

# What is the **INTRINSIC** **DIMENSION** of Your Data?

**University of Washington Seminar**

Wenhao Chai

**University of Washington Information Processing Lab Seminar**

What is the Intrinsic Dimension of Your Data?

Bridging the Parallel Decoding of LLMs with the Diffusion Process

DPO and RLHF for Large Language Model Post-training

Vision Representation Learning from Synthetic Data

From Large Language Models to Large Multi-modal Models

Seattle, WA

Jan 2025

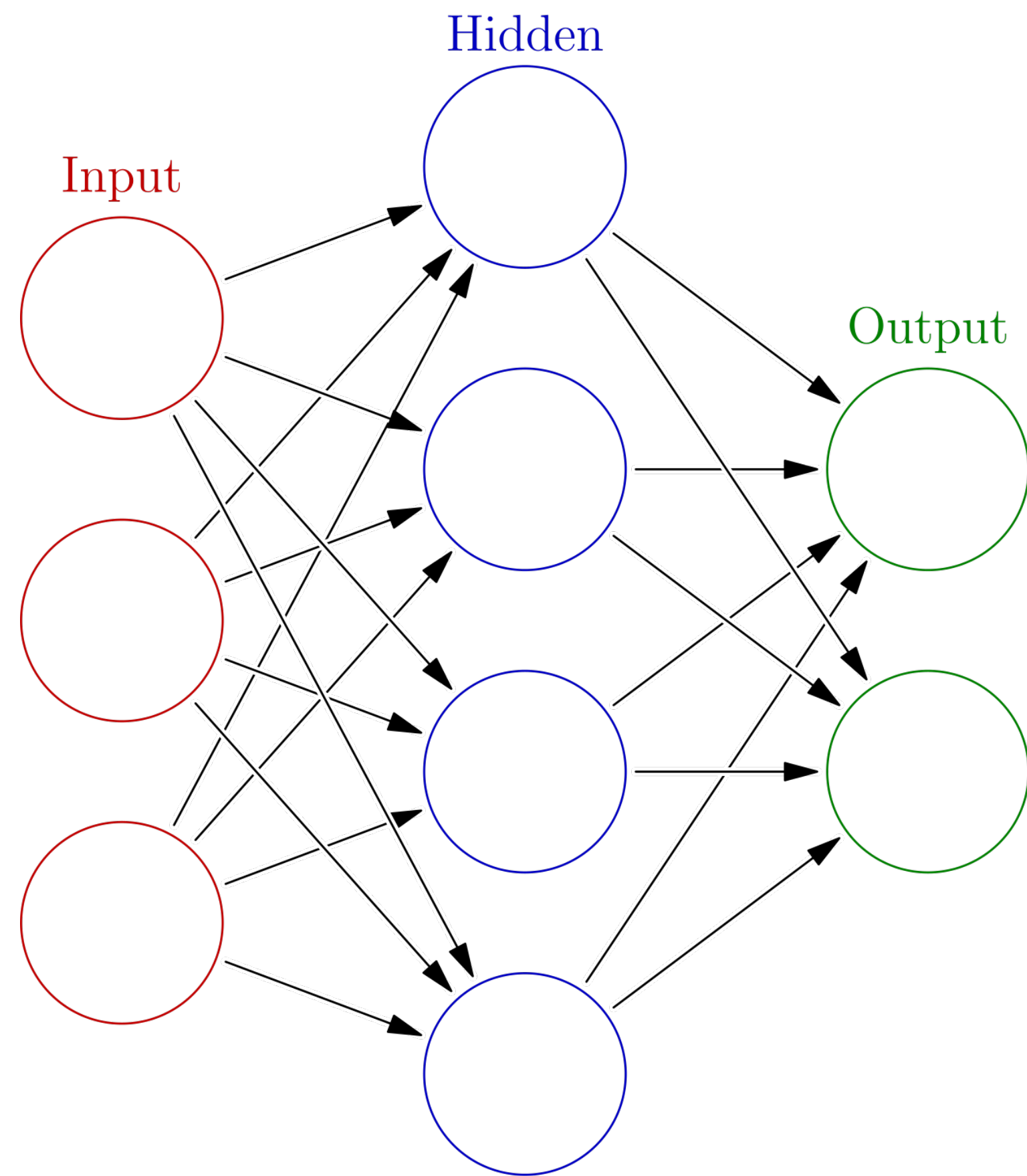
Oct 2024

Apr 2024

Jan 2024

Nov 2023

# Intrinsic Dimension



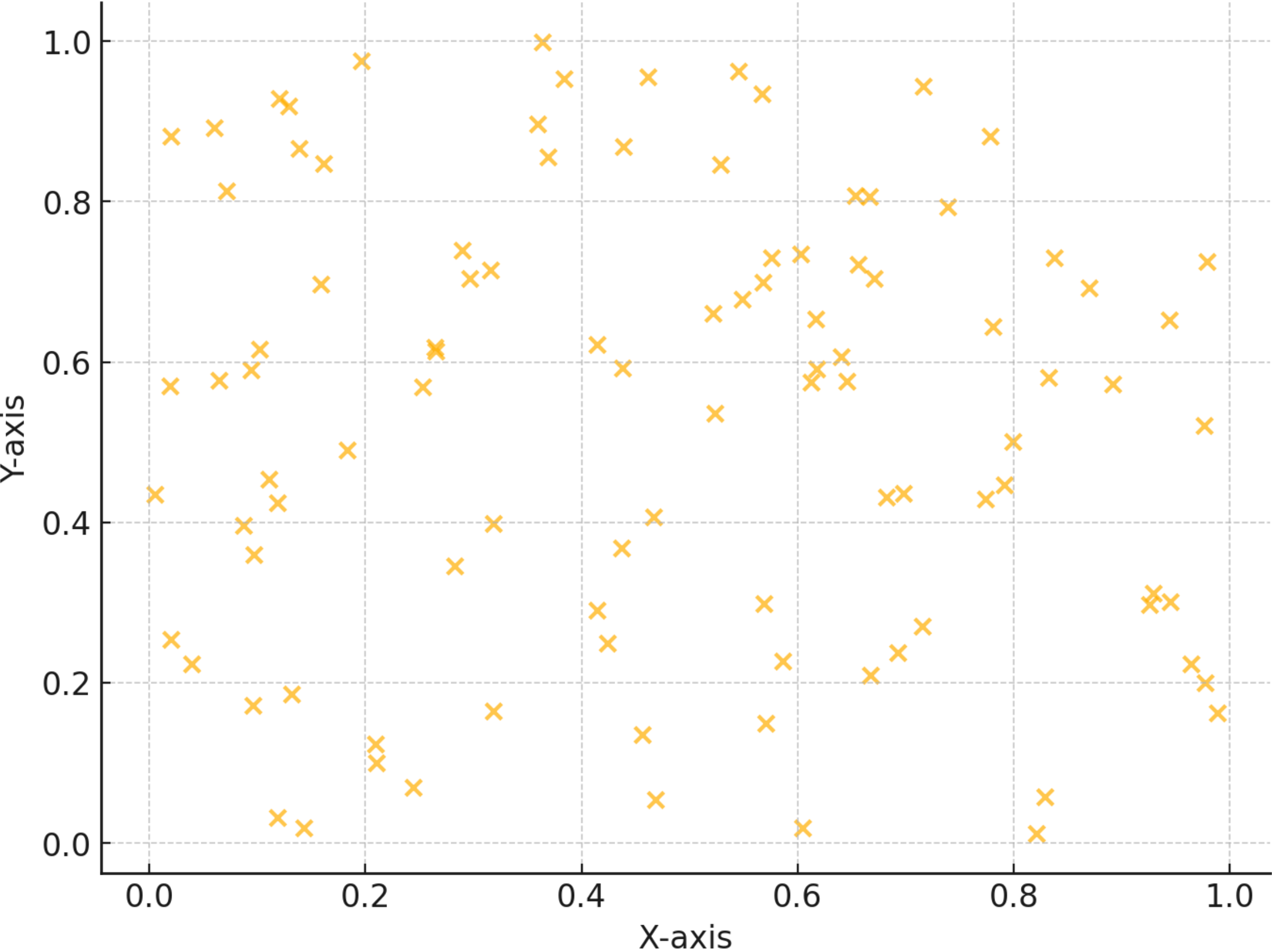
Hidden dim happened in NN design  
However, NN is overparameterized

The **intrinsic dimension** for a data set can be thought of as the number of variables needed in a minimal representation of the data

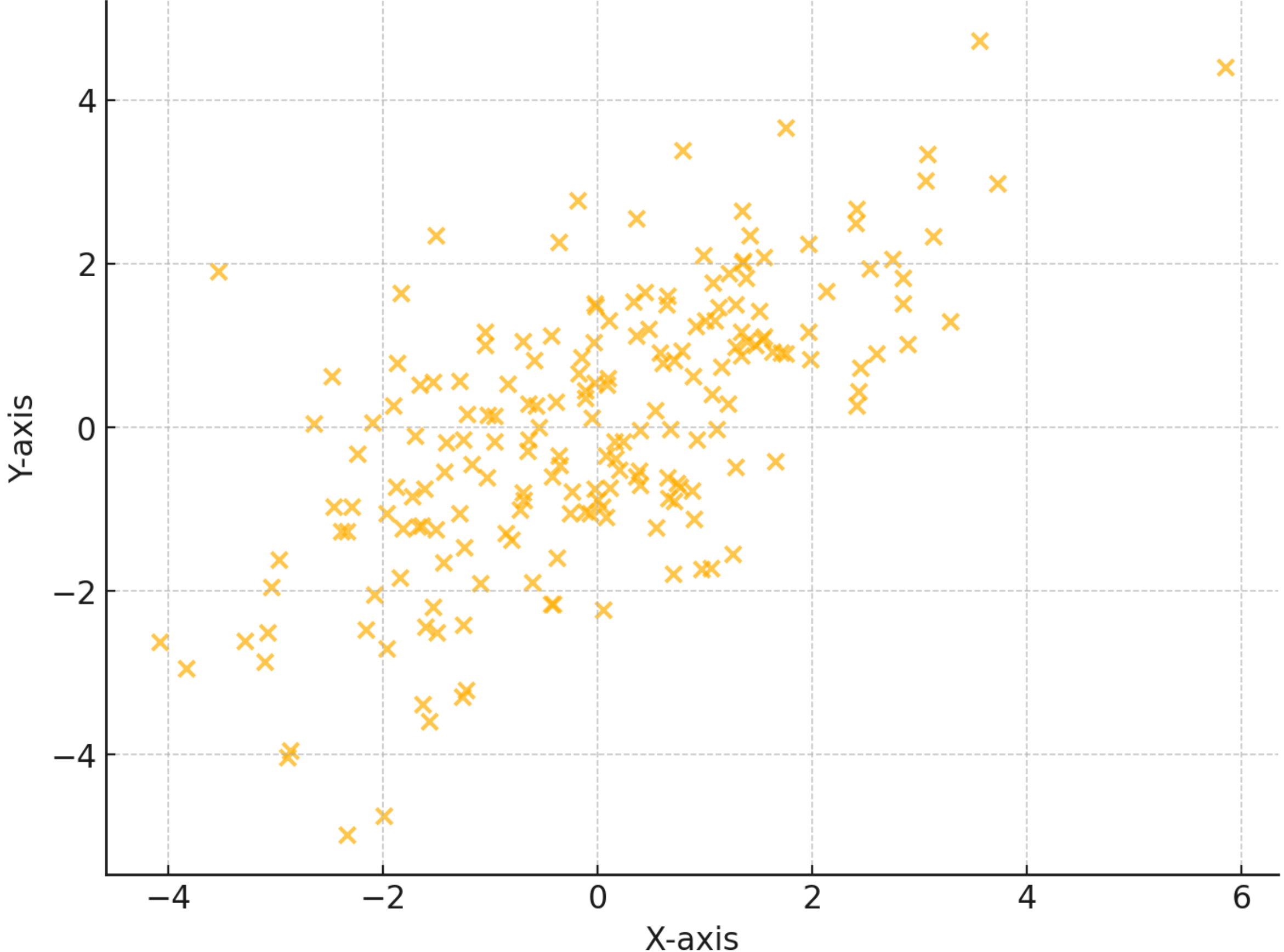
How to measure the intrinsic dimension of the original data?

# Toy Data Example

Randomly Generated Scatter Plot



Scatter Plot of PCA-Compatible Data





# More Complex Data Example



ImageNet

14 million images

more than 20,000 categories

224 x 224 resolution

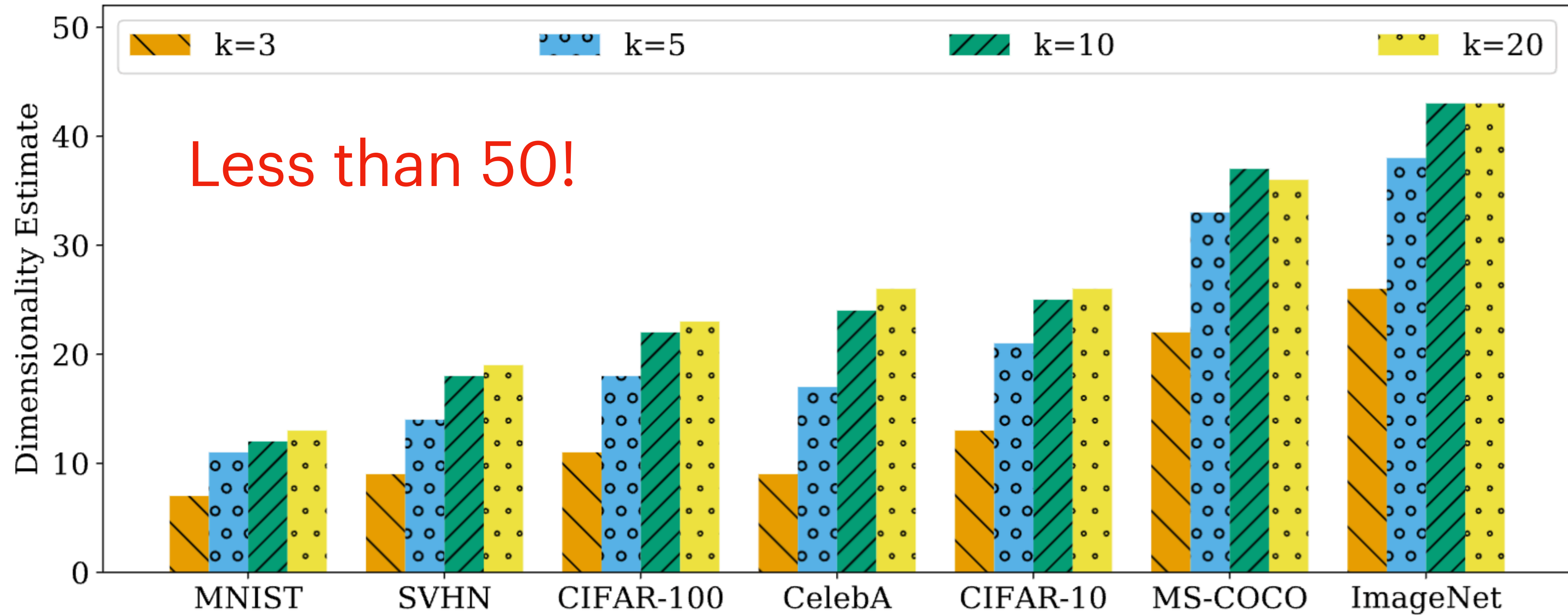
150,528 pixels per image

What is the intrinsic dimension of that?

Let's guess!



# Intrinsic Dimension of Some Dataset



\* k is a hyper-param they used

Pope, P., Zhu, C., Abdelkader, A., Goldblum, M., & Goldstein, T. The Intrinsic Dimension of Images and Its Impact on Learning. In *International Conference on Learning Representations*.

NeurIPS 2004

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Maximum Likelihood Estimation of  
Intrinsic Dimension

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Published as a conference paper at ICLR 2021

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# THE INTRINSIC DIMENSION OF IMAGES AND ITS IMPACT ON LEARNING

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# Notation and Assumption

$P \in \mathbb{R}^N$  data point

$M \subseteq \mathbb{R}^N$  manifold

$m = \dim(M) \ll N$  intrinsic dimension

density is constant within small neighborhoods    Local uniformity assumption

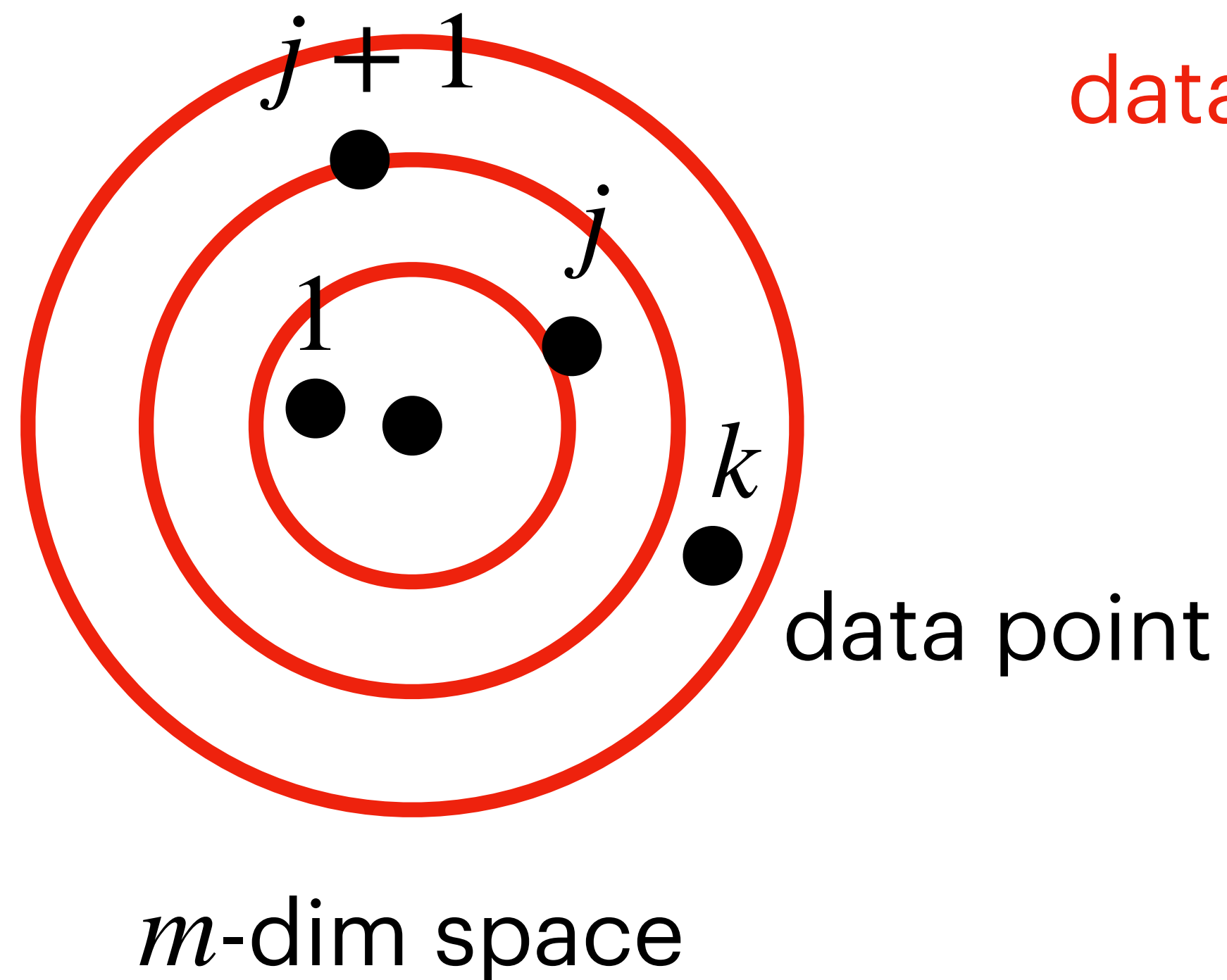


# Before Math ...

Find a relationship between **some var** and intrinsic dimension  $m$



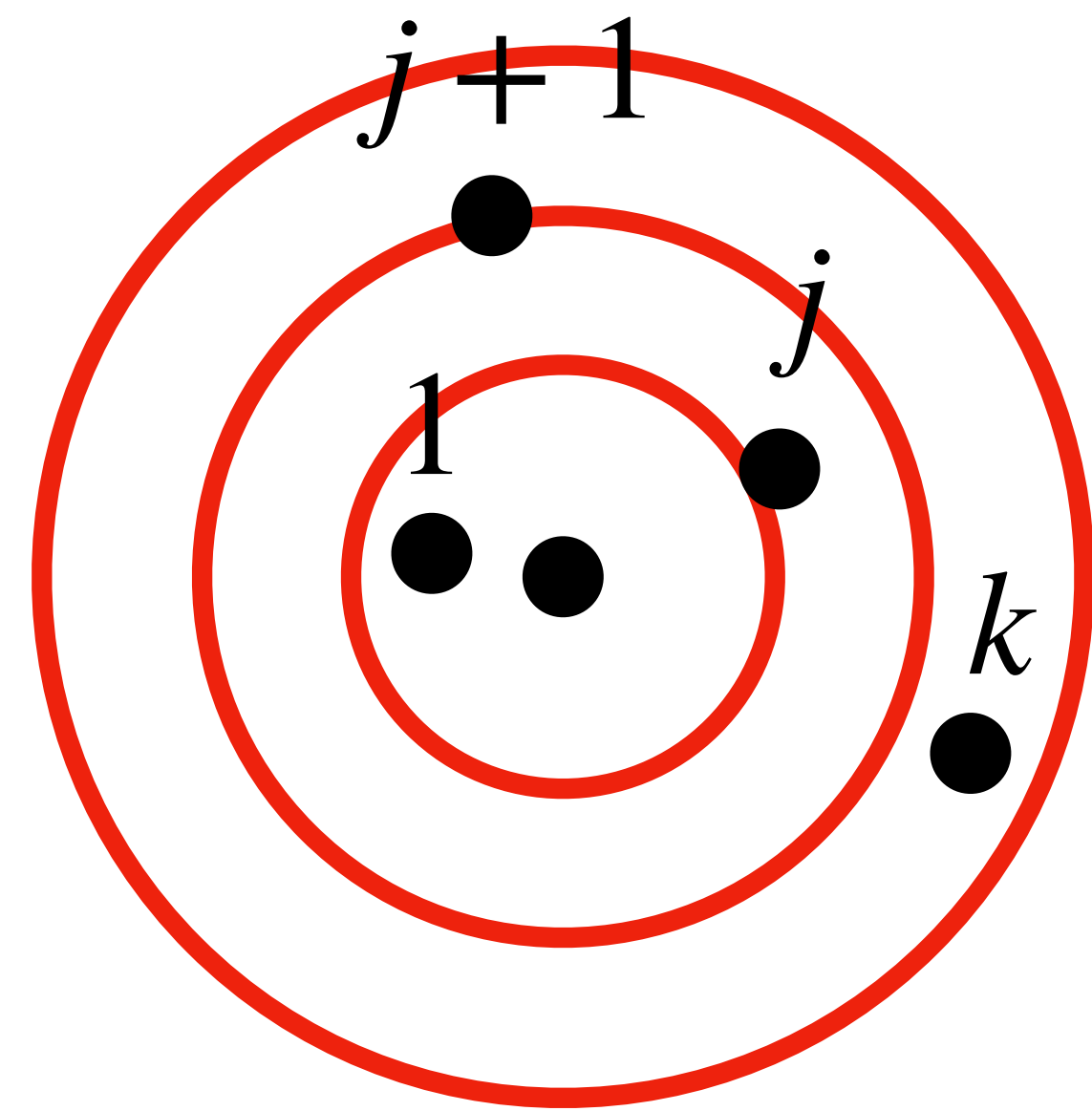
data density / distance



$$\mathbb{E}(\text{number of points}) = \rho V_m(r) \propto r^m$$

$$\text{e.g. } V_2(r) = \pi r^2, V_3(r) = \frac{4}{3} \pi r^3$$

# Maximum Likelihood Estimation of Poisson Process



$k$ -nearest neighbor

We observe  $r_1, r_2, r_3, \dots, r_k$

$$\mathbb{E}(\text{number of points}) = N(r) = \rho V_m(r) \propto r^m$$

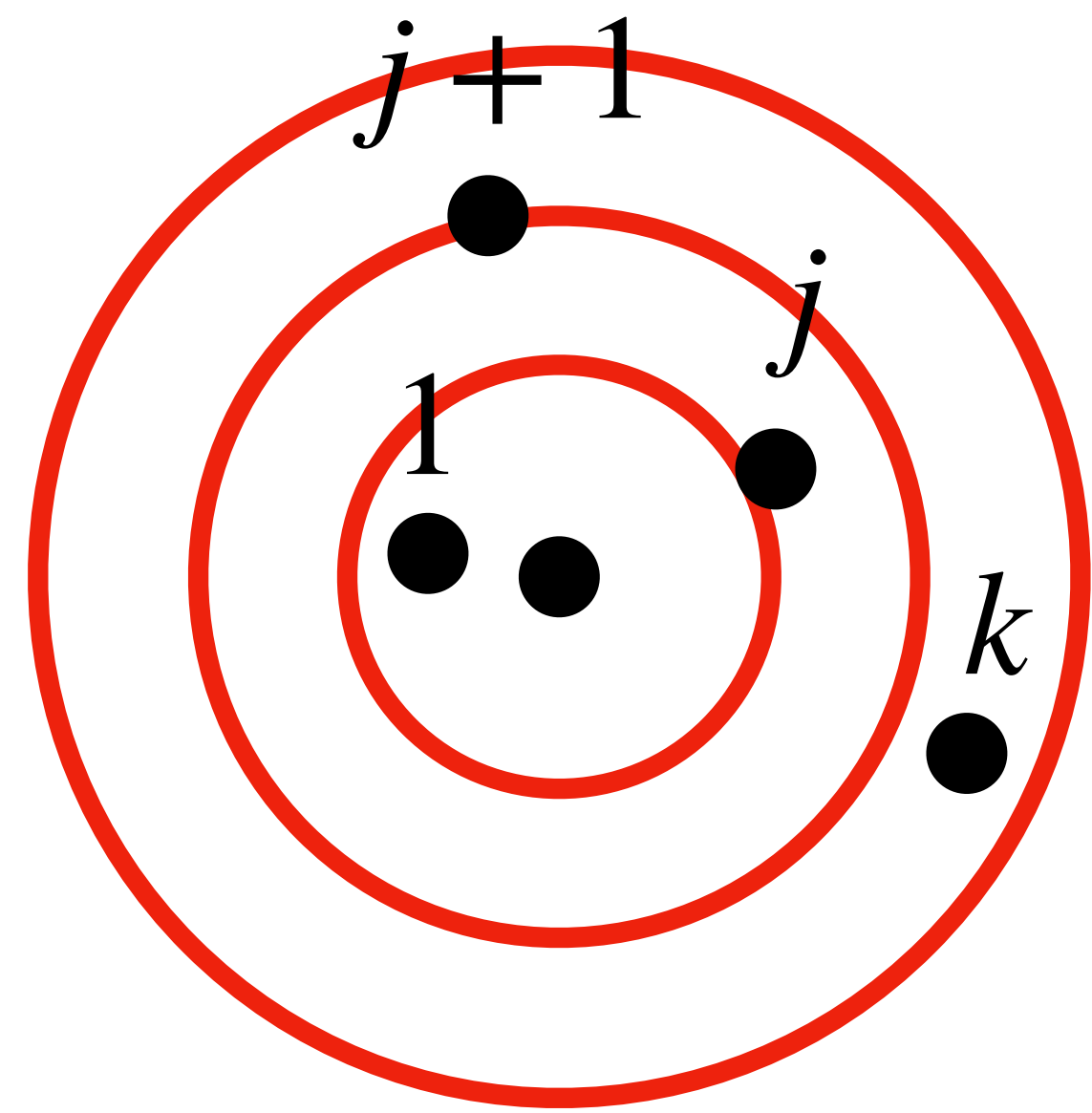
$$\lambda(r) \propto \frac{d}{dr} [r^m] = m \cdot r^{m-1}$$

$$P(N(r)) \propto \exp\left(-\int_0^R \lambda(r) dr\right) \prod_j \lambda(r_j),$$

$$L(m) = \int_0^R \log \lambda(r) dN(r) - \int_0^R \lambda(r) dr$$



# Maximum Likelihood Estimation of Poisson Process



$k$ -nearest neighbor

$$L(m) = \int_0^R \log \lambda(r) dN(r) - \int_0^R \lambda(r) dr$$

$$\frac{\partial L}{\partial m} = 0$$

$$\hat{m} = \left[ \frac{1}{k-1} \sum_{j=1}^{k-1} \log \frac{r_k}{r_j} \right]^{-1}$$



# Validating Dimension Estimation with Synthetic Data



Prepare:

Pretrained BigGAN with 128-dim latent set  $d$  when the others are 0 to make data

$k$	$\bar{d}$							GT
	2	4	8	16	32	64	128	
3	1.1	2.6	6.1	10.5	16.0	20.0	20.0	
4	1.5	3.6	8.2	14.0	21.0	26.0	26.0	
5	1.7	4.1	9.3	15.7	23.5	28.7	28.5	
6	1.8	4.4	9.9	16.6	24.9	30.3	29.9	
7	1.9	4.6	10.4	17.2	25.8	31.2	30.6	
8	1.9	4.7	10.7	17.6	26.4	31.7	31.1	
9	2.0	4.9	10.9	18.0	26.8	31.9	31.5	
10	2.0	5.0	11.1	18.2	27.1	32.1	31.7	
15	2.1	5.3	11.6	18.8	27.8	32.3	31.7	
20	2.2	5.5	11.8	19.0	27.9	31.9	31.3	
25	2.2	5.7	12.0	19.2	27.9	31.5	30.8	



# Why We Need to Know Intrinsic Dimension?

Measuring the difficulty in terms of classification

Dataset	MNIST	SVHN	CIFAR-100	CelebA	CIFAR-10	MS-COCO	ImageNet
MLE ( $k=3$ )	7	9	11	9	13	22	26
MLE ( $k=5$ )	11	14	18	17	21	33	38
MLE ( $k=10$ )	12	18	22	24	25	37	43
MLE ( $k=20$ )	13	19	23	26	26	36	43
SOTA Accuracy	99.84	99.01	93.51	-	99.37	-	88.55

Measuring the difficulty in terms of diffusion generation

Linear Convergence of Diffusion Models Under the Manifold Hypothesis

Number of diffusion steps =  $O(d)$

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# Why We Need to Know Intrinsic Dimension?

## Guidance of GAN design

*Accordingly, a latent code of size 512 is highly redundant, making the mapping network's task harder at the beginning of training. Consequently, the generator is slow to adapt and cannot benefit from Projected GAN's speed up. We therefore reduce StyleGAN's latent code  $z$  to 64*

## StyleGAN-XL: Scaling StyleGAN to Large Diverse Datasets

AXEL SAUER, KATJA SCHWARZ, and ANDREAS GEIGER

University of Tübingen and Max Planck Institute for Intelligent Systems, Tübingen, Germany





# Why We Need to Know Intrinsic Dimension

Detect AI-generated content

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## Intrinsic Dimension Estimation for Robust Detection of AI-Generated Texts

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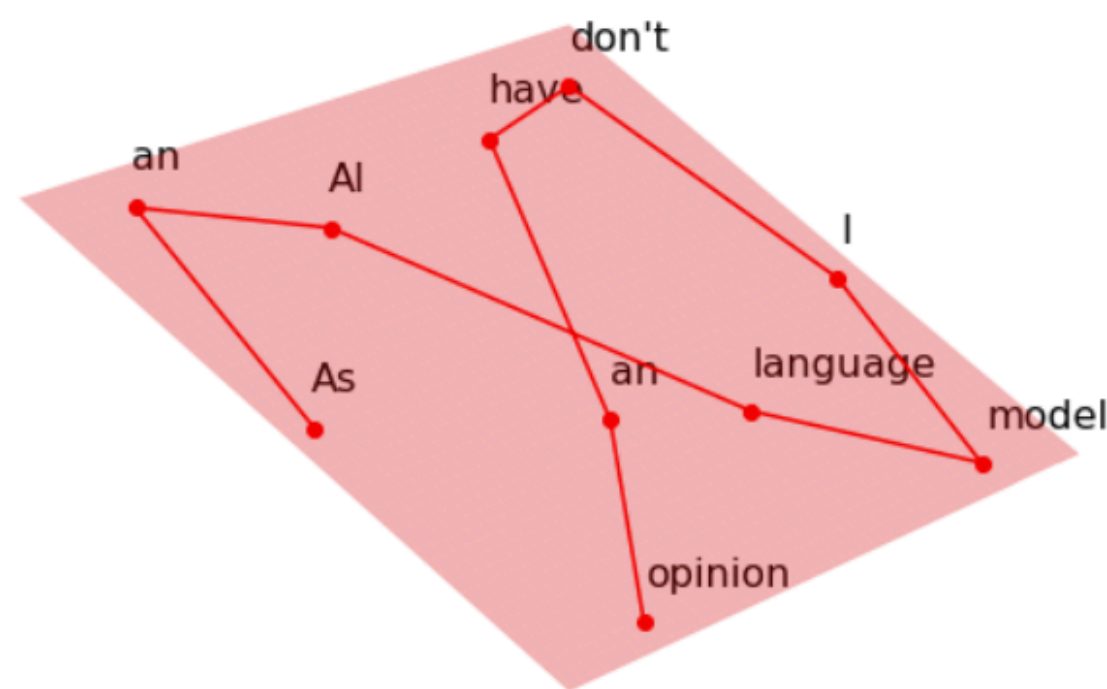
Eduard Tulchinskii<sup>1</sup>, Kristian Kuznetsov<sup>1</sup>, Laida Kushnareva<sup>2</sup>, Daniil Cherniavskii<sup>3</sup>,  
Sergey Nikolenko<sup>5</sup>, Evgeny Burnaev<sup>1,3</sup>, Serguei Barannikov<sup>1,4</sup>, Irina Piontkovskaya<sup>2</sup>

<sup>1</sup>Skolkovo Institute of Science and Technology, Russia;

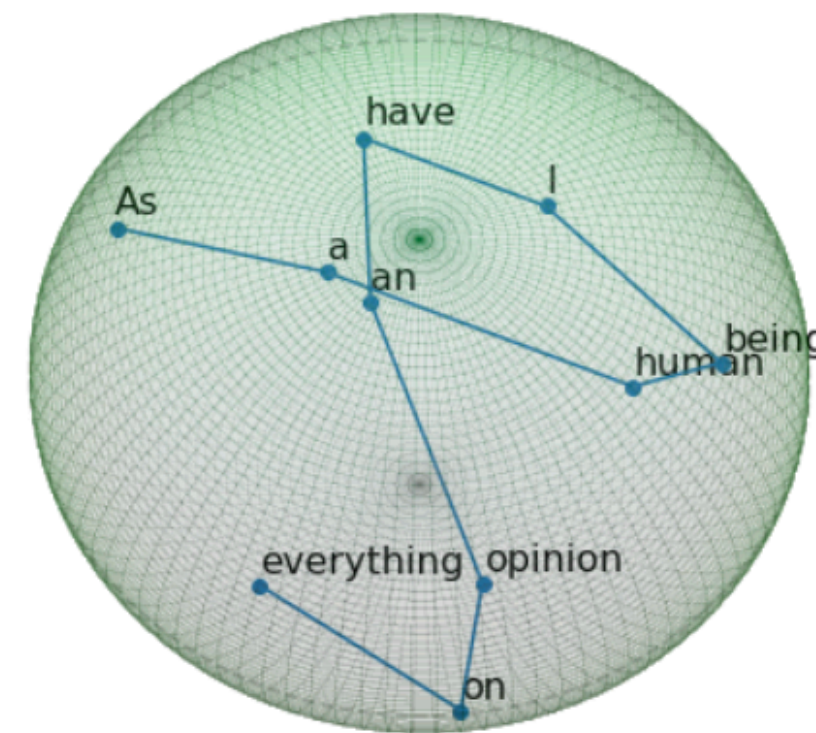
<sup>2</sup>AI Foundation and Algorithm Lab, Russia;

<sup>3</sup>Artificial Intelligence Research Institute (AIRI), Russia; <sup>4</sup>CNRS, Université Paris Cité, France;

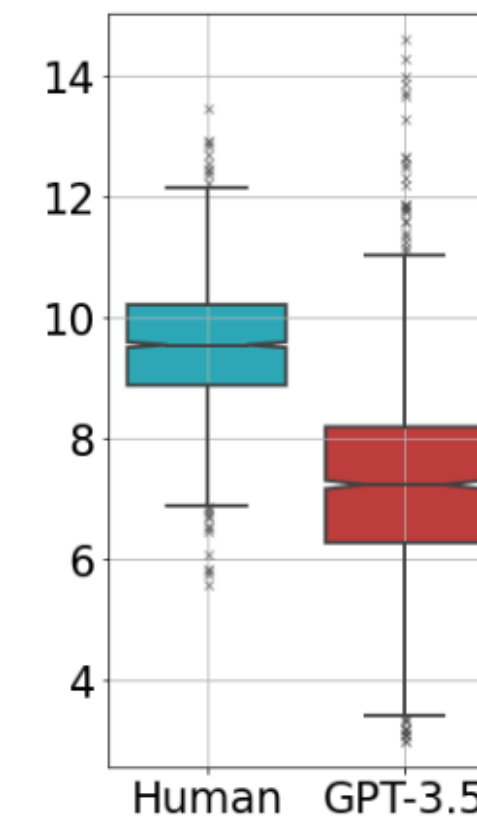
<sup>5</sup>St. Petersburg Department of the Steklov Institute of Mathematics, Russia



(a) AI generated



(b) human written



(c)