

How I Use Language Models for My Research

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STOR-C

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Disclaimer

- Just my personal opinions
- LLM is rapidly evolving
- Not going to cover the ethics
(e.g. data privacy, energy usage, monopolised technology ...)
- Nothing on Copilot

“It doesn't matter if a cat is black or white,
if it catches mice it's a good cat.”

Language Models

| Product Name | Company | Country | Subscription Fee |
|--------------|----------|---------|-----------------------------------|
| ChatGPT | OpenAI | USA | ~£15 / month |
| Claude | Antropic | USA | ~£13 / month |
| DeepSeek | DeepSeek | China | Free |
| Gemini | Google | USA | ~£19 / month (Free for students?) |

Using Language Models

- Via Browser
 - Open <https://chatgpt.com/>
 - Sign up for an account
 - Ready to play!
- Via API
 - More complicated ... Maybe next time ...

(My) Glossary

| Term | Meaning |
|---------------------|--|
| Prompt Engineering | Ask the question (nicely) |
| Modality | Types of allowed input (e.g. text, image, audio) |
| Role prompting | Assign roles to the LLM and the user |
| In-Context Learning | Give some examples, and ask the LLM to extrapolate |
| Hallucination | Wrong answer, but looks plausible |
| Chain-of-thought | Step by step description of how the answer is obtained |
| Pre-Training | Model with neural network weights learned using a large, general dataset |
| Fine-Tune | Use a specialised dataset to improve a pre-trained model on certain tasks. (e.g. LoRA) |
| Distillation | Train a smaller model using data from a large pre-trained model. |



Andrej Karpathy ✓

@karpathy



There's a new kind of coding I call "vibe coding", where you fully give in to the vibes, embrace exponentials, and forget that the code even exists. It's possible because the LLMs (e.g. Cursor Composer w Sonnet) are getting too good. Also I just talk to Composer with SuperWhisper so I barely even touch the keyboard. I ask for the dumbest things like "decrease the padding on the sidebar by half" because I'm too lazy to find it. I "Accept All" always, I don't read the diffs anymore. When I get error messages I just copy paste them in with no comment, usually that fixes it. The code grows beyond my usual comprehension, I'd have to really read through it for a while. Sometimes the LLMs can't fix a bug so I just work around it or ask for random changes until it goes away. It's not too bad for throwaway weekend projects, but still quite amusing. I'm building a project or webapp, but it's not really coding - I just see stuff, say stuff, run stuff, and copy paste stuff, and it mostly works.

11:17 PM · Feb 2, 2025 · **5M** Views



1.3K



5K



29K

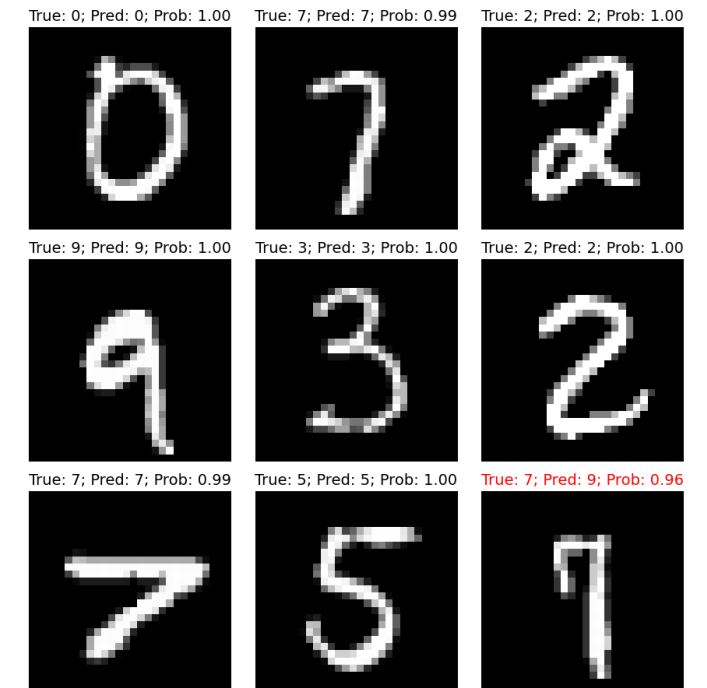


15K



Task 1

- Code up MNIST classification with 2-layer MLP in Torch



Task 2

- Get an overview of a new topic

JOURNAL ARTICLE



Conformal prediction with local weights: randomization enables robust guarantees

[Get access >](#)

[Rohan Hore](#) , [Rina Foygel Barber](#)

Journal of the Royal Statistical Society Series B: Statistical Methodology, Volume 87, Issue 2, April 2025, Pages 549–578, <https://doi.org/10.1093/jrsssb/qkae103>

Published: 11 November 2024 **Article history** ▼

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Abstract

In this work, we consider the problem of building distribution-free prediction intervals with finite-sample conditional coverage guarantees. Conformal prediction (CP) is an increasingly popular framework for building such intervals with distribution-free guarantees, but these guarantees only ensure marginal coverage: the probability of coverage is averaged over both the training and test data, meaning that there might be substantial undercoverage within certain subpopulations. Instead, ideally we would want to have local coverage guarantees that hold for each possible value of the test point's features. While the impossibility of achieving pointwise local coverage is well established in the literature, many variants of conformal prediction algorithm show favourable local coverage properties empirically. Relaxing the definition of local coverage can allow for a theoretical understanding of this empirical phenomenon. We propose randomly localized conformal prediction (RLCP), a method that builds on localized CP and weighted CP techniques to return prediction intervals that are not only marginally valid but also offer relaxed local coverage guarantees and validity under covariate shift. Through a series of simulations and real data experiments, we validate these coverage guarantees of RLCP while comparing it with the other local conformal prediction methods.

Keywords: [distribution free prediction intervals](#), [conformal prediction](#), [local coverage guarantees](#), [localized conformal prediction](#), [weighted conformal prediction](#), [distribution shift](#)

Task 3

- Scribblings to LaTeX / Rmd

$$L_1 A_1 L_1^T = \begin{bmatrix} \sqrt{2} & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \sqrt{2} & 0 \\ 0 & 0 \end{bmatrix} = \begin{bmatrix} 2 & 0 \\ 0 & 0 \end{bmatrix}$$

$$L_1 B_1 L_1^T = \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} \quad Z_{11} =$$

$$L_1 B_1 B_1^T L_1^T = \begin{bmatrix} \sqrt{2} & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \sqrt{2} & 0 \\ 0 & 0 \end{bmatrix}$$

MDP Expected reward with discount

$$V_t(s) = E_t[G_t | s_t, \pi] = E_t\left[\sum_{k=0}^{\infty} \gamma^k r_{t+k} | s_t, \pi\right]$$

$$Q_t(s, a) = E_t[G_t | s_t, a_t, \pi] = E_t\left[\sum_{k=0}^{\infty} \gamma^k r_{t+k} | s_t, a_t, \pi\right]$$

$$\pi_*$$
 s.t. $V_{\pi_*} \geq V_{\pi} \forall \pi \in \Pi$ optimal policy

V_* Q_* π_* (the unique policy, the unique V_* and Q_*)

Bellman Eqn
$$V_*(s) = \max_a R(s, a) + \gamma E_{p(s'|s, a)}[V_*(s')]$$

$$Q_*(s, a) = R(s, a) + \gamma E_{p(s'|s, a)}[\max_{a'} Q_*(s', a')]$$

$$\pi_*(s) = \arg\max_a Q_*(s, a) = \arg\max_a R(s, a) + \gamma E_{p(s'|s, a)}[V_*(s')]$$

$$V_{\pi}(s) = \max_a \left[R(s, a) + \gamma E_{p(s'|s, a)}[V_{\pi}(s')] \right] = \max_a \left[R(s, a) + \gamma \sum_{s'} p(s'|s, a) V_{\pi}(s') \right]$$

$$V_{\pi}(s) = \max_a \sum_{s'} \gamma^k R(s_k, a_k) \quad \text{s.t. } a_t \in \mathcal{A}(s_t) \quad s_{k+1} = T(s_k, a_k)$$


$$= R(s_0, a_0) + \max_{a_1} \sum_{s_1} \gamma R(s_1, a_1)$$

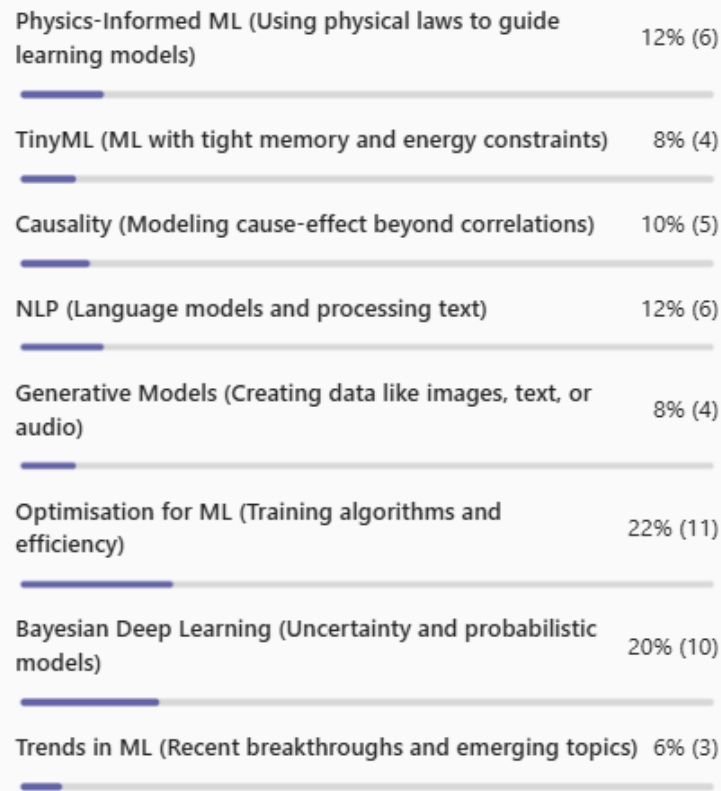
$$= R(s_0, a_0) + \gamma \left[\max_{a_1} \sum_{s_1} \gamma R(s_1, a_1) \right]$$

$$= R(s_0, a_0) + \gamma V_{\pi}(s_1)$$

Lancaster AI Reading Group



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16 responses

LAI Reading Group

Lancaster AI (**LAI**) reading group is a weekly reading group focusing on topics related to AI, including but not limited to: diffusion models, information geometry, stochastic optimisation, geometric deep learning. It will be more tutorial-styled, instead of seminar-styled, tailored more towards people who wish to learn more about the recent developments of AI. This reading group is supported by the [Prob_AI Hub](#).

In Term 3, we are doing **geometric deep learning**.

PSC Lab 2 and over Teams; Wednesday 2-3pm (mostly).

See [here](#) for the **full schedules**; [here](#) for **past sessions**.

Next Session

| Title | Location | Date | Time | Speaker |
|-------------|-----------|-------------|-------------|---------|
| GNNs for RL | PSC Lab 2 | 4 June 2025 | 2 pm - 3 pm | Jack |

Email [Andreas](#) or [Cass](#) for any question related to the reading group.

<https://lai-reading-group.github.io/>

