



Using Embeddings of Line Graph Powers to Retrieve Item Substitutes

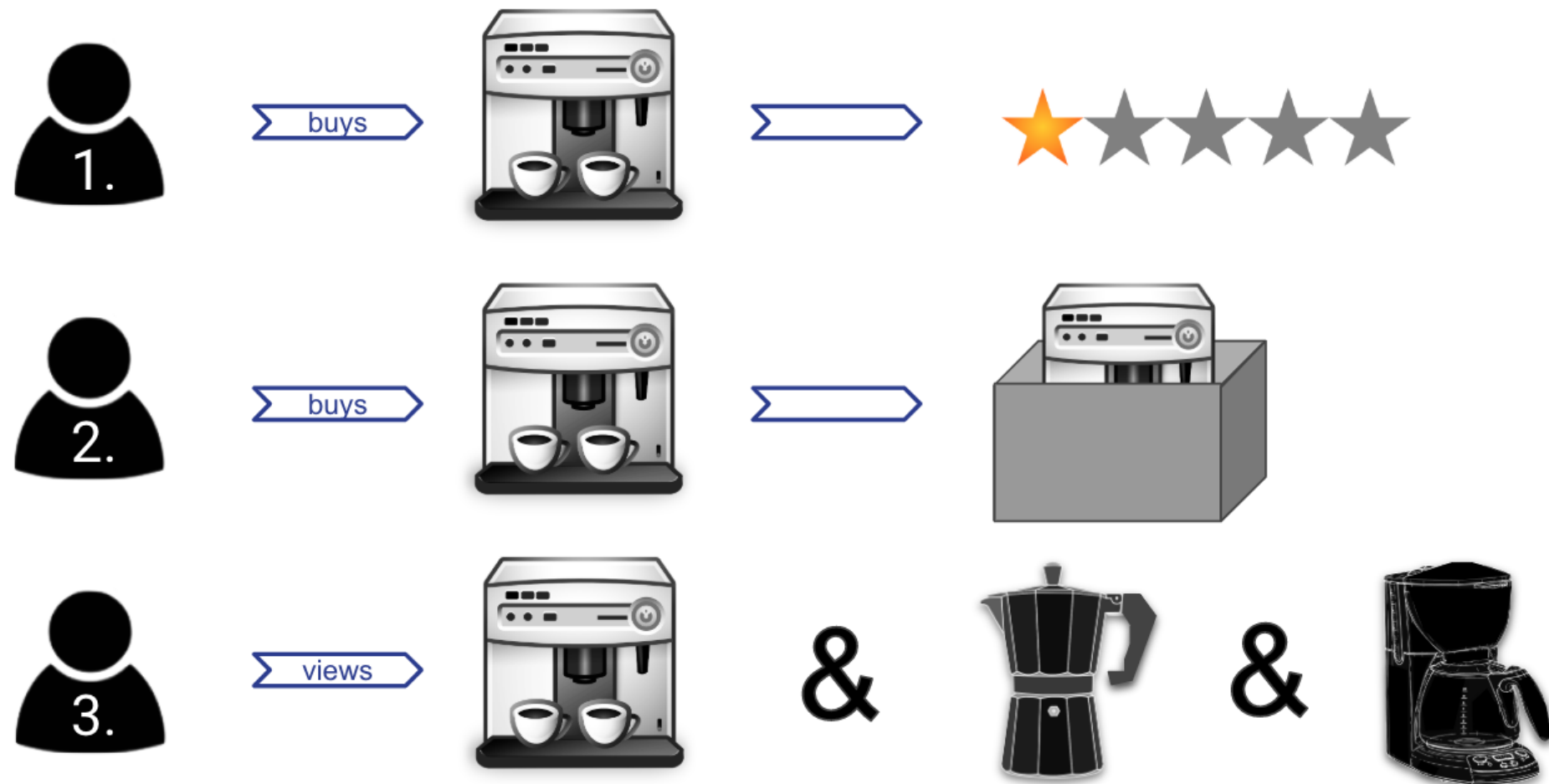
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Motivation

In real-world recommender systems, differentiating between substitutes and complement products is important in order to capture users' intent.



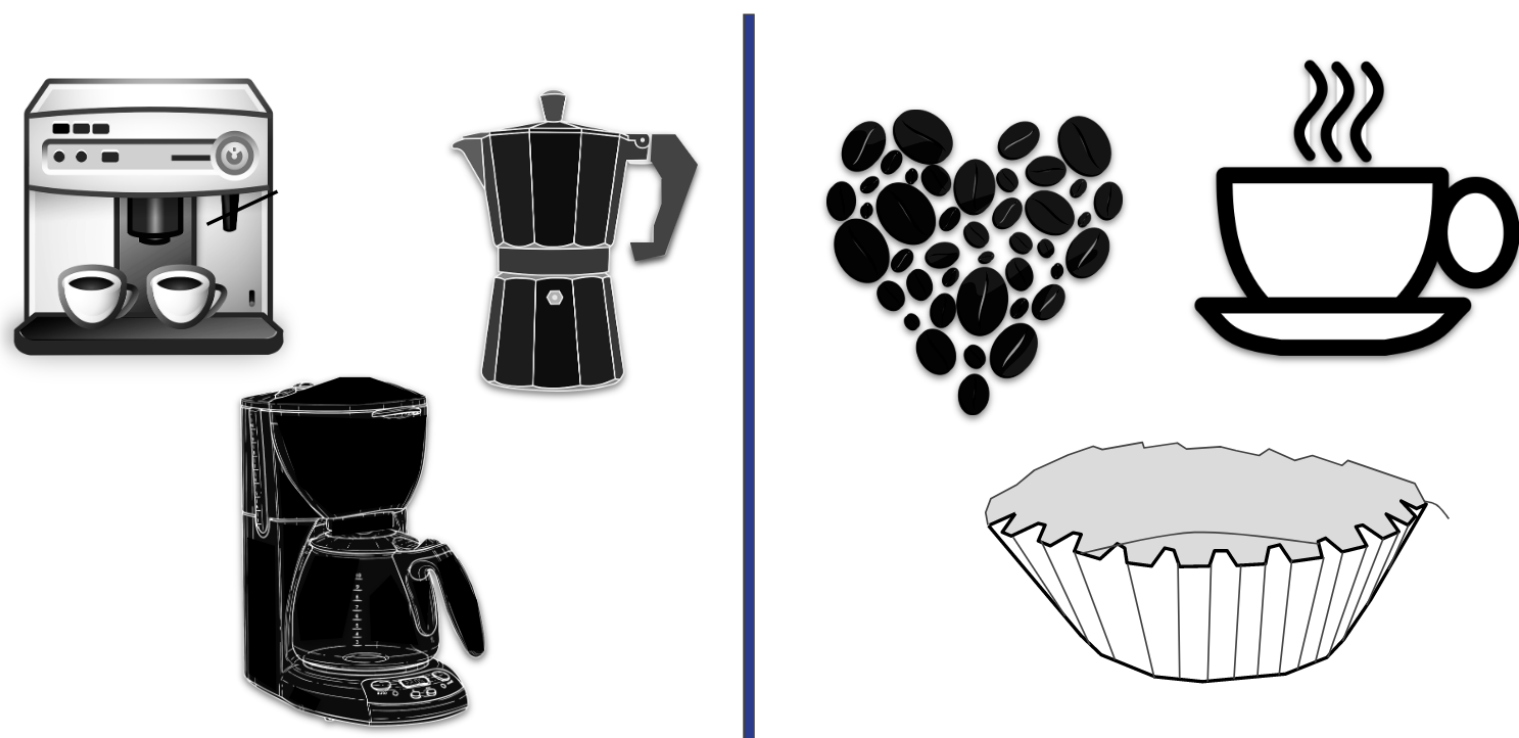
Our research question in this work is the following:

◇ Can we retrieve item substitutes by only leveraging structural information from users' purchase graph?

Complements & Substitutes

Consumer choice theory [1] defines compliments and substitutes as follows:

- ◇ **Complements:** Products used in conjunction with other products, often co-purchased by users.
- ◇ **Substitutes:** Products often perceived as the same or comparable. That means, having one product would make users desire the other substitutes less.



Previous Approaches

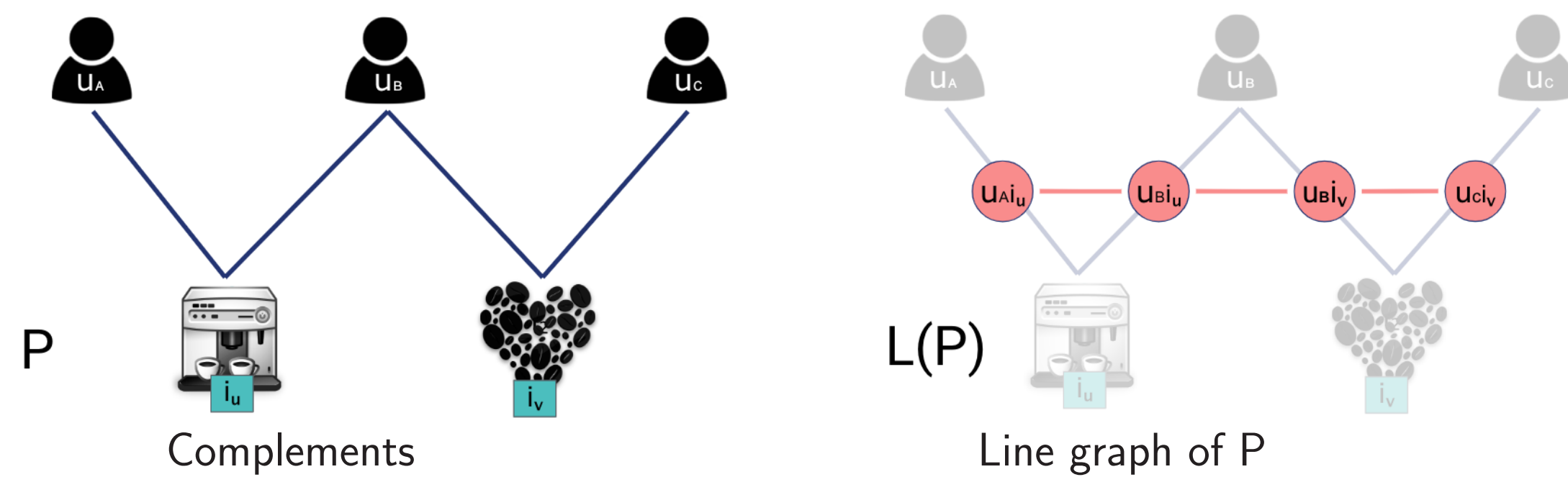
- ◇ Item-based collaborative filtering on users' navigation logs: heuristics are used to map navigation logs to either substitute or complement [2]
- ◇ Link prediction with supervised language modeling from users' navigation logs and item meta data [3]
- ◇ Node2Vec is a random-walk based method that learns node embeddings that can be used to retrieve relevant items, however it cannot identify substitutes [4]

Setup

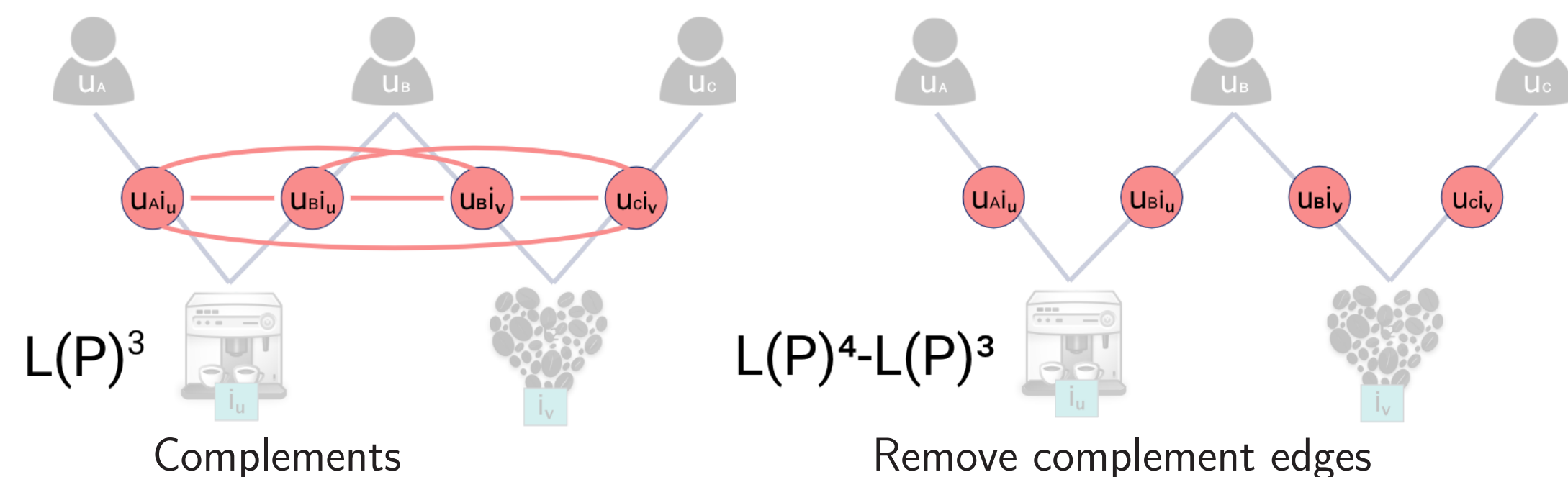
Let U be the set of users and I the set of items, and $P = (U \cup I, E)$ a bipartite purchase graph, with edges (u, i) , for $u \in U$, and $i \in I$ for each purchase of item i by user u .

Methodology

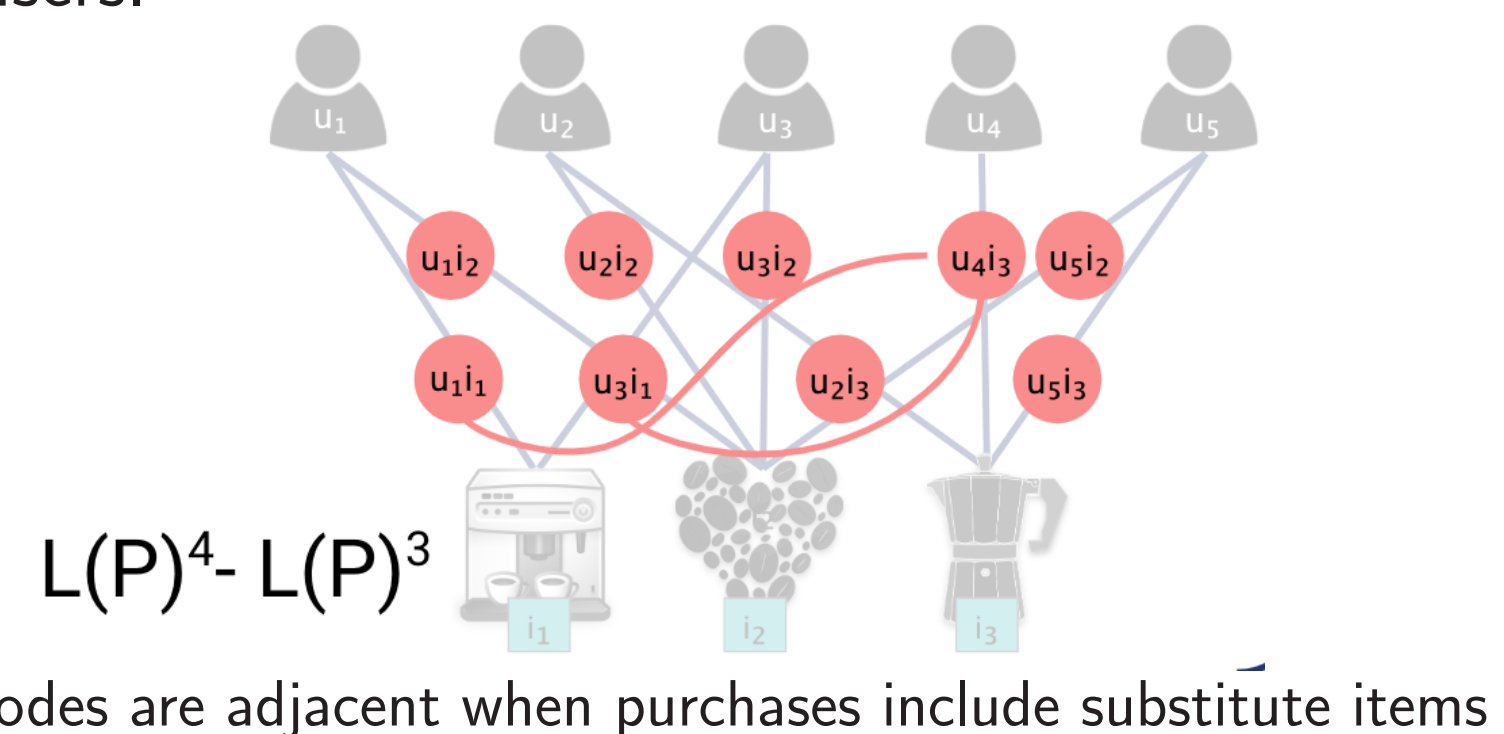
Our method is based on the assumption that generally users co-purchase complements, not substitutes. Let $L(P)$ denote the line graph of P , with nodes representing purchases by (u, i) pairs, and edges representing a shared item, or user between two nodes.



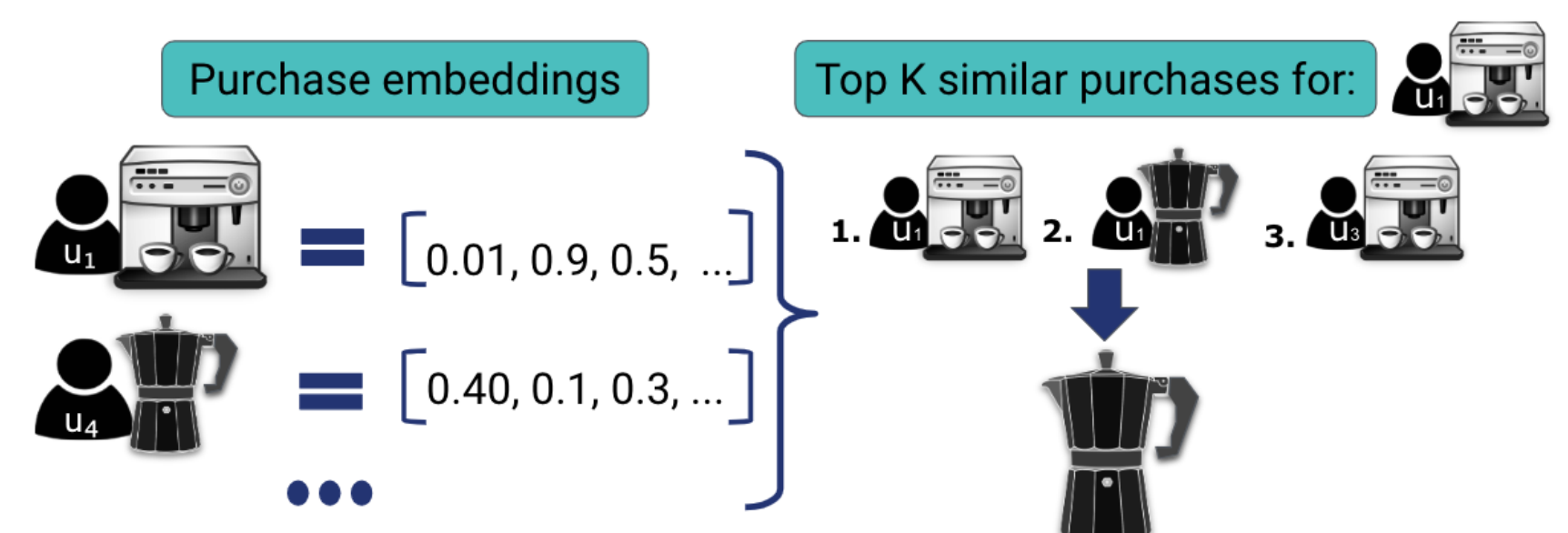
Let us now define $L(P)^k$, the k^{th} power of $L(P)$, a new graph with the same set of nodes, where two nodes are adjacent if their distance is at most k . $L(P)^3$ then captures all complements.



$L(P)^4 - L(P)^3$ then defines a graph where any two nodes (i.e. purchases) have items that are never in the same purchase set of any users.



Random-walk based techniques like [4] can help us generate node embeddings for $L(P)^4 - L(P)^3$ where substitutes are now closer in vector space.



Bibliography

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