Personalized Machine Learning

Invariant Models

Rodrigo Alves

November 12, 2024

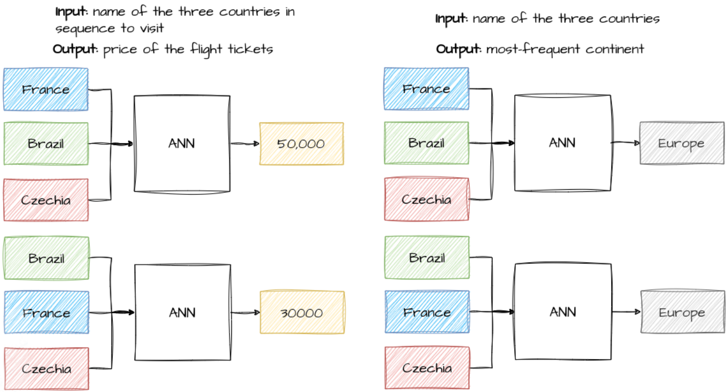
Bias in Recommender Systems

- Recommender systems are susceptible to biases, impacting fairness and accuracy.
- Types of bias: user, item, demographic, etc.
- Challenges: unfair treatment, limited diversity, stereotype reinforcement.

Position bias: it is a tendency to prioritize items in prominent positions, reinforcing popular items.

- Note that, however, often the recommender can be programmed to show some items in the first positions.
- Also, note that the models actually aim to **'bias'** the recommendation by putting the more relevant items in the first positions, and because of that, some PML algorithms focus on that.
- However, we can have some ML problems that are invariant by nature.

Invariant Models



Invariant Models

Domain invariance: For instance, Graph Neural Networks (GNNs) can be employed in Collaborative Filtering, where user-item interactions are modeled as a graph. GNNs are utilized to capture interactions, irrespective of their **domain**.

Time invariance: It is common to assume that the model is not influenced by **time**. For example, the order in which users rate the items is not considered in the evaluation of their taste.

Permutation-equivariant models: These models demonstrate equivariance concerning **input** permutations.

Odd-One-Out Problem

- The odd-one-out problem is a widely explored concept in Recommender Systems.
- Traditionally, it involves predicting user choices, such as identifying which item a user is most likely to click from a given list.
- Our lecture, however, focus to a more nuanced application within neuroscience, particularly in the context of triplets.
- **Triplets Problem:** Consider presenting three images to an individual: $\mathcal{I}_a, \mathcal{I}_b, \mathcal{I}_c$.
  - The task is to predict which pair of images exhibits the **closest conceptual similarity** based on given options.
  - Among goals we aim to develop models capable of **predicting similarity** within new triplets.
  - Simultaneously, we aim to **construct embeddings** that capture how humans perceive and understand conceptual relationships.

Triplets Problem

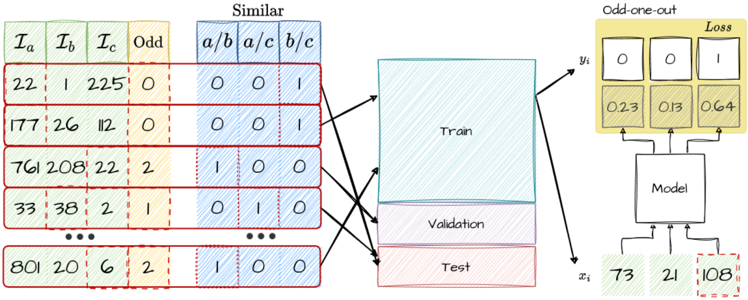
Triplets Problem: Data

$\mathcal{I}_a$	$\mathcal{I}_b$	$\mathcal{I}_c$	Odd
22	1	225	0
177	26	112	0
761	208	22	2
33	38	2	1
…	…	…	…
801	20	6	2

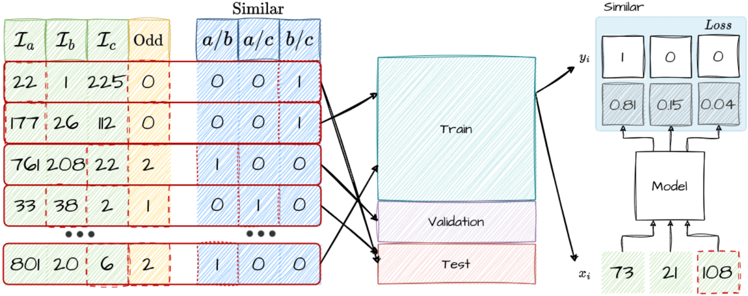
Similar

a/b	a/c	b/c
0	0	1
0	0	1
1	0	0
0	1	0
…	…	…
1	0	0

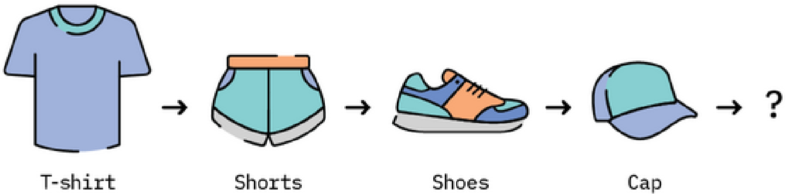
Triplets Problem: Odd-one-out



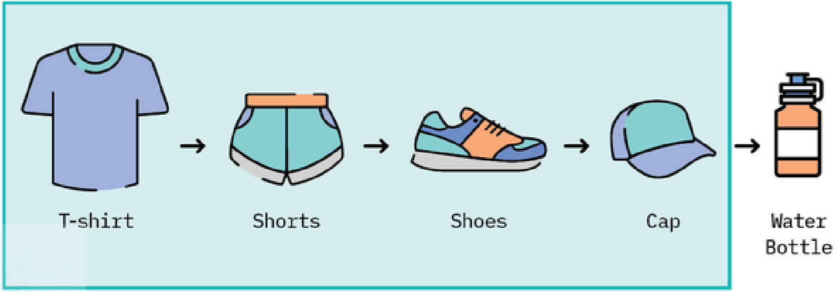
Triplets Problem: Similar



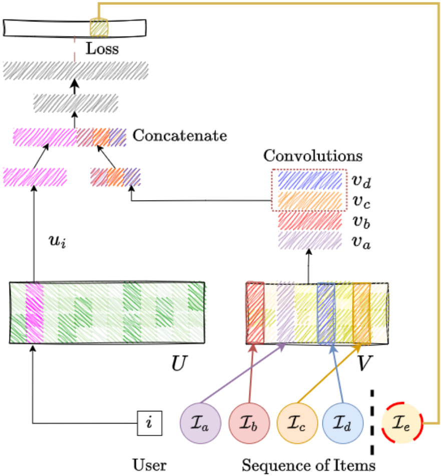
Sequential Recommendation (RECAP)



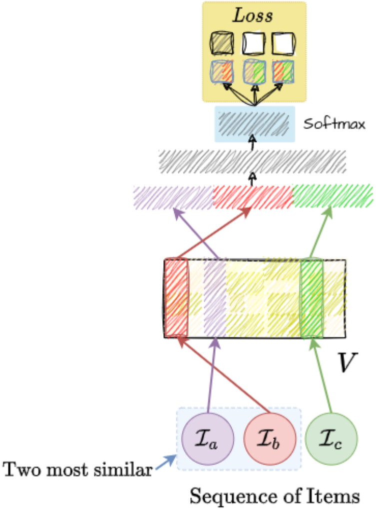
Sequential Recommendation (RECAP)



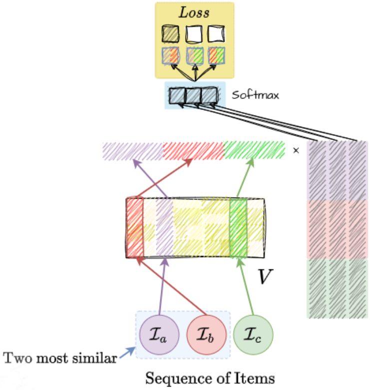
Sequential Recommendation (RECAP)

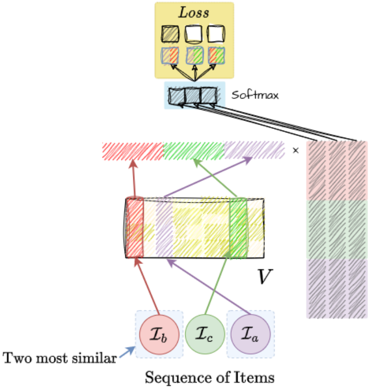


A First Try


Loss
Softmax
V
$\mathcal{I}_a$
$\mathcal{I}_b$
$\mathcal{I}_c$
Two most similar
Sequence of Items

Is it a Invariant Model?





SPoSE

- SPoSE is a model developed to learn individual representations from triplets.
- It is an acronym for **S**parse **Po**sitive **S**imilarity **E**mbedding.
- These representations predict a latent similarity structure between objects, capturing most of the explainable variance in human behavioral judgments.
- The model is based on the concept of probability. Let $S(a, b)$ be a function representing the similarity between a and b. One way to compute the probabilities of the three possible embeddings x_1, x_2, and x_3 such that they add up to one, can be given by:

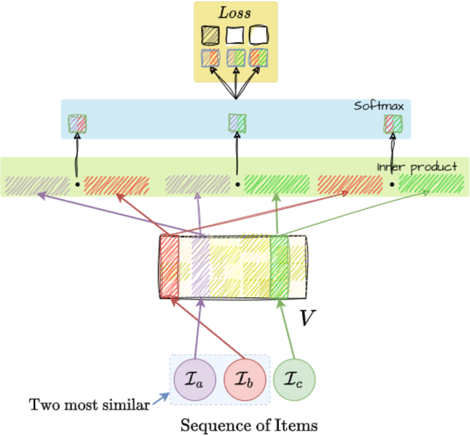
$$P(x_1, x_2) = \frac{e^{S(x_1,x_2)}}{e^{S(x_1,x_2)} + e^{S(x_1,x_3)} + e^{S(x_2,x_3)}}$$

SPoSE

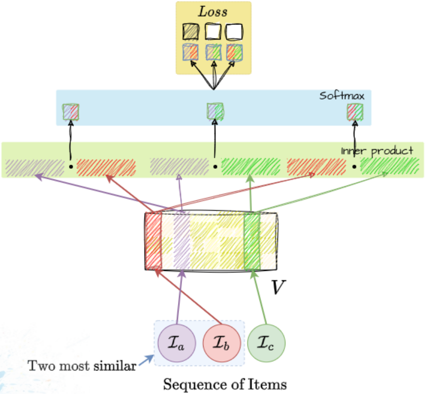
- Similarity can be computed in various ways.
- The authors of the SPoSE paper tried two methods: one based on **Euclidean distance** and another on **cosine similarity**.
- Experimentally, **cosine similarity** showed to be more effective.
- Given a set of triplets $T = \{t_1, t_2, \cdots t_n\}$,where $t_i = \{a_{i,1}, a_{i,2}, a_{i,3}\}$ and item $a_{i,1}$ is more similar to item $a_{i,2}$ (in other words, $a_{i,3}$ is the odd-one-out item),an embedding vector of item $a_{i,j}$ is represented by $x_{a_{i,j}}$. With the aim to learn $X = \{x_1, x_2, \cdots x_m\}$, we have

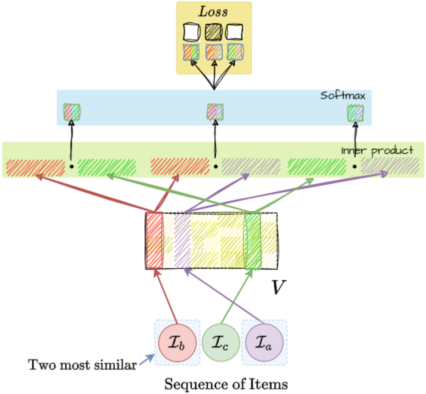
$$\text{argmin}_{x_j} \sum_{i=1}^{n} \log \frac{e^{x_{a_{i,1}}^\top x_{a_{i,2}}}}{e^{x_{a_{i,1}}^\top x_{a_{i,2}}} + e^{x_{a_{i,1}}^\top x_{a_{i,3}}} + e^{x_{a_{i,2}}^\top x_{a_{i,3}}}} + \lambda \sum_{j} |x_j|_1$$

SPoSE


Loss
Softmax
Inner product
V
$\mathcal{I}_a$
$\mathcal{I}_b$
$\mathcal{I}_c$
Two most similar
Sequence of Items

SPoSE

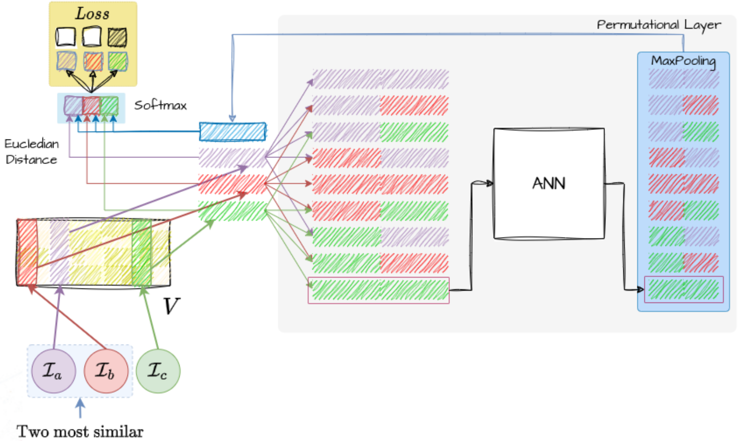

Loss
Softmax
Inner product
V
$\mathcal{I}_a$
$\mathcal{I}_b$
$\mathcal{I}_c$
Two most similar
Sequence of Items


Loss
Softmax
Inner product
V
$\mathcal{I}_b$
$\mathcal{I}_c$
$\mathcal{I}_a$
Two most similar
Sequence of Items

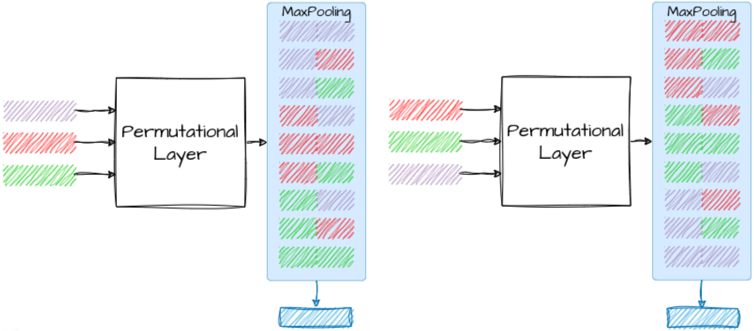
Permutational Layer

- Component of neural networks for handling variable-length input sequences.
- Processes **permutations of input elements**, allowing the model to handle different orders of sequence elements.
- Extracts features **irrespective of the original positions**, enhancing the model's understanding of relationships.
- Particularly useful in tasks where the order of elements should not influence the model's predictions, like set-based or graph-based data.
- Commonly applied in set classification tasks, where predictions are based on set properties rather than element order.

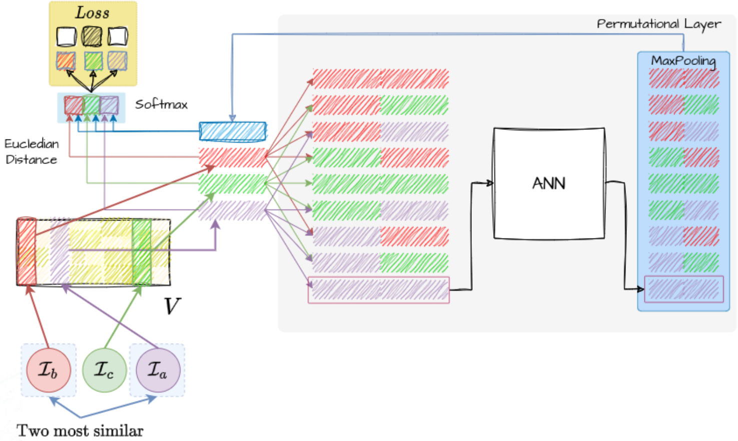
Permutational Layer



Permutational Layer



Permutational Layer



Obrigado :) - Faculty of Information Technology