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Human-Computation and Crowdsourcing

Online and Stochastic Learning with a Human Cognitive Bias

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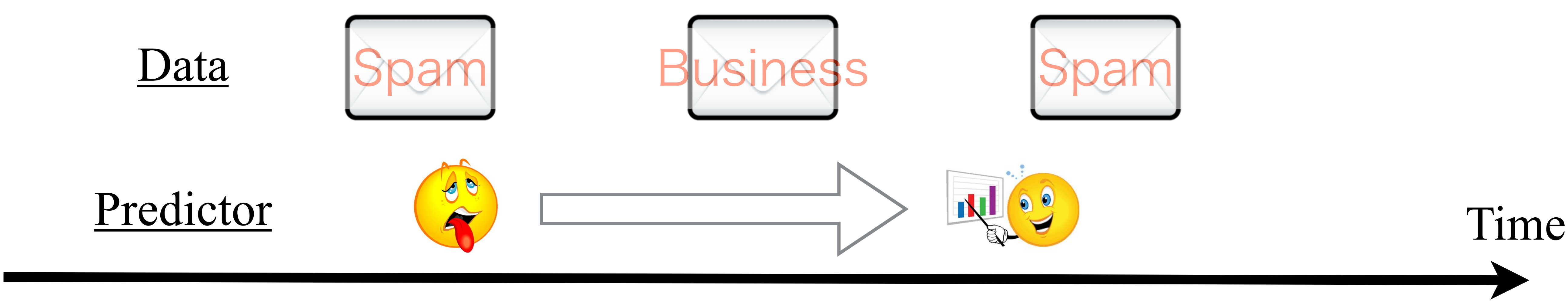
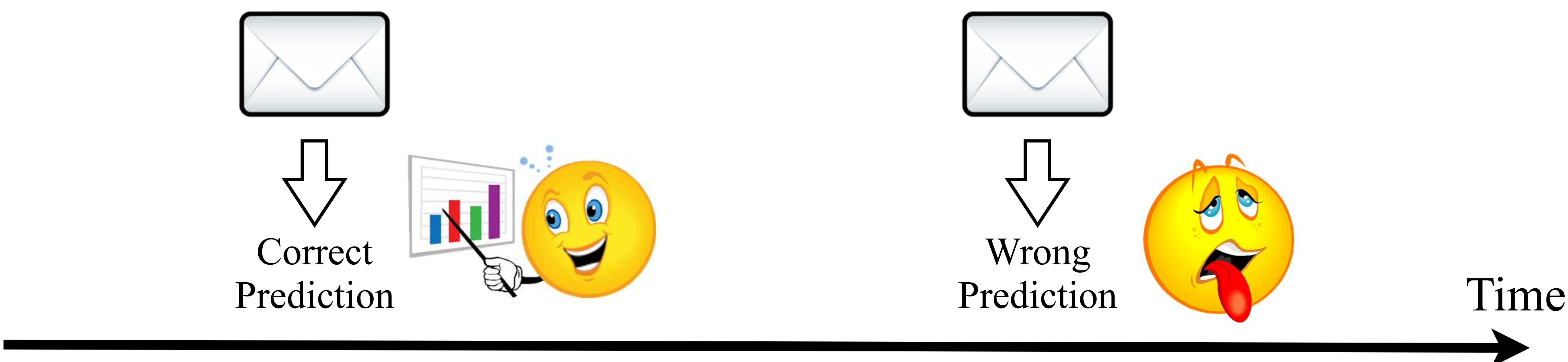
General Setting

- Supervised learning to learn **linear predictor** $\mathbf{w} \in \mathcal{W}$
  - to predict **label** $y \in \{-1, 1\}$ from **input** $x \in \mathcal{X}$
  - e.g. Spam Mail Filtering
- Approach: Sequential Learning
  - Update predictor each time algorithm receives one labeled datum
  - Advantageous to large-scale learning: Do not store processed data
  - e.g. Online / Stochastic Learning



Human Cognitive Bias

- When applying sequential learning to practical applications, conventional framework causes problem
  - Sometimes algorithms misclassify data that were correctly classified in the past
  - User utility may be crucially deteriorated in this case
- Utility Maximization $\neq$ Prediction Error Minimization
- We focus on sequential learning with human cognitive bias

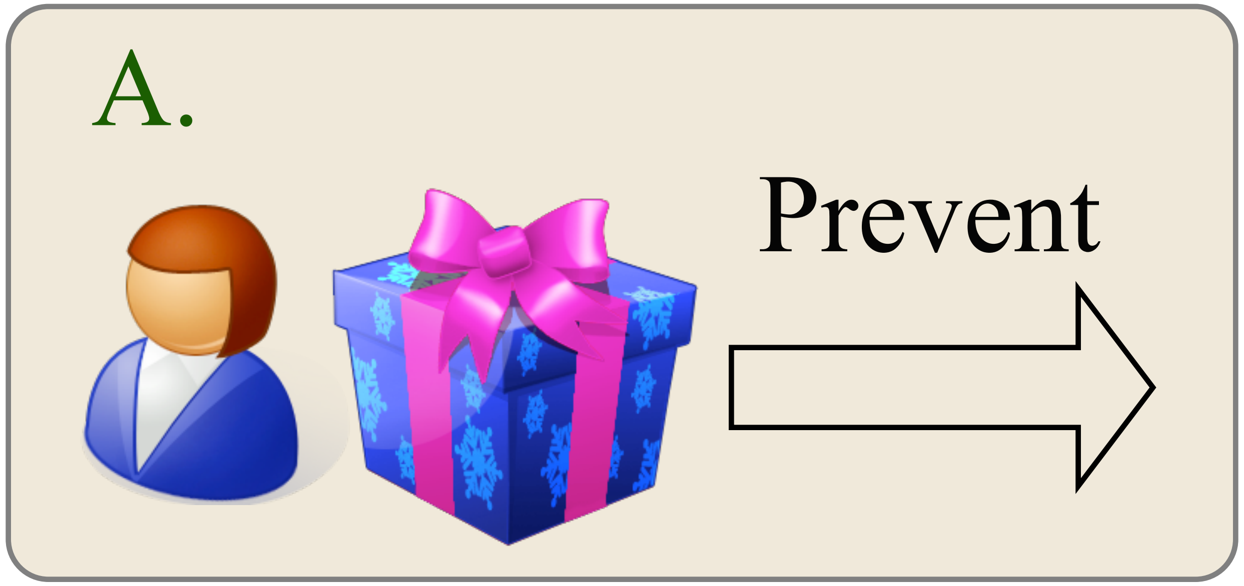


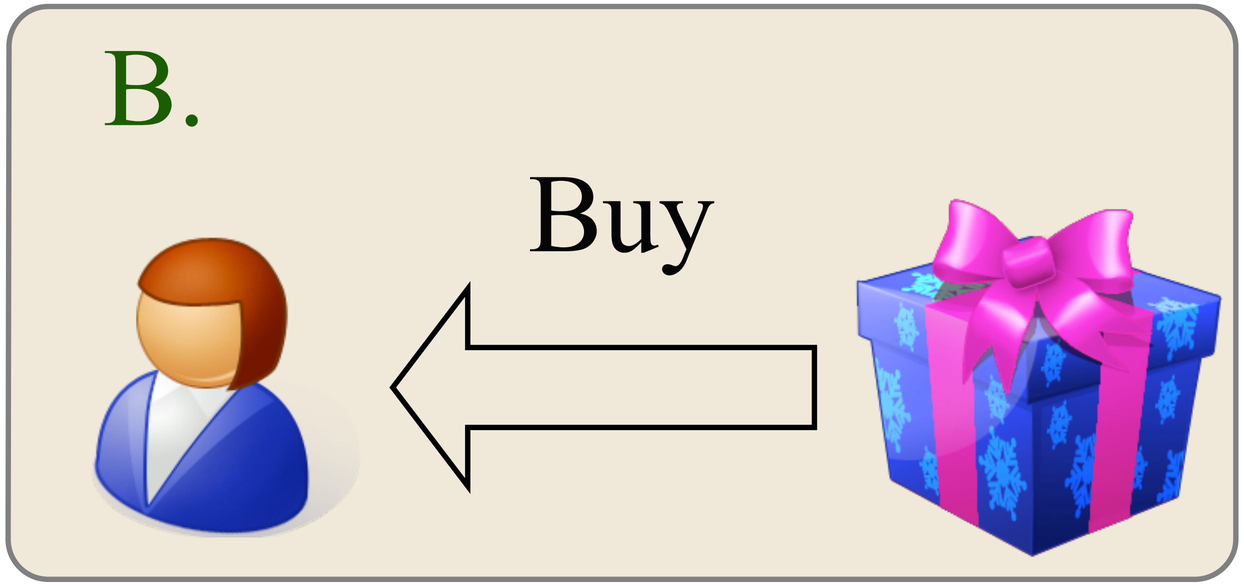
Outline

- Endowment Effect as a human cognitive bias
  - Empirical analysis of this effect toward utility maximization
- New framework: Online and Stochastic Learning with a Human Cognitive Bias
- Proposed Algorithm: Endowment-induced OGD
  - Theoretical Analysis
  - Experimental Analysis

Endowment Effect [Thaler+ 80]

- One of the major human cognitive biases
  - Human tends to pay more money in event A
    - A. Prevent loss of already possessed object
    - B. Buy a new object
- Human utility changes even if the outcome is the same

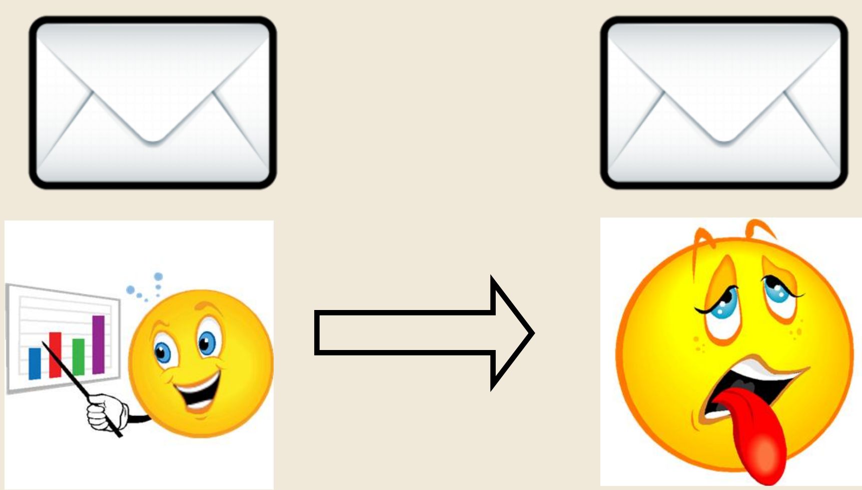




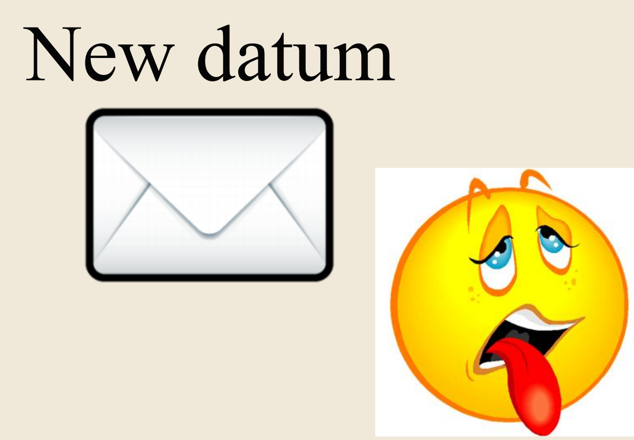
In the notion of Sequential Learning …

- Event A tends to decrease human utility
  - A. Misclassify data that we correctly predicted in the past
  - B. Misclassify unseen data
- Does this bias truly exist?

A.



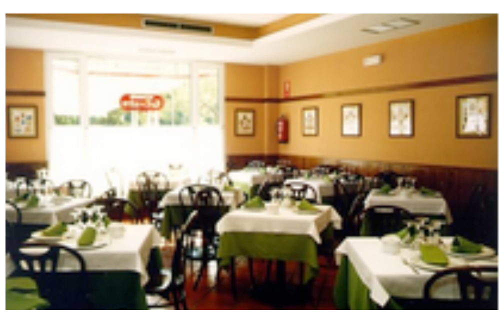
B.



Experiment on Endowment Effect

- Verify endowment effect for human utility
- Utilize crowdsourcing system to assign tasks
  - Set up scene recognition systems
  - Assign several tasks to each worker

<u>Training</u>



Predicted label
Restaurant

<u>Test</u>

Predicted label
Restaurant

Receive pictures and predicted labels
Send correct label if misclassified

Receive new pictures and labels
Evaluate learnability at a five scale

Experiment on Endowment Effect

- We assign two type tasks to each user
  - (type-I) Same image does not appear in both phases
  - (type-II) Images are redisplayed. They are correctly classified in training phase but misclassified in test phase
- Misclassification rates are fixed in both types
- **Result**: Type-II has lower evaluation than type-I with 1% level of significance
  - **Endowment effect badly affect worker's evaluation**

	1	2	3	4	5	Average
type-I	2	3	15	73	7	3.80
type-II (duplicate)	2	11	26	54	7	3.53

Sequential Learning with Endowment Effect

- Define this human cognitive bias as divestiture loss

$$\text{[Divestiture loss]} = \ell(\mathbf{w}; z)1_{\text{prev}}$$

  - $z = (\mathbf{x}, y)$: Datum
  - $\ell(\mathbf{w}; z)$: Loss function
  - 1_{prev} : This function becomes 1 when sample z was correctly classified in the past; 0 otherwise.
- We add this term to objective functions
  - Online learning: [Regret] + γ[Divestiture loss Regret]
  - Stochastic Learning: [Expected loss] + γ[Divestiture loss]

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Endowment-induced OGD (E-OGD)

- We propose a new algorithm based on Online Gradient Descent (OGD)

$$\mathbf{w}_{t+1} = \Pi_{\mathcal{W}}\left(\mathbf{w}_t - \eta_t \nabla \ell(\mathbf{w}_t; z_t)\right)$$

$$\text{where} \quad \eta_t = \begin{cases} c(1+\gamma)/\sqrt{t} & \text{if } \hat{y}_t = y_t \\ c/\sqrt{t} & \text{if } \hat{y}_t \neq y_t \end{cases}$$

- $\gamma \geq 0$: parameter to adjust importance of endowment effect
    - When $\gamma = 0$, E-OGD becomes normal OGD
- According to prediction result, adjust step width
    - When current datum is correctly classified, update parameters aggressively
    - This adjustment tend to prevent misclassification

Theoretical Analysis for Online Learning

- Regret Analysis
  - New objective: [Regret] + γ [Divestiture loss Regret]
  - We proved E-OGD achieves $O(\sqrt{T})$ upper bound
  - The same rate as OGD for normal setting [Zinkevich+ 03]

Theorem 3. *Let $\mathbf{w}_1, \ldots, \mathbf{w}_{T+1}$ be derived according to E-OGD's update rule. Assume that for all $\mathbf{w}_t$, $\|\mathbf{w}_t\|_2 \leq R$ and $\|\nabla \ell_t(\mathbf{w}_t)\|_2 \leq G$ are satisfied. If loss functions are convex and we set a sequence of step widths $\eta_{1:T}$ as denoted above, the upper bound of regret is obtained by setting $c = \sqrt{2}R/G(1+\gamma)$ as follows:*

$$\mathrm{Regret}(T) \leq 2\sqrt{2}RG(1+\gamma)\sqrt{T}\,. \qquad (9)$$

Theoretical Analysis for Stochastic Learning

- Expected Loss Analysis
  - New objective : [Expected loss] + γ [Divestiture loss]
  - E-OGD achieves $O(1/\sqrt{T})$ upper bound under some assumptions
  - The same rate as OGD for normal setting [Cesa-Bianchi+ 04]

Theorem 4. *Assume that the conditions in Theorem 3 are satisfied and there is an integer t_p such that $r_t(z) = r_{t_p}(z)$ for any $t \geq t_p$. In this setting, the following formula is satisfied for any $\mathbf{u} \in \mathcal{W}$.*

$$E_{\mathcal{D}^T}\left[E_{z\sim\mathcal{D}_P}\left[\ell(\bar{\mathbf{w}}; z)\right]\right] - E_{\mathcal{D}^T}\left[E_{z\sim\mathcal{D}_P}\left[\ell(\mathbf{u}; z)\right]\right] \leq \frac{\sqrt{2}RG(1+\gamma)}{(\sqrt{T}-(t_p+1)/\sqrt{T})/(2-\sqrt{t_p-1/\sqrt{T}})}, \quad (11)$$

where $\bar{\mathbf{w}} = \sum_{t=t_p}^{T} \mathbf{w}_t/(T - t_p + 1)$.

Experiment

- Five binary classification tasks by one-pass stochastic learning
  - Loss function : Logistic loss
  - Learning rate : $\eta_t = \eta/\sqrt{t}$
    - Constant factor is set to minimize the objective
  - Trade-off parameter : $\gamma = 1$
  - Evaluation: [Expected loss] + γ [Divestiture loss]

Table 2: Dataset Specifications. T is the number of training data. S is test data size. N is the number of features.

	T	S	N
news20	15,000	4,996	1,335,191
rcv1	20,242	677,399	47,236
algebra	8,407,752	510,302	20,216,830
BtA	19,264,097	748,401	29,890,095
webspam-t	315,000	35,000	16,609,143

Experimental Result

	Loss Type	E-OGD	OGD
news20	Expected	$\mathbf{3.11 \times 10^{-2}}$	3.85×10^{-2}
	Divestiture	$\mathbf{1.37 \times 10^{-2}}$	2.20×10^{-2}
	Cumulative	$\mathbf{4.48 \times 10^{-2}}$	6.05×10^{-2}
rcv1	Expected	$\mathbf{3.53 \times 10^{-2}}$	3.80×10^{-2}
	Divestiture	$\mathbf{1.25 \times 10^{-2}}$	1.78×10^{-2}
	Cumulative	$\mathbf{4.79 \times 10^{-2}}$	5.58×10^{-2}
algebra	Expected	3.35×10^{-1}	$\mathbf{3.13 \times 10^{-1}}$
	Divestiture	$\mathbf{5.89 \times 10^{-2}}$	1.02×10^{-1}
	Cumulative	$\mathbf{3.94 \times 10^{-1}}$	4.16×10^{-1}
BtA	Expected	3.29×10^{-1}	$\mathbf{3.11 \times 10^{-1}}$
	Divestiture	$\mathbf{7.64 \times 10^{-2}}$	1.17×10^{-1}
	Cumulative	$\mathbf{4.05 \times 10^{-1}}$	4.28×10^{-1}
webspam-t	Expected	$\mathbf{2.62 \times 10^{-2}}$	2.75×10^{-2}
	Divestiture	$\mathbf{8.29 \times 10^{-3}}$	1.16×10^{-2}
	Cumulative	$\mathbf{3.45 \times 10^{-2}}$	3.91×10^{-2}

Conclusion

- Online and stochastic learning with a human cognitive bias
  - Verifying endowment effect through subjective experiment
  - Mathematical modeling of endowment effect
- E-OGD heals negative effect of divestiture loss
  - Theoretical analyses of E-OGD
  - E-OGD obtains better empirical performance