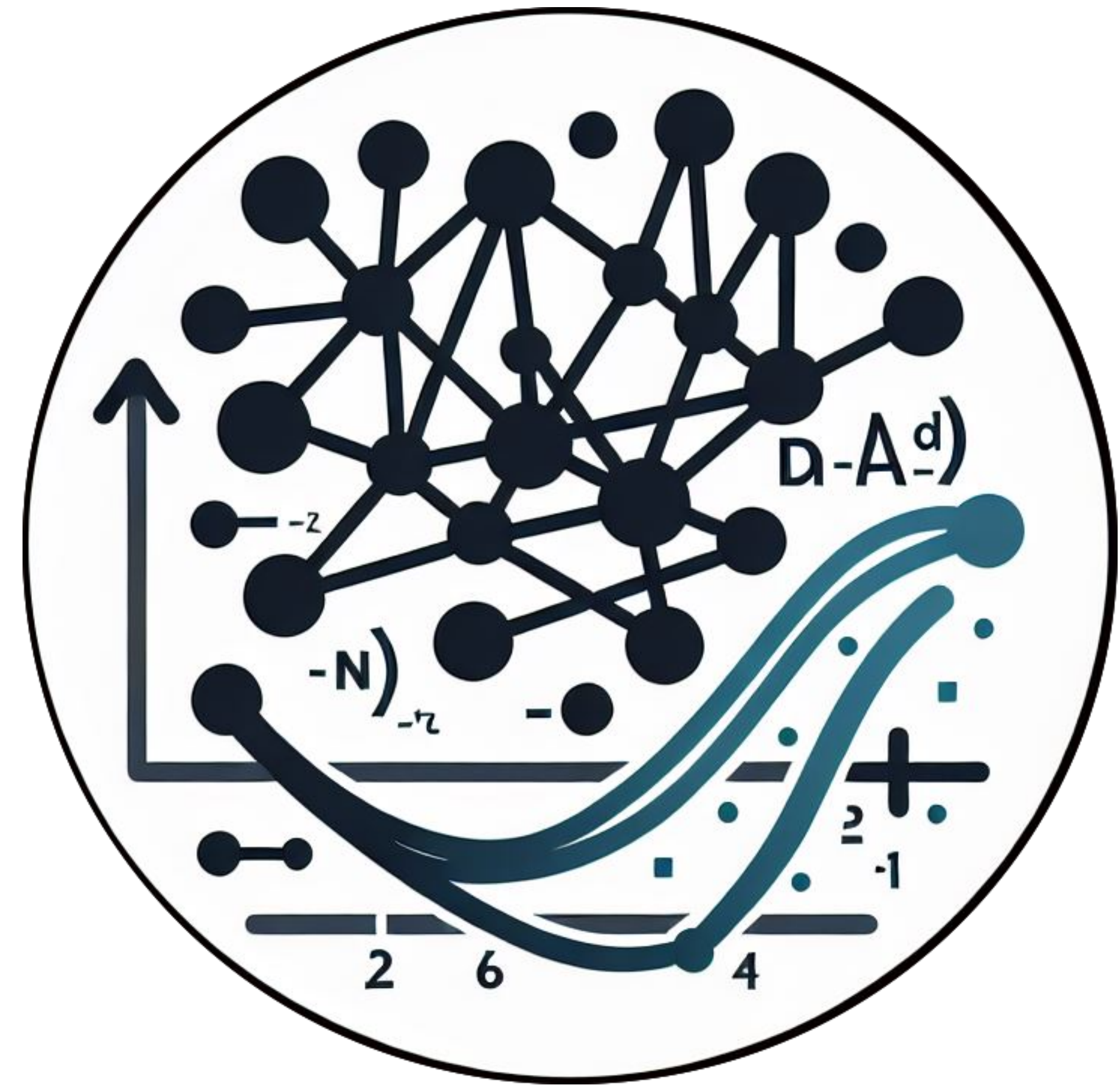


KAN Implementation Examples



Deep Learning for Engineers

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```
pip install pykan
```

(docs are not up to date. see examples in repo)

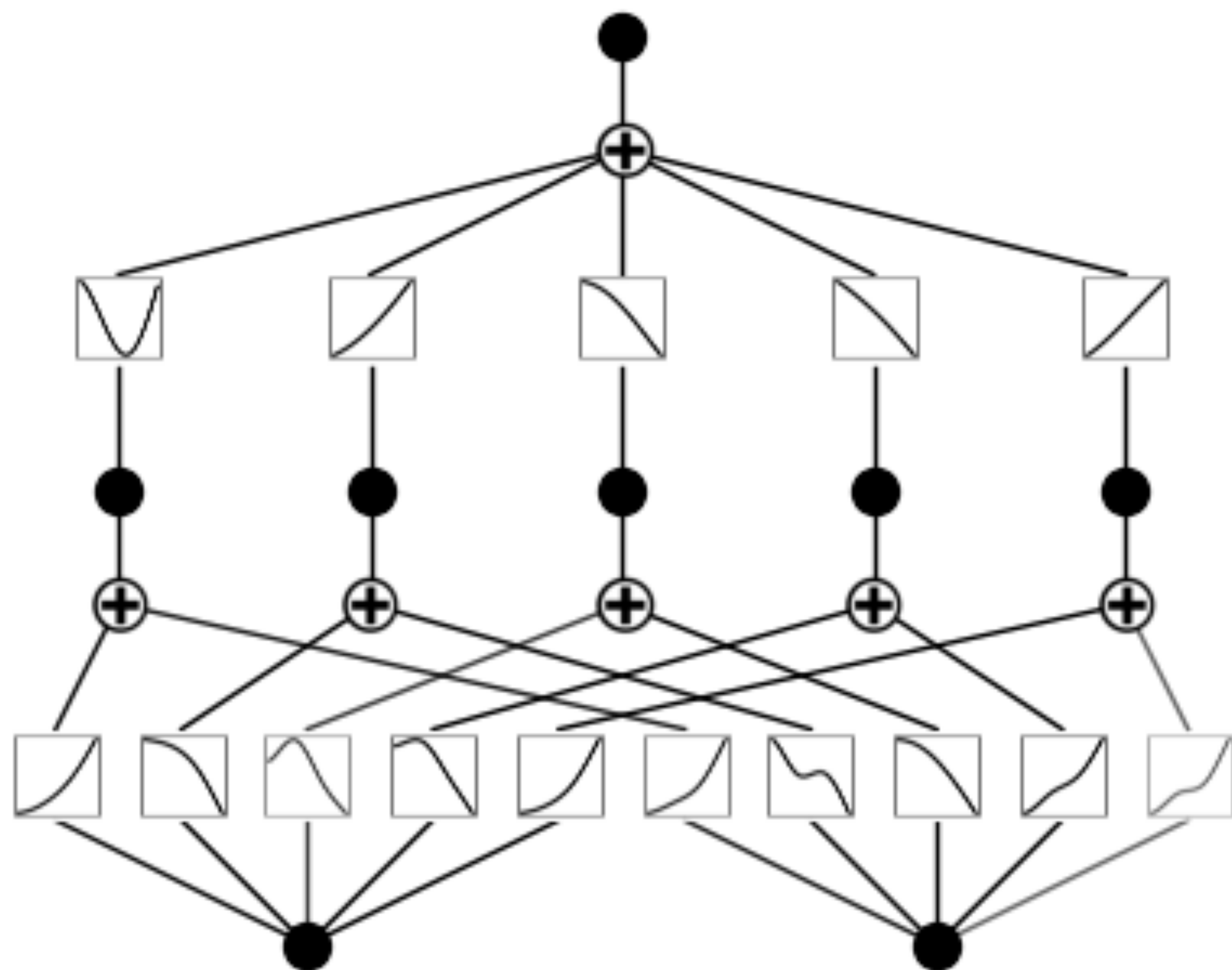
download [heat.csv](#) dataset linked on our website

```
import kan
import torch
import matplotlib.pyplot as plt

f = lambda x: torch.exp(torch.sin(torch.pi*x[:,[0]]))
+ x[:,[1]]**2)
dataset = kan.utils.create_dataset(f, n_var=2)
```

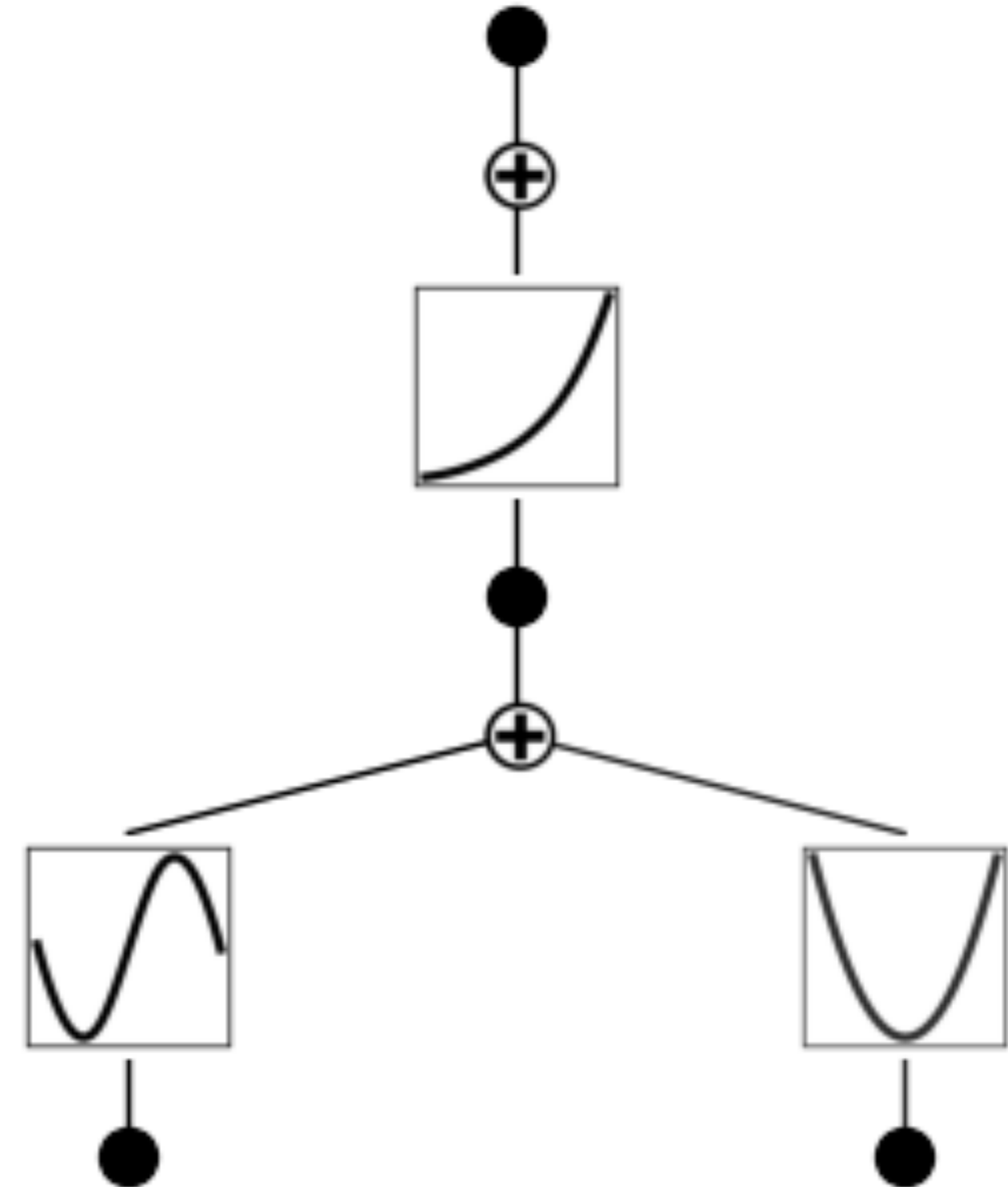
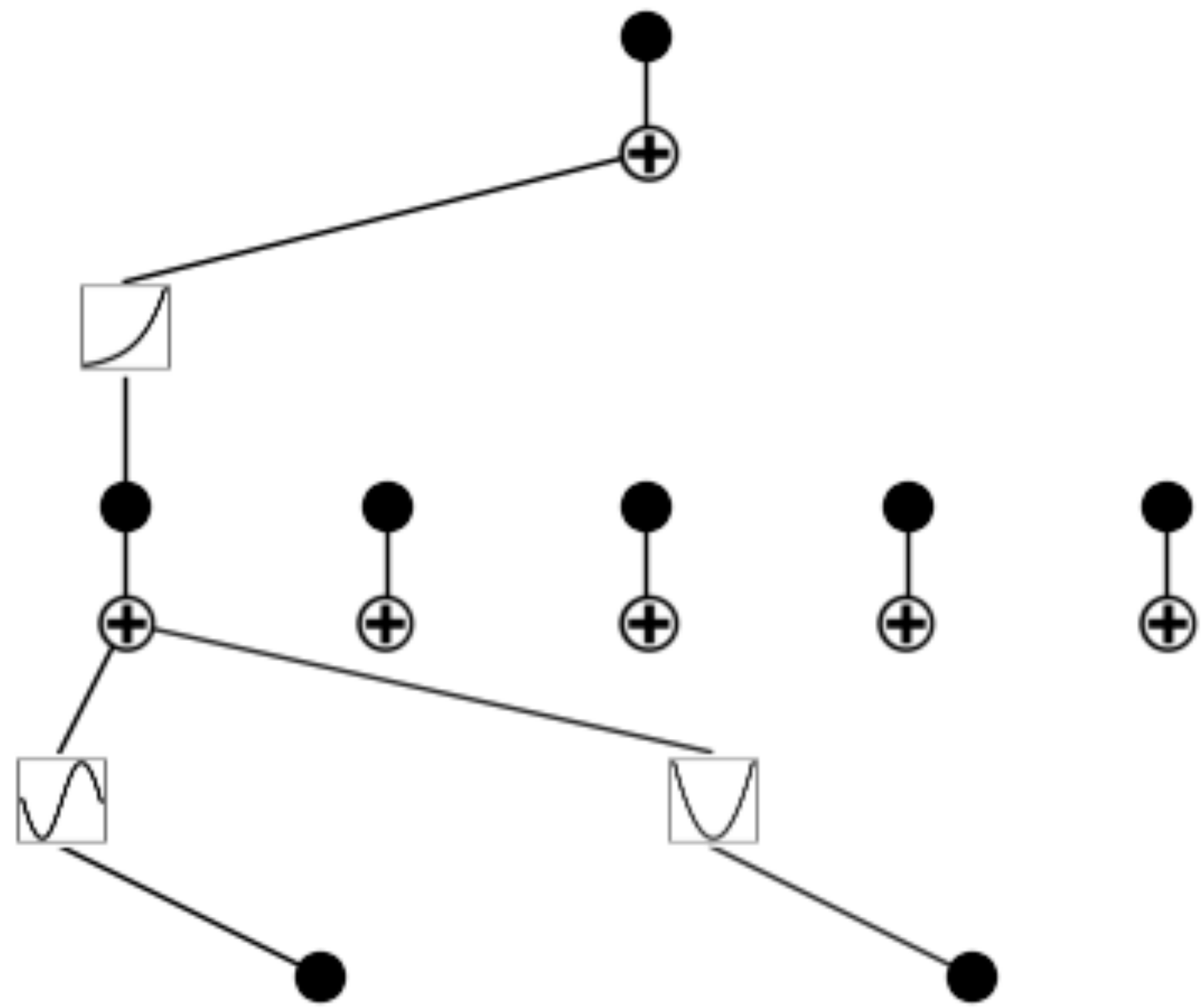
```
# 2 inputs, 5 hidden, 1 output, 3 grid intervals, cubic splines
model = kan.KAN(width=[2, 5, 1], grid=3, k=3, seed=42)

model(dataset['train_input'])
model.plot()
plt.show()
```



```
model.fit(dataset, opt="LBFGS", steps=50, lamb=0.001)  
model.plot()  
plt.show()
```

```
model = model.prune()  
model.plot()  
plt.show()
```



```
model = model.refine(10)
model.fit(dataset, opt="LBFGS", steps=50);
```

```
model.auto_symbolic()
```

```
model.fit(dataset, opt="LBFGS", steps=50);
```

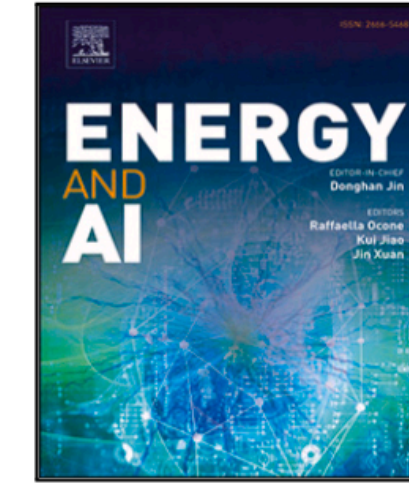
```
from kan.utils import ex_round
```

```
ex_round(model.symbolic_formula()[0][0], 4)
```




```
>>> 1.0*exp(1.0*x_2**2 + 1.0*sin(3.1416*x_1))
```

Contents lists available at [ScienceDirect](https://www.sciencedirect.com)

Energy and AI

journal homepage: www.elsevier.com/locate/egyai

Opening the AI black-box: Symbolic regression with Kolmogorov–Arnold Networks for advanced energy applications

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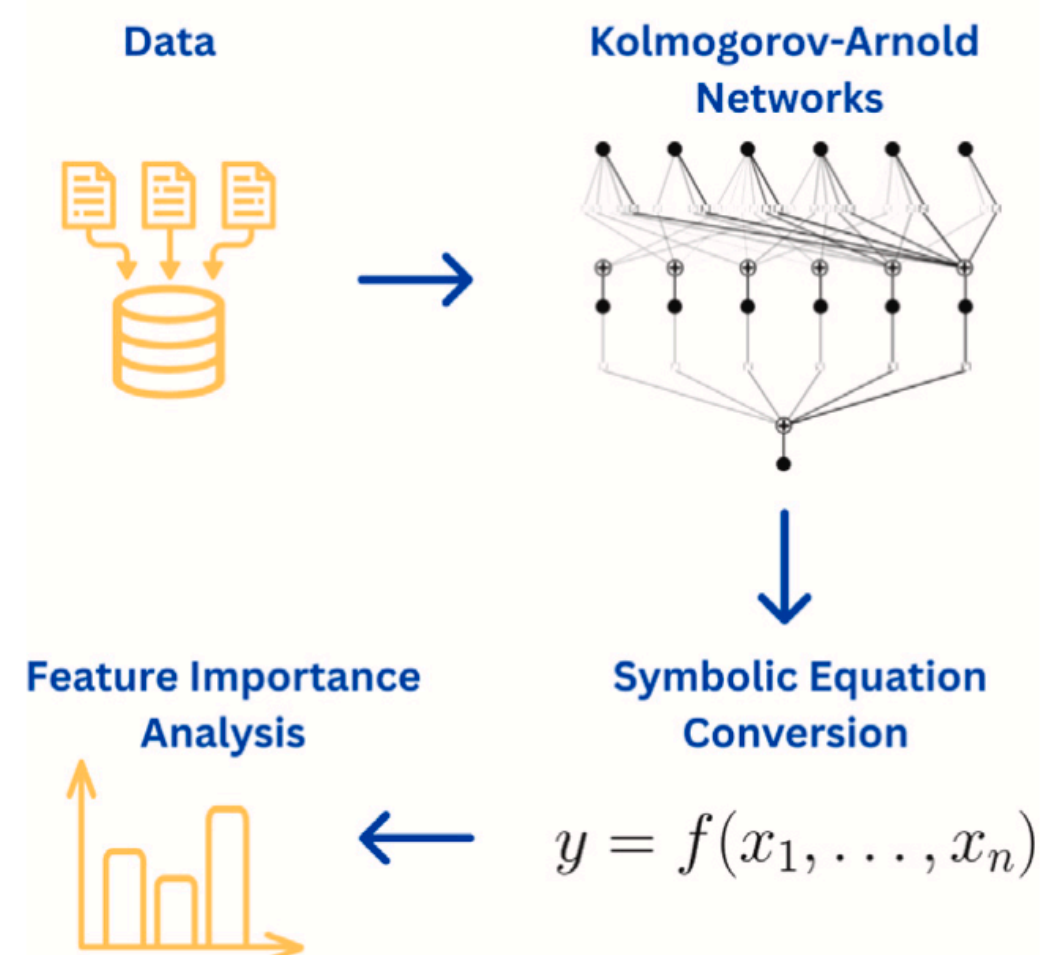
Department of Nuclear Engineering and Radiological Sciences, University of Michigan, Ann Arbor, MI 48109, United States

HIGHLIGHTS

- We find symbolic regressions for energy applications using Kolmogorov–Arnold Networks (KAN).
- KAN offers interpretability, explainability, and accuracy compared to black-box models.
- We compare KANs to feedforward neural networks in their ability to offer greater physical explanations.
- We benchmark KAN performance on eight different datasets derived from nuclear power.

GRAPHICAL ABSTRACT

Interpretable & Explainable AI



Heat Conduction Dataset

Inputs:

q_{prime} — linear heat generation rate [W/m]

\dot{m} — coolant mass flow rate [kg/s]

T_{in} — coolant inlet temperature [K]

R — fuel pellet radius [m]

L — fuel rod length [m]

C_p — specific heat of coolant [J/(kg·K)]

k — thermal conductivity of fuel [W/(m·K)]

Output:

T — fuel centerline temperature [K]

Hyperparameters

Best KAN hyperparameter tuning results for all datasets.

Dataset	Depth	Grid	k	λ	$\lambda_{entropy}$	LR_1	LR_2	Reg. Metric	Steps	Spline R^2	Symbolic R^2
FP	1	8	7	2.043e-05	5.03464	1.5	1.75	EFS	75	0.99144	0.99098
LWR	1	7	2	8.912e-04	7.48809	1.75	1.25	EFS	125	0.96004	0.90596
HEAT	1	7	3	1.899e-04	8.20921	1.5	2	EFSU	150	0.99308	0.99823
MICROREACTOR	1	8	3	1.217e-05	7.66581	0.75	1.25	EFS	25	0.99183	0.98926
PC-A	1	4	7	4.284e-05	0.02540	1.5	1.25	EFS	25	0.99859	0.99843
PC-B	1	8	3	1.112e-05	0.06268	0.75	1	EFS	250	0.99766	0.99745