Recommender Systems

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Notebook Link Here

Workshop Overview

Prereqs:

- Some basic ML knowledge
- Basic Linear Algebra

Goals:

- Start with basic architectures and build our way up in complexity
    - Basic Models
    - Models currently used in Industry
    - Emerging Architectures
- Implement our own recommendation systems

Workshop Outline

- What are Recommender Systems?
- Motivation
- History Timeline
- Level 1: Basic Models
  - Content Based Filtering (KNN)
  - Collaborative Filtering (Matrix Factorization)
- Level 2: Industry Models
  - Neural Collaborative Filtering
- Level 3: Emerging Architectures
  - Graph Neural Networks
- Notebook
- Useful Resources

What are Recommender Systems?

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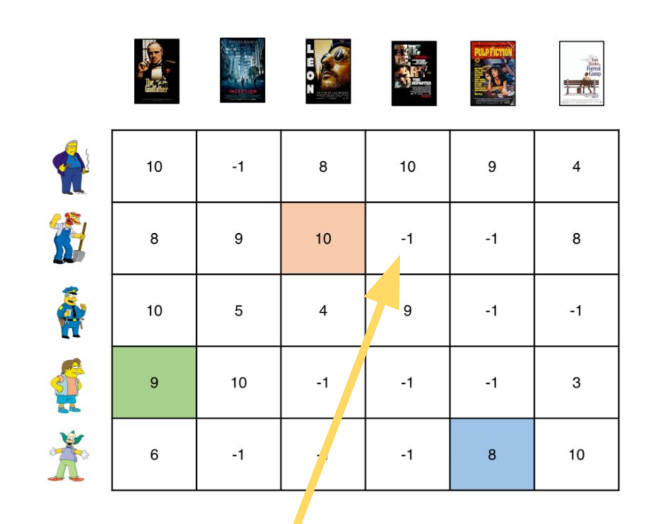
Recommender Systems (Rec Sys) are a class of ML model made to provide personalized recommendations relevant to users

Terminology:
Items - Info about objects being recommended (e.g. movies)
Users - Info about users
Embeddings - Representations of a user/items in a N-dimensional vector

Items ***j***

Users ***i***



10	-1	8	10	9	4
8	9	10	-1	-1	8
10	5	4	9	-1	-1
9	10	-1	-1	-1	3
6	-1	[illegible]	-1	8	10

How much user ***i*** ‘likes’ item ***j***

Motivation

- Rec Sys are one of the most relevant ML topics to industry
- They are a core aspect of revenue-generation for many B2C tech companies
- Aim to maximize customer retention

Facts:

- Rec Sys are responsible for **35%** of Amazon.com's revenue
- **80%** of Netflix stream time comes from its recommendations

Examples in Industry:

- Amazon.com Products
- Netflix Movies
- Youtube Home page
- Instagram Explore Page
- Steam Explore Page

And so on ...

History Timeline

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Basic Models

Industry Models

Emerging Architectures

Content Based Filtering

Collaborative Filtering

Matrix Factorization

Neural Collaborative Filtering

Reinforcement Learning, Graph Neural Networks ...

1990

2000

2010

2020

Level 1 - Content Based Filtering

Defn: Recommending **similar items** to what the user likes

Ex - Video Game Recommendations

Features

	F1	F2	F3
User 1	0	4	9
User 2	6	2	1
User 3	7	3	5

Features

	F1	F2	F3
Item 1	5	5	2
Item 2	9	7	9
Item 3	0	3	8

Feature Labels:

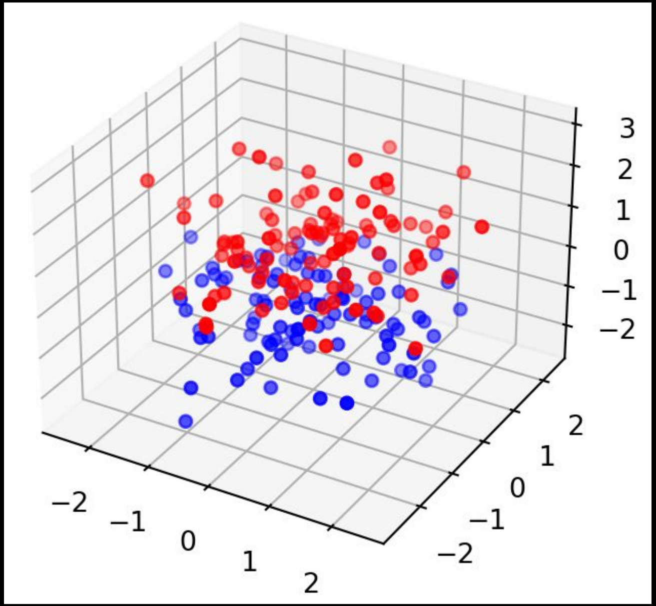
F1 - FPS

F2 - Adventure

F3 - Sports

Level 1 - Content Based Filtering

Given the user + item embeddings we can represent them in a N dimensional space:



Red Points - Users
Blue Points - Items

The Rec Sys has to find the most similar items for user ***i*** using a **similarity metric** that measures distance between embeddings/points

Level 1 - Content Based Filtering

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Similarity Metric: Euclidean Distance

$$d(x, y) = \sqrt{\sum_{i=1}^{n}(y_i - x_i)^2}$$

Magnitude of a straight line between two points in a N-dimensional space

Find Similar Points: K-Nearest Neighbors (KNN)

- Initialize value of K
- For every item embedding:
  - Calculate distance between item and user i
- Find the K smallest calculated distances
- The corresponding items are your “similar items”

Precision @ K:

$$\frac{\text{(\# of relevant items at K)}}{K}$$

Level 1 - Content Based Filtering

Pros	Cons
Easy to understand + High interpretability	Needs hand-engineered features beforehand
Scalable for lots of users (since users treated independently)	Needs information for each user and item beforehand (expensive & infeasible)

Level 1 - Collaborative Filtering

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Defn: Recommending items based on what **similar users** like

Feedback Matrix A_{MxN}

	Harry Potter	The Triplets of Belleville	Shrek	The Dark Knight Rises	Memento
	✓		✓	✓	
		✓			✓
	✓	✓	✓		
				✓	✓

$A_{i,j} = 1 \rightarrow$ User i interested in item j

$A_{i,j} = 0 \rightarrow$ User i not interested in item j (or unobserved)

Level 1 - Collaborative Filtering

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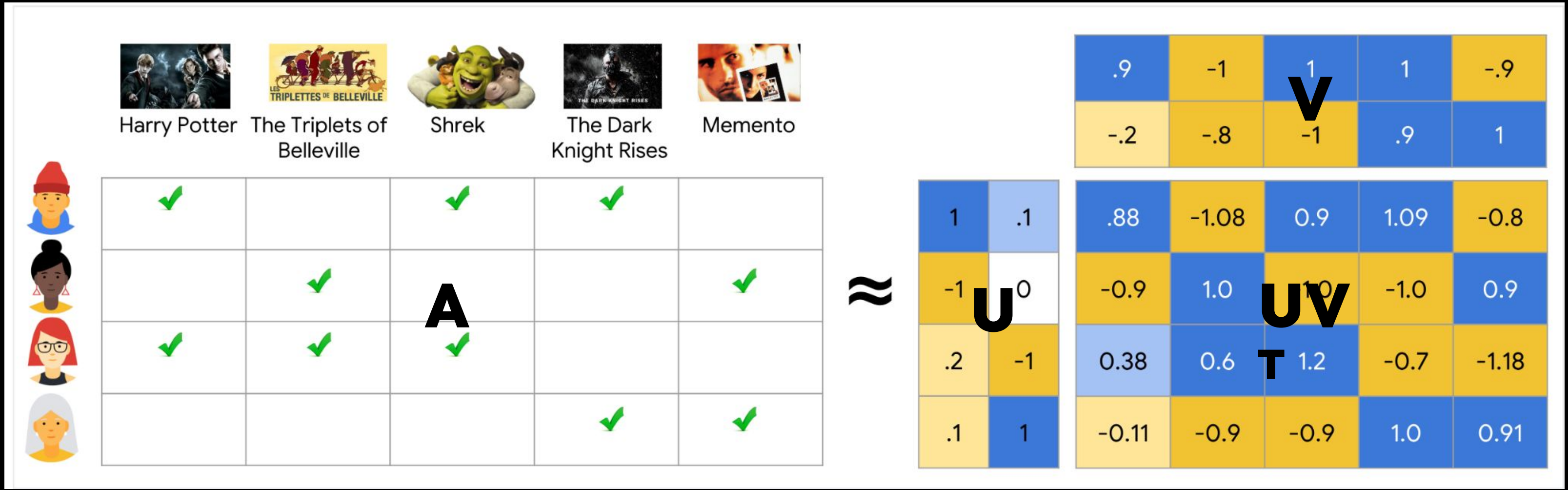
Item Embedding Matrix



Feedback Matrix

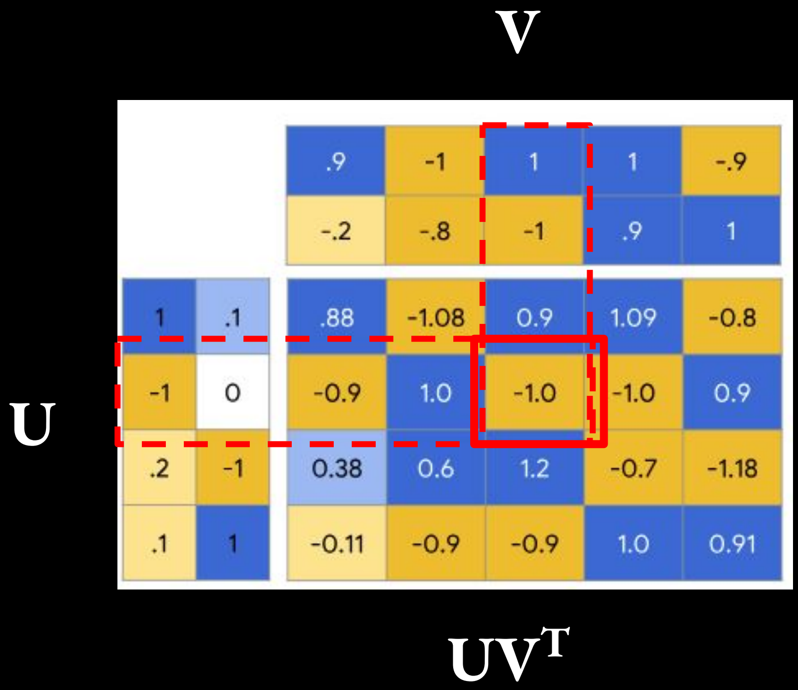
User Embedding Matrix

Level 1 - Collaborative Filtering

Matrix Factorization:
Finds user matrix *U* and item matrix *V* that minimizes the function

$$\min_{U \in \mathbb{R}^{m \times d},\, V \in \mathbb{R}^{n \times d}} \|A - UV^T\|_F^2.$$

Ways to solve
- Singular Value Decomposition (too slow)
- Stochastic Gradient Descent



Level 1 - Collaborative Filtering

Pros	Cons
Don't need to specify features beforehand	Unable to capture **non-linear relationships** between users and items
No domain knowledge required	(Since UV^T is made up of weighted sums)
Makes use of all data available for predictions	

Level 2 - Neural Collaborative Filtering

Was the next breakthrough in RecSys in 2017

Kickstarted the use of Deep Learning (Neural Networks) in Rec Sys.

Made the upgrade from the previous industry standard: Matrix Factorization

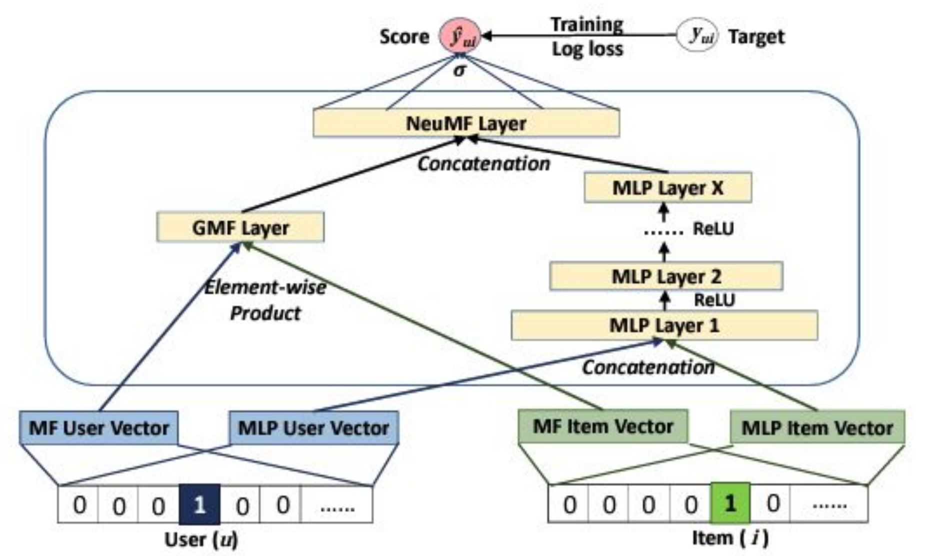


Figure 3: Neural matrix factorization model

Level 2 - Neural Collaborative Filtering

Purpose:
Model predicts interaction score between ***user u*** and **item *j***

Predicted score is denoted $\hat{y}_{ui}$

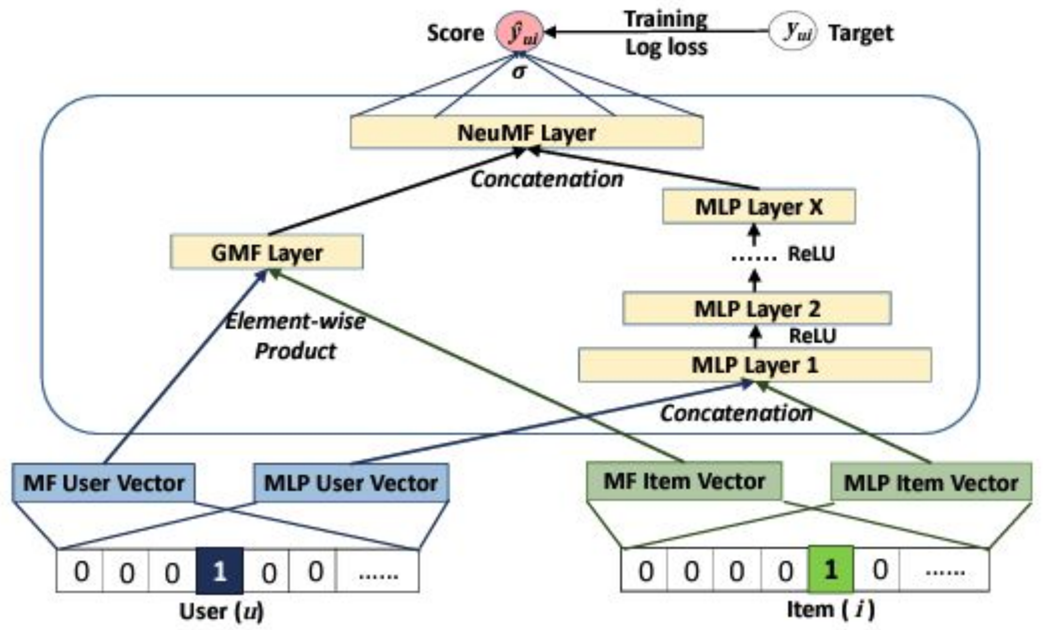


Figure 3: Neural matrix factorization model

Level 2 - Neural Collaborative Filtering

Input Layer:
IDs of (user, item) pair in sparse one hot encoded form

Ex:
4 → [0,0,0,1,0,0, ...]
5 → [0,0,0,0,1,0, ...]

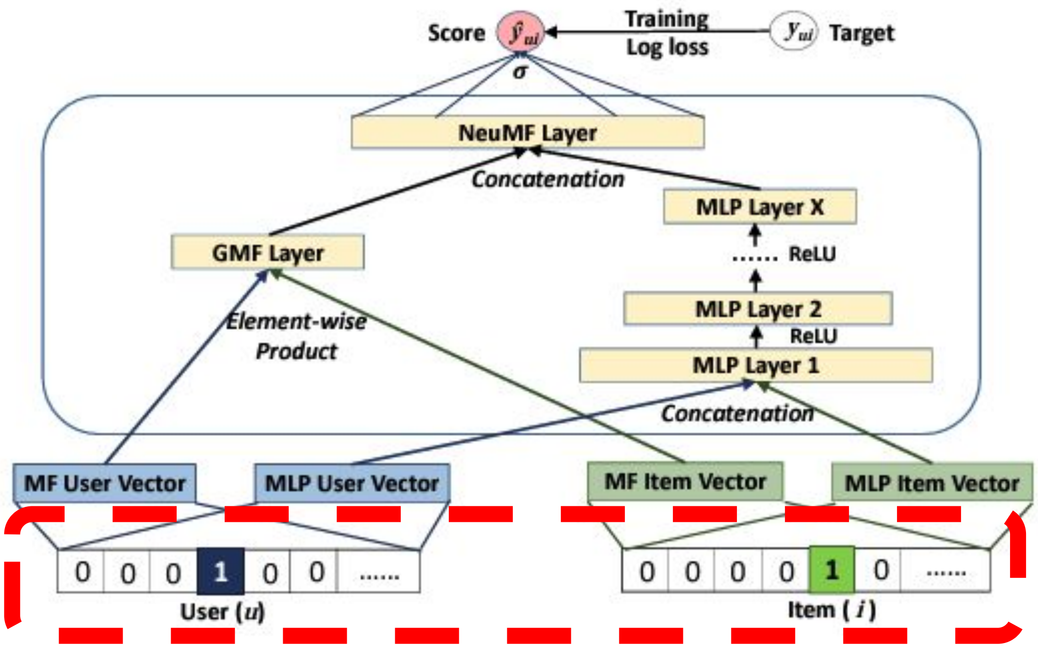
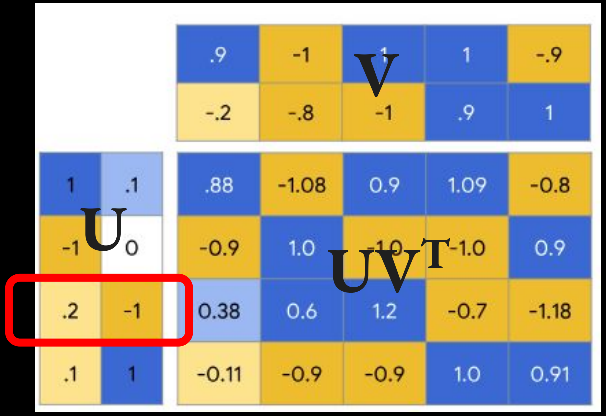


Figure 3: Neural matrix factorization model

Level 2 - Neural Collaborative Filtering

Embedding Layer:
The inputs converted to their corresponding embeddings from matrix factorization model

Embedding of user ID 3 below



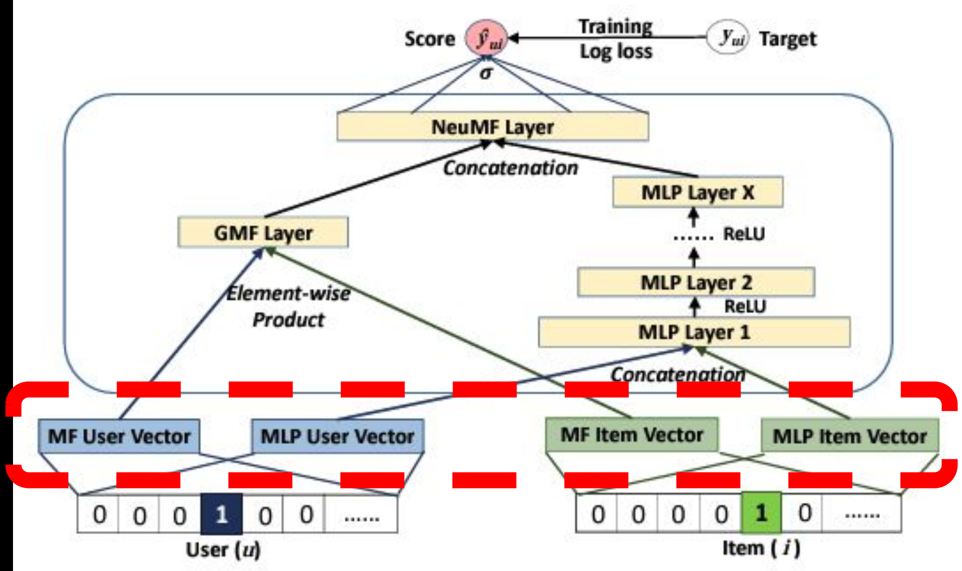


Figure 3: Neural matrix factorization model

Level 2 - Neural Collaborative Filtering

Generalized Matrix Factorization Layer:

$$\mathbf{x} = \mathbf{p}_u \odot \mathbf{q}_i$$
$$\hat{y}_{ui} = \alpha(\mathbf{h}^\top \mathbf{x}),$$

p_u = embedding for user u
q_i = embedding for item i
x = resulting input vector
a = activation function of NN
h = weights of NN
$\hat{y}_{ui}$ = prediction for user u, item i

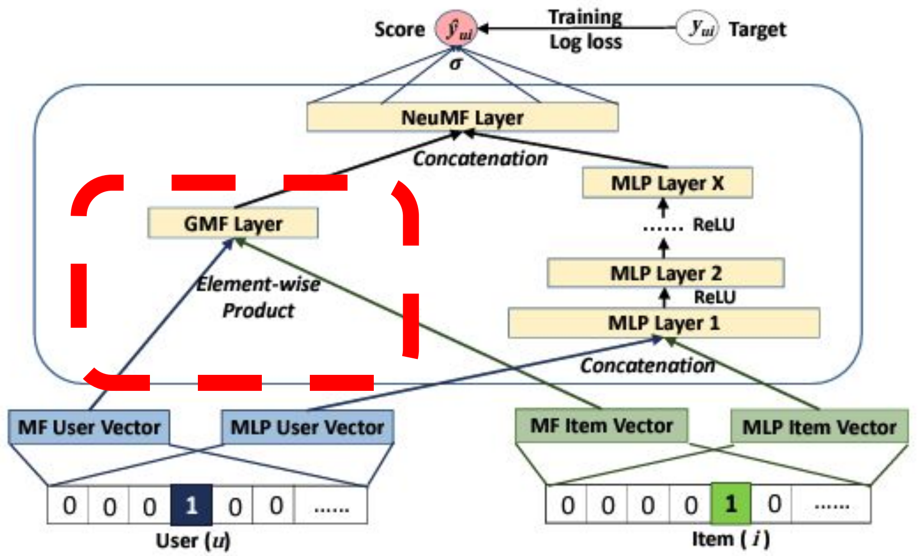


Figure 3: Neural matrix factorization model

Level 2 - Neural Collaborative Filtering

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Multi-Layer Perceptron Layer:

Responsible for capturing the non-linear patterns

$$z^{(1)} = \phi_1(\mathbf{U}_u, \mathbf{V}_i) = [\mathbf{U}_u, \mathbf{V}_i]$$
$$\phi^{(2)}(z^{(1)}) = \alpha^1(\mathbf{W}^{(2)} z^{(1)} + b^{(2)})$$
$$\cdots$$
$$\phi^{(L)}(z^{(L-1)}) = \alpha^L(\mathbf{W}^{(L)} z^{(L-1)} + b^{(L)}))$$
$$\hat{y}_{ui} = \alpha(\mathbf{h}^\top \phi^L(z^{(L-1)}))$$

W - weight matrix
b - bias vector
a - activation function
Φ - function of labelled layer
z - output of labelled layer
$\hat{y}_{ui}$ = prediction for user u, item i

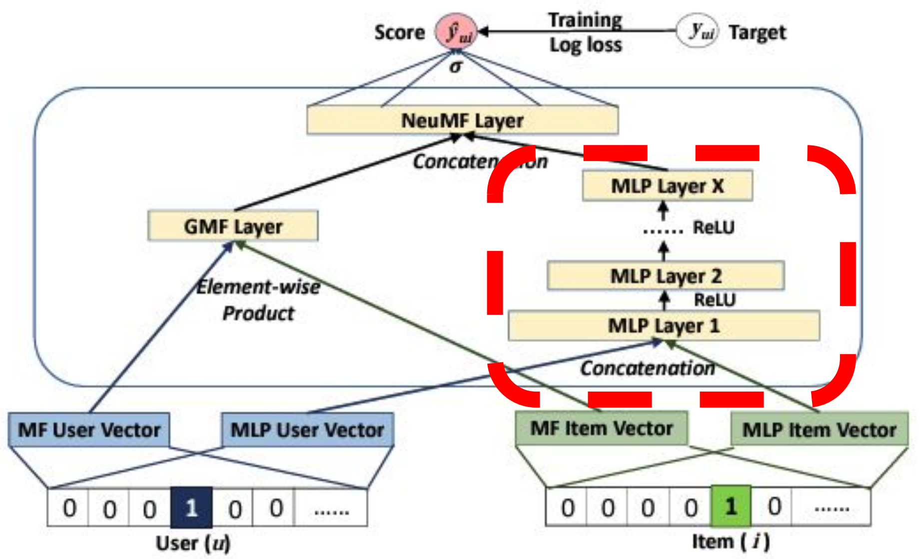


Figure 3: Neural matrix factorization model

Level 2 - Neural Collaborative Filtering

NeuMF Layer:
Combines results both networks

Concatenates the second last layers of the GMF and MLP networks to get:

$$\hat{y}_{ui} = \sigma(\mathbf{h}^{\top}[\mathbf{x}, \phi^{L}(z^{(L-1)})]).$$

σ - sigmoid activation function
h - projection matrix
$\hat{y}_{ui}$ = prediction for user u, item i

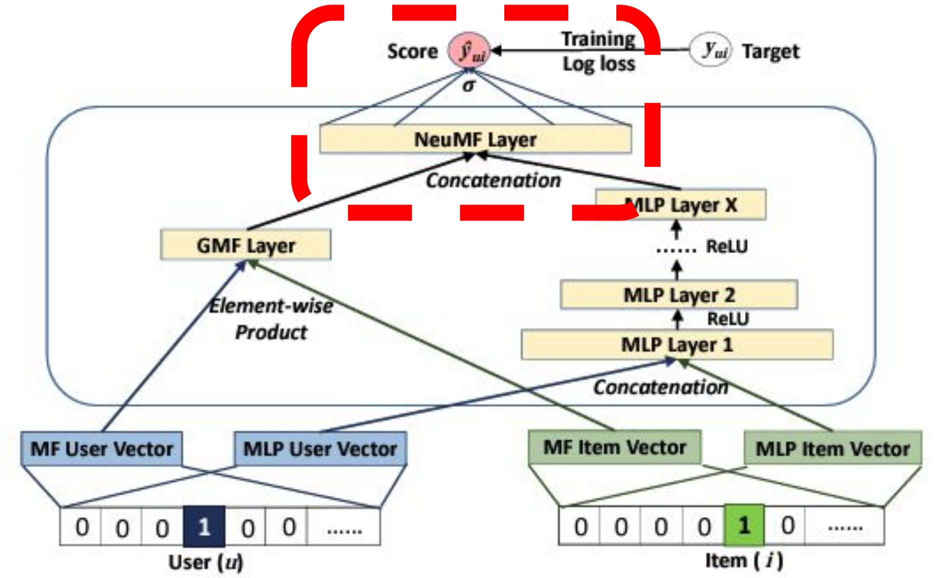


Figure 3: Neural matrix factorization model

Level 2 - Neural Collaborative Filtering

Loss Score:

Neural Collaborative Filtering uses pointwise loss:

$$L_{sqr} = \sum_{(u,i)\in\mathcal{Y}\cup\mathcal{Y}^-} w_{ui}(y_{ui} - \hat{y}_{ui})^2,$$

y - set of observed interactions

y^- - set of unobserved interactions

w_{ui} - weight hyperparameter

y_{ui} - target

$\hat{y}_{ui}$ - prediction

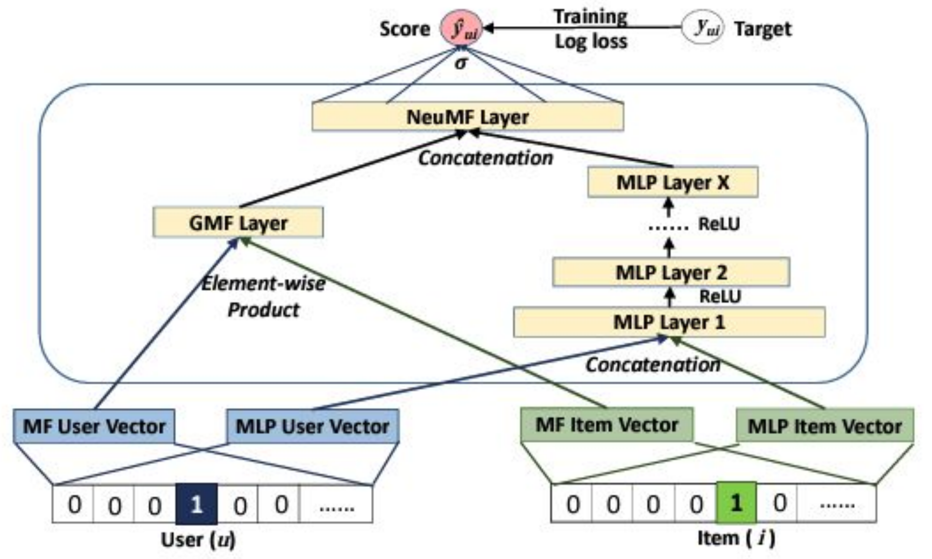


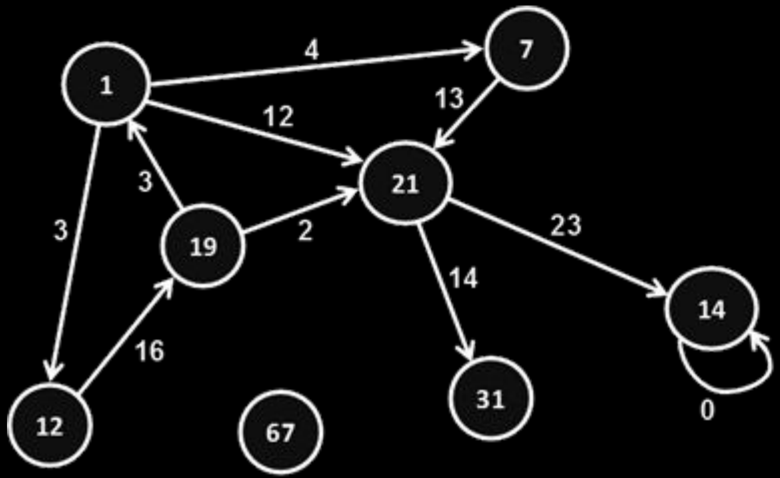
Figure 3: Neural matrix factorization model

Level 3 - Graph Neural Networks

Graph Based methods help capture **more complex relational dependencies** in the data, and have been gaining popularity since 2020

Work well for data with relational dependencies

- Social Media networks (mutual friends)
- Large Knowledge Graphs
- Citation Networks



Level 3 - Graph Neural Networks

Amazon - "Using graph neural networks to recommend related products"

- Using GNNs to model asymmetric product relationships leading to 30-160% performance improvements

Snap Inc - "Graph Neural Networks for Friend Ranking in Large-scale Social Platforms"

- Propose GNN model that uses messages, likes, & other interactions to generate higher quality user representations

Google Maps - "ETA Prediction with Graph Neural Networks in Google Maps"

- Use GNN to model connectivity of road networks to reduce inaccuracies of ETA calculations by more than 50%

Notebook

We will show how to implement basic recommender systems based on the ideas covered today

1. Content-Based Filtering (KNN method)
2. Collaborative Filtering (Matrix Factorization method)
3. Neural Collaborative Filtering

Useful Resources

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Datasets:

- [Recommender System Datasets]
- [Stanford Graph/Recommendation Datasets]
- [Netflix $1M Prize Competition Dataset]

Architectures:

- [Intro to Content-Based Filtering]
- [Intro to Collaborative Filtering]
- [Neural Collaborative Filtering Paper (2017)]

Future of Recommendation Systems:

- [Amazon Science: GNNs for related products]
- [Snap Inc: GNNs for Large Scale Friend Ranking]
- [Google Maps: ETA Prediction using GNNs]