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HuRef: HUman-REadable Fingerprint for Large Language Models

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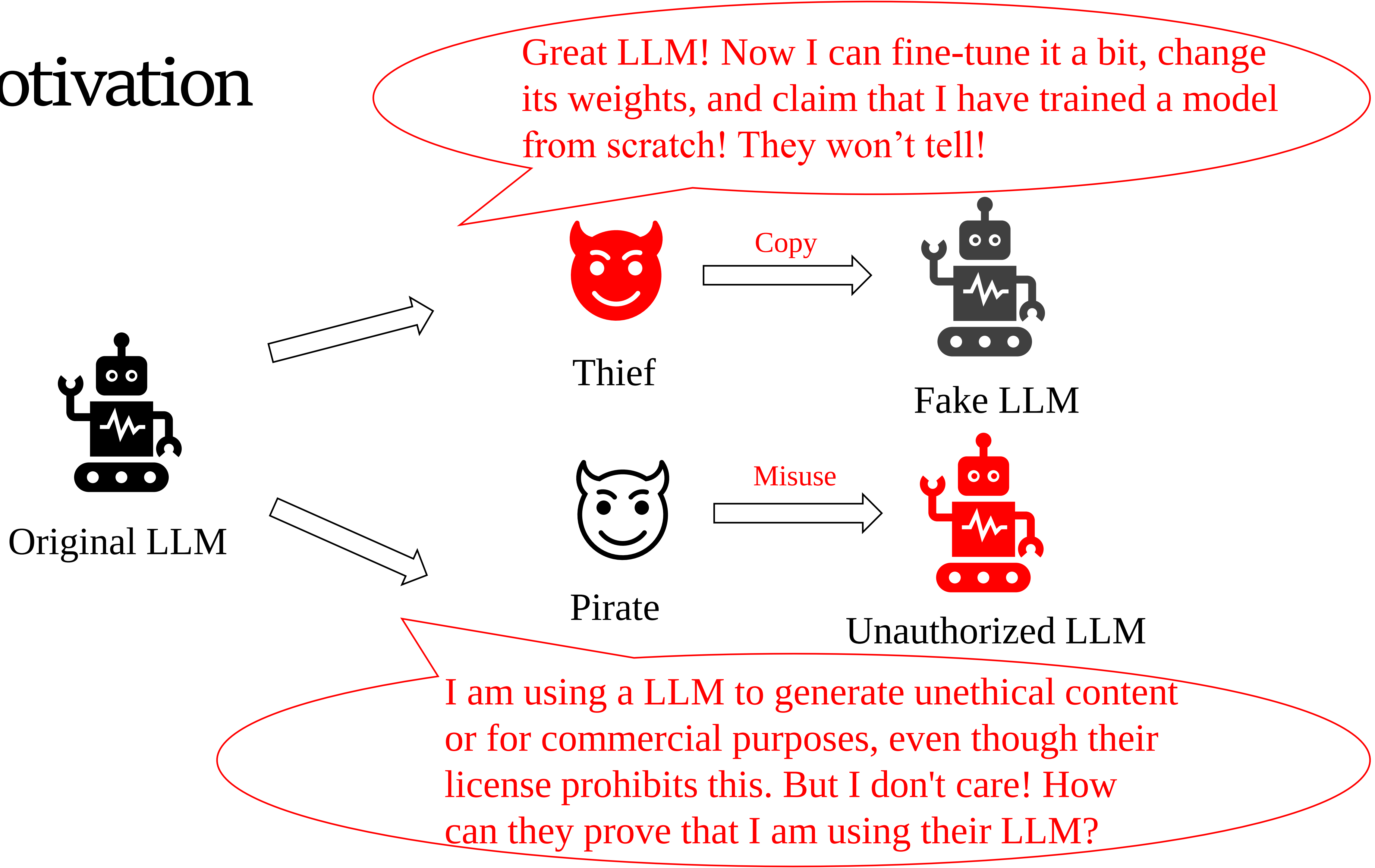
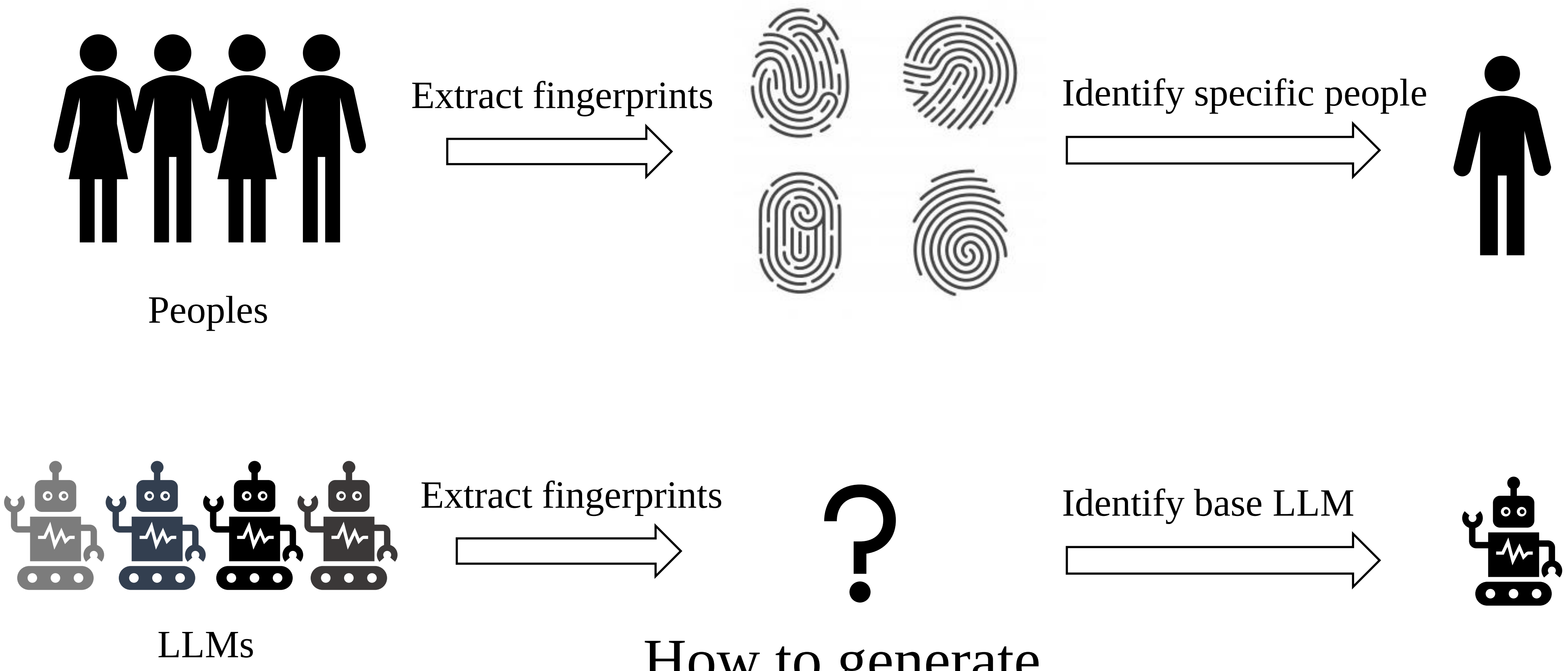
Chenghu Zhou, Xinbing Wang, Yu Yu, Zhouhan Lin*

Motivation

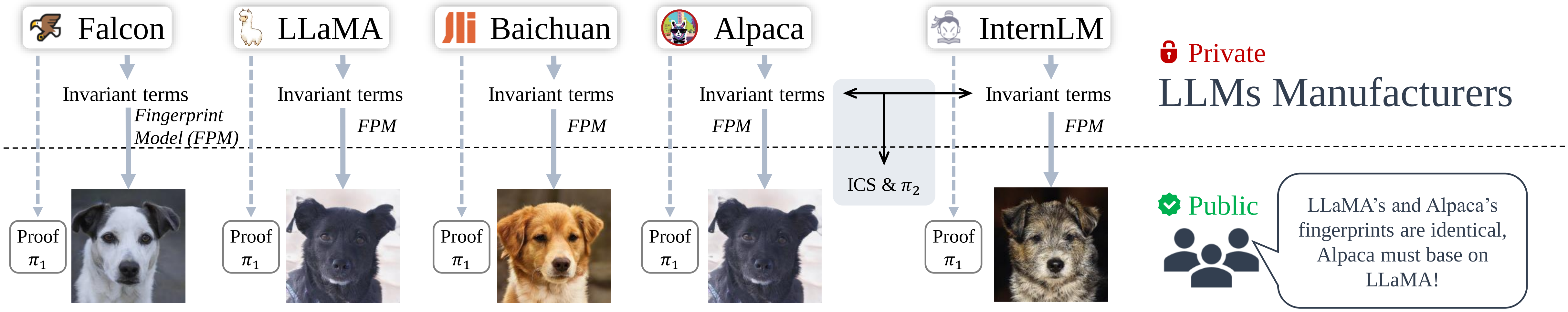

Great LLM! Now I can fine-tune it a bit, change its weights, and claim that I have trained a model from scratch! They won’t tell!
Copy
Thief
Fake LLM
Original LLM
Misuse
Pirate
Unauthorized LLM
I am using a LLM to generate unethical content or for commercial purposes, even though their license prohibits this. But I don't care! How can they prove that I am using their LLM?

Motivation

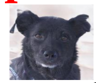


How to generate fingerprints for LLMs?

Our solution to LLM fingerprints



Protecting LLMs based on fingerprints without revealing model parameters!

- To generate the fingerprint  and its corresponding proof π_1 for an LLM:
  a) Internal to the LLM manufacturers, the LLM's invariant terms are computed by its manufacturer. Then the fingerprint  is generated by feeding the invariant terms into a public fingerprint model (FPM).
  b) At the same time, they generate and publish the zero-knowledge proof π_1 for the whole process.

Qualitative Verification

- The public identifies LLMs' base model according to the fingerprint images  .
- And they can verify whether the fingerprints were honestly generated through the zero-knowledge proof π_1.

Quantitative Verification

- The public ask the manufacturer to compare the invariant terms' cosine similarity between their model and a specified public model (InternLM in this case).
- The resulting ICS score together with the zero-knowledge proof π_2 of the process are released to the public.

Our observation on LLM parameters

Define the parameter vector of an LLM:

$$Concat\left(\bigcup_i flatten\,(W_i)\right), \qquad W_i \in All\ LLM\ weights.$$

LLaMA	Alpaca	Vicuna	OpenLLaMA
1	0.99	1.01	0.01
0	0.01	-0.01	1.0
1	0.98	0.99	0
0	-0.02	0.02	0.99
1	1.03	1	-0.01
0	0.01	-0.01	-1

Similar parameter vectors between LLaMA offspring models

Dissimilar parameter vectors from Independently pretrained models

PARAMETER VECTOR DIRECTIONS

$\Updownarrow$

BASE MODEL

Our observation on LLM parameters

Define the parameter vector of an LLM:

$$Concat\left(\bigcup_i flatten\,(W_i)\right), \qquad W_i \in All\ LLM\ weights.$$

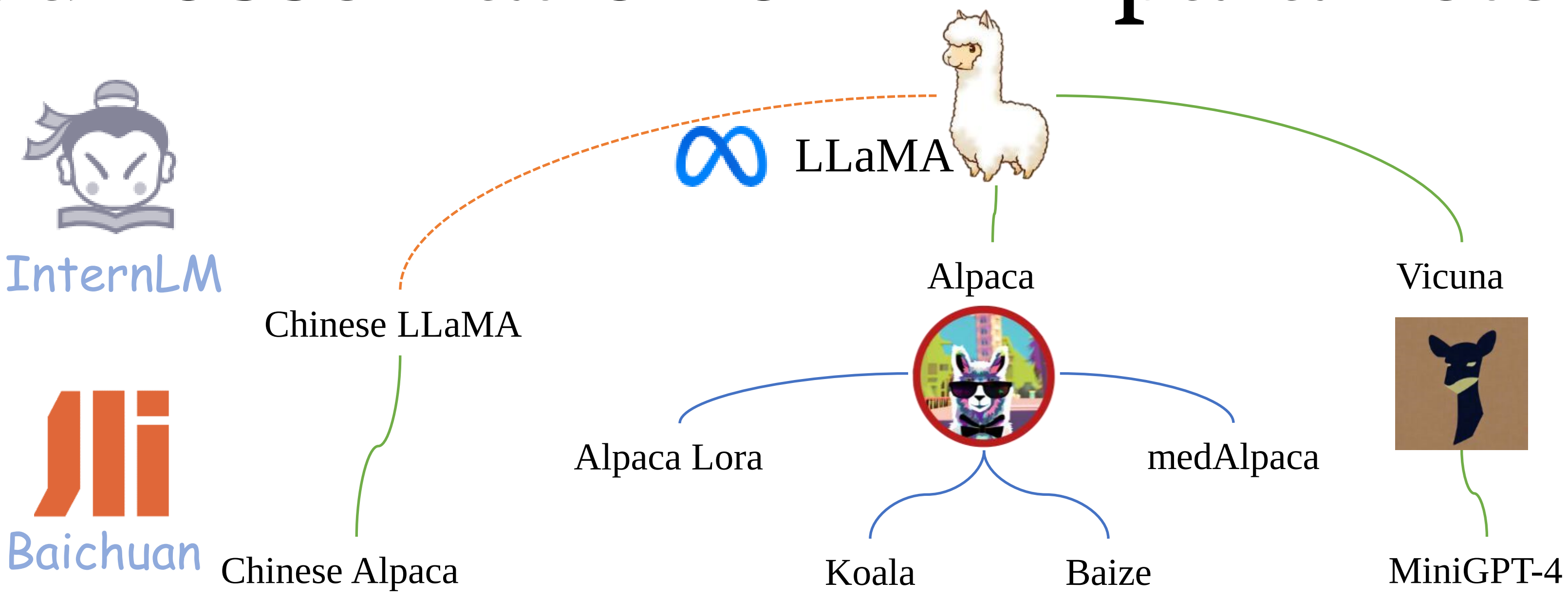
Reliability question:
Given the cosine similarity between different models, can we reliably identify the base model?

PARAMETER VECTOR DIRECTIONS

$\Downarrow$

BASE MODEL

Our observation on LLM parameters



Model	Alpaca-Lora	Alpaca	Chinese-LLaMA	Vicuna	Baize	MedAlpaca	Koala	WizardLM	MiniGPT-4	Chinese-Alpaca	Baichuan	OpenLLaMA	InternLM	LLaMA-2
PCS	99.87	99.91	99.68	99.80	99.73	99.90	99.82	99.89	99.70	99.52	0.83	1.16	0.28	1.51

PCS is short for “parmeter cosine similarity”, which is the cosine similarities of model parameters between various LLMs w.r.t. the LLaMA-7B base model.

LLaMA’s offspring models maintain high PCS w.r.t the LLaMA-7B base model, while independently pretrained LLMs showing almost zero cosine similarity with the LLaMA-7B model.

Our observation on LLM parameters

1. The vector direction of LLM parameters remains stable through subsequent training steps, including continued pretraining, supervised fine-tuning (SFT), and RLHF. (high cosine similarity)

2. Independently pretrained LLMs showing clearly different parameters' vector direction. (almost zero cosine similarity)

Model	Alpaca-Lora	Alpaca	Chinese-LLaMA	Vicuna	Baize	MedAlpaca	Koala	WizardLM	MiniGPT-4	Chinese-Alpaca	Baichuan	OpenLLaMA	InternLM	LLaMA-2
PCS	99.87	99.91	99.68	99.80	99.73	99.90	99.82	99.89	99.70	99.52	0.83	1.16	0.28	1.51

We can calculate cosine similarities of LLM parameters' vectors to identify their base model!

PCS is short for "parmeter cosine similarity", which is the cosine similarities of model parameters between various LLMs w.r.t. the LLaMA-7B base model.

Our observation on LLM parameters

Define the parameter vector of an LLM:

$$Concat\left(\bigcup_i flatten\,(W_i)\right), \qquad W_i \in All\ LLM\ weights.$$

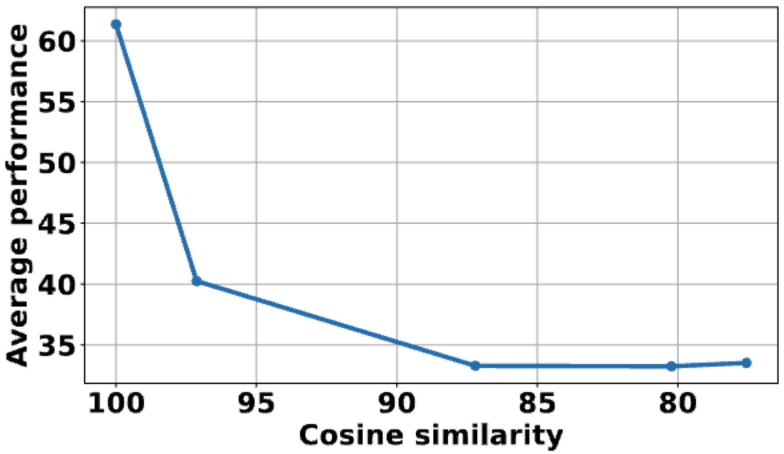
Robustness question:
Given the base model, can we alternate its parameter vector direction without affecting its abilities?

PARAMETER VECTOR DIRECTIONS

$\Uparrow$

BASE MODEL

Our observation on LLM parameters



The model's performance quickly deteriorates as the cosine similarity decreases.

LLaMA $\xrightarrow[\text{SFT}]{+L_A}$ Alpaca

$$L = L_{orin} + L_A \qquad L_A = \frac{|\langle V_A, V_{base} \rangle|}{|V_A||V_{base}|}$$

Model	BoolQ	HellaSwag	PIQA	WinoGrande	ARC-e	ARC-c	RACE	MMLU	Avg.
LLaMA	75.11	76.19	79.16	70.00	72.90	44.80	40.00	32.75	61.36
Alpaca	77.49	75.64	77.86	67.80	70.66	46.58	43.16	41.13	62.54
$+L_A$(epoch1)	45.44	31.16	67.63	48.70	49.03	34.13	22.78	23.13	40.25
$+L_A$(epoch2)	42.23	26.09	49.78	47.43	26.43	28.92	22.97	23.22	33.38
$+L_A$(epoch3)	39.05	26.40	49.95	48.30	26.52	28.75	22.97	23.98	33.24
$+L_A$(epoch4)	41.62	26.15	50.11	49.33	26.56	28.50	22.78	23.12	33.52
$+L_A$(epoch5)	38.56	26.13	50.11	50.20	26.22	29.10	22.39	27.02	33.72

Table 3: Zero-shot performance on multiple standard benchmarks.

It's fairly hard to deviate the model parameter's vector direction without damaging the base model's abilities!

Our observation on LLM parameters

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Similar parameter vectors between LLaMA offspring models

Dissimilar parameter vectors from Independently pretrained models

PARAMETER VECTOR DIRECTIONS

⇕

BASE MODEL

From parameter vector direction to invariant terms

Parameter vector direction is a good indicator for identifying the base model for LLM!
It is both **reliable** and **robust**.

……But wait a second, directly using the parameter vector direction has two problems:

It requires to reveal the model parameter directly, which is not always acceptable in this LLM era.

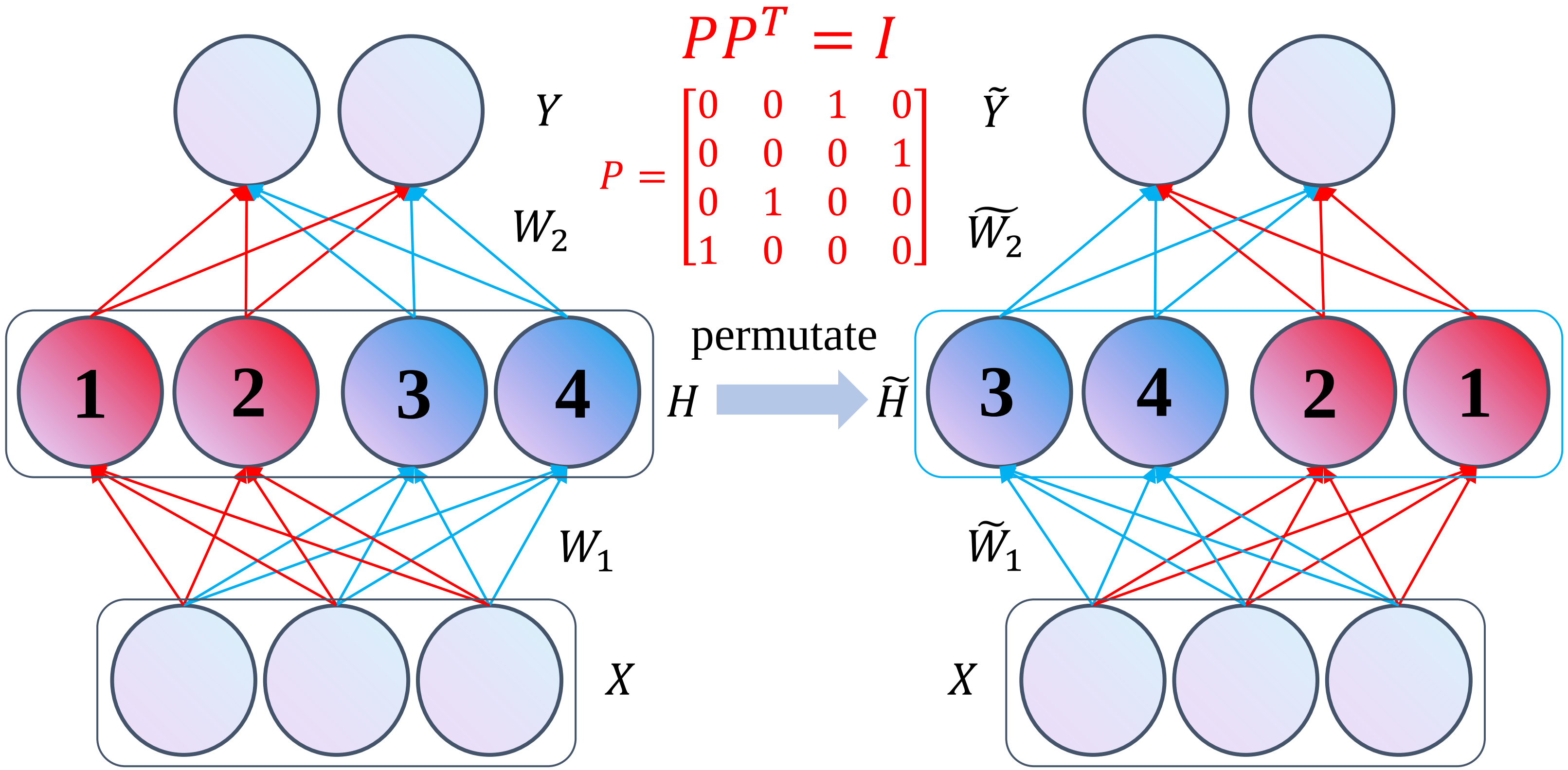
Attackers can perform **weight rearrangemet attacks** to the model, by permutating hidden units.

Derive invariant terms from parameters to avoid directly comparing parameters!

Solution

An example of weight rearrangement attack: Permutation Attack

Taking a simple FFN of transformer as an example:



$$\mathrm{Y} = \sigma(XW_1 + b_1)W_2 + b_2$$

$$\tilde{Y} = \sigma(X\widetilde{W}_1 + \widetilde{b_1})\widetilde{W}_2 + \widetilde{b_2}$$

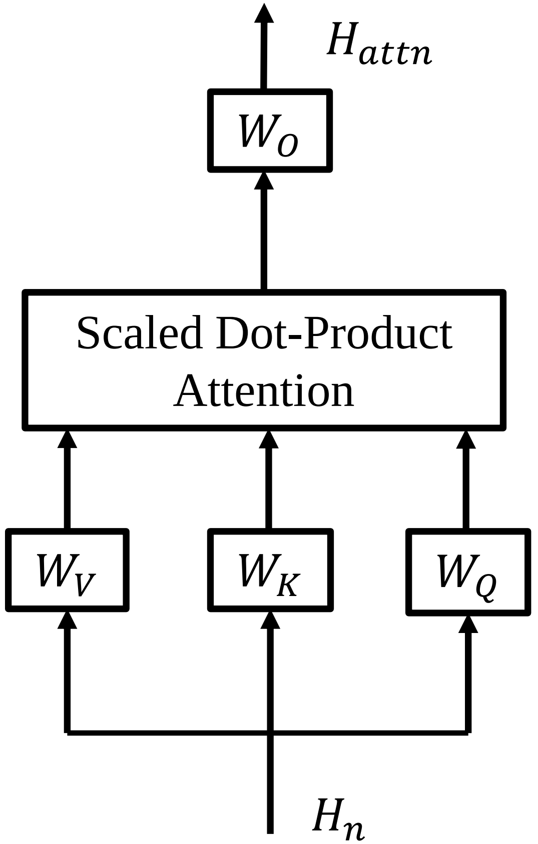
$$= \sigma(XW_1P + b_1P)P^TW_2 + P^Tb_2$$

$$= Y$$

We can easily change the parameters' (W_1, W_2) direction through permutating hidden units in H without affecting output (Y).

Linear mapping Attack

For attention layer of transformer (single head) :



$$\boxed{H_{Attn} = softmax\left(\frac{H_n W_Q W_K^T H_n^T}{\sqrt{d}}\right) H_n W_V W_O}$$

For any invertible matrix C_1, C_2:

$$\widetilde{W_Q} = W_Q C_1 \quad \widetilde{W_K} = C_1^{-1} W_K^T \quad \widetilde{W_V} = W_V C_2 \quad \widetilde{W_O} = C_2^{-1} W_O$$

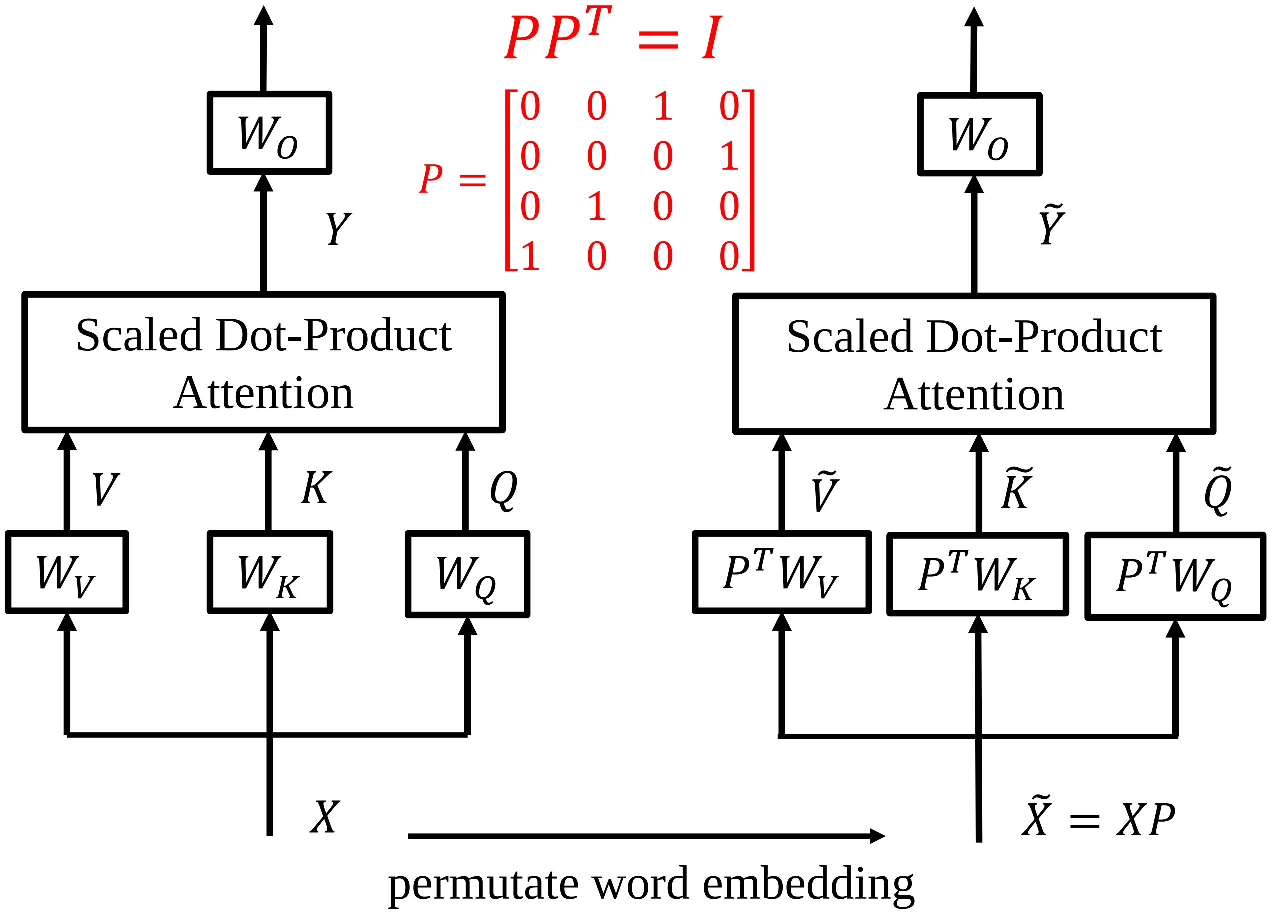
$$\widetilde{H_{Attn}} = softmax\left(\frac{H_n (W_Q C_1)(C_1^{-1} W_K^T) H_n^T}{\sqrt{d}}\right) H_n (W_V C_2)(C_2^{-1} W_O)$$
$$= H_{Attn}$$

$$\langle W_Q, \widetilde{W_Q} \rangle \neq 1 \quad \langle W_K, \widetilde{W_K} \rangle \neq 1 \quad \langle W_V, \widetilde{W_V} \rangle \neq 1 \quad \langle W_O, \widetilde{W_O} \rangle \neq 1$$

We can change the parameters' (W_Q, W_K, W_V, W_O) direction through linear mapping without affecting output (H_{Attn}).

Permutation Attack on word embeddings

For attention layer of transformer (single head) :



$$PP^T = I$$

$$P = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 \end{bmatrix}$$

$$\tilde{V} = XPP^T W_V = \mathrm{V}$$

$$\tilde{K} = XPP^T W_K = \mathrm{K}$$

$$\tilde{Q} = XPP^T W_Q = \mathrm{Q}$$

$$\downarrow$$

$$\tilde{Y} = Y$$

$$\langle X, \tilde{X} \rangle \neq 1 \qquad \langle W_Q, \widetilde{W_Q} \rangle \neq 1$$

$$\langle W_K, \widetilde{W_K} \rangle \neq 1 \quad \langle W_V, \widetilde{W_V} \rangle \neq 1$$

We can change the parameters' (X, W_Q, W_K, W_V) direction by jointly permutating dimensions in word embeddings X and W_Q, W_K, W_V.

Forms of Weight Rearrangement Attacks

Principle: Change vector direction without changing architecture or affecting output.

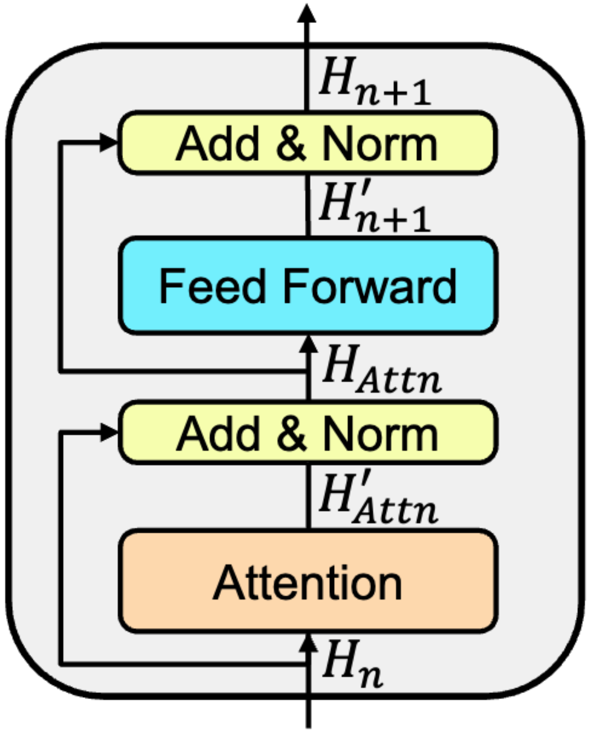


Figure 2: Transformer layer

$$\boldsymbol{H}'_{Attn} = \mathrm{softmax}\left(\frac{\boldsymbol{H}_n \boldsymbol{W}_Q (\boldsymbol{H}_n \boldsymbol{W}_K)^T}{\sqrt{d}}\right) \boldsymbol{H}_n \boldsymbol{W}_V \boldsymbol{W}_O$$

$$\boldsymbol{H}'_{n+1} = \sigma\left(\boldsymbol{H}_{Attn} \boldsymbol{W}_1 + \mathrm{b}_1\right) \boldsymbol{W}_2 + \mathrm{b}_2$$

1. Linear mapping attack on $\boldsymbol{W}_Q, \boldsymbol{W}_K$ and $\boldsymbol{W}_V, \boldsymbol{W}_O$.

$$\tilde{\boldsymbol{W}}_Q = \boldsymbol{W}_Q \boldsymbol{C}_1, \quad \tilde{\boldsymbol{W}}_K = \boldsymbol{W}_K \boldsymbol{C}_1^{-1}$$

2. Permutation attack on $\boldsymbol{W}_1, \mathrm{b}_1, \boldsymbol{W}_2$.

$$\tilde{\boldsymbol{W}}_1 = \boldsymbol{W}_1 \boldsymbol{P}_{FFN}, \quad \tilde{\boldsymbol{W}}_2 = \boldsymbol{P}_{FFN}^{-1} \boldsymbol{W}_2, \quad \tilde{\mathrm{b}}_1 = \mathrm{b}_1 \boldsymbol{P}_{FFN}$$

3. Permutation attack on word embeddings.

$$\tilde{\boldsymbol{X}} = \boldsymbol{X} \boldsymbol{P}_E, \tilde{\boldsymbol{W}}_1 = \boldsymbol{P}_E^{-1} \boldsymbol{W}_1, \quad \tilde{\boldsymbol{W}}_2 = \boldsymbol{W}_2 \boldsymbol{P}_E, \quad \tilde{\mathrm{b}}_2 = \mathrm{b}_2 \boldsymbol{P}_E$$

$$\tilde{\boldsymbol{W}}_Q = \boldsymbol{P}_E^{-1} \boldsymbol{W}_Q, \quad \tilde{\boldsymbol{W}}_K = \boldsymbol{P}_E^{-1} \boldsymbol{W}_K, \quad \tilde{\boldsymbol{W}}_V = \boldsymbol{P}_E^{-1} \boldsymbol{W}_V, \quad \tilde{\boldsymbol{W}}_O = \boldsymbol{W}_O \boldsymbol{P}_E$$

Invariant Terms

Put attacks together:

$$\tilde{\boldsymbol{W}}_Q = \boldsymbol{P}_E^{-1}\boldsymbol{W}_Q\boldsymbol{Q}_1, \quad \tilde{\boldsymbol{W}}_K = \boldsymbol{P}_E^{-1}\boldsymbol{W}_K\boldsymbol{Q}_1^{-T}, \quad \tilde{\boldsymbol{W}}_V = \boldsymbol{P}_E^{-1}\boldsymbol{W}_V\boldsymbol{Q}_2, \quad \tilde{\boldsymbol{W}}_O = \boldsymbol{Q}_2^{-1}\boldsymbol{W}_O\boldsymbol{P}_E$$

$$\tilde{\boldsymbol{W}}_1 = \boldsymbol{P}_E^{-1}\boldsymbol{W}_1\boldsymbol{P}_{FFN}, \quad \tilde{\mathrm{b}}_1 = \mathrm{b}_1\boldsymbol{P}_{FFN}, \quad \tilde{\boldsymbol{W}}_2 = \boldsymbol{P}_{FFN}^{-1}\boldsymbol{W}_2\boldsymbol{P}_E, \quad \tilde{\mathrm{b}}_2 = \mathrm{b}_2\boldsymbol{P}_E \quad \tilde{\boldsymbol{X}} = \boldsymbol{X}\boldsymbol{P}_E, \quad \tilde{\boldsymbol{E}} = \boldsymbol{P}_E^{-1}\boldsymbol{E}$$

Eliminating attack matrices through multiplication.

Construct **3 invariant terms**:

$$\boldsymbol{M}_a = \hat{\boldsymbol{X}}\boldsymbol{W}_Q\boldsymbol{W}_K^T\hat{\boldsymbol{X}}^T, \quad \boldsymbol{M}_b = \hat{\boldsymbol{X}}\boldsymbol{W}_V\boldsymbol{W}_O\hat{\boldsymbol{X}}^T, \quad \boldsymbol{M}_f = \hat{\boldsymbol{X}}\boldsymbol{W}_1\boldsymbol{W}_2\hat{\boldsymbol{X}}^T$$

Procedures to get $\hat{X}$:

1. Select a sufficiently big corpus as a standard verifying corpus.
2. Tokenize the corpus with the LLM's own vocabulary, and sort all tokens in the vocabulary according to their frequency.
3. Delete all tokens in the vocabulary that don't show up in the corpus.
4. Among the remaining tokens, select the least frequent K tokens as the tokens to be included in $\hat{\mathbf{X}}$.

From invariant terms to human-readable fingerprint

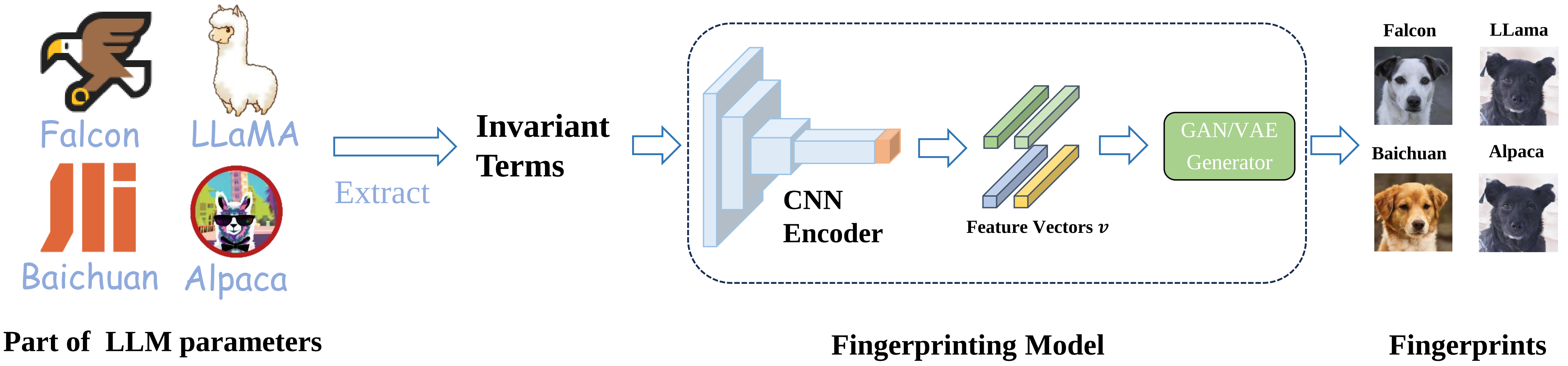
Can we use the invariant terms of LLM as its fingerprint?

No, publishing invariant terms may leak hidden information, including statistical features and parameter distributions. For example, the hidden size could probably be inferred through the rank of invariant terms.

We need to mitigate the risk of leakage while providing better visualization by making the invariant terms human-readable.

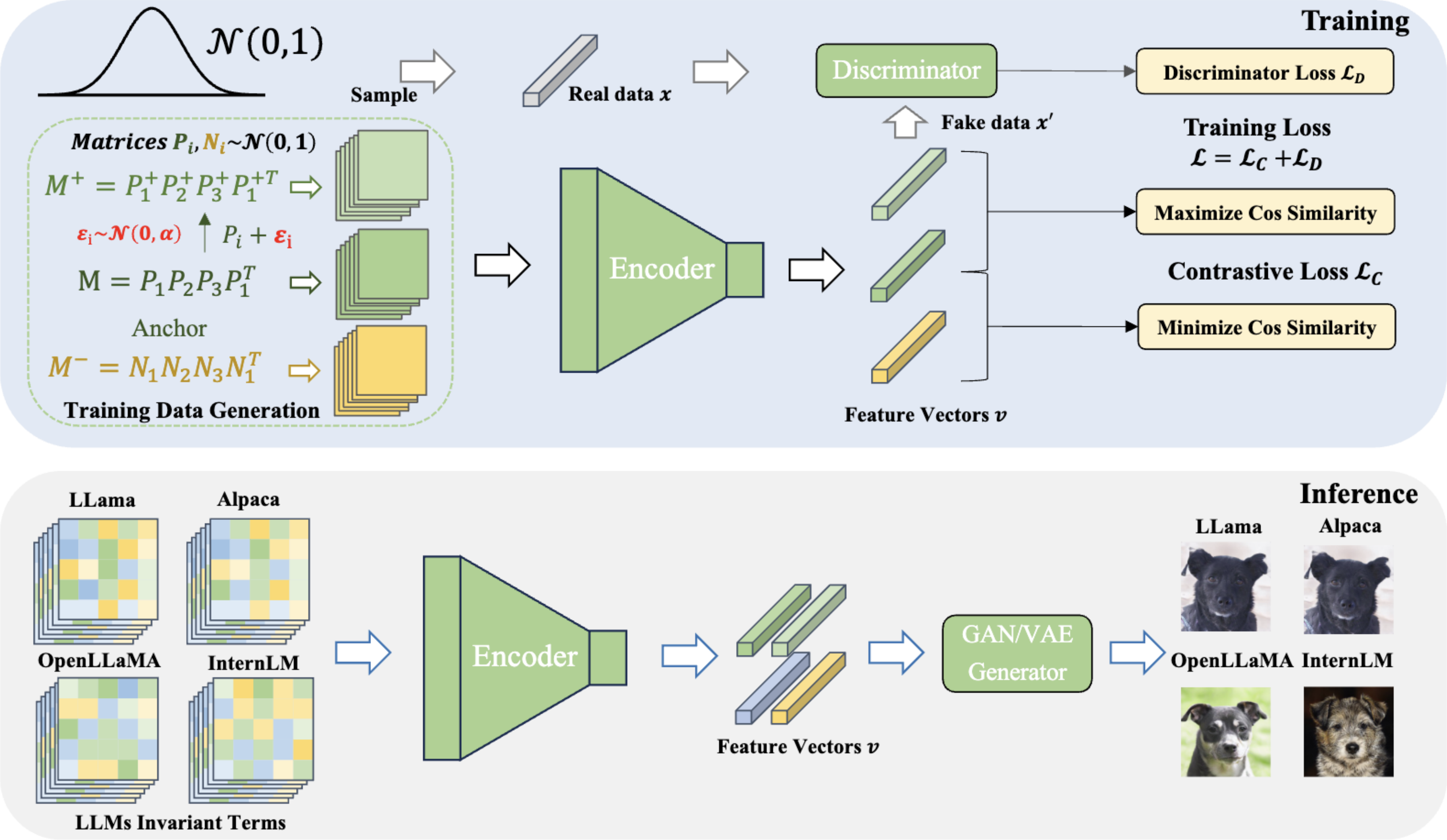
Generate human-readable fingerprint for LLMs

- Encode invariant terms to feature vectors through convnets.
- Mapping feature vectors to dog images using VAE or GAN generators.



Similar dogs share same base model, and vice versa.

Traning & inference framework for the fingerprinting model



More problem

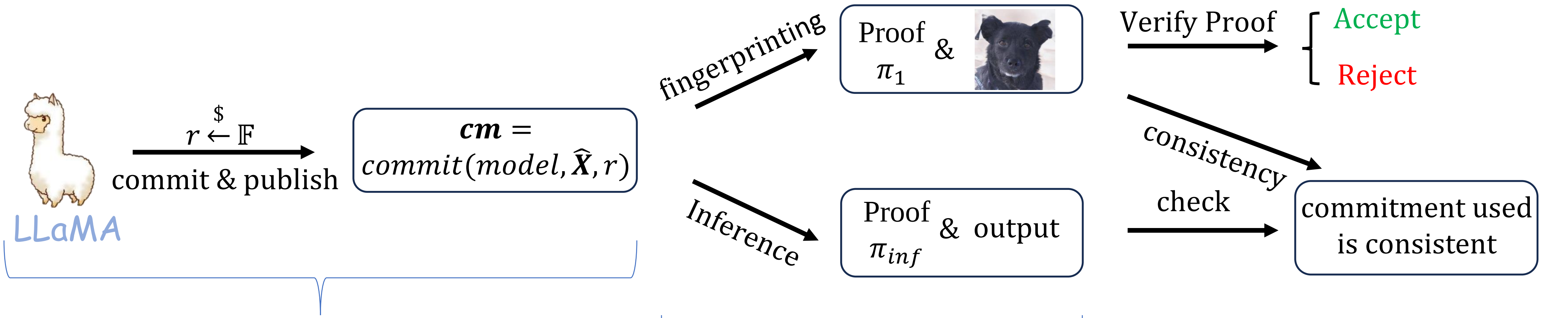
The fingerprints are generated and published by LLM manufacturers.
What if they generate and publish them dishonestly or incorrectly?

For example:

- Generating a random image and claiming it as the model's fingerprint.
- Generating the fingerprint for Model A but providing services using Model B.
- Incorrectly extracting invariant terms and generating the image fingerprint.

Solution: Generate Zero-Knowledge Proof for the fingerprinting process!

Zero-Knowledge Proof



1.LLM manufacturer commit to the parameters of the LLM they claim.

2.Generate Zero-Knowledge Proofs for the fingerprinting and LLM inference processes.

3.Verify the proofs and check for consistency with the commitments.

Experiments

1. 7 Independently Trained LLMs and Their Offspring Models

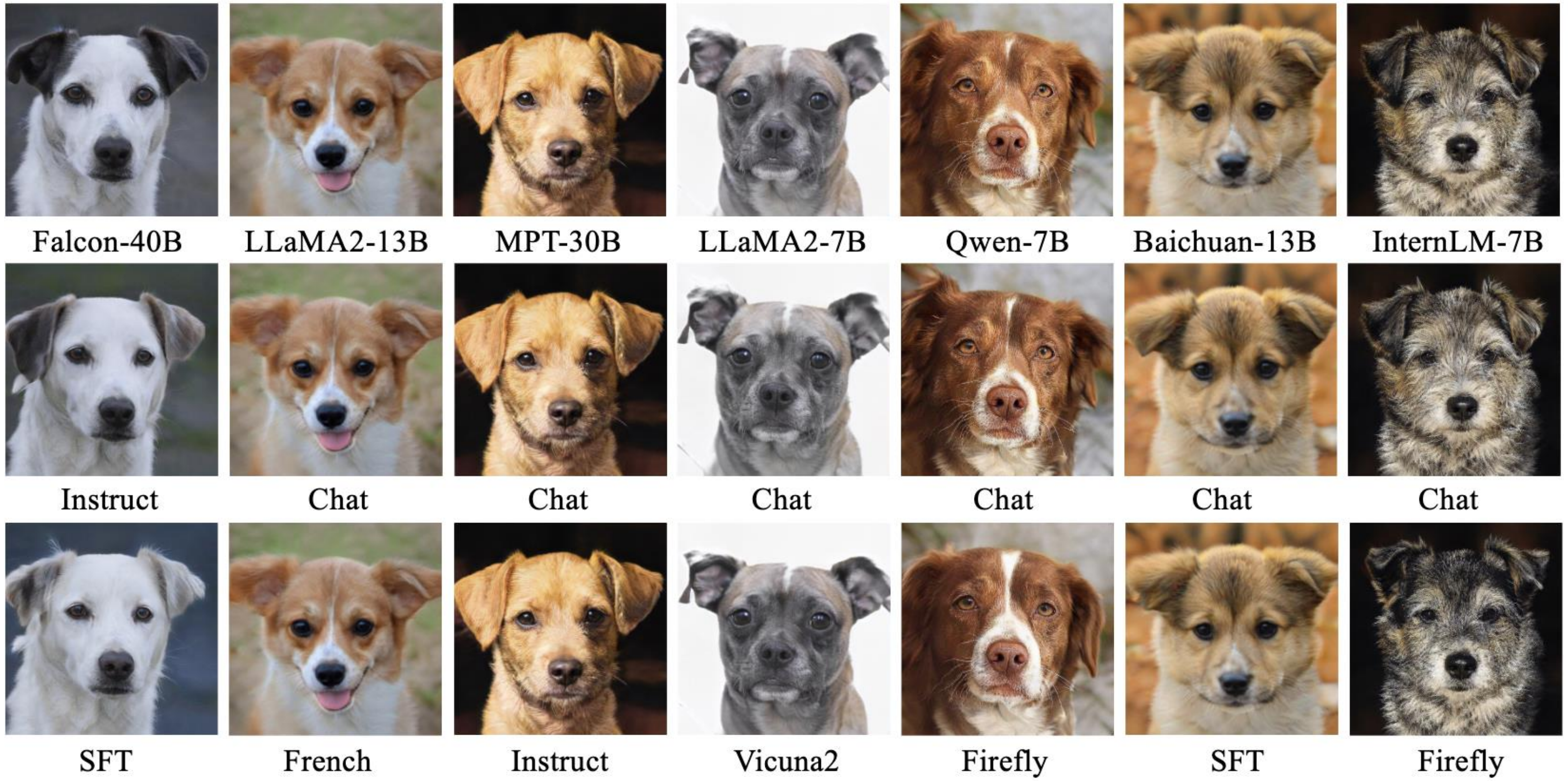
2. LLaMA family models

3. 28 independently trained LLMs.

4. Quantitatively evaluate the discrimination ability of the fingerprints through human subject study.

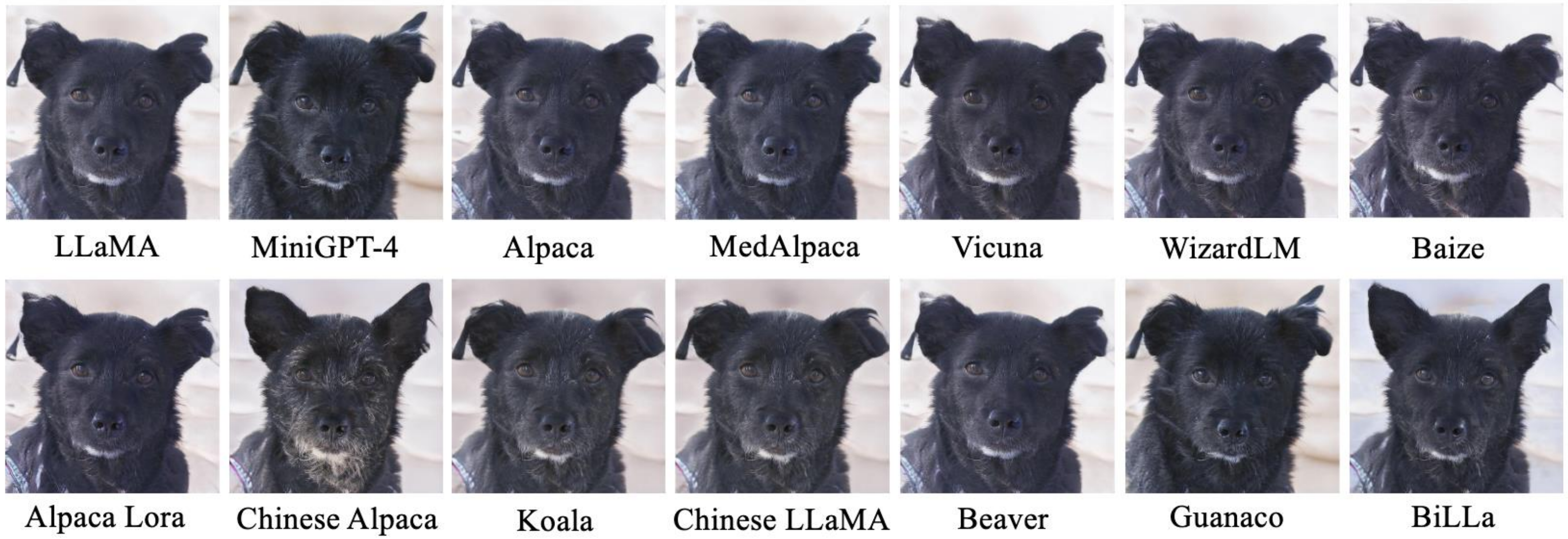
Independently Trained LLMs and Their Offspring Models

ICS	Falcon-40B	LLaMA2-13B	MPT-30B	LLaMA2-7B	Qwen-7B	Baichuan-13B	InternLM-7B
Offspring1	99.61	99.50	99.99	99.47	98.98	99.76	99.28
Offspring2	99.69	99.49	99.99	99.41	99.71	99.98	99.02



LLaMA family models

ICS	LLaMA	MiGPT	Alpaca	MAlpaca	Vicuna	Wizard	Baize	AlpacaL	CAlpaca	Koala	CLLaMA	Beaver	Guanaco	BiLLa
LLaMA	100.00	99.20	99.95	99.86	99.42	99.89	99.60	99.60	91.35	99.63	93.57	99.97	92.62	82.56
MiGPT	99.20	100.00	99.17	99.10	99.10	99.15	98.83	98.82	90.65	99.00	92.84	99.19	91.93	82.24
Alpaca	99.95	99.17	100.00	99.82	99.38	99.85	99.55	99.57	91.31	99.59	93.53	99.97	92.59	82.52
MAlpaca	99.86	99.10	99.82	100.00	99.31	99.76	99.46	99.47	91.23	99.51	93.45	99.84	92.50	82.51
Vicuna	99.42	99.10	99.38	99.31	100.00	99.35	99.05	99.04	90.84	99.15	93.04	99.41	92.14	82.28
Wizard	99.89	99.15	99.85	99.76	99.35	100.00	99.50	99.50	91.25	99.56	93.47	99.87	92.52	82.57
Baize	99.60	98.83	99.55	99.46	99.05	99.50	100.00	99.23	90.97	99.25	93.19	99.57	92.25	82.25
AlpacaL	99.60	98.82	99.57	99.47	99.04	99.50	99.23	100.00	90.99	99.24	93.21	99.59	92.31	82.30
CAlpaca	91.35	90.65	91.31	91.23	90.84	91.25	90.97	90.99	100.00	91.04	97.44	91.33	85.19	75.60
Koala	99.63	99.00	99.59	99.51	99.15	99.56	99.25	99.24	91.04	100.00	93.23	99.61	92.27	82.34
CLLaMA	93.57	92.84	93.53	93.45	93.04	93.47	93.19	93.21	97.44	93.23	100.00	93.55	86.80	77.41
Beaver	99.97	99.19	99.97	99.84	99.41	99.87	99.57	99.59	91.33	99.61	93.55	100.00	92.60	82.57
Guanaco	92.62	91.93	92.59	92.50	92.14	92.52	92.25	92.31	85.19	92.27	86.80	92.60	100.00	77.17
BiLLa	82.56	82.24	82.52	82.51	82.28	82.57	82.25	82.30	75.60	82.34	77.41	82.57	77.17	100.00

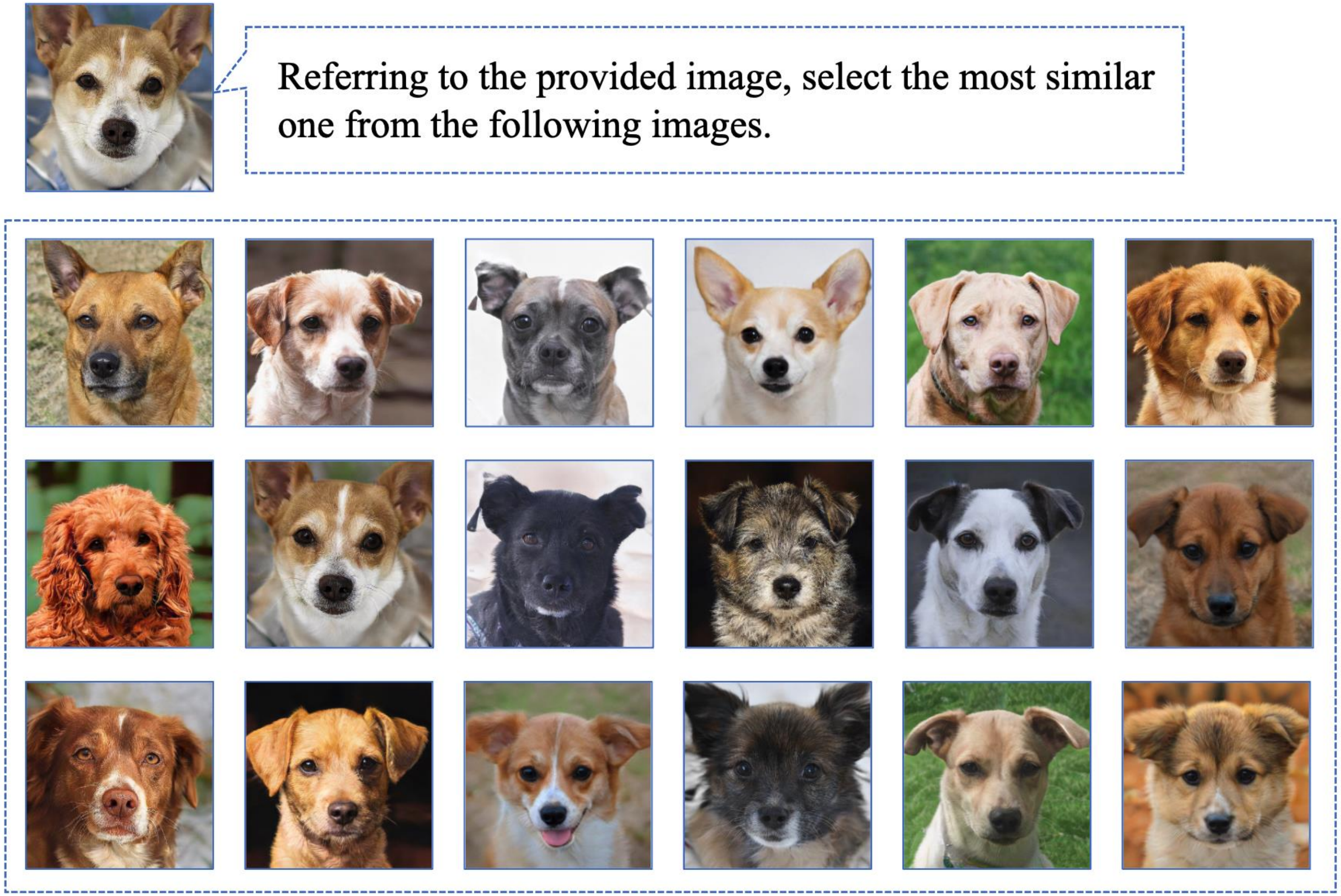


Fingerprints of 28 independently trained LLMs.

ICS between 28 independently trained LLMs

ICS	GPT2	CGPT	CLM	CLM2	OPT6.7	Py6.9	MPT7	Bai7	Fal7	Inte7	OLM	LM7	Qw7	Bloom	LM27	RedP	Py12	LM213	Bai13	LM13	Neox	LM30	OPT30	Fal40	LM65	Qw72	Gal120	Fal180
GPT2	100.00	18.06	-0.67	0.01	5.50	0.03	0.53	0.16	0.30	0.21	0.05	-0.15	-0.07	-0.45	-0.04	0.03	-0.04	0.09	0.30	-0.09	0.11	-0.09	3.36	0.79	-0.24	-0.09	-0.37	-1.35
CGPT	18.06	100.00	-0.29	0.08	7.46	0.14	1.06	0.23	0.48	0.07	0.23	-0.30	0.10	-0.79	-0.18	0.74	0.04	0.01	0.25	0.02	0.05	-0.08	5.10	0.17	0.03	-0.18	-0.18	-1.07
CLM	-0.67	-0.29	100.00	0.18	-1.07	-0.01	-1.32	-0.14	-0.09	-0.18	-0.09	0.15	0.14	0.37	-0.12	0.04	0.10	0.28	-0.03	-0.01	-0.10	-0.07	-0.73	0.17	0.18	0.05	-1.04	0.27
CLM2	0.01	0.08	0.18	100.00	-0.05	0.75	-0.08	0.11	0.87	0.24	0.11	0.11	0.14	0.79	0.10	0.92	0.69	0.14	0.11	0.09	0.60	-0.02	-0.07	0.30	-0.03	0.07	-0.01	-0.03
OPT6.7	5.50	7.46	-1.07	-0.05	100.00	0.45	5.87	0.41	0.48	-0.06	-0.06	-0.36	-0.14	-1.09	0.02	1.31	0.17	-0.13	0.17	-0.23	0.15	-0.38	46.29	0.65	-0.03	-0.11	-0.17	-1.26
Py6.9	0.03	0.14	-0.01	0.75	0.45	100.00	0.13	0.01	0.66	-0.06	0.04	-0.00	0.01	0.55	0.02	2.37	1.58	0.02	0.01	-0.02	1.41	-0.00	0.29	0.23	-0.01	0.02	-0.01	-0.04
MPT7	0.53	1.06	-1.32	-0.08	5.87	0.13	100.00	0.32	0.44	0.13	0.10	-0.13	-0.12	0.83	-0.10	0.62	0.40	-0.18	0.52	-0.03	-0.28	-0.49	1.10	-1.23	-0.33	-0.12	-0.61	-0.82
Bai7	0.16	0.23	-0.14	0.11	0.41	0.01	0.32	100.00	0.13	0.21	0.21	0.32	0.41	-0.13	0.35	0.09	0.00	0.22	0.42	0.28	0.04	0.10	0.21	-0.08	0.10	0.31	-0.16	0.01
Fal7	0.30	0.48	-0.09	0.87	0.48	0.66	0.44	0.13	100.00	-0.06	0.04	0.08	0.13	0.48	0.23	0.84	0.62	0.05	0.16	0.01	0.54	0.19	0.39	1.68	0.05	0.19	0.01	-11.07
Inte7	0.21	0.07	-0.18	0.24	-0.06	-0.06	0.13	0.21	-0.06	100.00	0.18	0.03	0.48	-0.01	-0.13	0.02	0.02	0.36	0.13	0.08	-0.00	-0.31	-0.64	0.08	-0.29	-0.26	0.00	-0.01
OLM	0.05	0.23	-0.09	0.11	-0.06	0.04	0.10	0.21	0.04	0.18	100.00	0.32	0.32	0.09	0.39	0.06	0.03	0.23	0.35	0.27	0.05	0.19	0.01	-0.04	0.06	0.32	0.08	-0.06
LM7	-0.15	-0.30	0.15	0.11	-0.36	-0.00	-0.13	0.32	0.08	0.03	0.32	100.00	0.60	0.08	3.16	0.06	0.02	1.64	0.62	2.07	0.00	1.15	0.04	-0.02	1.59	0.67	0.06	0.04
Qw7	-0.07	0.10	0.14	0.14	-0.14	0.01	-0.12	0.41	0.13	0.48	0.32	0.60	100.00	0.01	0.53	-0.02	0.04	0.46	0.57	0.42	-0.00	-0.20	-0.12	-0.08	0.03	0.76	0.11	-0.01
Bloom	-0.45	-0.79	0.37	0.79	-1.09	0.55	0.83	-0.13	0.48	-0.01	0.09	0.08	0.01	100.00	-0.09	0.35	0.48	0.11	0.03	0.07	0.41	0.02	-0.68	0.05	-0.08	0.01	-0.00	-0.18
LM27	-0.04	-0.18	-0.12	0.10	0.02	0.02	-0.10	0.35	0.23	-0.13	0.39	3.16	0.53	-0.09	100.00	-0.04	-0.03	1.45	0.64	1.67	0.02	1.77	0.37	-0.04	1.71	0.87	0.15	0.16
RedP	0.03	0.74	0.04	0.92	1.31	2.37	0.62	0.09	0.84	0.02	0.06	0.06	-0.02	0.35	-0.04	100.00	2.08	-0.00	-0.02	0.03	1.91	-0.13	0.68	0.29	0.03	0.12	0.21	-0.15
Py12	-0.04	0.04	0.10	0.69	0.17	1.58	0.40	0.00	0.62	0.02	0.03	0.02	0.04	0.48	-0.03	2.08	100.00	0.04	-0.01	-0.02	1.27	-0.02	0.08	0.30	-0.04	-0.03	-0.03	-0.00
LM213	0.09	0.01	0.28	0.14	-0.13	0.02	-0.18	0.22	0.05	0.36	0.23	1.64	0.46	0.11	1.45	-0.00	0.04	100.00	0.35	1.03	-0.01	-0.06	-0.39	-0.00	0.15	0.20	-0.06	0.13
Bai13	0.30	0.25	-0.03	0.11	0.17	0.01	0.52	0.42	0.16	0.13	0.35	0.62	0.57	0.03	0.64	-0.02	-0.01	0.35	100.00	0.41	-0.01	0.21	0.21	-0.14	0.25	0.59	0.02	-0.10
LM13	-0.09	0.02	-0.01	0.09	-0.23	-0.02	-0.03	0.28	0.01	0.08	0.27	2.07	0.42	0.07	1.67	0.03	-0.02	1.03	0.41	100.00	-0.01	0.39	0.13	-0.12	0.88	0.37	0.07	-0.04
Neox	0.11	0.05	-0.10	0.60	0.15	1.41	-0.28	0.04	0.54	-0.00	0.05	0.00	-0.00	0.41	0.02	1.91	1.27	-0.01	-0.01	-0.01	100.00	-0.00	0.14	0.34	0.02	0.03	0.11	0.01
LM30	-0.09	-0.08	-0.07	-0.02	-0.38	-0.00	-0.49	0.10	0.19	-0.31	0.19	1.15	-0.20	0.02	1.77	-0.13	-0.02	-0.06	0.21	0.39	-0.00	100.00	0.12	0.08	2.45	0.48	-0.13	0.06
OPT30	3.36	5.10	-0.73	-0.07	46.29	0.29	1.10	0.21	0.39	-0.64	0.01	0.04	-0.12	-0.68	0.37	0.68	0.08	-0.39	0.21	0.13	0.14	0.12	100.00	0.55	0.56	0.40	-0.06	-0.93
Fal40	0.79	0.17	0.17	0.30	0.65	0.23	-1.23	-0.08	1.68	0.08	-0.04	-0.02	-0.08	0.05	-0.04	0.29	0.30	-0.00	-0.14	-0.12	0.34	0.08	0.55	100.00	-0.05	-0.10	0.20	4.90
LM65	-0.24	0.03	0.18	-0.03	-0.03	-0.01	-0.33	0.10	0.05	-0.29	0.06	1.59	0.03	-0.08	1.71	0.03	-0.04	0.15	0.25	0.88	0.02	2.45	0.56	-0.05	100.00	0.44	-0.13	0.02
Qw72	-0.09	-0.18	0.05	0.07	-0.11	0.02	-0.12	0.31	0.19	-0.26	0.32	0.67	0.76	0.01	0.87	0.12	-0.03	0.20	0.59	0.37	0.03	0.48	0.40	-0.10	0.44	100.00	0.07	0.09
Gal120	-0.37	-0.18	-1.04	-0.01	-0.17	-0.01	-0.61	-0.16	0.01	0.00	0.08	0.06	0.11	-0.00	0.15	0.21	-0.03	-0.06	0.02	0.07	0.11	-0.13	-0.06	0.20	-0.13	0.07	100.00	0.19
Fal180	-1.35	-1.07	0.27	-0.03	-1.26	-0.04	-0.82	0.01	-11.07	-0.01	-0.06	0.04	-0.01	-0.18	0.16	-0.15	-0.00	0.13	-0.10	-0.04	0.01	0.06	-0.93	4.90	0.02	0.09	0.19	100.00

Human subject study

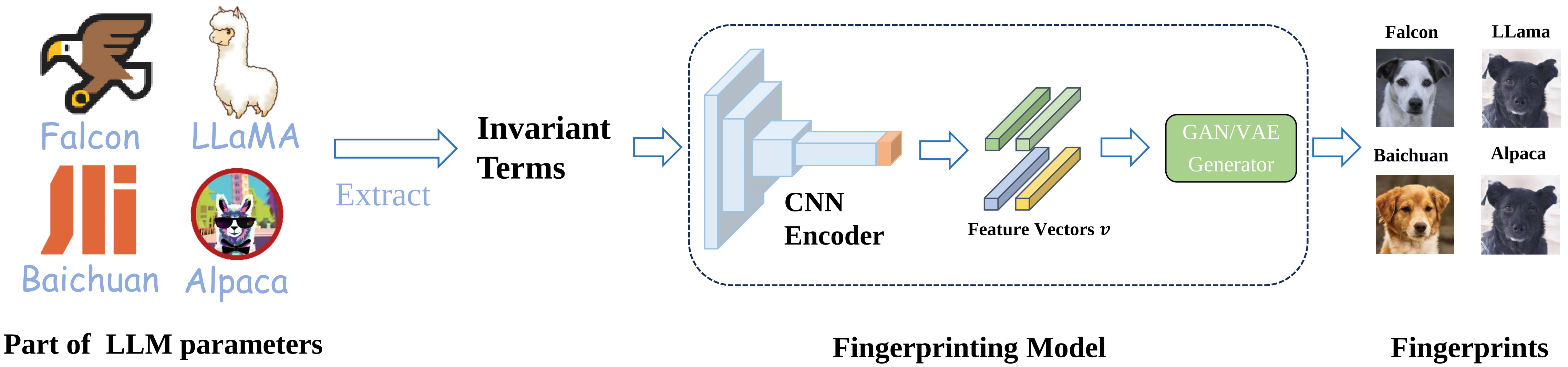


Yielded a **94.74%** accuracy rate among 72 college-educated individuals, each answering 51 questions.

Limitations

1. Our focus is solely on transformer-based LLMs, and generalizing our approach to other architectures requires further investigation

2. StyleGAN2's behavior exhibits occasional inconsistencies, leading to the generation of similar images for dissimilar models or dissimilar images for highly similar models.



Thank you!

https://arxiv.org/abs/2312.04828

https://github.com/LUMIA-Group/HuRef