



# **Amnesic Probing:**

#### **Behavioral Explanation with Amnesic Counterfactuals**

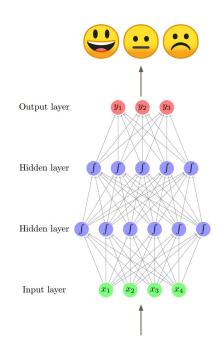
**Yanai Elazar**, Shauli Ravfogel, Alon Jacovi and Yoav Goldberg

TACL 2021

## The State of NLP (ML?)

Output

Model

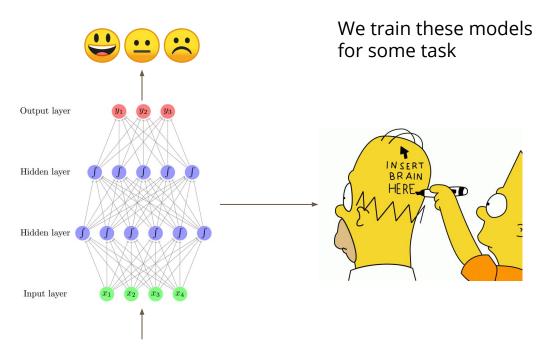


Input

#### The State of NLP

Output

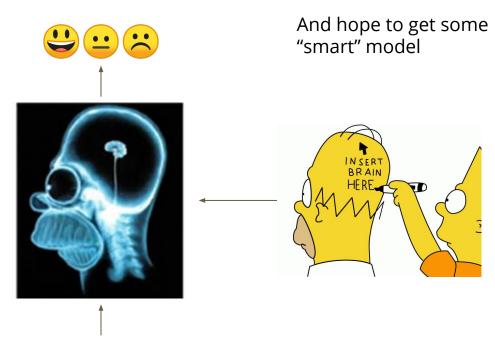
Model



#### The State of NLP

Output

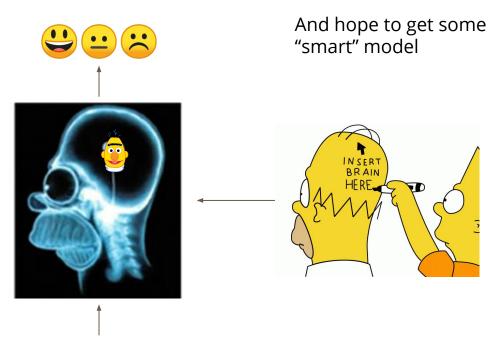
Model



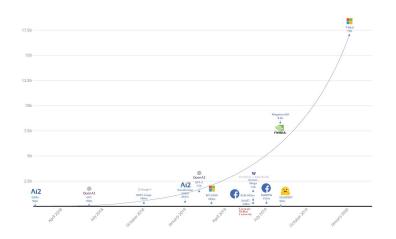
#### The State of NLP

Output

Model



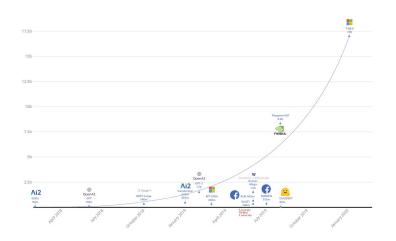
#### The State of NLP: Sesame Street







#### The State of NLP: Inside Sesame Street





#### The State of NLP: Inside Sesame Street



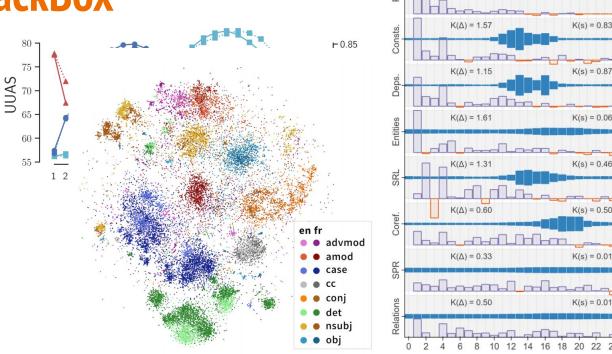
you cannot cram the meaning of a whole %&!\$# sentence into a single \$&!#\* vector

- -- Ray Mooney
- So what can be crammed into that?

- Sentence Length
- Word Order
- Tense
- POS
- Tree depth
- Entities
- Coref.
- ...

Adi et al., 2016, Conneau et al., 2018, Hewitt and Manning, 2019, Tenney et al., 2019, Chi et al., 2020

- Sentence Length
- Word Order
- Tense
- POS
- Tree depth
- **Entities**
- Coref.



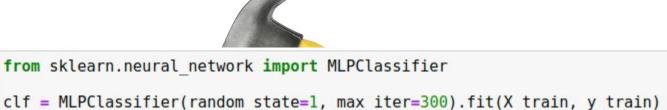
 $K(\Delta) = 1.60$ 

K(s) = 0.83

Adi et al., 2016, Conneau et al., 2018, Hewitt and Manning, 2019, Tenney et al., 2019, Chi et al., 2020

 $clf.predict proba(X test[:\overline{1}])$ 

#### But with what tool?

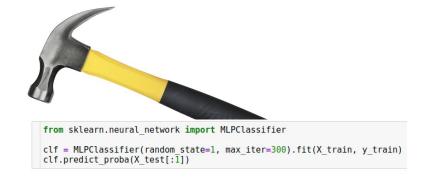




We (the community) found out that:

- Random Models perform surprisingly well (architecture inductive bias?)
- The hammer may have been too big





Conneau et al., 2018, Hewitt and Liang, 2019

- Looking at the representations we find that different properties are encoded
- The first step of a long journey



#### **Opening the BlackBox - This Work**

We ask a behavioral question:

What information does a model use in order to make a prediction?

Also,

Is there a connection between the structural analysis (standard probes) to behavioral analysis (e.g. this work)



## **Amnesic Probing: A Behavioral Probe**

#### **Amnesic Probing: A Behavioral Analysis**

- Understanding how our models work
- Interpretability and analysis tool, which allows to answer scientific questions (e.g. Does a LM use POS information?)
- Answer sensitive questions (e.g. Does the model use gender for making a decision)

#### **Amnesic Probing: The Intuition**

- Ablation Test (or Counterfactuals):
  - Removes a certain component
  - Test how it affects the results

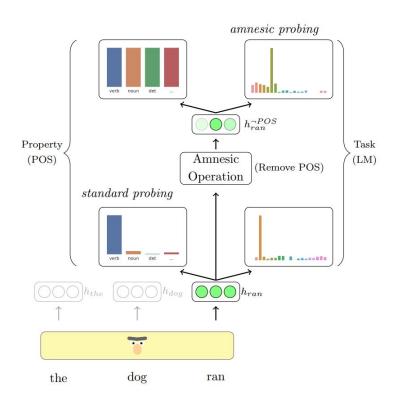


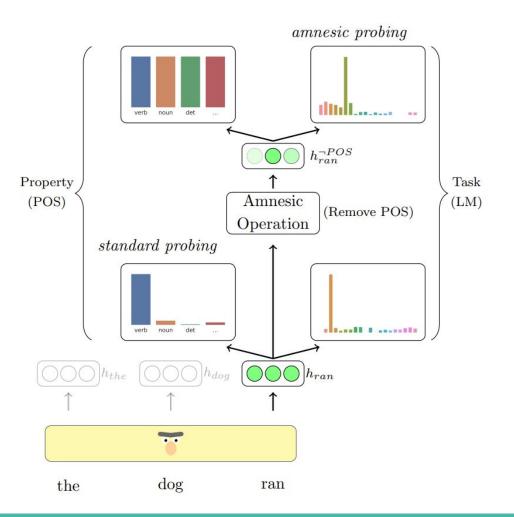
#### **Amnesic Probing: The Intuition**

- We remove a feature from the representation
- Does the model change its behavior?

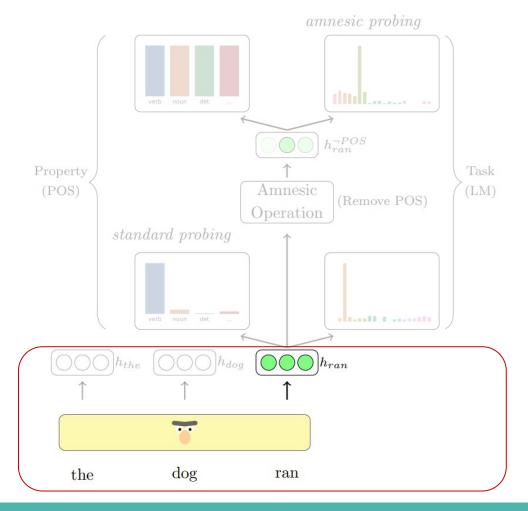
- Yes:
  - The model uses this information for its predictions
- No:
  - The model does not use this information for its predictions

## **Amnesic Probing: Overview**



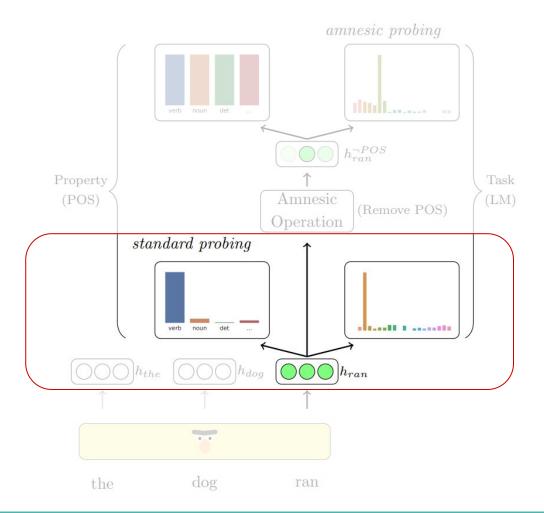


#### 1. Encode

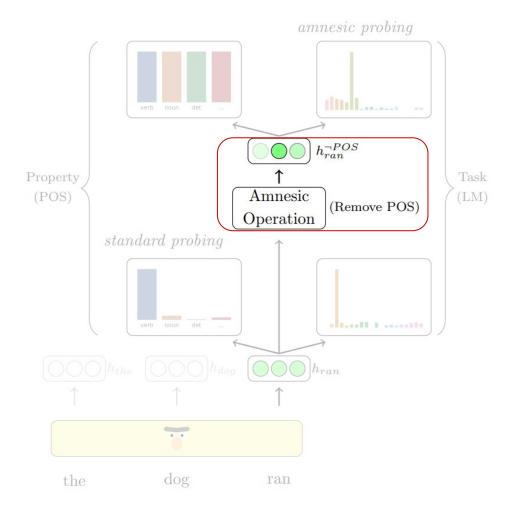


#### 1. Encode

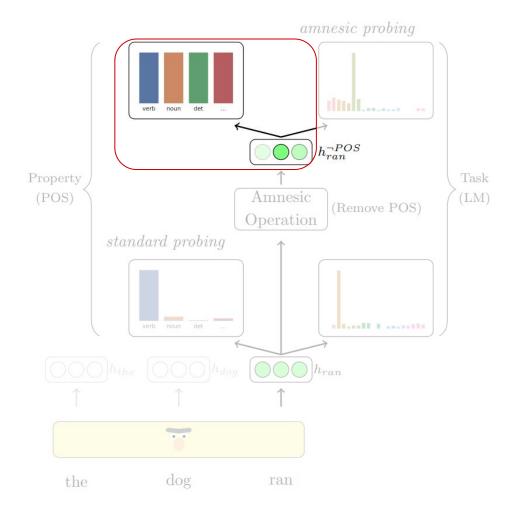
2. Probe



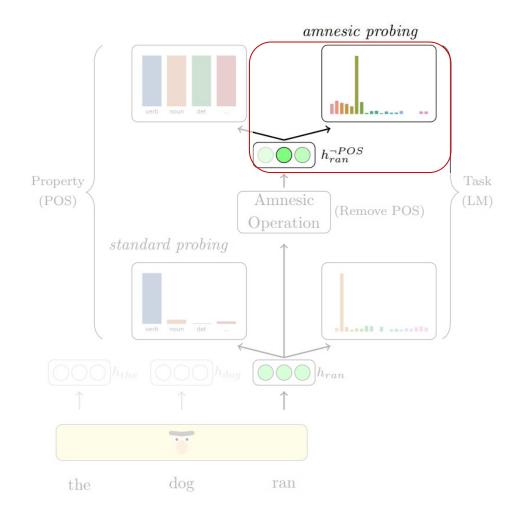
- 1. Encode
- 2. Probe
- 3. Amnesia



- 1. Encode
- 2. Probe
- 3. Amnesia
  - 3.1. Verify



- 1. Encode
- 2. Probe
- 3. Amnesia
  - 3.1. Verify
- 4. Amnesic Probing



#### **The Amnesia**

One option: Adversarial Training

#### Adversarial Removal of Demographic Attributes from Text Data

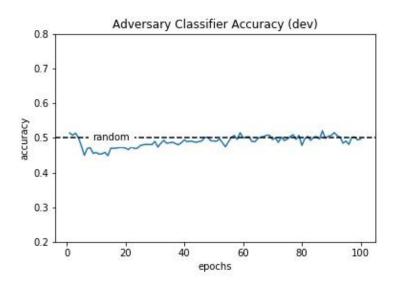
Yanai Elazar<sup>†</sup> and Yoav Goldberg<sup>†\*</sup>

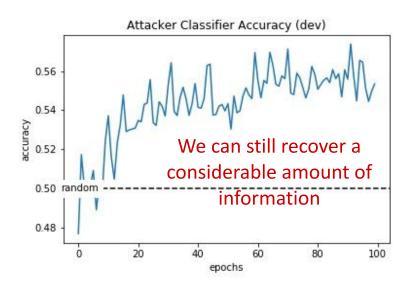
†Computer Science Department, Bar-Ilan University, Israel

\*Allen Institute for Artificial Intelligence

{yanaiela, yoav.goldberg}@gmail.com

One option: Adversarial Training

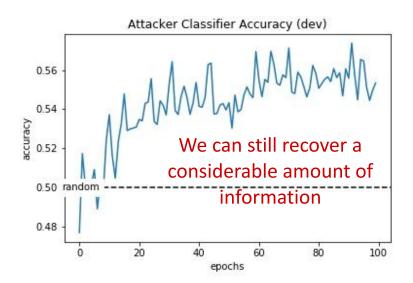




One option: Adversarial Training

#### But also:

- Slow & unstable training
- Is it the same model afterwards?



#### Null It Out: Guarding Protected Attributes by Iterative Nullspace Projection

Shauli Ravfogel<sup>1,2</sup> Yanai Elazar<sup>1,2</sup> Hila Gonen<sup>1</sup> Michael Twiton<sup>3</sup> Yoav Goldberg<sup>1,2</sup>

<sup>1</sup>Computer Science Department, Bar Ilan University

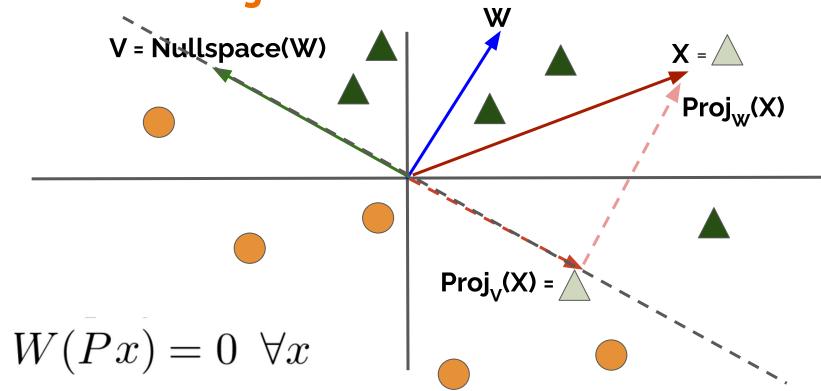
<sup>2</sup>Allen Institute for Artificial Intelligence

<sup>3</sup>Independent researcher

**INLP**: Iterative Nullspace Projection

Find a projection matrix P, which projects into the nullspace

$$N(W) = \{x | Wx = 0\}$$



- Each projection only removes a single direction
- Therefore the "iterative" part:
- We repeat this process until convergence

Debiasing applications (Ravfogel et al., 2020)

Check it out!

	BoW	FastText	BERT
Original	78.2	78.1	80.9
+INLP	80.1	73.0	75.2
Original	0.203	0.184	0.184
+INLP	0.124	0.089	0.095
	+INLP Original	Original 78.2 +INLP 80.1 Original 0.203	Original         78.2         78.1           +INLP         80.1         73.0           Original         0.203         0.184

Table 2: Fair classification on the Biographies corpus.

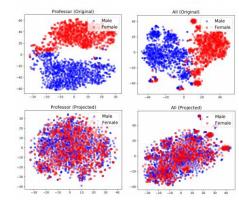


Figure 3: t-SNE projection of BERT representations for the profession "professor" (left) and for a random sample of all professions (right), before and after the projection.

#### **Amnesic Probing: Properties**

- The removed information is linear
- Guaranteed to remove linear all the linear information, given the usage of a good classifier
- No need to retrain a model (e.g. adversarial training)
- Post-hoc operation on a learned representation

#### **Amnesic Probing: Using INLP**

 We use INLP in this work, but this is a component that can be replaced with a future (non-linear) alternative

## **Amnesic Probing: Setup**

- We take a trained model
- Choose properties/features of interest
- Measure the difference (Behavioral!)
  - Accuracy (of predicting the "right" label)
  - KL Divergence (DKL): softer metric, but on the entire distribution

## **Amnesic Probing: Controls**

- Did the amnesic operation really had an effect?
- Did the amnesic operation remove too much information?













## **Amnesic Probing: Controls**

- Did the amnesic operation really had an effect?
- Did the amnesic operation remove too much information?



Removing random directions













## **Amnesic Probing: Controls**

- Did the amnesic operation really had an effect?
- Did the amnesic operation remove too much information?



- Removing random directions
- Control over Selectivity
  - Add back the "real" features, and retrain



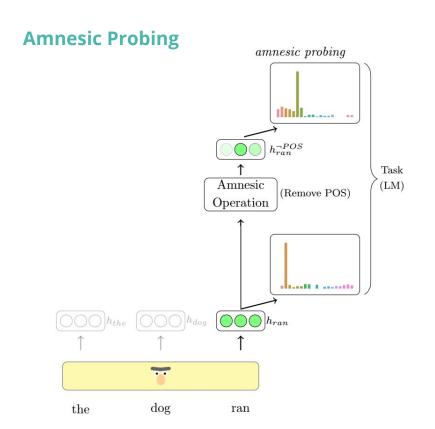


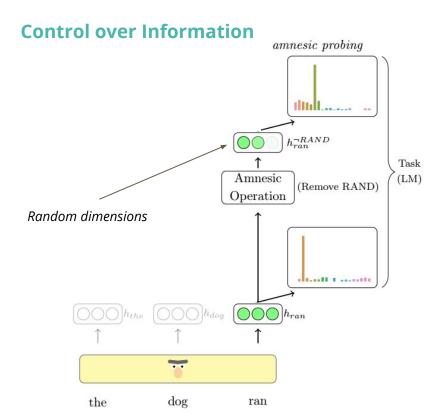






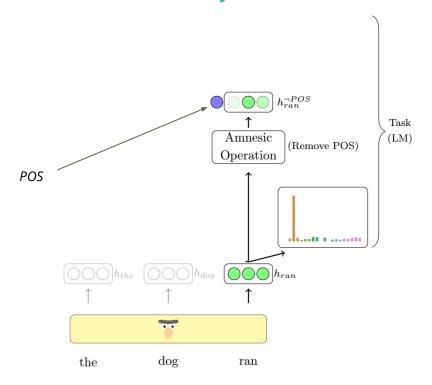






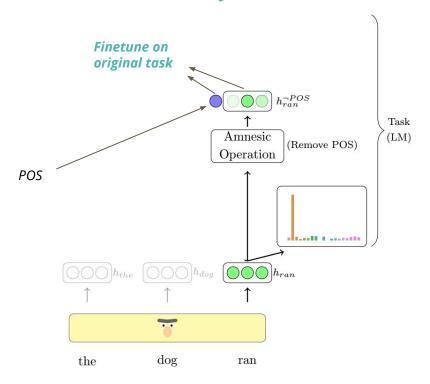
#### **Amnesic Probing** amnesic probing Illullarana a $h_{ran}^{\neg POS}$ Task Amnesic (LM) (Remove POS) Operation Alterest Consensation the dogran

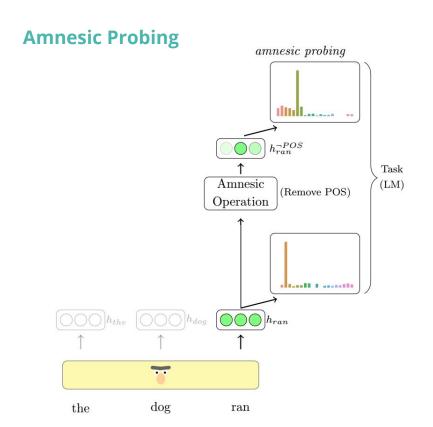
#### **Control over Selectivity**

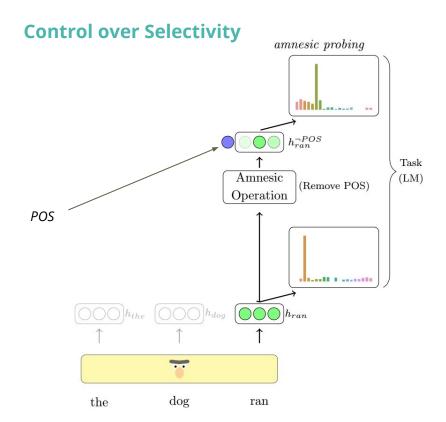


#### **Amnesic Probing** amnesic probing Illidi.... $h_{ran}^{\neg POS}$ Task Amnesic (LM) (Remove POS) Operation Alterest Consensation the dogran

#### **Control over Selectivity**







### **Amnesic Operation - Randomization**

#### First Align, then Predict: Understanding the Cross-Lingual Ability of Multilingual BERT

```
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<sup>1</sup>Inria, Paris, France <sup>2</sup>Sorbonne Université, Paris, France

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<sup>4</sup>Allen Institute for Artificial Intelligence

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yanaiela@gmail.com
```

#### **Amnesic Operation - Randomization**

- Study the role of a model component (e.g. MLP) in pretraining
- Randomize the layer and then fine-tune
- Measure difference in performance w/ and w/o the randomization.

# **Case Study: Pre-trained BERT**



• The Model: BERT-base

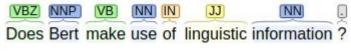


The Model: BERT-base

Properties:

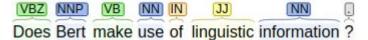
POS

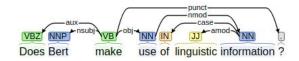




- The Model: BERT-base
- Properties:
  - o POS
  - Dependency edges



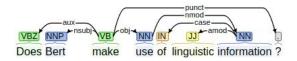




- The Model: BERT-base
- Properties:
  - o POS
  - Dependency edges
  - NER



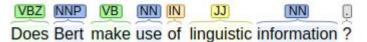


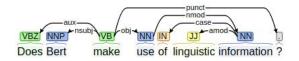


Does Bert make use of linguistic information ?

- The Model: BERT-base
- Properties:
  - o POS
  - Dependency edges
  - NER
  - Constituency boundaries









		dep	f-pos	c-pos	ner	phrase start	phrase end
	N. dir	738	585	264	133	36	22
<b>Properties</b>	N. classes	41	45	12	19	2	2
875	Majority	11.44	13.22	31.76	86.09	59.25	58.51
Probing	Vanilla	76.00	89.50	92.34	93.53	85.12	83.09
	Vanilla	94.12	94.12	94.12	94.00	94.00	94.00
IMAGO	Rand	12.31	56.47	89.65	92.56	93.75	93.86
LM-Acc	Selectivity	73.78	92.68	97.26	96.06	96.96	96.93
	Amnesic	7.05	12.31	61.92	83.14	94.21	94.32
IM D	Rand	8.11	4.61	0.36	0.08	0.01	0.01
$LM-D_{KL}$	Amnesic	8.53	7.63	3.21	1.24	0.01	0.01

*Linguistic Properties* 

	2	dep	f-pos	c-pos	ner	phrase start	phrase end
Properties	N. dir	738	585	264	133	36	22
	N. classes	41	45	12	19	2	2
	Majority	11.44	13.22	31.76	86.09	59.25	58.51
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$\mathrm{LM} ext{-}\mathrm{D}_{KL}$	Rand	8.11	4.61	0.36	0.08	0.01	0.01
	Amnesic	8.53	7.63	3.21	1.24	0.01	0.01

#### Standard Probing

		dep	f-pos	c-pos	ner	phrase start	phrase end
Properties	N. dir	738	585	264	133	36	22
	N. classes	41	45	12	19	2	2
	Majority	11.44	13.22	31.76	86.09	59.25	58.51
Probing	Vanilla	76.00	89.50	92.34	93.53	85.12	83.09
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	Amnesic	8.53	7.63	3.21	1.24	0.01	0.01

#### LM Accuracy Results

		dep	f-pos	c-pos	ner	phrase start	phrase end
	N. dir	738	585	264	133	36	22
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Probing	Vanilla	76.00	89.50	92.34	93.53	85.12	83.09
LM-Acc	Vanilla Rand Selectivity Amnesic	94.12 12.31 73.78 7.05	94.12 56.47 92.68 12.31	94.12 89.65 97.26 61.92	94.00 92.56 96.06 83.14	94.00 93.75 96.96 94.21	94.00 93.86 96.93 94.32
$LM-D_{KL}$	Rand Amnesic	8.11 8.53	4.61 7.63	0.36	0.08 1.24	0.01 0.01	0.01

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$LM-D_{KL}$	Rand Amnesic	8.11 8.53	4.61 7.63	0.36 3.21	0.08 1.24	0.01 0.01	0.01 0.01

Comparison to Control: Information

		dep	f-pos	c-pos	ner	phrase start	phrase end
	N. dir	738	585	264	133	36	22
Properties	N. classes	41	45	12	19	2	2
	Majority	11.44	13.22	31.76	86.09	59.25	58.51
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$LM-D_{KL}$	Rand Amnesic	8.11 8.53	4.61 7.63	0.36 3.21	0.08 1.24	0.01 0.01	0.01 0.01

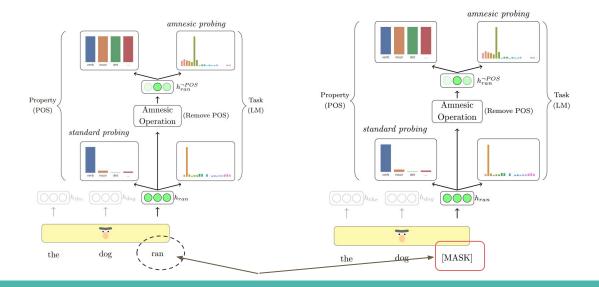
Comparison to Control: **Selectivity** 

		dep	f-pos	c-pos	ner	phrase start	phrase end
	N. dir	738	585	264	133	36	22
Properties	N. classes	41	45	12	19	2	2
F	Majority	11.44	13.22	31.76	86.09	59.25	58.51
Probing	Vanilla	76.00	89.50	92.34	93.53	85.12	83.09
	Vanilla	94.12	94.12	94.12	794.00	7 94.00	7 94.00
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	Vanilla	94.12	94.12	94.12	94.00	94.00	94.00	DKL Results
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LM-Acc	Selectivity	73.78	92.68	97.26	96.06	96.96	96.93	
	Amnesic	7.05	12.31	61.92	83.14	94.21	94.32	
$LM ext{-}D_{KL}$	Rand	8.11	4.61	0.36	0.08	0.01	0.01	•
LM-DKL	Amnesic	8.53	7.63	3.21	1.24	0.01	0.01	

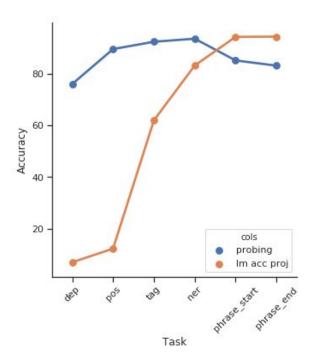
		dep	f-pos	c-pos	ner	phrase start	phrase end	
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$LM-D_{KL}$	Amnesic	8.53	7.63	3.21	1.24	0.01	0.01	<u>.</u>

- We perform the same experiments on another setup, where the words are masked
  - (Similar results, but we'll come back to it)



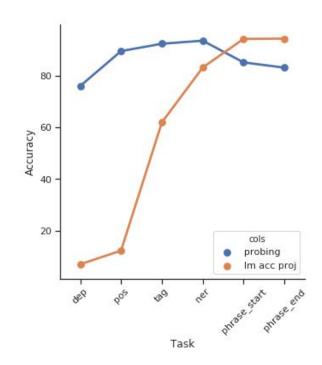
## **Amnesic Probing vs. Standard Probing**

- We plot the performance of regular probing vs.
   amnesic probing
- We observe no correlation between the two metrics



### **Amnesic Probing vs. Standard Probing**

- We plot the performance of regular probing vs.
   amnesic probing
- We observe no correlation between the two metrics
- Behavioural conclusions cannot be made from standard probing results



## **Amnesic Probing: Diving In**

small changes

## **Amnesic Probing Fine Grained**

- How individuals POS are affected by the removal of POS information?
- Open vs. Closed vocabulary

Large changes

c-pos	Vanilla	Rand	Amnesic	Δ
verb	46.72	44.85	34.99	11.73
noun	42.91	38.94	34.26	8.65
adposition	73.80	72.21	37.86	35.93
determiner	82.29	83.53	16.64	65.66
numeral	40.32	40.19	33.41	6.91
punctuation	80.71	81.02	47.03	33.68
particle	96.40	95.71	18.74	77.66
conjunction	78.01	72.94	4.28	73.73
adverb	39.84	34.11	23.71	16.14
pronoun	70.29	61.93	33.23	37.06
adjective	46.41	42.63	34.56	11.85
other	70.59	76.47	52.94	17.65

# **Amnesic Probing: Inside The Model**

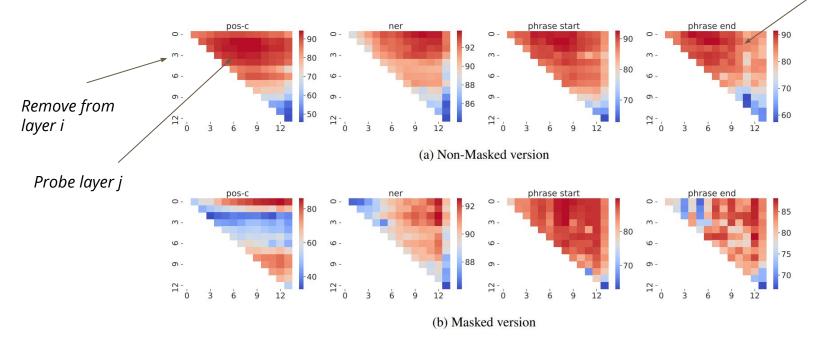
### The Inner Layers

- Until now, querying the last layer
  - o INLP removes linear information, last layer is only multiplied by a matrix
- We perform the same analysis on the Inner layers
- Standard Probe (after the amnesic operation)
- Behavioral Probe

## The Inner Layers: Probing

*Probe scores* 

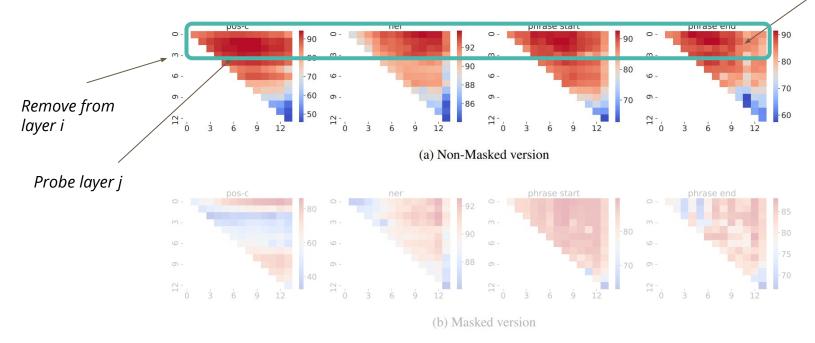
Removing information from layer i, and probing in layer j



## The Inner Layers: Probing

*Probe scores* 

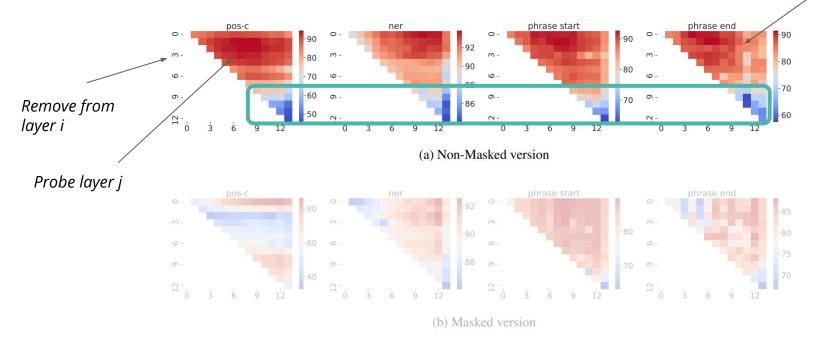
Removing information from layer i, and probing in layer j



## The Inner Layers: Probing

*Probe scores* 

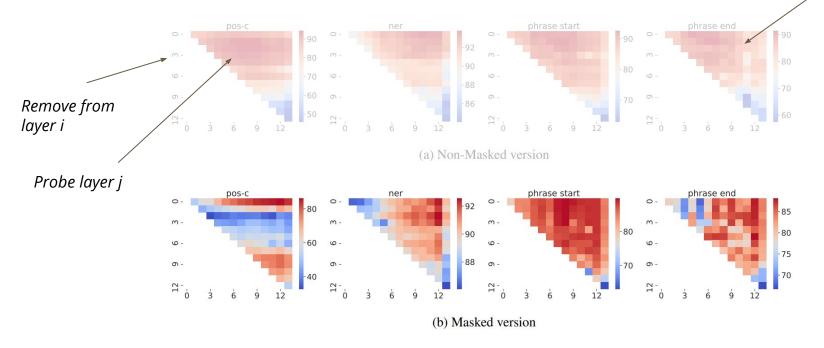
Removing information from layer i, and probing in layer j



## The Inner Layers: Probing

*Probe scores* 

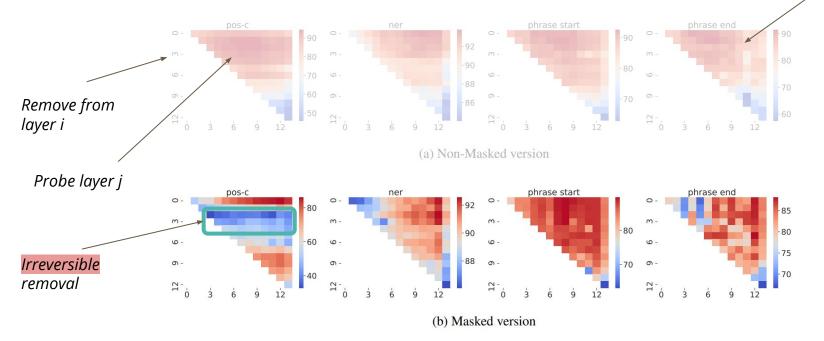
Removing information from layer i, and probing in layer j



## The Inner Layers: Probing

*Probe scores* 

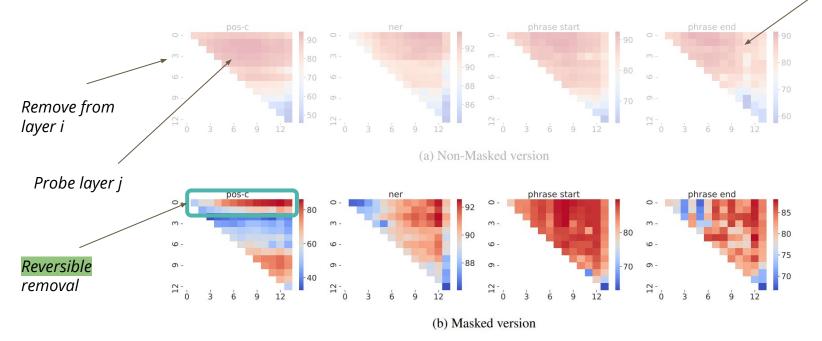
Removing information from layer i, and probing in layer j

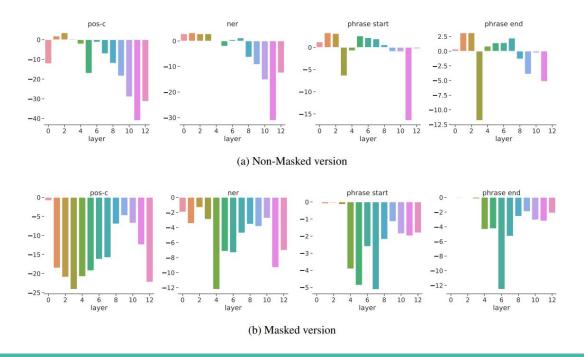


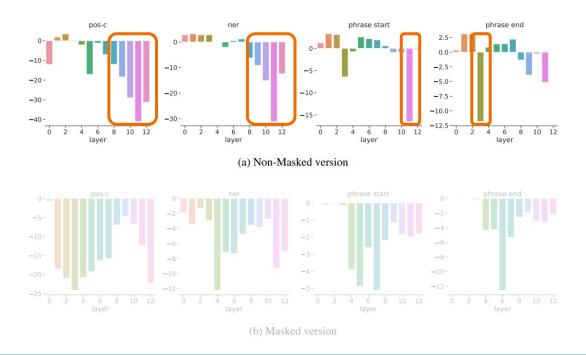
## The Inner Layers: Probing

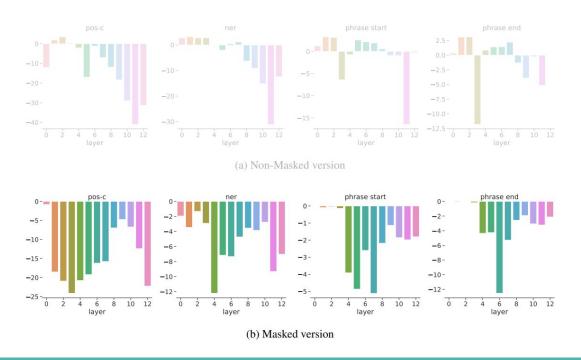
*Probe scores* 

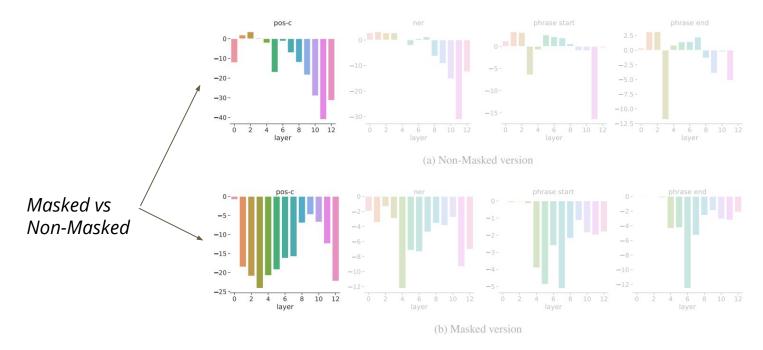
Removing information from layer i, and probing in layer j

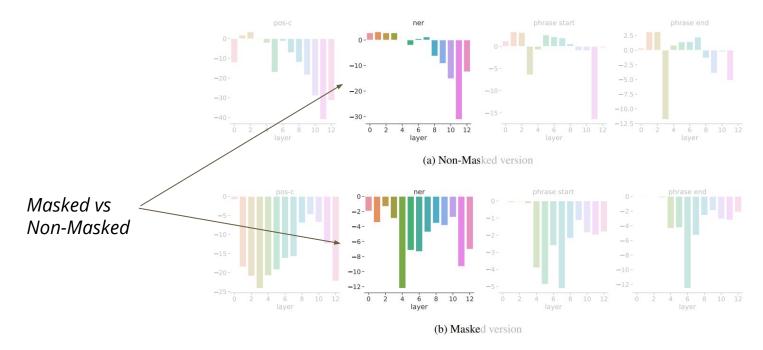


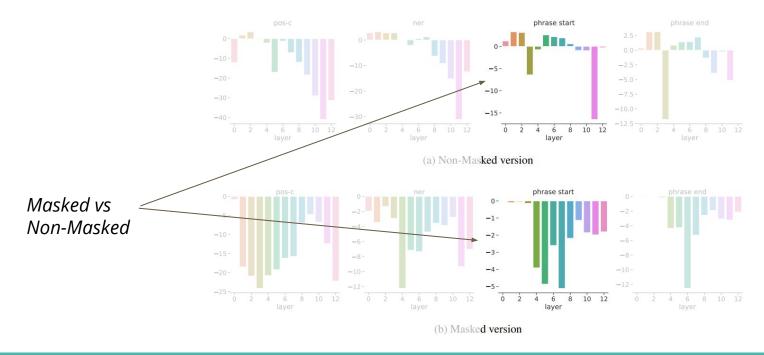


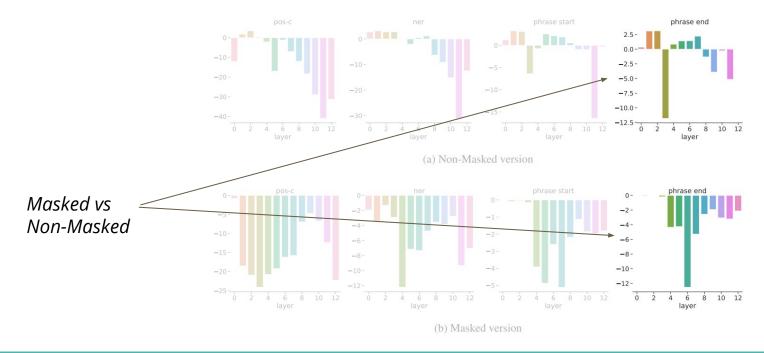




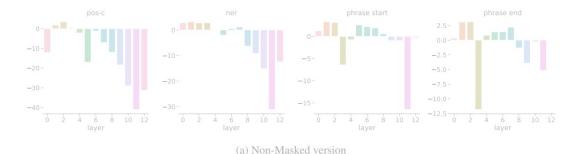




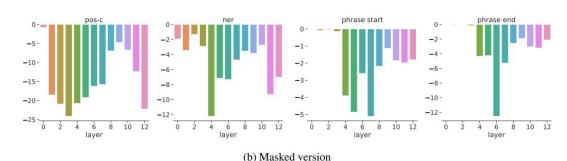




• Removing information from layer *i*, and inspecting the model's predictions



Strong impact in the first few layers!!



#### **Summary - Amnesic Probing**

- New method for answering questions about what properties are being used by models
- Analysis of different linguistic properties and how they are being used by the popular BERT MLM
- Structural Analysis != Behavioral Analysis

## **Going Forward**

- What does it mean that some information is extractable?
- ... or, why is it there from the first place?
- Algorithms that remove also non-linear information







# Thanks!



arxiv paper

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