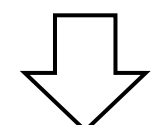


Motivation

➤ Explicit modeling of phrase structure

- Recent CCG supertagging and parsing models demonstrate high performance yet rely on **non-explicit modeling** of dependencies between words through neural networks.



➤ Explicit modeling of phrase structure with neural networks.

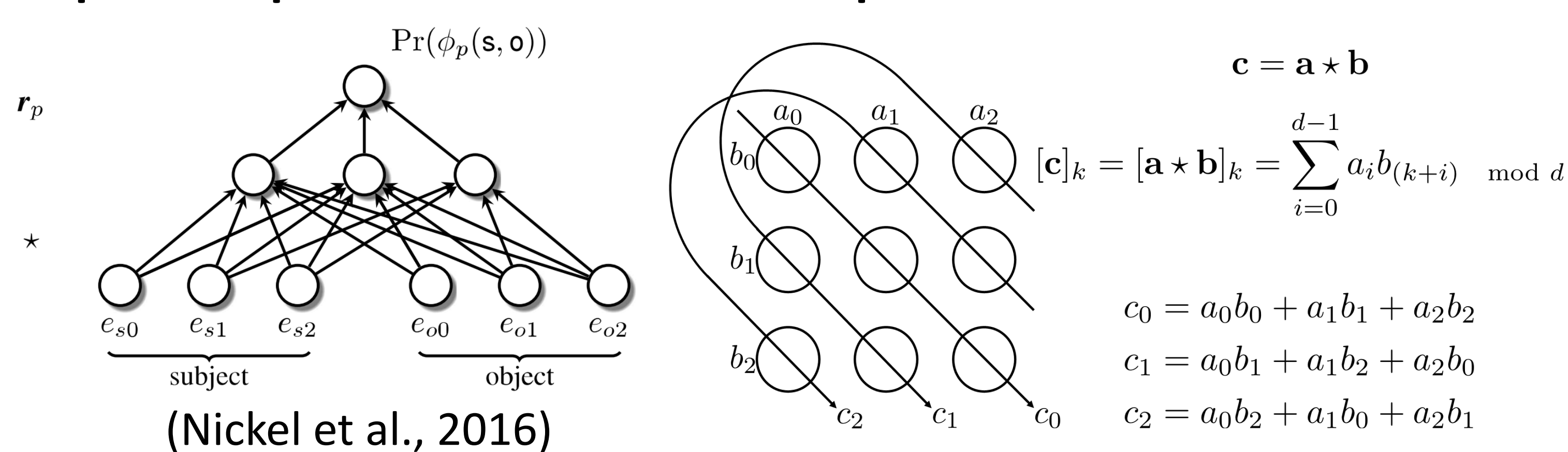
➤ Syntactic phrase-level representation

- Compose **syntactically rich phrase-level representations** while maintaining training efficiency.

Holographic CCG

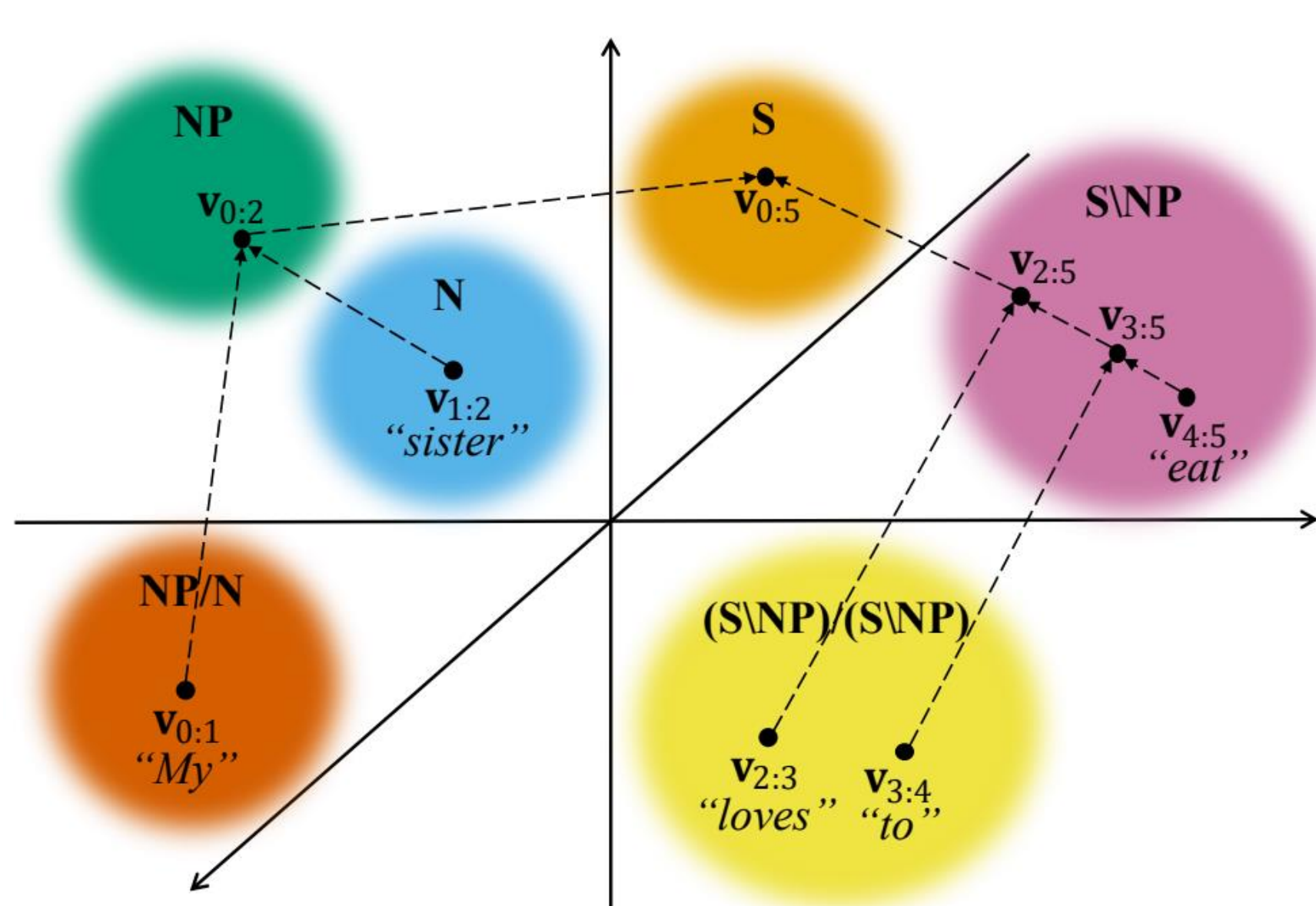
➤ Holographic Embeddings (Nickel et al., 2016)

- Embedding knowledge graphs into vector space for statistical modeling
- Vector composition using **circular correlation** to capture dependencies between entities
- Similarity of knowledge graphs and phrase structures that need to capture dependencies between components**



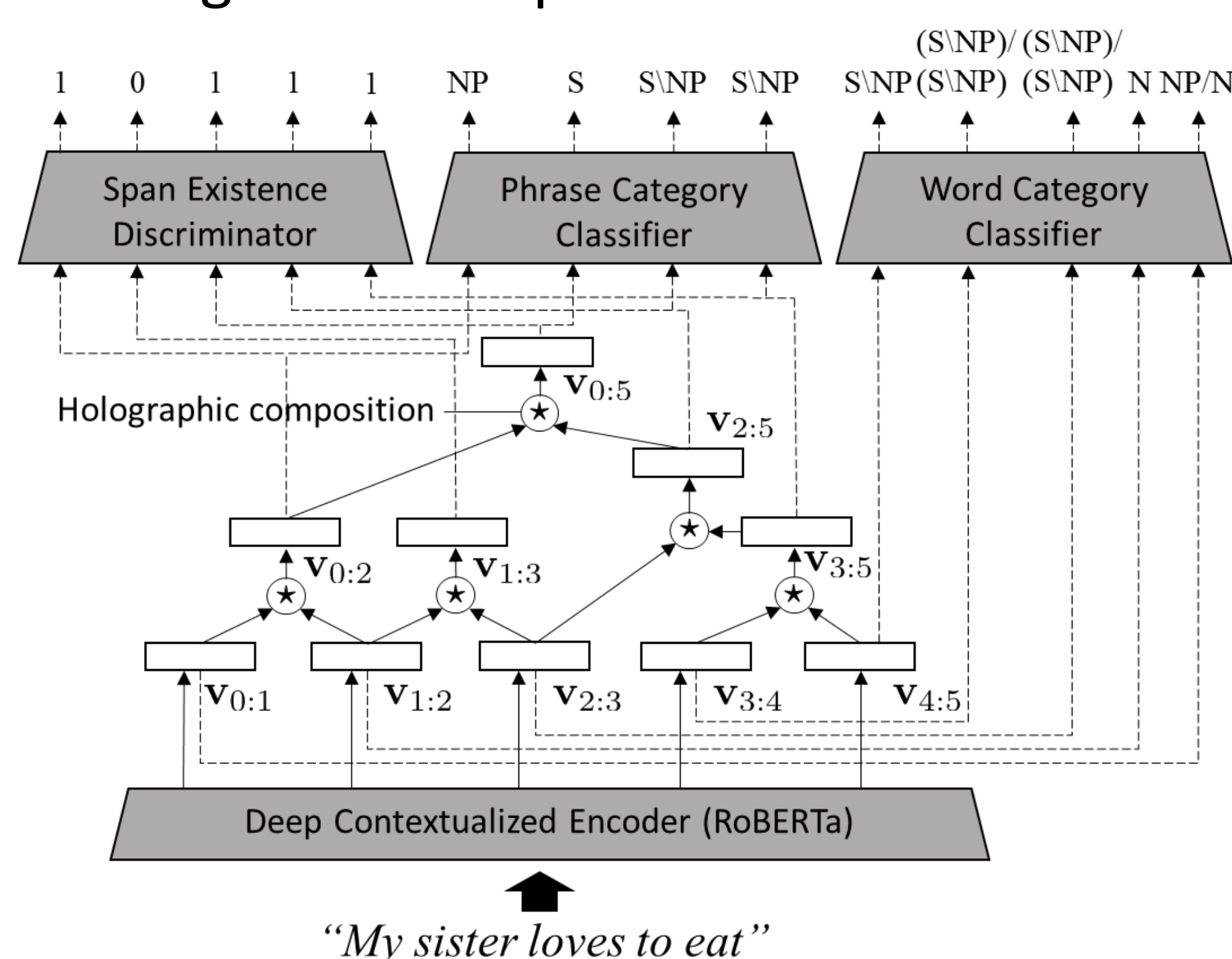
➤ Holographic CCG (Hol-CCG)

- Formulate CCG as a **recursive compositional operation** between distributed representations in a vector space.
- Applicable to **Supertagging** and **Span-based Parsing**.



➤ Model Structure

- Encode word sequence into distributed representations.
- Recursively compose phrase-level representations.
- Predict CCG categories and span existence.



➤ Span-based Parsing

- Store word-level representations.
- Recursively compose phrase-level representations.
- Directly evaluates category assignment to phrases.

Algorithm 1: Span-based CKY parsing

```

1 v0:1, v1:2, ..., vn-1:n = Encode(w1, w2, ..., wn);
2 for i = 0, ..., n - 1 do
3   Pw(i, i + 1) = SM(Qwσ(LN(Uwv_{i:i+1} + bw)) + cw);           ▷ Equation (11)
4   for C ∈ {X | Pw(i, i + 1)[X] > tw = 0.1} do
5     prob[i, i + 1, C] = log Pw(i, i + 1)[C];
6     vector[i, i + 1, C] = v_{i:i+1};
7 for ℓ = 2, ..., n do
8   for i = 0, ..., n - ℓ do
9     j = i + ℓ;
10    for k = i + 1, ..., j - 1 do
11      for C1 ∈ {X | prob[i, k, X] > 0} do
12        v_{i:k} = vector[i, k, C1];
13        for C2 ∈ {X | prob[k, j, X] > 0} do
14          v_{k:j} = vector[k, j, C2];
15          for C ∈ {X | C1, C2 → X ∈ R} do
16            v_{i:j} = v_{i:k} * v_{k:j};           ▷ Equations (4) and (5)
17            Ps(i, j) = SM(Qsσ(LN(Usv_{i:j} + bs)) + cs);           ▷ Equation (13)
18            if Ps(i, j)[e] > ts = 0.01 then
19              Pp(i, j) = SM(Qpσ(LN(Upv_{i:j} + bp)) + cp);           ▷ Equation (12)
20              if Pp(i, j)[C] > tp = 0.01 then
21                p = log Pp(i, j)[C] + log Ps(i, j)[e] + prob[i, k, C1] + prob[k, j, C2];
22
23                if p > prob[i, j, C] then
24                  prob[i, j, C] = p;
25                  backpointer[i, j, C] = (k, C1, C2);
26                  vector[i, j, C] = v_{i:j};

```

Experiment

- Dataset: CCGbank (Hockenmaier et al., 2007)
- Calculate the model's prediction error by cross entropy
 - Category assignment to words and phrases: $\mathcal{L}_w, \mathcal{L}_p$
 - Existence of span: \mathcal{L}_s
- Compare models by changing the combination of back-propagating errors (\mathcal{L})
 - Baseline: $\mathcal{L} = \mathcal{L}_w$
 - Hol-CCG: $\mathcal{L} = \mathcal{L}_w + \mathcal{L}_p + \mathcal{L}_s$
- Supertagging by Baseline and Hol-CCG
- Parsing using C&C Parser (Clark and Curran, 2007) and Hol-CCG's span-based parsing

Result & Discussion

- Hol-CCG outperforms baseline.
- Span-based Parsing outperforms C&C Parser.
- Explicit modeling of word/phrase dependencies** through composition of phrase representations is effective for both supertagging and parsing.

Training Objectives	Parser	Acc	LF
\mathcal{L}_w (baseline)	C&C	96.41 ± 0.03	91.77 ± 0.03
$\mathcal{L}_w + \mathcal{L}_p + \mathcal{L}_s$ (Hol-CCG)	C&C	96.59 ± 0.02	92.03 ± 0.04
	Span	-	92.61 ± 0.03

- Hol-CCG achieved SoTA in supertagging accuracy and LF with C&C Parser.
- Hol-CCG's span-based parsing is competitive with current SoTA performance.

Model	Parser	Acc	LF
Vaswani et al., 2016	C&C	94.5	88.32
Bhargava and Penn, 2020	C&C	96.00	90.9
Prange et al., 2021	C&C	96.22	90.91
Clark, 2021	C&C	-	91.9
	Span	-	92.9
Hol-CCG	C&C	96.60	92.12
	Span	-	92.67