Deep Learning Models for Information Retrieval

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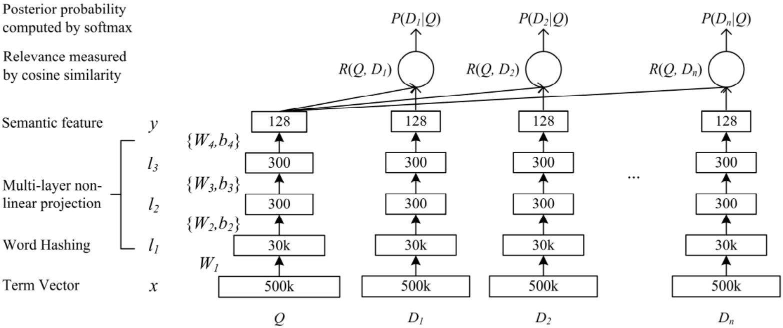
Outline

Deep Structured Semantic Model(DSSM)

- We strive to develop a series of new latent semantic models with a deep structure that project queries and documents into a common low-dimensional space.



Deep Structured Semantic Model(DSSM)

- Word Hashing
  - good : #go, goo, ood, od#
- The semantic relevance score between a query Q and a document D is measured as:

$$R(Q, D) = \cos(y_Q, y_D) = \frac{y_Q^T y_D}{\|y_Q\| \|y_D\|}.$$

- We compute the posterior probability of a document given a query :

$$P(D|Q) = \frac{\exp(\gamma R(Q, D))}{\sum_{D' \in \mathbf{D}} \exp(\gamma R(Q, D'))}$$

- We approximate $\mathbf{D}$ by including D^+ and four randomly selected unclicked documents, denote by $\{D_j^- : j = 1, ..., 4\}$.
- Learning the DSSM : we minimize the following loss function

$$L(\Lambda) = -\log \prod_{(Q, D^+)} P(D^+|Q)$$

Multi-task DNN for Semantic Classification and Information Retrieval

- Our multi-task model combines classification and ranking tasks:
  - Query Classification
    - In this study, we classify queries into four domains of interest: “Restaurant”, “Hotel”, “Flight”, “Nightlife”.
  - Web search
    - Given a query Q, we estimate $P(D|Q)$ for each document D.

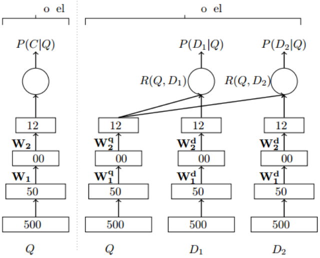
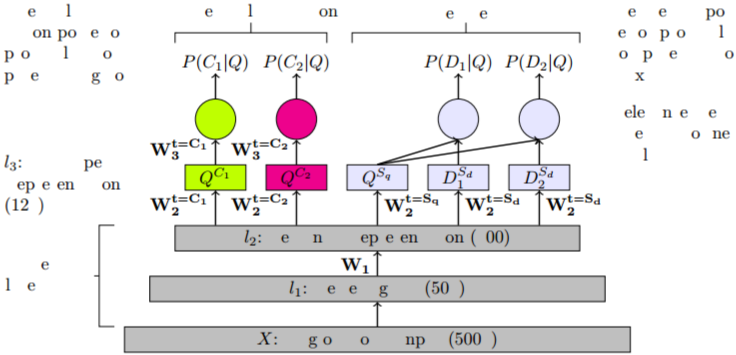


Figure 2: A DNN model for classification and a DSSM model (Huang et al., 2013) for ranking.

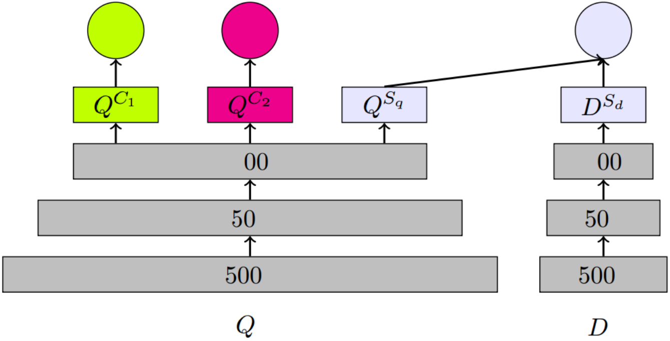
Multi-task DNN for Semantic Classification and Information Retrieval

- The Multi-task DNN for Semantic Classification and Information Retrieval :



Multi-task DNN for Semantic Classification and Information Retrieval

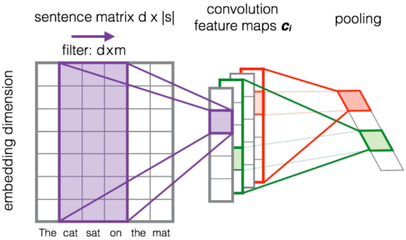
- Alternative Model :



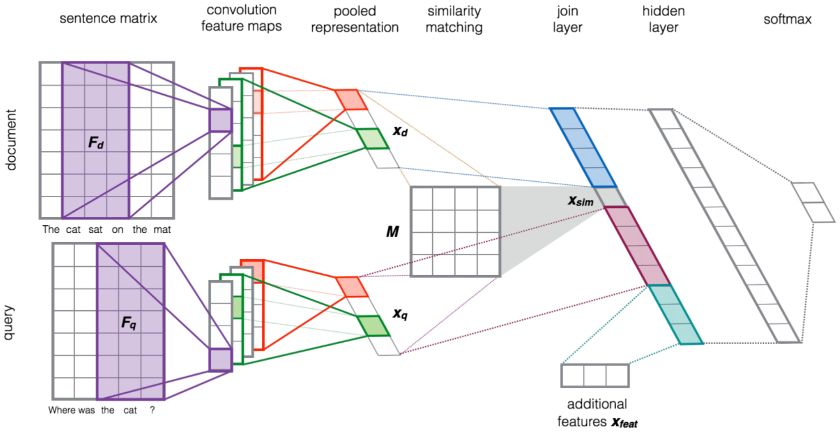
- It achieves good results in query classification at the expense of web search.

CNN for ranking pairs of short texts

- We are given a set of retrieved lists, where each query $q_i \in \mathbf{Q}$ comes together with its list of candidate documents $\mathbf{D}_i = \{d_{i_1}, d_{i_2}, ..., d_{i_n}\}$.
- The candidate set comes with their relevancy judgements $\{y_{i_1}, y_{i_2}, ..., y_{i_n}\}$, where documents that are relevant have labels equal to 1 and 0 otherwise.
- The goal is to build a model that for each query q_i and its candidate list $\mathbf{D}_i$ generates an optimal ranking.



CNN for ranking pairs of short texts



CNN for ranking pairs of short texts

- The similarity between x_q and x_d vectors as follows:

$$sim(x_q, x_d) = x_q^T M x_d$$

  where $M \in \mathbb{R}^{d \times d}$ is a similarity matrix.

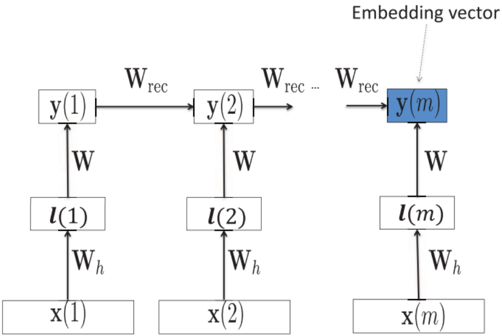
- The model is trained to minimize the cross-entropy function:

$$\begin{aligned} C &= -\log \prod_{i=1}^{N} p(y_i | q_i, d_i) + \lambda \|\theta\|_2^2 \\ &= -\sum_{i=1}^{N} [y_i \log a_i + (1 - y_i) \log(1 - a_i)] + \lambda \|\theta\|_2^2 \end{aligned}$$

  where a is the output from the softmax layer.

Deep Sentence Embedding Using LSTM

- The basic RNN structure



Deep Sentence Embedding Using LSTM

- We use the RNN with LSTM cells.
- We adopt the cosine similarity between the semantic vectors of two sentences as a measure for their similarity :

$$R(Q, D) = \frac{y_Q(T_Q)^T y_D(T_D)}{\|y_Q(T_Q)\| \|y_D(T_D)\|}.$$

  where T_Q and T_D are the lengths of the sentence Q and sentence D, respectively.
- Objective function :

$$L(\Lambda) = \min_{\Lambda} \left\{ -\log \prod_{r=1}^{N} P(D_r^+ | Q_r) \right\}$$

  where $P(D_r^+ | Q_r) = \frac{\exp(\gamma R(Q_r, D_r^+))}{\sum_{D' \in \mathbf{D}_r} \exp(\gamma R(Q_r, D'))}$ and $\mathbf{D}_r = \{D_r^+, D_{r,1}^-, ..., D_{r,n}^-\}$.

Deep Learning Based Query Expansion

- Each term t is represented by a vector of predefined dimension v_t.
  - e.g. Word2vec
- The similarity between two terms t_1 and t_2 is measured with the normalized cosine between their two vectors v_{t_1} and v_{t_2}.

$$SIM(t_1, t_2) = \widetilde{\cos}(v_{t_1}, v_{t_2})$$

- Based on this normalized cosine similarity between terms, we define the function that returns the k-most similar terms to a term t, $top_k(t)$.
- Building Expanded Query
  - The expanded query q' is defined as follows: $q' = q \cup_{t \in q} top_k(t)$.
  - The frequency of each $t \in q$ still the same in the expanded query q'.
  - The frequency of each expansion term $t' \in top_k(t)$ in the expanded query q' is given as follows :

$$\#(t', q') = \alpha \times \#(t, q') \times \widetilde{\cos}(v_t, v_{t'})$$

where $\alpha \in [0, 1]$ is a tuning parameter that determines the importance of expansion terms.

Reference

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