A Fast Unified Model for Parsing and Sentence Understanding

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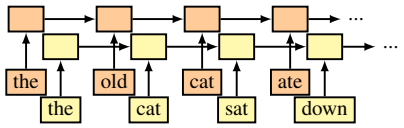
Abstract

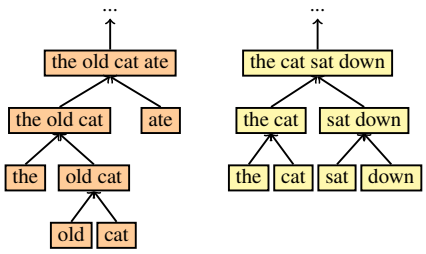
Tree-structured neural networks exploit valuable syntactic parse information as they interpret the meanings of sentences. However, they suffer from two key technical problems that make them slow and unwieldy for large-scale NLP tasks: they can only operate on parsed sentences and they do not directly support batched computation. We address these issues by introducing the Stack-augmented Parser-Interpreter Neural Network (SPINN), which combines parsing and interpretation within a single tree-sequence hybrid model by integrating tree-structured sentence interpretation into the linear sequential structure of a shift-reduce parser. Our model supports batched computation for a speedup of up to 25x over other tree-structured models, and its integrated parser allows it to operate on unparsed data with little loss of accuracy. We evaluate it on the Stanford NLI entailment task and show that it significantly outperforms other sentence-encoding models.

1 Introduction

A wide range of current models in NLP are built around a neural network component that produces vector representations of sentence meaning (e.g., Sutskever et al., 2014; Tai et al., 2015). This component, the sentence encoder, is generally formulated as a learned parametric function from a sequence of word vectors to a sentence vector, and this function can take a range of different forms. Common sentence encoders include sequence-based recurrent neural network models (RNNs, see Figure 1a) with Long Short-Term Memory (LSTM, Hochreiter and Schmidhuber, 1997), which accumulate information over the sentence sequentially; convolutional neural networks (Kalchbrenner et al., 2014; Zhang et al., 2015), which accumulate information using filters over short local sequences of words or characters; and tree-structured recursive neural networks (TreeRNNs, Goller and Küchler, 1996; Socher et al., 2011a, see Figure 1b), which propagate information up a binary parse tree.



(a) A conventional sequence-based RNN for two sentences.



(b) A conventional TreeRNN for two sentences.

Figure 1: An illustration of two standard designs for sentence encoders. The TreeRNN, unlike the sequence-based RNN, requires a substantially different connection structure for each sentence, making batched computation impractical.

Of these, the TreeRNN appears to be the principled choice, since meaning in natural language sentences is known to be constructed recursively according to a tree structure (Dowty, 2007, i.a.). TreeRNNs have shown promise (Tai et al., 2015; Li et al., 2015; Bowman et al., 2015b), but have largely been overlooked in favor of sequence-based RNNs because of their incompatibility with

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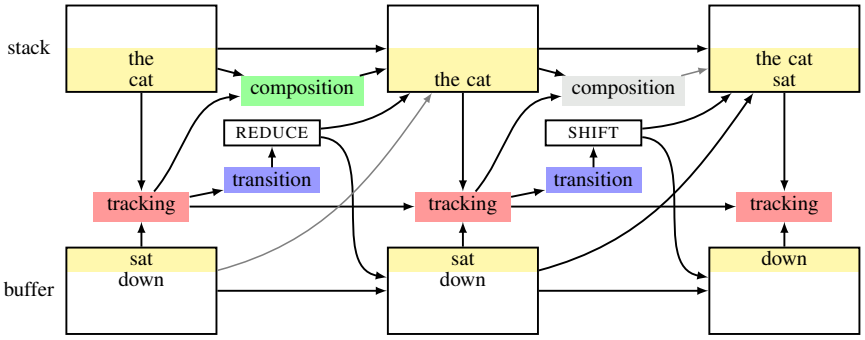
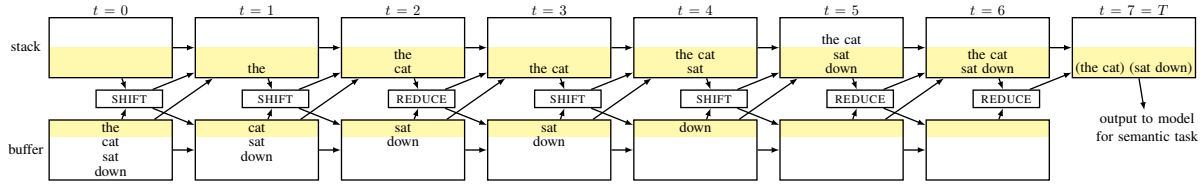


(a) The SPINN unrolled for two transitions during the processing of the sentence *the cat sat down*. 'Tracking', 'transition', and 'composition' are neural network layers. Gray arrows indicate connections which are blocked by a gating function.



(b) The fully unrolled SPINN for *the cat sat down*, with neural network layers omitted for clarity.

Figure 2: Two views of the SPINN.

batched computation and their reliance on external parsers. Batched computation—performing synchronized computation across many examples at once—yields order-of-magnitude improvements in model run time, and is crucial in enabling neural networks to be trained efficiently on large datasets. Because TreeRNNs use a different model structure for each sentence, as in Figure 1, batching is impossible in standard implementations. In addition, standard TreeRNN models can only operate on sentences that have already been processed by a syntactic parser, which slows and complicates the use of these models at test time for most applications.

This paper introduces a new model to address both these issues: the Stack-augmented Parser-Interpreter Neural Network, or SPINN, shown in Figure 2. SPINN executes the computations of a tree-structured model in a linearized sequence, and can incorporate a neural network parser that produces the required parse structure on the fly. This design improves upon the TreeRNN architecture in three ways: At test time, it can simultaneously parse and interpret unparsed sentences without incurring a substantial additional computational cost, removing the dependence on an external parser. In addition, it supports batched computation for both parsed and unparsed sentences, which yields dramatic speedups over standard TreeRNNs. Finally, it supports a novel tree-sequence hybrid mechanism for handling local context in sentence interpretation that yields substantial gains in accuracy over pure sequence- or tree-based models.

We evaluate SPINN on the Stanford Natural Language Inference entailment task (SNLI, Bowman et al., 2015a), and find that it significantly outperforms other sentence-encoding-based models, and that it yields speed increases of up to 25x over a standard TreeRNN implementation.

2 Related work

There is a fairly long history of work on building neural network-based parsers that use the core operations and data structures from transition-based parsing, of which shift-reduce parsing is a variant (Henderson, 2004; Emami and Jelinek, 2005; Titov and Henderson, 2010; Chen and Manning, 2014; Buys and Blunsom, 2015; Dyer et al., 2015; Kiperwasser and Goldberg, 2016). In addition, there has been recent work proposing models designed primarily for generative language modeling tasks that use this architecture as well (Zhang et al., 2016; Dyer et al., 2016). To our knowledge, SPINN is the first model to use this architecture for the purpose of sentence interpretation, rather than parsing or generation.

Socher et al. (2011a,b) present versions of the TreeRNN model which are capable of operating over unparsed inputs. However, these methods re-

quire an expensive search process at test time. Our model presents a fast alternative approach.

3 Our model: SPINN

3.1 Background: Shift-reduce parsing

SPINN is inspired by the shift-reduce parsing formalism (Aho and Ullman, 1972), which builds a tree structure over a sequence (e.g., a natural language sentence) by a single left-to-right scan over its tokens. The formalism is widely used in natural language parsing (e.g., Shieber, 1983; Nivre, 2003).

A shift-reduce parser accepts a sequence of input tokens $\mathbf{x} = (x_0, \ldots, x_{N-1})$ and consumes transitions $\mathbf{t} = (t_0, \ldots, t_{T-1})$, where each $t_t \in \{\text{SHIFT}, \text{REDUCE}\}$ specifies one step of the parsing process. In general a parser may also generate these transitions on the fly as it reads the tokens. It proceeds left-to-right through a transition sequence, combining the input tokens $\mathbf{x}$ incrementally into a tree structure. For any binary-branching tree structure over N words, this requires $2N - 1$ transitions.

The parser uses two auxiliary data structures: a stack S of partially completed subtrees and a buffer B of tokens yet to be parsed. The parser is initialized with the stack empty and the buffer containing the tokens $\mathbf{x}$ of the sentence in order. Let $\langle S, B \rangle = \langle \emptyset, \mathbf{x} \rangle$ denote this starting state. It next proceeds through the transition sequence, where each transition t_t selects one of the two following operations. Below, the $|$ symbol denotes the *cons* (concatenation) operator. We arbitrarily choose to always *cons* on the left in the notation below.

SHIFT: $\langle S, x \mid B \rangle \rightarrow \langle x \mid S, B \rangle$. This operation pops an element from the buffer and pushes it onto the top of the stack.

REDUCE: $\langle x \mid y \mid S, B \rangle \rightarrow \langle (x, y) \mid S, B \rangle$. This operation pops the top two elements from the stack, merges them into a binary tree with children (x, y), and pushes the result back onto the stack.

3.2 Composition and representation

SPINN is based on a shift-reduce parser, but it is designed to produce a vector representation of a sentence as its output, rather than a tree as in standard shift-reduce parsing. It modifies the shift-reduce formalism by using fixed length vectors to represent each entry in the stack and the buffer. Correspondingly, its REDUCE operation combines two vector representations from the stack into another vector using a neural network function.

The composition function When a REDUCE operation is performed, the vector representations of two tree nodes are popped off of the stack and fed into a *composition function*, which is a neural network function that produces a representation for a new tree node that is the parent of the two popped nodes. This new node is pushed on to the stack.

The TreeLSTM composition function (Tai et al., 2015) generalizes the LSTM neural network layer to tree- rather than sequence-based inputs, and it shares with the LSTM the idea of representing intermediate states as a pair of a fast-changing state representation $\vec{h}$ and a slower-changing memory representation $\vec{c}$. Our version is formulated as:

$$\text{(1)} \quad \begin{bmatrix} \vec{i} \\ \vec{f}_l \\ \vec{f}_r \\ \vec{o} \\ \vec{g} \end{bmatrix} = \begin{bmatrix} \sigma \\ \sigma \\ \sigma \\ \sigma \\ \tanh \end{bmatrix} \left(W_{\text{comp}} \begin{bmatrix} \vec{h}_s^1 \\ \vec{h}_s^2 \\ \vec{e} \end{bmatrix} + \vec{b}_{\text{comp}} \right)$$

$$\text{(2)} \quad \vec{c} = \vec{f}_l \odot \vec{c}_s^2 + \vec{f}_r \odot \vec{c}_s^1 + \vec{i} \odot \vec{g}$$

$$\text{(3)} \quad \vec{h} = \vec{o} \odot \vec{c}$$

where σ is the sigmoid activation function, $\odot$ is the elementwise product, the pairs $\langle \vec{h}_s^1, \vec{c}_s^1 \rangle$ and $\langle \vec{h}_s^2, \vec{c}_s^2 \rangle$ are the two input tree nodes popped off the stack, and $\vec{e}$ is an optional vector-valued input argument which is either empty or comes from from an external source like the tracking LSTM (see Section 3.3). The result of this function, the pair $\langle \vec{h}, \vec{c} \rangle$, is placed back on the stack. Each vector-valued variable listed is of dimension D except $\vec{e}$, of the independent dimension D_{tracking}.

The stack and buffer The stack and the buffer are arrays of N elements each (for sentences of up to N words), with the two D-dimensional vectors $\vec{h}$ and $\vec{c}$ in each element.

Word representations We use word representations based on the standard 300D vector package provided with GloVe (Pennington et al., 2014). We do not update these representations during training. Instead, we use a learned linear transformation to map each input word vector $\vec{x}_{\text{GloVe}}$ into a vector pair $\langle \vec{h}, \vec{c} \rangle$ that is stored in the buffer:

$$\text{(4)} \quad \begin{bmatrix} \vec{h} \\ \vec{c} \end{bmatrix} = W_{\text{wd}} \vec{x}_{\text{GloVe}} + \vec{b}_{\text{wd}}$$

3.3 The tracking LSTM

In addition to the stack, the buffer, and the composition function, our full model includes an additional component: the tracking LSTM. This is a simple low-dimensional sequence-based LSTM RNN that operates in tandem with the model, taking inputs from the buffer and stack at each step. It is meant to maintain a low-resolution summary of the portion of the sentence that has been processed so far, which is used for two purposes: it supplies feature representations to the transition classifier, which allows the model to stand alone as a parser, and it additionally supplies a secondary input $\vec{e}$ (see Equation 1) to the composition function, allowing context information to leak into the construction of sentence meaning, and forming what is effectively a tree-sequence hybrid model.

The tracking LSTM's inputs (yellow in Figure 2) are the top element of the buffer $\vec{h}_b^1$ (which would be moved in a SHIFT operation) and the top two elements of the stack $\vec{h}_s^1$ and $\vec{h}_s^2$ (which would be composed in a REDUCE operation).

Why a tree-sequence hybrid? Lexical ambiguity is ubiquitous in natural language. Most words have multiple senses or meanings, and it is generally necessary to use the context in which a word occurs to determine which of its senses or meanings is meant in a given sentence. Even though TreeRNNs are much more effective at composing meanings in principle, this ambiguity can give simpler sequence-based sentence-encoding models an advantage: when a sequence-based model first processes a word, it has direct access to a state vector that summarizes the left context of that word, which acts as a cue for disambiguation. In contrast, when a standard tree-structured model first processes a word, it only has access to the constituent that the word is merging with, which is often just a single additional word. Feeding a context representation from the tracking LSTM into the composition function is a simple and efficient way to mitigate this disadvantage of tree-structured models.

It would be straightforward to augment SPINN to support the use of some amount of right-side context as well, but this would add complexity to the model that we think is largely unnecessary: humans are very effective at understanding the beginnings of sentences before having seen or heard the ends, suggesting that it is possible to get by without the unavailable right-side context.

t	$S[t]$	Q_t
0		—
1	a	$\underline{1}$
2	b	$\underline{1}\ \underline{2}$
3	c	$1\ \underline{2}\ \underline{3}$
4	$(c\ b)$	$\underline{1}\ \underline{4}$
5	$((c\ b)\ a)$	$\underline{5}$

Table 1: The thin-stack algorithm computing a SHIFT-SHIFT-SHIFT-REDUCE-REDUCE sequence on the input sentence (a, b, c). S is shown in the second column and represents the top of the stack at each step t. The last two elements of Q (underlined) specify which rows t would be involved in a REDUCE operation at the next step.

3.4 Parsing: Predicting transitions

For SPINN to operate on unparsed inputs, it needs to be able to produce its own transition sequence $\mathbf{t}$ rather than relying on an external parser to supply it as part of the input. To do this, the model predicts t_t at each step using a simple two-way softmax classifier whose input is the state of the tracking LSTM:

$$\vec{p}_{\mathrm{t}} = \mathrm{softmax}(W_{\mathrm{trans}}\vec{h}_{\mathrm{tracking}} + \vec{b}_{\mathrm{trans}}) \quad (5)$$

At test time, the model uses whichever transition (i.e., SHIFT or REDUCE) is assigned a higher probability. The prediction function is trained to mimic the decisions of an external parser, and these decisions are used as the inputs to the model during training. For SNLI, we use the binary Stanford PCFG Parser parses that are included with the corpus. We did not find scheduled sampling (Bengio et al., 2015)—allowing the model to use its own transition decisions in some instances at training time—to help.

3.5 Implementation issues

Representing the stack efficiently A naïve implementation of SPINN would require representing a stack of size N for each timestep of each input sentence at training time to support backpropagation. This implies a per-example space requirement of $N \times T \times D$, which is prohibitively large for significant batch sizes or sentence lengths N. Such a naïve implementation would also require copying a largely unchanged stack at each timestep, since each SHIFT or REDUCE operation writes only one new representation to the stack.

Algorithm 1 The thin stack algorithm

```
function STEP(bufferTop, op, t, S, Q)
    if op = SHIFT then
        S[t] := bufferTop
    else if op = REDUCE then
        right := S[Q.pop()]
        left := S[Q.pop()]
        S[t] := COMPOSE(left, right)
    Q.push(t)
```

We propose an alternative space-efficient stack representation inspired by the zipper technique (Huet, 1997), that we call *thin stack*. For each input sentence, we represent the stack with a single $T \times D$ matrix S. Each row S_t represents the top of the actual stack at timestep t. We maintain a queue of backpointers onto S that indicates which elements would be involved in a REDUCE operation at any given step. Algorithm 1 describes the full mechanics of a stack feedforward in this compressed representation. It operates on the compressed $T \times D$ matrix S and a backpointer queue Q. Table 1 shows an example run.

This stack representation requires substantially less space. It stores each element involved in the feedforward computation exactly once, meaning that this representation can still support efficient backpropagation. Furthermore, all of the updates to S and Q can be performed batched and in-place on a GPU, yielding substantial speed gains. We describe speed results in Section 3.7.

A simpler variant of this technique can be used to represent the buffer, since information is not written to the buffer during model operation. It can be stored as a single fixed matrix with a scalar pointer variable indicating which element is the head at each step.

Preparing the data At training time, SPINN requires both a transition sequence $\mathbf{t}$ and a token sequence $\mathbf{x}$ as its inputs for each sentence. The token sequence is simply the words in the sentence in order. $\mathbf{t}$ can be obtained from any constituency parse for the sentence by first converting that parse into an unlabeled binary parse, then linearizing it (with the usual in-order traversal), then taking each word token as a SHIFT transition and each ')' as a REDUCE transition, as here:

Unlabeled binary parse: ((the cat) (sat down))

$\mathbf{t}$: SHIFT, SHIFT, REDUCE, SHIFT, SHIFT, REDUCE, REDUCE

$\mathbf{x}$: the, cat, sat, down

Handling variable sentence lengths For any sentence model to be trained with batched computation, it is necessary to pad or crop sentences to a fixed length. We fix this length at $N = 25$ words, longer than about 98% of sentences in SNLI. Transition sequences $\mathbf{t}$ are cropped at the left or padded at the left with SHIFTs. Token sequences $\mathbf{x}$ are then cropped or padded with empty tokens at the left to match the number of SHIFTs added or removed from $\mathbf{t}$, and can then be padded with empty tokens at the right to meet the desired length N.

3.6 TreeRNN-equivalence

Without the addition of the tracking LSTM, SPINN (in particular the SPINN-PI-NT variant, for *parsed input, no tracking*) is precisely equivalent to a conventional tree-structured neural network model in the function that it computes, and therefore also has the same learning dynamics. In both, the representation of each sentence consists of the representations of the words combined recursively using a TreeRNN composition function (in our case, the TreeLSTM function). The SPINN, however, is dramatically faster, and supports both integrated parsing and a novel approach to context through the tracking LSTM.

3.7 Inference speed

In this section, we compare the test time speed of our SPINN-PI-NT with an equivalent TreeRNN implemented in the conventional fashion and with a standard RNN sequence model. While the full models evaluated below are implemented and trained using Theano (Bergstra et al., 2010; Bastien et al., 2012), which is reasonably efficient but not perfect for our model, we wish to compare well-optimized implementations of all three models. To do this, we reimplement the feedforward[1] of SPINN-PI-NT and an LSTM RNN baseline in C++/CUDA, and compare that implementation with a CPU-based C++/Eigen TreeRNN implementation from Irsoy and Cardie (2014), which we modified to perform exactly the same computations as SPINN-PI-NT.[2] TreeRNNs like this can

[1] We chose to reimplement and evaluate only the feedforward/inference pass, as inference speed is the relevant performance metric for most practical applications.

[2] The original code for Irsoy & Cardie's model is available at `https://github.com/oir/deep-recursive`. We plan to release our modified code at publication time, alongside the optimized C++/CUDA models and the Theano source code for the full SPINN.

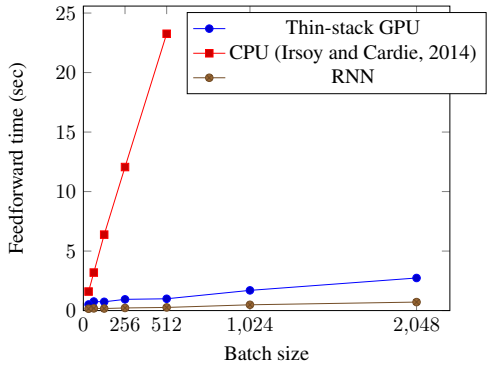


Figure 3: Feedforward speed comparison.

only operate on a single example at a time and are thus poorly suited for GPU computation.

Each model is restricted to run on sentences of 30 tokens or fewer. We fix the model dimension D and the word embedding dimension at 300. We run the CPU performance test on a 2.20-GHz 16-core Intel Xeon E5-2660 processor with hyper-threading enabled. We test our thin-stack implementation and the RNN model on an NVIDIA Titan X GPU.

Figure 3 compares the sentence encoding speed of the three models on random input data. We observe a substantial difference in runtime between the CPU and thin-stack implementations that increases with batch size. With a large but practical batch size of 512, the largest we on which we tested the TreeRNN, our model is about 25x faster than the standard CPU implementation, and about 4x slower than the RNN baseline.

Though this experiment only covers SPINN-PI-NT, the results should be similar for the full SPINN model: most of the computation involved in running SPINN is involved in populating the buffer, applying the composition function, and manipulating the buffer and the stack, with the low-dimensional tracking and parsing components adding only a small additional load.

4 NLI Experiments

We evaluate SPINN on the task of natural language inference (NLI, a.k.a. recognizing textual entailment, or RTE; Dagan et al., 2006). NLI is a sentence pair classification task, in which a model reads two sentences (a premise and a hypothesis), and outputs a judgment of *entailment*, *contradiction*, or *neutral*, reflecting the relationship between the meanings of the two sentences, as in this example from the SNLI corpus, which we use:

Premise: Girl in a red coat, blue head wrap and jeans is making a snow angel.

Hypothesis: A girl outside plays in the snow.

Label: entailment

Although NLI is framed as a simple three-way classification task, it is nonetheless an effective way of evaluating the ability of some model to extract broadly informative representations of sentence meaning. In order for a model to perform reliably well on NLI, it must be able to represent and reason with the core phenomena of natural language semantics, including quantification, coreference, scope, and several types of ambiguity.

SNLI is a corpus of 570k human-labeled pairs of scene descriptions like the one above. We use the standard train–test split and ignore unlabeled examples, which leaves about 549k examples for training, 9,842 for development, and 9,824 for testing. SNLI labels are roughly balanced, with the most frequent label, *entailment*, making up 34.2% of the test set.

4.1 Applying SPINN to SNLI

Creating a sentence-pair classifier To classify an SNLI sentence pair, we run two copies of SPINN with shared parameters: one on the premise sentence and another on the hypothesis sentence. We then use their outputs (the $\vec{h}$ states at the top of each stack at time $t = T$) to construct a feature vector $\vec{x}_{\text{classifier}}$ for the pair. This feature vector consists of the concatenation of these two sentence vectors, their difference, and their elementwise product (following Mou et al., 2015):

$$\vec{x}_{\text{classifier}} = \begin{bmatrix} \vec{h}_{\text{premise}} \\ \vec{h}_{\text{hypothesis}} \\ \vec{h}_{\text{premise}} - \vec{h}_{\text{hypothesis}} \\ \vec{h}_{\text{premise}} \odot \vec{h}_{\text{hypothesis}} \end{bmatrix} \quad (6)$$

Following Bowman et al. (2015a), this feature vector is then passed to a series of 1024D ReLU neural network layers (i.e., an MLP; the number of layers is tuned as a hyperparameter), then passed into a linear transformation, and then finally passed to a softmax layer, which yields a distribution over the three labels.

The objective function Our objective combines a cross-entropy objective $\mathcal{L}_s$ for the SNLI classification task, a cross-entropy objective $\{\mathcal{L}_t^p, \mathcal{L}_t^h\}$ for each parsing decision for each of the sentences at each step t, and an L2 regularization term on the

Model	Params.	Trans. acc. (%)	Train acc. (%)	Test acc. (%)
Previous non-NN results				
Lexicalized classifier (Bowman et al., 2015a)	—	—	99.7	78.2
Previous sentence encoder-based NN results				
100D LSTM encoders (Bowman et al., 2015a)	221k	—	84.8	77.6
1024D pretrained GRU encoders (Vendrov et al., 2015)	15m	—	98.8	81.4
300D Tree-based CNN encoders (Mou et al., 2015)	3.5m	—	83.4	82.1
Our results				
300D LSTM RNN encoders	3.0m	—	83.9	80.6
300D SPINN-PI-NT (*parsed input, no tracking*) encoders	3.4m	—	84.4	80.9
300D SPINN-PI (*parsed input*) encoders	3.7m	—	89.2	**83.2**
300D SPINN (unparsed input) encoders	2.7m	92.4	87.2	82.6

Table 2: Results on SNLI 3-way inference classification. Params. is the approximate number of trained parameters (excluding word embeddings for all models). Trans. acc. is the model's accuracy in predicting parsing transitions at test time. Train and test are SNLI classification accuracy.

trained parameters. The terms are weighted using the tuned hyperparameters α and λ:

$$\mathcal{L}_{\mathrm{m}} = \mathcal{L}_{\mathrm{s}} + \alpha \sum_{t=0}^{T-1} (\mathcal{L}_{\mathrm{t}}^{p} + \mathcal{L}_{\mathrm{t}}^{h}) + \lambda |\theta|_2^2 \quad (7)$$

Initialization, optimization, and tuning We initialize the model parameters using the nonparametric strategy of He et al. (2015), with the exception of the softmax classifier parameters, which we initialize using random uniform samples from $[-0.005, 0.005]$.

We use minibatch SGD with the RMSProp optimizer (Tieleman and Hinton, 2012) and a tuned starting learning rate that decays by a factor of 0.75 every 10k steps. We apply both dropout (Srivastava et al., 2014) and batch normalization (Ioffe and Szegedy, 2015) to the output of the word embedding projection layer and to the feature vectors that serve as the inputs and outputs to the MLP that precedes the final entailment classifier.

We train each model for 250k steps in each run, using a batch size of 32. We track each model's performance on the development set during training and save parameters when this performance reaches a new peak. We use early stopping, evaluating on the test set using the parameters that perform best on the development set.

An appendix discusses hyperparameter tuning.

4.2 Models evaluated

We evaluate four models. The four all use the sentence-pair classifier architecture described in Section 4.1, and differ only in the function computing the sentence encodings. First, a single-layer LSTM RNN (similar to that of Bowman et al., 2015a) serves as a baseline encoder. Next, the minimal SPINN-PI-NT model (equivalent to a TreeLSTM) introduces the SPINN model design. SPINN-PI adds the tracking LSTM to that design. Finally, the full SPINN adds the integrated parser.

We compare our models against several baselines, including the strongest published non-neural network-based result from Bowman et al. (2015a) and previous neural network models built around several types of sentence encoders.

4.3 Results

Table 2 shows our results on SNLI inference classification. For the full SPINN, we also report a measure of agreement between this model's parses and the parses included with SNLI, calculated as classification accuracy over transitions averaged across timesteps.

We find that the bare SPINN-PI-NT model performs little better than the RNN baseline, but that SPINN-PI with the added tracking LSTM performs well. The success of SPINN-PI, which is a hybrid tree-sequence model, suggests that the tree- and sequence-based encoding methods are at least partially complementary. The full SPINN model with its relatively weak internal parser performs slightly less well, but nonetheless robustly exceeds the performance of the RNN baseline.

Both SPINN-PI and the full SPINN significantly outperform all previous sentence-encoding models. Most notably, these models outperform the tree-based CNN of Mou et al. (2015), which also uses tree-structured composition for local feature extraction, but uses simpler pooling techniques to build sentence features in the interest of efficiency. Our results show that a model that uses

tree-structured composition fully (SPINN) outperforms one which uses it only partially (tree-based CNN), which in turn outperforms one which does not use it at all (RNN).

The full SPINN performed moderately well at reproducing the Stanford Parser's parses of the SNLI data at a transition-by-transition level, with 92.4% accuracy at test time. However, its transition prediction errors were fairly evenly distributed across sentences, and most sentences were assigned partially invalid transition sequences that either left a few words out of the final representation or incorporated a few padding tokens into the final representation.

4.4 Discussion

The use of tree structure improves the performance of sentence-encoding models for SNLI. We suspect that this improvement is largely attributable to the more efficient learning of accurate generalizations overall, and not to any particular few phenomena. However, some patterns are identifiable in the results. In particular, it seems that tree-structured models are better able to focus on the key actors and events named in a sentence (possibly by learning an approximation of the linguistic notion of headedness), and that this allows them to better focus on the central actors and events described in a sentence. For example, this pair was classified successfully by all three SPINN variants, but not by the RNN baseline (key words emphasized):

Premise: A *woman* in red blouse is *standing* with small blond *child* in front of a small folding chalkboard.

Hypothesis: a *woman stands* with her *child*

Label: neutral

The tree-sequence hybrid models seem to be especially good at reasoning over pairs of sentences with very different structures, for which it is helpful to use strict compositionality with the tree-structured component to get the meanings of the sentence parts, but then to also accumulate a broad sentence summary that abstracts away from the precise structures of each sentences. For example, this pair is classified correctly by both hybrid models, but not by the RNN or the SPINN-PI-NT:

Premise: Nurses in a medical setting conversing over a plastic cup.

Hypothesis: The nurses are discussing a patient.

Label: neutral

We suspect that the hybrid nature of the full SPINN model is also responsible for its ability to perform better than an RNN baseline even when its internal parser is relatively ineffective at producing correct full-sentence parses. We suspect that it is acting somewhat like the tree-based CNN, only with access to larger trees: using tree structure to build up local phrase meanings, and then using the tracking LSTM, at least in part, to combine those meanings.

5 Conclusions and future work

We introduce a model architecture (SPINN-PI-NT) that is equivalent to a TreeLSTM, but an order of magnitude faster at test time. We expand that architecture into a tree-sequence hybrid model (SPINN-PI), and show that this yields significant gains on the SNLI entailment task. Finally, we show that it is possible to exploit the strengths of this model without the need for an external parser by integrating a fast parser into the model (as in the full SPINN), and that the lack of external parse information yields little loss in accuracy.

Because this paper aims to introduce a general purpose model for sentence encoding, we do not pursue the use of soft attention (Bahdanau et al., 2015; Rocktäschel et al., 2015), despite its demonstrated effectiveness on the SNLI task.[3] However, we expect that it should be possible to productively combine our model with soft attention to reach state-of-the-art performance.

Our tracking LSTM uses only simple, quick-to-compute features drawn from the head of the buffer and the head of the stack. It is plausible that giving the tracking LSTM access to more information from the buffer and stack at each step would allow it to better represent the context at each tree node, yielding both better parsing and better sentence encoding. One promising way to pursue this goal would be to encode the full contents of the stack and buffer at each time step following the method used by Dyer et al. (2015).

For a more ambitious goal, we expect that it should be possible to implement a variant of SPINN on top of a modified stack data structure with differentiable PUSH and POP operations (as in Grefenstette et al., 2015; Joulin and Mikolov, 2015). This would make it possible for the model to learn to parse using guidance from the semantic representation objective, essentially allowing it

[3] Attention based models like Rocktäschel et al. (2015) and the unpublished Cheng et al. (2016) have shown accuracies as high as 89.0% on SNLI, but are more narrowly engineered to suit the task, and do not yield sentence encodings.

to learn to produce parses that are, in aggregate, better suited to supporting semantic interpretation than those supplied in the training data.

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A Hyperparameters

We use random search to tune the hyperparameters of the model, setting the ranges for search for each hyperparameter heuristically (and validating the reasonableness of the ranges on the development set), and then launching eight copies of each experiment each with newly sampled hyperparameters from those ranges. Table 3 (on the following page) shows the hyperparameters used in the best run of each model.

Param.	Range	Strategy	RNN	SPINN-PI-NT	SPINN-PI	SPINN
Initial LR	2e-4–2e-2	LOG	5e-3	3e-4	7e-3	2e-3
L2 regularization λ	8e-7–3e-5	LOG	4e-6	3e-6	2e-5	3e-5
Transition cost α	0.5–4.0	LIN	—	—	—	3.9
Embedding transformation dropout keep rate	80–95%	LIN	—	83%	92%	86%
Classifier MLP dropout keep rate	80–95%	LIN	94%	94%	93%	94%
Tracking LSTM size D_{tracking}	24–128	LOG	—	—	61	79
Classifier MLP layers	1–3	LIN	2	2	2	1

Table 3: Hyperparameter ranges and values. *Range* shows the hyperparameter ranges explored during random search. *Strategy* indicates whether sampling from the range was uniform, or log–uniform.