SFU

NLPCorps

E-Ranked: Product Search Relevance Tool

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Contributions

- We provided a method that will help E-commerce companies to provide better search results.
- Our method extends (Ahmad et al., 2019)'s Context Attentive Document Ranking approach.
- We provide examples that shows our method is better than current search suggestions used in the industry.

Example Corpus

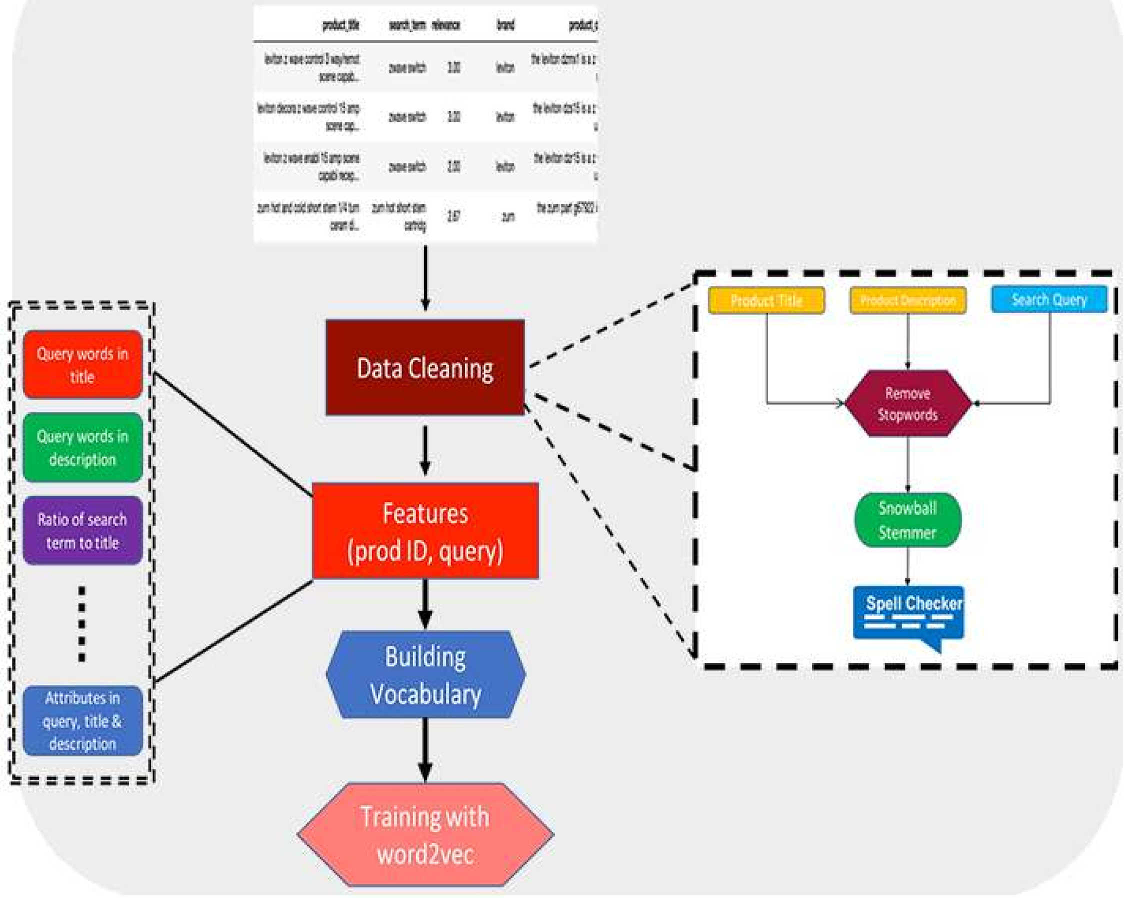
Query entered by the user — Relevancy of search result as per query — Rank of result as per relevancy

id	product_uid	product_title	search_term	relevance	brand	product_description	rank
122225	141628	leviton z wave control 3 way/remot scene capab...	zwave switch	3.00	leviton	the leviton dzmx1 is a z wave enabl univers di...	2
123081	142033	leviton decora z wave control 15 amp scene cap...	zwave switch	3.00	leviton	the leviton dzs15 is a z wave enabl univers sw...	3
107899	134888	leviton z wave enabl 15 amp scene capabl recep...	zwave switch	2.00	leviton	the leviton dzr15 is a z wave enabl univers sw...	7
186707	179212	zurn hot and cold short stem 1/4 turn ceram di...	zurn hot short stem cartridg	2.67	zurn	the zurn part g67922 is a cartridg repair kit ...	1

Objectives

1. Combine novel architecture to real world issue
2. Improve e-commerce experience for users by providing relevant results
3. Uniquely working on context of product information rather than just words.
4. Ranking two similar relevancies (with different product information) according to their cosine score.

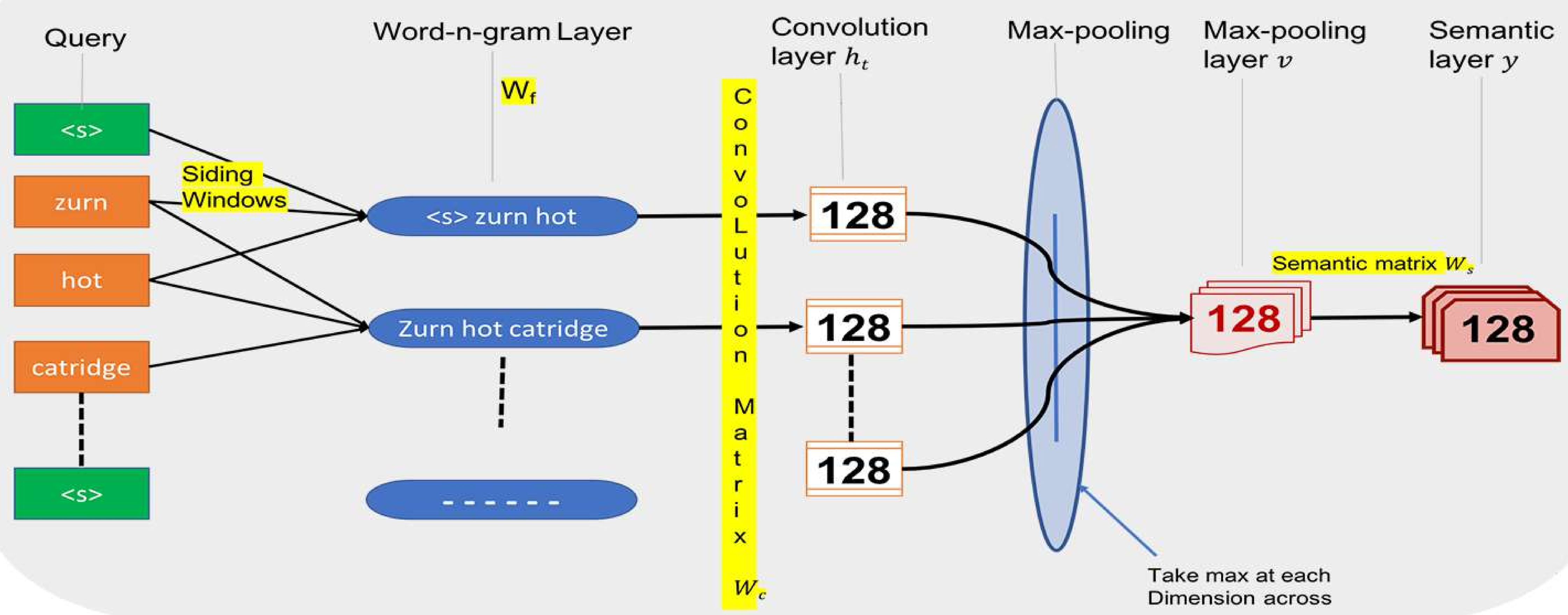
Baseline Model



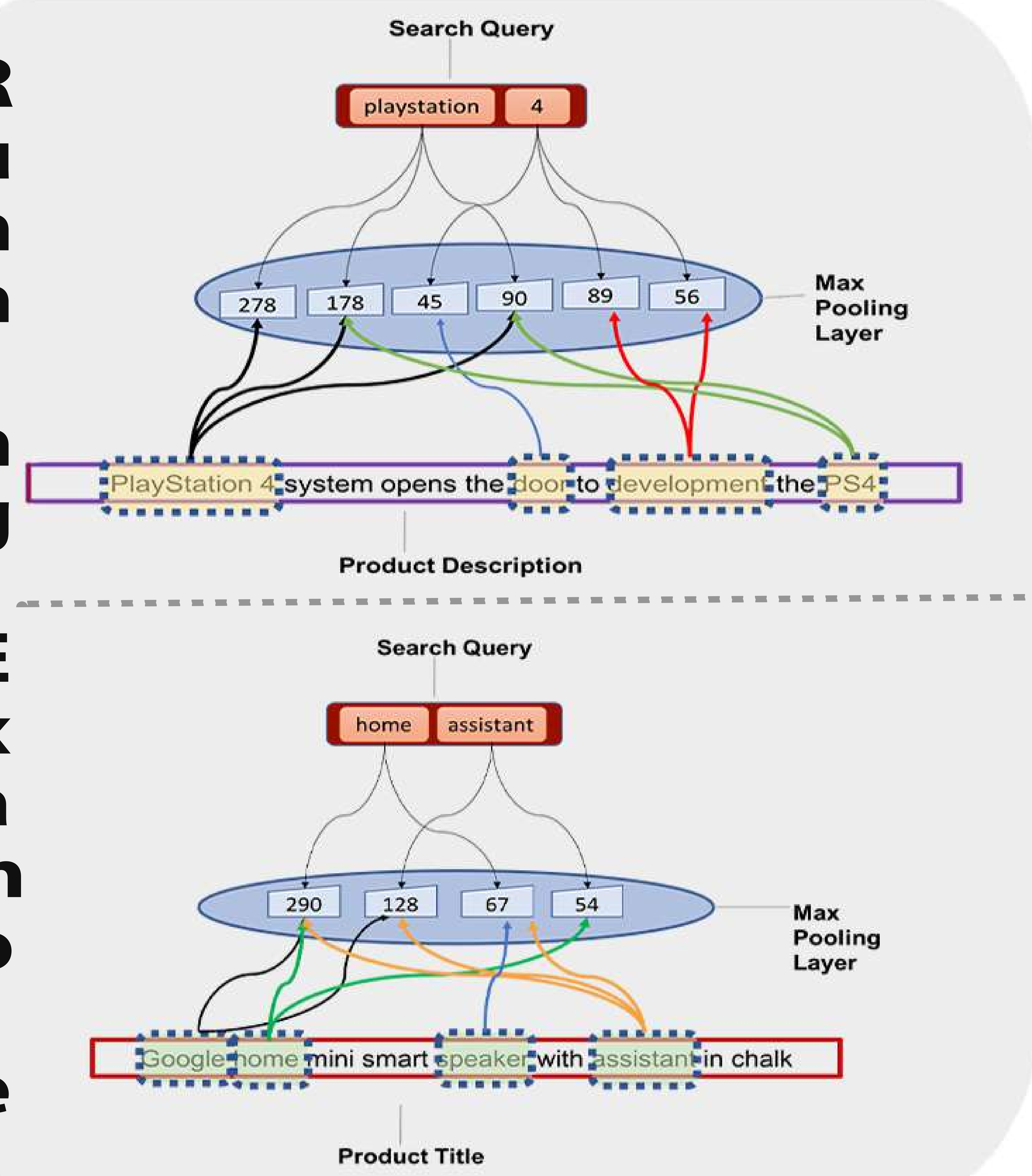
Deep-Learning Algorithm

- **Word-n-gram Representation**:
  $lt = [f_{t-d}^T, \dots, f_t^T, \dots, f_{t+d}^T]^T, t = 1, \dots, T \text{ and } d = (n-1)/2$
  l_t=representation of word-n-gram and f_t is t^{th} word and n is the sliding window of size n=2d+1
- **Convolution Layer:**
  $h_t = \tanh(Wc \cdot lt)$
  ht is contextual feature vector and Wc is feature transformation matrix
- **Max Pooling:**
  $v(i) = \max_{t=1\dots t}[h_t(i)], i = 1, \dots, k$
  Retain most useful features, k= dimension of h_t
- **Semantic layer:**
  $y = \tanh(Ws \cdot v)$
  Ws is semantic projection matrix and y is vector representation of input query
- **Semantic relevance Score calculation:**
  $R(Q, D) = cosine(y_Q, yD) = \frac{y_Q^T yD}{\|y_Q\| \|y_D\|}$, y_Q and yD are semantic vectors of query Q and text D
- **Training:**
  $P(D^+|Q) = \frac{exp(\gamma R(Q, D^+))}{\sum_{D' \in D} exp(\gamma R(Q, D'))}$, γ is smoothing factor
- **Loss:**
  $l(x, y) = \{l_1, \dots l_N\}^T; l_n = (x_n - y_n)^2$

ARCHITECTURE

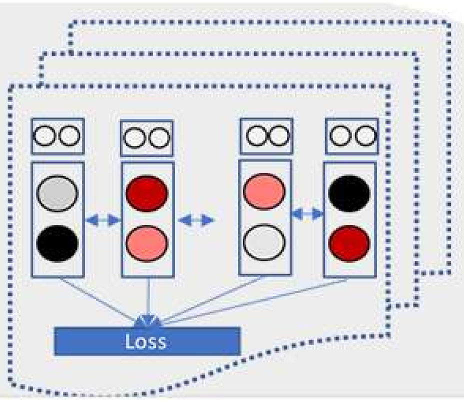


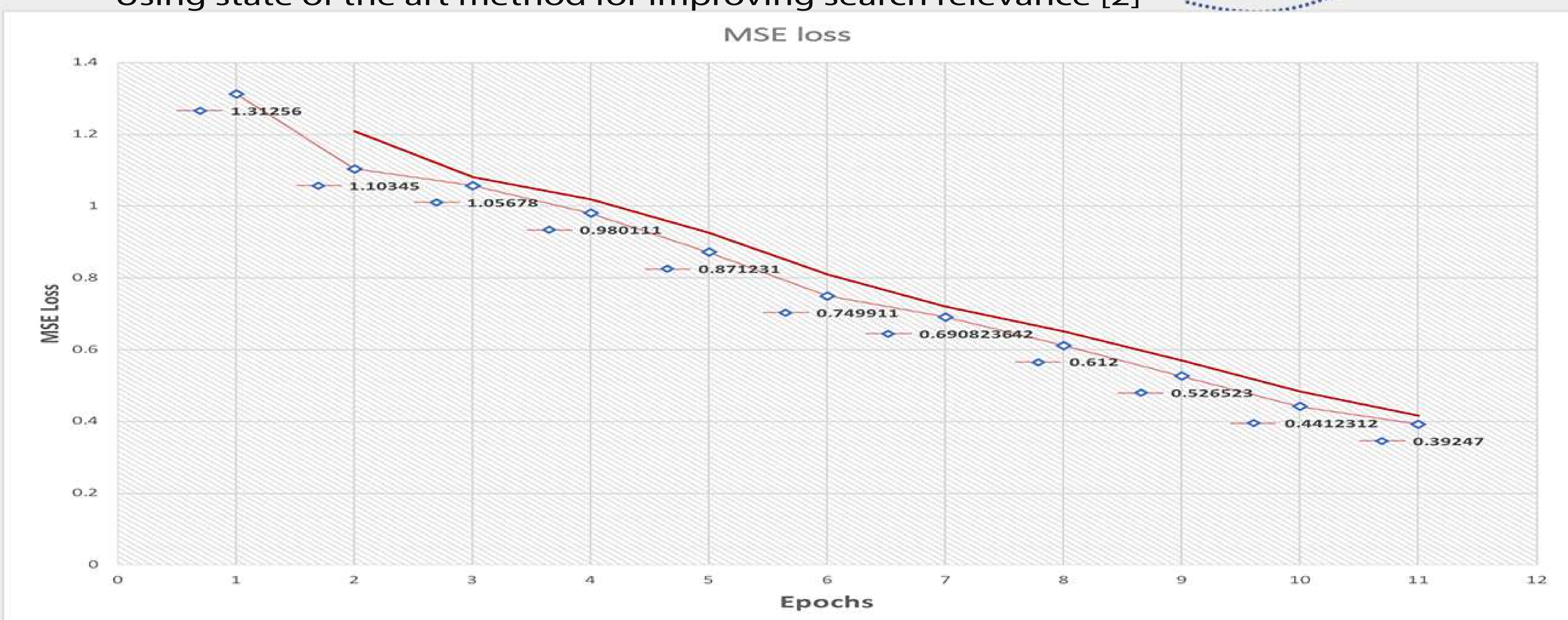
Running Example



Result

- **Task:** Improve loss on ranked searches
- **Training/Tuning** the search data:
  -Home Depot + crowdflower's data
- **Methods:**
  - Using Gensim modelling by vocab building [1]
  - Using state of the art method for improving search relevance [2]





- ***Reduced the loss to ~ 0.39 for giving relevant results***

Model Comparison

Working
- Baseline model finds the suitable match for every single word in query.
- E-Ranked model sees the query and finds the similar context.

Modelling
- Building vocabulary and pretrained embeddings for lookups
- Follows a complex architecture of making a pool and finding semantic relations with product information.

Uniqueness/Improvement
- Most companies follow this approach of finding relations according to each word and miss out on the context.
- E-Ranked provides a unique way of utilizing state-of-the-art model in a real-world problem to better user-experience.

Future Work

1. Understanding the context of product features based on the search query (a good metric to break the tie).
2. Given more data of user clicks, add as an additional feature to determine the relevance being produced by the model.
3. In the future, we also plan to use pre-trained embeddings coupled with our changes to enhance the performance of our model.
4. We plan to find a more diverse set of data.

References

[1] gensim: modelling using word2vec (n.d.). Retrieved from https://radimrehurek.com/gensim/models/word2vec.html.
[2] Shen, Yelong.et al."A Latent Semantic Model with Convolutional-Pooling Structure for Information Retrieval." Proc of the 23rd ACM CIKM 2014