



A Deep Relevance Model for Zero-Shot Document Filtering

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Overview:

- **Document filtering** is the task to separate relevant documents from the irrelevant ones for a specific topic
- **Zero-shot** means the instances of targeted categories are unseen during training phase

Motivation and Objective:

- In the era of big data, the potentially possible categories covered by documents would be limitless, we have to do filtering for **unseen** categories in many situations
- We propose a novel **deep relevance model** for **zero-shot document filtering** (named **DAZER**) by modeling the hidden feature interactions between the documents and category in the word embedding space

Approach:

➤ Interaction-based representation

- A category is represented by a set of seed words $|S_c|$, the embedding of category can be obtained as follow:

$$e_c = \frac{1}{|S_c|} \sum_{s \in S_c} e_s$$

- Interaction-based representation between word and category can be got as follow:

$$e_{c,w}^{diff} = e_c - e_w, e_{c,w}^{prod} = e_c \odot e_w$$

$$e_w^c = [e_w \oplus e_{c,w}^{diff} \oplus e_{c,w}^{prod}]$$

➤ Relevance signal extraction

- Convolution with k-max pooling:

$$r_i = W_1 e_{i-l:i+l}^c + b_1, r_d = [r_{k-max}^1 \oplus r_{k-max}^2 \oplus \dots \oplus r_{k-max}^m]$$

- Category-specific gate mechanism is applied after convolution operation to control the information flow:

$$a_c = \sigma(W_2 e_c + b_2), r_i = a_c \odot (W_1 e_{i-l:i+l}^c + b_1)$$

➤ Relevance aggregation

- Two fully-connected layers are applied to get relevance score:

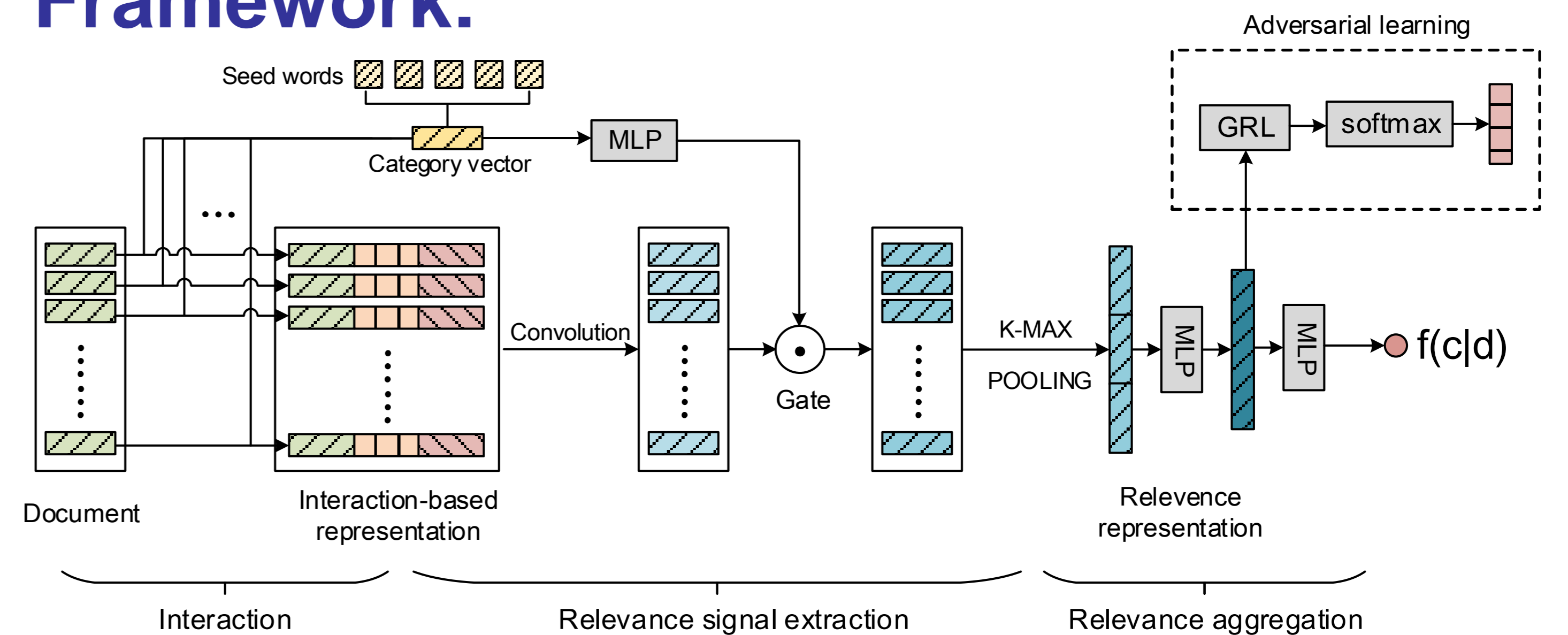
$$h_{c,d} = g_a(W_3 r_{c,d} + b_3), f(c|d) = \tanh(W^T h_{c,d} + b)$$

➤ Adversarial learning

- To ensure the extracted hidden feature $h_{c,d}$ contain no category-specific information, we introduce an adversarial classifier over hidden feature $h_{c,d}$:

$$p_{cat}(\cdot | h_{c,d}) = \text{softmax}(W_4 h_{c,d} + b_4)$$

Framework:



Experimental Results

- Dataset: 20-Newsgroup (18,846 documents) and Movie Review (5,006 movie reviews)
- Mean average precision

Dataset	Category	DAZER	DRMM	K-NRM	DeepRank	DSSM	SSVM	BM25
20NG	pc	0.535	<u>0.382</u> †	0.369†	0.144†	0.222†	0.117	0.313
	med	0.826	<u>0.662</u> †	0.645†	0.033†	0.192†	0.104	0.403
	baseball	0.764	0.731†	<u>0.735</u> †	0.294†	0.373†	0.291	0.414
	space	0.780	0.593†	<u>0.671</u> †	0.285†	0.142†	0.140	0.641
	med-space	0.805	0.640†	<u>0.666</u> †	0.101†	0.174†	0.122	0.522
	atheism-electronics	0.464	0.242†	0.346†	<u>0.418</u> †	0.219†	0.132	0.263
	christian-mideast	0.712	<u>0.662</u> †	0.657†	0.298†	0.327†	0.161	0.579
	baseball-hockey	0.782	0.642†	<u>0.736</u> †	0.332†	0.135†	0.438	0.444
	pc-windows-electronics	0.489	0.274†	<u>0.379</u> †	0.183†	0.278†	0.120	0.314
Movie Review	very negative	0.290	0.119†	0.114†	0.097†	<u>0.216</u> †	0.080	0.134
	negative	0.807	0.528†	<u>0.557</u> †	0.423†	0.478†	0.236	0.090
	neural	0.798	<u>0.764</u> †	0.749†	0.686†	0.678†	0.365	0.007
	Positive	0.862	0.696	0.706†	0.655†	<u>0.753</u> †	0.300	0.090
	very positive	0.479	0.250†	<u>0.339</u> †	0.217†	0.271†	0.063	0.066
Avg		0.671	0.513	<u>0.548</u>	0.298	0.318	0.191	0.306

➤ Ablation test

Setting	very negative	negative	neural	positive	very positive
DAZER	0.29	0.807	0.798	0.862	0.479
- $e_{c,w}^{diff}$	0.246	0.773	0.776	0.847	0.453
- $e_{c,w}^{prod}$	0.258	0.779	0.785	0.847	0.43
-Gate	0.278	0.755	0.785	0.848	0.429
-Adv	0.261	0.779	0.776	0.827	0.444

➤ Zero-shot document filtering is more like a semantic matching task

➤ Proposed DAZER significantly achieves much better filtering performance on all tasks

➤ Each component contributes significantly positive for the filtering performance