

Analogies Explained: Towards Understanding Word Embeddings



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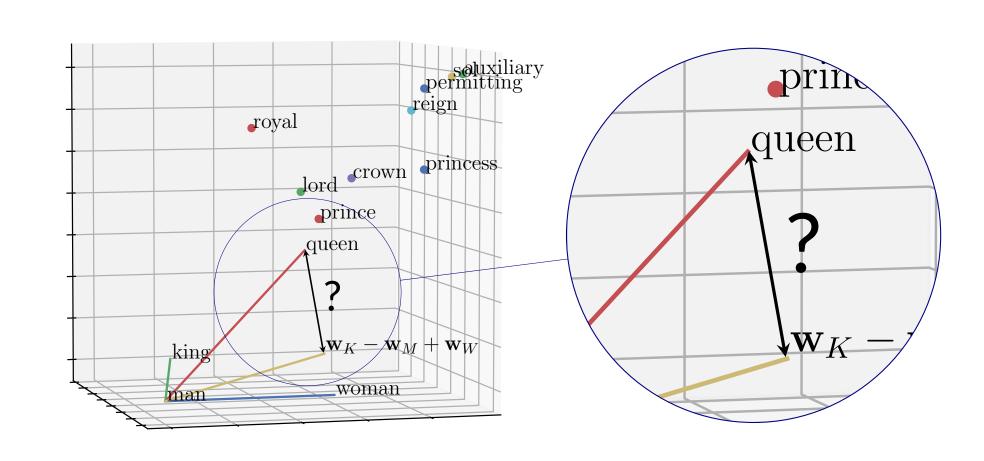


The Problem: linking semantics to geometry

from:

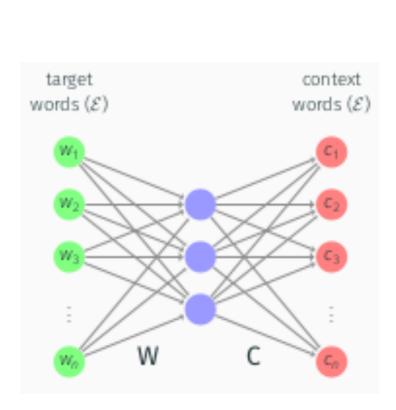
"man is to king as woman is to queen" explain:

 $\mathbf{w}_{king} - \mathbf{w}_{man} + \mathbf{w}_{woman} \approx \mathbf{w}_{queen}$ or rather:



Word2Vec: SkipGram with Negative Sampling

Mikolov et al. (2013a,b)

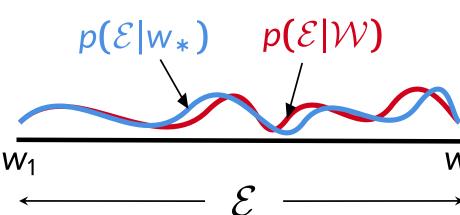


- $p(c_i|w_i)$ by **softmax** expensive
- use sigmoid with negative sampling (k)
- Levy and Goldberg (2014) $\mathbf{w}_{i}^{\mathsf{T}}\mathbf{c}_{j} \approx \log \frac{p(w_{i}, c_{j})}{p(w_{i})p(c_{i})} - \log k$

$$\mathbf{W}^{\mathsf{T}}\mathbf{C} \approx \mathbf{PMI} - \log k$$

Paraphrase[†] of W by w_*

Word $w_* \in \mathcal{E}$ paraphrases words $\mathcal{W} = \{w_1, ..., w_m\} \subseteq \mathcal{E}$, if w_* and W are semantically interchangeable.



Definition (D1): $w_* \in \mathcal{E}$ paraphrases $\mathcal{W} \subseteq \mathcal{E}$, $|\mathcal{W}| < I$, if paraphrase error $\rho^{w,w_*} \in \mathbb{R}^n$ is (element-wise) small:

$$\rho_j^{w,w*} = \log \frac{p(c_j|w_*)}{p(c_j|w)}, c_j \in \mathcal{E}$$

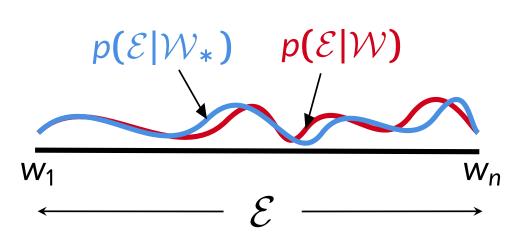
Paraphrase: $PMI_1 + PMI_2 \approx PMI_*$?

$$\begin{aligned} & \mathsf{PMI}(w_*, c_j) - \left(\mathsf{PMI}(w_1, c_j) + \mathsf{PMI}(w_2, c_j)\right) \\ &= \underbrace{\mathsf{log} \frac{p(c_j|w_*)}{p(c_j|\mathcal{W})}}_{\rho_j^{\mathcal{W}, w_*}} + \underbrace{\mathsf{log} \frac{p(\mathcal{W}|c_j)}{p(w_1|c_j)p(w_2|c_j)}}_{\sigma_j^{\mathcal{W}}} - \underbrace{\mathsf{log} \frac{p(\mathcal{W})}{p(w_1)p(w_2)}}_{\tau^{\mathcal{W}}} \\ & \mathsf{paraphrase} \\ & \mathsf{error} \end{aligned} \quad \underbrace{\mathsf{conditional}}_{\substack{\mathsf{independence} \\ \mathsf{error}}} \quad \underbrace{\mathsf{independence}}_{\substack{\mathsf{error}}} \end{aligned}$$

Lemma 1: For any word
$$w_* \in \mathcal{E}$$
, words $\mathcal{W} \subseteq \mathcal{E}$, $|\mathcal{W}| < I$:
$$PMI_* = \sum_{w \in \mathcal{W}} PMI_i + \rho^{\mathcal{W},w*} + \sigma^{\mathcal{W}} - \tau^{\mathcal{W}} 1$$

Generalised Paraphrase

Replace word w_* with word set $\mathcal{W}_* \subseteq \mathcal{E}$:



Lemma 2: For word sets W, $W_* \subseteq \mathcal{E}$, |W|, $|W_*| < l$: $\sum PMI_i = \sum PMI_i + \rho^{w,w_*} + \sigma^{w} - \sigma^{w_*} - (\tau^{w} - \tau^{w_*})1$

Linking semantics to geometry

So, if: $W = \{ woman, king \}$ paraphrases $\mathcal{W}_* = \{man, queen\},$ then: $PMI_{aueen} \approx PMI_{king} - PMI_{man} + PMI_{woman}$

Geometry links to semantics, but to the wrong relationship.

Word Transformation: changing perspective

A paraphrase w_* of \mathcal{W} can be thought of as a **word transformation** from some $w \in \mathcal{W}$ to w_* by adding: $\{man, royal\} \approx_p king \implies$

Adding *context* \implies induced distributions better align.

Similarly, consider paraphrase W of W_* as word transformation from a $w \in \mathcal{W}$ to $w_* \in \mathcal{W}_*$ by adding:

or adding to one side and *subtracting* from the other:



A generalised paraphrase *is* a word transformation from $w \in \mathcal{W}$ to $w_* \in \mathcal{W}_*$:

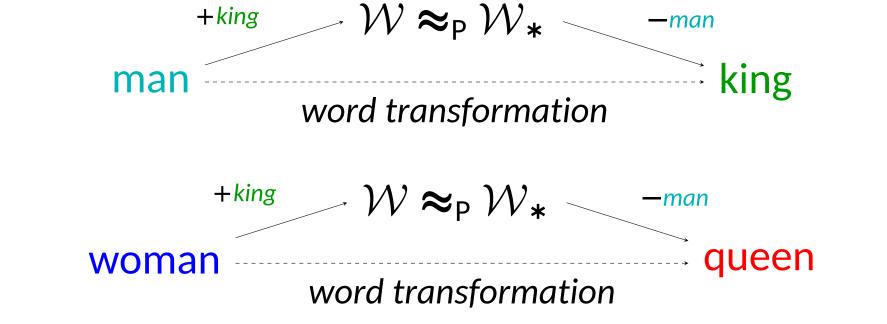
- added words narrow context
- subtracted words broaden context

Providing a "richer dictionary" to explain the difference between w and w_* , or, how "w is to w_* ".

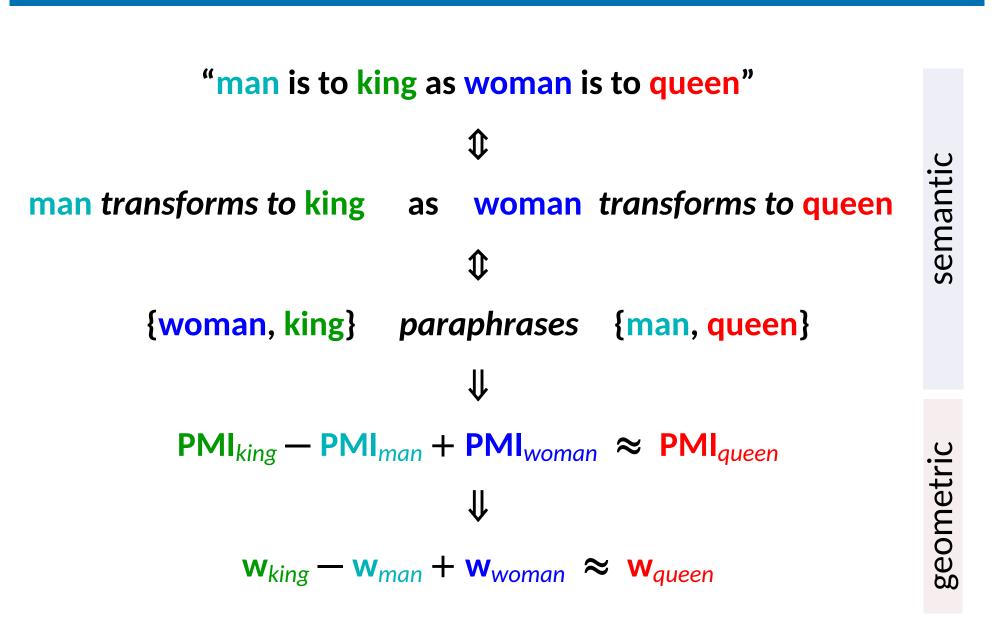
Definition (D4): We say " w_a is to w_{a*} as w_b is to w_{b^*} " iff there exist \mathcal{W}^+ , $\mathcal{W}^- \subseteq \mathcal{E}$ that simultaneously transform w_a to w_{a*} and w_b to w_{b*} .

We say: "man is to king as woman is to queen" iff $\exists \mathcal{W}^+, \mathcal{W}^- \subseteq \mathcal{E}$ that transform man to king and woman to queen.

w.l.o.g. choose $\mathcal{W}^+ = \{king\}, \mathcal{W}^- = \{man\}.$



Routemap

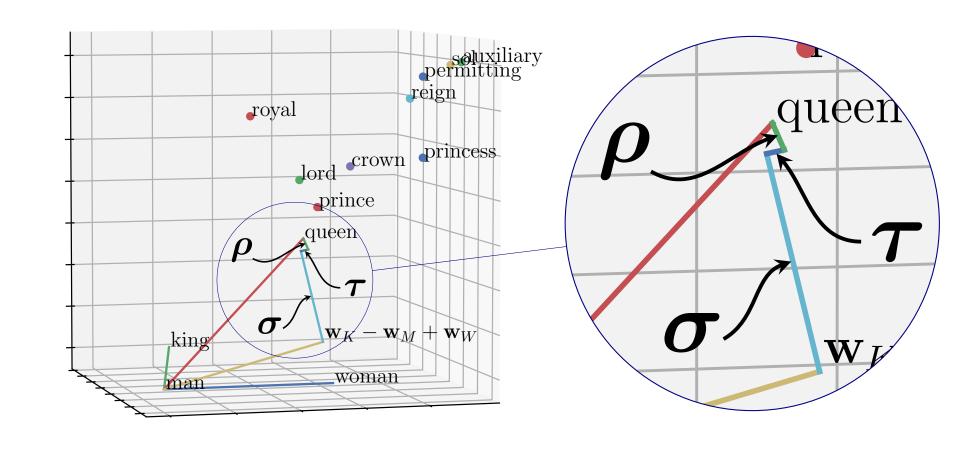


The Solution: linking semantics to geometry

"man is to king as woman is to queen"

implies:





References

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[†]Inspired by Gittens et al. (2017)