A Primer on Deep Learning
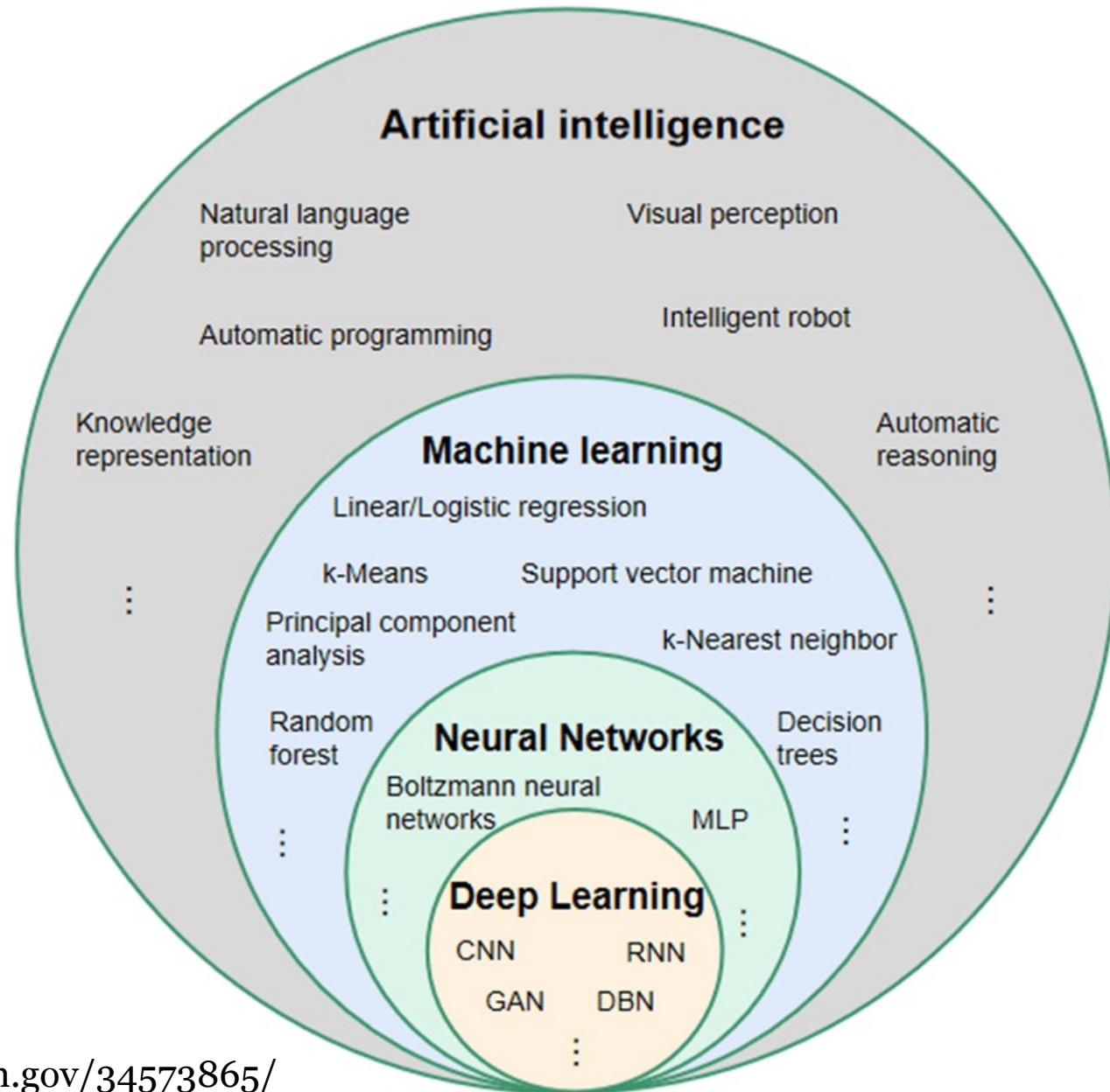
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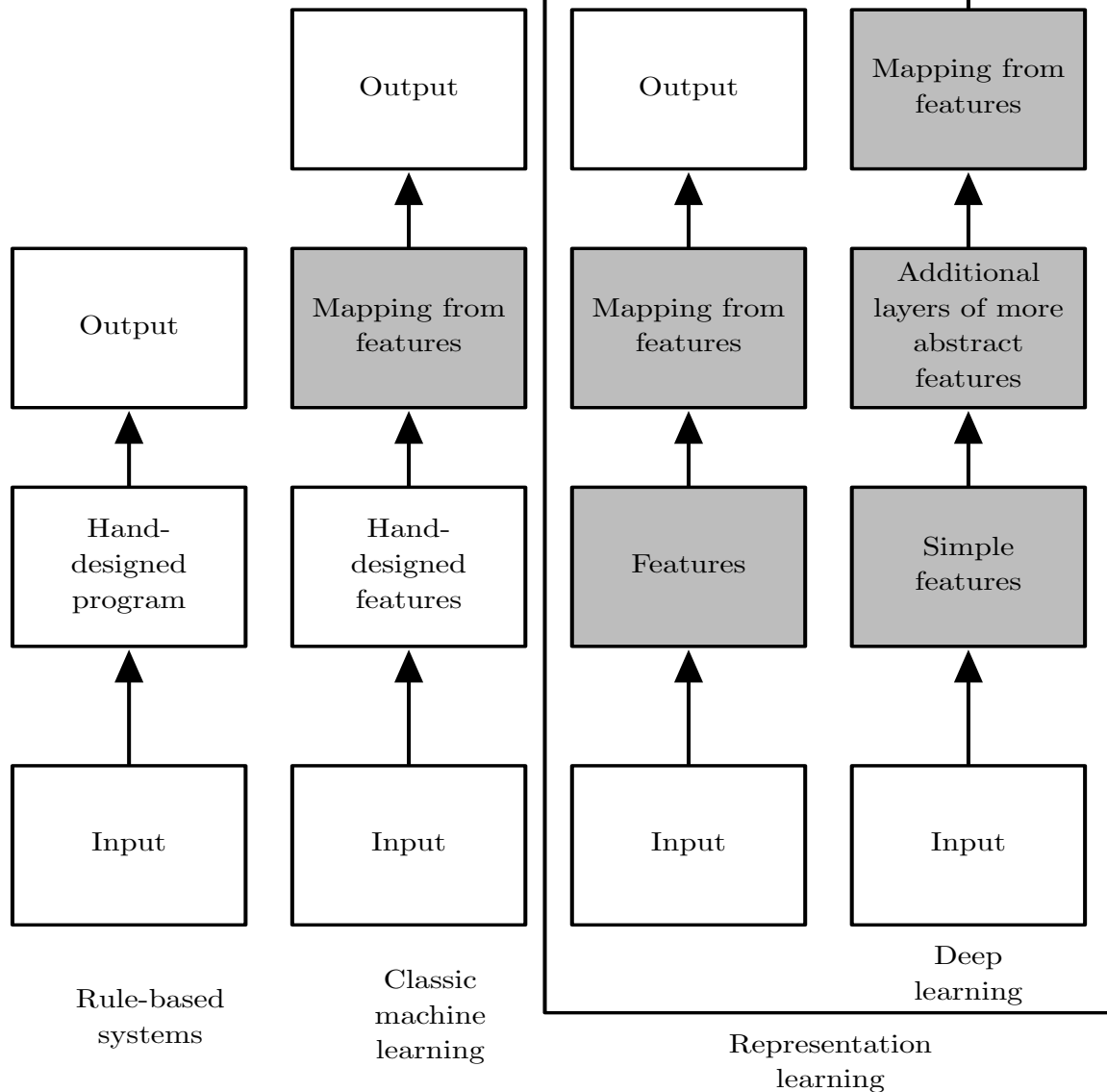*http://digbio.missouri.edu*

AI Scope

Artificial intelligence

Natural language processing

Visual perception

Automatic programming

Intelligent robot

Knowledge representation

Automatic reasoning

⋮

Machine learning

Linear/Logistic regression

k-Means   Support vector machine

Principal component analysis

k-Nearest neighbor

Random forest

Neural Networks

Decision trees

Boltzmann neural networks

MLP

⋮

Deep Learning

CNN   RNN

GAN   DBN

⋮

⋮

⋮

https://pubmed.ncbi.nlm.nih.gov/34573865/

Different Approaches

			Output
	Output	Output	Mapping from features
Output	Mapping from features	Mapping from features	Additional layers of more abstract features
Hand-designed program	Hand-designed features	Features	Simple features
Input	Input	Input	Input
Rule-based systems	Classic machine learning	Representation learning	Deep learning

Supervised Machine learning

- Apply a prediction function to a feature representation of the image to get the desired output:

$$f(\text{}) = \text{``apple''}$$

$$f(\text{}) = \text{``tomato''}$$

$$f(\text{}) = \text{``cow''}$$

Supervised Machine learning

$$y = f(\mathbf{x})$$

output   prediction   Image
          function   feature
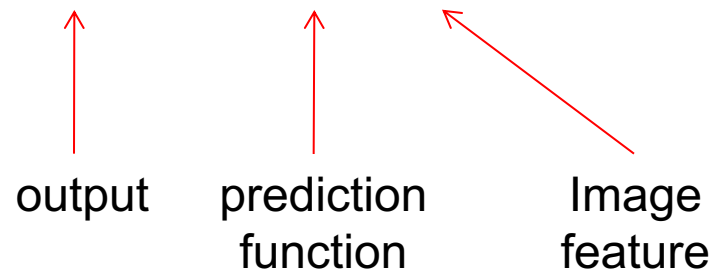
- **Training:** given a *training set* of labeled examples $\{(\mathbf{x}_1,y_1), ..., (\mathbf{x}_N,y_N)\}$, estimate the prediction function f by minimizing the prediction error on the training set

- **Testing:** apply f to a never before seen *test example* $\mathbf{x}$ and output the predicted value $y = f(\mathbf{x})$

Generalization

Training set (labels known)

Test set (labels unknown)

- How well does a learned model generalize from the data it was trained on to a new test set?

Learning Hierarchical Representations

Low-level features → Mid-level features → High-level features → Trainable classifier → output

Increasing level of abstraction
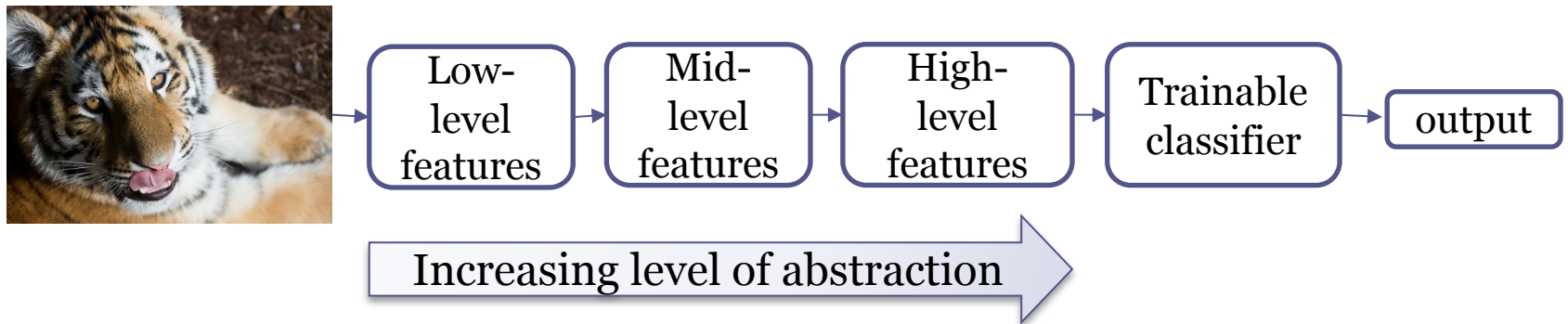
- Hierarchy of representations with increasing level of abstraction. Each stage is a kind of trainable nonlinear feature transform
- Image recognition

  Pixel → edge → texton → motif → part → object
- Text

  Character → word → word group → clause → sentence → story

Example Application

- Handwriting Digit Recognition

$$f: R^{256} \rightarrow R^{10}$$
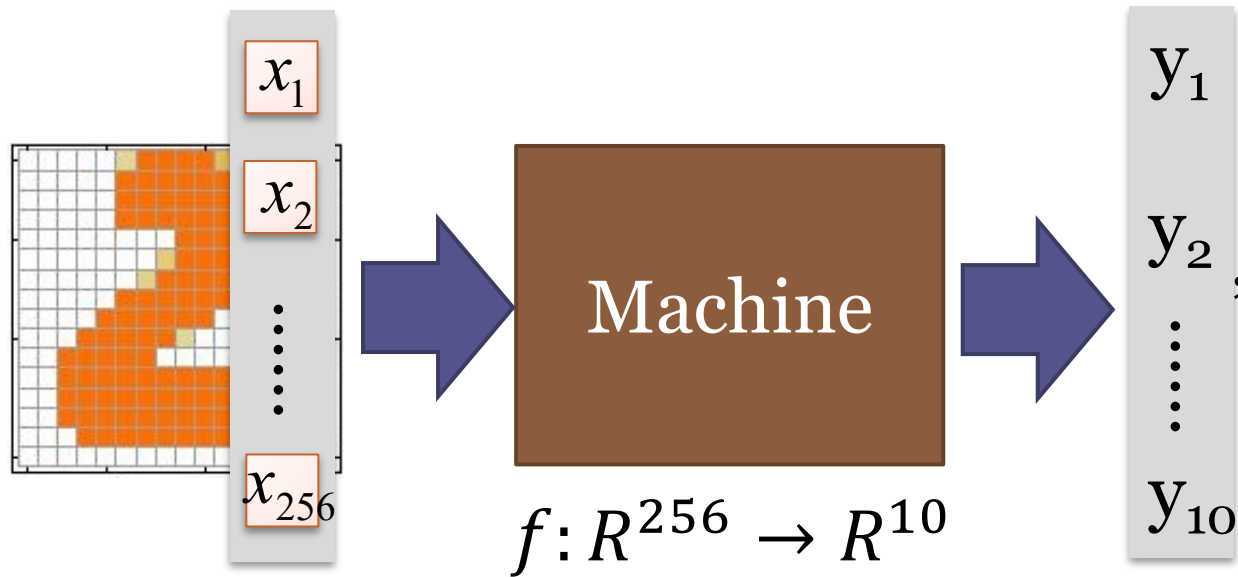
Handwriting Digit Recognition

Input

16 x 16 = 256

Ink → 1
No ink → 0

Output

0.1	is 1
0.7	is 2
0.2	is 0

The image is "2"
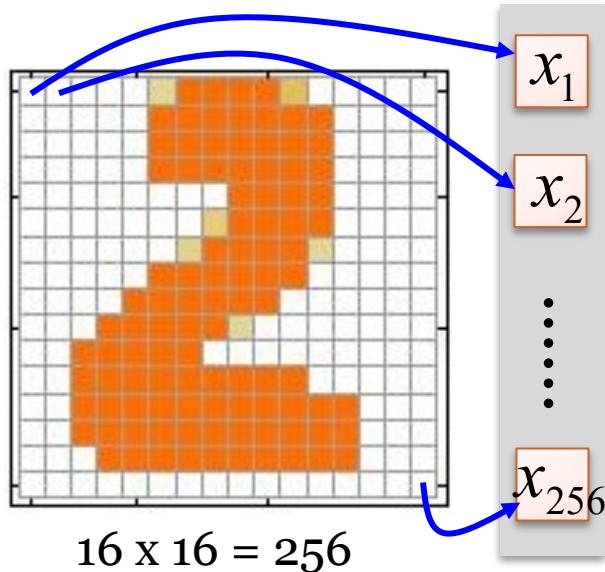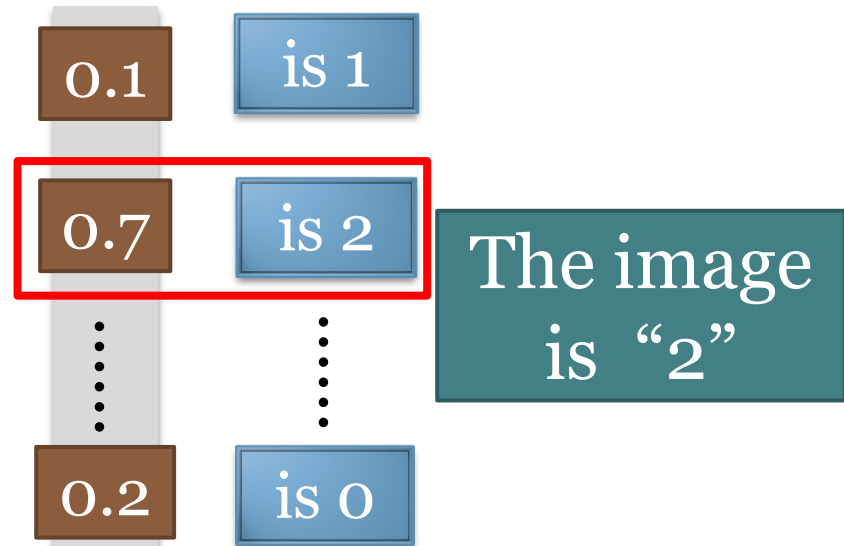
Each dimension represents the confidence of a digit.

Deep Neural Network (DNN)

neuron

Input Layer Layer Layer Output

x_1

x_2

x_N

...... y_1

...... y_2

...... y_M

**Input
Layer**

**Hidden
Layers**

**Output
Layer**
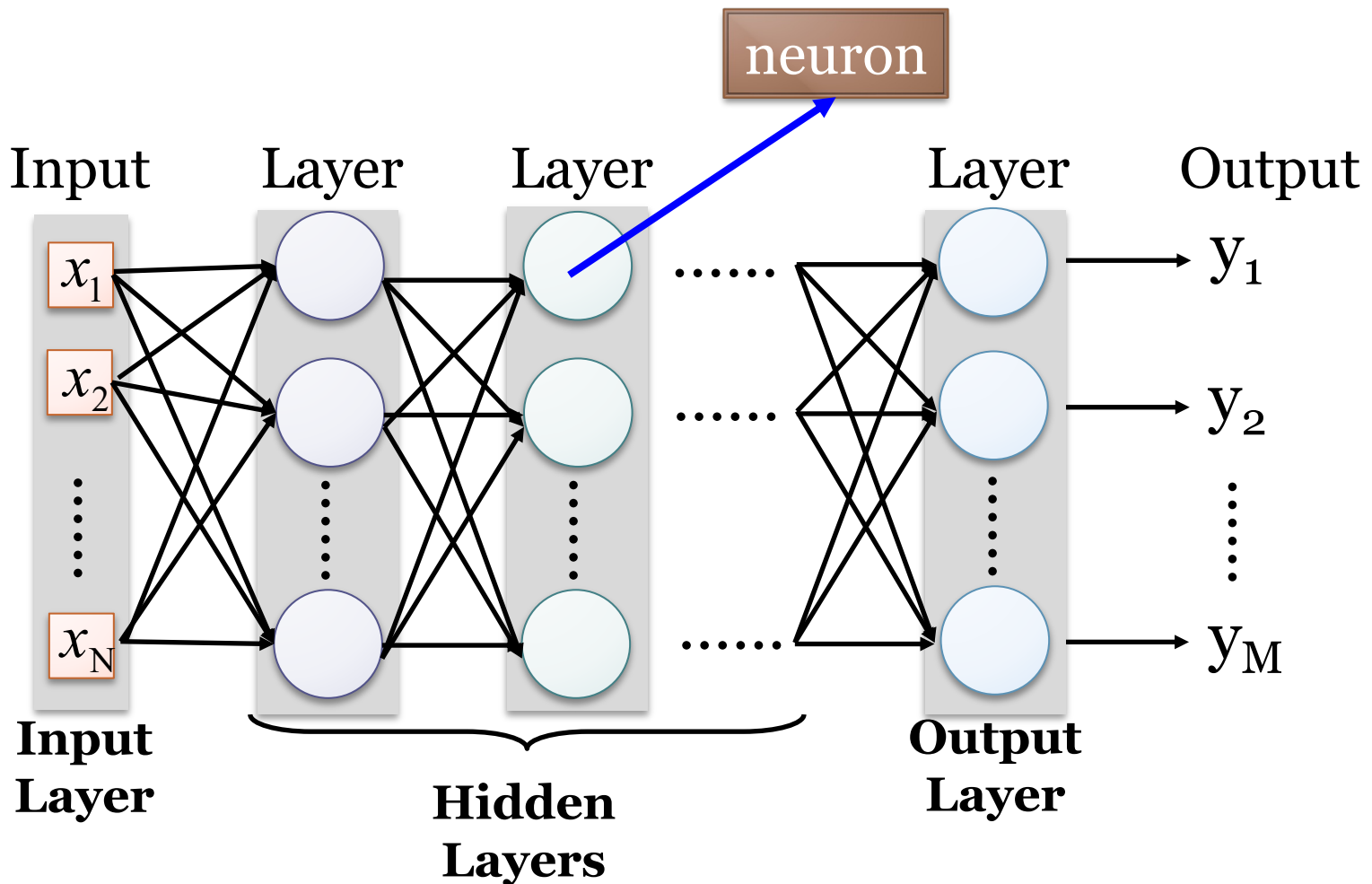
Deep means many hidden layers

Abstraction and Representation

physical space → latent/embedding space (manifold)

photo	impressionism	expressionism	cubism	abstract expressionism

Latent Representation
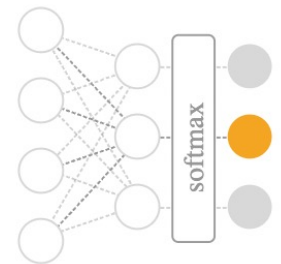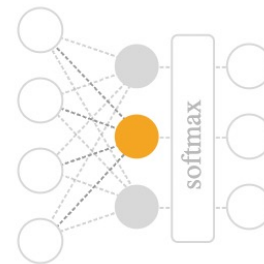
Neuron
$layer_n[x,y,z]$
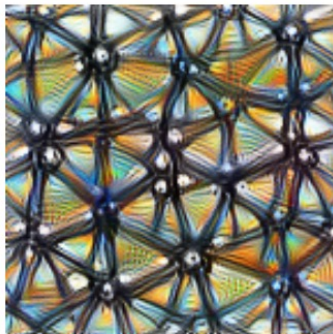
Channel
$layer_n[:,:,z]$

Layer/DeepDream
$layer_n[:,:,:]^2$

Class Logits
$pre\_softmax[k]$
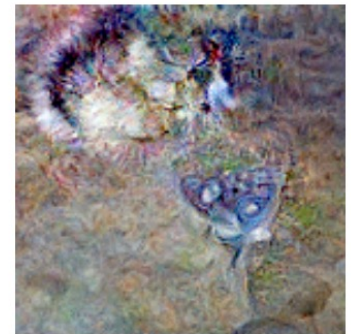
Class Probability
$softmax[k]$

https://distill.pub/2017/feature-visualization/

Unsupervised Learning & Embedding

High-dimensional signals
in a signal space S

Embedding space
(e.g., low-dimension,
small number of bits)
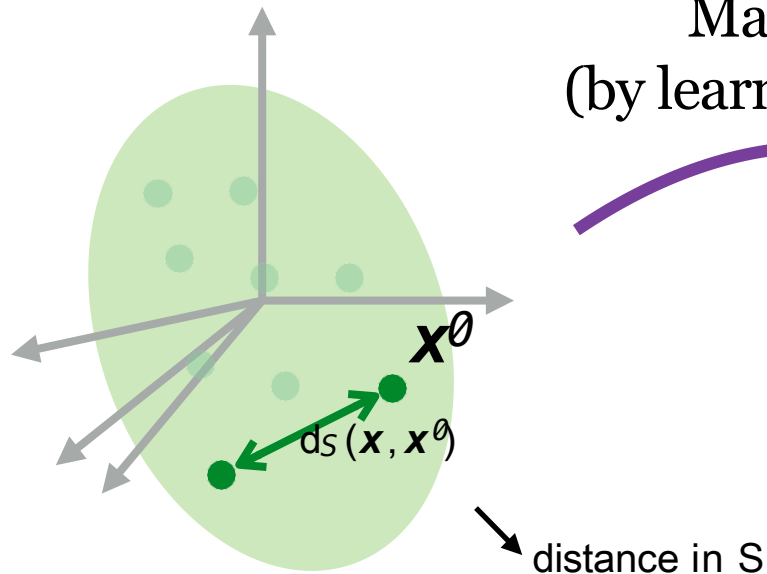
Mapping
(by learning in DL)

$\boldsymbol{X^0}$

$d_S(\boldsymbol{x}, \boldsymbol{x^0})$

distance in S

$f(\boldsymbol{x^0})$

$f(\boldsymbol{x})$

$d_E(f(\boldsymbol{x}), f(\boldsymbol{x^0}))$
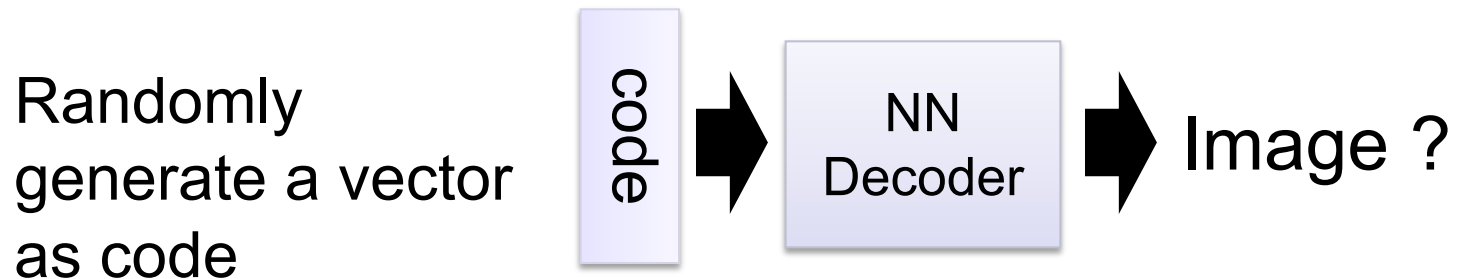
distance in E
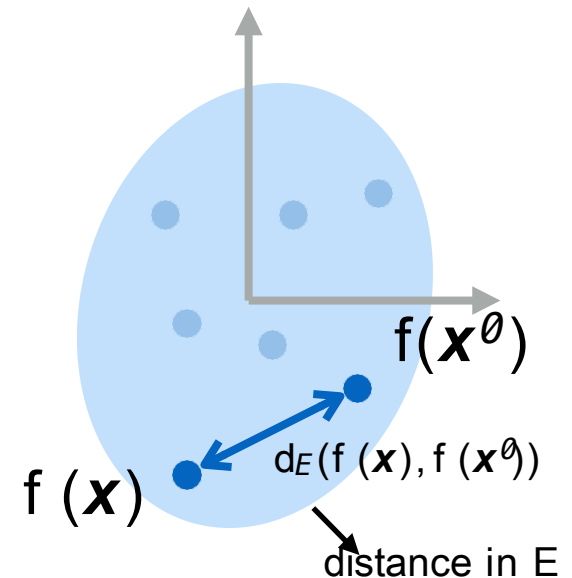
An embedding is a function from an original space to an embedding
space that preserves aspects of the geometry of the original space

Autoencoder
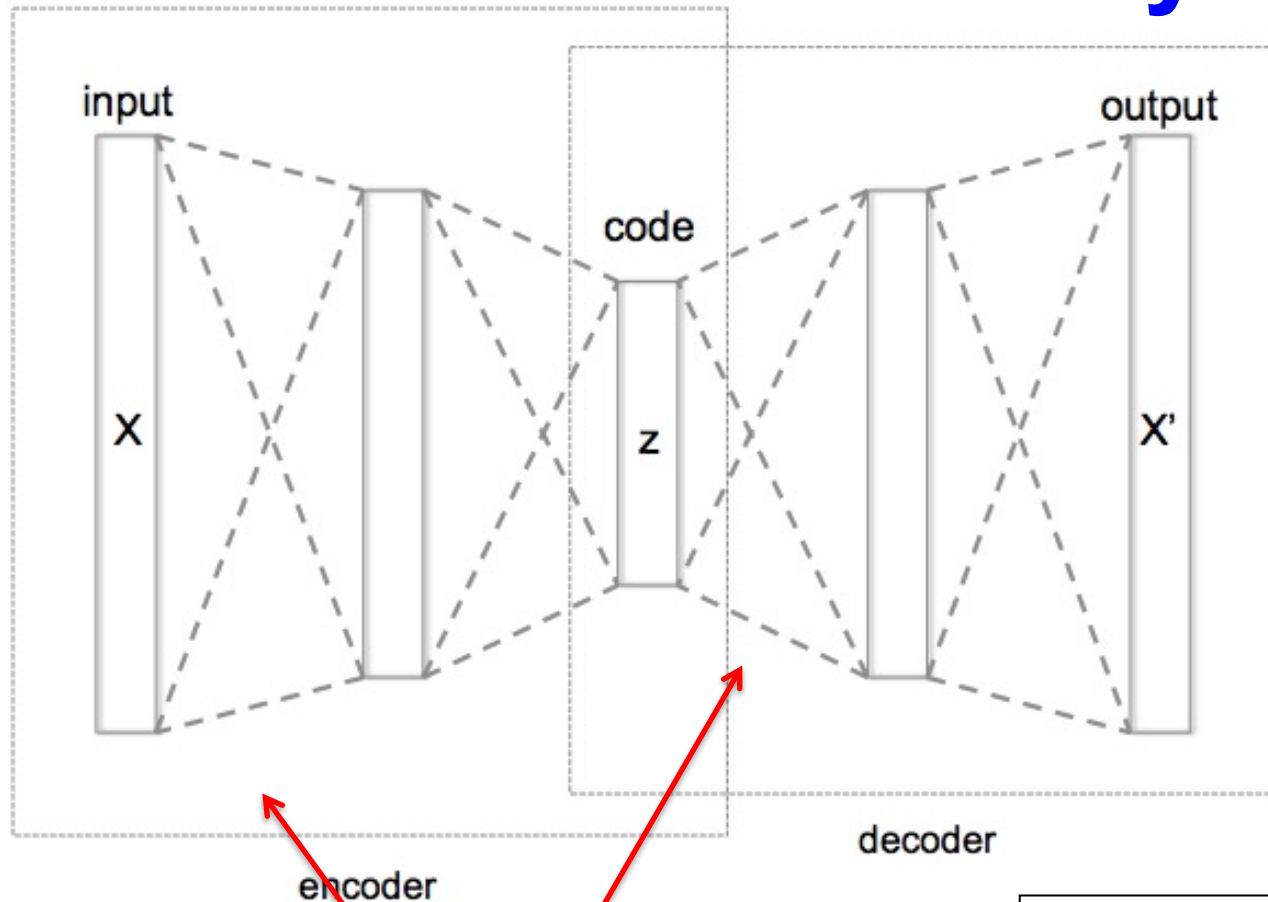
As close as possible
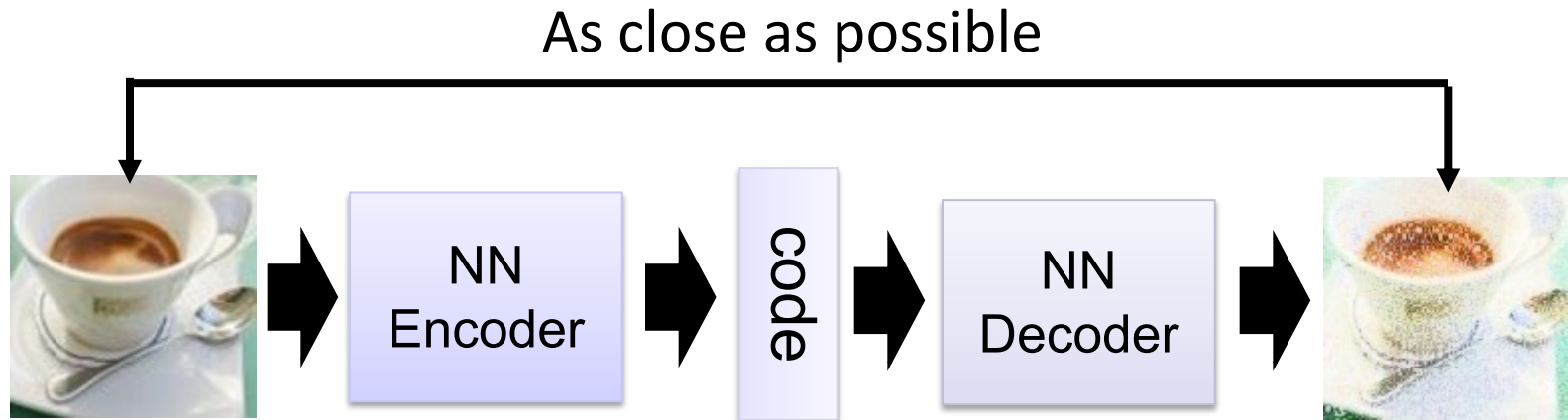
A type of unsupervised learning which discovers generic features of the data (**learn data patterns**)

Randomly generate a vector as code   code → NN Decoder → Image ?

Autoencoder with 3 Layers

input

output

code

X

z

X'

encoder

decoder
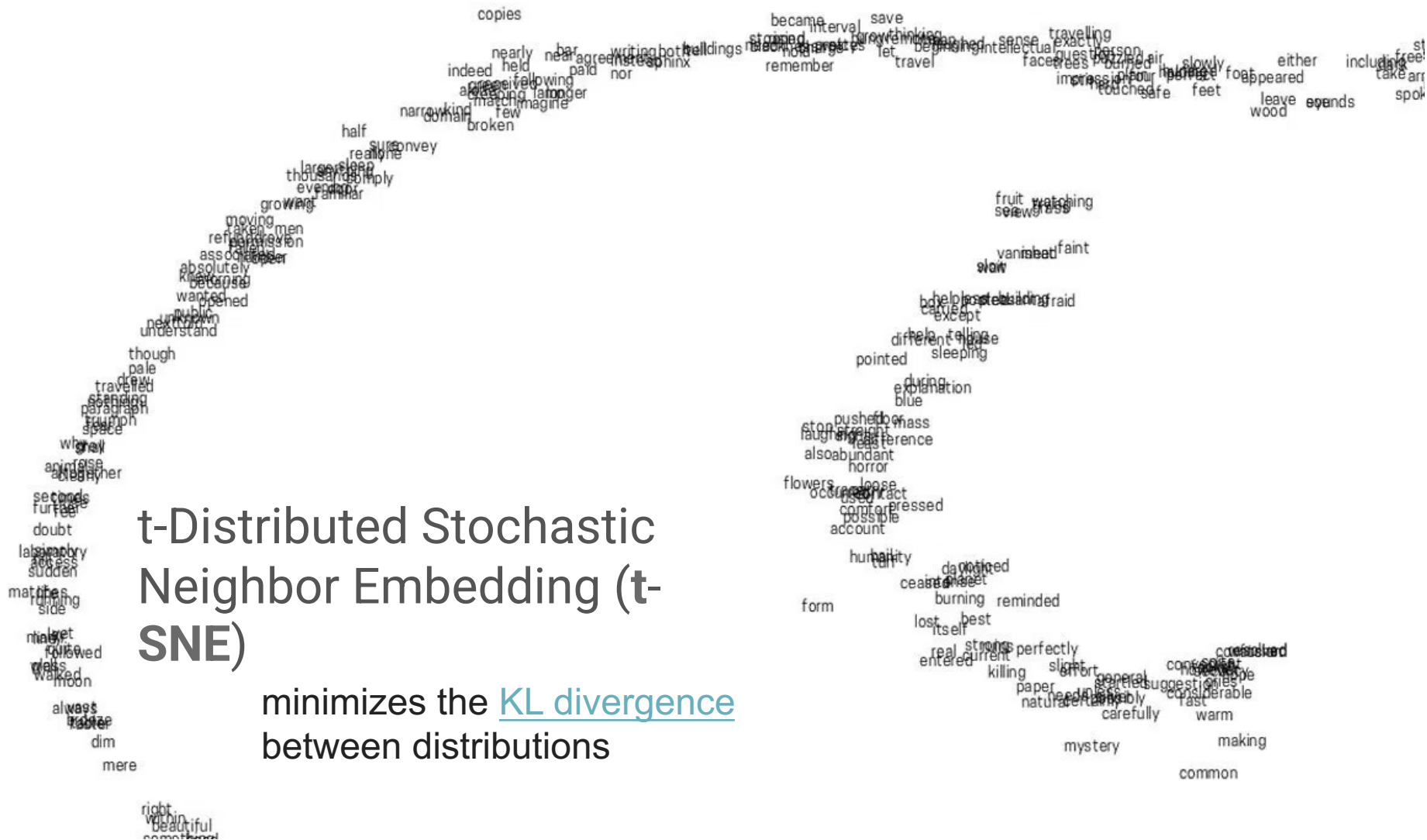
Large → small, learn to compress

Z: Latent variable; embedding

Training: model.fit(X,X)
Cost function: $\Sigma_{k=1..N} (x_k - x'_k)^2$

T-SNE Visualization

t-Distributed Stochastic Neighbor Embedding (**t-SNE**)
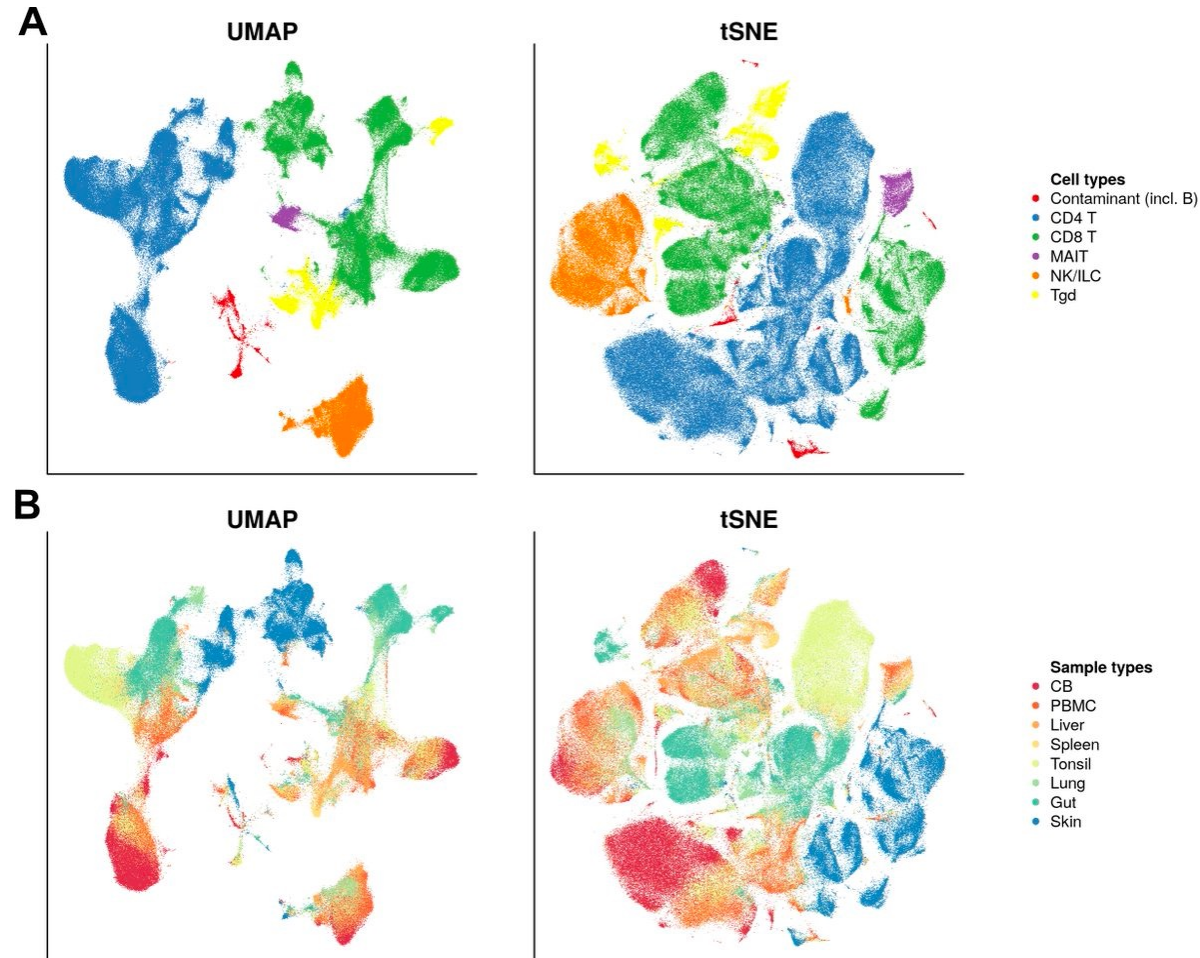
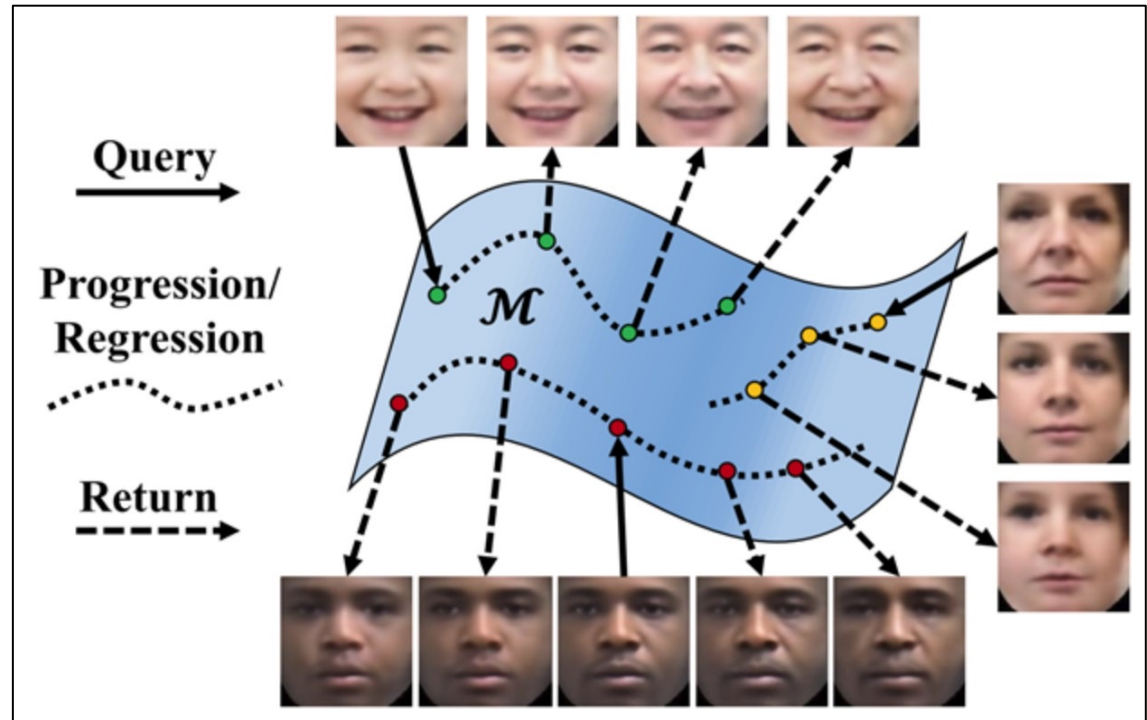minimizes the KL divergence between distributions

U-Map

Uniform Manifold Approximation and Projection (UMAP)

**find a topological representation of the data in a lower dimensional space through manifold learning technique**

https://github.com/lmcinnes/umap

Manifold

- A Manifold is a topological space that locally resembles Euclidean space near each point
- n-dim manifold → topological space M, every point x ∈ M has a neighbor homeomorphic (isomorphismic) to Euclidean space Rn

Manifold Hypothesis

- **DL Central Hypothesis**: Data concentrates around a low-dim manifold (**relevant dimension**)
- Mimic human learning
- Not all embeddings produce manifold
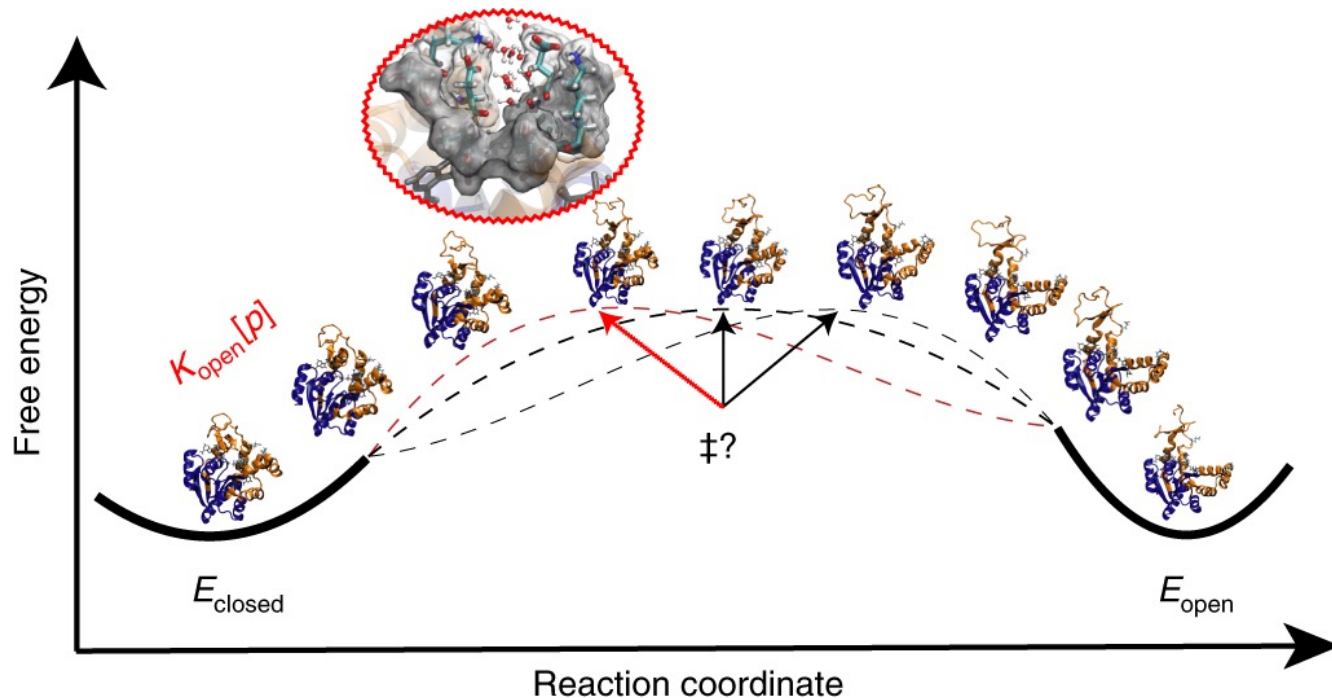
Self-supervised learning
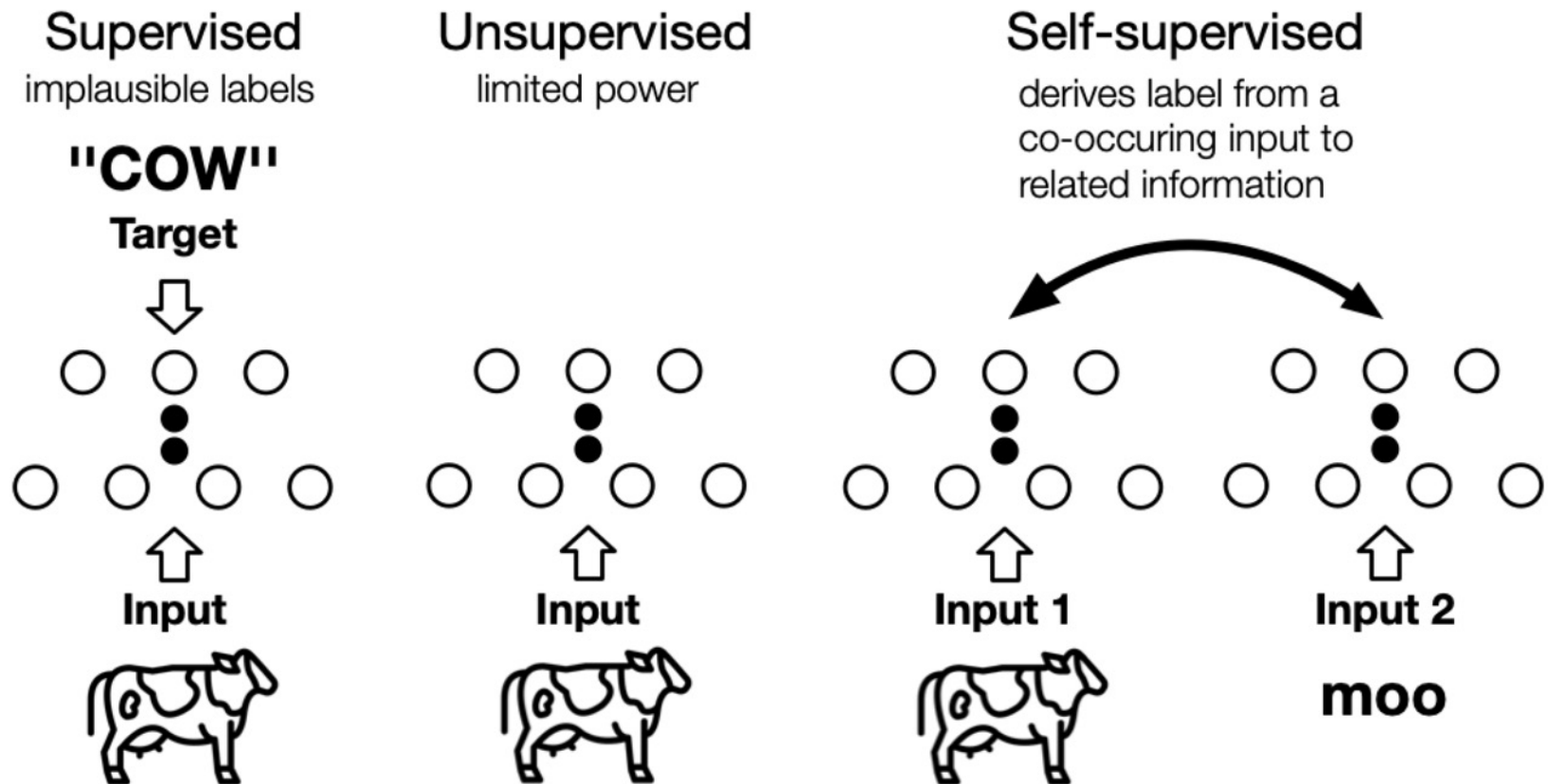
representation learning that enables learning good data representation from unlabeled dataset.

Foundation model era

- Machine learning paradigms

   Feature engineering: manual feature extraction (SVM, LightGBM, XGBoost)

   Architecture engineering: raw features, design deep network (CNN, LSTM)

   Objective engineering: pre-train large model and fine-tune it (ResNet50, Bert)

   Prompt engineering: prompt **foundation model** in zero/few shots

- Industrial era of artificial intelligence

AM radio receiver circuit

ElecCircuit.com