

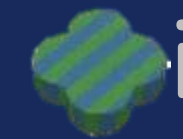


# Metric supervision enables LLMs to learn structured token geometry.

which is useful for...


## Reward Modelling

Input: [Instruction]  
[Sample response]  
Output: Helpfulness: **4**,  
Safety: **1**,  
Verbosity: **3**,...

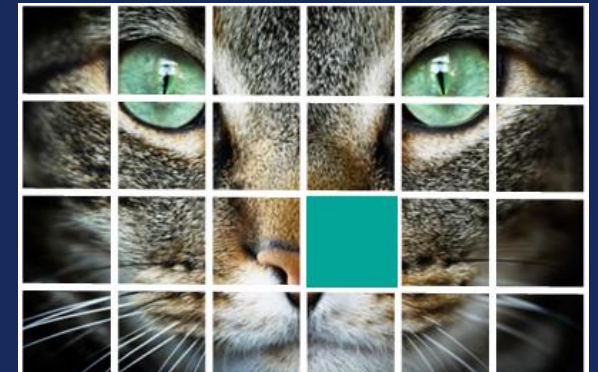
## Robotic Manipulation

Input: Put  into the   
  
Output: Move arm to **(0.2,0.4)**  
and Rotate **108°**

## Visual Grounding

Input: Detect the full zebra.  
  
Output: The full zebra is at  
[[**(49,10)**],[**(540,465)**]]

## Text-to-Image

Input: Draw a cat.  
  
Output: <IMG28>, <IMG10>  
<IMG32>.....



## Motivation

- Standard autoregressive models do not learn that nearby tokens can be better than distant ones.
- Our goal is to teach LLMs the geometry of structured tokens, such as coordinates, angles.

## Methods

- We augment one-hot CE with a **distance-aware soft target distribution**.

$$p_d(v | x, t) = \frac{\exp(-d(v, x, t)/\tau)}{\sum_{v' \in \mathcal{V}_d} \exp(-d(v', x, t)/\tau)}$$

- Tokens closer to the target under metric  $d(\cdot, \cdot)$  receive higher probability mass.

Instruction (Non-Target Tokens)



Detect location of the full zebra .

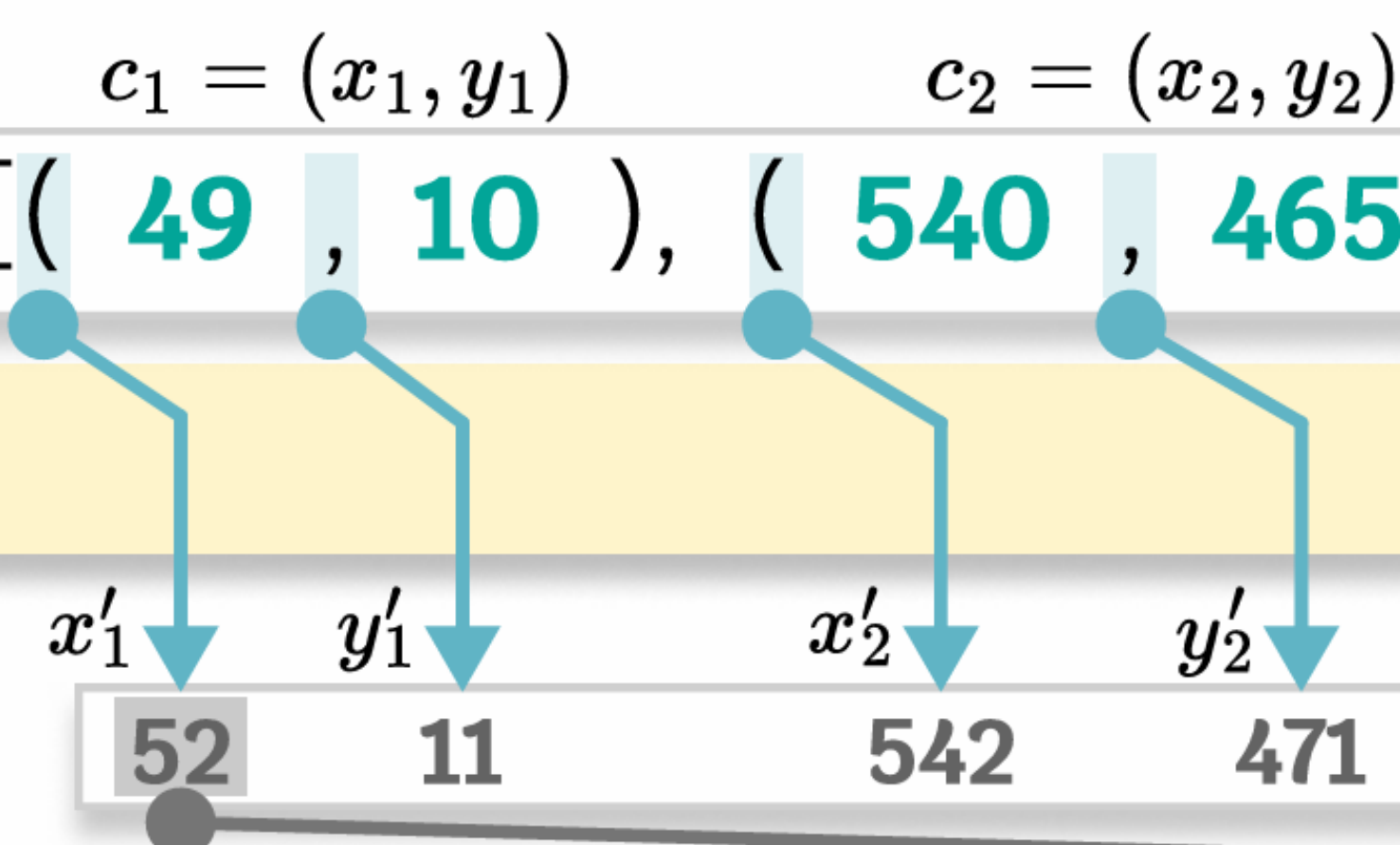
Target Tokens

The full zebra is at [( **49** , **10** ) , ( **540** , **465** )].

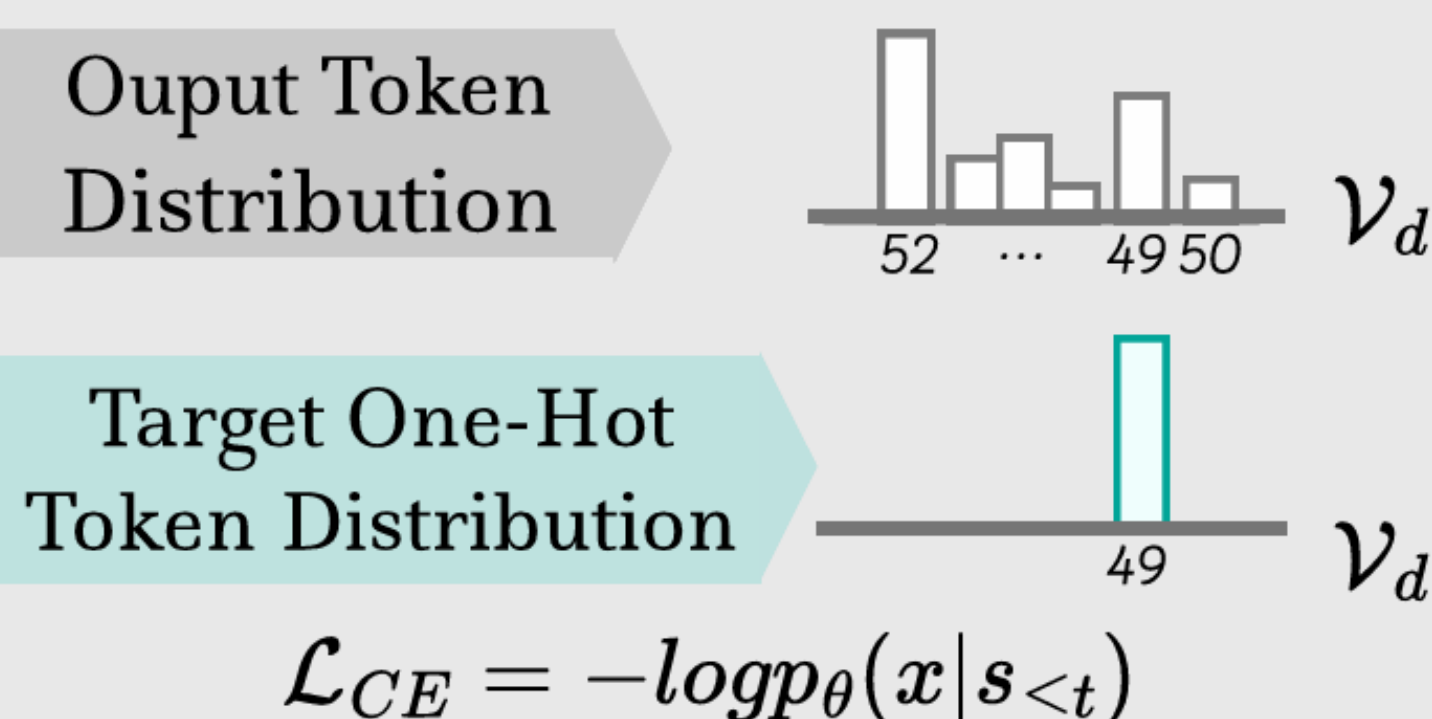
## Discrete Autoregressive Model

**DIST<sup>2</sup>Loss in the SFT scenario**

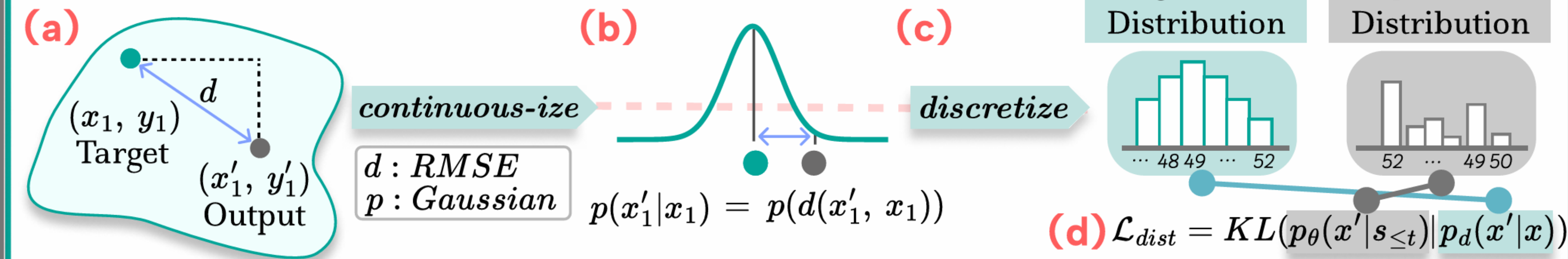
Model's Next-Token Predictions  
(Causal Language Modeling)



## Base Cross-Entropy Loss



## Discretized Distance Loss



## Results

### Reward Modelling

Models	Chat	Chat Hard	RewardBench			Average
			Safety	Reasoning		
Tulu-v2.5-RM-13B	93.6	68.2	77.3	88.5		81.9
GPT-3.5	92.2	44.5	65.5	59.1		65.3
Claude-3-haiku	73.7	92.7	52.0	79.5		70.6
Prometheus-2-7B	85.5	49.1	77.1	76.5		72.0
Llama-binary	83.8	34.7	39.9	73.5		58.0
Llama-sft	89.1	49.3	79.2	83.9		75.3
Llama-dist	95.0 ( <b>↑4.9</b> )	69.1 ( <b>↑19.8</b> )	86.5 ( <b>↑7.3</b> )	90.4 ( <b>↑6.5</b> )		85.3 ( <b>↑10.0</b> )

### Robotic Manipulation

#Data	L1			L2		
	1K	10K	100K	1K	10K	100K
RT-2	1.9	21.9	73.1	3.8	17.7	70.4
LLaRA-sft	49.6	82.3	88.5	46.2	78.1	84.6
LLaRA-vocab	50.8	81.0	87.0	44.6	77.2	83.5
LLaRA-dist	<b>53.9</b>	<b>83.4</b>	<b>89.5</b>	<b>51.5</b>	<b>82.8</b>	<b>86.1</b>

### Visual Grounding

Models	#PT	#FT	val	RefCOCO	
				test-A	test-B
Ferretv2	1.1M	127K	92.8	94.7	88.7
Florence-2-B	126M	127K	92.6	94.8	91.5
Florence-2-L	126M	127K	93.4	95.3	92.0
Phi3V-sft	0	127K	94.3	93.5	86.0
Phi3V-vocab	0	127K	94.5 ( <b>↑0.2</b> )	93.2 ( <b>↓0.3</b> )	86.0 (-)
Phi3V-dist	0	127K	94.8 ( <b>↑0.5</b> )	94.5 ( <b>↑1.0</b> )	87.3 ( <b>↑1.3</b> )

### Text-to-Image

Models	Epoch #Params	50		Full (300)	
		FID ↓	IS ↑	FID ↓	IS ↑
VQGAN	227M	-	-	18.65	80.4
VQGAN	1.4B	-	-	15.78	74.3
LlamaGen-sft	111M	10.03	116.37	6.44	157.17
LlamaGen-dist	111M	9.41	127.44	6.27	164.32
LlamaGen-sft	343M	4.24	206.74	3.08	256.07
LlamaGen-dist	343M	<b>4.18</b>	<b>209.41</b>	<b>3.04</b>	<b>258.19</b>

Across various downstream tasks, Adding Discretized distance loss improves performance, with particularly strong gains in **low-data regimes**

# Teaching Metric Distance to Discrete Autoregressive Language Models

Jiwan Chung, Saejin Kim, Yongrae Jo, Jaewoo Park, Dongjun Min, and Youngjae Yu

jiwan.chung.research@gmail.com



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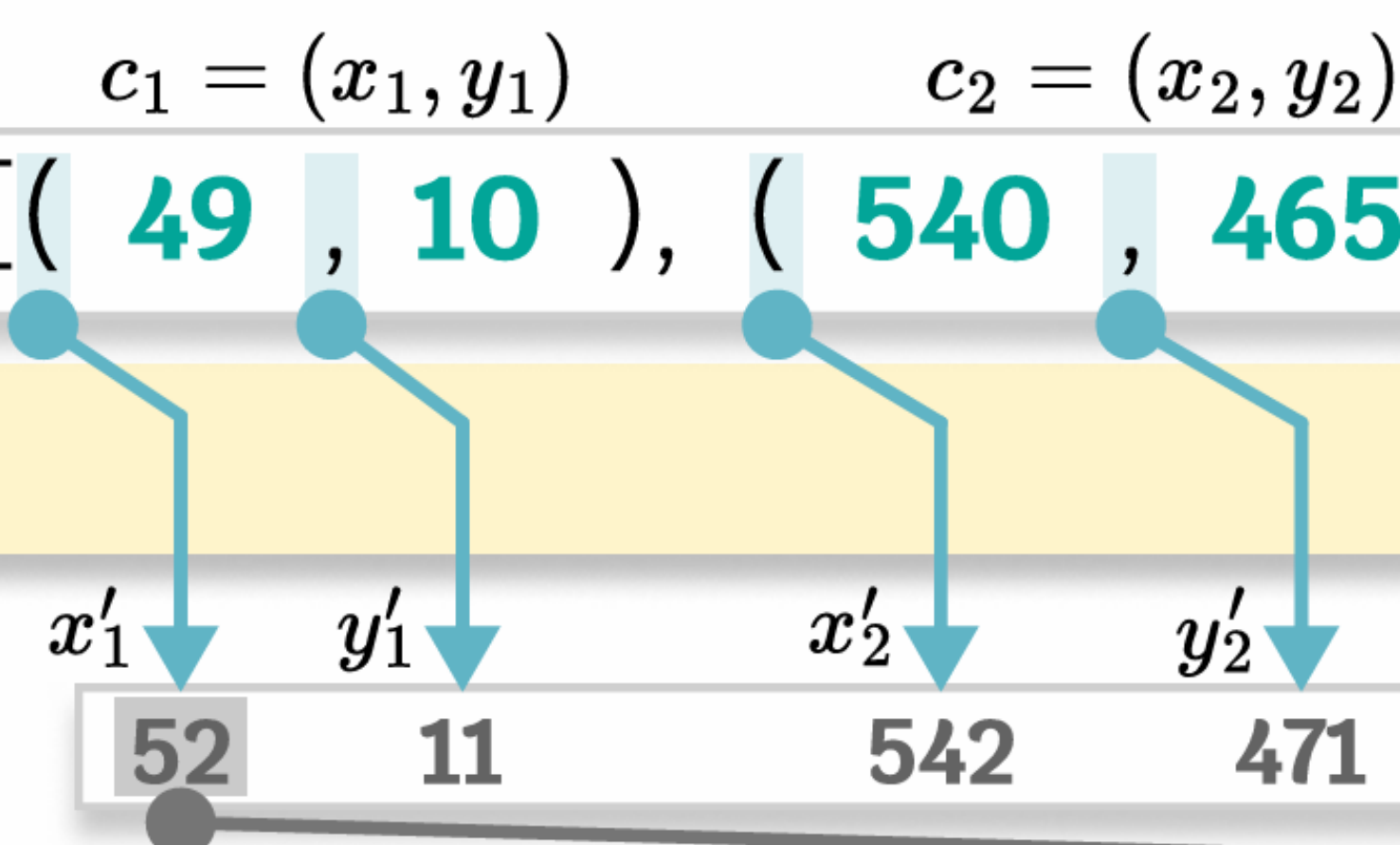
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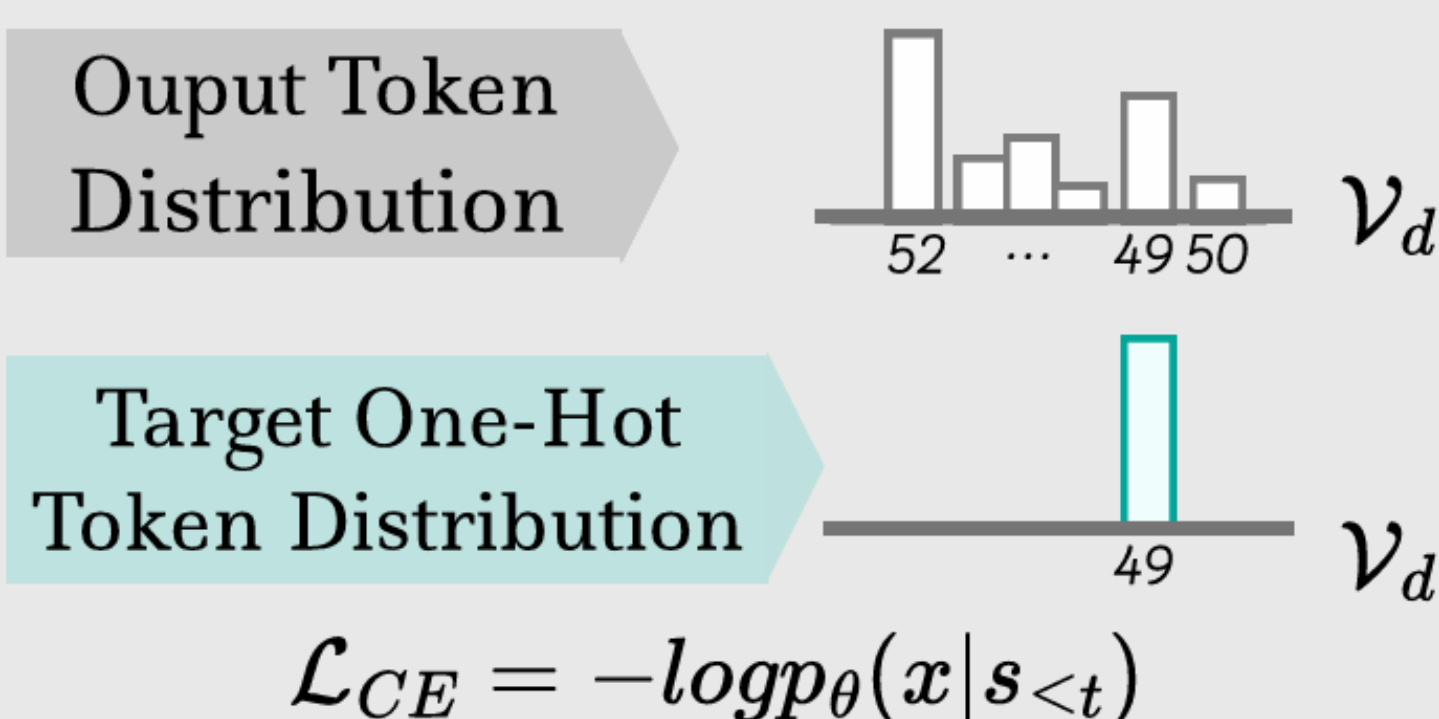
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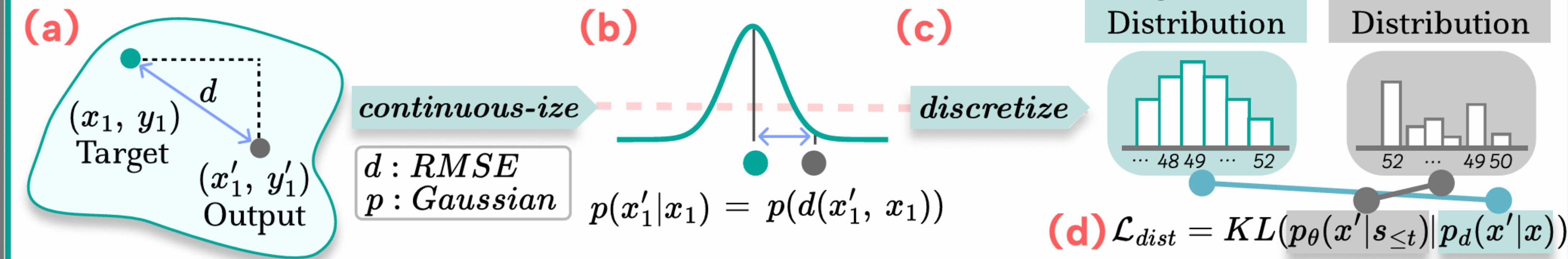
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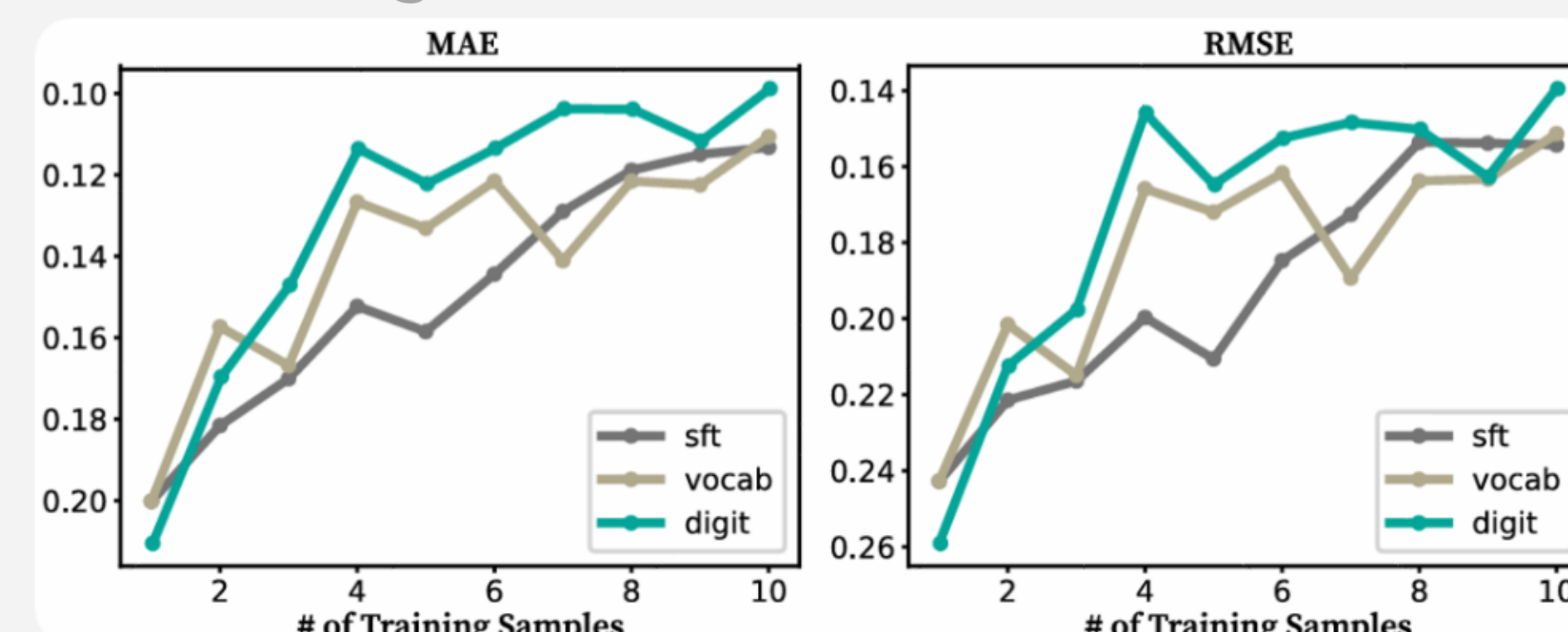


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### Linear Regression



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