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Attention-based Encoder-Decoder Networks for Spelling and Grammatical Error Correction

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Introduction

Automatic spelling and grammar correction is the task of automatically correcting errors in written text.

- This cake is *basicly* sugar, butter, and flour. [$\rightarrow$ basically]
- We went to the store and bought *new stove*. [$\rightarrow$ a new stove]
- *i*'m *entirely* awake. [$\rightarrow$ {I, wide}]

The ability to correct errors accurately will improve

- the reliability of the underlying applications
- the construction of software to help foreign language learning
- to reduce noise in the entry of NLP tools
- better processing of unedited texts on the Web.

Problem definition

Given a N-character source sentence $S = s_1, s_2, ..., s_N$ with its reference sentence $T = t_1, t_2, ..., t_M$, we define an error correction system as:

Definition

$$\widehat{T} = MC(S) \tag{1}$$

where $\widehat{T}$ is a correction hypothesis.

Question: How can the MC function can be modeled?

Background

Various algorithms propose different approaches:

- **Error detection**: involves determining whether an input word has an equivalence relation with a word in the dictionary.
  - Dictionary lookup
  - n-gram analysis
- **Error correction**: refers to the attempt to endow spell checkers with the ability to correct detected errors.
  - Minimum edit distance technique
  - Similarity key technique
  - Rule-based techniques
  - **Probabilistic techniques**

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Probabilistic techniques

We assume the task of error correction as a type of monolingual *machine translation* where the source sentence is potentially erroneous and the target sentence should be the corrected form of the input.

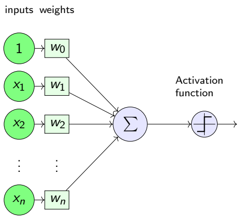
Aim

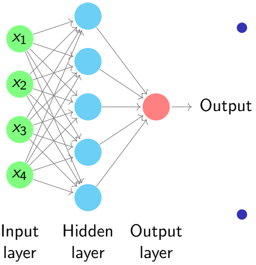
To create a probabilistic model in such a way that:

$$\widehat{T} = \underset{T}{argmax} P(T|S;\theta) \tag{2}$$

where θ is the parameters of the model.
This is called the Fundamental Equation of Machine Translation [Smith, 2012].

Neural networks as a probabilistic model





- Mathematical model of the biological neural networks
- Computes a single output from multiple real-valued inputs:

$$z = \sum_{i=1}^{n} w_i x_i + b = W^T x + b \tag{3}$$

- Putting the output into a non-linear function:

$$tanh(z) = \frac{e^{2z} - 1}{e^{2z} + 1} \tag{4}$$

- Back-propagates in order to minimize the loss function H:

$$\theta^* = \underset{\theta}{argmin} \mathbf{H}(\hat{y} - y) \tag{5}$$

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NLP challenges in Machine Translation

Large input state spaces → **word embedding**

No upper limit on the number of words.

Long-term dependencies

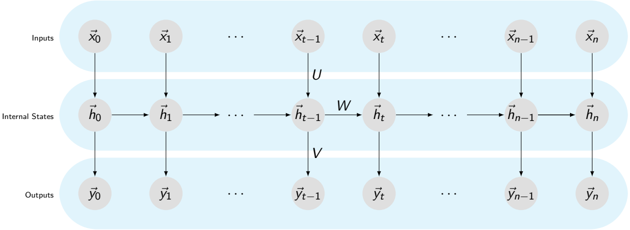
- Constraints: **He** did not even think about **himself**.
- Selectional preferences: **I** ate salad with **fork** NOT ~~rake~~.

Variable-length output sizes

- This structure have anormality → **30** characters
- This structure has an abnormality. → **34** characters

Recurrent Neural Network

Unlike a simple MLP, can make use of all the previous inputs. Thus, it provides a memory-like functionality.



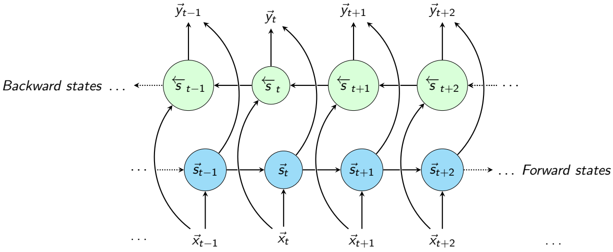
$$h_t = tanh(Wx_t + Uh_{t-1} + b) \tag{6}$$

$$\widehat{y}_t = softmax(Vh_t) = \tag{7}$$

W, U an V are the parameters of our network we want to learn.

Bidirectional Recurrent Neural Network

We can use two RNN models; one that reads through the input sequence forwards and the other backwards, both with two different hidden units but connected to the same output.

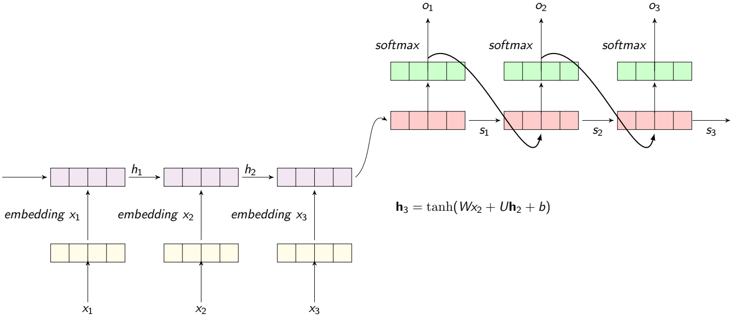


$$\vec{h}_t = tanh(\vec{W}x_t + \vec{U}\vec{h}_{t-1} + \vec{b}) \tag{8}$$

$$\overleftarrow{h}_t = tanh(\overleftarrow{W}x_t + \overleftarrow{U}\overleftarrow{h}_{t-1} + \overleftarrow{b}) \tag{9}$$

Sequence-to-sequence models

The sequence-to-sequence model is composed of two processes : *encoding* and *decoding*.



$$h_t = RNN(x_t, h_{t-1}) \tag{10}$$

$$c = tanh(h_T) \tag{11}$$

where h_t is a hidden state at time t, and c is the context vector of the hidden layers of the encoder.

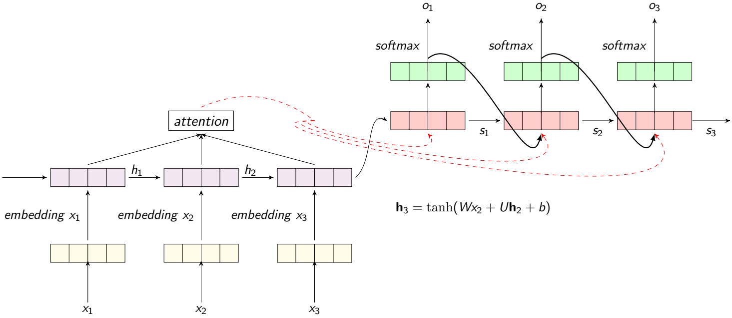
Attention mechanism

The attention mechanism calculates a new vector c_t for the output word y_t at the decoding step t.

$$c_t = \sum_{j=1}^{T} a_{tj} h_j \quad 2\text{mm} \tag{12}$$

$$\alpha_{ij} = \frac{exp(e_{ij})}{\sum_{k=1}^{T} exp(e_{ik})} \tag{13}$$

$$e_{ij} = attentionScore(s_{i-1}, h_j) \tag{14}$$



where h_j is the hidden state of the word x_j, and a_{tj} is the weight of h_j for predicting y_t. This vector is also called *attention vector*.

Experiments

Various metrics are used to evaluate the correction models, including MaxMatch M^2 [Dahlmeier, 2012], I-measure [Felice, 2015], BLEU and GLEU [Napoles, 2015].

Model	M^2 scorer		
	P	R	$F_{0.5}$
Baseline	1.0000	0.0000	0.0000
RNN	0.5397	0.2487	0.4373
BiRNN	0.5544	0.2943	0.4711
Encoder-decoder	**0.5835**	**0.3249**	**0.5034**
Attention	0.5132	0.2132	0.4155

Table: Evaluation results of the models using MaxMatch M^2 metric. Bold numbers indicate the scores of the best model.

Qualitative comparison

Source sentence	306 characters
لا زال كبير الشبيحه يظن ان ارواح وآلام الناس اقل كلفه من تخليه عن منصبه ، فلذلك اذا كان السوريون لا يرتضون بهذه المعادله المهينه ، فعليهم ان يهبوا هبه قويه واحده وياخذو حقوقهم من هذه العصابه عنوه ، اننا يا أحبائي ندفع ثمن اكثر من اربعين عام ومن الخنوع والذل والثمن سيكون غاليا ولكنه يستأهل هذه التضحيات	
Gold standard reference	309 characters
لازال كبير الشبيحة يظن أن أرواح وآلام الناس أقل كلفة من تخليه عن منصبه ، فلذلك إذا كان السوريون لا يرتضون بهذه المعادلة المهينة ، فعليهم أن يهبوا هبة قوية واحدة ويأخذوا حقوقهم من هذه العصابة عنوة . إننا يا أحبائي ندفع ثمن أكثر من أربعين عاما ، ومن الخنوع ، والذل والثمن سيكون غاليا ولكنه يستأهل هذه التضحيات .	
Recurrent neural network model prediction	307 characters
لا زال كبير الشبيحة يظن ان ارواح وآلام الناس اقل كلفه من تخليه عن منصبه ، فلذلك اذا كان السوريون لا يرتضون بهذه المعادلة المهينه ، فعليهم ان يهبوا هبه قويه واحده وياخذاذو حقوهم نن ههه العابه عنوه أننا يا أحبائي ندفع ثمن أكثر من أربعين عام ، ومن الخنوع ،، واللا والمن سيكنن ااااا ولنن يستتهههههه الضحي	
Bidirectional recurrent neural network prediction	307 characters
لا زال كبير الشبيحة يظن أن أرواح والأم الناس أقل كلفه من تخليه عن منصبه ، فلذلك إذا كان السوريون لا يرتضون بهذه المعادلة المهينة ، فعليهم أن يهبوا هبه قويه واحده وياخذو ققهممم ههه االعصبب عوهه ننا ياأأحائي ندف من ككثرمن رربعن امم ، وومن النووع ،،والذل والمثن سيكوننغغايا وككنههستههل ههه التضحيت	
Sequence-to-sequence model prediction	306 characters
لا زال كبير الشبيحة يظن أن أرواح وللام الناس أقل كلفه من تخليه عن منصبه ، فلذلك إذا كان السوريون لا يرتضون بهذه المعادله المهينة ، فعليهم أن يهبوا هبه قويه واحده وياخذو وحققهمممنهه اللصابب عنوه أننا يا حبائيندفع ثمم أككر ن رربعن ع من الخنوو واللل واللمنن ييون ااايي ووكنهههستهألههذهاااتتضا	
Attention-based sequence-to-sequence model prediction	309 characters
لا زال كبير الشبيحه يظن ان ارواح وللام الناس اقل كلفه من تخليه عن منصبه ، فلذلك اذا كان السوريون لا يرتضون بهذه المعادلة المهينة ، فعليهم ان يهبوا هبه قويه واحده وياخذ واحققهم من هذه اعصابة عنوه إنا يا حبائي ندف من أكثر من أربيين عام ، ومن الخخوع ، واللل والثمن سيكون االيا وككنه يتتههههذه التضضي	

Conclusion and future work

Conclusion

- Modeling correction error for any language.
- Variant results using different metrics.
- Reducing precision in correction of long sentences.

Future studies

- Models to be explored in more levels, e.g., word-level, phrase-level.
- Limiting the length of the sequences in training models.
- Using deeper networks with larger embedding size.
- Preventing over-learning of models by not training them over correct input tokens (action ="OK").

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