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Reasoning About Sequential Decisions for Customer Management

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Customer Lifetime Value (CLV)

Kotler and Armstrong (1996)—A profitable customer is a person whose

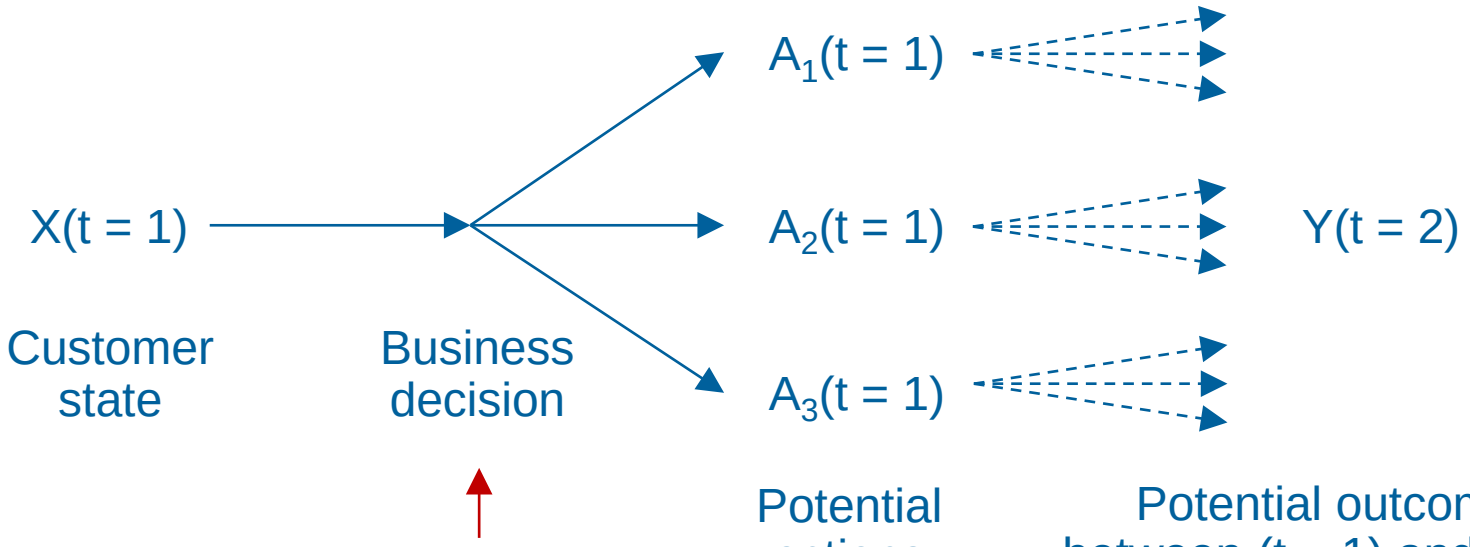
"revenues over time exceed, by an acceptable amount, the company costs of attracting, selling and servicing that customer."

CLV is the excess, defined as

"the present value of the future cash flows attributed to the customer during his/her entire relationship with the company."

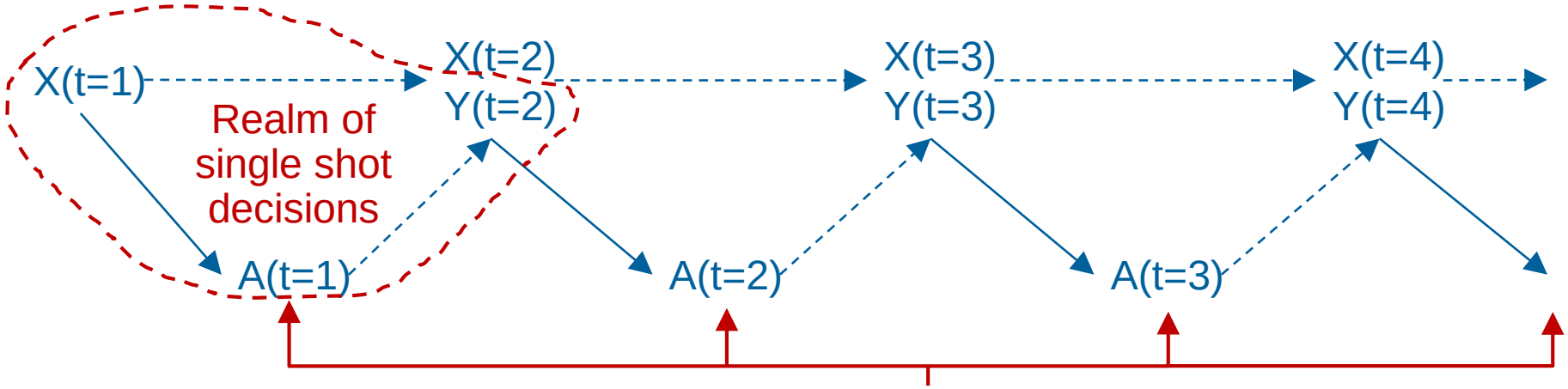
Wikipedia: http://en.wikipedia.org/wiki/Customer_lifetime_value

Single-Shot Perspective on Decision Optimization



Sequential View of Customer Relationship and Planning

- Decision sequence has cumulative effect on all future outcomes and on CLV



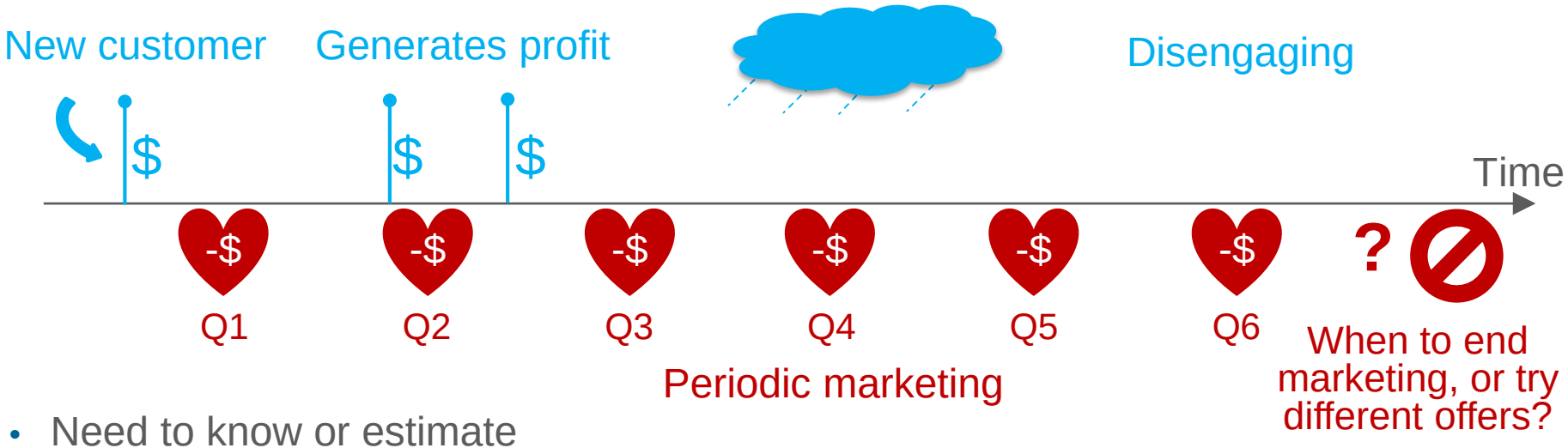
Better rationale:
Plan action sequence to maximize CLV

Sequential Problems Are Ubiquitous, Impact Bottom Line

- Customer acquisition
  - Targeting and offer design
- Customer/account management
  - Changing card limits and pricing
  - Influencing migration to profitable states
  - Managing inactive customers
  - Orchestrating customer dialogue for more relevant offers
- Collections
  - Optimizing treatment sequences/scenarios

How to Treat Inactive Customers?

A Customer Journey



- Need to know or estimate
  - Profit contributions, marketing costs per period
  - Probability that customer makes purchase during next period

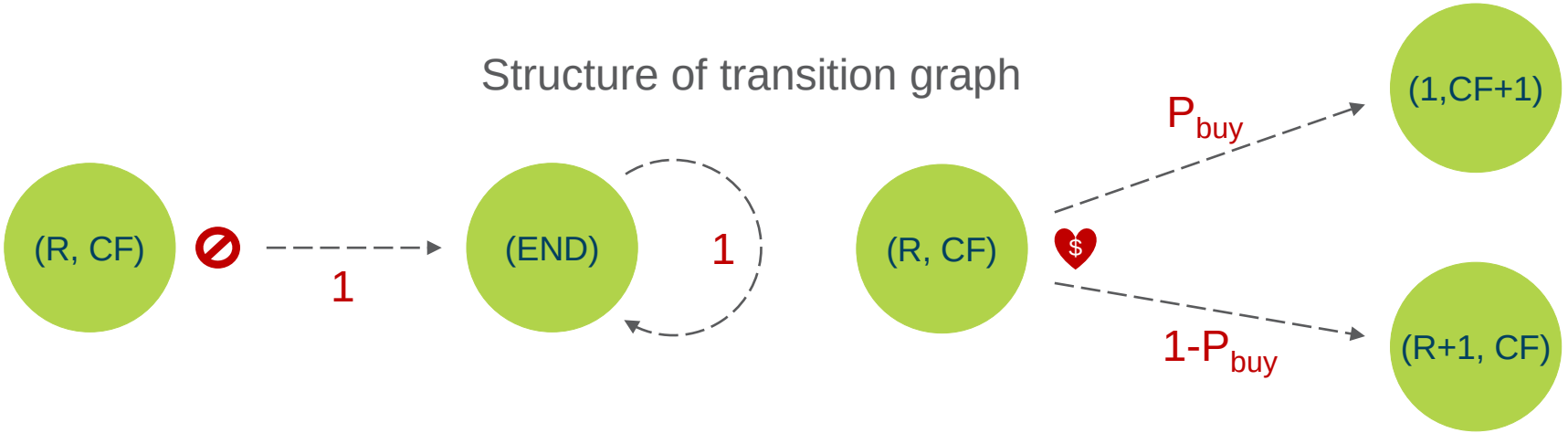
→ Can compute optimal marketing policy via Markov Decision Process (MDP) model

1. Define “State Space”

- Current state and action should suffice to predict next state (Markov property)
- States should inform actions (Marketing  / No Marketing ) and associated rewards
- May chose State = (Recency, Cumulative Frequency) = (R, CF)[1]
  - New customer: State = (1, 1)
  - Customer who made 3 purchases, then did not buy for 4 periods: State = (4, 3)
- Add a special terminal State = (END) for customers no longer marketed to
  - What goes there stays there

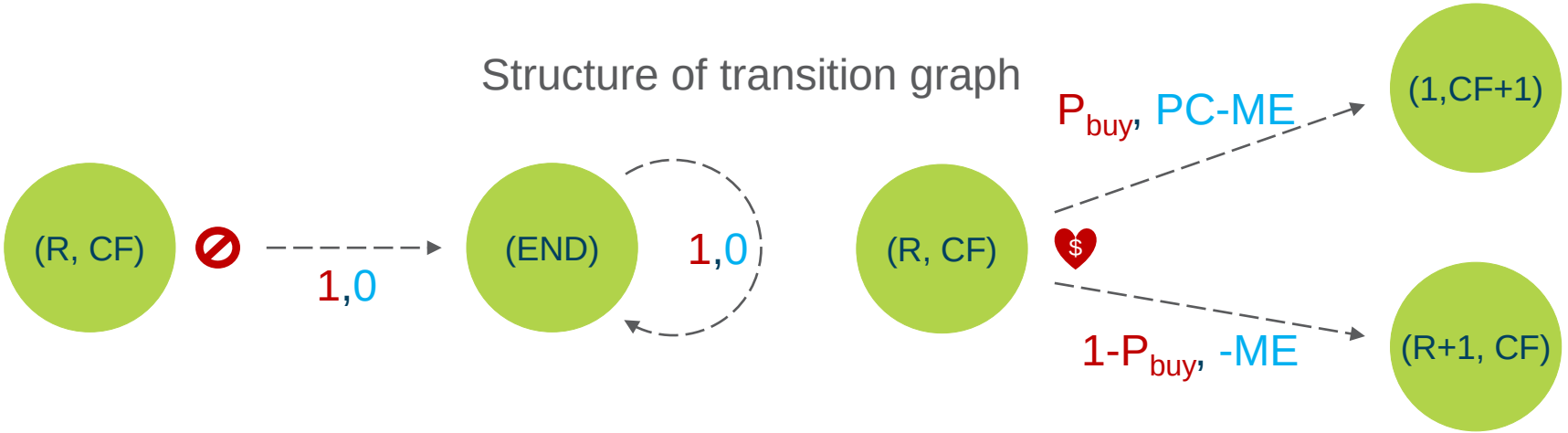
2. Estimate State Transition Probabilities

- Customers experience state transitions between discrete time periods
- Empirical purchase probabilities that customers will buy in next period: $P_{buy}(R,CF)$
  - Marketed customer makes purchase: (R, CF) → (1, CF+1), with probability P_{buy}
  - Marketed customer makes no purchase: (R, CF) → (R+1, CF), with probability $1-P_{buy}$
  - Customer is no longer marketed to: (R, CF) → (END), (END) → (END) with probability 1



3. Specify “Reward” Structure

- Business collects (or loses) rewards during each time period
- Profit Contribution PC, Marketing Expense ME are reward parameters
  - Marketed customer makes purchase: PC – ME, with probability P_{buy}
  - Marketed customer makes no purchase: – ME, with probability $1\text{-}P_{buy}$
  - Customer is no longer marketed to: 0, with probability 1



Estimating and Optimizing CLV

CLV is a concept based on an indefinite time horizon

– Present value of all future cash flows attributed to customer during entire relationship with the company

Markov model can estimate CLV from finite data window

– State transition probabilities and reward structure can be learned from finite data window

Model entails assumptions

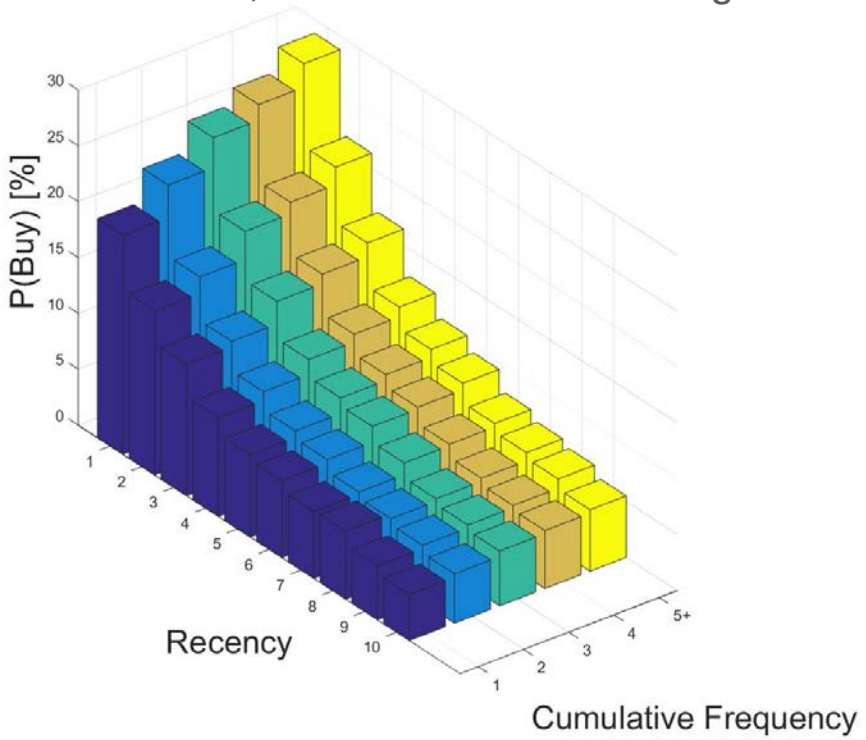
– Transition probabilities and rewards depend only on current state and action and are independent of time

George E. P. Box (1919–2013)
"Essentially, all models are wrong, but some are useful"

Modeling Hypothetical Portfolio

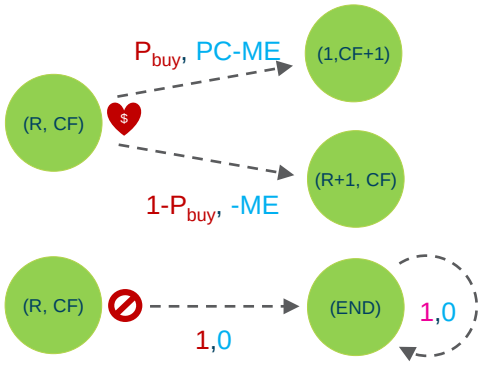
- New customers observed over 3 years
- Historic policy markets to customers until Recency = 10 quarters, then marketing ends
- Discretize time into quarters
- Define 50 active states by Recency, Cumulative Frequency
  - R = {1, …, 10⊗} CF = {1, …, 5+}
  - Estimate P_{buy} for active states conditional on marketing
- Assume P_{buy} = 0 if no marketing
- Reward parameters: PC = $100, ME = $10
- Discount rate = 12% p.a.

Estimated purchase probabilities for active states, conditional on marketing



Calculating CLV Using Matrix Algebra

Model structure and parameters



For any fixed policy

Matrix algebra[1]

$$CLV = \left(I - \frac{P}{1+d} \right)^{-1} R$$

P : Transition Matrix

I : Identity Matrix

R : Reward Vector

d : Per - period discount rate

Historic Policy and Associated CLV

All customers marketed (♡) until Recency = 10

Optimal Policy and Associated CLV

Solved by Policy Iteration[2]

Value of Optimizing Sequential Marketing Decisions for a New Customer

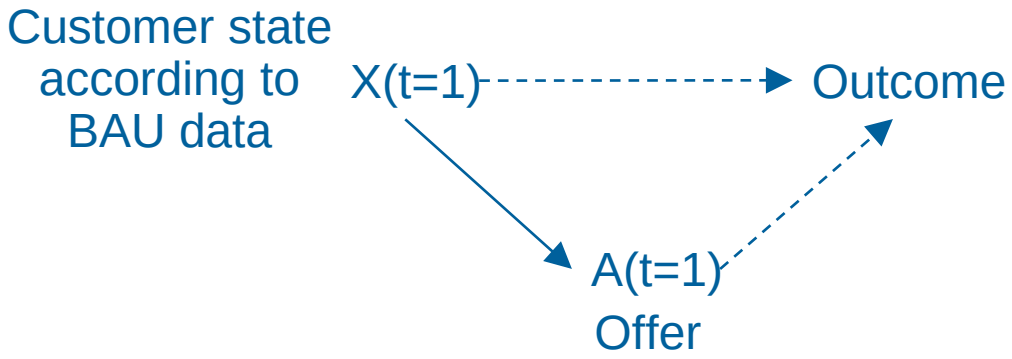
	Policy	
	Historic	Optimal
CLV(1,1) (new customer)	$131.03	$134.92
Profit Contribution from initial purchase	$100.00	$100.00
Expected present value from future cash flows	$31.03	$34.92
% Improvement of future cash flow	**+12.5%**	

Agenda

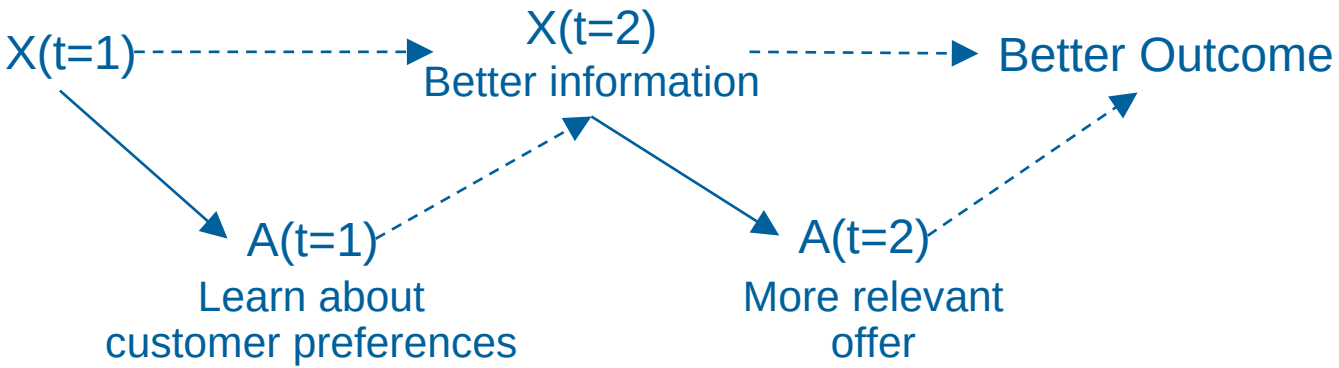
- Managing Inactive Customers
- Orchestrating Customer Dialogue for More Relevant Offers

Could Best Next Action Be Asking a Question?

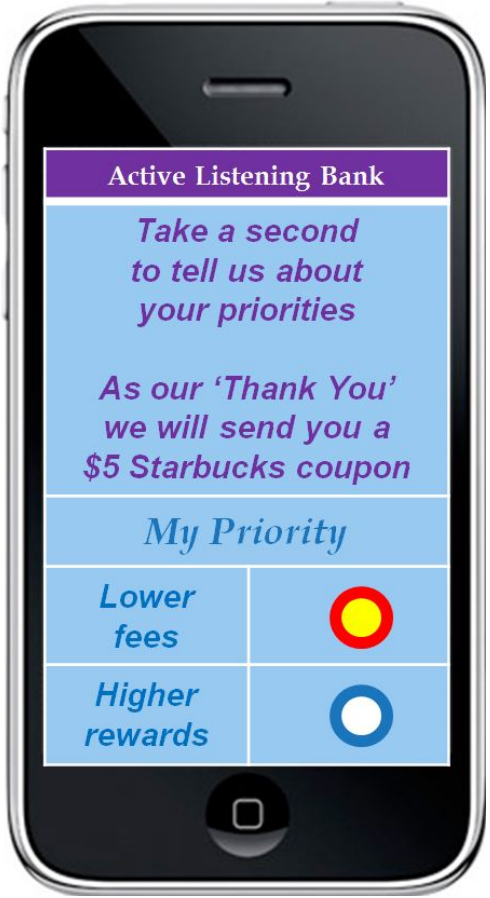
- Single-shot offer decision



- Sequential approach: (i) Customer dialogue → (ii) More relevant offer



Customer Dialogue App Example



- Ideal
  - Trusted dialogue
  - Truthful response (in customer's self-interest)
  - No incentive needed
- What is realistic?
  - May need to incentivize responses
  - Responses my not always be truthful
  - Customer may not always know her preferences
- When does imperfect information generated by dialogue outweigh cost of entertaining dialogue?

Simulation Parameters

States

Initial, End

Dialogue (non)responses

Offer (non)responses

Actions

Do nothing

Start dialogue

Offers

Reward Structure	
Customer engages in dialogue	-$5
Customer responds to offer	$100

No discounting

From State	Action	To State	Prob
Initial state	Do nothing	Initial state	1
Initial state	Offer: LOWER FEES	Offer response: ACCEPTED	0.5
Initial state	Offer: LOWER FEES	Offer response: NONE	0.5
Initial state	Offer: HIGHER REWARDS	Offer response: ACCEPTED	0.3
Initial state	Offer: HIGHER REWARDS	Offer response: NONE	0.7
Initial state	Start dialogue	Dialogue response: LOWER FEES	0.41
Initial state	Start dialogue	Dialogue response: HIGHER REWARDS	0.35
Initial state	Start dialogue	Dialogue response: NONE	0.24
Dialogue response: LOWER FEES	Do nothing	End state	1
Dialogue response: HIGHER REWARDS	Do nothing	End state	1
Dialogue response: NONE	Do nothing	End state	1
Dialogue response: LOWER FEES	Offer: LOWER FEES	Offer response: ACCEPTED	0.7
Dialogue response: LOWER FEES	Offer: LOWER FEES	Offer response: NONE	0.3
Dialogue response: LOWER FEES	Offer: HIGHER REWARDS	Offer response: ACCEPTED	0.25
Dialogue response: LOWER FEES	Offer: HIGHER REWARDS	Offer response: NONE	0.75
Dialogue response: HIGHER REWARDS	Offer: LOWER FEES	Offer response: ACCEPTED	0.15
Dialogue response: HIGHER REWARDS	Offer: LOWER FEES	Offer response: NONE	0.85
Dialogue response: HIGHER REWARDS	Offer: HIGHER REWARDS	Offer response: ACCEPTED	0.8

Optimal Policy and Best Next Action

Solution to MDP

State	Optimal Action
Initial state	Start dialogue
Dialogue response: HIGHER REWARDS	Offer: HIGHER REWARDS
Dialogue response: LOWER FEES	Offer: LOWER FEES
Dialogue response: NONE	Offer: LOWER FEES

Choices from initial state

Action	Customer Value	
Do nothing	$0.00	
Offer: HIGHER REWARDS	$30.00	
Offer: LOWER FEES	$50.00	← Best next action
Start dialogue	$57.70	

Discussion

- Optimizing sequential decisions and customer dialogue promise to increase customer value
- MDP's provide a framework—be aware of Markov assumptions
- Understanding effects of actions on state transition probabilities is a key task
  - Opportunities in informing model parameters through Test—and—Learn

- Where do you see your sequential decision opportunities?

References

[1] *Modeling customer relationships as Markov chains*. Phillip E. Pfeifer and Robert L. Carraway, John Wiley & Sons, Inc. and Direct Marketing Educational Foundation, Inc. Journal of Interactive Marketing Volume 14, Issue 2 (2000), pp. 43–55.

[2] *Dynamic Programming and Markov Processes.* Ronald A. Howard, The M.I.T. Press, 1960.

Thank You

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