EntRGi: Entropy-Aware Reward Guidance for Diffusion Language Models

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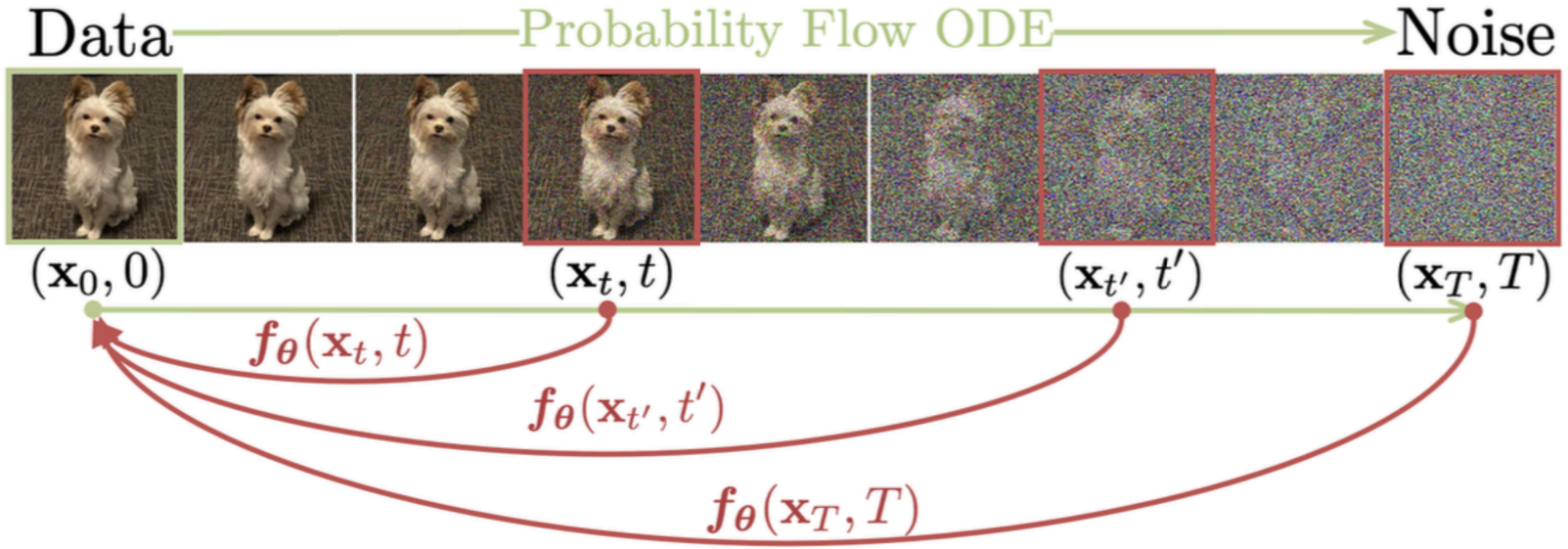
Diffusion Models



- Start with a clean Image
- Add noise at various ‘levels’
- Train a network to reconstruct the original image
- Inference - Start from noise and run the network with time ‘backwards’

https://lilianweng.github.io/posts/2021-07-11-diffusion-models/

(Discrete) Diffusion Language Models

- Almost the same as continuous/image diffusion
- Follows an “Absorbing State Markov chain” — where the Noise is just a sequence of mask tokens
- Data is sequences (tokens) of text

(Masked) Diffusion Language Models

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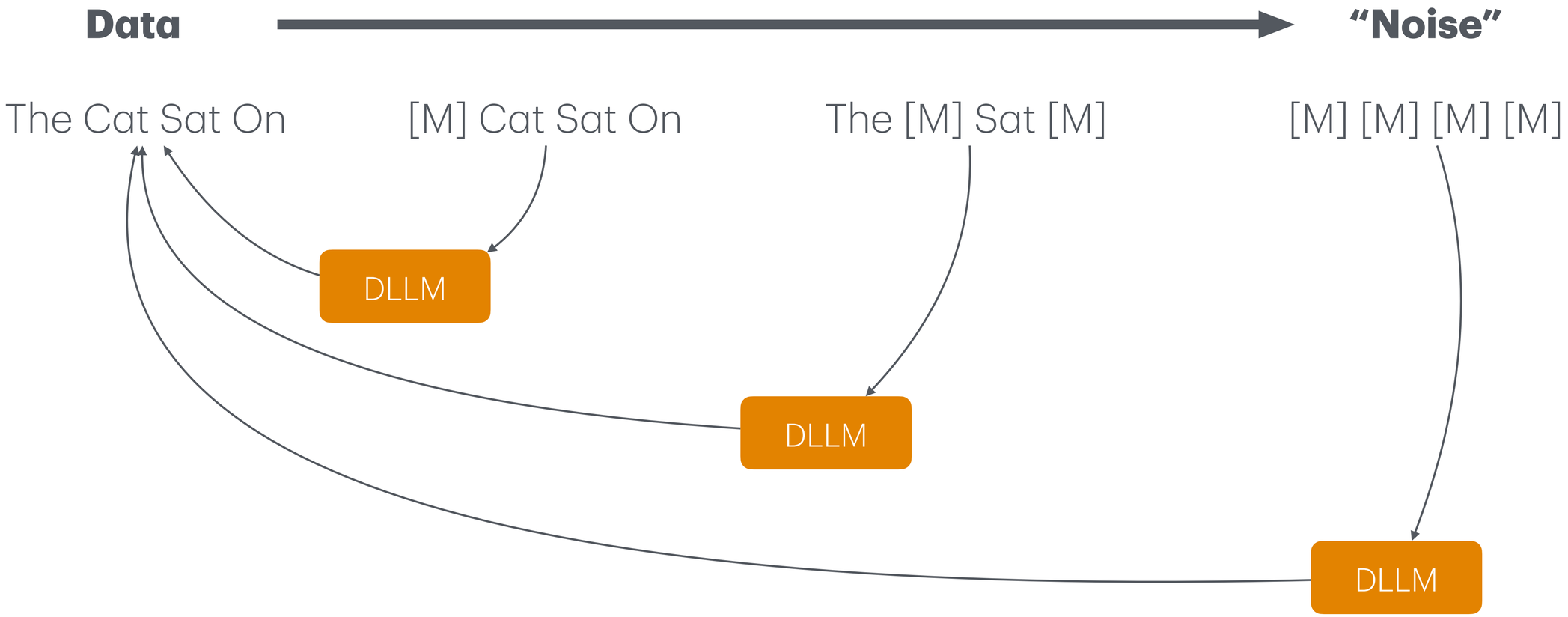

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Autoregressive vs Masked Diffusion LLMs

AR Generates Left to Right

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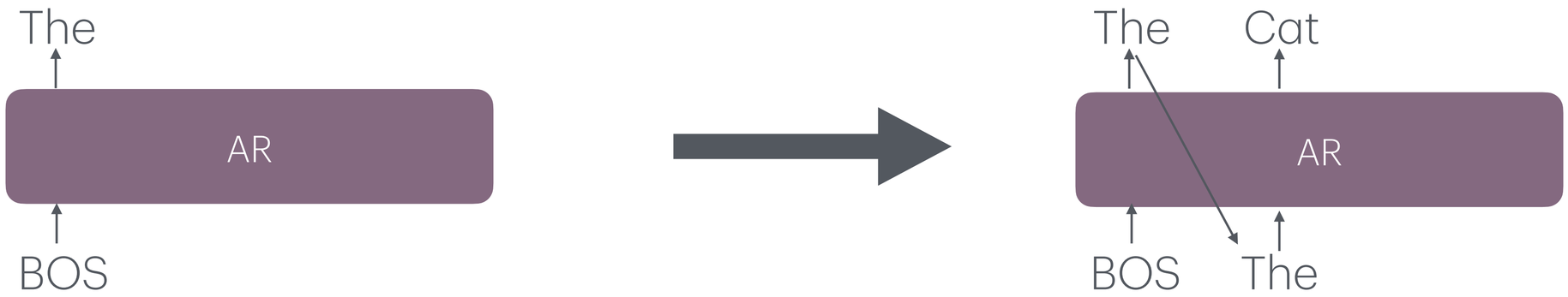

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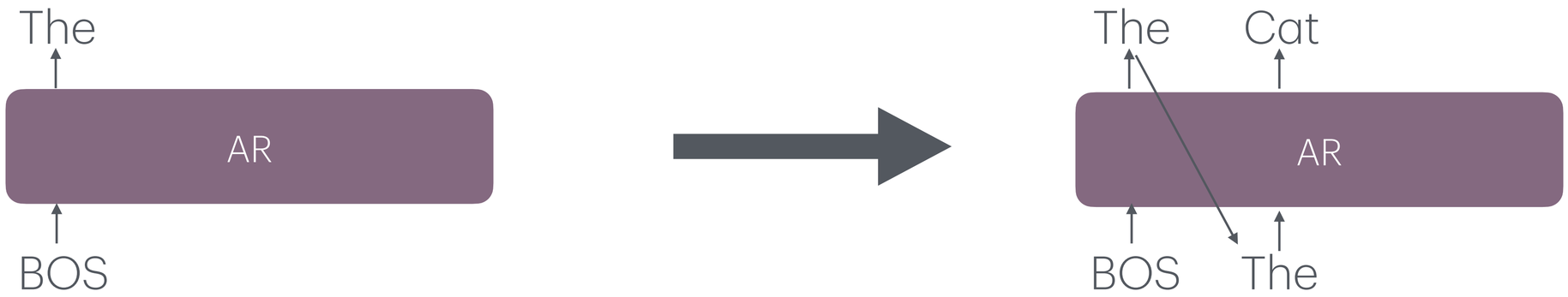
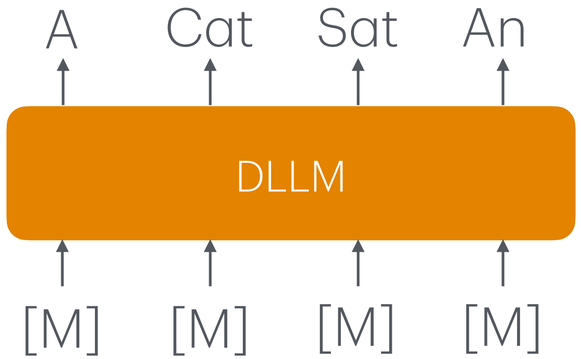


Discrete Diffusion (Sahoo et. al.) starts from mask tokens and iteratively selects tokens in an arbitrary/selected order



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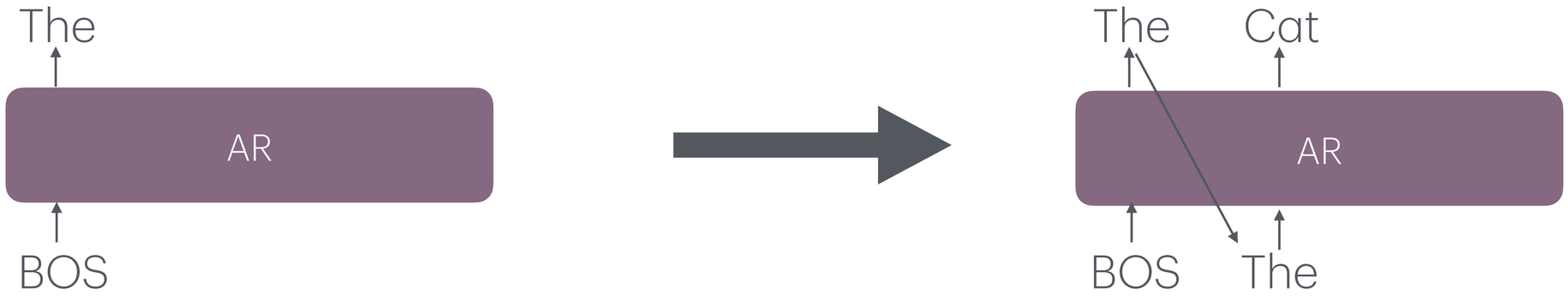

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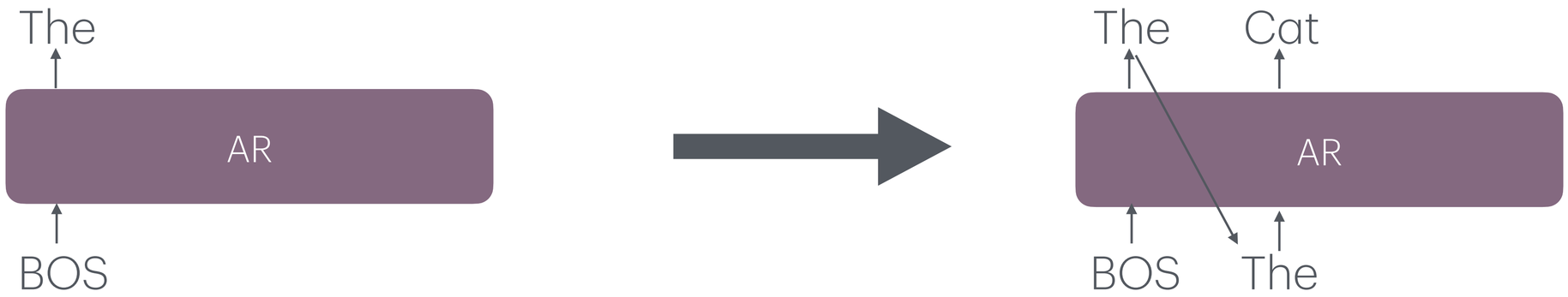

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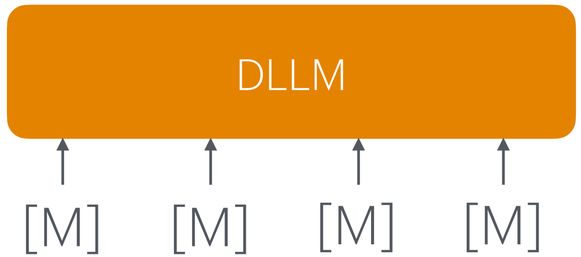
DLLMs generate a probability distribution at ALL masked positions



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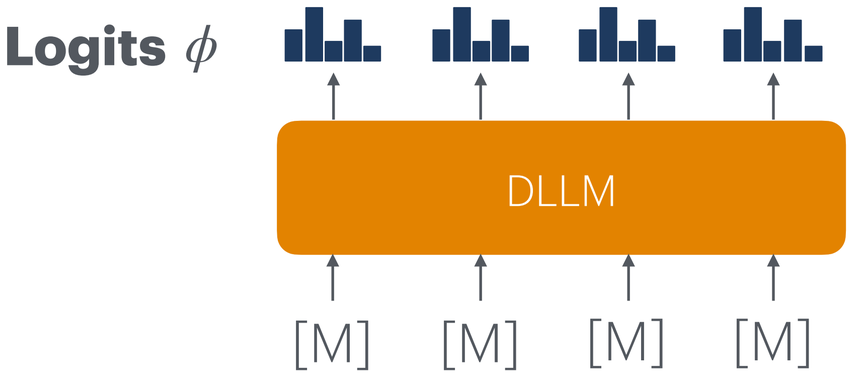

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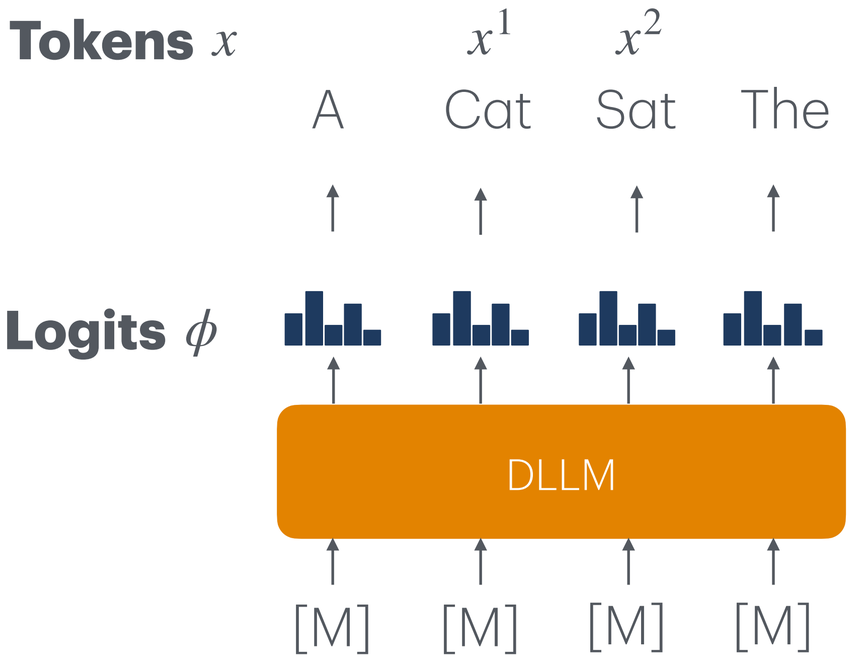

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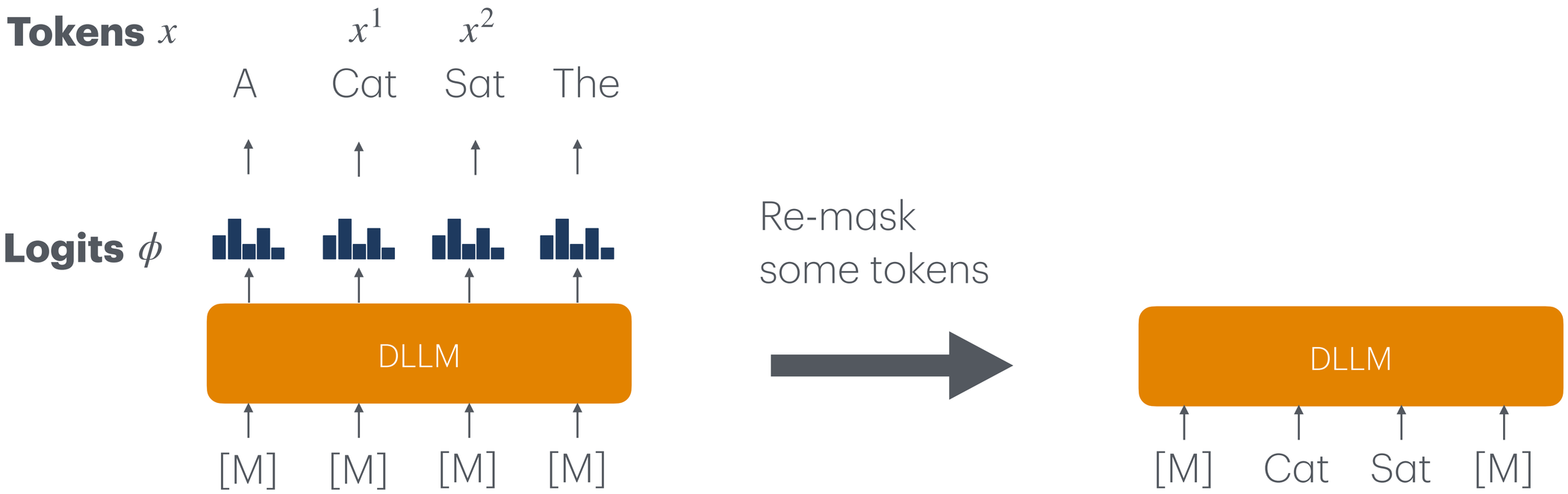

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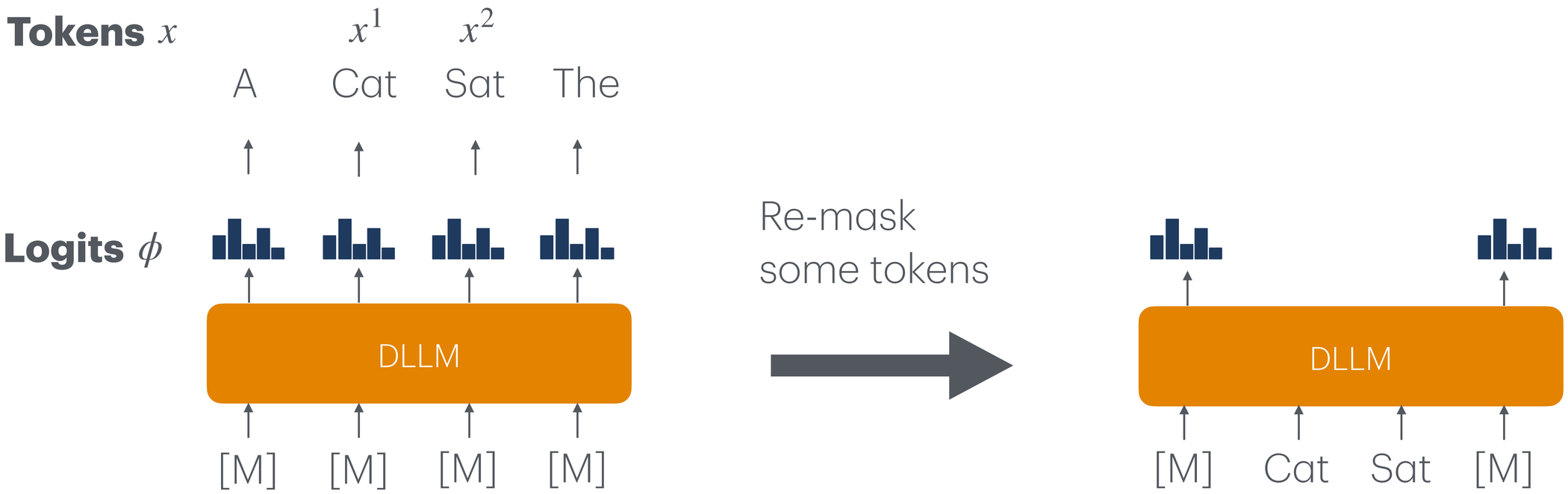

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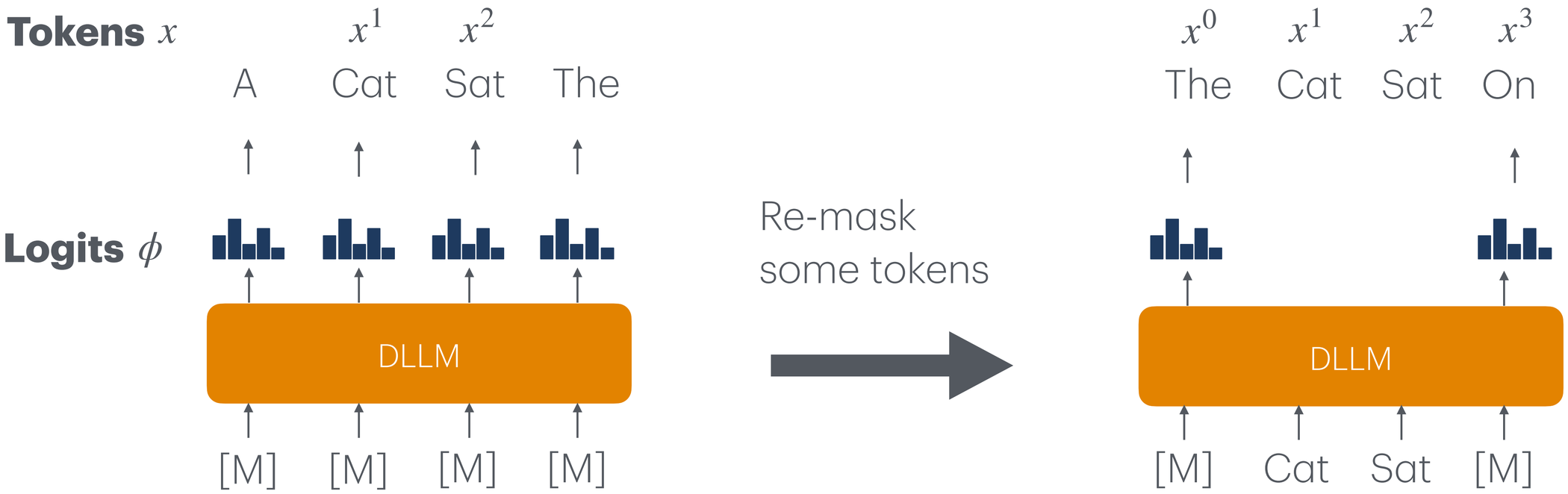
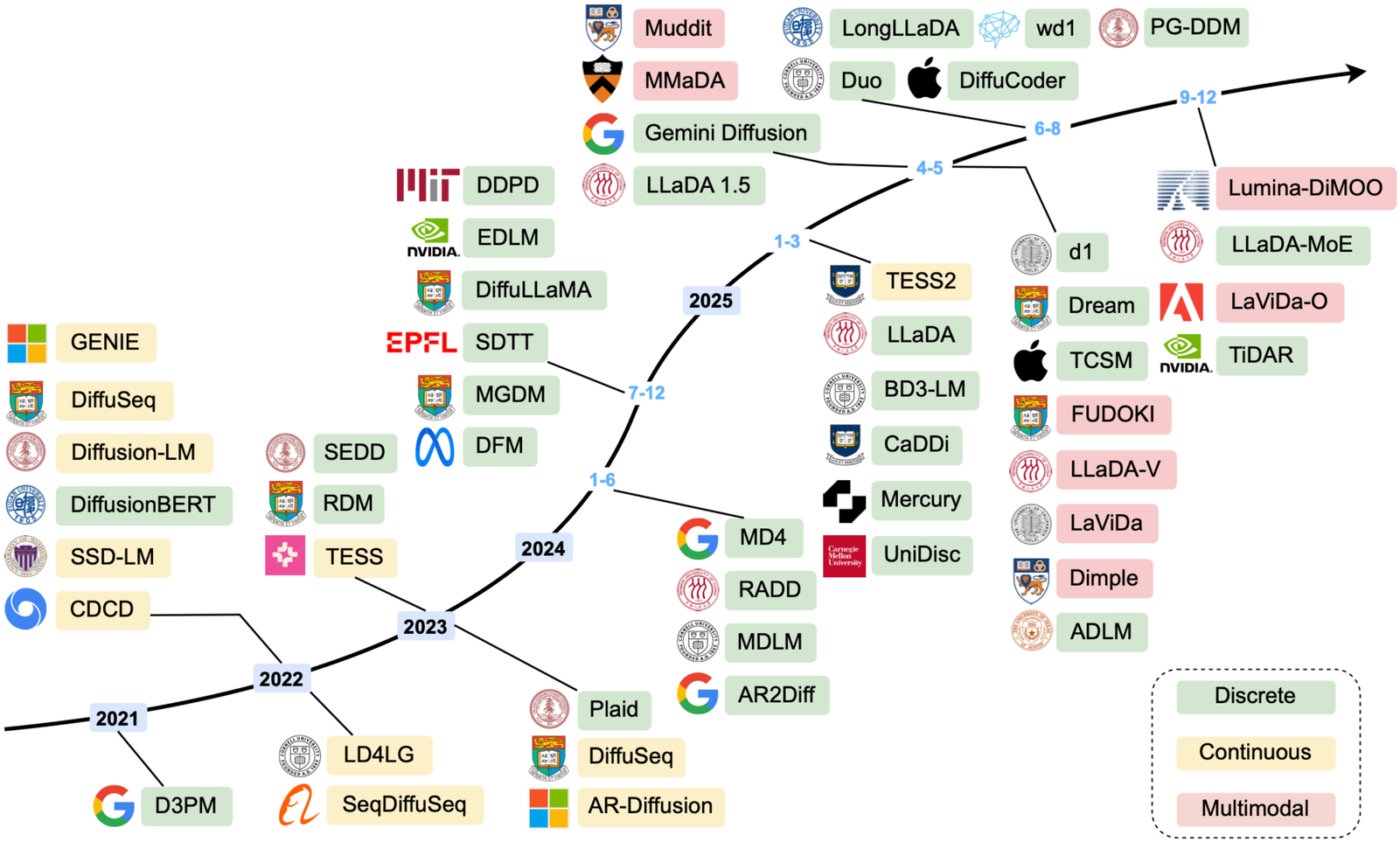


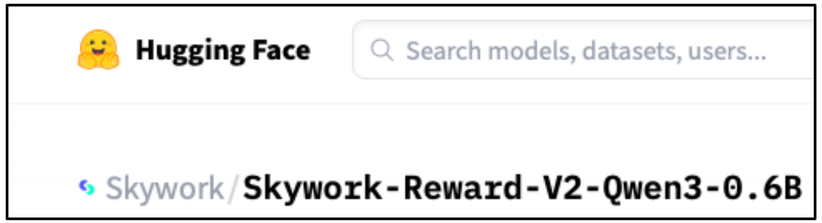
DLLMs are gaining widespread interest



Li et. al. 2025. A Survey on Diffusion Language Models

Reward models

Trained and evaluated in certain domains eg: Instruction Following, Factuality



Trained with Preference Data

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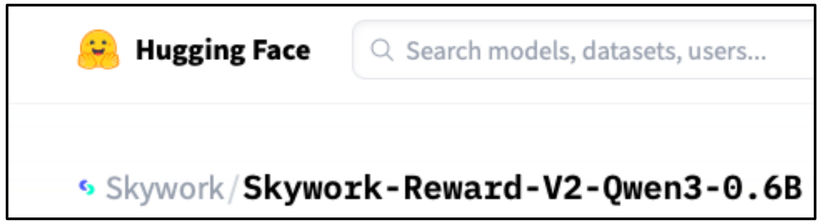
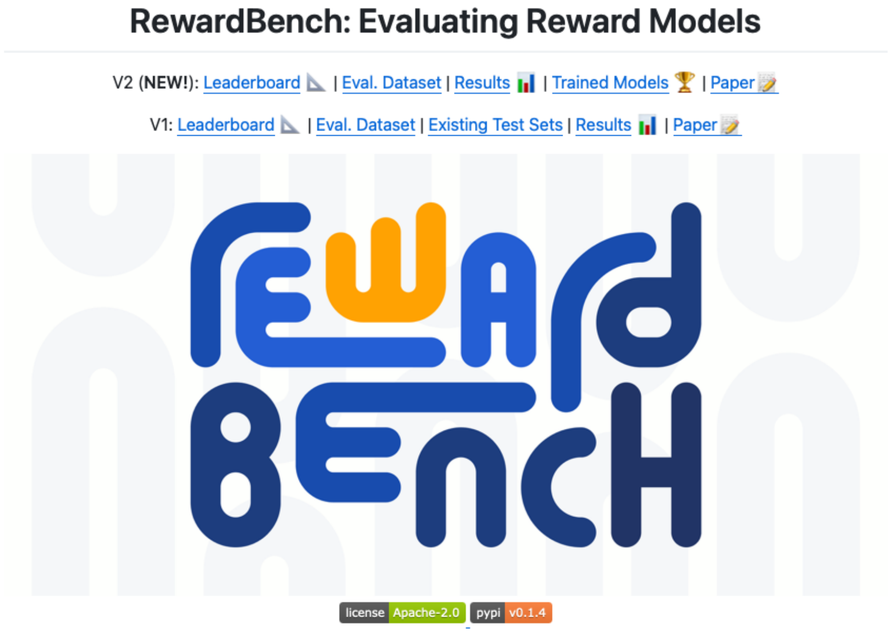
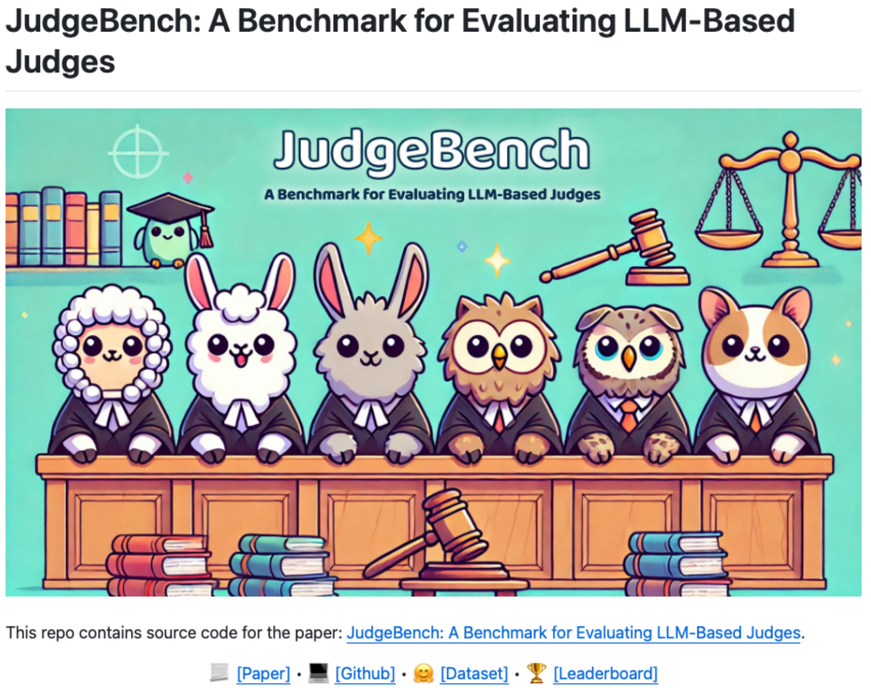


Trained with Preference Data

Evaluate the Reward Model





Goal: Generate high reward samples

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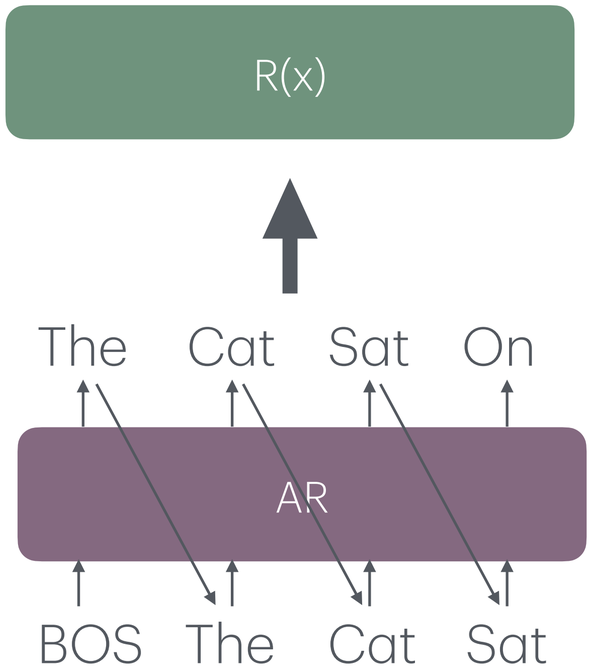
Typically R(x) is small-ish so you can make as many calls to R(x) as you want



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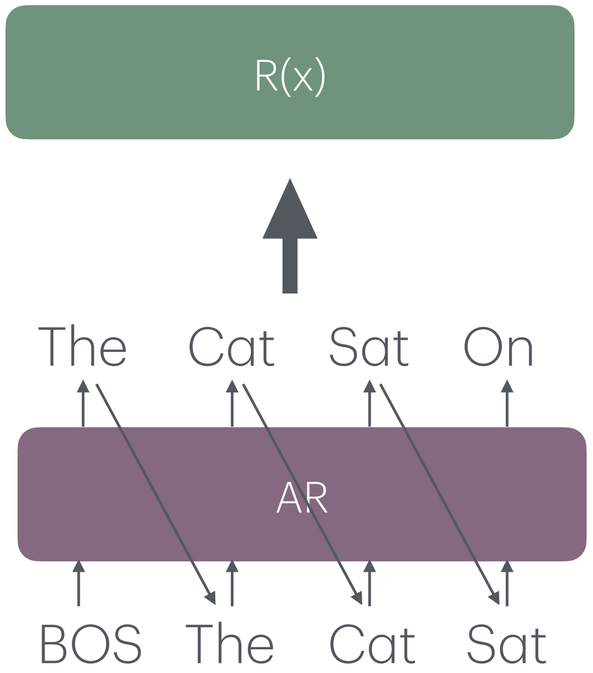

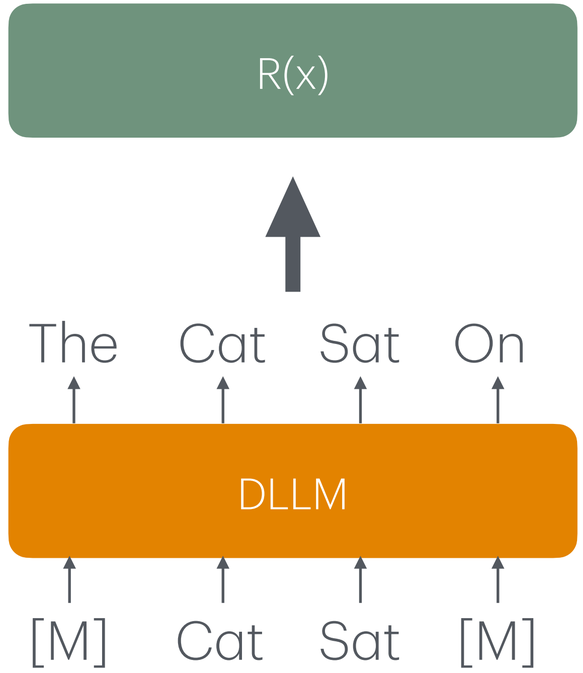

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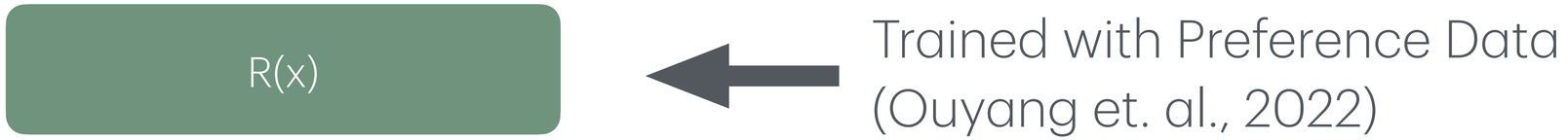
One way - we can update the parameters of the model



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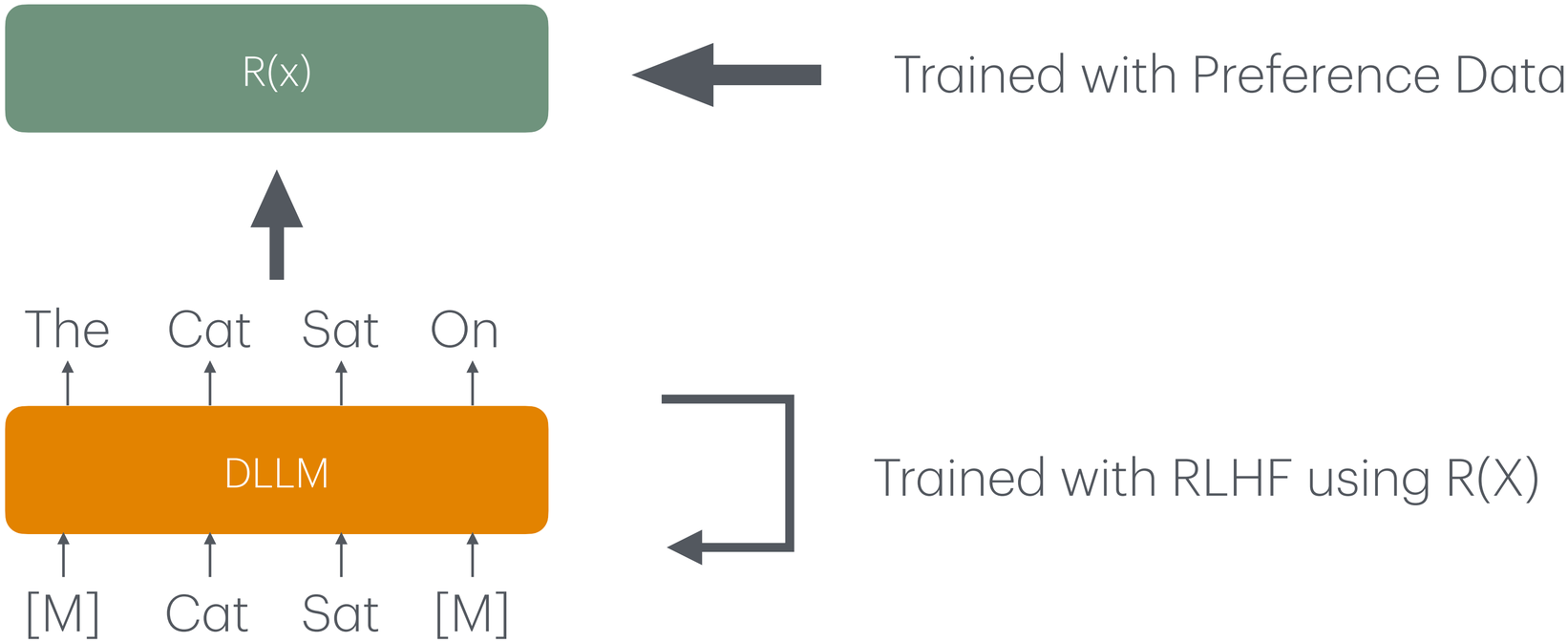

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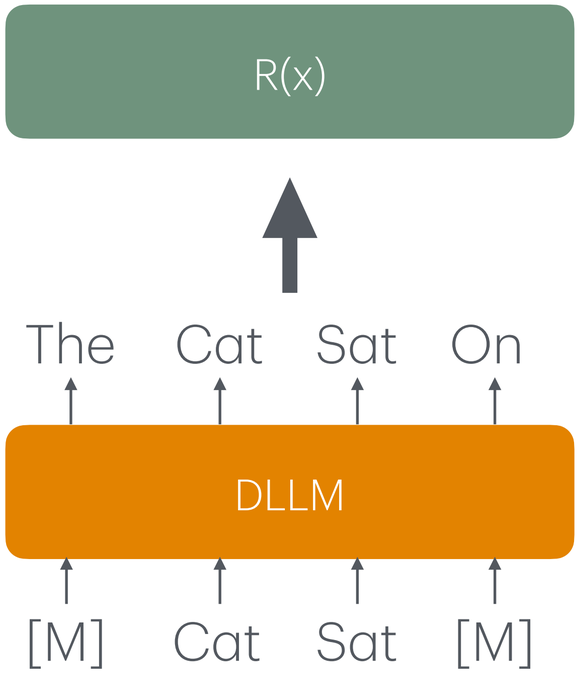

Trained with Preference Data

We don't want to modify weights!

Trained with RLHF using R(X)

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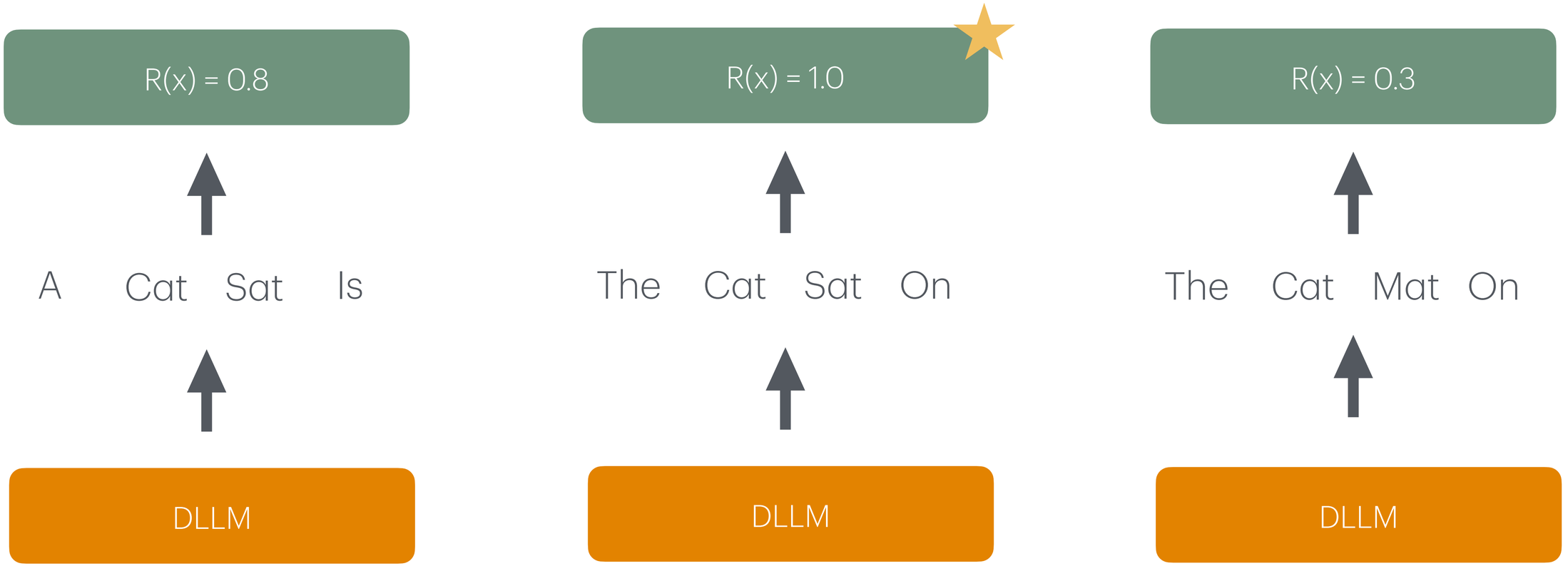
Best-of-N Sampling - Generate ’N’ and pick the best one



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Recall - DLLMs produce a distribution at ALL positions

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- Or use Process Reward Models to assess intermediate completions

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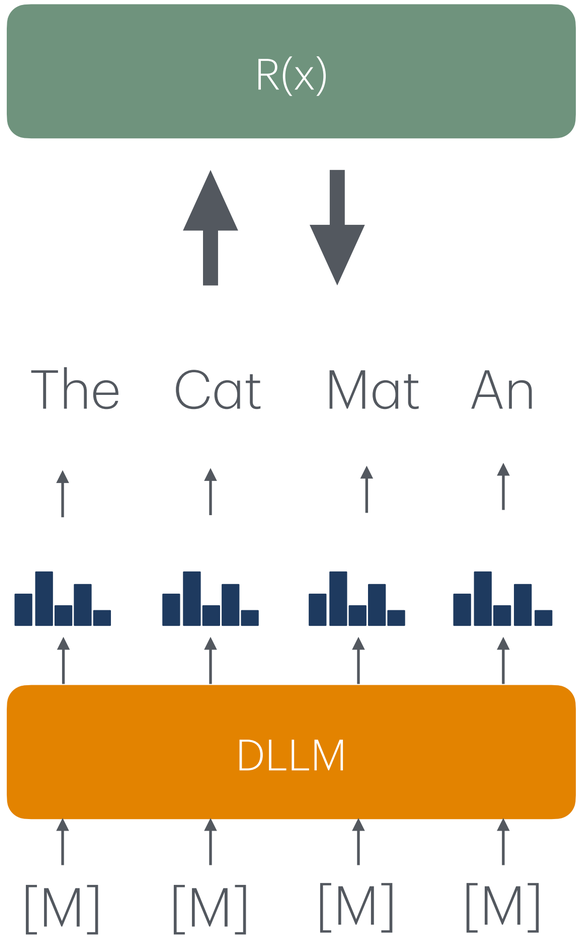
- With AR -> need to generate full string ‘x’ before assessing quality
- Or use Process Reward Models to assess intermediate completions
- With DLLMs -> you can sample (imperfect strings) at ALL stages
- Can we use this observation to update logits at each step?



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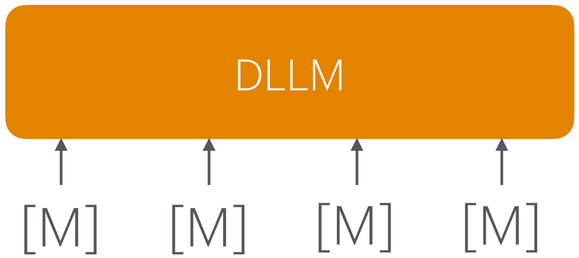

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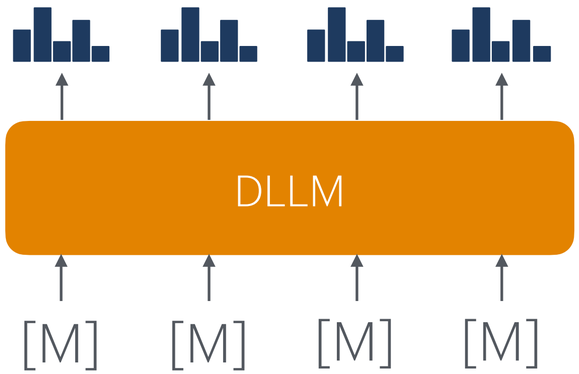

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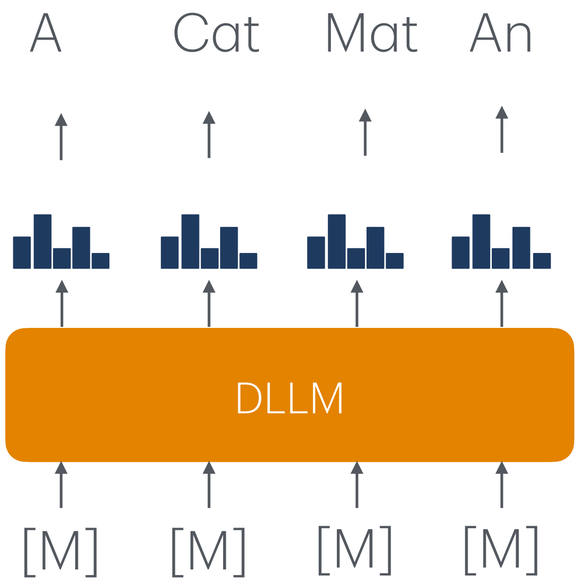

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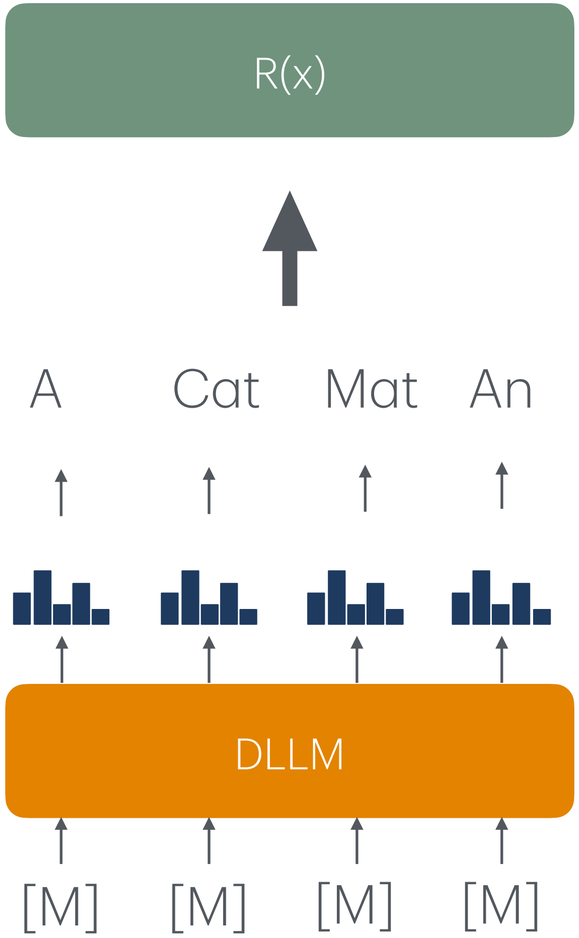

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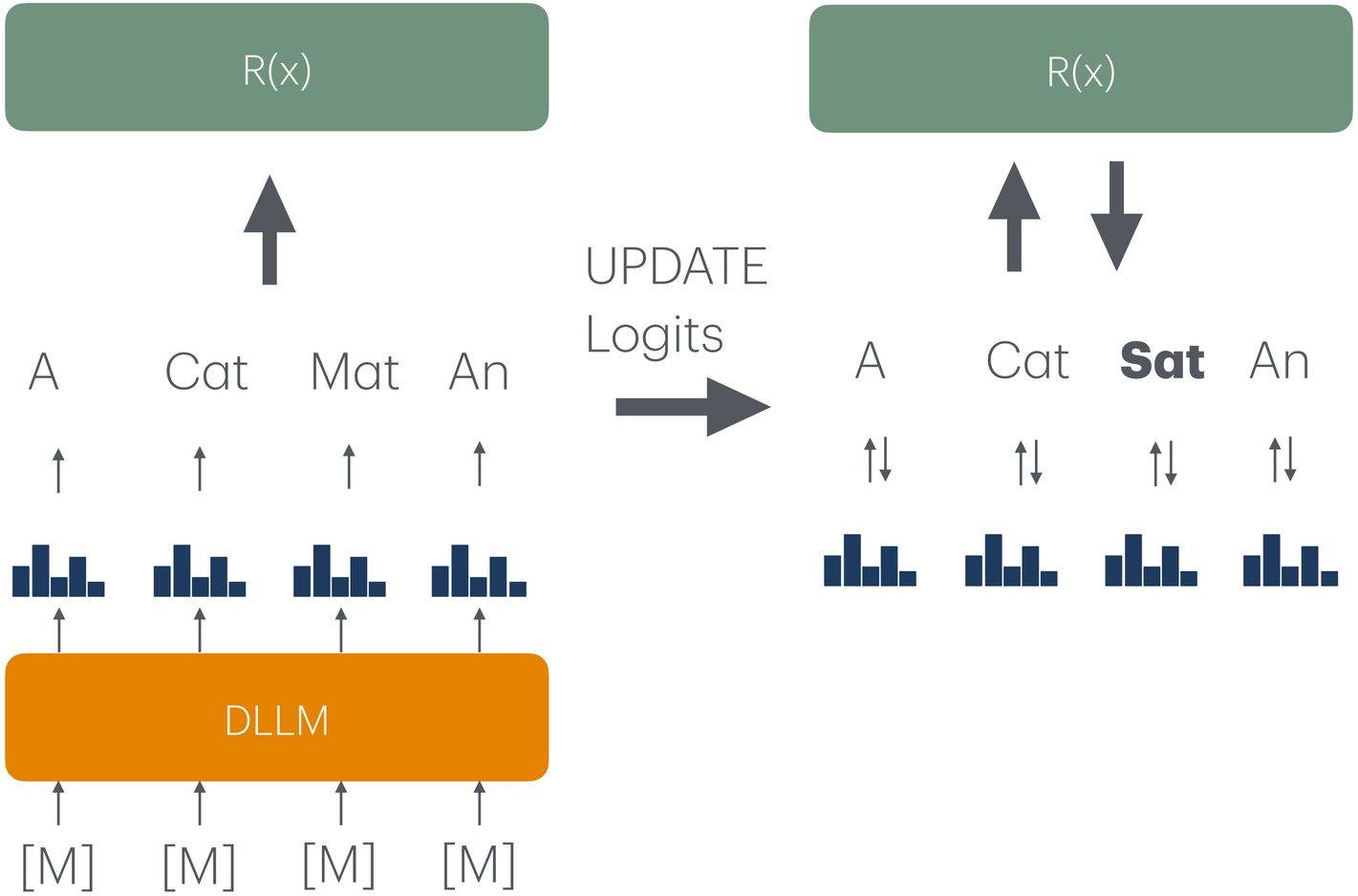

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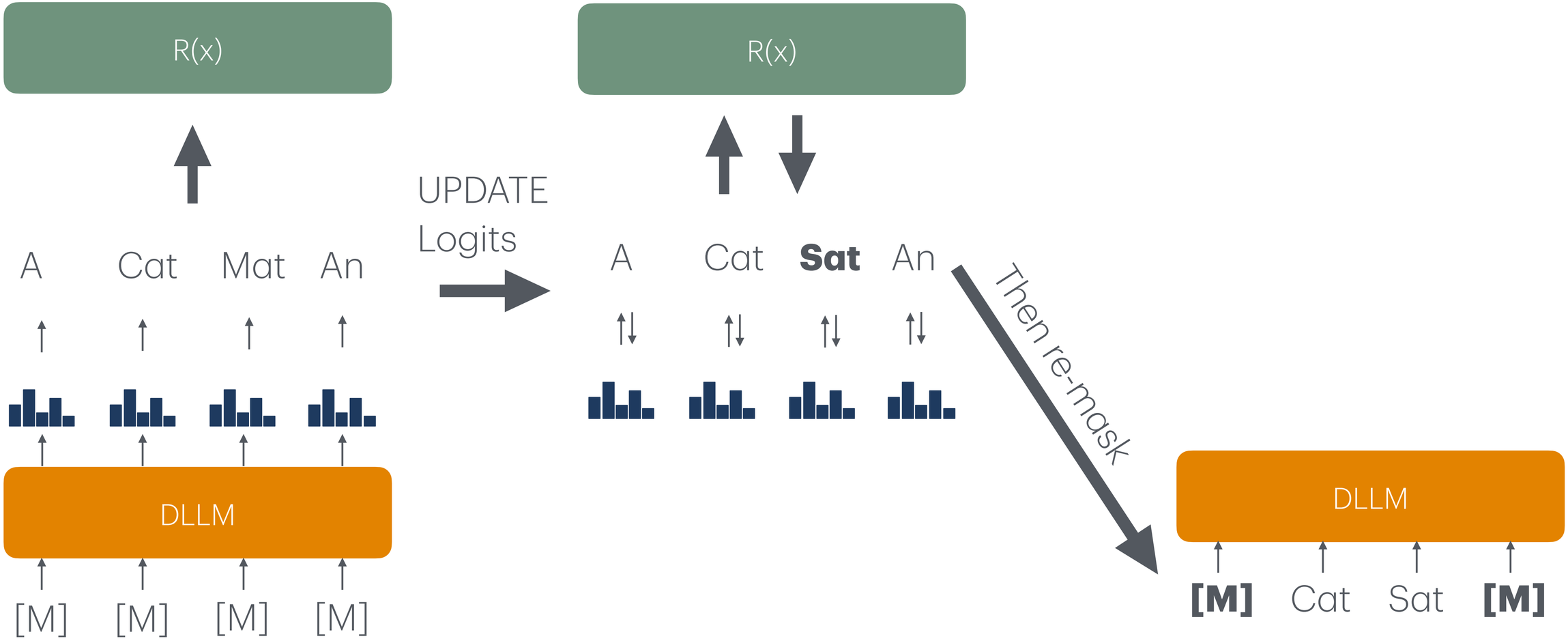

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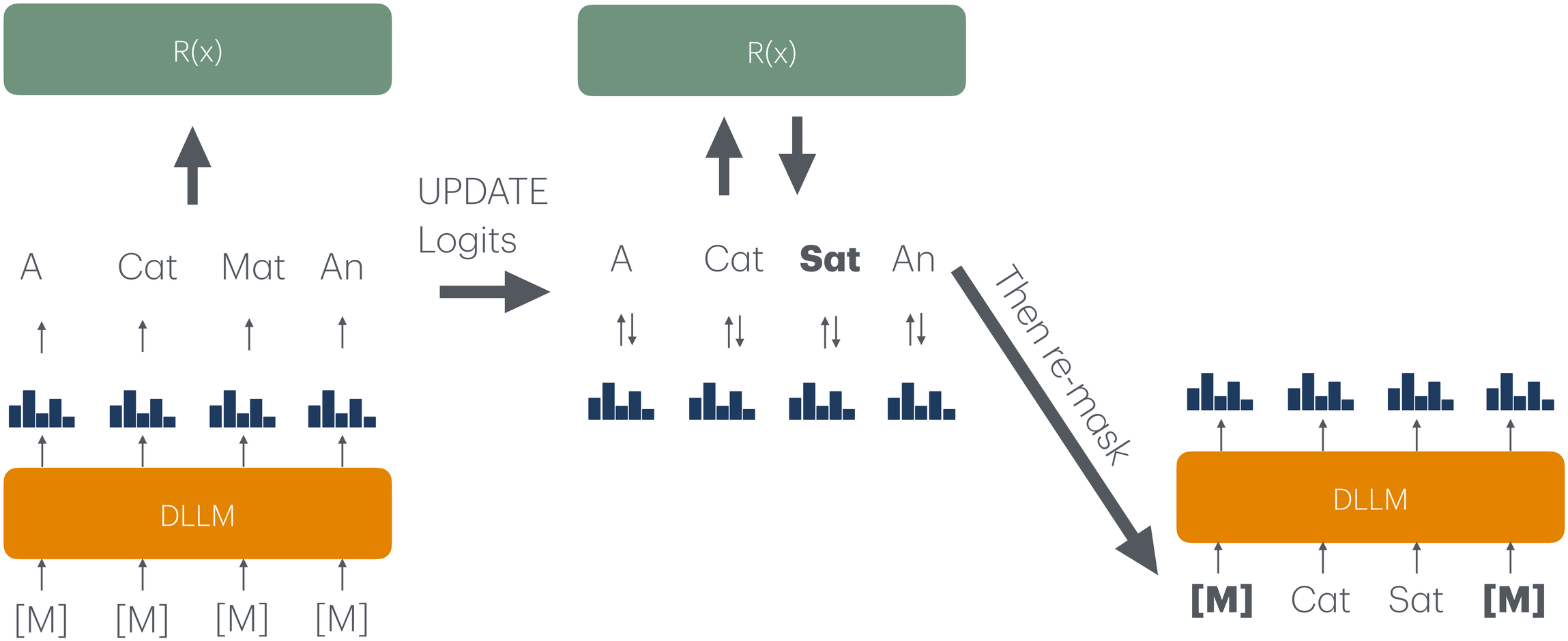

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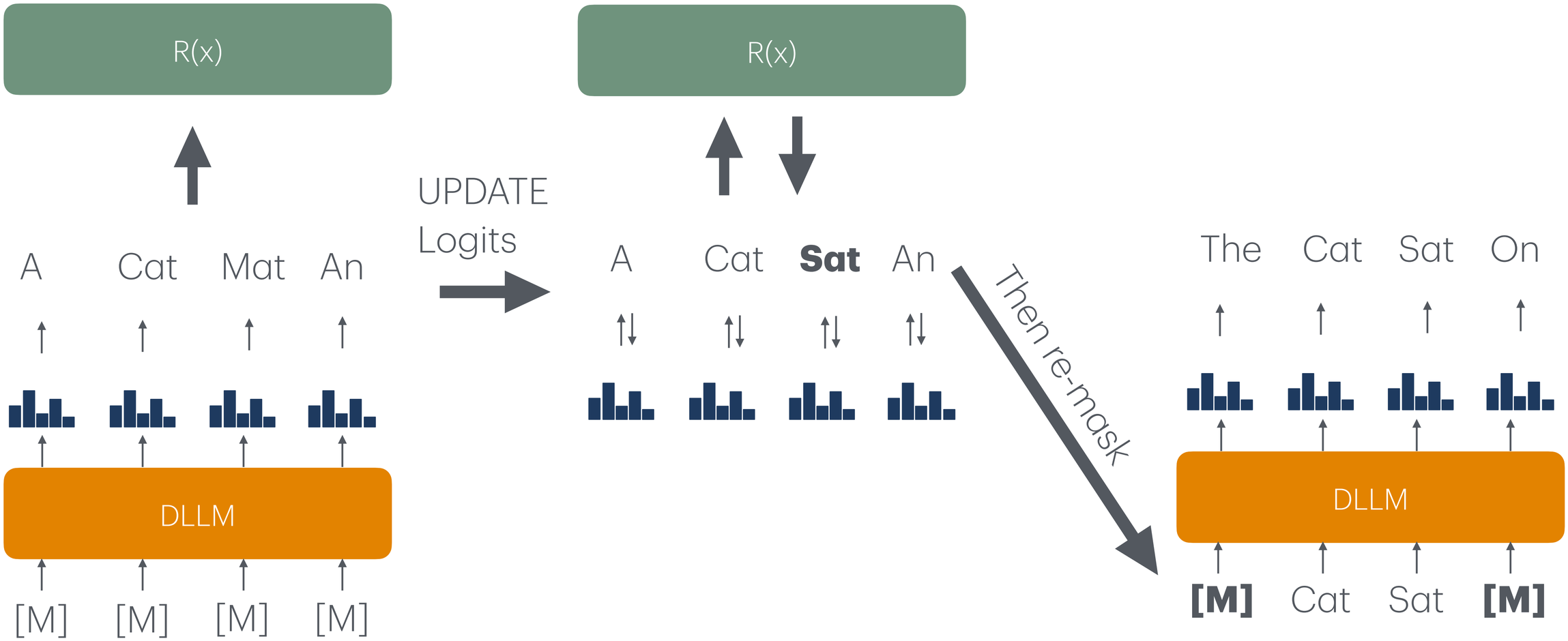

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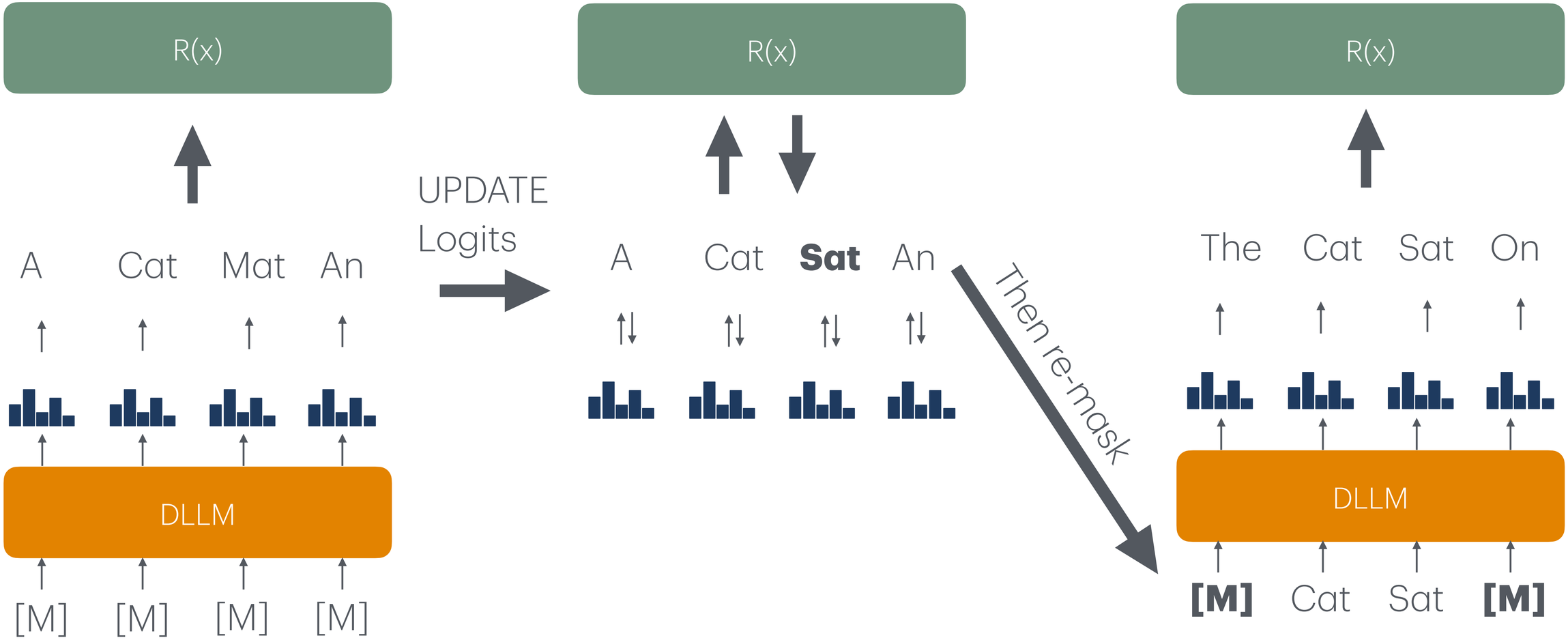
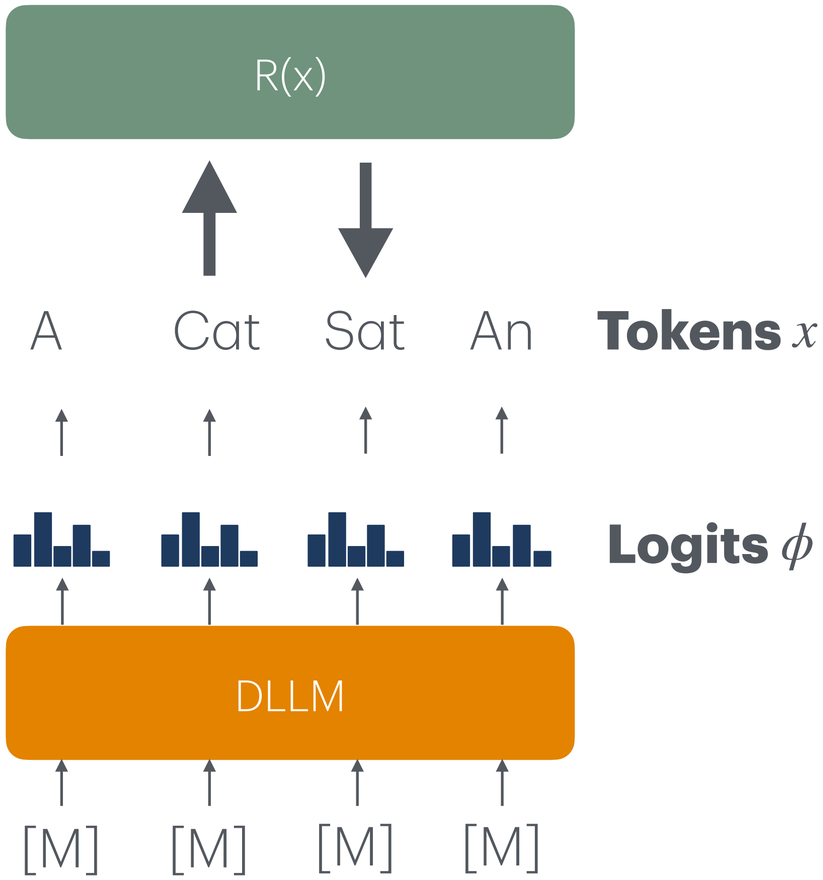


Gradient/Classifier Guidance (Dhariwal & Nichol et. al.)

If R(x) is differentiable, we can (potentially) update the logits. Successful in Continuous (Image) Diffusion



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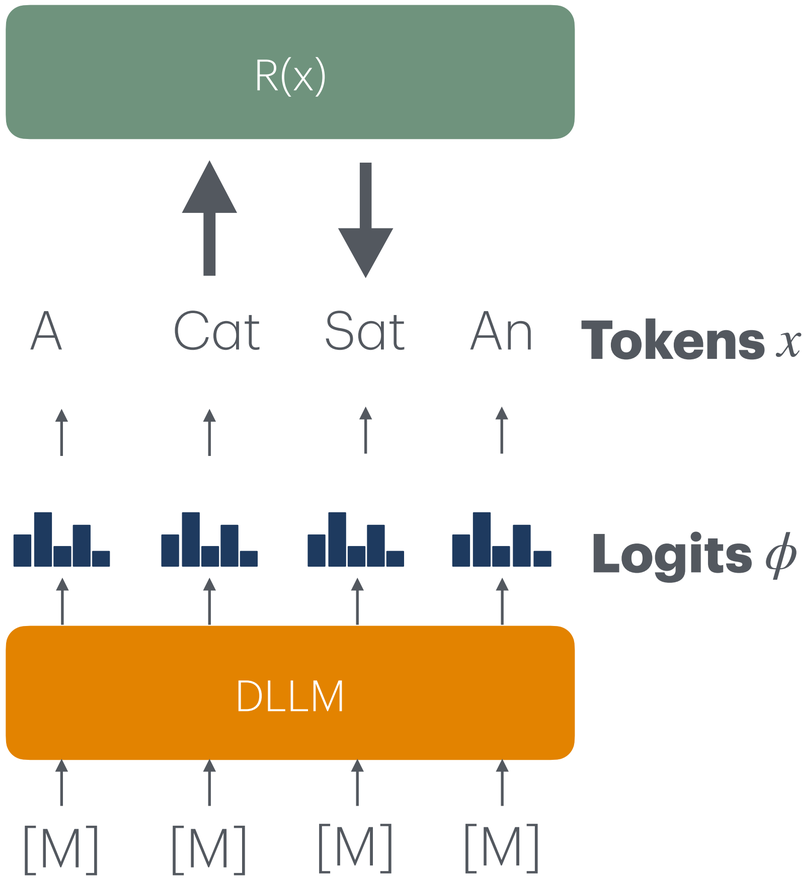

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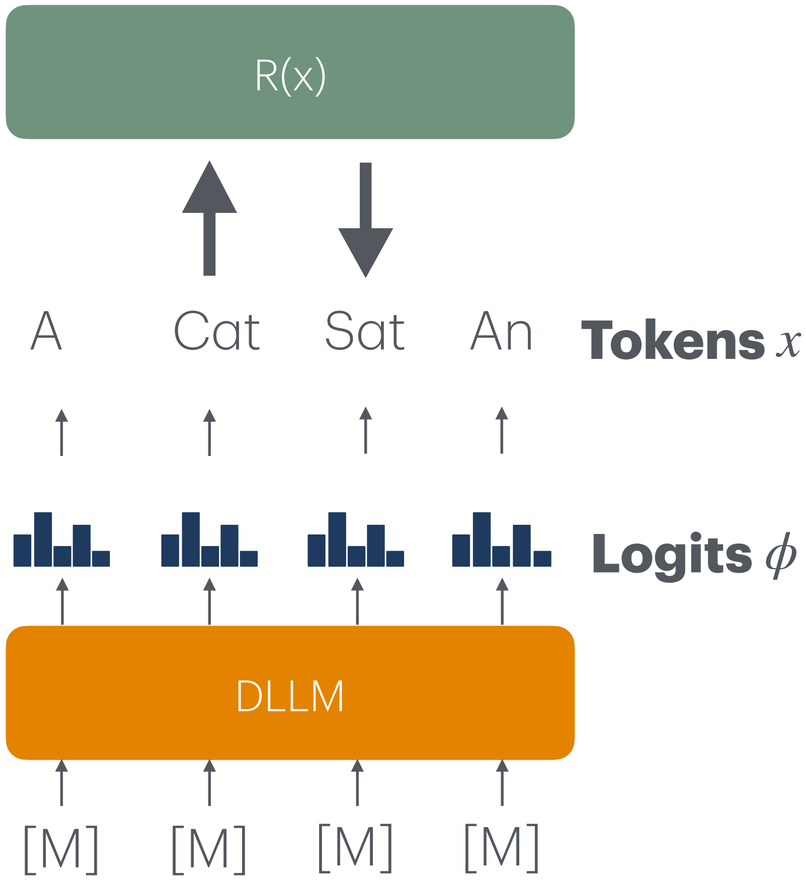

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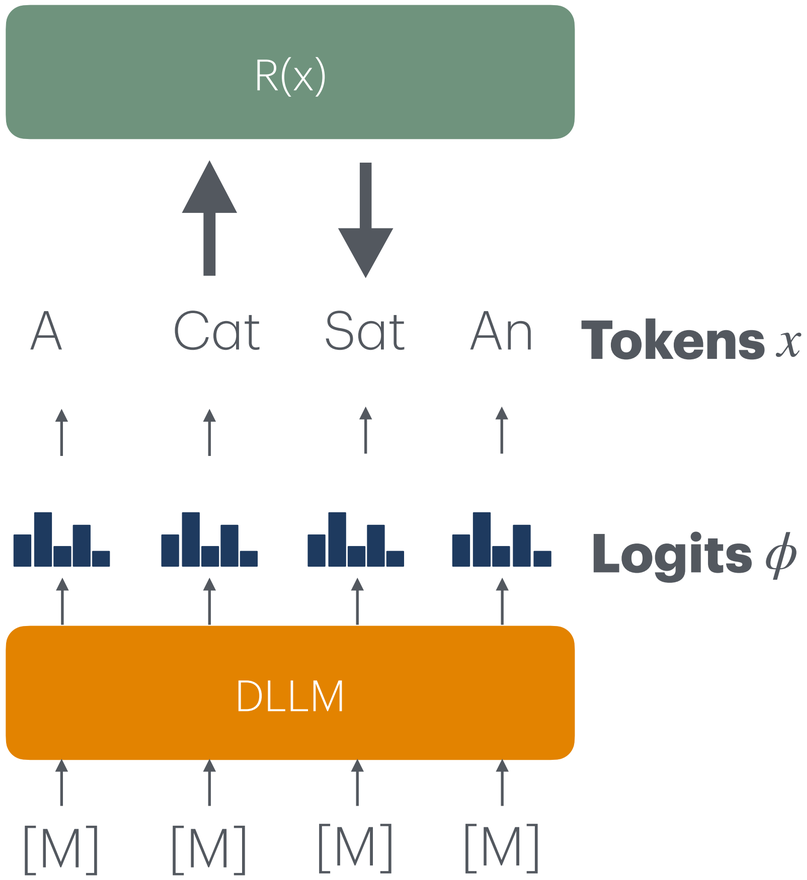

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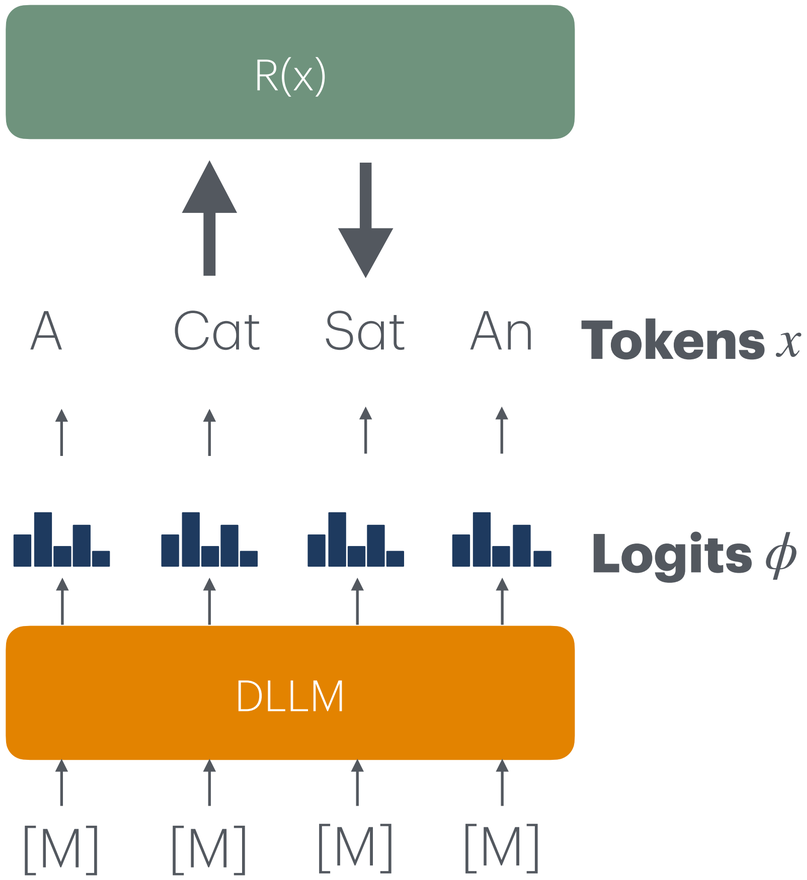

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Score function equivalent

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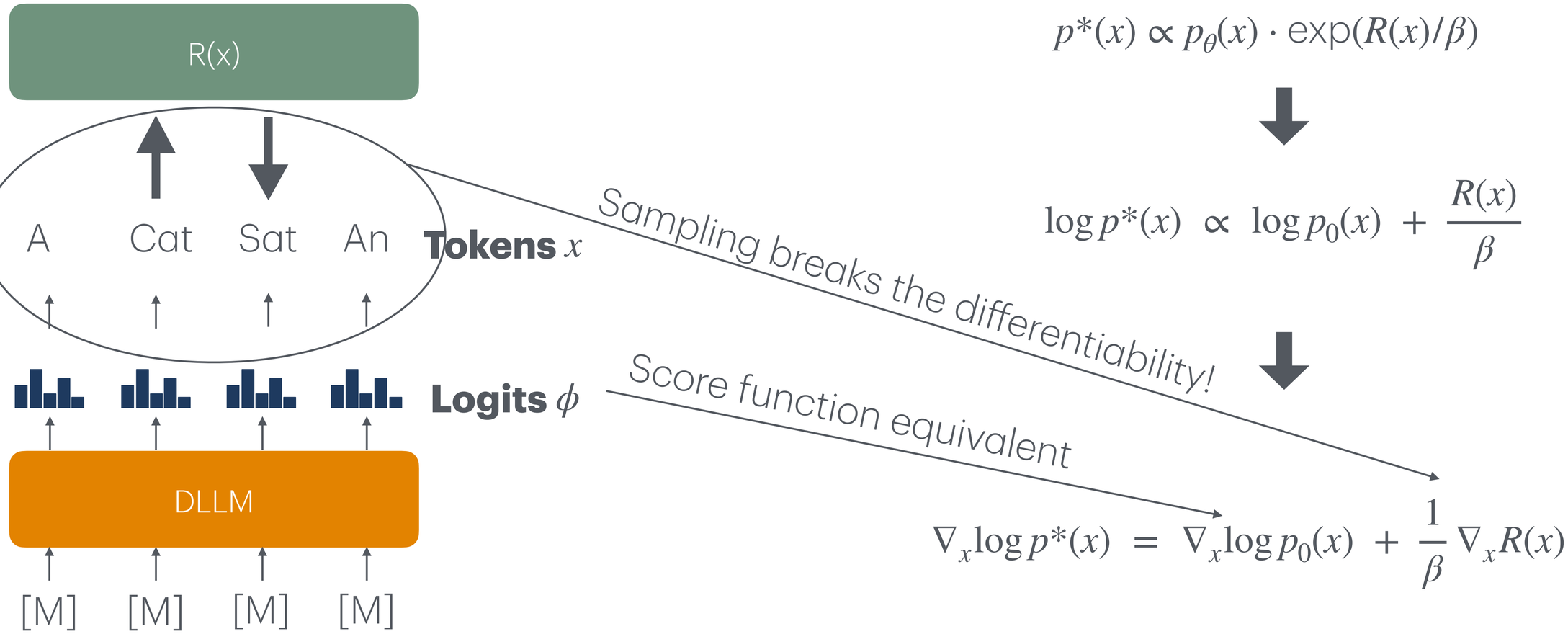
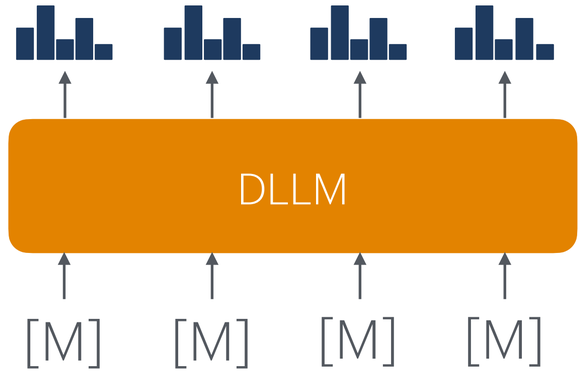


We can pretend the problem doesn't exist

Feed the `expected token` to R

- Let E_R be the embedding table of the reward model R



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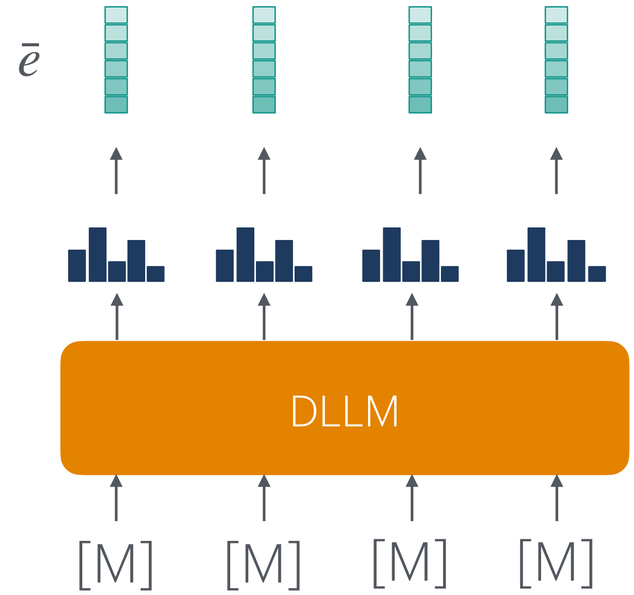
  $\bar{e} = \sum_{i \in \mathcal{V}} \text{softmax}(\phi) \cdot E_R^i$



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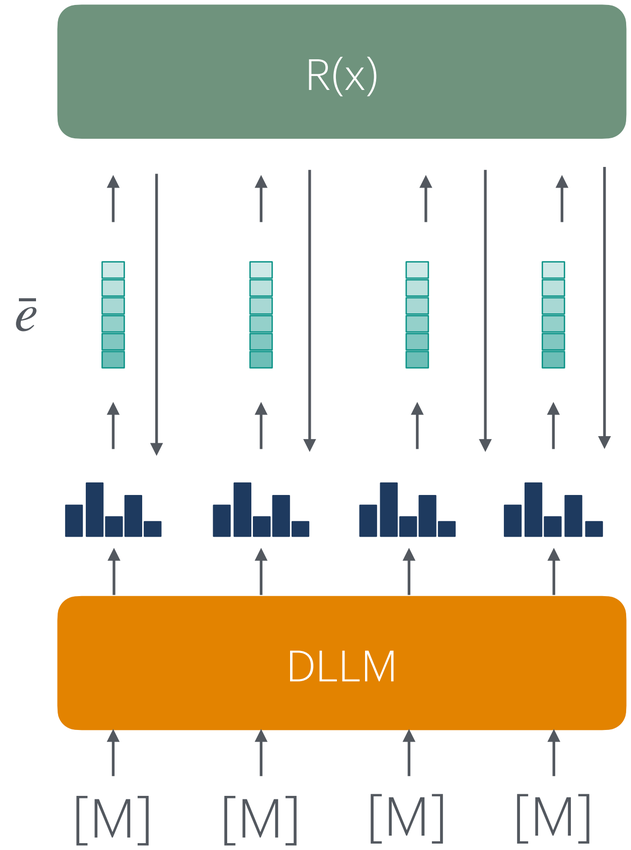

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May not always know what $\bar{e}$ means!

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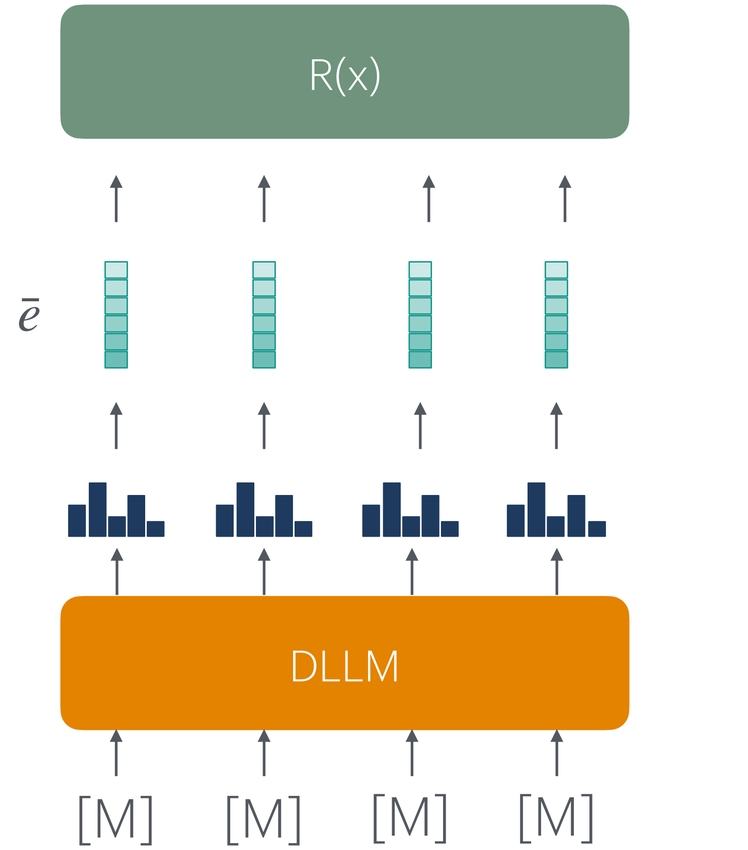
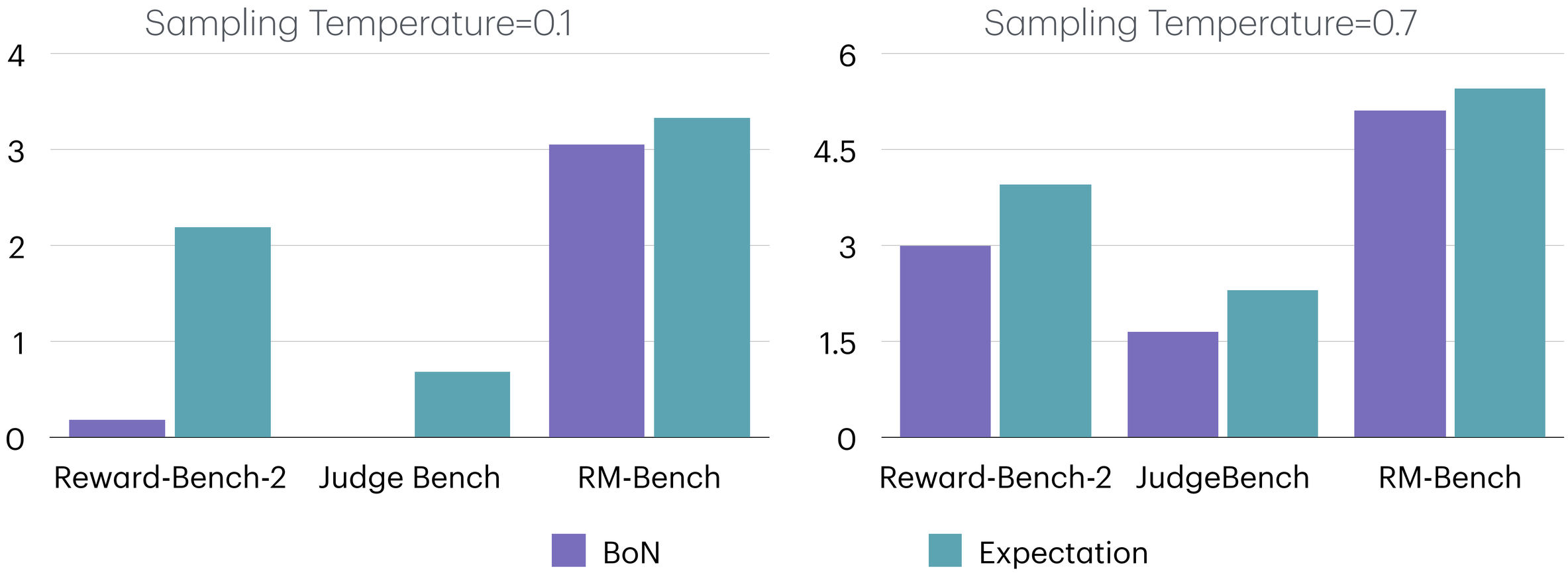
- Update logits as : $\phi \leftarrow \phi + \frac{1}{\beta} \nabla_\phi R(\bar{e})$
- $\bar{e}$ may not be close to any real token embedding E_R^i



We can pretend the problem doesn't exist

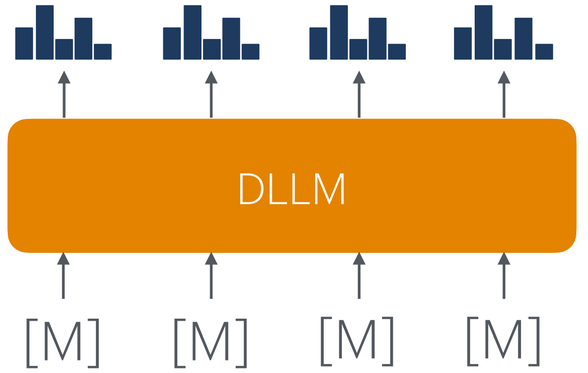
Feed the `expected token` to R



APS (Rout et al.) for Image Discrete Diffusion

Feed a discrete token, but compute gradient at the soft token (Bengio et. al., Jang et. al.)

- Sample a token x
- Get its embedding $\tilde{e} = E_R[x]$



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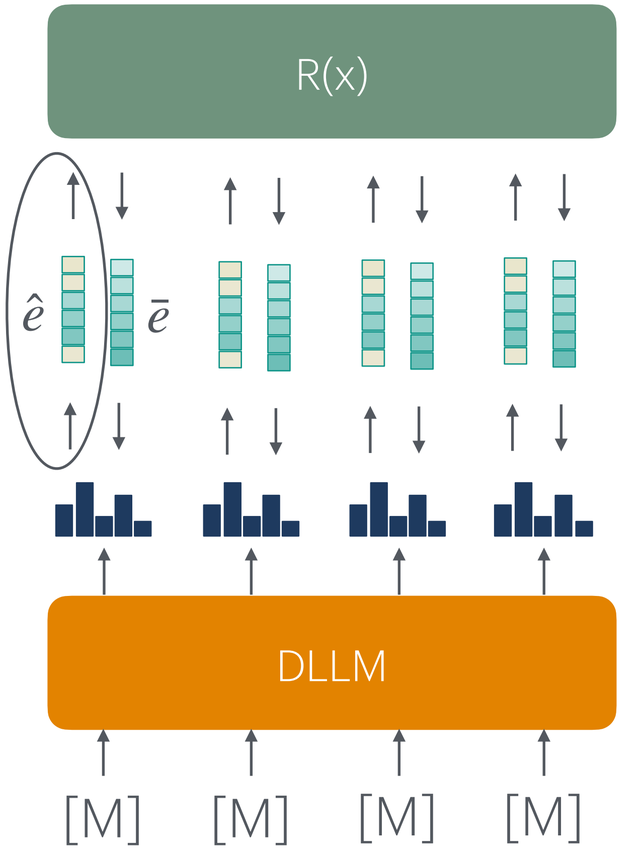

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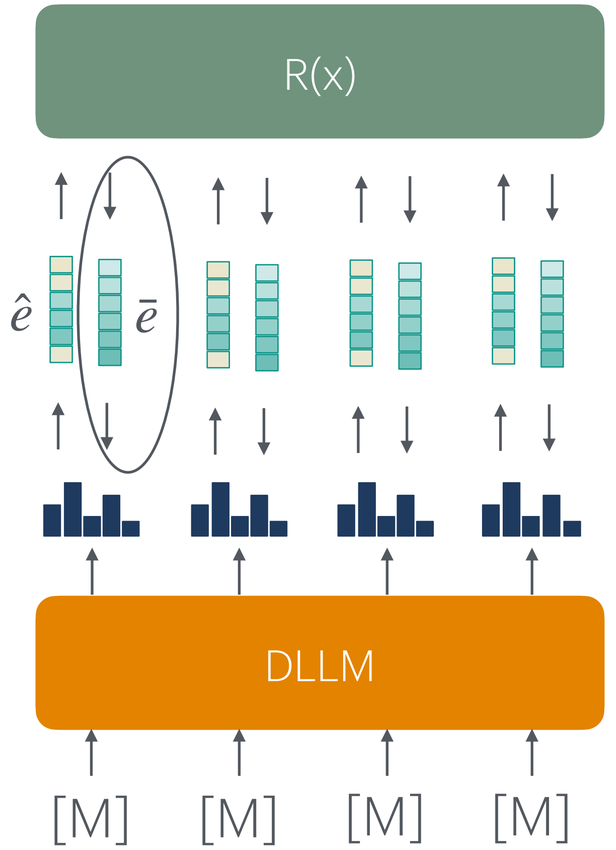
- Intuition: R effectively 'sees' $\tilde{e}$ but computes gradient at $\bar{e}$



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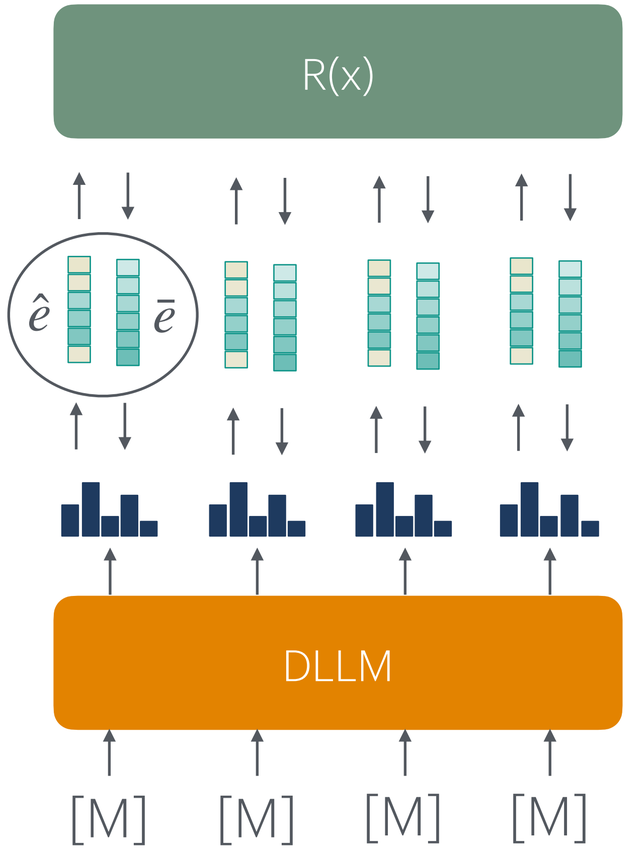
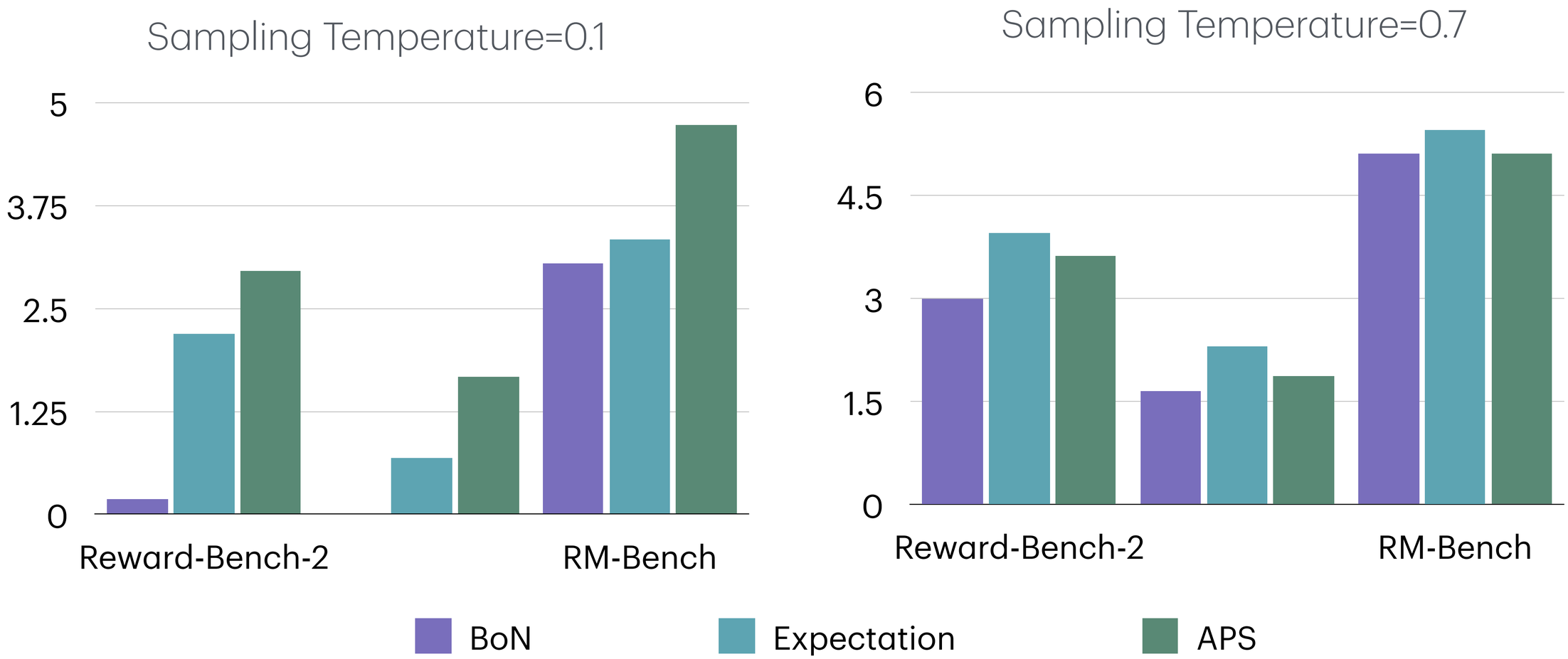
  $\hat{e} = \bar{e} + \text{stop-grad}(\tilde{e} - \bar{e})$
- Intuition: R effectively 'sees' $\tilde{e}$ but computes gradient at $\bar{e}$
- Issue: If $\bar{e}$ is far away from $\tilde{e}$, the gradients are wrong
- VQ-VAE in images, so this issue is not as catastrophic



APS (Rout et al.) for Image Discrete Diffusion

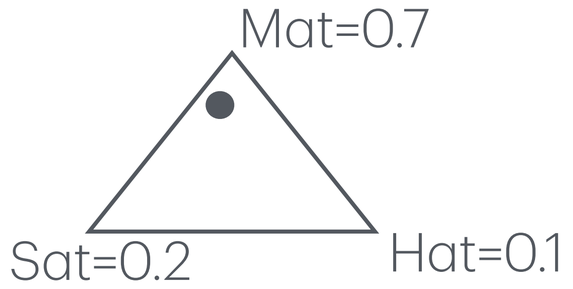
If gradients are wrong, performance drops!



EntRGi: Let the Model's Entropy Decide

The right choice depends on the confidence of the model (see paper for gradient analysis)

- Low Entropy -> Model is close to a real token -> don't sample, use the expected (soft) embedding



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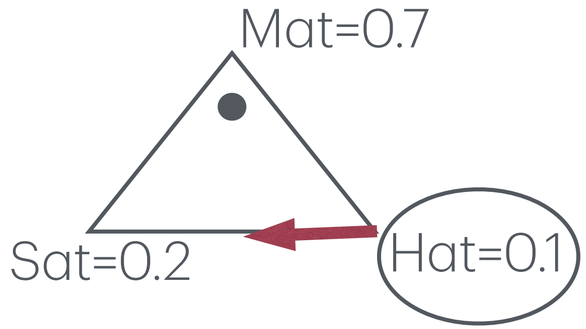

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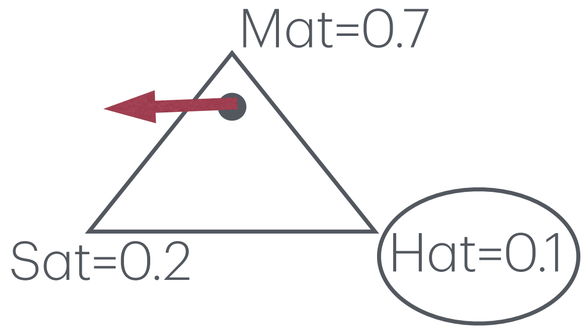

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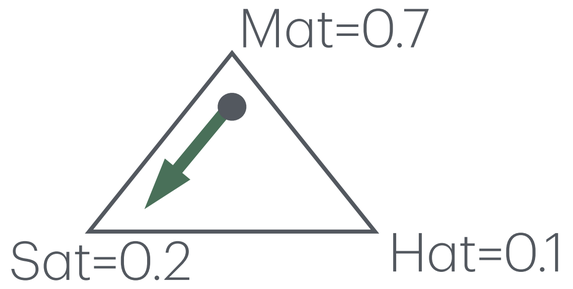

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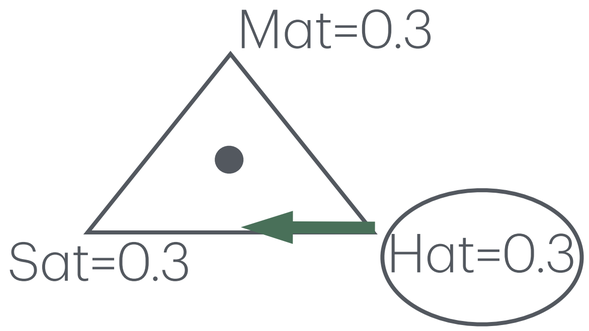
The right choice depends on the confidence of the model (see paper for gradient analysis)

- Low Entropy -> Model is close to a real token -> don't sample, use the expected (soft) embedding
- High Entropy -> R(x) becomes unreliable, fall back to STE



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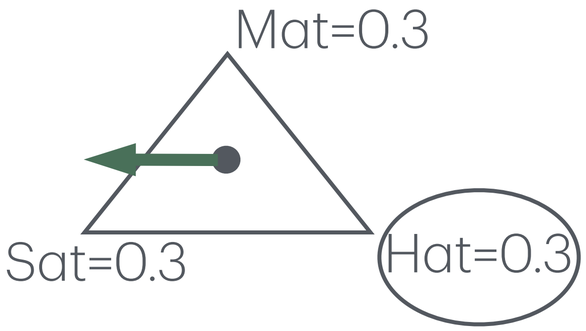

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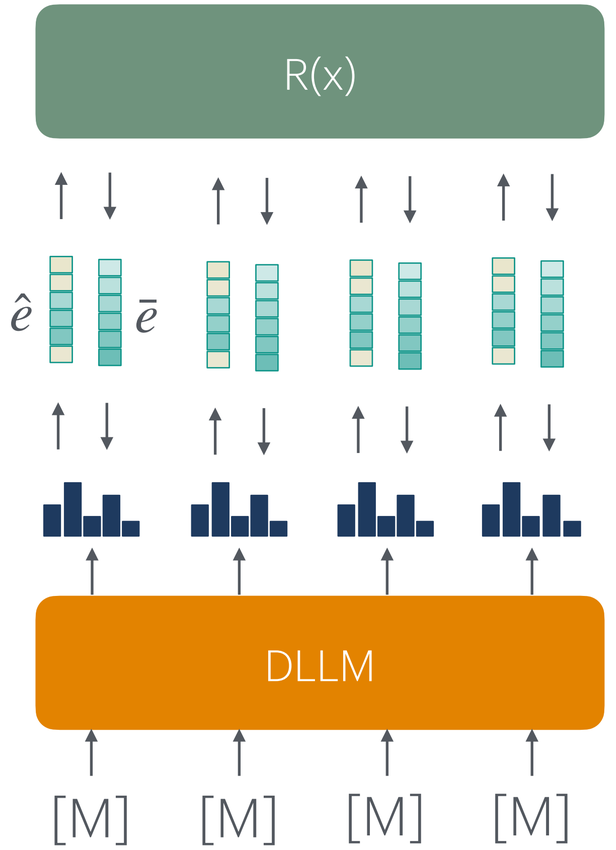
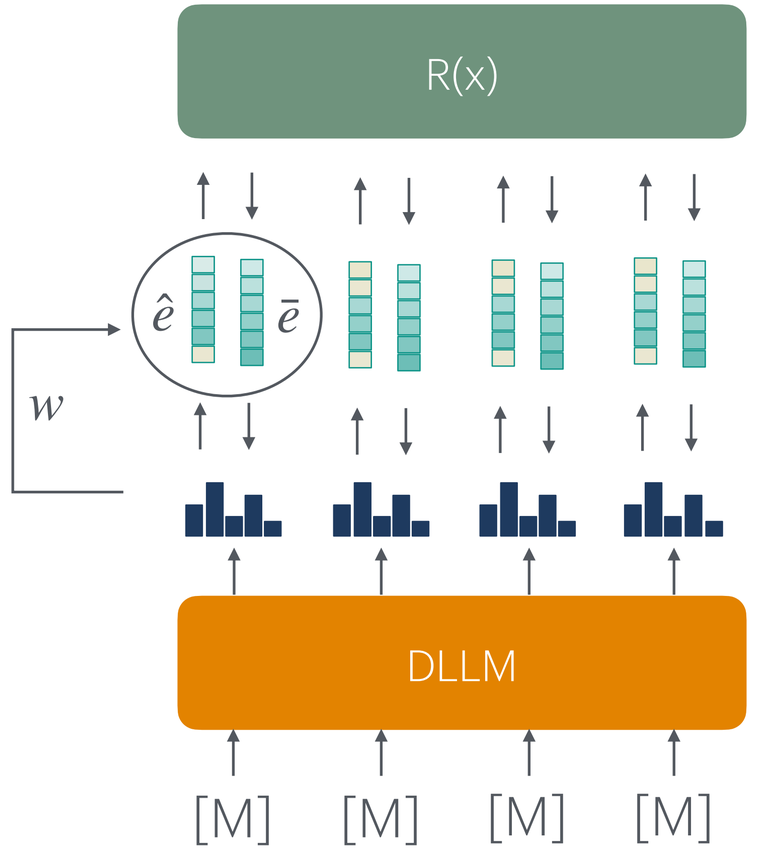
- High Entropy -> R(x) becomes unreliable, fall back to STE
- Construct input embedding to R as
  $\hat{e} = \bar{e} + \text{stop-grad}(w(\tilde{e} - \bar{e}))$
- Where $w = \dfrac{H(\text{softmax}(\phi))}{\log |\mathcal{V}|} \in [0,1]$



EntRGi: Let the Model's Entropy Decide

The right choice depends on the confidence of the model (see paper for gradient analysis)

- Low Entropy -> Model is close to a real token -> don't sample, use the expected embedding
- High Entropy -> RM becomes unreliable, fall back to STE
- Construct input embedding to R as
  $\hat{e} = \bar{e} + \text{stop-grad}(w(\tilde{e} - \bar{e}))$
- Where $w = \dfrac{H(\text{softmax}(\phi))}{\log |\mathcal{V}|} \in [0,1]$



Results

Dream-7B-Instruct with Skywork-Reward-V2-0.6B

External model to measure reward hacking

Method	Reward-Bench-2			JudgeBench			RM-Bench		
	Top@1	**Avg@4**	**LMUnit**	**Top@1**	**Avg@4**	**LMUnit**	**Top@1**	**Avg@4**	**LMUnit**
Temperature ($\tau = 0.1$)									
BoN	0.18±0.22	0.05±0.23	3.74±0.04	0.00±0.15	-0.07±0.16	3.75±0.03	3.05±0.05	3.02±0.05	3.93±0.01
Expectation	2.19±0.19	**1.62**±0.17	4.12±0.03	0.68±0.19	**-0.06**±0.21	3.81±0.02	3.33±0.20	2.59±0.12	3.89±0.04
APS	2.95±0.21	1.47±0.20	4.19±0.01	**1.67**±0.11	-0.17±0.14	3.89±0.03	4.72±0.13	2.46±0.17	4.01±0.03
EntRGi	**3.07**±0.22	**1.62**±0.18	**4.22**±0.02	**1.73**±0.14	-0.11±0.18	**3.94**±0.01	**4.90**±0.13	**2.75**±0.14	**4.06**±0.01
Temperature ($\tau = 0.7$)									
BoN	2.99±0.23	1.38±0.29	4.15±0.02	1.65±0.18	-0.84±0.16	3.91±0.02	5.11±0.20	2.98±0.15	4.02±0.03
Expectation	**3.95**±0.28	**2.23**±0.24	4.22±0.02	2.30±0.08	**0.13**±0.07	**3.97**±0.01	5.45±0.16	3.29±0.13	4.02±0.03
APS	3.62±0.27	1.80±0.24	4.22±0.02	1.87±0.14	-0.63±0.10	3.93±0.02	5.11±0.14	2.66±0.15	4.00±0.02
EntRGi	**3.91**±0.30	**2.20**±0.26	**4.25**±0.02	**2.44**±0.06	0.02±0.10	**3.98**±0.02	**5.70**±0.12	**3.41**±0.14	**4.04**±0.01

Try it Out!

TEXAS
The University of Texas at Austin

Paper

Code