# Deep Learning for Natural Language Processing

Autoregressive Sequence Models



CHALMERS

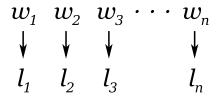


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## structured prediction: basic terminology

- sequence labeling is a structured prediction task
- ▶ input: a sequence x
- ightharpoonup output: a sequence  $m{y}$  of the same length as  $m{x}$



## Algorithmic approaches

#### Exhaustive search

Cast structured prediction as a combinatorial optimisation problem over the set of target representations.

Viterbi algorithm, Eisner algorithm

#### Greedy search

Cast structured prediction as a sequence of classification problems: at each point in time, predict one of several options.

window-based part-of-speech tagging, arc-standard algorithm

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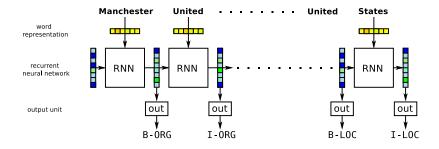
Viterbi algorithm, Eisner algorithm

#### Greedy search

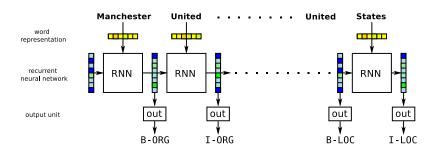
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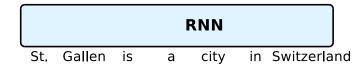
## RNN-based sequence labeling

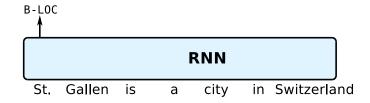


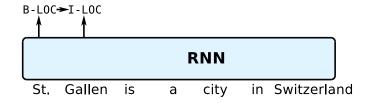
#### a limitation of our current model

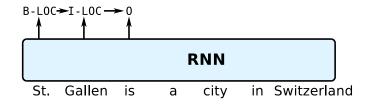


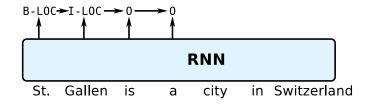
- our output decisions don't affect each other
- can we model the interdependency between labels?
  - ▶ for instance, that B-LOC+I-LOC is good
  - but B-LOC+I-ORG is bad

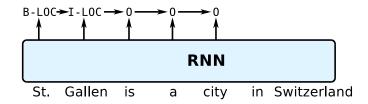


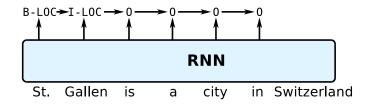


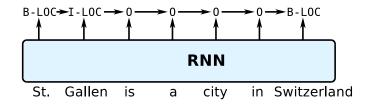






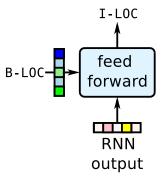






## implementation of autoregressive sequence models

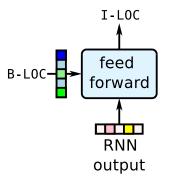
example of a model that depends on the previous output



if the prediction model is an RNN, it depends on the full history

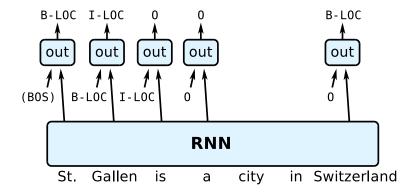
## training autoregressive sequence models

how do we train a model that depends on its own predictions?



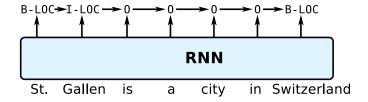
- the classical solution is to use the gold-standard label
- this idea is called teacher forcing

# implementing teacher forcing



## after training: running the system

- at prediction time, we run the system incrementally
- ▶ in this case, the previous label is a predicted label



## limitations of teacher forcing

- training-time and prediction time data distributions are different
  - ▶ at prediction time, some of the previous labels will be incorrect
- if we make a mistake, the system might be in a situation it has never seen before!
  - this is called exposure bias
- risk of compounding errors



## limitations of autoregressive models

the predictions are influenced by past predictions but not by future predictions

```
Paris Hilton is a media celebrity B-LOC I-PER O O O O
```

- because the prediction algorithm is greedy, the model can't change its mind!
- in the next lecture, we will see a non-greedy approach

#### exercise 2

we will continue our NER experiments

Manchester	United	will	return	to	the	United	States
B-ORG	I-ORG	Ο	0	Ο	Ο	B-LOC	I-LOC

 we will investigate autoregressive models and conditional random fields (next lecture)