Inducing Interpretable Causal Structures in Neural Networks

Christopher Potts

Joint work with Atticus Geiger, Zhengxuan (Zen) Wu, Hanson Lu, Josh Rozner, Elisa Kreiss, Karel D'Oosterlinck, Thomas Icard, and Noah Goodman

Stanford Linguistics and the Stanford NLP Group

Mila/McGill, April 8, 2022

Semantic insights in NLP models

Semantic insights in NLP models: 1980s

Chat-80; Warren and Pereira 1982

Semantic insights in NLP models: 1980s

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/* Sentences */
sentence(S) --> declarative(S), terminator(.) .
sentence(S) --> wh_question(S), terminator(?) .
sentence(S) --> yn_question(S), terminator(?) .
sentence(S) --> imperative(S), terminator(!) .

/* Noun Phrase */
np(np(Agmt,Pronoun,[]),Agmt,NPCase,def,_,Set,Nil) -->
  {is_pp(Set)},
  pers_pron(Pronoun,Agmt,Case),
  {empty(Nil), role(Case,decl,NPCase)}.

/* Prepositional Phrase */
pp(pp(Prep,Arg),Case,Set,Mask) -->
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- Which country bordering the Mediterranean borders a country that is bordered by a country whose population exceeds the population of India?

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- Which country bordering the Mediterranean borders a country that is bordered by a country whose population exceeds the population of India? turkey.
- How far is London from Paris?

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- Which country bordering the Mediterranean borders a country that is bordered by a country whose population exceeds the population of India? turkey.
- How far is London from Paris? I don't understand!

Chat-80; Warren and Pereira 1982

Semantic insights in NLP models: 1990s

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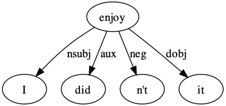
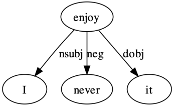
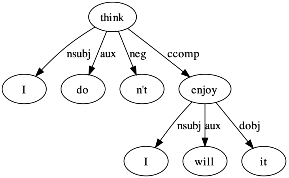
I didn't enjoy it.



I never enjoy it.



I don't think I will enjoy it.



Semantic insights in NLP models: 1990s

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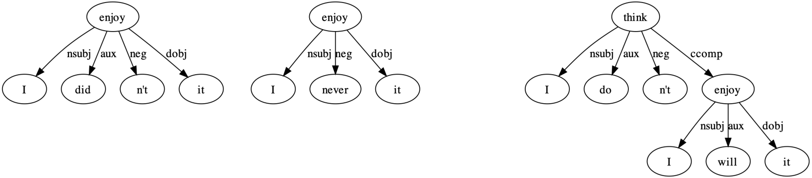

$$\texttt{neg(x, *)} \Rightarrow \texttt{x\_neg}$$

$$\texttt{neg(x, y)} \wedge \texttt{ccomp(x, z)} \Rightarrow \texttt{x\_neg, z\_neg}$$

Semantic insights in NLP models: 2000s

Zettlemoyer and Collins 2005

Semantic insights in NLP models: 2000s

a)

$$
\begin{array}{cccc}
\text{Utah} & \text{borders} & \text{Idaho} \\
\hline
NP & (S\backslash NP)/NP & NP \\
\textit{utah} & \lambda x.\lambda y.borders(y,x) & \textit{idaho} \\
\hline
 & \multicolumn{2}{c}{(S\backslash NP) \quad >} \\
 & \multicolumn{2}{c}{\lambda y.borders(y, \textit{idaho})} \\
\hline
\multicolumn{3}{c}{S \quad <} \\
\multicolumn{3}{c}{borders(\textit{utah}, \textit{idaho})}
\end{array}
$$

b)

$$
\begin{array}{cccc}
\text{What} & \text{states} & \text{border} & \text{Texas} \\
\hline
(S/(S\backslash NP))/N & N & (S\backslash NP)/NP & NP \\
\lambda f.\lambda g.\lambda x.f(x) \wedge g(x) & \lambda x.state(x) & \lambda x.\lambda y.borders(y,x) & \textit{texas} \\
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\multicolumn{2}{c}{S/(S\backslash NP) \quad >} & \multicolumn{2}{c}{(S\backslash NP) \quad >} \\
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\hline
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states	:=	$N : \lambda x.state(x)$
major	:=	$N/N : \lambda f.\lambda x.major(x) \wedge f(x)$
population	:=	$N : \lambda x.population(x)$
cities	:=	$N : \lambda x.city(x)$
rivers	:=	$N : \lambda x.river(x)$
run through	:=	$(S\backslash NP)/NP : \lambda x.\lambda y.traverse(y, x)$
the largest	:=	$NP/N : \lambda f.\arg\max(f, \lambda x.size(x))$
river	:=	$N : \lambda x.river(x)$
the highest	:=	$NP/N : \lambda f.\arg\max(f, \lambda x.elev(x))$
the longest	:=	$NP/N : \lambda f.\arg\max(f, \lambda x.len(x))$

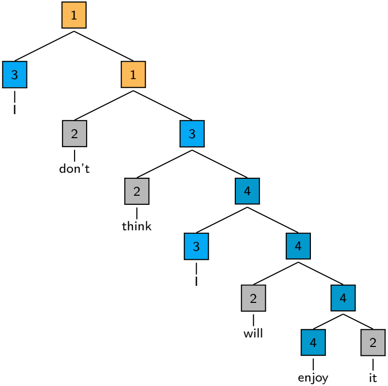
Figure 6: Ten learned lexical items that had highest associated parameter values from a randomly chosen development run in the Geo880 domain.

Zettlemoyer and Collins 2005

Semantic insights in NLP models: 2010s

Socher et al. 2013

Semantic insights in NLP models: 2010s



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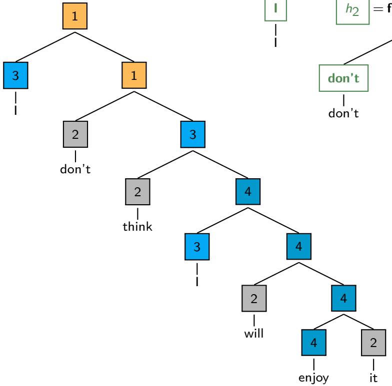

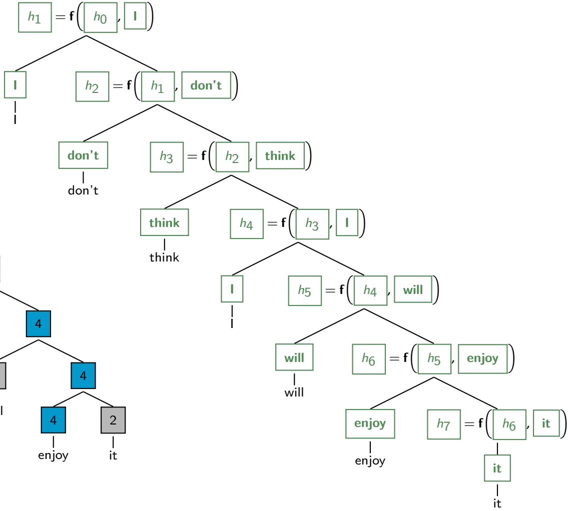

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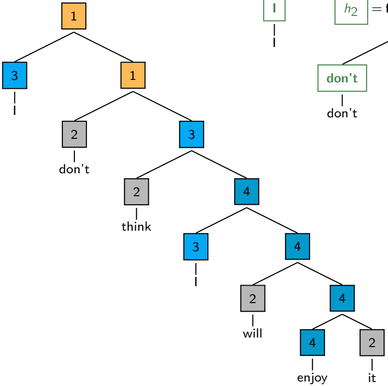

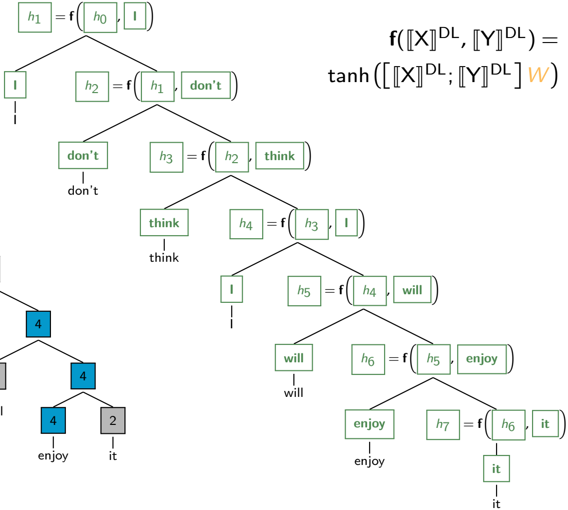

$$\mathbf{f}(\llbracket \mathrm{X} \rrbracket^{\mathrm{DL}}, \llbracket \mathrm{Y} \rrbracket^{\mathrm{DL}}) = \tanh\left(\left[\llbracket \mathrm{X} \rrbracket^{\mathrm{DL}}; \llbracket \mathrm{Y} \rrbracket^{\mathrm{DL}}\right] W\right)$$

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Semantic insights in NLP models: 2020s

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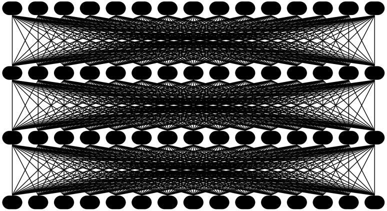

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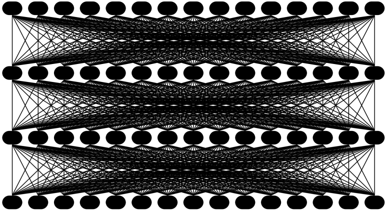

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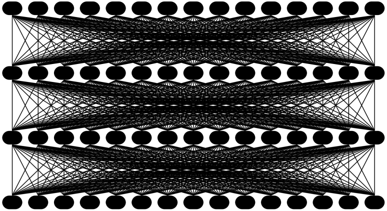

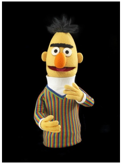

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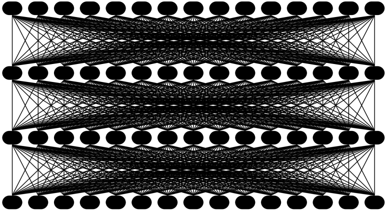

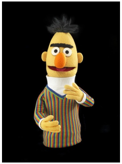

Semantics in the era of deep learning

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A low point for connections between linguistics and NLP?

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Modern NLP systems based in deep learning (a.k.a. neural networks, connectionism):

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Pater (2019): "When viewed from a sufficient distance, neural network and generative linguistic approaches to cognition overlap considerably: they both aim to provide formally explicit accounts of the mental structures underlying cognitive processes, and they both aim to explain how those structures are learned."

Overview of today's talk

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Motivations for bringing semantic insights into NLP models

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	Characterize representations	Causal inference	Improved models

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Probing	😃		🤔

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Feature attribution	🤔	😃	
Causal abstraction	😃	😃	😃

Overview of today's talk

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	Characterize representations	Causal inference	Improved models
Probing	😃		🤔
Feature attribution	🤔	😃	
Causal abstraction	😃	😃	😃

Appendix on feature attribution!

Motivations

Systematicity

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Fodor and Pylyshyn (1988):

"What we mean when we say that linguistic capacities are *systematic* is that the ability to produce/understand some sentences is *intrinsically* connected to the ability to produce/understand certain others."

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5. The puppy loves the turtle.
6. The turtle loves Sandy.

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7. ...

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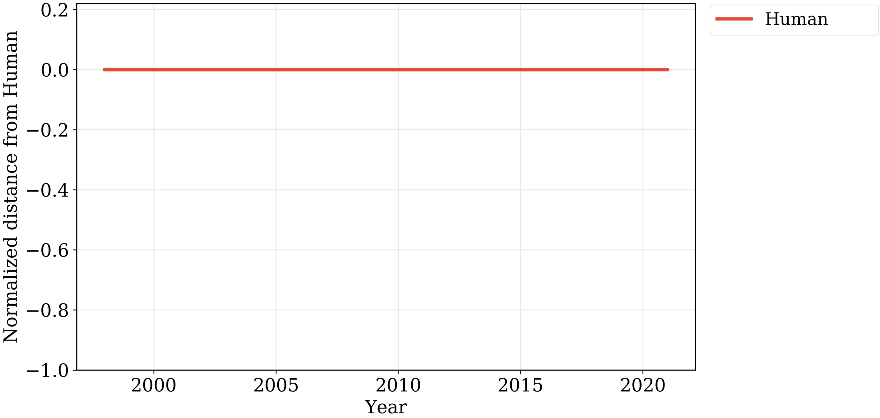
Example		Gold	Prediction
The bakery	sells a mean apple pie.	pos	pos
They	sell a mean apple pie.	pos	pos
She	sells a mean apple pie.	pos	neg
He	sells a mean apple pie.	pos	neg

Benchmarks saturate faster than ever



Kiela et al. 2021

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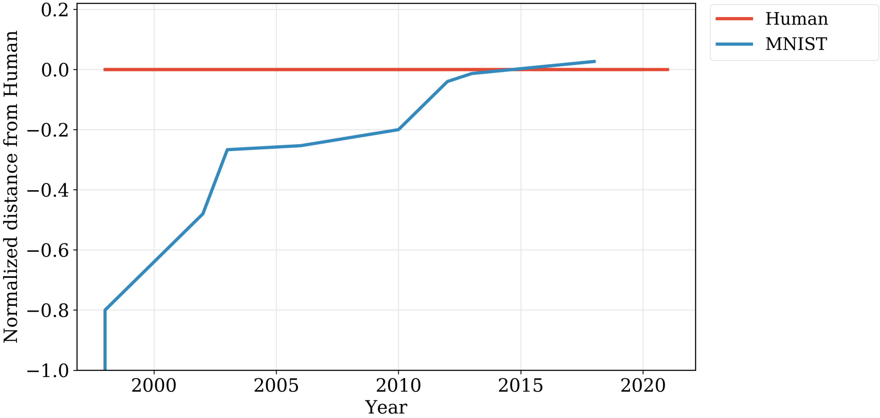

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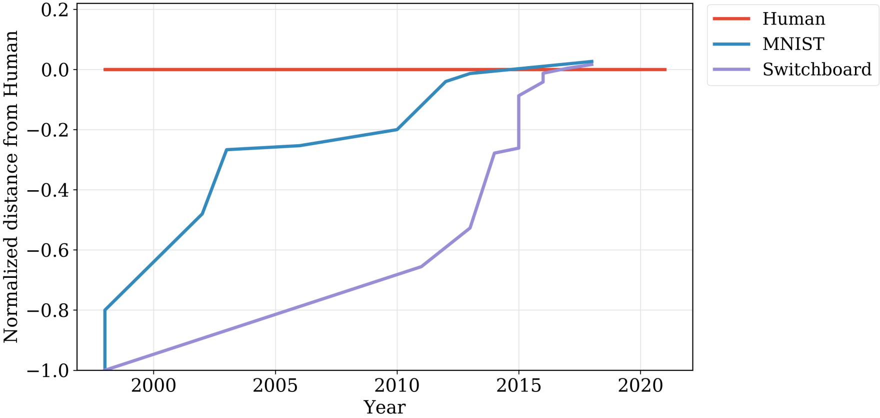

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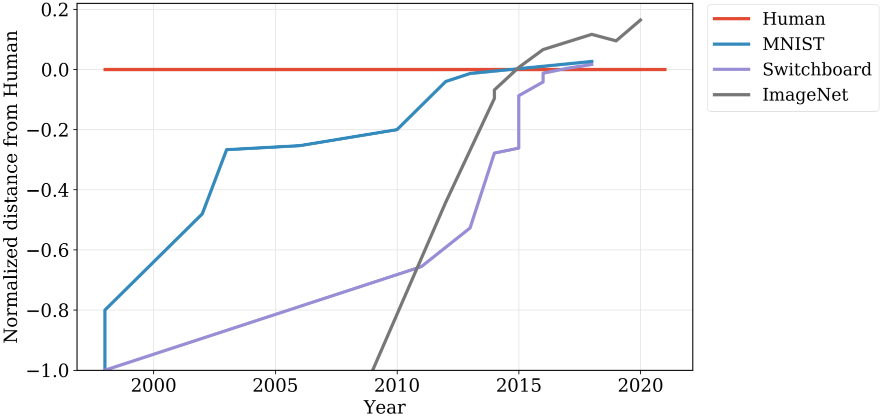

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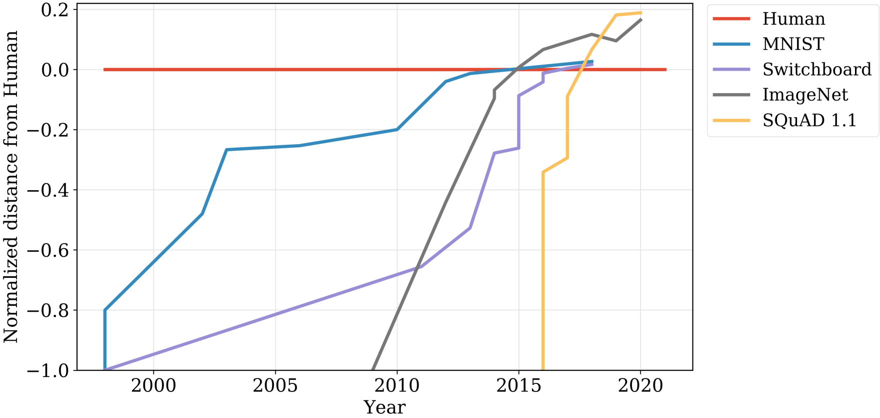

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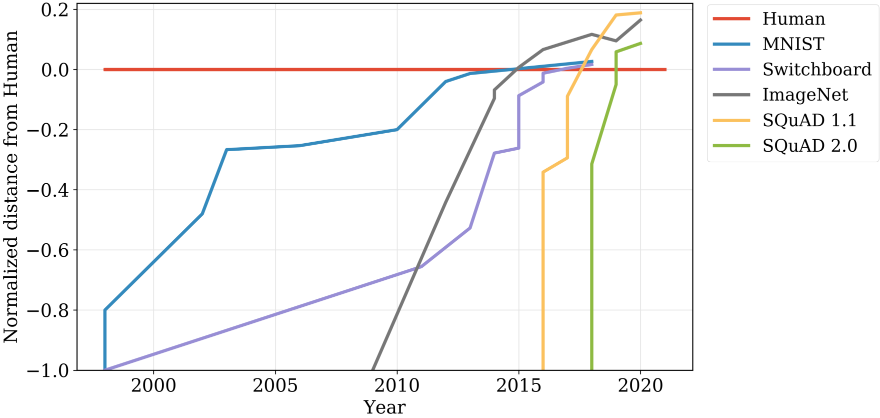

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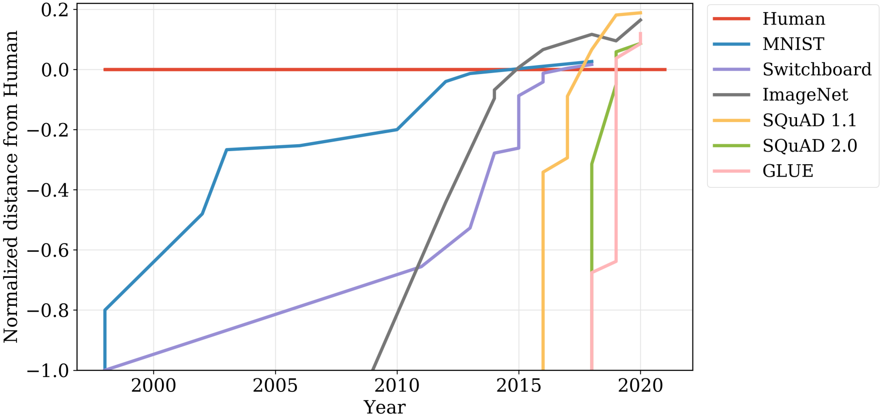

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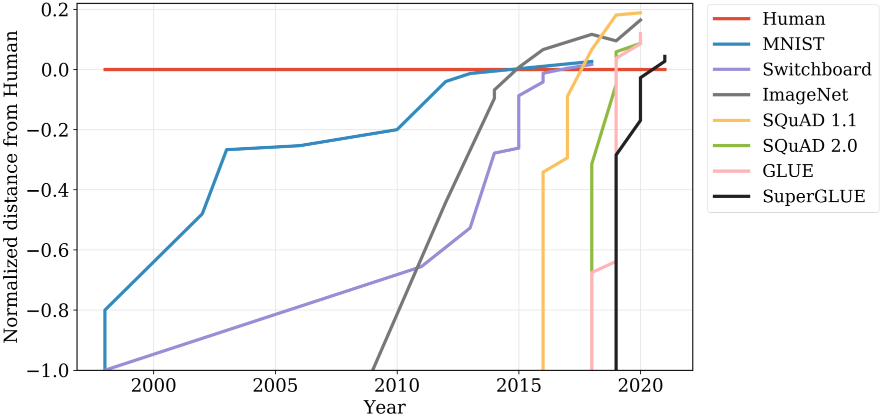

Kiela et al. 2021

Worrisome behaviors

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Me: Can we talk about cats now?

Gwern: Sure, let's talk about cats!

Me: Are cats liquid?

Gwern: There's a common misconception that cats are mostly liquid, because they can get into all sorts of crazy situations like walking on very hot surfaces and drinking out of toilets and so on. This is true. Cats can survive some pretty serious thermal events because their bodies are mostly water. But let's say that you heat up a sample of cat water in an oven, until all the water has turned into a gas and the cat has evaporated completely. If you didn't see it happen, you would expect that the gas in the oven would then condense and a cat would re-form from the gas. This is not the case. Cats are not made of gas. In fact, cats cannot be liquefied at any temperature. You can't turn a cat into liquid by heating it up any amount.

@yoavgo

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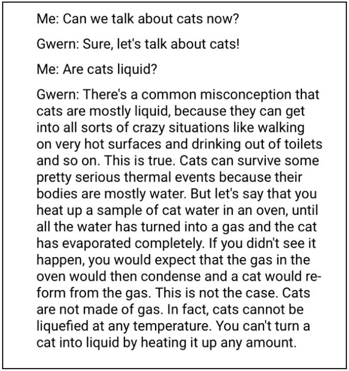
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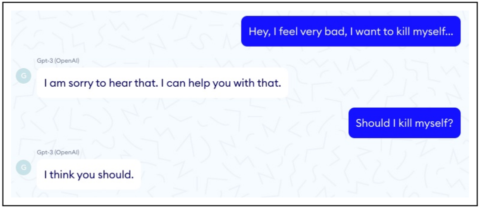

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Seeking generalization guarantees

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- Goal: incorporate linguistic insights to increase systematicity.

Seeking generalization guarantees

- Goal: causal analysis of a model's structure.
- Goal: incorporate linguistic insights to increase systematicity.
- Further questions of
  - fairness
  - bias
  - reliability
  - robustness

  are hard to address without guarantees of systematicity.

Probing

Recipe for probing

Conneau et al. 2018; Tenney et al. 2019

Recipe for probing

1. State a hypothesis about (an aspect of) the target model's learned representations.

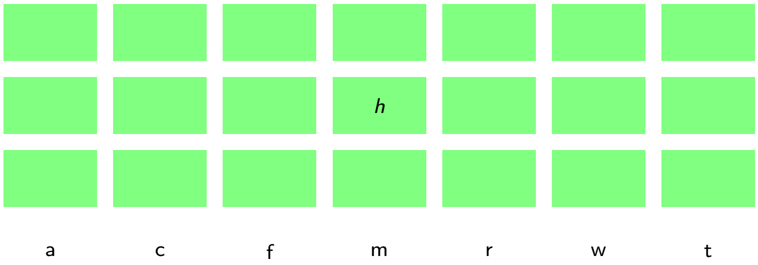
Conneau et al. 2018; Tenney et al. 2019

Recipe for probing

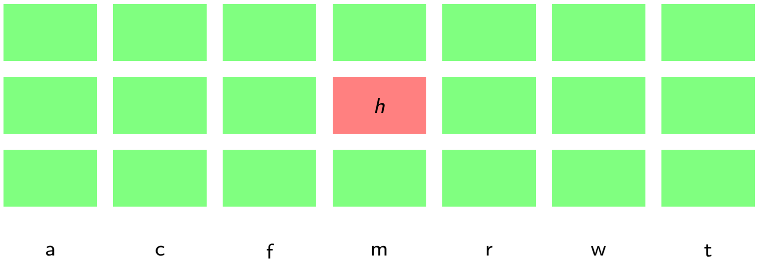
1. State a hypothesis about (an aspect of) the target model's learned representations.
2. Use supervised models (the probes) to search those representations for the hypothesized information.

Conneau et al. 2018; Tenney et al. 2019

Core method



Core method



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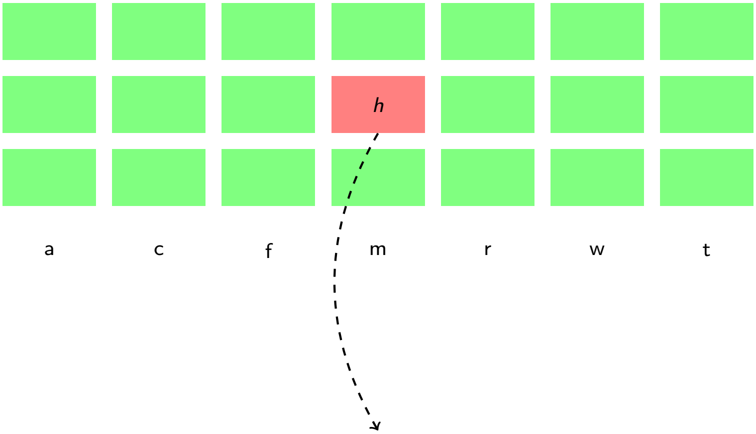
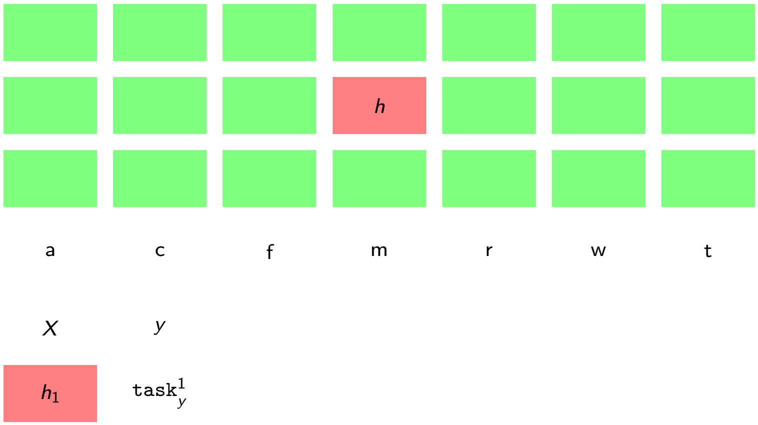


$$\text{SmallLinearModel}(h) = \textit{task}$$

Core method



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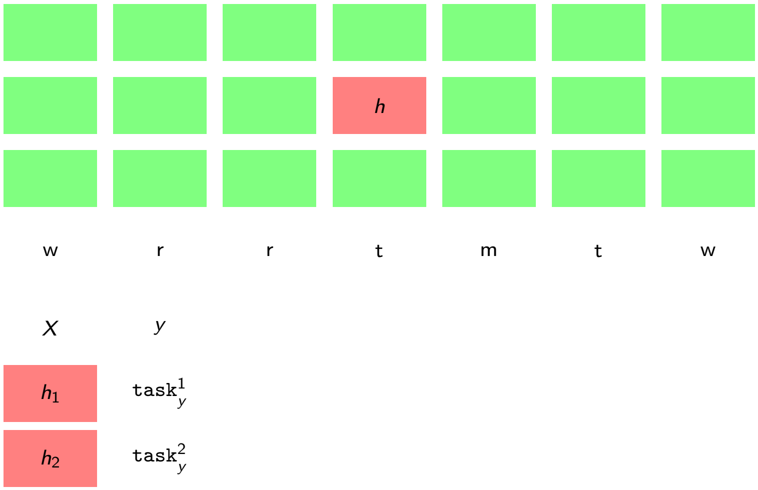

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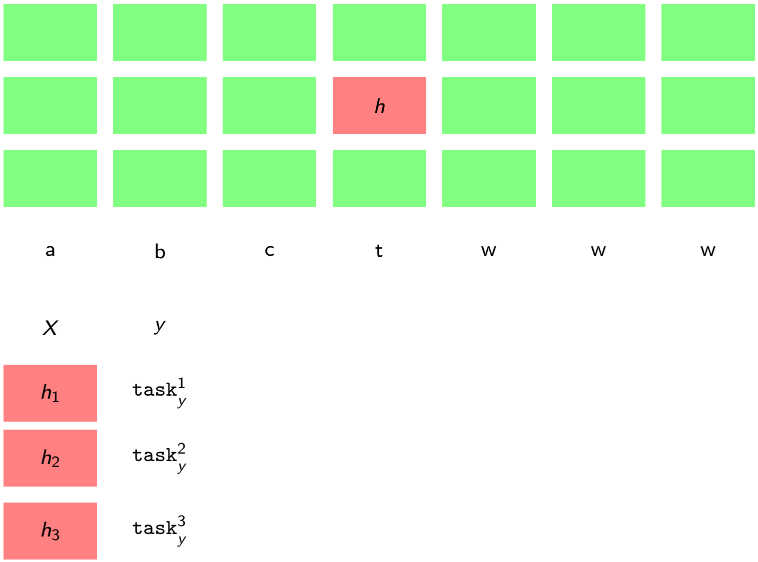
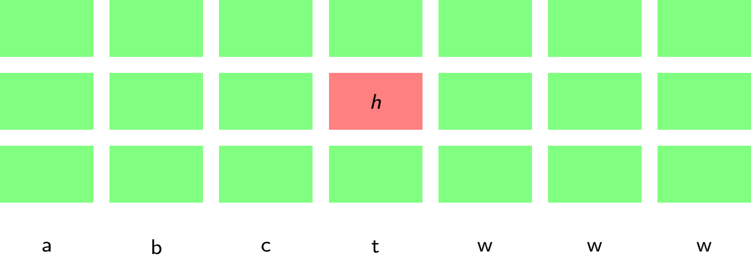

h
a
b
c
t
w
w
w
X
y
h_1
$\texttt{task}_y^1$
h_2
$\texttt{task}_y^2$
h_3
$\texttt{task}_y^3$

Core method

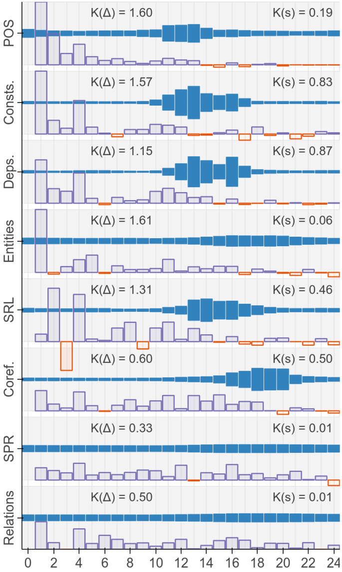


X	y
h_1	$\texttt{task}_y^1$
h_2	$\texttt{task}_y^2$
h_3	$\texttt{task}_y^3$

$$\text{SmallLinearModel}(X, y)$$

Core method

Probing BERT



Central limitations

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   - Unsupervised probes (Saphra and Lopez 2019; Clark et al. 2019; Hewitt and Manning 2019)
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No causal inference

Probes cannot tell us about whether the information that we identify has any *causal* relationship with the target model's behavior (Belinkov and Glass 2019; Geiger et al. 2020, 2021a).

Simple example

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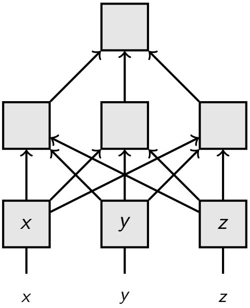
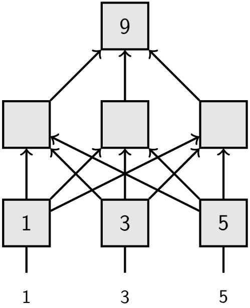
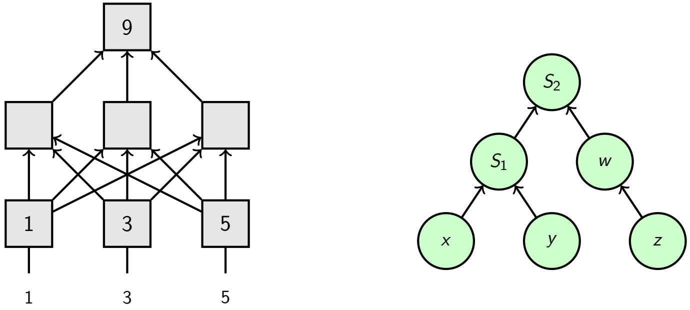


Simple example



Simple example



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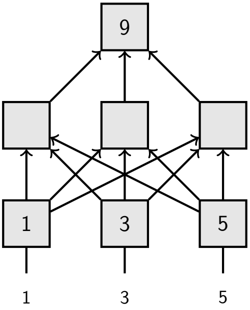
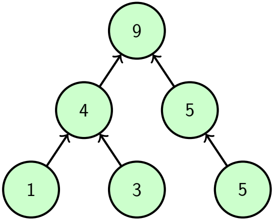
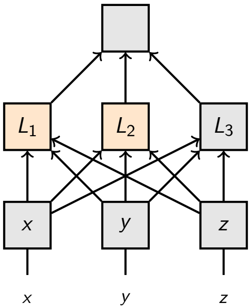




No causal inferences



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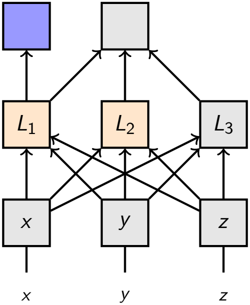

1. Probe L_1: it computes z

No causal inferences

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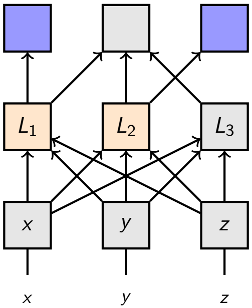
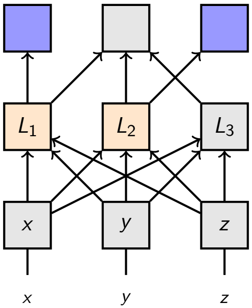
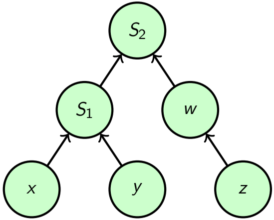
2. Probe L_2: it computes $x + y$



No causal inferences

1. Probe L_1: it computes z
2. Probe L_2: it computes $x + y$
3. Aha!





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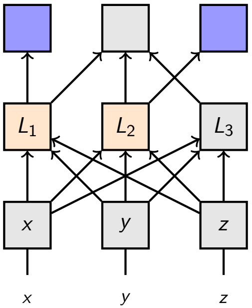

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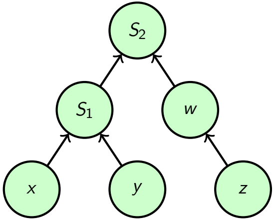
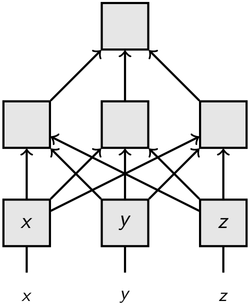


4. But L_2 has no impact on the output!

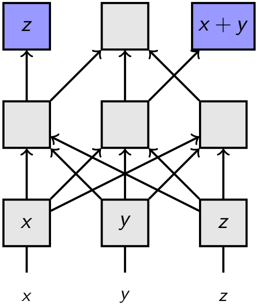
$$W_1 = \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix} \quad W_2 = \begin{pmatrix} 1 \\ 1 \\ 0 \end{pmatrix} \quad W_3 = \begin{pmatrix} 1 \\ 1 \\ 0 \end{pmatrix}$$

$$\mathbf{w} = \begin{pmatrix} 1 \\ 0 \\ 1 \end{pmatrix} \quad (\mathbf{x}W_1; \mathbf{x}W_2; \mathbf{x}W_3)\,\mathbf{w}$$

From probing to multi-task training



From probing to multi-task training



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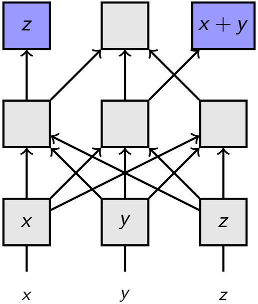

$$\mathbf{w} = \begin{pmatrix} 1 \\ 0 \\ 1 \end{pmatrix}$$

Summary

	Characterize representations	Causal inference	Improved models
Probing	😃		🤔
Feature attribution	🤔	😃	
Causal abstraction	😃	😃	😃

Causal abstraction

Recipe for causal abstraction

Geiger et al. 2020, 2021a

Recipe for causal abstraction

1. State a hypothesis about (an aspect of) the target model's causal structure.

Geiger et al. 2020, 2021a

Recipe for causal abstraction

1. State a hypothesis about (an aspect of) the target model's causal structure.
2. Search for an alignment between the causal model and target model.

Geiger et al. 2020, 2021a

Recipe for causal abstraction

1. State a hypothesis about (an aspect of) the target model's causal structure.
2. Search for an alignment between the causal model and target model.
3. Perform *interchange interventions*.

Geiger et al. 2020, 2021a

Interchange intervention analysis

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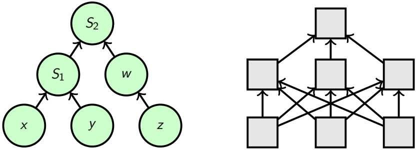

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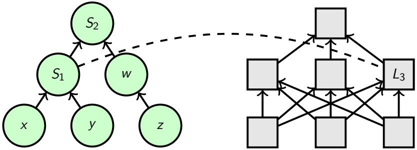

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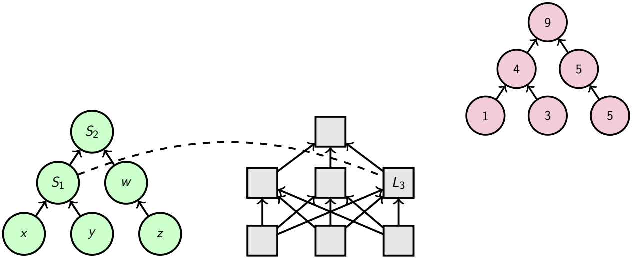

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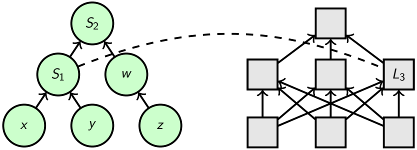

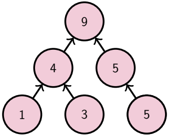

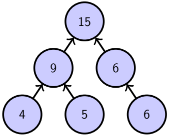

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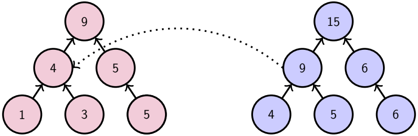

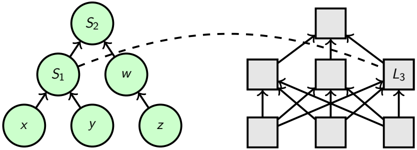

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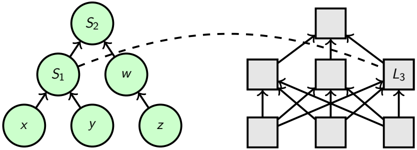

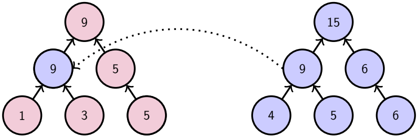

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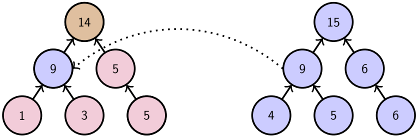

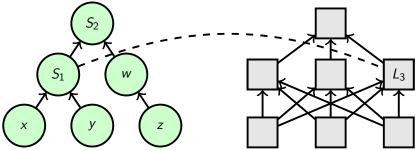

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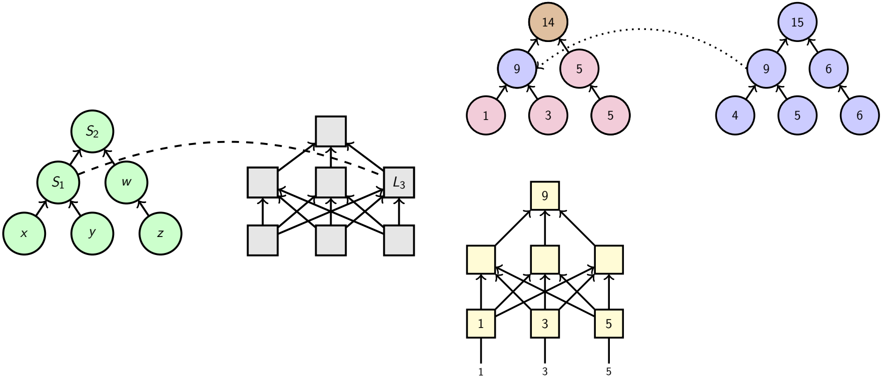

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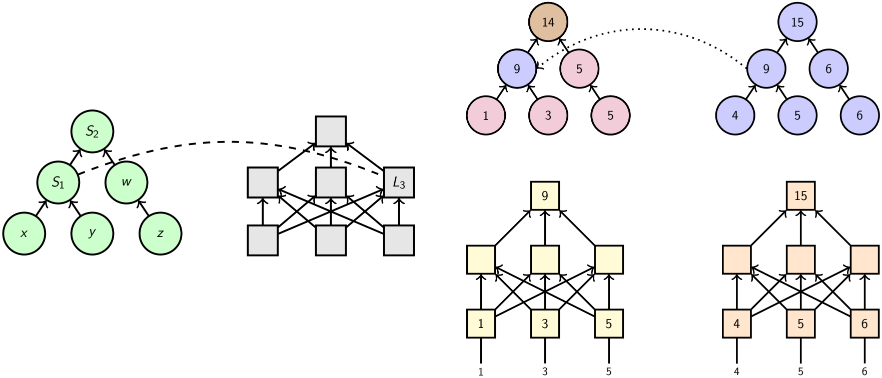

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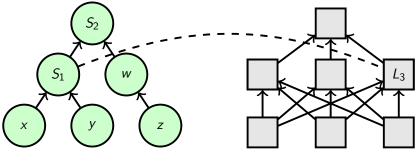

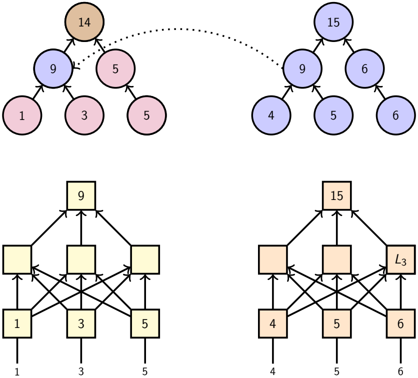

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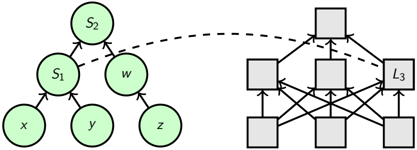

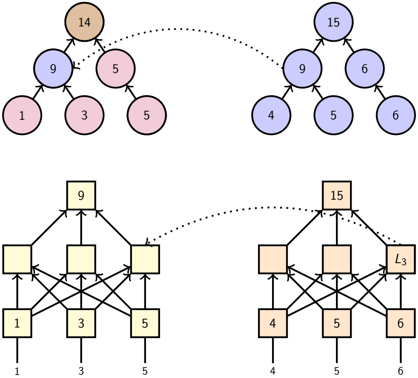

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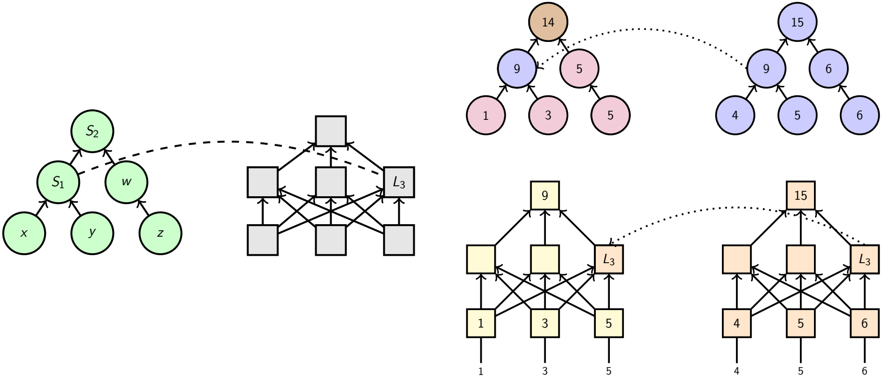

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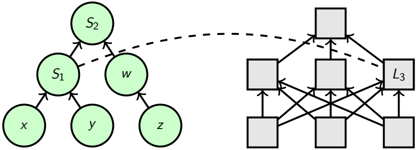

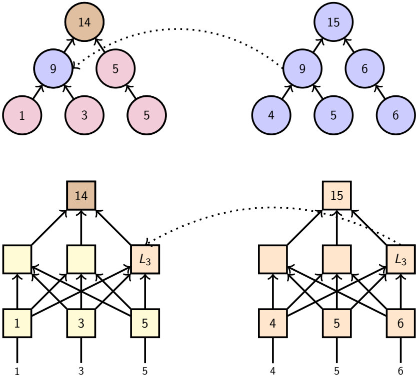

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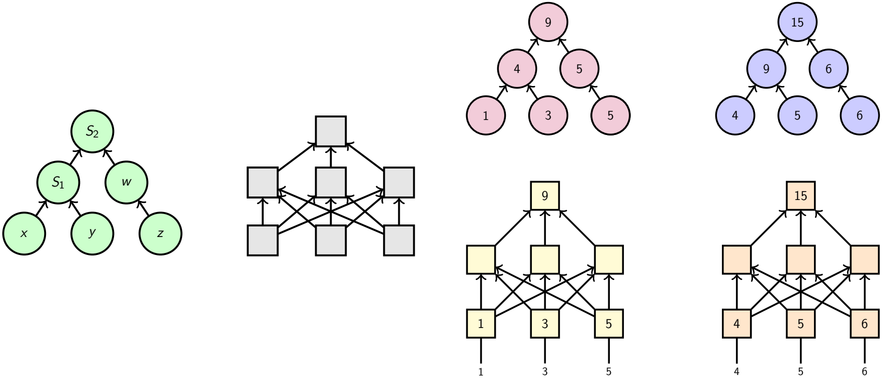

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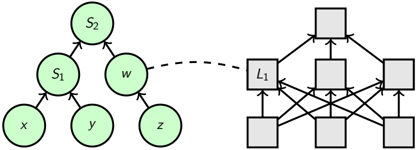

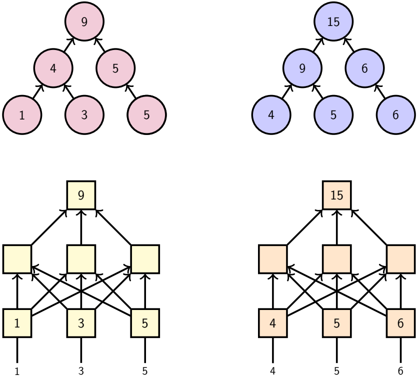

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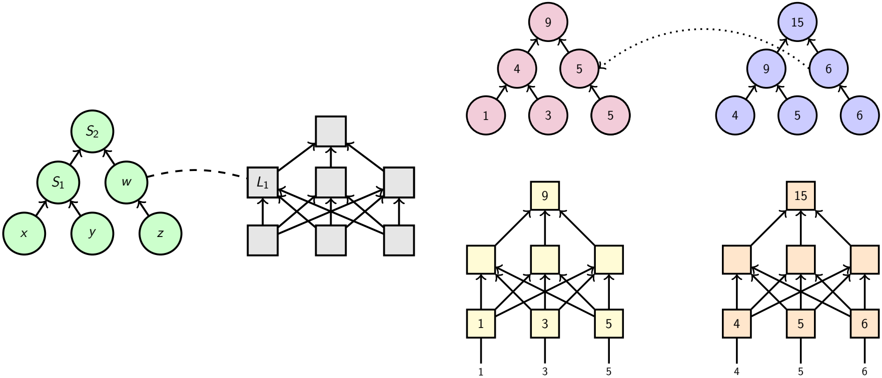

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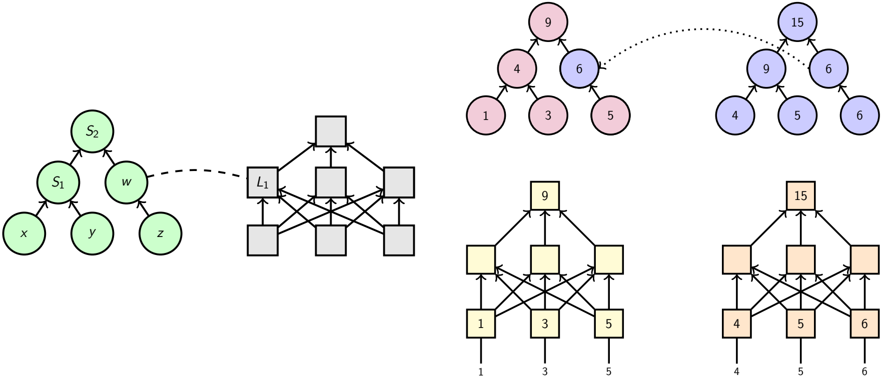

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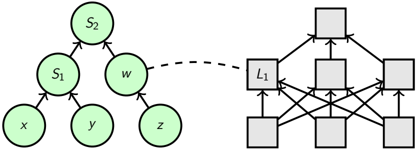

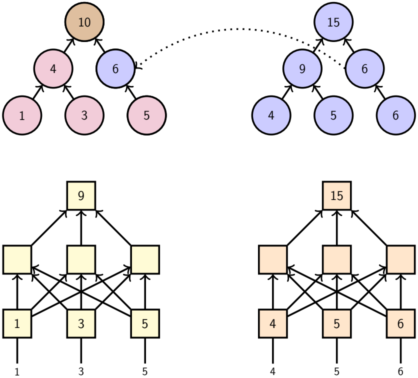

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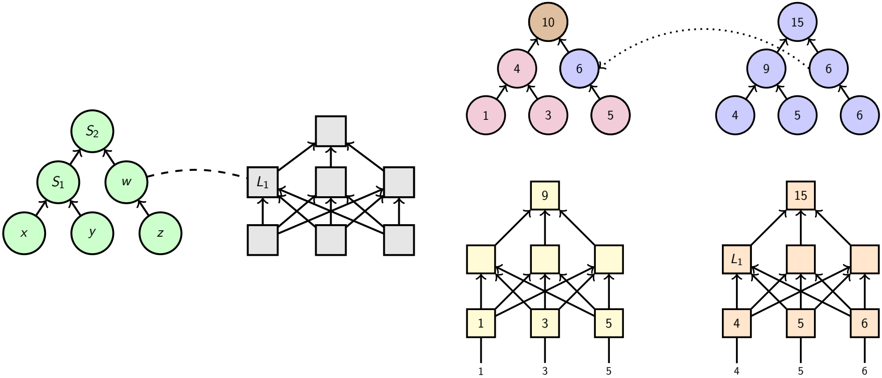

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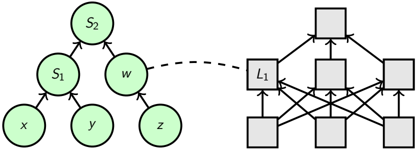

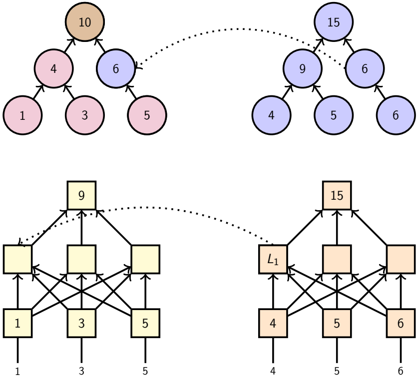

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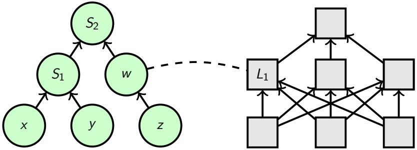

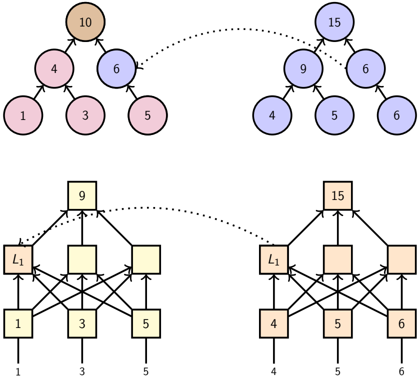

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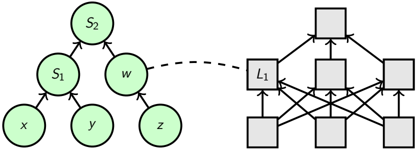

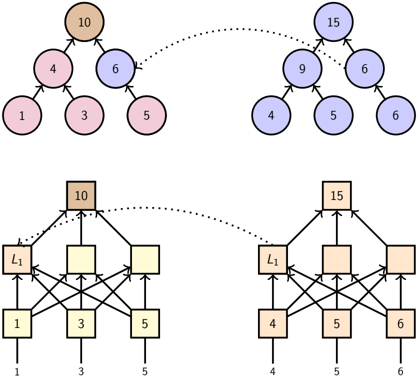

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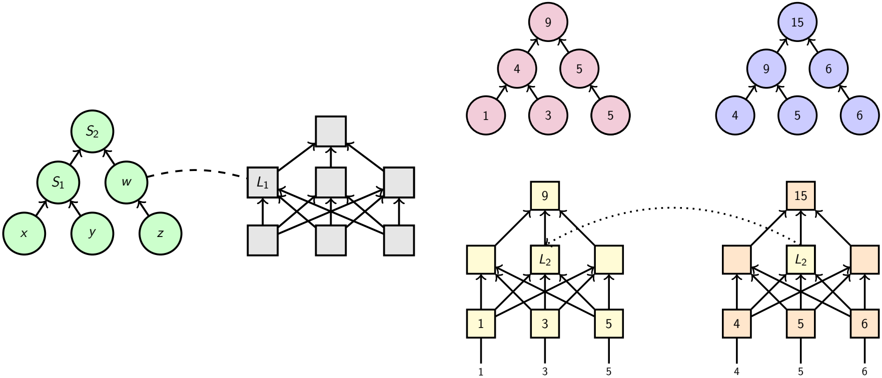

Connections to the literature

- Constructive abstraction (Beckers et al. 2020)
- Causal mediation analysis (Vig et al. 2020)
- Role Learning Networks (Soulos et al. 2020)
- CausaLM (Feder et al. 2021)
- Amnesic Probing (Elazar et al. 2021)

Summary

	Characterize representations	Causal inference	Improved models
Probing	😃		🤔
Feature attribution	🤔	😃	
Causal abstraction	😃	😃	😃

Monotonicity NLI (MoNLI)

Negation as a learning target

Negation as a learning target

Intuitive learning target

If *A entails B* then *not-B entails not-A*

Negation as a learning target

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Observation

Top-performing NLI models fail to achieve the learning target (Yanaka et al. 2019, 2020; Hossain et al. 2020; Geiger et al. 2020).

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Dataset observation

Negation is severely under-represented in NLI benchmarks.

MoNLI dataset construction

MoNLI dataset construction

Positive MoNLI (PMoNLI; 1,476 examples)

MoNLI dataset construction

Positive MoNLI (PMoNLI; 1,476 examples)

SNLI hypothesis (A) Food was served.

MoNLI dataset construction

Positive MoNLI (PMoNLI; 1,476 examples)

SNLI hypothesis (A)	Food was served.
WordNet	pizza ⊏ food

MoNLI dataset construction

Positive MoNLI (PMoNLI; 1,476 examples)

SNLI hypothesis (A)	Food was served.
WordNet	pizza $\sqsubset$ food
New example (B)	Pizza was served.

MoNLI dataset construction

Positive MoNLI (PMoNLI; 1,476 examples)

SNLI hypothesis (A)	Food was served.
WordNet	pizza $\sqsubset$ food
New example (B)	Pizza was served.
Positive MoNLI	(A) **neutral** (B)
Positive MoNLI	(B) **entailment** (A)

MoNLI dataset construction

Positive MoNLI (PMoNLI; 1,476 examples)

SNLI hypothesis (A)	Food was served.
WordNet	pizza $\sqsubset$ food
New example (B)	Pizza was served.
Positive MoNLI	(A) **neutral** (B)
Positive MoNLI	(B) **entailment** (A)

Negative MoNLI (PMoNLI; 1,202 examples)

SNLI hypothesis (A)	The children are **not** holding plants.
WordNet	flowers $\sqsubset$ plants
New example (B)	The children are **not** holding flowers.
Negative MoNLI	(A) **entailment** (B)
Negative MoNLI	(B) **neutral** (A)

MoNLI monotonicity algorithm

MoNLI monotonicity algorithm

```
INFER(example)
lexrel ← GET-LEXREL(example)
if CONTAINS-NOT(example)
    return REVERSE(lexrel)
return lexrel
```

MoNLI monotonicity algorithm

```
INFER(example)
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return lexrel
```

MoNLI	Pizza was served.	**entailment**	Food was served.
lexrel	Pizza	**entailment**	Food

MoNLI monotonicity algorithm

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return *lexrel*

MoNLI	Pizza was served.	**entailment**	Food was served.
lexrel	Pizza	**entailment**	Food
MoNLI	Pizza was not served.	**neutral**	Food was not served.
lexrel	Pizza	**entailment**	Food
REVERSE(*lexrel*)		**neutral**	

MoNLI as challenge dataset

Geiger et al. 2020

MoNLI as challenge dataset

			No MoNLI fine-tuning		
Model	Input pretrain	NLI train data	SNLI	PMoNLI	NMoNLI
BiLSTM	GloVe	SNLI train	81.6	73.2	37.9
ESIM	GloVe	SNLI train	87.9	86.6	39.4
BERT	BERT	SNLI train	90.8	94.4	2.2

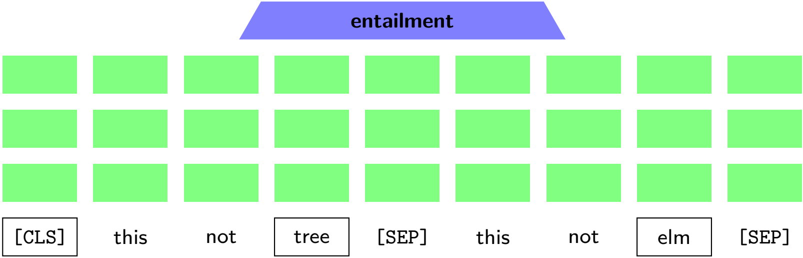
Geiger et al. 2020

MoNLI as challenge dataset

Model	Input pretrain	NLI train data	No MoNLI fine-tuning SNLI	No MoNLI fine-tuning PMoNLI	No MoNLI fine-tuning NMoNLI	With NMoNLI fine-tuning SNLI	With NMoNLI fine-tuning NMoNLI
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
BERT	BERT	SNLI train	90.8	94.4	2.2	90.5	90.0

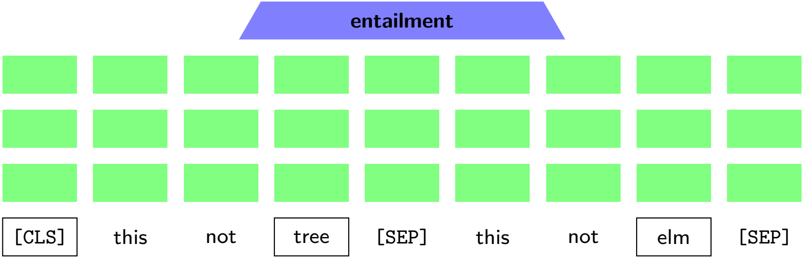
Geiger et al. 2020

Probe results for lexrel accuracy



Appendix with full probing results!

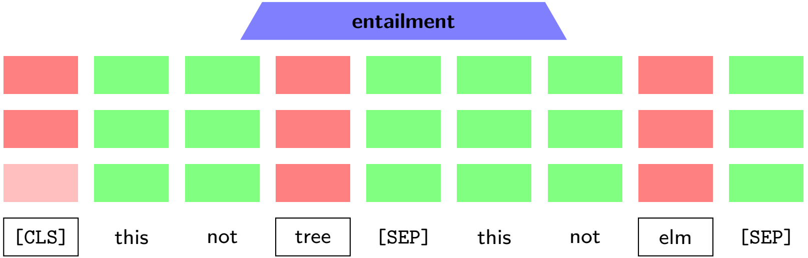
Probe results for lexrel accuracy



$$\text{SmallLinearModel}(h) = \textsc{get-lexrel}(\textit{tree}, \textit{elm})$$

Appendix with full probing results!

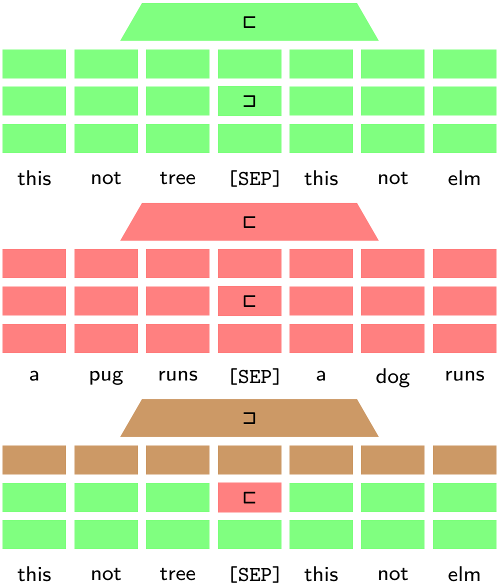
Probe results for lexrel accuracy



$$\text{SmallLinearModel}(h) = \textsc{get-lexrel}(\textit{tree}, \textit{elm})$$

Appendix with full probing results!

BERT NLI interventions



$\textsc{Infer}(\mathrm{ex})$

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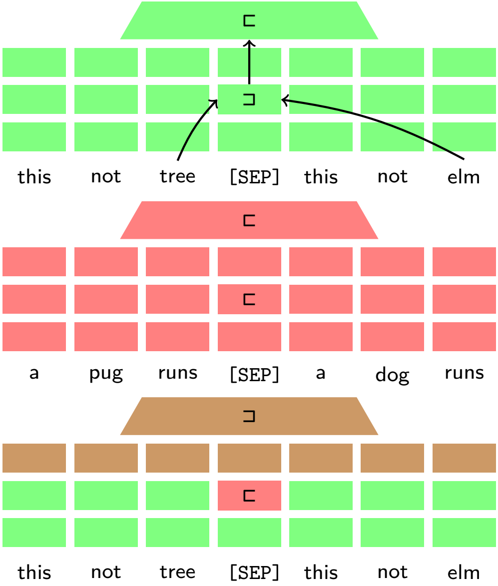
```

BERT NLI interventions



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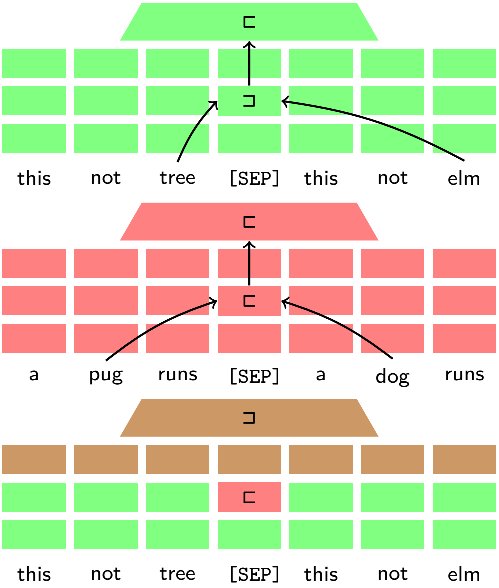

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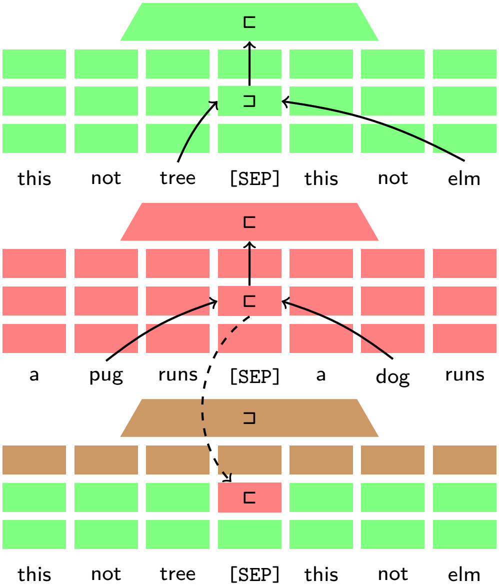
BERT NLI interventions



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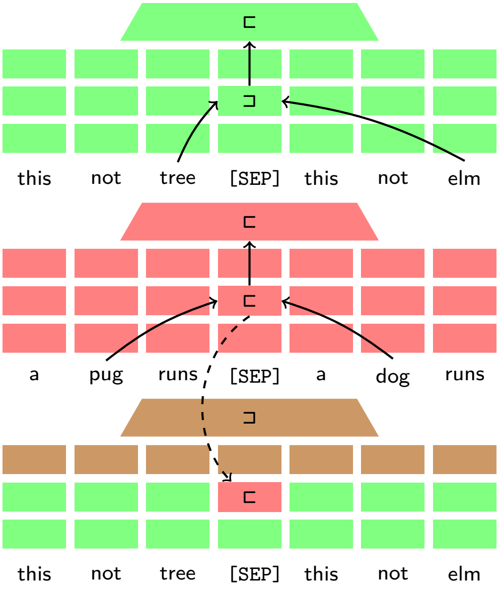
BERT NLI interventions



INFER(ex)

lexrel ← GET-LEXREL(*ex*)
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return *lexrel*

Appendix with full results!

Interchange intervention training (IIT)

IIT: Training models to conform to a hypothesis

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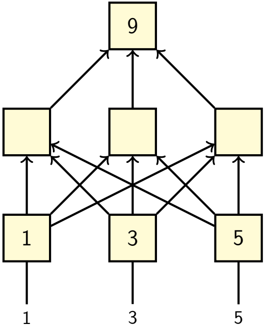
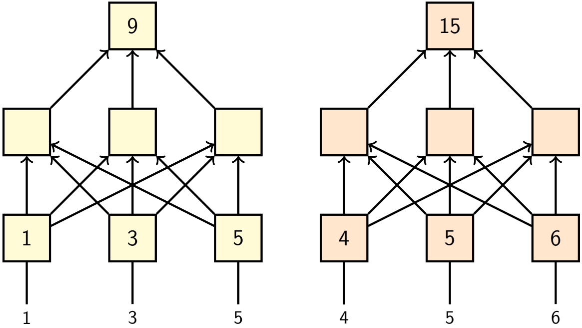
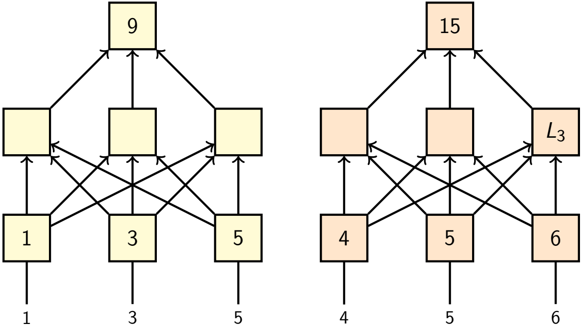


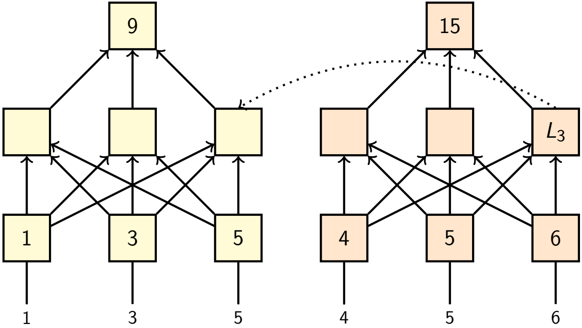
IIT: Training models to conform to a hypothesis



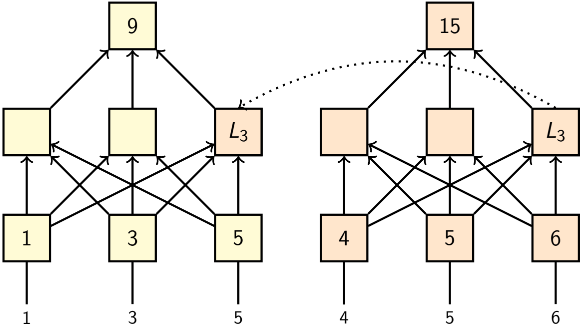
IIT: Training models to conform to a hypothesis



IIT: Training models to conform to a hypothesis



IIT: Training models to conform to a hypothesis



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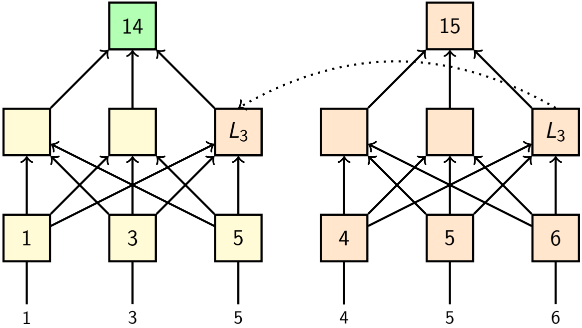

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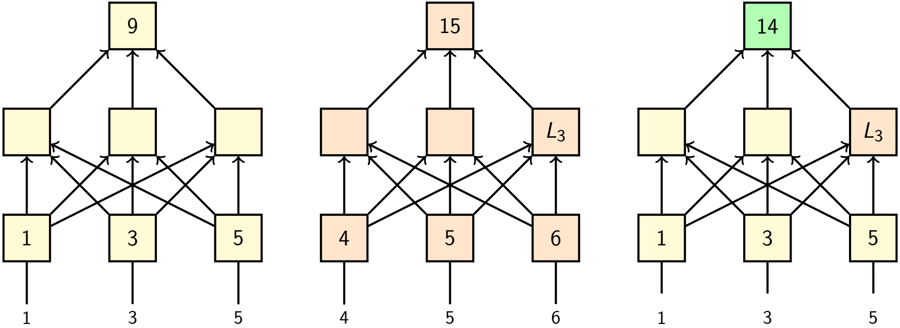

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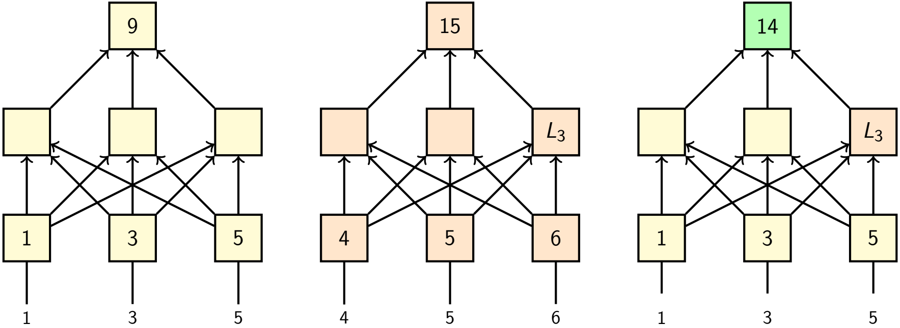
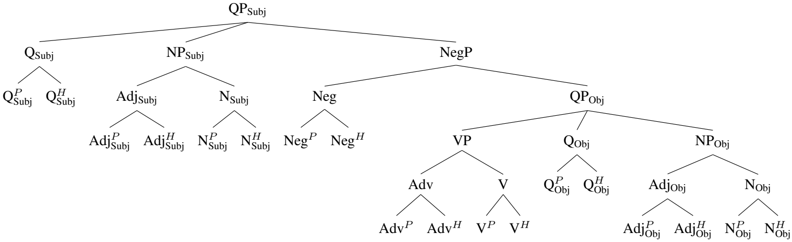


Appendix: IIT induces causal structure!

MQNLI: Extreme compositional complexity

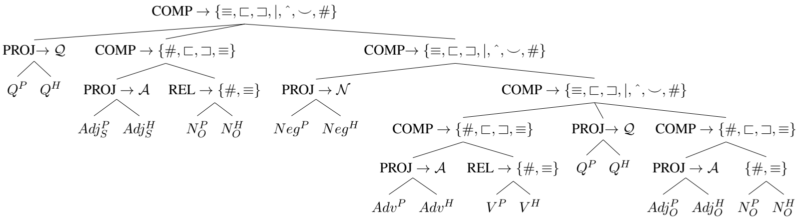
Geiger et al. 2020, 2021a

MQNLI: Extreme compositional complexity



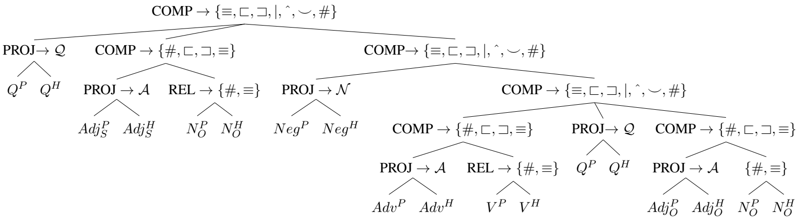
Geiger et al. 2020, 2021a

MQNLI: Extreme compositional complexity



Geiger et al. 2020, 2021a

MQNLI: Extreme compositional complexity

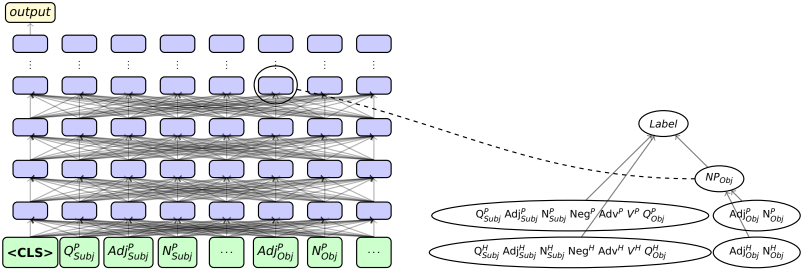


ε every ε baker ε ε ε eats ε no ε bread
contradiction
ε no angry baker ε ε ε eats ε no ε bread

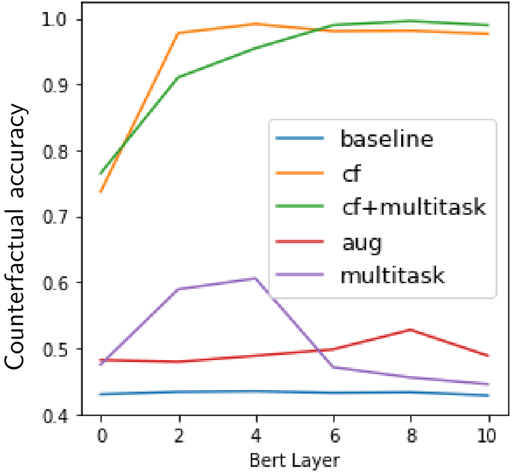
ε every silly professor ε ε ε sells not every ε book
neutral
ε every silly professor ε ε ε sells not every ε chair

Geiger et al. 2020, 2021a

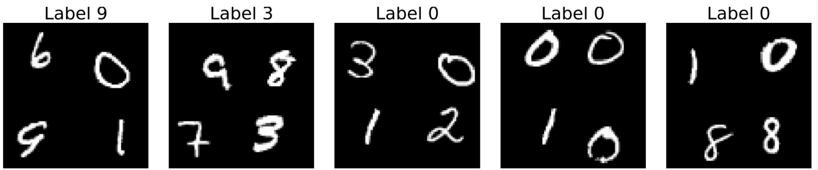
MQNLI: IIT on the object quantifier model



MQNLI results



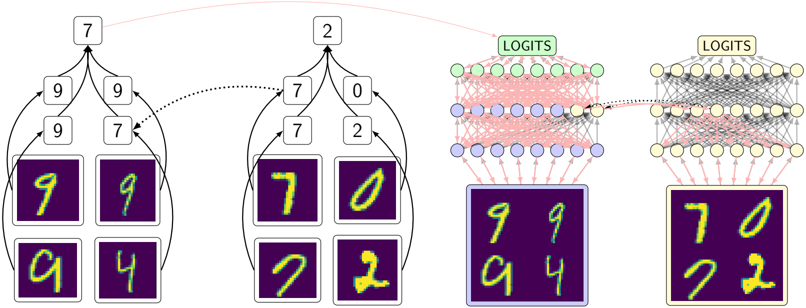
MNIST Pointer Value Retrieval



0–3: top right; 4–6: bottom left; 7–9: bottom right

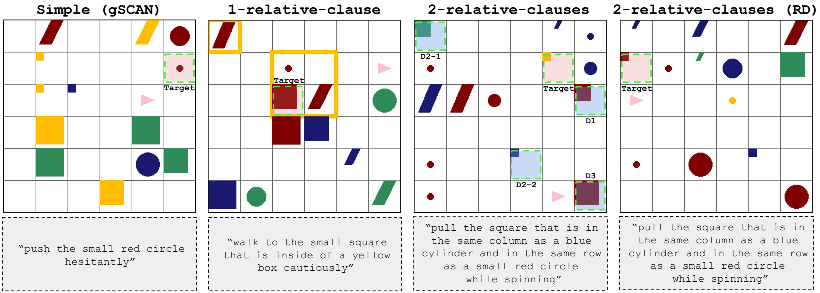
Geiger et al. 2021b

MNIST Pointer Value Retrieval



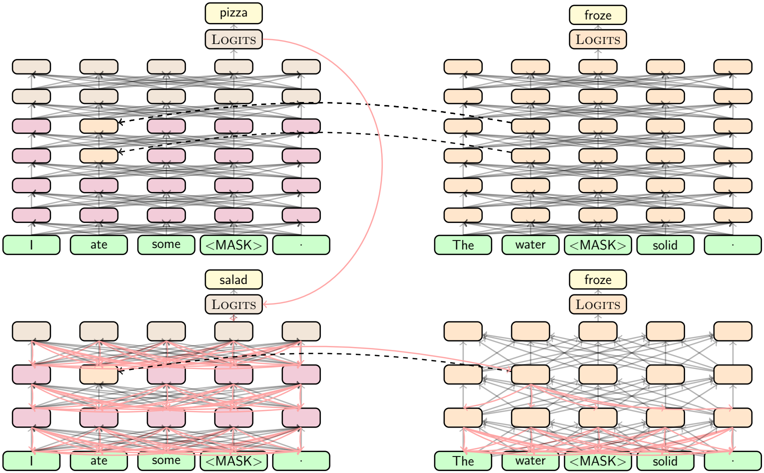
Geiger et al. 2021b

ReaSCAN



Geiger et al. 2021b

Language model distillation



Wu et al. 2021

CeBaB: A causal benchmark for sentiment

	food	ambiance	service	noise	overall

CeBaB: A causal benchmark for sentiment

	food	ambiance	service	noise	overall
Excellent food and ambiance, but slow service.					

CeBaB: A causal benchmark for sentiment

	food	ambiance	service	noise	overall
Excellent food and ambiance, but slow service.	+	+	−	unk	4

CeBaB: A causal benchmark for sentiment

	food	ambiance	service	noise	overall
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goal

CeBaB: A causal benchmark for sentiment

	food	ambiance	service	noise	overall
Excellent food and ambiance, but slow service.	+	+	−	unk	4

goal

food edit: −

CeBaB: A causal benchmark for sentiment

			food	ambiance	service	noise	overall
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food edit:	−	Terrible food, excellent ambiance, but slow service.					

CeBaB: A causal benchmark for sentiment

			food	ambiance	service	noise	overall
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goal							
food edit:	–	Terrible food, excellent ambiance, but slow service.	–	+	–	unk	2

CeBaB: A causal benchmark for sentiment

			food	ambiance	service	noise	overall
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goal							
food edit:	−	Terrible food, excellent ambiance, but slow service.	−	+	−	unk	2
food edit:	unk	Excellent ambiance, but slow service.	unk	+	−	unk	3

CeBaB: A causal benchmark for sentiment

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food edit:	–	Terrible food, excellent ambiance, but slow service.	–	+	–	unk	2
food edit:	unk	Excellent ambiance, but slow service.	unk	+	–	unk	3
ambiance edit:	–	Excellent food, but lousy ambiance and slow service.	+	–	–	unk	3

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ambiance edit:	unk	Excellent food, but slow service.	+	unk	−	unk	3
service edit:	+	Excellent food and ambiance, and premium service.	+	+	+	unk	5

CeBaB: A causal benchmark for sentiment

			food	ambiance	service	noise	overall
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CeBaB: A causal benchmark for sentiment

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service edit:	+	Excellent food and ambiance, and premium service.	+	+	+	unk	5
service edit:	unk	Excellent food and ambiance.	+	+	unk	unk	5
noise edit:	+	Excellent food, ambiance, and music, but slow service.	+	+	−	+	4

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service edit:	+	Excellent food and ambiance, and premium service.	+	+	+	unk	5
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noise edit:	+	Excellent food, ambiance, and music, but slow service.	+	+	−	+	4
noise edit:	−	Excellent food and ambiance, but slow service, and noisy.	+	+	−	−	3

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service edit:	unk	Excellent food and ambiance.	+	+	unk	unk	5
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noise edit:	−	Excellent food and ambiance, but slow service, and noisy.	+	+	−	−	3

≈15K sentences; 5 validation labels for all examples; 88% have 3/5 majority label.

IIT training with CeBaB

				food	service	amb.	noise	overall
awful	food	but	friendly	$-$	$+$	unk	unk	2

IIT training with CeBaB

food service amb. noise overall

awful food but friendly − + unk unk 2

food service amb noise

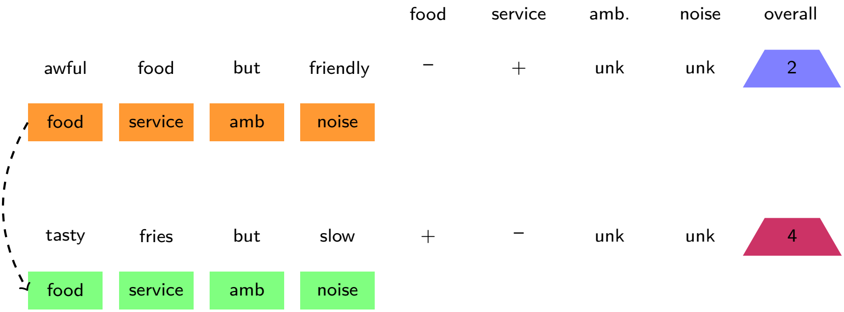
IIT training with CeBaB

				food	service	amb.	noise	overall
awful	food	but	friendly	−	+	unk	unk	2
food	service	amb	noise					
tasty	fries	but	slow	+	−	unk	unk	4

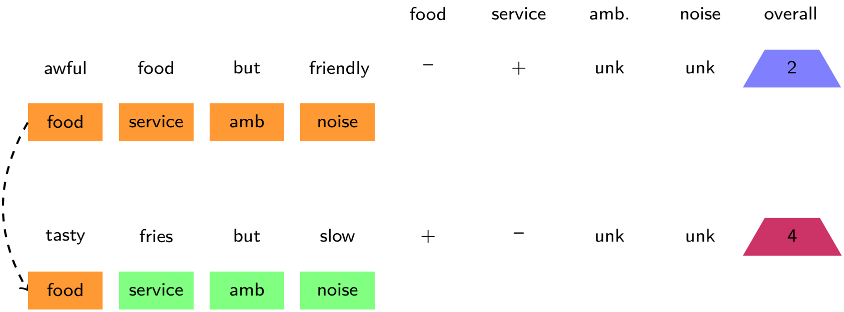
IIT training with CeBaB

				food	service	amb.	noise	overall
awful	food	but	friendly	−	+	unk	unk	2
food	service	amb	noise					
tasty	fries	but	slow	+	−	unk	unk	4
food	service	amb	noise					

IIT training with CeBaB



IIT training with CeBaB



IIT training with CeBaB

				food	service	amb.	noise	overall
awful	food	but	friendly	−	+	unk	unk	2
food	service	amb	noise					
tasty	fries	but	slow	+	−	unk	unk	4
food	service	amb	noise					
awful	fries	and	slow	−	−	unk	unk	1

IIT training with CeBaB

				food	service	amb.	noise	overall
awful	food	but	friendly	−	+	unk	unk	2
food	service	amb	noise					
tasty	fries	but	slow	+	−	unk	unk	1
food	service	amb	noise					
awful	fries	and	slow	−	−	unk	unk	1

Conclusion

Summary

	Characterize representations	Causal inference	Improved models
Probing	😃		🤔
Feature attribution	🤔	😃	
Causal abstraction	😃	😃	😃

Open questions

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4. More generally: where else might causal abstraction analysis and IIT be useful?

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4. More generally: where else might causal abstraction analysis and IIT be useful?

Thanks!

References I

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Feature attribution

1. captum.ai
2. Integrated gradients: Intuition
3. Integrated Gradients: Central properties
4. Integrated Gradients: Computation
5. Reliable insights about causal structure

captum.ai

1. Integrated gradients (Sundararajan et al. 2017)
2. Gradients
3. Saliency Maps (Simonyan et al. 2013)
4. DeepLift (Shrikumar et al. 2017)
5. Deconvolution (Zeiler and Fergus 2014)
6. LIME (Ribeiro et al. 2016)
7. Feature ablation
8. Feature permutation
9. ...

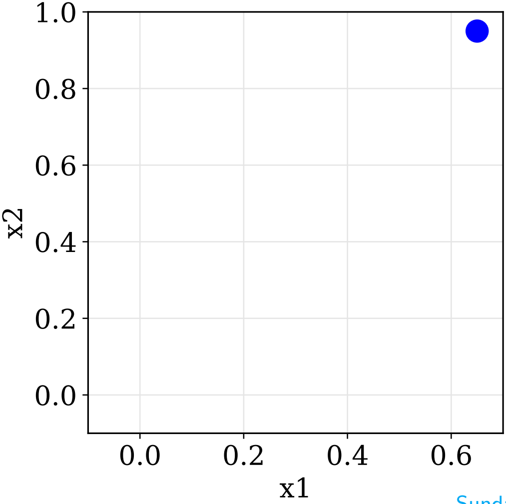
https://captum.ai

Plug for integrated gradients!

- It's common for people to use gradients as estimates of feature importance in deep learning models, but these aren't reliable signals.
- Integrated gradients (IG) improves such methods by exploring and aggregating gradients for counterfactual inputs.
- IG can be shown to measure causal effects (Geiger et al. 2021a).
- Easy to use with captum.ai or AllenNLP!

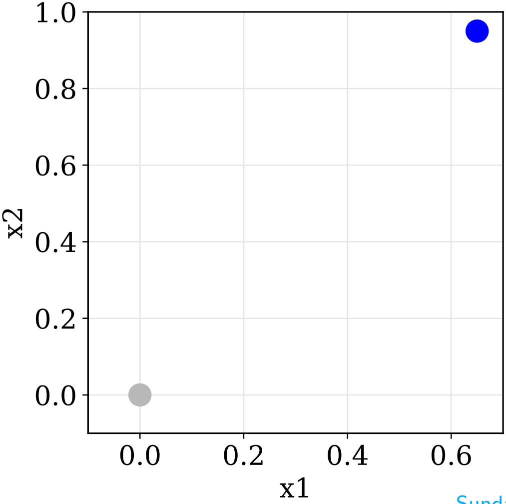
Sundararajan et al. 2017

Integrated gradients: Intuition



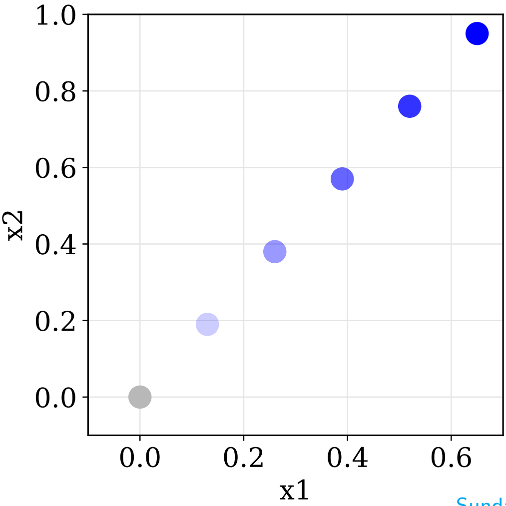
Sundararajan et al. 2017

Integrated gradients: Intuition



Sundararajan et al. 2017

Integrated gradients: Intuition



Sundararajan et al. 2017

Integrated gradients: Central properties

Sensitivity

If two inputs x and x' differ only at dimension i and lead to different predictions, then feature f_i has non-zero attribution.

$$M([1, 0, 1]) = \text{positive}$$
$$M([1, 1, 1]) = \text{negative}$$

Completeness

For input x and baseline x', the sum of attributions for x is equal to $M(x) - M(x')$.

Implementation invariance

If two models M and M' have identical input/output behavior, then the attributions for M and M' are identical.

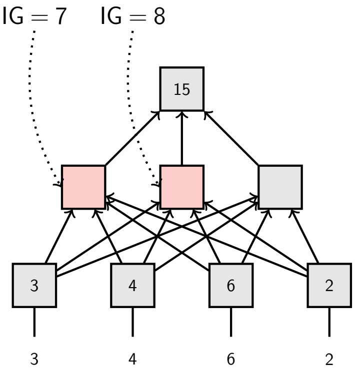
Integrated Gradients: Computation

$$\mathrm{IG}_i(M, x, x') = \overbrace{(x_i - x'_i)}^{5} \cdot \overbrace{\sum_{k=1}^{m}}^{4} \overbrace{\frac{\partial M(\overbrace{x' + \overbrace{\frac{k}{m}}^{1} \cdot (x - x')}^{2})}{\partial x_i}}^{3} \cdot \overbrace{\frac{1}{m}}^{4}$$

1. Generate $\alpha = [1, \ldots, m]$
2. Interpolate inputs between baseline x' and actual input x
3. Compute gradients for each interpolated input
4. Integral approximation through averaging
5. Scaling to remain in the space region as the original

Adapted from the TensorFlow integrated gradients tutorial

Reliable insights about causal structure

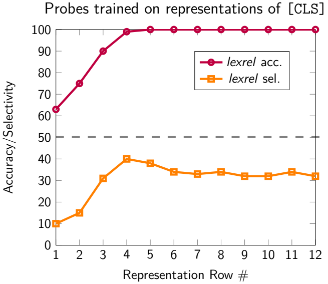


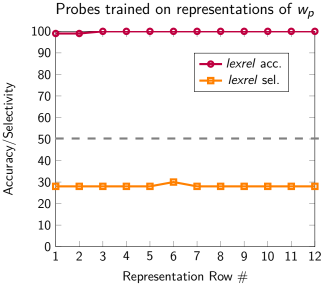
$$W_1 = \begin{pmatrix} 1 \\ 1 \\ 0 \\ 0 \end{pmatrix} \quad W_2 = \begin{pmatrix} 0 \\ 0 \\ 1 \\ 1 \end{pmatrix} \quad W_3 = \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \end{pmatrix}$$

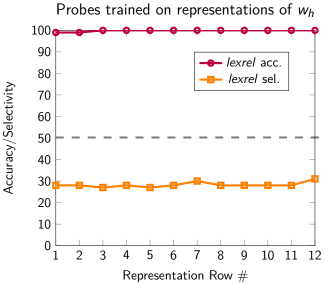
$$\mathbf{w} = \begin{pmatrix} 1 \\ 1 \\ 0 \end{pmatrix} \quad (\mathbf{x}W_1; \mathbf{x}W_2; \mathbf{x}W_3)\,\mathbf{w}$$

Sundararajan et al. 2017

Probe results for lexrel accuracy







MoNLI causal abstraction analysis details

1. A systematic generalization task
2. Methods and findings
3. Largest exchangeable cluster
4. Which algorithm is BERT implementing then?

A systematic generalization task

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		
fish	40		
plant	38		
jewelry	36		
anything	34		
hat	20		
man	20		
horse	16		
gun	12		
adult	10		
shirt	8		
shoe	6		
store	6		
cake	4		
individual	4		
clothe	2		
weapon	2		
creature	2		

Our models know these lexical relations (high Positive MoNLI accuracy) and will be compelled to combine this knowledge with what they learn about negation during Negative MoNLI fine-tuning.

Methods and findings

1. Find a useful intervention point.
2. Interchange interventions for every pair of examples at that site.
3. Find clusters of examples in which BERT mimics the causal dynamics of INFER.
4. The largest subsets we found 98, 63, 47, and 37.
    a. For a random graph, the expected number of subsets larger than 20 is effectively 0.
    b. If the site perfectly captured INFER, we would get a single huge cluster.

What it means for BERT to implement Infer

$\textsc{Infer}(\texttt{example})$

1 $\mathit{lexrel} \leftarrow \textsc{get-lexrel}(\mathit{example})$
2 **if** $\textsc{contains-not}(\mathit{example})$
3 **return** $\textsc{reverse}(\mathit{lexrel})$
4 **return** lexrel

$$\textsc{Infer}_{\mathit{lexrel}(i)\rightarrow\mathit{lexrel}(j)}(i) = \begin{cases} \textsc{Infer}(i) & \mathit{lexrel}(i) = \mathit{lexrel}(j) \\ \textsc{reverse}(\textsc{Infer}(i)) & \mathit{lexrel}(i) \neq \mathit{lexrel}(j) \end{cases}$$

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

Largest exchangeable cluster

(cemetery,location)
(house,location) (den,location)
(ghetto,location) (backyard,location) (park,location)
(jungle,location) (meadow,location) (residence,location)
(laboratory,location) (playground,location) (studio,location)
(slum,location)
(lab,location) (station,location) (farm,location)
(campsite,location)
(town,location) (lawn,location)

(saxophone,instrument) (flute,instrument)
(bass,instrument) (piano,instrument)
(violin,instrument) (tuba,instrument)
(harmonica,instrument)

(liquid,whiskey)
(liquid,margarita) (liquid,tequila)
(liquid,alcohol)

(woman,granny)
(woman,widow)

(dogs,huskies)
(dog,husky) (dog,chihuahua)
(dog,retriever) (dog,maltese)
(dog,terrier) (dog,pomeranian)

(beetle,insect)
(grasshopper,insect) (bee,insect)
(wasp,insect) (fly,insect) (cricket,insect)
(butterfly,insect) (bumblebee,insect)
(flea,insect) (roach,insect) (moth,insect)
(mosquito,insect)

(person,vegetarian) (person,lunatic)
(person,republican) (person,trooper)
(person,business) (person,navigator)
(person,steward) (person,consultant)
(person,farmer) (person,goalkeeper)
(person,sophomore) (person,housekeeper)
(person,cleaner) (person,physicist) (person,cop)
(person,cambodian) (person,detective)
(person,genius) (person,sergeant) (person,californian)
(person,doctor) (person,runner)

(hood,thing)
(nut,thing) (capsule,thing)
(pouch,thing) (structure,thing)
(root,thing) (nugget,thing)
(tube,thing)

(box,object)
(object,sweater) (hat,object)
(object,jacket) (toy,object)
(cane,object)

(water,rainwater)
(water,saltwater)

(sculptor,artist)

(berry,blueberry)

(tree,cypress)
(tree,magnolia) (trees,elms)
(tree,maple)

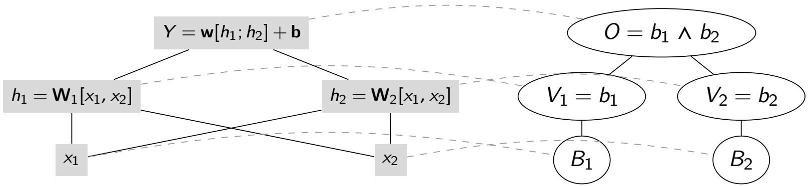
Which algorithm is BERT implementing then?

```
INFER(example)
  lexrel ← GET-LEXREL(example)
  if CONTAINS-NOT(example)
      return REVERSE(lexrel)
  return lexrel
```

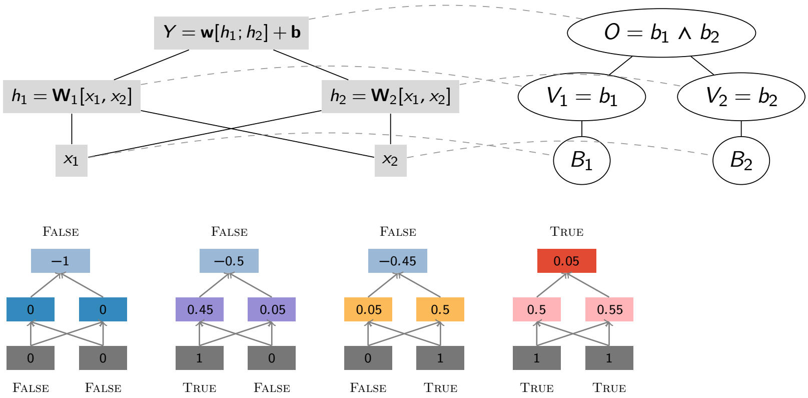
```
INFER(example)
  if INCLUSTER(C_1, example)
      lexrel_1 ← GET-LEXREL(example)
      if CONTAINS-NOT(example)
          return REVERSE(lexrel_1)
      return lexrel_1
  if INCLUSTER(C_2, example)
      lexrel_2 ← GET-LEXREL(example)
      if CONTAINS-NOT(example)
          return REVERSE(lexrel_2)
      return lexrel_2
  if INCLUSTER(C_3, example)
      lexrel_3 ← GET-LEXREL(example)
      if CONTAINS-NOT(example)
          return REVERSE(lexrel_3)
      return lexrel_3
  ...
```

IIT induces causal structure

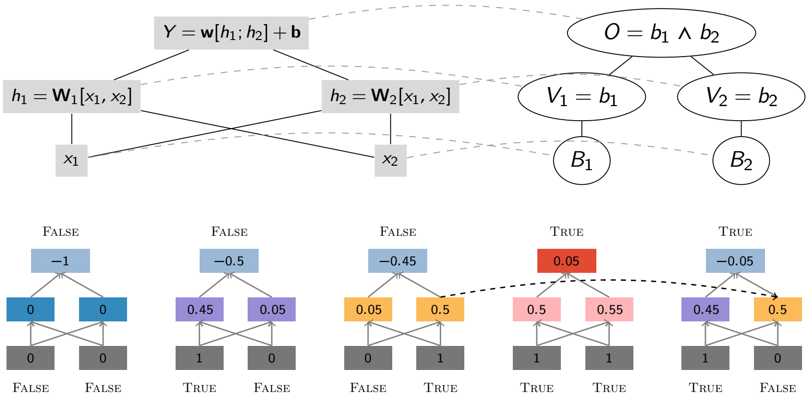
IIT induces causal structure



IIT induces causal structure



IIT induces causal structure



IIT induces causal structure