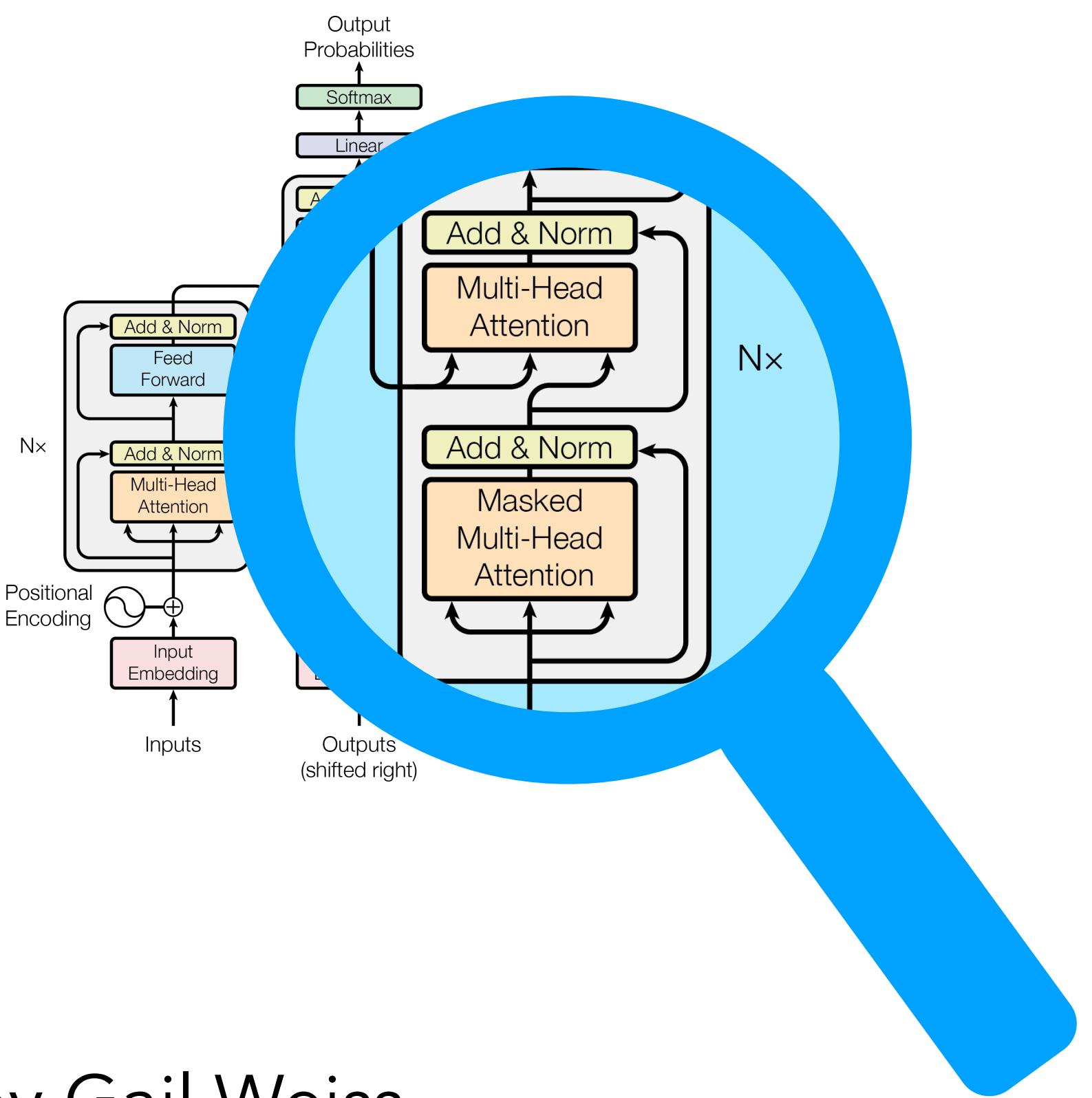


Interpretability



EPFL

Given by Gail Weiss



Outline

◆ Introduction

◆ Methods and Concepts

- Several black and white box methods, intuition vs hypotheses, observation vs intervention
- Background interrupt: Classical NLP tasks

◆ Friends

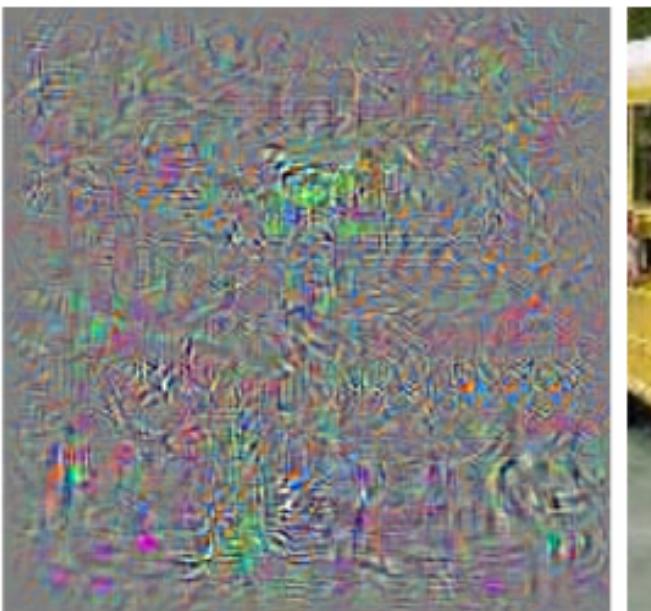
- Formal Analysis; Extraction

◆ Conclusion

Can we trust neural networks?

Introduction

Why did my model do that?

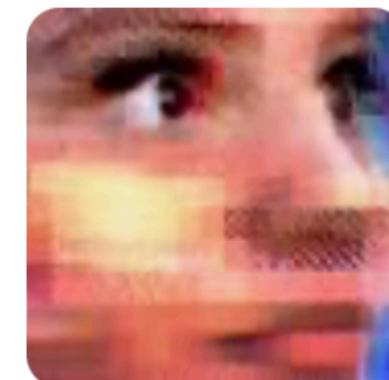


CBS News

Microsoft shuts down AI chatbot, Tay, after it turned into a Nazi

Microsoft got a swift lesson this week on the dark side of social media. Yesterday the company launched "Tay," an artifi

25 Mar 2016



bus



Introduction

“Interpretability is the degree to which a human can understand the cause of a decision”

Tim Miller, 2017

“Interpretability is the degree to which a human can consistently predict the model’s result”

Been Kim et al, 2016

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A: Intrinsic Interpretability:

Rule Based Models

Decision Trees; Linear
Models; Finite State
Machines...

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B: Post Hoc Interpretability

Extraction

Converting to decision trees;
FSMs; other rules...



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B: Post Hoc Interpretability

Investigating trained models

Feature Visualisation; LIME; SHAP;
Leave-one-out; Saliency maps;
Probing; Causal Tracing; De-
embedding space; Key-Value Pairs;
...

Extraction

Converting to decision trees;
FSMs; other rules...

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...



Extraction

Converting to decision trees;
FSMs; other rules...



Intuitions and Visualisations

Cell sensitive to position in line:

```
The sole importance of the crossing of the Berezina lies in the fact  
that it plainly and indubitably proved the fallacy of all the plans for  
cutting off the enemy's retreat and the soundness of the only possible  
line of action--the one Kutuzov and the general mass of the army  
demanded--namely, simply to follow the enemy up. The French crowd fled  
at a continually increasing speed and all its energy was directed to  
reaching its goal. It fled like a wounded animal and it was impossible  
to block its path. This was shown not so much by the arrangements it  
made for crossing as by what took place at the bridges. When the bridges  
broke down, unarmed soldiers, people from Moscow and women with children  
who were with the French transport, all--carried on by vis inertiae--  
pressed forward into boats and into the ice-covered water and did not,  
surrender.
```

Cell that turns on inside quotes:

```
"You mean to imply that I have nothing to eat out of.... On the  
contrary, I can supply you with everything even if you want to give  
dinner parties," warmly replied Chichagov, who tried by every word he  
spoke to prove his own rectitude and therefore imagined Kutuzov to be  
animated by the same desire.
```

```
Kutuzov, shrugging his shoulders, replied with his subtle penetrating  
smile: "I meant merely to say what I said."
```

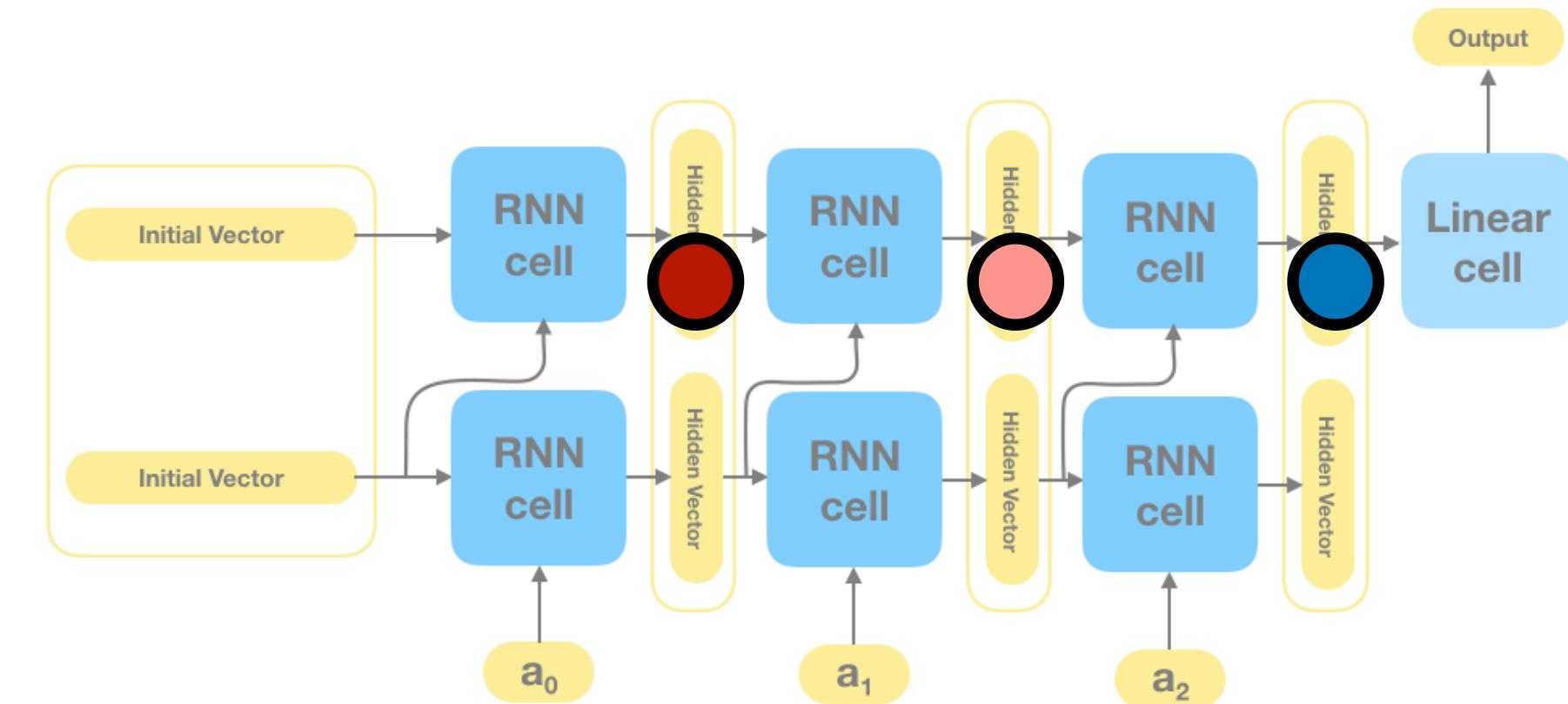
Cell that robustly activates inside if statements:

```
static int __dequeue_signal(struct sigpending *pending, sigset_t *mask,  
    siginfo_t *info)  
{  
    int sig = next_signal(pending, mask);  
    if (sig) {  
        if (current->notifier) {  
            if (sigismember(current->notifier_mask, sig)) {  
                if (!!(current->notifier)(current->notifier_data)) {  
                    clear_thread_flag(TIF_SIGPENDING);  
                    return 0;  
                }  
            }  
        }  
        collect_signal(sig, pending, info);  
    }  
    return sig;  
}
```

A large portion of cells are not easily interpretable. Here is a typical example:

```
/* Unpack a filter field's string representation from user-space  
 * buffer. */  
char *audit_unpack_string(void **bufp, size_t *remain, size_t len)  
{  
    char *str;  
    if (!*bufp || (len == 0) || (len > *remain))  
        return ERR_PTR(-EINVAL);  
    /* Of the currently implemented string fields, PATH_MAX  
     * defines the longest valid length.  
    */
```

Individual cells in an RNN hidden state



Architecture	White box embedder
Required data	None
Explains	Neuron, Sample
Focus	Neuron
Use for...	Intuition

Intuitions and Visualisations

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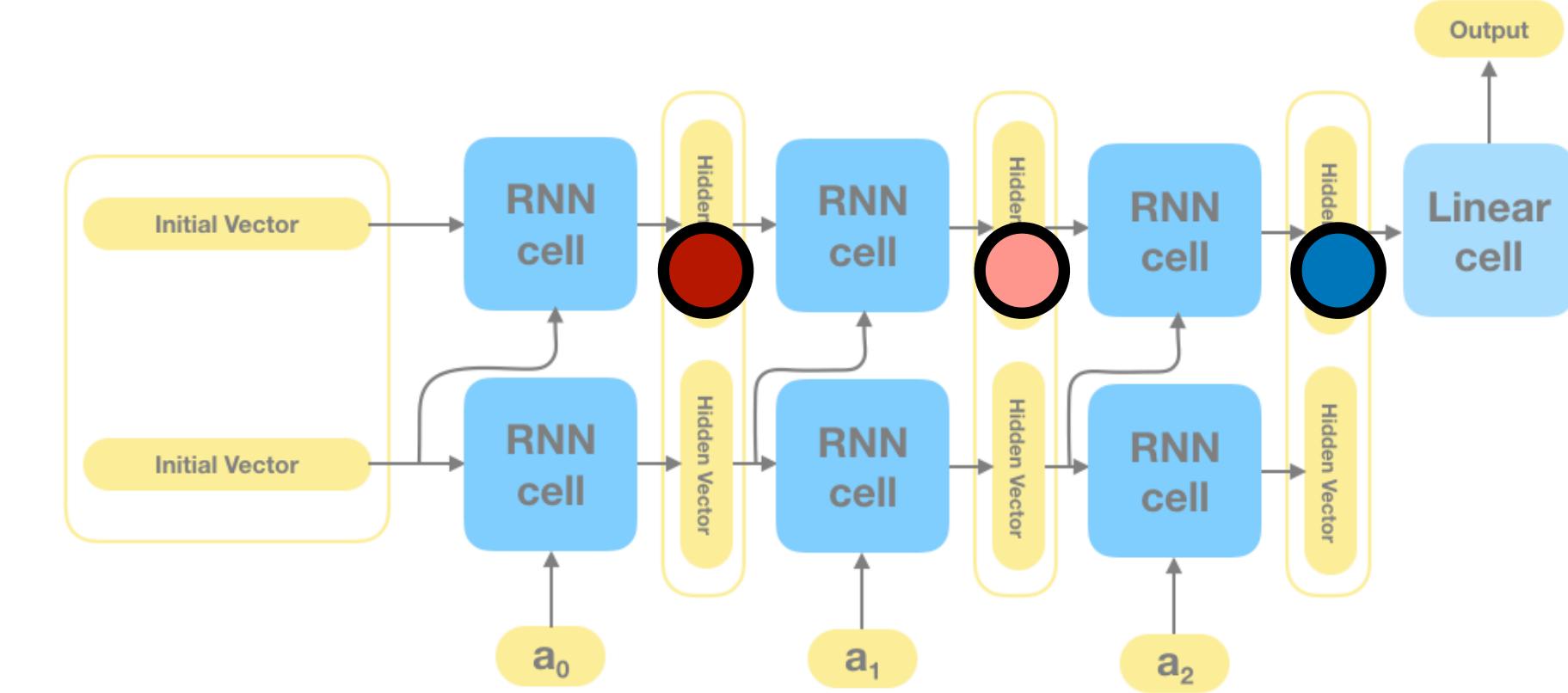
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            if (sigismember(current->notifier_mask, sig)) {  
                if (!!(current->notifier)(current->notifier_data)) {  
                    clear_thread_flag(TIF_SIGPENDING);  
                    return 0;  
                }  
            }  
            collect_signal(sig, pending, info);  
        }  
        return sig;  
    }  
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```

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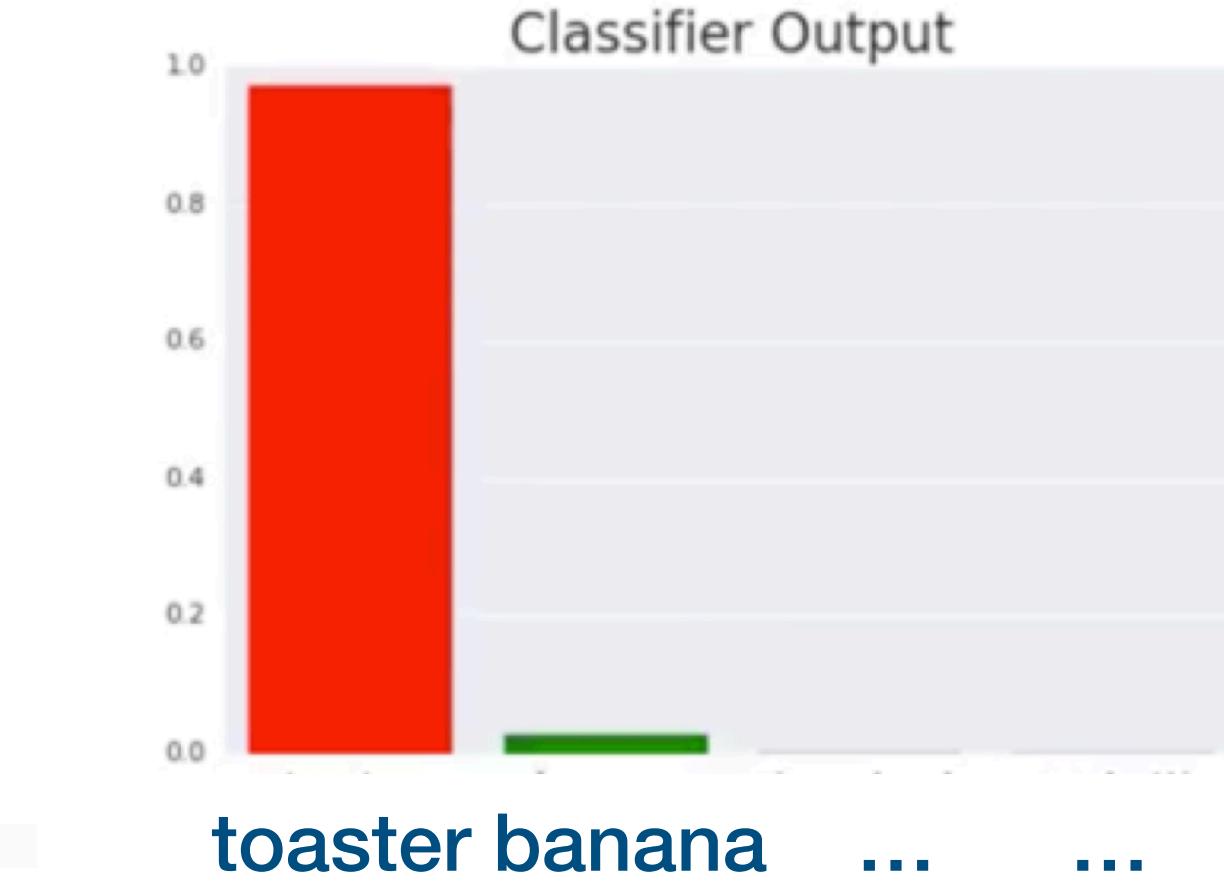
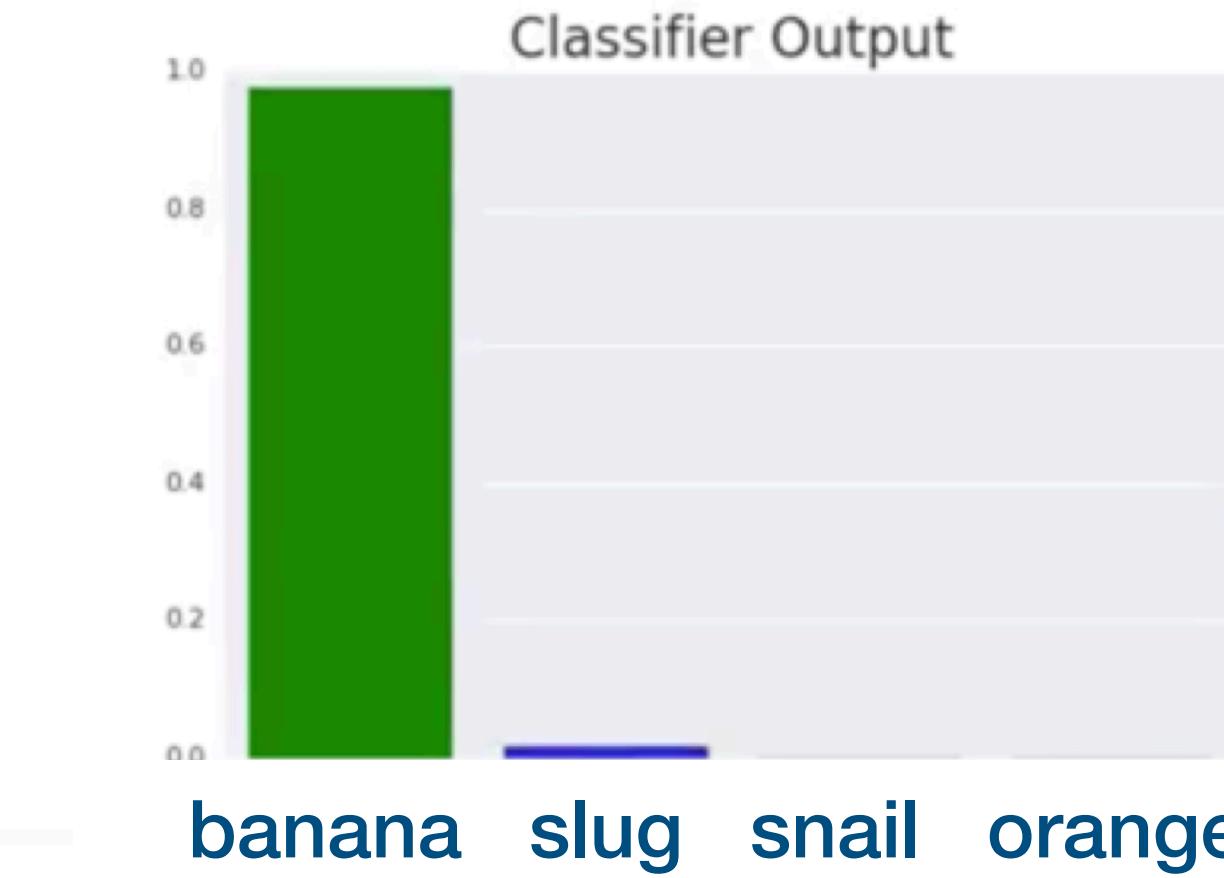
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     */
```

Individual cells in an RNN hidden state



Architecture	White box classifier
Required data	None
Explains	Model
Focus	Class
Use for...	Modifying output across samples!

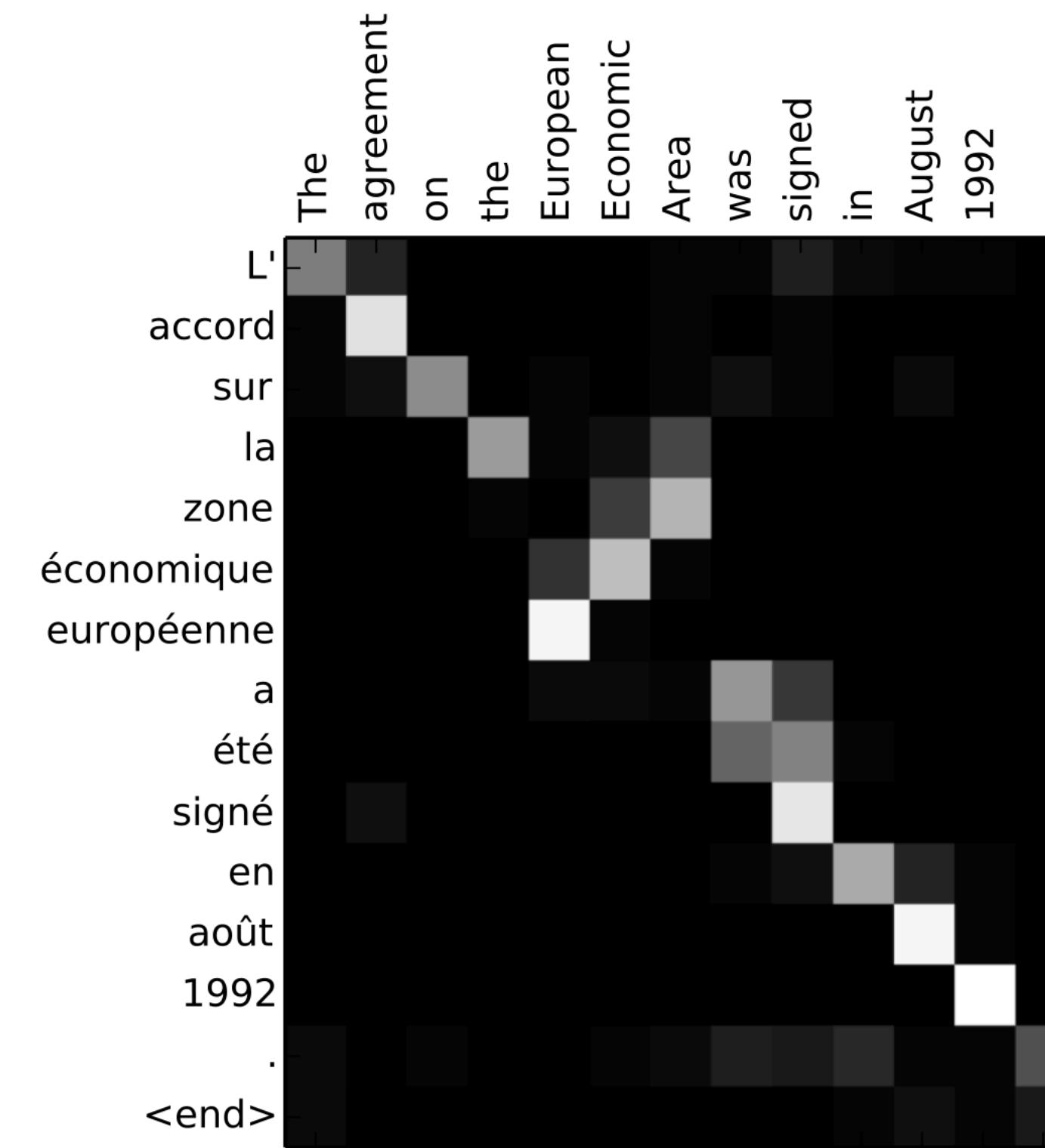
Intuitions and Visualisations



Adversarial patch, Brown et al, 2018

Architecture	White box with attention
Required data	None
Explains	Model
Focus	Partial Computation
Use for...	Intuition

Intuitions and Visualisations



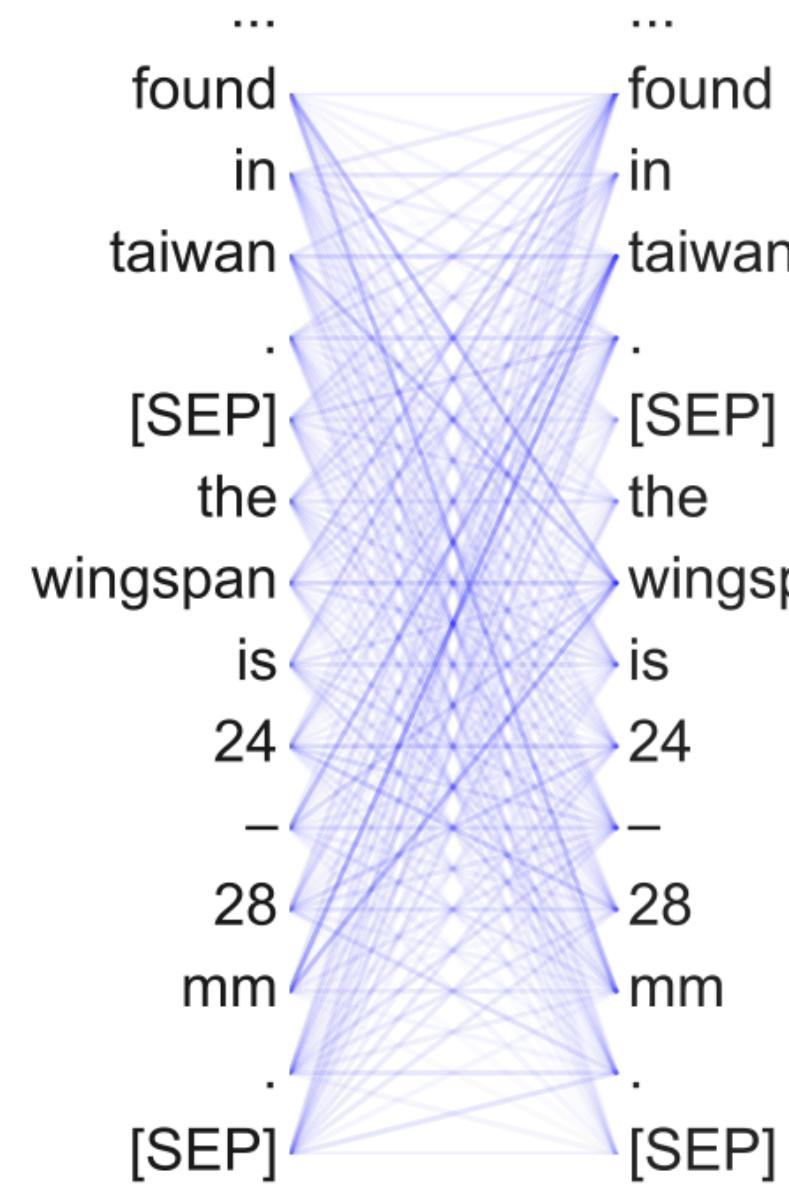
Attention!

Neural Machine Translation by Jointly Learning to Align and Translate, Bahdanau et al, 2014

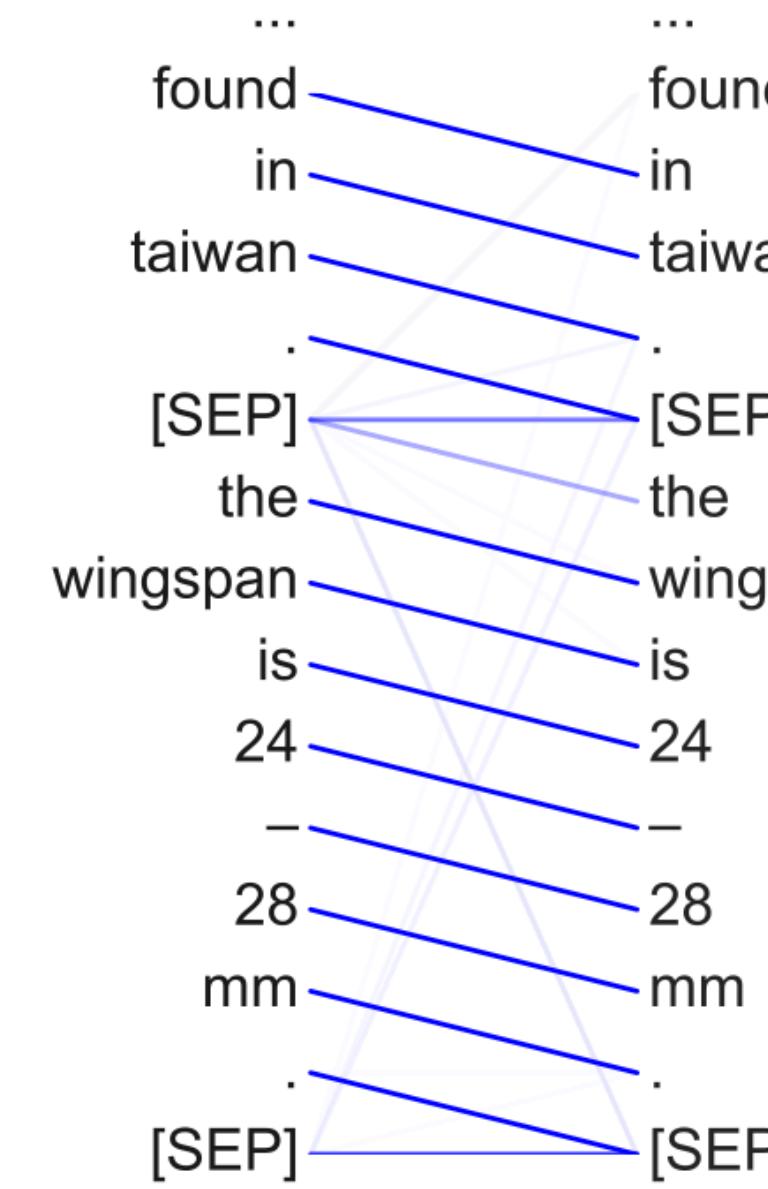
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Required data	None
Explains	Model
Focus	Partial Computation
Use for...	Intuition

Intuitions and Visualisations

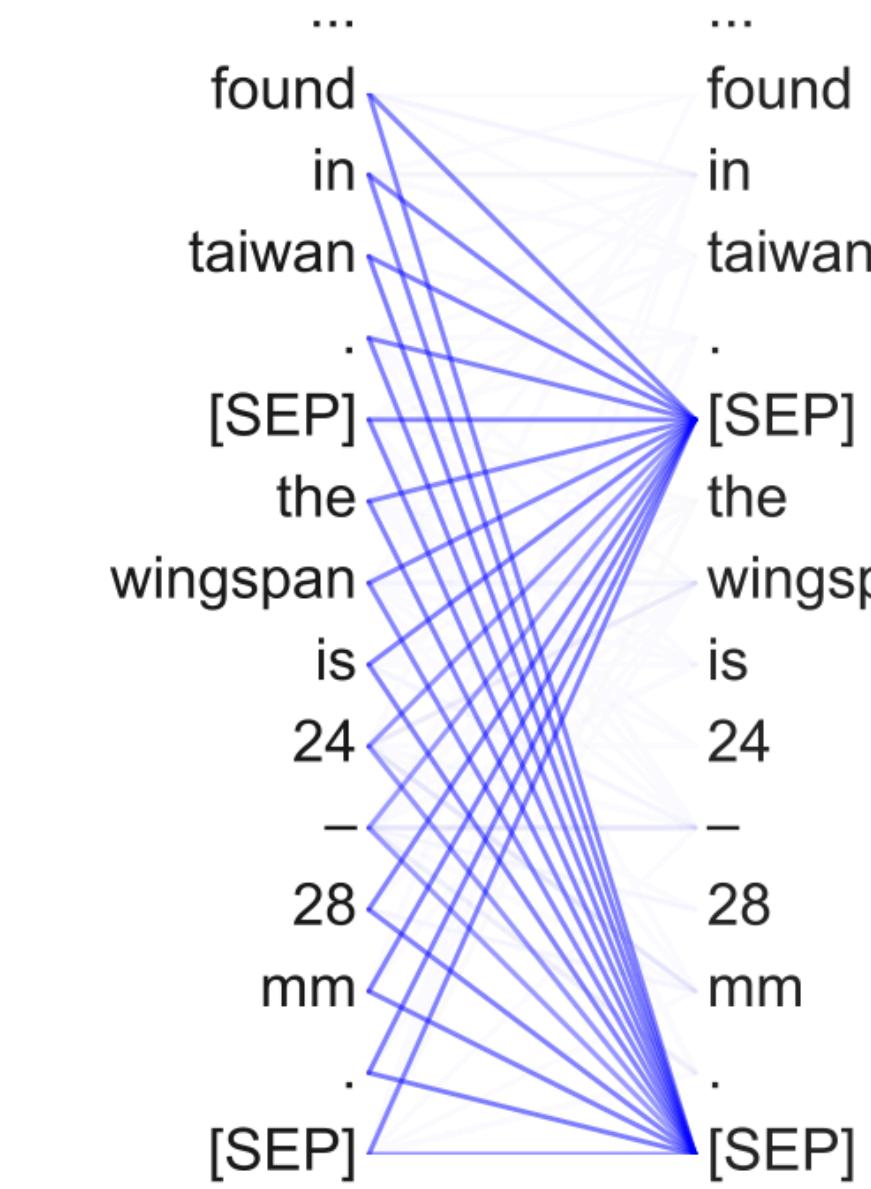
Head 1-1
Attends broadly



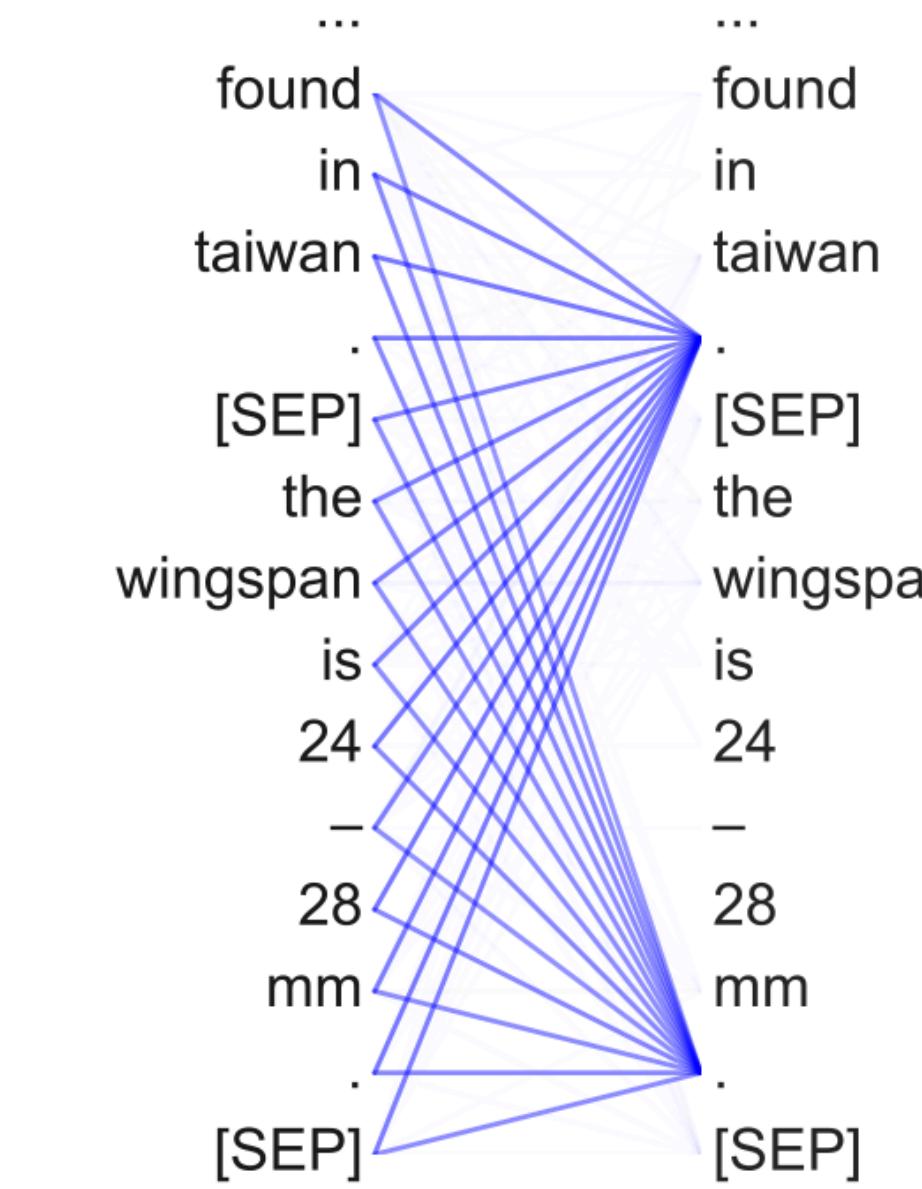
Head 3-1
Attends to next token



Head 8-7
Attends to [SEP]



Head 11-6
Attends to periods



What does BERT look at? An analysis of BERT's attention, Clark et al, 2019

Attention is not explanation, Jain and Wallace, 2019

Attention is not not explanation, Wiegreffe and Pinter, 2019

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- Formal Analysis; Extraction

◆ Conclusion

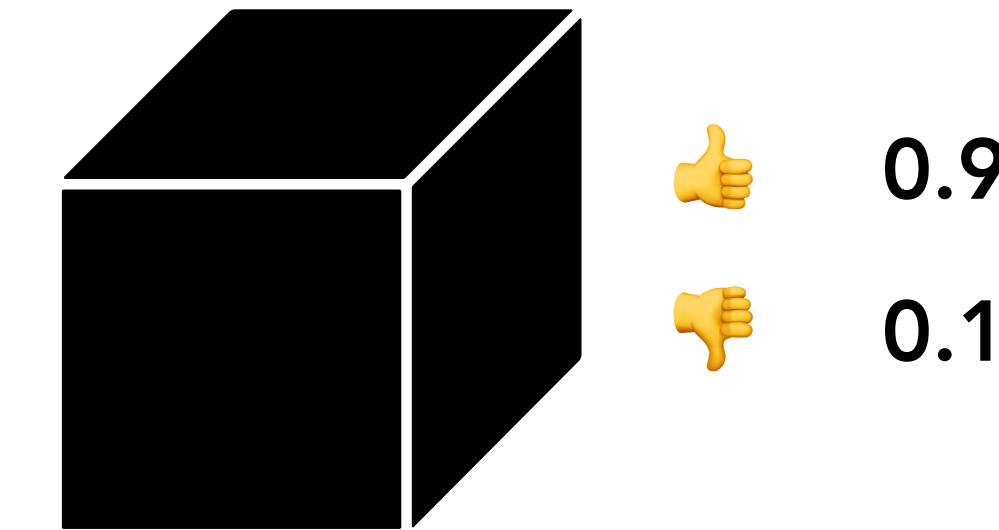
We have a model and a
classification - what can we
check?

Basic approaches
complete black box

Architecture	Black box
Required data	None
Explains	Sample area
Focus	Features
Use for...	Intuition

Leave One Out

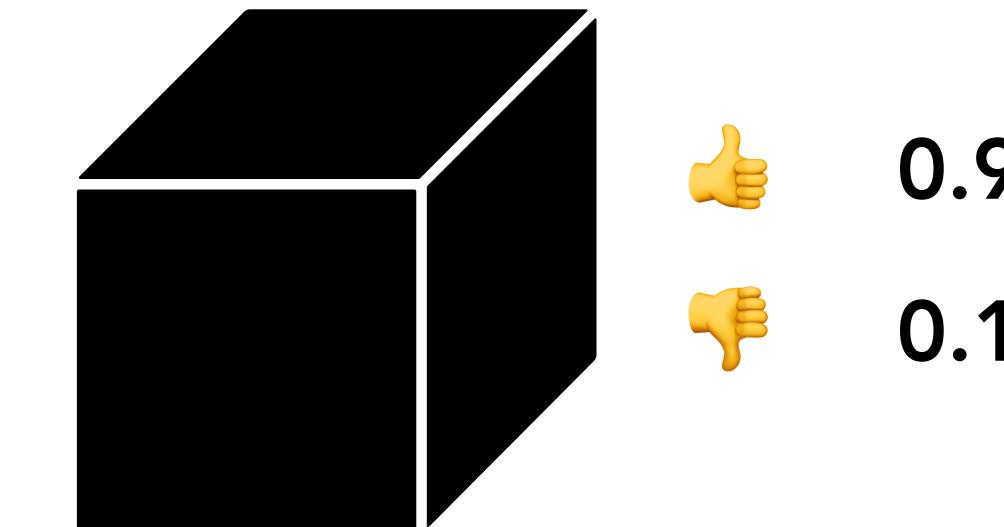
I couldn't like this more!



Architecture	Black box
Required data	None
Explains	Sample area
Focus	Features
Use for...	Intuition

Leave One Out

I couldn't like this more!

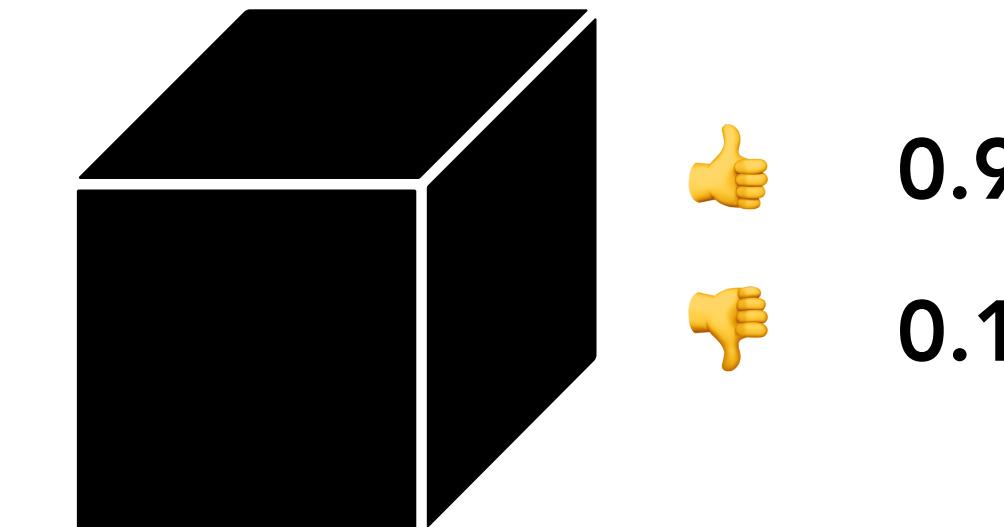


Manipulation	Result	Conclusion?
I couldn't like this more!	拇指图标 0.9	"I" and "couldn't" were not very important in this sample
I couldn't like this more!	拇指图标 0.7	

Architecture	Black box
Required data	None
Explains	Sample area
Focus	Features
Use for...	Intuition

Leave One Out

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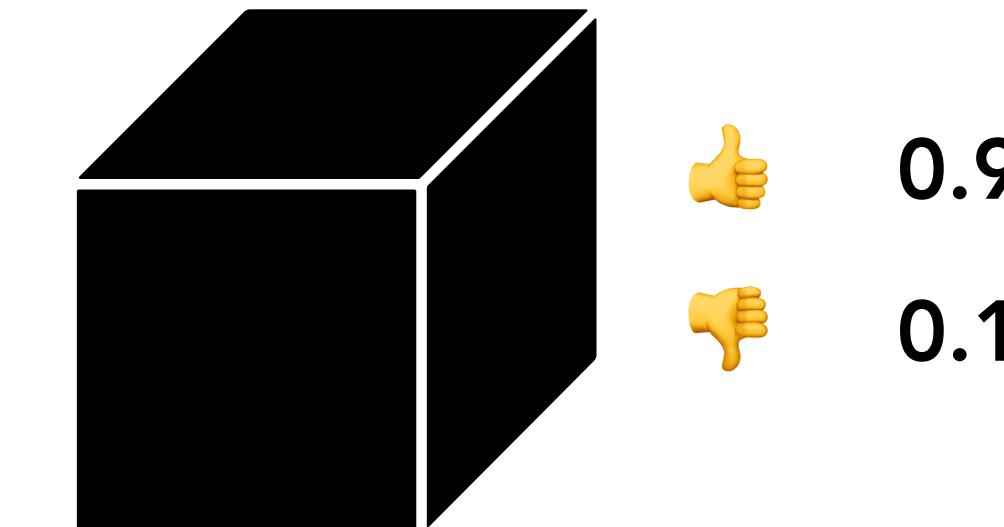


Manipulation	Result	Conclusion?
I couldn't like this more!	拇指 0.9	"I" and "couldn't" were not very important in this sample
I couldn't like this more!	拇指 0.7	"like" quite important
I couldn't like this more!	拇指 0.5	

Architecture	Black box
Required data	None
Explains	Sample area
Focus	Features
Use for...	Intuition

Leave One Out

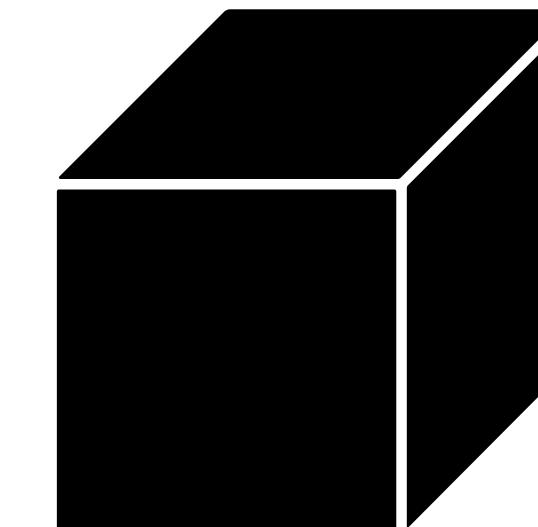
I couldn't like this more!



Manipulation	Result	Conclusion?
I couldn't like this more!	0.9	"I" and "couldn't" were not very important in this sample
I couldn't like this more!	0.7	"like" quite important
I couldn't like this more!	0.3	"this", "more" critical???
I couldn't like this more!	0.1	

Architecture	Black box
Required data	None
Explains	Sample area
Focus	Features
Use for...	Intuition

Leave One Out



👍 0.9
👎 0.1

I couldn't like this more!

Manipulation	Result	Conclusion?
I couldn't like this more!	👍 0.9	"I" and "couldn't" were not very important in this sample
I couldn't like this more!	👍 0.7	"like" quite important
I couldn't like this more!	👍 0.5	"this", "more" critical???
I couldn't like this more!	👍 0.3	
I couldn't like this more!	👍 0.1	

Architecture	Black box
Required data	None
Explains	Sample area
Focus	Features
Use for...	Intuition

Weaknesses

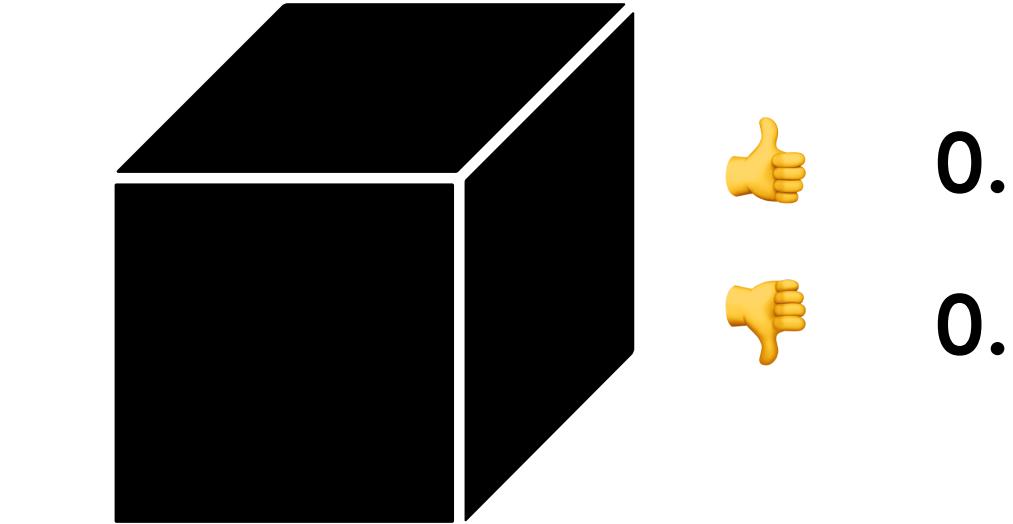
- Doesn't catch interactions between features
- Explanation can be based on illegal (i.e. OOD) inputs

Can we consider multiple
features?

Architecture	Black box
Required data	None
Explains	Sample area
Focus	Features
Use for...	Intuition

Local Surrogates

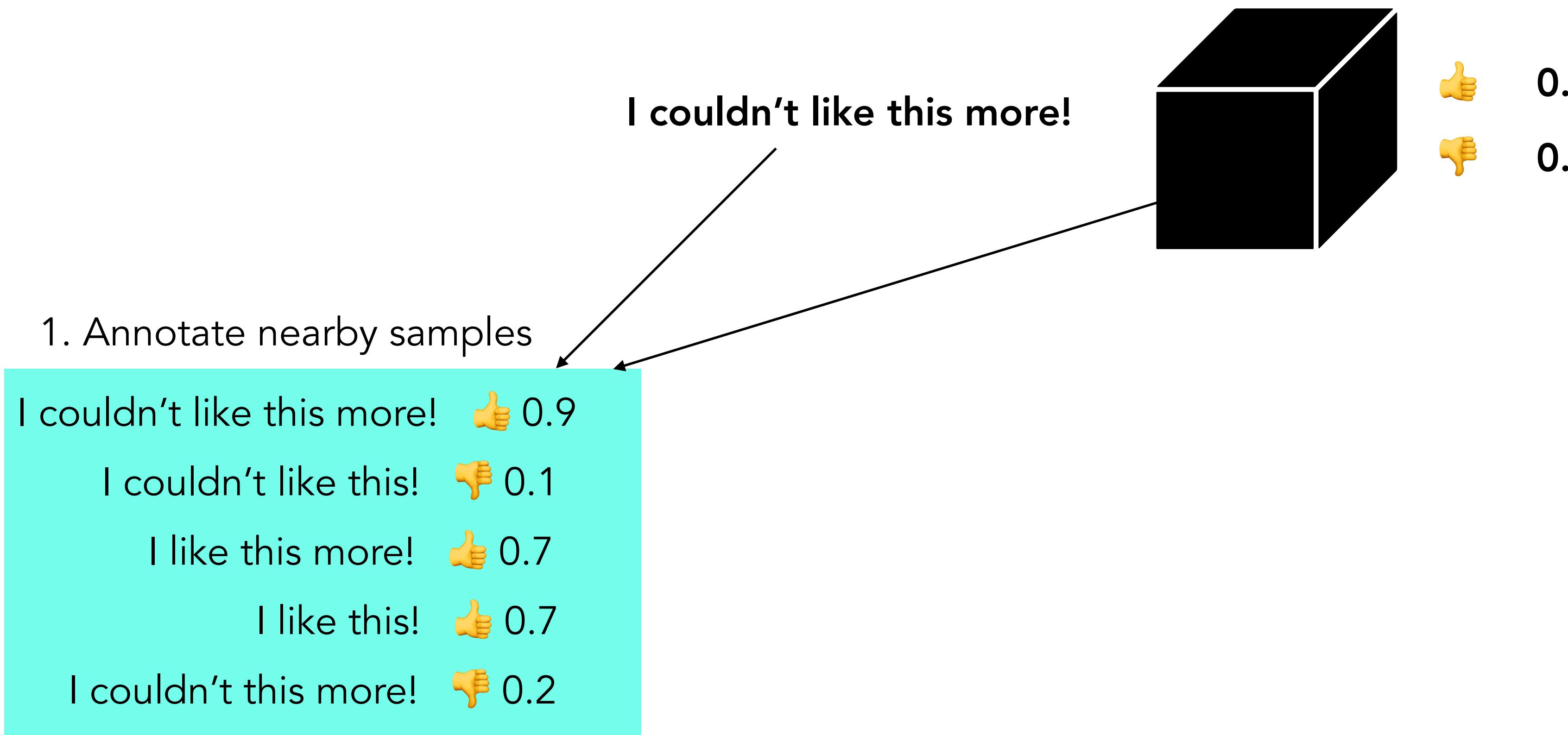
I couldn't like this more!



"Why Should I Trust You?" Explaining the Predictions of Any Classifier, Ribeiro et al, 2016

Architecture	Black box
Required data	None
Explains	Sample area
Focus	Features
Use for...	Intuition

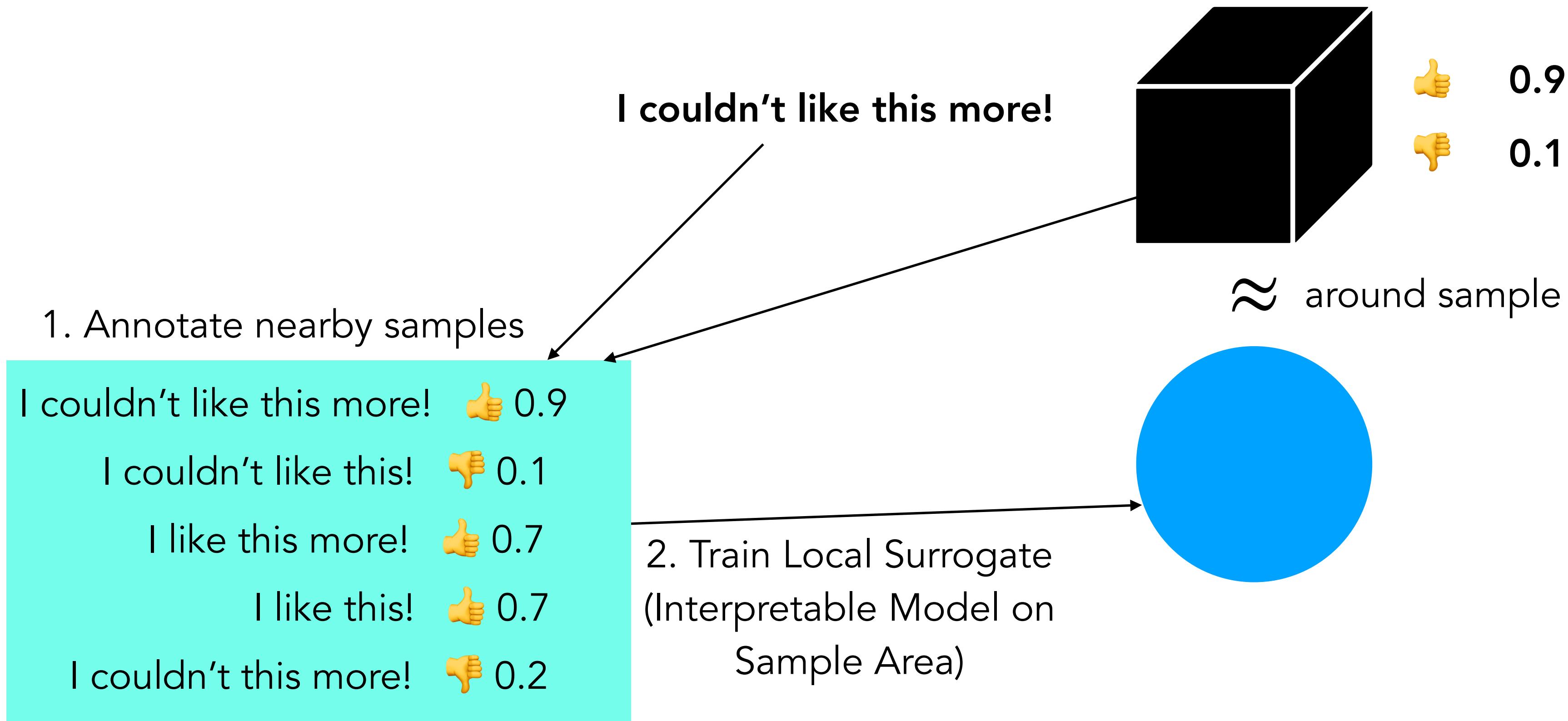
Local Surrogates



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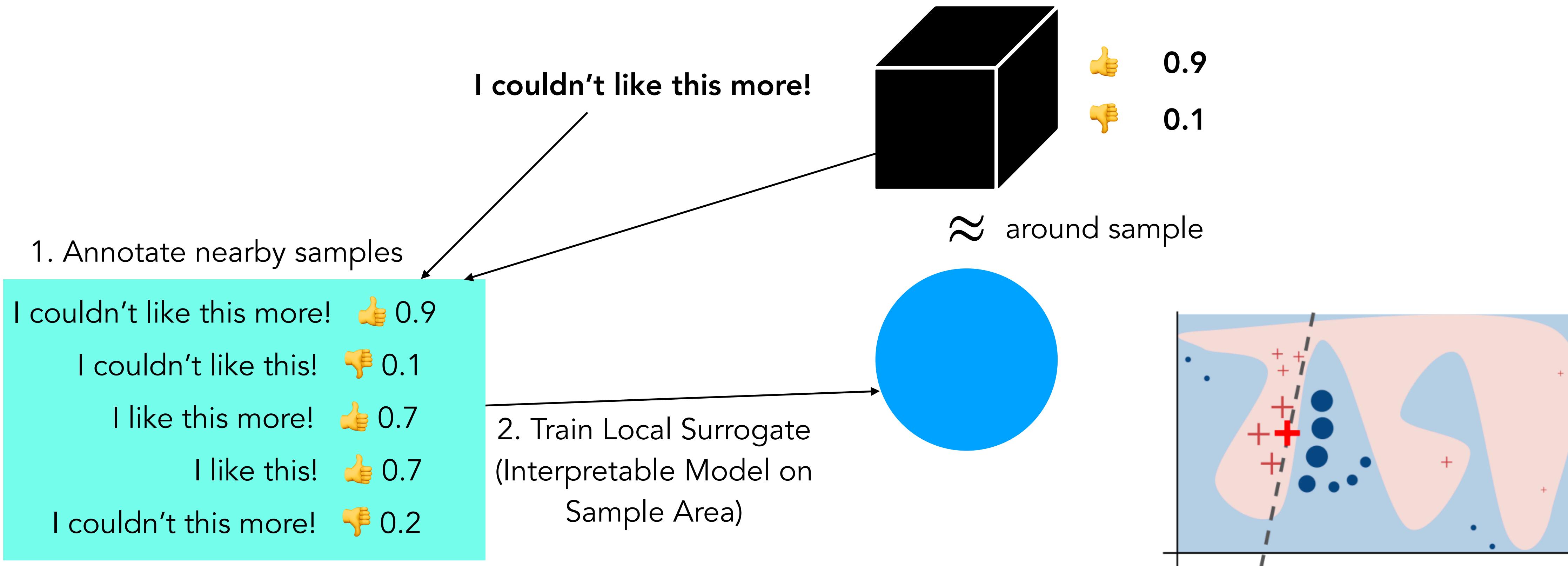
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Architecture	Black box
Required data	None
Explains	Sample area
Focus	Features
Use for...	Intuition

Local Surrogates

LIME: Local Interpretable Model-agnostic Explanations



On images: use “superpixels”
Include and exclude similarly to tokens in sequences



“Why Should I Trust You?” Explaining the Predictions of Any Classifier, Ribeiro et al, 2016

Architecture	Black box
Required data	None
Explains	Sample area
Focus	Features
Use for...	Intuition

Local Surrogates

LIME: Local Interpretable Model-agnostic Explanations

Weaknesses

Unstable - kernel (sample “area”) can change explanation!

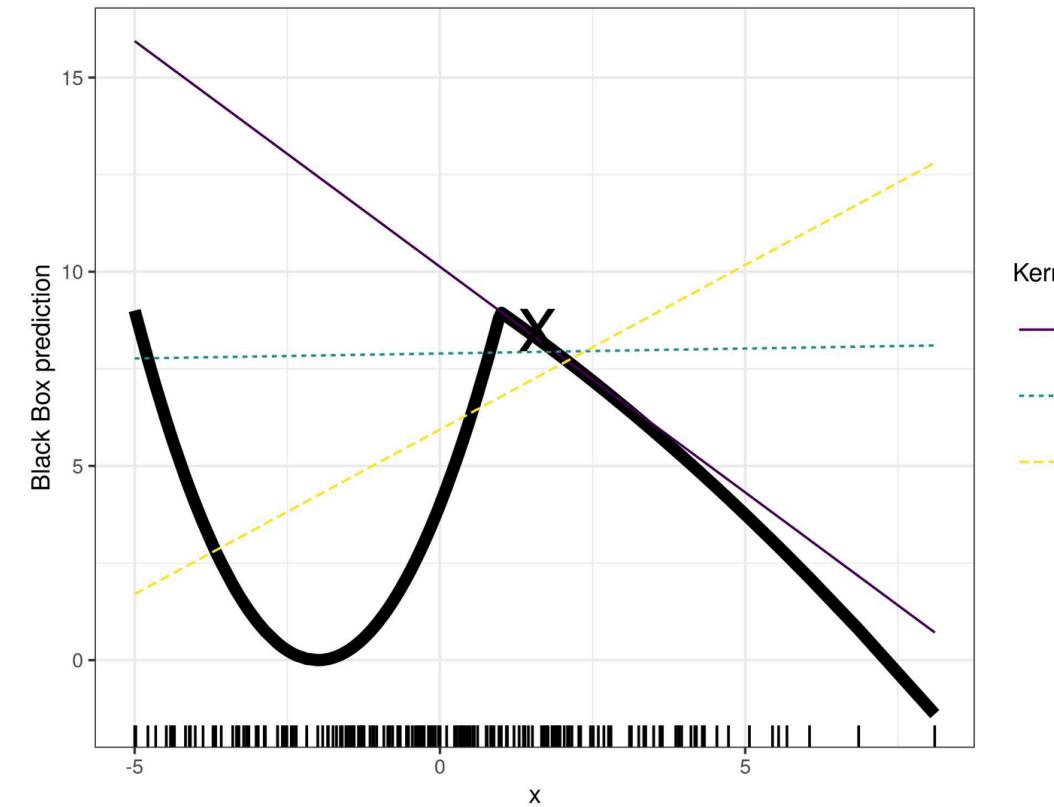


Image: Interpretable Machine Learning:
A guide for making black boxes
explainable, Molner, 2023

Explanation may be based on illogical (OOD) inputs

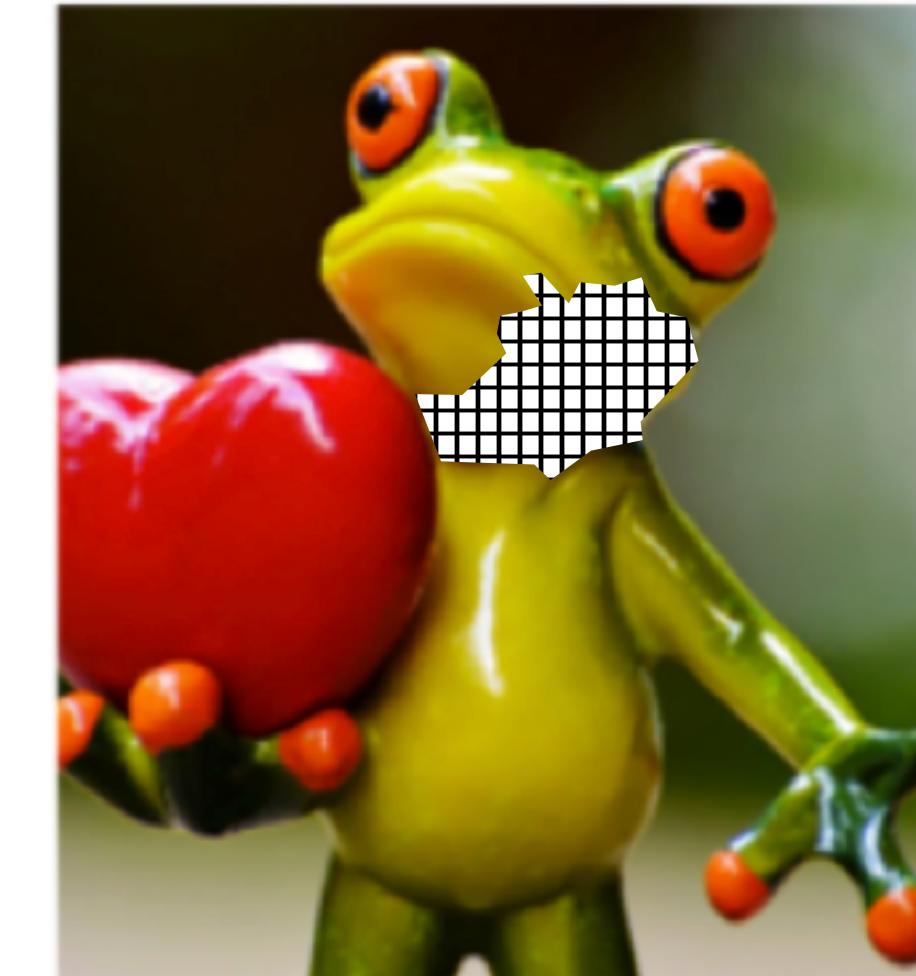


Image: Introduction to Model Interpretability, Jonathan Mak

“Why Should I Trust You?” Explaining the Predictions of Any Classifier, Ribeiro et al, 2016

Architecture	Black box
Required data	None
Explains	Sample area
Focus	Features
Use for...	Intuition

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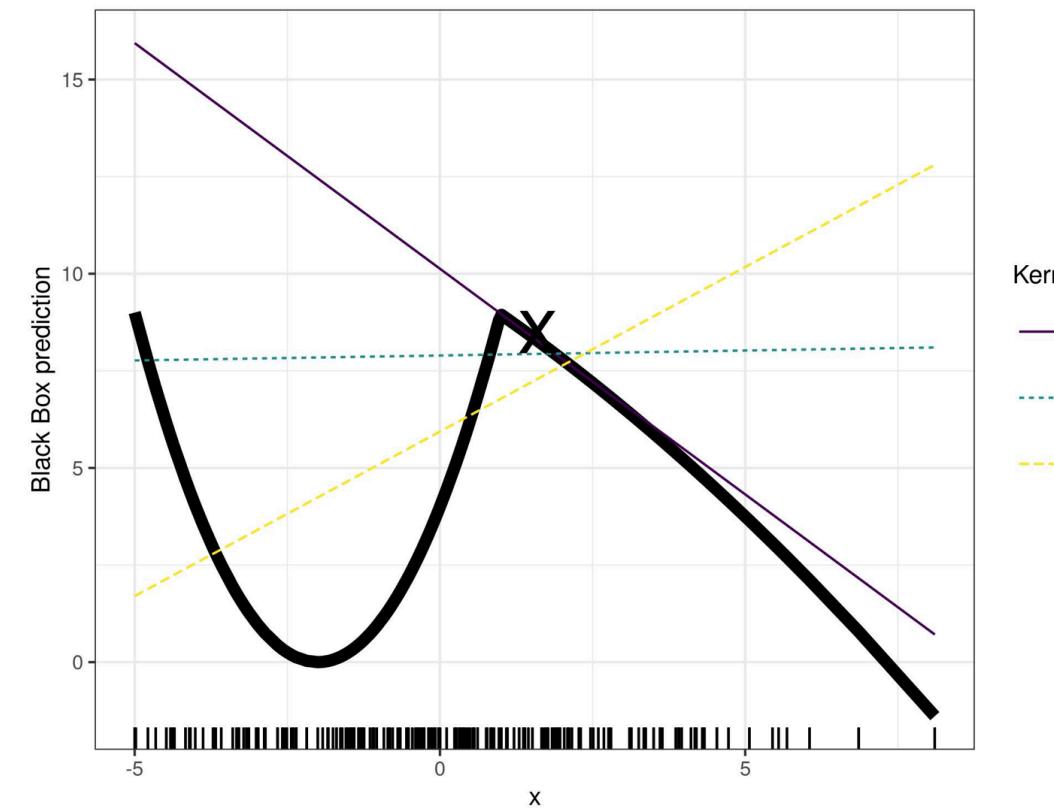


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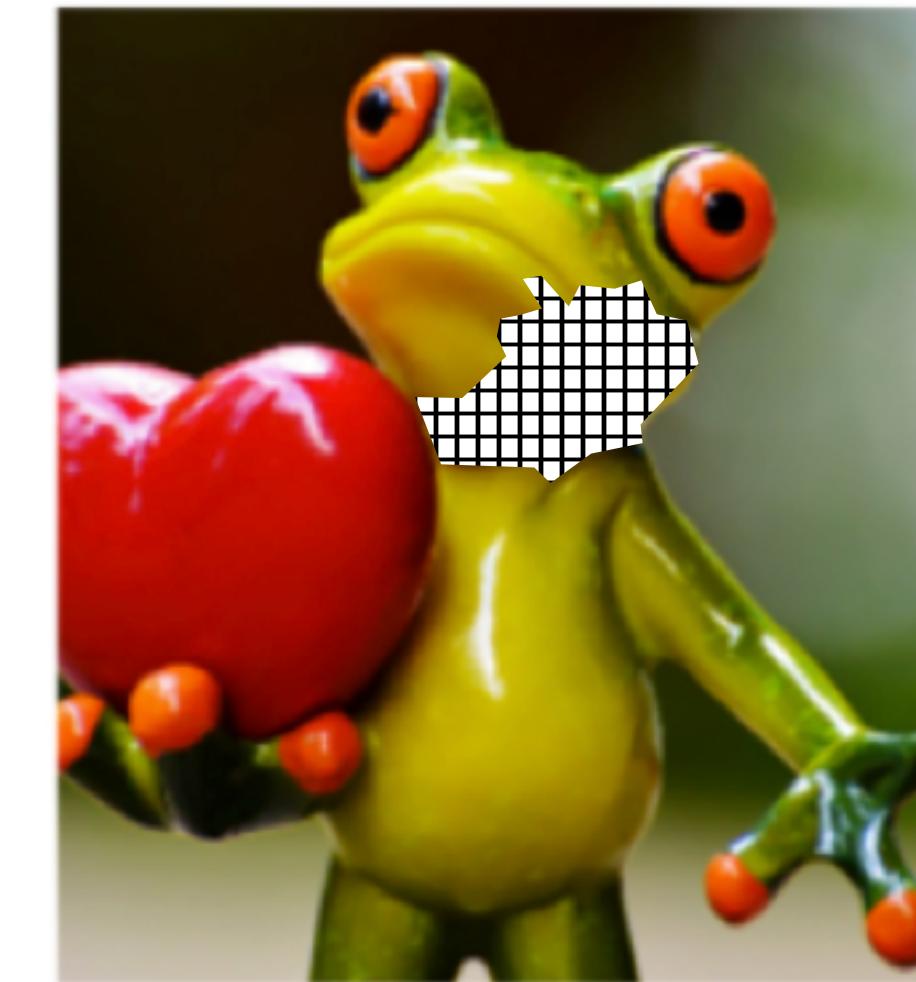


Image: Introduction to Model
Interpretability, Jonathan Mak

Architecture	Black box
Required data	None
Explains	Sample area
Focus	Features
Use for...	Intuition

"Why Should I Trust You?" Explaining the Predictions of Any Classifier, Ribeiro et al, 2016

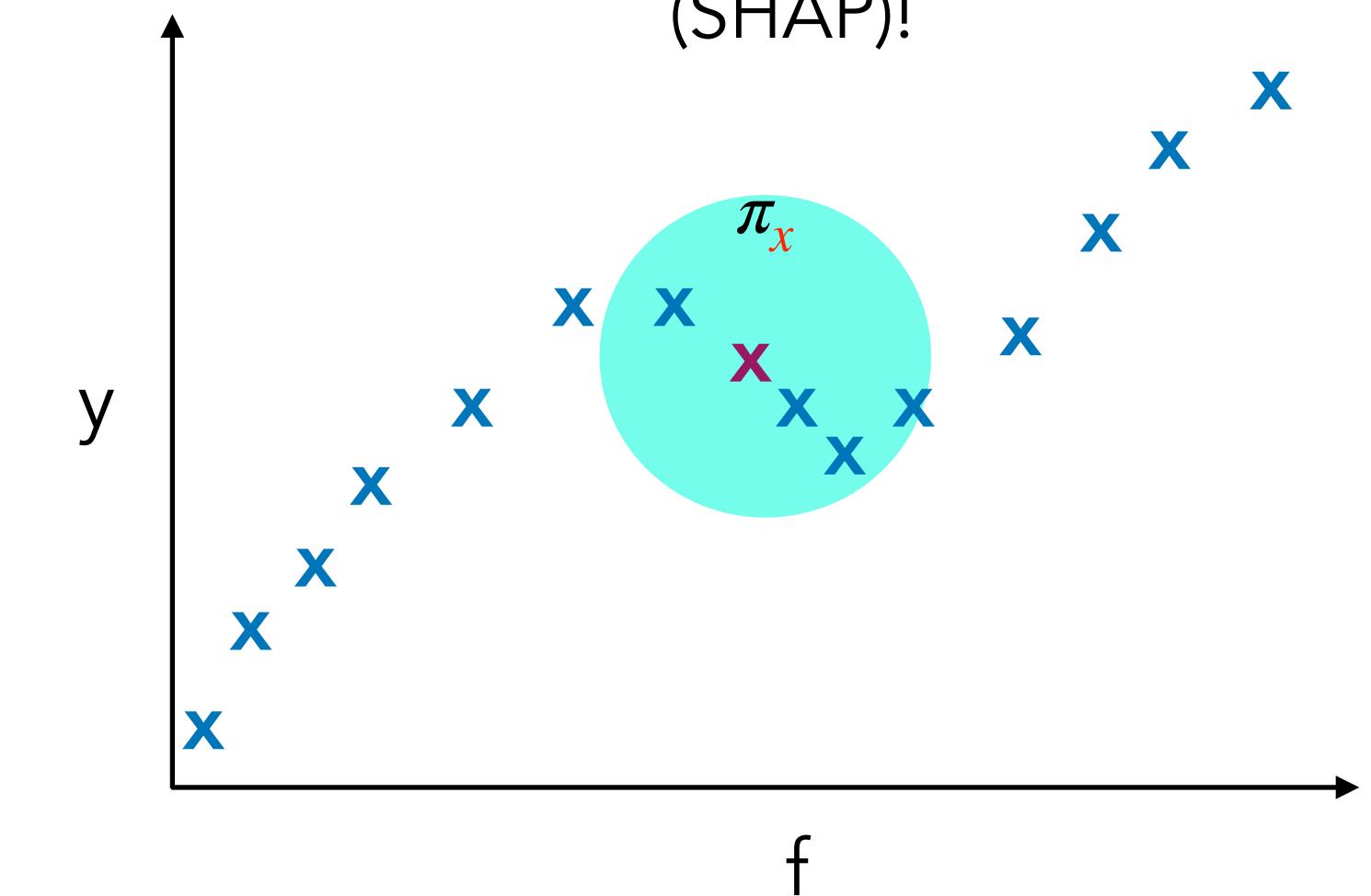
SHAP

LIME	
Architecture	Black box
Required data	None
Explains	Sample area
Focus	Features
Use for...	Intuition

SHAP	
Architecture	Black box
Required data	Train samples
Explains	Model
Focus	Features
Use for...	Intuition

Warning

A feature can have negative correlation with output locally (LIME), and positive globally (SHAP)!



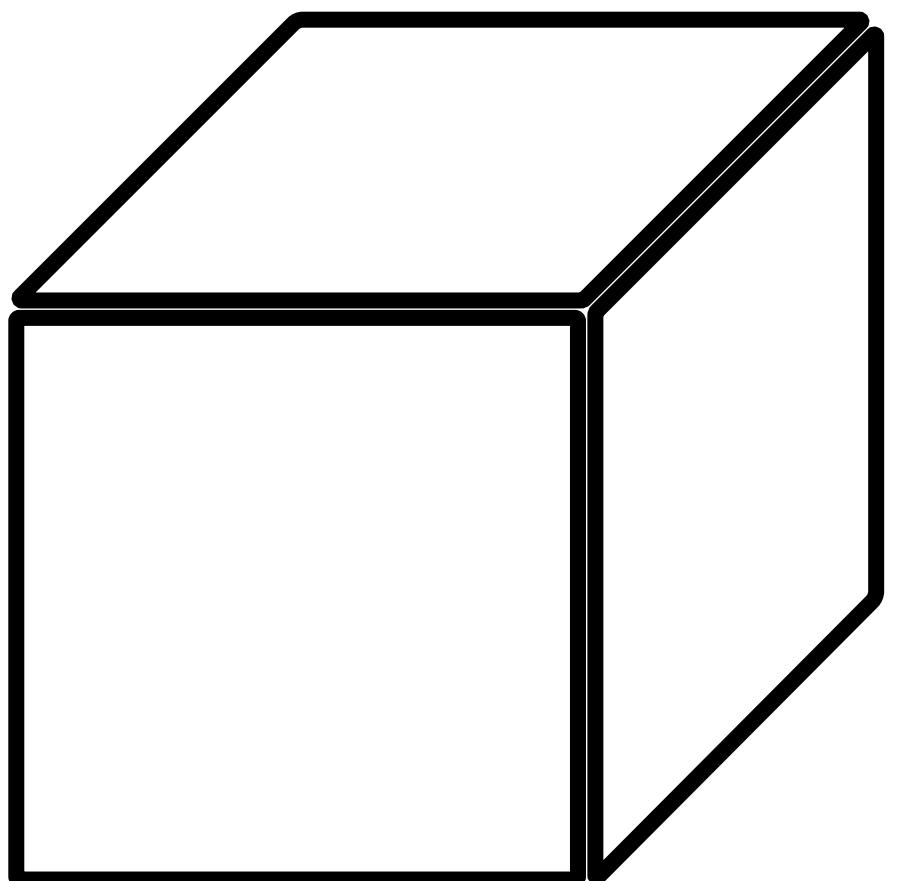
Interpreter Beware!

"An adversarial entity [can] craft an arbitrary desired explanation" -

Fooling LIME and SHAP: Adversarial Attacks on Post hoc Explanation Methods, Slack et al, 2020

A Unified Approach to Interpreting Model Predictions, Lundberg and Lee, 2017

Looking inside
White Box

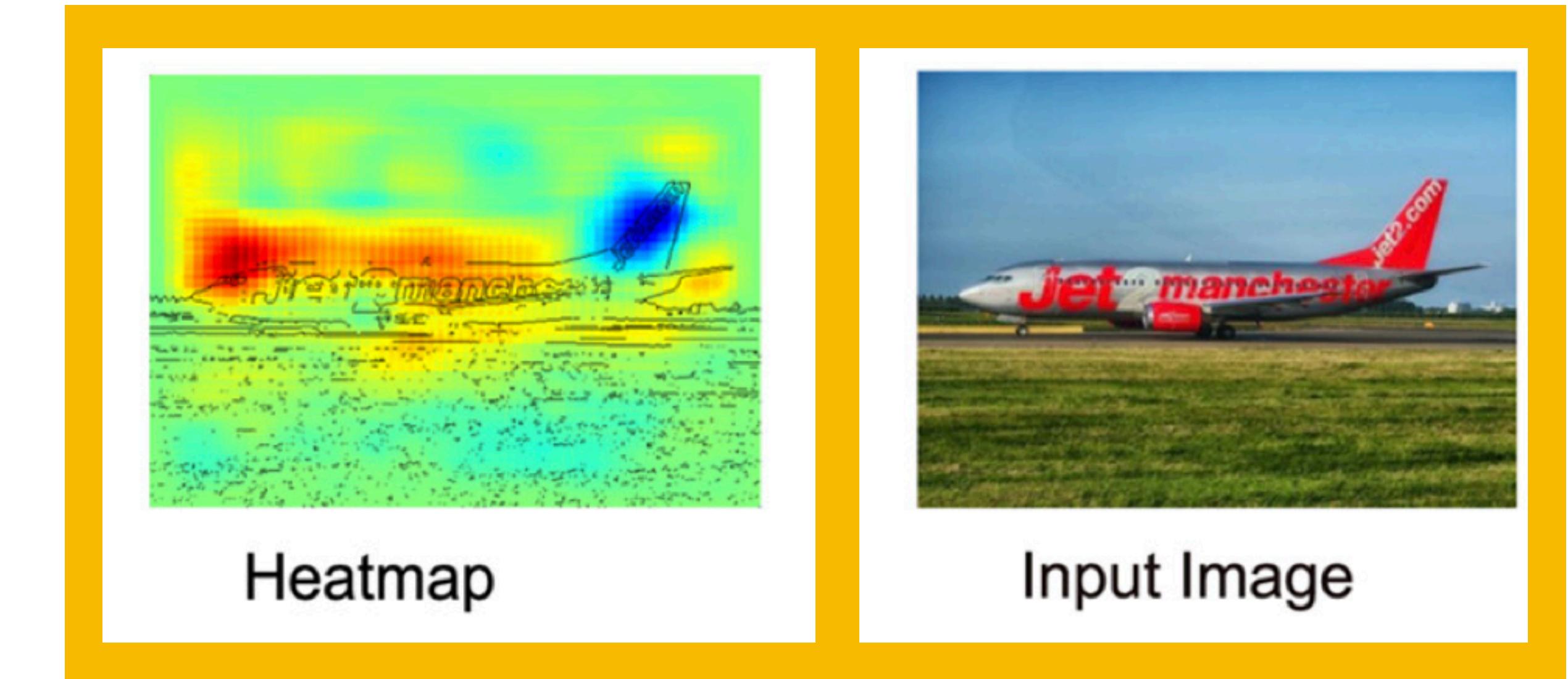


Architecture	White box with layers
Required data	None
Explains	Sample
Focus	Class in sample
Use for...	Intuition

Layer-Wise Relevance Propagation

Iteratively propagate output class score through layers of network, assigning relevance scores to the neurons at each layer

Adapted for deeper models, which have deep non linear “path” from input to output



On pixel-wise explanations for non-linear classifier decisions by layer-wise relevance propagation, Bach et al, 2015

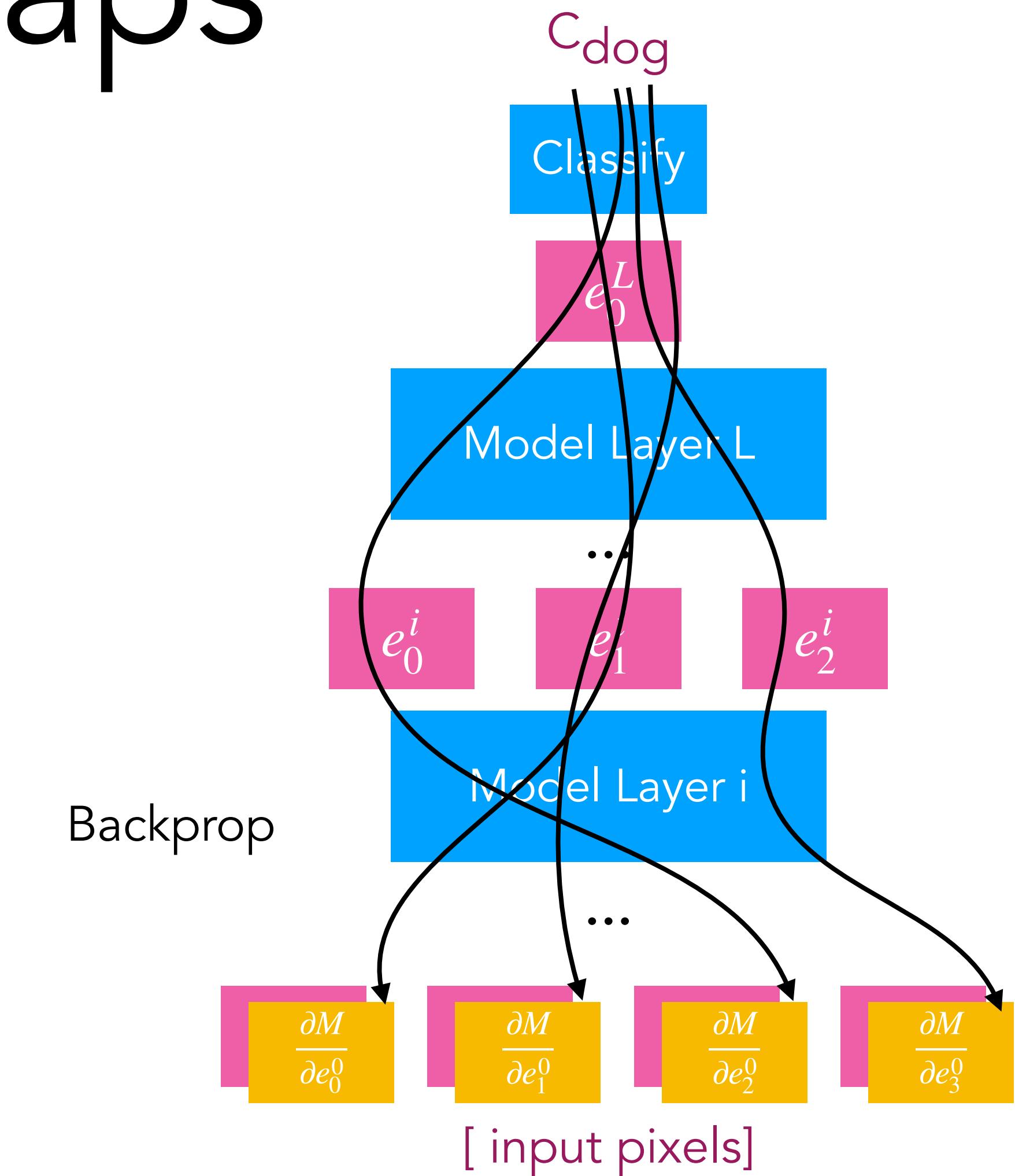
Architecture	Differentiable White box
Required data	None
Explains	Sample
Focus	Class in sample
Use for...	Intuition

Saliency Maps

AKA Pixel Attribution



$$\frac{\partial M}{\partial p}(C_{\text{dog}})$$

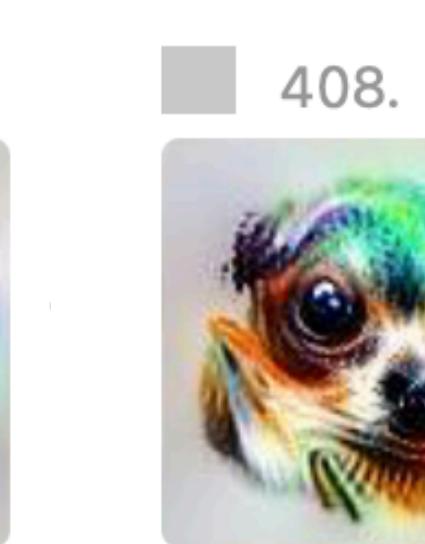
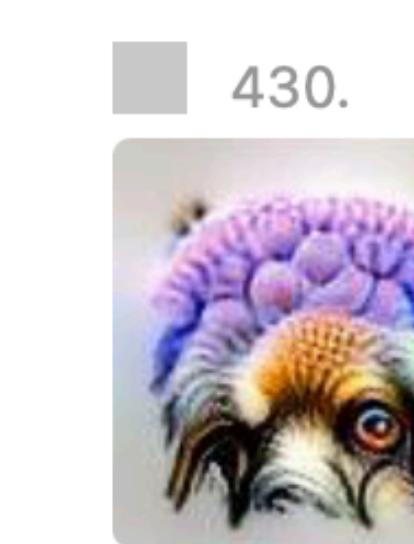
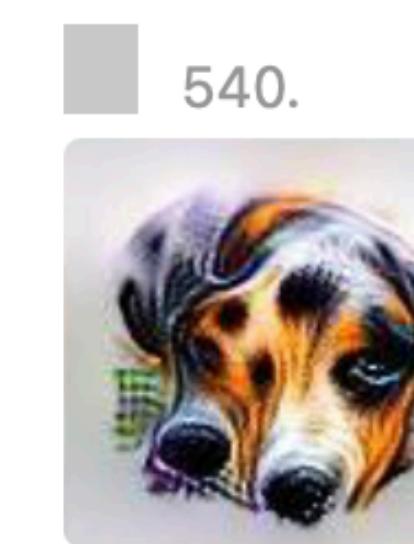
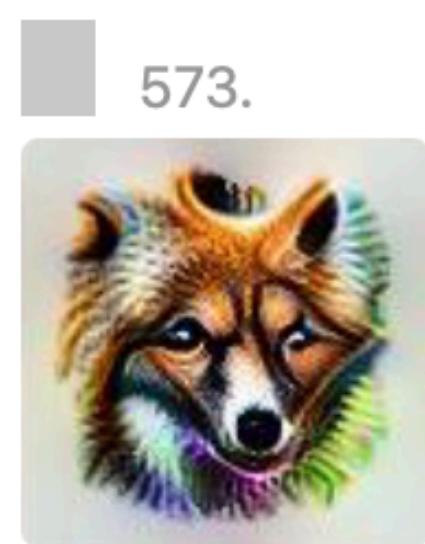
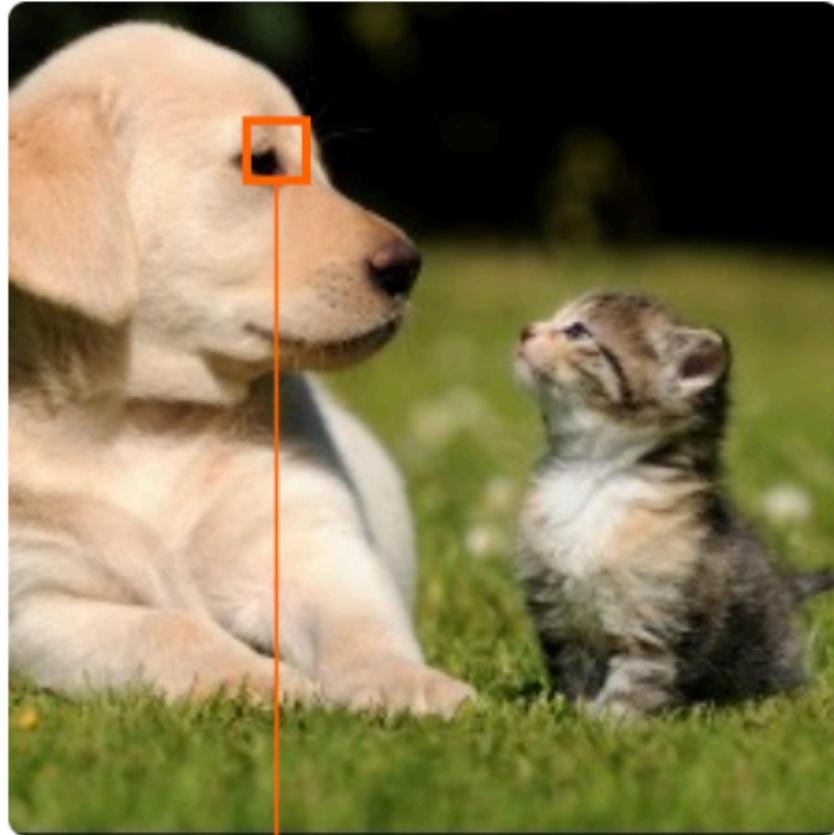


Deep inside convolutional networks: Visualising image classification models and saliency maps, Simonyan et al, 2013

Can we do better?
Gradients

Architecture	Differentiable white box embedder
Required data	None
Explains	Model
Focus	Neuron
Use for...	Intuition

Activation Maximisation

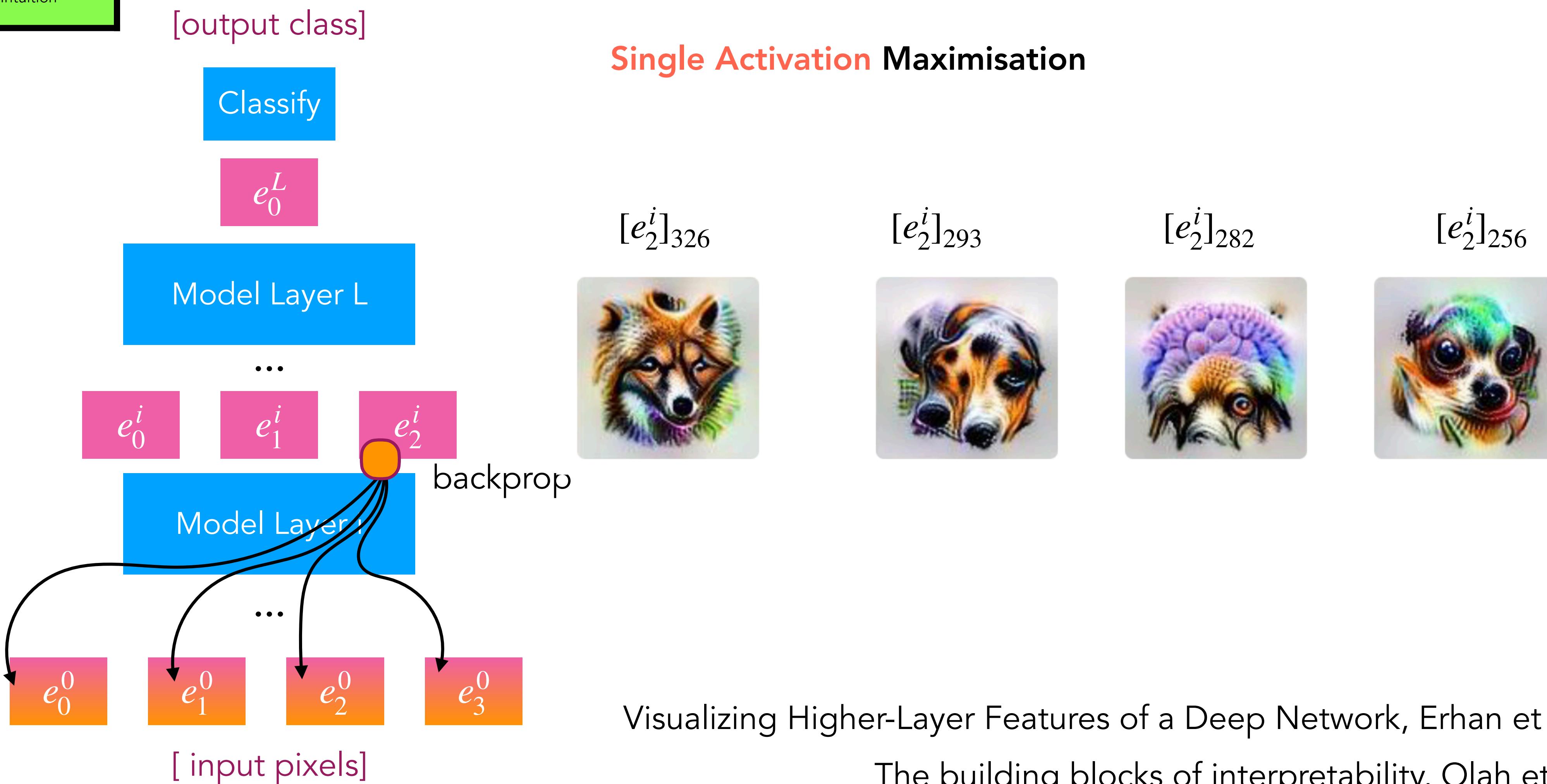


Visualizing Higher-Layer Features of a Deep Network, Erhan et al, 2009

The building blocks of interpretability, Olah et al, 2018

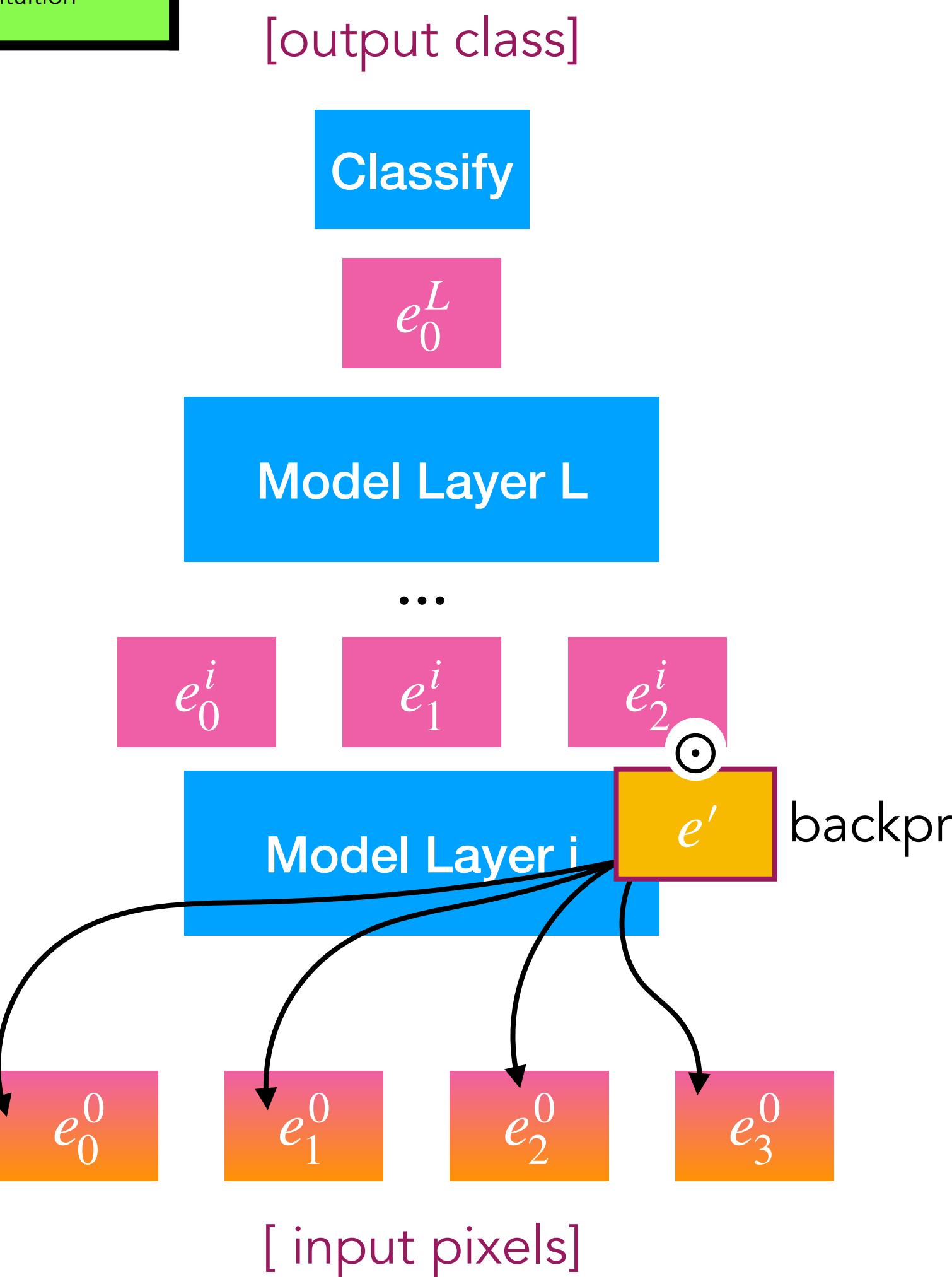
Architecture	Differentiable white box embedder
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Activation Maximisation



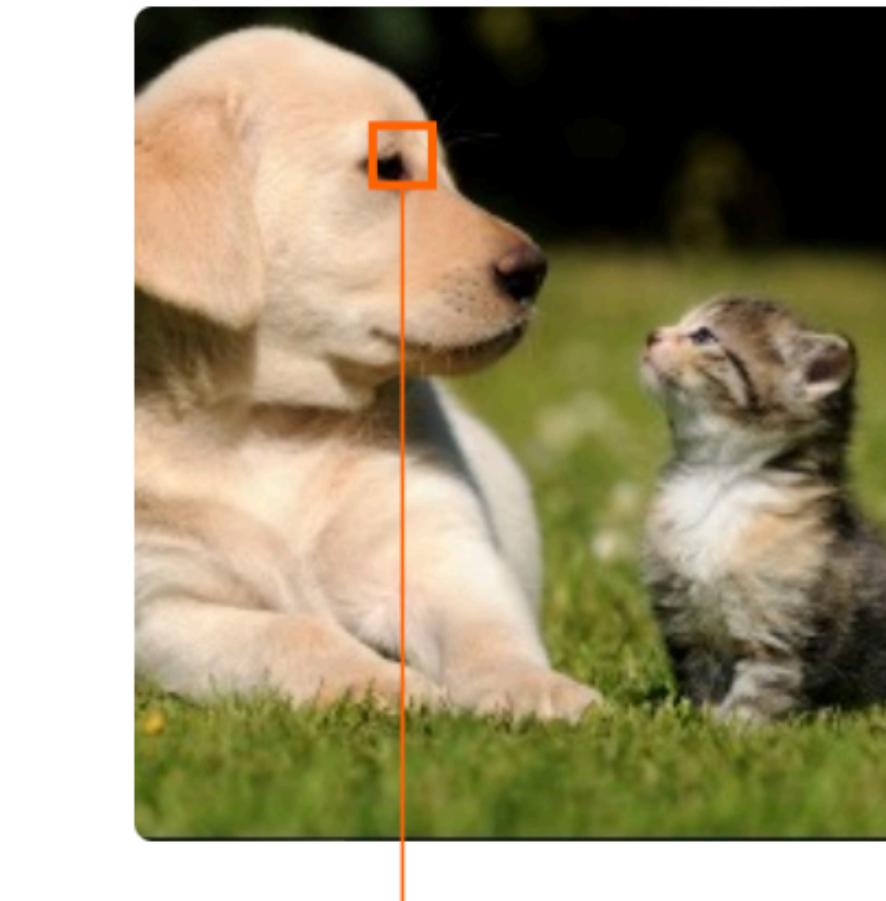
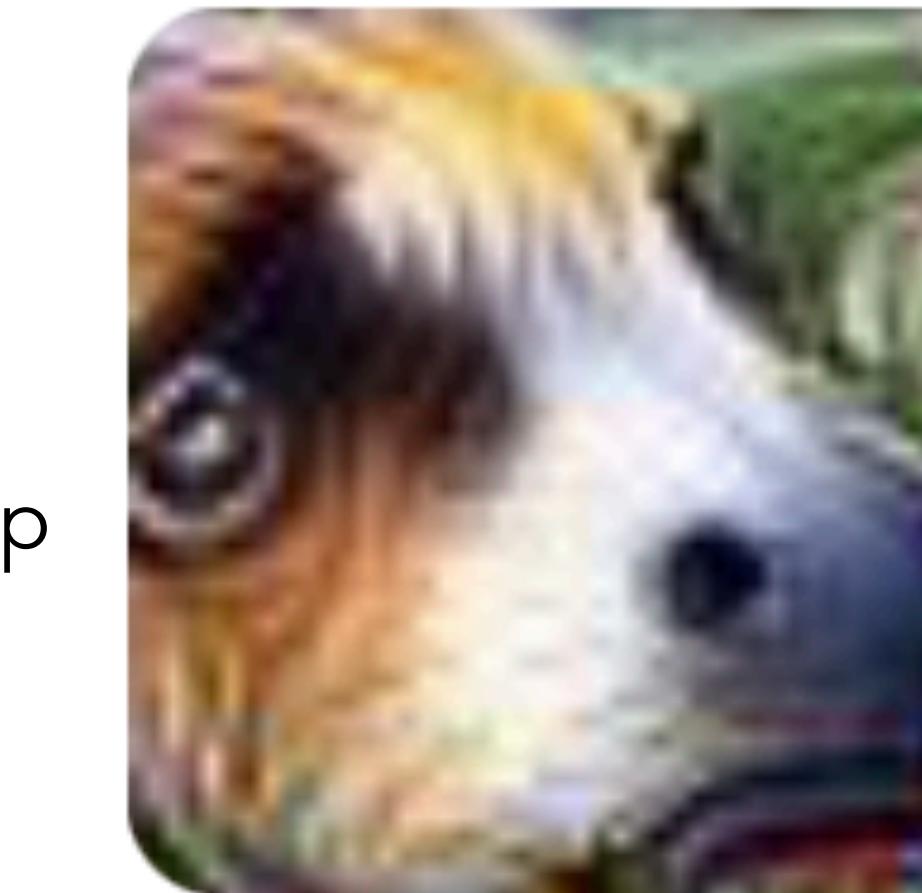
Architecture	Differentiable white box embedder
Required data	None
Explains	Sample
Focus	Layer
Use for...	Intuition

Activation Maximisation



Activation Vector Maximisation

image optimised for $[e_2^i]$
(input position "2", layer i)

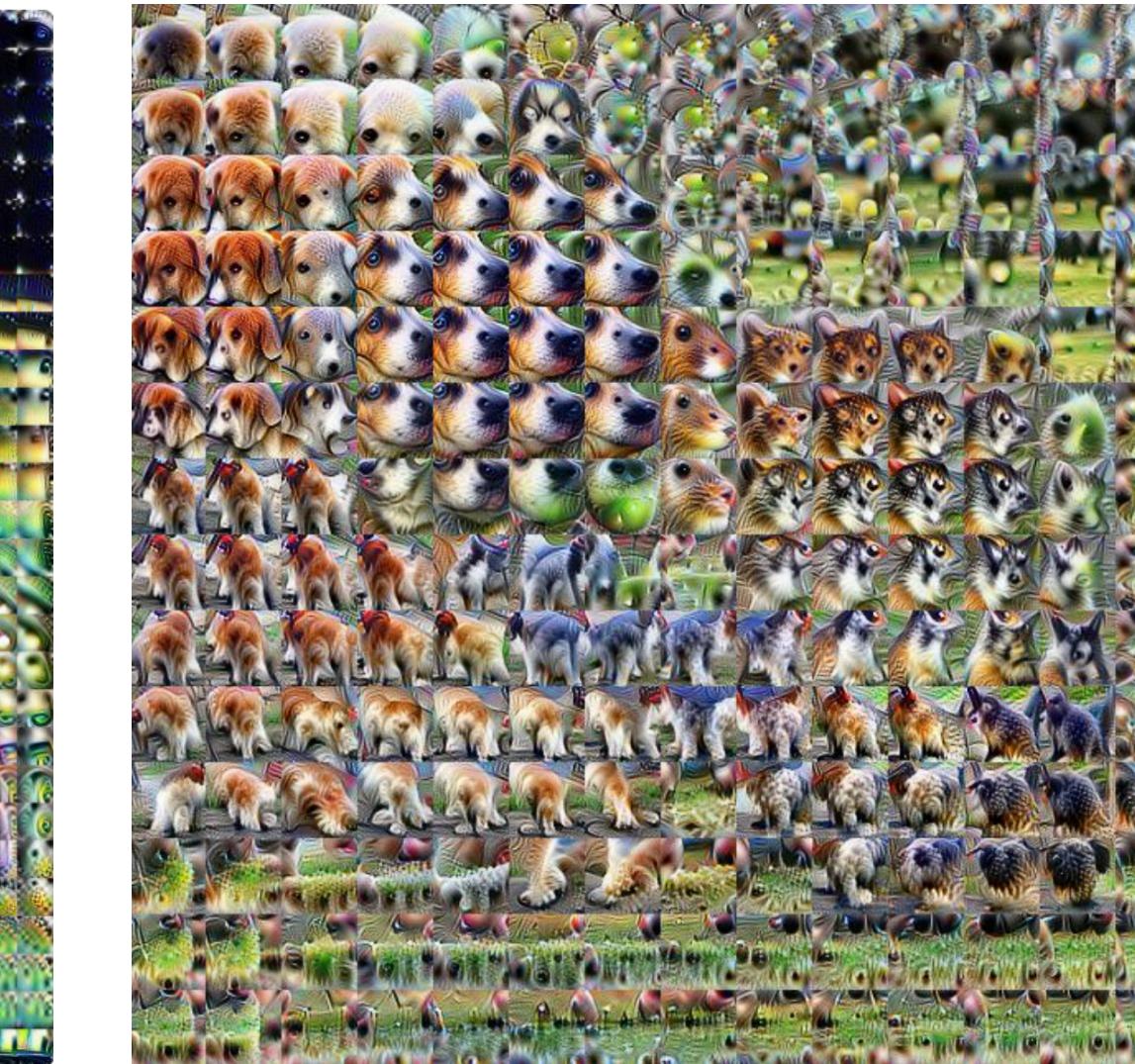
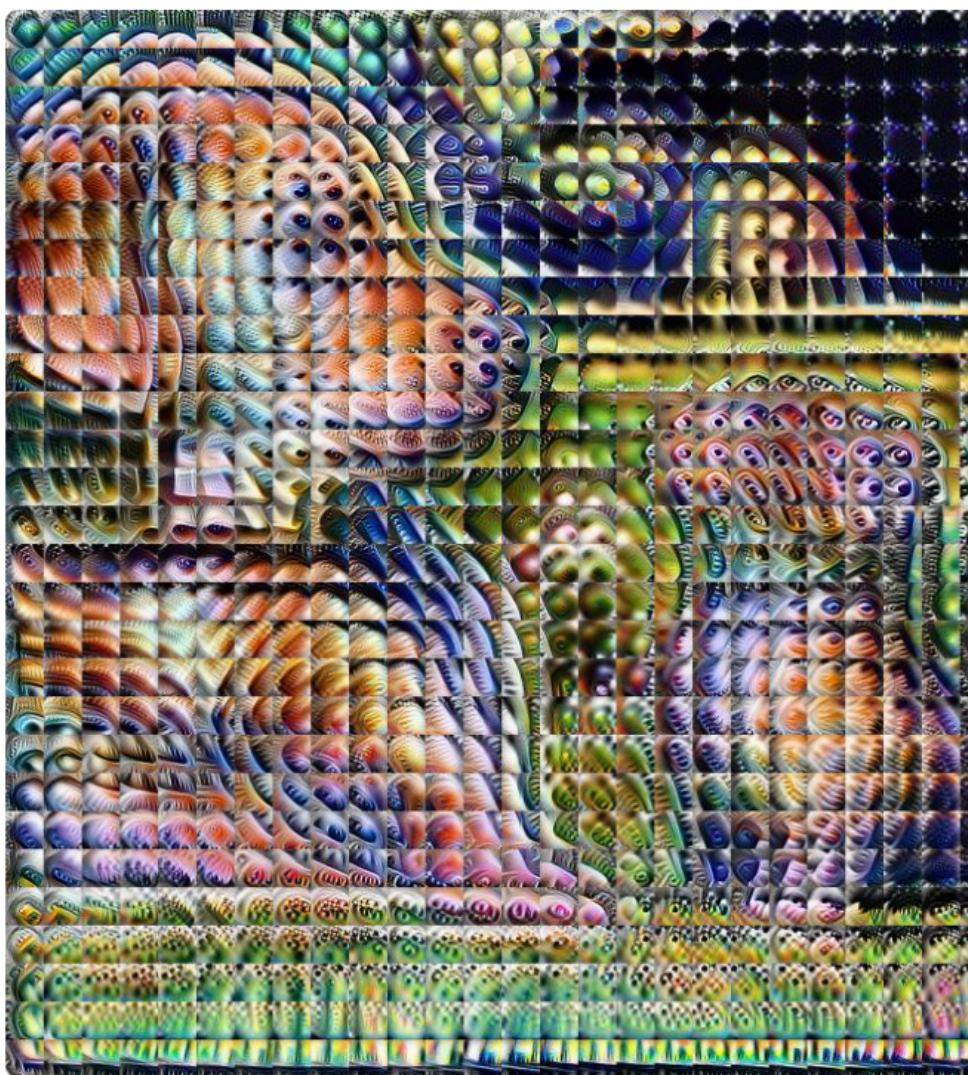


Visualizing Higher-Layer Features of a Deep Network, Erhan et al, 2009

The building blocks of interpretability, Olah et al, 2018

Architecture	Differentiable white box embedder
Required data	None
Explains	Sample
Focus	Layer
Use for...	Intuition

Activation Maximisation



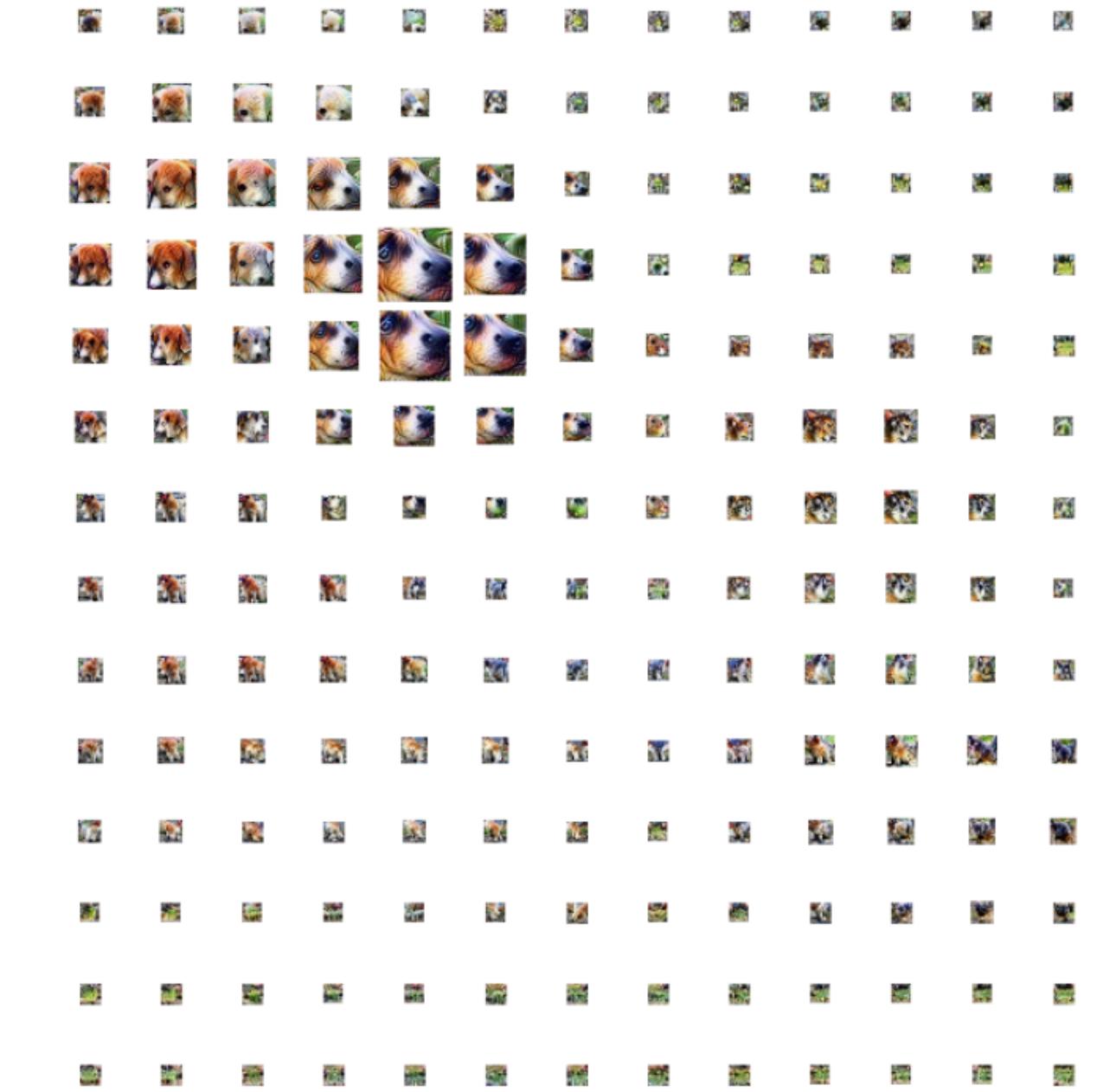
(kind of like local caricatures...)

Visualizing Higher-Layer Features of a Deep Network, Erhan et al, 2009

The building blocks of interpretability, Olah et al, 2018

Architecture	Differentiable white box embedder
Required data	None
Explains	Sample
Focus	Layer
Use for...	Intuition

Activation Maximisation + scaling



The “activation atlas”:

<https://distill.pub/2019/activation-atlas/>

Visualizing Higher-Layer Features of a Deep Network, Erhan et al, 2009

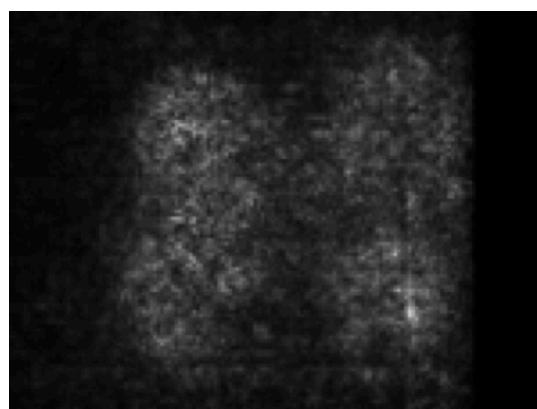
The building blocks of interpretability, Olah et al, 2018

Visualisations

Saliency Maps

Architecture	Differentiable white box
Required data	None
Explains	Sample
Focus	Class in sample
Use for...	Intuition

Backprop to input, no train



Activation (Neuron) Maximisation

Architecture	Differentiable white box embedder
Required data	None
Explains	Model
Focus	Neuron
Use for...	Intuition

Neuron-specific optimisation of input



Activation Vector Maximisation

Architecture	Differentiable white box embedder
Required data	None
Explains	Sample
Focus	Layer
Use for...	Intuition

Sample-specific optimisation of input



Nice images, I have convinced
myself of all my pre existing
beliefs 🙏

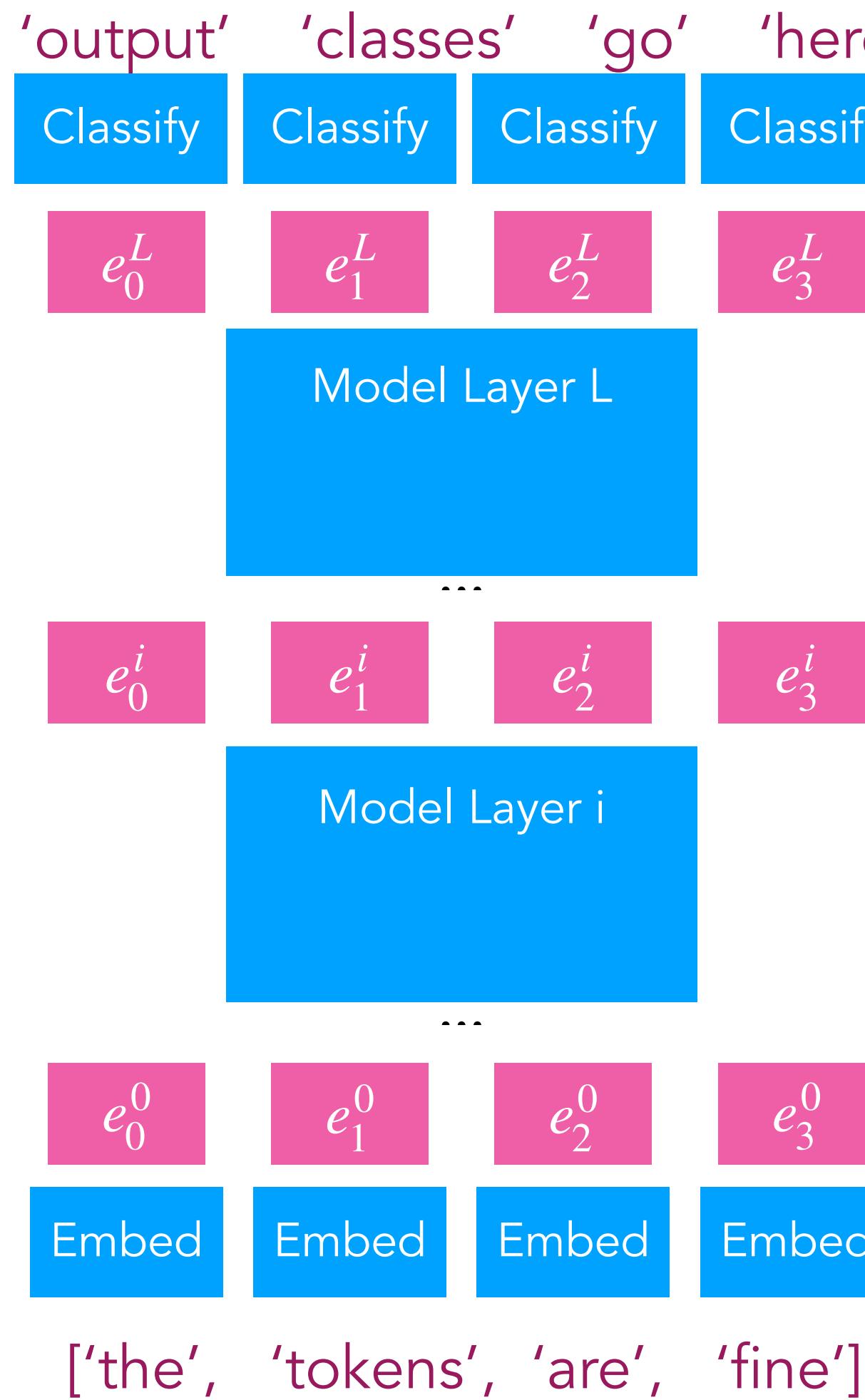


Evaluating partial computations

Attention

Architecture	White box with attention
Required data	Annotated task
Explains	Model
Focus	Partial Computation
Use for...	Evaluating hypotheses

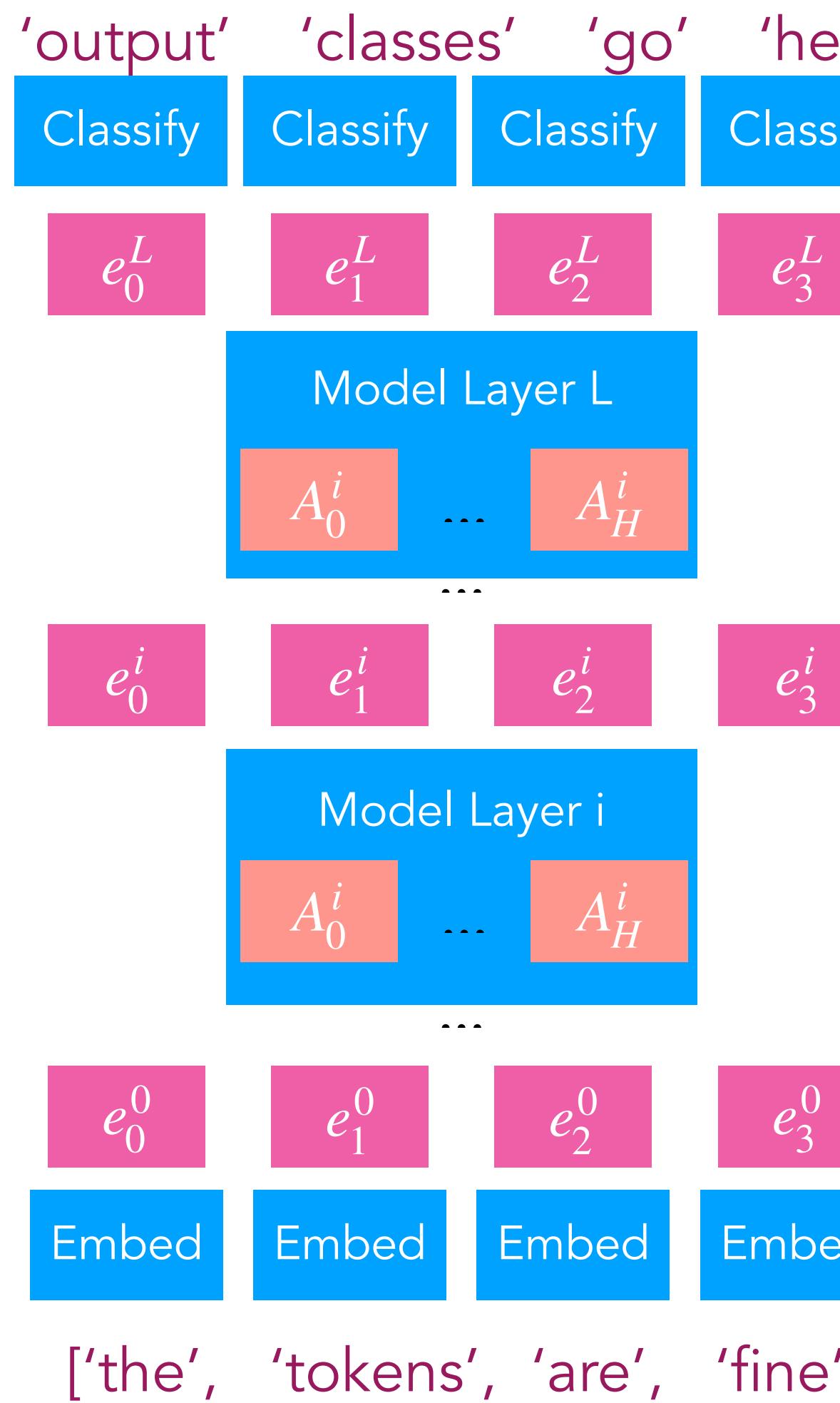
Specialised Attention Heads



Analyzing Multi-Head Self-Attention: Specialized Heads Do the Heavy Lifting,
the Rest Can Be Pruned, Voita et al, 2019

Architecture	White box with attention
Required data	Annotated task
Explains	Model
Focus	Partial Computation
Use for...	Evaluating hypotheses

Specialised Attention Heads



In trained NMT encoder-decoder models, encoder contains:

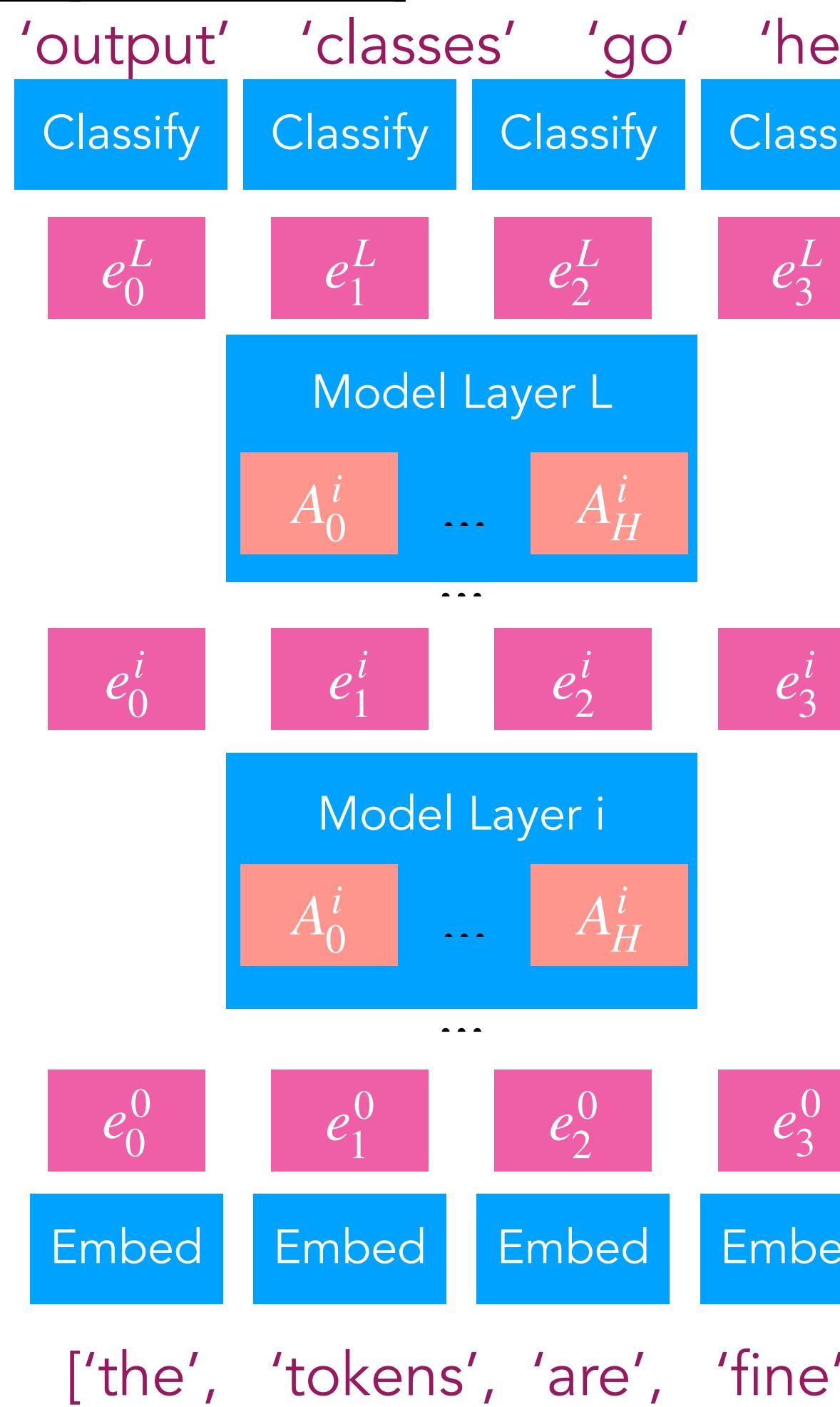
Positional Heads: 90% of time, max focus is +1 or -1

Syntactic Heads: 10% higher than majority baseline
for some dependency relation (e.g. advmod: adverb
modifier)

Rare Word Head: in sequences with tokens not from
top 500, frequently attends to rarest token(s) (post-
hoc description..)

Architecture	White box with attention
Required data	Annotated task
Explains	Model
Focus	Partial Computation
Use for...	Evaluating hypotheses

Specialised Attention Heads



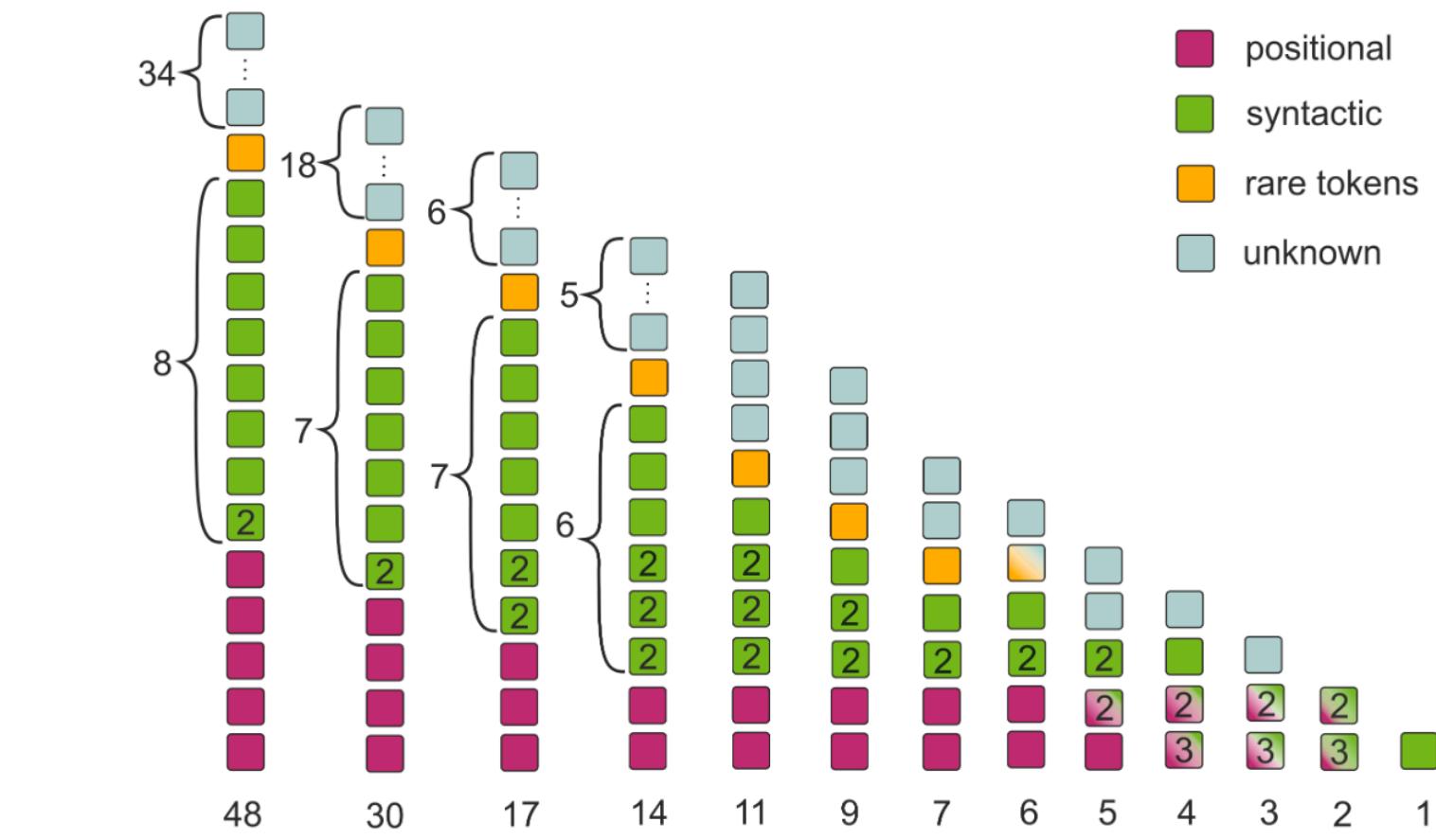
Finding: In trained NMT encoder-decoder models, encoder contains:

Positional Heads: 90% of time, max focus is +1 or -1

Syntactic Heads: 10% higher than majority baseline for some dependency relation (e.g. advmod: adverb modifier)

Rare Word Head: in sequences with tokens not from top 500, frequently attends to rarest token(s)

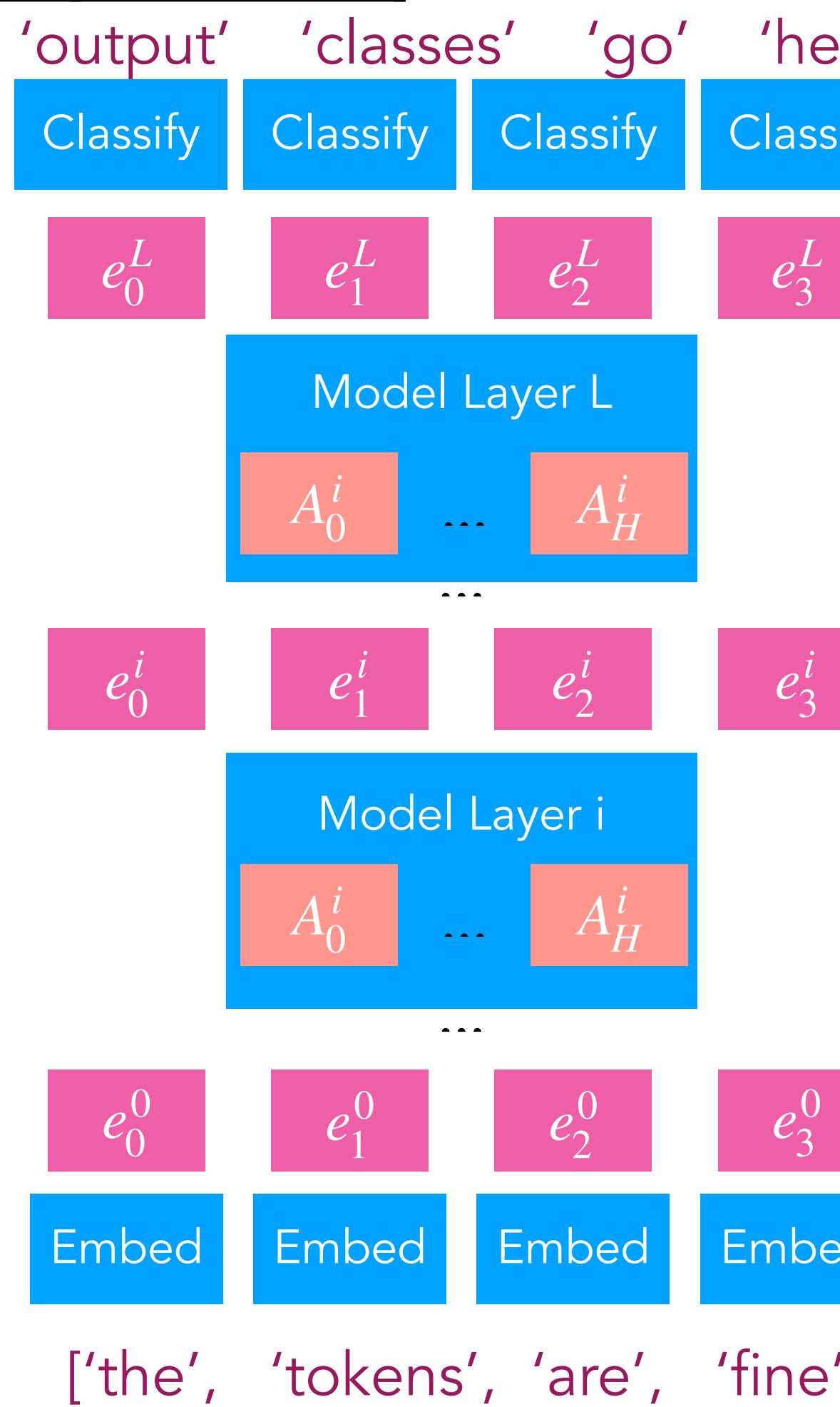
When pruning the network,
these heads are removed last!



Analyzing Multi-Head Self-Attention: Specialized Heads Do the Heavy Lifting, the Rest Can Be Pruned, Voita et al, 2019

Architecture	White box with attention
Required data	Annotated task
Explains	Model
Focus	Partial Computation
Use for...	Evaluating hypotheses

Specialised Attention Heads



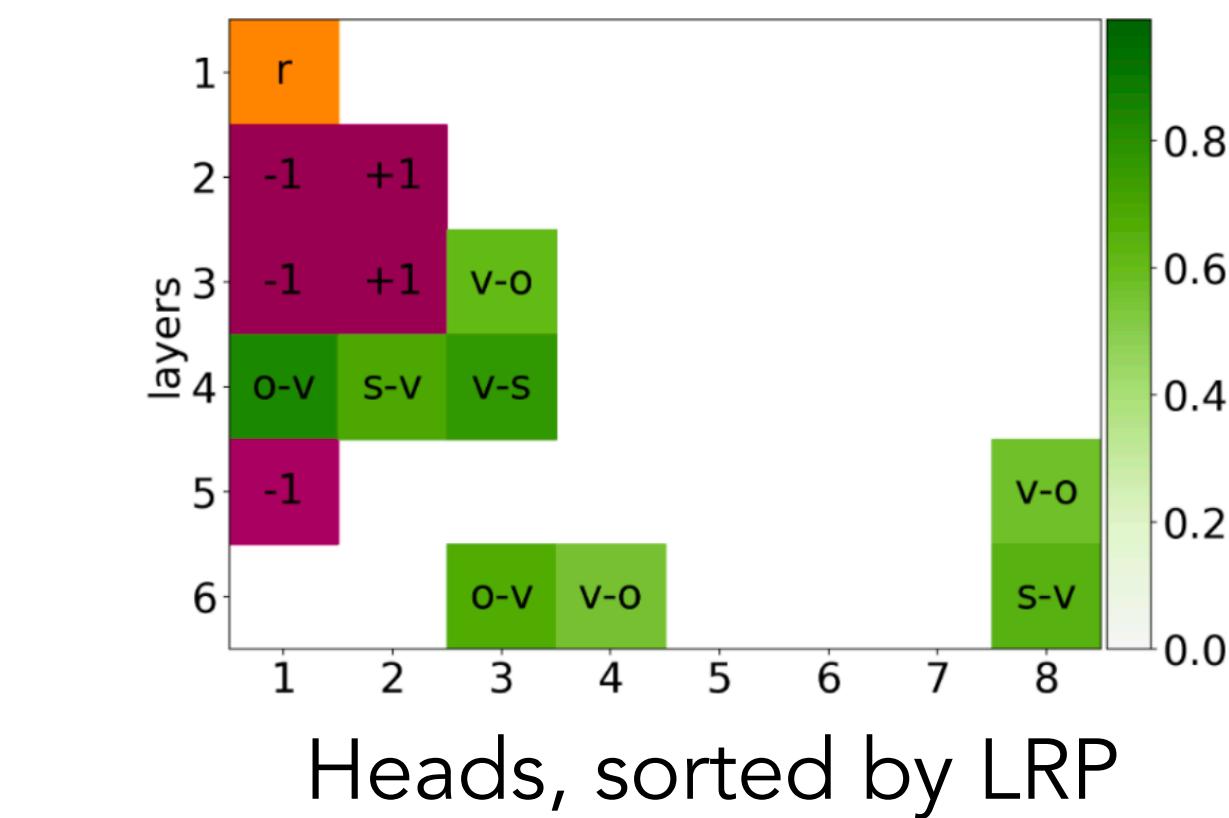
Finding: In trained NMT encoder-decoder models, encoder contains:

Positional Heads: 90% of time, max focus is +1 or -1

Syntactic Heads: 10% higher than majority baseline for some dependency relation (e.g. advmod: adverb modifier)

Rare Word Head: in sequences with tokens not from top 500, frequently attends to rarest token(s)

We see correlation between LRP score and having a clear task



Visualising and Understanding Neural Machine Translation, Ding et al, 2017

Analyzing Multi-Head Self-Attention: Specialized Heads Do the Heavy Lifting, the Rest Can Be Pruned, Voita et al, 2019

Evaluating partial computations Embeddings

Architecture	White box with internal embeddings
Required data	Annotated task
Explains	Model, single samples if good
Focus	Partial Computation
Use for...	Evaluating hypothesis, Single samples if good

Probing

Architecture	White box with internal embeddings
Required data	Annotated task
Explains	Model, single samples if good
Focus	Partial Computation
Use for...	Evaluating hypothesis, Single samples if good

Probing

Sequence/Image/...

51

Next token/Classification/...

'output' 'classes' 'go' 'here'

Classify Classify Classify Classify

e_0^L e_1^L e_2^L e_3^L

Model Layer L
...
RNN/
Transformer/
CNN*...

e_0^i e_1^i e_2^i e_3^i

Model Layer i
...
...

e_0^0 e_1^0 e_2^0 e_3^0

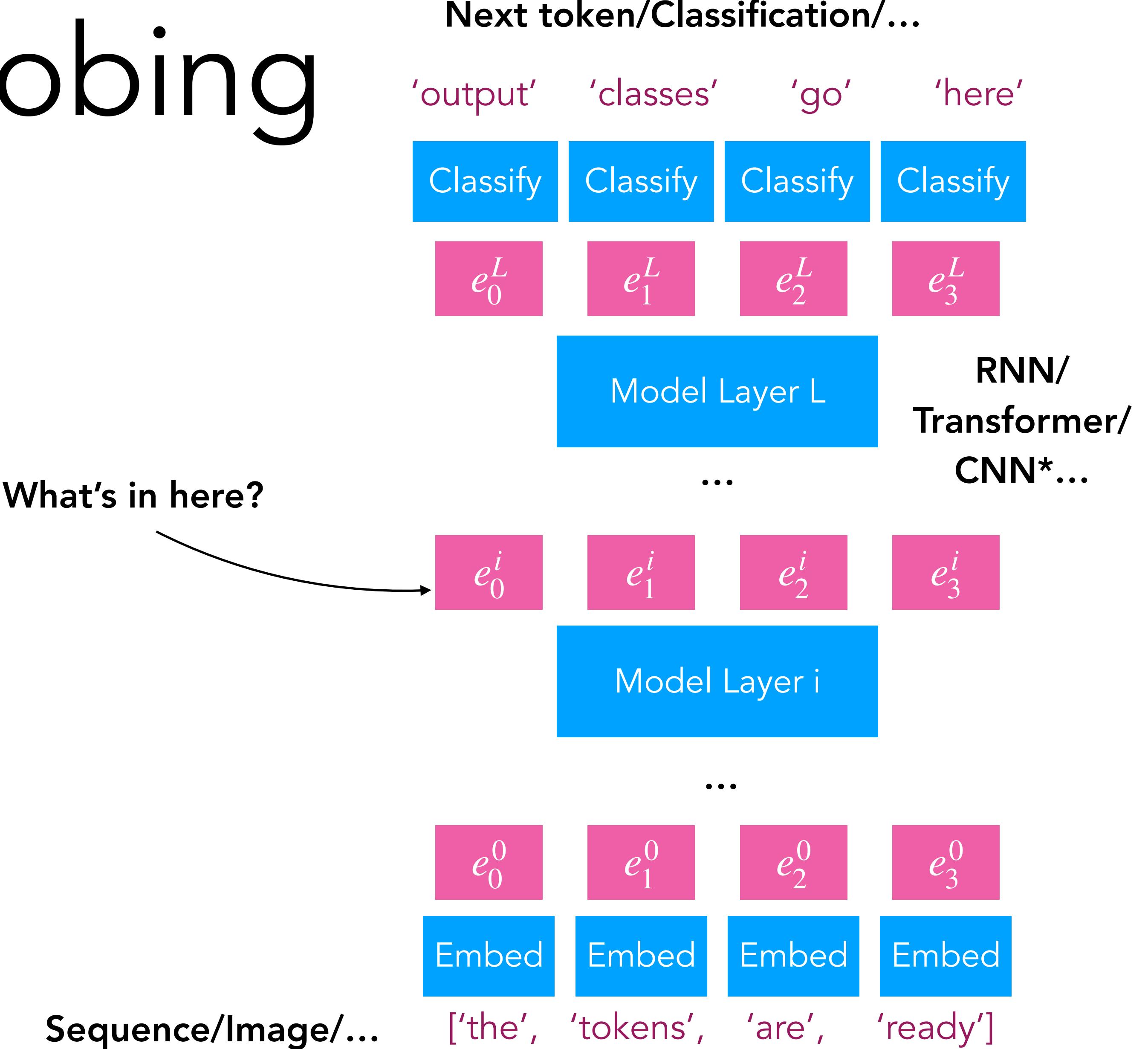
Embed Embed Embed Embed

['the', 'tokens', 'are', 'ready']

Architecture	White box with internal embeddings
Required data	Annotated task
Explains	Model, single samples if good
Focus	Partial Computation
Use for...	Evaluating hypothesis, Single samples if good

Probing

What's in here?



Architecture	White box with internal embeddings
Required data	Annotated task
Explains	Model, single samples if good
Focus	Partial Computation
Use for...	Evaluating hypothesis, Single samples if good

Probing

Next token/Classification/...

'output' 'classes' 'go' 'here'

Classify Classify Classify Classify

e_0^L e_1^L e_2^L e_3^L

RNN/
Transformer/
CNN*

the tokens are ready

Probe Probe Probe Probe

Model Layer L

...

e_0^i e_1^i e_2^i e_3^i

Model Layer i

...

e_0^0 e_1^0 e_2^0 e_3^0

Embed Embed Embed Embed

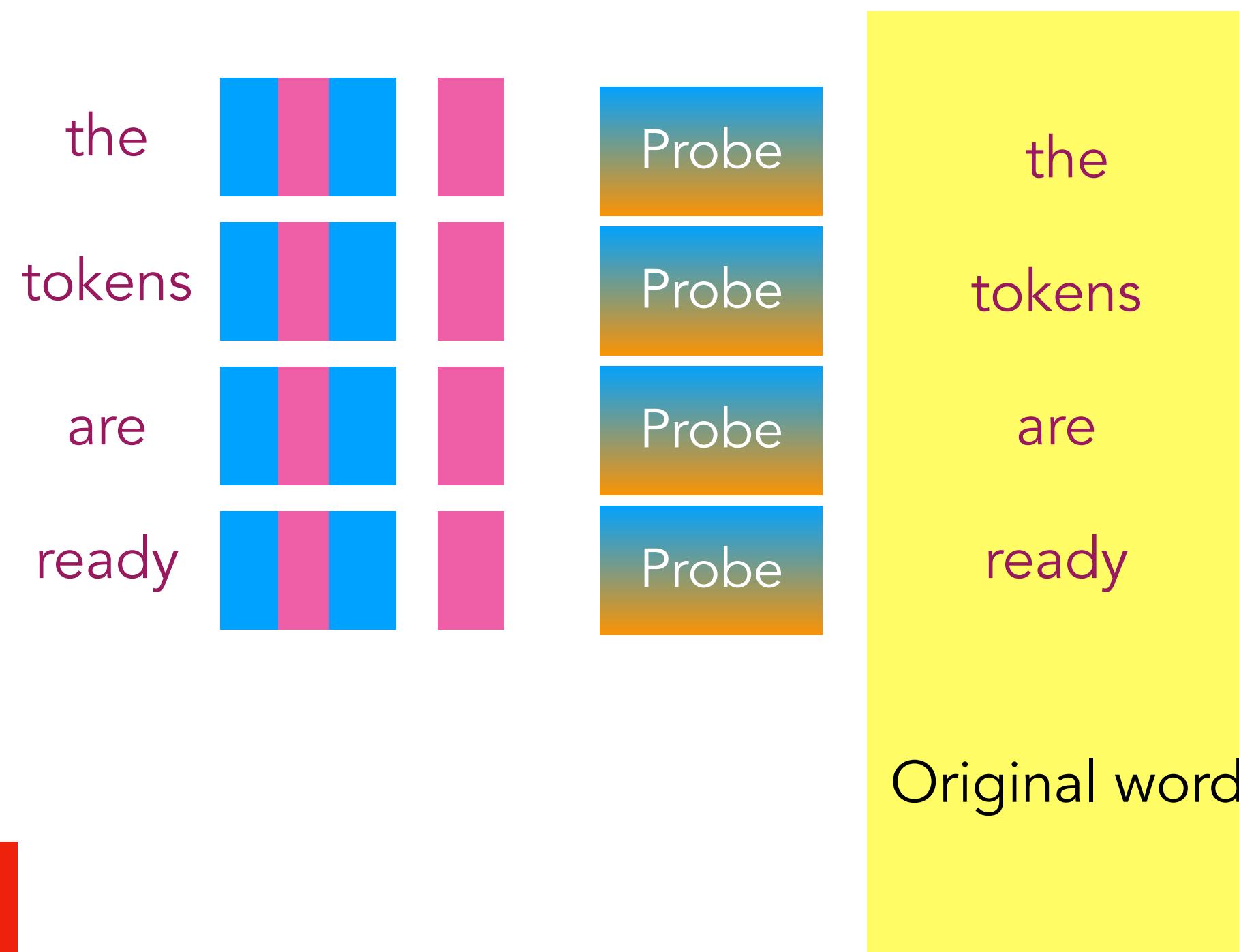
Sequence/Image/...

['the', 'tokens', 'are', 'ready']

Architecture	White box with internal embeddings
Required data	Annotated task
Explains	Model, single samples if good
Focus	Partial Computation
Use for...	Evaluating hypothesis, Single samples if good

Probing

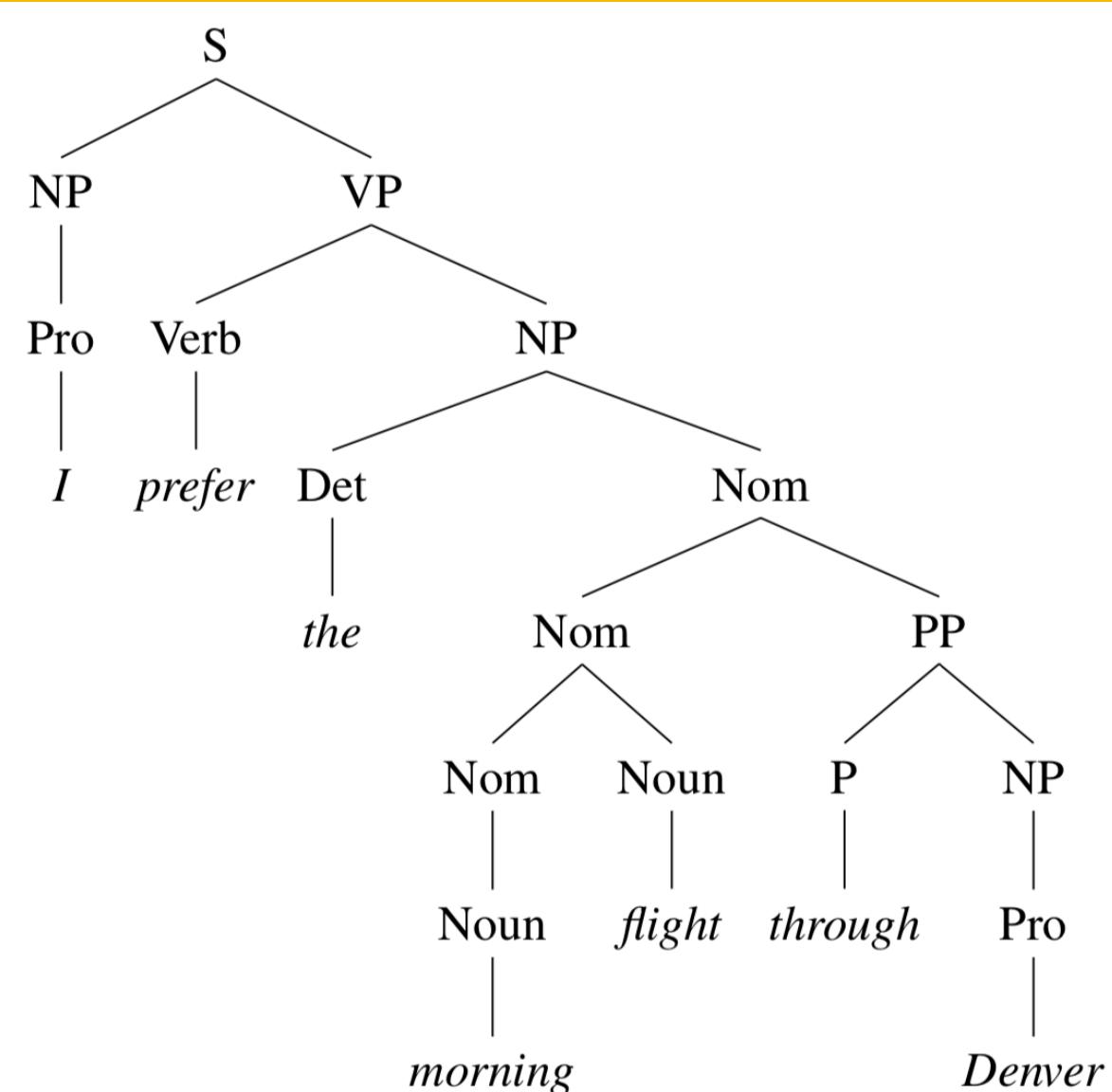
Example: Word-level Tasks



Classical NLP Tasks

Explicitly assigning structure to sentences

Constituency Parsing

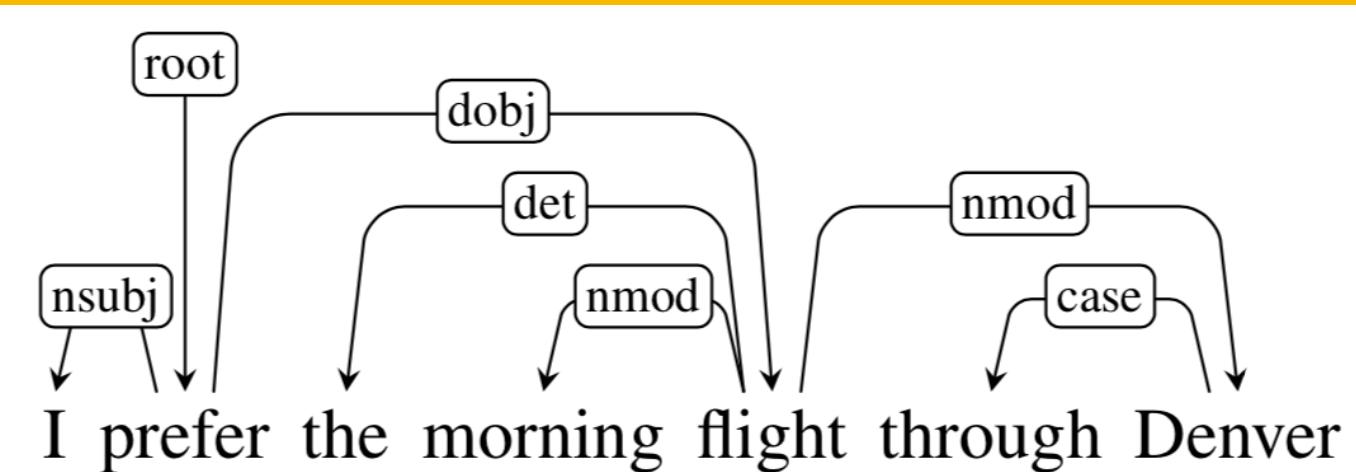


e.g.:

Penn Treebank

Marcus et al, 1999

Dependency Parsing



e.g.:
Universal Dependencies
Nivre et al, 2017

Named Entity Recognition

[Jim]person prefers the [6am]time
flight from [Denver]place

e.g.:
CoNLL-2003 shared task: Language Independent NER
Tjong et al, 2003

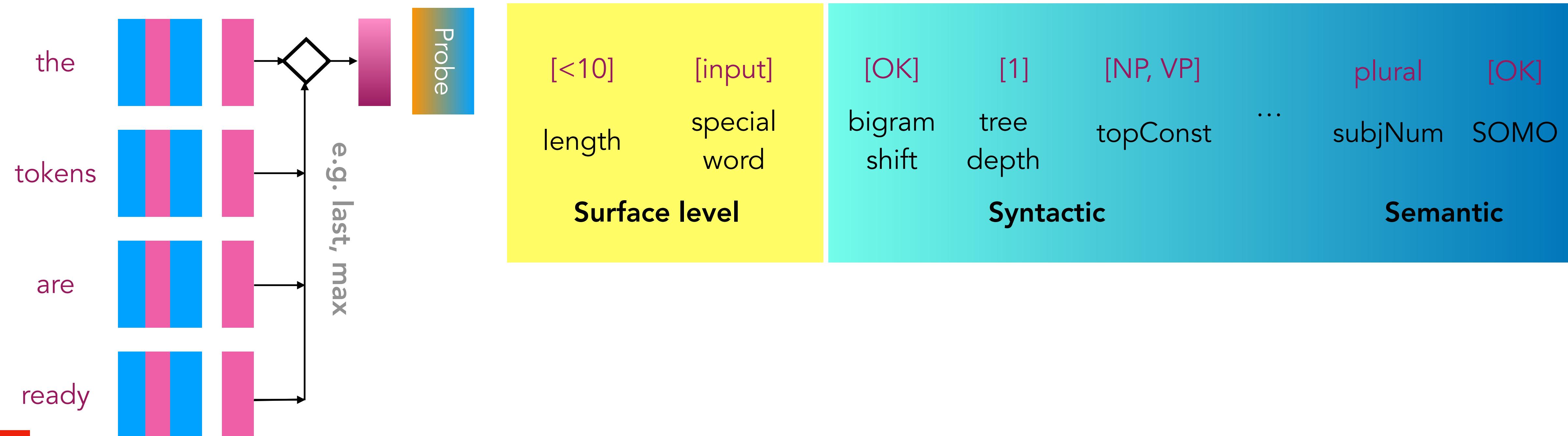
NLP researchers invested a lot of effort in solving these tasks explicitly, in pursuit of successful sentence parsing

Do modern models solve them too, or are they doing something else?

Architecture	White box with internal embeddings
Required data	Annotated task
Explains	Model, single samples if good
Focus	Partial Computation
Use for...	Evaluating hypothesis, Single samples if good

Probing

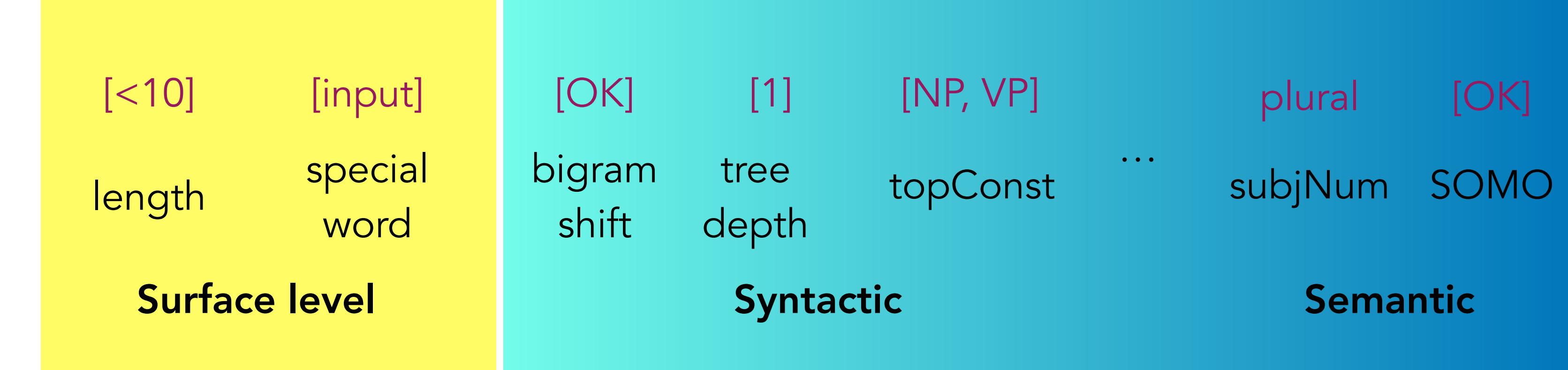
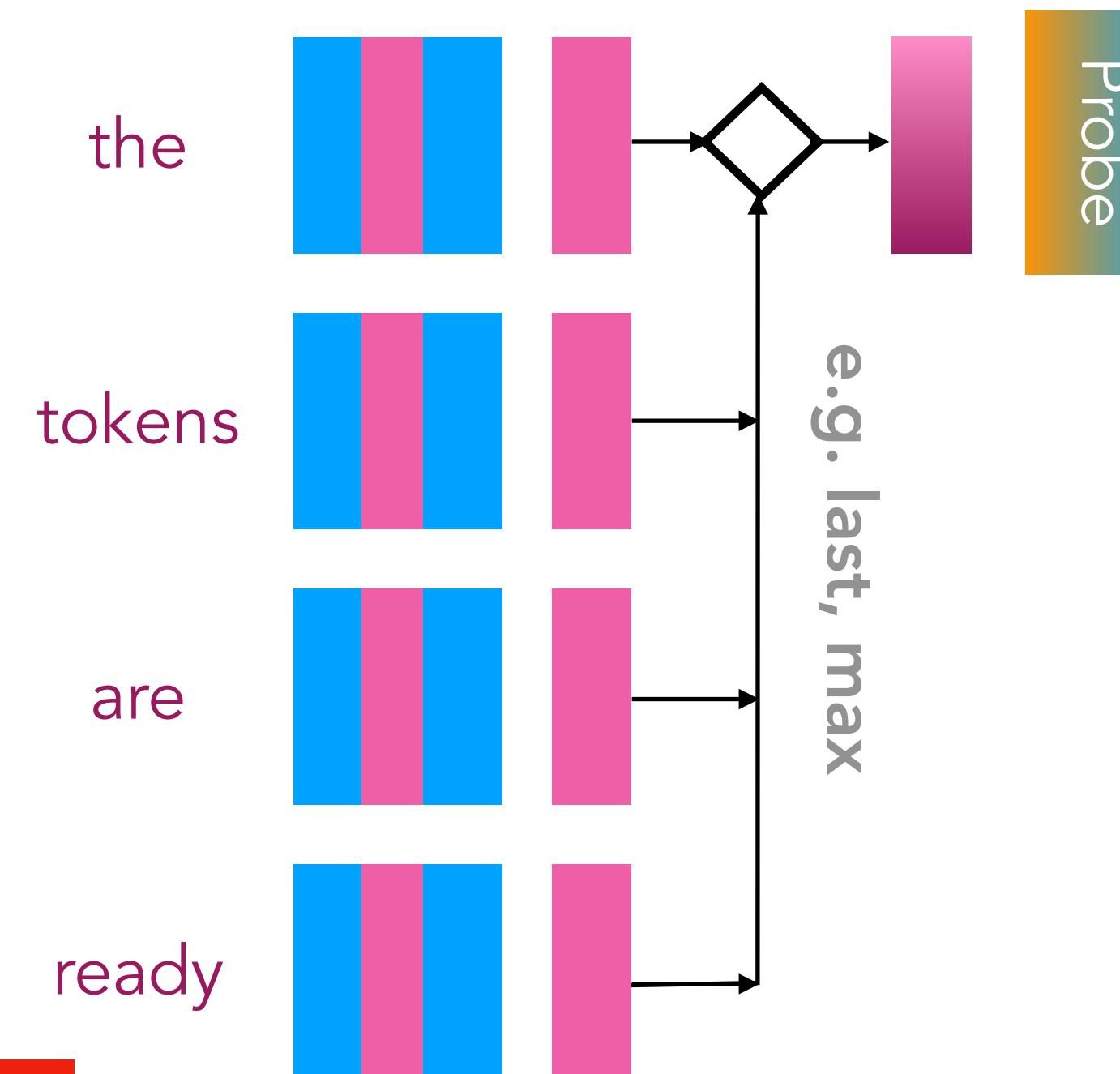
Examples: Sentence-level Tasks



What you can cram into a single \$&!#* vector: Probing sentence embeddings for linguistic properties, Conneau et al, 2018

Architecture	White box with internal embeddings
Required data	Annotated task
Explains	Model, single samples if good
Focus	Partial Computation
Use for...	Evaluating hypothesis, Single samples if good

Probing



Note: Can also probe over subspans ("Edge Probing"):
 What do you learn from context? Probing for sentence structure in contextualized word representations, Tenney et al, 2019

Architecture	White box with internal embeddings
Required data	Annotated task
Explains	Model, single samples if good
Focus	Partial Computation
Use for...	Evaluating hypothesis, Single samples if good

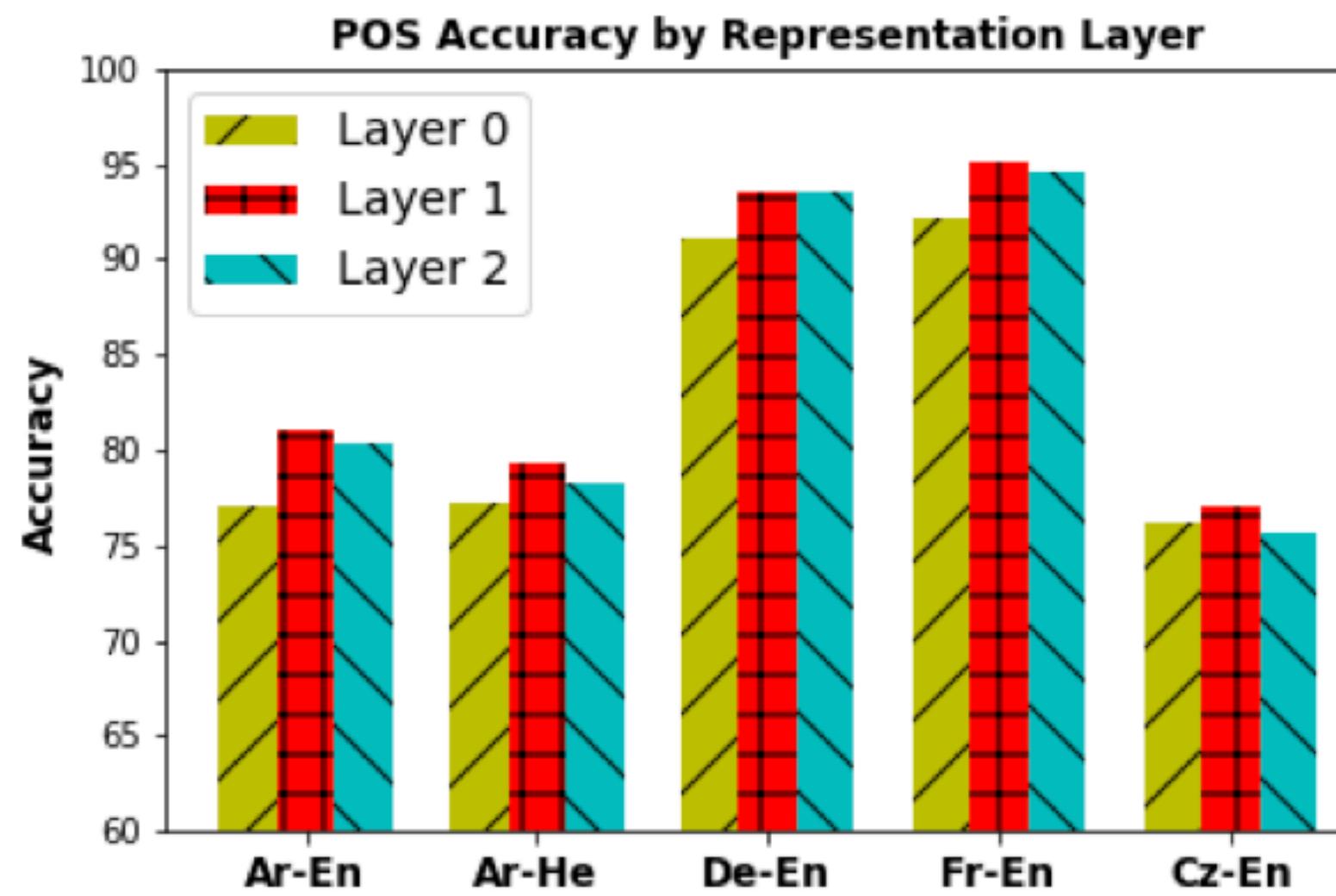
Probing

Example: Word-level Tasks



Architecture	White box with internal embeddings
Required data	Annotated task
Explains	Model, single samples if good
Focus	Partial Computation
Use for...	Evaluating hypothesis, Single samples if good

Probing



The embeddings of trained Neural Networks contain ‘solutions’ to a variety of classical NLP tasks

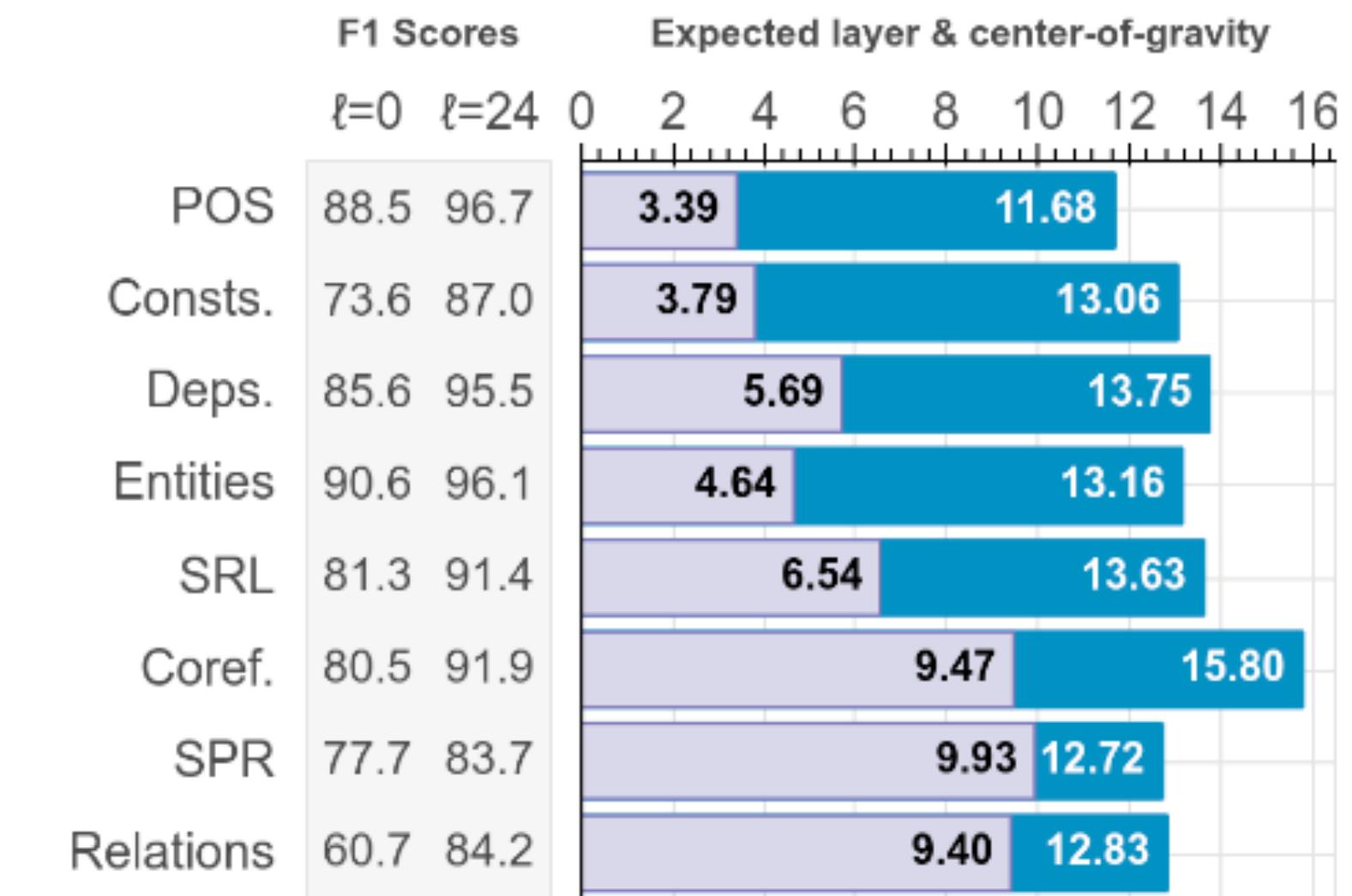
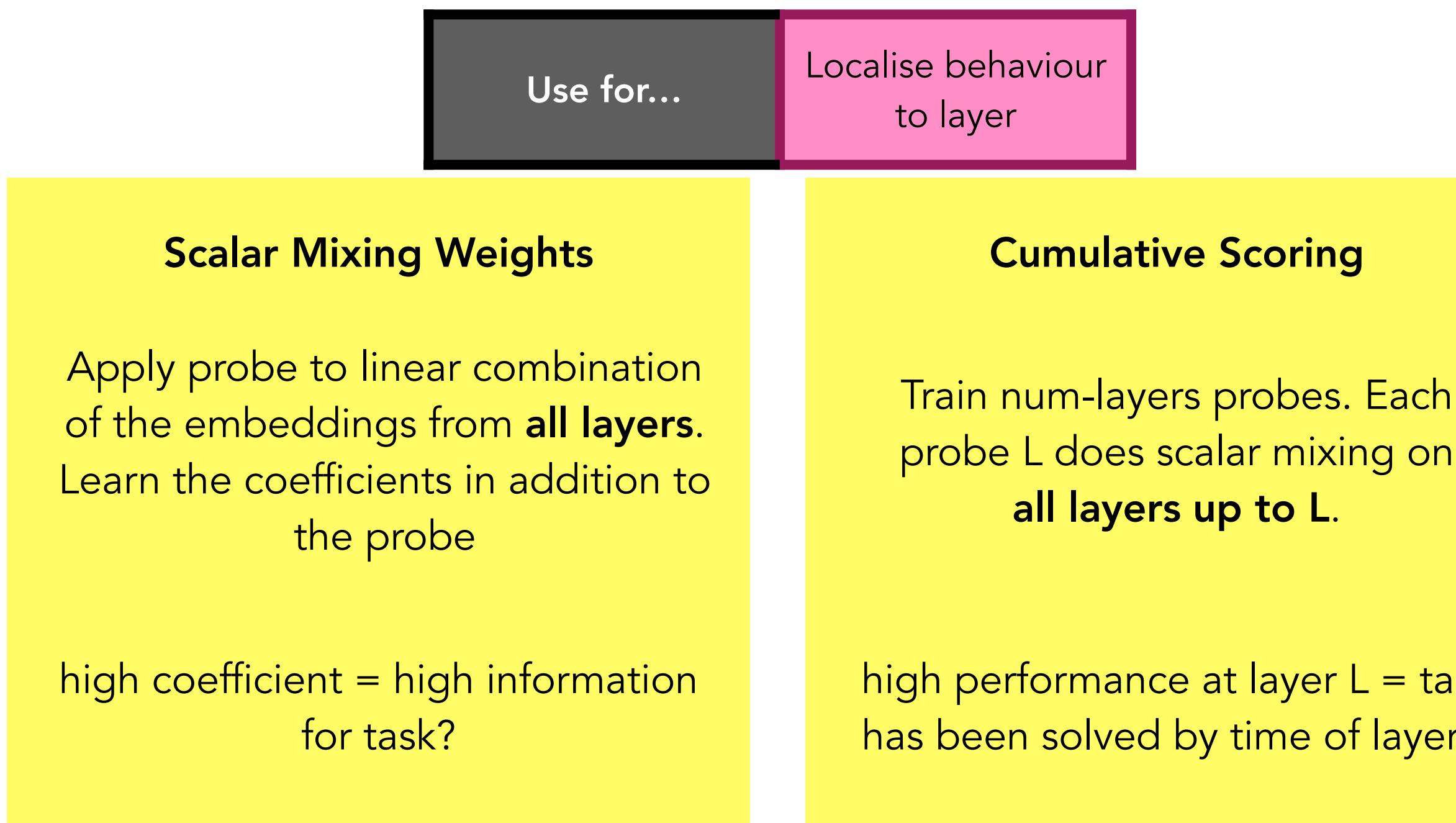
Lower layers appear better at syntax (structure), higher layers at semantics (meaning)

What do Neural Machine Translation Models Learn about Morphology?, Belinkov et al, 2017
Evaluating Layers of Representation in Neural Machine Translation on Part-of-Speech and Semantic Tagging Tasks, Belinkov et al, 2018

Architecture	White box with internal embeddings
Required data	Annotated task
Explains	Model, single samples if good
Focus	Partial Computation
Use for...	Evaluating hypothesis, Single samples if good

Probing

Is BERT solving classical NLP tasks as part of its solution? Is it solving them in the order we expect?



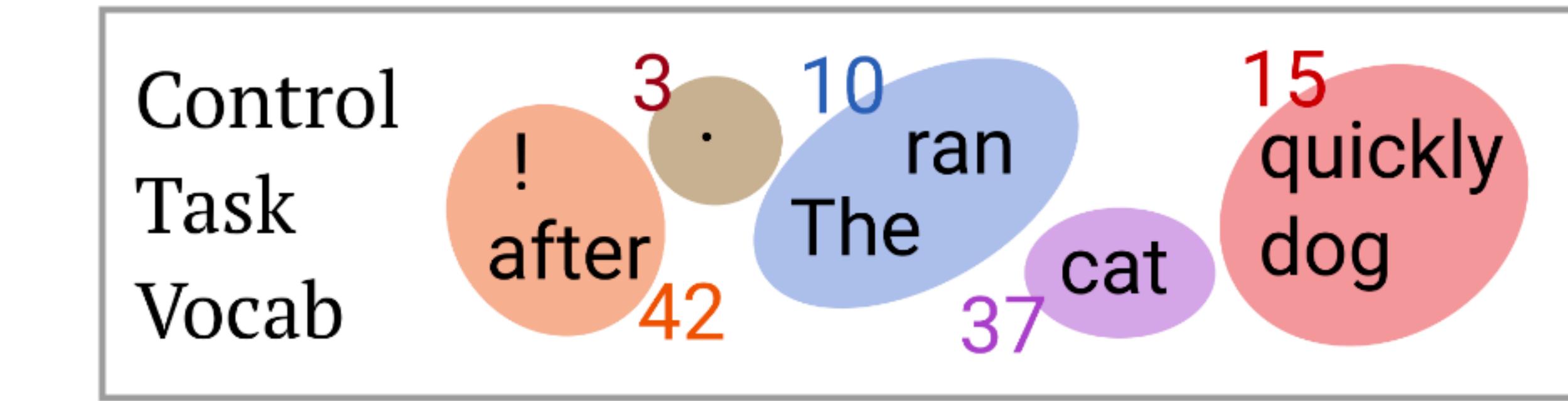
Light purple: time (layer) by which task is solved
Semantic tasks solved later in model

Architecture	White box with internal embeddings
Required data	Annotated task
Explains	Model, single samples if good
Focus	Partial Computation
Use for...	Evaluating hypothesis, Single samples if good

Probing

Selectivity

- If our probe is too strong, and our model embeddings very rich, the probe might solve the task regardless of whether the model is doing so itself
- Evaluate the probe on control tasks to stay grounded
- Design random tasks that can only be learned by memorisation - no generalisation



	Sentence 1	The	cat	ran	quickly	.
Part-of-speech		DT	NN	VBD	RB	.
Control task	10	37	10	15	15	3

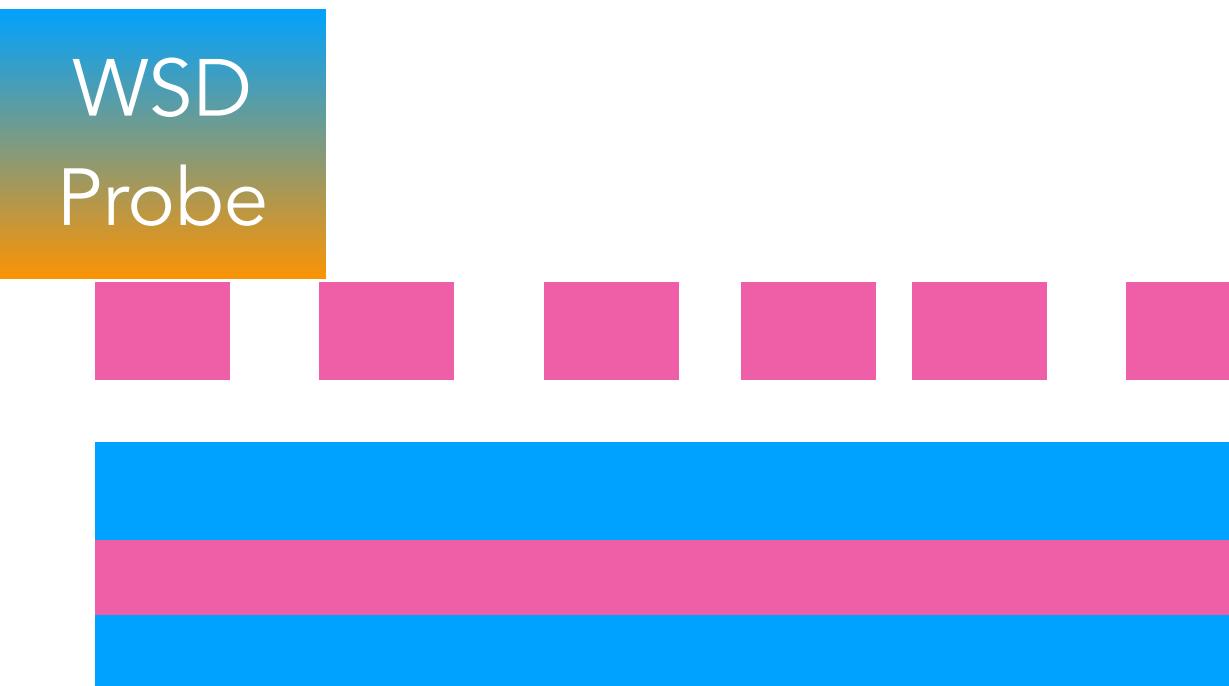
	Sentence 2	The	dog	ran	after	!
Part-of-speech		DT	NN	VBD	IN	.
Control task	10	15	10	42	42	

Architecture	White box with internal embeddings
Required data	Annotated task
Explains	Model, single samples if good
Focus	Partial Computation
Use for...	Evaluating hypothesis, Single samples if good

Probing

Note: won't give new classes, but could reveal unexpected associations!

le **X** should be la!



The doctor said she was tired

Architecture	White box with internal embeddings
Required data	Annotated task
Explains	General Behaviour, Single samples if good
Localises	Partial Computation
Use for...	Evaluating hypothesis, Single samples if good

Any ready made probes?
Embedding space

Architecture	White box with internal embeddings
Required data	None
Explains	Model, single samples when good
Focus	Partial Computation
Use for...	Evaluating hypotheses, samples when good

Embedding Space

aka logit lens

'output' 'classes' 'go' 'here'

Classify Classify Classify Classify

e_0^L e_1^L e_2^L e_3^L

Model Layer L

...

e_0^i e_1^i e_2^i e_3^i

Model Layer i

...

e_0^0 e_1^0 e_2^0 e_3^0

Embed Embed Embed Embed

['the', 'tokens', 'are', 'ready']

Idea: Treat classifier as probe

Architecture	White box with internal embeddings
Required data	None
Explains	Model, single samples when good
Focus	Partial Computation
Use for...	Evaluating hypotheses, samples when good

Embedding Space

aka logit lens

'output' 'classes' 'go' 'here'



Model Layer L

...



where
there
out



Model Layer i

...



['the', 'tokens', 'are', 'ready']

Idea: Treat classifier as probe

Architecture	White box with internal embeddings
Required data	None
Explains	Model, single samples when good
Focus	Partial Computation
Use for...	Evaluating hypotheses, samples when good

Embedding Space

aka logit lens

'output' 'classes' 'go' 'here'

Classify Classify Classify Classify

e_0^L e_1^L e_2^L e_3^L

Model Layer L

...

Classify

where
there
out

e_0^i e_1^i e_2^i e_3^i

Model Layer i

...

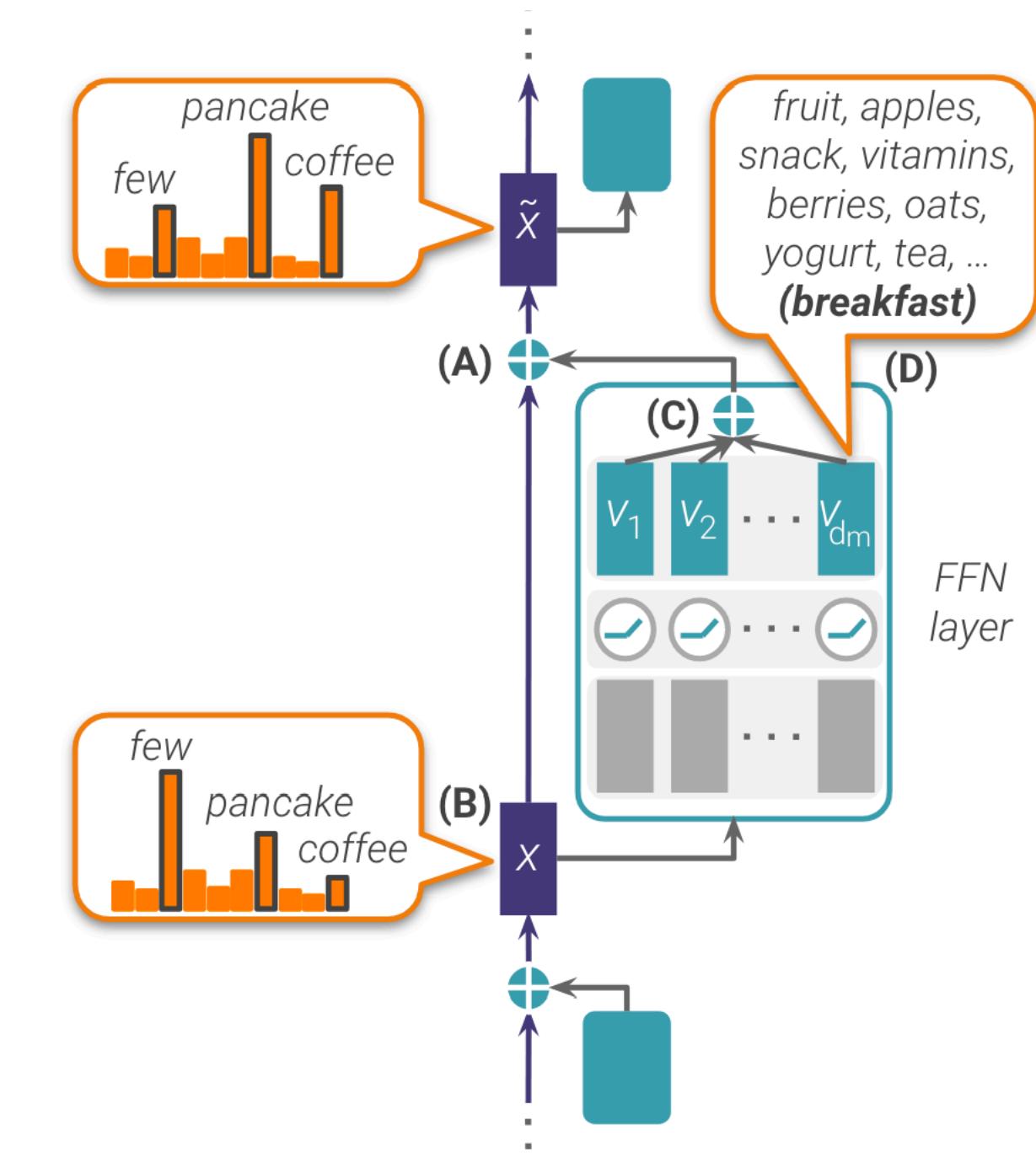
e_0^0 e_1^0 e_2^0 e_3^0

Embed Embed Embed Embed

['the', 'tokens', 'are', 'ready']

Idea: Treat classifier as probe

Results seem plausible/interpretable:

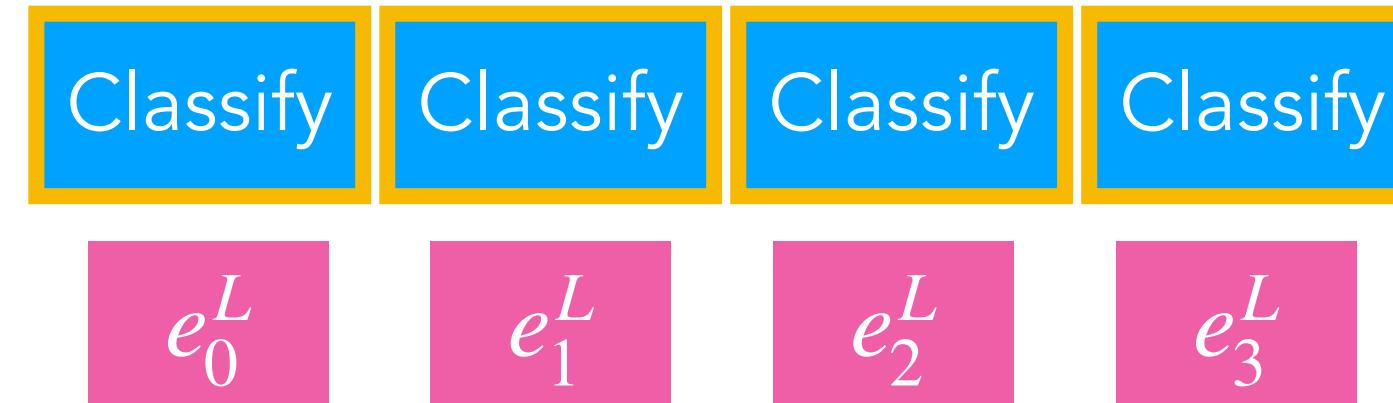


Transformer feed-forward layers build predictions by promoting concepts in the vocabulary space, Geva et al, 2022

anything interesting with this?

Transformer FFs as Key-Value Pairs

'output' 'classes' 'go' 'here'



Model Layer L

...



Model Layer i

...



Embed Embed Embed Embed

['the', 'tokens', 'are', 'ready']

$$FF_i(e) = W_i^B R(W_i^A e)$$

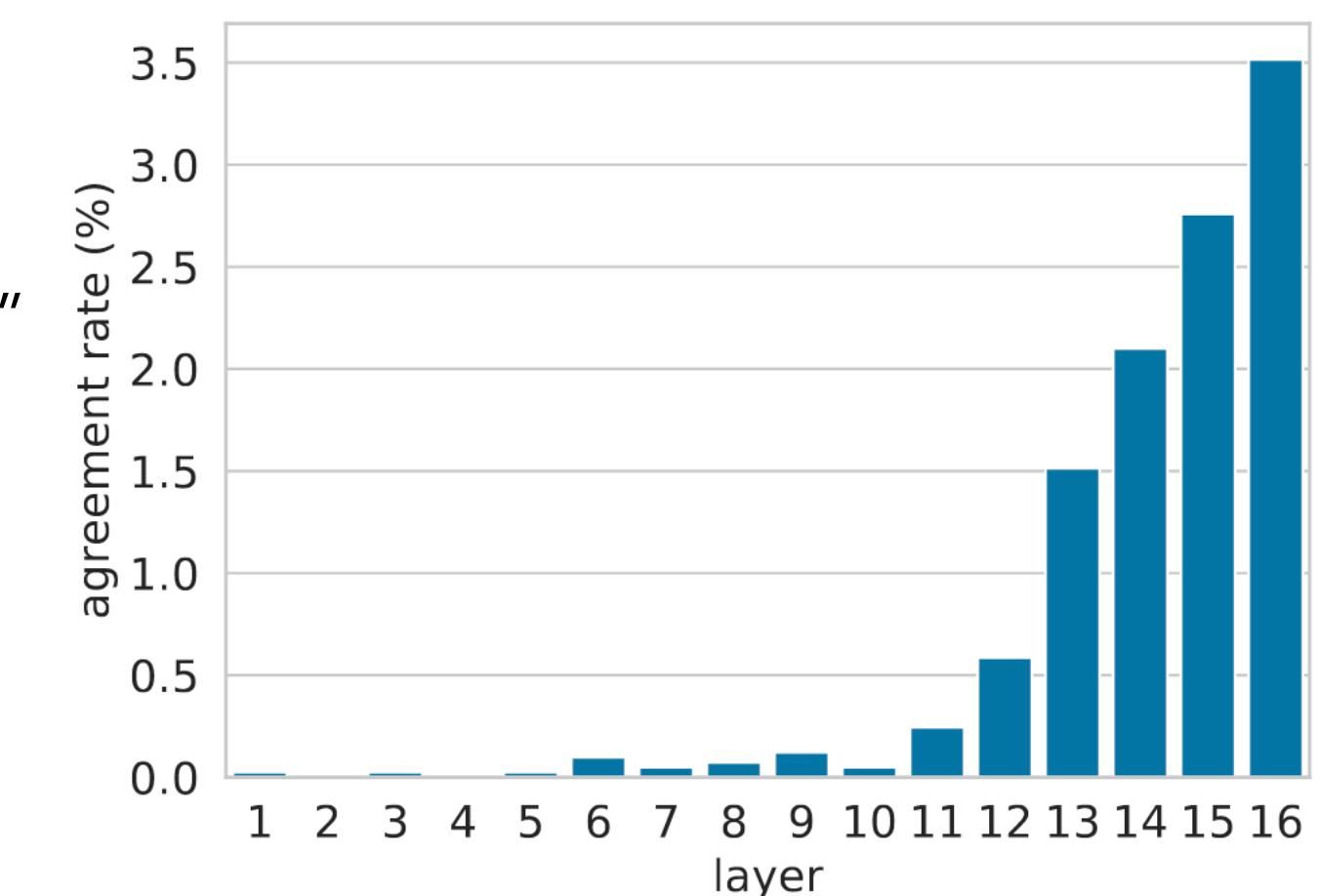
w_i^A

w_i^B

"keys"
(rows respond to
"trigger" inputs)

"values"
(columns meaningful in
embedding space)

%:
key's "top trigger"
next token
==
value's top token



Transformer feed-forward networks are
key-value memories, Geva et al, 2021

Was that a hint of associations
coming up

Architecture	Black box LM
Required data	Knowledge Triplets
Explains	Model
Focus	No
Use for...	Assert presence of/ extract knowledge

Knowledge

The **LAMA** probe*:
LAnguage Model Analysis

Take knowledge triplet, and present as sentence with object as last token:
(Dante,Born in,Florence)
→ **Dante was born in Florence**

Mask object, feed to LM, and asses ability
to recover the object

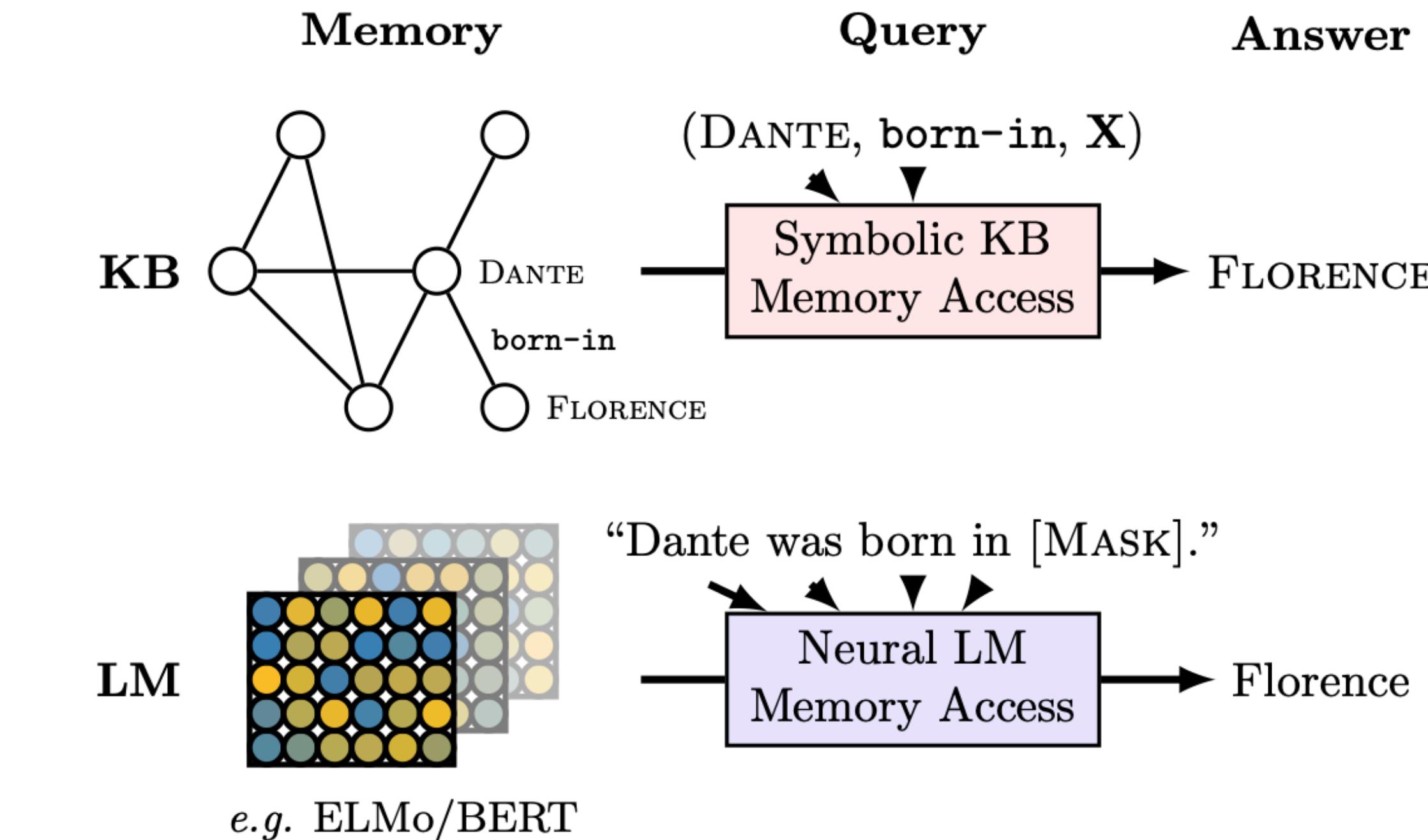


Figure 1: Querying knowledge bases (KB) and language models (LM) for factual knowledge.

*task, prompt

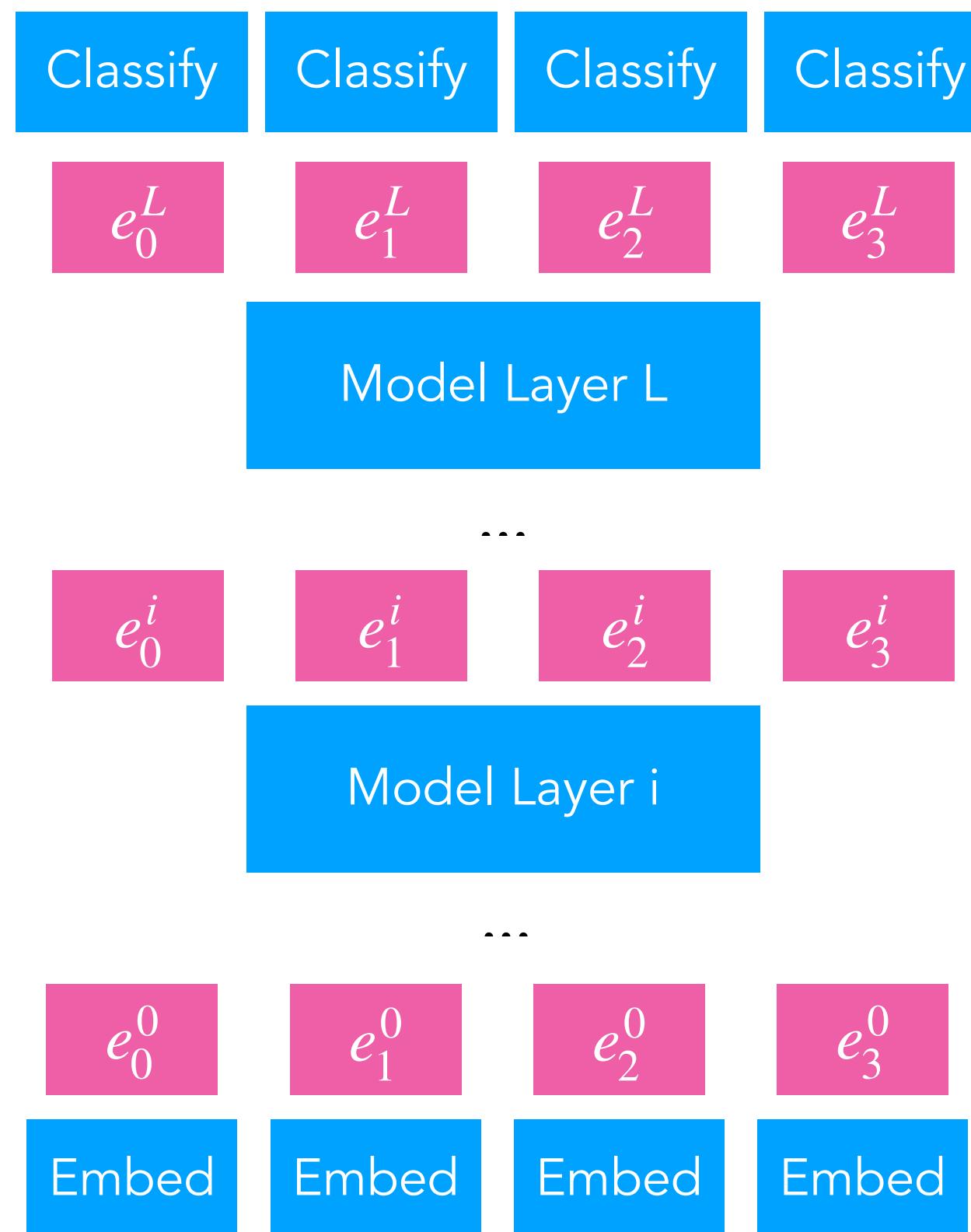
Locating knowledge Interventions

Architecture	White box
Required data	No
Explains	Model
Focus	Input x Layer
Use for...	Locating computation

Causal Tracing

AKA Activation Patching

'output' 'classes' 'go' 'here'



['the', 'tokens', 'are', 'fine']

Inspiration: Causal Mediation Analysis, Pearl, 2001

Architecture	White box
Required data	Samples of interest
Explains	General behaviour
Localises	Input x Layer
Use for...	Locating computation

Causal Tracing

AKA Activation Patching

'output' 'classes' 'go' 'here'

Classify Classify Classify Classify

e_0^L e_1^L e_2^L e_3^L

Model Layer L

'output' 'is' 'garbage' 'now'

Classify Classify Classify Classify

e_0^L e_1^L e_2^L e_3^L

Model Layer L

e_0^i e_1^i e_2^i e_3^i

Model Layer i

e_0^i e_1^i e_2^i e_3^i

Model Layer i

e_0^0 e_1^0 e_2^0 e_3^0

Embed Embed Embed Embed

['the', 'tokens', 'are', 'fine']

1. corrupt input

corrupt **tokens** or embedding
or FF hidden or attention

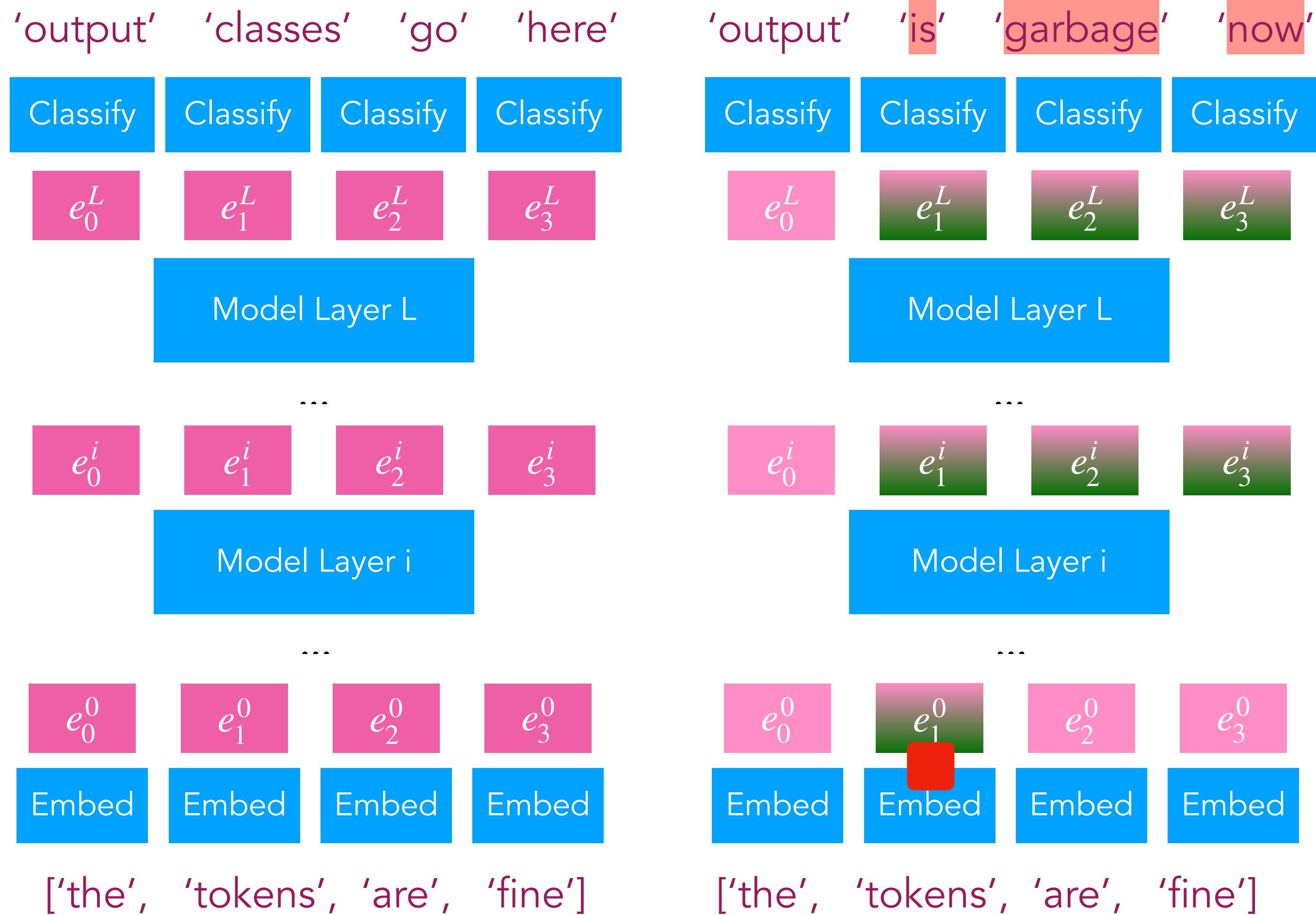
⇒ output gets broken

Inspiration: Causal Mediation Analysis, Pearl, 2001

Architecture	White box
Required data	Samples of interest
Explains	General behaviour
Localises	Input x Layer
Use for...	Locating computation

Causal Tracing

AKA Activation Patching



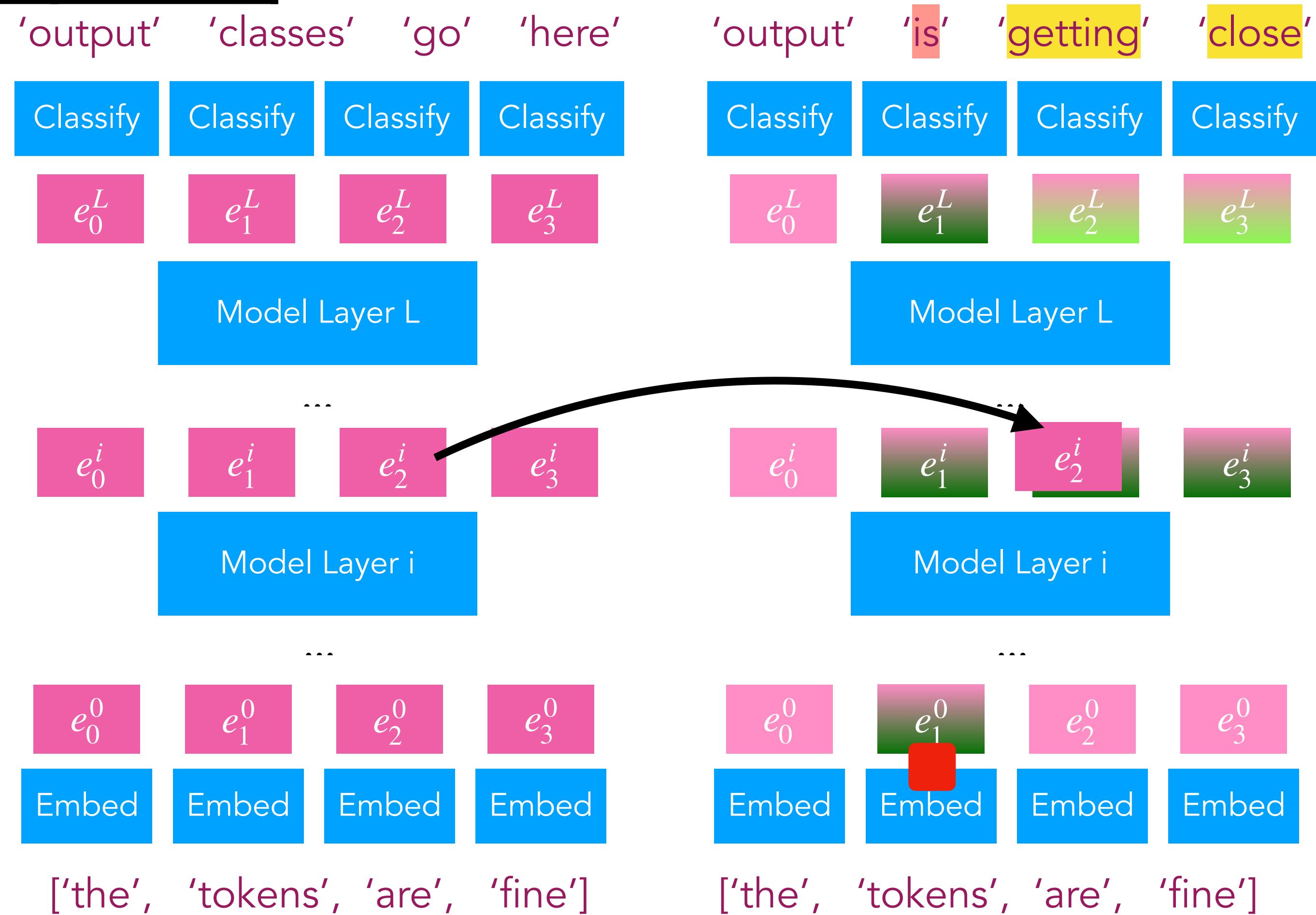
1. corrupt input
corrupt tokens or **embedding**
or FF hidden or attention
⇒ output gets broken

Inspiration: Causal Mediation Analysis, Pearl, 2001

Architecture	White box
Required data	Samples of interest
Explains	General behaviour
Localises	Input x Layer
Use for...	Locating computation

Causal Tracing

AKA Activation Patching



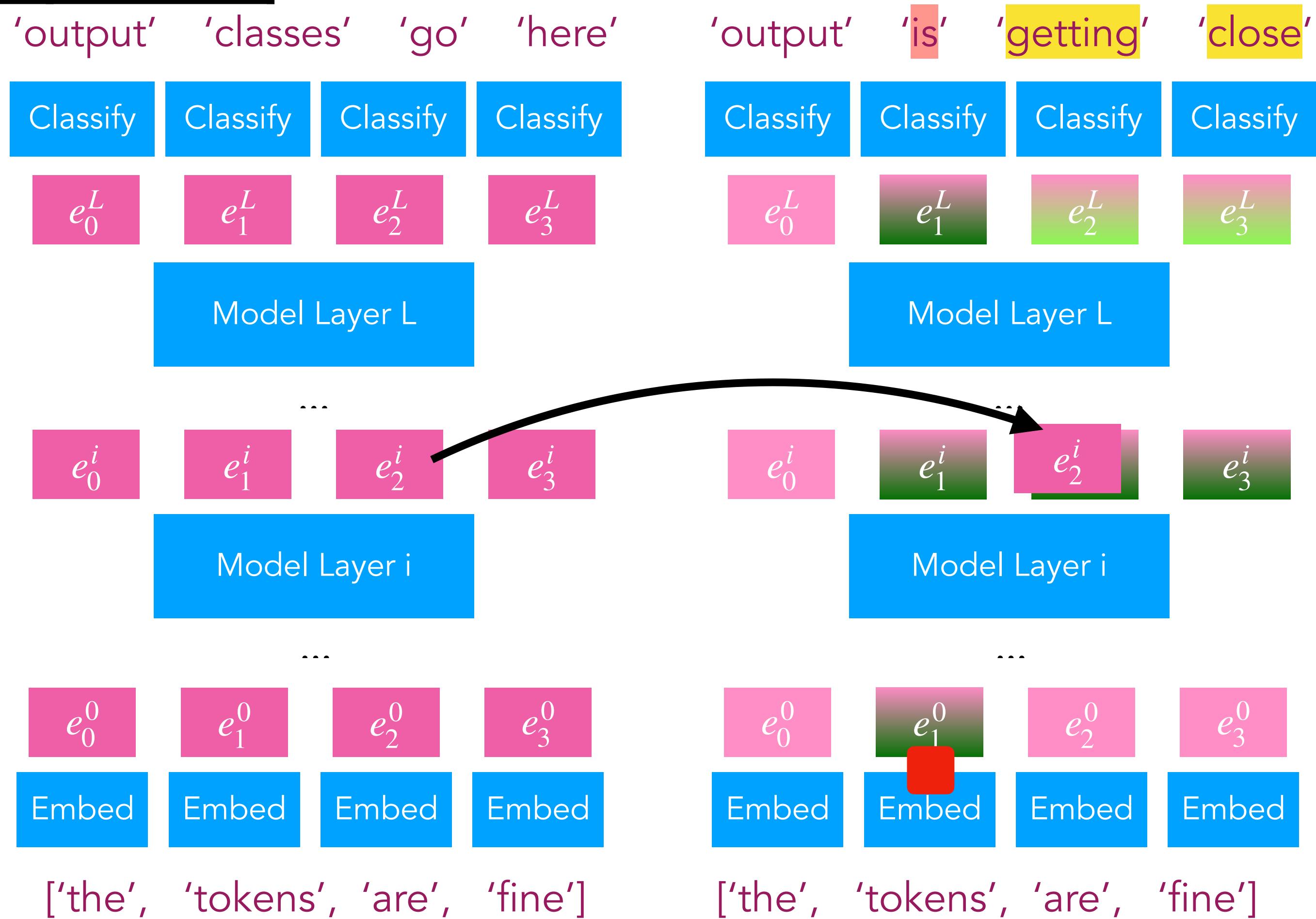
1. corrupt input
corrupt tokens or embedding
or FF hidden or attention
 \implies output gets broken
2. patch in embeddings
from correct input
different layers and positions

Inspiration: Causal Mediation Analysis, Pearl, 2001

Architecture	White box
Required data	Samples of interest
Explains	General behaviour
Localises	Input x Layer
Use for...	Locating computation

Causal Tracing

AKA Activation Patching



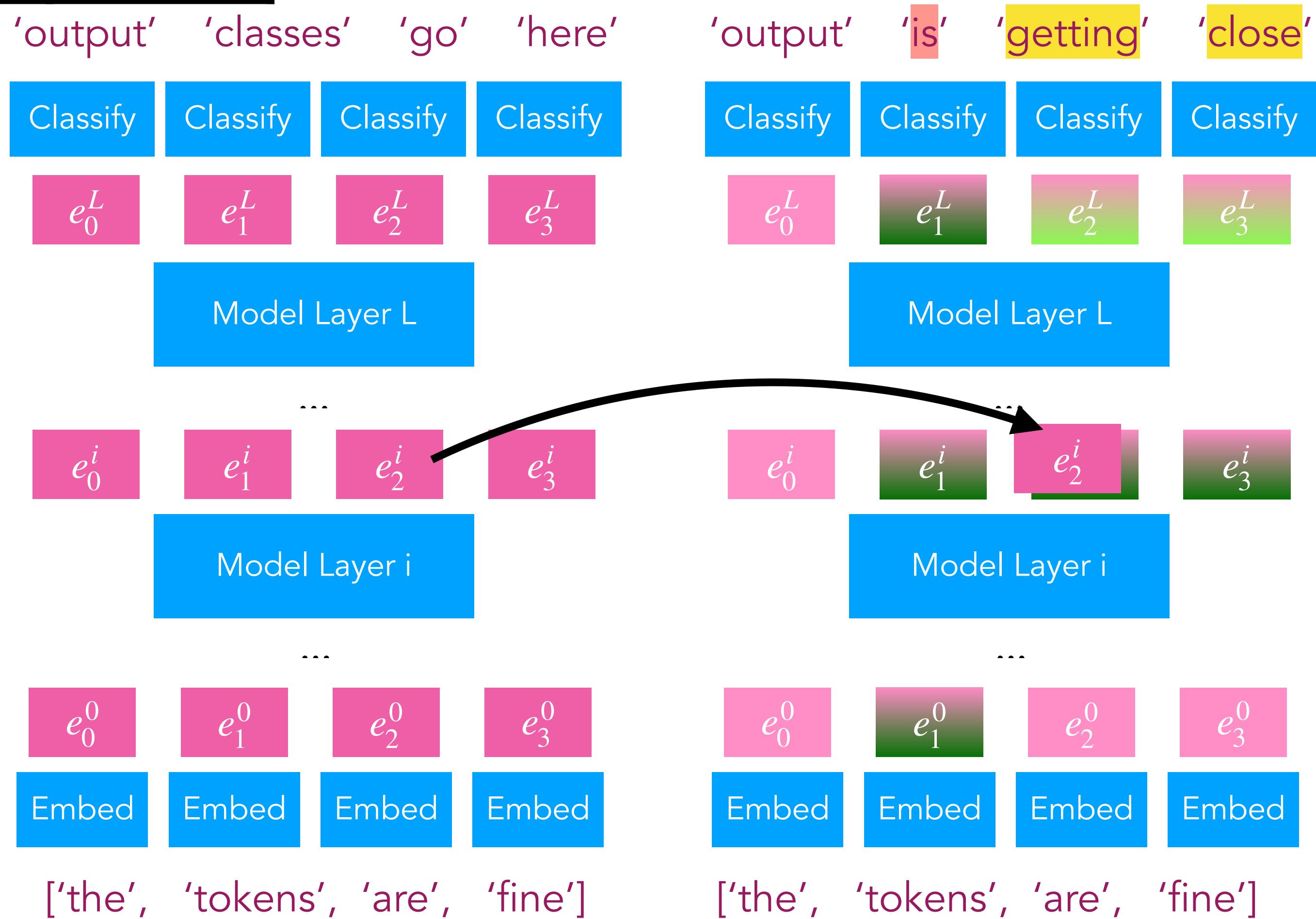
1. corrupt input
corrupt tokens or embedding
or FF hidden or attention
 \Rightarrow output gets broken
 2. patch in embeddings
from correct input
different layers and positions
- is output fixed?**

Inspiration: Causal Mediation Analysis, Pearl, 2001

Architecture	White box
Required data	Samples of interest
Explains	General behaviour
Localises	Input x Layer
Use for...	Locating computation

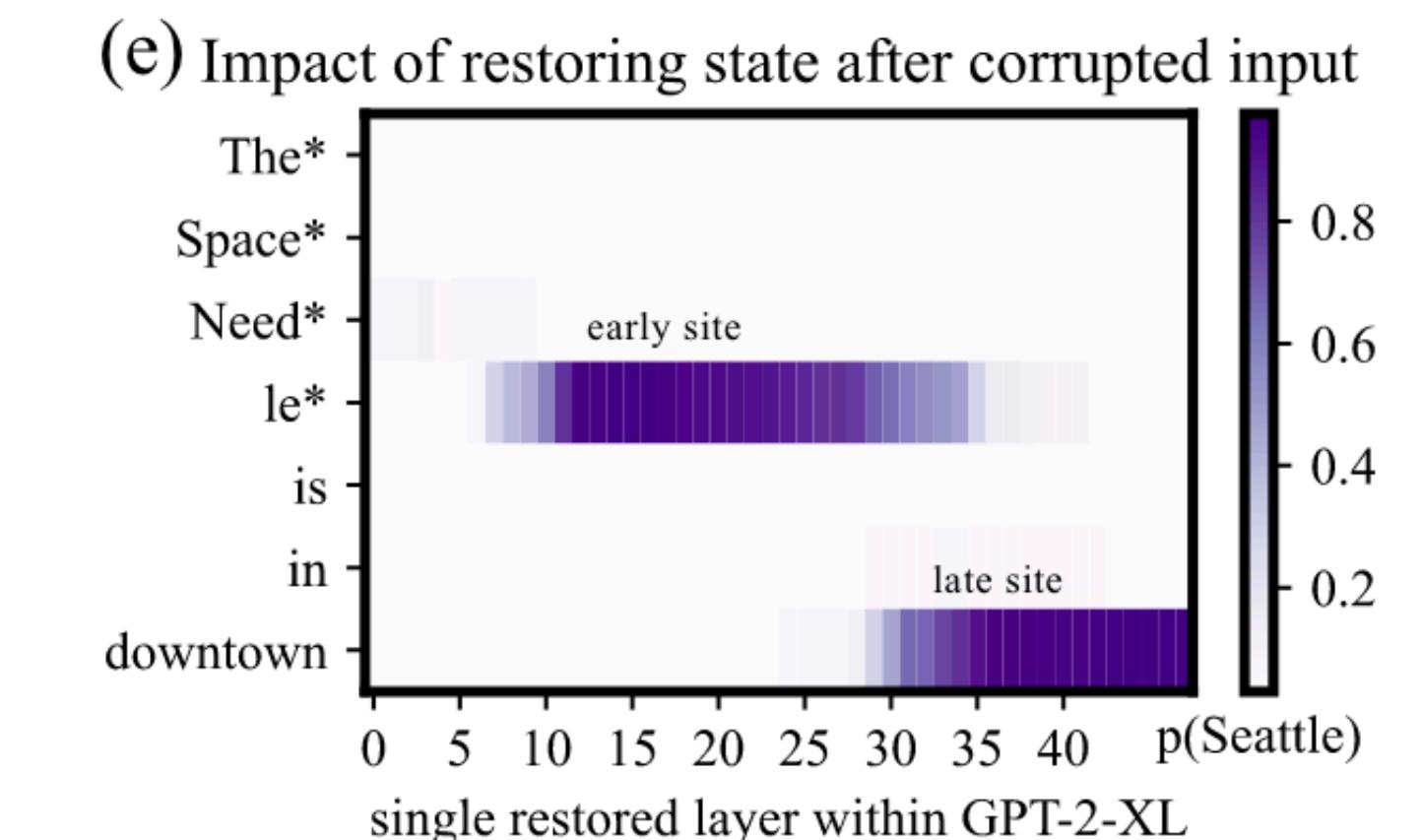
Causal Tracing

AKA Activation Patching



1. corrupt input
corrupt tokens or embedding
or FF hidden or attention
 \implies output gets broken
 2. patch in embeddings
from correct input
different layers and positions
- is output fixed?**

Result: localise position of associations in network

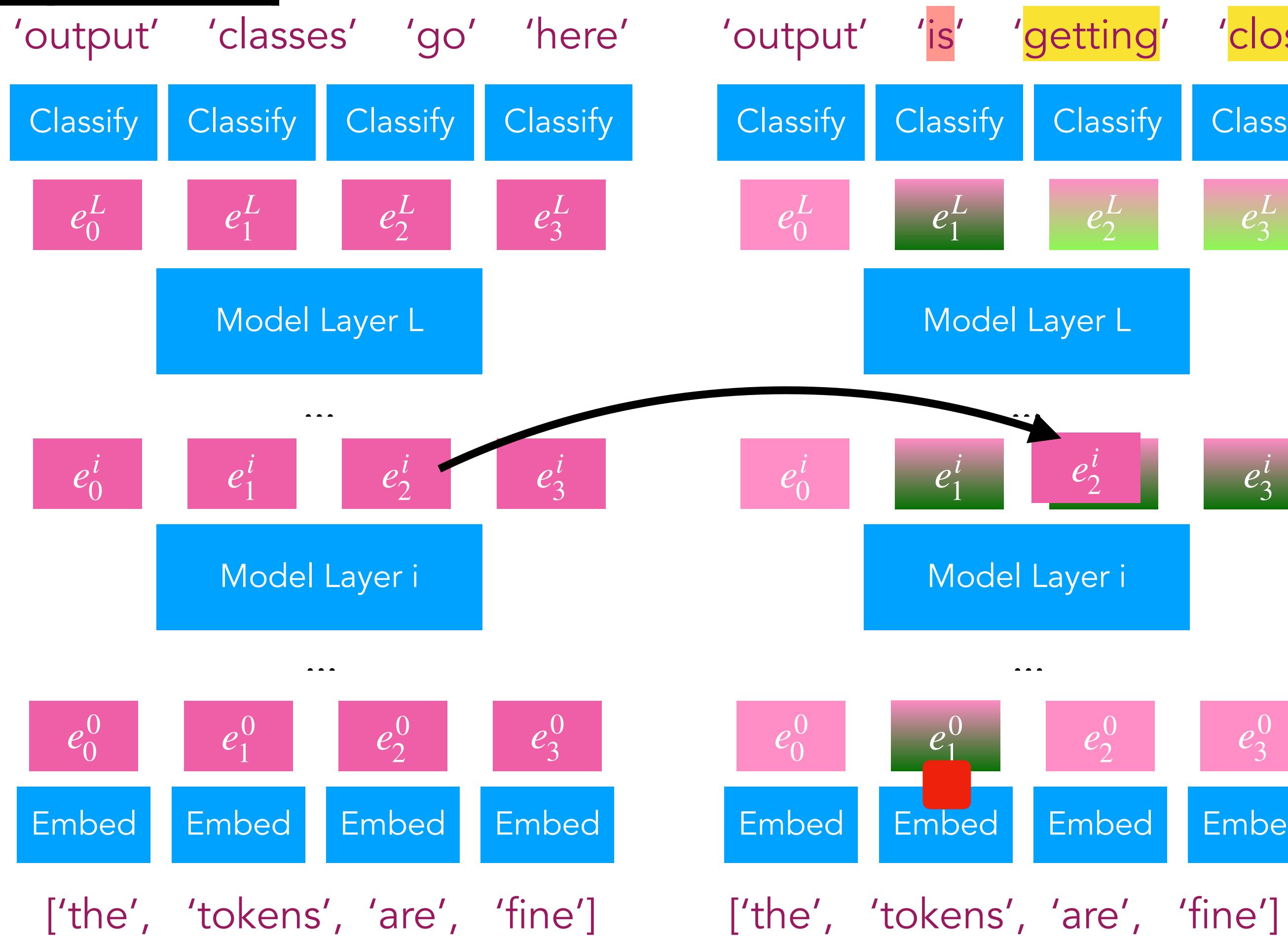


Inspiration: Causal Mediation Analysis, Pearl, 2001

Architecture	White box
Required data	Samples of interest
Explains	General behaviour
Localises	Input x Layer
Use for...	Locating computation

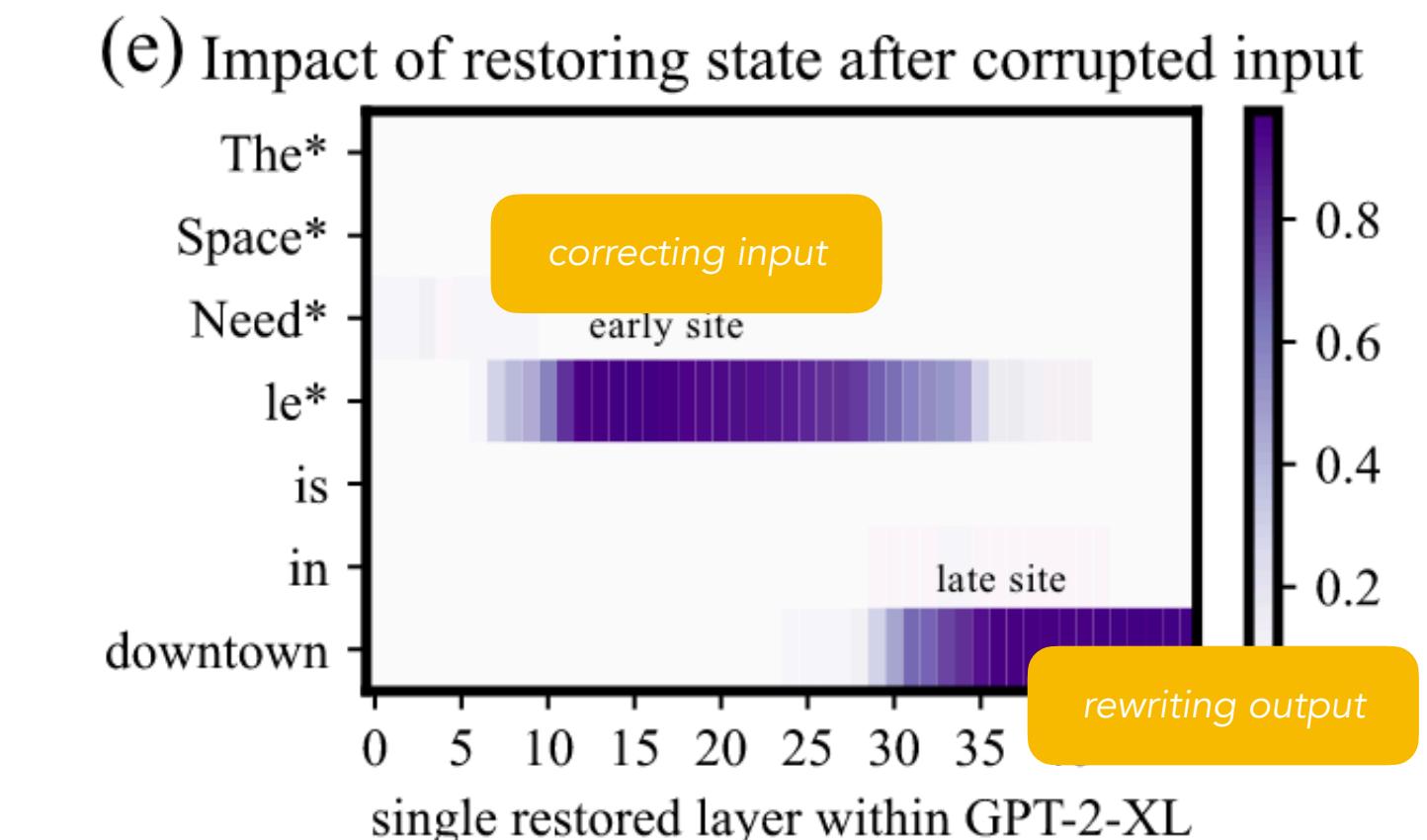
Causal Tracing

AKA Activation Patching



1. corrupt input
corrupt tokens or embedding
or FF hidden or attention
 \implies output gets broken
2. patch in embeddings
from correct input
different layers and positions
is output fixed?

Result: localise position of associations in network



Inspiration: Causal Mediation Analysis, Pearl, 2001

Locating knowledge **Modifications**

Architecture	White box LM
Required data	Knowledge Phrases
Explains	Model
Focus	All weights
Use for...	Blocking knowledge

Knowledge-Critical Subnets

Learn a mask over model parameters to remove knowledge

Optimise for:

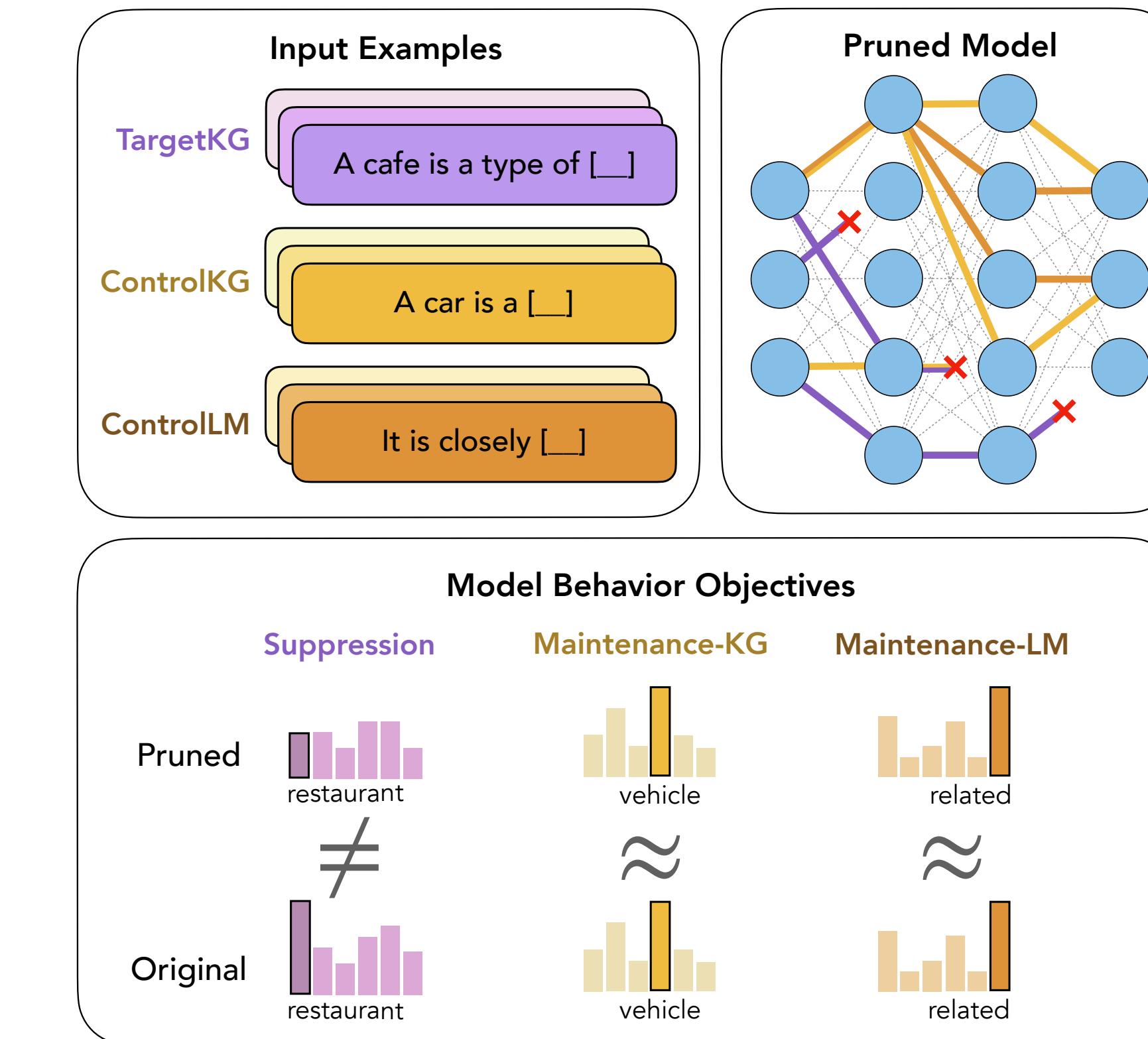
Keep mask minimal

+

Remove target knowledge

+

Maintain other behaviours



*task, prompt

Breathe

Recap

	Leave one out	LIME	SHAP	Layerwise Relevance Propagation	Saliency Maps	Activation Neuron Maximisation	Activation Vector Maximisation	Attention head eval	Probing	Embedding Space	LAMA	Causal Tracing	Knowledge Critical Subnets
Architecture	Black box	Black box	Black box	White box (with layers)	Differentiable white box	Differentiable white box embedder	Differentiable white box embedder	White box with attention	White box with internal embeddings	White box with internal embeddings	Black box LM	White box	White box
Required data	None	None	Train Samples	None	None	None	None	Annotated task	Annotated task	None	Knowledge Triples	No	Knowledge Phrases
Explains	Sample area	Sample area	Model	Sample	Sample	Model	Sample	Model	Model, single samples if good	Model, single samples (when good)	Model	Model	Model
Focus	All features	All features	All features	All sample (locates class)	All sample (locates class)	Neuron	Layer	Partial Computation	Partial Computation	Partial Computation	No	Input X Layer	All weights
Use for...	Intuition	Intuition	Intuition	Intuition	Intuition	Intuition	Intuition	Evaluating hypotheses	Evaluating hypotheses, single samples if good	Evaluating hypotheses, single samples (when good)	Assert presence of/ extract knowledge	Locating computation/ knowledge	Blocking knowledge

Used creatively for
attention relevance!

Not in here: pruning/ablations in general: knocking out whole sub-components to see if model needs them

Outline

◆ Introduction

◆ Methods and Concepts

- Several black and white box methods, intuition vs hypotheses, observation vs intervention
- Background interrupt: Classical NLP tasks

◆ Friends

- Mechanistic interpretability; Formal analysis; Extraction

◆ Conclusion

I keep hearing about
mechanistic interpretability

Mechanistic Interpretability

Circuits

Individual subcomponents of the transformer computation, ideally with intuitive meaning - e.g. induction heads

Induction Heads

specific "circuits" that perform:
 $[A][B] \dots [A] \rightarrow [B]$

the "attention circuit" (KQ) finds [A],
and then sends [B] (VO)

Polysemy/Privileged Basis

Features tracked by the partial computations are not necessarily aligned with the standard basis: single neuron not always fun to follow (contrast with e.g. Karpathy RNN demo)

Path/attribution patching

Similar to causal tracing, but with finer grained/more deliberate interventions

Cell sensitive to position in line:
The sole importance of the crossing of the Berezina lies in the fact that it plainly and indubitably proved the fallacy of all the plans for cutting off the enemy's retreat and the soundness of the only possible line of action - the one Kutuzov had demanded namely, simply to follow the enemy up the French army fled at a continually increasing speed and all its energy was directed to reaching its goal. It fled like a wounded animal and it was impossible to block its path. This was shown not so much by the arrangements it made for crossing as by what took place at the bridges. When the bridges broke down, under the weight of people from Moscow, women with children who were with the French, transporatation all - carried on by vis inertiae - pressed forward into boats and into the ice-covered water and did not surrender.

Cell that turns on inside quotes:
"You mean to imply that I have nothing to eat out of... On the contrary, I can supply you with everything even if you want to give dinner parties," warmly replied Chichagov, who tried by every word he spoke to prove his own rectitude and therefore imagined Kutuzov to be animated by the same desire.

Kutuzov, shrugging his shoulders, replied with his subtle penetrating smile: "I meant merely to say what I said."

Mechanistic Interpretability

Induction Heads

Provided intuition: $[A][B] \dots [A] \rightarrow [B]$

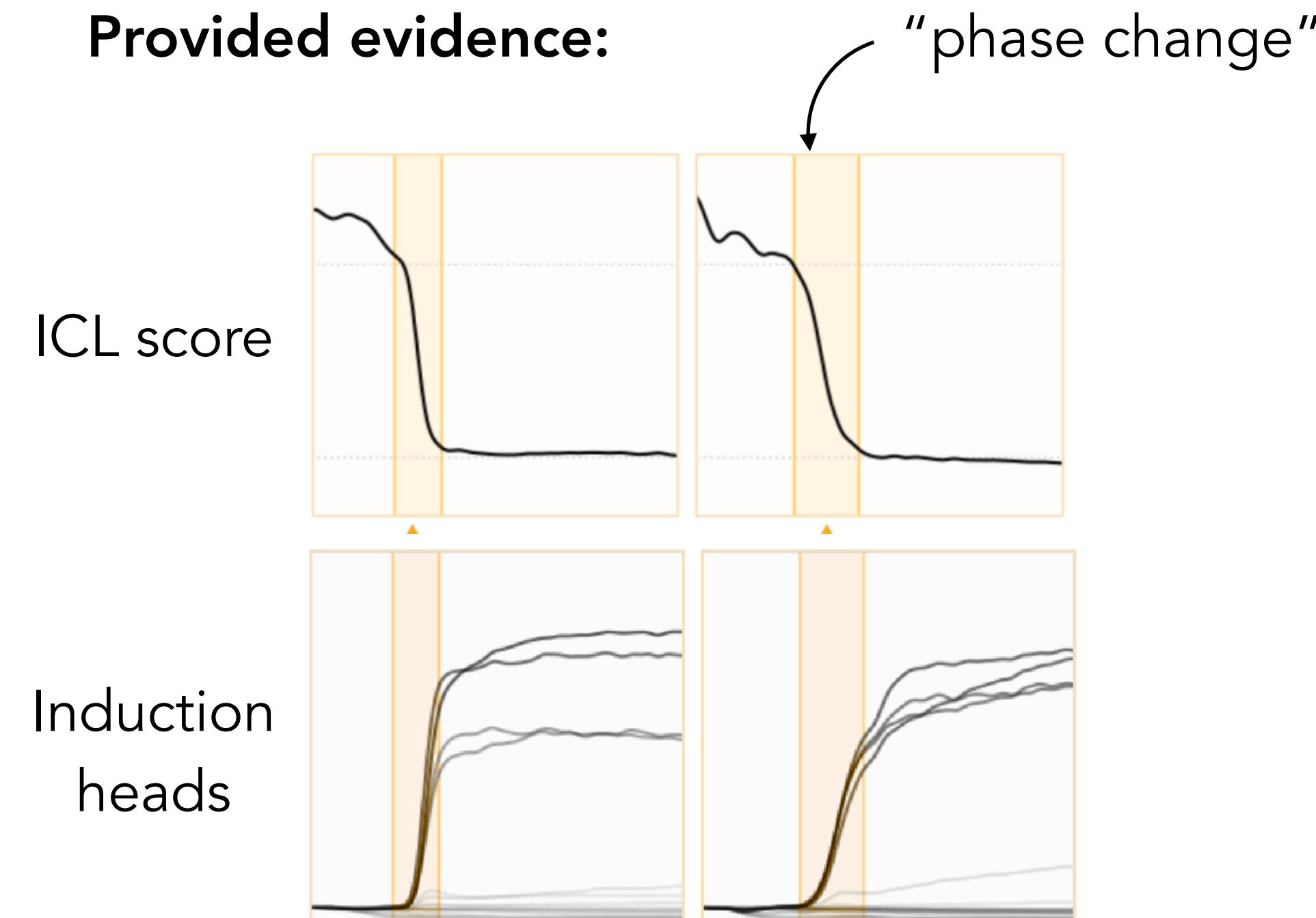
Provided definition: Heads for which, on input sample x , attention from position i tends to positions j for which $x_j = x_{i+1}$

Claim: Models that do in-context learning learn induction heads, and these heads are very helpful for ICL

Provided definition: In context learning score:

$$\frac{1}{N} \sum_{n \in [N]} L(x_{500} | x_{\leq 500}) - L(x_{50} | x_{\leq 50})$$

Provided evidence:



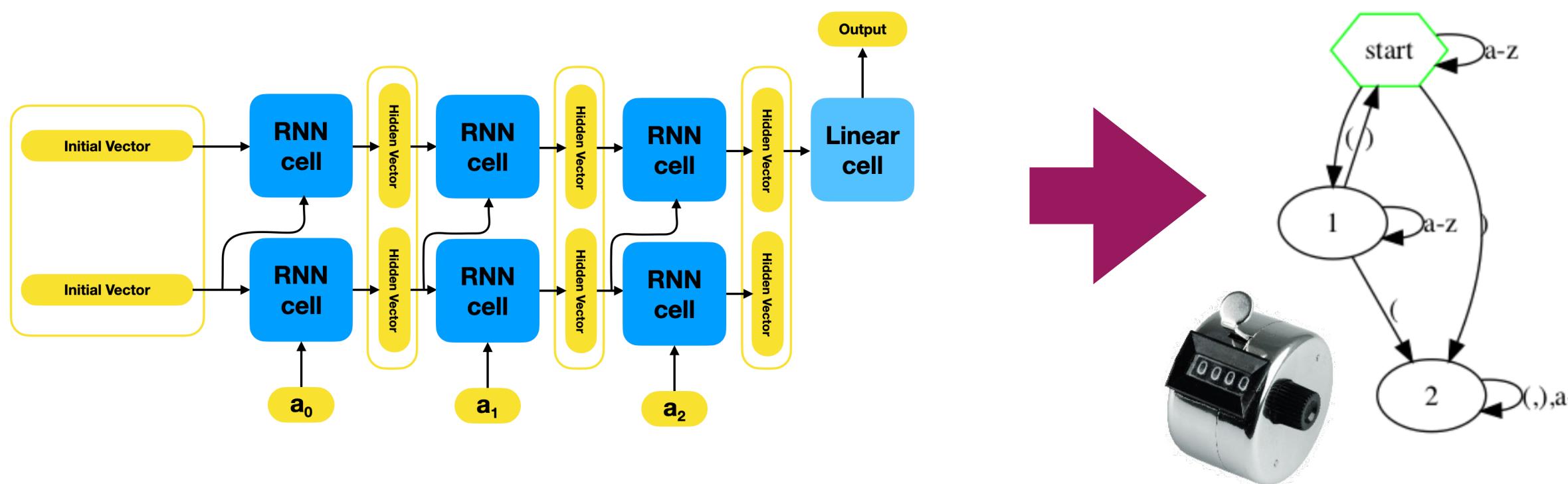
ablations too - manipulating time of IH appearance, removing IHs

In-context learning and induction heads, Olsson et al, 2022

Recent investigation: What needs to go right for an induction head? A mechanistic study of in-context learning circuits and their formation, Singh et al, 2024

Can't we just turn the networks
into interpretable models?

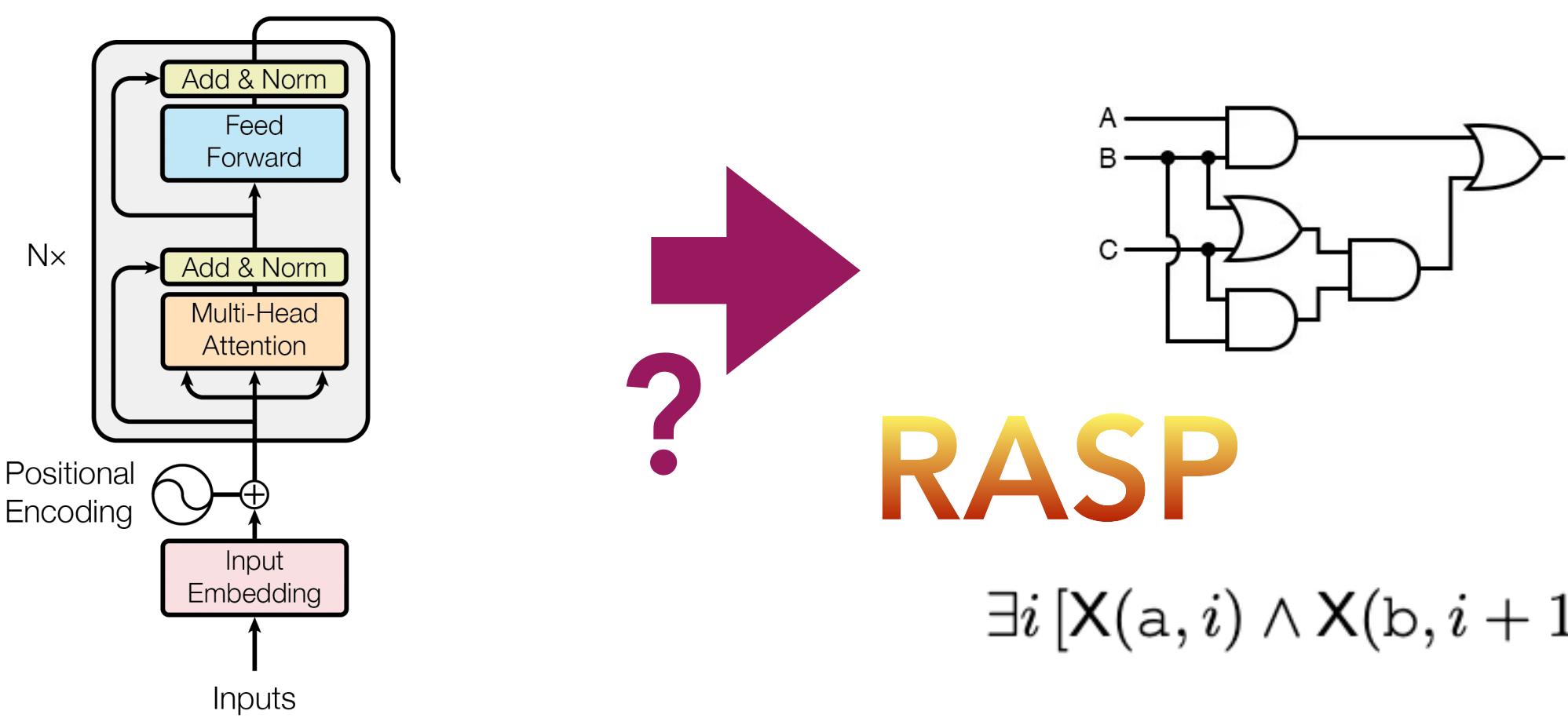
Extraction



Extraction of rules from discrete-time recurrent neural networks,
Omlin and Giles, 1996

Extracting automata from recurrent neural networks using queries and
counterexamples,
Weiss et al, 2018

Extracting context-free grammars from recurrent neural networks using tree-
automata learning and A* search,
Barbot et al, 2021



Proposes relevant model (RASP):
Thinking like transformers, Weiss et al, 2021

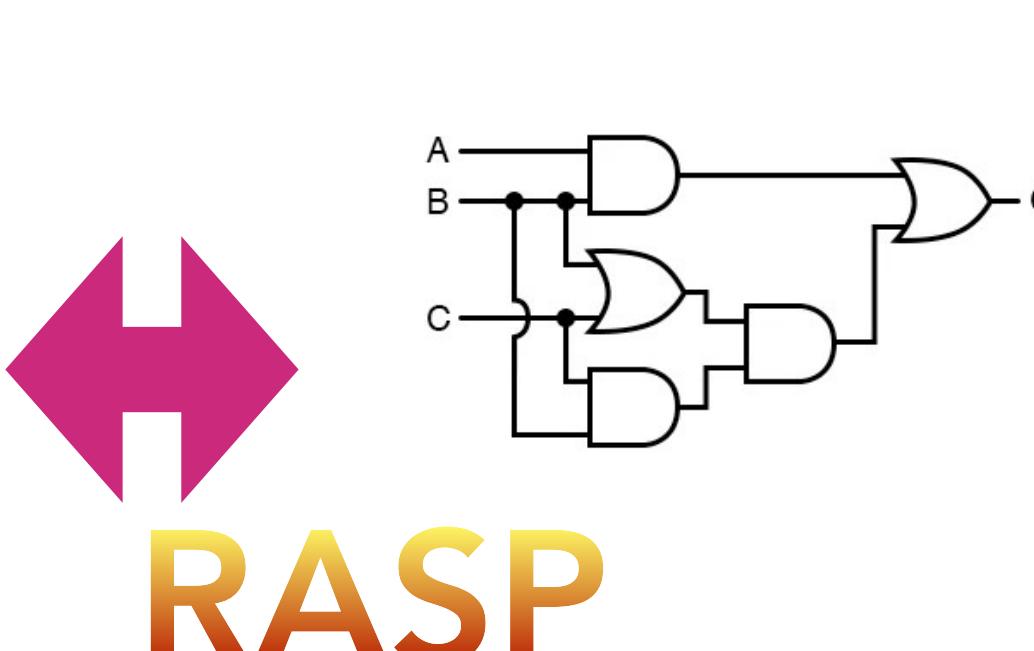
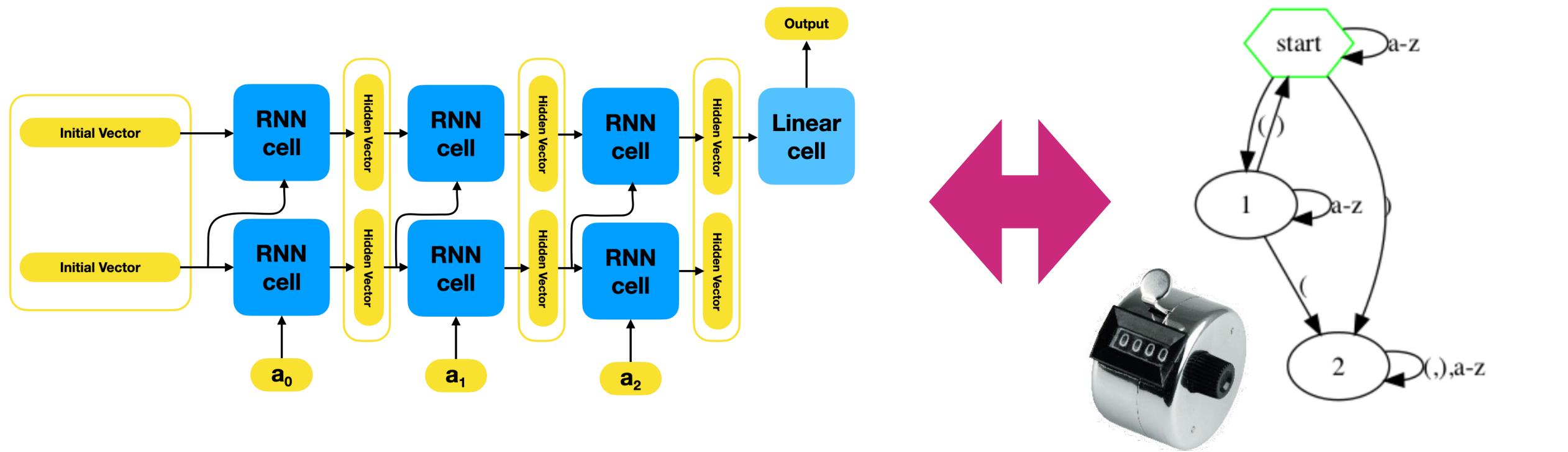
Proposes relevant playground (Tracr):
Compiled transformers as a laboratory for interpretability, Lindner et al, 2023

Proposes inherently interpretable models:
Learning transformer programs, Friedman et al, 2023

What about some theory

Formal Analysis/Expressivity

Understanding NN power with the help of formal tasks



$$\exists i [X(a, i) \wedge X(b, i + 1)]$$

For example:

RNNs can learn regular languages!

Transformers struggle, but can learn shortcuts...

RNNs can't practically reverse or copy

Transformers can

Insights could inspire architecture design

A survey of neural networks and formal languages: Ackerman and Cybenko, 2020

Formal language theory meets modern NLP, Merrill, 2021

Formal aspects of language modeling, Cotterell et al, 2023

Transformers as recognizers of formal languages: a survey on Expressivity, Strobl et al, 2023

Conclusion

NNs have taken over, but **we don't understand them**

A huge variety of methods to attempt explaining decisions has sprung up in response

We must be careful to not fool ourselves when working with them: **we must not draw conclusions from intuitions alone**

Good understanding facilitates **adversarial input discovery, model editing, ...**

Nice resource (though doesn't cover everything here):
Interpretable Machine Learning, Christoph Molnar, 2023
<https://christophm.github.io/interpretable-ml-book/>