Geometry-Aware Supertagging

with Heterogeneous Dynamic Convolutions

Konstantinos Kogkalidis[1,2] & Michael Moortgat[2]

1 Aalto University

2 Utrecht Institute of Linguistics OTS, Utrecht University

LSD, Sept 12, Göteborg

A composition calculus for vector-based semantic modelling with a localization for Dutch

NWO 360-89-070, 2017-2023

Utrecht University

Categorial Grammars 101

what are they?

A **family** of syntactic formalisms; each instance consists of:

- a **lexicon**
  a map assigning *categories* to words: (quasi-)logical formulas (or ADTs)
- a small set of **inference rules**
  ways to combine and reduce *expressions* based on their categories

Categorial Grammars 101

Many variations: TLG, ACG, CCG, …(*CG)

common points

- **Lexicalized**
  words come packed with their combinatorics
- **Formal**
  proximal to logics, type theory & functional programming
- **Transparent**
  neat syntax-semantics interface

Categorial Grammars 101

Many variations: TLG, ACG, CCG, ...(*CG)

divergences

different background logics $\implies$

- different linguistic aspects captured
  e.g. surface order, non-local syntax, dependency relations
- different parsing complexity
- different computational semantics
- ...

Categorial Grammars 101

but! the **parsing pipeline** is always the same

given an input sentence:

1. Assign a category to each word
2. Build the syntactic derivation bottom-up
3. ???
4. Profit

Supertagging: the task

For some input sentence $w_1, \ldots w_n$ find the category assignment $c_1, \ldots c_n$ s.t.

$$argmax_{(c_1, \ldots c_n)} \; p(c_1, \ldots c_n \mid w_1, \ldots w_n)^*$$

Supertagging: the task

For some input sentence $w_1, \ldots w_n$ find the category assignment $c_1, \ldots c_n$ s.t.

$$argmax_{(c_1, \ldots c_n)}\ p(c_1, \ldots c_n \mid w_1, \ldots w_n)^*$$

**In practice*:
build the best statistical model possible given current technology and available data

(pre-)history

$p(t_1, \ldots t_n \mid w_1, \ldots w_n) \approx$

- $\prod_i^n (t_i \mid w_i)$
  co-occurrence-based statistical models (90s)
- $\prod_i^n (t_i \mid w_{i-\kappa} \ldots w_{i+\kappa})$
  window-based n-gram models (00s), FFNs (early 10s)
- $\prod_i^n (t_i \mid w_1, \ldots w_n)$
  sequence encoders (mid 10s)
- $\prod_i^n (t_i \mid t_1, \ldots t_{i-1}, w_1, \ldots w_n)$
  seq2seq (late 10s)

$\square^{det}(n \multimap np)$	n	$*$	np	$\diamond^{obj} np \multimap \diamond^{su} np \multimap s_{\mathrm{sub}}$
the	role	that	types	play

$* := \diamond^{body}(\diamond^{obj1} np \multimap s_{\mathrm{sub}}) \multimap \square^{mod}(np \multimap np)$

(pre-)history

$p(t_1, \ldots t_n \mid w_1, \ldots w_n) \approx$

- $\prod_i^n (t_i \mid w_i)$
  co-occurrence-based statistical models (90s)
- $\prod_i^n (t_i \mid w_{i-\kappa} \ldots w_{i+\kappa})$
  window-based n-gram models (00s), FFNs (early 10s)
- $\prod_i^n (t_i \mid w_1, \ldots w_n)$
  sequence encoders (mid 10s)
- $\prod_i^n (t_i \mid t_1, \ldots t_{i-1}, w_1, \ldots w_n)$
  seq2seq (late 10s)

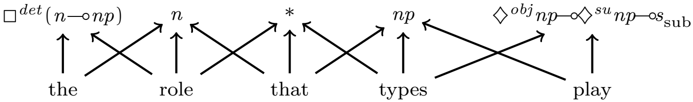
$\Box^{det}(n \multimap np)$	n	$*$	np	$\Diamond^{obj} np \multimap \Diamond^{su} np \multimap s_{\text{sub}}$
$\uparrow$	$\uparrow$	$\uparrow$	$\uparrow$	$\uparrow$
the	role	that	types	play

$* := \Diamond^{body}(\Diamond^{obj1} np \multimap s_{\text{sub}}) \multimap \Box^{mod}(np \multimap np)$

(pre-)history

$p(t_1, \ldots t_n \mid w_1, \ldots w_n) \approx$

- $\prod_i^n (t_i \mid w_i)$
  co-occurrence-based statistical models (90s)
- $\prod_i^n (t_i \mid w_{i-\kappa} \ldots w_{i+\kappa})$
  window-based n-gram models (00s), FFNs (early 10s)
- $\prod_i^n (t_i \mid w_1, \ldots w_n)$
  sequence encoders (mid 10s)
- $\prod_i^n (t_i \mid t_1, \ldots t_{i-1}, w_1, \ldots w_n)$
  seq2seq (late 10s)



$* := \diamond^{body}(\diamond^{obj1} np \multimap s_{\text{sub}}) \multimap \square^{mod}(np \multimap np)$

(pre-)history

$p(t_1, \dots t_n \mid w_1, \dots w_n) \approx$

- $\prod_i^n (t_i \mid w_i)$
  co-occurrence-based statistical models (90s)
- $\prod_i^n (t_i \mid w_{i-\kappa} \dots w_{i+\kappa})$
  window-based n-gram models (00s), FFNs (early 10s)
- $\prod_i^n (t_i \mid w_1, \dots w_n)$
  sequence encoders (mid 10s)
- $\prod_i^n (t_i \mid t_1, \dots t_{i-1}, w_1, \dots w_n)$
  seq2seq (late 10s)

$\Box^{det}(n \multimap np)$	n	$*$	np	$\Diamond^{obj} np \multimap \Diamond^{su} np \multimap s_{\text{sub}}$
the	role	that	types	play

the $\longleftrightarrow$ role $\longleftrightarrow$ that $\longleftrightarrow$ types $\longleftrightarrow$ play

$* := \Diamond^{body}(\Diamond^{obj1} np \multimap s_{\text{sub}}) \multimap \Box^{mod}(np \multimap np)$

(pre-)history

$p(t_1, \ldots t_n \mid w_1, \ldots w_n) \approx$

- $\prod_i^n (t_i \mid w_i)$
  co-occurrence-based statistical models (90s)
- $\prod_i^n (t_i \mid w_{i-\kappa} \ldots w_{i+\kappa})$
  window-based n-gram models (00s), FFNs (early 10s)
- $\prod_i^n (t_i \mid w_1, \ldots w_n)$
  sequence encoders (mid 10s)
- $\prod_i^n (t_i \mid t_1, \ldots t_{i-1}, w_1, \ldots w_n)$
  seq2seq (late 10s)

$$
\begin{array}{ccccccccc}
\Box^{det}(n \multimap np) & & n & & * & & np & & \Diamond^{obj} np \multimap \Diamond^{su} np \multimap s_{\text{sub}} \\
\uparrow & & \uparrow & & \uparrow & & \uparrow & & \uparrow \\
\text{the} & \longleftrightarrow & \text{role} & \longleftrightarrow & \text{that} & \longleftrightarrow & \text{types} & \longleftrightarrow & \text{play}
\end{array}
$$

$* := \Diamond^{body}(\Diamond^{obj1} np \multimap s_{\text{sub}}) \multimap \Box^{mod}(np \multimap np)$

(pre-)history

$$p(t_1, \ldots t_n \mid w_1, \ldots w_n) \approx$$

- $\prod_i^n (t_i \mid w_i)$
  co-occurrence-based statistical models (90s)
- $\prod_i^n (t_i \mid w_{i-\kappa} \ldots w_{i+\kappa})$
  window-based n-gram models (00s), FFNs (early 10s)
- $\prod_i^n (t_i \mid w_1, \ldots w_n)$
  sequence encoders (mid 10s)
- $\prod_i^n (t_i \mid t_1, \ldots t_{i-1}, w_1, \ldots w_n)$
  seq2seq (late 10s)

$$\begin{array}{ccccccccc}
\square^{det}(n \multimap np) & & n & & * & & np & & \diamond^{obj} np \multimap \diamond^{su} np \multimap s_{\text{sub}} \\
\uparrow & & & & & & & & \\
\text{the} & \longleftrightarrow & \text{role} & \longleftrightarrow & \text{that} & \longleftrightarrow & \text{types} & \longleftrightarrow & \text{play}
\end{array}$$

$$* := \diamond^{body}(\diamond^{obj1} np \multimap s_{\text{sub}}) \multimap \square^{mod}(np \multimap np)$$

(pre-)history

$p(t_1, \ldots t_n \mid w_1, \ldots w_n) \approx$

- $\prod_i^n (t_i \mid w_i)$
  co-occurrence-based statistical models (90s)
- $\prod_i^n (t_i \mid w_{i-\kappa} \ldots w_{i+\kappa})$
  window-based n-gram models (00s), FFNs (early 10s)
- $\prod_i^n (t_i \mid w_1, \ldots w_n)$
  sequence encoders (mid 10s)
- $\prod_i^n (t_i \mid t_1, \ldots t_{i-1}, w_1, \ldots w_n)$
  seq2seq (late 10s)

$$
\begin{tikzcd}
\square^{det}(n \multimap np) \arrow[r] & n & * & np & \diamond^{obj} np \multimap \diamond^{su} np \multimap s_{\text{sub}} \\
\text{the} \arrow[u] \arrow[r, leftrightarrow] & \text{role} \arrow[u] \arrow[r, leftrightarrow] & \text{that} \arrow[r, leftrightarrow] & \text{types} \arrow[r, leftrightarrow] & \text{play}
\end{tikzcd}
$$

$* := \diamond^{body}(\diamond^{obj1} np \multimap s_{\text{sub}}) \multimap \square^{mod}(np \multimap np)$

(pre-)history

$$p(t_1, \dots t_n \mid w_1, \dots w_n) \approx$$

- $\prod_i^n (t_i \mid w_i)$
  co-occurrence-based statistical models (90s)
- $\prod_i^n (t_i \mid w_{i-\kappa} \dots w_{i+\kappa})$
  window-based n-gram models (00s), FFNs (early 10s)
- $\prod_i^n (t_i \mid w_1, \dots w_n)$
  sequence encoders (mid 10s)
- $\prod_i^n (t_i \mid t_1, \dots t_{i-1}, w_1, \dots w_n)$
  seq2seq (late 10s)

$$\begin{tikzcd}
\Box^{det}(n \multimap np) \arrow[r] & n \arrow[r] & * & np & \Diamond^{obj} np \multimap \Diamond^{su} np \multimap s_{\mathrm{sub}} \\
\text{the} \arrow[u] \arrow[r, leftrightarrow] & \text{role} \arrow[u] \arrow[r, leftrightarrow] & \text{that} \arrow[u] \arrow[r, leftrightarrow] & \text{types} \arrow[r, leftrightarrow] & \text{play}
\end{tikzcd}$$

$$* := \Diamond^{body}(\Diamond^{obj1} np \multimap s_{\mathrm{sub}}) \multimap \Box^{mod}(np \multimap np)$$

(pre-)history

$p(t_1, \ldots t_n \mid w_1, \ldots w_n) \approx$

- $\prod_i^n (t_i \mid w_i)$
  co-occurrence-based statistical models (90s)
- $\prod_i^n (t_i \mid w_{i-\kappa} \ldots w_{i+\kappa})$
  window-based n-gram models (00s), FFNs (early 10s)
- $\prod_i^n (t_i \mid w_1, \ldots w_n)$
  sequence encoders (mid 10s)
- $\prod_i^n (t_i \mid t_1, \ldots t_{i-1}, w_1, \ldots w_n)$
  seq2seq (late 10s)

$$
\begin{tikzcd}
\square^{det}(n \multimap np) \arrow[r] & n \arrow[r] & * \arrow[r] & np & \Diamond^{obj} np \multimap \Diamond^{su} np \multimap s_{\mathrm{sub}} \\
\text{the} \arrow[u] \arrow[r, leftrightarrow] & \text{role} \arrow[u] \arrow[r, leftrightarrow] & \text{that} \arrow[u] \arrow[r, leftrightarrow] & \text{types} \arrow[u] \arrow[r, leftrightarrow] & \text{play}
\end{tikzcd}
$$

$* := \Diamond^{body}(\Diamond^{obj1} np \multimap s_{\mathrm{sub}}) \multimap \square^{mod}(np \multimap np)$

(pre-)history

$p(t_1, \dots t_n \mid w_1, \dots w_n) \approx$

- $\prod_i^n (t_i \mid w_i)$
  co-occurrence-based statistical models (90s)
- $\prod_i^n (t_i \mid w_{i-\kappa} \dots w_{i+\kappa})$
  window-based n-gram models (00s), FFNs (early 10s)
- $\prod_i^n (t_i \mid w_1, \dots w_n)$
  sequence encoders (mid 10s)
- $\prod_i^n (t_i \mid t_1, \dots t_{i-1}, w_1, \dots w_n)$
  seq2seq (late 10s)

$$\begin{tikzcd}
\square^{det}(n \multimap np) \arrow[r] & n \arrow[r] & * \arrow[r] & np \arrow[r] & \Diamond^{obj} np \multimap \Diamond^{su} np \multimap s_{\text{sub}} \\
\text{the} \arrow[u] \arrow[r, leftrightarrow] & \text{role} \arrow[u] \arrow[r, leftrightarrow] & \text{that} \arrow[u] \arrow[r, leftrightarrow] & \text{types} \arrow[u] \arrow[r, leftrightarrow] & \text{play} \arrow[u]
\end{tikzcd}$$

$* := \Diamond^{body}(\Diamond^{obj1} np \multimap s_{\text{sub}}) \multimap \square^{mod}(np \multimap np)$

(pre-)history

$p(t_1, \ldots t_n \mid w_1, \ldots w_n) \approx$

- $\prod_i^n (t_i \mid w_i)$
  co-occurrence-based statistical models (90s)
- $\prod_i^n (t_i \mid w_{i-\kappa} \ldots w_{i+\kappa})$
  window-based n-gram models (00s), FFNs (early 10s)
- $\prod_i^n (t_i \mid w_1, \ldots w_n)$
  sequence encoders (mid 10s)
- $\prod_i^n (t_i \mid t_1, \ldots t_{i-1}, w_1, \ldots w_n)$
  seq2seq (late 10s)

what have we done?

- more arrows (=more context)
- auto-regression (price: temporal delay)
- what about the co-domain?

Intermezzo: the curse(?) of sparsity

The majority of unique categories in common datasets are rare

the "*fix*": ignore rare categories

- small penalty in accuracy
- less so for coverage..
- meta: sparse grammars = bad

the **fix**: decompose categories & build them up during decoding

- ↯ unlimited ~~power~~ generalization
- meta: sparse grammars = ok

Intermezzo: the curse(?) of sparsity

The majority of unique categories in common datasets are rare

the "*fix*": ignore rare categories

- small penalty in accuracy
- less so for coverage..
- meta: sparse grammars = bad

the **fix**: decompose categories & build them up during decoding

- ↯ unlimited ~~power~~ generalization
- meta: sparse grammars = ok

Intermezzo: the curse(?) of sparsity

The majority of unique categories in common datasets are rare

the "*fix*": ignore rare categories

- small penalty in accuracy
- less so for coverage..
- meta: sparse grammars = bad

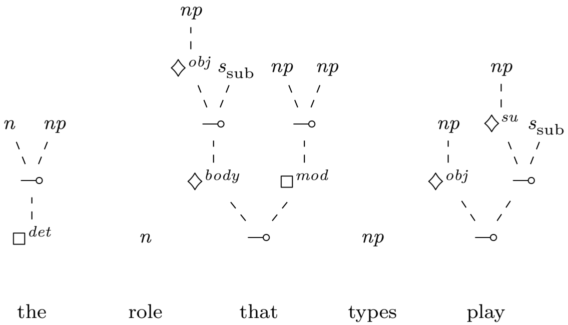
the **fix**: decompose categories & build them up during decoding

- ↯ unlimited ~~power~~ generalization
- meta: sparse grammars = ok

Modern Times

$$p(\sigma_1, \ldots \sigma_m \mid w_1, \ldots w_n) \approx$$

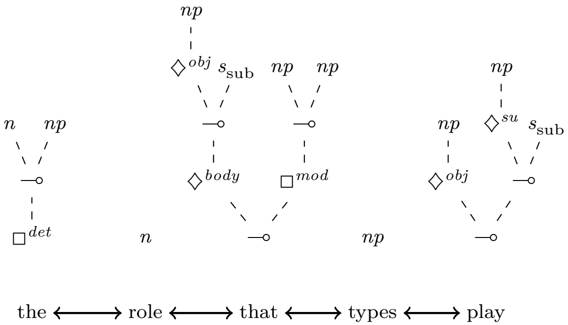
- $\prod_i^m(\sigma_i \mid \sigma_1, \ldots \sigma_{i-1}, w_1, \ldots w_n)$
  sequential constructive (w/ Moortgat & Deoskar, 2019)
- $\prod_i^m(\sigma_i \mid \mathrm{anc}(\sigma_i), w_1, \ldots w_n)$
  tree-recursive (Prange et. al 2020)



Modern Times

$p(\sigma_1, \ldots \sigma_m \mid w_1, \ldots w_n) \approx$

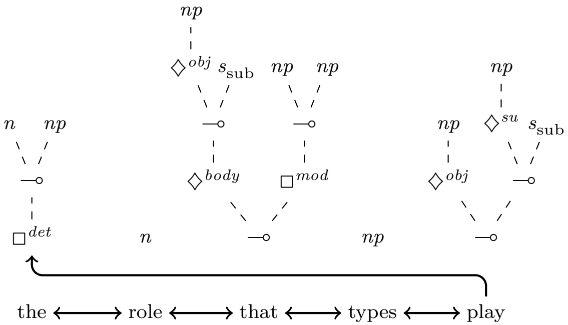
- $\prod_i^m (\sigma_i \mid \sigma_1, \ldots \sigma_{i-1}, w_1, \ldots w_n)$
  sequential constructive (w/ Moortgat & Deoskar, 2019)
- $\prod_i^m (\sigma_i \mid \mathrm{anc}(\sigma_i), w_1, \ldots w_n)$
  tree-recursive (Prange et. al 2020)



Modern Times

$p(\sigma_1, \ldots \sigma_m \mid w_1, \ldots w_n) \approx$

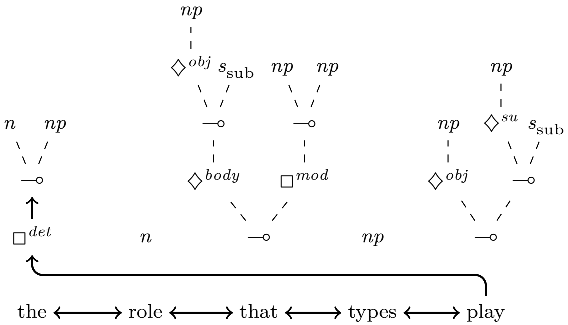
- $\prod_i^m (\sigma_i \mid \sigma_1, \ldots \sigma_{i-1}, w_1, \ldots w_n)$
  sequential constructive (w/ Moortgat & Deoskar, 2019)
- $\prod_i^m (\sigma_i \mid \mathrm{anc}(\sigma_i), w_1, \ldots w_n)$
  tree-recursive (Prange et. al 2020)



Modern Times

$p(\sigma_1, \ldots \sigma_m \mid w_1, \ldots w_n) \approx$

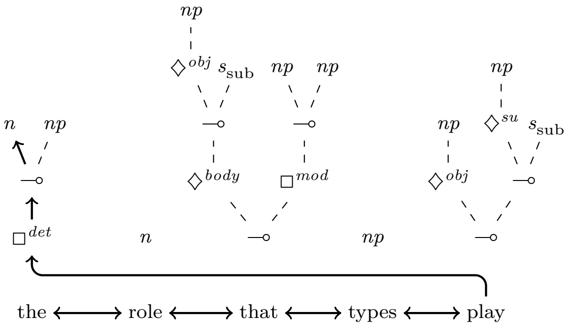
- $\prod_i^m (\sigma_i \mid \sigma_1, \ldots \sigma_{i-1}, w_1, \ldots w_n)$
  sequential constructive (w/ Moortgat & Deoskar, 2019)
- $\prod_i^m (\sigma_i \mid \mathrm{anc}(\sigma_i), w_1, \ldots w_n)$
  tree-recursive (Prange et. al 2020)



Modern Times

$p(\sigma_1, \dots \sigma_m \mid w_1, \dots w_n) \approx$

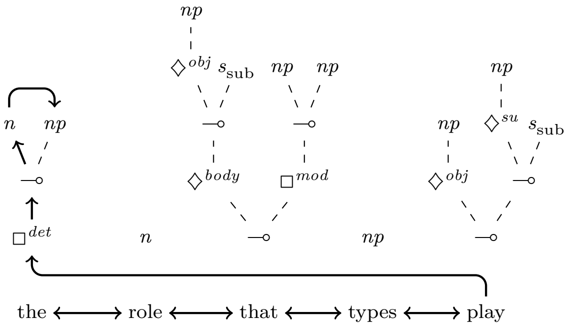
- $\prod_i^m(\sigma_i \mid \sigma_1, \dots \sigma_{i-1}, w_1, \dots w_n)$
  sequential constructive (w/ Moortgat & Deoskar, 2019)
- $\prod_i^m(\sigma_i \mid \text{anc}(\sigma_i), w_1, \dots w_n)$
  tree-recursive (Prange et. al 2020)



Modern Times

$p(\sigma_1, \dots \sigma_m \mid w_1, \dots w_n) \approx$

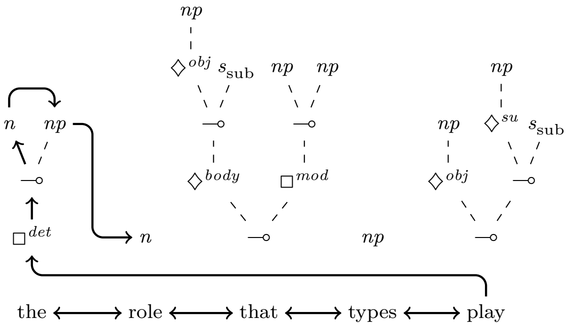
- $\prod_i^m (\sigma_i \mid \sigma_1, \dots \sigma_{i-1}, w_1, \dots w_n)$
  sequential constructive (w/ Moortgat & Deoskar, 2019)
- $\prod_i^m (\sigma_i \mid \text{anc}(\sigma_i), w_1, \dots w_n)$
  tree-recursive (Prange et. al 2020)



Modern Times

$p(\sigma_1, \ldots \sigma_m \mid w_1, \ldots w_n) \approx$

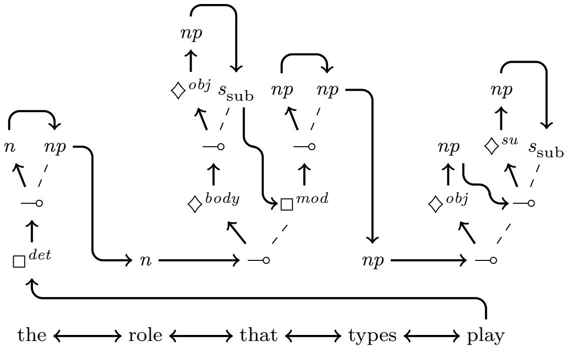
- $\prod_i^m (\sigma_i \mid \sigma_1, \ldots \sigma_{i-1}, w_1, \ldots w_n)$
  sequential constructive (w/ Moortgat & Deoskar, 2019)
- $\prod_i^m (\sigma_i \mid \mathrm{anc}(\sigma_i), w_1, \ldots w_n)$
  tree-recursive (Prange et. al 2020)



Modern Times

$p(\sigma_1, \dots \sigma_m \mid w_1, \dots w_n) \approx$

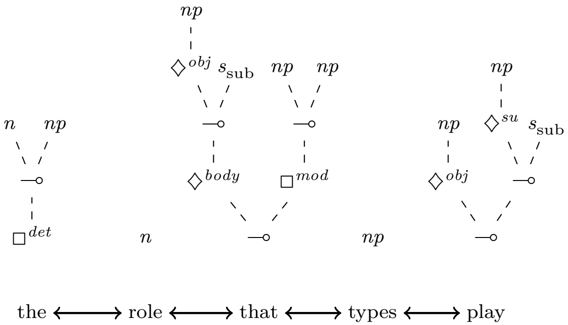
- $\prod_i^m (\sigma_i \mid \sigma_1, \dots \sigma_{i-1}, w_1, \dots w_n)$
  sequential constructive (w/ Moortgat & Deoskar, 2019)
- $\prod_i^m (\sigma_i \mid \mathrm{anc}(\sigma_i), w_1, \dots w_n)$
  tree-recursive (Prange et. al 2020)



Modern Times

$p(\sigma_1, \ldots \sigma_m \mid w_1, \ldots w_n) \approx$

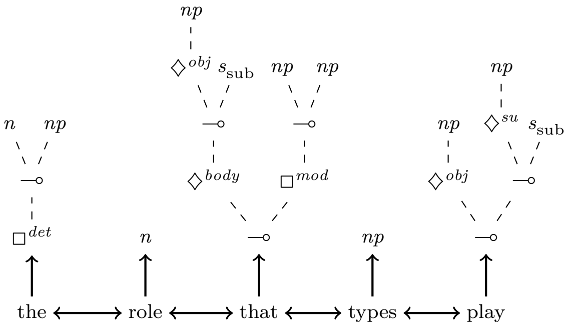
- $\prod_i^m (\sigma_i \mid \sigma_1, \ldots \sigma_{i-1}, w_1, \ldots w_n)$
  sequential constructive (w/ Moortgat & Deoskar, 2019)
- $\prod_i^m (\sigma_i \mid \mathrm{anc}(\sigma_i), w_1, \ldots w_n)$
  tree-recursive (Prange et. al 2020)



Modern Times

$p(\sigma_1, \ldots \sigma_m \mid w_1, \ldots w_n) \approx$

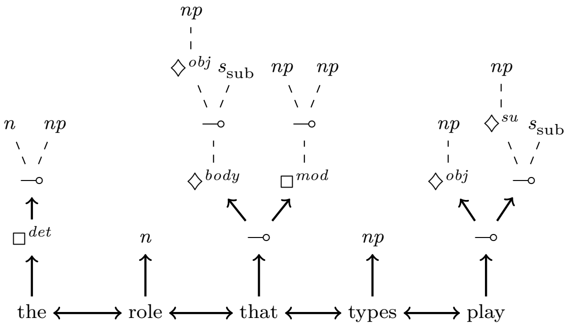
- $\prod_i^m (\sigma_i \mid \sigma_1, \ldots \sigma_{i-1}, w_1, \ldots w_n)$
  sequential constructive (w/ Moortgat & Deoskar, 2019)
- $\prod_i^m (\sigma_i \mid \mathrm{anc}(\sigma_i), w_1, \ldots w_n)$
  tree-recursive (Prange et. al 2020)



Modern Times

$p(\sigma_1, \dots \sigma_m \mid w_1, \dots w_n) \approx$

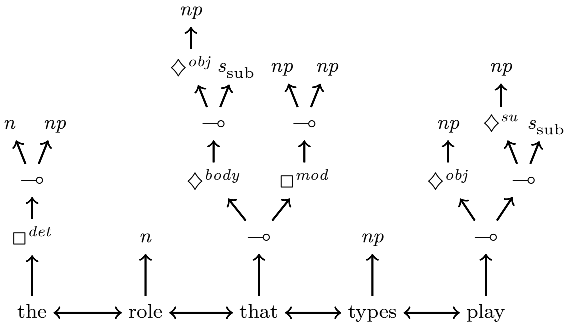
- $\prod_i^m(\sigma_i \mid \sigma_1, \dots \sigma_{i-1}, w_1, \dots w_n)$
  sequential constructive (w/ Moortgat & Deoskar, 2019)
- $\prod_i^m(\sigma_i \mid \mathrm{anc}(\sigma_i), w_1, \dots w_n)$
  tree-recursive (Prange et. al 2020)



Modern Times

$p(\sigma_1, \ldots \sigma_m \mid w_1, \ldots w_n) \approx$

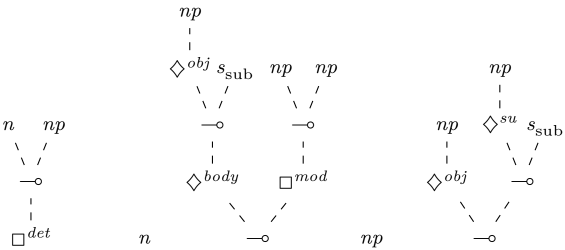
- $\prod_i^m (\sigma_i \mid \sigma_1, \ldots \sigma_{i-1}, w_1, \ldots w_n)$
  sequential constructive (w/ Moortgat & Deoskar, 2019)
- $\prod_i^m (\sigma_i \mid \mathrm{anc}(\sigma_i), w_1, \ldots w_n)$
  tree-recursive (Prange et. al 2020)



Post-modernity

neither sequence nor tree but sequence of trees

$p(\sigma_1, \ldots \sigma_m \mid w_1, \ldots w_n) \approx \prod_i^m (\sigma_i \mid \sigma_j : \mathrm{depth}(\sigma_j) < \mathrm{depth}(\sigma_i), w_1, \ldots w_n)$



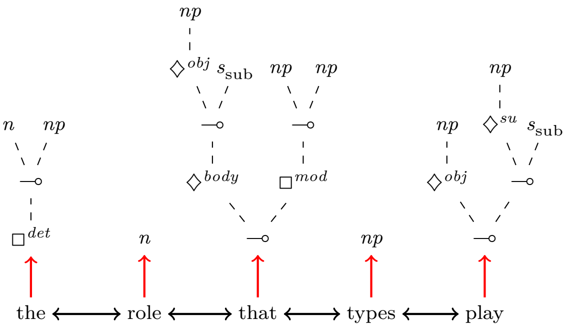
the $\longleftrightarrow$ role $\longleftrightarrow$ that $\longleftrightarrow$ types $\longleftrightarrow$ play

(encode)

Post-modernity

neither sequence nor tree but sequence of trees

$p(\sigma_1, \ldots \sigma_m \mid w_1, \ldots w_n) \approx \prod_i^m (\sigma_i \mid \sigma_j : \mathrm{depth}(\sigma_j) < \mathrm{depth}(\sigma_i), w_1, \ldots w_n)$

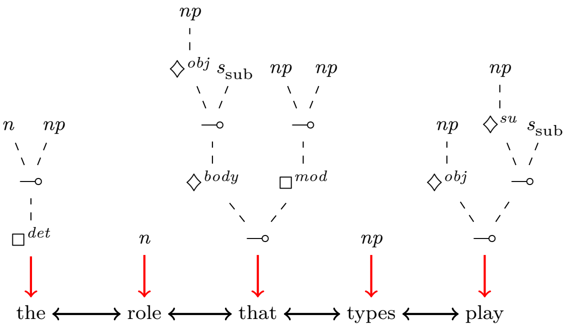


(predict)

Post-modernity

neither sequence nor tree but sequence of trees

$p(\sigma_1, \ldots \sigma_m \mid w_1, \ldots w_n) \approx \prod_i^m (\sigma_i \mid \sigma_j : \mathrm{depth}(\sigma_j) < \mathrm{depth}(\sigma_i), w_1, \ldots w_n)$

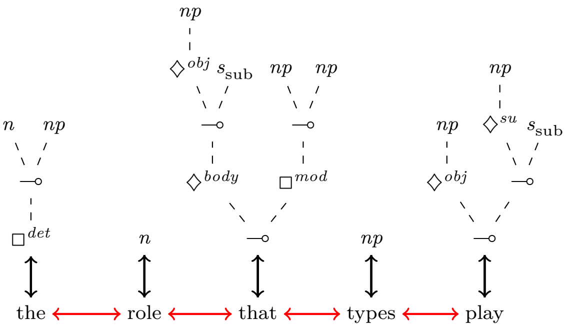


(feedback)

Post-modernity

neither sequence nor tree but sequence of trees

$p(\sigma_1, \ldots \sigma_m \mid w_1, \ldots w_n) \approx \prod_i^m (\sigma_i \mid \sigma_j : \mathrm{depth}(\sigma_j) < \mathrm{depth}(\sigma_i), w_1, \ldots w_n)$

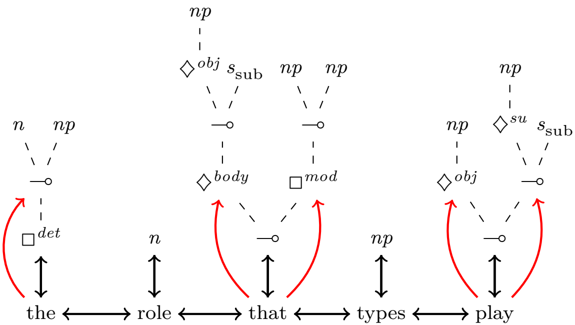


(contextualize)

Post-modernity

neither sequence nor tree but sequence of trees

$p(\sigma_1, \ldots \sigma_m \mid w_1, \ldots w_n) \approx \prod_i^m (\sigma_i \mid \sigma_j : \mathrm{depth}(\sigma_j) < \mathrm{depth}(\sigma_i), w_1, \ldots w_n)$

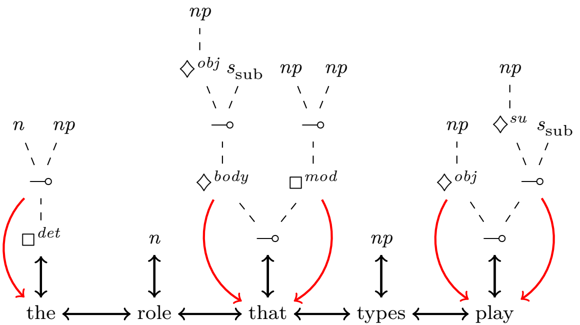


(predict)

Post-modernity

neither sequence nor tree but sequence of trees

$p(\sigma_1, \ldots \sigma_m \mid w_1, \ldots w_n) \approx \prod_i^m(\sigma_i \mid \sigma_j : \mathrm{depth}(\sigma_j) < \mathrm{depth}(\sigma_i), w_1, \ldots w_n)$

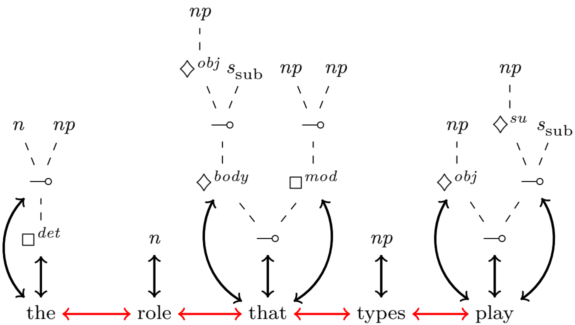


(feedback)

Post-modernity

neither sequence nor tree but sequence of trees

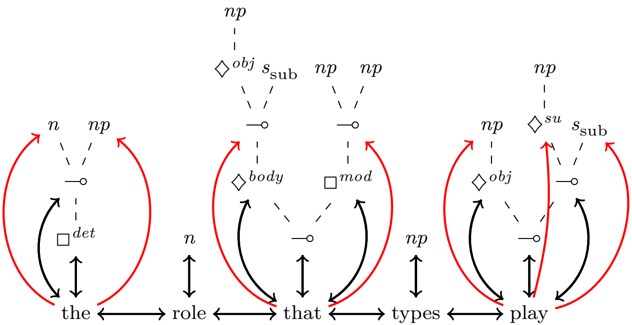
$p(\sigma_1, \ldots \sigma_m \mid w_1, \ldots w_n) \approx \prod_i^m (\sigma_i \mid \sigma_j : \text{depth}(\sigma_j) < \text{depth}(\sigma_i), w_1, \ldots w_n)$



(contextualize)

Post-modernity

neither sequence nor tree but sequence of trees
$p(\sigma_1, \ldots \sigma_m \mid w_1, \ldots w_n) \approx \prod_i^m (\sigma_i \mid \sigma_j : \text{depth}(\sigma_j) < \text{depth}(\sigma_i), w_1, \ldots w_n)$



(predict)

Implementation: dynamic graph convolutions

1 decoding step per tree depth; 3 message-passing rounds per step

- *contextualize: states* $\rightarrow$ *states*
  universal transformer encoder w/ relative weights
  (many-to-many, update states with neighborhood context)
- *predict: state* $\rightarrow$ *nodes*
  token classification w/ dynamic tree embeddings
  (one-to-many, predict fringe nodes from current state)
- *feedback: nodes* $\rightarrow$ *state*
  heterogeneous graph attention
  (many-to-one, update state with last predicted nodes)

Table with numbers

model	accuracy (%) overall	frequent	uncommon	rare	unseen
CCGbank *(Combinatory Categorial Grammar, en)*					
Sequential RNN	95.10	95.48	65.76	26.02	0.00
Tree Recursive	96.09	96.44	68.10	$\boxed{37.40}$	3.03
Attentive Convolutions	96.25	$\boxed{96.64}$	71.04	–	–
this work	$\boxed{96.29}$	96.61	$\boxed{72.06}$	34.45	$\boxed{4.55}$
CCGrebank *(ditto, improved version)*					
Sequential RNN	94.44	94.93	66.90	27.41	1.23
Tree Recursive	94.70	95.11	68.86	36.76	$\boxed{4.94}$
this work	$\boxed{95.07}$	$\boxed{95.45}$	$\boxed{71.40}$	$\boxed{37.19}$	3.70
TLGBank *(Lambek calculus & control modalities, fr)*					
ELMo LSTM	93.20	95.10	75.19	25.85	–
this work	$\boxed{95.93}$	$\boxed{96.40}$	$\boxed{81.48}$	$\boxed{55.37}$	$\boxed{7.26}$
Æthel *(van Benthem calculus & dependency modalities, nl)*					
Sequential Transformer	83.67	84.55	64.70	50.58	$\boxed{24.55}$
this work	$\boxed{93.67}$	$\boxed{94.72}$	$\boxed{73.45}$	$\boxed{53.83}$	15.78

Color coded summary

decoder	seq2seq[t]	seq2seq[σ]	tree	dynamic graph
codomain	fixed	open	constrained	constrained
context	left	preorder (global)	ancestors (local)	levels (global)
complexity	# words	# symbols	tree depth	tree depth
treeness	ignored	implicit	explicit	explicit
sequencess	explicit	misaligned	ignored	explicit
search?	✓	✓	?	?

legend

- green = good
- yellow = meh
- red = bad

Take home messages

use hammers for nails only

sparsity.. a *friend*?

- more rare cats $\implies$ better acquisition of rare cats
- cascading effect on performance

thanks!