

«Personalized Recommendations will replace the navigation grid on Netflix»  
Neil Hunt, CPO of Netflix

## SUMMARY

So far, recommender systems have been mostly evaluated on **accuracy** → **one-click analysis**

We extend this evaluation towards **sequences of dependent clicks** → **multiple-click analysis**

## RESULTS

Recommendation networks are **poorly navigable**, but explorative and variable scenarios are better supported.

**Collaborative Filtering produces more navigable networks** than content-based recommendations.

More attention to **recommendation networks** is needed to improve navigability, e.g., by specifically replacing some recommendations.

## RESEARCH QUESTIONS

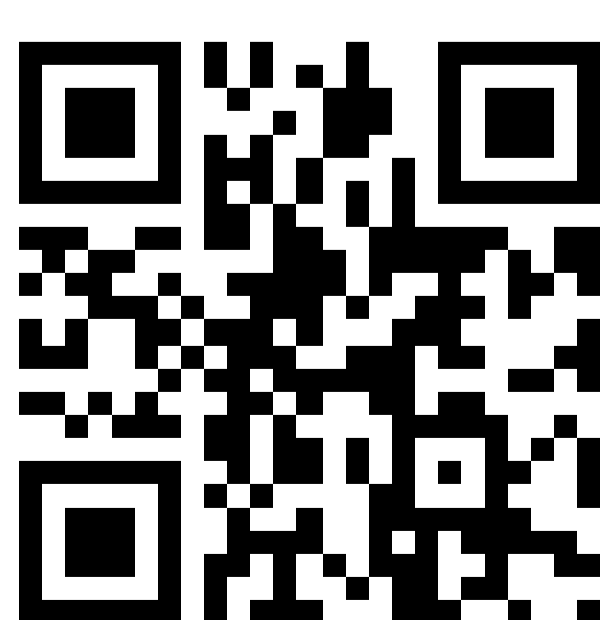
1) How well are recommendation networks suited for navigation and exploratory search?

2) What is the influence of parameters (e.g., recommendation algorithms and the number of recommendations shown) on navigability?

## REFERENCES

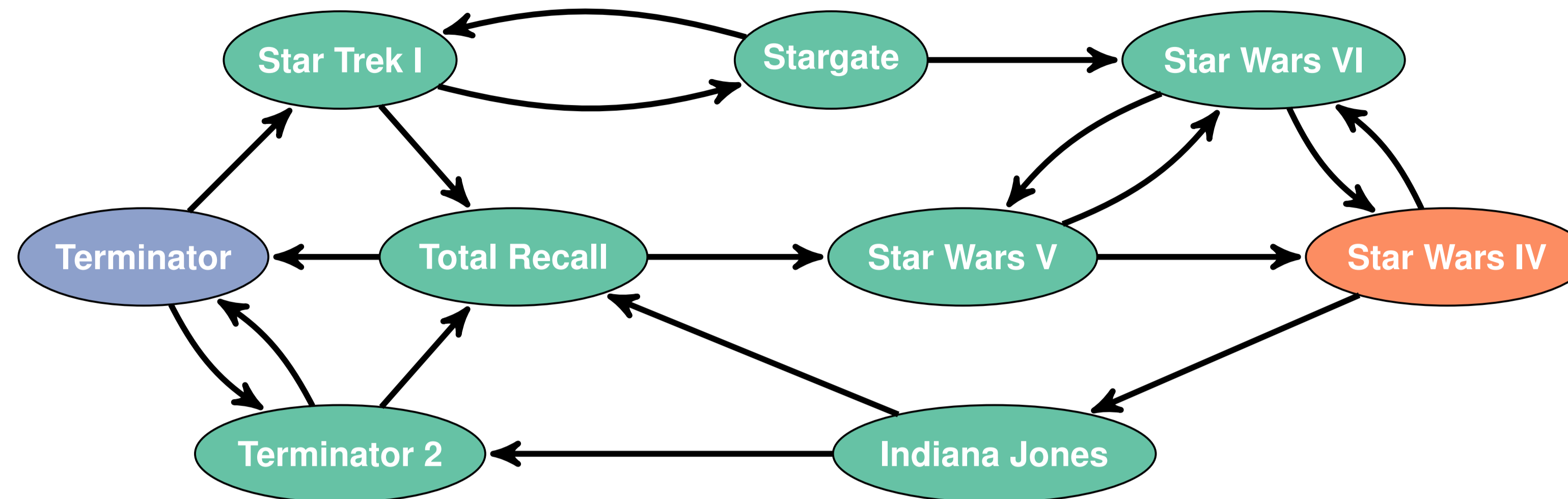
- [1] M. J. Bates. The design of browsing and berrypicking techniques for the online search interface. *Online Information Review*, 13(5):407–424, 1989.
- [2] J. Kleinberg. Complex networks and decentralized search algorithms. In *Proceedings of the International Congress of Mathematicians (ICM)*, volume 3, pages 1019–1044, 2006.
- [3] P. Pirolli. *Information Foraging Theory: Adaptive Interaction with Information*. Oxford University Press, 2007.

## CONTACT



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## METHOD



### Legend

- Start Node
- Intermediate Node
- Target Node
- Recommendation

We build **recommendation networks** with **movies** from **MovieLens** and **books** from **BookCrossing**, taking the items as nodes and a fixed number of unpersonalized outgoing recommendations per node as links.

We use two types of recommendations:

- **Collaborative Filtering** recommendations from user ratings
- **Content-based** recommendations via text similarity of Wikipedia articles for items.

## NAVIGATION

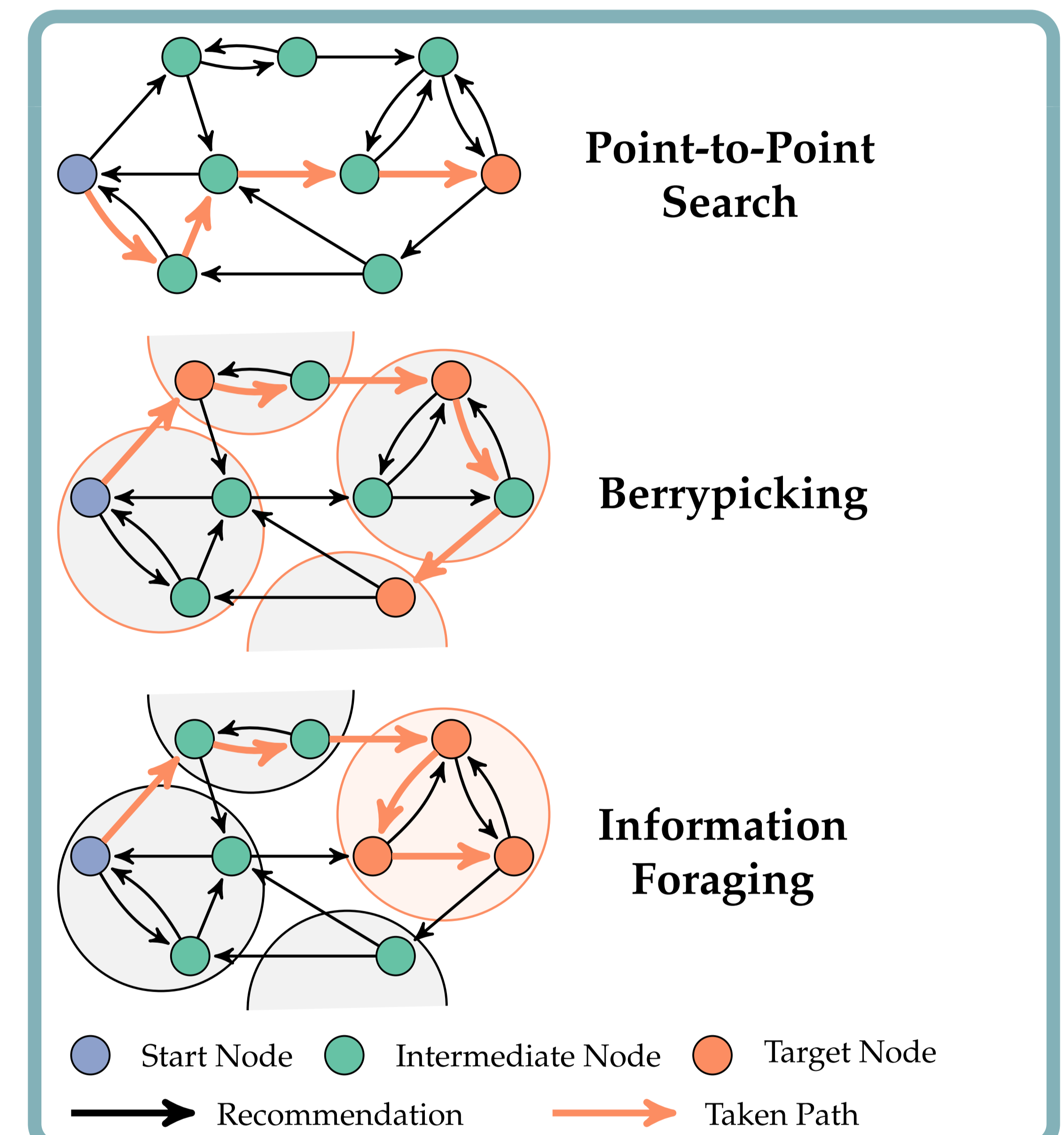
We model navigation with **Decentralized Search** [2], based on of the following intuitions:

1. **Title Similarity** (*Star Wars* and *Star Trek*)
2. **Shared Neighbors** (i.e., *What neighbor shares the most neighbors with the target?*)

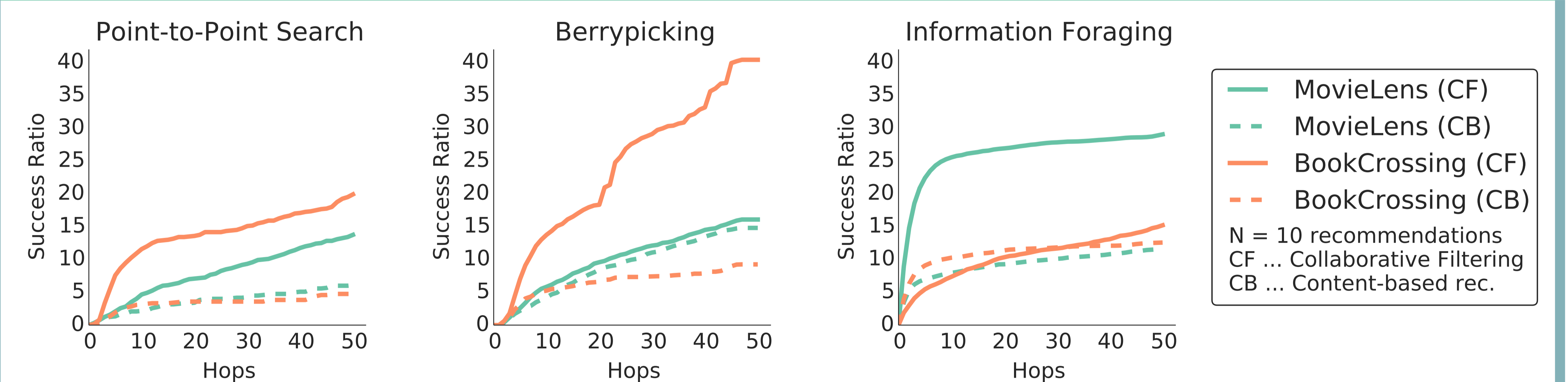
Navigation uses one of these types of local knowledge for greedily picking the next hop.

## SCENARIOS

- 1) **Point-to-Point Search** as a static start-to-target navigation.
- 2) **Berrypicking** [1] as a dynamic and explorative scenario picking one item (berry) from several clusters.
- 3) **Information Foraging** [3] as a dynamic and explorative scenario searching (foraging) for a whole cluster of items.



## FINDINGS



**In general we find recommendation networks to be poorly navigable.** We evaluate scenarios based on **Success Ratio** (the fraction of successfully found targets) over the number of **Hops** (the maximum number of allowed steps).

**Point-to-Point** search is only poorly supported (Success Ratio < 20%). This suggests that current recommender systems do not support static navigation scenarios.

**Berrypicking** and **Information Foraging**, examples of explorative scenarios, are better supported.

**Collaborative Filtering produces more navigable networks than content-based recommendations.**

## CONCLUSIONS

- We present a **general approach for evaluating navigation dynamics** in recommendation networks.
- We find that **the recommender systems are poorly navigable** in our scenarios, if practical constraints are applied.
- **Our approach is useful for assessing current recommendation algorithms** w.r.t. the produced recommendation networks.
- **Navigability could be improved by increasing serendipity**, e.g., by replacing some recommendations by specifically (or randomly) selected links.