Word Vectors (Part 2)

CS114B Lab 7

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Distributed Representations of Words

- Representations of (contexts of) words as embeddings in some vector space
- Two approaches to distributed, distributional representations (Baroni et al. 2014):
  - Count-based
    - Count occurrences of words in contexts, optionally followed by some mathematical transformation (e.g. tf-idf, PPMI, SVD)
  - Prediction-based
    - Given some context vector(s) $\mathbf{c}$, predict some word $\mathbf{x}$ (or vice versa)
    - a.k.a. language modeling-based

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    - Examples: n-gram language models
      - Unigram: predict $P(\mathbf{x}_i)$
      - Bigram: predict $P(\mathbf{x}_i|\mathbf{x}_{i-1})$
      - Trigram: predict $P(\mathbf{x}_i|\mathbf{x}_{i-2}, \mathbf{x}_{i-1})$

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    - Examples: neural network language models
      - Feedforward: word2vec (Mikolov et al. 2013a, 2013b)
      - Recurrent:  (Peters et al. 2018)
      - Transformer:  (Devlin et al. 2019)

word2vec

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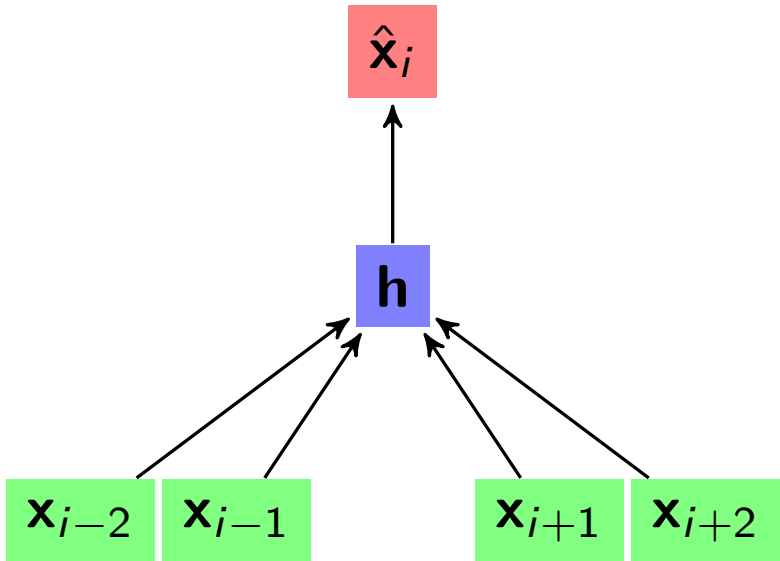
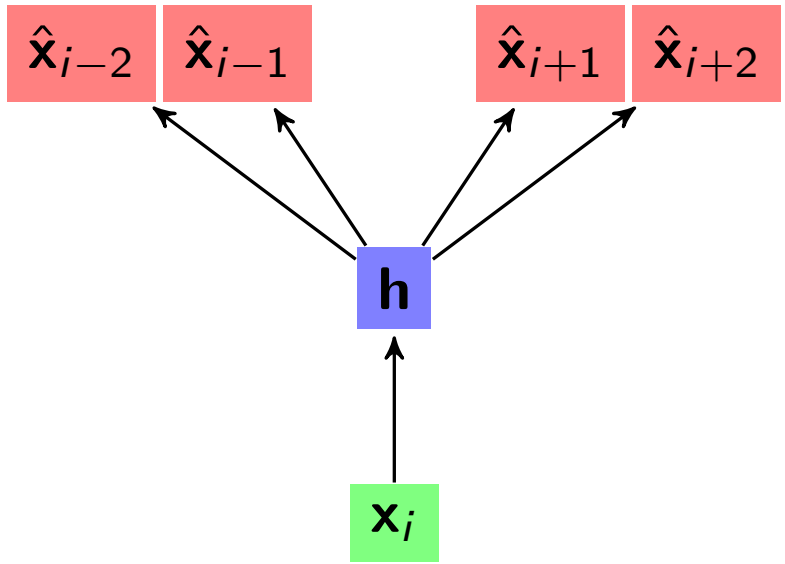


CBOW



Skip-gram

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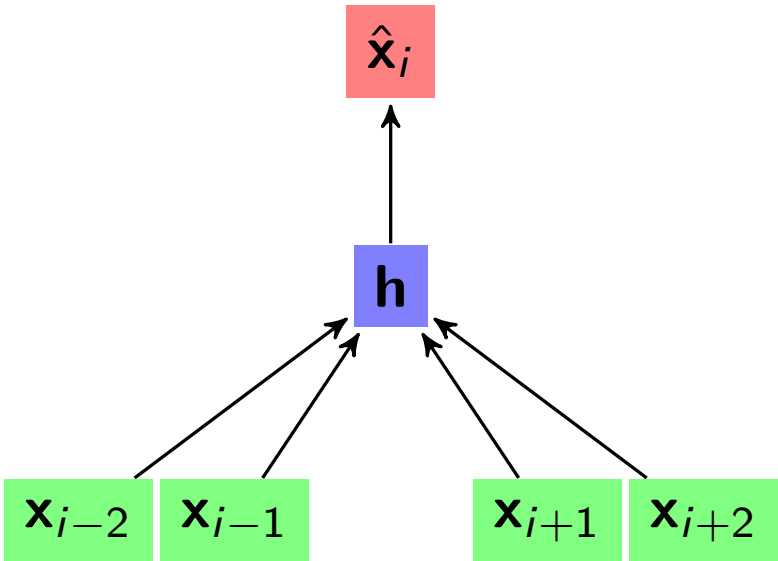

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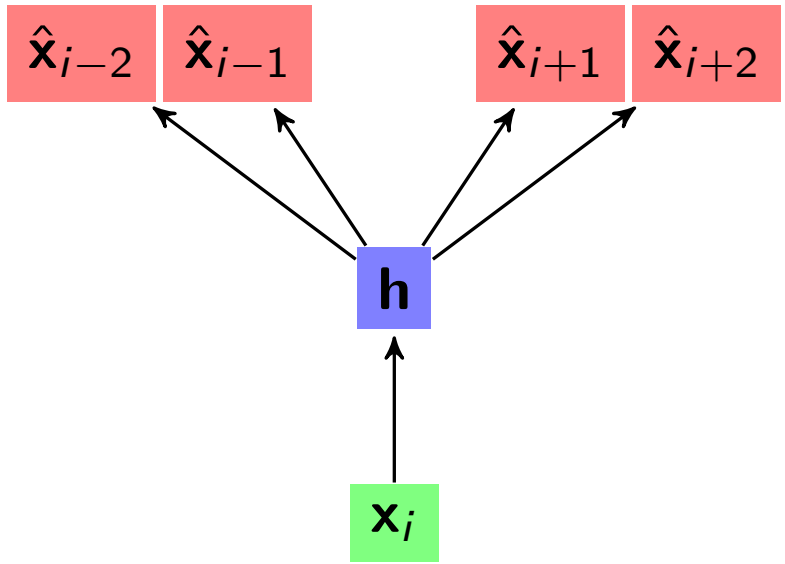

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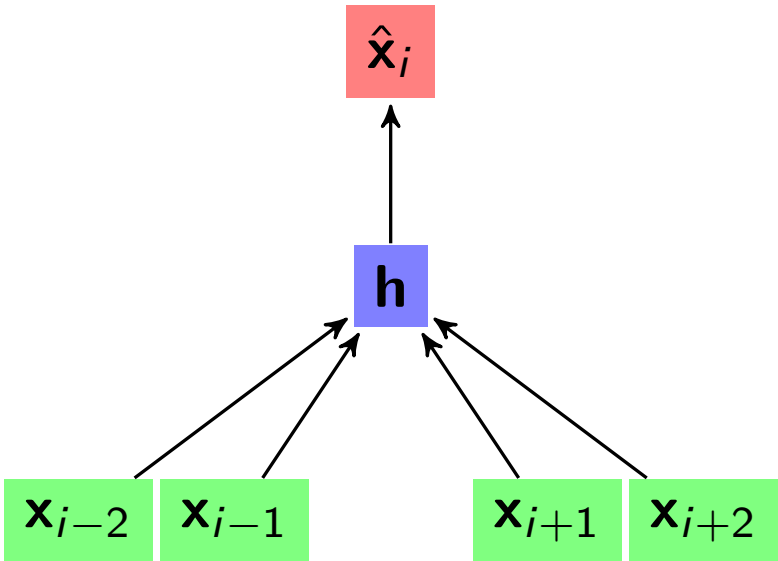

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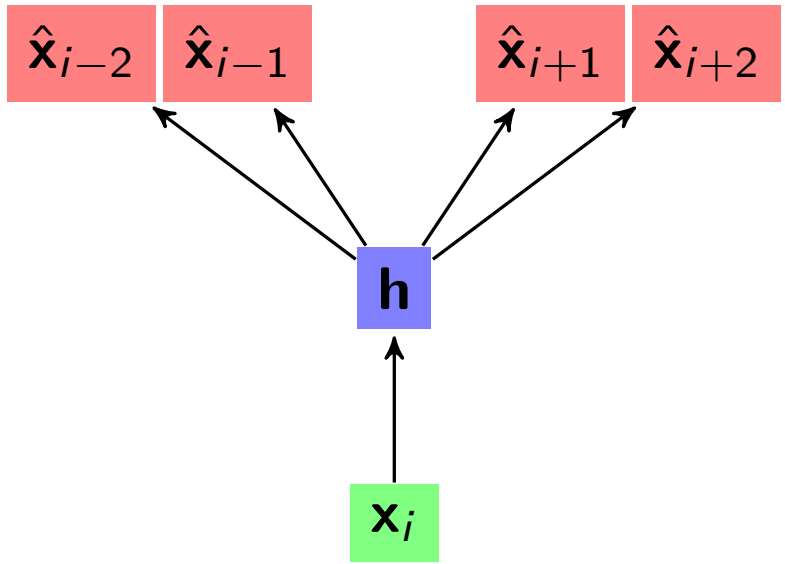

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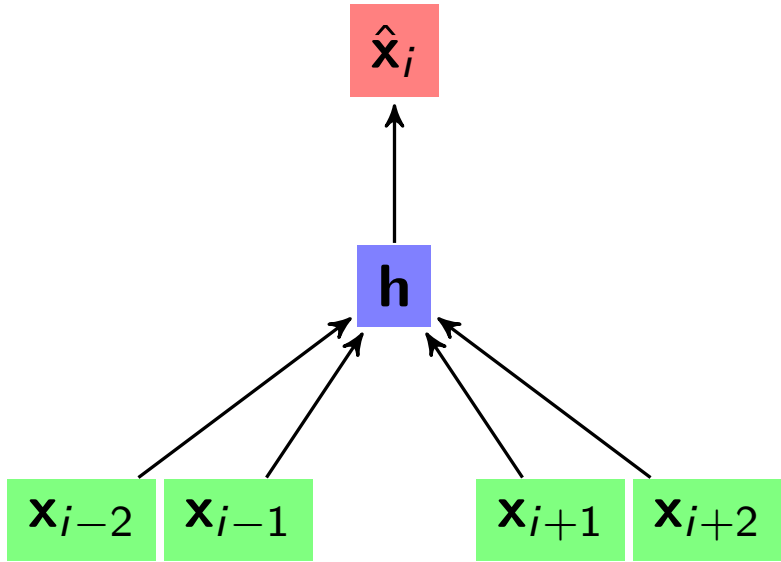

- Input layer: one-hot word vectors
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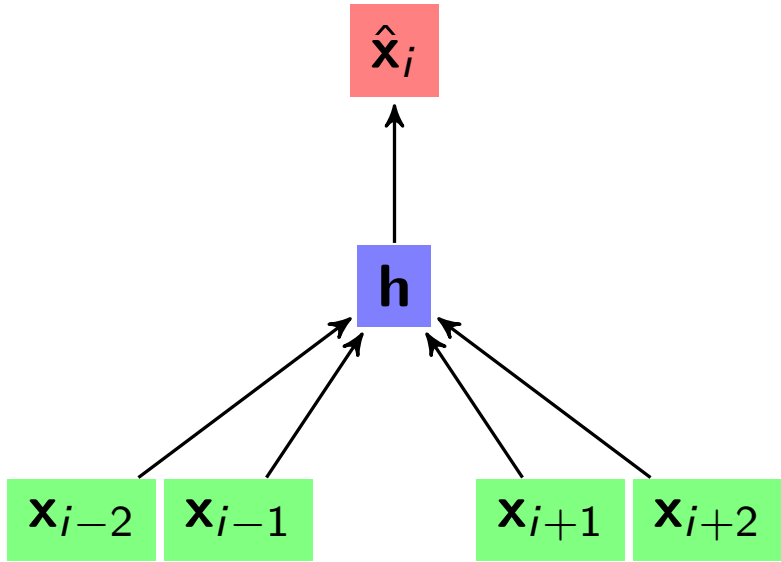

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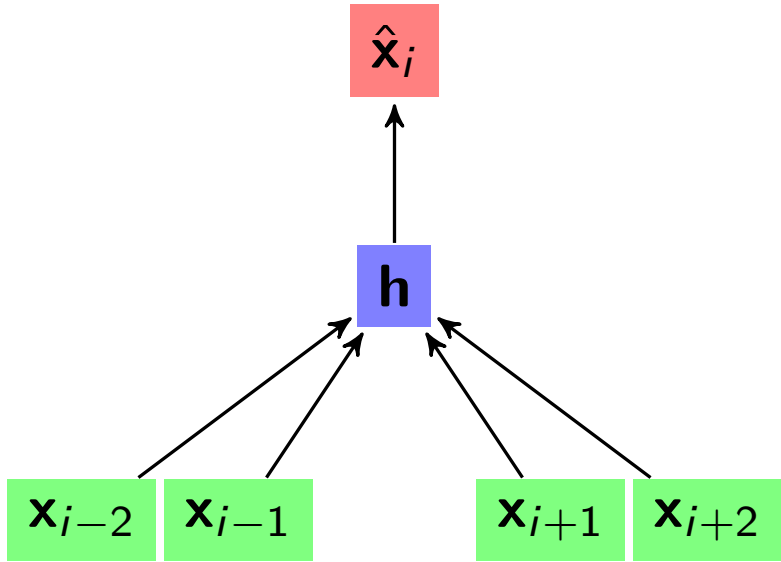

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  - Weight matrix shared for all context words

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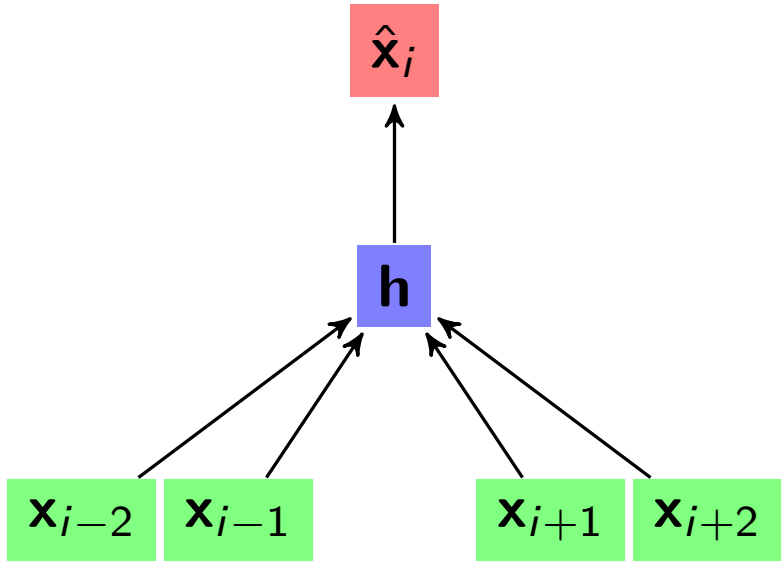

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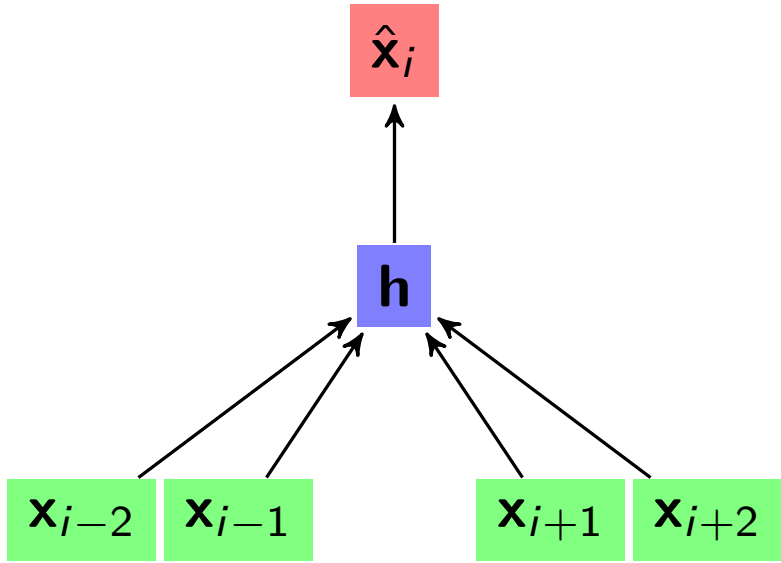

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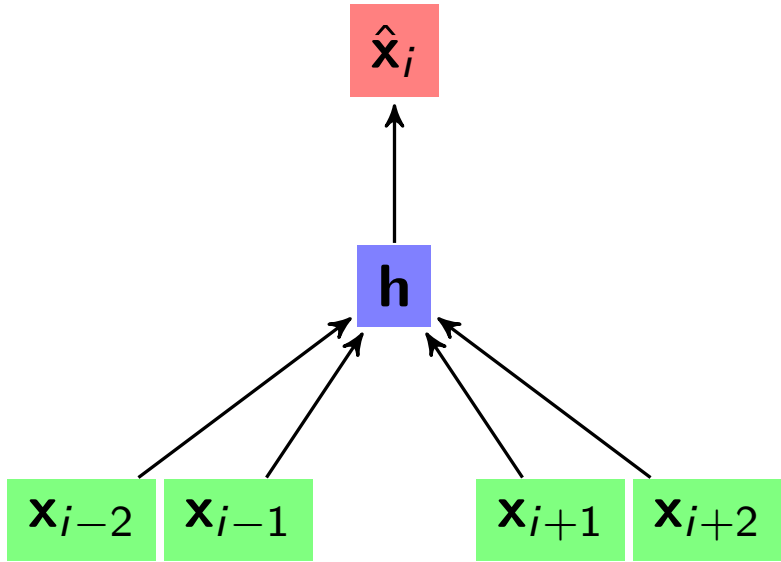
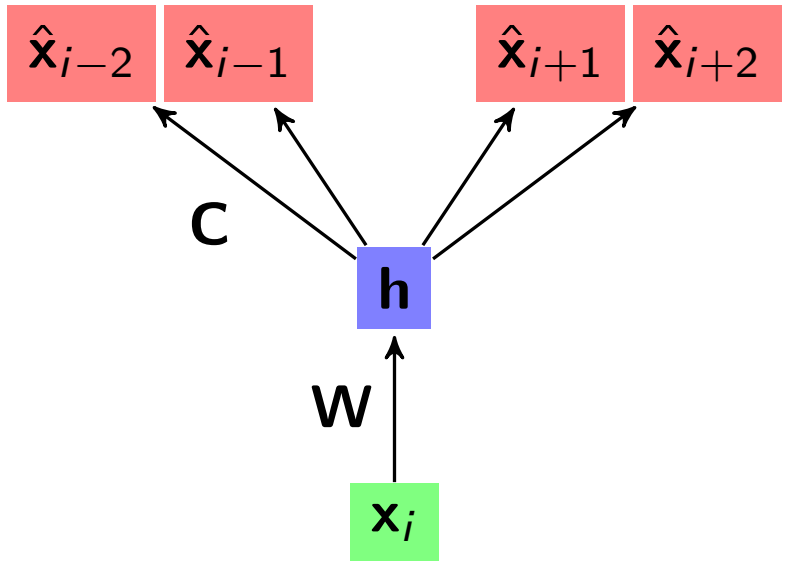


- Output layer: softmax activation function
  - Numbers $\rightarrow$ probabilities

Skip-gram



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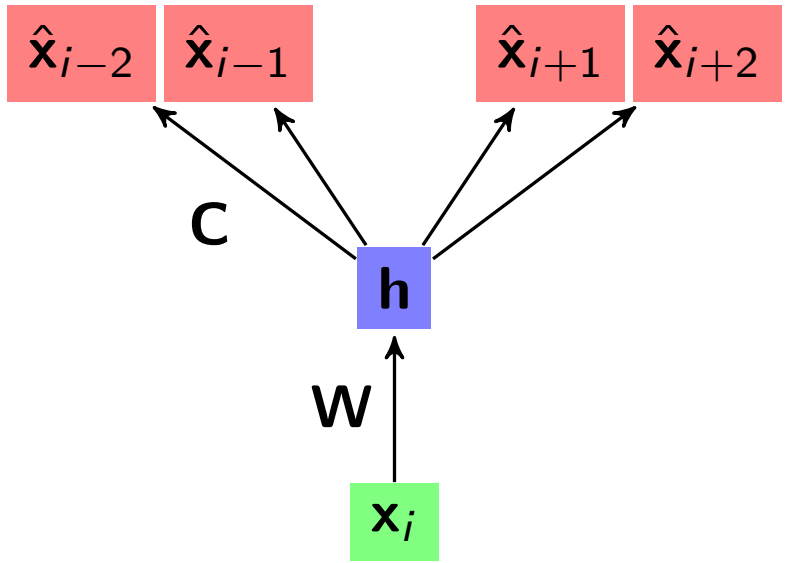

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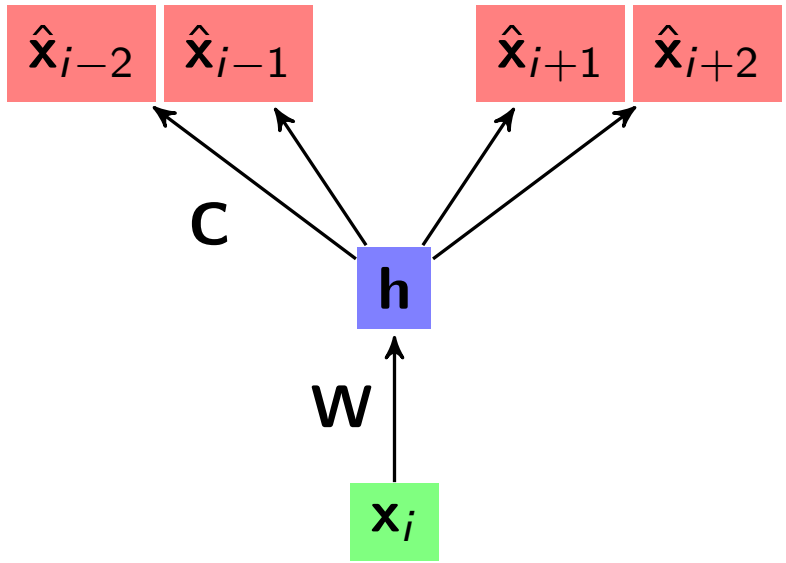

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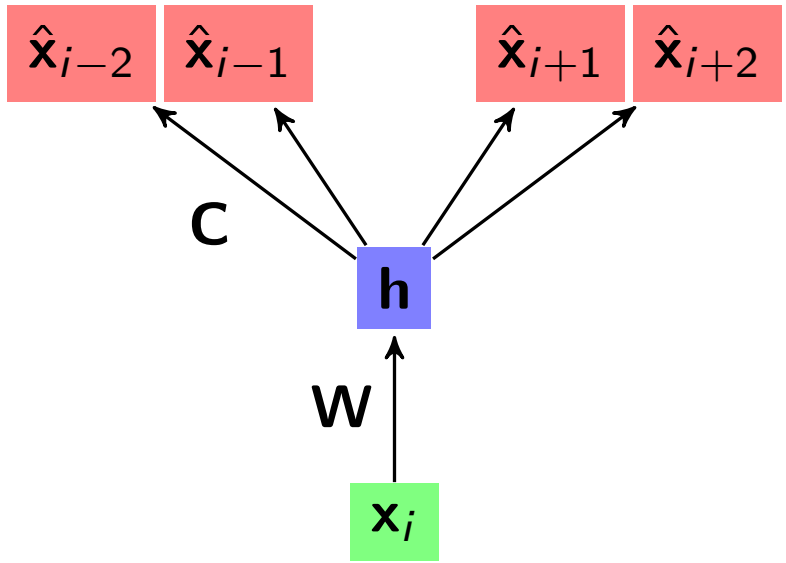

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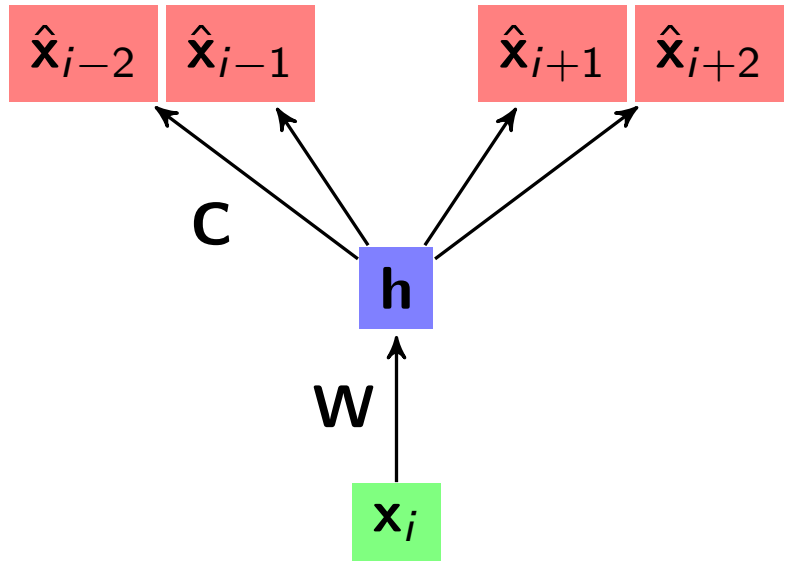

- Output layer: softmax activation function
  - Predict context words within some window
  - Separate classification for each context word
  - Closer context words sampled more than distant context words

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$$L = -\left[\log \sigma(\mathbf{w} \cdot \mathbf{c}_{pos}) + \sum_{i=1}^{k} \log \sigma(\mathbf{w} \cdot -\mathbf{c}_{neg})\right]$$

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  - Maximize the (log-)probability of positive samples (true context words)

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  - Minimize the (log-)probability of k negative samples (random non-context words)

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  - Target word vector $\mathbf{w}$ (row of $\mathbf{W}$, = output of hidden layer)
  - Context word vector $\mathbf{c}$ (column of $\mathbf{C}$)
- Common final word embeddings
  - Add $\mathbf{w} + \mathbf{c}$
  - Just $\mathbf{w}$ (throw away $\mathbf{c}$)

References

- Baroni, Marco, Georgiana Dinu, and Germán Kruszewski. "Don't count, predict! a systematic comparison of context-counting vs. context-predicting semantic vectors." Proceedings of ACL. 2014.
- Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding." Proceedings of NAACL-HLT. 2019.
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