IIC3670 Procesamiento de Lenguaje Natural

https://github.com/marcelomendoza/IIC3670

Generación condicional con atención

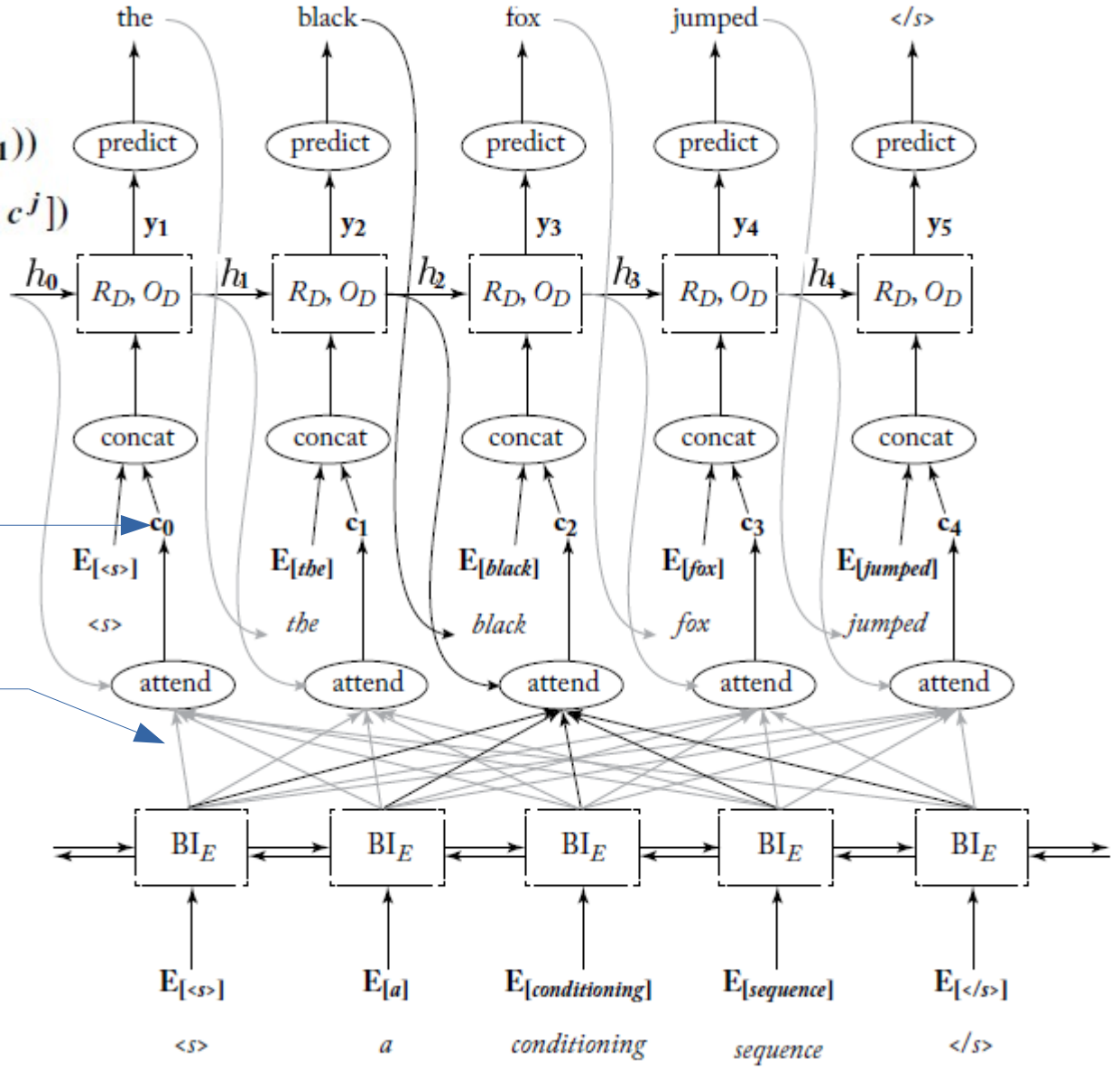
$$p(t_{j+1} = k \mid \hat{t}_{1:j}, x_{1:n}) = f(O_{\text{dec}}(h_{j+1}))$$

$$h_{j+1} = R_{\text{dec}}(h_j, [\hat{t}_j; c^j])$$

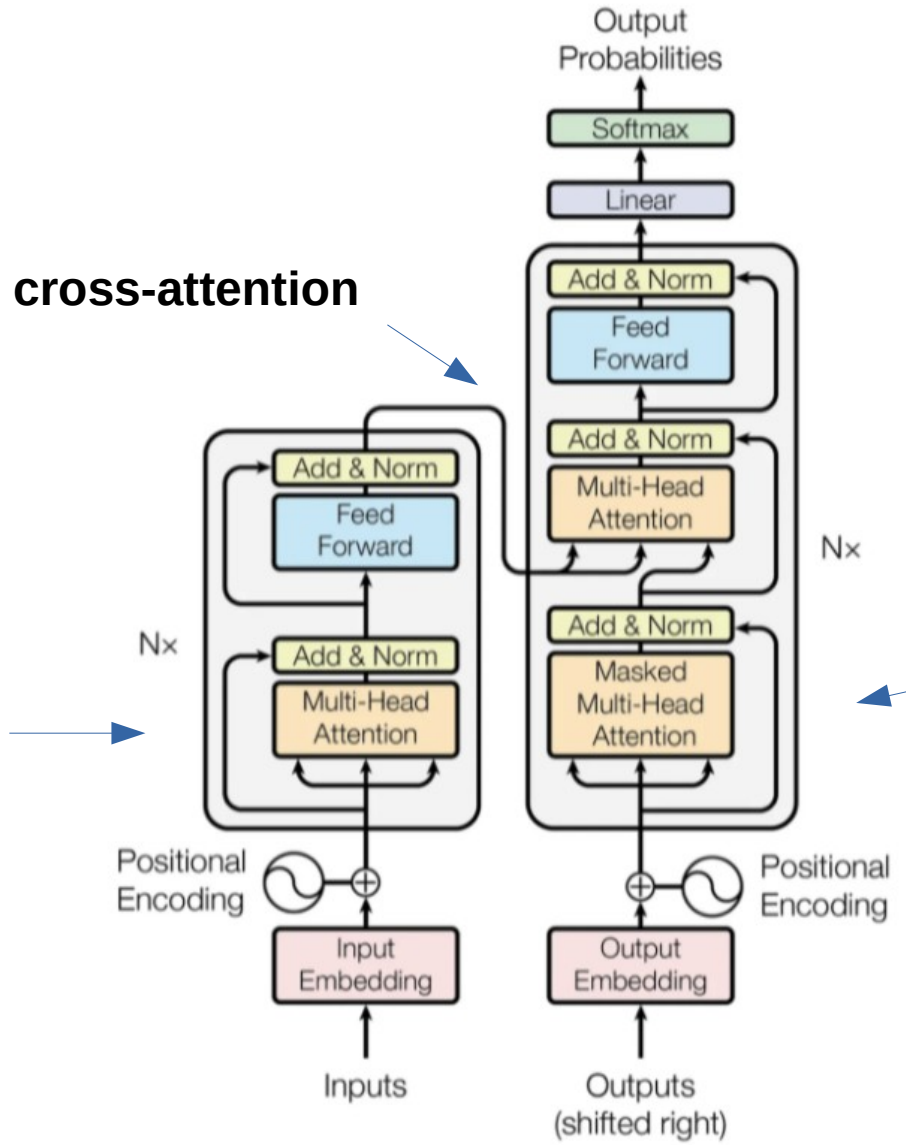
$$c^j = \sum_{i=1}^{n} \alpha^j_{[i]} \cdot c_i$$

$$\bar{\alpha}^j_{[i]} = \text{MLP}^{\text{att}}(h_j; c_i])$$

$$c_{1:n} = \text{biRNN}^{\star}_{\text{enc}}(x_{1:n})$$



Generación condicional con atención (transformer seq2seq)



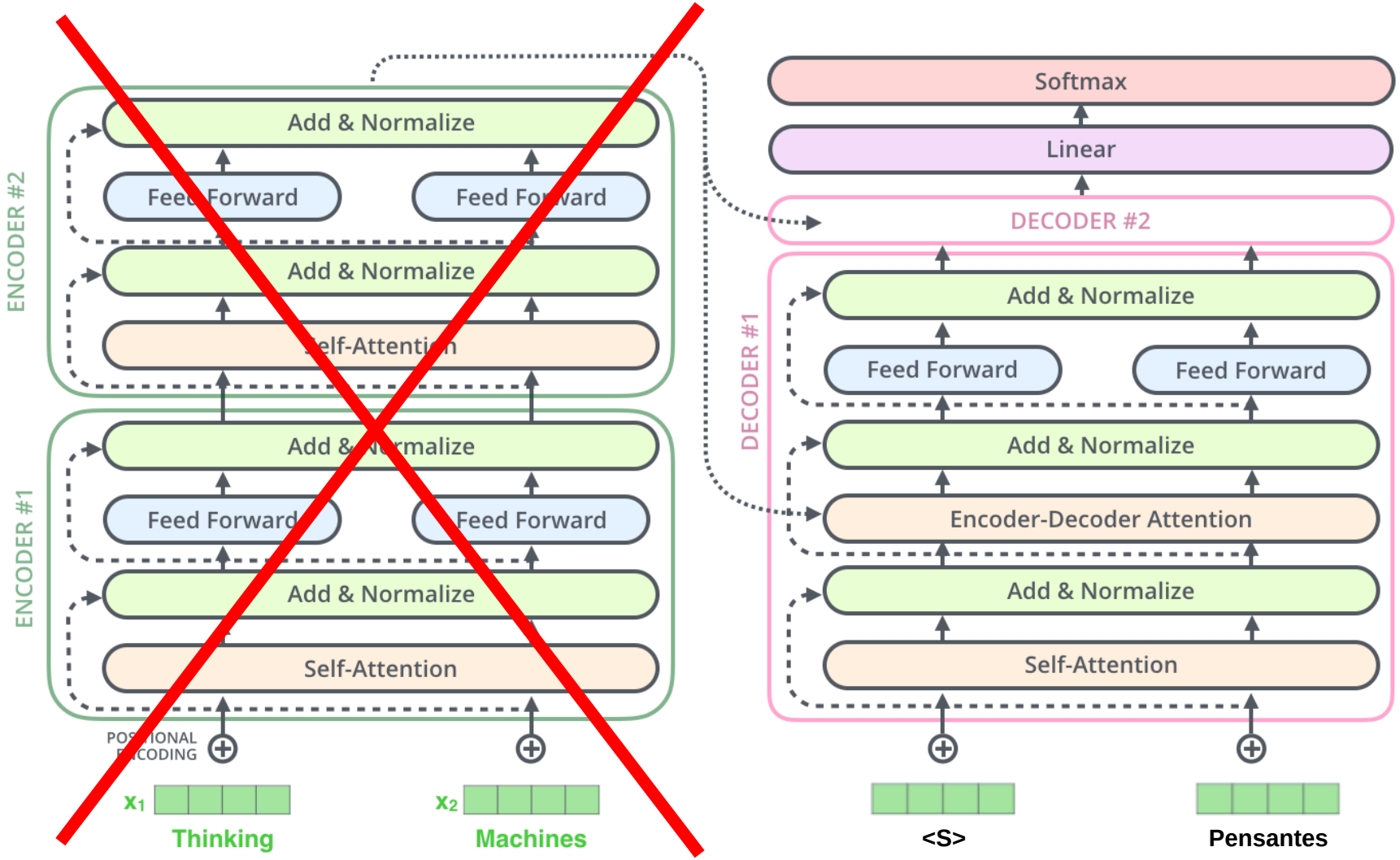
cross-attention

global attention

causal attention

- GENERATIVE PRETRAINED TRANSFORMERS -

Se elimina el encoder!!!



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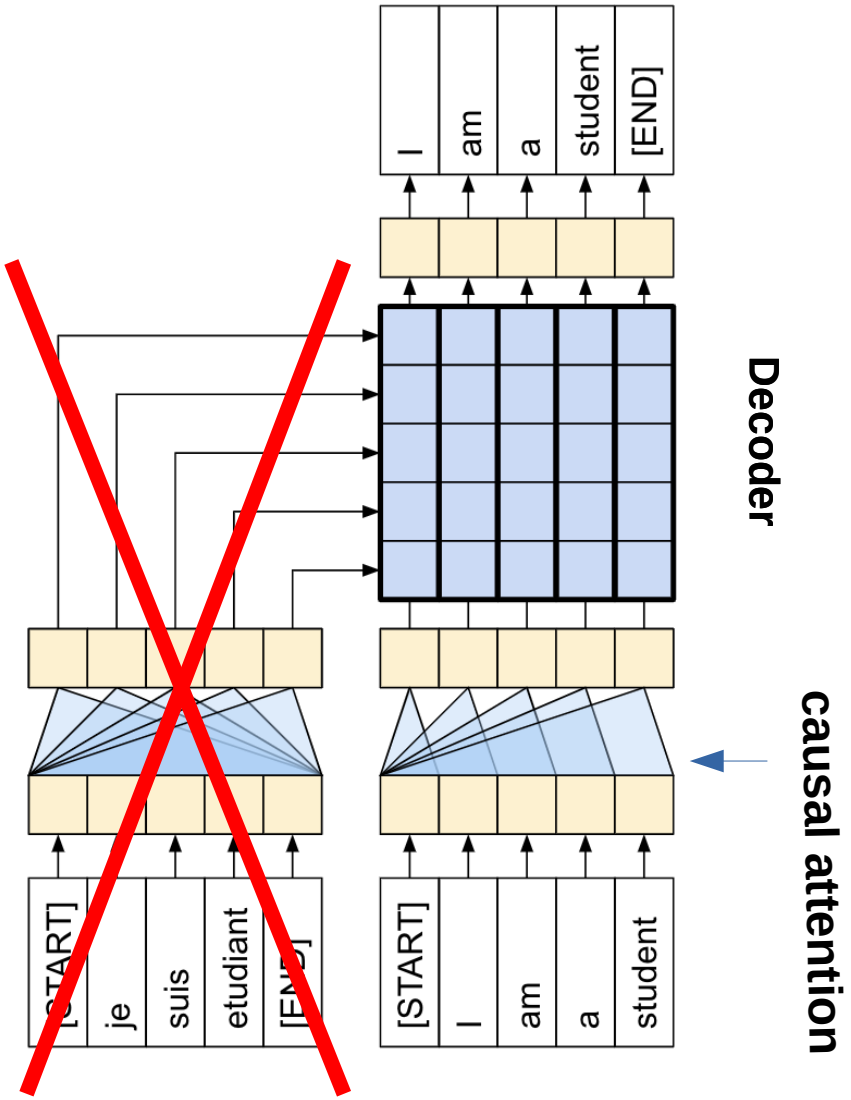


Transformer decoder

Seq2seq

- Cada secuencia $(m^1, ..., m^n) \mapsto (y^1, ..., y^\eta)$

se transforma en:

Símbolo separador

$$(w^1, ..., w^{n+\eta+1}) = (m^1, ..., m^n, \delta, y^1, ..., y^\eta)$$

- Luego, el **decoder** resuelve la siguiente tarea:

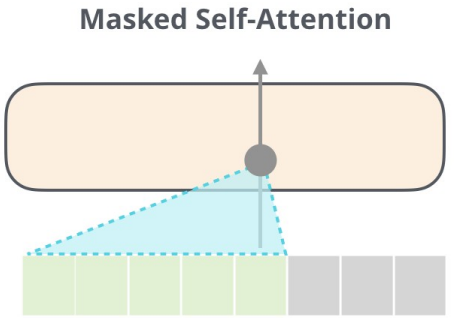
secuencias largas

$$p(w^1, ..., w^{n+\eta}) = \prod_{j=1}^{n+\eta} p(w^i | w^1, ..., w^{j-1})$$

Transformer decoder

Las oraciones van a ser más largas

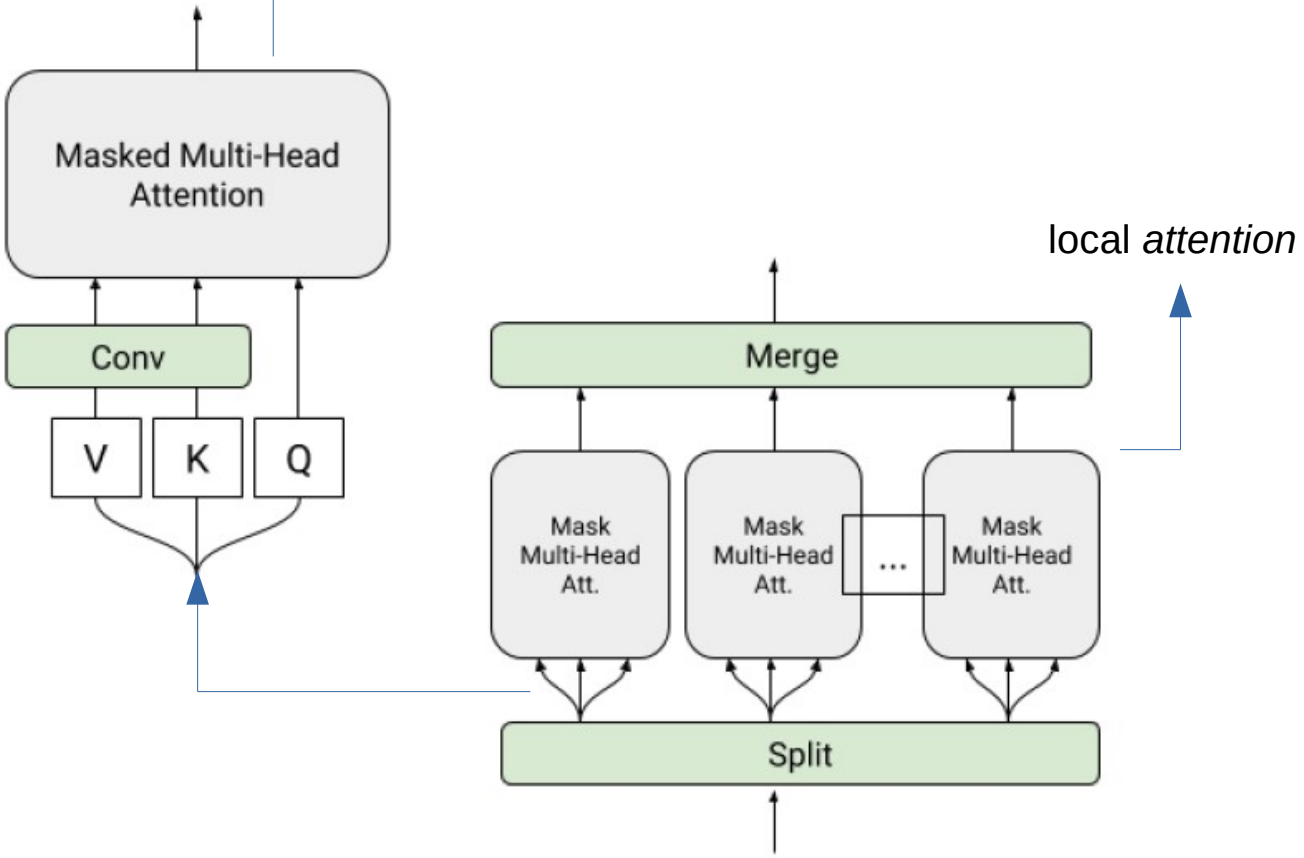
Modelo **abstractivo**



Causal LM

Memory-compressed attention

local *attention*



Reduce las V y K usando kernels de 3x3

Divide la oración en *batches* del mismo tamaño

Transformer decoder

LLM

Mecanismo auto-regresivo

tokens

$$L_1(\mathcal{U}) = \sum_i \log P(u_i | u_{i-k}, \ldots, u_{i-1}; \Theta)$$

$$U = (u_{-k}, \ldots, u_{-1})$$ **contexto de u**

Token embedding matrix

$$h_0 = UW_e + W_p$$ Position embedding matrix

$$h_l = \texttt{transformer\_block}(h_{l-1}) \forall i \in [1, n]$$

#_layers

task $$P(u) = \texttt{softmax}(h_n W_e^T)$$

Idea propuesta en:

GENERATING WIKIPEDIA BY SUMMARIZING LONG SEQUENCES
Peter J. Liu, Mohammad Saleh,
Etienne Poty, Ben Goodrich, Ryan Sepassi, Łukasz Kaiser, Noam Shazeer
ICLR 2018

GPT 1

Transformer decoder + supervised fine tuning

$$L_1(\mathcal{U}) = \sum_i \log P(u_i | u_{i-k}, \ldots, u_{i-1}; \Theta)$$

Transformer decoder

$$P(y|x^1, \ldots, x^m) = \texttt{softmax}(h_l^m W_y).$$

Supervised fine-tuning

label

Última capa del transformer decoder

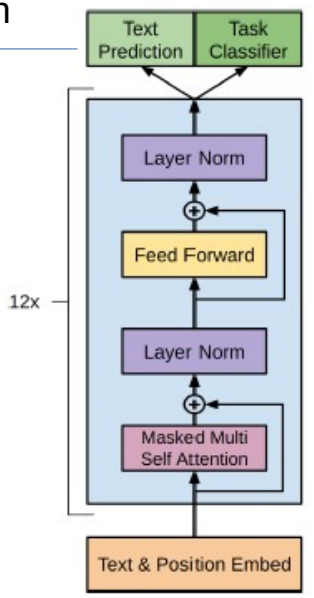
en LM *y* es un token

$$L_2(\mathcal{C}) = \sum_{(x,y)} \log P(y|x^1, \ldots, x^m).$$

La pérdida combinada es:

$$L_3(\mathcal{C}) = L_2(\mathcal{C}) + \lambda * L_1(\mathcal{C})$$

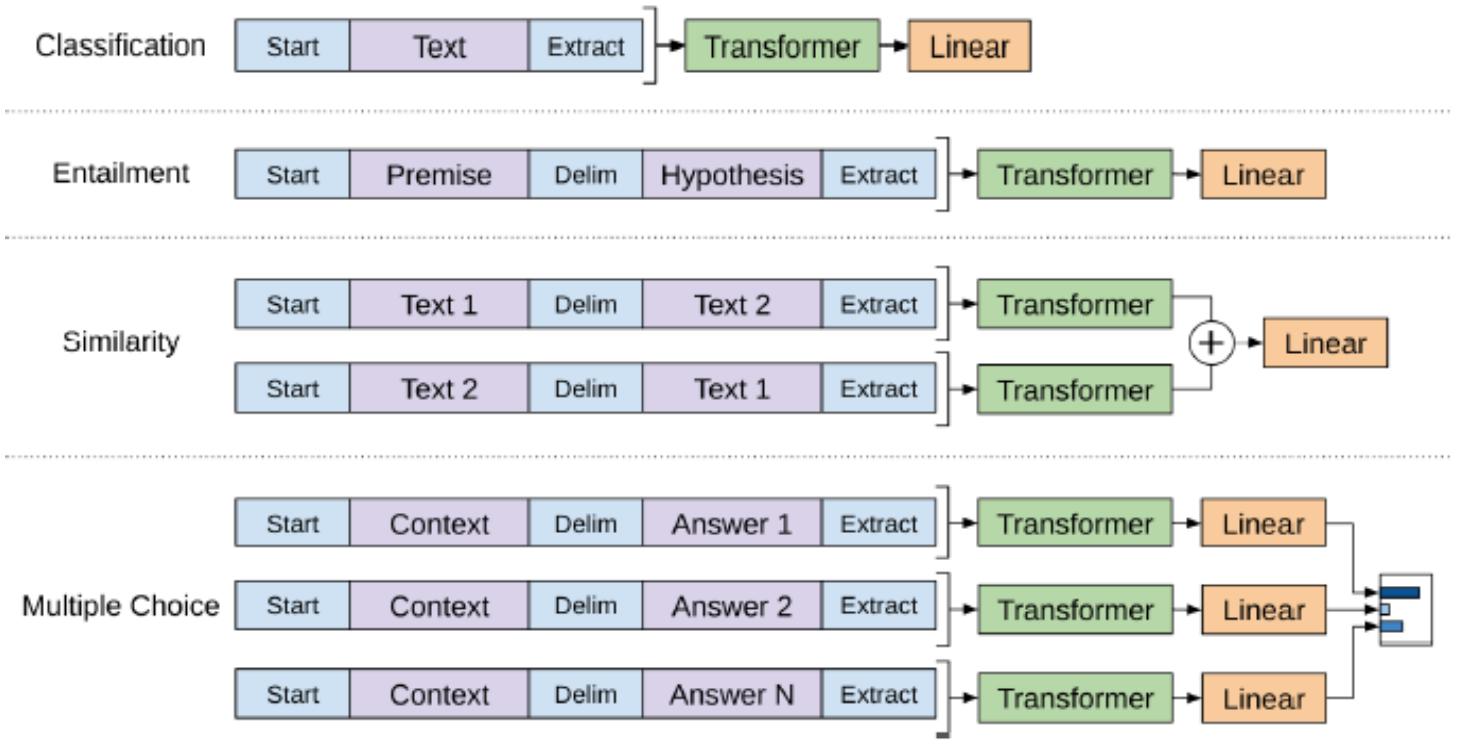
GPT 1 resuelve ambas tareas simultáneamente (LM y specific task)



GPT 1

Supervised fine-tuning

La secuencia de entrada depende de la tarea



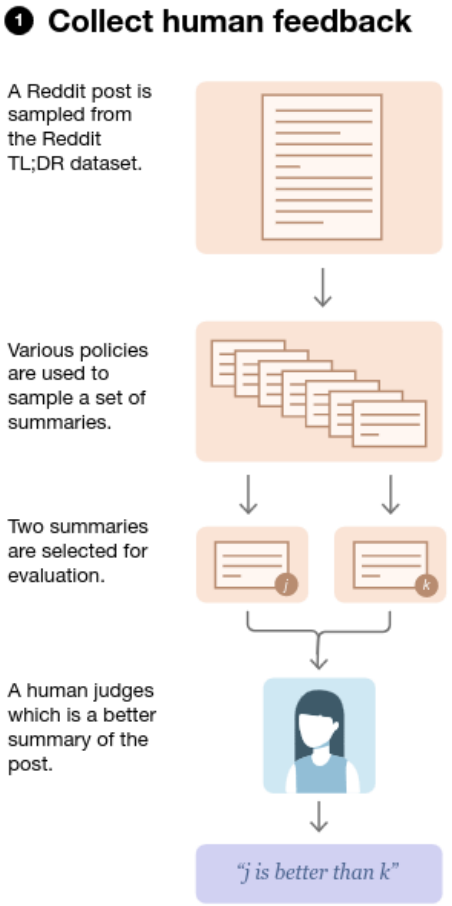
GPT 1

Radford, A., Narasimhan, K., Salimans, T., Sutskever, I. Improving language understanding by generative pre-training, 2018.

- INSTRUCT GPT -

Human in the loop

Inicialmente este tema se abordó para construcción de resúmenes



Stiennon et al. Learning to summarize from human feedback, NeurIPS 2020

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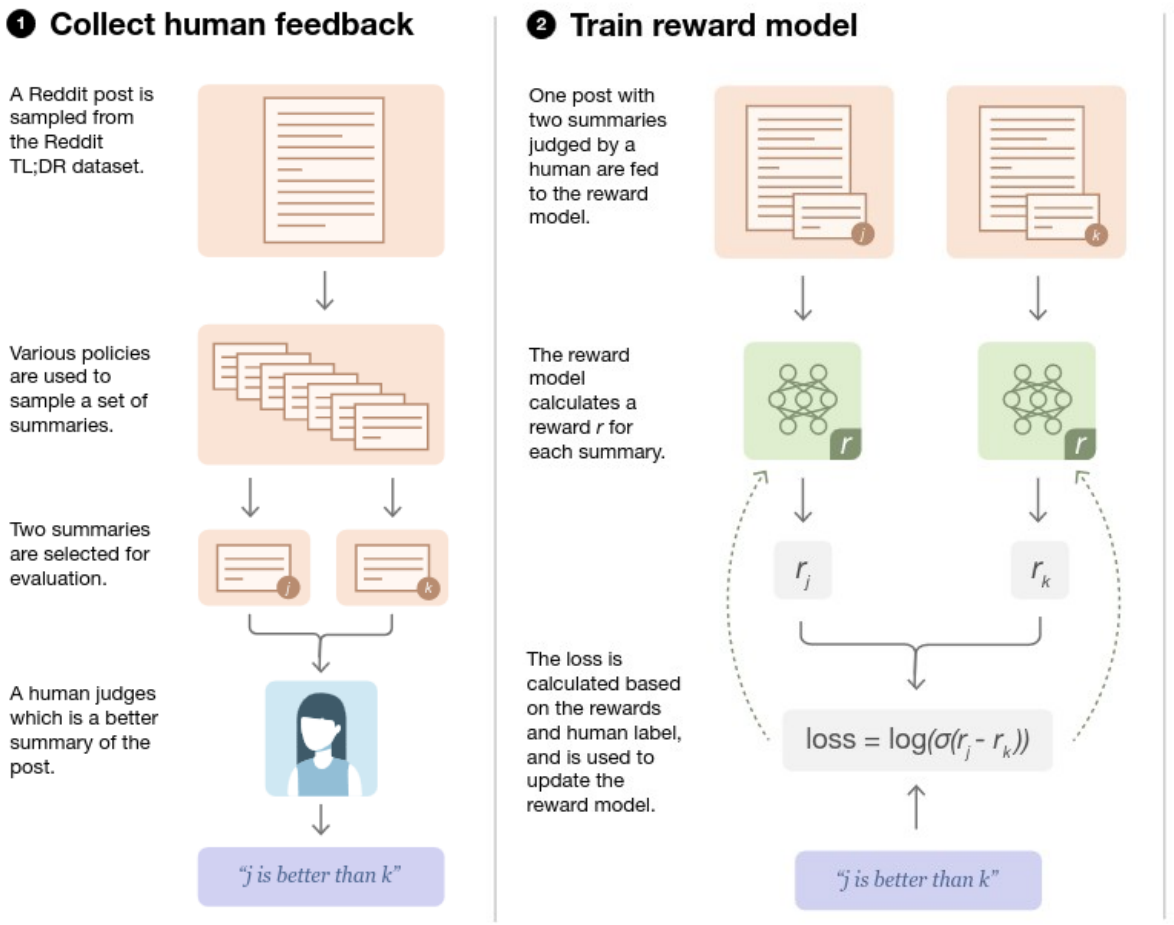

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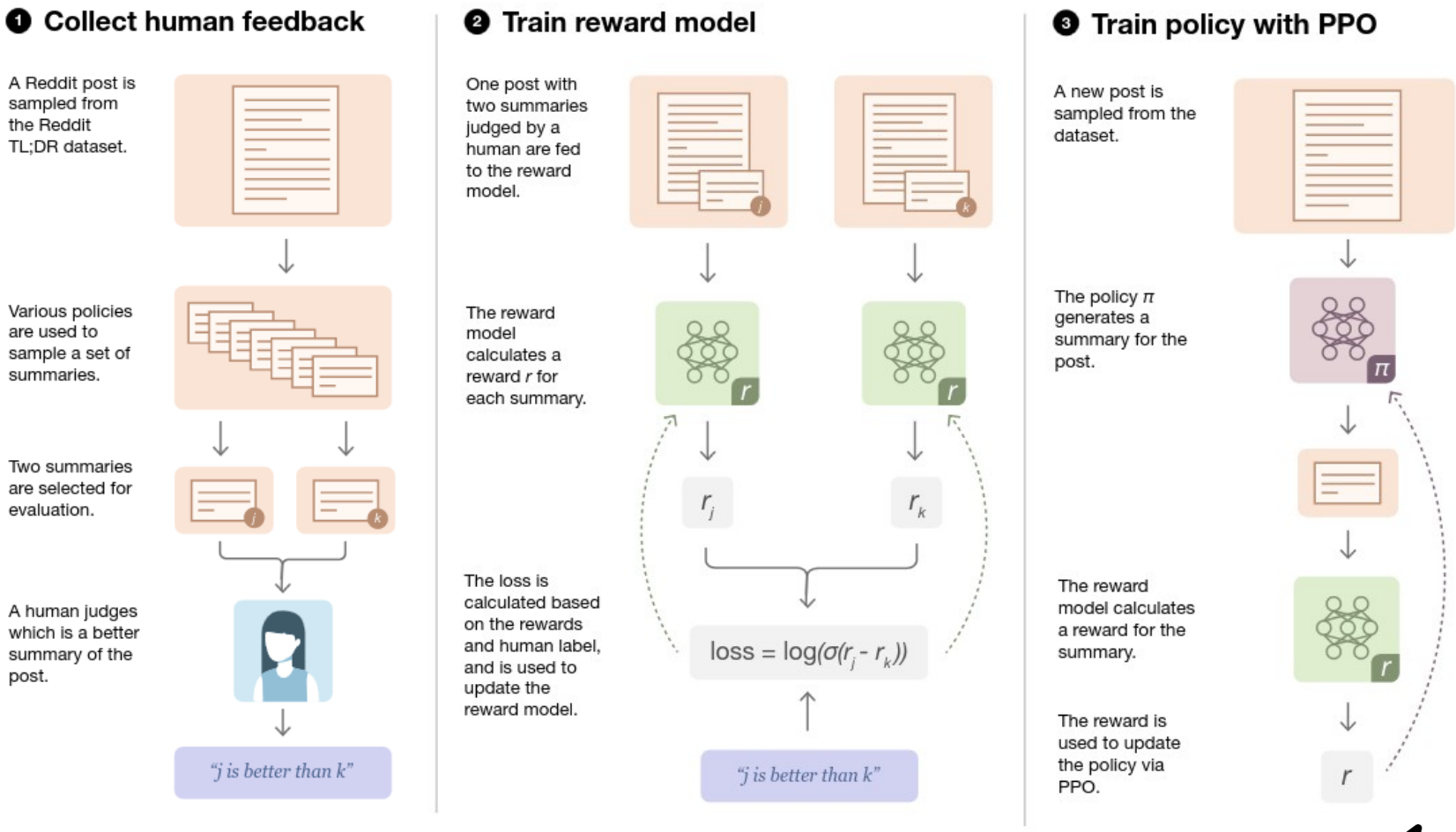

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Reward Model (RM)

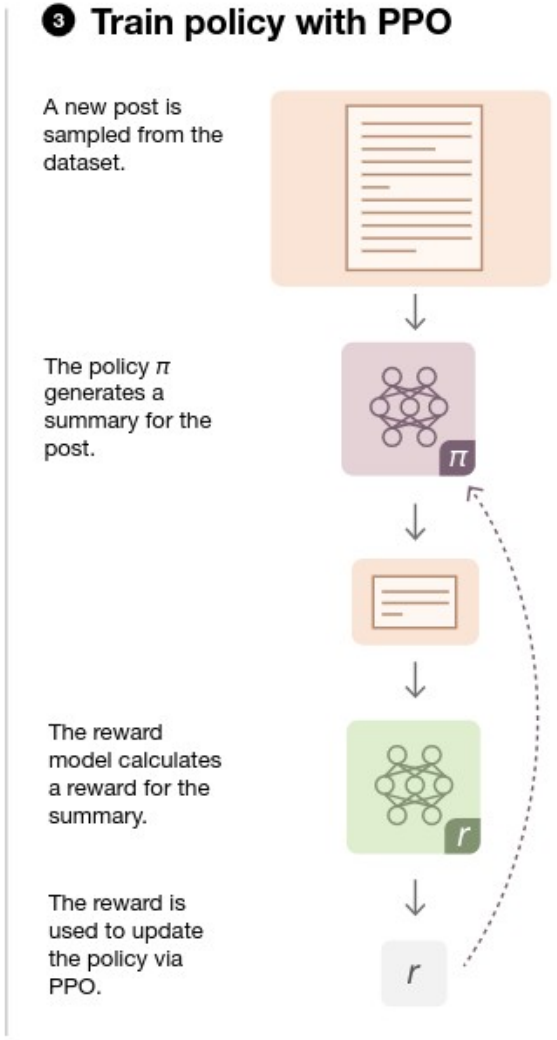
- El RM es un modelo lineal que entrega un escalar (regresión).
- Se entrena el modelo para predecir a partir de resúmenes cuál es mejor:

$$\text{loss}(r_\theta) = -E_{(x,y_0,y_1,i)\sim D}[\log(\sigma(r_\theta(x, y_i) - r_\theta(x, y_{1-i})))]$$

resumen preferido $y \in \{y_0, y_1\}$

- Una vez que termina el entrenamiento, se normaliza el RM para que el reward tenga un score medio en 0.

Proximal Policy Optimization (PPO)



- La salida del RM es un reward para el sistema.

- Se penaliza la divergencia entre el modelo mejorado (RL) y el original SFT para evitar que las salidas de los modelo sean muy distintas a las vistas por el RM durante el entrenamiento.

- El full reward queda dado por:

$$R(x, y) = r_\theta(x, y) - \beta \log[\pi_\phi^{\text{RL}}(y|x)/\pi^{\text{SFT}}(y|x)]$$