



**Figure 3: Causal effects with a modified computation graph.** (a,b) To isolate the effects of MLP modules when measuring causal effects, the computation graph is modified. (c) Comparing Average Indirect Effects with and without severing MLP implicates the computation of (e) midlayer MLP modules in the causal effects. No similar gap is seen when attention is similarly severed.

## 2.2 Causal Tracing Results

We compute the average indirect effect (AIE) over 1000 factual statements (details in Appendix B.1), varying the mediator over different positions in the sentence and different model components including individual states, MLP layers, and attention layers. Figure 2 plots the AIE of the internal components of GPT-2 XL (1.5B parameters). The ATE of this experiment is 18.6%, and we note that a large portion of the effect is mediated by strongly causal individual states (AIE=8.7% at layer 15) at the last subject token. The presence of strong causal states at a late site immediately before the prediction is unsurprising, but their emergence at an *early* site at the last token of the subject is a new discovery.

Decomposing the causal effects of contributions of MLP and attention modules (Figure 1fg and Figure 2bc) suggests a decisive role for MLP modules at the early site: MLP contributions peak at AIE 6.6%, while attention at the last subject token is only AIE 1.6%; attention is more important at the last token of the prompt. Appendix B.2 further discusses this decomposition.

Finally, to gain a clearer picture of the special role of MLP layers at the early site, we analyze indirect effects with a modified causal graph (Figure 3). (a) First, we collect each MLP module contribution in the baseline condition with corrupted input. (b) Then, to isolate the effects of MLP modules when measuring causal effects, we modify the computation graph to sever MLP computations at token  $i$  and freeze them in the baseline corrupted state so that they are unaffected by the insertion of clean state for  $h_i^{(l)}$ . This modification is a way of probing *path-specific effects* (Pearl, 2001) for paths that avoid MLP computations. (c) Comparing Average Indirect Effects in the modified graph to those in the original graph, we observe (d) the lowest layers lose their causal effect without the activity of future MLP modules, while (f) higher layer states’ effects depend little on the MLP activity. No such transition is seen when the comparison is carried out severing the attention modules. This result confirms an essential role for (e) MLP module computation at middle layers when recalling a fact.

Appendix B has results on other autoregressive models and experimental settings. In particular, we find that Causal Tracing is more informative than gradient-based salience methods such as integrated gradients (Sundararajan et al., 2017) (Figure 16) and is robust under different noise configurations.

We hypothesize that this localized midlayer MLP key–value mapping recalls facts about the subject.

## 2.3 The Localized Factual Association Hypothesis

Based on causal traces, we posit a specific mechanism for storage of factual associations: each midlayer MLP module accepts inputs that encode a subject, then produces outputs that recall memorized properties about that subject. Middle layer MLP outputs accumulate information, then the summed information is copied to the last token by attention at high layers.

This hypothesis localizes factual association along three dimensions, placing it (i) in the MLP modules (ii) at specific middle layers (iii) and specifically at the processing of the subject’s last token. It is consistent with the Geva et al. (2021) view that MLP layers store knowledge, and the Elhage et al. (2021) study showing an information-copying role for self-attention. Furthermore, informed by the Zhao et al. (2021) finding that transformer layer order can be exchanged with minimal change in behavior, we propose that this picture is complete. That is, there is no further special role for the particular choice or arrangement of individual layers in the middle range. We conjecture that any fact