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Deep Neural Networks in Natural Language Processing

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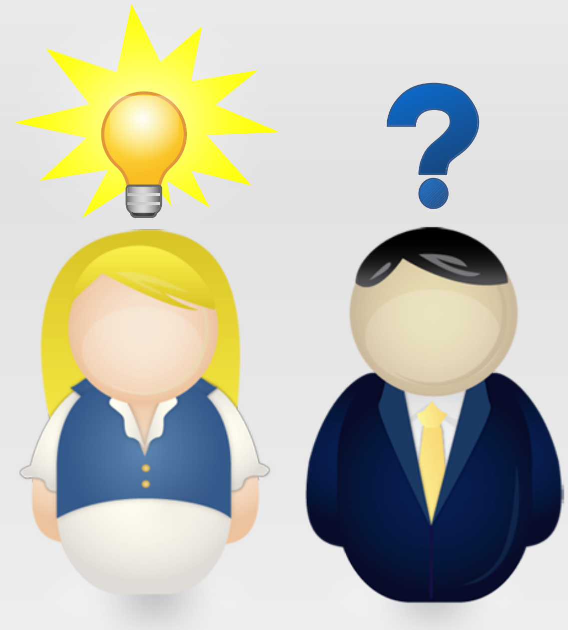
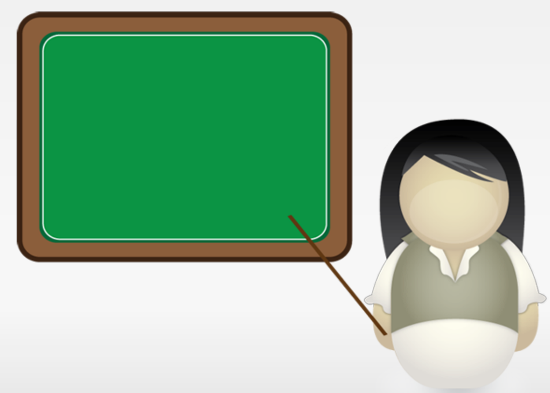
Background check: do you know...

- Machine learning? (ML)
- Artificial neural networks? (NN)
- Deep neural networks? (DNN)
- Convolutional neural networks? (CNN)
- Recurrent neural networks? (RNN)
  - Long short-term memory units? (LSTM)
  - Gated recurrent units? (GRU)
- Attention mechanism? (Bahdanau+, 2014)
  - Self-attentive networks? (SAN, Transformer)
- Word embeddings? (Bengio+, 2003)
  - Word2vec? (Mikolov+, 2013)



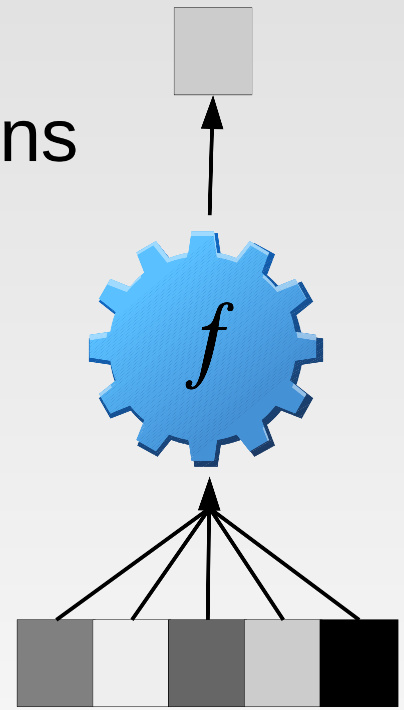


ML in Natual Language Processing

- Before: complex multistep pipelines
  - Preprocessing, low-level processing, high-level processing, classification, post-processing…
  - Massive feature engineering, linguistic knowledge…
- Now: monolitic end-to-end systems (or nearly)
  - text → deep neural network → output
  - Little or no linguistic knowledge required
  - Little or no feature engineering
  - Little or no dependence on external tools
  - → so now is a good time for **anyone** to get into NLP!

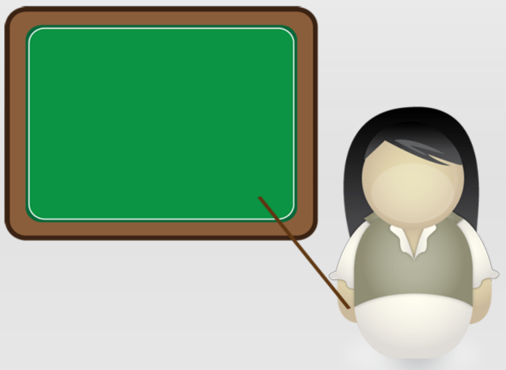
Neural networks & text processing

- Input to a neuron: <u>fixed-dimension</u> <u>real</u> vector
  - Dimension should be reasonable ($<10^3$)
  - Neural net: fixed-sized network of neurons
- Text input: sequence processing
  - Sentence = sequence of words
  - Words: discrete (but interrelated)
    - Massively multi-valued ($\sim 10^6$)
    - Very sparse (Zipf distribution)
  - Sentences: variable length (~1 to 100)
    - Complex and hidden internal structure



Outline of the talk

- Problem 1: Words
  - There are too many
  - They are discrete
  - *Representing massively multi-valued discrete data by continuous low-dimensional vectors*



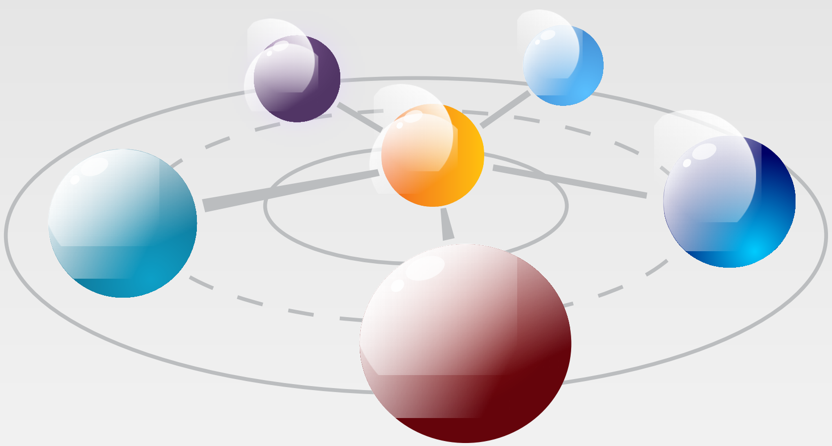
- Problem 2: Sentences
  - They have various lengths
  - They have internal structure
  - *Handling variable-length input sequences with complex internal relations by fixed-sized neural units*

Warnings

- I am not a ML expert, rather a ML *user*
  - Please excuse any errors and inaccuracies
- Focus of talk: input representation (“encoding”)
  - Key problem in NLP, interesting properties
- Leaving out
  - Generating output (“decoding”) – that’s also interesting
    - Sequence generation
      - Seq. elements discrete, large domain (softmax over 10^6)
      - Sequence length not a priori known
  - Decision at encoder/decoder boundary (if any)

Problem 1: Words

Massively multi-valued discrete data
(words)



Continuous low-dimensional vectors
(word embeddings)

Simplification

- For now, forget sentences

Word is positive/neutral/negative,
Definition of the word,
Hyperonym (dog → animal),
…

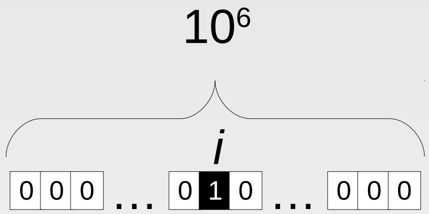
1 word → 

→ some output

- Situation
  - We have labelled training data for **some** words (10^3)
  - We want to generalize (ideally) to **all** words (10^6)

The problem with words

- How many words are there? Too many!
  - Many problems with counting words, cannot be done
  - ~10^6 (but potentially infinite – new words get created every day)
- Long-standing problem of NLP
- Natural representation: 1-hot vector



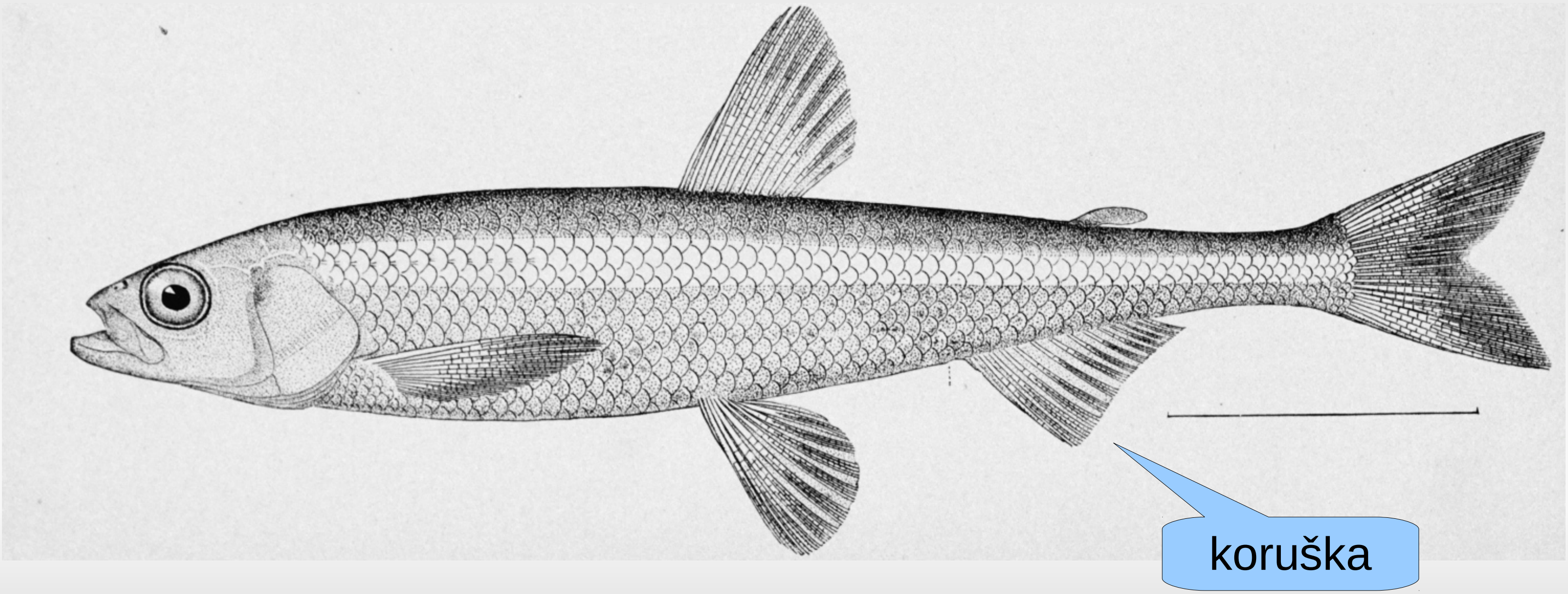
  - ML with ~10^6 binary features on input 
  - Pair of words: ~10^{12} 
  - No generalization, meaning of words not captured
    - dog~puppy, dog~~cat, dog~~~platypus, dog~~~~whiskey

Split the words

- Split into characters M O C K
  - Not that many (~10^2)
  - Do not capture meaning
    - Starts with “m-”, is it positive or negative?
- Split into subwords/morphemes mis class if ied
  - Word starts with “mis-”: it is probably negative
    - *misclassify, mistake, misconception…*
  - Helps, used in practice
    - Potentially infinite set covered by a finite set of subwords
  - Meaning-capturing subwords still too many (~10^5)

Distributional hypothesis

- *smelt* (assume you don’t know this word)
  - *I had a **smelt** for lunch.* → noun, meal/food
  - *My father caught a **smelt**.* → <u>animal</u>/illness
  - ***Smelts** are disappearing from oceans.* → plant/<u>fish</u>



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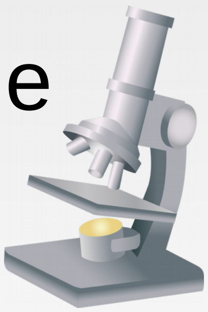
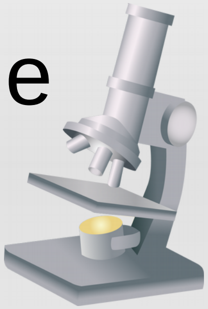
- Harris (1954): "Words that occur in the same contexts tend to have similar meanings."



Distributional hypothesis



- Harris (1954): “Words that occur in the same contexts tend to have similar meanings.”
- Cooccurrence matrix
  - # of sentences containing both WORD and CONTEXT

WORD	CONTEXT				
	lunch	caught	oceans	doctor	green
smelt	10	10	10	1	1
salmon	100	100	100	1	1
flu	1	100	1	100	10
seaweed	10	1	100	1	100

  - Cheap plentiful data (webs, news, books…): ~10^9

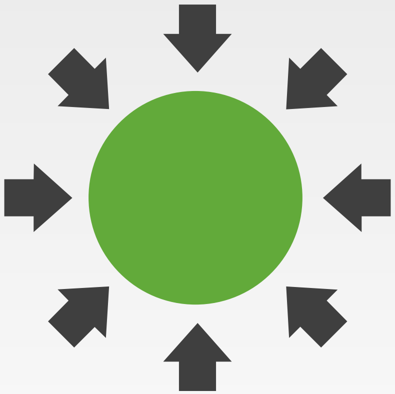
From cooccurence to PMI

- Cooccurrence matrix
  - $M_C[i, j] = count(word_i \ \& \ context_j)$
- Conditional probability matrix
  - $M_P[i, j] = P(word_i \mid context_j) = M_C[i, j] / count(context_j)$
- Conditional log-probability matrix
  - $M_{LogP}[i, j] = \log P(word_i \mid context_j) = \log M_P[i, j]$
- Pointwise mutual information matrix
  - $M_{PMI}[i, j] = \log [P(word_i \mid context_j) / P(word_i)]$

Association measures

From cooccurence to PMI

- Word representation still impratically huge
  - $M_{PMI}[i] \in \mathbf{R}^N$, $N \sim 10^6$
- But better than 1-hot
  - Meaningful continuous vectors (e.g. cos similarity)
- Just need to compress it!
  - Explicitly: matrix factorization
    - post-hoc, not used
  - Implicitly: word2vec
    - widely used

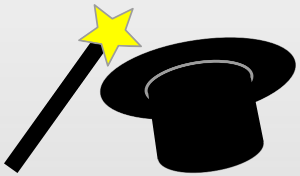


Matrix factorization

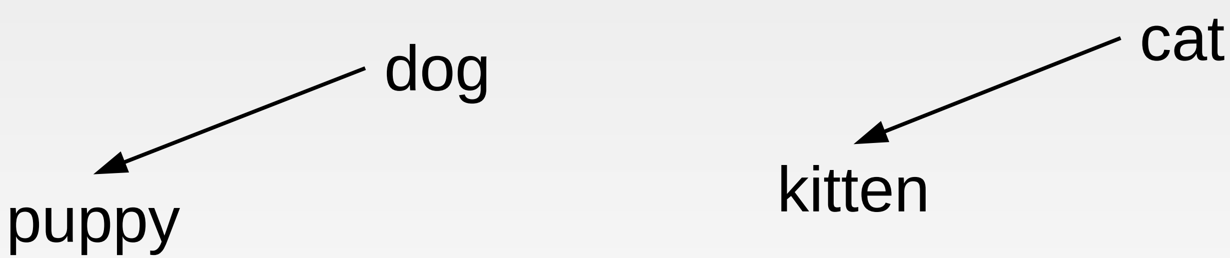
- Levy&Goldberg (2014)
- Take M_{LogP} or M_{PMI}
- Shift the matrix to make it positive (- min)
- Truncated Singular Value Decomposition:
  - $\overline{M} = UDV^T$ $M \in \mathbf{R}^{NxN} \rightarrow U \in \mathbf{R}^{Nxd}, D \in \mathbf{R}^{dxd}, V \in \mathbf{R}^{Nxd}$
- Word embedding matrix: $W = UD \in \mathbf{R}^{Nxd}$
  - Embedding $vec(word_i) = W[i] \in \mathbf{R}^d$
  - Continuous low-dimensional vector
  - Meaningful (cos similarity, algebraic operations)

$N \sim 10^6$
$d \sim 10^2$

Word embeddings magic



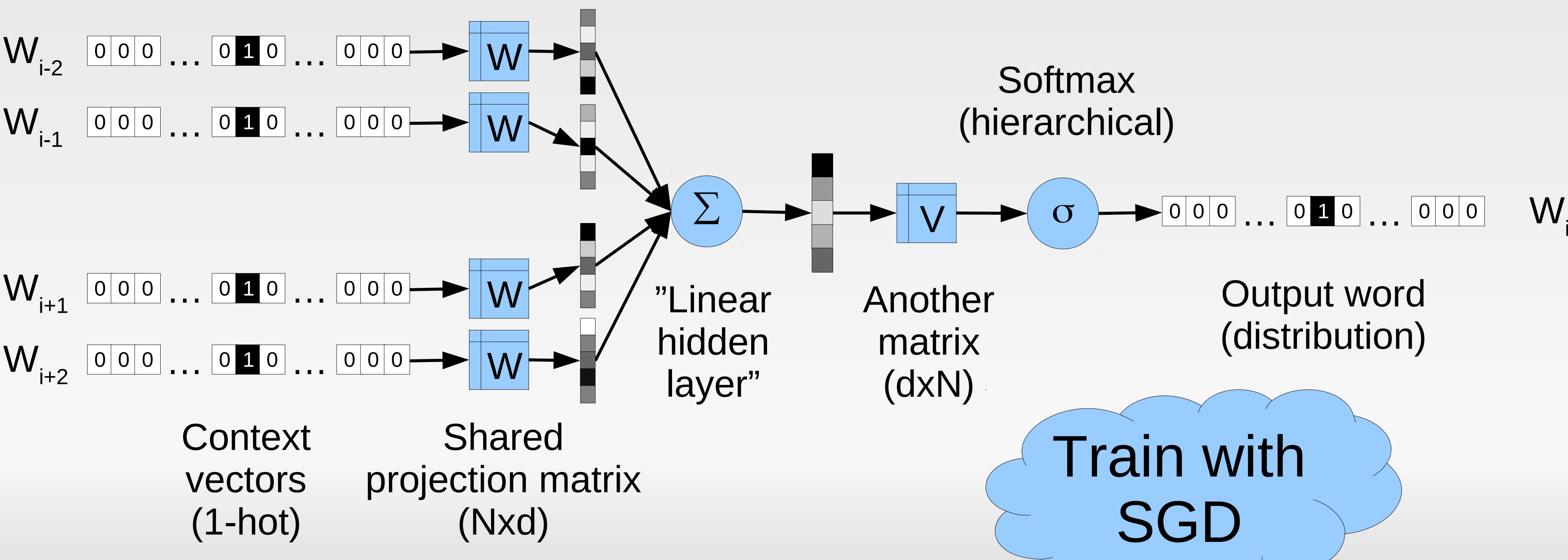
- Word similarity (cos)
  - vec(dog) ~ vec(puppy),   vec(cat) ~ vec(kitten)
- Word meaning algebra
  - Some relations parallel across words
  - vec(puppy) - vec(dog) ~ vec(kitten) - vec(cat)



  - => vec(puppy) - vec(dog) + vec(cat) ~ vec(kitten)
    - vodka – Russia + Mexico, teacher – school + hospital…

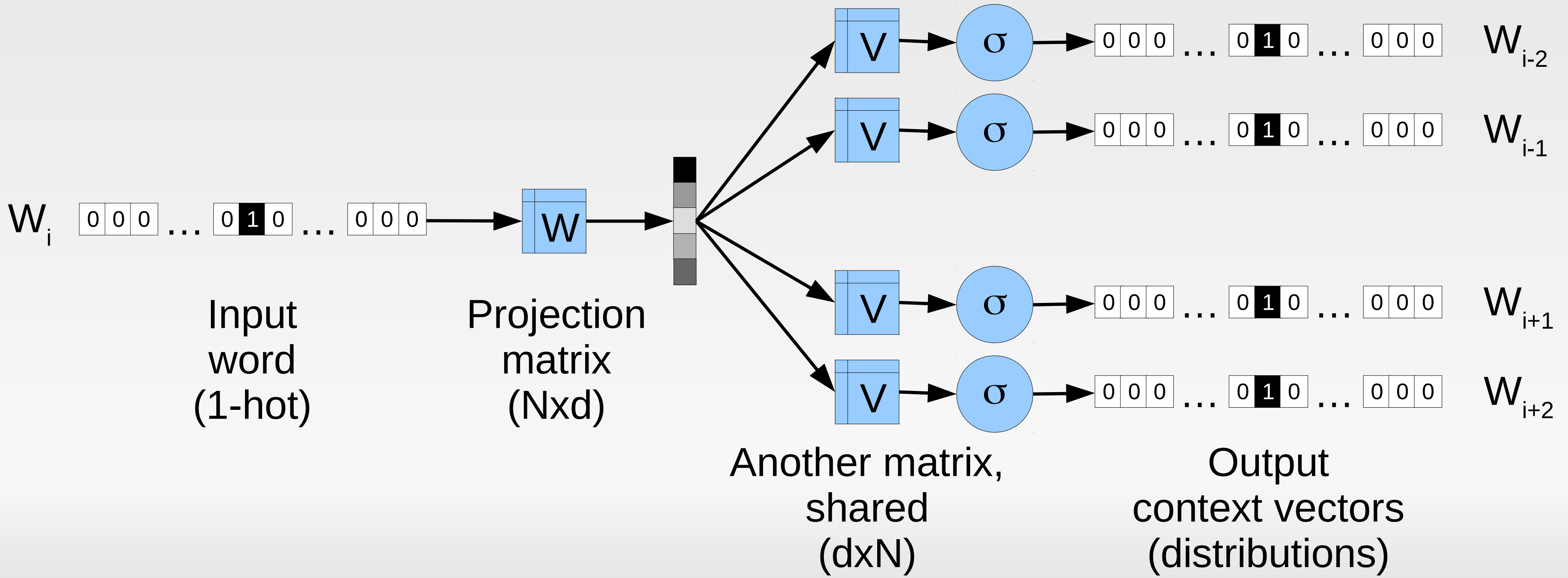
word2vec (Mikolov+, 2013)

- Predict word w_i from its context (CBOW)
  - E.g.: “*I had ______ for lunch*”
  - Sentence: … w_{i-2} w_{i-1} $\mathbf{w_i}$ w_{i+1} w_{i+2} …

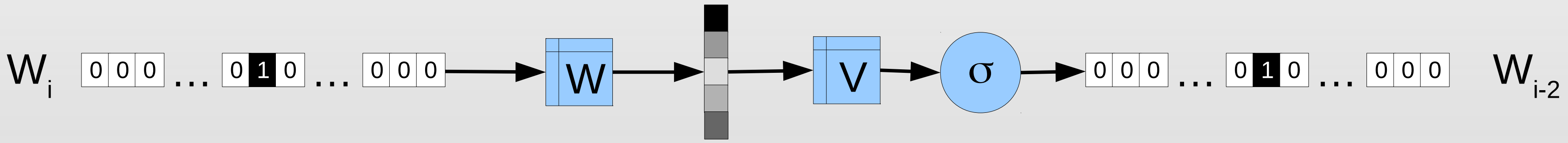


word2vec (Mikolov+, 2013)

- Predict context from a word w_i (SGNS)
  - E.g.: "_____ ______ *smelt* ______ ______"
  - Sentence: … $\mathbf{w_{i-2}}$ $\mathbf{w_{i-1}}$ w_i $\mathbf{w_{i+1}}$ $\mathbf{w_{i+2}}$ …



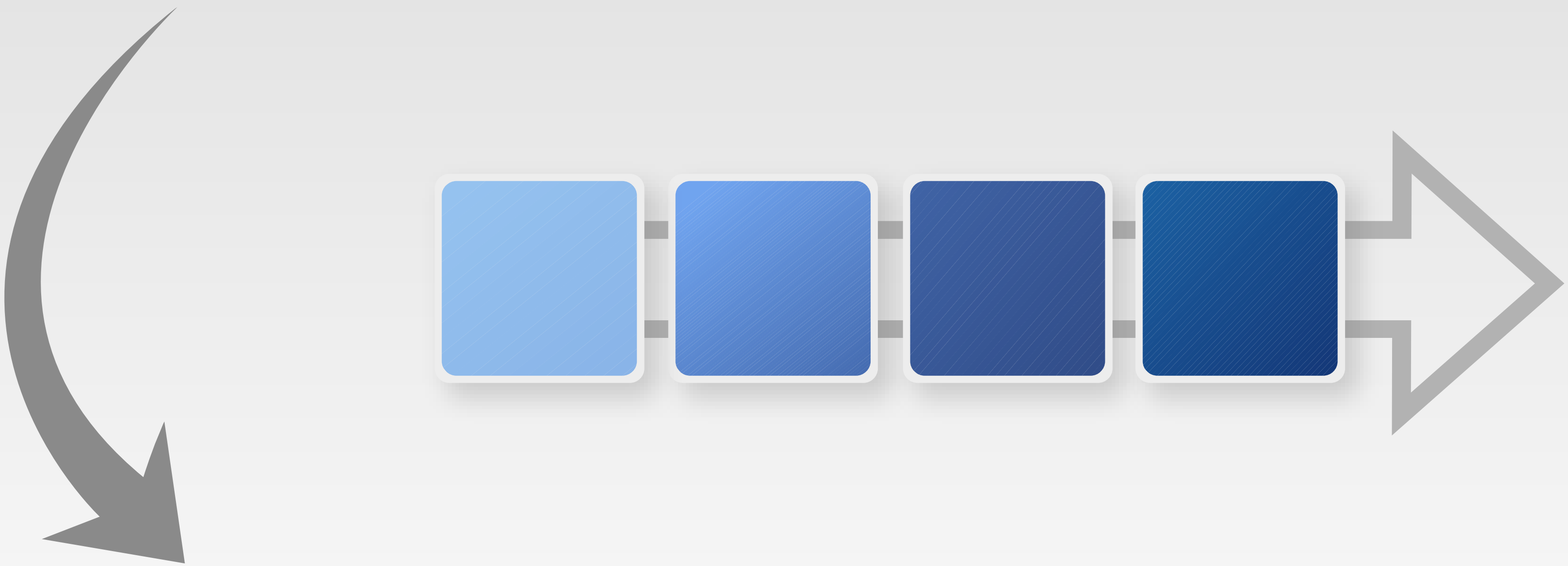
word2vec ~ implicit factorization



- Word embedding matrix $W \in \mathbf{R}^{N x d}$
  - embedding($word_i$) = $W[i] \in \mathbf{R}^d$
- Levy&Goldberg (2014)
  - word2vec SGNS implicitly factorizes M_{PMI}
  - $M_{PMI}[i, j] = \log [P(word_i \mid context_j) / P(word_i)]$
  - SGNS: $M_{PMI} = WV$
  - $M_{PMI} \in \mathbf{R}^{N x N} \rightarrow W \in \mathbf{R}^{N x d}, V \in \mathbf{R}^{d x N}$

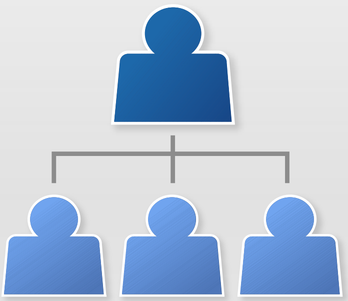
Problem 2: Sentences

Variable-length input sequences with long-distance relations between elements (sentences)



Fixed-sized neural units (attention mechanisms)

Convolutional neural networks



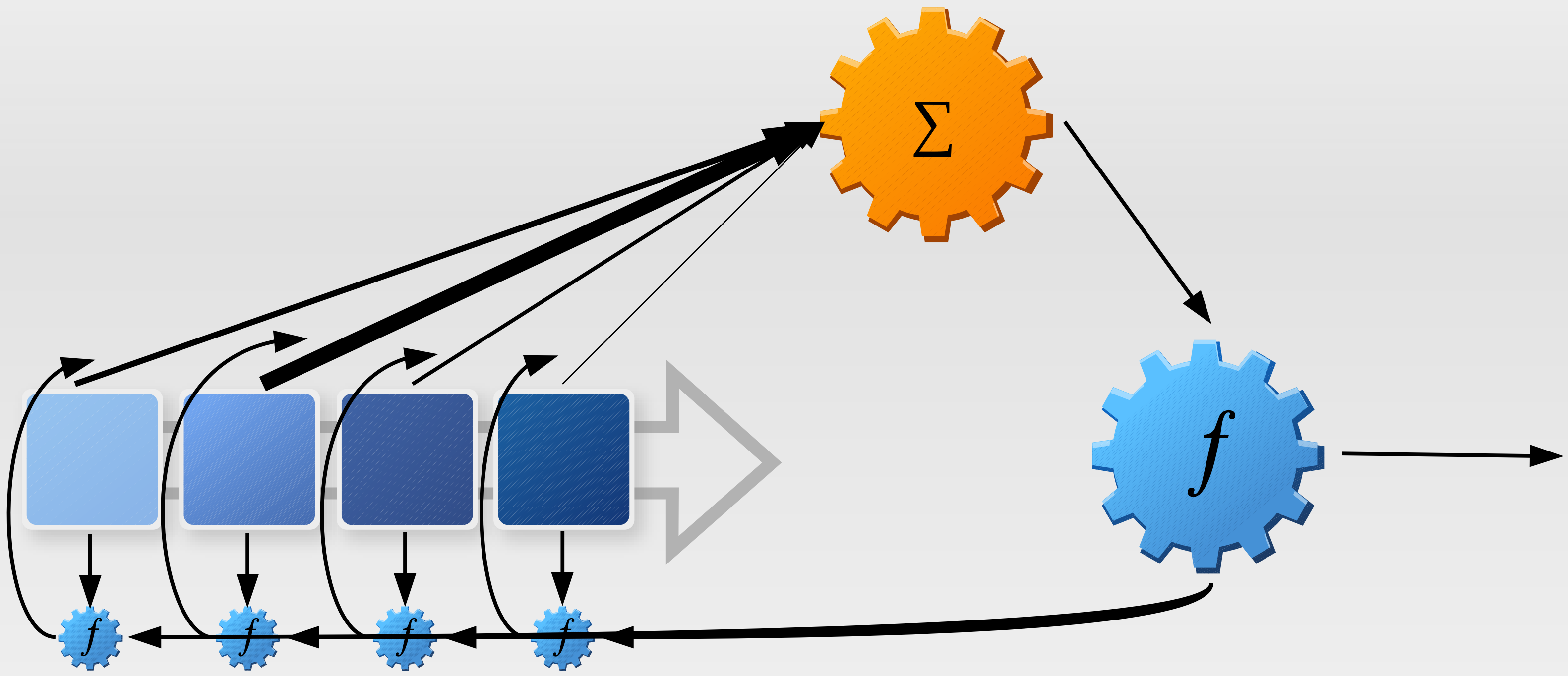
- Input: sequence of word embeddings
- Filters (size 3-5), norm, maxpooling
- Training deep CNNs hard → residual connections
  - Layer input averaged with output, skips non-linearity
- Problem: capturing long-range dependencies
  - Receptive field of each filter is limited
  - *My <u>computer</u> works, but I have to buy a new <u>mouse</u>.*
- Good for word *n*gram spotting
  - Sentiment analysis, named entity detection…

Recurrent neural networks

- Input: sequence of word embeddings
- Output: final state of RNN
- Problems

  - Vanishing gradient → memory cells (LSTM, GRU)
  - Long distance dependencies not perfectly captured
  - Final state is biased (“forgetting”)
    - …sentence end better captured than sentence start
    - Bidirectional RNN, output = concat of both final states
      - Still may not well capture the middle parts…
    - Using all hidden states as output, not just the final one
      - We loose the fixed-sized representation

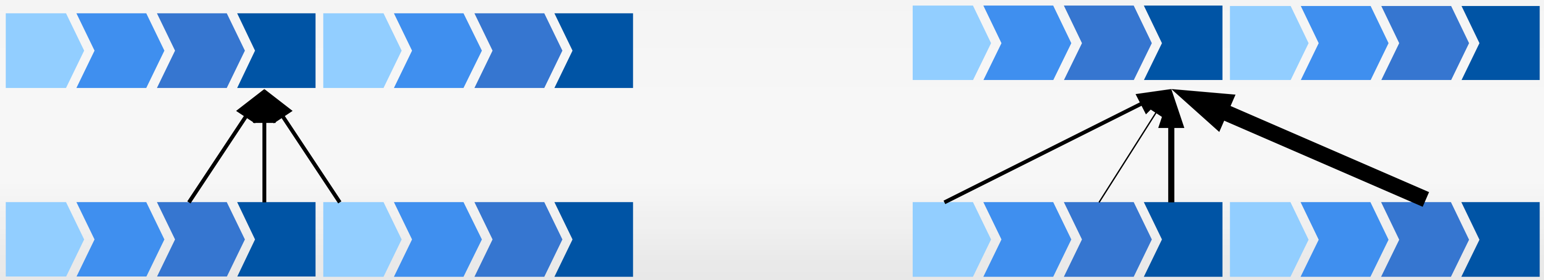
Attention (on top of a RNN)



- Classifier/decoder gets a fixed-size context vector
  - Weighted average of encoder hidden states
  - Attention weights computed by a feed-forward subnet
    - $\text{weight}_i \sim \text{NN}(\text{state}_i, \text{state}_{\text{decoder}})$

Advanced attention

- Multi-head attention
  - Multiple attention heads (~8), each has its own distro
  - Resulting context vectors concatenated
- Self-attentitive encoder (SAN)
  - CNN/attention hybrid
  - CNN: cell gets small local context via filters
  - SAN: cell gets global context via attention heads



Conclusion

- Words → word embeddings
  - Too many, too sparse
  - Word meaning ~ context in which it appears
  - Cooccurrence matrix, implicit/explicit factorization
- Sentences → attention
  - Variable length, complex internal structure
  - biRNN (LSTM, GRU), CNN+residuals
  - Attention: weighted sum of encoder hidden states
  - Self-attention: à la CNN, filters → attention

References

- **Word embeddings:**
  - **Distributional hyp.:** Harris: *Distributional structure.* Word, 1954
  - **First:** Bengio+: *A neural probabilistic language model.* JMLR, 2003
  - **Efficient implicit (word2vec):** Mikolov+: *Linguistic Regularities in Continuous Space Word Representations.* NAACL, 2013
  - **Explicit (TSVD):** Levy&Goldberg: *Neural Word Embedding as Implicit Matrix Factorization.* NIPS, 2014
- **Recurrent neural networks and attention:**
  - **LSTM:** Hochreiter+: *Long short-term memory.* NeCo, 1997
  - **Attention:** Bahdanau+: *Neural Machine Translation by Jointly Learning to Align and Translate.* CoRR, 2014
  - **Tranformer SAN:** Vaswani+: *Attention is all you need.* NIPS, 2017

Thank you for your attention

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