

## Lec 4 Sequence Modelling

### # Motivation

Lots of seqs in NLP

- words
- characters
- documents

Long-distance dependencies

- gender agreements
- semantic/factual dependencies
- what 'it' refers to

Winograd schema ← linguistic challenge with minimal pairs

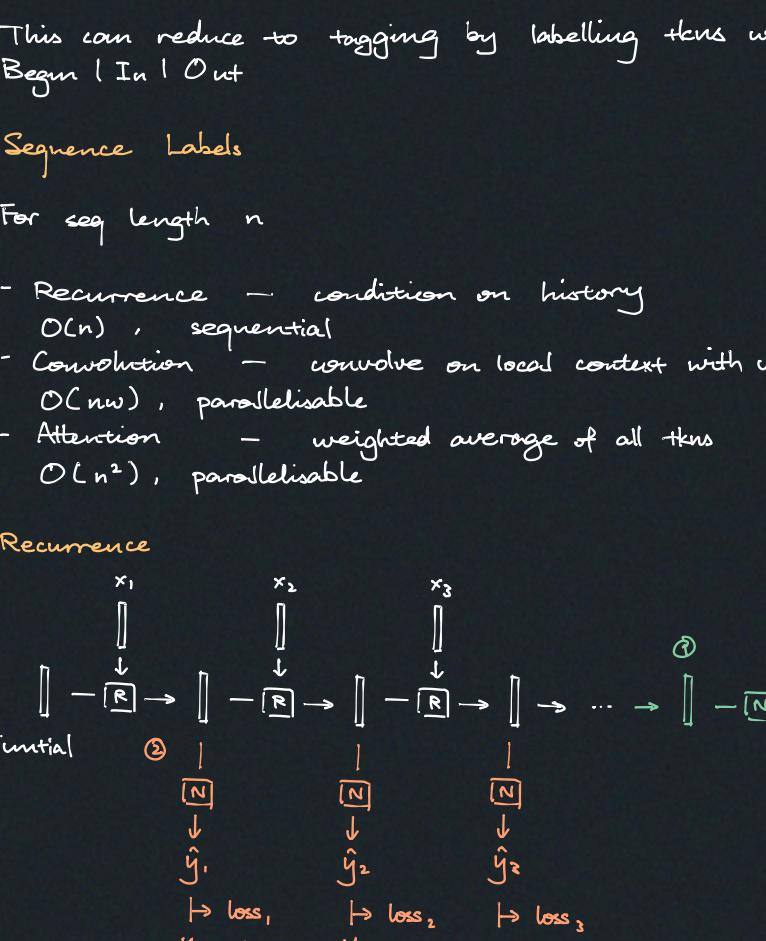
trophy won't fit in bag, it is too small

trophy won't fit in bag, it is too big

→ Figurative language

### # Sequential prediction problems

- Binary
- Multi-class
- Structured
  - ↳ part of speech labelling  
I hate this movie → PRP VBP DT NN
  - ↳ translation  
I hate this movie → kono eiga ga kirei



Paradigm: extract feature → predict

### ▷ Sequence Labelling

$$X \rightarrow Y \text{ st. } |Y| = |X|$$

- Part of speech
- Lemmatisation
- Morphological tagging

saw → tense: past

{ stemming only  
chose things off

### ▷ Span Labelling

- NER
- Carnegie Mellon University → ORG

- Syntactic Chunking

VP, NP, etc.

- Semantic Role Labelling

actor, predicate, location

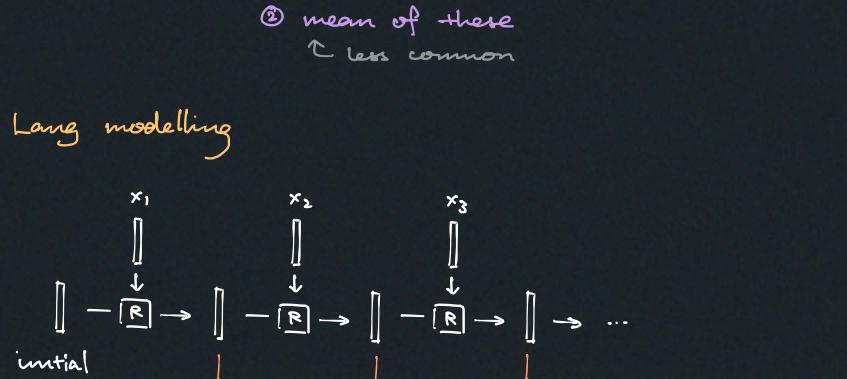
This can reduce to tagging by labelling tokens with  
Begin | In | Out

### # Sequence Labels

For seq length  $n$

- Recurrence - condition on history  $O(n)$ , sequential
- Convolution - convolve on local context with window size  $w$   $O(nw)$ , parallelisable
- Attention - weighted average of all tks  $O(n^2)$ , parallelisable

### # Recurrence



→ Bidirectional RNN

- Vanishing/exploding gradient if long recurrence
  - ↳ try to put more direct path from important info to loss and unimportant ones further
  - ↳ residual connections in other situations

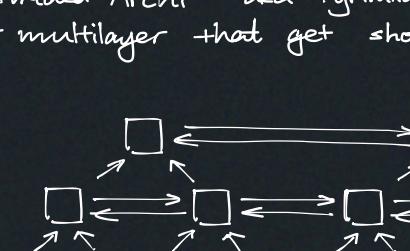
### # LSTM - useful for very long sequences

Idea: additive input between every time step

### # Convolution - useful in speech/image proc

many frames many pixels

### → Convolution auto-regressive



### # Attention

- Cross attention: attend to another seq
- Self attention: attend to context in same seq

Calculation:

query := current decoder state  
key := encoder states  
values := things to combine together



The score func a:

- MLP (original paper)  $a(q, k) = w_2^\top \tanh(w_1[q; k])$

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- bilinear  $a(q, k) = q^\top W k$

- dot product  $a(q, k) = q^\top k$

- scaled dot prod  $a(q, k) = \frac{q^\top k}{\sqrt{|k|}}$  ← normalise

:

Note we sometimes want the model to not look at future information. We can make attention mask to make attention score to future token  $-\infty$  (softmax turns them 0)

### ▷ Seq encoding

- RNN could be harder to change if long distance
- attention has direct connection so learns long distance quickly
- attention models becomes sequential when generating

Exists: translation with strong Trans encoder + fast RNN decoder

### # Efficiency Considerations

Sequences have different length : C

- Padding and masking
  - ↳ when calculating loss, multiply pad locs by 0

- Bucketing / sorting
  - ↳ put similar length in same batch
  - ↳ BUT this disrupts random data distribution

- Strided Archi aka Pyramidal RNN aka sparse attention

↳ multilayer that get shorter to save compute



### → Truncated BPTT

↳ break into smaller seqs, subsequent passes take prev pass out

↳ backprop into shorter distances

