Stable Coactive Learning via Perturbation

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Coactive Learning

Learning model

Repeat forever:

- System receives context $\mathbf{x}_t$.

Coactive Learning

e.g. : Search Engine

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Ranking

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  Full information: $U(\mathbf{x}_t, \mathbf{y}^{(1)}), U(\mathbf{x}_t, \mathbf{y}^{(2)}), \ldots$

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Perceptron has regret $O(\frac{1}{\alpha\sqrt{T}})$ for linear utility $(U(\mathbf{x}, \mathbf{y}) = \mathbf{w}_*^\top \phi(\mathbf{x}, \mathbf{y}))$.

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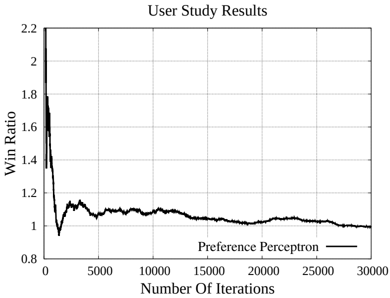

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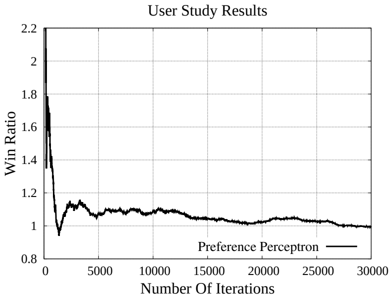

Perceptron performs poorly!

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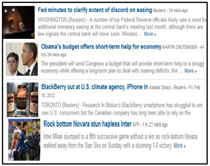
Preference Perceptron Algo:

1. Initialize weight vector $\mathbf{w}_1 \leftarrow \mathbf{0}$.
2. Given context $\mathbf{x}_t$ present $\mathbf{y}_t \leftarrow \text{argmax}_{\mathbf{y}} \mathbf{w}_t^\top \phi(\mathbf{x}_t, \mathbf{y})$.

Presented Ranking (y)



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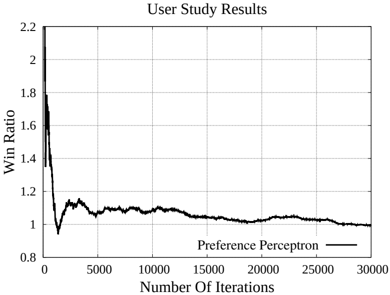

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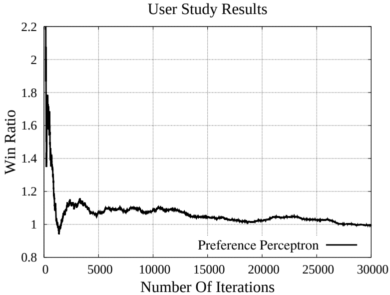

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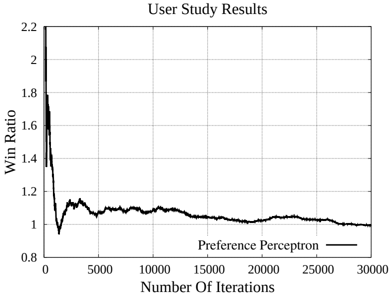

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3. Observe clicks and construct feedback ranking $\bar{\mathbf{y}}_t$.
4. $\mathbf{w}_{t+1} \leftarrow \mathbf{w}_t + \phi(\mathbf{x}_t, \bar{\mathbf{y}}_t) - \phi(\mathbf{x}_t, \mathbf{y}_t)$.
5. Repeat from step 2.

Presented Ranking (y) Feedback Ranking ($\bar{\text{y}}$)

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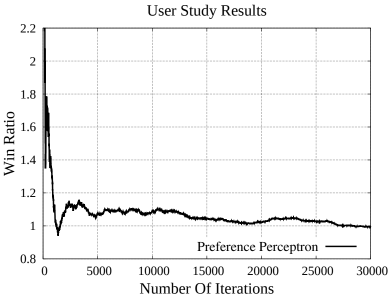
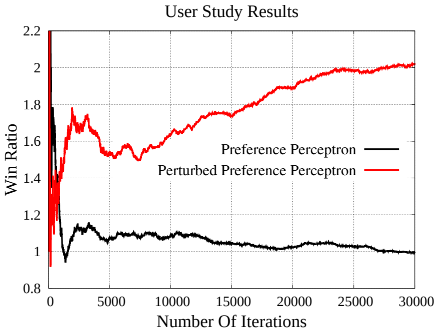


Perceptron performs poorly!

Perturbed Preference Perceptron

1. Initialize weight vector $\mathbf{w}_1 \leftarrow \mathbf{0}$.
2. Given context $\mathbf{x}_t$ compute $\hat{\mathbf{y}}_t \leftarrow \operatorname{argmax}_{\mathbf{y}} \mathbf{w}_t^\top \phi(\mathbf{x}_t, \mathbf{y})$.
3. Present $\mathbf{y}_t \leftarrow \mathit{Perturb}(\hat{\mathbf{y}}_t)$ (Randomly swap adjacent pairs).
4. Observe clicks and construct feedback ranking $\bar{\mathbf{y}}_t$.
5. $\mathbf{w}_{t+1} \leftarrow \mathbf{w}_t + \phi(\mathbf{x}_t, \bar{\mathbf{y}}_t) - \phi(\mathbf{x}_t, \mathbf{y}_t)$.
6. Repeat from step 2.



Predicted Ranking ($\hat{y}$)

Presented Ranking (y)

Please come to our poster

I will tell you:

- Why the preference perceptron performs poorly?
- Why does perturbation fix the problem?
- What are the regret bounds for the algorithm?
- How do we do this more generally for non-ranking problems?