

## Problem Definition & Motivation

- Previous studies show the effectiveness of using the word2vec's related terms for document retrieval when applying Generalized and Extended Translation models. (Rekabsaz et al. CIKM 2016, ECIR 2017, SIGIR 2017)
- The translation models however extend each query term independently and don't consider other query terms.
- To address the problem, we introduce a novel *explicit representation* based on the Skip-Gram (SG) model.
- We discuss our ideas of using the explicit representation and local information for query-specific related terms.

## Background

### Embedding with Negative Sampling

The SG model has two sets of vectors: term and context vectors and aims to optimize the following probability:

$$p(c|w) = \frac{\exp(V_w \tilde{V}_c)}{\sum_{c' \in W} \exp(V_w \tilde{V}_{c'})}$$

The Negative Sampling redefines it with the probability that the co-occurrence of terms is genuine:

$$p(y = 1|w, c) = \frac{\exp(V_w \tilde{V}_c)}{\exp(V_w \tilde{V}_c) + 1} = \sigma(V_w \tilde{V}_c)$$

$$J = - \sum_{\langle w, c \rangle \in X} \left[ \log p(y = 1|w, c) + k \mathbb{E}_{\tilde{c}_i \sim \mathcal{N}} \log p(y = 0|w, \tilde{c}_i) \right]$$

+ *subsampling* and *context distribution smoothing (cdfs)*

### Explicit Representation

PMI also assesses a genuine co-occurrence:

$$PMI(w, c) = \log \frac{p(w, c)}{p(w)p(c)}$$

$$PPMI(w, c) = \max(PMI(w, c), 0).$$

$$SPPMI(w, c) = \max(PMI(w, c) - \log(k), 0)$$

Levy and Goldberg 2014

SPPMI also considers *subsampling* and *cdfs* as follows:

$$PMI_\alpha(w, c) = \log \frac{p(w, c)}{p(w)p_\alpha(c)} \quad p_\alpha(c) = \frac{f(\langle w, . \rangle, X)^\alpha}{\sum_{w' \in W} f(\langle w', . \rangle, X)^\alpha}$$

## Explicit Skip-Gram Representation

### Theory & Definition

$$ExpSG(w, c) = p(y = 1|w, c) = \sigma(V_w \tilde{V}_c)$$

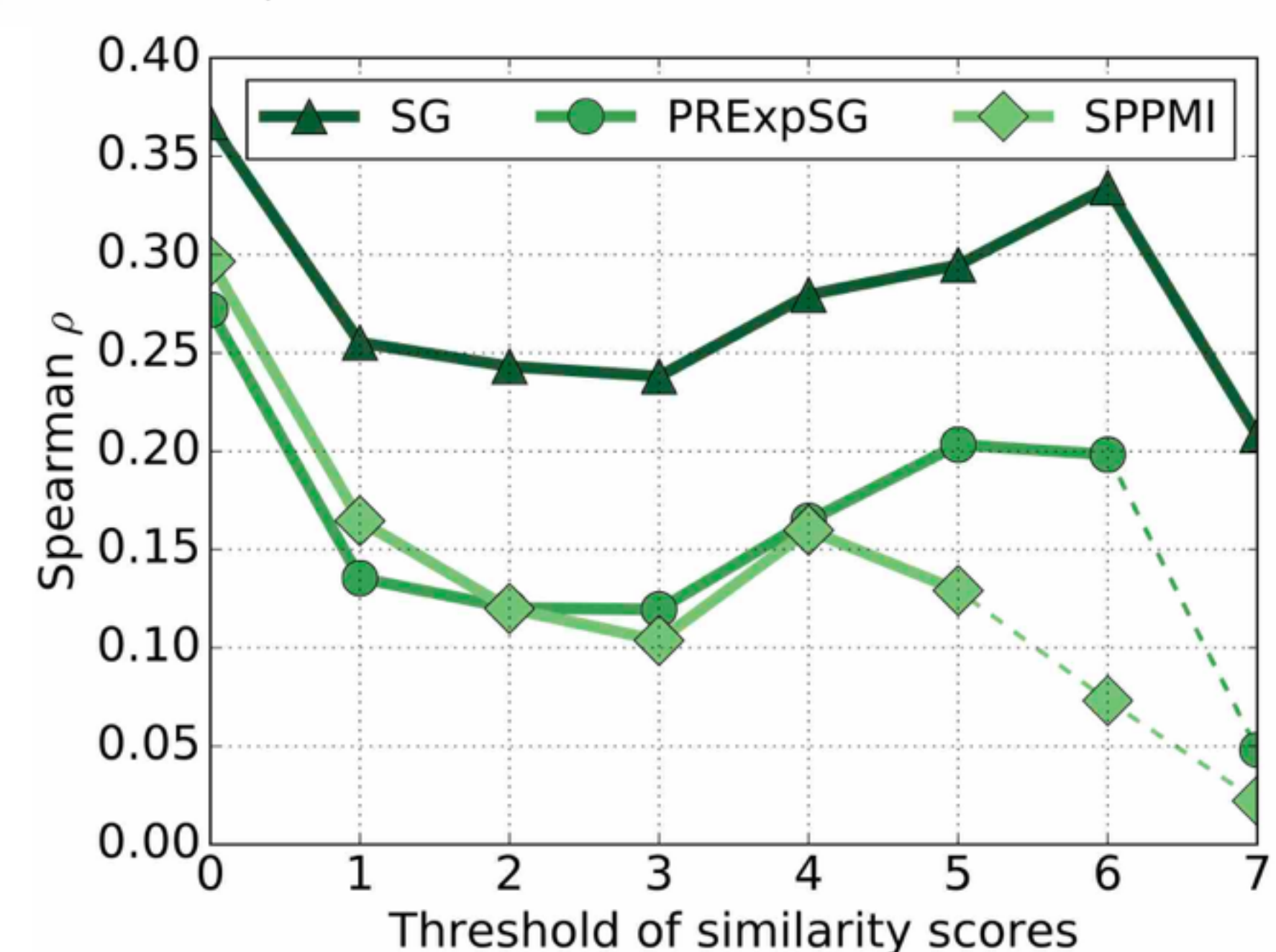
$$RExpSG(w, c) = ExpSG(w, c) - \mathbb{E}_{\tilde{c} \sim \mathcal{N}} p(y = 1|w, \tilde{c}) - \mathbb{E}_{\tilde{w} \sim \mathcal{N}} p(y = 1|\tilde{w}, c)$$

$$\mathbb{E}_{\tilde{w} \sim \mathcal{N}} p(y = 1|\tilde{w}, c) = \frac{\sum_{i=1}^{|W|} f(\tilde{w}_i, C) \cdot \sigma(V_{\tilde{w}_i} \tilde{V}_c)}{\sum_{i=1}^{|W|} f(\tilde{w}_i, C)} \quad \mathbb{E}_{\tilde{c} \sim \mathcal{N}} p(y = 1|w, \tilde{c}) = \frac{\sum_{i=1}^{|W|} f(\tilde{c}_i, C)^\alpha \cdot \sigma(V_w \tilde{V}_{\tilde{c}_i})}{\sum_{i=1}^{|W|} f(\tilde{c}_i, C)^\alpha}$$

$$PRExpSG(w, c) = \max(RExpSG(w, c), 0)$$

### Evaluation

Method	Sparsity	WS Sim.	WS Rel.	MEN	Rare	SCWS	SimLex
PPMI	98.6%	.681	.603	.702	.309	.601	.284
SPPMI	99.6%	<b>.722</b>	<b>.661</b>	.704	.394	.571	<b>.296</b>
ExpSG	0%	.596	.404	.645	.378	.549	.231
RExpSG	0%	.527	.388	.606	.311	.507	.215
PRExpSG	94.1%	.697	.626	<b>.711</b>	<b>.406</b>	<b>.614</b>	.272
SG	0%	<u>.770</u>	.620	<u>.750</u>	<u>.488</u>	<u>.648</u>	<u>.367</u>



## Integration of Local Information

Let us refer to each cell of the matrix of explicit vector representations as  $v(w, c)$

Based on the set of local documents ( $F$ ), we alter the cell values with the following formula:

Here are different suggestions for the function  $f$

$$f_1(w, c, F) = f_1(c, F) = \mathbb{1}[f(c, F) > 0]$$

$$f_2(w, c, F) = f_2(c, F) = \frac{p(c|F)}{p(c|C)} = \frac{f(c, F)/\sum_{d \in F} |d|}{f(c, C)/\sum_{d \in C} |d|}$$

$$f_3(w, c, F) = \frac{p(w, c|X_F)}{p(w, c|X_C)} = \frac{f(\langle w, c \rangle, X_F)/|X_F|}{f(\langle w, c \rangle, X_C)/|X_C|}$$

$$\hat{v}(w, c) = \frac{1}{1 + e^{-(a+b \cdot f(w, c, F))}} v(w, c)$$

$$f_4(w, c, F) = f_4(c) = p(c|\Theta_F) = \sum_{\theta_d \in \Theta_F} p(c|\theta_d) \prod_{q \in Q} p(q|\theta_d)$$

$$f_5(w, c, F) = p(w, c|\Theta_F) = \sum_{\theta_d \in \Theta_F} p(w|\theta_d) p(c|\theta_d) \prod_{i \in Q} p(q|\theta_d)$$