

## 1 Variable definition

$$X, X' \in R^{b \times t \times d_{\text{model}}} \quad (1)$$

$$Z, Z' \in R^{b \times t \times d_{\text{ff}}} \quad (2)$$

$$W_U, W_G \in R^{b \times d_{\text{model}} \times d_{\text{ff}}} \quad (3)$$

$$W_D \in R^{b \times d_{\text{ff}} \times d_{\text{model}}} \quad (4)$$

## 2 Forward Path

$$X' = \text{norm}(X) \times W_N \quad (5)$$

$$Z = X' W_U \quad (6)$$

$$Z' = \text{Silu}(X' W_G) \times Z \quad (7)$$

$$Y = Z' W_D + X \quad (8)$$

## 3 Problem setting

Given a question  $(s, r)$  that can't be answered by model  $f$ 's knowledge but can be answered by being given fact  $(s, r, o)$  through In-Context Learning. We want to build a new model  $\hat{f}$  that doesn't need In-Context Learning to answer the question. This is what we call an Edit Success.

$$\hat{f}((s, r)) \approx f(\text{Concat}((s, r, o), (s, r))) = o \quad (9)$$

$$\hat{f}(\text{"Who won 2026 UEFA Champions league ?"}) \approx f(\text{"Manchester City won 2026 UEFA Champions league. Who won 2026 UE"}) \quad (10)$$

If we then give a question  $(s', r)$  or  $(s, r')$  with  $s$  paraphrasing  $s'$  and  $r$  paraphrasing  $r'$ , the new model should generalize by answering without In-Context Learning. This is what we call respectively subject generalization and relation generalization.

$$\hat{f}((s', r)) \approx f(\text{Concat}((s, r, o), (s, r))) = o \quad (11)$$

$$\hat{f}(\text{"Who won 2026 most famous European football league ?"}) \approx f(\text{"Manchester City won 2026 UEFA Champions league. Who"}) \quad (12)$$

$$\hat{f}((s, r')) \approx f(\text{Concat}((s, r, o), (s, r))) = o \quad (13)$$

$$\hat{f}(\text{"Who got the trophy of the 2026 UEFA Champions league ?"}) \approx f(\text{"Manchester City won 2026 UEFA Champions league. Who"}) \quad (14)$$

If we now give a question  $(s'', r)$  or  $(s, r'')$  with  $s \neq s''$  and  $r \neq r''$  that shouldn't be modified by knowing fact  $(s, r, o)$ , our new model should behave the same as the base model. This is what we call respectively subject specificity and relation specificity.

$$\hat{f}((s'', r)) \approx f((s'', r)) = o'' \quad (15)$$

$$\hat{f}(\text{"Who won 2024 UEFA Champions league ?"}) \approx f(\text{"Who won 2024 UEFA Champions league ?"}) = \text{"Real Madrid"} \quad (16)$$

Or

$$\hat{f}((s, r'')) \approx f((s, r'')) = o'' \quad (17)$$

$$\hat{f}(\text{"When does the 2026 UEFA Champions league starts ?"}) \approx f(\text{"When does the 2026 UEFA Champions league starts?") = "S} \quad (18)$$

Given a fact  $(s, r''', o'''')$  already known by the base model without In-Context Learning, the model should be able to answer a multihop question such as  $((s, r), r''')$ .

$$\hat{f}(((s, r), r''')) \approx f(Concat((s, r, o), ((s, r), r'''))) = o''' \quad (19)$$

$$\hat{f}(\text{"From which country is the team that won 2026 UEFA Champions league ?"}) \approx f(\text{"Manchester City won 2026 UEFA Champ}) \quad (20)$$

## 4 Update weight

$$W_U^{new} = Concat(W_U, W_U^{update}) \quad (21)$$

$$W_G^{new} = Concat(W_G, W_G^{update}) \quad (22)$$

$$W_D^{new} = Concat(W_D, W_D^{update}) \quad (23)$$

$$Z^{update}, Z'^{update} \in R^{(b \times t) \times (n_{edit} \times n_{tok})} \quad (24)$$

$$W_U^{update}, W_G^{update} \in R^{b \times d_{model} \times (n_{edit} \times n_{tok})} \quad (25)$$

$$W_D^{update} \in R^{b \times (n_{edit} \times n_{tok}) \times d_{model}} \quad (26)$$

## 5 New variables defintion

$$Z^{new}, Z'^{new} \in R^{b \times t \times (d_{ff} + (n_{edit} \times n_{tok}))} \quad (27)$$

$$W_U^{new}, W_G^{new} \in R^{b \times d_{model} \times (d_{ff} + (n_{edit} \times n_{tok}))} \quad (28)$$

$$W_D^{new} \in R^{b \times (d_{ff} + (n_{edit} \times n_{tok})) \times d_{model}} \quad (29)$$

## 6 Updated forward path

$$W_U^{update} = W_G^{update} = \frac{X'^{err}}{\|X'^{err}\|_2^2} \quad (30)$$

$$Z^{update} = X'^{err} W_U^{update} \quad (31)$$

$$Z'^{update} = Silu(X'^{err} W_G^{update}) \times Z^{update} \quad (32)$$

$$Z'^{update} = Silu(X'^{err} W_U^{update}) \times Z^{update} \quad (33)$$

$$Z'^{update} = Silu(Z^{update}) \times Z^{update} \quad (34)$$

$$Z'^{update} = Z^{update}^2 \times Sigmoid(Z^{update}) \quad (35)$$

$$Z'^{update} W_D^{update} = Y^{gld} - Y^{err} \quad (36)$$

## 7 Details of $W_D^{update}$ computation

$$Y^{new} = Z'^{new} W_D^{new} \quad (37)$$

$$Y^{new} = Concat(Z', Z'^{update}) Concat(W_D, W_D^{update}) + X \quad (38)$$

$$Y^{new} = Z' W_D + Z'^{update} W_D^{update} + X_{err} \quad (39)$$

$$Y^{new} = Y^{err} + Z'^{update} W_D^{update} \quad (40)$$

$$Y^{gld} = Y^{err} + Z'^{update} W_D^{update} \quad (41)$$

$$Y^{gld} - Y^{err} = Z'^{update} W_D^{update} \quad (42)$$

$$W_D^{update} = Z'^{update-1} (Y^{gld} - Y^{err}) \quad (43)$$

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