Warm-starting contextual bandits: robustly combining supervised and bandit feedback

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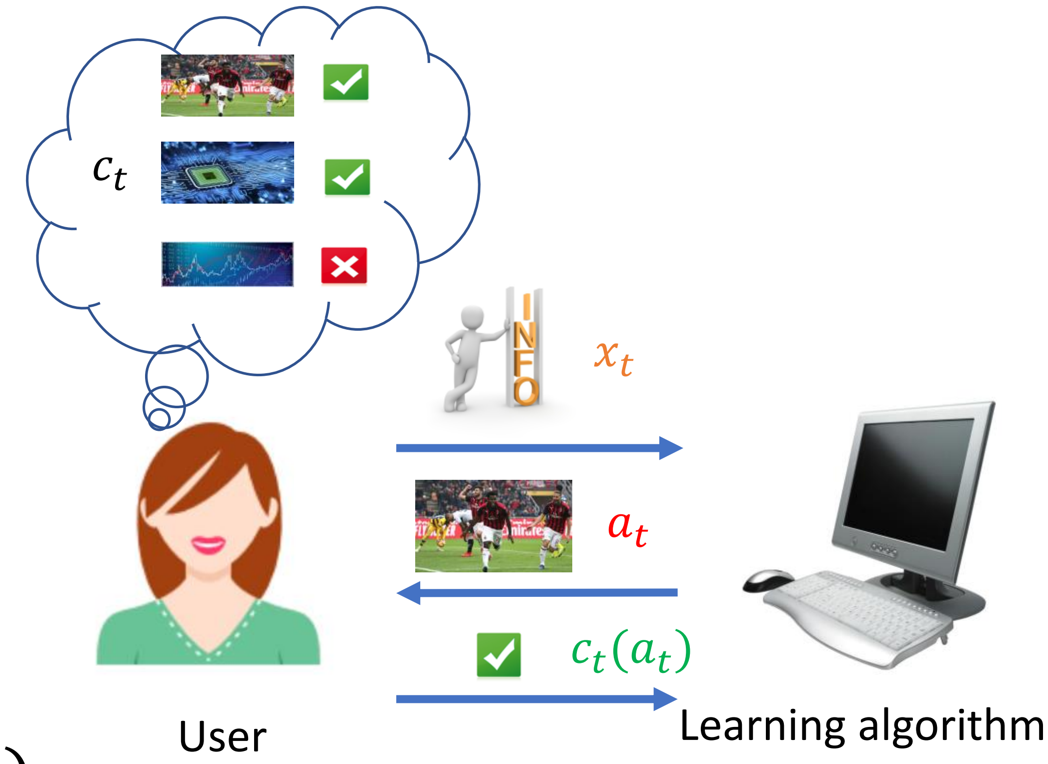
Warm-starting contextual bandits

- For timestep $t = 1,2,..T$:
  - Observe context x_t
    with associated cost $c_t = (c_t(1), \dots, c_t(K))$
    from distribution D
  - Take an action $a_t \in \{1, \dots K\}$
  - Receive cost $c_t(a_t) \in [0,1]$
- **Goal:** incur low cumulative cost: $\sum_{t=1}^{T} c_t(a_t)$



Warm-starting contextual bandits

- Receive warm-starting examples $S = \{(x, c)\} \sim W$
- For timestep $t = 1,2, .. T$:
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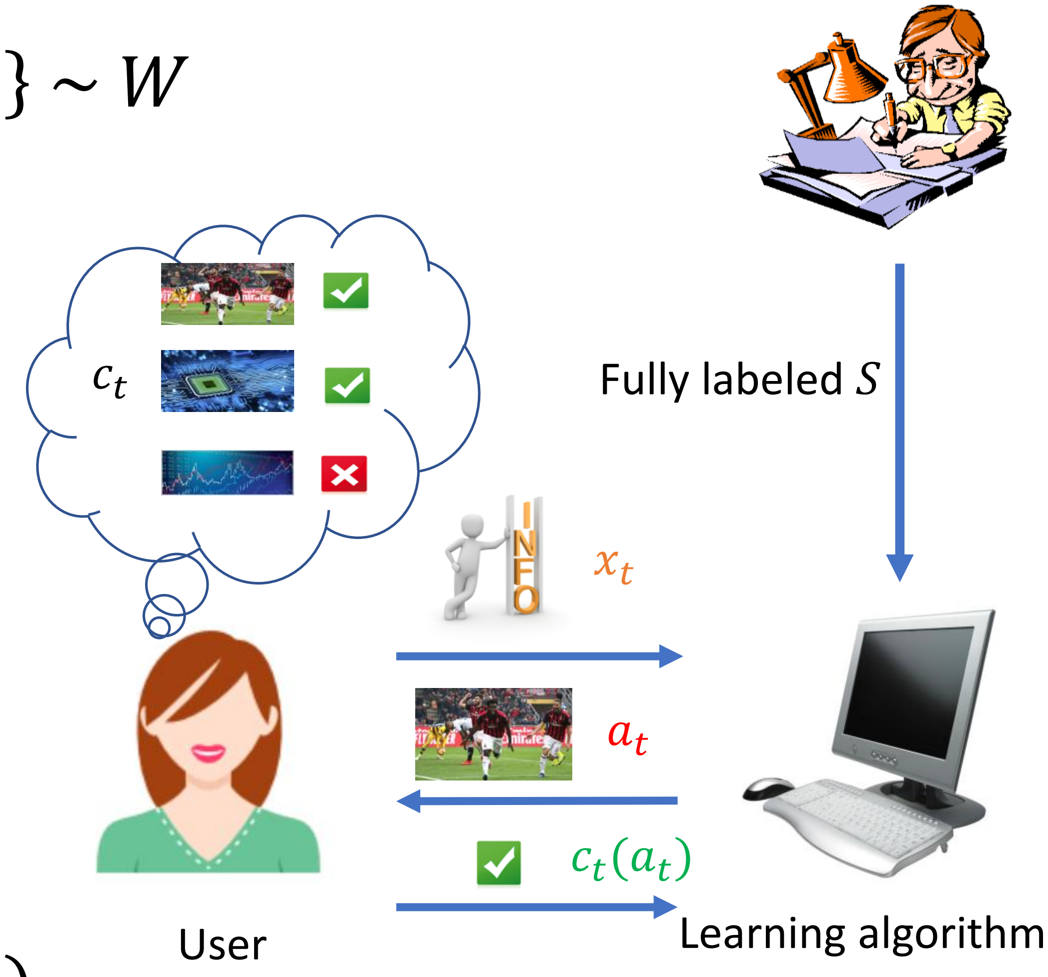

Warm-starting contextual bandits: motivation

- Some labeled examples often exist in applications, e.g.
  - News recommendation: editorial relevance annotations
  - Healthcare: historical medical records w/ prescribed treatments

- Leveraging historical data can reduce unsafe exploration

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Key Challenge: W may not be the same as D

- Editors fail to capture users' preferences
- Medical record data from another population

How to utilize the warm-starting examples robustly and effectively?

Algorithm & performance guarantees

ARRoW-CB: iteratively finds the best relative weighting of warm-start and bandit examples to rapidly learn a good policy

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- **Theorem (informal):**

Compared to algorithms that ignore S,* the regret of ARRoW-CB is

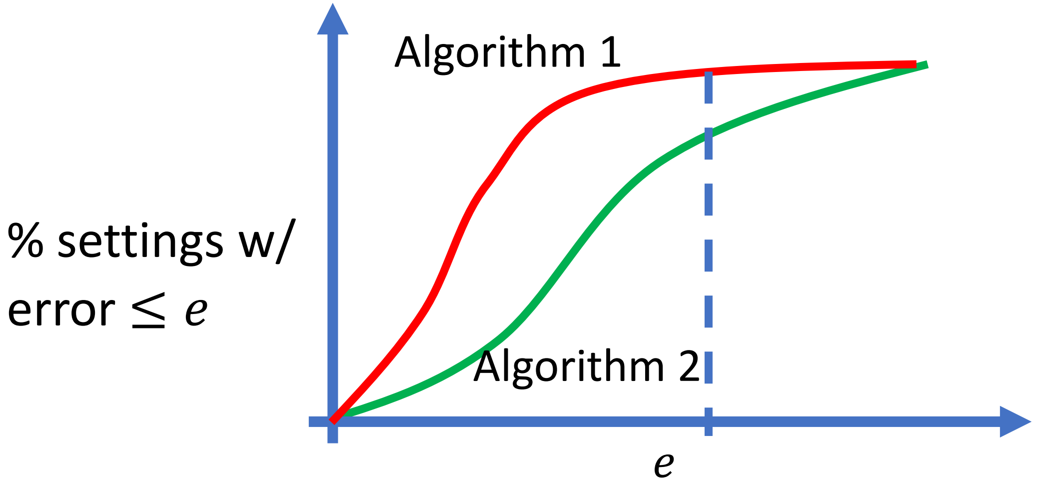
- never much worse (robustness)

- much smaller, if W and D are close enough, and $|S|$ is large enough

*$S \sim W$ is the warm start data

Empirical evaluation

- 524 datasets from openml.org
- CDFs of normalized errors



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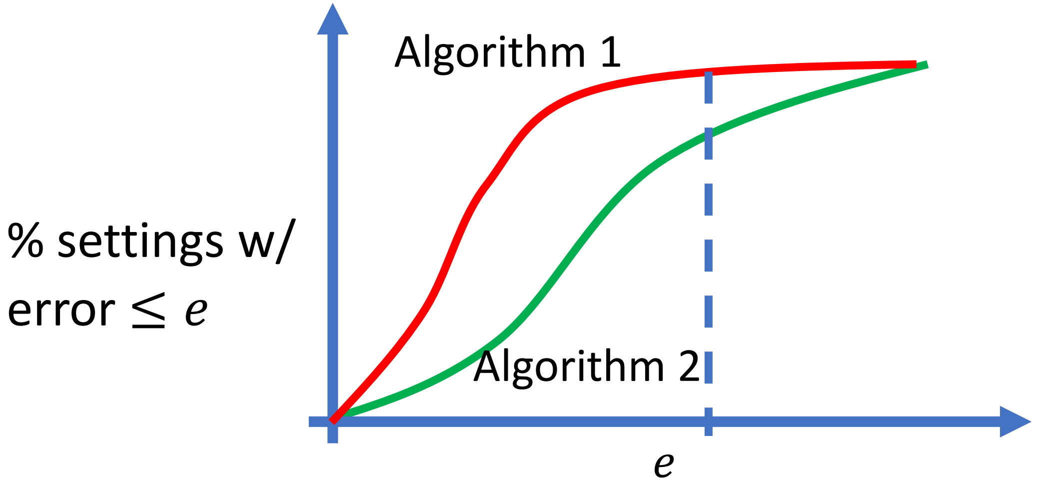
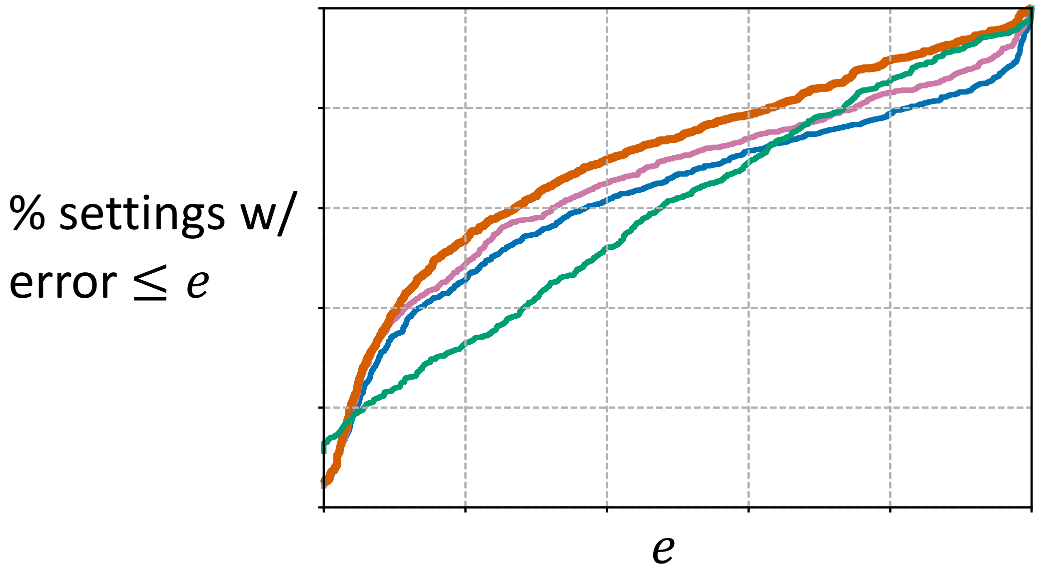


- Moderate noise setting
- Algorithms:
  ARRoW-CB,
  Sup-Only,
  Bandit-Only,
  Sim-Bandit (uses both sources)



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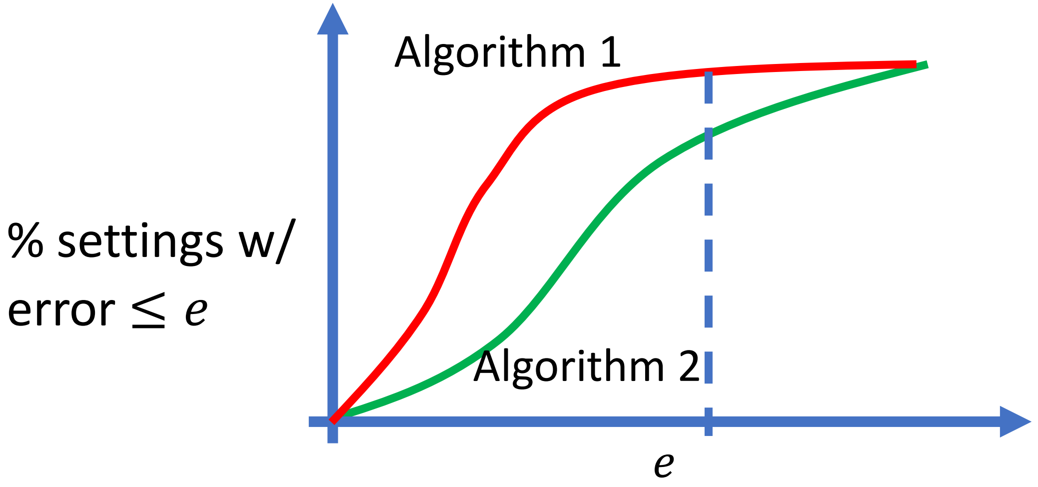

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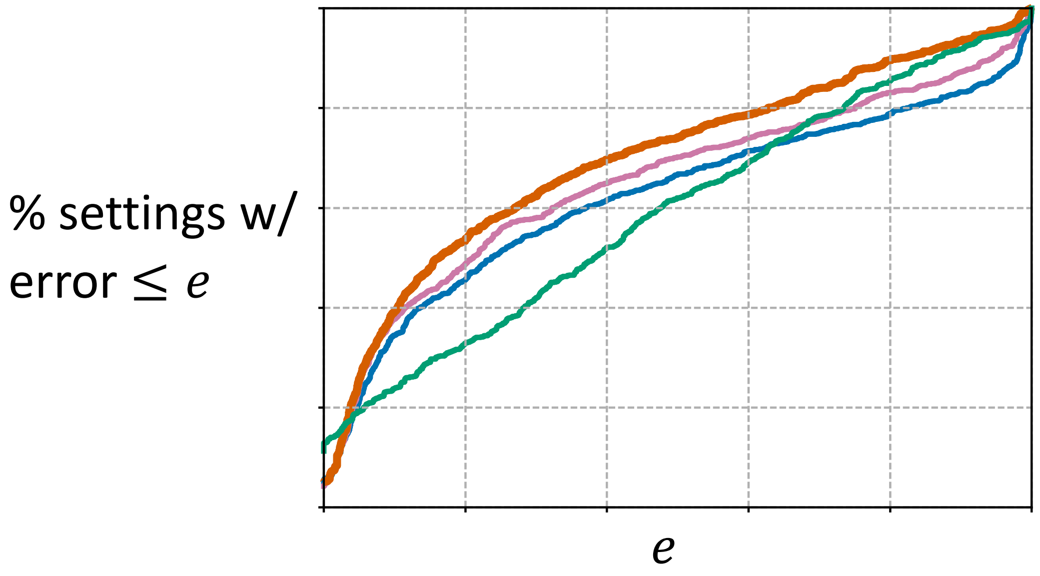

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