Can Dependency Aid Natural Language Generation?

Cases from English and Japanese

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Outline

Who am I?

- Gyu-min Lee
- Graduated from Handong University (Pohang, ROK)
  - B.A. in Studies of English & Counseling Psychology
  - Minored in Computer Science
- Student at Korea University Graduate School (Seoul, ROK)
  - For M.A. in Linguistics
  - Majoring in Computational Linguistics
  - Under the guidance of Prof. Sanghoun Song

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- A little background
  - "I would like to help others to understand the information written in other languages through (automatic) translation." – ME (2003)
  - "Programming is so fun!" – also ME (2008)
  - Science track at high school
  - Started as Computer Science major
  - Eventually, English & Counseling Psychology
  - "Deep understanding of syntax can help others (including machines) to understand the language!" – ME as well (2015)

Who am I?

- Research Interests
  - Syntactic analysis of human language
  - Machine natural language generation
  - Introduction of rich grammar to NLP
- Project Participation
  - In writing a proposal for deep analysis of KFL learners
  - In writing a proposal for Korean NER development
  - In building a library for syntactic experiments for Korean language using neural LMs (present)

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- Why this topic?
  - "NLP is so successful that it does not require feature engineering"
  - But NLP still requires a lot of resources and still "sounds" computer...
  - What if we "teach" the neural language model grammar?
- Where to go from here?
  - More ways to teach neural LMs grammar
  - Neural LMs are learning grammars – how? How can we even facilitate that?
  - Probing neural LMs' language acquisition
  - See how much grammar we can teach for the best performance and efficiency

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What Is This?

- Master's Thesis
  - Offering a (yet another) case where *linguistics matters to NLP*
- The ultimate goal
  - To probe the "neural language acquisition"
  - The understanding of how neural networks acquire a language

The Current Status of NLG

- Natural language generation (NLG) is important from summarization to MT
- Introduction of neural networks greatly improved the surface performance of NLG
- Introduction of Seq2Seq structure further improved the NLG
- ...and once again with Attention-only Seq2Seq (a.k.a. Transformer)

Seq2Seq

- Encoder
  - Makes a sentence embedding vector out of source sentence vectors
  - Similar to sentence classification RNN models
- Decoder
  - A conditional neural network language model
  - Current time-step word is based on the sentential embedding vector from the Encoder and the words generated so far through translation.
- Generator
  - Make probability out of the vector resulting from the decoder per time-step with Softmax function

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Problems with current NLG

- Room for improvement for E2E neural NLG
  - Domain-general
  - Grammatical appropriateness and naturalness
  - More predictability

A Fundamental Issue with NLG

- *Human language is hierarchical*
  - Yet, neural LMs treat language to be linear

Various Methods...

- Revisiting the template-based method with information extraction
- Teaching the machine the *un*likely tokens
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Let's teach deep learning syntax!

- Not all the syntax – rich but not efficient
- The argument structure – perhaps a good balance between efficiency and linguistic richness?
- In the form of dependency
- i.e. *Grammatical Relation*
- Minimal Recursion Semantics?

Didn't They Learn Syntax Already?

- Recent findings showing that neural language models have acquired some syntax
- If language models can perform that well with that little bit of syntactic knowledge. . .
- It would do much better with explicit syntax!

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Data

- Gold Data
  - Redwoods Treebank
  - Hinoki Treebank
- Silver Data
  - Following Hajdik et al. (2019) that found using silver data as well improved NLG compared to gold only
  - MRS generated with ERG/JACY
  - Brown...?
  - Japanese corpora...?

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Model

- Baseline from Hajdik et al. (2019) for English
    - From MRS
    - Encoder-decoder design
    - Bi-LSTM Encoder
    - Attention Decoder
- Transformer
- BERT/XLNet/ELECTRA. . . ?

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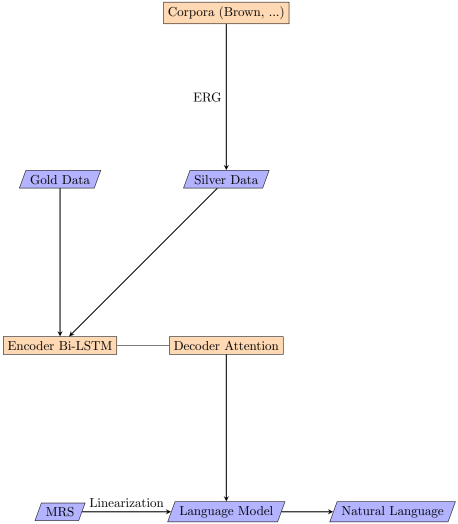
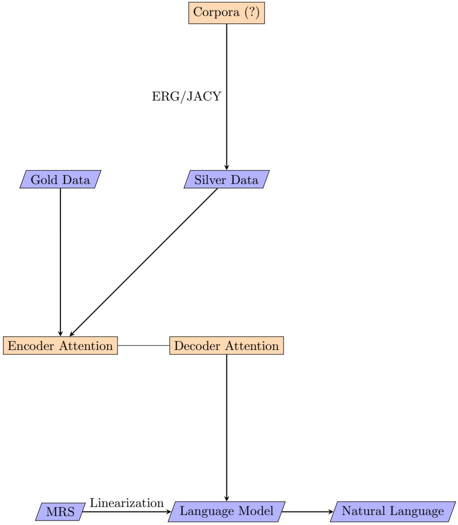
Model from Hajdik et al. (2019)

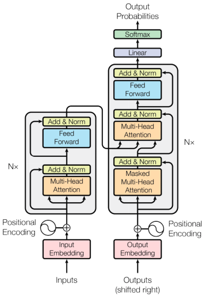


Suggested Model



Transformer

- Vaswani et al. (2017)
- Seq2Seq with only Attention mechanism
- Without any variant of recurrent neural network
- Thus, *Attention is All You Need*



Attention Mechanism

- Because long term dependency even with LSTM & GRU
- To get a good result at Google, you should QUERY well
- Given the vectors of *QUERY, KEY, & VALUE*,
- Attention helps us to perform the correct queries.
- i.e., attention governs how “important” each word are.

Why Transformer?

- This task is a translation between the source language of MRS representation and the target language of English and Japanese
- Linearized MRS is not free from long term dependency problem
- Using attention would help in letting the machine to understand which grammatical feature matters the most
- In other words, each attention heads will “look at” certain linguistic features, thus “learning” the syntax better

Why Not BERT and others?

- Their strength comes from being pre-trained
- Models pre-trained with MRS representation of ERG/JACY?
- If there isn't one, we can train MRS BERT, etc.
- But is it really beneficial for now?

Expected result

- Would score higher BLEU
- Would show better qualitative result
  - Hajdik et al. (2019) already showed an improvement of around 15 BLEU by implementing MRS
  - Because of the implementation of the newer model, my model would perform better
  - As Transformer outperforms RNN-based Seq2Seq *in general* in MT tasks
  - Transformer would benefit from syntax as well
- Would have learned more syntax than the general Transformer models

Implications

- Significance of rule-based, hard-coded computational grammar
- Importance of syntactic information for neural NLG
- Extension of Hajdik et al. (2019) to more languages
  - Extension to another language
  - Increased language independency of the finding
  - Implementation of a newer technology

State of the research

- In early steps
  - Literature reviews on NLG
  - Literature reviews on neural LM's acquisition of syntax
  - Literature reviews on machine translation
- Collecting data
  - Getting Redwoods
  - Getting Hinoki
  - Deciding on the corpora for silver dataset
- reproducing Hajdik et al. (2019)
  - Translating from their data to English
  - Using Transformer via OpenNMT

State of the research

```
**SENTENCE**
The Cathedral and the Bazaar
**PREDICTED**
A bunch of the view .
**LINEARIZED MRS**
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**SENTENCE**
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Open Publication License , version card0 .
**PREDICTED**
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(|_ _license_n_1|num=SG|pers=3 RSTR-H-of|_ (|_ _the_q|_ )|_ ARG1-EQ-of|_ (|_
```

State of the research

- Trained with a small portion of the data from Hajdik et al. (2019)
- Using OpenNMT implementation of Transformer
- for 40 steps
- In short, Transformer is applicable

Agenda

- Write out the literature reviews
- Get the data
- Make the preprocessor (i.e. linearizer for MRS representation)
- Run the experiment with bigger epochs

Problems

- Where exactly do I get the Redwoods & Hinoki?
- Any model pre-trained with MRS representation of English/Japanese?
- Is OpenNMT the best choice for the task?
- Baseline model for Japanese?