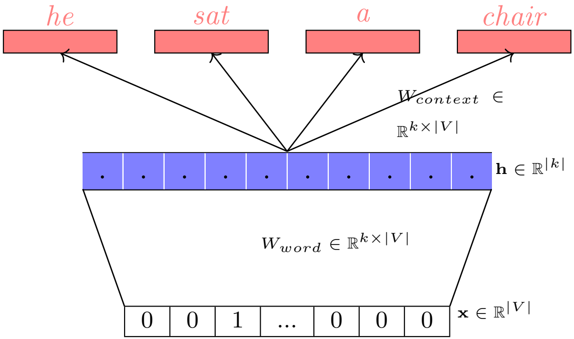
Module 10.10: Relation between SVD & word2Vec

The story ahead ...

- Continuous bag of words model
- Skip gram model with negative sampling (the famous word2vec)
- GloVe word embeddings
- Evaluating word embeddings
- Good old SVD does just fine!!



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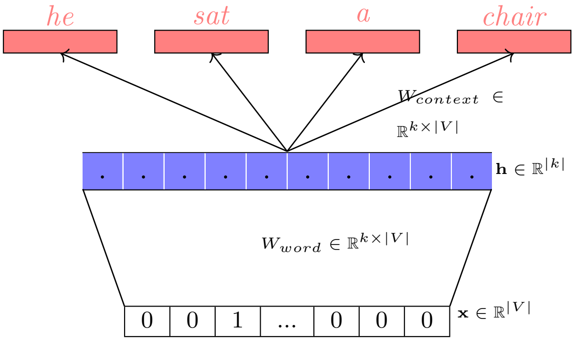

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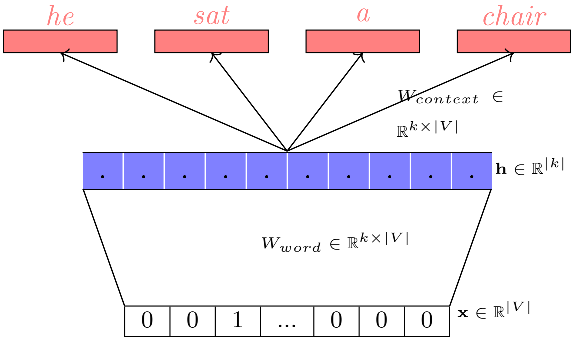

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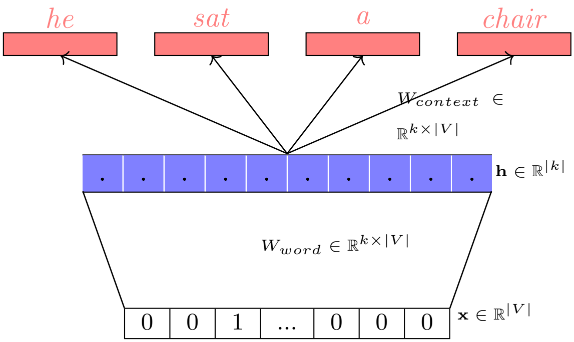

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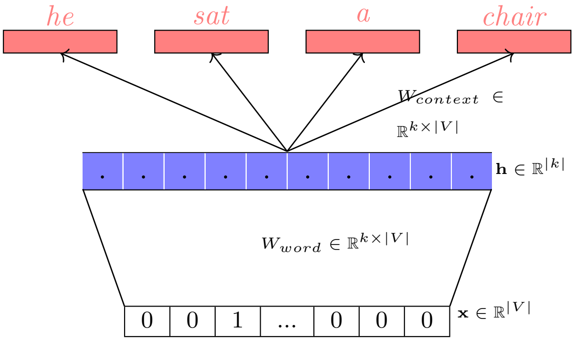

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- Turns out that we can also show that

$$M = W_{context} * W_{word}$$

where

$$M_{ij} = PMI(w_i, c_i) - log(k)$$

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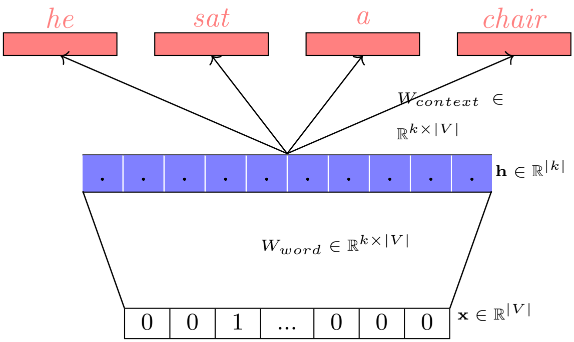

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- So essentially, word2vec factorizes a matrix M which is related to the PMI based co-occurrence matrix (very similar to what SVD does)