Learning Syntactic Properties with Deep Neural Networks

Deep Learning and the Nature of Linguistic Representation

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Outline

Machine Learning of Syntactic Properties

- Both symbolic and statistical machine learning methods have been applied to syntactic learning tasks for many years, with varying levels of success.
- These include, *inter alia*, part of speech tagging, phrasal chunking, and sentential parsing.
- DL has made significant progress across these, and other syntactic applications.
- Identifying subject-verb agreement is a particularly interesting domain, because it involves long distance relations, and hierarchical structure.

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Agreement and Intervening Attractors

The subject-verb pairs are in italics, and the attractors are indicated in boldface.

1(a) *The students submit* a final project to complete the course.

(b) *The students* enrolled in **the program** *submit* a final project to complete the course.

(c) *The students* enrolled in **the program** in **the Department** *submit* a final project to complete the course.

(d) *The students* enrolled in **the program** in **the Department** where **my colleague** teaches *submit* a final project to complete the course.

Supervised Learning of Agreement

- Linzen et al. use a dependency parser to identify the controlling subject of each verb in their corpus of examples.
- This identification is necessary to compute the number of attractors, but it is not used in the training for the number prediction task.
- The number of the verb is morphologically manifest in the raw data.
- They train their LSTM on $\sim$121,500 examples (9% of the total corpus) by showing it the correct number feature of the verb.
- They test the LSTM's number predictions on $\sim$1.21 million examples (90% of their corpus).

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Accuracy of The Model

- Linzen et al. encode input words as vectors in 50 dimensions, and their LSTM has 50 hidden units.
- They report that their system achieves 99% accuracy in the number prediction task for cases with 0 attractors between the subject and its verb.
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Unsupervised Learning with a Language Model

- Linzen et al. also train a generative language model (predicting the next word) to predict the number of the verb in an unsupervised manner.
- In contrast to their supervised LSTM, their language model scores below chance in its predictions for 4 attractor cases.
- The much larger Google LM (Jozefowicz et al., 2016) does better, at a $\sim$45% error rate for 4 attractors, but it is still well below their supervised RNN.
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Bernardy and Lappin's (2017) Agreement Experiments

- Bernardy and Lappin (2017) (BL) experiment with several DNN architectures, and alternative values for a variety of parameters, for the subject-verb agreement task.

- The architectures include an LSTM, a CNN, and a Gated Recurrent Unit (GRU, Cho et al., 2014).

- The parameters are
  - Ratio of training to testing as a partition of the corpus
  - Number of hidden units (memory size)
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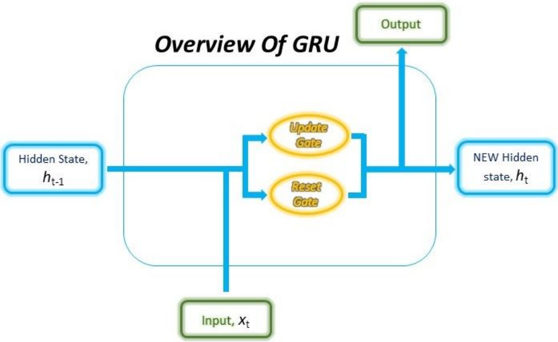
GRU Architecture



From Gabriel Loye, "Gated Recurrent Unit (GRU) With PyTorch", *FloydHub*, July 22, 2019

BL's CNN Design

- BL's CNN has 6 levels, with filtering successively compressing vector dimensions from 15 through 20, 15, 10 to 5.
- Convolution at these levels yields 7, 5, 5, and 3 features, respectively.
- Every convolution layer uses a ReLU activation function.
- The last layer is a dense layer with sigmoid activation.

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BL's CNN

$$
\begin{tikzcd}
\text{class} \\
\mathbb{R}^5 \arrow[u, "\text{dense}"'] \\
\mathbb{R}^{10} \arrow[u, "\text{6-dilated convolution, filter size = 3}"'] \\
\mathbb{R}^{15} \arrow[u, "\text{4-dilated convolution, filter size = 5}"'] \\
\mathbb{R}^{20} \arrow[u, "\text{2-dilated convolution, filter size = 5}"'] \\
\mathbb{R}^{50} \arrow[u, "\text{convolution, filter size = 7}"'] \\
\{0,1\}^{\text{voc. size}} \arrow[u, "\text{embedding}"']
\end{tikzcd}
$$

Training and Test Corpus

- BL use the WaCkypedia English corpus (Baroni et al., 2009), which contains ∼24 million example cases of present tense subject-verb agreement.
- The corpus is annotated with POS tags by TreeTagger (Schmid, 1995), and with dependency relations by the MaltParser (Nivre et al., 2007).
- Linzen et al. restrict training and testing to one agreement case per sentence in their corpus.
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- The benchmark is an LSTM with one layer of 150 units and no dropout, a data-set constructed with 10,000 words, lexical embeddings of dimension 50, and a training regimen of 90% of the corpus.
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Different Parameters Values

BL experiment with the following parameter values for their DNNs:

- Training on 10%, 50%, and 90% of the corpus, testing on the remainder for each split,
- 50, 150, 450 and 1350 units for the LSTM layers,
- Embedding vocabulary sizes of 100, 10k and 100k words, substituting corresponding POS tags for the rest,
- 1, 2 and 4 layers for the LSTM,
- Dropout rates of 0, 0.1, 0.2 and 0.5, applied to the weights within the LSTM layers, but not at the final dense layer, and
- Lexical embedding dimension sizes of 17, 50, 150, and 450.

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- BL hypothesise that a DNN will learn the target syntactic dependency pattern more efficiently if it is exposed to input consisting largely of POS sequences in which number features are marked on noun and verb tags.
- They conjecture that such input would highlight the dependency relations more clearly by abstracting away from possibly confounding distributional lexical information contained in richer embeddings.
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- The LSTM has two layers of 1200 units per layer, and a dropout rate of 0.5.
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- BL use their neural LM for unsupervised prediction of agreement in two ways.
- Let $p(w_i|w_{i-1},...,w_{i-k})$ be the predicted probability of a word w in a string, given the prefix of $w_{i-1},...,w_{i-k}$ of preceding words in that string.
- On the first approach, they determine, for each sentence in the test set, whether the following condition holds: $\sum_{V^n} p(V_i^n|w_{i-1},...,w_{i-k}) > \sum_{V^{\neg n}} p(V_i^{\neg n}|w_{i-1},...,w_{i-k})$, where V^n ranges over verbs with the correct number feature (n) in a particular string, and $V^{\neg n}$ ranges over verbs with the wrong number feature in that string.
- On the second method BL test to see if the following condition holds: $p(Verb_i^n|w_{i-1},...,w_{i-k}) > p(Verb_i^{\neg n}|w_{i-1},...,w_{i-k})$.

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- The second procedure compares the predicted probability of the correctly number-marked form of the actual verb in this position with that of its incorrectly marked form (*the verb targeted method*).
- While in the summing method the LM is not given any semantic cue, in the verb targeted method it is priimed to expect a specific verb.
- This bias contributes minimal semantic information, given that the BL LM's 100-word vocabulary contains only the inflectional verb forms "to be", "to have", and "to state", with other verbs represented by the "VV" part of speech code.

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- The first method measures the summed conditional probabilities of all correctly number inflected verbs after the prefix in a string against the summed predicted probabilities of all incorrectly number inflected verbs appearing in this position (*the summing method*).
- The second procedure compares the predicted probability of the correctly number-marked form of the actual verb in this position with that of its incorrectly marked form (*the verb targeted method*).
- While in the summing method the LM is not given any semantic cue, in the verb targeted method it is priimed to expect a specific verb.
- This bias contributes minimal semantic information, given that the BL LM's 100-word vocabulary contains only the inflectional verb forms "to be", "to have", and "to state", with other verbs represented by the "VV" part of speech code.

Results of BL Experiments

- In all the following graphs, except for the last one (number of test examples per number of attractors) the *y*-axis gives the accuracy rate, and the *x*-axis the number of NP attractors.
- 73% of the verbs in the test sets are singular.
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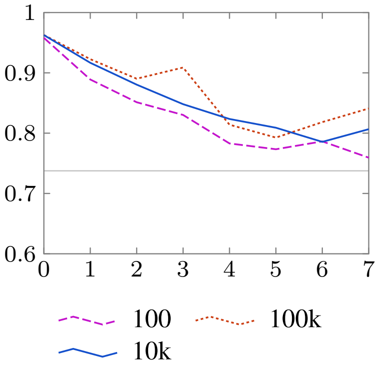
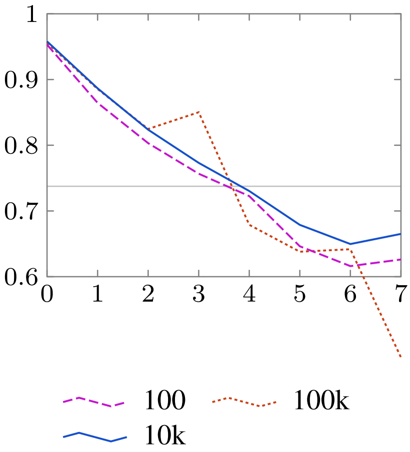
LSTM Vocabulary Size

A reduced vocabulary of the 100 most common words, with POS tags for the remainder, reduces accuracy across DNN architectures, for supervised learning.

Increasing the vocabulary to 100k words yields a significant improvement for the LSTM, but gives mixed results for the CNN.

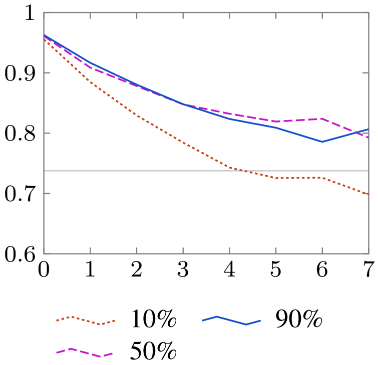


CNN Vocabulary Size



Training Size

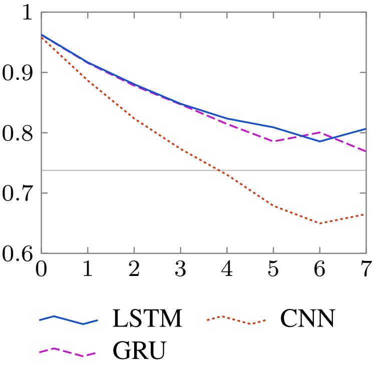
Increasing the ratio of training to testing examples from 10% to 50% significantly improves the performance of the LSTM (with 150 units and a vocabulary of 10,000 word embeddings).
Further increasing it to 90% does not make much of a difference, even degrading accuracy slightly at 6 attractors.



Architecture

The LSTM and GRU perform at a comparable level.

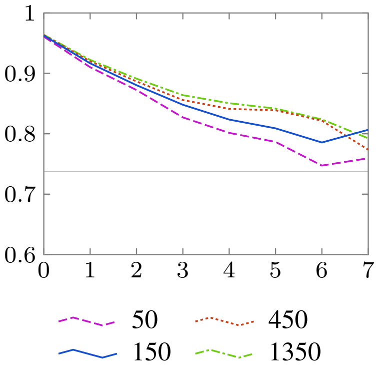
Both achieve significantly better accuracy than the CNN.



Memory Size

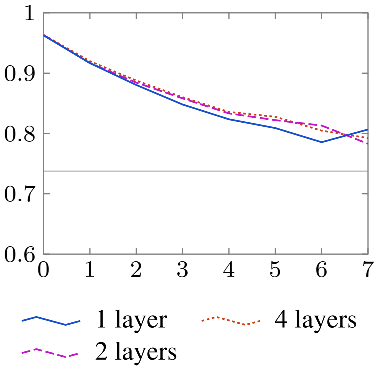
Increasing the number of units in an LSTM improves accuracy relative to the number of attractors.

Each three-fold increase in units achieves a similar improvement in percentage points for a higher number of attractors, up to 450 units.



Number of Layers

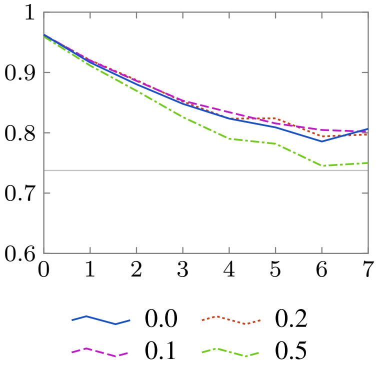
Increasing the number of layers for an LSTM from 1 150-unit layer to 2 such layers marginally improves its performance.
A further increase to 4 150-unit layers makes no clear difference.



Dropout Rates

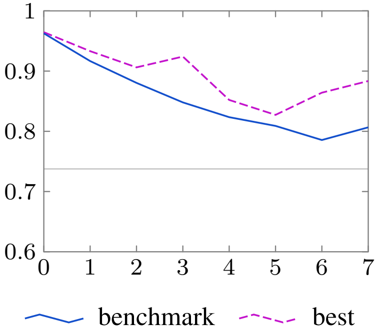
A dropout rate of 0.1 for the LSTM RNN (1 layer with 150 units) improves LSTM performance slightly.

An increase to 0.2 provides no clear benefit, while increasing the rate to 0.5 degrades performance.



Model with the Best Parameters

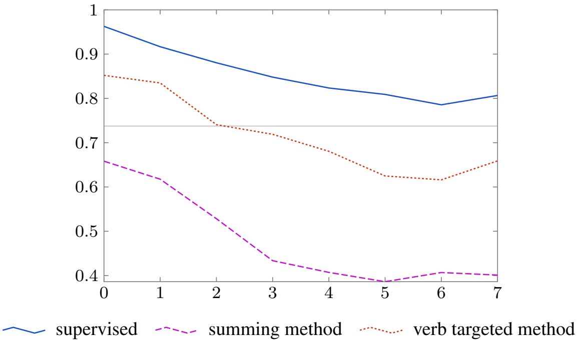
The DNN configured with the best observed parameter values is an LSTM with 2 layers, 1350 units, a dropout rate of 0.1, a vocabulary size of 100k, trained on 90% of the corpus, and lexical embedding size of 150 dimensions.



Unsupervised Language Model

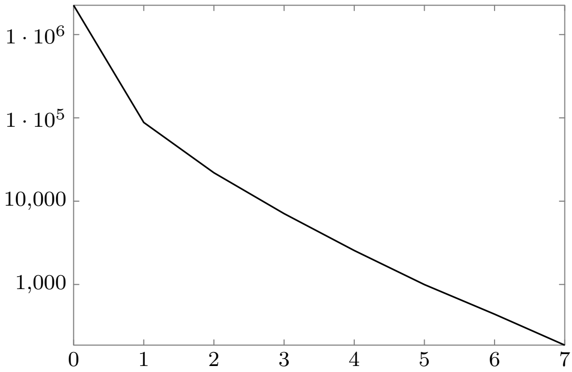
The BL LM prediction of verb number with the summing method is comparable to Linzen et al.'s LM.

The verb targeted method achieves a far higher level of accuracy than their model, and than the much larger Google LM, but it is still below BL's best supervised results.



Training Examples and Attractors

There is an inverse relation between the number of examples in the corpus and the number of attractor NPs in these sentences.



Significance of BL's Experiments

- BL's results support Linzen et al.'s finding that RNNs (both LSTMs and GRUs) learn long distance syntactic dependencies within extended, complex sequences.
- Their success in learning subject-verb agreement scales with the size of the data set on which they train.
- Training DNNs on data that is lexically impoverished, but highlights the syntactic elements of a relation, does not (for this task) facilitate learning, but degrades it, contrary to their initial hypothesis.
- This suggests that DNNs extract syntactic patterns incrementally from lexical embeddings, through recognition of their distributional regularities.
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The Nature of Syntactic Representation

- It is an open question as to how DNN learning resembles and diverges from human learning.
- BL make no cognitive claims concerning the relevance of their experiments to human syntactic representation.
- It is interesting to note that some recent work in neurolinguistics indicates that syntactic knowledge is distributed through different language centres in the brain, and closely integrated with lexical-semantic representations (Blank et al., 2016).
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Neural LMs and Hierarchical Syntactic Structure

- Gulordava et al. (2018) use an LSTM LM for unsupervised learning of subject-verb agreement, with tests sets in Italian, English, Hebrew, and Russian.
- They extract test sentences from a dependency tree bank, and convert them into nonsense (nonce) sentences by substituting arbitrary lexical items with corresponding POS, from the LM's vocabulary, for the the nouns and verbs in the originals.
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Gulordava et al.'s Experimental Results

	Italian	English	Hebrew	Russian
Unigram Majority Baseline				
Original	54.6	65.9	67.8	60.2
Nonce	54.1	42.5	63.1	54.0
5-ngram Kneser-Ney smoothing				
Original	63.9	63.4	72.1	73.5
Nounce	52.8	43.4	61.7	56.8
Perplexity	147.8	168.9	122.0	166.6
5-gram LSTM				
Original	81.8	70.2	90.9	91.5
Nounce	78.0	58.2	77.5	85.7
Perplexity	62.6	71.6	59.9	61.1
LSTM				
Original	92.1	81.0	94.7	96.1
Nounce	85.5	74.1	80.8	88.8
Perplexity	45.2	52.1	42.5	48.9

Gulordava et al.'s Results

- Gulordava et al.'s LM significantly outperforms the three baseline systems.
- The fact that it yields reasonable accuracy for nonce sentences indicates that it learns hierarchical syntactic structure independently of semantic cues.
- But its predictive accuracy is still significantly higher for the original sentences, suggesting that these cues facilitate syntactic learning, as BL's work suggests.
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- They report that the LSTM model approaches the human level of performance.
- For the original sentences, average human accuracy is 94.5, and the LSTM LM is 92.1.
- For the nonce sentences, average human accuracy is 88.4, and the LSTM LM is 85.5.
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Agreement Across Different Structures

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Applying BERT to the Marvin-Linzen Test Set

- Goldberg (2019) uses BERT (Base and Large, both untuned) as a LM on Marvin and Linzen's test set.
- He masks the contrasting verbs in each minimal pair, and uses BERT's pre-softmax logit scores as quasi-probability values to test its prediction for each of these verbs.
- By virtue of its bidirectional processing of input, BERT conditions its predicted scores on both the left and right contexts of the masked verb.
- In 9 of the 10 syntactic constructions BERT approaches or surpasses Marvin and Linzen's reported human judgment accuracy, in some cases by a significant margin.
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- Their RNNG LM contains a stack and a composition operator for predicting the constituency structure of a string.
- It assigns joint probability to a string and a phrase structure.
- This RNNG and their best sequential LSTM LM achieve approximately the same level of accuracy in predicting agreement for sentences with 0-2 attractors (98%, 96.5%, and 95%, respectively).
- However, the RNNG outperforms the LSTM LM for cases with higher numbers of attractors, with 93% vs 87% at 4 attractors, and 88% vs 82% at 5 attractors).

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Syntactic Structure as an Architectural Bias

- An RNNG is designed to induce hierarchical structure on a string.
- The fact that it outperforms an LSTM lacking this architectural feature, on the agreement task, for more complex cases, suggests that it is better able to learn long distance syntactic dependencies.
- However, Kuncoro et al. only test their RNNG LM on a limited set of English data.
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Tree RNNs

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- These models have achieved improved performance on tasks like natural language inference (NLI) and sentiment analysis.
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- Choi et al.'s (2018) latent tree RNN (ST-Gumbel) outperformed all other systems, scoring accuracy rates of 83.7 on SNLI, and 69.5 on MNLI.
- The other systems scored between 81.3 and 82.6 on SNLI, and between 66.2 and 69.1 on MNLI.
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Significance of Tree Representations in the NLI Task

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- Given these results, and the fact that the non-tree LSTM baseline achieves results comparable to Choi et al.'s model, it is unclear to what extent tree representations, latent or supervised, contribute to the NLI task.
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Implicit Representation of Trees in Transformers

- Hewitt and Manning (2019) (HM) use a supervised probe to test for the presence of syntactic tree structures in the word vectors of DNNs.
- The probe consists of a squared L2 distance measure, which determines the distance (number of nodes) between word pairs in a tree, and a squared L2 norm, which identifies the relative depth (chain of nodes from the root) of each word in a tree.
- This metric defines a mapping from the word vectors in the sentence representation of a DNN into a parse tree structure.
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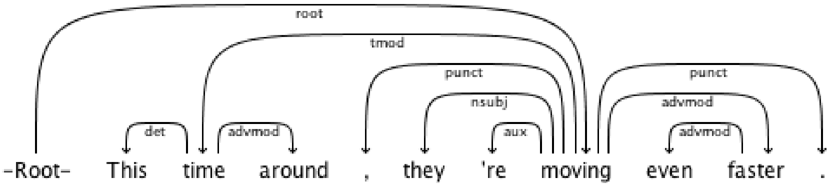
Stanford Dependency Parser



Labelled dependency parse tree from

`https://nlp.stanford.edu/software/nndep.html`

Transformer Accuracy on Parse Prediction

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- ELM01 scores an average Spearman correlation of 0.87 on word distances, and 0.87 on word depth.
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Conclusions

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- This information is implicit in the distributed lexical embeddings of a DNN, and it is encoded in the vector representations of the words, phrases, and sentences that the DNN produces.
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