Recommender Systems & Embeddings

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Outline

Recommender Systems

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Architecture and Regularization

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Personnalized 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: Mean Square Error, Mean Absolute Error...

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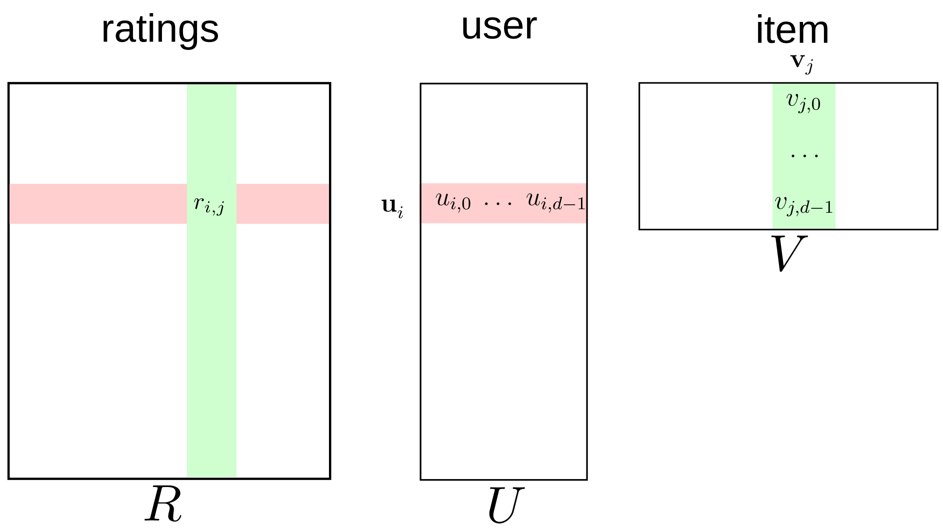
Implicit (and Explicit) feedback distribution **impacted by UI/UX changes** and the **RecSys deployment** itself.

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 $r_{i,j}$

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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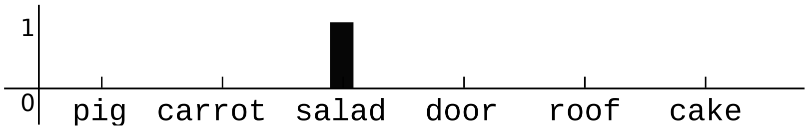
Notation:

Symbol s in vocabulary V

One-hot representation

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



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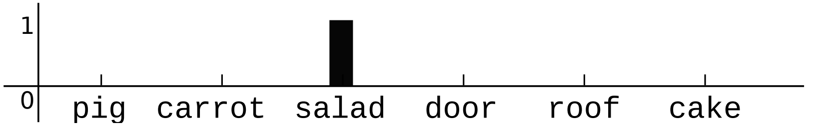

- Sparse, discrete, large dimension $|V|$
- Each axis has a meaning
- Symbols are equidistant from each other

Embedding

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

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- Continuous and dense
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- Axis have no meaning *a priori*
- Embedding metric can capture semantic distance

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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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- Equivalent to one-hot encoding multiplied by a weight matrix $\mathbf{W} \in \mathbb{R}^{V \times K}$:

$$embedding(x) = onehot(x).\,\mathbf{W}$$

Distance and similarity in Embedding space

Euclidean distance

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

- Simple with good properties
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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

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

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

Visualizing Embeddings

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- 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 keep relative distance between nearest neighbors

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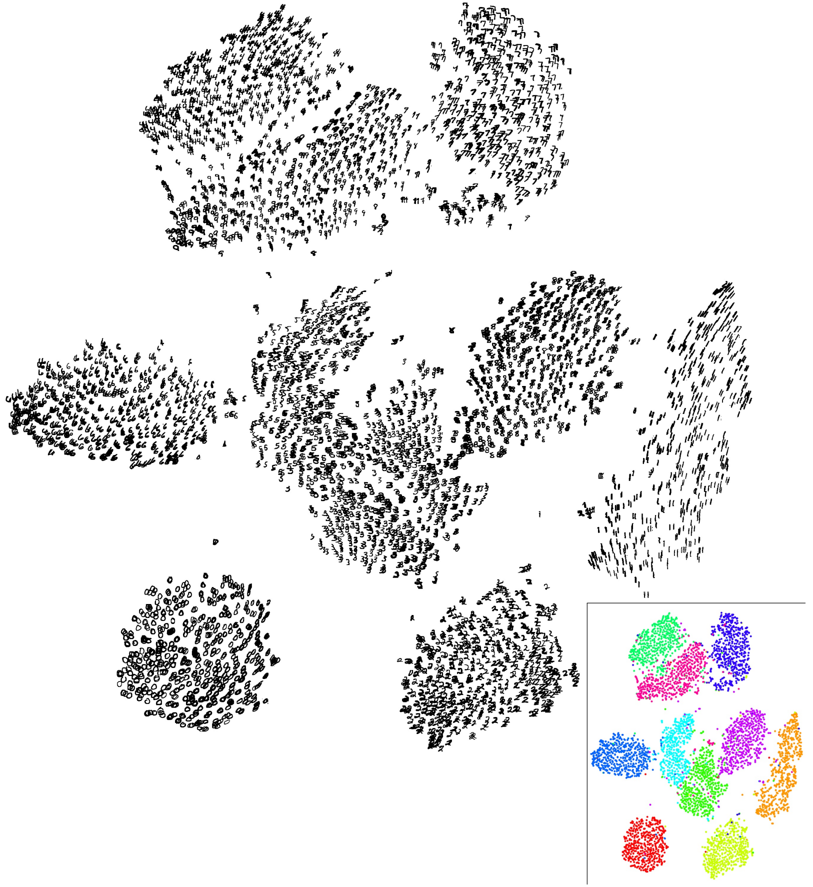
t-SNE projection is non deterministic (depends on initialization)

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

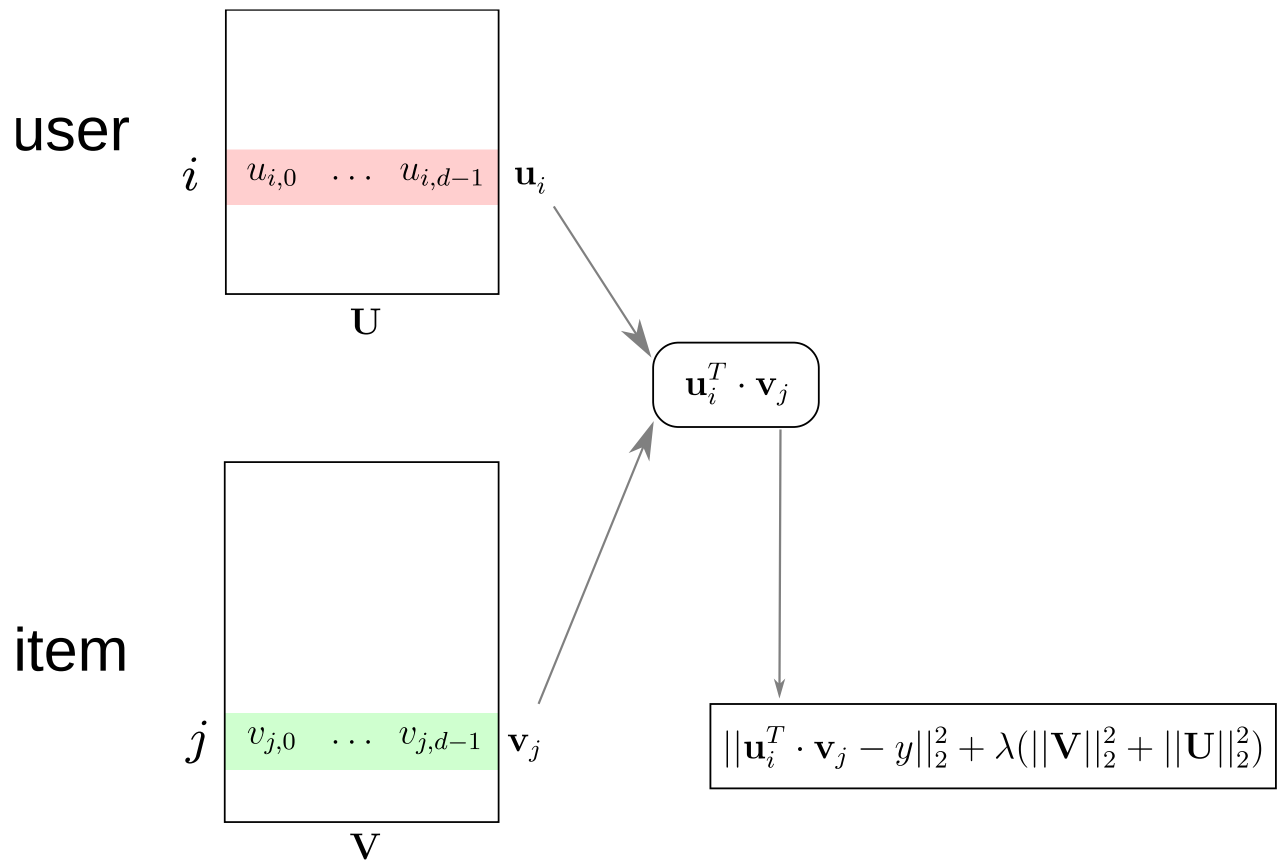
Example word vectors

Visualizing Mnist

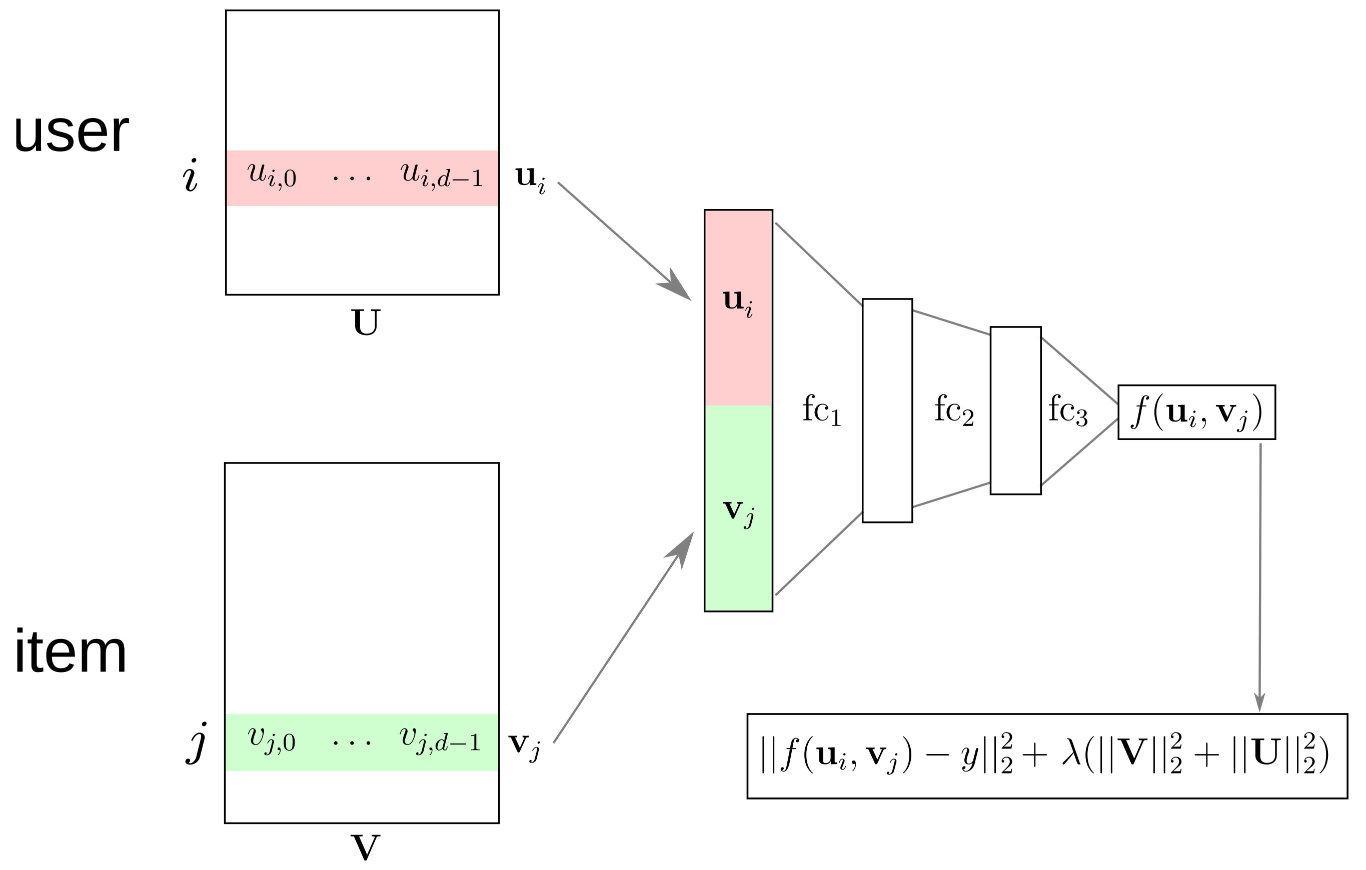


Architecture and Regularization

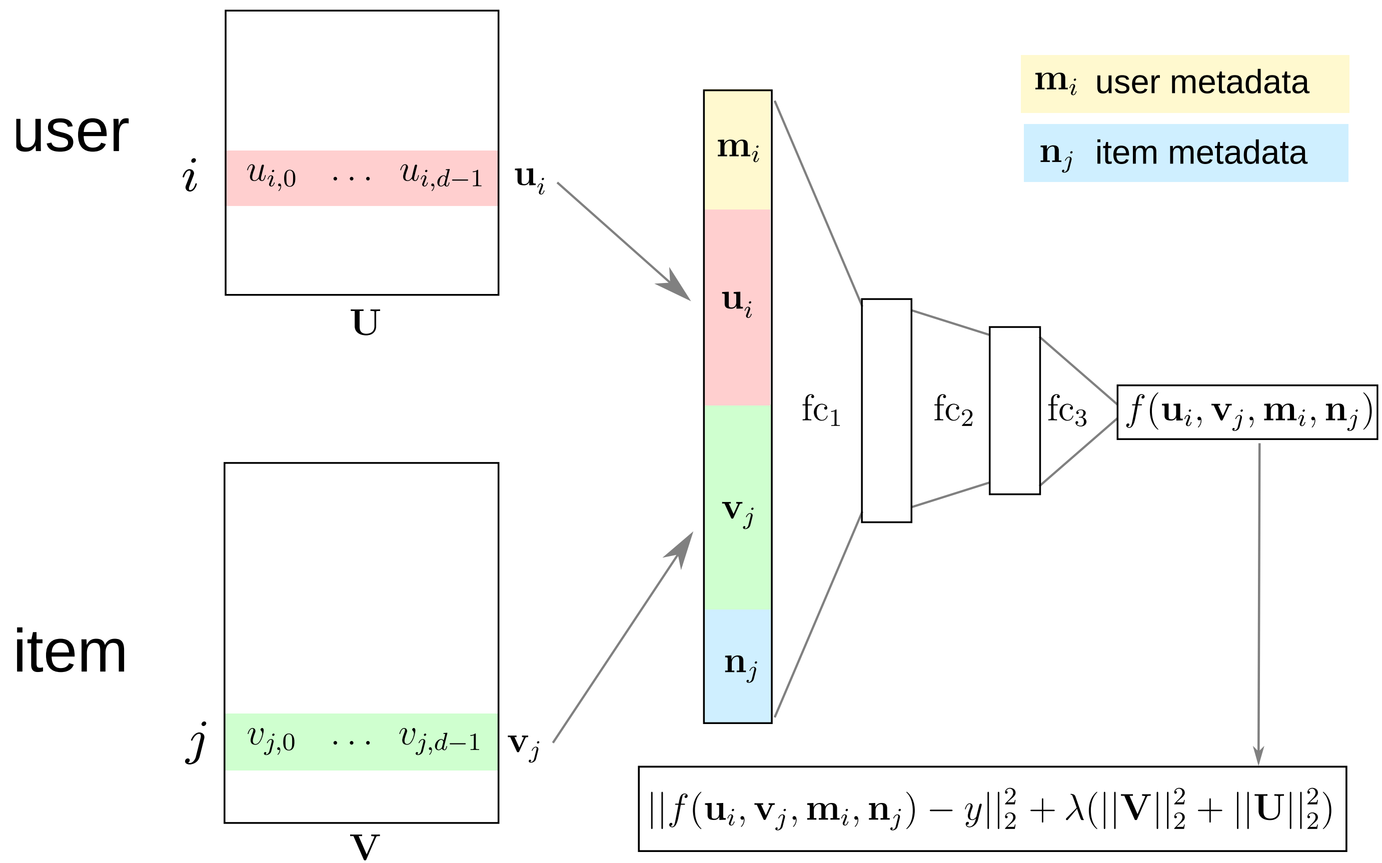
RecSys with Explicit Feedback



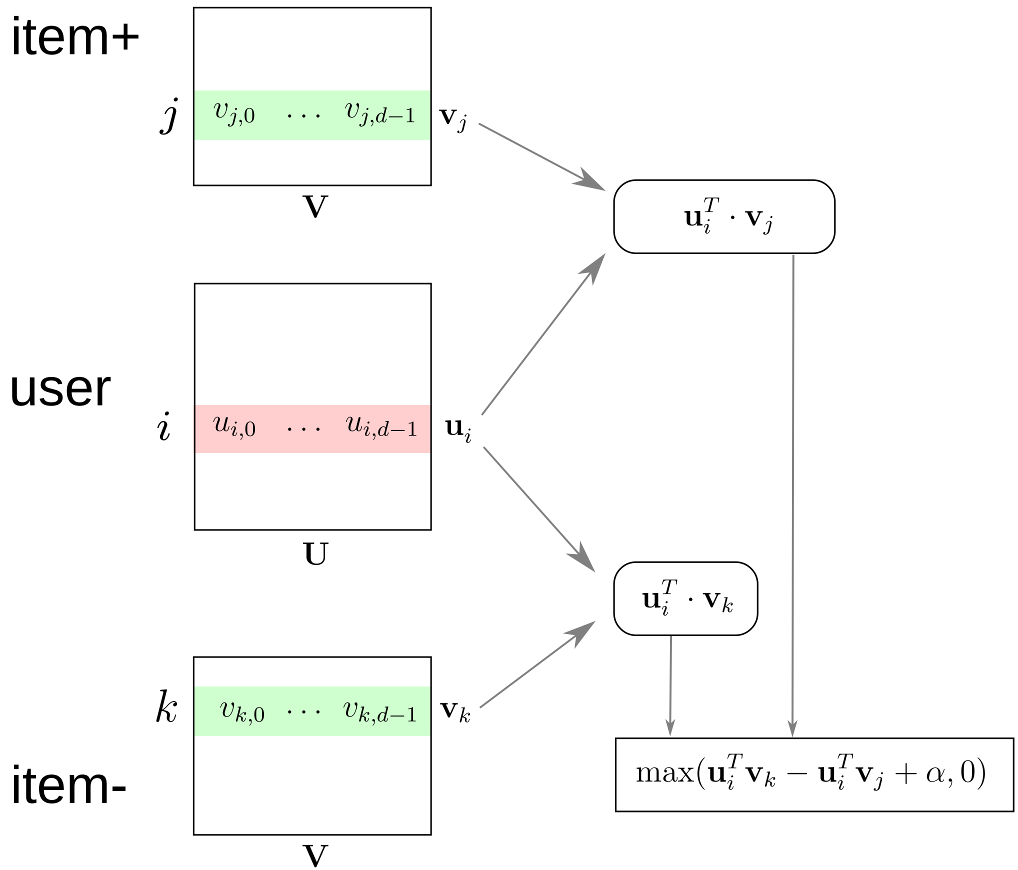
Deep RecSys Architecture



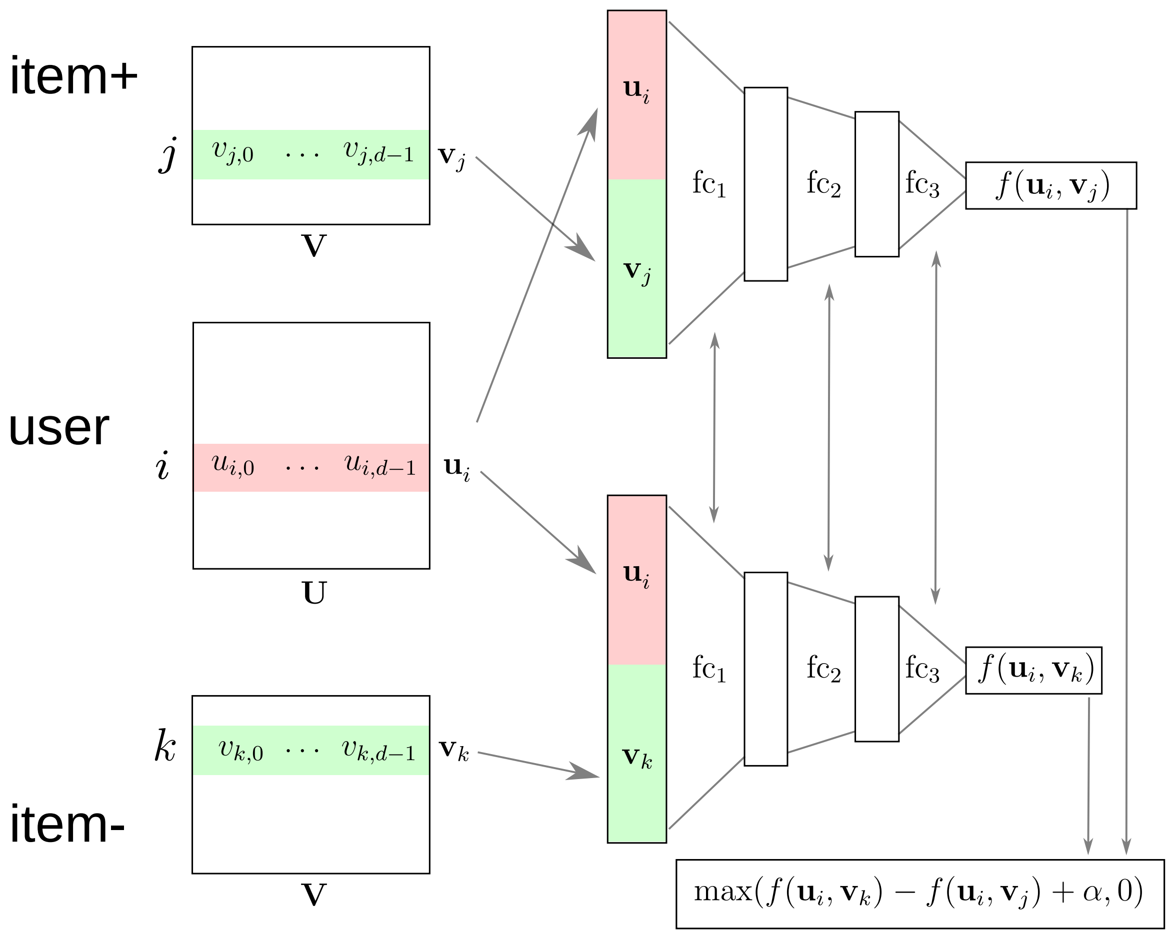
Deep RecSys with metadata



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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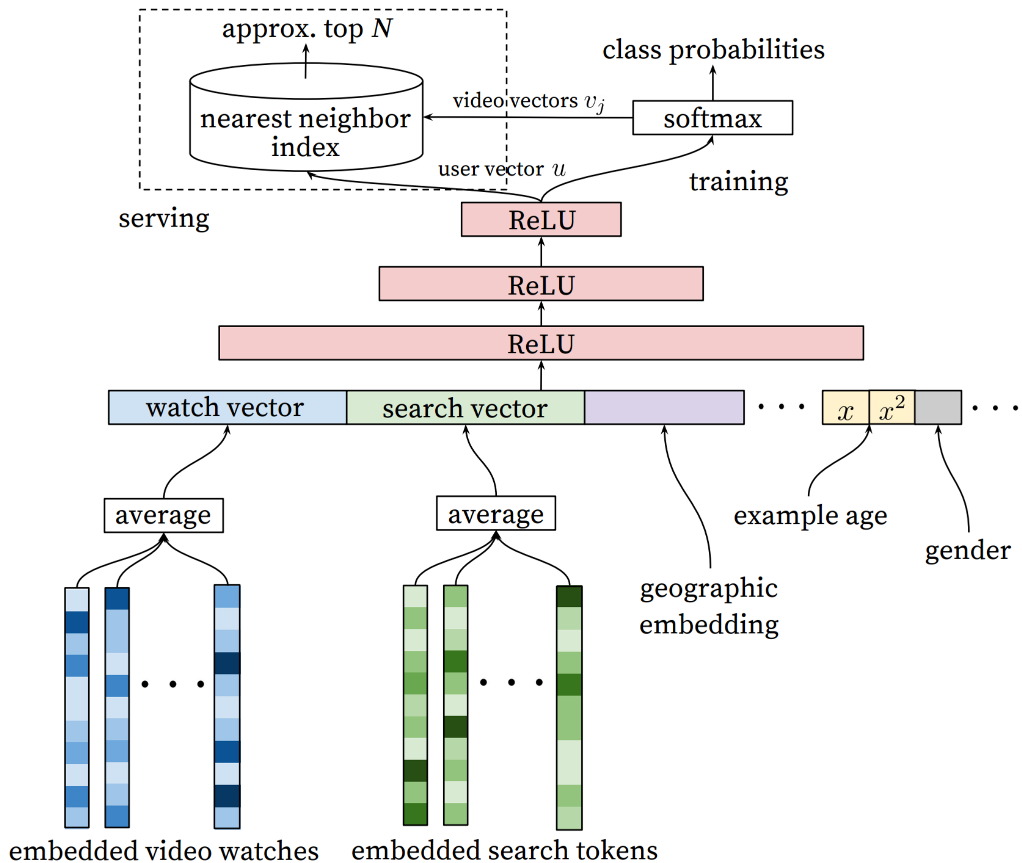
    - Call item k a negative item for user i
    - Train model on triplet (i, j, k)



Deep Neural Networks for YouTube Recommendations

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

Regularization

Size of the embeddings

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Size of the embeddings

Depth of the network

Regularization

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L_2 penalty on embeddings

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Size of the embeddings

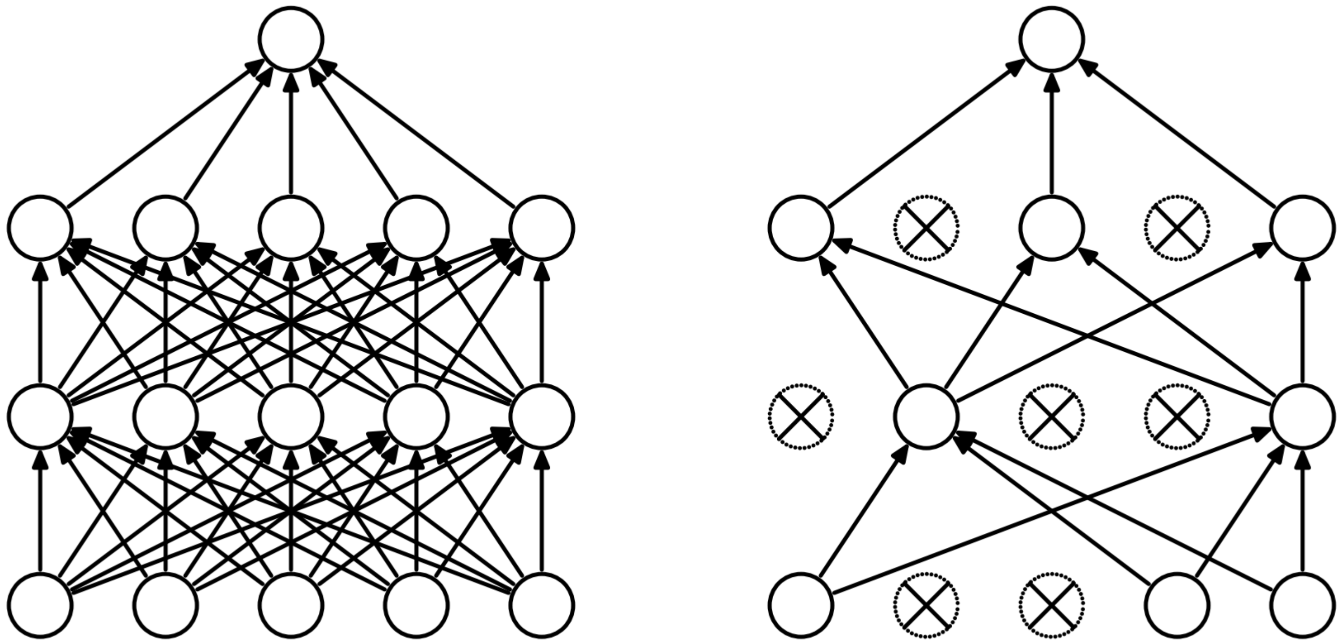
Depth of the network

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

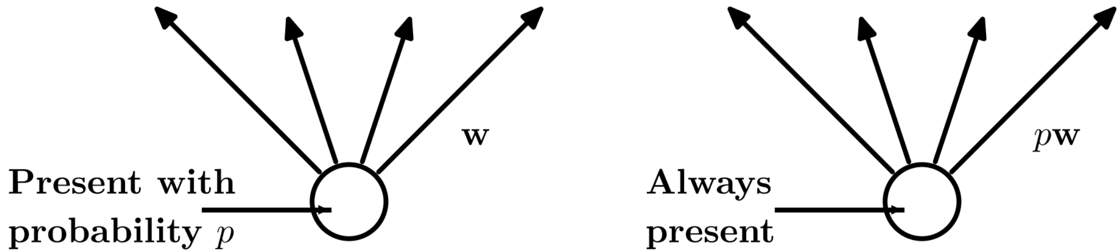
Interpretation

- 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

Dropout

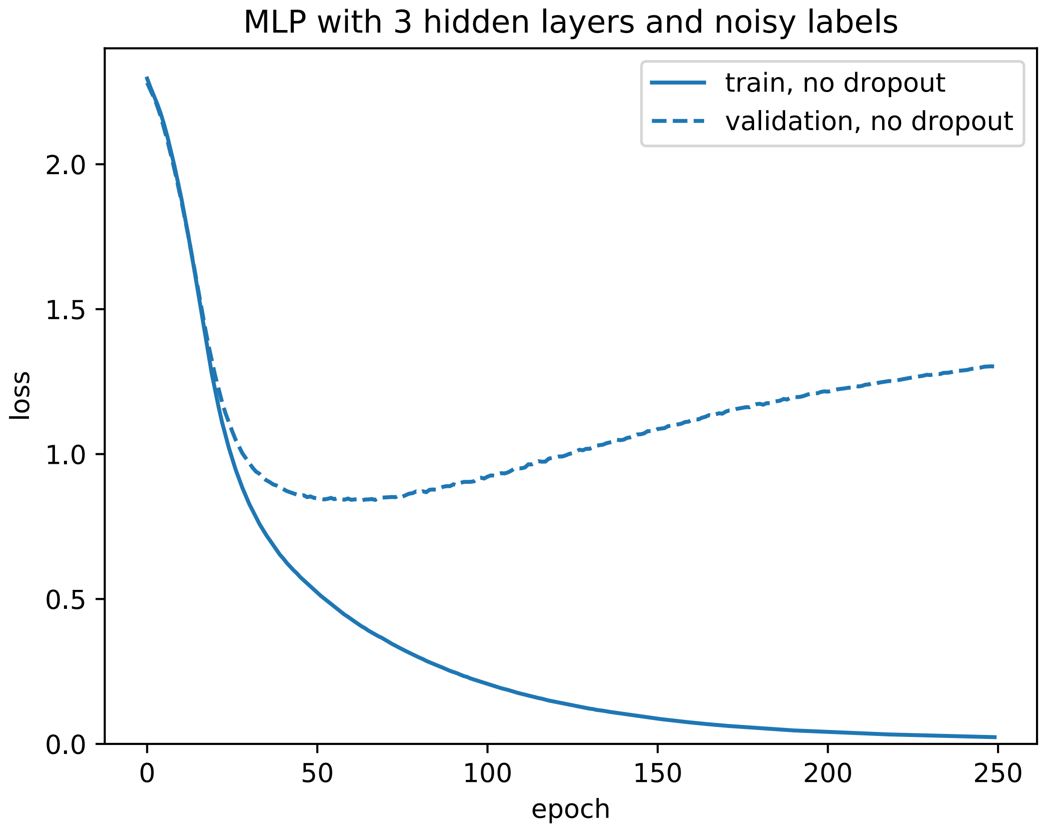


(a) At training time (b) At test time

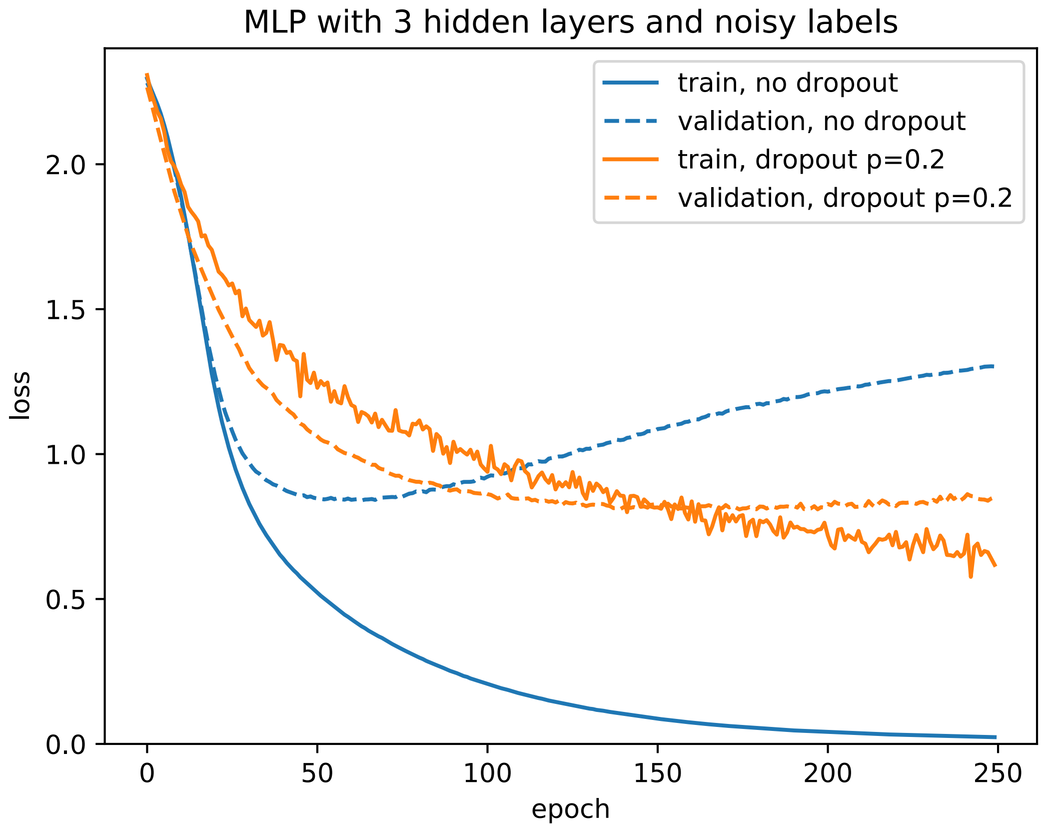
At test time, multiply weights by p to keep same level of activation

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

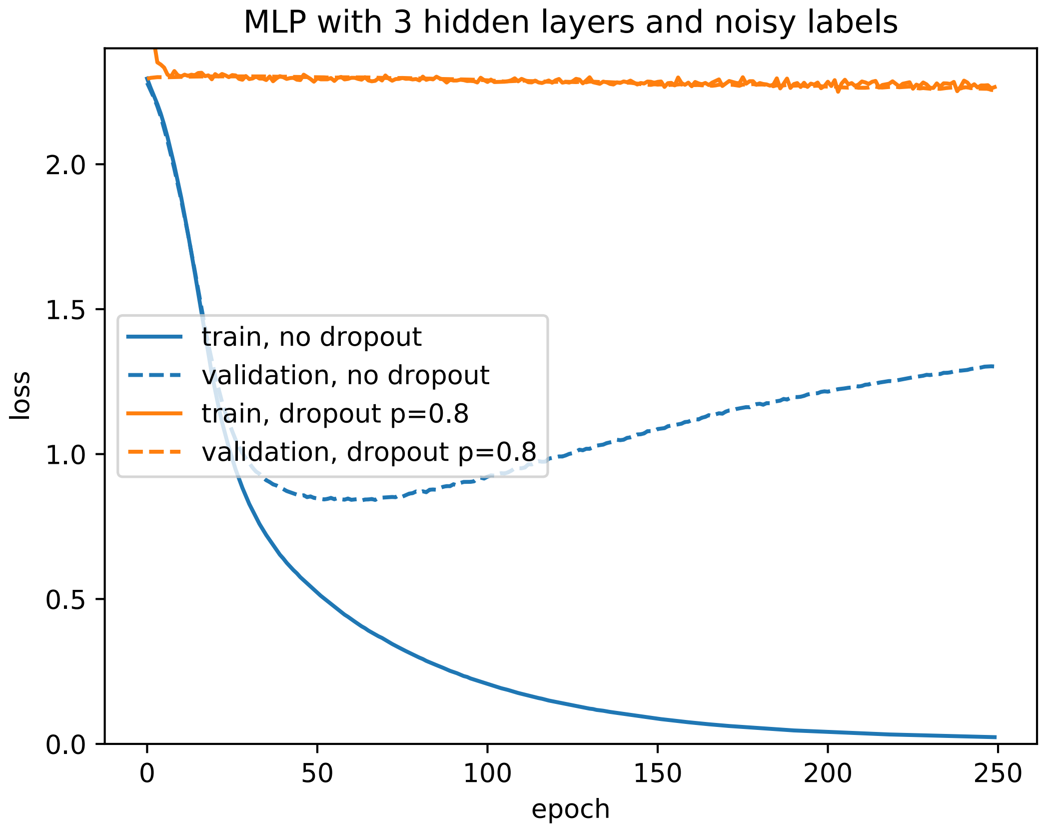
Overfitting Noise



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'))
```

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

- People tend to unfollow people they don't agree with
- Ranking / filtering systems can further amplify this issue

Call to action

Designing Ethical Recommender Systems

- Wise modeling choices (e.g. use of "firstname" as feature)
- Conduct internal audits to detect fairness issues
- Learning representations that actively enforce fairness?

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- 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 2: Room C017 and F900 in 15min!