Redes Neurais Aplicadas a Sistemas de Recomendação

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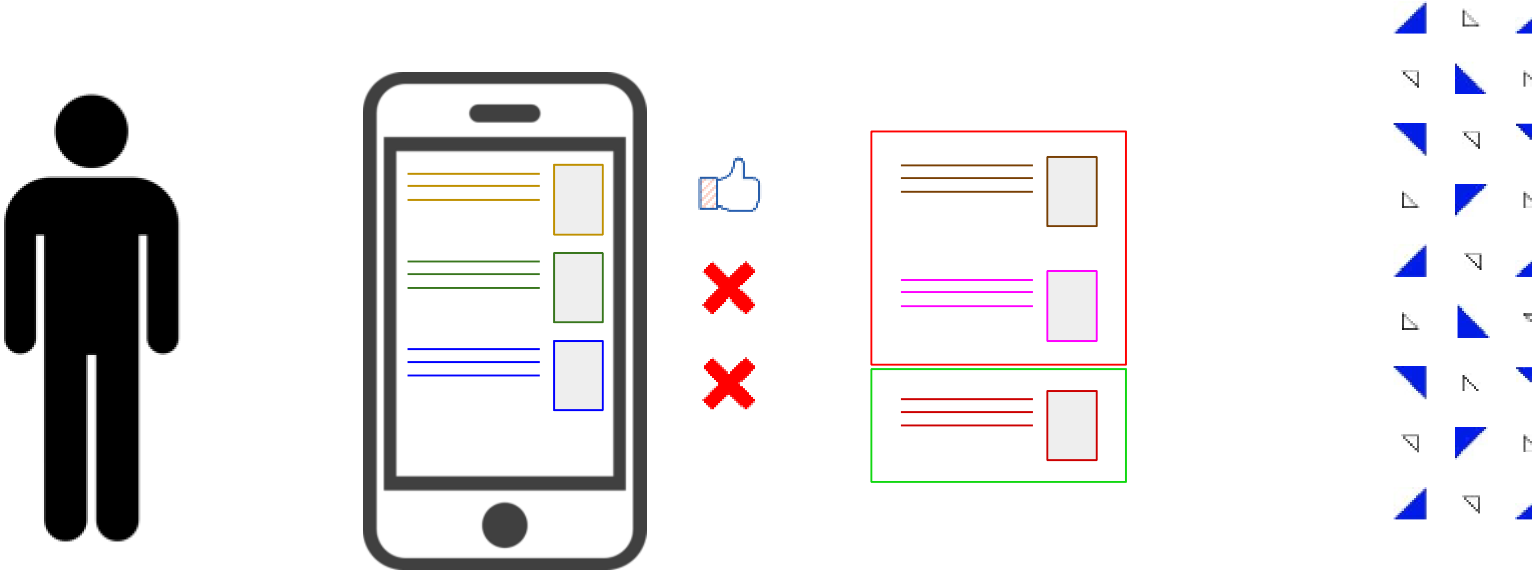
Conceitos fundamentais

Conceitos fundamentais



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Conceitos fundamentais

Explicit Feedback

Implicit Feedback

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Conceitos fundamentais

- **Explicit Feedback:** quando usuário deixa claro, de forma ativa, qual é sua preferência por um item.

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Conceitos fundamentais

- **Implicit Feedback:** Quando o usuário não deixa de forma ativa o interesse ou preferência dele para um determinado item.

Exemplos:

- Tempo que o usuário passou em uma determinada categoria do site
- Número de acessos
- Número de cliques

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Conceitos fundamentais

	GLADITOR	GODFTHER	BEN-HUR	GOODFELLAS	SCARFACE	SPARTACUS
U_1	1			5		2
U_2		5			4	
U_3	5	3		1		
U_4			3			4
U_5				3	5	
U_6	5		4			

(a) Ordered ratings

	GLADIATOR	GODFATHER	BEN-HUR	GOODFELLAS	SCARFACE	SPARTACUS
U_1	1			1		1
U_2		1			1	
U_3	1	1		1		
U_4			1			1
U_5				1	1	
U_6	1		1			

(b) Unary ratings

Conceitos fundamentais

Collaborative Filtering

Content Based

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Conceitos fundamentais

Collaborative Filtering

The basic idea of collaborative filtering methods is that these unspecified ratings can be imputed because the observed ratings are often highly correlated across various users and items. For example, consider two users named Alice and Bob, who have very similar tastes. If the ratings, which both have specified, are very similar, then their similarity can be identified by the underlying algorithm. In such cases, it is very likely that the ratings in which only one of them has specified a value, are also likely to be similar. This similarity can be used to make inferences about incompletely specified values. Most of the models for collaborative filtering focus on leveraging either inter-item correlations or inter-user correlations for the prediction process. Some models use both types of correlations.

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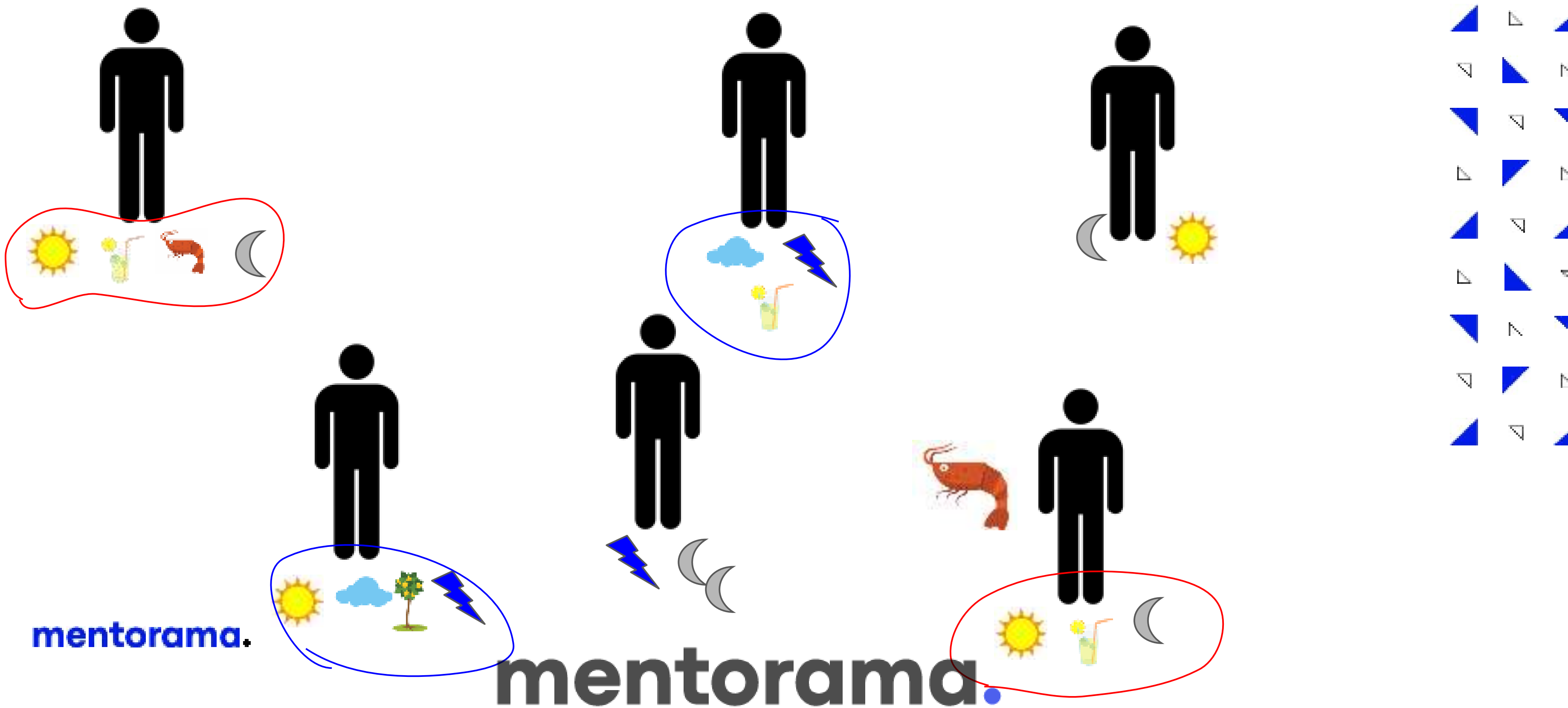
Conceitos fundamentais



Conceitos fundamentais

Content
Based

Título
Legenda
Imagem
Vídeo

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Abordagens Modernas para Construção de Sistemas de Recomendação

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Abordagens Modernas para Sistemas de Recomendação

Rule Based

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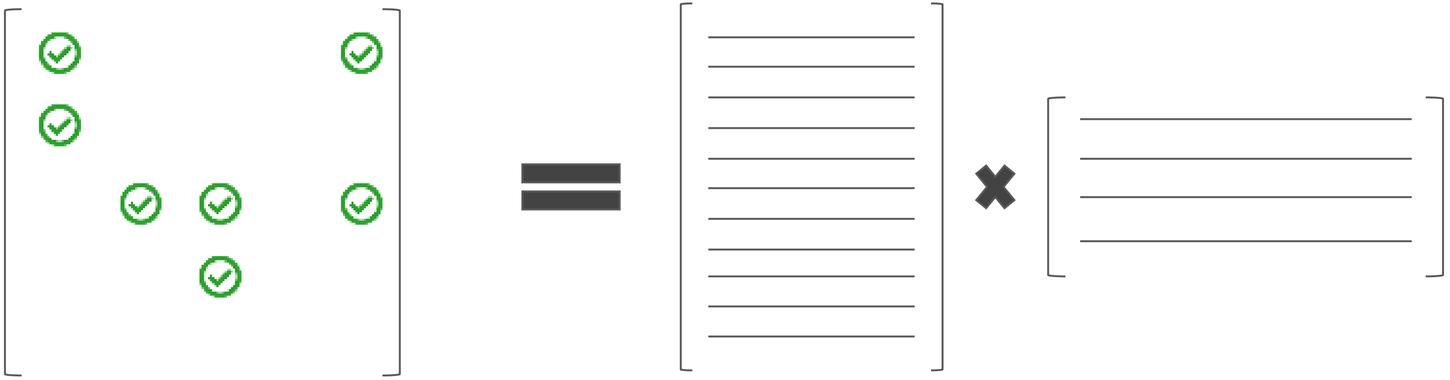
Fatoração de matrizes



Alternating Least Squares

- Método de otimização
- Alterna entre as matrizes

Possível função para otimizar:

$$\arg\min_{x_u, y_i} \sum_{u,i} (r_{ui} - x_u^T y_i)^2 + \lambda \left(\sum_u ||x_u||^2 + \sum_i ||y_i||^2 \right)$$

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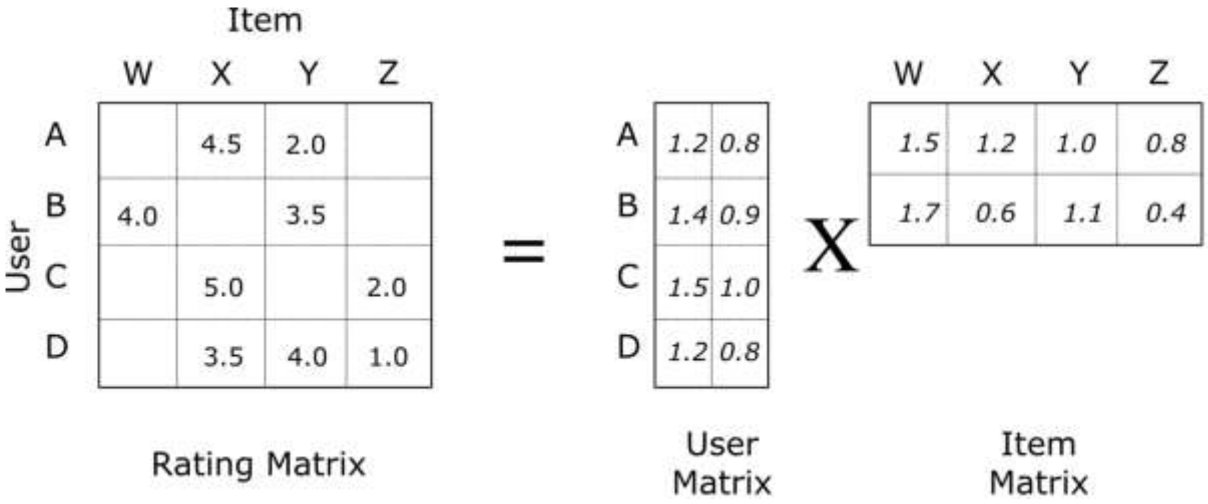
Abordagens Modernas para Sistemas de Recomendação



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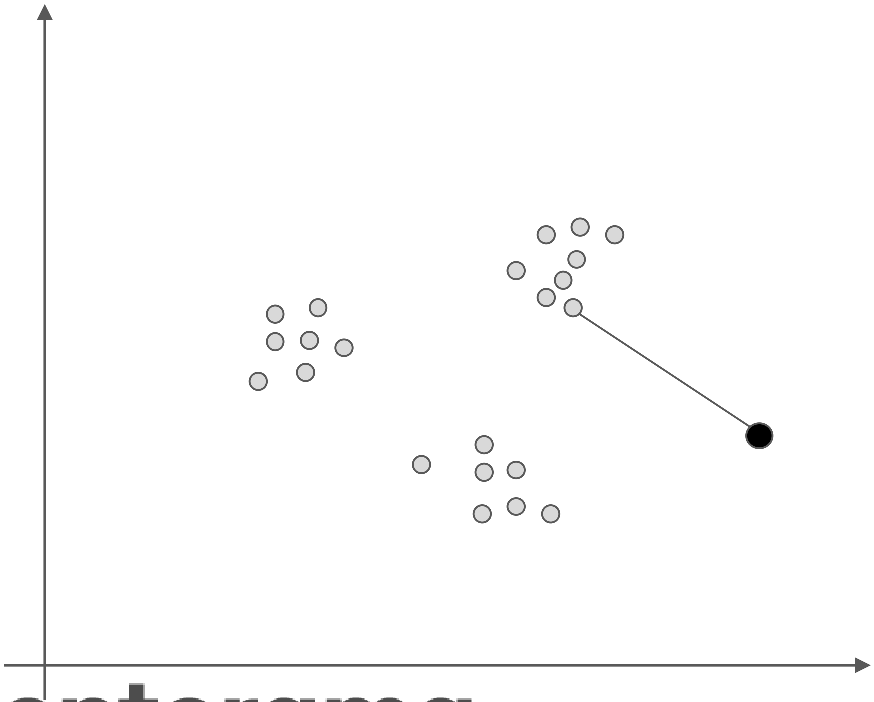
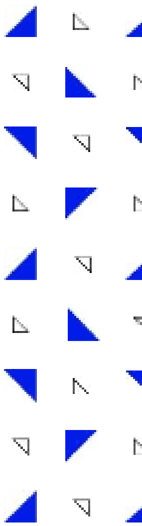
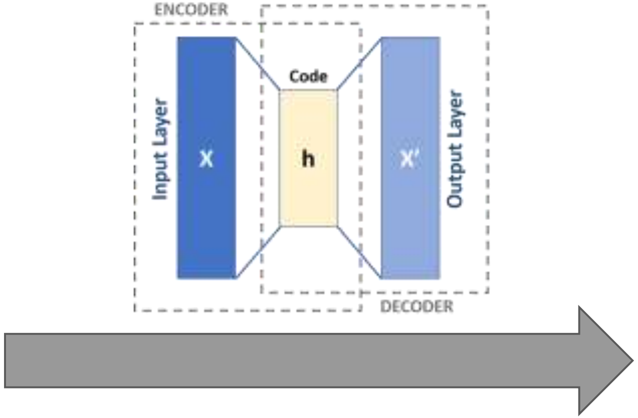
Abordagens Modernas para Sistemas de Recomendação

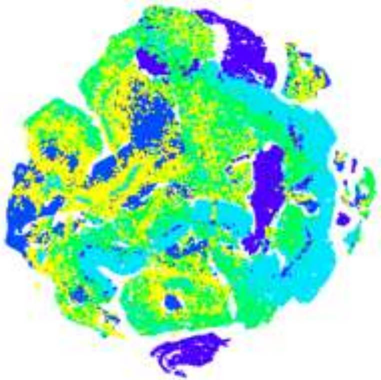
Neighborhood-based Recommendations

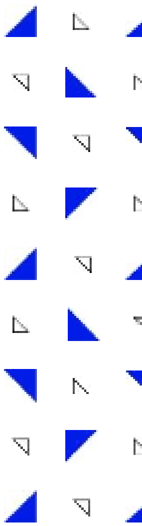




Autoencoder + k-NN







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Abordagens Modernas para Sistemas de Recomendação

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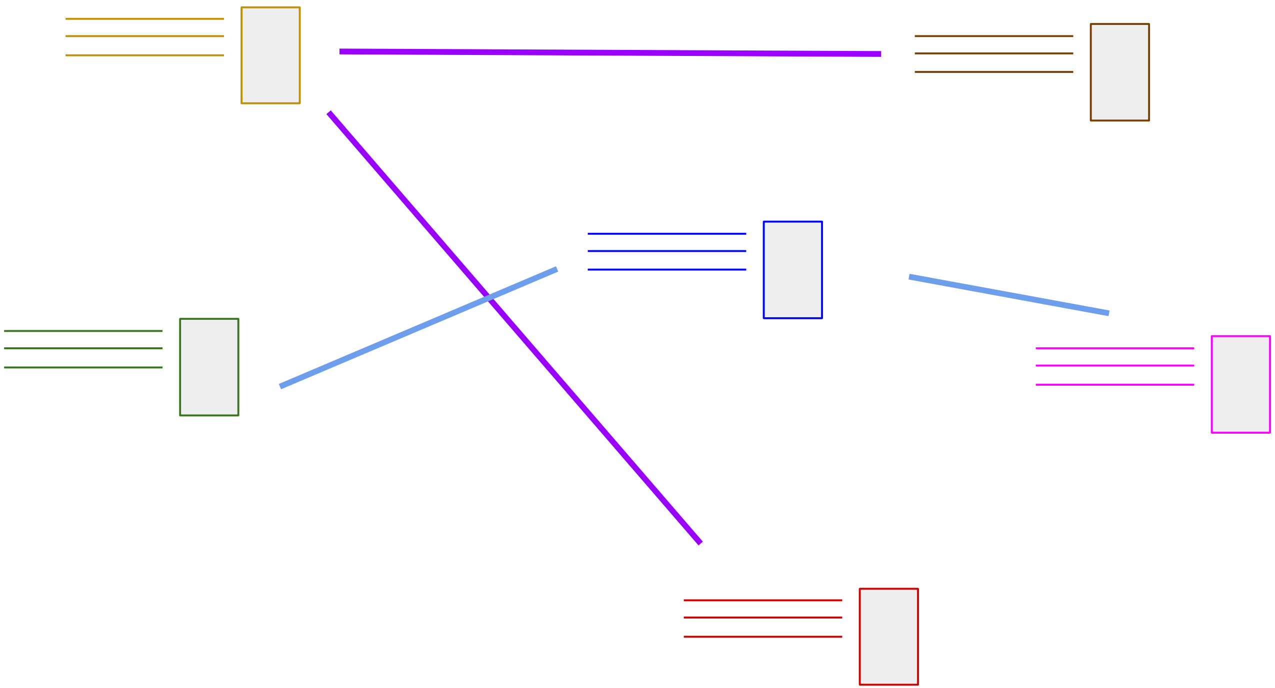
Sistemas de recomendação com Base de Conhecimento

Sistemas de recomendação com Base de Conhecimento



Neural Collaborative Filtering

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Neural Collaborative Filtering

$$\hat{y}_{ui} = f(u, i|\mathbf{p}_u, \mathbf{q}_i) = \mathbf{p}_u^T \mathbf{q}_i = \sum_{k=1}^{K} p_{uk} q_{ik}$$

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Neural Collaborative Filtering

- Generalized Matrix Factorization - GMF
- Evolução do GMF com MLP
- Neural Matrix Factorization - NeuralMF

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Neural Collaborative Filtering

GMF

$$\phi_1(\mathbf{p}_u, \mathbf{q}_i) = \mathbf{p}_u \odot \mathbf{q}_i$$

where $\odot$ denotes the element-wise product of vectors. We then project the vector to the output layer:

$$\hat{y}_{ui} = a_{out}(\mathbf{h}^T(\mathbf{p}_u \odot \mathbf{q}_i))$$

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Neural Collaborative Filtering

Evolução do GMF com MLP

$$\mathbf{z}_1 = \phi_1(\mathbf{p}_u, \mathbf{q}_i) = \begin{bmatrix} \mathbf{p}_u \\ \mathbf{q}_i \end{bmatrix},$$
$$\phi_2(\mathbf{z}_1) = a_2(\mathbf{W}_2^T \mathbf{z}_1 + \mathbf{b}_2),$$
$$\ldots\ldots$$
$$\phi_L(\mathbf{z}_{L-1}) = a_L(\mathbf{W}_L^T \mathbf{z}_{L-1} + \mathbf{b}_L),$$
$$\hat{y}_{ui} = \sigma(\mathbf{h}^T \phi_L(\mathbf{z}_{L-1})),$$

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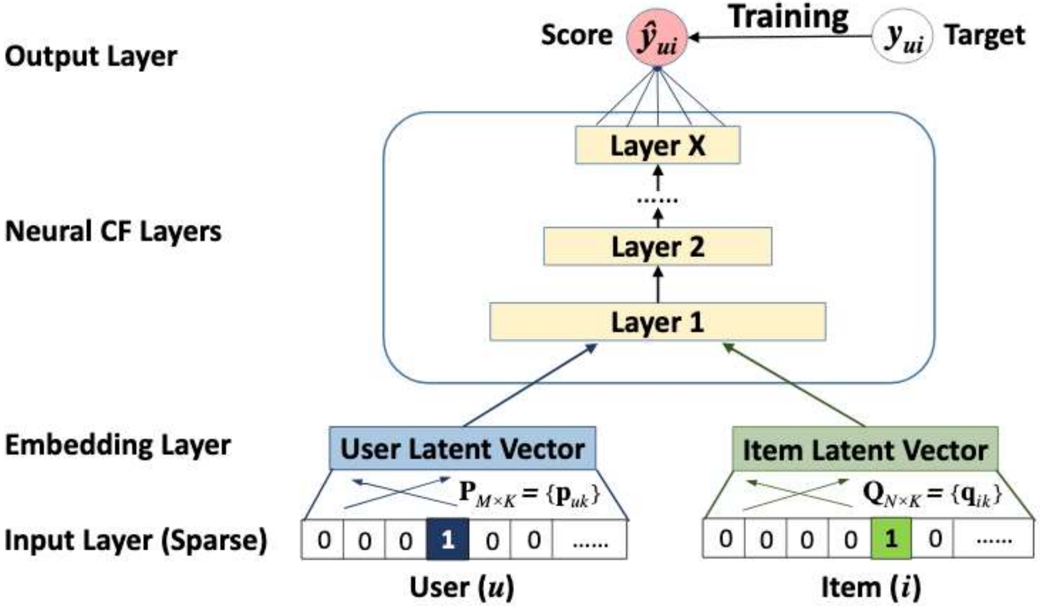
Neural Collaborative Filtering

Evolução do GMF com MLP



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Neural Collaborative Filtering

Evolução do GMF com MLP

$$\phi^{GMF} = \mathbf{p}_u^G \odot \mathbf{q}_i^G$$

$$\phi^{MLP} = a_L(\mathbf{W}_L^T(a_{L-1}(...a_2(\mathbf{W}_2^T \begin{bmatrix} \mathbf{p}_u^M \\ \mathbf{q}_i^M \end{bmatrix} + \mathbf{b}_2)...)) + \mathbf{b}_L)$$

$$\hat{y}_{ui} = \sigma(\mathbf{h}^T \begin{bmatrix} \phi^{GMF} \\ \phi^{MLP} \end{bmatrix})$$

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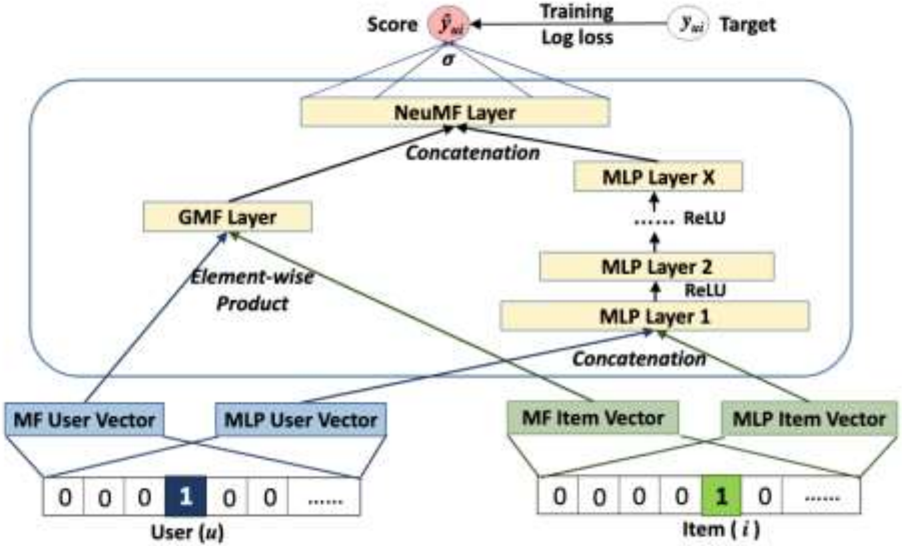
Neural Collaborative Filtering

Evolução do GMF com MLP



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