Neuro-symbolic Models for NLP (6.884), Oct. 23, 2020

Modular Computation

Geiger et al. 2020 & Parte 1984

Carina

Matthew

Yixuan

Hang

Outline

1. Monotonicity Reasoning (Hang)	11:35-11:50
2. Discussion	
3. Geiger et al. 2020 (Yixuan)	11:55-12:10
4. Breakout Room + Discussion	12:10-12:30
5. 10-minute Break	
6. Compositionality + MCP (Carina)	12:40-12:55
7. Challenges (Matthew)	12:55-1:10
8. Breakout Room + Discussion	1:10-1:25

Question

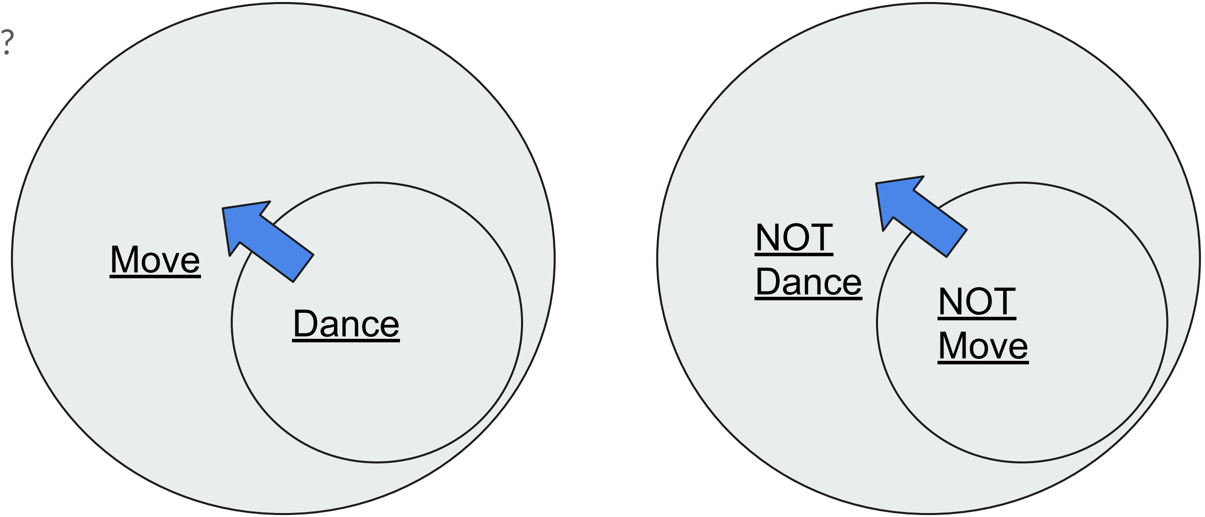
How can we know the model is doing the linguistic task vs. learning linguistic knowledge/reasoning?

Monotonicity Reasoning

What is monotonicity?

Entailment

Negation



Paper Outline

1. Challenge Test Sets
2. Systematic Generalization Task
3. Probing
4. Intervention

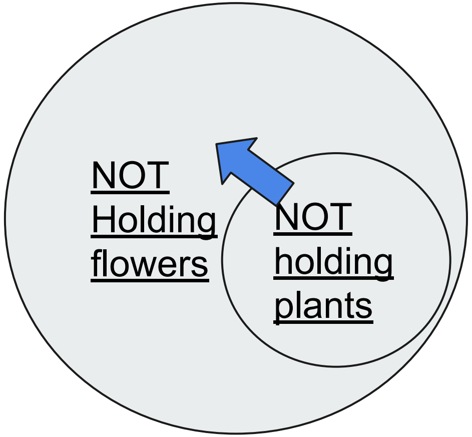
MoNLI Dataset

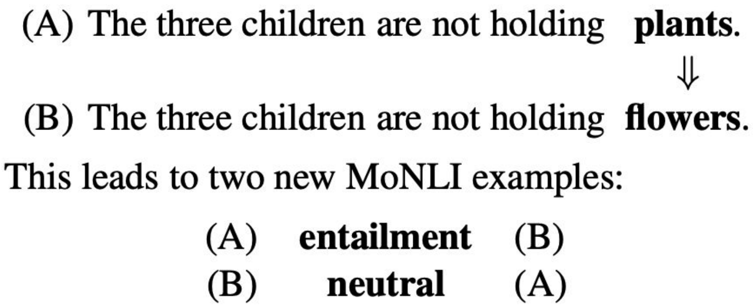
Procedure

- Ensure the hypernym / hyponym occurs in SNLI
- Ensure substitution generates a grammatically coherent sentence
- Generate one **entailment** and one **neutral** example

NMoNLI (1,202 examples)

PMoNLI (1,476 examples)




(A) The three children are not holding **plants**.

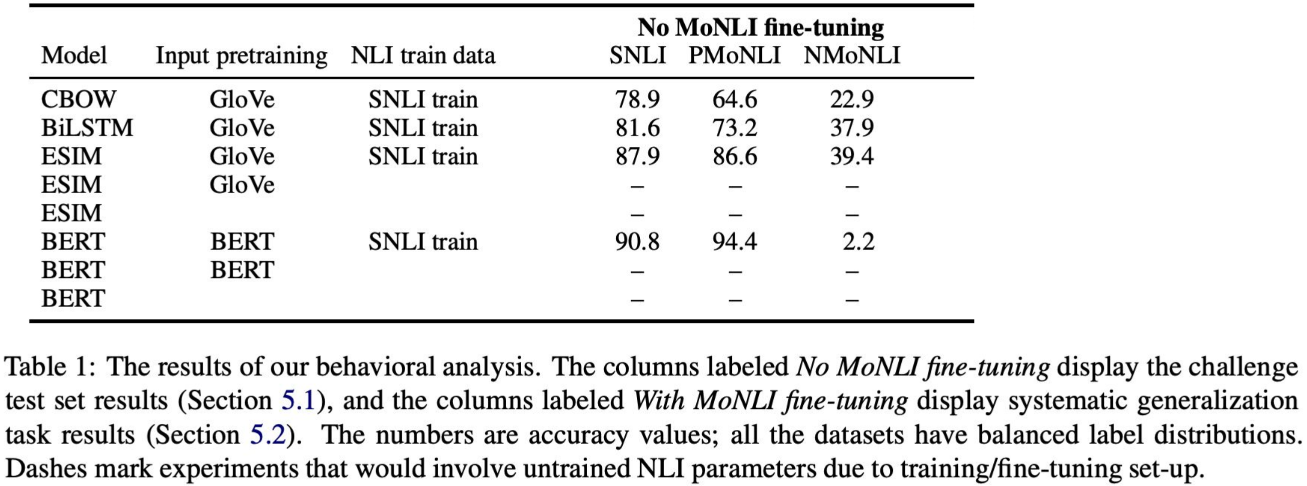
⇓

(B) The three children are not holding **flowers**.

This leads to two new MoNLI examples:

(A)	**entailment**	(B)
(B)	**neutral**	(A)

Results



			No MoNLI fine-tuning		
Model	Input pretraining	NLI train data	SNLI	PMoNLI	NMoNLI
CBOW	GloVe	SNLI train	78.9	64.6	22.9
BiLSTM	GloVe	SNLI train	81.6	73.2	37.9
ESIM	GloVe	SNLI train	87.9	86.6	39.4
ESIM	GloVe		–	–	–
ESIM			–	–	–
BERT	BERT	SNLI train	90.8	94.4	2.2
BERT	BERT		–	–	–
BERT			–	–	–

Table 1: The results of our behavioral analysis. The columns labeled *No MoNLI fine-tuning* display the challenge test set results (Section 5.1), and the columns labeled *With MoNLI fine-tuning* display systematic generalization task results (Section 5.2). The numbers are accuracy values; all the datasets have balanced label distributions. Dashes mark experiments that would involve untrained NLI parameters due to training/fine-tuning set-up.

Observations on the Challenge Test Set

- No MoNLI fine-tuning,
  - Comparable results on PMoNLI
  - All models consistently fail on NMoNLI
  - 38 data points (ish) +++
- Combining MNLI + SNLI to have more negation examples yields a similar results
  - ~4% (18K) negation examples

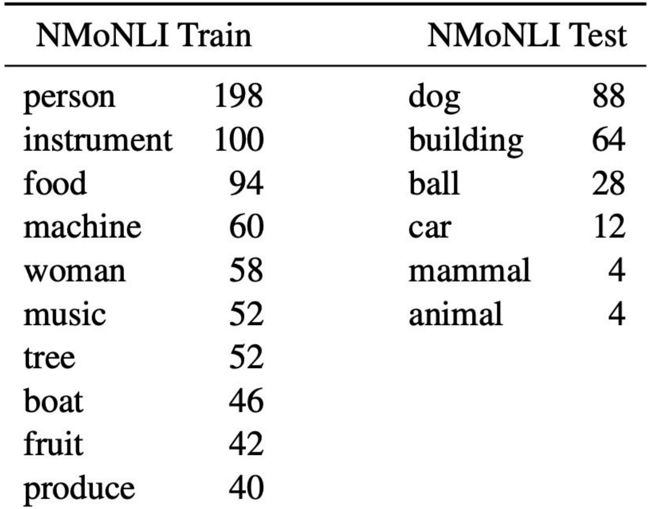
A Systematic Generalization Task

Can models learn the general theory of entailment and negation beyond lexical relationship?

Experiment Design

1. train/test split: substitution words must be in disjoint
2. Inoculation on NMoNLI

Train/Test data split -- disjoint



NMoNLI Train		NMoNLI Test	
person	198	dog	88
instrument	100	building	64
food	94	ball	28
machine	60	car	12
woman	58	mammal	4
music	52	animal	4
tree	52		
boat	46		
fruit	42		
produce	40		

Make sure there is no overlapping

Otherwise, models just memorize negation

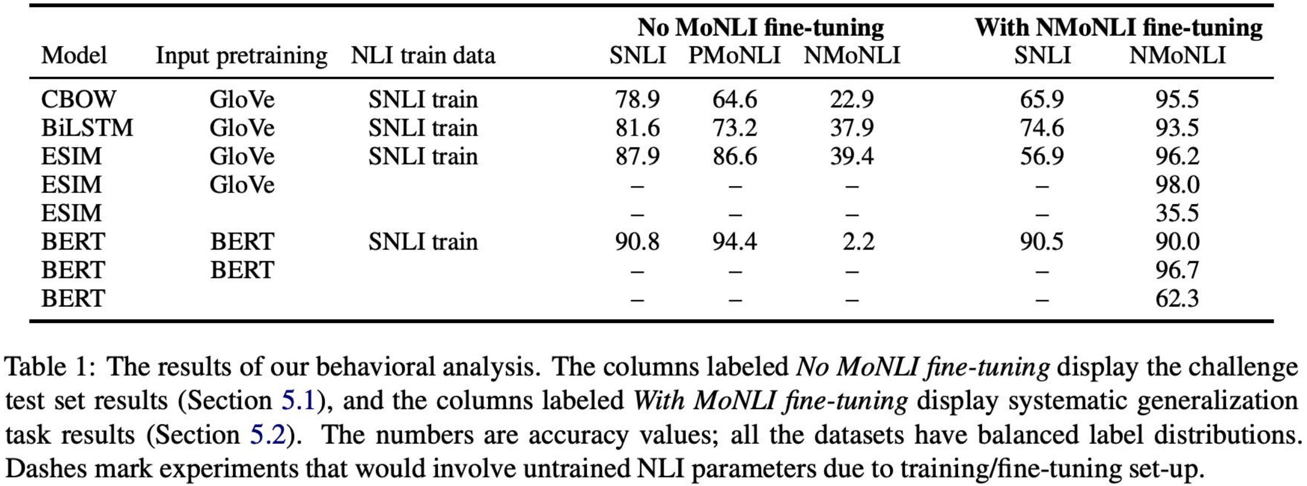
Inoculation

Two stage fine-tuning on both SNLI and NMoNLI datasets respectively

A pre-trained model is further fine-tuned on different small amounts of adversarial data while performance on the original dataset and the adversarial dataset is tracked

- choose the highest average accuracy between both datasets

Results



			No MoNLI fine-tuning			With NMoNLI fine-tuning	
Model	Input pretraining	NLI train data	SNLI	PMoNLI	NMoNLI	SNLI	NMoNLI
CBOW	GloVe	SNLI train	78.9	64.6	22.9	65.9	95.5
BiLSTM	GloVe	SNLI train	81.6	73.2	37.9	74.6	93.5
ESIM	GloVe	SNLI train	87.9	86.6	39.4	56.9	96.2
ESIM	GloVe		–	–	–	–	98.0
ESIM			–	–	–	–	35.5
BERT	BERT	SNLI train	90.8	94.4	2.2	90.5	90.0
BERT	BERT		–	–	–	–	96.7
BERT			–	–	–	–	62.3

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Observations on systematic generalization

1. All models solved the task
2. Only BERT maintain high accuracy on SNLI
3. Removing pre-training on SNLI has little influence on results for BERT and ESIM
4. Removing pre-training for BERT and ESIM make them fail the task
    a. Note: BERT’s score is double that of ESIM with random initialization
5. Weak evidence from behavioral evaluation

Discussion

1. Why does combining SNLI + MNLI **NOT** improve the model's generalization on NMoNLI?
2. What would happen if we combine MoNLI and SNLI instead of doing the two-stage fine-tuning?
3. Do we need to create a specific adversarial dataset for each linguistic phenomenon of interest?

Structural Evaluation

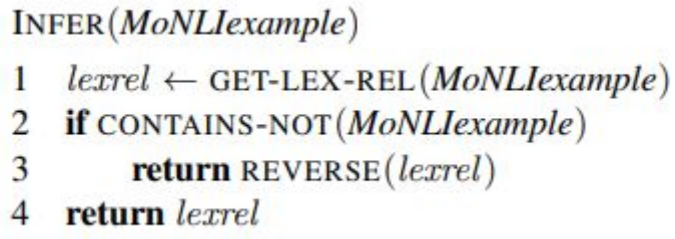
Trying to determine internal dynamics to ‘conclusively evaluate systematicity’

- Probing & Intervention
  - Not well understood methodologies
  - Have to be tailored to the model
- BERT
  - Fine tuned on NMoNLI
  - Chosen because it does well without sacrificing SNLI performance

INFER and Intuition

- Question is if BERT (at the algorithmic level) implements lexical entailment and negation
- *INFER*
  - Algorithmic description of entailment
  - *lexrel:* The lexical entailment relation between the substituted **words** in the MoNLI example

- Intuition behind storing and using *lexrel*
  - If BERT implements algorithm (loosely) then it will *store* a rep and *use* it
  - Storing → probe
  - Using → Intervention



```
INFER($MoNLIexample$)
lexrel ← GET-LEX-REL($MoNLIexample$)
if CONTAINS-NOT($MoNLIexample$)
    return REVERSE($lexrel$)
return $lexrel$
```

Probing

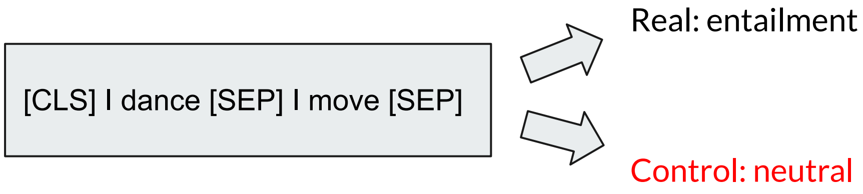
$$e = \langle \texttt{[CLS]}, p, \texttt{[SEP]}, h, \texttt{[SEP]} \rangle$$

- Idea: We want to see if *lexrel* (entailment relationship between words) is represented, and where
- BERT structure (12 layers of transformer encoders), get 1 vector rep/word per layer as a contextual embedding
  - Per word, this vector is not *just* info on the word like it would be for word2vec, heavily contextualized as BERT uses the words around it to inform
- **Assumption:** *lexrel* is stored in one of these vectors
- Specifically, one of the vectors for CLS, w_p, and w_h
- Try to find the vector which most likely stores this linguistic information
- Train the probe on all MoNLI

Probing and Selectivity

Takeaway (Hewitt and Manning 2019):

- Probes: use representations to predict linguistic properties
- Good probe: need high accuracy and high selectivity
- Probe design: use linear probes with fewer units



[CLS] I dance [SEP] I move [SEP]

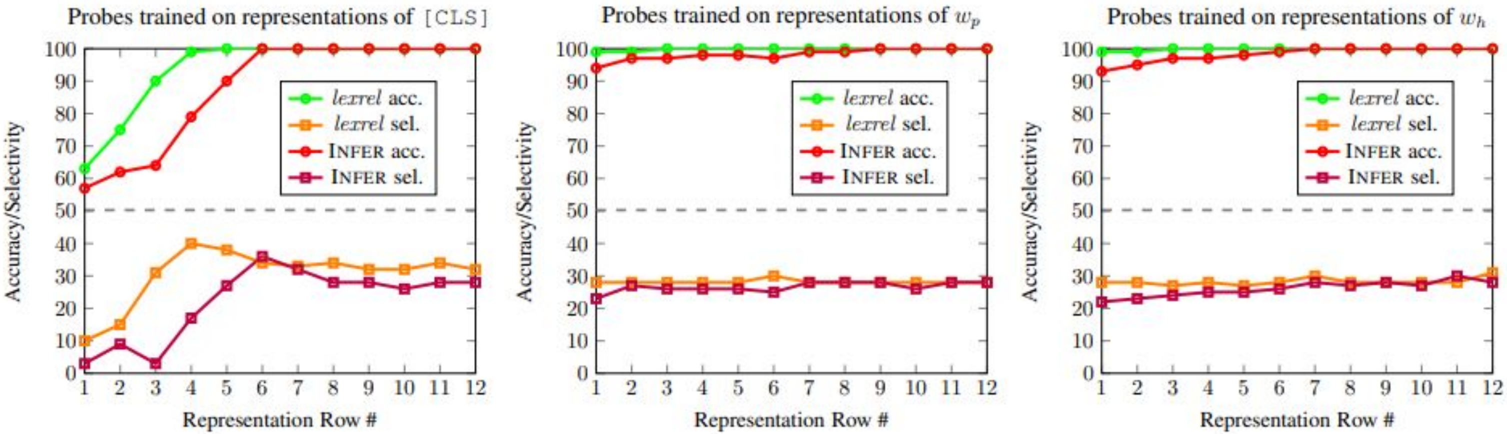
Real: entailment

Control: neutral

Experiment

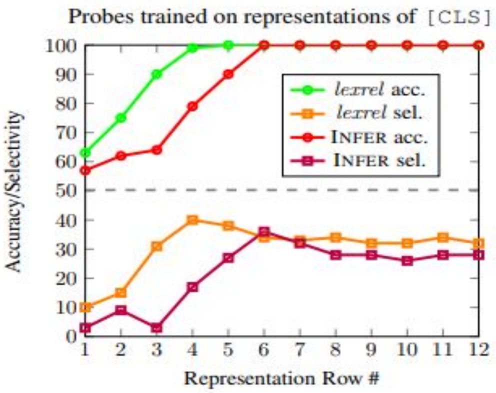
- Simple model with 4 Hidden Units
- Predict the value of *lexrel* from the contextual embedding as the only input
    - Accuracy and selectivity are both plotted

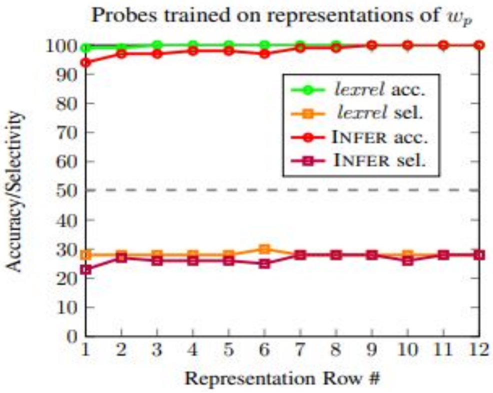
Probe Results

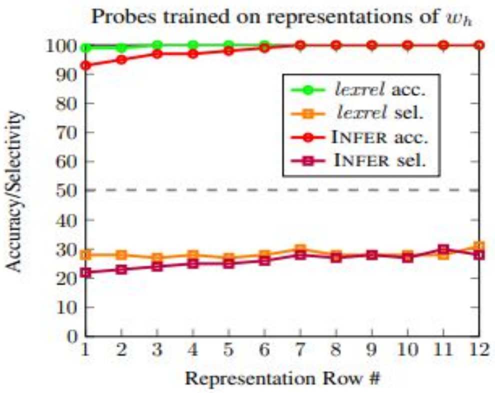


Interpretation

- Why do the first couple of vectors for the [CLS] token not perform great?
- Essentially all vectors not 1-4 for the [CLS] token perform well for the task
  - *Lexrel* info is encapsulated in all of these places

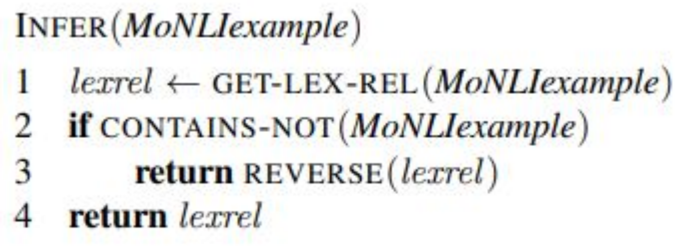






Interventions

- Verifying whether the lexrel rep is *used* and where it is
- Want to show that the causal dynamics of *INFER* are mimicked by BERT
  - Not enough to show output of *INFER* and BERT match
  - *lexrel* is the only variable
  - Causal role can be determined with counterfactuals on how changing value of *lexrel* causes output to change



```
INFER(MoNLIexample)
  lexrel ← GET-LEX-REL(MoNLIexample)
  if CONTAINS-NOT(MoNLIexample)
      return REVERSE(lexrel)
  return lexrel
```

Example:

[CLS] this not tree [SEP] this not elm [SEP]

lexrel **:** tree is hypernym of elm

negation : true

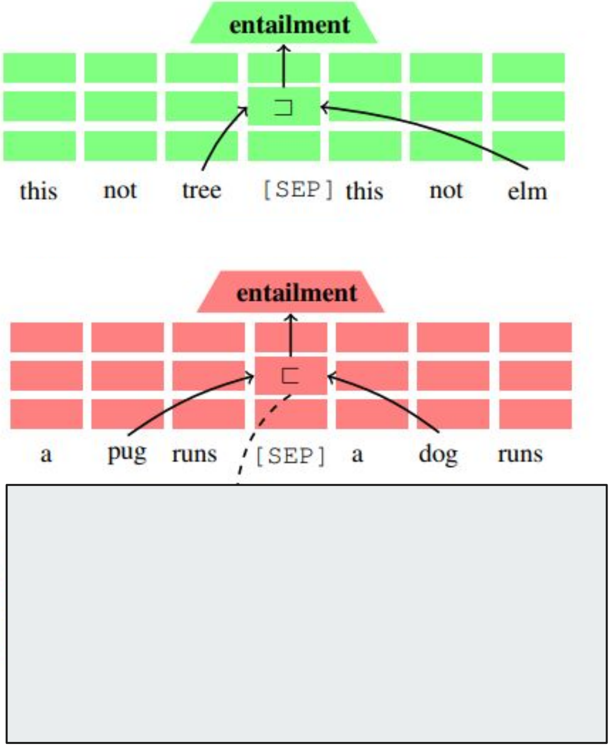
INFER: entailment

Idea: if you flip *lexrel*, the output of *INFER* will change

Intervention Cont.

How would this work with BERT?

For a guess, *L*, of where the vector is and 2 examples, we can say that BERT mimics *INFER* on those 2 examples if the interchange behaves as expected.



Formalization and Experiment

Let *L* be the hypothesis that *lexrel* is stored at a specific location of 36, suppose *L* with input *i* is replaced with *L* with input *j*, and feed *i* into this modified bert. We call this

$$\mathrm{BERT}_{L(i)\rightarrow L(j)}(i)$$

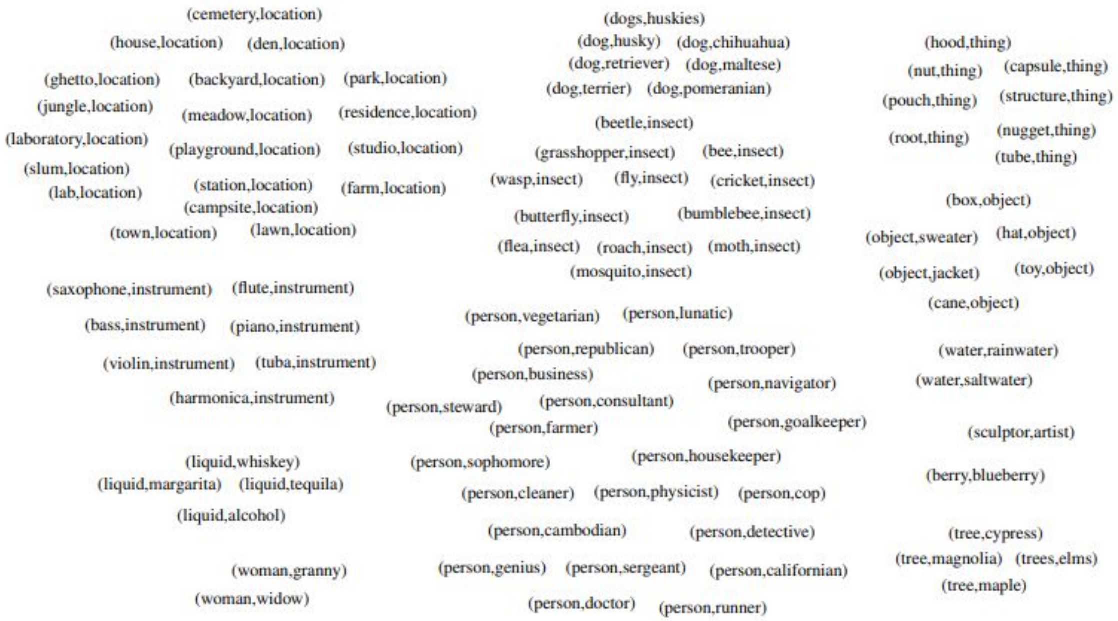
For some subset of MoNLI, if we believe BERT is storing value of *lexrel* at L and using info to make final prediction, than for all i,j in S we should have

$$\textsc{Infer}_{lexrel(i)\rightarrow lexrel(j)}(i) = \mathrm{BERT}_{L(i)\rightarrow L(j)}(i)$$

Experiment

- For any pair of examples *i,j*, draw an edge between *i and j* if the interchange of the *lexrel* vector leads to the expected behavior
- Conducted interchange experiments at 36 different locations and chose most promising after partial graph
  - BERT^3 _wh
- 7 Million interchanges at this location
  - One for every pair of examples in MoNLI
- Greedy algorithm to discover large subsets of MoNLI where BERT mimics causal dynamics of INFER

Graph Visualization



Results

- Found large subsets of 98, 63, 47, and 37
- Expected number of subsets larger than 20 with this property if interchange had random effect is 10^-8
- Same causal dynamics on 4 large subsets of MoNLI

Takeaway?

- Seems promising!
  - Interventions seem to show that the probability that BERT isn’t at some level implementing this algorithm is extremely low
- A lot of assumptions and shortcuts taken for the sake of reducing computation though

Breakout Rooms

10 min

- Did this approach show whether the model is able to just pass the entailment reasoning task or whether it was able to implement entailment reasoning?

- Does the probing/intervention approach seem promising to understand other linguistic tasks

- Why weren’t the clusters bigger? What assumptions made by the authors do you think were more/less valid or had bigger effects?

Compositionality

Partee 1984

Principle of Compositionality

> The meaning of an expression **is a function of** the **meanings** of its parts and of the way they are **syntactically** combined

> theory-dependent as highlighted terms can have different interpretations

Montague’s strong version of the compositionality principle (MCP)

Compositionality as a homomorphism between the syntactic and semantic algebra

What is an Algebra?

An *algebra* is a tuple < **A**, f_1, … , f_n > consisting of

- a set **A**
- one or more operations (functions) f_1, … , f_n ,

where A is *closed* under each of f_1, … , f_n

An *algebra* is a tuple < **A**, $f_1, \dots, f_n$> consisting of

- a set **A**
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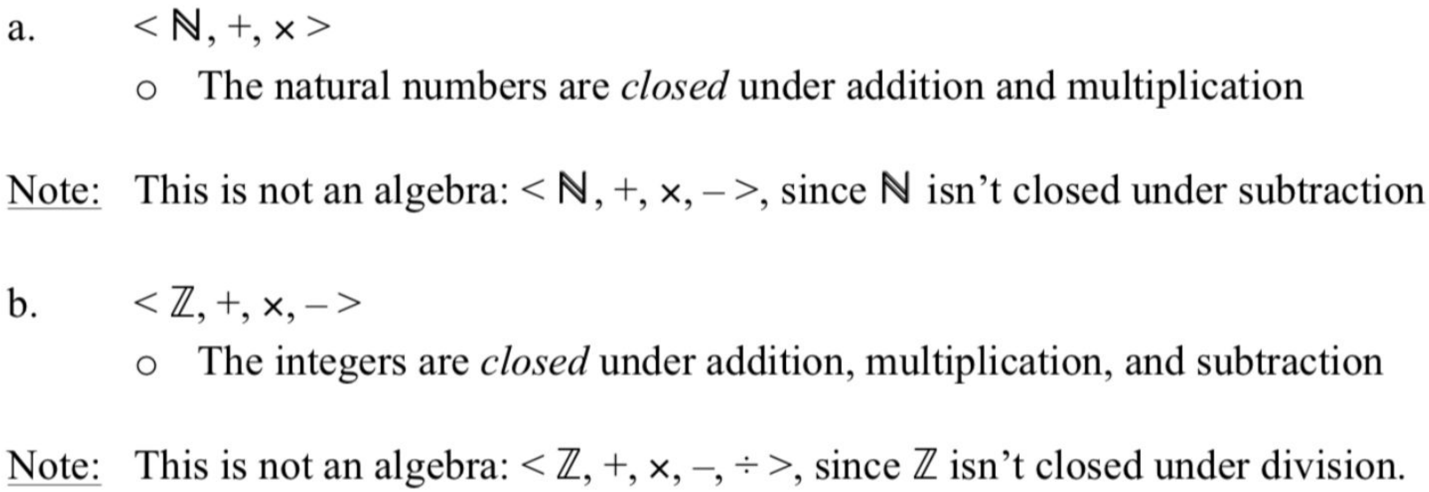
What is an Algebra?



a. < ℕ, +, × >

- The natural numbers are *closed* under addition and multiplication

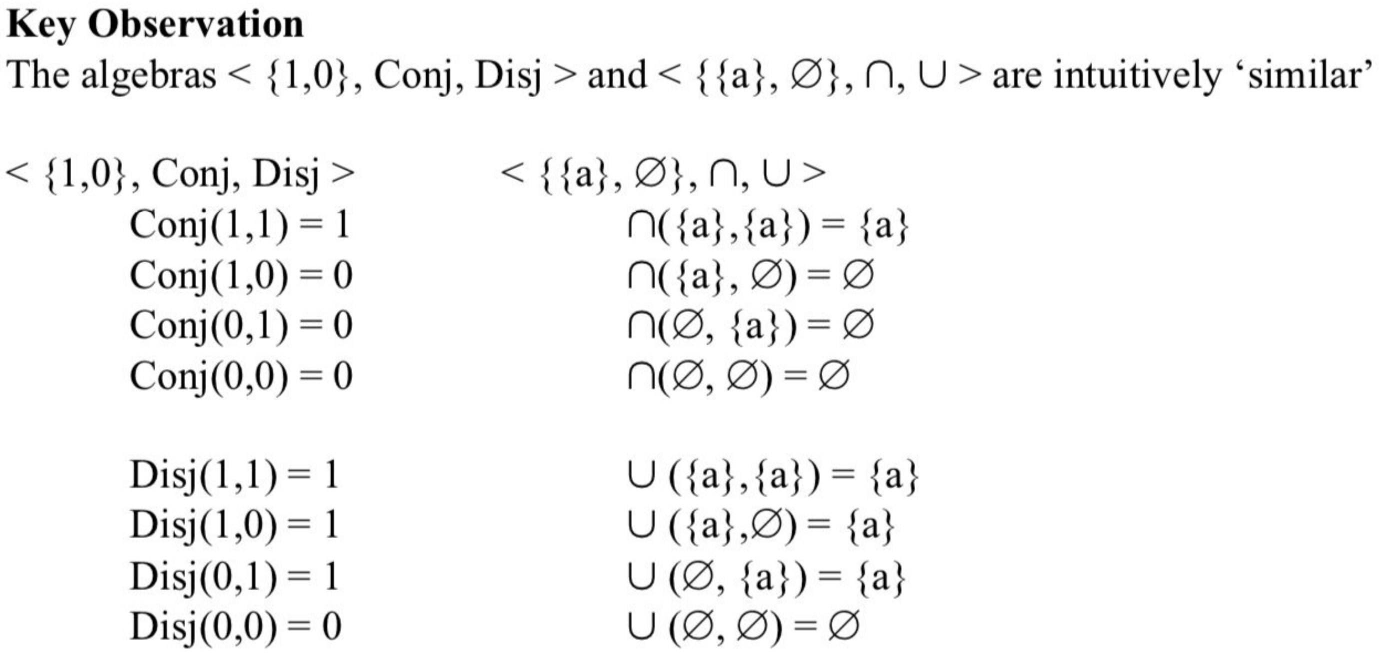
Note: This is not an algebra: < ℕ, +, ×, – >, since ℕ isn't closed under subtraction

b. < ℤ, +, ×, – >

- The integers are *closed* under addition, multiplication, and subtraction

Note: This is not an algebra: < ℤ, +, ×, –, ÷ >, since ℤ isn't closed under division.

Different Algebras Can Be Similar!

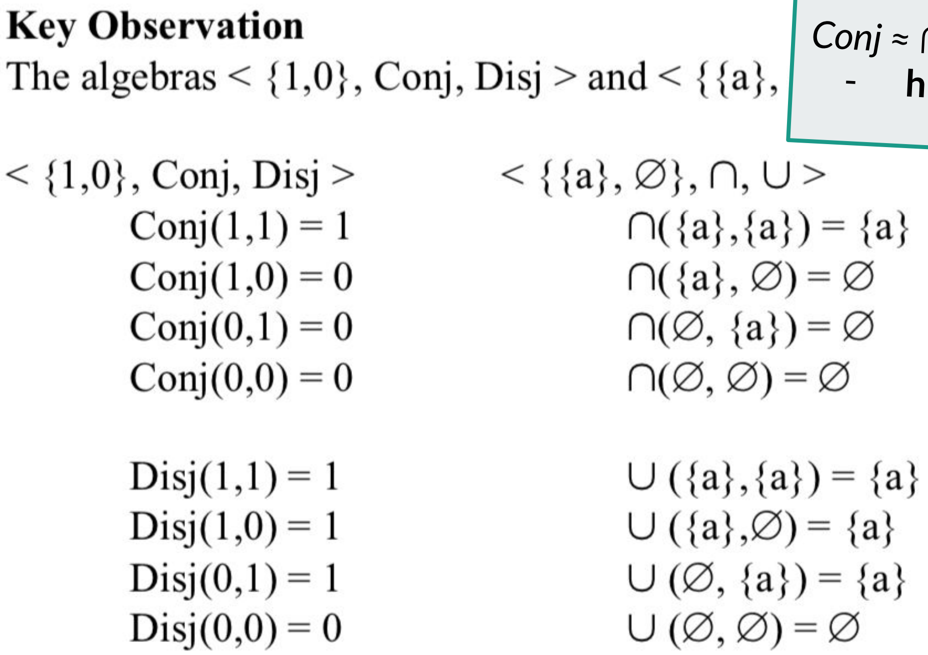


Key Observation

The algebras $< \{1,0\}, \text{Conj}, \text{Disj} >$ and $< \{\{a\}, \varnothing\}, \cap, \cup >$ are intuitively ‘similar’

$< \{1,0\}, \text{Conj}, \text{Disj} >$	$< \{\{a\}, \varnothing\}, \cap, \cup >$
$\text{Conj}(1,1) = 1$	$\cap(\{a\},\{a\}) = \{a\}$
$\text{Conj}(1,0) = 0$	$\cap(\{a\}, \varnothing) = \varnothing$
$\text{Conj}(0,1) = 0$	$\cap(\varnothing, \{a\}) = \varnothing$
$\text{Conj}(0,0) = 0$	$\cap(\varnothing, \varnothing) = \varnothing$
$\text{Disj}(1,1) = 1$	$\cup(\{a\},\{a\}) = \{a\}$
$\text{Disj}(1,0) = 1$	$\cup(\{a\},\varnothing) = \{a\}$
$\text{Disj}(0,1) = 1$	$\cup(\varnothing, \{a\}) = \{a\}$
$\text{Disj}(0,0) = 0$	$\cup(\varnothing, \varnothing) = \varnothing$

Different Algebras Can B



Key Observation

The algebras < {1,0}, Conj, Disj > and < {{a},

< {1,0}, Conj, Disj >	< {{a}, ∅}, ∩, ∪ >
Conj(1,1) = 1	∩({a},{a}) = {a}
Conj(1,0) = 0	∩({a}, ∅) = ∅
Conj(0,1) = 0	∩(∅, {a}) = ∅
Conj(0,0) = 0	∩(∅, ∅) = ∅
Disj(1,1) = 1	∪ ({a},{a}) = {a}
Disj(1,0) = 1	∪ ({a},∅) = {a}
Disj(0,1) = 1	∪ (∅, {a}) = {a}
Disj(0,0) = 0	∪ (∅, ∅) = ∅

Intuitive similarity can be formalized as **homomorphism** between algebras!

$$h = \begin{pmatrix} 1 \rightarrow \{a\} \\ 0 \rightarrow \varnothing \end{pmatrix}$$

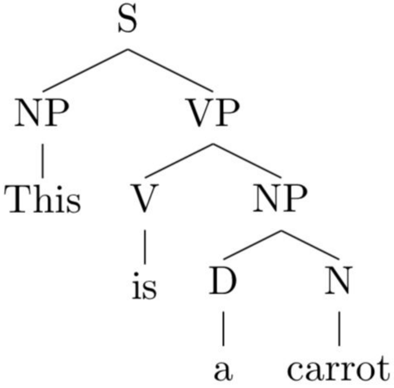
Conj ≈ ∩

- **h(Conj(1,1))** = h(1) = {a} = ∩({a},{a}) =**∩(h(1), h(1))**

MCP Compositionality: Homomorphism Between Syntactic and Semantic Algebra

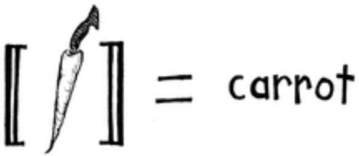
Syntax:

Arrangement of words and phrases into well-formed sentences

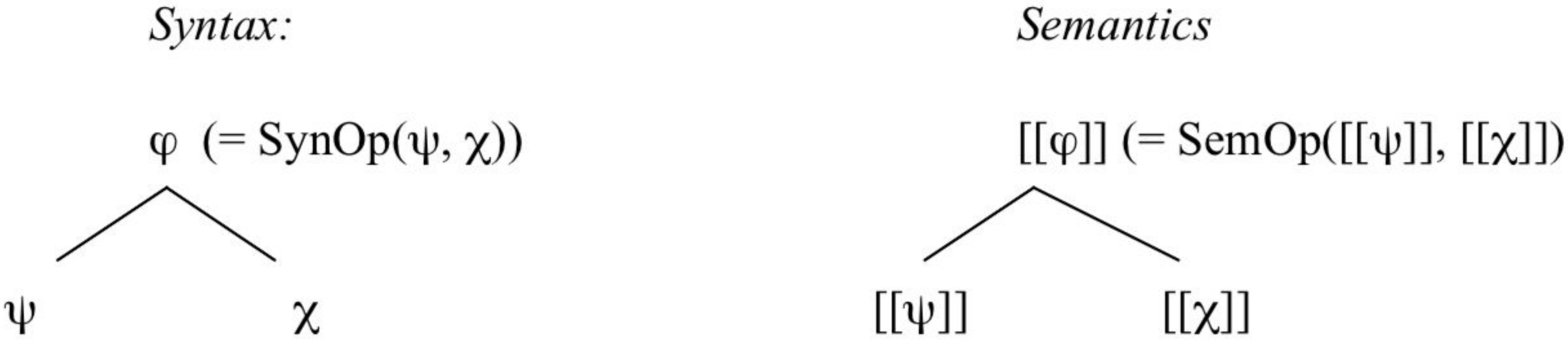


Semantics

Meaning of words, phrases, and sentences

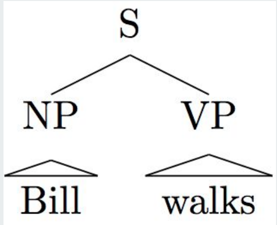


MCP Compositionality: Homomorphism Between Syntactic and Semantic Algebra

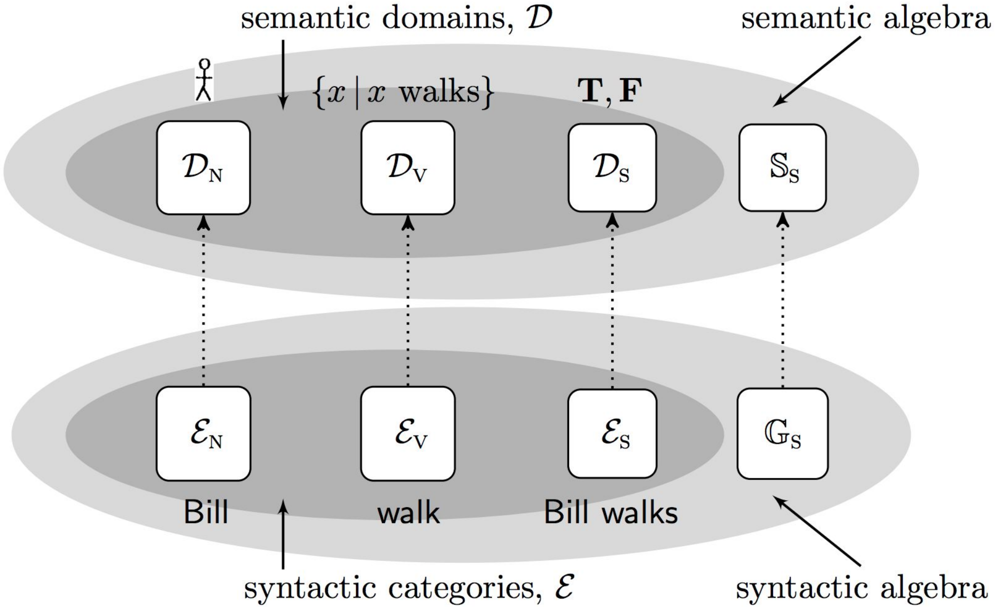


Source

Building Blocks



[[Bill]] = 🧍
[[walks]] = function that takes one argument, x, and yields 1 iff x walks
[[Bill walks]] = 1 iff 🧍 walks


semantic domains, $\mathcal{D}$

semantic algebra

🧍 $\{x \mid x \text{ walks}\}$ $\mathbf{T}, \mathbf{F}$

$\mathcal{D}_N$ $\mathcal{D}_V$ $\mathcal{D}_S$ $\mathbb{S}_S$

$\mathcal{E}_N$ $\mathcal{E}_V$ $\mathcal{E}_S$ $\mathbb{G}_S$

Bill walk Bill walks

syntactic categories, $\mathcal{E}$

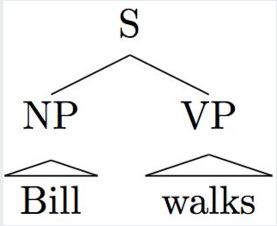
syntactic algebra

$\mathbb{S}_S$. $\left[\!\!\left[\begin{smallmatrix} A \\ B \quad C \end{smallmatrix} \right]\!\!\right] = [\![B]\!]\ ([\![C]\!]\ )$

$\mathbb{G}_S$. Merge (X,Y) → $<_Z$ X,Y> or $\begin{smallmatrix} Z \\ X \quad Y \end{smallmatrix}$

Image source

Building Blocks



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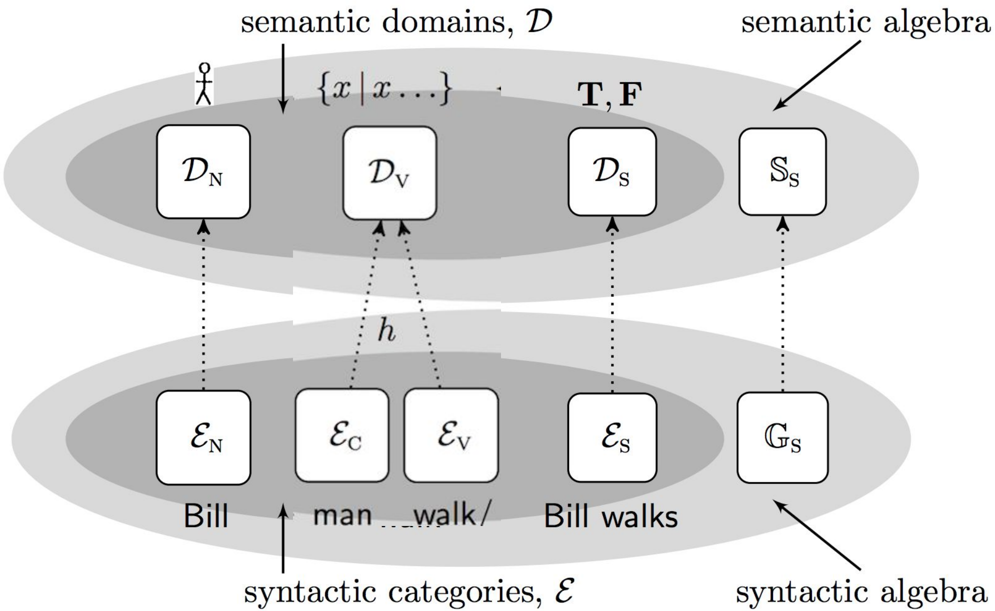
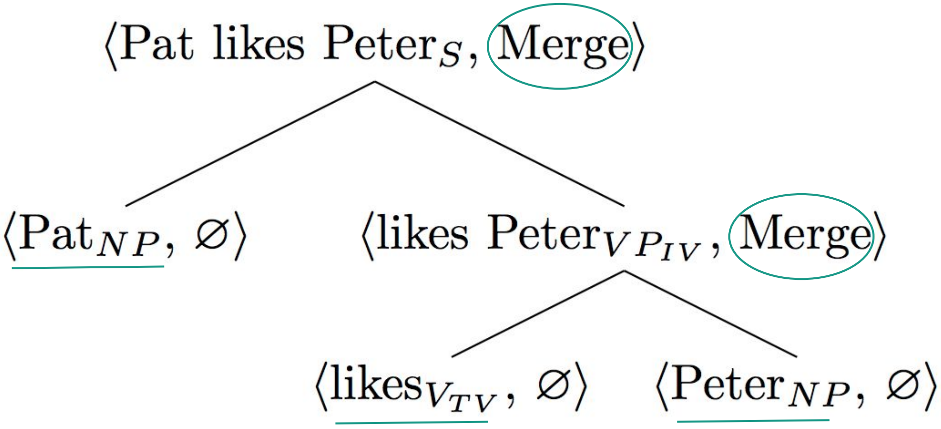

semantic domains, $\mathcal{D}$
semantic algebra
$\{x \mid x \ldots\}$
$\mathbf{T}, \mathbf{F}$
$\mathcal{D}_{\mathrm{N}}$
$\mathcal{D}_{\mathrm{V}}$
$\mathcal{D}_{\mathrm{S}}$
$\mathbb{S}_{\mathrm{S}}$
h
$\mathcal{E}_{\mathrm{N}}$
$\mathcal{E}_{\mathrm{C}}$
$\mathcal{E}_{\mathrm{V}}$
$\mathcal{E}_{\mathrm{S}}$
$\mathbb{G}_{\mathrm{S}}$
Bill
man
walk/
Bill walks
syntactic categories, $\mathcal{E}$
syntactic algebra

$\mathbb{S}_{\mathrm{S}}$. $\left[\!\left[\begin{array}{c} A \\ B\ \ C \end{array} \right]\!\right] = [\![B]\!]\ ([\![C]\!]\ )$

$\mathbb{G}_{\mathrm{S}}$. Merge (X,Y) → $<_Z$ X,Y> or $\begin{array}{c} Z \\ X\ \ Y \end{array}$

Montague's Paradise: Perfect Homomorphism

Syntax



$\langle \text{Pat likes Peter}_S, \text{Merge} \rangle$

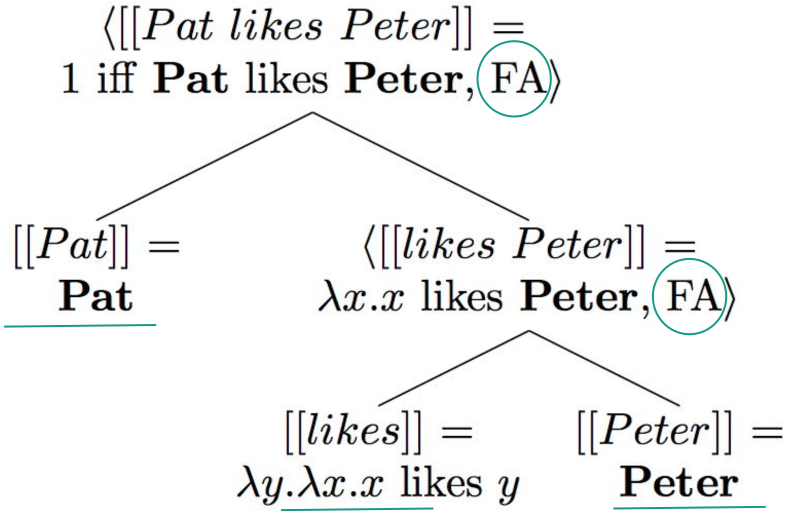
$\langle \text{Pat}_{NP}, \varnothing \rangle$

$\langle \text{likes Peter}_{VP_{IV}}, \text{Merge} \rangle$

$\langle \text{likes}_{V_{TV}}, \varnothing \rangle$

$\langle \text{Peter}_{NP}, \varnothing \rangle$

Simplified semantics



$\langle [[\textit{Pat likes Peter}]] =$ 1 iff **Pat** likes **Peter**, FA$\rangle$

$[[\textit{Pat}]] =$ **Pat**

$\langle [[\textit{likes Peter}]] = \lambda x.x$ likes **Peter**, FA$\rangle$

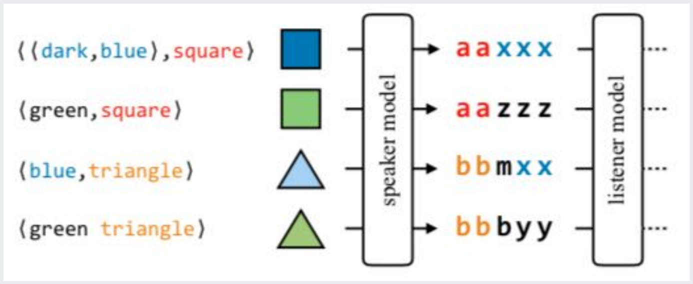
$[[\textit{likes}]] = \lambda y.\lambda x.x$ likes y

$[[\textit{Peter}]] =$ **Peter**

Key features: Bottom-up!

Meanings of leaves are independent!

This Seems Familiar!



Derivations: Assumption of prior knowledge (**oracle** on derivation primitives)

Compositionality: homomorphism from inputs to representations

For any x with $D(x) = \langle D(x_a), D(x_b) \rangle$: $f(x) = f(x_a) * f(x_b)$

Challenges overcome by Montague

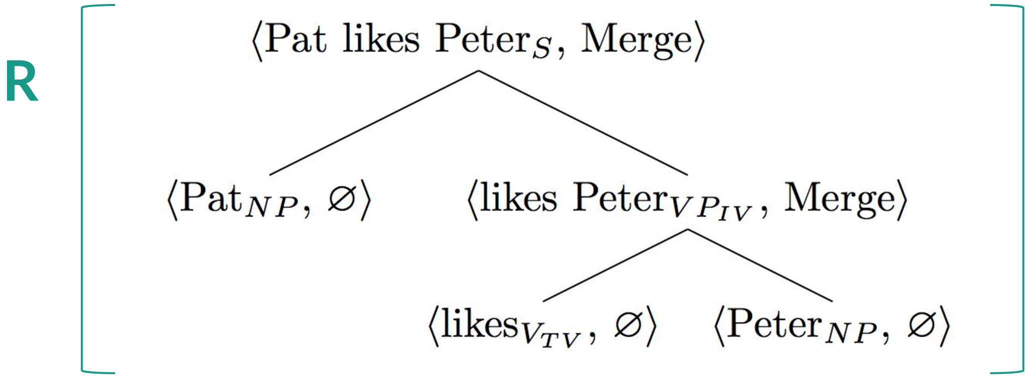
- Structural ambiguity
  - Syntactic structure vs. Phonological Form (=spell-out)
- Context-(in)dependent meanings
  - Intensions (Senses) vs. Extensions (Denotations)

Structural Ambiguity

It’s not the case that Pat likes Peter and Megan smokes.

When is this sentence true?

Syntactically Ambiguous Languages



R

$\langle \text{Pat likes Peter}_S, \text{Merge} \rangle$

$\langle \text{Pat}_{NP}, \varnothing \rangle$

$\langle \text{likes Peter}_{VP_{IV}}, \text{Merge} \rangle$

$\langle \text{likes}_{V_{TV}}, \varnothing \rangle$

$\langle \text{Peter}_{NP}, \varnothing \rangle$

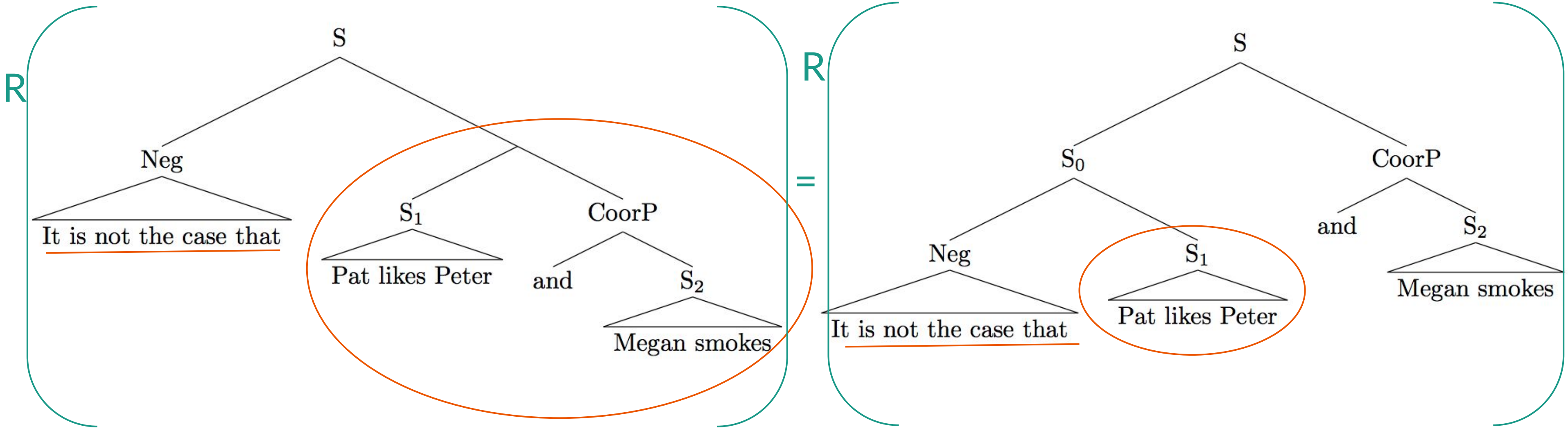
= Pat likes Peter

(“Phonological spell-out” of the structure”)

Syntactically ambiguous natural language like English:

- **Disambiguated expressions** are the analysis trees themselves
- **Ambiguation Relation R** maps analysis tree to string in the tree root

Disambiguation structures



Same spell-out, but different meaning!

It’s not the case that Pat likes Peter and Megan smokes.

Context (In)dependent Meaning: Why We Need Intensions I

The president of the United States is blonde = S

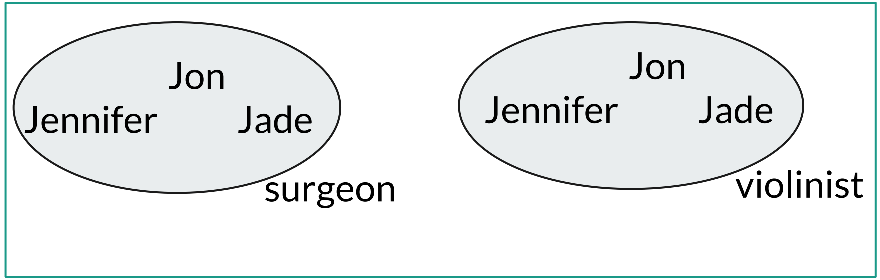
Truth of statement evaluated on 23-10-2020: [[S]] = True
Truth of statement evaluated on 23-10-2021: [[S]] = ?

How can there be different meanings?

Intension/Sense: [[the president of the US]]^{w} = the president of the US at w (type <s,e>)
> the presidential concept (function: context → president in that context)

Extension/Denotation: [[the president of the US]]^{w0} = Donald Trump (type <e>)
> the presidential referent (current person picked out by that function)

Why We Need Intensions II



Toy context w0: [[surgeon]]^{w0} = [[violinist]]^{w0}

Substitution should go through via MCP!

(1) Jon is a skillful surgeon.
(2) Jon is a skillful violinist.
BUT: One can be true without the other!
Why?

Solution:

- adjective denotes a function that applies to the **intension** of the common noun phrase.
- [[surgeon]]^{w} ≠ [[violinist]]^{w} >> Intensions are clearly different!
- So (1) and (2) can have different truth values even if the **extensions** pick out the same people!

Caveat: Implemented via more complex types of functions in Montague grammar! (<s,<e,t>>, etc.)

Challenges to MCP

Generic Interpretation of Noun Phrases

A. The horse is widespread	**Generic**
B. The horse is in the barn	**Non-generic**
C. The horse is growing stronger	**Ambiguous**

Where is the disambiguating information?

$$\underbrace{\text{The horse}}_{\textbf{NP}}\ \underbrace{\text{is in the barn}}_{\textbf{VP}}$$

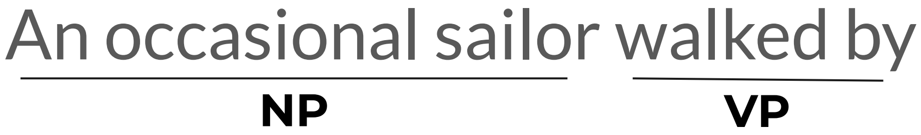
Genericness as Local Ambiguity

The teacher was explaining the diesel engine

Non-Generic

Generic

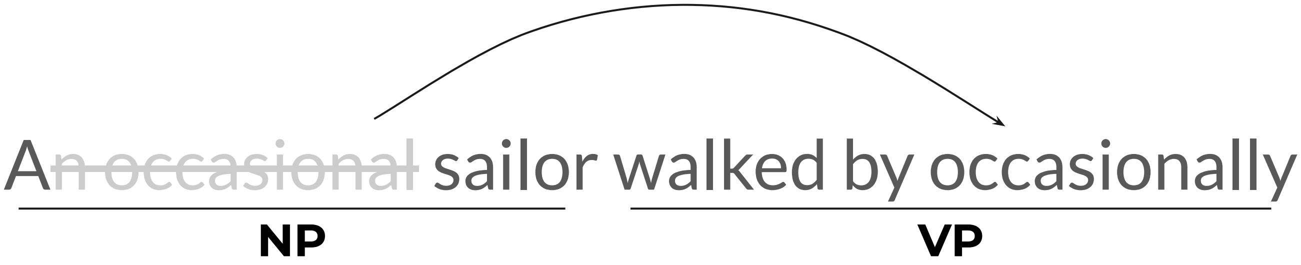
Things in the Wrong Place



An occasional sailor walked by

NP VP

Things in the Wrong Place



A~~n occasional~~ sailor walked by occasionally

NP

VP

Constructions with Extra Meanings

A. Being a master of disguise, Bill would fool anyone **Single Event**

(Since Bill is)

B. Wearing his new outfit, Bill would fool anyone **Two Events**

Implicit Argument Differences

A. Every man in this room is a father

Father of his own child

B. Every man in this room is an enemy

Enemy of the same entity

Breakout Rooms

10 min

“the horse” has two distinct senses. What are the implications of this for our models, especially regarding word embeddings?

Do we still have a robust definition of compositionality after accounting for these examples?

To what extent do we want our algorithms to model this principle of compositionality? How can we best adapt existing models to handle it?