

# Online Learning to Diversify from Implicit Feedback

Karthik Raman

Cornell University  
karthik@cs.cornell.edu

Pannaga Shivaswamy

Cornell University  
pannaga@cs.cornell.edu

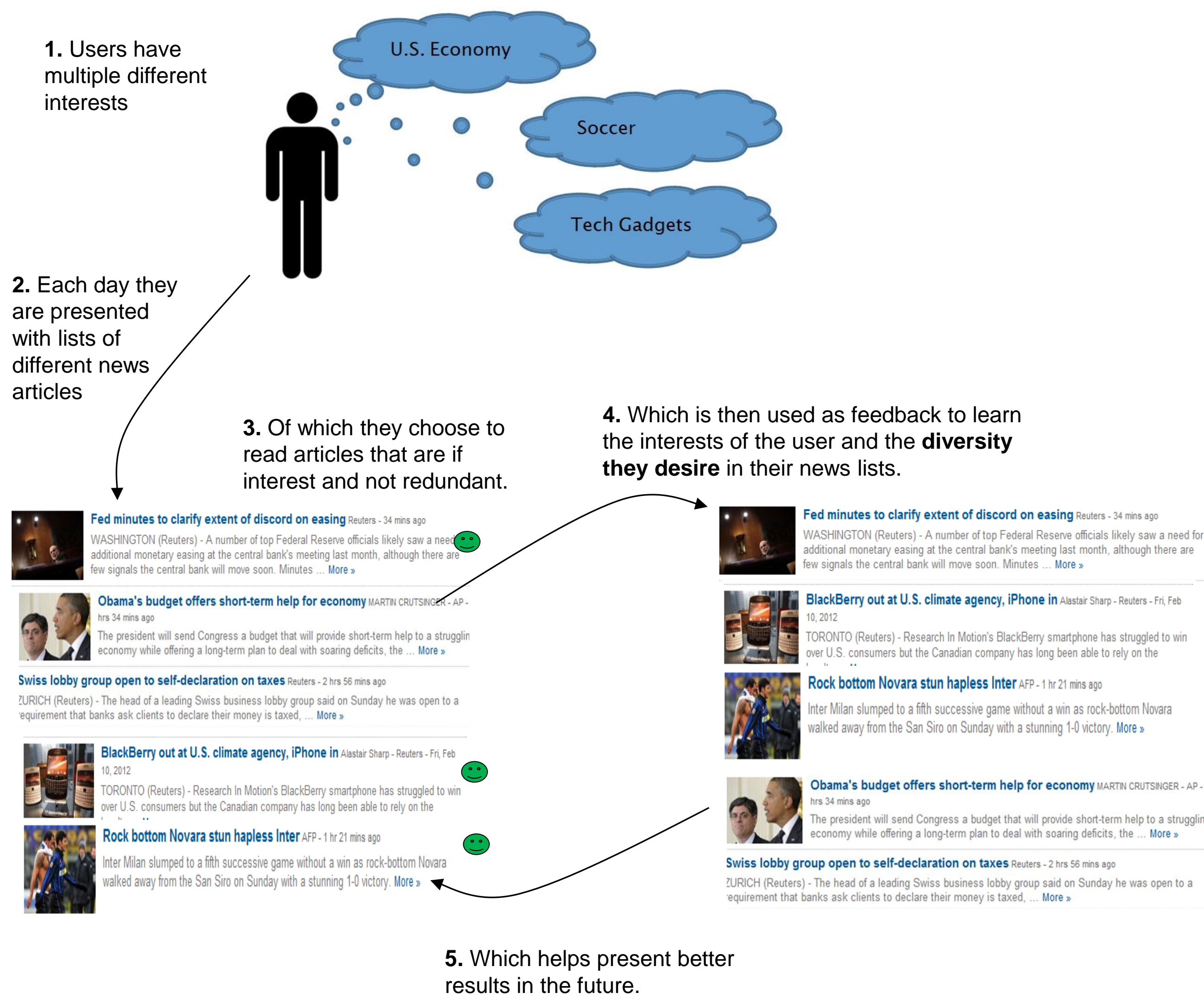
Thorsten Joachims

Cornell University  
tj@cs.cornell.edu

## Overview

Present simple, efficient **online learning** algorithms for learning both relevance and **diversity** in rankings, which are shown to be theoretically and empirically robust.

## Example: News Recommendation

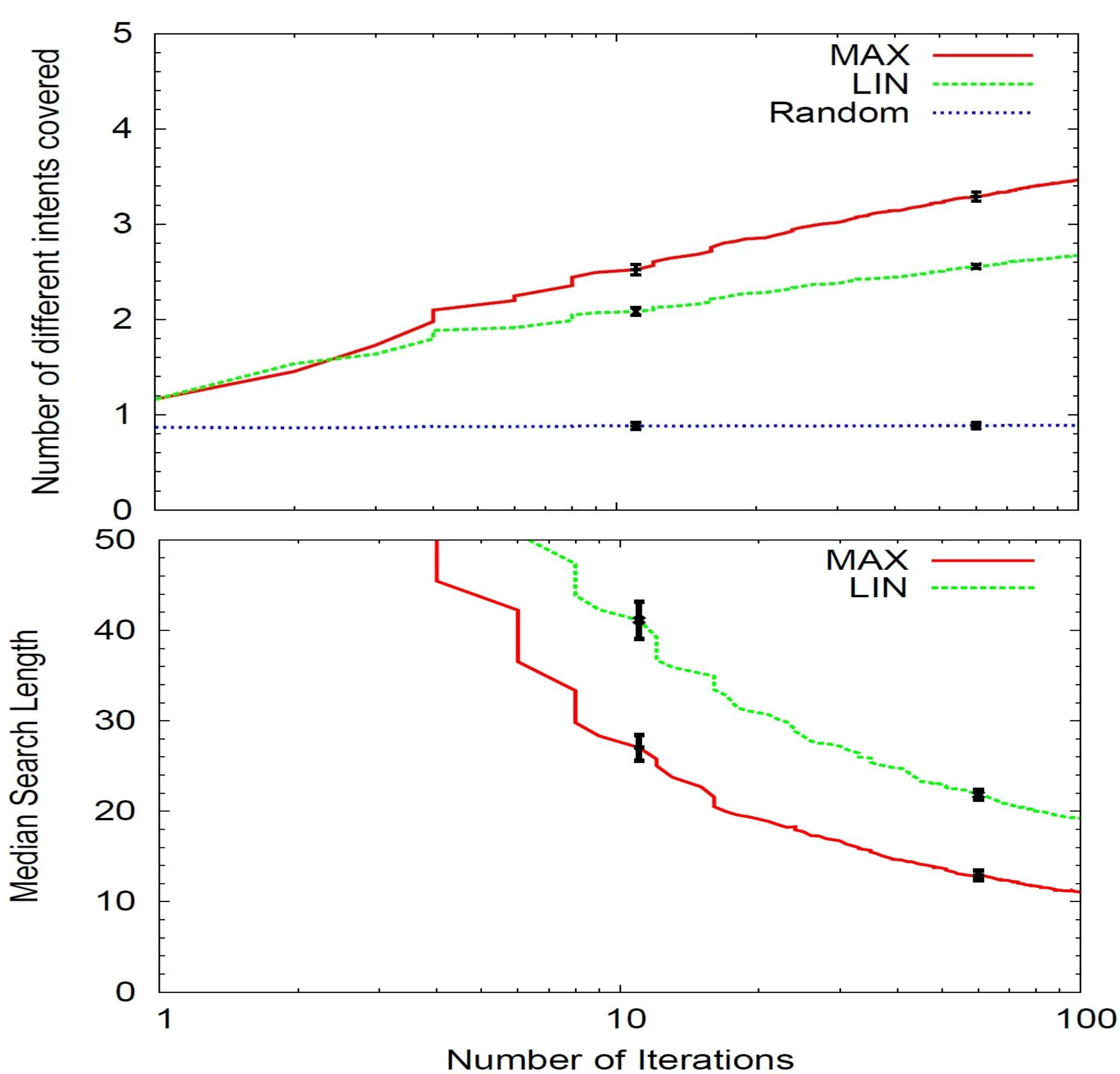


## Experiments:

- Used 2 news datasets: RCV1 and 20NG
- Simulated diverse users with 5 interests.
- TFIDF values used for document features,

## Findings:

- Highly robust to noisy user feedback and quality of feedback.
- Able to learn desired amount of diversity.



**Fig1:** Change in the number of intents covered (above) and search length (below) over time.

## Motivation:

- Most research on focused on **extrinsic** diversity.
- Intrinsic Diversity:** Diversity in the aspects of a single information need.
- No previous method for learning required amount of diversity from user feedback/click data.

## Learning Diversity:

- Capture diversity via **non-linear combination** of document feature vectors:

$$\phi^j(\mathbf{x}, \mathbf{y}) = F(\{\phi^j(d_{i_1}), \phi^j(d_{i_2}), \dots, \phi^j(d_{i_k})\})$$

- Choice of  $F$  determines how much redundancy in predicted rankings. Couple of examples:

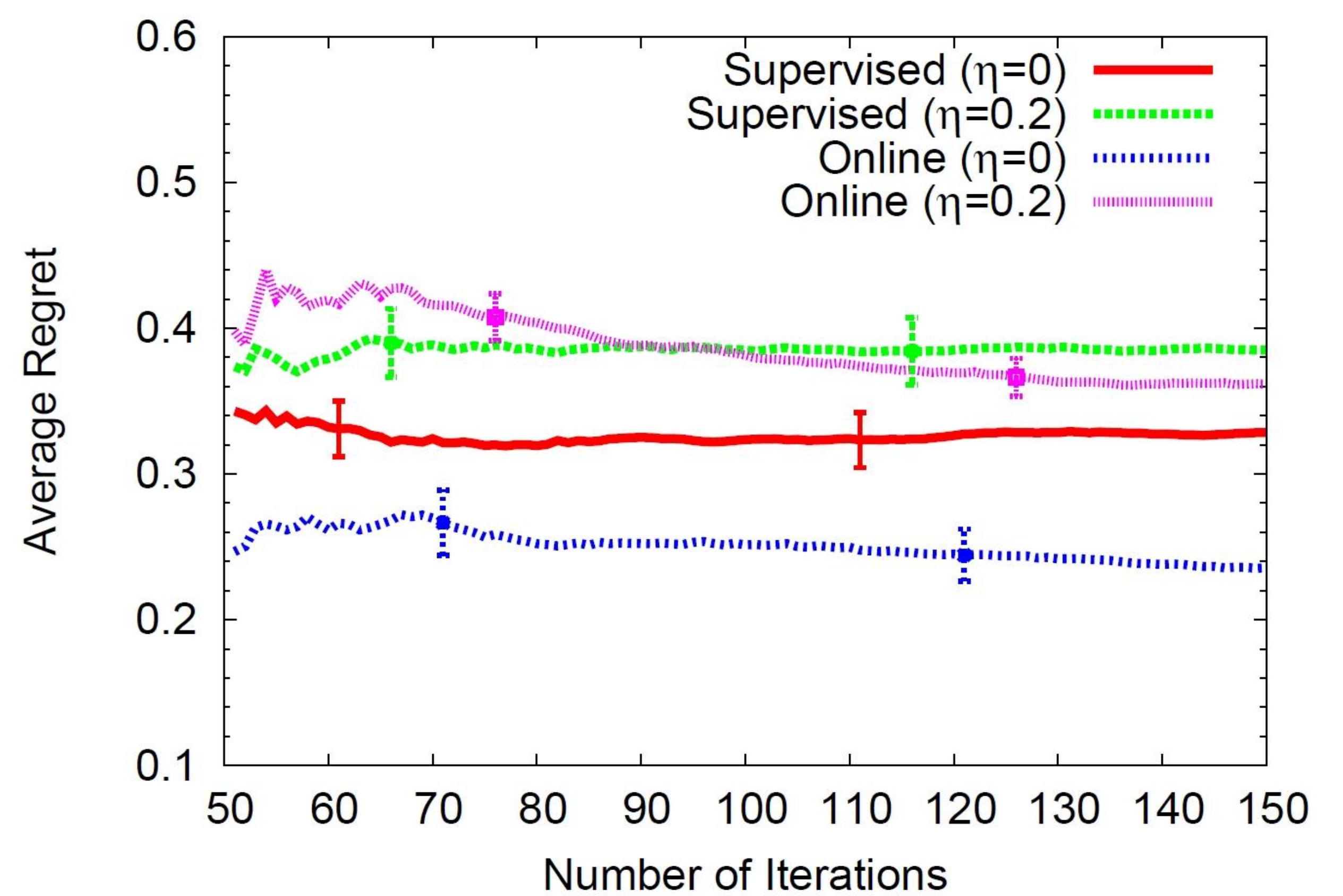
| Name | $F(A)$                    |
|------|---------------------------|
| LIN  | $F(A) = \sum_{a \in A} a$ |
| MAX  | $F(A) = \max_{a \in A} a$ |

## Algorithm:

- Start with  $\mathbf{w} = \mathbf{0}$
- Present ranking as per current  $\mathbf{w}$
- Observe user feedback.
- Perceptron Update:  
 $\mathbf{w} += \text{Feedback FeatVec} - \text{Presented FeatVec}$
- Repeat from step 2 for next user session

- Simple and efficient
- Theoretically guaranteed to converge to optimal
- Ranking in step 2 can be easily computed via simple **greedy** algorithm for any **submodular**  $F$ .

- Outperforms supervised learning within few iterations despite not receiving true labels.



**Fig2:** Comparison with supervised learning.

## Future Directions:

- User study of model in recommendation system.
- Extending to extrinsic diversity.