Statistical Machine Translation: Neural Machine Translation

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Outline

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1. Neural Networks
2. RNN Encoder-Decoder
3. RNN Encoder-Decoder: Extentions

Neural networks

Abstraction

- Each neural network (NN) is simply a *function* with a set of *parameters*
- For instance from $\mathcal{R}^n$ to $\mathcal{R}^m$ for some $n, m > 0$

Construction

Construction of NNs is based on:

- Elementary building blocks (simple NNs: $\mathbb{A}, \mathbb{B}, \mathbb{C}, \ldots$)
- Combination operators (e.g. function composition $\mathbb{A} \circ \mathbb{B}$)
  $\rightarrow$ functional programming paradigm

However:

- We cannot use just any building block and any combination operation
- The building blocks should be *differentiable*
- The combination operators should preserve this property

Fortunately:

- Frameworks/domain specific languages make sure that we only build sane NNs

Network networks

Example

- **Code**: `https://github.com/kawu/bpfun` (look in the ‘src‘ directory)
- **Library**: backprop (`https://backprop.jle.im/index.html`)
  → automatic heterogeneous back-propagation library
  → allows to safely construct complex networks
- **Plan**: build a simple neural translation system

Feed-forward network

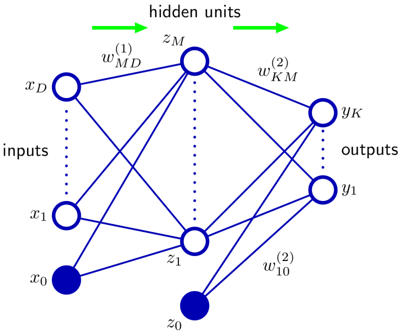
Network function:

$$y_k(\mathbf{x}, \mathbf{w}) = f\left(\sum_{j=0}^{M} w_{kj}^{(2)} z_j\right)$$

$$z_j = h\left(\sum_{i=0}^{D} w_{ji}^{(1)} x_i\right)$$

Graphical representation:

- Input, hidden, and output variables represented by nodes
- Weight parameters represented by links between nodes
- Arrows represent information flow during forward propagation
- (Source: [Bishop, 2006])



Expression power

Advantages:

- Neural networks are said to be *universal approximators*:

  "A two-layer [feed-forward] network with linear outputs can uniformly approximate any continuous function on a compact input domain to arbitrary accuracy provided the network has a sufficiently large number of hidden units." [Bishop, 2006]
- Seamless integration of word embeddings

Price to pay:

- Relatively complex model → lack of transparency
- Parameters hard to learn

Word embeddings

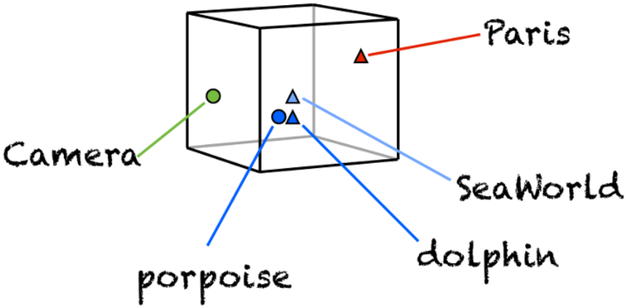


Figure: Representing words as N-dimensional vectors

Outline

Basic NMT System

Encoder-Decoder

- **Input**: concatenation of input word embeddings

$$v = x_1 \cdot x_2 \cdot \ldots \cdot x_n$$

- **Encoder**: calculate a vector representation of the output sentence

$$w = \mathbb{A}(v)$$

- **Decoder**: generate the output sentence from its hidden vector representation *w*

Basic NMT System

Encoder-Decoder

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Issues

- The size of the input vector v is not constant – it depends on the input length
- Feed-forward networks calculate vectors – how can we generate a sequence of words?

Recursive Neural Network

Recursive Neural Network (RNN)

- **Input**: sequence of vectors $\boldsymbol{x} = (x_1, \ldots, x_n)$
- **Output**: sequence of vectors $\boldsymbol{h} = (h_1, \ldots, h_n)$
- **Recursive definition**:

$$\begin{aligned} h_i &= \mathbb{A}(x_i, h_{i-1}) \\ &= \mathbb{A}(x_i, \mathbb{A}(x_{i-1}, h_{i-2})) \\ &= \mathbb{A}(x_i, \mathbb{A}(x_{i-1}, \mathbb{A}(x_{i-2}, h_{i-3}))) \\ &= \mathbb{A}(x_i, \mathbb{A}(x_{i-1}, \mathbb{A}(x_{i-2}, \mathbb{A}(\ldots \mathbb{A}(x_1, h_0) \ldots)))) \end{aligned} \tag{1}$$

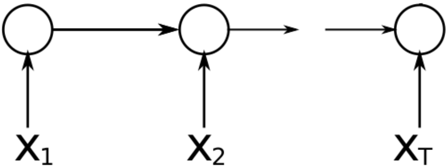
- **Parameters**: h_0 + those of $\mathbb{A}$

Intuitions

- h_i provides a summary of the prefix $x_1, \ldots, x_i$
- h_n provides a summary of the entire input sequence $\boldsymbol{x}$
  $\rightarrow$ **precisely what we need for encoding**

Recursive Neural Network

Graphical representation



Recursive Neural Network

Generative RNN

- **Input**: vector h_0 (here: representation of the the input sentence)
- **Hidden**: sequence of vectors $\boldsymbol{h} = (h_1, \ldots, h_m)$
- **Output**: sequence of words $\boldsymbol{y} = (y_1, \ldots, y_m)$ with $y_m = \text{EOS}$
- **Recursive definition**:

$$P(y_i \mid y_1, \ldots, y_{i-1}, \boldsymbol{x}) = \mathtt{softmax}(\mathbb{G}(h_{i-1})) \tag{2}$$

$$h_i = \mathbb{B}(y_i, h_{i-1}) \tag{3}$$

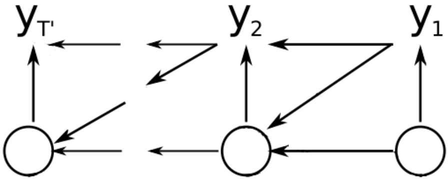
- **Parameters**: those of $\mathbb{B}$ and $\mathbb{G}$

Intuitions

- h_i provides a summary of the generated sentence $y_1, \ldots, y_i$, as well as information on what part of the input sentence has been already translated
- $\boldsymbol{y}$ represents the output sentence → **precisely what we need for decoding**

Recursive Neural Network

Graphical representation



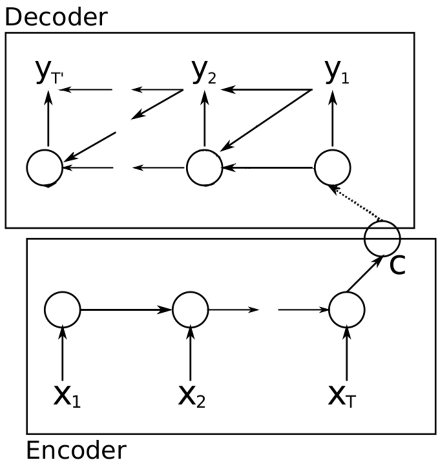
RNN Encoder-Decoder

Architecture

- **Input**: sequence of vectors $\boldsymbol{x} = (x_1, \ldots, x_n)$
- **Encoding**: transform $\boldsymbol{x}$ into a **fixed-length** vector c
  $\rightarrow$ using standard RNN
- **Decoding**: generate a translation $\boldsymbol{y}$ from the encoded vector c
  $\rightarrow$ using „generative" RNN

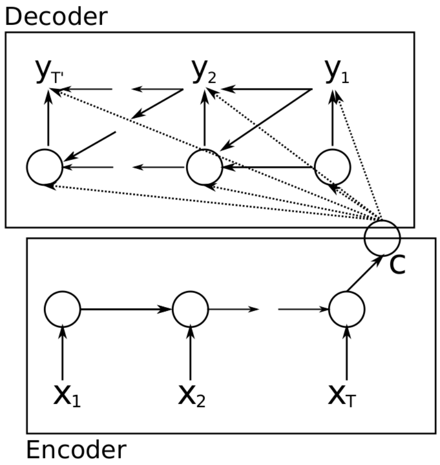
RNN Encoder-Decoder

Graphical representation



RNN Encoder-Decoder

Alternative architecture



RNN Encoder-Decoder

Training

- The two components of the RNN Encoder–Decoder are jointly trained to maximize the conditional likelihood of the training data:

$$\ell(D) = \prod_{(\boldsymbol{x},\boldsymbol{y}) \in D} P(\boldsymbol{y} \mid \boldsymbol{x}) \tag{4}$$

- Probability for a particular sentence pair is defined as:

$$P(\boldsymbol{y} \mid \boldsymbol{x}) = \prod_{i=1}^{m} P(y_i \mid y_1, \ldots, y_{i-1}, \boldsymbol{x}) \tag{5}$$

where the individual $P(y_i \mid y_1, \ldots, y_{i-1}, \boldsymbol{x})$ are calculated by the network (see Eq. 2)

Encoder-Decoder in Practice

Phrase-based [Cho et al., 2014]

- Use the RNN Encoder-Decoder as a part of a standard phrase-based architecture
- Update the phrase translation probabilities using the RNN Encoder-Decoder
- Use the standard decoding algorithm on the modified phrase translation table

Seq2seq [Sutskever et al., 2014]

- The RNN Encoder-Decoder is directly used to translate
- The input sentence is encoded in a reversed direction (from end to start)

Outline

RNN Encoder-Decoder

Issues

RNN Encoder-Decoder

- is very simplistic
- works poorly for long sentences
- ignores 80% of what we have learned
- of course we can apply better optimization techniques, but is it all we can do?

Trends

One of the trends in deep learning for NLP:

- Benefit from what we know (about formal languages, linguistically inspired formalisms, classical computational models, etc.) in order to design better network architectures (see e.g. `https://sites.google.com/view/delfol-workshop-acl19`)

Possible Extensions

Encoder: ,,additive" semantics

- Assumption: the meaning of a sentence is the sum of the meanings of its words
  → that's obviously naive (and not true)
  → but a better prior assumption that nothing

Encoder: compositional semantics

- Assumption: the meaning of a sentence is a function of the meaning of its words and its syntactic (tree) structure
  → much more plausible
  → we could apply ,,tree2seq" network architectures
  → not easy because we typically don't know the structure of the input

Possible Extensions

Phrase-based-like decoding

Each time a new word is to be generated:

- Pick the relevant fragment (≈ phrase) in the input sentence
- Combine the vector representations of its words
- Based on that (and the previously generated words), generate the next word

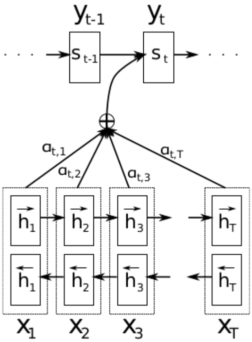


Figure: RNN Encoder-Decoder with Attention [Bahdanau et al., 2014]

RNN Encoder-Decoder with Attention

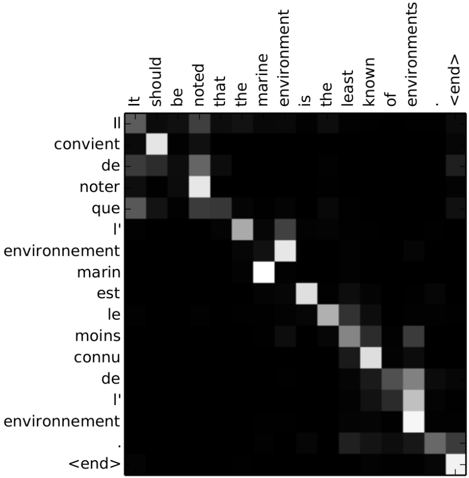


Figure: Example of alignments produced with attention-based RNN Encoder-Decoder

Discussion

Discussion

- Attention-based encoder-decoder can be seen as a variant of the phrase-based translation model couched in the framework of NNs
- It is one of the most influential NMT architectures nowadays
- Not necessarily SOTA, but attention is also employed in higher-scoring systems [Vaswani et al., 2017]

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