Deep Learning for NLP

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Lecture 7 – Word Embeddings 3 (Sentence Embeddings)

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Natural Language Learning Group (NLLG)

This lecture

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1. **Embeddings of sentences (or even documents)**

2. (Problems with) Evaluation of Sentence Embeddings

Embedding of sentences

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- Our methods so far only embedded *words* in a low dimensional dense space

- How about larger objects such as phrases, sentences, or even whole documents?

  - Would be cool if we could represent the meaning of a sentence in a low-dimensional space
    - Why?

Why sentence/document embeddings?

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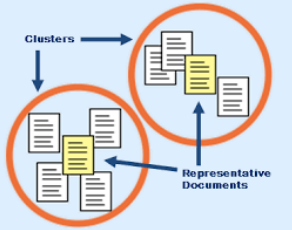
- For clustering



- For retrieval
  - Given question, give me an answer
  - Given sentence, give me a similar sentence
  - Given sentence, give me a translated sentence

- As an alternative to sentence representations learned from word-level models (e.g. CNN)
  - Particularly, when task-specific training data is small

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Sentence Embeddings: Naive approaches

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- **Naïve approach number 1:**
  - Treat sentence as long word, predict surrounding sentences like in CBOW or SKIP-GRAM
    - The cat sat on the mat → The_cat_sat_on_the_mat
  - Problems with this approach? Extreme data sparsity

- **Naïve approach number 2:**
  - Concatenate word embeddings
  - Problems?
    - No fixed size representation
    - Sparseness

Sentence Embeddings: Naive approaches

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- **Naïve approach number 3:**
  - Take some sort of mean (e.g. arithmetic mean of words in the sentences = centroid)
    - Embedding of “cat sat on the mat” is the average embedding of all of words in the sentence
    - Problems with this:
      - Half of all words in a sentence are function words (“noise”) which shouldn’t contribute a lot
        - Have to discard high frequency words (e.g. use stop word list or determine them by counting)
        - Or even better: weight them down via, e.g., inverse document frequency
      - Word order is ignored. Embedding for “cat sat on the mat” and “mat cat sat on the” are the same
    - However, the mean (weighted) word vector is often a reasonable baseline

Sentence Embeddings

- To outline more sophisticated approaches, we briefly need to peek ahead

- And introduce so-called **encoder-decoder models**, discussed in more detail in Lecture 9
  - To understand these, we first need to understand **recurrent neural nets** (Lecture 8)

Excursion 1: RNNs

Motivation

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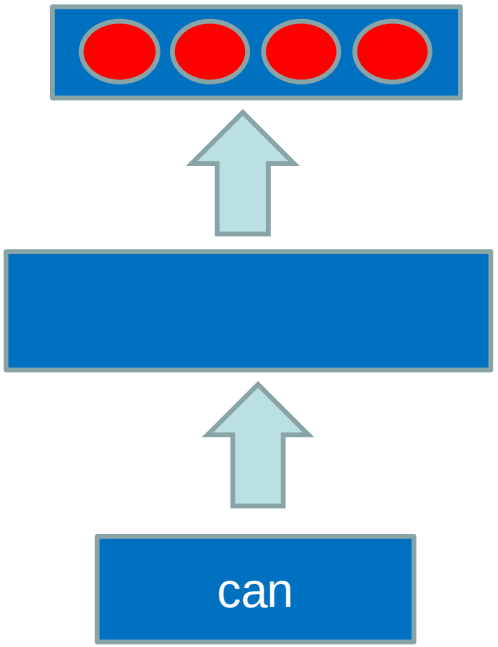
We want to do POS tagging

- That is, label each token in a sentence with its part-of-speech (= word class)
- I can see the cat



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Motivation

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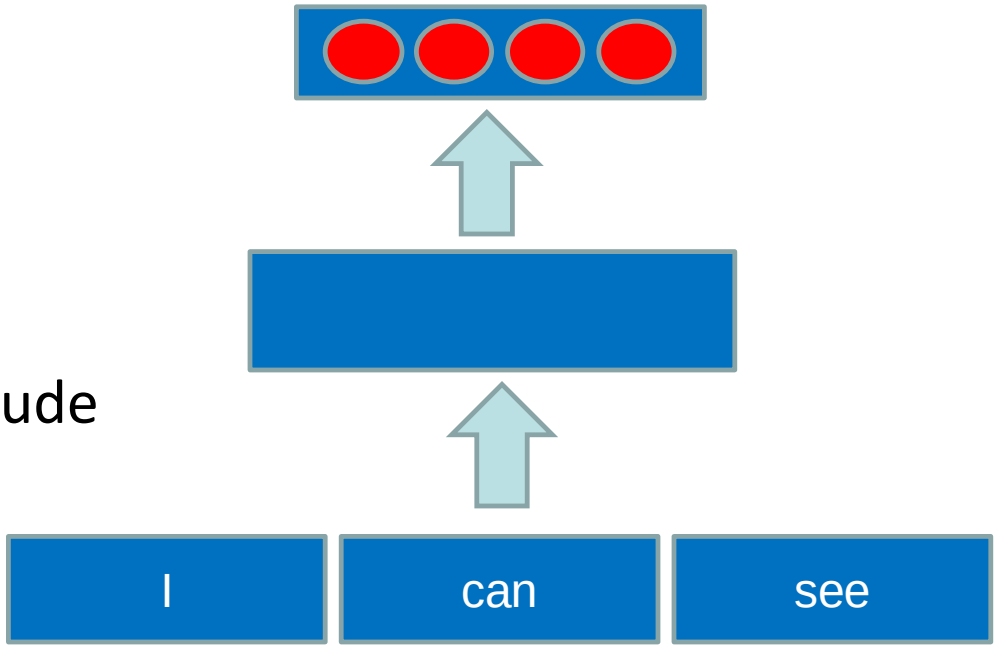

- It's better to include context

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Motivation

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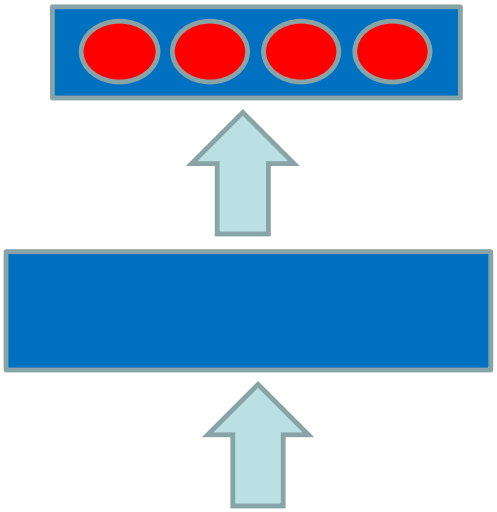

- It's better to include more context

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Motivation

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We want to do POS tagging

- That is, label each token in a sentence with its part-of-speech (= word class)
- I can see the cat

- Problem 1: How much context?
- Problem 2: We cannot simply add more and more context because
  - We have many more parameters then

    → Overfitting

    → Speed

Motivation

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We want to do POS tagging

- That is, label each token in a sentence with its part-of-speech (= word class)
- I can see the cat

- We want a different architecture
  - with infinite context size
  - that has few parameters
  - makes a prediction at each time step

RNN model

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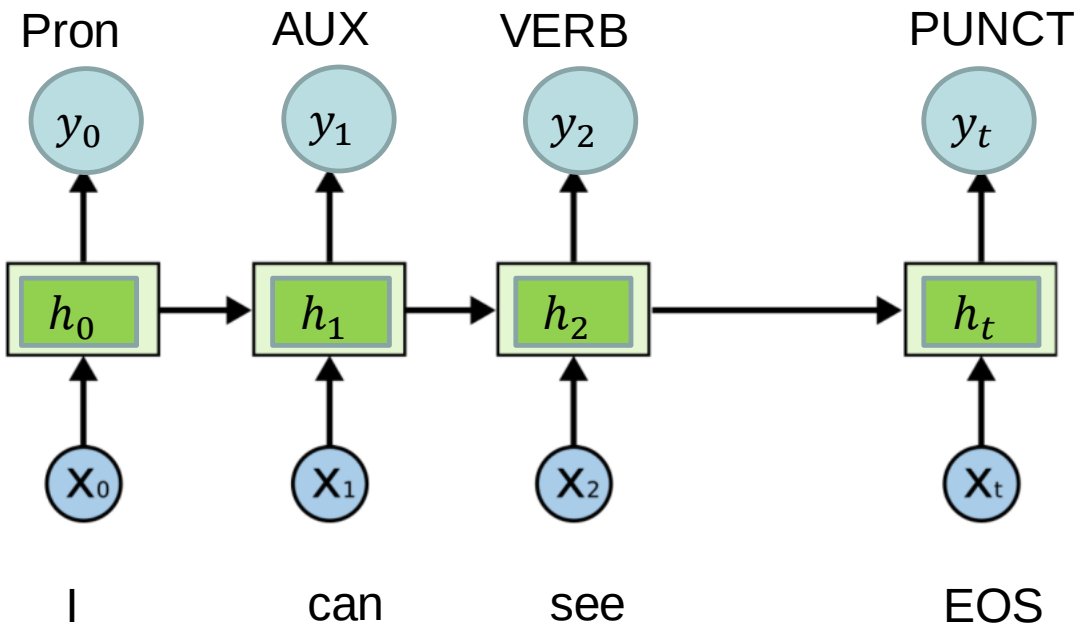

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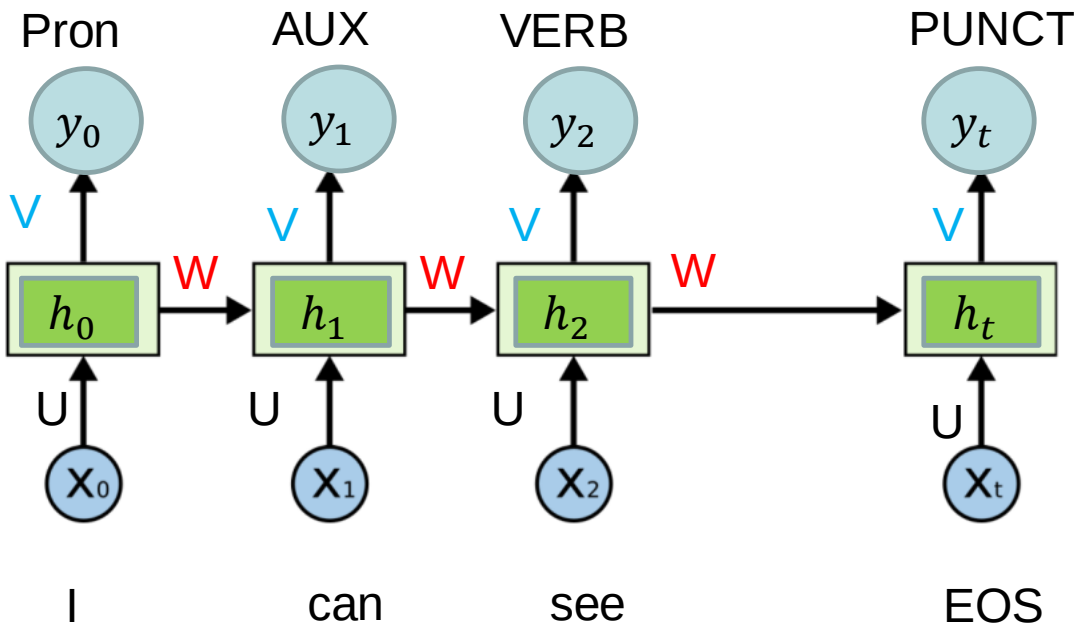
RNN model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RNN model

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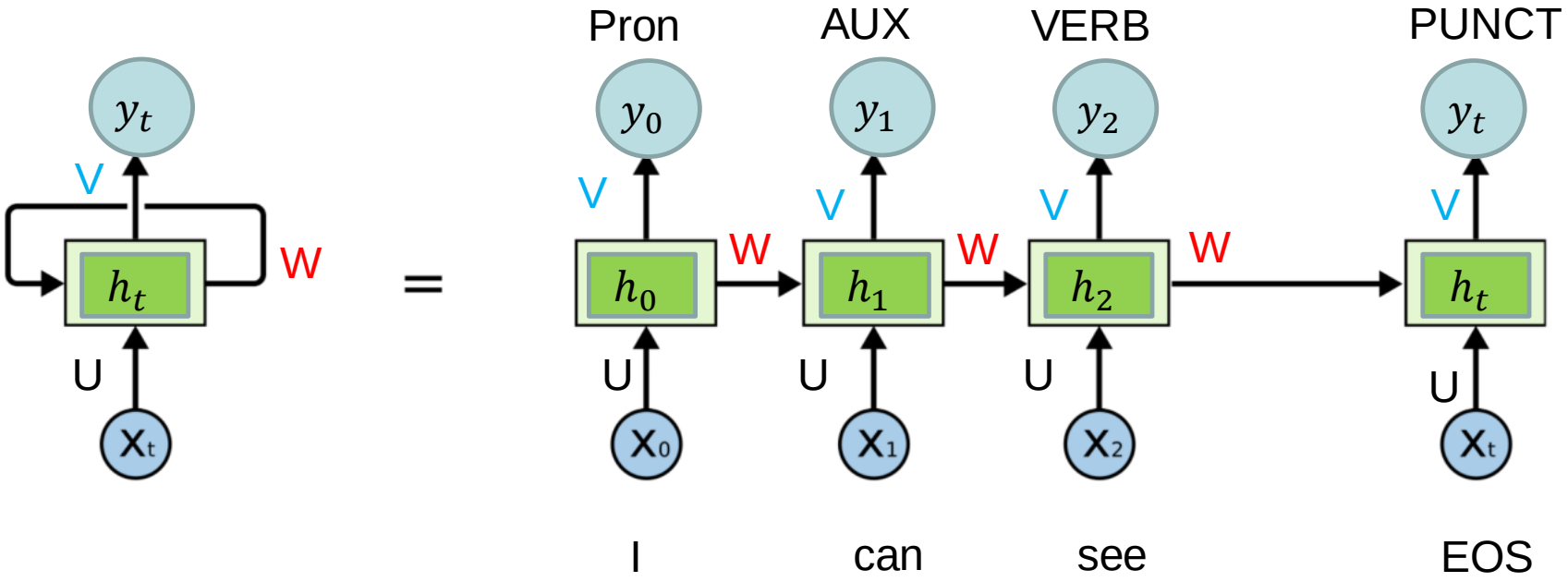

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Math

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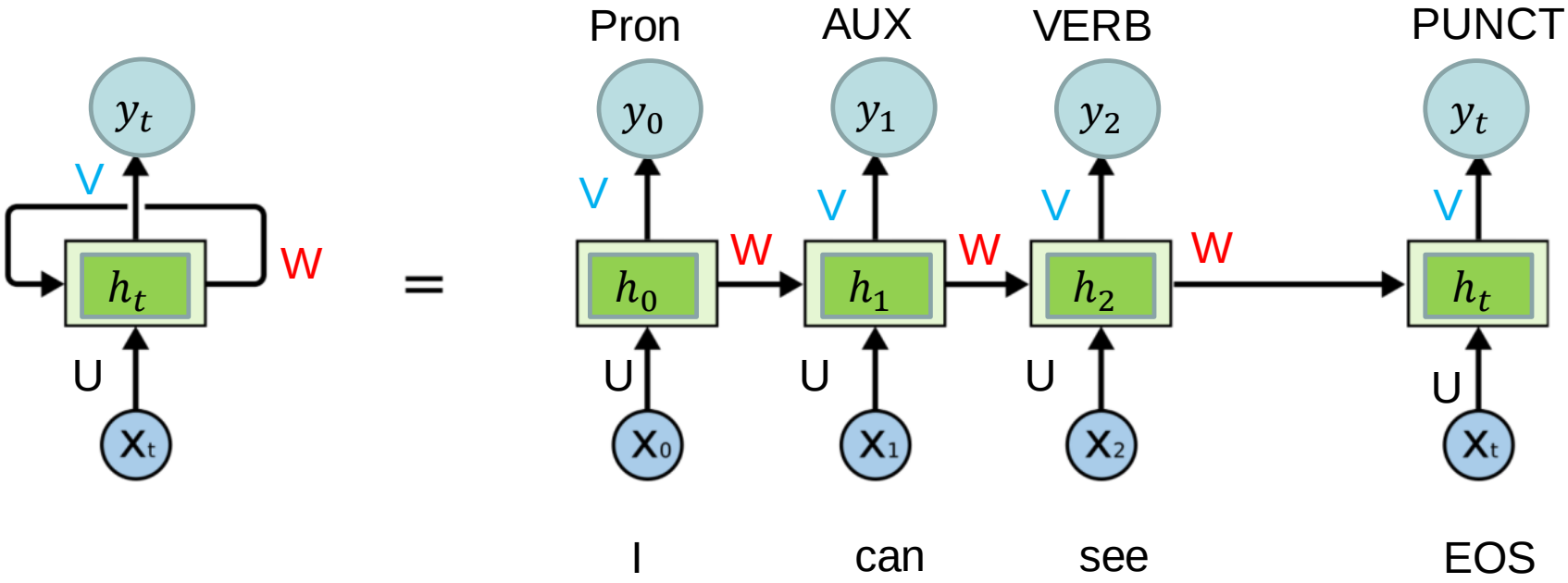
Math: $\boldsymbol{h}_t = f(\boldsymbol{x}_t \boldsymbol{U} + \boldsymbol{h}_{t-1} \boldsymbol{W} + \boldsymbol{b})$

$\boldsymbol{y}_t = \text{softmax}(\boldsymbol{h}_t \boldsymbol{V} + \boldsymbol{c})$



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Benefits

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- Infinite influence from the past – in theory
  - If you make this bidirectional, you also have infinite influence from the future
- Few parameters, via parameter sharing and “small” matrices U, V, W

RNN – Example

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- Input: “A rusty can”
- Embeddings: $\boldsymbol{x}_1 = (1,0,0), \boldsymbol{x}_2 = (1,1,2), \boldsymbol{x}_3 = (1,-1,1)$
- Truth: DET,ADJ,NOUN, encoded as 1-hot vectors (in a 4-d label space)
- Activations: ReLU for hidden layer, Softmax for output layer

RNN – Example

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Initialization:

- $\boldsymbol{U} = \begin{pmatrix} 1 & 1 \\ 2 & 0 \\ 0.5 & 1 \end{pmatrix}$
- $\boldsymbol{W} = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix}$
- $\boldsymbol{V} = \begin{pmatrix} 0 & 1 & 0 & 0 \\ 1 & 0 & \frac{1}{3} & -1 \end{pmatrix}$
- $\boldsymbol{b} = \boldsymbol{c} =$ zero-vectors of appropriate size
- $\boldsymbol{h}_0 = (0,0)$

RNN – Example

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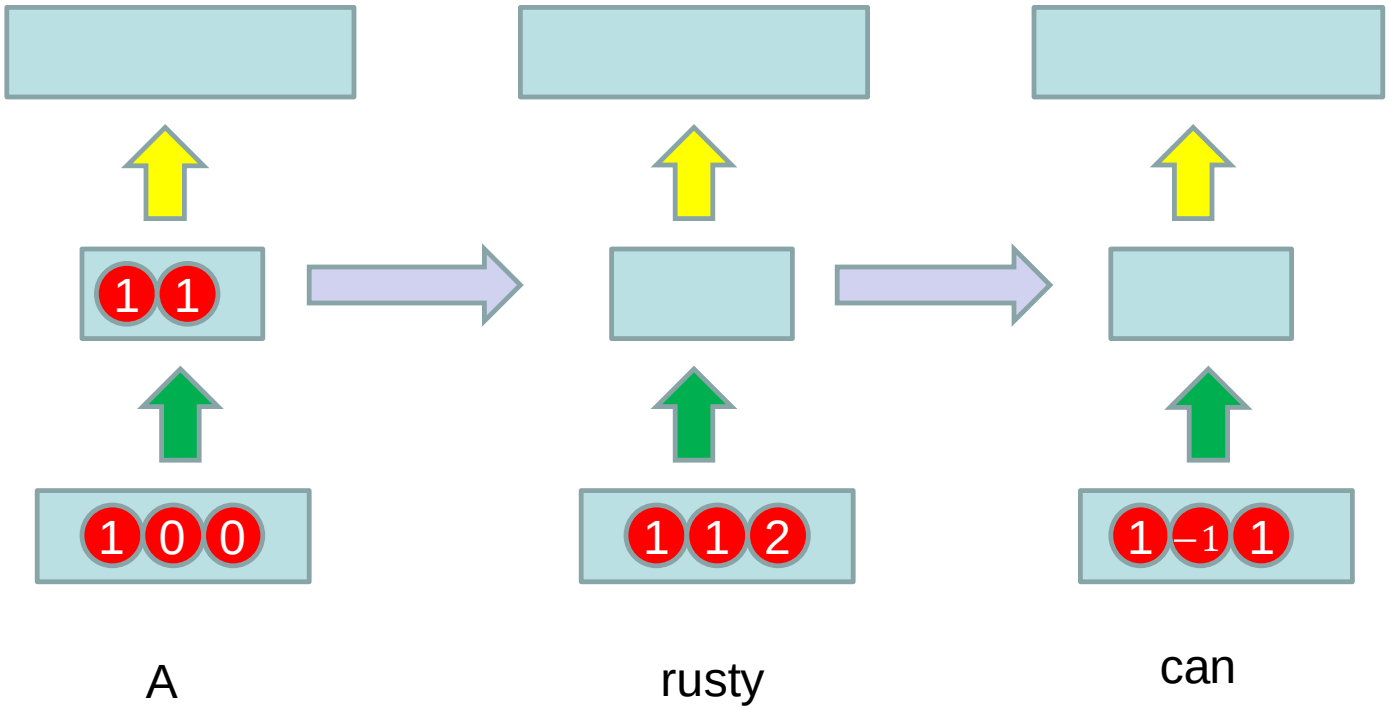
$$\boldsymbol{h}_1 = \sigma_H(\boldsymbol{x}_1\boldsymbol{U} + \boldsymbol{h}_0\boldsymbol{W} + \boldsymbol{b})$$
$$\boldsymbol{h}_1 = (1,1)$$



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RNN – Example

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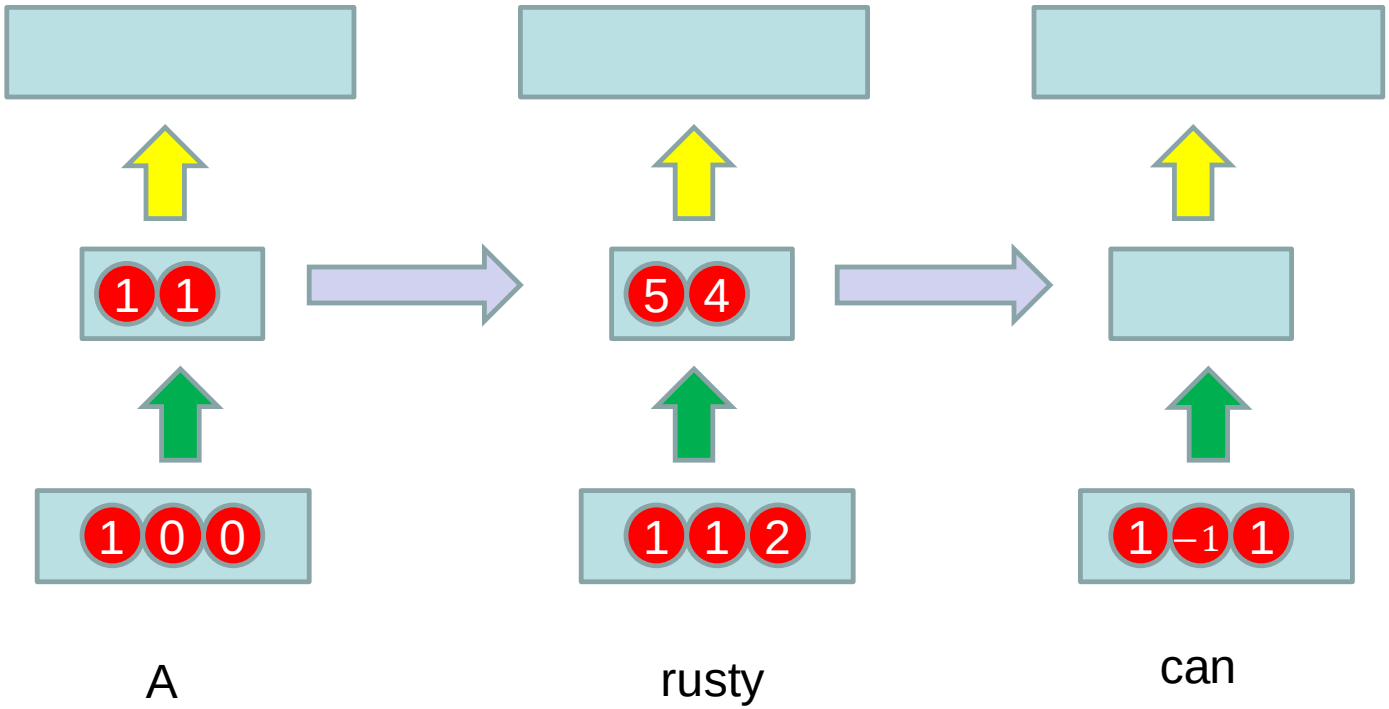
$$\boldsymbol{h}_2 = \sigma_H(\boldsymbol{x}_2\boldsymbol{U} + \boldsymbol{h}_1\boldsymbol{W} + \boldsymbol{b})$$
$$\boldsymbol{h}_2 = (5,4)$$



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RNN – Example

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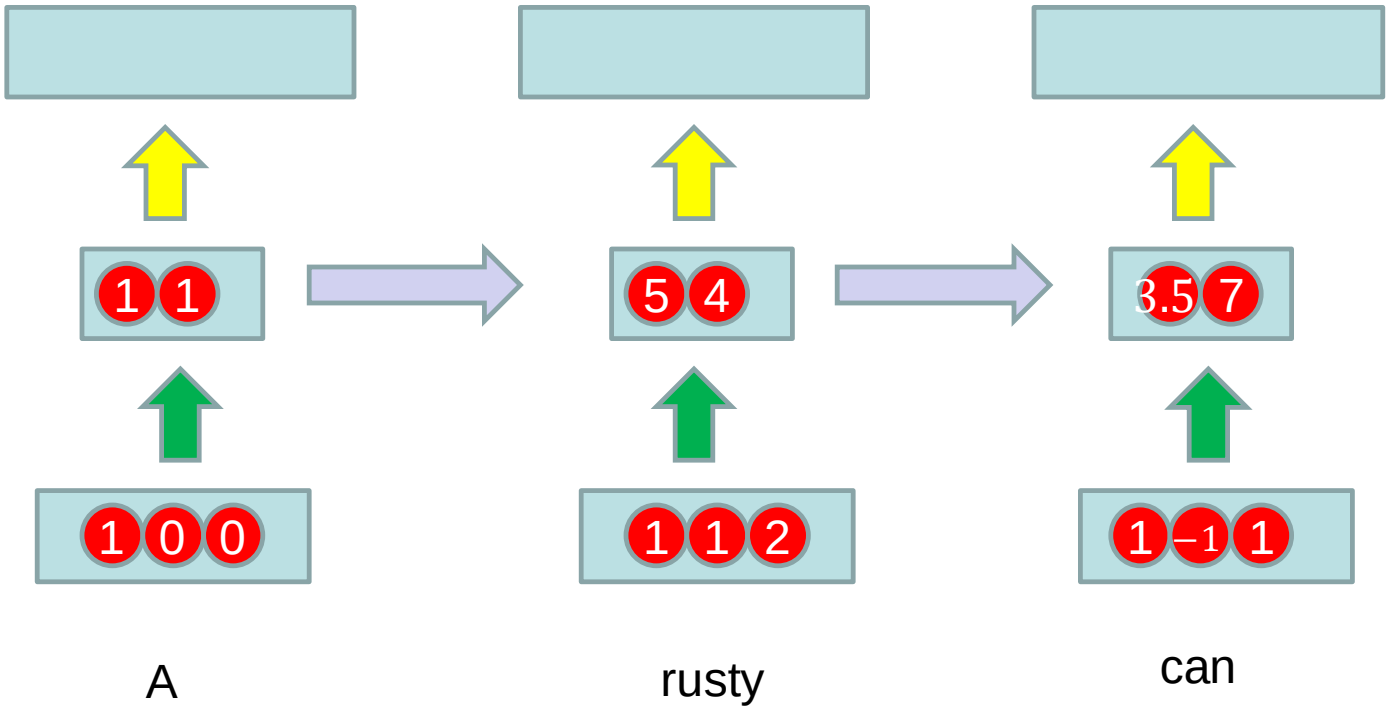
$$\boldsymbol{h}_3 = \sigma_H(\boldsymbol{x}_3\boldsymbol{U} + \boldsymbol{h}_2\boldsymbol{W} + \boldsymbol{b})$$
$$\boldsymbol{h}_3 = (3.5,7)$$



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RNN – Example

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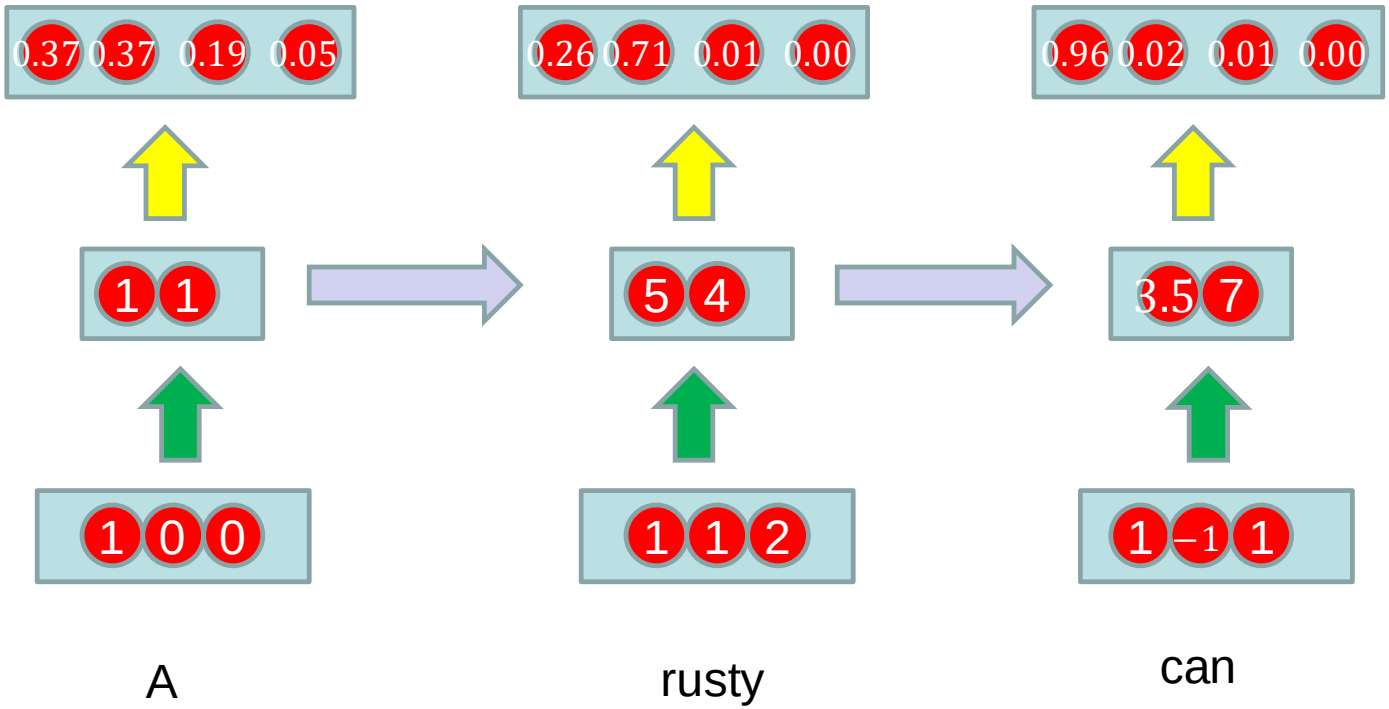
$$\boldsymbol{y}_t = \sigma_Y(\boldsymbol{h}_t \boldsymbol{V} + \boldsymbol{c})$$



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RNN – Example

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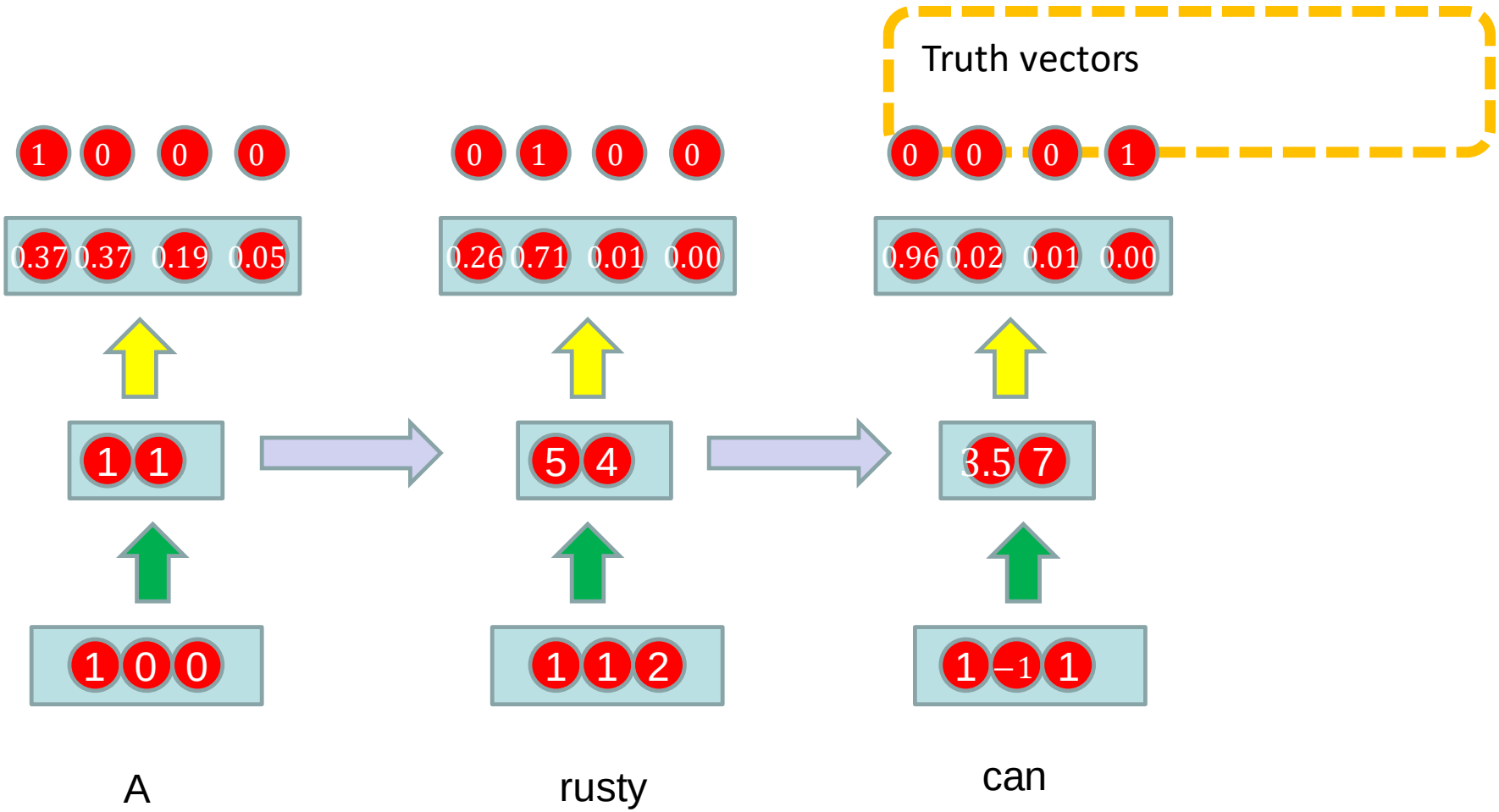

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Excursion 2: Encoder-Decoder Models

RNNs

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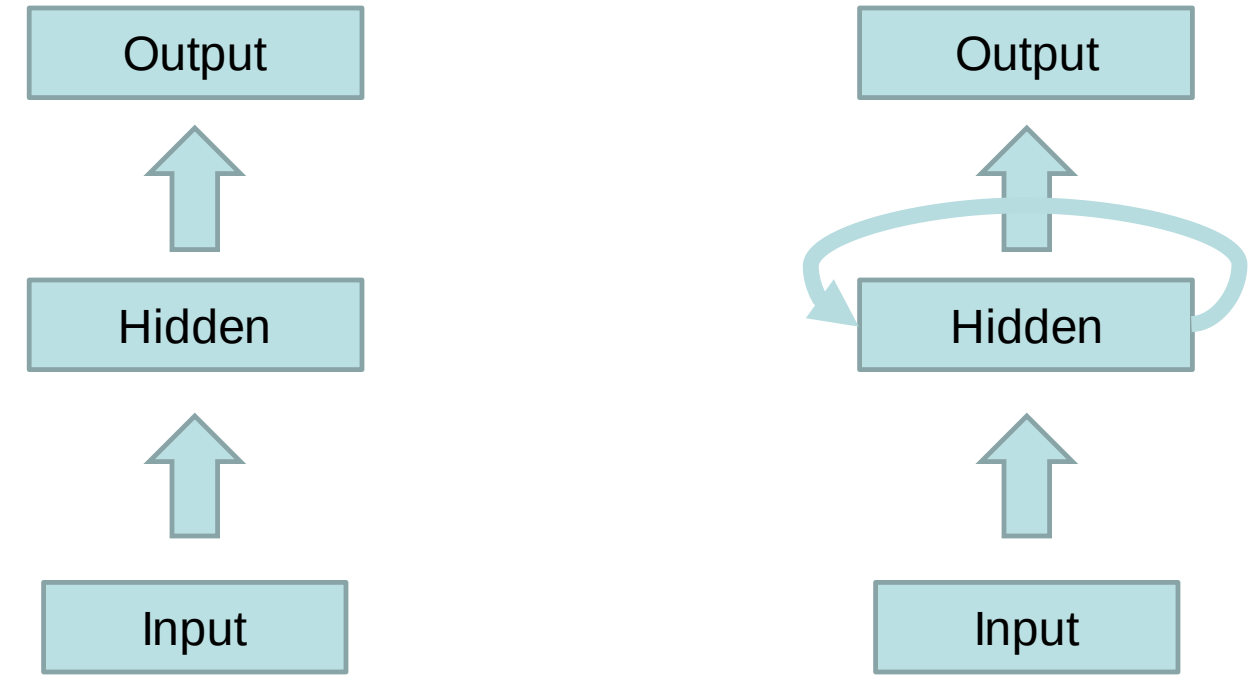
A recurrent neural net (RNN) is a MLP with additional feedback loop



Standard MLP

RNN

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RNNs

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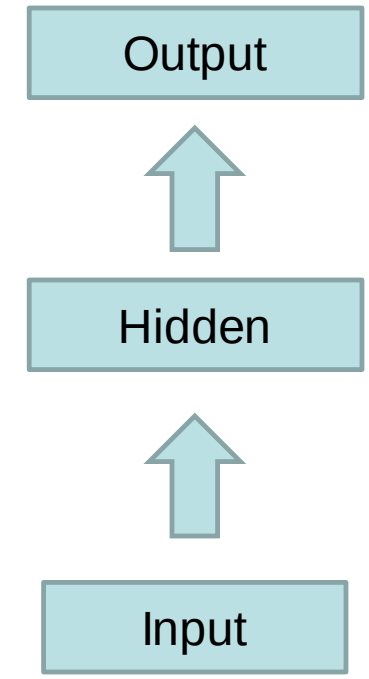
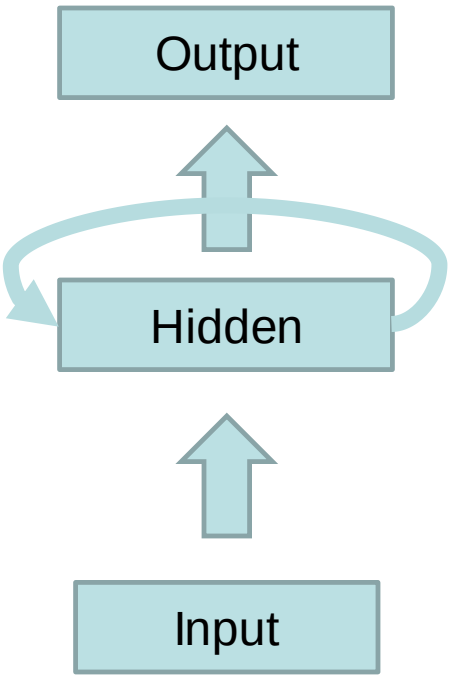


Standard MLP



But with a time delay!

RNN

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From RNNs to Encoder-Decoder Models

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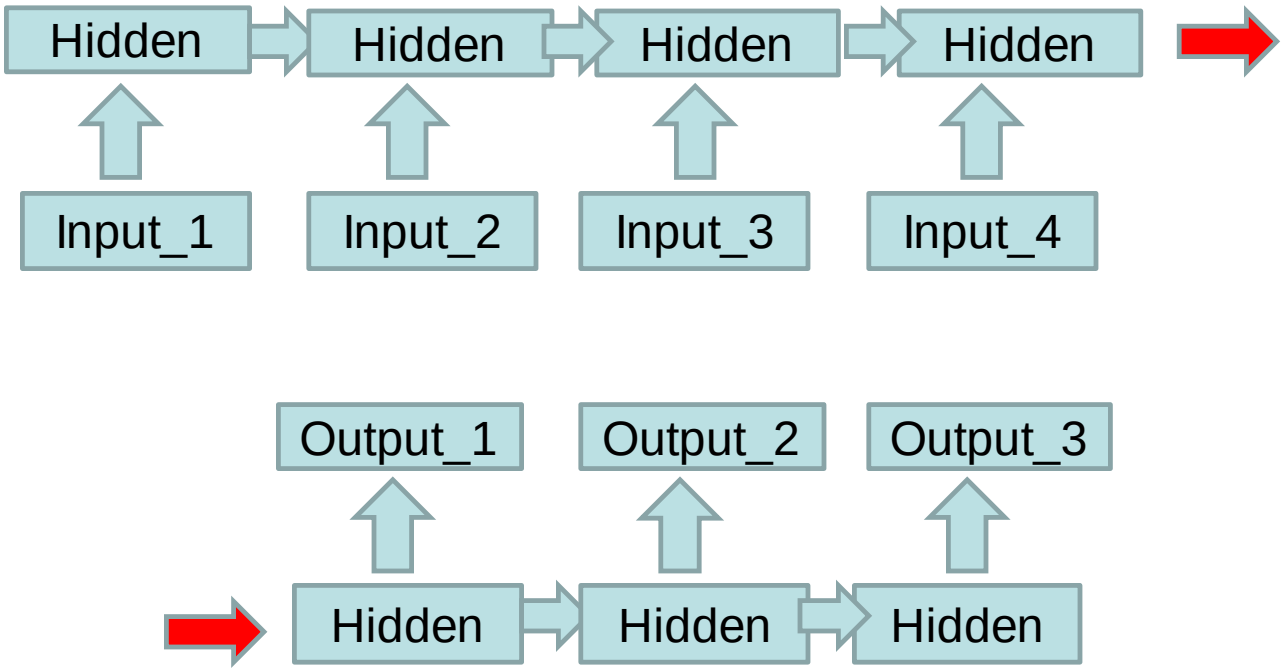
- Encoder-Decoder Models: We stack two RNNs together
- And make some further design changes



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Encoder-Decoder models

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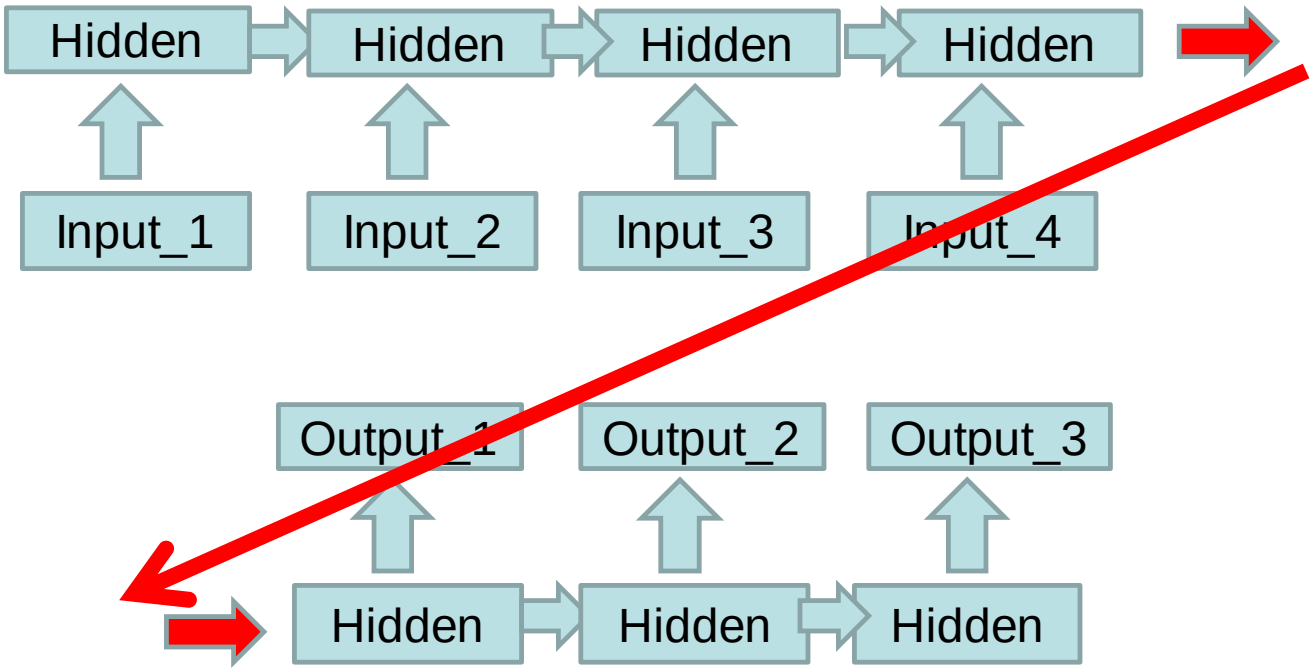
- Encoder-Decoder Models: We stack two RNNs together
- And make some further design changes



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Encoder-Decoder models

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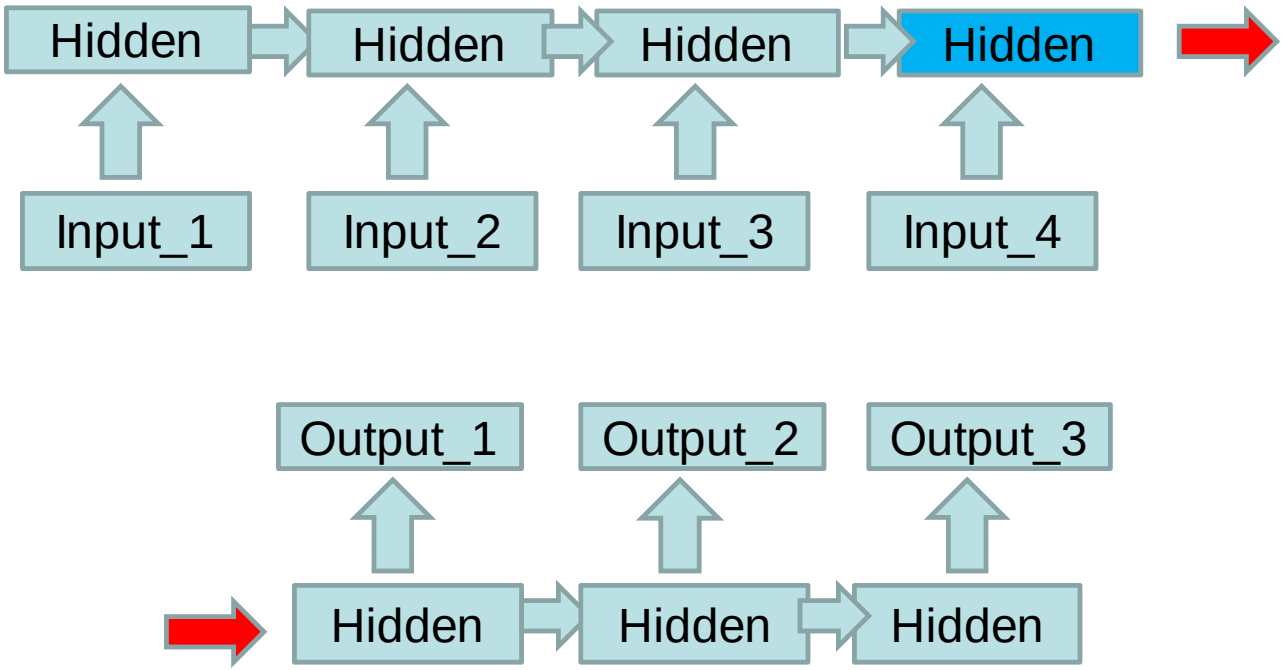
- Encoder-Decoder Models: We stack two RNNs together
- The last hidden layer in the input is taken as representation of the input



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Application of Encoder-Decoder models

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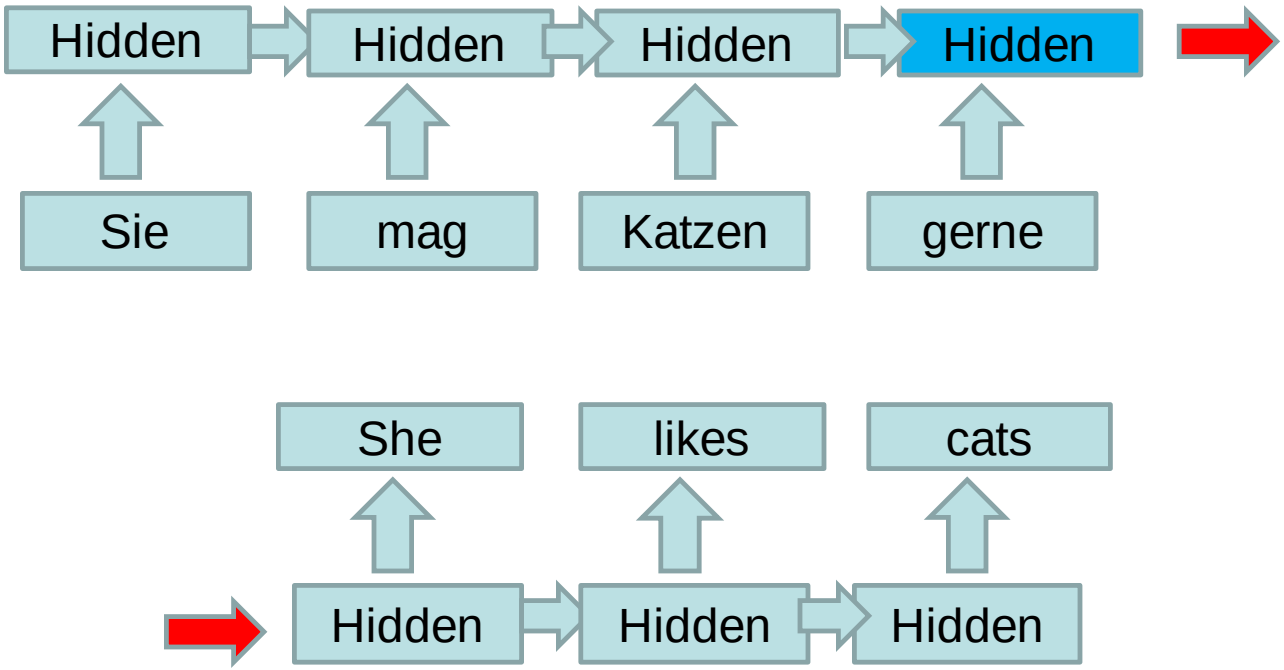
- Encoder-Decoder Models are typically emloyed in Machine Translation
- E.g. Translate a German sentence into an English sentence



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Back to SE: Complex/costly methods

Idea

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- For sentence embeddings, we can exactly take such encoder-decoder models

- E.g. take an encoder-decoder model, let the input sequence equal the output sequence, and take the final hidden vector on the input side to be the **sentence representation**

  - Such an approach is sometimes called an *auto-encoder*

Sequential Denoising Autoencoders

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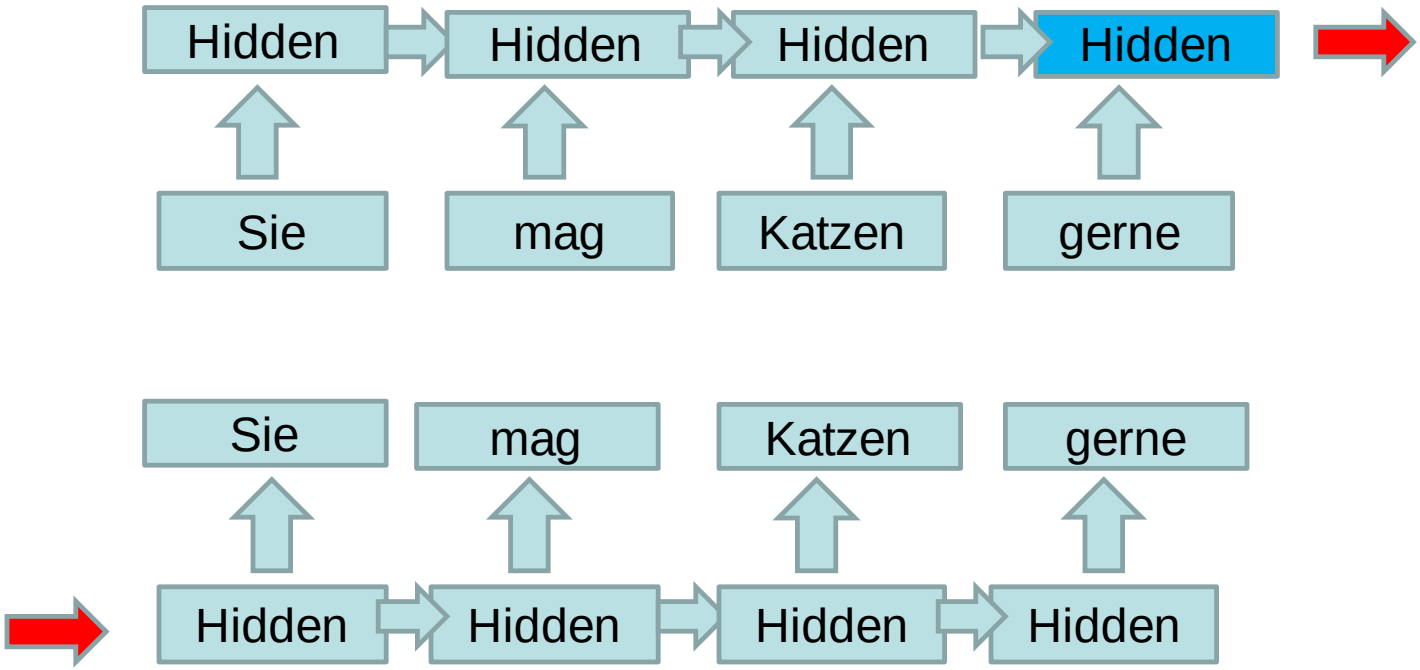
- This is the idea of Hill et al. (2015): **SDAE**
- They in addition do something called *denoising* – they corrupt the input a little



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Skip-thought vectors

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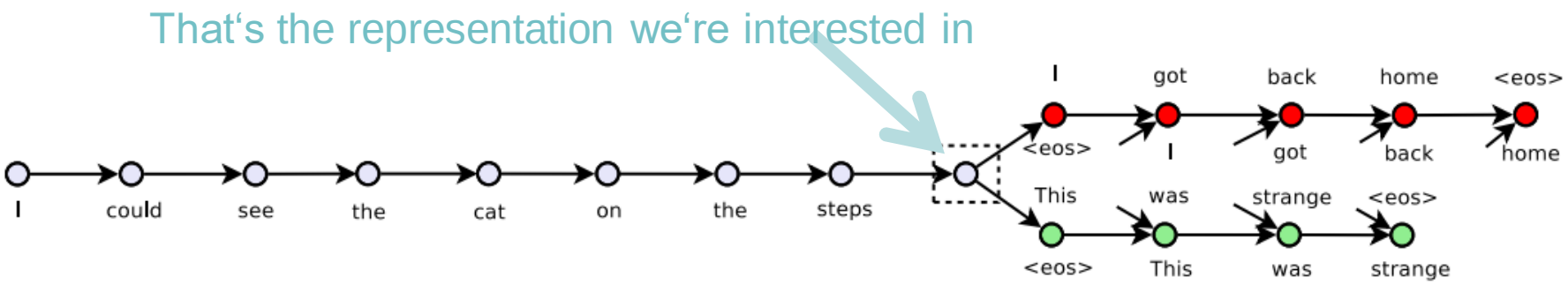
- Another possibility is to predict the *context sentences*, similarly as in Skip-Gram
- This is the idea of Kiros et al. (2015): **Skip-Thought Vectors**



- One can of course easily extend these ideas
  - E.g. predict the current, previous and next sentence, etc.
- What is the difference to our naïve idea number 1?

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Comparison: Skip-thoughts vs. SDAE

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- Skip-thoughts requires text in context – e.g. a novel where preceding and following sentences are coherent

- SDAE only requires individual sentences without context
  - Could be applied easier to, e.g., Twitter etc.
  - Can make use of more data

InferSent

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- It is **supervised** rather than unsupervised as the two methods before
- It trains on high-quality data (Stanford Natural Language Inference Data - SNLI)
- Paper: Supervised Learning of Universal Sentence Representations from Natural Language Inference Data

InferSent – SNLI Training data

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SNLI Corpus

- Stanford Natural Language Inference corpus

  Premise: Girl in a red coat, blue head wrap and jeans is making a snow angel.

  Hypothesis: A girl outside plays in the snow.

  Label: entailment

- 570k premise/hypothesis/label triplets
- Labels: “entailment”, “contradiction”, “neutral”
- http://nlp.stanford.edu/projects/snli/

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InferSent – SNLI Training data

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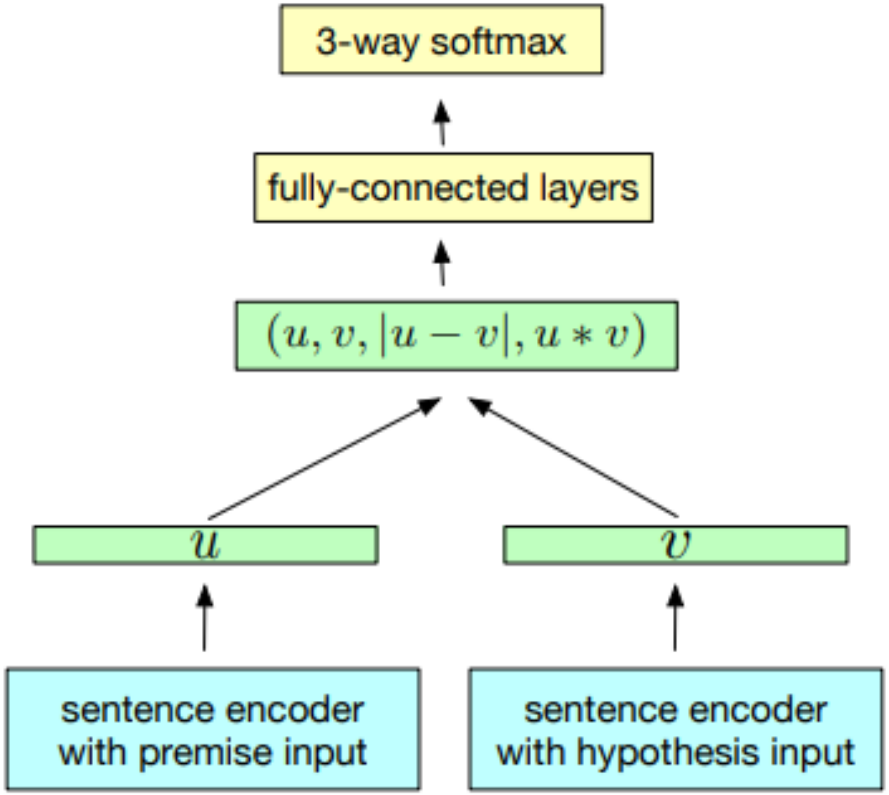

Figure 1: **Generic NLI training scheme.**

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InferSent – General Outline

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Sentence Embedding

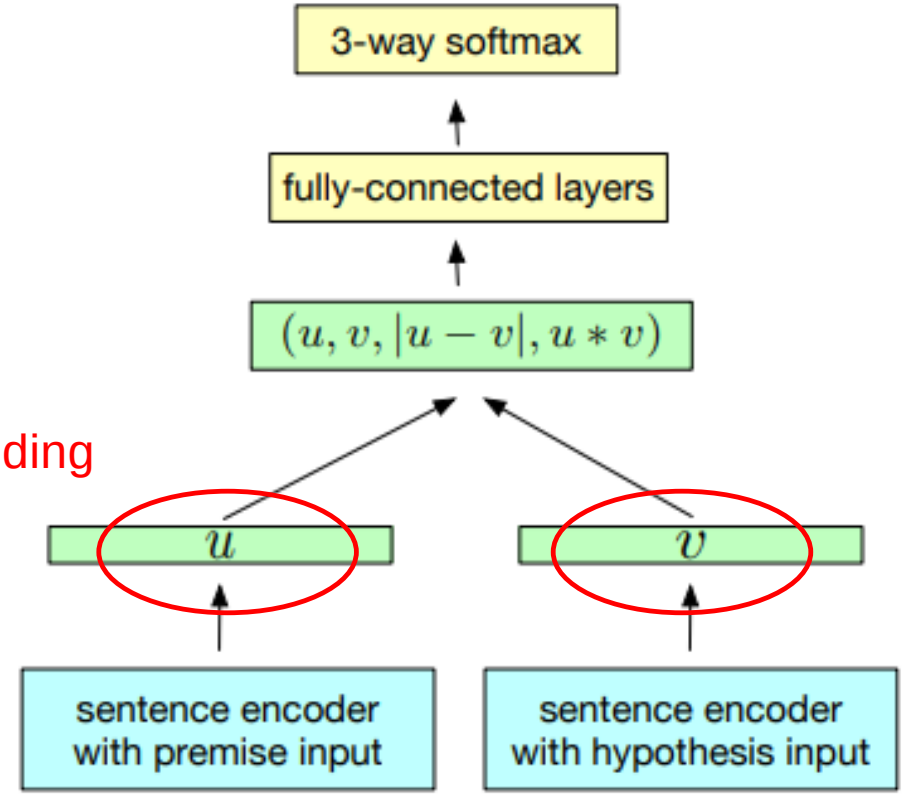

Figure 1: **Generic NLI training scheme.**

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InferSent – Computing the sentence embedding

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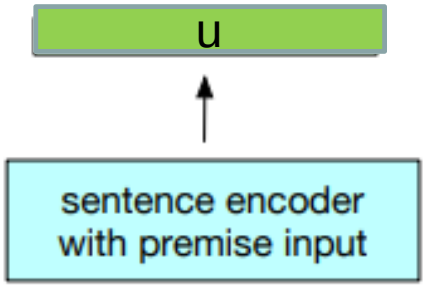
- They use an LSTM, an RNN variant (see Lecture 8)
- Their LSTM is bidirectional



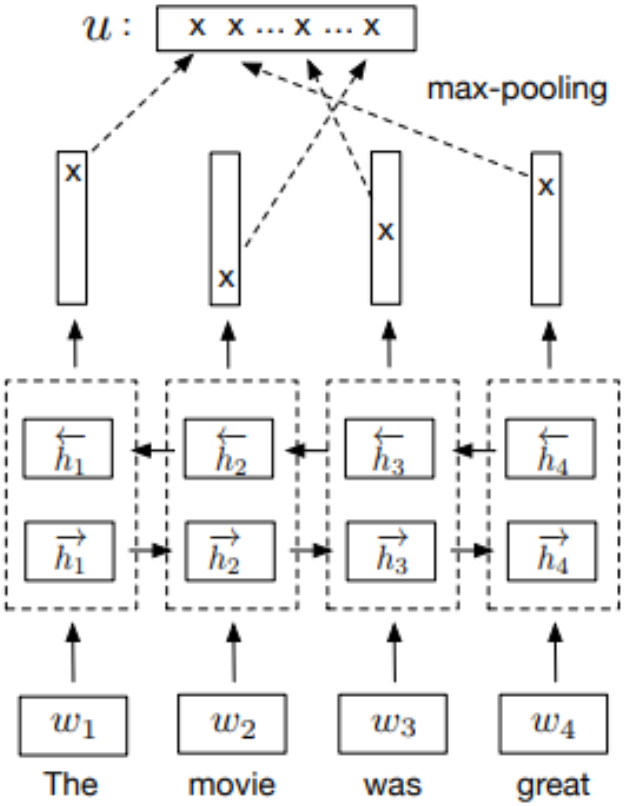


Figure 2: **Bi-LSTM max-pooling network.**

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Back to SE: Simple/cheap methods

Why simple?

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- The previous models were costly, because **at test time** one would have to run a new sentence through an RNN to embed
  - There are many matrix-vector multiplications involved
  - May be slow and memory intensive

- Now we discuss simpler techniques, especially at test time

Concatenated Power Mean Embeddings

(https://github.com/UKPLab/arxiv2018-xling-sentence-embeddings)

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- Proposed by Rücklé et al. (2018)
- 1st Idea is to generalize the average to the so-called *power mean*
  - Power mean of numbers $x_1, \ldots, x_n$
  - $M_p(x_1, \ldots, x_n) = \left(\frac{1}{n}\sum_i x_i^p\right)^{1/p}$
    - $p = -\infty$: $M_p = \min(x_1, \ldots, x_n)$
    - $p = +\infty$: $M_p = \max(x_1, \ldots, x_n)$
    - $p = 1$: ?
    - $p = 2$: quadratic mean
    - $p = 0$: geometric mean
    - .....

Concatenated Power Mean Embeddings

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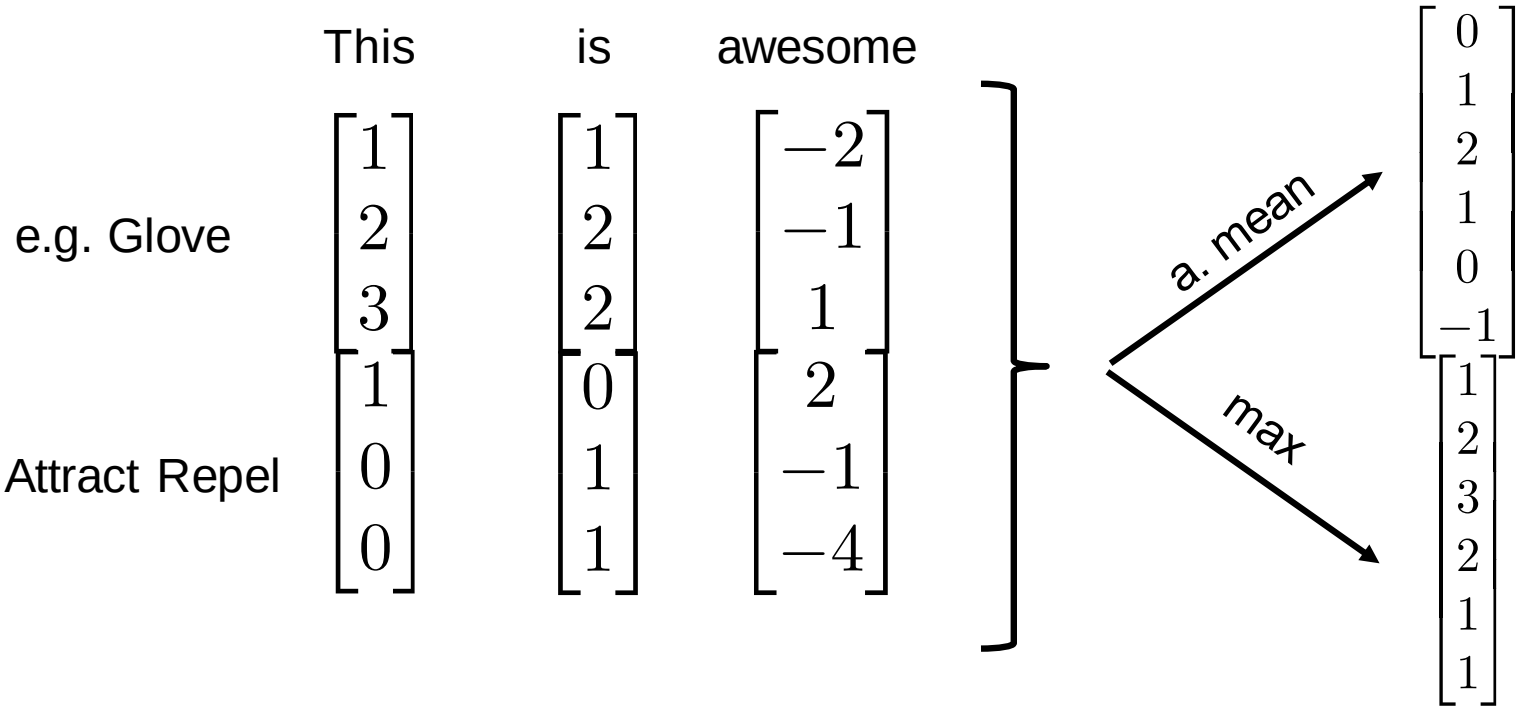
- 1st Idea is to generalize the average to the so-called *power mean*
  - Now instead of taking a per-dimension standard average
  - One takes a per-dimension power mean average
    - Concatenate different power mean representations
  - Why?
- 2nd Idea is to concatenate **diverse** power mean word embeddings
  - Such as Glove,Word2Vec,….
  - Why?

Example



Sentence Embedding

SBERT

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- Sentence BERT
- Fine-tunes BERT on NLI
- Averages BERT embeddings as sentence representation

- Very easy to use software
- Solid results
- Check it out
  - https://www.sbert.net

Multlingual SBERT

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- SBERT across multiple languages
- Idea:
  - Use parallel data to map monolingual representations across languages
  - Using knowledge distillation

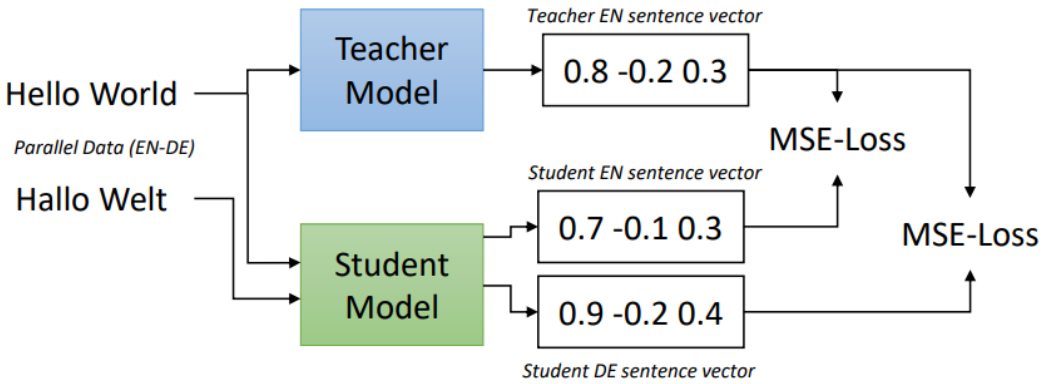

Figure 1: Given parallel data (e.g. English and German), train the student model such that the produced vectors for the English and German sentences are close to the teacher English sentence vector.

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This lecture

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1. Embeddings of sentences (or even documents)

2. **(Problems with) Evaluation of Sentence Embeddings**

Evaluation of Sentence Embeddings

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As for word embeddings

- Extrinsic
  - Feed in to some task
  - Usually apply simple classifier on top of embeddings
    - E.g. logistic regression
- Intrinsic
  - Direct introspection of embeddings

Extrinsic evaluation - Scheme

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A) Take your sentence embedding model

B) Embed sentences in an extrinsic task

C) Train classifier on embedded sentences

D) Repeat with different sentence embedding model and compare performances

Extrinsic tasks

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name	N	task	C	examples
MR	11k	sentiment (movies)	2	"Too slow for a younger crowd , too shallow for an older one." (neg)
CR	4k	product reviews	2	"We tried it out christmas night and it worked great ." (pos)
SUBJ	10k	subjectivity/objectivity	2	"A movie that doesn't aim too high , but doesn't need to." (subj)
MPQA	11k	opinion polarity	2	"don't want"; "would like to tell"; (neg, pos)
TREC	6k	question-type	6	"What are the twin cities ?" (LOC:city)
SST	70k	sentiment (movies)	2	"Audrey Tautou has a knack for picking roles that magnify her [..]" (pos)

Table 1: **Classification tasks**. C is the number of class and N is the number of samples.

Intrinsic evaluation - Scheme

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A) Take your sentence embedding model

B) Embed sentence pairs in an intrinsic task

C) Use cosine to measure distance between pairs

D) Correlate with human judgments

Intrinsic tasks

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name	task	N	premise	hypothesis	label
SICK-R	STS	10k	"A man is singing a song and playing the guitar"	"A man is opening a package that contains headphones"	1.6
STS14	STS	4.5k	"Liquid ammonia leak kills 15 in Shanghai"	"Liquid ammonia leak kills at least 15 in Shanghai"	4.6

Table 2: **Natural Language Inference and Semantic Textual Similarity tasks**. NLI labels are contradiction, neutral and entailment. STS labels are scores between 0 and 5.

Problems with Evaluation of Sentence (and Word!) Embeddings

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(1) Researchers come up with models of vastly different sizes
   - 300d, 600d, 700d, 3600d, 4096d, 4800d
   - Comparison is unfair

(2) Different models trained on different datasets (Wikipedia, common crawl, Toronto Book corpus, …)

(3) Which classifier to use on top of embeddings in extrinsic tasks?

Sizes

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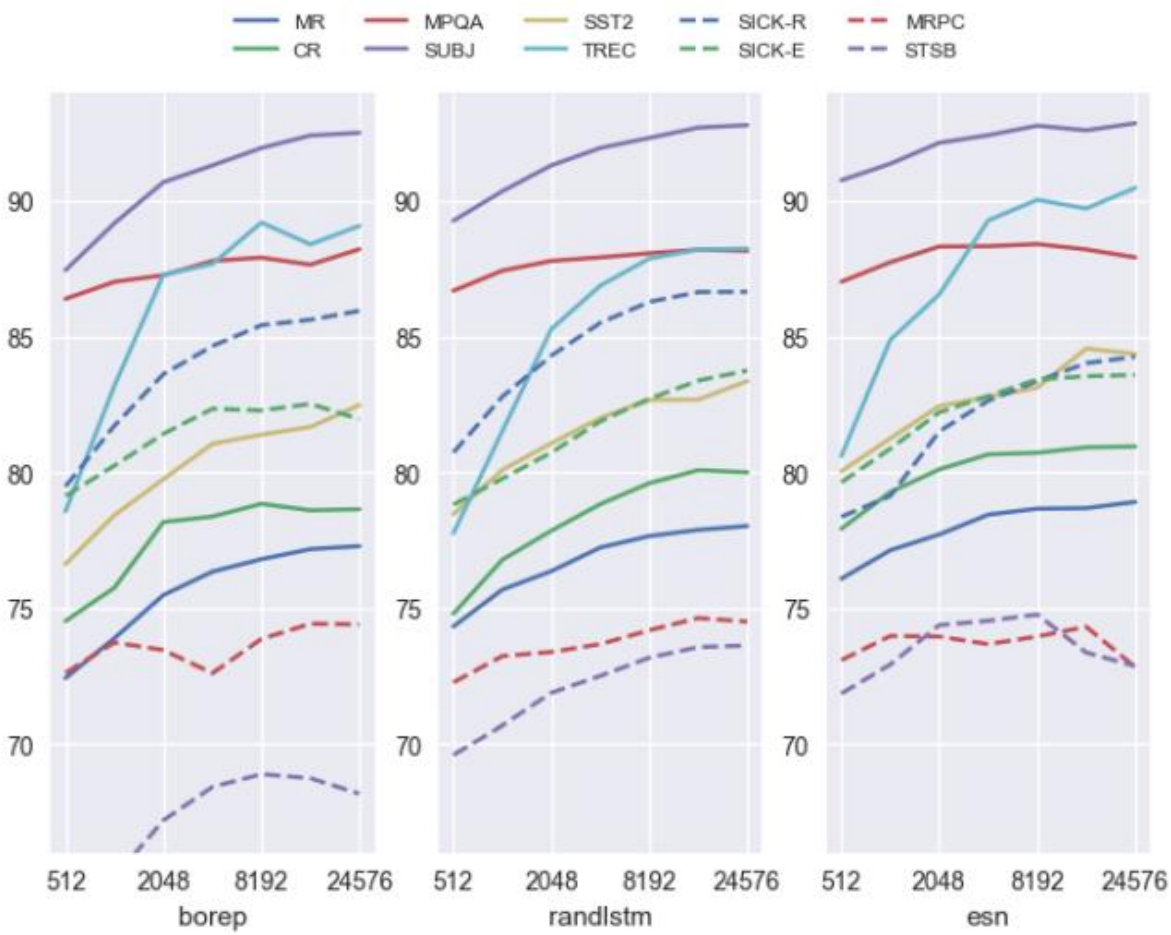
Wieting and Kiela (2019), ICLR



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Sizes

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Eger et al. (2019), Problems with Eval of Sentence Emb., Repl4NLP

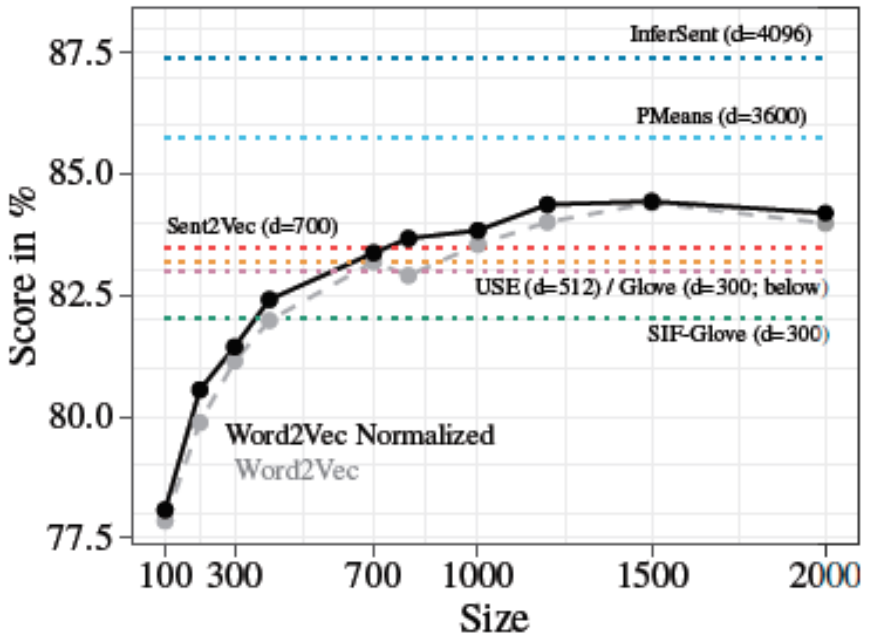

Figure 1: Avg. score across 6 transfer tasks for different sizes of Word2Vec embeddings vs. scores of other encoders (with constant embedding sizes as given in Table 1). 'Word2Vec Normalized' is discussed below.

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Introspection of Sentence Embeddings

Linguistic Probing Tasks

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- What linguistic information is captured in embeddings?
  - Sentence length
  - Word order
  - Whether a certain word is in the sentence
  - Agreement between subject and verb (*she likes cats* vs. *she like cats*)

- Extrinsic and intrinsic evaluation give limited insights
  - Because they are complex tasks and may require several knowledge nuggets

- Probing tasks introspect embeddings → help to **interpret** them

Linguistic Probing Tasks

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Table 4: Linguistic probing tasks description and samples.

Task	Description	Example	Output
Bigram Shift (BShift)	Whether two words (tokens) in a sentence have been inverted	This is my Eve Christmas .	Inverted
Coordination Inversion (CoordInv)	Sentences comprised of two coordinate clauses. Detect whether clauses are inverted	I returned to my work , and Lisa headed for her office .	Inverted
Object Number (ObjNum)	Number of the direct object in the main clause (singular and plural)	He received the 200 points .	NNS (Plural)
Sentence Length (SentLen)	Predict the sentence length among 6 classes, which are length intervals	I can 't wait to show you and Mr. Taylor .	9 – 12 words
Semantic Odd Man Out (SOMO)	Random noun or verb replaced in the sentence by another noun or verb. Detect whether the sentence has been modified	Tomas surmised as well .	Changed

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Linguistic Probing Tasks

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Subject Number (SubjNum)	Number of the subject in the main clause (singular and plural)	If there was ever a time to let loose , this vacation would have to be it .	Singular
Past Present (Tense)	Whether the main verb in the sentence is in the past or present tense	She smiled at him , her eyes alight with love .	Present
Top-Constituent (TopConst)	Classification task, where the classes are given by the 19 most common top-constituent sequences in the corpus	Did he buy anything from Troy ?	VBD_NP_VP_
Depth of Syntactic Tree (TreeDepth)	Predict the maximum depth of the syntactic tree of the sentence	The leaves were in various of stages of life .	10
Word Content (WC)	Predict which of the target words (among 1000) appear in the sentence	She eyed him skeptically .	eyed

Summary

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- Representation learning for sentences or whole documents
  - For information retrieval
  - Clustering
  - Classification
- Approaches:
  - Complex approaches based on RNNs (InferSent, SkipThought, …)
  - Simple approaches like (generalized) averaging
- Also looked at Evaluation of Sentence Representations
  - Intrinsic
  - Extrinsic

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