

# CLSM - Convolutional Latent Semantic Model

## A Latent Semantic Model with Convolutional-Pooling Structure for Information Retrieval

G10 - Moustafa AboulAtta, Martin Achtner, Ridon Arifi, Daniel Ehrhardt and Lukas Fichtner

### Introduction

- Modern search engines rely on semantic models for the retrieval of Web documents with search queries.
- These perform better than simple lexical models by combining words that appear in a similar context into semantic clusters.
- However existing models do mostly not consider the context of the words which can lead to unwanted results. (e.g. microsoft *office* ↔ apartment *office*)
- CLSM is taking the context into account and is thus able to achieve a better performance.

### CLSM Architecture

The CLSM consists of five layers (c. Figure 1) in the following order:

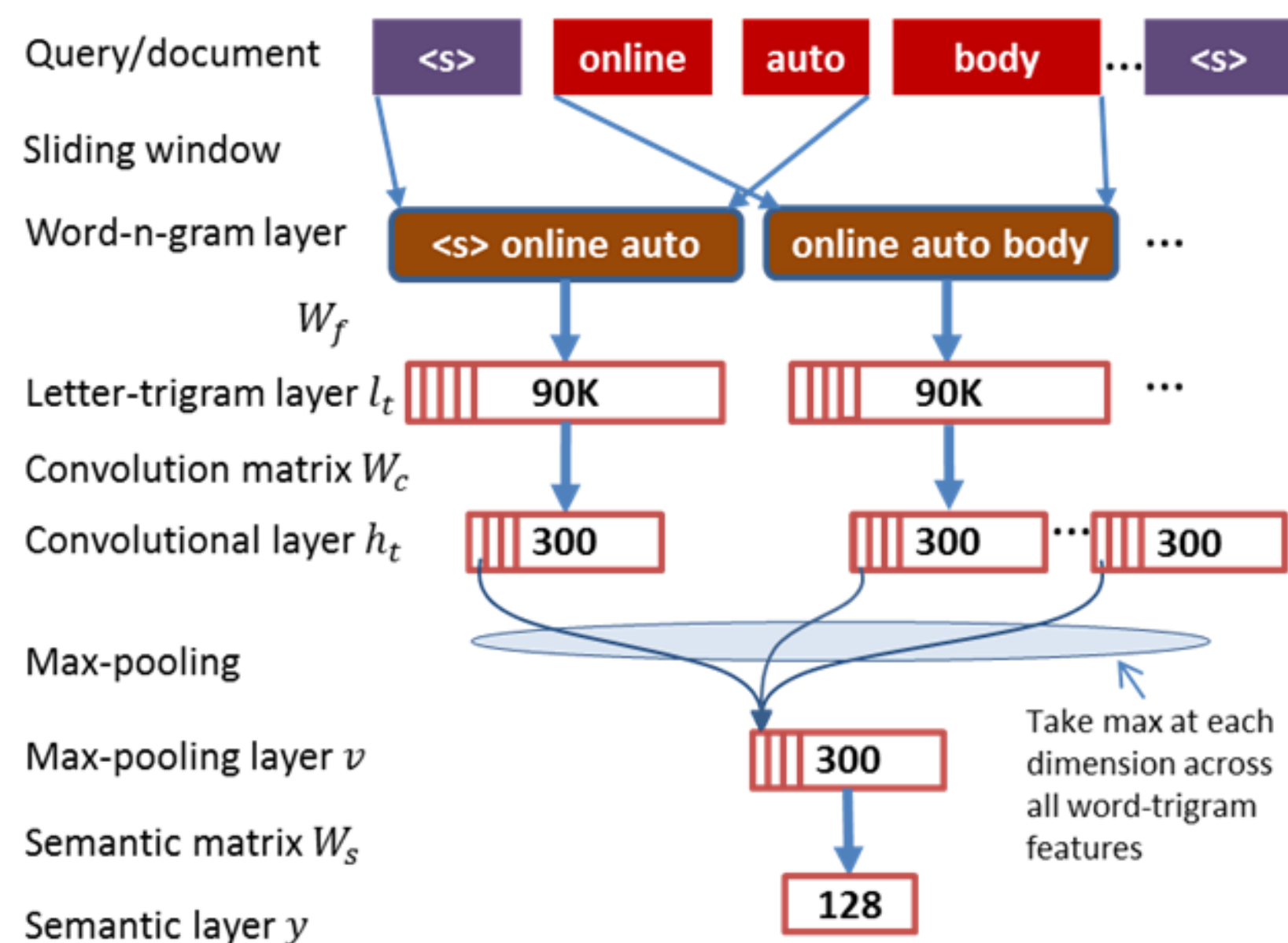


Figure 1: The Architecture of CLSM, Shen et al.

### Usage

- Use the CLSM model on the query and the documents
- Determine the matching documents via the cosine distance of the resulting vectors

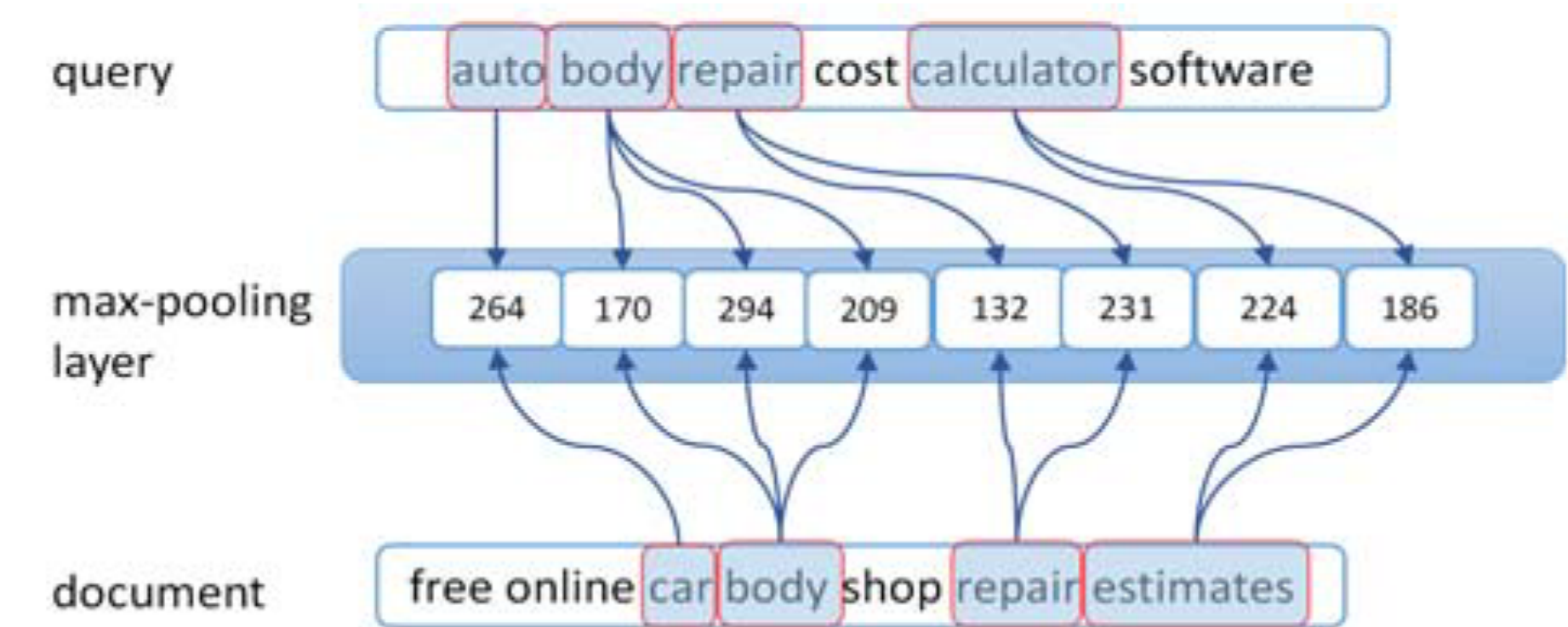


Figure 2: Semantic Matching on Maxpooling Layer, Shen et al.

### Learning

- Model parameters are trained to maximize the likelihood  $P(D+|Q)$  through the loss function.

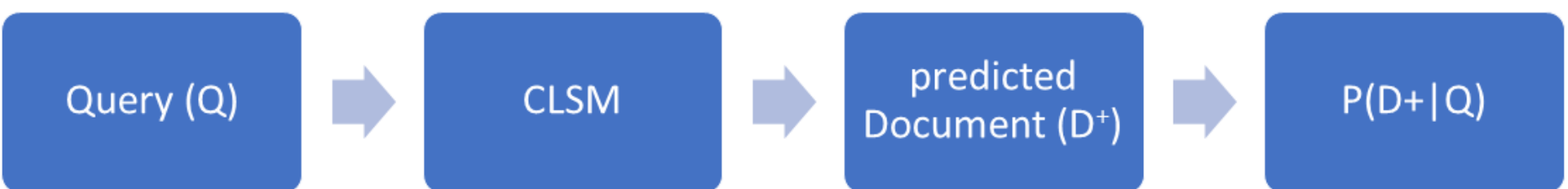


Figure 3: CLSM learning process

### Experiments and Results

| #   | Models               | NDCG@1                     | NDCG@3                     | NDCG@10                    |
|-----|----------------------|----------------------------|----------------------------|----------------------------|
| 1   | BM25                 | 0.305                      | 0.328                      | 0.388                      |
| 2   | ULM                  | 0.304                      | 0.327                      | 0.385                      |
| ... | ...                  | ...                        | ...                        | ...                        |
| 11  | PTM (maxlen = 3)     | 0.319 <sup>α</sup>         | 0.347 <sup>α</sup>         | 0.413 <sup>α</sup>         |
| 12  | DSSM (J = 4)         | 0.320 <sup>α</sup>         | 0.355 <sup>α</sup>         | 0.431 <sup>α</sup>         |
| 13  | DSSM (J = 50)        | 0.327 <sup>αβ</sup>        | 0.355 <sup>αβ</sup>        | 0.431 <sup>αβ</sup>        |
| 14  | CLSM (J = 4)         | 0.342 <sup>αβγ</sup>       | 0.374 <sup>αβγ</sup>       | 0.447 <sup>αβγ</sup>       |
| 15  | <b>CLSM (J = 50)</b> | <b>0.348<sup>αβγ</sup></b> | <b>0.379<sup>αβγ</sup></b> | <b>0.449<sup>αβγ</sup></b> |

Table 1: Comparison between state-of-the-art approaches. Superscripts  $\alpha, \beta$ , and  $\gamma$  indicate statistically significant improvements over **BM25**, **PTM**, and **DSSM (J = 50)**, respectively.

- DSSM and CLSM are closely related in terms of the architecture and it is therefore feasible to compare them closer:

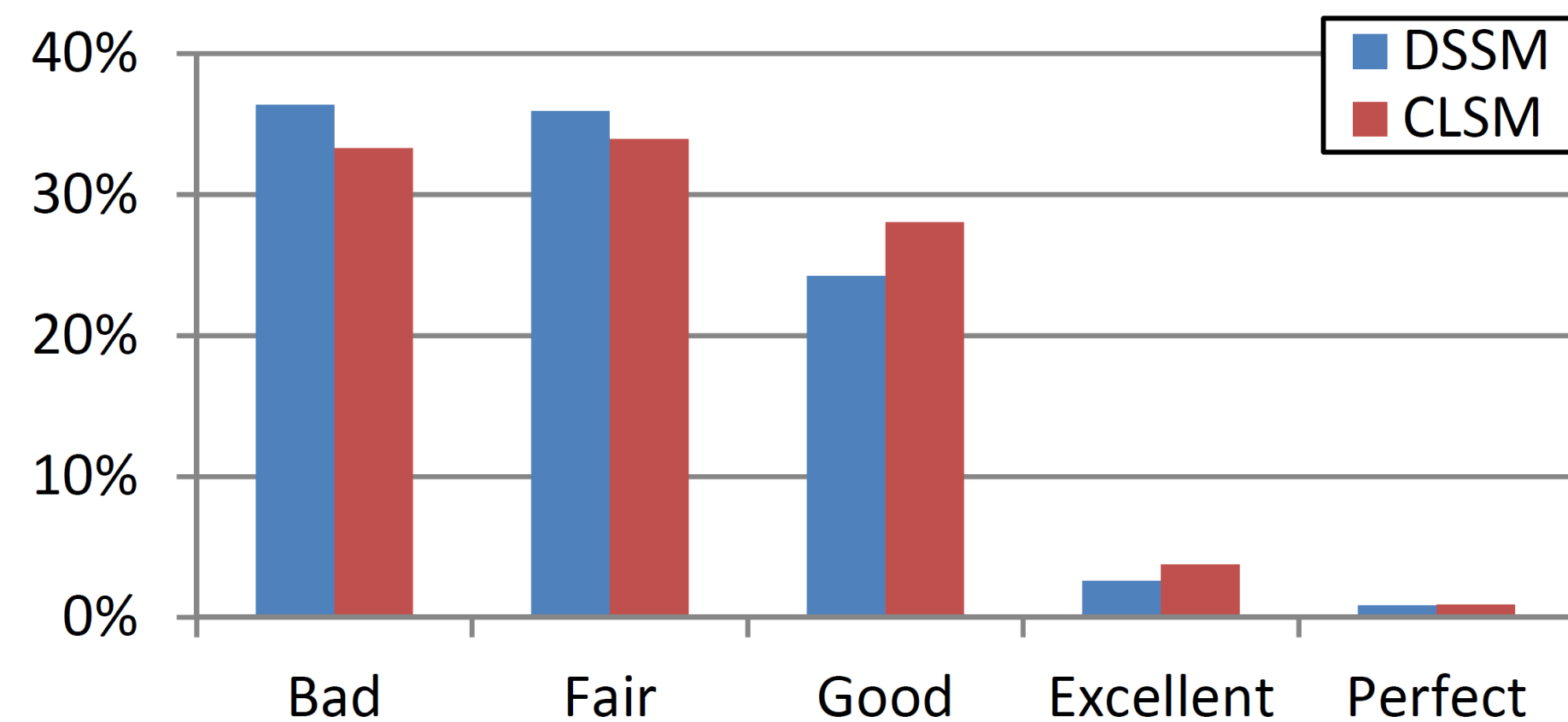


Figure 4: Comparison of DSSM <sup>a</sup> and CLSM regarding qualification quality  
<sup>a</sup> Deep Structured Semantic Model