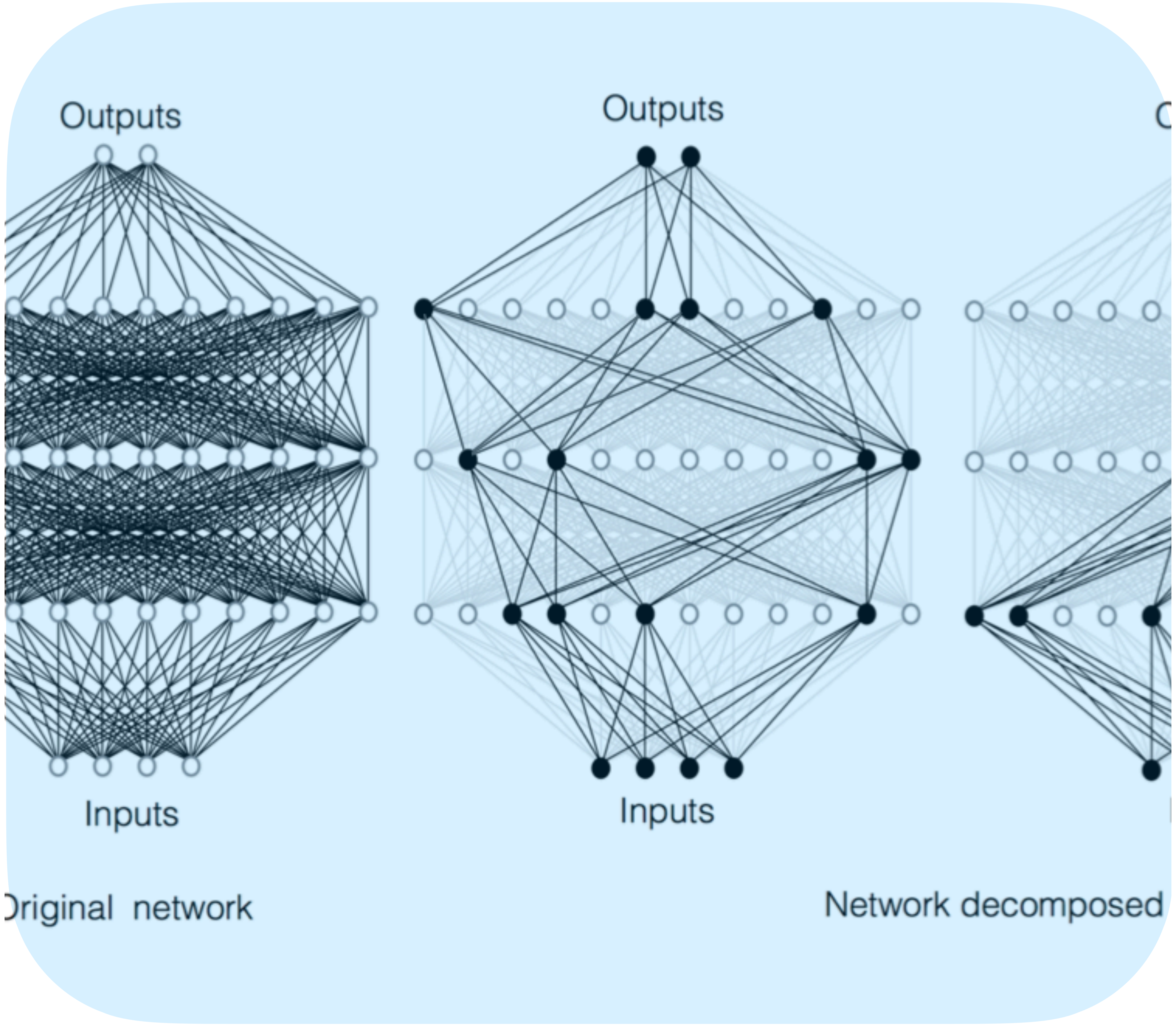
Leveraging Sparse Input and Sparse Models: Efficient Distributed Learning in Resource-Constrained Environments

Emmanouil Kariotakis[1*], Grigorios Tsagkatakis[2,3], Panagiotis Tsakalides[2,3], **Anastasios Kyrillidis[4]**
[1]KU Leuven, [2]Institute of CS - FORTH, [3]University of Crete (CS), [4]Rice University CS

Conference on Parsimony and Learning (CPAL)

Presented by: Daniel LeJeune (Stanford)
Thank you, Daniel!

Motivation for this work: End-2-end sparse training



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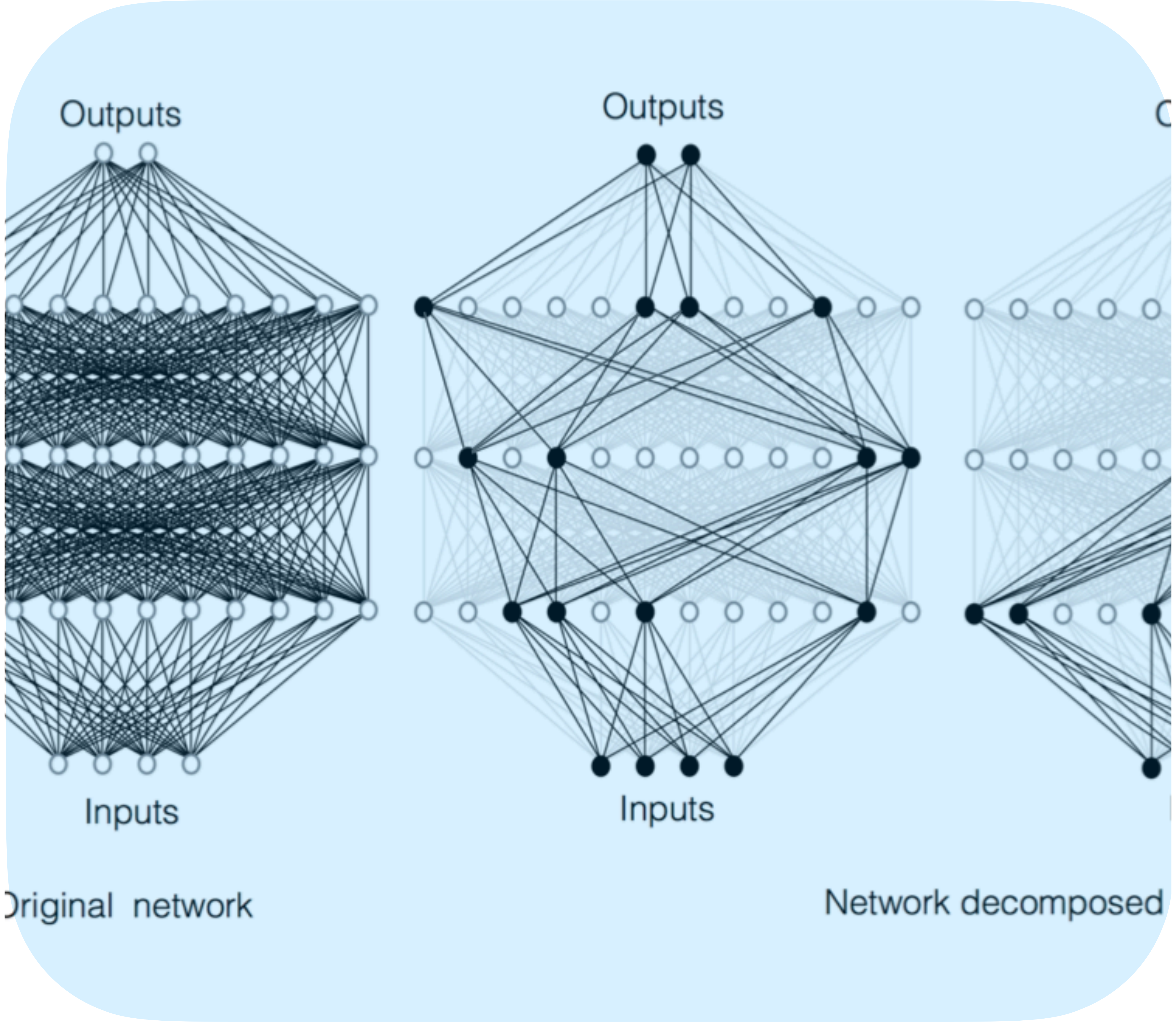

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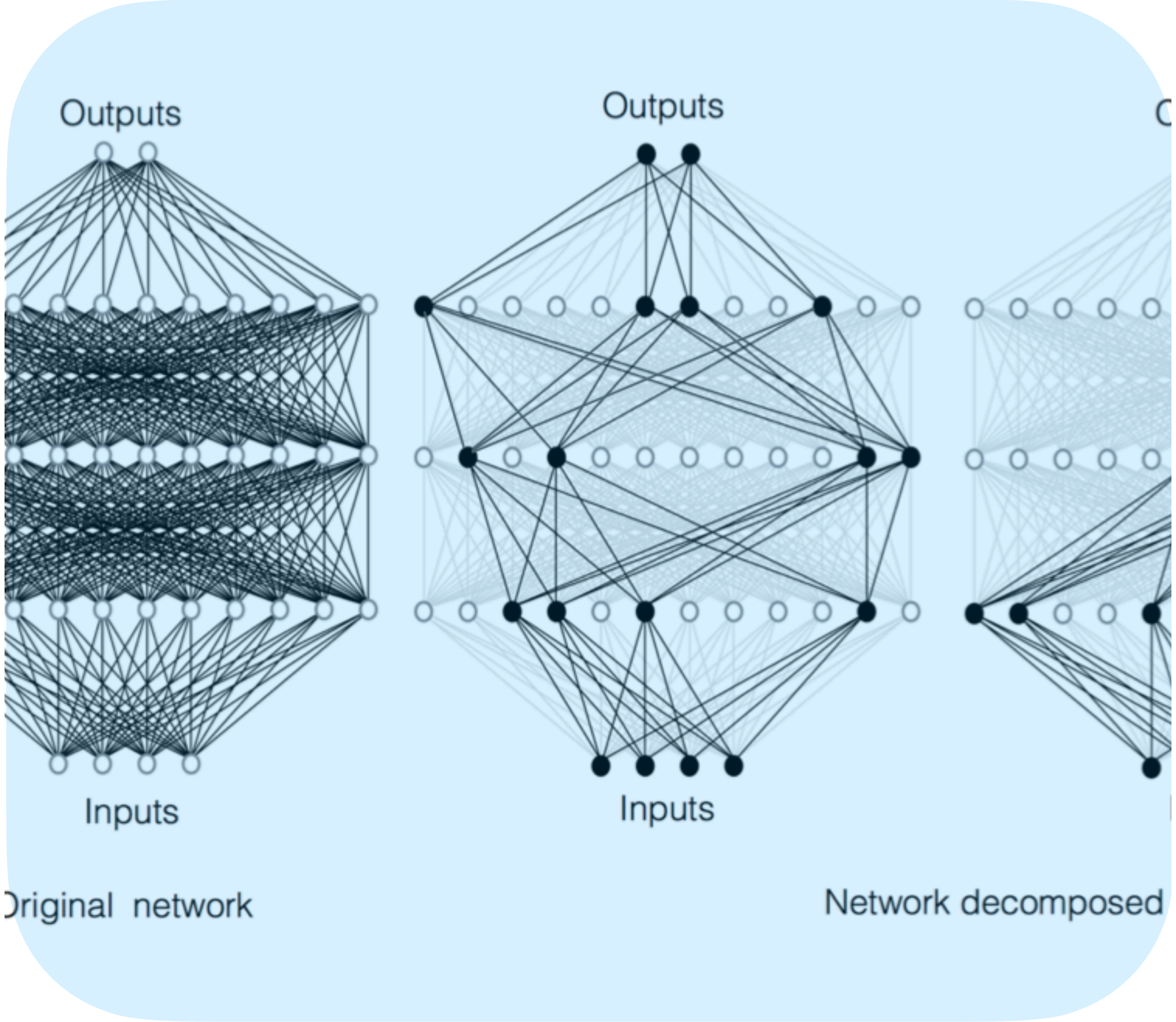

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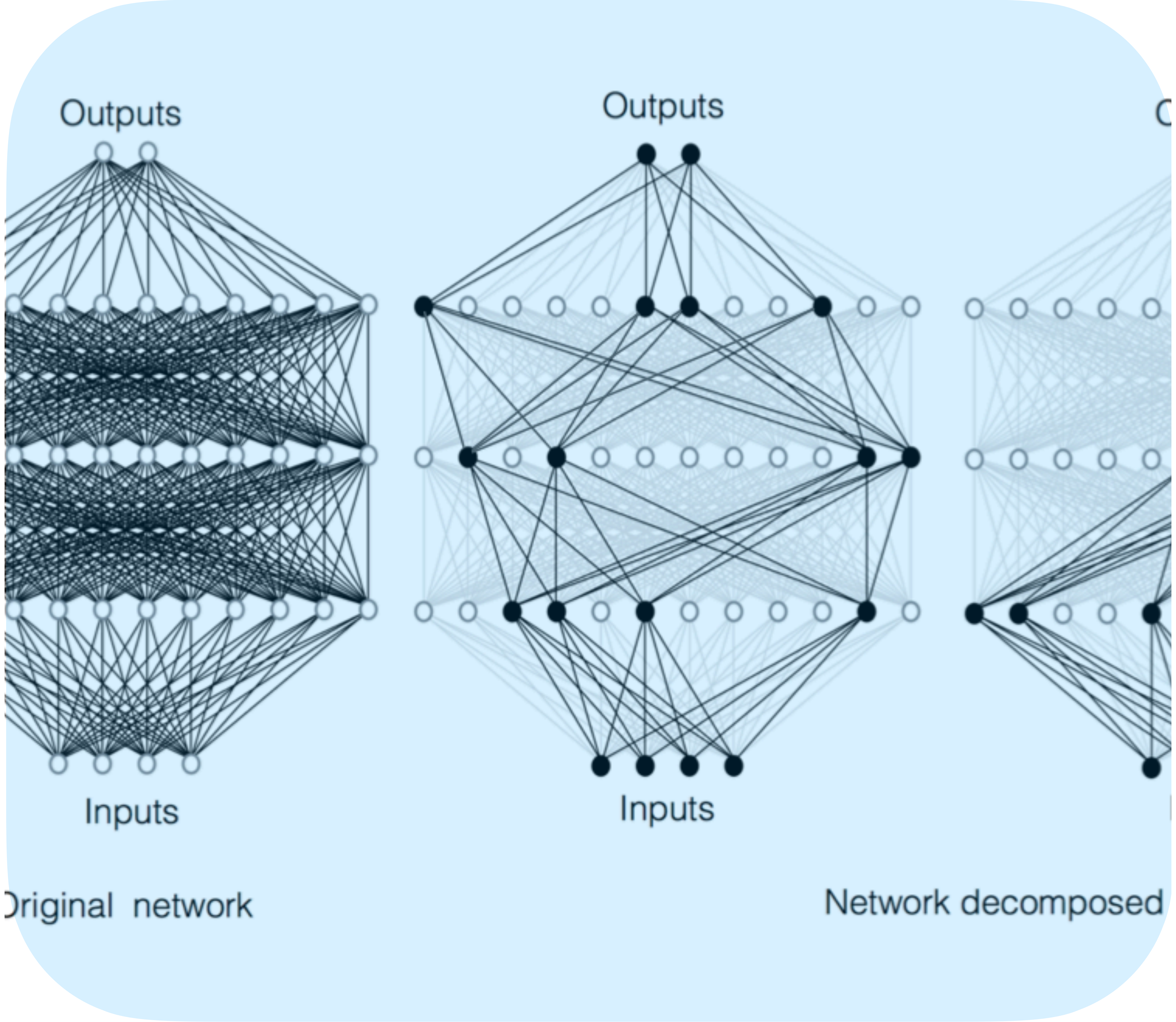

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- Past work answered this question affirmatively:

  Advertising own work: IST

  [Yuan et al. 2022, Liao et al 2021, Dun et al., 2022-23; Wan et al. 2022, Hu et al., 2023, Wang et al. 2023;...]

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  [So many works, just look around you...]

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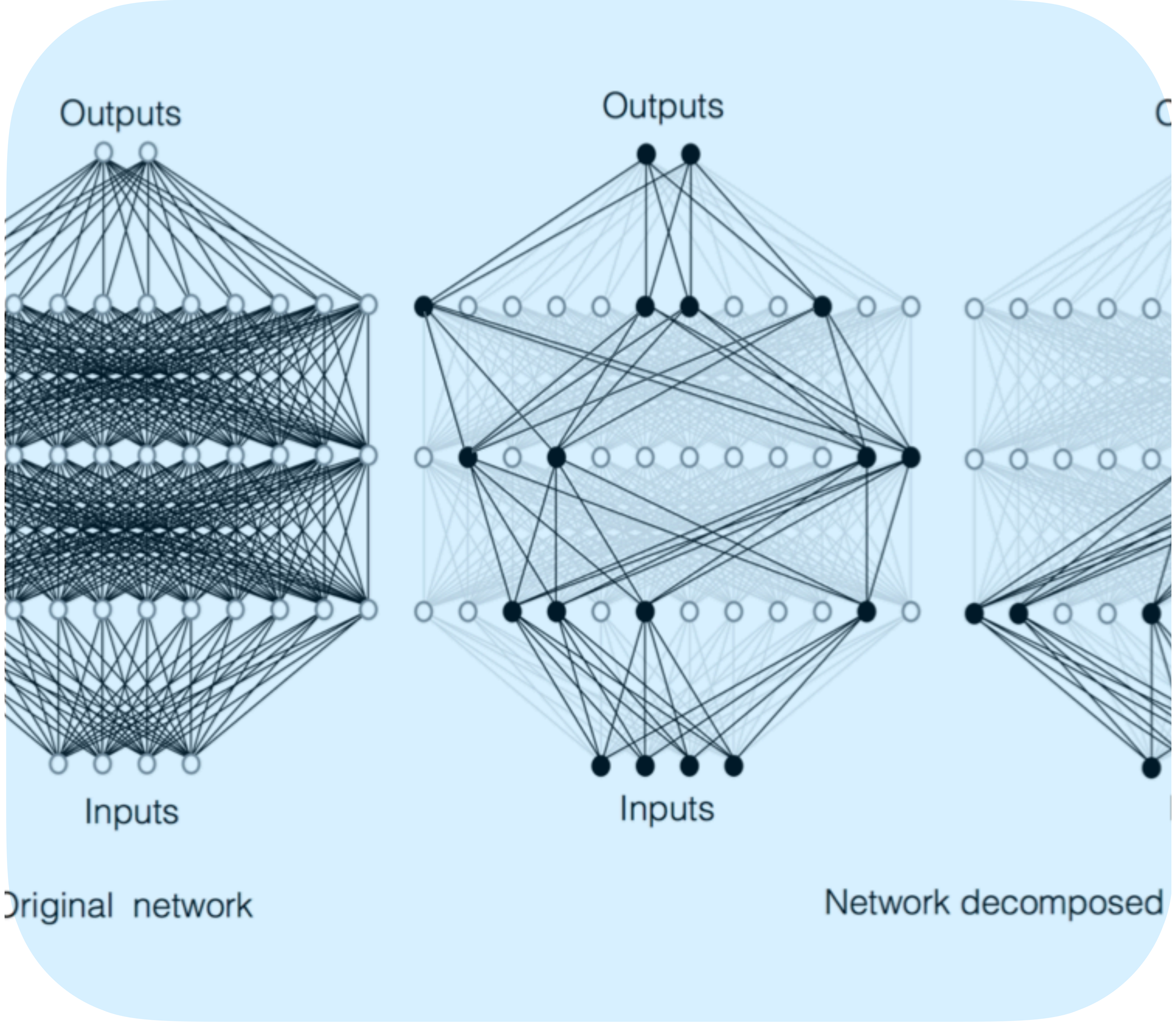

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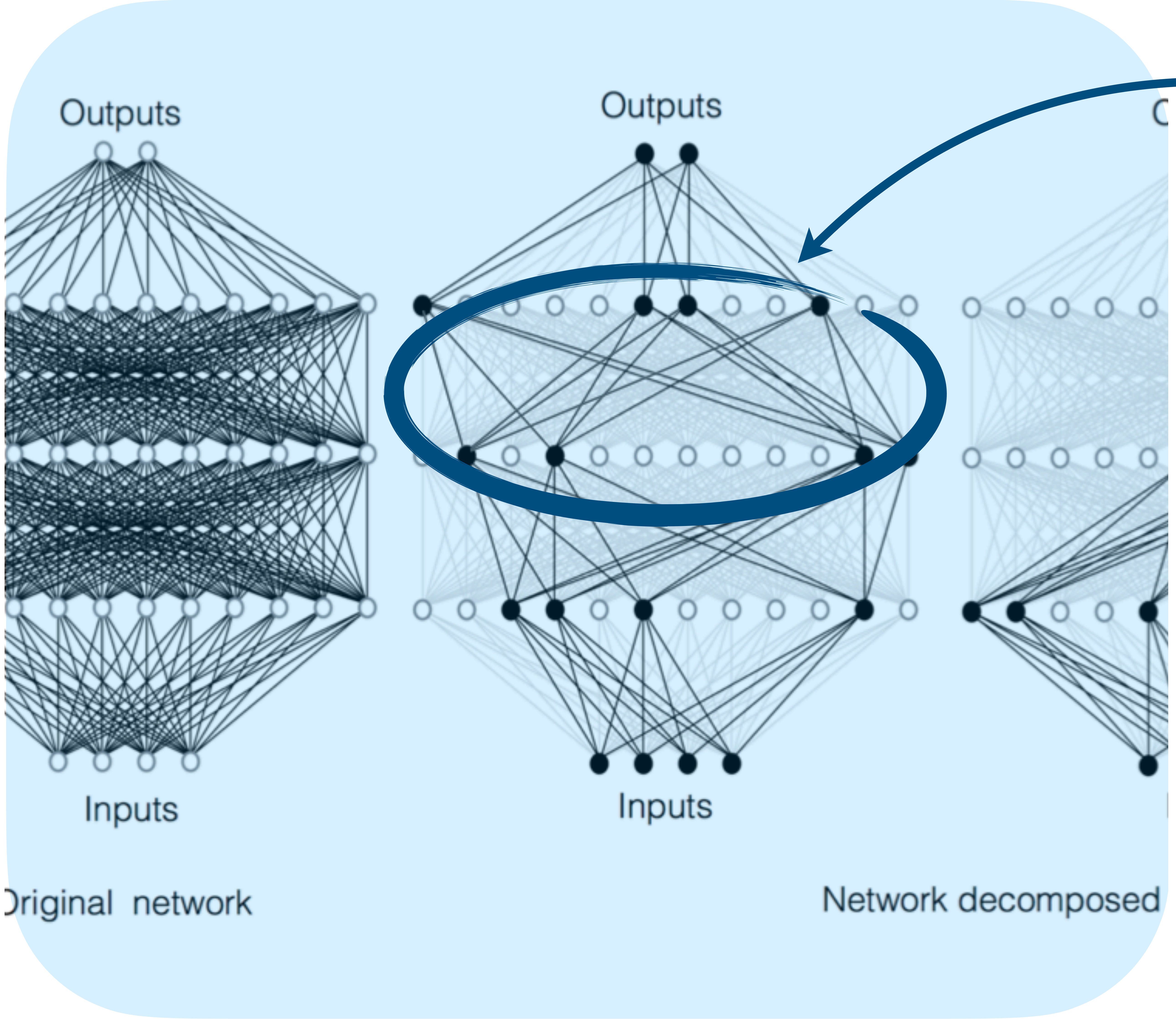
  Sparse training methods

  [So many works, just look around you...]
- Motivation: efficiency; "do we need all these parameters?"; curiosity..

How does this work differentiate?



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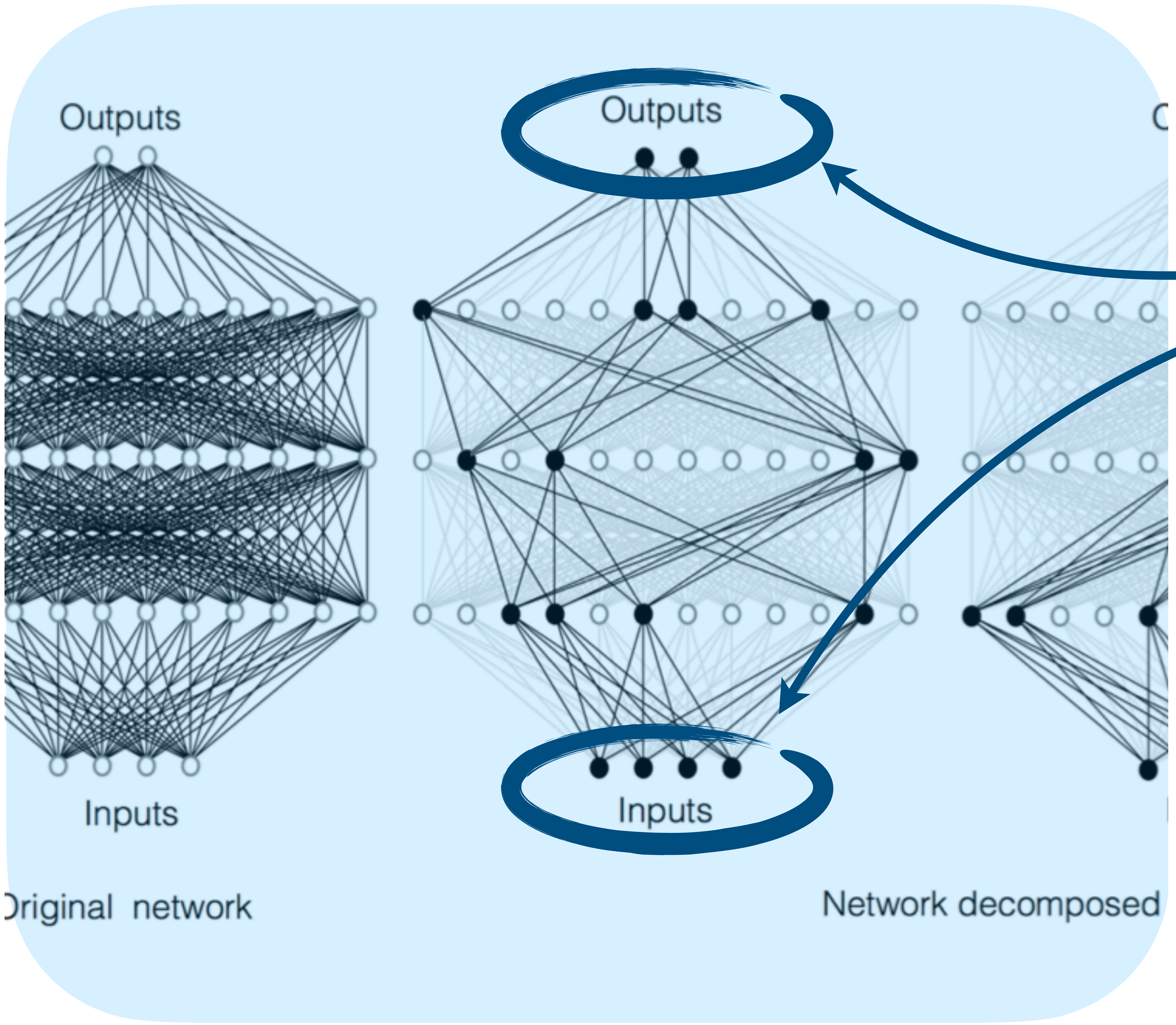

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- There are cases where input/output layers create the bottleneck:

Number of classes in original ImageNet: 21K

Number of products in recomm. datasets: Amazon 670K

Number of inputs: Amazon 670K has 135K input feature

32K token input for GPT-4?

.... (many more examples)

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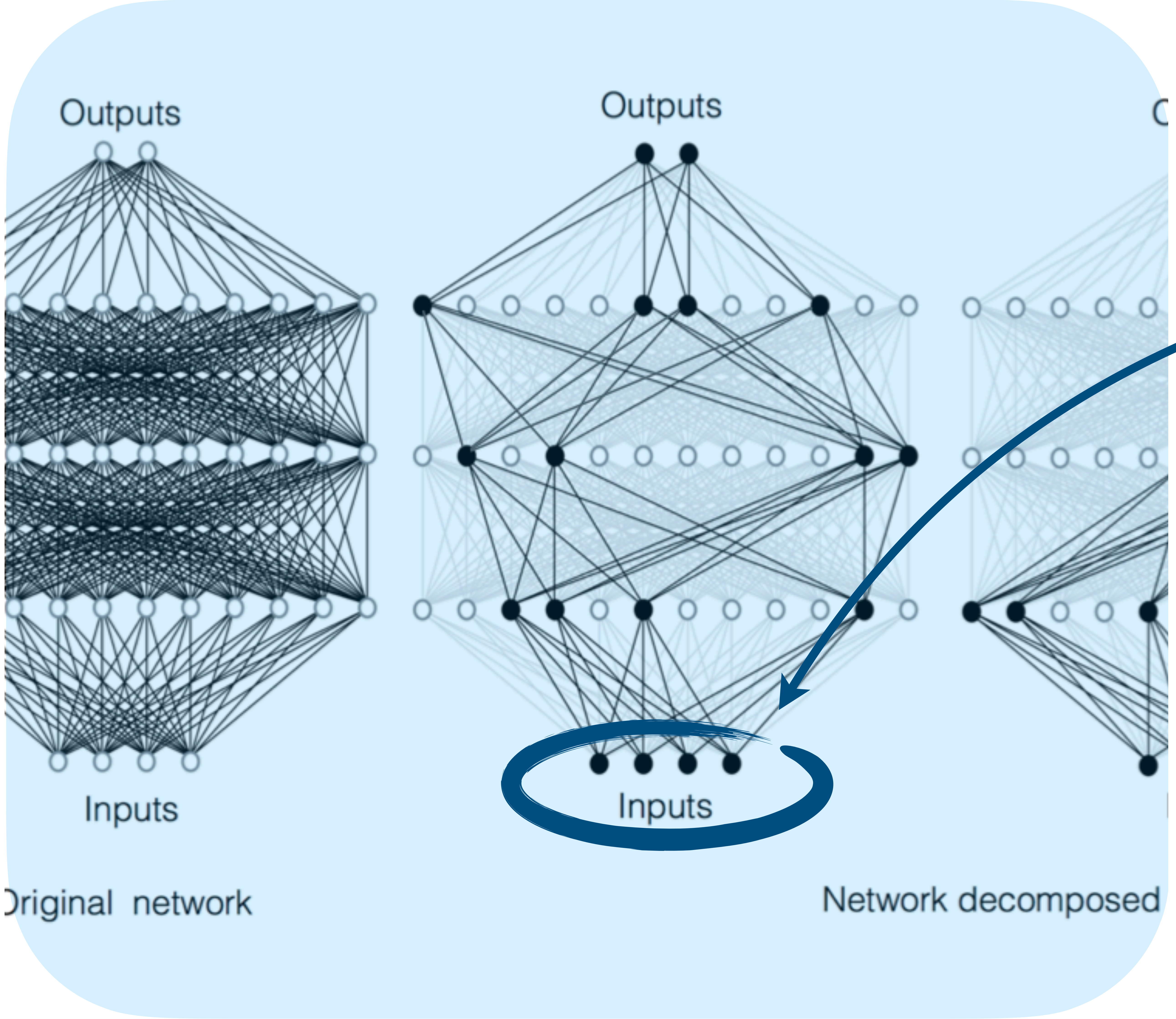

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- In this work: we focus on input sparsity and combine this with other sparse-training methods (here IST - more later)

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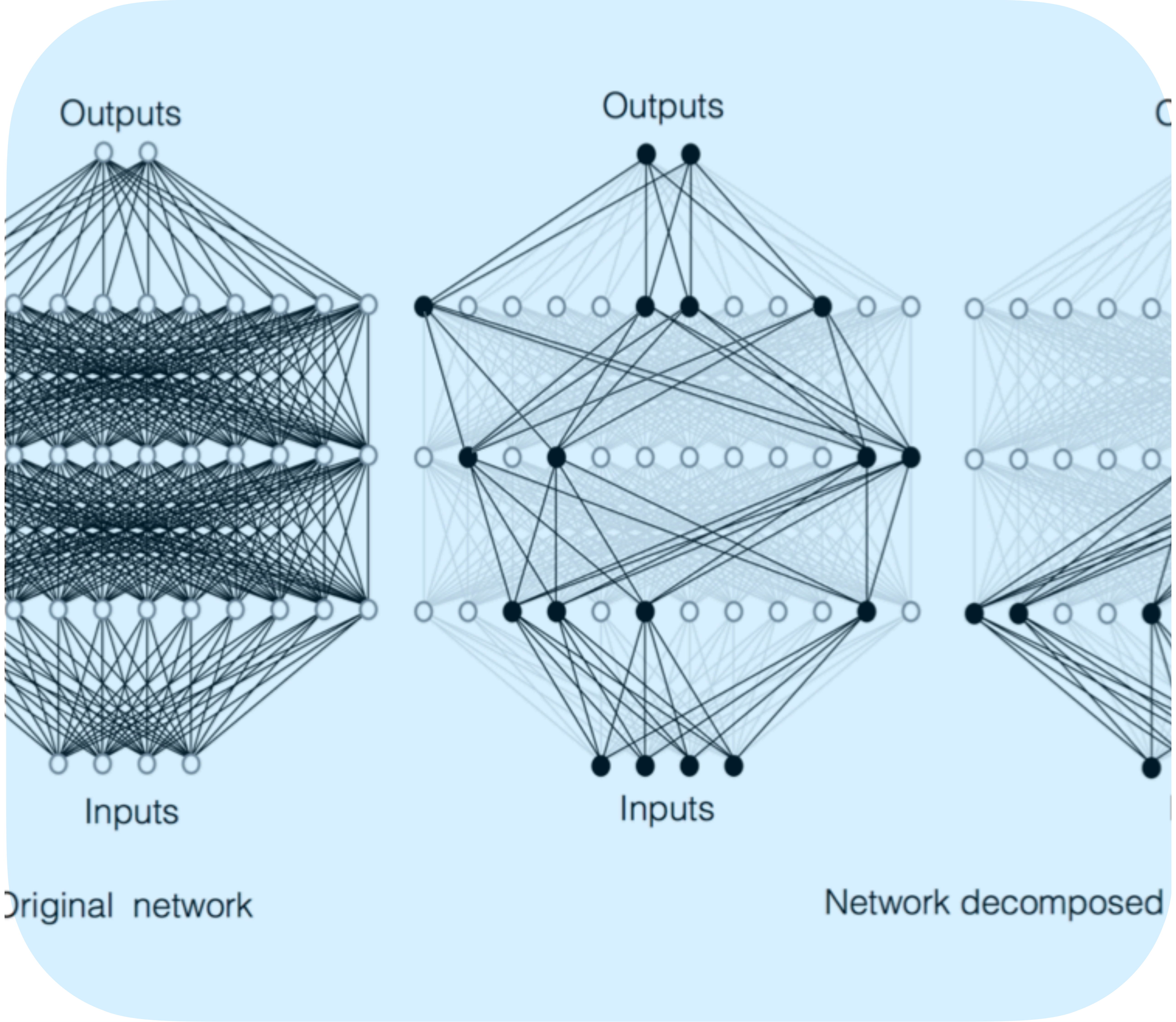

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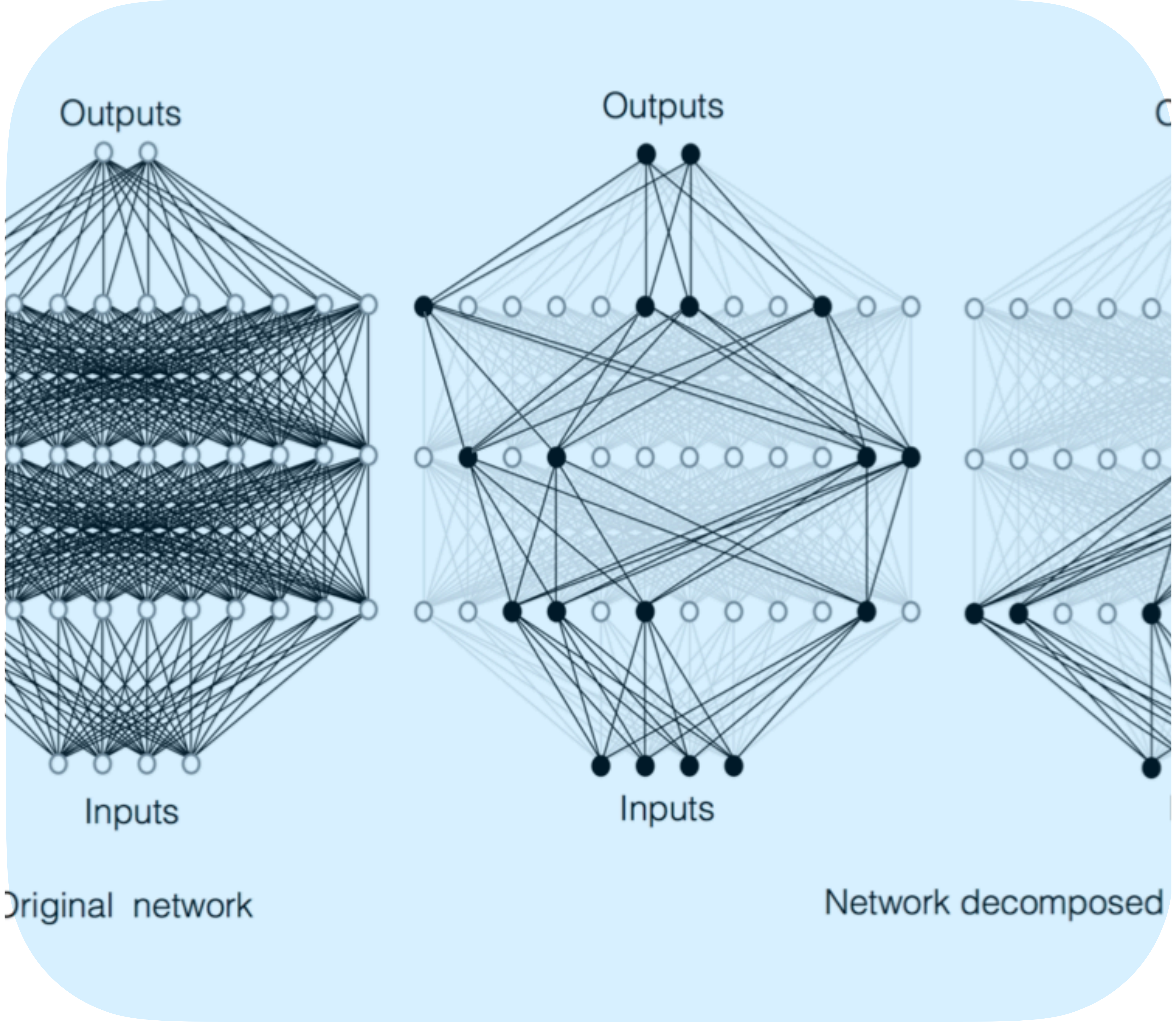

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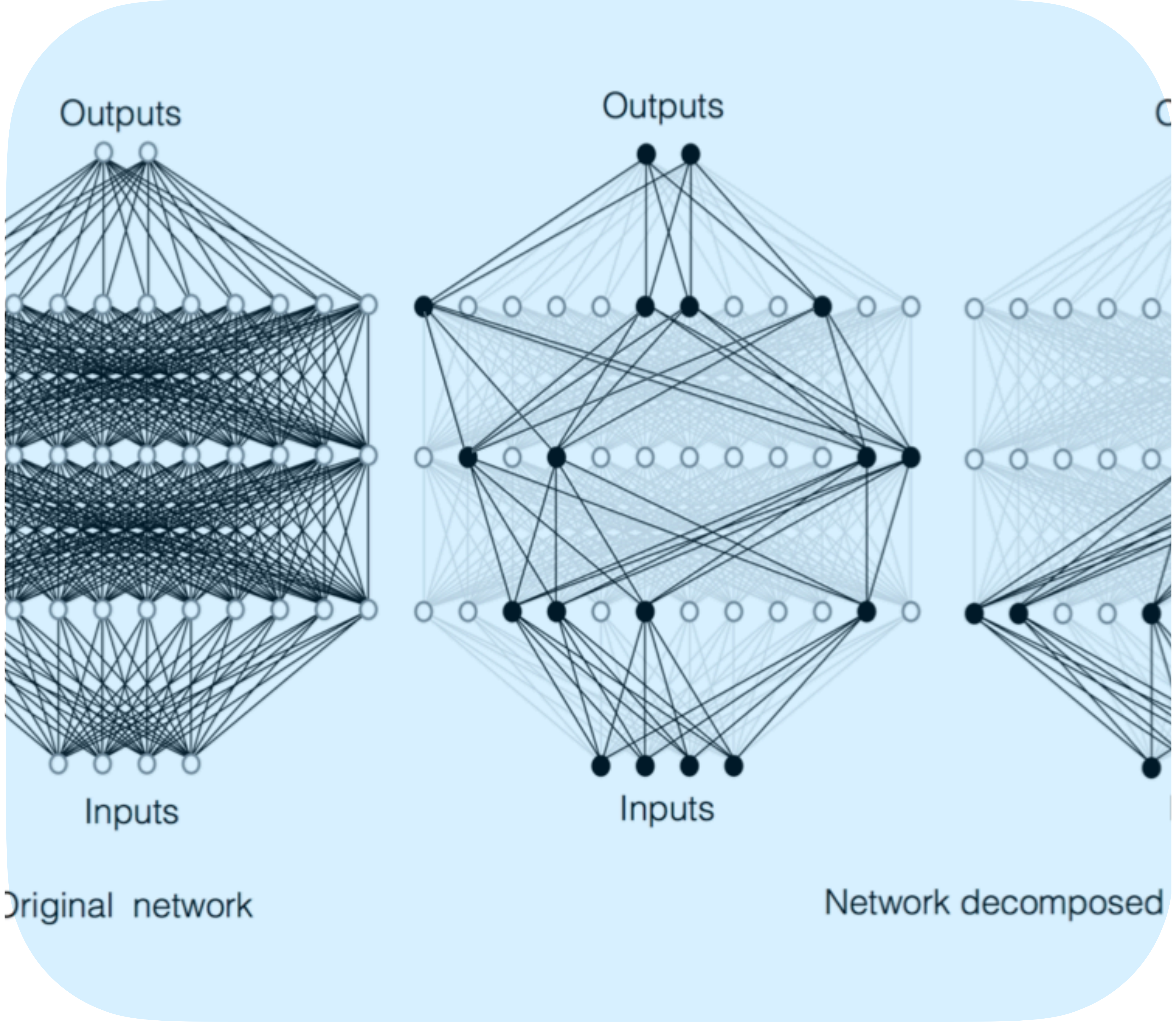

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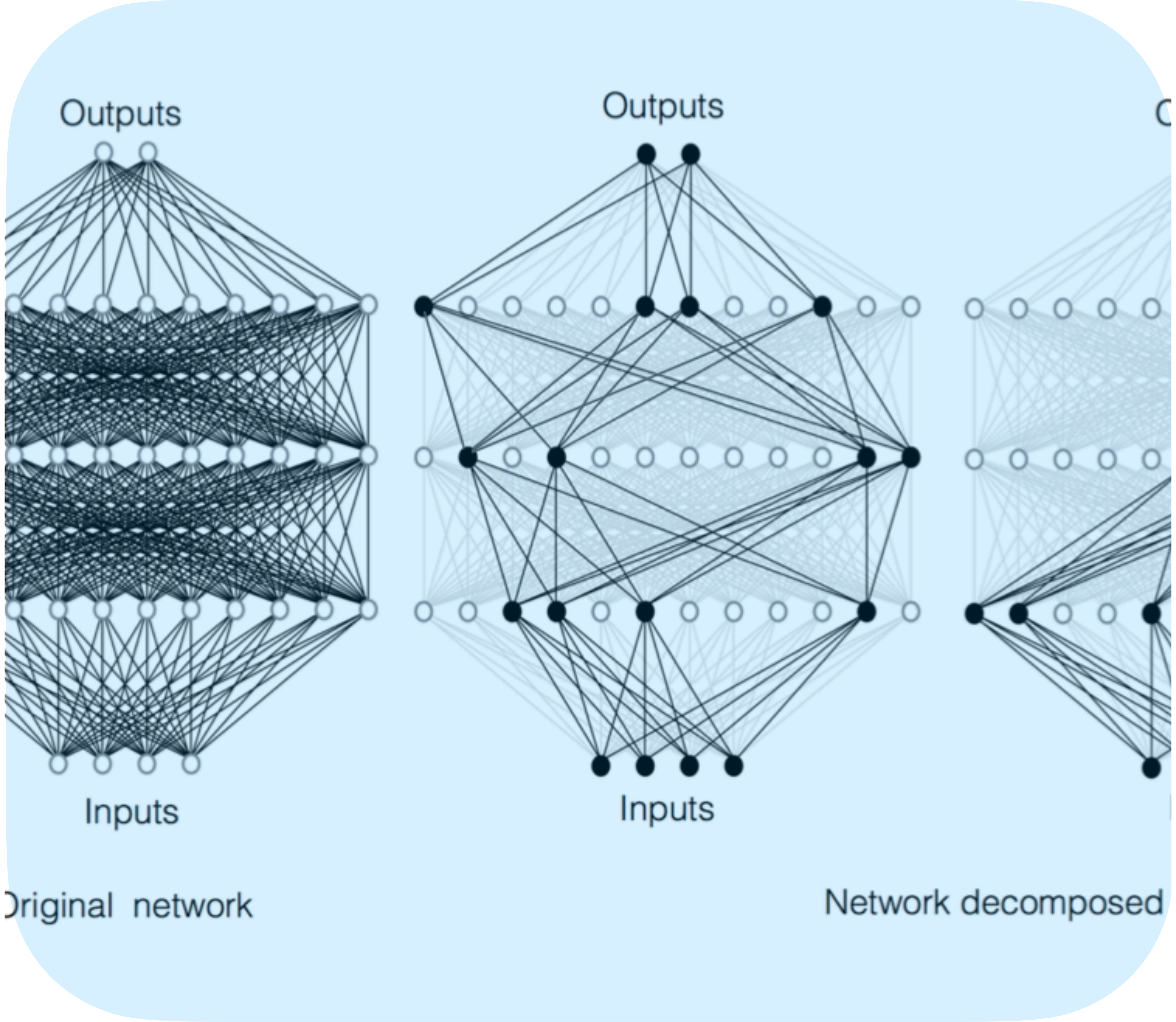

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- Consider also a distributed scenario

    Either regular distributed or FL

    Not much power to do intensive work
    Not much memory to keep large models

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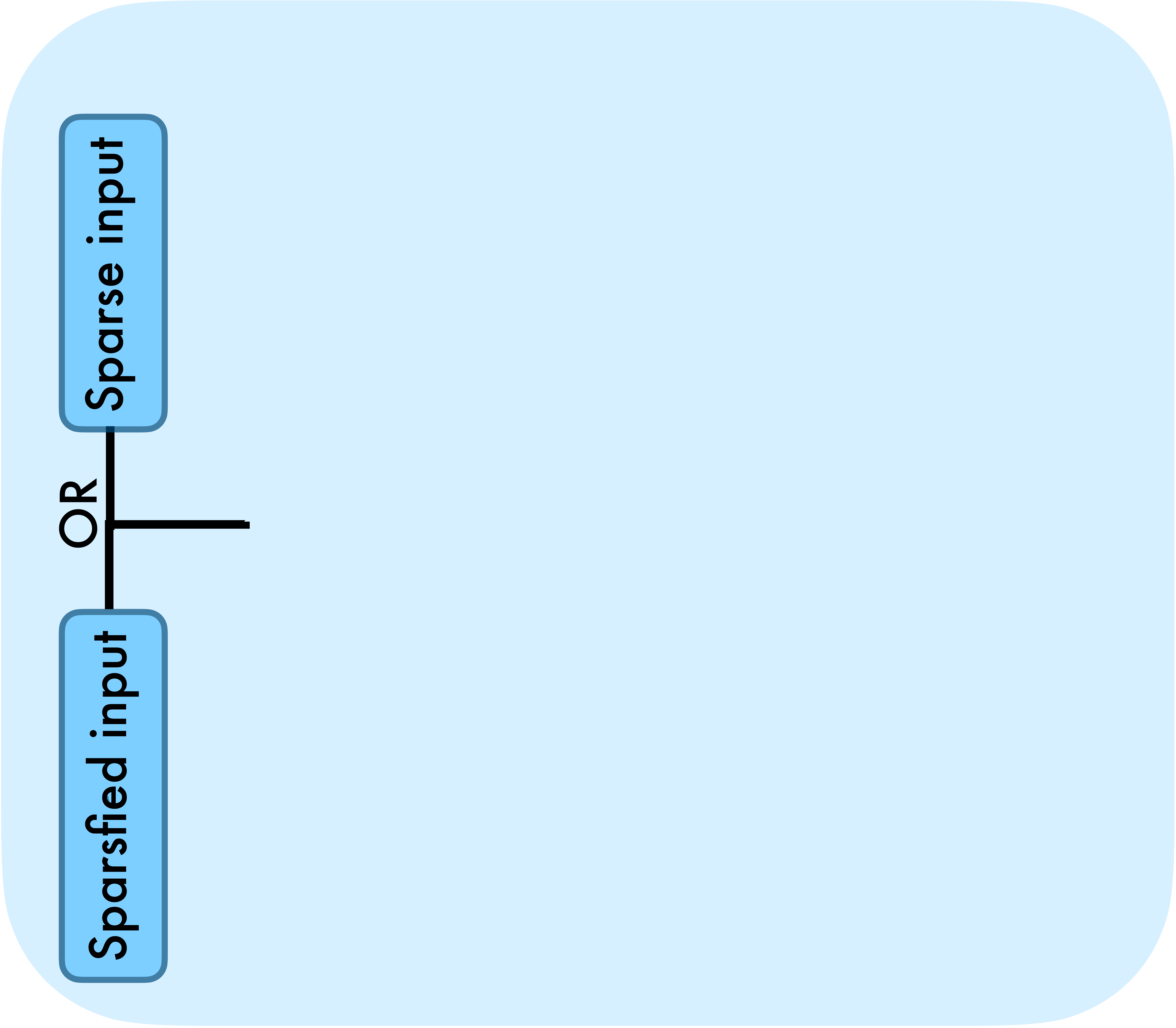

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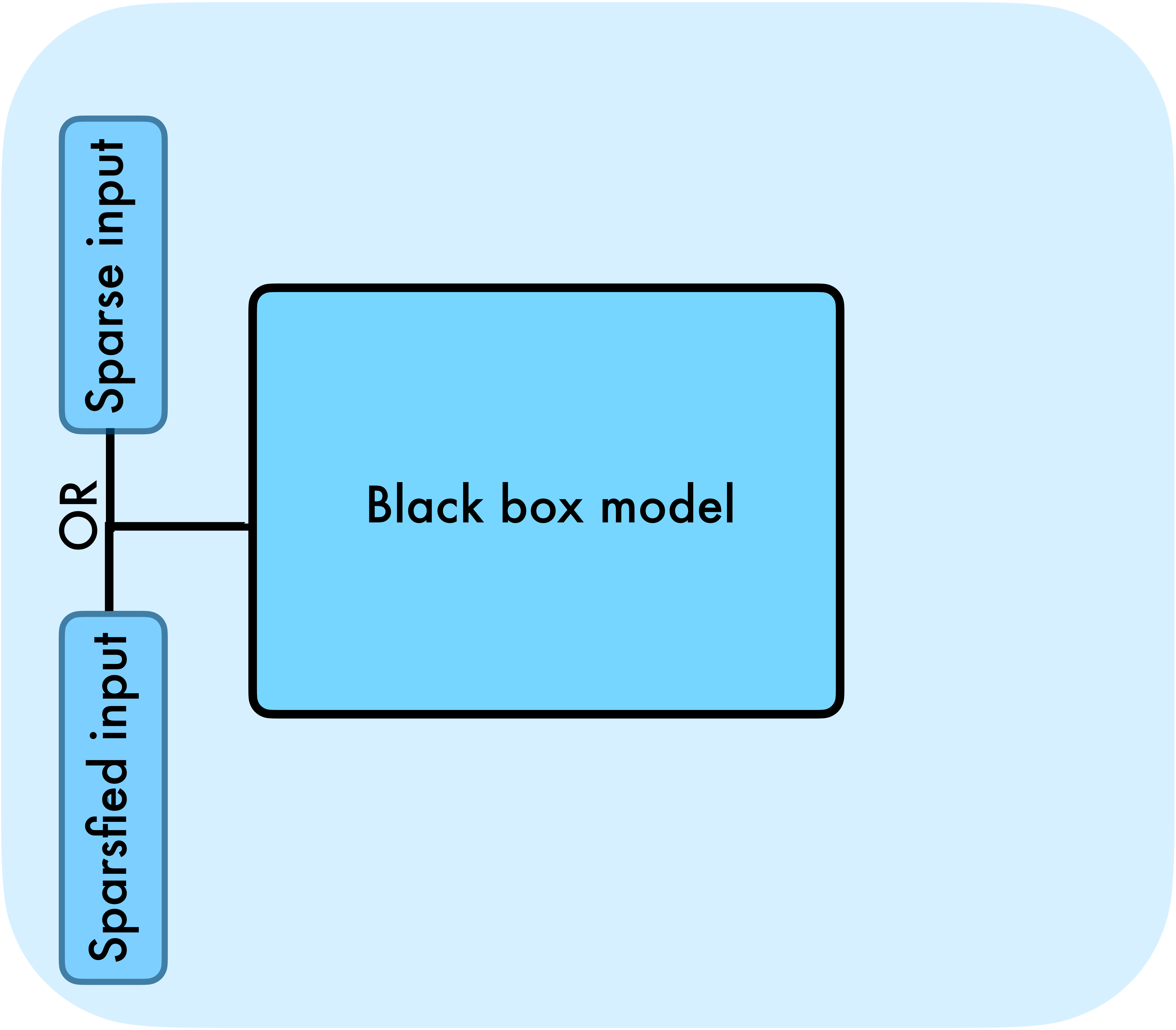

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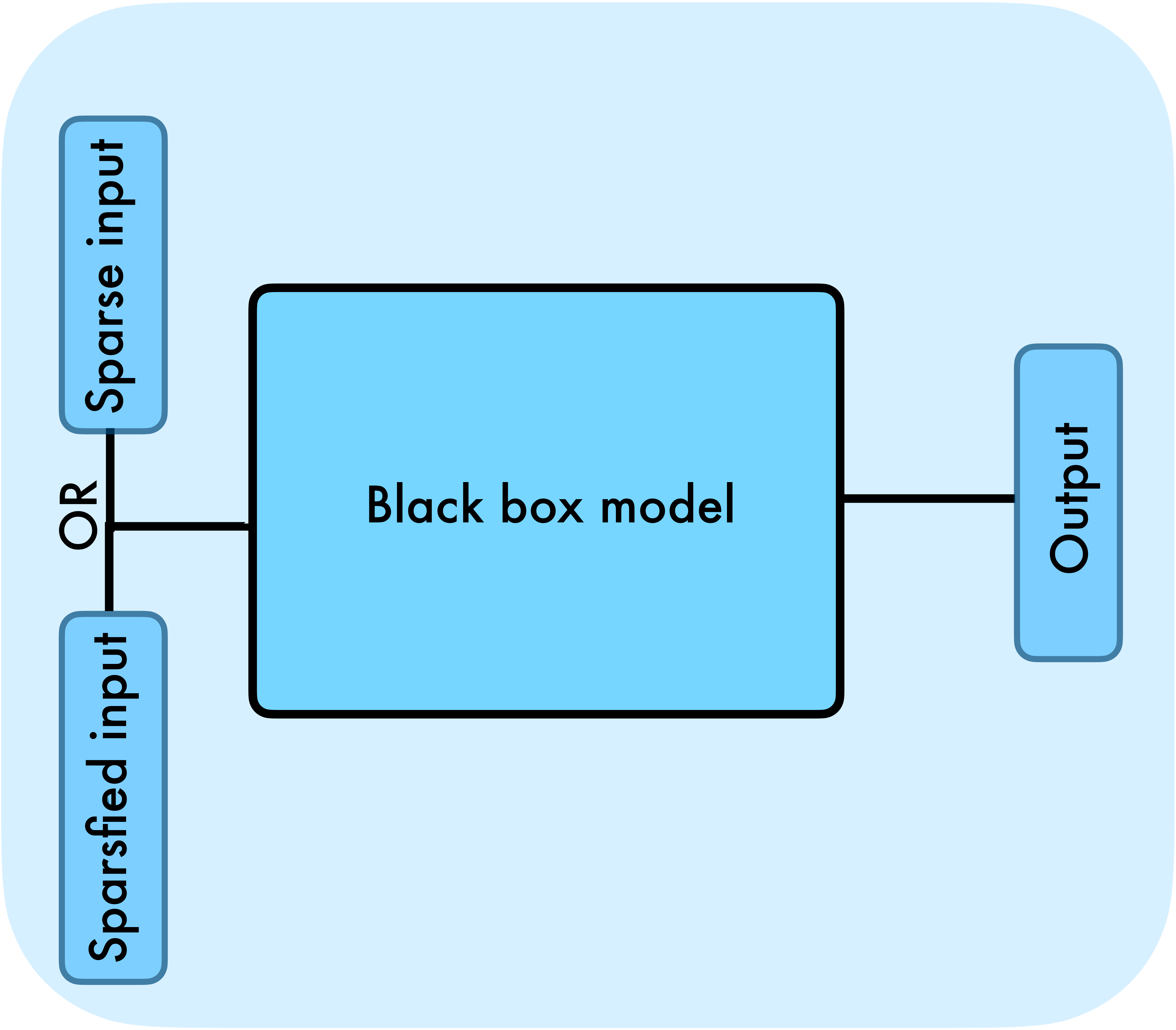

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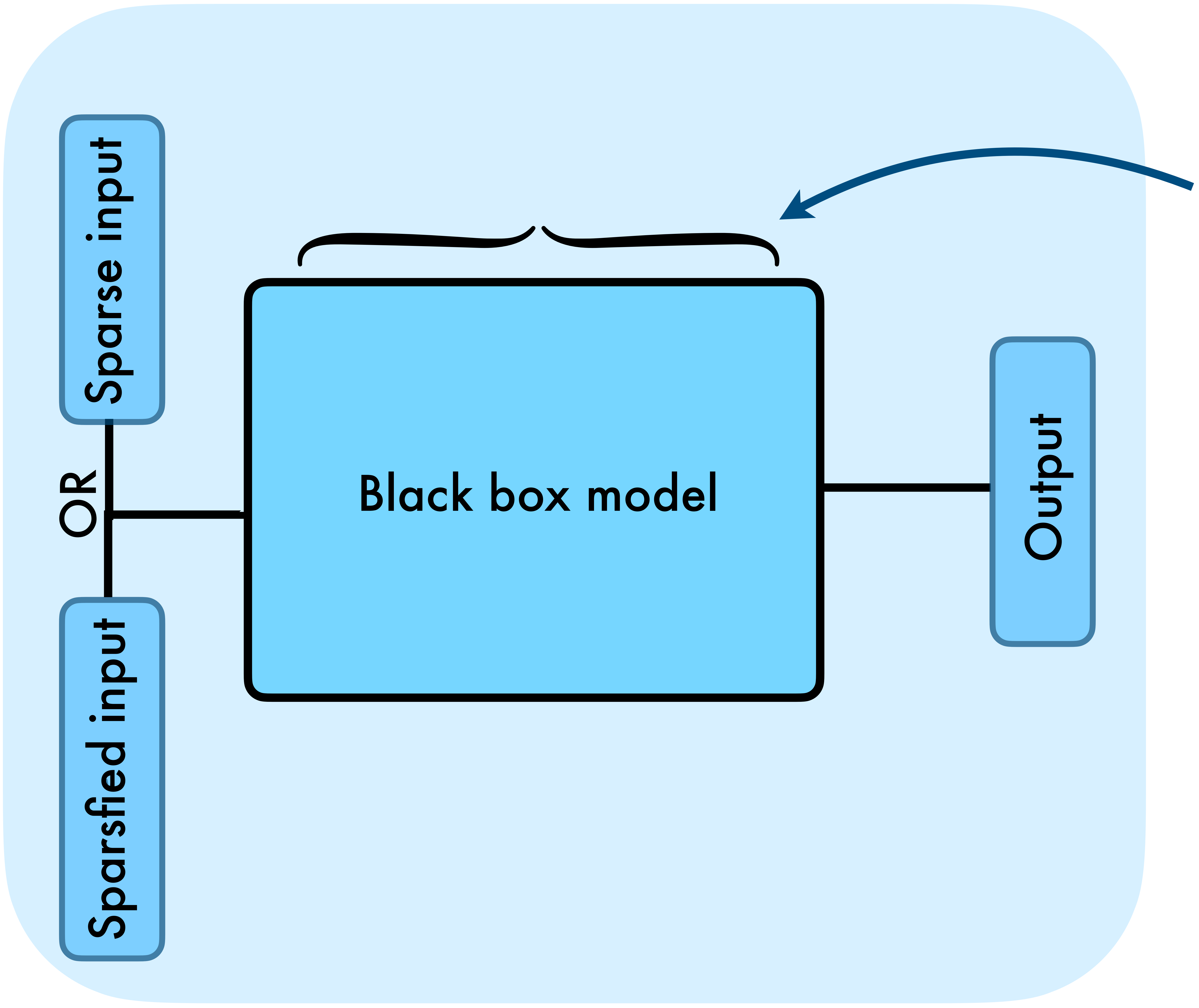

- Sparse input
- What about the intermediate layers?

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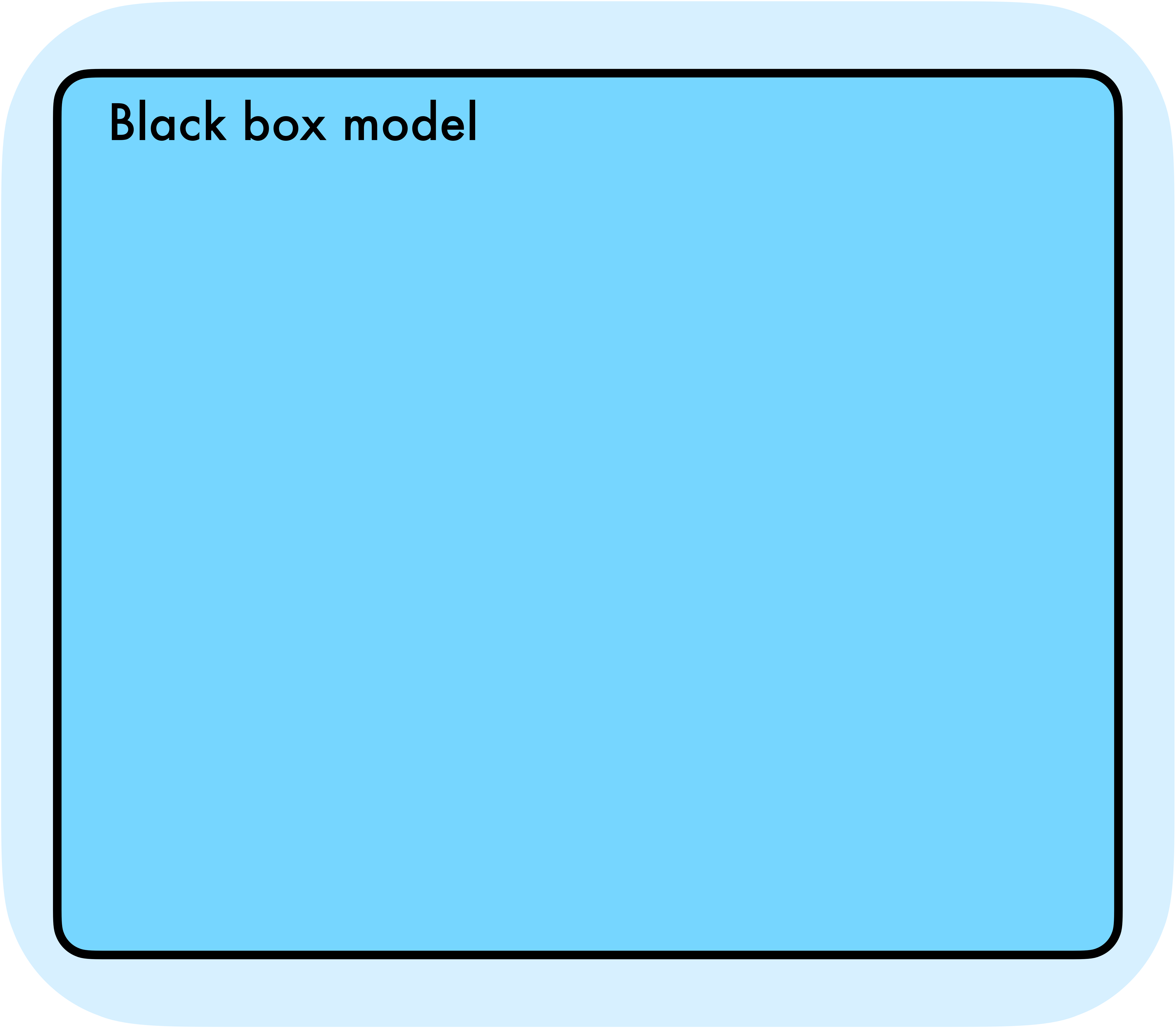

- "Zooming in" the black box model...

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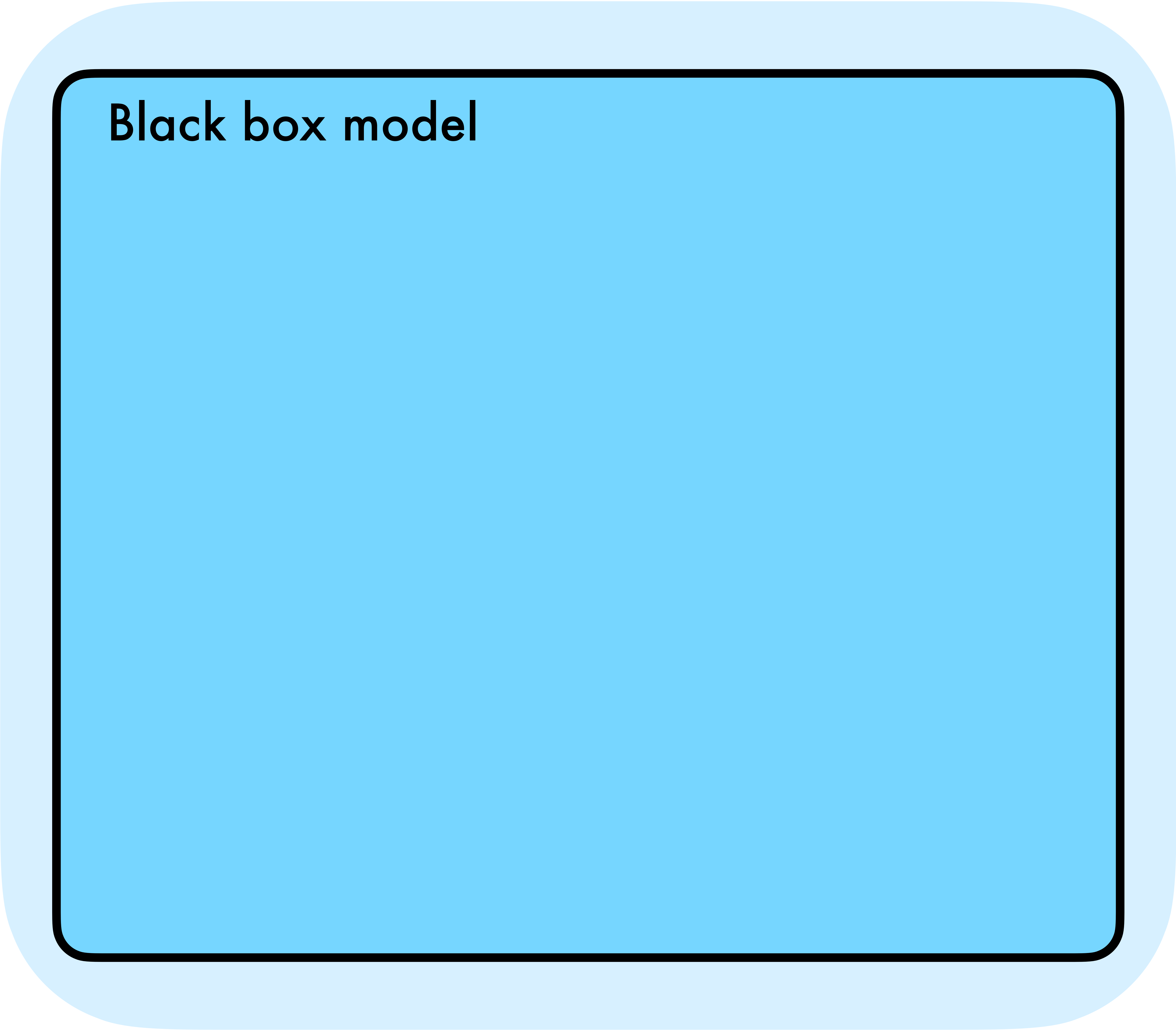

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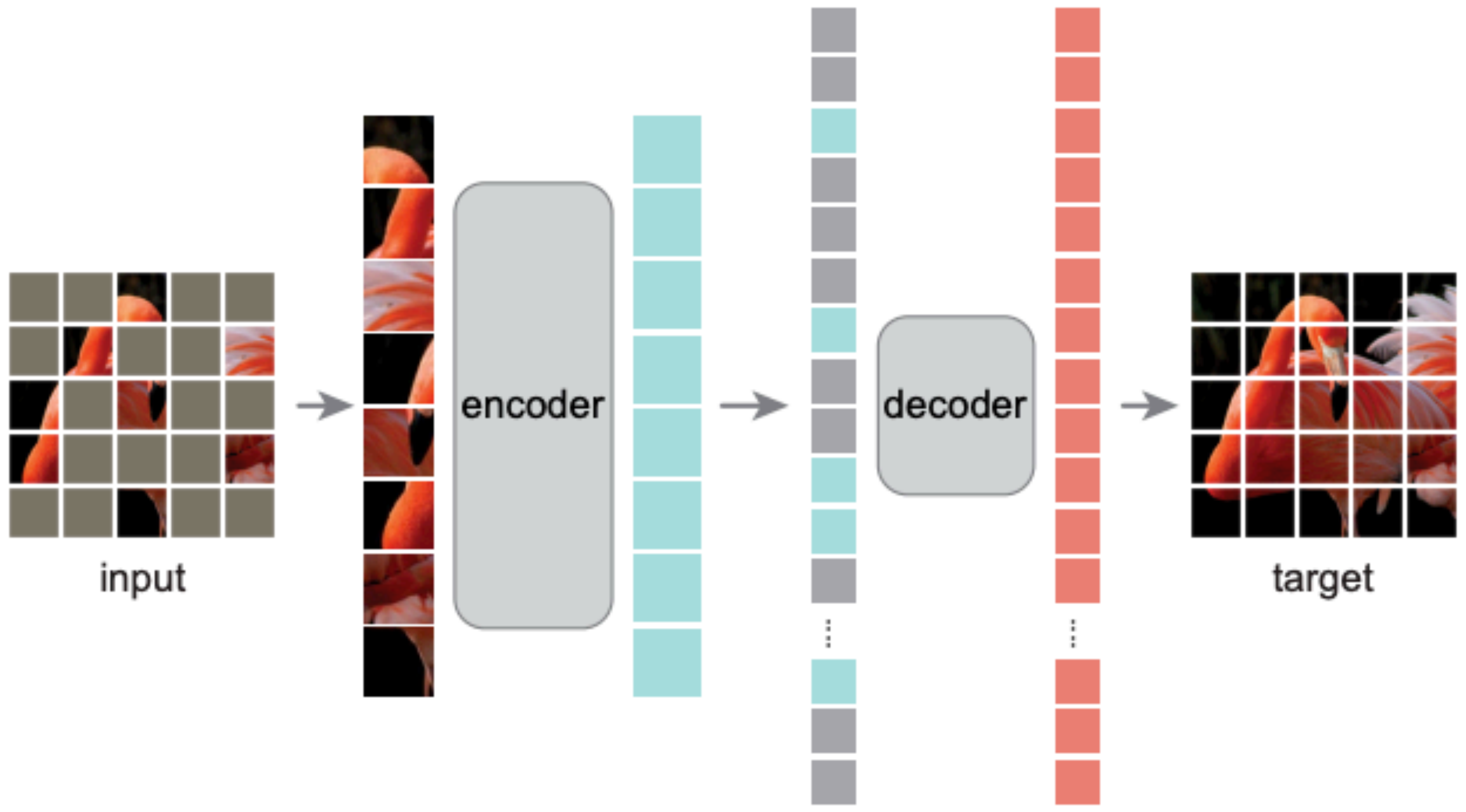
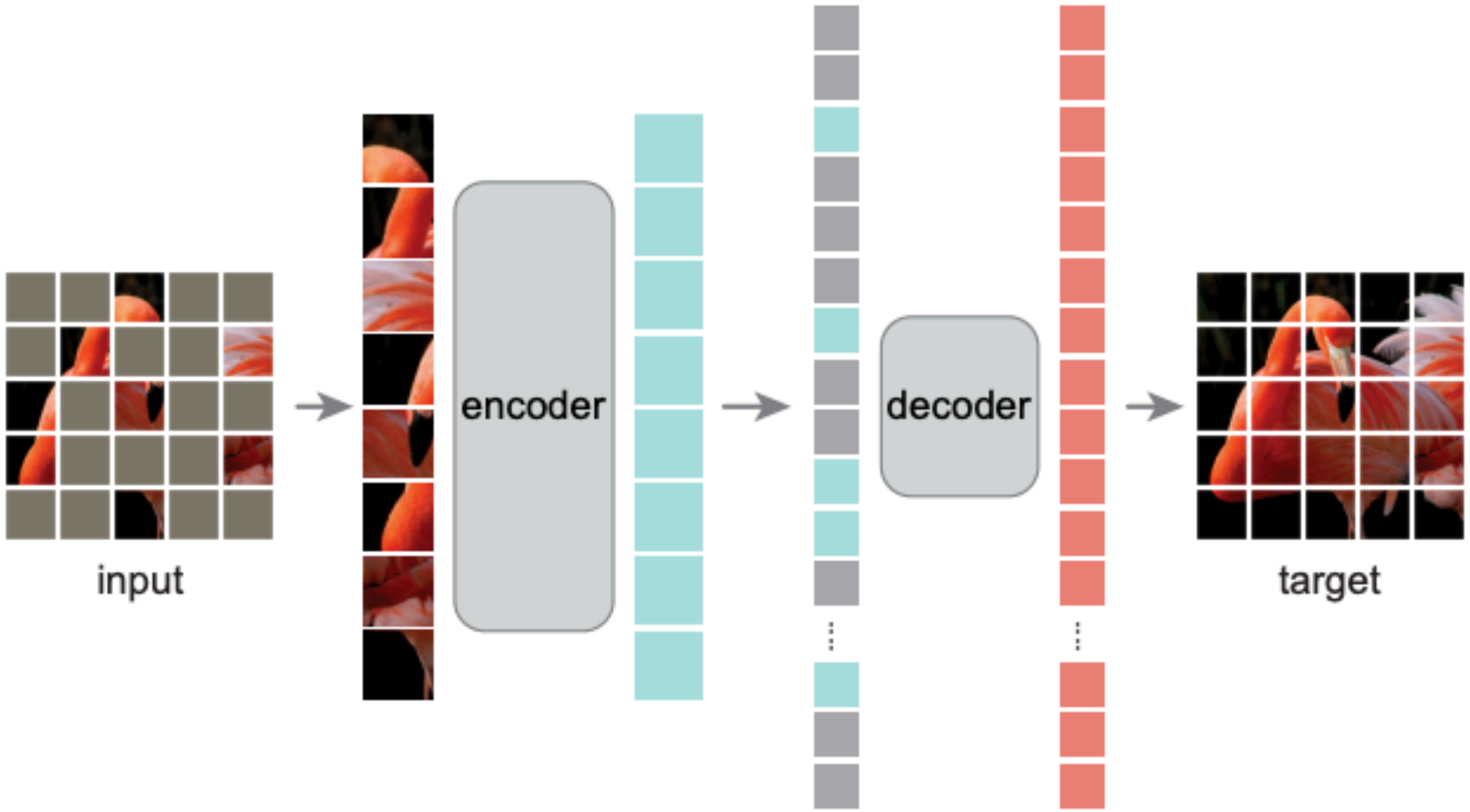
Masked autoencoders (MAEs)



MAEs [He et al., 2021]

- The idea is that of regression (reconstruction) from sparse input (images)



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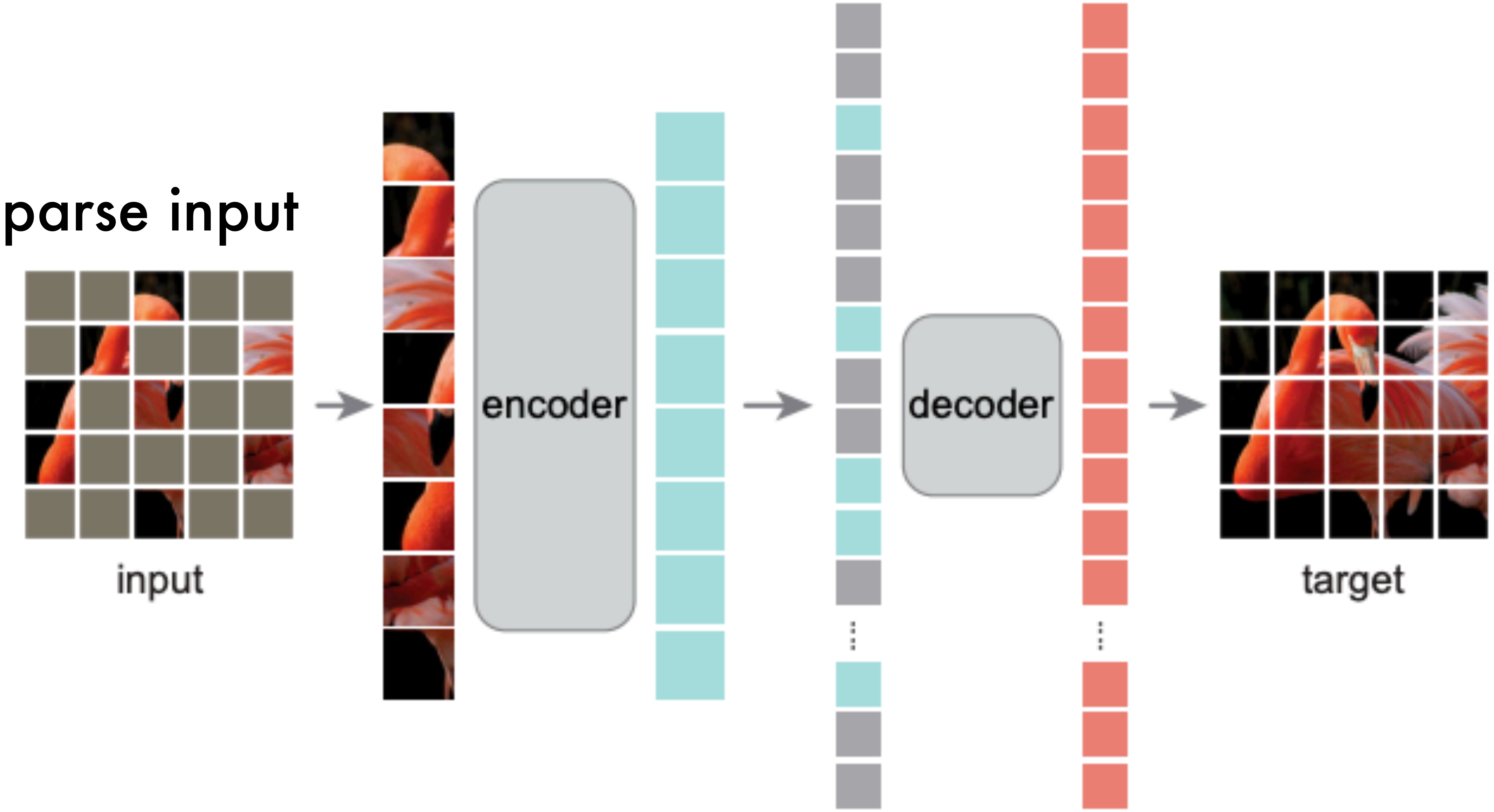

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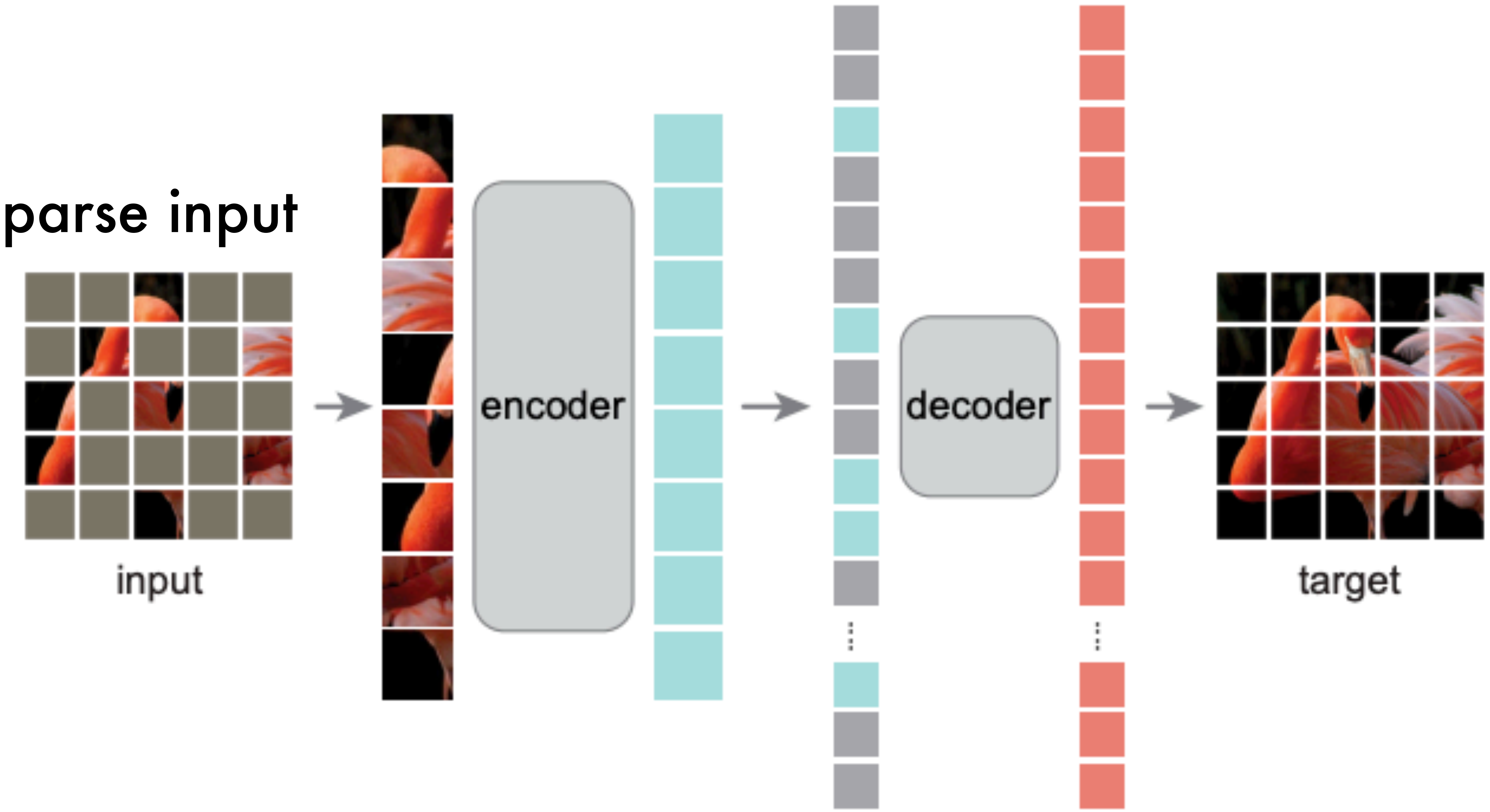

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Decoding (image reconstruction)

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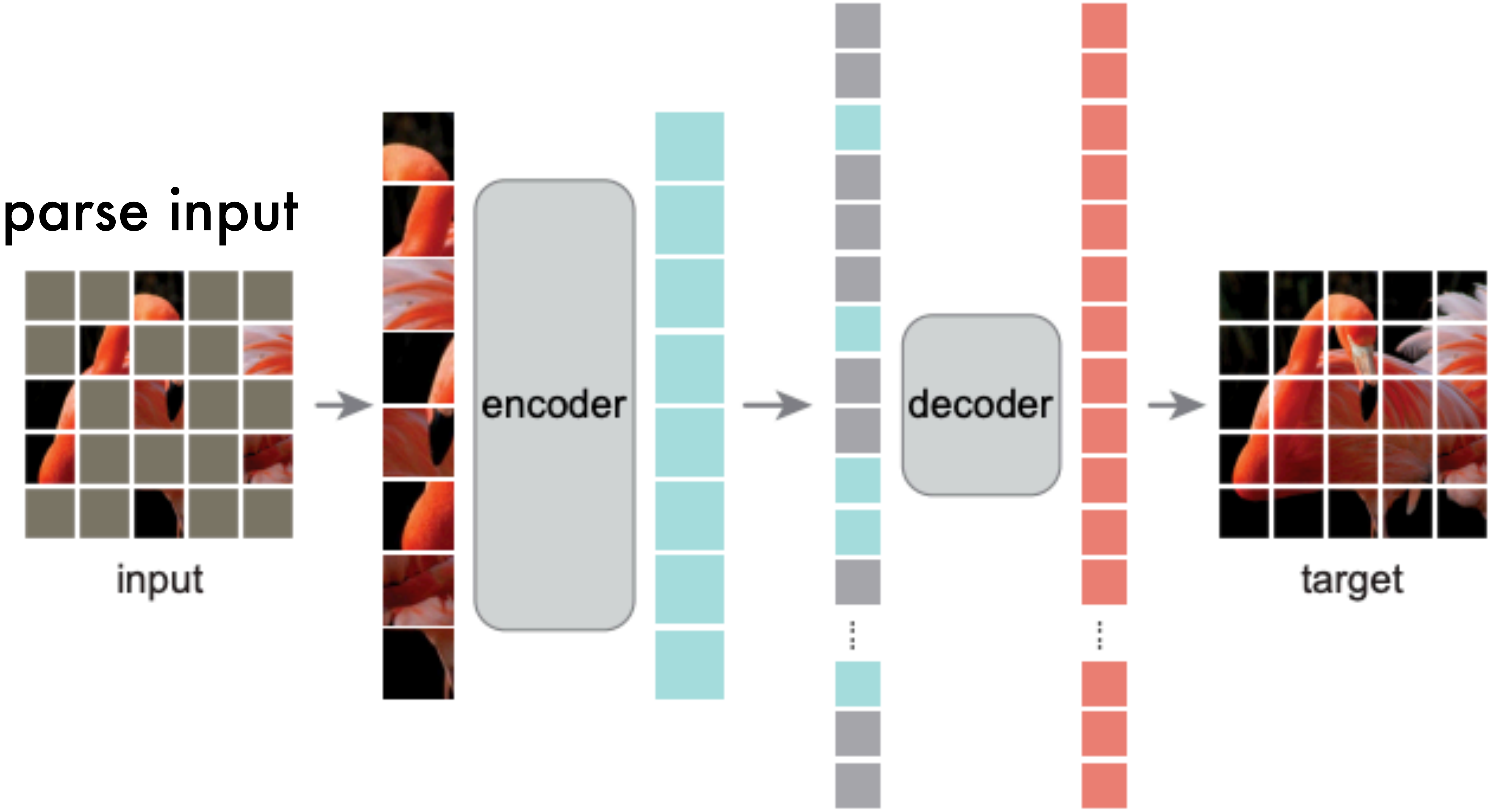

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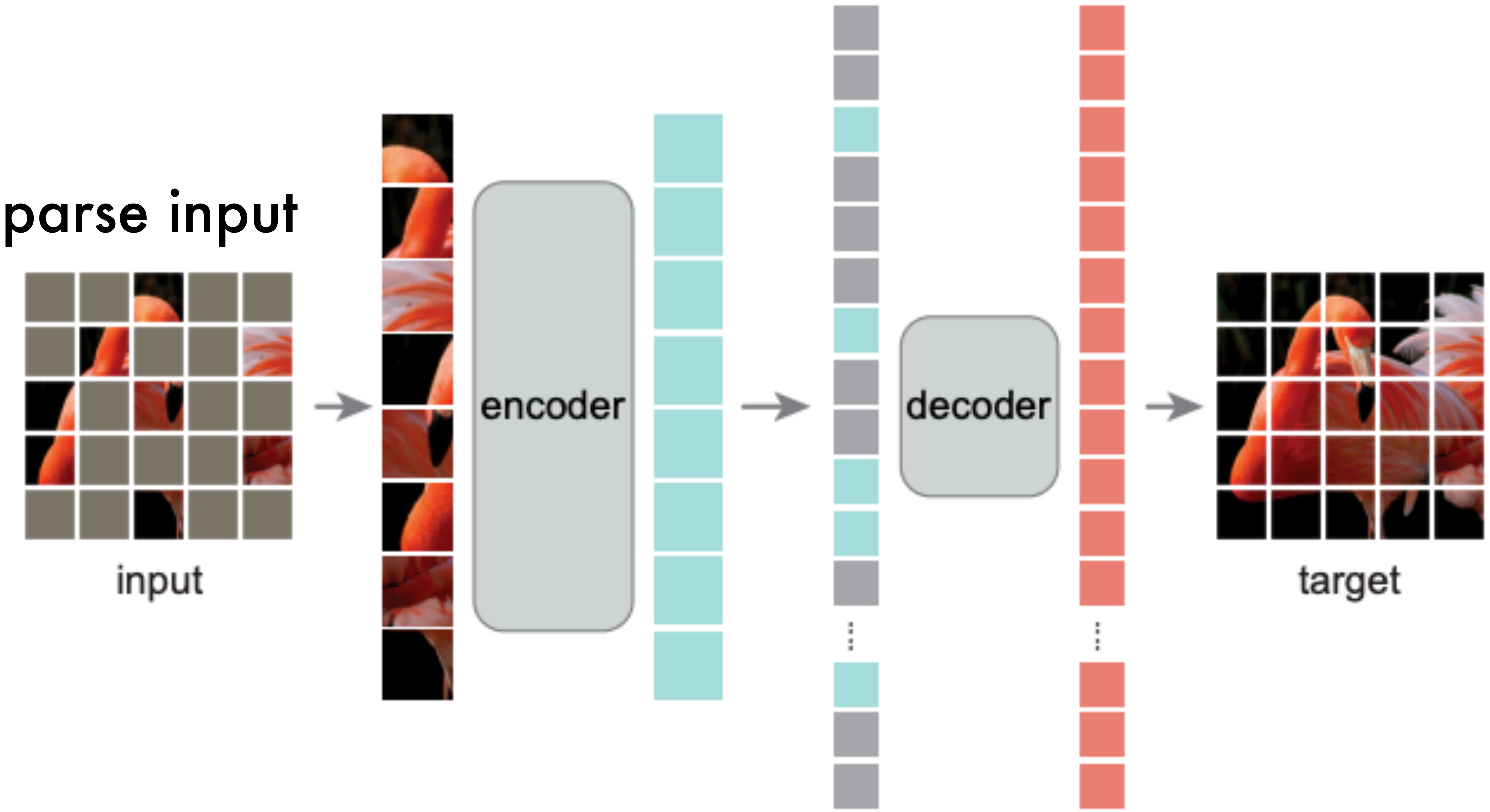

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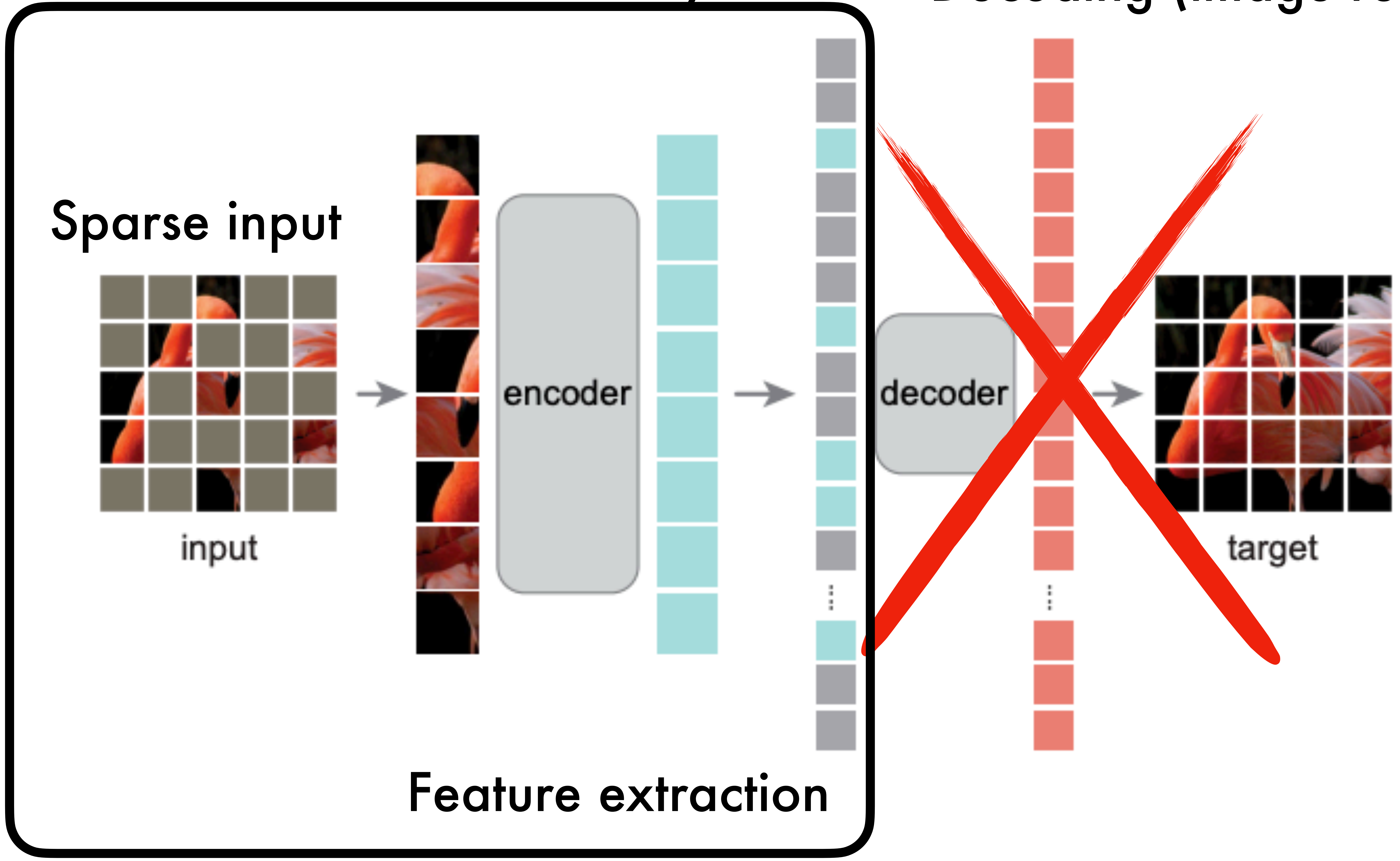
- In our case: we use the feature extractor only!



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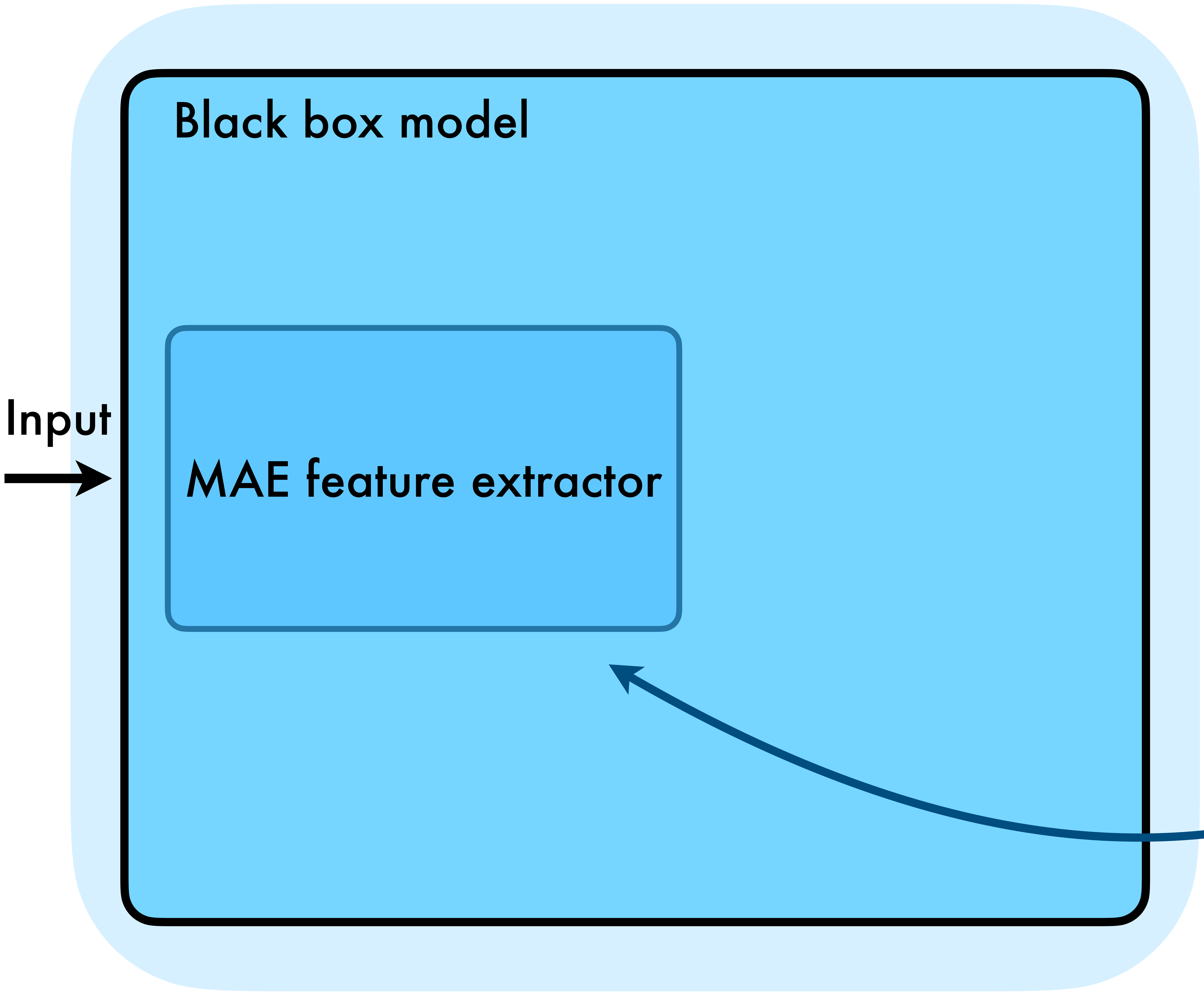

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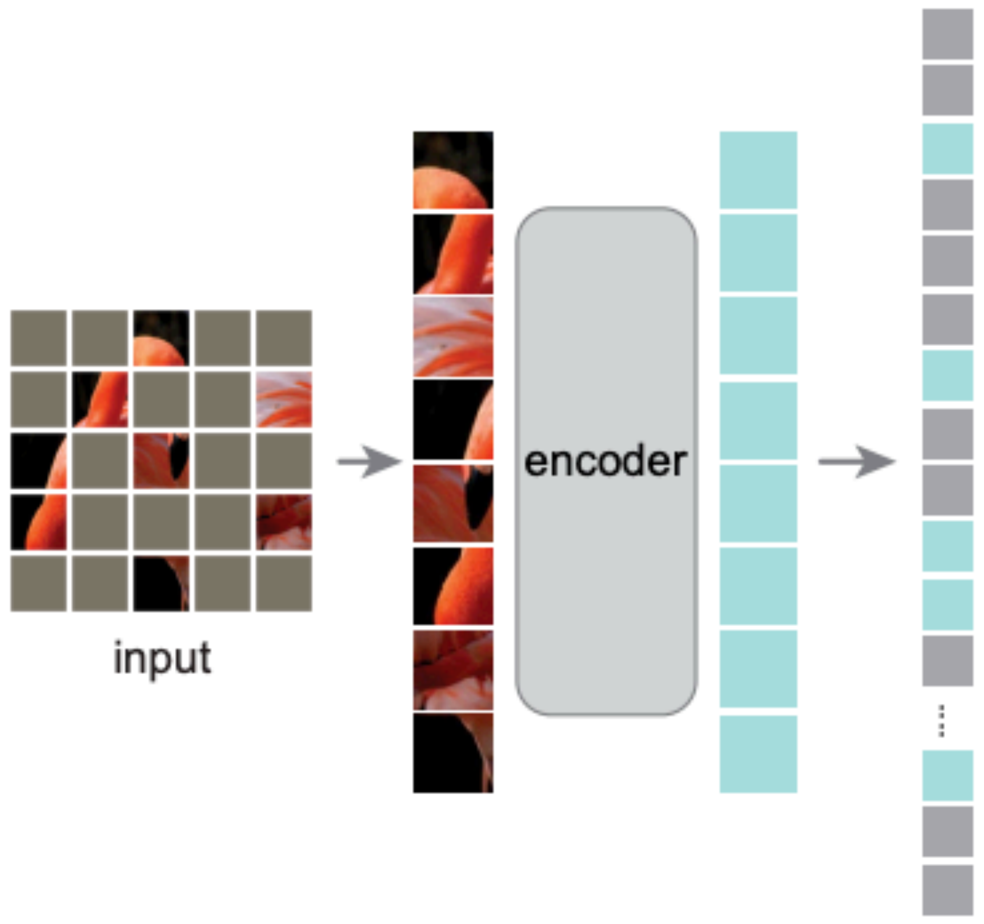

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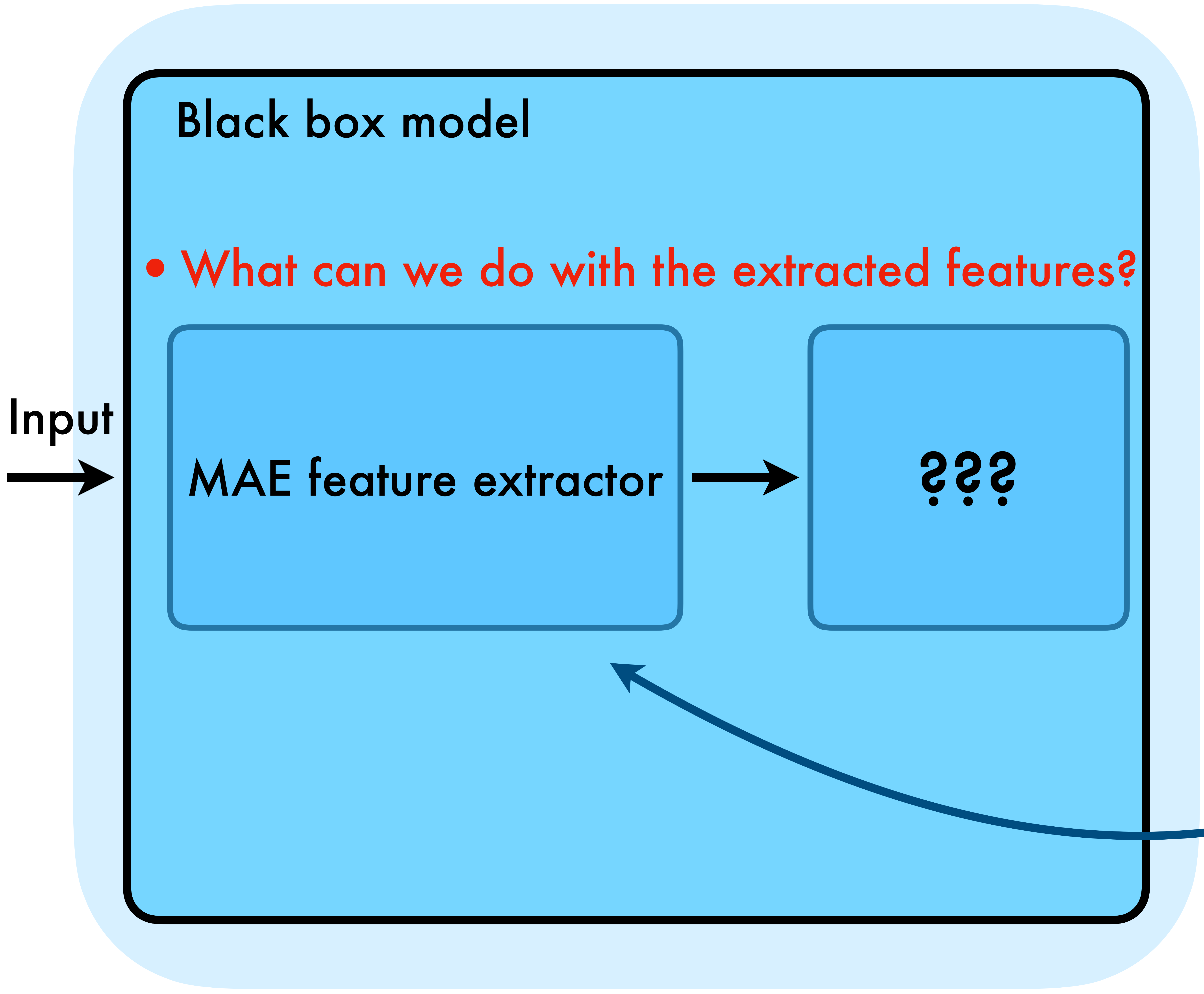

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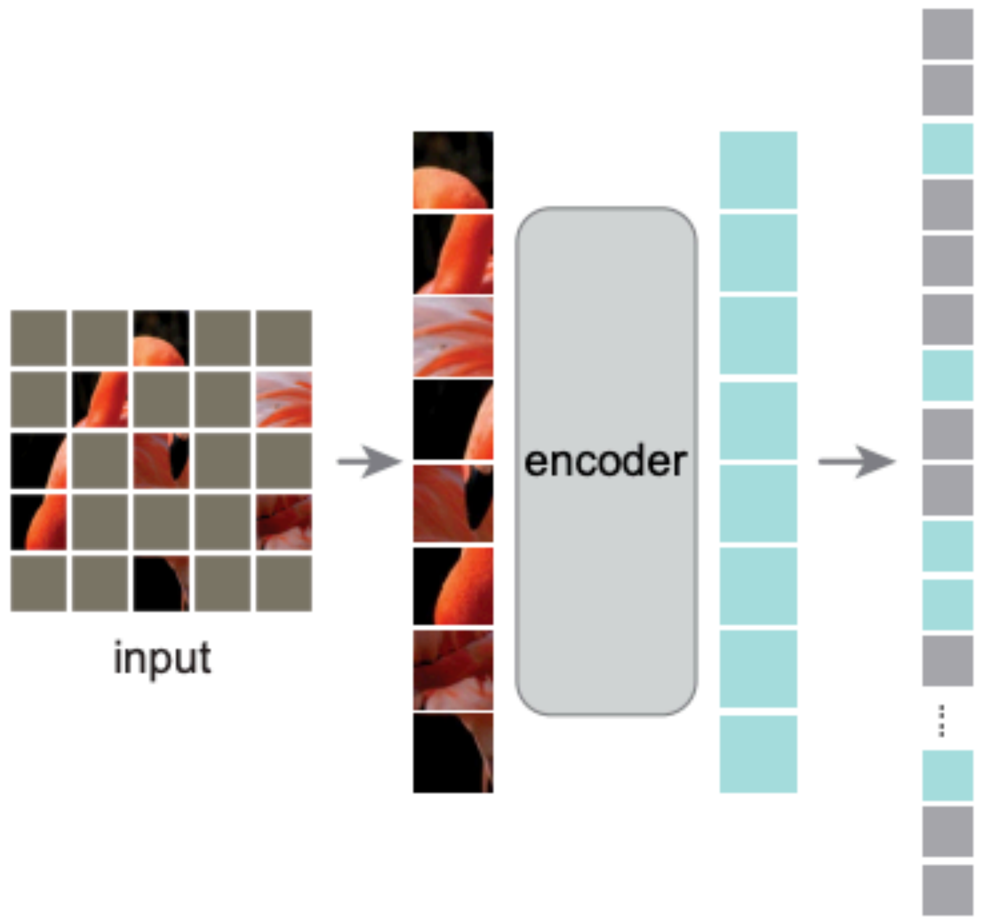

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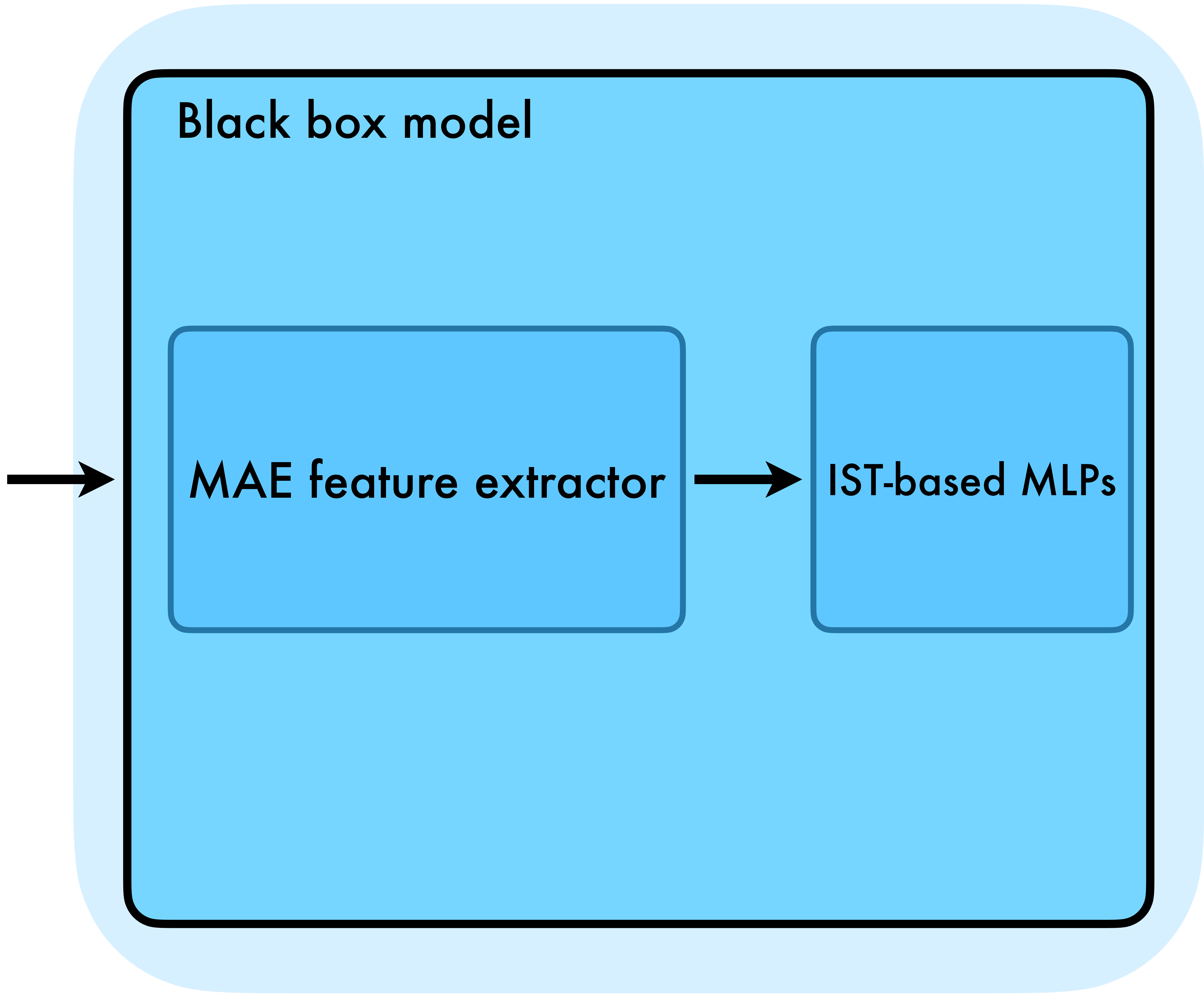

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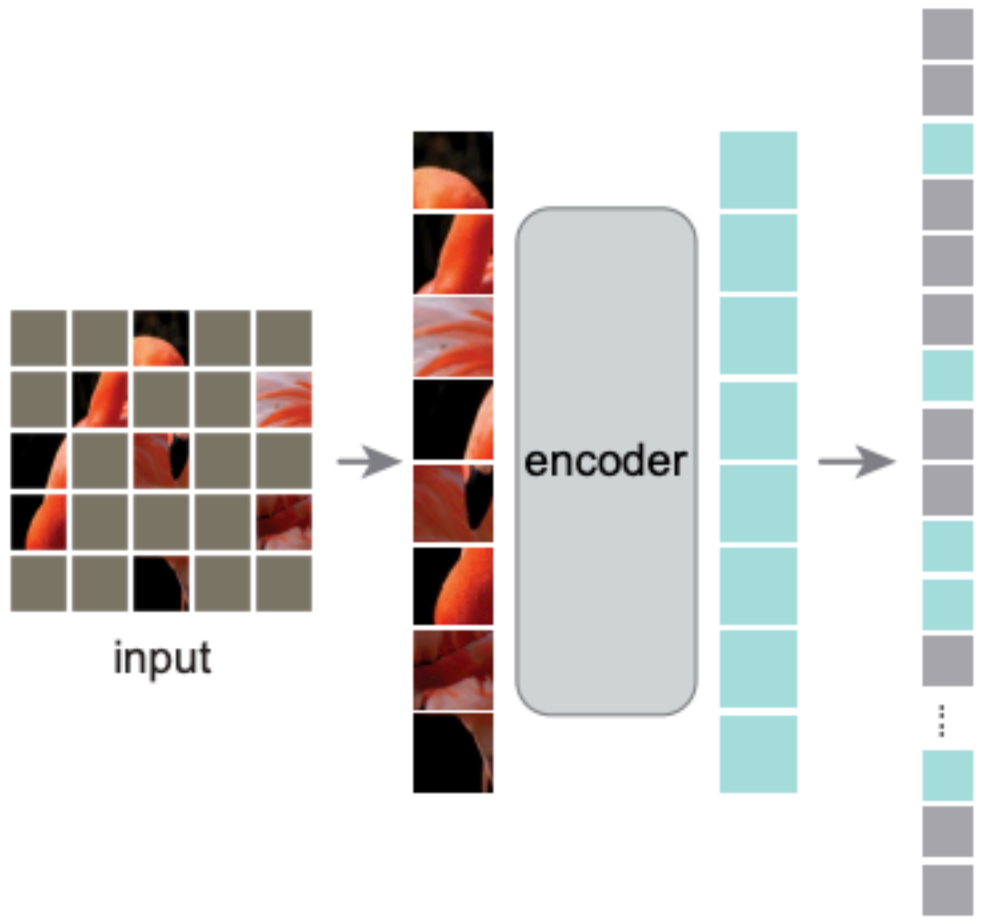
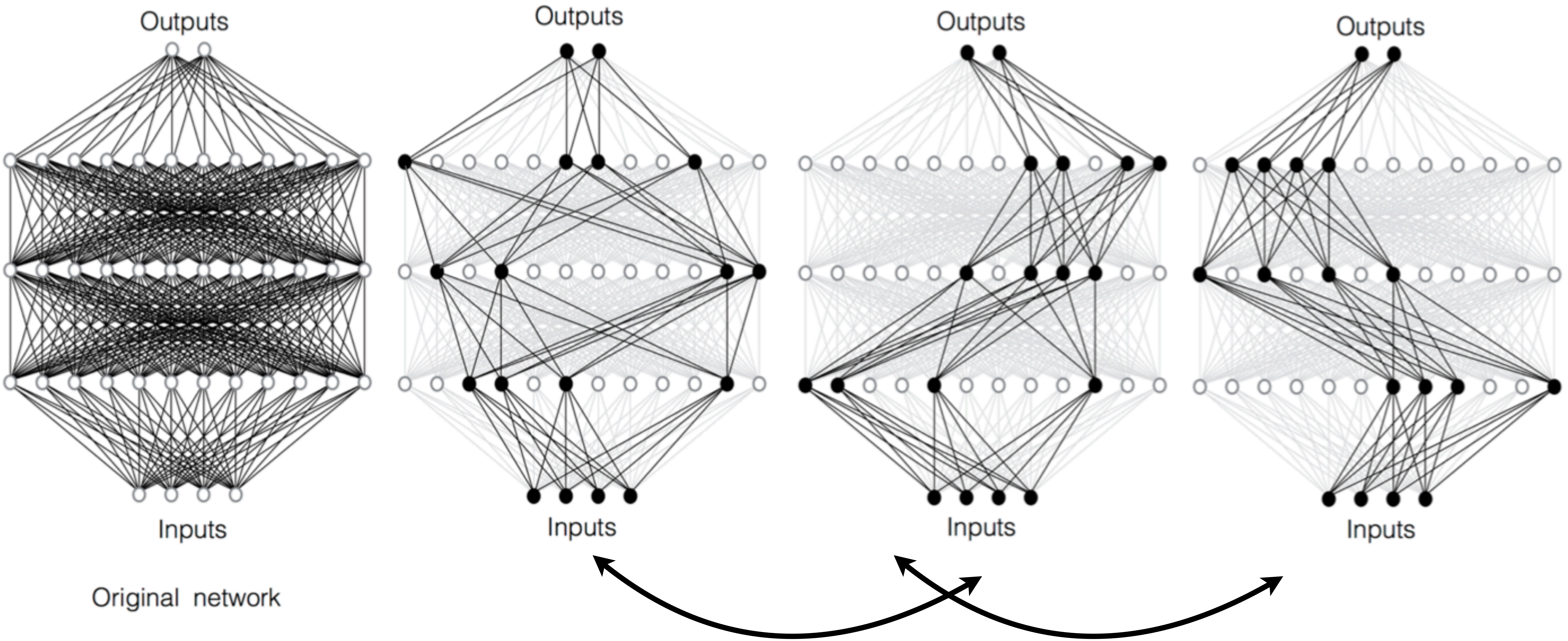


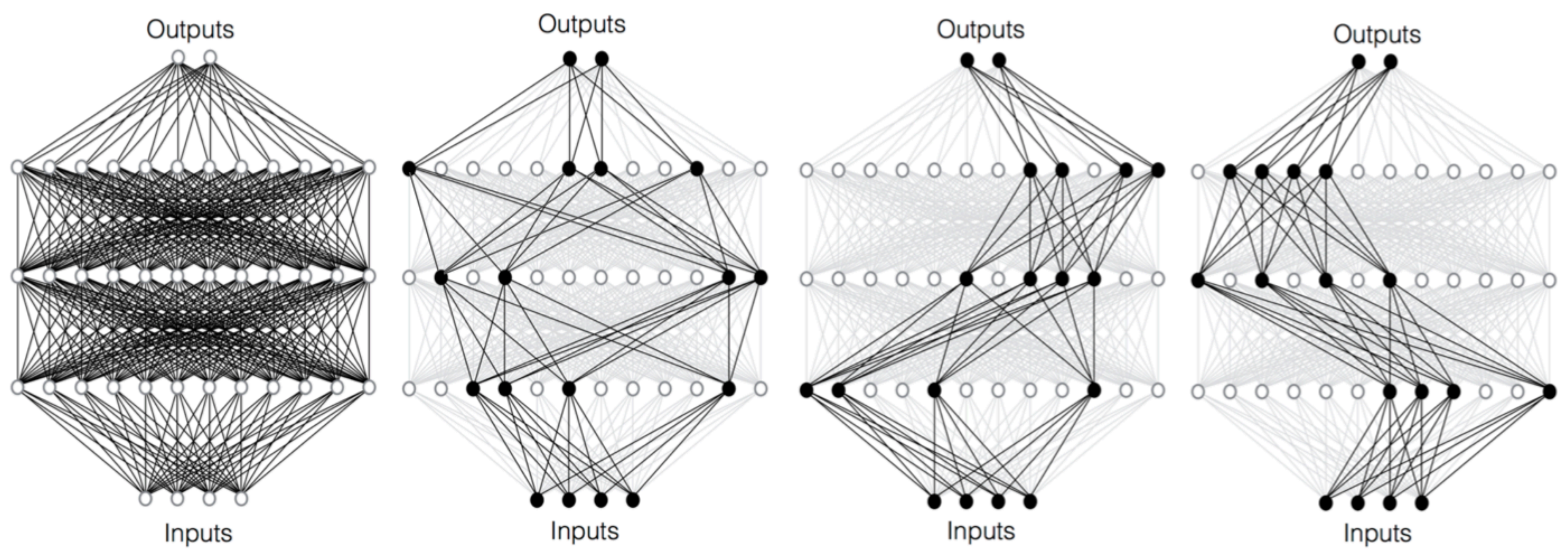
IST: Independent Subnet Training



Union of neurons make original network
(Note: union of parameters do not make original network necessarily)

IST: Independent Subnet Training

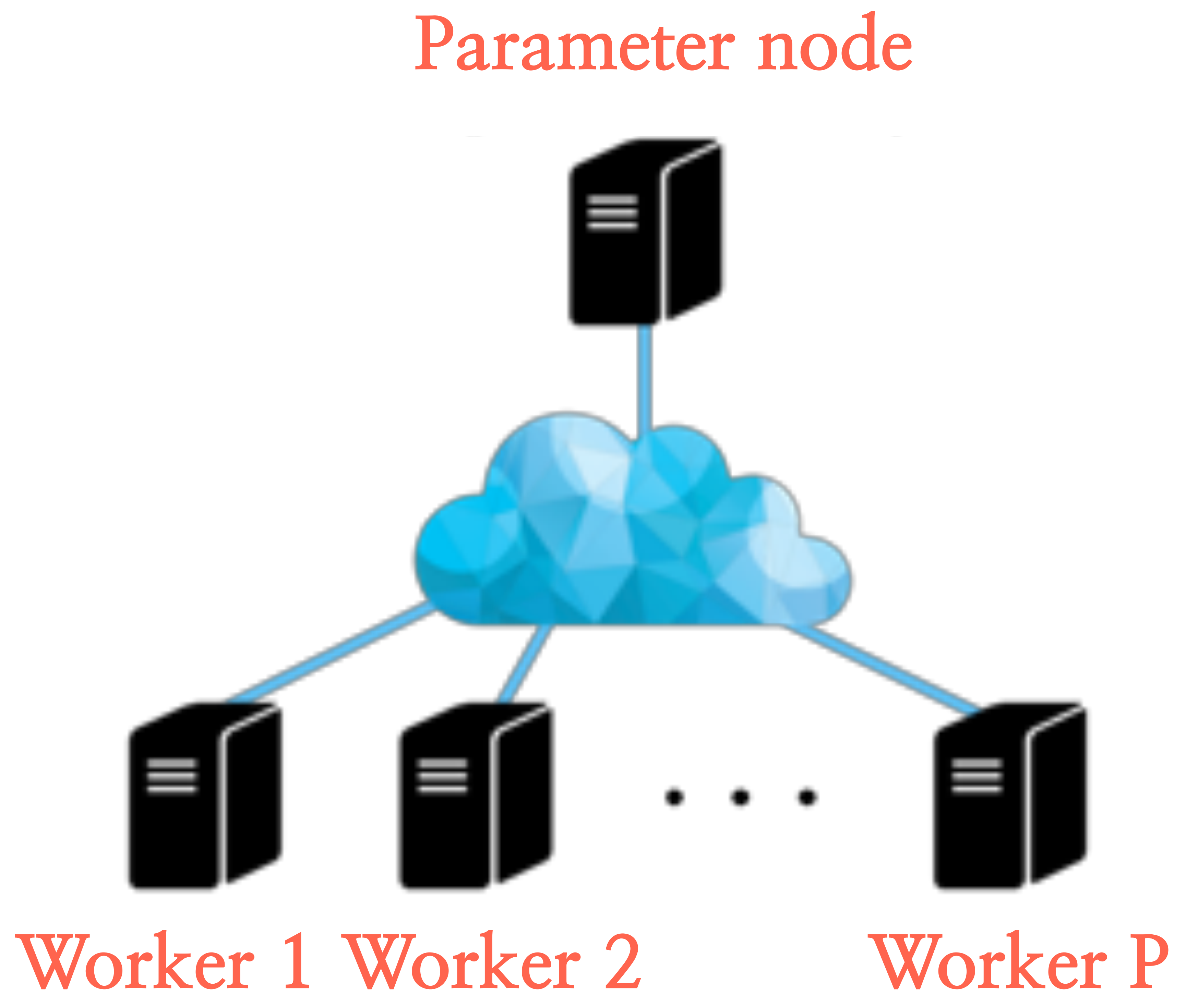
How to decompose a NN:



Original network

Network decomposed into three cascades for training

How to train NN in a distributed fashion:



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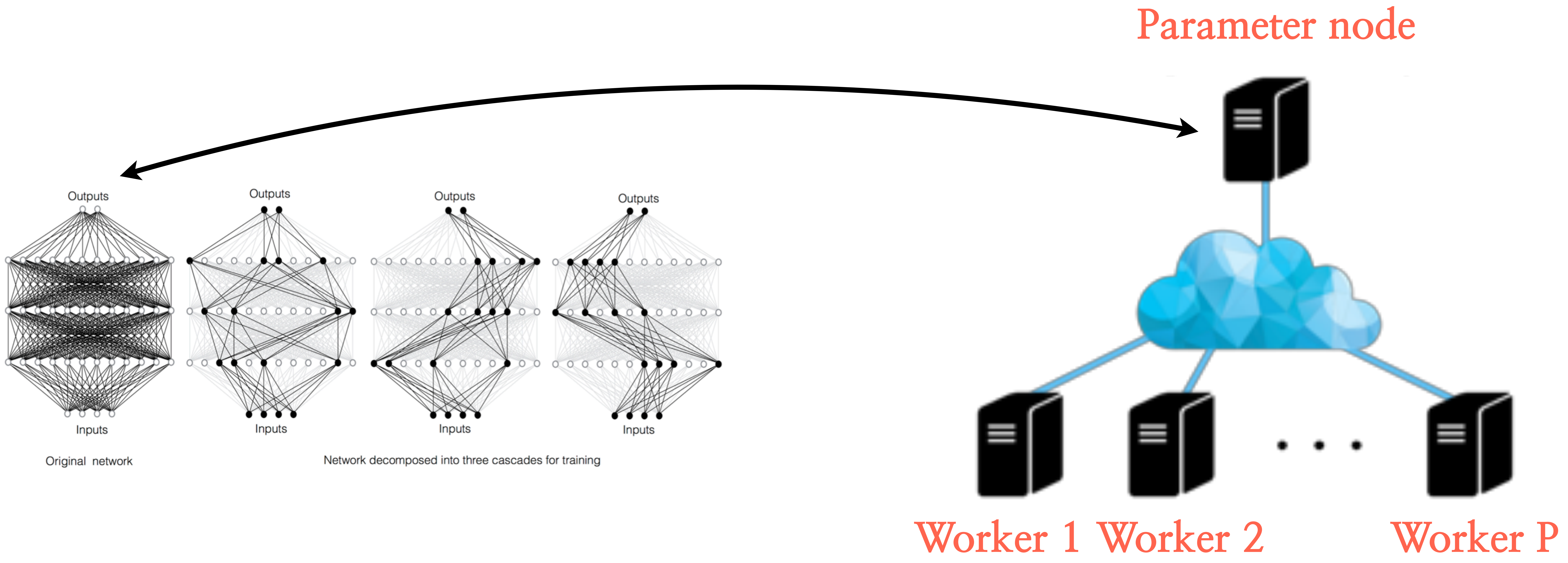

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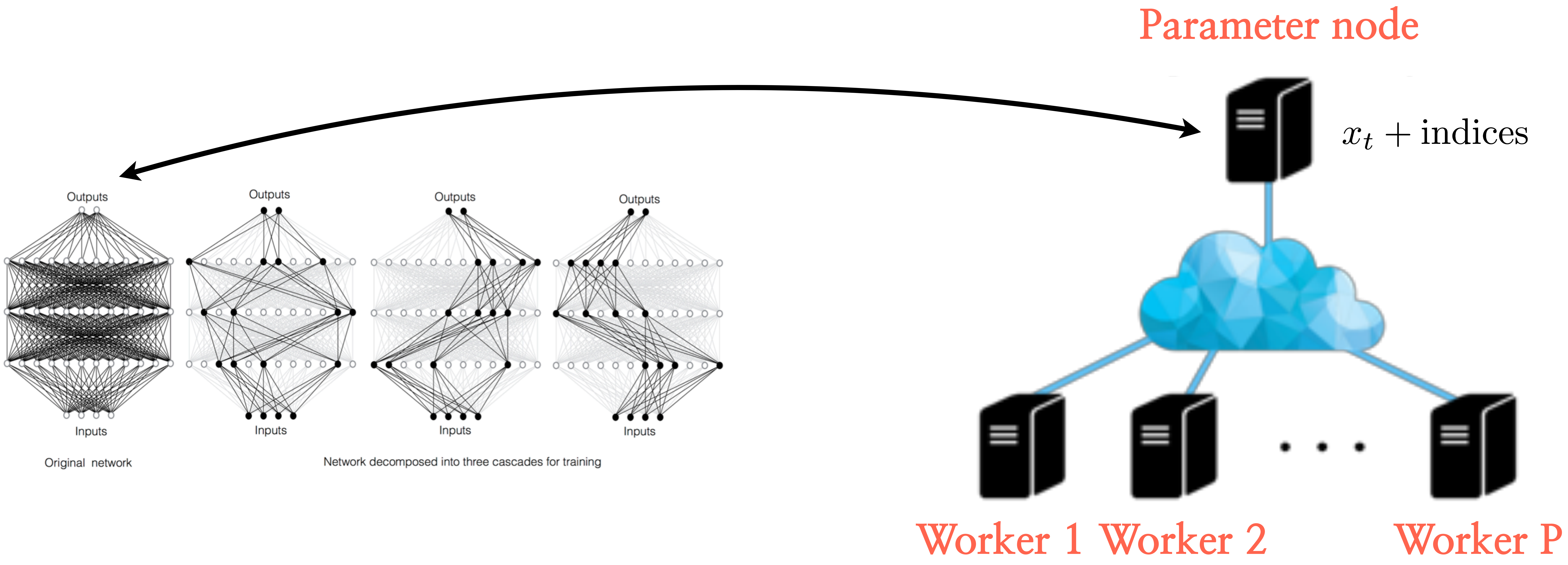

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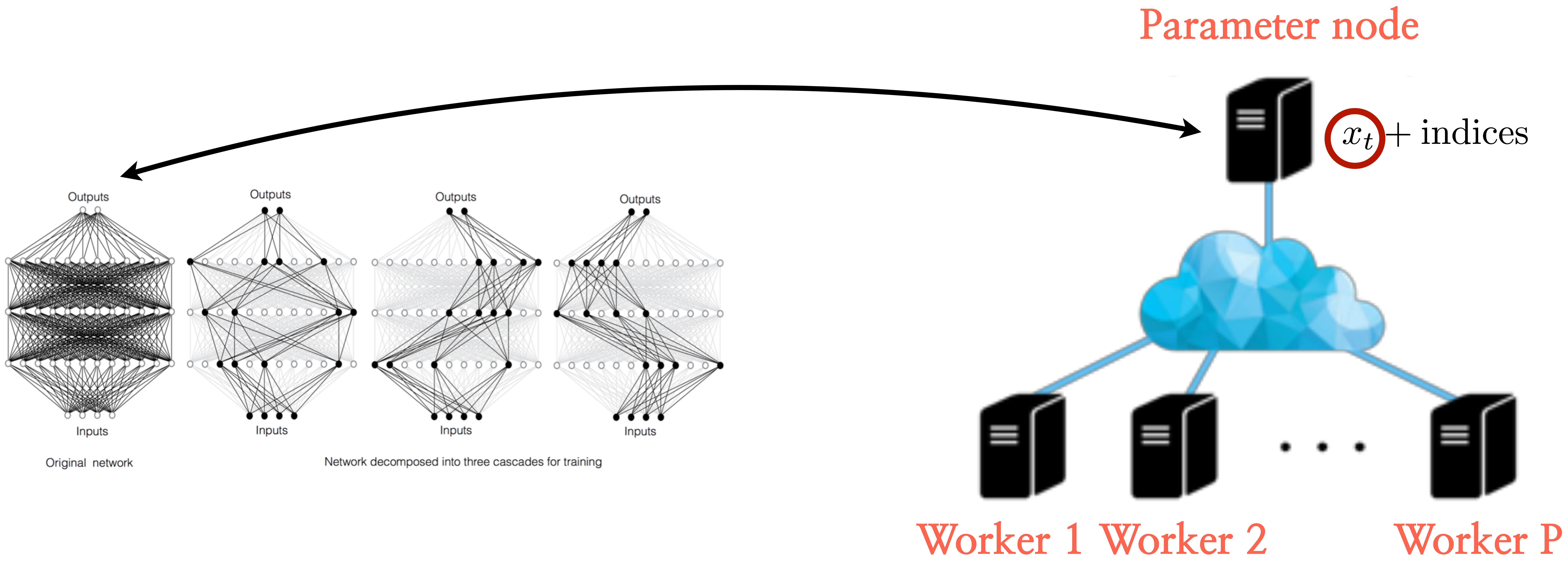

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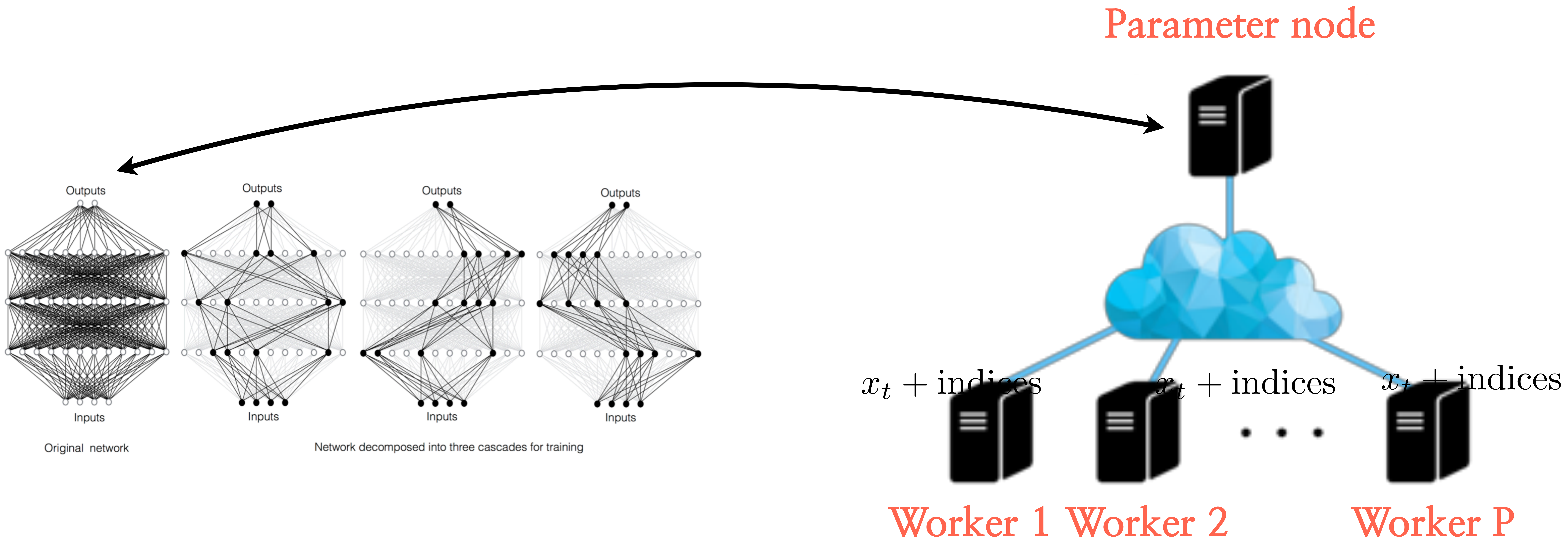

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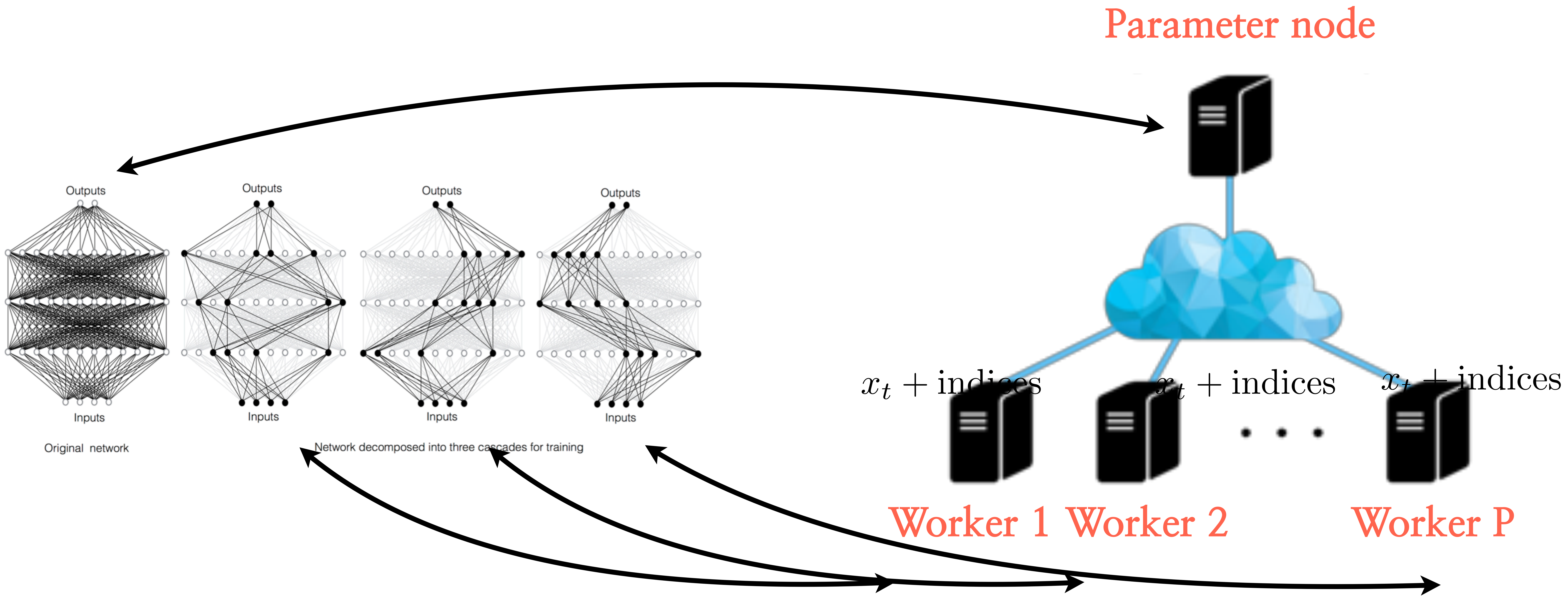

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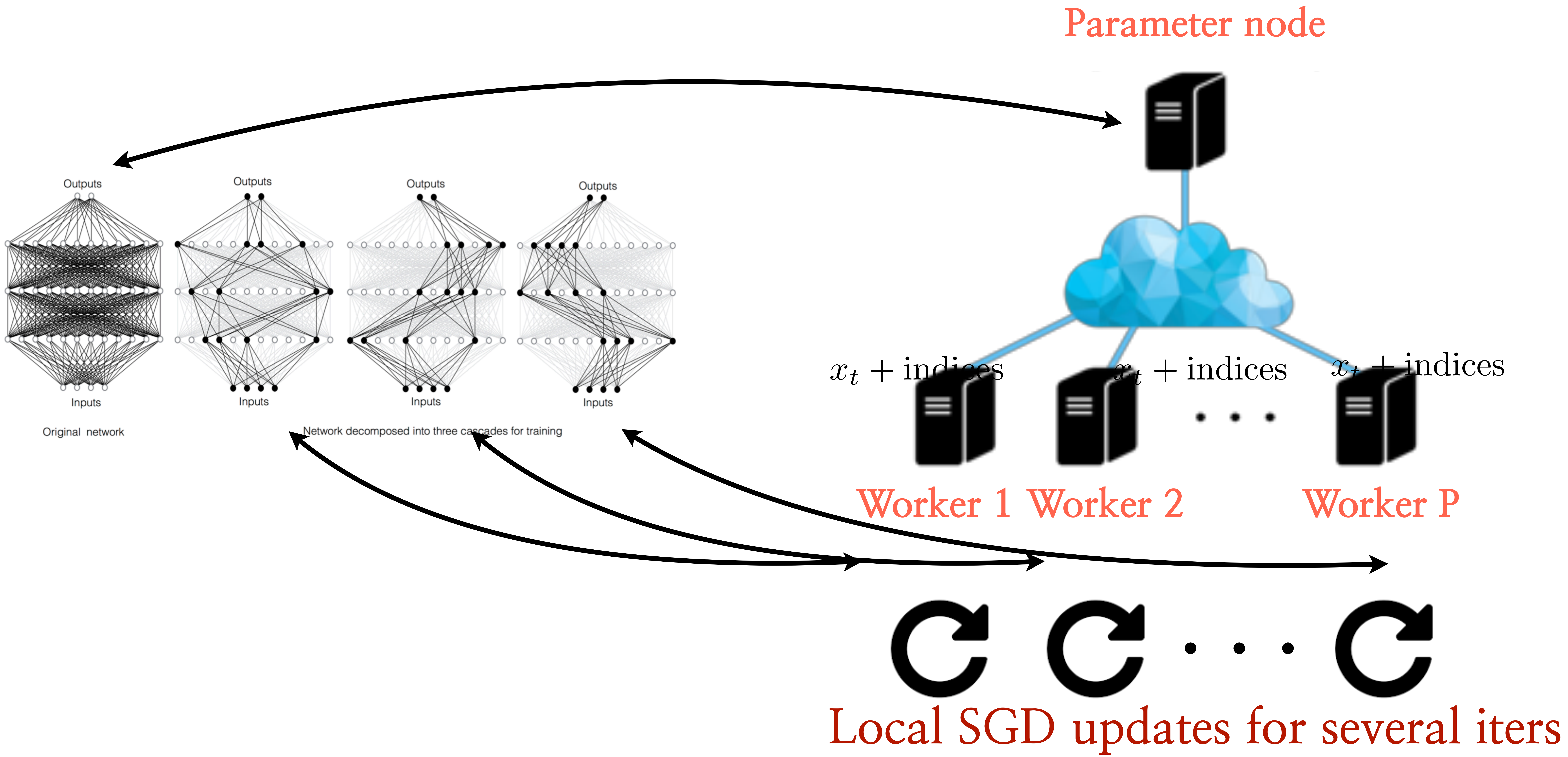

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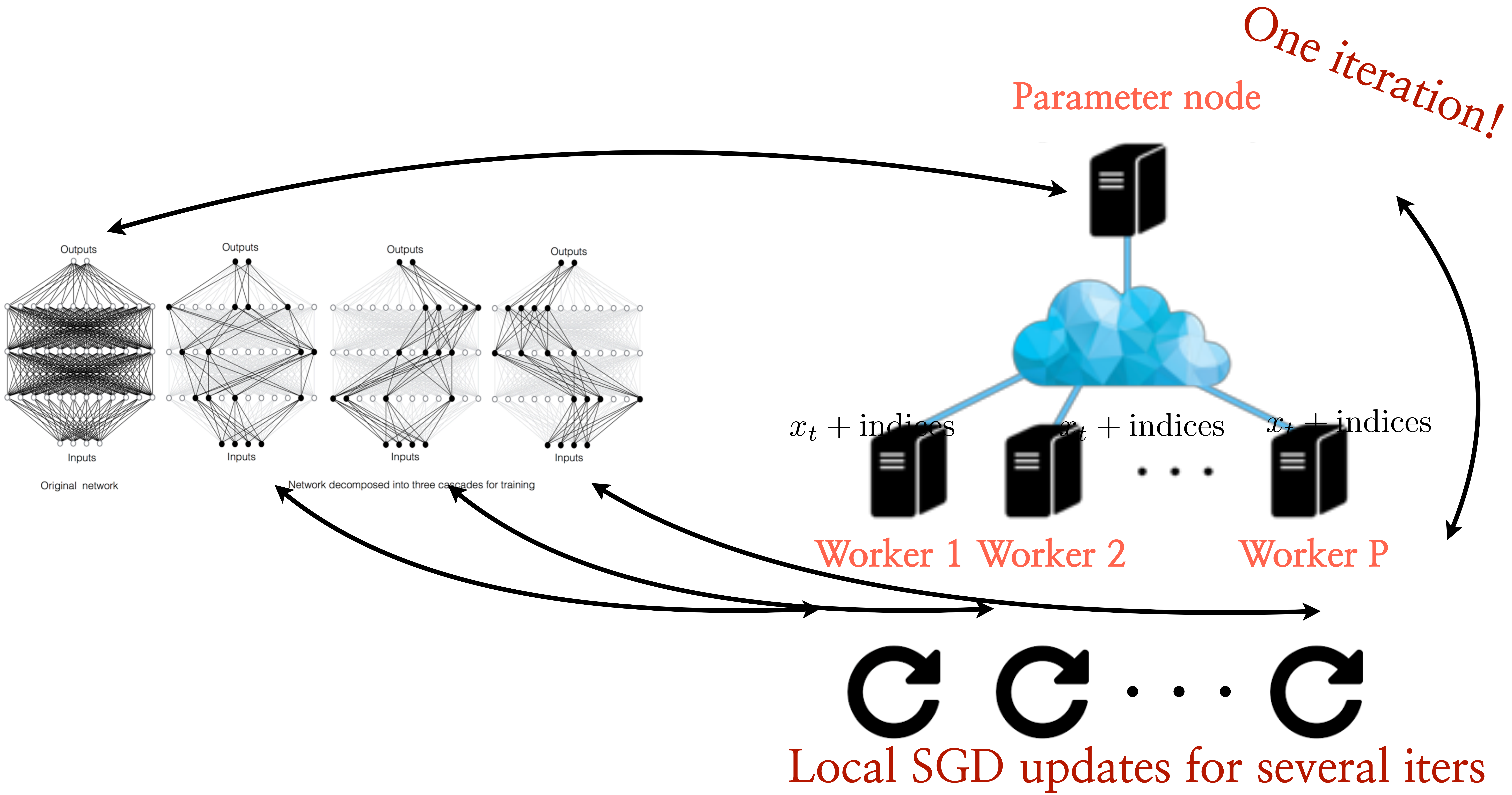

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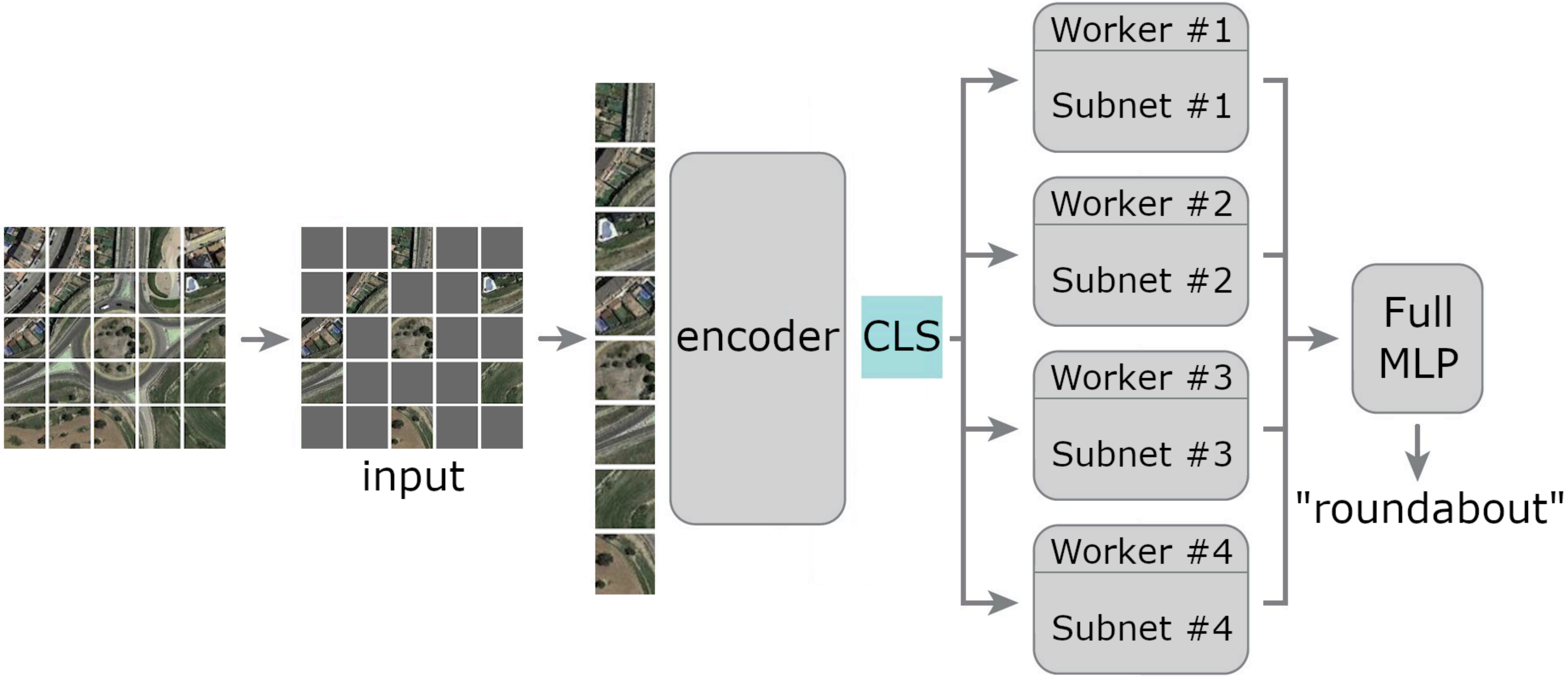

IST-style

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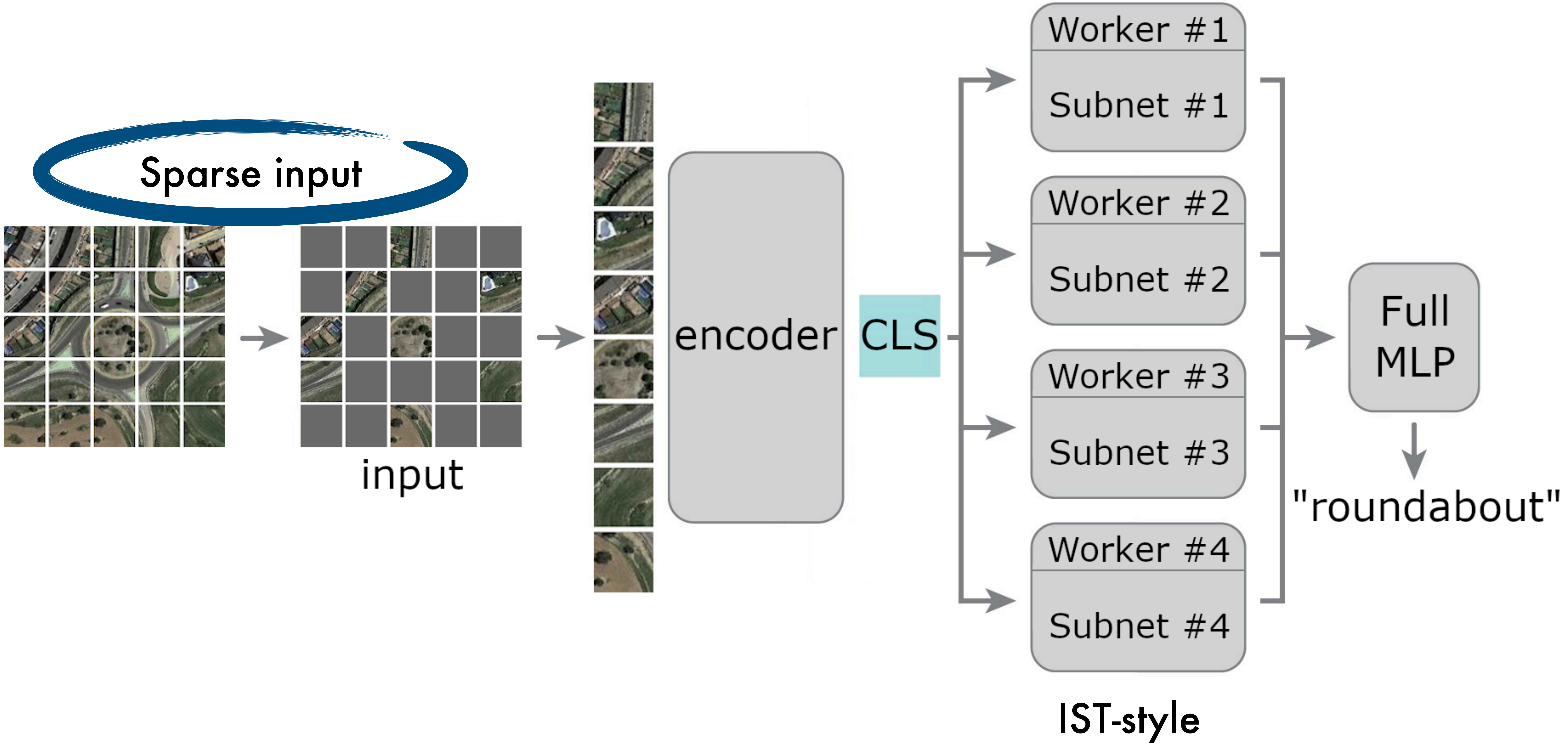

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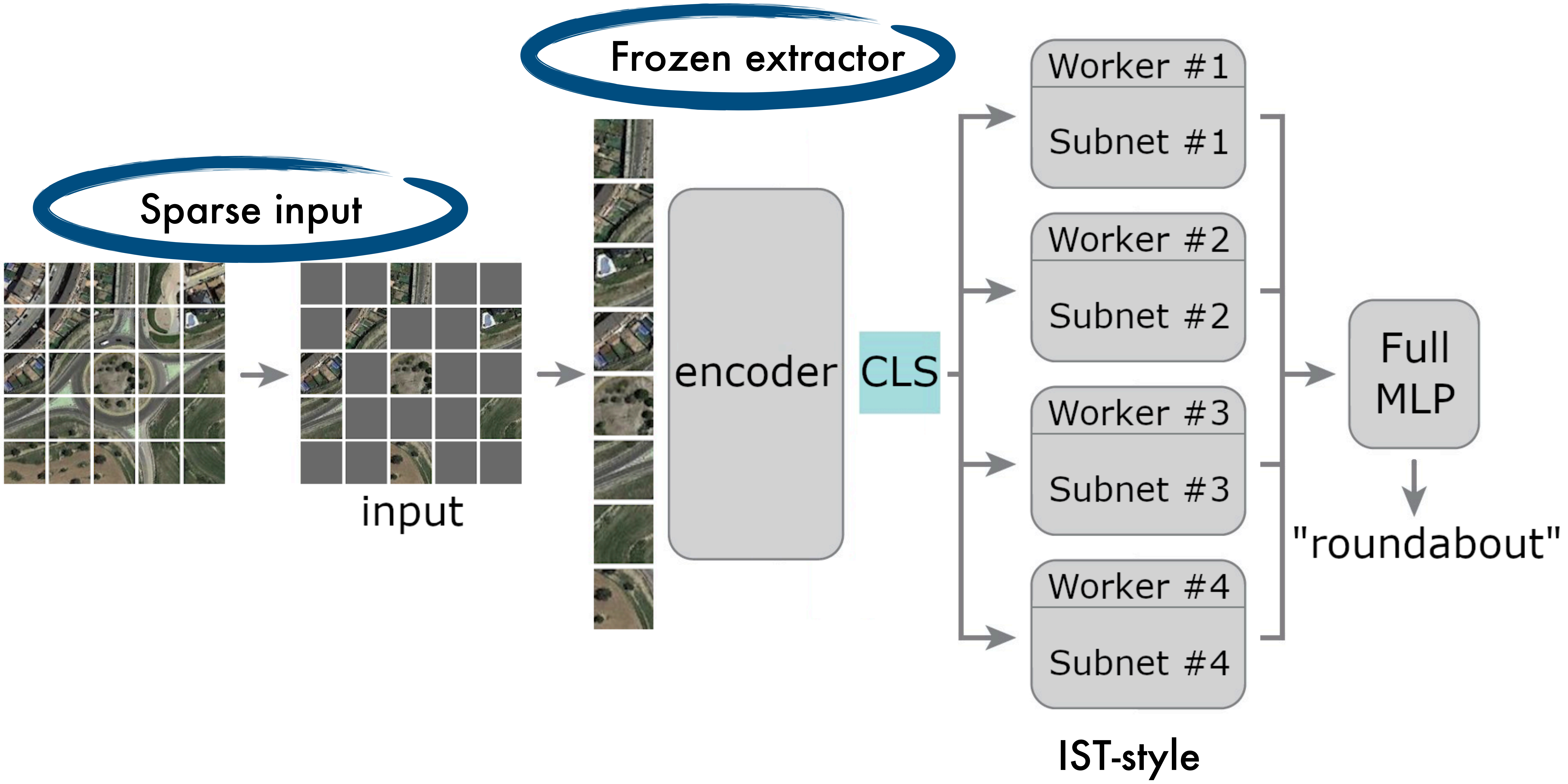

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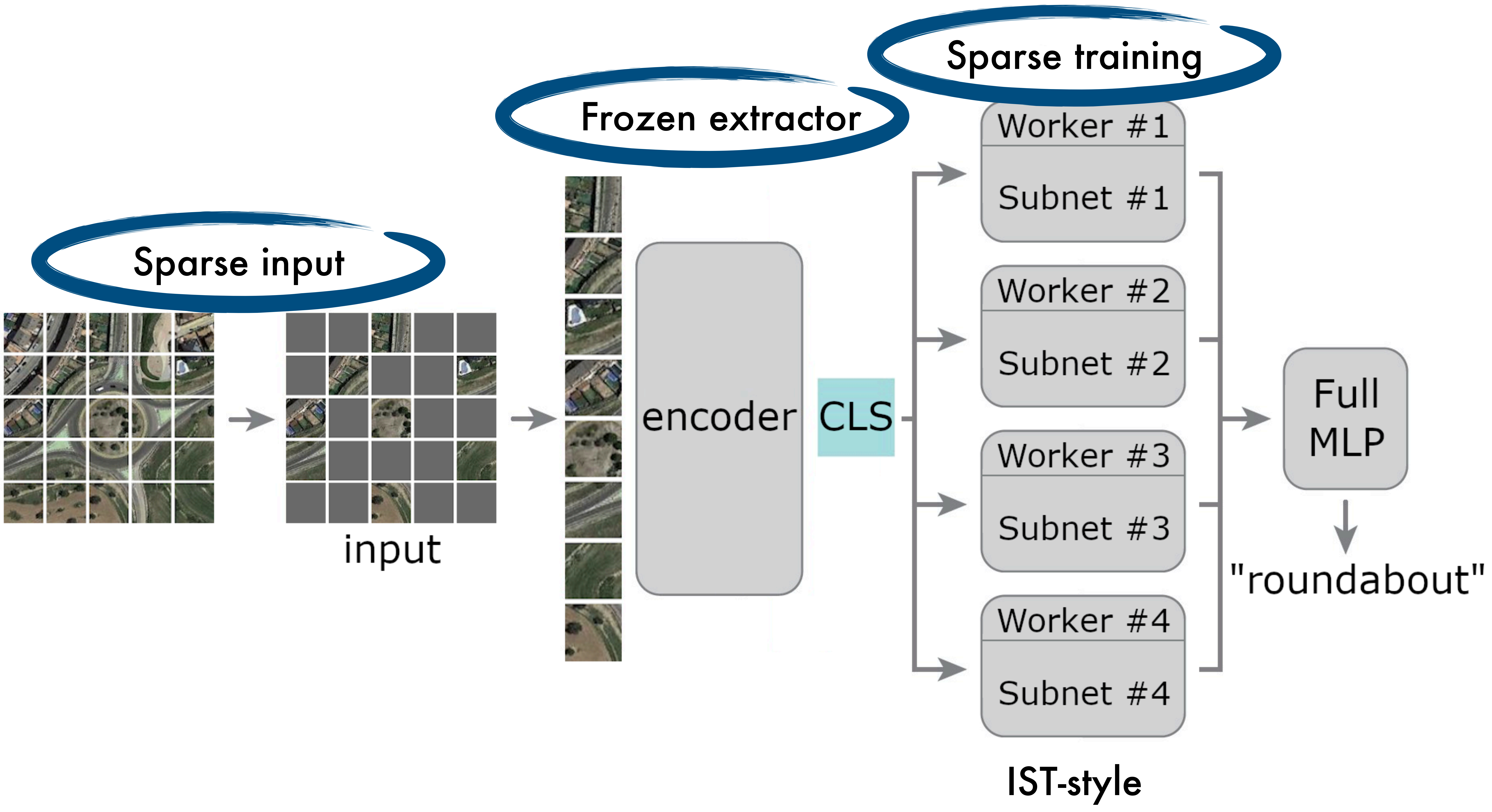

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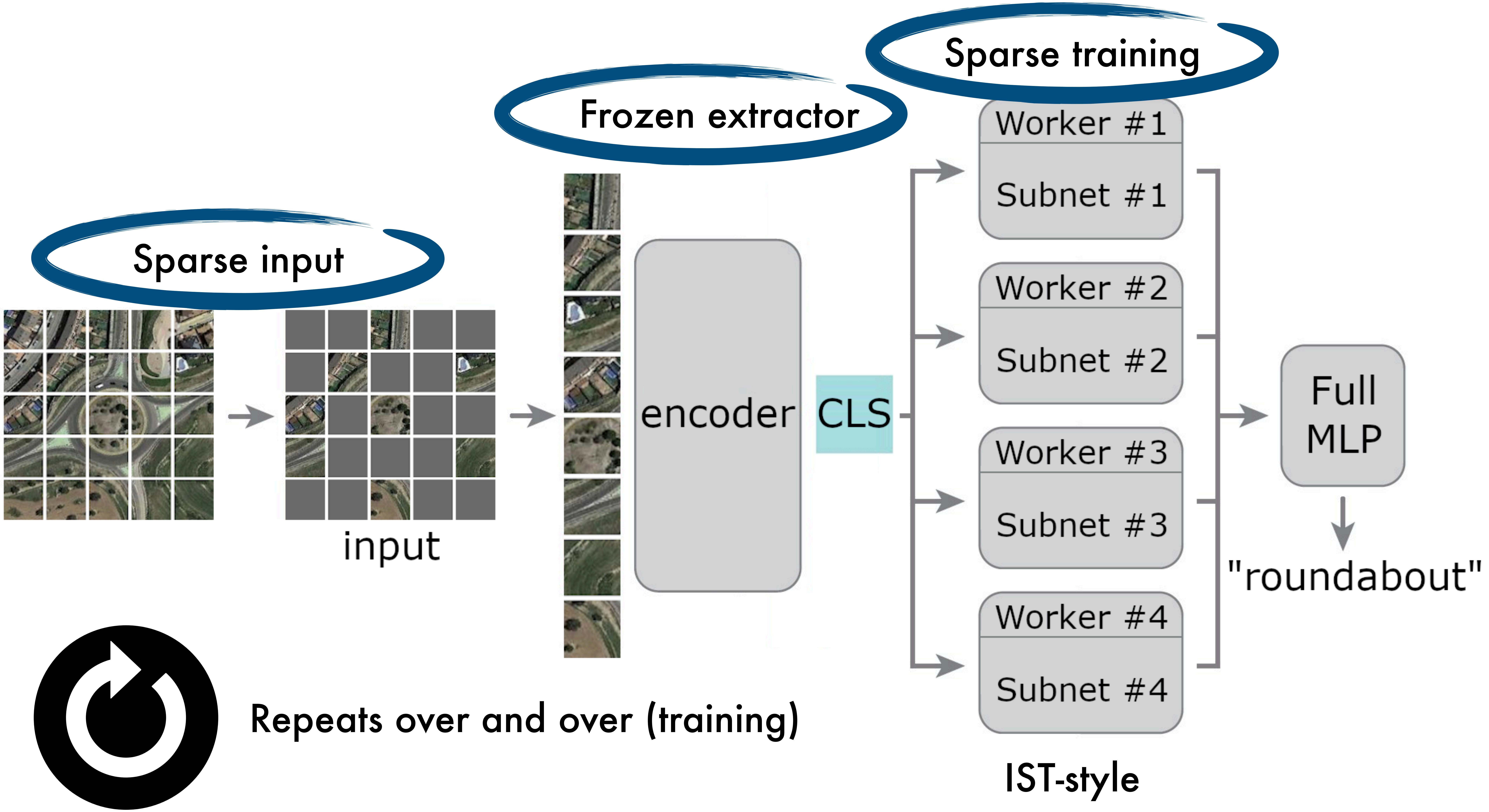

Repeats over and over (training)

Does it work?

- Simple tasks (Disclaimer: we need to do a better job on this moving forward)

Dataset	Classes	Image Size	Images per Class	Total (Training - Test Set)
CIFAR10	10	32×32	$6,000$	$60,000$ ($50,000$ - $10,000$)
RESISC45	45	256×256	700	$31,500$ ($27,000$ - $4,500$)
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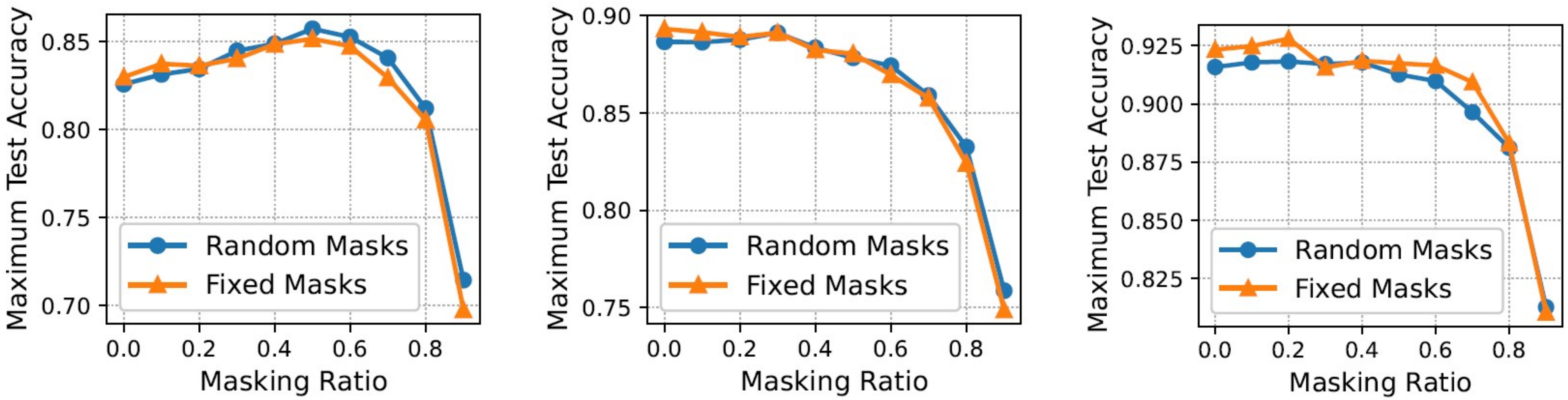

(a) CIFAR10 (b) RESISC45 (c) AID

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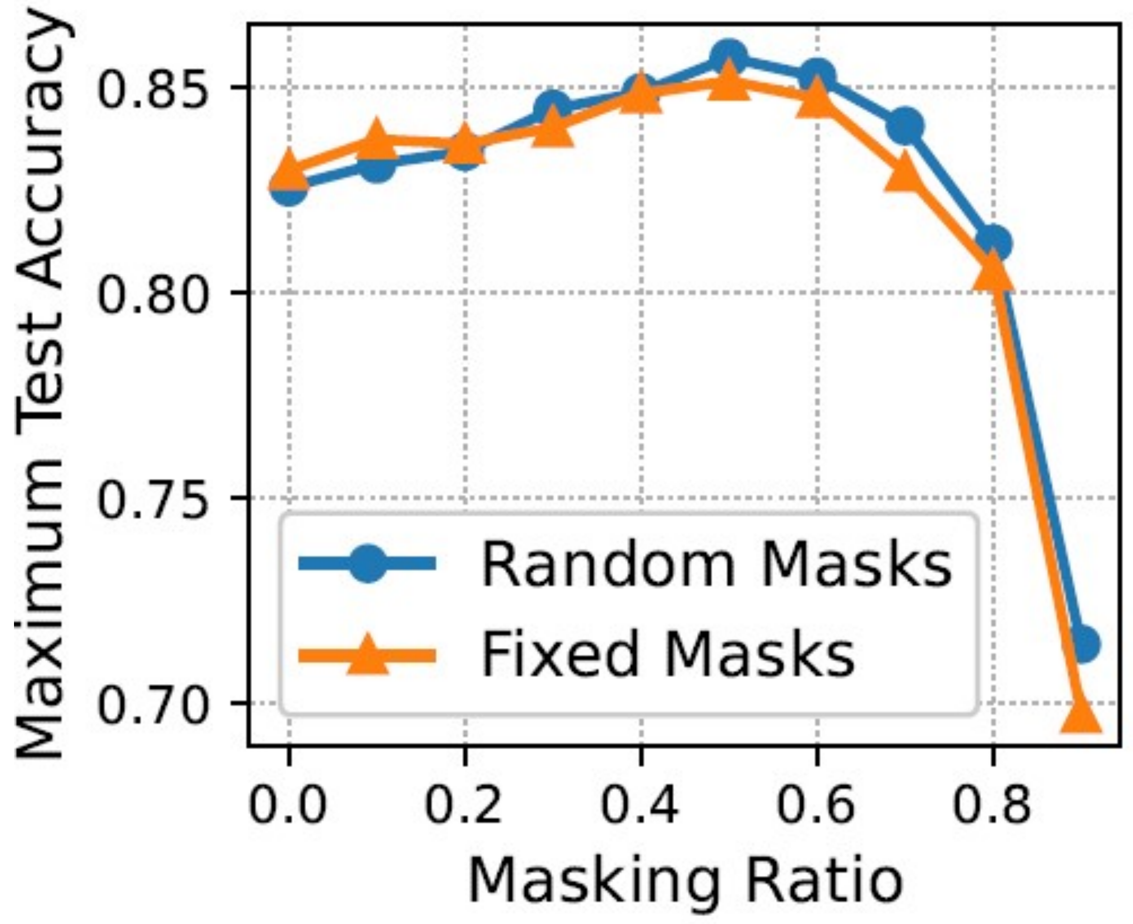

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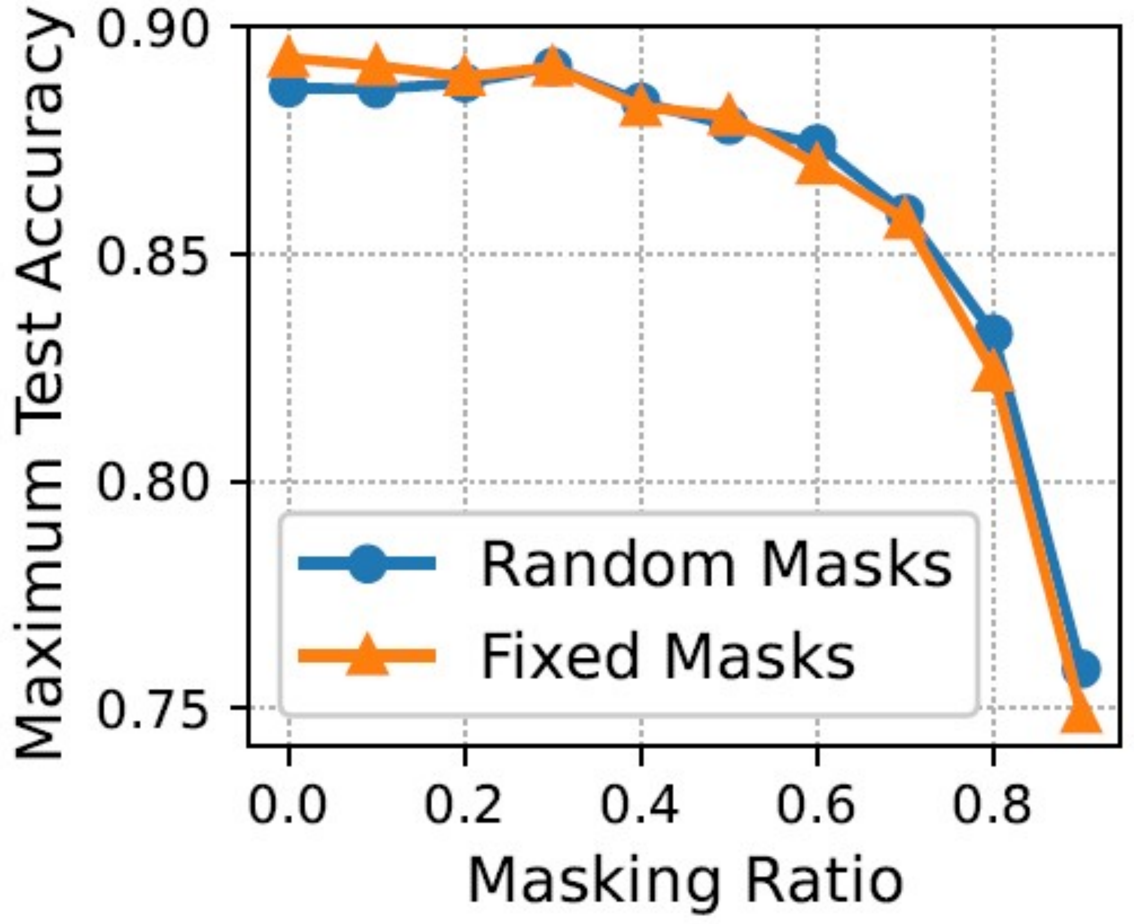

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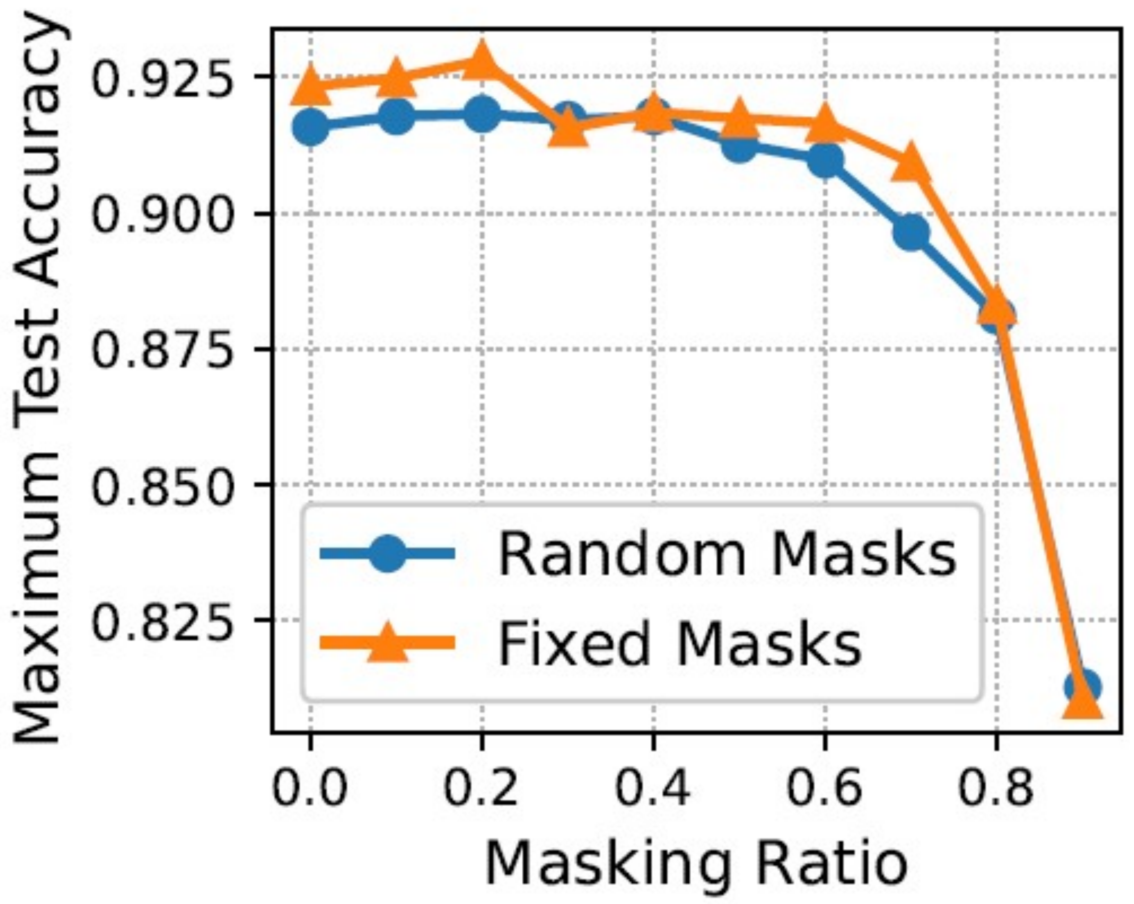

(c) AID

This means that:

- Applications with natural sparsity could be solved fine (given enough data points)

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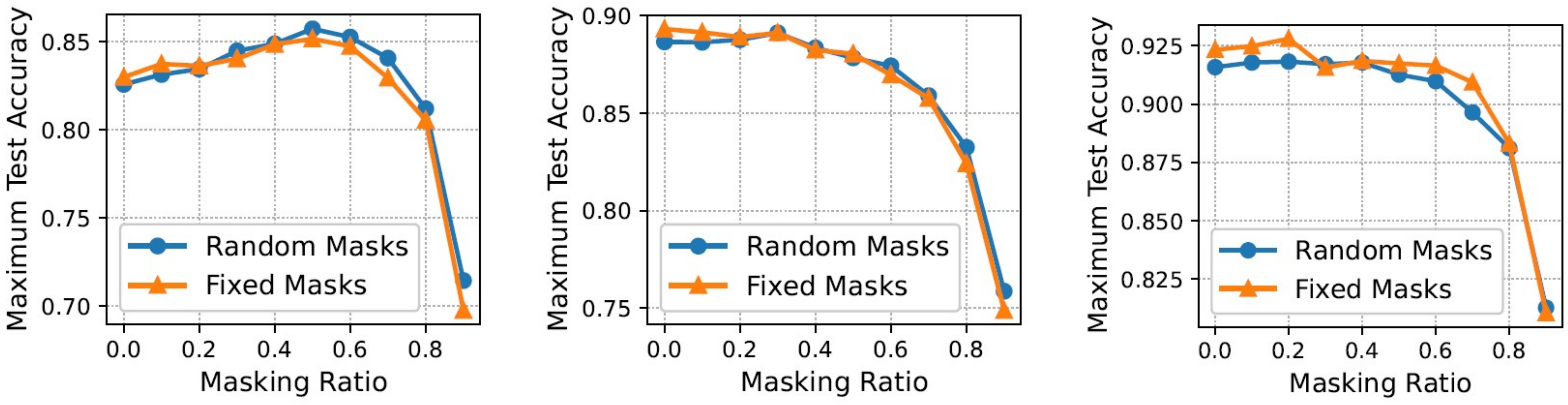
AID	30	600×600	$220 \sim 420$	$10,000$ ($8,500$ - $1,500$)

- Ablation study: *Can we use fixed masks to sparsity inputs?* Seems so!



(a) CIFAR10 (b) RESISC45 (c) AID

This means that:

- Applications with artificial input sparsity do not require random mask generation per iteration

Does it work?

- The system works for various masking ratios, preserving accuracy

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	Masking Ratio	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
CIFAR10	Masked Images Size (in GB)	0.205	0.184	0.164	0.143	0.123	0.102	0.082	0.061	0.041	0.020
	CLS Tokens Size (in GB)	0.1536									
	Max Accuracy	0.823	0.837	0.836	0.840	**0.848**	**0.851**	0.847	0.829	0.805	0.697
RESISC45	Masked Images Size (in GB)	7.078	6.370	5.662	4.954	4.247	3.539	2.831	2.123	1.416	0.708
	CLS Tokens Size (in GB)	0.083									
	Max Accuracy	**0.893**	**0.891**	0.889	**0.891**	0.882	0.880	0.869	0.857	0.824	0.749
AID	Masked Images Size (in GB)	12.240	11.016	9.792	8.568	7.344	6.120	4.896	3.672	2.448	1.224
	CLS Tokens Size (in GB)	0.026									
	Max Accuracy	0.923	**0.925**	**0.928**	0.916	0.918	0.917	0.916	0.909	0.883	0.810

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Accuracy even improved!

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  - Can we theoretically characterize the input layer sparsity?
    - Even an NTK analysis would be a great start

I would love to be there :(- Thank you Daniel!

For questions: anastasios@rice.edu