

# KAN based Autoencoders for Factor models

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#### Introduction

- Factor models describe relationships between asset returns and factors.
- Standard form:  $r \square^{=} \beta \square factor \square^{+} \epsilon \square$
- Some popular models: Fama French, CAPM, etc.

## What's the problem?

- Real world data isn't linear or independent.
- It is:
  - 1. Collinearity Gram Schmidt Process, PCA
  - 2. Multidimensional representation Feature engineering
  - 3. Noise PCA
- Factors aren't enough, PCA can't go back

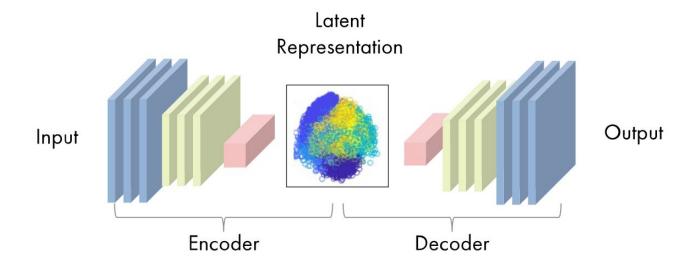
### **Experiment Setup**

- Risk Weighted Portfolio Construction of Russell 3000 dataset
- Winsorized Outliers
- OLS for getting factor weights,  $r \Box = \beta \Box factor \Box + \epsilon \Box$
- One reason to do this, faster and efficient, however entire dataset could be better (However, [1.5 million \* 26 factors] v/s [15120 \* 26 factors]).



#### Autoencoders

- Neural networks that learn to compress and reconstruct data
- Goal: Learn efficient representations while preserving important information





# **Kolmogorov Arnold Networks**

Based on Kolmogorov-Arnold Representation theorem, any continuous function of several variables can be constructed using only:

Addition, Composition, Functions of a single variable

It showed complex multivariate functions could be built from simple building blocks.

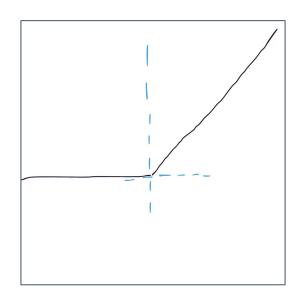
Neural nets are black-box equation solvers, Researchers at MIT thought why not use the kolmogorov's work in neural nets.

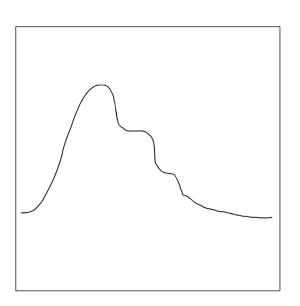


# **Kolmogorov Arnold Networks**

Activation functions in DL: ReLU, sigmoid, GeLU, etc.

KAN has flexible and learnable activation functions.







# **Kolmogorov Arnold Networks**

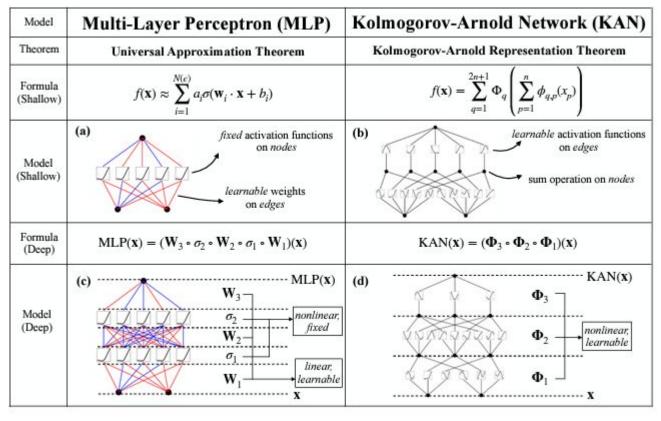


Figure 0.1: Multi-Layer Perceptrons (MLPs) vs. Kolmogorov-Arnold Networks (KANs)

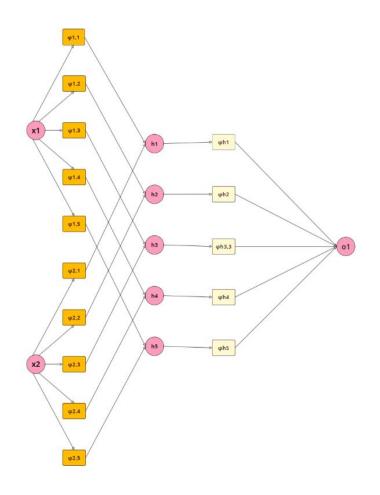
KANs are flexible and interpretable, paper has examples.

Unfortunately, our work hasn't proved interpretability yet.



# **Model Design**

- KAN based encoder for getting latent representations as model factors
- Use a simple decoder to reconstruct a factor model explaining returns
- Solve to minimize the loss function (Actual returns vs approximated returns)



#### Loss

Creating a loss function for factor model

• predicted return ->  $r\Box^{\text{predicted}} = \beta\Box factor\Box^+ \epsilon\Box$ 

Loss = 
$$r \square^{\text{actual}}$$
 -  $r \square^{\text{predicted}}$ 



### **Results**

Dataset: 60 years of stock data (1957-2016)

Training: 1957-1987 (30 yr) Validation: 1987-1999 (12 yr) Testing: 2000-2016 (16yr)

Table 1: R<sup>2</sup> Scores

Model	FF	CA	KAN-CA
1 factor	<0	11.06	11.02
3 factors	<0	11.39	11.26
6 factors	<0	11.29	11.32

Table 2: Predictive R<sup>2</sup> Scores

Model	FF	CA	KAN-CA
1 factor	<0	0.202	0.203
3 factors	<0	0.168	0.203
6 factors	<0	0.188	0.214

Table 3: Sharpe Ratio

Model	1 factor	3 factors	6 factors
CA	0.86	0.87	0.91
KAN-CA	0.84	0.86	0.96



#### **Future Research Directions**

- Demonstrate KAN's interpretability, so we have better interpretable factor models.
- Establish statistical significance of performance improvements through extended validation periods and comprehensive sensitivity analysis across market conditions.
- Optimize model architecture through systematic hyperparameter studies, adding more neurons and longer training periods, with standardized benchmarking against more state-of-the-art factor models.
- Add Mean Variance Portfolio, Random Portfolio Tests, Q-test



# Feedback and questions

Paper link: <a href="https://www.arxiv.org/abs/2408.02694">https://www.arxiv.org/abs/2408.02694</a>

