Predefined Sparseness in Recurrent Sequence Models

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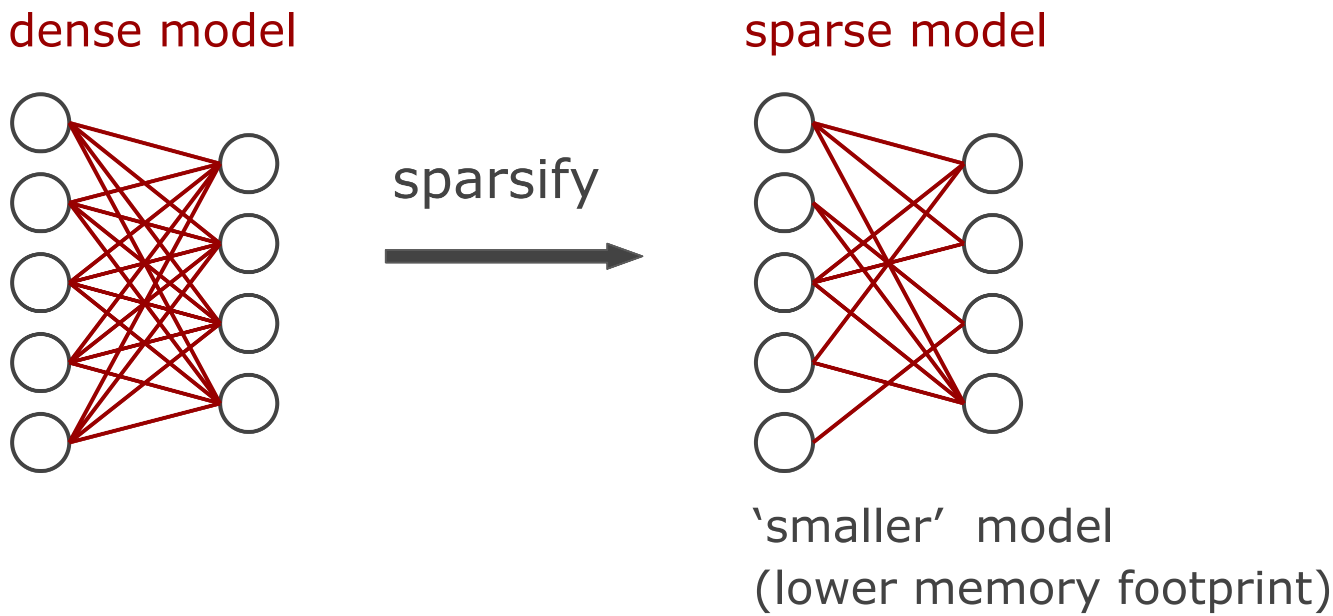
Sparse Neural Networks



Sparsifying by weight pruning

Highly sparse with accuracy close to dense models [1]

Large sparse networks can be better than small dense models [2]

BUT THEN: large *dense* network needed during training!

GOAL: models that are sparse from the start?

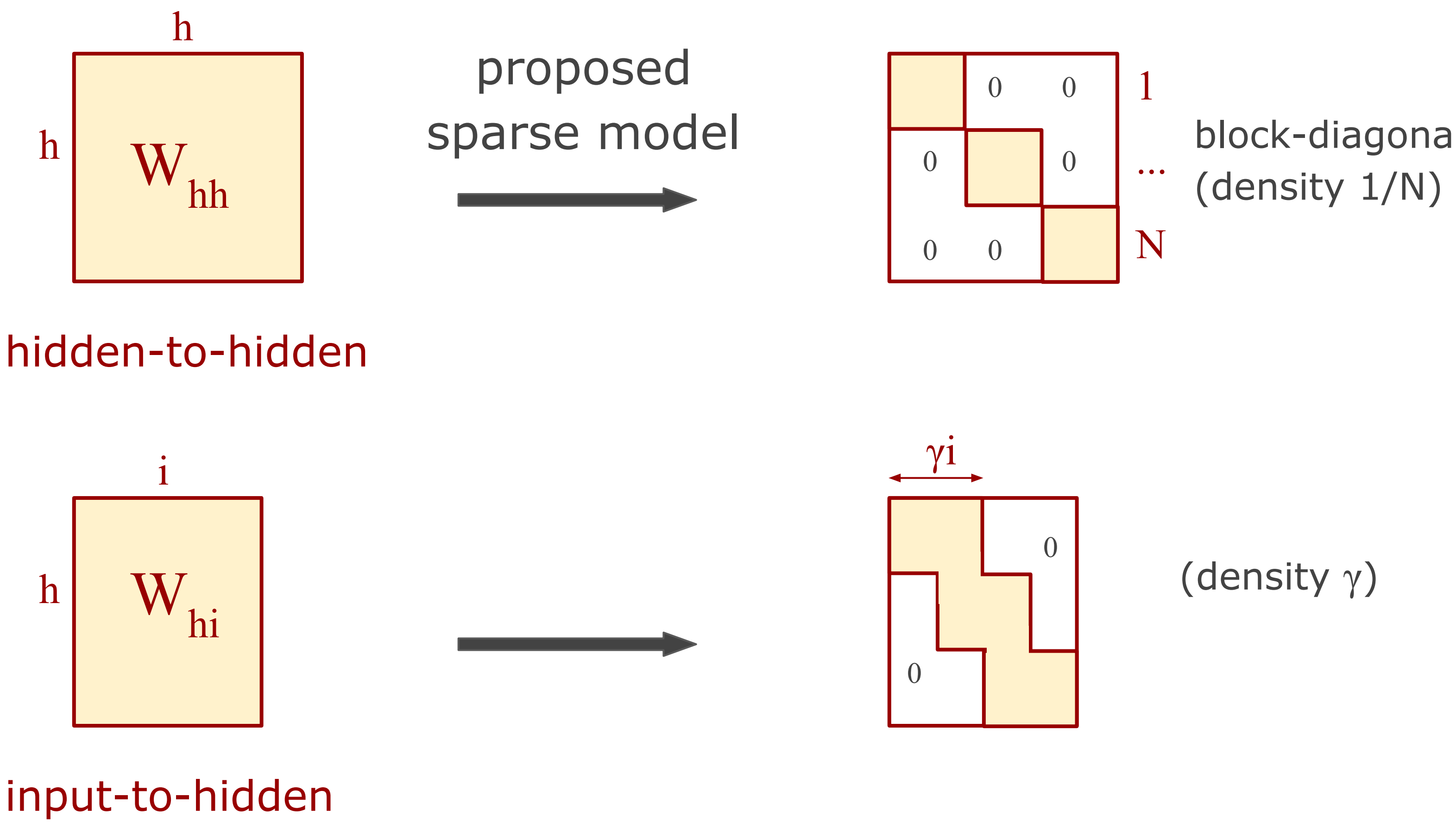
"predefined sparseness"

[1] Narang *et al.* "Exploring Sparsity in RNNs" (ICLR 2017)

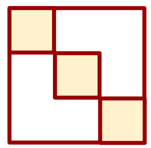
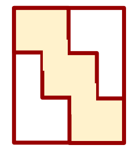
[2] Kalchbrenner *et al.* "Efficient Neural Audio Synthesis" (ICML 2018)

Predefined sparseness for RNNs

Any recurrent cell (RNN, LSTM, GRU...): 2 types of matrices



Predefined sparseness for RNNs

With sparse W_{hh}  and W_{hi} 

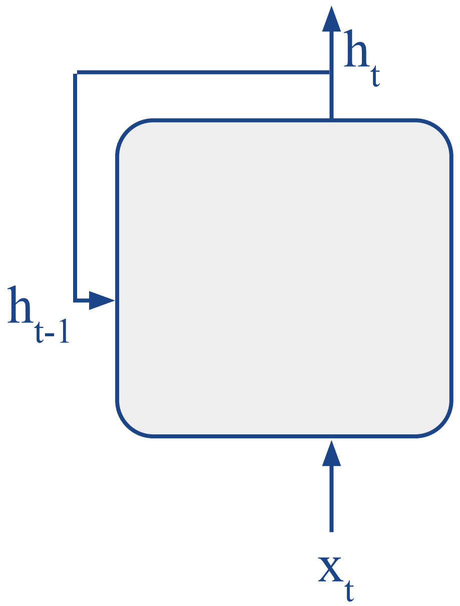
- strongly reduced number of hidden-to-hidden interactions (cfr. weight dropping in W_{hh} [5])
- not all hidden dimensions have access to each input dimension.

why this particular choice?

[5] Merity et al. "Regularizing and Optimizing LSTM Language Models." ICLR 2018.

Predefined sparseness for RNNs

Consider vanilla RNN



Predefined sparseness for RNNs

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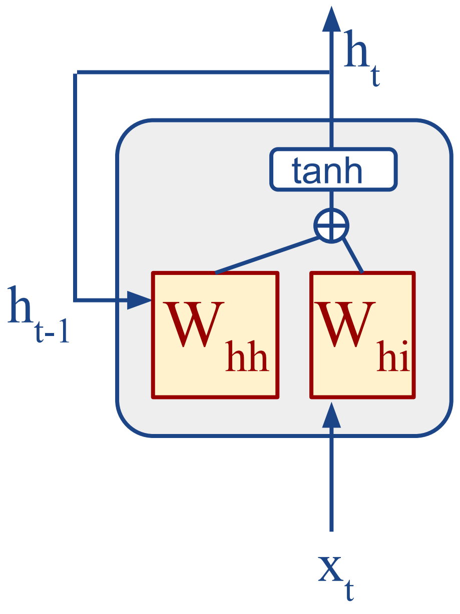
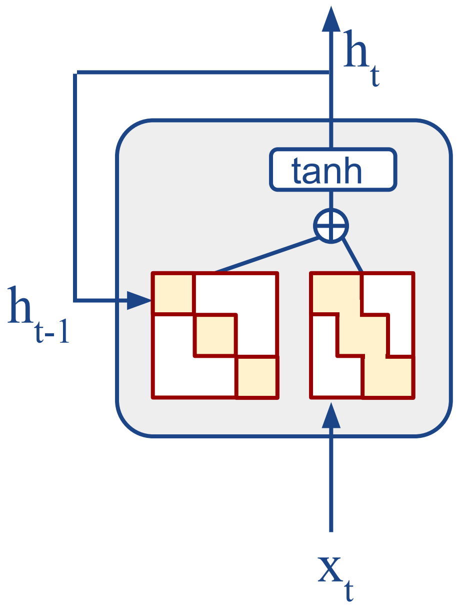


Predefined sparseness for RNNs

Consider vanilla RNN - made sparse



Predefined sparseness for RNNs

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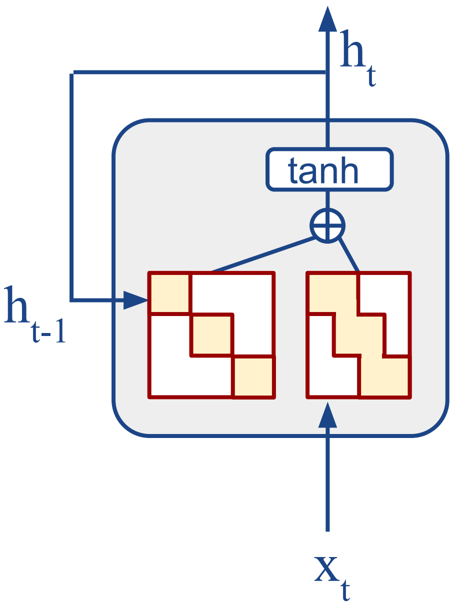

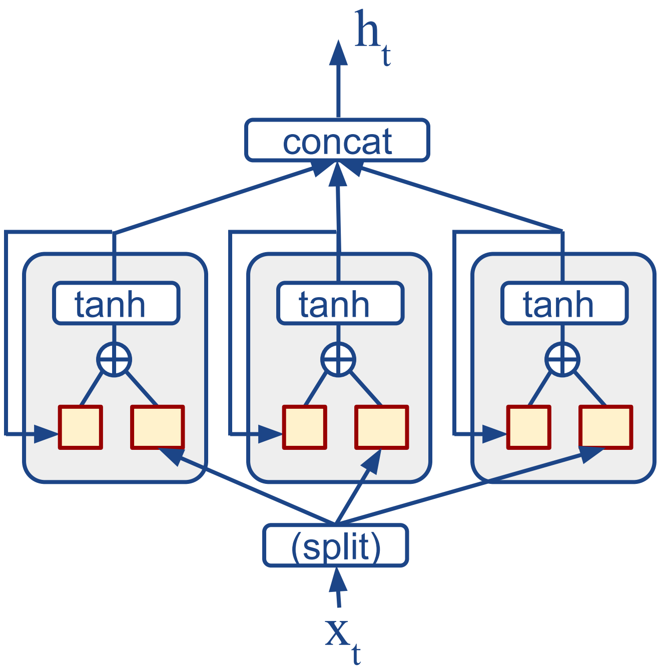

Resulting RNN equivalent to N smaller dense RNNs in parallel

- only possible with output divided into disjoint segments
- but input can be (partly) shared between components
- holds for vanilla RNN, LSTM, GRU,...
- allows standard tools (CuDNN) / parallel processing

Language modeling with sparse LSTM

- baseline: AWD-LSTM model [5] with 3-layer stacked LSTM

- sparse counterpart:
  - middle LSTM hidden size x 1.5 (from 1150 to 1725)
  - sparse; same number of parameters
  - same regularization settings

[5] Merity et al. "Regularizing and Optimizing LSTM Language Models." ICLR 2018.

Language modeling with sparse LSTM

- first train run (500 epochs)

Model	Penn Treebank test perplexity
reported [5]	58.8
baseline	58.8 ± 0.3
sparse LSTM	57.9 ± 0.3

- train further (‘finetune’) : sparse model overfits

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Language modeling with sparse LSTM

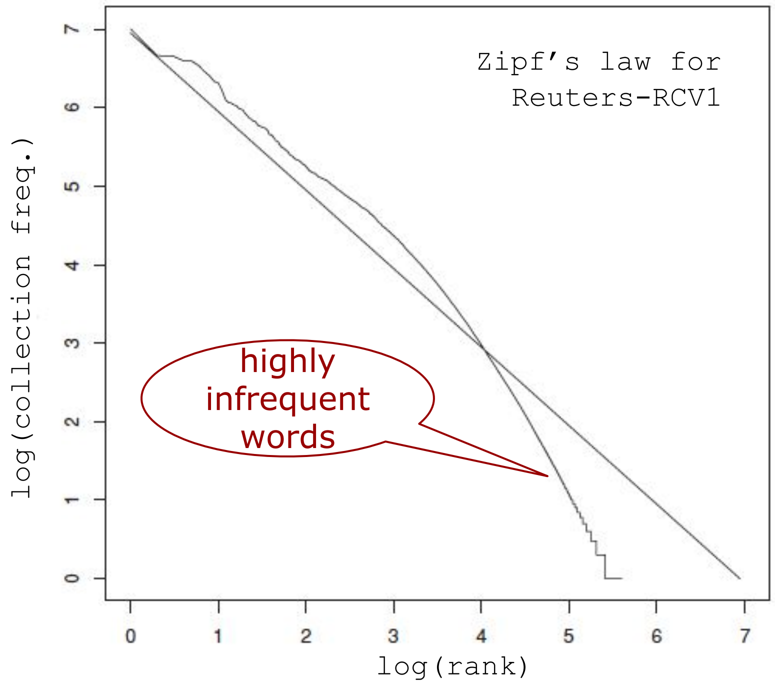
- hypothesis:

  the regularization effect of
  a priori limiting interactions between dimensions
  does not compensate for increased expressiveness
  due to larger hidden state size

- supported by additional experiment “learning to recite” (see paper 😀)

Predefined sparseness in word embeddings

- Goal:
  decide upfront which entries in embedding matrix $\mathbf{E} \in \mathbb{R}^{V\mathrm{x}k}$ are 0.
- Word occurrence frequencies
  have Zipfian nature



source: Manning, Schütze, Raghavan, "Introduction to Information Retrieval", Cambridge UP, 2009

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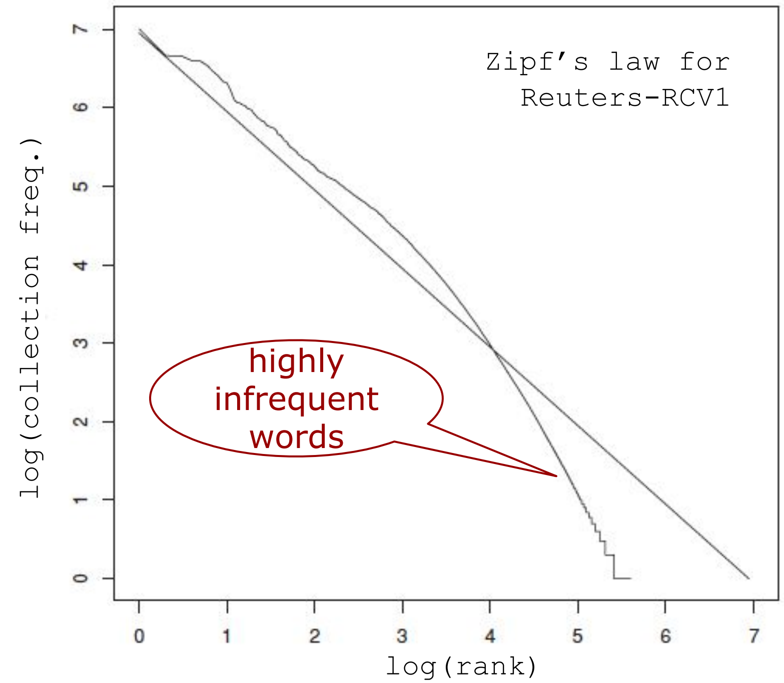

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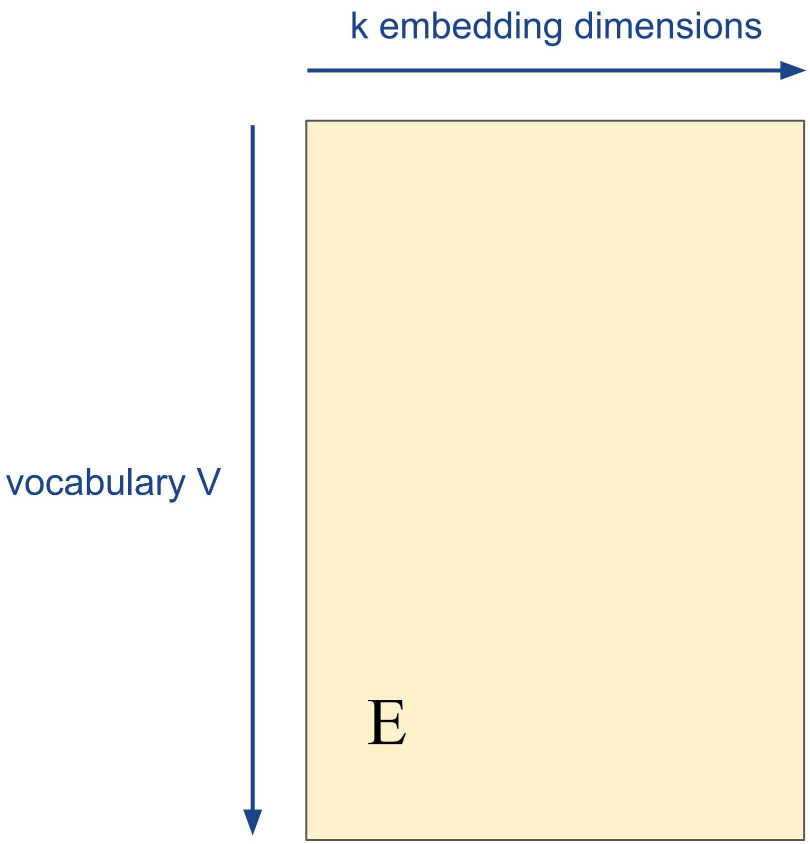
representing long tail of rare terms with short embeddings would greatly reduce memory requirements

Predefined sparseness in word embeddings

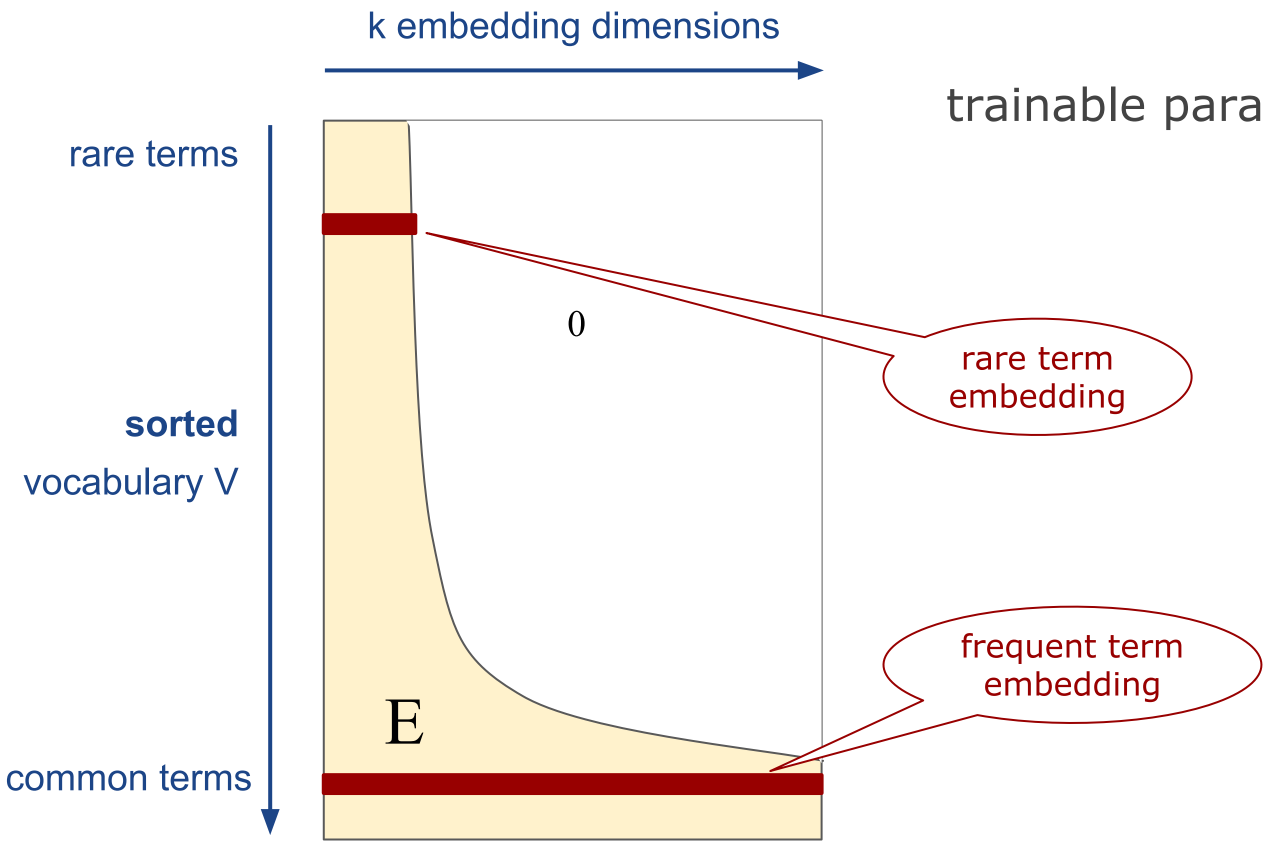
Predefined sparse embedding matrix E ?



trainable parameters $= \mathrm{kV}$

Predefined sparseness in word embeddings

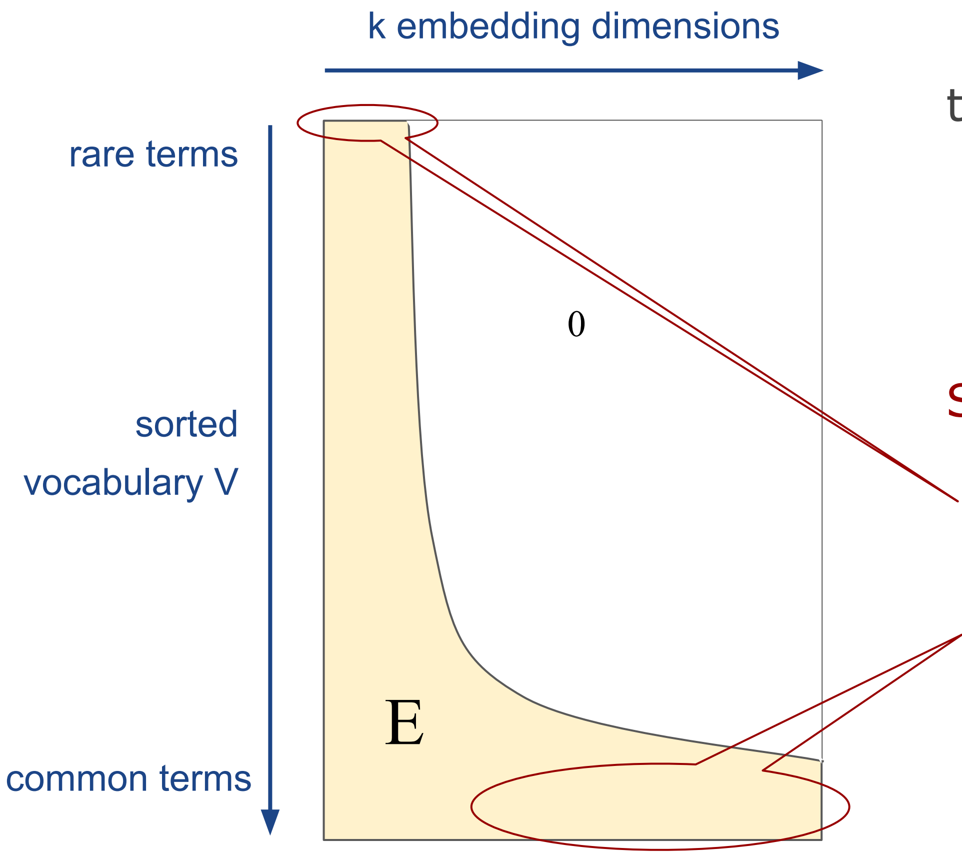
Predefined sparse embedding matrix E?



trainable parameters $= kV\delta_E$

Predefined sparseness in word embeddings

Predefined sparse embedding matrix E?



trainable parameters $= kV\delta_E$

Sparse embedding space

- 'first' dimensions model many rare terms
- remaining dimensions model few frequent terms

Predefined sparseness in word embeddings

- Experimental setup:
  - POS tagging on Penn Treebank
  - very small model (else too easy!)
  - 20-D word embeddings (876k params)
  - BiLSTM state size 10+10 (3k params)

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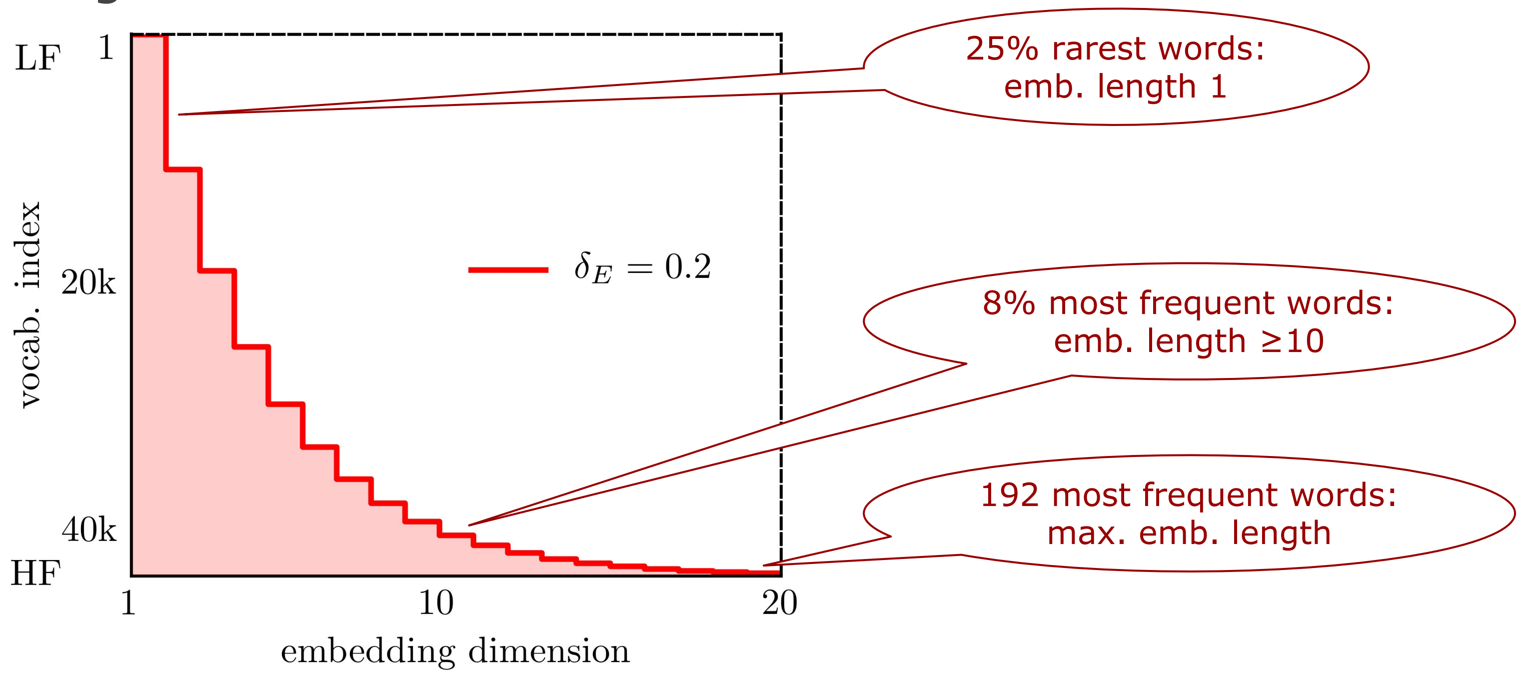
- Embedding matrix



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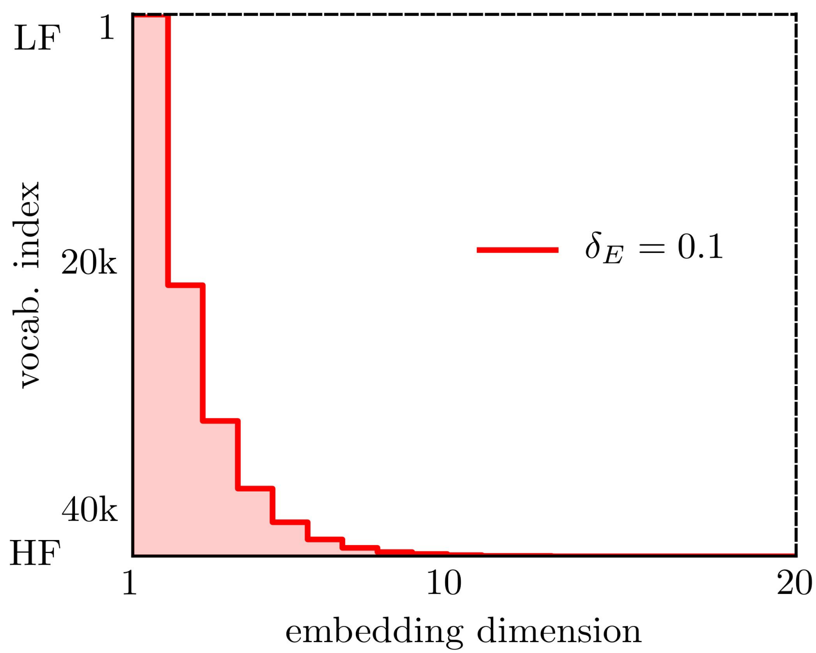
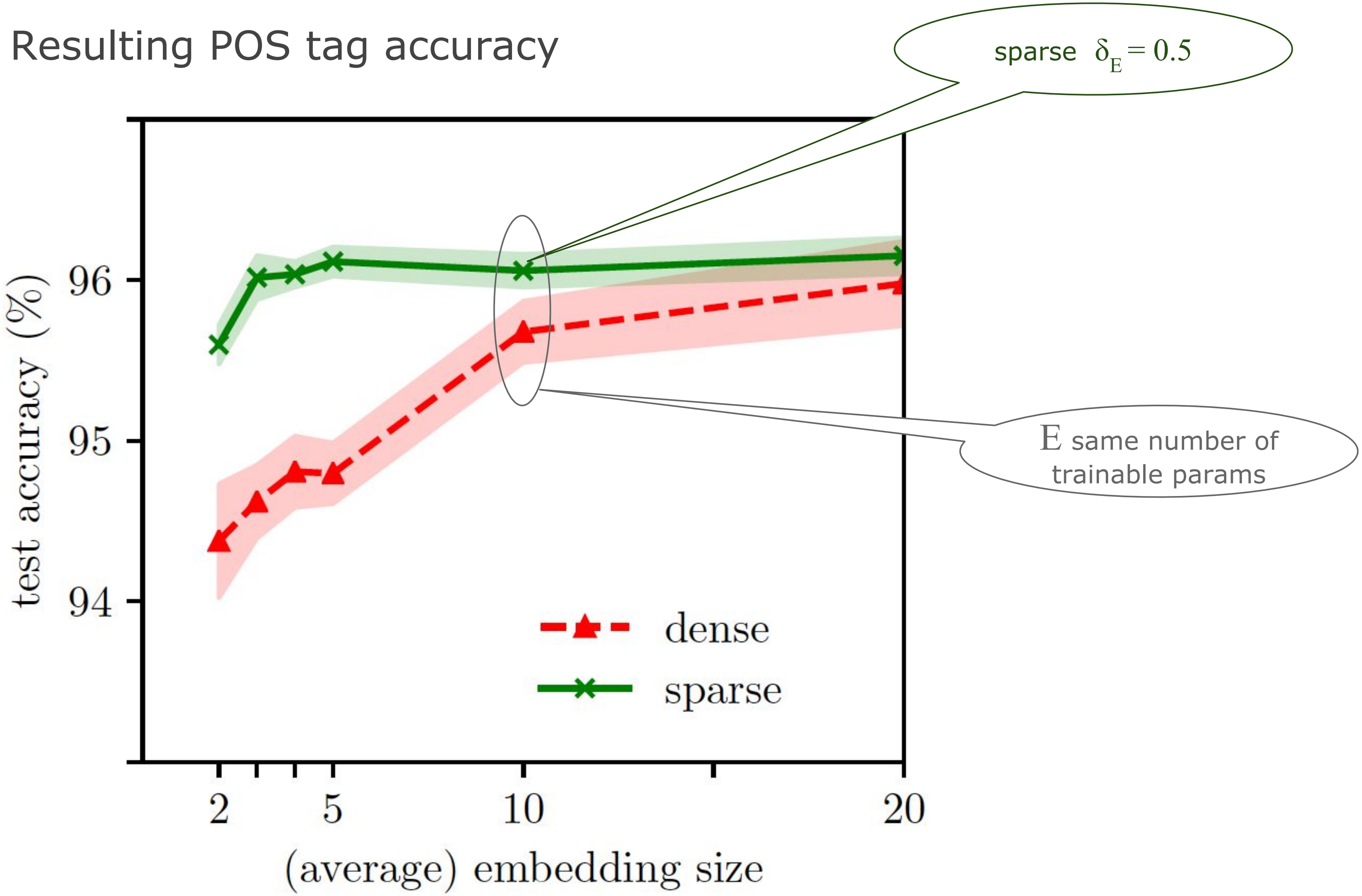


Predefined sparseness in word embeddings

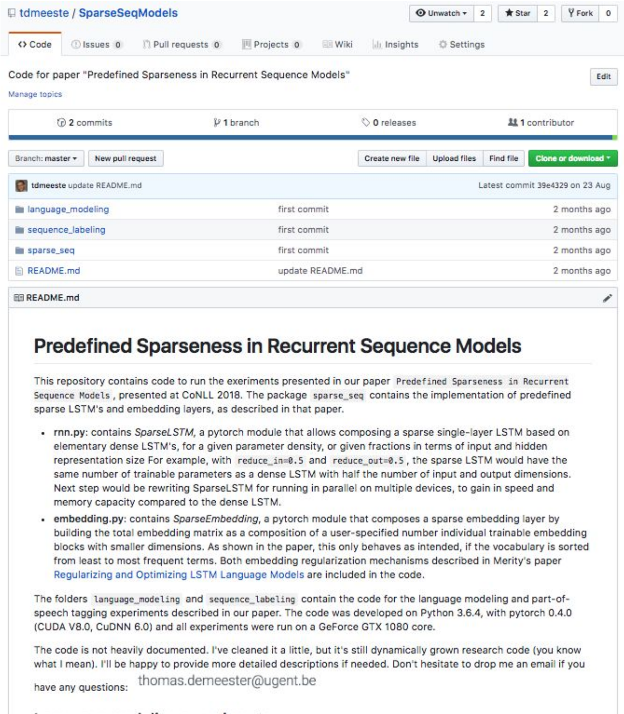
- Resulting POS tag accuracy



Conclusions

- Simple ideas for predefined sparseness in RNNs and embedding layers
- Predefined Sparseness has potential in NLP
- Further investigation needed
  (for very large representation sizes for large vocabularies, etc.)
- Need some "predefined sparseness" code?

  https://github.com/tdmeeste/SparseSeqModels



Thank you!

Language modeling with sparse LSTM

- baseline:
  - AWD-LSTM model [5]
  - 400D word embeddings, 10k words; 4M params
  - 3-layer stacked LSTM (dimensions 400 - 1150 - 400); 20M params

- sparse counterpart:
  - similar 3-layer LSTM; 20M params
  - but: middle LSTM scaled from 1150 to 1725 units (factor 1.5)
    sparse: to retain same number of parameters
  - no tuning (exactly same regularization parameters)

[5] Merity et al. "Regularizing and Optimizing LSTM Language Models." ICLR 2018.

Inspiration from literature

“application of sparse coding in language processing is far from extensive, when compared to speech processing” [3]

Need for sparse models in NLP!

“natural language is high-rank” [4]

How to train large sparse representations despite memory constraints?

[3] Wang et al. “Deep and sparse learning in speech and language processing: An overview.” BICS 2016

[4] Yang et al. “Breaking the softmax bottleneck: a high-rank rnn language model.” ICLR 2018

Language modeling with sparse LSTM

- first train run (500 epochs)

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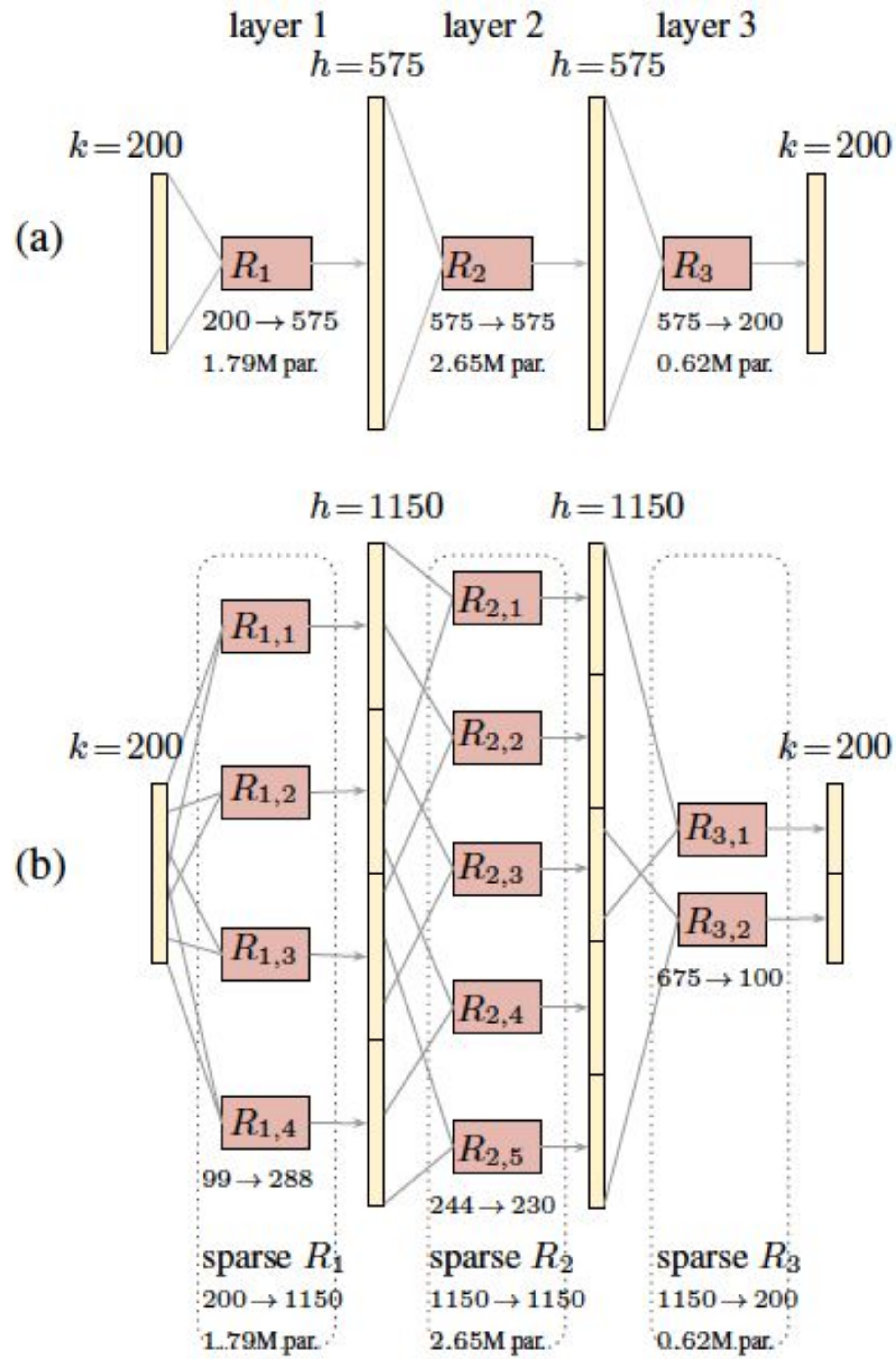
Language modeling with sparse LSTM

- train again (“finetune step” [5])

Model	Penn Treebank test perplexity
reported [5]	57.3
baseline	56.6 ± 0.2
sparse LSTM	57.0 ± 0.2

sparse model
starts overfitting

[5] Merity et al. “Regularizing and Optimizing LSTM Language Models.” ICLR 2018.



layer 1
layer 2
layer 3
h = 575
h = 575
k = 200
k = 200
(a)
R1
R2
R3
200 → 575
1.79M par.
575 → 575
2.65M par.
575 → 200
0.62M par.
h = 1150
h = 1150
k = 200
k = 200
(b)
R1,1
R1,2
R1,3
R1,4
R2,1
R2,2
R2,3
R2,4
R2,5
R3,1
R3,2
99 → 288
244 → 230
675 → 100
sparse R1
200 → 1150
1.79M par.
sparse R2
1150 → 1150
2.65M par.
sparse R3
1150 → 200
0.62M par.