Why-Not Explainable Graph Recommender

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40th IEEE International Conference on **Data Engineering**
Utrecht, Netherlands | 13th - 17th May
2024

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Recommendation Systems

Recommendation systems are personalizing our web experience.
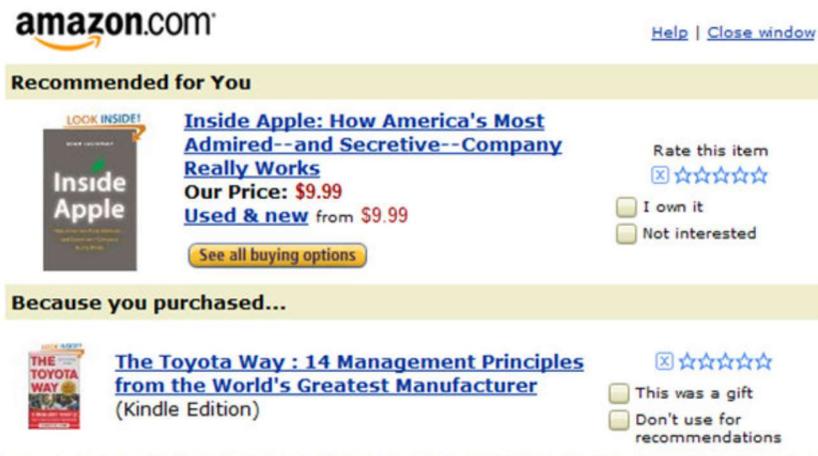

What to buy
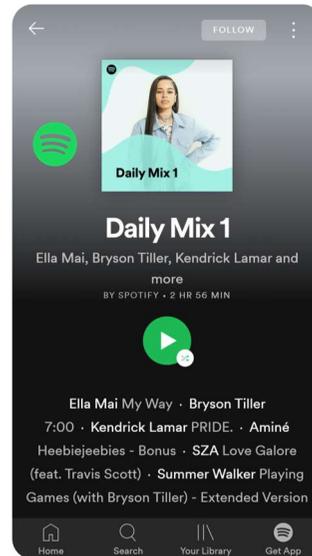
What to listen
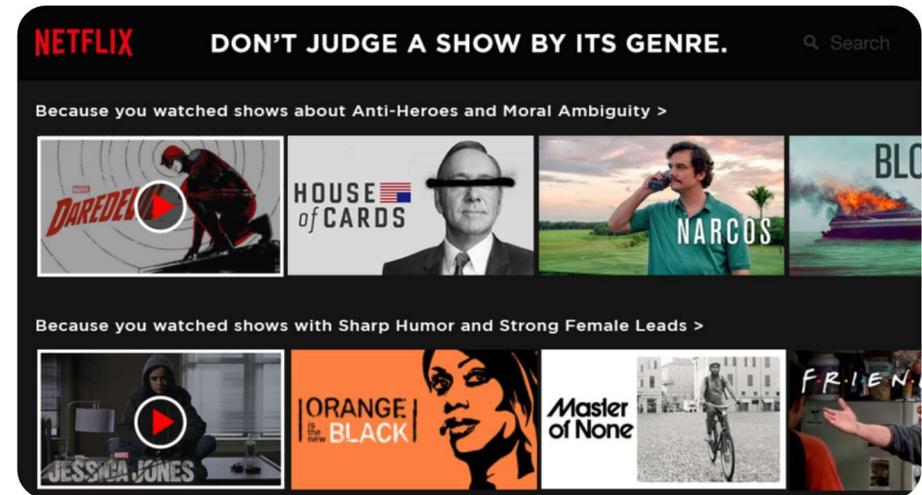
What to watch

Recommendation Systems
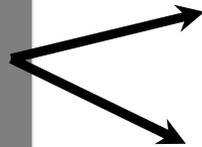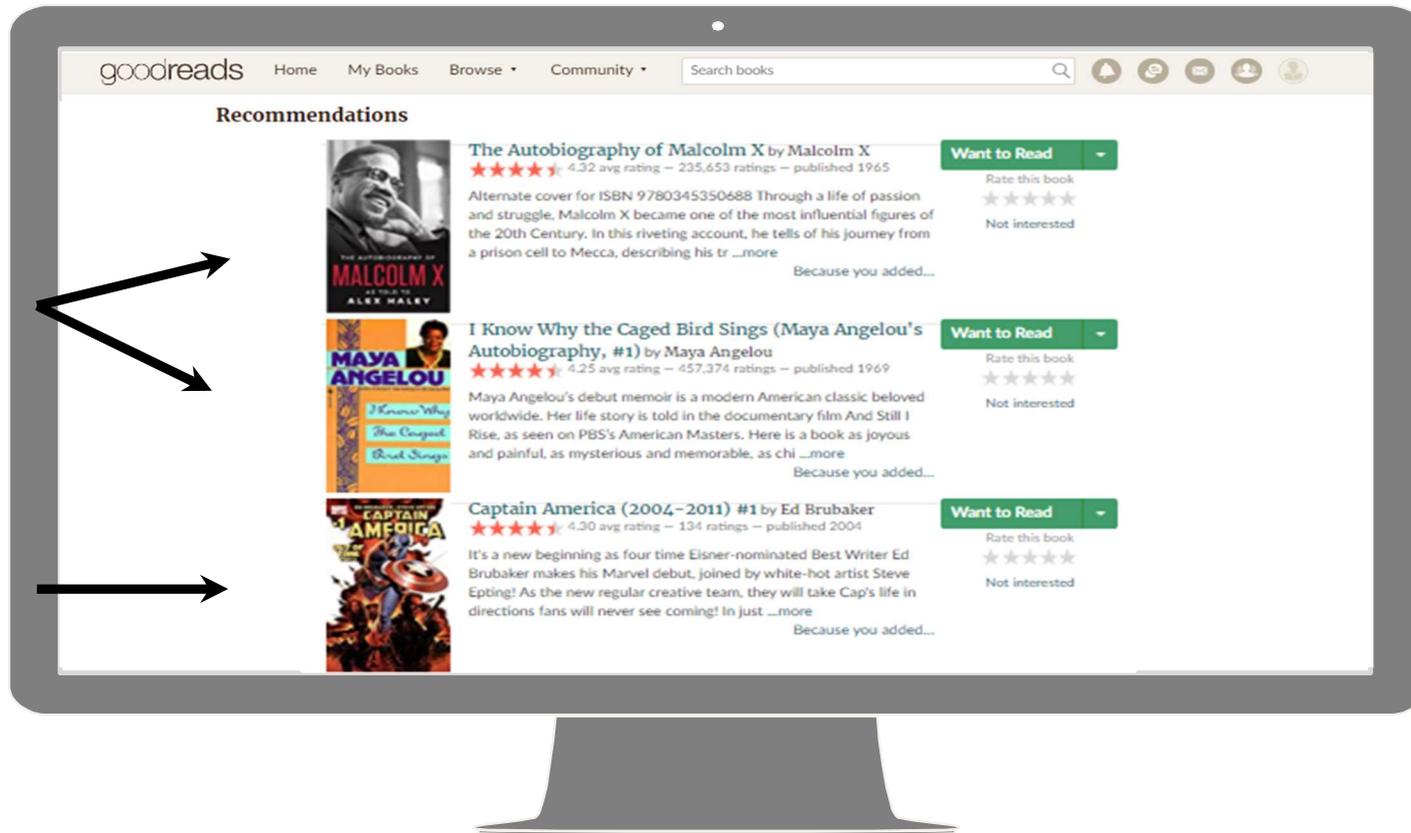
Biography

Comics

Book recommendations from Goodreads when logging in with an Amazon account.

Explainable Recommendation Systems
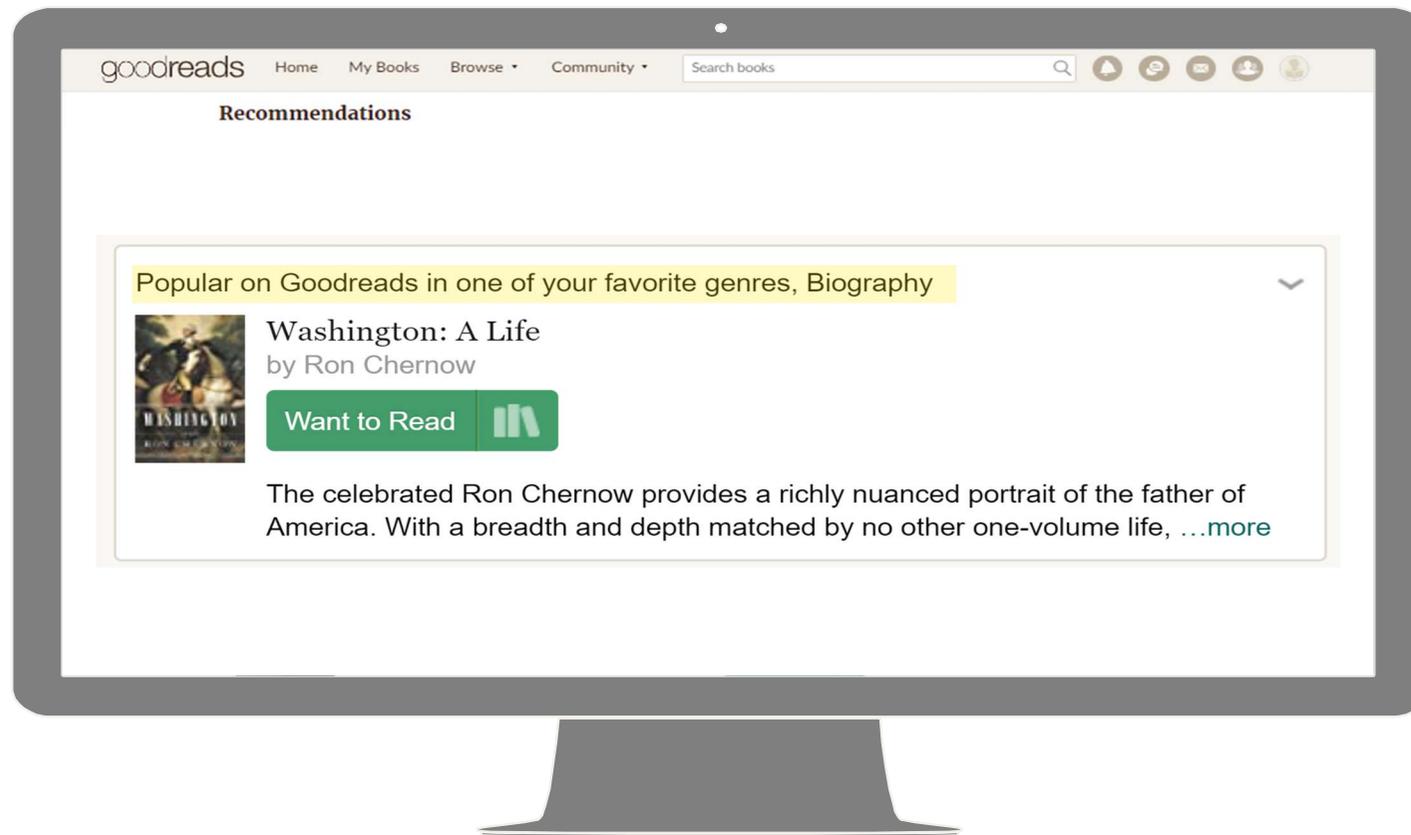
Example **explanation** for a recommendation.

Explainable Recommendation Systems

Biography
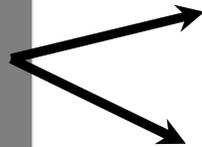
Comics
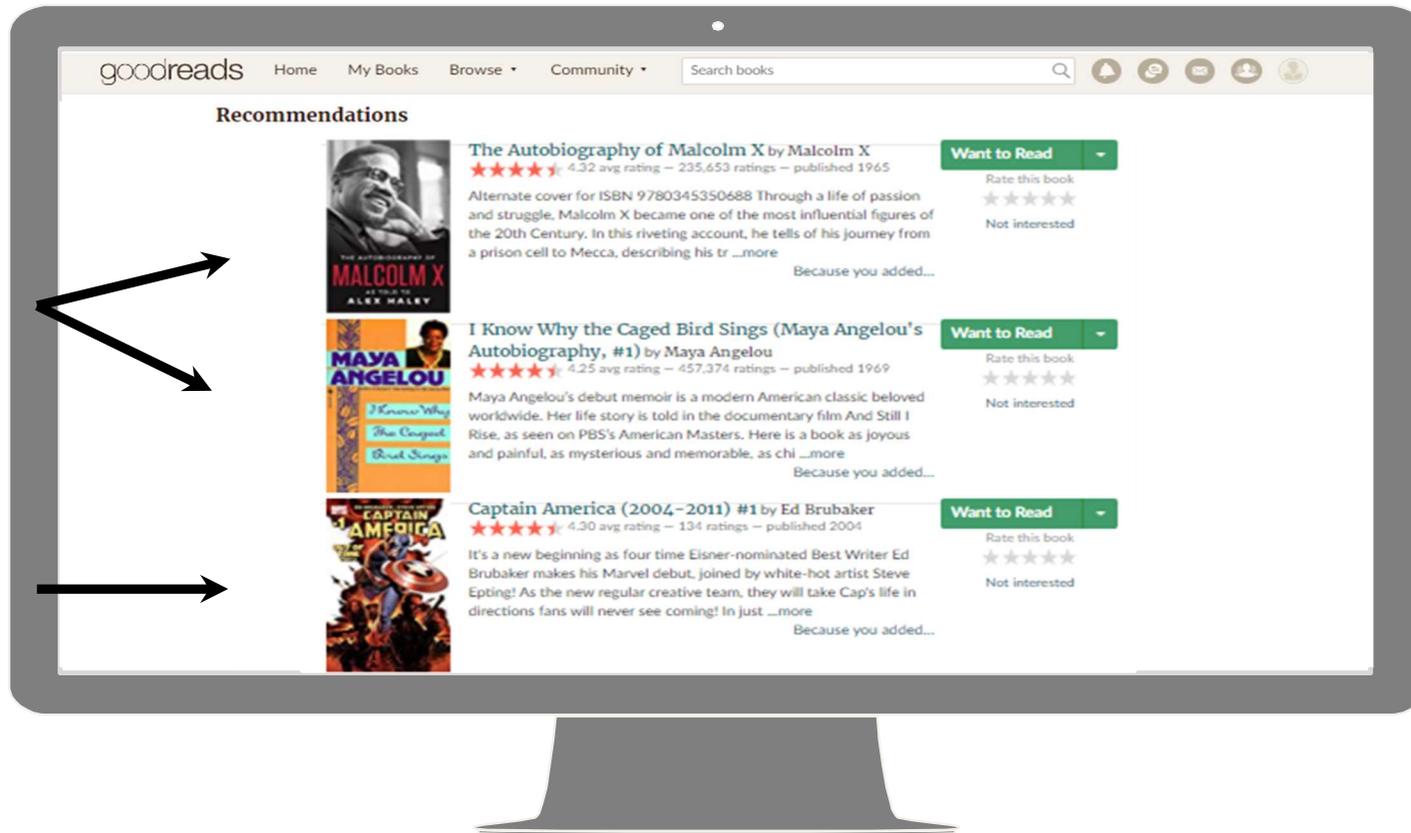
Why-Not Question:

Why don't I get recommended any Computer Science books ❓ 5

Why-Not Explanations

Why-Not Question:

- **Why** an item or category of items is **not** in the recommendation list ?
- **Why** an item or category of items is **not** ranked in a higher position ?

Why-Not Explanations:

- **Explain the absence** of certain options from a user's recommendation list.
- **Provide more information** to the system designer.
- Promote decision **transparency** and strengthen fairness.
- **Detect discriminative** systems and biases in the original data.

Related & Backgound Work

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Related work

Recommenders

- Collaborative Filtering [12]
- Content-Based Filtering [8]
- Context-Based Recommenders [17]
- …

Explainable Recommenders

- Explainable Matrix Factorization [1]
- Rule Mining [21]
- Graph Based [5]
- Black-Box Explanations [20]
- Counterfactual Explanation for ML
- …

Why-Not Questions

- Why-Not Questions In Databases [6, 14],
- Top-K Spatial Queries [7] Workflow Analysis [4]
- …

- Why-Not Questions In Collaborative Filtering [13]

- **Why-Not Explainable Recommenders**

Why-Not Explanations for Recommenders   ICDE2024

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Background: Heterogeneous graph
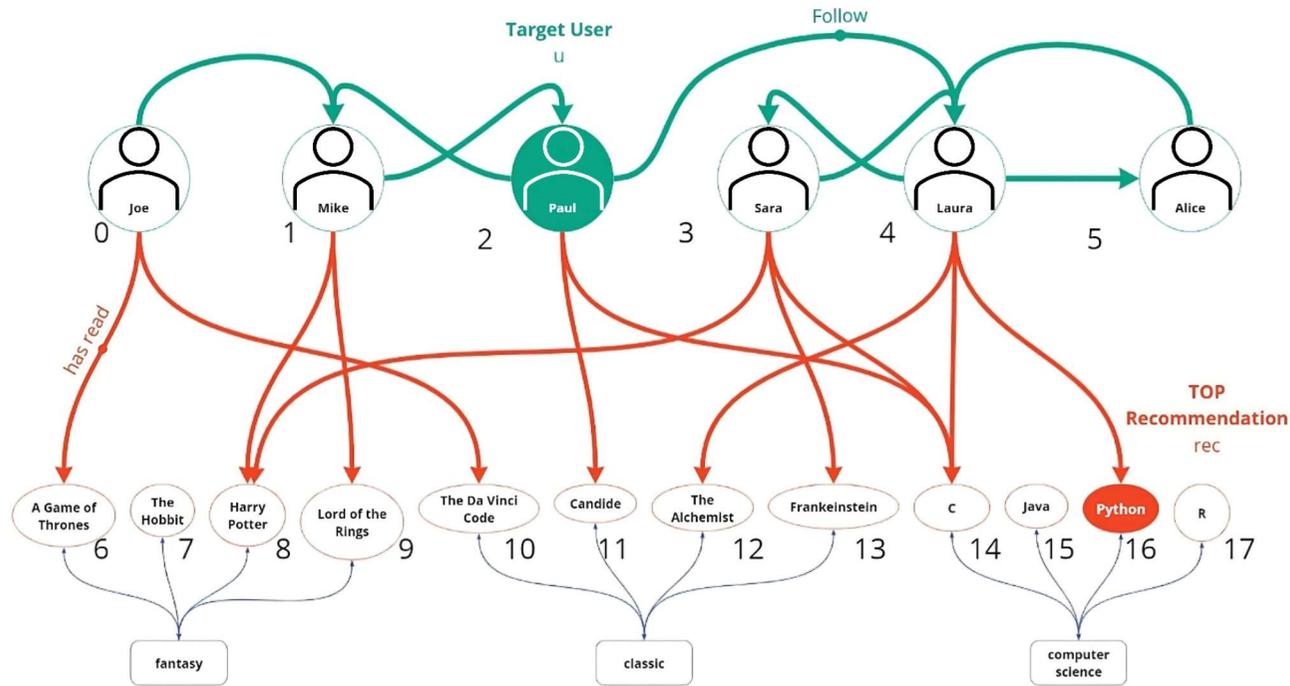
An heterogeneous graph G = (V, E, θ) consists of a set of nodes V, a set of edges E ⊆ V ×V, and a mapping θ from each node and each edge to their types, such that $\theta_V : V \to T_V$ and $\theta_E : E \to T_E$ with $|T_V|+|T_E| > 2$.

In this work a heterogeneous graph generally contains at least two node types:
* **users** $U \in T_V$
* **items** $I \in T_V$

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Background: Recommendation Algorithm: Personalized PageRank (PPR)

$$PPR(u, \cdot) = \alpha \sum_{l=0}^{\infty} (1 - \alpha)^l e_u W^l$$

The distribution of a random walk in G, starting at u:

- with probability α: teleports to a set of seed nodes {s}
- with probability 1 − α: continues the walk to a randomly chosen outgoing edge.

$$rec = \arg\max_{i \in I \setminus N_{\text{out}}(u)} PPR(u, i)$$

The item i with the highest PPR(u,i) will be recommended.

α → teleportation probability
s → single seed
e_s → the one-hot vector
W → the transition matrix

Athanasios N. Nikolakopoulos and George Karypis. RecWalk: Nearly Uncoupled Random Walks for Top-N Recommendation. February 2019.

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**Problem
Definition
&
Solution**
———

Why-Not Explanations for
Graph Recommender Systems

Problem Definition

Given:
- a graph $G = (V, E, \theta)$,
- a user u,
- a Why-Not Item **WNI**,
- and an initial recommendation *rec*

a **Why-Not explanation** is the set of edges
$A^* \subseteq A$, $A \in \{A^+, A^-\}$, with:
- $A^+ = \{a^+ \mid a^+ = (u,i) \notin E, i \in I\}$, and
- $A^- = \{a^- \mid a^- = (u,i) \in E, i \in I\}$

such that $G' = (V, E', \theta)$, with $E' = E \cup A^+ \setminus A^-$
generates **WNI** as the top-1 recommendation.
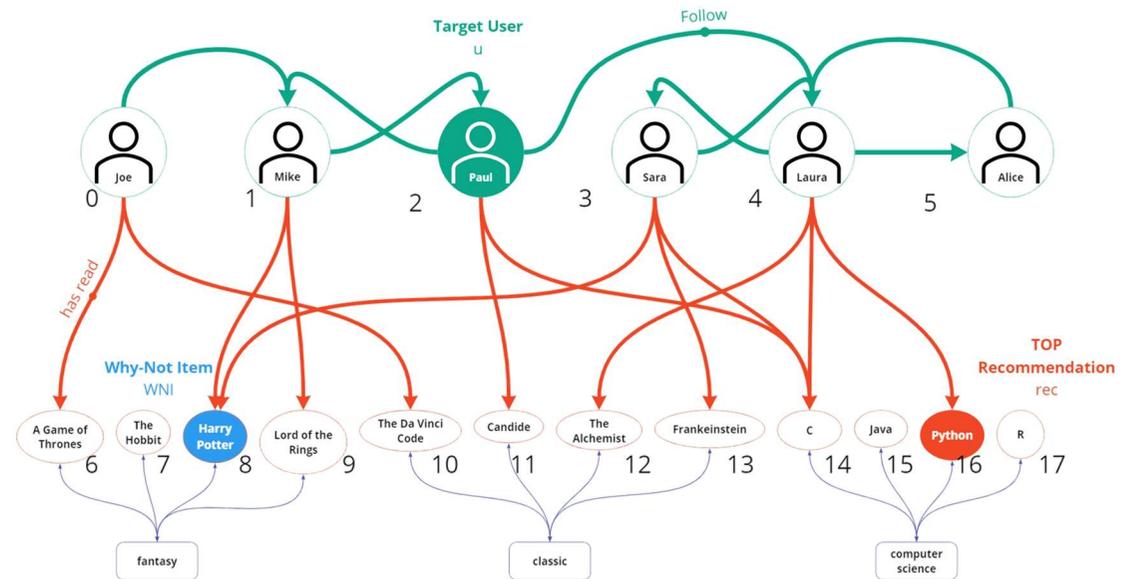
Example of Why-Not explanations

*Why Harry Potter is **not** my recommendation?*

Add Mode
Suggests **NEW ACTIONS**
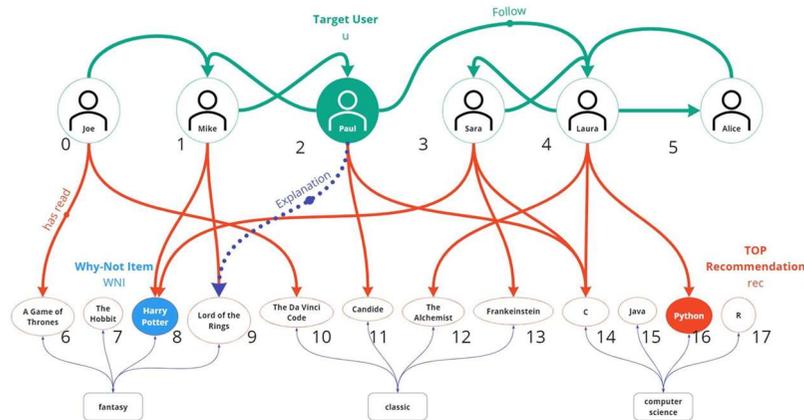
$A^+ = \{(2,9)\}$

"If Paul reads ***Lord of the Rings,*** the recommendation will be ***Harry Potter***"

Remove Mode
Pinpoints **PAST ACTIVITY**
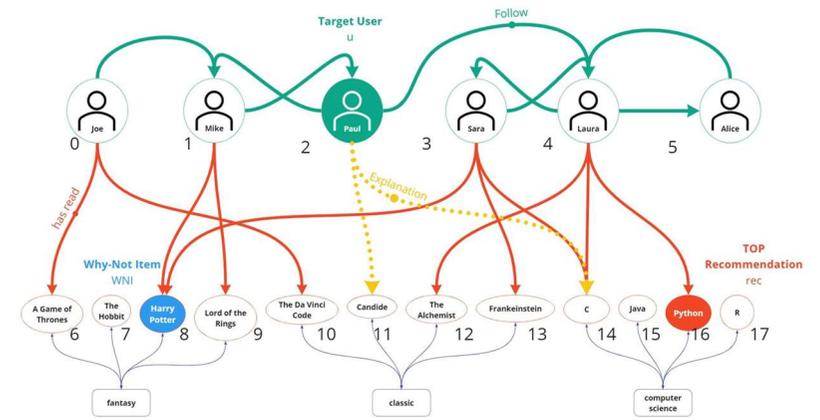
$A^- = \{(2,11), (2,14)\}$

"If Paul had not read ***Candide*** and ***C*** the recommendation, would have been ***Harry Potter***"

Example of Why-Not explanations

*Why Harry Potter is **not** my recommendation?*

Add Mode

Suggests **NEW ACTIONS**
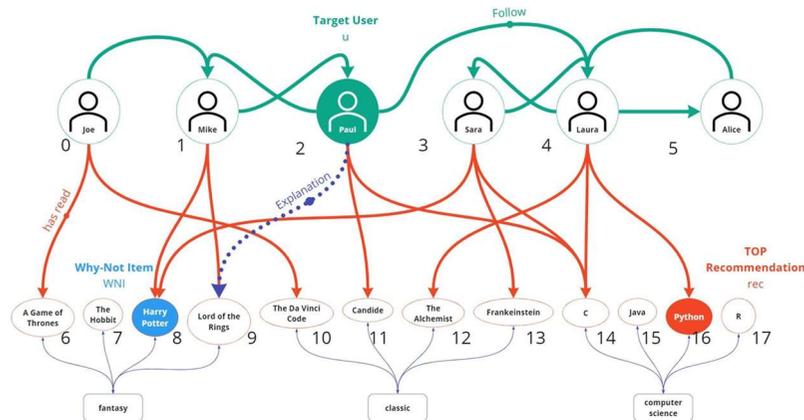
Remove Mode

Pinpoints **PAST ACTIVITY**
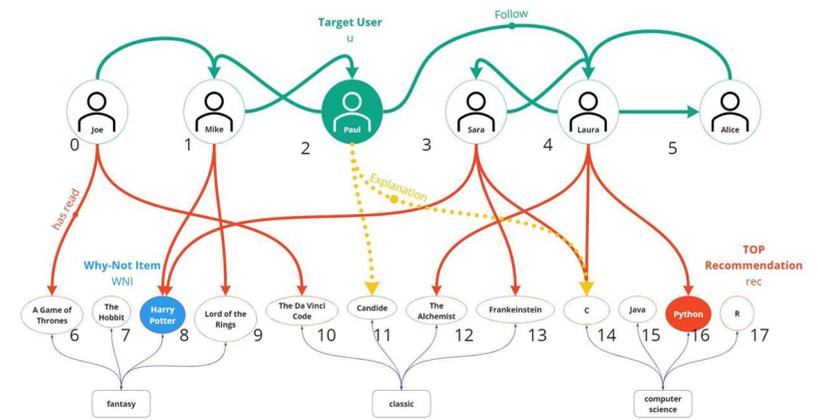
1. List the **existing**/**potential** neighbors by their contribution to the current recommendation compared to Why-Not Item.

2. **Disconnect**/**Connect** a set of neighbors so that the recommendation changes to the Why-Not Item.

EMiGRe: a Framework for Explaining Missing Graph Recommendations
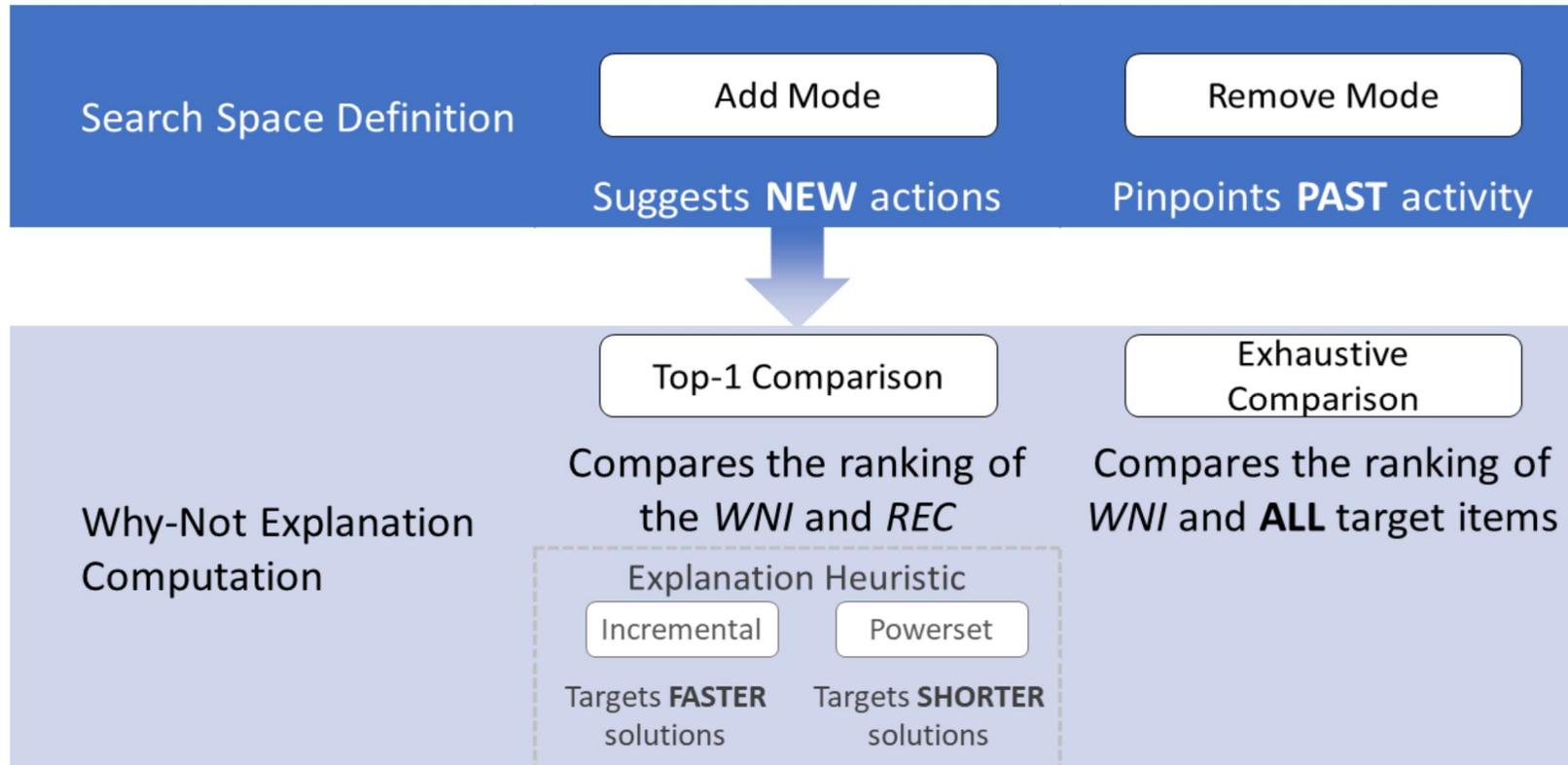
$$contribution_{add}(n_i) = PPR(n_i, WNI \mid A) - PPR(n_i, \text{rec} \mid A)$$

$$contribution_{rmv}(n_i) = W(u, n_i) \cdot (PPR(n_i, rec \mid A) - PPR(n_i, WNI \mid A))$$

Example

— — —

Incremental heuristic in Remove Mode

Follow

Target User
u

Joe 0 Mike 1 Paul 2 Sara 3 Laura 4 Alice 5

has read

Why-Not Item
WNI

TOP
Recommendation
rec

A Game of Thrones 6   The Hobbit 7   Harry Potter 8   Lord of the Rings 9   The Da Vinci Code 10   Candide 11   The Alchemist 12   Frankeinstein 13   C 14   Java 15   Python 16   R 17

fantasy

classic

computer science

Follow

Target User
u

Joe 0 Mike 1 Paul 2 Sara 3 Laura 4 Alice 5

has read

Why-Not Item
WNI

TOP
Recommendation
rec

A Game of Thrones 6 The Hobbit 7 Harry Potter 8 Lord of the Rings 9 The Da Vinci Code 10 Candide 11 The Alchemist 12 Frankeinstein 13 C 14 Java 15 Python 16 R 17

fantasy

classic

computer science

PPR(2,12) = 0.034

PPR(2,16) = 0.039

Target User
u

Follow

Joe
0

Mike
1

Paul
2

Sara
3

Laura
4

Alice
5

Why-Not Item
WNI

TOP
Recommendation
rec

has read

A Game of
Thrones
6

The
Hobbit
7

Harry
Potter
8

Lord of the
Rings
9

The Da Vinci
Code
10

Candide
11

The
Alchemist
12

Frankeinstein
13

C
14

Java
15

Python
16

R
17

fantasy

classic

computer
science

$$contribution_{rmv}(n_i) = W(u, n_i) \cdot (PPR(n_i, rec \mid A) - PPR(n_i, WNI \mid A))$$

$$contribution_{rmv}(n_i) = W(u, n_i) \cdot (PPR(n_i, rec \mid A) - PPR(n_i, WNI \mid A))$$

After removing the explanation …

PPR(2,12) = 0.047

PPR(2,16) = 0.023
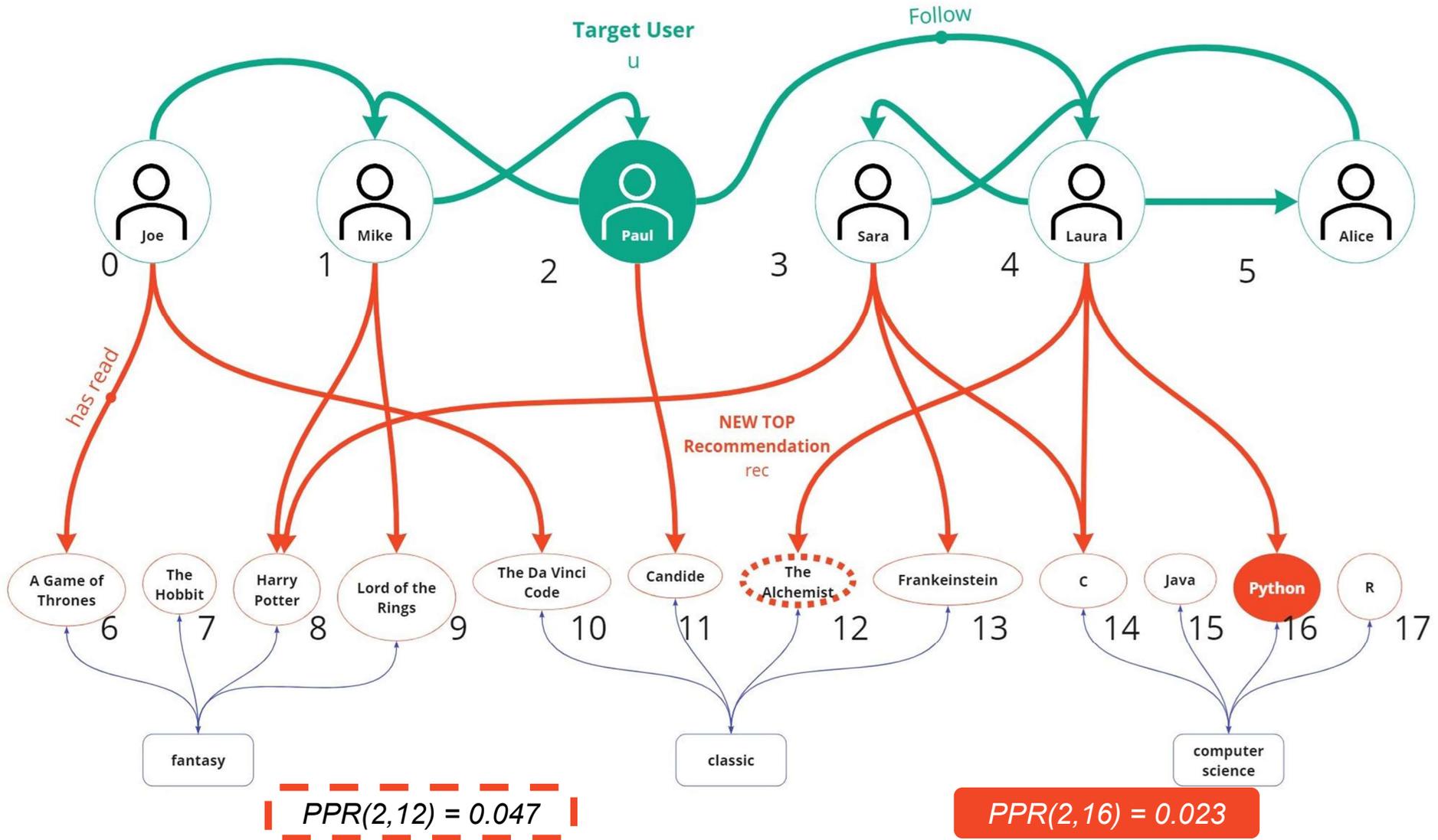
Experimental Evaluation

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Dataset Analysis

Why-Not scenario definition:

- **Target users**: 100 random *"normal"* users from an Amazon Dataset
- **Graph:** 4 radius subgraph around the target user node
- **Why-Not item**: items ranked 2 to 10 in the recommendation list

Dataset	#nodes	#edges	#users	#items	#reviews	#categories
Amazon	114 002	687 184	1 999	53 727	58 233	43

Edge Types	
type	**nodes**
"rated"	(user↔item)
"reviewed"	(user↔review)
"has-review"	(item↔review)
"belongs-to"	(item↔category)

Algorithms and Baselines

Algorithms:

- add_Powerset, Powerset heuristic, Add Mode;
- add_Incremental, Incremental heuristic, Add Mode;
- add_ex Exhaustive Comparison heuristic, Add Mode;

- remove_Powerset Powerset heuristic, Remove Mode;
- remove_Incremental Incremental heuristic, Remove Mode;
- remove_ex Exhaustive Comparison heuristic, Remove Mode.

Baselines:

- Brute force (remove mode) : to evaluate the computation time and explanation size
- Exhaustive Comparison Direct : to evaluate the need for the check step

Evaluation metrics

- **Explanation size** : a good explanation is a short explanation

- **Success rate**: we need the algorithm to provide the explanations

- **Time**: we need the algorithm to be as fast as possible

Explanation success rate per method
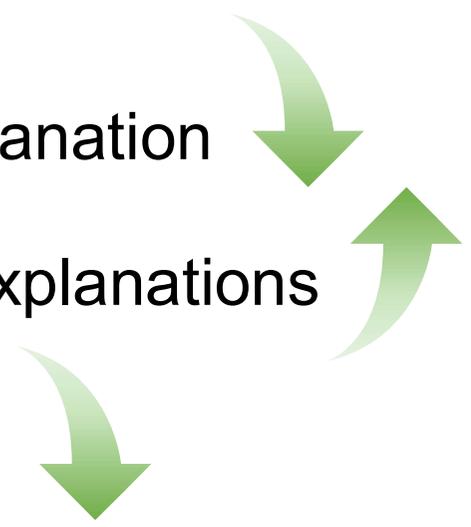
explanation success rate per method
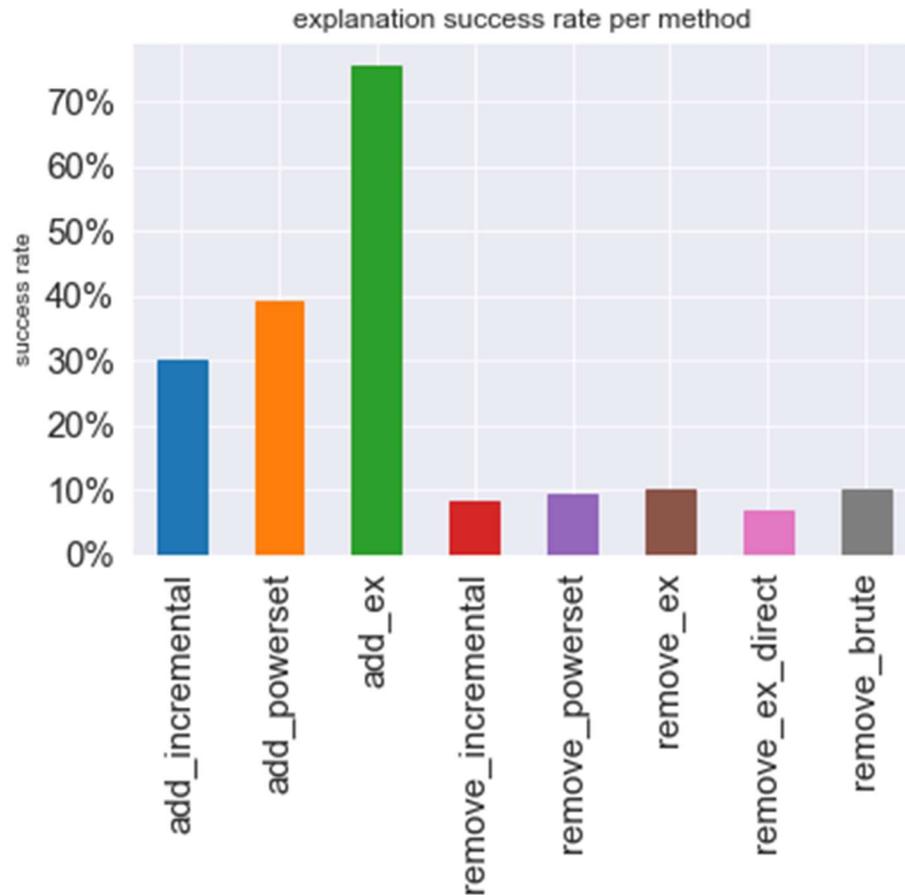
- Low success rate in Remove Mode because of the limited candidate space.

- Add Mode is more successful than Remove Mode.

- Best heuristic: Exhaustive Method in Add Mode.

Average explanation size per method

average explanation size per method
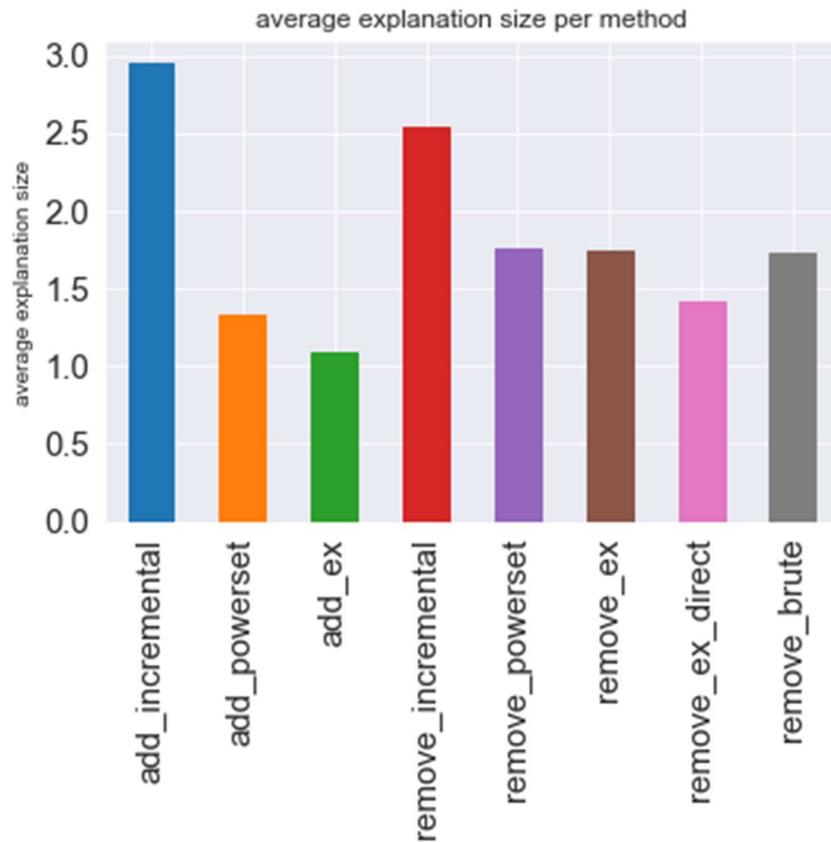
- Low explanation size (smaller than 3 edges on average) for all heuristics.

- Remove Mode, best heuristics: Exhaustive and Powerset.

- Add Mode: low (or minimum) explanation size for all.

Average computation time

Method		(a)	(b)	(c)
add_Incremental		*6,54*	*8,31*	*5,78*
add_Powerset		57,55	133,96	8,19
add_ex		21618,32	23924,37	14646,56
remove_Incremental		*9,07*	*8,20*	*9,15*
remove_Powerset		287,91	15,32	315,31
remove_ex		173,44	24,48	190,13
remove_ex_direct		25,14	21,81	25,38
remove_brute		908,73	22,37	1008,07

Average runtime in seconds per method (a) in the general case, (b) when an explanation is found, and (c) when no explanation is found.

- The Exhaustive Comparison method in Remove Mode is comparable to brute force when successful.

- Incremental Methods give faster results, both in Add and Remove Modes.

Conclusion & Future Work

Conclusion & Future Work

Conclusions

1. We proposed counterfactual-like explanations for missing recommendations, in the form of a set of user-rooted, existing or potential edges.
2. We proposed various heuristics for computing why-not explanations, targeting small explanations or fast computation.
3. Our experiments on real-world data showed the feasibility of our solution.

Future Work

- Improve the success rate by extending the expressiveness of our explanations (considering edge weights, creating meta-explanations, etc).
- Further evaluate the quality of the explanations, e.g., by evaluating the user satisfaction property.

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For more, check:

https://git.cyu.fr/hattolou/why-not-explainable-graph-recommender

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