7. Machine Translation, Seq2seq

LING-581-Natural Language Processing 1

Instructor: Hakyung Sung

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*Acknowledgment: These course slides are based on materials from CS224N @ Stanford University

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Review

Review

- RNNs
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- LSTMs
- Bidirectional RNNs

Review: Problems with RNNs

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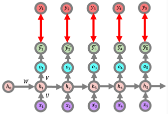

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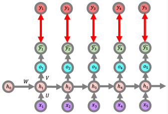

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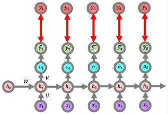

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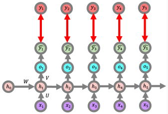

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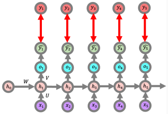

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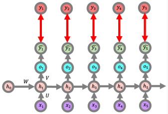

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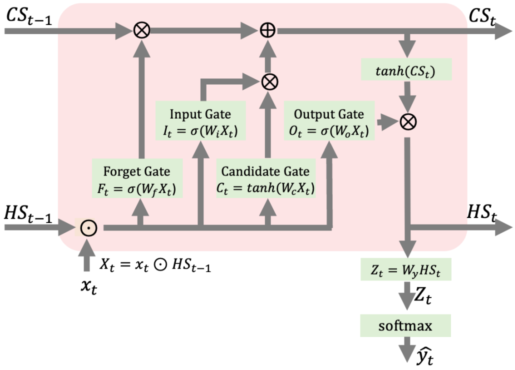
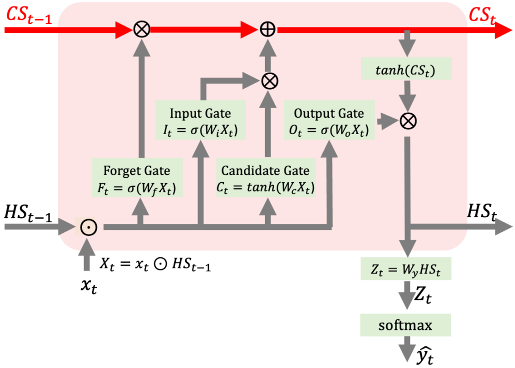
- If each multiplication factor:
  - is < 1, gradients shrink exponentially (vanishing).
  - is > 1, gradients grow exponentially (exploding).
- Standard feedforward nets have limited depth, so this extreme behavior is less pronounced.

Vanishing problem: Solution

Separate memory cell with gating mechanisms to add/erase information.

Review: LSTMs





CS_{t-1}
CS_t
$tanh(CS_t)$
Input Gate
$I_t = \sigma(W_i X_t)$
Output Gate
$O_t = \sigma(W_o X_t)$
Forget Gate
$F_t = \sigma(W_f X_t)$
Candidate Gate
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x_t
$Z_t = W_y HS_t$
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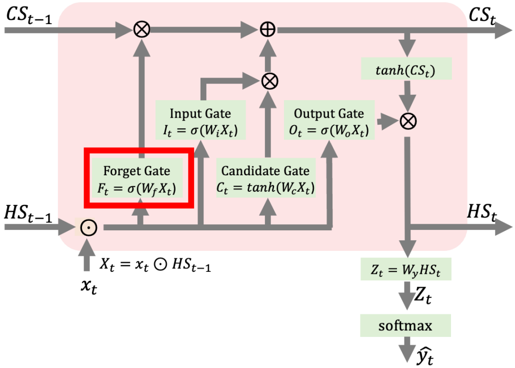
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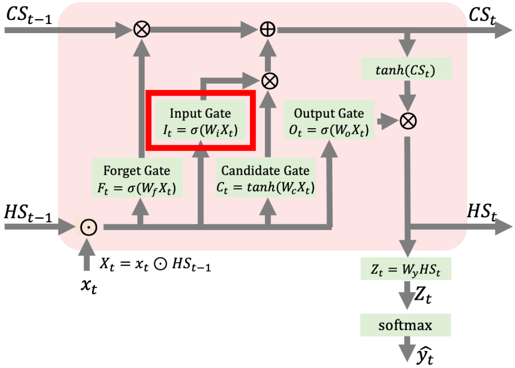
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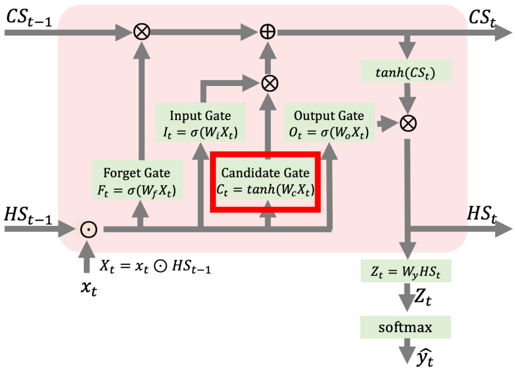

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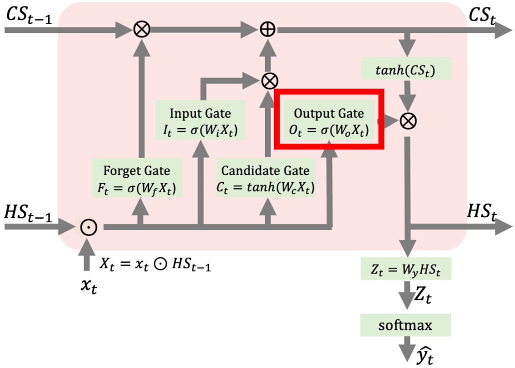
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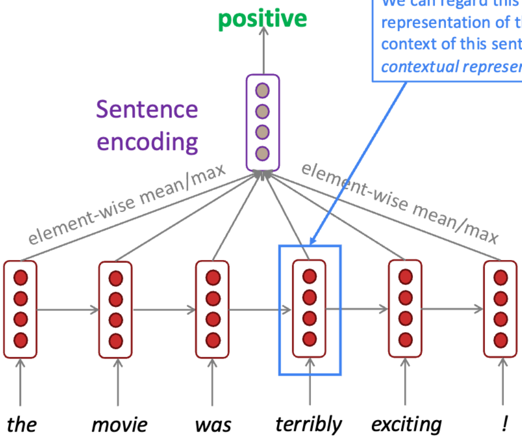
Review: Bidirectional RNNs

- A standard RNN only uses past context.
- Bidirectional RNNs process the sequence in both directions.

Task: Sentiment Classification

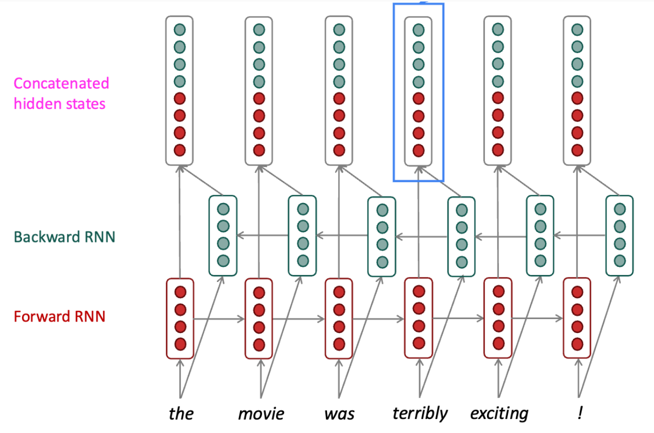


We can regard this hidden state as a representation of the word *"terribly"* in the context of this sentence. We call this a *contextual representation.*

These contextual representations only contain information about the *left* context (e.g. *"the movie was"*).

What about *right* context?

In this example, *"exciting"* is in the right context and this modifies the meaning of *"terribly"* (from negative to positive)


Concatenated hidden states
Backward RNN
Forward RNN
the
movie
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terribly
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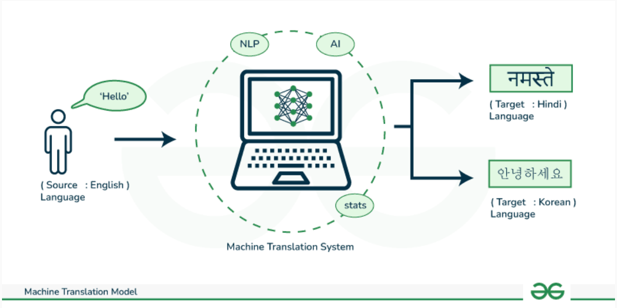
!

Machine translation

Pre-neural machine translation

- Machine Translation (**MT**) is the task of translating a sentence x from one language (source language) to a sentence y in another language (target language)



Source: *https://www.geeksforgeeks.org/nlp/machine-translation-of-languages-in-artificial-intelligence/*

The early history of MT: 1950s

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- MT heavily funded by military, but basically just **simple rule-based systems** doing word substitution
- Human language is more complicated than that, and varies more across languages
- Little understanding of natural language syntax, semantics, pragmatics … problem soon appeared intractable…

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- **Idea:** Learn a probabilistic model of translation from data.

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- Directly modeling $P(y \mid x)$ is difficult!

1990s-2010s: SMT

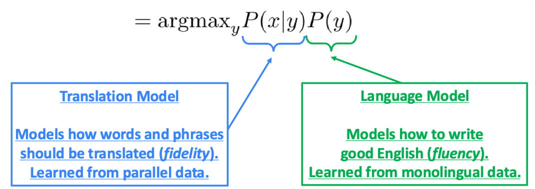
- Using *Bayes*' Theorem:

$$P(y \mid x) = \frac{P(x \mid y)\, P(y)}{P(x)}$$

- Since $P(x)$ is <u>fixed</u> (bc we cannot change the input), we can rewrite the search as:

$$\text{argmax}_y \; P(x \mid y) \cdot P(y)$$

- This gives two components to be learned separately:
  - Translation Model: $P(x \mid y)$
  - Language Model: $P(y)$



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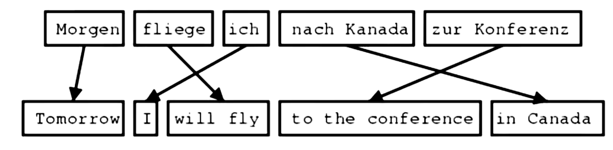
- How do we build a language model?
- How can we learn a translation model $P(x \mid y)$?
- Requirement: A large amount of parallel data (e.g., pairs of human-translated French/English sentences)

Learning alignment of SMT

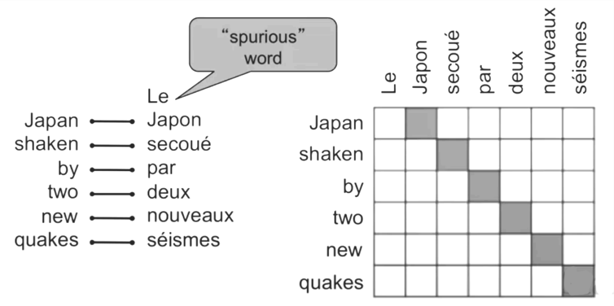
- How to learn translation model $P(x \mid y)$ from the parallel corpus?
- Break it down further: Introduce latent *a* variable into the model $P(x, a \mid y)$
- where *a* is the *alignment* (i.e., word-level correspondence between source sentence *x* and target sentence *y*)



More notes: Alignment

Alignment is the correspondence between particular words in the translated sentence pair.

- Typological differences between languages lead to complicated alignments
- Some words might have no counterpart (or too many); not one-to-one correspondence



More notes: Learning alignment

We learn $P(x, a \mid y)$ where:

- y: source sentence (e.g., English)
- x: target sentence (e.g., French)
- a: word alignment (latent mapping between words in y and x)

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- e.g., Expectation-Maximization algorithm
  - **E-step:** given current parameters, estimate how likely each possible alignment is (soft alignment).
  - **M-step:** re-estimate translation probabilities $t(x \mid y)$ using those expectations.

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- Required compiling and maintaining extra resources
    - Like tables of equivalent phrases
- Lots of human effort to maintain

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- The best systems were extremely complex
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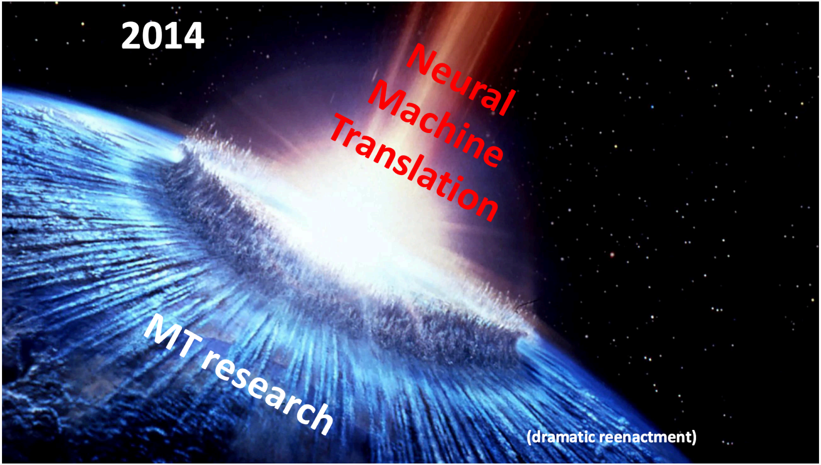
Neural machine translation


2014
Neural
Machine
Translation
MT research
(dramatic reenactment)

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- Neural machine translation (NMT) is a way to do machine translation with a single end-to-end neural network.
- The neural network architecture is called a sequence-to-sequence (seq2seq) and it involves two RNNs (more generally, *neural networks*).

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  - Modern models: Transformer encoder–decoder

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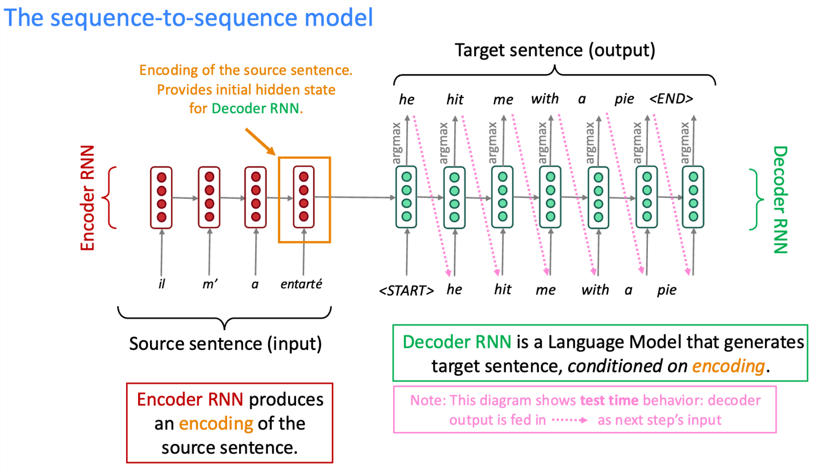

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- e.g., The encoder processes the French sentence and compresses it into a single vector representation.

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- The decoder takes the context vector as its initial state and generates the output sequence one token at a time.
- At each step, it uses the previous hidden state, the previously generated token, and the context vector to compute the next hidden state.

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Seq2Seq: Inference

(Decoding at Test Time)

- At inference time, the true target words are not available.
- The decoder must use its own **predicted word** from the previous step as the next input.
- The process starts with a special *`<start>`* token and continues until an *<end>* token is generated.
- Example:
  - Step 1: input *`<start>`* $\to$ model predicts “I”
  - Step 2: feed predicted “I” $\to$ model predicts “love”
  - Step 3: feed predicted “love” $\to$ model predicts “cats”

Seq2seq

- Q: How do we train a seq2seq/NMT system?

Seq2seq

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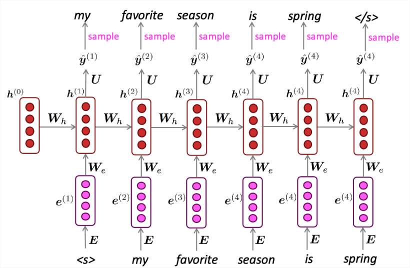
- A: Use a large parallel corpus and optimize parameters to maximize the likelihood of the correct target sequence given the source.

Seq2Seq: Multi-layer RNNs

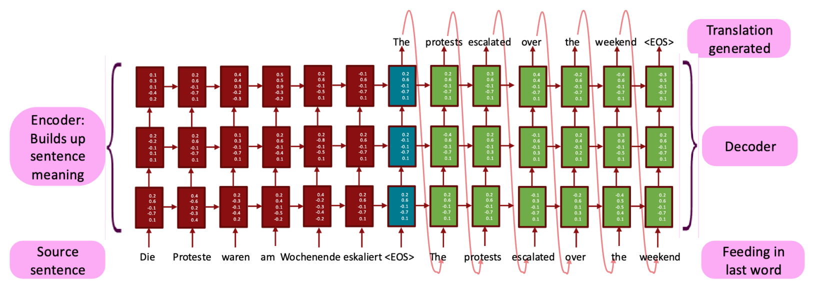
- RNNs are already *deep* in time: At each timestep, an RNN passes information from the previous hidden state to the next, effectively stacking computations across many steps.



Seq2Seq: Multi-layer RNNs

- We can also add depth in layers: Instead of using just one RNN layer, we can stack multiple RNNs on top of each other, where the output of one layer becomes the input of the next (**multi-layer RNNs, stacked RNNs**)

Seq2Seq: Multi-layer RNNS



Seq2Seq: Multi-layer RNNS (in practice)

- High-performing RNNs are usually multi-layer (but aren't as deep as convolutional or feed-forward networks)
- e.g., Britz et al. (2017) found that NMT, 2 to 4 layers, is the best for the encoder RNN, and 4 layers is best for the decoder RNN
  - Often 2 layers is a lot better than 1 layer.
  - 3 might be a little better than 2 layers.
- Transformer-based networks (e.g., BERT) are usually deeper, like 12 or 24 layers.

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    - Same methods for all languages

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- Hard to debug
- Difficult to control (e.g., can’t easily specify rules or guidelines for translation)

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- BLUE is useful but imperfect
    - There are many valid ways to translate a sentence
    - So a good translation can get a poor BLUE score because it has low *n*-gram overlap with the human translation

NMT: the first big success story of NLP deep learning

NMT went from a fringe research attempt in 2014 to the learning standard method in 2016

2014: First seq2seq paper published [Sutskever et al. 2014]

2016: Google Translate switches from SMT to NMT – and by 2018 everyone has

This is amazing!

- SMT systems, built by hundreds of engineers over many years, outperformed by NMT systems trained by small groups of engineers in a few months

So, is MT solved?

No, many difficulties remain:

- Out-of-vocabulary words
- Domain mismatch between train and test data
- Maintaining context over longer text
- Low-resource language pairs
- Failures to accurately capture sentence meaning
- Pronoun (or zero pronoun) resolution errors
- Morphological agreement errors

Wrap-up

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- New task: Machine translation
- SMT $\rightarrow$ NMT

Review: Dependency parser training

Approaches

- SpaCy: 11
- PyTorch: 5
- Graph-based parser: 1

LAS scoreboard (Top 5)

Rank	LAS
1	92.76
2	91.66
3	87.02
4	86.76
5	85.04

Average: 74.5

Reminder

1. Background research brief

Released on Tuesday 09/16/2025

Each groups should submit the following to prepare your background-research presentation and to seed your final presentation/paper. Please aim to have a working draft ready for your group check-in on October 9th. After the group meeting, the final version of the draft should be submitted by October 10th (Friday). This is not a graded assignment.

Things to include

1. **Topic / Area**
   - One sentence stating the focus
   - 3–5 keywords
2. **Research question / Problem**
   - 1–2 sentences clearly stating the core question or hypothesis
3. **Mini annotated bibliography (3–5 papers)** — for **each** paper include:

   - Full citation (consistent style)
   - 1-sentence contribution (key finding/idea)
   - Method/Data (e.g., corpus, model, experiment)
   - Relevance (why it matters for your group project)