Recommender Systems & Embeddings

Charles Ollion - Olivier Grisel

Outline

Embeddings

Outline

Embeddings

Dropout Regularization

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Dropout Regularization

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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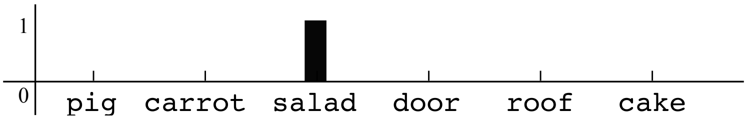
Notation:

Symbol s in vocabulary V

One-hot representation

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



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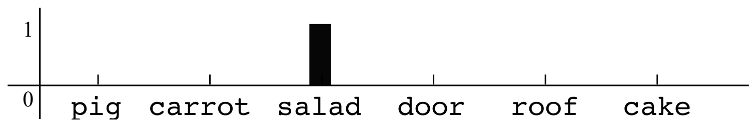

- Sparse, discrete, large dimension $|V|$
- Each axis has a meaning
- Symbols are equidistant from each other:

euclidean distance = $\sqrt{2}$

Embedding

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

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- Continuous and dense
- Can represent a huge vocabulary in low dimension, typically: $d \in \{16, 32, \ldots, 4096\}$
- 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 unconstrained)

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Cosine similarity

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

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

Distance and similarity in Embedding space

If x and y both have unit norms:

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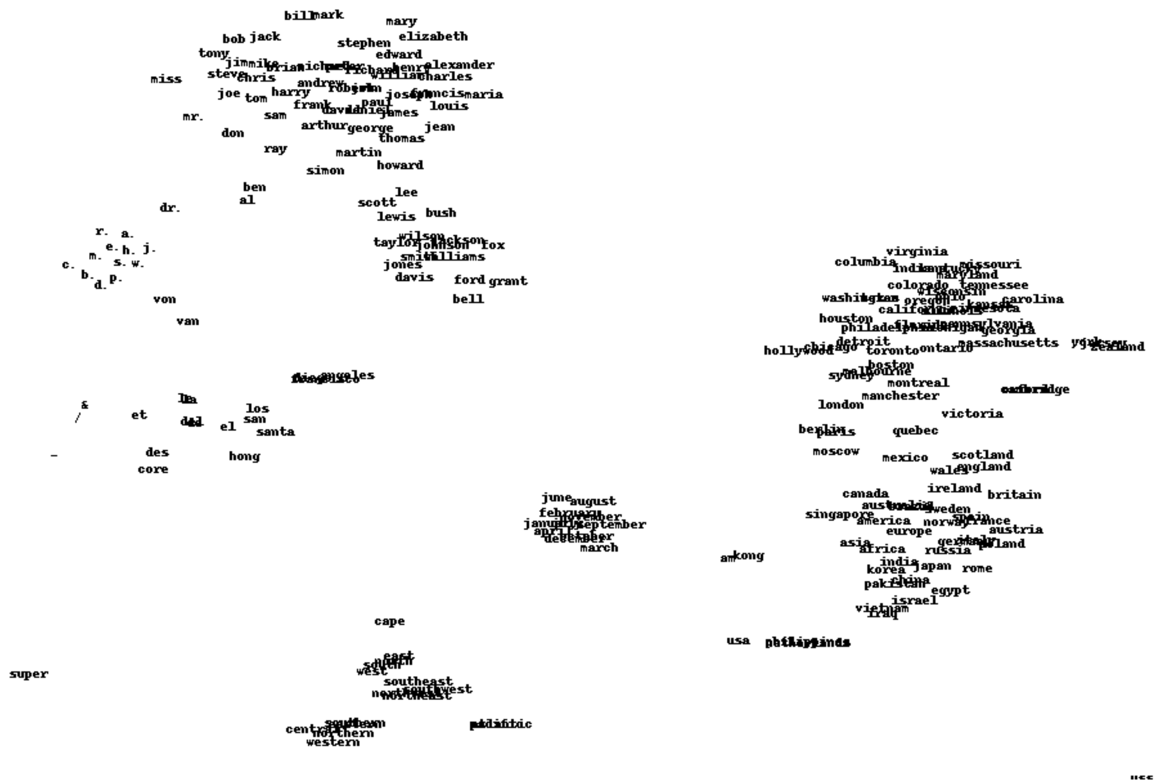
t-SNE projection is non deterministic (depends on initialization)

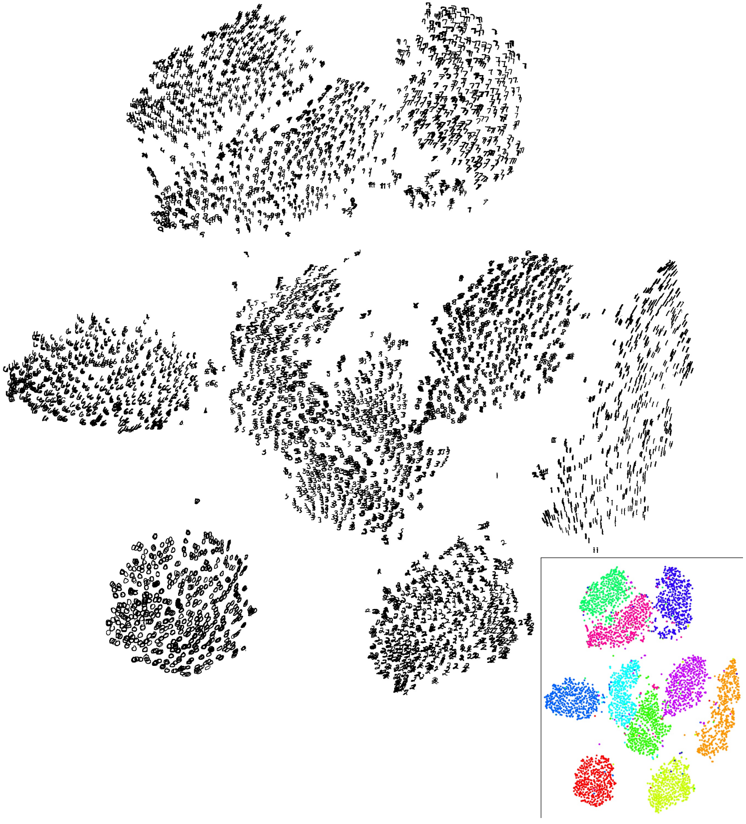
- Critical parameter: perplexity, usually set to 20, 30
- See http://distill.pub/2016/misread-tsne/

Example word vectors



excerpt from work by J. Turian on a model trained by R. Collobert et al. 2008

Visualizing Mnist



Dropout Regularization

Regularization

Size of the embeddings

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Size of the embeddings

Depth of the network

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L_2 penalty on embeddings

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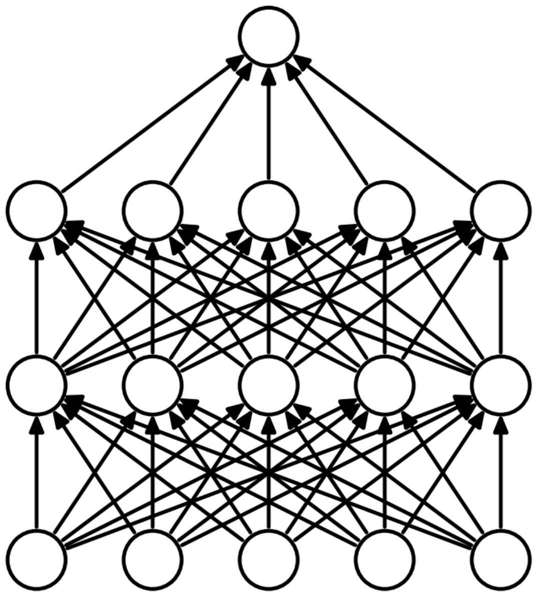
L_2 penalty on embeddings

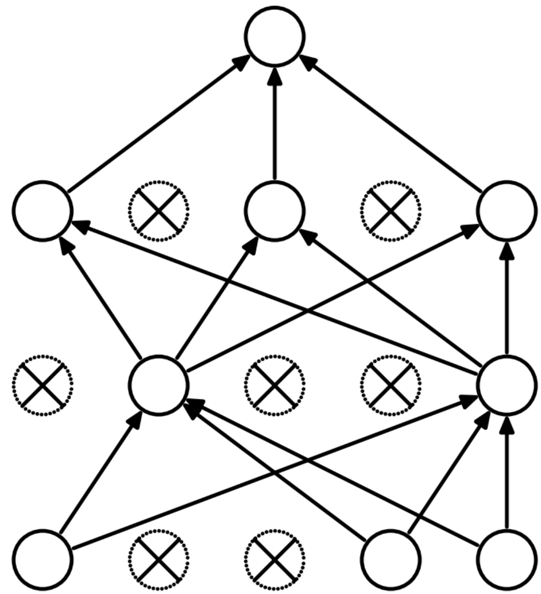
Dropout

- 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

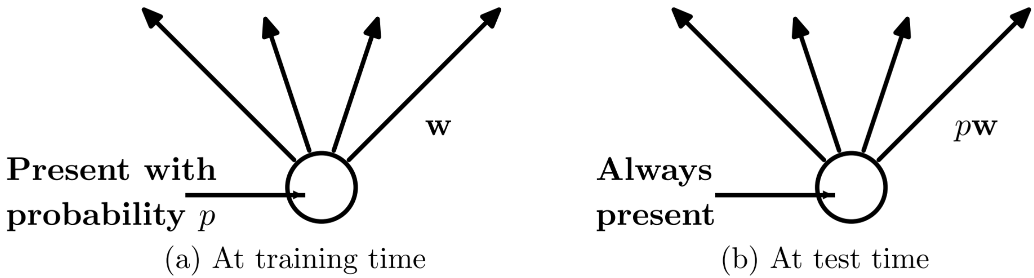
Interpretation

- 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

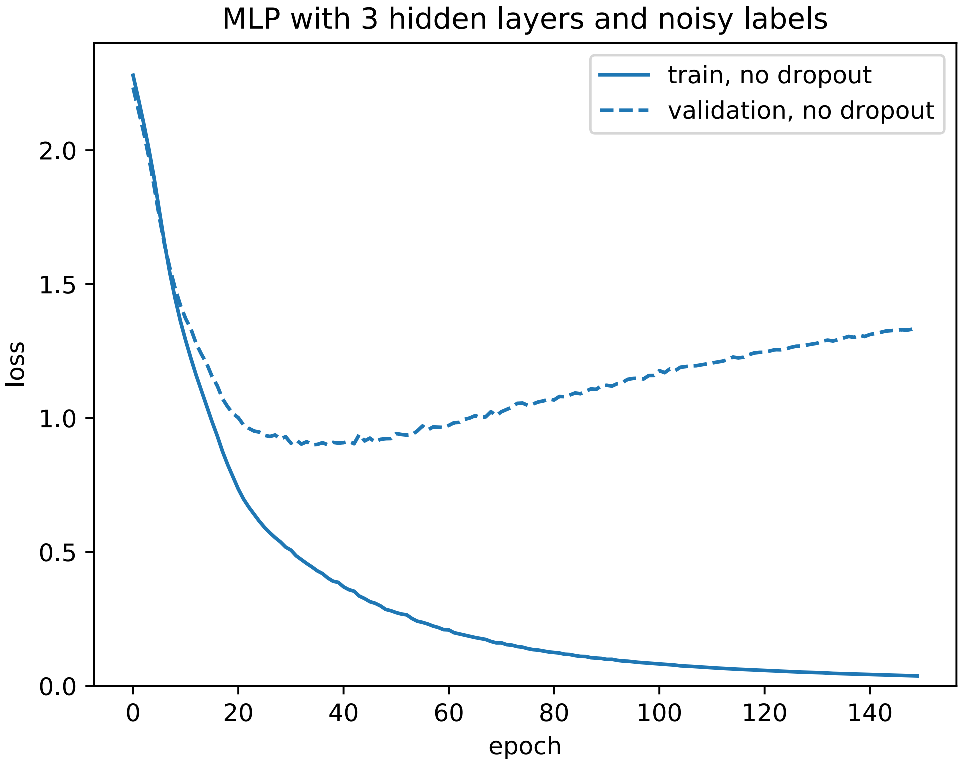
Dropout



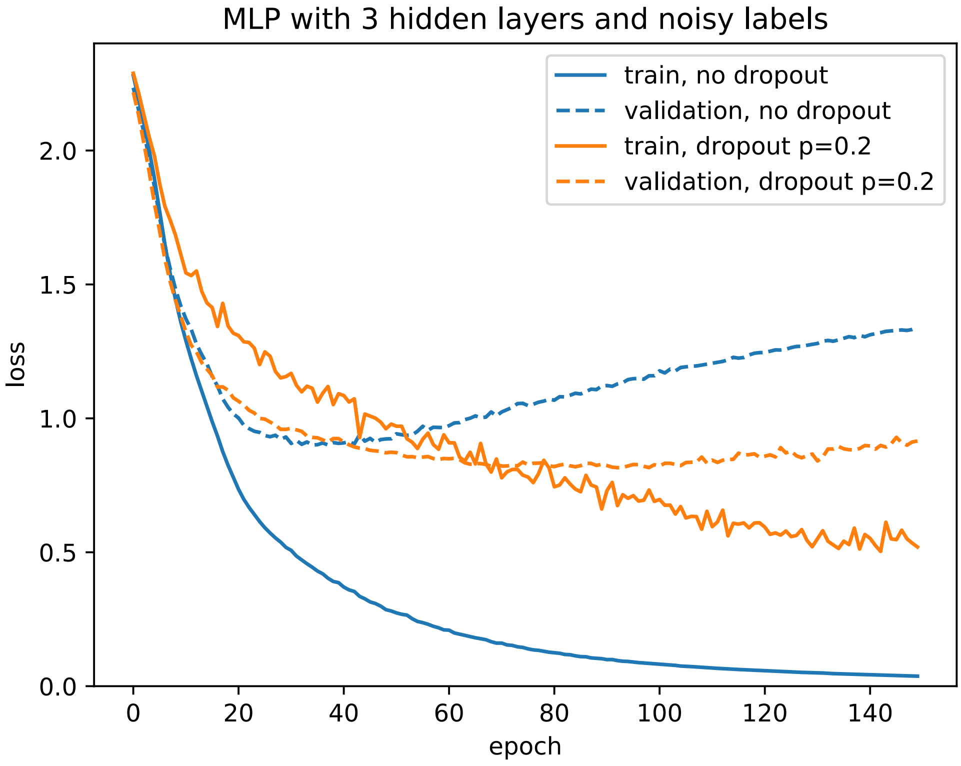
At test time, multiply weights by p to keep same level of activation

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

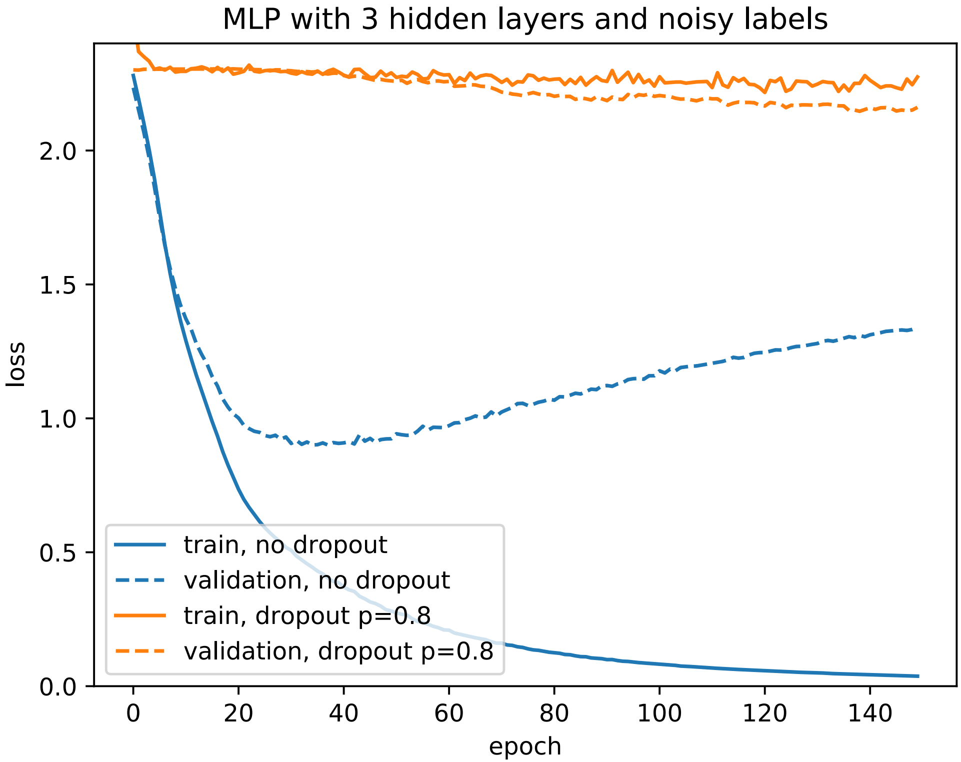
Overfitting Noise



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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Prioritized social media status updates

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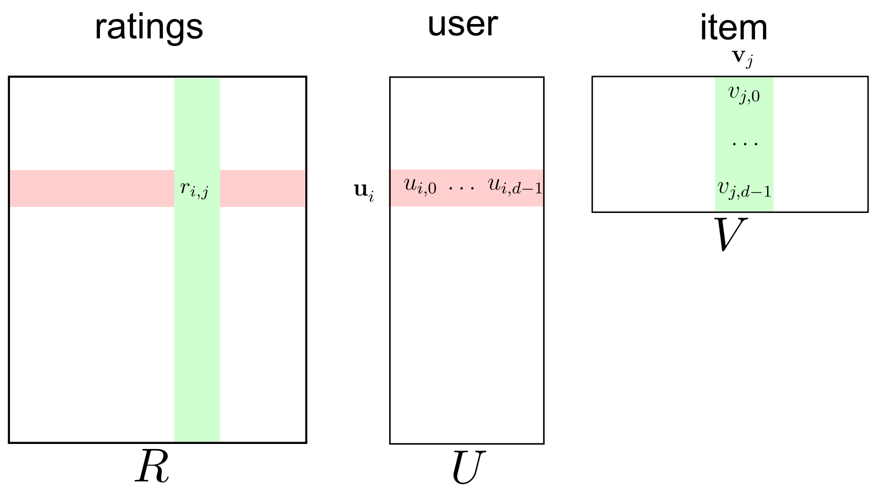
Implicit (and Explicit) feedback distribution **impacted by UI/UX changes** and the **RecSys deployment** itself.

Matrix Factorization for CF

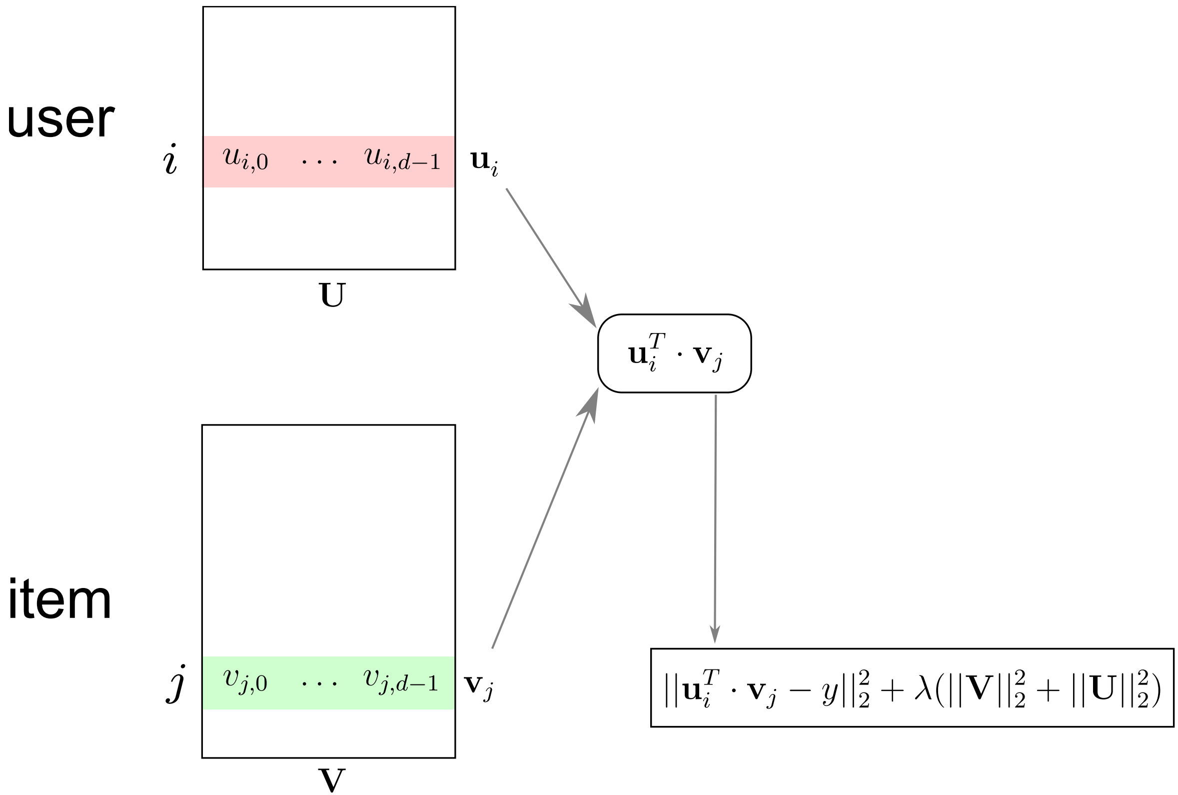


$$L(U,V) = \sum_{(i,j)\in D} ||r_{i,j} - \mathbf{u}_i^T \cdot \mathbf{v}_j||_2^2 + \lambda(||U||_2^2 + ||V||_2^2)$$

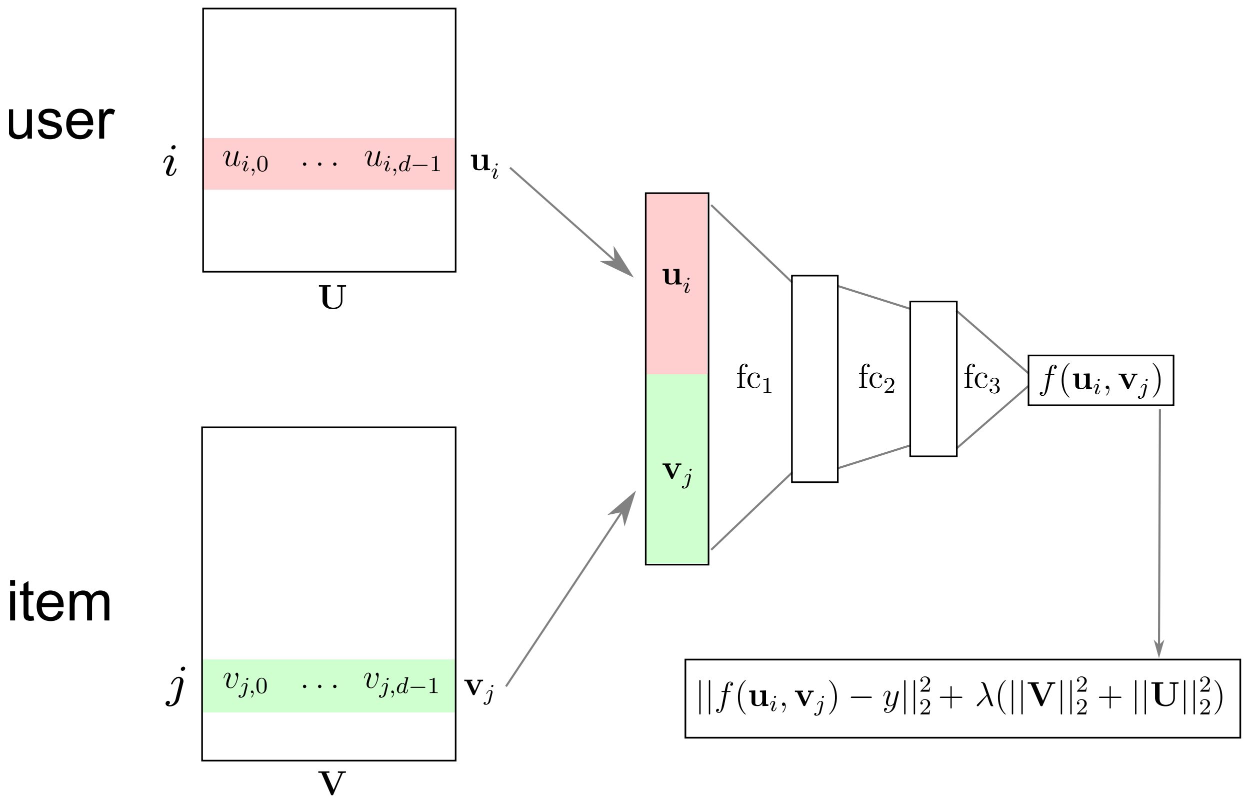
- Train U and V on observed ratings data $r_{i,j}$

Architecture and Regularization

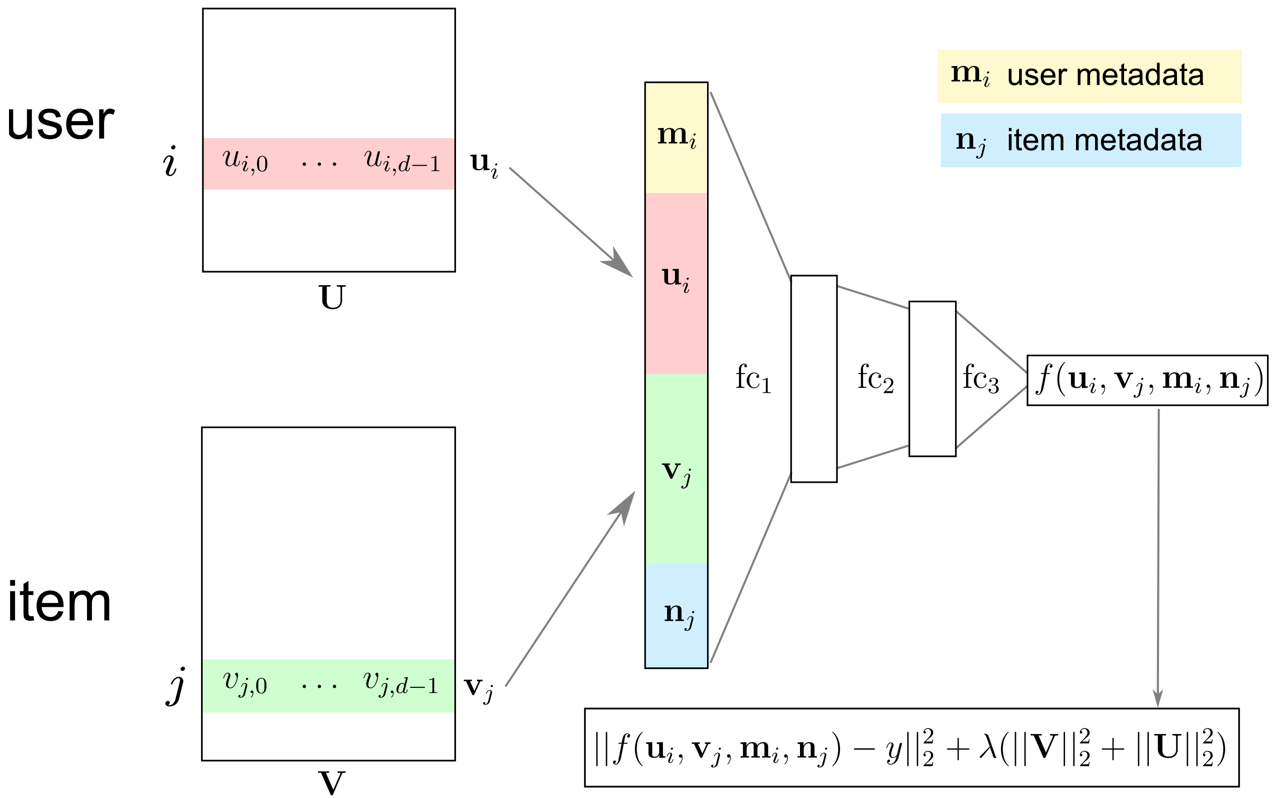
RecSys with Explicit Feedback



Deep RecSys Architecture

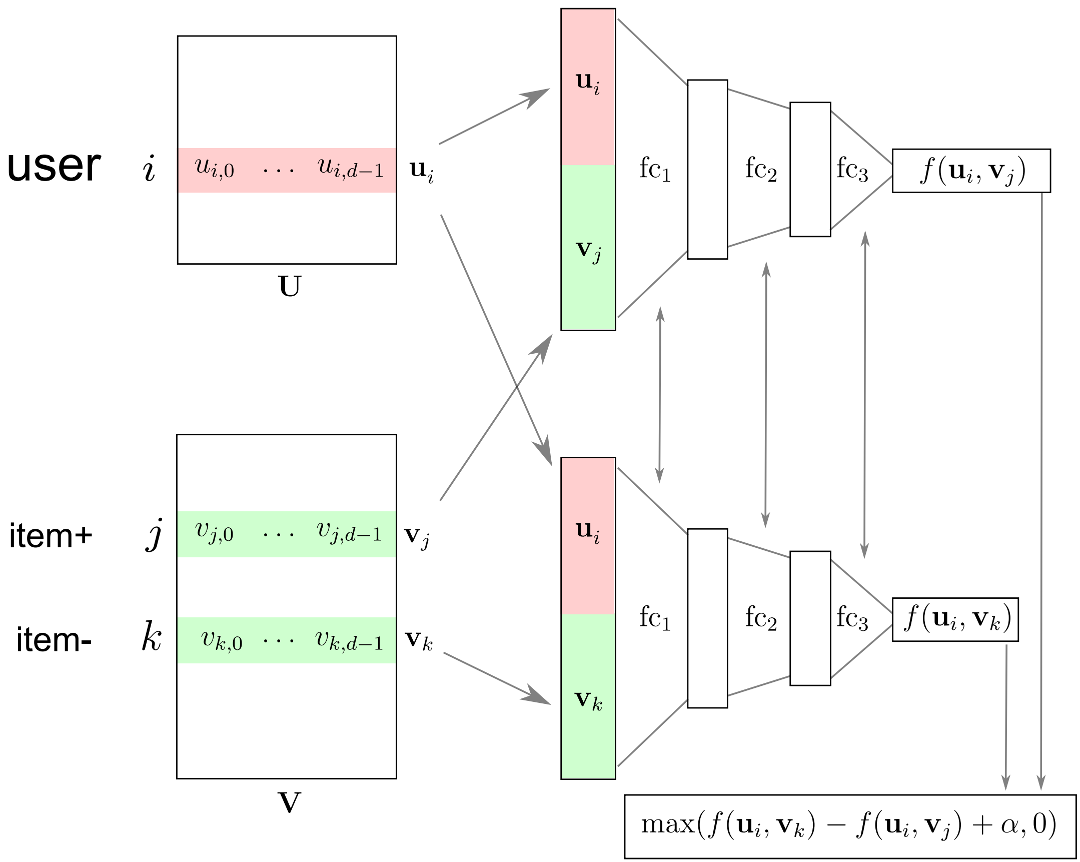


Deep RecSys with metadata



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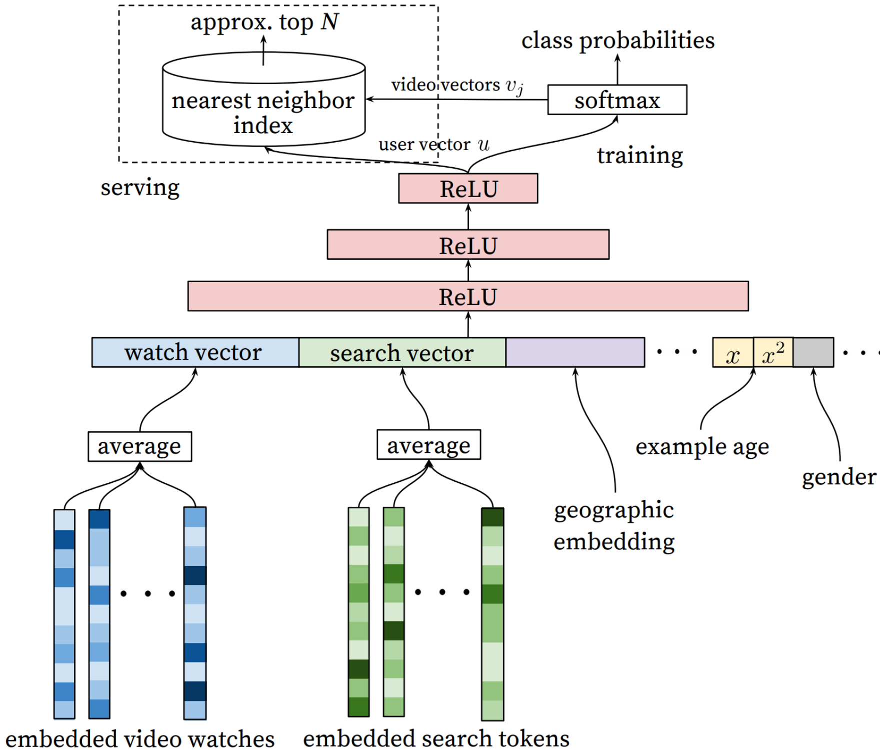
    - Train model on triplet (i, j, k)



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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- Educate decision makers and the general public
- How to allow users to assess fairness by themselves?
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Lab 3: Back here in 15min!