Gradient Based Circuits Discovery

by Pablo Talavante

Goal

Have an easy to implement method that can provide insights when looking for circuits

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Have an easy to implement method that can provide insights when looking for circuits

General method that tell us *where to look*

Hypothesis

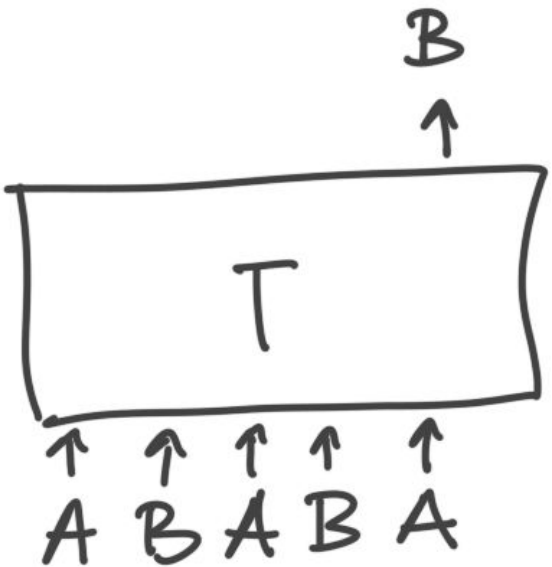
Given a transformer-based model **M**, and a task **T**, for which obtaining a correct answer **only** a (correctly working) circuit **C** is needed, the **gradients** in **M** for the weights involved in **C** will be maximal in a backward pass where the prediction is compared (via a loss function) to a **maximally wrong** answer.

Hypothesis

If we consider this scenario, to **detect** a circuit we would have to choose a **task** for which know **just C** is needed, get a prediction and get the **gradients** of the loss function comparing the prediction with the **maximally wrong answer**.

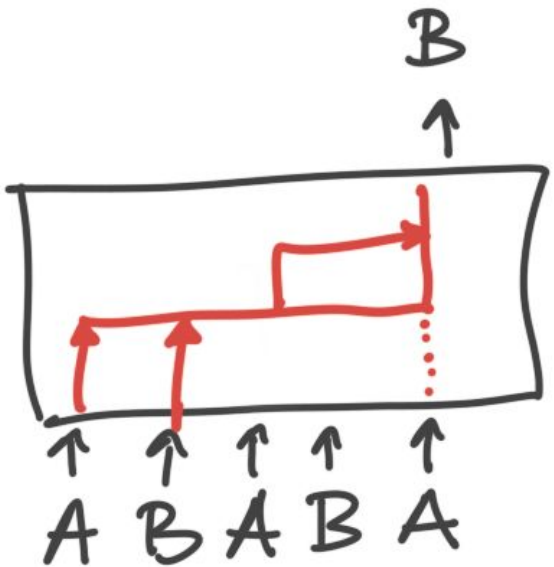
Eg.: induction circuits, IOI circuits

Task example



$\mathcal{L}(B, \bar{B})$

Task example



$\mathcal{L}(B, \bar{B})$

$\nabla \mathcal{L}(B, \bar{B})$

Task example

(as described in ACDC paper)

Task	Example Prompt	Output	Metric
1: IOI (Appendix E.2)	"When John and Mary went to the store, Mary gave a bottle of milk to"	"_John"	Logit difference

2: Docstring (Appendix G.1)	`def f(self, files, obj, state, size, shape, option):`
	`  """document string example`
	
	`  :param state: performance analysis`
	`  :param size: pattern design`
	`  :param`
		"_shape"	Logit difference

3: Greater-Than (Appendix F)	"The war lasted from 1517 to 15"	"18" or "19" or ... or "99"	Probability difference
4: tracr-xproportion (Appendix H.1)	`["a", "x", "b", "x"]`	`[0, 0.5, 0.33, 0.5]`	Mean Squared Error
5: tracr-reverse (Appendix H.2)	`[0, 3, 2, 1]`	`[1, 2, 3, 0]`	Mean Squared Error
6: Induction (Section 4.2)	"Vernon *Durs*ley and Petunia *Durs*"	"ley"	Negative log-probability

Maximally wrongness

How we define the maximally (optimally) wrong answer?

Possible definitions:

- most dissimilar token ?
- inverse of the logits ?
- logit difference ?
- semantics ?

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OPEN (?) QUESTION

Implementation (on GPT2-small)

```
idx_john = t2idx[' John']
idx_mary = t2idx[' Mary']

text_A = 'When Mary and John went to the store, Mary gave a drink to'
text_B = 'When Mary and John went to the store, John gave a drink to'
input_ids_A, hidden_state_A, out_A = generate_sequence(text_A)
input_ids_B, hidden_state_B, out_B = generate_sequence(text_B)

loss = F.mse_loss(out_A[:, -1, idx_john],
                  out_A[:, -1, idx_mary]) + \
       F.mse_loss(out_B[:, -1, idx_john],
                  out_B[:, -1, idx_mary])
loss.backward()
```

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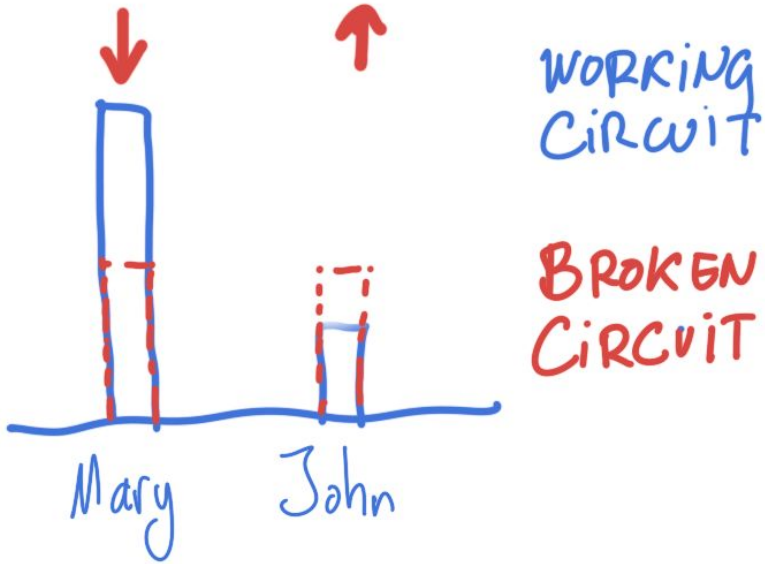
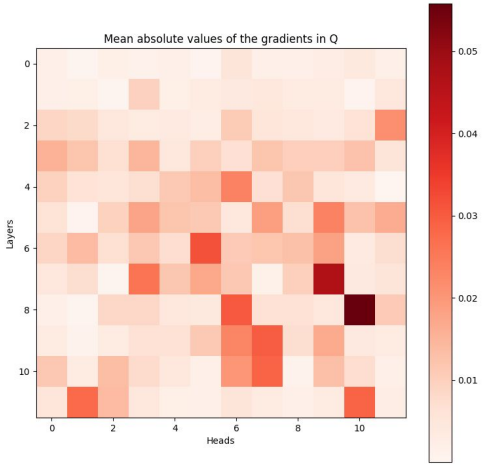
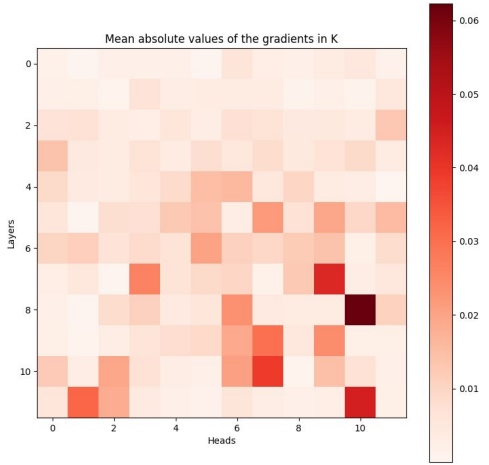
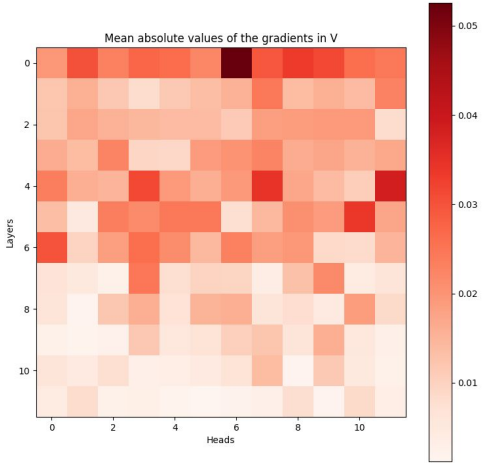
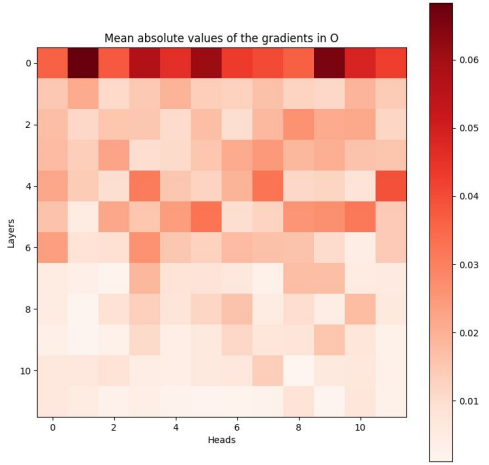


Results

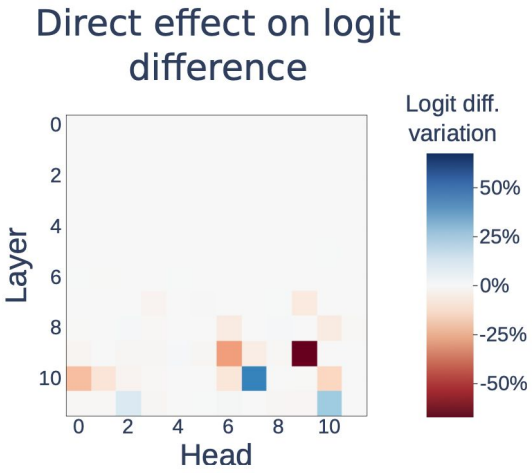

Mean absolute values of the gradients in Q
Layers
Heads
0
2
4
6
8
10
0.05
0.04
0.03
0.02
0.01

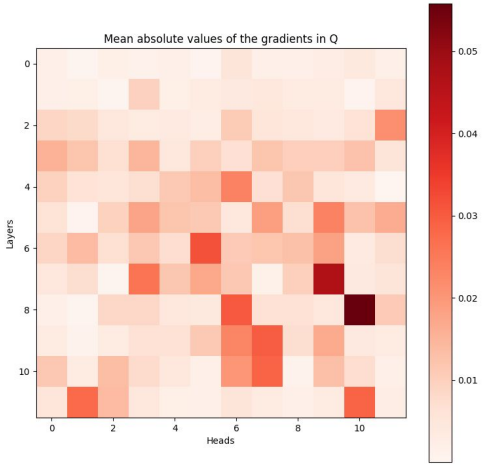

Mean absolute values of the gradients in K
Layers
Heads
0
2
4
6
8
10
0.06
0.05
0.04
0.03
0.02
0.01

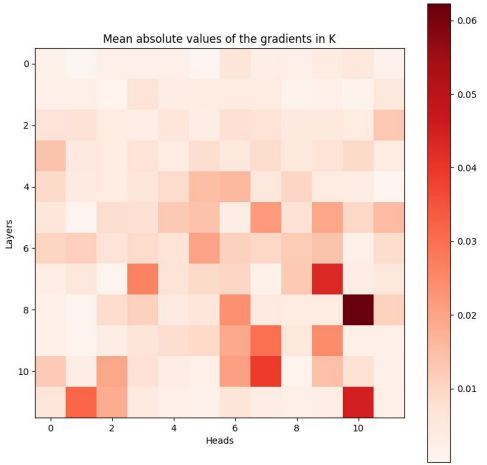

Mean absolute values of the gradients in V
Layers
Heads
0
2
4
6
8
10
0.05
0.04
0.03
0.02
0.01

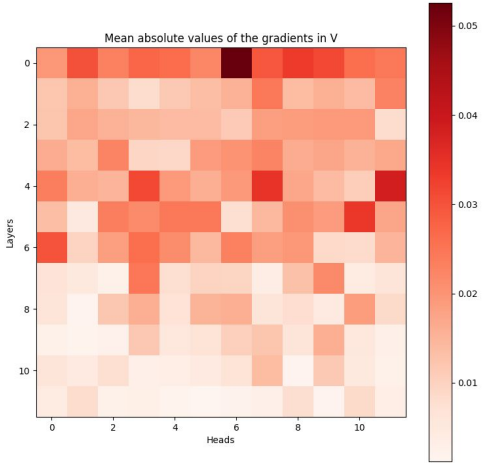

Mean absolute values of the gradients in O
Layers
Heads
0
2
4
6
8
10
0.06
0.05
0.04
0.03
0.02
0.01

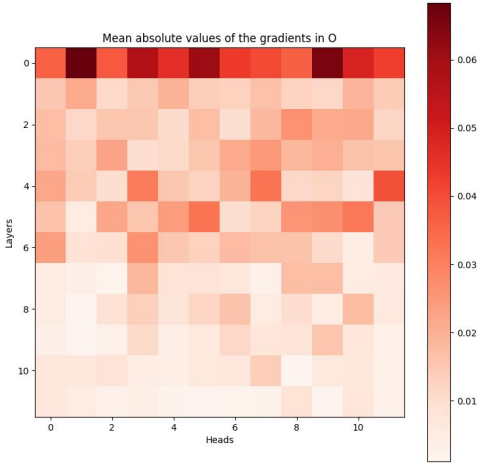
Results


Direct effect on logit difference
Logit diff. variation
50%
25%
0%
-25%
-50%
Layer
Head
0
2
4
6
8
10

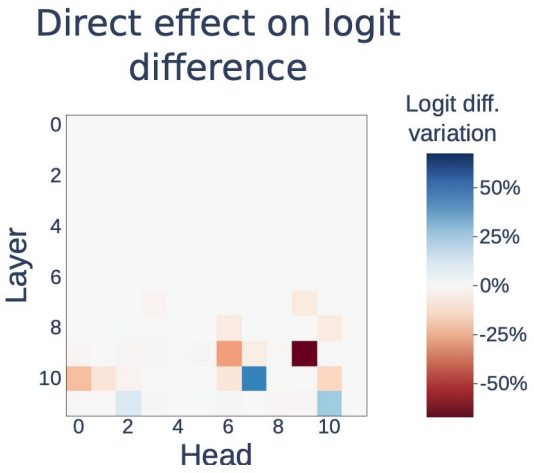

Mean absolute values of the gradients in Q
Layers
Heads


Mean absolute values of the gradients in K
Layers
Heads


Mean absolute values of the gradients in V
Layers
Heads


Mean absolute values of the gradients in O
Layers
Heads

Results


Direct effect on logit difference
Logit diff. variation
50%
25%
0%
-25%
-50%
Layer
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0
2
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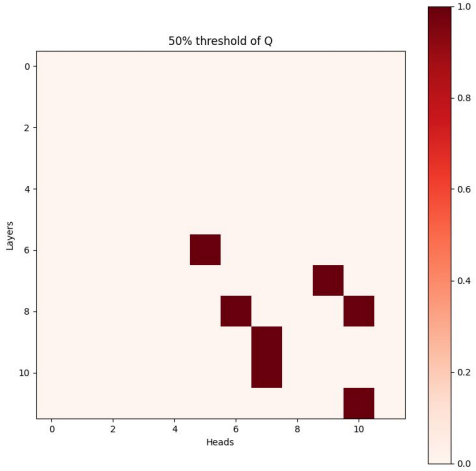
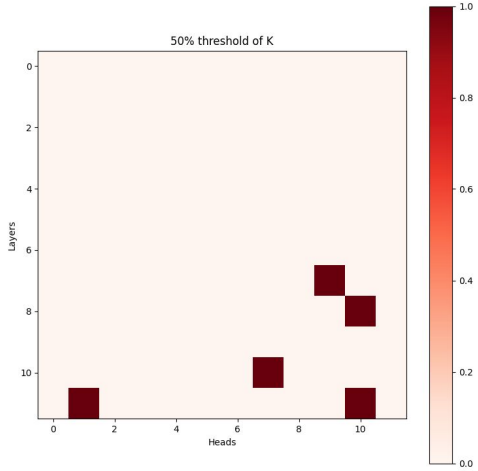
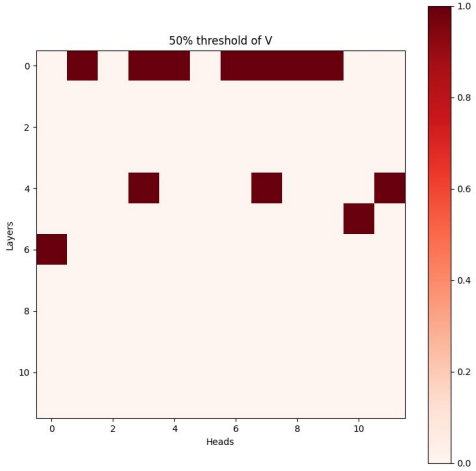
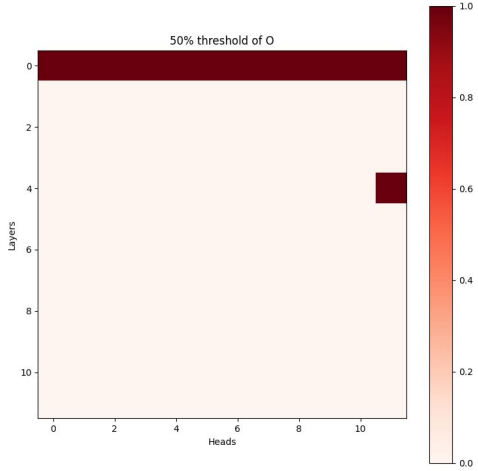
10


50% threshold of Q
Layers
Heads


50% threshold of K
Layers
Heads


50% threshold of V
Layers
Heads


50% threshold of O
Layers
Heads

Pros

- There are no causal interventions
- Easy to implement
- Can give first insights on where to look

Cons

- There are no causal interventions
- Noisy outputs (due to circuit interference?)
- You work with gradients, which have a much larger dimensionality than activations

Thanks for your attention