

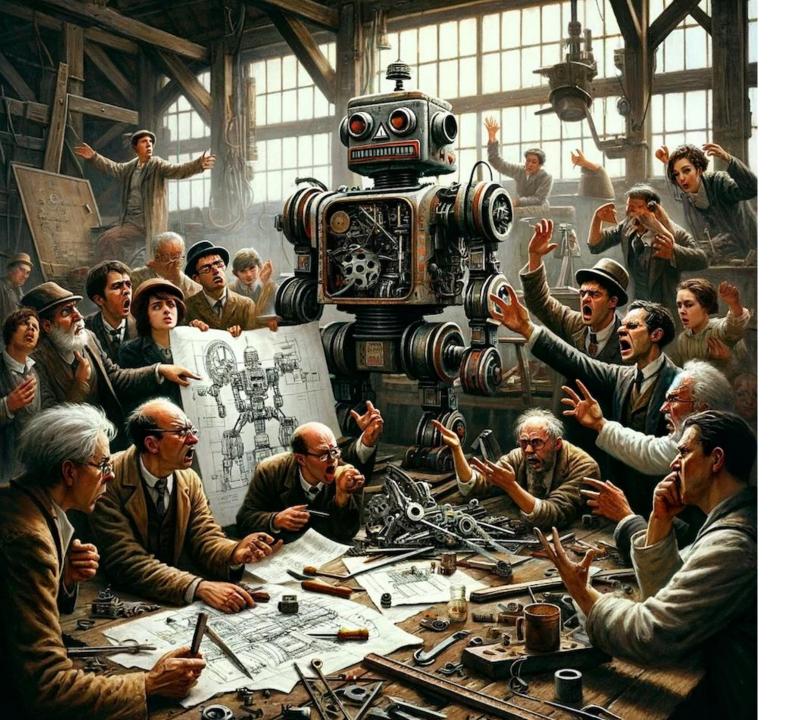
Is Prompting Enough?

The Process of Making a Copilot for UI-based Chatbot Builders

Emanuel Lacić

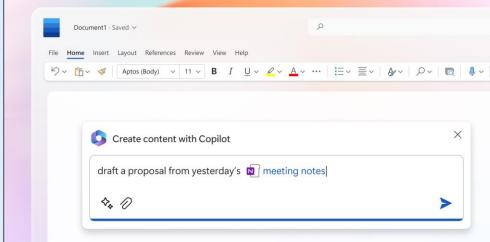
Principal Engineer @ Infobip





Companies everywhere are launching copilots

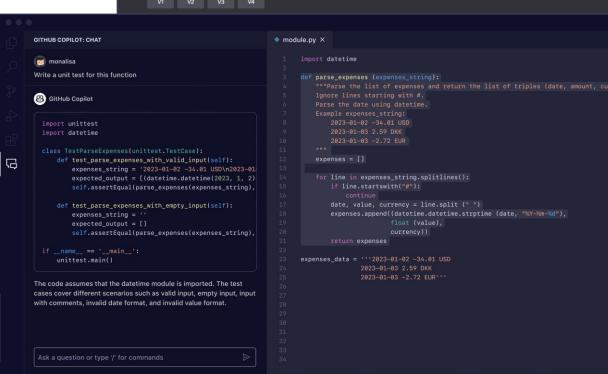
Al assistants that leverage LLMs to help solving a specific task



MS Office Copilot

Github

Copilot



Midjourney

air, She is happily looking at the photoframes floating around her, bold and pleasent colours, 8k, cinematic, detailed, unreal engine, --ar 2:1--v 5

//s.mj.run/S7FZLGUVVxA An illustration, unique and colourful, A long shot of a dreamy land, a girls is floating in the

Get answers to complex questions

For example, you could ask "Help me plan for my fishing trip."

Copilot

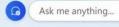
Take actions on your PC

Control your Windows environment with actions like "Adjust my settings so I can focus."

Work across documents

Summarize and compose text from any app start by copying text to clipboard.

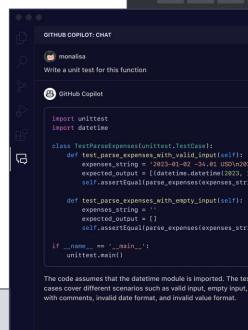
Let's learn together. Windows copilot is powered by AI, so surprises and mistakes are possible. Make sure to check the facts, and share feedback so we can learn and improve!

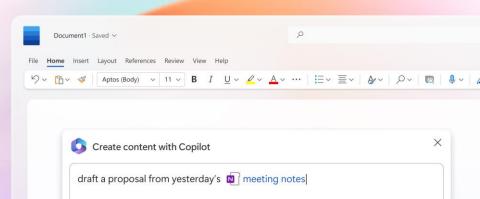






Windows Copilot









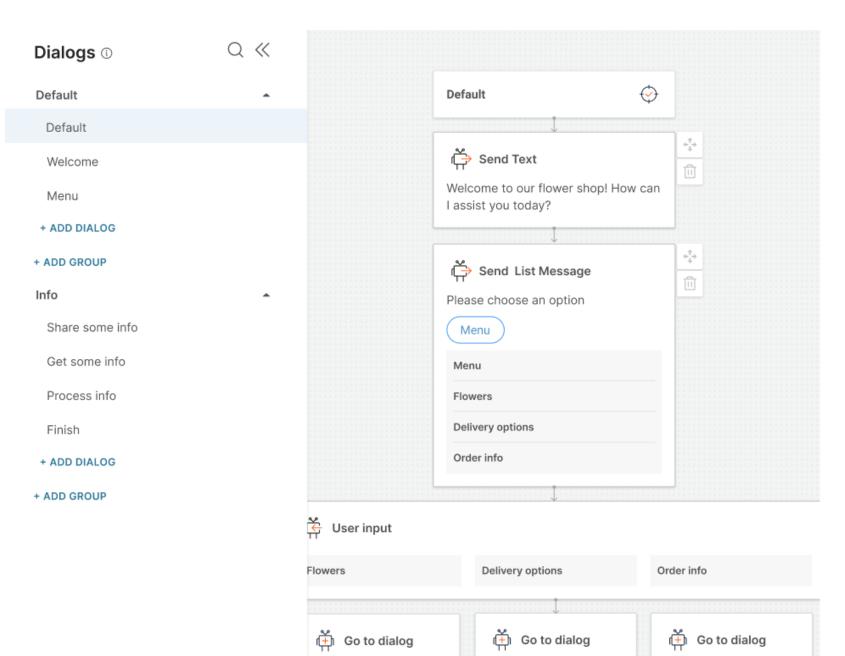
Building Your Own Product Copilot: Challenges, Opportunities, and Needs

Chris Parnin, Gustavo Soares, Rahul Pandita, Sumit Gulwani, Jessica Rich, Austin Z. Henley {chrisparnin,gustavo.soares}@microsoft.com,rahulpandita@github.com,{sumitg,jessrich,austinhenley}@microsoft.com
Microsoft, GitHub Inc.

USA

Exploration Implementation Evaluation Productization Model **Business** model **Business** Prompt crafting comparison Guardrails Safety, privacy, Prompt testing scenarios **Processing input** Company data **Processing** System testing and compliance Benchmarks AI tooling and User experience output models Orchestration **Finetuning** User feedback Al best practices **Embedding** Training custom Deployment and models Proof of concepts management monitoring





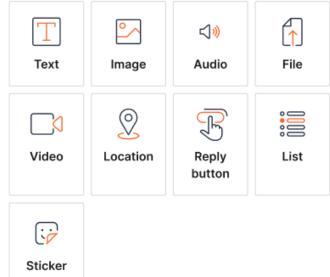


Build

Drag and drop the following elements to build and define your bot interactions or choose to build with Al copilot.



Chatbot sends



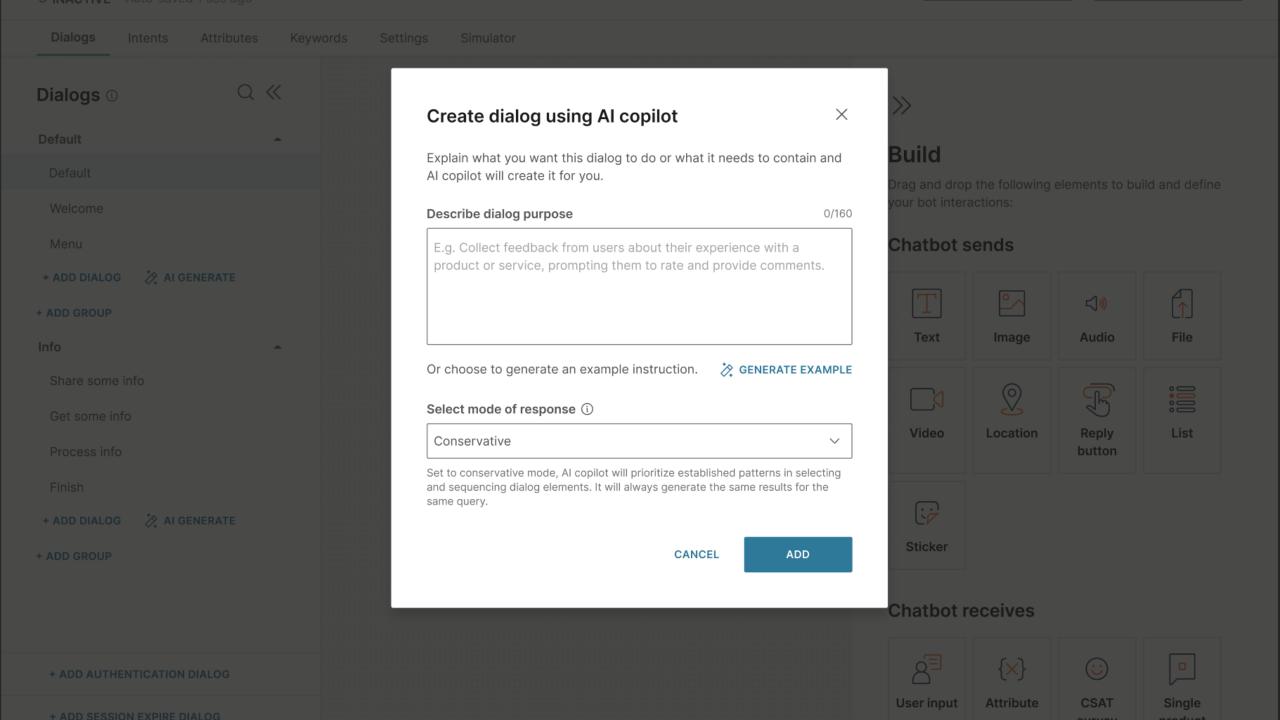
Chatbot receives





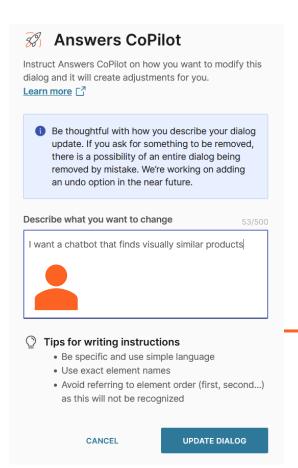


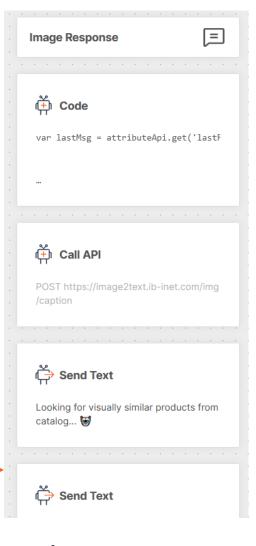






Prompting





OpenAl Visual Elements
API [...]



Prompting

Test out prompt engineering baselines with API from Microsoft (GPT3.5-turbo)

Strategies:

- Zero-Shot
 - A prompt that <u>describes the problem</u> of building a chatbot dialog as well as states the <u>vocabulary</u> of the available visual elements
- Few-Shot
 - Add multiple examples of input task descriptions and their expected outputs
- Few-Shot with Instructions
 - Add the information about specific <u>rules that need to be enforced</u> to render the generated output in the UI



Performance

Hallucinations

Percentage of **predictions that contain hallucinations**. Hallucinations are unexpected predictions which include (1) <u>format validation</u>, (2) <u>vocabulary validation</u> and (3) <u>rule validation</u>

HitRate

Is 1 when the prediction 100% matches what is expected, else 0

	Hallucinations	HitRate	
Zero-Shot	30.67 %	1.31 %	
Few-Shot	20.22 %	2.13 %	T = 0.0
Few-Shot with Instructions	23.57 %	0.68 %	
Zero-Shot	46.44 %	2.09 %	
Few-Shot	12.63 %	1.75 %	T = 0.7
Few-Shot with Instructions	25.70 %	0.69 %	





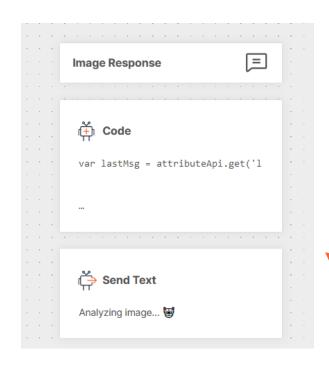


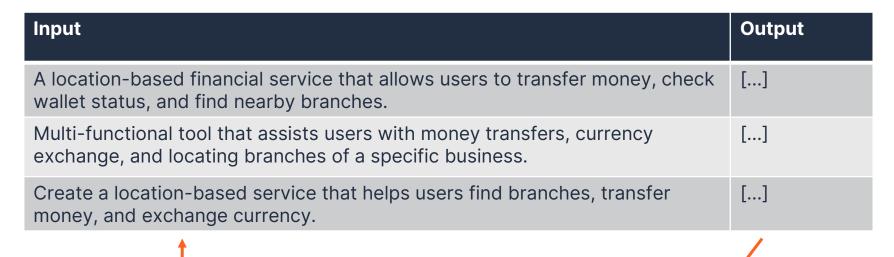
Adapting LLMs

- OpenAl GPT3.5-turbo (large)
 - https://learn.microsoft.com/en-us/azure/ai-services/openai/tutorials/fine-tune
- Mistral 7B Instruct (mid)
 - https://arxiv.org/pdf/2310.06825.pdf
- LLaMa 3B (small)
- https://arxiv.org/pdf/2302.13971.pdf
- Sheared LLaMA 1.3B (tiny)
 - https://arxiv.org/pdf/2310.06694.pdf



Training Data





What does this

dialog do?

Domain-specific configuration of visual elements



Training Data



Input	Output
A location-based financial service that allows users to transfer money, check wallet status, and find nearby branches.	[]
Multi-functional tool that assists users with money transfers, currency exchange, and locating branches of a specific business.	[]
Create a location-based service that helps users find branches, transfer money, and exchange currency.	[]

BUT WE DON'T HAVE THIS KIND OF DATA!!!



Synthetic Data

Hypothesis: You can use GenAl (e.g., GPT3.5-turbo) to synthetically create description data

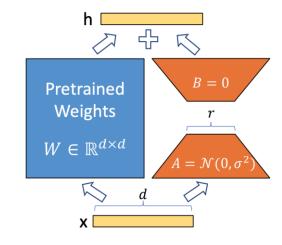
```
import json
instruction = """
You are a chabtot generator. Your job is to find out and desribe what a bot is based on the provided attributes.
prompt = """
You just got the following information about the attributes of the chatbot which will be built:
{attributes}
Describe in one sentence what this chatbot is about?
def parse json(json str):
    attributes = []
        for obj in json.loads(json str):
            attributes.append(obj["name"])
    except json.JSONDecodeError:
        return None
    messages=[
                {"role": "system", "content": instruction},
                {"role": "user", "content": prompt.format(attributes=attributes)}
    bot desc = chat complete(messages, temperature=0.0)
    return bot desc
```

NEED FOR PRIOR
DATA CLEANING,
TEXT STANDARDIZATION,
ANONYMIZATION
&
PROMPT ENGINEERING



Fine-Tuned Models

Use LoRA to fine-tune visual element generation on own data

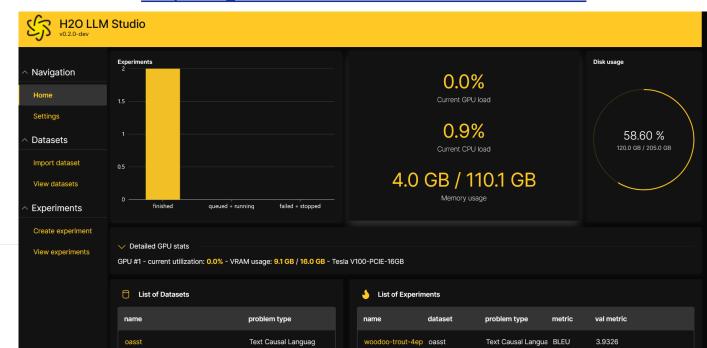




State-of-the-art Parameter-Efficient Fine-Tuning (PEFT) methods

https://github.com/huggingface/peft

https://github.com/h2oai/h2o-llmstudio

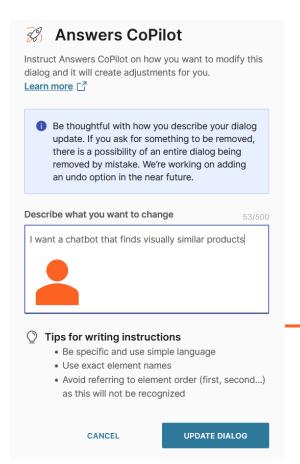


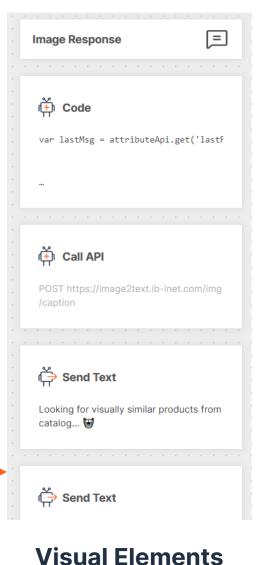


Fine-Tuned Models

LLMs fine-tuned

on relevant data







Fine-Tuned Models

Fine-tuned LLMs were able to achieve

- Number of Hallucinations significantly lowered from 12.63% → the best performance of 0.04%
- A <u>HitRate</u> that improved from 0.68% 2.13% → 18.81% 26.72%

	Hallucinations	HitRate
Sheared LLaMA 1.3B (tiny)	0.04 %	18.81 %
LLaMa 3B (small)	0.19 %	18.89 %
Mistral 7B Instruct (mid)	15.34 %	26.72 %
OpenAl GPT3.5-turbo (large)	1.96 %	15.78 %



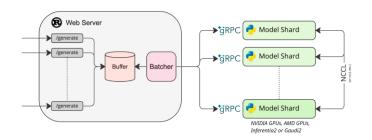
Inference

For inference, you can use Huggingface's text generation API

https://github.com/huggingface/text-generation-inference

Text Generation Inference

Fast optimized inference for LLMs



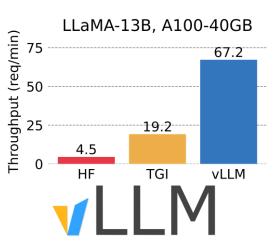
docker run --detach --gpus all --shm-size 1g -p 9999:80 -v /var/lib/docker/volumes/h2o-llmstudio-shared/output/user:/dataghcr.io/huggingface/text-generation-inference:1.1.0 --model-id /data/mymodel

Mistral-7B on NVIDIA's Volta architecture requires the use of **Ilama.cpp**

https://github.com/ggerganov/llama.cpp



	VRAM
Sheared LLaMA 1.3B (tiny)	5.1 GB
LLaMa 3B (small)	9.5 GB
Mistral 7B Instruct (mid)	13.6 GB



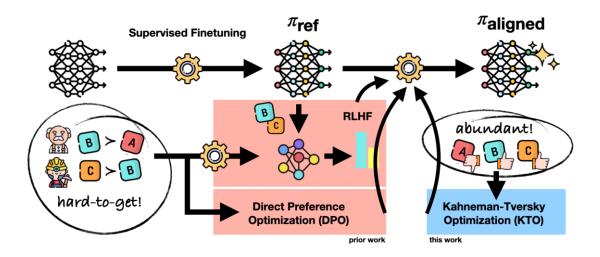
https://github.com/vllm-project/vllm







Human-Aware Loss Functions



https://github.com/ContextualAI/HALOs

KTO: Model Alignment as Prospect Theoretic Optimization

Kawin Ethayarajh 1 Winnie Xu 2 Niklas Muennighoff 2 Dan Jurafsky 1 Douwe Kiela 12

Abstract

Kahneman & Tversky's prospect theory tells us that humans perceive random variables in a biased but well-defined manner (1992); for example, humans are famously loss-averse. We show that objectives for aligning LLMs with human feedback implicitly incorporate many of these biases—the success of these objectives (e.g., DPO) over cross-entropy minimization can partly be ascribed to them being human-aware loss functions (HA-LOs). However, the utility functions these meth-

the mathematically equivalent DPO (Rafailov et al., 2023)—take preference data as input.

To understand why these alignment methods work so well, and whether feedback needs to be in the form of preferences, we frame them through the lens of *prospect theory* (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992). Prospect theory explains why humans make decisions about uncertain events that do not maximize expected value. It formalizes how humans perceive random variables in a biased but well-defined manner; for example, relative to some reference point, humans are more sensitive to losses

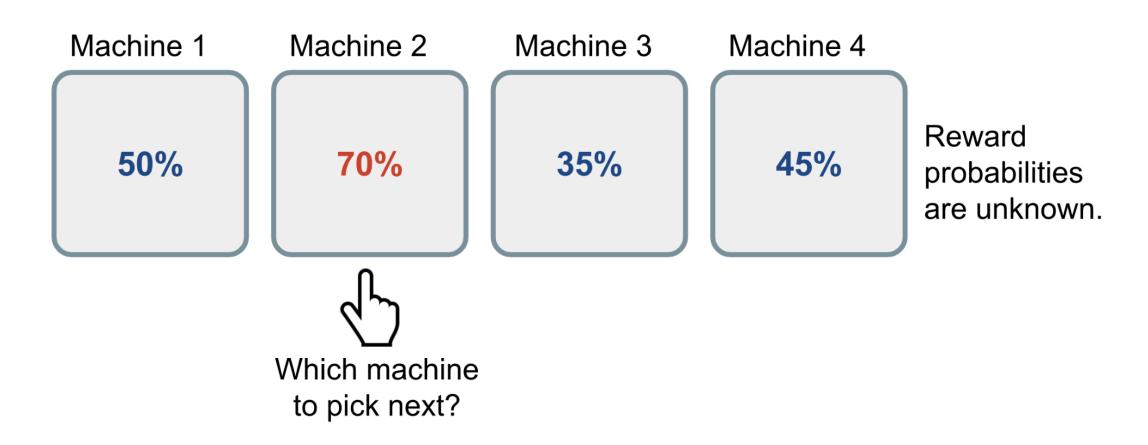
Human feedback is in a binary format?

There is an **imbalance** between the number of **desirable** and **undesirable examples?**

In that case, KTO is the natural choice!

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Let:

- \blacksquare $\Pi_0 = (\pi_1^0, \dots, \pi_K^0)$ be a prior distribution over $(\theta_1, \dots, \theta_K)$
- $\Lambda_t = (\lambda_1^t, \dots, \lambda_K^t)$ be the posterior over the means (μ_1, \dots, μ_K) a the end of round t

The Bayes-UCB algorithm chooses at time t

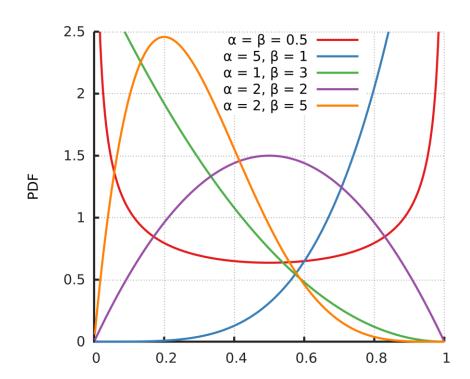
$$A_t = \operatorname*{argmax}_{a} Q \left(1 - \frac{1}{t (\log t)^c}, \lambda_a^{t-1} \right)$$

where $Q(\alpha, \pi)$ is the quantile of order α of the distribution π .

Bernoulli reward with uniform prior: $heta=\mu$ and $\Pi_t=\Lambda_t$

$$A_t = \operatorname*{argmax}_a Q \left(1 - rac{1}{t(\log t)^c}, \operatorname{Beta}(S_a(t) + 1, N_a(t) - S_a(t) + 1)
ight)$$

Kaufmann, E. Bayesian and Frequentist Methods in Bandit Models. 2013





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Kaufmann, E. Bayesian and Frequentist Methods in Bandit Models. 2013

```
class BayesianUCBBandit:
    def init (self, n arms):
        self.n arms = n arms
        self.alpha = np.ones(n arms)
        self.beta = np.ones(n_arms)
        self.t = 0
        self.c = 5 # exploration parameter
        self.totals = np.zeros(n arms, dtype=int)
    def select arm(self):
        self.t += 1
        quantile level = 1 - 1 / self.t
        # avoid division by \theta when t = 1
        if self.t > 1:
            quantile level = 1 - 1 / (self.t * (np.log(self.t) ** self.c))
       ucb_values = [beta.ppf(quantile_level, a, b) for a, b in zip(self.alpha, self.beta)]
        return np.argmax(ucb values)
    def update(self, chosen arm index, feedback):
        if feedback == 1:
            self.alpha[chosen arm index] += 1 # Positive
        elif feedback == -1:
            self.beta[chosen_arm_index] += 1 # Negative
        # Else, do nothing (no feedback was given)
        # we could also have different weights for feedback
```



```
chosen_LLM_index = bandit.select_arm()

output = generate(input_text, chosen_LLM_index)

# feedback aquisition needs to be defined
feedback = get_feedback(chosen_LLM_index, input_text, output)

bandit.update(chosen_LLM_index, feedback)
```

```
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Questions?



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