





Unsupervised Human Preference Learning

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All datasets are available at

TL;DR

Problems:

- Powerful LMs produce *impersonal* outputs.
- Finetuning big LMs is too *expensive at scale*. Even LoRA!

Opportunity: People have *personal* preferences that can be learnt from!

Our Solution: LLM Personalization via lexicalized rules:

- Train a *small, local model* on personalization rules.
- Use it to *guide foundational models* in tasks, aligning with user preferences.

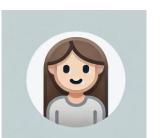


complete and ready for legal review, and that it should be available by tomorrow morning.



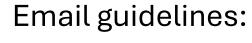
Dear Sylvia, Thank you for your email regarding the status of the NG Energy contract. I'm pleased to let you know that the contract is now complete and ready for an attorney review. [...]

Best regards, <Your Name Here>



Write an email to Sylvia informing her that the NG contract is complete and ready for legal review, and that it should be available by tomorrow morning.





- Start with talking about NG Energy Contract
- Don't use an introductory name
- Use direct tone, concise sentences

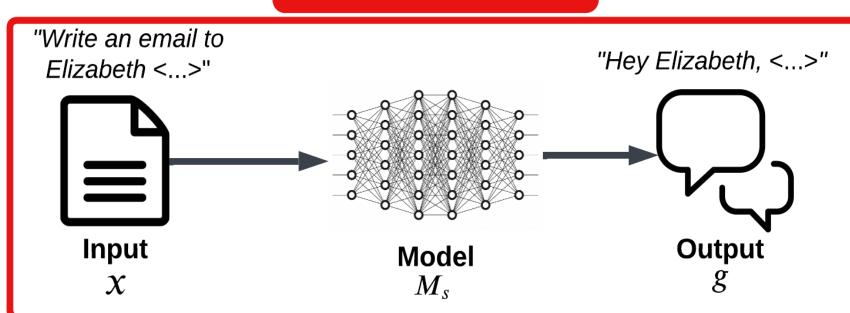


The NG Energy contract is finished. I need a lawyer to review it. It will be ready in the morning.



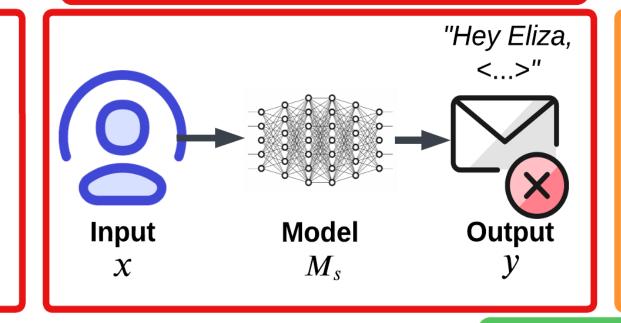
How can we efficiently personalize language model outputs? **Naive Finetuning**

"Write an email to

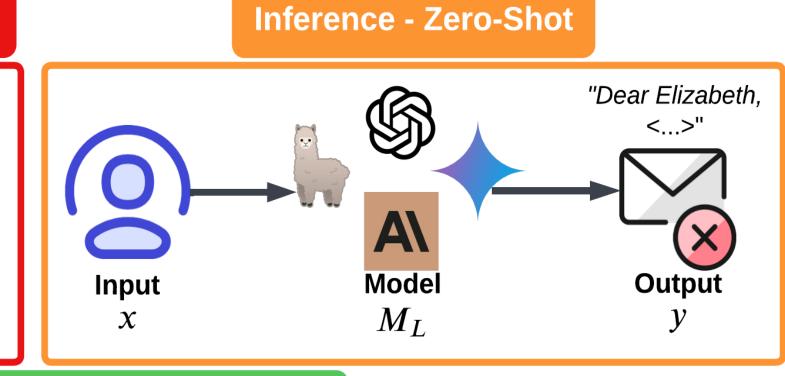


Rule Finetuning

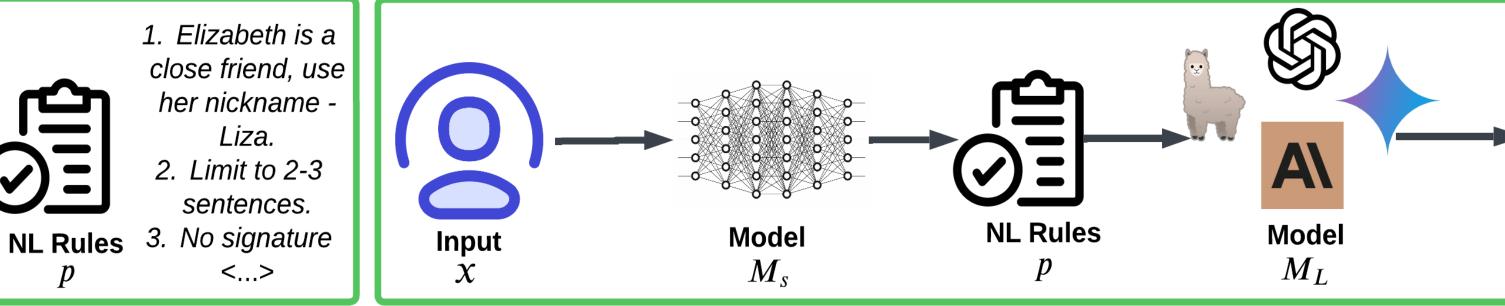
Model



Inference - Naive Finetuning

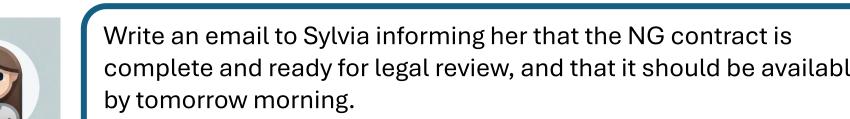


Inference - Rule Finetuning



	Ablation Study								
	benjamin rogers	1.709599	0.278687	-0.625471	-1.264398	-0.098432			
er	bill williams	1.122283	1.312860	-0.907662	-0.648935	-0.878586			
Email Sender	debra perlingiere	-0.435813	-0.160073	1.942809	-0.446755	-0.900193			
ᄪ	dutch quigley	0.743530	-0.997835	-0.477245	1.581549	-0.849957			
	gerald nemec	1.199673	0.287342	-0.336556	-1.737809	0.587341			
		benjamin rogers	bill williams Pers	debra perlingiere onalized A	dutch quigley gent	gerald nemec			

Empirical Examples







Preference Agents	New Yorker			Enron		LAMP 3U			Aggregated		
$M_L ightarrow \ ext{vs} \downarrow$	Llama3 70B Instruct	Claude 3.5 Sonnet	Gemini 1.5 Pro	Llama3 70B Instruct	Claude 3.5 Sonnet	Gemini 1.5 Pro	Llama3 70B Instruct	Claude 3.5 Sonnet	Gemini 1.5 Pro	LLM Evaluation	Human Evaluation
Small Baseline	77.4	91.5	80.0	88.4	96.1	89.8	74.6	84.0	75.3	84.1	91.0
Large Baseline	67.7	75.2	66.9	85.6	83.7	88.2	66.5	69.5	63.8	74.1	84.5
Few Shot	68.3	62.0	66.7	61.1	68.0	57.4	58.3	57.4	59.4	62.0	73.4
Naive Finetune	80.3	82.4	81.8	75.3	87.8	81.3	85.0	92.7	89.0	83.9	92.2
No Baseline Agent	65.1	68.8	63.8	58.4	61.3	62.5	63.8	67.2	60.4	63.4	52.0

Results

Table 1: Win Rates of Llama 38B M_s combined with various M_L , evaluated by GPT40 and human evaluation.

PeFT on User Data vs Rules

"Hi Liza!

Output

