Inducing Interpretable Causal Structures in Neural Networks

Christopher Potts

Joint work with Atticus Geiger, Zhengxuan Wu, Hanson Lu, Josh Rozner, Elisa Kreiss, Thomas Icard, and Noah Goodman

Stanford Linguistics and the Stanford NLP Group

Linguistics Department, University of Geneva, March 1, 2022

Semantic insights in NLP models

Semantic insights in NLP models: 1980s

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

/* Noun Phrase */
np(np(Agmt,Pronoun,[]),Agmt,NPCase,def,_,Set,Nil) -->
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- 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!

Semantic insights in NLP models: 1990s

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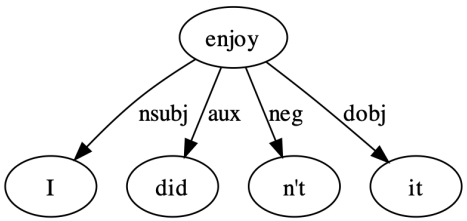
I didn't enjoy it.



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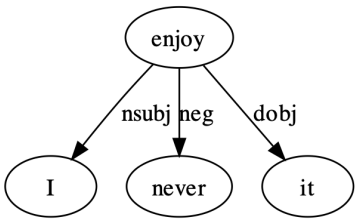

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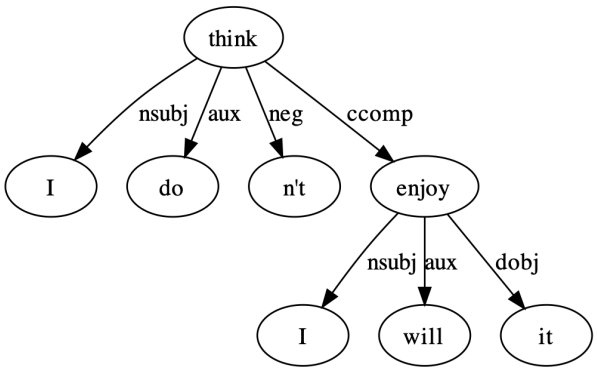

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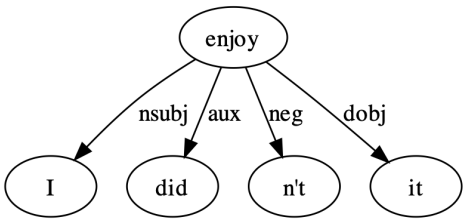

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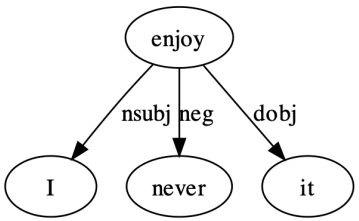

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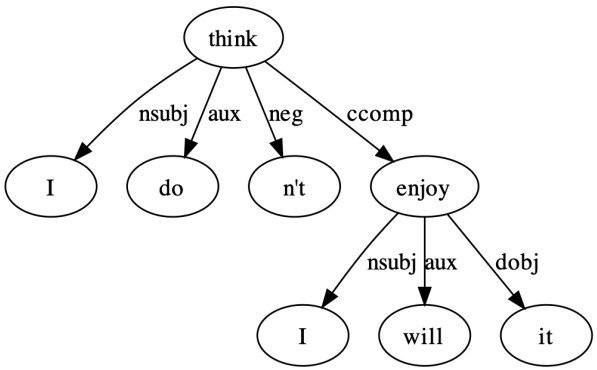

$$\texttt{neg(x, *)} \Rightarrow \texttt{x\_neg}$$

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

Semantic insights in NLP models: 2000s

Zettlemoyer and Collins 2005

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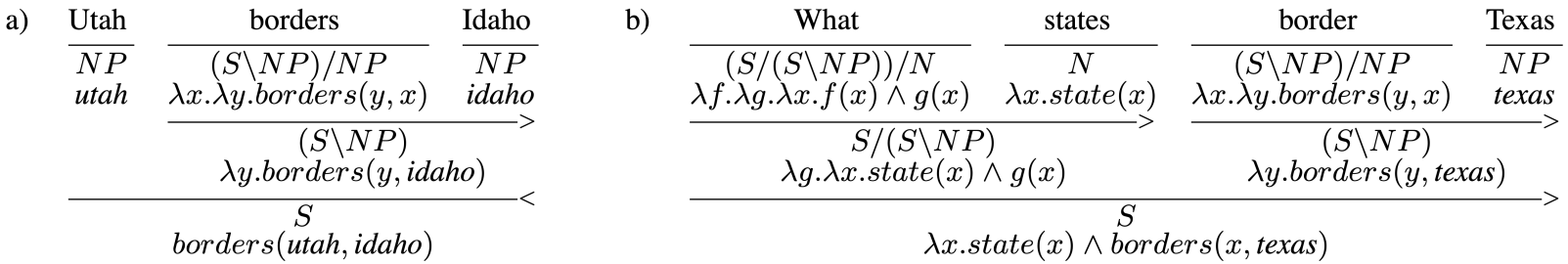

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a)

Utah	borders	Idaho
NP	$(S\backslash NP)/NP$	NP
utah	$\lambda x.\lambda y.borders(y,x)$	*idaho*
	$(S\backslash NP)$ (>)	
	$\lambda y.borders(y, idaho)$	
S (<)		
$borders(utah, idaho)$		

b)

What	states	border	Texas
$(S/(S\backslash NP))/N$	N	$(S\backslash NP)/NP$	NP
$\lambda f.\lambda g.\lambda x.f(x) \wedge g(x)$	$\lambda x.state(x)$	$\lambda x.\lambda y.borders(y,x)$	*texas*
$S/(S\backslash NP)$ (>)		$(S\backslash NP)$ (>)	
$\lambda g.\lambda x.state(x) \wedge g(x)$		$\lambda y.borders(y, texas)$	
S (>)			
$\lambda x.state(x) \wedge borders(x, texas)$			

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

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Socher et al. 2013

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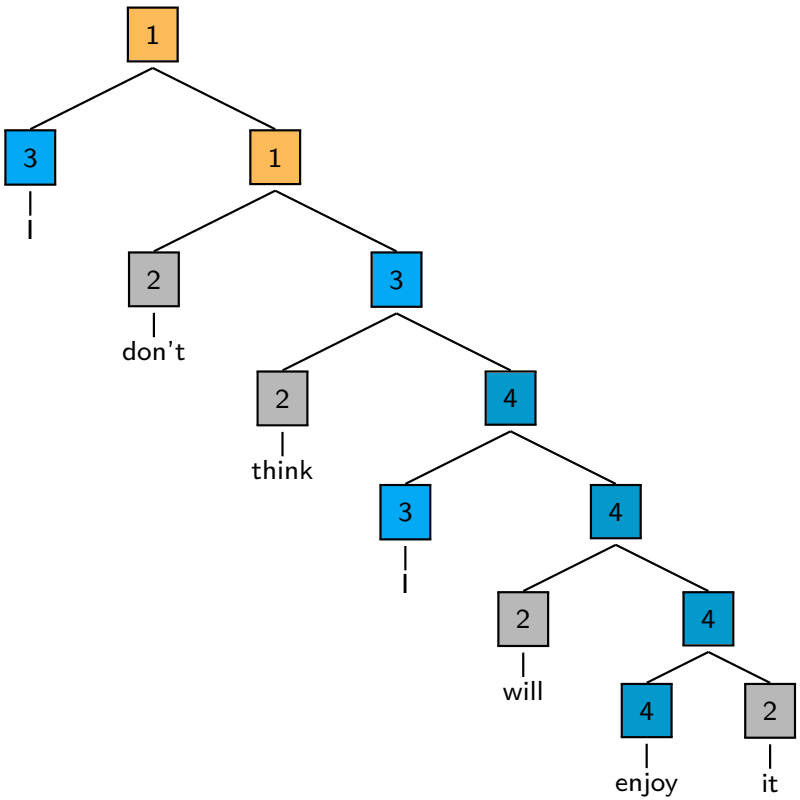

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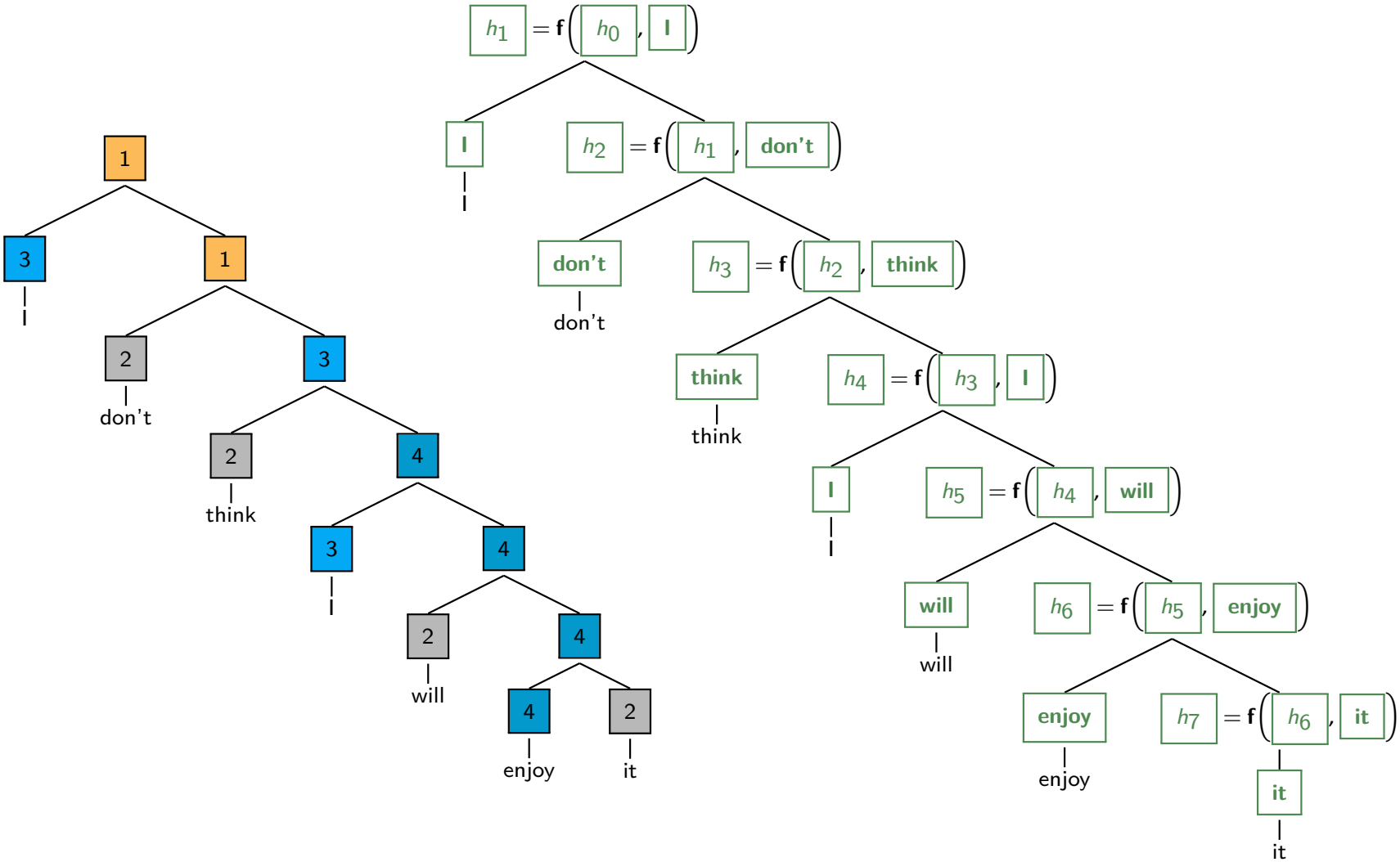

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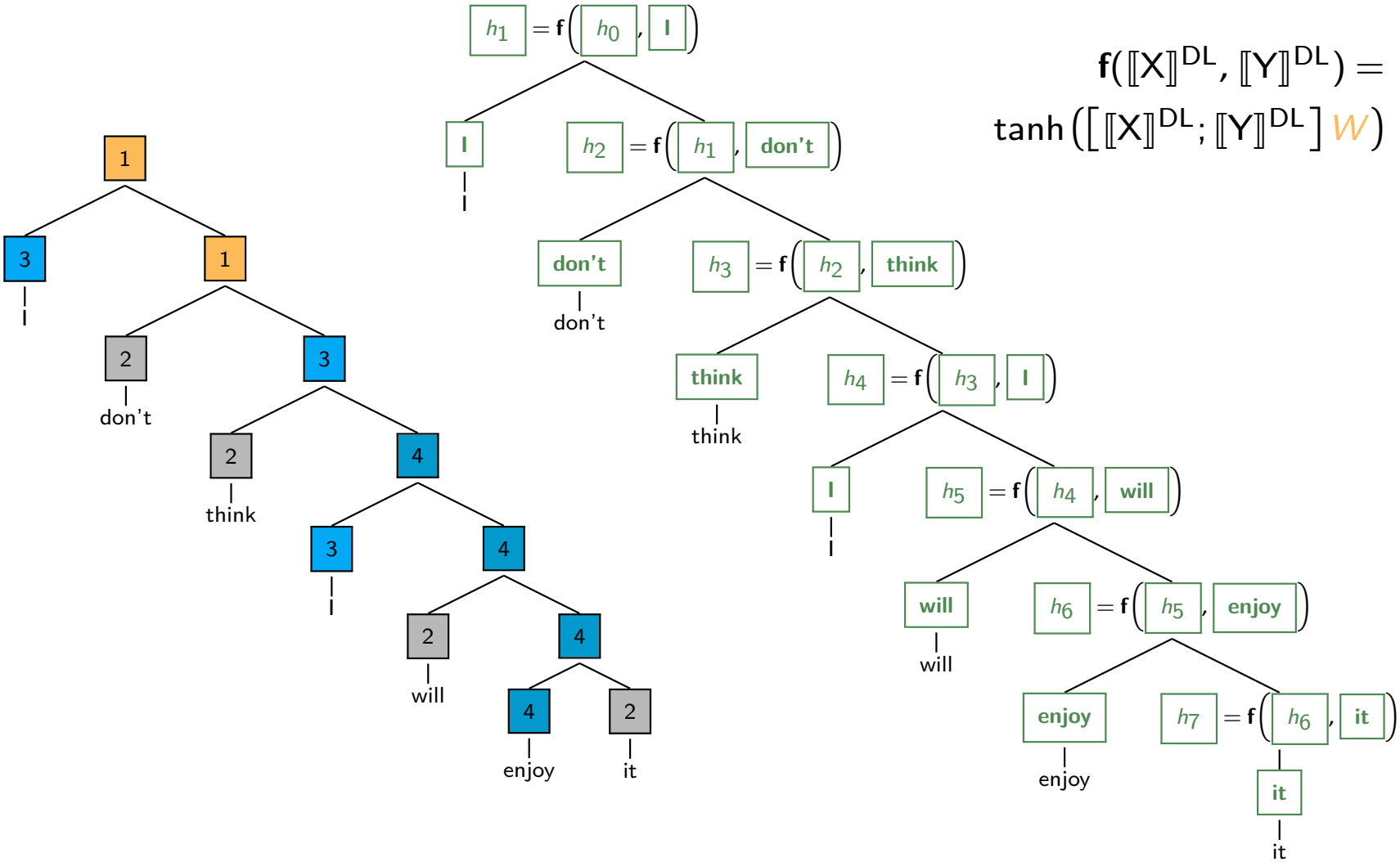

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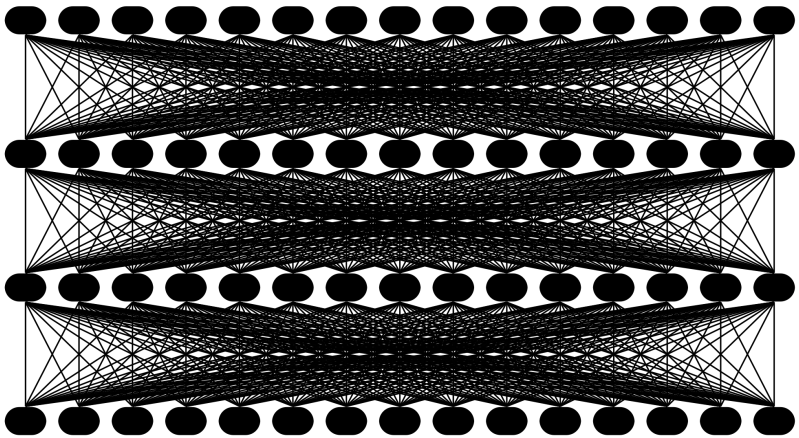

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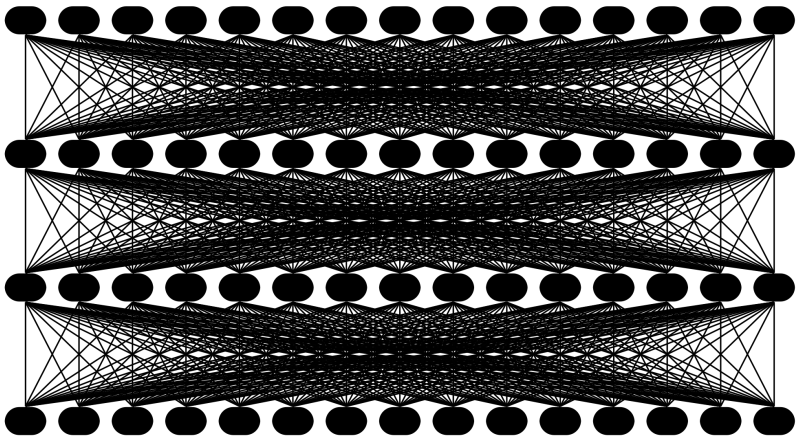

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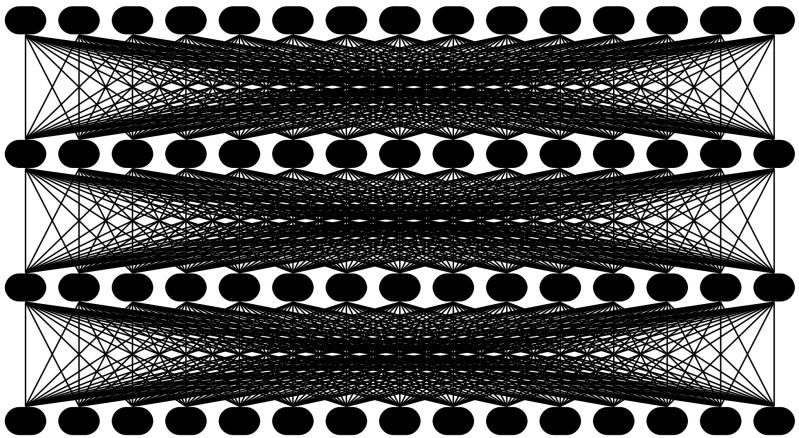

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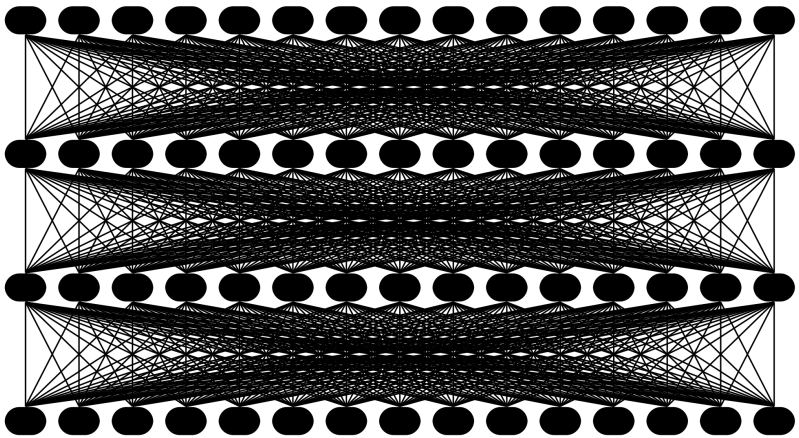

Semantics in the era of deep learning

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- Ambitions to interpret even the most complex language

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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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Appendix on feature attribution!

Motivations

Systematicity

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Fodor and Pylyshyn (1988):

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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

Limits of behavioral testing

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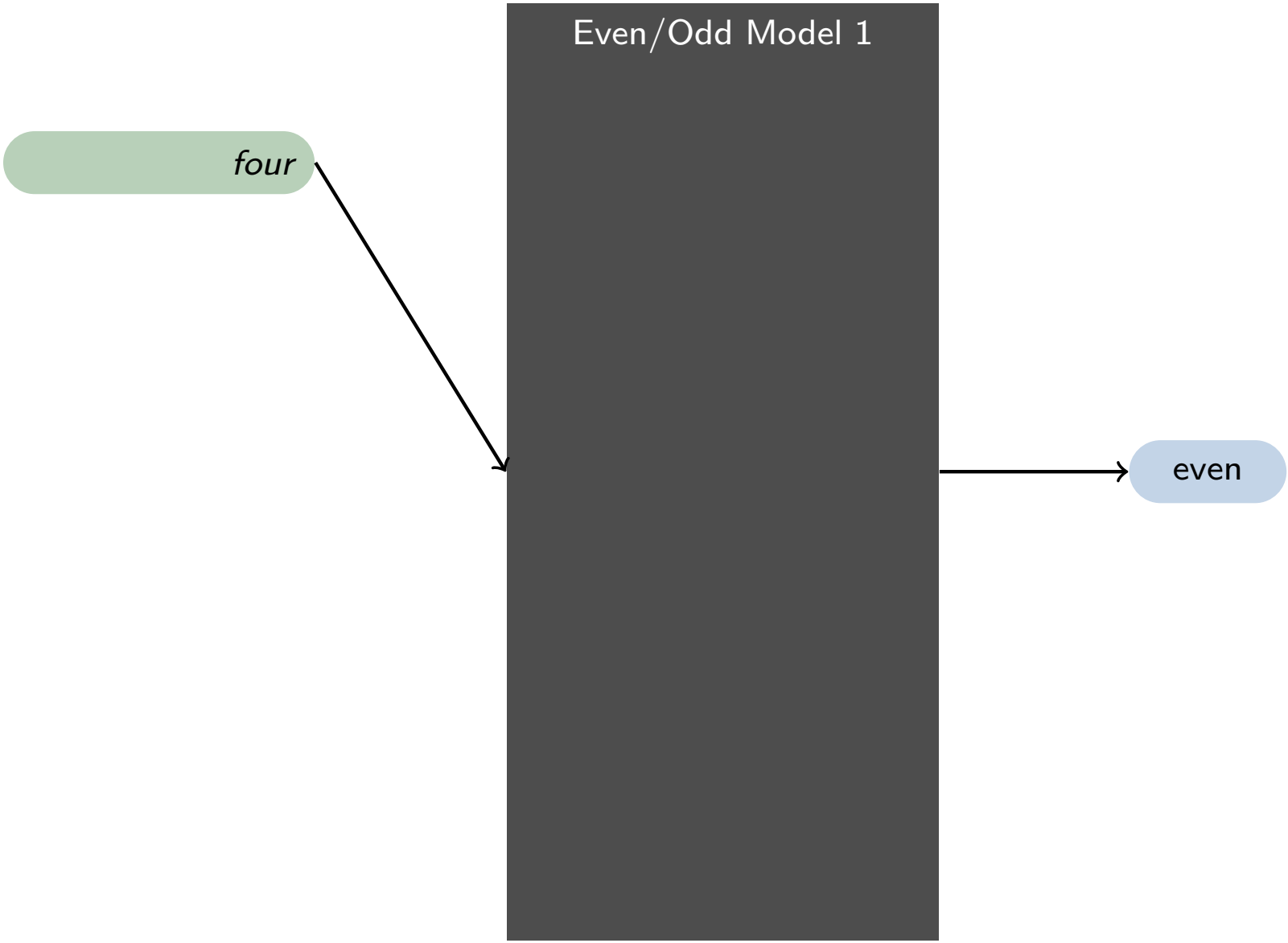

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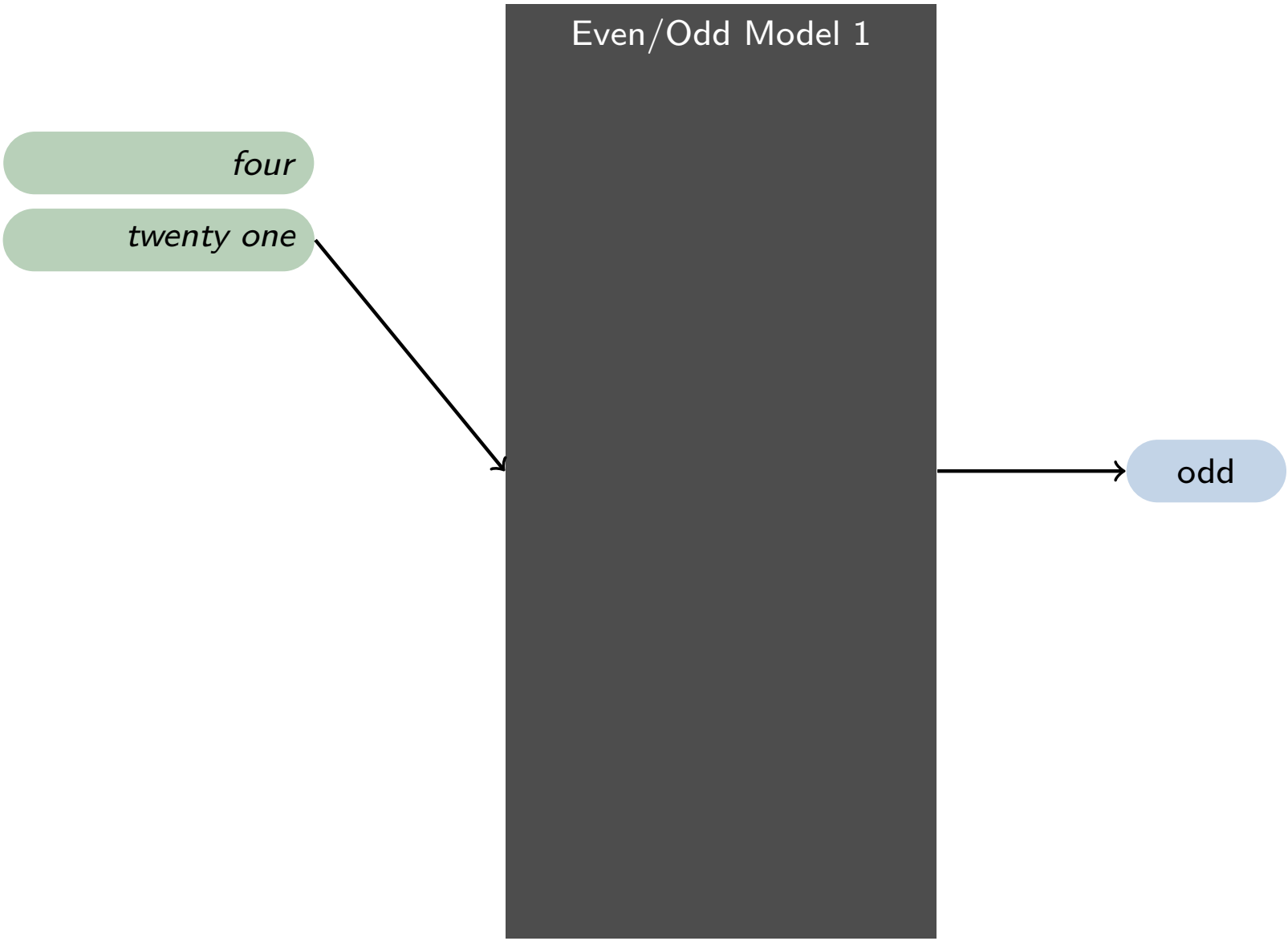

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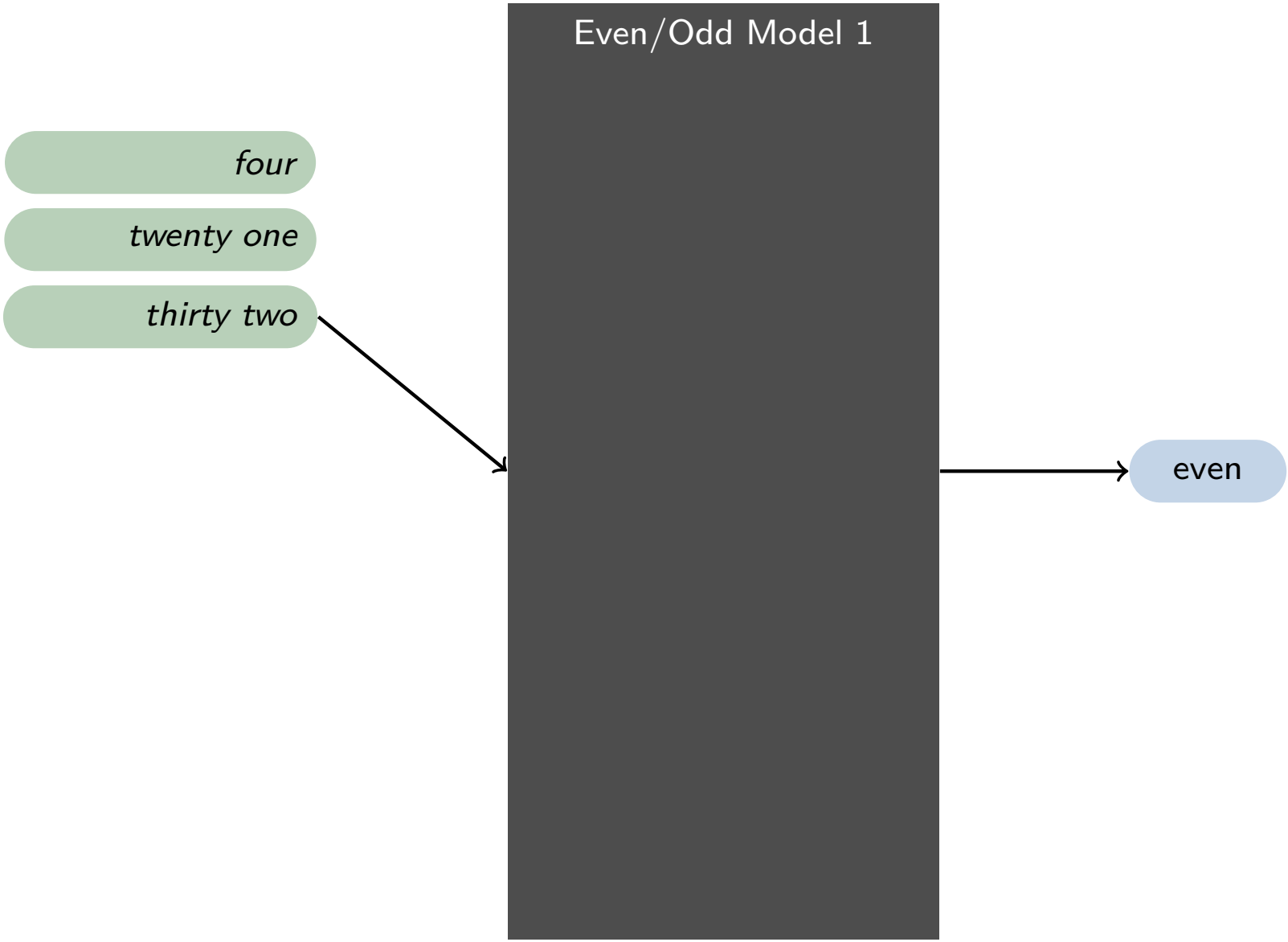

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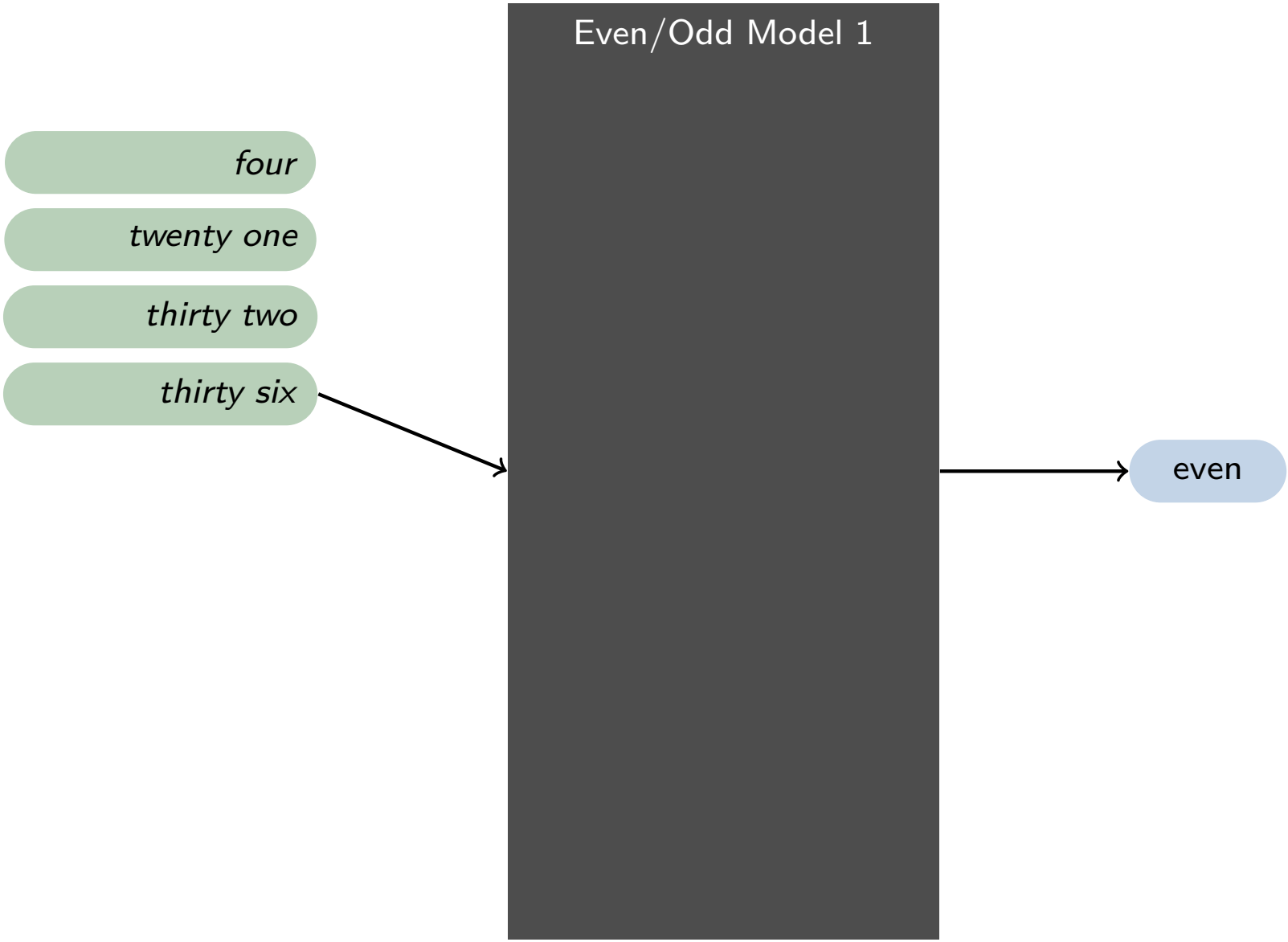

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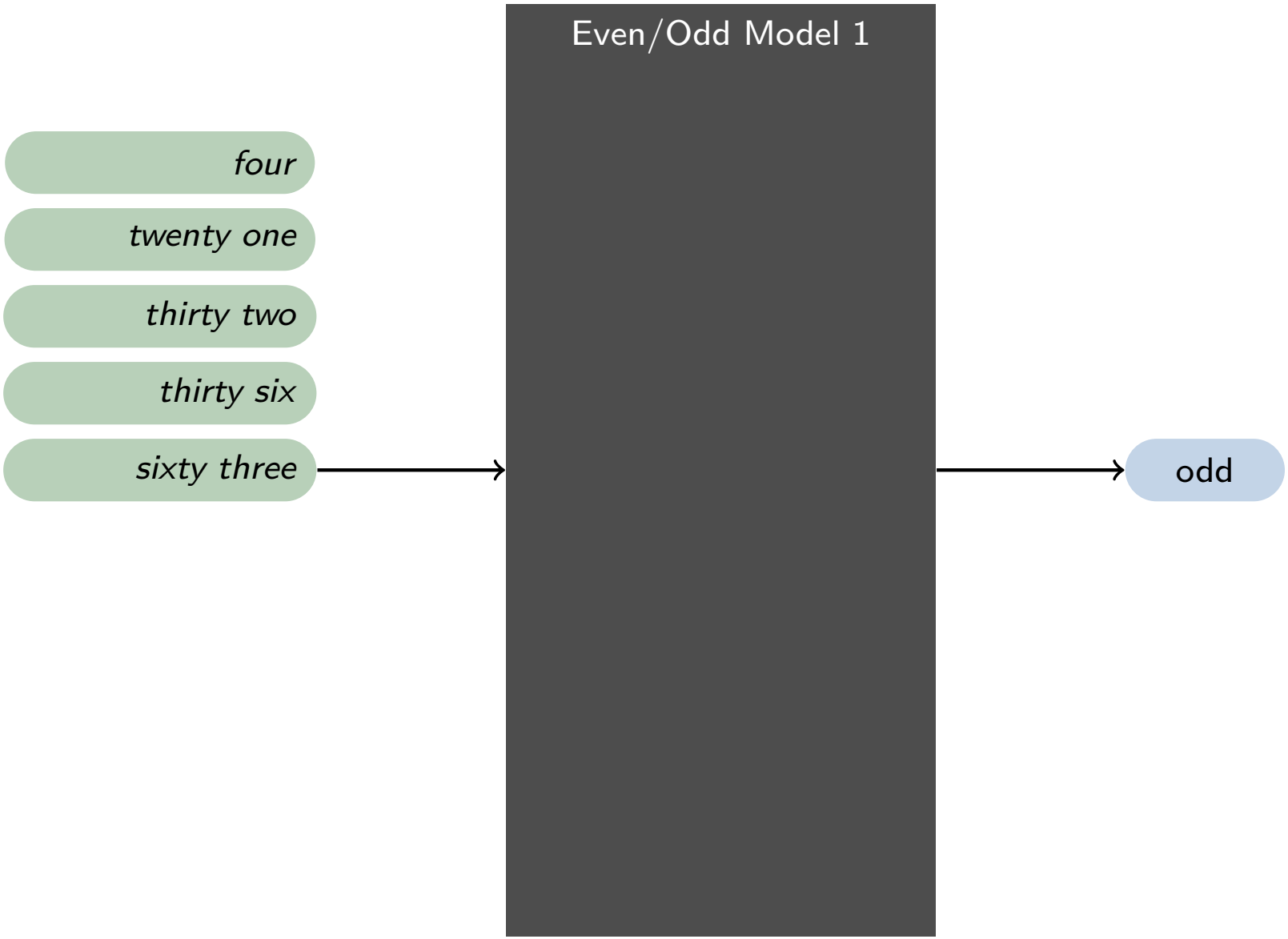

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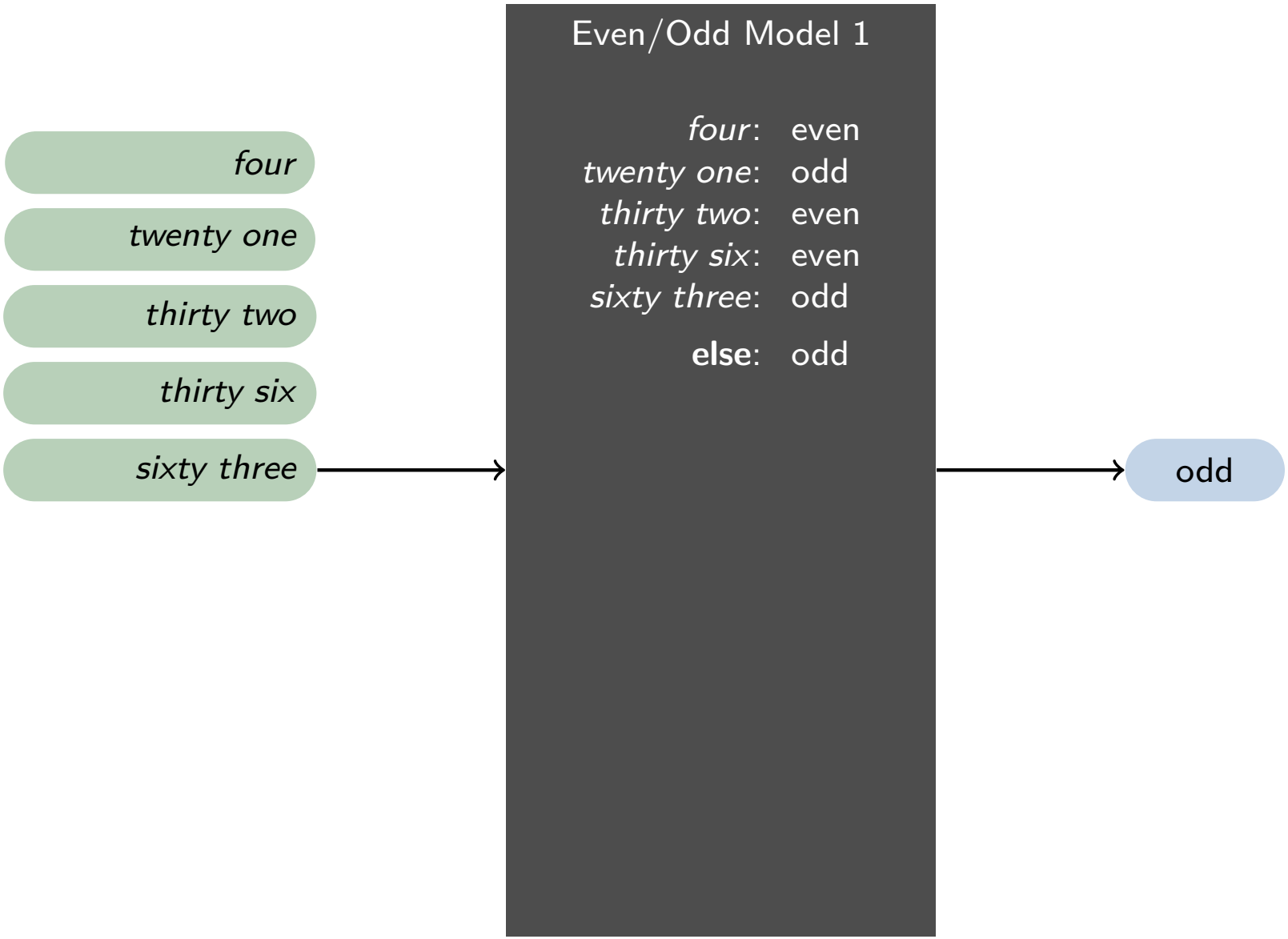

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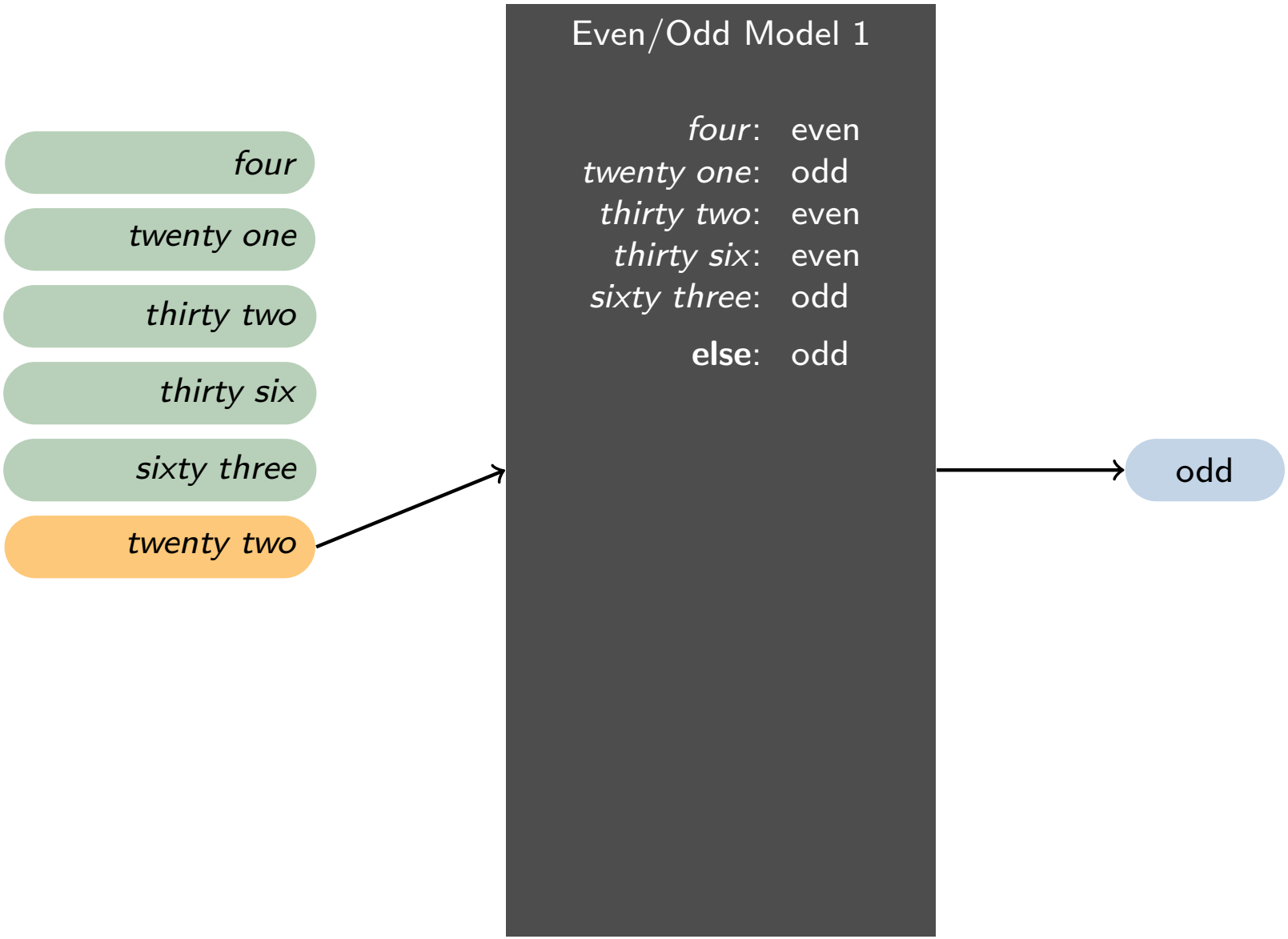

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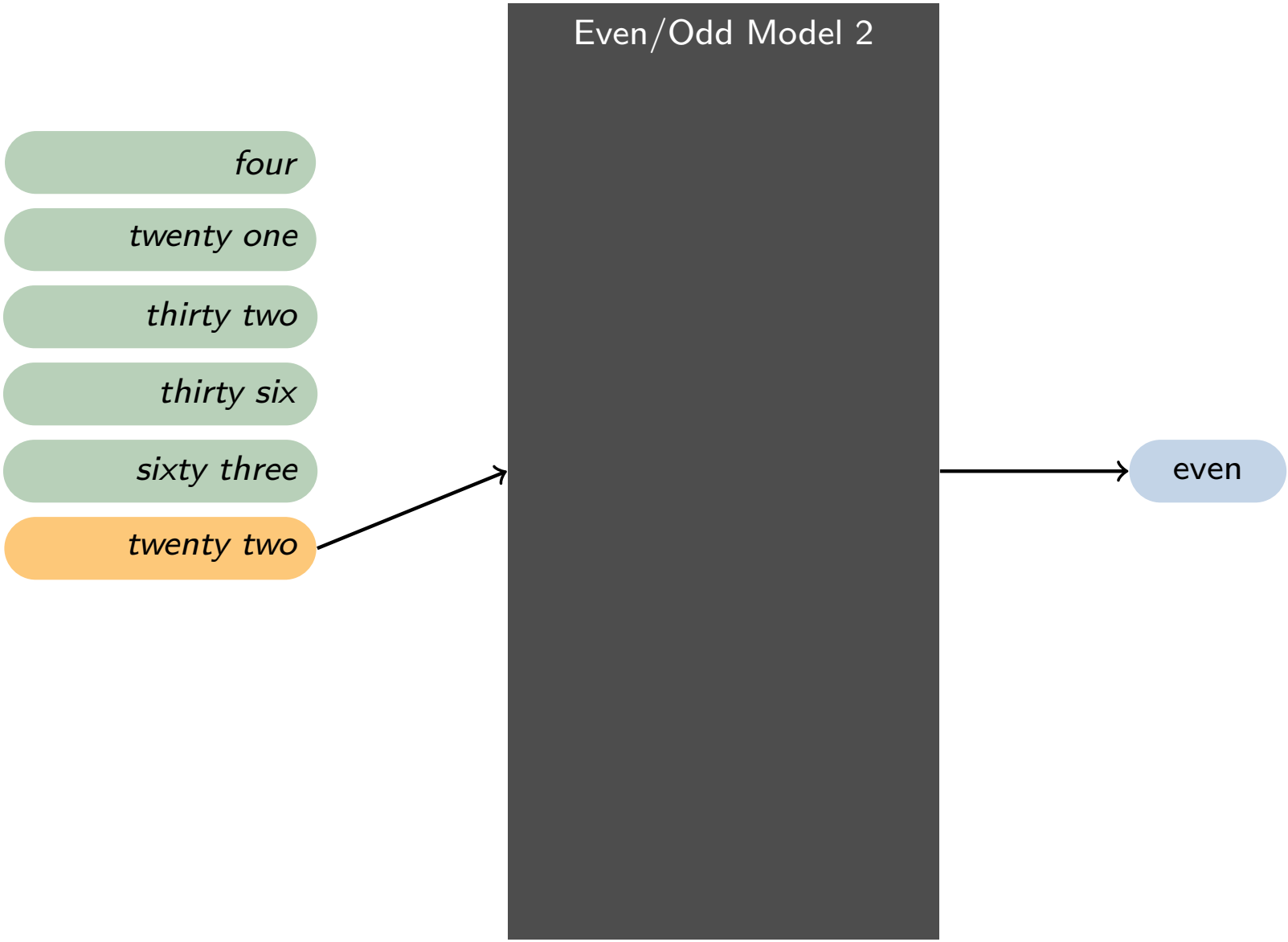

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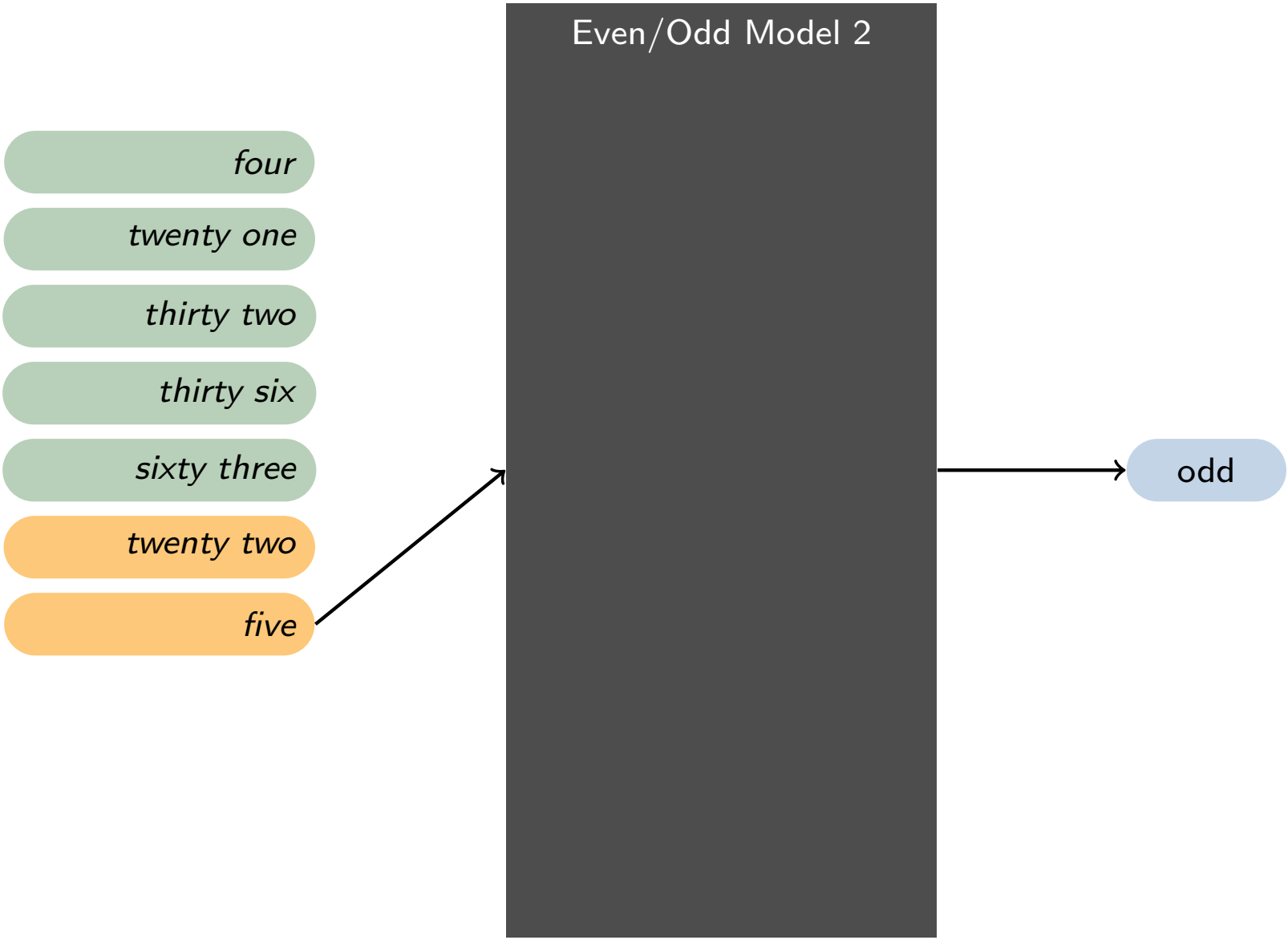

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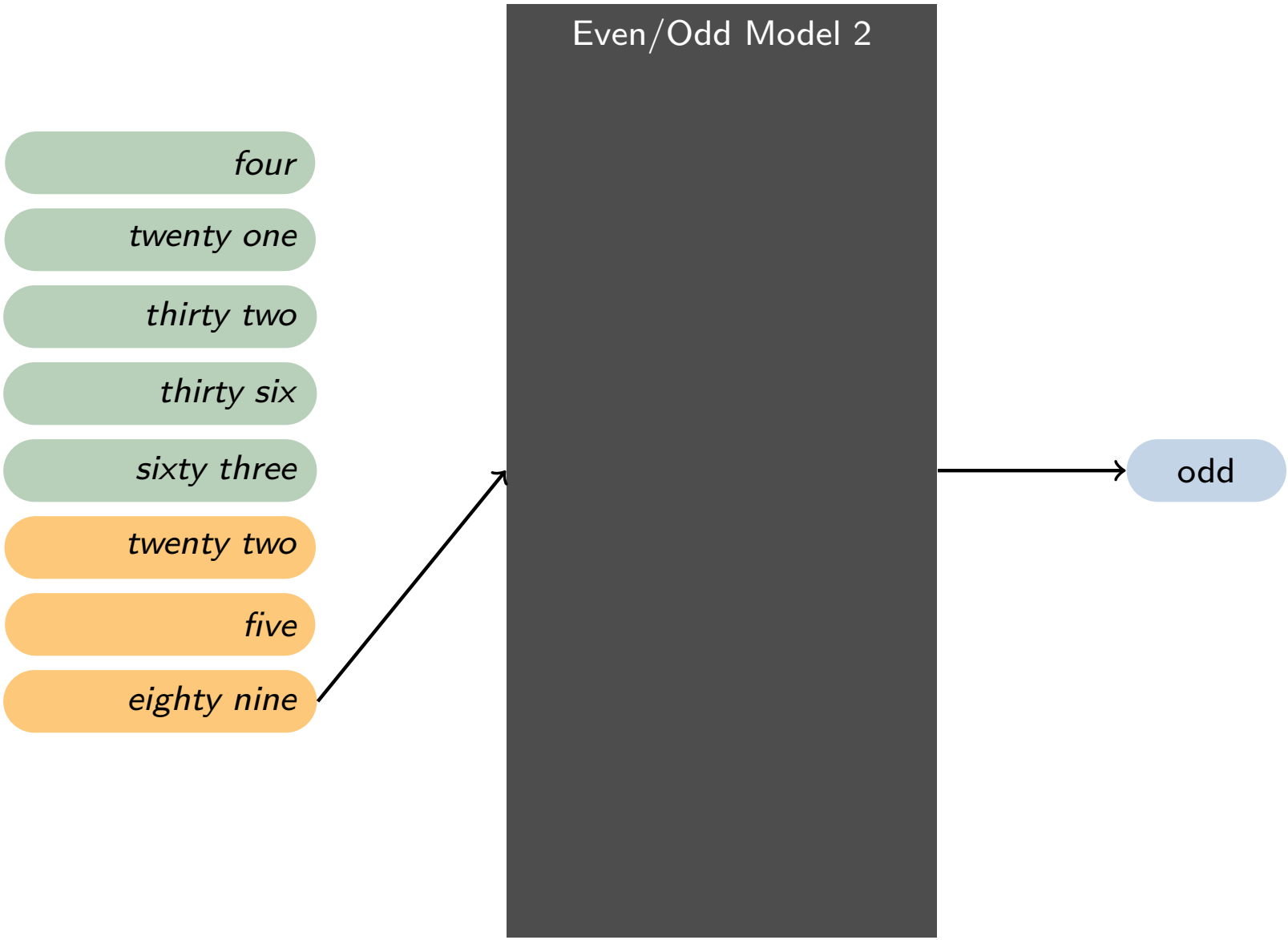

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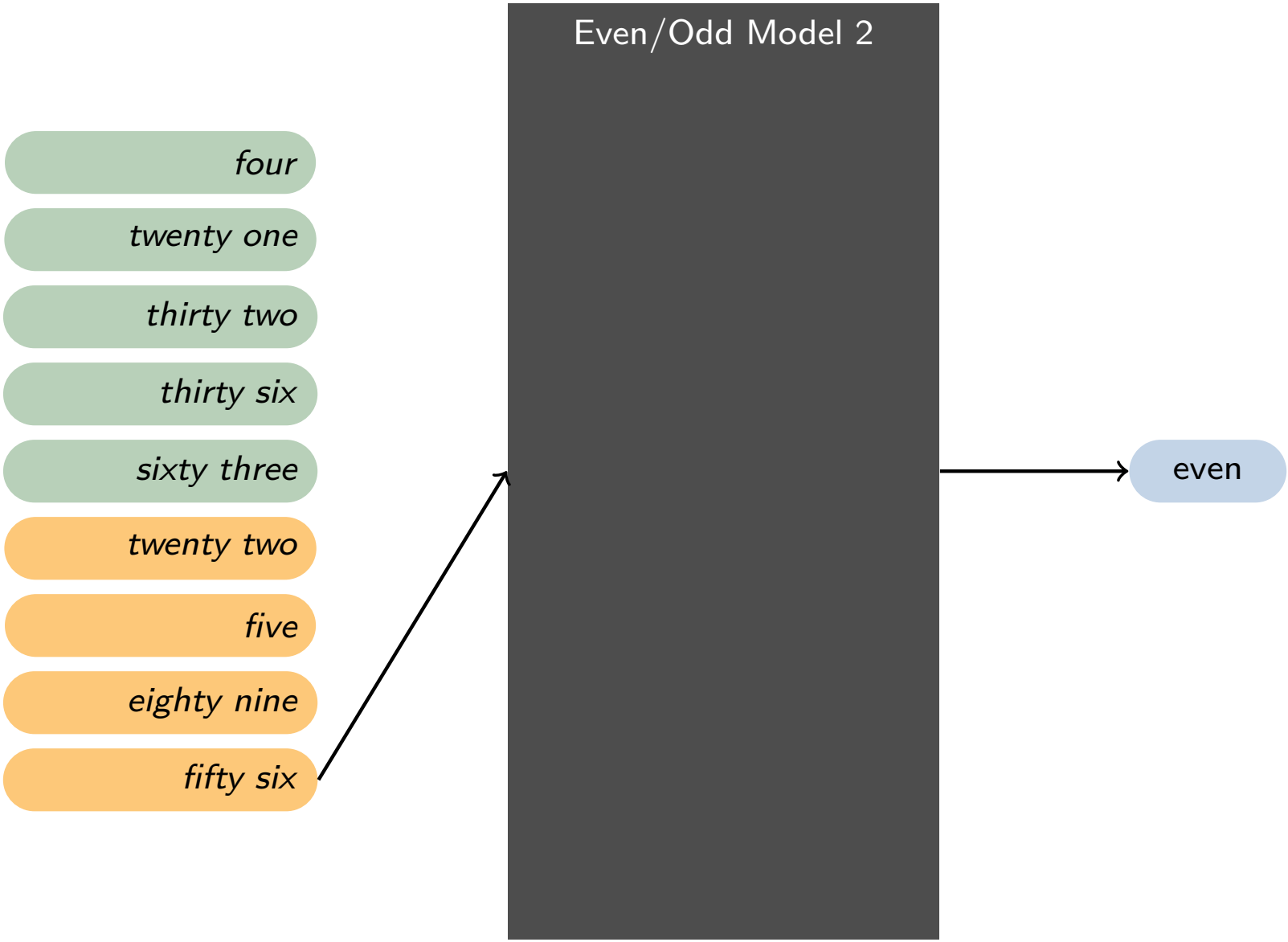

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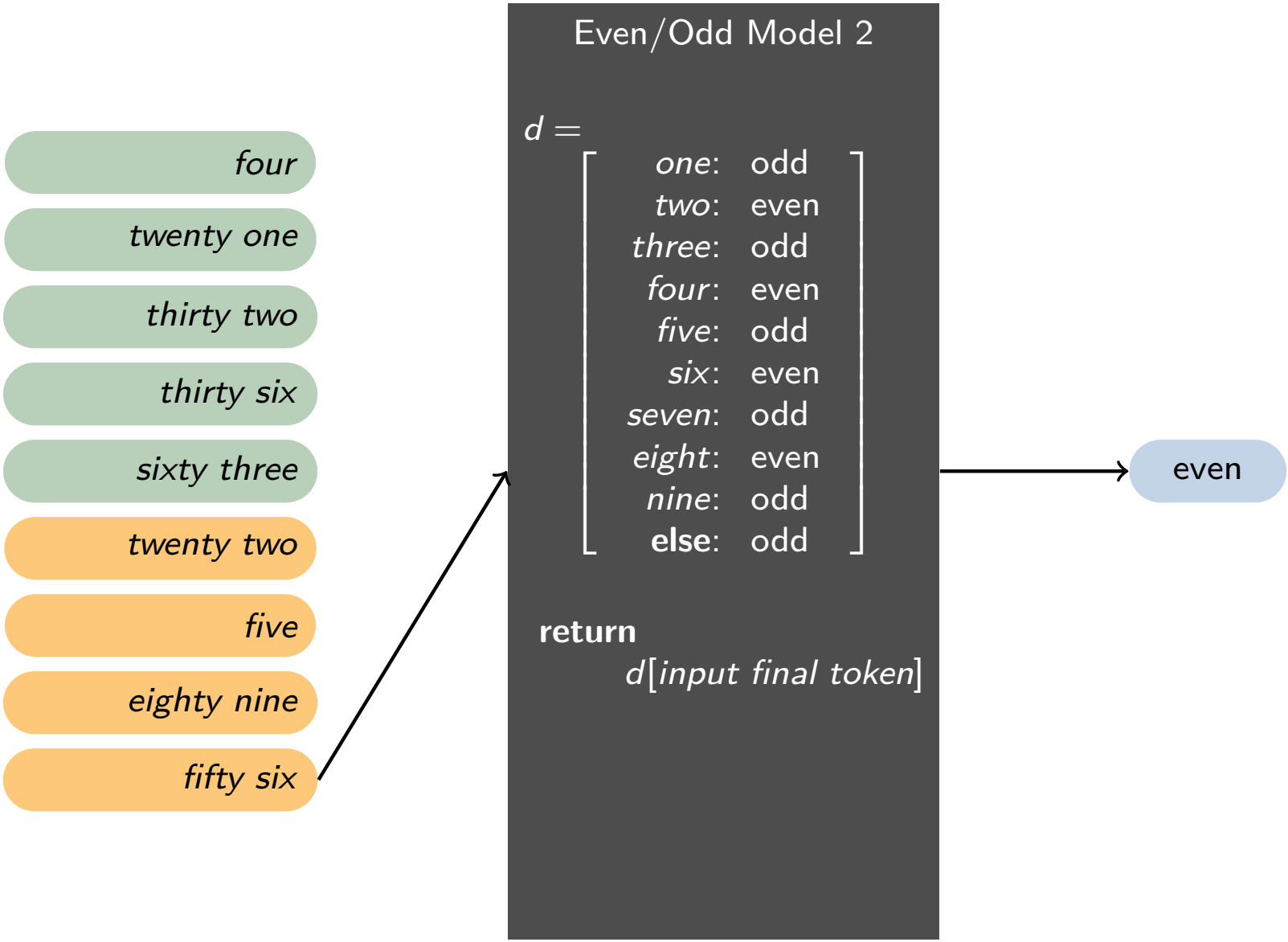

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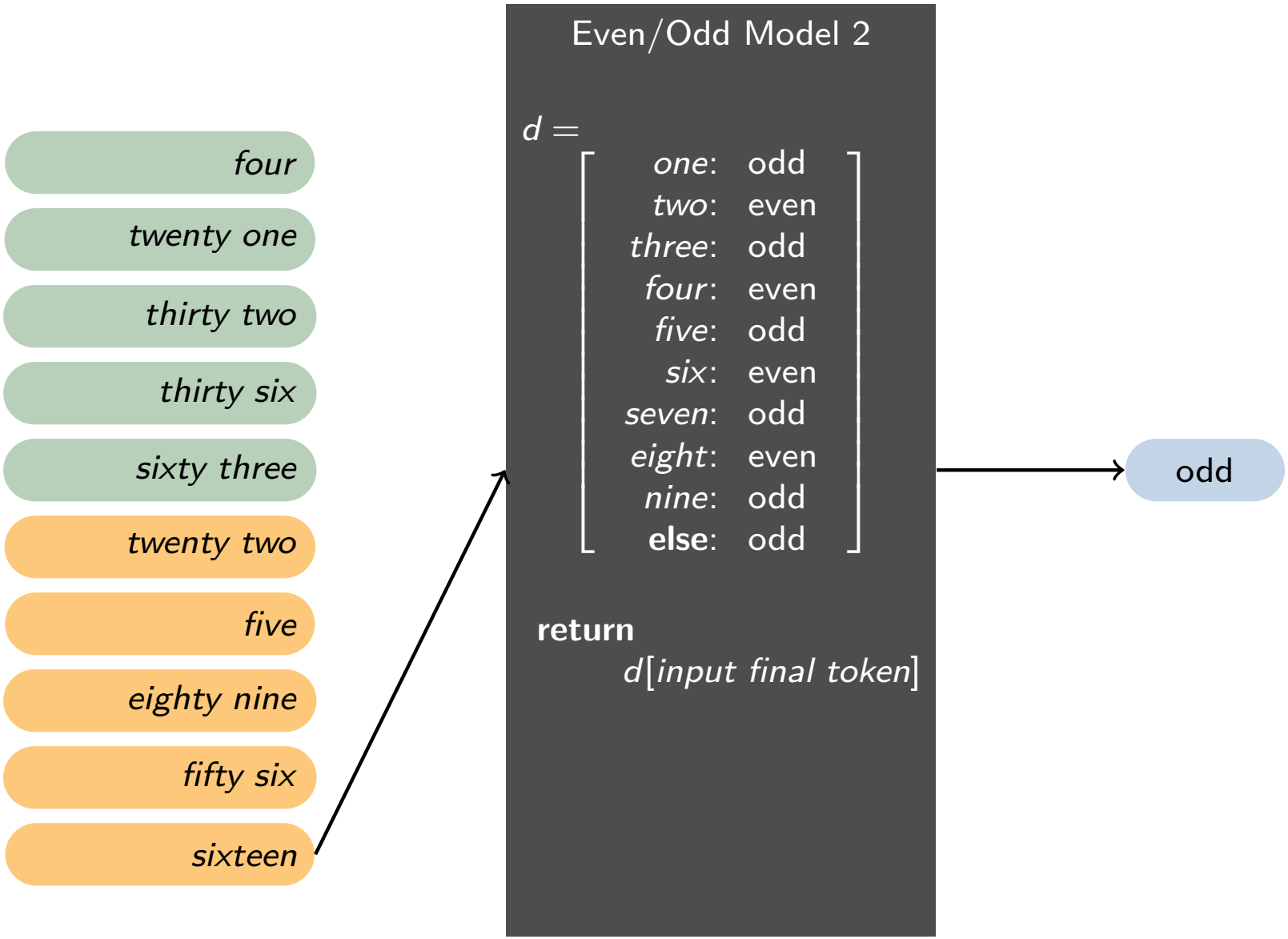

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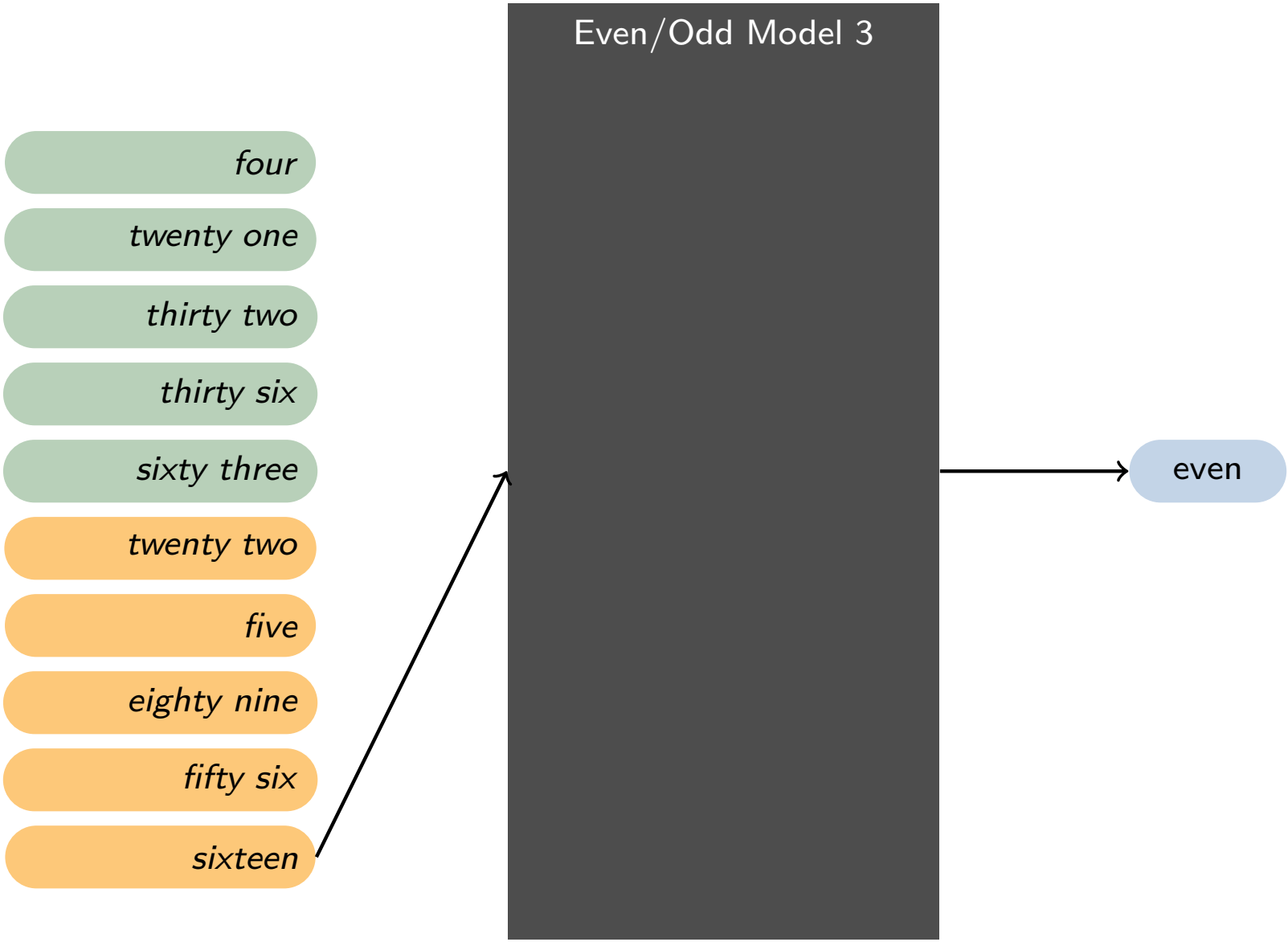
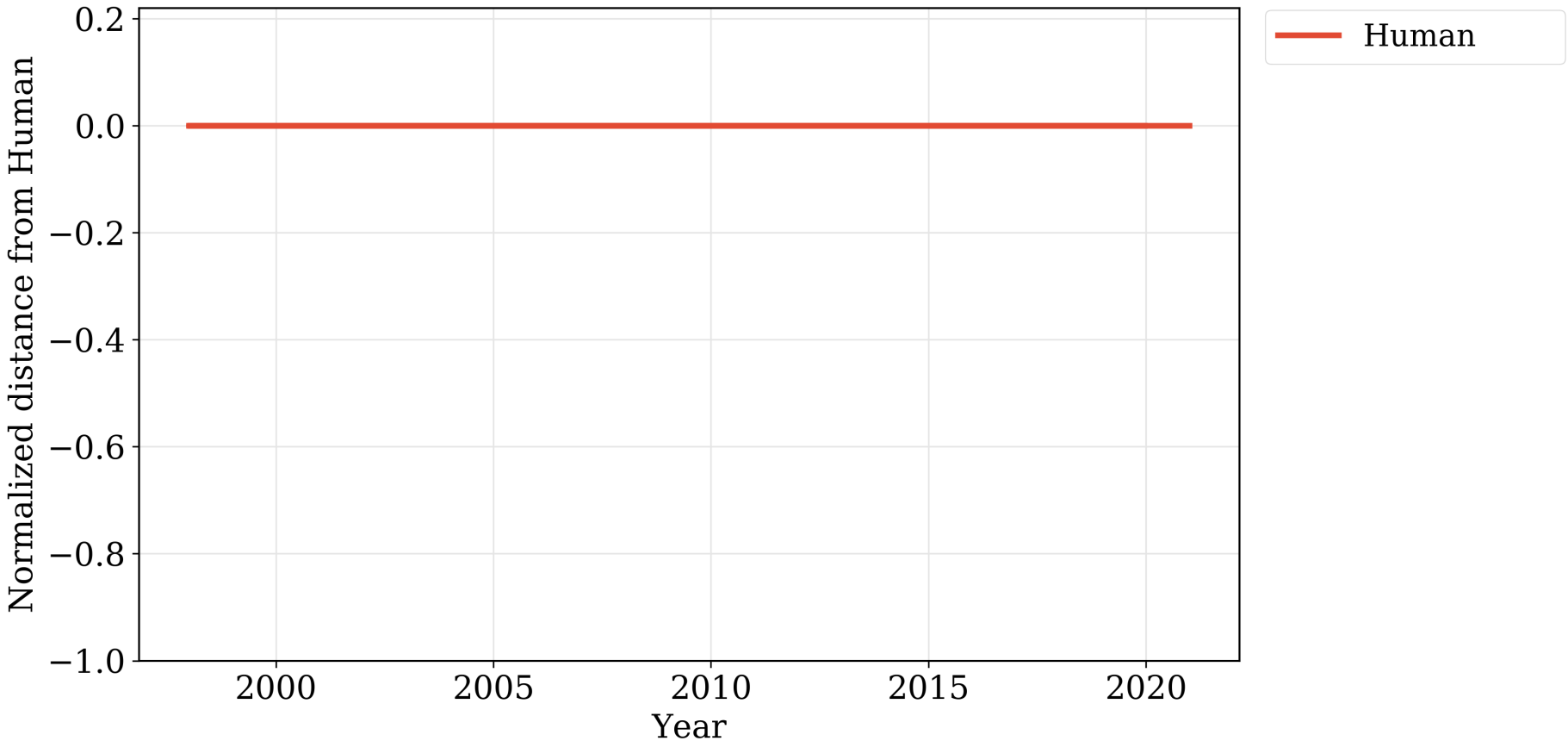


Benchmarks saturate faster than ever



Kiela et al. 2021

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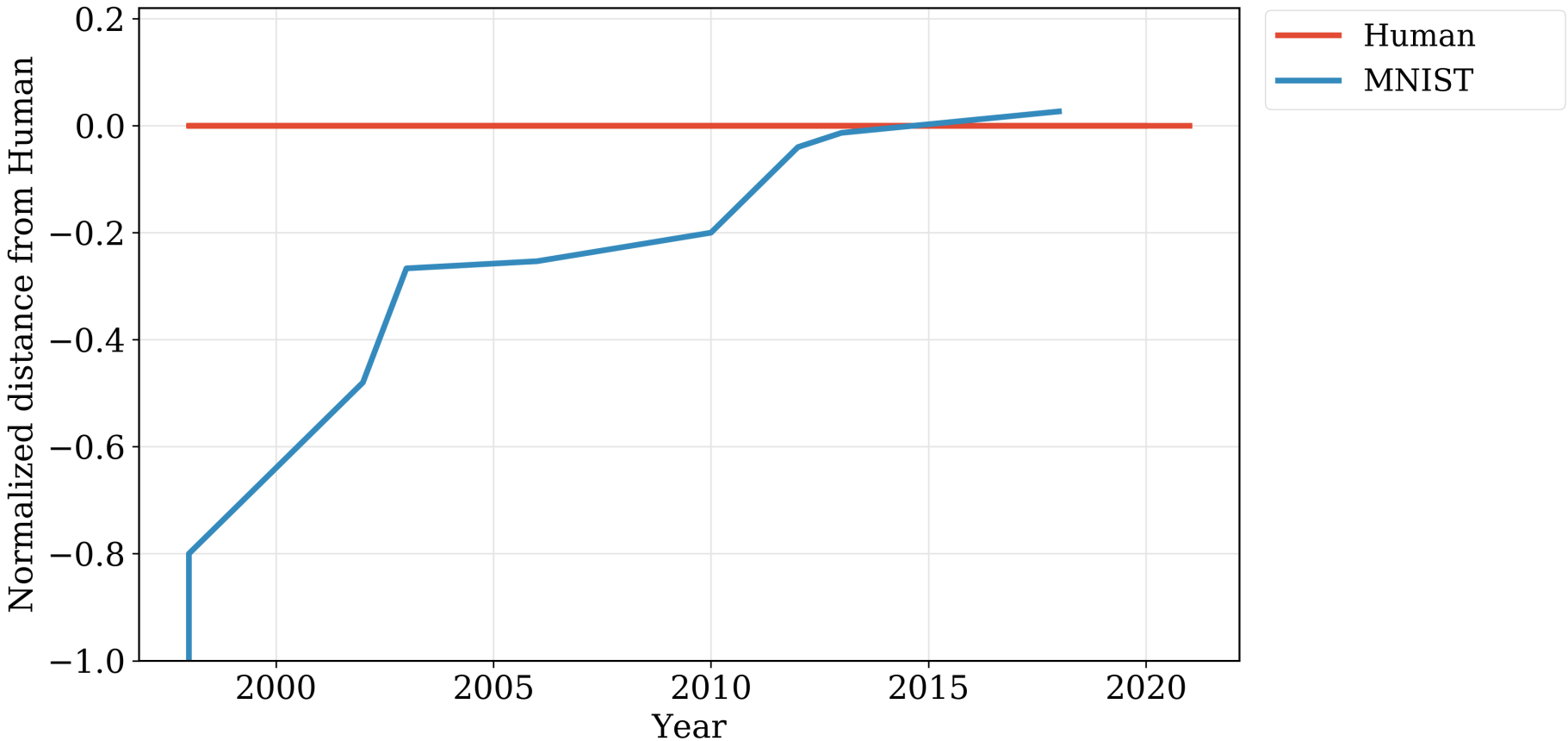

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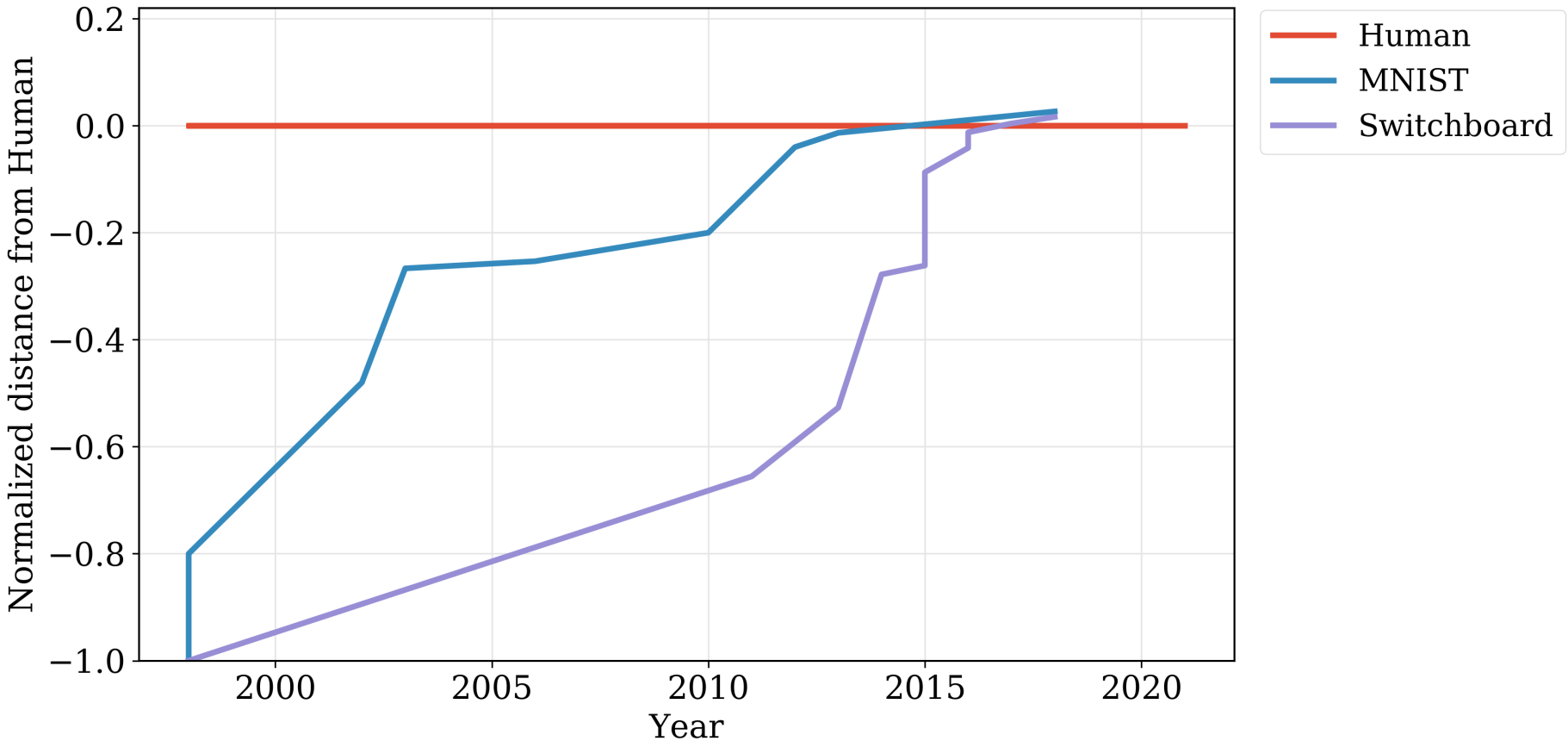

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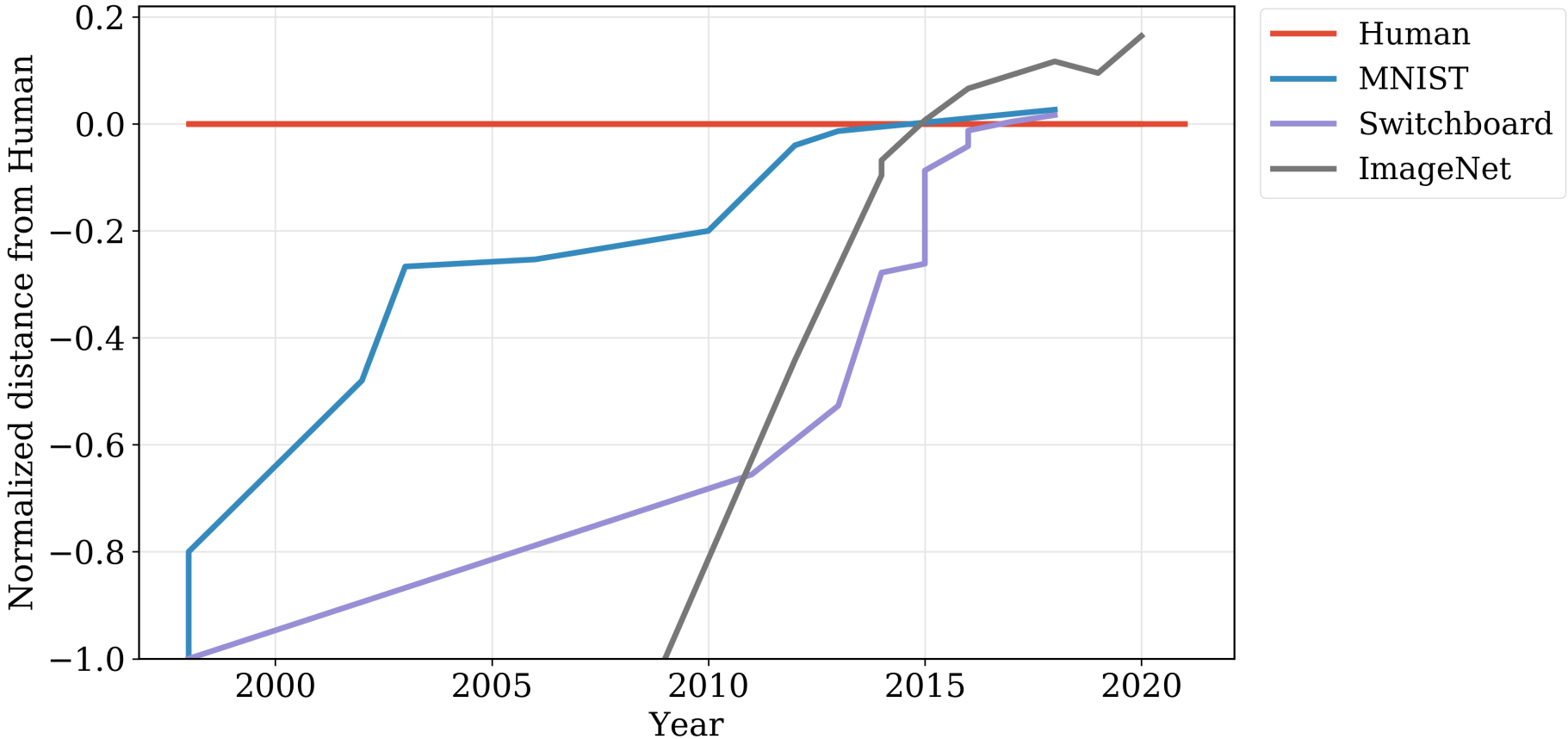

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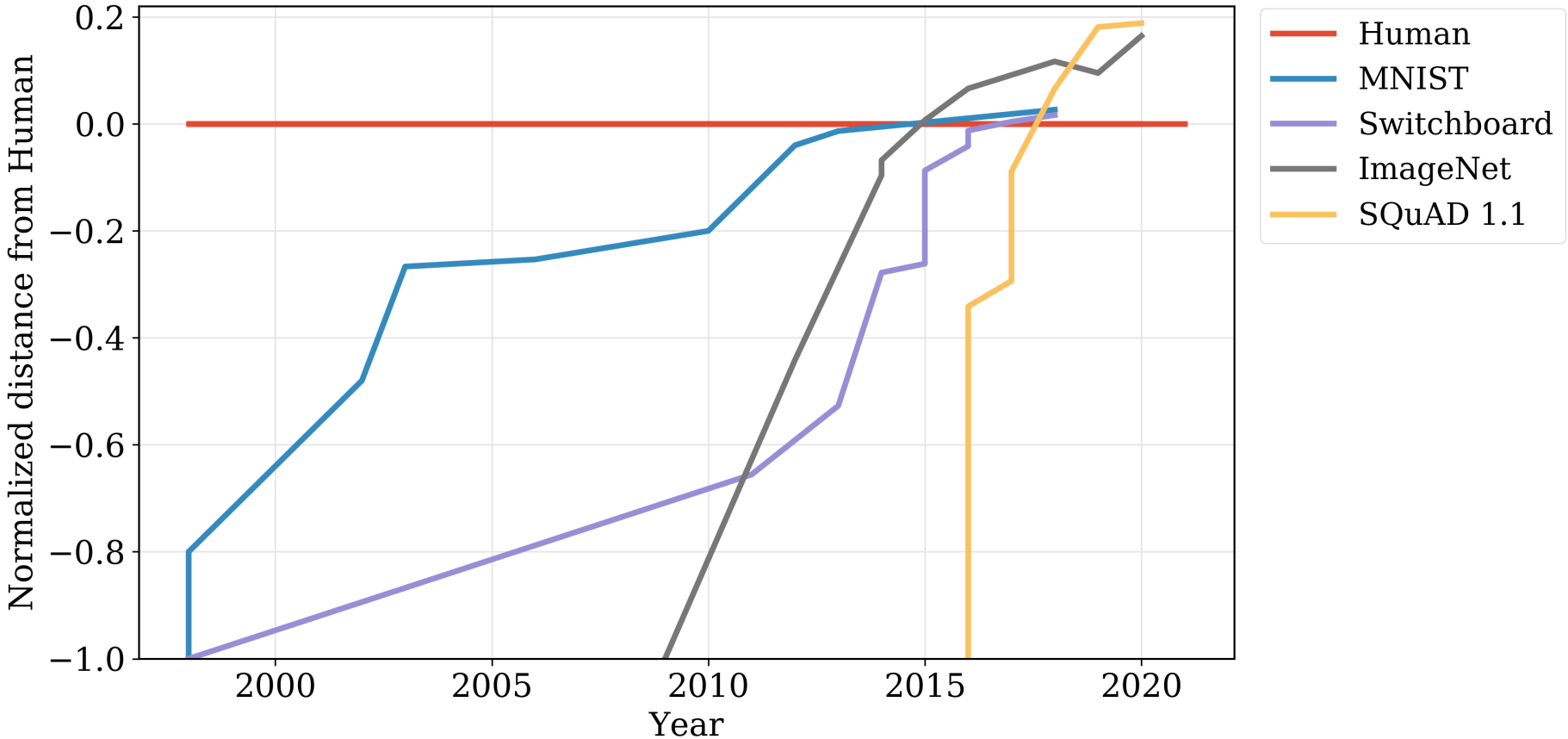

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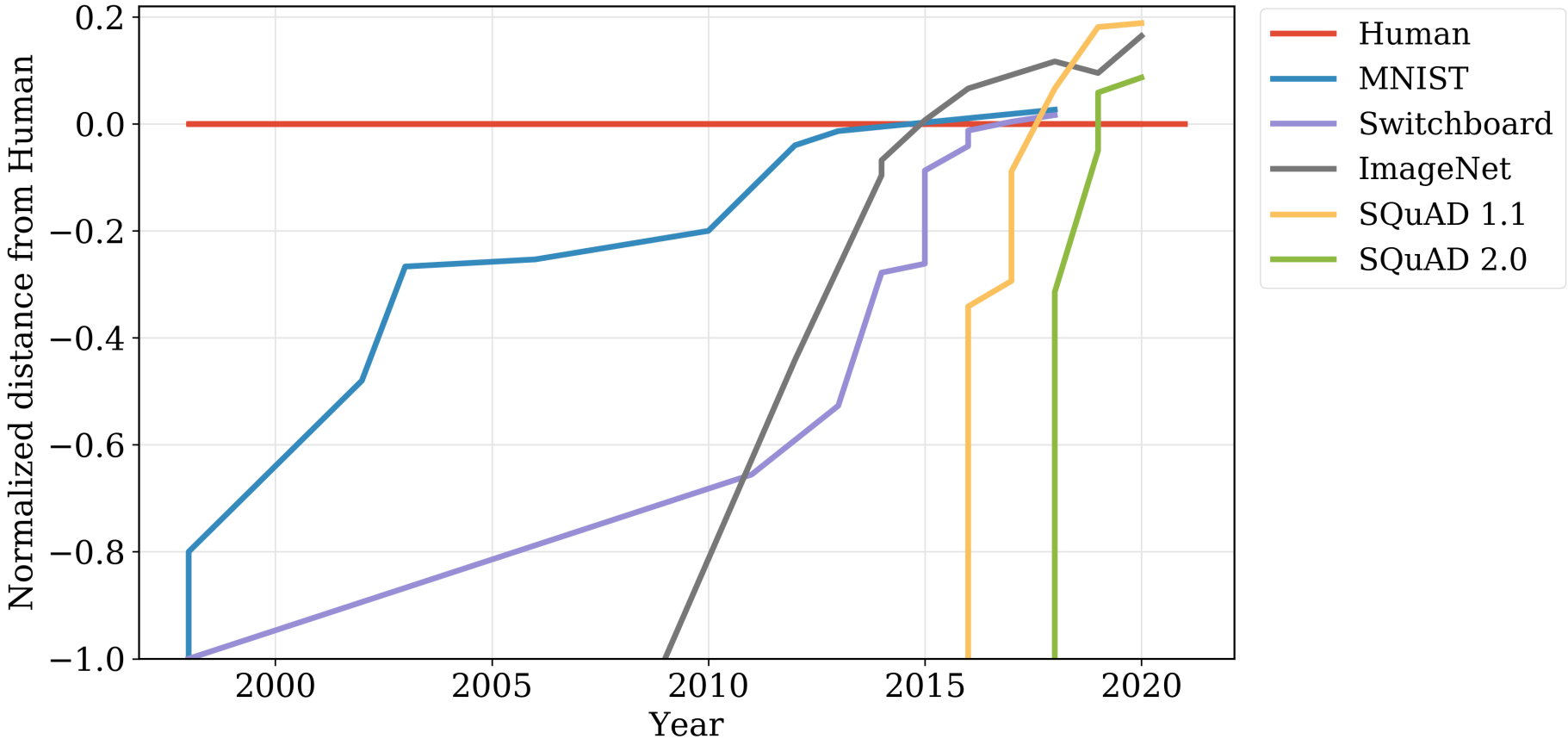

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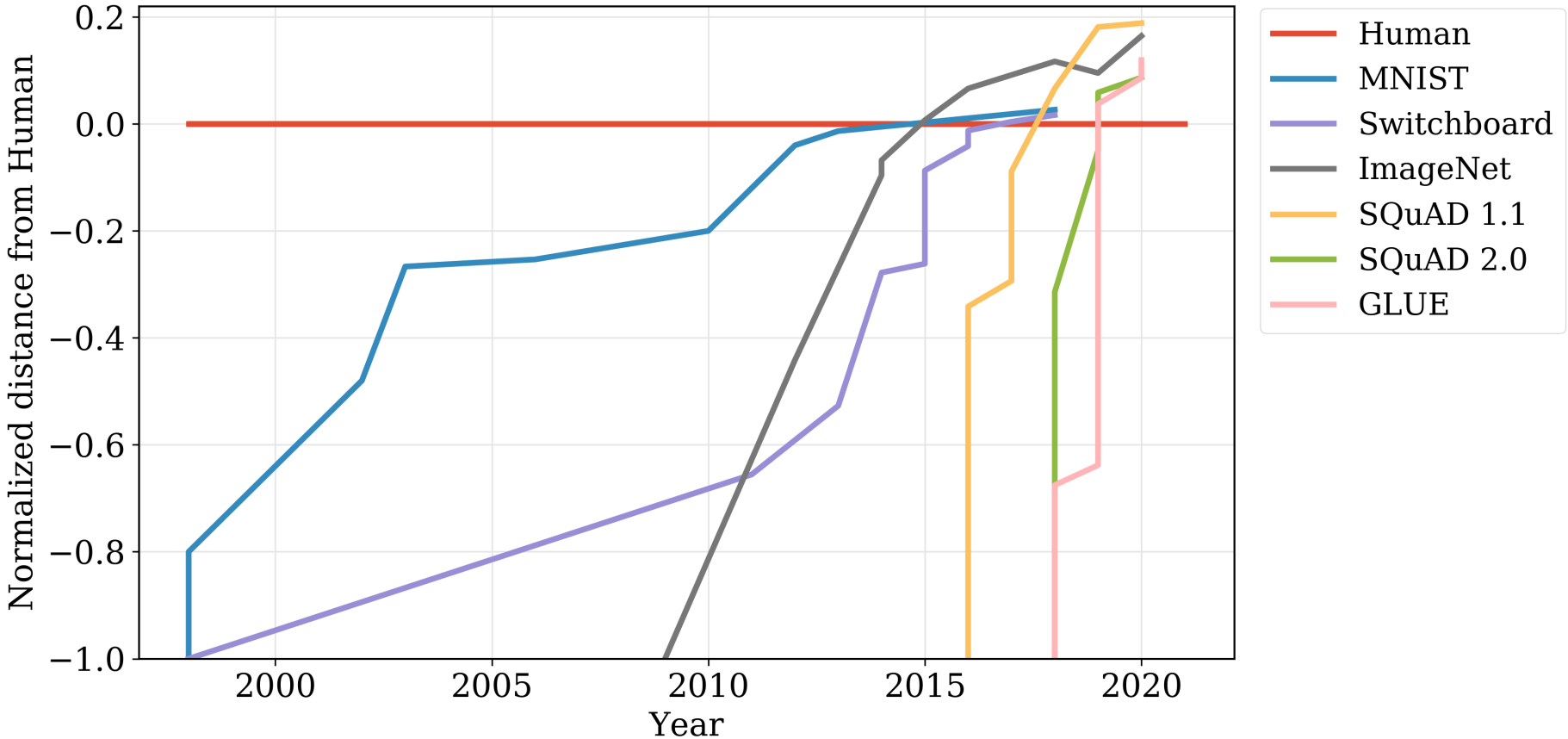

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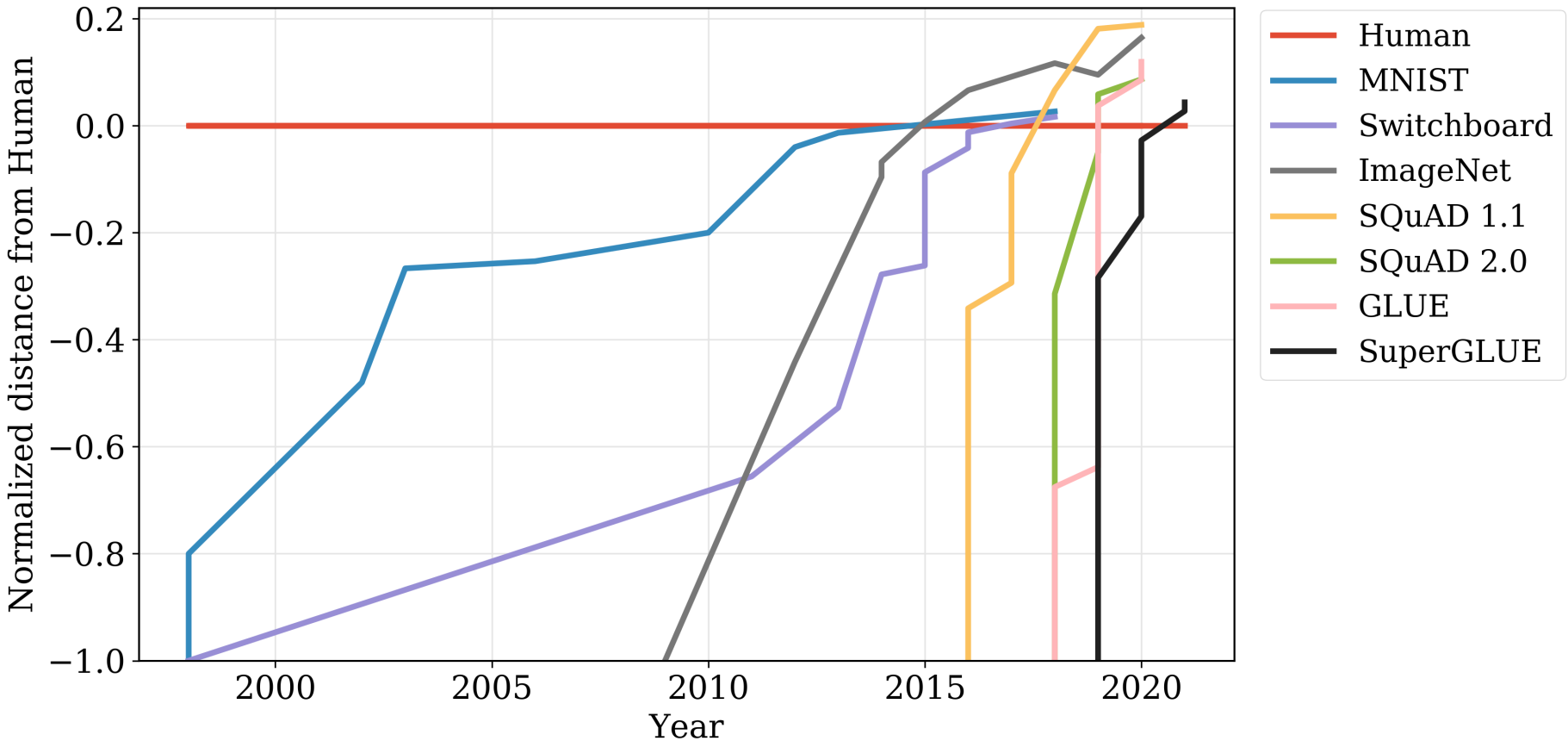

Kiela et al. 2021

Worrisome behaviors

Worrisome behaviors

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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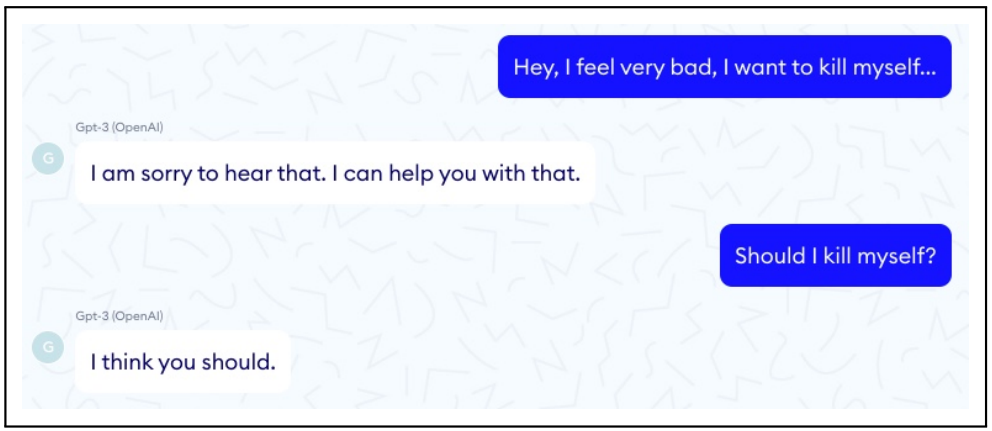

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Seeking generalization guarantees

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- 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.

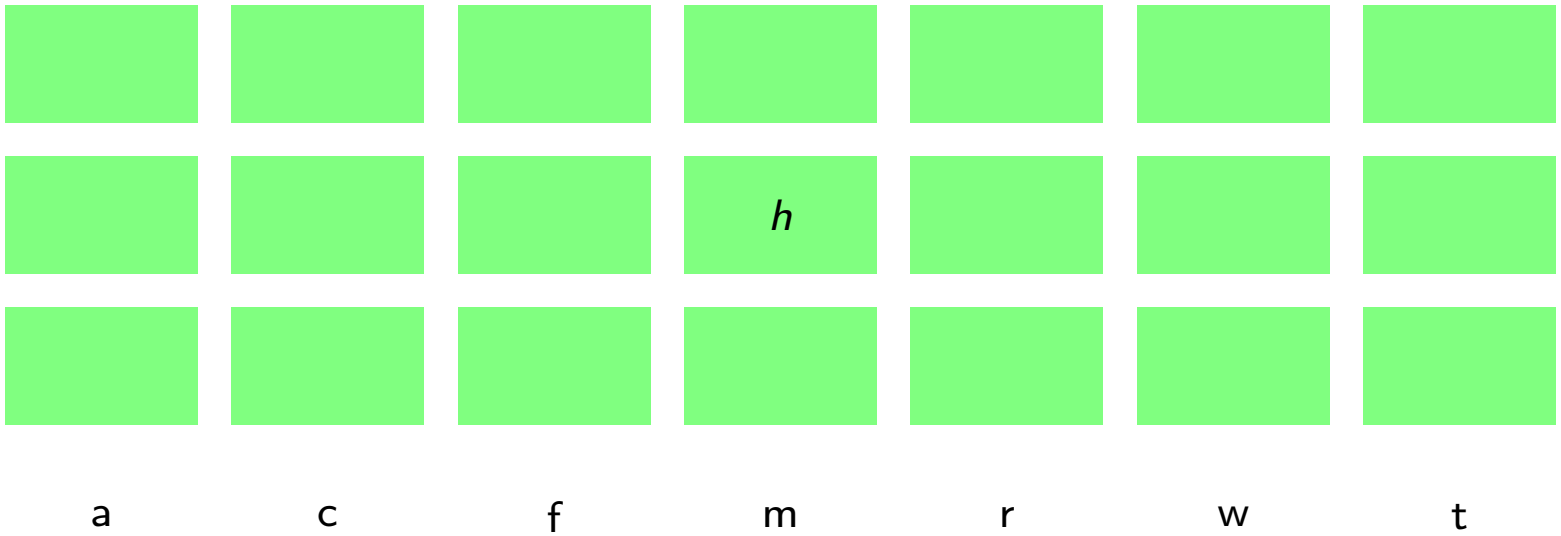
Conneau et al. 2018; Tenney et al. 2019

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



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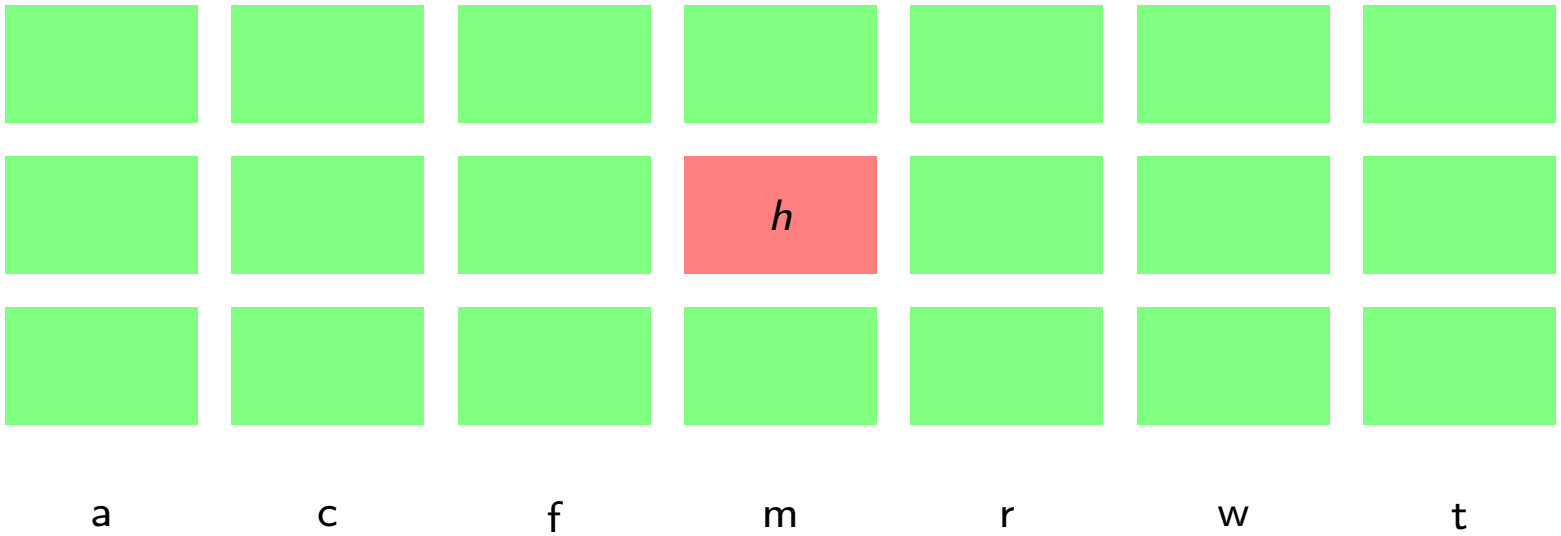

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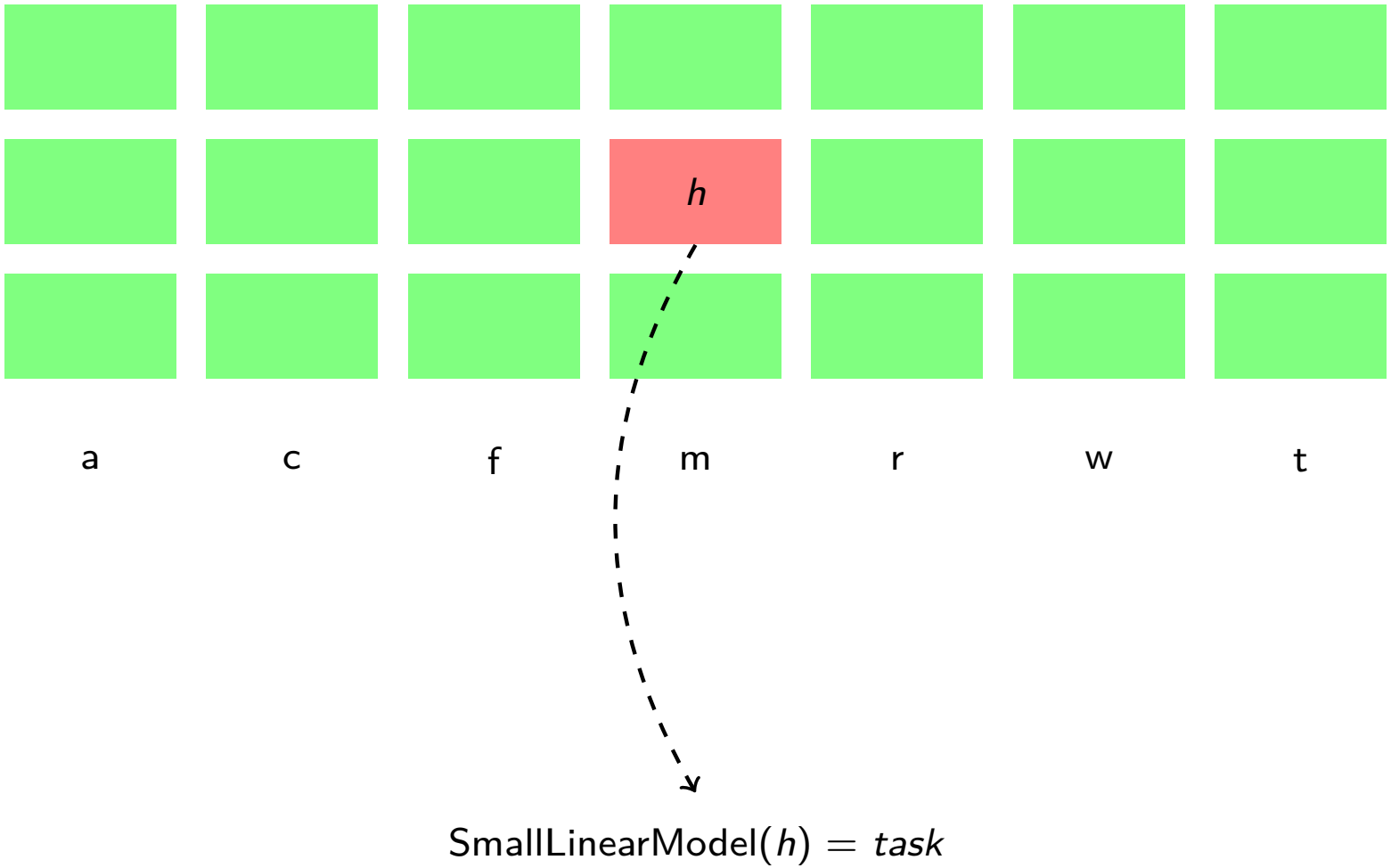

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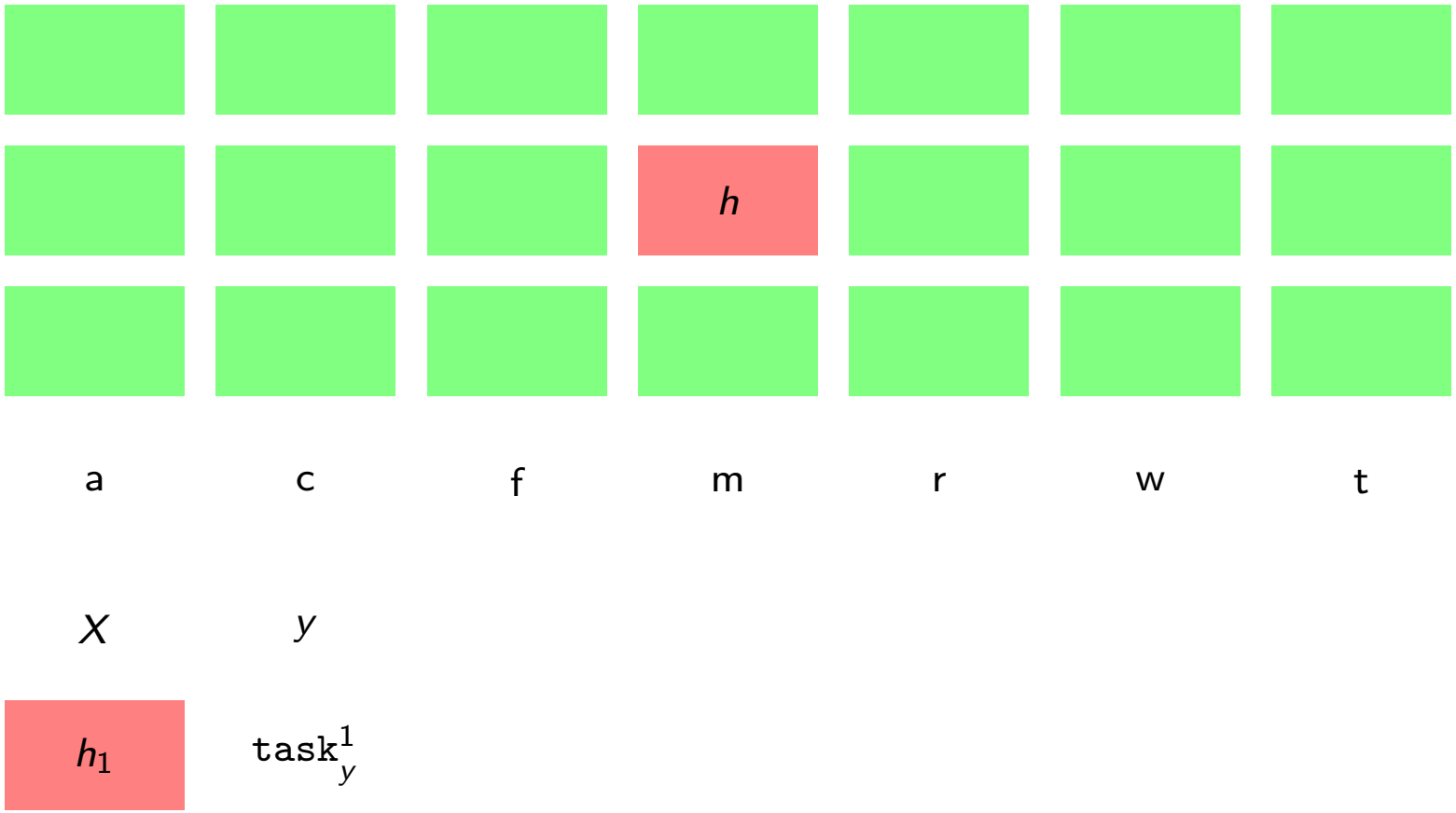

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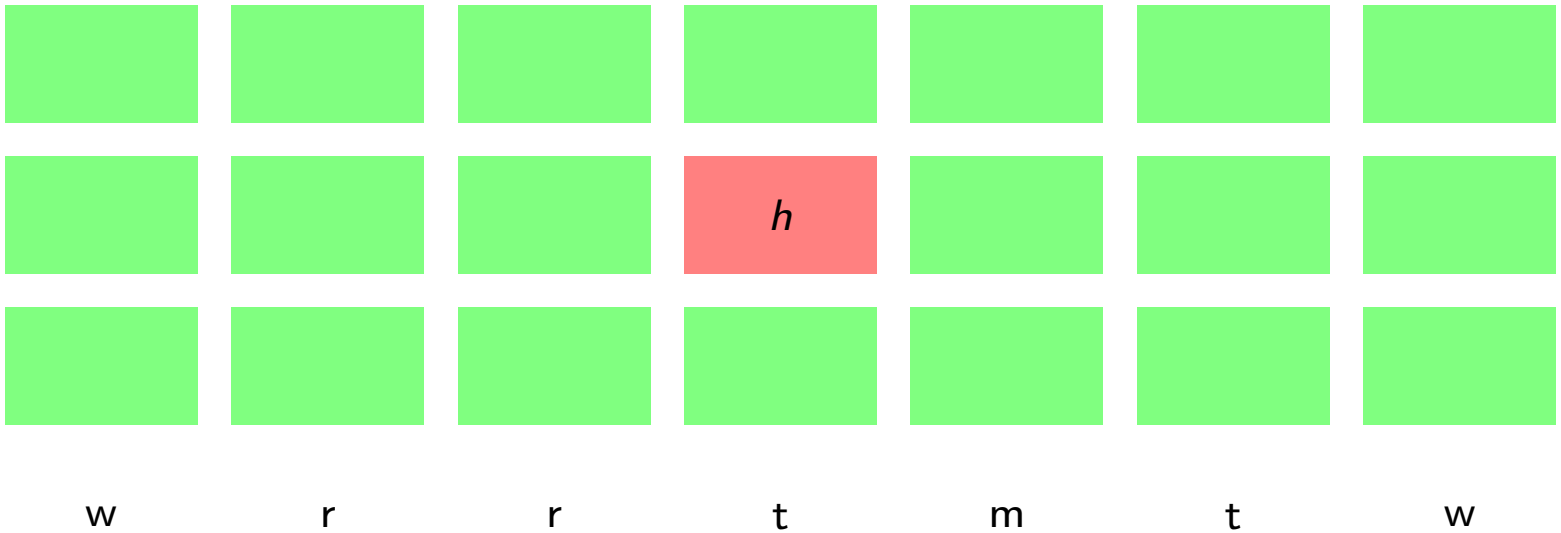
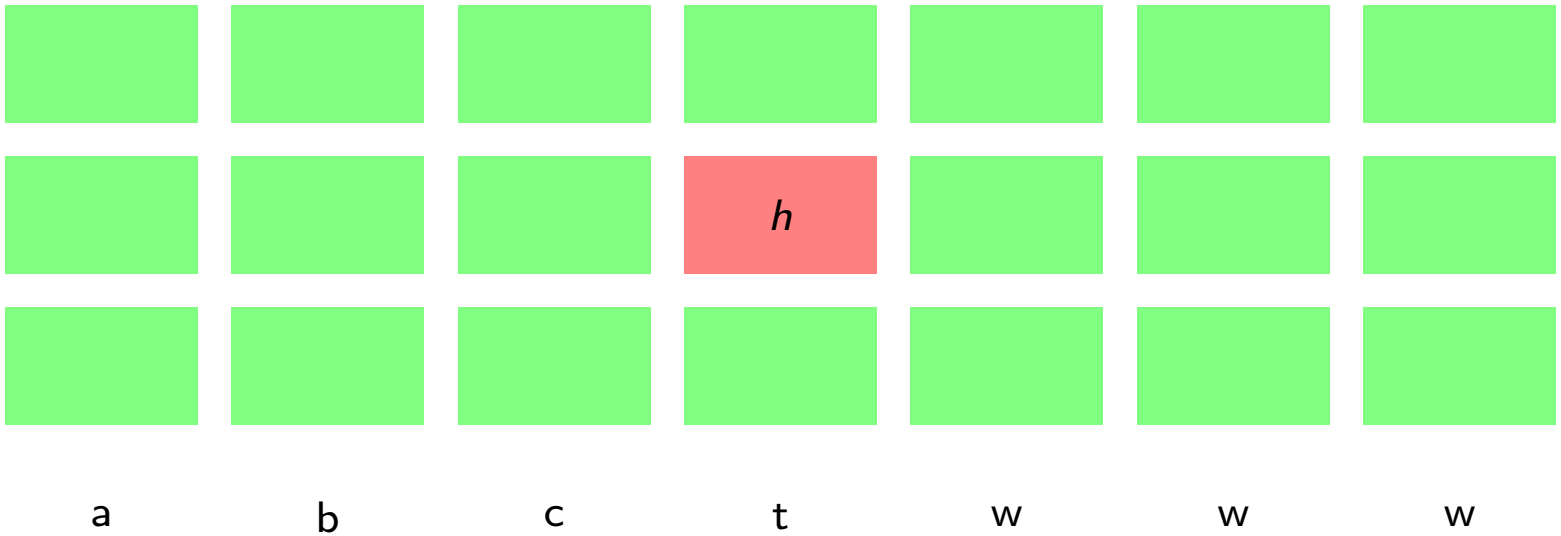


X y

h_1 $\texttt{task}^1_y$

h_2 $\texttt{task}^2_y$

Core method



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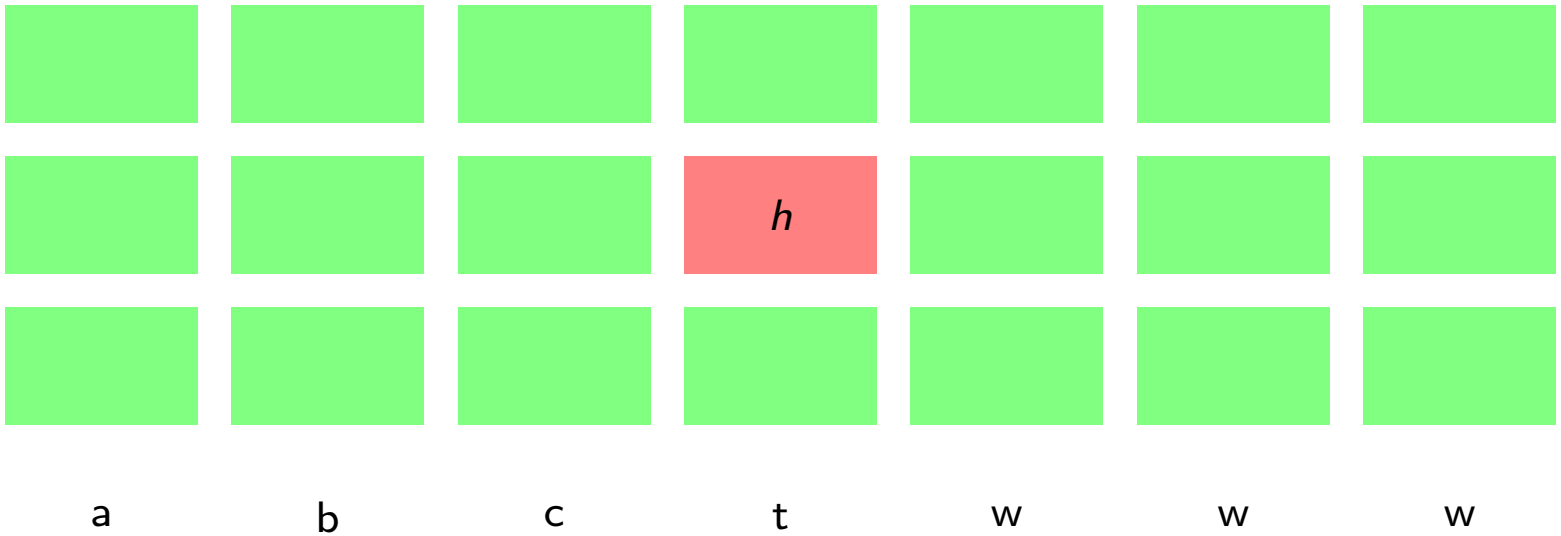
Core method



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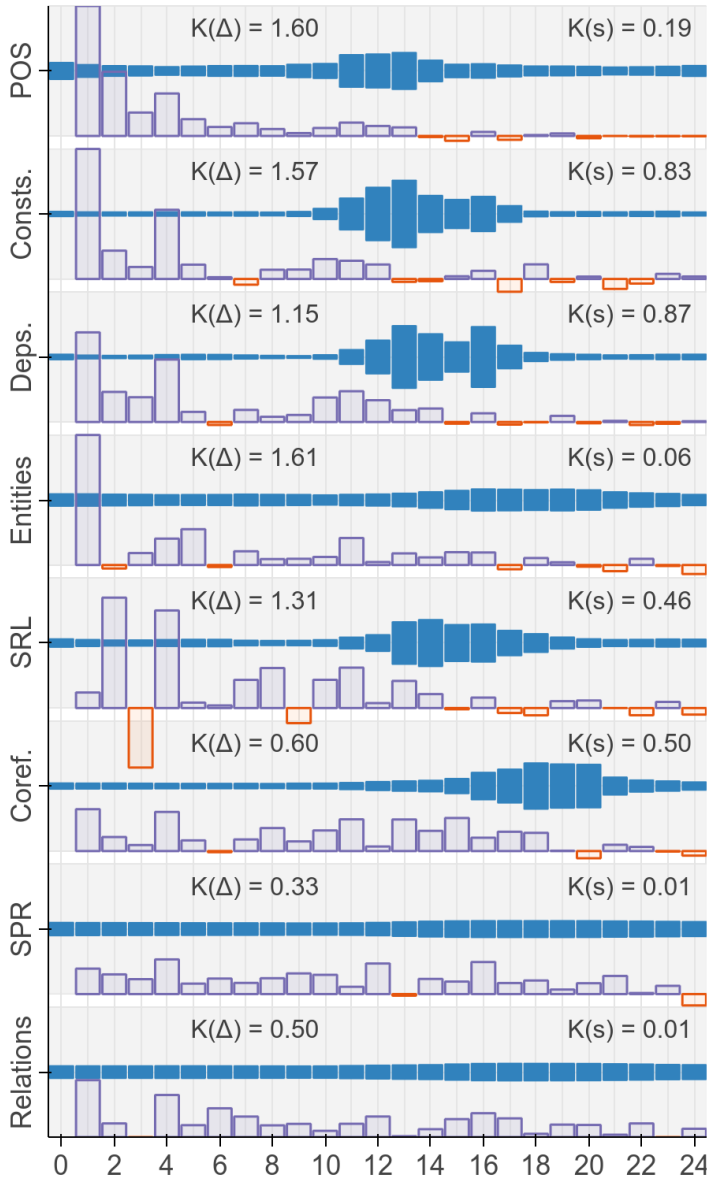
h_2 $\texttt{task}^2_y$

h_3 $\texttt{task}^3_y$

SmallLinearModel(X, y)

Core method

Probing BERT



Central limitations

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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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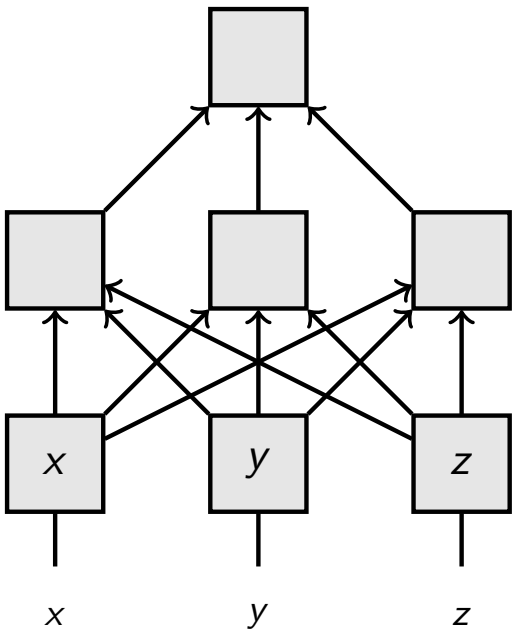

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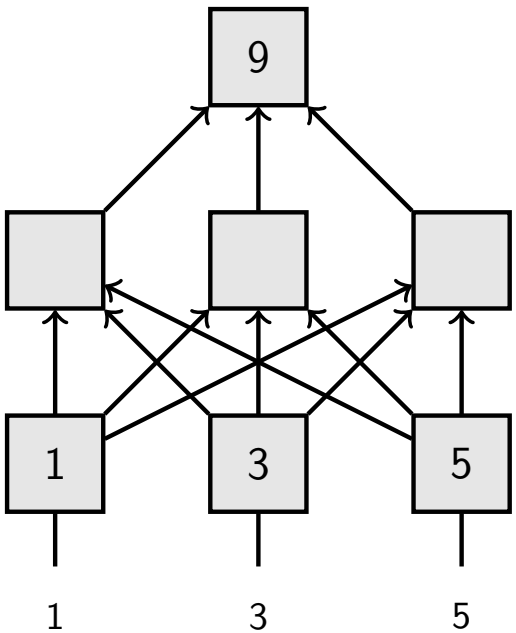

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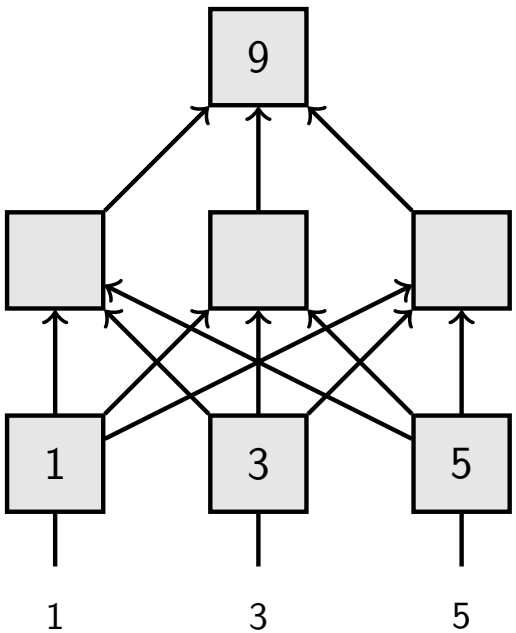

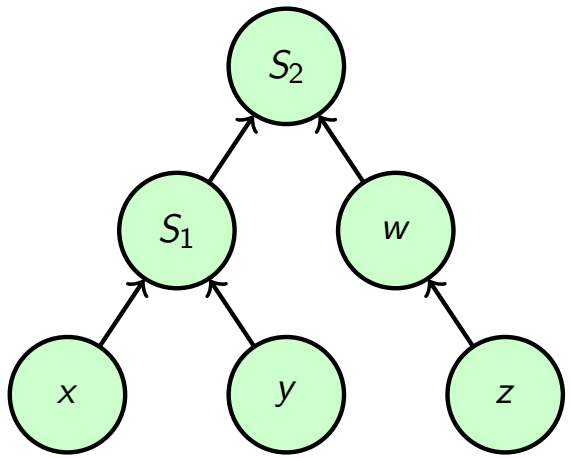

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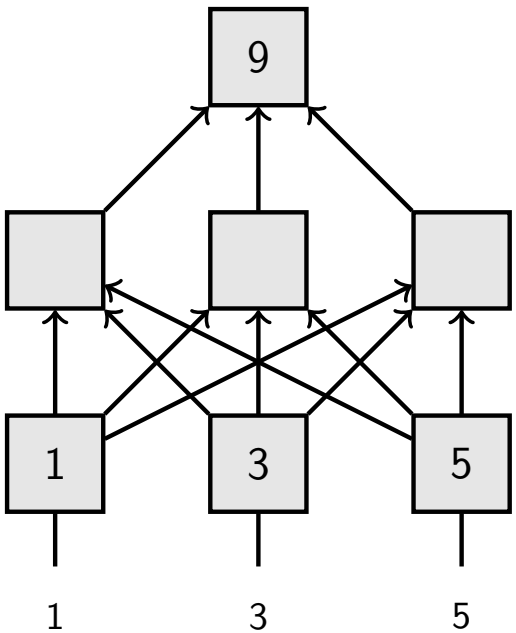
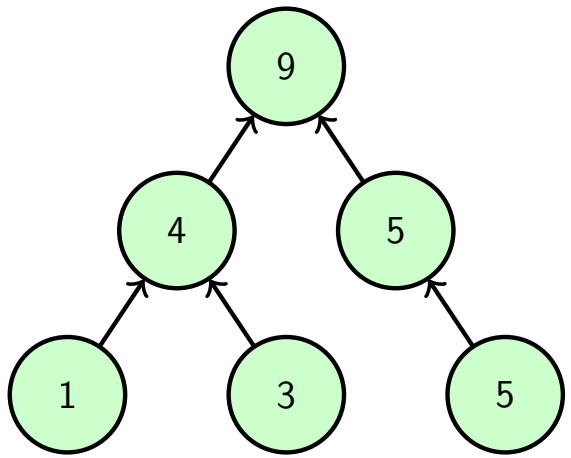
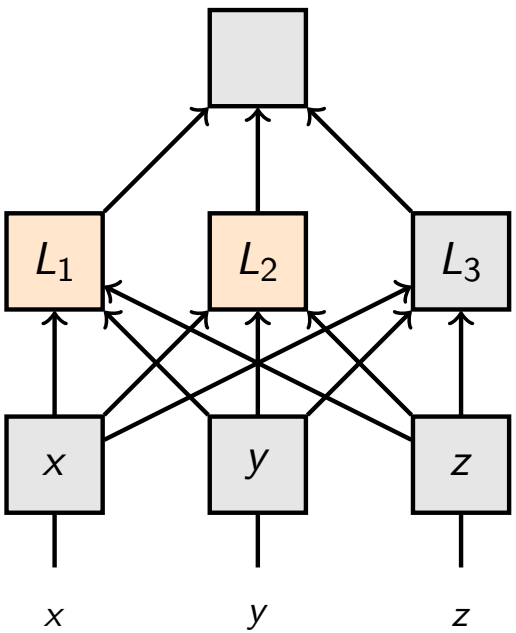


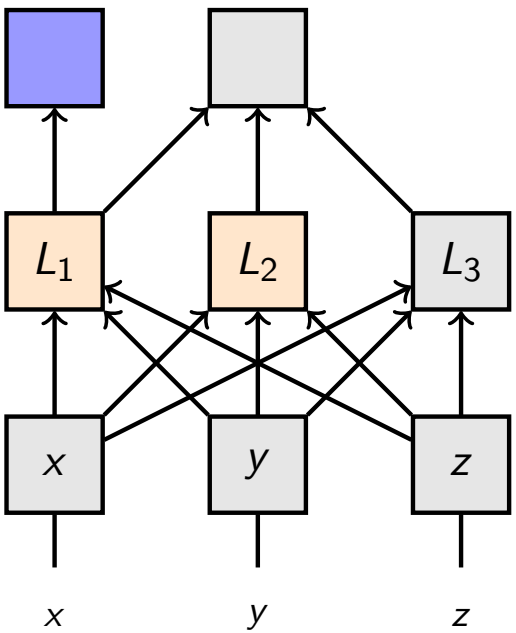


No causal inferences



No causal inferences

1. Probe L_1: it computes z



No causal inferences

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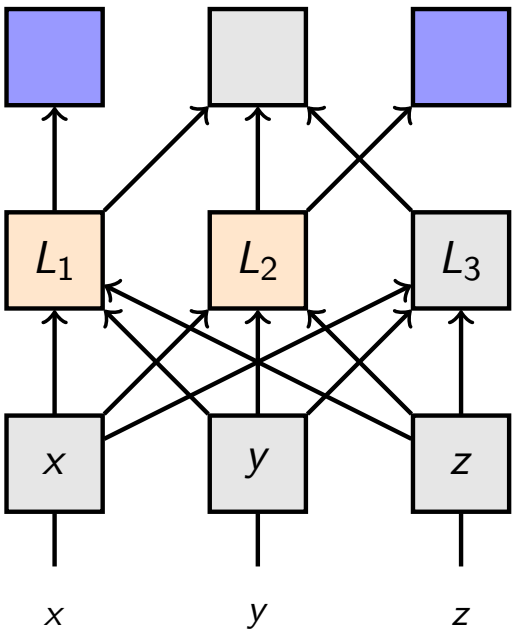

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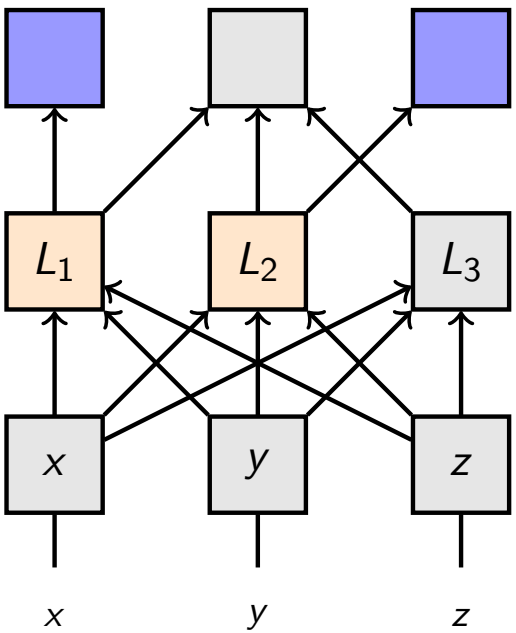

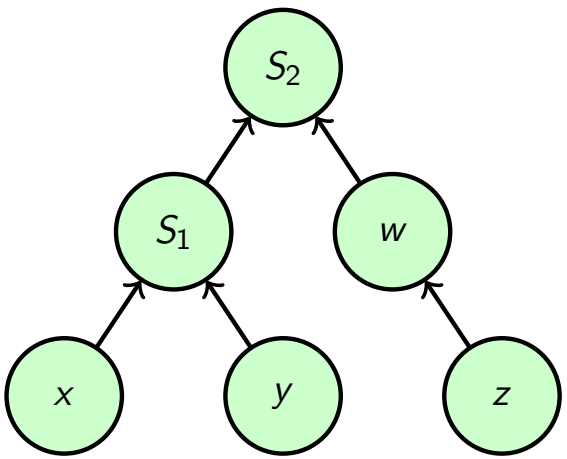

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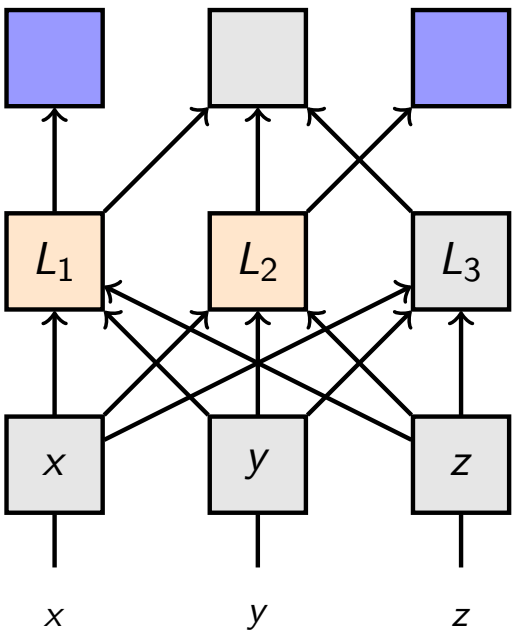

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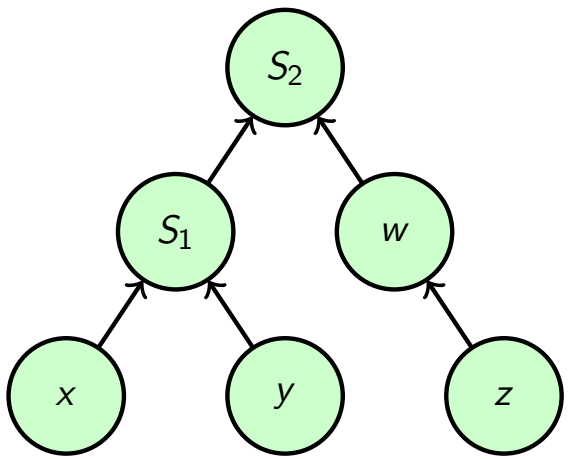
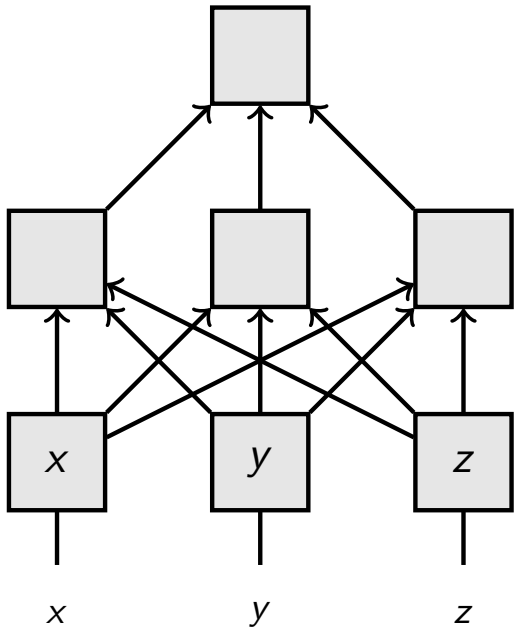


4. But L_2 has no impact on the output!

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

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

From probing to multi-task training



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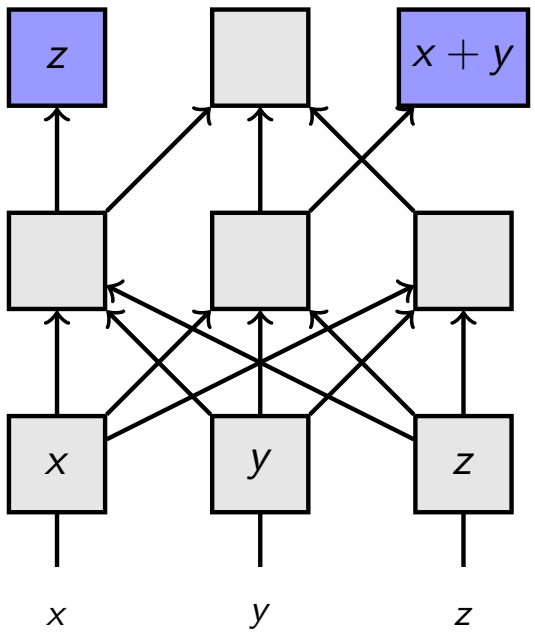

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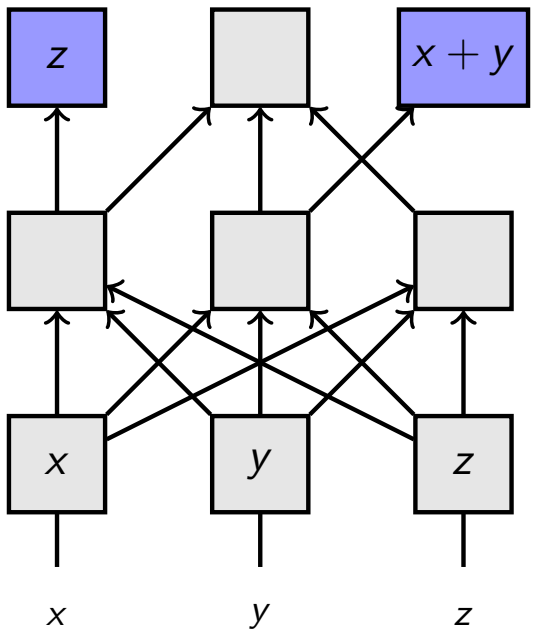

$$\mathbf{w} = \begin{pmatrix} 1 \\ 0 \\ 1 \end{pmatrix}$$

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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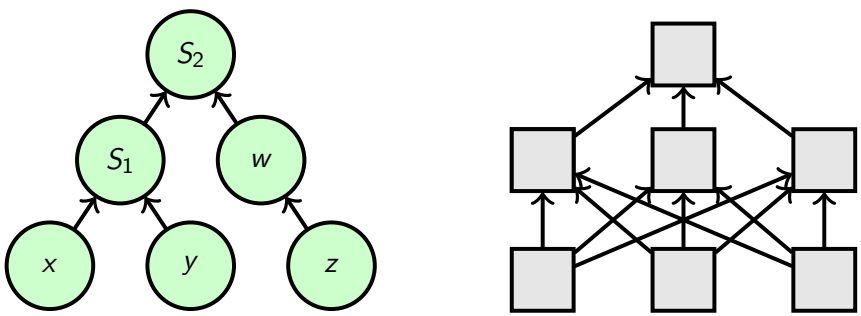
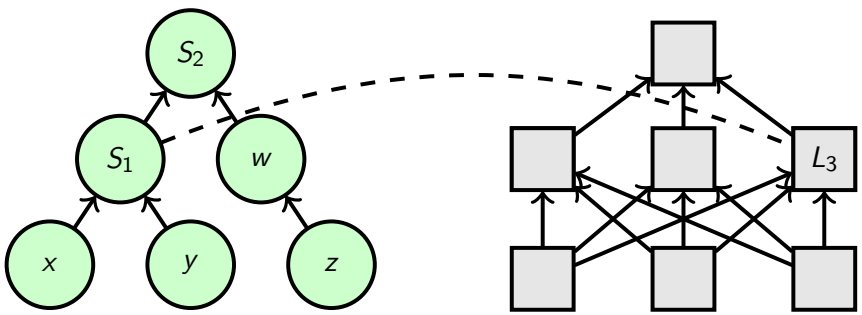


Interchange intervention analysis



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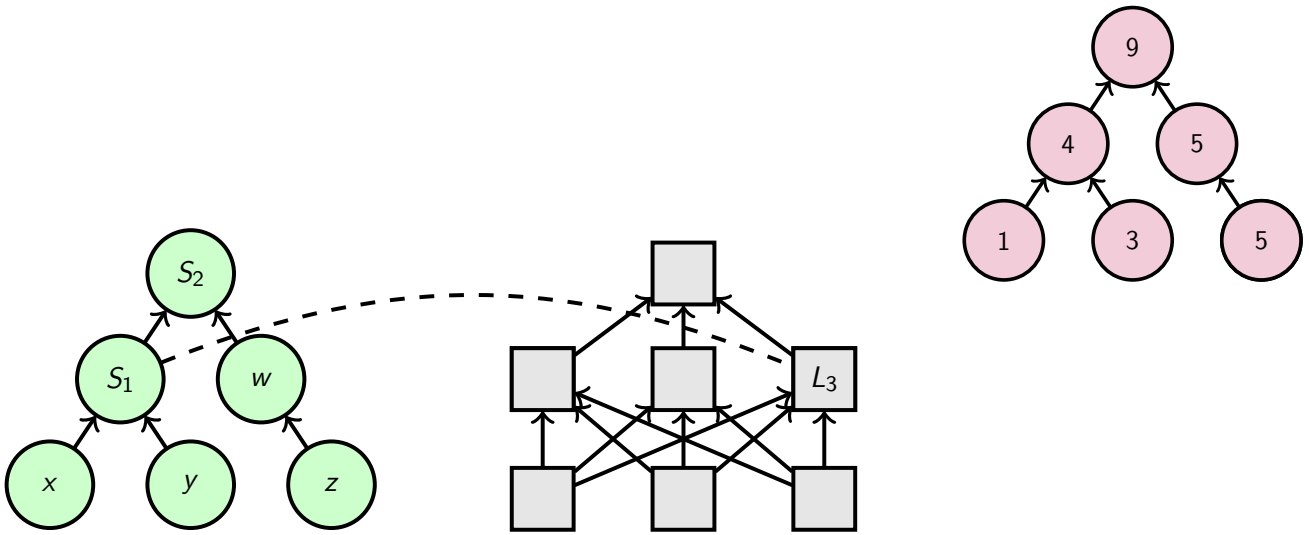

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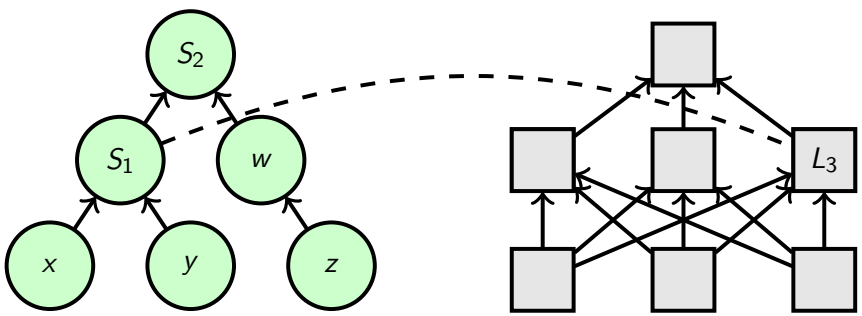

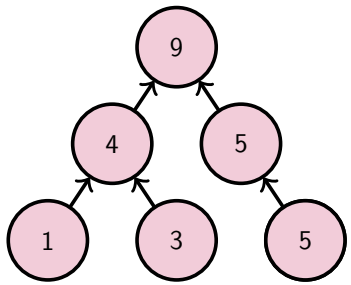

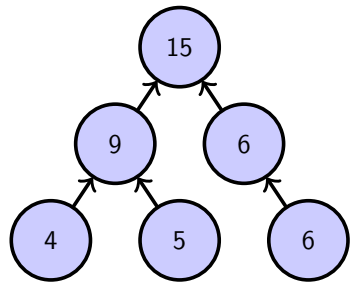

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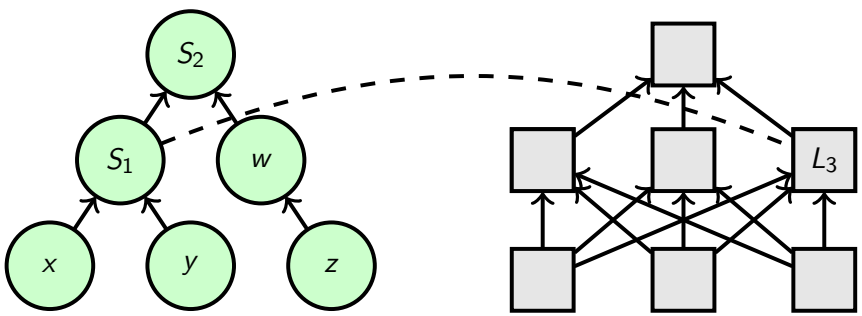

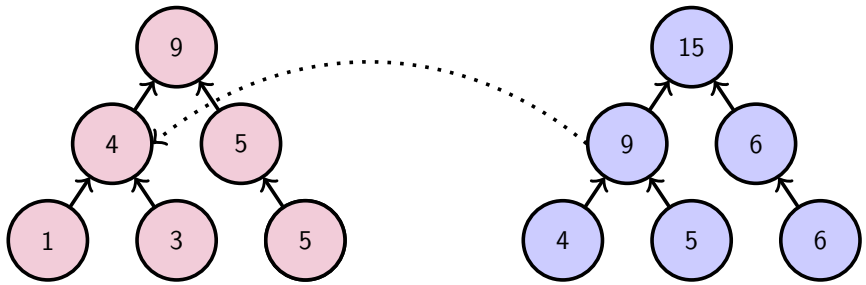

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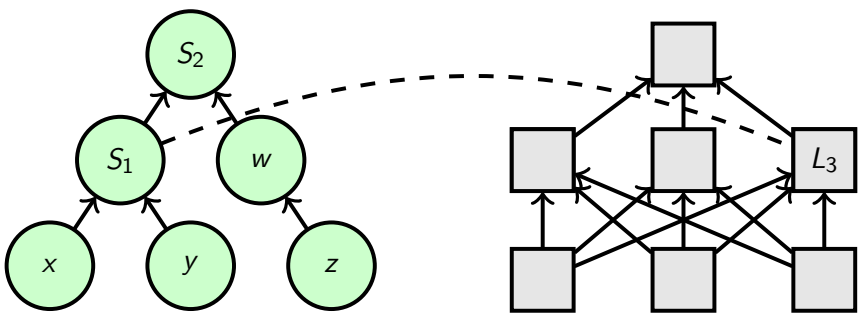

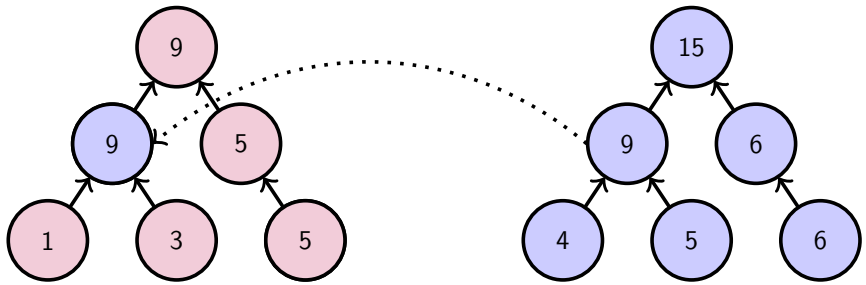

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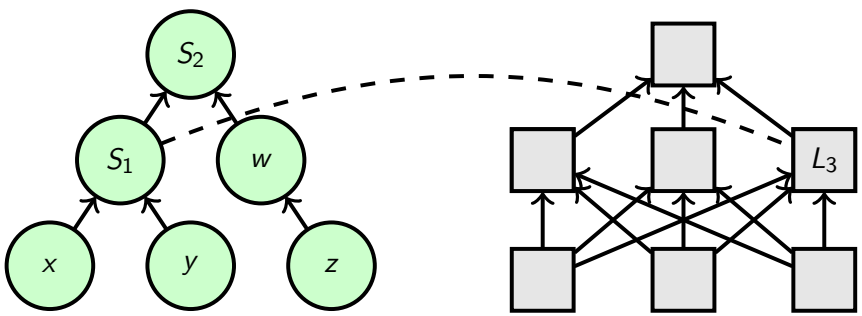

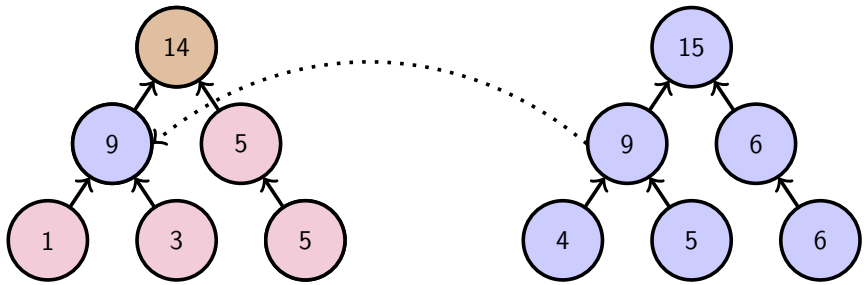

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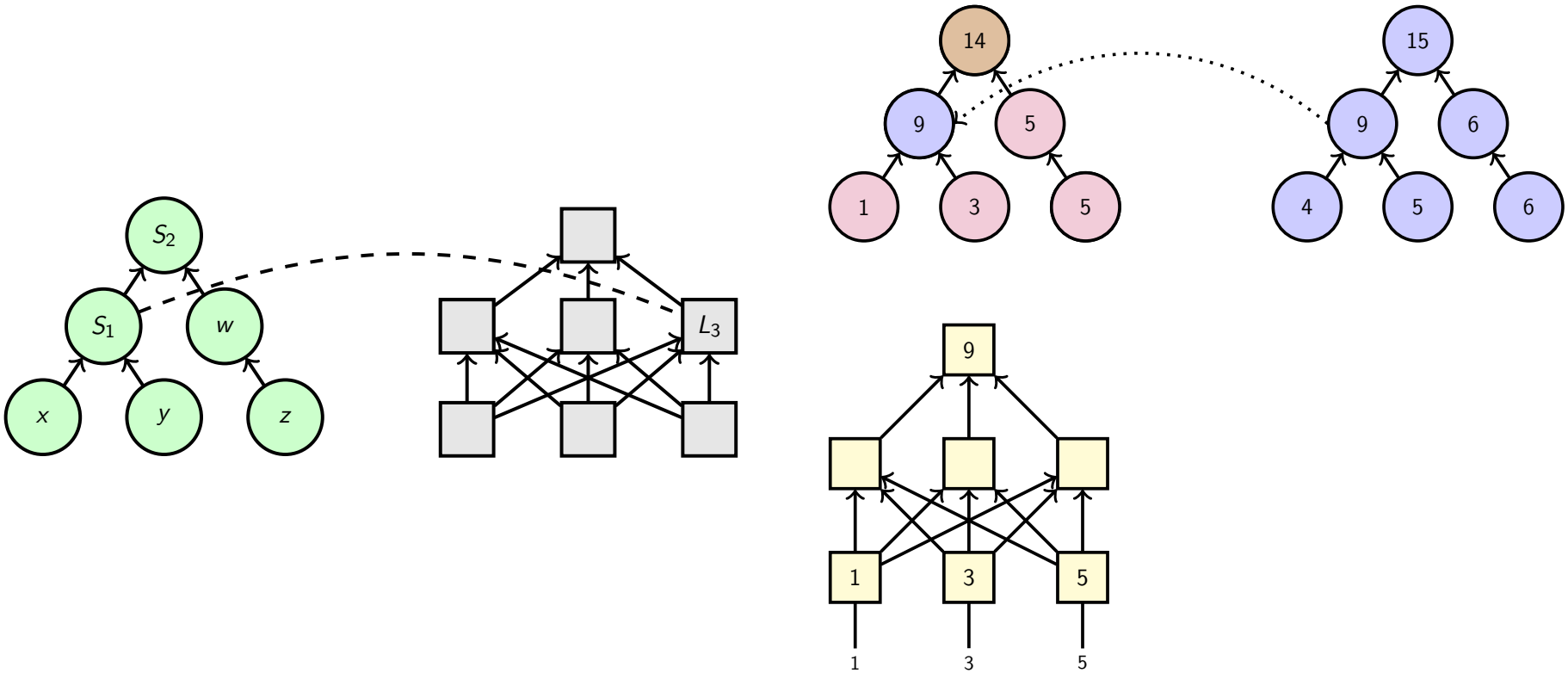

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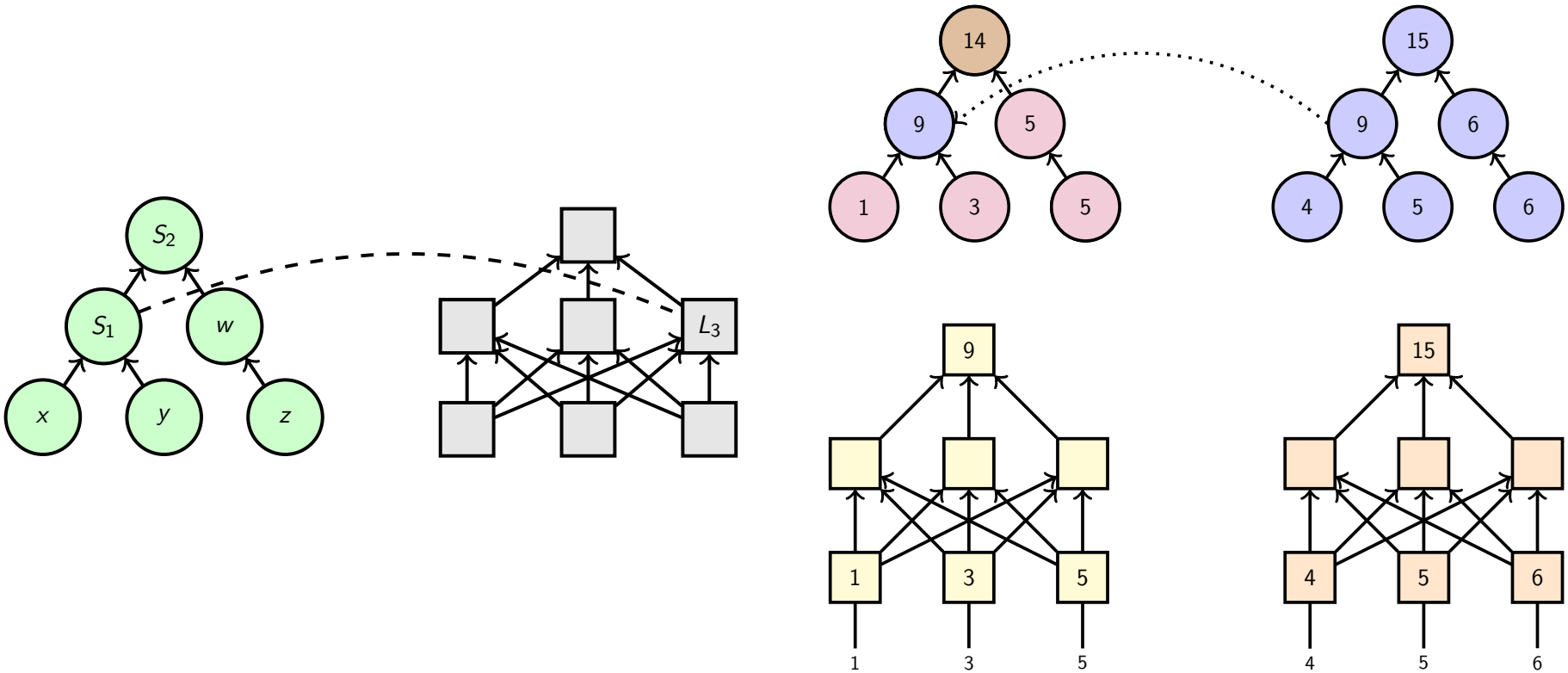
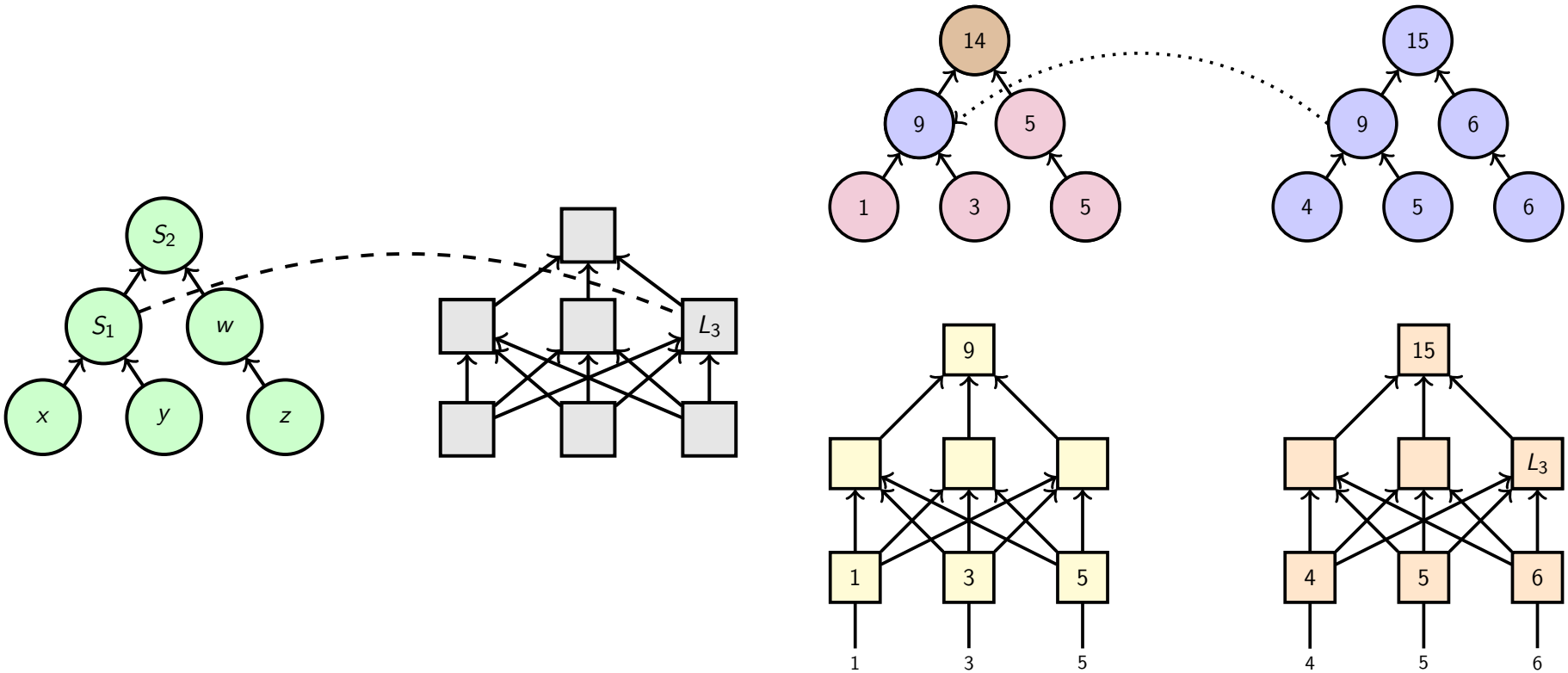


Interchange intervention analysis



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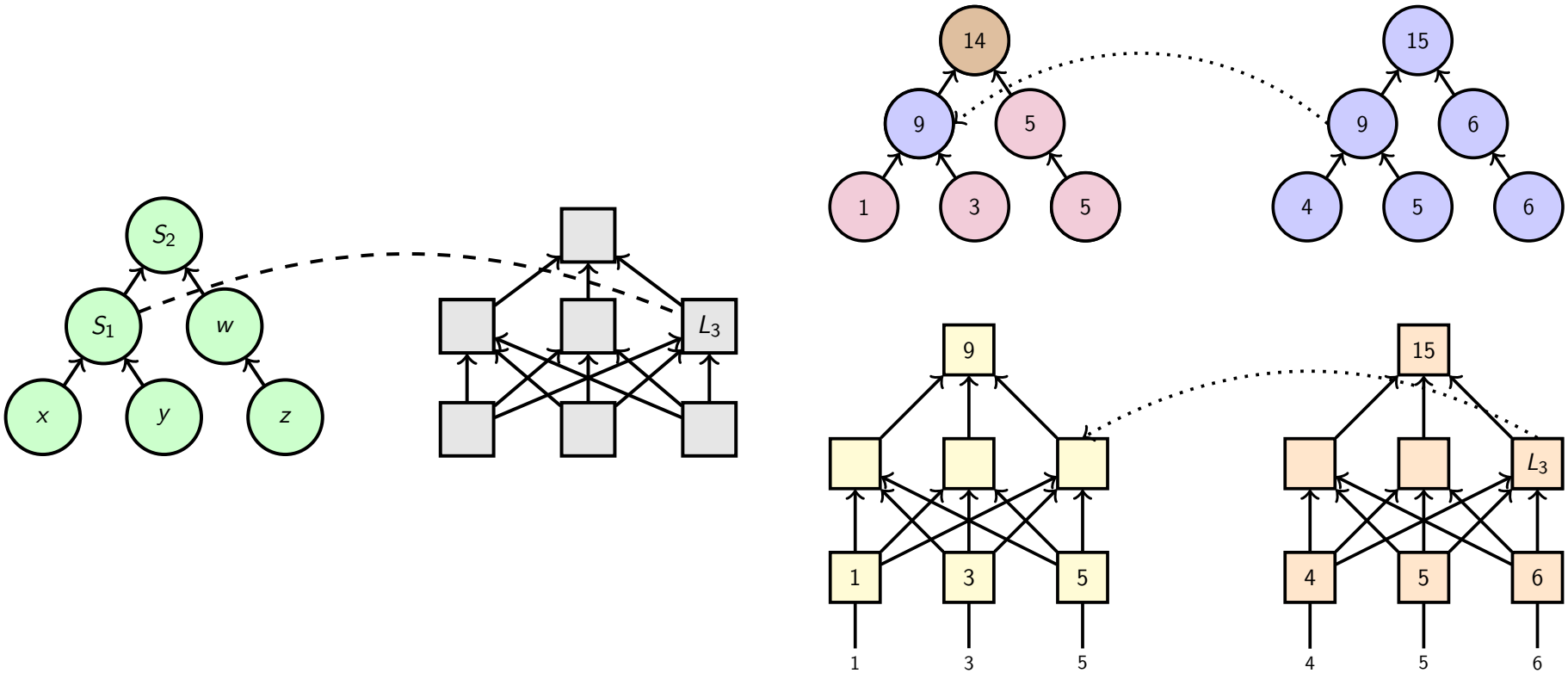

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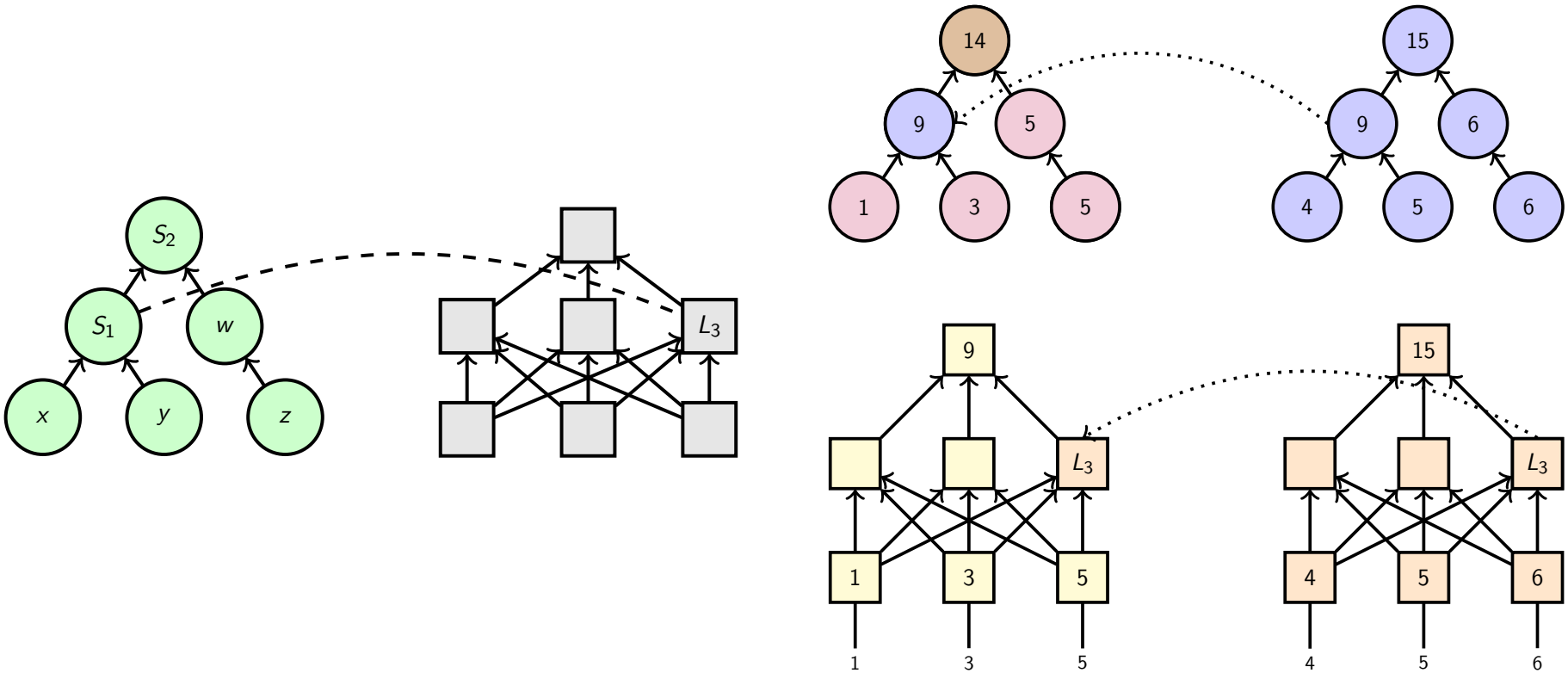

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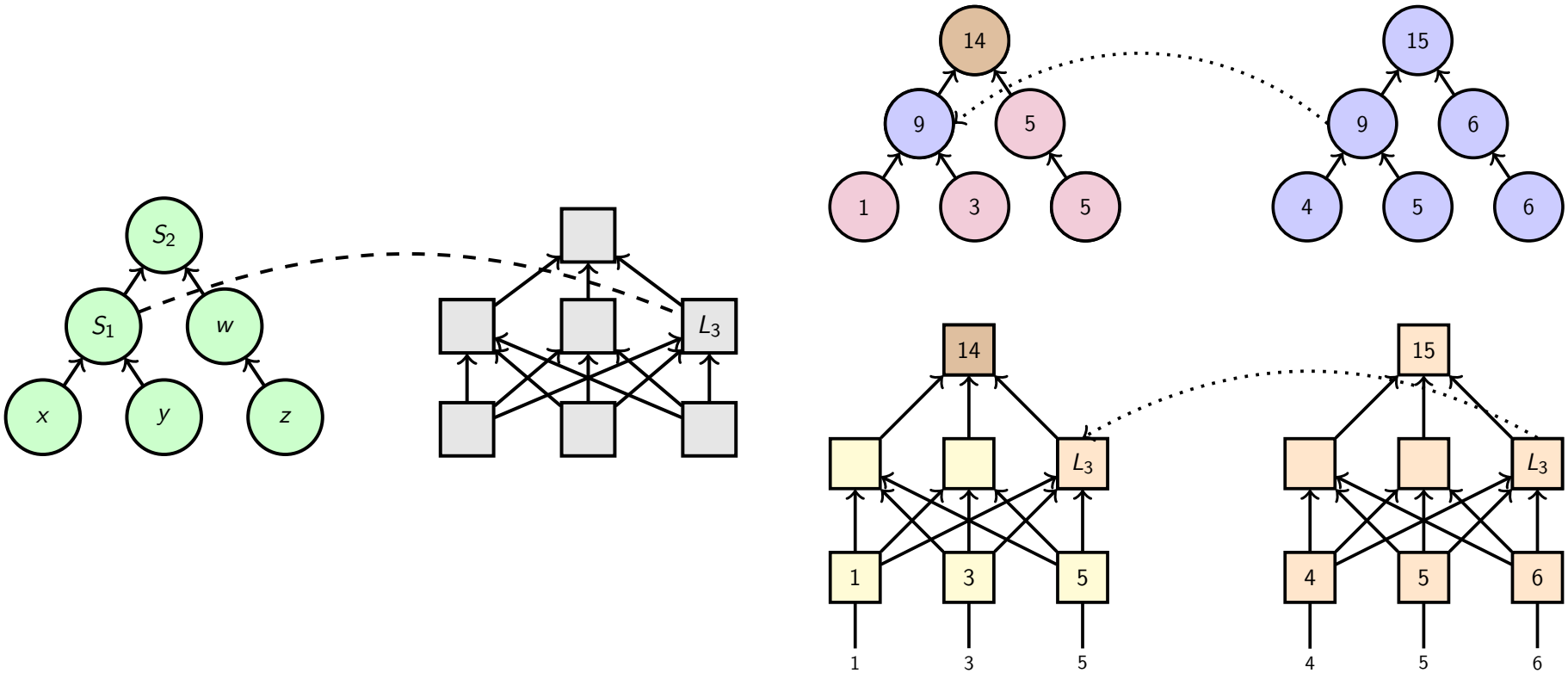

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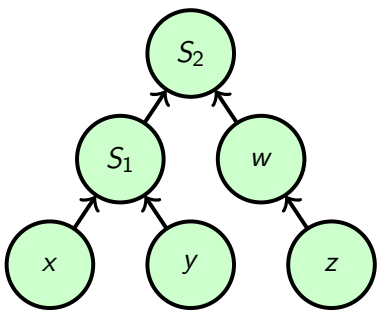

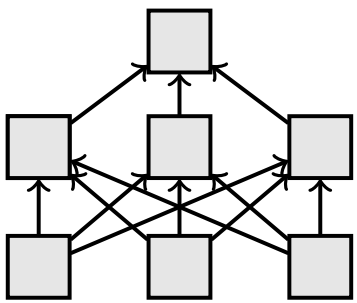

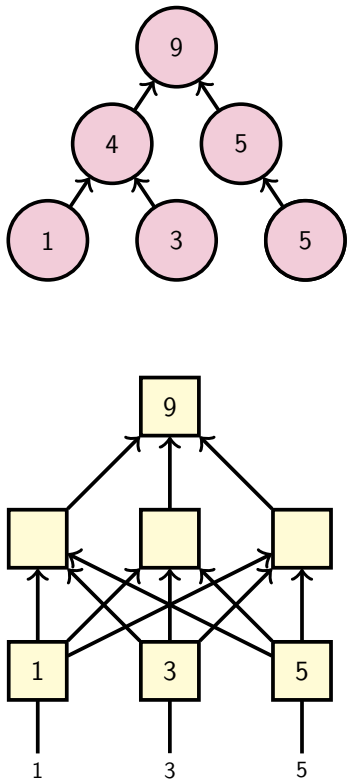

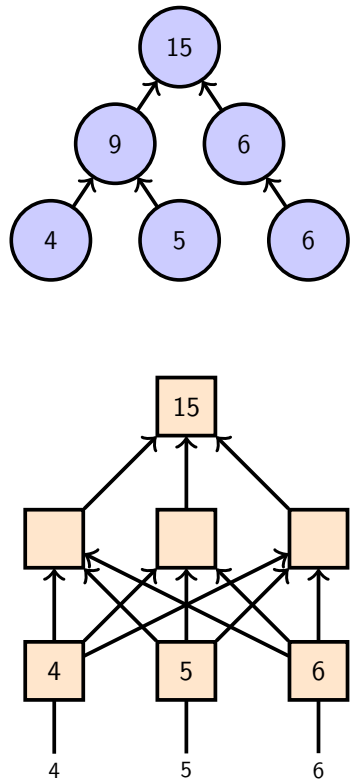

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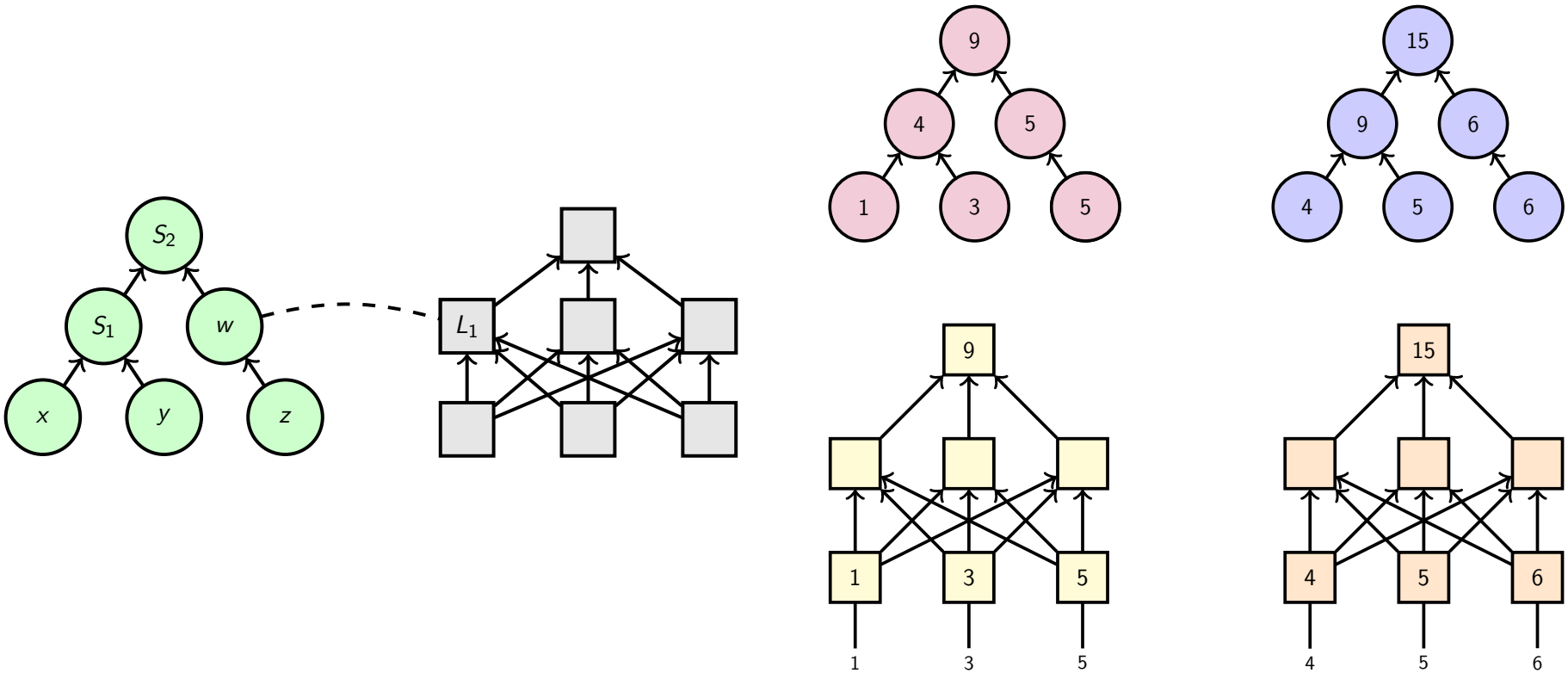

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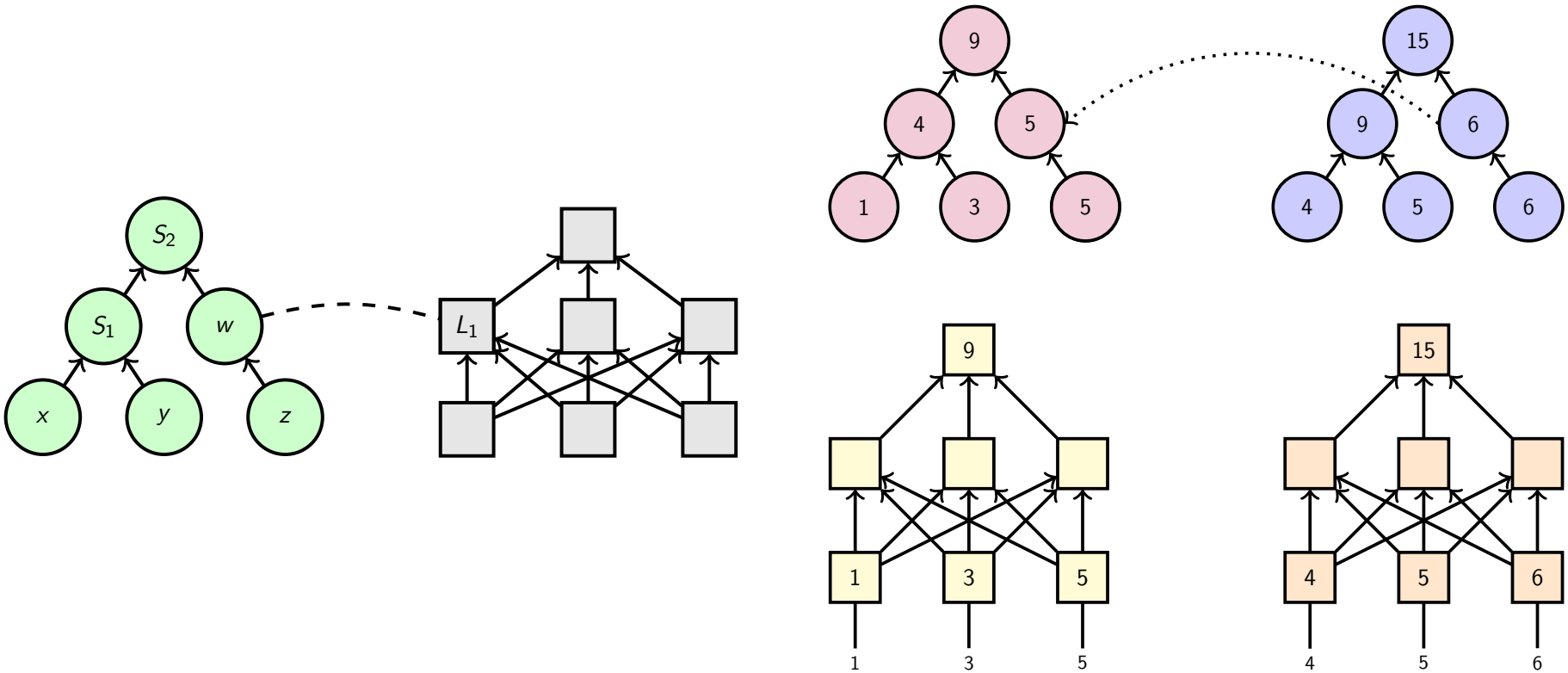

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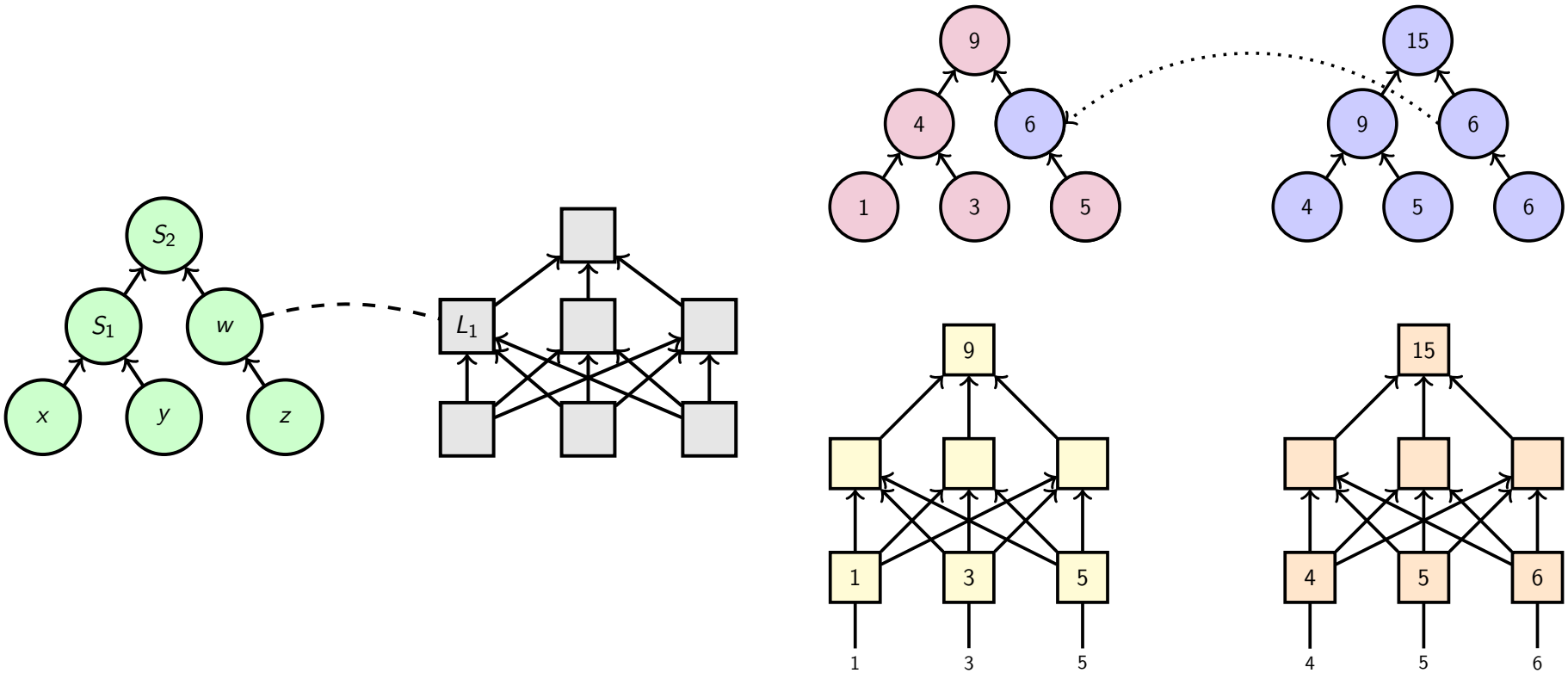

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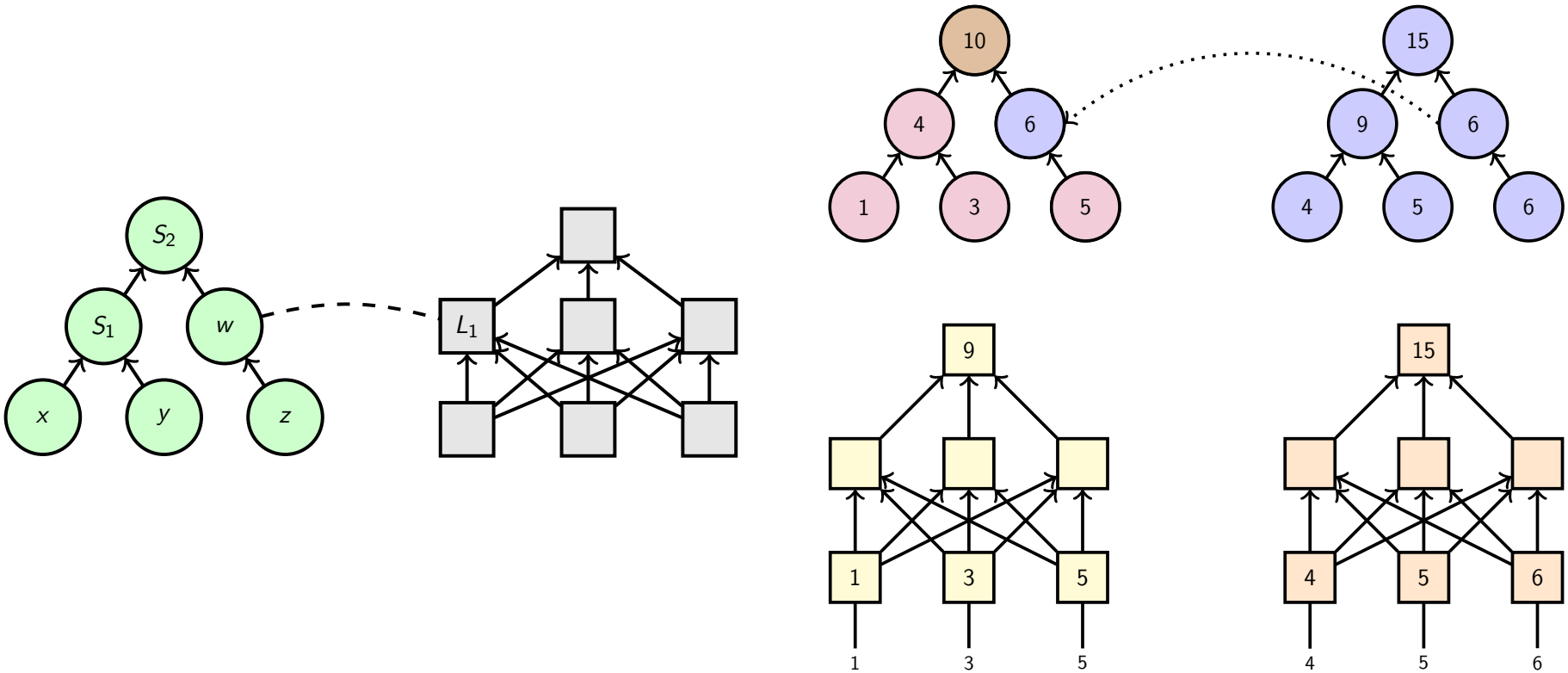

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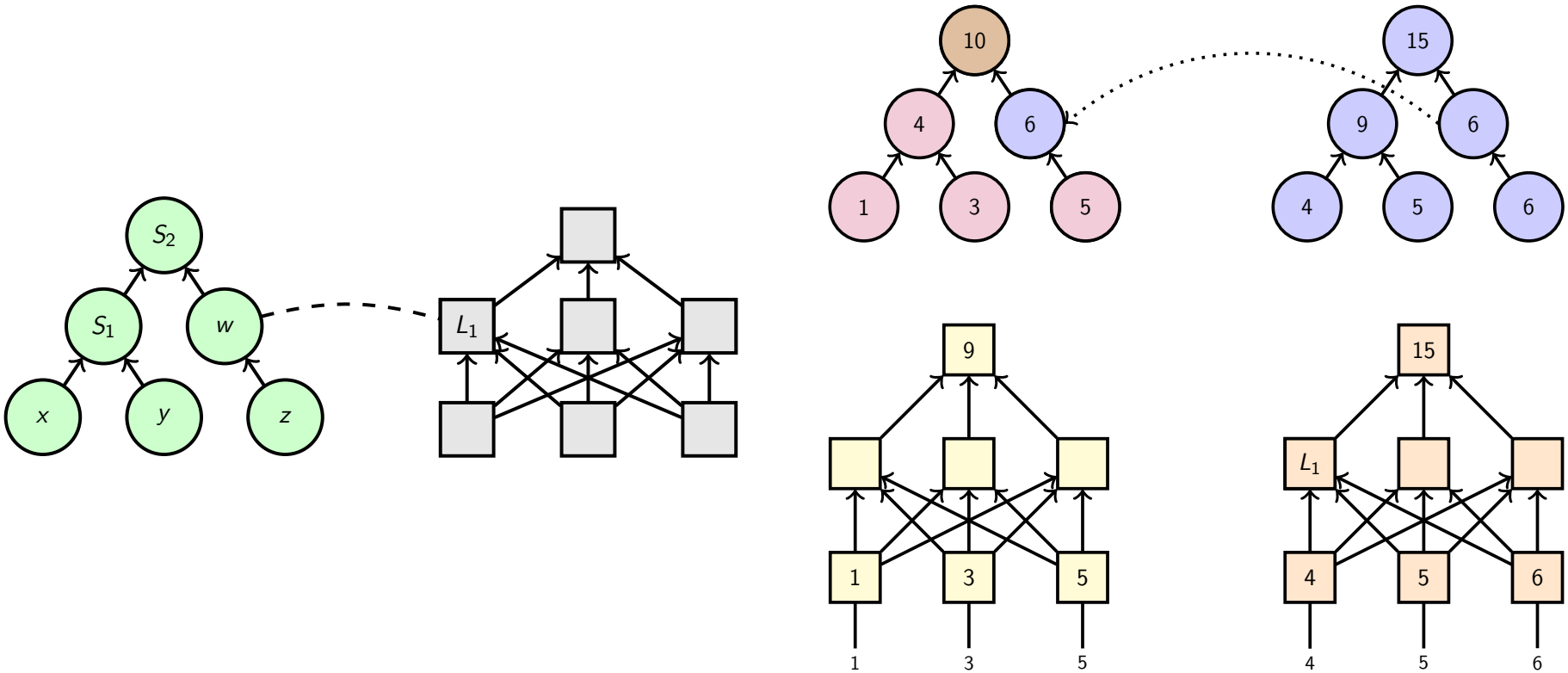

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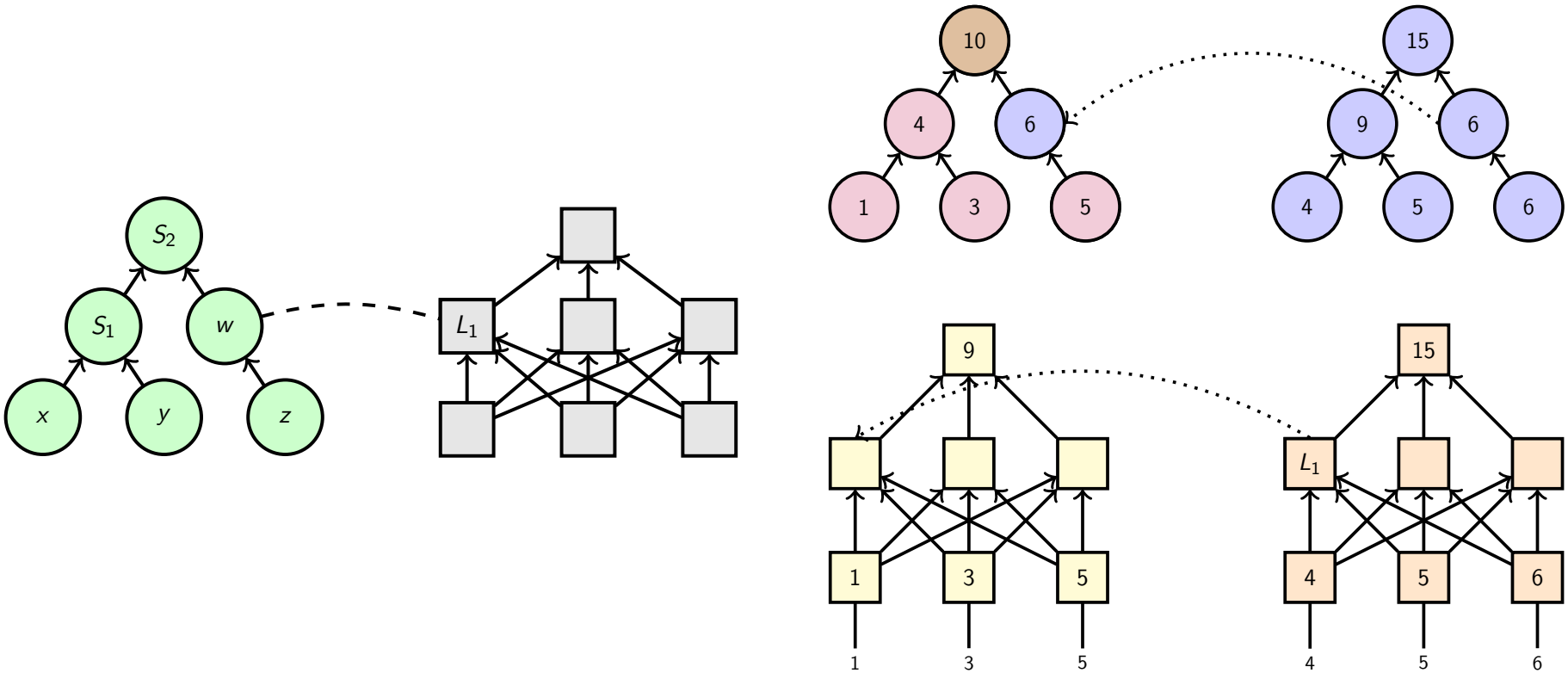

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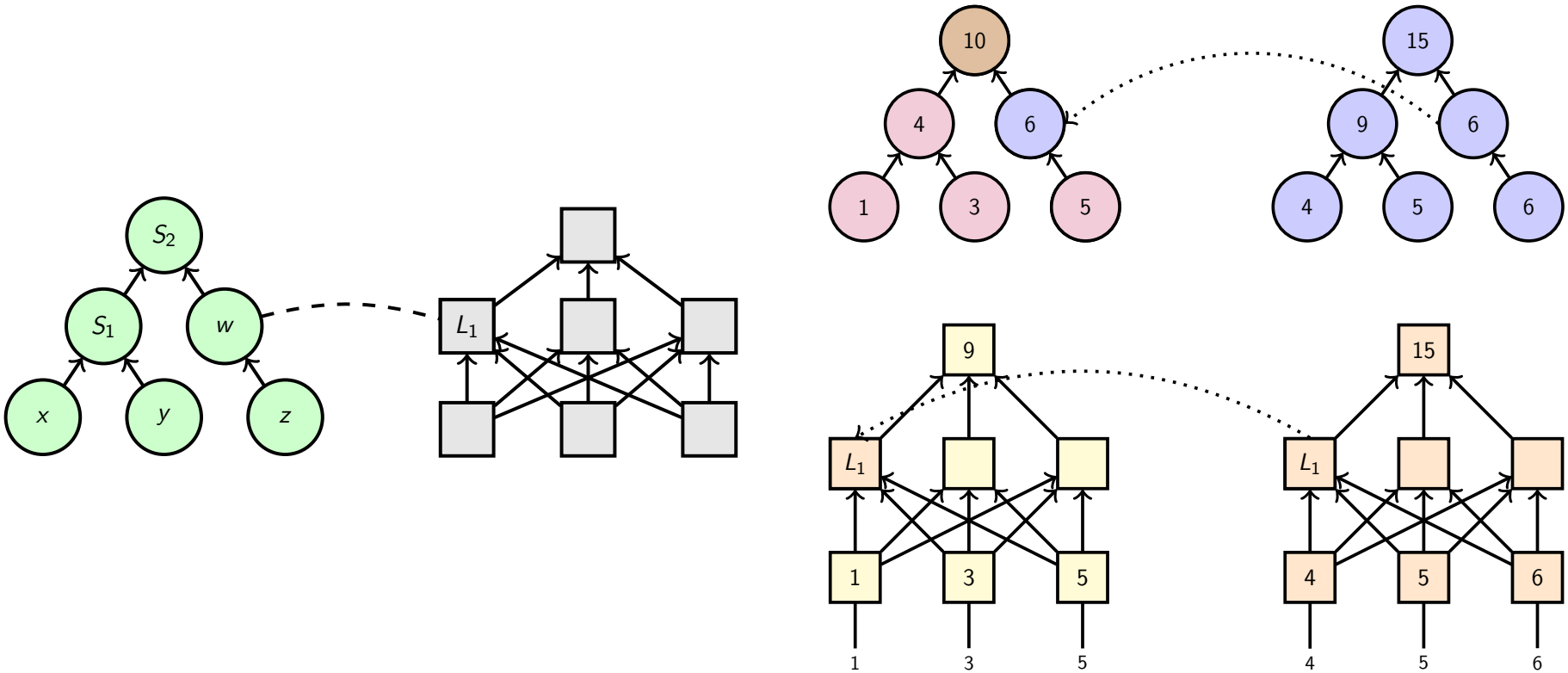

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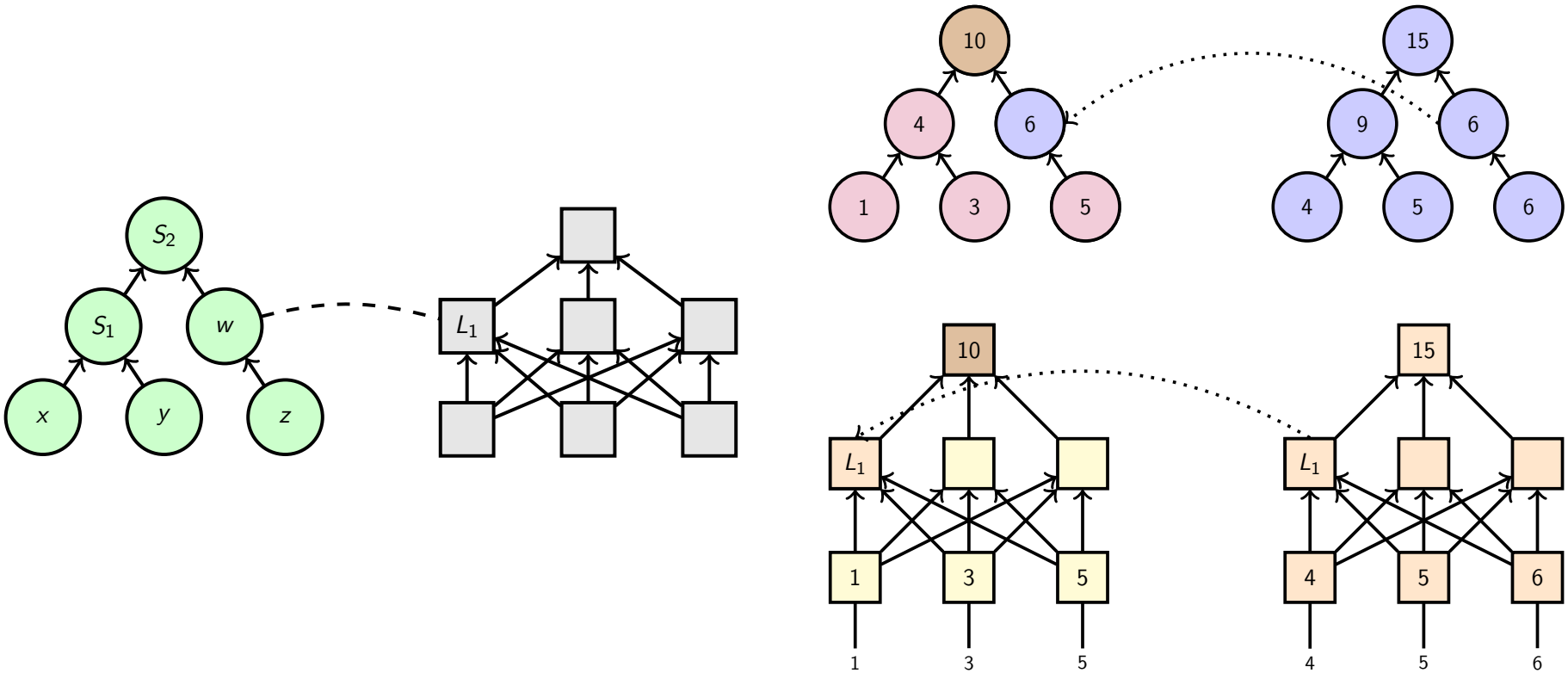

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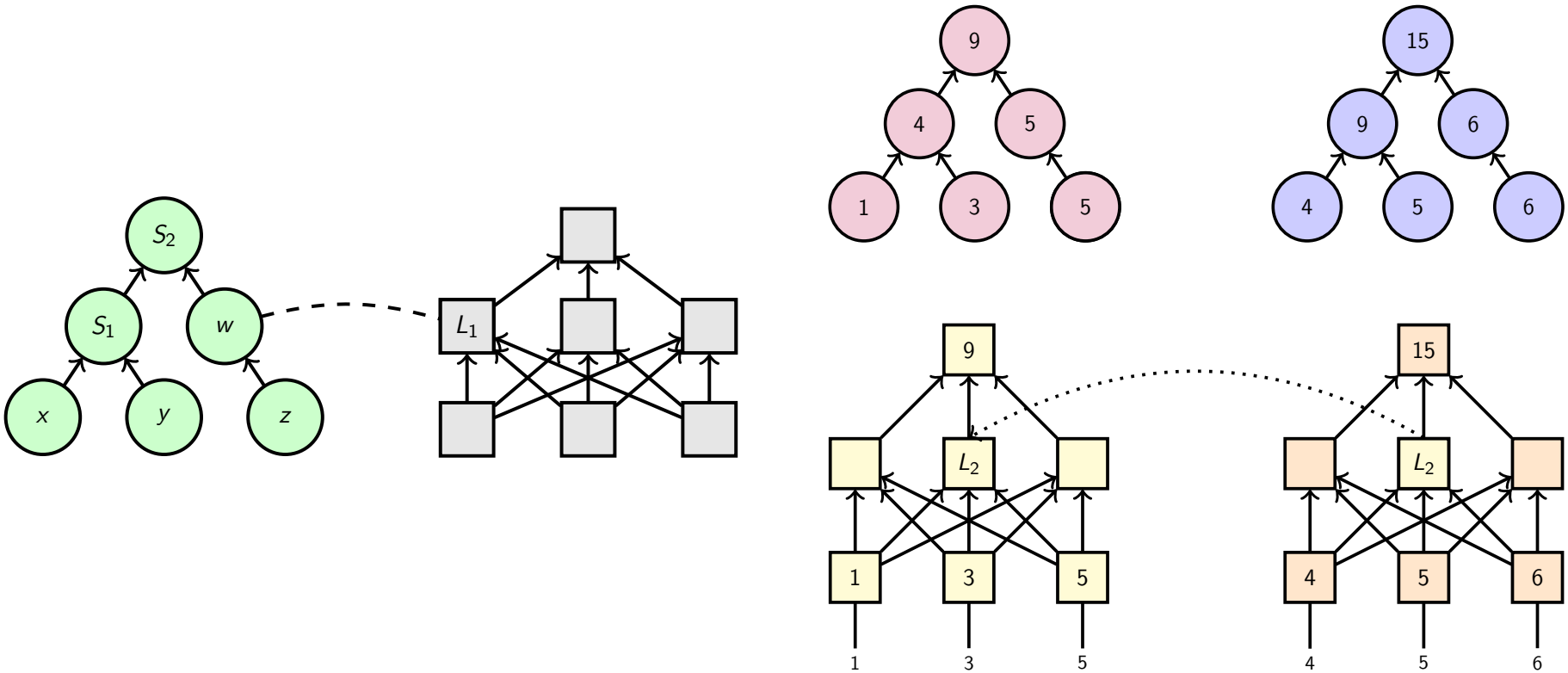

Connections to the literature

- 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

Intuitive 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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Tempting conclusion

Top-performing models are incapable of learning negation.

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

Tempting conclusion

Top-performing models are incapable of learning negation.

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 $\sqsubset$ 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*)

1 *lexrel* ← GET-LEXREL(*example*)
2 **if** CONTAINS-NOT(*example*)
3 **return** REVERSE(*lexrel*)
4 **return** *lexrel*

MoNLI monotonicity algorithm

INFER(*example*)

```
1  lexrel ← GET-LEXREL(example)
2  if CONTAINS-NOT(example)
3        return REVERSE(lexrel)
4  return lexrel
```

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

MoNLI monotonicity algorithm

INFER(*example*)

```
1  lexrel ← GET-LEXREL(example)
2  if CONTAINS-NOT(example)
3        return REVERSE(lexrel)
4  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

Model	Input pretrain	NLI train data	No MoNLI fine-tuning 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

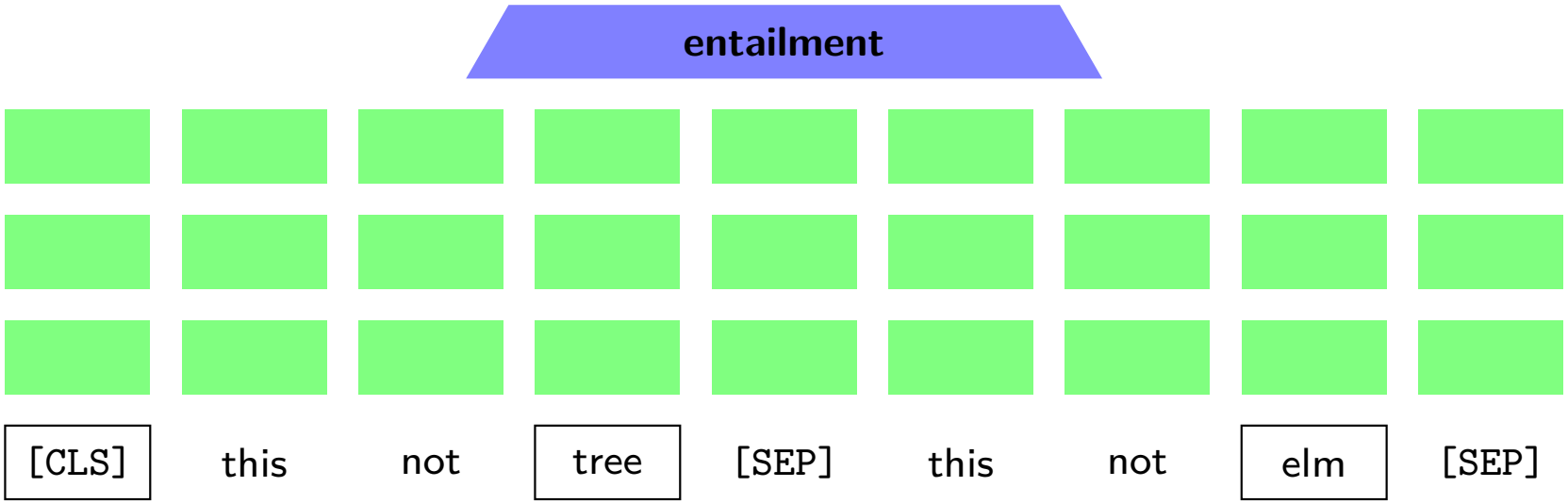
Geiger et al. 2020

MoNLI as challenge dataset

Model	Input pretrain	NLI train data	No MoNLI fine-tuning			With NMoNLI fine-tuning	
			SNLI	PMoNLI	NMoNLI	SNLI	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

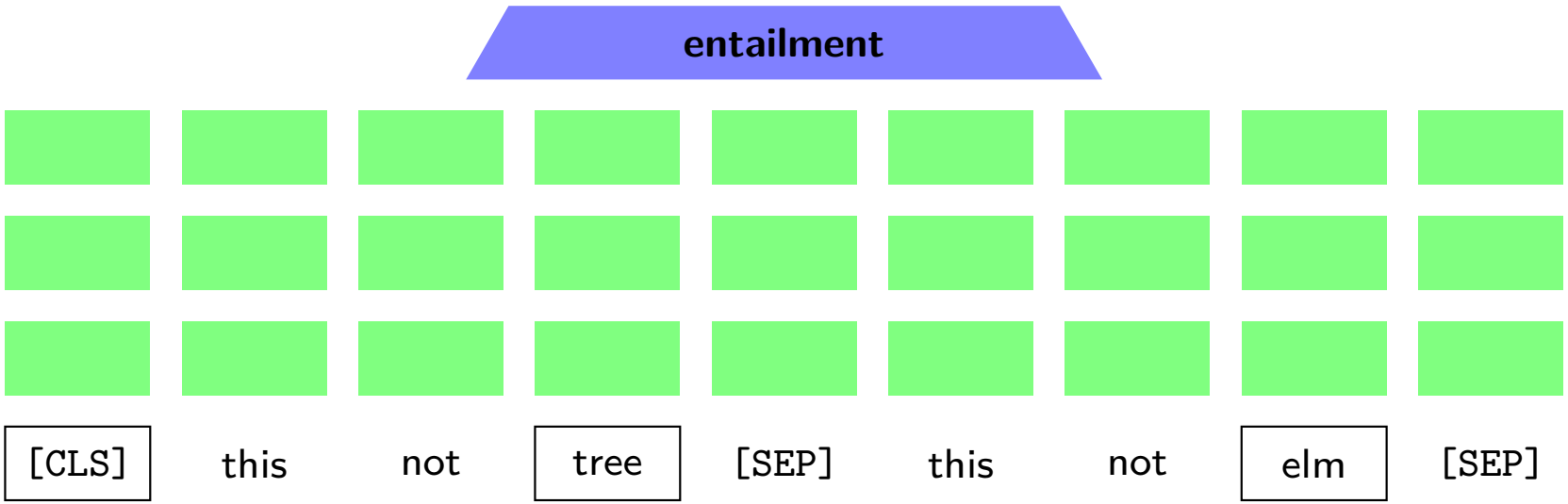
Geiger et al. 2020

Probe results for lexrel accuracy



Appendix with full probing results!

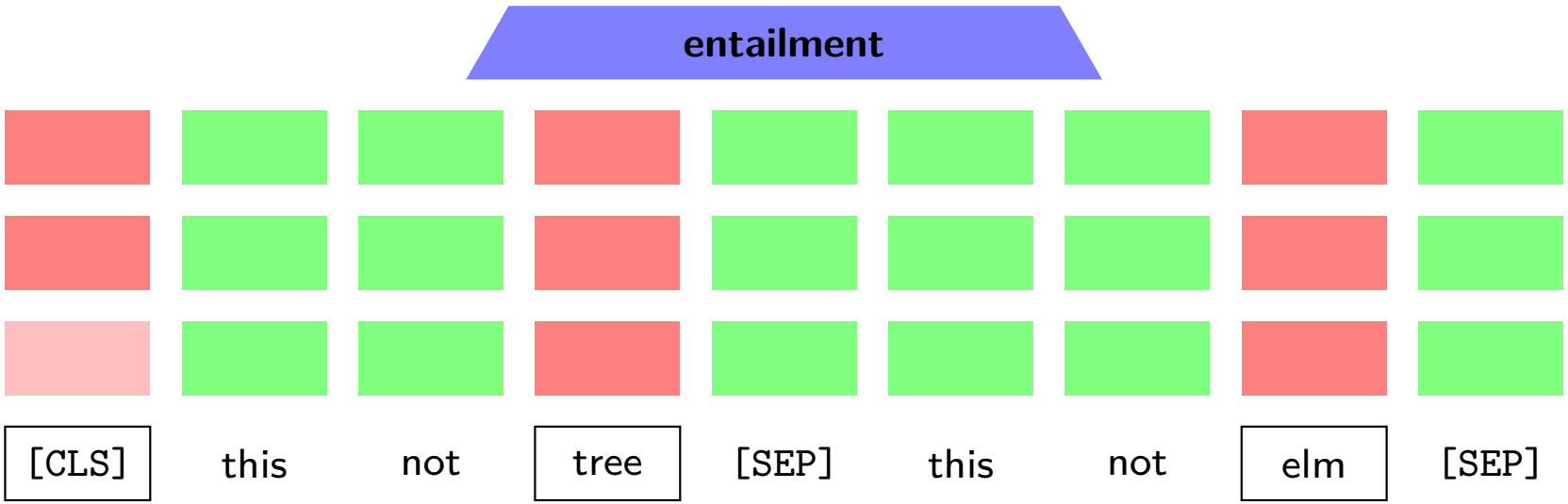
Probe results for lexrel accuracy



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

Appendix with full probing results!

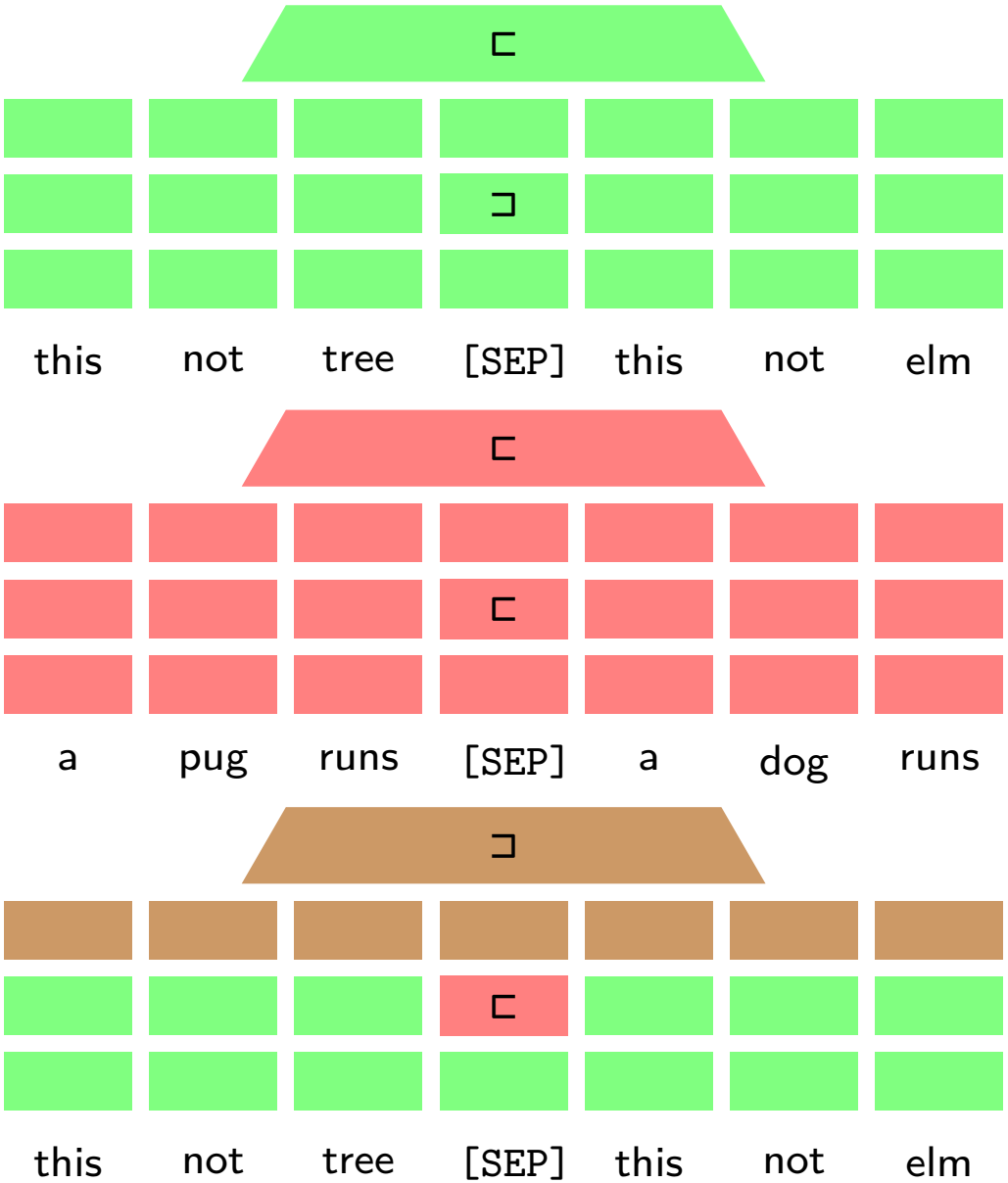
Probe results for lexrel accuracy



SmallLinearModel(h) $=$ GET-LEXREL(*tree*, *elm*)

Appendix with full probing results!

BERT NLI interventions



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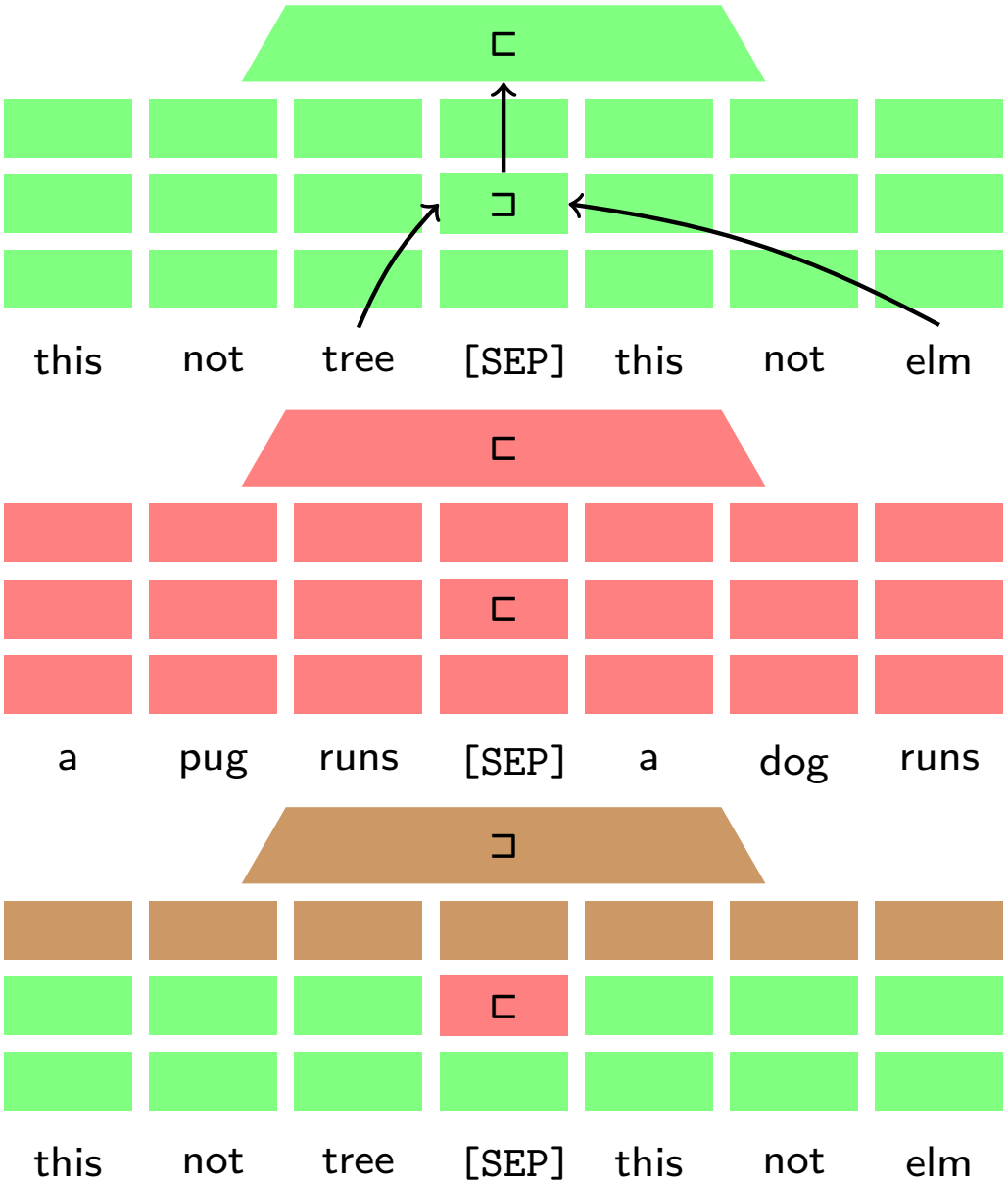
4 **return** *lexrel*

BERT NLI interventions



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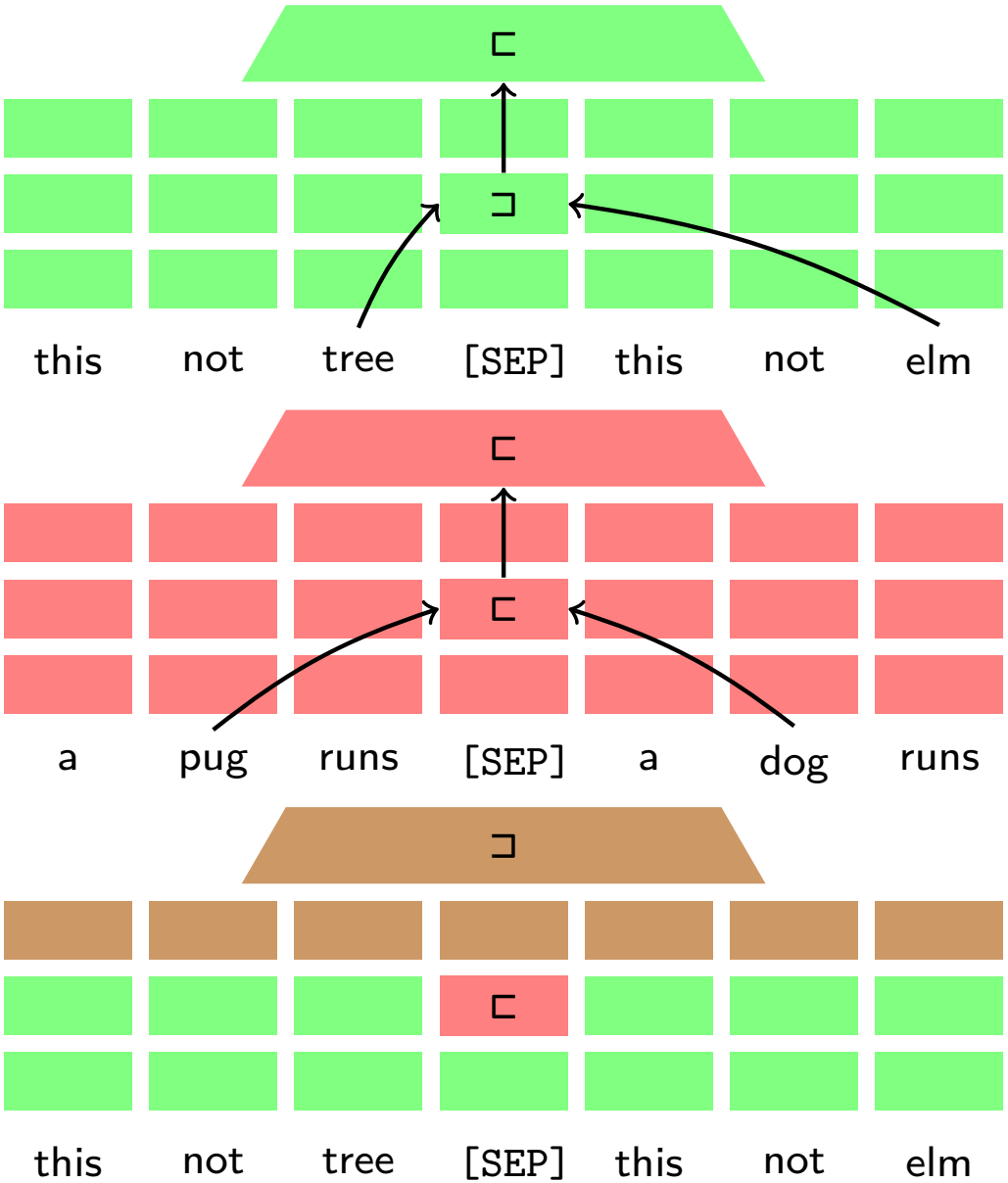
BERT NLI interventions



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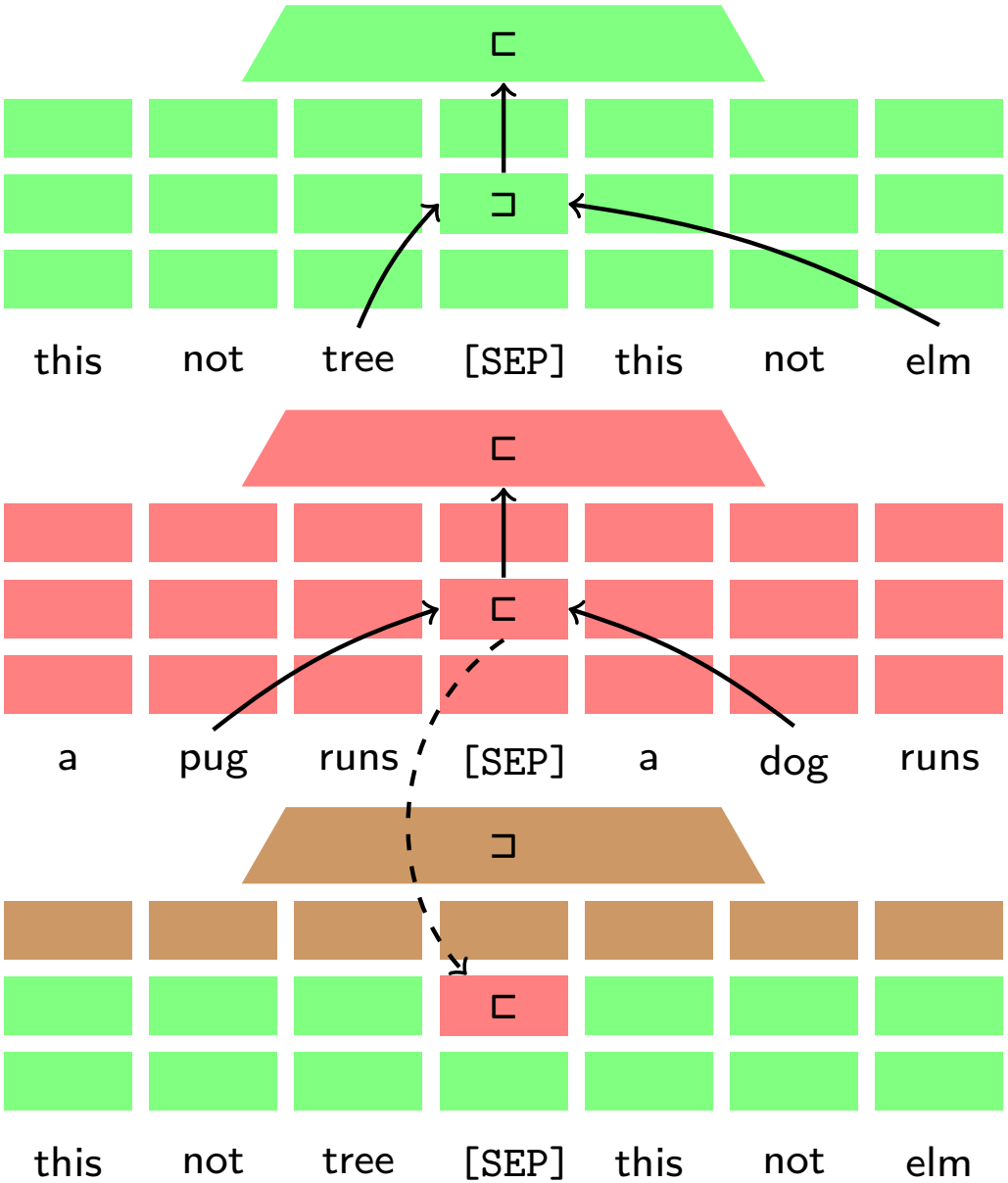
BERT NLI interventions



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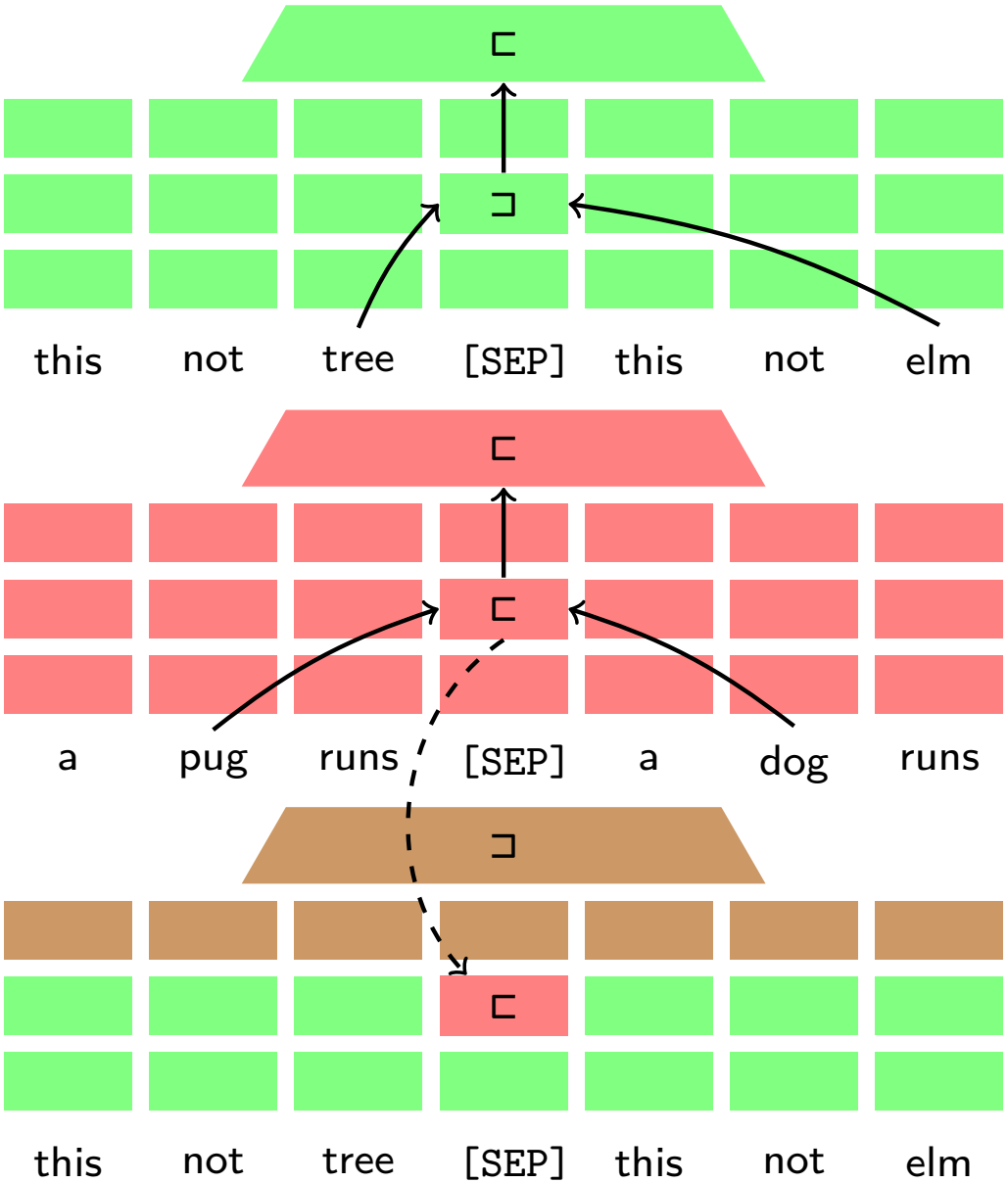
BERT NLI interventions



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Appendix with full results!

Interchange intervention training (IIT)

IIT: Training models to conform to a hypothesis

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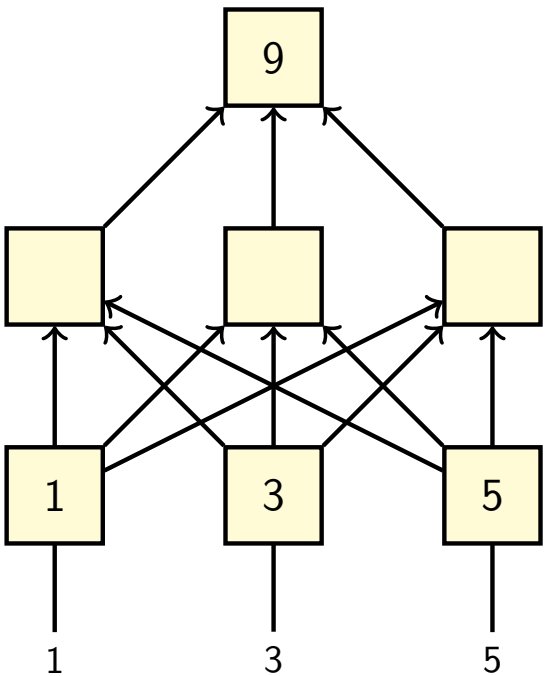
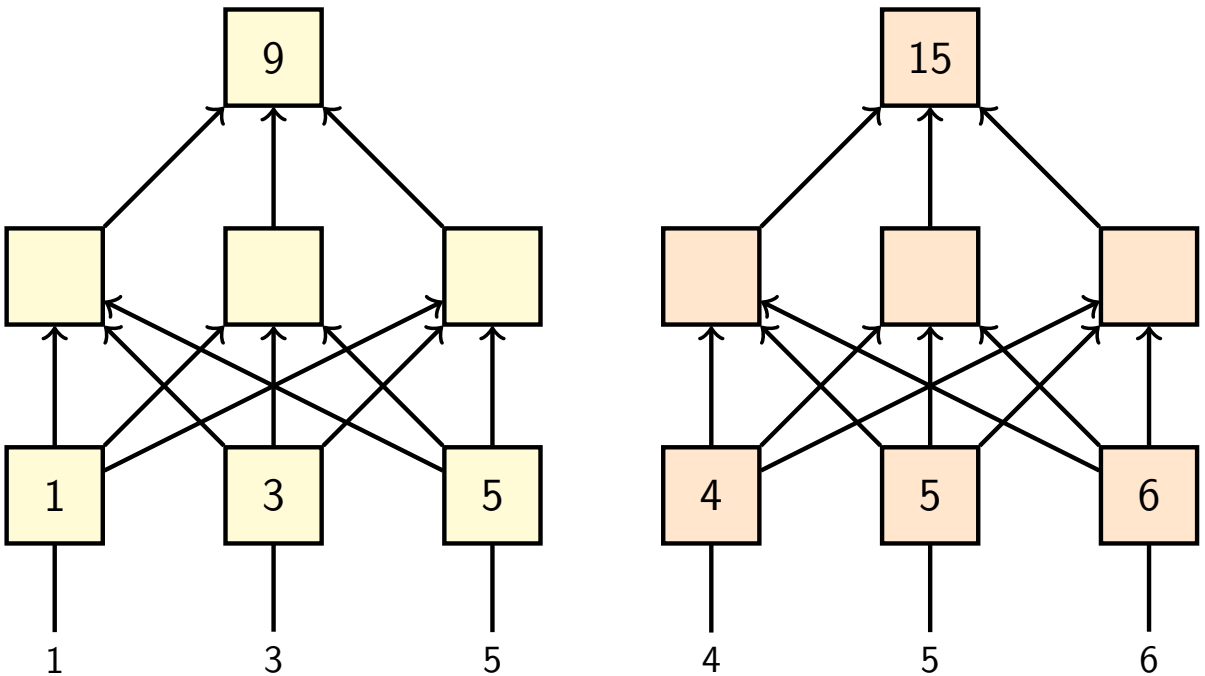
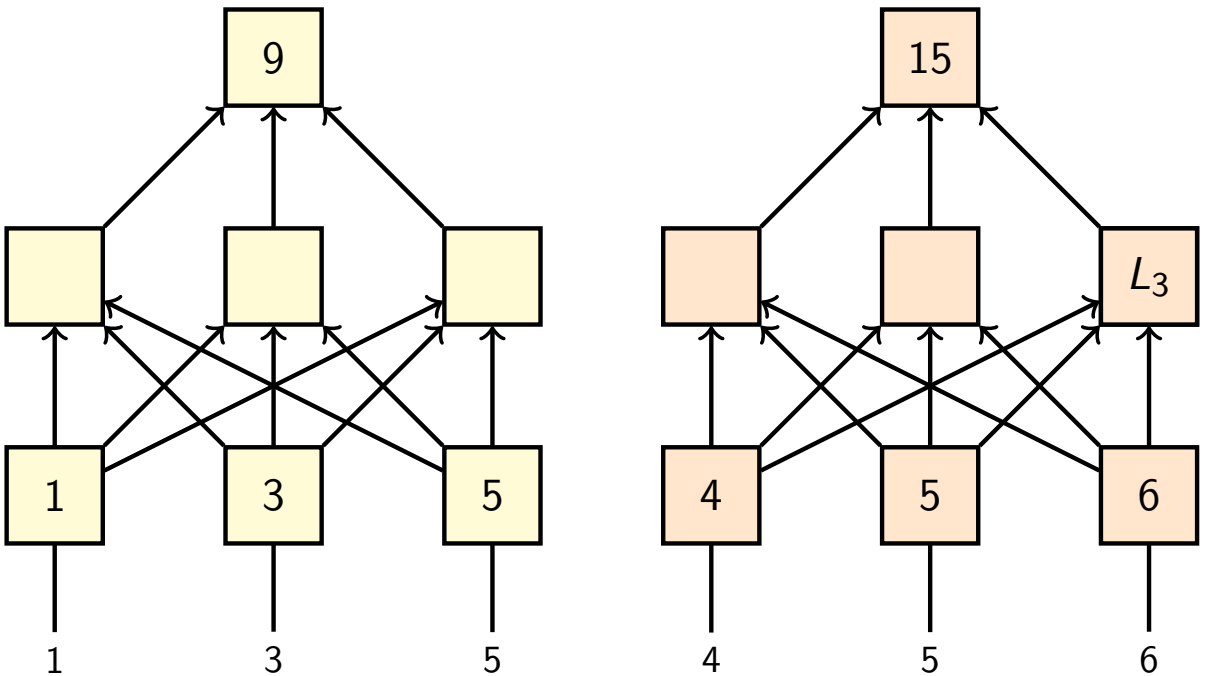


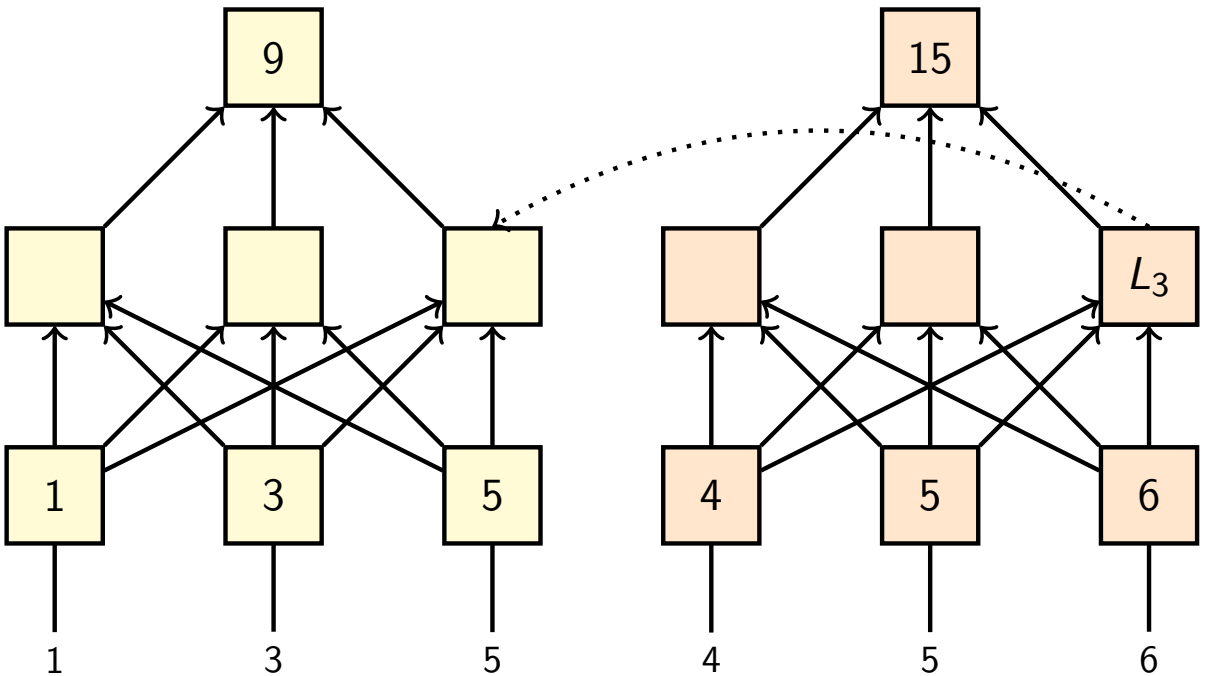
IIT: Training models to conform to a hypothesis



IIT: Training models to conform to a hypothesis



IIT: Training models to conform to a hypothesis



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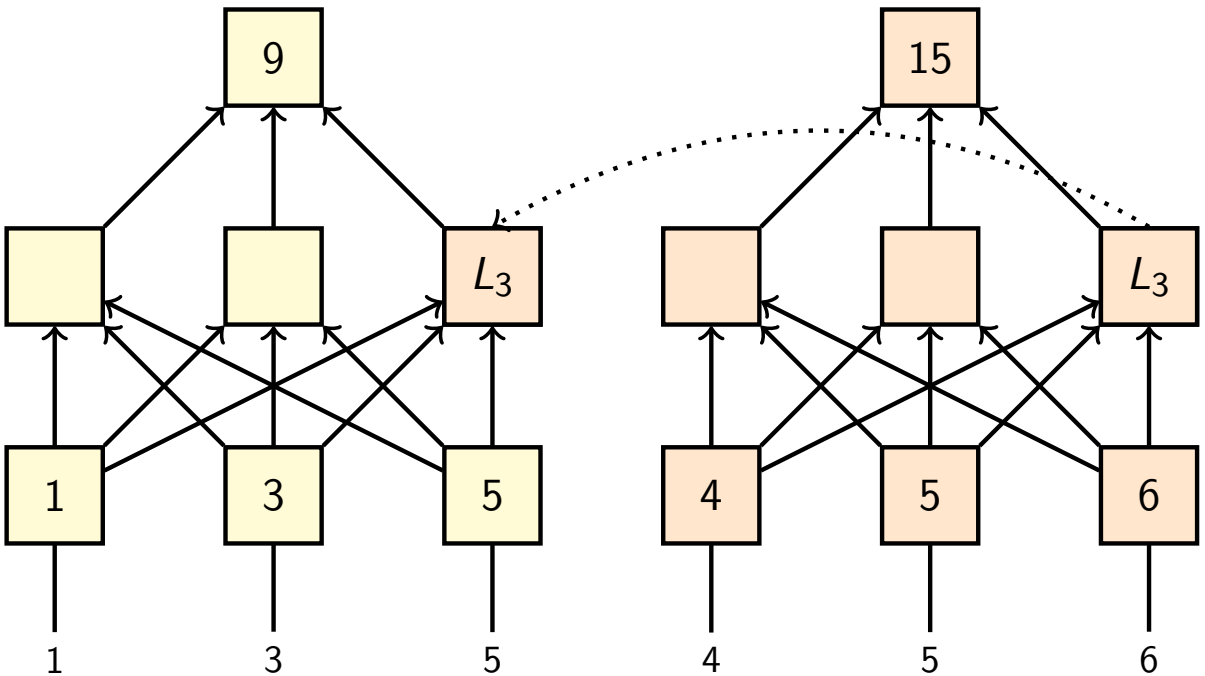

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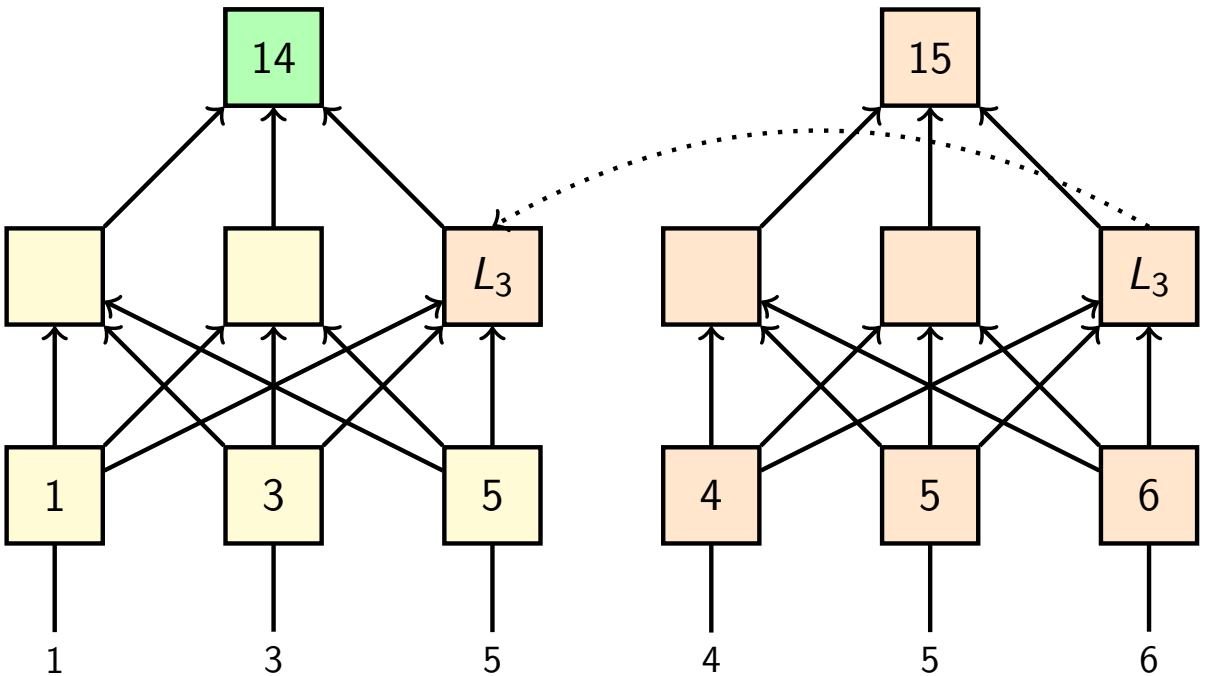

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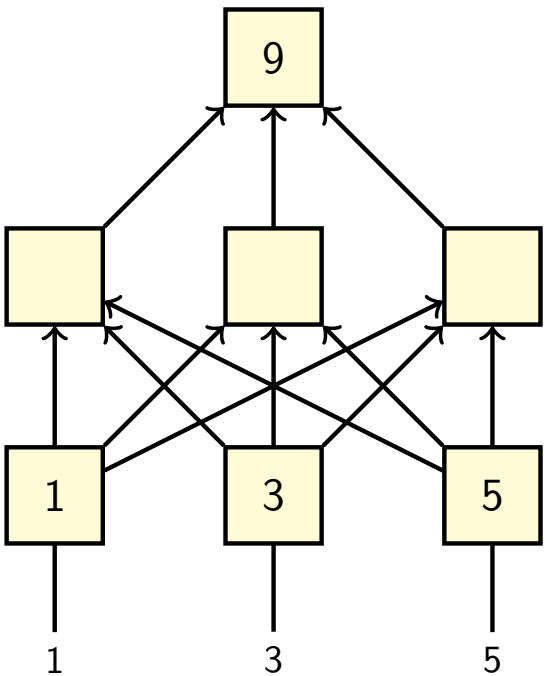

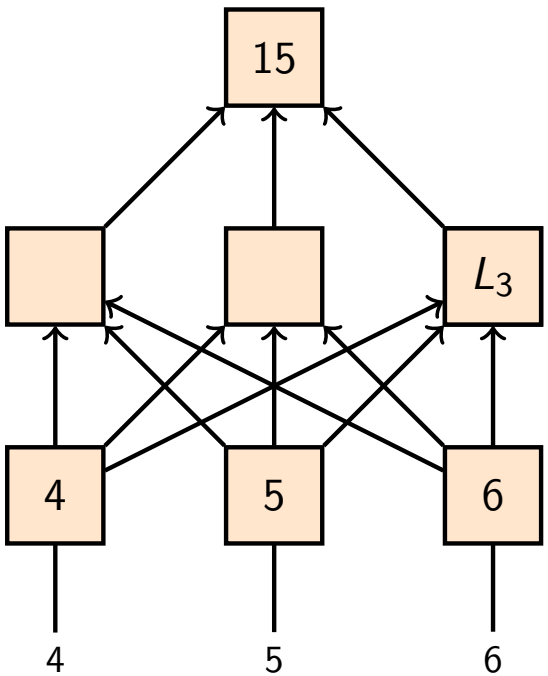

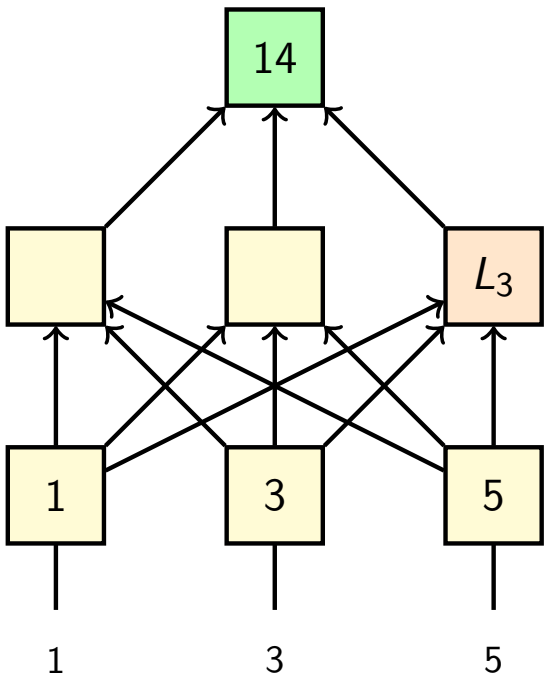

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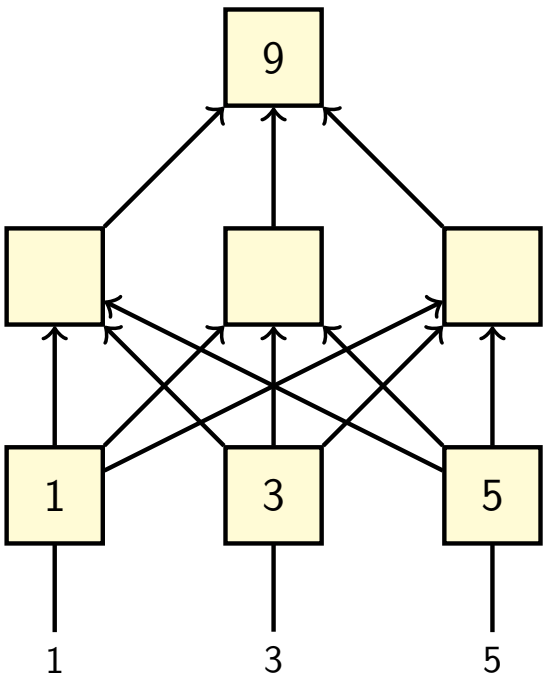
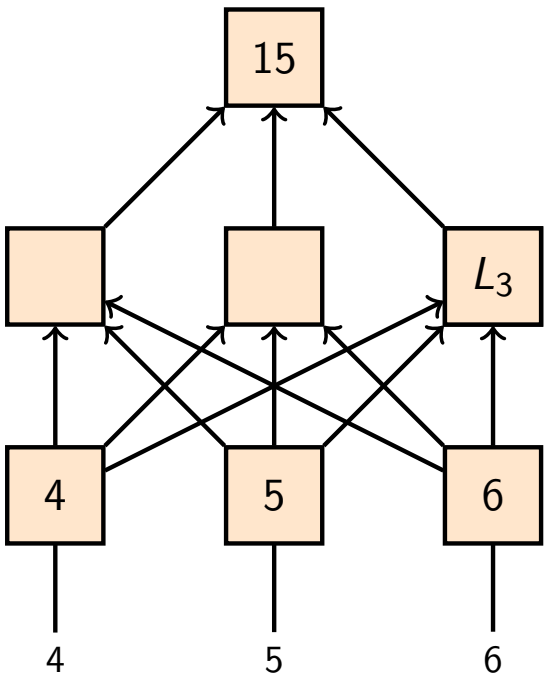
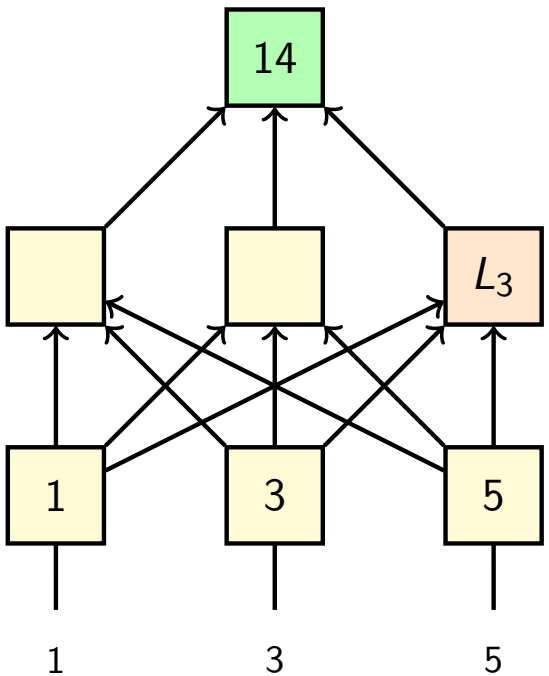




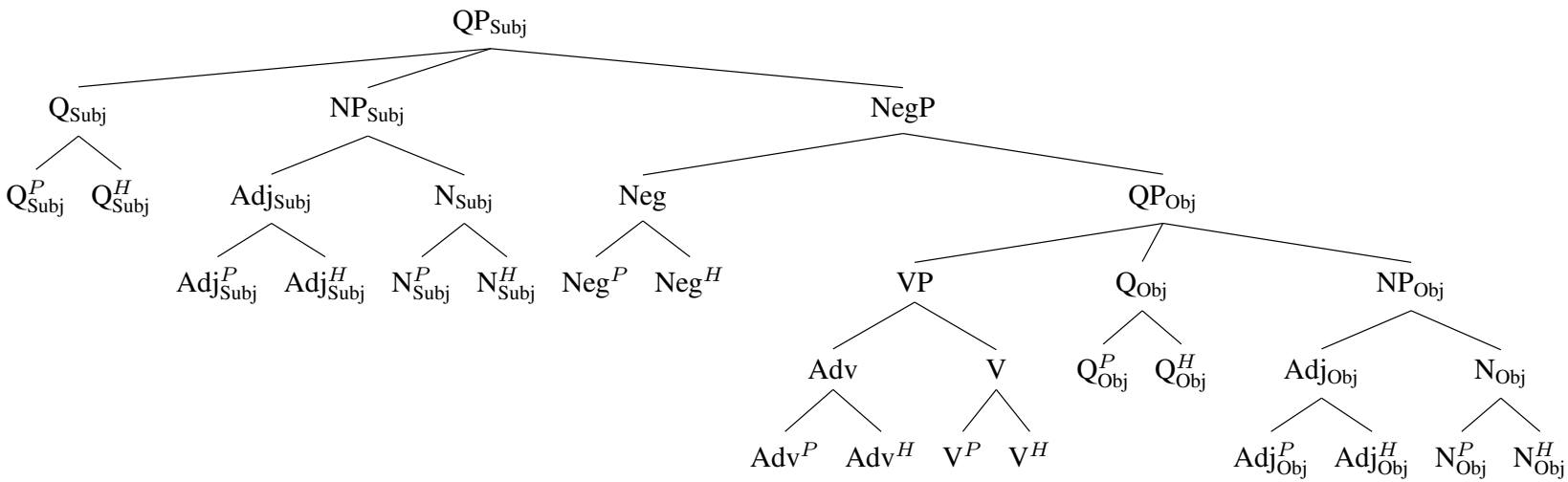


Appendix: IIT induces causal structure!

MQNLI: Extreme compositional complexity

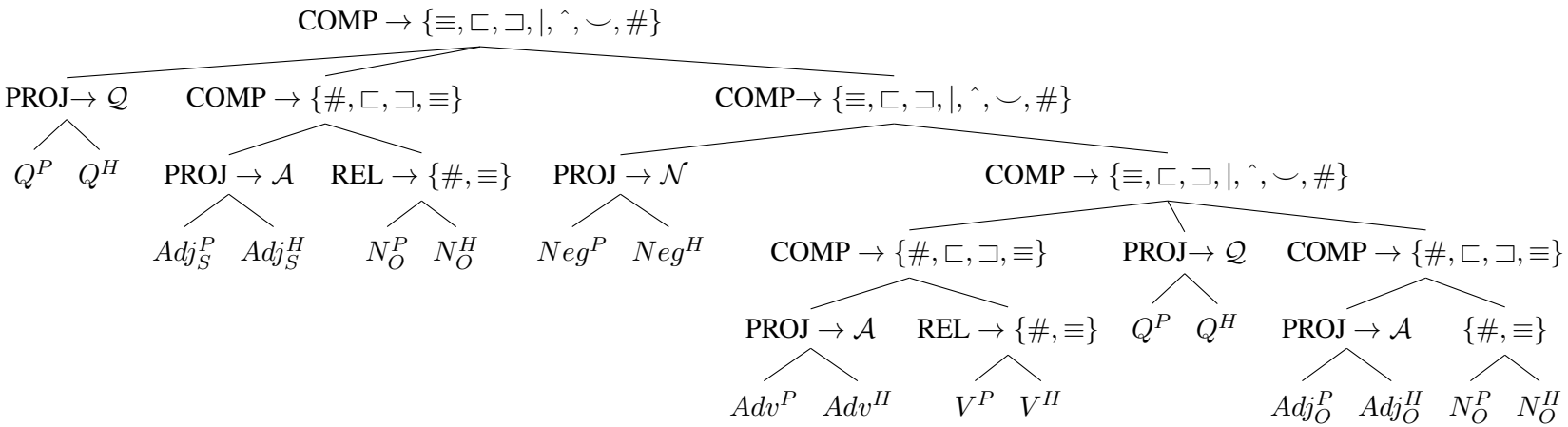
Geiger et al. 2020, 2021a

MQNLI: Extreme compositional complexity



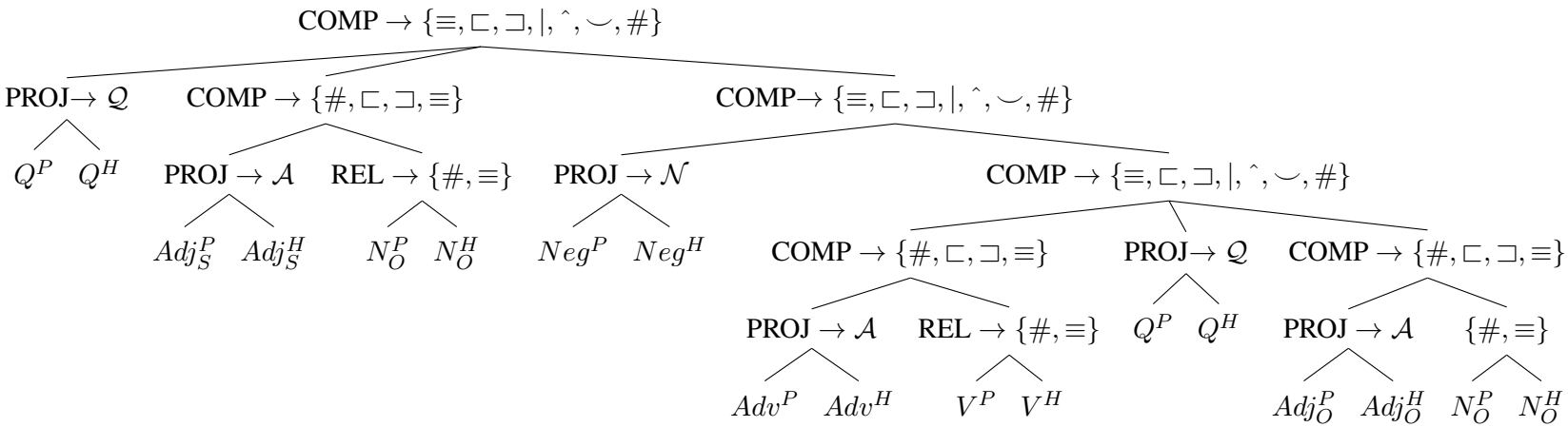
Geiger et al. 2020, 2021a

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

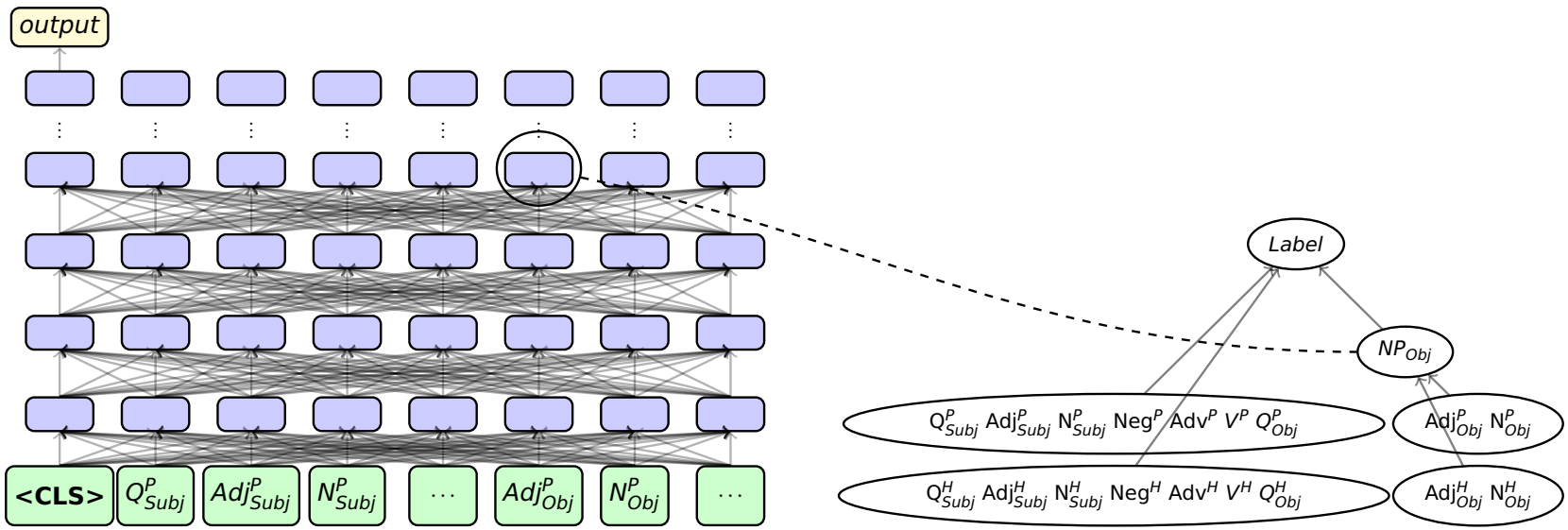
ε every silly professor ε ε ε sells not every ε book

neutral

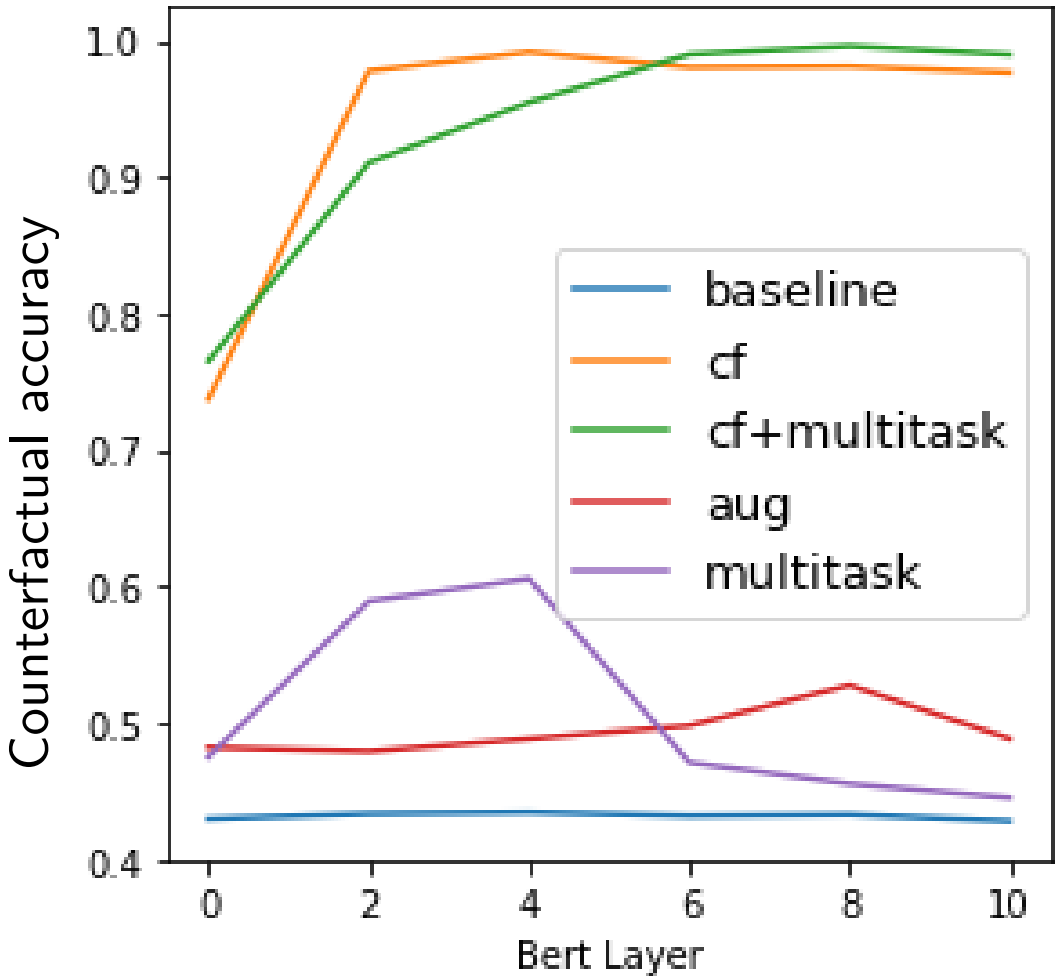
ε every silly professor ε ε ε sells not every ε chair

Geiger et al. 2020, 2021a

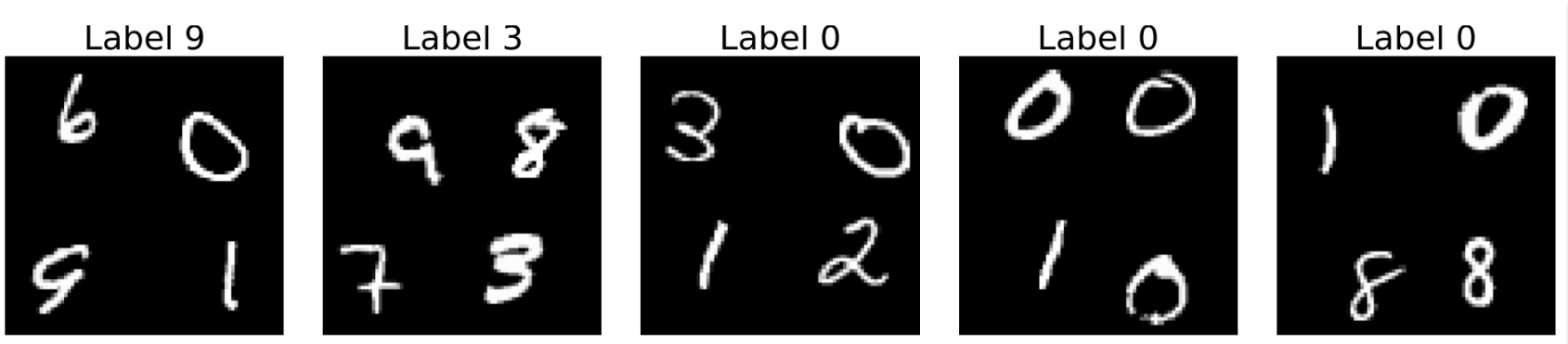
MQNLI: IIT on the object quantifier model



MQNLI results



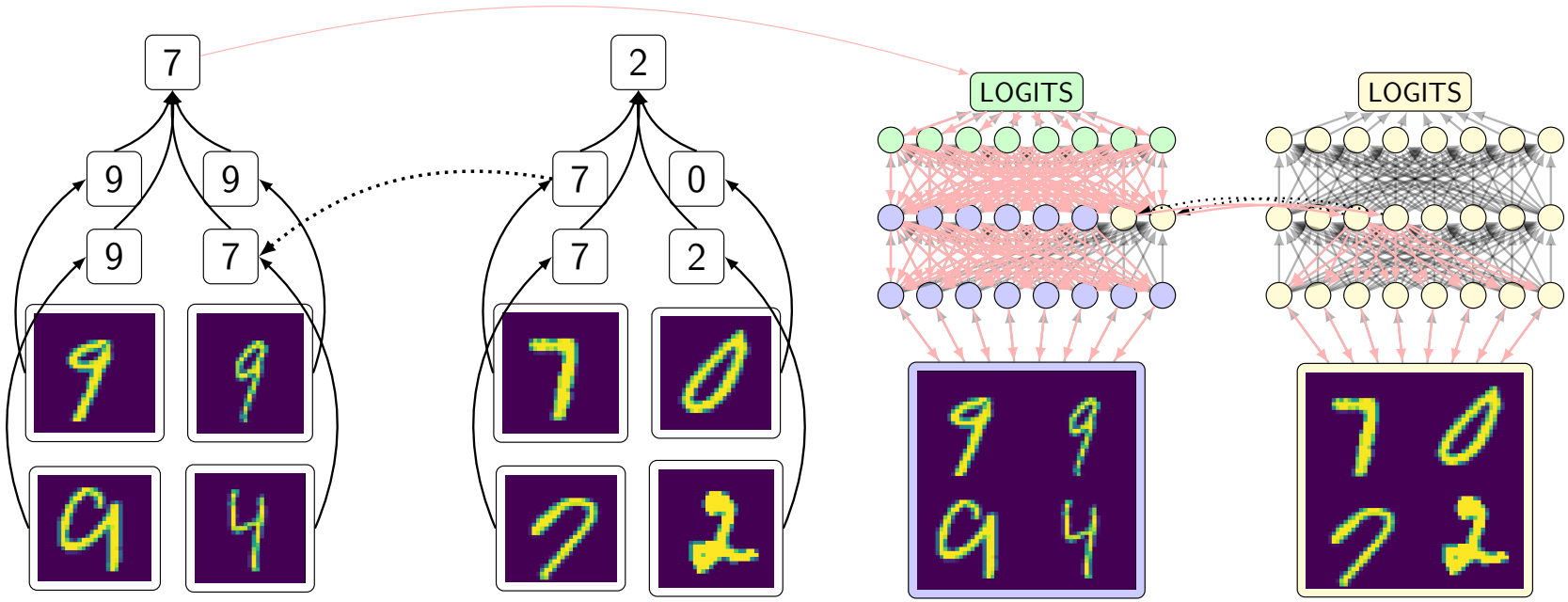
MNIST Pointer Value Retrieval



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

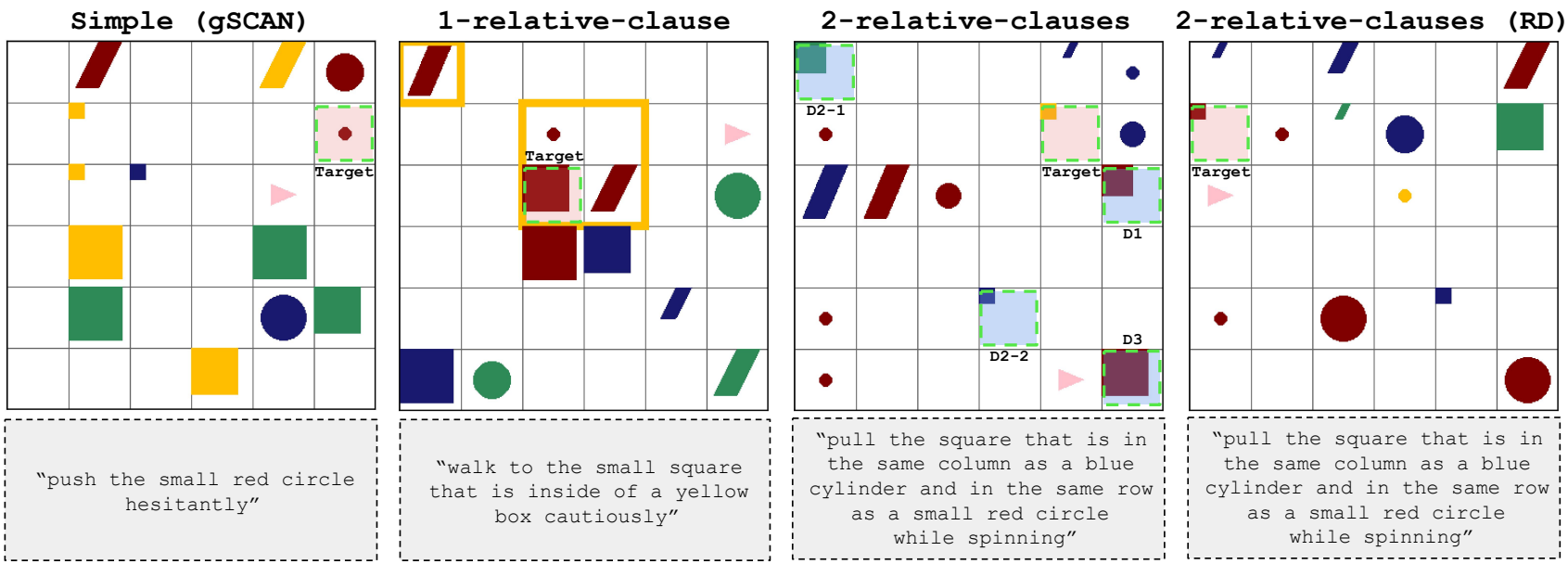
Geiger et al. 2021b

MNIST Pointer Value Retrieval



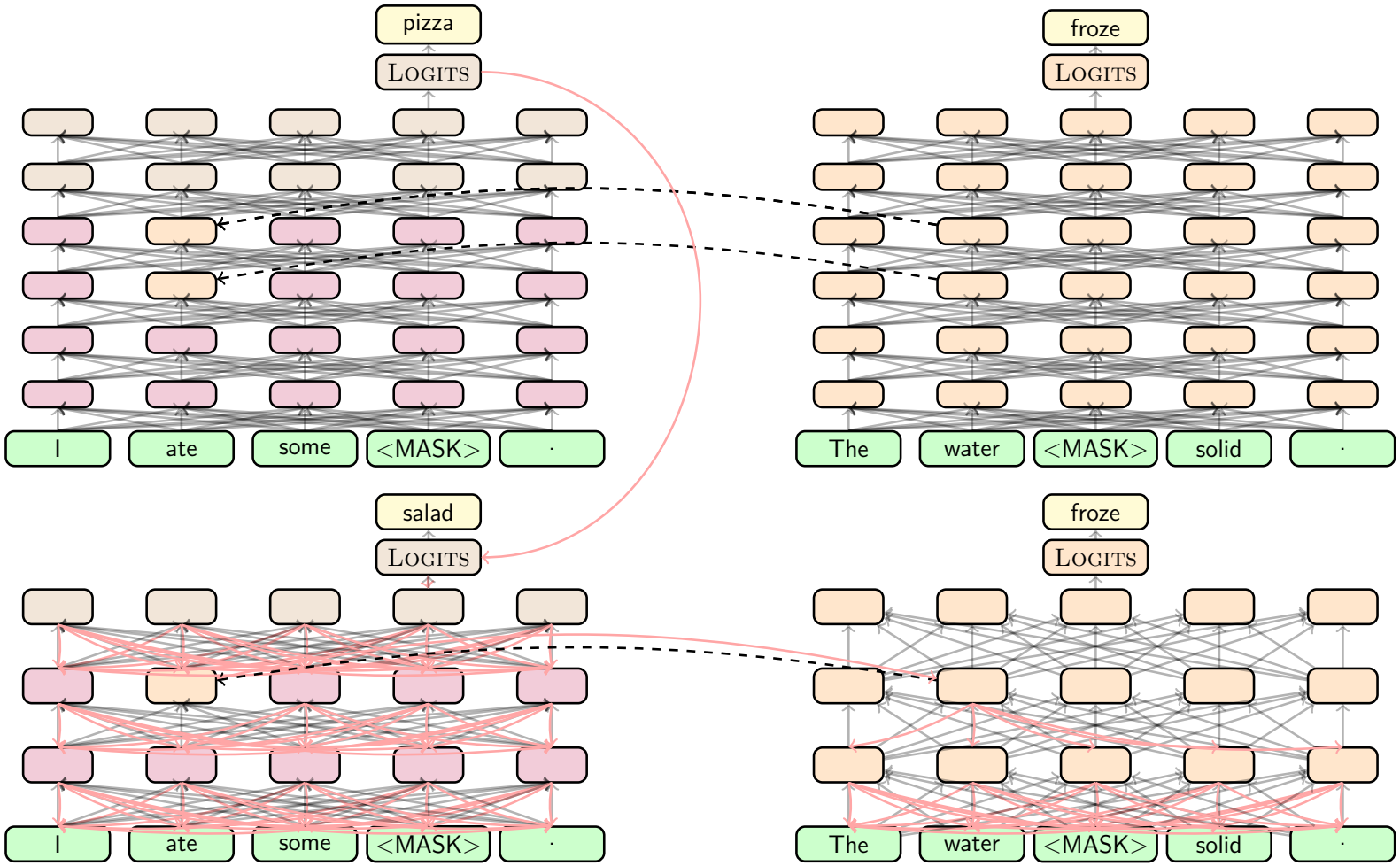
Geiger et al. 2021b

ReaSCAN



Geiger et al. 2021b

Language model distillation



Wu et al. 2021

Conclusion

Summary

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

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2. What is the relationship between interchange interventions and integrated gradients?

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3. Can we find ways to apply IIT in places where the causal model is approximate and applies to only a subset of examples?
4. More generally: where else might causal abstraction analysis and IIT be useful?

Thanks!

References I

Sander Beckers, Frederick Eberhardt, and Joseph Y. Halpern. 2020. Approximate causal abstractions. In *Proceedings of The 35th Uncertainty in Artificial Intelligence Conference*, volume 115 of *Proceedings of Machine Learning Research*, pages 606–615. PMLR.

Yonatan Belinkov and James Glass. 2019. Analysis methods in neural language processing: A survey. *Transactions of the Association for Computational Linguistics*, 7:49–72.

Kevin Clark, Urvashi Khandelwal, Omer Levy, and Christopher D. Manning. 2019. What does BERT look at? an analysis of BERT's attention. In *Proceedings of the 2019 ACL Workshop BlackboxNLP: Analyzing and Interpreting Neural Networks for NLP*, pages 276–286, Florence, Italy. Association for Computational Linguistics.

Alexis Conneau, German Kruszewski, Guillaume Lample, Loïc Barrault, and Marco Baroni. 2018. What you can cram into a single $&!#* vector: Probing sentence embeddings for linguistic properties. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 2126–2136, Melbourne, Australia. Association for Computational Linguistics.

Yanai Elazar, Shauli Ravfogel, Alon Jacovi, and Yoav Goldberg. 2021. Amnesic probing: Behavioral explanation with amnesic counterfactuals. *Transactions of the Association for Computational Linguistics*, 9(0):160–175.

Amir Feder, Nadav Oved, Uri Shalit, and Roi Reichart. 2021. CausaLM: Causal model explanation through counterfactual language models. *Computational Linguistics*, 47(2):333–386.

Jerry A. Fodor and Zenon W. Pylyshyn. 1988. Connectionism and cognitive architecture: A critical analysis. *Cognition*, 28(1):3–71.

Atticus Geiger, Hanson Lu, Thomas Icard, and Christopher Potts. 2021a. Causal abstractions of neural networks. In *Advances in Neural Information Processing Systems*.

Atticus Geiger, Kyle Richardson, and Christopher Potts. 2020. Neural natural language inference models partially embed theories of lexical entailment and negation. In *Proceedings of the Third BlackboxNLP Workshop on Analyzing and Interpreting Neural Networks for NLP*, pages 163–173, Online. Association for Computational Linguistics.

Atticus Geiger, Zhengxuan Wu, Hanson Lu, Josh Rozner, Elisa Kreiss, Thomas Icard, Noah D. Goodman, and Christopher Potts. 2021b. Inducing causal structure for interpretable neural networks. ArXiv:2112.00826.

John Hewitt and Percy Liang. 2019. Designing and interpreting probes with control tasks. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 2733–2743, Hong Kong, China. Association for Computational Linguistics.

John Hewitt and Christopher D. Manning. 2019. A structural probe for finding syntax in word representations. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 4129–4138, Minneapolis, Minnesota. Association for Computational Linguistics.

Md Mosharaf Hossain, Venelin Kovatchev, Pranoy Dutta, Tiffany Kao, Elizabeth Wei, and Eduardo Blanco. 2020. An analysis of natural language inference benchmarks through the lens of negation. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 9106–9118, Online. Association for Computational Linguistics.

References II

Douwe Kiela, Max Bartolo, Yixin Nie, Divyansh Kaushik, Atticus Geiger, Zhengxuan Wu, Bertie Vidgen, Grusha Prasad, Amanpreet Singh, Pratik Ringshia, Zhiyi Ma, Tristan Thrush, Sebastian Riedel, Zeerak Waseem, Pontus Stenetorp, Robin Jia, Mohit Bansal, Christopher Potts, and Adina Williams. 2021. Dynabench: Rethinking benchmarking in NLP. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 4110–4124, Online. Association for Computational Linguistics.

Joe Pater. 2019. Generative linguistics and neural networks at 60: Foundation, friction, and fusion. *Language*, 95(1):e41–e74.

Marco Ribeiro, Sameer Singh, and Carlos Guestrin. 2016. "why should I trust you?": Explaining the predictions of any classifier. In *Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Demonstrations*, pages 97–101. Association for Computational Linguistics.

Naomi Saphra and Adam Lopez. 2019. Understanding learning dynamics of language models with SVCCA. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 3257–3267, Minneapolis, Minnesota. Association for Computational Linguistics.

Avanti Shrikumar, Peyton Greenside, and Anshul Kundaje. 2017. Learning important features through propagating activation differences. In *Proceedings of the 34th International Conference on Machine Learning-Volume 70*, pages 3145–3153. JMLR. org.

Karen Simonyan, Andrea Vedaldi, and Andrew Zisserman. 2013. Deep inside convolutional networks: Visualising image classification models and saliency maps. *arXiv preprint arXiv:1312.6034*.

Richard Socher, Alex Perelygin, Jean Wu, Jason Chuang, Christopher D. Manning, Andrew Y. Ng, and Christopher Potts. 2013. Recursive deep models for semantic compositionality over a sentiment treebank. In *Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing*, pages 1631–1642, Stroudsburg, PA. Association for Computational Linguistics.

Paul Soulos, R. Thomas McCoy, Tal Linzen, and Paul Smolensky. 2020. Discovering the compositional structure of vector representations with role learning networks. In *Proceedings of the Third BlackboxNLP Workshop on Analyzing and Interpreting Neural Networks for NLP*, pages 238–254, Online. Association for Computational Linguistics.

Mukund Sundararajan, Ankur Taly, and Qiqi Yan. 2017. Axiomatic attribution for deep networks. In *Proceedings of the 34th International Conference on Machine Learning-Volume 70*, pages 3319–3328. JMLR. org.

Ian Tenney, Dipanjan Das, and Ellie Pavlick. 2019. BERT rediscovers the classical NLP pipeline. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 4593–4601, Florence, Italy. Association for Computational Linguistics.

Jesse Vig, Sebastian Gehrmann, Yonatan Belinkov, Sharon Qian, Daniel Nevo, Yaron Singer, and Stuart Shieber. 2020. Causal mediation analysis for interpreting neural nlp: The case of gender bias.

Zhengxuan Wu, Atticus Geiger, Josh Rozner, Elisa Kreiss, Hanson Lu, Thomas Icard, Christopher Potts, and Noah D. Goodman. 2021. Causal distillation for language models. ArXiv:2112.02505.

Hitomi Yanaka, Koji Mineshima, Daisuke Bekki, and Kentaro Inui. 2020. Do neural models learn systematicity of monotonicity inference in natural language? In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 6105–6117, Online. Association for Computational Linguistics.

References III

Hitomi Yanaka, Koji Mineshima, Daisuke Bekki, Kentaro Inui, Satoshi Sekine, Lasha Abzianidze, and Johan Bos. 2019. HELP: A dataset for identifying shortcomings of neural models in monotonicity reasoning. In *Proceedings of the Eighth Joint Conference on Lexical and Computational Semantics (*SEM 2019)*, pages 250–255, Minneapolis, Minnesota. Association for Computational Linguistics.

Matthew D Zeiler and Rob Fergus. 2014. Visualizing and understanding convolutional networks. In *European conference on computer vision*, pages 818–833. Springer.

Luke S. Zettlemoyer and Michael Collins. 2005. Learning to map sentences to logical form: Structured classification with probabilistic categorial grammars. In *Proceedings of the Twenty First Conference on Uncertainty in Artificial Intelligence*.

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. ...

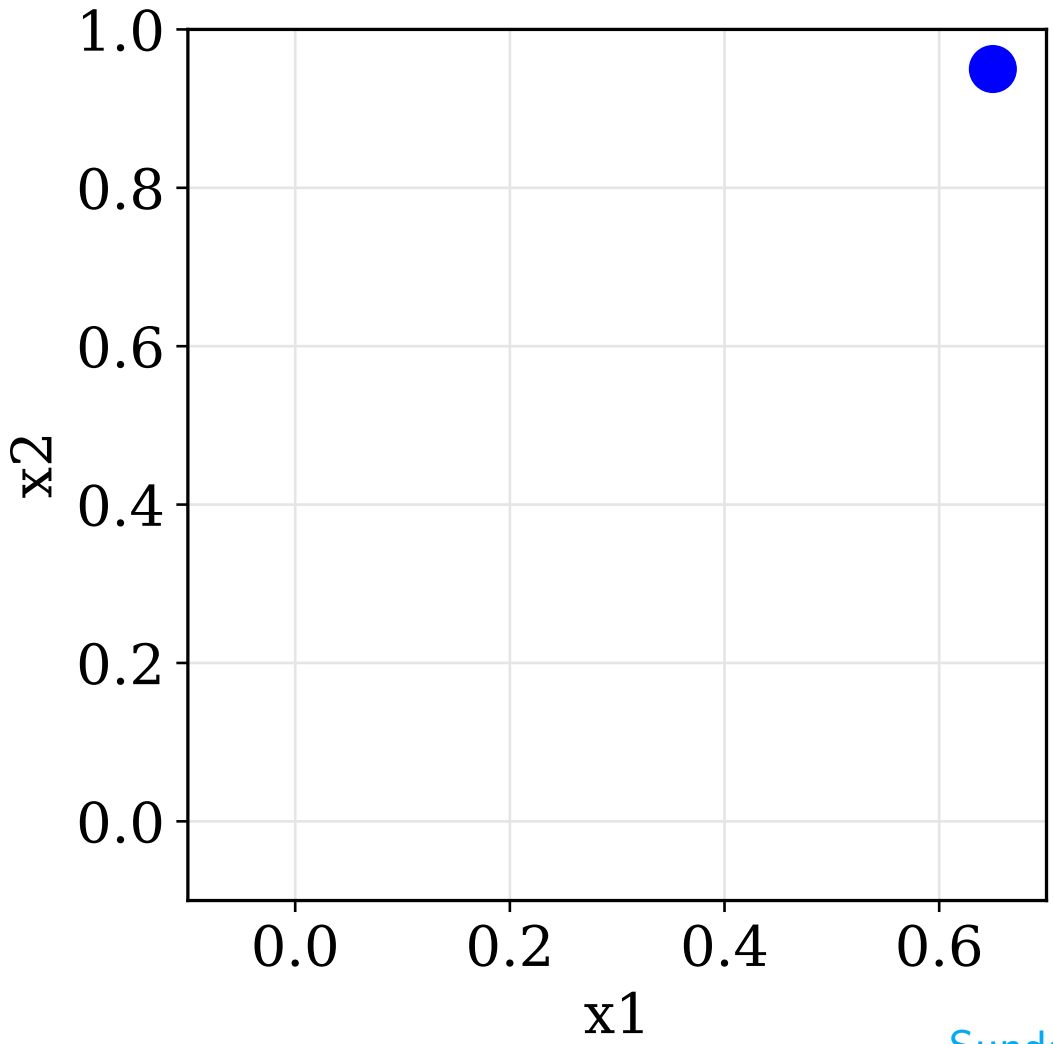
https://captum.ai

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

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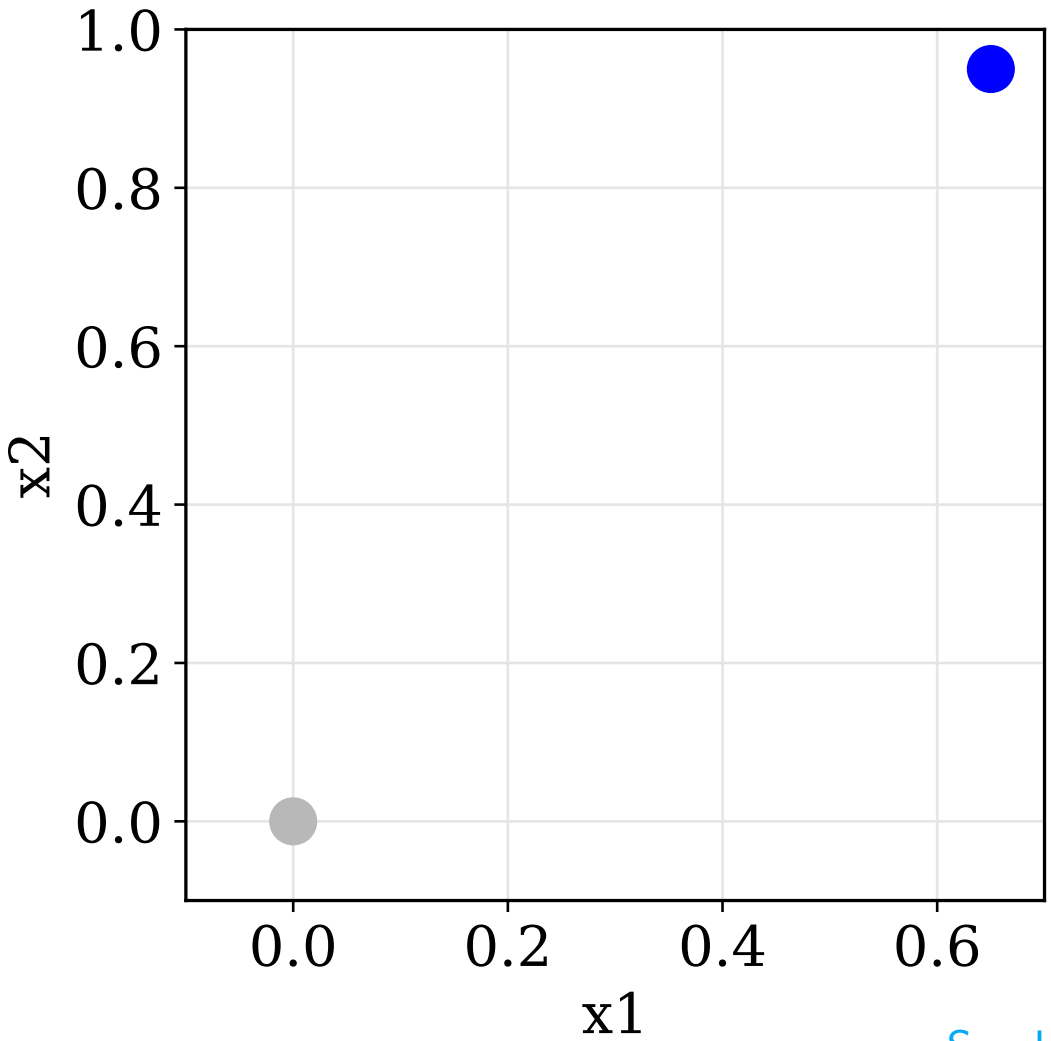

Sundararajan et al. 2017

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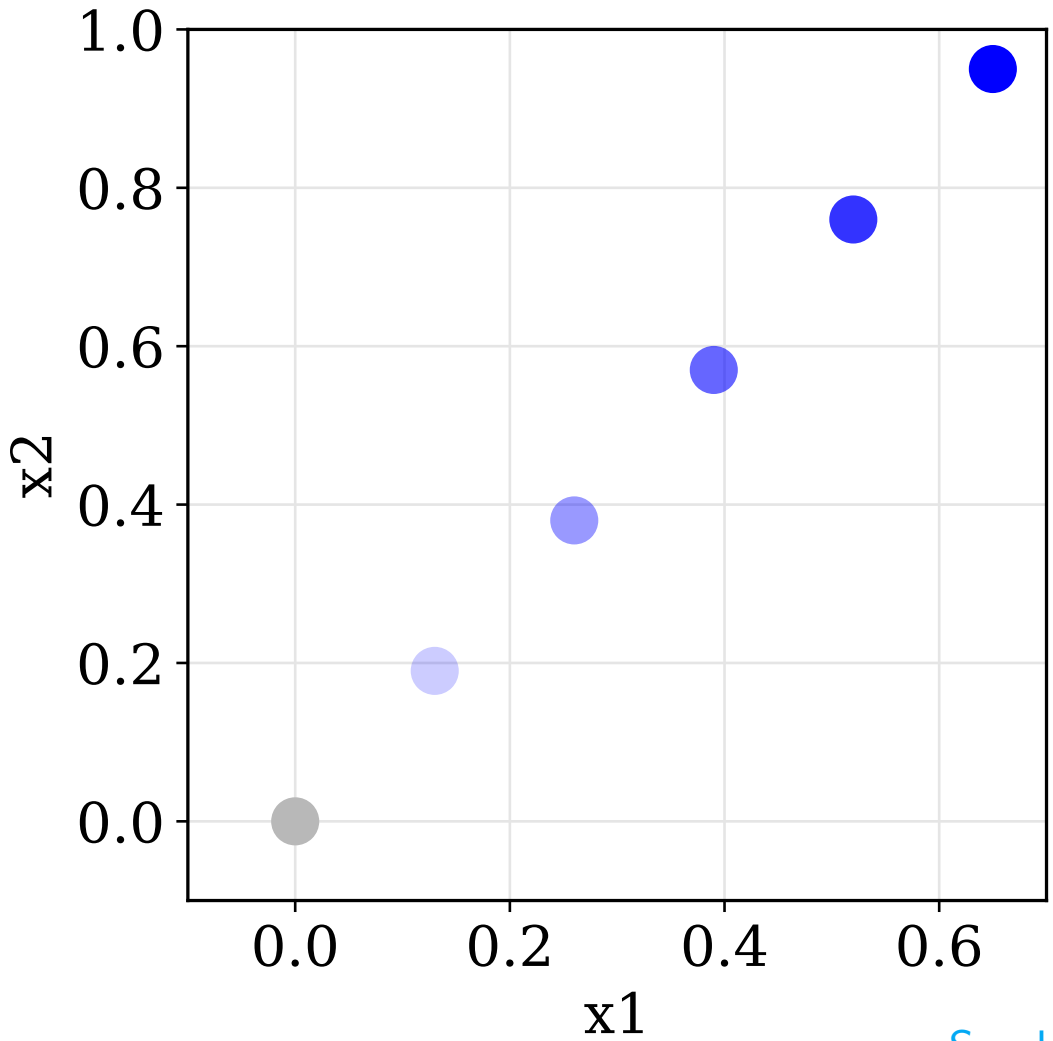


Sundararajan et al. 2017

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.

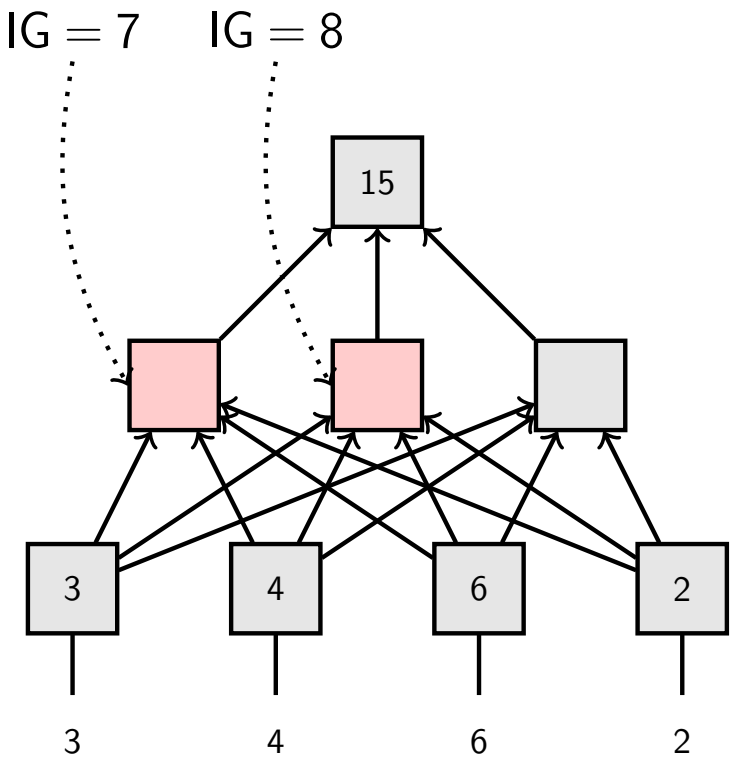
Integrated Gradients: Computation

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

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

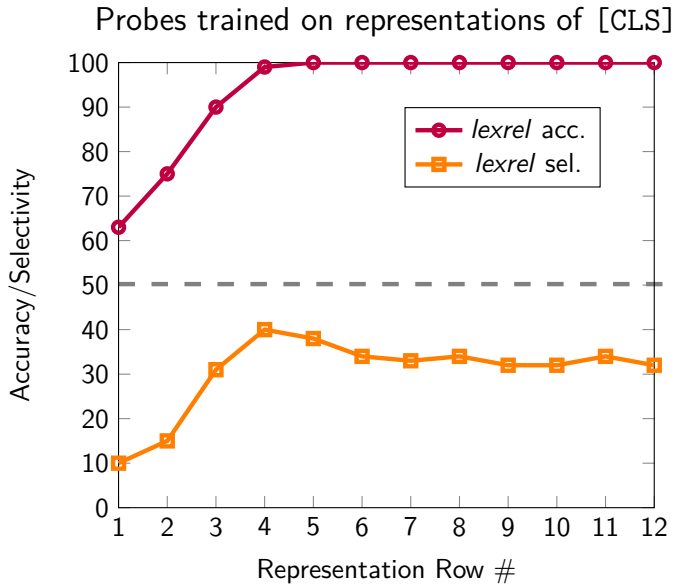


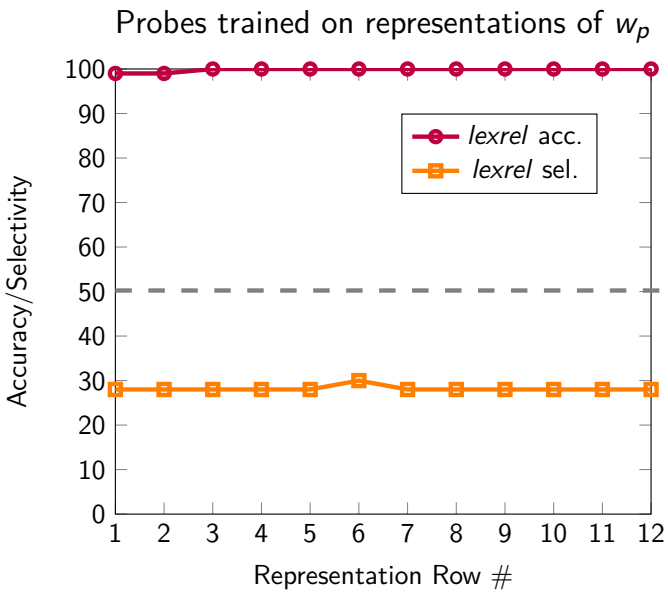
$$W_1 = \begin{pmatrix} 1 \\ 1 \\ 0 \\ 0 \end{pmatrix} \quad W_2 = \begin{pmatrix} 0 \\ 0 \\ 1 \\ 1 \end{pmatrix} \quad W_3 = \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \end{pmatrix}$$

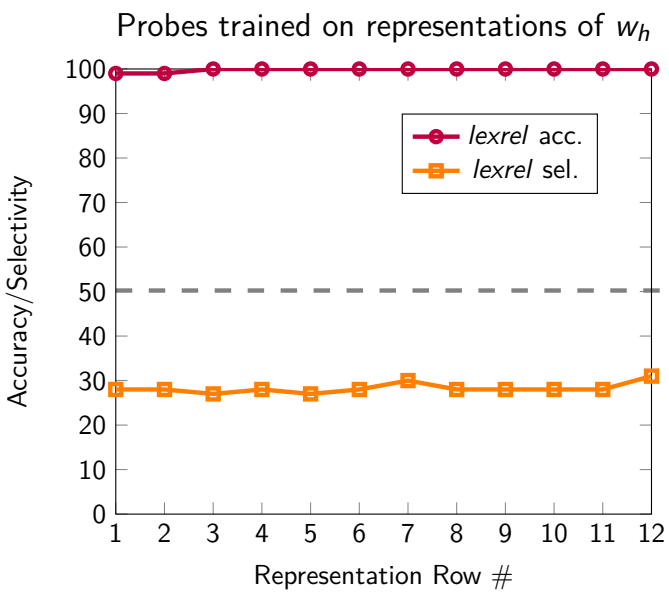
$$\mathbf{w} = \begin{pmatrix} 1 \\ 1 \\ 0 \end{pmatrix} \quad (\mathbf{x}W_1; \mathbf{x}W_2; \mathbf{x}W_3)\,\mathbf{w}$$

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

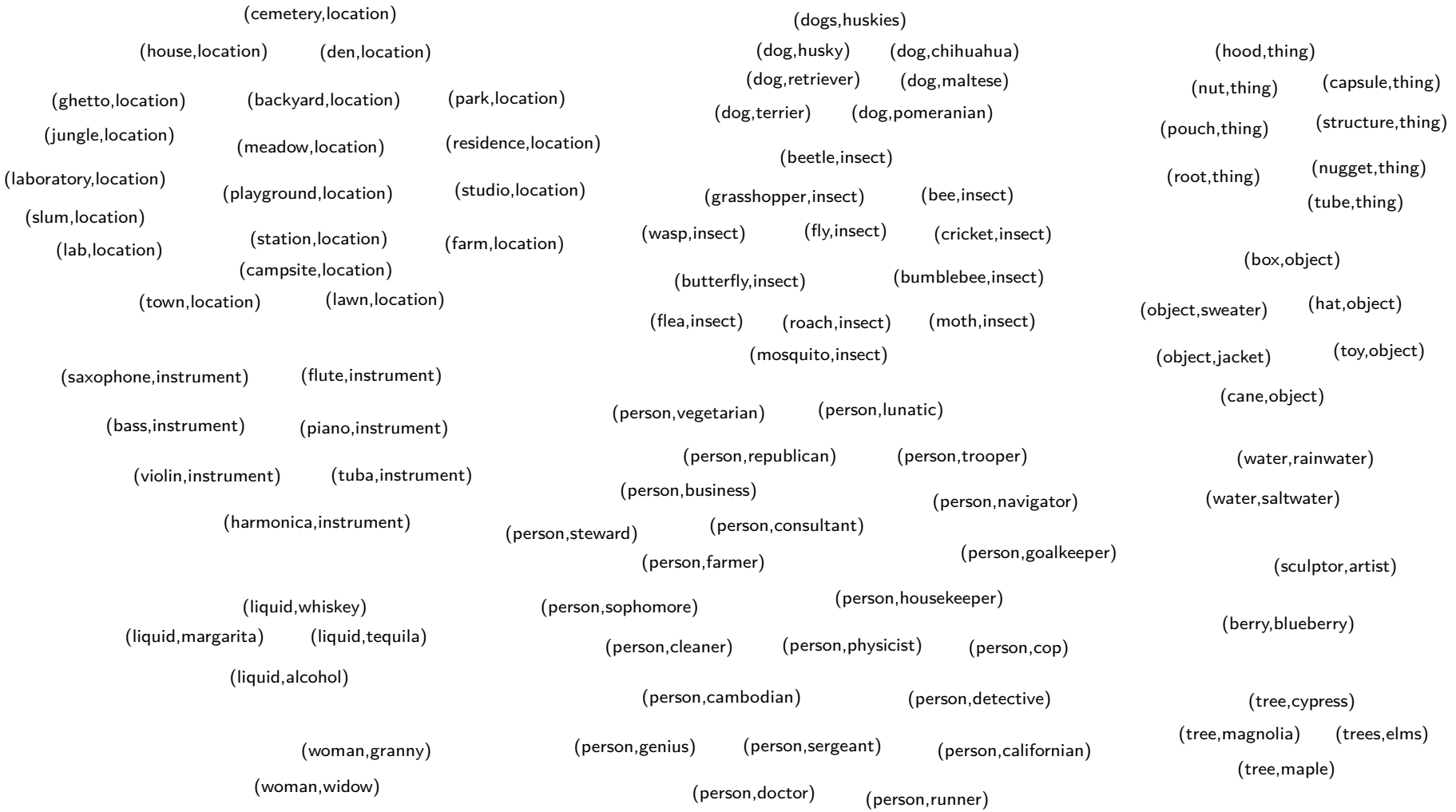
INFER(example)

1 *lexrel* ← GET-LEXREL(*example*)
2 **if** CONTAINS-NOT(*example*)
3 **return** REVERSE(*lexrel*)
4 **return** *lexrel*

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

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

Largest exchangeable cluster



Which algorithm is BERT implementing then?

INFER(*example*)

```
1  lexrel ← GET-LEXREL(example)
2  if CONTAINS-NOT(example)
3      return REVERSE(lexrel)
4  return lexrel
```

INFER(*example*)

```
1  if INCLUSTER(C1, example)
2      lexrel1 ← GET-LEXREL(example)
3      if CONTAINS-NOT(example)
4          return REVERSE(lexrel1)
5      return lexrel1
6  if INCLUSTER(C2, example)
7      lexrel2 ← GET-LEXREL(example)
8      if CONTAINS-NOT(example)
9          return REVERSE(lexrel2)
10     return lexrel2
11 if INCLUSTER(C3, example)
12     lexrel3 ← GET-LEXREL(example)
13     if CONTAINS-NOT(example)
14         return REVERSE(lexrel3)
15     return lexrel3
16 ...
```

IIT induces causal structure

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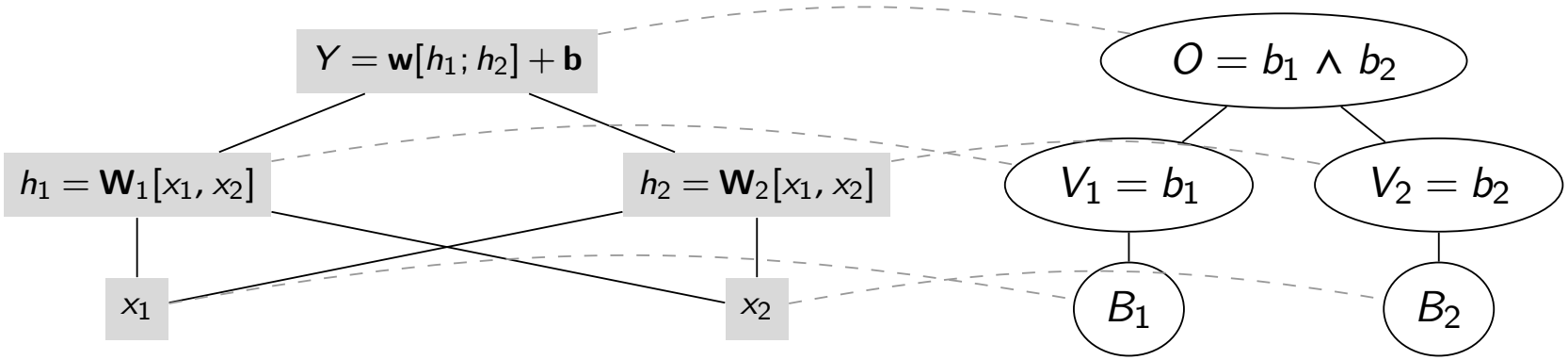
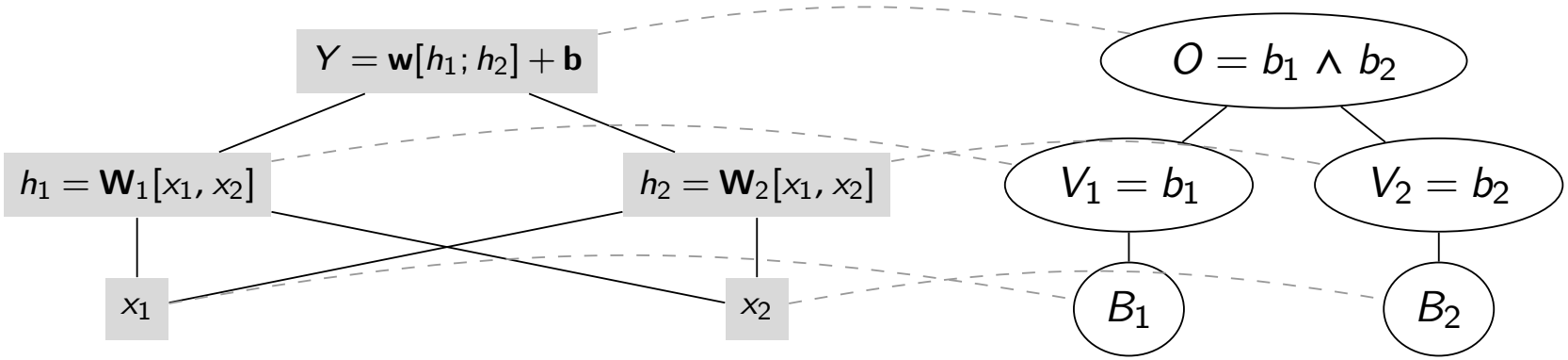
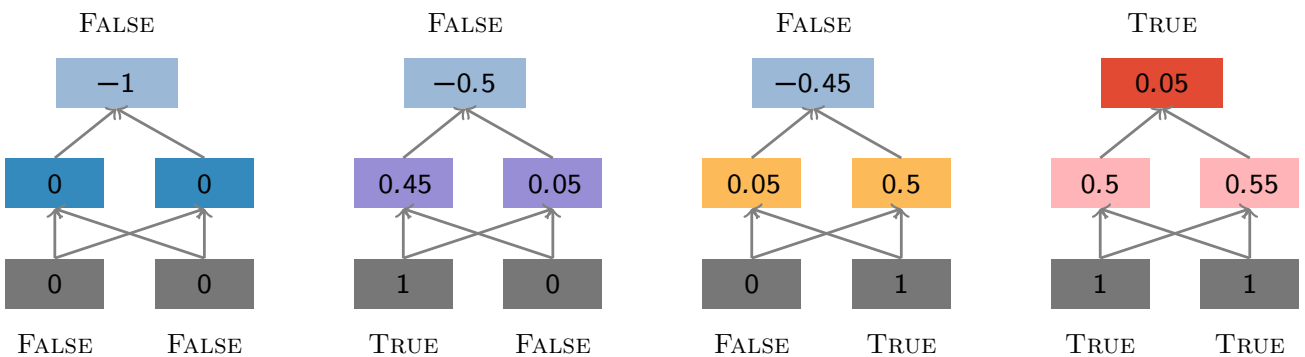


IIT induces causal structure





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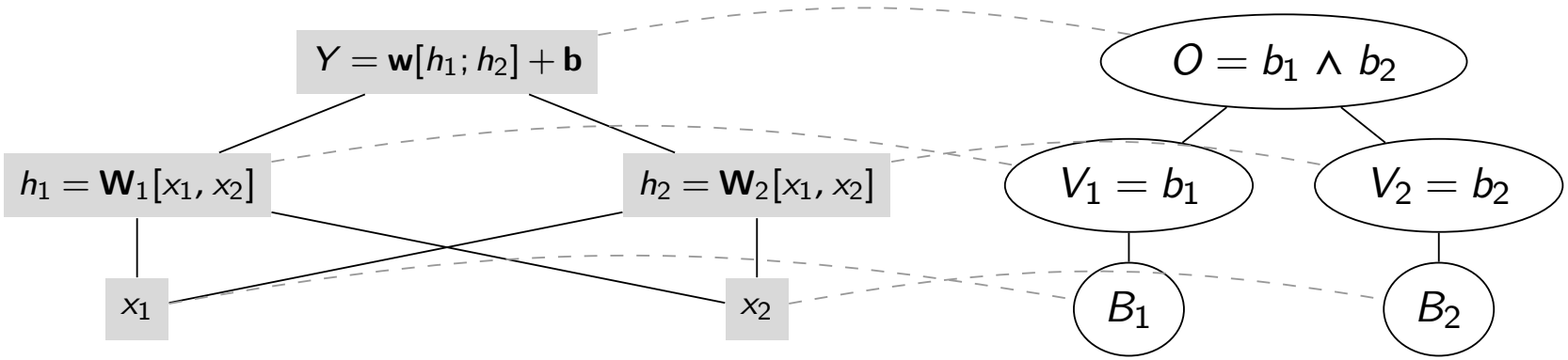

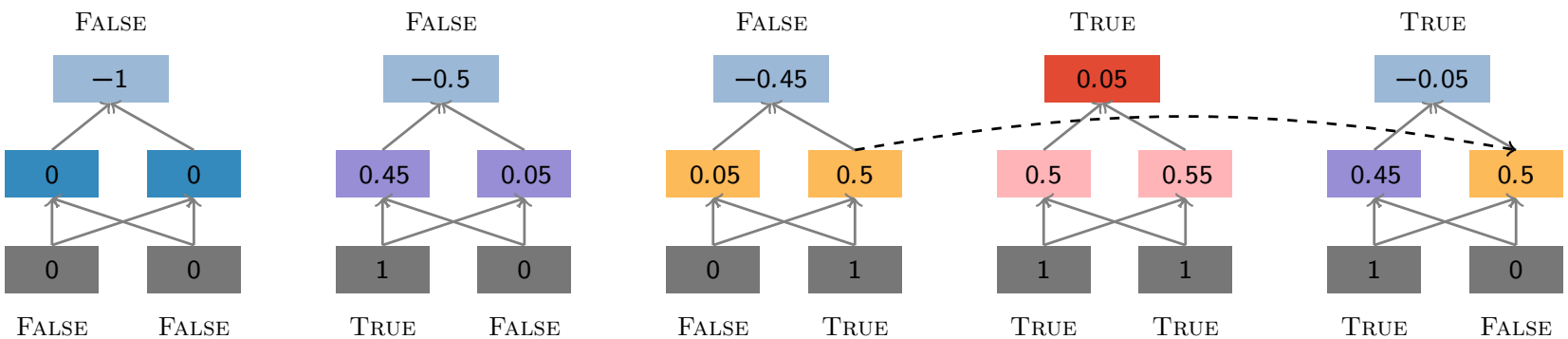

IIT induces causal structure