Never Start from Scratch: Expediting On-Device LLM Personalization via Explainable Model Selection

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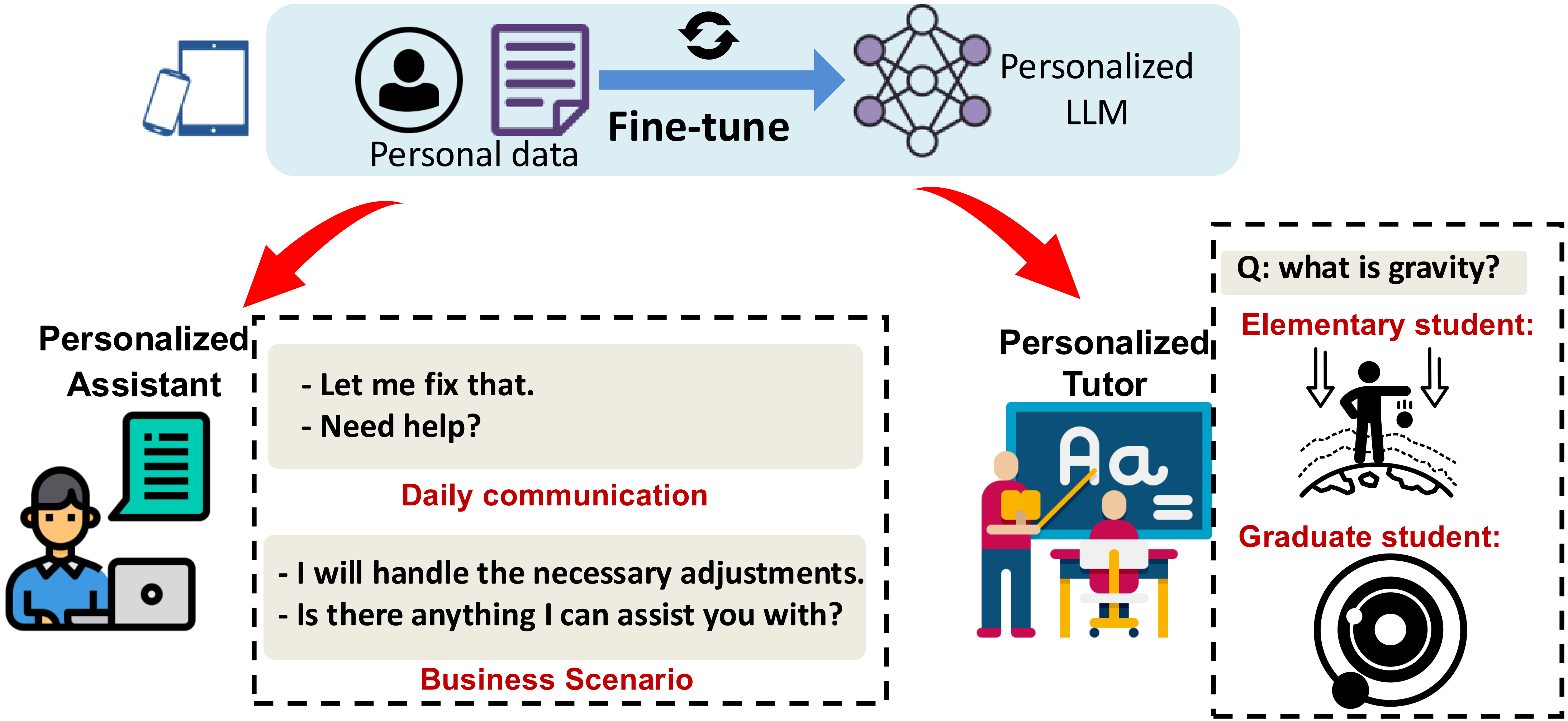
University of Pittsburgh

***ACM MobiSys* 2025**

LLM personalization on Mobile Devices



Personal data

Fine-tune

Personalized LLM

Personalized Assistant

- Let me fix that.
- Need help?

Daily communication

- I will handle the necessary adjustments.
- Is there anything I can assist you with?

Business Scenario

Personalized Tutor

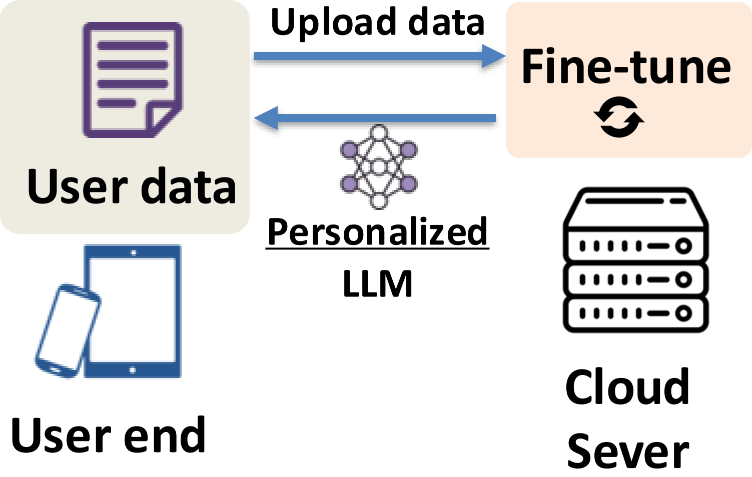
Q: what is gravity?

Elementary student:

Graduate student:

Existing Solutions

Upload user data to the cloud


User data

Upload data

Fine-tune

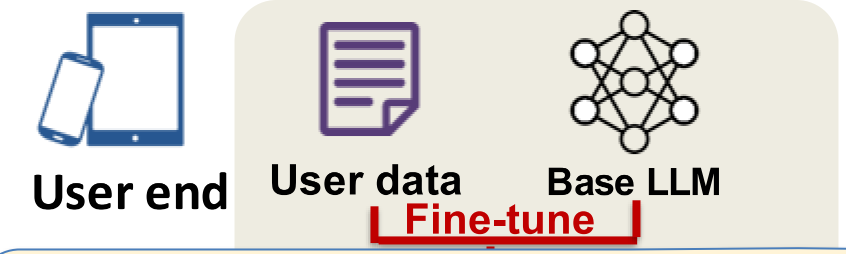
Personalized LLM

User end

Cloud Sever

Impairing user's data privacy

Fine-tune LLM at the local device


User end

User data

Base LLM

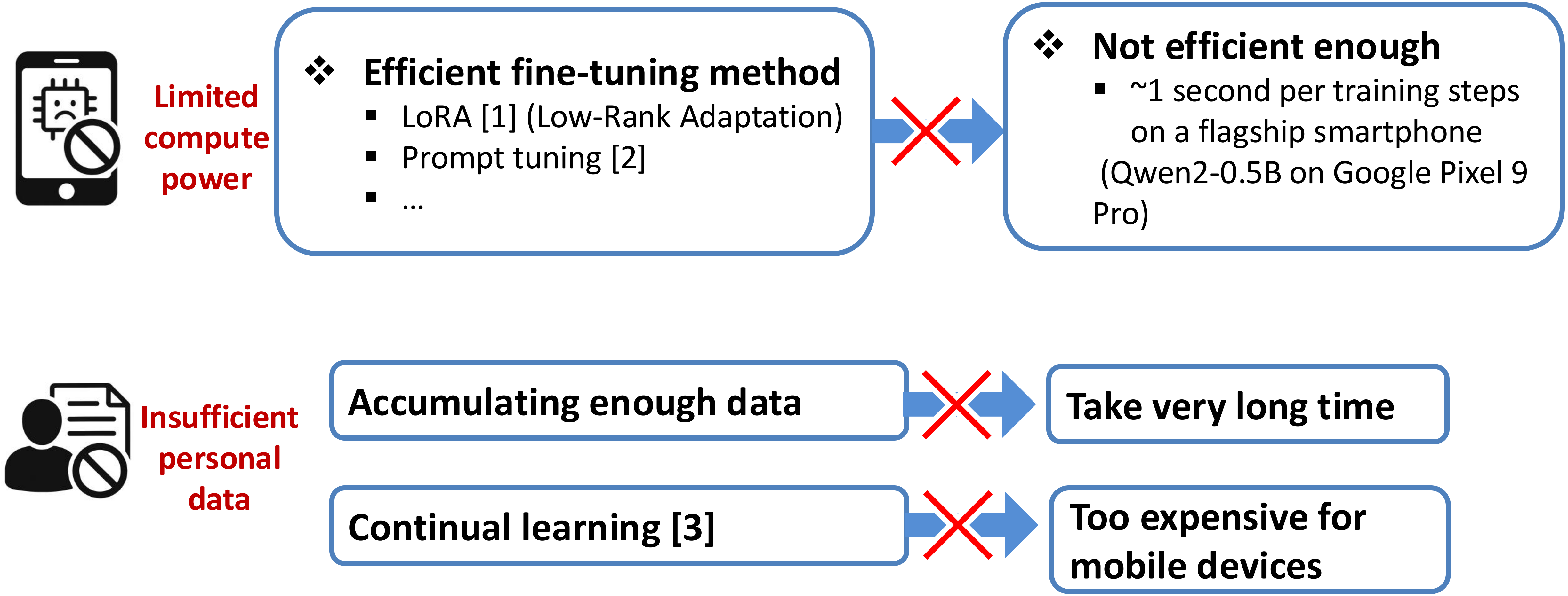
Fine-tune

How to address such on-device challenges?

Limited compute power

Insufficient personal data

On-device personalization challenges



Limited compute power

- ❖ **Efficient fine-tuning method**
  - ▪ LoRA [1] (Low-Rank Adaptation)
  - ▪ Prompt tuning [2]
  - ▪ …

- ❖ **Not efficient enough**
  - ▪ ~1 second per training steps on a flagship smartphone (Qwen2-0.5B on Google Pixel 9 Pro)

Insufficient personal data

Accumulating enough data

Take very long time

Continual learning [3]

Too expensive for mobile devices

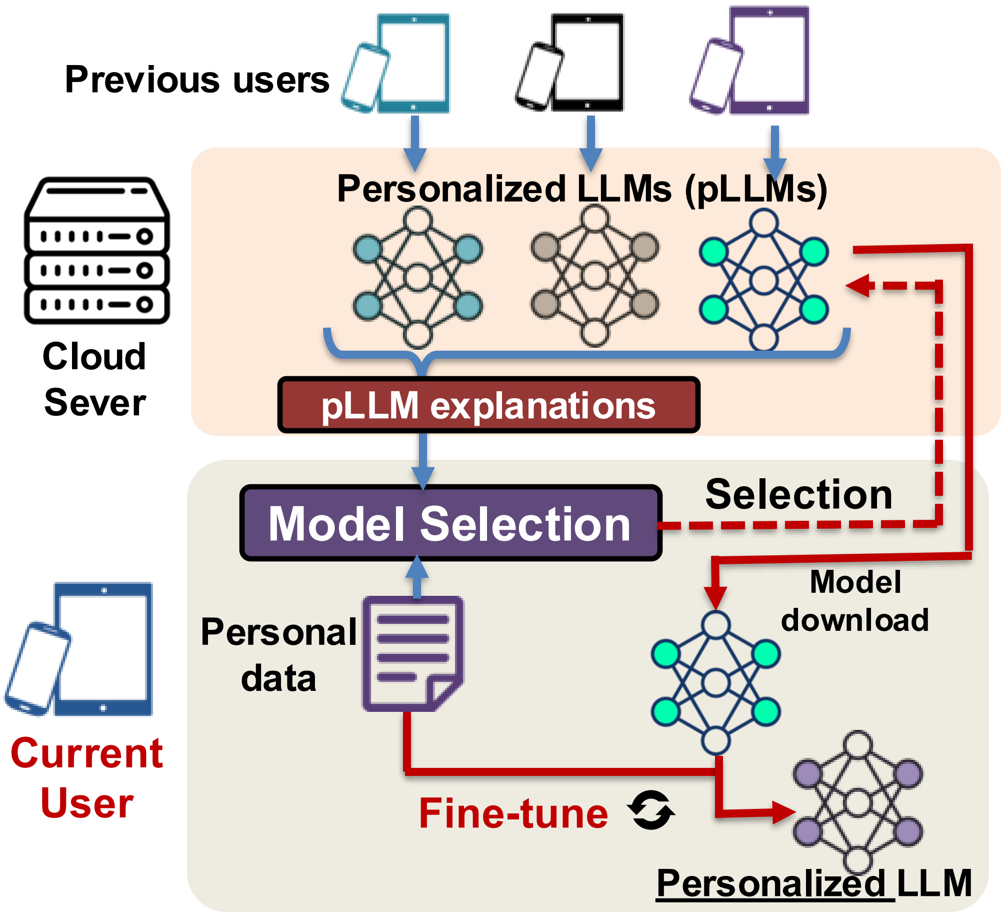
[1] J Lin, et al. Lora: Low-rank adaptation of large language models. ICLR 2022

[2] B Lester, et al. The Power of Scale for Parameter-Efficient Prompt Tuning. Arxiv 2021

[3] A Razdaibiedina, et al. Progressive prompts: Continual learning for language models. ICLR 2023

Our Solution: Never Start from Scratch!

Initialize personalization from the existing personalized LLMs



Server end:

(1) Personalized LLM pre-cached on the cloud server

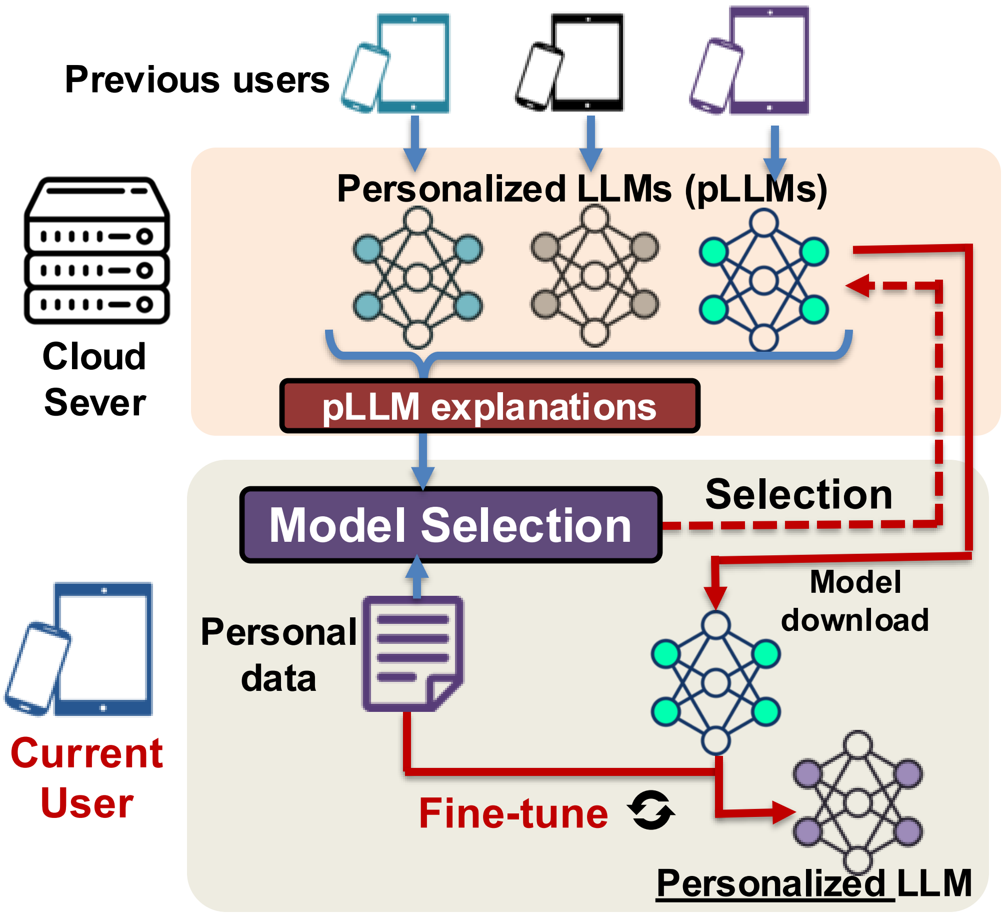
(2) Pre-compute the explanations for pLLMs

On device :

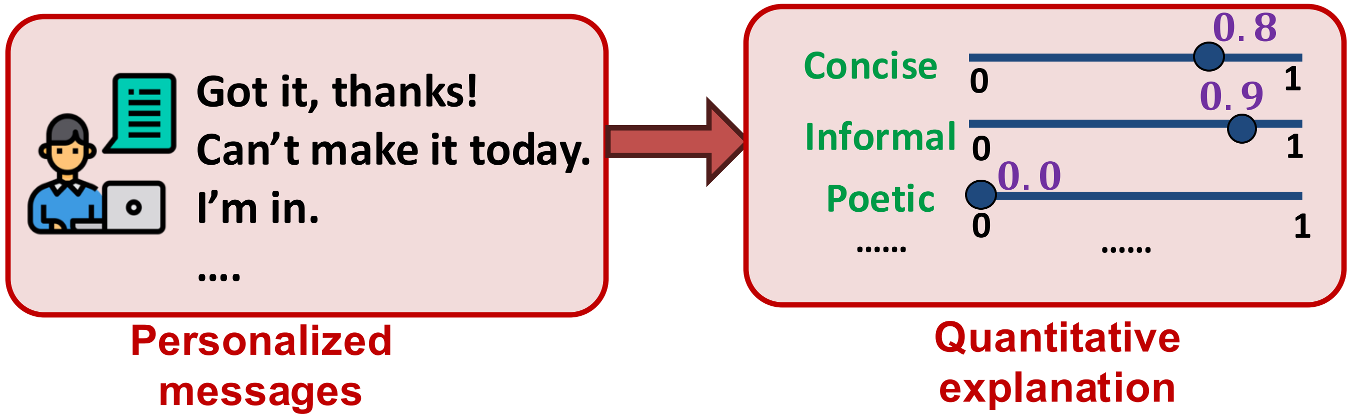
(3) Select the pLLM that best resembles the personal data based on the explanations of pLLMs

(4) Locally fine-tune the selected pLLM with personal data

Our Solution: Never Start from Scratch!

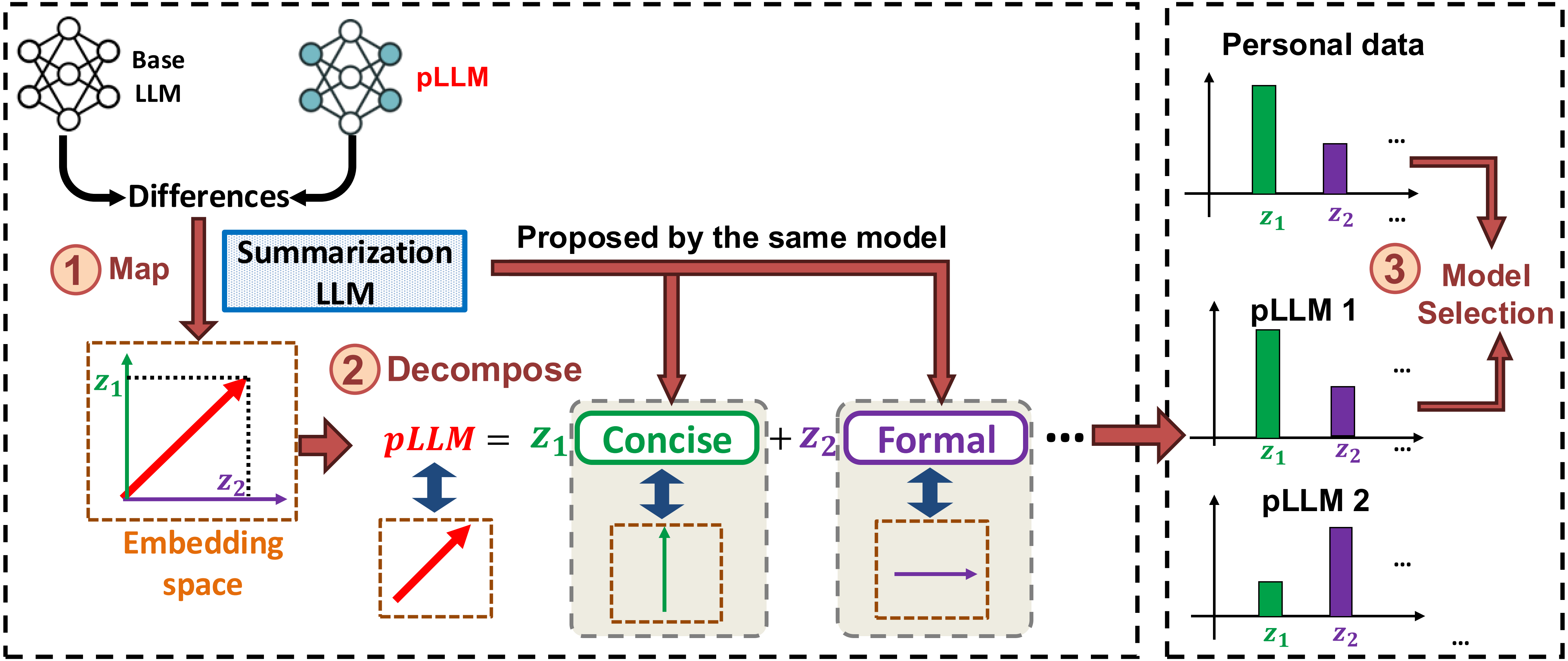


- **Requirements for pLLM explanations:**
  - **Explainable**: in natural language to ensure users' trust
  - **Quantitative:** facilitate model selection
- **Format of explanations:**



Got it, thanks!
Can't make it today.
I'm in.
....

eXplainable Personalized Tuning (XPerT)



Base LLM

pLLM

Differences

1 Map

Summarization LLM

Proposed by the same model

Embedding space

2 Decompose

$pLLM = z_1$ Concise $+ z_2$ Formal ...

Personal data

pLLM 1

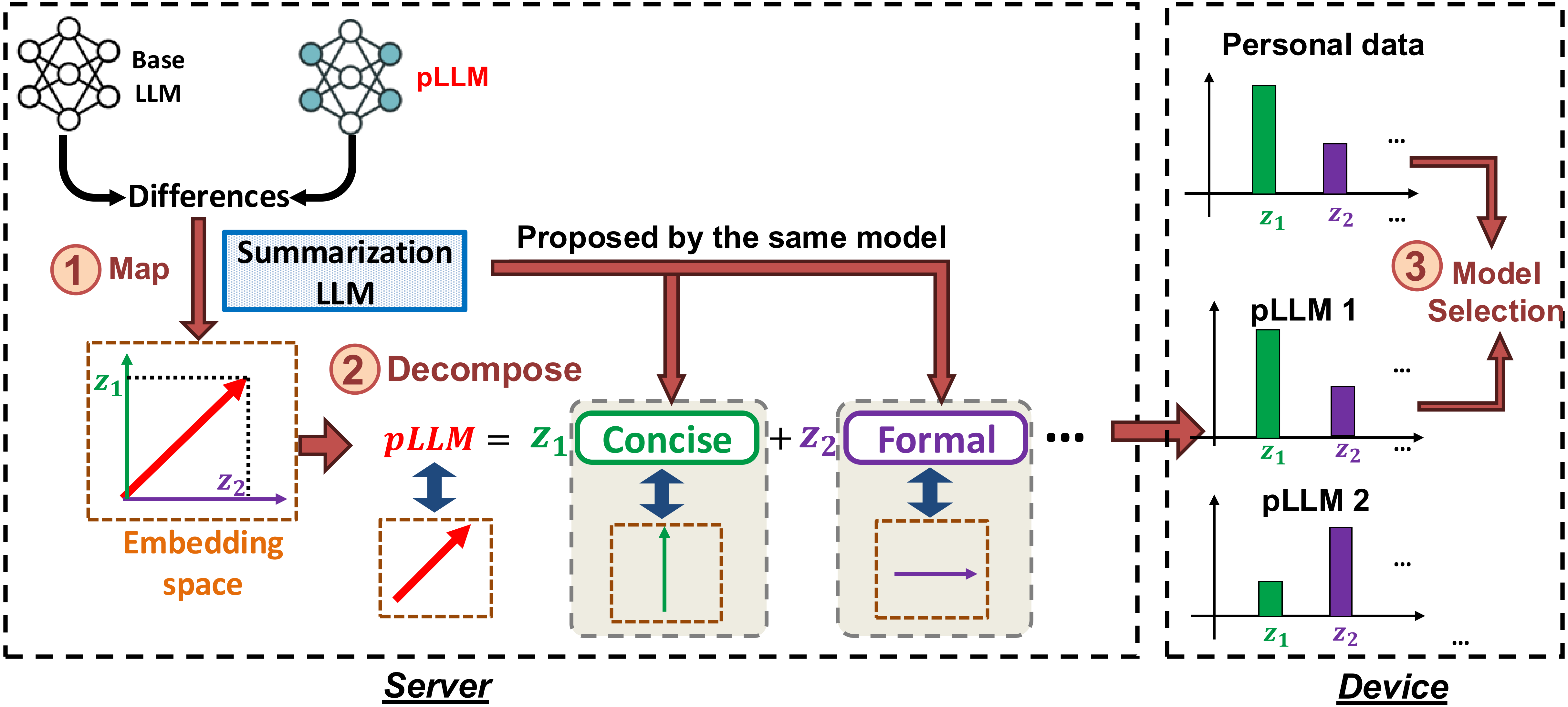
pLLM 2

3 Model Selection

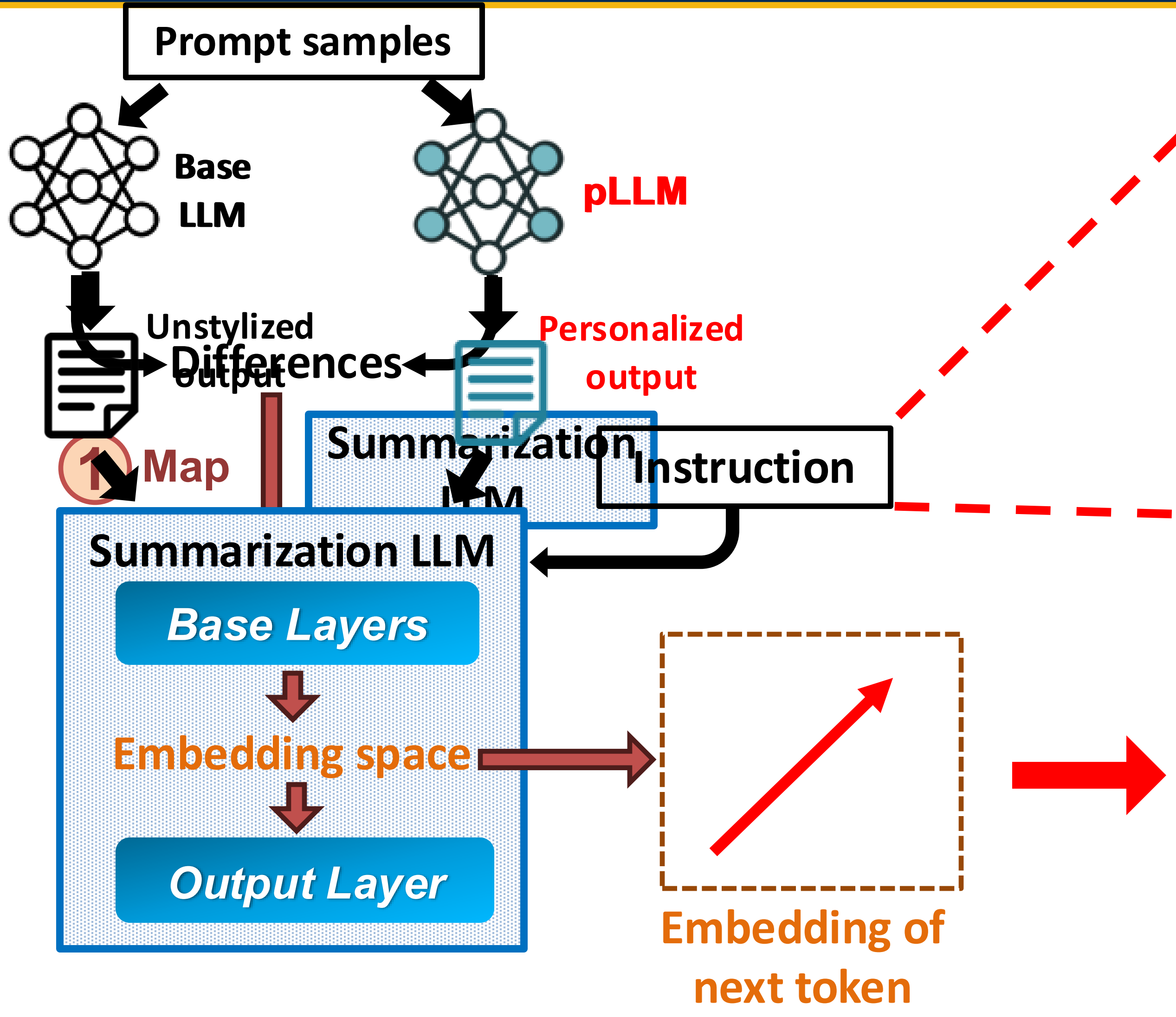
Server

Device

XPerT: ① Mapping differences to Embedding space



XPerT: ① Mapping Differences to Embedding Space

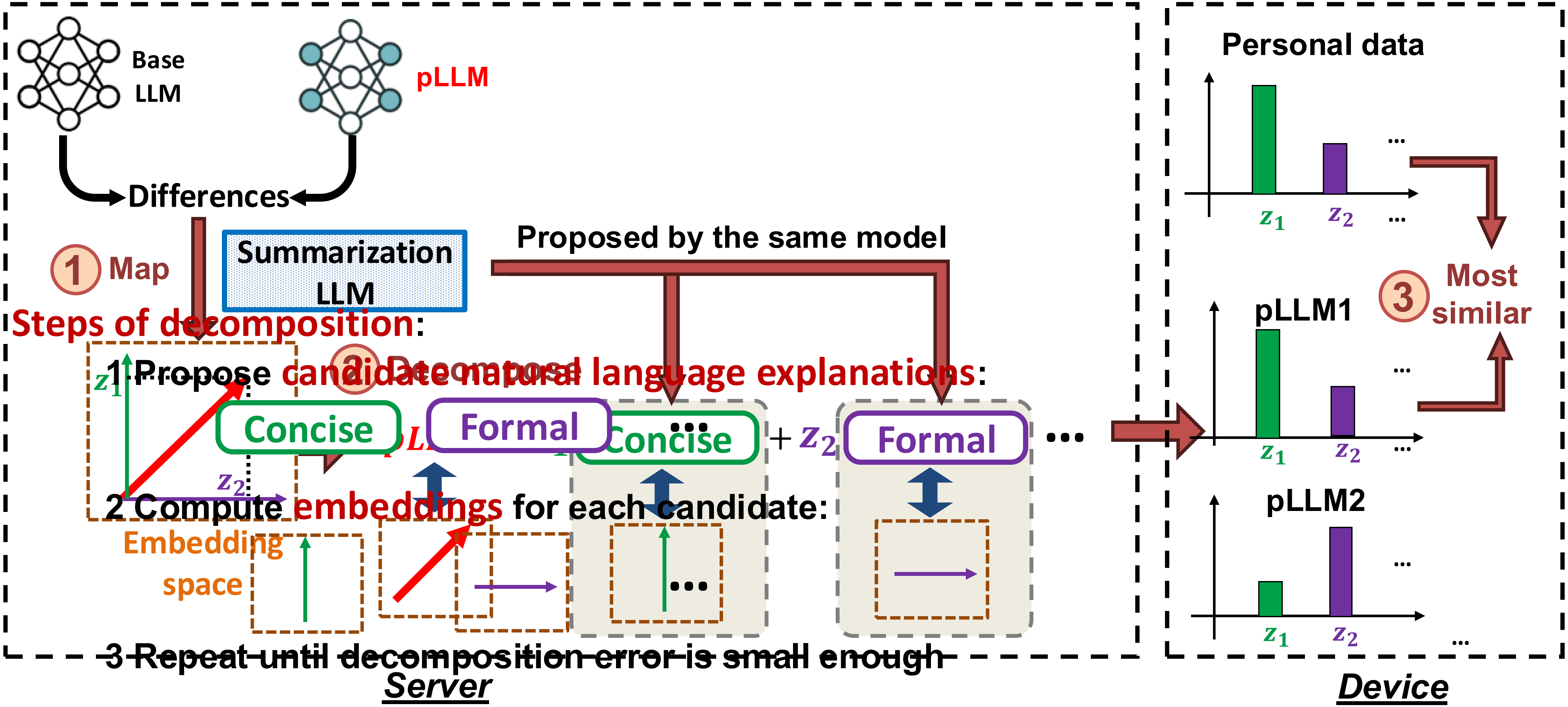


which language style is more characteristic of
<Unstylized output>
than
<Personalized output>

Reply with only one adjective

Averaged over multiple inferences

XPerT: ② Decomposing the Embedding



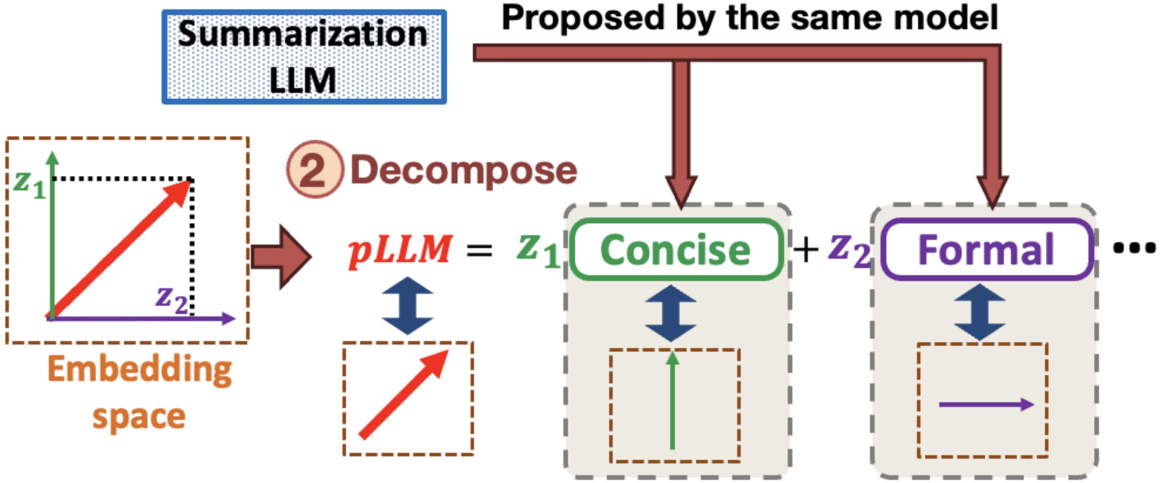
Steps of decomposition:

1 Propose candidate natural language explanations:

2 Compute embeddings for each candidate:

3 Repeat until decomposition error is small enough

XPerT: ② Decomposing the Embedding

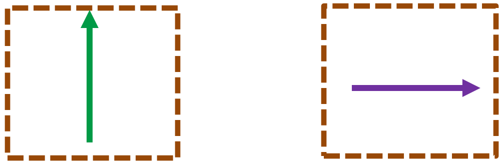

Summarization LLM
Proposed by the same model
z_1
z_2
Embedding space
② Decompose
$pLLM = z_1$ Concise $+ z_2$ Formal …

Steps of decomposition:

1 Propose **candidate natural language explanations**:

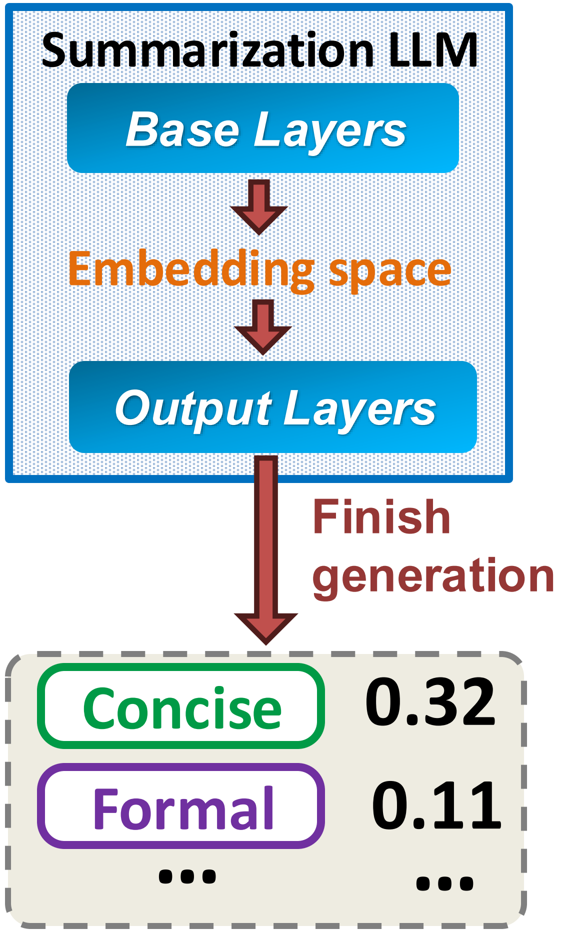
Concise Formal …

2 Compute **embeddings** for each candidate:



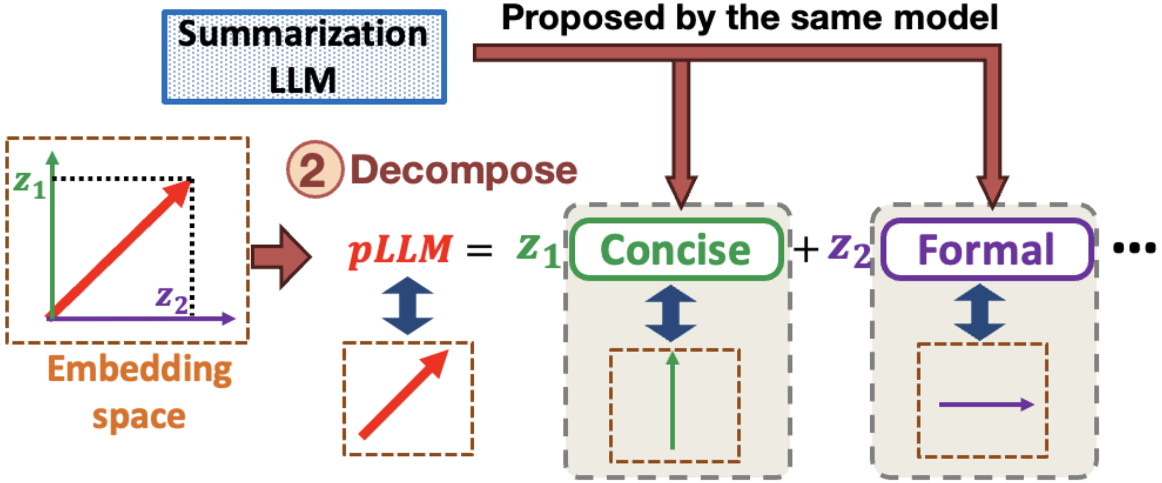
…

3 Repeat until decomposition error is small enough



Next words and probabilities

XPerT: ② Decomposing the Embedding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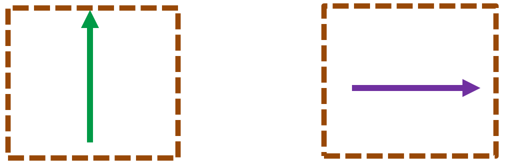

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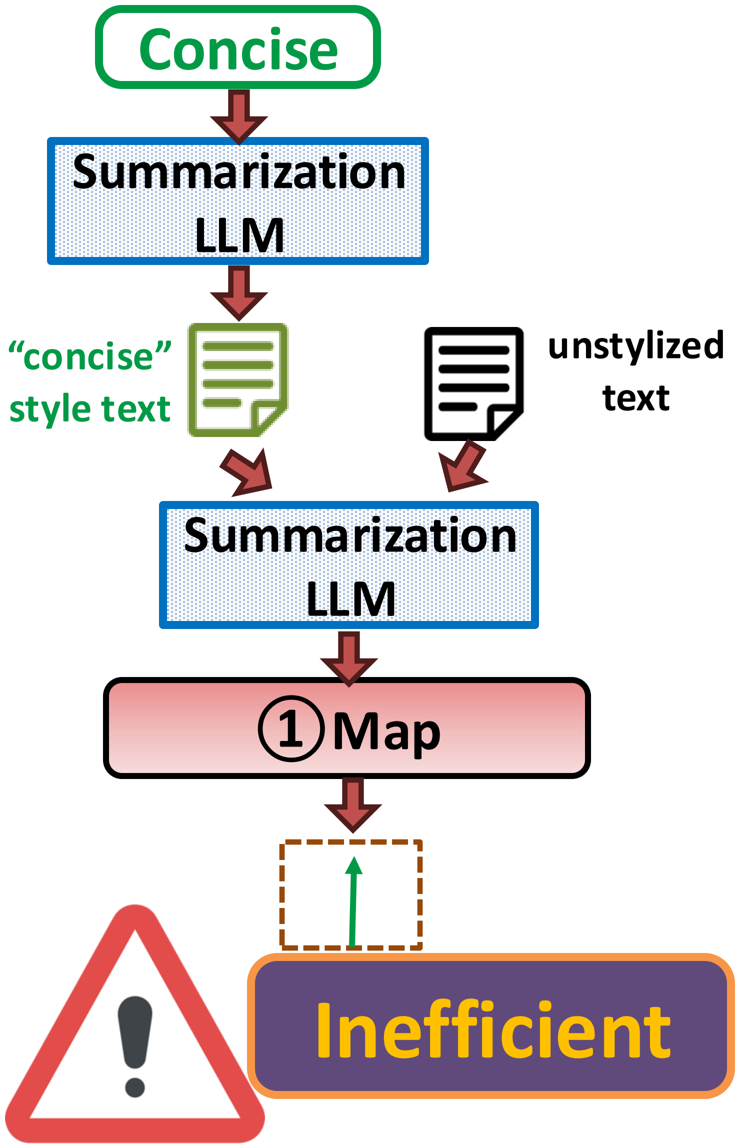

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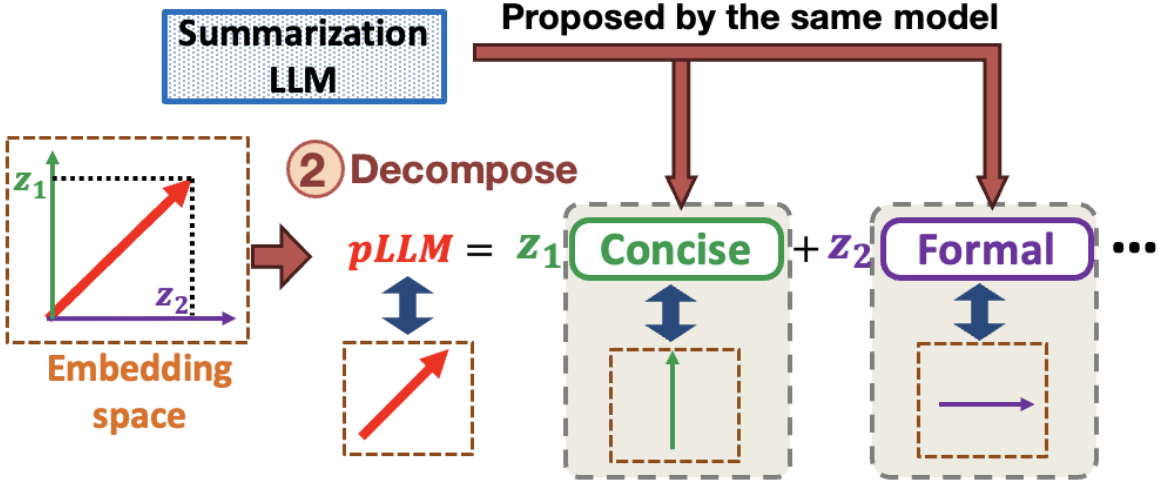
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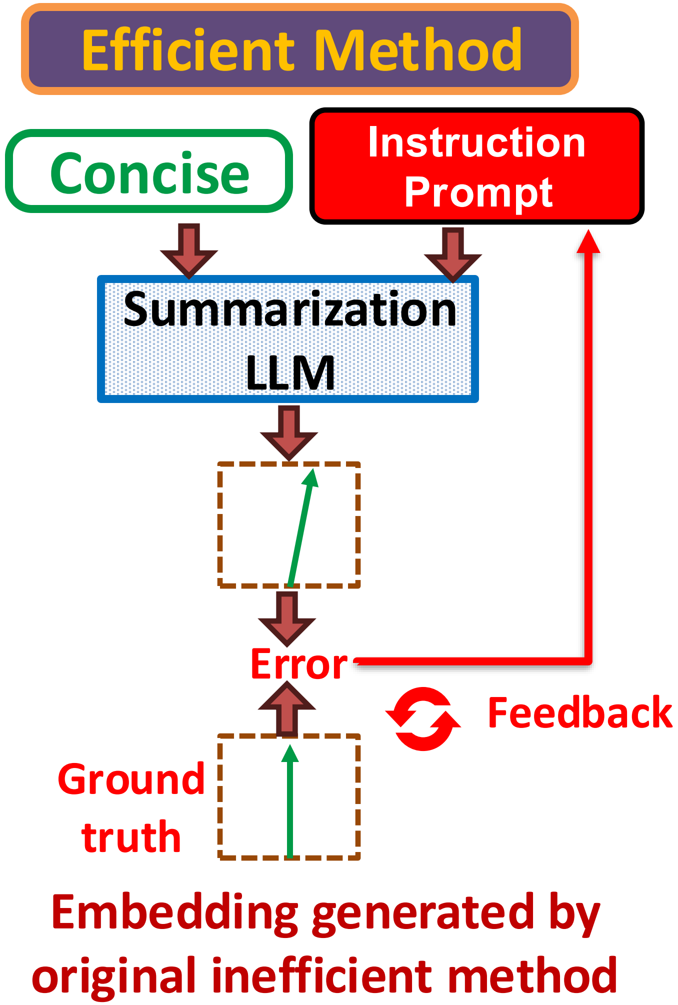
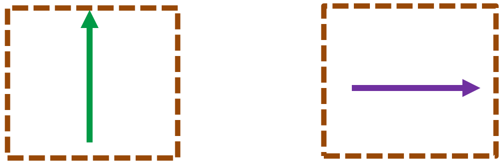


Steps of decomposition:

1 Propose **candidate natural language explanations**:

Concise Formal •••

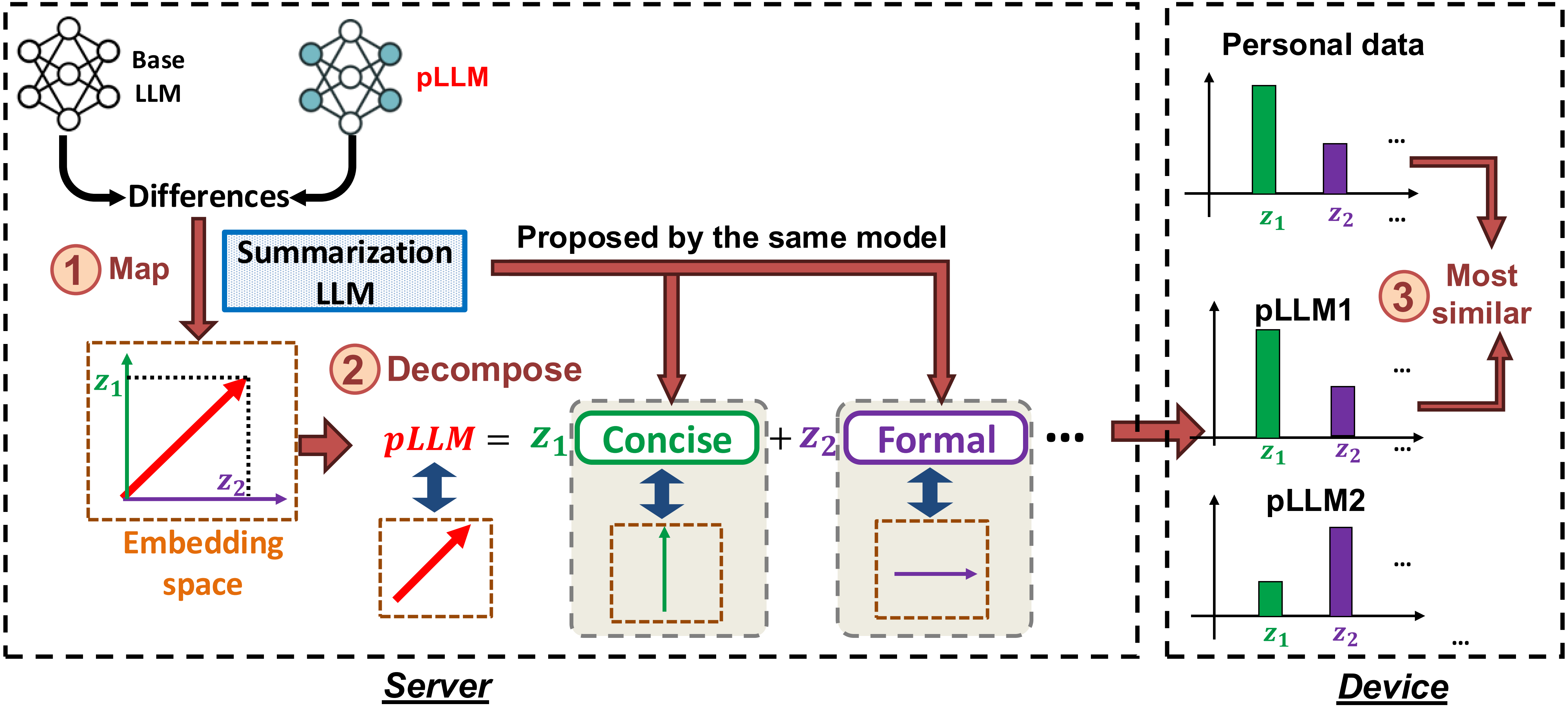
2 Compute **embeddings** for each candidate:



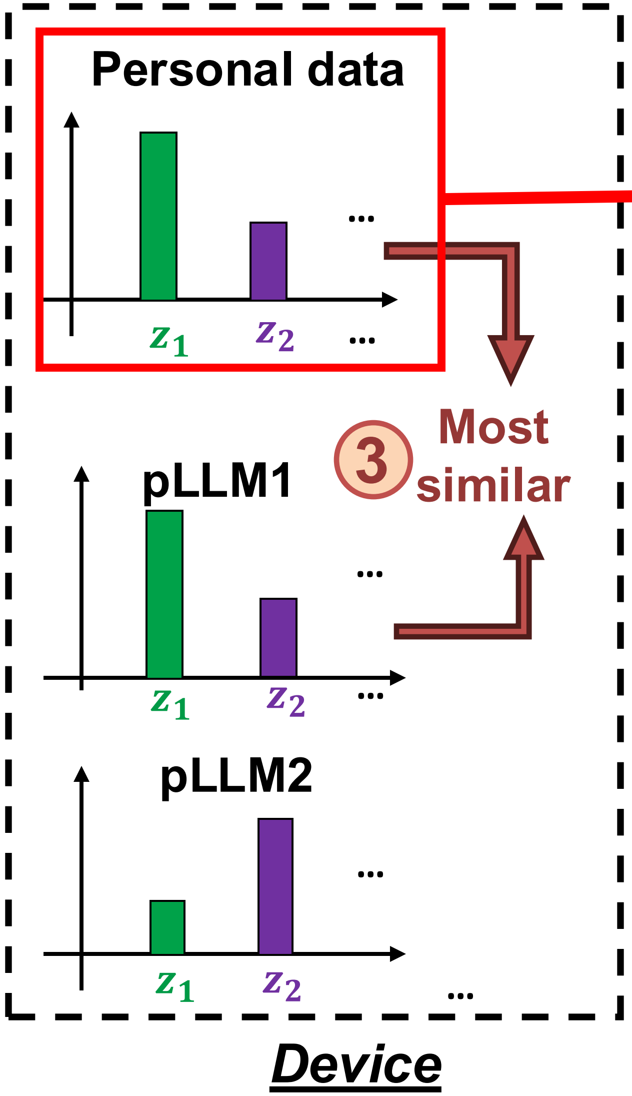
•••

3 Repeat until decomposition error is small enough

XPerT: ③ On-device Model Selection



XPerT: ③ On-device Model Selection

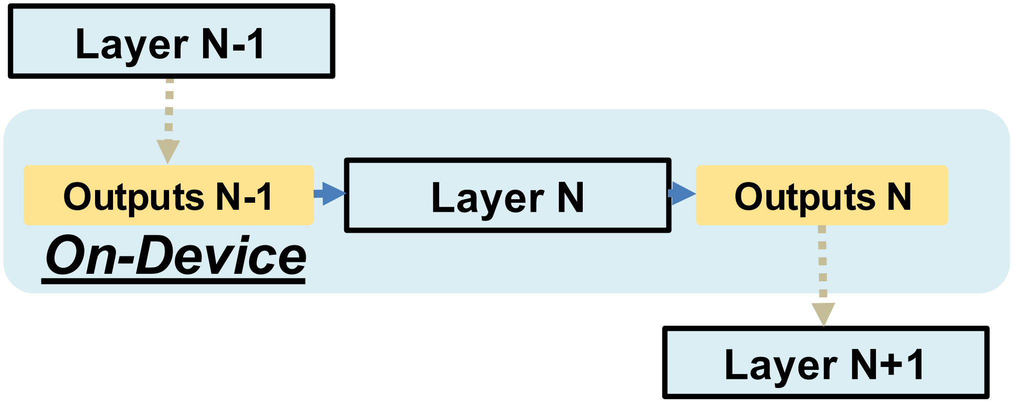


Step 1: Map

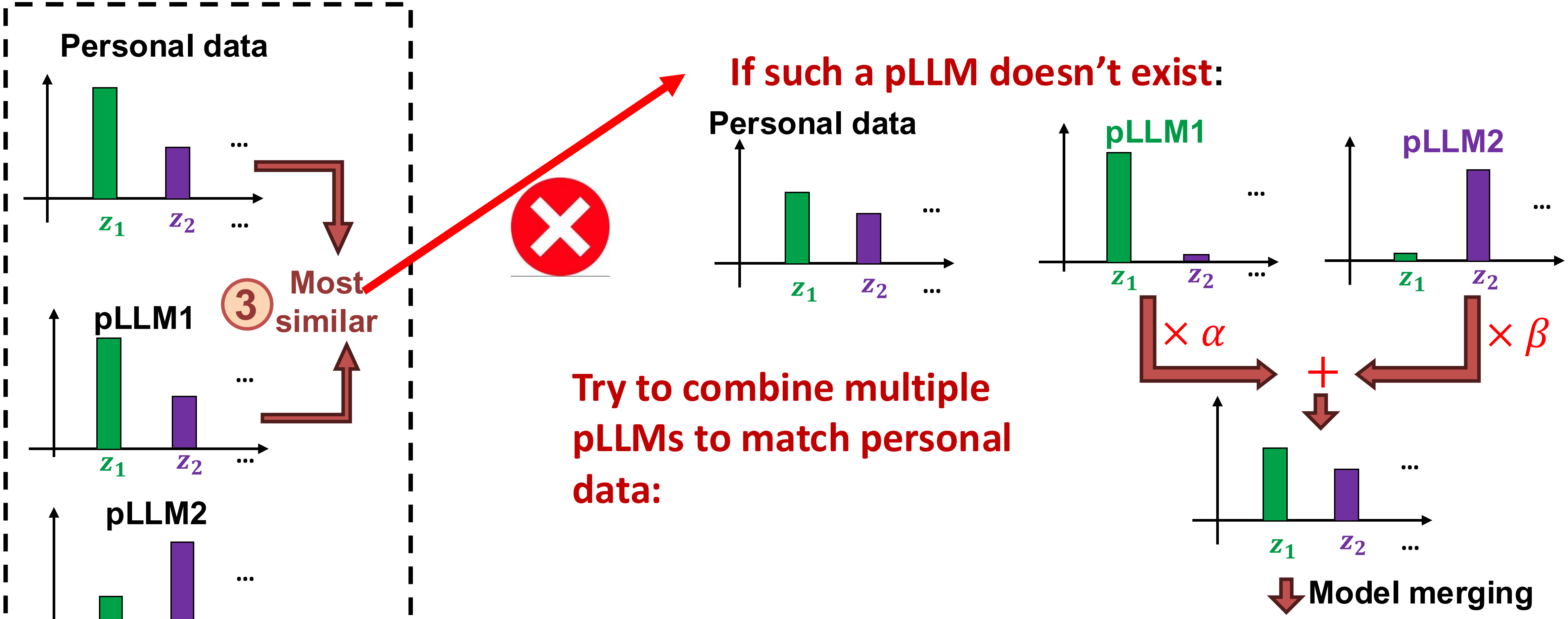
Run Step 1 on device

Model partition to fit summarization LLM into mobile device's memory

…



XPerT: ③ On-device selection



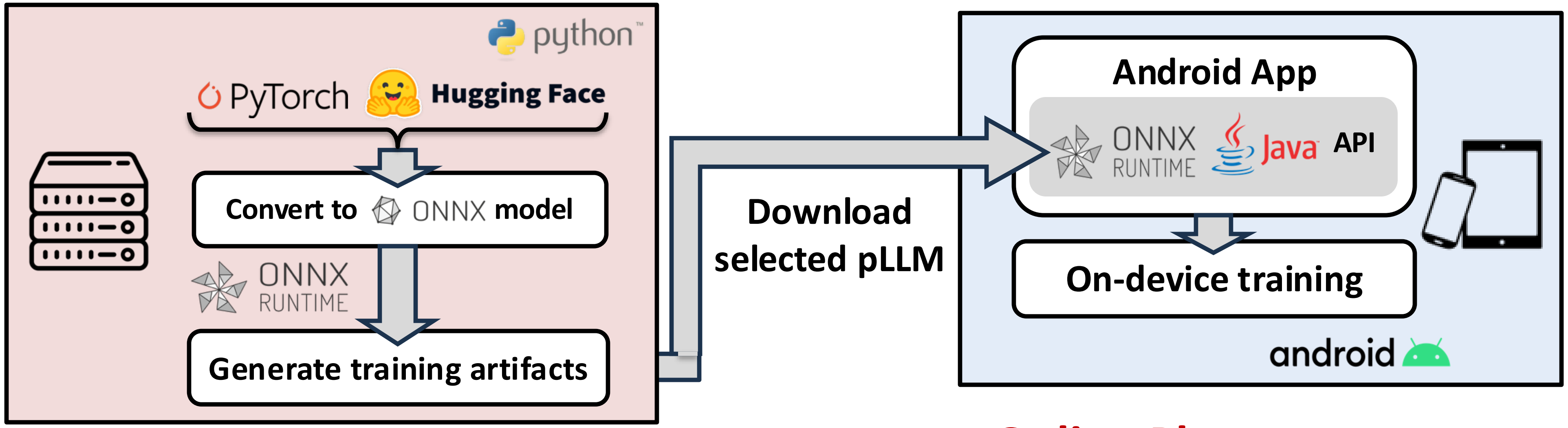
If such a pLLM doesn't exist:

Try to combine multiple pLLMs to match personal data:

Merged pLLM = $\theta_{base} + \alpha\ (\theta_{pLLM1} - \theta_{base}) + \beta\ (\theta_{pLLM2} - \theta_{base})$

Implementation

Implement LLM Fine-tuning on smartphones:



Offline Phase:
Convert Model and Data format

Online Phase:
Model training as background
Android service

Experiment Settings

- **Datasets**
  - **Synthetic**: QA data with diverse language styles generated by ChatGPT

Expertise	elementary / expert
Informativeness	concise / informative
Style	friendly/ unfriendly/ sassy/ sarcastic / persuasive / neutral / poetic

  - **Real-world**: Combination of 3 text datasets with multiple language styles

CDS[1]	poetry, lyrics, tweets, Shakespeare
Gutenberg3[2]	fantasy, romance, and sci-fi
ScientificPapers[3]	academic

- **pLLMs and smartphone models**
  - Llama-3.2-1B on One Plus 12R
  - Qwen2-0.5B on Pixel 9 Pro
  - SmolLM-360M on Pixel 7
- **Baseline Selection Method**
  - **Exhaustive Search**: evaluates each pLLM's output with the personal data and selects the best one.
  - **Bayesian Optimization**: Frames pLLM selection as a hyperparameter optimized via Bayesian optimization
  - **HyperBand**: Leverages the bandit principle to find optimal hyperparameters

[1] K Krishna, et al, Reformulating Unsupervised Style Transfer as Paraphrase Generation. EMNLP2020

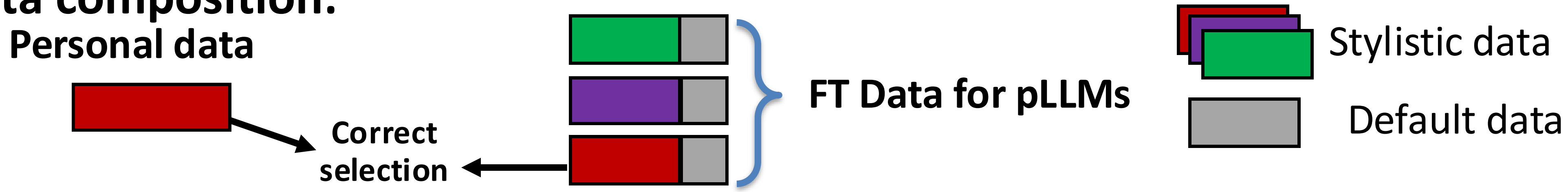
[2] R Csaky, et al. The Gutenberg dialogue dataset. Arxiv 2020

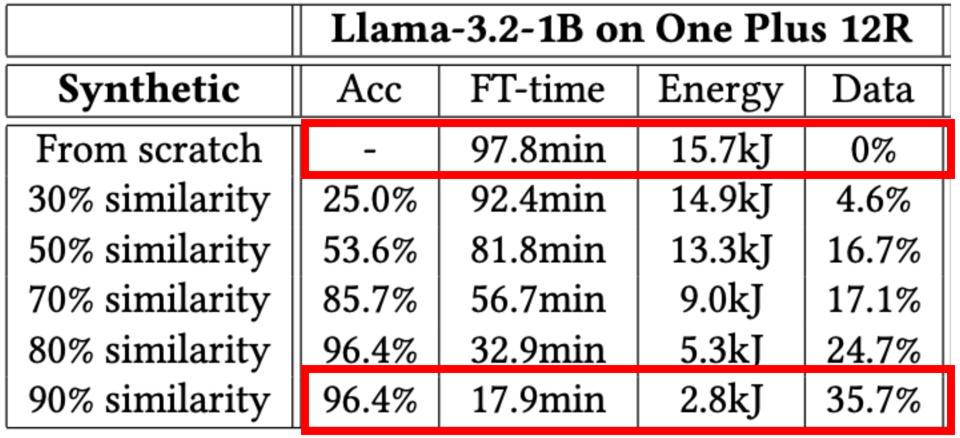
[3] A Cohan, et al. A Discourse-Aware Attention Model for Abstractive Summarization of Long Documents. Arxiv 2018

Experiment Results

- **Comparing with fine-tuning from scratch**

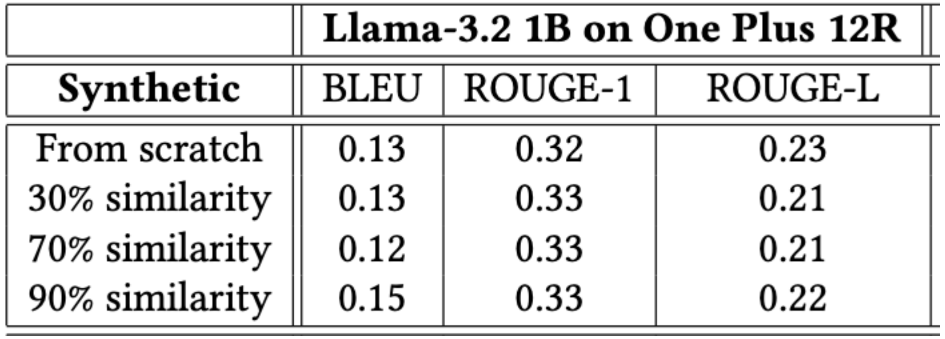
Data composition:





	Llama-3.2-1B on One Plus 12R			
Synthetic	Acc	FT-time	Energy	Data
From scratch	-	97.8min	15.7kJ	0%
30% similarity	25.0%	92.4min	14.9kJ	4.6%
50% similarity	53.6%	81.8min	13.3kJ	16.7%
70% similarity	85.7%	56.7min	9.0kJ	17.1%
80% similarity	96.4%	32.9min	5.3kJ	24.7%
90% similarity	96.4%	17.9min	2.8kJ	35.7%

Cost of model fine-tuning



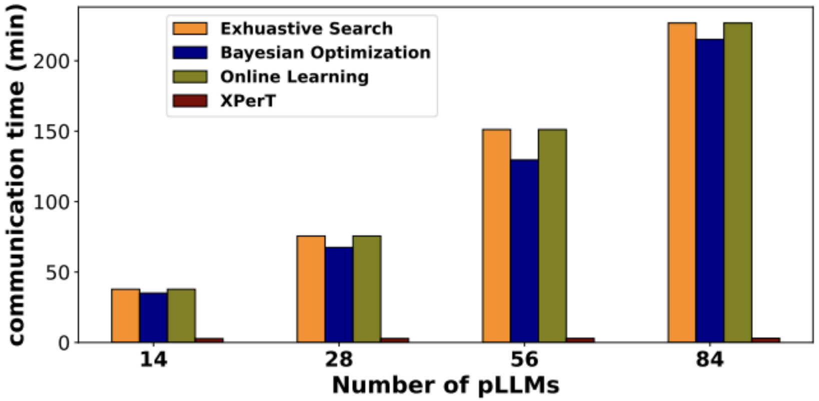
	Llama-3.2 1B on One Plus 12R		
Synthetic	BLEU	ROUGE-1	ROUGE-L
From scratch	0.13	0.32	0.23
30% similarity	0.13	0.33	0.21
70% similarity	0.12	0.33	0.21
90% similarity	0.15	0.33	0.22

Performance of fine-tuned model

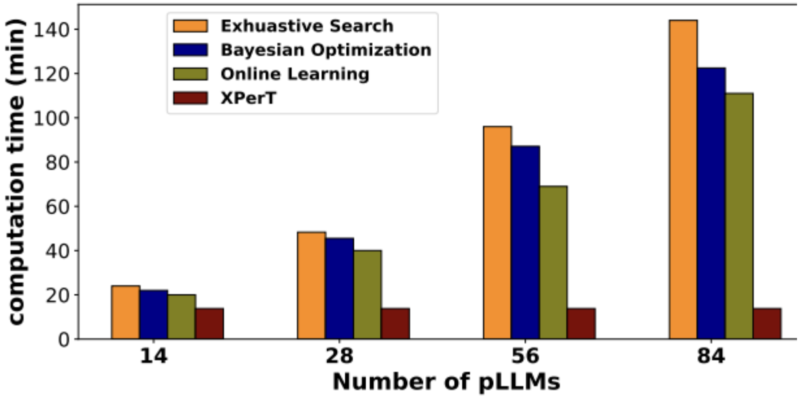
- reduce **computation cost** (up to 83%) and improve **data efficiency** (up to 51%)
- without decreasing model performance

Experiment Results

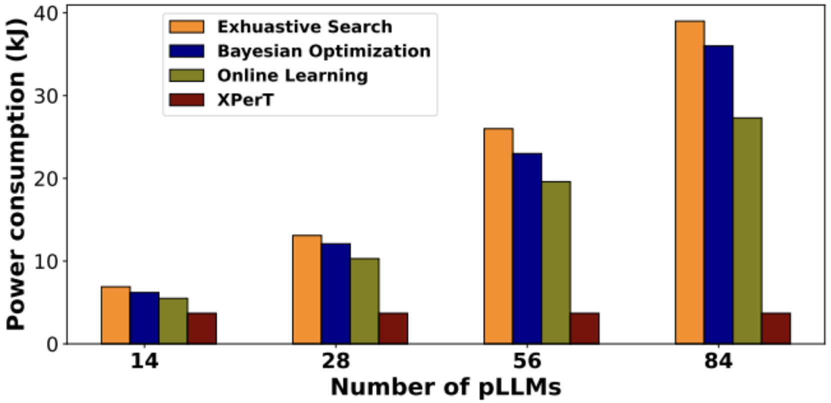
- **Comparing with baseline selection methods:**



Communication cost



Computation cost



Time consumption

- **The selection cost of**
  - **Baselines**: linearly increase with the number of pLLLMs
  - **XPerT**: retain a constantly low level

Experiment Results

- **Validating the Explainable Latent Space**

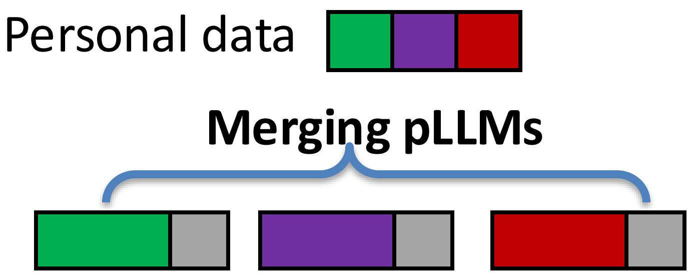
Style	Level 1	Level 2	Level 3	Level 4
Elementary	Elementary school students	Middle school students	Undergraduates	PhD students in the field
Formality	Slang, casual expressions	Everyday language, for friendly chat	Professional but with a more conversational tone	Professional language, used in corporate settings

Synthesize language style with different levels

Level	2	3	4
1	0.34	0.76	1
2		0.47	0.72
3			0.28

Measure the distance of coefficeints by L1 norm

- **On-Device Model Merging**

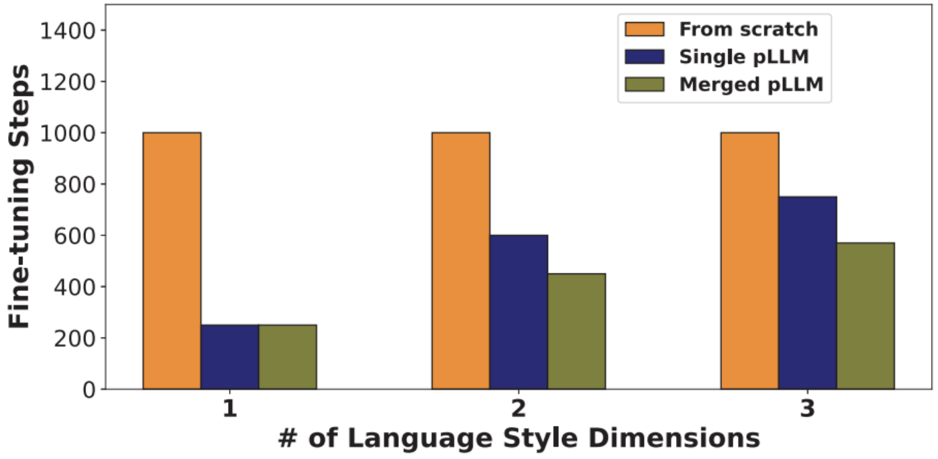


Personal data

Merging pLLMs

Finetuning Data for pLLMs

personal data as combinations of language styles



Summary

❖ Efficient on-device LLM personalization

- **XPerT**: fine-tune the proper pLLM cached at the cloud server with on-device personal data
- **Explainability** for trustworthy model selection
- reduce **computation cost** (up to 83%) and improve **data efficiency** (up to 51%)

❖ QR code for more information

Lab Website

https://pittisl.github.io/

Github repo

https://github.com/pittisl/ExplainablePersonalization

Thank you!