

# The four ingredient recipe for AI



Data



Model Architecture



Learning Algorithm



Compute Resources

# The 5 modalities of data



Images/Videos (or  
Computer Vision)



3D Vision



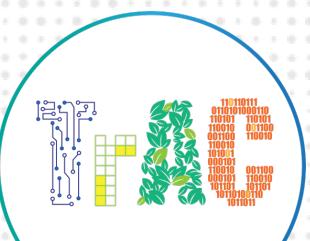
Speech/Audio



Text – natural  
language



Sensor Data



# Key architectures

## AlexNet (2012)

The network was made up of

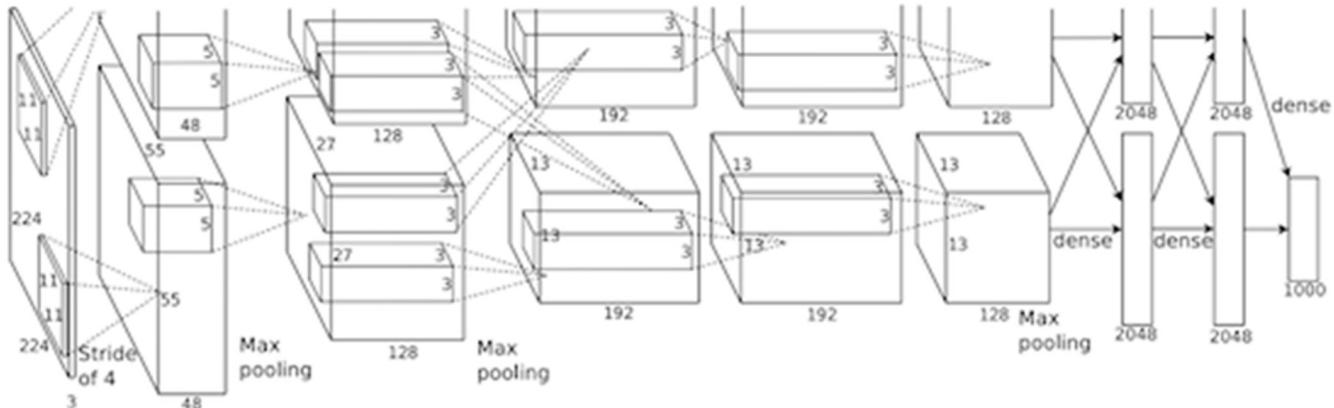
- 5 Conv layers
- Max-Pooling la
- Dropout layers
- 3 Fully Connec
- layers.

### Main Points

- Trained the network on ImageNet data, which contained over 15 million annotated images from a total of over 22,000 categories.
- Used ReLU for the nonlinearity functions (Found to decrease training time as ReLUs are several times faster than the conventional tanh function).
- Used data augmentation techniques that consisted of image translations, horizontal reflections, and patch extractions.
- Implemented dropout layers in order to combat the problem of overfitting to the training data.
- Trained the model using batch stochastic gradient descent, with specific values for momentum and weight decay.
- Trained on two GTX 580 GPUs for **five to six days**.

### Why It's Important

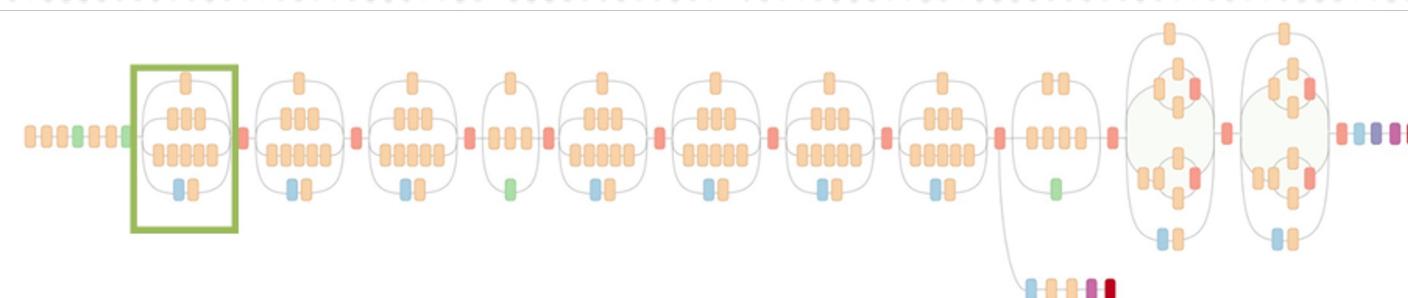
The neural network developed by Krizhevsky, Sutskever, and Hinton in 2012 was the coming out party for CNNs in the computer vision community. This was the first time a model performed so well on a historically difficult ImageNet dataset. Utilizing techniques that are still used today, such as data augmentation and dropout, this paper really illustrated the benefits of CNNs and backed them up with record breaking performance in the competition.



AlexNet architecture (May look weird because there are two different "streams". This is because the training process was so computationally expensive that they had to split the training onto 2 GPUs)

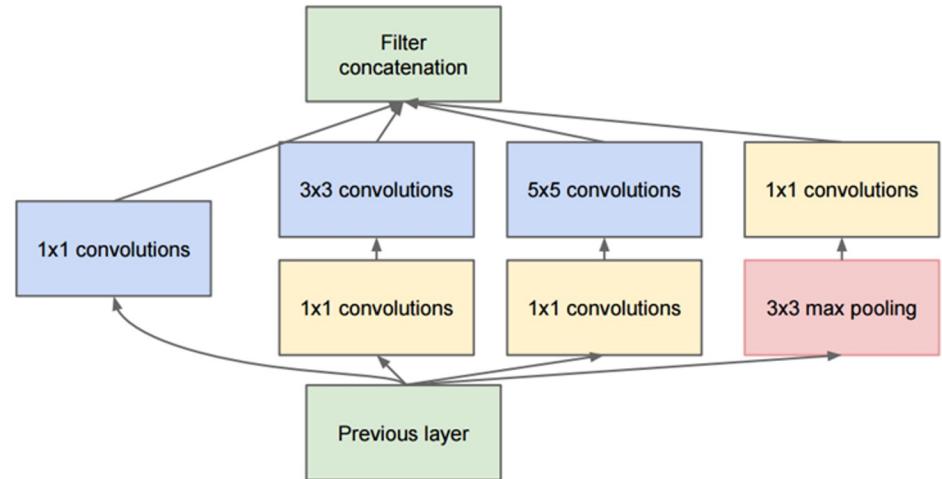
## GoogLeNet (2015)

- Used 9 Inception modules in the whole architecture, with over 100 layers in total! Now that is deep...
- No use of fully connected layers! They use an average pool instead, to go from a  $7 \times 7 \times 1024$  volume to a  $1 \times 1 \times 1024$  volume. This saves a huge number of parameters.
- Uses 12x fewer parameters than AlexNet.



Legend:  
Convolution  
AvgPool  
MaxPool  
Concat  
Dropout  
Fully connected  
Softmax

Green box shows parallel region of GoogLeNet



Full Inception module



Well said Leo, well said

## Microsoft ResNet (2015)

- 152 layers...
- Interesting note that after only the *first 2* layers, the spatial size gets compressed from an input volume of 224x224 to a 56x56 volume.
- Authors claim that a naïve increase of layers in plain nets result in higher training and test error (Figure 1 in the [paper](#)).
- The group tried a 1202-layer network, but got a lower test accuracy, presumably due to overfitting.

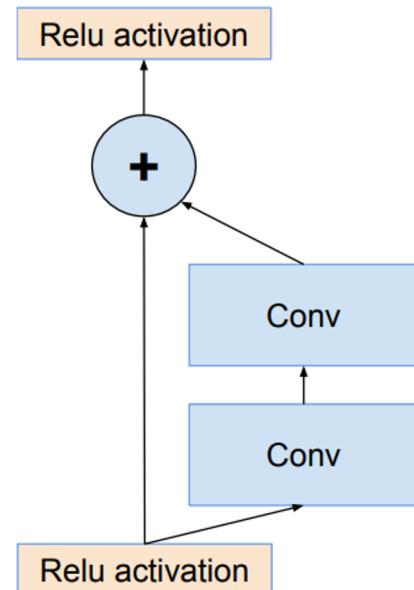
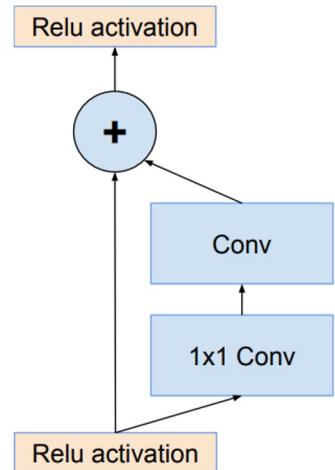
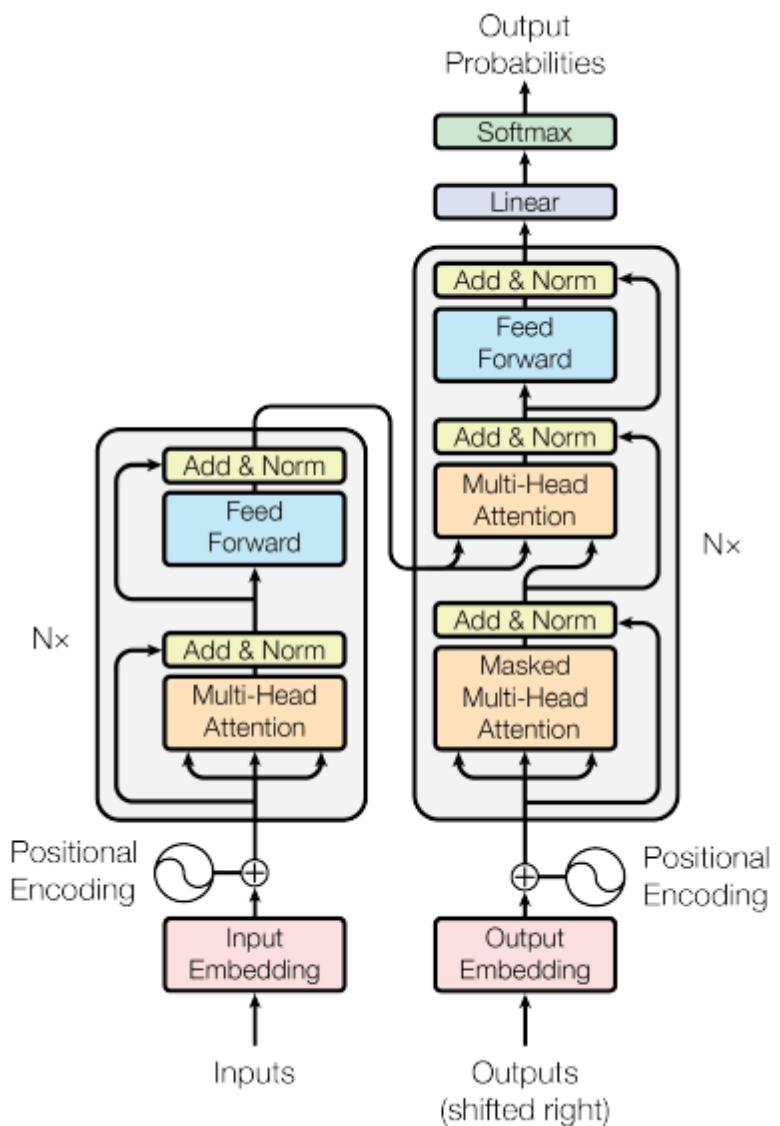


Figure 2. Optimized version of ResNet connections by [5] to shield computation.

# Transformer architecture

- *Attention is All You Need* (Vaswani, 2017)
- The GPT-n series of models uses this architecture with only minor adjustments
  - PreNorm layers – move normalization layers before attention/feed forward blocks
  - Encoder – Self Attention
  - Decoder – Cross Attention



# Concluding Remarks

Parameter Count  
Num Training Samples

Alexnet  
p/n: 28

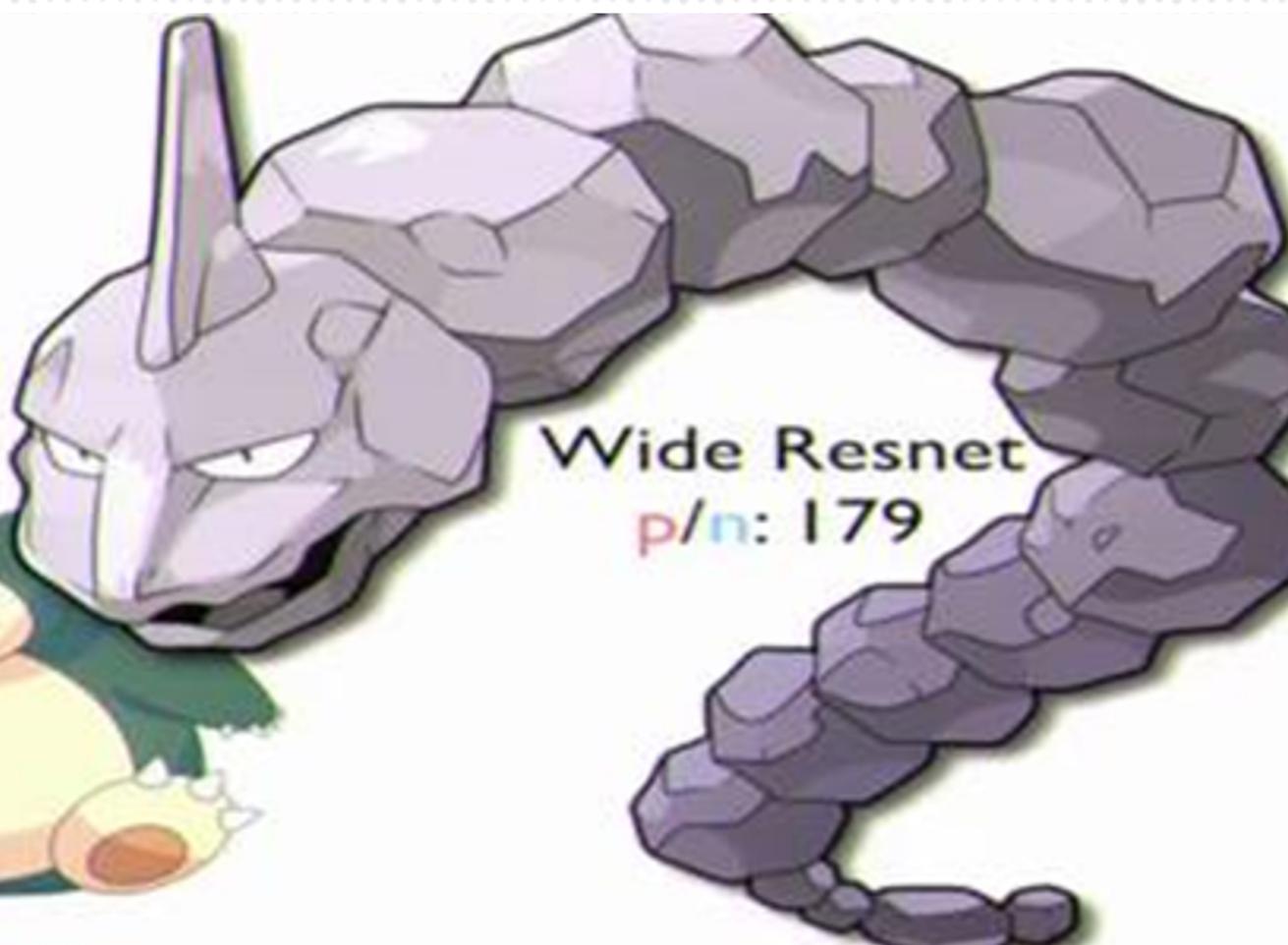
MLP 1x512  
p/n: 24

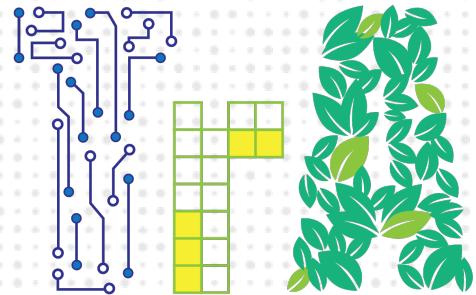


Inception  
p/n: 33



Wide Resnet  
p/n: 179





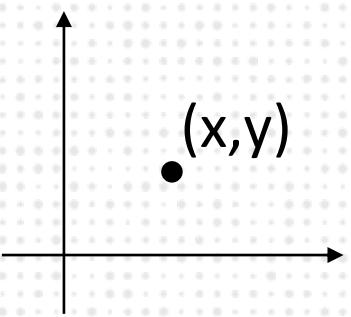
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10110100110  
10110111

Translational AI Center

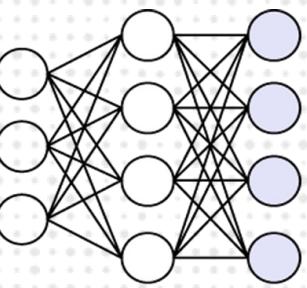
# Neural Fields (or INRs)

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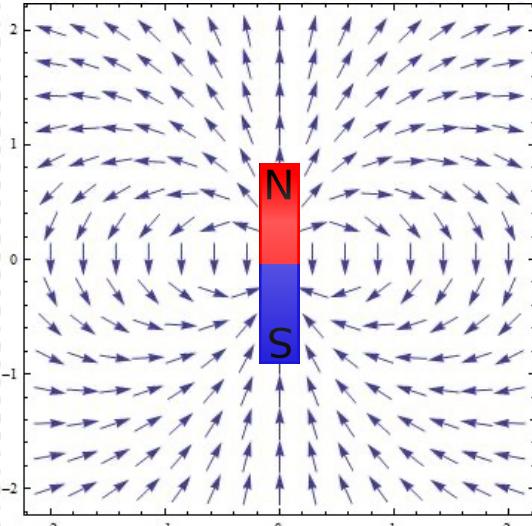
# What are neural fields?



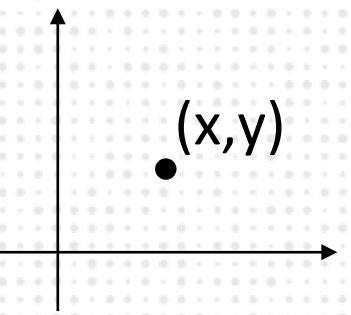
$$\Phi: \mathbb{R}^2 \rightarrow \mathbb{R}^2$$



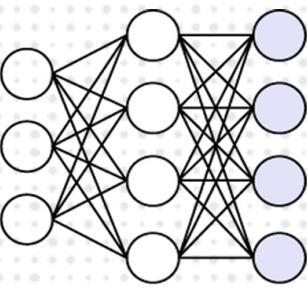
Neural Network  
( $\Phi$ )



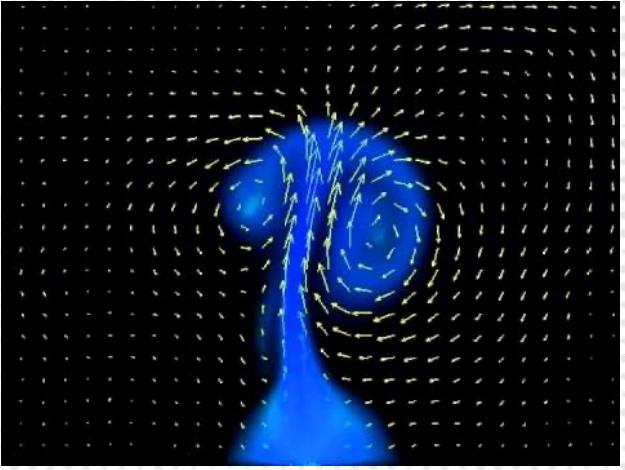
Magnetic Field



$$\Phi: \mathbb{R}^2 \rightarrow \mathbb{R}^2$$

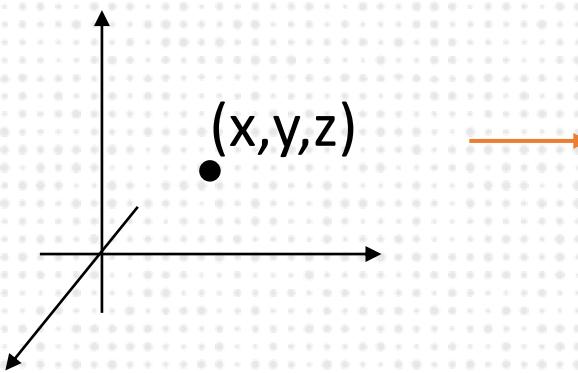


Neural Network  
( $\Phi$ )

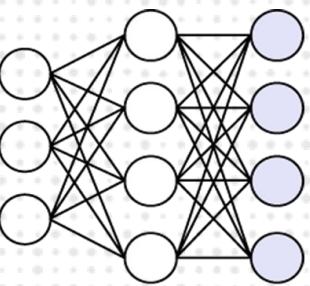


Eulerian Flow Field of a  
Fluid  
[Koldora CC]

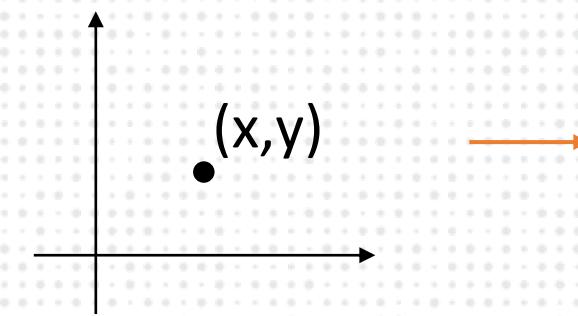
# What are neural fields?



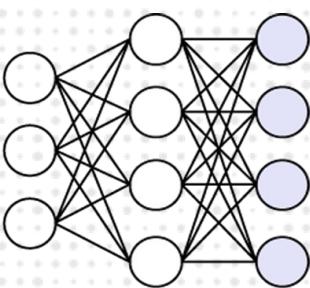
$$\Phi: \mathbb{R}^n \rightarrow \mathbb{R}$$



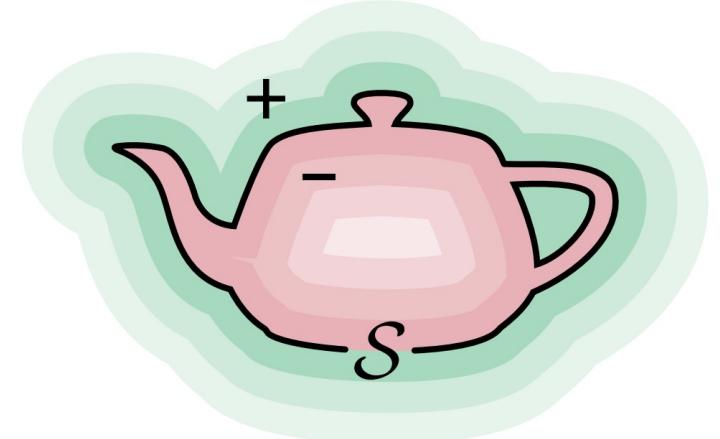
Neural Network  
( $\Phi$ )



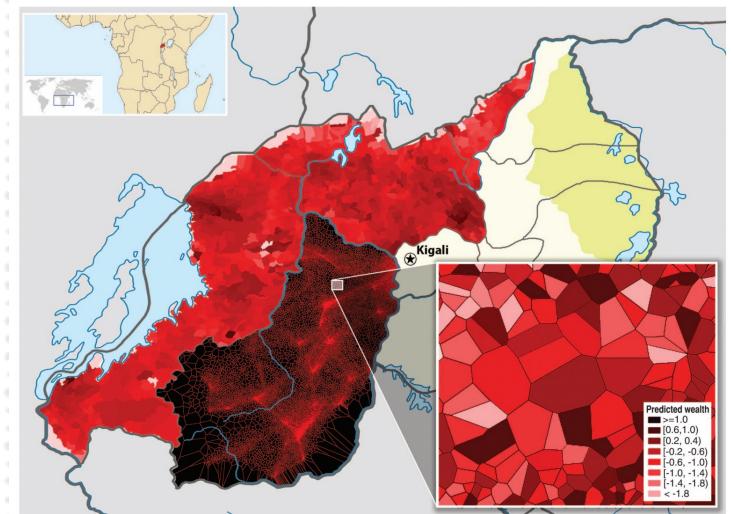
$$\Phi: \mathbb{R}^2 \rightarrow \mathbb{R}^n$$



Neural Network  
( $\Phi$ )



Signed Distance Function (SDF)



Geospatial Data  
[Blumenstock et al. 2015]

# Neural Fields for Vision and Graphics



[@smallfly, Müller et al. 2022]

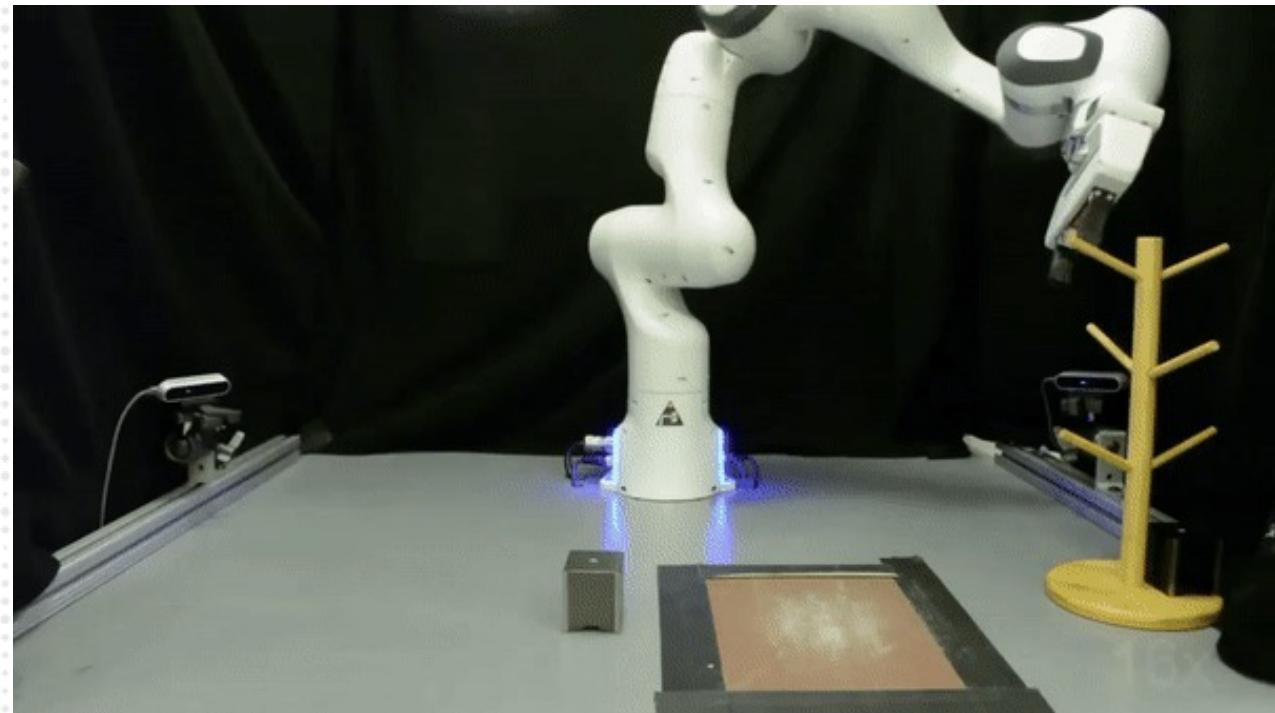
# Normal Fields for Vision and Graphics



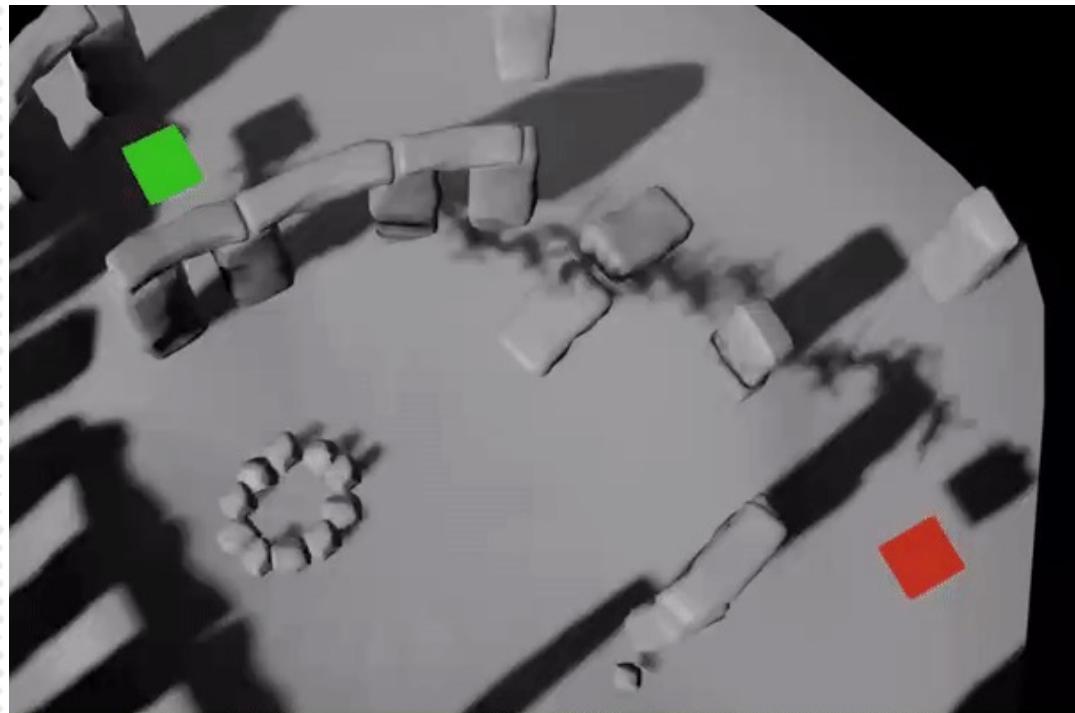
[Chan et al. 2021]

[Saito et al. 2020 (PIFu)]

# Neural Fields for Robotics

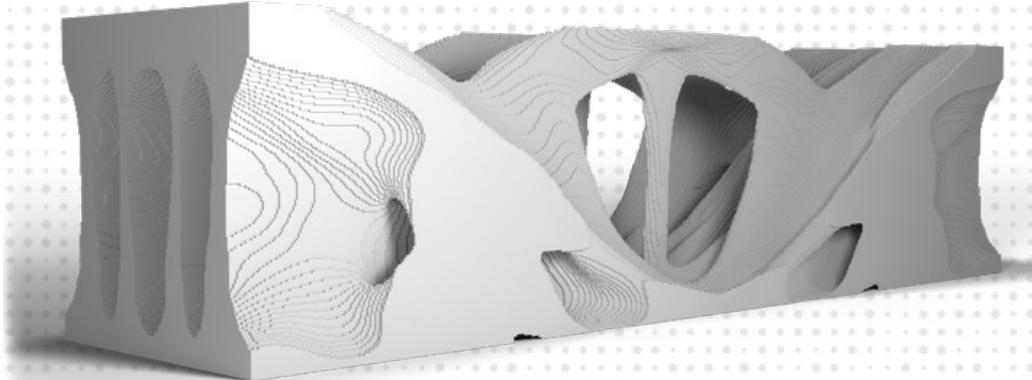


[Simeonov et al. 2021 (Neural Descriptor Fields)]

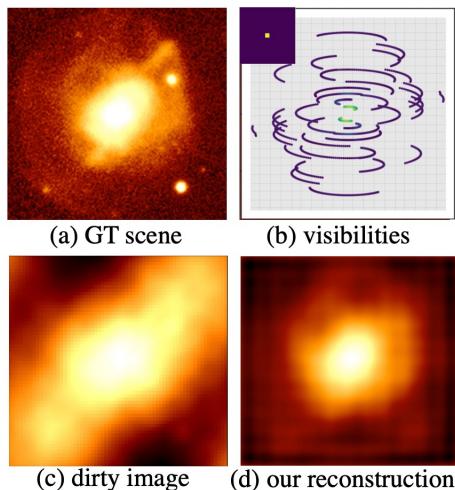


[Adamkiewicz, Chen et al. 2021]

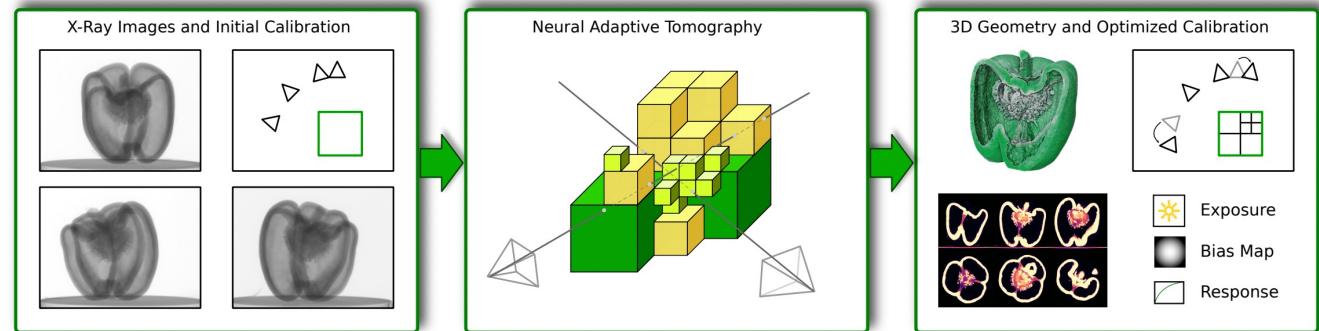
# Neural Fields for Science and Engineering



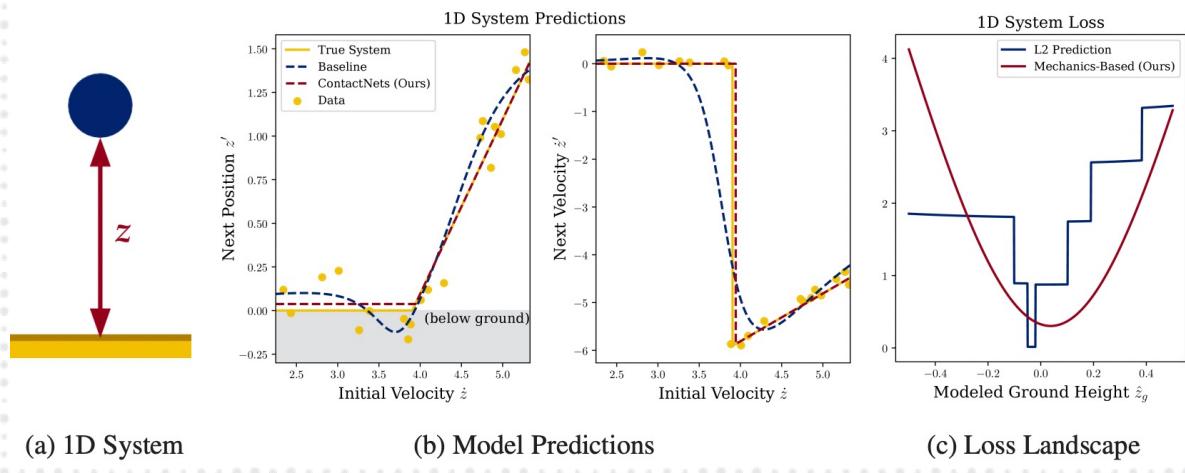
Topology Optimization [Doosti et al. 2021]



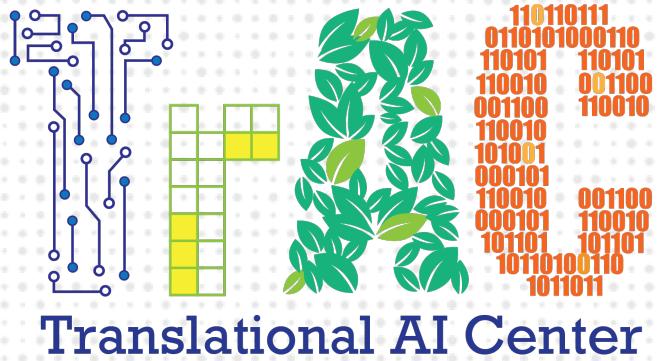
Astronomical Interferometry [Wu et al. 2021]



Tomographic Reconstruction [Ruckert et al. 2022]

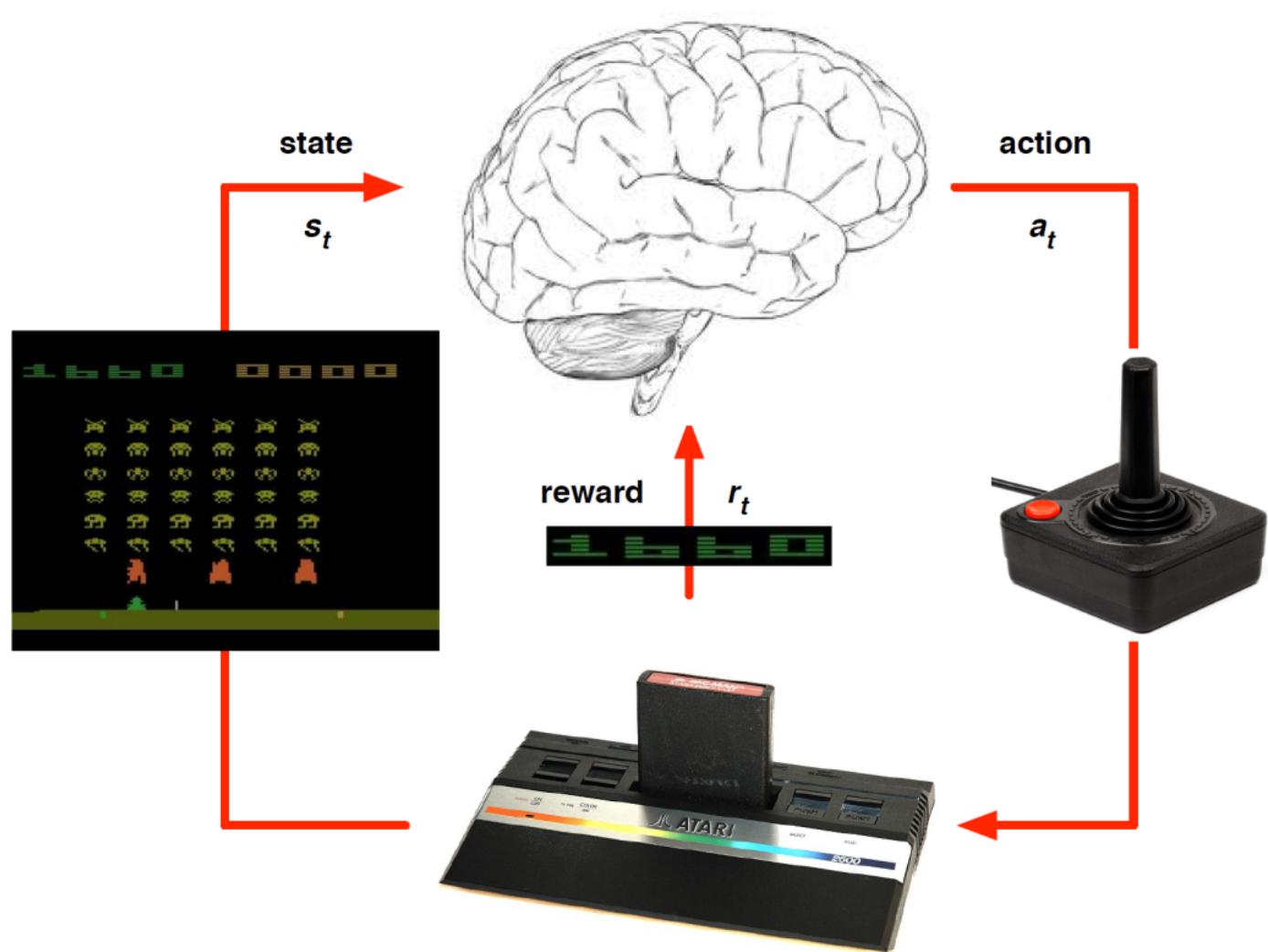


Contact Dynamics [Pfrommer, Halm et al. 2022]

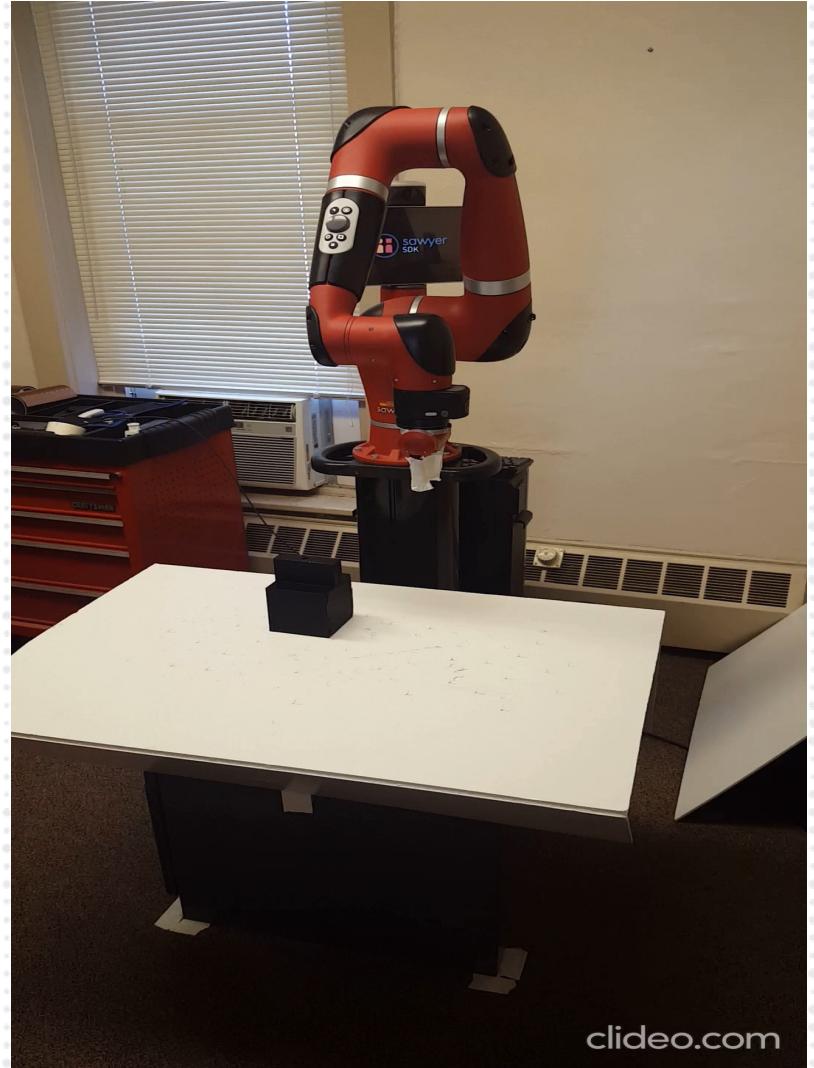
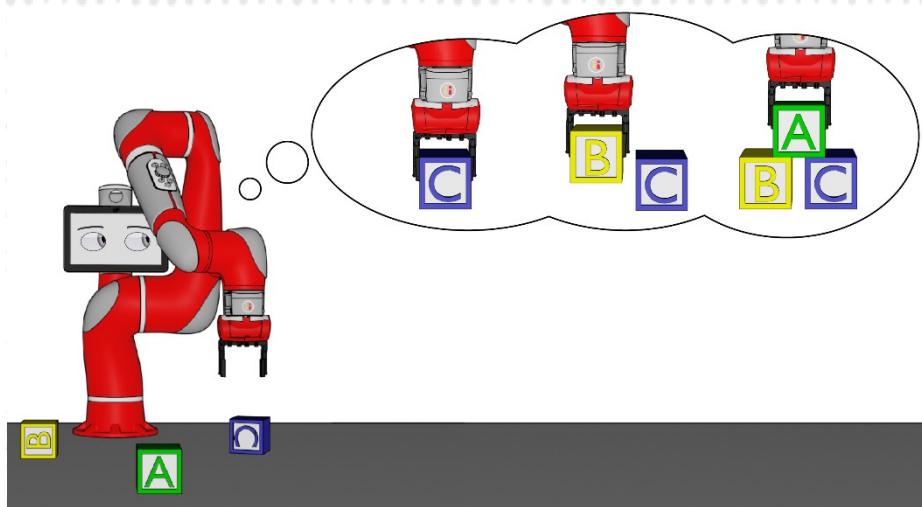


# Reinforcement Learning

# Learning from feedback



# From playing games to robotic manufacturing



# Some initial success stories



Kohl and Stone, 2004



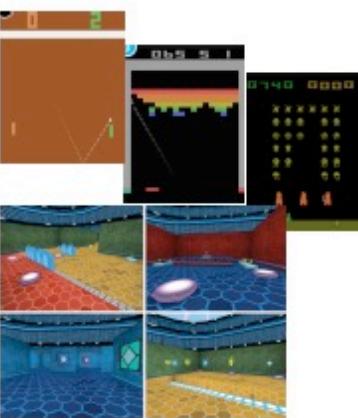
Ng et al, 2004



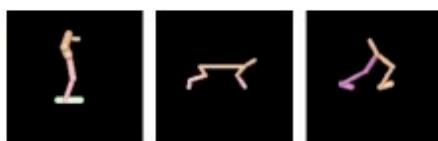
Tedrake et al, 2005



Kober and Peters, 2009



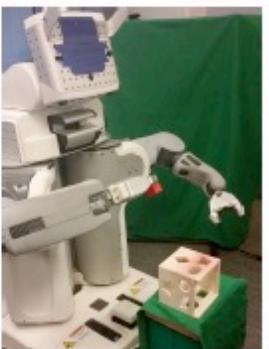
Mnih et al 2013 (DQN)  
Mnih et al, 2015 (A3C)



Silver et al, 2014 (DPG)  
Lillicrap et al, 2015 (DDPG)



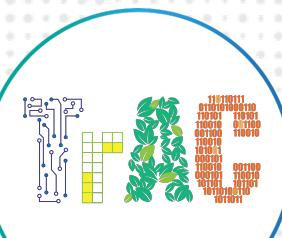
Schulman et al,  
2016 (TRPO + GAE)



Levine\*, Finn\*, et  
al, 2016  
(GPS)



Silver\*, Huang\*, et  
al, 2016  
(AlphaGo)



# ChatGPT – RL with human feedback

Step 1

Collect demonstration data  
and train a supervised policy.

A prompt is  
sampled from our  
prompt dataset.



A labeler  
demonstrates the  
desired output  
behavior.

This data is used  
to fine-tune GPT-3.5  
with supervised  
learning.

Step 2

Collect comparison data and  
train a reward model.

A prompt and  
several model  
outputs are  
sampled.



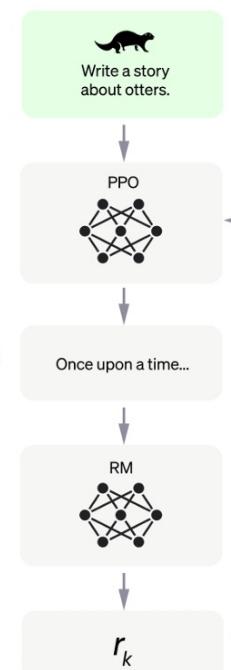
A labeler ranks the  
outputs from best  
to worst.

This data is used  
to train our  
reward model.

Step 3

Optimize a policy against the  
reward model using the PPO  
reinforcement learning algorithm.

A new prompt is  
sampled from  
the dataset.

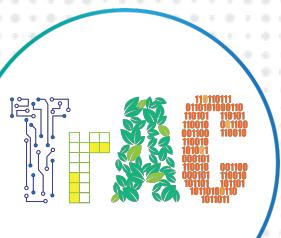


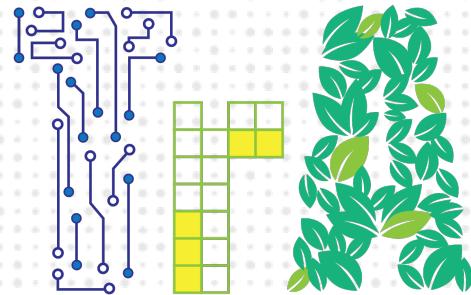
The PPO model is  
initialized from the  
supervised policy.

The policy generates  
an output.

The reward model  
calculates a reward  
for the output.

The reward is used  
to update the  
policy using PPO.





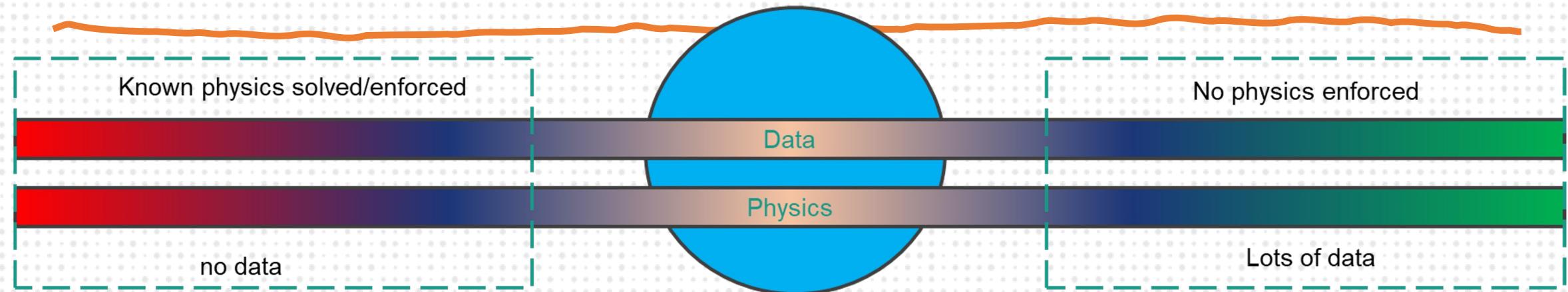
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10110111

Translational AI Center

# Scientific Machine Learning

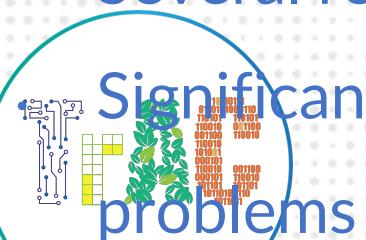
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# SciML Overview

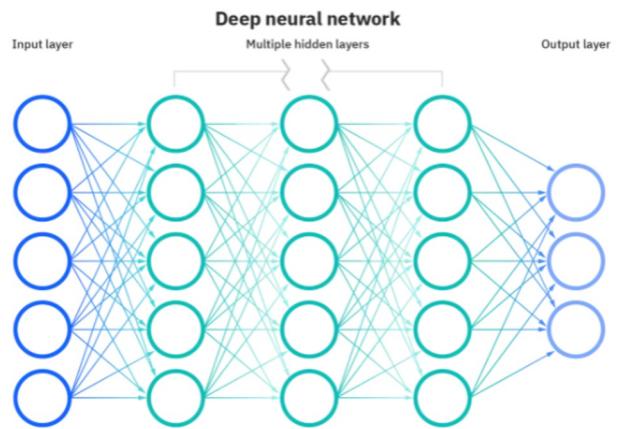


- Look at ML through the lens of amount of data vs amount of information
- Information (or domain knowledge) considered in terms of constraints
- Spectrum of methods being developed by the community
- Several recent works on 'neural PDE' solvers

Significant implication for multi-scale simulations, real time control, design, inverse



# SciML Overview



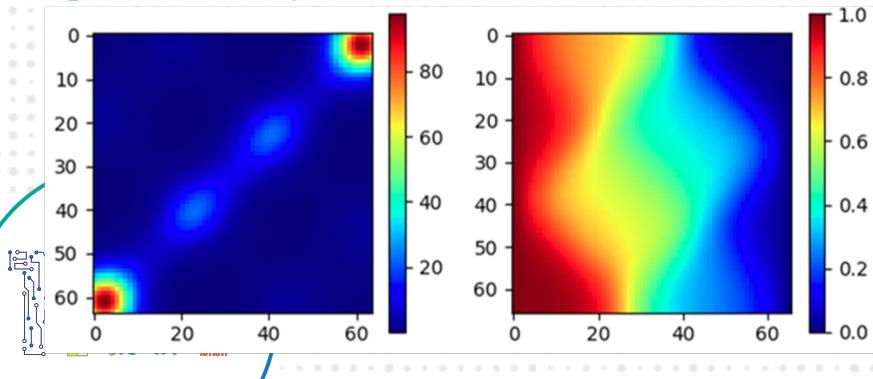
<https://www.ibm.com/cloud/learn/neural-networks>

Basic ML: Input output data pairs

Know some underlying physics

- constraints, invariances
- Perhaps know the equations themselves

input (diffusivity  $v$ )



Can integrate these 'domain knowledge' into the network

# AI in Molecular Synthesis

AI allows scientists to determine what potential drugs are worth evaluating in the lab and the effective ways of synthesizing them

CHEMICAL SYNTHESIS PLANS BENCHMARK: TOP-1 TEST ACCURACY

Source: Schwaller, 2020 | Chart: 2021 AI Index Report

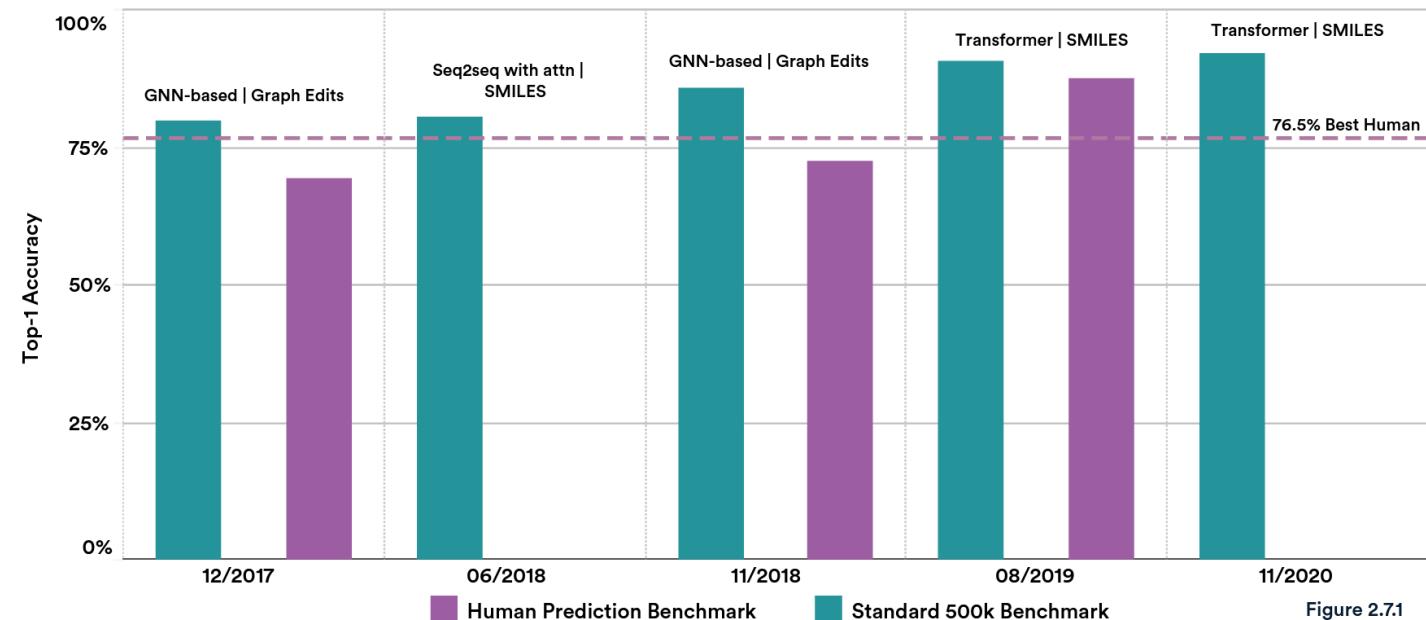
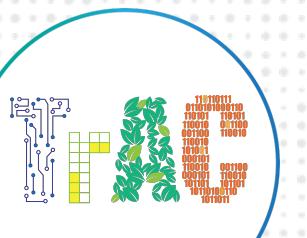


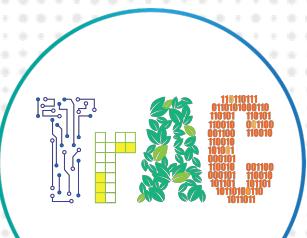
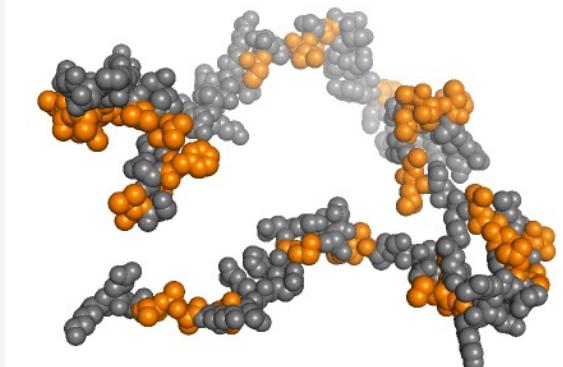
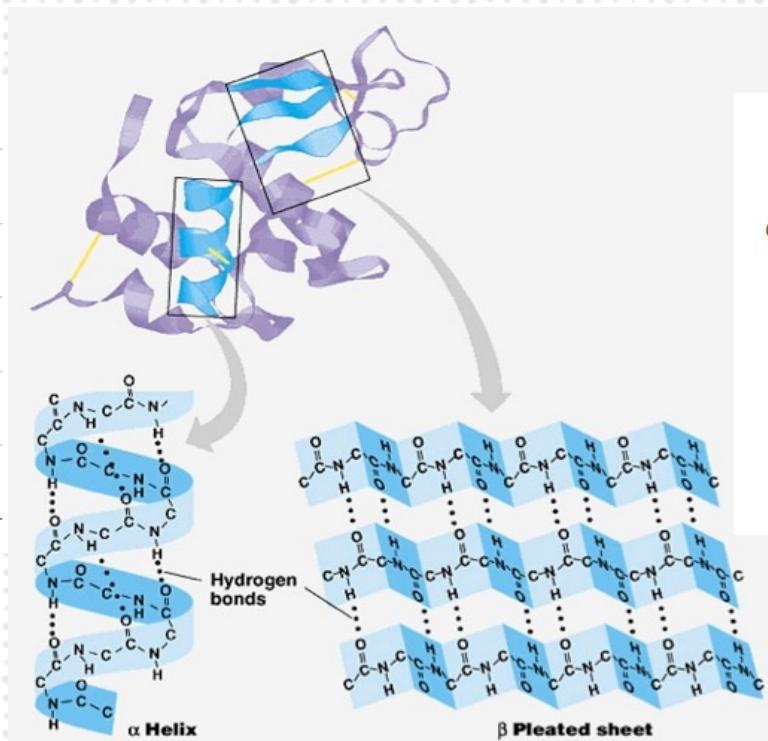
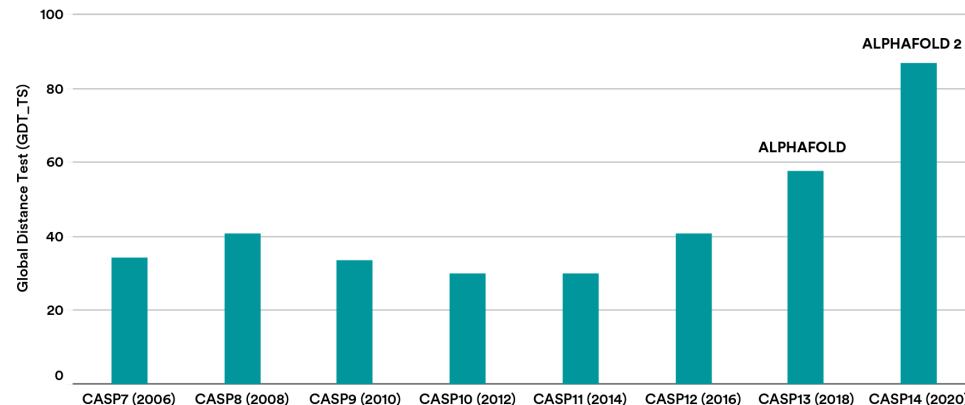
Figure 2.7.1



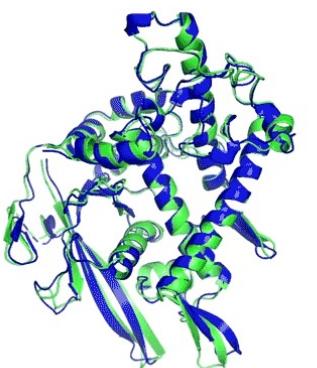
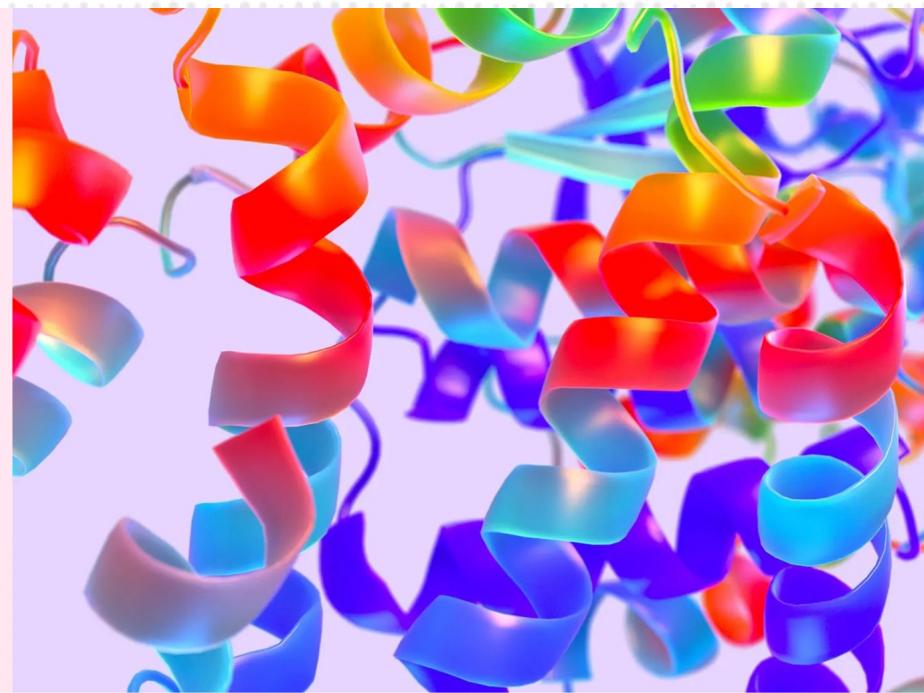
# AlphaFold and Protein Folding

The protein folding problem is to determine the 3D structures of proteins from sequences of amino acids

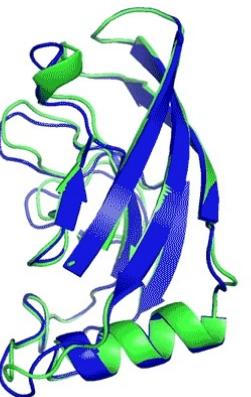
CASP: MEDIAN ACCURACY of PREDICTIONS in FREE-MODELING by THE BEST TEAM, 2006-20  
Source: DeepMind, 2020 | Chart: 2021 AI Index Report



# AlphaFold 1

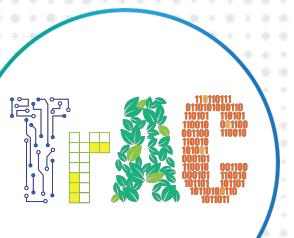


T1037 / 6vr4  
90.7 GDT  
(RNA polymerase domain)



T1049 / 6y4f  
93.3 GDT  
(adhesin tip)

26

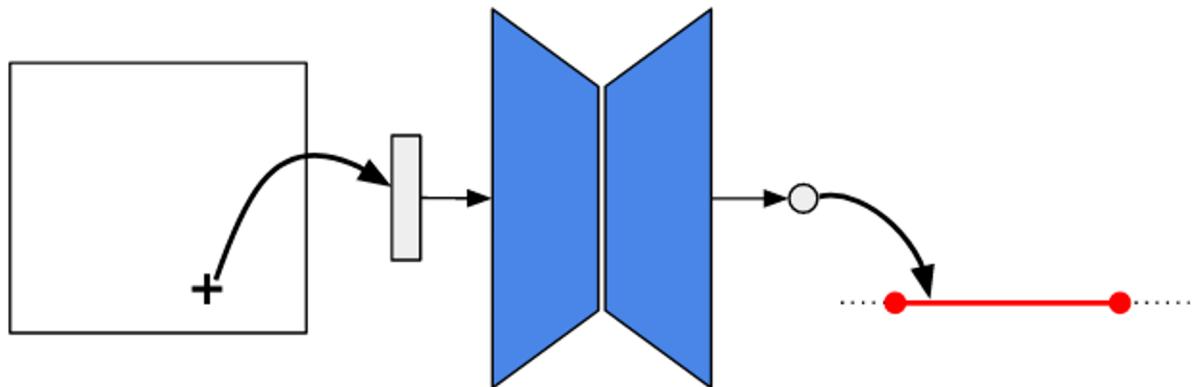


- Experimental result
- Computational prediction

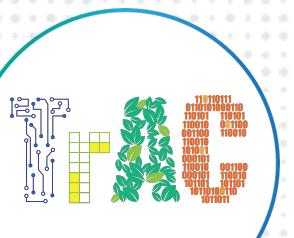
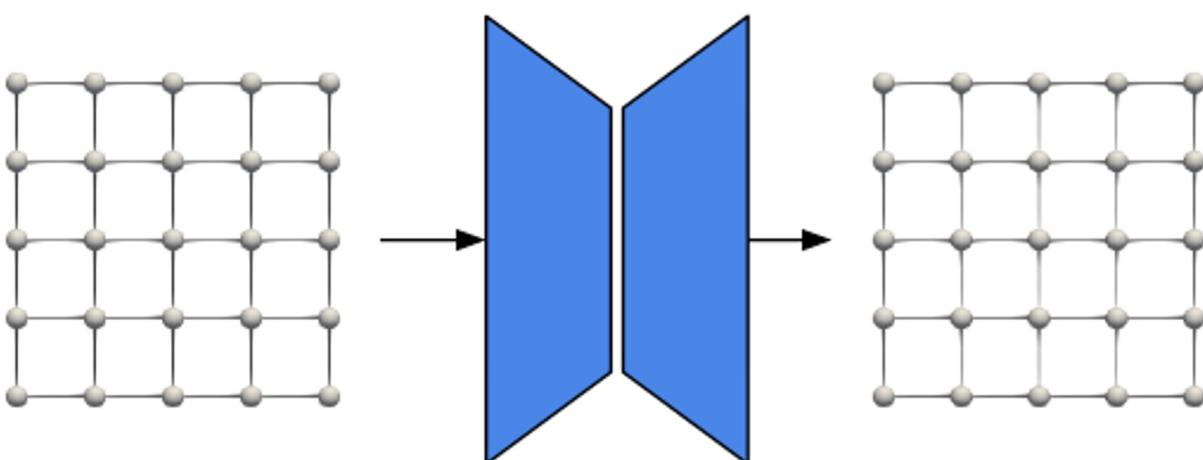
# SciML: Architecture and loss functions

Pointwise architectures:

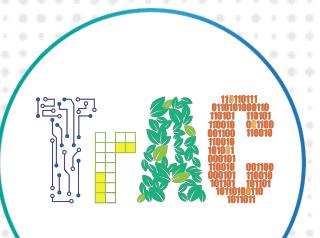
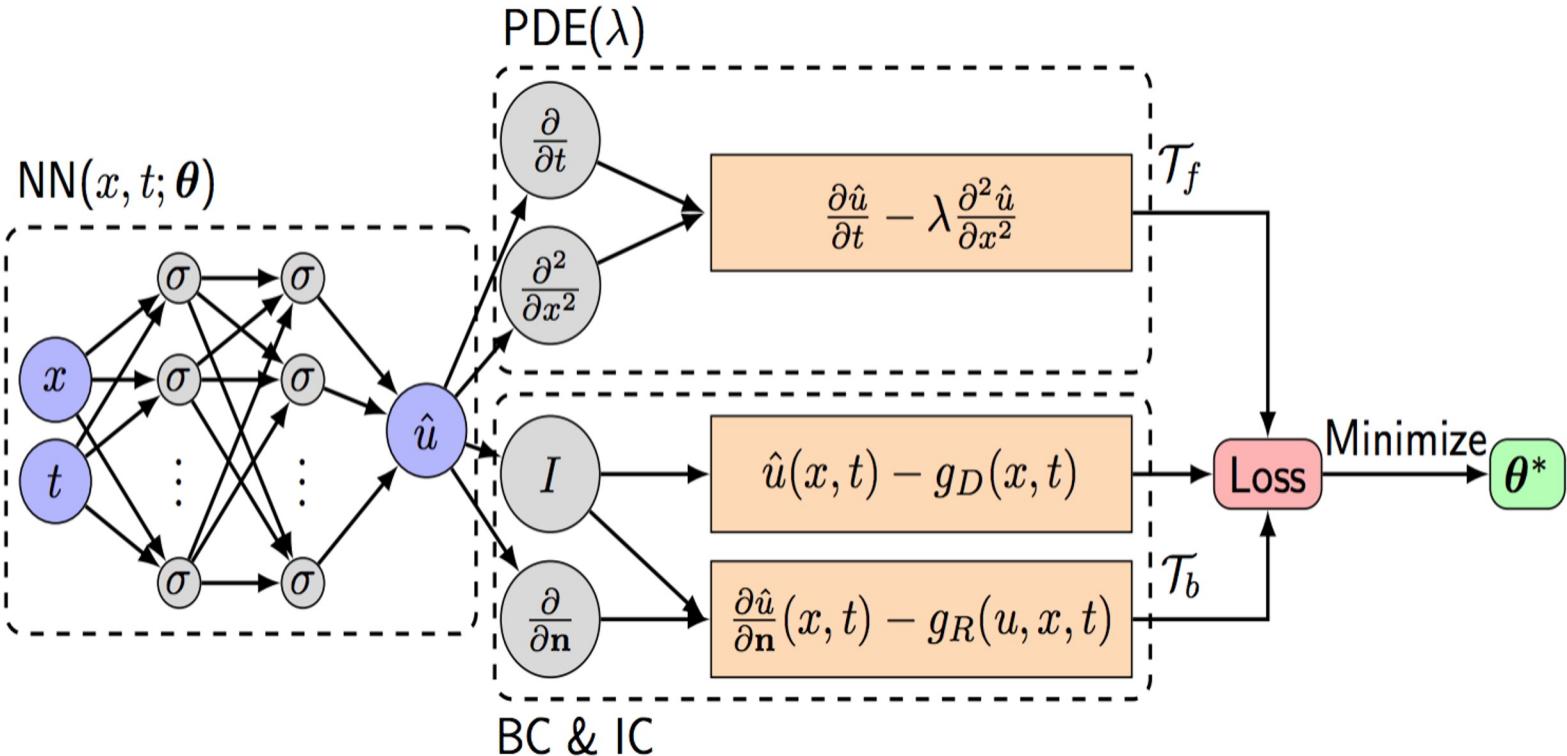
PINNs Physics Informed Neural Networks



Field based architectures



# Physics Informed Neural Networks for point-wise solutions

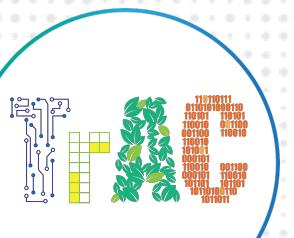
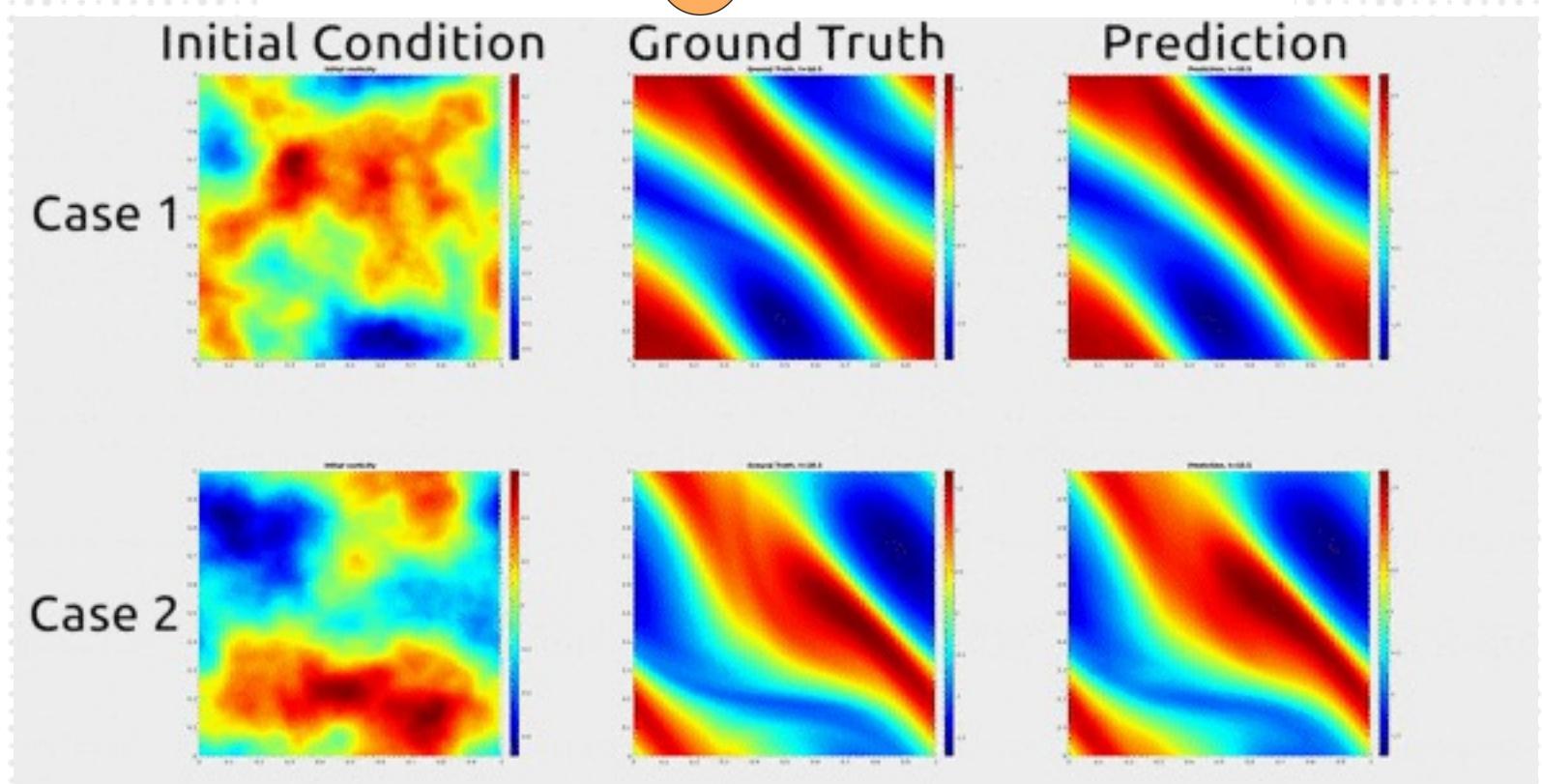
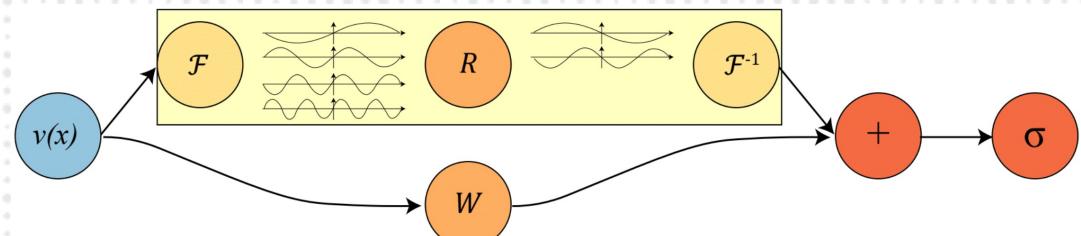


# Fourier Neural Operators

*Operator learning can be taken as an image-to-image problem. The Fourier layer can be viewed as a substitute for the convolution layer.*

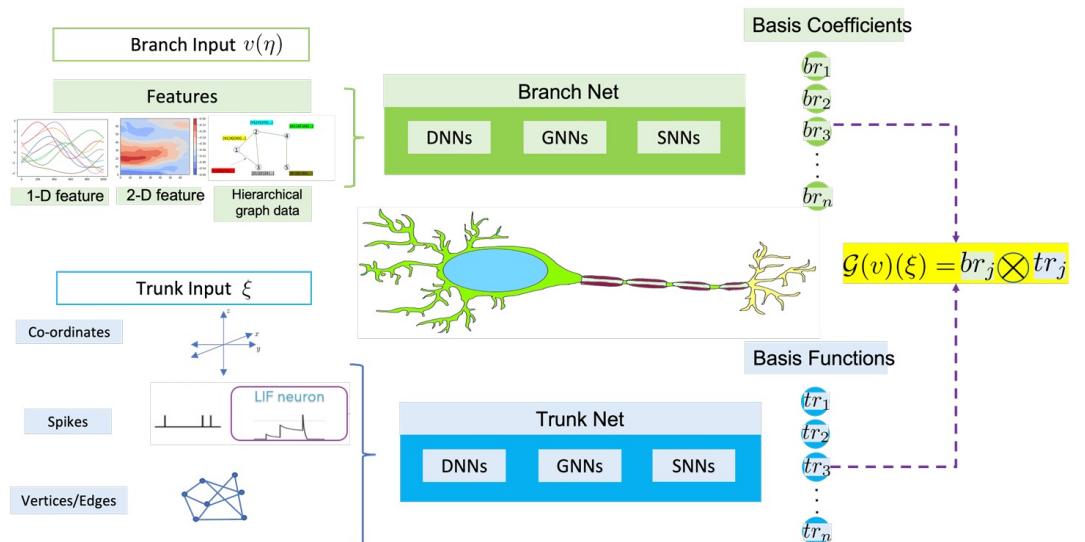
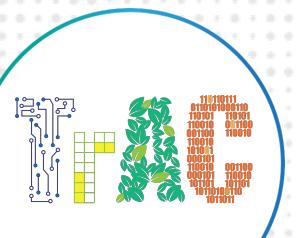
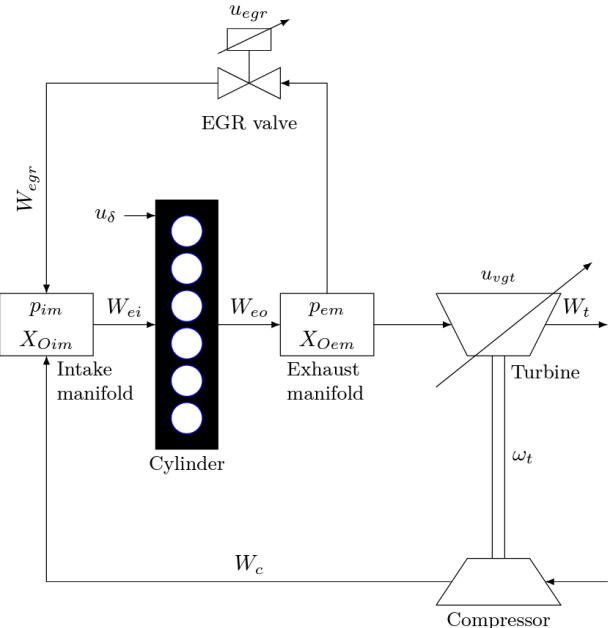
The Fourier layer just consists of three steps:

1. Fourier transform  $\mathcal{F}$
2. Linear transform on the lower Fourier modes  $R$
3. Inverse Fourier transform  $\mathcal{F}^{-1}$



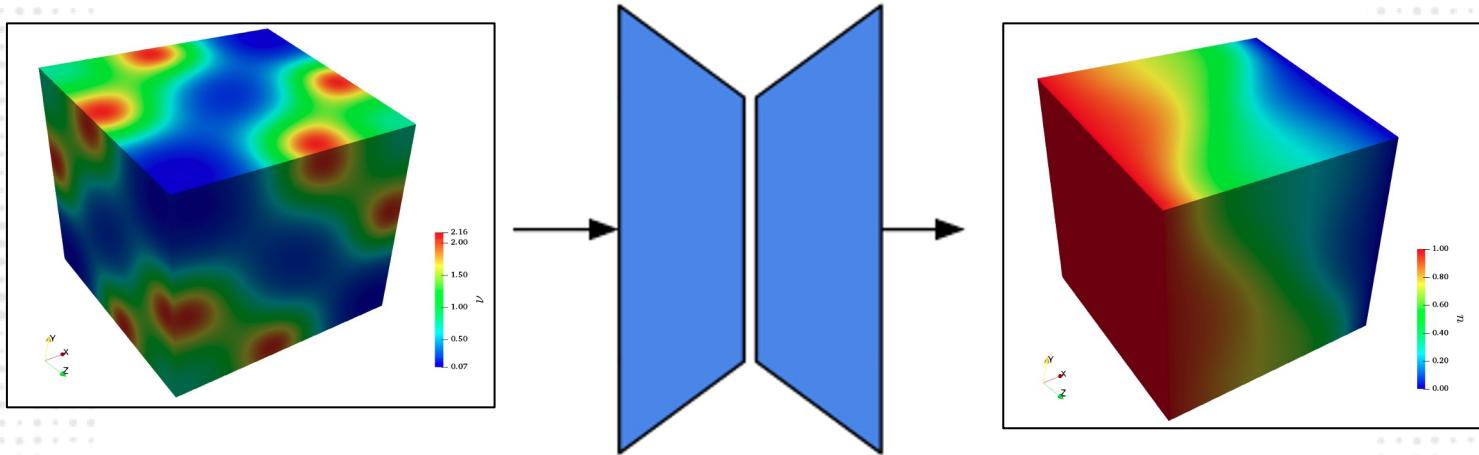
# DeepONets

Extends PINNs to arbitrary geometries and parametric datasets etc.



# SciML: Forward problems vs Inverse problems

Forward solvers:  
Neural PDE solvers



SciML for inverse and design

