

# You Only Ever Look Once

Experiments in...  
Fine Tuning Domain-Specific Code Generating LLMs

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Bolts

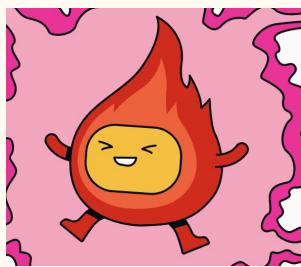
1. Why fine tune 
2. How 
3. Why experiments are more important than ever for our industry 

# DOMAIN SPECIFIC



## C++ Patterns

RAll, Concepts, Templates



## Mojo/MAX

GPU programming  
>= CUDA



## Kubernetes

Dynamic clusters  
Autoscalers  
When it isn't simply



## Secure Envs

Egress is NOT an option

## BUT LLMS ARE ...?

- Perfect enough
- LMBenchmark number go up
- Is already working
- Depends on what your definition of *is* is
- How to define what *is* is?



# CUE: DESIGN THINKING

Interviewer: How's it going?

Interviewee: Meh.

“I recently told my team they don't have to use LLMs anymore, the time we spent reviewing generated code became too costly”

”

Engineering Manager  
Series B InsurTech  
Startup

“Cursor [an AI development environment] makes up documentation that does not even exist”

”

Senior Engineer  
Major FinTech

“The GPT5 update broke all of my system prompts and I have to fall back to earlier and earlier versions to keep my workflows running”

”

Engineering Manager  
Not Google

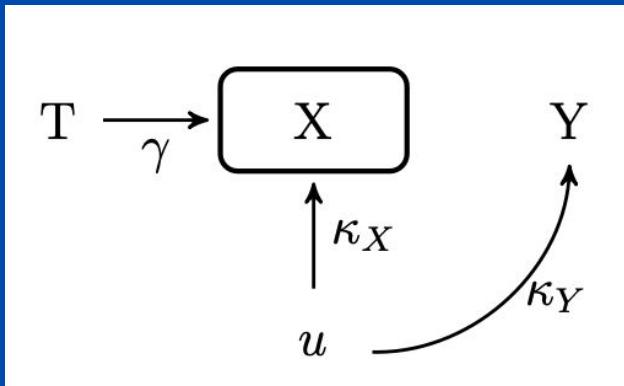
“[Our] internal code agent is 90% correct. [I use] it [only] for writing documents because I am a bad writer. My domain knowledge is still absolutely necessary”

”

Senior Quant  
Relentless.com

# REACH FOR TOOLS TO...

Avoid benchmark overfitting ↓



## Formal Hypothesis

Let

$$P_{\text{default}}$$

represent the performance of default coding LLMs and

$$P_{\text{finetuned}}$$

represent the performance of fine-tuned coding LLMs on language-specific tasks, where performance is measured as a score of execution validity, operational validity, and troubleshooting utility.

**Null Hypothesis (H):**

$$H_0 : P_{\text{default}} = P_{\text{finetuned}}$$

**Alternative Hypothesis (H):**

$$H_a : P_{\text{default}} \neq P_{\text{finetuned}}$$

## Performance Evaluation Framework

Performance can be operationalized as a weighted score:

$$P = w_1 \cdot E_v + w_2 \cdot O_v + w_3 \cdot T_u$$

Where: -

$$E_v$$

= Execution validity (binary: 0 or 1) -

$$O_v$$

= Operational validity (binary: 0 or 1) -

$$T_u$$

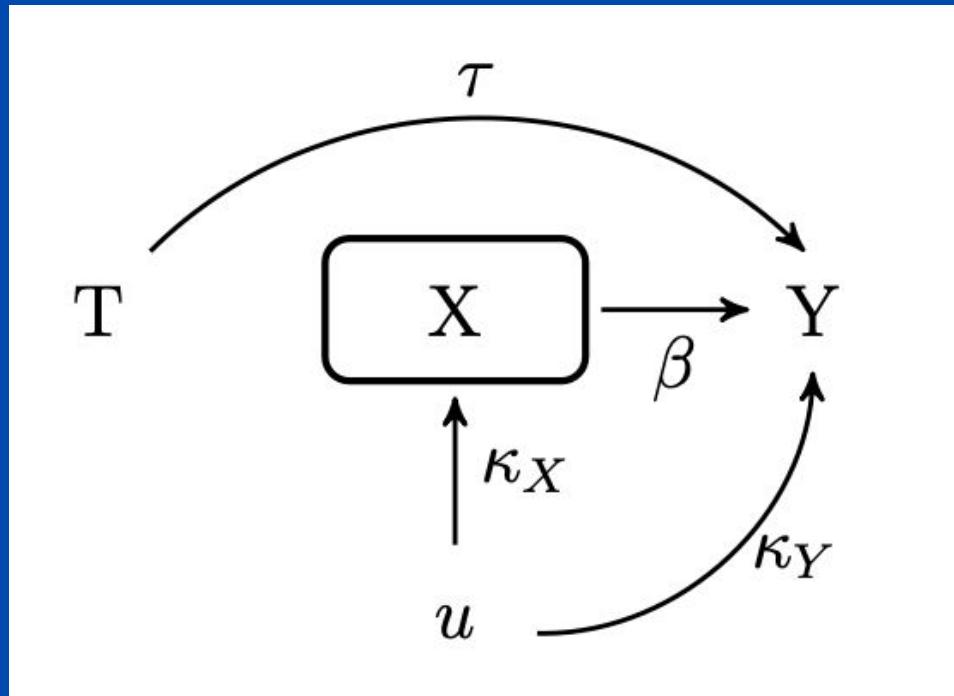
= Troubleshooting utility (binary: 0 or 1) -

$$w_1, w_2, w_3$$

= weights such that

$$w_1 + w_2 + w_3 = 1$$

## EXPERIMENTS GOOD



Does X cause Y?  
How much X causes Y? If at all.

Attributes of Proper Experiment:

- Treatment and Control
- Regression
- Likelihood Estimator
- Notion of Odds

probably...

## RESULTS SNAPSHOT

stdout	return_code	flag	flag_detail
{ "apiVersion": "v1", "kind": "Namespace", "metadata": { "annotations": { "kubectl.kubernetes.io/last-applied- "apiVersion": "v1", "kind": "Namespace", "metadata": { "annotations": { "kubectl.kubernetes.io/last-applied-	0	false	Resource fulfills the task: it is a Namespace with only the requested simple organization labels and no extra user-defined elements.
{ "apiVersion": "v1", "kind": "Namespace", "metadata": { "annotations": { "kubectl.kubernetes.io/last-applied- "apiVersion": "v1", "kind": "Namespace", "metadata": { "annotations": { "kubectl.kubernetes.io/last-applied-	0	true	The provided Namespace resource lacks ResourceQuota that would enforce CPU and memory constraints, thereby failing the explicit task requirement.

FIN

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