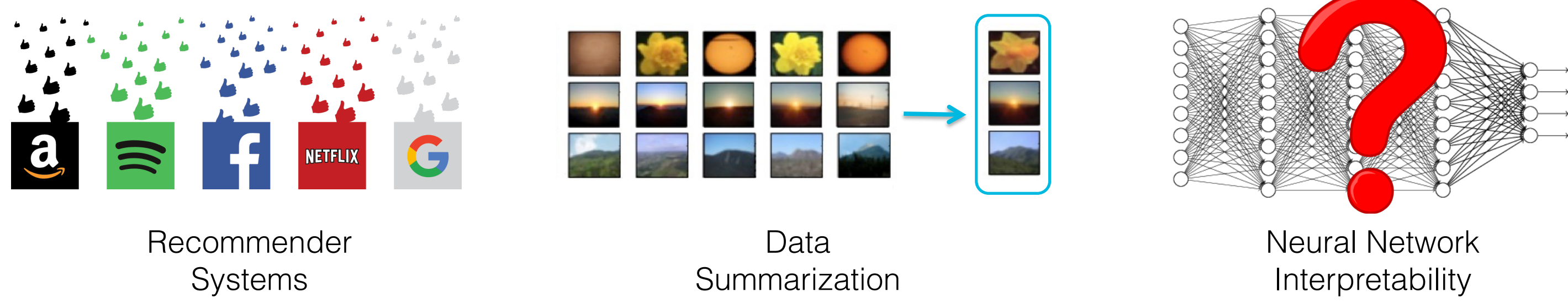


1. Background

- In a nutshell, submodular functions are the class of functions that exhibit diminishing returns. As such, many machine learning applications fall under the umbrella of submodularity:



- Mathematically, a function is said to be **submodular** if for all sets $A \subseteq B$ and all elements $v \in V \setminus B$:

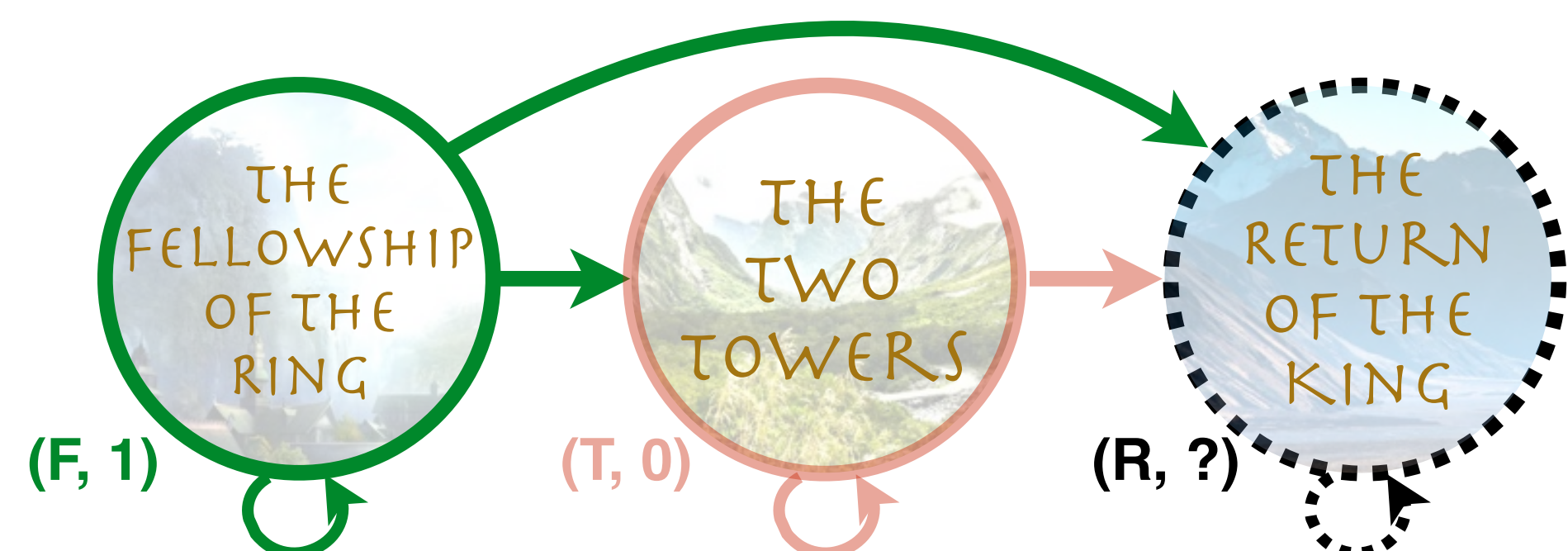
$$f(A \cup \{v\}) - f(A) \geq f(B \cup \{v\}) - f(B)$$

- In other words, the marginal value of any item is non-increasing as our set grows. For example, suppose we want to summarize a set of images about Vancouver. Once we already have one image of the convention centre, additional images of the convention centre will be much less valuable.



2. Problem Statement

- We view the problem of adaptive and sequential decision making through the lens of submodularity.
- We assume there is a directed graph $G = (V, E)$, where each item in our ground set is represented as a vertex $v \in V$, and the edges encode the additional value intrinsic to picking certain items in certain orders.
- A sequence of items σ induces a set of edges $E(\sigma) = \{(\sigma_i, \sigma_j) \mid (\sigma_i, \sigma_j) \in E, i \leq j\}$
- To include adaptivity, we assume that each vertex has some (initially unknown) state $o \in O$, each edge has a state $q \in Q$ that is determined entirely by the states of its endpoints. Another way to look at this is to say a realization ϕ of the vertices induces a realization ϕ^E of the edges.
- This allows us to define $f(\sigma, \phi) = h(E(\sigma), \phi^E)$, where h is a weakly-adaptive set submodular function, σ induces $E(\sigma)$, and ϕ induces ϕ^E



- This example gives a possible partial realization of the vertices ψ_1 and an associated partial realization of the edges ψ_1^E . In this case, the state of an edge is equal to the state of its start point.
- Suppose our function h counts all induced edges that are in state 1. Furthermore, let us simply assume that any unknown vertex is equally likely to be in state 0 or state 1. This means that the self-loop (R, R) is also equally likely to be in either state 0 or state 1. Therefore,
 $\Delta((R, R) \mid \psi_1^E) = \frac{1}{2} \times 0 + \frac{1}{2} \times 1 = \frac{1}{2}$.

3. Algorithm and Theoretical Results

Algorithm 1 Adaptive Sequence Greedy Policy π

```

1: Input: Directed graph  $G = (V, E)$ , weakly adaptive sequence submodular  $f(\sigma, \phi) = h(E(\sigma), \phi^E)$ , and cardinality constraint  $k$ 
2: Let  $\sigma \leftarrow ()$ 
3: while  $|\sigma| \leq k - 2$  do
4:    $\mathcal{E} = \{e_{ij} \in E \mid v_j \notin \sigma\}$ 
5:   if  $\mathcal{E} \neq \emptyset$  then
6:      $e_{ij} = \arg \max_{e \in \mathcal{E}} \Delta(e \mid \psi_\sigma^E)$ 
7:     if  $v_i = v_j$  or  $v_i \in \sigma$  then
8:        $\sigma = \sigma \oplus v_j$  and observe state of  $v_j$ 
9:     else
10:       $\sigma = \sigma \oplus v_i \oplus v_j$  and observe states of  $v_i, v_j$ 
11:     end if
12:   else
13:     break
14:   end if
15: end while
16: Return  $\sigma$ 

```

Theorem 1. For adaptive monotone and weakly adaptive sequence submodular function f , the Adaptive Sequence Greedy policy π represented by Algorithm 1 achieves

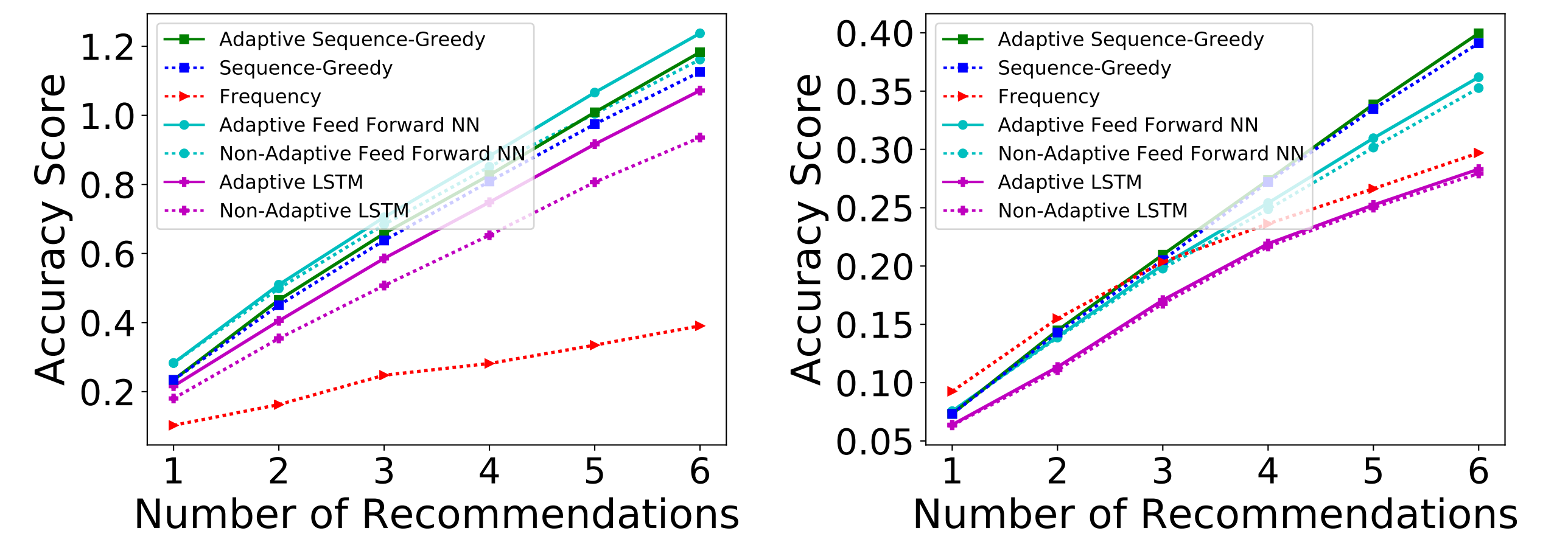
$$f_{avg}(\pi) \geq \frac{\gamma}{2d_{in} + \gamma} \cdot f_{avg}(\pi^*),$$

where γ is the weakly adaptive submodularity parameter, π^* is the policy with the highest expected value and d_{in} is the largest in-degree of the input graph G .

4. Applications

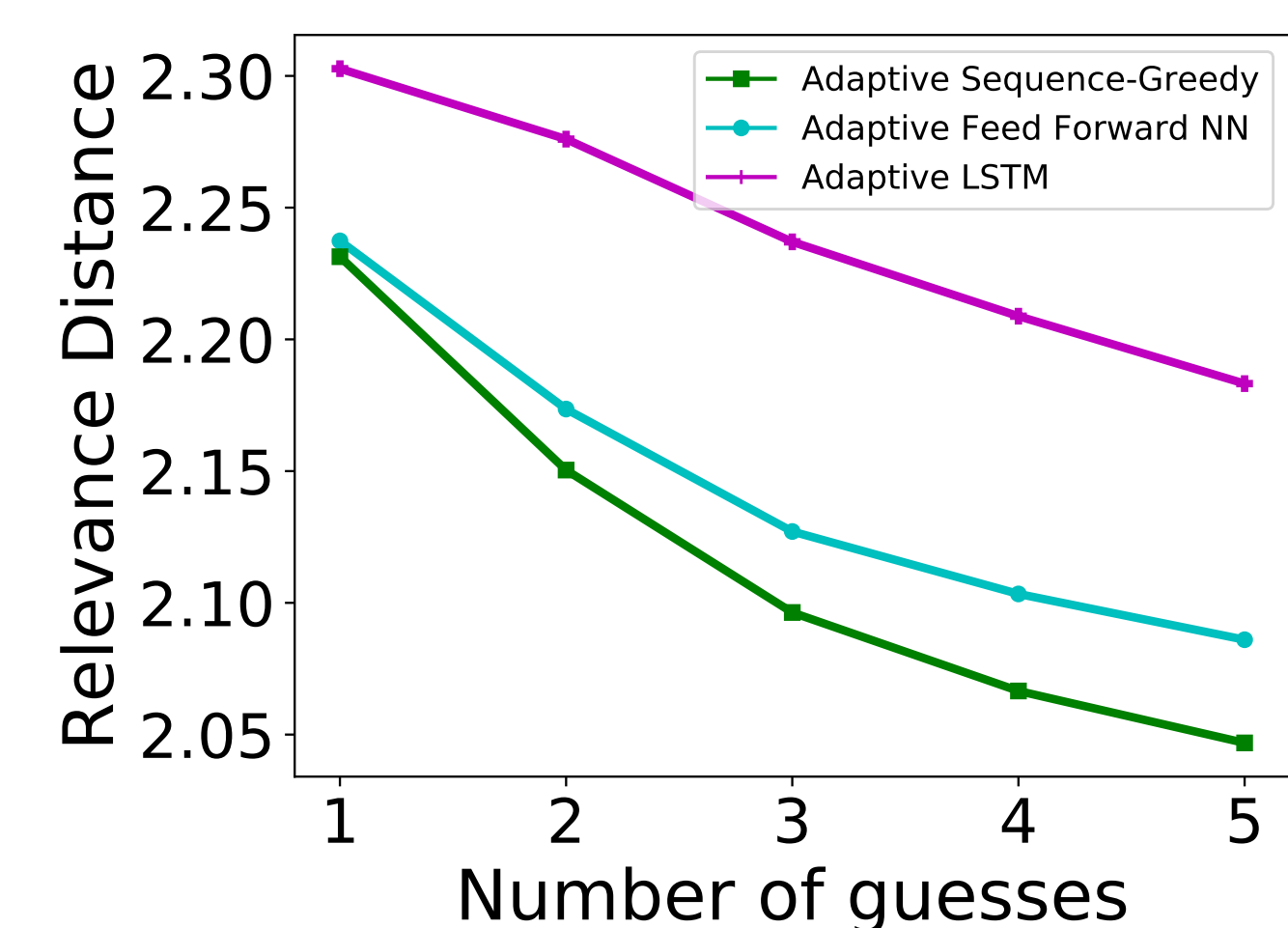
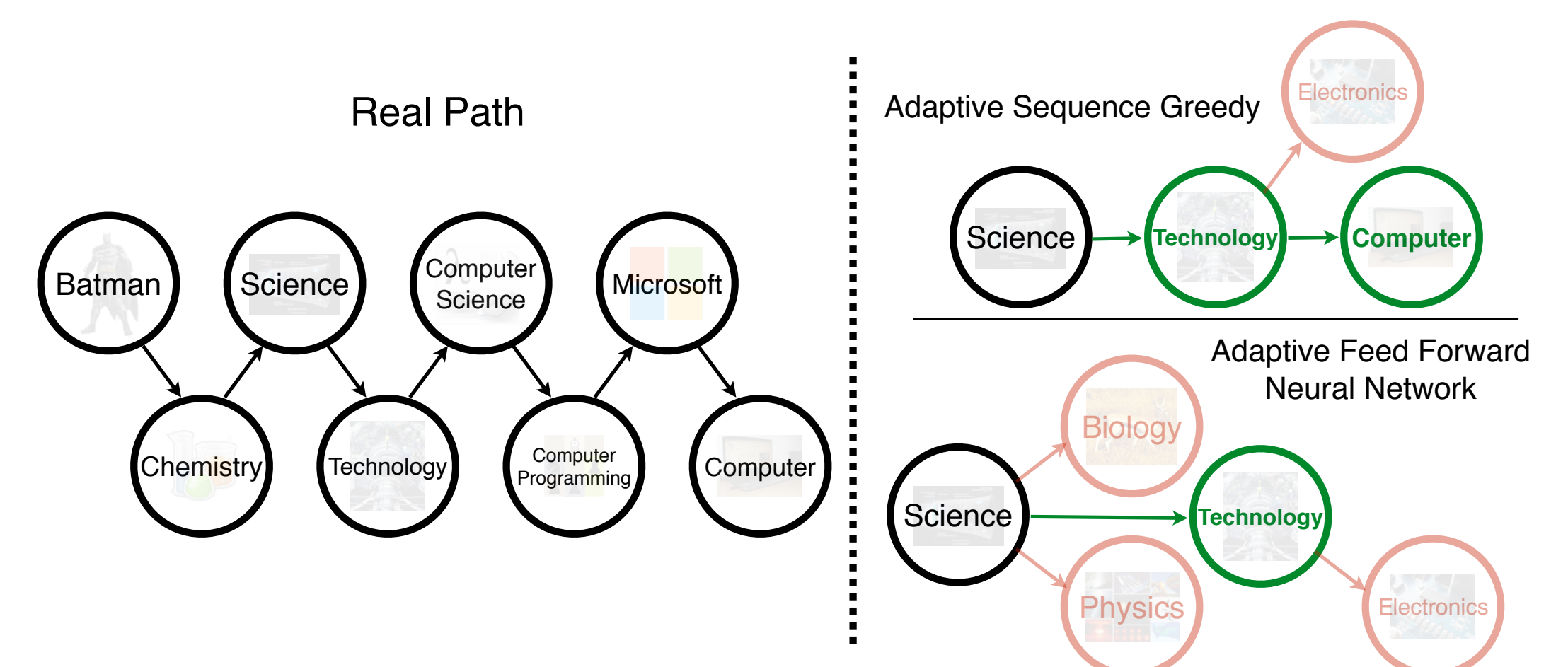
- Product Recommendation

- We use the Amazon Video Games dataset (McAuley et al., 2015), which contains 10,672 products, 24,303 users, and 231,780 confirmed purchases.
- Given the first 4 products that a user has purchased, our goal is to recommend k products that we think she will purchase.



- Wikipedia Link Prediction

- We use the Wikispeedia dataset (West et al., 2009), which consists of 51,138 completed search paths on a condensed version of Wikipedia that contains 4,604 pages and 119,882 links between them.
- Given the first 3 pages a user has visited, we want to guide her to her target page.



5. Acknowledgements

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