

Recommender Systems & Embeddings

Charles Ollion - Olivier Grisel



Outline

Embeddings

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Dropout Regularization

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Recommender Systems

Embeddings

Symbolic variable

- Text: characters, words, bigrams...
- Recommender Systems: item ids, user ids
- Any categorical descriptor: tags, movie genres, visited URLs, skills on a resume, product categories...

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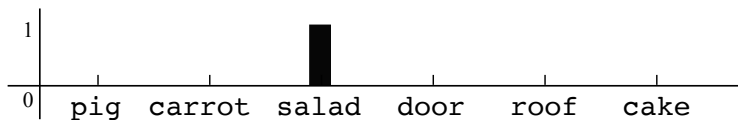
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Notation:

Symbol s in vocabulary V

One-hot representation

$$\text{onehot}(\text{'salad'}) = [0, 0, 1, \dots, 0] \in \{0, 1\}^{|V|}$$



One-hot representation

$$\text{onehot}(\text{'salad'}) = [0, 0, 1, \dots, 0] \in \{0, 1\}^{|V|}$$



- Sparse, discrete, large dimension $|V|$
- Each axis has a meaning
- Symbols are equidistant from each other:

$$\text{euclidean distance} = \sqrt{2}$$

Embedding

$$\textit{embedding}(\text{'salad'}) = [3.28, -0.45, \dots 7.11] \in \mathbb{R}^d$$

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- Continuous and dense
- Can represent a huge vocabulary in low dimension, typically:
 $d \in \{16, 32, \dots, 4096\}$
- Axis have no meaning *a priori*
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Neural Networks compute transformations on continuous vectors

Implementation with Keras

Size of vocabulary $n = |V|$, size of embedding d

```
# input: batch of integers  
Embedding(output_dim=d, input_dim=n, input_length=1)  
# output: batch of float vectors
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- \mathbf{W} are trainable parameters of the model

Distance and similarity in Embedding space

Euclidean distance

$$d(x, y) = ||x - y||_2$$

- Simple with good properties
- Dependent on norm
(embeddings usually
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Cosine similarity

$$\text{cosine}(x, y) = \frac{x \cdot y}{||x|| \cdot ||y||}$$

- Angle between points, regardless of norm
- $\text{cosine}(x, y) \in (-1, 1)$
- Expected cosine similarity of random pairs of vectors is 0

Distance and similarity in Embedding space

If x and y both have unit norms:

$$||x - y||_2^2 = 2 \cdot (1 - \text{cosine}(x, y))$$

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or alternatively:

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Alternatively, dot product (unnormalized) is used in practice as a pseudo similarity

Visualizing Embeddings

- Visualizing requires a projection in 2 or 3 dimensions
- Objective: visualize which embedded symbols are similar

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t-SNE

Visualizing data using t-SNE, L van der Maaten, G Hinton, *The Journal of Machine Learning Research*, 2008

t-Distributed Stochastic Neighbor Embedding

- Unsupervised, low-dimension, non-linear projection
- Optimized to preserve relative distances between nearest neighbors
- Global layout is not necessarily meaningful

t-Distributed Stochastic Neighbor Embedding

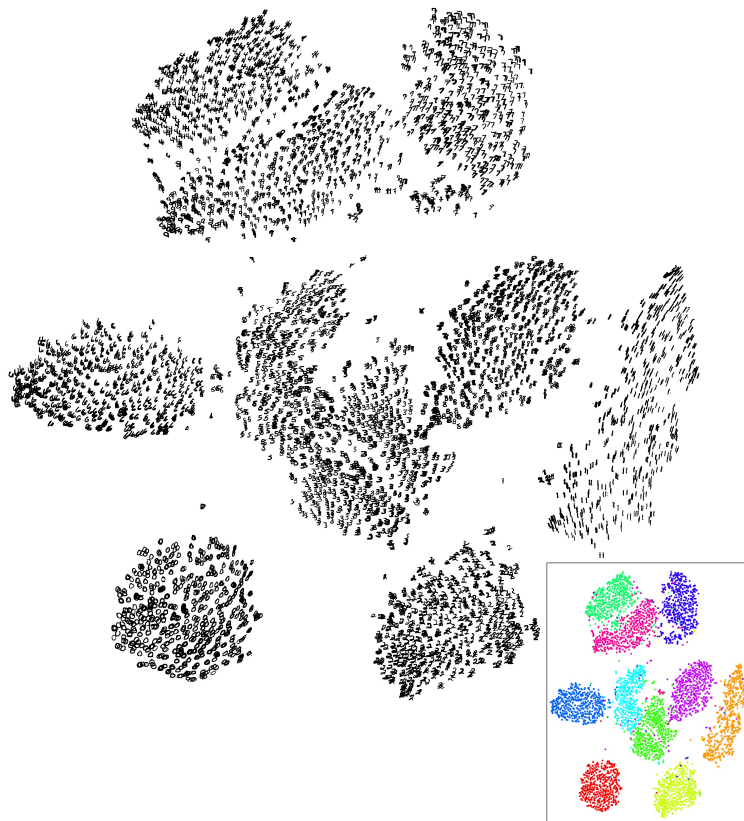
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t-SNE projection is non deterministic
(depends on initialization)

- Critical parameter: perplexity, usually set to 20, 30
- See <http://distill.pub/2016/misread-tsne/>

[illegible]

Visualizing Mnist



Dropout Regularization

Regularization

Size of the embeddings

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Size of the embeddings

Depth of the network

Regularization

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Depth of the network

L_2 penalty on embeddings

Regularization

Size of the embeddings

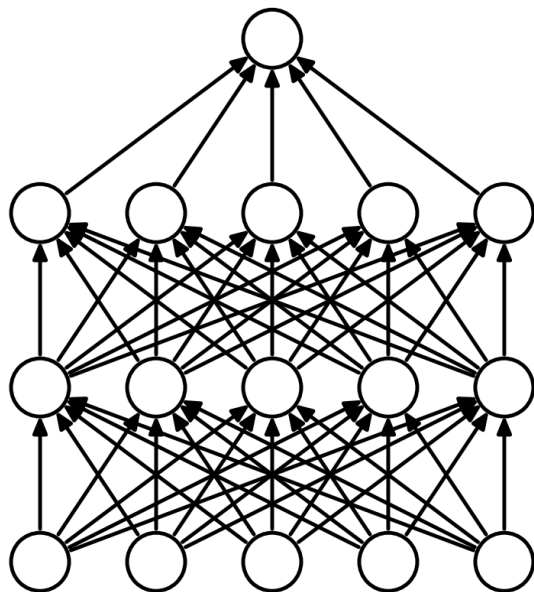
Depth of the network

L_2 penalty on embeddings

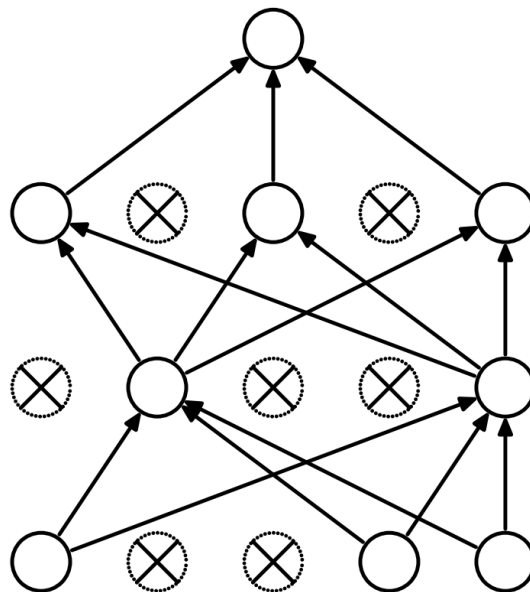
Dropout

- Randomly set activations to 0 with probability p
- Bernoulli mask sampled for a forward pass / backward pass pair
- Typically only enabled at training time

Dropout



(a) Standard Neural Net



(b) After applying dropout.

Dropout: A Simple Way to Prevent Neural Networks from Overfitting, Srivastava et al.,
Journal of Machine Learning Research 2014

Dropout

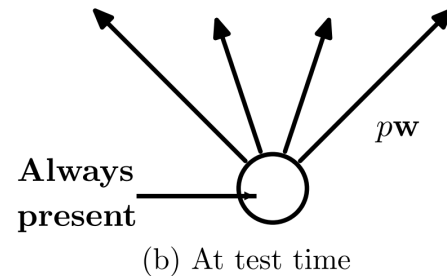
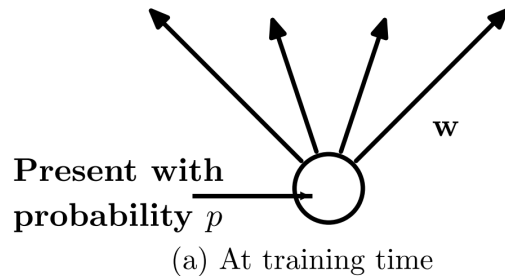
Interpretation

- Reduces the network dependency to individual neurons
- More redundant representation of data

Ensemble interpretation

- Equivalent to training a large ensemble of shared-parameters, binary-masked models
- Each model is only trained on a single data point

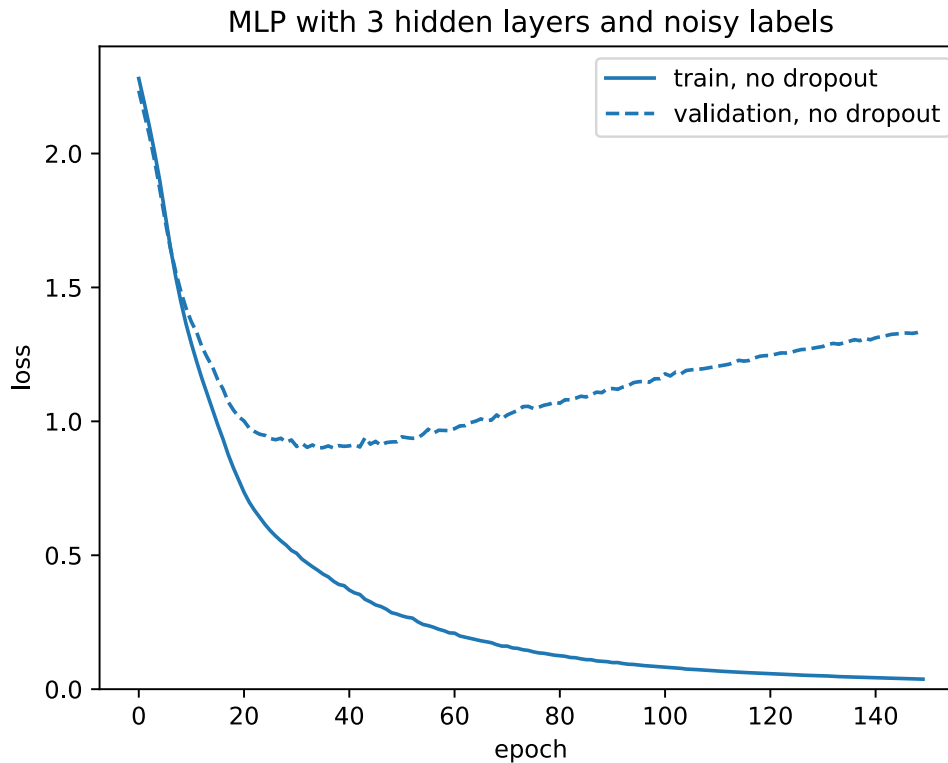
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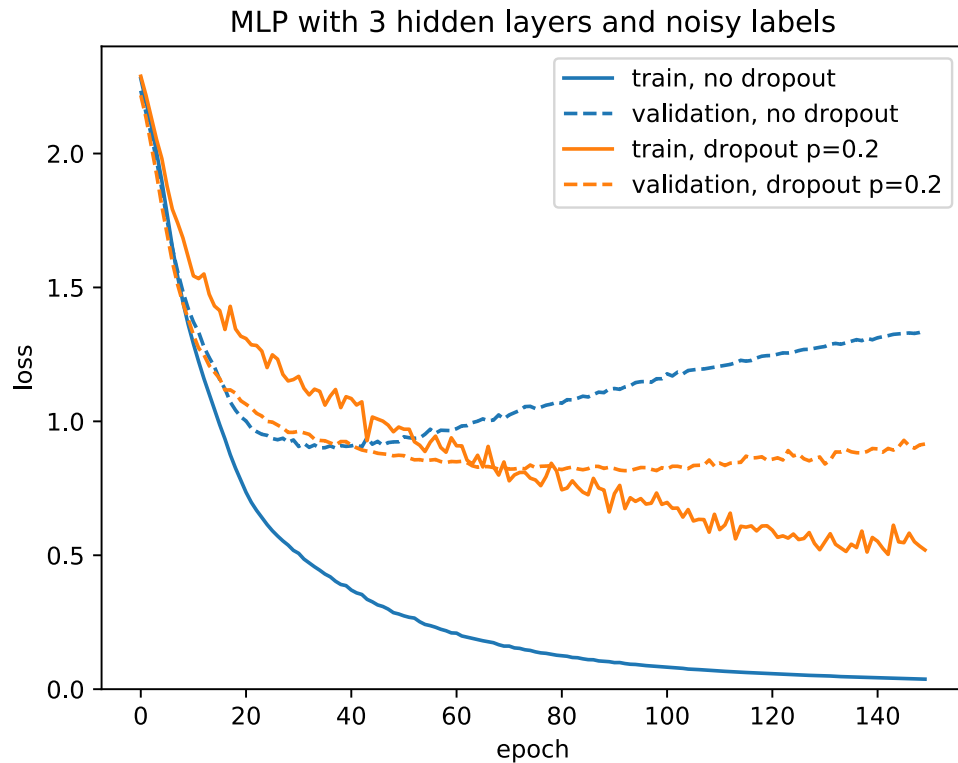
At test time, multiply weights by p to keep same level of activation

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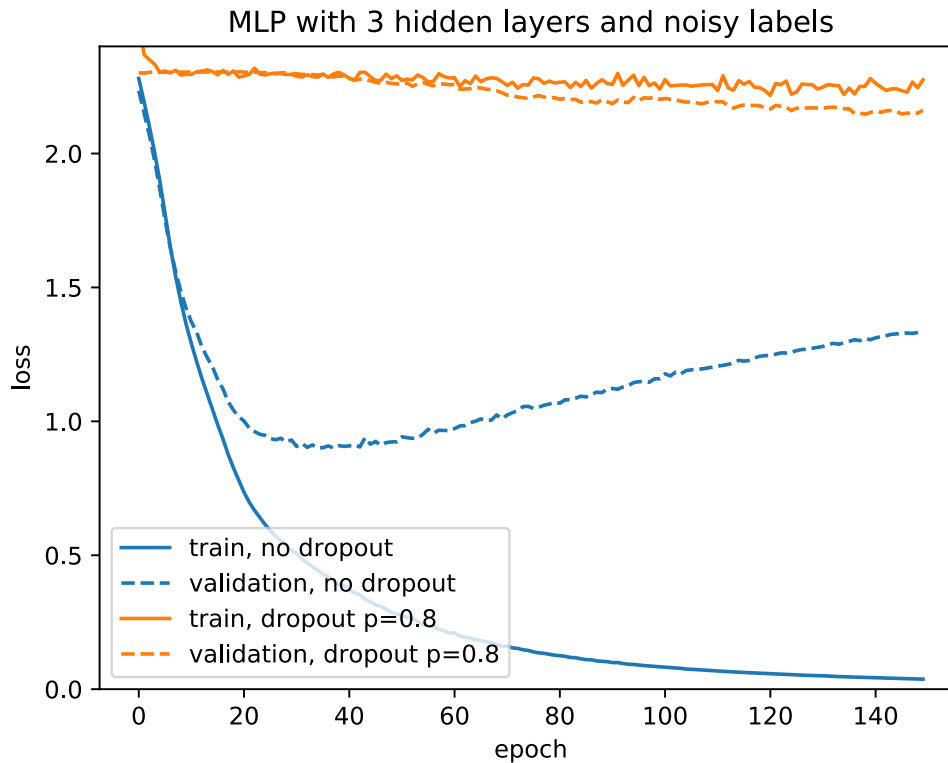
Overfitting Noise



A bit of Dropout



Too much: Underfitting



Implementation with Keras

```
model = Sequential()  
model.add(Dense(hidden_size, input_shape, activation='relu'))  
model.add(Dropout(p=0.5))  
model.add(Dense(hidden_size, activation='relu'))  
model.add(Dropout(p=0.5))  
model.add(Dense(output_size, activation='softmax'))
```

Recommender Systems

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Recommend contents and products

Movies on Netflix and YouTube, weekly playlist and related
Artists on Spotify, books on Amazon, related apps on app stores,
"Who to Follow" on twitter...

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Recommend contents and products

Movies on Netflix and YouTube, weekly playlist and related Artists on Spotify, books on Amazon, related apps on app stores, "Who to Follow" on twitter...

Prioritized social media status updates

Personalized search engine results

Personalized ads and RTB

RecSys 101

Content-based vs Collaborative Filtering (CF)

Content-based: user metadata (gender, age, location...) and item metadata (year, genre, director, actors)

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Content-based: user metadata (gender, age, location...) and item metadata (year, genre, director, actors)

Collaborative Filtering: passed user/item interactions: stars, plays, likes, clicks

Hybrid systems: CF + metadata to mitigate the cold-start problem

Explicit vs Implicit Feedback

Explicit: positive and negative feedback

- Examples: review stars and votes
- Regression metrics: Root Mean Squared Error (RMSE), Mean Absolute Error (MAE)...

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Implicit: positive feedback only

- Examples: page views, plays, comments...
- Ranking metrics: ROC AUC, precision at rank, NDCG...

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Implicit feedback much more **abundant** than explicit feedback

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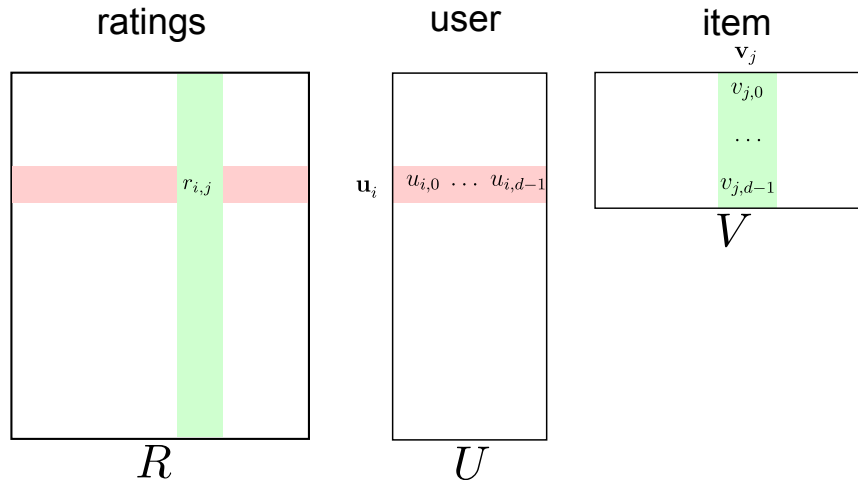
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Implicit (and Explicit) feedback distribution **impacted by UI/UX changes** and the **RecSys deployment** itself.

Matrix Factorization for CF

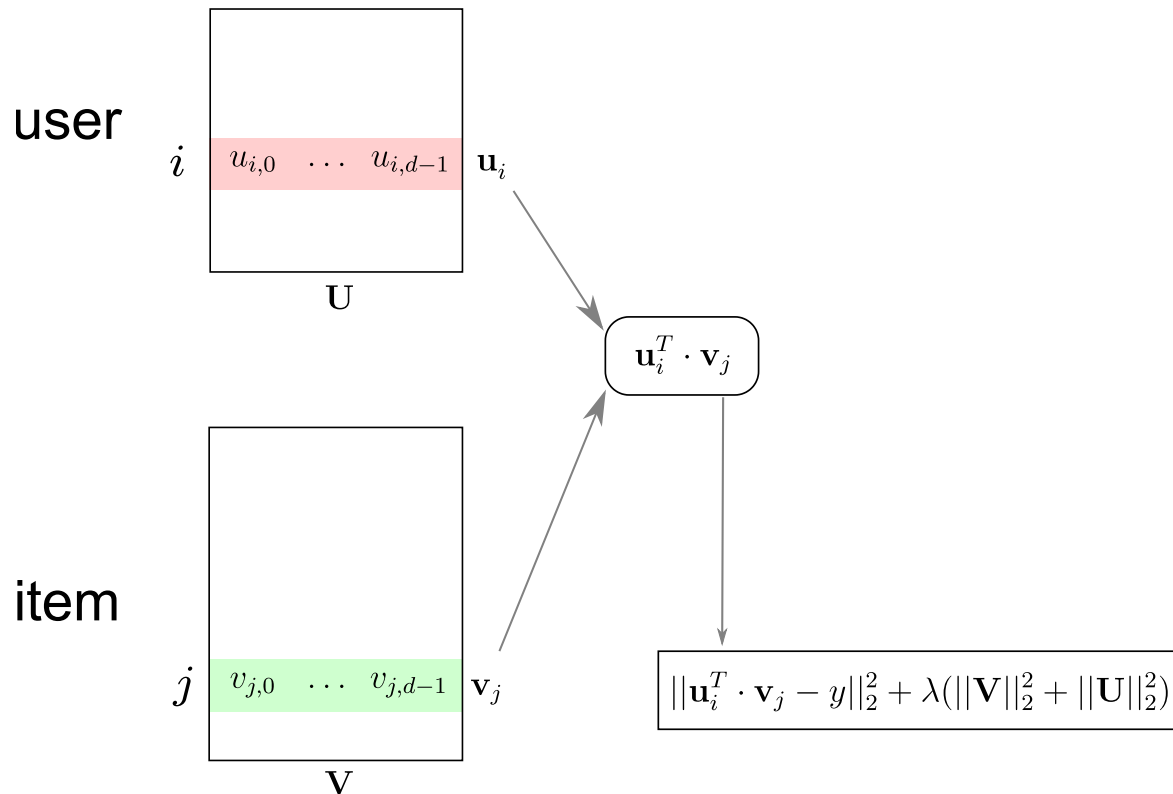


$$L(U, V) = \sum_{(i,j) \in D} ||r_{i,j} - \mathbf{u}_i^T \cdot \mathbf{v}_j||_2^2 + \lambda(||U||_2^2 + ||V||_2^2)$$

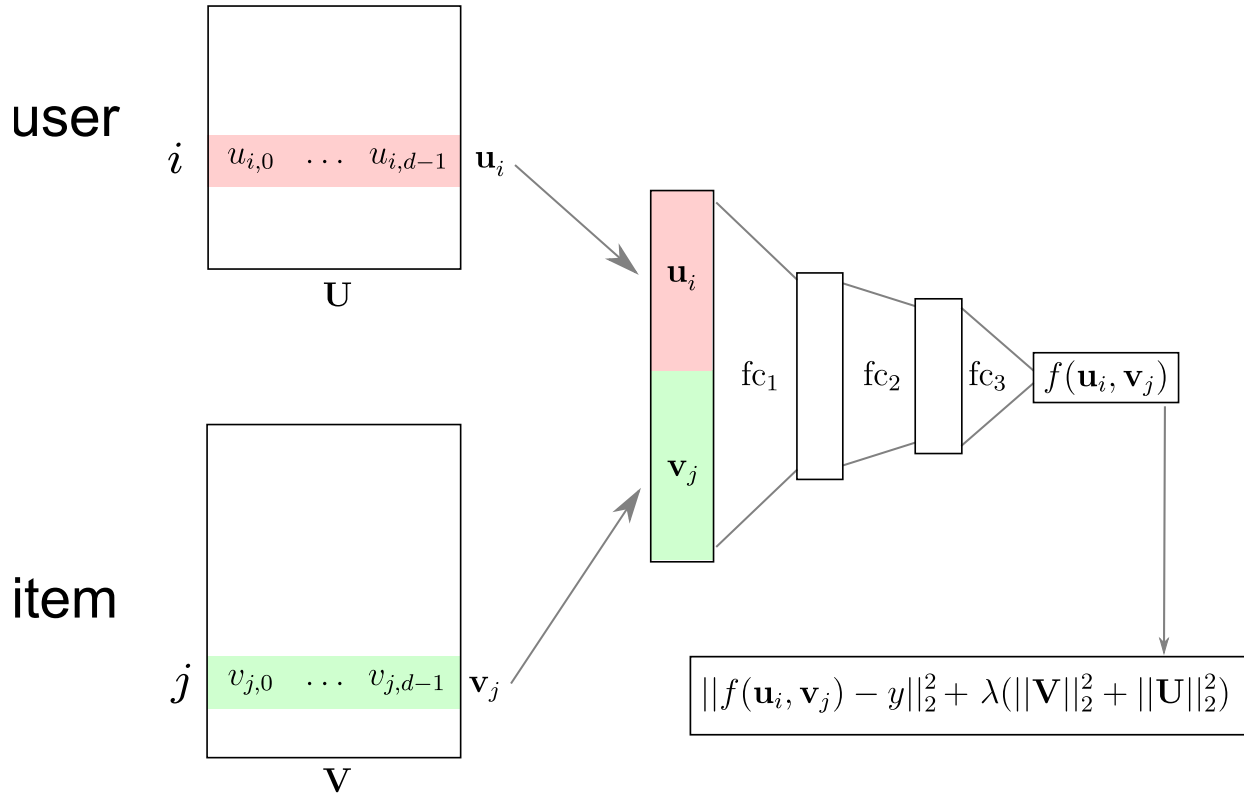
- Train U and V on observed ratings data $r_{i,j}$
- Use $U^T V$ to find missing entries in sparse rating data matrix R

Architecture and Regularization

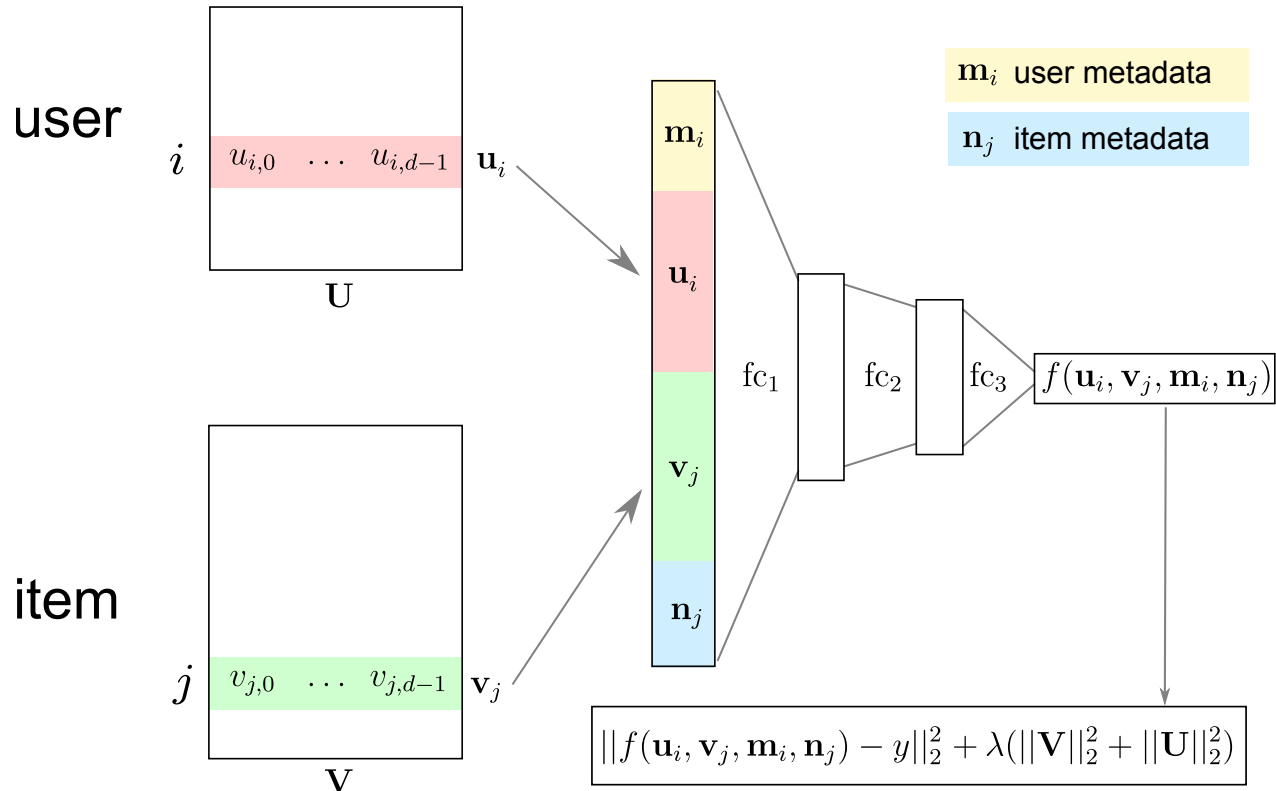
RecSys with Explicit Feedback



Deep RecSys Architecture

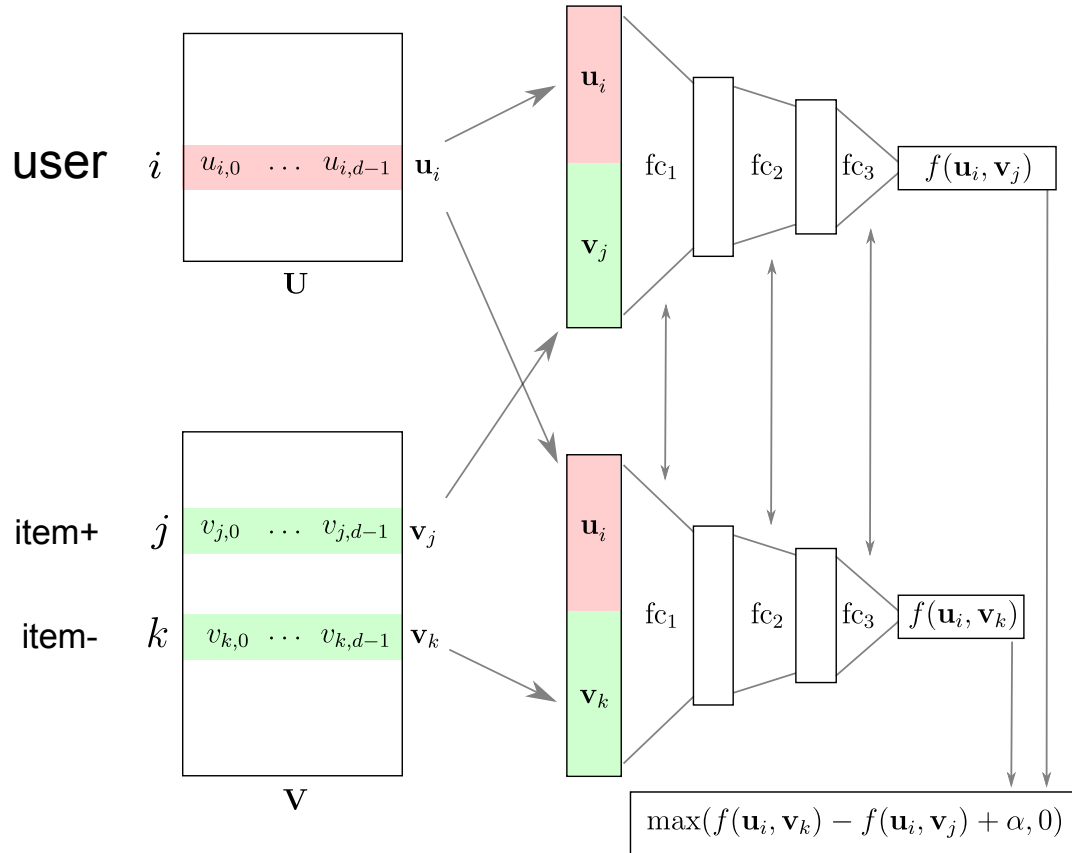


Deep RecSys with metadata



Implicit Feedback: Triplet loss

Deep Triplet Networks



Training a Triplet Model

- Gather a set of positive pairs user i and item j
- While model has not converged:

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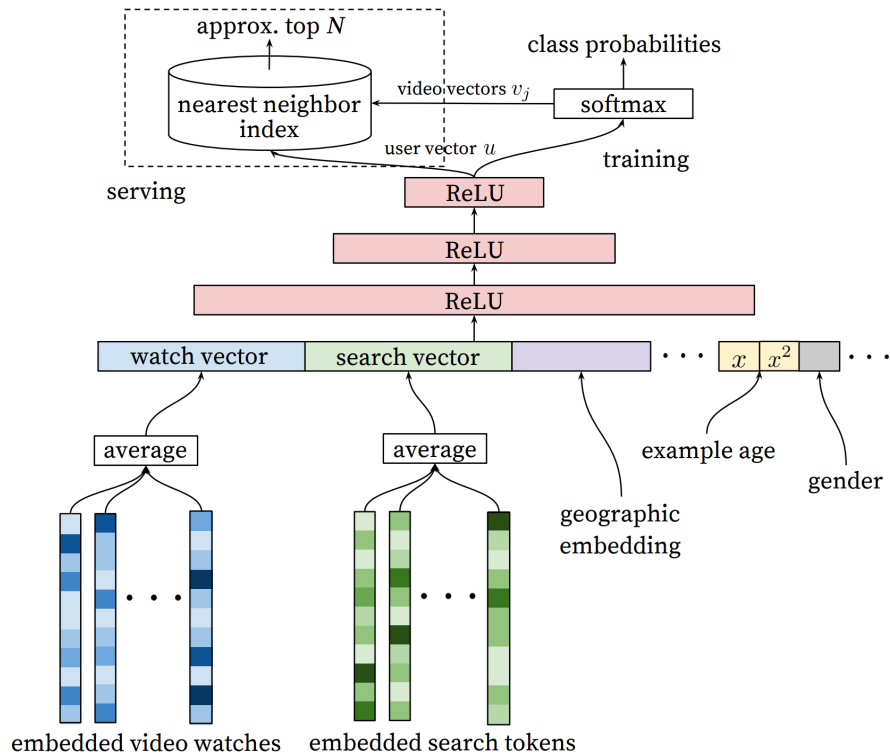
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 - Train model on triplet (i, j, k)



Deep Neural Networks for YouTube Recommendations

<https://research.google.com/pubs/pub45530.html>

Ethical Considerations of Recommender Systems

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Amplification of existing discriminatory and unfair behaviors / bias

- Example: gender bias in ad clicks (fashion / jobs)
- Using the firstname as a predictive feature

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Amplification of the filter bubble and opinion polarization

- Personalization can amplify "people only follow people they agree with"
- Optimizing for "engagement" promotes content that cause strong emotional reaction (and turns normal users into *haters?*)
- RecSys can exploit weaknesses of some users, lead to addiction

Call to action

Designing Ethical Recommender Systems

- Wise modeling choices (e.g. use of "firstname" as feature)
- Conduct internal audits to detect fairness issues: [SHAP](#), [Integrated Gradients](#)
- Learning [representations that enforce fairness](#)?

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Transparency

- Educate decision makers and the general public
- How to allow users to assess fairness by themselves?
- How to allow for independent audits while respecting the privacy of users?

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Lab 3: Back here in 15min!