When all you have are Logits...

Towards (Closed-Source) LLM Accountability via Logit Signatures

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Assistant Professor, USC Viterbi CS
NSF - OSGAI Workshop
March 26, 2024

2

olmo

LLM360

MISTRAL AI_

2

Gemini

GPT - 4

Claude AI

OLMo

LLM360

MISTRAL AI_

GP 4

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Logits of API-Protected LLMs Leak Proprietary Information

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Finlayson, Ren & **Swayamdipta**, Under Submission 2024

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Logits can reveal the hidden dimensionality!

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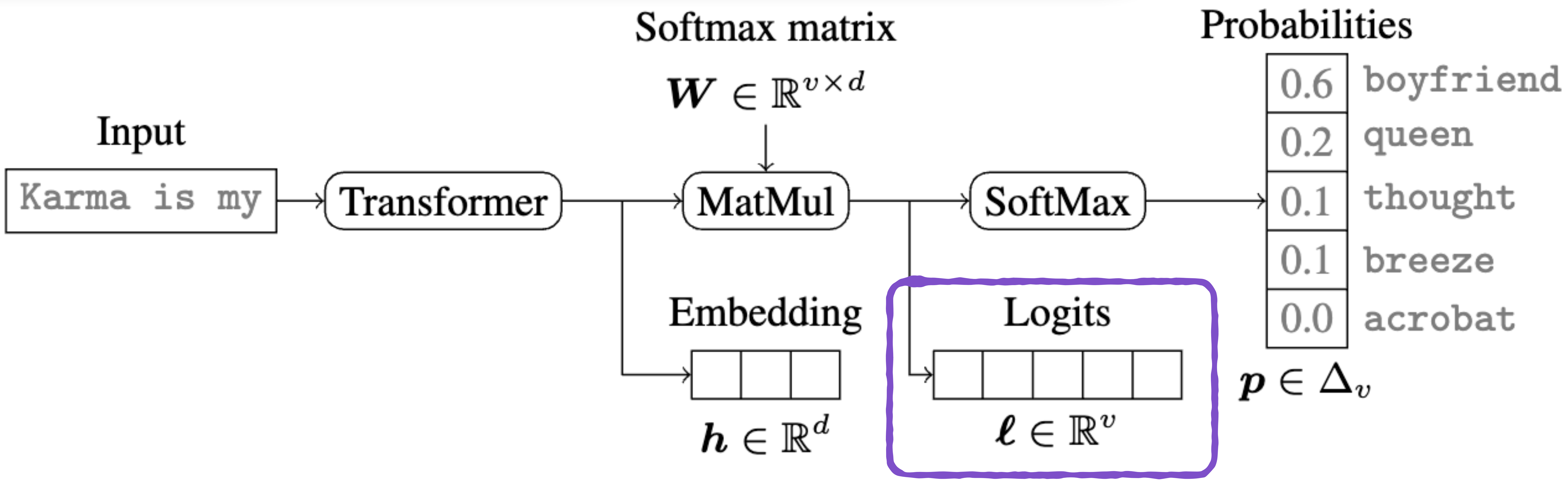

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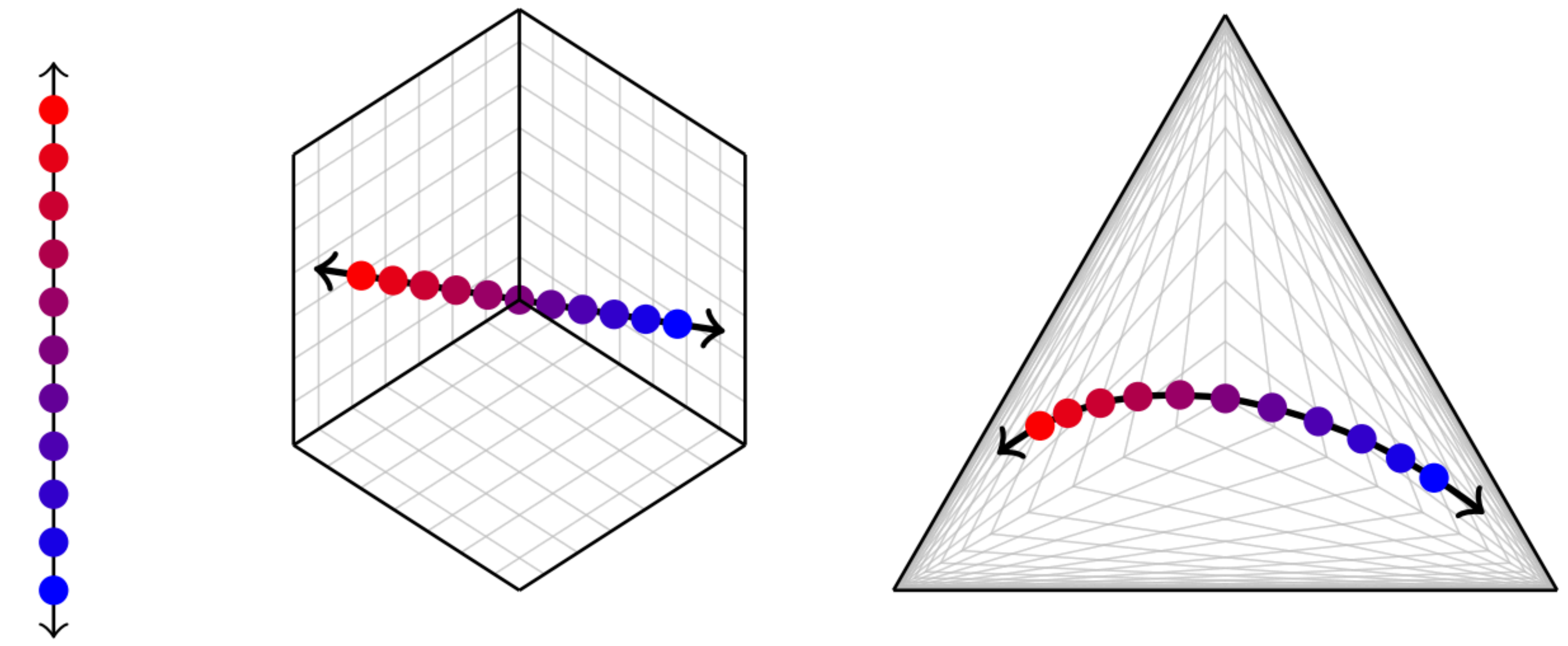
$$\mathbf{h} \qquad \mathbf{l} = \mathbf{W}\mathbf{h} \qquad \mathbf{p} = \mathrm{softmax}(\mathbf{l})$$

$$\mathbb{R}^d \xrightarrow{\boldsymbol{W}} \mathbb{R}^v \xrightarrow{\text{softmax}} \Delta_v$$



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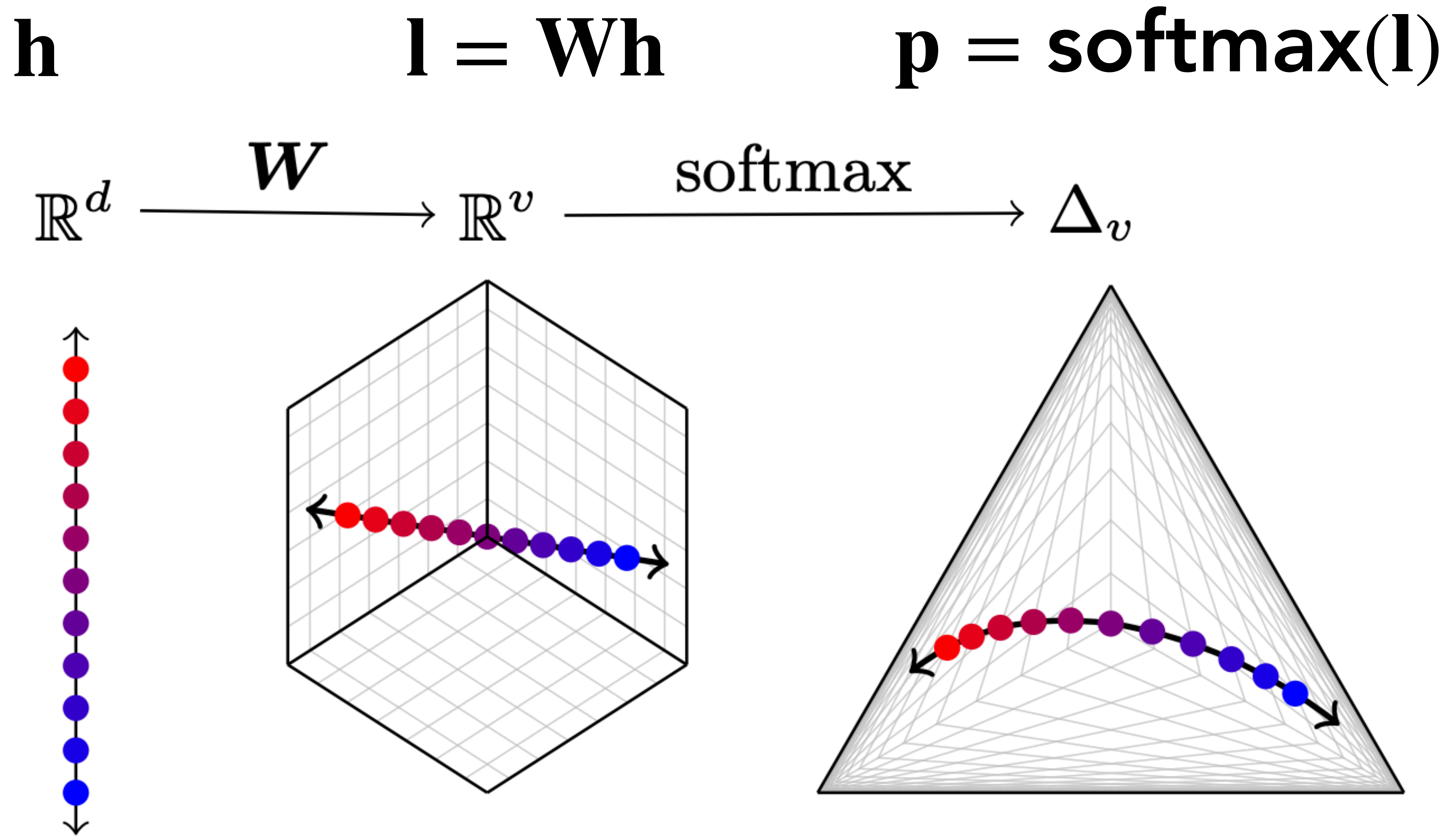
- LM outputs are projected from the hidden dimension d to v-dimensional logit and probability vectors, thus occupying a d-dimensional subspace of $\mathbb{R}^v$ or Δ_v, respectively



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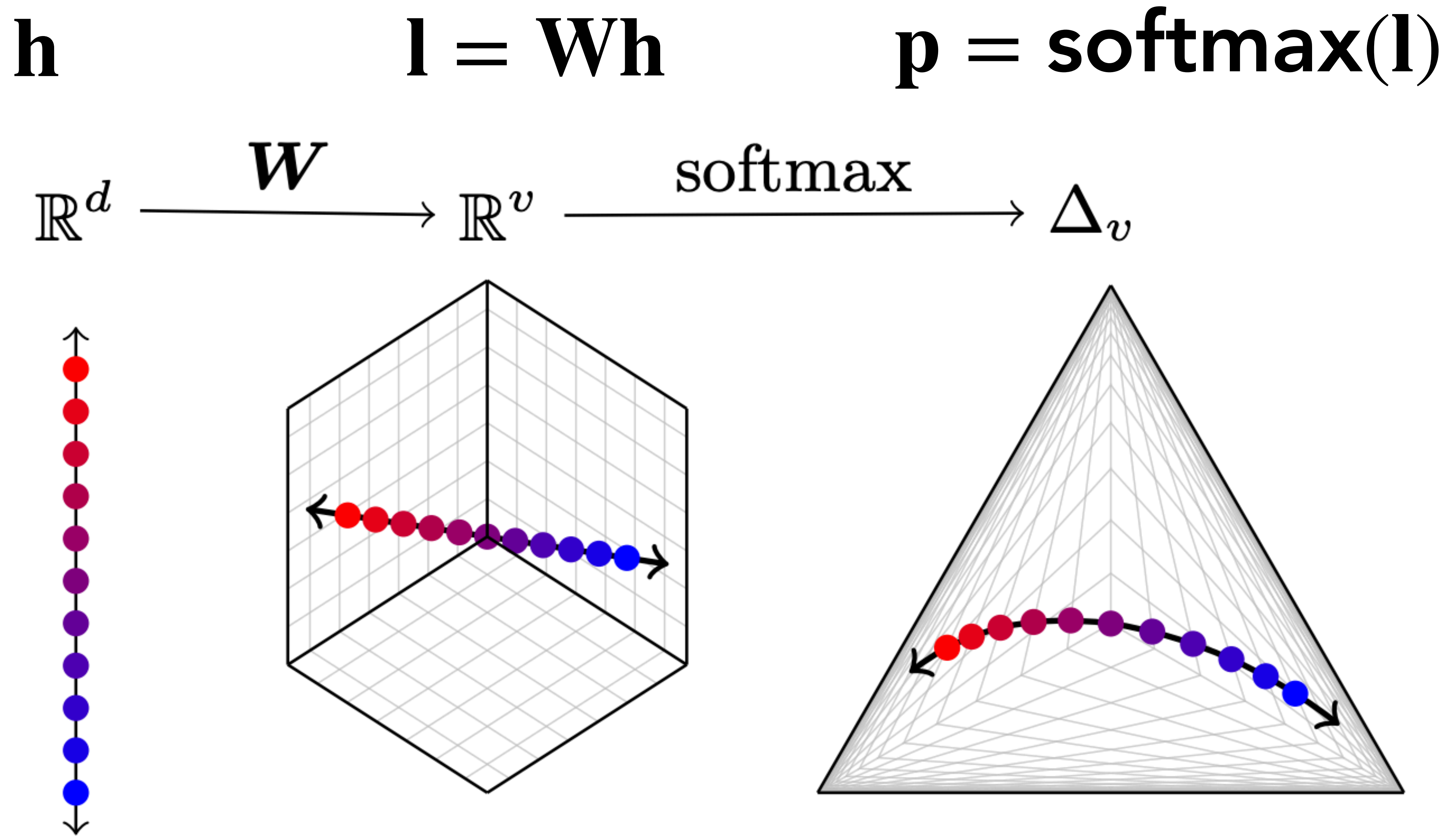

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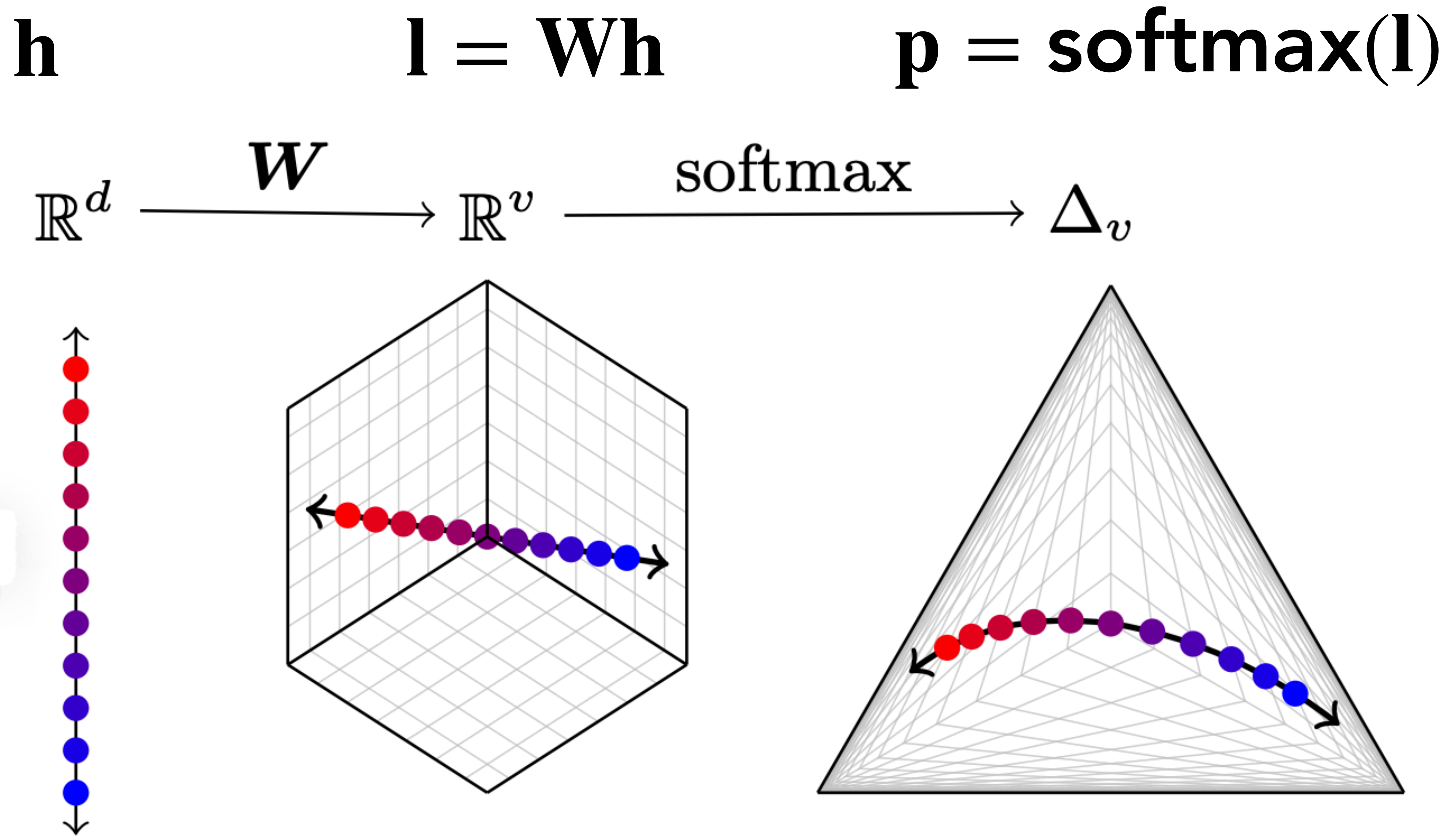

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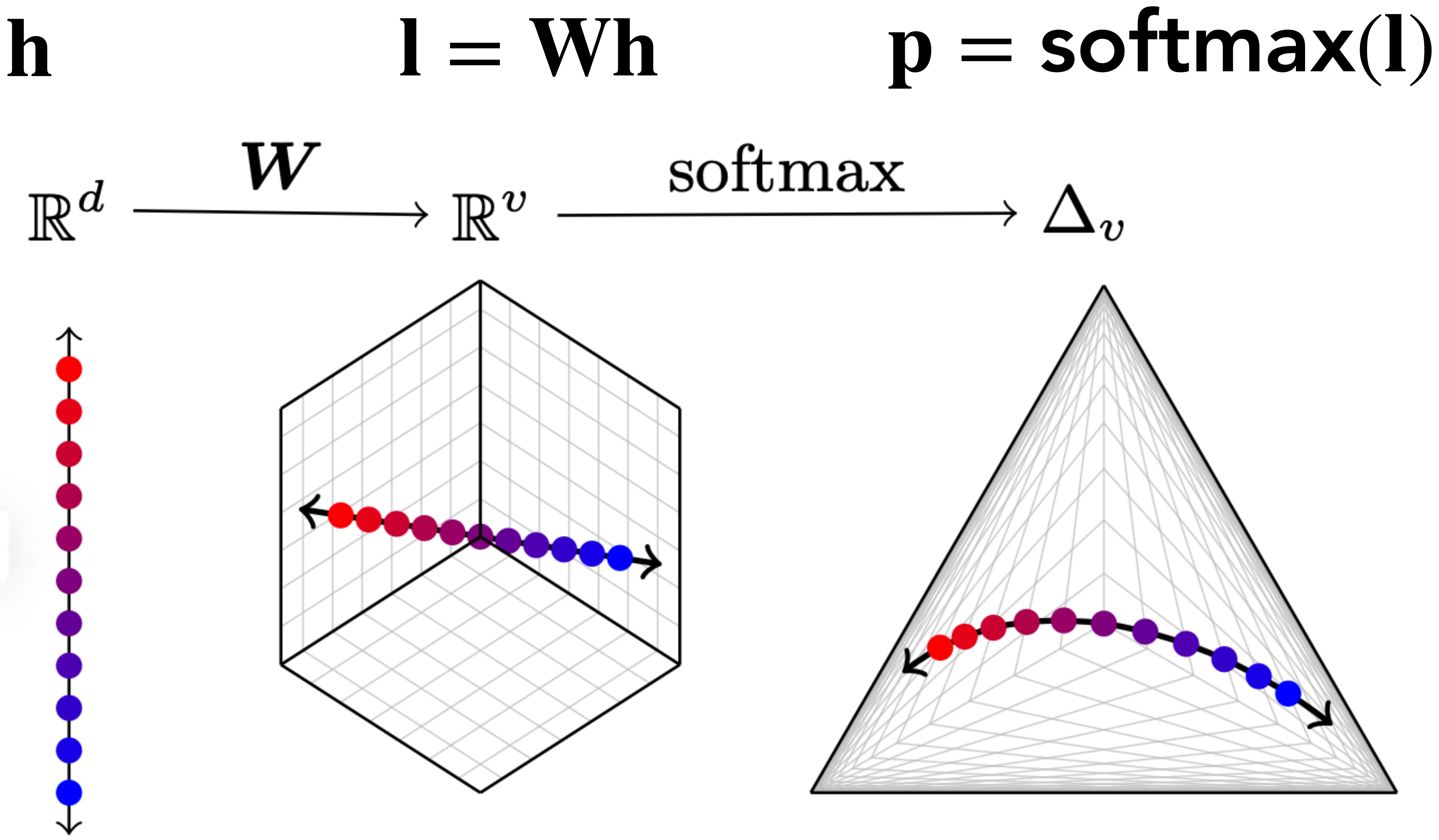
- A collection of d linearly independent outputs $\mathbf{p}^1, \mathbf{p}^2, \ldots, \mathbf{p}^d \in \Delta_v$ from the model will form a basis for the model's image



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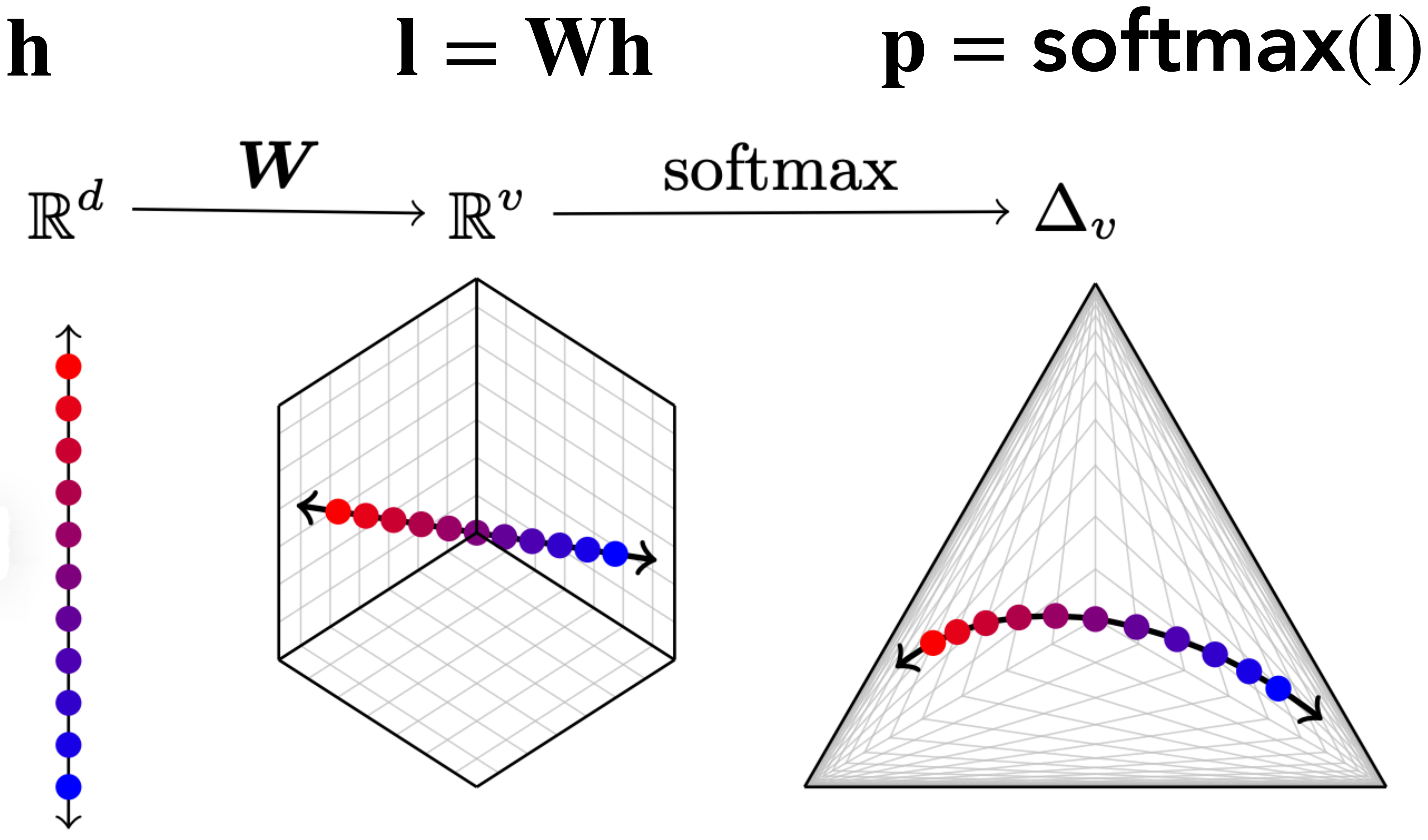

Targeted queries to the LM's API to extract $n > d$ logit vectors will result in extracting its hidden dimension, d and related information

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How to recover model logits from APIs?

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- If the hidden size is known, this can be done in d API calls; in general, in $O(d)$ calls

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Key Result: Hidden Dimensionality

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- We collect outputs $\mathbf{p}^i$ one at a time until the number of linearly independent outputs in the collection (obtained via SVD) stops increasing, which will occur when we have collected $d + 1$ outputs

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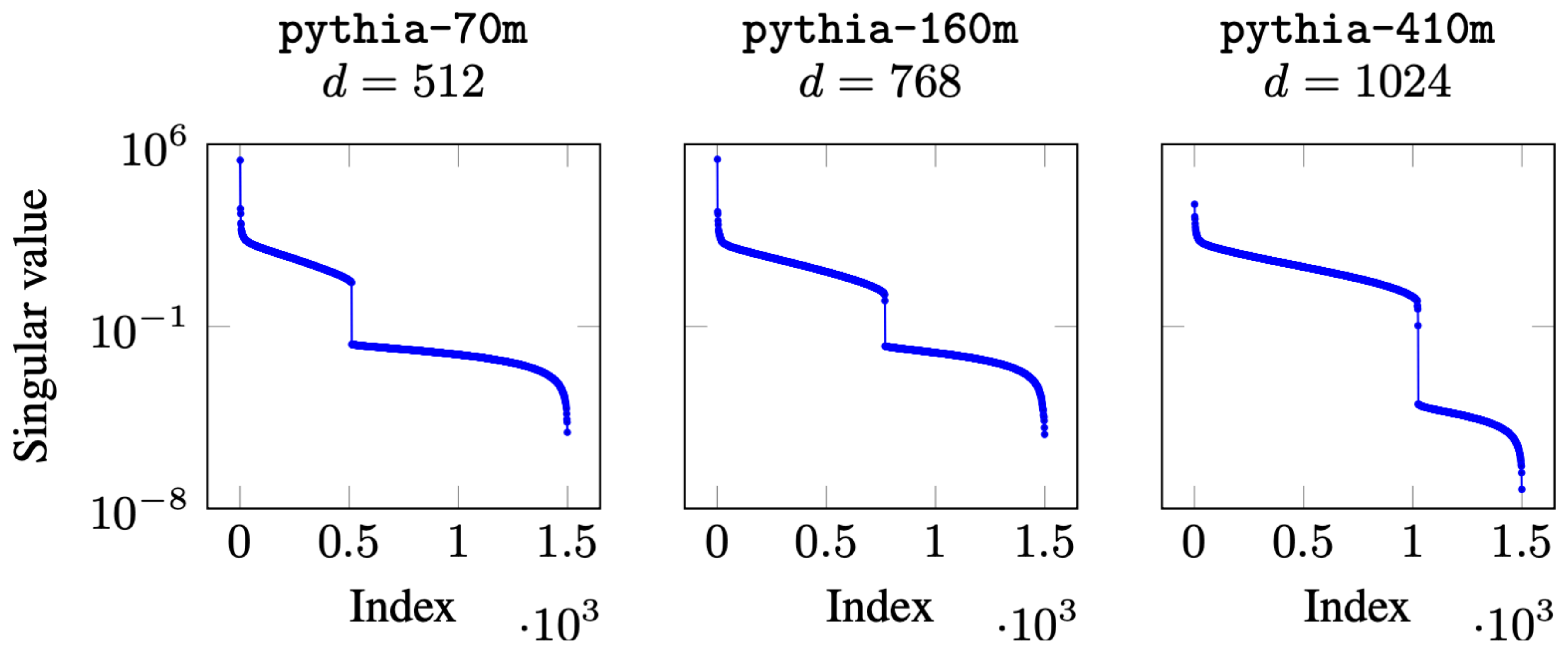

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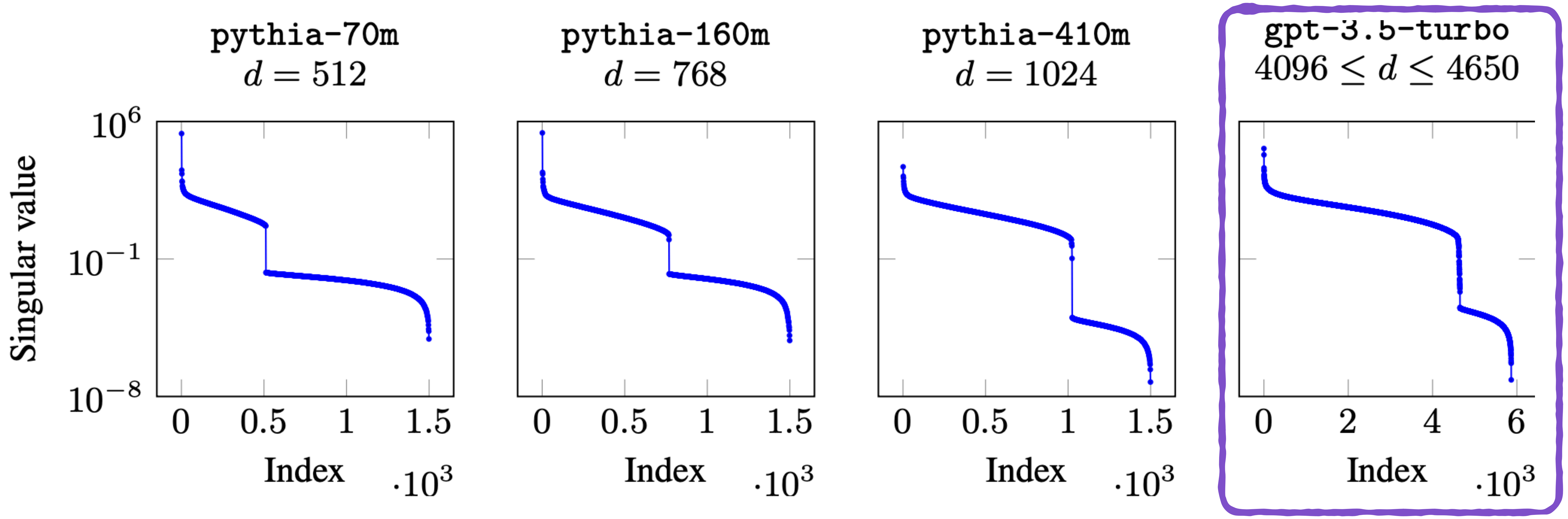

- We collect outputs $\mathbf{p}^i$ one at a time until the number of linearly independent outputs in the collection (obtained via SVD) stops increasing, which will occur when we have collected $d + 1$ outputs
- GPT-3.5-Turbo has hidden dimension close to 4096 and is likely a 7B model!

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Model Signature

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- Model signatures are unique!

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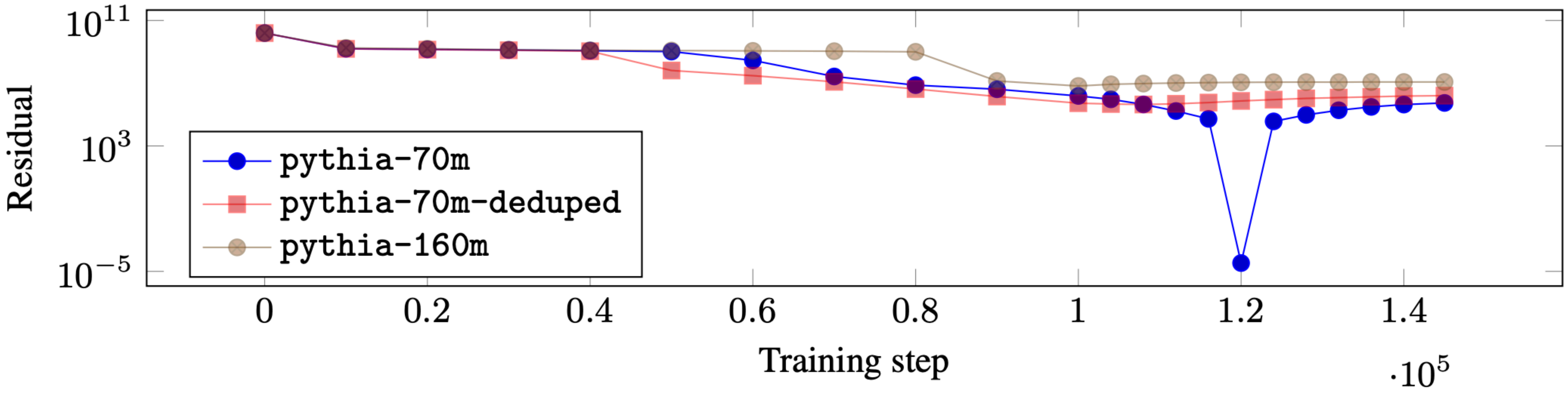

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Other Applications of Model Signatures

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- Detecting model updates and changes to hidden prompts
- Improved LLM Inversion

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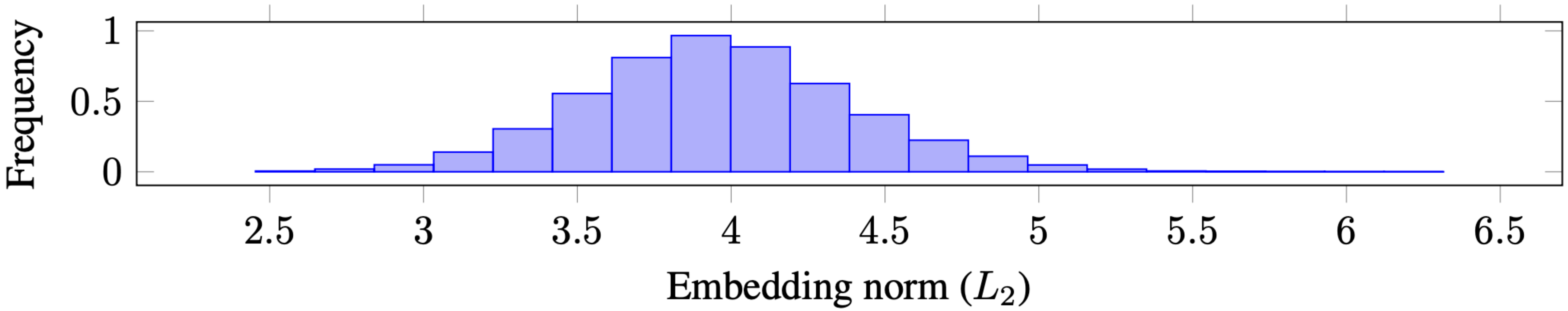
  Demeter et al., 2020; Grivas et al., 2023
- Recovering the softmax parameter matrix $\mathbf{W}$ (up to a rotation)



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  - Building trust between API users and providers
  - Implementing efficient protocols for model auditing
  - Verifying LM identity and ownership

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Stealing Part of a Production Language Model

Nicholas Carlini [1] Daniel Paleka [2] Krishnamurthy (Dj) Dvijotham [1] Thomas Steinke [1] Jonathan Hayase [3]
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Simultaneous Discovery!

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