# **KAN**

Kolmogorov–Arnold Networks

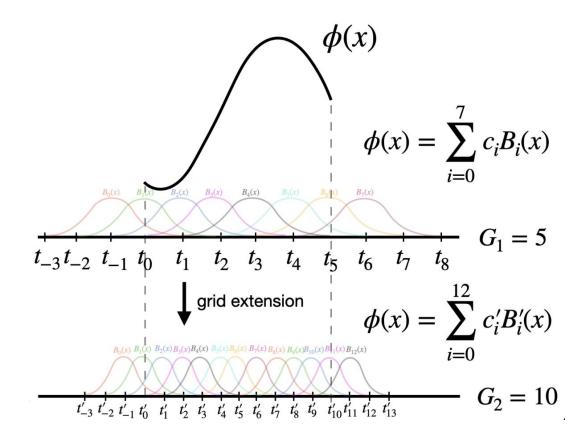
### Summary

- Komolgorov-Arnold Theorem
- How B-Splines works?
- A Brief Context
- What is KAN?
- Advantages and Challenges
- Variations of KAN
- Applications
- Conclusion

### Komolgorov-Arnold Theorem

"Kolmogorov-Arnold Representation Theorem establishes that if **f** a **multivariate continuous function** on a bounded domain, then **f** can be written as a **finite composition** of **continuous functions** of a **single variable** and the binary operation of addition."

## Komolgorov-Arnold Theorem



### Komolgorov-Arnold Theorem

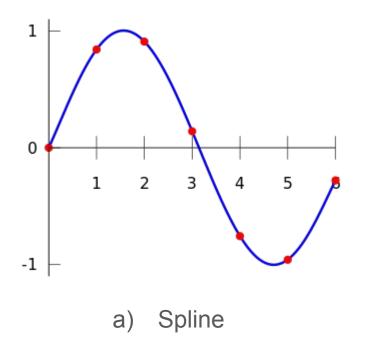
$$f(x_1,...,x_n) = \sum_{q=1}^{2n+1} \Phi_q \left( \sum_{p=1}^n \phi_{q,p}(x_p) 
ight)$$

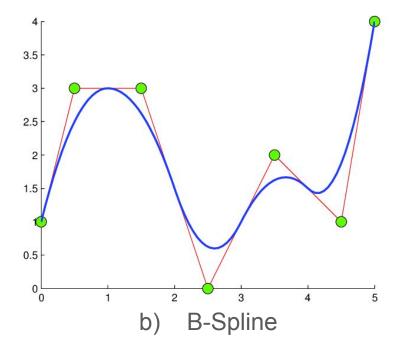
#### In this expression:

- $f(x_1,...,x_n)$  is the original multivariate continuous function.
- ullet  $\phi_{q,p}$  are univariate continuous functions that map each input variable  $x_p$ .
- ullet  $\Phi_q$  are continuous functions that combine the outputs of the univariate functions.

### How B-Splines works?

- Spline: a piecewise-defined polynomial function used in interpolation.
- B-Splines: a type of spline function used to create smooth curves.

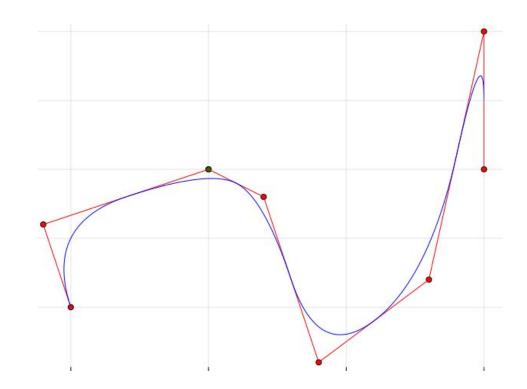




### How B-Splines works?

### • B-Splines properties:

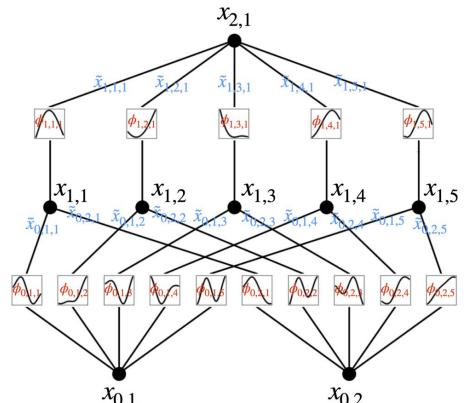
- Local Control: The influence of each control point is limited to a specific region of the curve.
- Continuity: Ensure a certain level of continuity at the knots
- Stability: Numerically stable and less prone to oscillations compared to other polynomial interpolation methods.



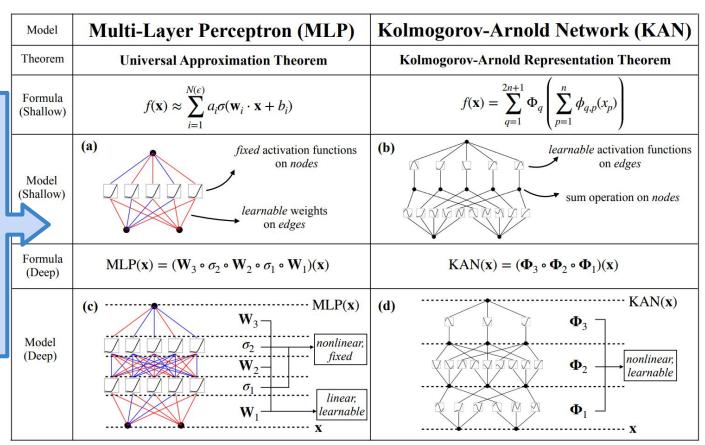
### A Brief Context

- Most functions in science and daily life are often smooth and have sparse compositional structures.
- MLP require many parameters, being inefficient in memory and computation.
- MLPs use predefined activation functions, limiting their ability to model complex non-linear relationships.
- NNs are considered "black boxes", making it difficult to understand the decision-making process.

Kolmogorov-Arnold Networks
 (KANs) are a neural network
 architecture that uses
 learnable univariate spline
 as activation functions, to
 capture complex, non-linear
 relationships more efficiently
 and interpretably.



MLPs treat linear transformations and nonlinearities separately as W and σ, while KANs treat them all together in Φ



In matrix form, this reads

$$\mathbf{x}_{l+1} = \underbrace{\begin{pmatrix} \phi_{l,1,1}(\cdot) & \phi_{l,1,2}(\cdot) & \cdots & \phi_{l,1,n_{l}}(\cdot) \\ \phi_{l,2,1}(\cdot) & \phi_{l,2,2}(\cdot) & \cdots & \phi_{l,2,n_{l}}(\cdot) \\ \vdots & \vdots & & \vdots \\ \phi_{l,n_{l+1},1}(\cdot) & \phi_{l,n_{l+1},2}(\cdot) & \cdots & \phi_{l,n_{l+1},n_{l}}(\cdot) \end{pmatrix}}_{\mathbf{\Phi}_{l}} \mathbf{x}_{l},$$

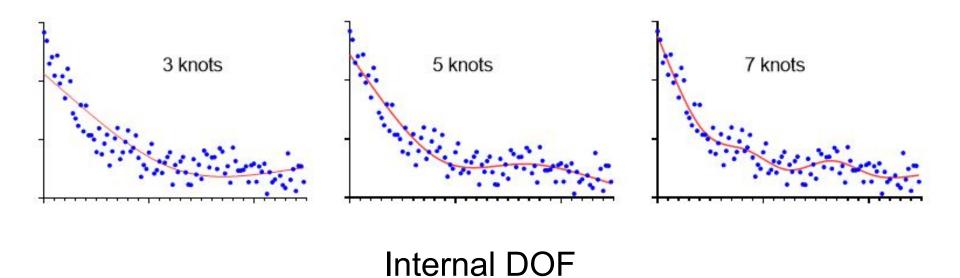
where  $\Phi_l$  is the function matrix corresponding to the  $l^{\text{th}}$  KAN layer. A general KAN network is a composition of L layers: given an input vector  $\mathbf{x}_0 \in \mathbb{R}^{n_0}$ , the output of KAN is

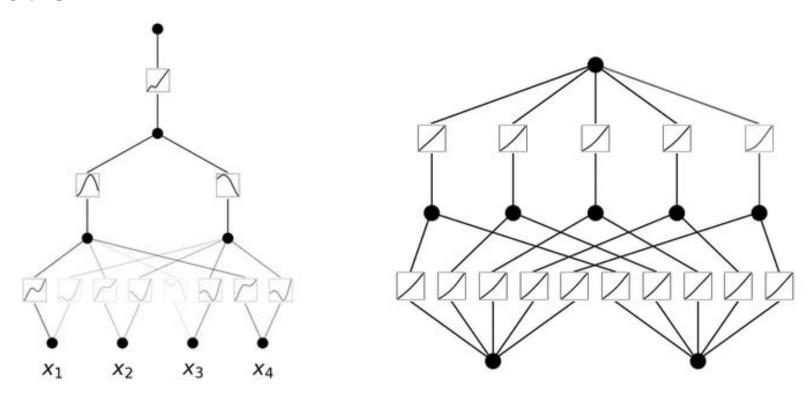
$$KAN(\mathbf{x}) = (\mathbf{\Phi}_{L-1} \circ \mathbf{\Phi}_{L-2} \circ \cdots \circ \mathbf{\Phi}_1 \circ \mathbf{\Phi}_0)\mathbf{x}.$$

#### KANs Concepts:

- Internal DOF: Grid points of the Spline (Activation Function).
  - Responsible for learning univariate functions.

- External DOF: The edges of the KAN layer.
  - Responsible for learning compositional structures of multiple variables.

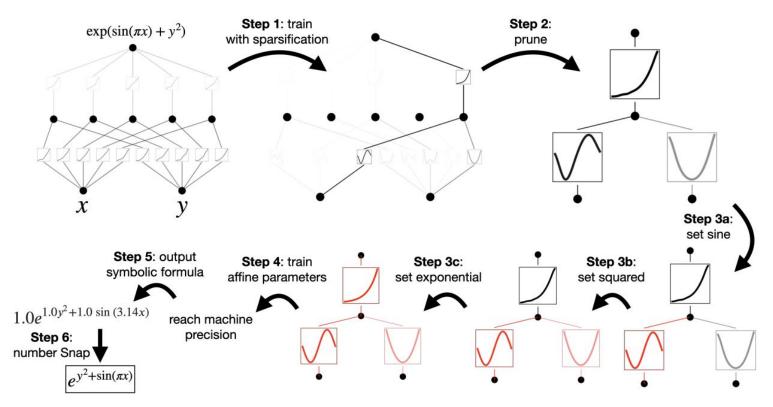




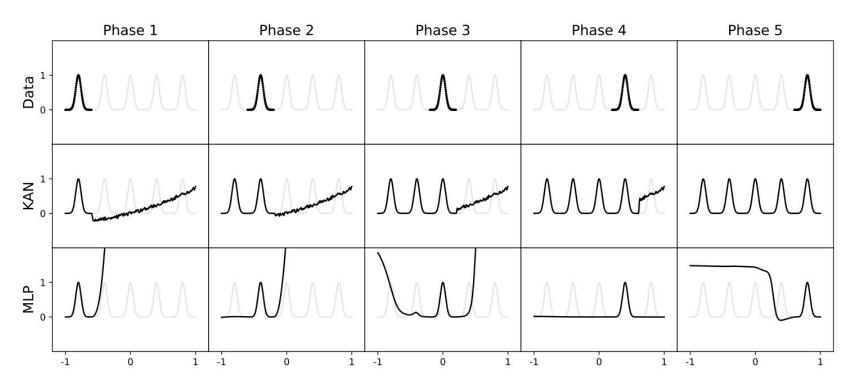
**External DOF** 

#### KANs Concepts:

- Interpretability: Smaller KANs can be interpreted by analyzing their activation functions.
  - Sparsity allow prune and reduce KANs.
  - The way we visualize KANs is like displaying KANs' "brain" to users, and users can perform "surgery" (debugging) on KANs.
- Learning: KANs can learn both the compositional structure and the univariate functions.
  - By internal and external DOFs.



The idea is to start from a large enough KAN and train it with sparsity regularization followed by pruning.



**Catastrophic forgetting** is a serious problem in current machine learning. KANs have **local plasticity** and can avoid catastrophic forgetting by leveraging the locality of splines.

### Advantages and Challenges

#### **Advantages**

- Interpretability: KANs are easier to understand and visualize.
- Efficiency: KANs achieve comparable or superior results with fewer parameters than MLPs.
- Precision: Learnable activation functions enable KANs to model complex data relationships with high accuracy.

### Challenges

- Training Speed: KANs train slowly because different activation functions cannot leverage batch computation.
- Implementation Complexity: Using splines and complex functions makes KANs harder to implement and optimize.
- Further Research Needed: More studies are needed to explore the robustness of KANs across diverse datasets and their compatibility with other deep learning architectures.

#### Variations of KAN

- U-KAN: Integrates KANs into the U-Net architecture, commonly used for image segmentation tasks.
- **Diffusion U-KAN:** Applies U-KAN for noise prediction in diffusion models.
- FourierKAN-GCF: Combines KANs with Fourier transforms for Graph Collaborative Filtering (GCF).
- KA2NCD: Uses KANs in Cognitive Diagnostic Networks (CDNs).
- **iKAN:** Designed for Human Activity Recognition (HAR) using wearable sensor data.
- T-KAN: Temporal KAN for univariate time series prediction.

### Variations of KAN

- Wav-KAN: Integrates wavelets into KANs, replacing traditional splines.
- MT-KAN: Multivariate Temporal KAN for modeling interactions between multiple time
- ReLU-KAN: Uses ReLU activation functions instead of splines.
- DeepOKAN: Combines KANs with Deep Operator Networks (DeepONets).
- Chebyshev Polynomial-Based KAN: Uses Chebyshev polynomials as an alternative
   to splines.
- **TKAT (Temporal Kolmogorov-Arnold Transformer):** Integrates KANs with Long Short-Term Memory (LSTM) networks.

### **Applications**

- Time Series Prediction
- Image Segmentation and Generation
- Image Classification
- Human Activity Recognition (HAR)
- Signal Analysis
- Function Approximation

### Conclusions

- KANs offer significant benefits in precision, interpretability, and efficiency compared
   to
- They show potential across various applications, with improved interpretability being a key advantage.
- However, KANs face challenges like slower training speeds and implementation
- Future research is essential to fully unlock their potential and address current limitations.