UNIVERSITY OF AMSTERDAM

Using users
for online evaluation and learning

Anne Schuth
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ILPS, University of Amsterdam

Recommender Meetup, December 8, 2014

Information Retrieval

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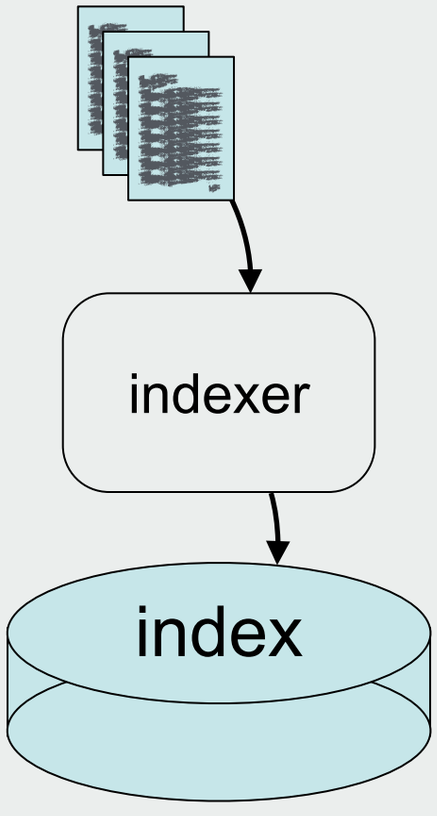

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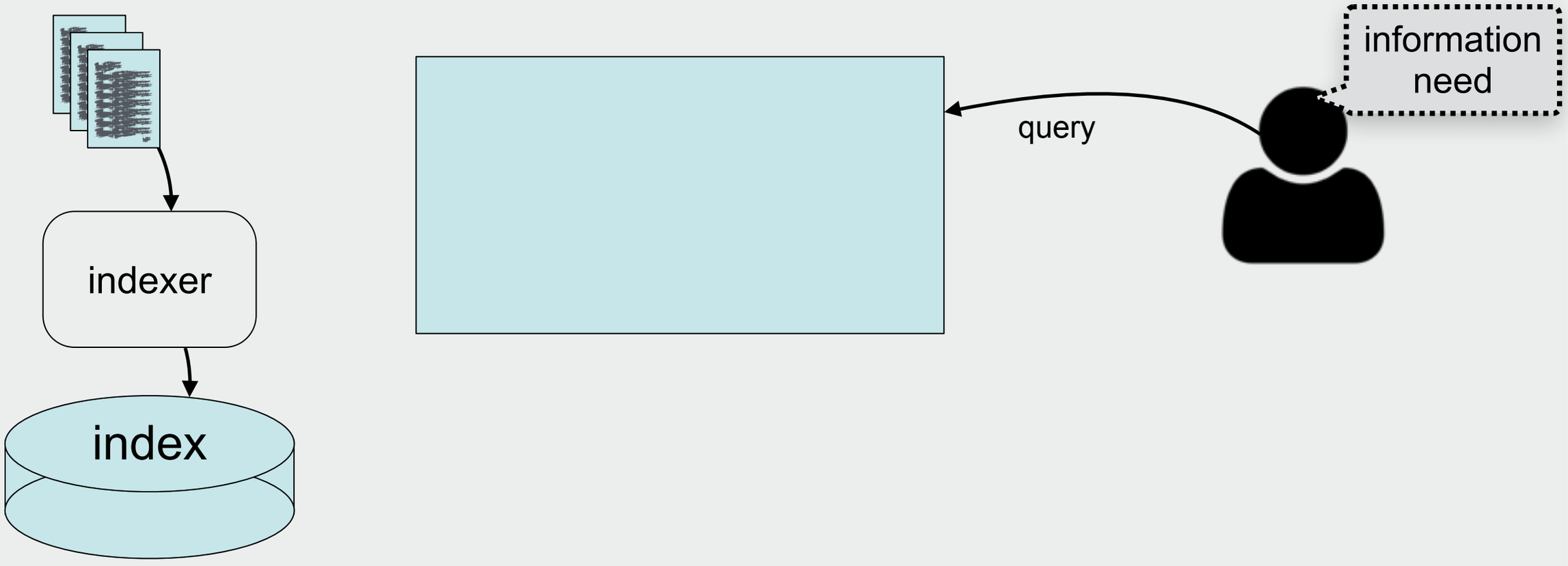

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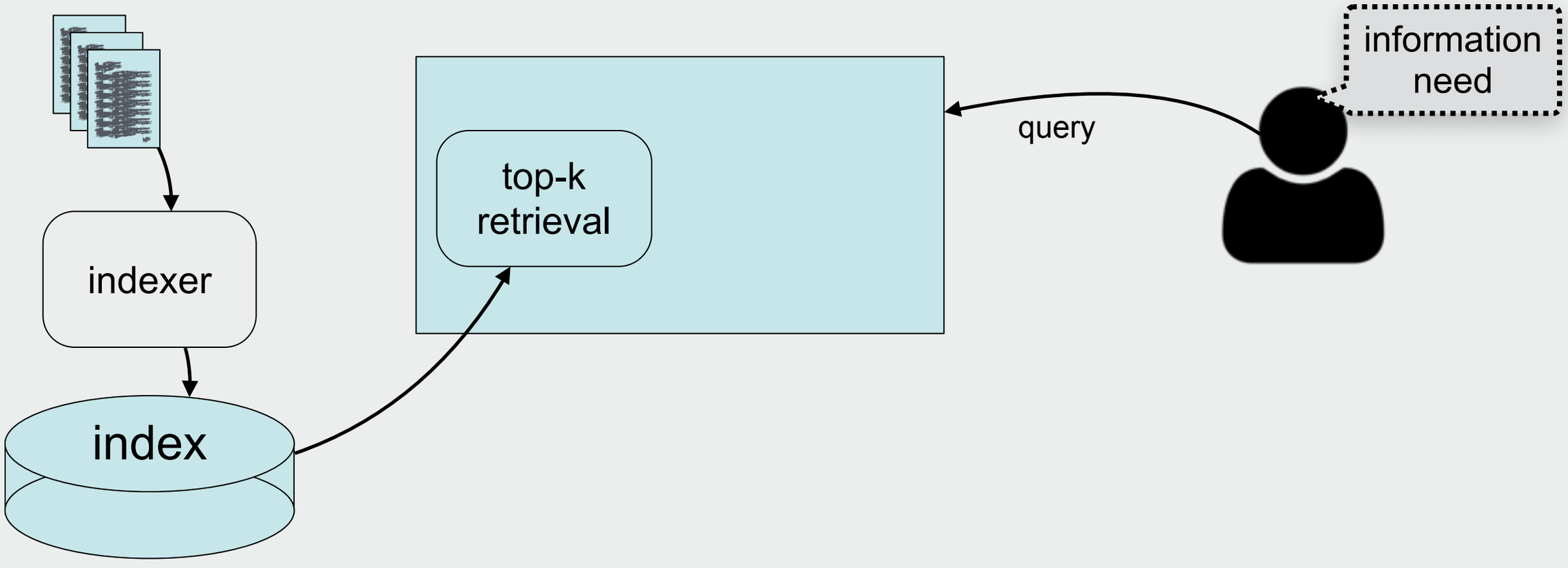

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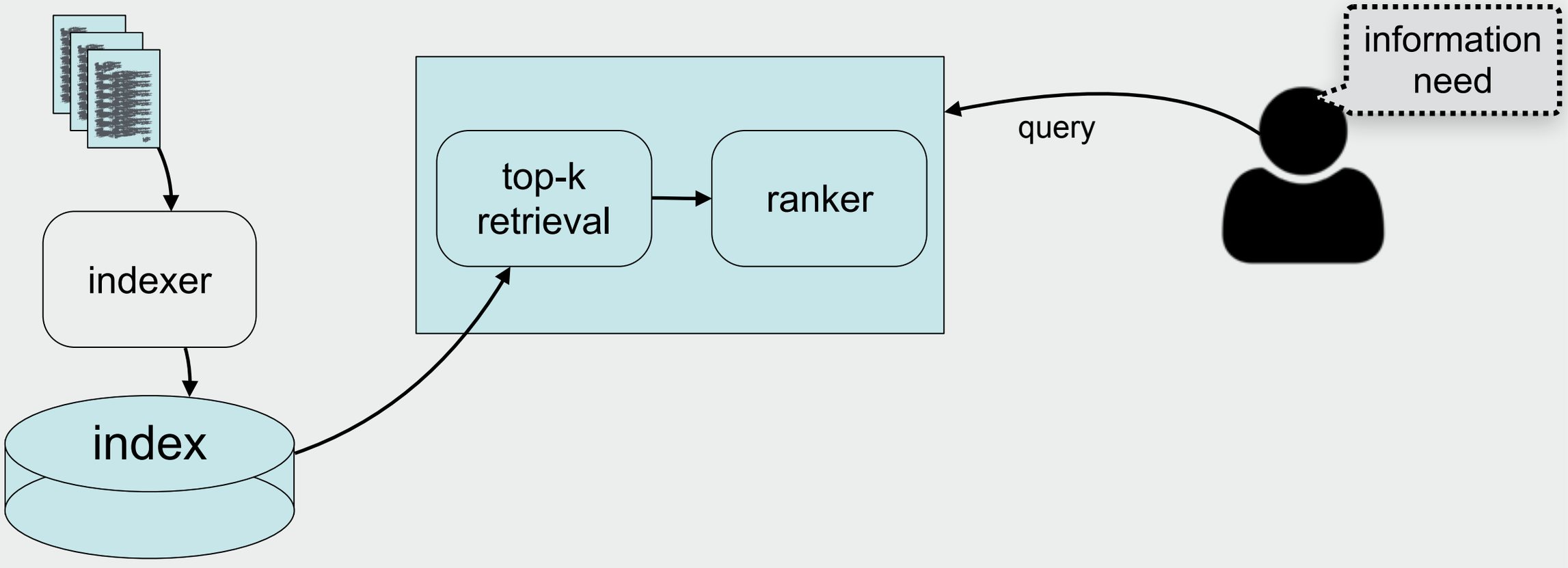

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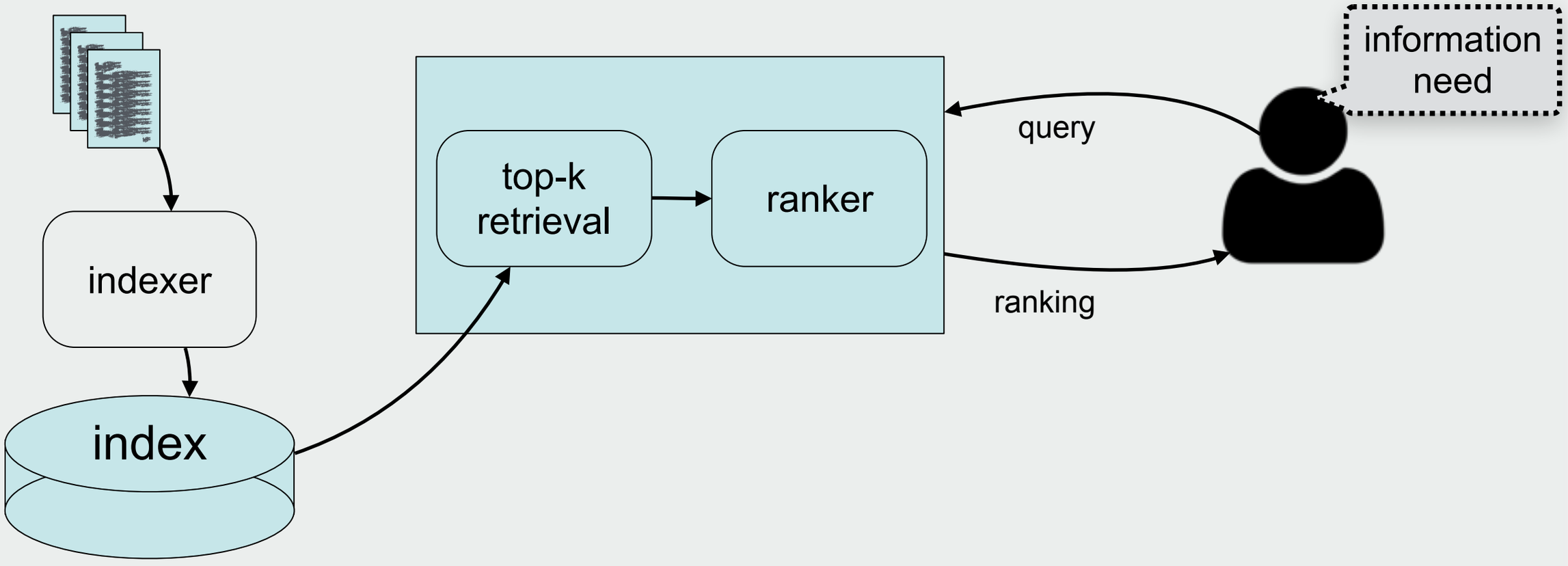

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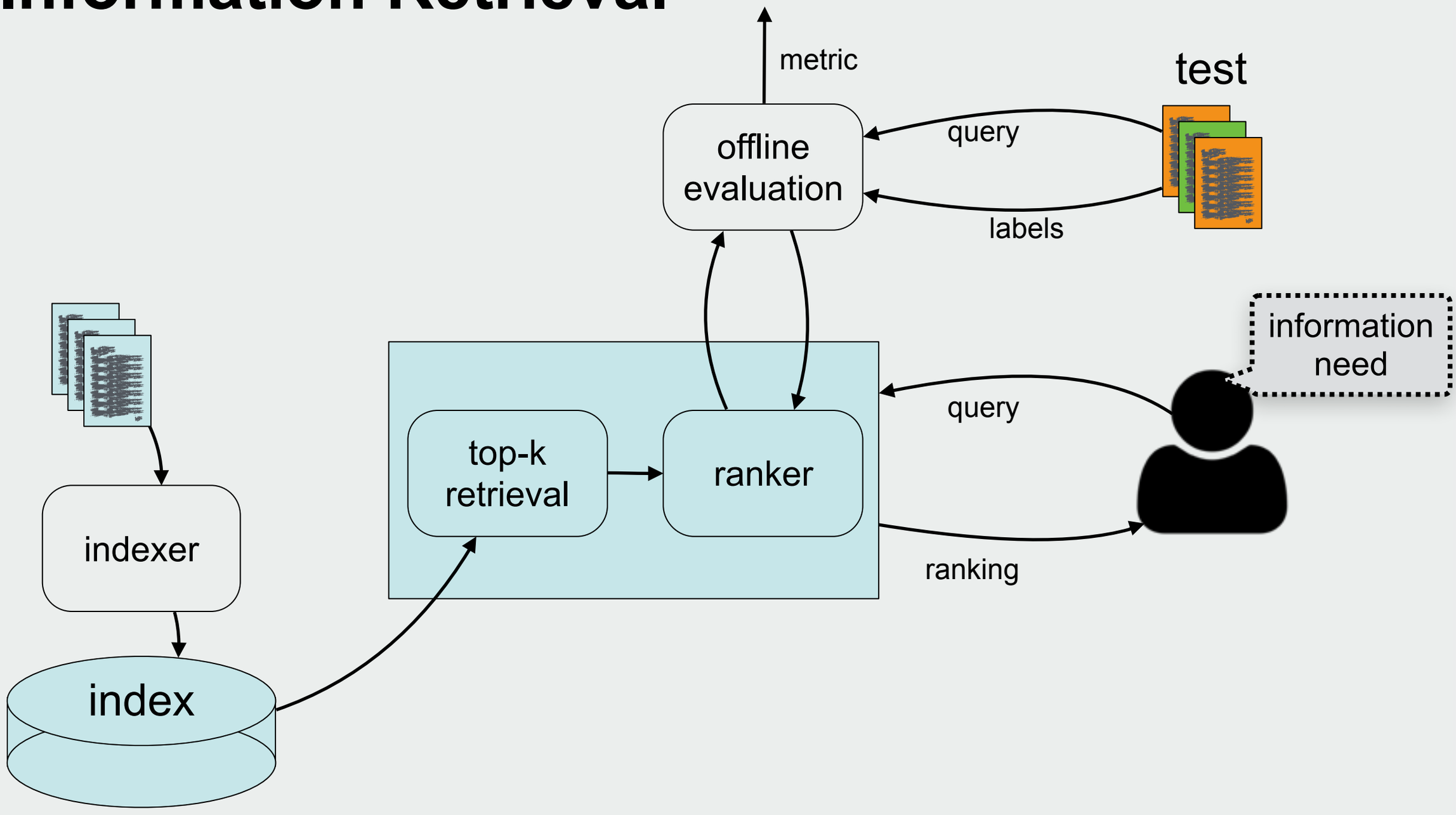

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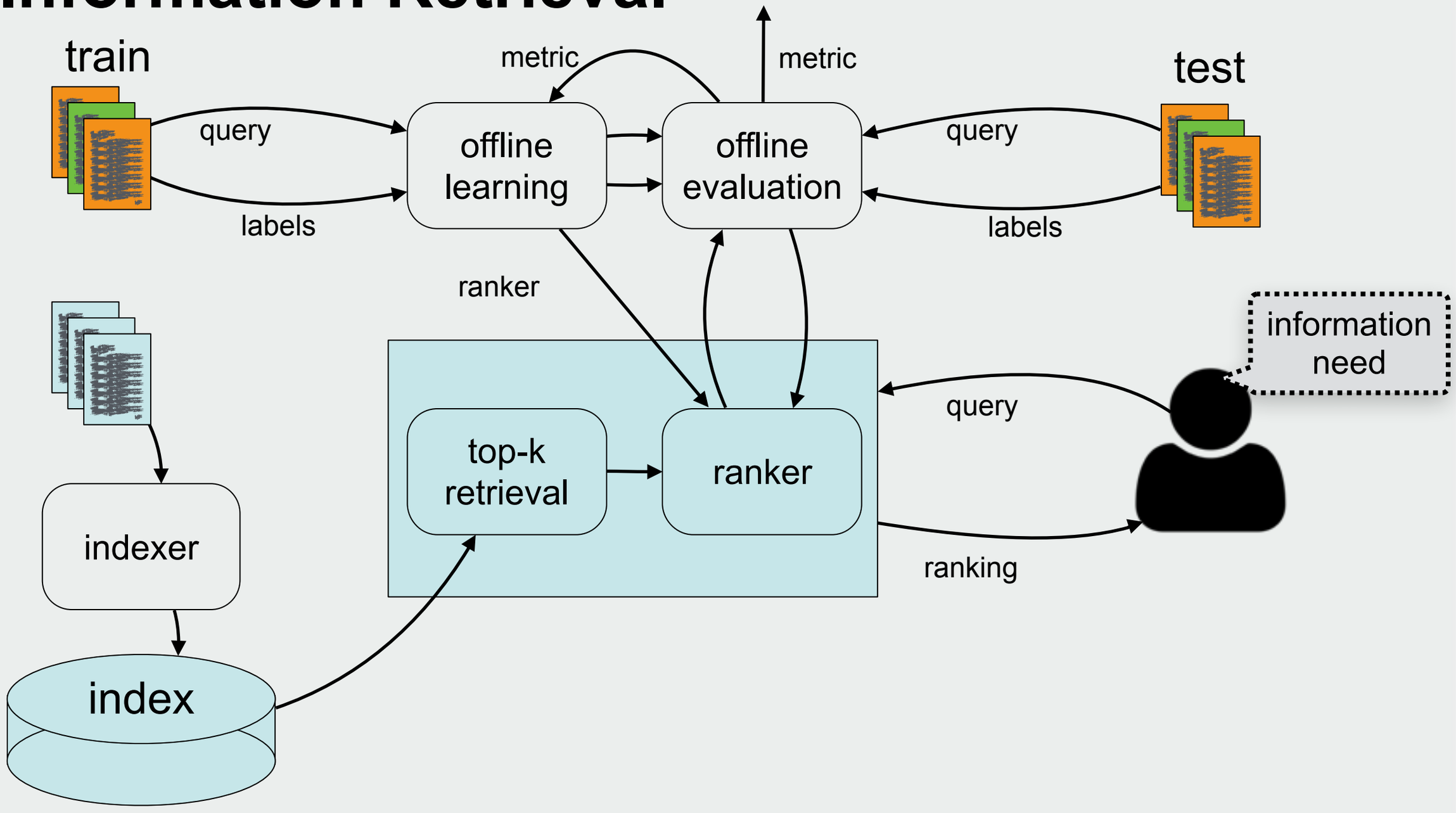

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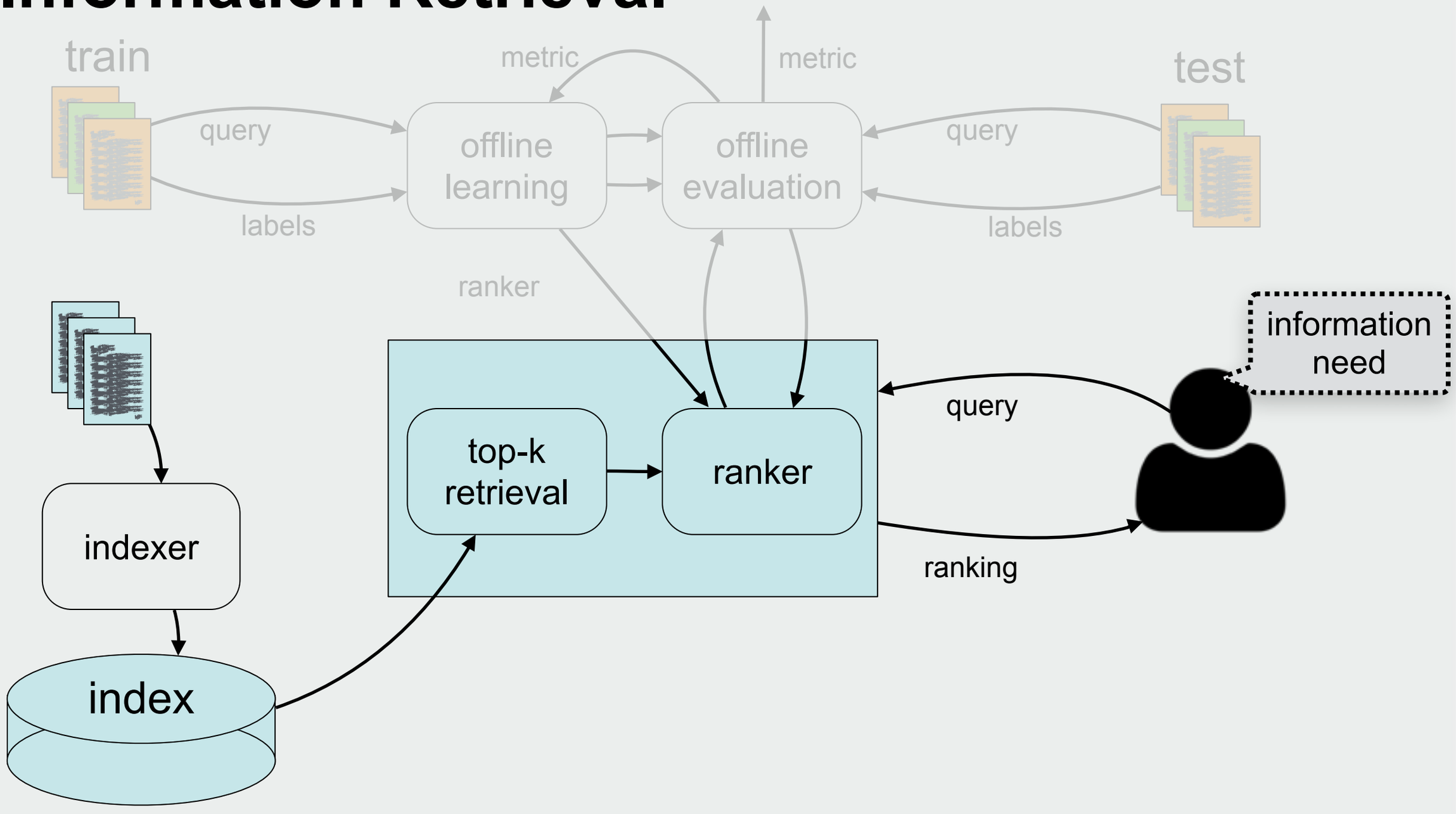

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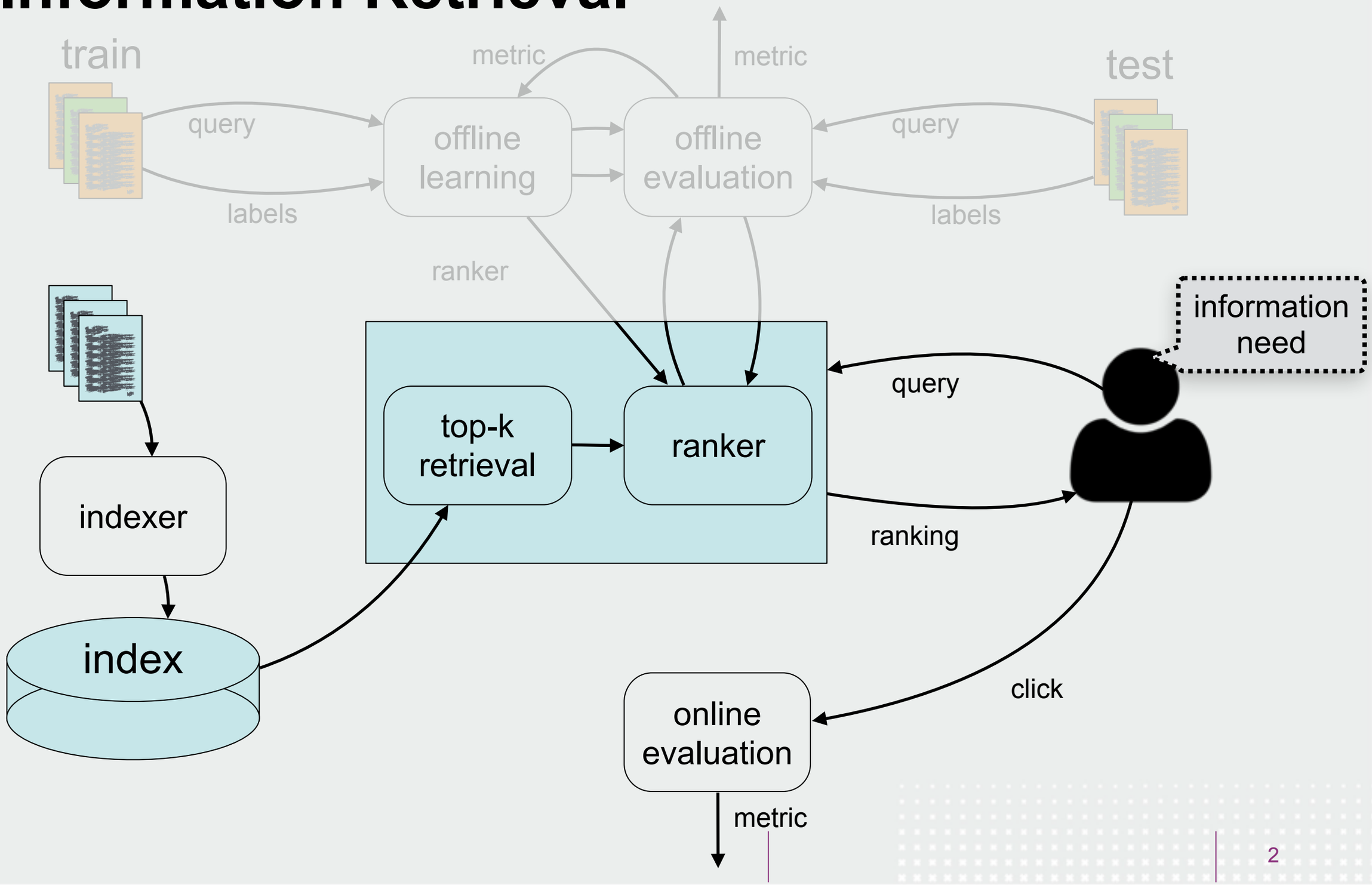

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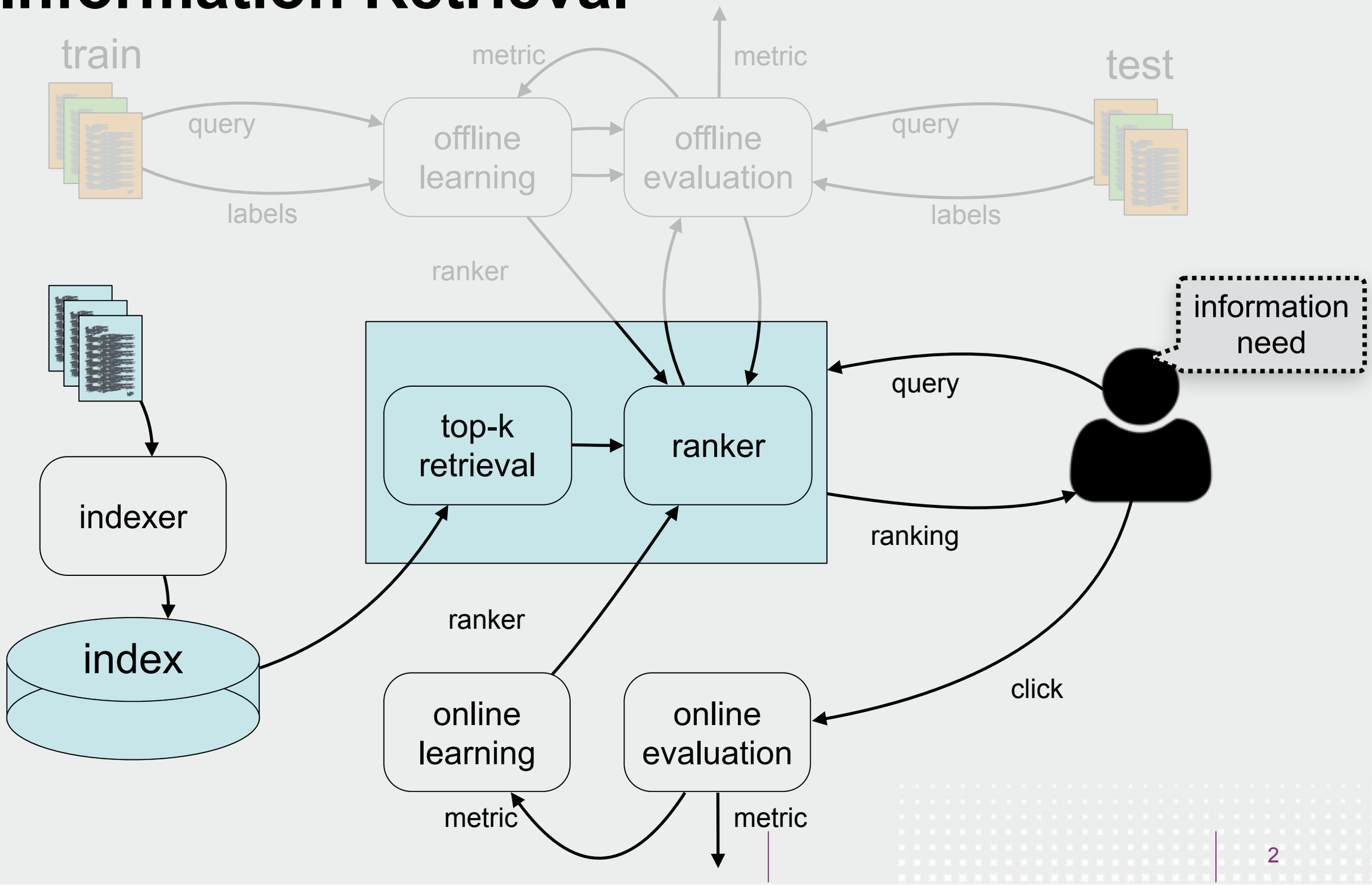

Information Retrieval

Information Retrieval

- **Users** have an **information need**

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- **Search engine**'s task is to **retrieve** documents **relevant** to information need

Recommender Systems

Information Retrieval

- **Users** have an implicit information need
- User come to a recommender system because they hope (or know) the answer is in the **collection**
- Information need is translated into a **query** (implicit (users are the query))
- Search engine / recommender system's task is to **retrieve** documents **relevant** to information need / the user

Outline

- Information Retrieval
- Online
  - Evaluation
  - Learning to Rank
  - Issues
- Living Labs
- Wrap up

Recommender Systems

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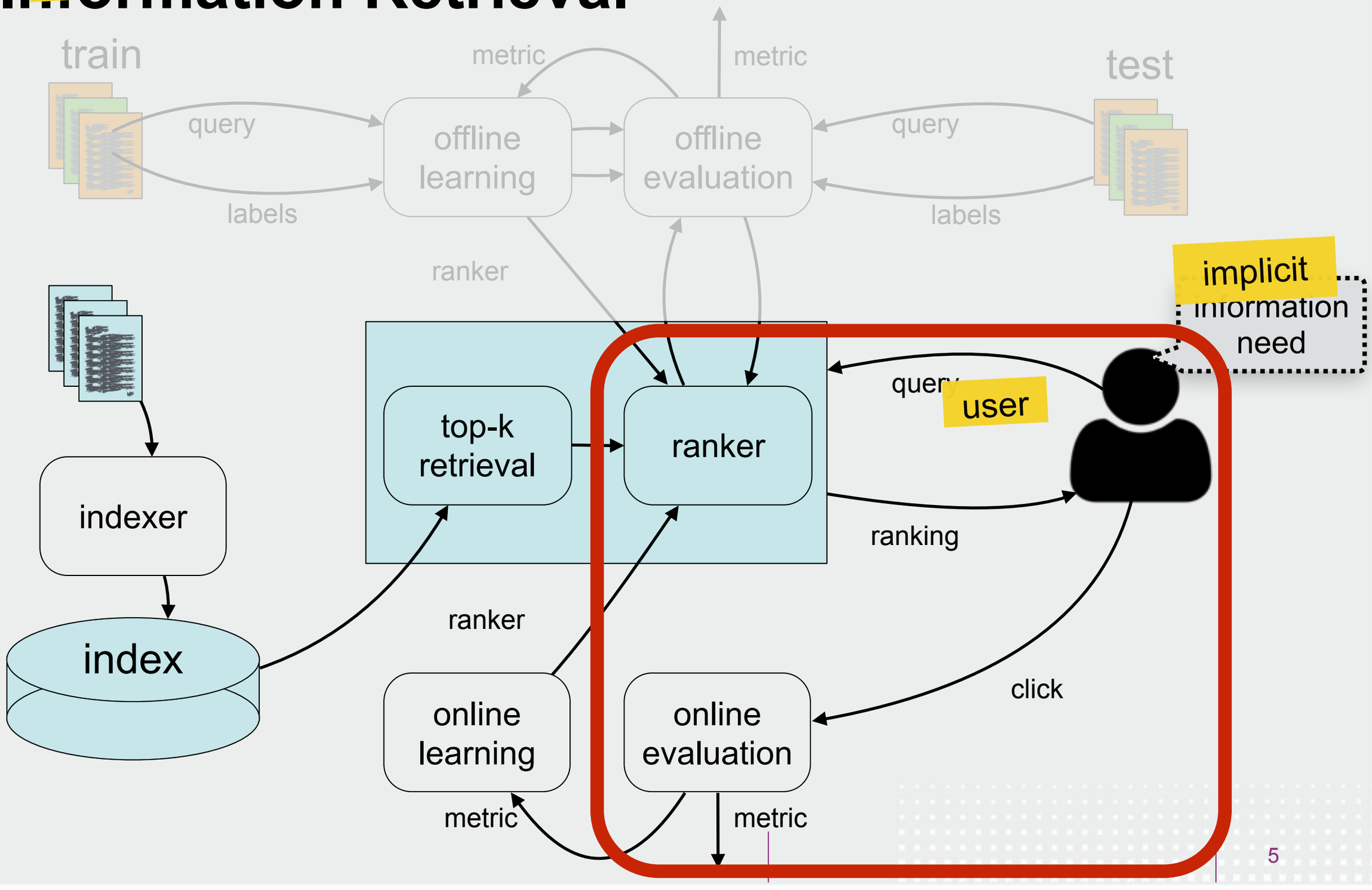

What about Observational Studies?

Why not compare with historical data?
Here's an example of Kindle Sales over time.
You changed the site, and there was an amazing spike

Kohavi, R. (2013). Online Controlled Experiments. SIGIR '13.

External Events can Dwarf Your Changes

Oprah calls Kindle "her new favorite thing"

- In this example of an A/B test, you'd be better off with version A
- In controlled experiments, both versions are impacted the same way by external events

Kohavi, R. (2013). Online Controlled Experiments. SIGIR '13.

Online Evaluation

- Basic Idea:

  User can tell you what works and what not

- A/B testing
  - “Bucket” users, show A to one bucket, B to the other
  - Between subject design
- Interleaving
  - For ranking evaluation only
  - Avoid buckets, within subject design
  - Reduce variance

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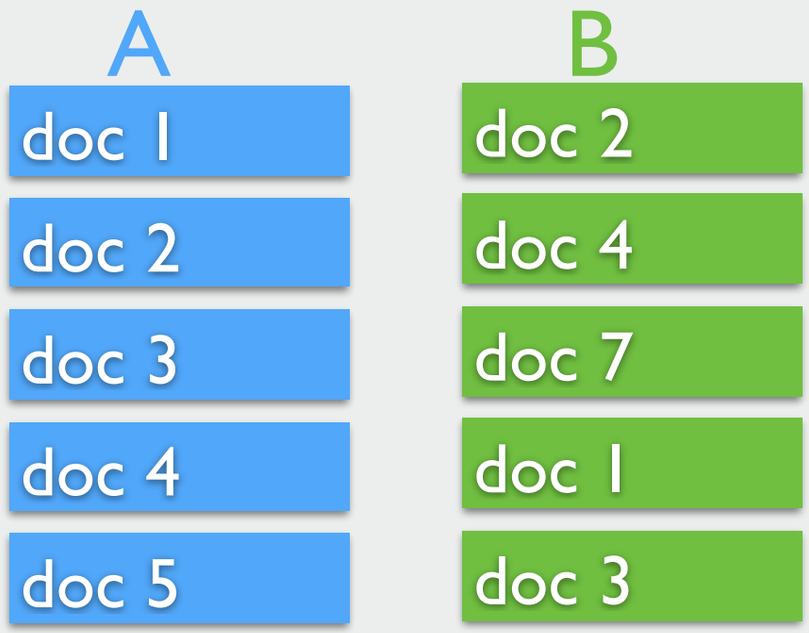
Interleaving



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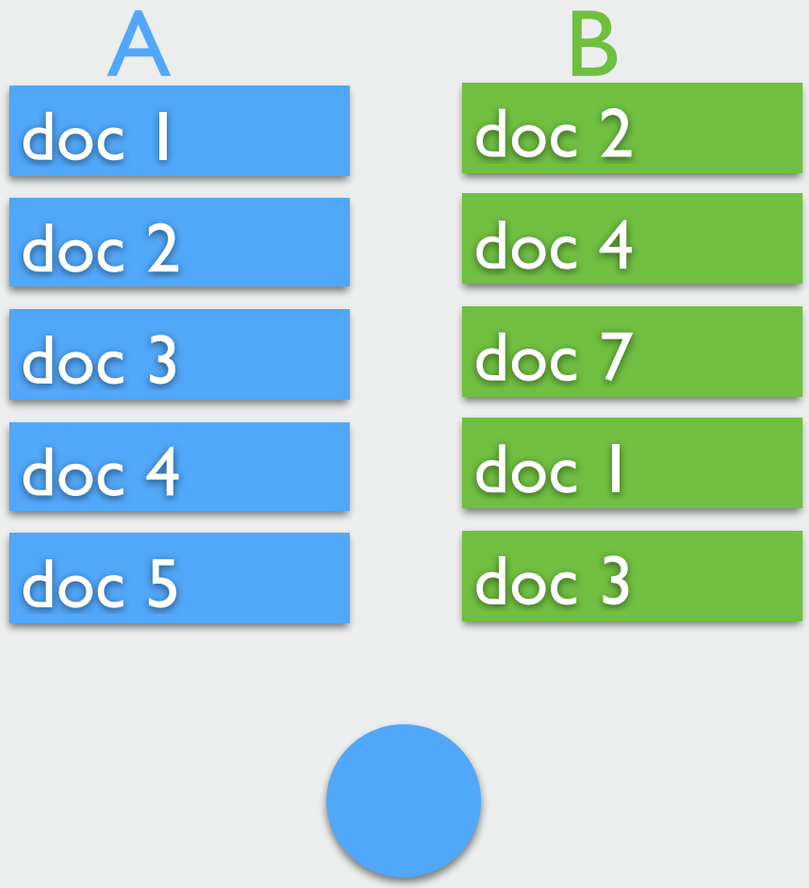
Interleaving



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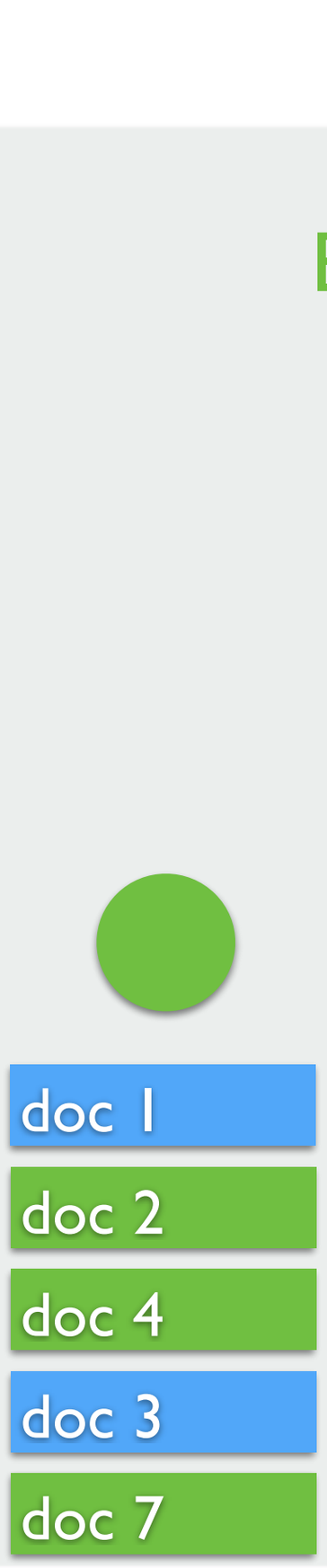
A B



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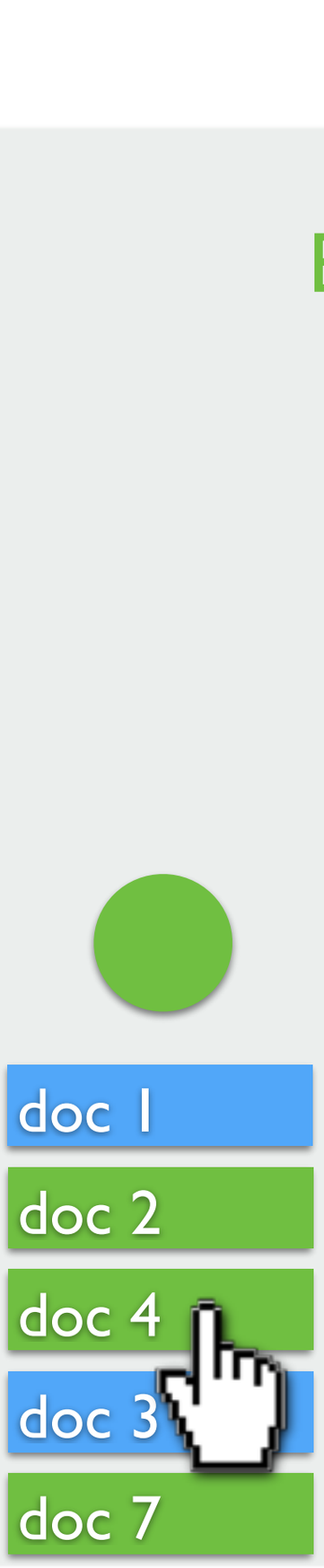

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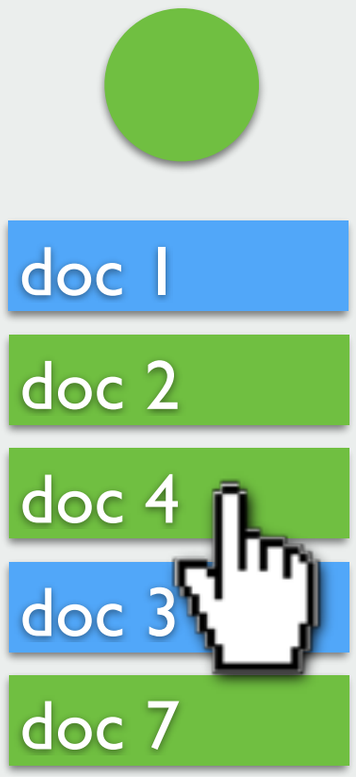

Inference:

B > A

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Online Evaluation - Clicks

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Why not Just Use Clicks?

greenfield, mn accident

Annandale man dies in car/truck crash in Greenfield

Article by: Star Tribune Updated: January 12, 2010 - 8:59 PM

resize text | print | buy reprints

Recommend 0 Tweet 0 share +

more from west metro

A 21-year-old man from Annandale, Minn., was killed Tuesday afternoon in a car-truck crash on Hwy. 55 in Greenfield, according to the Minnesota State Patrol.

Battle over plan to restrict access to metro lakes

Time spent on page: 38 seconds

Microsoft Research

Hassan, A., Shi, X., Craswell, N., & Ramsey, B. (2013). Beyond Clicks: Query Reformulation as a Predictor of Search Satisfaction. In CIKM '13.

Why not Just Use Clicks?

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Woman dies in a fatal accident in greenfield, minnesota

Session Ends

Microsoft Research

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Why not Just Use Clicks?

- User performed this search on July 1st
- User was probably looking for

Car-truck crash in Greenfield kills woman, 34

Updated: June 30, 2012 - 9:46 PM

0 comments | resize text | print | buy reprints

Recommend 38 Tweet share +

A 34-year-old woman was killed shortly after 6 p.m. Saturday when the car she was driving collided with a pickup truck at the intersection of County Road 50 and Vernon Street in Greenfield.

more from local

Minn. man sentenced for fake sports apparel

Microsoft Research

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Why not Just Use Clicks?

- User clicked on a result
- The dwell time is long
- But, user was not satsified

Query **Click** Query

Clicks do not always mean satisfaction

Microsoft Research

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  - they don't always mean what you hope
  - absence of clicks is not always negative

Why not Just Use Clicks?

Lack of clicks does not always mean dissatisfaction

Microsoft Research

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Online Evaluation - Clicks

- Clicks are biased
  - understand the bias
  - correct for it

- Clicks are noisy
  - repeat

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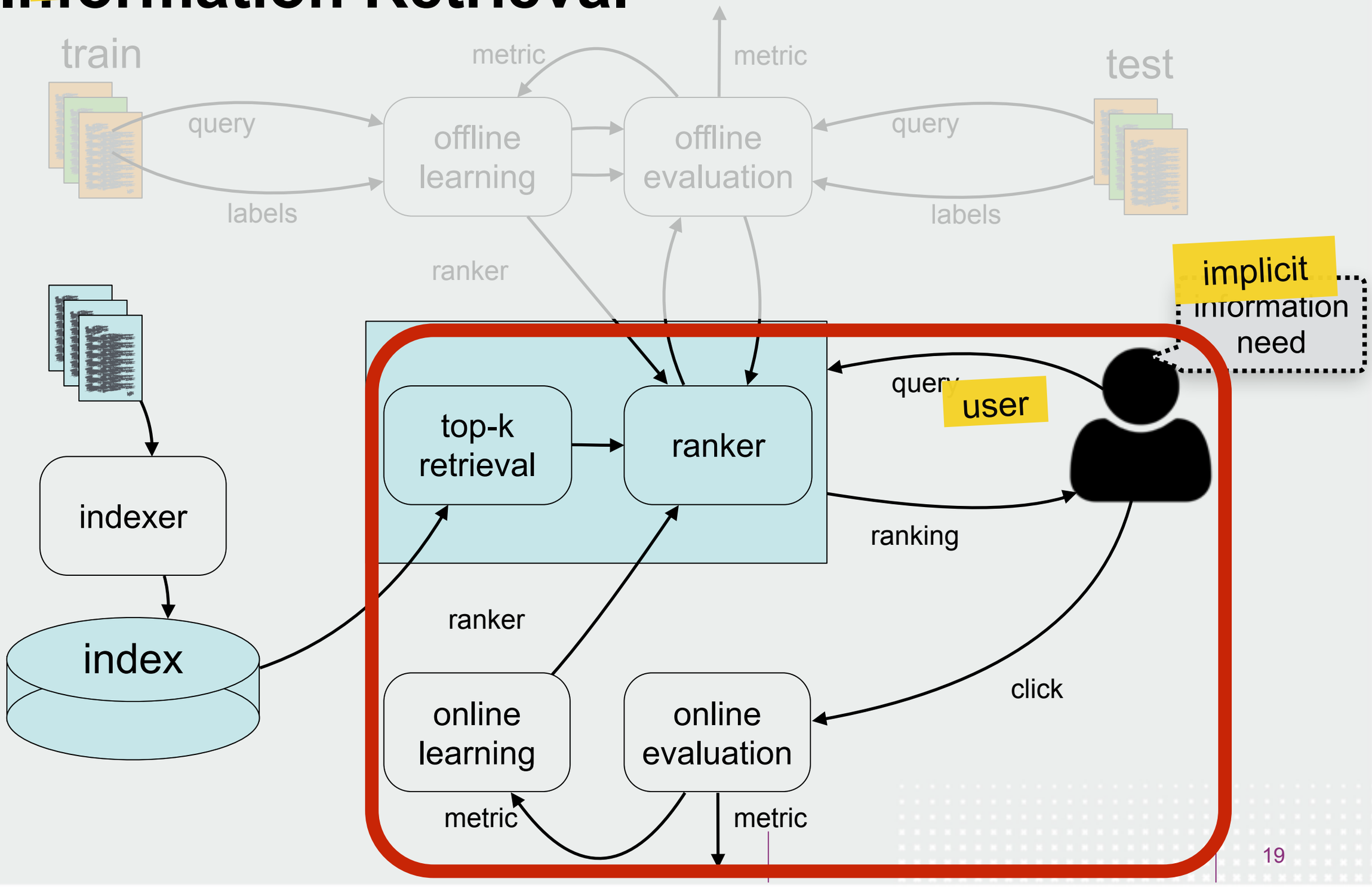
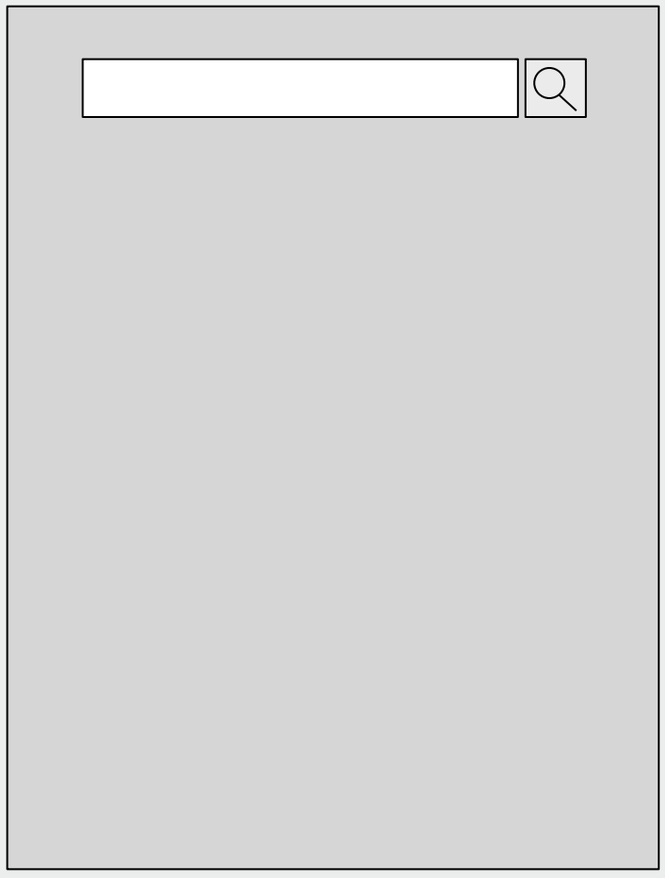


Dueling Bandit Gradient Descent



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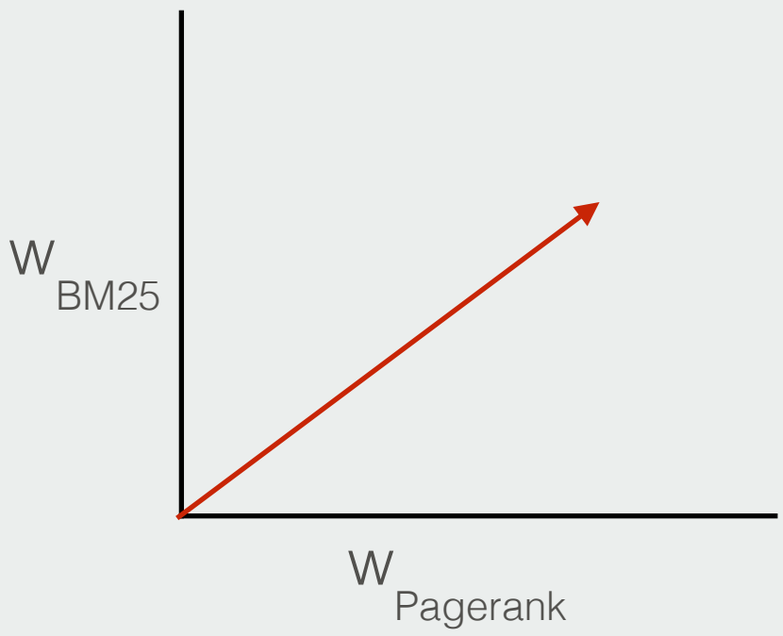

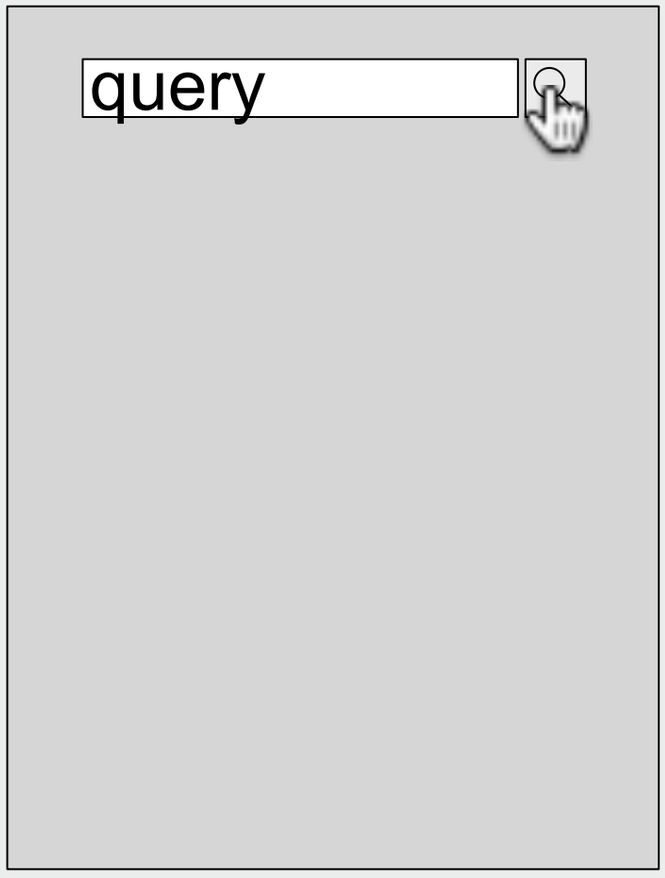

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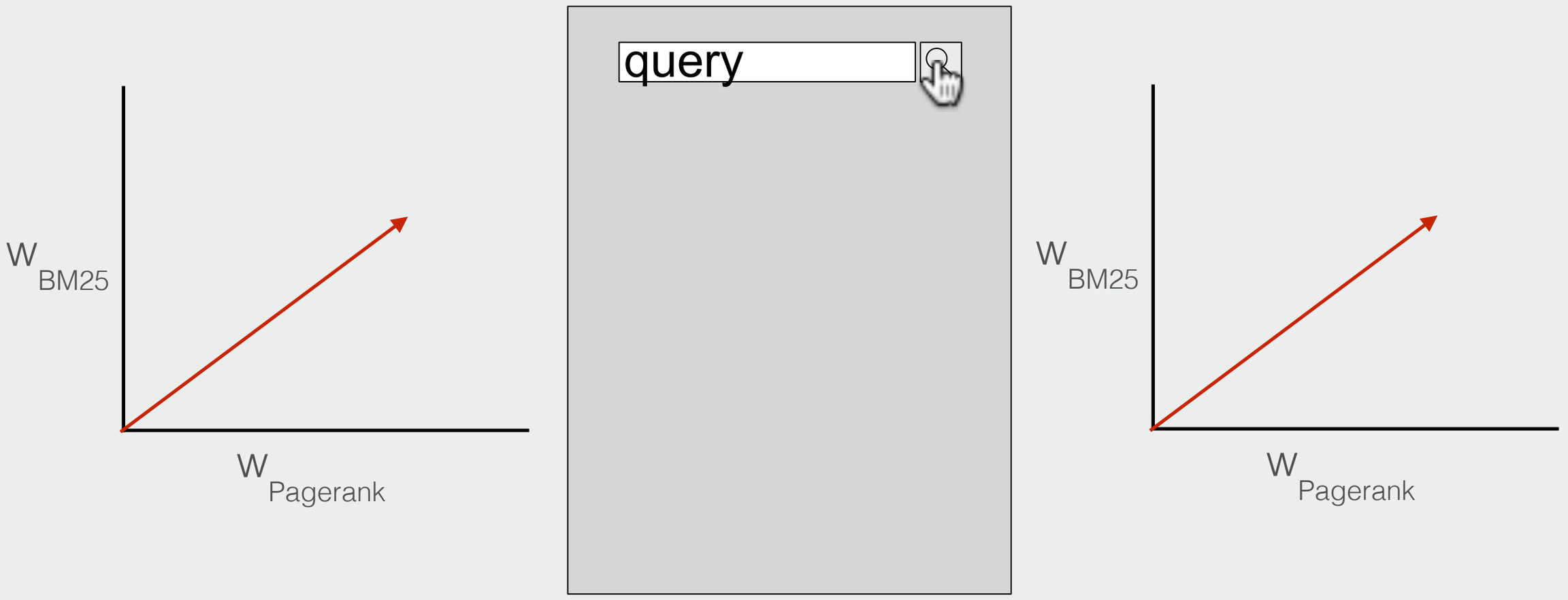

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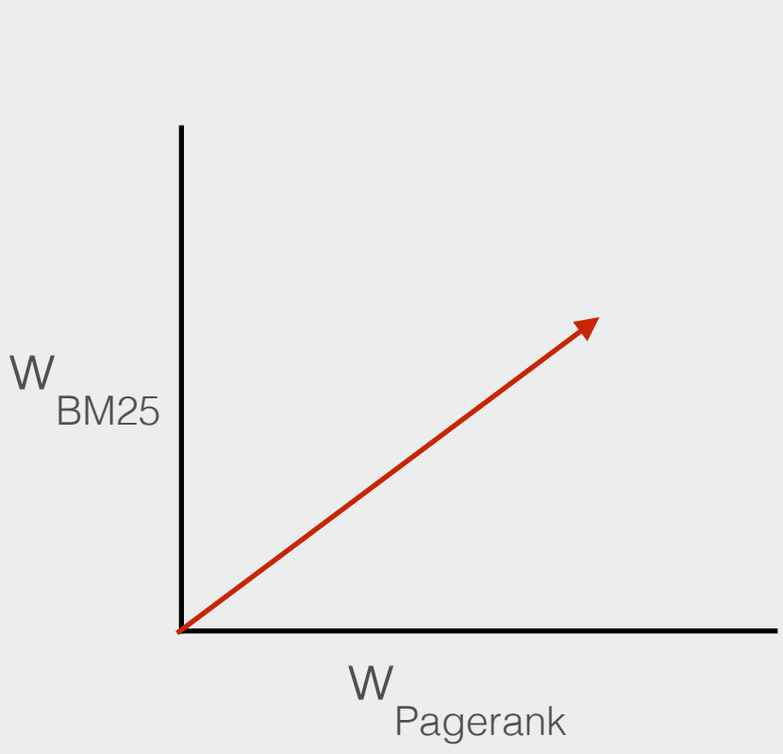

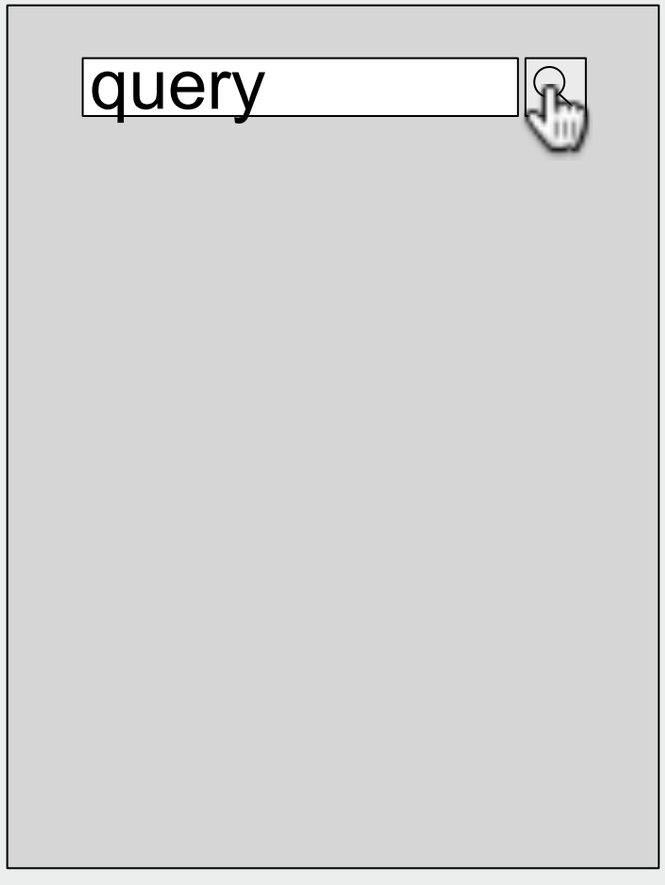

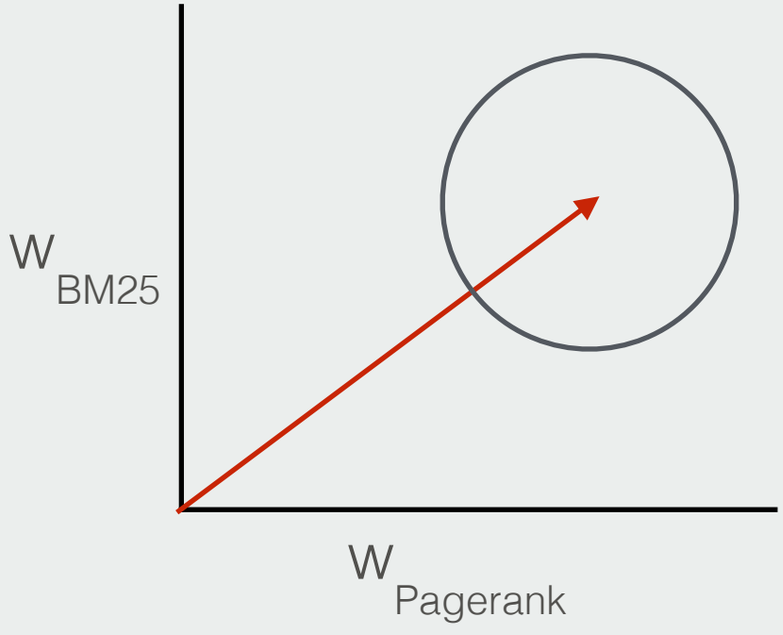

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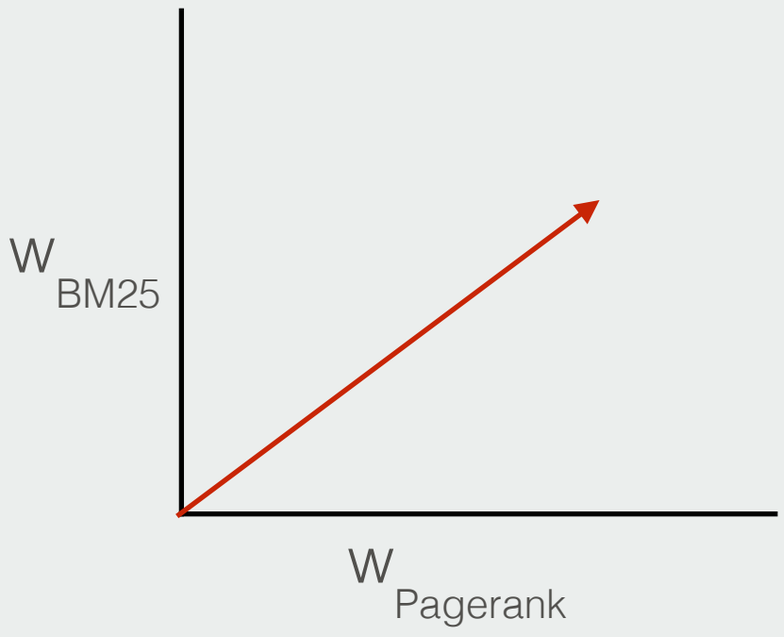

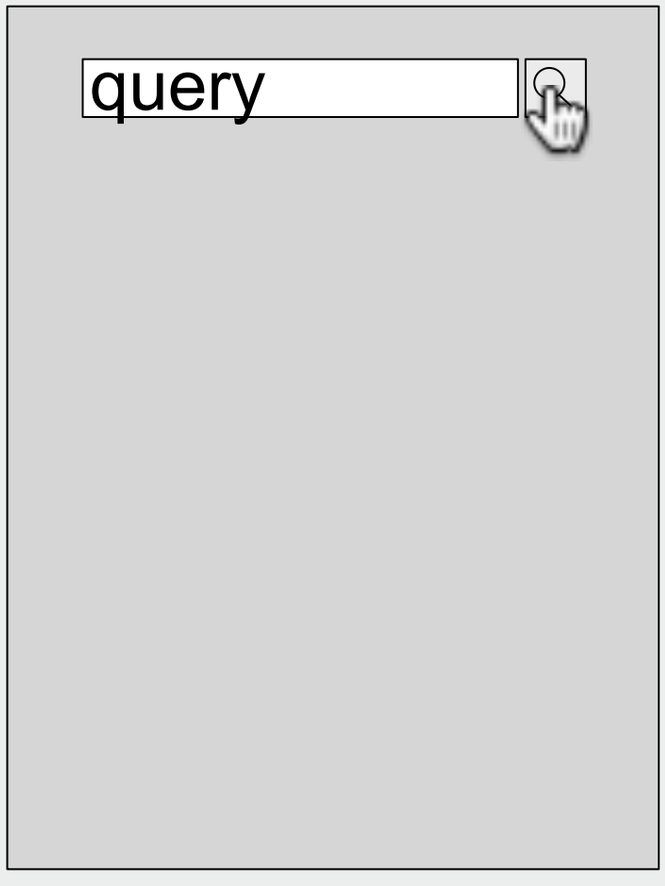

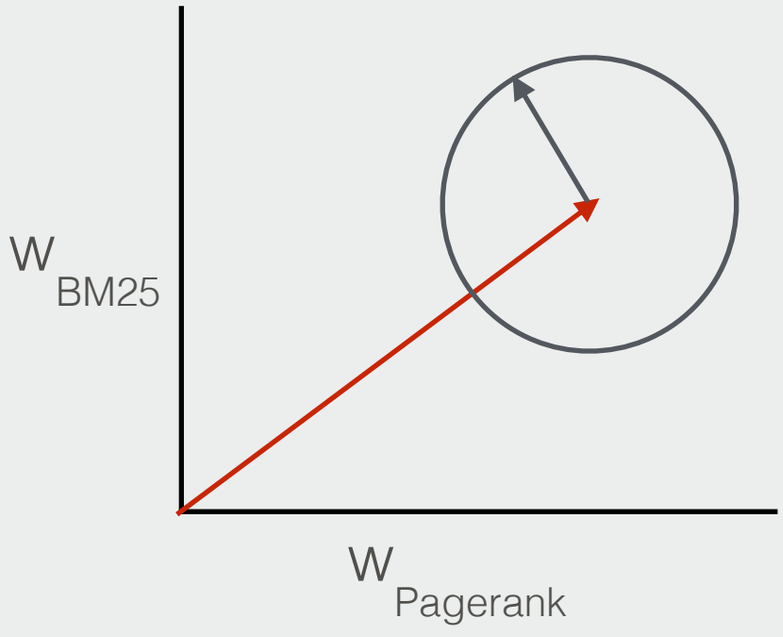

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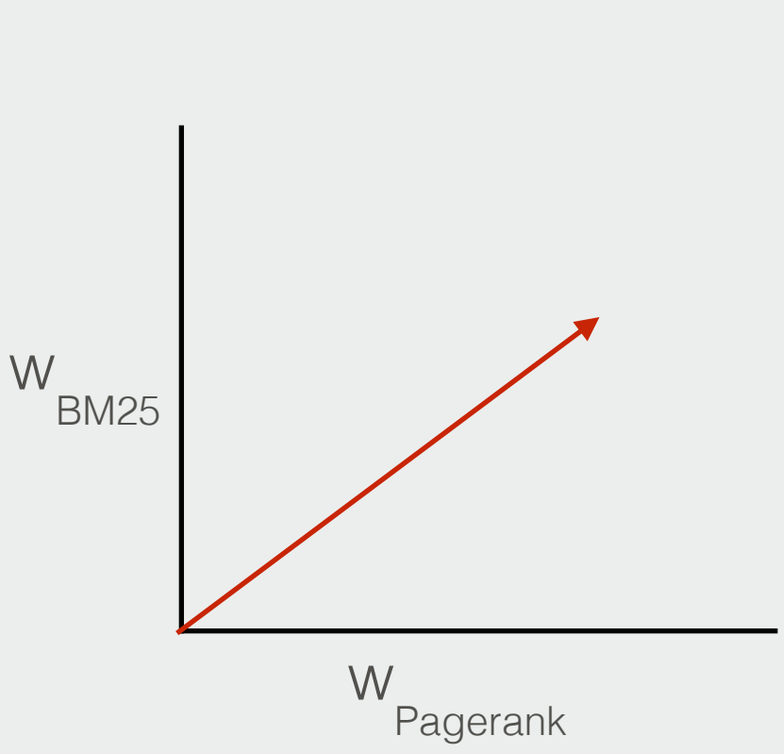

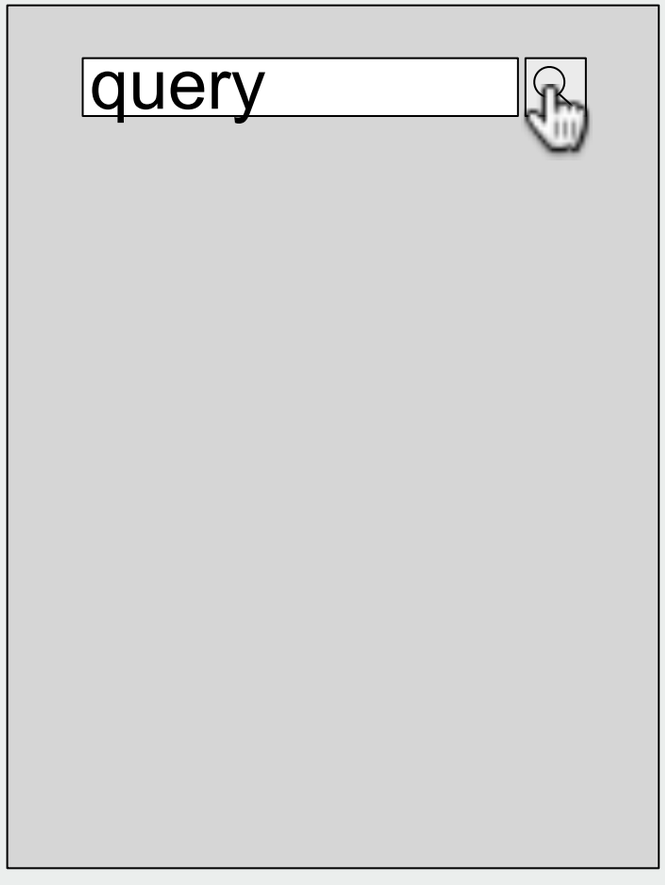

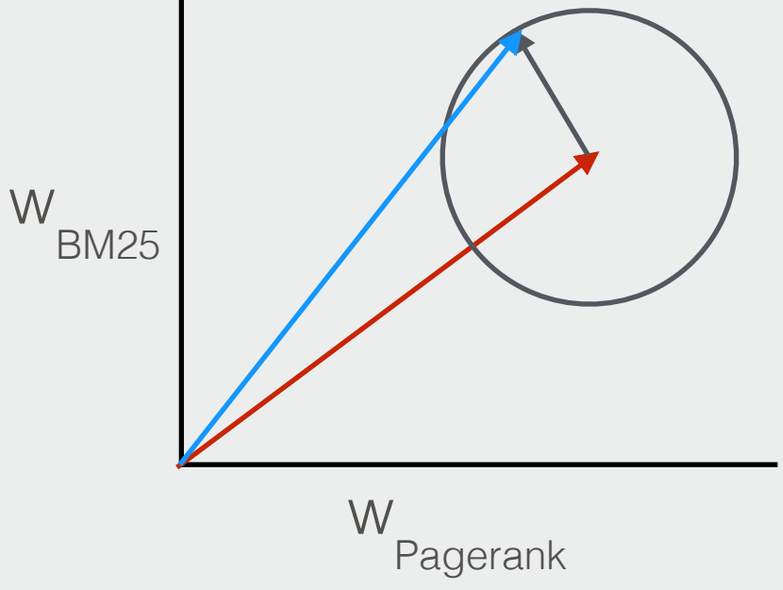

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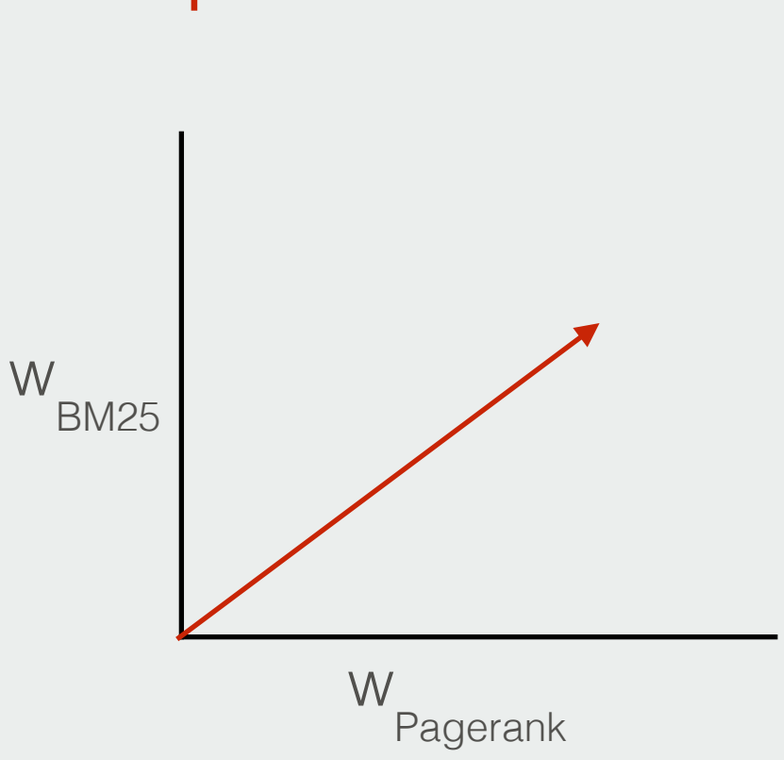
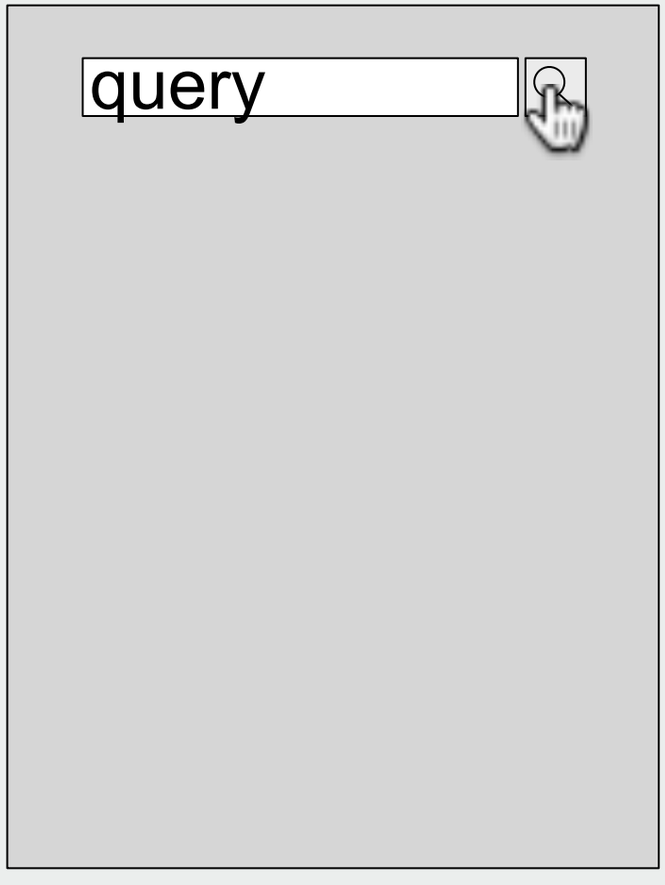
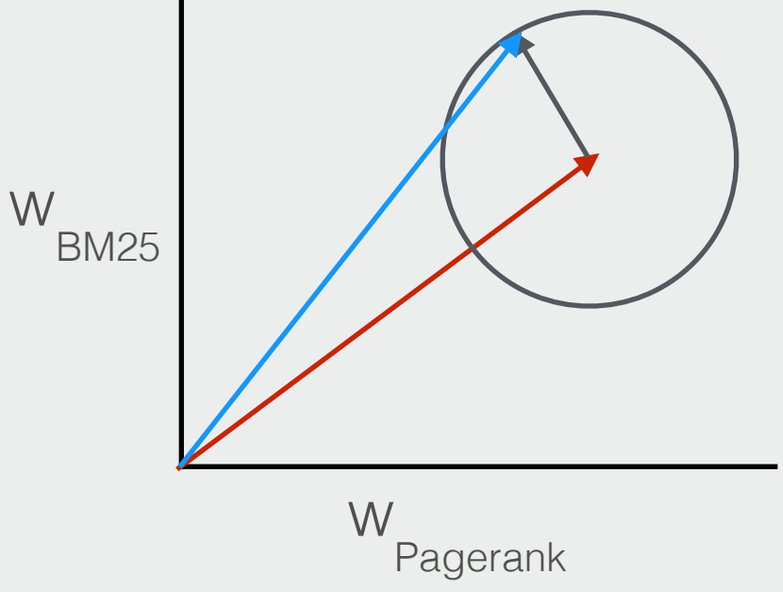
Dueling Bandit Gradient Descent

Exploitative Ranker







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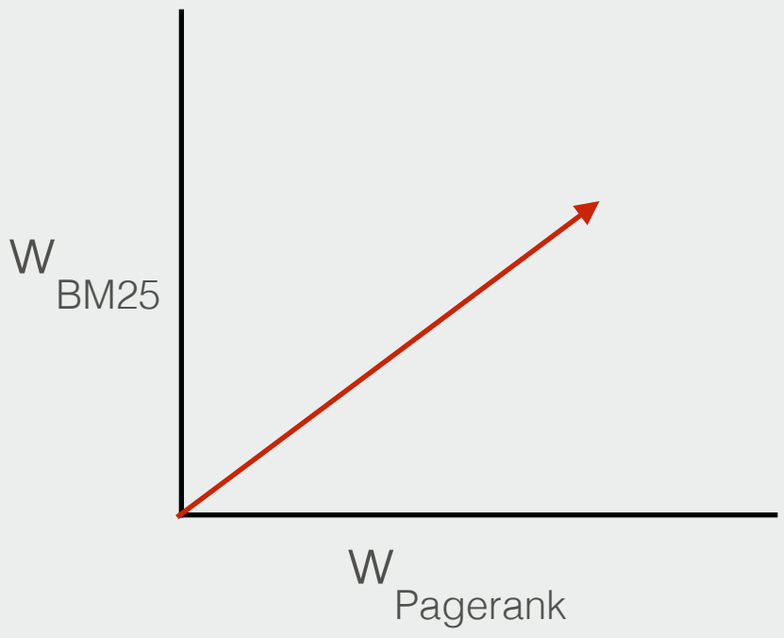

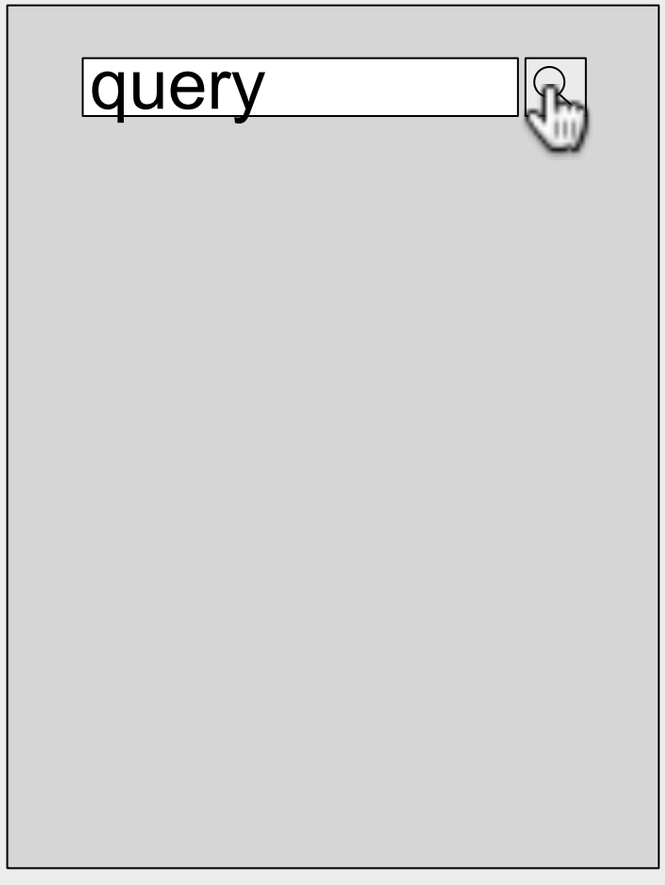

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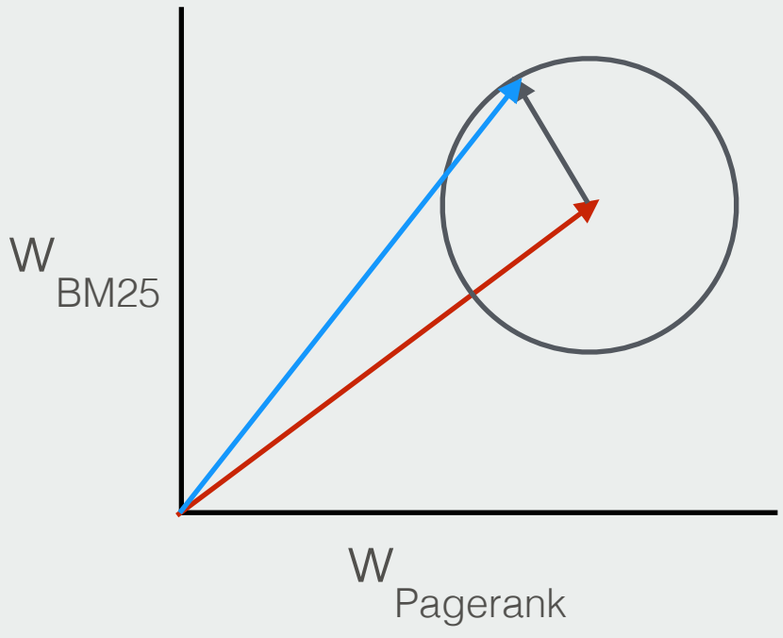
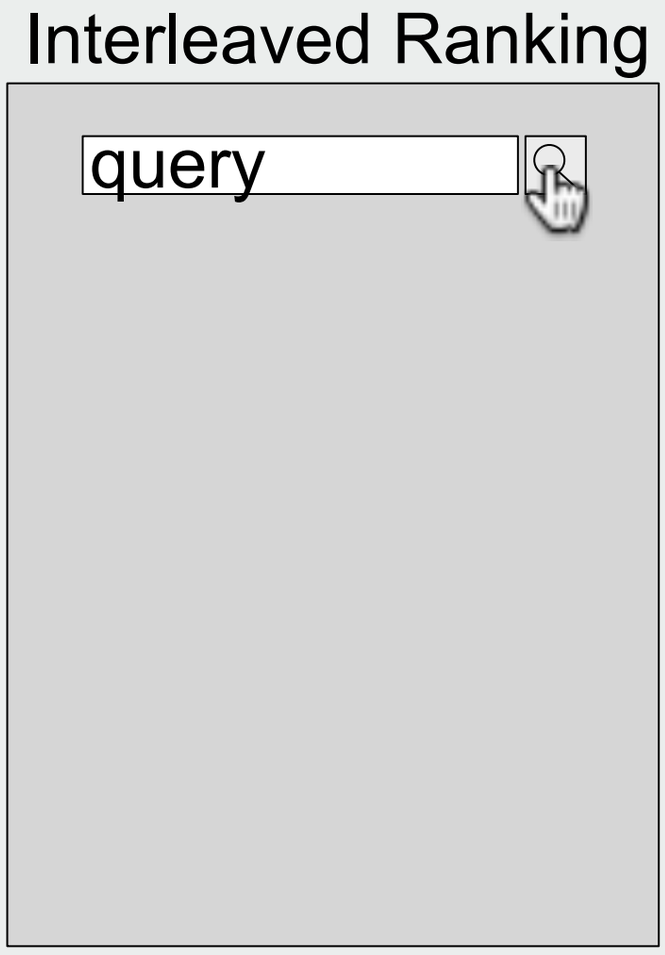


, 2009; Hofmann et al., 2011]

TeamDraft Interleave



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TeamDraft Interleave

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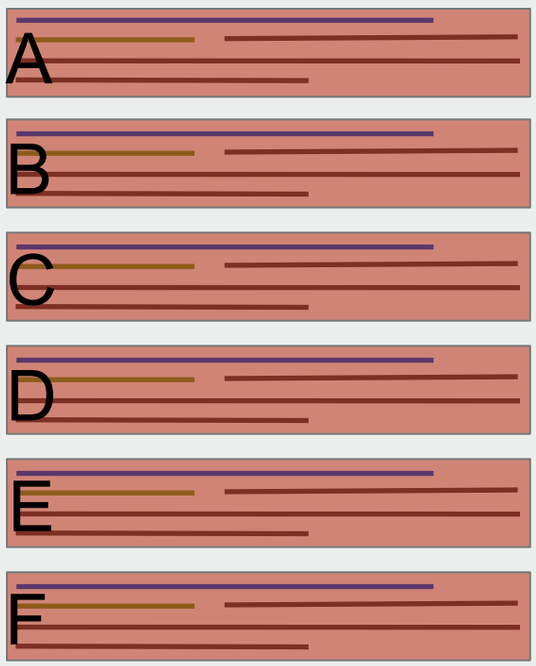
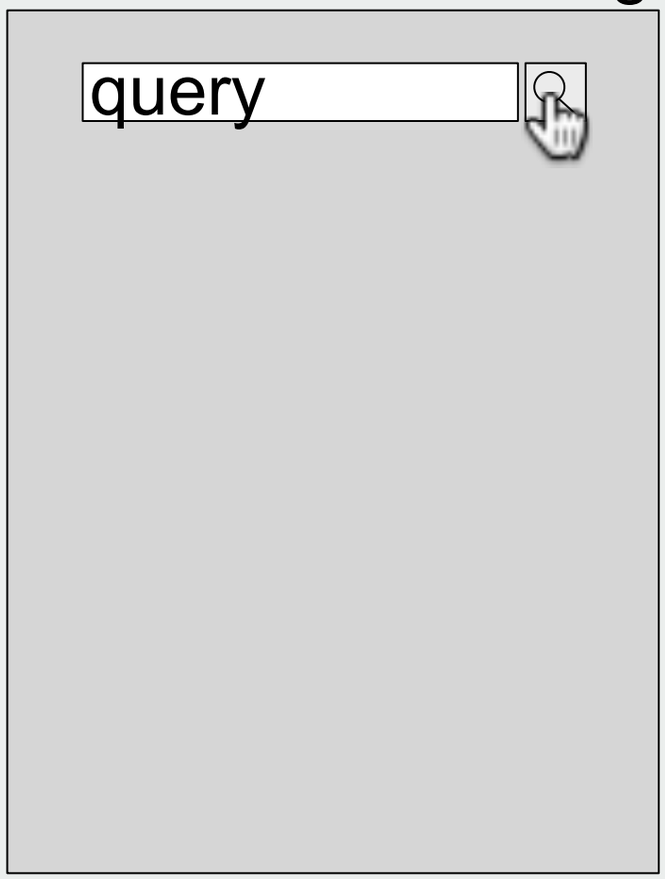


Interleaved Ranking



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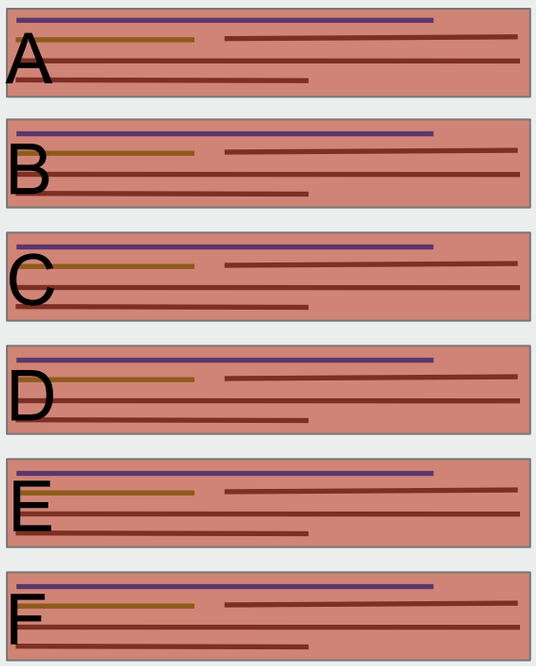

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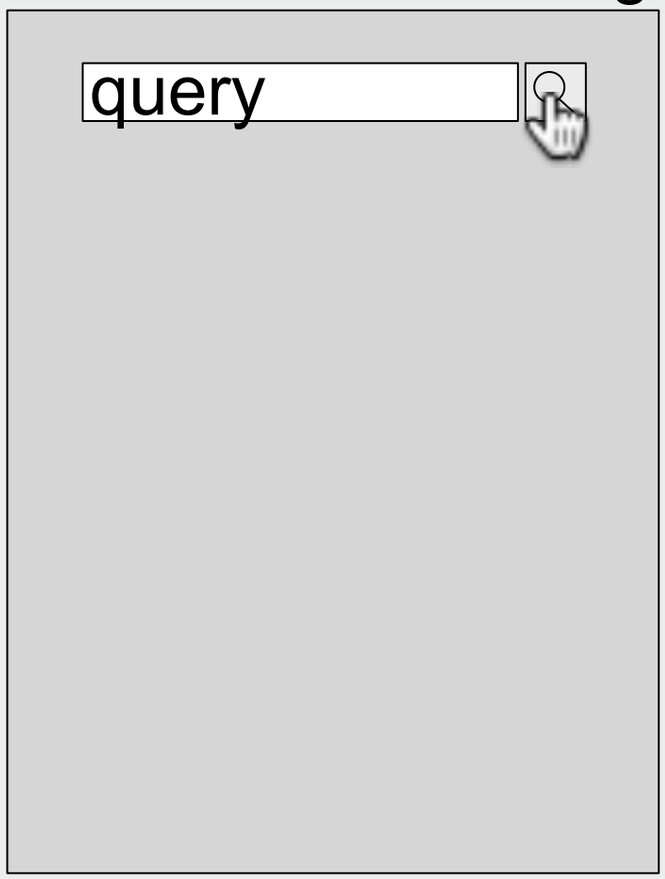

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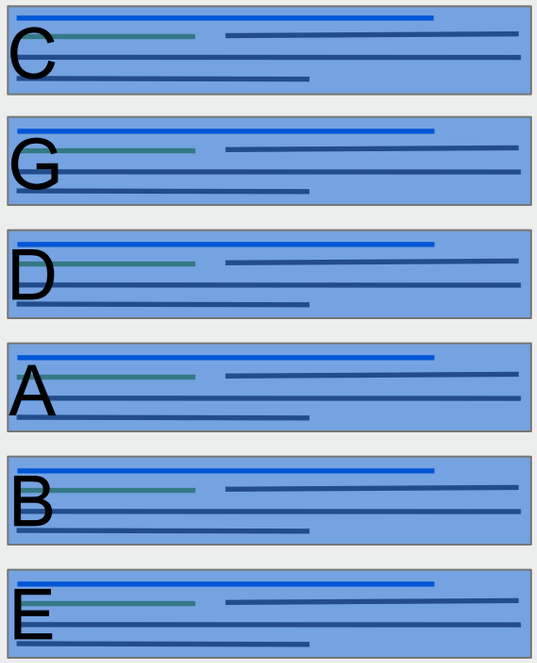

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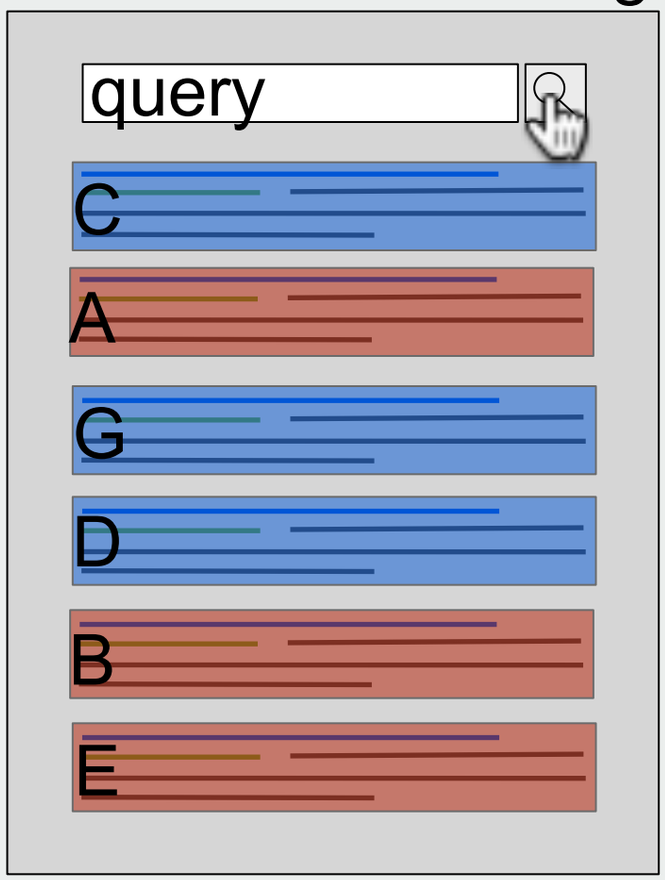

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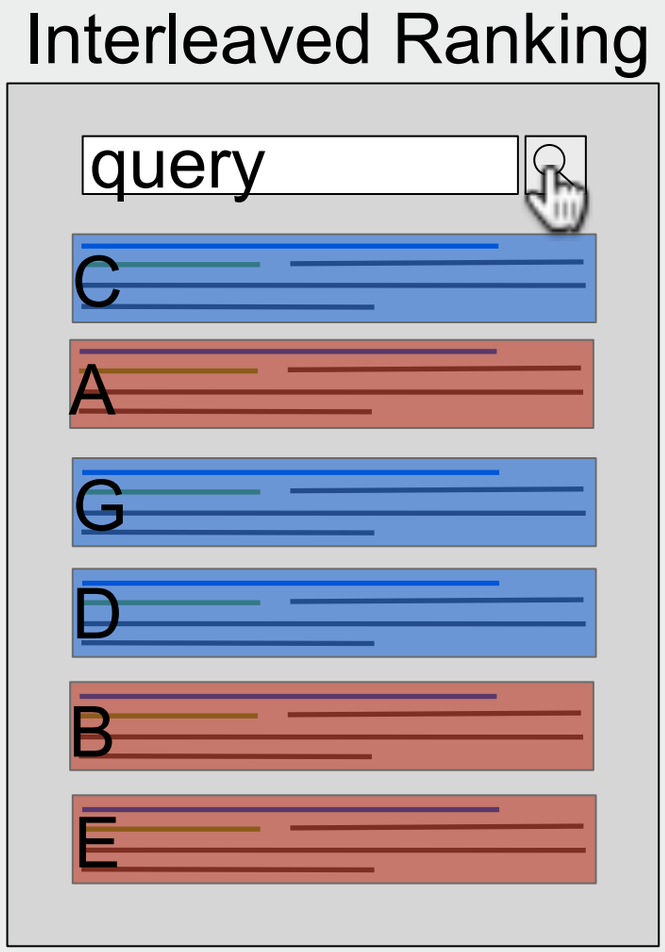

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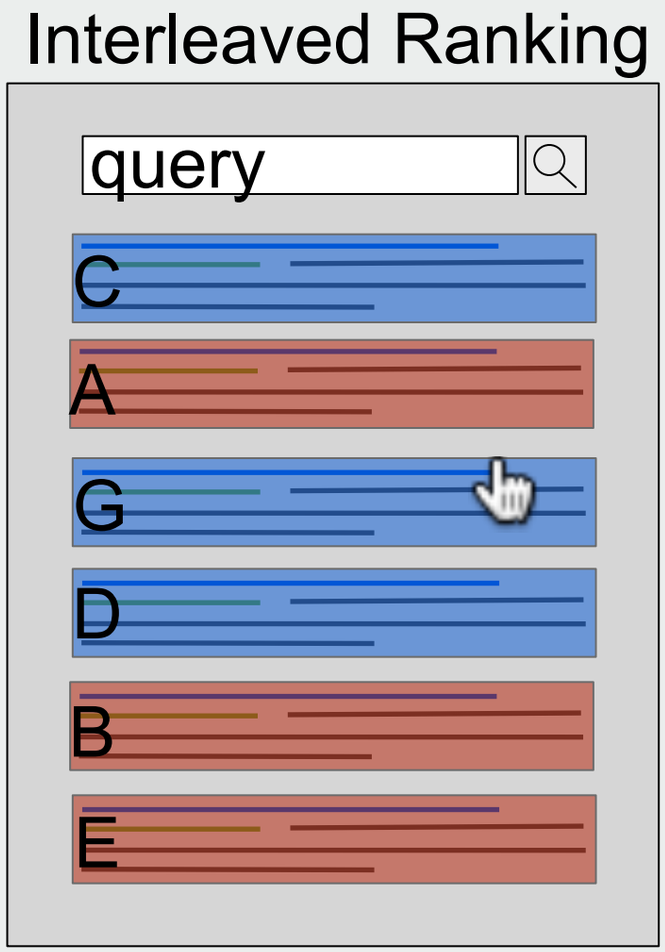

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Dueling Bandit Gradient Descent

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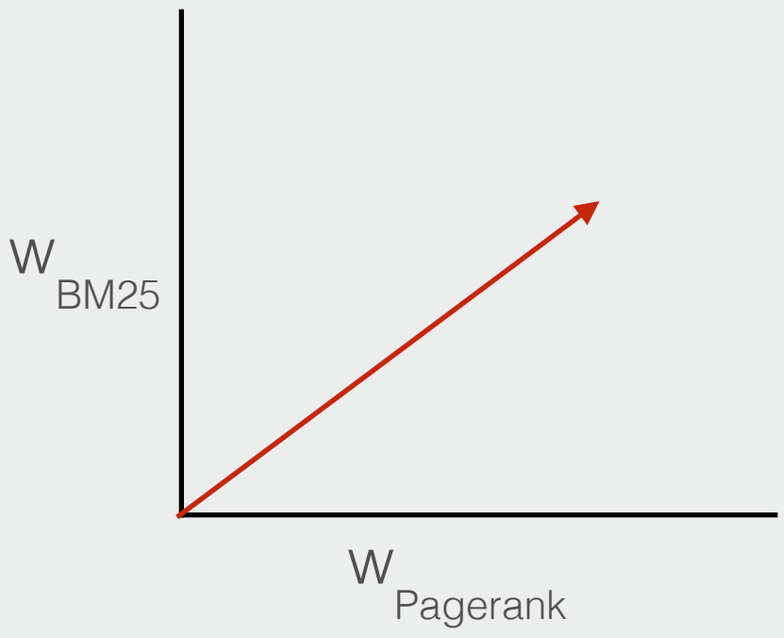

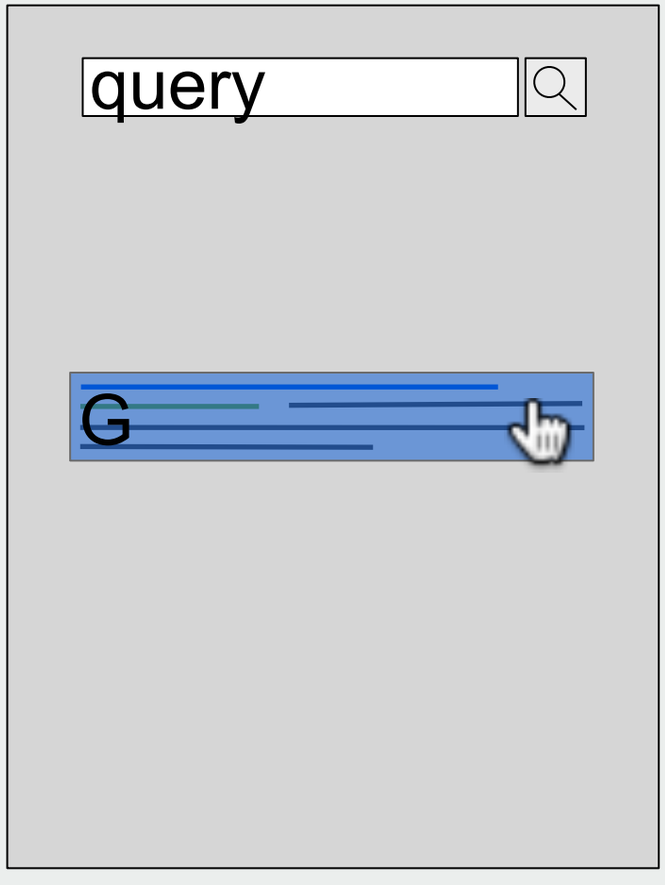

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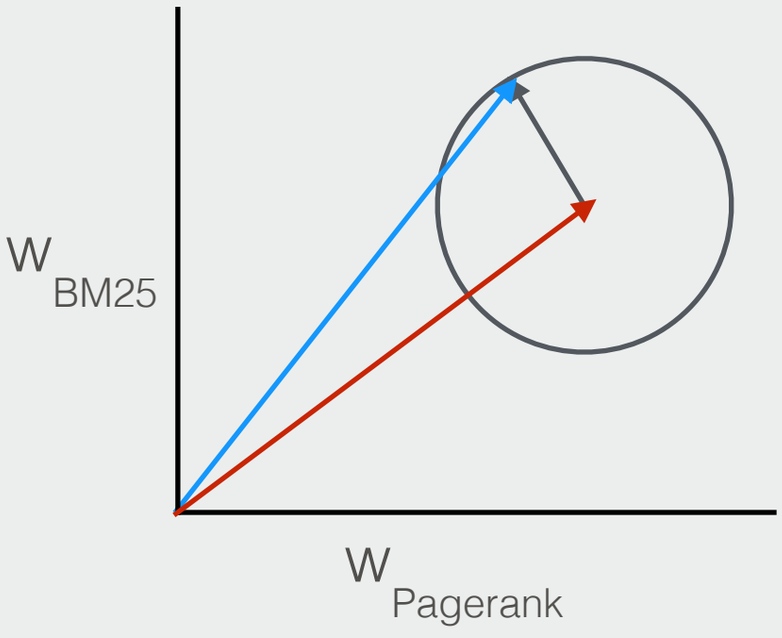

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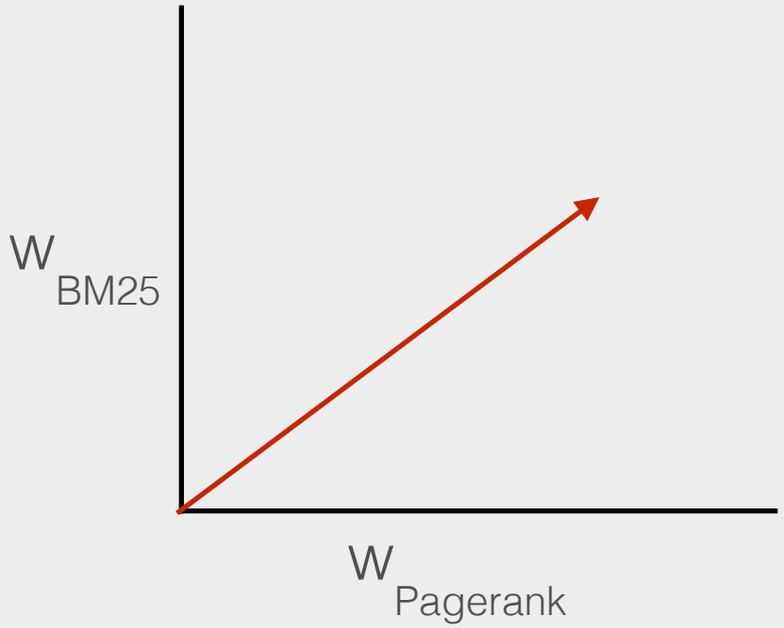

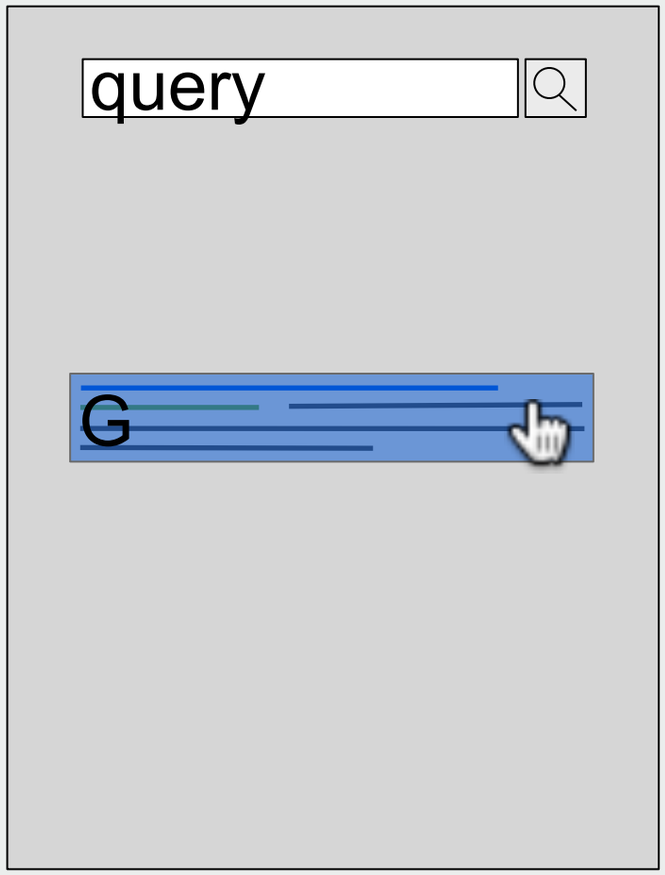

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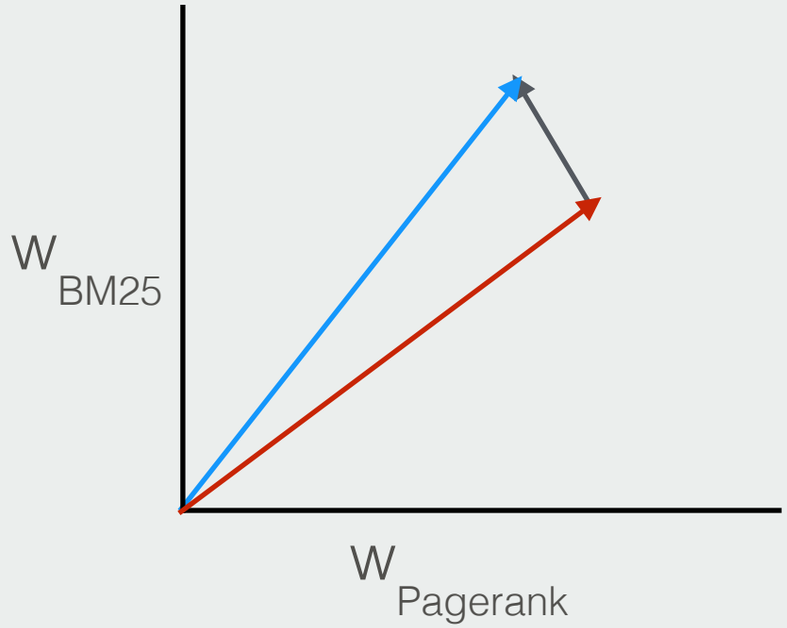

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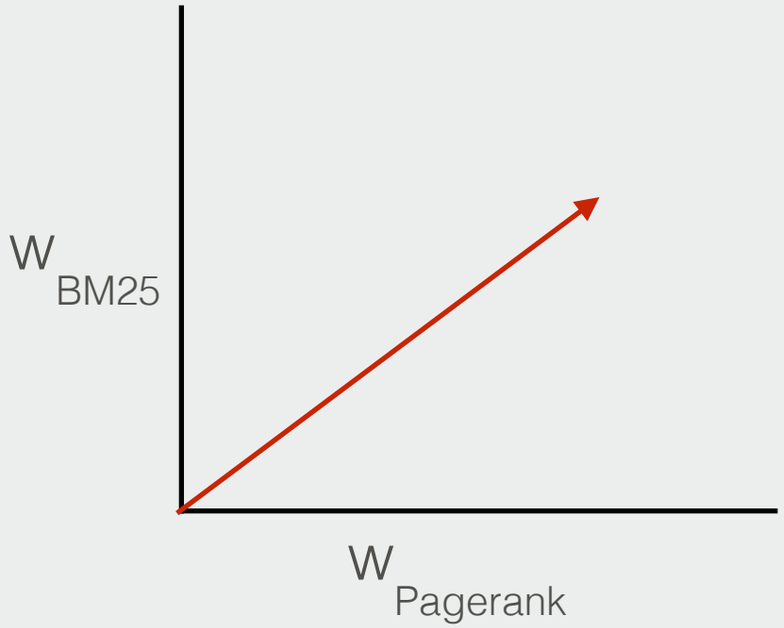

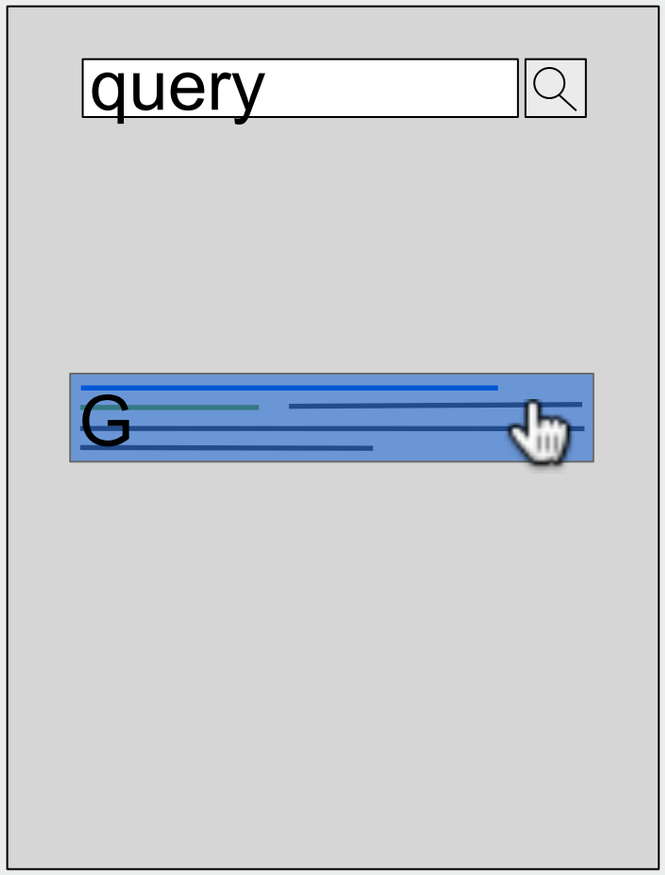

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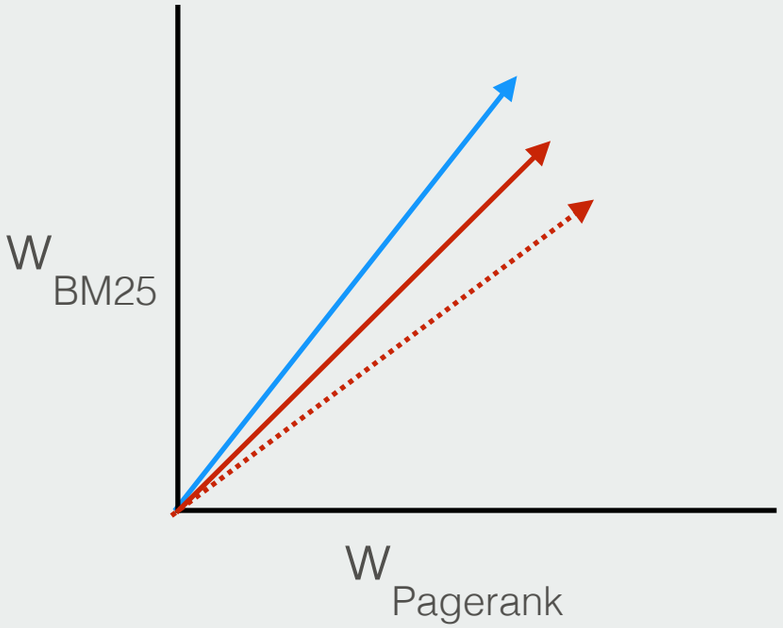

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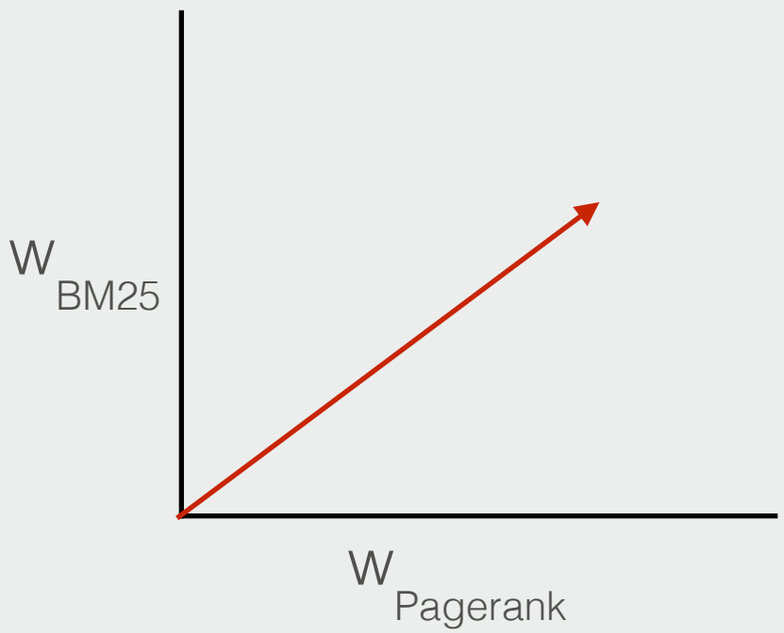

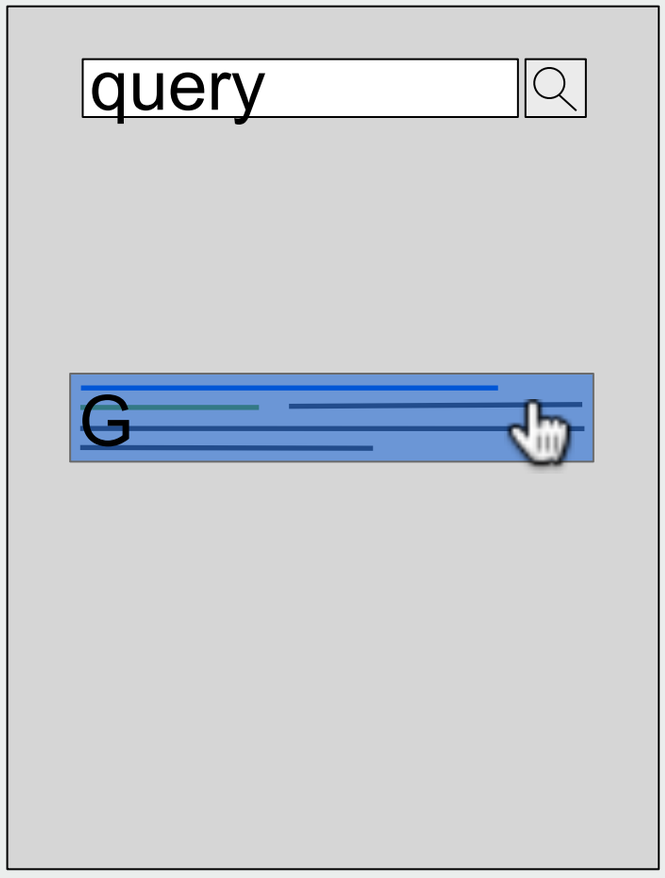

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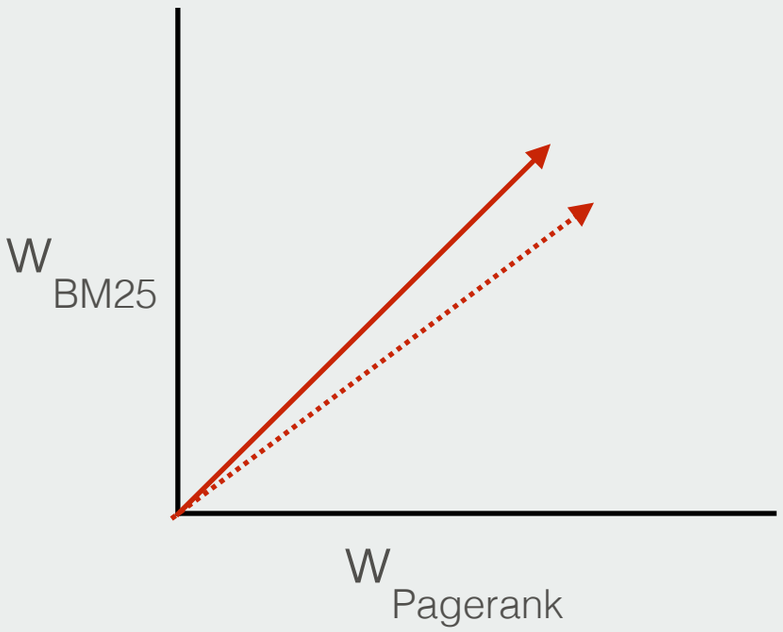

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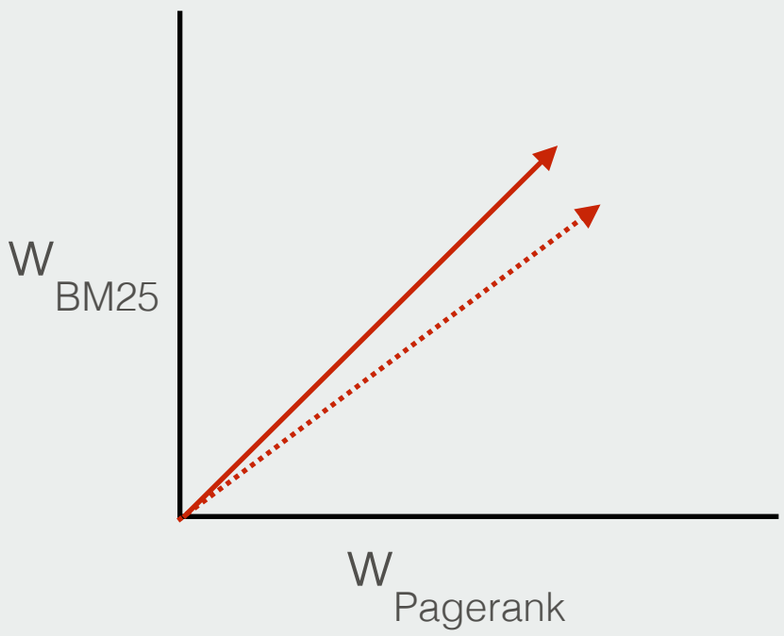

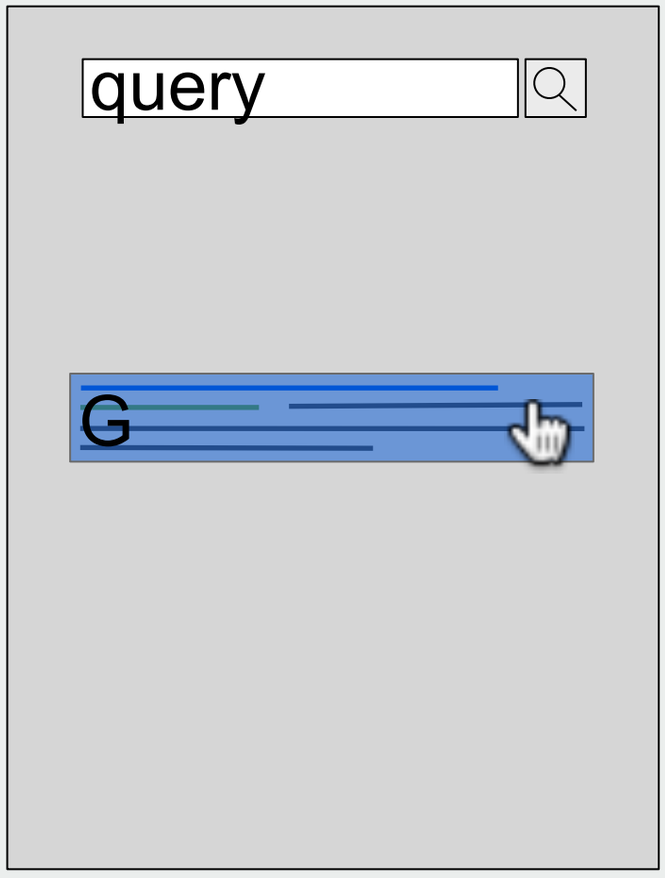

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Outline

- Information Retrieval
- Online
  - Evaluation
  - Learning to Rank
  - Issues
- Living Labs
- Wrap up

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- You may hurt a user
- **Users…**
  - **always limiting factor**
  - **no access for researchers**

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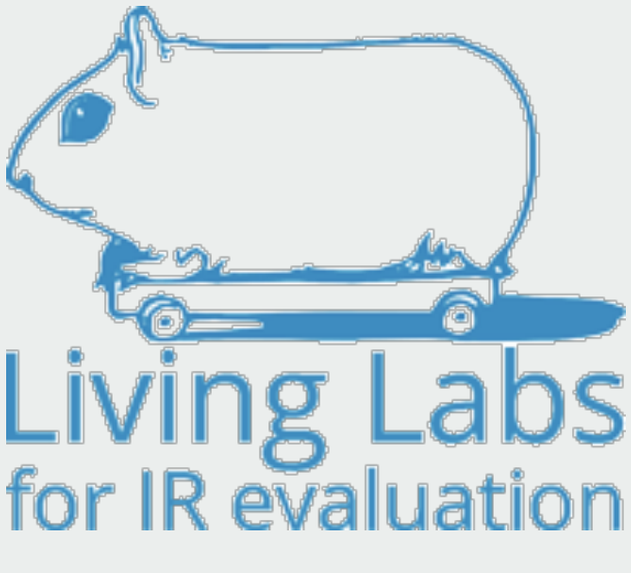
Living Lab for IR Evaluation



- If you are a researcher:
  - “Give us your ranking, we’ll have it clicked!”

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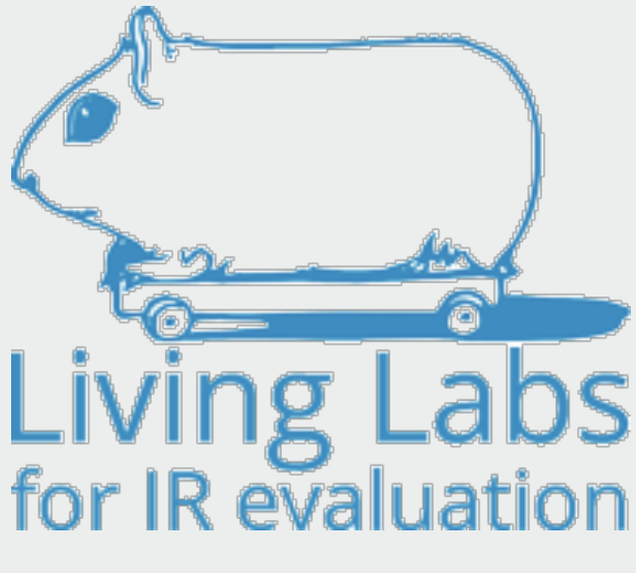

- If you are a researcher:
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- If you own a search engine:
  - "Give us your clicks, we'll solve your ranking problem!"

Living Lab for IR Evaluation

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- Sites (real search engines) provide queries
  - sample of ~100 queries
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- Participants use clicks on their own rankings
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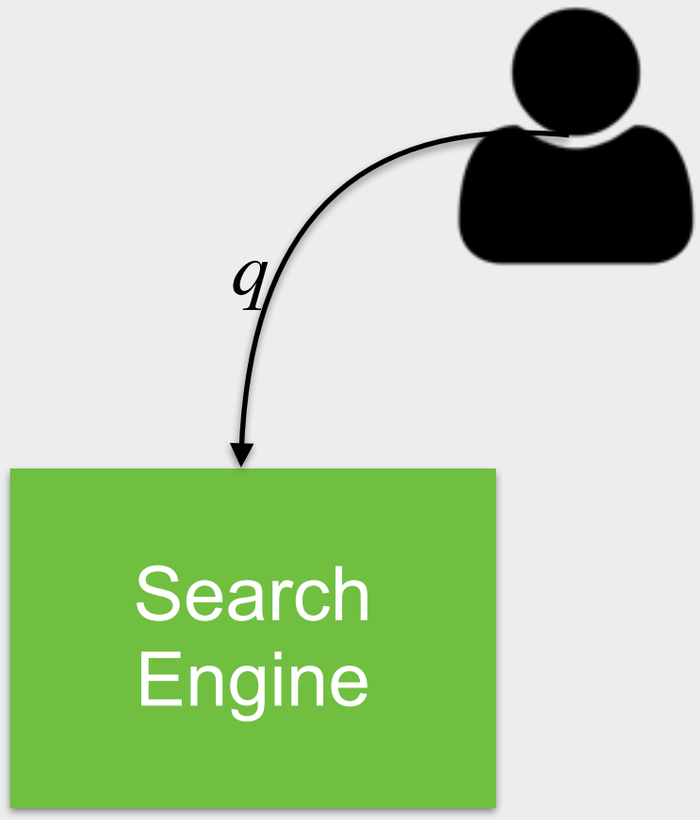
  - to improve rankings

Living Lab for IR Evaluation

Living Lab for IR Evaluation

Search Engine

Living Lab for IR Evaluation



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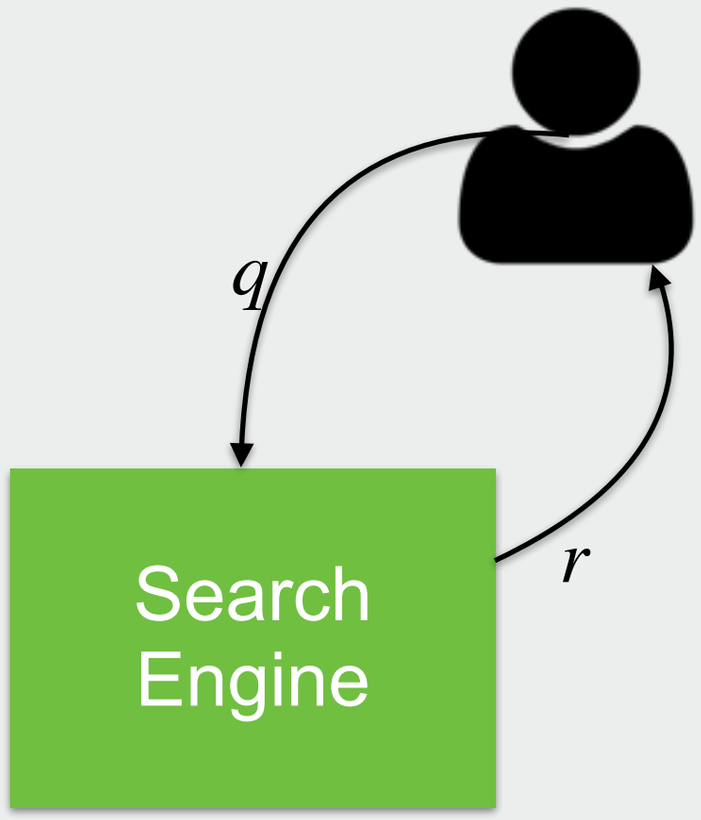

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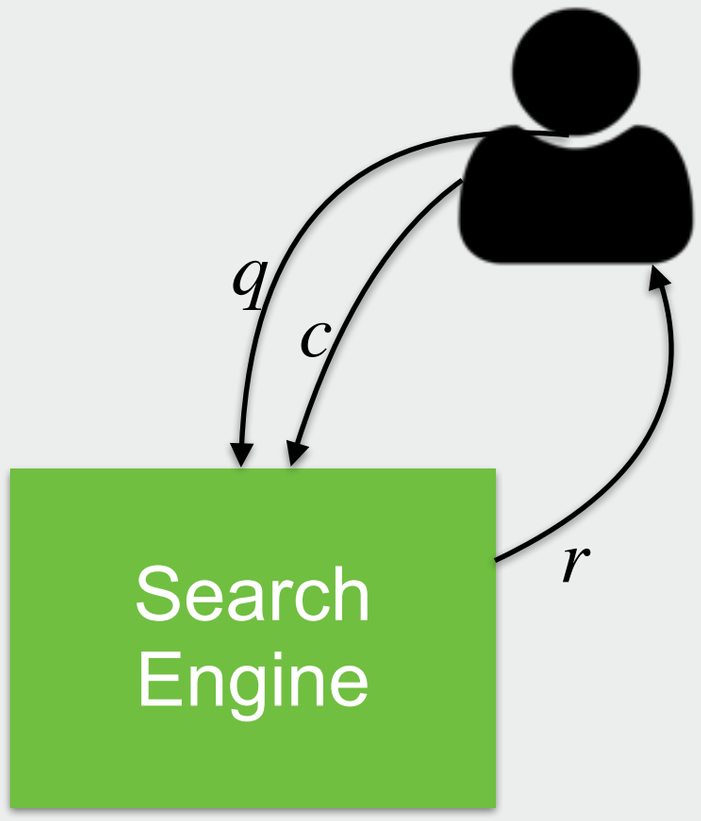

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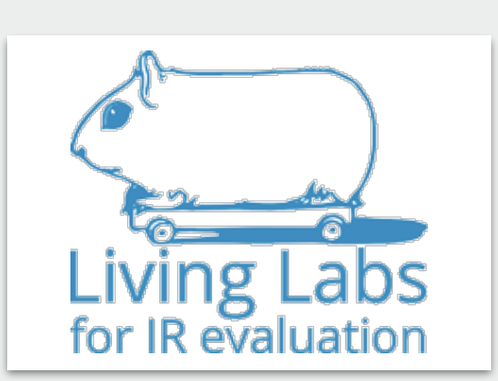

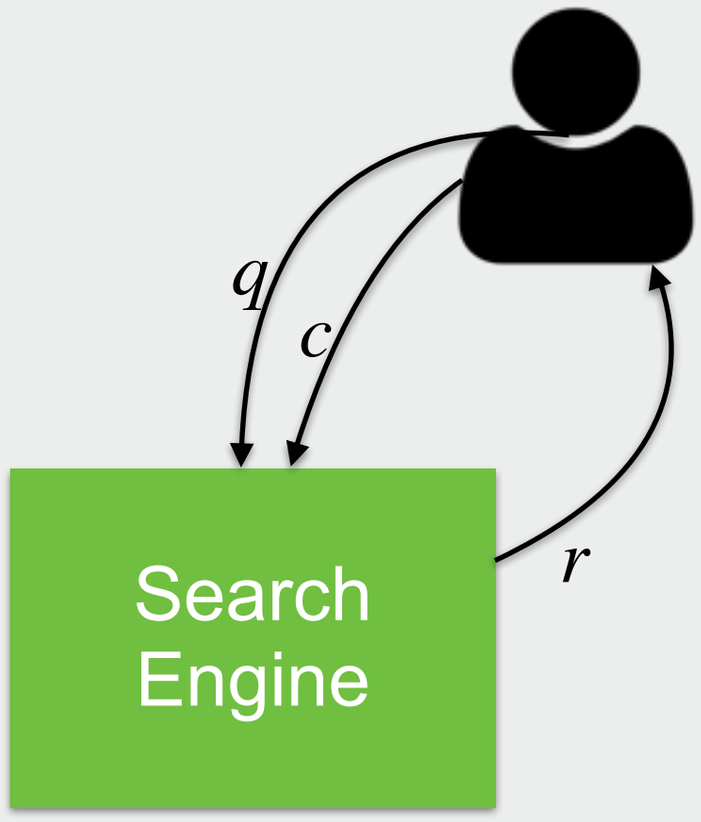

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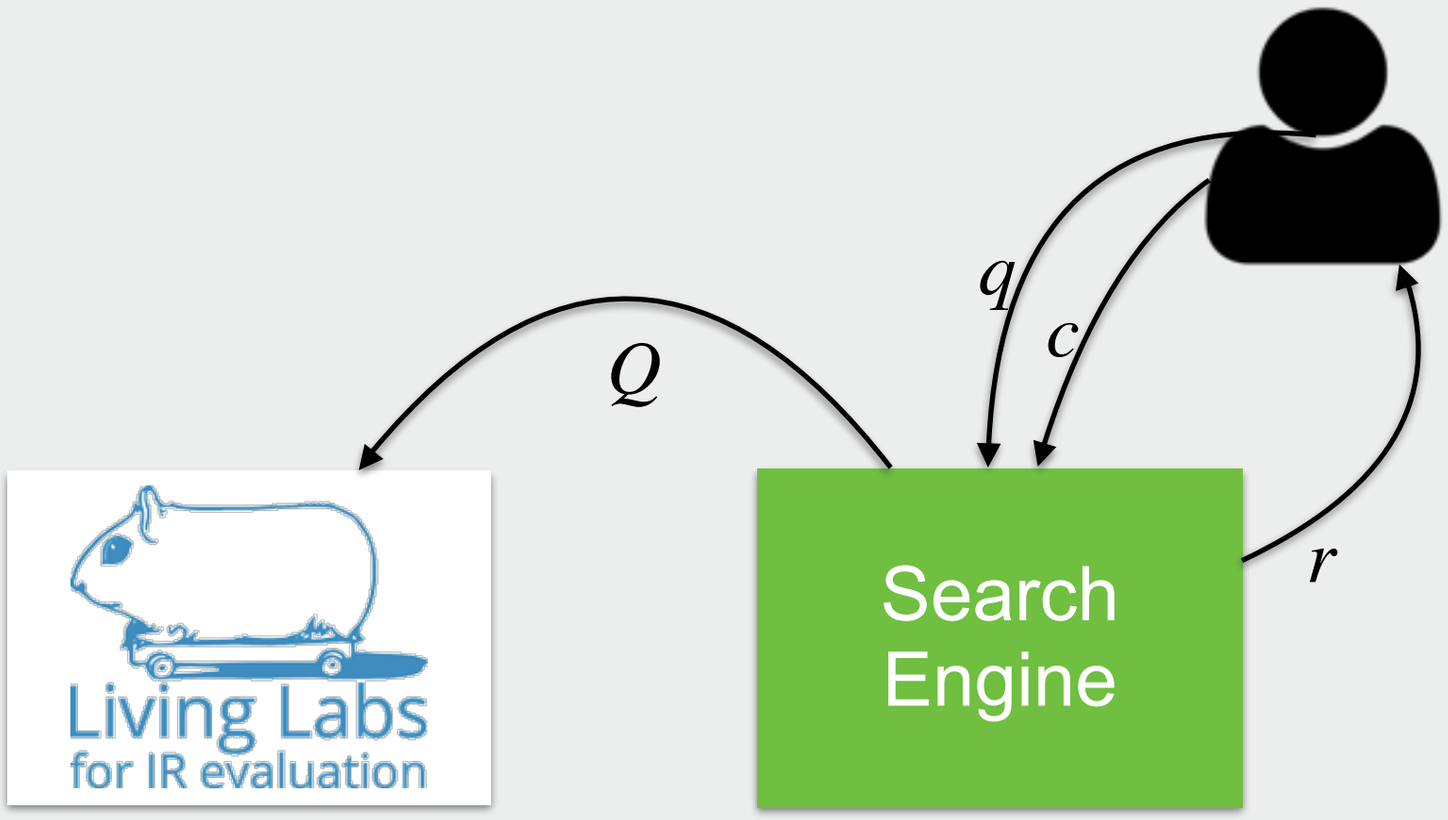

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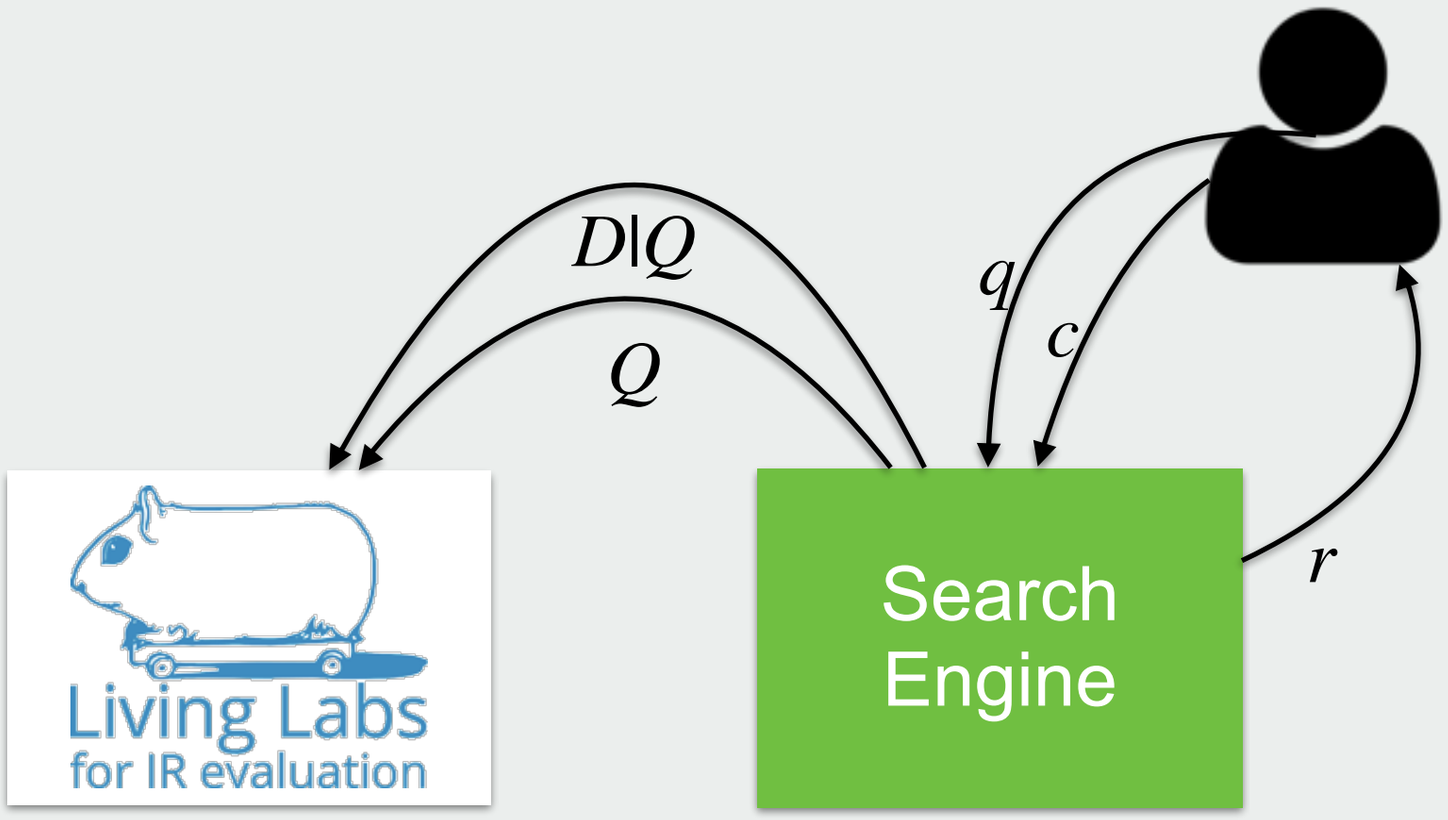

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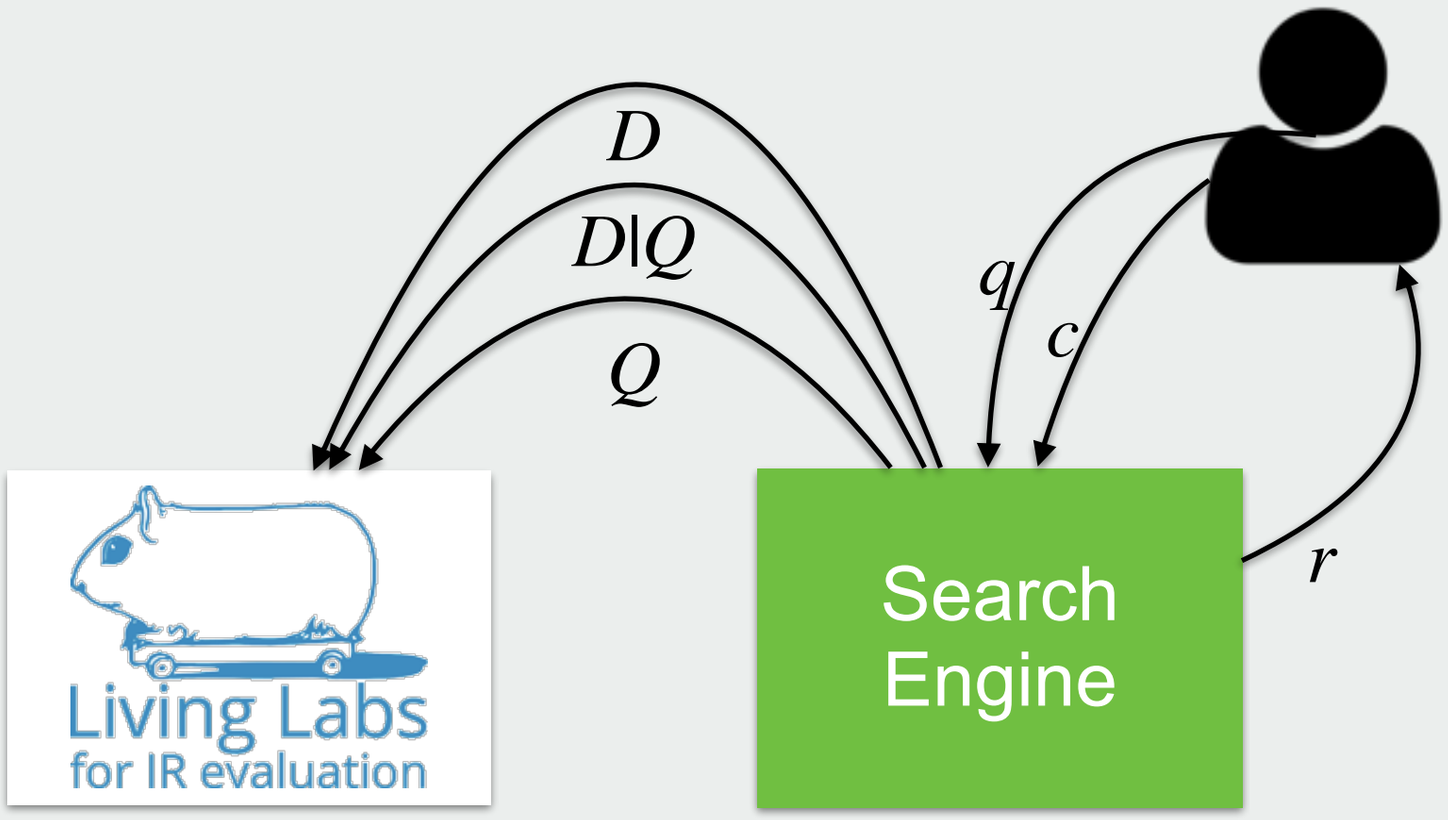

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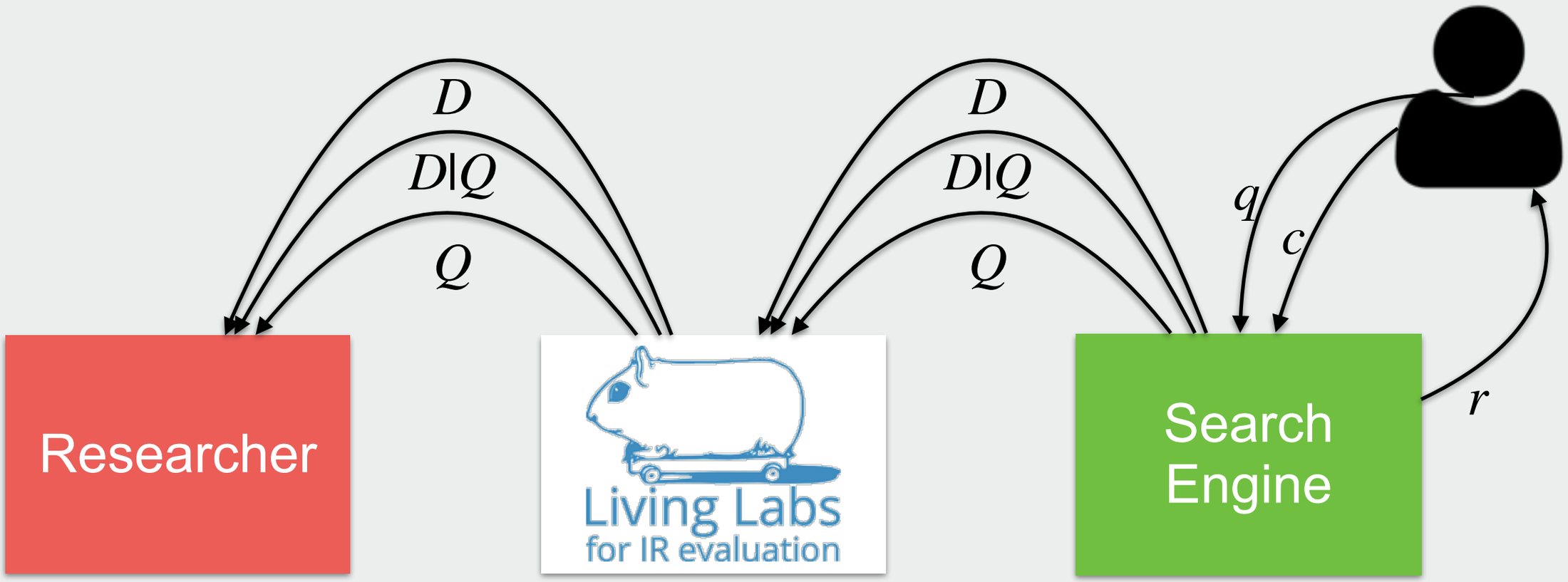

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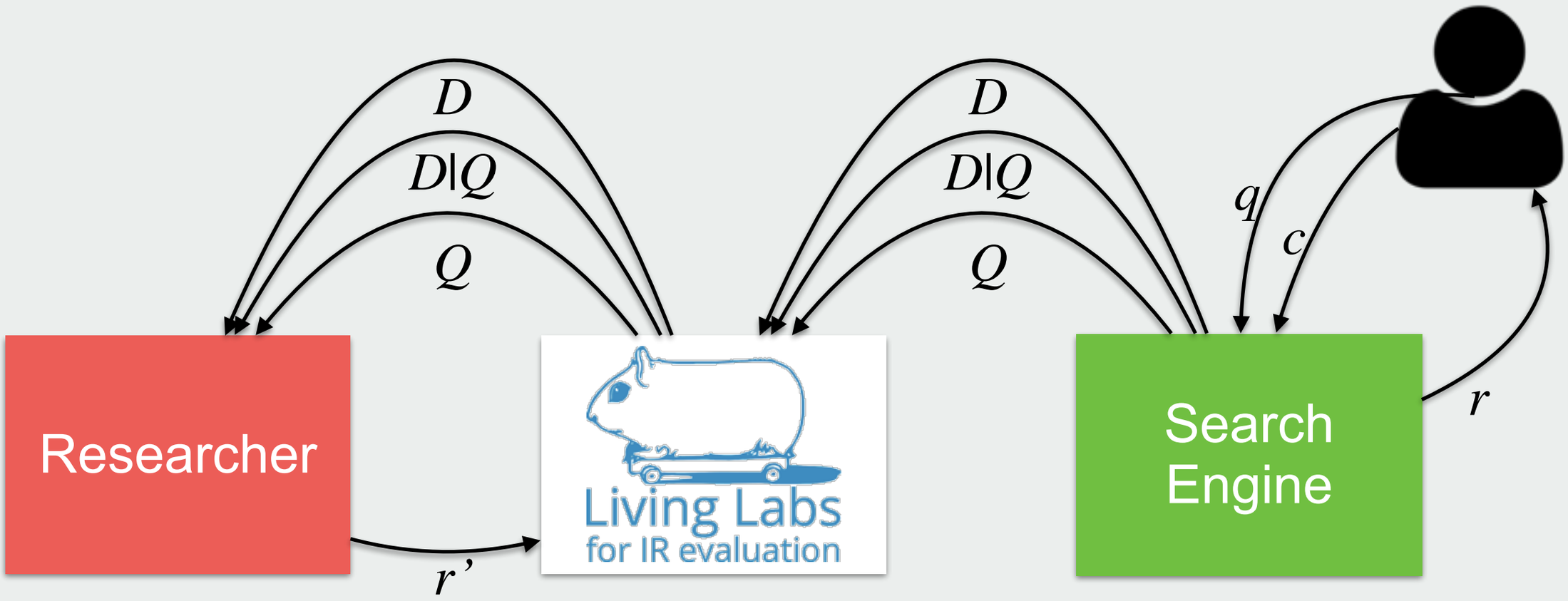

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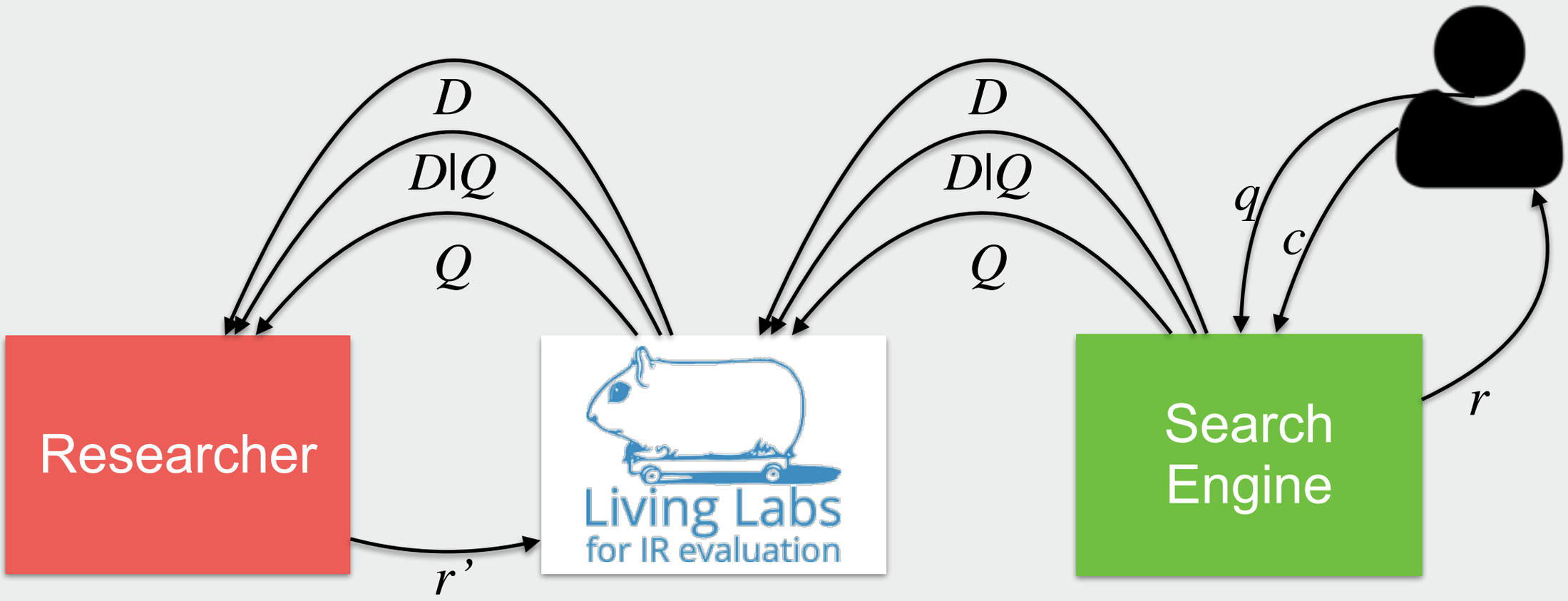

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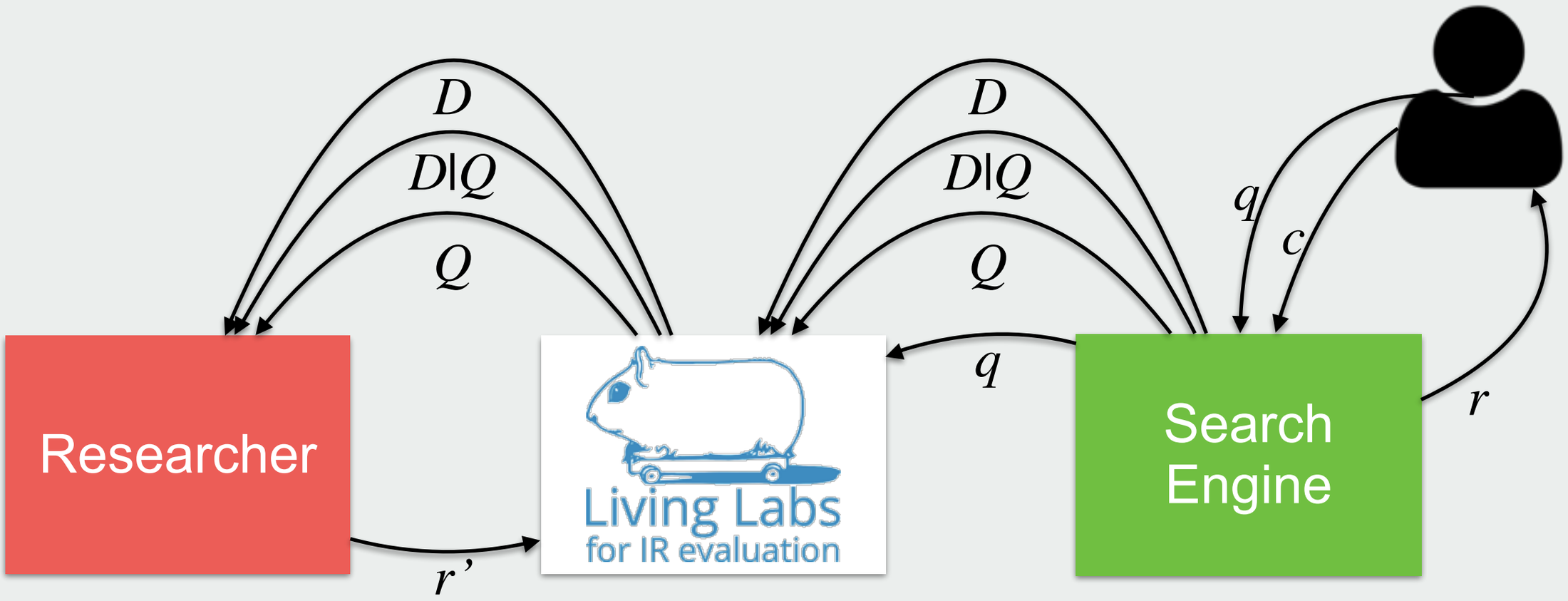

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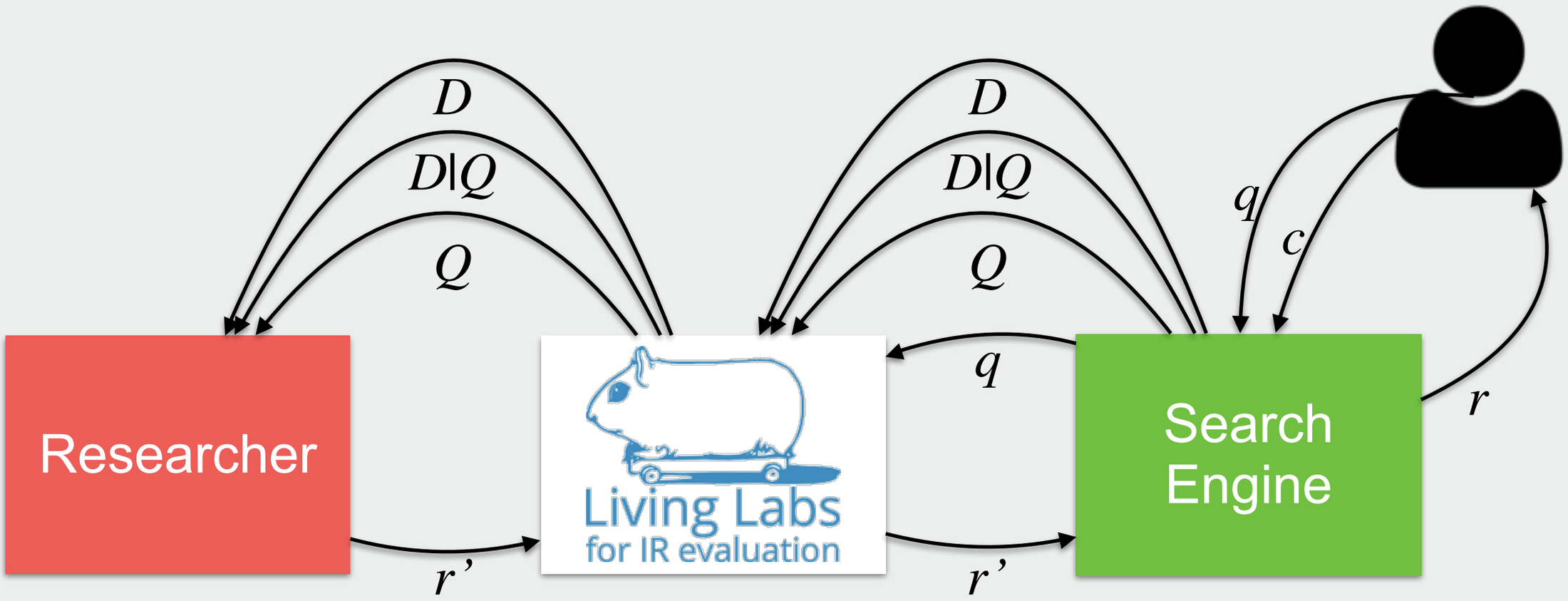

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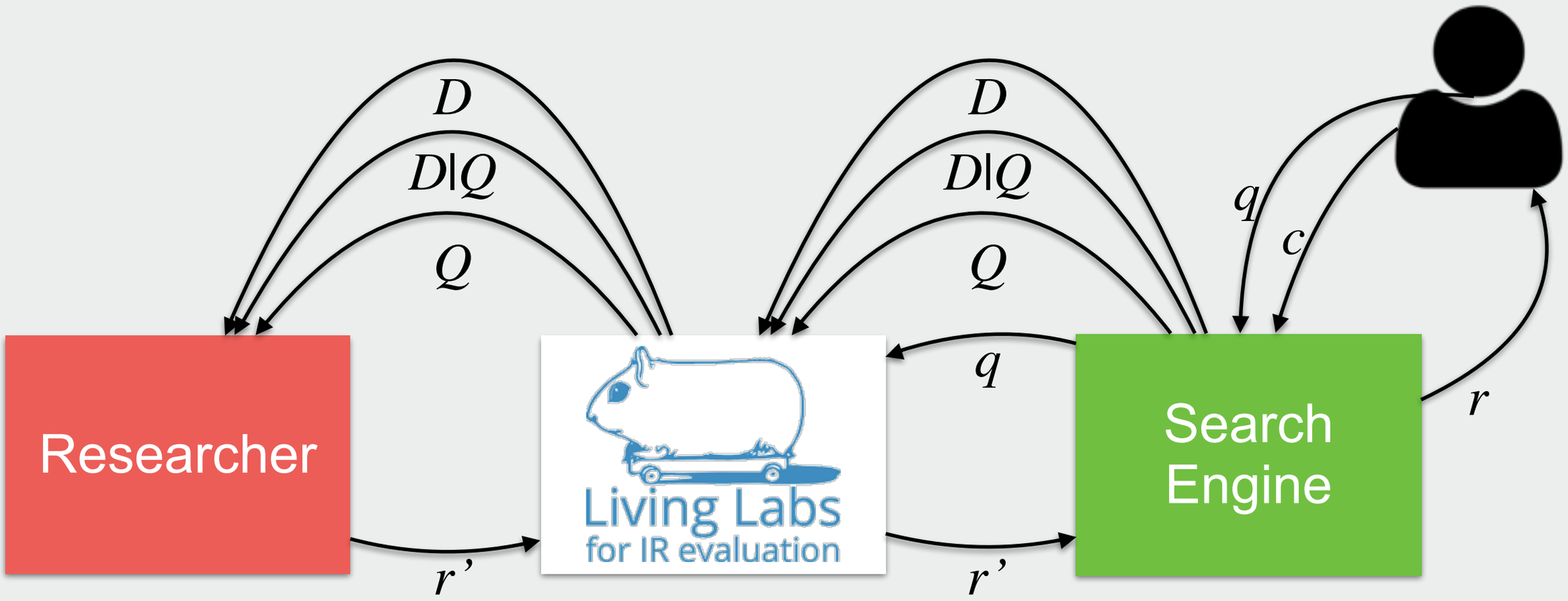

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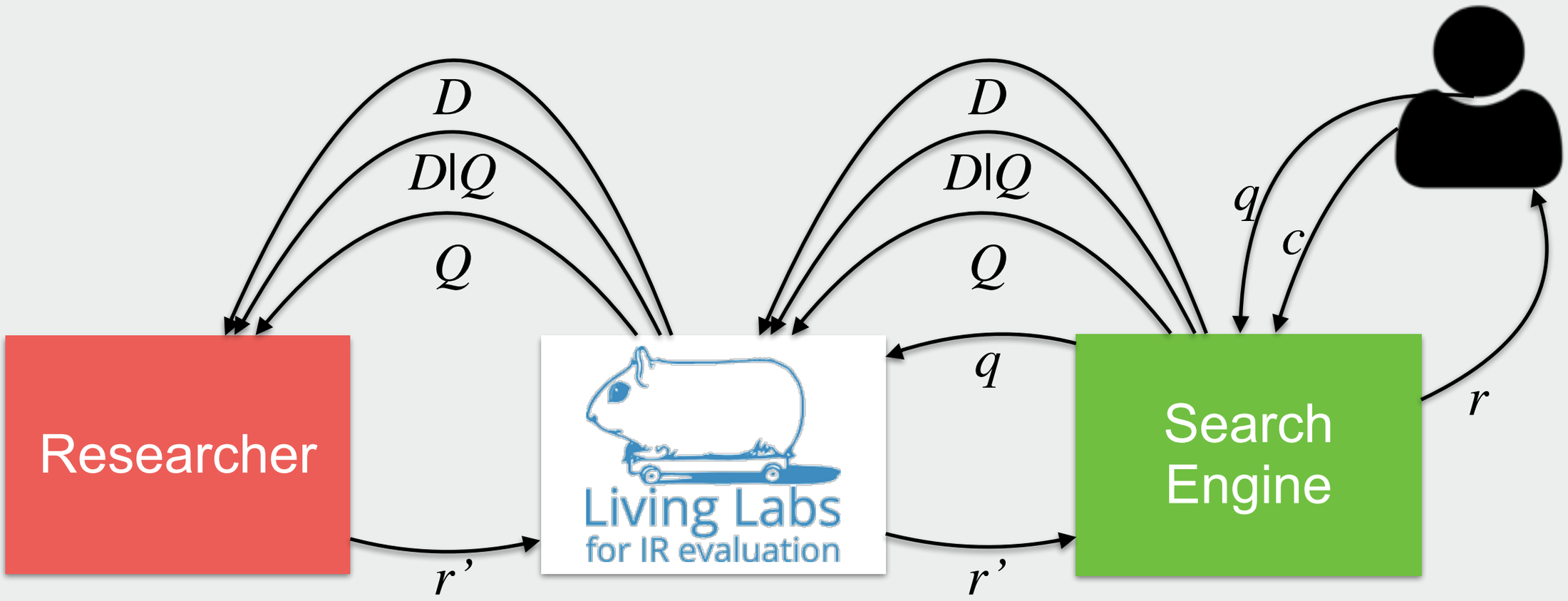

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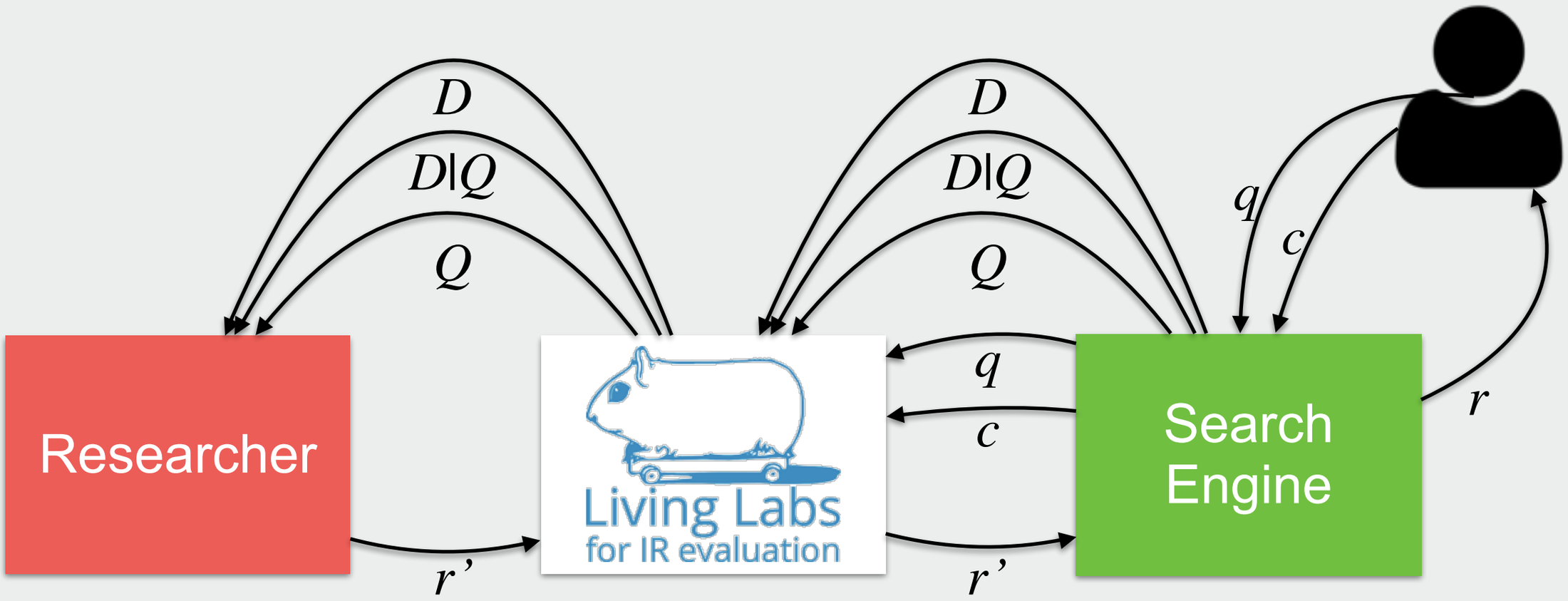
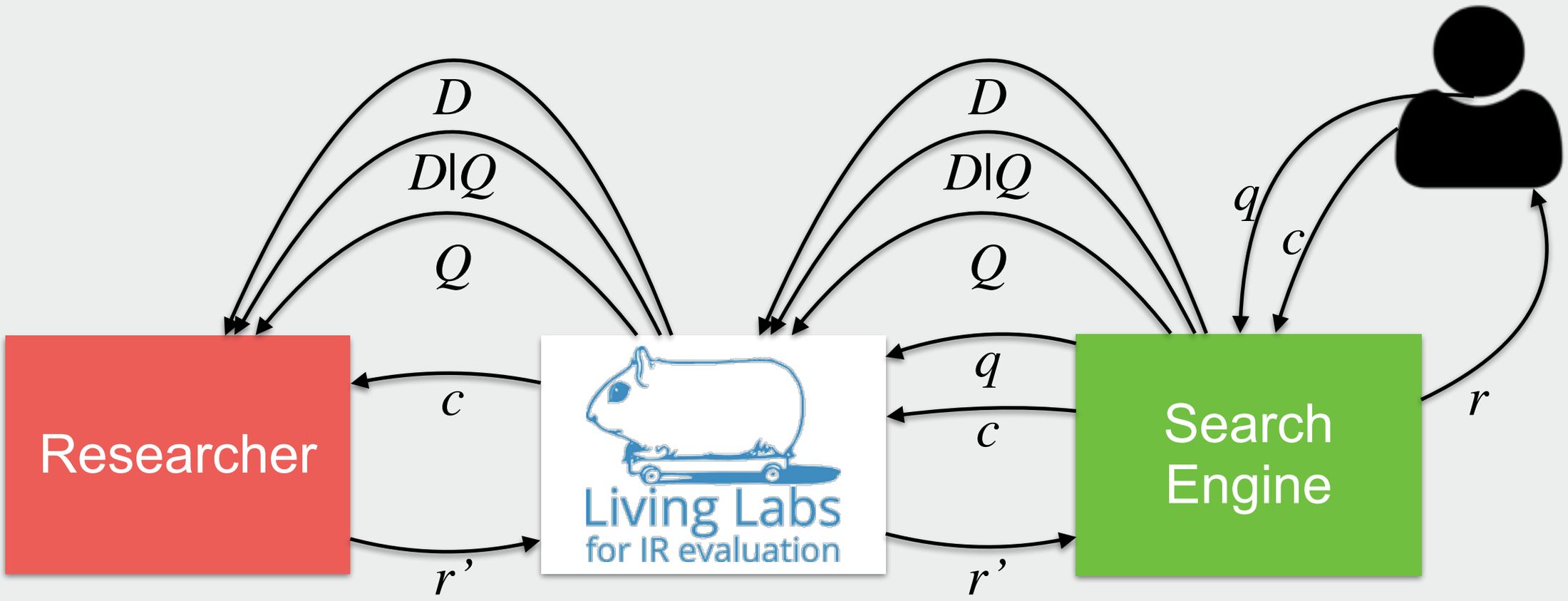


Living Lab for IR Evaluation



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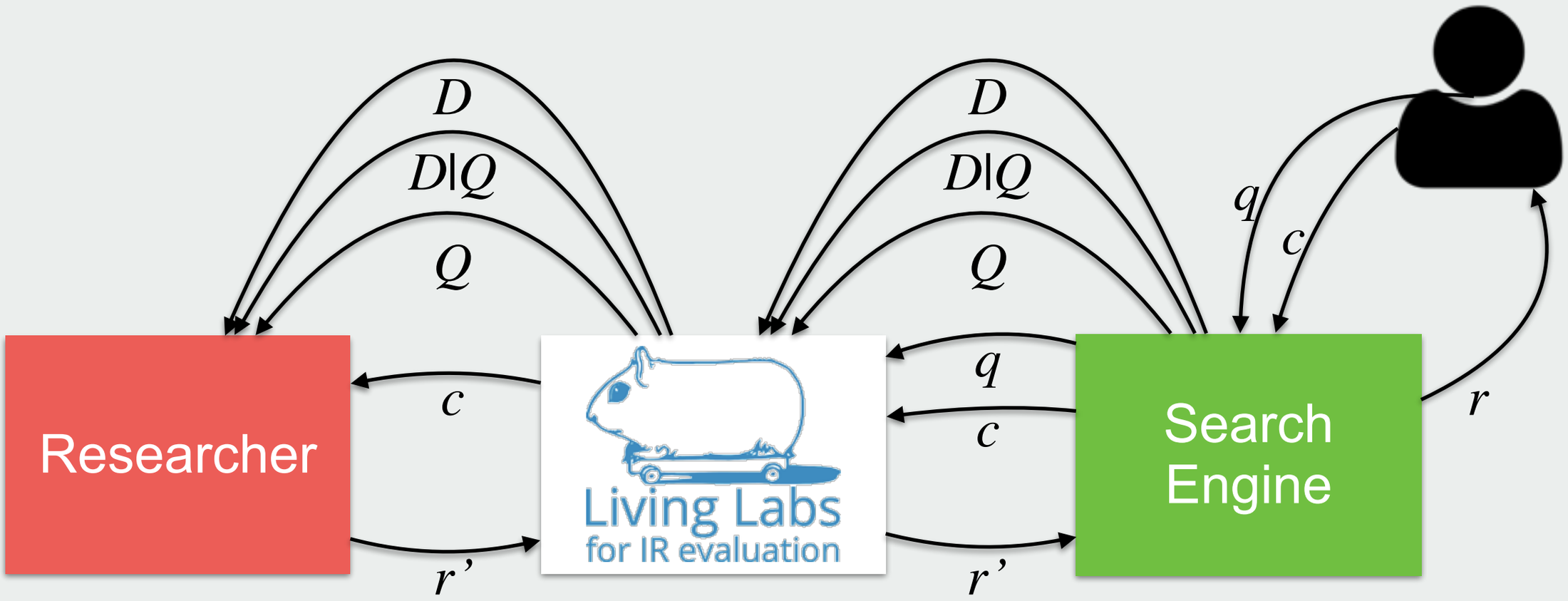

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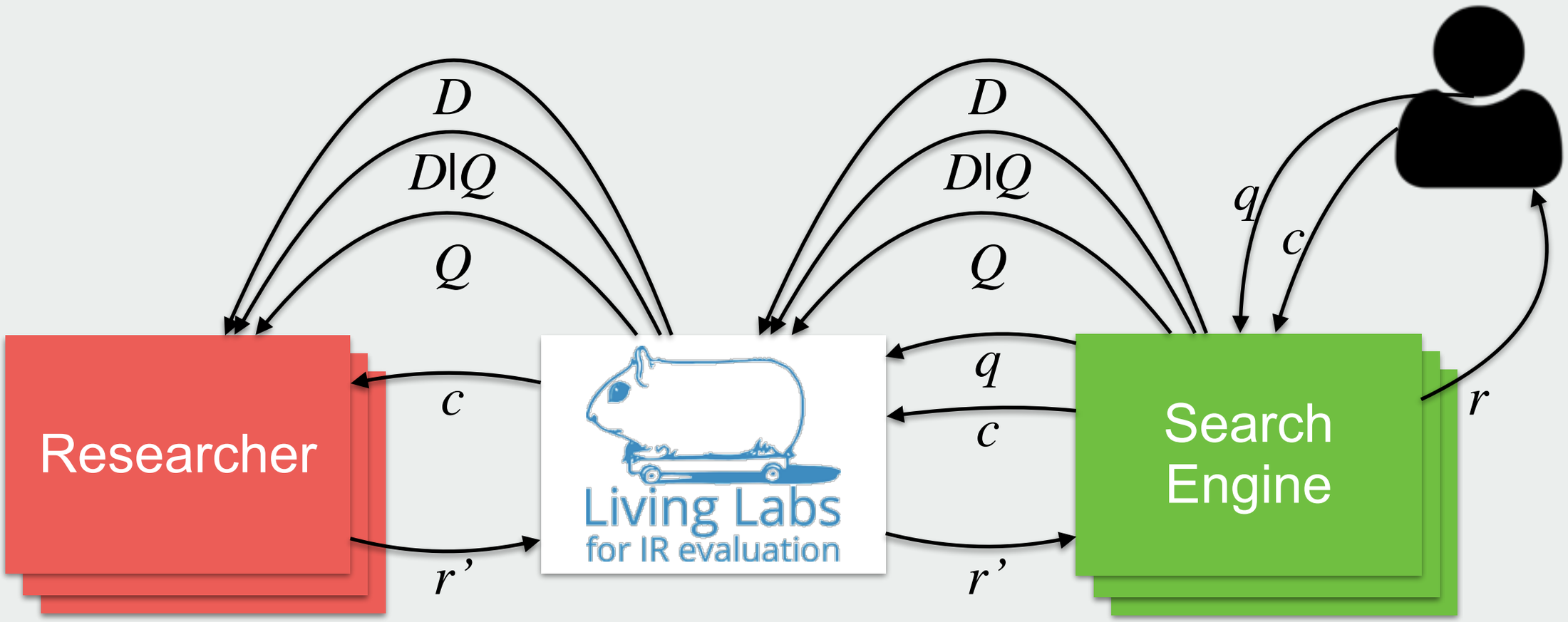

Living Lab for IR Evaluation

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- Overcome lack of users for researchers

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- Provide search engines with researchers

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- Runs as a CLEF Lab
  - http://living-labs.net/clef-lab/

Outline

- Information Retrieval
- Online
  - Evaluation
  - Learning to Rank
  - Issues
- Living Labs
- Wrap up

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- Living Labs
  - Users for researchers
  - Researchers for search engines

Thanks

Living Labs for IR evaluation

living-labs.net/clef-lab

Lerot

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