Information Filtering for arXiv.org:

Bandits, Exploration vs. Exploitation, and the Cold Start Problem

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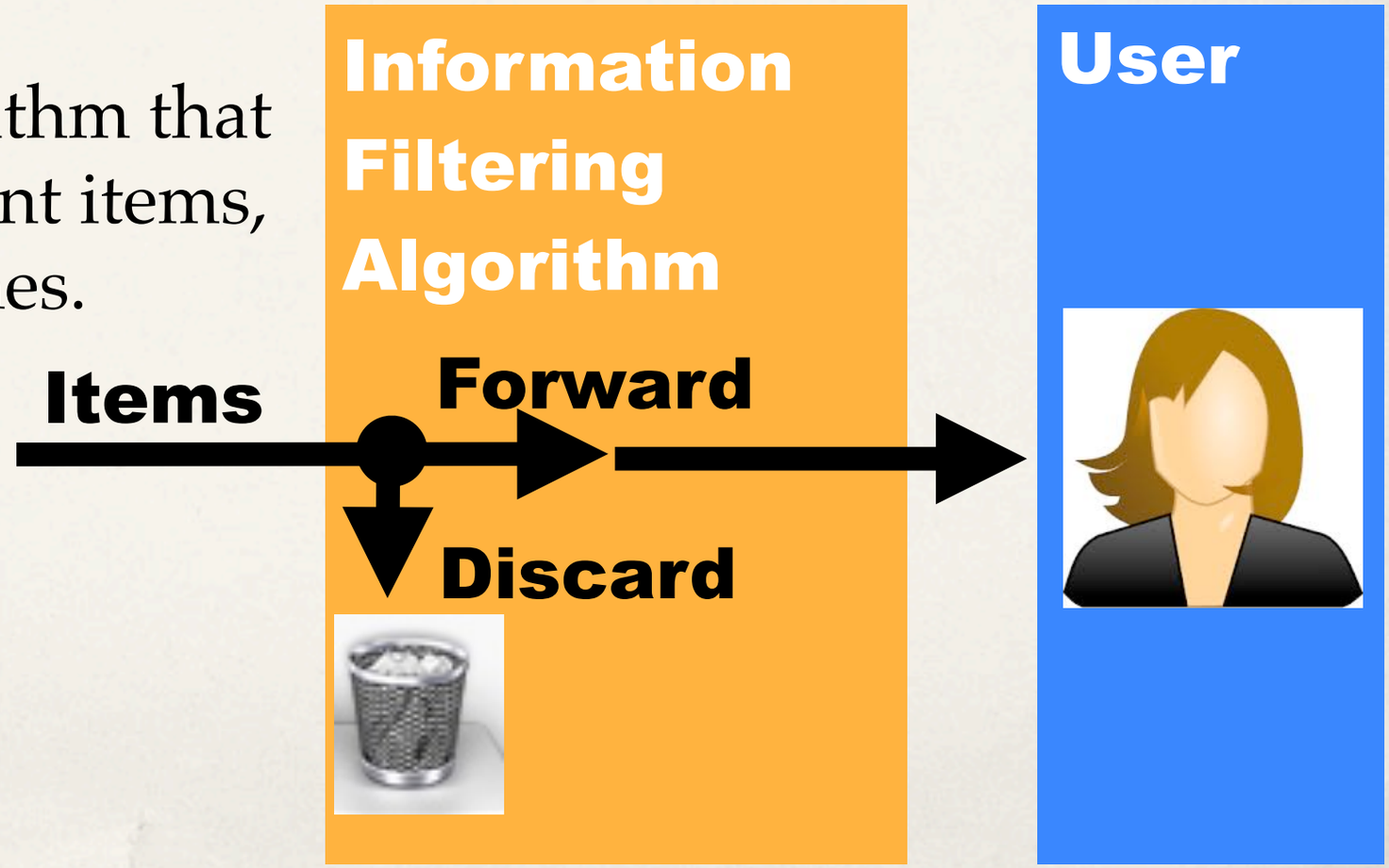
We are interested in

information filtering

- We face a sequence of time-sensitive items (emails, blog posts, news articles).
- A human is interested in some of these items.
- But, the stream is too voluminous for her to look at all of them.
- We wish to design an algorithm that forwards most of the relevant items, and few of the irrelevant ones.



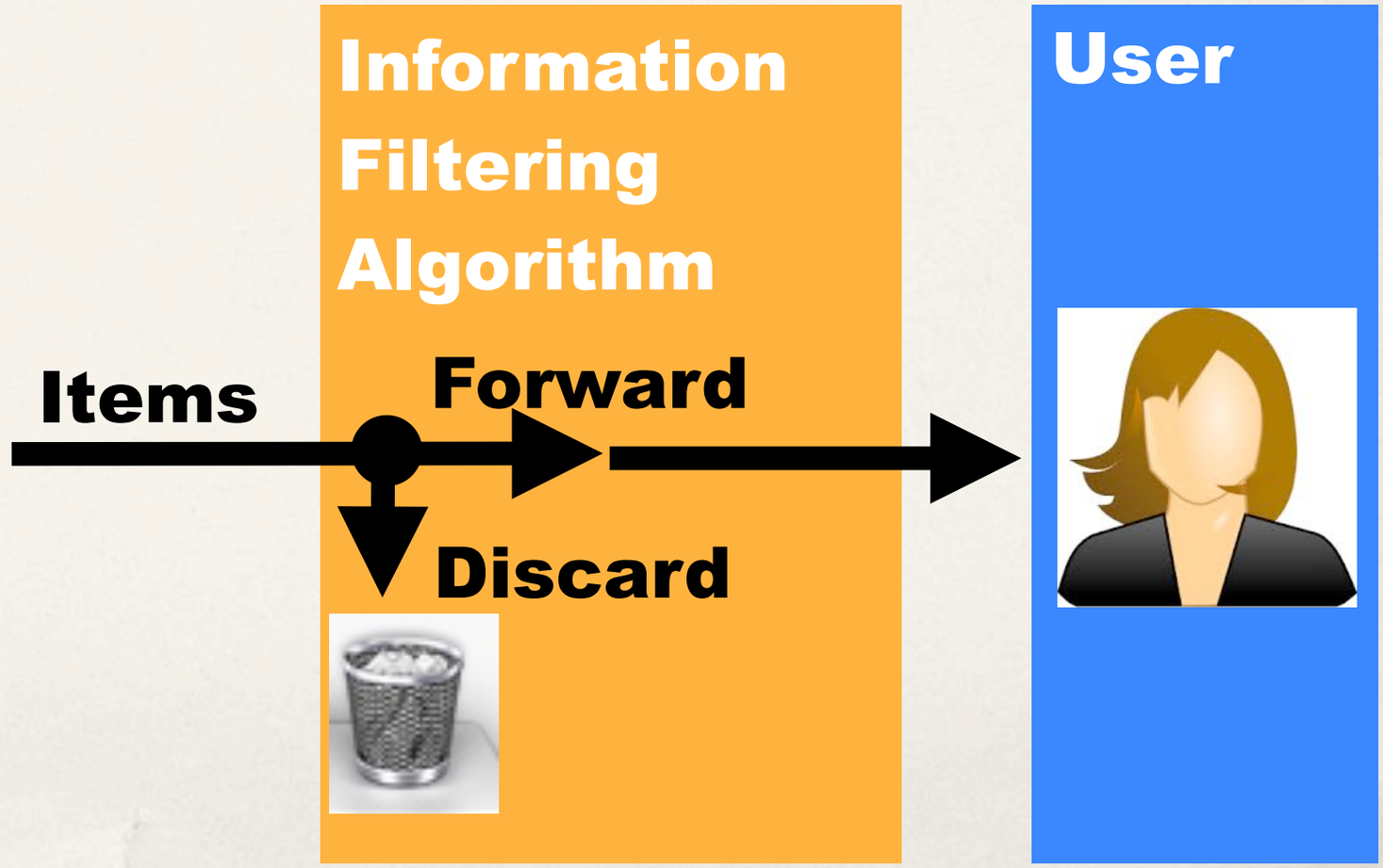
We are interested in

information filtering

- If we had lots of historical data, we could train a machine learning classifier to predict which items would be relevant to this user.

- But what if we are doing information filtering for a new user, i.e., from a **cold start**?

- How can we quickly learn user preferences, without forwarding too many irrelevant items?



We are interested in

exploration vs. exploitation

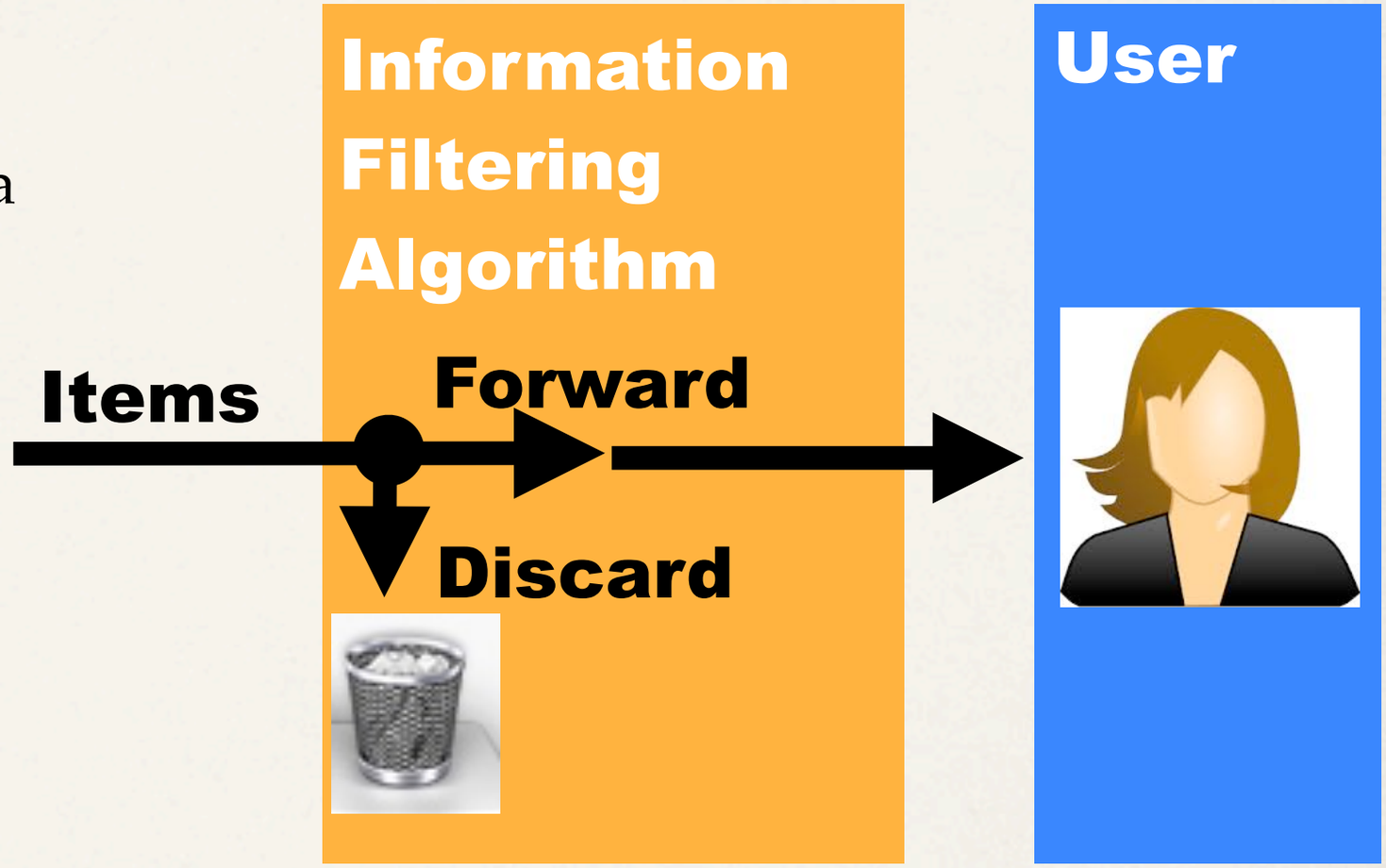
in information filtering

- What if we are filtering for a new user, or filtering items of a type we haven't seen before?

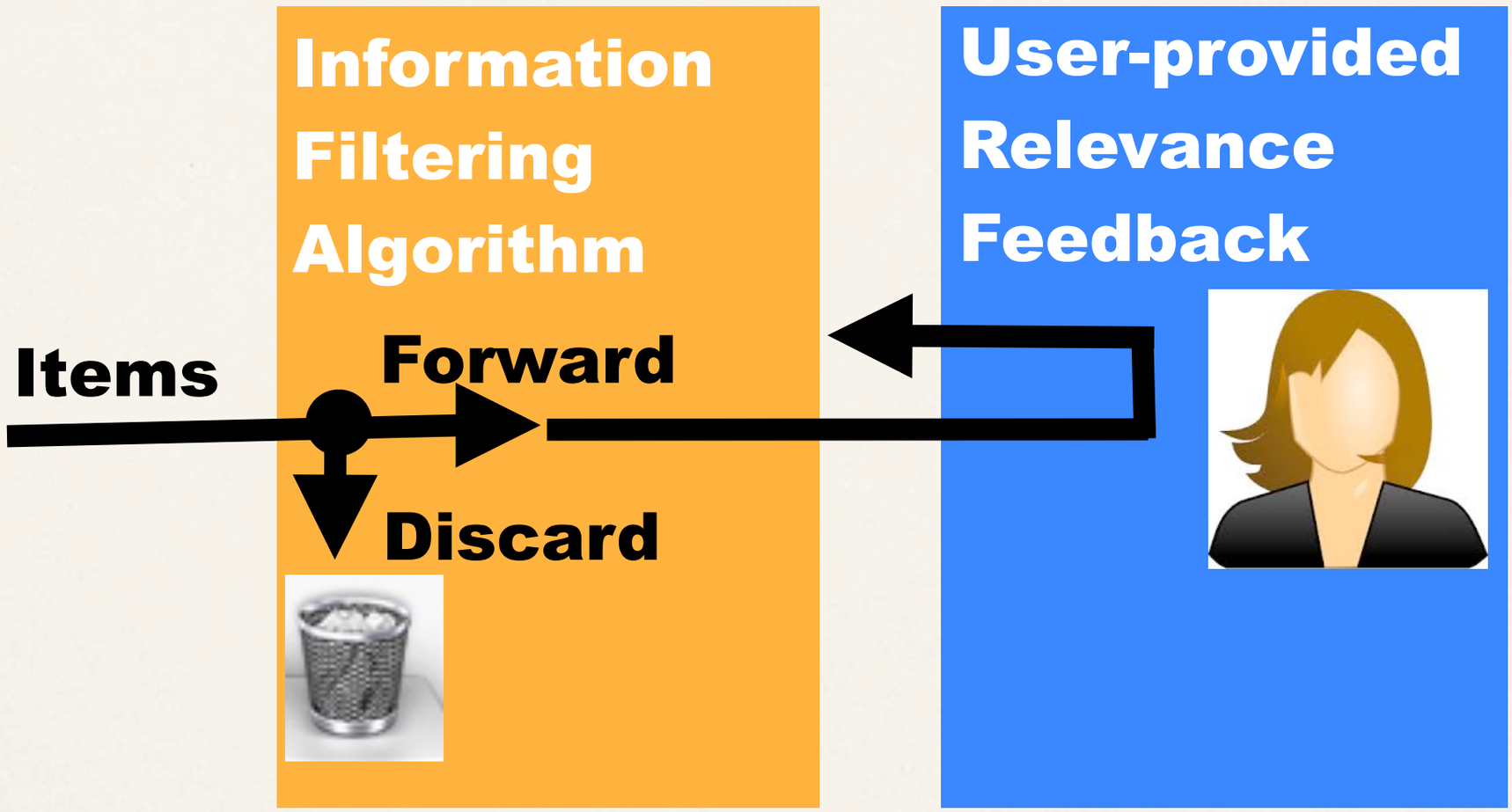
- We may want to **EXPLORE**, i.e., forward a few items of unknown relevance, to allow learning.

- But, we may want to **EXPLOIT** what little training data we have, which may suggest these items type is irrelevant.

- What should we do?

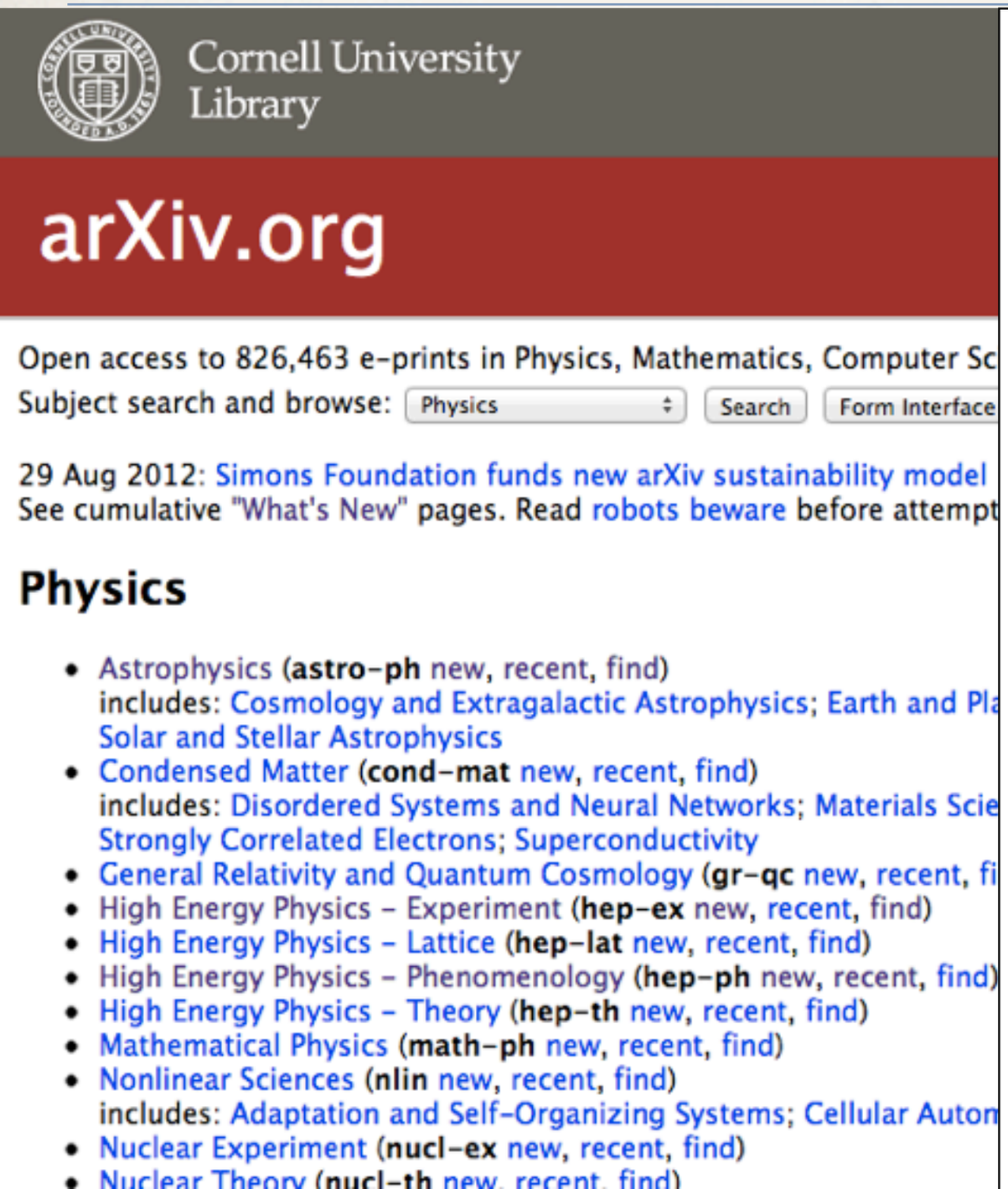


We develop an information filtering algorithm that trades exploration vs. exploitation



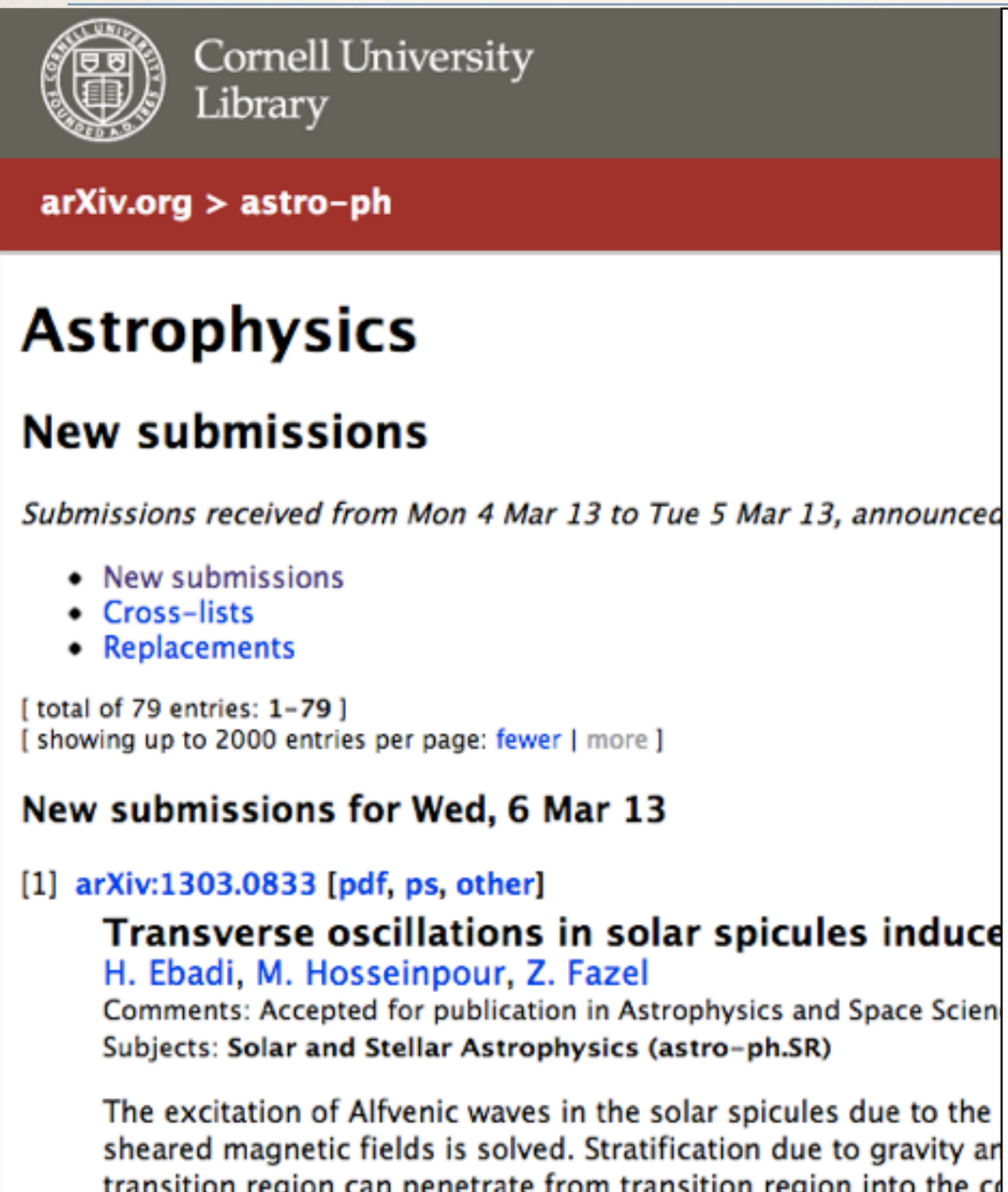
- We use **dynamic programming** and a **Bayesian analysis** to provide an algorithm that is **average-case optimal** for a particular version of the information filtering problem.

We are motivated by an information filtering system we are building for arxiv.org



- arXiv.org is an electronic repository of scientific papers hosted by Cornell.
- Papers are in physics, math, CS, statistics, finance, and biology.
- arXiv currently has ≈800,000 articles, and 16 million unique users accessing the site each month.

Our goal is to improve daily & weekly new-article feeds



- Many physicists visit the arXiv every day to browse the list of new papers, to stay aware of the latest research.
- There are lots of new papers: e.g., 15 new papers / day in arxiv category astro.GA, "Astrophysics of Galaxies."
- Problem 1: Browsing this many papers is a lot of work for researchers.
- Problem 2: Researchers still miss important developments.

Literature Review

- Exploration vs. exploitation has been studied extensively in the multi-armed bandit problem:
  - Bayesian treatments: [Gittins & Jones, 1974; Whittle 1980] ...
  - non-Bayesian treatments: [Auer, Cesa-Bianchi, Freund, Schapire, 1995; Auer, Cesa-Bianchi & Fischer, 2002] ...
- Exploration vs. exploitation has been studied in information retrieval: [Zhang, Xu & Callan 2003; Agarwal, Chen & Elango 2009; Yue, Broder, Kleinberg & Joachims 2009; Hofmann, Whitestone & Rijke 2012]

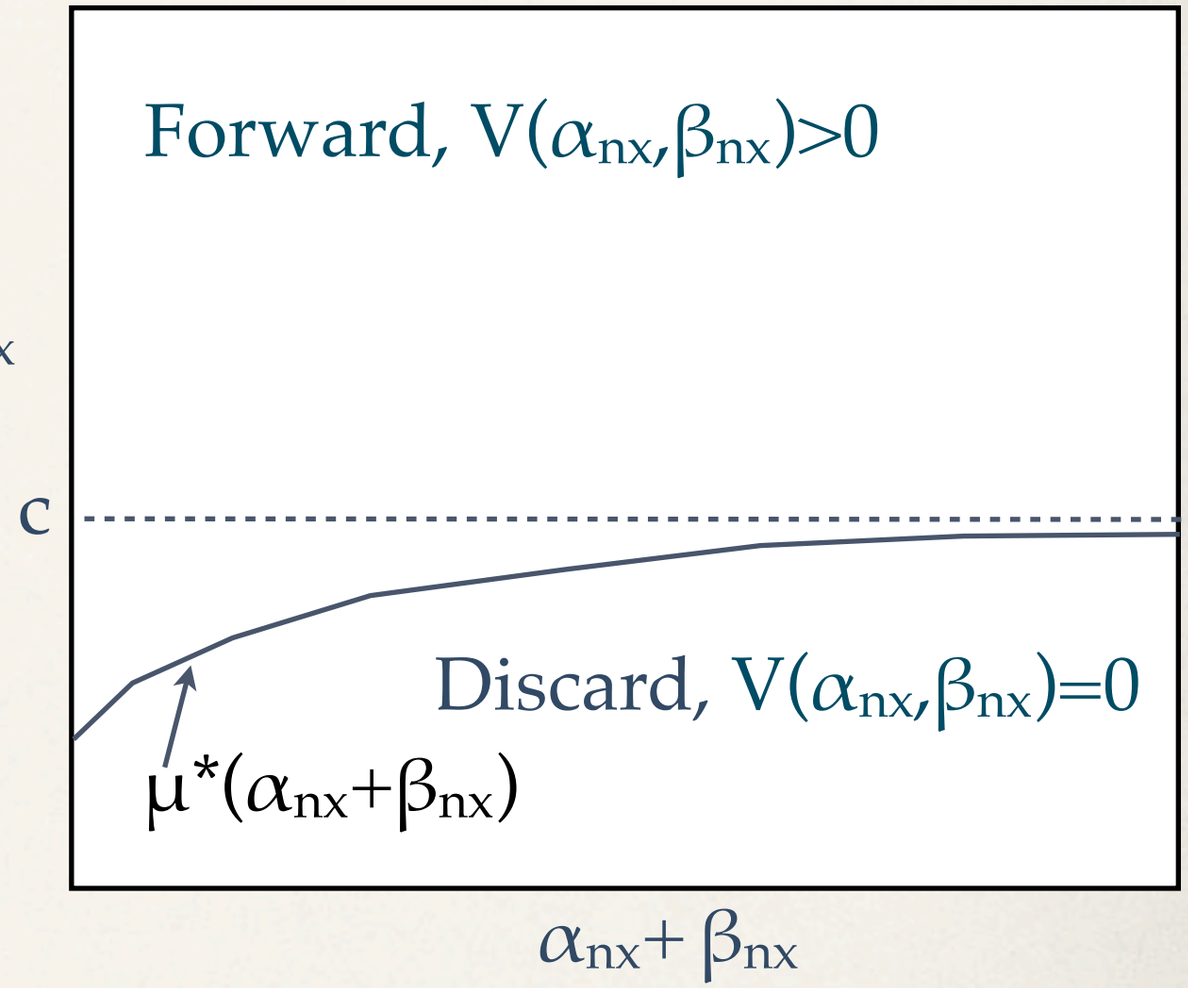
I'll use a simple model to explain the main idea.

- Items are pre-categorized into one of k categories, and the category is the only information about them we use.
- Items within category x are relevant with probability θ_x.
- θ_x is unknown, but we have a Beta(α_{0x}, β_{0x}) prior on it, learned from historical data.
- We only observe relevance of forwarded items. [So **the only way to learn is to forward**.]
- For each forwarded item, we get a reward of 1-c if it is relevant, and pay a penalty of -c if it is irrelevant.
- The user spends a random geometrically-distributed amount of time using our system.
- We wish to maximize expected total reward over the user's time using our system.

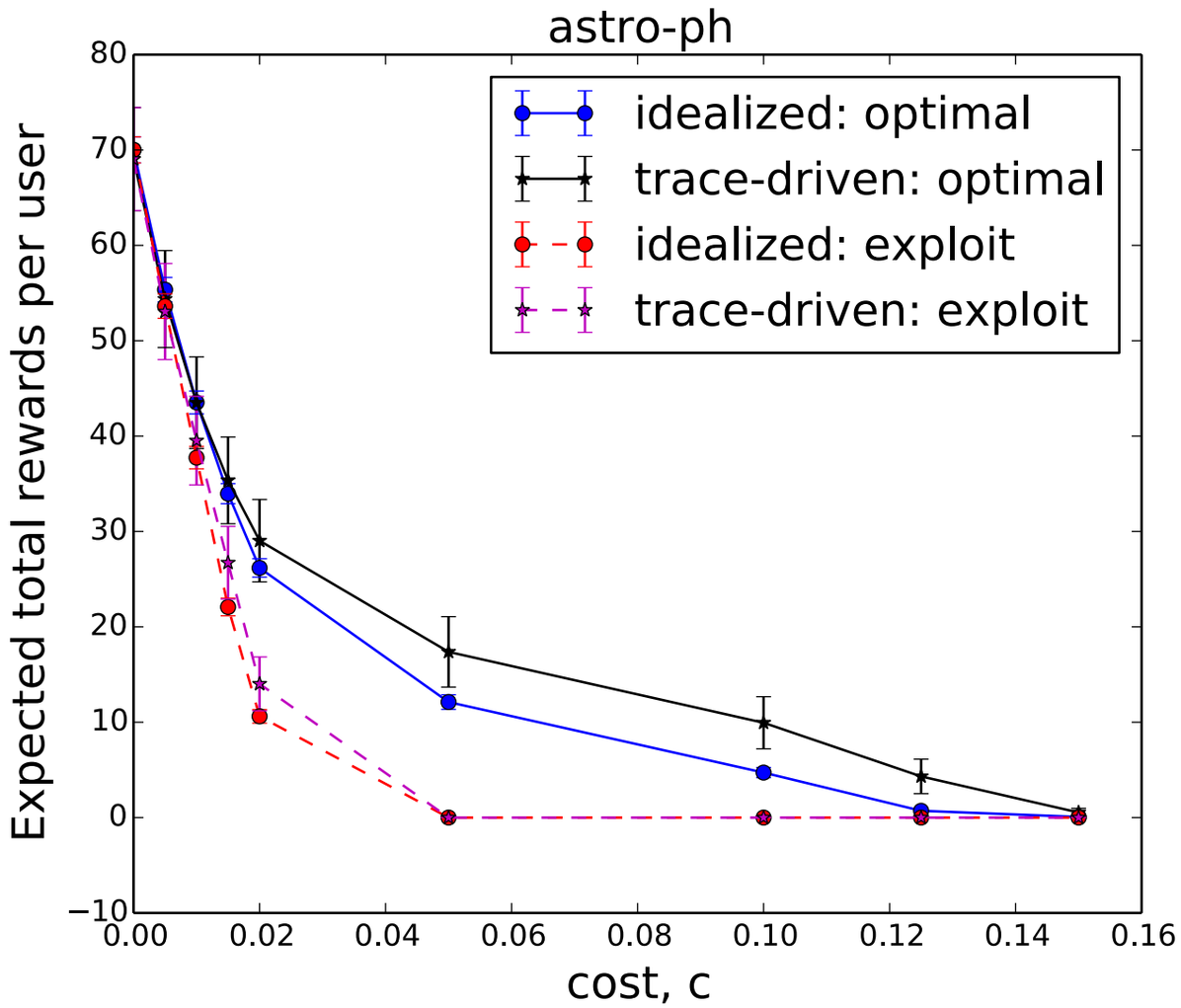
The optimal algorithm looks like this, and can be computed using stochastic dynamic programming.

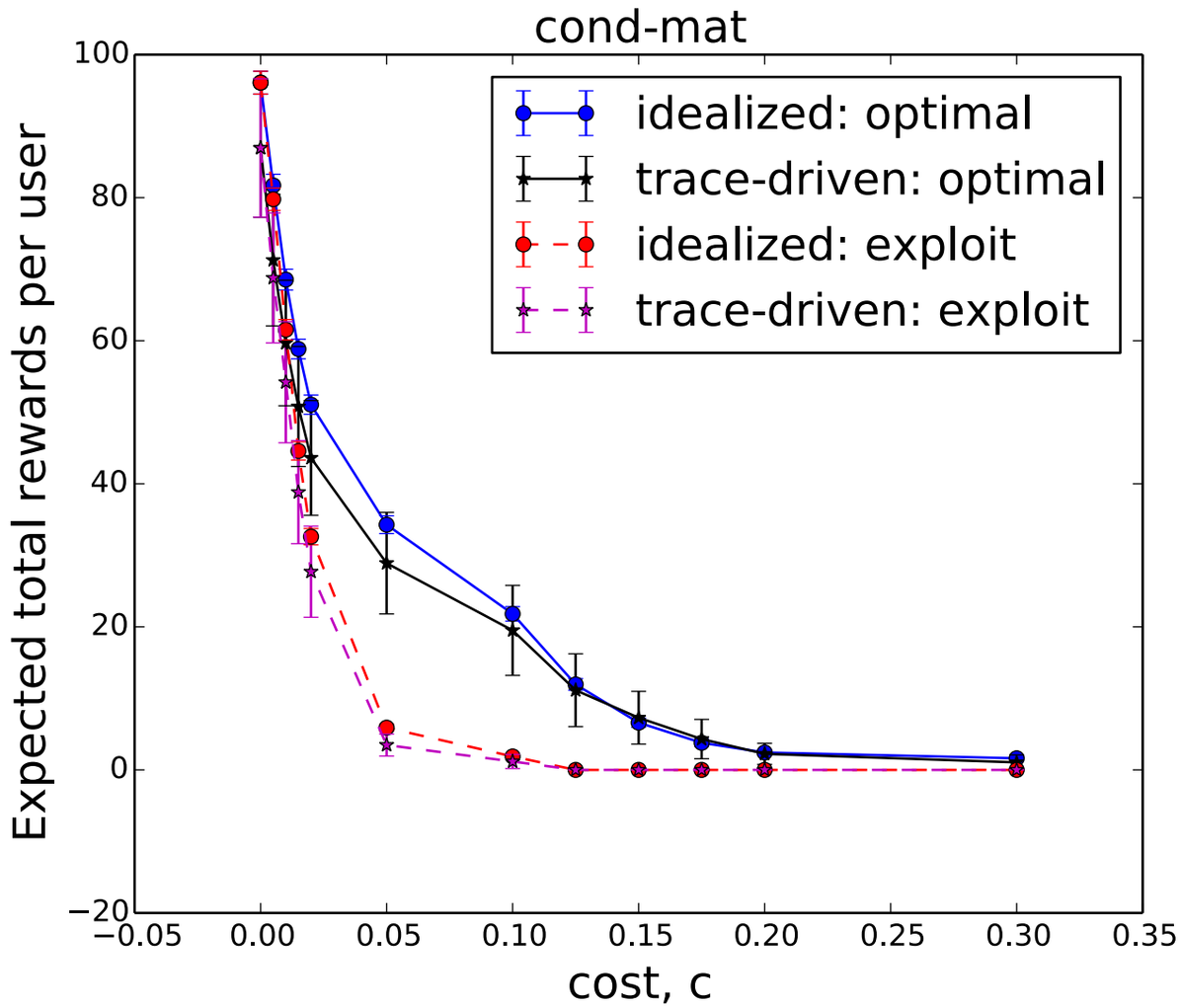
- **Theorem 1**: There exists a function $\mu^*(\cdot)$ such that it is optimal to forward when $\mu_{nx} \geq \mu^*(\alpha_{nx}+\beta_{nx})$ and to discard otherwise.

- **Theorem 2**: $\mu^*(\alpha+\beta)$ has the following properties:
  - it is bounded above by c;
  - it is increasing in $\alpha+\beta$;
  - it goes to c as $\alpha+\beta \to \infty$.



Optimal outperforms myopic in the multi-category problem, in idealized and trace-driven simulations.





We build on this analysis to study more complex models

- **Periodic review**: If the user responds to forwarded items not immediately but only periodically when visiting our website, then our decision is the # of items from each category to show.

- **Rankings**: If the user does not tell us the cost of his time c, and instead examines papers from a ranked list on each visit until his "patience budget" is exhausted, then we can view c as a Lagrange multiplier, and use our analysis to provide a ranking. [Analysis gives an upper bound on the value of the Bayes-optimal procedure.]

- **Linear models**: If items are described by feature vectors rather than categories, and user preference is described by a linear model, then upper bounds on the Bayes-optimal procedure may be derived.

Conclusion

- We presented an information filtering problem arising in the design of a recommender system for arXiv.org
  - We gave details of a simple model, which assumed a known cost, and instantaneous feedback from the user.
  - This model can be extended to periodic review, in which the user provides feedback on items in batches, and to provide rankings over items.
- We are in the process of testing this system, and rolling it out to users of the arXiv.