Recommender Systems & Embeddings

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Outline

- Embeddings

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- Dropout Regularization

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- Recommender Systems

Embeddings

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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

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

One-hot representation

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

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

euclidean distance = $\sqrt{2}$

Embedding

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- Continuous and dense
- Can represent a huge vocabulary in low dimension, typically: $d \in \{16, 32, \ldots, 4096\}$
- Embedding metric can capture semantic distance
- 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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- Equivalent to one-hot encoding multiplied by a weight matrix $\mathbf{W} \in R^{n \times d}$:

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

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- $\mathbf{W}$ are trainable parameters of the model.

Distance and similarity in Embedding space

Euclidean distance

$$d(\boldsymbol{x}, \boldsymbol{y}) = \|\boldsymbol{x} - \boldsymbol{y}\|_2$$

- Simple with good properties
- Dependent on norm (embeddings usually unconstrained)

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Cosine similarity

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

- Angle between points, regardless of norm
- $\boldsymbol{cosine}(\boldsymbol{x}, \boldsymbol{y}) \in [-\mathbf{1}, \mathbf{1}]$
- 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

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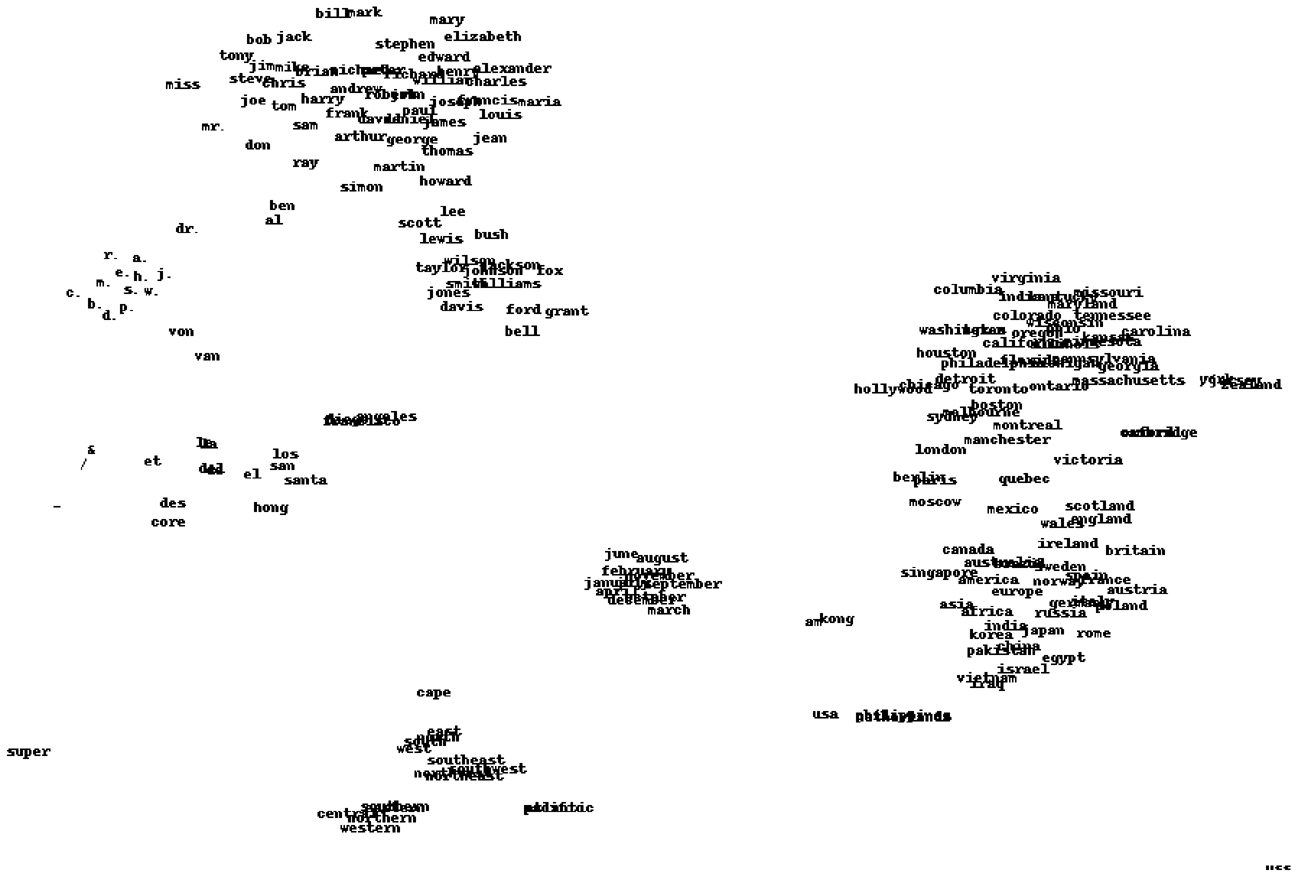
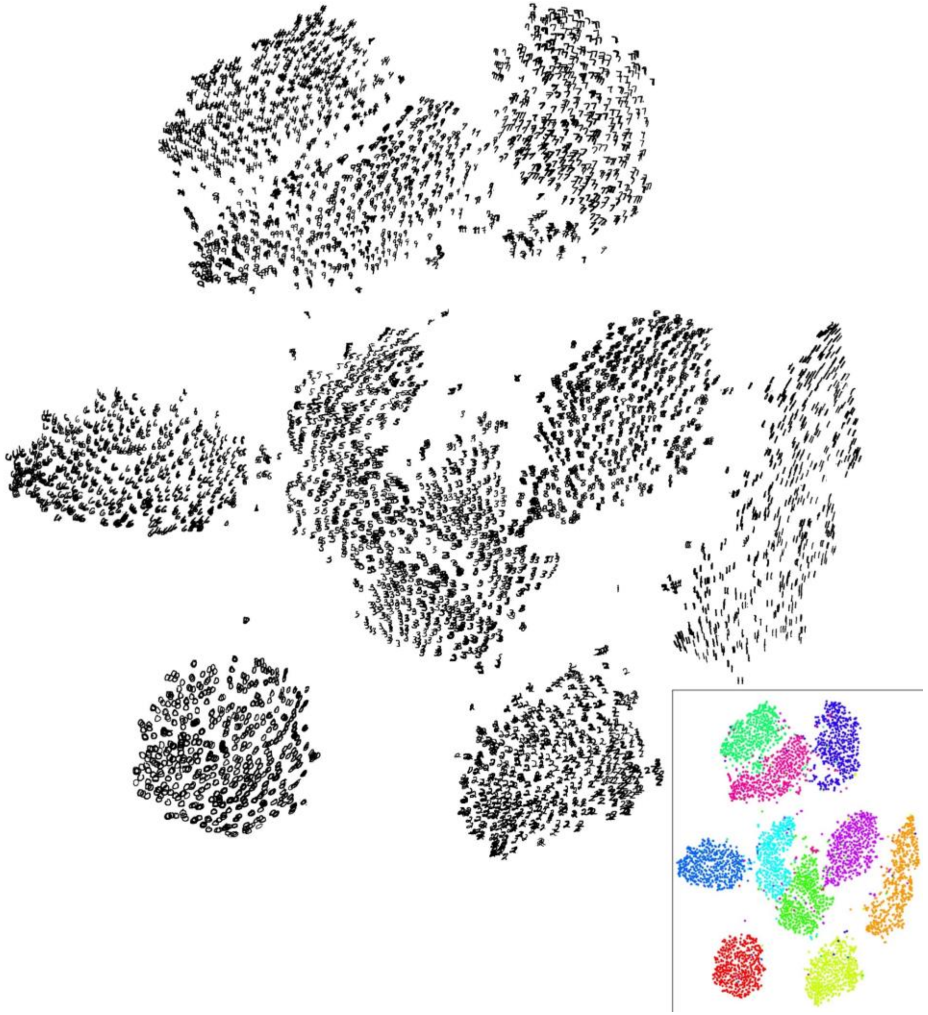
t-SNE projection is non deterministic (depends on initialization)

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

Example word vectors



Visualizing Mnist



Dropout Regularization

Regularization

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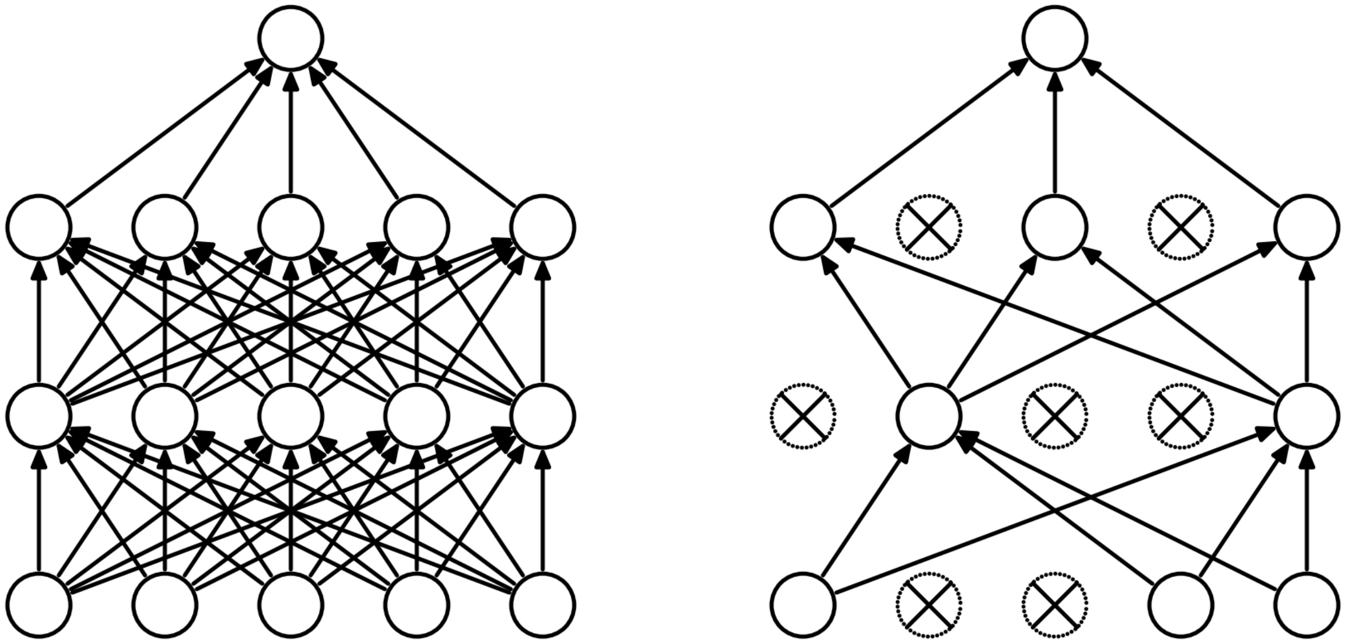
- Size of the embeddings
- Depth of the network
- L_2 penalty on embeddings
- Dropout
    - Randomly set activations to 0 with probability p
    - Bernoulli mask sampled for a forward pass / backward pass pair
    - Typically only enabled at training time

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

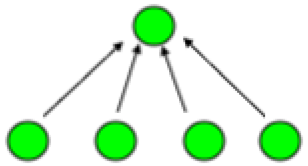
Interpretation

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

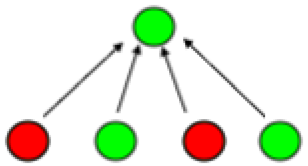
Ensemble interpretation

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

Dropout



(Image a)



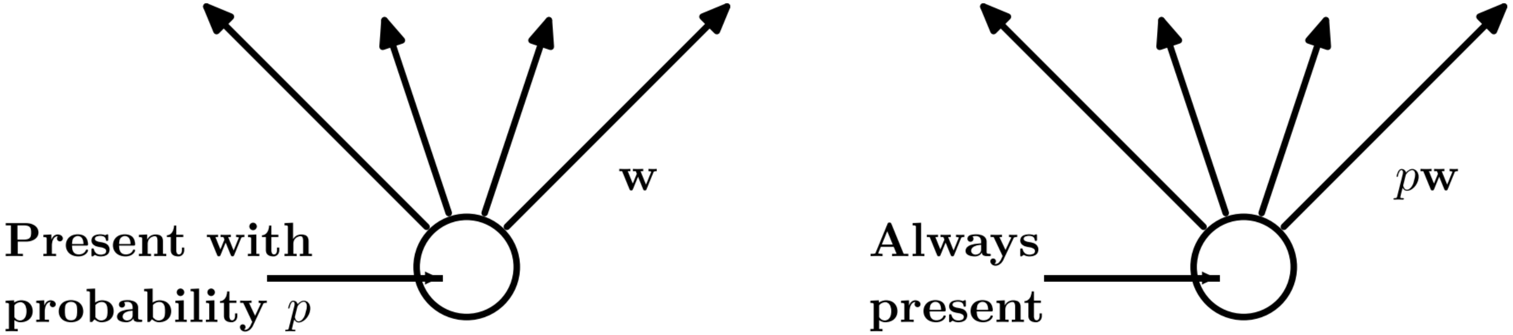
(Image b)

The weight on each unit will initially be ¼ = 0.25.

If we apply dropout with $p = 0.5$ to this layer, it could end up looking like image b. Since only two units are considered, they will each have an initial weight of ½ = 0.5. But we don't want these weights to be fixed at this high number during testing.

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

Dropout



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

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

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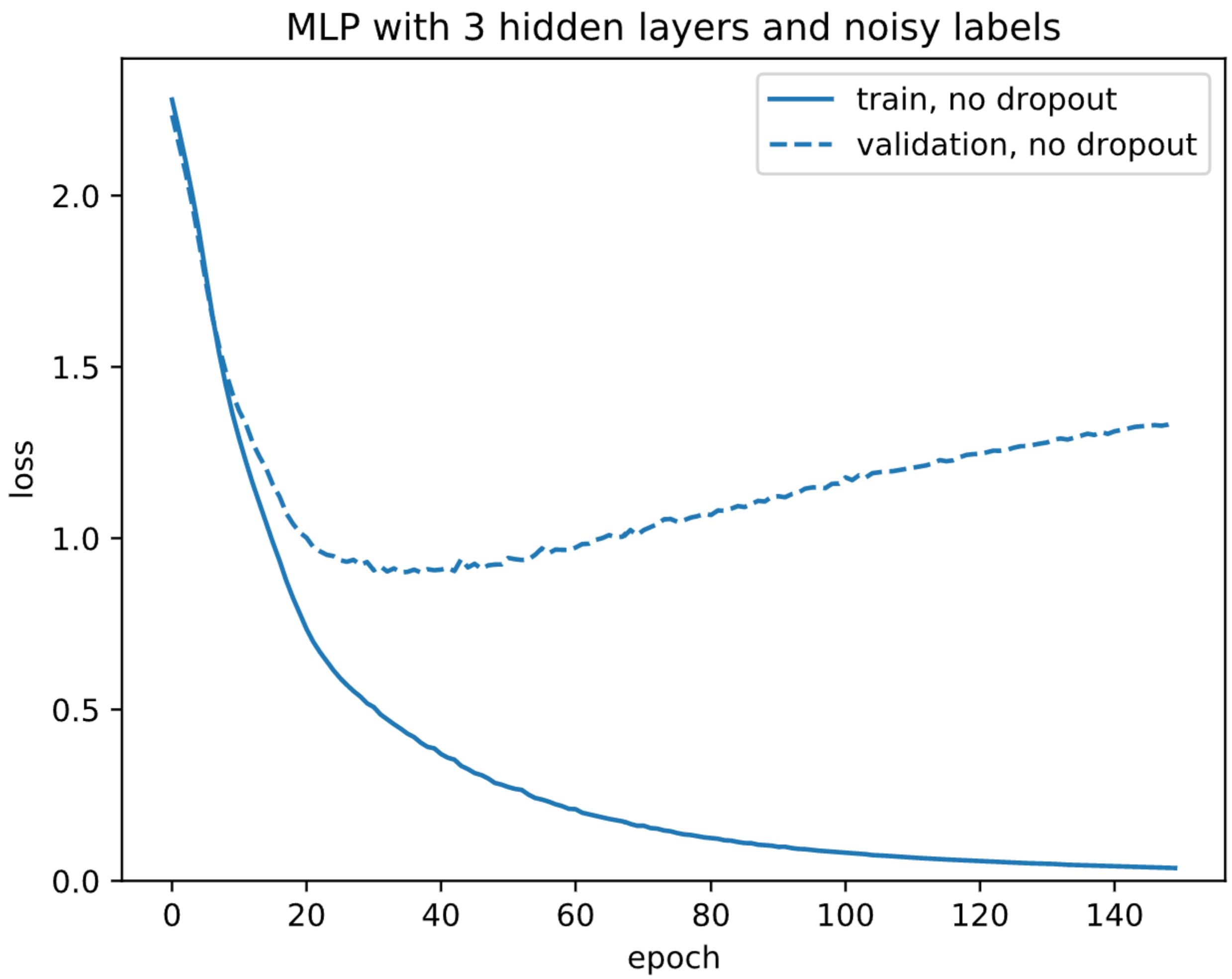
Overfitting Noise



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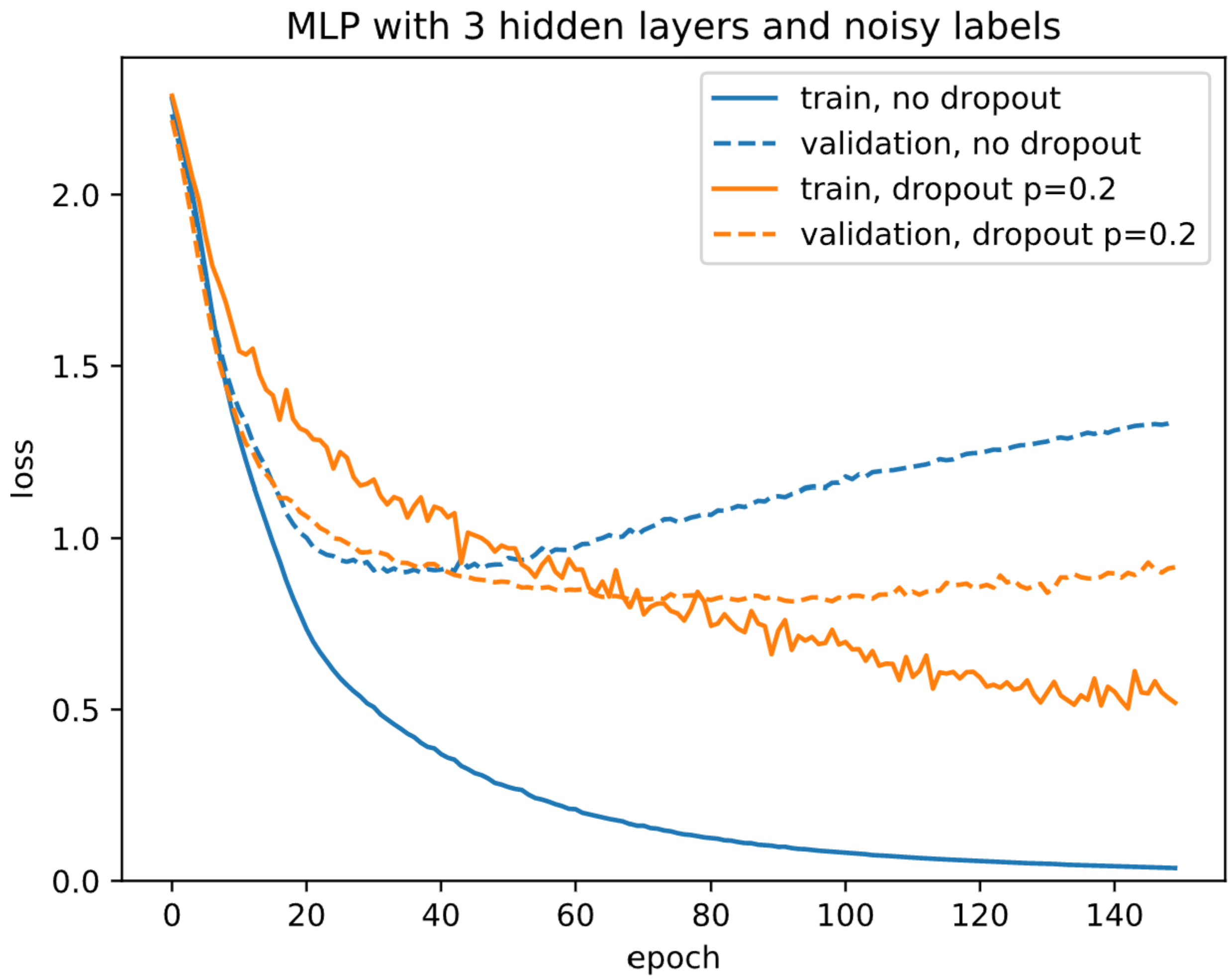

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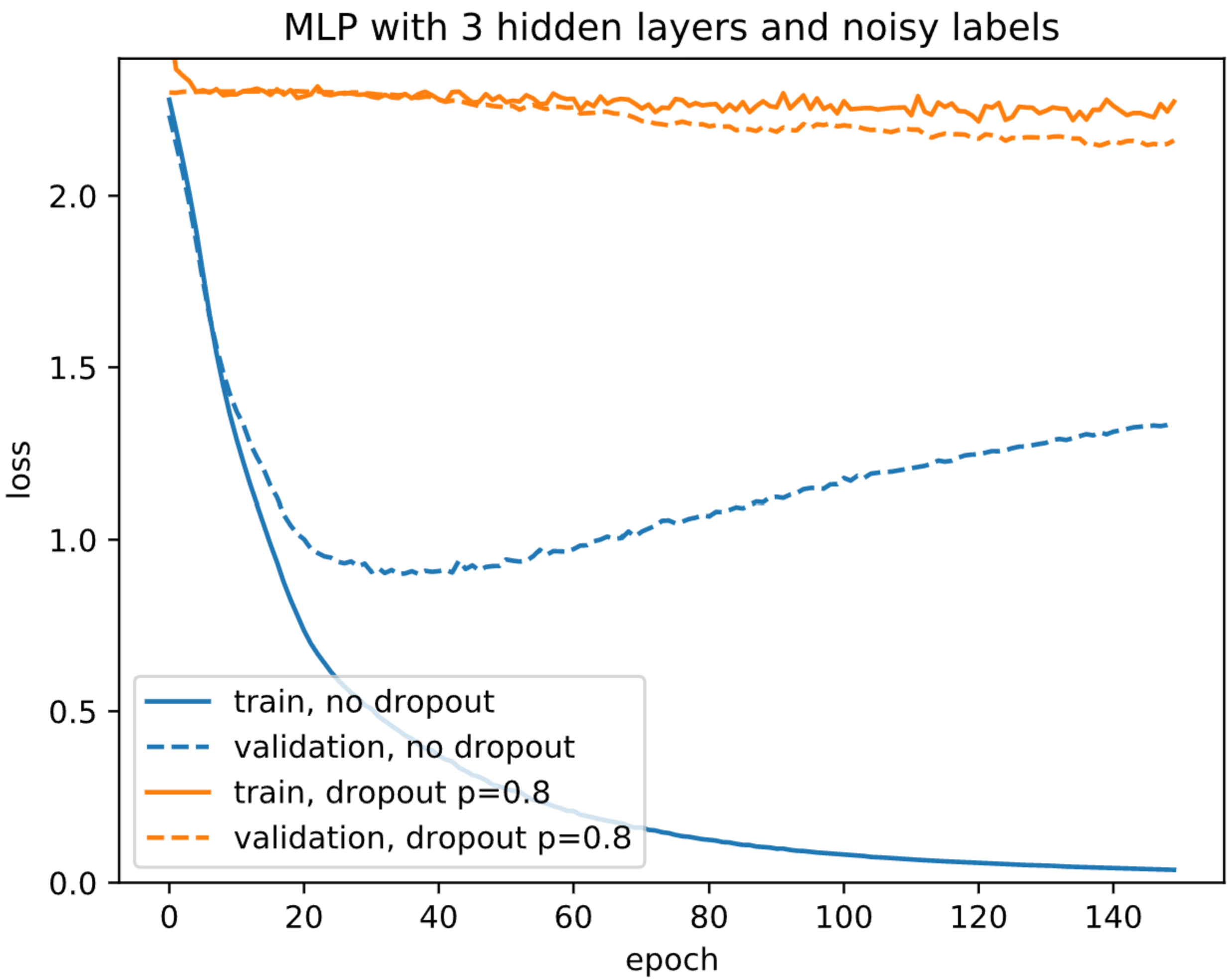

Implementation with Keras

```
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'))
```

Recommendation 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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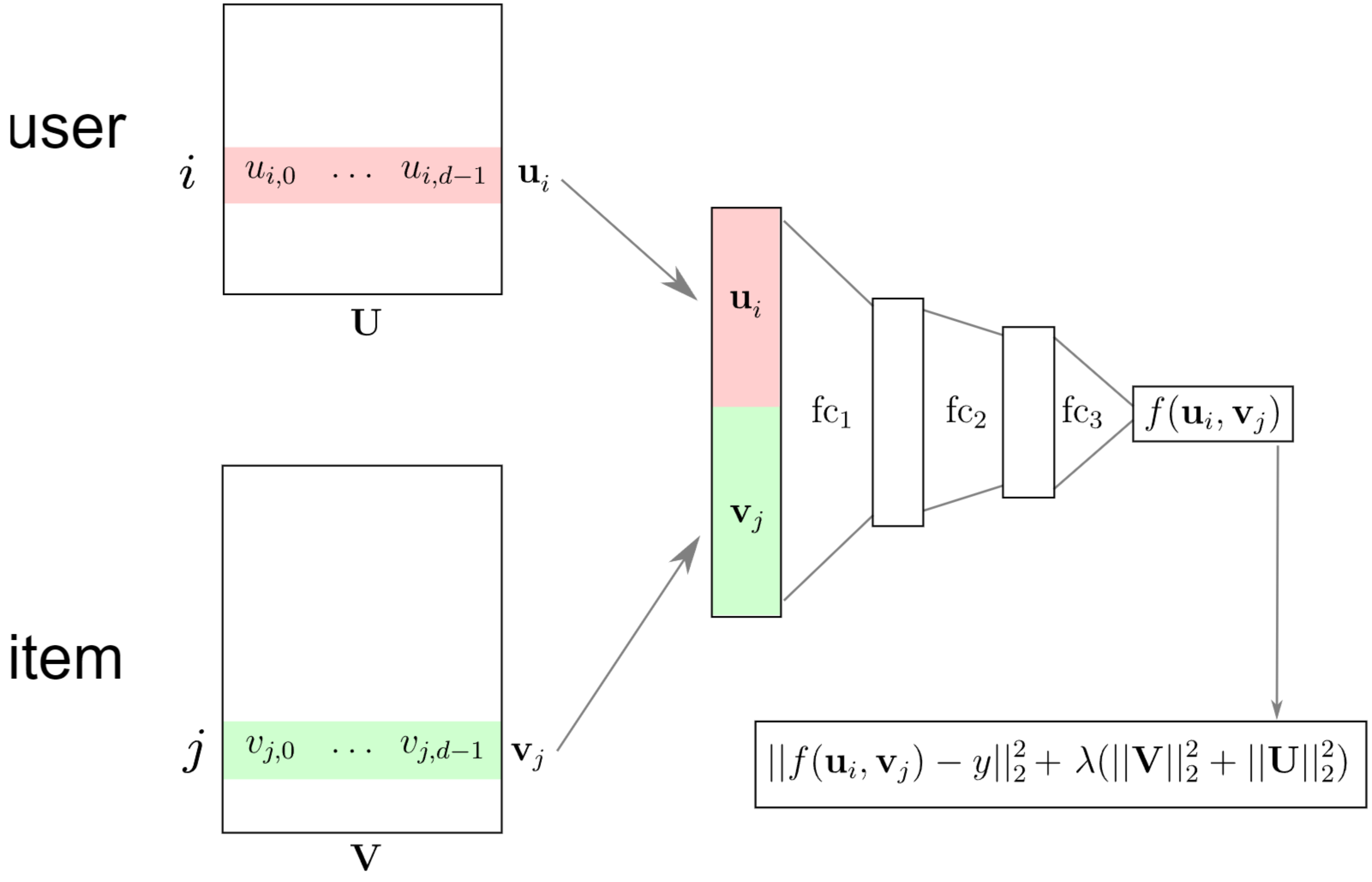
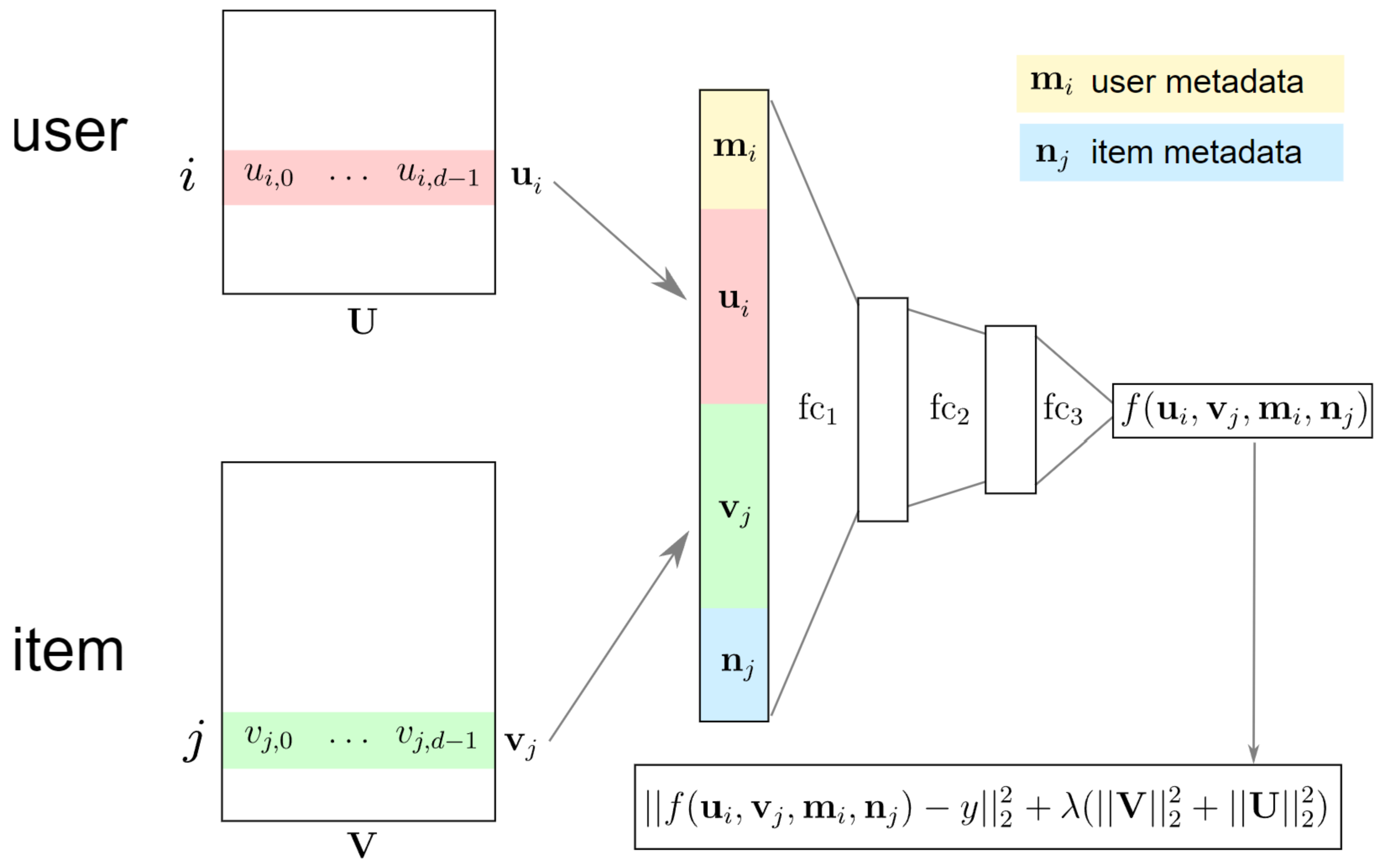
Personalized ads

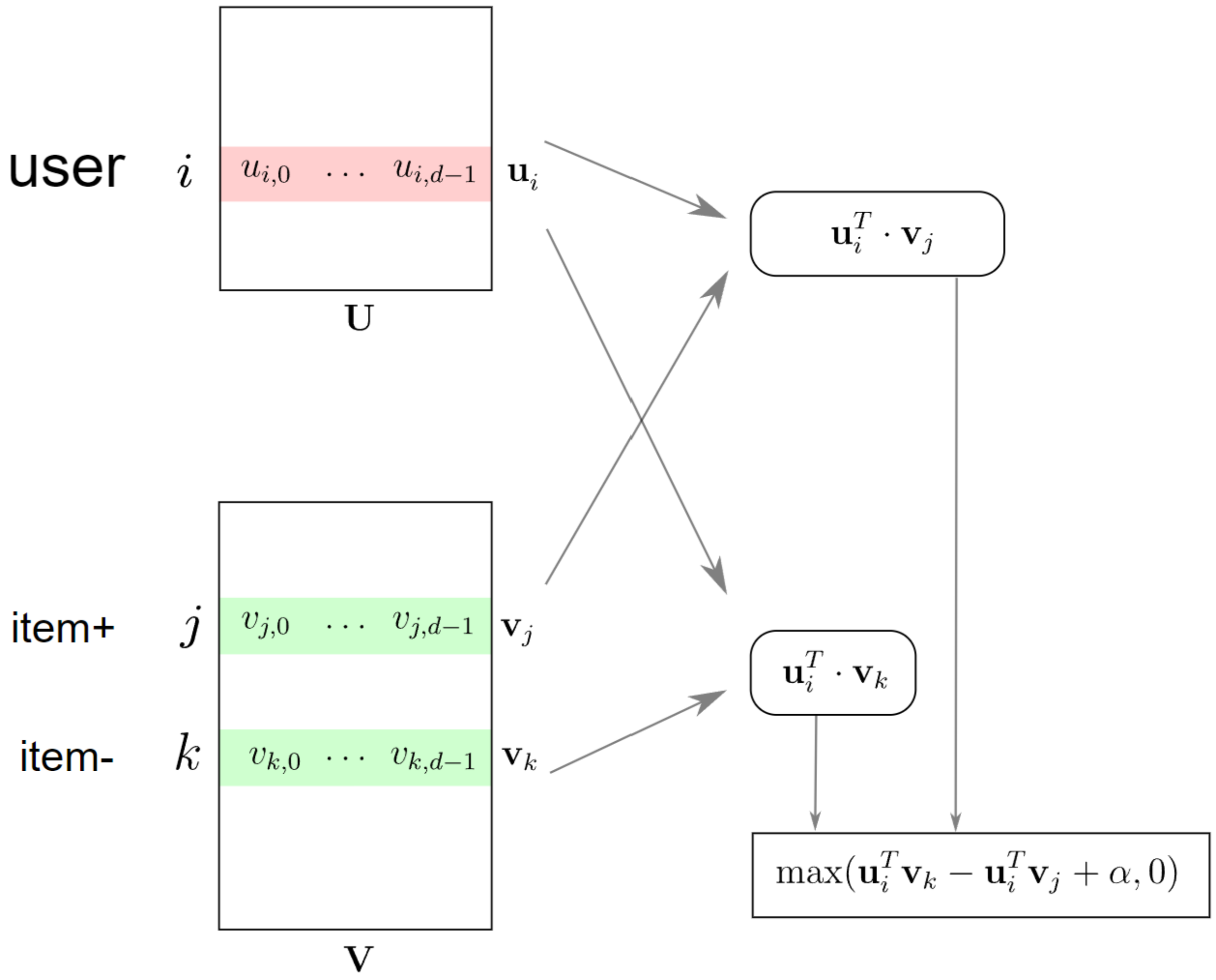
Deep RecSys Architecture



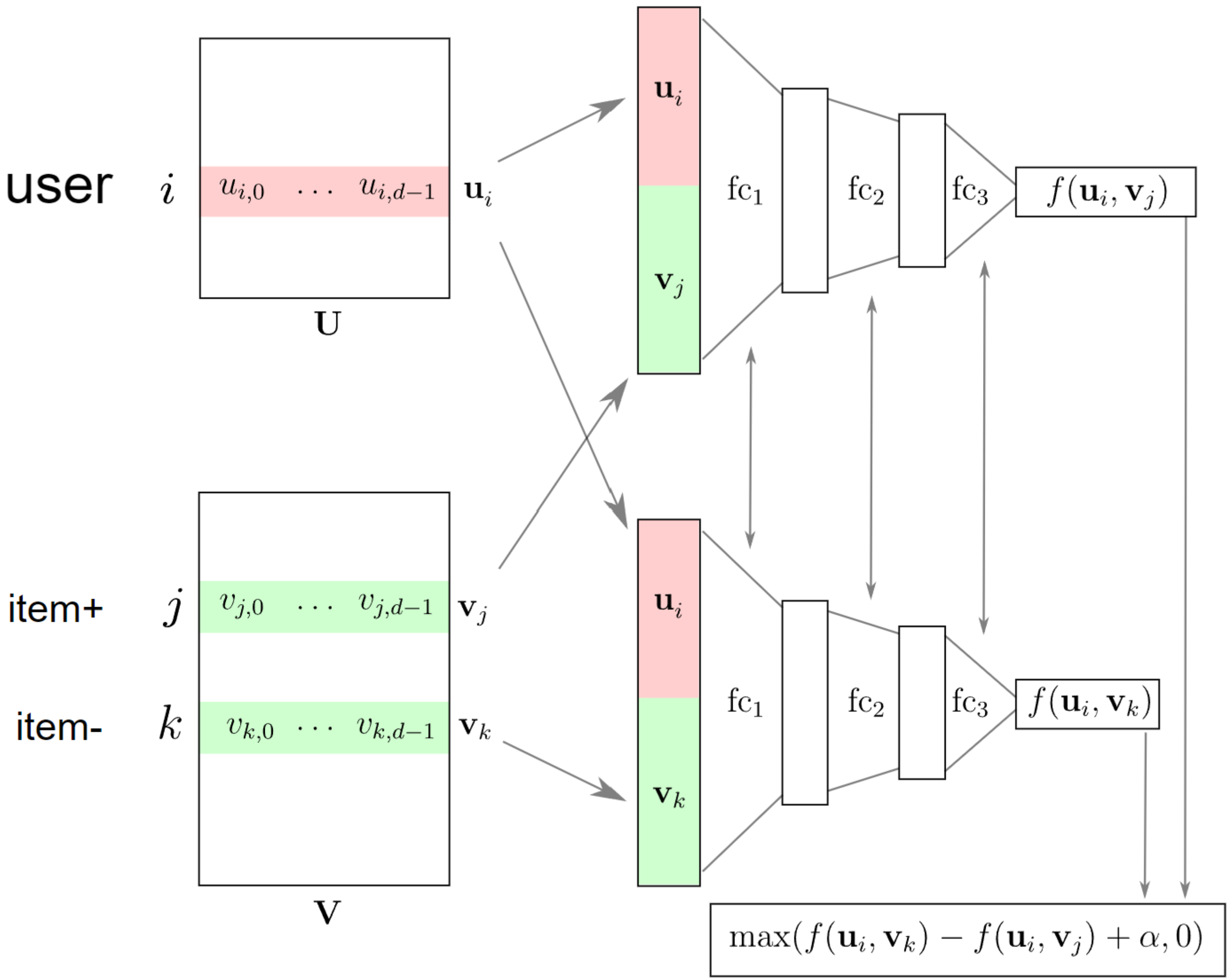
Deep RecSys with metadata



Implicit Feedback: Triplet loss



Deep Triplet Networks



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- Gather a set of positive pairs user i and item j

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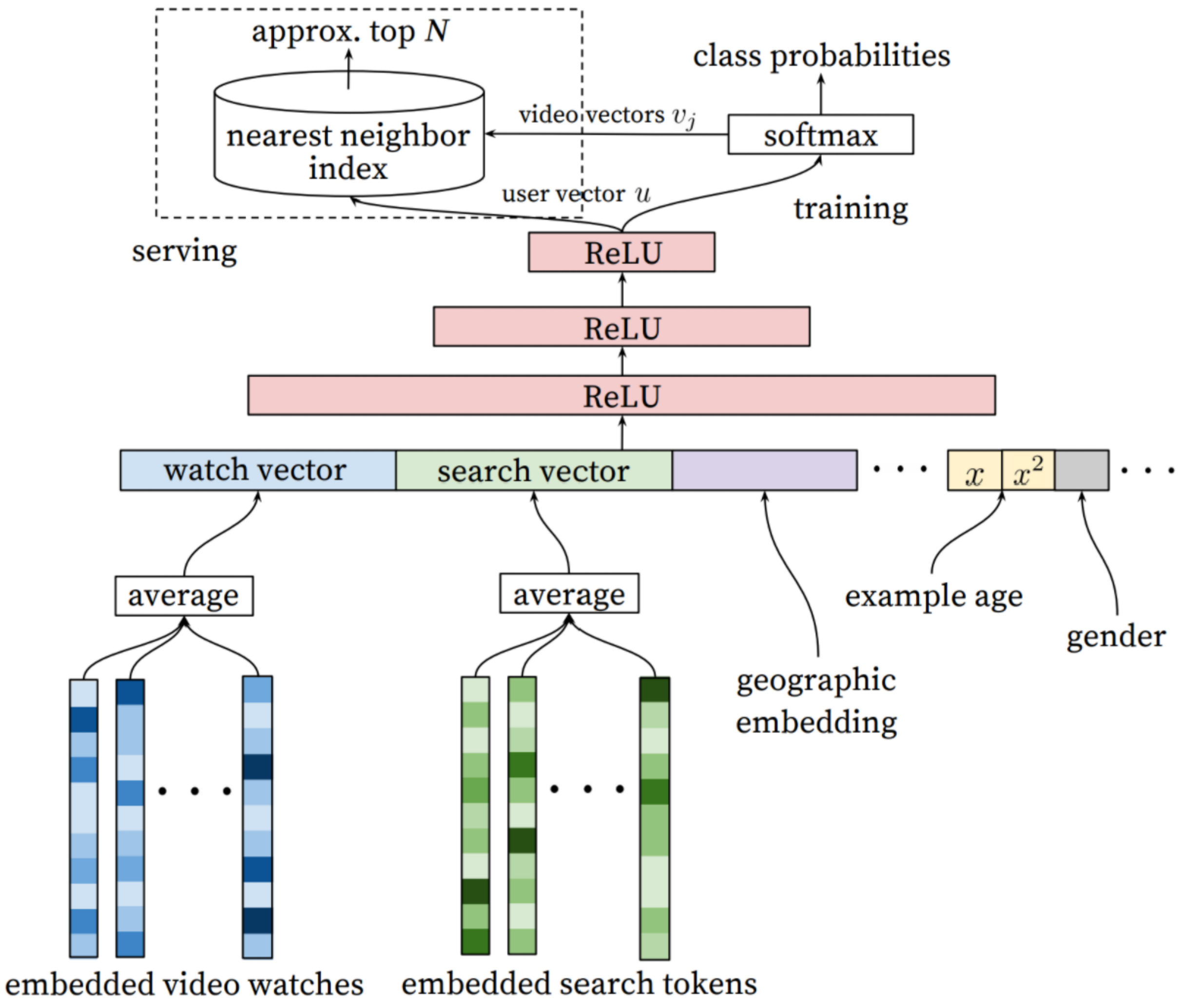

Deep Neural Networks for YouTube Recommendations https://research.google.com/pubs/pub45530.html

Ethical Considerations of Recommender Systems

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Amplification of existing discriminatory and unfair behaviors /

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

Facebook Under Fire For Alleged Gender Discrimination In Job Advertisements

- 96% of the people shown the ad for mechanic jobs were men.
- 95% of those shown the ad for preschool nurse jobs were women.
- 75% of those shown the ad for pilot jobs were men.
- 77% of those shown the ad for psychologist jobs were women.

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
- Addicted users clicks over-represented in future training data

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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Active Area of Research