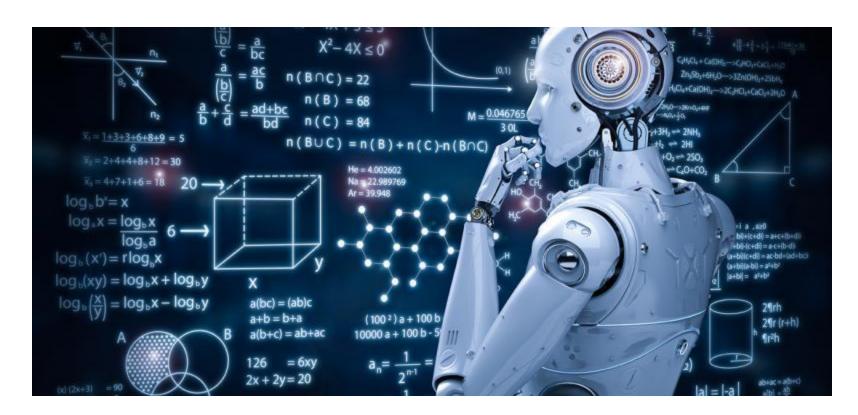
## Part III – Machine learning (ML)



1





## What is machine learning?



- Machine Learning is the most popular technique of **predicting** the **future** or **classifying information** to help people in making necessary decisions.
- Machine Learning algorithms are trained over instances or examples through which they learn from past experiences and also analyze the historical data.
- Therefore, as it trains over the examples, again and again, it is able to identify patterns in order to make predictions about the future.



## Machine learning, Deep learning, and Artificial Intelligence (AI)



- Machine Learning: branch of AI knowledge analysis that automates analytical model building
- **Deep learning:** broader family of ML methods supported artificial neural networks with representation learning
- AI is the greater pool that contains an amalgamation of all the above-discussed technologies.



Where do you encounter ML/AI in your day-2-day live?





## ML is everywhere



5

• Correction when you type on your phone

Speech recognition
Which advert to pu
SPAM filter
Prediction which m
Predict your friends
Autonomous car dr
single cell analysis predicting protein s

ChatGPT – and friends – does it all for you?

ALL BASED on collection of large data amount!

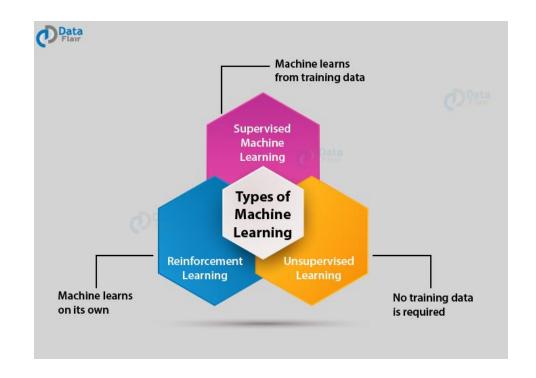


## My approach



- Realise, it is everywhere
- What are the dangers?
- General concept of types
- No math ⊗
- Some examples





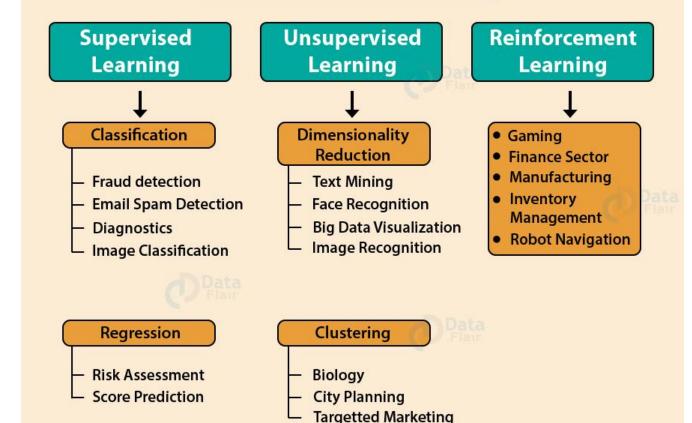




## Types of Machine Learning



8





## **Machine Learning Algorithms**



- **1.** Regression Linear Regression
- **2. Decision Tree Learning** supervised methods to take decisions based on user input.
- 3. Support Vector Machines to classify data into two categories or classes.
- **4. Association Rule Learning -** customer will buy item Y if he has purchased the item X
- 5. Artificial Neural Networks (ANN) mirror the brain layers of neuros –
- **6. Inductive Logic Programming -** produce a rule-like learning model.
- 7. Reinforcement Learning self driving car: series of trials and errors to get better
- **8.** Clustering unsupervised methods we did that!
- 9. Similarity and Metric Learning learns to map similar objects together
- 10. Bayesian Networks P(A/B) = P(B/A)\*P(A)/P(B)
- 11. Representation Learning algorithms are able to preserve the input data and essential information
- 12. Sparse Dictionary Learning extension of representation learning
- **13.** Transformers pay attention
- **14.** Natural Language Processing (NLP) makes chatGPT talk to you



## So far



- Clustering
- T-SNE / UMAP

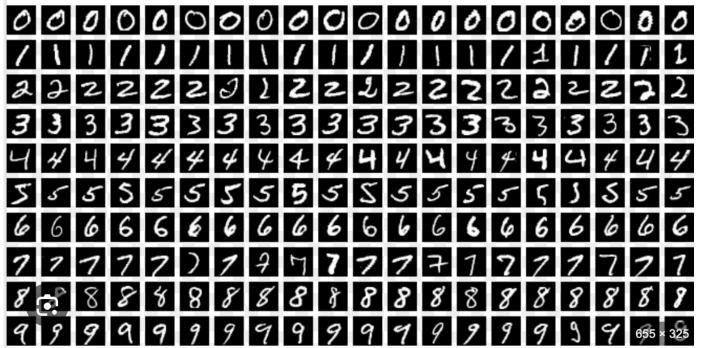
How can we use AI/ML in der interpretation of our data?



## Classifier – perceptron - a simplified approach



- A classifier of numbers from 0-9
- How easy?

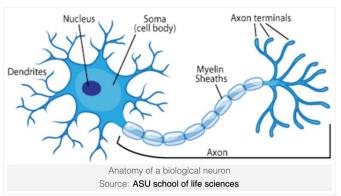


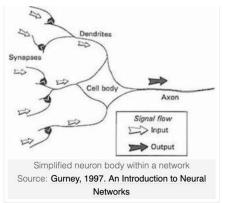


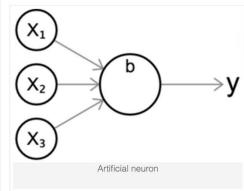
#### What we need...

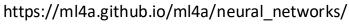


- We give it a number and want out, what number it is.
- Difficult as not clear
- Let's use a neural network







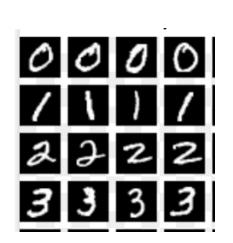


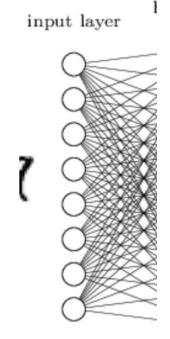


## What is the input?



- Yes the number?
- What how are we going to give it to the network?





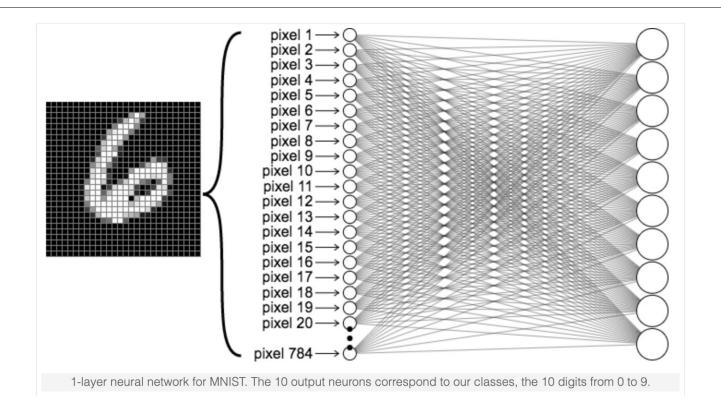
We need an "embedding"

Any ideas?



## Dimension of image + gray values



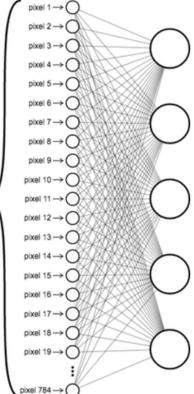




## Or back to 2 D



pixel 1 → pixel 2→ pixel 5→ pixel 10 → pixel 11 → pixel 12→ pixel 13→ pixel 14→ 28 x 28 pixel 15→ 784 pixels pixel 16→ pixel 17 → pixel 18→ pixel 19→

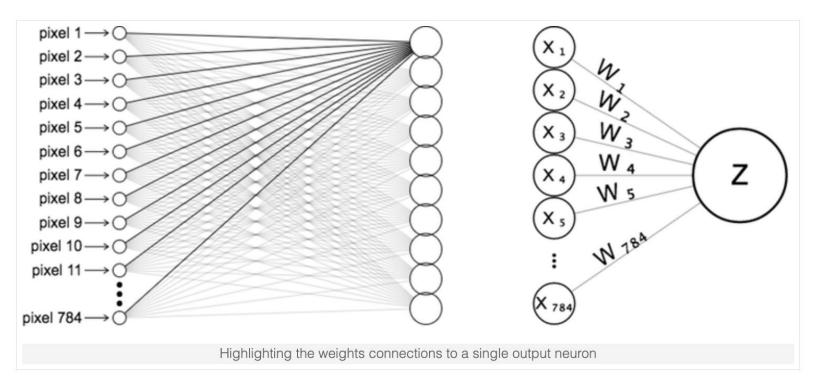


How to input an image into a neural network



## Which output fits to the correct numbers?



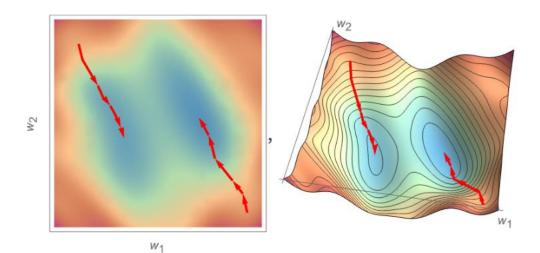




## Learning

BERNHARD NOCHT INSTITUTE FOR TROPICAL MEDICINE

- Split the data into training and testing
- Train, iteratively, optimise a cost function
- Try to find the global minimum of the cost function
- Hope that the system converges







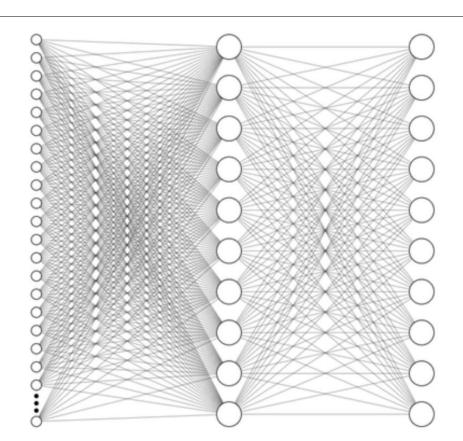


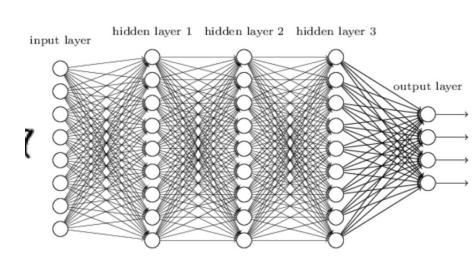
Der	Demo: Looking inside neural nets						[demo page]			rce]		MNIST ordinary v View numbers v sa		
		predi	ncted 0 predi	cted 1	icted 2 predi	icted 3	icted 4 predi	icted 5 predi	icted 6	icted 7 predi	cted 8	gicted 9 3 misclassified as 9		
	actual 0		0	0	7	1	10	6	3	7	3	96% 89% 82% 72% 71%		
	actual 1	0	1031	4	3	1	4	1	2	16	2	97%		
	actual 2	12	21	852	18	11	8	14	20	29	5	86% 5 5 3		
	actual 3	2	5	9	899	1	71	0	12	23	7	87% 70% 57% 51%		
	actual 4	2	8	2	2	861	7	7	1	4	89	88%		
	actual 5	7	5	9	24	3	833	12	8	12	2	91%		
	actual 6	11	6	2	0	6	31	902	0	8	1	93%		
	actual 7	3	10	5	3	7	7	1	1041	0	14	95%		
ow to	ow to improve??? 29					2	31	1	9	882	21	87%		
	actual 9	7	3	1	7	10	11	1	44	4	873	91%		
												accuracy		
	precision	95%	92%	96%	91%	95%	82%	95%	91%	90%	86%			



## Adding an internal layer!







99.4 % correctness



## If doing this, you need to read about



- Sample size
- Overfitting: a model learns patterns that are specific to the training data but don't generalize

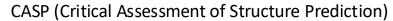


## Example of AI: Alpha fold v1



#### AlphaFold v1 (2018)

- Used convolutional and recurrent (LSTM) networks.
- Architecture was relatively shallow by today's standards: around 8–10 layers in its main modules.
- Achieved impressive accuracy for its time but had limits on long-range residue interactions.

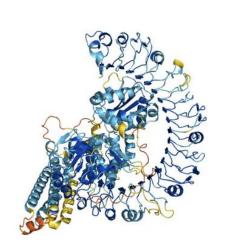


**Accuracy:** It predicted **~25 out of 43 protein structures** *more accurately than any other method*.

Average GDT TS: ≈ 58.9

#### **Second-best method**

- The **second-ranked group** at CASP13 was typically listed as **Zhang Lab** (University of Michigan, team "Zhang-Server").
- Their models were the best for about **3 to 5** targets (depending on subcategory).
- Average GDT\_TS: ≈ 49.6 (FM category)





#### AF version 2



- AlphaFold v2 at CASP14 (2020)
- **Competition:** CASP14 (2020)
- **Result:** Transformed the field entirely.
- Average GDT\_TS: 92.4 (out of 100) across all categories essentially experimental accuracy.

So here we can see that AI – deep neural networks, do "something correct"



## AlphaFold v2 (2021)



- Completely redesigned with transformer-style modules.
- Uses two key components:

**Evoformer** – a deep stack of *transformer blocks* processing sequence and pairwise residue information.

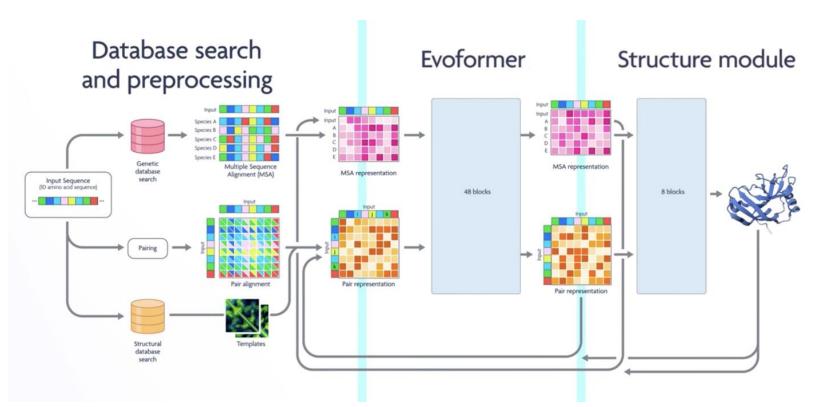
**Structure Module** – a geometric deep-learning component that predicts 3D atomic coordinates.

- Each Evoformer contains about **48 transformer blocks**, and each block includes **multiple attention layers** (so, effectively hundreds of sublayers when expanded).
- So depending on how you count, AlphaFold2 has on the order of hundreds of neural layers, far deeper than a standard MLP.



## The trick is the transformer and putting things one after the other









Transformers let the model learn what to pay attention to.

Provided proper attribution is provided, Google hereby grants permission to reproduce the tables and figures in this paper solely for use in journalistic or scholarly works.

#### **Attention Is All You Need**

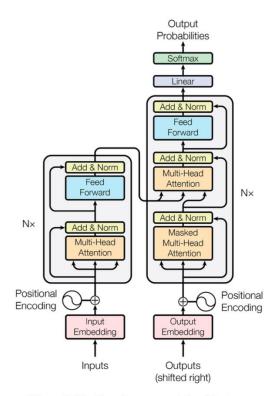


Figure 1: The Transformer - model architecture.

I still need to read this paper!



## What is the attention part exactly?



- "The cat sat on the mat because it was soft."
- The It refers to the mat that is not easy to get the of neural network
- For each token (word) it computes three vectors: Query (Q), Key (K), and Value (V).

$$\operatorname{Attention}(Q,K,V) = \operatorname{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$



#### How does ChatGPT works?



- https://writings.stephenwolfram.com/2023/02/what-is-chatgpt-doing-and-why-does-it-work/
- Just decided "randomly" what the next word will be

a ranked list of words that might follow, together with "probabilities":

The best thing about AI is its ability to

learn	4.5%
predict	3.5%
make	3.2%
understand	3.1%
do	2.9%

- Probability is learn from billions of texts of the internet
- There is a random value, which word to take in the list... so every answer is the same

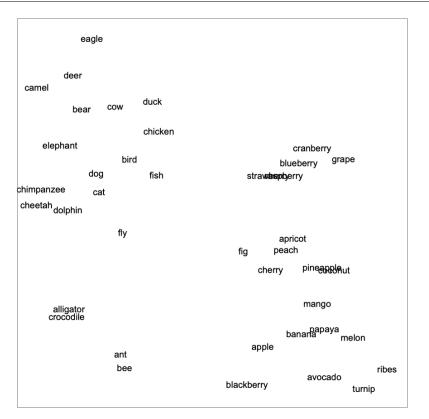


## The Concept of Embeddings



- Words get transformed into numbers
- if we project down to 2D
- Train on 5 billion words from the web and some words like crocodile and alligator will often appear almost interchangeably in otherwise similar sentences

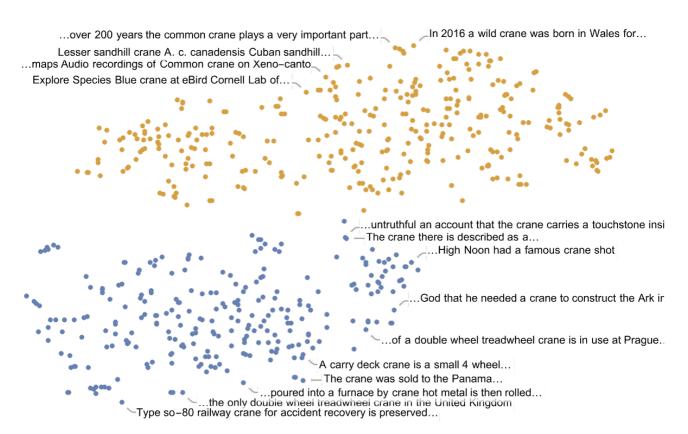
• 175 billion neural net weights





## Store more concepts

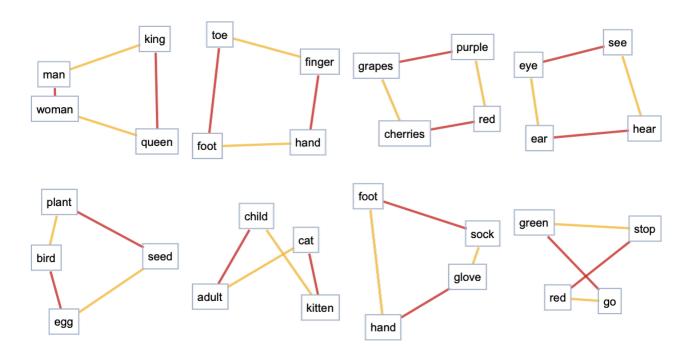






Is there for example some kind of notion of "parallel transport" that would reflect "flatness" in the space? One way to get a handle on that is to look at analogies:





And, yes, even when we project down to 2D, there's often at least a "hint of flatness", though it's certainly not universally seen.



## But why am I telling you that?



Could we train a LLM based on scRNA-Seq data, that "knows" which gene to express next?





#### **Article**

# Transfer learning enables predictions in network biology

https://doi.org/10.1038/s41586-023-06139-9

Received: 29 March 2022

Accepted: 27 April 2023

Published online: 31 May 2023

Check for updates

Christina V. Theodoris<sup>1,2,3,4 ⋈</sup>, Ling Xiao<sup>2,5</sup>, Anant Chopra<sup>6</sup>, Mark D. Chaffin<sup>2</sup>, Zeina R. Al Sayed<sup>2</sup>, Matthew C. Hill<sup>2,5</sup>, Helene Mantineo<sup>2,5</sup>, Elizabeth M. Brydon<sup>6</sup>, Zexian Zeng<sup>1,7</sup>, X. Shirley Liu<sup>1,7,8</sup> & Patrick T. Ellinor<sup>2,5 ⋈</sup>

Mapping gene networks requires large amounts of transcriptomic data to learn the connections between genes, which impedes discoveries in settings with limited data,



#### GeneFormer - the model

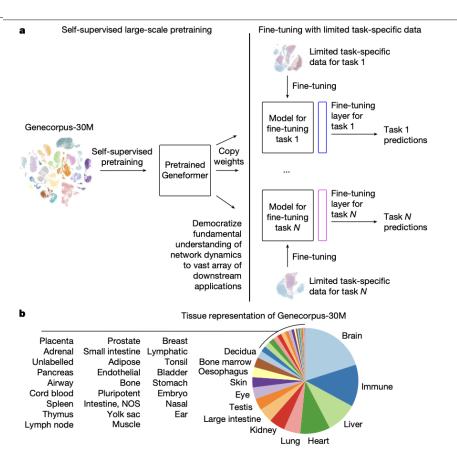


а Standard approach: training on task-specific learning objective for each application Supervised Labeled training Predictions on specific Trained task-specific task for which model model training data was initially trained b Limited task-specific One self-supervised data for task 1 large-scale pretraining on generalizable Fine-tuning learning objective Model for Large-scale Task 1 fine-tuning pretraining corpus predictions task 1 Self-supervised Fine-tuning with pretraining Pretrained limited task-specific data on model task-specific learning objectives for a multitude of downstream applications Model for Task N fine-tuning Democratize predictions task N fundamental understanding of learning Fine-tuning domain Limited task-specific data for task N



## The training data

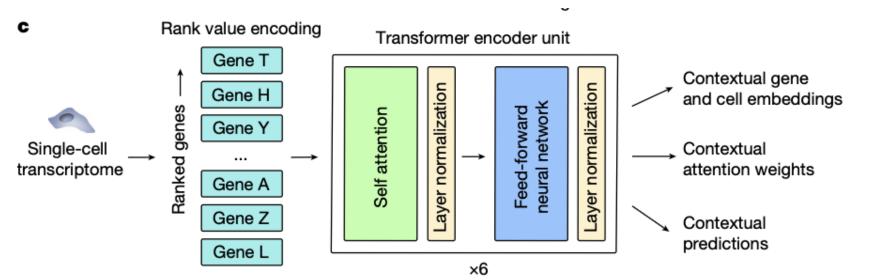






## **Application**

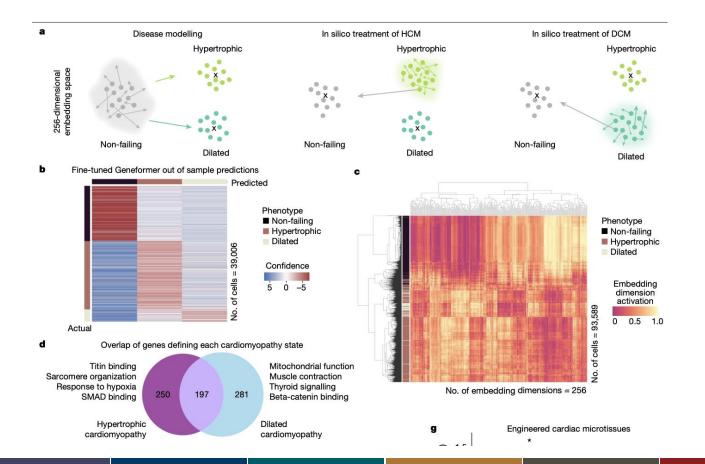






### In silico perturbation







Now, think you have your own data, what could you do?

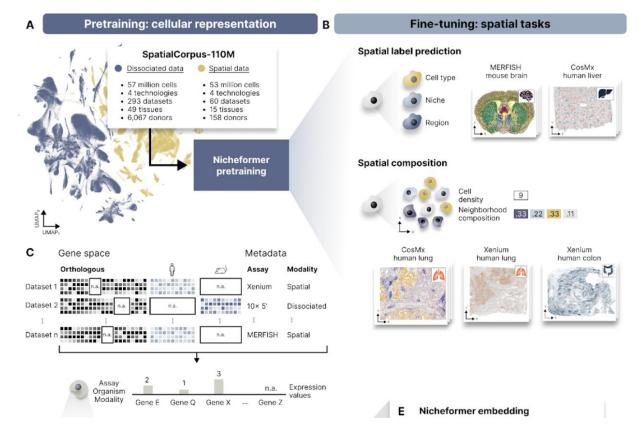




#### More datasets to come

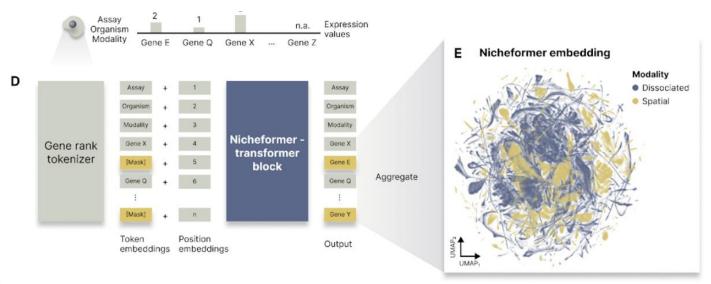


Niechformer – Schaar et al, Theis lab, BioRxiv 20205 - From 90 million to 300 cells?









130 Figure 1 | Nicheformer, a foundation model for spatial transcriptomics. A) Nicheformer is pretrained on the

129



Again, how could you used that?





## Thank you for inviting me to Montevideo



