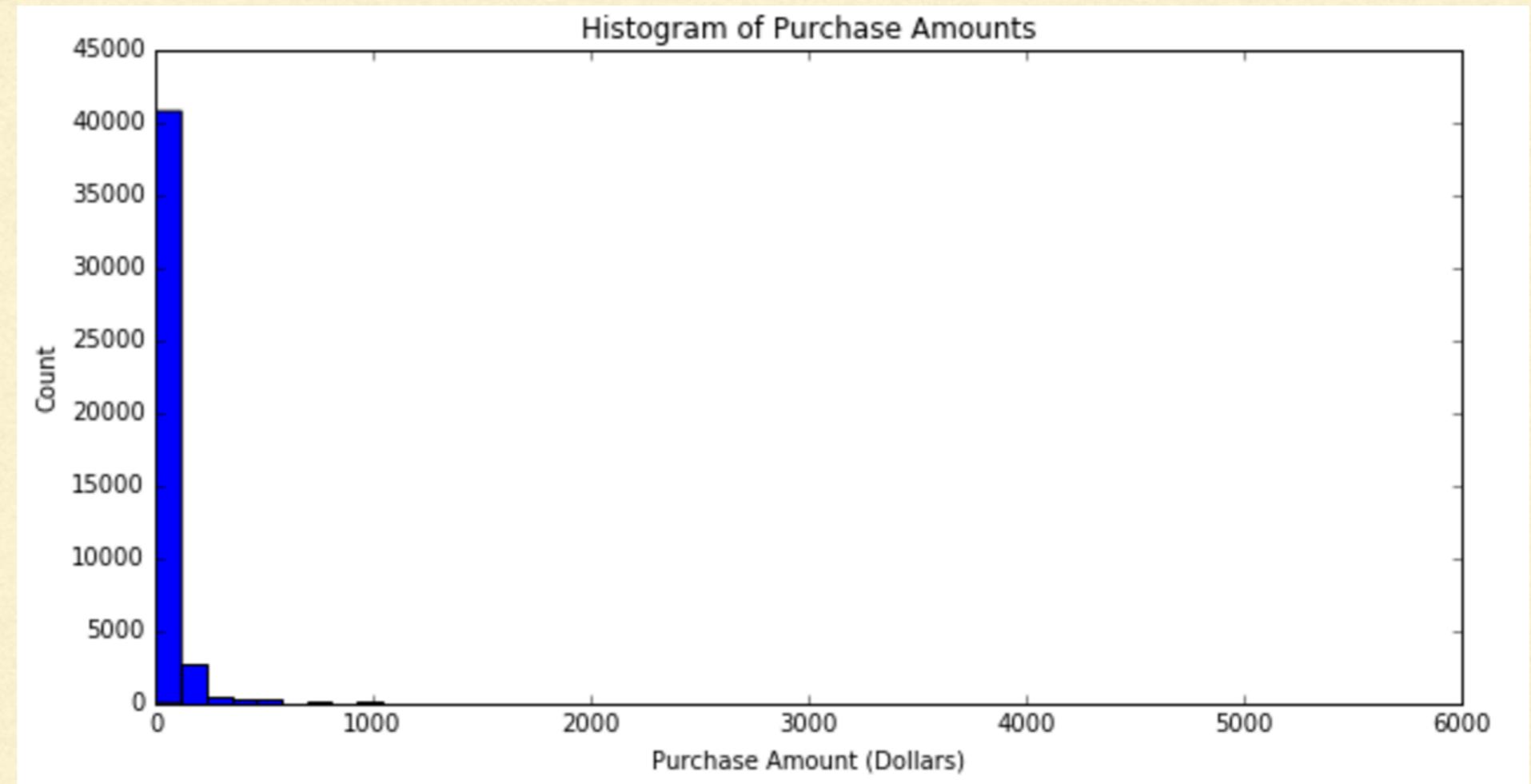
- Purchase amounts extremely right skewed

- Mean: \$71

- Median: \$40

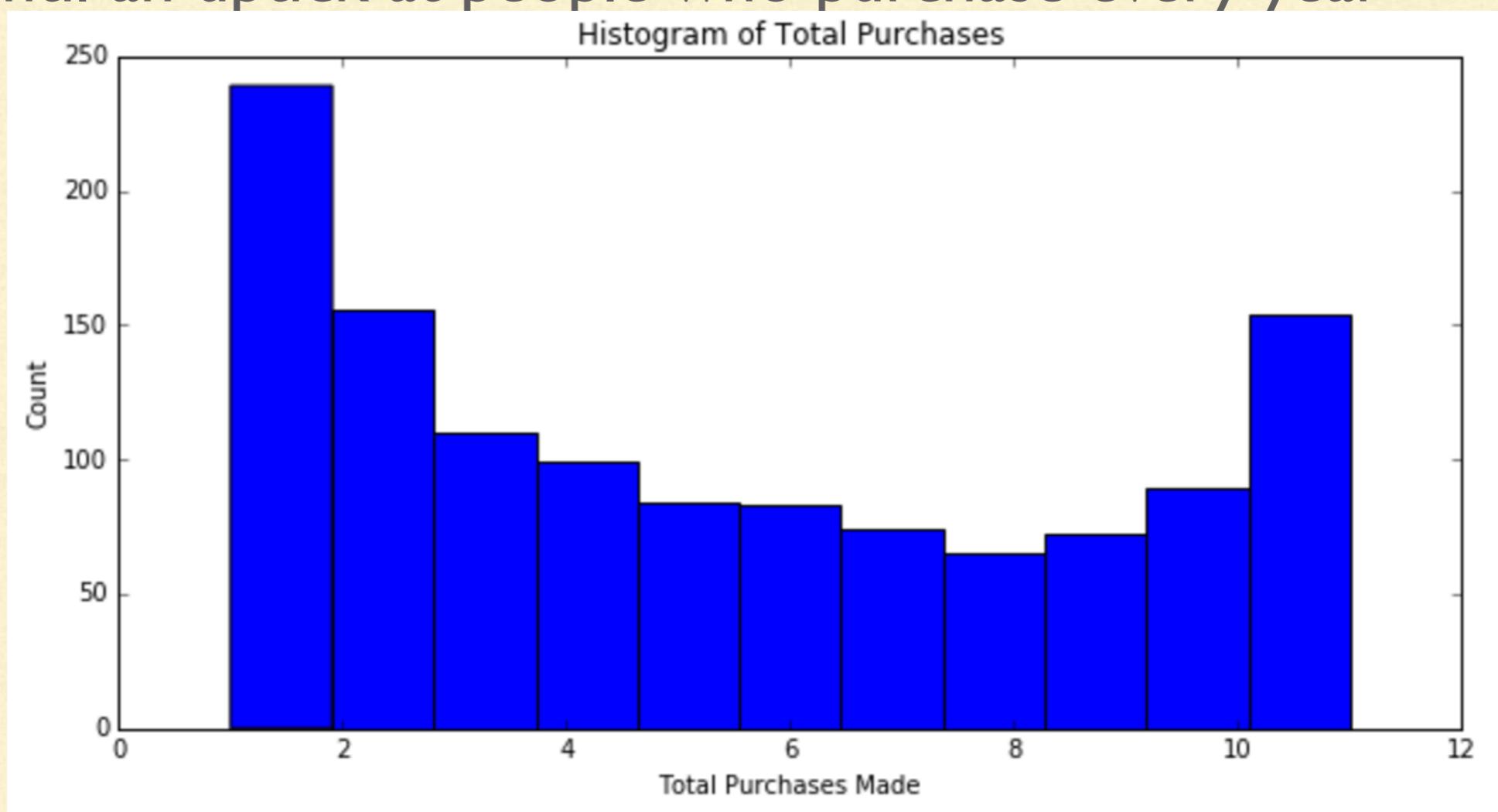
- Max: \$5750

- 90%  $\leq$  \$100



# EDA: TOTAL PURCHASES MADE

- Decrease until an uptick at people who purchase every year
- Median: 5



# EDA: BOOLEAN MATRIX

- Vast majority of customers only make one purchase per year
- Markov transition period: one year

| year    | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 |
|---------|------|------|------|------|------|------|------|------|------|------|------|
| cust_id |      |      |      |      |      |      |      |      |      |      |      |
| 10      | 1    | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    |
| 80      | 1    | 0    | 1    | 0    | 1    | 0    | 1    | 0    | 1    | 1    | 1    |
| 90      | 1    | 1    | 1    | 1    | 1    | 1    | 1    | 1    | 1    | 0    | 0    |
| 130     | 1    | 0    | 1    | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    |
| 190     | 1    | 1    | 1    | 1    | 1    | 0    | 0    | 0    | 0    | 0    | 0    |

# RECENCY TRANSITION MATRIX

- At  $R \geq 7$ , probability is < 5%: churn state

# SEGMENTATION

- Recency:
  - $R = 0$  //  $1 < R < 7$  //  $R \geq 7$
- Frequency:
  - $F \leq 5$  //  $F > 5$
- Monetary:
  - $M \leq 30$  //  $30 < M \leq 50$  //  $M > 50$
- $(3)(2)(3) = 18$  total RFM states
- All states with  $R \geq 7$  are absorbing states



# STATE MATRIX

- Calculate RFM tuples from boolean matrix
- Convert to state values using segments

| <b>year</b>    | <b>2005</b> | <b>2006</b> | <b>2007</b> | <b>2008</b> | <b>2009</b> | <b>2010</b> | <b>2011</b> | <b>2012</b> | <b>2013</b> | <b>2014</b> | <b>2015</b> |
|----------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|
| <b>cust_id</b> |             |             |             |             |             |             |             |             |             |             |             |
| <b>10</b>      | 6           | 12          | 12          | 12          | 12          | 12          | 18          | 18          | 18          | 18          | 18          |
| <b>80</b>      | 5           | 11          | 4           | 10          | 4           | 10          | 4           | 10          | 4           | 1           | 1           |
| <b>90</b>      | 4           | 4           | 4           | 4           | 4           | 1           | 1           | 1           | 1           | 7           | 7           |
| <b>130</b>     | 5           | 11          | 4           | 10          | 10          | 10          | 10          | 10          | 16          | 16          | 16          |
| <b>190</b>     | 5           | 4           | 6           | 4           | 4           | 10          | 10          | 10          | 10          | 10          | 16          |

# RFM TRANSITION MATRIX

- Calculate transition matrix from state matrix
- Matrix too large to show here



# REWARD VECTOR

- $M = \sim \$71$
- mean purchase amount
- $C = \$25$
- Flopkart's marketing cost per year

```
[[ 46.03911622 ],  
 [ 46.03911622 ],  
 [ 46.03911622 ],  
 [ 46.03911622 ],  
 [ 46.03911622 ],  
 [ 46.03911622 ],  
 [-25.          ],  
 [-25.          ],  
 [-25.          ],  
 [-25.          ],  
 [-25.          ],  
 [  0.          ],  
 [  0.          ],  
 [  0.          ],  
 [  0.          ],  
 [  0.          ]]]
```

# FLOPKART CLV

- States 9-12 are unchurned but have negative CLV
- Policy implication
- Stop spending money on people in these states

```
[ 164.97606887 ],  
[ 163.53654628 ],  
[ 132.88523581 ],  
[ 141.27641545 ],  
[ 133.1715939 ],  
[ 94.75529752 ],  
[ 13.41616067 ],  
[ 11.0259514 ],  
[ -7.17343942 ],  
[ -5.88976893 ],  
[ -4.71694682 ],  
[ -18.15269545 ],  
[ 0. ],  
[ 0. ],  
[ 0. ],  
[ 0. ],  
[ 0. ] ]
```

# REVENUE CALCULATION

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- Calculate based on previous equation using  $T = 10$
- 2144 new customers each year
  - Average observed in historical data
  - Distributed according to observed entrance states

# REVENUE: NO POLICY

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- Total revenue: \$2.6M

|      |               |
|------|---------------|
| 2016 | 117192.674744 |
| 2017 | 213756.539922 |
| 2018 | 274843.715024 |
| 2019 | 292909.959191 |
| 2020 | 295450.852444 |
| 2021 | 292481.817299 |
| 2022 | 287665.24994  |
| 2023 | 282355.970819 |
| 2024 | 277062.491102 |
| 2025 | 271977.620176 |

# REVENUE: WITH POLICY

- Total revenue: \$3.7M

|      |               |
|------|---------------|
| 2016 | 242931.3269   |
| 2017 | 339495.192079 |
| 2018 | 387466.427388 |
| 2019 | 400117.133611 |
| 2020 | 399549.233561 |
| 2021 | 394034.374733 |
| 2022 | 386729.05203  |
| 2023 | 378889.023419 |
| 2024 | 371044.570756 |
| 2025 | 363435.328919 |



Any  
Questions