Framework and Principles of Matching Technologies

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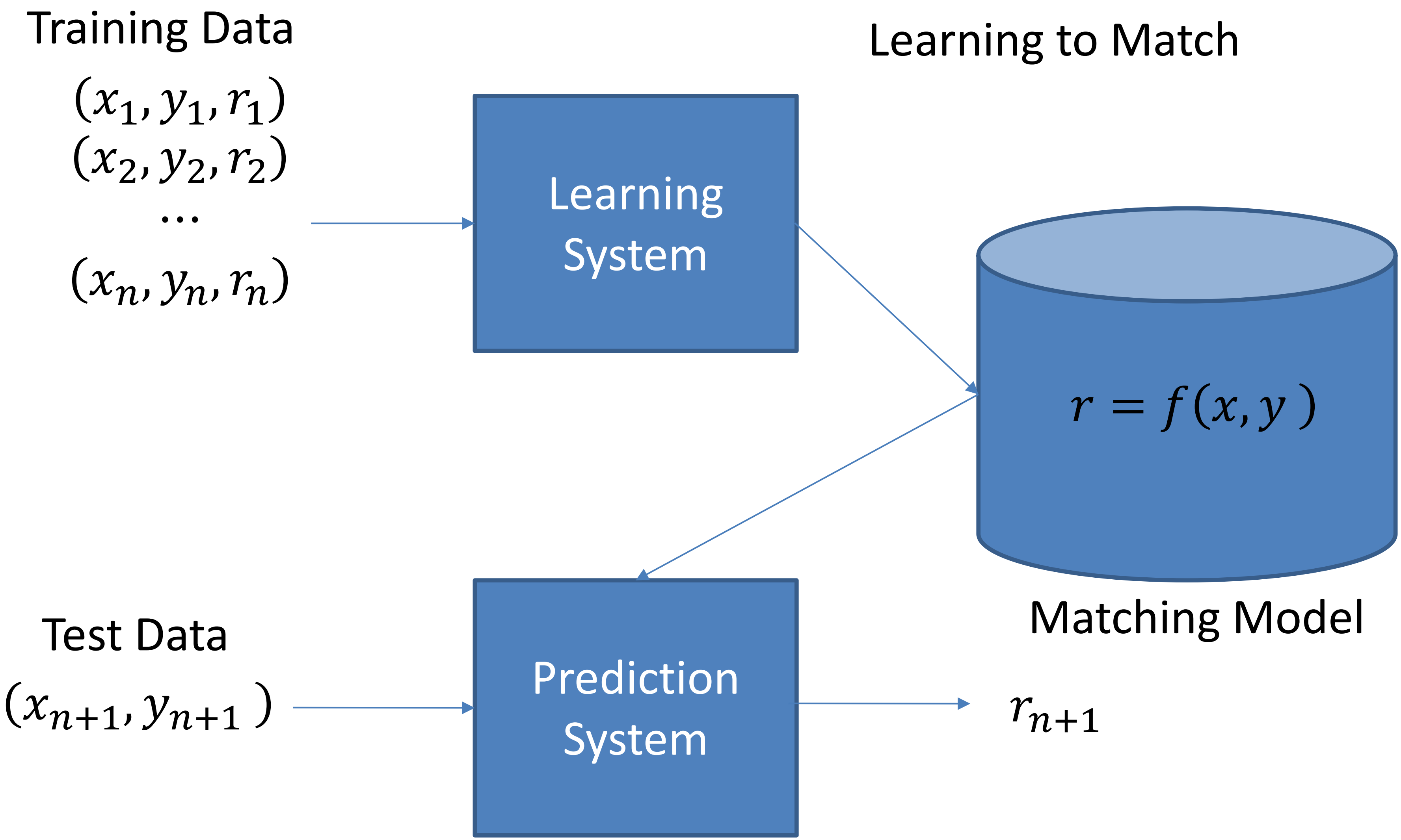
This talk gives a high-level review of matching technologies in search and recommendation

Outline of Talk

- *Matching Problem*
- Framework and Principles of Matching
- State-of-the-Art Techniques for Matching
- Summary

Matching Problem



Matching vs Classification and Regression

- Matching model: $f(x, y)$
- Classification and regression models: $f(x)$
- Matching can be viewed as special case of classification and regression
- But, there are also differences
- Features need to be carefully designed to represent the interactions between inputs x and y

Matching and Ranking

- Matching model: $f(x, y)$
- Ranking model: $g(x, y)$
- In search and recommendation:
- Matching models can be features of ranking model
- Ranking model is more 'content-agnostic' than matching models, its features = BM25, PageRank
- Sometimes, matching model and ranking model are combined and trained together with pairwise loss

Learning to Rank

- Pointwise loss: $L(f(x,y),r)$
- Pairwise loss: $L(f(x,y_1),f(x,y_2),r_1,r_2)$
- Listwise loss: $L(f(x,y_1),f(x,y_2),\cdots f(x,y_m),r_1,r_2,\cdots r_m)$
- Pairwise approach and listwise approach work better than pointwise approach
- Pairwise approach is more widely used
- Sometimes listwise approach works best

Text Matching and Entity Matching

- Matching between two sets of objects
- Text matching
  - Order exists between objects in each set (i.e., words in each sentence)
  - E.g., query title matching in search
- Entity matching
  - No order exists between objects in each set
  - E.g., user item matching in recommendation

Matching in Search

- Text matching: query-title matching
- Lexical matching is more important
- Asymmetric matching: query to title (document)
- Query can consist of multiple phrases (i.e., partial order)
- Query term importance may need to be considered
- E.g., “talk geoffrey hinton deep learning” → “Prof. Hinton’s Lecture at University of Toronto on Deep Learning”

Matching in Question Answering

- Text matching: question-answer matching
- Semantic matching is more important
- Asymmetric matching: question to answer
- E.g., "how far is sun from earth" → "distance between sun and earth"

Matching in Paraphrasing

- Text matching: sentence-sentence matching
- Semantic matching is more important
- Symmetric matching: text to text
- E.g., “Harry Potter 4”, v.s.
  “Harry Potter and the Goblet of Fire”
- E.g., “Harry Potter 4”, v.s. “Harry Potter 5”

Matching in Recommendation

- Entity matching: user-item matching
- Interactions (similarities) between entities are useful information
- Data is sparse
- Hidden structure of interactions (obtained via matrix factorization) is powerful

Natural Language Processing Problems

- Classification: $x \to c$
- Matching: $x, y \to \mathcal{R}$
- Sequence-to-Sequence: $x \to y$
- Structured Prediction: $x \to [x]$
- Sequential Decision Process: $\pi: s \to a$

Li 2017

Natural Language Problems

- Classification
  - Text classification
  - Sentiment analysis
- Matching
  - Search
  - Question answering
  - Single-turn dialogue (retrieval)
- Sequence to Sequence
  - Machine translation
  - Summarization
  - Single-turn dialogue (generation)
- Structured Prediction
  - Sequential labeling
  - Semantic parsing
- Sequential Decision Process
  - Multi turn dialogue

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Overview of Matching

- Deep learning (neural networks) is state-of-the-art in search and recommendation
- Different network architectures are needed for different tasks
- There are general framework and principles

Deep Learning

Mimicking human behaviors
using deep learning tools

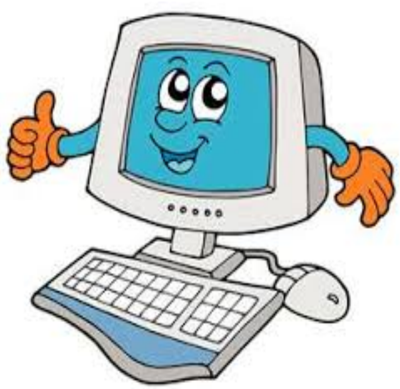
x

y

$$y = f(x)$$

$$\max_f P_f\,(y|x)$$

x



y

Deep Learning Techniques

- Models and Tools
  - Feedforward Neural Network
  - Convolutional Neural Network
  - Recurrent Neural Network
  - Sequence-to-Sequence Model
  - Attention
  - .....
- Learning algorithm: back propagation
- Regularization, e.g., dropout, early-stopping

Framework of Matching

Output: MLP

Aggregation: Pooling, Concatenation

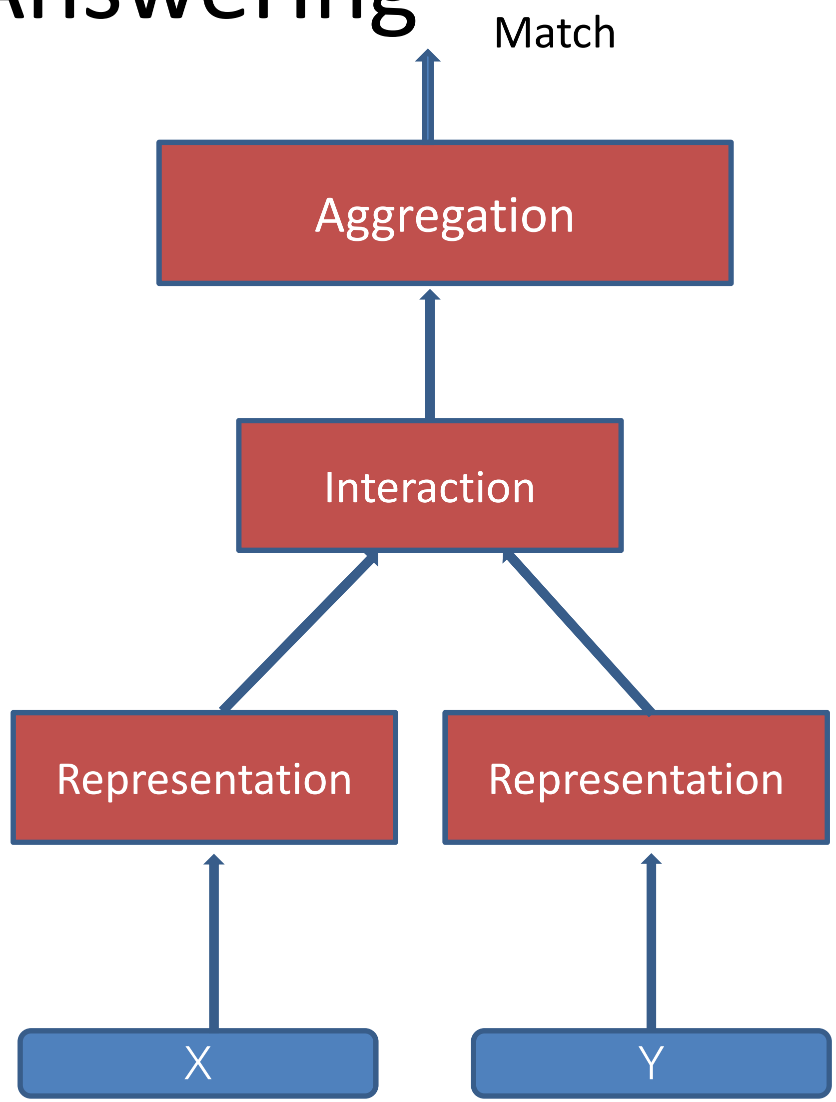
Interaction: Matrix, Tensor

Representation: MLP, CNN, LSTM

Input: ID Vectors, Feature Vectors

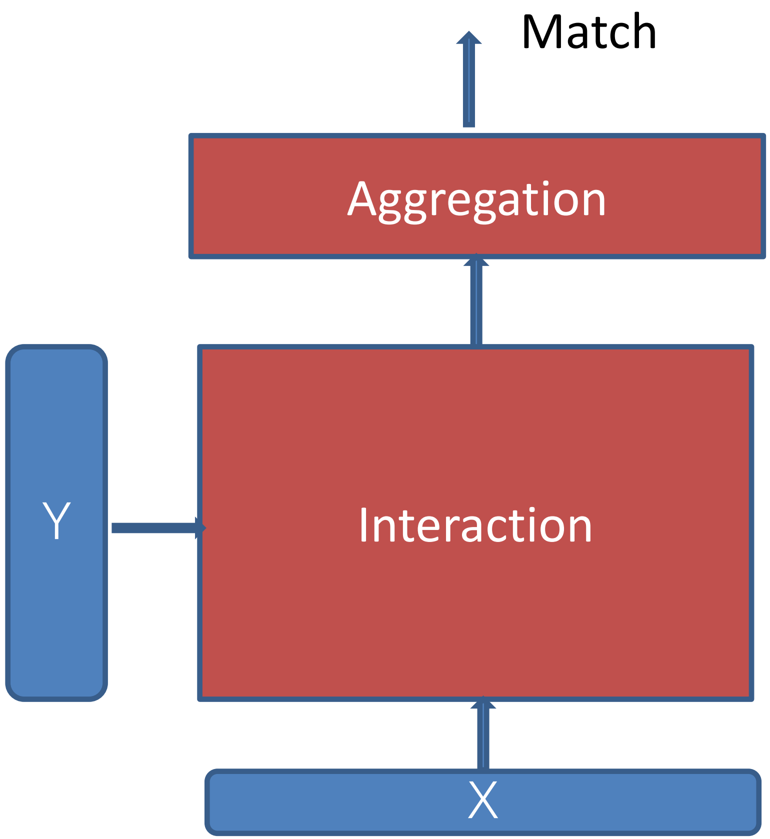
Typical Architecture for Search and Question Answering

- Input: two sequences of word embeddings
- First, create *semantic* representations of two inputs
- Next, make interaction between the two representations
- Finally, make aggregation

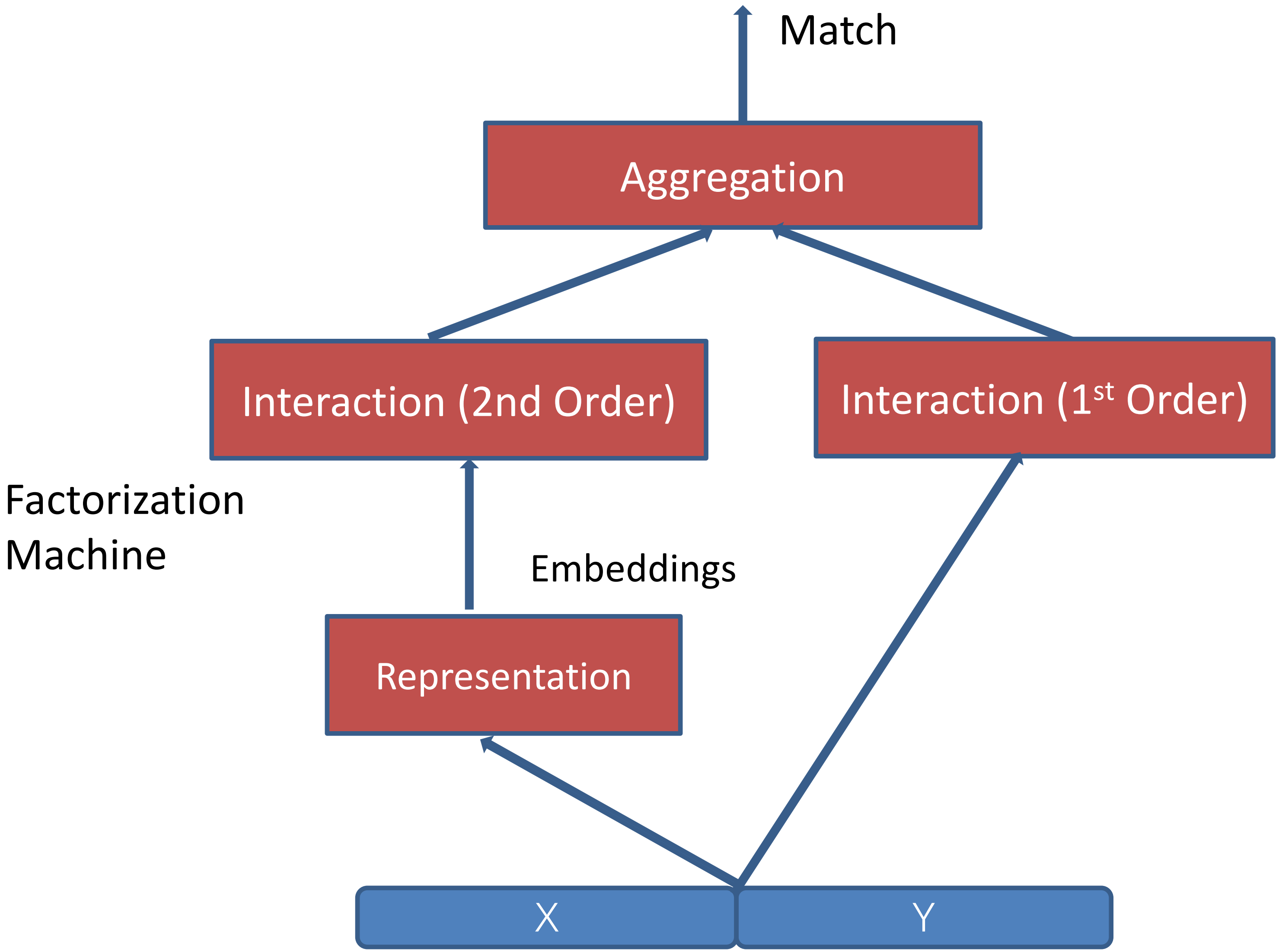


Typical Architecture for Search

- Input: two sequences of word embeddings
- First, make *lexical* interaction between two inputs
- Next, make aggregation of interaction



Typical Architecture for Recommendation



Typical Architecture for Recommendation

- Input: two vectors are combined
- First, create embeddings of combined inputs
- Next, make interactions using factorization machine (1^{st} order feature interaction and 2^{nd} order feature interaction)
- Finally, make aggregation of interactions

Two Principles

- Modular Principle: System consists of different modules (functions) implemented with different techniques
  - Representation: CNN, RNN, MLP
  - Interaction: matrix, tensor
  - Aggregation: pooling, concatenation
- Hybrid Principle: Combination of dichotomic techniques may be necessary
  - Deep model and wide model
  - Nonlinear model and linear model
  - Factorization and non-factorization (2^{nd} order interaction and 1^{st} order interaction)

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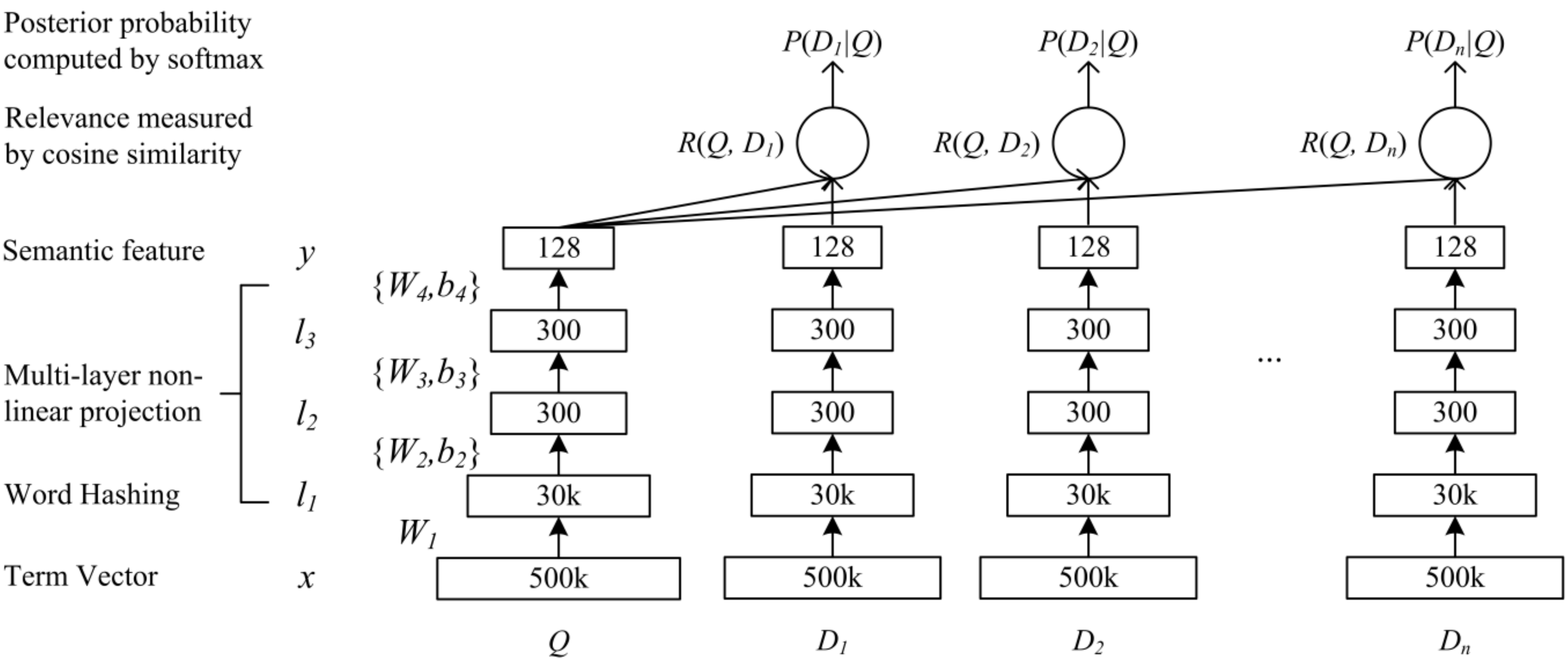
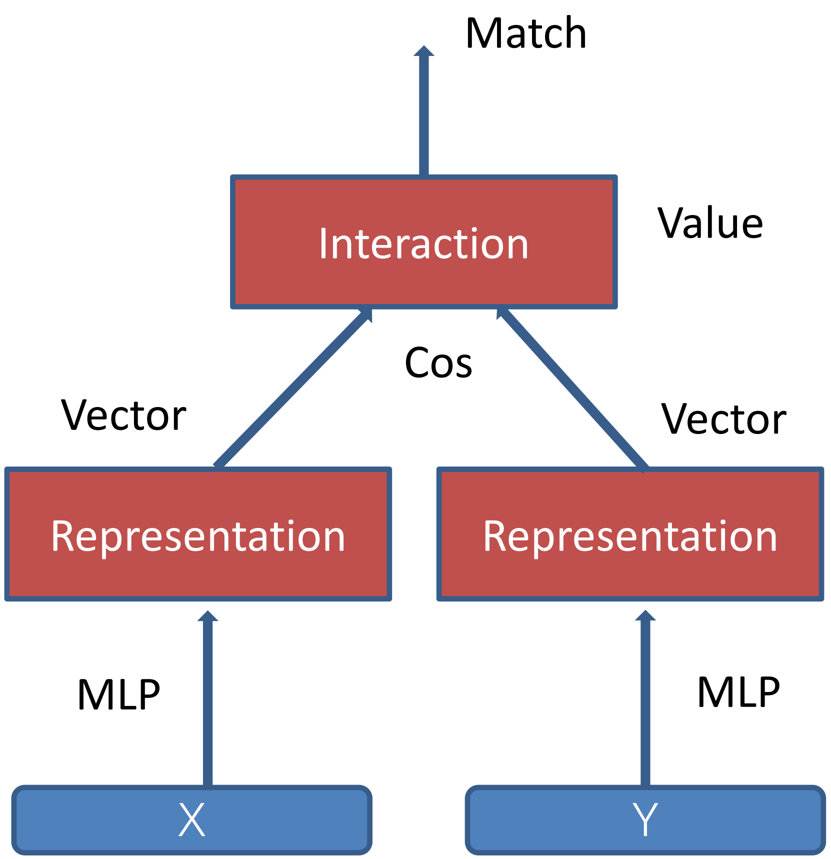
Search: DSSM



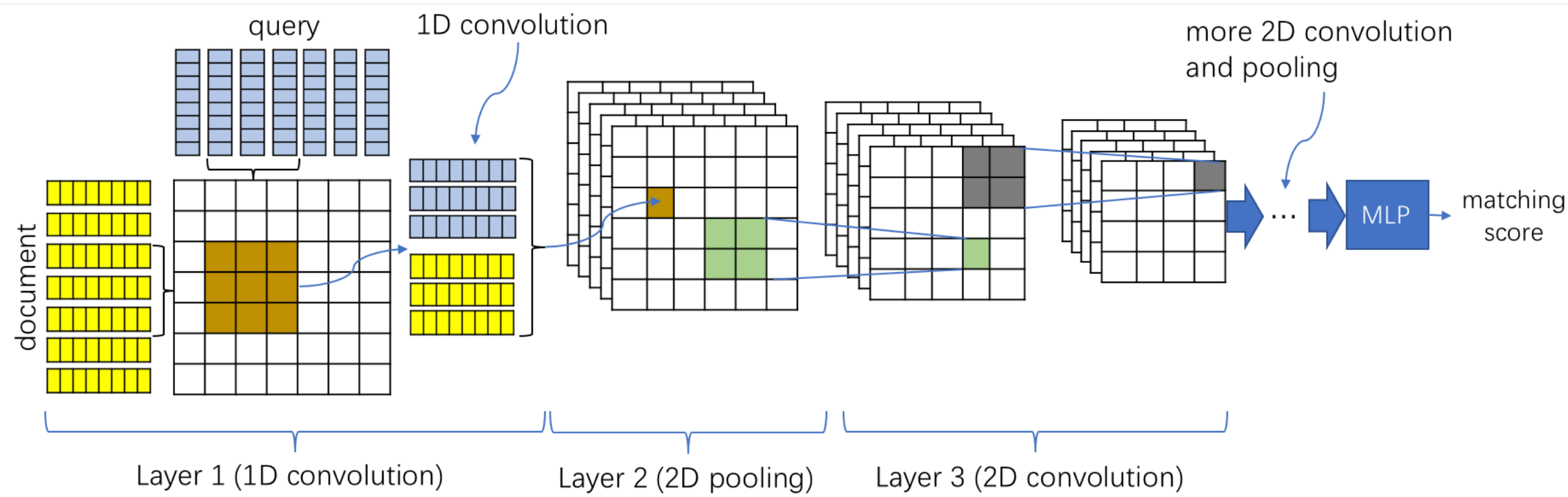
Huang at al. CIKM 2013

Search: DSSM

- Input: two vectors of letter n-grams
- Representations: two vectors created by MLP
- Interaction: cos between two vectors
- Alternatives: representations created by using CNN, RNN



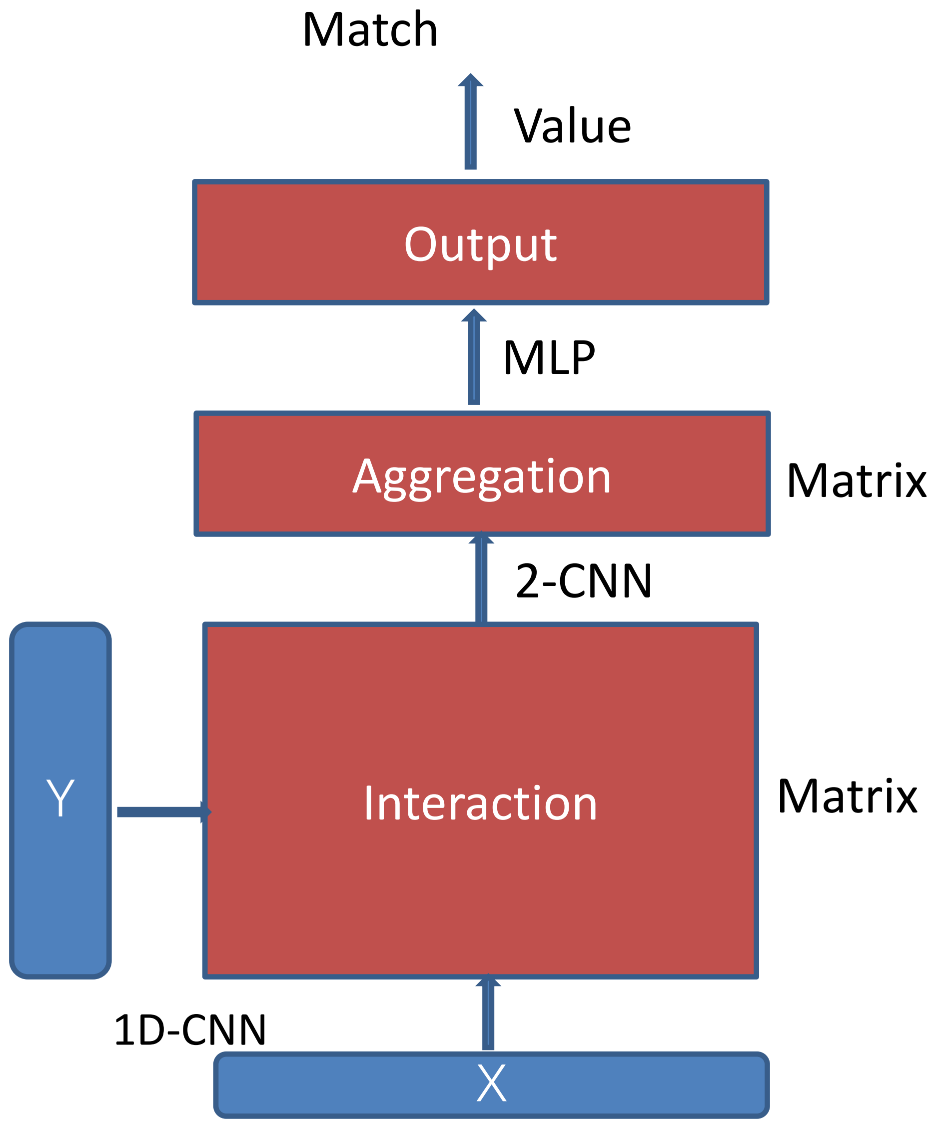
Question Answering: Arc II



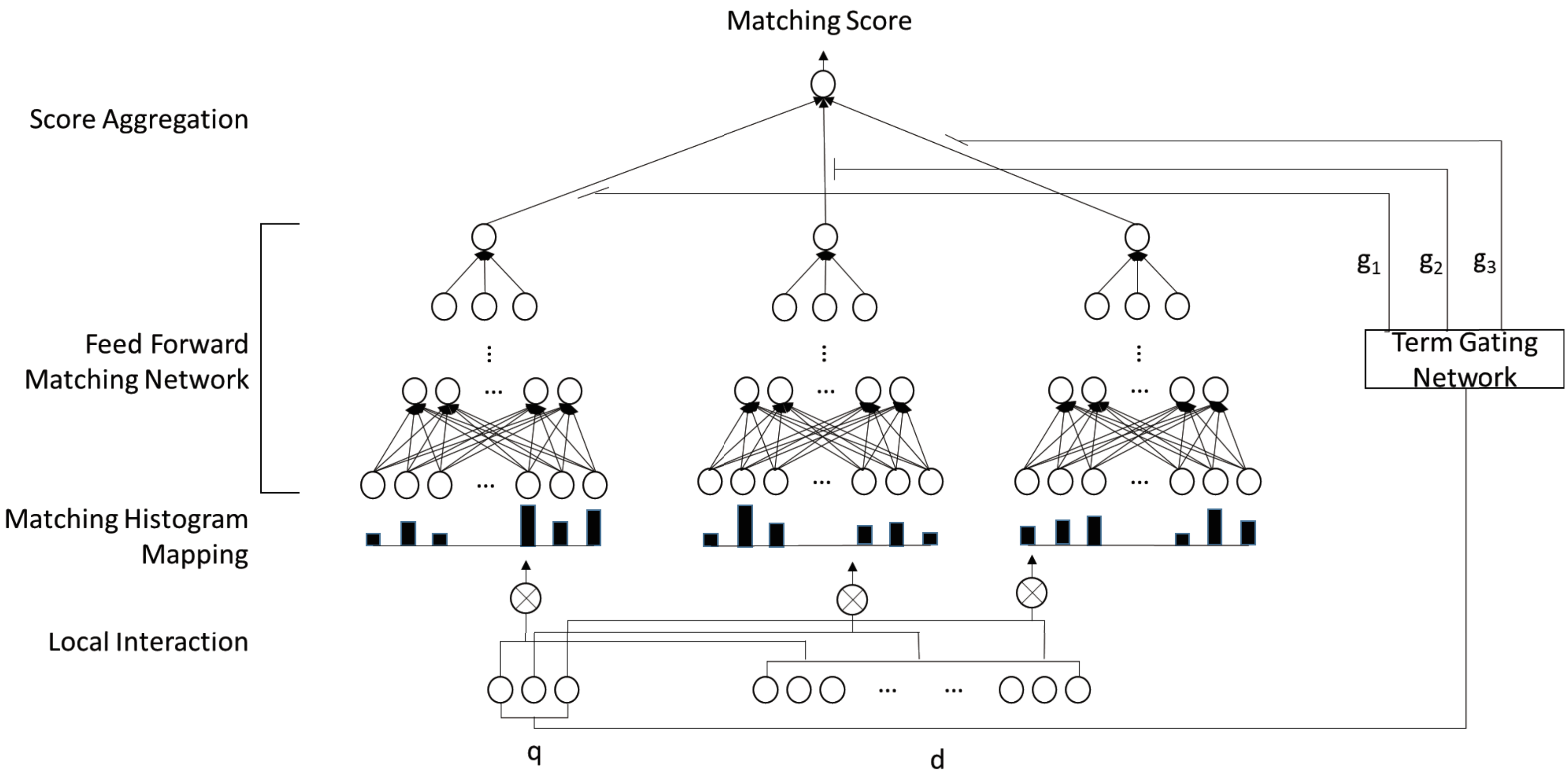
Hu at al. NIPS 2014

Question Answering: Arc II

- Input: two sequences of word embeddings
- Interaction: matrix created by 1-D CNN
- Aggregation: vector created by 2-D CNN
- Output: value generated by MLP



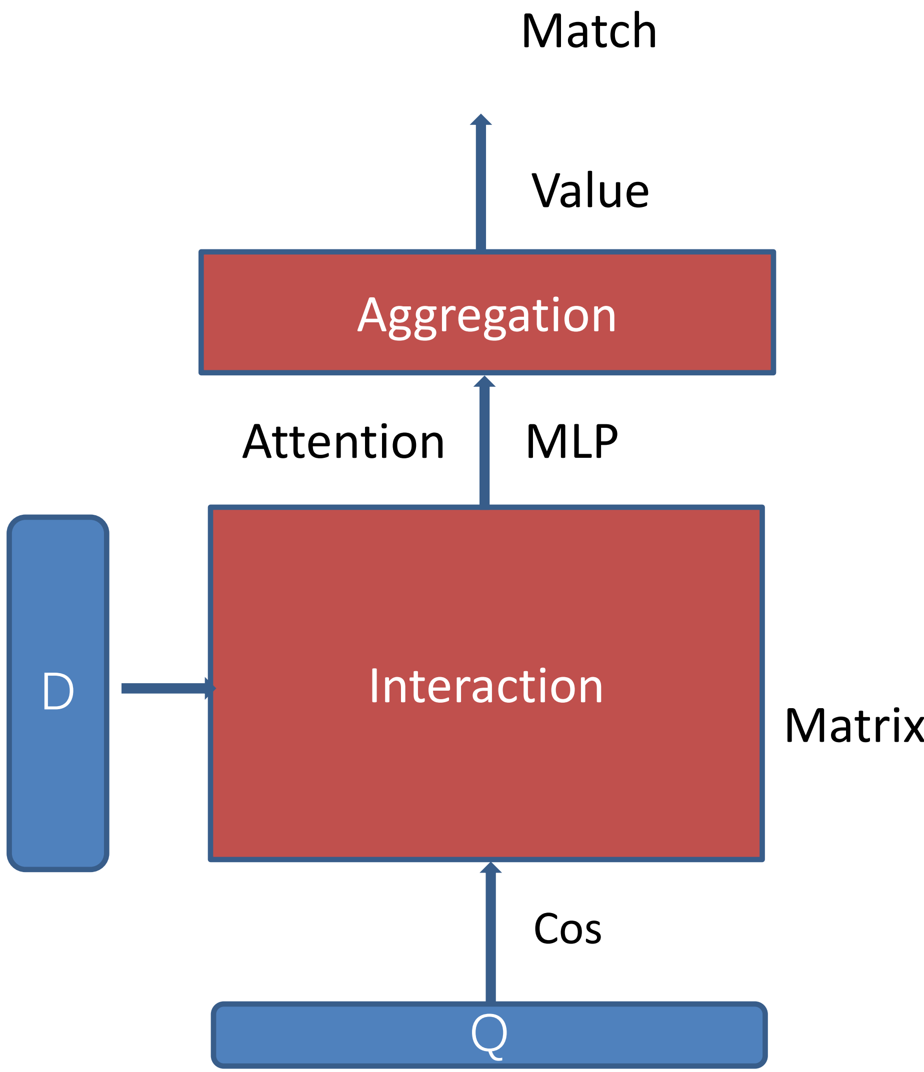
Search: DRMM



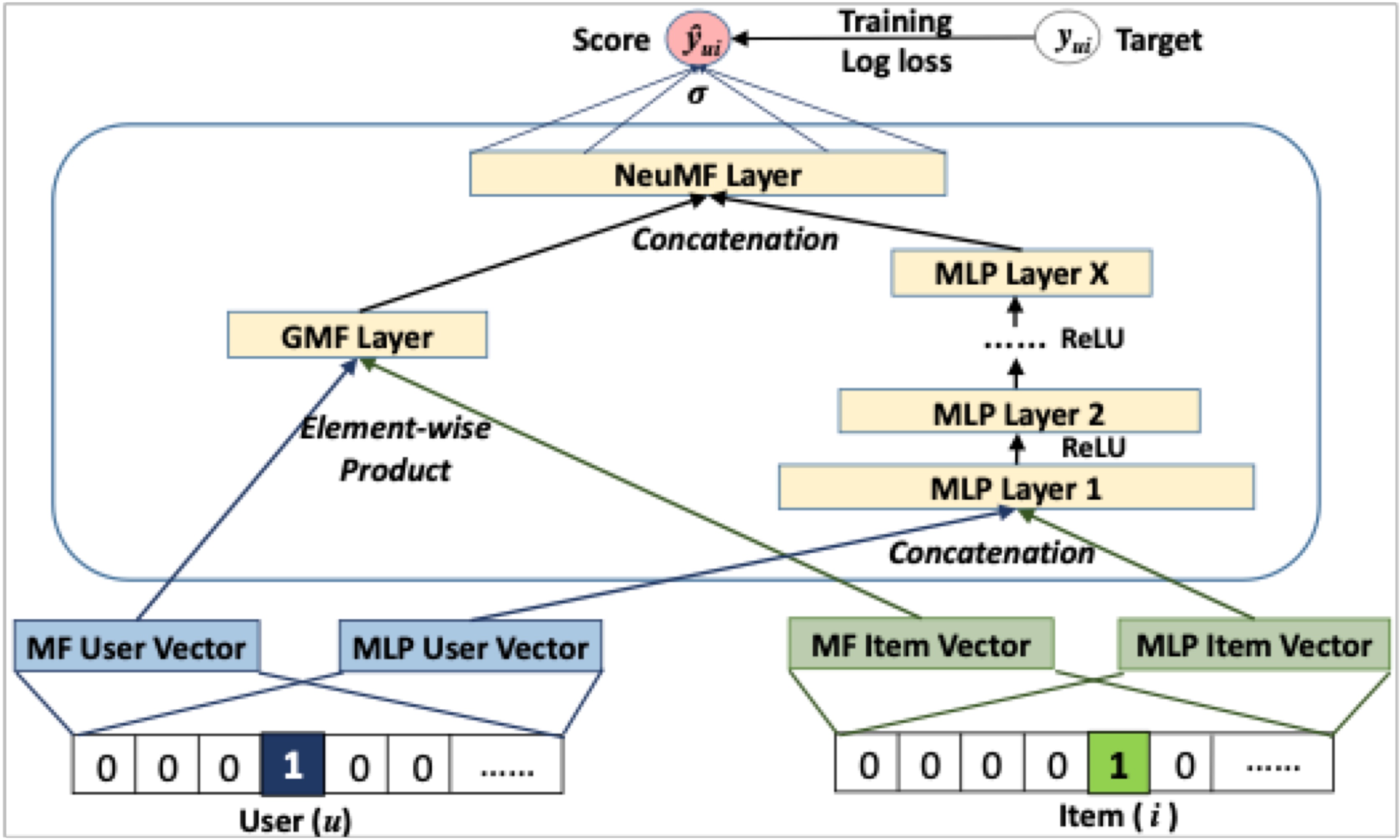
Guo at al. CIKM 2016

Search: DRMM

- Input: two sequences of word embeddings
- Interaction: lexical interaction matrix, asymmetric
- Aggregation: weighted sum created by MLP
- Attention: query term weighting
- Alternative: aggregation by kernel pooling or max pooling

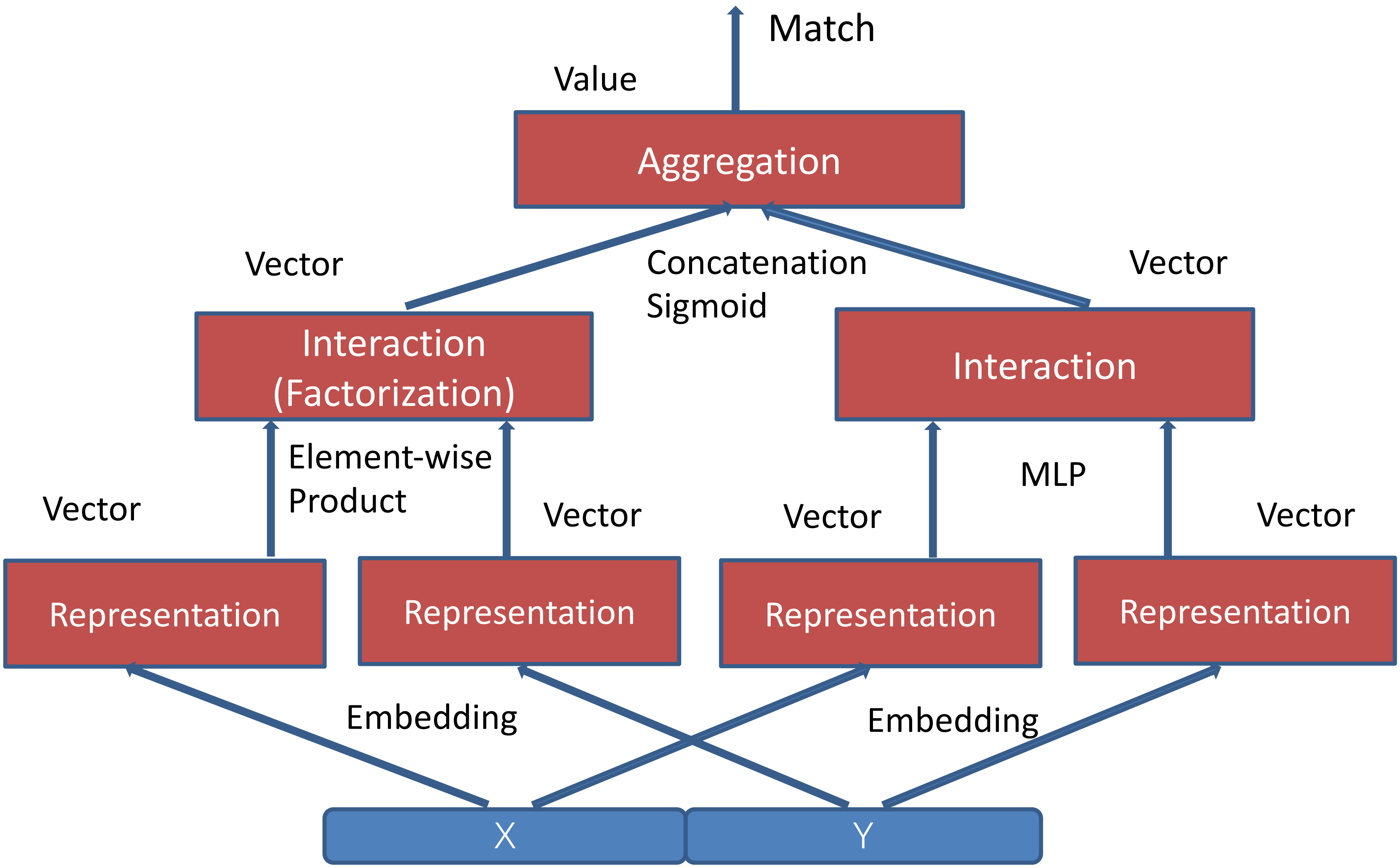


Recommendation: NeuMF



He at al. WWW 2017

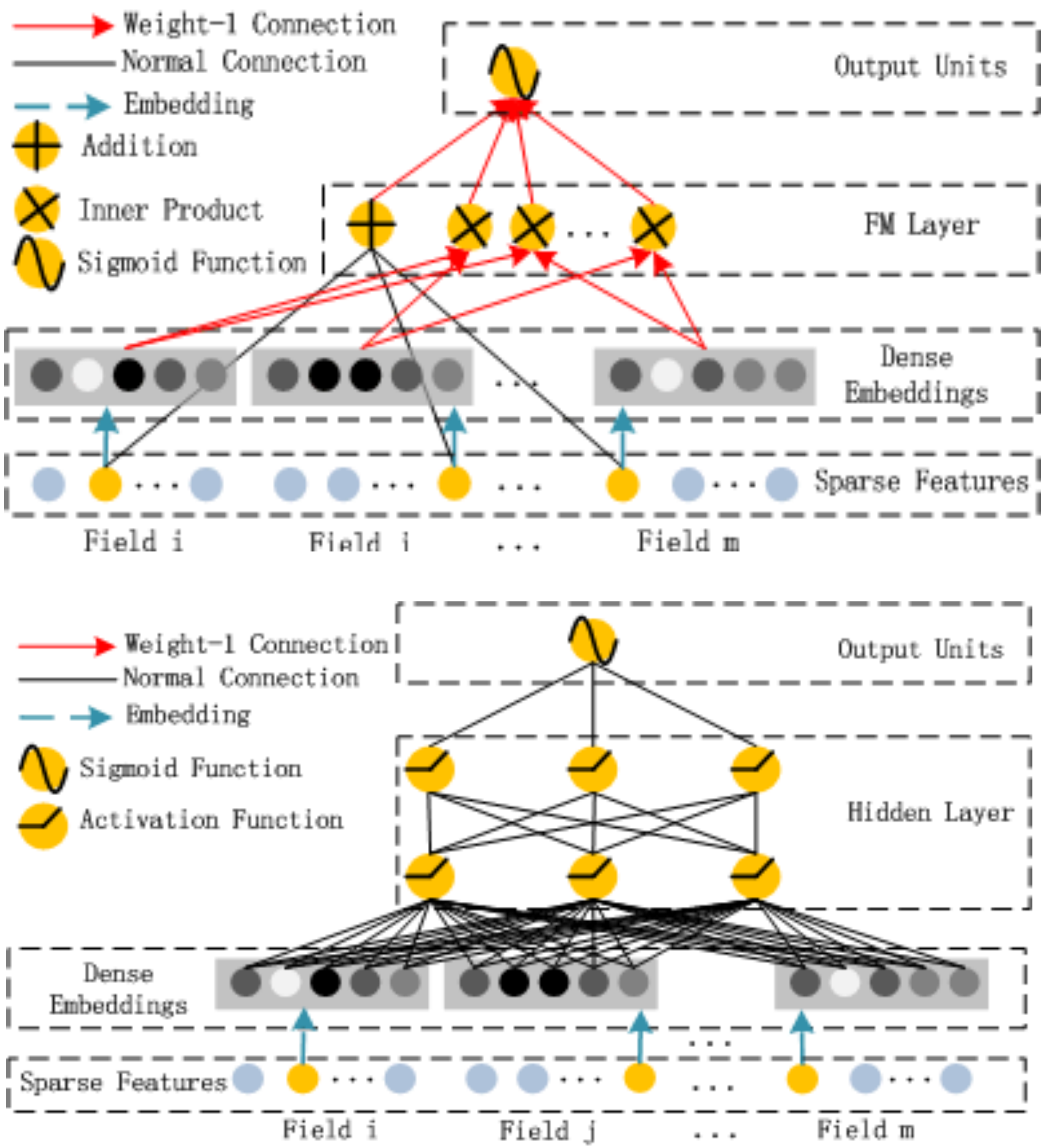
Recommendation: NeuMF



Recommendation: NeuMF

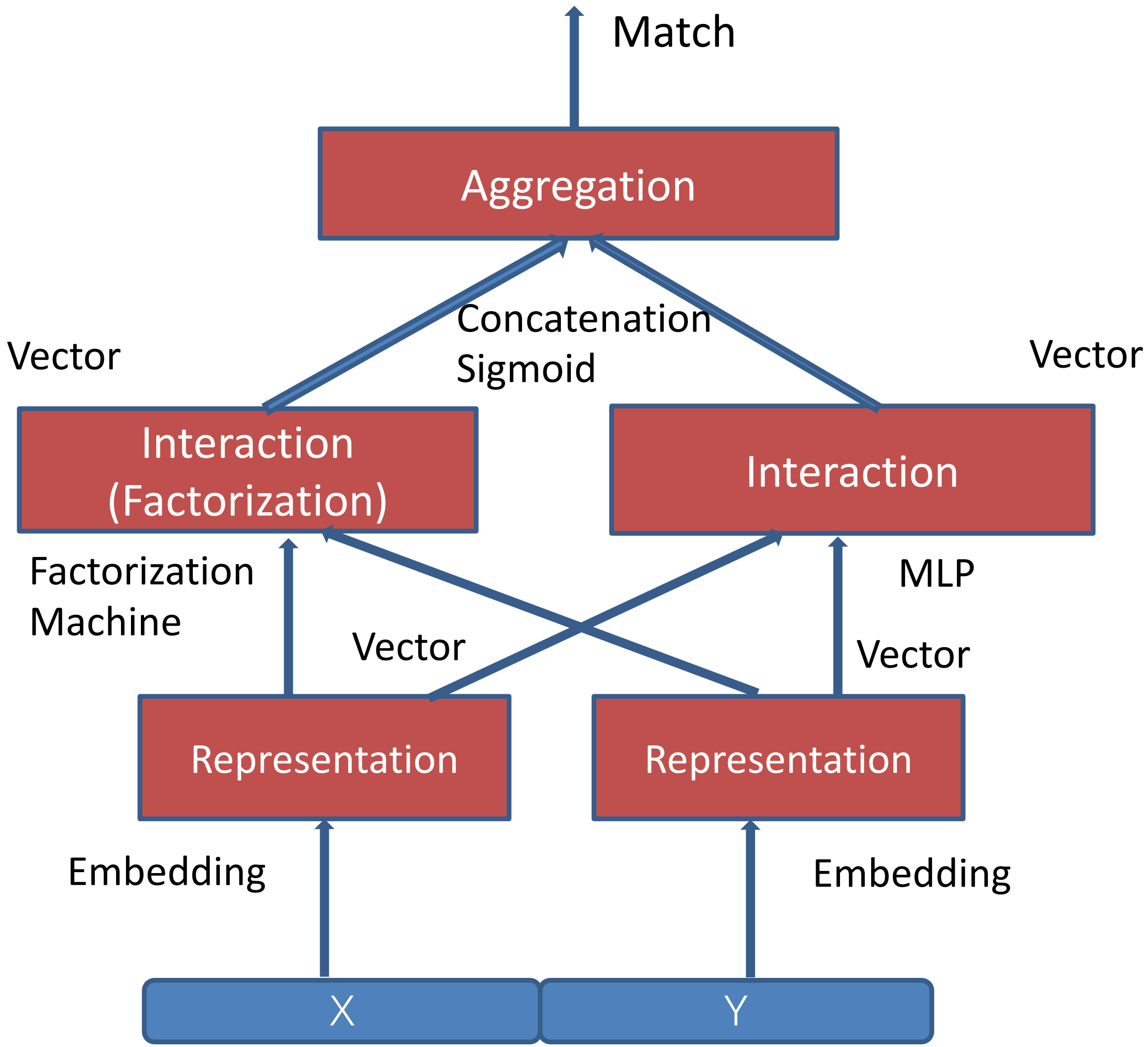
- Input
  - Combined user ID vector and item ID vector
- Representation
  - Two vectors (embeddings) for factorization and for neural network respectively
- Interaction
  - Two vectors obtained by factorization and neural network
- Aggregation
  - Value generated by concatenation and sigmoid function

Recommendation: DeepFM



Guo at al. IJCAI 2017

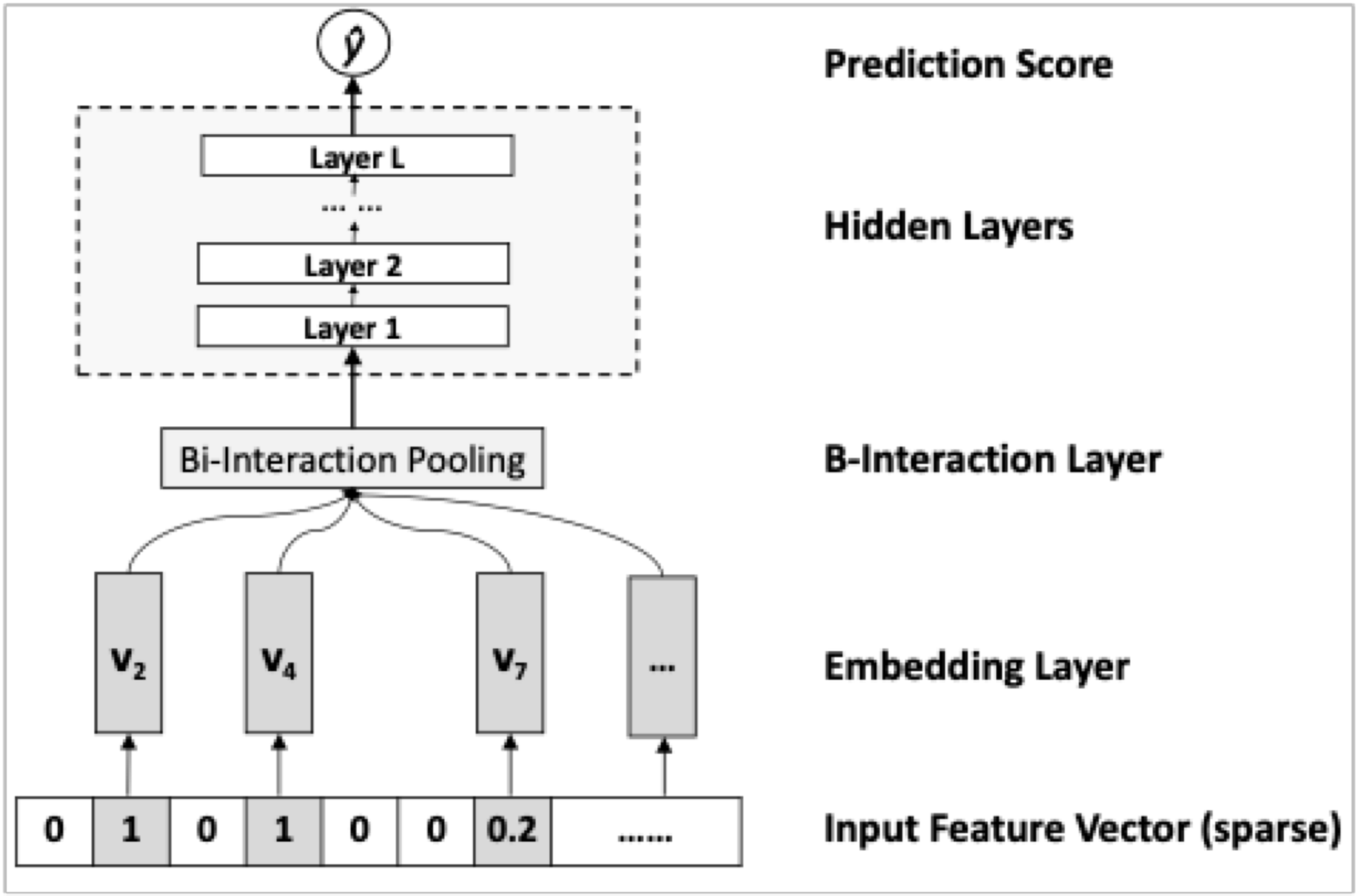
Recommendation: DeepFM



Recommendation: DeepFM

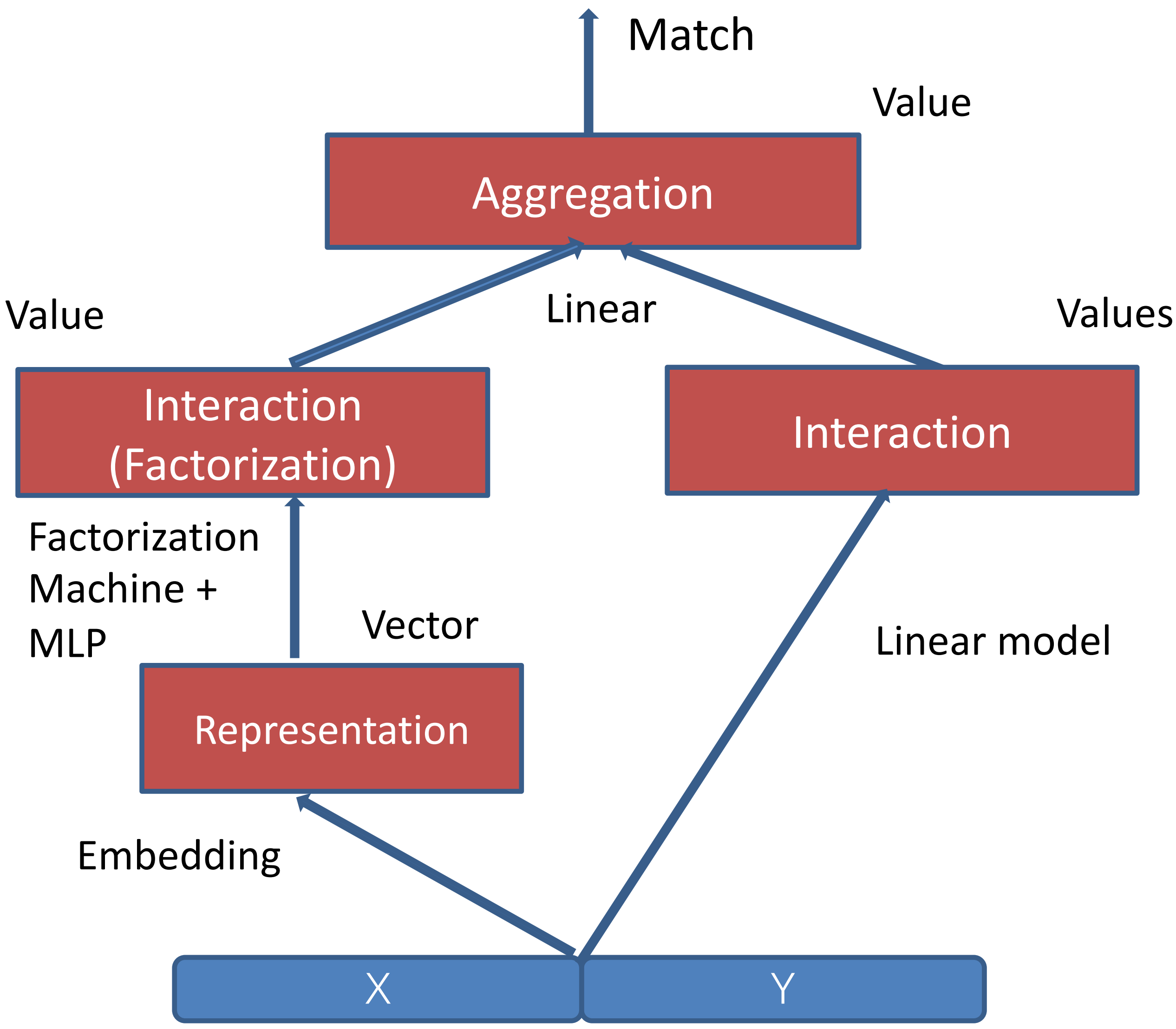
- Input
  - Combined user feature vector and item feature vector
- Representation
  - Two shared vectors (embeddings) for factorization machine and neural network
- Interaction
  - Two vectors by factorization machine and neural network
- Aggregation
  - Value generated by concatenation and sigmoid function

Recommendation: NFM



He at al. SIGIR 2017

Recommendation: NFM



Recommendation: NFM

- Input
  - Combined user feature vector and item feature vector
- Representation
  - Vector (embedding) from combined vectors
- Interaction
  - Vector by factorization machine plus neural network, as well as values by linear model
- Aggregation
  - Value generated by linear combination

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Summary

- Matching is key technology for search and recommendation
- Text matching and entity matching
- Deep learning is state-of-the-art
- Framework: input, representation, interaction, aggregation, output
- Principles: modular and hybrid

Acknowledgement

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References

- Jun Xu, Xiangnan He, Hang Li, Deep Learning for Matching in Search and Recommendation, WSDM 2019 Tutorial
- Hang Li, Deep Learning for Natural Language Processing, National Science Review, Perspective, 2017.

Thank you!

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