Neural Constituency Parsing

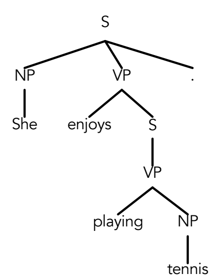
Berkeley N L P

Dan Klein
CS 288

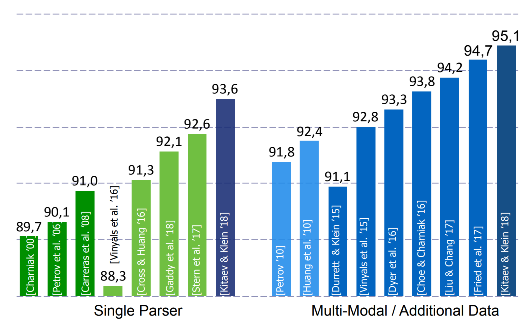
Syntactic Parsing

She enjoys playing tennis.

Syntactic Parsing

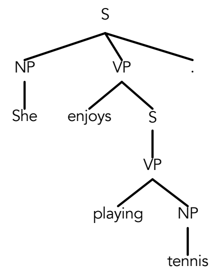


Historical Trends



[Slide from Slav Petrov]

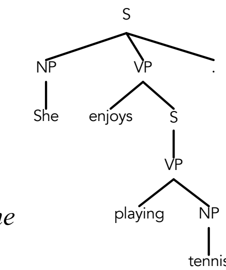
Output Correlations



6

Grammars

S → NP VP



VP[*enjoys*] : S[*playing*]

NP^S → *she*

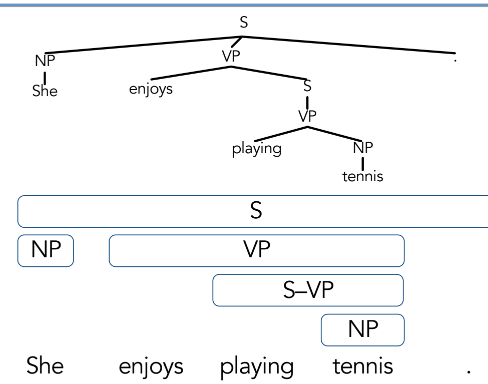
7

Input-Output Correlations

She enjoys playing tennis.

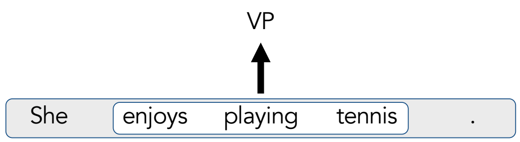
8

Span-Based Parsing



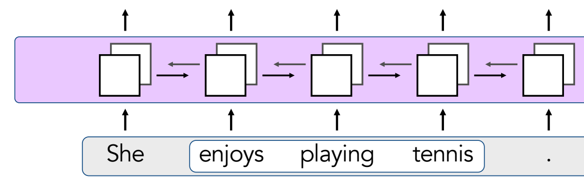
9

Parsing as Span Classification



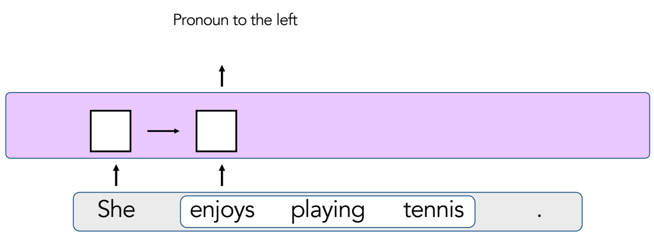
10

Routing with LSTMs



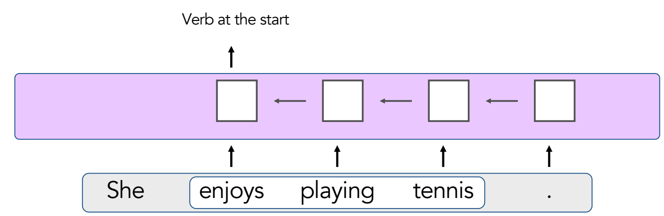
11

Routing with LSTMs



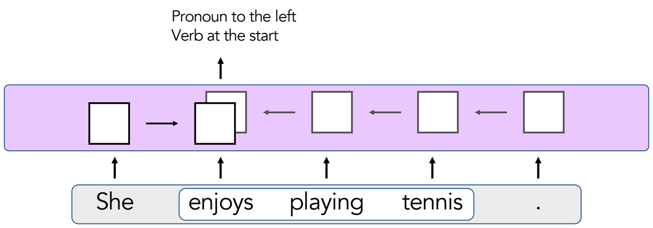
12

Routing with LSTMs

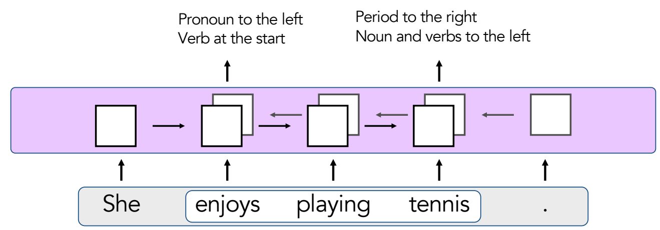


13

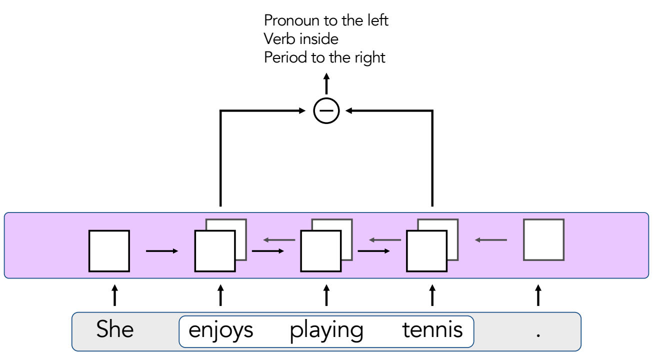
Routing with LSTMs



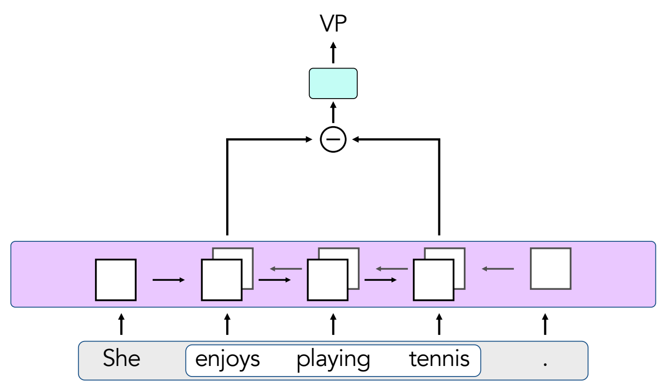
Routing with LSTMs



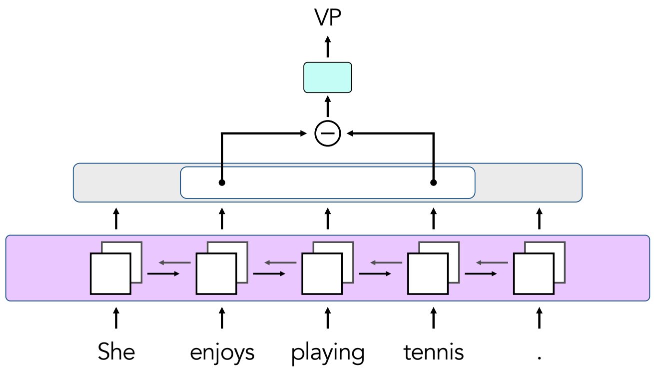
Span Classification



Span Classification

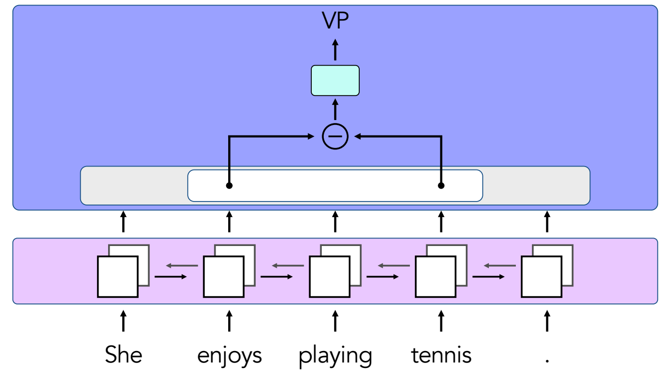


Span Classification



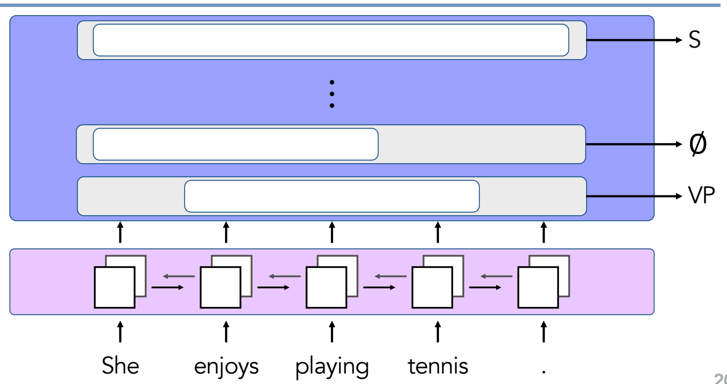
18

Span Classification



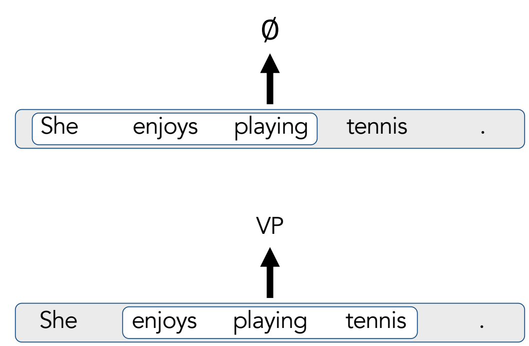
19

Span Classification



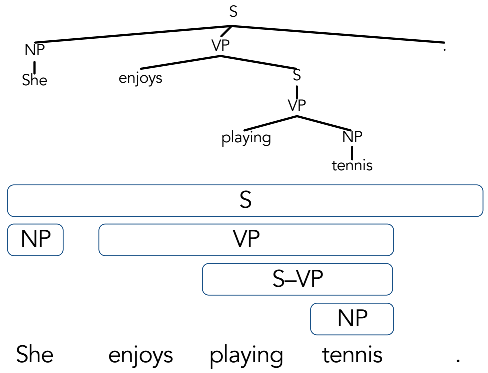
20

Non-Constituents



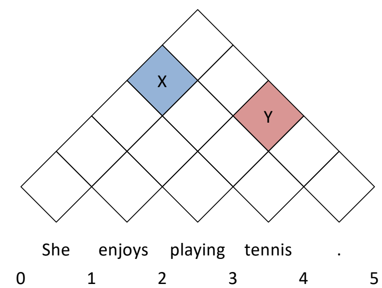
21

… But Will We Get a Tree Out?



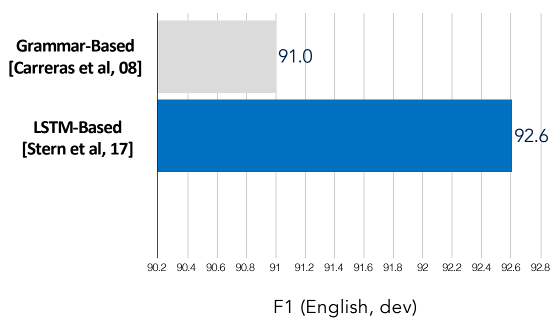
22

Reconciliation



23

Does It Work?



24

What's Going on in There?

Neural parsers no longer have much of the model structure provided to classical parsers.

How do they perform so well without it?

25

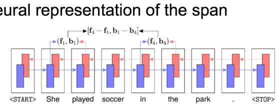
What's Going on in There?

Why don't we need a grammar?

Adjacent tree labels are redundant with LSTM features

If we can predict surrounding tree labels from our LSTM representation of the input, then this information doesn't need to be provided explicitly by grammar production rules

We find that for **92.3%** of spans, the label of the span's parent can predicted from the neural representation of the span



What's Going on in There?

Do we need tree constraints?

Not for F1

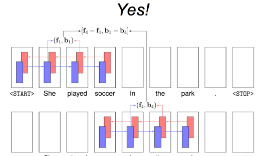
Many neural parsers no longer model output correlations with grammar rules, but still use output correlations from tree constraints

Predicting span brackets independently gives **nearly identical performance** on PTB development set F1 and produces valid trees for **94.5%** of sentences

What's Going on in There?

Is distant context important?

Yes!



Almost a full point of F1 is lost by truncating context 5 words away from span endpoints and half a point with 10 words

What's Going on in There?

What word representations do we need?

A character LSTM is sufficient

Word Only	91.44
Word and Tag	92.09
Character LSTM Only	**92.24**
Character LSTM and Word	92.22
Character LSTM, Word, and Tag	92.24

What's Going on in There?

What about lexicon features?

The character LSTM captures the same information

Heavily engineered lexicons used to be critical to good performance, but neural models typically don't use them

Word features from the Berkeley Parser (Petrov and Klein 2007) can be predicted with over **99.7%** accuracy from the character LSTM representation

30

What's Going on in There?

Do LSTMs introduce useful inductive bias compared to feedforward networks?

Yes!

We compare a truncated LSTM with feedforward architectures that are given the same inputs

The LSTM outperformed the best feedforward by **6.5 F1**

31

Routing with Transformers

Query:
verb

She enjoys playing tennis .

32

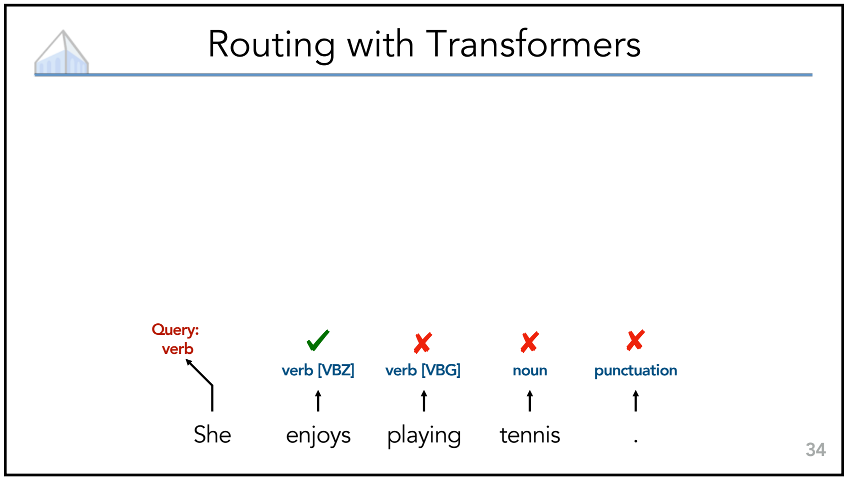
Routing with Transformers

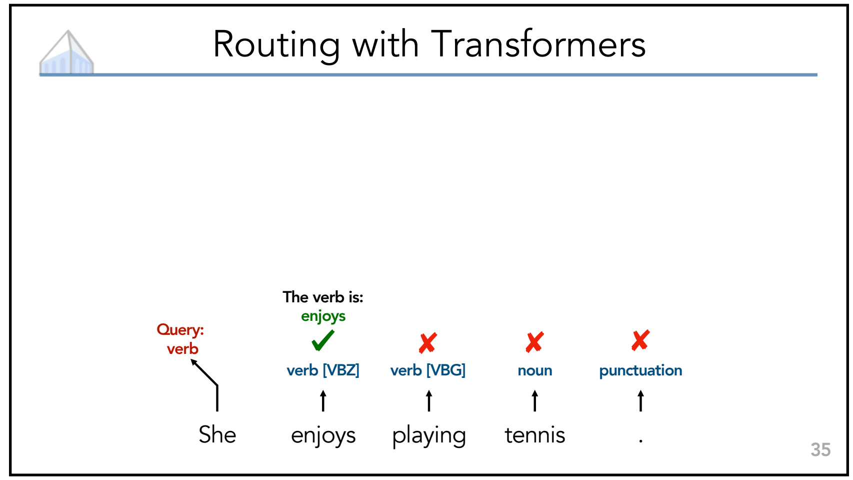
Query:
verb

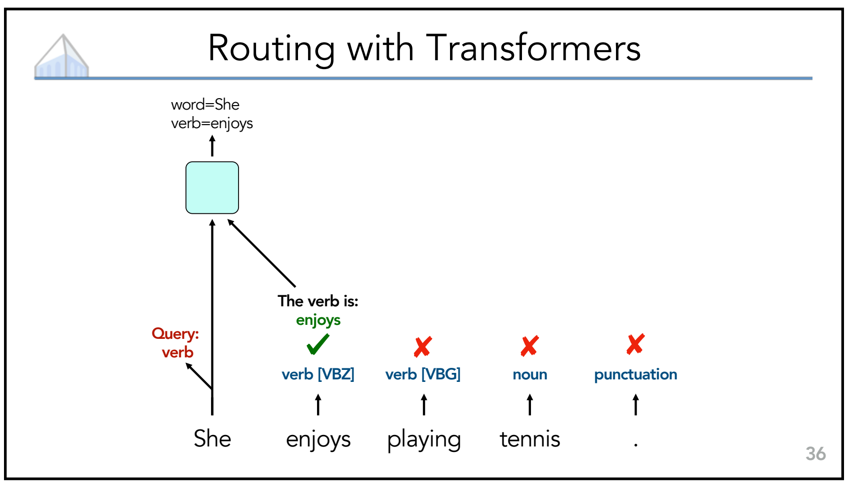
verb [VBZ] verb [VBG] noun punctuation

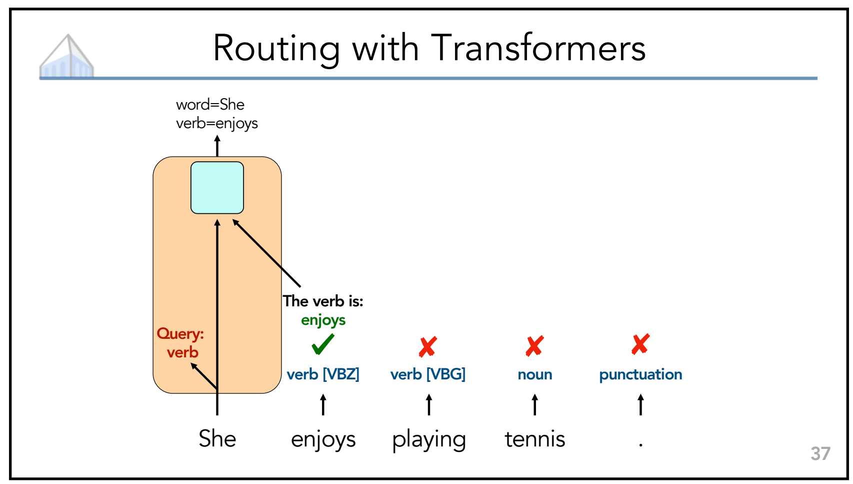
She enjoys playing tennis .

33

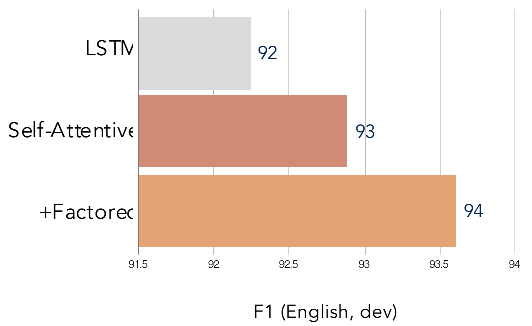

Routing with Transformers
Query:
verb
verb [VBZ]
verb [VBG]
noun
punctuation
She
enjoys
playing
tennis
.
34


Routing with Transformers
The verb is:
enjoys
Query:
verb
verb [VBZ]
verb [VBG]
noun
punctuation
She
enjoys
playing
tennis
.
35

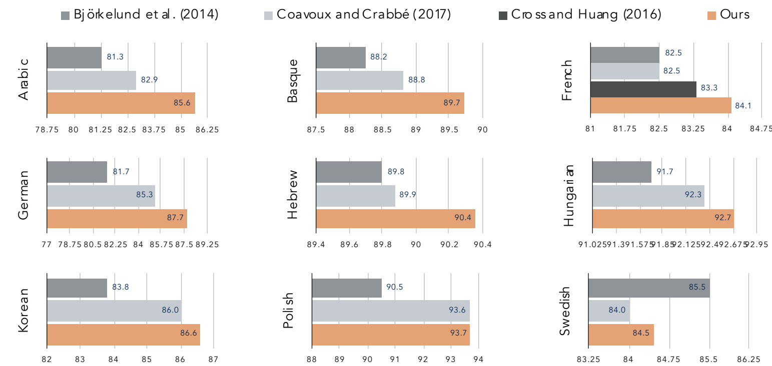

Routing with Transformers
word=She
verb=enjoys
The verb is:
enjoys
Query:
verb
verb [VBZ]
verb [VBG]
noun
punctuation
She
enjoys
playing
tennis
.
36


Routing with Transformers
word=She
verb=enjoys
The verb is:
enjoys
Query:
verb
verb [VBZ]
verb [VBG]
noun
punctuation
She
enjoys
playing
tennis
.
37

What Helps?



Results: Multilingual

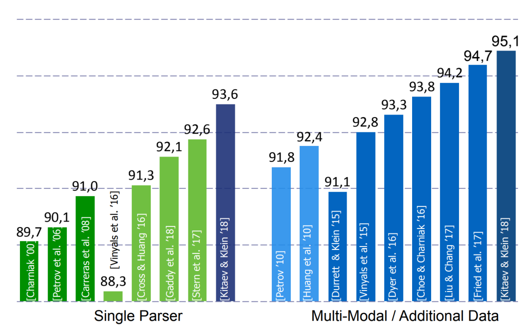


Data Hunger

Problem: Input has more variation than output

Need to handle:
- Rare words not seen during training
- Word forms in morphologically rich languages

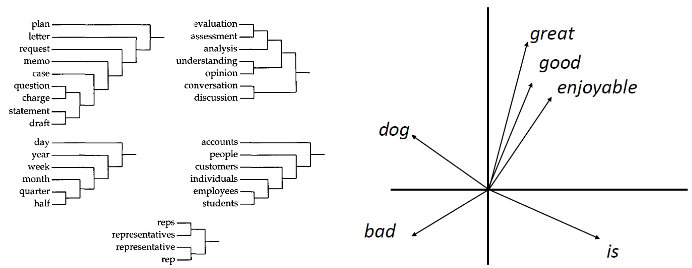
Historical Trends



[Slide from Slav Petrov]

Knowledge Modularity

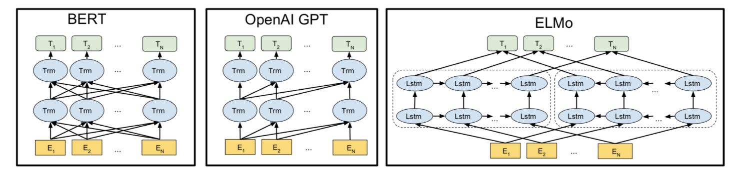
- Knowledge modularity: Learn domain-general knowledge from one data source and use it solve specific problems elsewhere



Context Embeddings and Pretraining

Key Idea: Embed contexts, not words. Use these embeddings for other tasks.

Example: BERT (Devlin et al., 2019) -- bidirectional Transformer trained on masked language modeling and next-sentence prediction



Recent Explosion of Pretraining Work

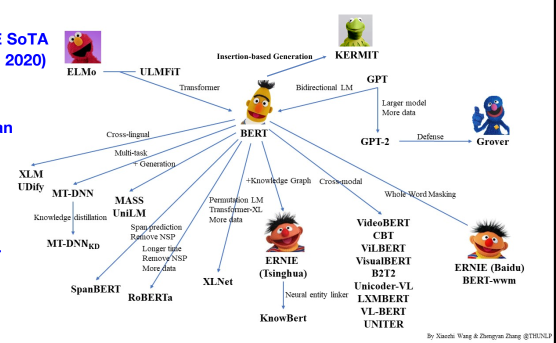
Model	URL	Score
ALBERT (Ensemble)		89.4
ALICE v2 large ensemble (Alibaba DAMO NLP)	↗	89.0
FreeLB-RoBERTa (ensemble)	↗	88.8
RoBERTa	↗	88.5
XLNet-Large (ensemble)	↗	88.4
MT-DNN-ensemble	↗	87.6
GLUE Human Baselines	↗	87.1
Snorkel MeTaL	↗	83.2
XLM (English only)	↗	83.1
SemBERT	↗	82.9
SpanBERT (single-task training)	↗	82.8
BERT + BAM	↗	82.3
Span-Extractive BERT on STILTs	↗	82.3
BERT on STILTs	↗	82.0
RGLM-Base (Huawei Noah's Ark Lab)		81.3
BERT: 24-layers, 16-heads, 1024-hidden	↗	80.5
BERT + Single-task Adapters	↗	80.2
Macaron Net-base	↗	79.7
SesameBERT-Base		78.6
MobileBERT		78.5
StackingBERT-Base	↗	78.4
TinyBERT	↗	75.4
BiLSTM+ELMo+Attn	↗	70.0

GLUE SoTA (ICLR 2020)

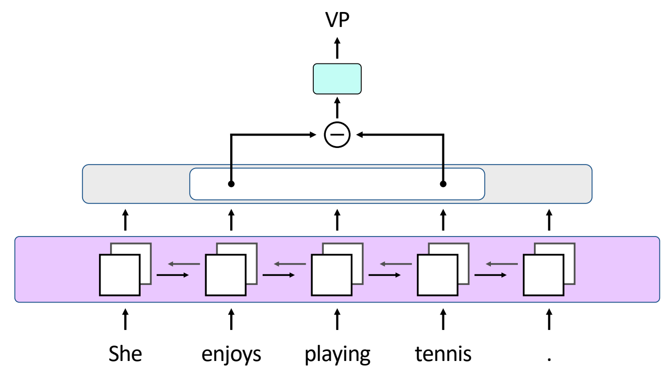
Human

BERT

GLUE Baseline (ICLR 2019)

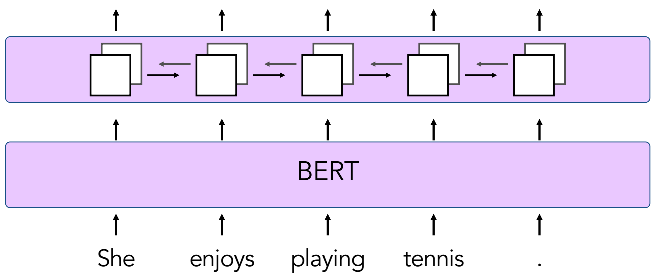


Parsing as Span Classification

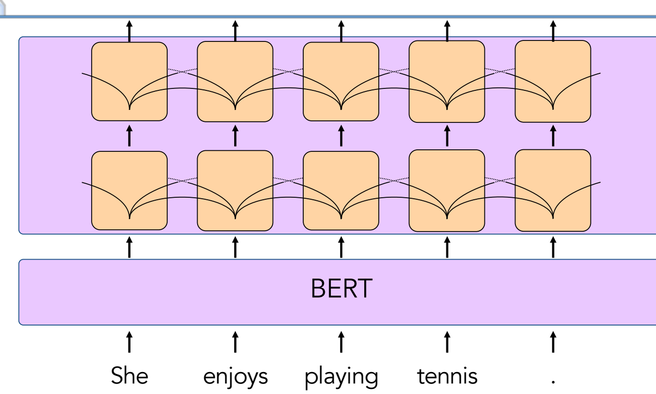


47

Pretraining



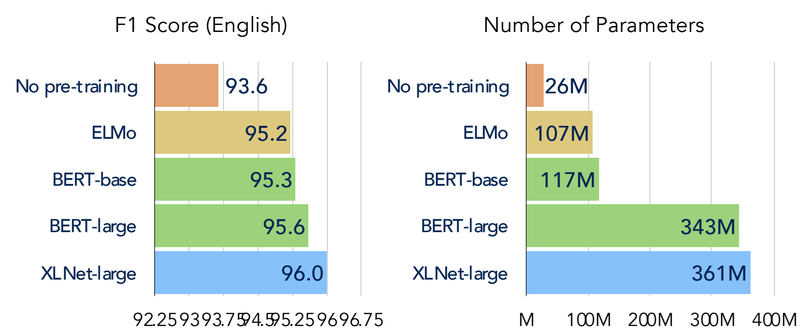
Architecture



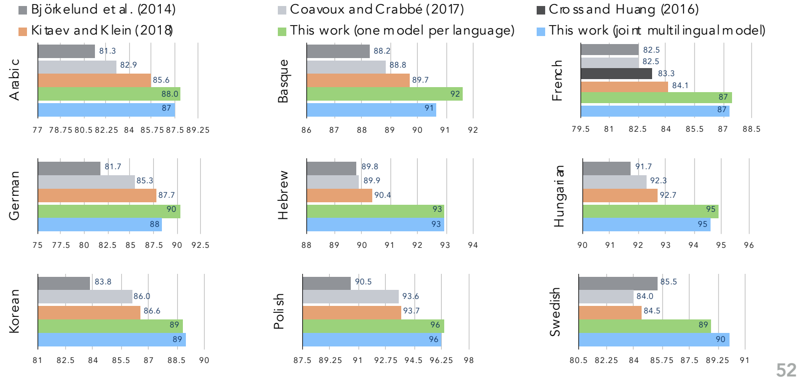
Encoder Architectures

	LSTM	Self-Attention
No pre-training	92.08 F1 [Gaddy+ 2018]	93.55 F1 [Kitaev & Klein 2018]
Pre-training	95.13 F1 (with ELMo) [Kitaev & Klein 2018]	95.60 F1 (with BERT)

Encoder Architectures



Results: Multilingual



52

Does Structure Help?

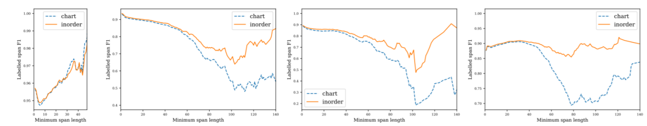


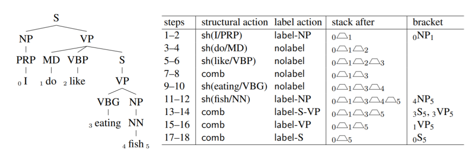
Figure 1: Labelled bracketing F1 versus minimum span length for the English corpora. F1 scores for the In-Order parser with BERT (orange) and the Chart parser with BERT (cyan) start to diverge for longer spans.

Out of Domain Parsing

	Berkeley		BLLIP		In-Order		Chart	
	F1	Δ Err.	F1	Δ Err.	F1	Δ Err.	F1	Δ Err.
WSJ Test	90.06	+0.0%	91.48	+0.0%	91.47	+0.0%	93.27	+0.0%
Brown All	84.64	+54.5%	85.89	+65.6%	85.60	+68.9%	88.04	+77.7%
Genia All	79.11	+110.2%	79.63	+139.1%	80.31	+130.9%	82.68	+157.4%
EWT All	77.38	+127.6%	79.91	+135.8%	79.07	+145.4%	82.22	+164.2%

Neural parsers improve out-of-domain numbers, but not more than in-domain numbers

Other Neural Constituency Parsers



- Back to at least Henderson 1998!
- Recent directions:
  - Shift-Reduce, eg Cross and Huang 2016
  - SR/Generative, eg Dyer et al 2016 (RNNG)
  - In-Order Generative, eg Liu and Zhang 2017

Thank You!

Berkeley NLP

nlp.cs.berkeley.edu