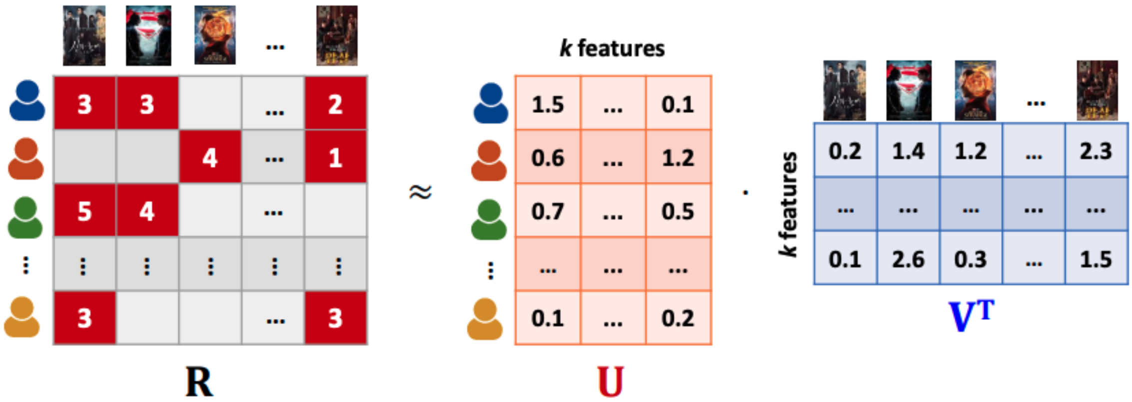
Lec 06-1. Neural Collaborative Filtering

Recap : Latent Factor Models

- Existing latent models assume that **user-item interactions are represented by linear combination.**

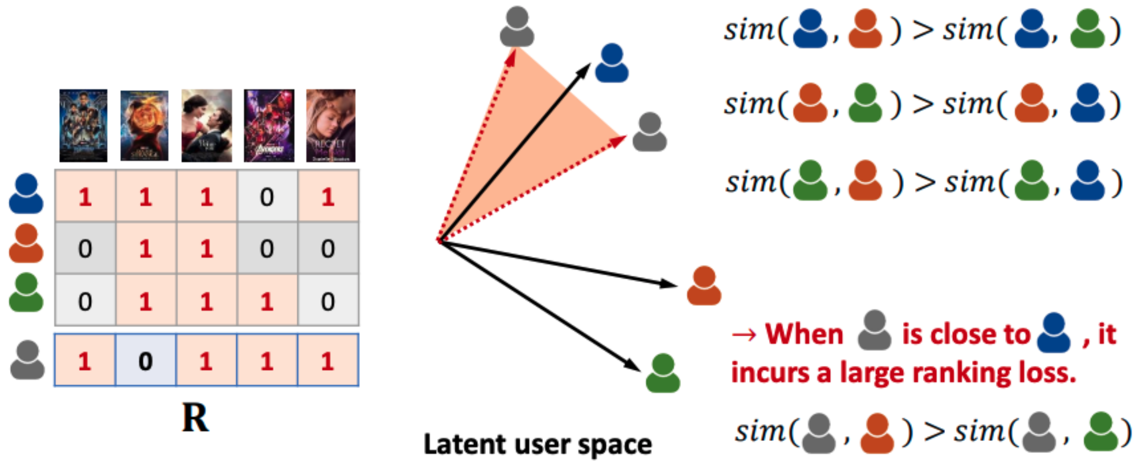
$$\min \frac{1}{2} \sum_{(u,i)\in\mathcal{S}} e_{ui}^2 = \frac{1}{2} \sum_{(u,i)\in\mathcal{S}} (r_{ui} - \mathbf{u}_u \mathbf{v}_i^T)^2$$

$\mathcal{S}$: a set of observed user-item pairs in $\mathbf{R}$

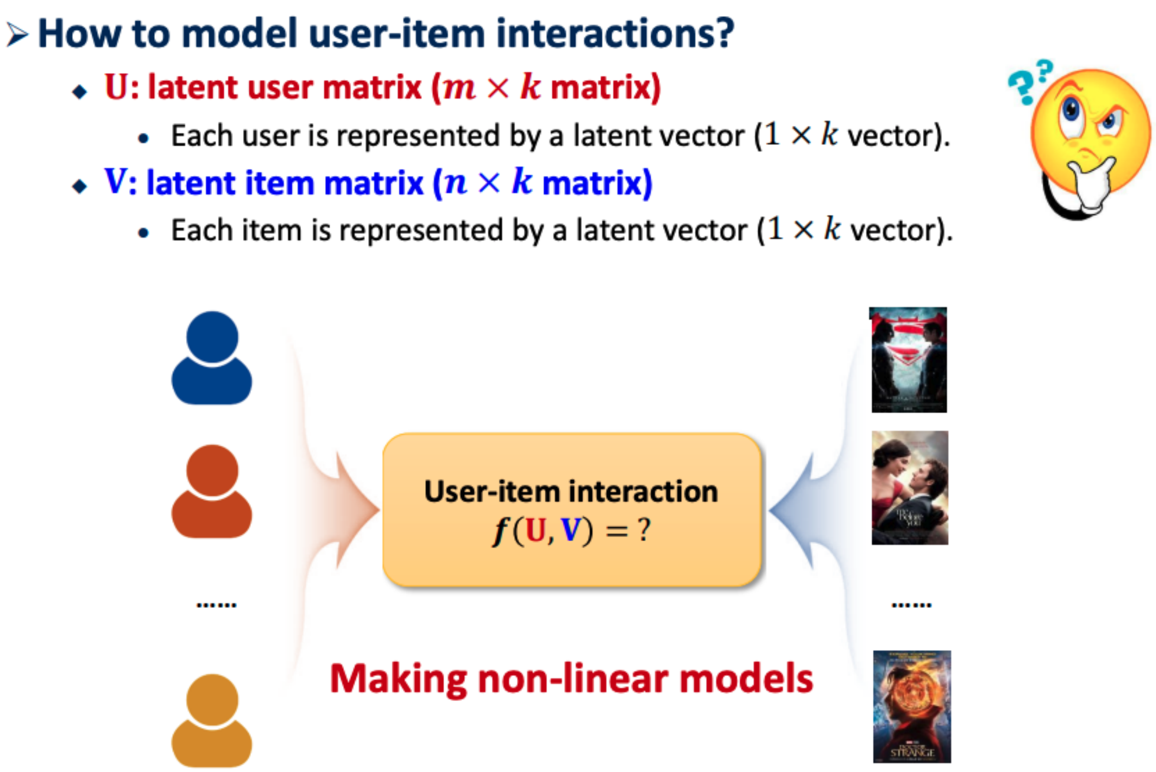


Example : Limitation of Linear Models

- Given a user-item rating matrix, the linear factor model represents users in the latent space.
  - It is difficult to preserve the true ranking order in the original space.



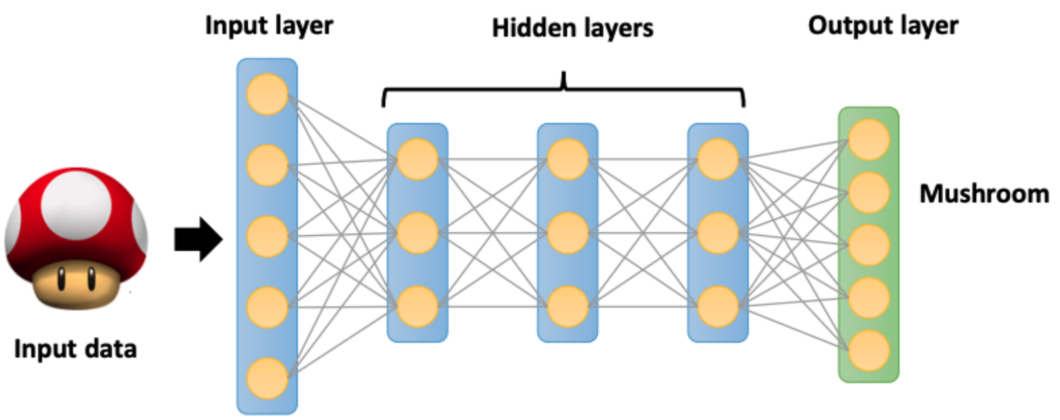
How to Design Latent Factor Models?



Feed-forward Neural Network

➢ **It is a typical artificial neural network.**

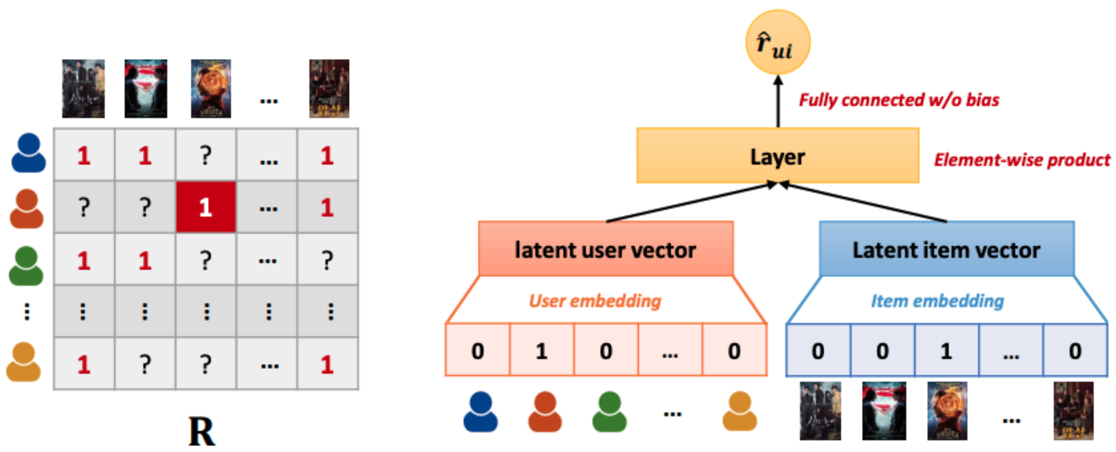
- The neurons in each layer feed their output forward to the next layer until we get the final output from the neural network.
  - Each node is a **neuron** that uses a **(non-linear) activation function**.
- There can be any number of hidden layers in a feedforward network.



Generalized Matrix Factorization (GMF)

➢ **Element-wise product is same as existing matrix factorization.**

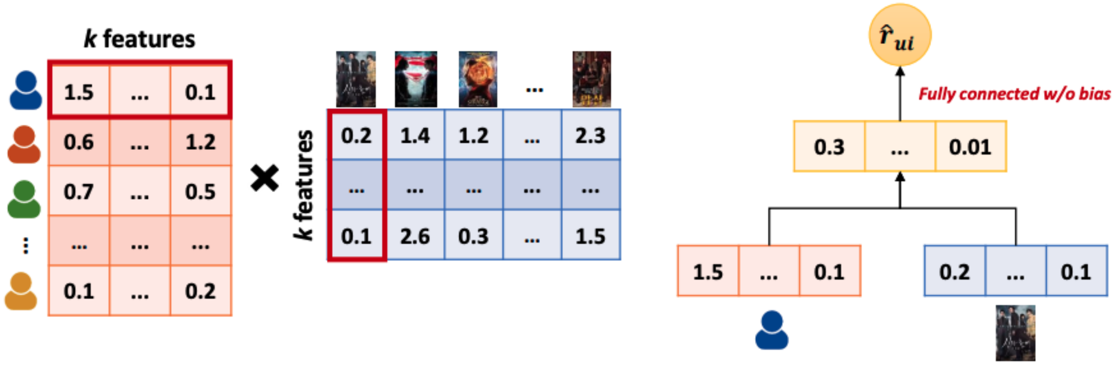
- **Input**: one-hot feature vector for user u and item i
- **Output**: predicted score $\hat{r}_{ui}$



- **When combining user and item latent vectors, different weights are used.**

w_j is the weight for the j-th latent feature.

$$\hat{r}_{ui} = \sum_{j=1}^{k} w_j \, u_{uj} v_{ij}^T$$

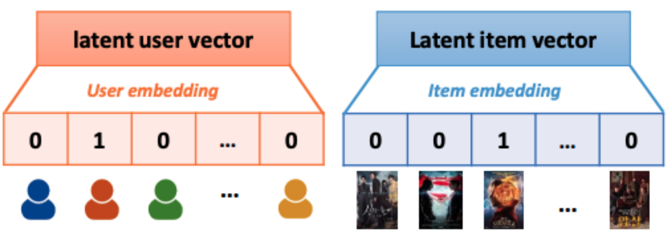


Embedding for Users and Items

- **User and item projection layers**

$$\begin{bmatrix} 0.1 & 1.5 & 1.9 & \dots & 1.2 \\ 0.2 & 2.3 & 0.5 & \dots & 1.1 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0.3 & 0.1 & 2.1 & \dots & 0.2 \end{bmatrix} \cdot \begin{bmatrix} 0 \\ 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix} = \begin{bmatrix} 1.5 \\ 2.3 \\ \vdots \\ 0.1 \end{bmatrix}$$

$\boldsymbol{U} \in \mathbb{R}^{k \times m}$ $\quad x_i \in \mathbb{R}^{m \times 1}$ $\quad \boldsymbol{U_u} \in \mathbb{R}^{k \times 1}$



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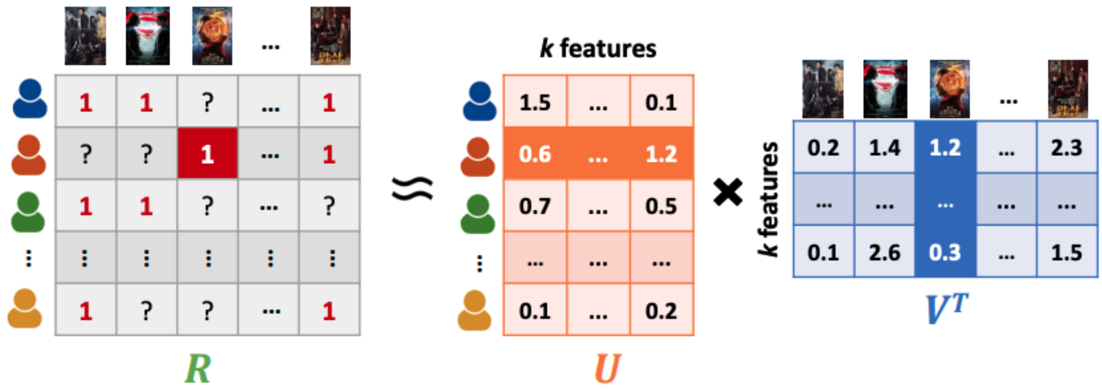

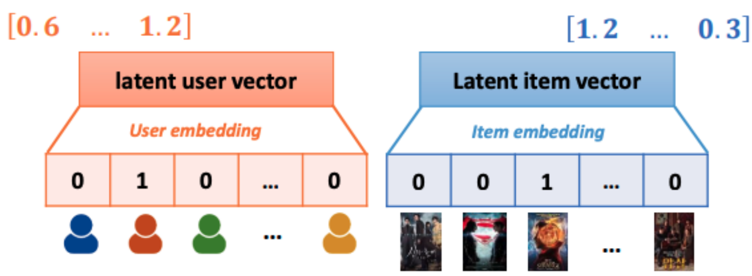

User and item latent vectors are represented by user and item embedding layers.

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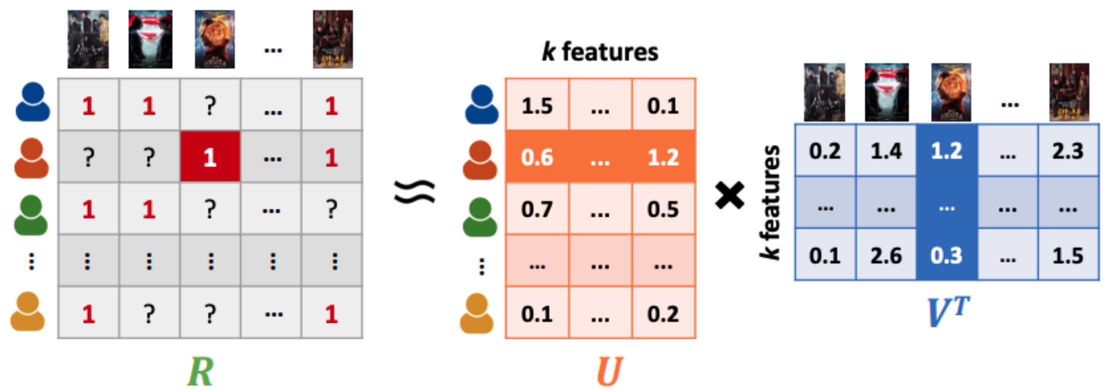
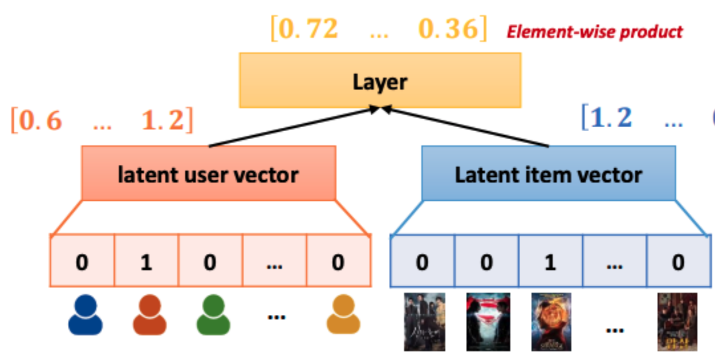
Element-wise Product





This is same as the linear combination of U_u and V_i^T.

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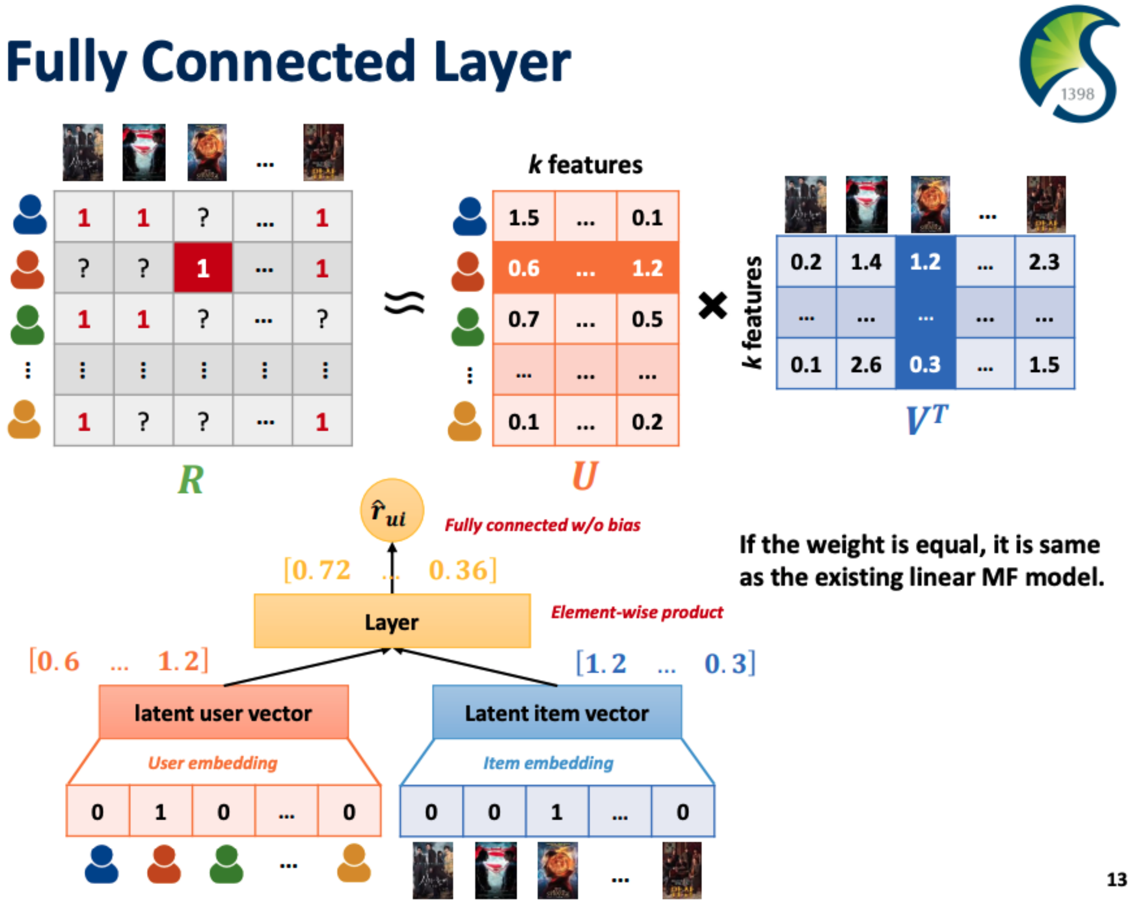
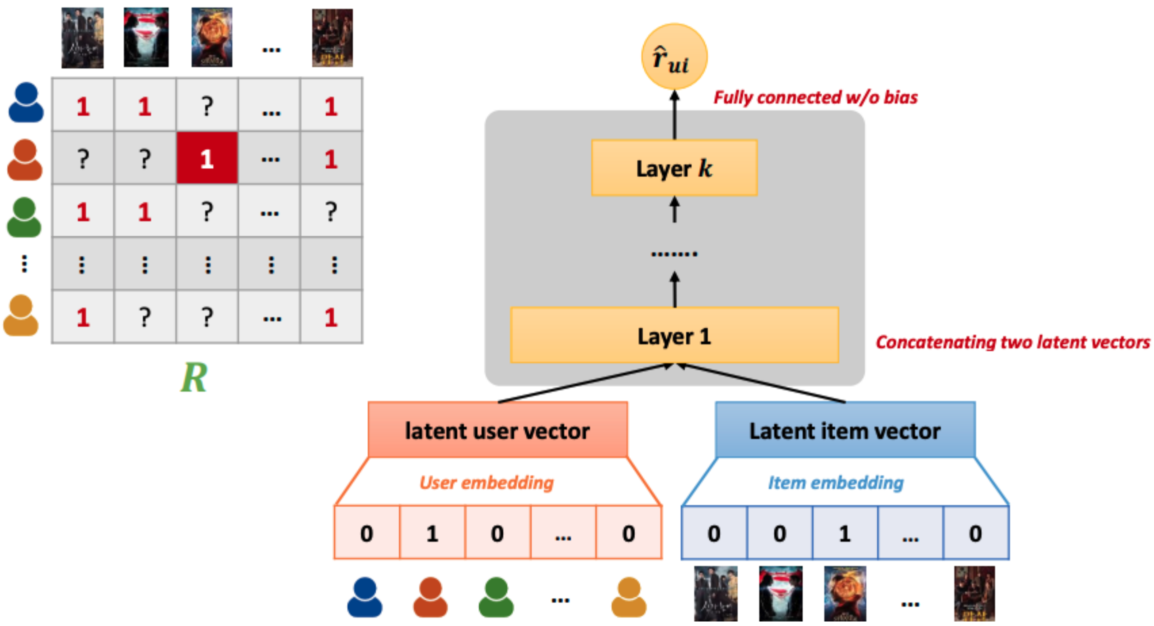
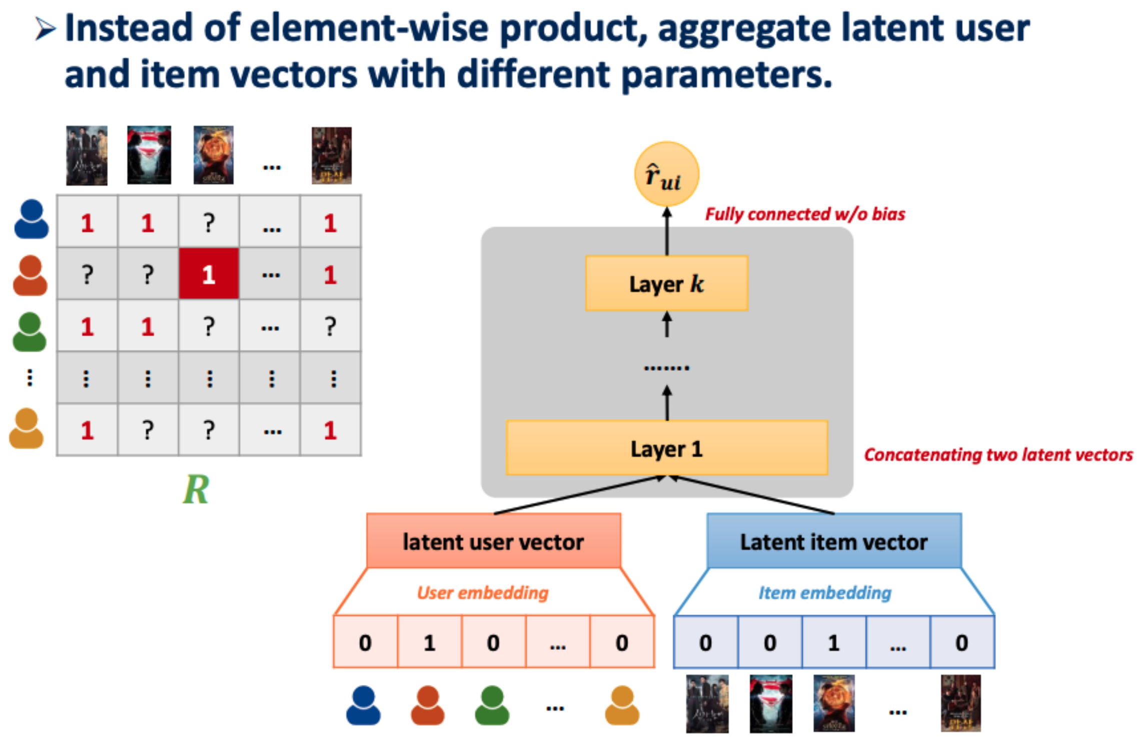
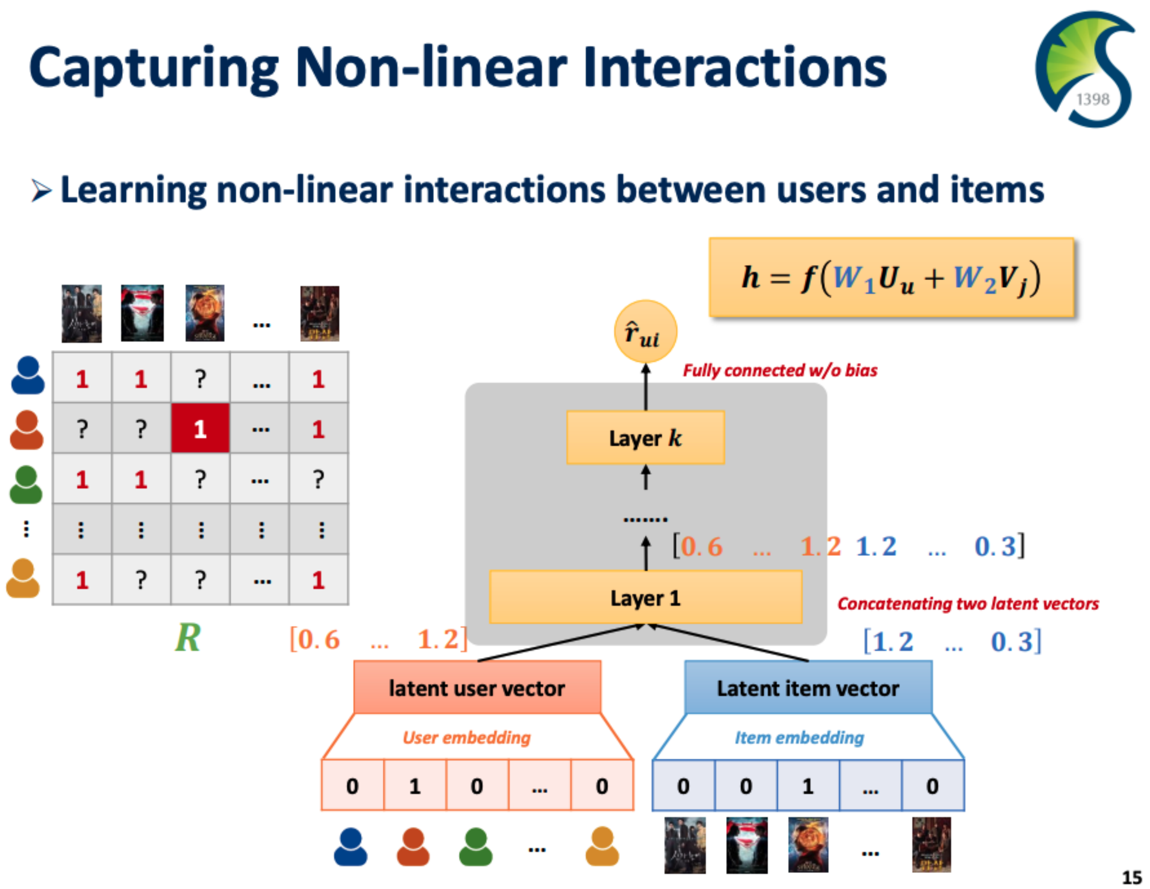


MLP-based Matrix Factorization

- Instead of element-wise product, aggregate latent user and item vectors with different parameters.







Neural Collaborative Filtering (NCF)

➢ **It utilizes both GMF and MLP layers.**