

Online Learning to Rank with Features

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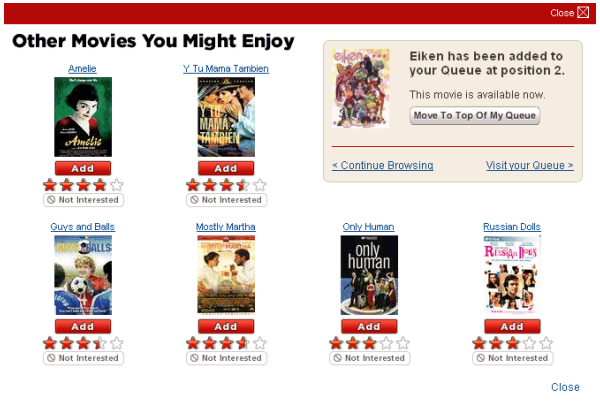
Learning to Rank



Amazon, YouTube, Facebook, Netflix, Taobao

Online Learning to Rank

- There are $\hat{I}$ items and $\hat{E}$ $\hat{I}$ positions
- At each time $^{?} = 1; 2; : : :$,
  - Choose an ordered list $_{?} = (\mathcal{E}_1^{?}; : : : ; \mathcal{E}_{\hat{E}}^{?})$
  - Show the user the list
  - Receive click feedback $G_{?1}; : : : ; G_{?\hat{E}}$ 2 $f0; 1g$, per position
- Objective: Maximize the expected number of clicks

$$\mathrm{E}\left[\sum_{?=1}^{\hat{}} \sum_{\zeta=1}^{\hat{E}} G_{?\zeta}\right]$$

Click Models

- Click models describe how users interact with item lists
- Cascade Model (CM)
  - Assumes the user checks the list from position 1 to position $\hat{E}$, clicks at the first satisfying item and stops
- Dependent Click Model (DCM)
  - Further assumes there is a satisfaction probability after click
- Position-Based Model (PBM)
  - Assumes the user click probability on an item a of position k can be factored into item attractiveness and position bias
- Generic model
  - Make as few assumptions as possible about the click model

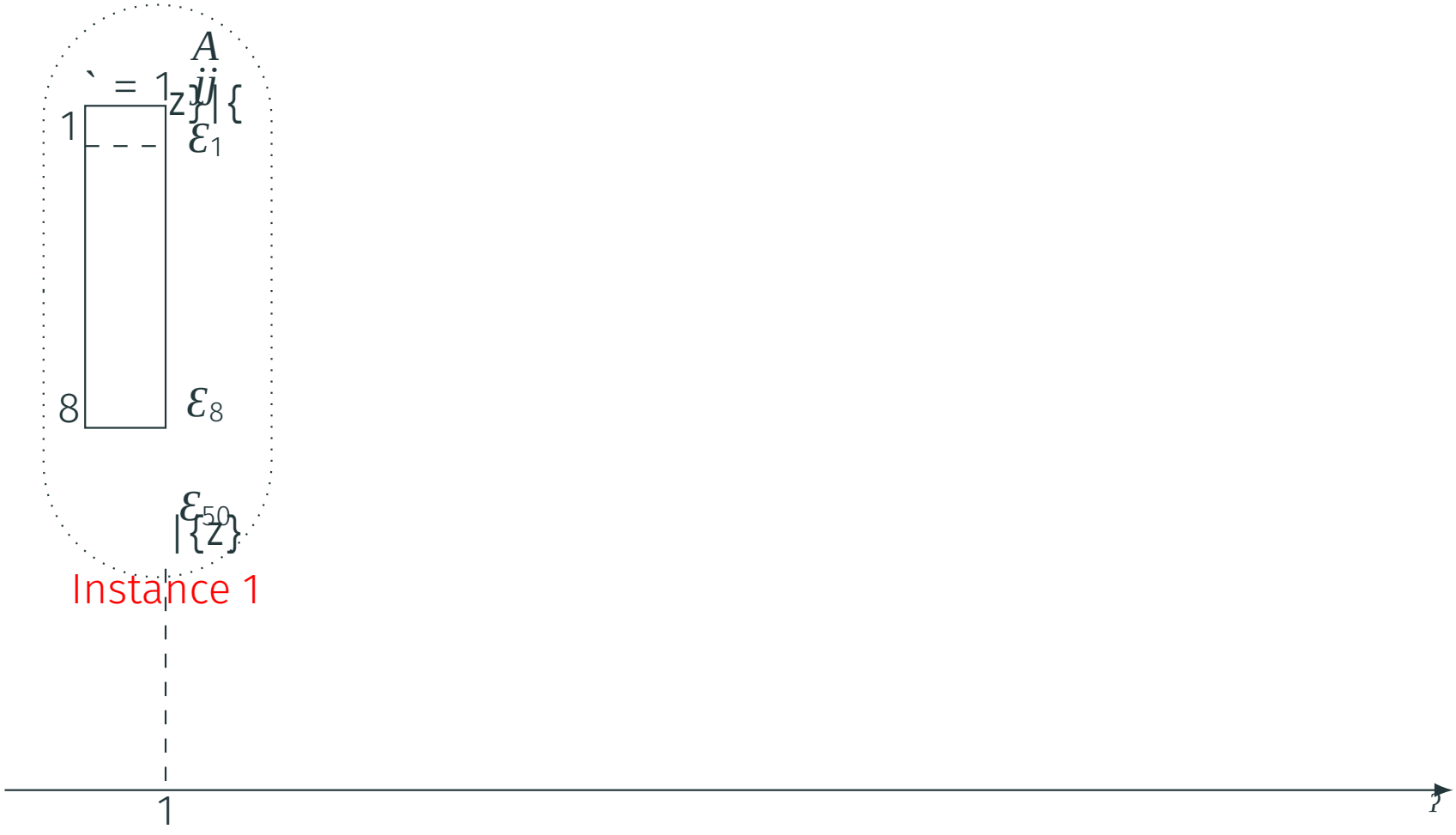
✗
✓
✗
✓
✗

RecurRank

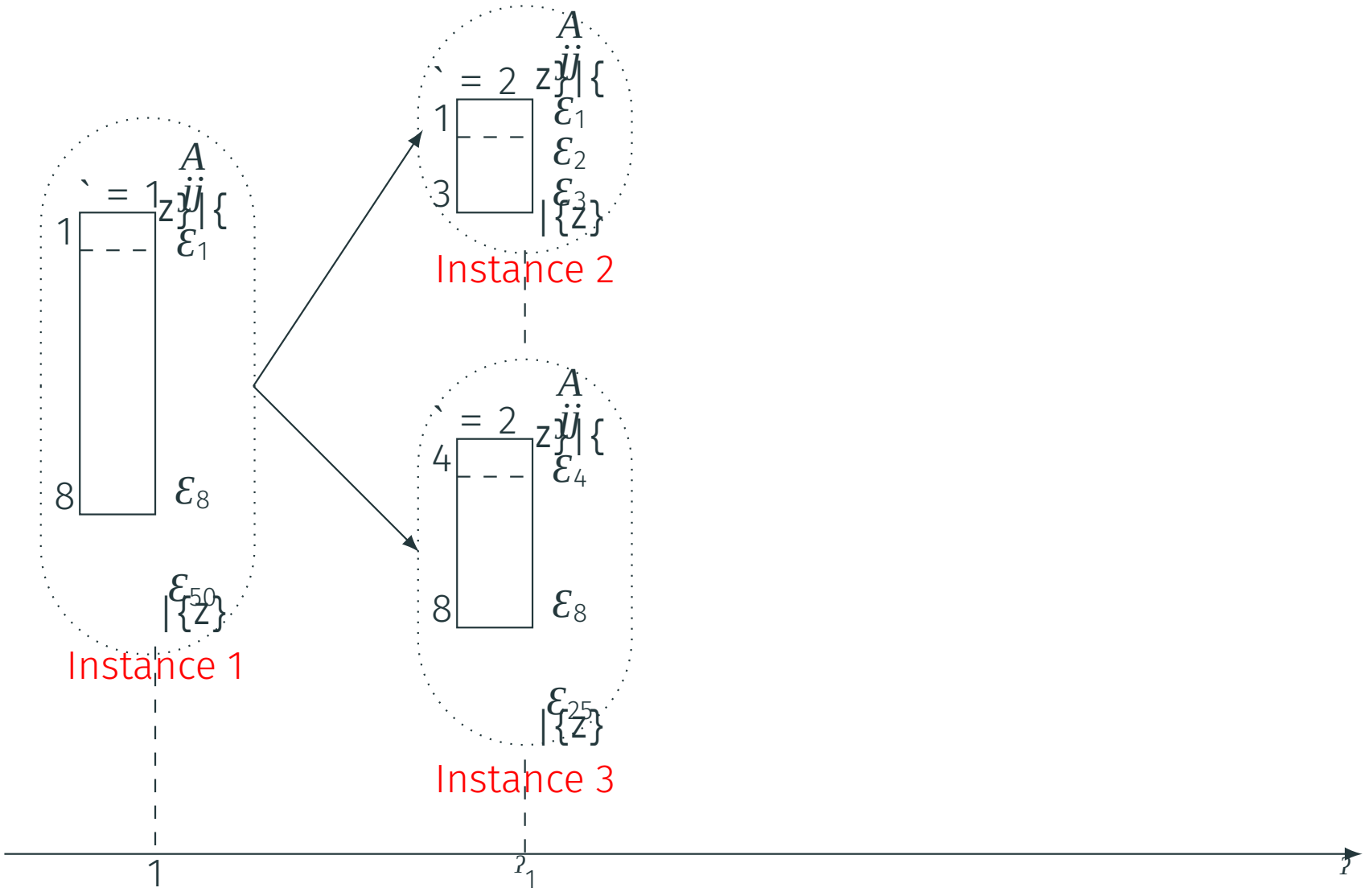
- Each item $\mathcal{E}$ is represented by a feature vector $\llcorner_{\mathcal{E}}\ 2\ \mathbf{R}^{Lj}$
- The attractiveness of item $\mathcal{E}$ is $(\mathcal{E}) = {}^{\top}\llcorner_{\mathcal{E}}$
- Click probability factors: $\mathbf{P}_{?}(G_{?\zeta} = 1) = (\mathcal{E}^{?}_{\zeta})\ (\ _{?};\zeta)$ where is the examination probability, which satisfies reasonable assumptions

- RecurRank (Recursive Ranking)
- For each phase `
  - Use first position for exploration
  - Use remaining positions for exploitation, rank best items first
- Split items and positions when the phase ends
- Recursively call the algorithm with increased phase

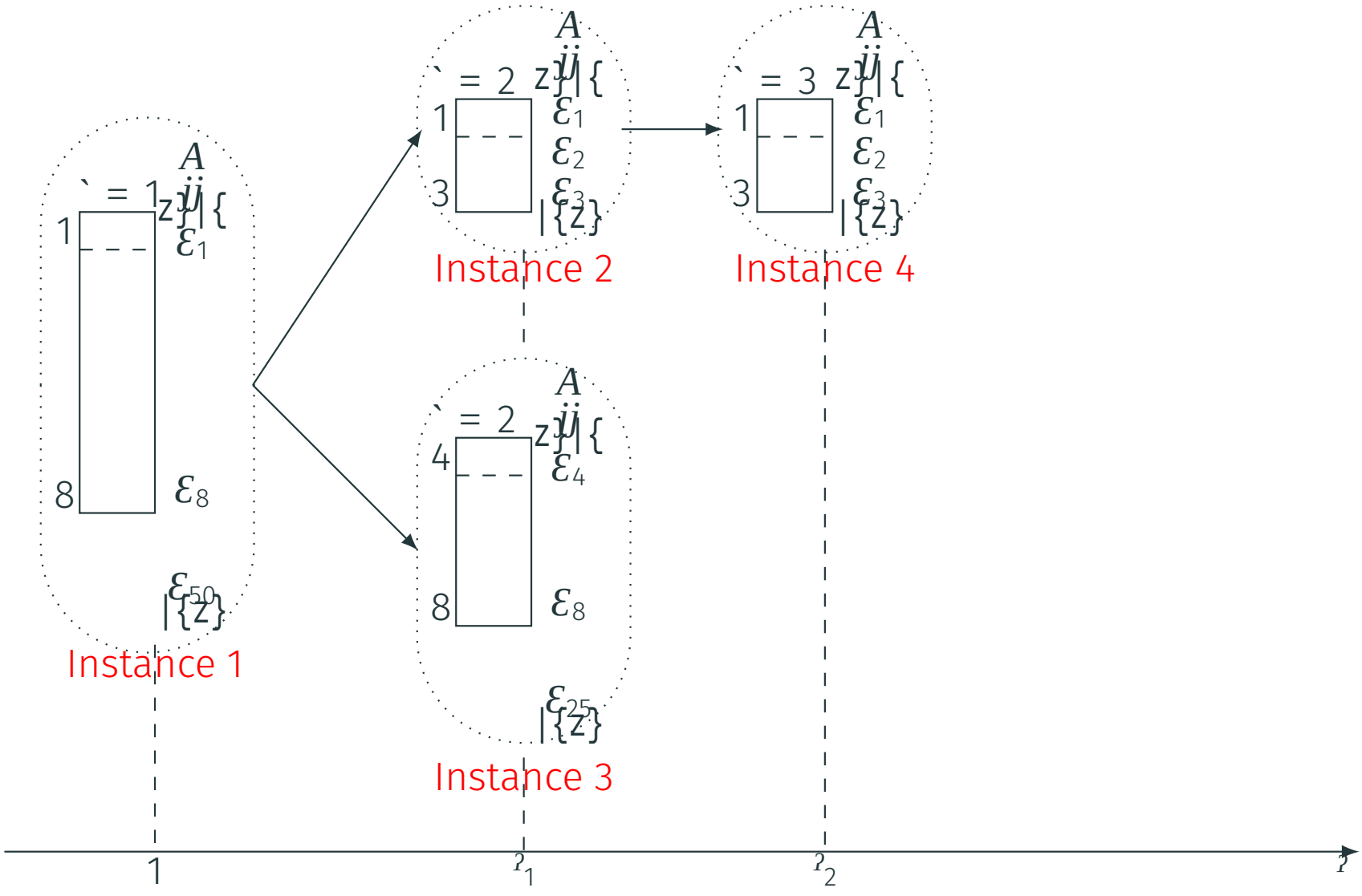
Example



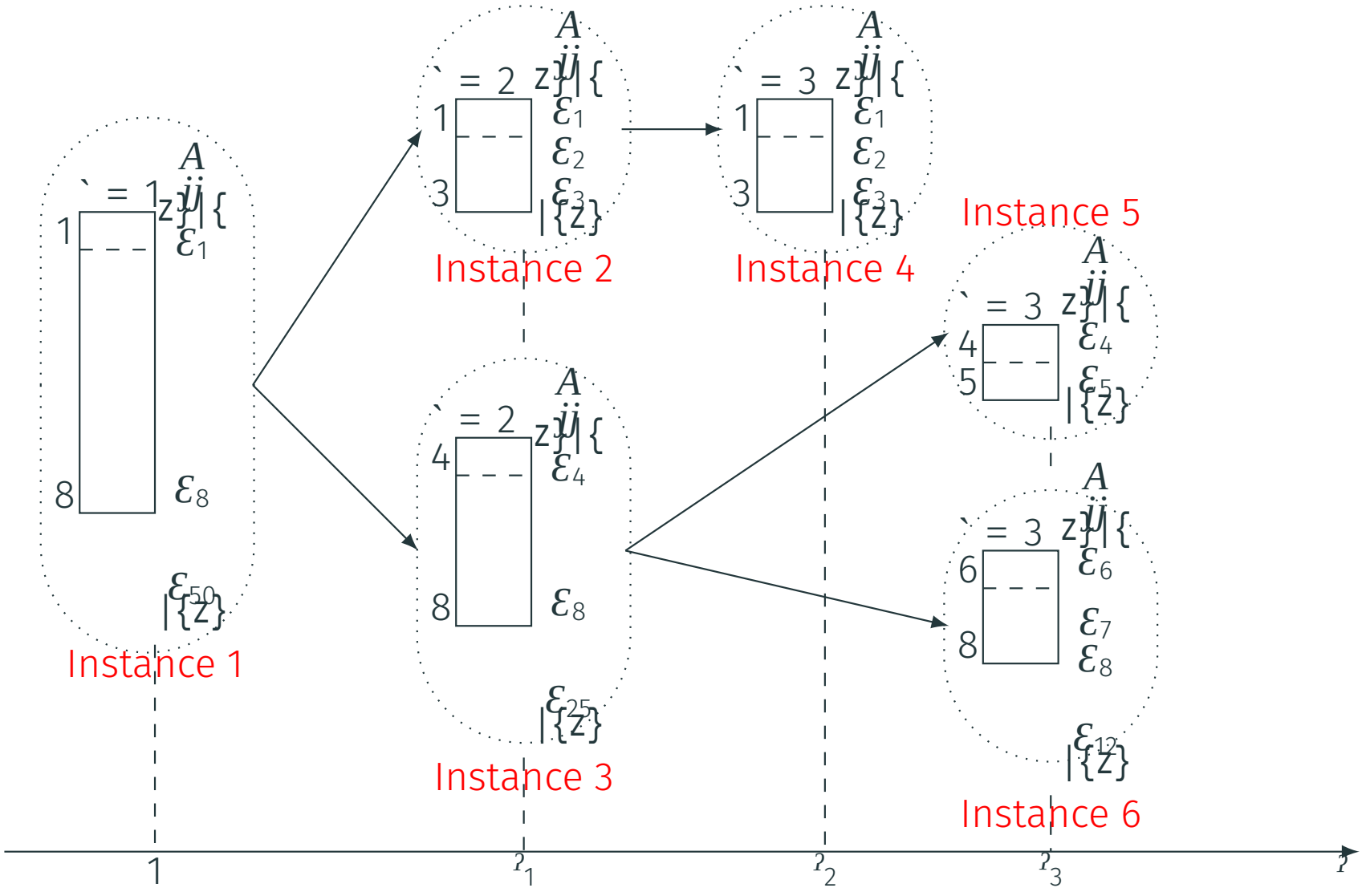
Example



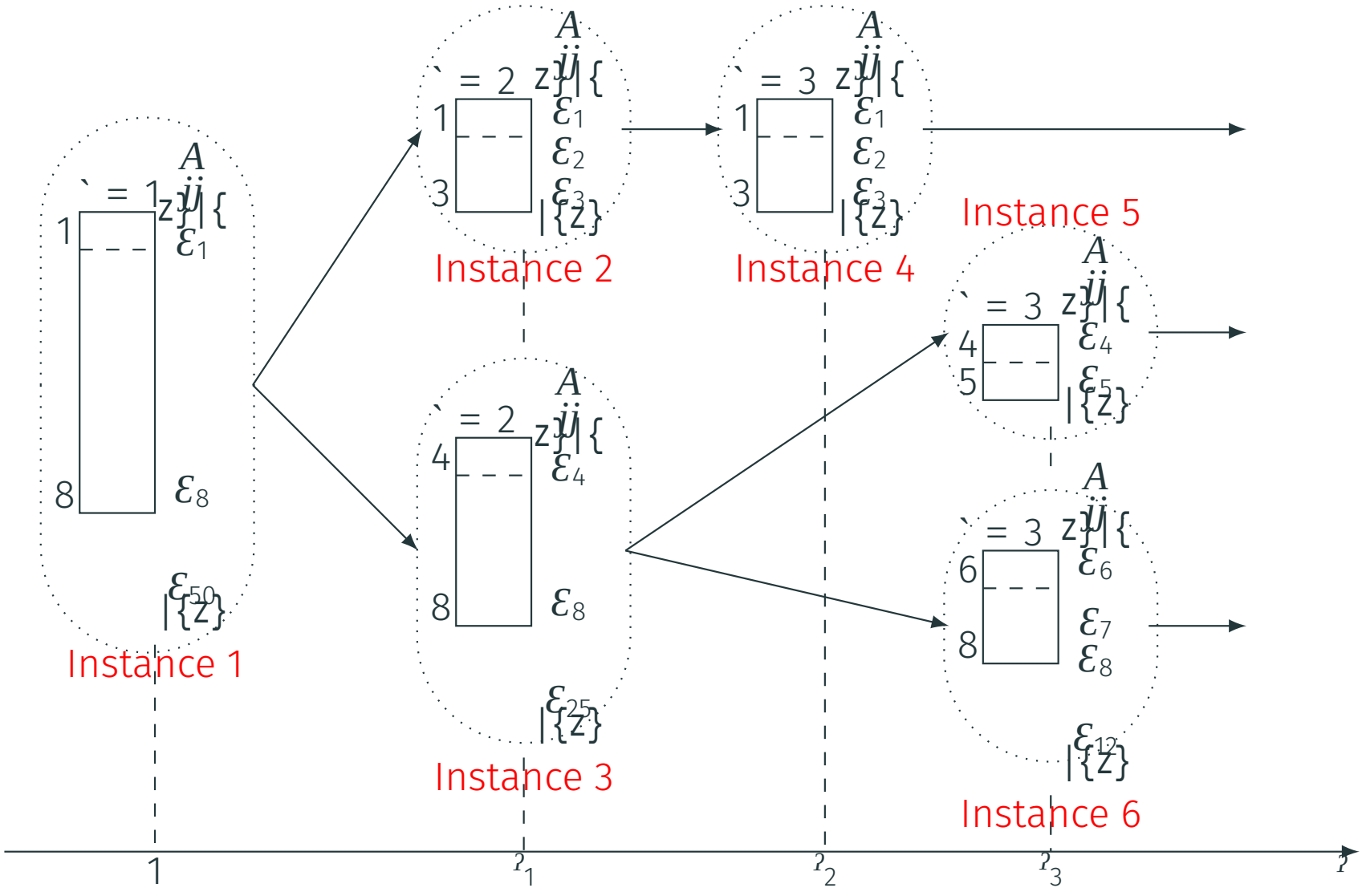
Example



Example


Instance 1
Instance 2
Instance 3
Instance 4
Instance 5
Instance 6
1
r_1
r_2
r_3
t

Example


Instance 1
Instance 2
Instance 3
Instance 4
Instance 5
Instance 6

Results

- Regret bound

$$\hat{g}(\imath) = \grave{\imath}\,(\hat{E}\,\sqrt{Lj\imath\,\log(\hat{I}\,\imath)})$$

- Improves over existing bound $\grave{\imath}\,\sqrt{\hat{E}^3\hat{I}\,\imath\,\log(\imath)}$

Results

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—RecurRank —CascadeLinUCB —TopRank

Thank you!

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