Deep Biaffine Attention for Neural Dependency Parsing

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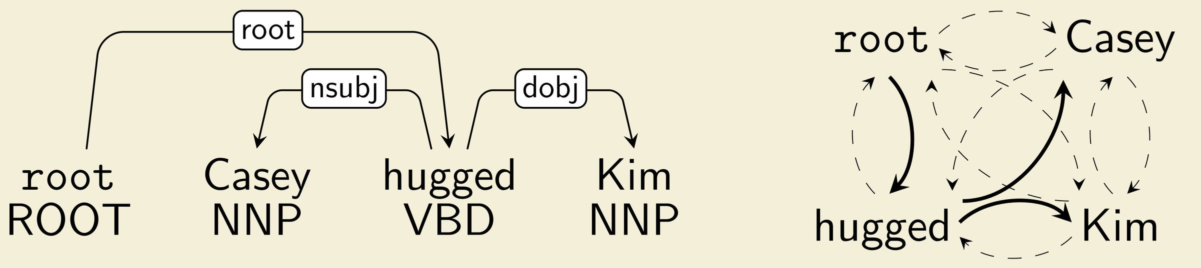
Goals

- Much research has been devoted to developing neural dependency parsers with complex, task-specific architecture
- Typical approach: use specialized neural networks to predict discrete actions in a dedicated, transition-based parsing algorithm
  SyntaxNet AKA Parsey McParseface (Andor et al., 2016): Feedforward network with beam search and CRF loss
  Ablated RNN Grammar (Kuncoro et al., 2016): Stack-LSTM with bidirectional LSTM for phrase composition (SOTA)
- **Can we get competitive (or even superior) parsing results with a simple architecture using general-purpose components?**

Dependency Parsing

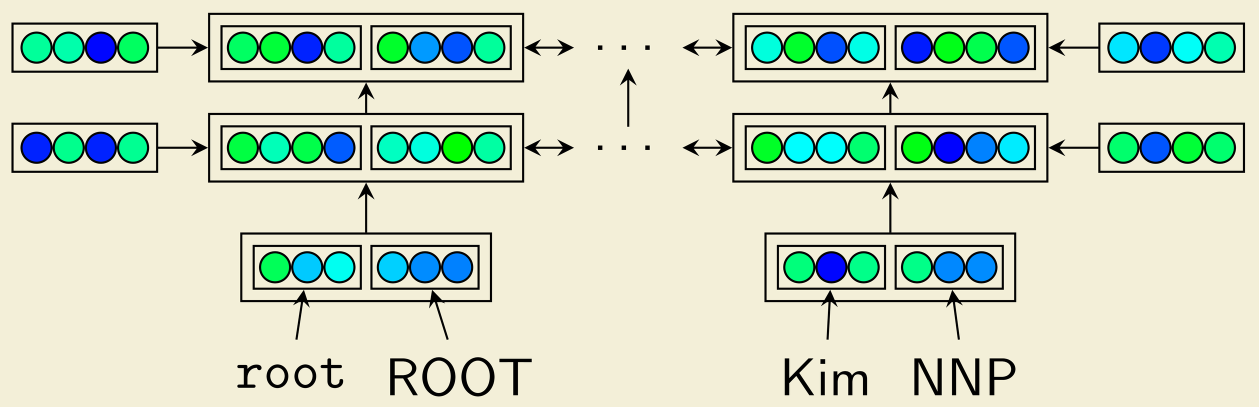
- Automatically annotate sentences, focusing on the functional role each phrase plays
  Head: Edge source, more contentful role (predicate → arguments)
  Dependent: Edge target
  Label: Edge type (*N*ominal *SUBJ*ect, *A*djectival *CL*ause)



- Particularly useful for NLU tasks, such as semantic parsing or knowledge base population
- Graph-based approach to parsing: assign weights to each possible edge, construct a maximum spanning tree

LSTM

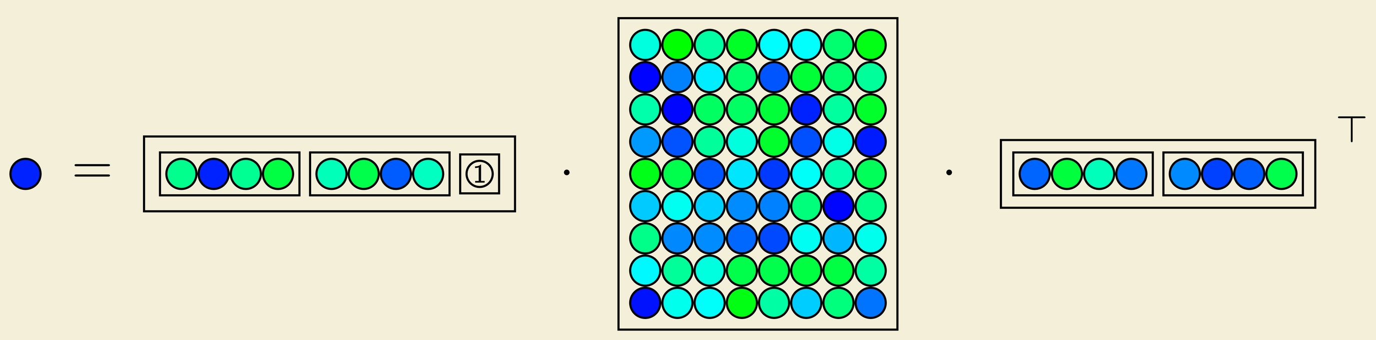
Step one: BiLSTM over the sequence of word and part of speech tag embeddings, take all topmost LSTM states R ($=\text{stack}_{i=1}^{n}(\mathbf{r}_i)$)



Variable-class classification (= attention)

- We want to predict heads (classes) given dependents (inputs), but the number of possible heads changes from sentence to sentence
- Thus, we want to predict $P(y_i^{(edge)} = j|\mathbf{r}_i; \mathbf{r}_j)$
- softmax$(RU^{(1)}\mathbf{r}_i + R\mathbf{u}^{(2)})$ achieves this naturally

$$P(j|\mathbf{r}_i; \mathbf{r}_j) \propto \exp\left(\mathbf{r}_i^\top U^{(1)}\mathbf{r}_j\right) \exp\left(\mathbf{u}^{\top(2)}\mathbf{r}_j\right)$$



- After deciding on an edge from j to i, we want to predict the label
- This time, we want to predict $P(y^{(label)} = l|\mathbf{r}_i, \mathbf{r}_{y_i^{(edge)}})$
- We can use softmax$(\mathbf{r}_{y_i}^\top \mathbf{U}^{(1)}\mathbf{r}_i + U^{(2)}(\mathbf{r}_{y_i} \oplus \mathbf{r}_i) + \mathbf{b})$ to model this

$$P(l|\mathbf{r}_i, \mathbf{r}_{y_i^{(edge)}}) \propto \exp\left(\mathbf{r}_i^\top U_l^{(1)}\mathbf{r}_{y_i}\right) \exp\left(\mathbf{r}_i^\top \mathbf{u}_l^{(2)}\right) \exp\left(\mathbf{r}_{y_i}^\top \mathbf{u}_l^{(3)}\right) \exp\left(b_l\right)$$

- Closely related to linear models with interactions

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scores ~ head.vector * dep.vector
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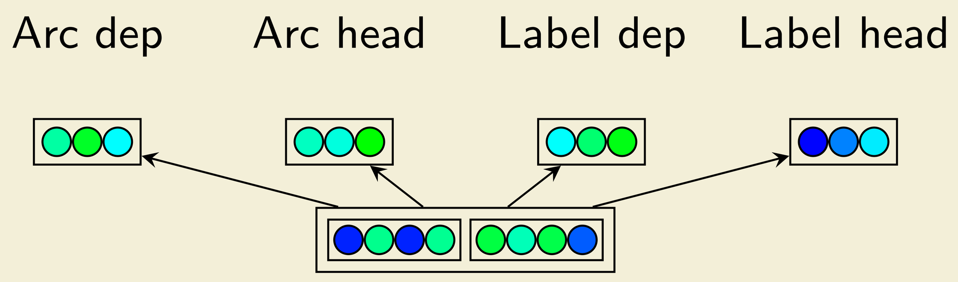
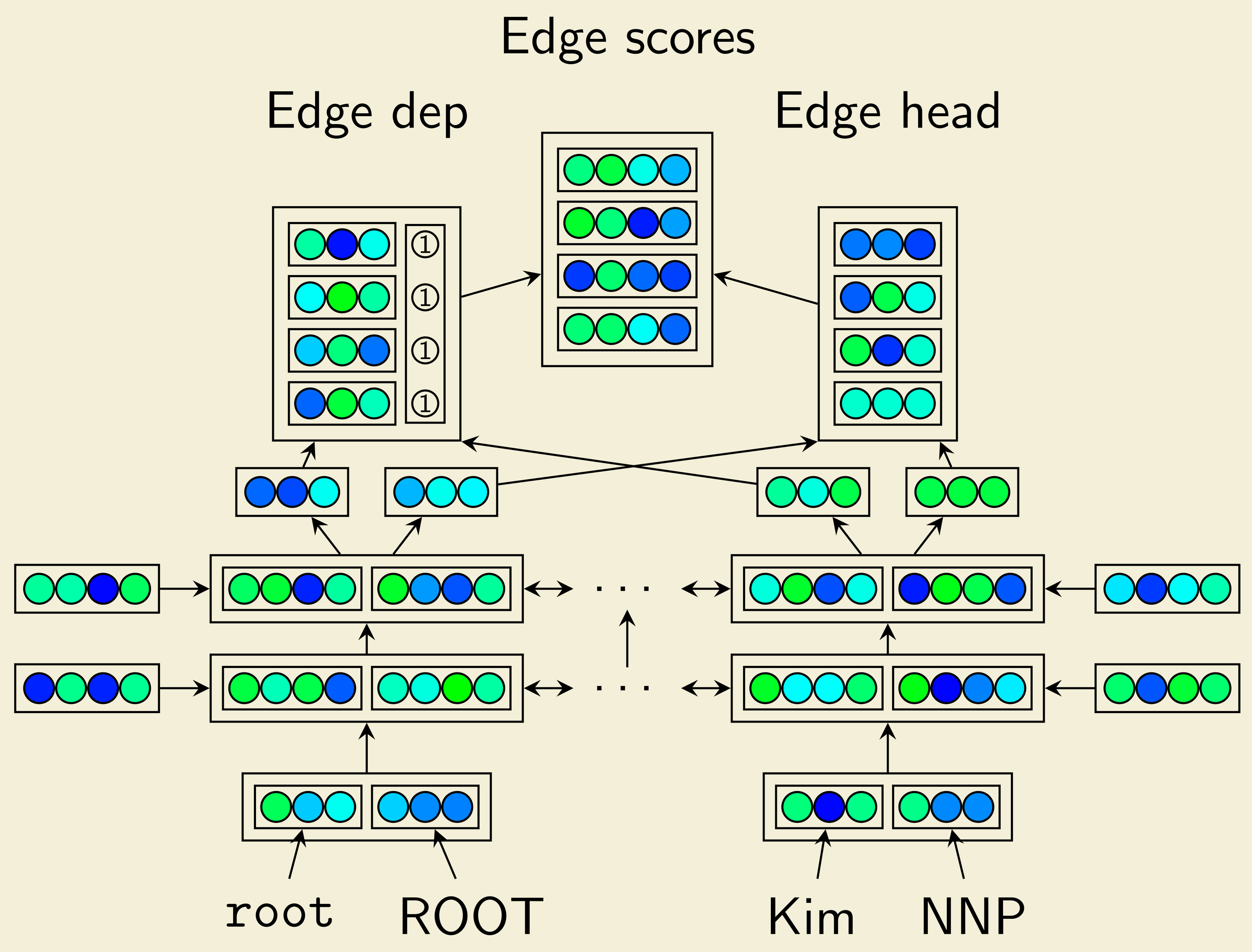
Practical modifications

- Everything is so big!
- We can get more control over the tradeoffs between speed, overfitting, and underfitting by shrinking $\mathbf{r}_i$ with smaller MLPs before the biaffine output layers (*deep biaffine* model as opposed to *shallow biaffine*)
- Result: four representations for each word
- Naturally reflects the intuition that the relationships we want to capture are asymmetric



Final model (edge scorer)



Hyperparameters

Param	Value	Param	Value
Embedding size	100	Embedding dropout	33%
LSTM size	400	LSTM dropout	33%
Edge MLP size	500	Edge MLP dropout	33%
Label MLP size	100	Label MLP dropout	33%
LSTM depth	3	MLP depth	1
α	$2e^{-3}$	β_1,β_2	.9
Annealing	$.75^{\frac{t}{5000}}$	t_{max}	50,000

- Relatively large network (other models use ∼ 100 LSTM dims)
- Highly regularized with dropout
- Reducing *Adam*'s β_2 from .999 to .9 significantly improved performance ($p < .05$)

Related work

- Transition-based
  Nivre et al. (2006): Feature-based
  Chen and Manning (2014): First successful neural parser
  Andor et al. (2016): Extend with beam search / CRF loss
  Kuncoro et al. (2016): Extend with LSTMs (SOTA)
- Graph-based
  McDonald and Pereira (2006): Feature-based
  Kiperwasser and Goldberg (2016): First neural graph-based parser
  Cheng et al. (2016): Keep track of previous decisions
  Hashimoto et al. (2016): Jointly learn tagging & chunking

PTB Results

Type	Model	SD 3.3.0 UAS	SD 3.3.0 LAS	CTB UAS	CTB LAS
Transition	Ballesteros et al. (2016)	93.6	91.4	87.7	86.2
	Andor et al. (2016)	94.6	92.8	–	–
	Kuncoro et al. (2016)	**95.8**	**94.6**	–	–
Graph	Kiperwasser and Goldberg (2016)	93.9	91.9	87.6	86.1
	Cheng et al. (2016)	94.1	91.5	88.1	85.7
	Hashimoto et al. (2016)	94.7	92.9	–	–
	Deep biaffine	95.7	94.1	**89.3**	**88.2**

CoNLL 09 Results

Model	Catalan UAS	Catalan LAS	Chinese UAS	Chinese LAS	Czech UAS	Czech LAS
Andor et al.	92.7	89.8	84.7	80.9	88.9	84.6
Deep biaffine	**94.7**	**92.0**	**88.9**	**85.4**	**92.1**	**87.4**

Model	English UAS	English LAS	German UAS	German LAS	Spanish UAS	Spanish LAS
Andor et al.	93.2	91.2	90.9	89.2	92.6	90.0
Deep biaffine	**95.2**	**93.2**	**93.5**	**91.4**	**94.3**	**91.7**

Affect of classifier type (SD 3.5.0)

Model	Classifier UAS	Classifier LAS	Classifier Sents/sec
Deep biaffine	**95.8**	**94.2**	**410.9**
Shallow biaffine	95.7	94.0*	299.0
Shallow b. (50% MLP dropout)	95.7	94.1*	300.1
Shallow b. (300d LSTM)	95.6*	93.9*	373.2
Traditional attention	95.5*	93.9*	367.4

(Statistical significances are marked with an asterisk)

Conclusion

- Our simple, straightforward parser uses only neural components, effectively no task-specific architecture
- **Substantially outperforms most more complex neural transition-based parsers**
- **Substantially outperforms all other neural graph-based parsers**
- The biaffine approach to attention is theoretically justified, here beats the more traditional approach
- Adding final MLP layers to the LSTM helps to maximize speed and performance, captures head-dependent asymmetries
- This work provides a fast, simple, high-performing baseline against which to test more complex architectures

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