Introduction to Neural Machine Translation

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Outline

Goal: Understand how Google Translate worked circa 2015.

1. Introduction
2. Preliminaries
3. Encoder-Decoder Recurrent Neural Networks
4. $f(\text{Final Remarks}) = \text{Remarques finales}$

My Background

- CS fourth year, Math third year
- Interests in language processing and machine learning.
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  - Dr. Bridget McInnes - VCU NLP Lab
  - Dr. Bartosz Krawczyk - VCU ML and Datastream Mining Lab

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What this talk is not:

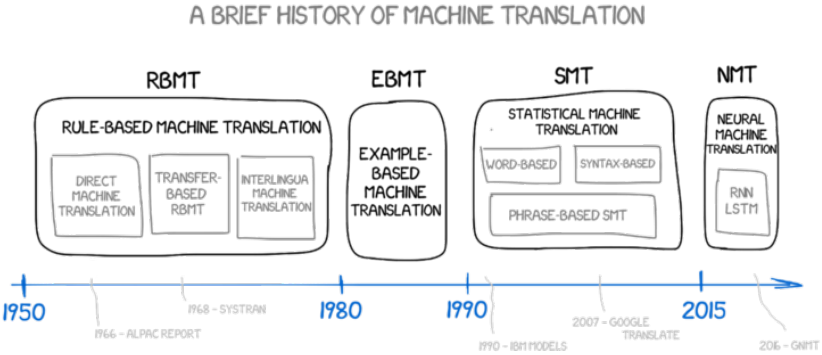
- Exhaustive.
- A demonstration of state-of-the-art techniques (2014).
- Consistent with transposition of matrices (readability).

Talk Pro Tips

- Stop me for questions. If something is unclear to you, then it is surely unclear to someone else.
- It's alright to get more food in the middle of the talk.

Problem

Given a text in language L_1 output a text in language L_2 that humans concede captures the same semantic meaning, obeys language grammar rules and is useful.



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Definitions and Notation: Representing Words

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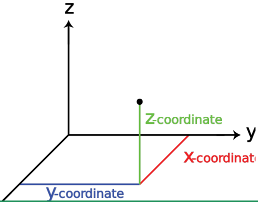

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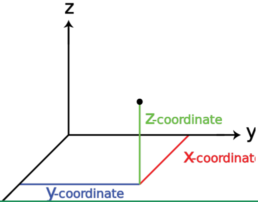

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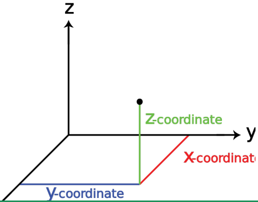
  - A hot research area in NLP:
    - How can we incorporate context when representing a token?



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  - Ex. Our sequence of 6 tokens with a one-hot encoding (assume $d = 5$) yields a matrix $\mathbb{R}^{6 \times 5}$

$$[\vec{\text{the}}, \vec{\text{girl}}, \vec{\text{walks}}, \vec{\text{the}}, \vec{\text{dog}}, \vec{.}] = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

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We now have the tools to be precise:

- **Translation**: Given languages L_1, L_2 with lexicons V_1, V_2 a translation is a function $f : \mathbb{R}^{T \times d} \rightarrow \mathbb{R}^{T' \times d}$ mapping a length T sequence of tokens over V_1 to a length T' sequence of tokens over V_2.

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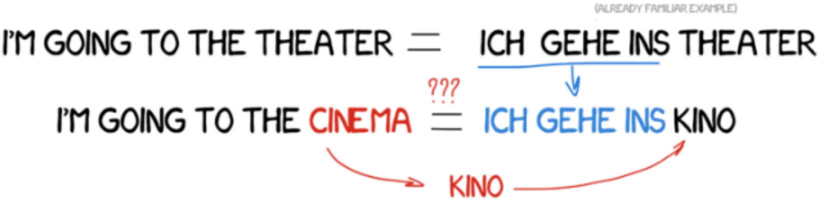
$$\{(x)^i, (y)^i : i \in \{1, ..., n\}\}$$

Almost there!

How do we estimate such a model? What properties should it possess?

- Independent of L_1, L_2.



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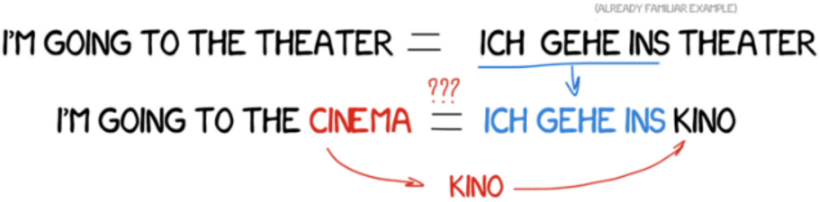

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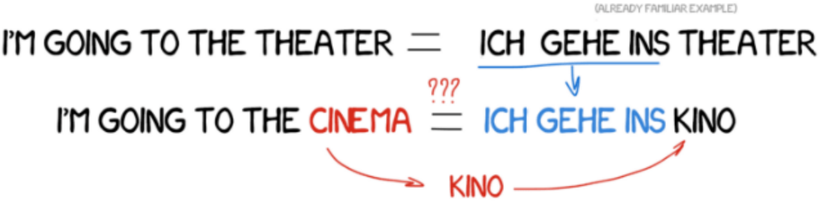
- Independent of L_1, L_2.
- Capable of handling translations that require the generation of both short and long sequences.
- Be able to translate input sequences **un-seen** during creation (training). This means **generalize**!



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Framework

Idea: Consider translation as estimating a conditional distributional!

- Assume the output of a translation $Y = (y)_{T'}$ is a random variable conditioned on the input $X = (x)_T$:

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- Why conditional estimation? Why can we factorize?

Framework cont.

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  1. p can be parameterized by a recurrent neural network.
  2. Our sequences are appropriately pre-processed.
     - Special tokens are added to vocabulary indicating end of sentences.
     - Vocabulary is shrunk down (lower casing inputs, etc).

  Ex. the, girl, walked, the, dog, . $\rightarrow$ the, girl, walked, the, dog, ., <EOS>

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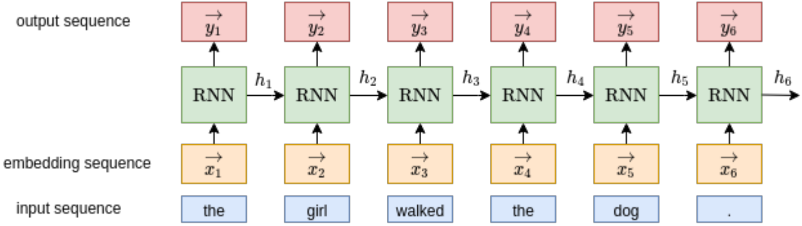

Recurrent Neural Networks (high level)

$$\mathrm{RNN}(x_t, h_{t-1}) = y_t$$

- At each time-step (token embedding!), the affine-linear[1] transformations

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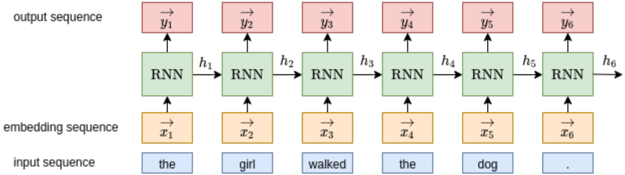

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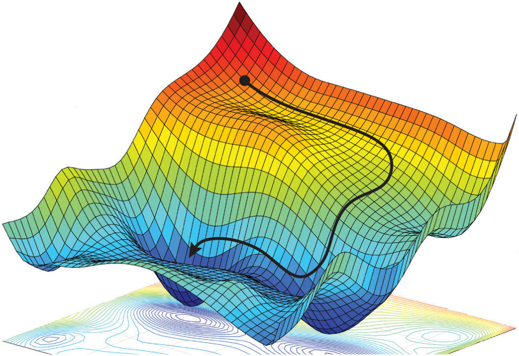

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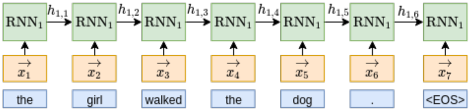
  - Why?
    Given new X we can auto-regressively decode Y by sampling p with tokens from V_2!

Encoder-Decoder RNN's

Idea:

1. Encoder RNN_1 unrolls over input sequence $(x)_T$.



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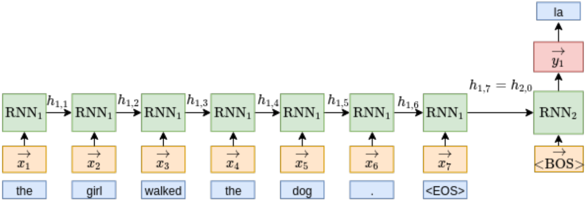

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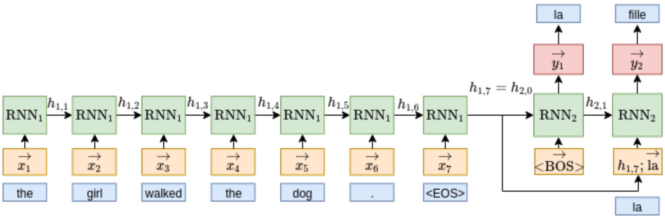

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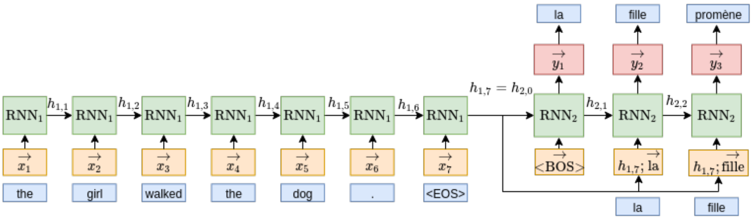

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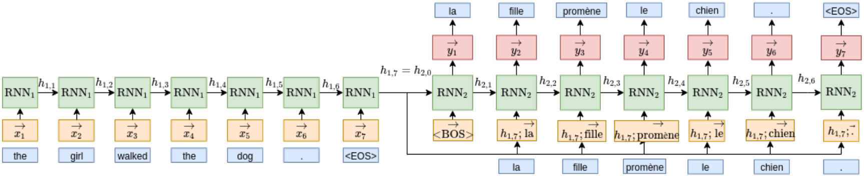
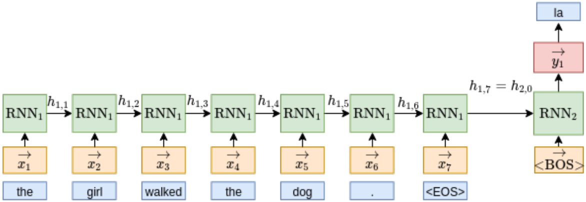


Encoder-Decoder RNN Training

- Encoder-Decoder RNN's parameterize our factorized distribution[1]!

$$p(Y|X) = \prod_{t=1}^{T'} p(y_t|x_1, x_2, ..., x_T; y_1, ..., y_{t-1})$$

$$= p(y_1|X) \cdot ...$$



[1] With appropriate output constraints.

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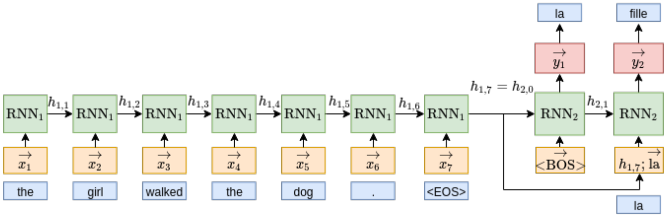

Encoder-Decoder RNN Training/Inference

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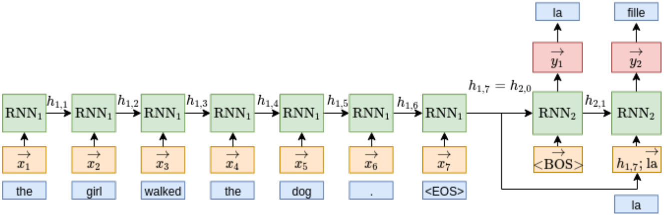

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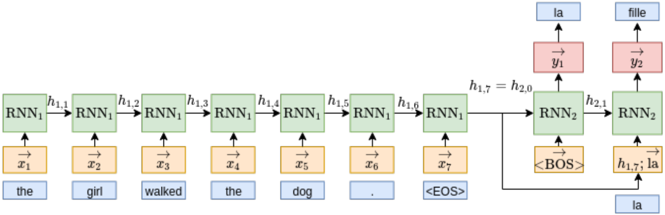
- At each time step, parameters of both RNNs are adjusted to assign higher probability to the correct sub-translation (via modified form of gradient descent).



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  - $V_1 = 160k, V_2 = 80k$.
    - Parallelized **parameters** and data across 8 GPU's during training. Still took 10 days.

How well does this work?

- The Seq2Seq learning paradigm was first applied successfully to MT in (Sutskever, 2014).
- First time a purely machine learning based approach was competitive with traditional statistical and phrase-based machine translation.
- Sutskever trained on a massive English-French parallel corpus.
  - 12 million sentence pairs.
  - Encoder-Decoder contained 348M parameters.
  - $V_1 = 160k, V_2 = 80k$.
    - Parallelized **parameters** and data across 8 GPU's during training. Still took 10 days.
  - BLEU score: ~ 34.8 (current SOTA sits at ~ 45)
    - BLEU (Bilingual Evaluation Understudy) is a metric assessing MT performance with high correlation to human judgement.

Outline

So - how does this *actually* work.

- This presentation showcased a vanilla RNN cell.
  - In practice, a RNN cell with more parameters and differing connections, the **LSTM**, is utilized.
    - **LSTM** - Long Short Term Memory RNN

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- And finally ... as of 2017 top performing MT models **do not** use recurrent neural networks!
  - Same encoder-decoder framework holds, but non-recurrent seq2seq based neural network architectures now prevail. Why?
    - Transformer

Conclusion

Thank you for your attention!
Questions?

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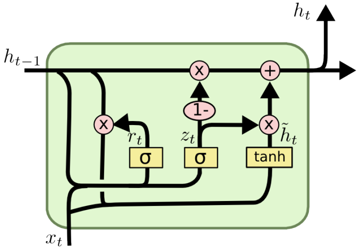
Supplement: LSTM



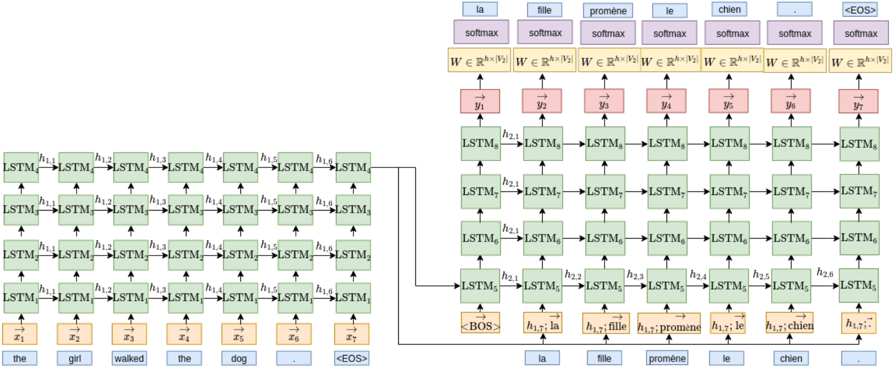
$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$

$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$

$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

- I did say 340M weights right?
- Note that this is really during inference - during training we need need to incorporate our objective!



Supplement: Decoding at Inference

- But decoding is difficult too (recalled p is but an estimate)!
- Usually several most likely next translations are explored and pruned in a tree like fashion:
  - **Beam Search**