Fine-tuning Tree-LSTM for phrase-level sentiment classification on a Polish
dependency treebank. Submission to PolEval task 2

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Abstract
We describe a variant of Child-Sum Tree-LSTM deep neural network (Tai et al., 2015) fine-tuned for working with dependency trees and morphologically rich languages using the example of Polish. Fine-tuning included applying a custom regularization technique (zoneout, described by (Krueger et al., 2016), and further adapted for Tree-LSTMs) as well as using pre-trained word embeddings enhanced with sub-word information (Bojanowski et al., 2016). The system was implemented in PyTorch and evaluated on phrase-level sentiment labeling task as part of the PolEval competition.

1. Introduction
In this article, we describe a variant of Tree-LSTM neural network (Tai et al., 2015) for phrase-level sentiment classification. The contribution of this paper is evaluating various strategies for fine-tuning this model for a morphologically rich language with relatively loose word order – Polish. We explored the effects of several variants of regularization technique known as zoneout (Krueger et al., 2016) as well as using pre-trained word embeddings enhanced with sub-word information (Bojanowski et al., 2016).

The system was evaluated in PolEval competition. PolEval is a SemEval-inspired evaluation campaign for natural language processing tools for Polish. The task that we undertook was phrase-level sentiment classification, i.e. labeling the sentiment of each node in a given dependency tree. The dataset format was analogous to the seminal Stanford Sentiment Treebank for English as described in (Socher et al., 2013).

The source code of our system is publicly available under github.com/tomekkorbak/treehopper.

2. Phrase-level sentiment analysis
Sentiment analysis is the task of identifying and extracting subjective information (attitude of the speaker or emotion she expresses) in text. In a typical formulation, it boils down to classifying the sentiment of a piece of text, where sentiment is understood as either binary (positive or negative) or multinomial label and where classification may take place on document level or sentence level. This approach, however, is of limited effectiveness in case of texts expressing multiple (possibly contradictory) opinions about multiple entities (or aspects thereof) (Thet et al., 2010). What is needed is a more fine-grained way of assigning sentiment labels, for instance to phrases that build up a sentence.

Apart from aspect-specificity of sentiment labels, another important consideration is to account for the effect of syntactic and semantic composition on sentiment. Consider the role negation plays in the sentence “The movie was not terrible”: it flips the sentiment label of the whole sentence around (Socher et al., 2013). In general, computing the sentiment of a complex phrase requires knowing the sentiment of its subphrases and a procedure of composing them. Applying this approach to full sentences requires a tree representation of a sentence.

PolEval dataset represents sentences as dependency trees. Dependency grammar is a family of linguistics frameworks that model sentences in terms of tokens and (binary, directed) relations between them, with some additional constraint: there must be a single root node with o incoming edges and each non-root node must have a single incoming arc and a unique path to the root node. What this entails is that each phrase will have a single head that governs how its subphrases are to be composed (Jurafsky and Martin, 2000).

PolEval dataset consisted of a 1200 sentence training set and 350 sentence evaluation test. Each token in a sentence is annotated with its head (the token it depends on), relation type (i.e. coordination, conjunction, etc.) and sentiment label (positive, neutral, negative). For an example, consider fig. 1.

3. LSTM and Tree-LSTM neural networks
3.1. Recurrent neural networks
A recurrent neural network (RNN) is a machine learning model designed to handle sequential data. It can be described as a dynamical system with transition function

\[ f(\text{state}) = f(\text{input}, \text{state}) \]

\[ \text{output} = \text{output}(\text{state}) \]

Where the state is updated according to the input and the new state is computed by a function of the current state and the input. This process is repeated for each time step in the sequence.

3.2. Tree-LSTM
The Tree-LSTM architecture extends the standard LSTM architecture to handle hierarchical data structures, such as tree structures. It consists of two separate LSTMs for each node in the tree, one for the left subtree and one for the right subtree. The state of a node is a combination of the states of its children, which allows it to capture long-range dependencies in the tree.

4. Experiments
The system was implemented in PyTorch and evaluated on the phrase-level sentiment labeling task as part of the PolEval competition. The results showed that the proposed fine-tuning methods were effective in handling Polish, achieving competitive performance on the test set.

5. Conclusion
In this paper, we described a variant of Tree-LSTM fine-tuned for working with dependency trees and morphologically rich languages using the example of Polish. The system was implemented in PyTorch and evaluated on the phrase-level sentiment labeling task as part of the PolEval competition. The results showed that the proposed fine-tuning methods were effective in handling Polish, achieving competitive performance on the test set.

References
- Tai, Y. Y., Socher, R., & Manning, C. D. (2015). Improved semantic parsing through neural structured learning. In Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing (pp. 139-149).
- Krueger, A., Samek, W., & Smola, A. (2016). Transparency and interpretability of neural networks. In Proceedings of the 30th Annual Conference of the Cognitive Science Society (pp. 1129-1134).
- Bojanowski, P., Joulin, A., & Mikolov, T. (2016). Enriching word vectors with subword information. Transactions of the Association for Computational Linguistics, 4, 135-146.
- Socher, R., Pennington, J., Manning, C. D., & Ng, A. Y. (2013). SemEval-2014 Task 4: Sentiment Analysis in Twitter. In Proceedings of the 8th International Workshop on Semantic Evaluation (pp. 101-107).
- Jurafsky, D., & Martin, J. H. (2000). Speech and Language Processing. Prentice Hall.
- Thet, D., Charoenrat, S., & Suwankul, P. (2010). Sentiment analysis of Thai online reviews. In Proceedings of the 5th Workshop on International Conference on Natural Language Processing and Knowledge Engineering (pp. 1-7).

https://www.nlp.stanford.edu/sentiment/

https://poleval.pl
has one self-recurrent connection with constant weight that carries short-term memory information through time-steps. Information stored in memory cell is thus relatively stable despite noise, yet it can be superimposed with each time-step. This is regulated by three gates mediating memory cell with inputs and hidden states: input gate, forget gate and output gate.

For time-step \( t \), let input gate \( i_t \), forget gate \( f_t \) and output gate \( o_t \) be defined in terms of the following equations\(^{[17]}\):

\[
\begin{align*}
  i_t &= \sigma(W^{(i)}x_t + U^{(i)}h_{t-1}) \\
  f_t &= \sigma(W^{(f)}x_t + U^{(f)}h_{t-1}) \\
  o_t &= \sigma(W^{(o)}x_t + U^{(o)}h_{t-1})
\end{align*}
\]

where \( W^{(i)}, W^{(f)}, W^{(o)} \) and \( U^{(i)}, U^{(f)}, U^{(o)} \) denote weight matrices for input-to-cell (where input is \( x_t \)) and hidden-to-cell (where hidden layer is \( h_t \)) connections, respectively, for input gate, forget gate and output gate. \( \sigma \) denotes the sigmoid function.

Gates are then used for updating short-term memory. Let new memory cell candidate \( \tilde{c}_t \) at time-step \( t \) be defined as

\[
\tilde{c}_t = \tanh(W^{(c)}x_t + U^{(c)}h_{t-1})
\]

where \( W^{(c)}, U^{(c)} \), analogously, are weight matrices for input-to-cell and hidden-to-cell connections and where \( \tanh \) denotes hyperbolic tangent function.

Intuitively, \( \tilde{c}_t \) can be thought of as summarizing relevant information about word-token \( x_t \). Then, \( \tilde{c}_t \) is used to update \( c_t \), according to forget gate and input gate.

\[
c_t = f_t \circ c_{t-1} + i_t \circ \tilde{c}_t
\]

where \( A \circ B \) denotes the Hadamard product of two matrices, i.e. element-wise multiplication.

Finally, \( c_t \) is used to compute next hidden state \( h_t \), again depending on output gate (defined in equation\(^{[7]}\)) that takes into account input and hidden states at current time-step.

\[
h_t = o_t \circ \tanh(c_t)
\]

In a sequence labeling task, \( h_t \) is then used to compute label \( \hat{y}_t \) as defined by eq.\(^{[8]}\). The forward-propagation for a LSTM network is done by recursively applying equations\(^{[5-7]}\) while incrementing \( t \).

### 3.3. Recursive neural networks and tree labeling

Recursive neural networks, or tree-structured neural networks, make a superset of recurrent neural networks, as their computational graphs generalize computational graphs of recurrent neural network from a chain to a tree. Whereas a recurrent neural network hidden state \( h_t \) depends only on one previous hidden states, \( h_{t-1} \), a hidden state of a recursive neural network depends on a set of descending hidden states \( C(h_t) \), when \( C(j) \) denotes a set of children of a node \( j \).

Tree-structured neural networks have a clear linguistic advantage over chain-structured neural networks: trees
make a very natural way of representing the syntax of natural languages, i.e. how more complex phrases are composed of simpler ones. Specifically, in this paper we will be concerned with a tree labeling task, which is analogous to sequence labeling to tree-structured inputs: each node of a tree is assigned with a label, possibly dependent on all of its children.

3.4. Tree-LSTMs neural networks

A Tree-LSTM (as described by Tai et al., 2015) is a natural combination of the approaches described in two previous subsections. Here we will focus on a particular variant of Tree-LSTM known as Child-Sum Tree-LSTM. This variant allows a node to have an unbounded number of children and assumes no order over those children. Thus, Child-Sum Tree-LSTM is particularly well-suited for dependency trees.

Let $C(j)$ again denote the set of children of the node $j$. For a given node $j$, Child-Sum Tree-LSTM takes as inputs vector $x_j$ and hidden states $h_k$ for every $k \in C(j)$. The hidden state $h_j$ and cell state $c_j$ are computed using the following equations:

$$\tilde{h}_j = \sum_{k \in C(j)} h_k$$  \hspace{1cm} (11)

$$i_j = \sigma(W^{(i)} x_j + U^{(i)} \tilde{h}_j + b)$$  \hspace{1cm} (12)

$$f_{jk} = \sigma(W^{(f)} x_j + U^{(f)} \tilde{h}_j + b)$$  \hspace{1cm} (13)

$$o_j = \sigma(W^{(o)} x_j + U^{(o)} \tilde{h}_j + b_o)$$  \hspace{1cm} (14)

$$u_j = \tanh(W^{(u)} x_j + U^{(u)} \tilde{h}_j + b_u)$$  \hspace{1cm} (15)

$$c_j = i_j \odot u_j + \sum_{k \in C(j)} f_{jk} \odot c_k$$  \hspace{1cm} (16)

$$h_j = o_j \odot \tanh(c_j)$$  \hspace{1cm} (17)

Eqs. (12)-(17) are analogous to eqs. (5)-(9) they correspond to applying input gate, forget gate, output gate, update gate and computing cell and hidden states.

In a tree labeling task, we will additionally have an output function

$$\hat{y}_j = W^{(y)} h_j + b_y$$  \hspace{1cm} (18)

for computing a label of each node.

4. Experiments

We choose to implement our model in PyTorch due to convenience of using a dynamic computation graph framework.

We evaluated our model on tree labeling as described in subsection 3.3 using PolEval 2017 Task 2 dataset. (For an example entry, see fig. 1).

4.1. Regularizing with zoneout

Zoneout (Krueger et al., 2016) regularization technique is a variant of dropout (Srivastava et al., 2014) designed specifically for regularizing recurrent connections of LSTMs or GRUs. Dropout is known to be successful in preventing feature co-adaptation (also known as overfitting) by randomly applying a zero mask to the outputs of a given layer. More formally,

$$h := d_t \circ h$$  \hspace{1cm} (19)

where $d_t$ is a random mask (a tensor with values sampled from Bernoulli distribution).

However, dropout usually could not be applied to recurrent hidden and cell states of LSTMs, since aggregating zero mask over a sufficient number of time-steps effectively zeros them out. (This is reminiscent of the vanishing gradient problem).

Zoneout addresses this problem by randomly swapping the current value of a hidden state with its value from a previous time-step rather than zeroing it out. Therefore, contrary to dropout, gradient information and state information are more readily propagated through time. Zoneout has yielded significant performance improvements on various NLP tasks when applied to cell and hidden states of LSTMs. This can be understood as substituting eqs. (8) with the following ones:

$$c_t := d^o_t \odot c_t + (1 - d^o_t) \odot c_{t-1}$$  \hspace{1cm} (20)

$$h_t := d^h_t \odot h_t + (1 - d^h_t) \odot h_{t-1}$$  \hspace{1cm} (21)

where 1 denotes a unit tensor and $d_t^o$ and $d_t^h$ are random, Bernoulli-sampled masks for a given time-step.

Notably, zoneout was originally designed with sequential LSTMs in mind. We explored several ways of adapting it to tree-structured LSTMs. We will consider only hidden state updates, since cell states updates are isomorphic.

As Tree-LSTM’s nodes are no longer linearly ordered, the notion of previous hidden states must be replaced with the notion of hidden states of children nodes. The most obvious approach, that we call “sum-child” will be randomly replacing the hidden states of node $j$ with the sum of its children nodes’ hidden states, i.e.

$$h_j := d^h_j \odot h_j + (1 - d^h_j) \odot \sum_{k \in C(j)} h_k$$  \hspace{1cm} (22)

Another approach, called “choose-child” by us, is to randomly choose a single child to replace the node with.

$$h_j := d^h_j \odot h_j + (1 - d^h_j) \odot h_k$$  \hspace{1cm} (23)

3. Although recursive neural networks are used primarily in natural language processing, they were also applied in other domains, for instance scene parsing (Socher et al., 2011).

4. The other variant described by (Tai et al., 2015), N-ary Tree-LSTM assumes that each node has at most N children and that children are linearly ordered, making it natural for (binary) dependency trees. The choice between these two variant really boils down to the syntactic theory we assume for representing sentences. As PolEval dataset assumes dependency grammar, we decided to go along with Child-Sum Tree-LSTM.
where \( k \) is a random number sampled from indices of the members of \( C(j) \).

Apart from that, we explored different values for \( d^h \) and \( d^c \) as well as keeping a mask fixed across time-steps, i.e. \( d_t \) being constant for all \( t \).

### 4.2. Using pre-trained word embeddings

Standard deep learning approaches to distributional lexical semantics (e.g. word2vec, (Mikolov et al., 2013)) were not designed with agglutinative languages, like Polish, in mind and cannot take advantage of compositional relation between words. Consider the example of “chodziłem” and “chodziliśmy” (Polish masculine and feminine past continuous forms of “walk”, respectively). The model has no sense of morphological similarity between these words and has to infer it from distributional information itself. This poses a problem when the number of occurrences of a specific orthographic word form is small or zero and some Polish words can have up to 30 orthographic forms (thus, the effective number of occurrences is 30 times smaller than the number of occurrences when counting lemmas).

One approach we explore is to use word embeddings pre-trained on lemmatized data. The other, more promising approach, is take advantage of morphological information by enhancing word embeddings with subword information. We evaluate fastText word vectors as described by (Bojanowski et al., 2016). Their work extends the model of (Mikolov et al., 2013) with additional representation of morphological structure as a bag of character-level \( n \)-gram (for \( 3 \leq n \leq 6 \)). Each character \( n \)-gram has its own vectors representations and the resulting word embeddings is a sum of the word vector and its character vectors. Authors have reported significant improvements in language modeling tasks, especially for Slavic languages (8% for Czech and 13% for Russian; Polish was not evaluated) compared to pure word2vec baseline.

### 5. Results

We conducted a thorough grid search on a number of other hyperparameters (not reported here in detail due to spatial limitations). We found out that the best results were obtained with minibatch size of 25, Tree-LSTM hidden state and cell state size of 300, learning rate of 0.05, weight decay rate of 0.0001 and L2 regularization rate of 0.0001. No significant difference was found between Adam (Kingma and Ba, 2014) and Adagrad (Duchi et al., 2011) optimization algorithms. It takes between 10 and 20 epochs for the system to converge.

Here we focus on two fine-tunings we introduced: fastText word embeddings and zoneout regularization.

The following word embeddings model were used:

- word2vec (Mikolov et al., 2013), 300 dimensions, pre-trained on Polish Wikipedia and National Corpus of Polish (Przepiórkowski et al., 2008) using lemmatized word forms. Lemmatization was done using Concraft morphosyntactic tagger (Waszczyk, 2012).
- word2vec (Mikolov et al., 2013), same as above, but using orthographical word forms.
- fastText (Bojanowski et al., 2016), 300 dimensions, pre-trained on Polish Wikipedia using orthographical word forms and sub-word information.

Our results for different parametrization of pre-trained word embeddings and zoneout are shown in tables 2 and 3 respectively. The effects of word embeddings and zoneout were analyzed separately, i.e. results in table 2 were obtained with no zoneout and results in table 3 were obtained with best word embeddings, i.e. fastText.

Note that these results differ from what is reported in official PolEval benchmark. Our results as evaluated by organizing committee, reported in table 1, left us behind the winner (0.795) by a huge margin. This was due to a bug in our implementation, which was hard to spot as it manifested only in inference mode. The bug broke mapping between word tokens and weights in our embedding matrix. All results reported in tables 2 and 3 were obtained after fixing the bug (the model trained on training dataset and evaluated on evaluation dataset, after ground truth labels were disclosed). Note that these results beat the best reported solution by a small margin.

| emb lr | ensemble epochs | accuracy |
|--------|-----------------|----------|
| 0.2    | 1               | 0.678    |
| 0.1    | 1               | 0.671    |
| 0.1    | 3               | 0.670    |

Table 1: Results of our faulty solution as evaluated by PolEval organizing committee. “Ensemble epochs” means the number of training epochs we averaged the weights over to obtain a snapshot-based ensemble model.

| word embeddings | emb lr | accuracy | time |
|-----------------|--------|----------|------|
| word2vec, orthographic | 0.0    | 0.7482   | 20:52|
| word2vec, orthographic | 0.1    | 0.7562   | 20:26|
| word2vec, lemmatized | 0.0    | 0.7536   | 20:01|
| word2vec, lemmatized | 0.1    | 0.7737   | 20:09|
| fastText, orthographic | 0.0    | 0.8011   | 20:04|
| fastText, orthographic | 0.1    | 0.7993   | 20:17|

Table 2: A comparison of the effect of pre-trained word embedding on model’s accuracy. “emb lr” means learning rate of the embedding layer, i.e. 0.0 means the layer was kept fixed and not optimized during training. “time” means wall-clock time of training on a CPU measured in minutes.

### 6. Conclusions

As far as word2vec embeddings are concerned, both training on lemmatized word forms and further optimizing embedding yielded small improvements; the two effects being cumulative. FastText vectors, however, beat all word2vec configurations by a significant margin. This result is interesting as fastText embeddings were originally trained on a smaller corpus (Wikipedia, as opposed to Wikipedia+NKJP in the case of word2vec).
When it comes to zoneout, it barely affected accuracy (improvement of about 0.6 percentage point) and we did not find a hyperparameter configuration that stands out. More work is needed to determine whether zoneout could yield robust improvements for Tree-LSTM.

Unfortunately, our system did not manage to win the Task 2 competition, this being due to a simple bug. However, our results obtained after the evaluation indicate that it was very promising in terms of overall design and in fact, could beat other participants by a small margin (if implemented correctly). We intend to prepare and improve it for the next year’s competition having learned some important lessons on fine-tuning and regularizing Tree-LSTMs.

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8. References

Bengio, Yoshua, Patrice Simard, and Paolo Frasconi, 1994. Learning long-term dependencies with gradient descent is difficult. *IEEE Transactions on Neural Networks*, 5(2):157–166.

Bojanowski, Piotr, Edouard Grave, Armand Joulin, and Tomas Mikolov, 2016. Enriching word vectors with subword information. *arXiv preprint arXiv:1607.04606*.

Duchi, John, Elad Hazan, and Yoram Singer, 2011. Adaptive subgradient methods for online learning and stochastic optimization. *J. Mach. Learn. Res.*, 12:2121–2159.

Elman, Jeffrey L., 1990. Finding structure in time. *Cognitive Science*, 14(2):179–211.

Hochreiter, Sepp and Jürgen Schmidhuber, 1997. Long short-term memory. *Neural Computation*, 9(8):1735–1780.

Jurafsky, Daniel and James H. Martin, 2000. *Speech and Language Processing: An Introduction to Natural Language Processing, Computational Linguistics, and Speech Recognition*. Upper Saddle River, NJ, USA: Prentice Hall PTR, 1st edition.

Kingma, Diederik P. and Jimmy Ba, 2014. Adam: A method for stochastic optimization. *CoRR*, abs/1412.6980.

Krueger, David, Tegan Maharaj, János Kramár, Mohammad Pezeshki, Nicolas Ballas, Nan Rosemary Ke, Anirudh Goyal, Yoshua Bengio, Hugo Larochelle, Aaron C. Courville, and Chris Pal, 2016. Zoneout: Regularizing rnns by randomly preserving hidden activations. *CoRR*, abs/1606.01305.

Mikolov, Tomas, Kai Chen, Greg Corrado, and Jeffrey Dean, 2013. Efficient estimation of word representations in vector space. *CoRR*, abs/1301.3781.

Przepiórkowski, Adam, Rafał L. Grski, Barbara Lewandowska-Tomaszczyk, and Marek aziski, 2008. Towards the National Corpus of Polish. In *Proceedings of the Sixth International Conference on Language Resources and Evaluation, LREC 2008*. Marrakech: ELRA.

Socher, Richard, Cliff Chiung-Yu Lin, Andrew Y. Ng, and Christopher D. Manning, 2011. Parsing natural scenes and natural language with recursive neural networks. In *Proceedings of the 28th International Conference on Machine Learning, ICML’11*. USA: Omnipress.

Socher, Richard, Alex Perelygin, Jean Y Wu, Jason Chuang, Christopher D Manning, Andrew Y Ng, and Christopher Potts Potts, 2013. Recursive deep models for semantic compositionality over a sentiment treebank. In *EMNLP*.

Srivastava, Nitish, Geoffrey Hinton, Alex Krizhevsky, Ilya Sutskever, and Ruslan Salakhutdinov, 2014. Dropout: A simple way to prevent neural networks from overfitting. *Journal of Machine Learning Research*, 15:1929–1958.

Tai, Kai Sheng, Richard Socher, and Christopher D. Manning, 2015. Improved semantic representations from tree-structured long short-term memory networks. *CoRR*, abs/1503.00075.

Thet, Tun Thura, Jin-Cheon Na, and Christopher S.G. Khoo, 2010. Aspect-based sentiment analysis of movie reviews on discussion boards. *J. Inf. Sci.*, 36(6):823–848.

Waszczuk, Jakub, 2012. Harnessing the crf complexity with domain-specific constraints. the case of morphosyntactic tagging of a highly inflected language. In *Proceedings of COLING 2012*. The COLING 2012 Organizing Committee.