

Relative representations

enable zero-shot latent space communication

Luca Moschella Valentino Maiorca

Marco Fumero Antonio Norelli Francesco Locatello Emanuele Rodolà



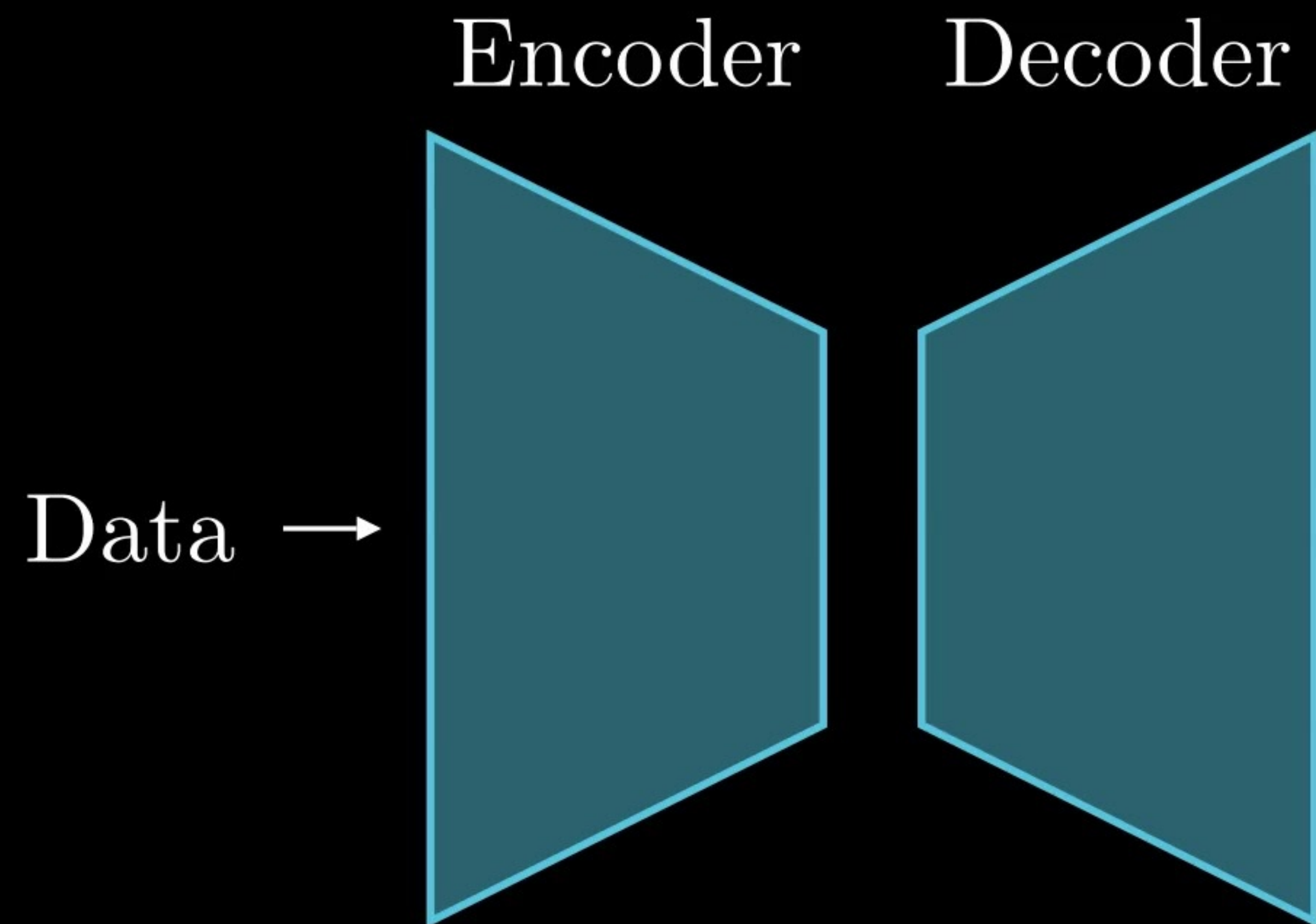
Neural Networks

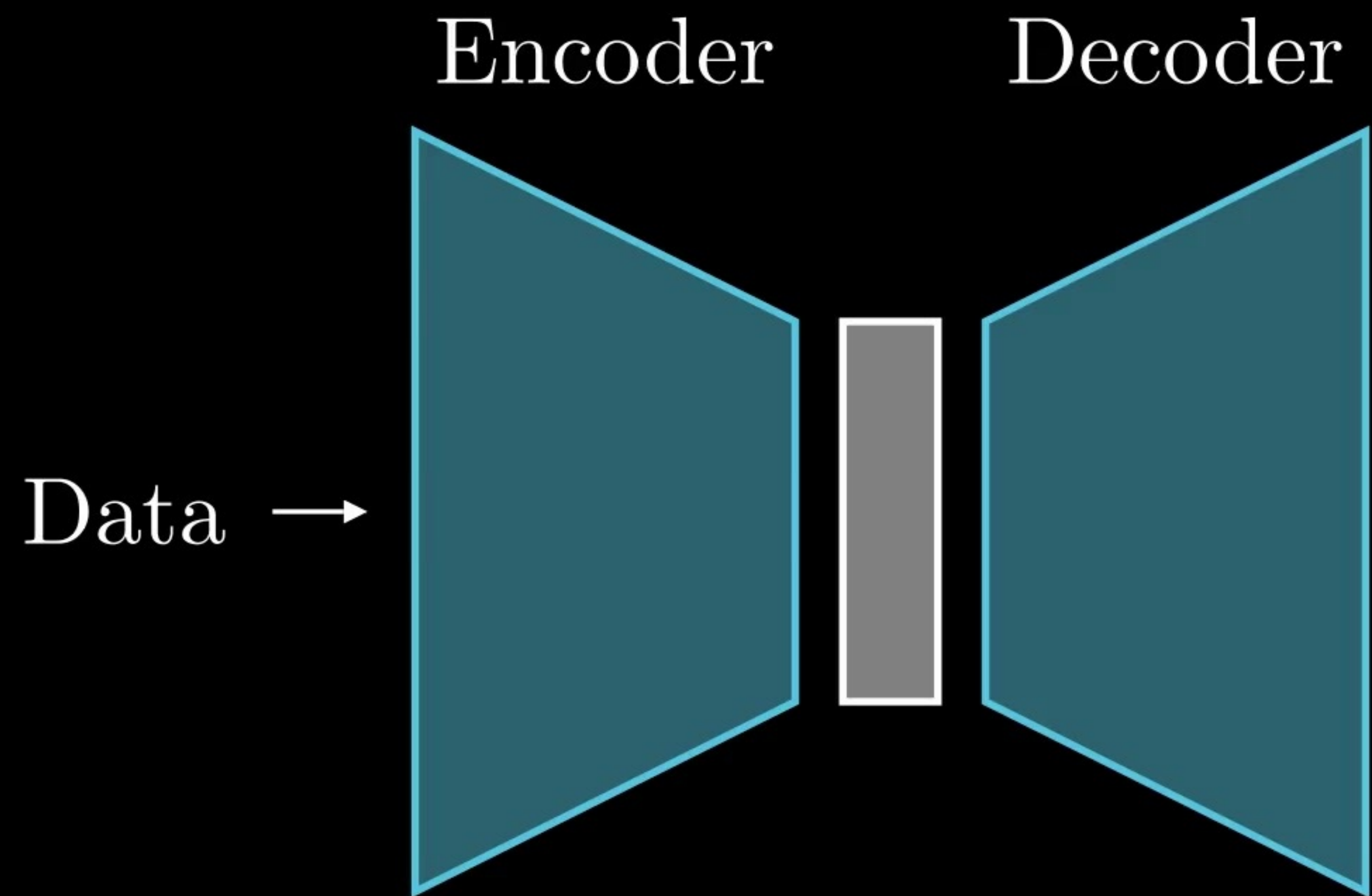
Encoder

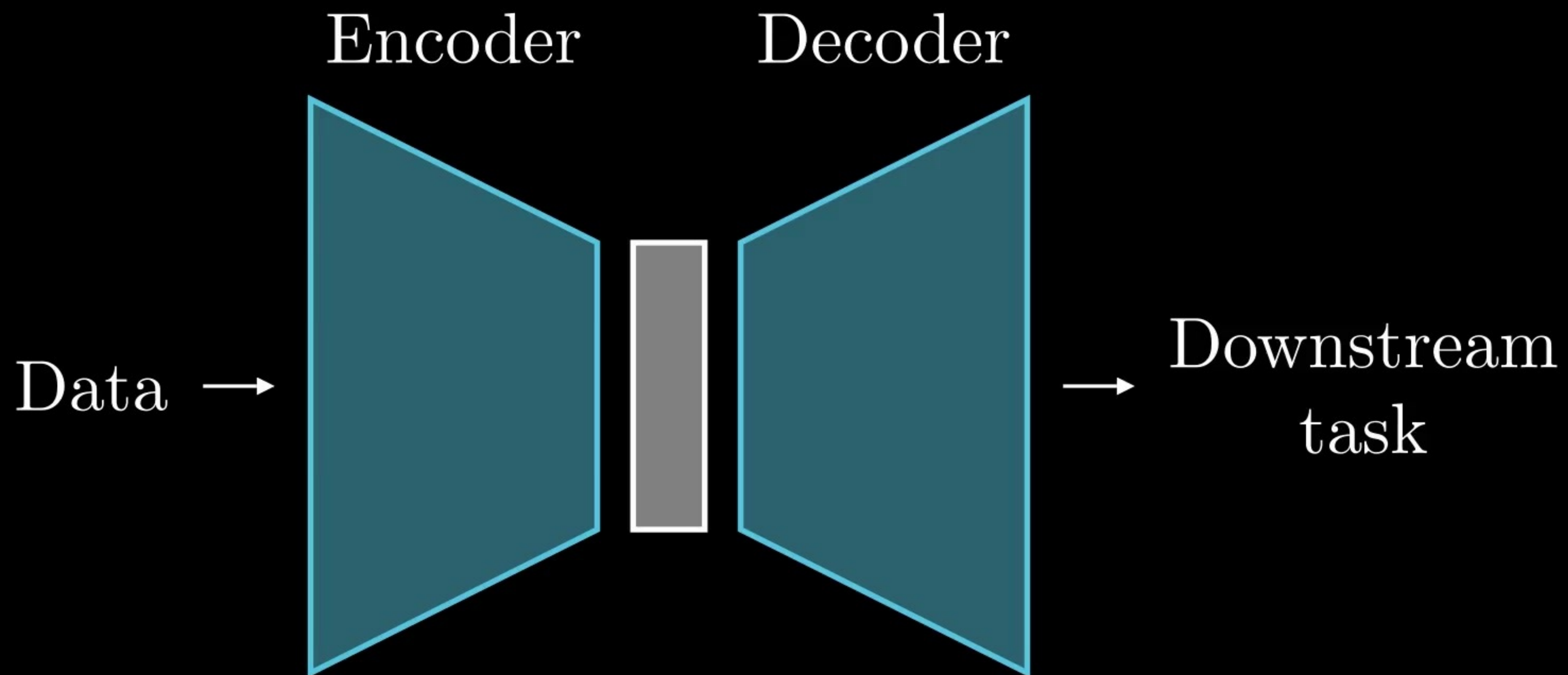


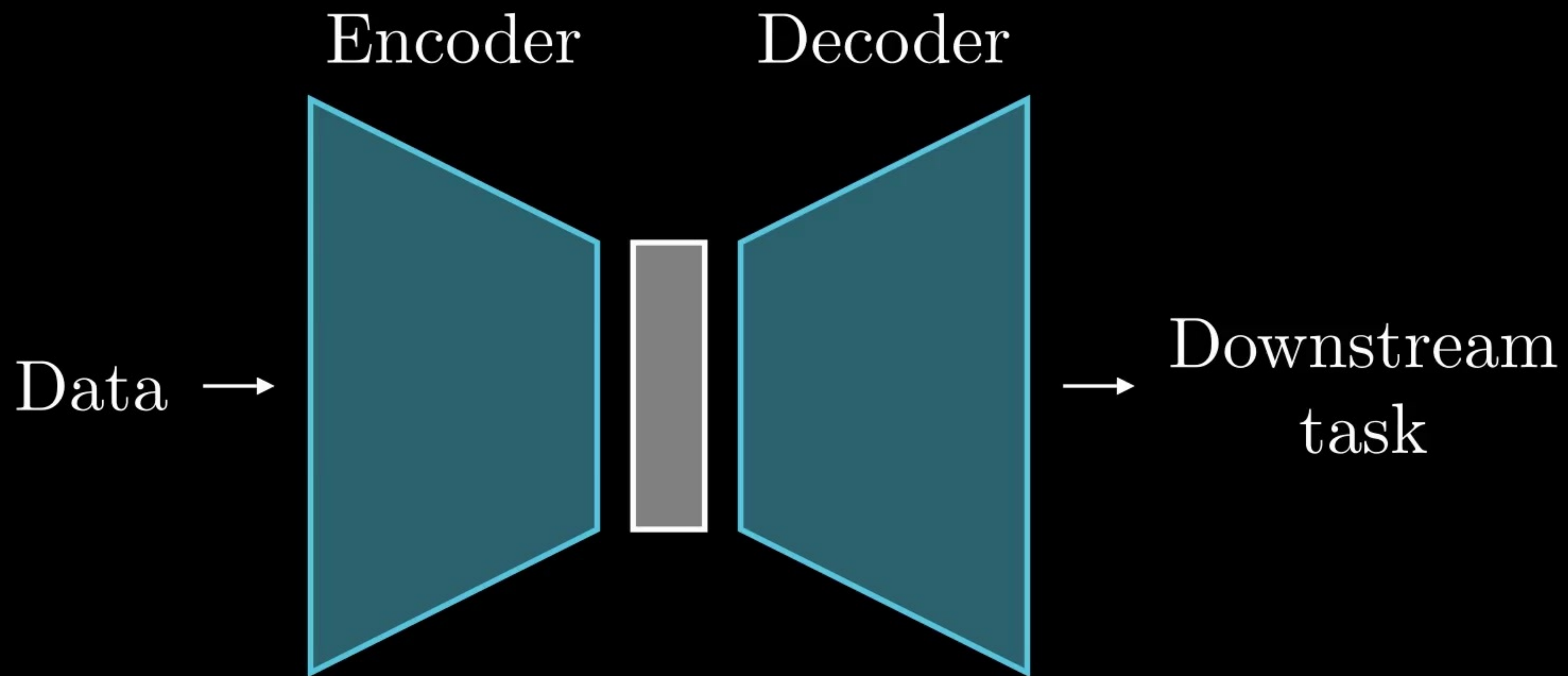
Decoder

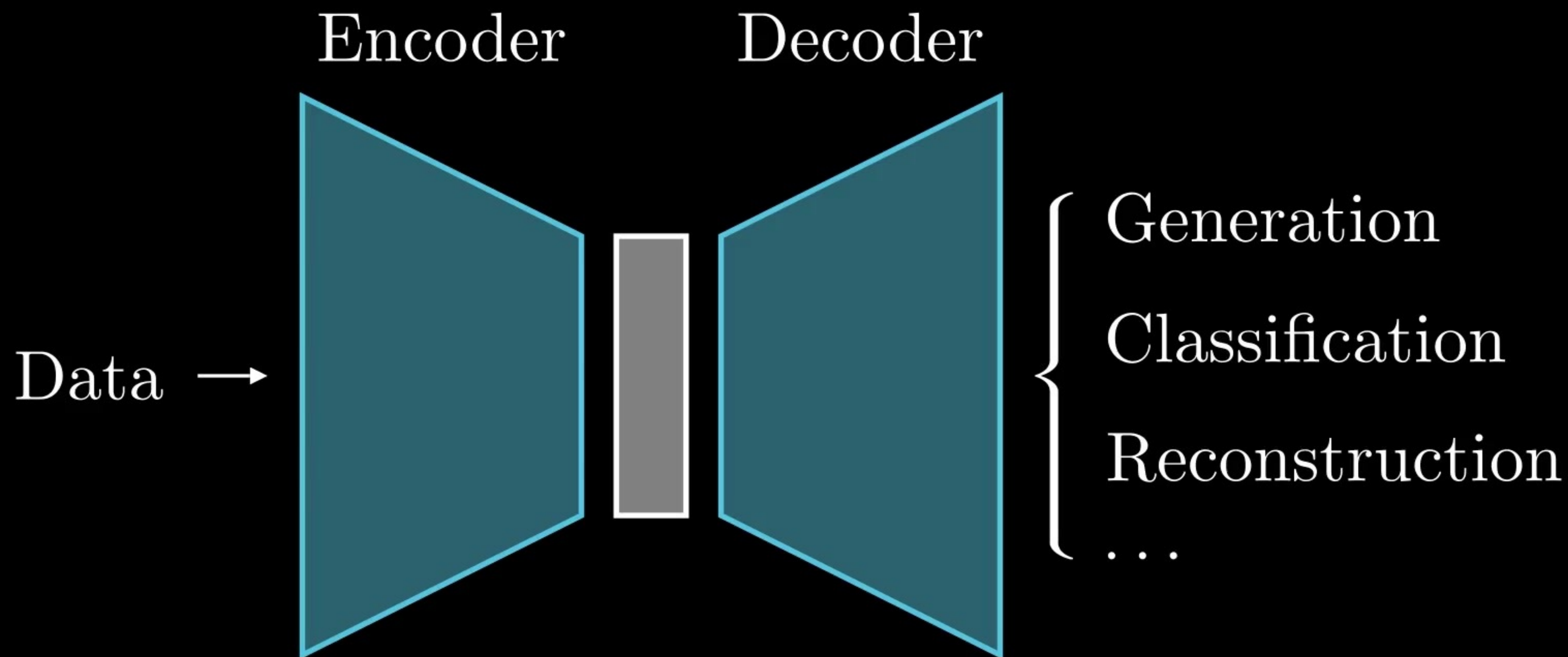






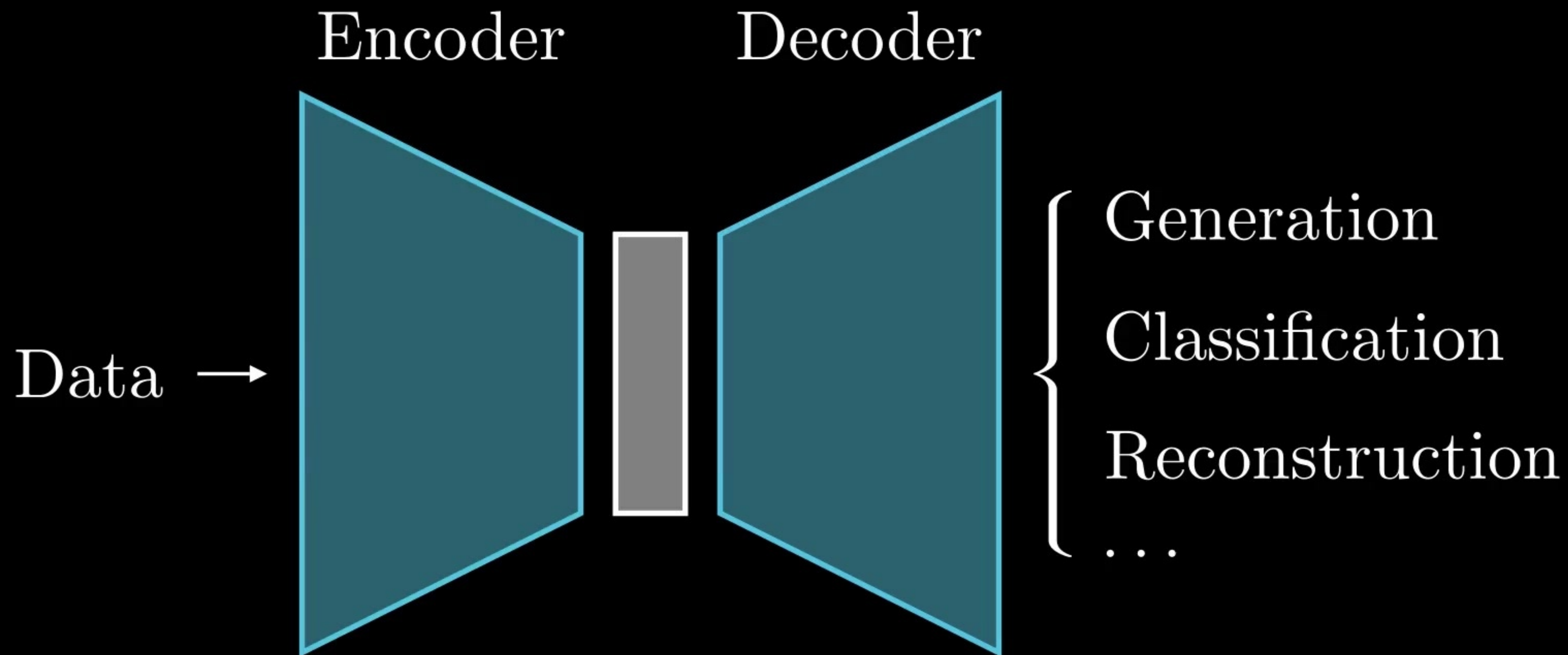




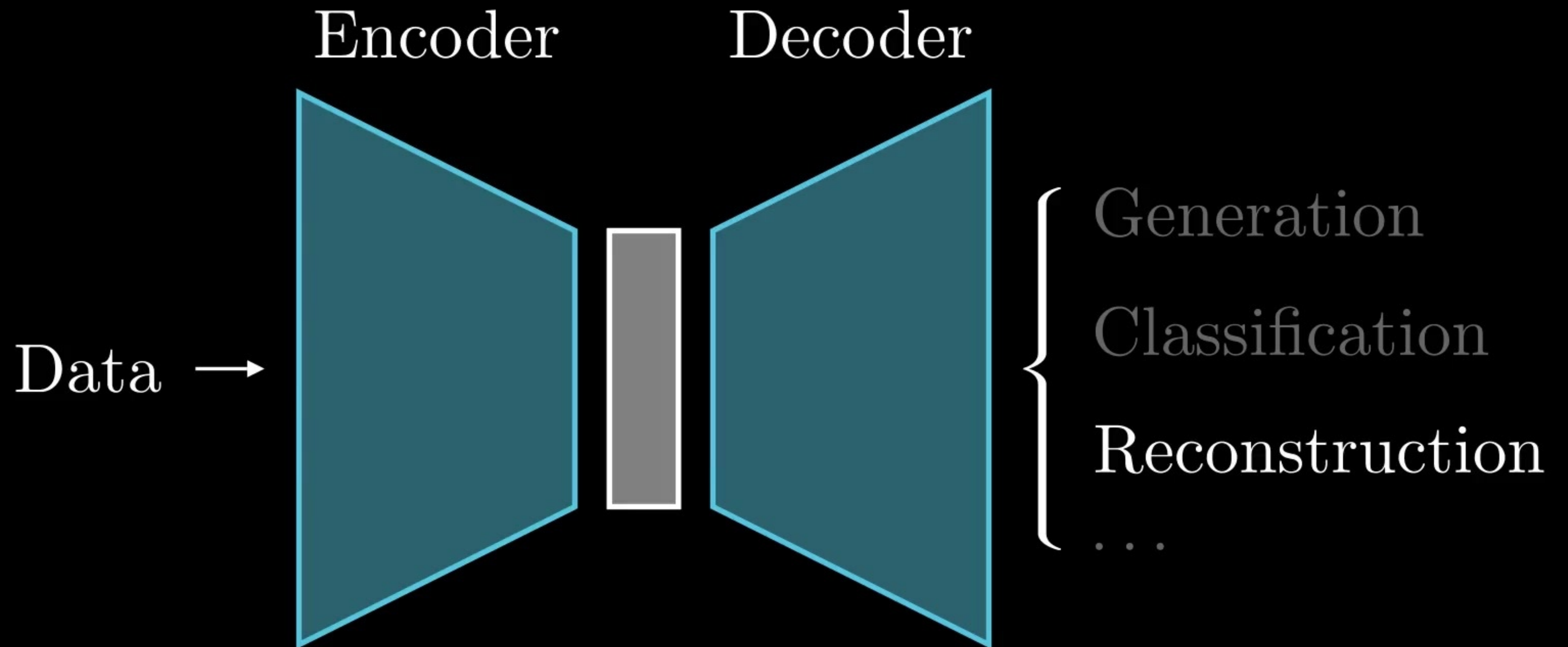


The shape of the latent space

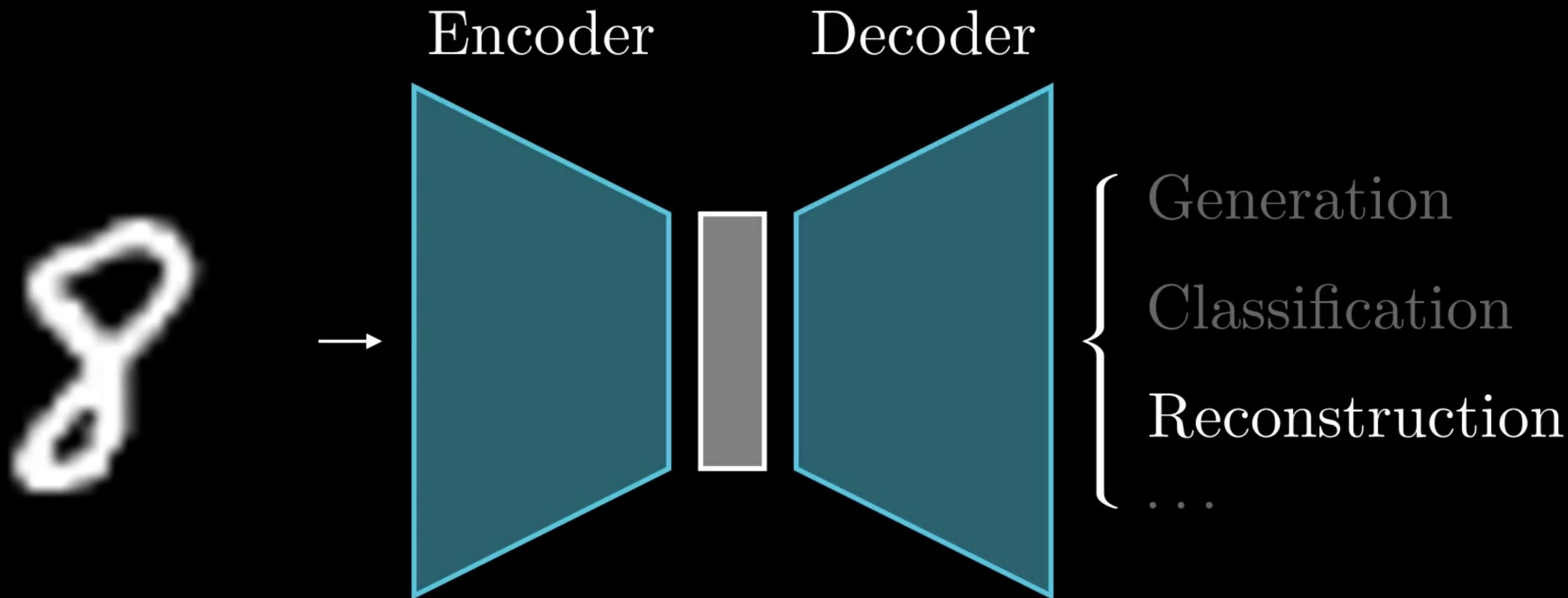
Toy AutoEncoder



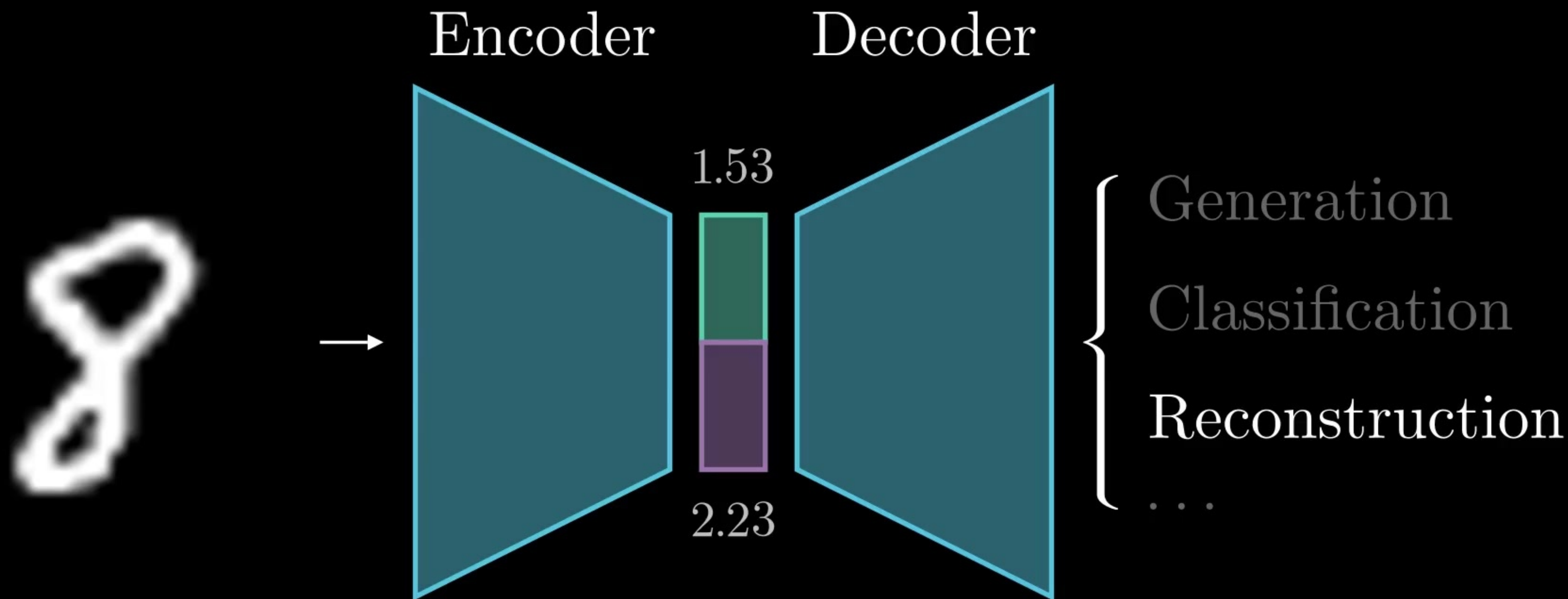
Toy AutoEncoder



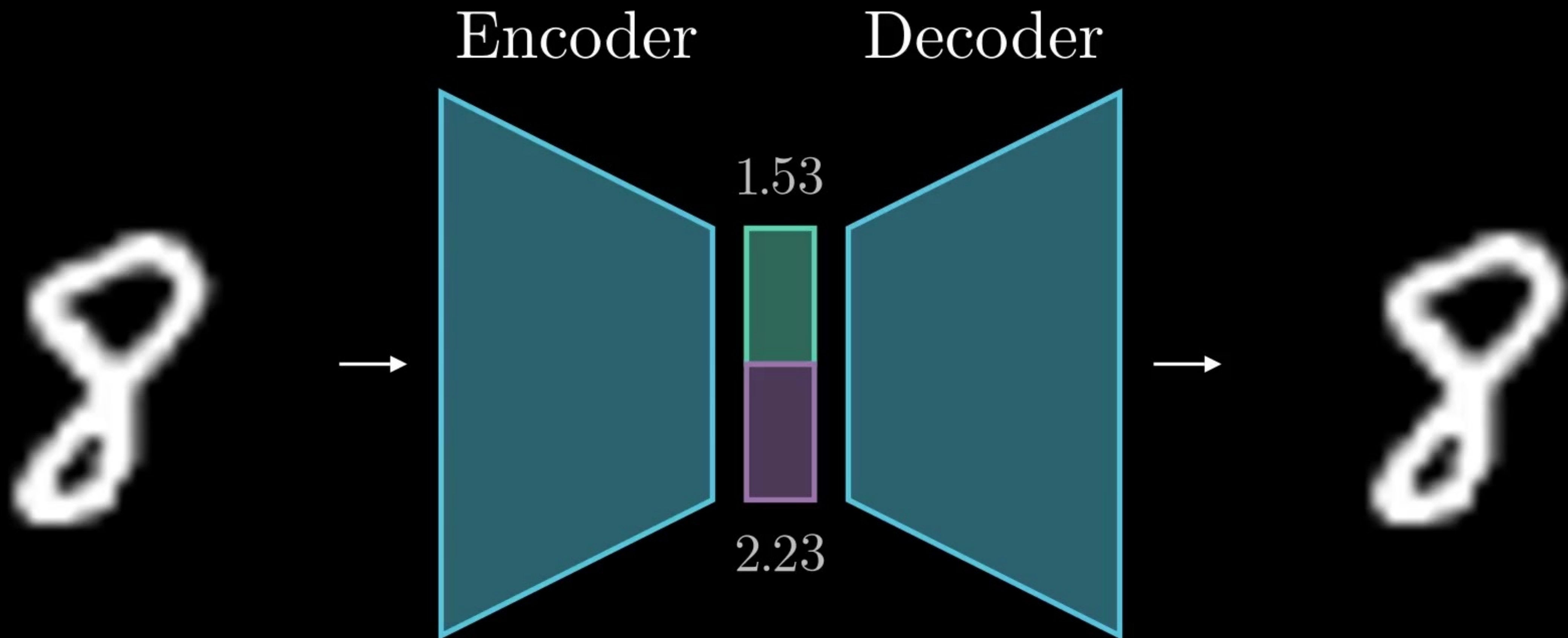
Toy AutoEncoder



Toy AutoEncoder



Toy AutoEncoder



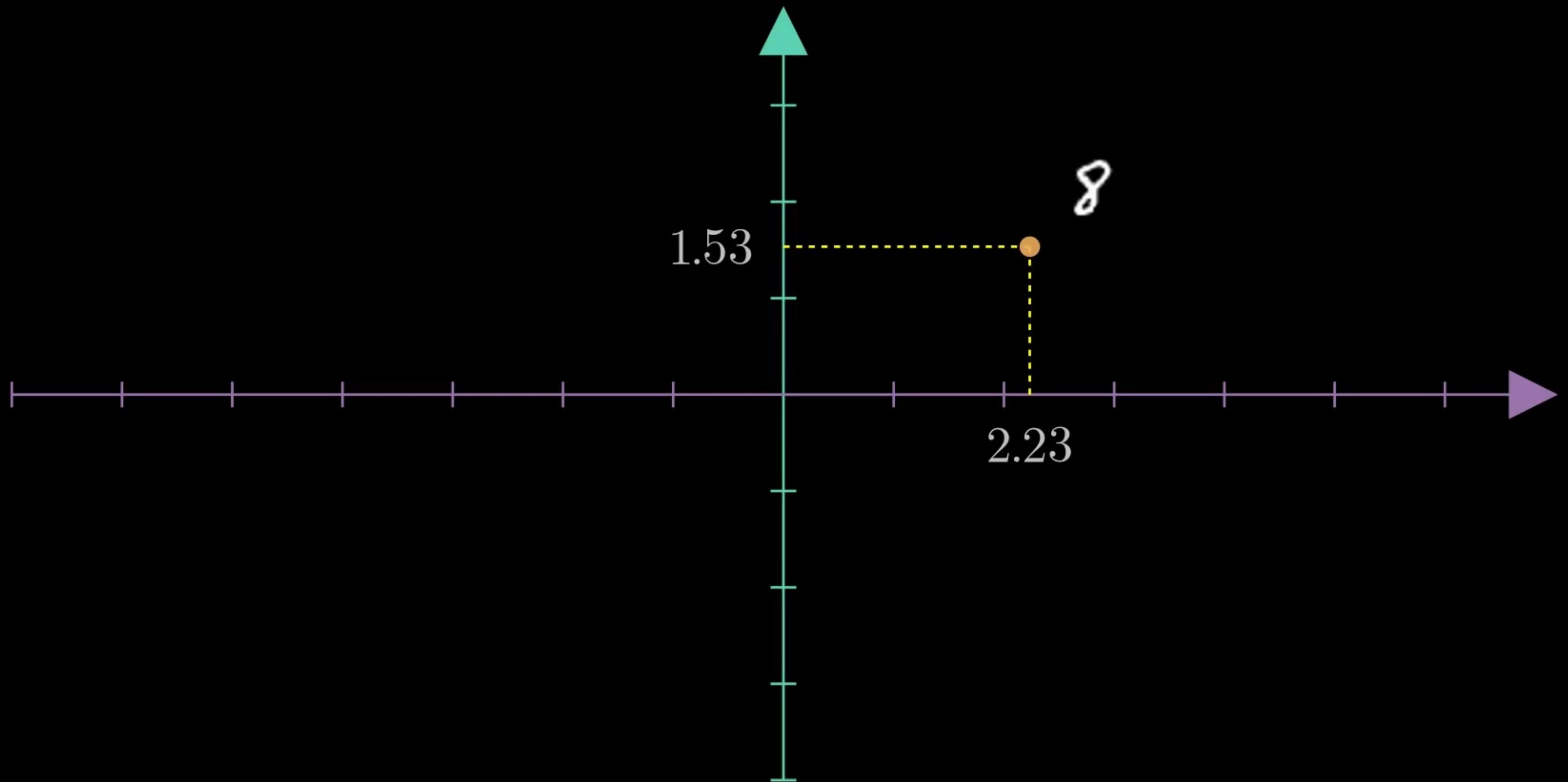
Toy AutoEncoder

1.53



2.23

Toy AutoEncoder



MNIST

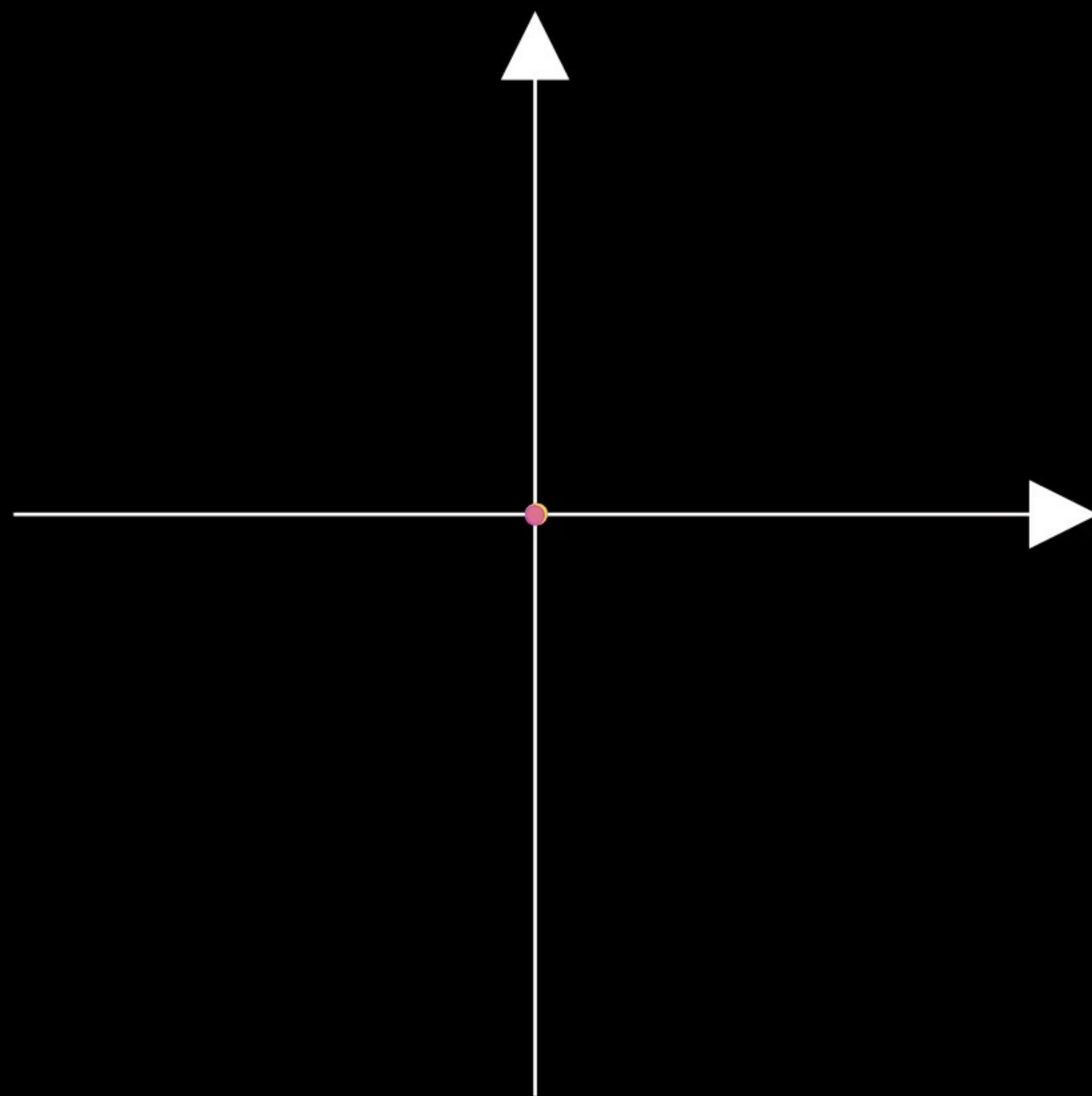
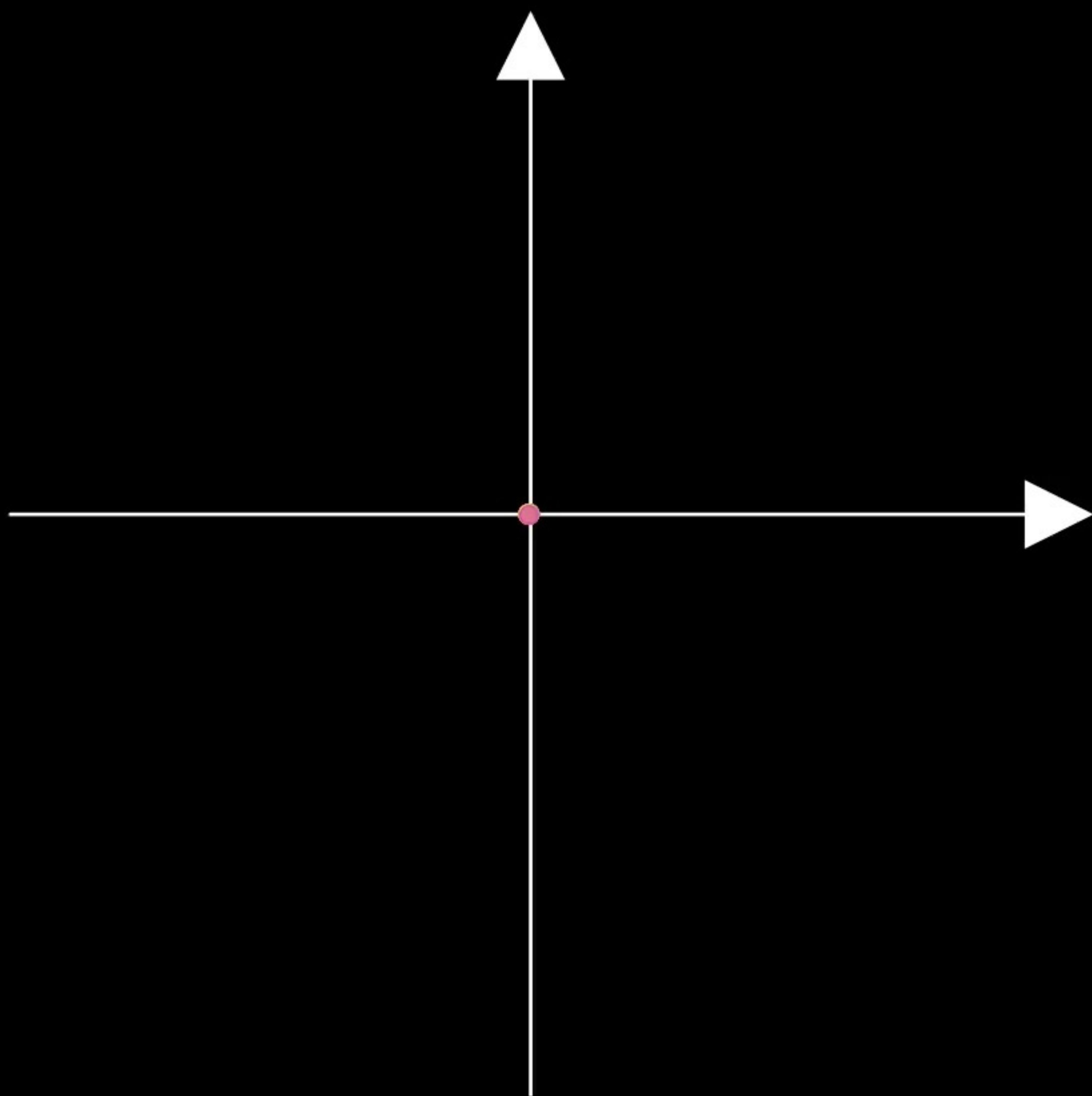
1 0 0 7 5 4 9 8 0 5 9 2 3 4
6 1 2 4 6 2 3 6 2 5 2 3 5 5
6 4 9 7 6 7 0 5 3 1 1 7 3 8
0 9 4 1 5 6 6 0 6 2 8 0 0 6
0 3 6 5 0 9 7 4 6 0 1 2 9 6
0 9 7 3 8 5 0 9 1 1 \ 0 4 2
6 7 8 9 0 2 9 6 1 7 1 0 6 4
4 9 4 5 8 3 3 4 8 2 3 9 6 4
0 9 8 1 1 7 9 7 3 2 9 2 5 5
1 2 7 4 1 4 4 9 5 7 6 9 3 7
0 3 1 1 3 6 3 6 4 4 5 6 4 6
8 1 7 8 3 9 2 1 8 8 7 4 8 6
3 1 8 5 6 1 7 7 2 6 3 7 1 7
5 0 4 6 2 3 3 2 1 5 5 6 3 8

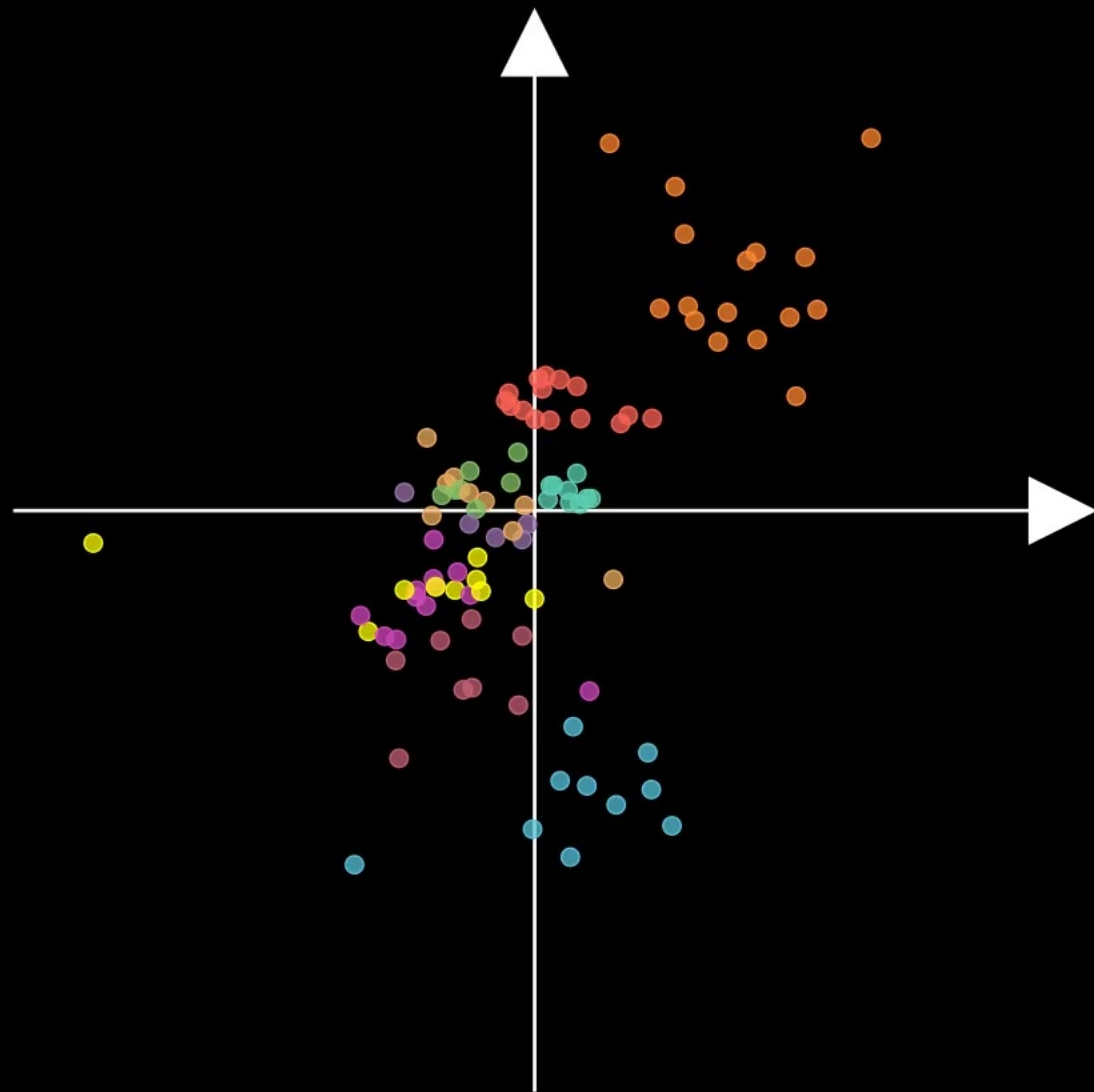
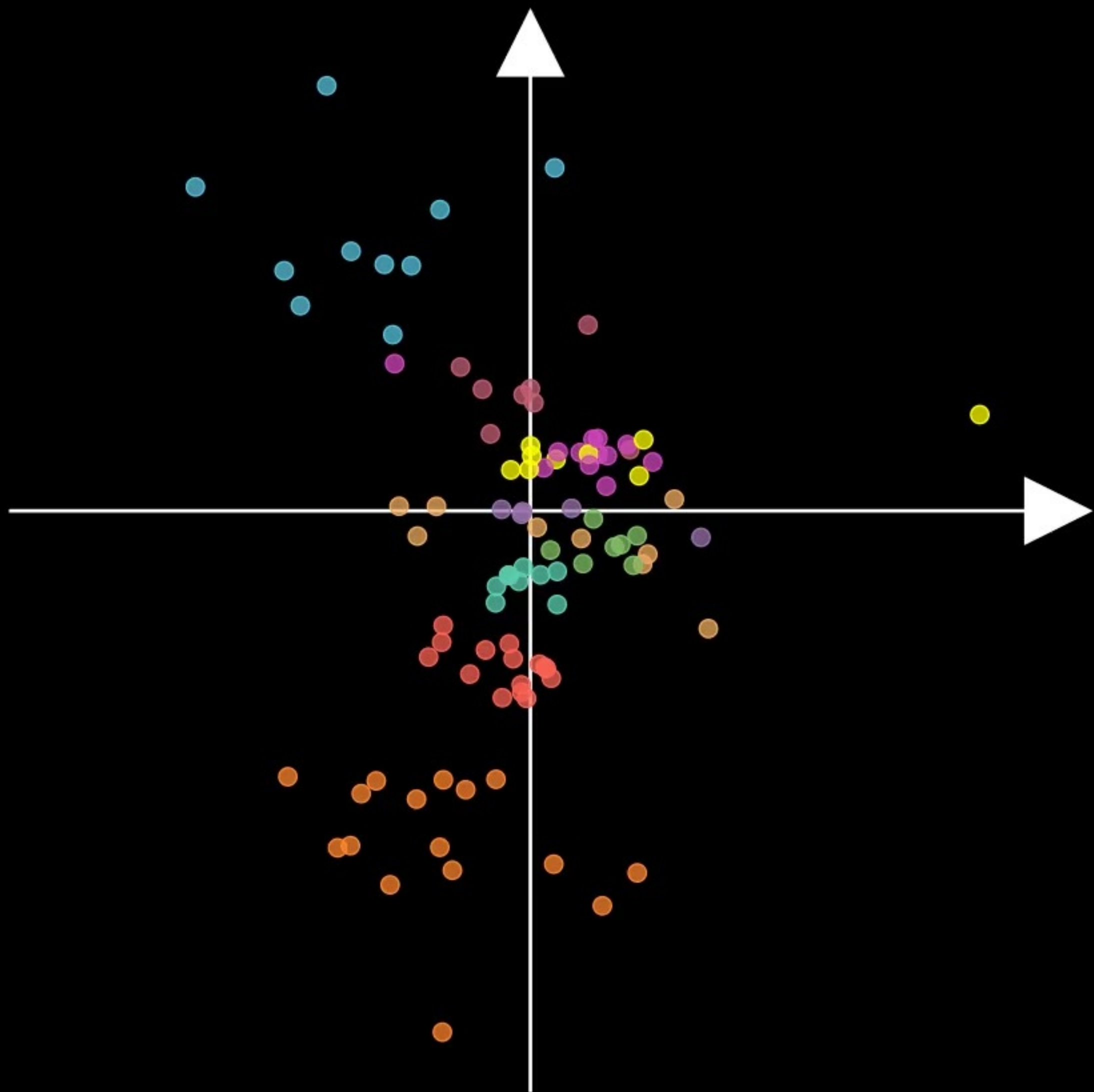
MNIST

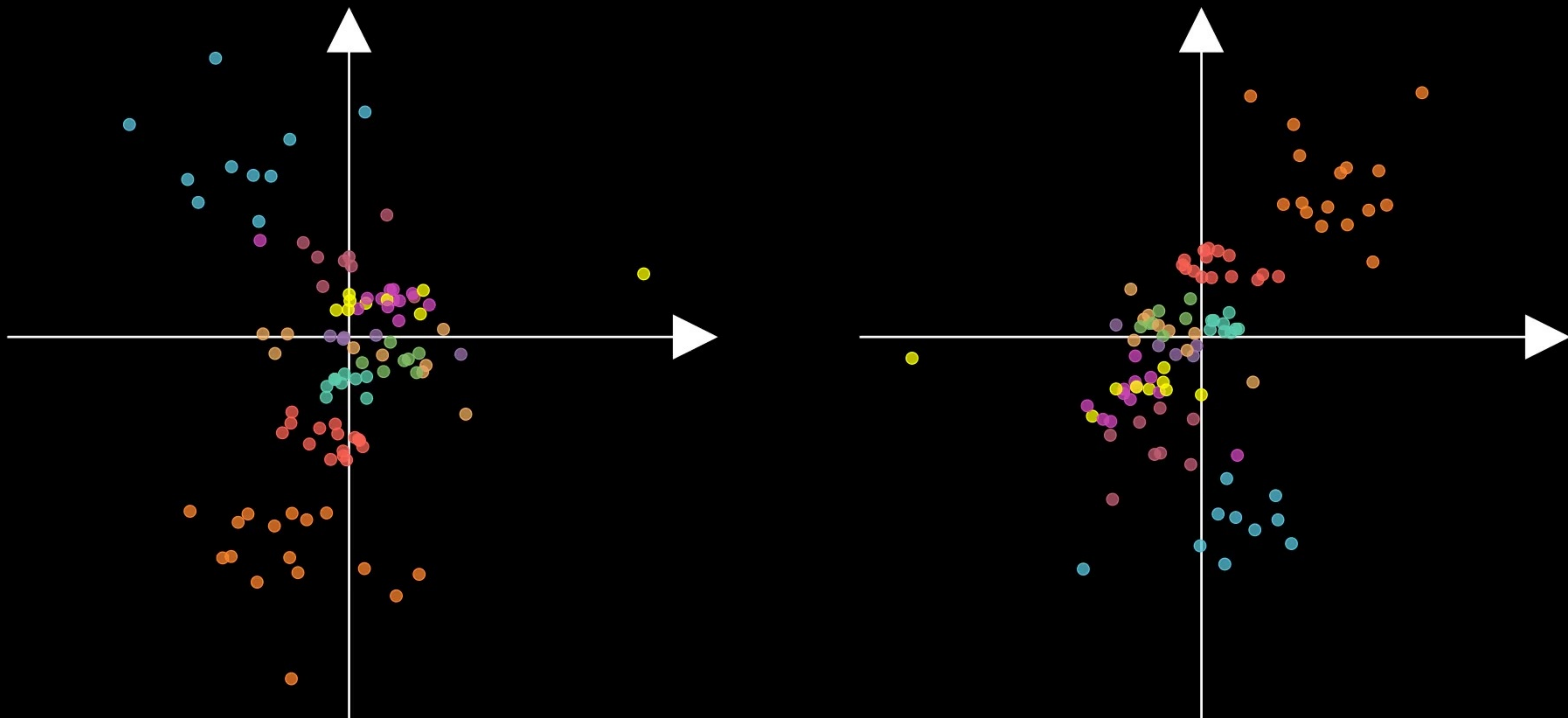
1 0 0 7 5 4 9 8 0 5 9 2 3 4
6 1 2 4 6 2 3 6 2 5 2 3 5 5
6 4 9 7 6 7 0 5 3 1 1 7 3 8
0 9 4 1 5 6 6 0 6 2 8 0 0 6
0 3 6 5 0 9 7 4 6 0 1 2 9 6
0 9 7 3 8 5 0 9 1 1 \ 0 4 2
6 7 8 9 0 2 9 6 1 7 1 0 6 4
4 9 4 5 8 3 3 4 8 2 3 9 6 4
0 9 8 1 1 7 9 7 3 2 9 2 5 5
1 2 7 4 1 4 4 9 5 7 6 9 3 7
0 3 1 1 3 6 3 6 4 4 5 6 4 6
8 1 7 8 3 9 2 1 8 8 7 4 8 6
3 1 8 5 6 1 7 7 2 6 3 7 1 7
5 0 4 6 2 3 3 2 1 5 5 6 3 8

MNIST

1 9 2 3 9 9 0 0 9 5 7 2 8 6
4 8 4 6 4 6 5 0 1 6 1 3 6 1
1 5 9 7 3 0 6 0 6 3 4 5 3 6
0 2 6 7 5 2 4 3 5 9 7 0 0 2
3 7 7 2 4 6 4 2 6 2 1 2 9 7
2 7 1 3 2 2 4 3 0 7 6 0 0 1
5 9 6 3 6 1 4 1 1 7 5 6 1 4
5 3 1 8 9 2 9 2 8 4 3 5 6 6
4 9 0 7 0 6 7 5 8 8 7 1 0 4
7 1 3 0 3 5 3 4 8 0 1 0 3 6
5 5 8 2 4 8 3 8 5 4 3 6 6 7
1 7 1 7 4 8 8 6 4 9 6 2 9 4
9 5 9 2 8 9 1 7 6 1 0 0 5 3
8 7 3 4 6 3 8 6 1 1 9 1 5 9







...different latent spaces?

The shape of the latent space

Contributing factors...

The shape of the latent space

Contributing factors...

Ideally

- Data Distribution
- The task
- Additional constraints (implicit or explicit)

The shape of the latent space

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In practice

- Parameter initialization
- Data shuffling
- Training seed
- Hyperparameters
- ...

The shape of the latent space

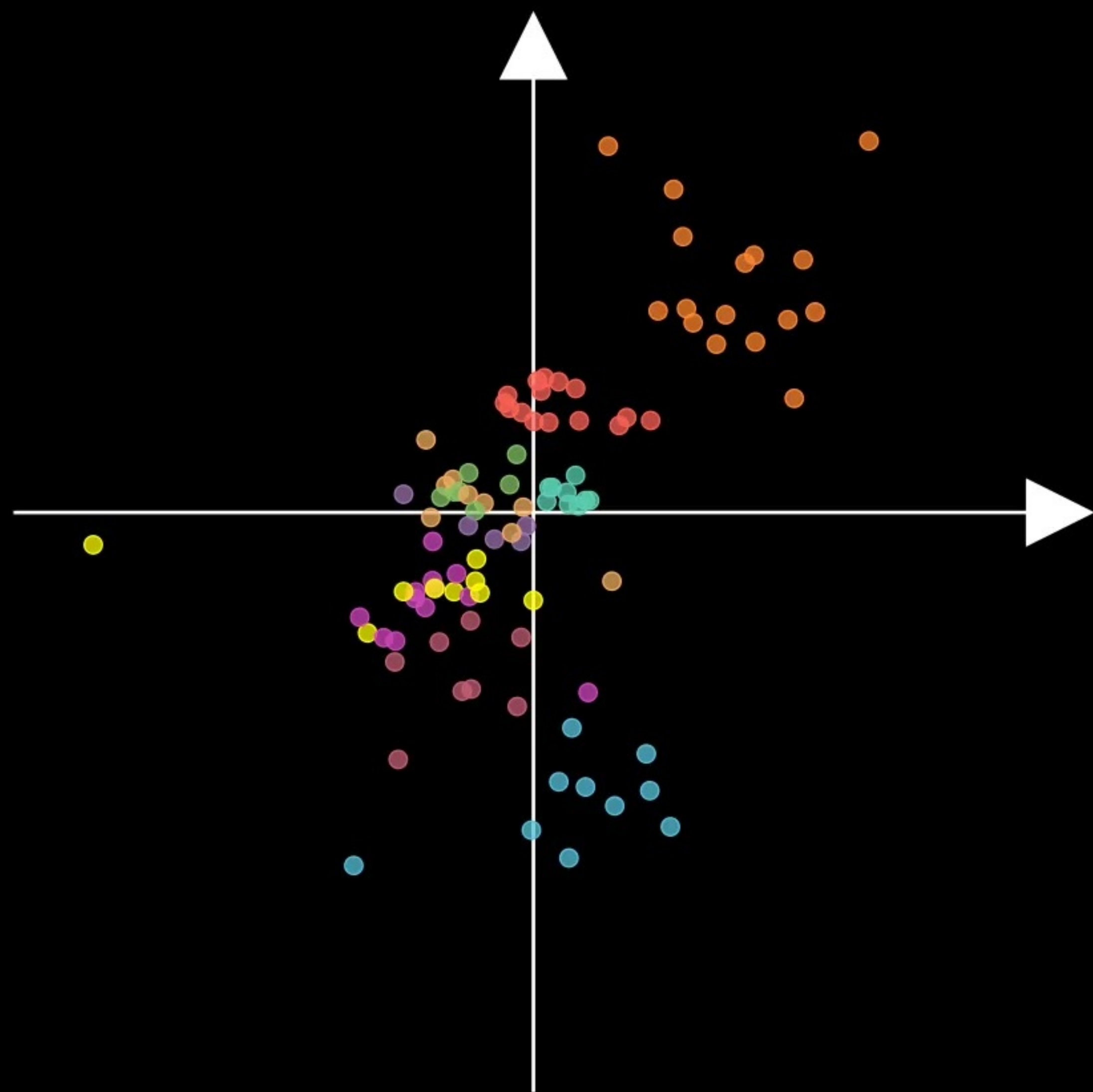
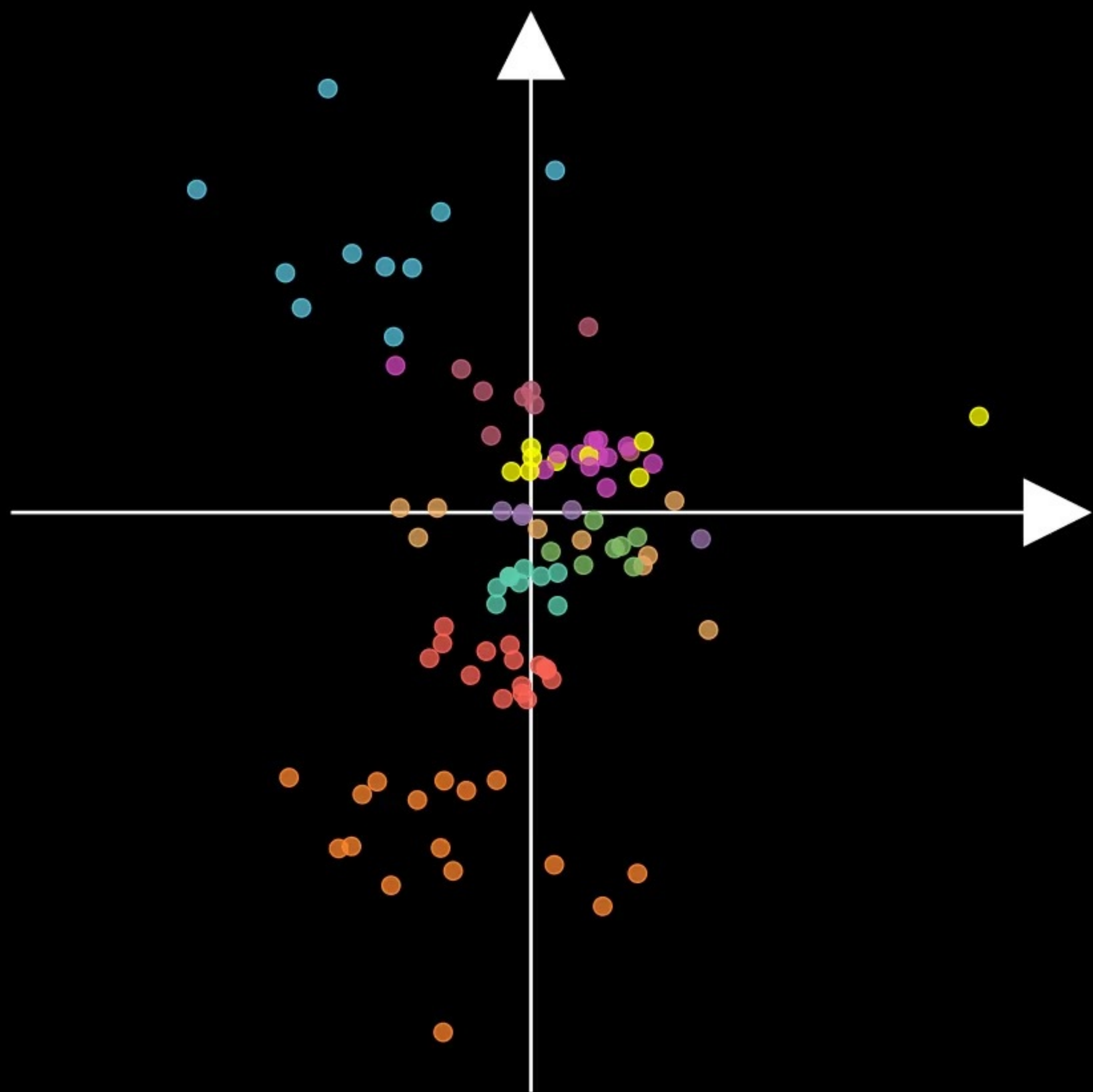
Contributing factors...

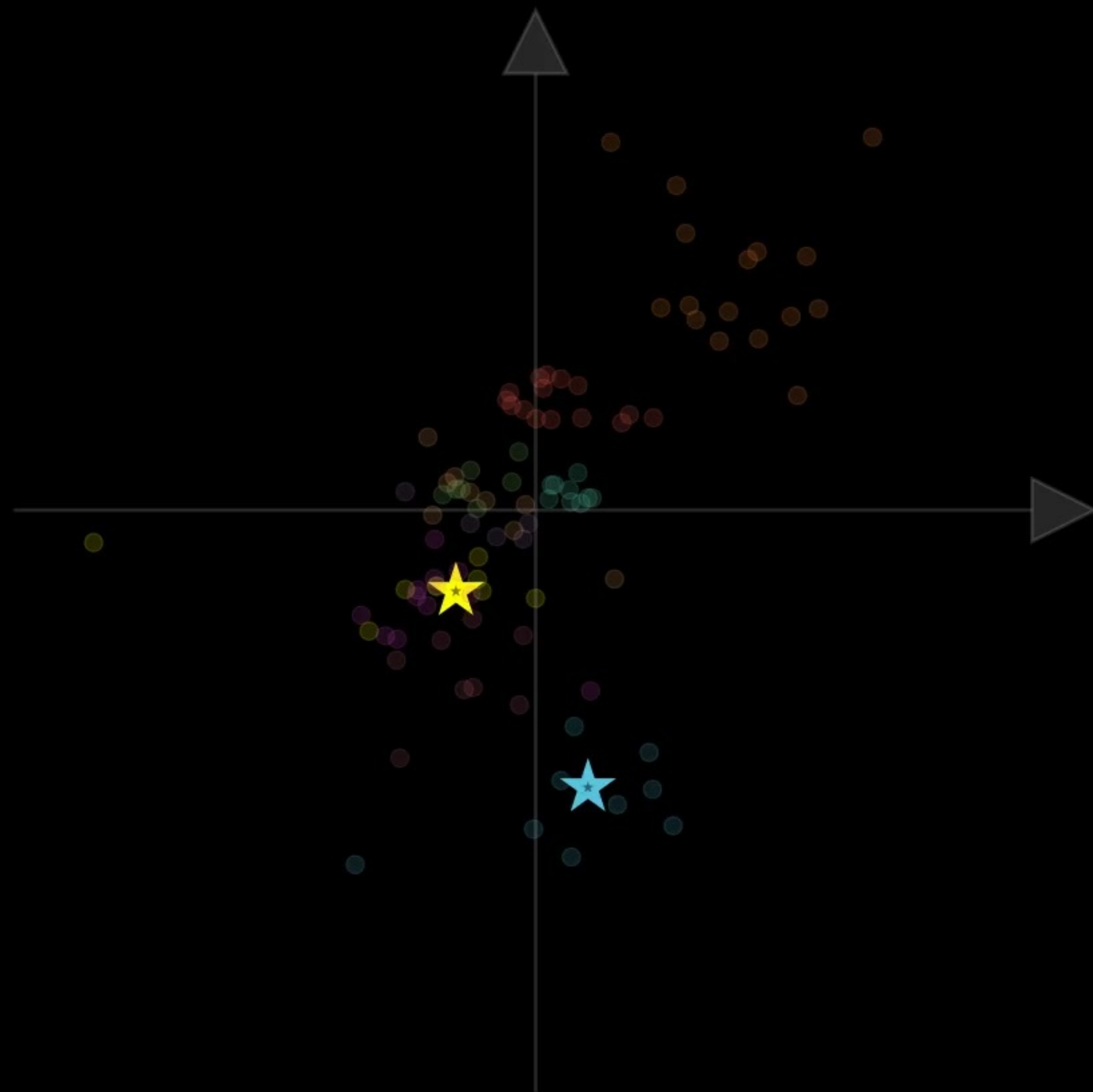
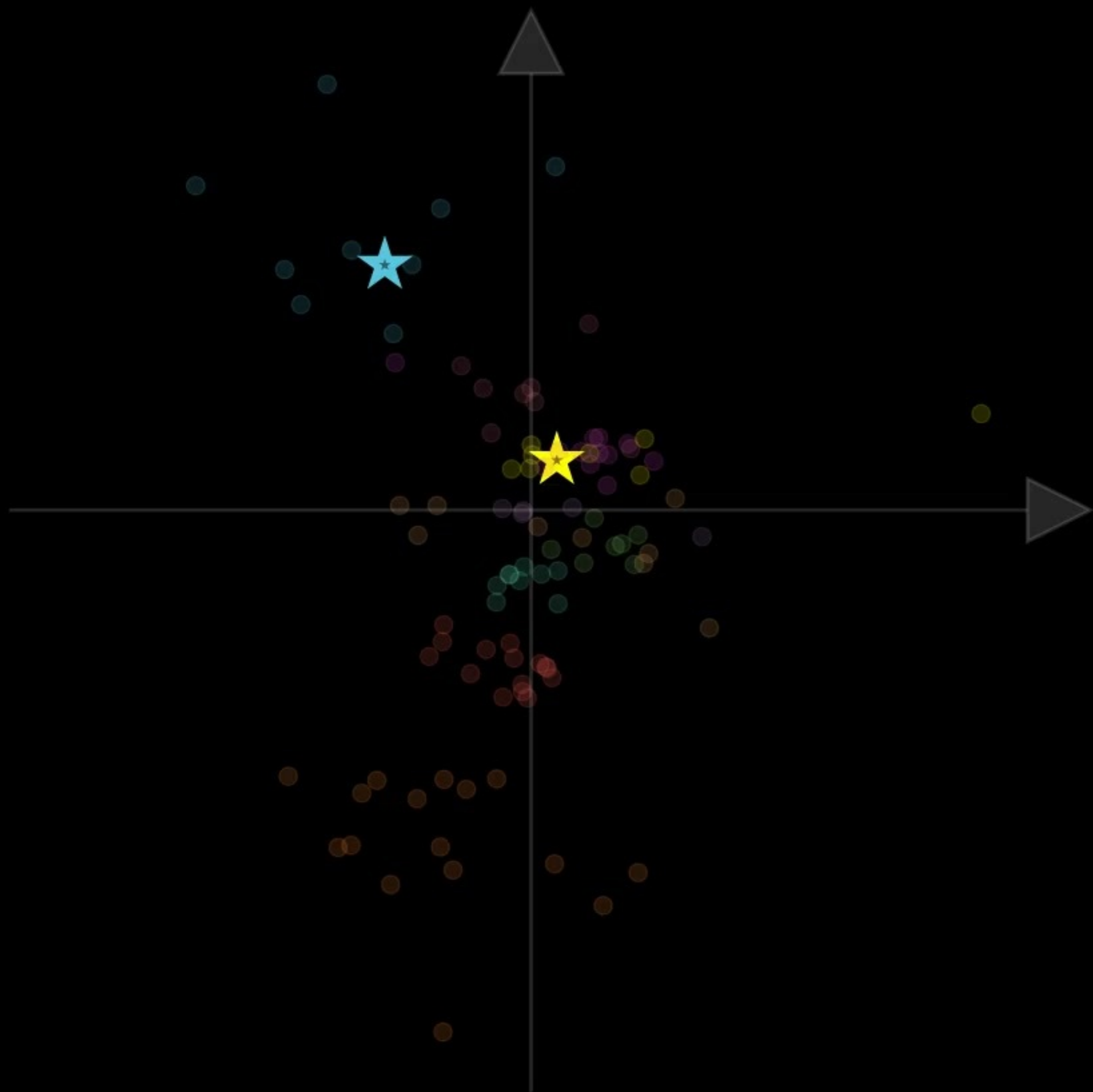
Ideally

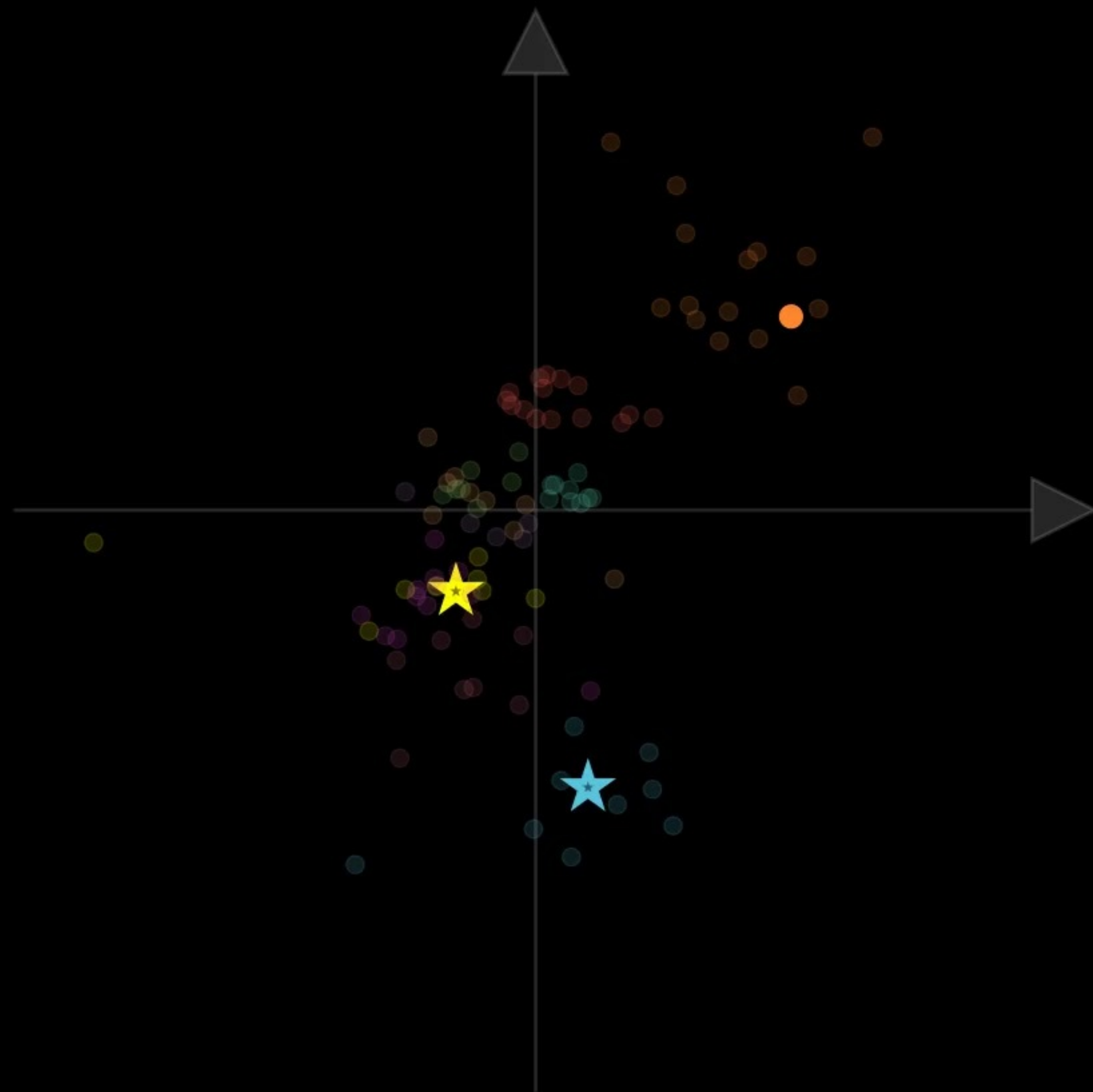
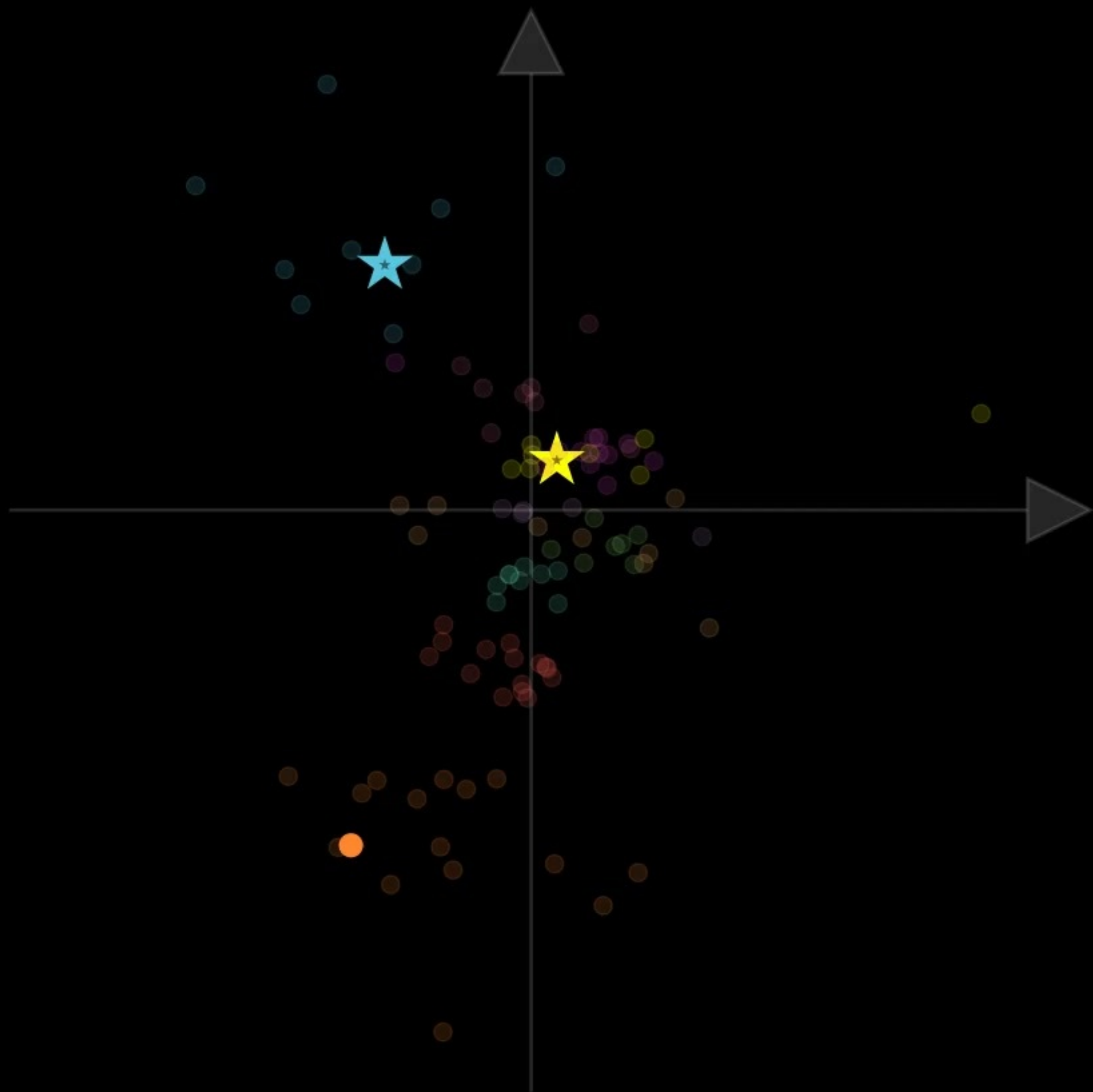
- Data Distribution
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- Additional constraints (implicit or explicit)

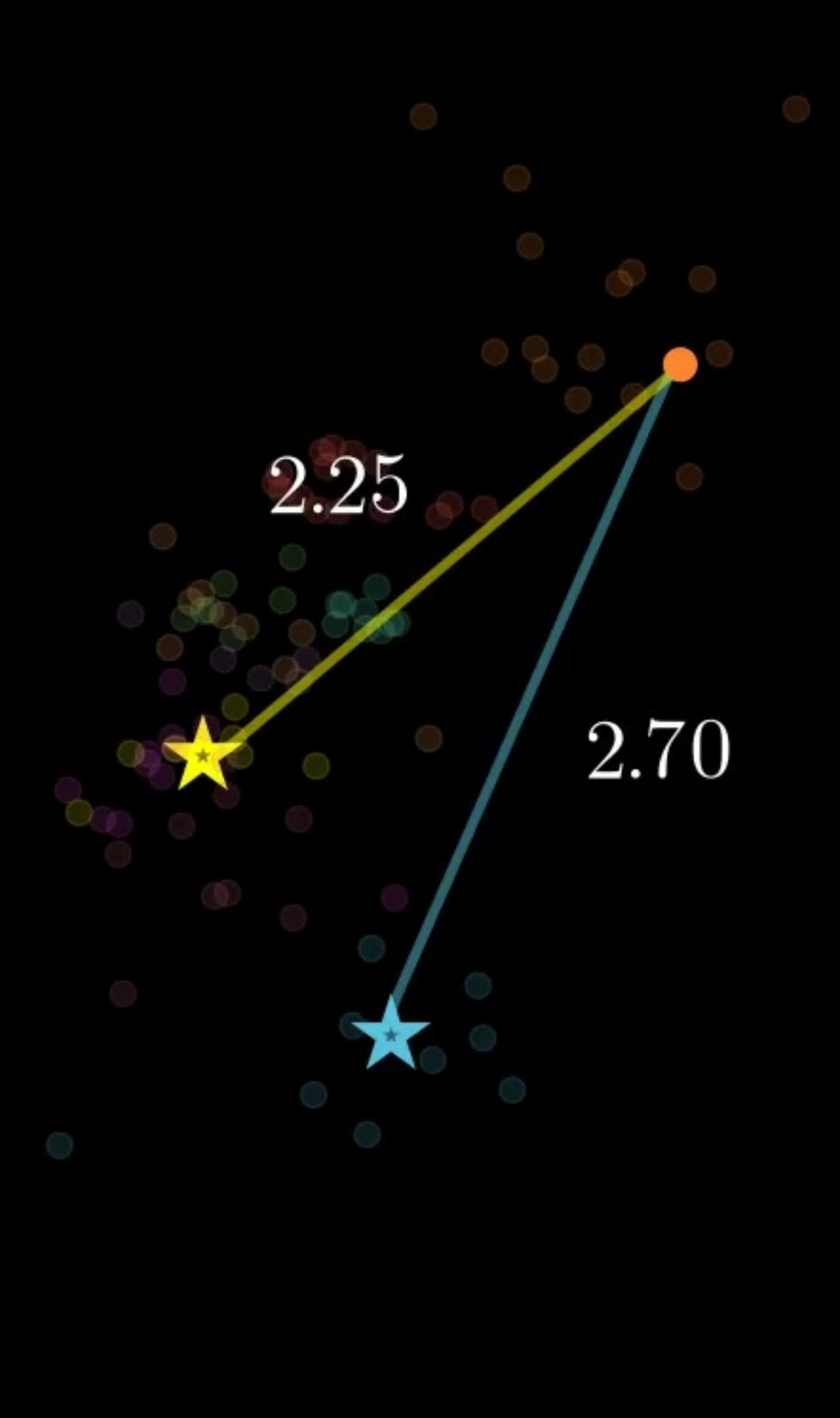
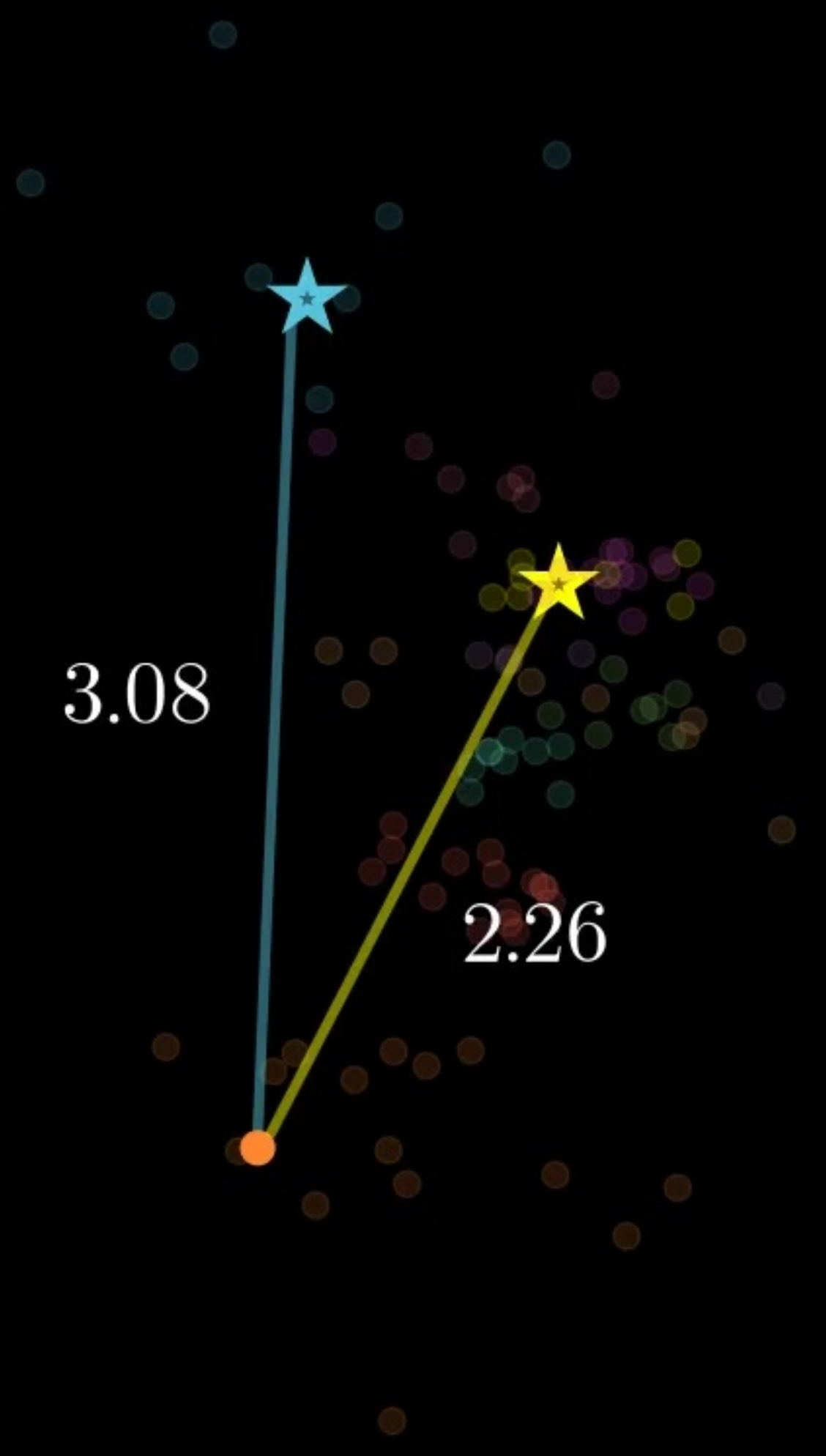
In practice

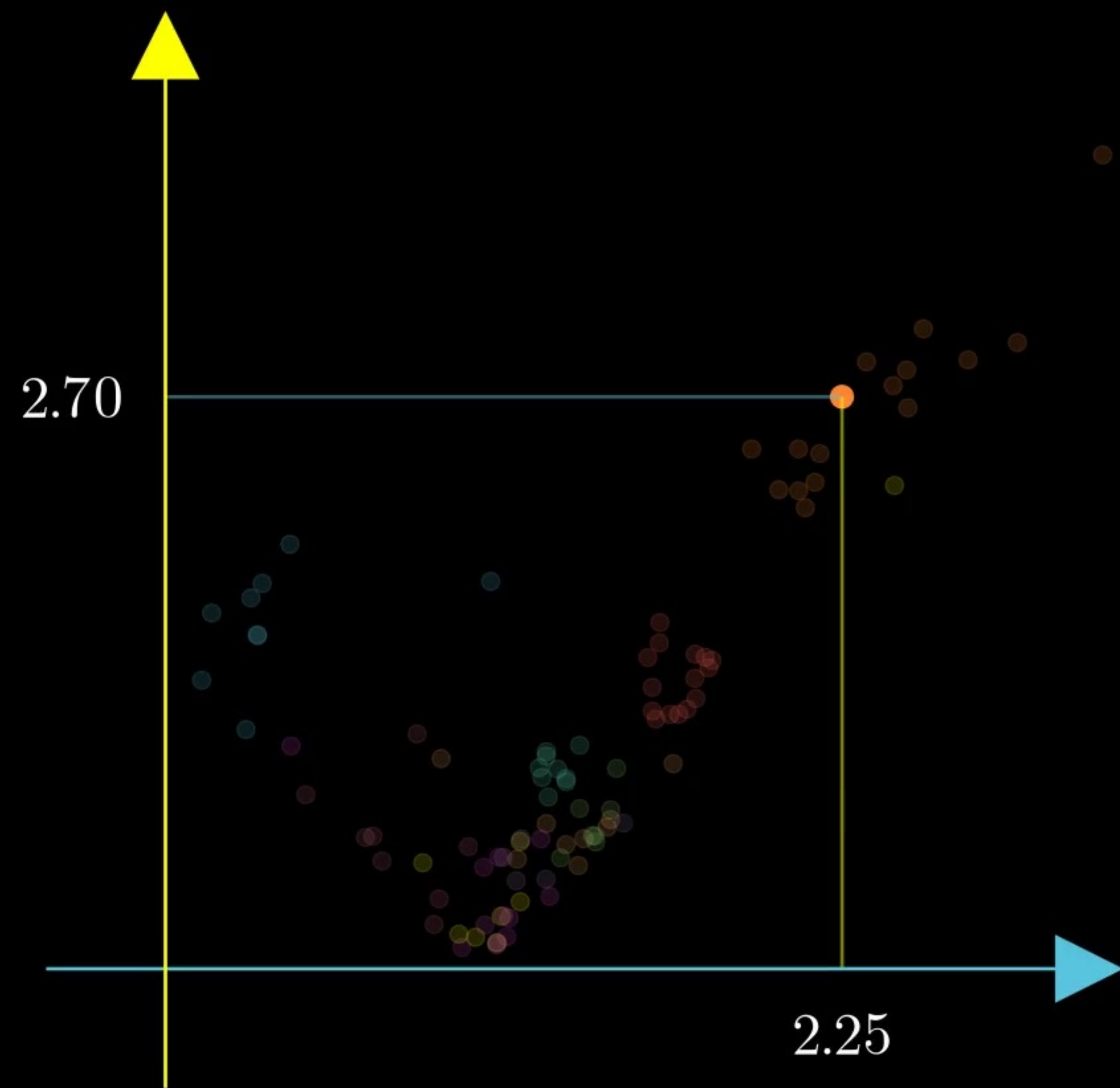
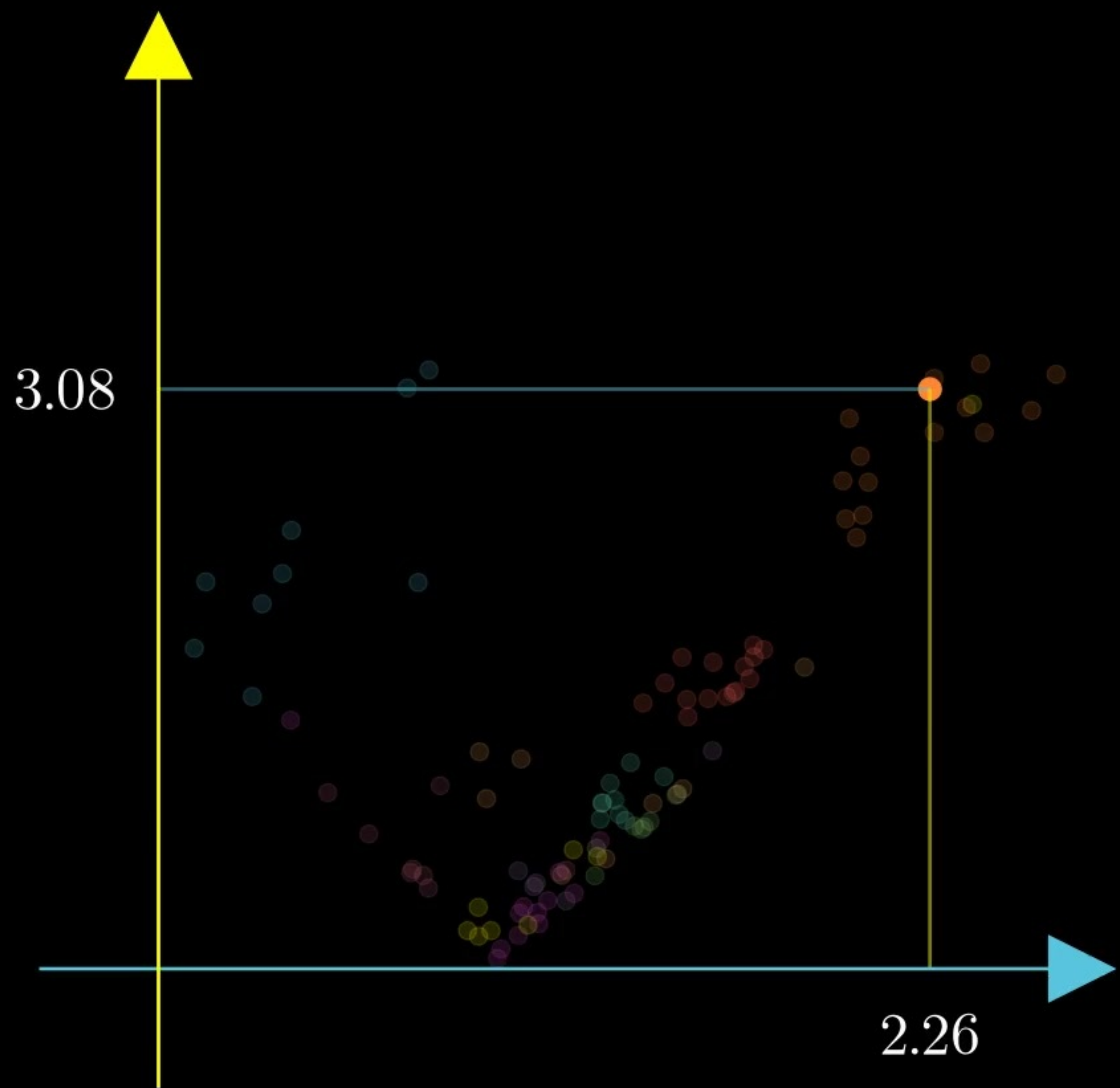
- Parameter initialization
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- Hyperparameters
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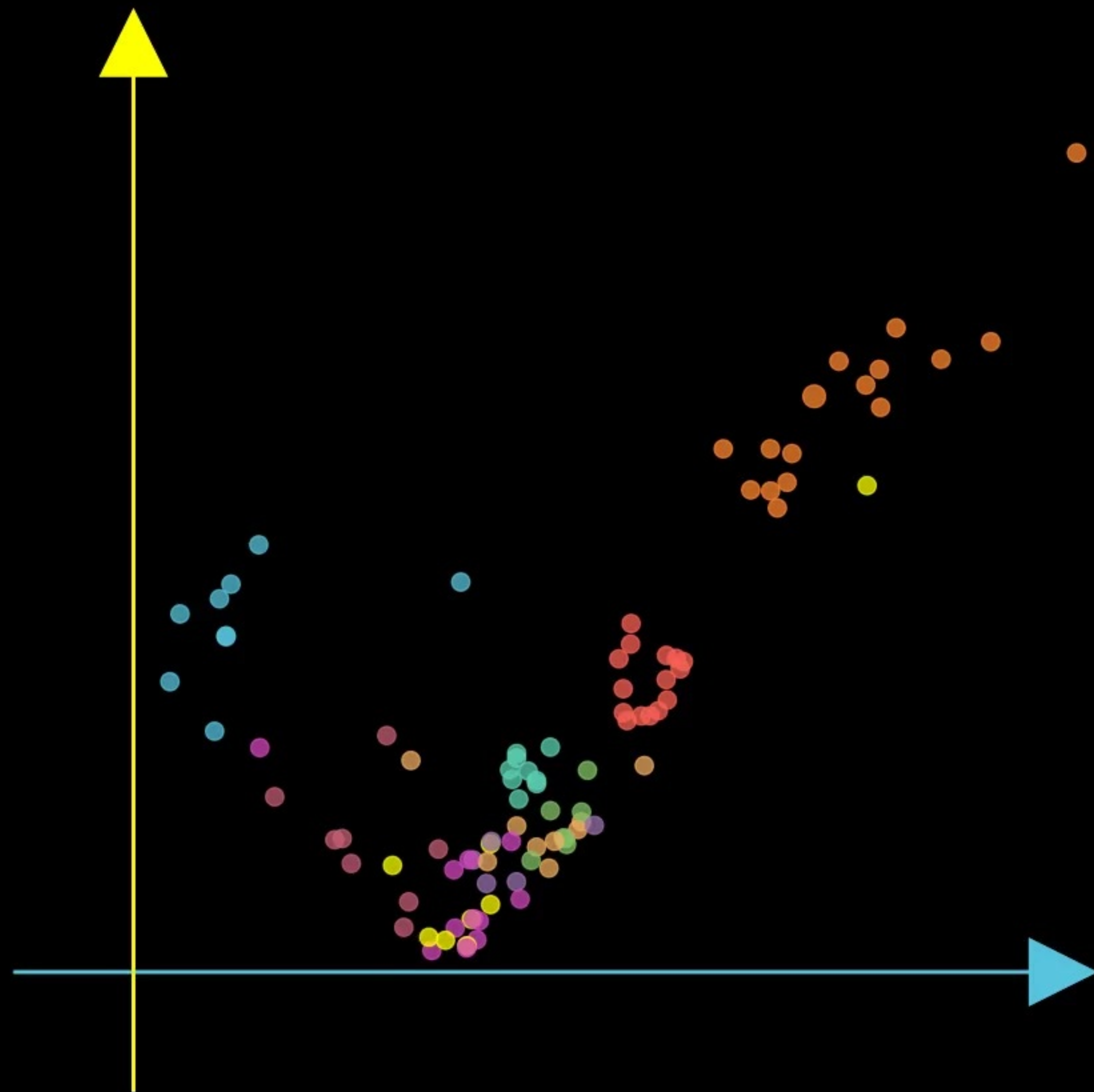
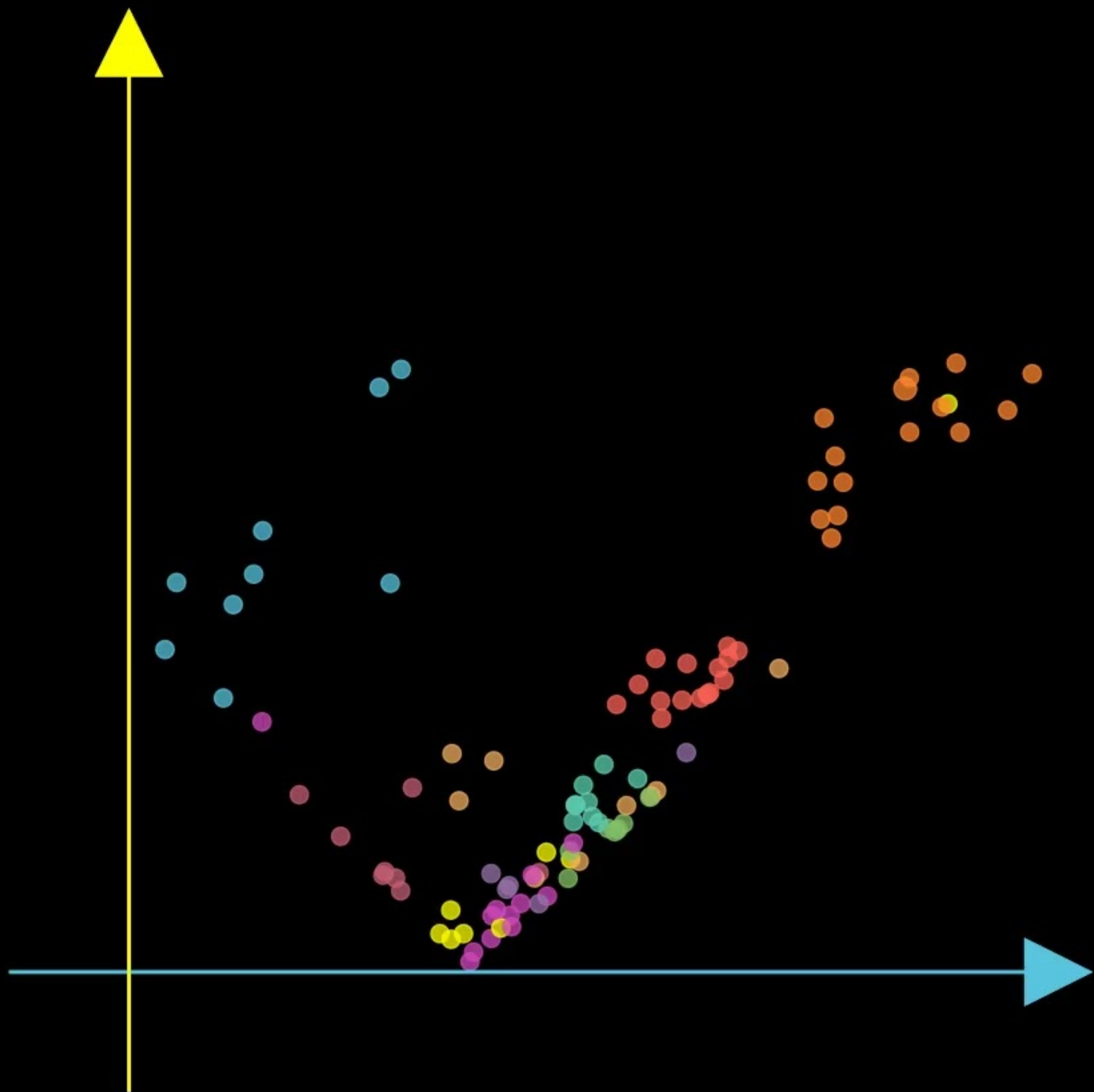












Sources of variations in the training process



distinct latent spaces

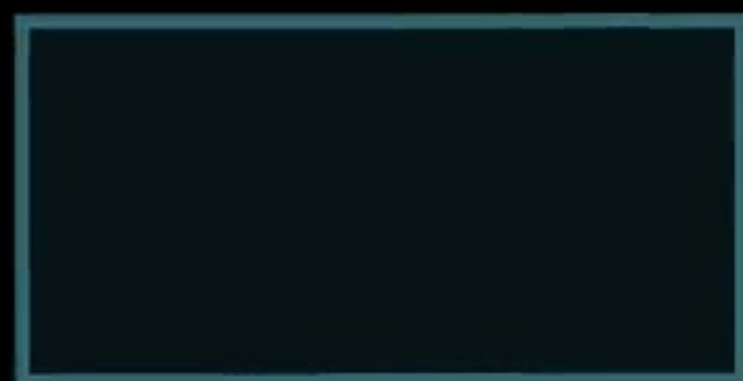
Can we model how the latent spaces are affected?

Yes!

As a near-isometric + rescaling transformation \mathcal{T} of the latent space

Yes!

As a near-isometric + rescaling transformation \mathcal{T} of the latent space



Yes!

As a near-isometric + rescaling transformation \mathcal{T} of the latent space

...we need a representation invariant to \mathcal{T}

e

T

Relative Representations

Algorithm

- Select a subset \mathbb{A} of the training set \mathbb{X} , denoted **anchors**
- Consider each **sample** x
- Consider an encoding function E
- The **relative representation** of x is:

$$\mathbf{r}_{\mathbf{x}^{(i)}} = \left(\text{sim}(\mathbf{e}_{\mathbf{x}^{(i)}}, \mathbf{e}_{\mathbf{a}^{(1)}}), \text{sim}(\mathbf{e}_{\mathbf{x}^{(i)}}, \mathbf{e}_{\mathbf{a}^{(2)}}), \dots, \text{sim}(\mathbf{e}_{\mathbf{x}^{(i)}}, \mathbf{e}_{\mathbf{a}^{(|\mathbb{A}|)}}) \right)$$

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anchors

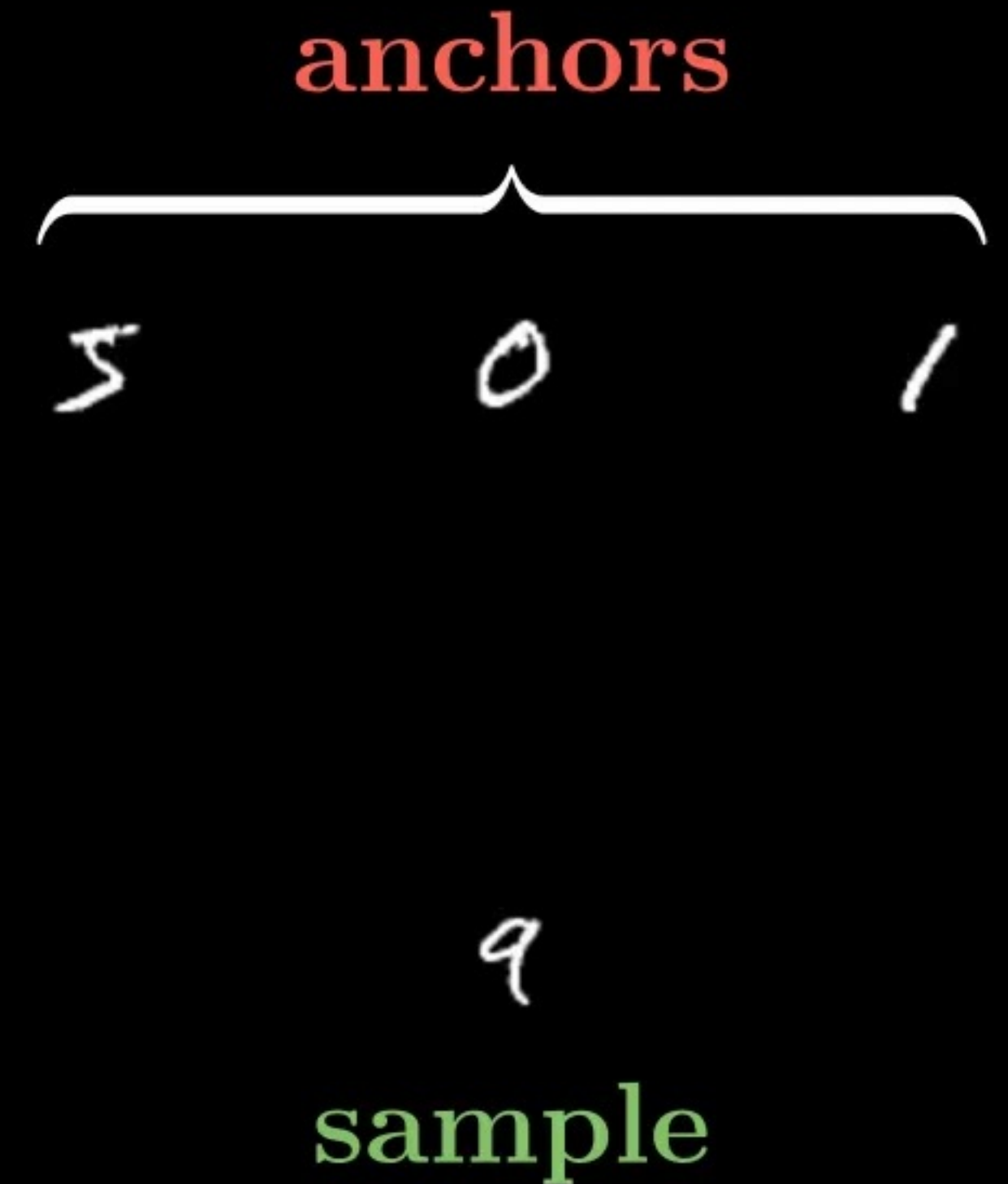


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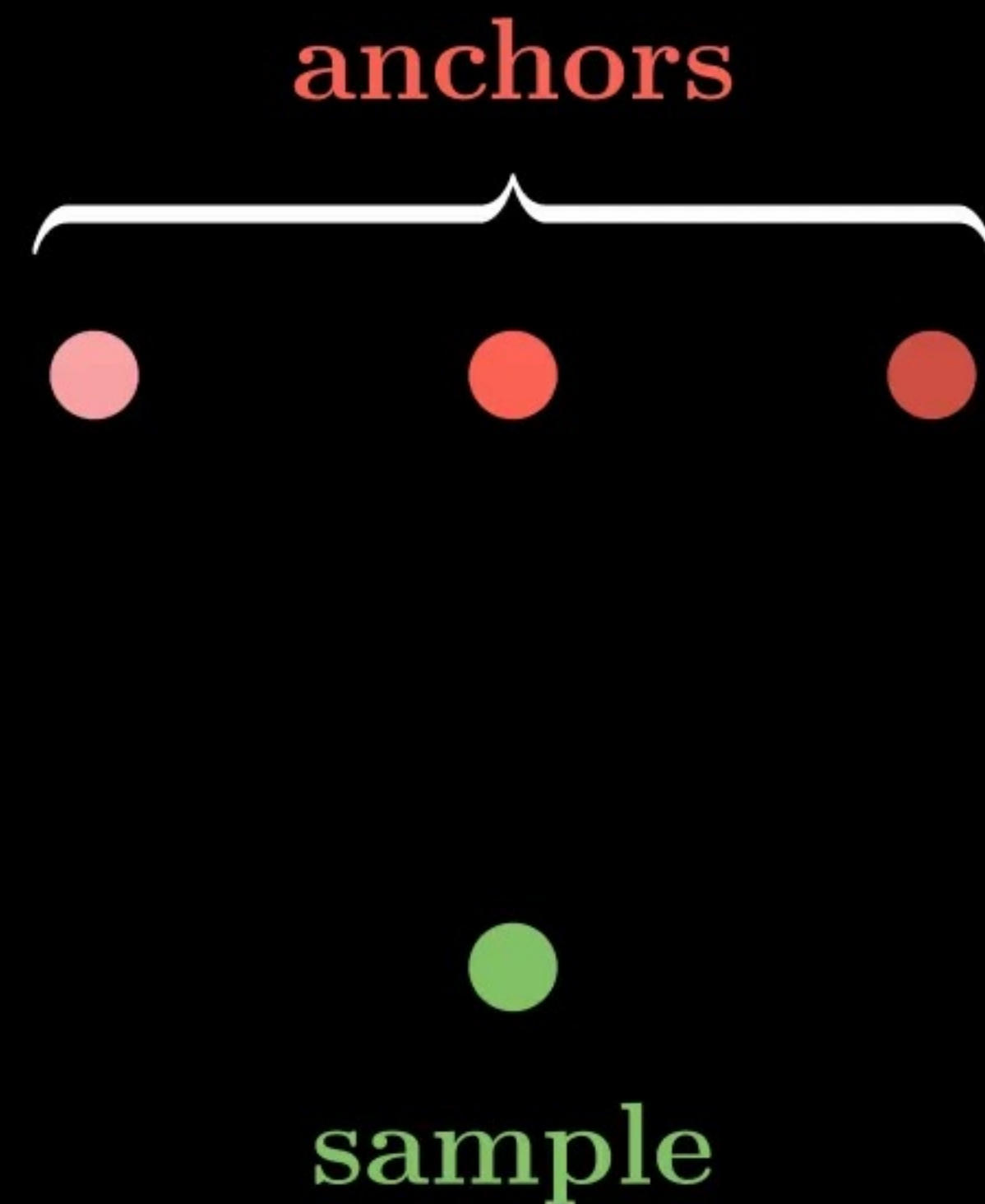


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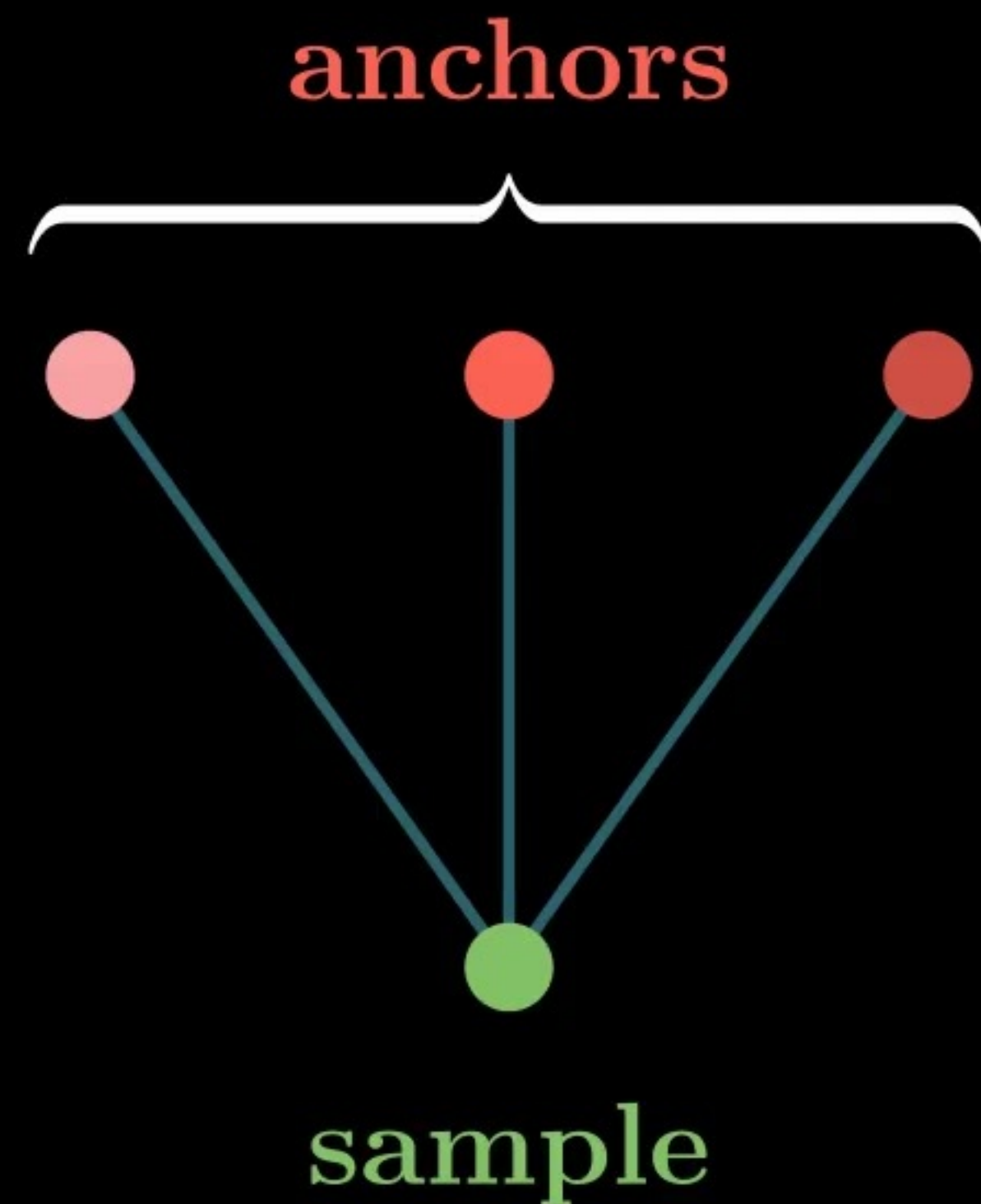
$$\mathbf{r}_{\mathbf{x}^{(i)}} = (\text{sim}(\mathbf{e}_{\mathbf{x}^{(i)}}, \mathbf{e}_{\mathbf{a}^{(1)}}), \text{sim}(\mathbf{e}_{\mathbf{x}^{(i)}}, \mathbf{e}_{\mathbf{a}^{(2)}}), \dots, \text{sim}(\mathbf{e}_{\mathbf{x}^{(i)}}, \mathbf{e}_{\mathbf{a}^{(|\mathbb{A}|)}}))$$



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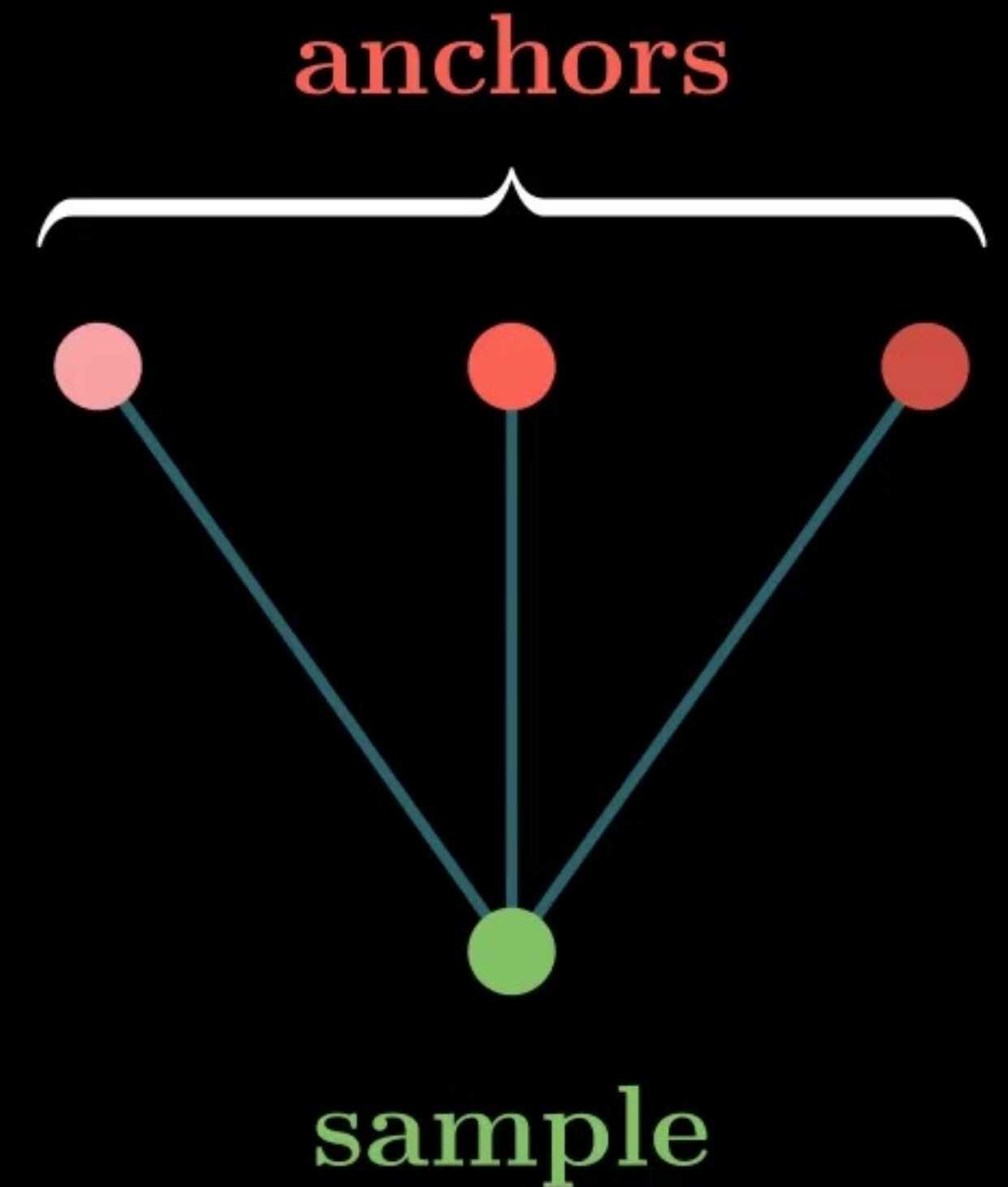
Algorithm

sim = cosine similarity

```
import torch
import torch.nn.functional as F

def relative_projection(x, anchors):
    x = F.normalize(x, p=2, dim=-1)
    anchors = F.normalize(anchors, p=2, dim=-1)
    return torch.einsum("bm, am -> ba", x, anchors)
```

differentiable!



Properties

- The size of $\mathbf{r}_{\mathbf{x}^{(i)}}$ depends on the number of anchors
- The anchors and similarity function choices determine the representation properties

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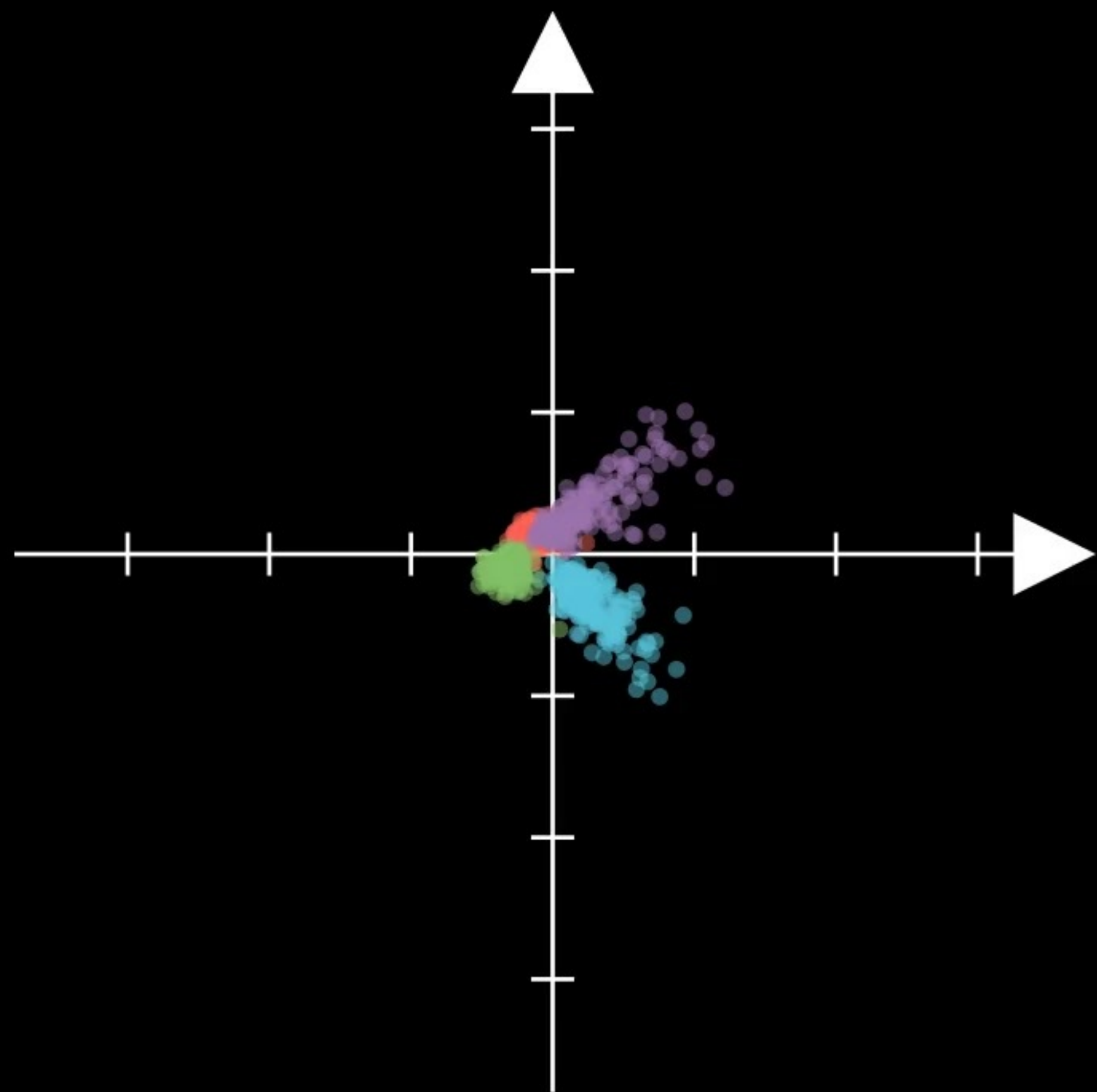
invariant to **rescaled isometric transformations** of the latent space

Semantic Invariance

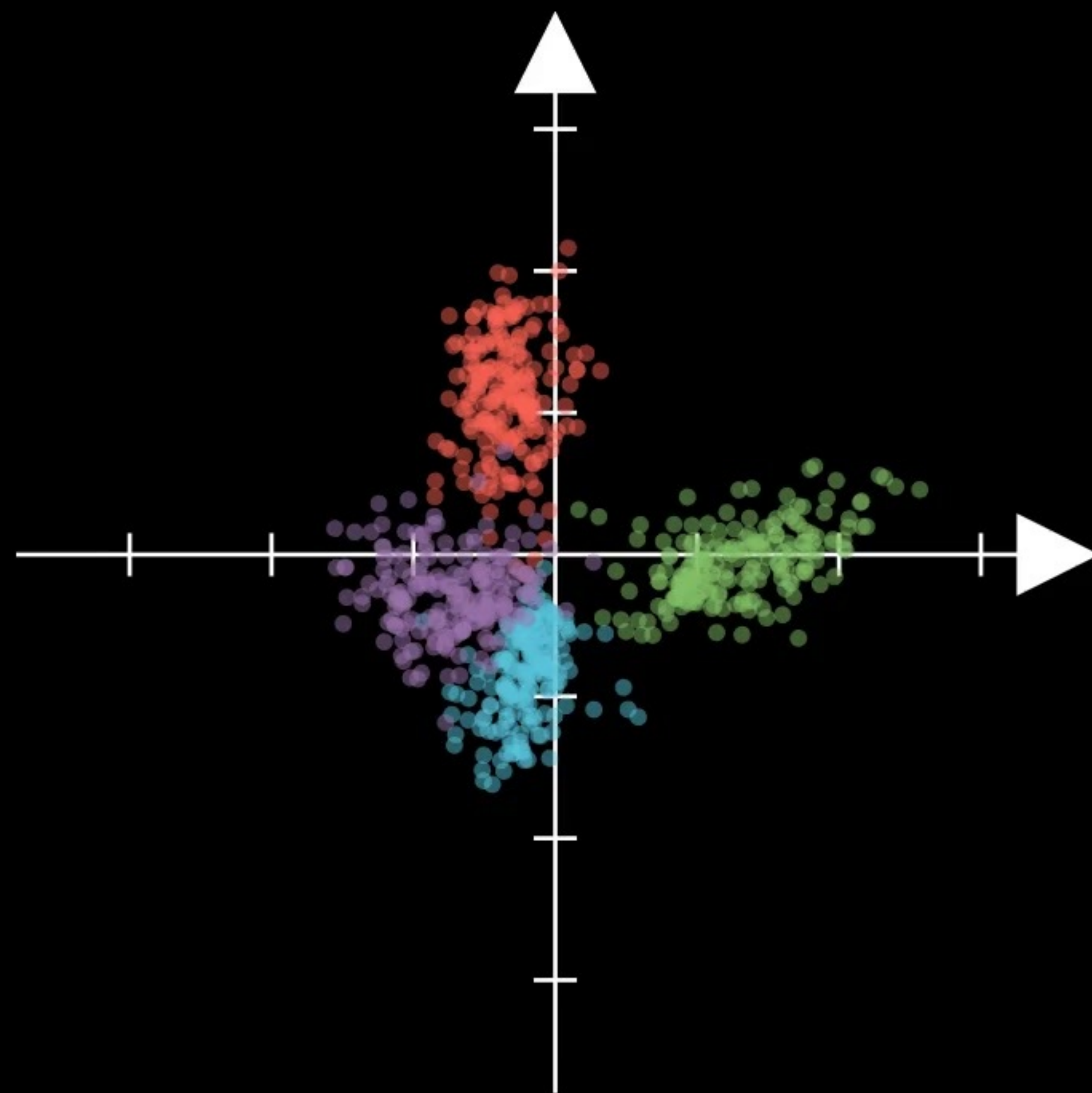
Given some *words*...

...consider their *embeddings* in different spaces

FastText



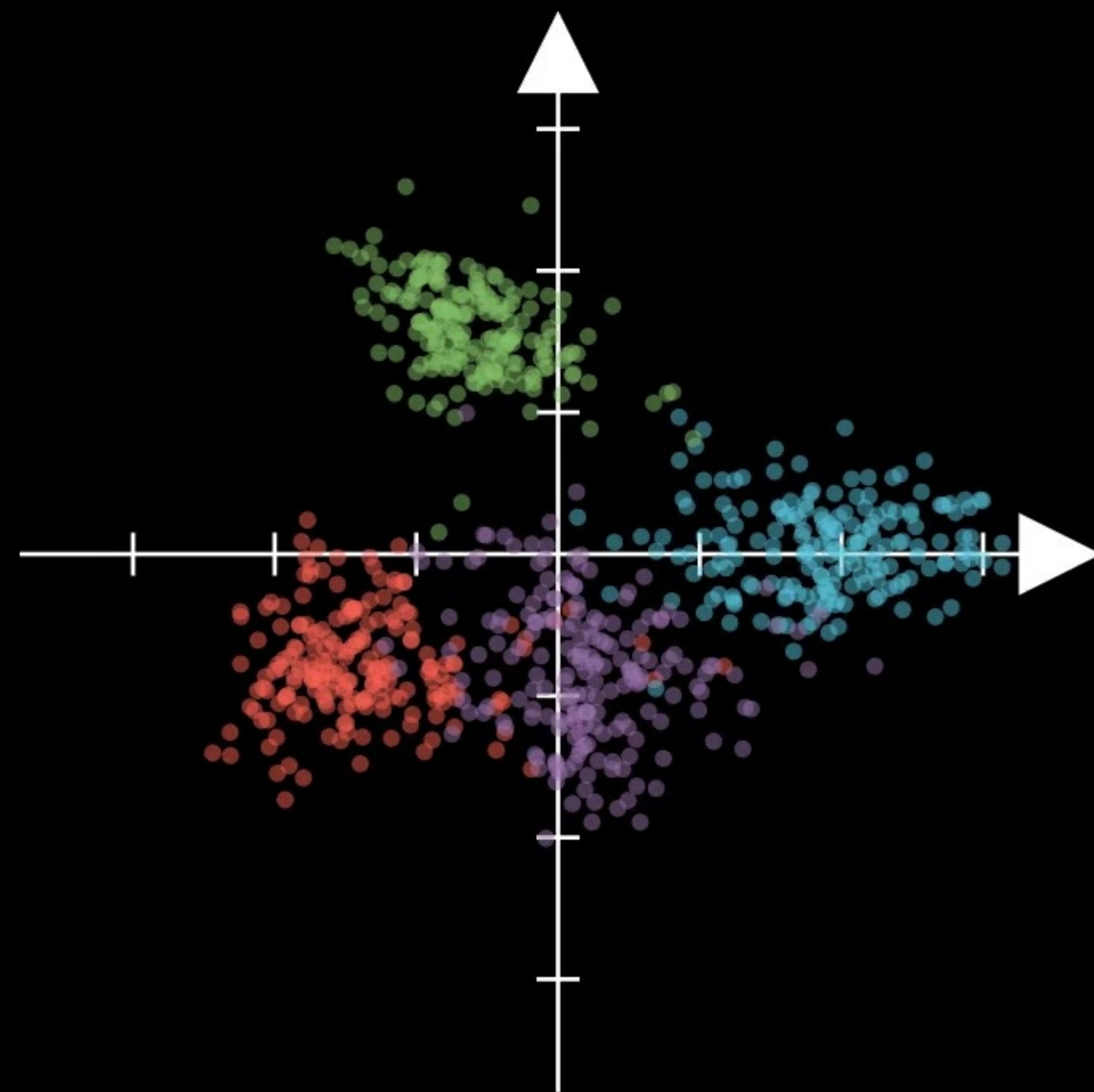
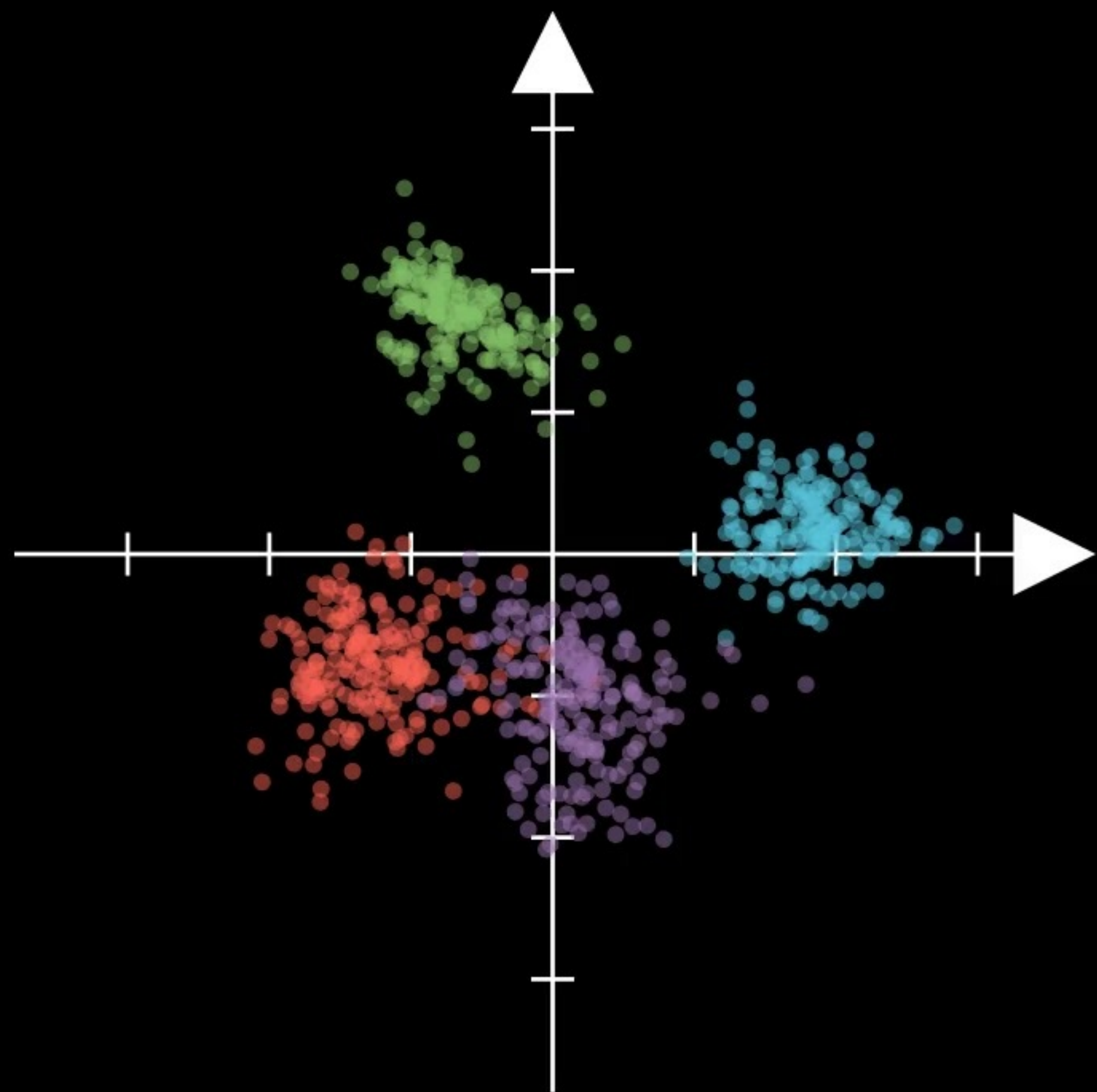
Word2Vec



Absolute Spaces

FastText

Word2Vec



Relative Spaces

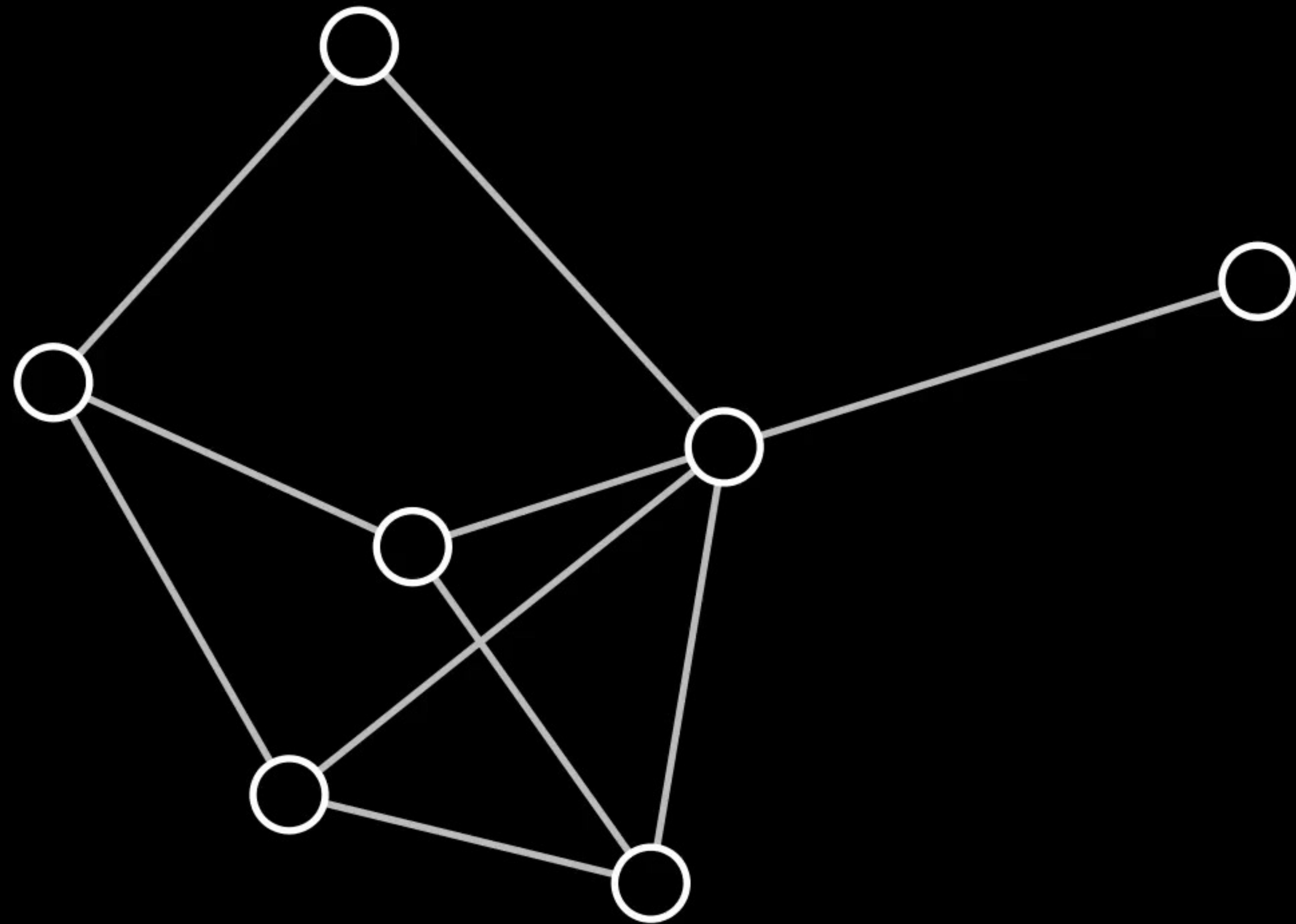
latent spaces with the same semantics



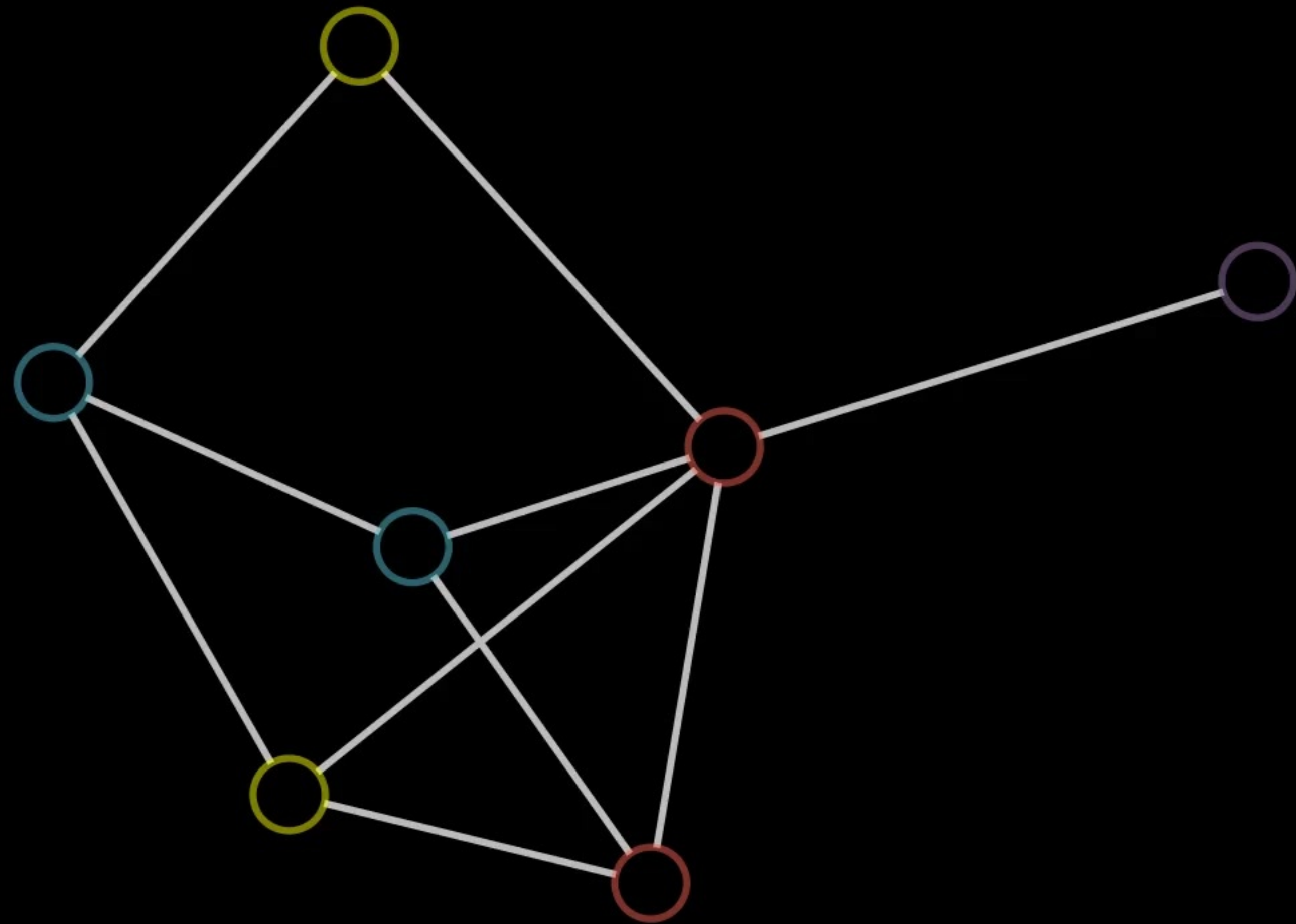
represented **similarly** in the relative space

Latent Performance Metric

Consider a node classification task...

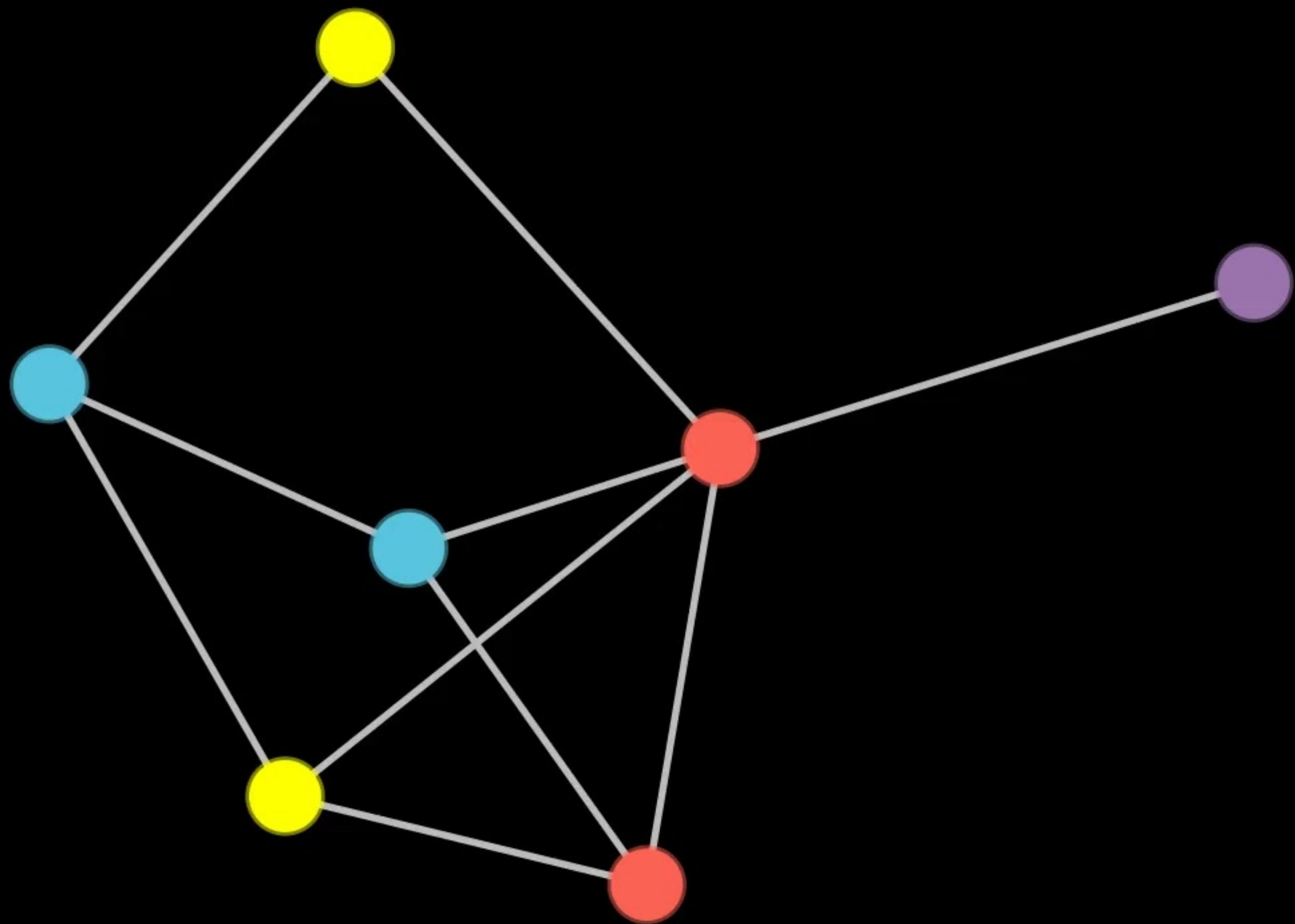


Cora dataset

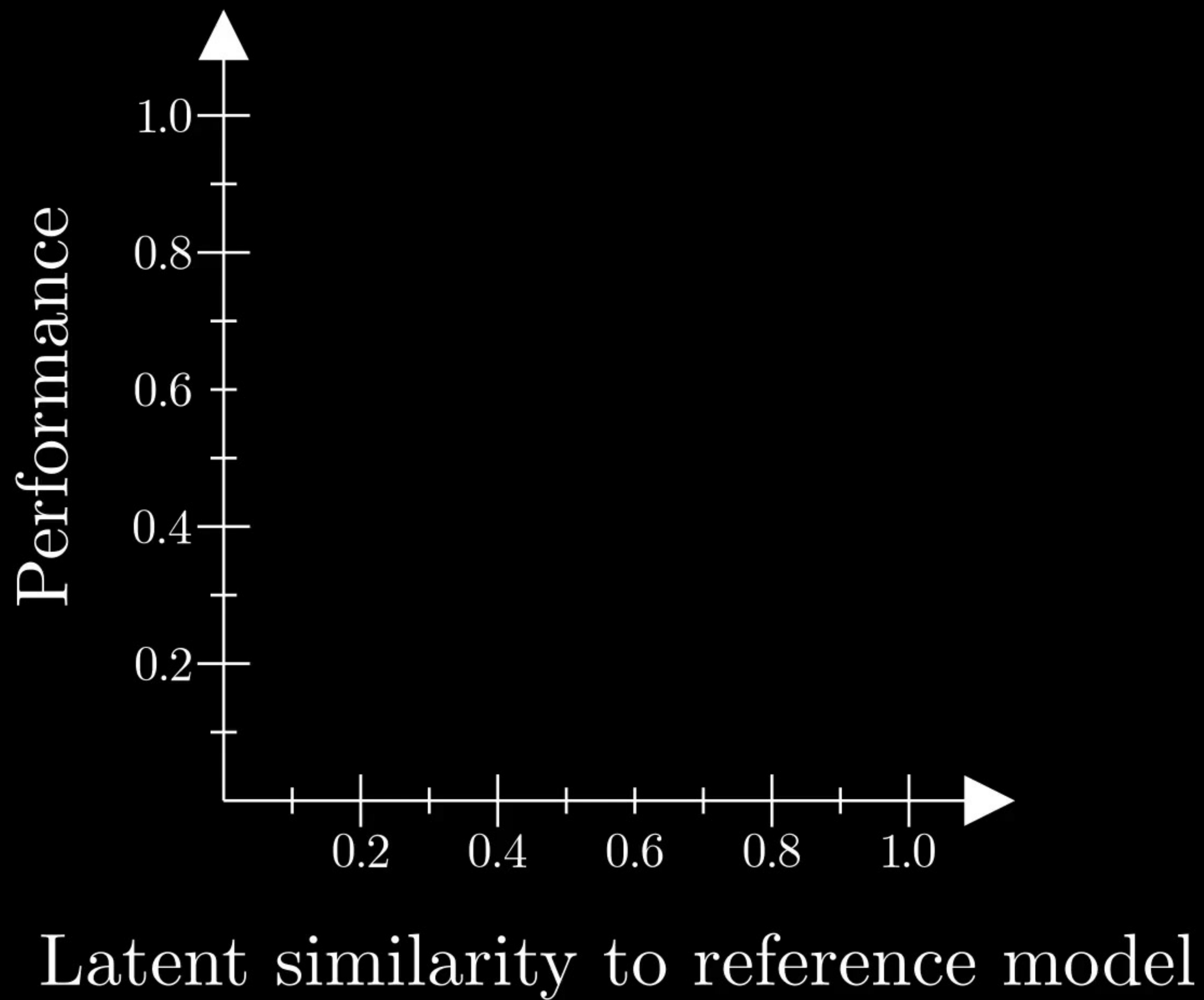


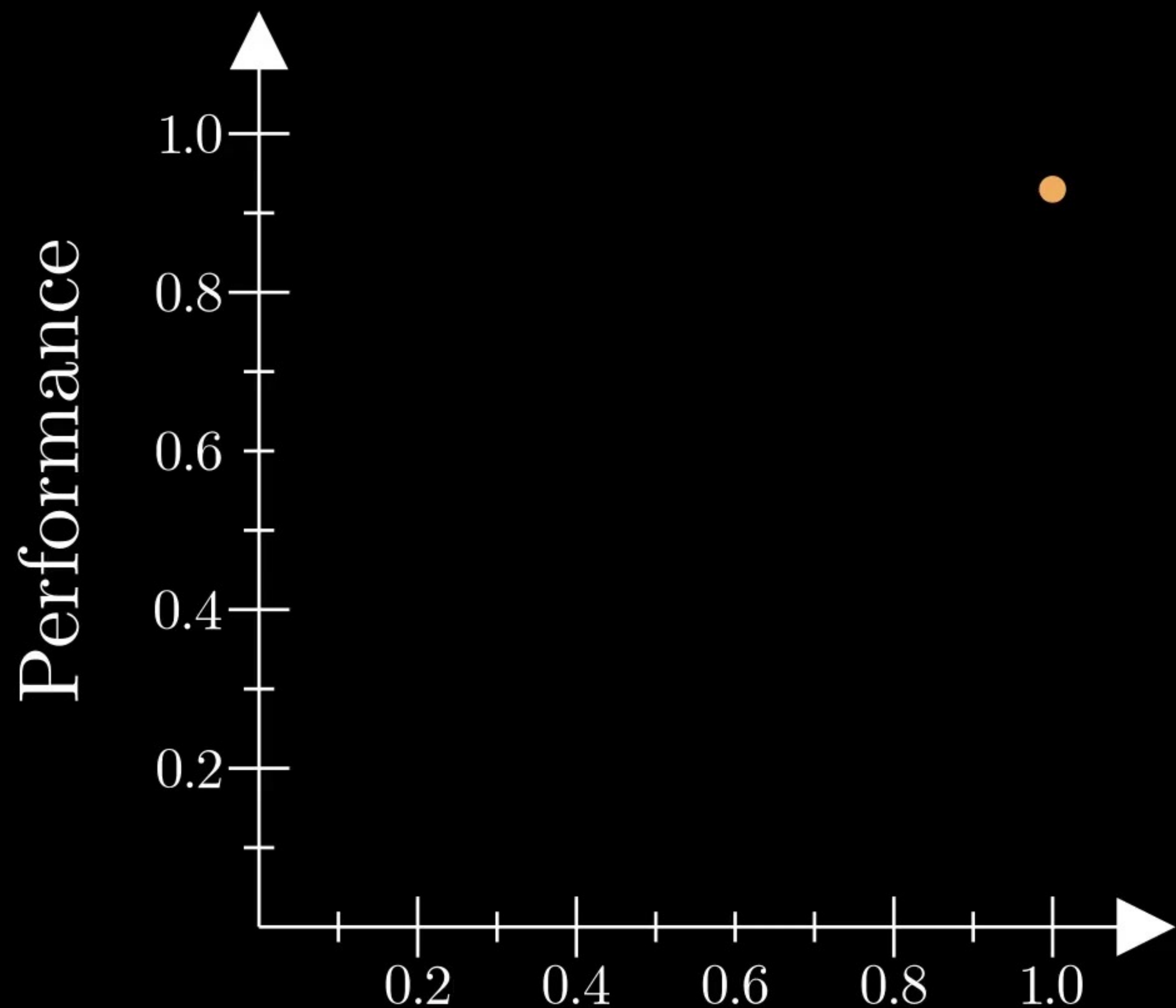
Cora dataset

given a good
reference model



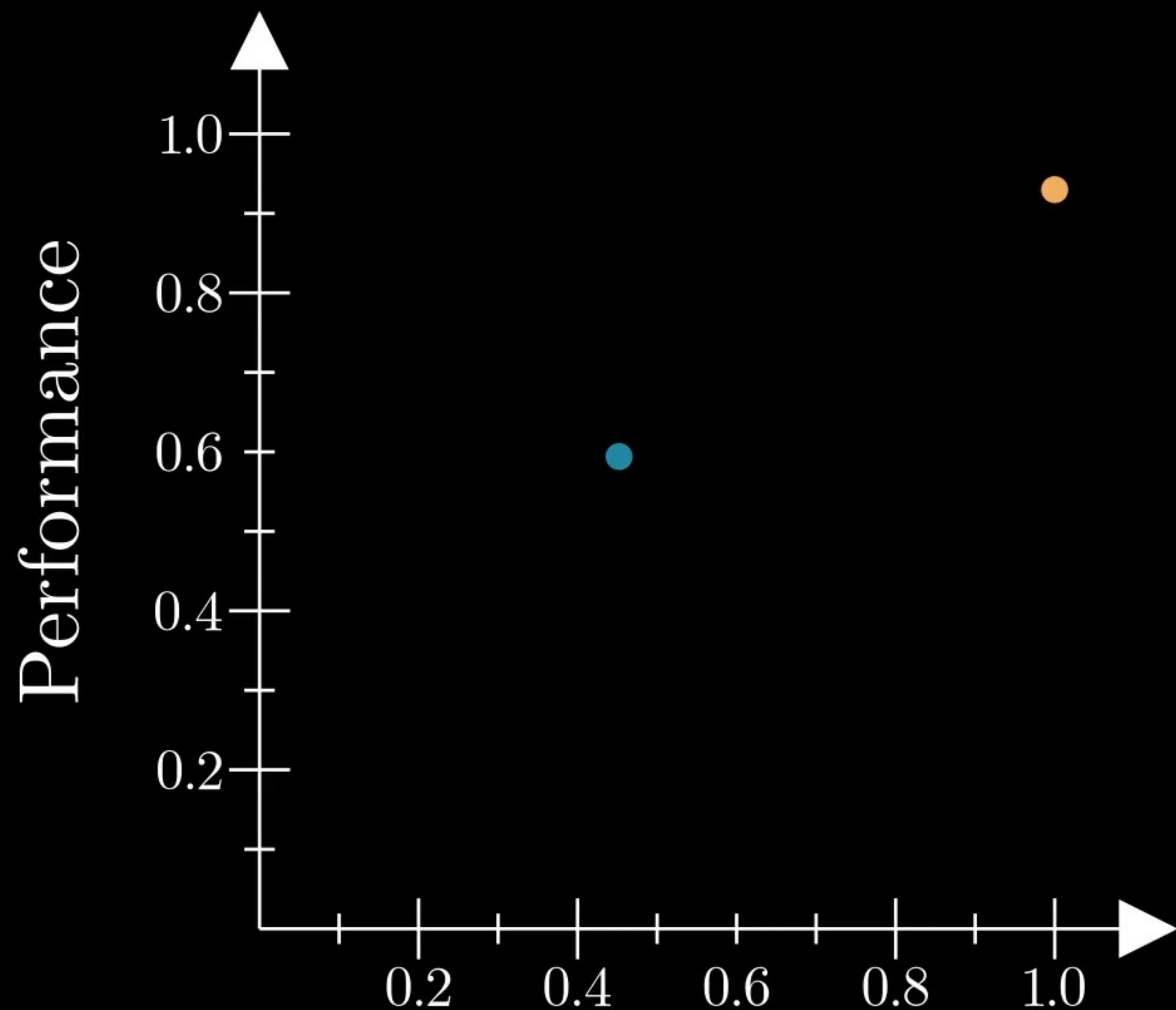
We train other models...





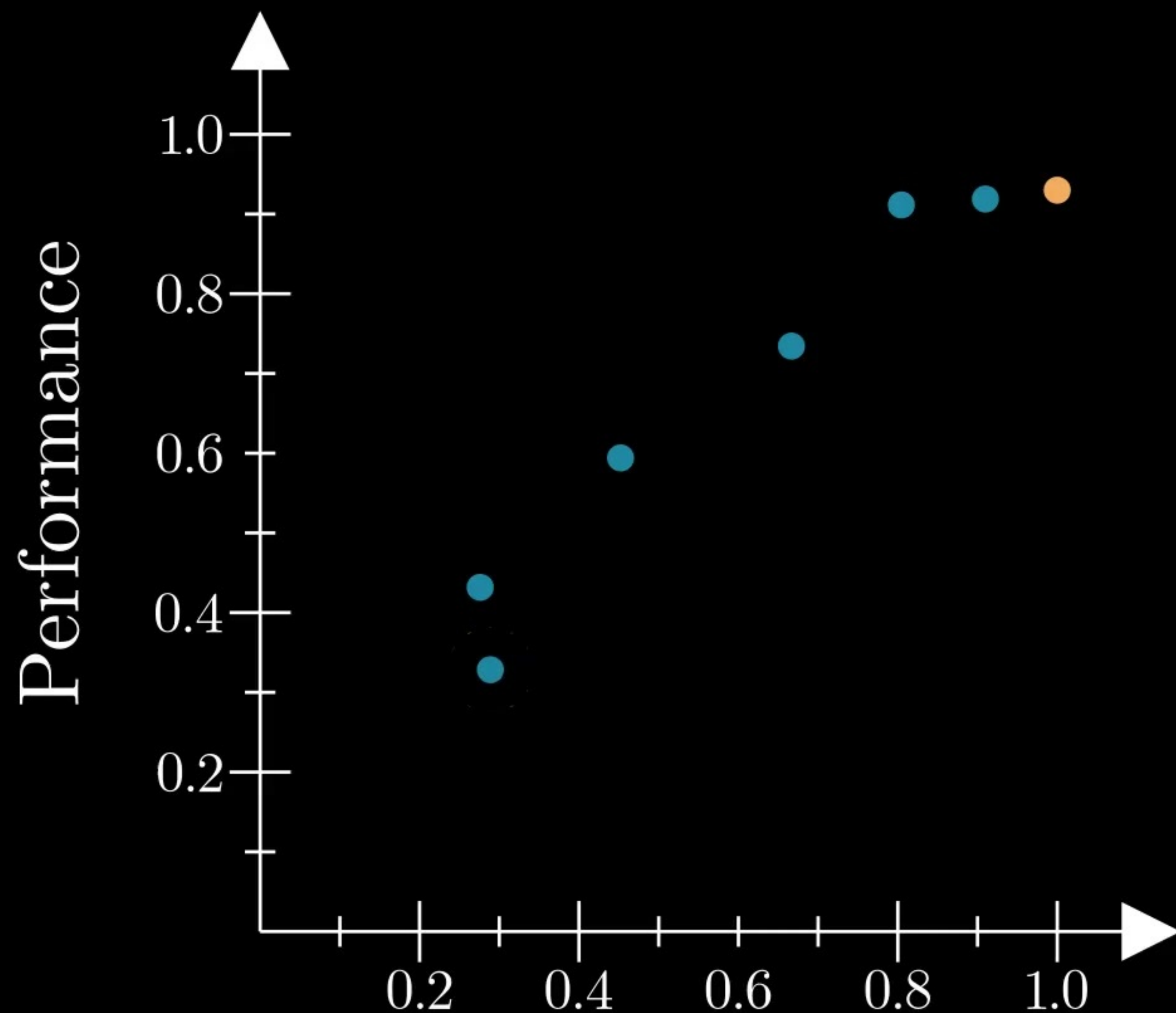
Seed	1
Epochs	500
Layers	32
Dropout	0.5
Hidden act.	ReLU
Conv. act.	ReLU
Optimizer	Adam
Learning rate	0.02
Encoder	GCN2Conv

Latent similarity to reference model



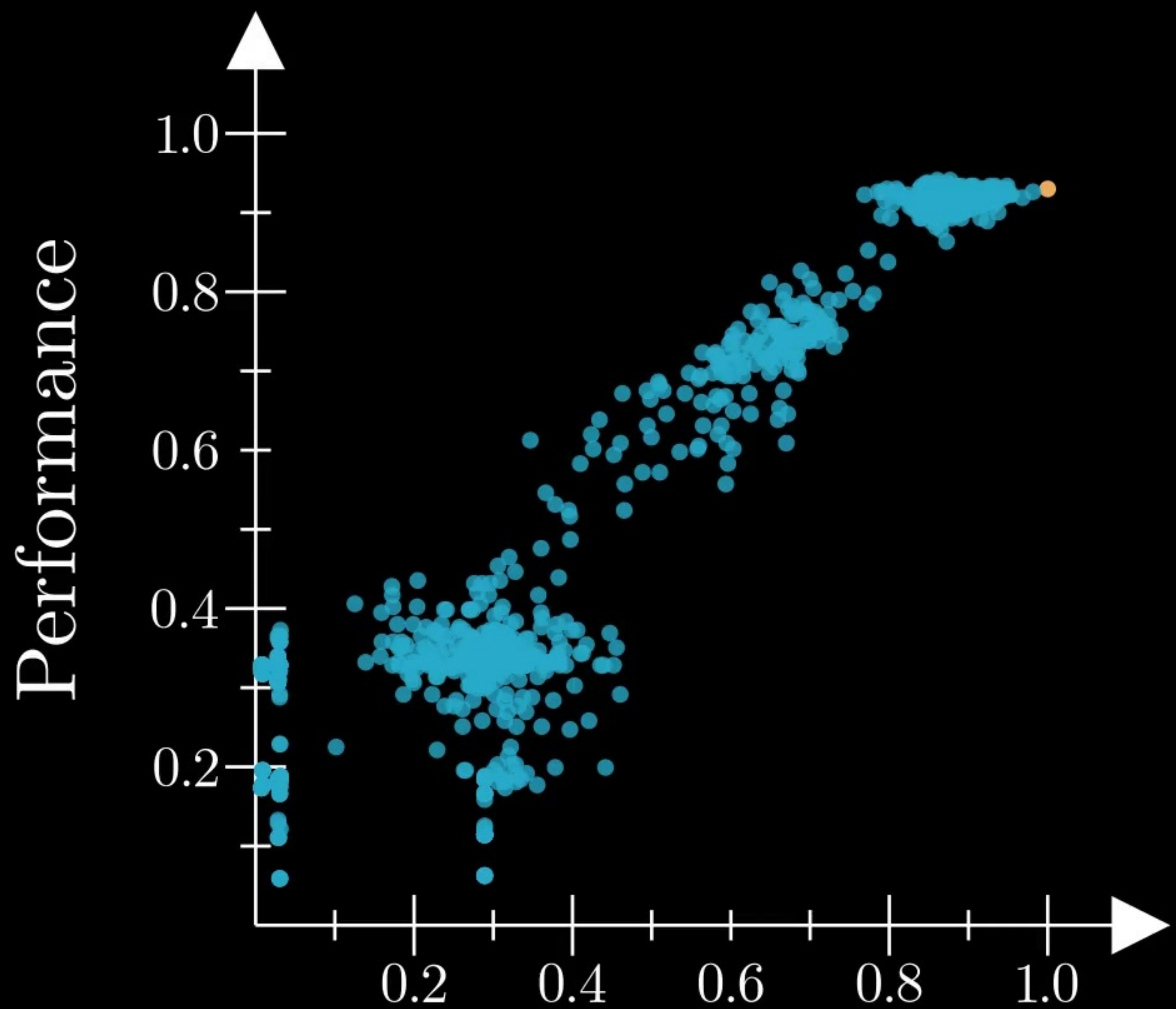
Seed	0
Epochs	10
Layers	32
Dropout	0.1
Hidden act.	ReLU
Conv. act.	ReLU
Optimizer	Adam
Learning rate	0.02
Encoder	GCN2Conv

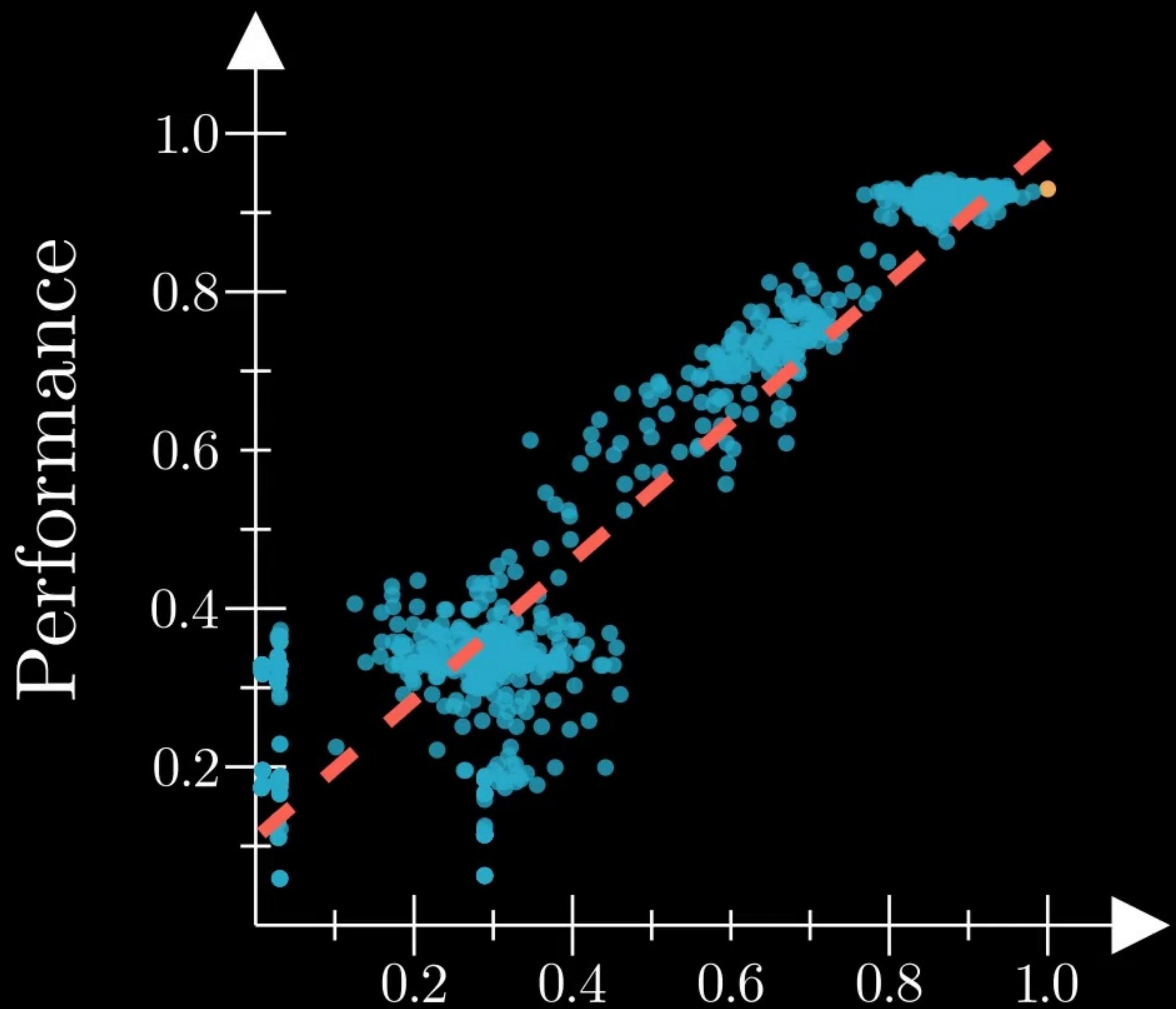
Latent similarity to reference model



Seed	2
Epochs	30
Layers	64
Dropout	0.1
Hidden act.	Tanh
Conv. act.	Tanh
Optimizer	Adam
Learning rate	0.02
Encoder	GINConv

Latent similarity to reference model





Latent similarity to reference model

relative space similar to the reference model



good performance

relative space similar to the reference model

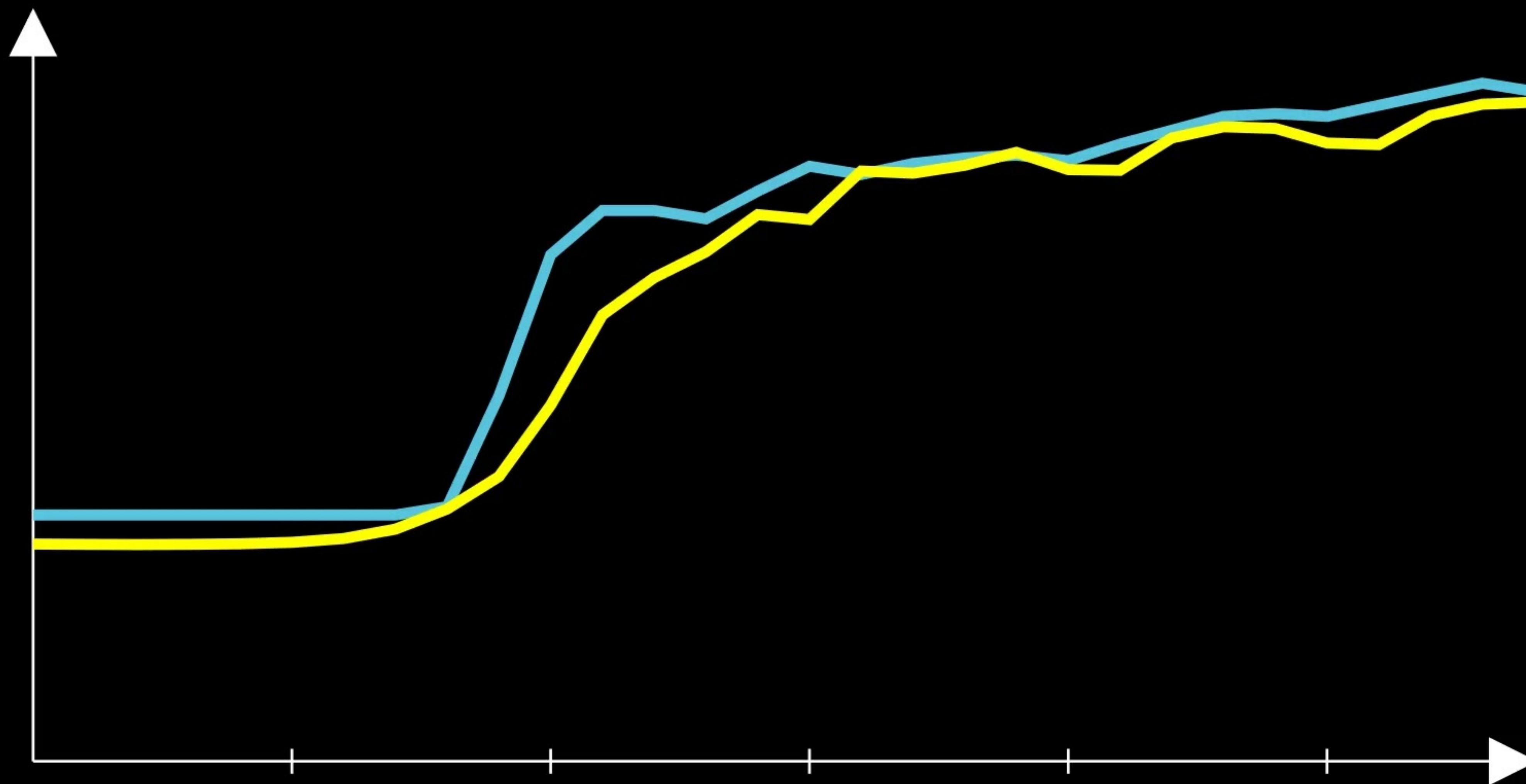


good performance

...zooming into
a single model training

● Performance

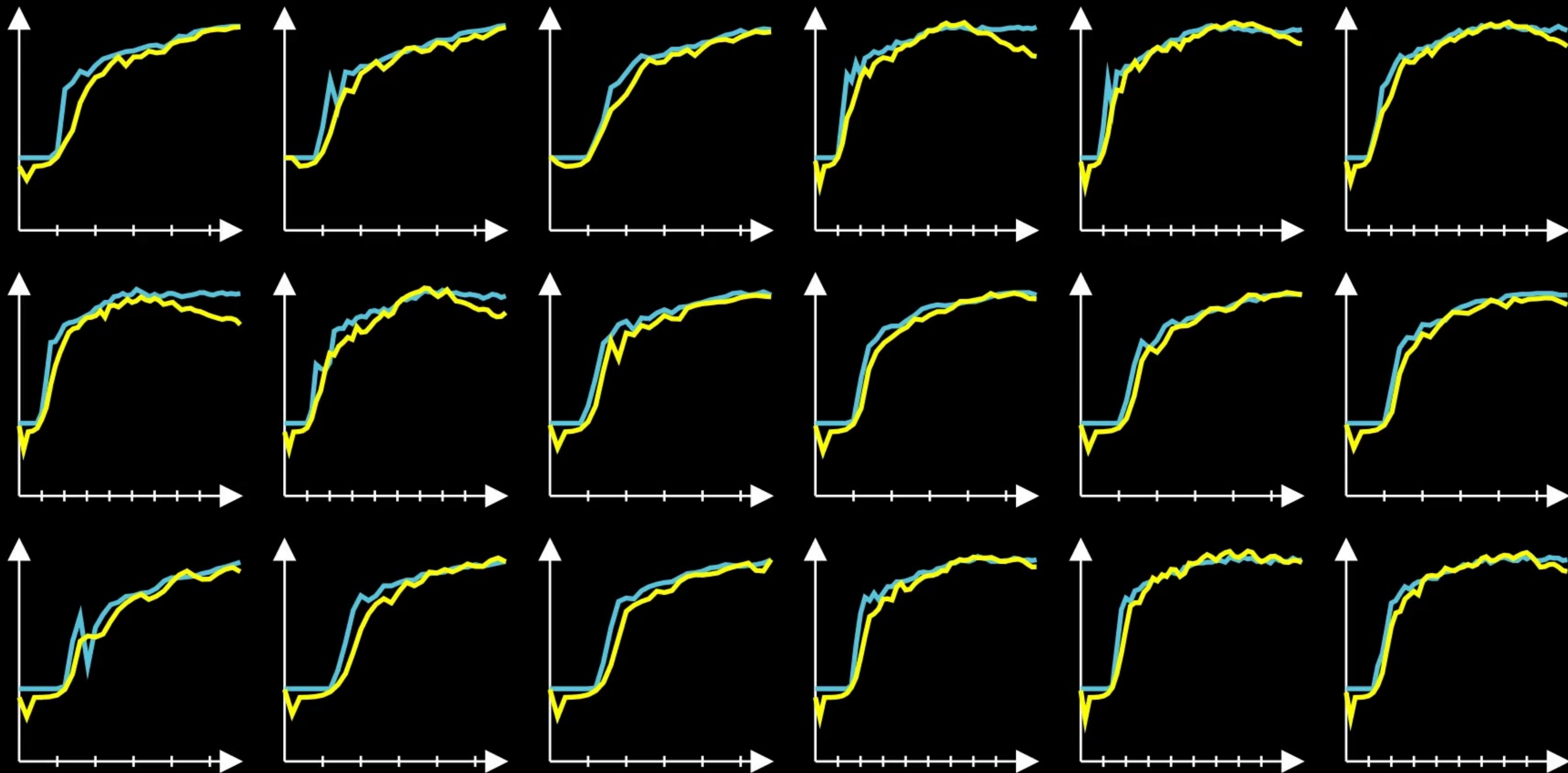
● Similarity



Epoch: 29

● Performance

● Similarity



Zero-shot Stitching

Encoder 1



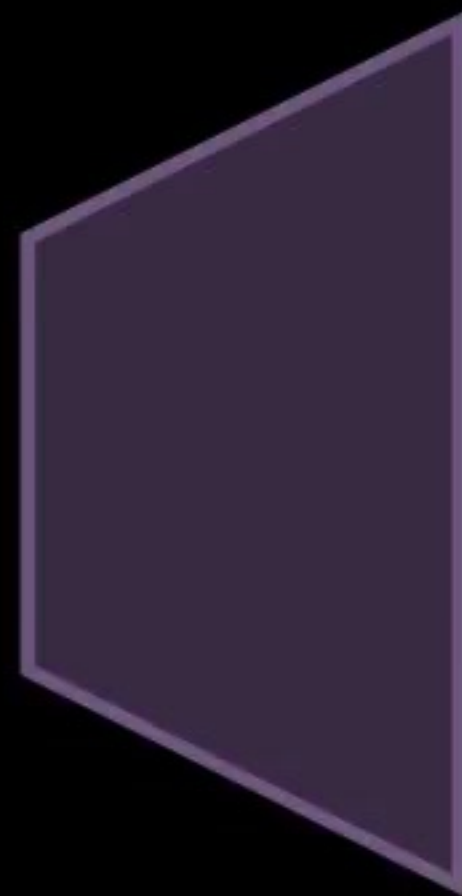
Decoder 1



Encoder 2



Decoder 2



Encoder 1



Decoder 1

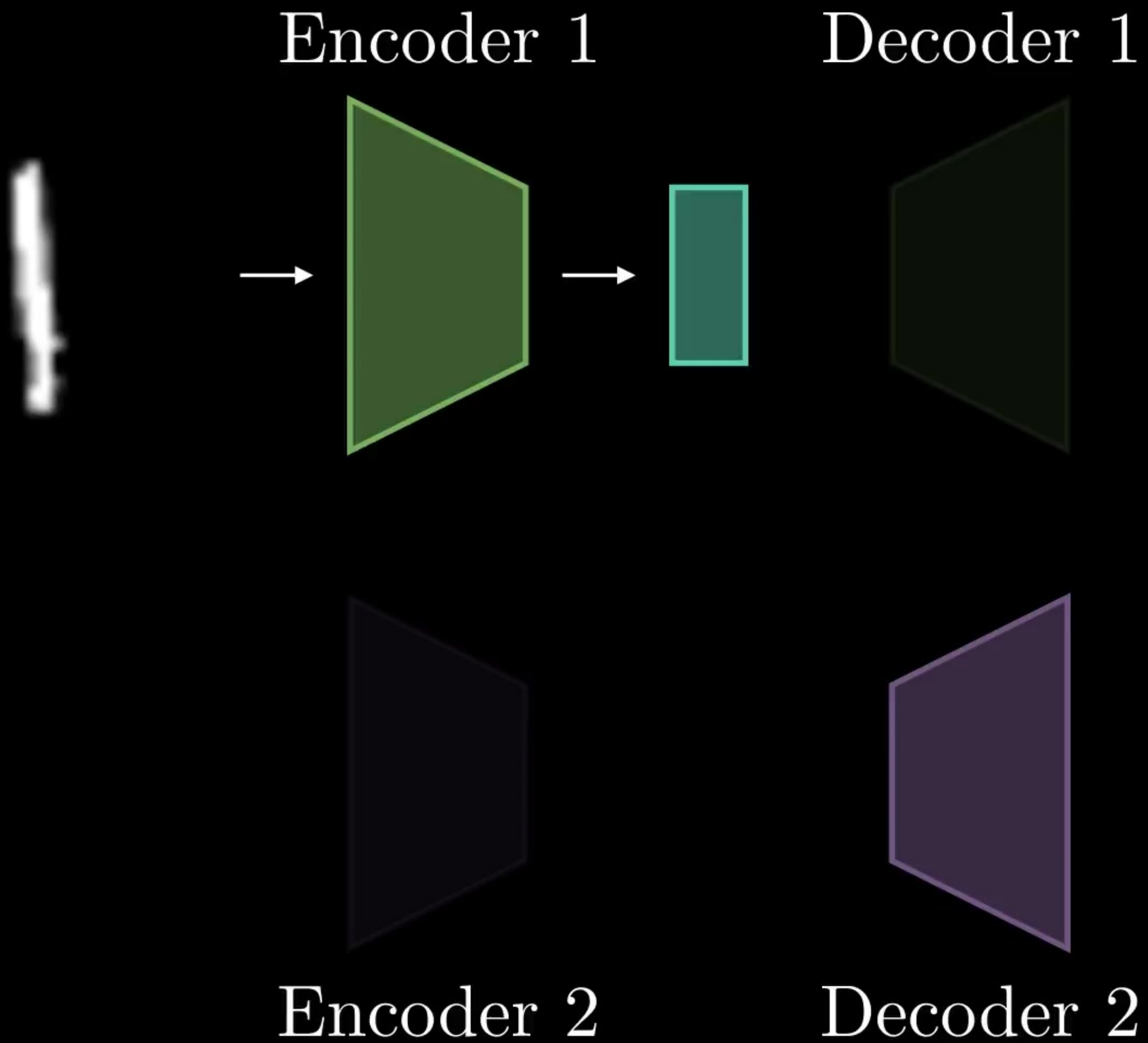


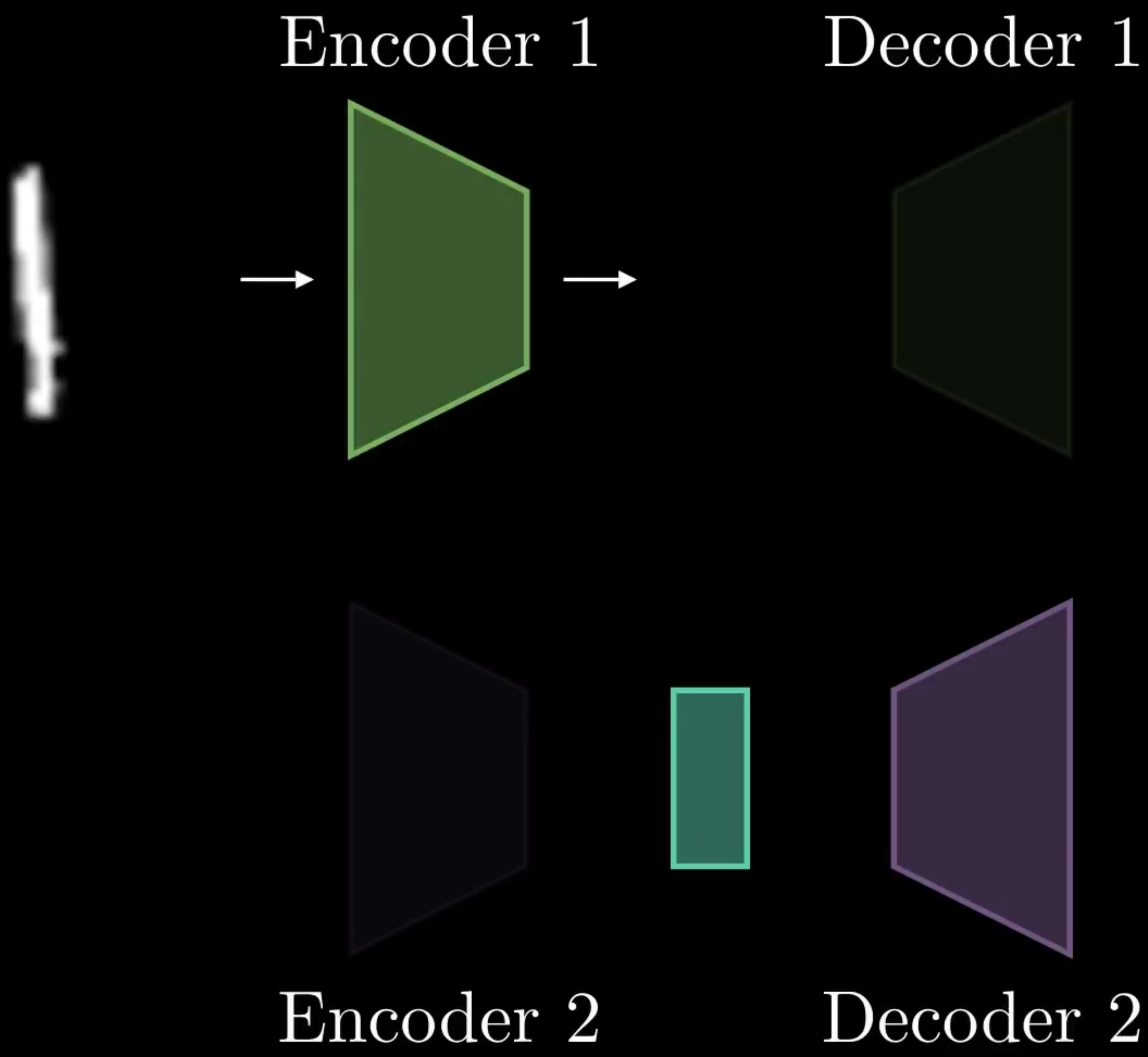
Encoder 2

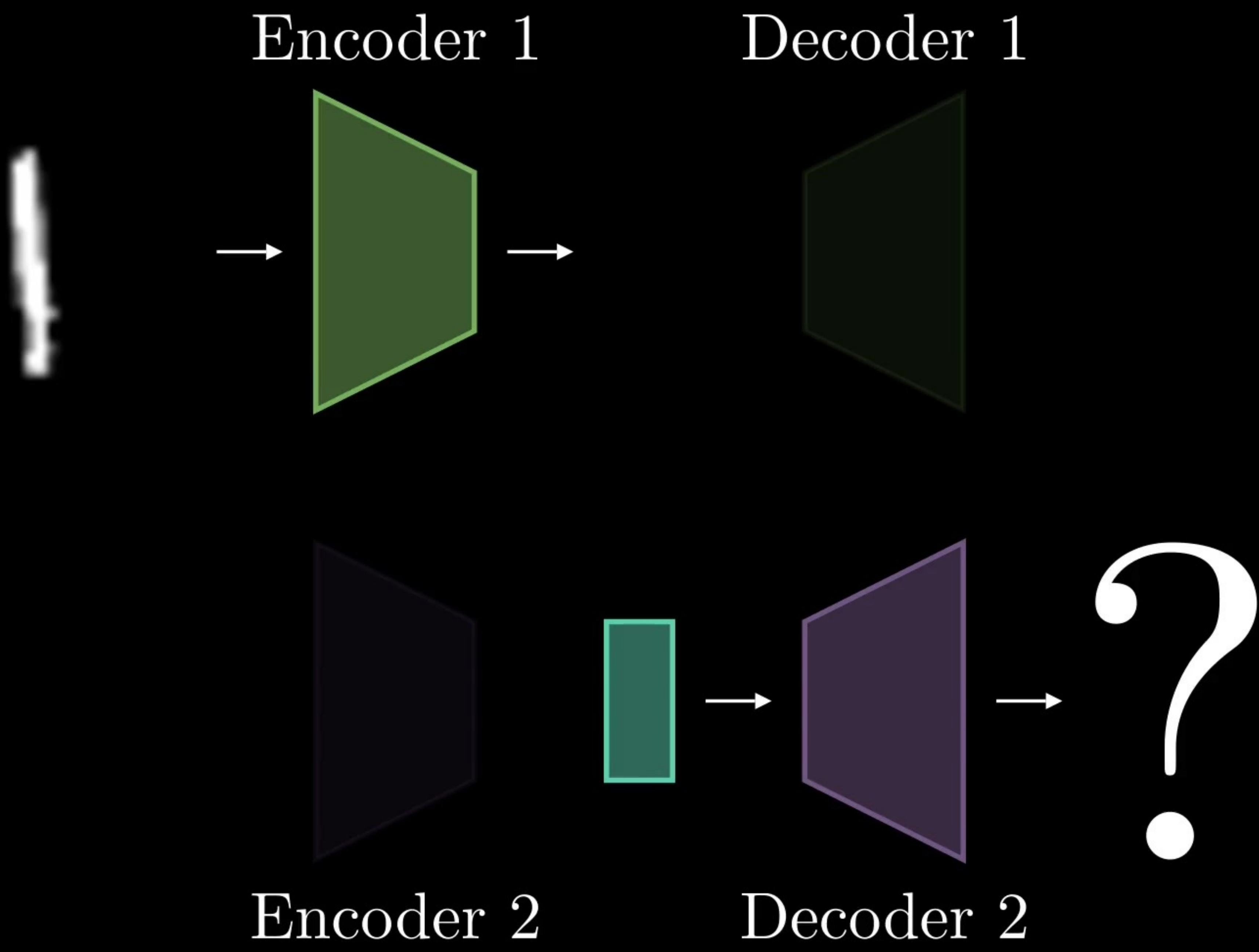


Decoder 2





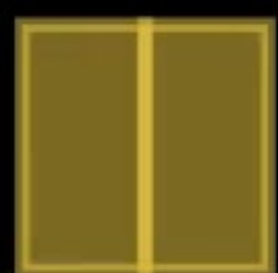




Fashion – MNIST

MNIST

Identity



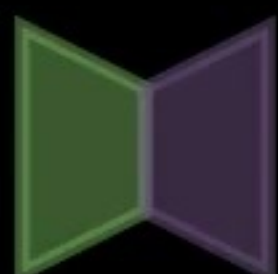
AE



Variational AE



Relative AE

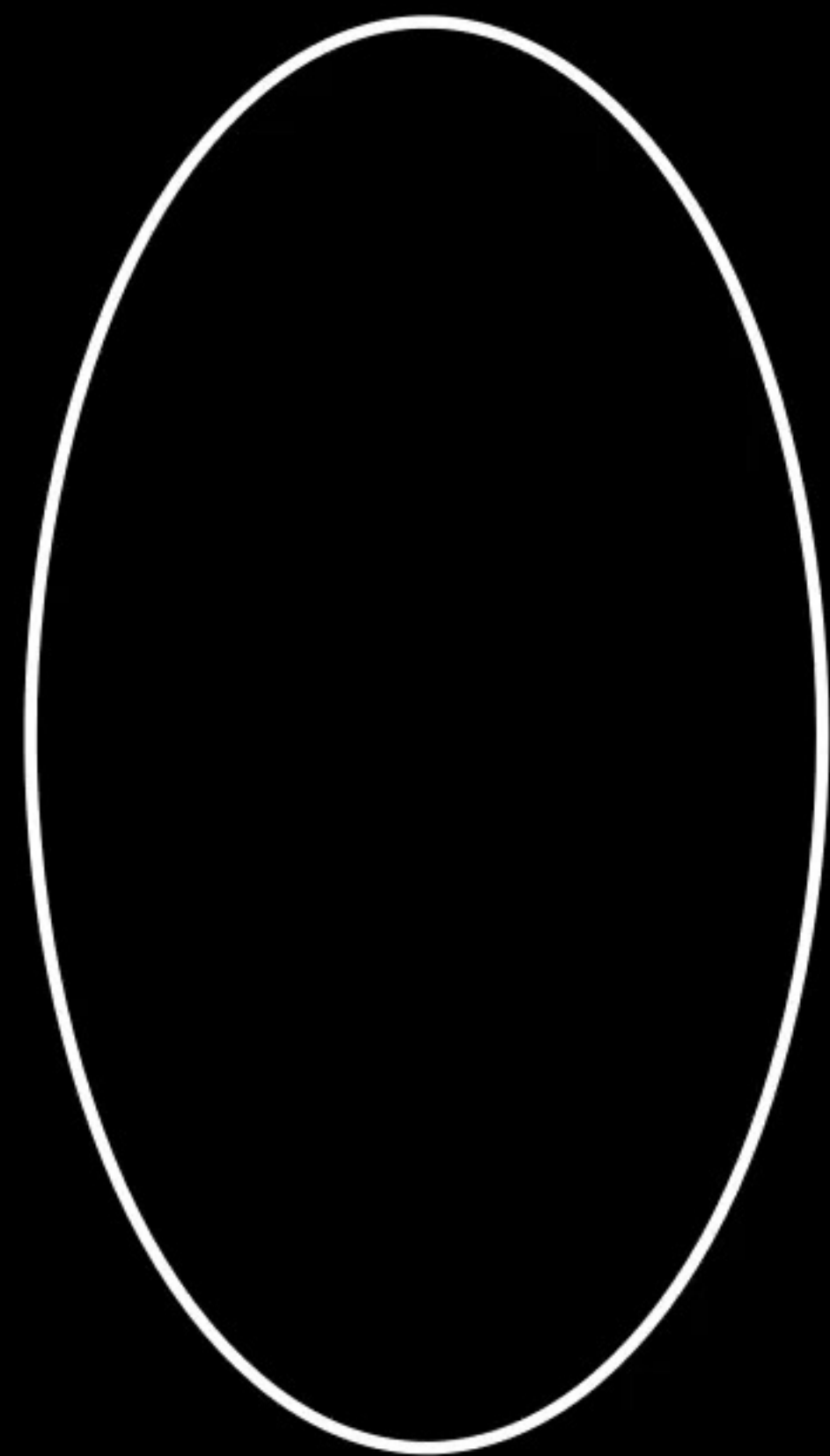


E

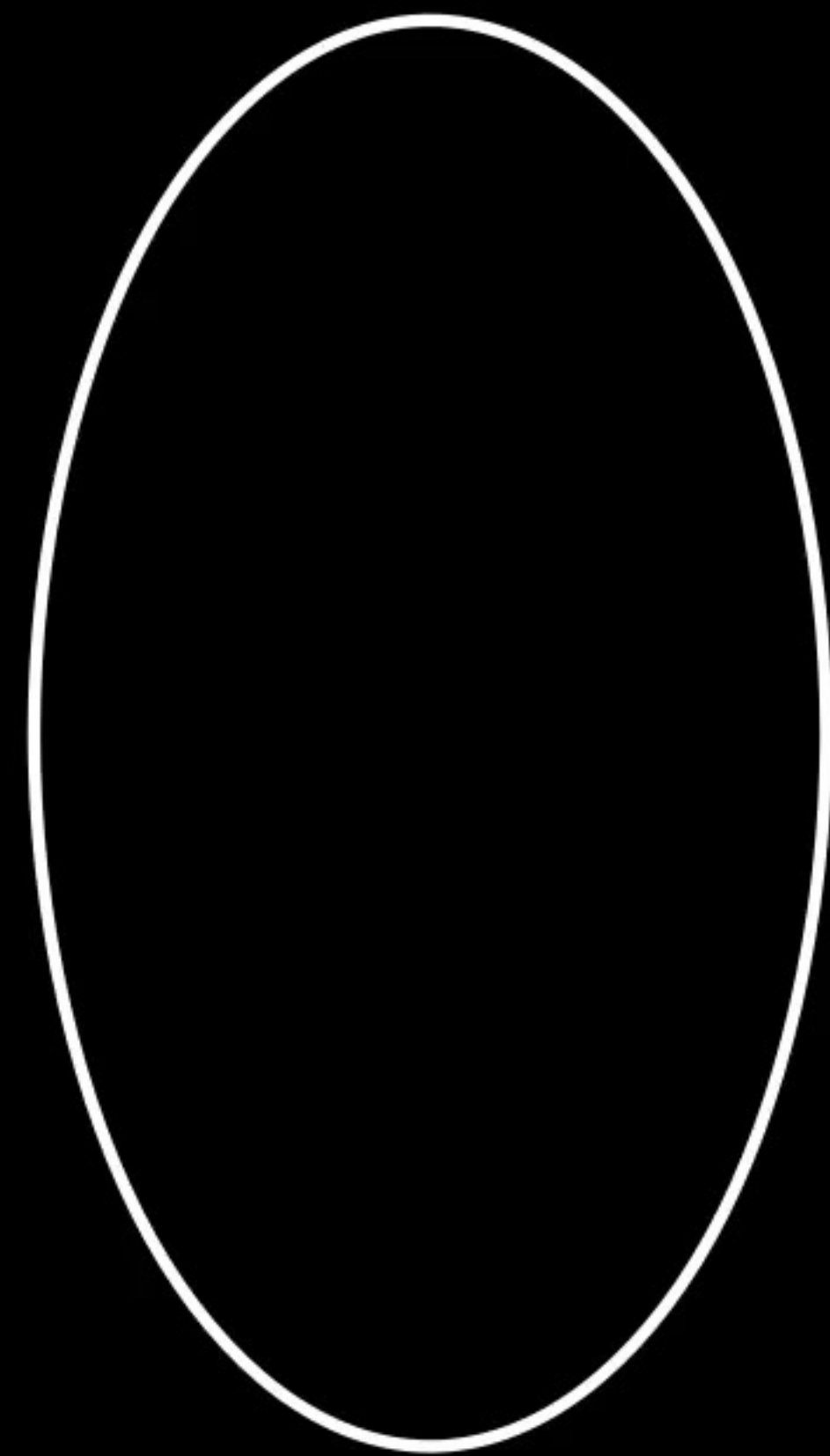
Parallel Anchors

...stitching between multiple domains?

English Space



Italian Space

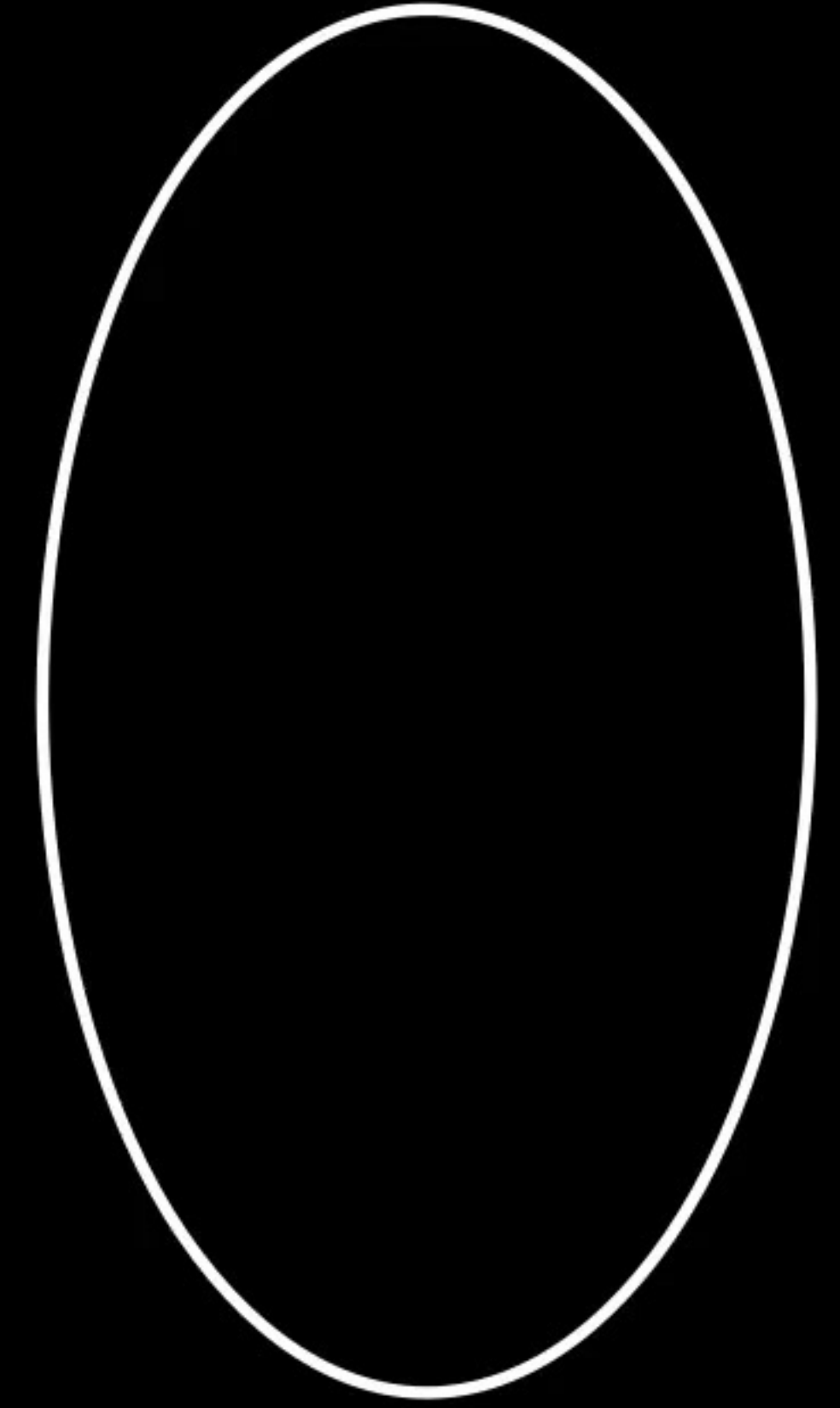
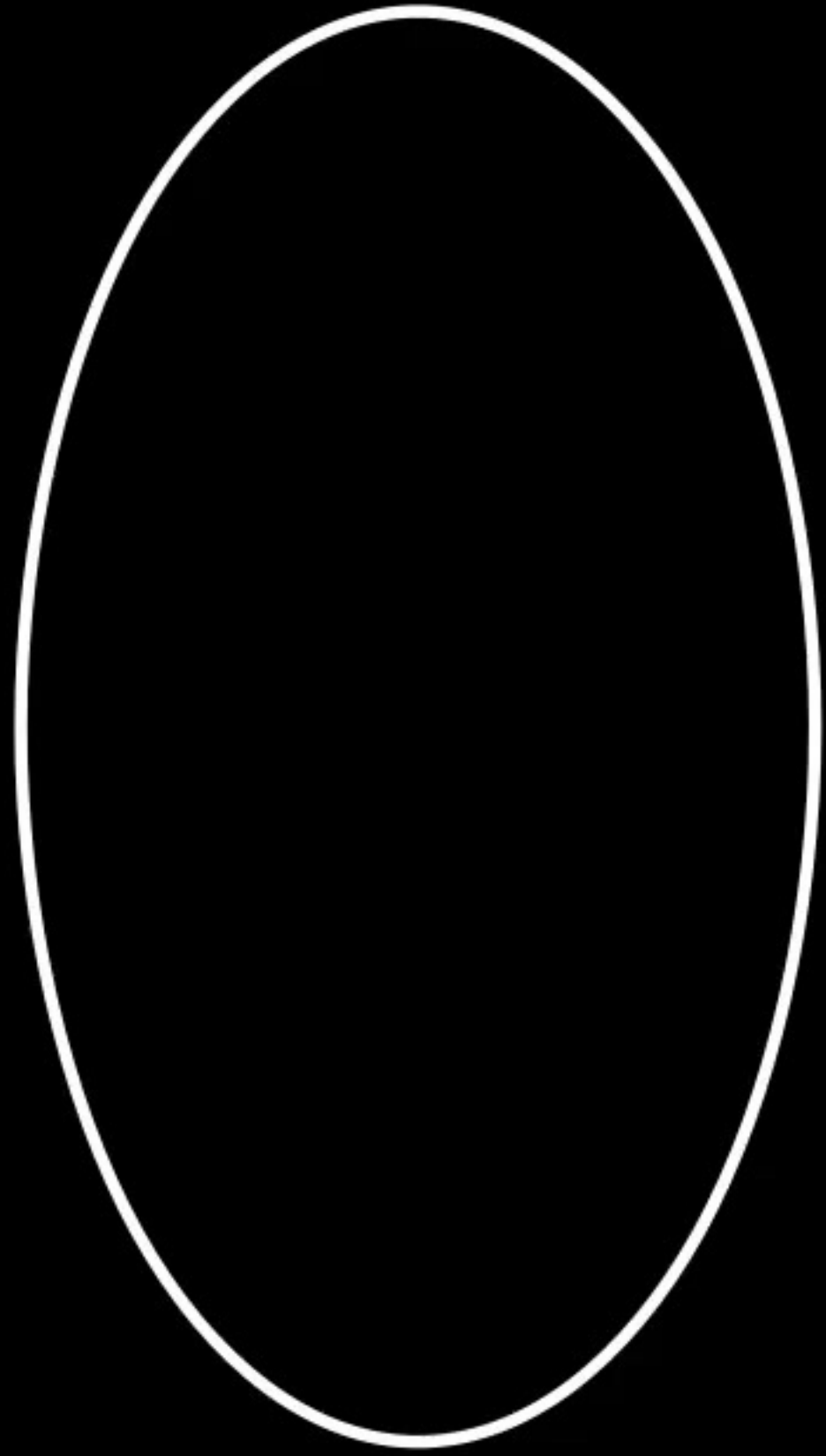


...solve a downstream task **once for both spaces**

Parallel Anchors

English Space

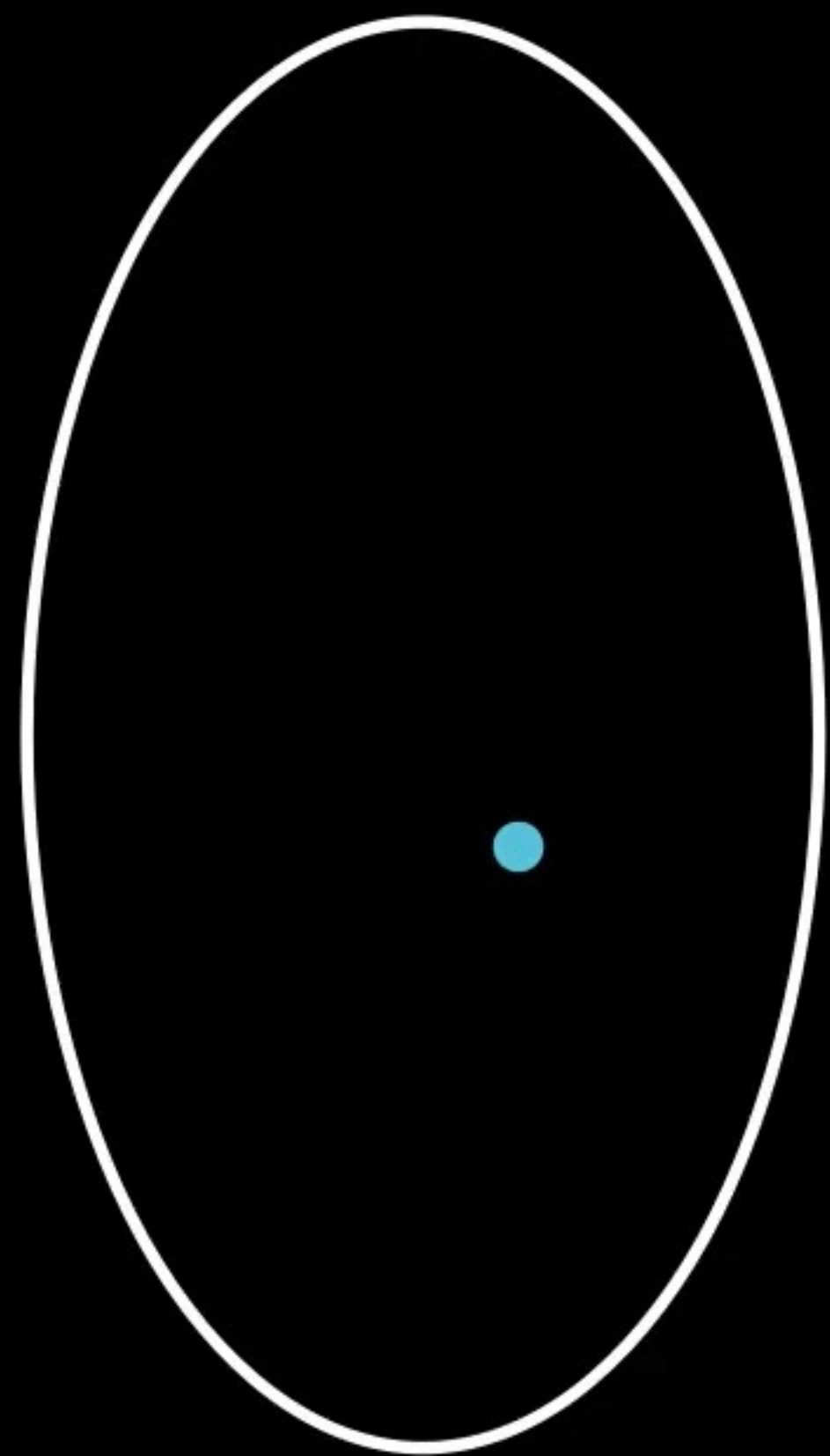
Italian Space



...

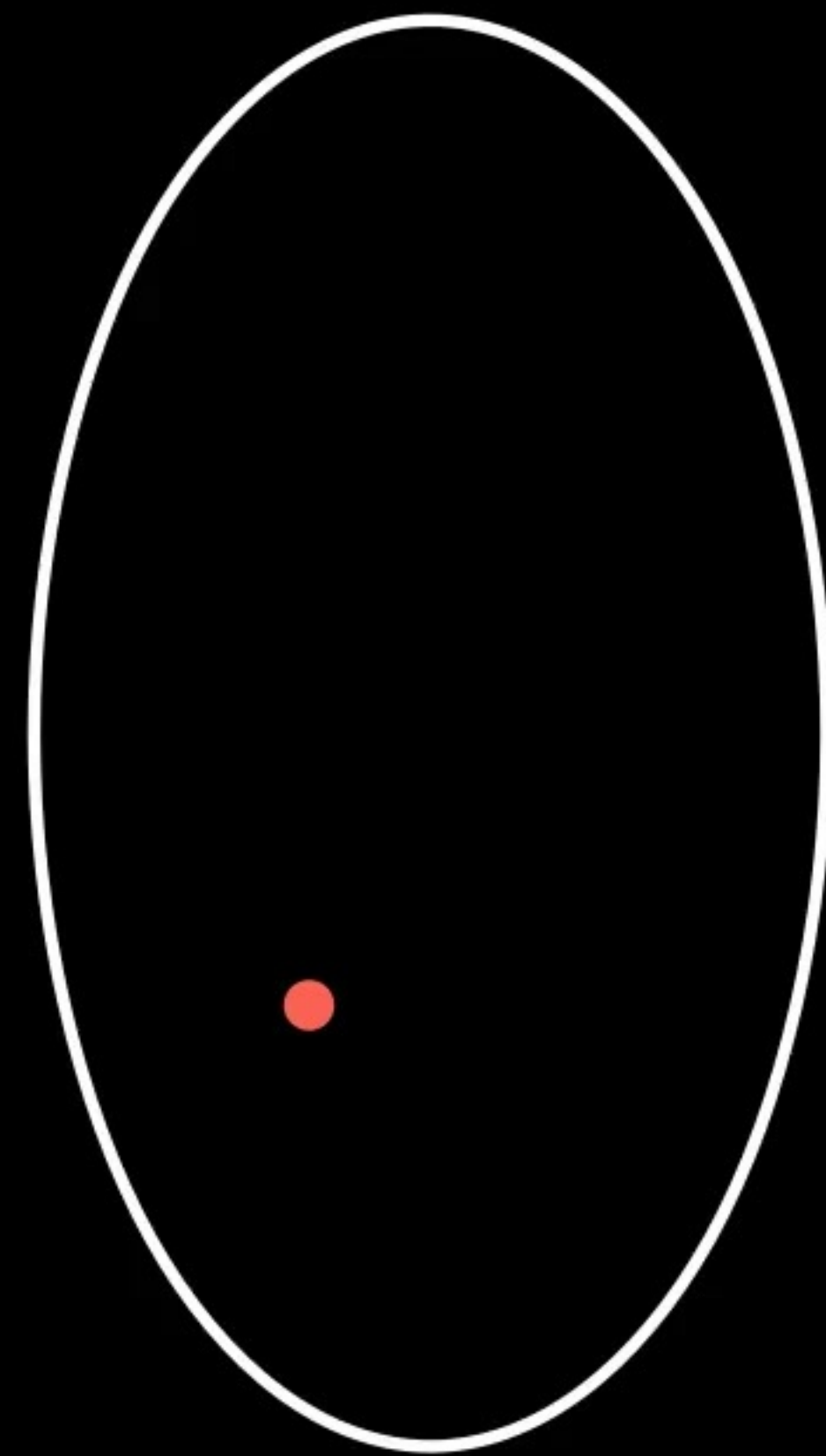
Parallel Anchors

English Space



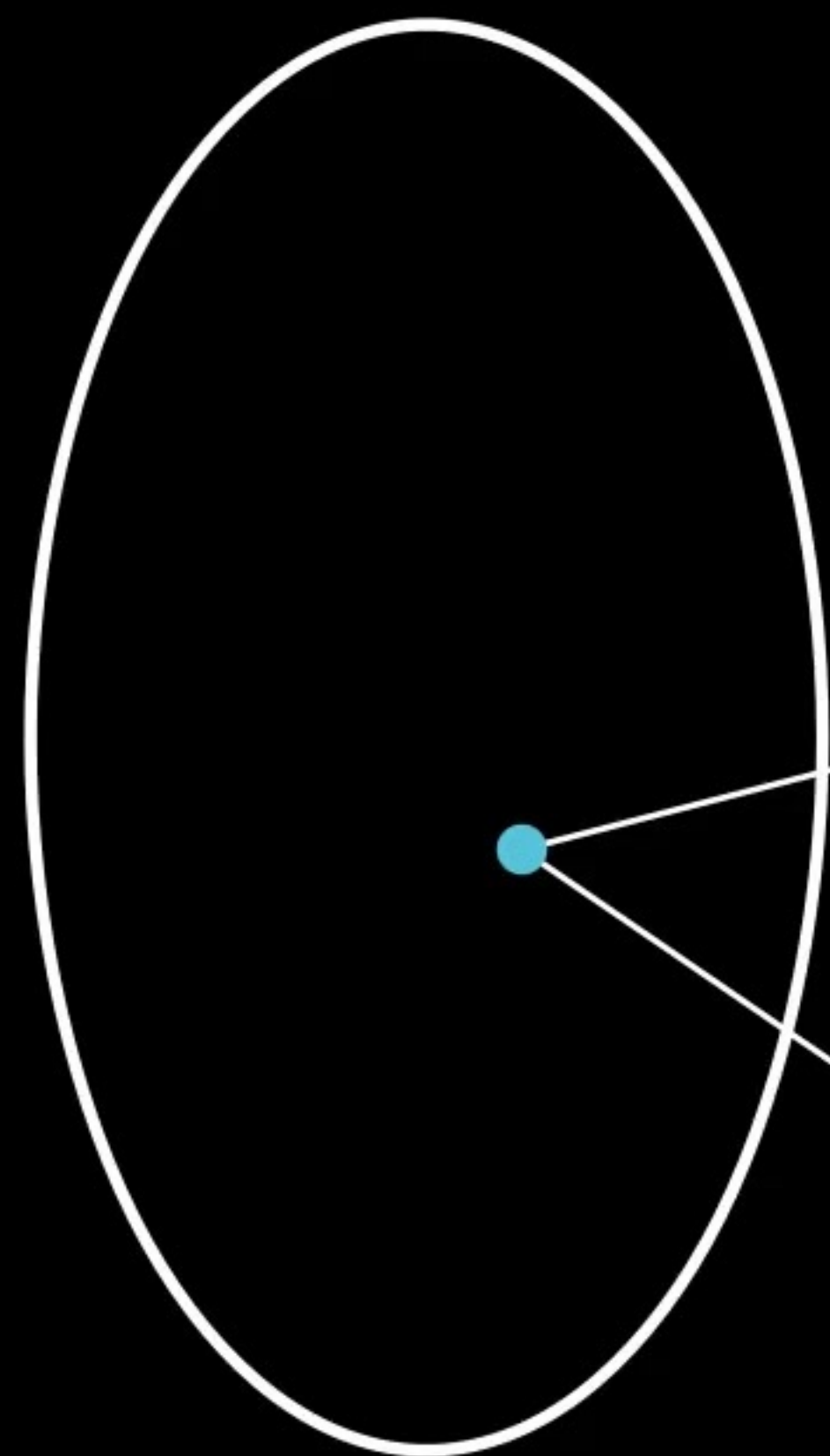
...

Italian Space

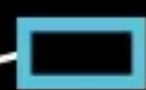


Parallel Anchors

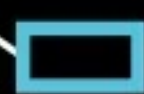
English Space



cat

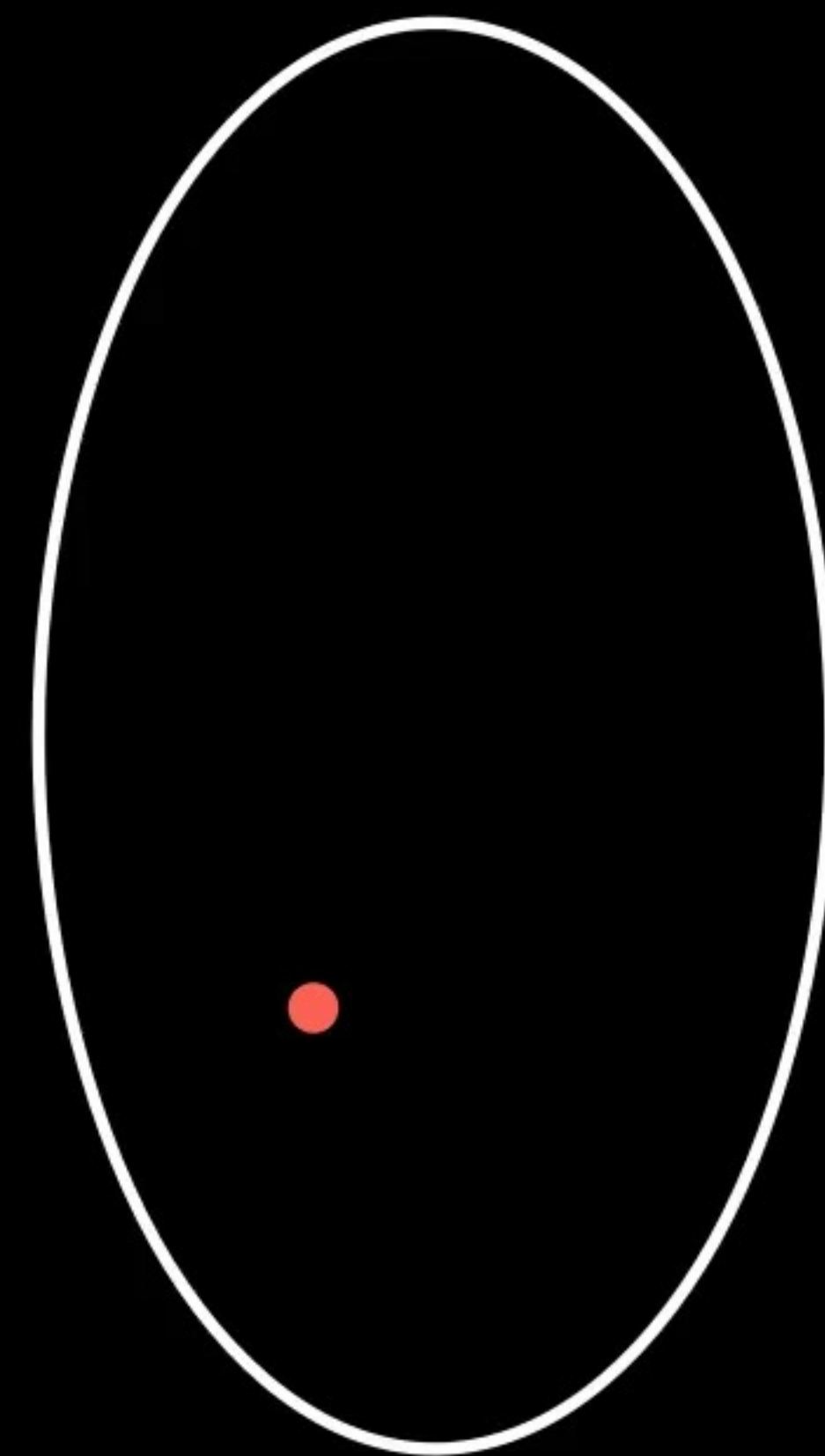


elephant



...

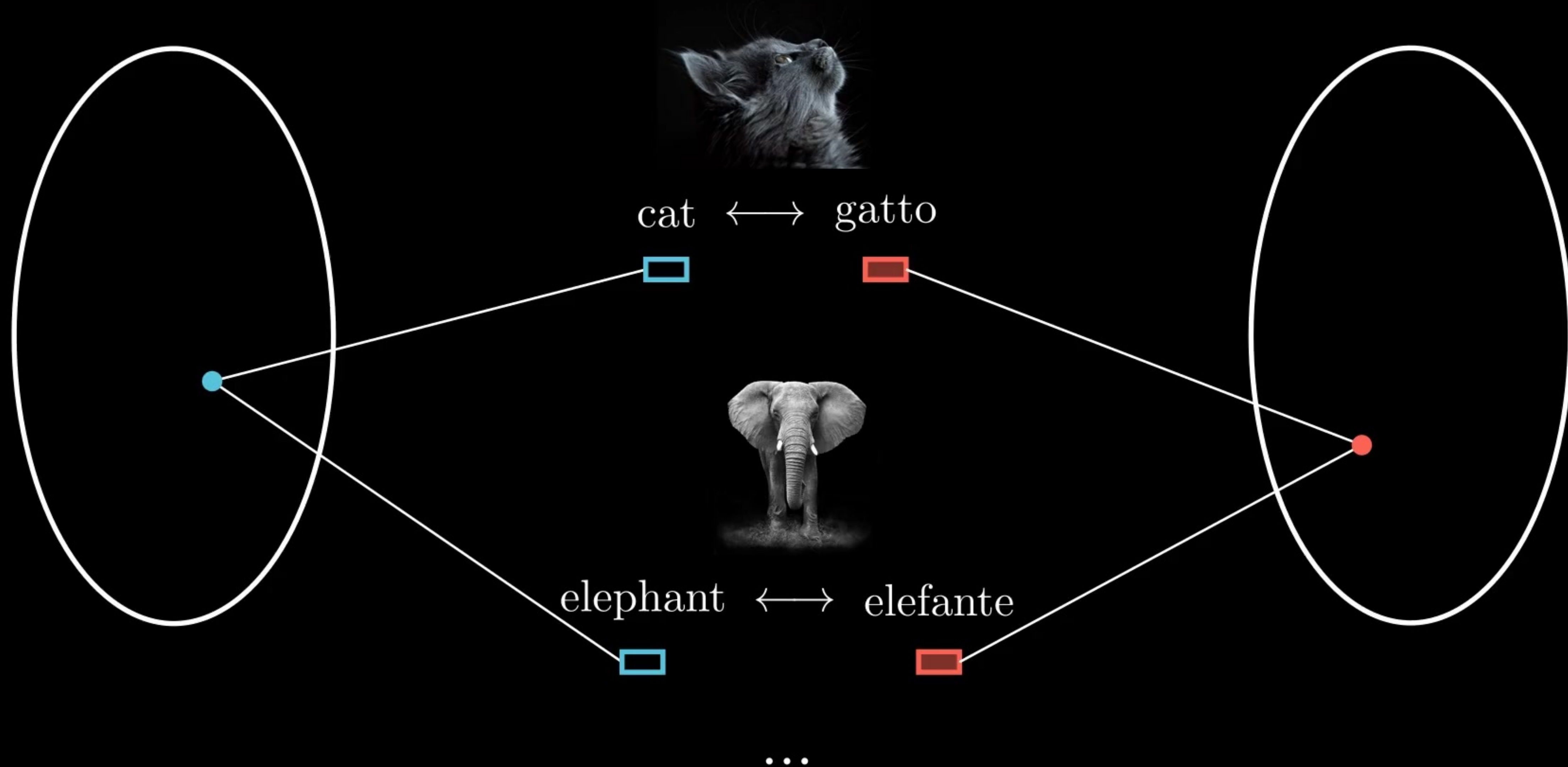
Italian Space



Parallel Anchors

English Space

Italian Space



...bridging data modalities

ASIF: Coupled Data
Turns Unimodal Models to Multimodal Without Training

Antonio Norelli

Marco Fumero Valentino Maiorca Luca Moschella

Francesco Locatello Emanuele Rodolà

<https://arxiv.org/abs/2210.01738>



A green bird from New Zealand

Conclusions

Zero-shot communication between different latent spaces

Applications in:

- Model stitching
- Measuring the performance of neural models
- Generalizing unimodal to multimodal models

Future directions:

- Different similarity/anchors choice \rightarrow different invariances/properties
- Relative space similarity as supervision signal

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Thank you!

...slides by Luca Moschella & Valentino Maiorca