Information Filtering for arXiv.org:

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

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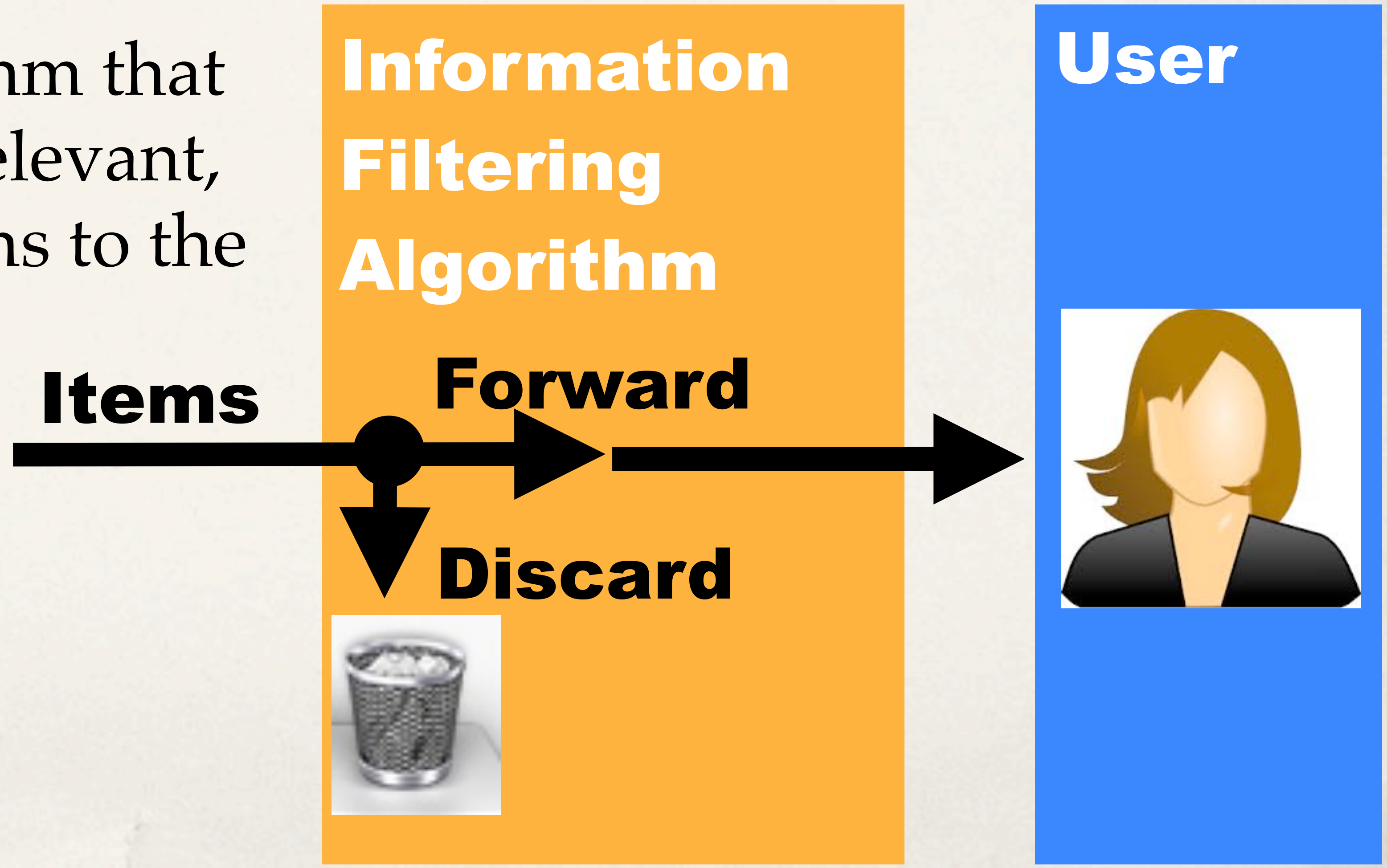
Supported by NSF IIS-1247696

Mostly OM 2014, Tsinghua University, June 14, 2014

We are interested in

information filtering

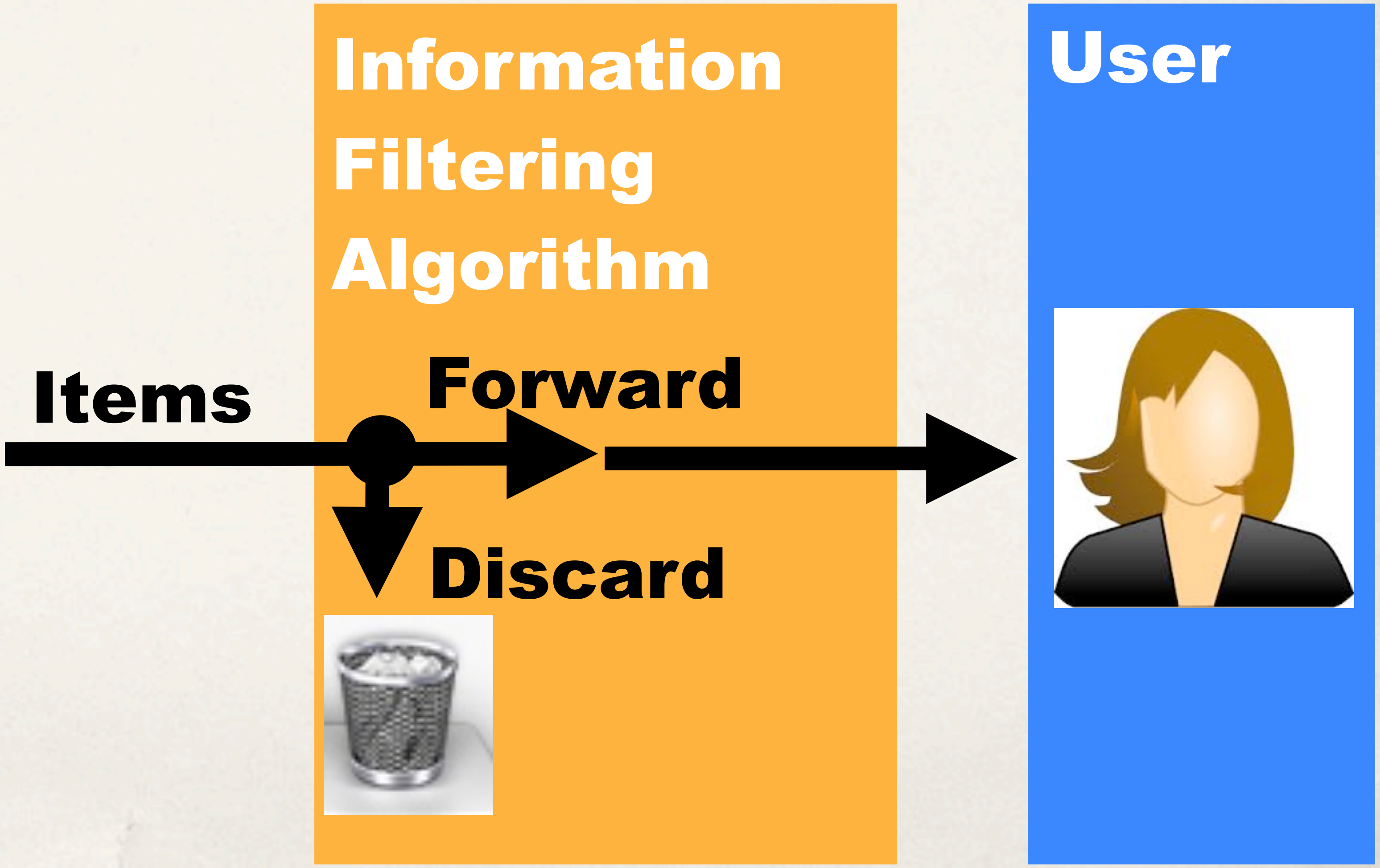
- We face a sequence of time-sensitive items (emails, blog posts, news articles).
- A human is interested in some of these items.
- But, the stream is too voluminous for her to look at all of them.
- **Our goal**: design an algorithm that can learn which items are relevant, and forward only these items to the user.



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?
- **Research Question:** How can we quickly learn user preferences, without forwarding too many irrelevant items?
- This is called the **cold start** problem.

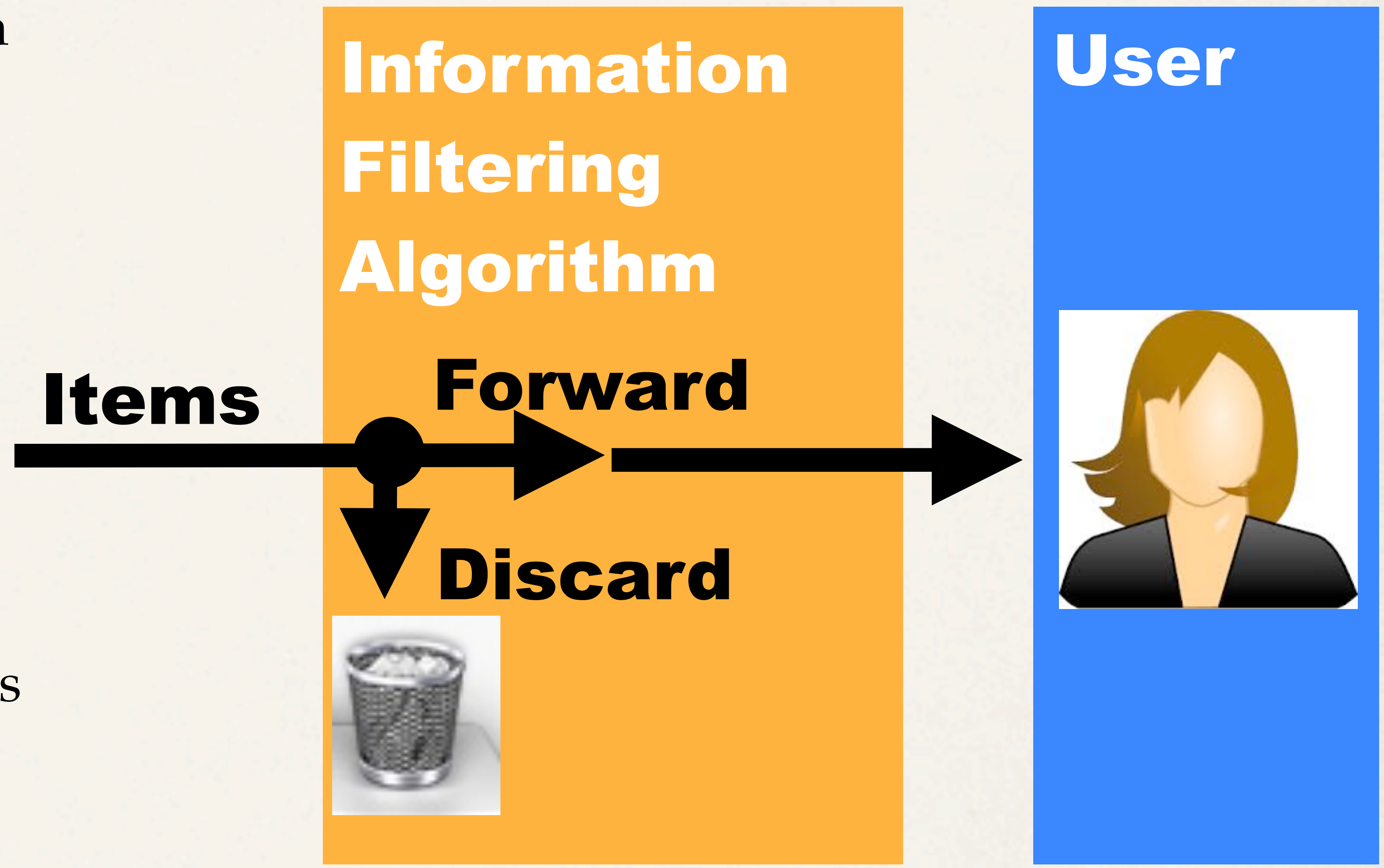


We are interested in

exploration vs. exploitation

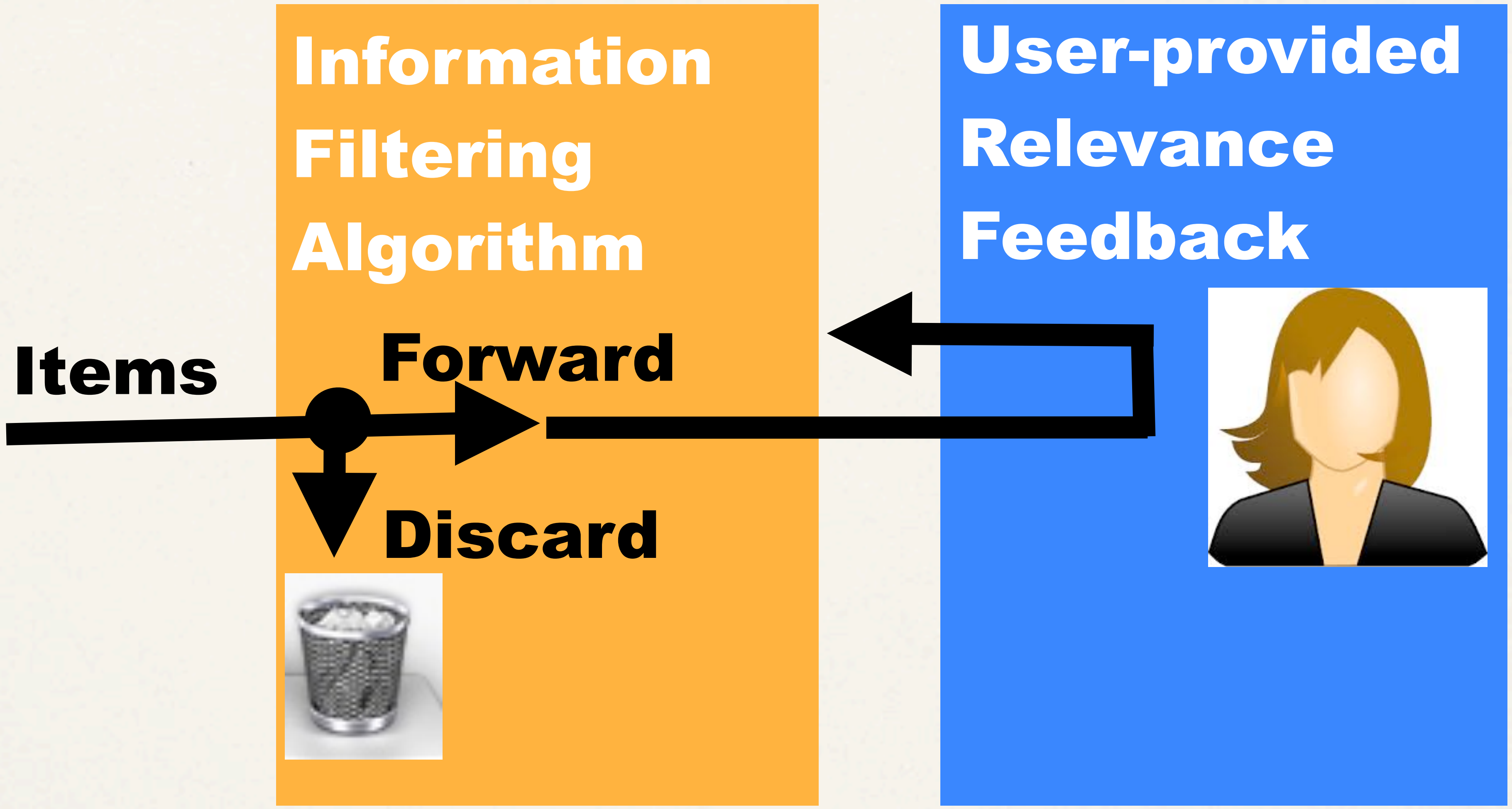
in information filtering

- More generally, suppose there is an item type with little historical data from this user.
- This can arise because:
    - this is a new user;
    - the item mix is changing;
    - the information filtering alg. has not forwarded items of this type.



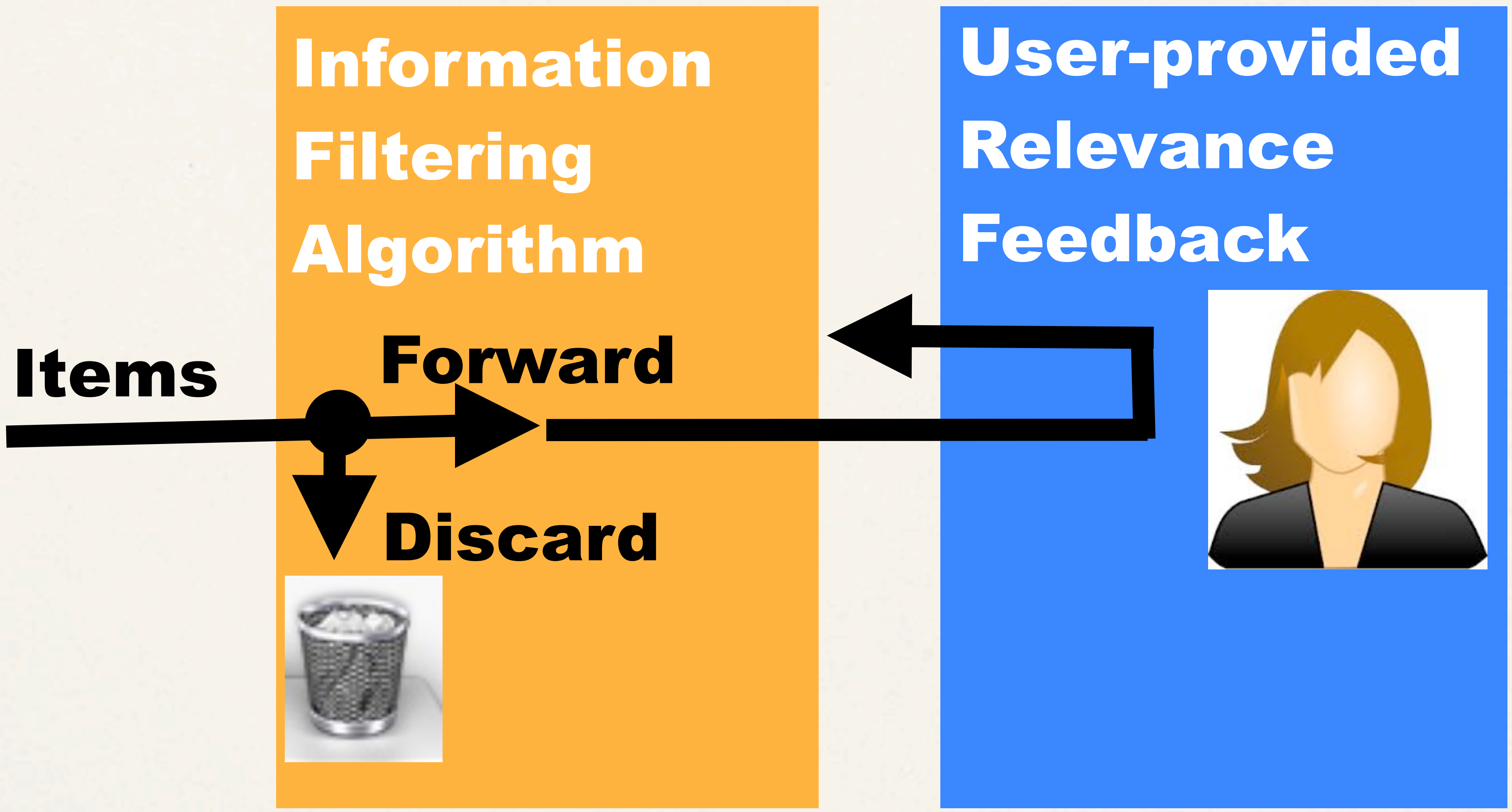
- We may **EXPLORE**, i.e., forward a few items of this type, to better learn this type's relevance.
- But, we may want to **EXPLOIT** what little training data we have, which may suggest this item type is irrelevant.
- What should we do?

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



- We use an **optimal learning** approach, which relies on **Bayesian statistics** and **dynamic programming**.

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

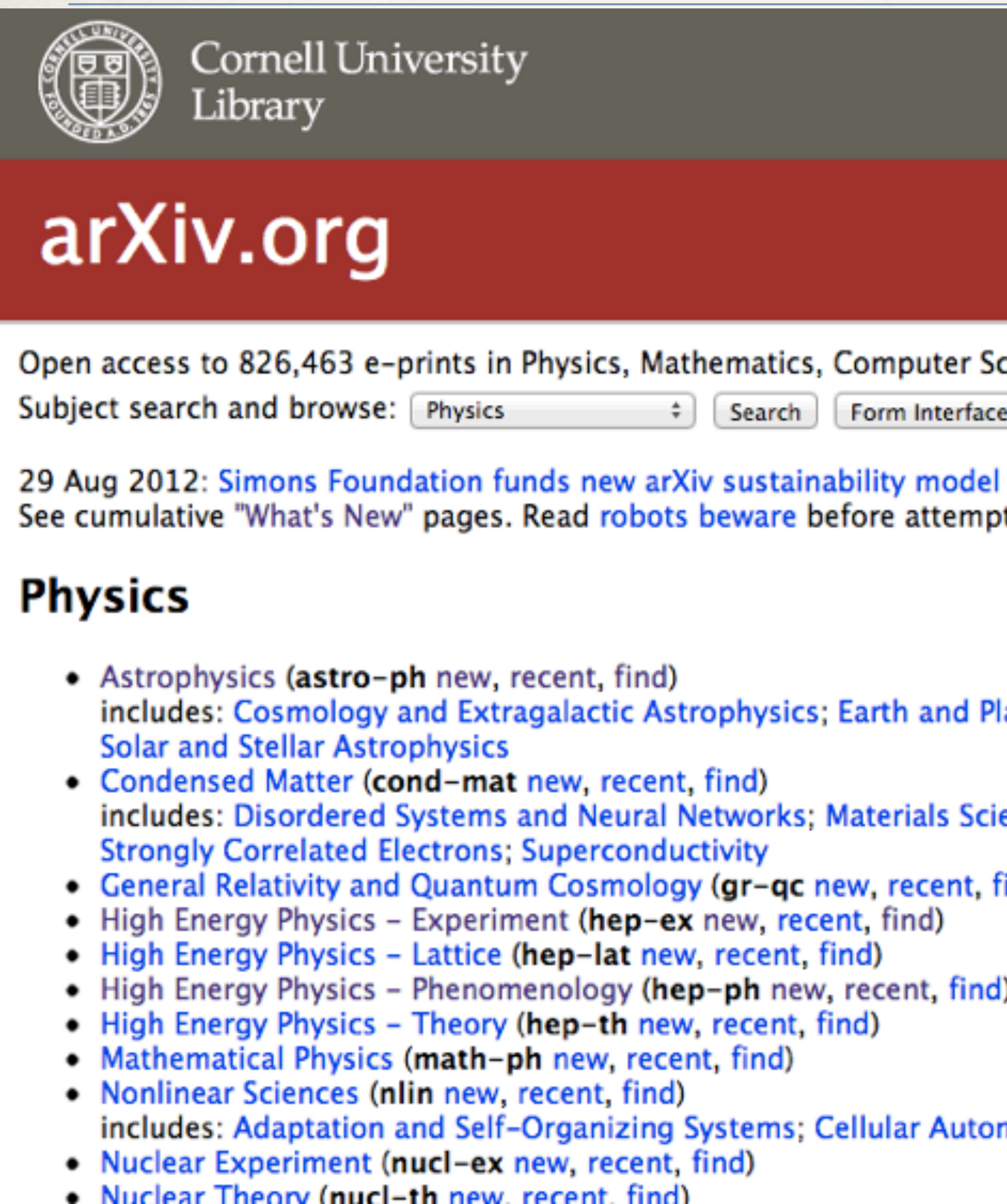


- We focus on the **value of the information** in the user's relevance feedback.

Information filtering & recommender systems are useful

- Recommender systems are closely related to information filtering systems.
- A recommender system is a computer system that makes personalized recommendations to users based on their browsing history.
- Many businesses have, or should have, a recommender system, or an information filtering system.

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

Open access to 826,463 e-prints in Physics, Mathematics, Computer Sc
Subject search and browse: Physics Search Form Interface

29 Aug 2012: Simons Foundation funds new arXiv sustainability model
See cumulative "What's New" pages. Read robots beware before attempt

Physics

- Astrophysics (**astro-ph** new, recent, find)
  includes: Cosmology and Extragalactic Astrophysics; Earth and Pla
  Solar and Stellar Astrophysics
- Condensed Matter (**cond-mat** new, recent, find)
  includes: Disordered Systems and Neural Networks; Materials Scie
  Strongly Correlated Electrons; Superconductivity
- General Relativity and Quantum Cosmology (**gr-qc** new, recent, fi
- High Energy Physics - Experiment (**hep-ex** new, recent, find)
- High Energy Physics - Lattice (**hep-lat** new, recent, find)
- High Energy Physics - Phenomenology (**hep-ph** new, recent, find)
- High Energy Physics - Theory (**hep-th** new, recent, find)
- Mathematical Physics (**math-ph** new, recent, find)
- Nonlinear Sciences (**nlin** new, recent, find)
  includes: Adaptation and Self-Organizing Systems; Cellular Auton
- Nuclear Experiment (**nucl-ex** new, recent, find)
- Nuclear Theory (**nucl-th** new, recent, find)

- 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.

The arXiv is an important repository of scientific articles

Google Scholar

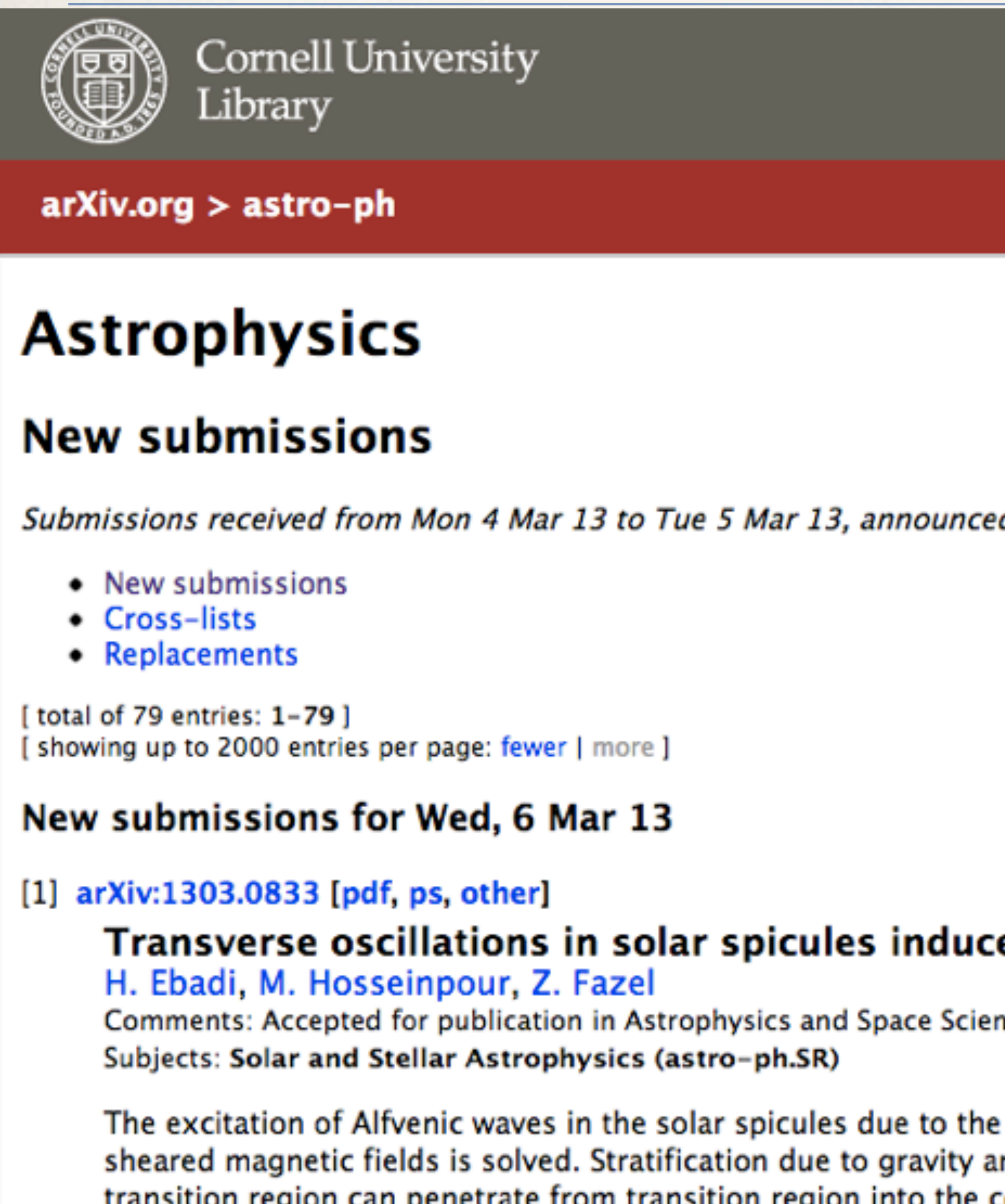
physics

Top 20 publications matching *physics*

	Publication	h5-index	h5-median
1.	arXiv High Energy Physics - Theory (hep-th)	137	180
2.	arXiv High Energy Physics - Phenomenology (hep-ph)	135	182
3.	arXiv Mesoscale and Nanoscale Physics (cond-mat.mes-hall)	132	193
4.	arXiv Quantum Physics (quant-ph)	126	181
5.	Journal of High Energy Physics	124	167
6.	Applied Physics Letters	121	147
7.	Nature Physics	117	160
8.	Reviews of Modern Physics	94	210
9.	Physics Letters B	89	130
10.	The Journal of Chemical Physics	80	112
11.	arXiv High Energy Physics - Experiment (hep-ex)	78	113

- In several research areas in physics, the arXiv's impact factor is higher than that of any journal.

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



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arXiv.org > astro-ph

Astrophysics

New submissions

Submissions received from Mon 4 Mar 13 to Tue 5 Mar 13, announced

- New submissions
- Cross-lists
- Replacements

[total of 79 entries: 1-79]
[showing up to 2000 entries per page: fewer | more]

New submissions for Wed, 6 Mar 13

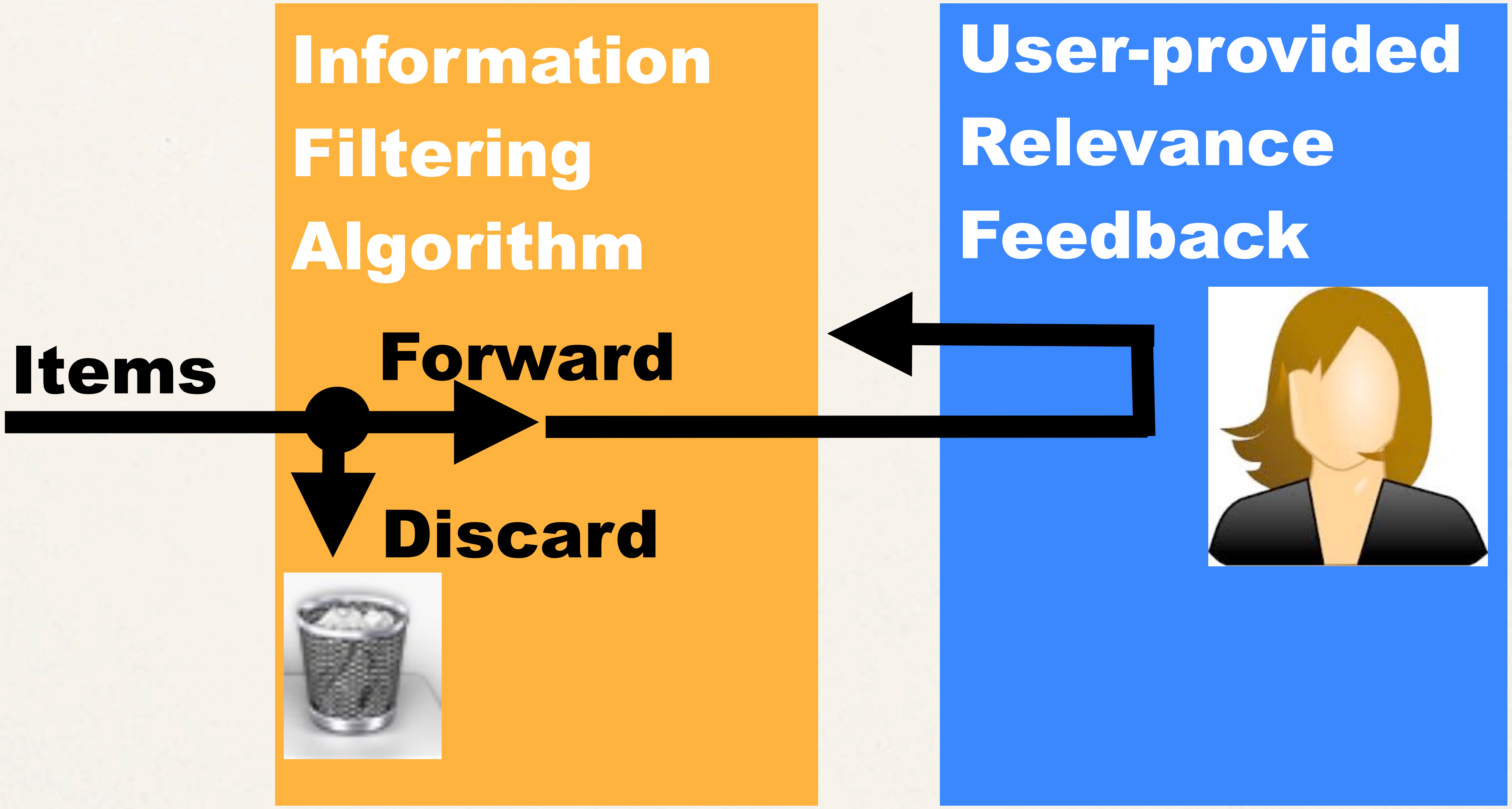
[1] arXiv:1303.0833 [pdf, ps, other]

Transverse oscillations in solar spicules induce
H. Ebadi, M. Hosseinpour, Z. Fazel
Comments: Accepted for publication in Astrophysics and Space Scien
Subjects: **Solar and Stellar Astrophysics (astro-ph.SR)**

The excitation of Alfvenic waves in the solar spicules due to the
sheared magnetic fields is solved. Stratification due to gravity ar
transition region can penetrate from transition region into the co

- 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 (roughly 80 new papers / day in astrophysics.)
- Problem 1: Browsing this many papers is a lot of work for researchers.
- Problem 2: Researchers still miss important developments.

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



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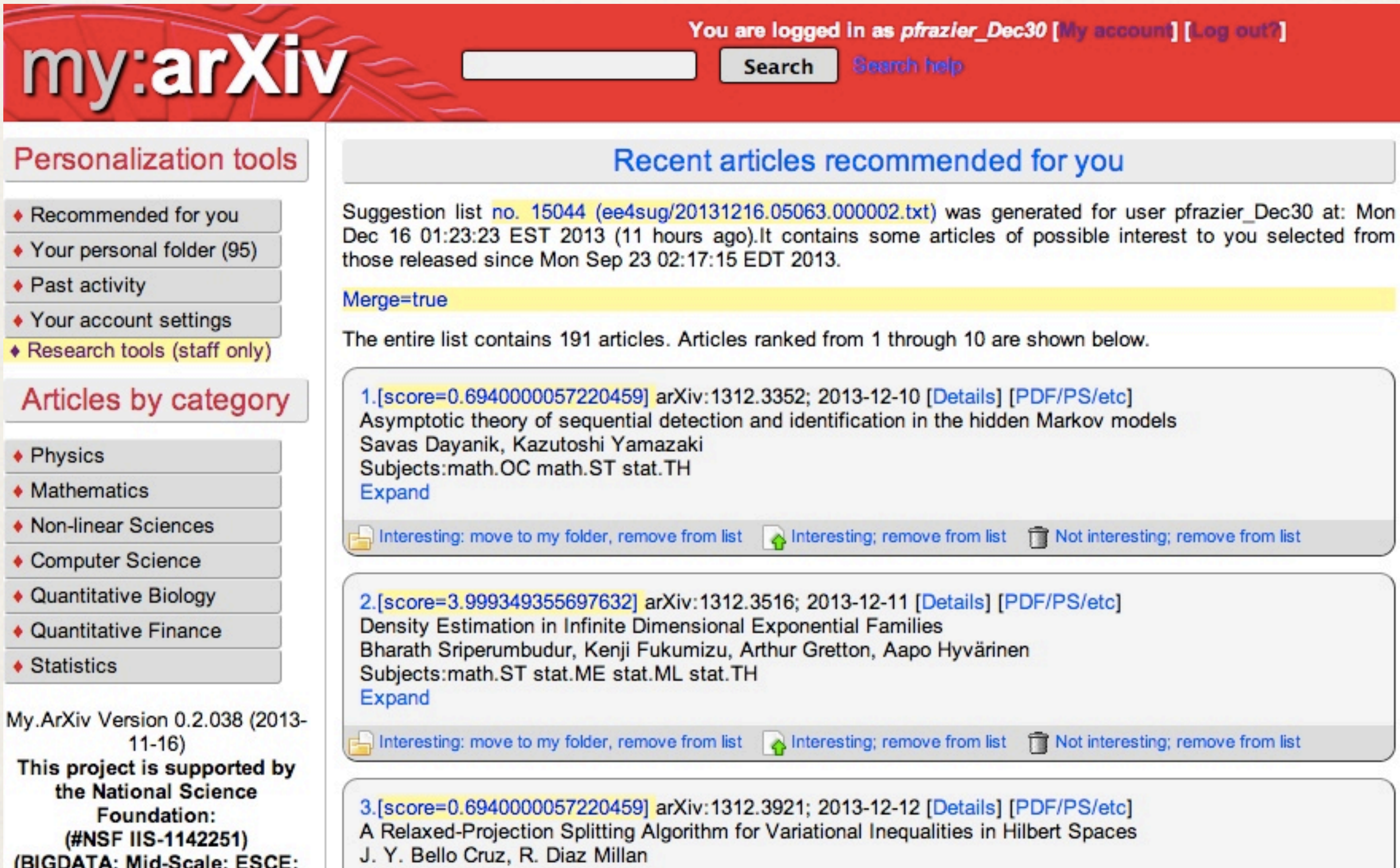

We also want to **understand** exploration vs. exploitation in information retrieval

- In this talk, we focus on the simplest of three models.
- The simplicity of this model makes clear the exploration vs. exploitation tradeoff.
- However, building a system that provides value to users requires extending this simple model in two ways.
- We will discuss these extensions at the end of the talk.

Exploration vs. exploitation has been studied in many research communities

- Multi-armed bandits (operations research and computer science):
  - Bayesian treatments: [Robbins 1952; Gittins and Jones, 1974; Whittle 1980]
  - non-Bayesian treatments: [Lai & Robbins 1985; Auer, Cesa-Bianchi, Freund, Schapire, 1995; Auer, Cesa-Bianchi and Fischer, 2002]
- Reinforcement learning: [Kaelbling et al., 1998, Sutton and Barto, 1998].
- Operations management: [Lariviere and Porteus, 1999; Ding, Puterman and Bisi 2002; Araman and Caldentey 2009; Besbes and Zeevi 2009; den Boer & Zwart 2013]
- Information retrieval: [Zhang, Xu and Callan 2003; Agarwal, Chen and Elango 2009; Yue, Broder, Kleinberg & Joachims 2009; Hofmann, Whitestone & Rijke 2012]

Outline

- Categorizing items
- Mathematical Model
- Extension #1: Periodic Review
- Extension #2: Unknown Costs

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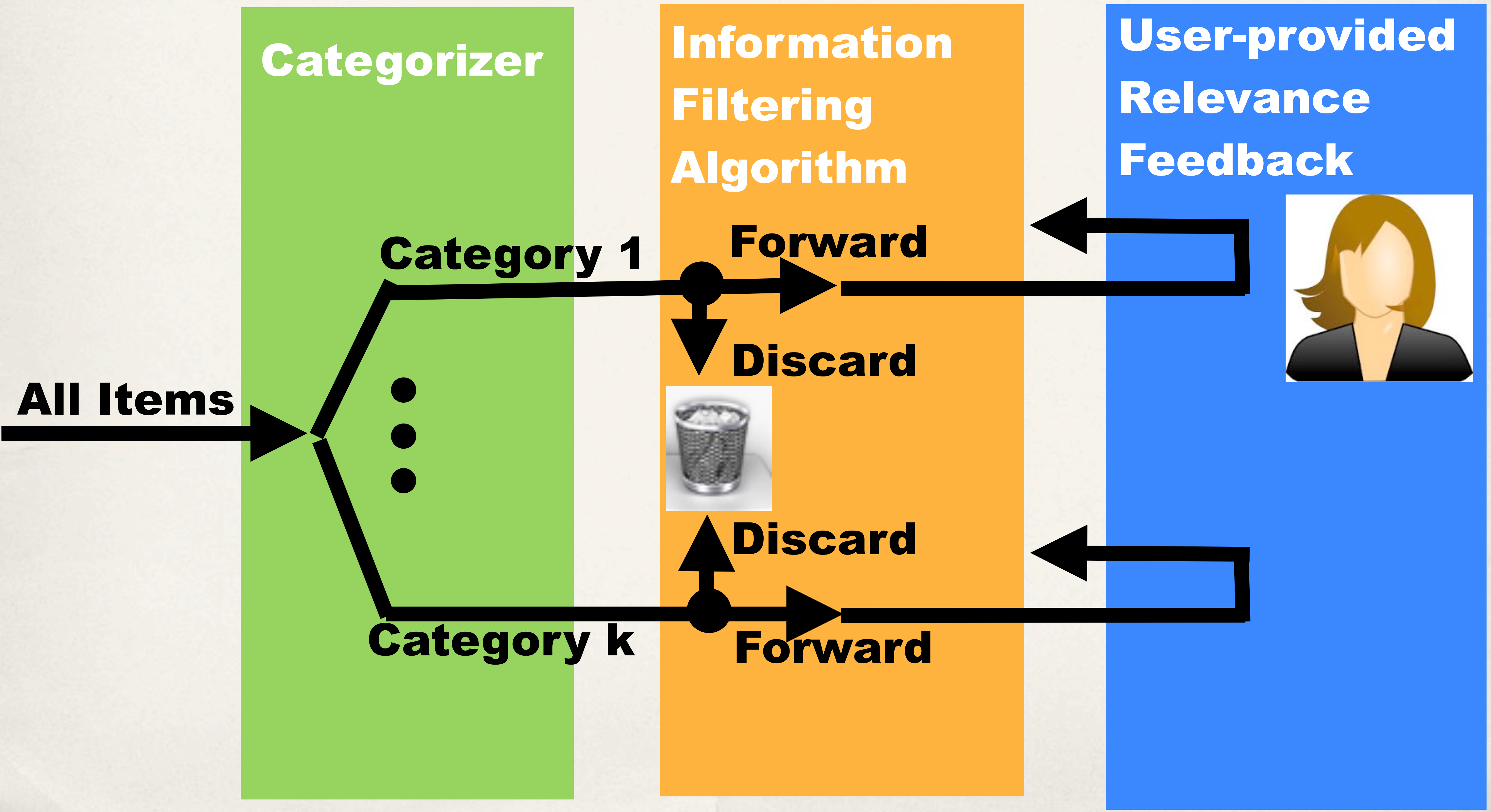
We use a pre-processing step that divides items into categorizes



We use a pre-processing step that divides items into categories

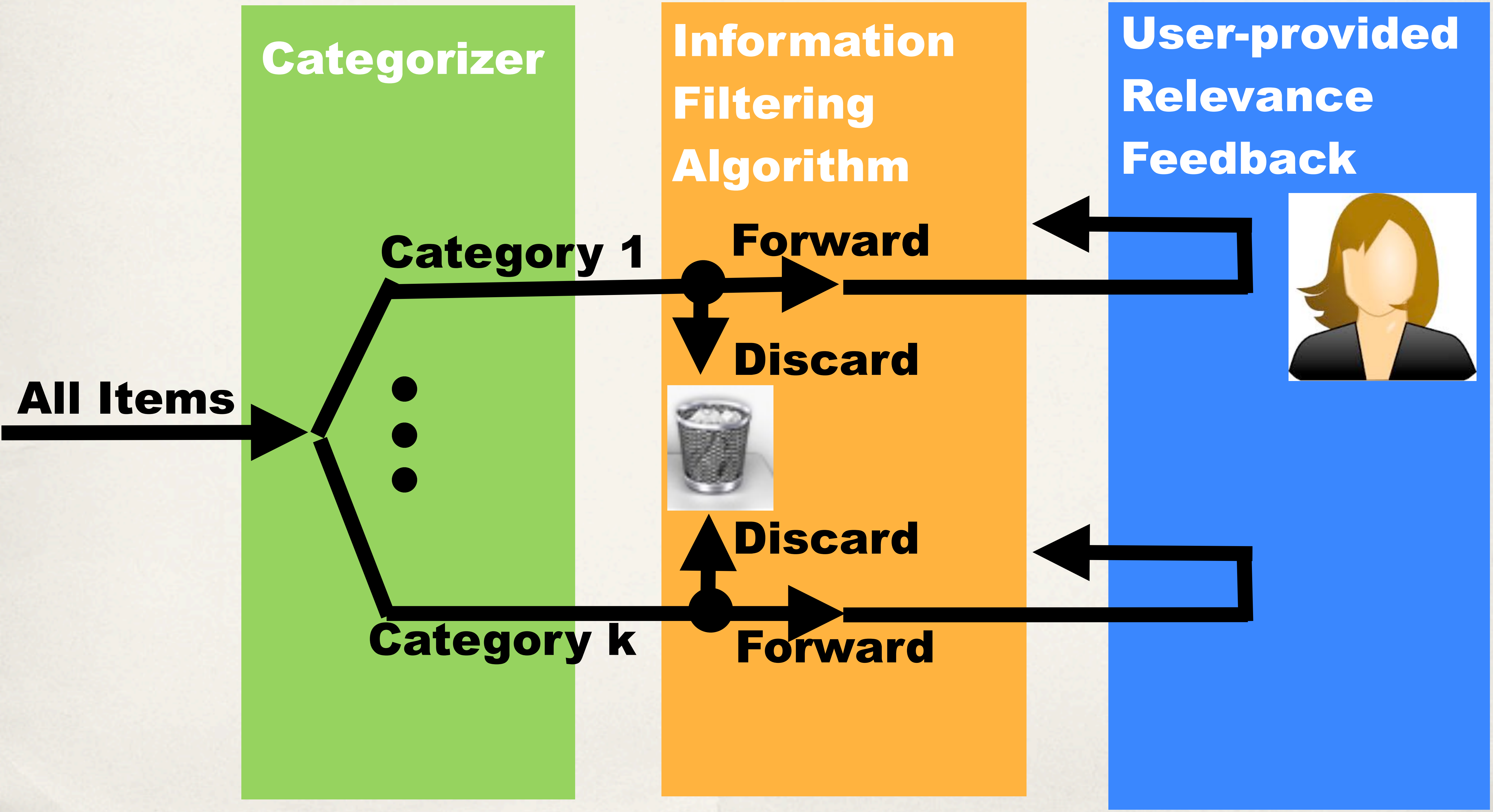
- **Step 1**: We use historical data to create a ratings matrix with older items and users with lots of history.
- **Step 2:** We use a singular value decomposition to represent older items as points in a low-dimensional space. Dimensions correspond roughly to "topics".
- **Step 3:** We use kmeans clustering on the low-dimensional space to cluster older items.
- **Step 4**: We train a multi-class SVM to predict the cluster from item features, e.g., the words in a paper, or the authors.

Other categorization methods are also possible

- Alternative Method 1: Use labels provided by authors: e.g., Artificial Intelligence; Computation and Language; Computational Complexity; Computational Engineering, Finance, and Science; Computational Geometry; Computer Science and Game Theory; Computer Vision and Pattern Recognition; ...

- Alternative Method 2: Compute vector representations of documents from the words in them (e.g., using TF-IDF, or word2vec), and cluster these vectors directly using k-means.

We now take the categorizer as given, and move on to the information filtering algorithm



Outline

- Categorizing items
- Mathematical Model
- Extension #1: Periodic Review
- Extension #2: Unknown Costs
- Lessons

Mathematical Model

- An item from category x is relevant to the user with probability θ_x.
- We begin with a Bayesian prior distribution on θ_x, which is independent across x.

$$\theta_x \sim \mathrm{Beta}(\alpha_{0x}, \beta_{0x})$$

- Items arrive according to a Poisson process with rate λ.
- An item falls into category x with probability p_x. An item's category is observable. Thus, items from category x arrive according to a Poisson process with rate $\lambda_x = \lambda p_x$.
- When each paper arrives, we decide whether to forward or discard. For the n^{th} item from category x, let $U_{nx}=1$ if we forward it, and 0 if not.

Mathematical Model

- When each item arrives, we decide whether to forward or discard. For the n^{th} item from category x, let $U_{nx}=1$ if we forward it, and 0 if not.

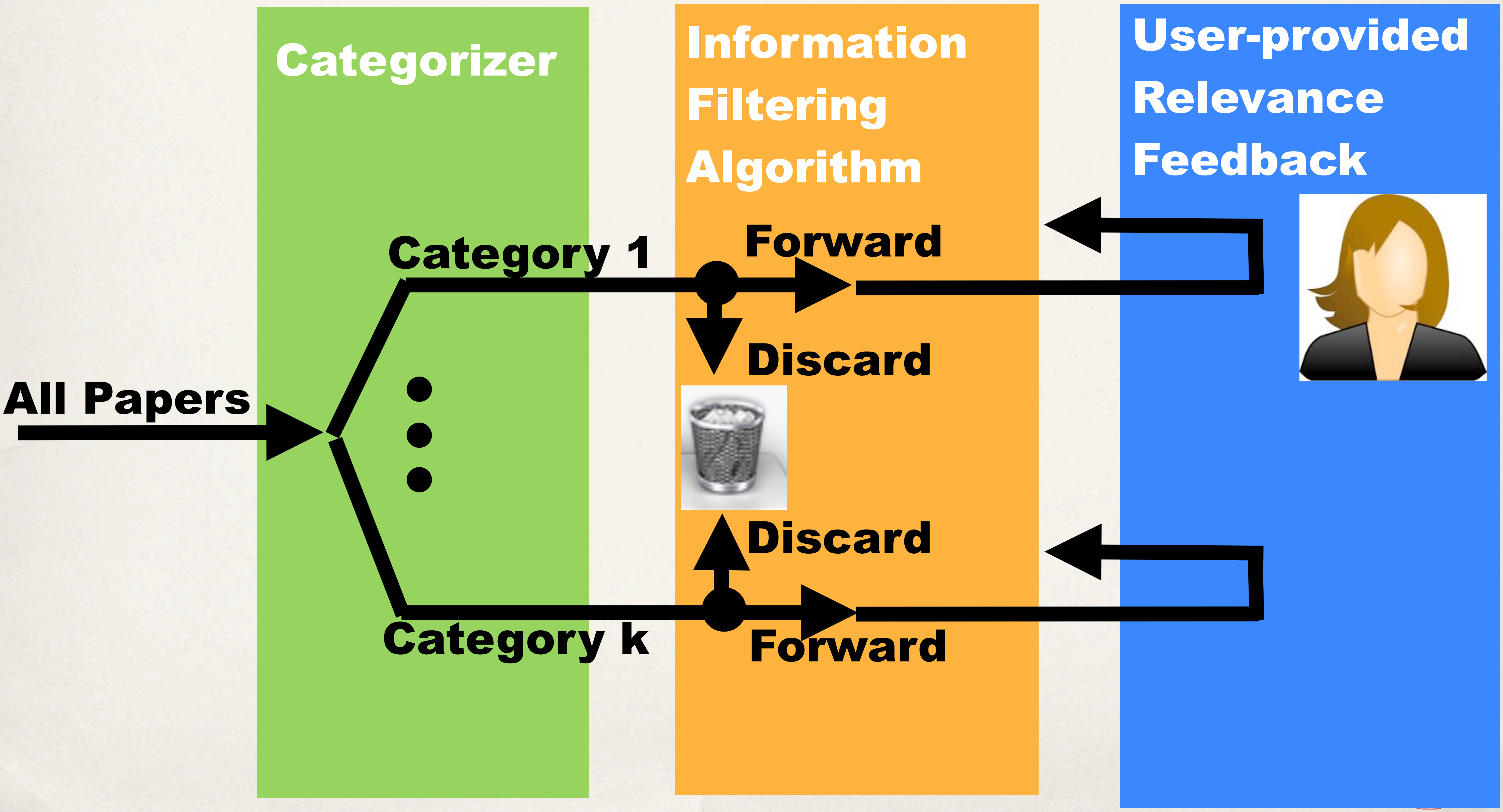
- If $U_{nx}=1$, we then observe Y_{nx}, which is 1 if the item was relevant to the user, and 0 if not.

$$Y_{nx}|\theta_{nx} \sim \text{Bernoulli}(\theta_x)$$

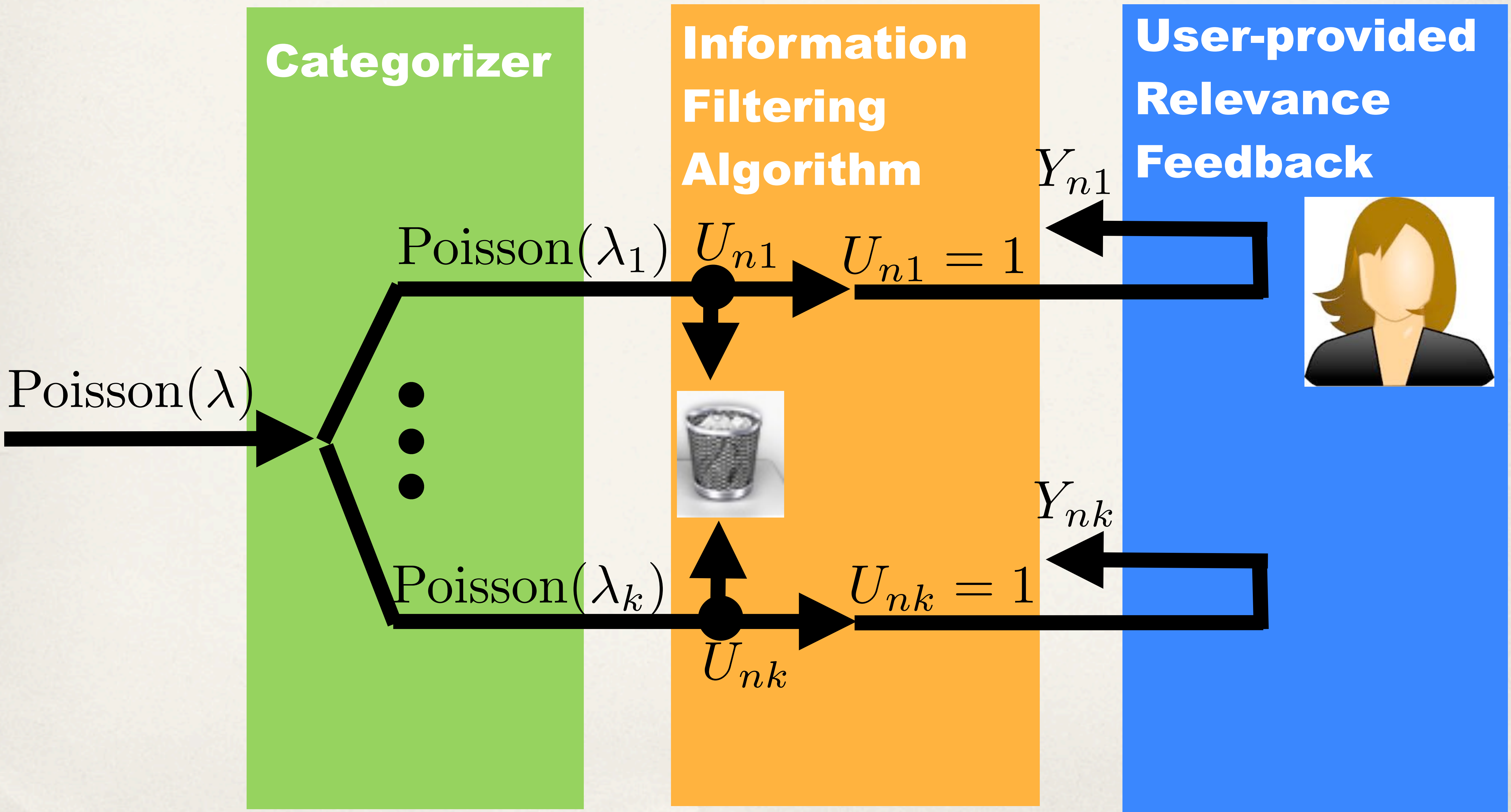
- We can then update our posterior distribution on θ_x, which will still be Beta-distributed (details later),

$$\theta_x|(Y_{mx} : m \leq n, U_{mx} = 1) \sim \text{Beta}(\alpha_{nx}, \beta_{nx})$$

Mathematical Model



Mathematical Model



Mathematical Model

- To model the cost of the user's time, we penalize ourselves with a cost c for forwarding an item. [more on the choice of c later]
- We give ourselves a reward of 1 for showing a relevant item.
- Our net reward is U_{nx} (Y_{nx}-c).
- Our goal is to design an algorithm π that maximizes

$$E^{\pi}\left[\sum_{x=1}^{k}\sum_{n=1}^{N_x} U_{nx}(Y_{nx}-c)\right]$$

- Here, N_x is the # of items available for forwarding from category x, before some random time horizon T.

Mathematical Model

- Recall: N_x is the # of items available for forwarding from category x, before some random time horizon T.
- More formally, $N_x = \sup\{n : t_{nx} \leq T\}$, where t_{nx} is the arrival time of the n^{th} item in category x.
- For mathematical convenience, we assume T~Exponential(r). We set r so that E[T] is the lifetime in system of a typical user.
- Then, $N_x \sim \text{Geometric}(\lambda_x/(\lambda_x+r))$. This will make it easier to solve an upcoming dynamic program.

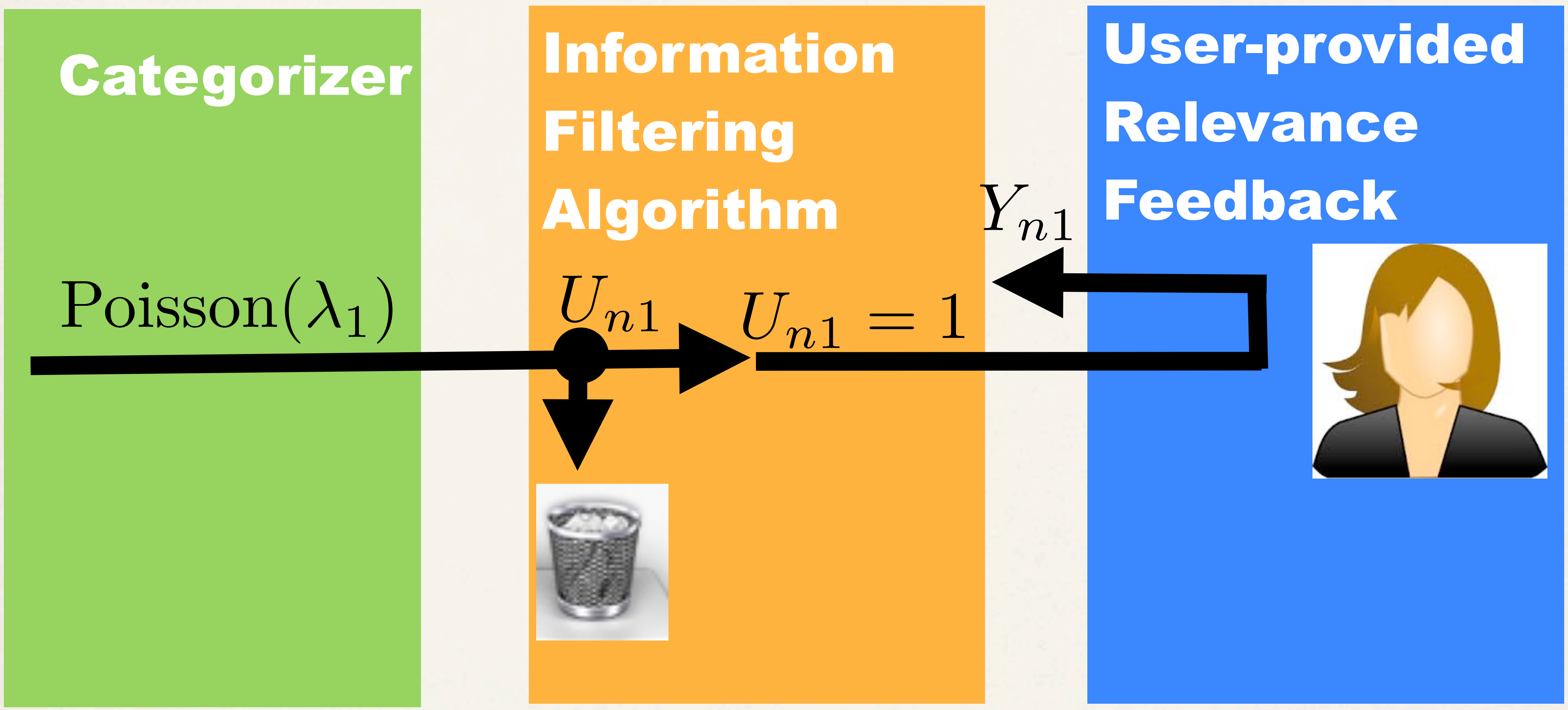
Mathematical Model

- Putting all of this together, our goal is to solve:

$$\sup_{\pi} E^{\pi}\left[\sum_{x=1}^{k}\sum_{n=1}^{N_x} U_{nx}(Y_{nx} - c)\right]$$

- Here, an algorithm π is a rule for choosing each U_{nx} based only on previously observed feedback (Y_{mz} : $U_{mz}=1$, $t_{mz} < t_{nx}$).

Let's first solve the problem for a single category



Let's first solve the problem for a single category

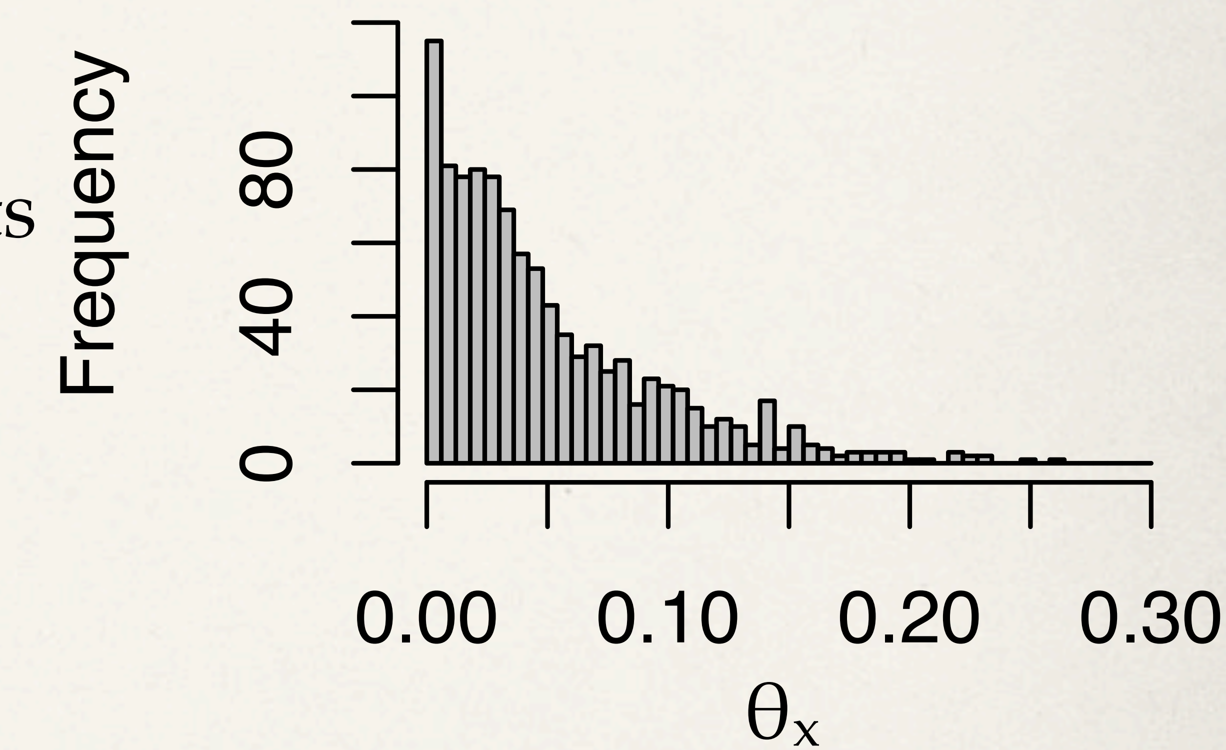
- For a given cluster x, let's figure out how to maximize the reward from just that cluster,

$$\sup_{\pi} E^{\pi}\left[\sum_{n=1}^{N_x} U_{nx}(Y_{nx} - c)\right]$$

- When choosing U_{nx}, it is sufficient to consider feedback only from previous items in our category x, $(Y_{mx} : U_{mx}=1, m<n)$

We use a standard Bayesian statistical model

- Recall that we model $\theta_x \sim \mathrm{Beta}(\alpha_{0x}, \beta_{0x})$.
- Here's how we choose α_{0x} and β_{0x}.
    - We first find a few users with lots of historical data in this cluster.
    - We estimate θ_x for each of these users, using their average relevance feedback.
    - We then make a histogram.



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- Recall that we model $\theta_x \sim \text{Beta}(\alpha_{0x},\beta_{0x})$.
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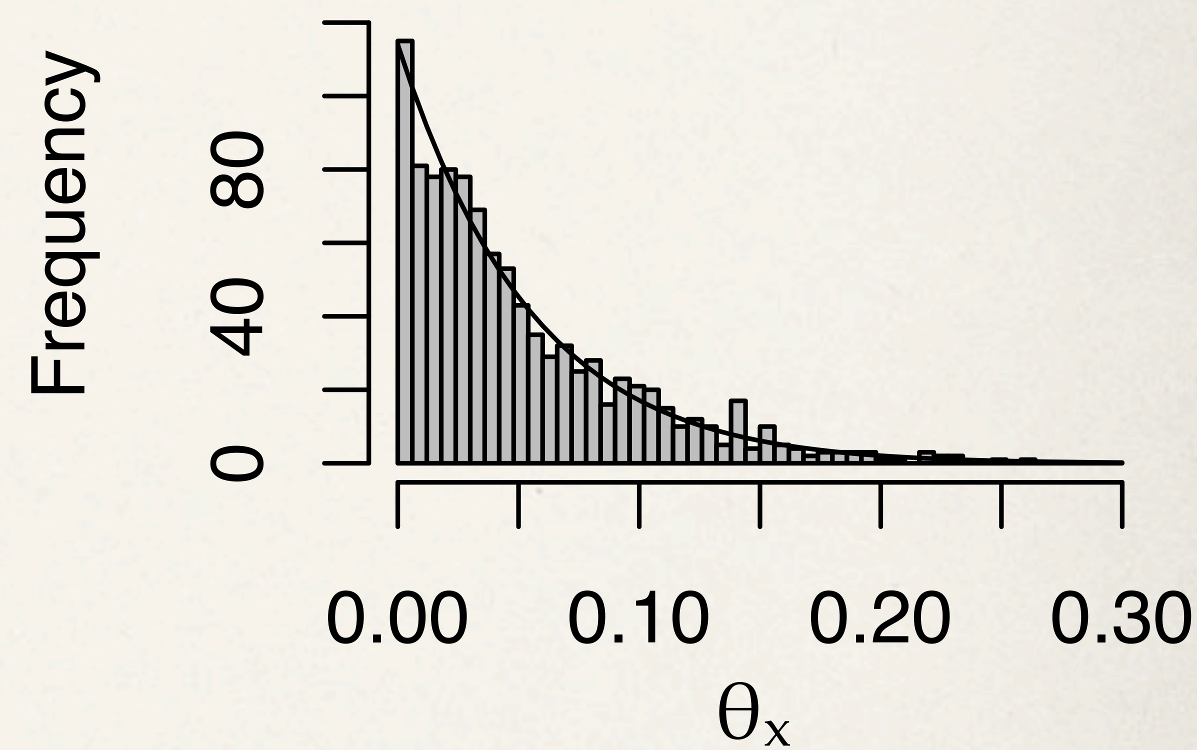
    - We then fit a beta density to this empirical distribution, using maximum likelihood estimation.
    - We set α_{0x} and β_{0x} to their values from the fitted distribution.
    - A beta distribution is analytically convenient, and fits the data well.



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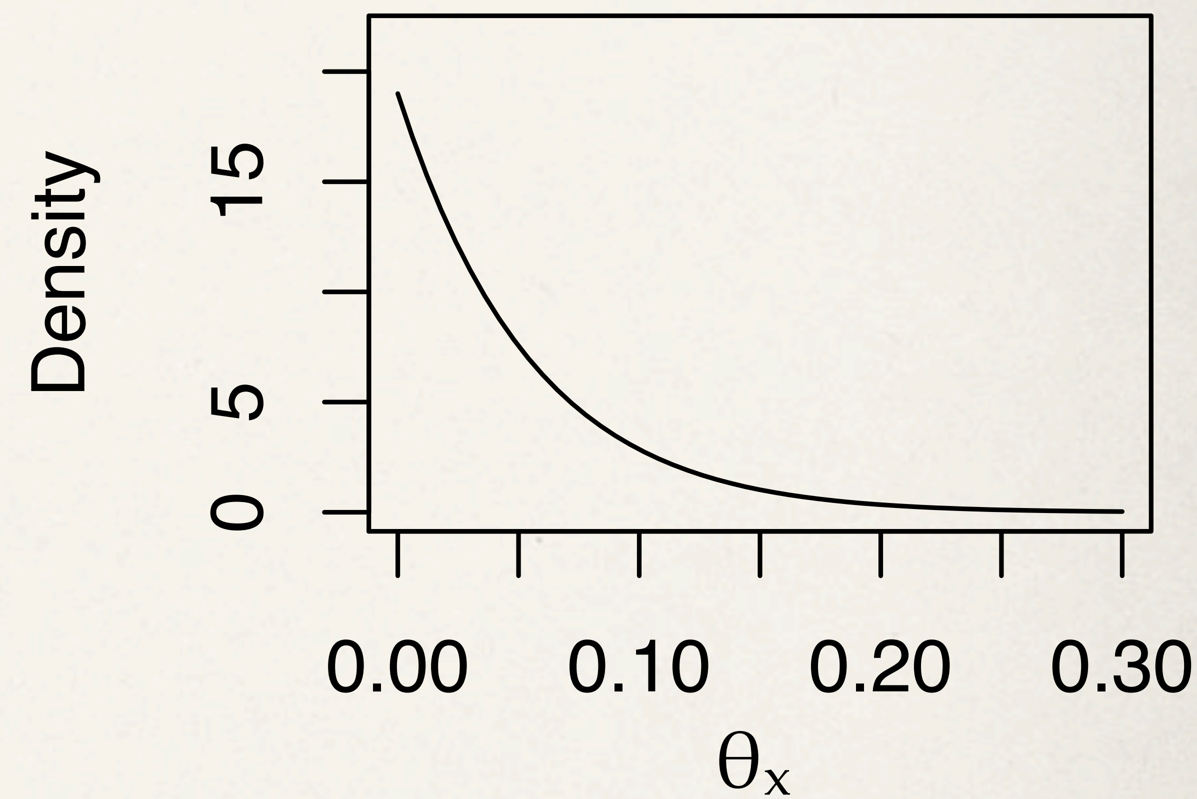


We use a standard Bayesian statistical model

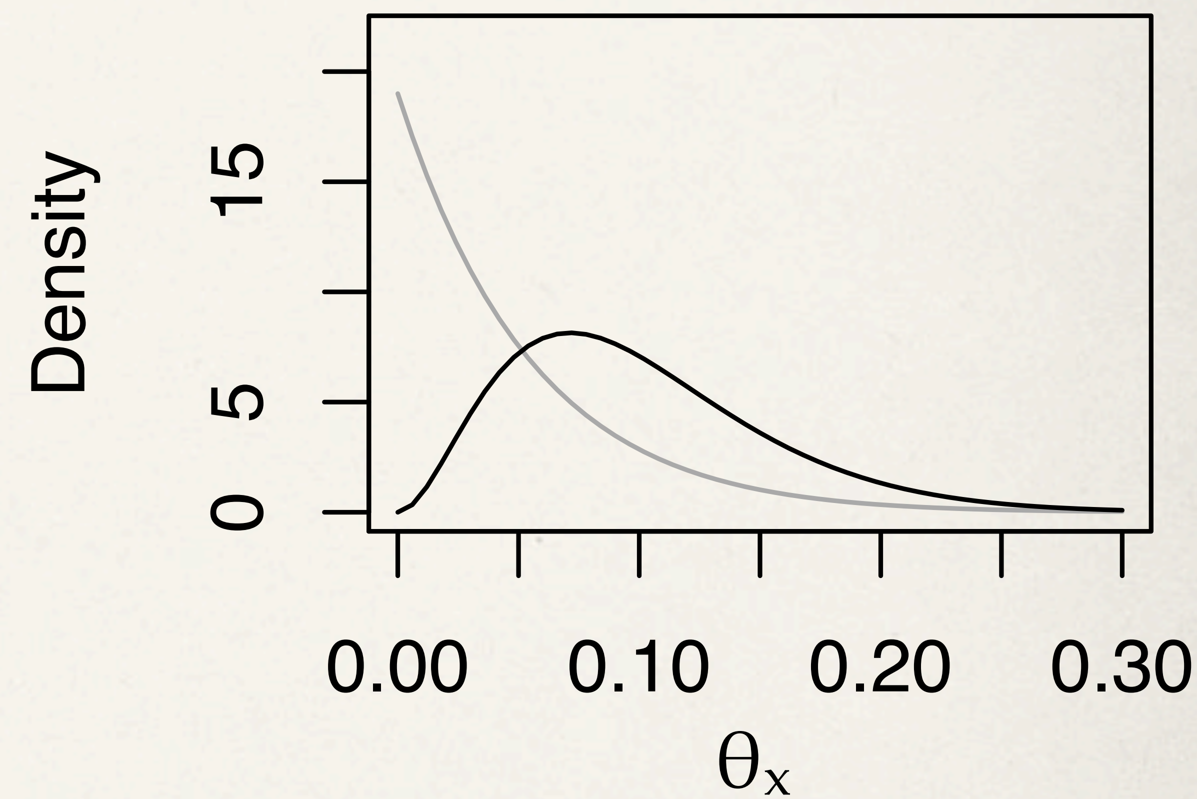
- After observing our data, we update our prior to obtain a posterior distribution using Bayes rule.

$$\theta_x | (Y_{mx} : m \le n, U_{mx} = 1)$$
$$\sim \mathrm{Beta}(\alpha_{nx}, \beta_{nx})$$

- Here, α_{nx} and β_{nx} count the effective numbers of relevant and irrelevant items shown:

$$\alpha_{nx} = \alpha_{0x} + \sum_{m=1}^{n} U_{mx} Y_{mx}$$

$$\beta_{nx} = \beta_{0x} + \sum_{m=1}^{n} U_{mx}(1 - Y_{mx})$$



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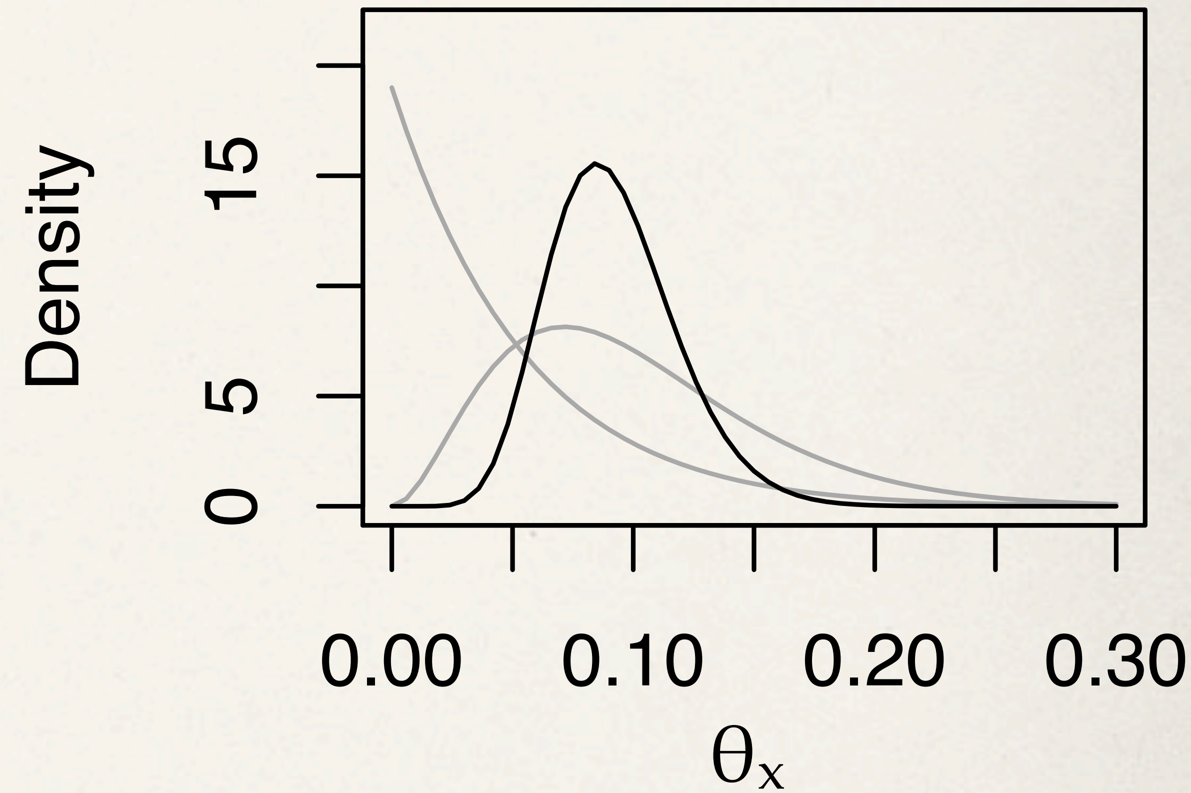


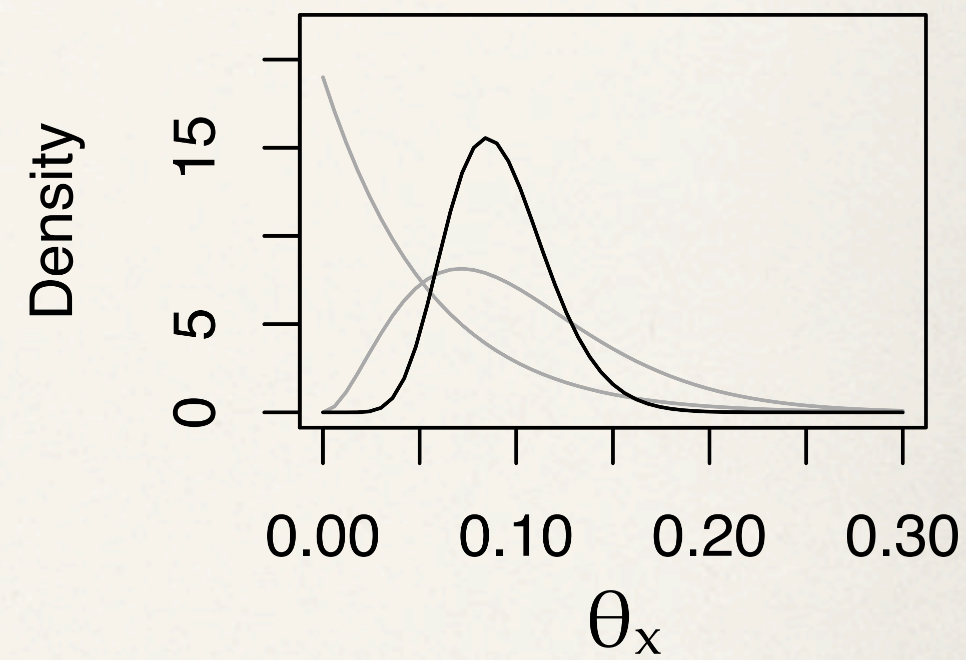
We use a standard Bayesian statistical model

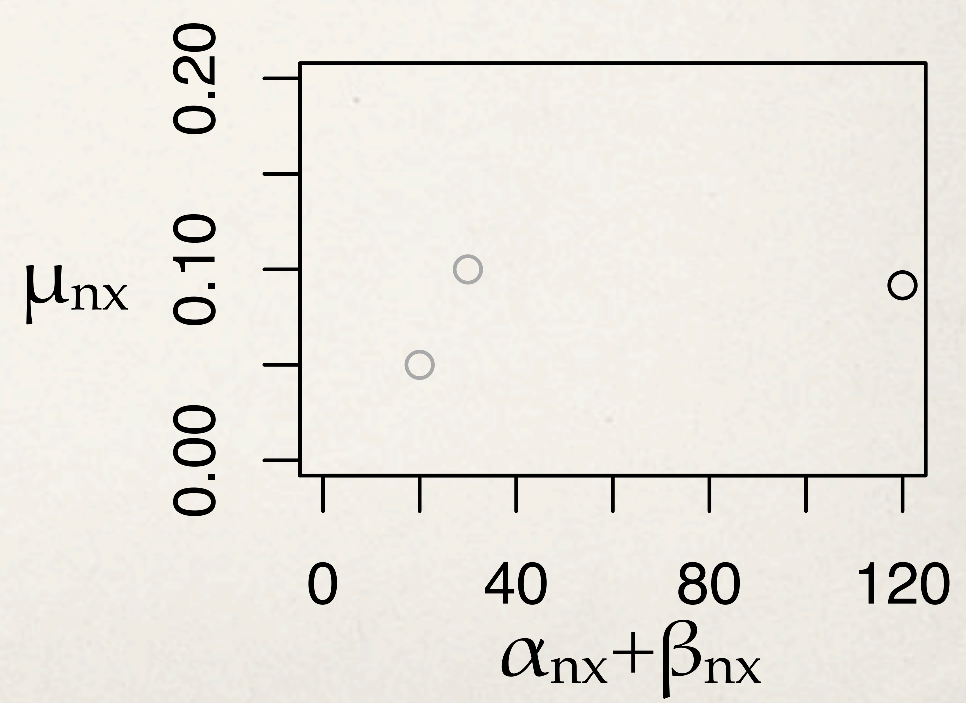
- Our posterior is

$$\theta_x | (Y_{mx} : m \leq n, U_{mx} = 1)$$
$$\sim \mathrm{Beta}(\alpha_{nx}, \beta_{nx})$$

- We can parameterize this posterior with (μ_{nx}, $\alpha_{nx}+\beta_{nx}$) where

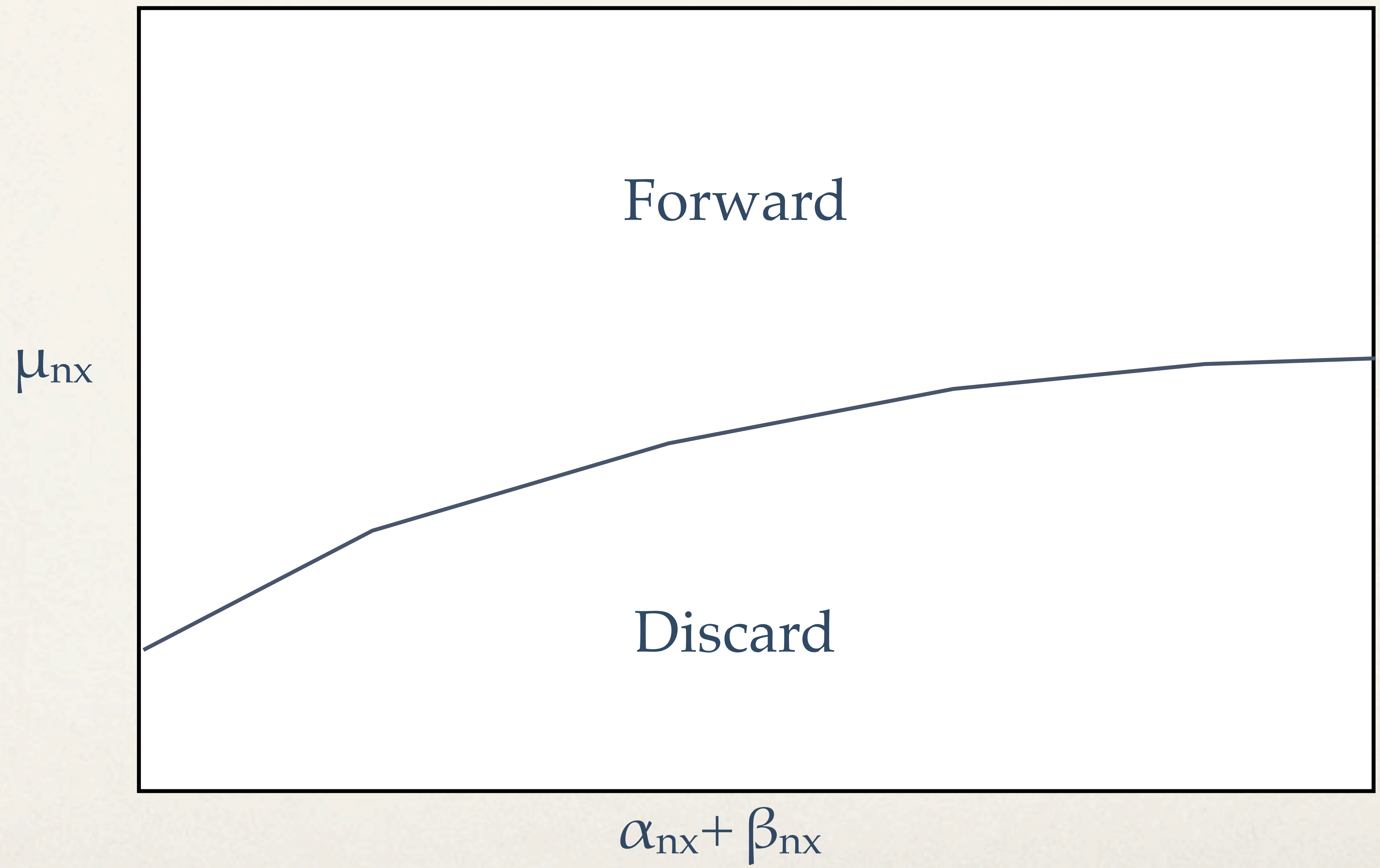
$$\mu_{nx} = E_n\left[\theta_x\right] = \frac{\alpha_{nx}}{\alpha_{nx} + \beta_{nx}}$$





An algorithm partitions the space of posteriors into "Forward" and "Discard"

- Here is one possible algorithm:



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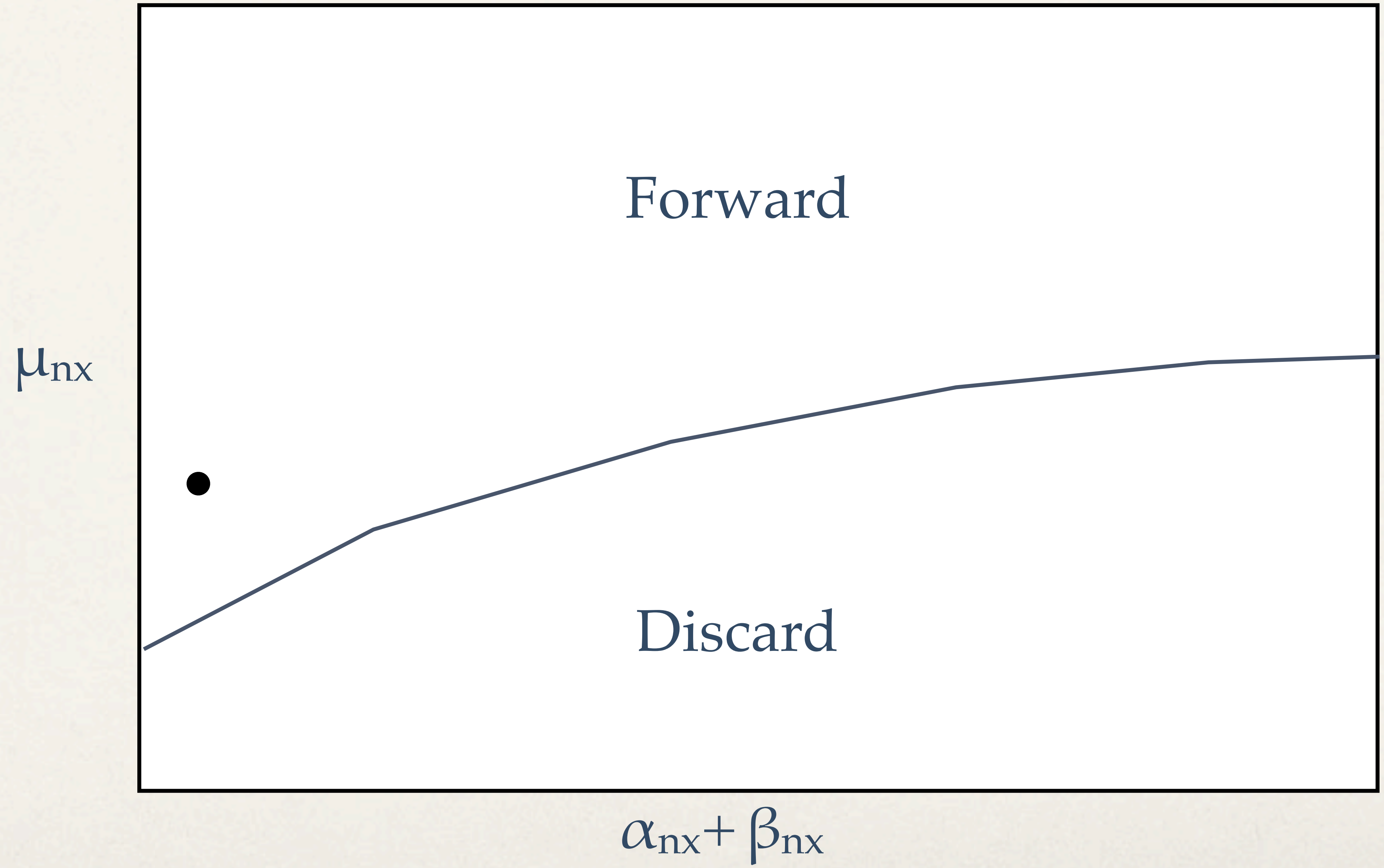

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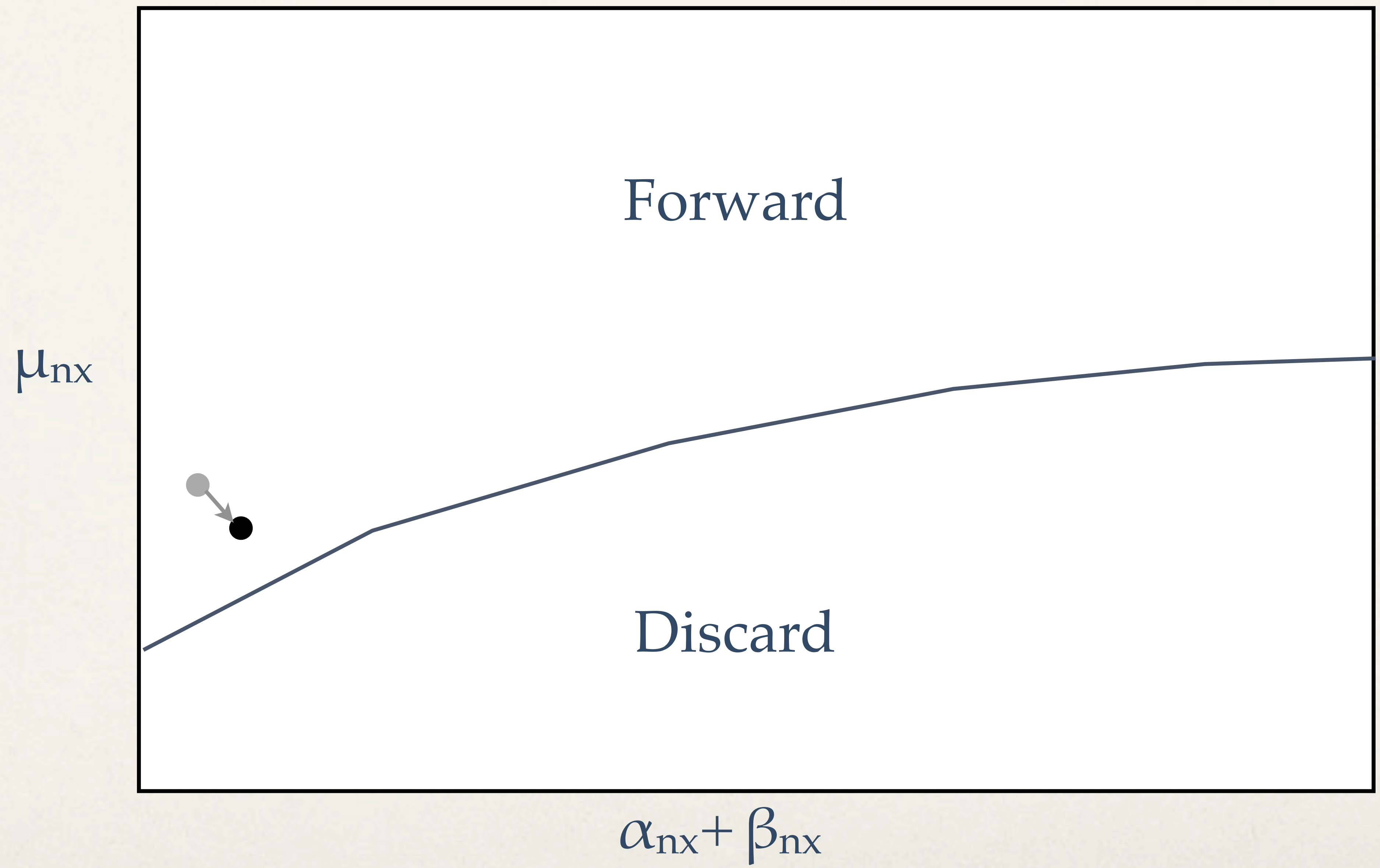

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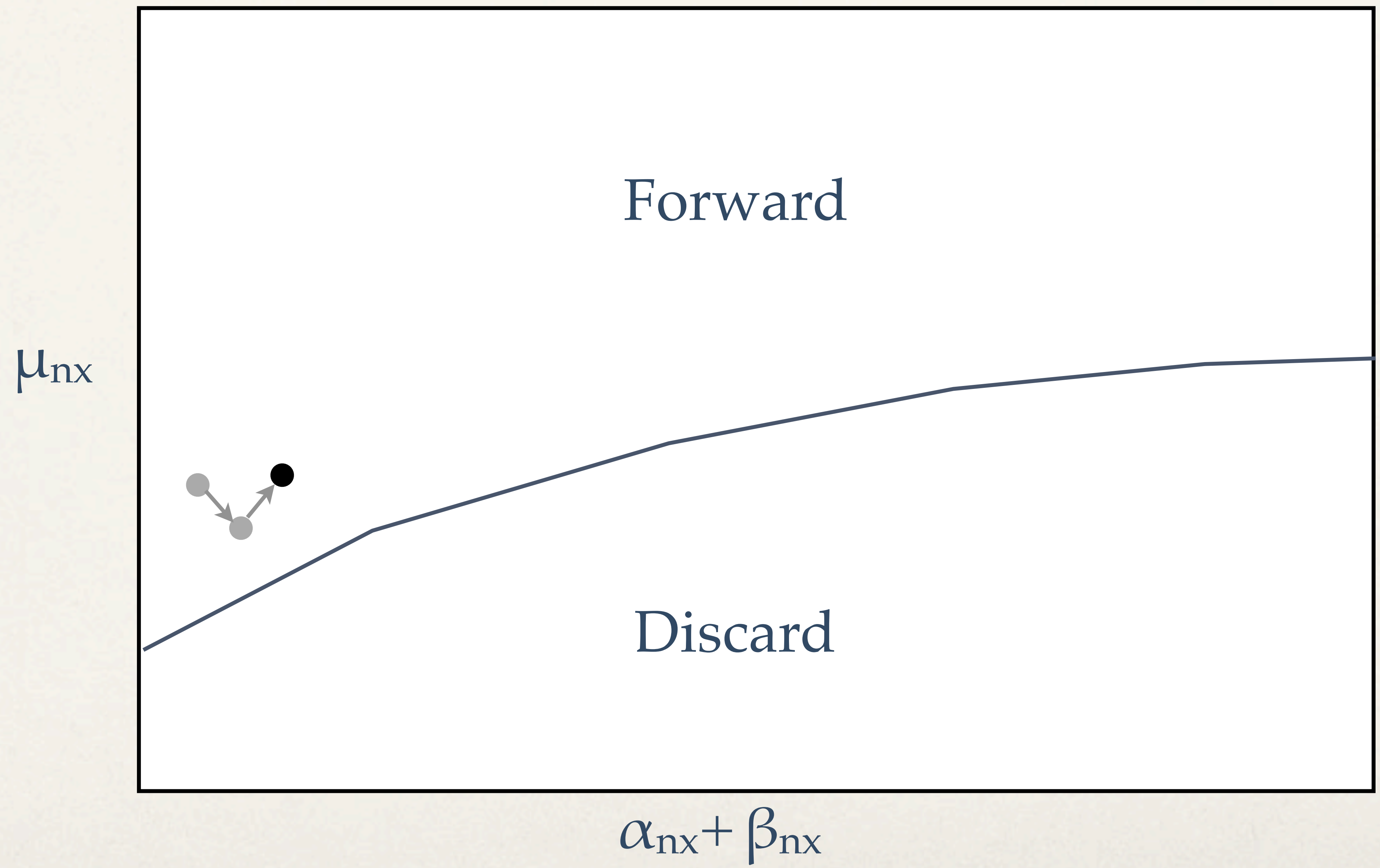

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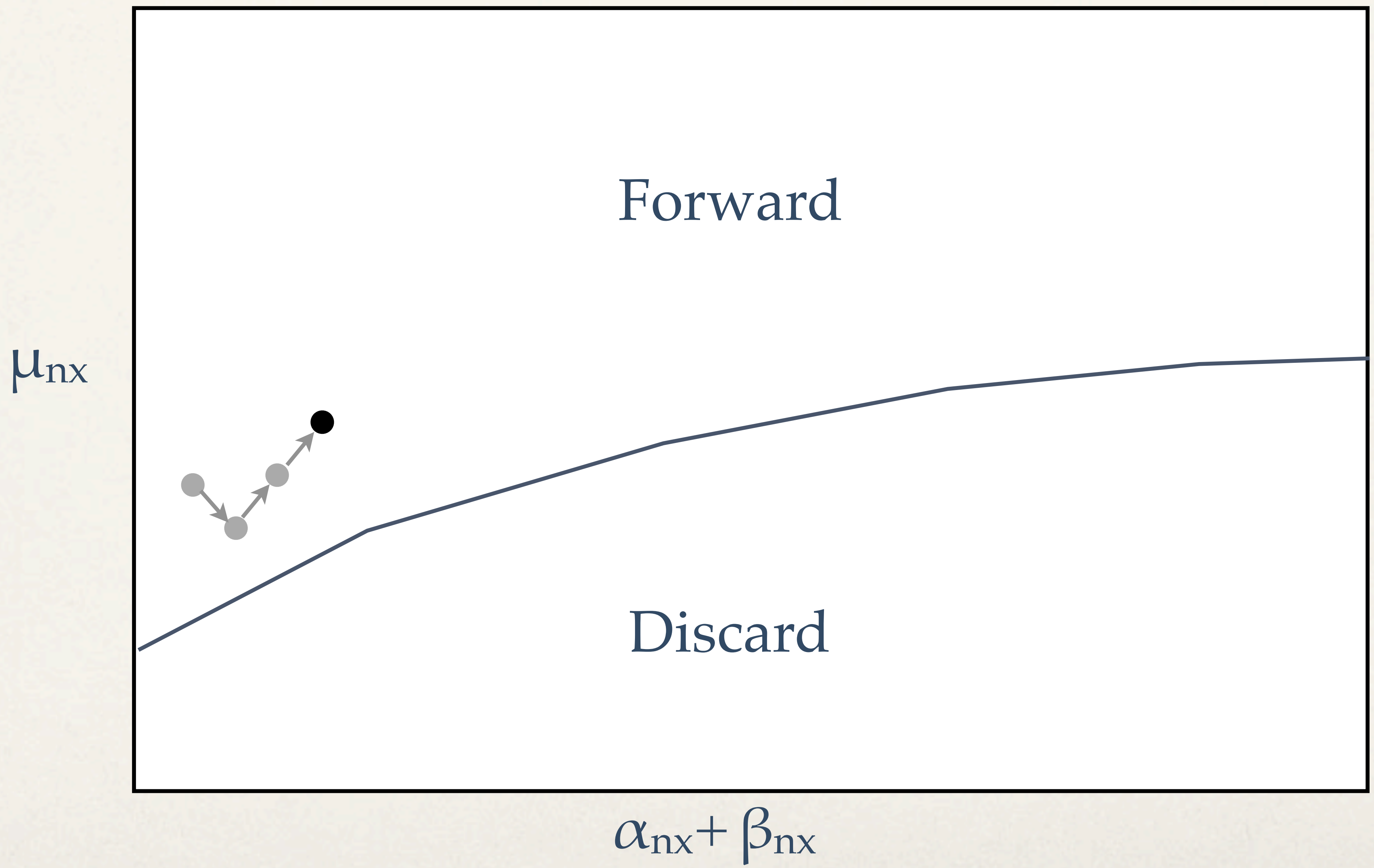

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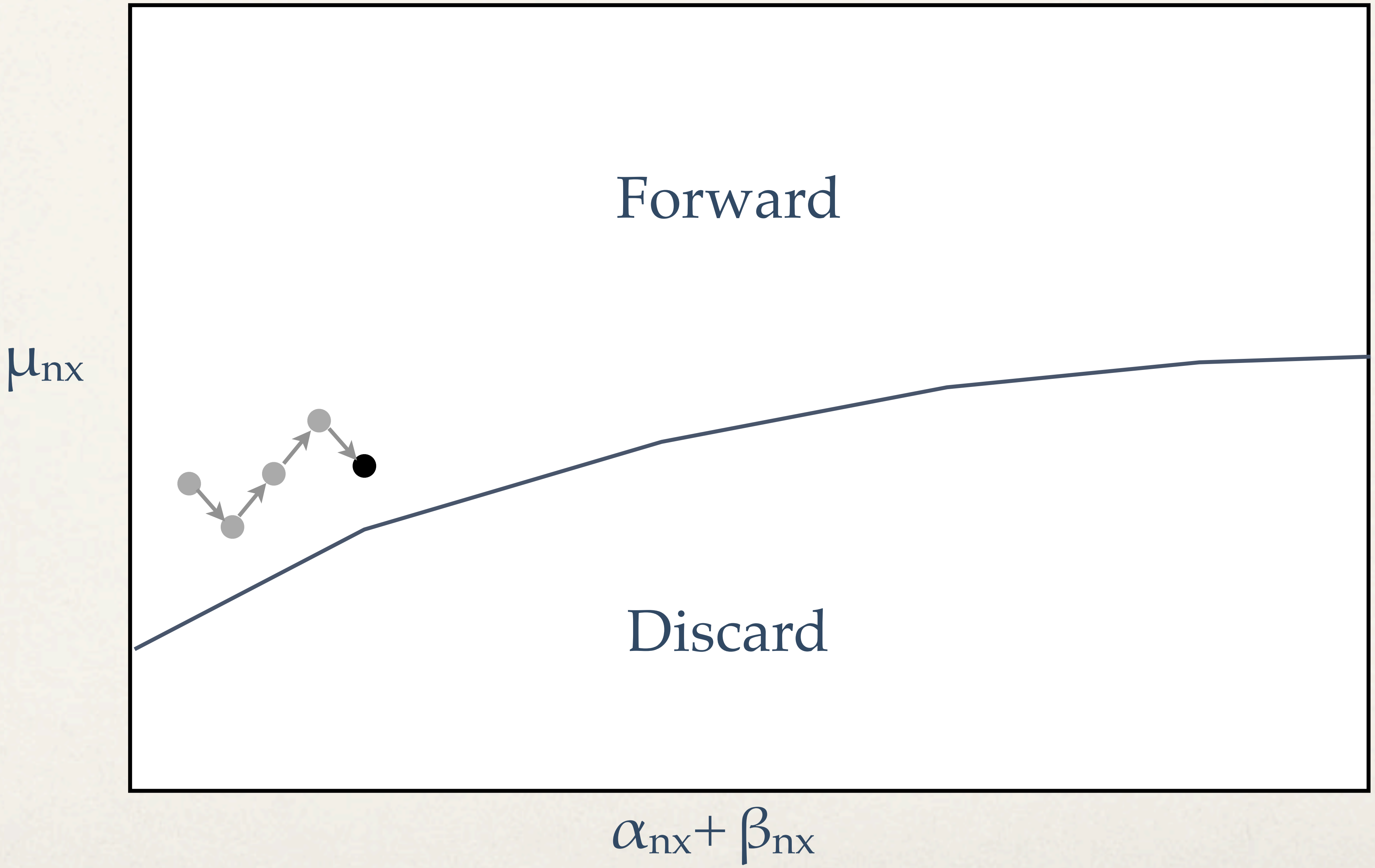

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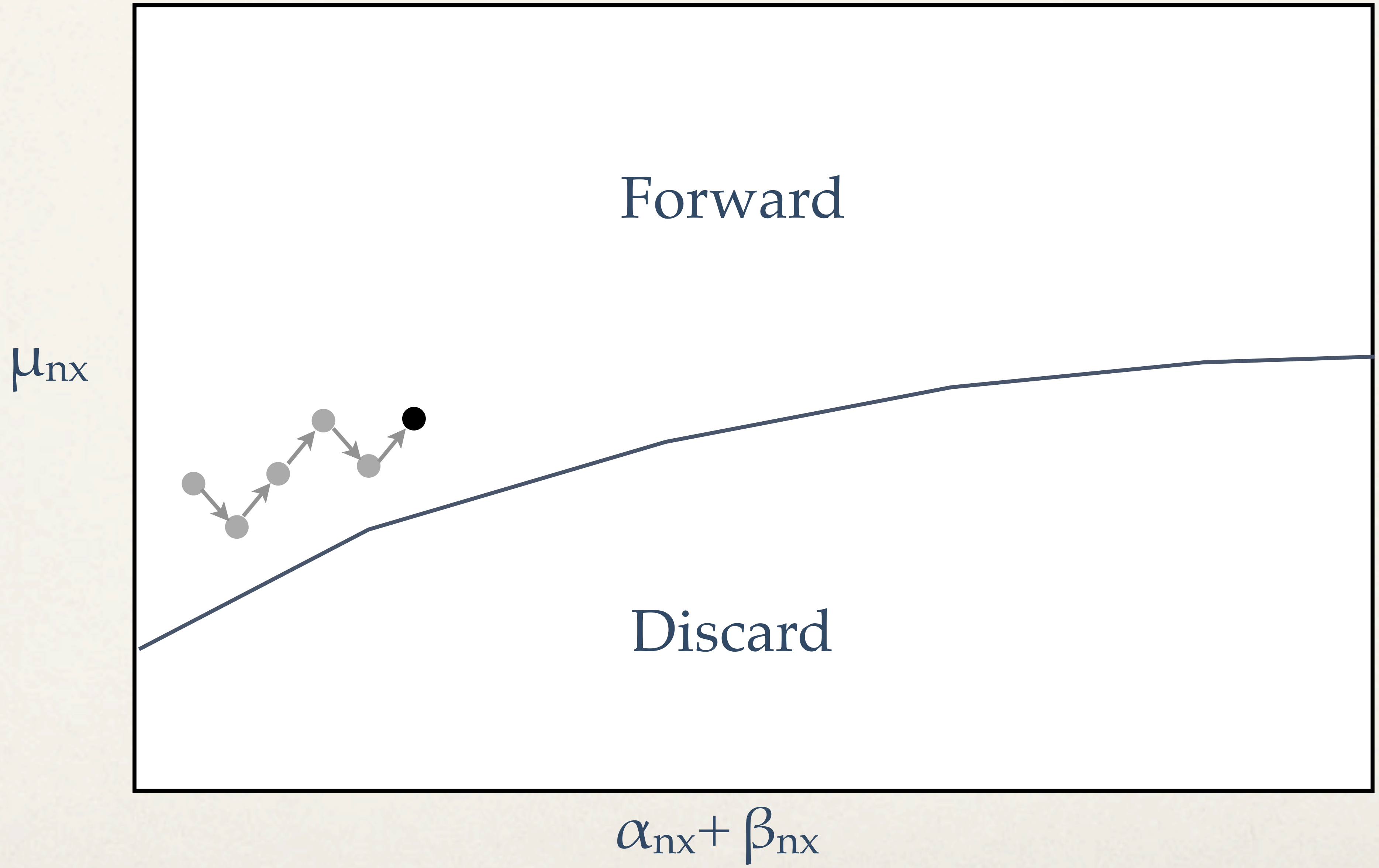

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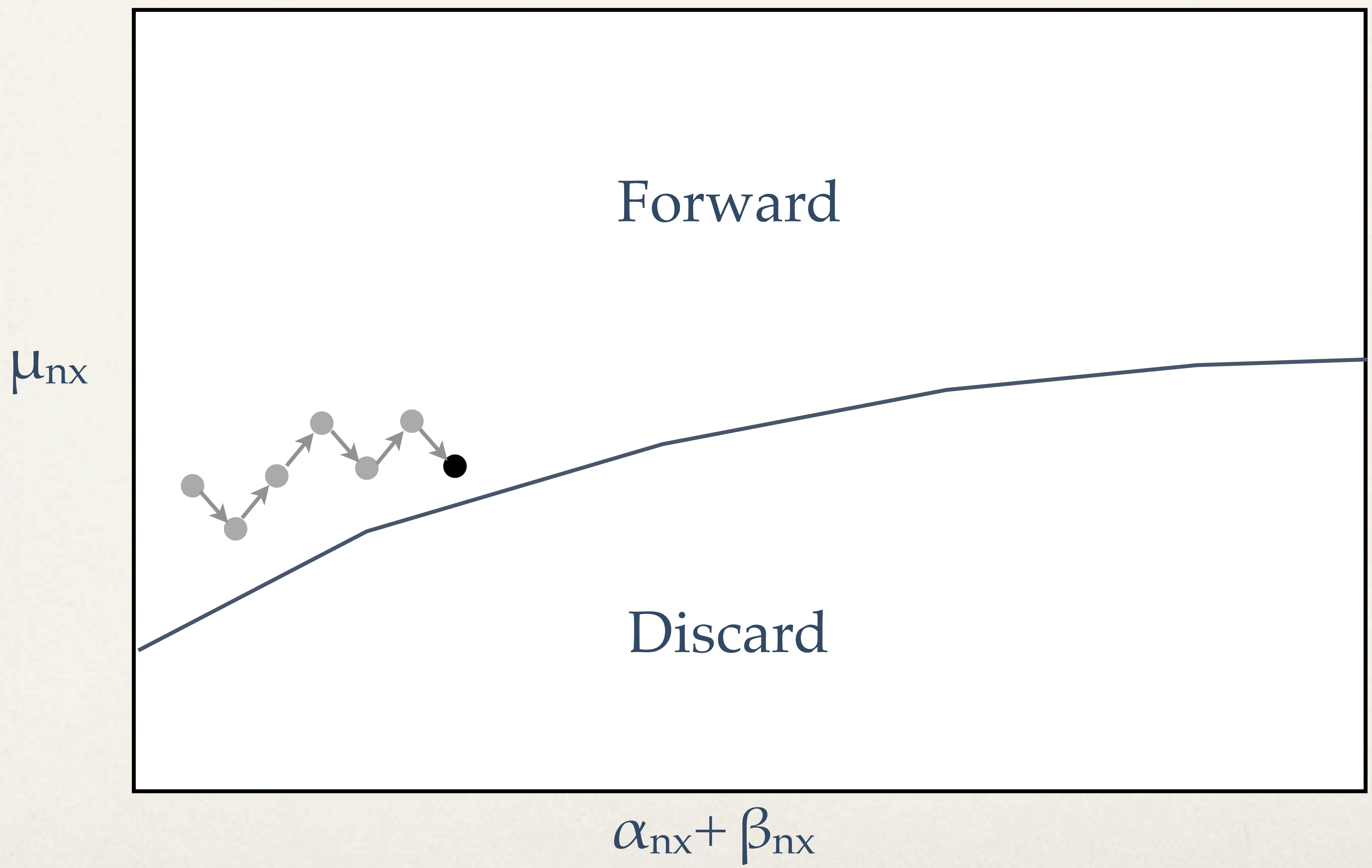

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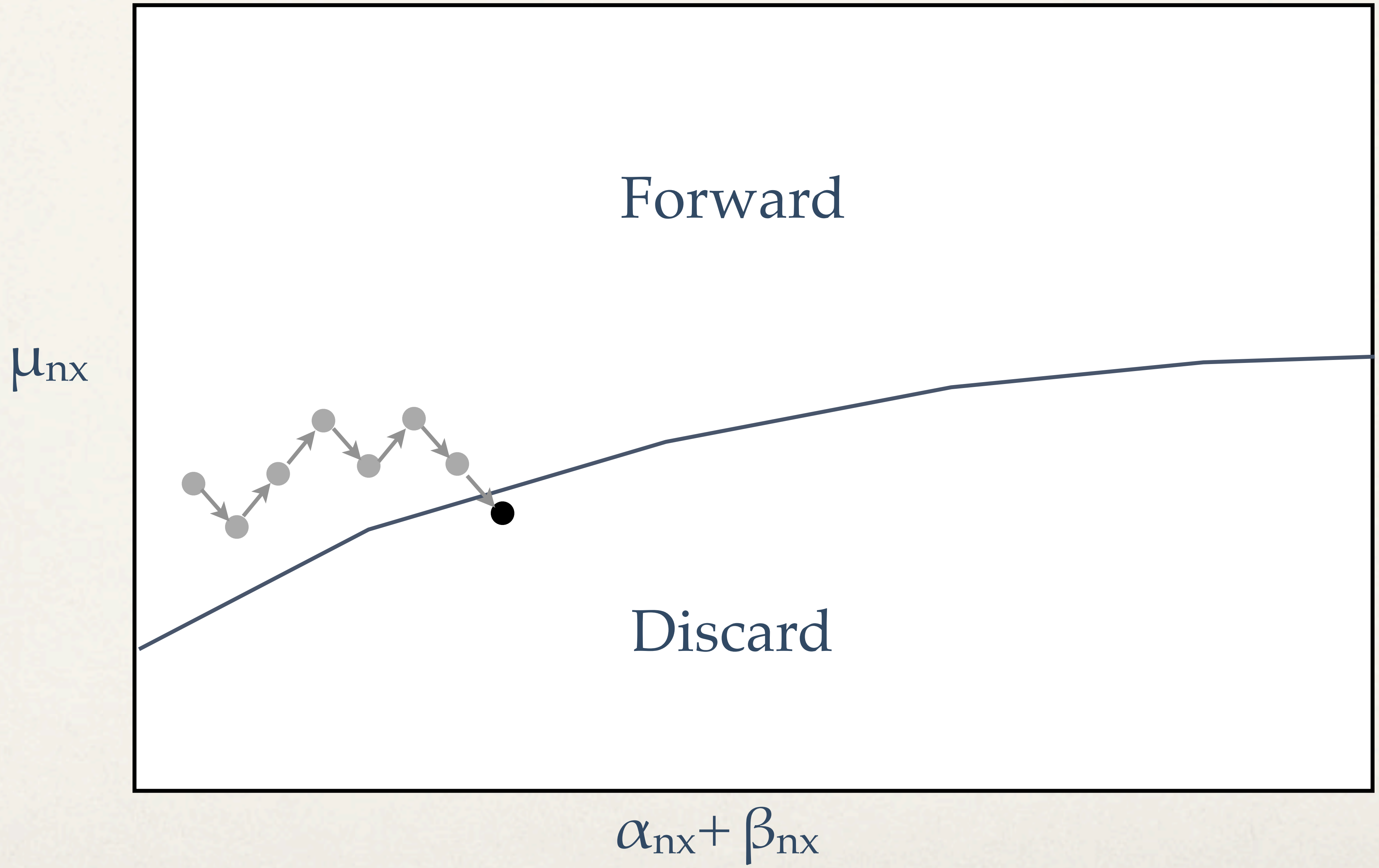

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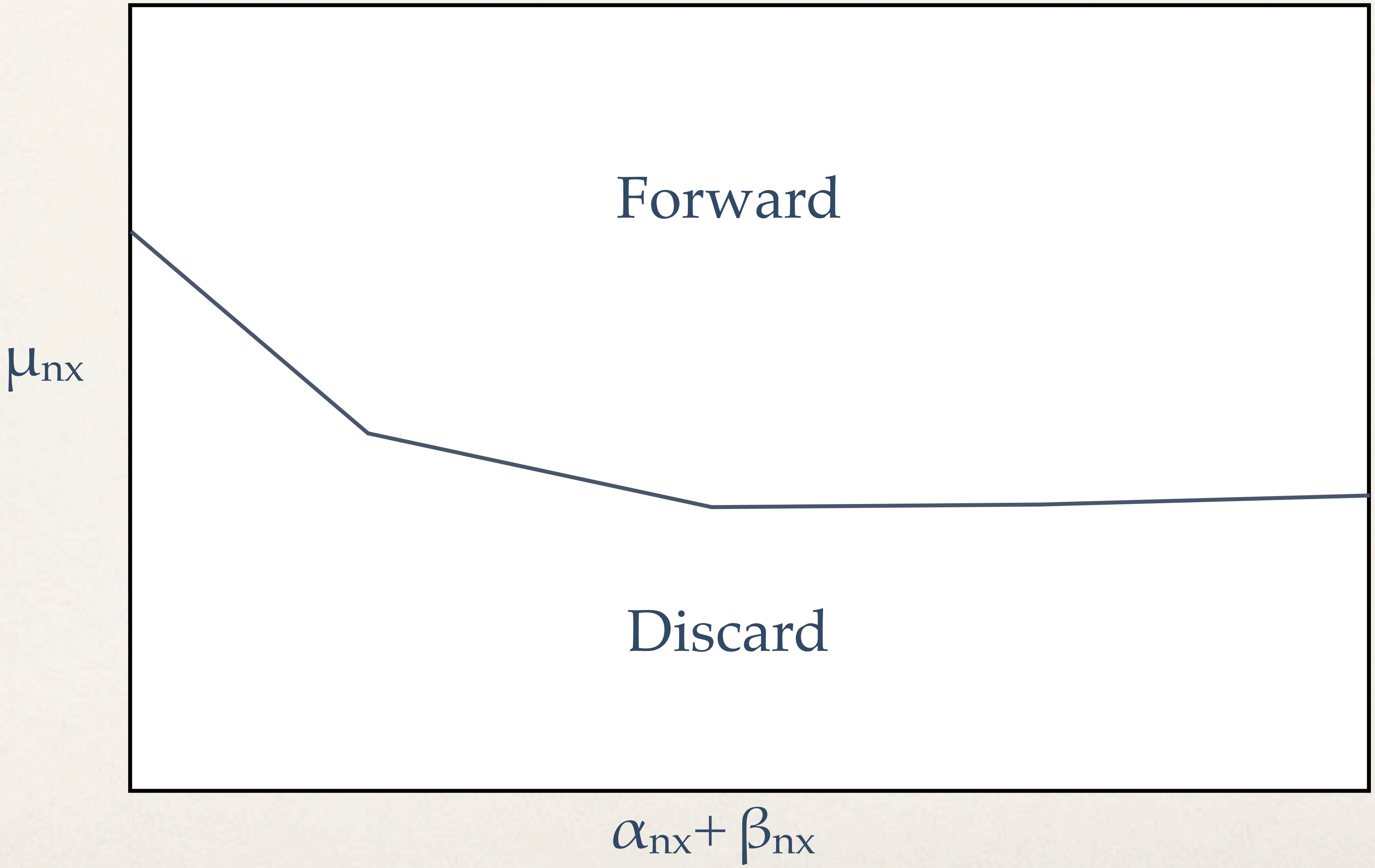
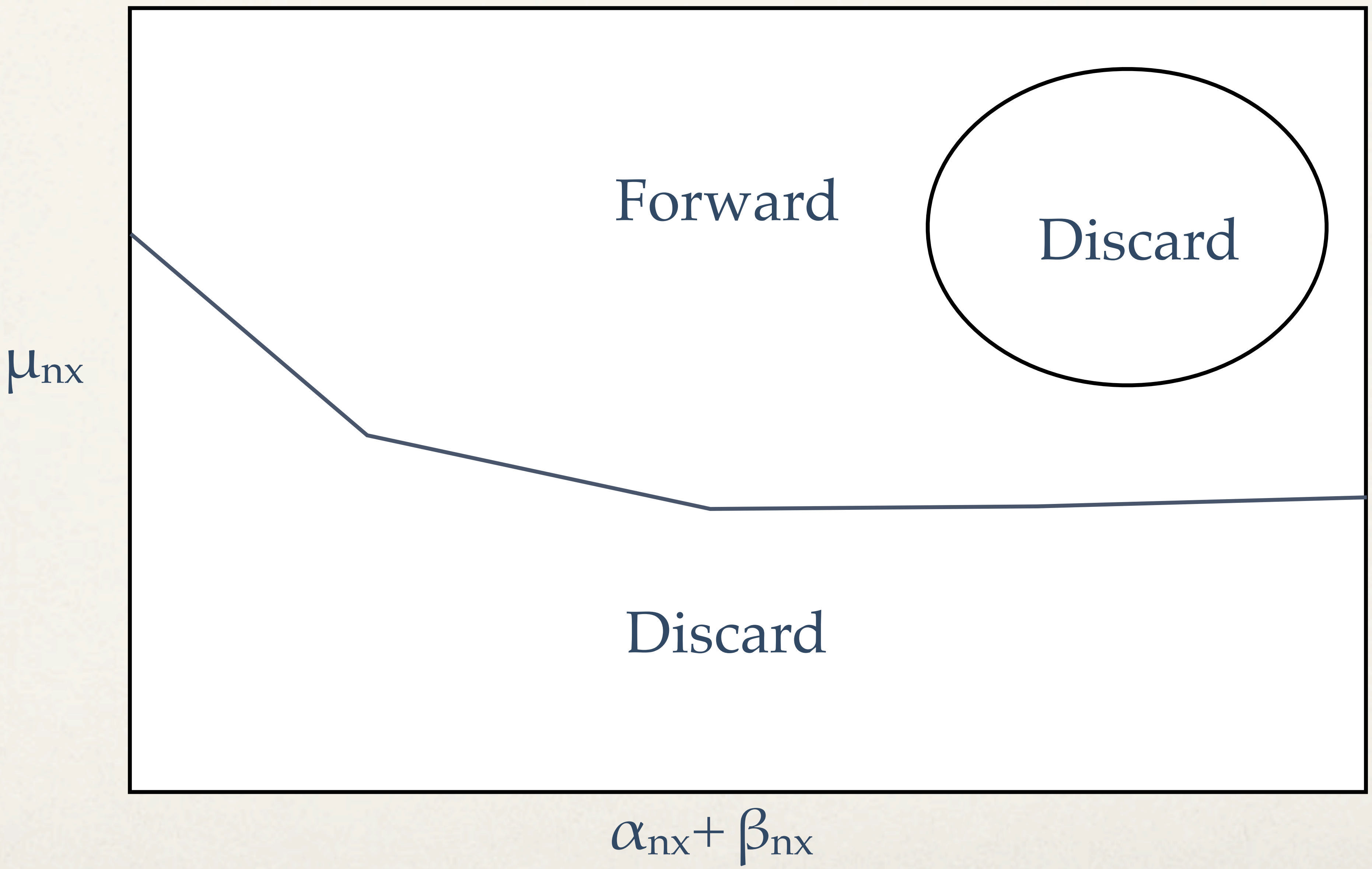


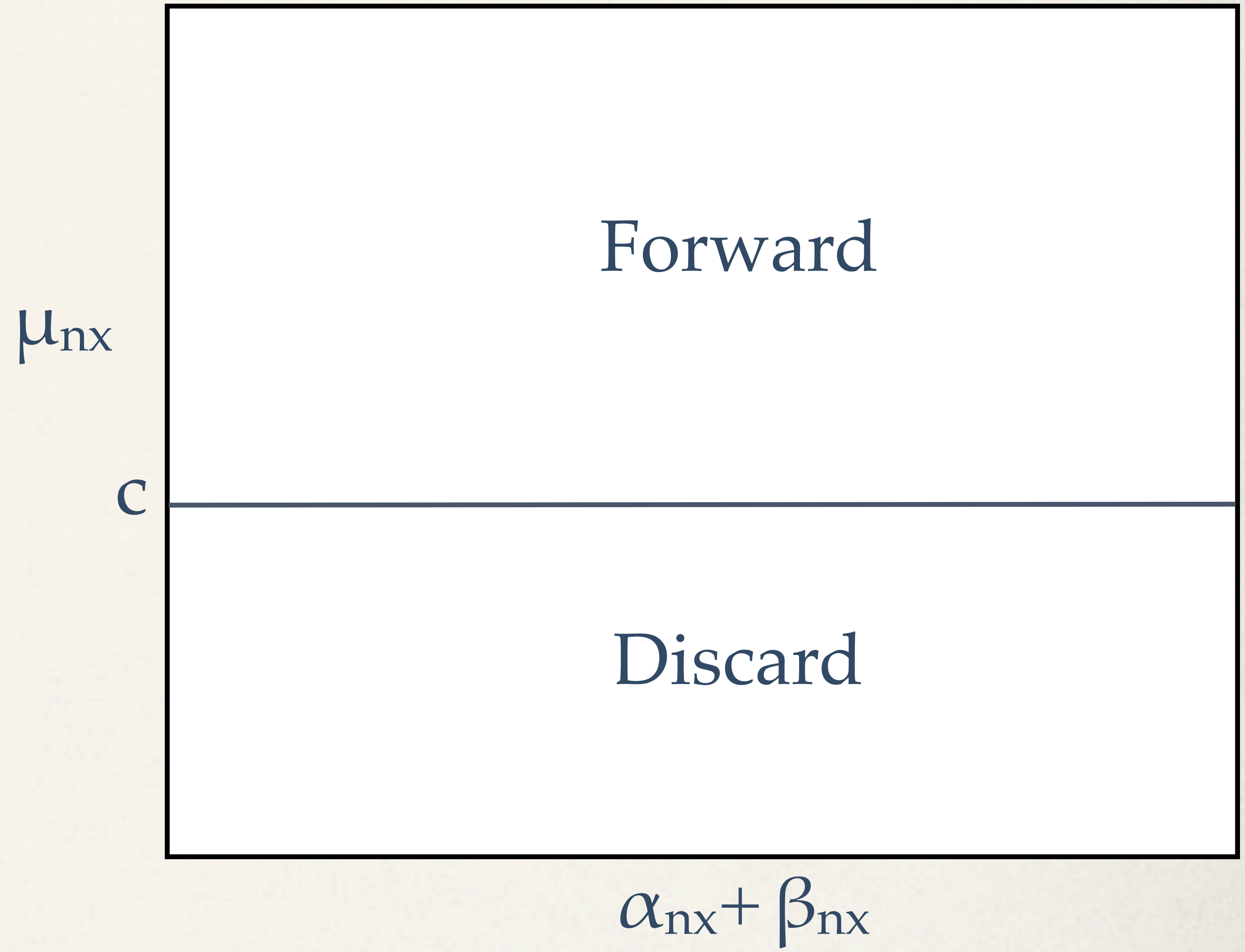
An algorithm partitions the space of posteriors into "Forward" and "Discard"

- Here is yet another possible algorithm:



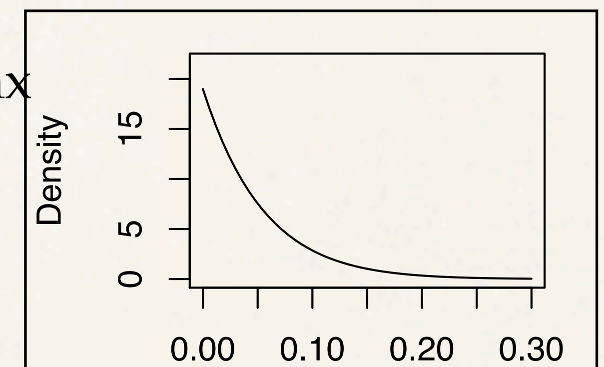
The myopic algorithm can be expressed in this way.

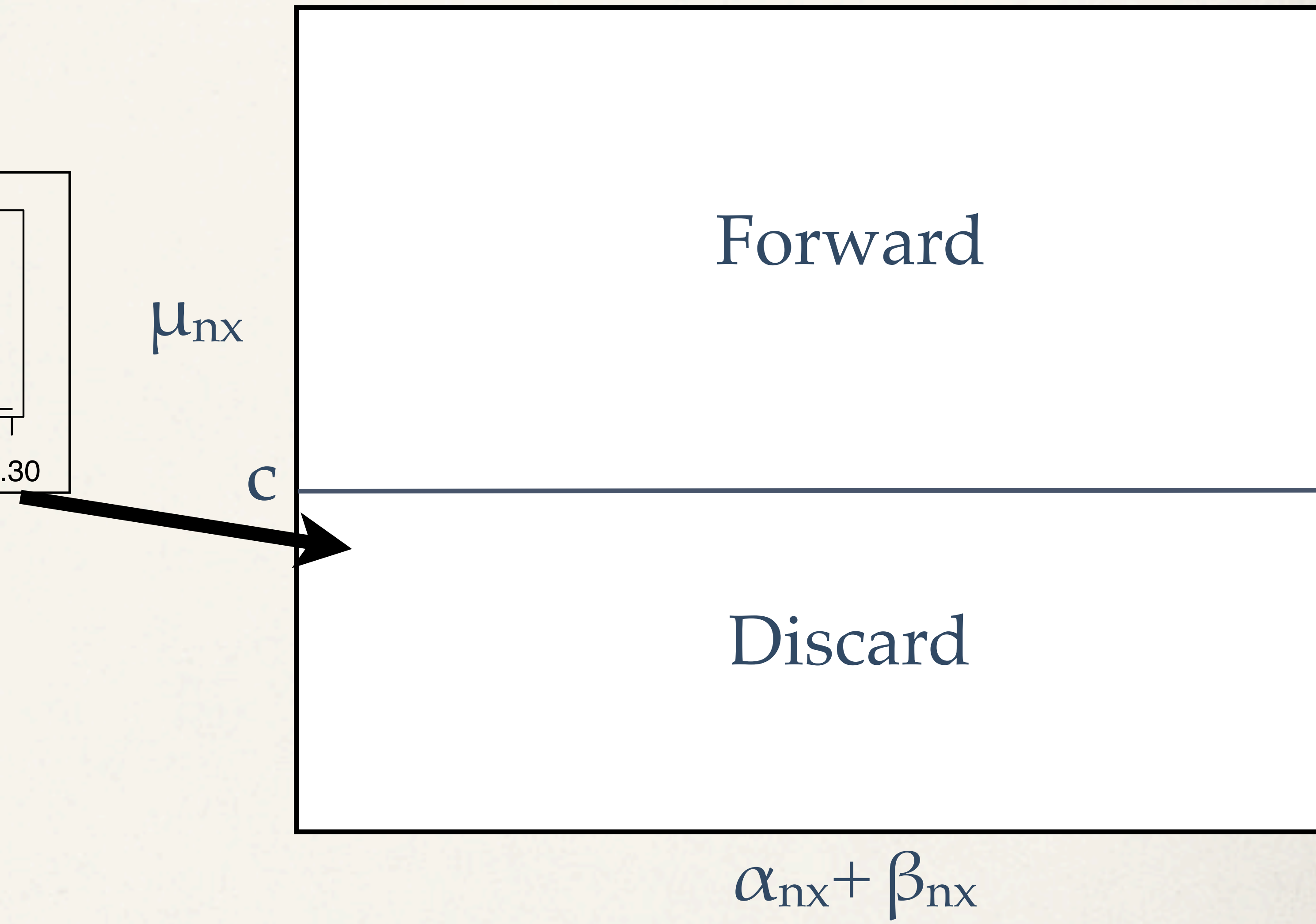
- The expected *immediate* payoff of forwarding is $E_n[\theta_x - c] = \mu_{nx} - c$
- The expected immediate payoff of discarding is 0.
- The rule that maximizes expected immediate reward is:
    - Forward if $\mu_{nx} > c$
    - Discard if not.



The myopic algorithm ignores the value of **exploring**

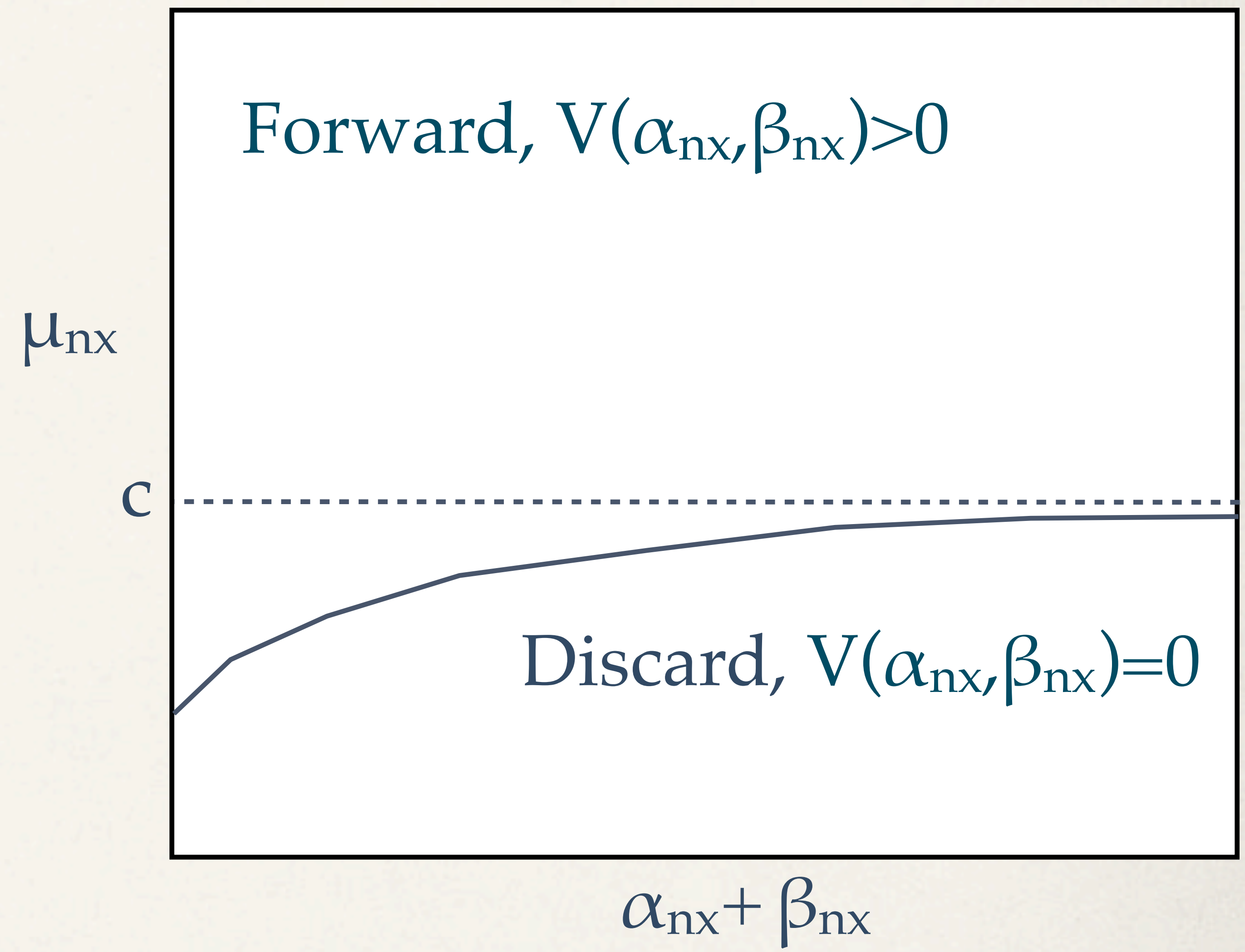
- If our current posterior has:
  - small $\alpha_{nx} + \beta_{nx}$
  - μ_{nx} close to c





- then it might be worth forwarding, just to learn more about θ_x.
- If it turns out $\theta_x > c$, we can take advantage of this in future forwarding decisions.

We can compute the optimal algorithm through stochastic dynamic programming



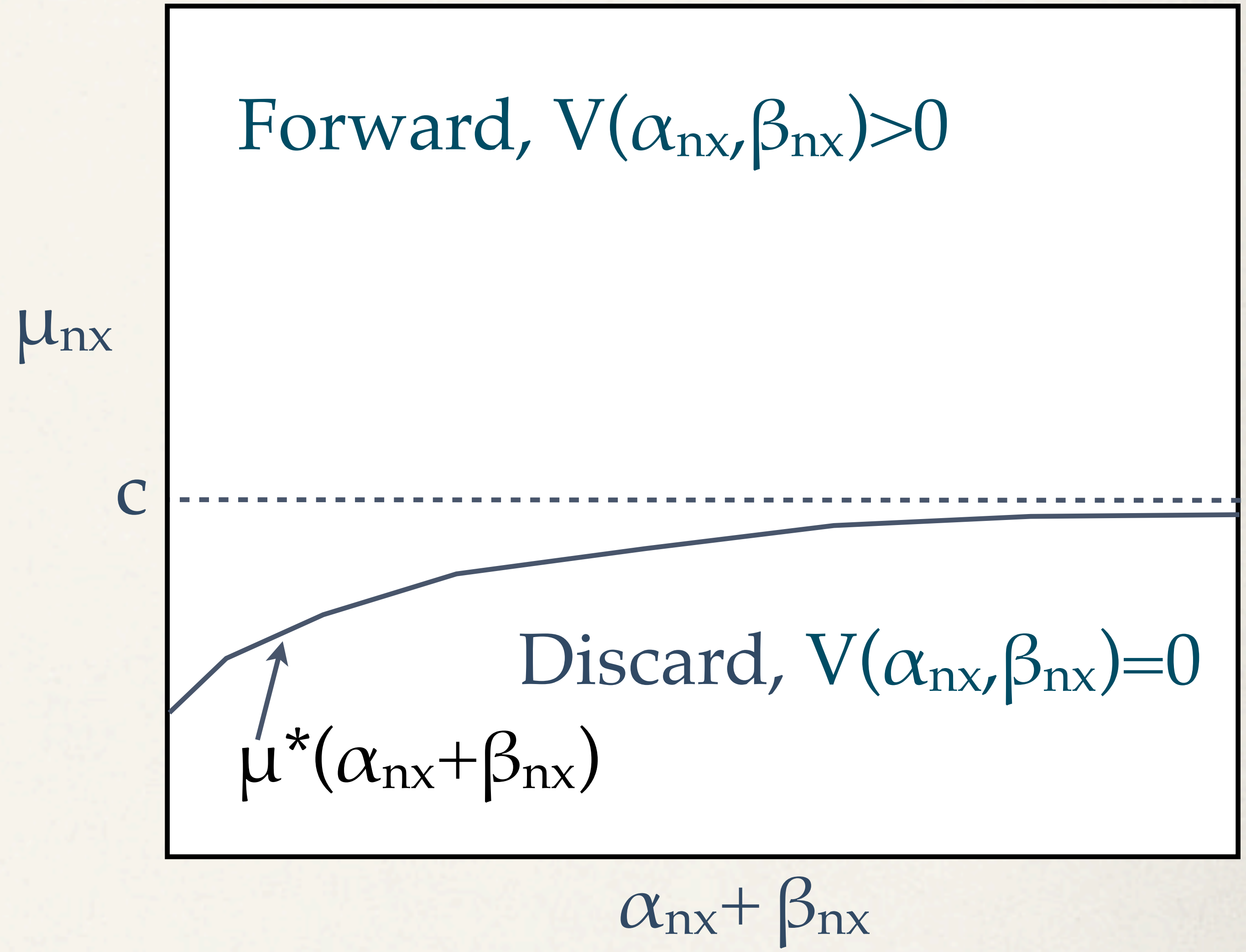
- Let $V(\alpha_{nx},\beta_{nx})$ be the expected future reward under the optimal policy, given n documents of history, and given $N_x \geq n$.
- V satisfies the dynamic programming recursion:

$$V(\alpha_{nx},\beta_{nx})=P(N_x\geq n+1 \mid N_x\geq n)\max(0,\mu_{nx}-c+E_n[V(\alpha_{n+1,x},\beta_{n+1,x})])$$

The optimal algorithm trades **exploration vs. exploitation**

- **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.

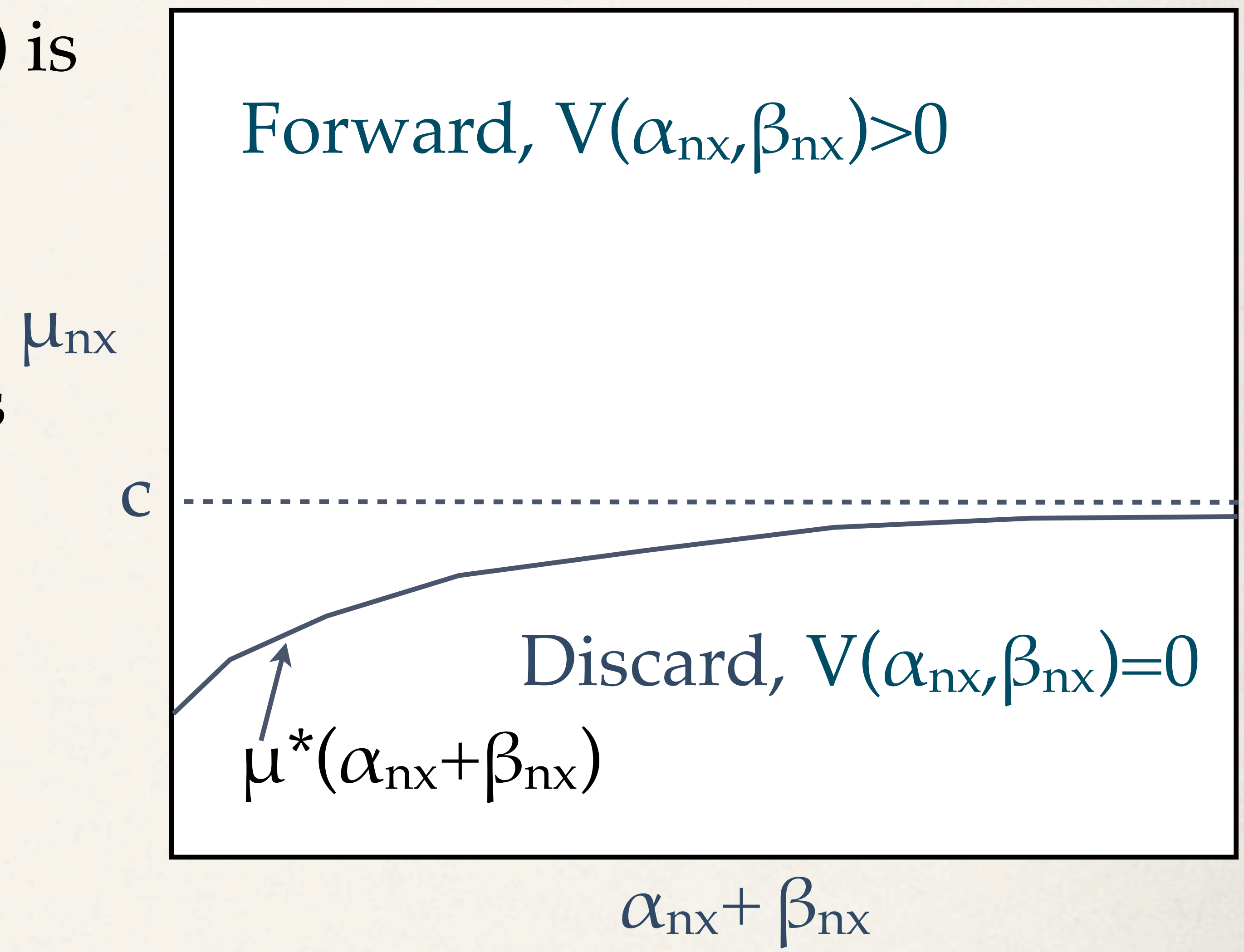
- **Theorem 2**: $\mu^*(\alpha+\beta)$ has the following properties:
  - it is bounded above by c;
  - it is increasing in $\alpha+\beta$;
  - it goes to c as $\alpha+\beta\to\infty$.



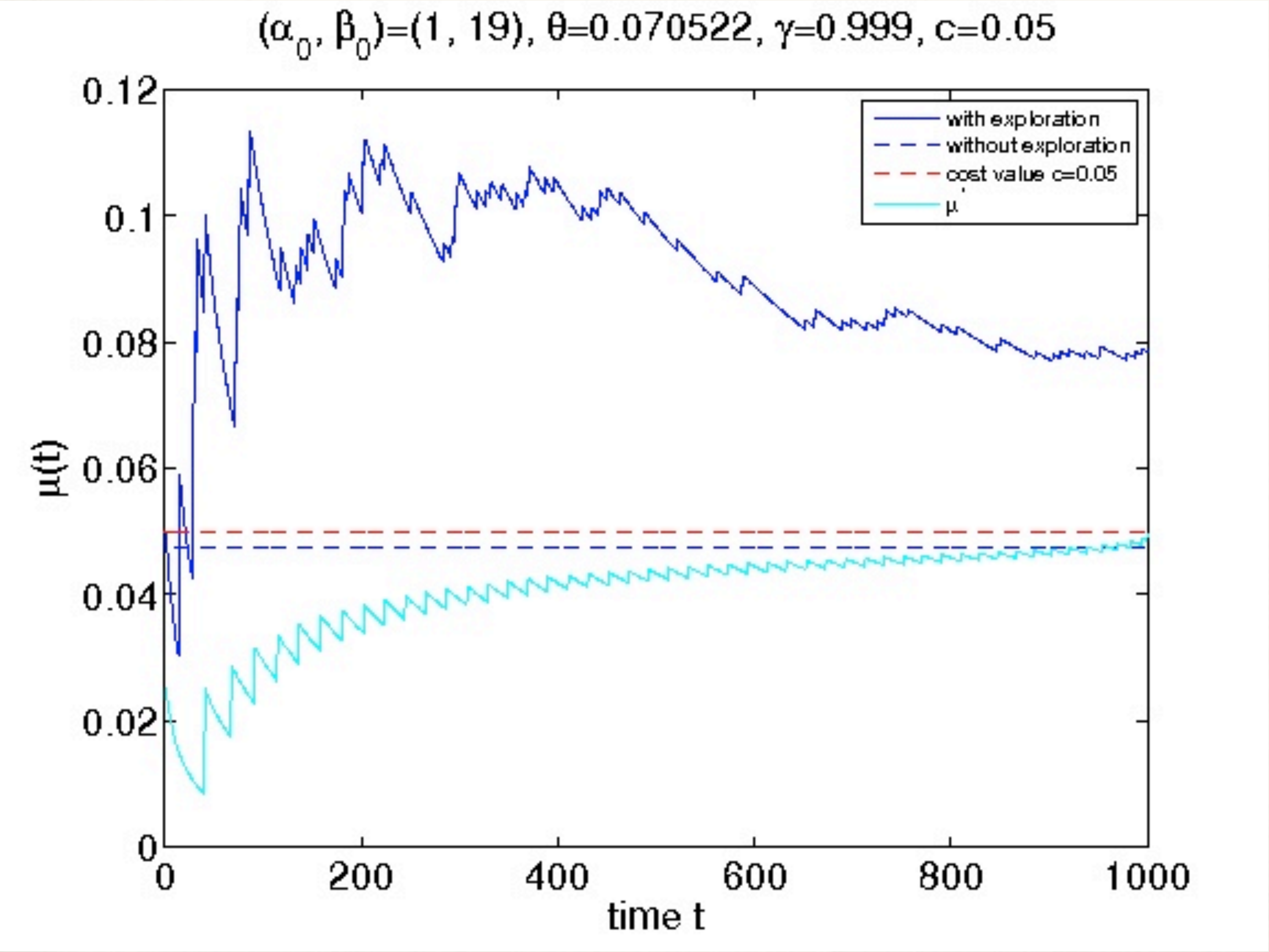
The optimal algorithm trades **exploration vs. exploitation**

- When $\alpha_{nx}+\beta_{nx}$ is small, $\mu^*(\alpha_{nx}+\beta_{nx})$ is much less than c, and we favor **exploration**.

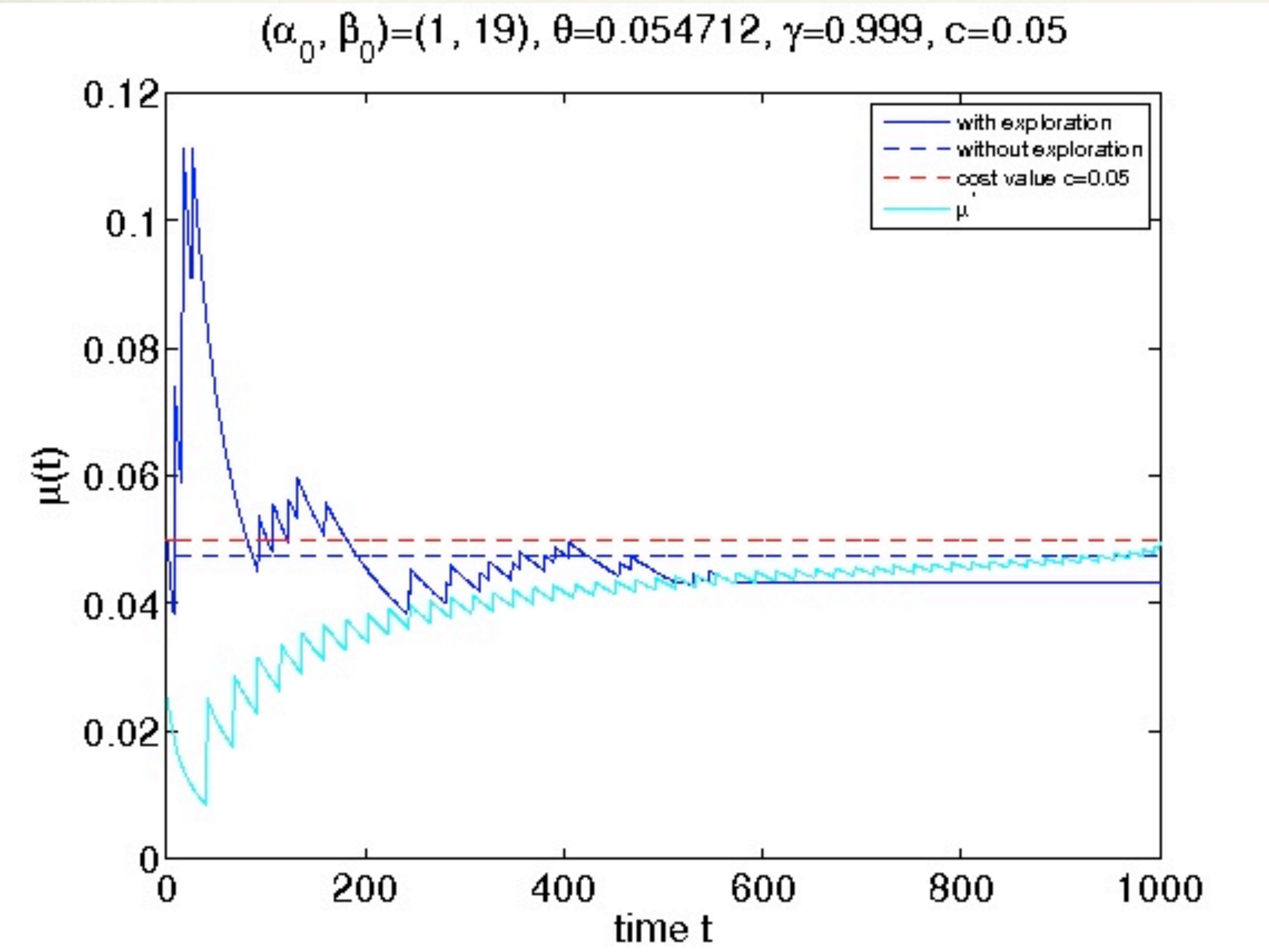
- When $\alpha_{nx}+\beta_{nx}$ is big, $\mu^*(\alpha_{nx}+\beta_{nx})$ is close to c, and we favor **exploitation**.



Here's a sample path where optimal is **better** than myopic



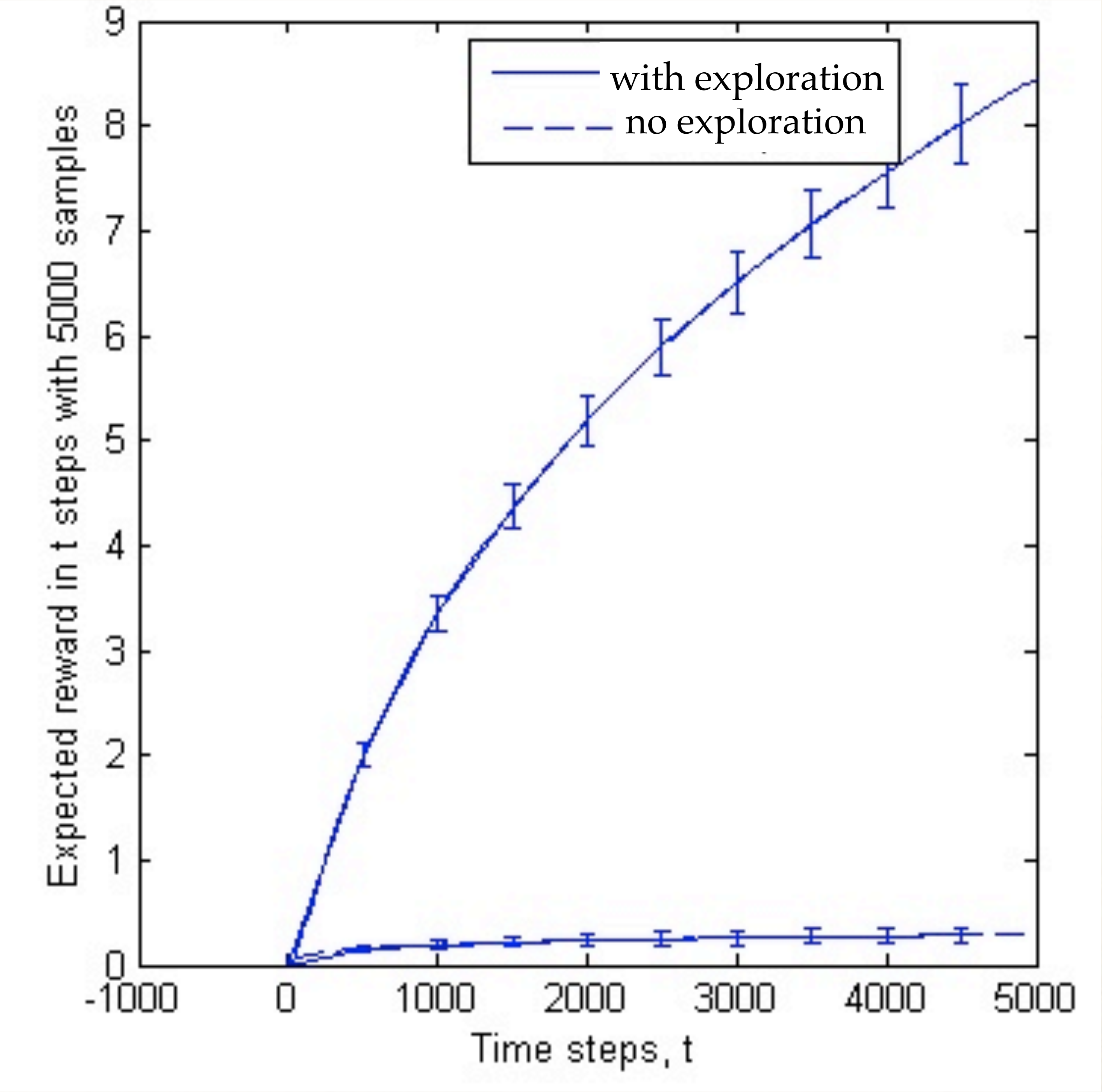
Here's a sample path where optimal is **worse** than myopic

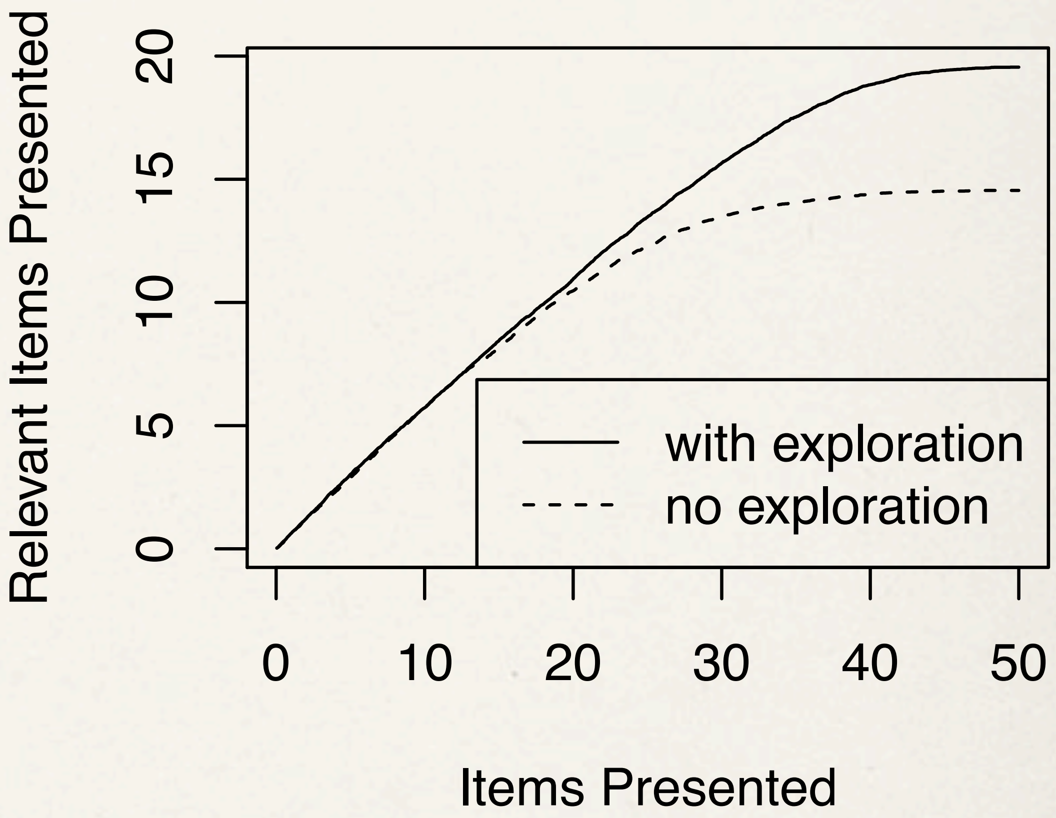


This is actually a bandit problem

- Deciding whether to forward or discard is really a 2-armed bandit problem.
  - Arm 0 corresponds to discarding, and always gives reward 0.
  - Arm 1 corresponds to forwarding, and gives reward Y_{nx}-c
- Each arm has associated with it a Gittins index, and the optimal policy is to pull the arm with the highest Gittins index.
  - The Gittins index of arm 0 is 0.
  - The Gittins index of arm 1 is $\nu(\alpha_{nx},\beta_{nx})$.
- $\nu(\alpha_{nx},\beta_{nx})>0 \Leftrightarrow \mu^*(\alpha_{nx}+\beta_{nx})>c$.

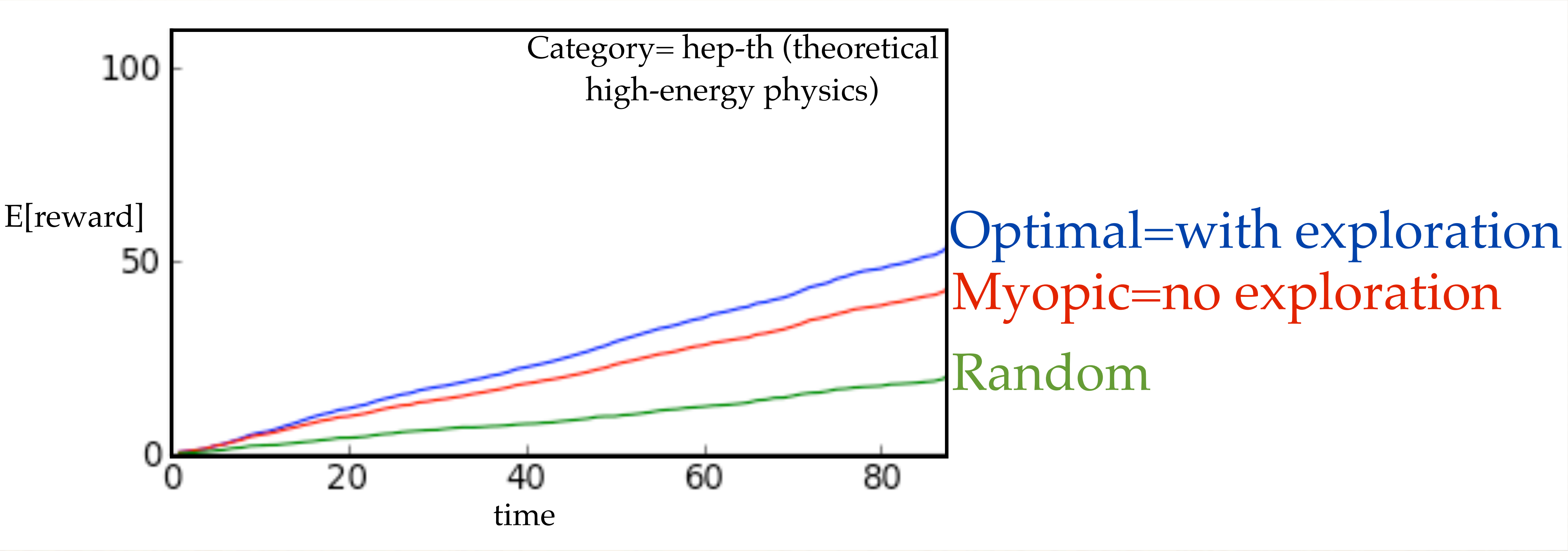
Optimal outperforms myopic (in idealized simulations)



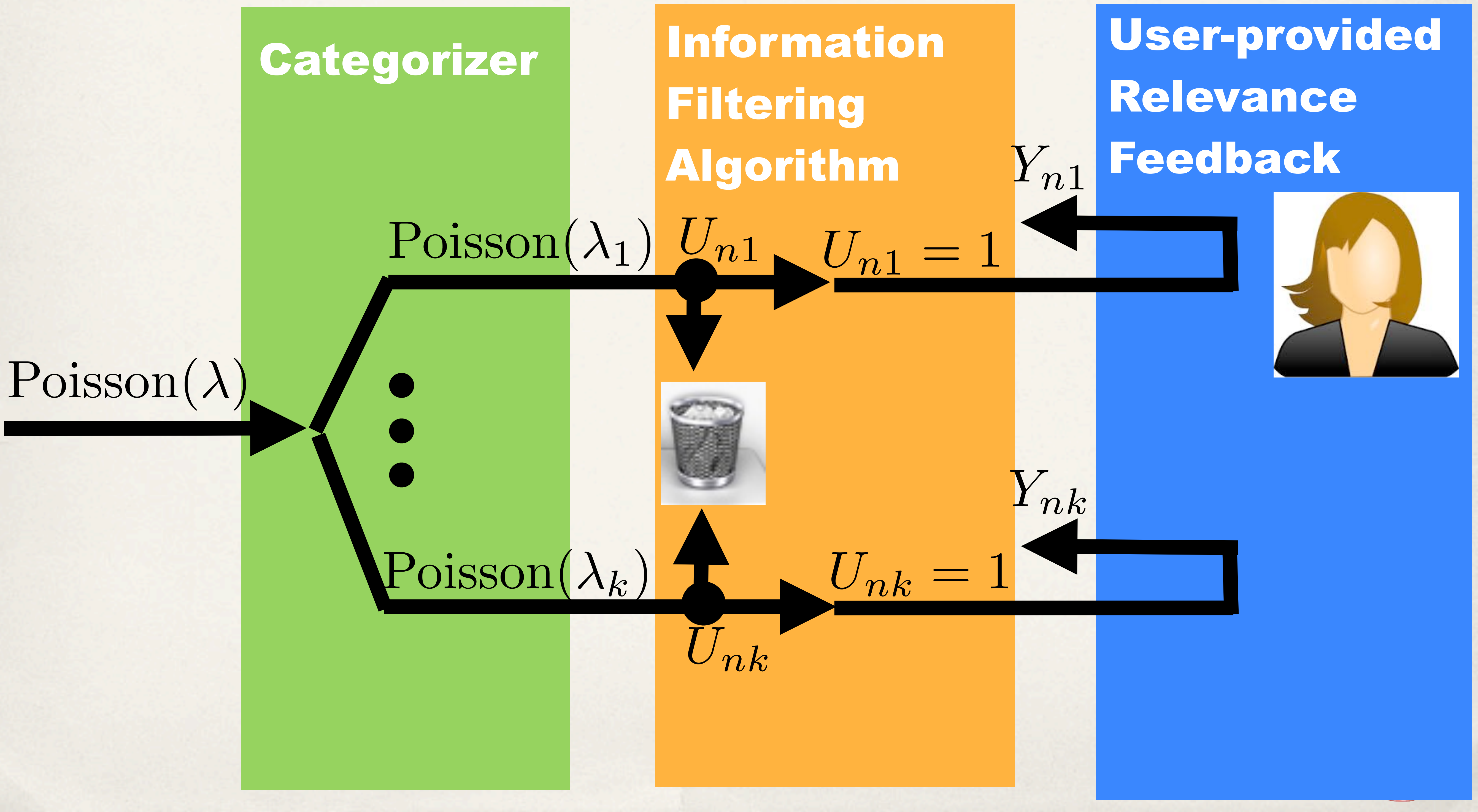


In these graphs,
"with exploration"=optimal
"no exploration"=myopic

Optimal outperforms myopic (in trace-driven simulations with historical data)



Combining single-category solutions solves the multi-category problem



Combining single-category solutions solves the multi-category problem

- We know the optimal forwarding/discarding strategy for a single category.

- To deal with multiple categories, simply apply this strategy independently to each individual category.

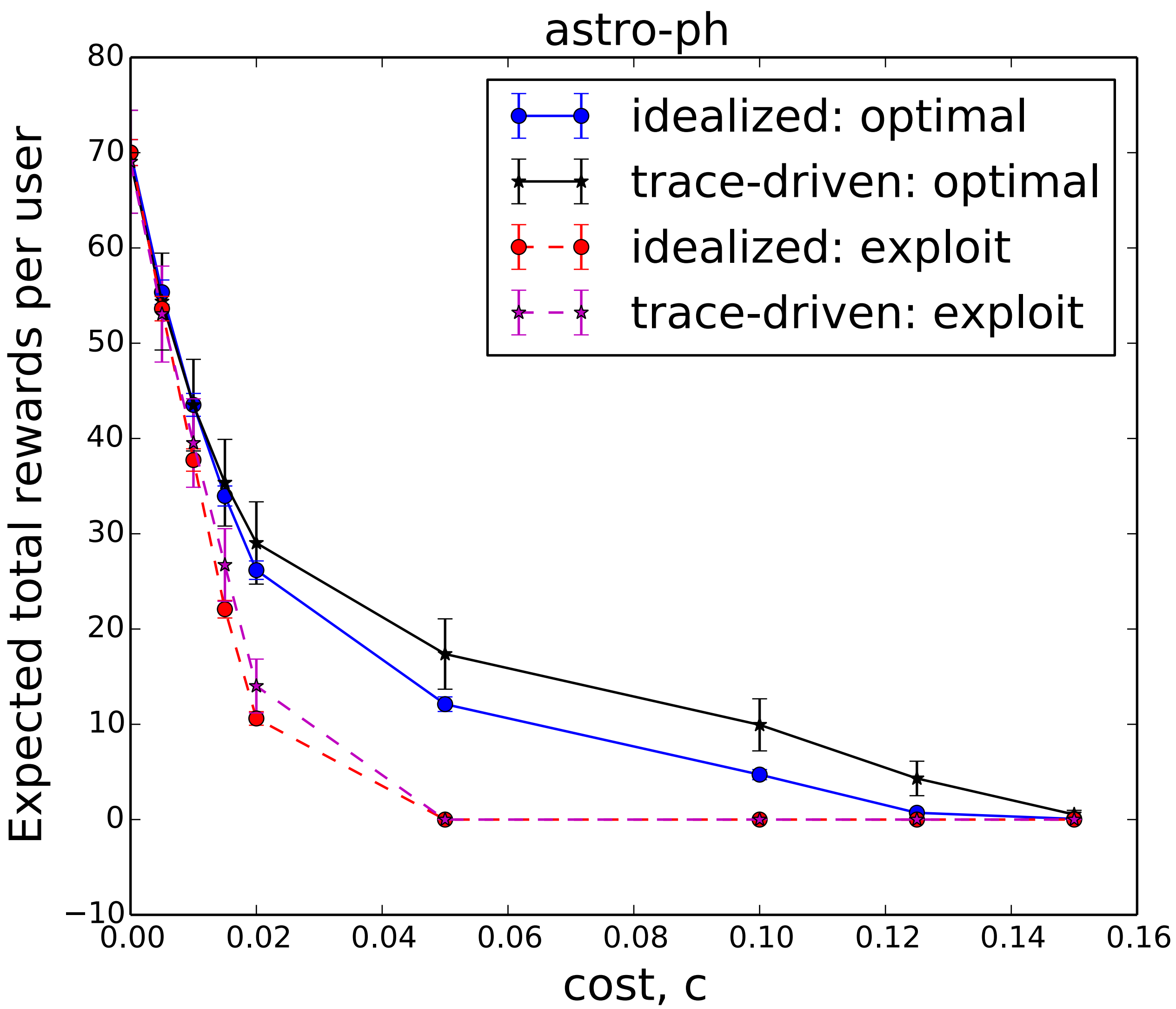
- The value of this optimal multi-category strategy is the sum of the values of the optimal single-category strategies:

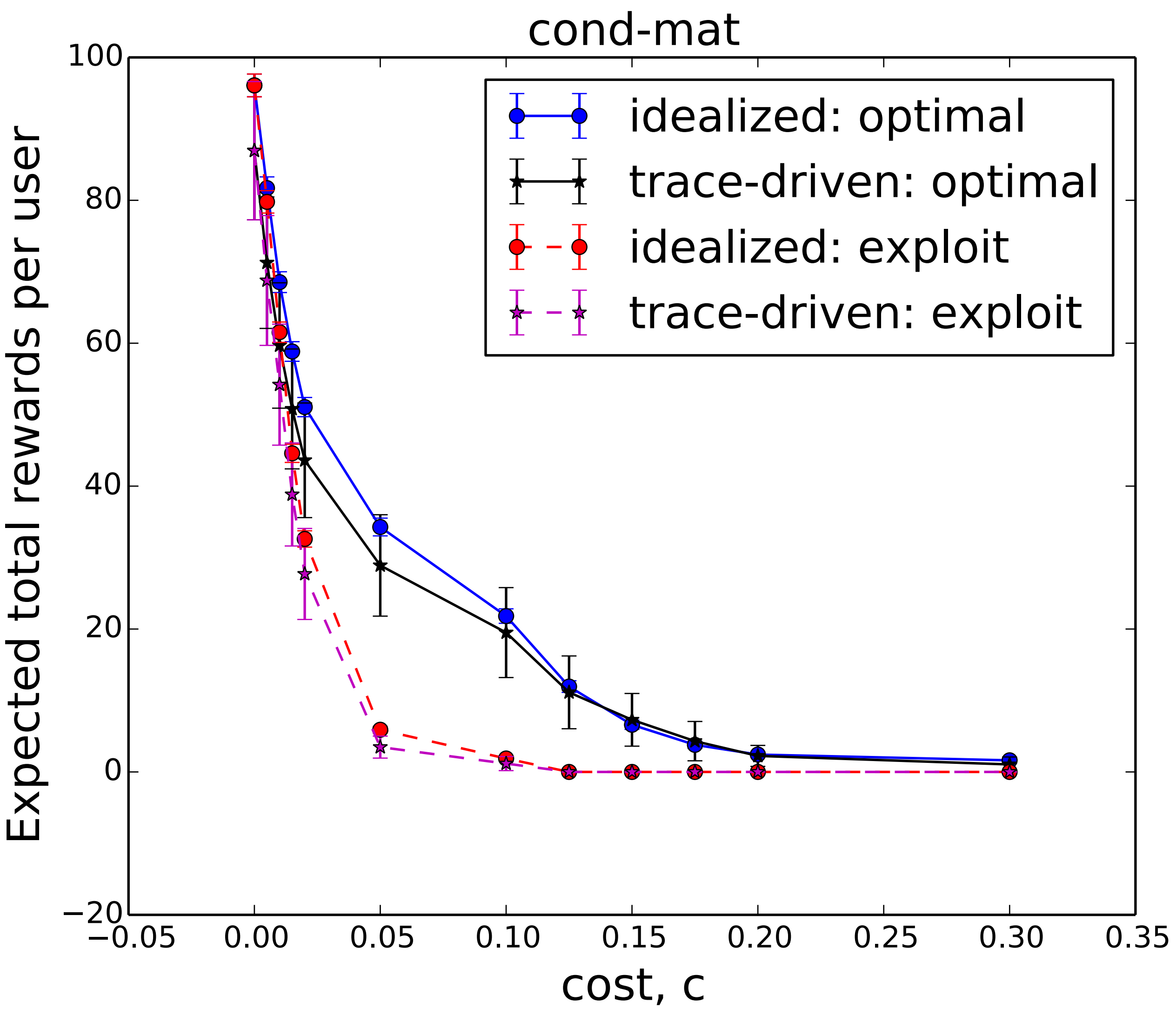
$$\sup_{\pi} E^{\pi}\left[\sum_{x=1}^{k}\sum_{n=1}^{N_x} U_{nx}(Y_{nx}-c)\right] = \sum_{x=1}^{k}\sup_{\pi} E^{\pi}\left[\sum_{n=1}^{N_x} U_{nx}(Y_{nx}-c)\right]$$

This decomposition technique avoids the curse of dimensionality

- We designed our mathematical problem to make it possible to solve for each category separately.
- The dynamic program for a single category has a 2-dimensional state variable (α_{nx},β_{nx}), and is thus easy to solve.
- The multi-category problem can also be solved directly as a dynamic program, but its state variable $(\alpha_{nx},\beta_{nx}: x=1,\ldots,k)$ has 2k dimensions, and is very hard to solve directly when k is large.

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





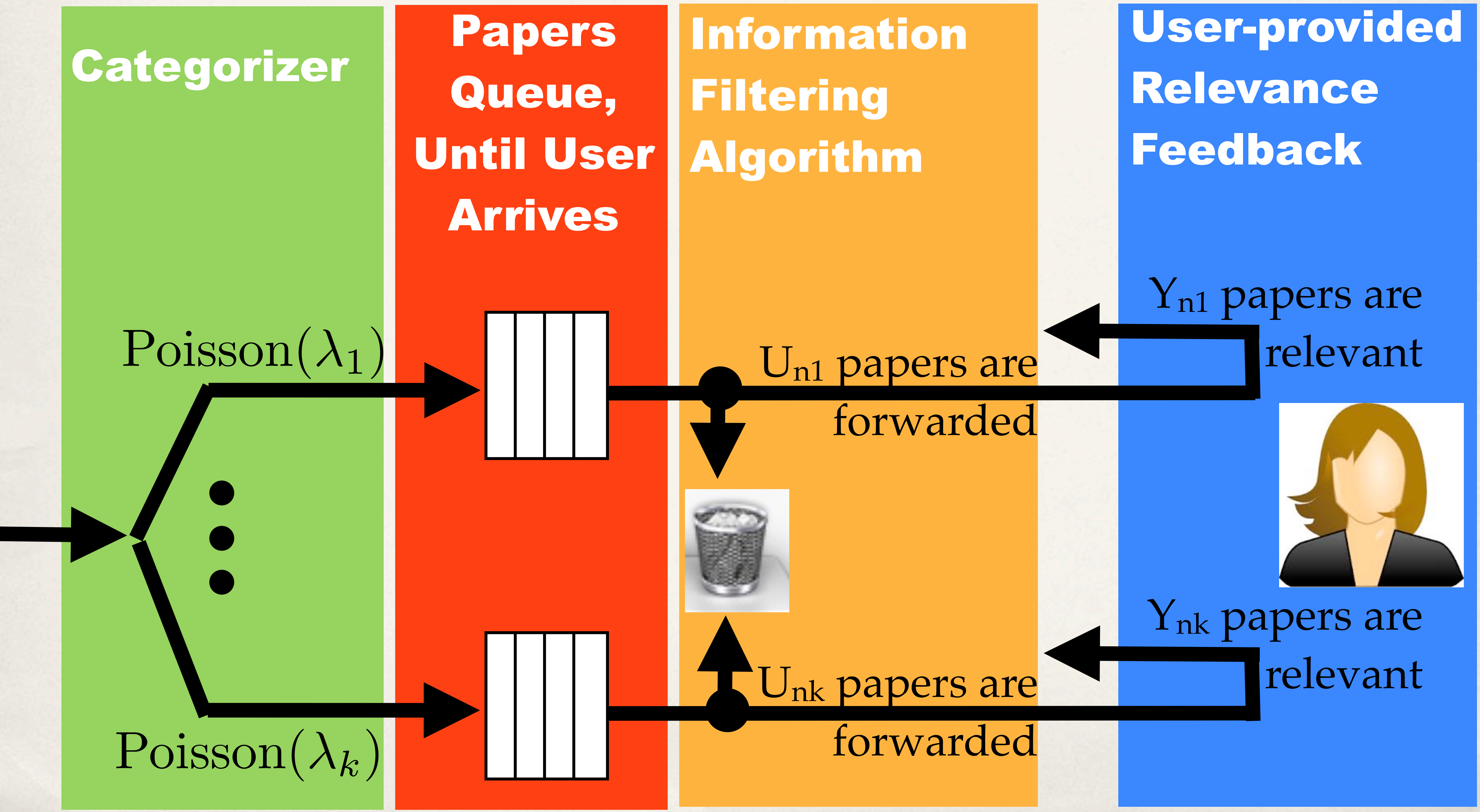
Outline

- Categorizing items
- Mathematical Model
- Extension #1: Periodic Review
- Extension #2: Unknown Costs

In reality, users review papers periodically, not instantaneously

- In the arxiv, users do not respond instantaneously. Instead they visit the arxiv periodically (once per day) to read papers.
- We allow papers to accumulate in a queue until the user arrives.
- When the user arrives, we decide which papers to forward/discard.
- We revise our analysis to handle this new model.

In reality, users review papers periodically, not instantaneously



We use a new mathematical model to handle periodic review

- We assume the user arrives to our website with interrarival times that are iid exponential, with known rate parameter.
  - Let N be the number of arrivals until the user's exponential time in system T elapses, so N is geometric.
  - Let n count user arrivals.
  - Let L_{nx} be the # of papers available for forwarding from category x, at the n^{th} user arrival, which is also geometrically distributed.
- Finding the optimal solution is also possible under other assumptions on user interarrival times.

We use a new mathematical model to handle periodic review

- The posterior on θ_x at the n^{th} user arrival will be Beta(α_{nx},β_{nx}) for some α_{nx},β_{nx}.
- Based on (α_{nx},β_{nx}), we choose U_{nx}, the max # of items to show from category x. [For simplicity, we choose U_{nx} before observing L_{nx}].
- Recall L_{nx} is the # of items available for forwarding from category x.
- We show $Z_{nx} = \min(L_{nx}, U_{nx})$ items from cluster x.

We use a new mathematical model to handle periodic review

- We observe relevance feedback for each of the Z_{nx} items shown.
- The number of relevant items is:
  - $Y_{nx} \mid \theta_x, Z_{nx} \sim \text{Binomial}(\theta_x, Z_{nx})$
- As before, the posterior that results is beta-distributed, with parameters that count the number of relevant and irrelevant items shown.

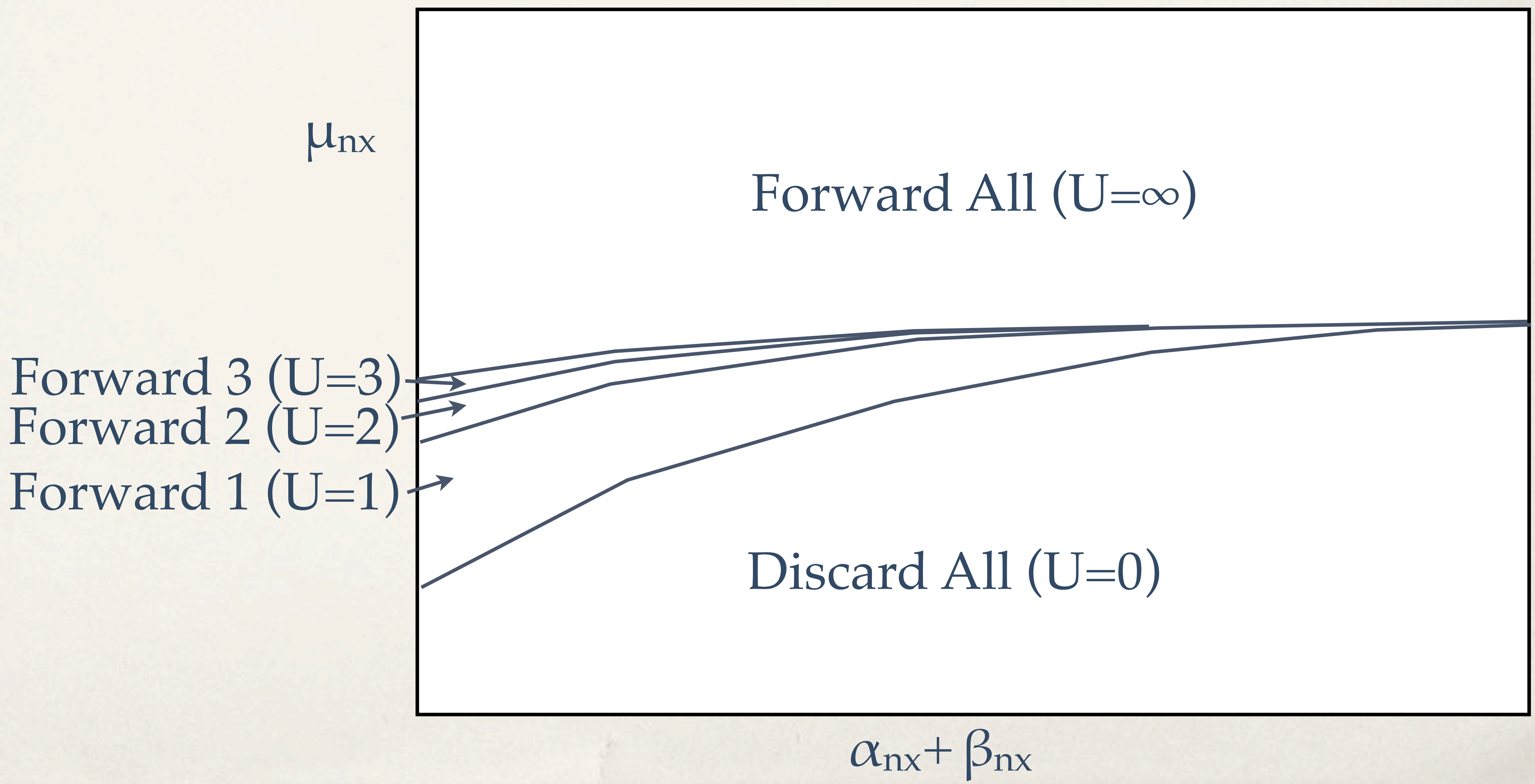
We use a new mathematical model to handle periodic review

- As before, our reward is the total number of **relevant** items shown, minus the cost of **all** items shown.
- The resulting stochastic dynamic program we wish to solve is:

$$\sup_{\pi} E^{\pi} \left[\sum_{x=1}^{k} \sum_{n=1}^{N} (Y_{nx} - cZ_{nx}) \right]$$

Here is what a single-category policy looks like

- In the previous single-category problem, we divided into "Forward" (U=1) and "Discard" (U=0). Now we divide into more levels.



As before, we avoid the curse of dimensionality by decomposing the multi-category problem into k single-category problems

- We can compute the optimal forwarding/discarding strategy for the single-category problem via stochastic dynamic programming.
- To deal with multiple categories, simply apply this strategy independently to each individual category.
- The value of this optimal multi-category strategy is the sum of the values of the optimal single-category strategies.

$$\sup_{\pi} E^{\pi}\left[\sum_{x=1}^{k}\sum_{n=1}^{N}(Y_{nx} - cZ_{nx})\right] = \sum_{x=1}^{k} E^{\pi}\left[\sum_{n=1}^{N}(Y_{nx} - cZ_{nx})\right]$$

Outline

- Categorizing items
- Mathematical Model
- Extension #1: Periodic Review
- Extension #2: Unknown Costs

In reality, we do not know c, the cost of the user's time.

- Rather than forwarding a set of papers based on c, we present **all** of the available items, in a ranked list.

- A user typically starts at the top of the list, and looks at papers in the presented order until he or she decides to stop.

We rank papers by building on our previous analysis

- Compute $c^*(m,x)$ for each cluster, which is the largest cost c in the periodic review model such that $U_{nx} \geq m$, i.e., such that we would be willing to forward at least m papers from cluster x.

- In each cluster x, put papers in a random order [since papers are indistinguishable within a cluster], and assign the m^{th} paper in the cluster a "value" $c^*(m,x)$.

- $c^*(m,x)$ is the largest price we would be willing to pay to see the m^{th} paper from cluster x.

- Present papers in a ranked list in decreasing order of $c^*(m,x)$.

This method is optimal in special cases, but not in general.

- If we model the user as knowing his own c, and looking at papers from top to bottom, stopping immediately before the first paper with $c^*(m,x) < c$, then this algorithm **is optimal**.

- If we model the user as looking at the top q papers in the list each time, this algorithm **is not optimal**, but we can obtain tractable upper and lower bounds on the optimal policy's value.

- If $q=1$, and all categories always have at least one paper available, this algorithm **is optimal**, and is equivalent to the Gittins index policy for multi-armed bandits.

Conclusion

- We presented an information filtering problem arising in the design of a recommender system for arXiv.org
  - We started with a very simple model, which assumed a know cost, and instantaneous feedback from the user.
  - We extended this model to allow periodic review, in which the user provides feedback on items in batches.
  - Finally, we extended this model to unknown cost for the user’s time.
- We are in the process of testing this system, and rolling it out to users of the arXiv.

Thanks to my collaborators!

- Paul Ginsparg, Thorsten Joachims, Xiaoting Zhao, Darlin Alberto, Karthik Raman, Ziyu Fan, Akilesh Potti (**Cornell**)
- Paul Kantor & Vladimir Menkov (**Rutgers**)
- Dave Blei & Laurent Charlin (**Princeton**)








Thank you for your attention!

Backup Slides

Extensions we did not discuss: Time-varying user preferences

- User preferences change over time.
- Our Bayesian statistical model may be extended to allow θ_x to change over time.
- The analysis is still tractable.

Extensions we did not discuss: Correlated prior distributions

- Our model assumed an independent prior on θ_x.
- In the data, a user's strong interest in one category (e.g., theoretical high-energy physics) may make a strong interest in another category more likely (e.g., experimental high-energy physics).
- We can model this with a correlated prior on θ_x.
- The dynamic program is no longer tractable, but we can compute $\mu^*(\alpha_{nx}+\beta_{nx})$ using independence, but update our posterior using a correlated prior.

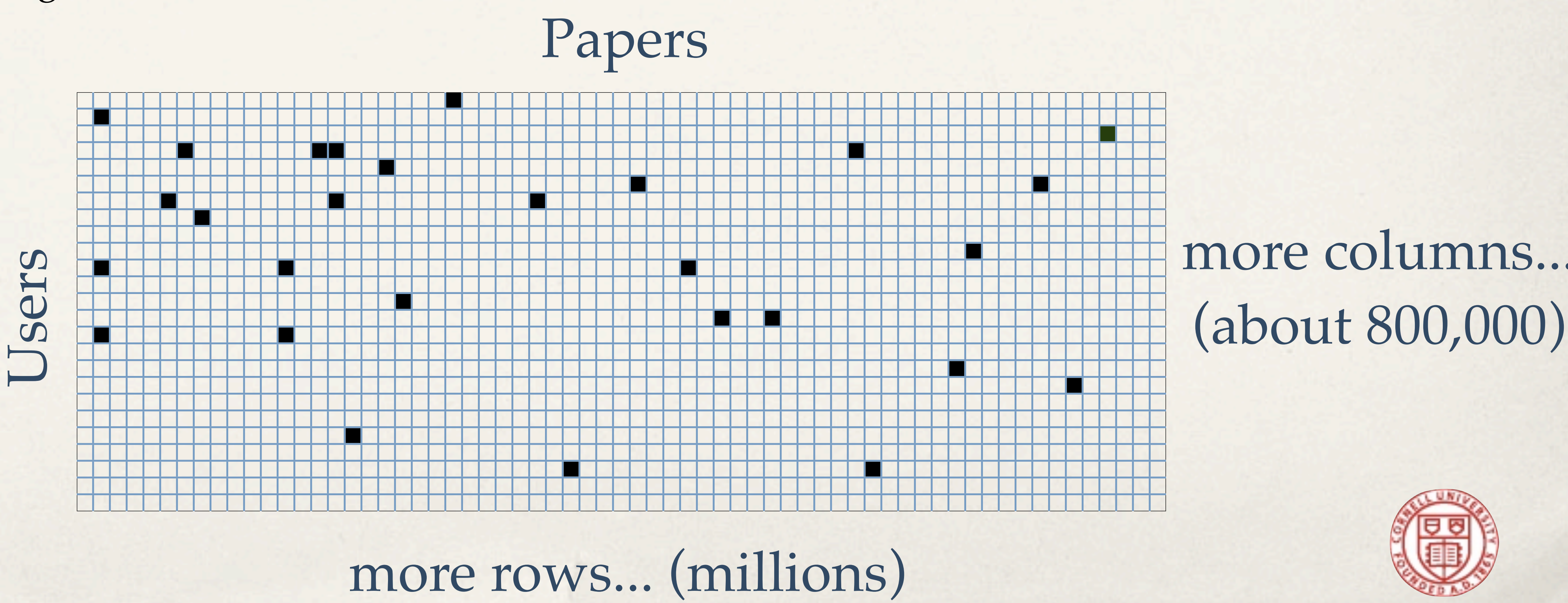
Additional details about our categorization method

Here’s a summary of our categorization method

- **Step 1**: We use historical data to create a ratings matrix for older items and users with lots of history.
- **Step 2:** We use a singular value decomposition to represent older items as points in a low-dimensional space. Dimensions correspond roughly to “topics”.
- **Step 3:** We use kmeans clustering on the low-dimensional space to cluster older items.
- **Step 4**: We train a multi-class SVM to predict the cluster from item features, e.g., the words in a paper, or the authors.

Step 1 in creating our categorizer is to create a ratings matrix

- **Step 1**: We use historical data to create a "ratings" matrix.
  - Each row i is a user. Only established users, with lots of history, are used in the ratings matrix.
  - Each column j is a paper. Only older papers, with lots of history, are used in the ratings matrix.
  - Cell (i,j) is 1 if user i downloaded paper j, and 0 if not.
  - This is a big matrix: 800,000 columns, and a similar number of rows

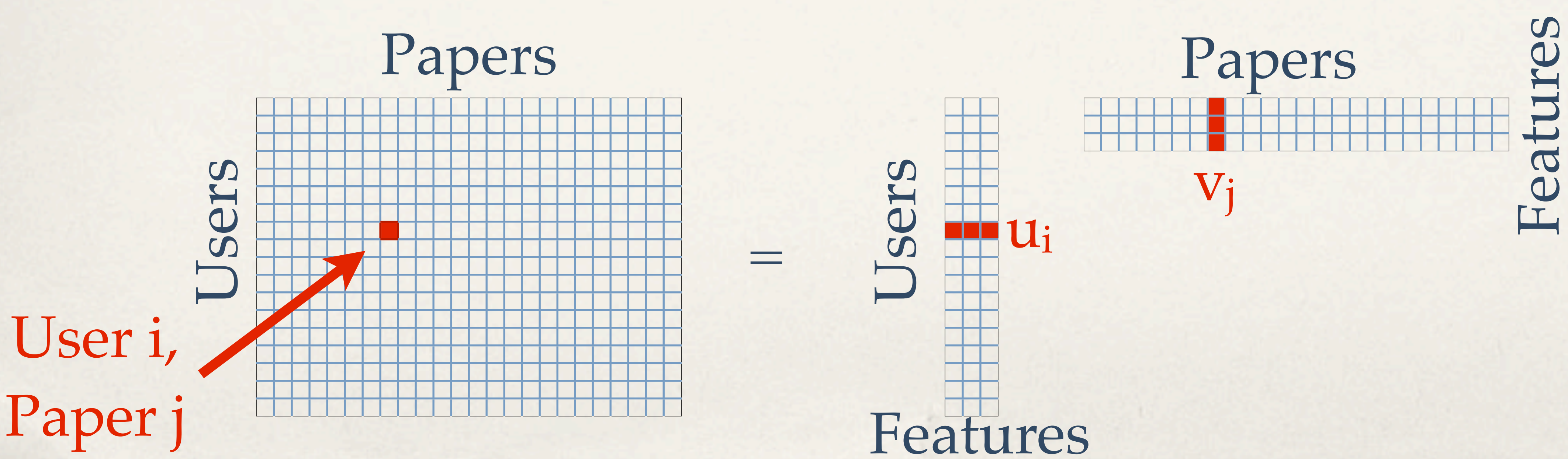


Step 2 in creating our categorizer is to do low-rank matrix factorization

- **Step 2:** We use a standard technique, called "low-rank matrix factorization", which will be described shortly.
- This technique will output a vector for each paper.
- Each component in the vector corresponds to some latent feature, e.g., "parallel computing" or "Bayesian statistics", and tells us how much of this feature this paper has.

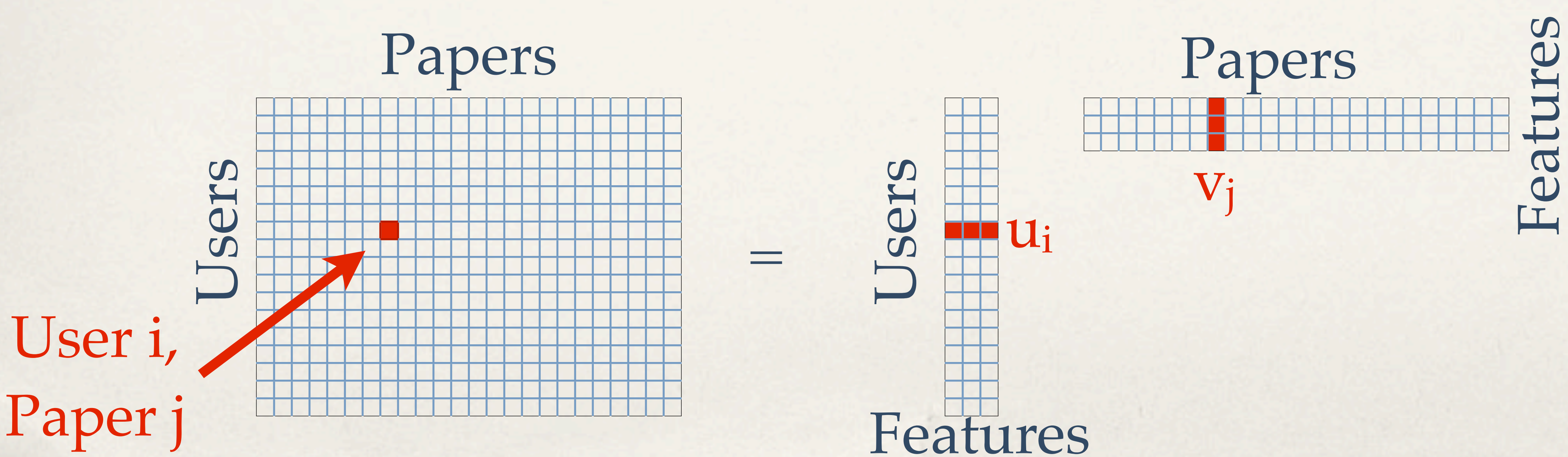
Step 2 in creating our categorizer is to do low-rank matrix factorization

- We suppose each (older) paper j is described by a vector v_j of length K.
  - Entry v_{jk} is the "amount of feature k" in paper j. (where k=1,...,K)
- We describe each (older) user i is described by a vector u_i of length K.
  - Entry u_{ik} is user i's "interest in feature k". (again, k=1,...,K)
- We suppose that user i's interest in paper j is approximated by $u_i(v_j)^T$



Step 2 in creating our categorizer is to do low-rank matrix factorization

- User i's interest in paper j is approximated by $u_i(v_j)^T$
- Put all the row vectors u_i into a "tall & skinny" matrix U, and all of the column vectors v_j into a "long & skinny" matrix V.
- Then, our approximation of the ratings matrix is UV.



Step 2 in creating our categorizer is to do low-rank matrix factorization

- We don't know the U and V matrices, so we choose their values to make the approximation as good as possible.

- This is really an optimization problem:

$$\min_{U,V} ||\text{RatingsMatrix} - UV||$$

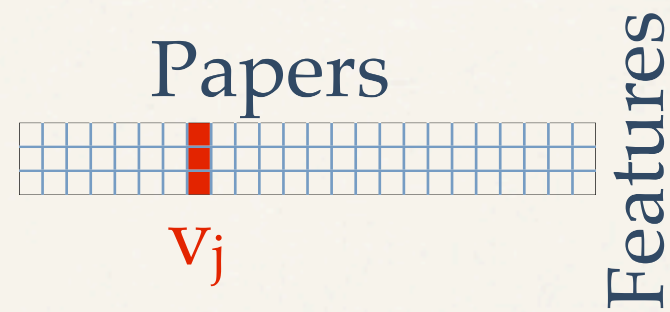
- where the matrices are constrained to have skinny dimension K, and where we usually use the sum of squared entries as our matrix norm.

- This optimization problem can be solved efficiently:

  - 1. Perform a singular value decomposition (SVD) of RatingsMatrix
  - 2. Take the largest K singular values, and the corresponding singular vectors, to create U and V.

Step 2 in creating our categorizer is to do low-rank matrix factorization

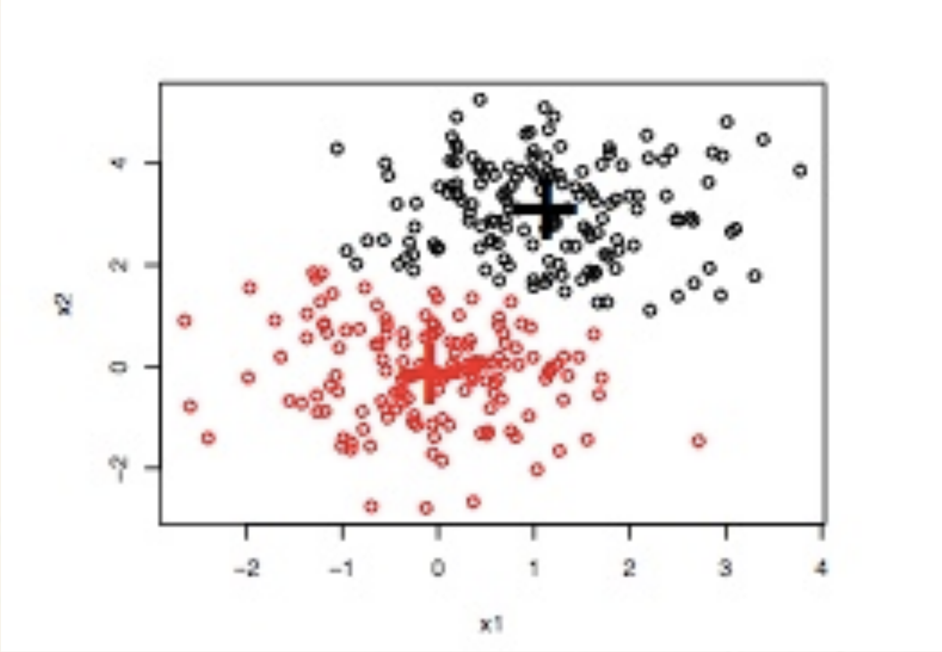
- This process gives us the matrix **V**:



- Each column of this matrix is a paper, and describes what the paper is about.
- We will feed these columns into the next step of our categorizer
- The matrices U and V can also be used to recommend old papers to old users:
  - Predict the rating for an unknown user / paper pair (i,j) from the estimated values for U and V. Then recommend papers for which this prediction is large.
- However, we want to filter **new papers**, and we want to do this well for **all users**, old & new.

We use a pre-processing step that divides items into categories

- **Step 3:** We think each paper j as the point v_j in R^K. We then use a clustering algorithm (kmeans) to cluster nearby papers together.



- All of the papers in a single cluster are about similar things.

- Our categorizer will try to reproduce these clusters in the categories it creates. It must do so based on things that can be directly observed from the paper, rather than how it was viewed by users.

We use a pre-processing step that divides items into categories

- **Step 4**: We train a multi-class support vector machine to predict the cluster from observable paper features: the words in a paper.

Paper	Cluster	Word 2: **a**	Word 2: **aa**	Word 2: **aardvark**	Word 2: **aardwolf**	Word3: **aargh**	Word4: **Aarhus**	....
1	16	Yes	No	Yes	No	No	No	...
2	11	Yes	No	No	No	No	No	...
3	1	Yes	No	No	No	No	No	...
4	2	Yes	No	No	No	No	Yes	...
5	11	Yes	No	No	No	No	No	...
...	...	...	...	....	....	....	....	...

- Once we have trained it, the SVM **can predict the category for new papers, based only on the words in them**. No ratings data is needed for new papers.

Additional details / alternate slides for periodic review

We use a new mathematical model to handle periodic review

- Let n count user arrivals (not papers).
- The posterior on θ_x at the n^{th} user arrival will be Beta(α_{nx},β_{nx}) for some α_{nx},β_{nx}.
- Based on (α_{nx},β_{nx}), we choose U_{nx}, the max # of papers to show from category x.
- Let L_{nx} be the # of papers available for forwarding from category x.
  - The stochastic process describing the user's interarrival times determines the distribution of L_{nx}. We assume these interarrival times are iid exponential, but other assumptions are possible.
- We show min(L_{nx}, U_{nx}) papers from cluster x. [U_{nx} is chosen before observing L_{nx}].
- We observe relevance feedback for each paper shown. All that we need to update our posterior is the # of relevant papers:
  - $Y_{nx} \mid \theta_x, L_{nx}, U_{nx} \sim \text{Binomial}(\theta_x, \min(L_{nx}, U_{nx}))$

We use a new mathematical model to handle periodic review

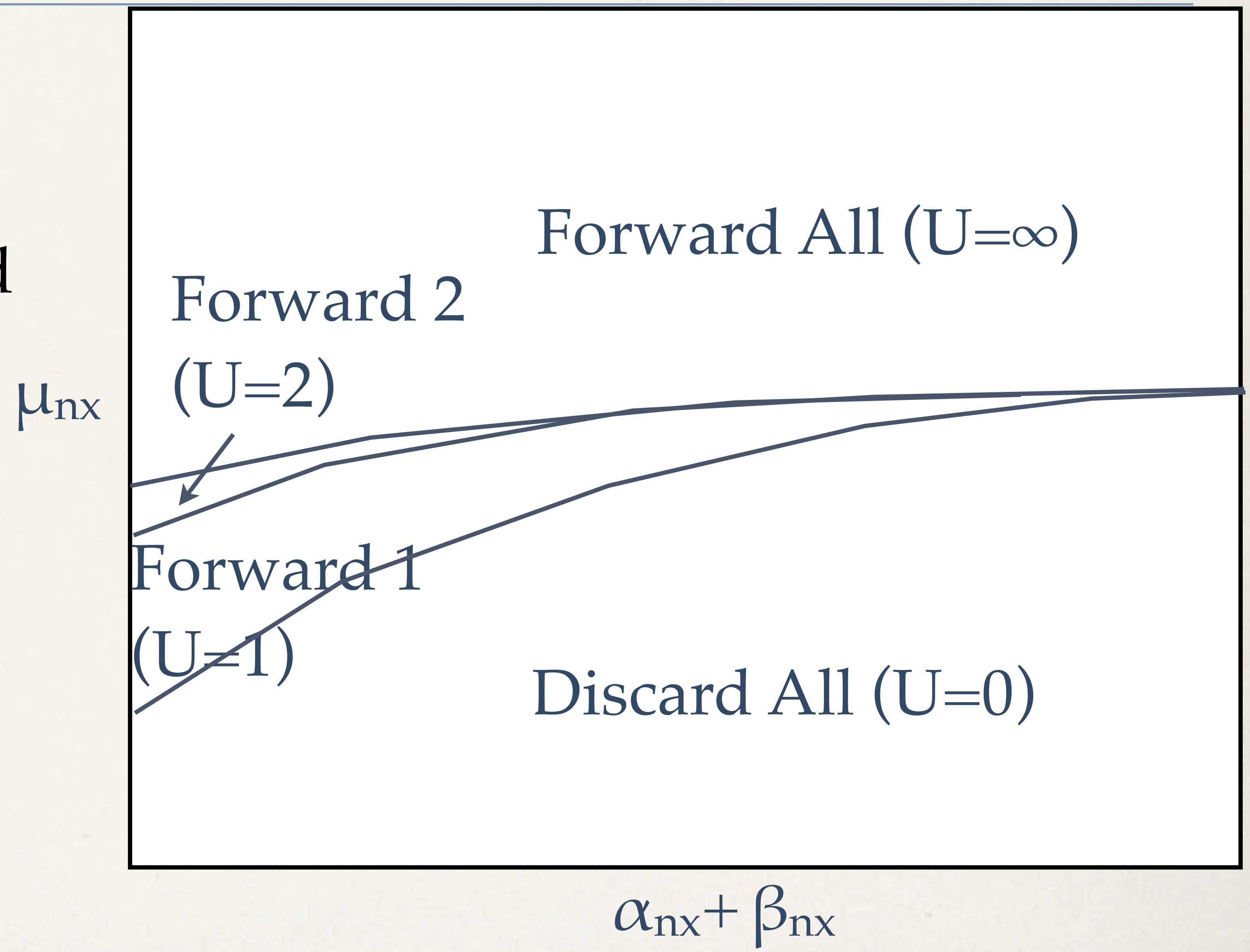
- Let n count user arrivals (not papers), and let $N_x = N$ be the number of arrivals until leaving the system.
- At each arrival we will show some **number** of papers from each cluster, up to the maximum available.
- We observe relevance feedback for each presented paper.
- As before, the posterior on θ_x at time n will be Beta(α_{nx},β_{nx}).
- Based on (α_{nx},β_{nx}), at time n, we choose U_{nx}, the max # of papers to show from category x.
- Let L_{nx} be the # of papers available for forwarding from category x.
  - The stochastic process describing the user's interarrival times determines the distribution of L_{nx}. To keep things simple, we assume interarrival times are iid.
  - For example, if the user goes exactly Δ time units between arrivals, then $L_{nx} \sim \text{Poisson}(\lambda_x \Delta)$. We also allow other assumptions about L_{nx}.
- We show $\min(L_{nx}, U_{nx})$ papers from cluster x.
- We observe relevance feedback for each of these:
  - $Y_{nx} \mid \theta_x, L_{nx}, U_{nx} \sim \text{Binomial}(\theta_x, \min(L_{nx}, U_{nx}))$

We can still avoid the curse of dimensionality

- Assume the times between a user's arrival are iid exponential.
- Let n count user arrivals, and let N
- As before, the posterior on θ_x at time n will be Beta(α_{nx},β_{nx}).
- Based on (α_{nx},β_{nx}), at time n, we choose U_{nx}, the max # of papers to show from category x.
- Let L_{nx} be the # of papers available for forwarding from category x.
    - The stochastic process describing the user's interarrival times determines the distribution of L_{nx}. To keep things simple, we assume interarrival times are iid.
    - For example, if the user goes exactly Δ time units between arrivals, then L_{nx}~Poisson($\lambda_x\Delta$). We also allow other assumptions about L_{nx}.
- We show min(L_{nx}, U_{nx}) papers from cluster x.
- We observe relevance feedback for each of these:
    - $Y_{nx} \mid \theta_x, L_{nx}, U_{nx} \sim \text{Binomial}(\theta_x, \min(L_{nx}, U_{nx}))$

Again, we solve the single category problem using stochastic dynamic programming

- Let $V(\alpha_{nx},\beta_{nx})$ be the expected future reward for a single category x under the optimal policy, given n documents of history.
- V satisfies the dynamic programming recursion:



$$V(\alpha_{nx},\beta_{nx}) = P(N_x \geq n+1 | N_x \geq n) \max_{u=0,1,2,\ldots} (\mu_{nx}-c)E[\min(u, L_{N+1,x})] + E_n\left[V(\alpha_{n+1,x},\beta_{n+1,x}) | U_{n+1,x}=u\right].$$