

# The Inverse Swarm Problem with Neural Networks

Vinit Kumar Singh  
Indian Institute of Technology, Kharagpur.

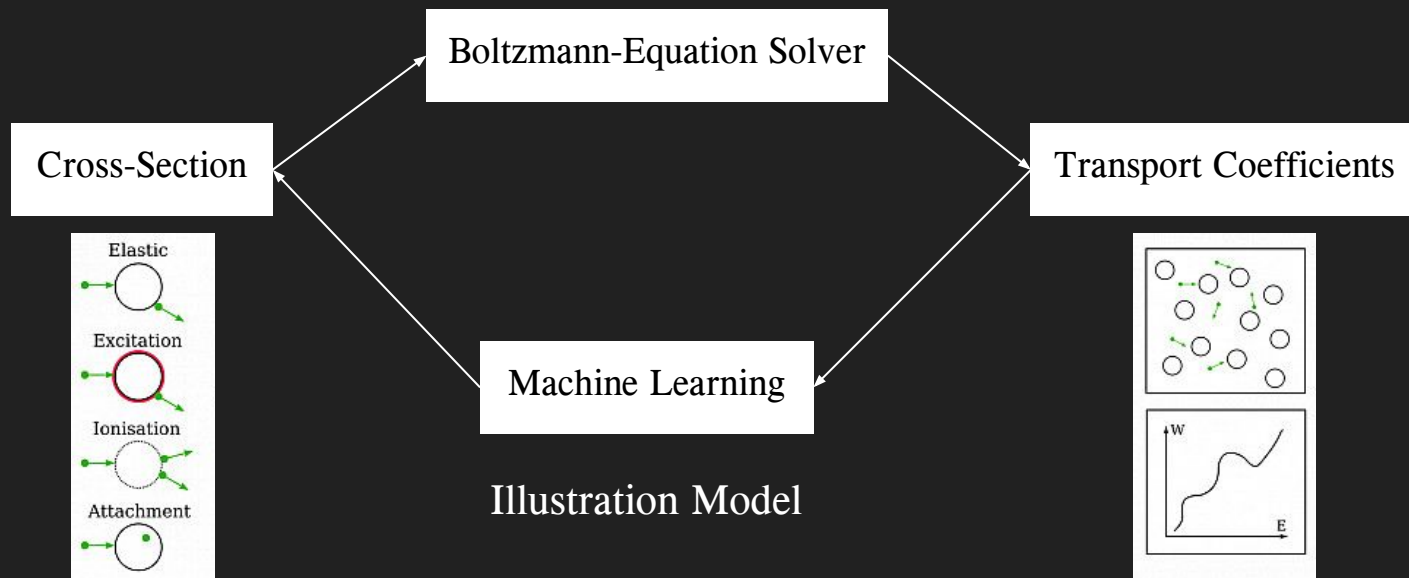
Supervisors: Daniel Cocks, James Sullivan, and Joshua Machacek  
Australian National University

# Outline

- Inverse Swarm Problem
- Neural Network
- PCA vs VAE
- Surge Function
- Mixture Density Networks
- Recurrent Neural Networks
- Future Applications

# Inverse Swarm Problem

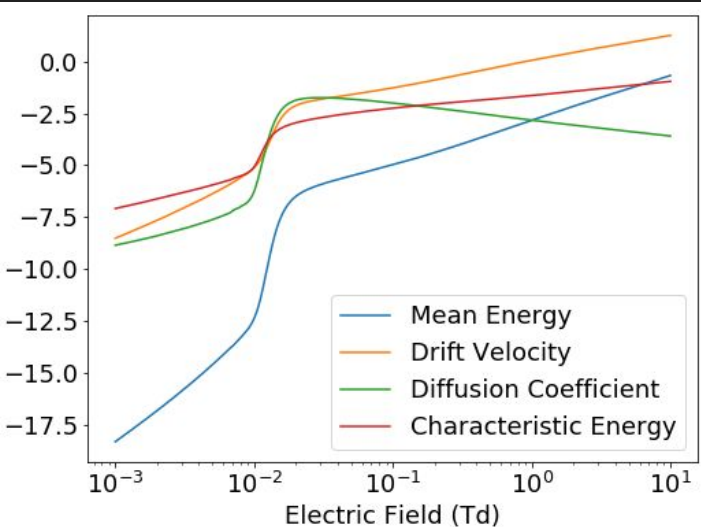
- Unknown if a unique functional exists
- Regardless, not an invertible problem due to sensitivity and uncertainty



# Sequence to Sequence Prediction

- Logarithmic spaced grid points.

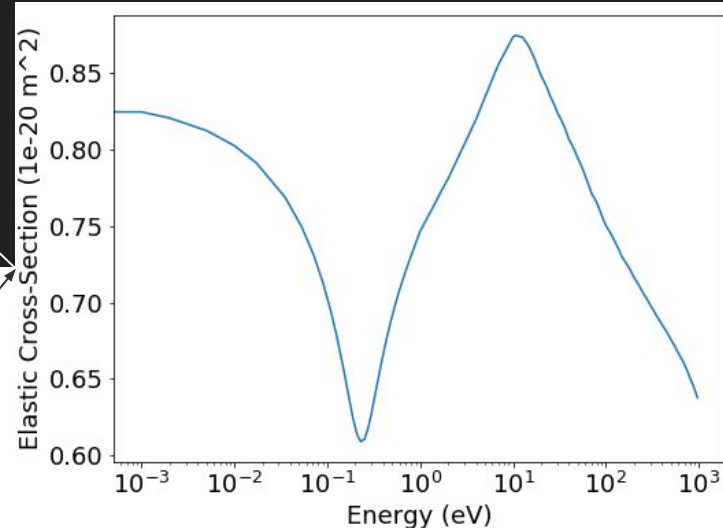
Transport  
Coefficient



BOLTZMANN  
EQUATION

NEURAL  
NETWORK

Cross Section



# Boltzmann Equation

- Use cross section in Boltzmann Equation find Electron Distribution.

$$\left[ \frac{q^2 E^2}{3m^2 \nu_m(v)} \right] \frac{d^2 f^{(0)}(v)}{dv^2} + \left[ \frac{mv\nu_m}{m_0} + \frac{2q^2 E^2}{3m^2 v\nu_m} \right] \frac{df^{(0)}(v)}{dv} + \frac{m}{m_0} [3\nu_m(v) + v\nu'_m(v)] f^{(0)}(v) = 0$$

- Transport Coefficients: functionals of EDF.

$$\epsilon = \frac{m}{2n} \int_0^\infty dv v^4 f^{(0)}(v)$$

$$W = \frac{1}{3} \int_0^\infty dv v^3 f^{(1)}(v)$$

- Calculating from cross section is easy.
- Calculating cross section from transport coefficient is impossible?

$\nu_m(v)$ : collision frequency

$f(v)$ : Electron Distribution Function

$E$ : Electric Field

$\epsilon$ : Mean Energy

$W$ : Drift Velocity

$V$ : Velocity

# Bolsig (Forward Problem)

## Boltzmann Equation Solver

Have also written my own test code to understand the working.

ELASTIC

Argon

Mol wt. = 0.136e-4

EFFECTIVE MOMENTUM TRANSFER

CROSS SECTION

U(eV)	$\sigma(\text{\AA}^2)$
0	0.75E-19
0.01	0.75E-19
... ..	
1E5	0.49E-22

CONDITIONS

0.1E-2 / Electric field / N (Td)

300. / Gas temperature (K)

200 / # of grid points

200. / Manual maximum energy (eV)

1e-10 / Precision

1000 / Maximum # of iterations

OUTPUT

E/N (Td)	Mean energy (eV)
0.1000E-02	0.3863E-01
0.1012E-02	0.3863E-01
0.1023E-02	0.3863E-01

... ..

E/N (Td)	Mobility *N (1/m/V/s)
0.1000E-02	0.2156E+27
0.1012E-02	0.2156E+27
0.1023E-02	0.2156E+27

... ..

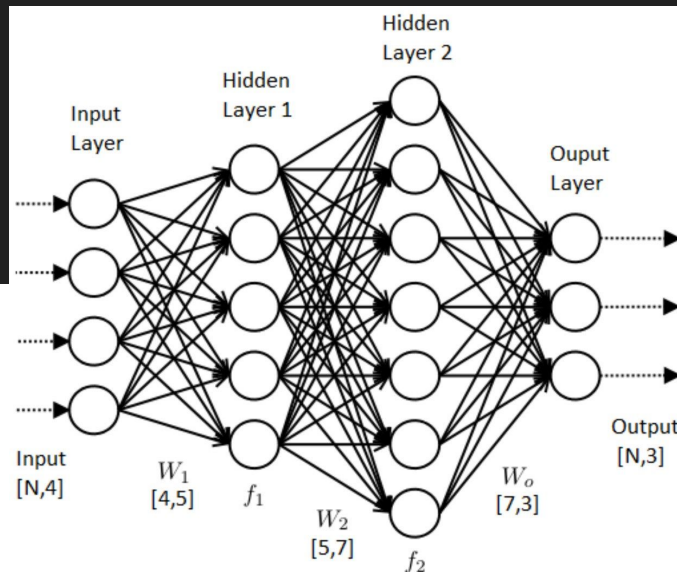
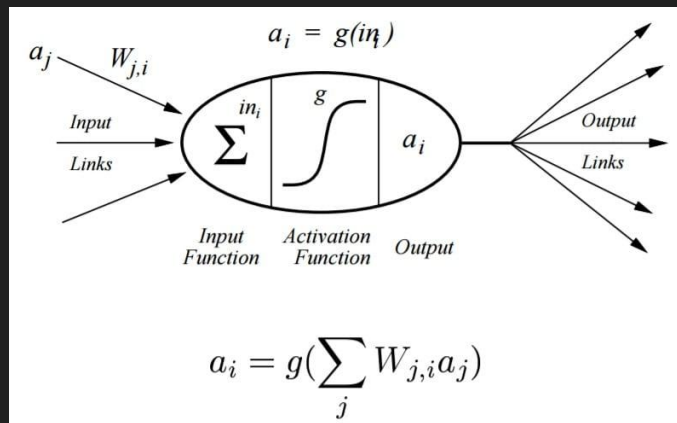
E/N (Td)	Diffusion coefficient *N (1/m/s)
0.1000E-02	0.5586E+25
0.1012E-02	0.5586E+25
0.1023E-02	0.5586E+25

... ..

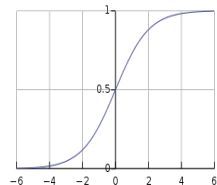
# Neural Network

- Widely used
- Function Approximator.
- Perceptron: Artificial Neuron
- Architecture.
- Non-linearity (Activation Function)

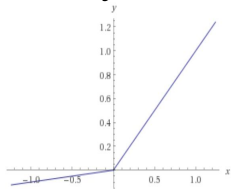
Ex. DFT



Sigmoid

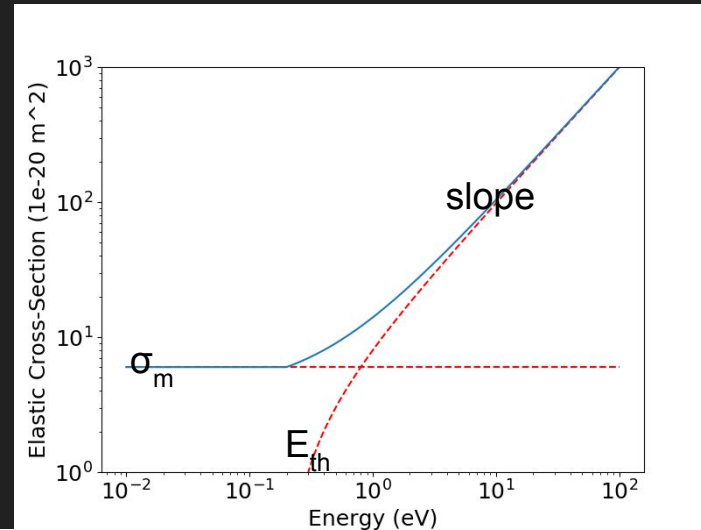


Leaky ReLu



# Reid's Ramp Model

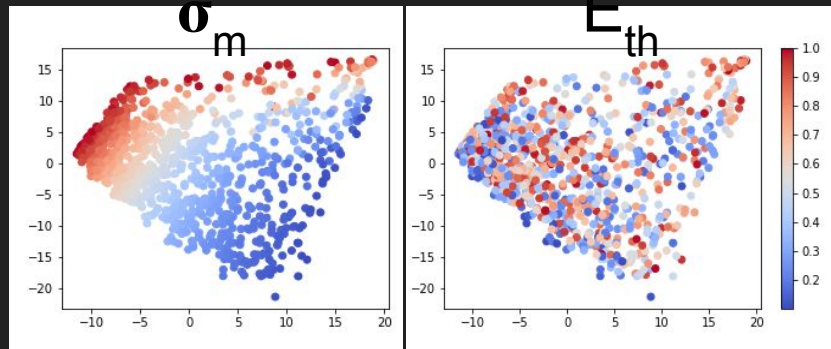
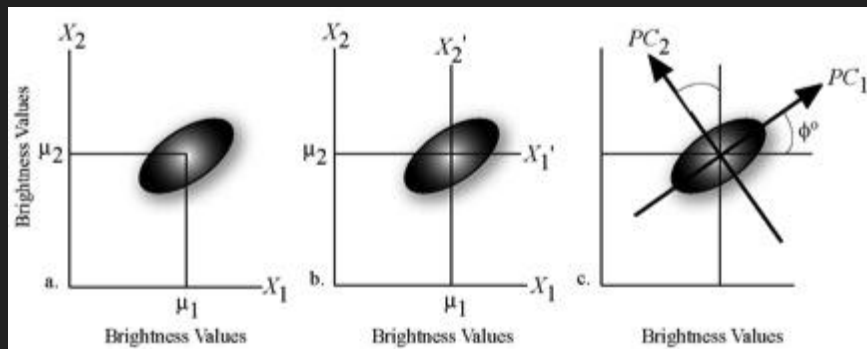
- A simple cross-section for a start.
- Sequence to Parameter prediction





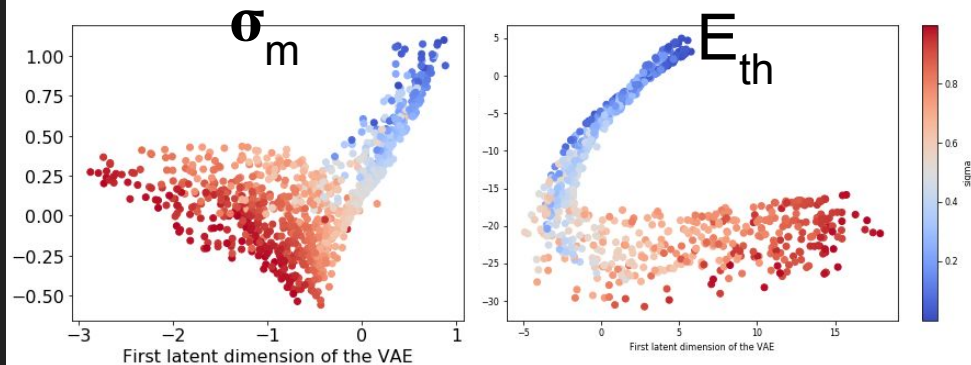
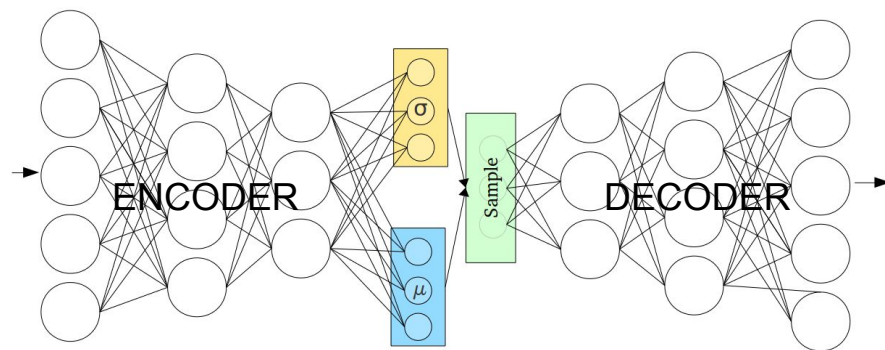
# Principal Component Analysis

Linear



# Variational Autoencoder.

Non-linear



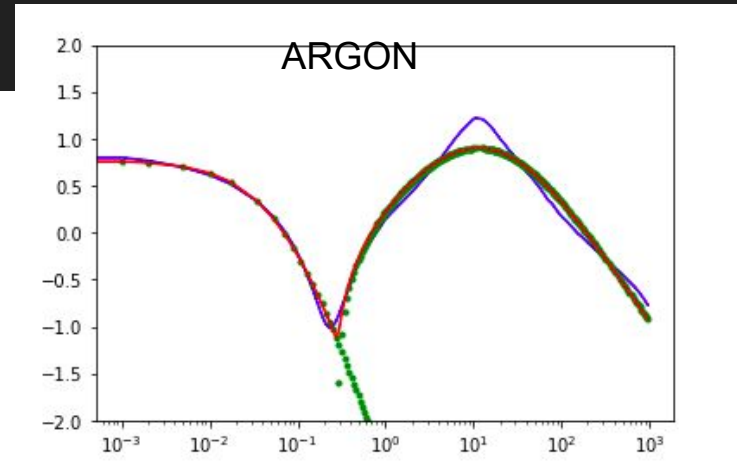
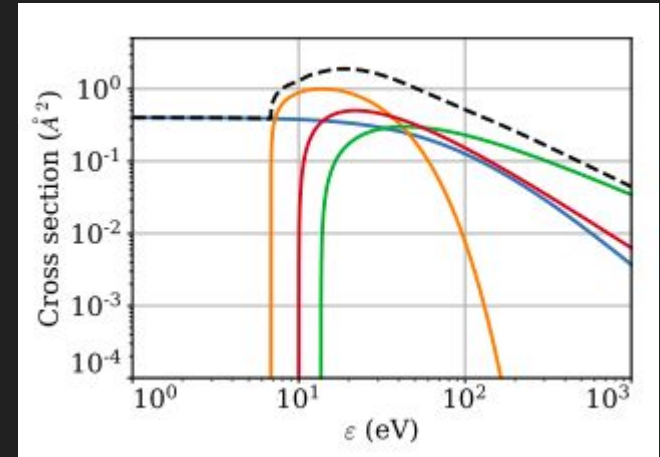
# Training Set: Surge Function

- A realistic model for cross-sections
- Parameters:
  - $A$  : magnitude
  - $\lambda$  : Width
  - $E_{th}$  : Threshold Energy
  - $P$  : Power-law decay
- Combination of Surge Functions fits realistic cross-sections. (LXCat)

$$x = E - E_{th}$$

$$S_{pwr}(x; p, \lambda) = \begin{cases} 0 & x < 0, \\ \lambda^p (p+1)^{p+1} \frac{x}{(x+p\lambda)^{p+1}} & x \geq 0, \end{cases}$$

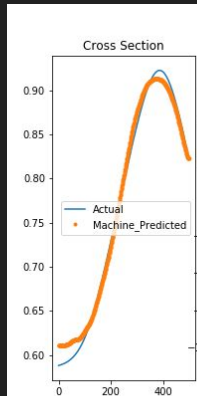
$$S_{exp}(x; p, \lambda) = \begin{cases} 0 & x < 0, \\ \left(\frac{e}{\lambda}\right)^p x^p e^{-px/\lambda} & x \geq 0, \end{cases}$$



# Fully Connected Neural Network

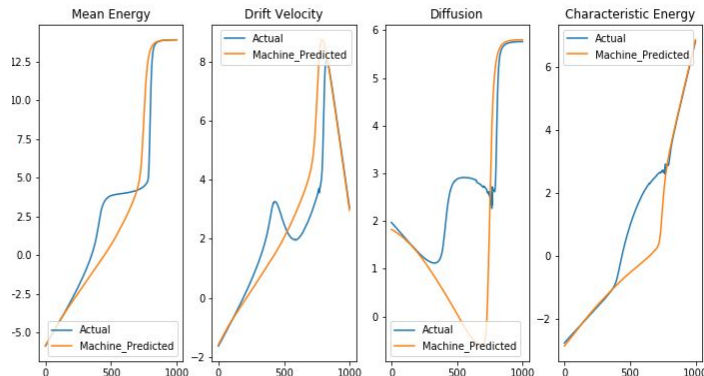
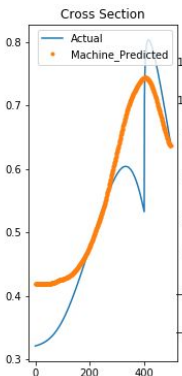
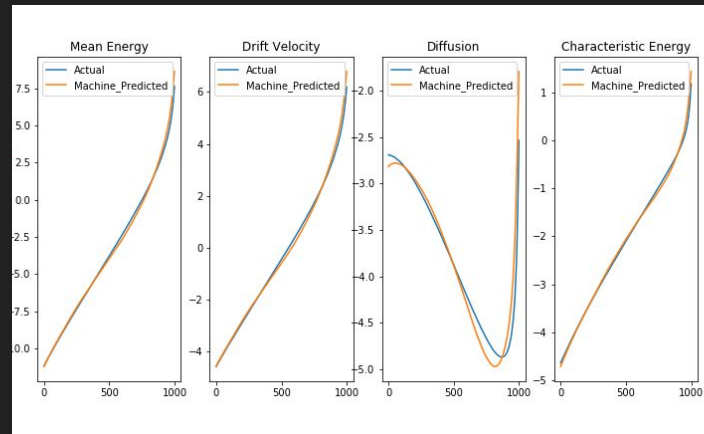
- Fairly good prediction for simple cross sections.
- Predicted cross-sections fed into Bolsig to see how well it machine does on the transport coefficient prediction.
- Smooth curves. Behaves like a low-pass filter.
- Fails to capture deep minimas and sharp peaks.

Cross Section



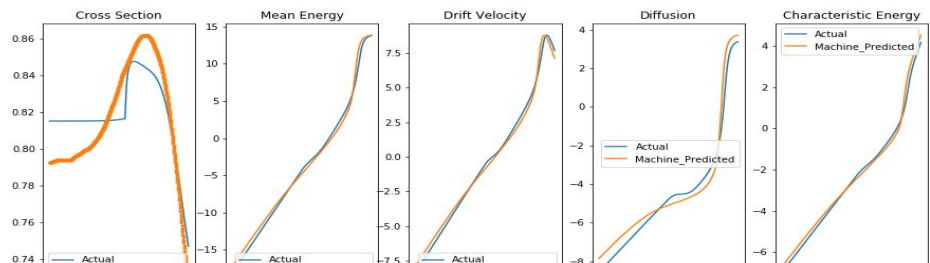
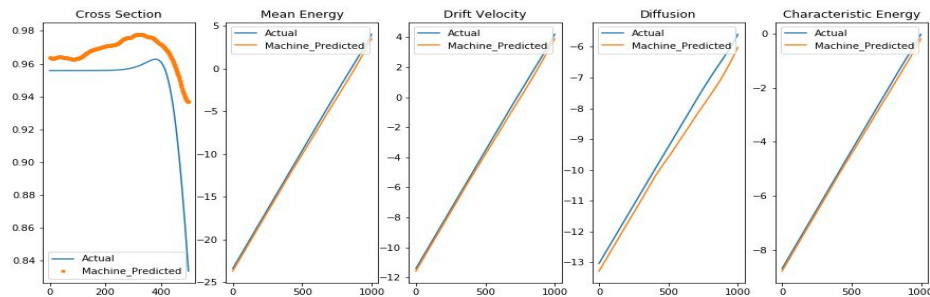
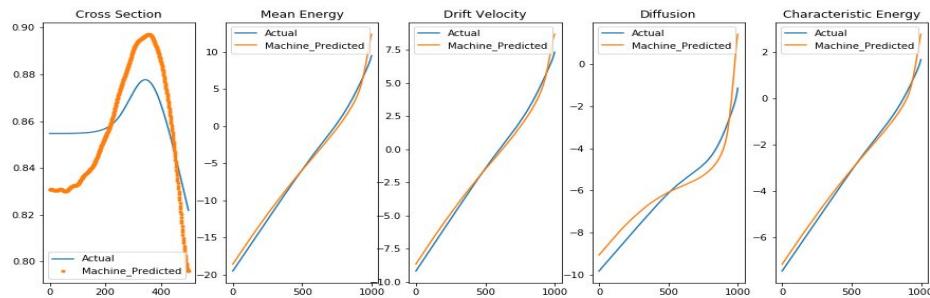
BOLSIG

Transport Coefficient



# Is the problem Invertible?

- Is the Inverse Swarm mapping many-to-one?
- Similar transport coefficient for very different looking cross-sections.
- Is it a good idea to try to exactly predict the cross-section?

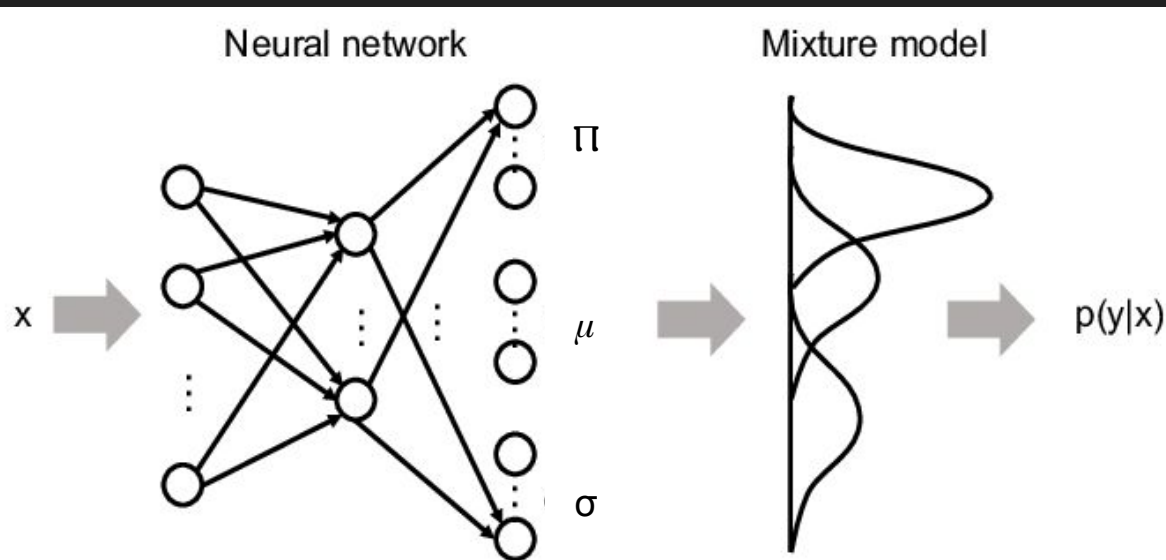


# Mixture Density Network

- Successful in predicting many to one functions.
- Predicting Probability Distribution instead of exact values.
- MDN Architecture.

Normal Distribution

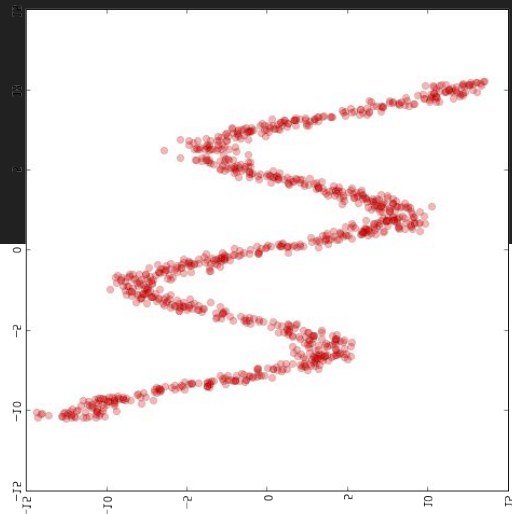
$$P(\hat{y}_i) = \sum_j \Pi_j N(\hat{y}_i | \mu_i, \sigma_i)$$



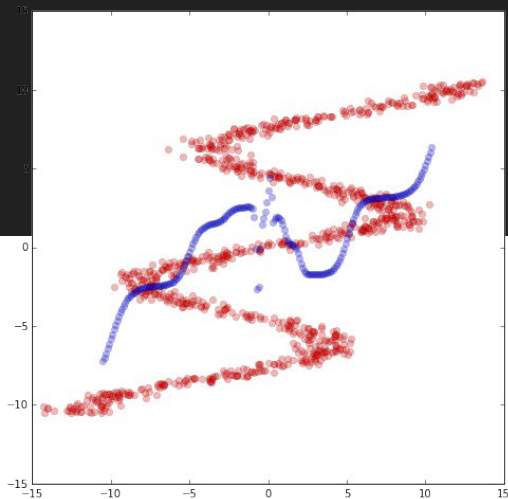
# Mixture Density Network

Toy Problem: One-to-Many function.

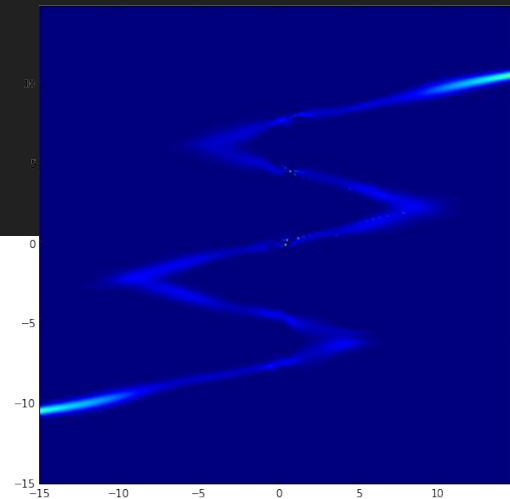
Training input



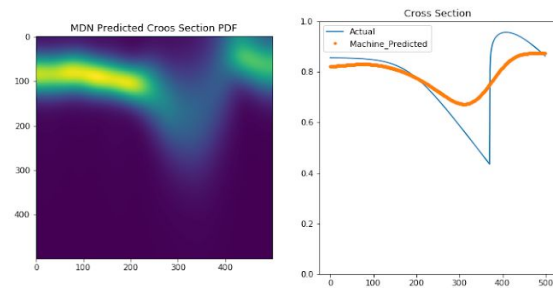
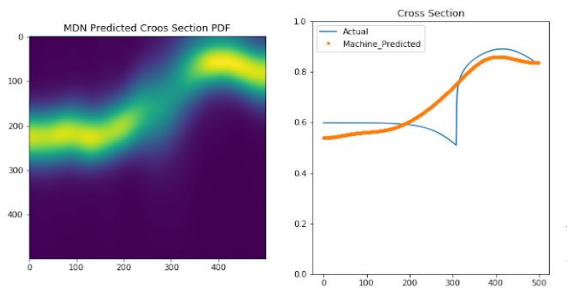
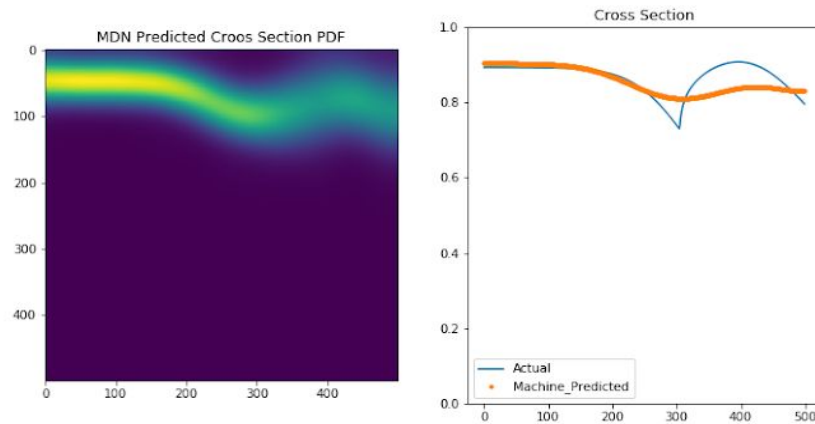
Simple NN prediction



MDN prediction



# Mixture Density Network



# Post-MDN Optimization

(Work in Progress)

After constraining the value of cross-section with the Probability Distribution Function, we can tweak it slightly away from the expectation value using Bolsig such that they evaluate the transport coefficients accurately.

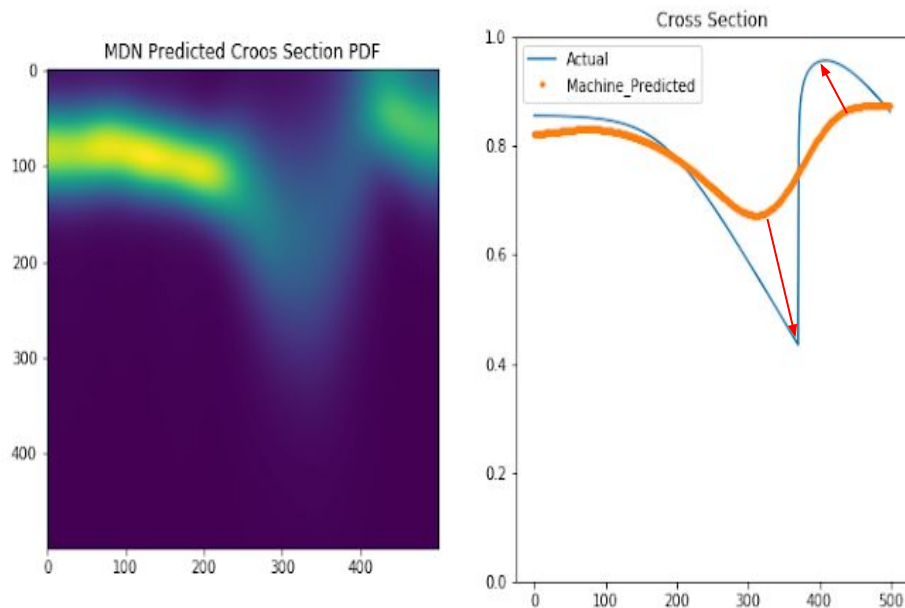
$$\text{Cost Function} = \Sigma(W-W')^2 - \lambda \log(\text{PDF}_{\sigma}(\sigma'))$$

$W$ : Transport Coefficients

$\sigma$ : Cross section

$(')$  denotes Machine Predicted values

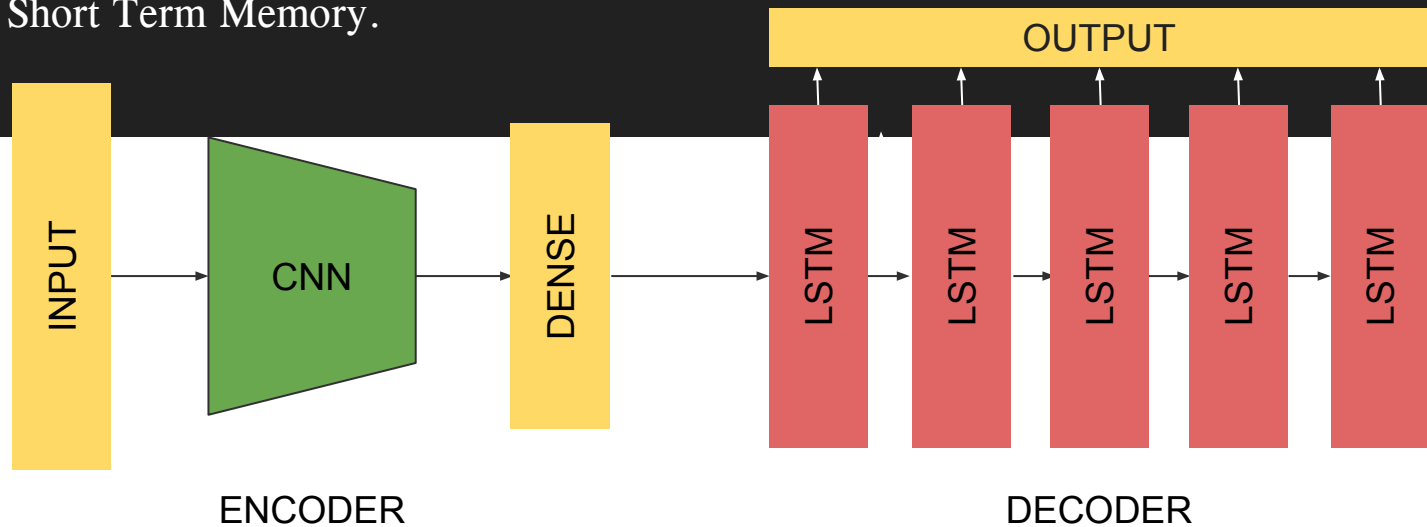
$\lambda$ : A tunable hyperparameter





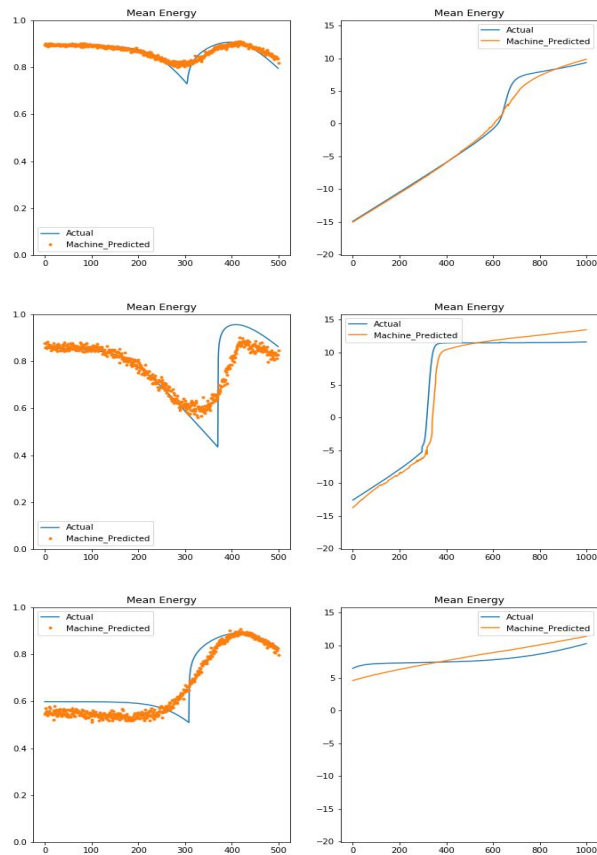
# Recurrent Neural Network

- Dealing with sequential data.
- Natural Language Processing Analogy.
- Attempt to capture Ramseur Minima better.
- Convolutional Neural Network.
- Long Short Term Memory.

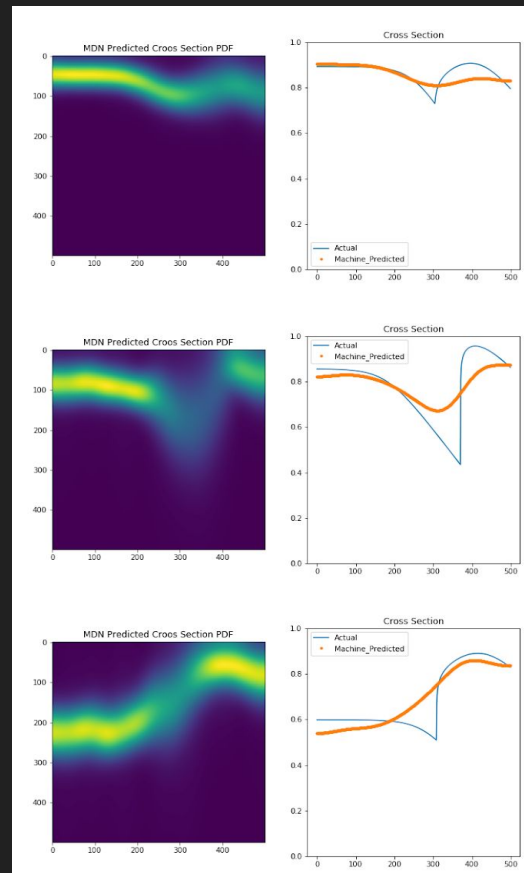


CNN-LSTM Encoder-Decoder Model.

# Recurrent Neural Network

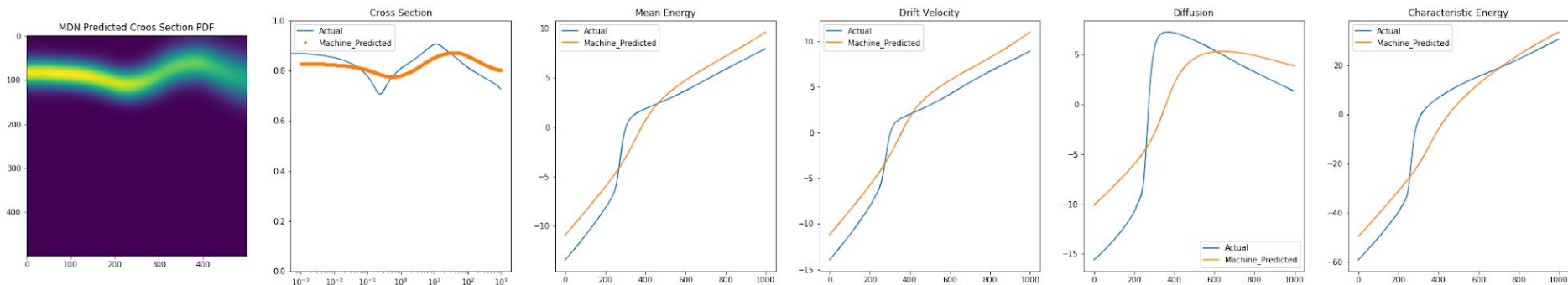


# Mixture Density Network



# Argon

Machine learned using simulated data but predicting real data.



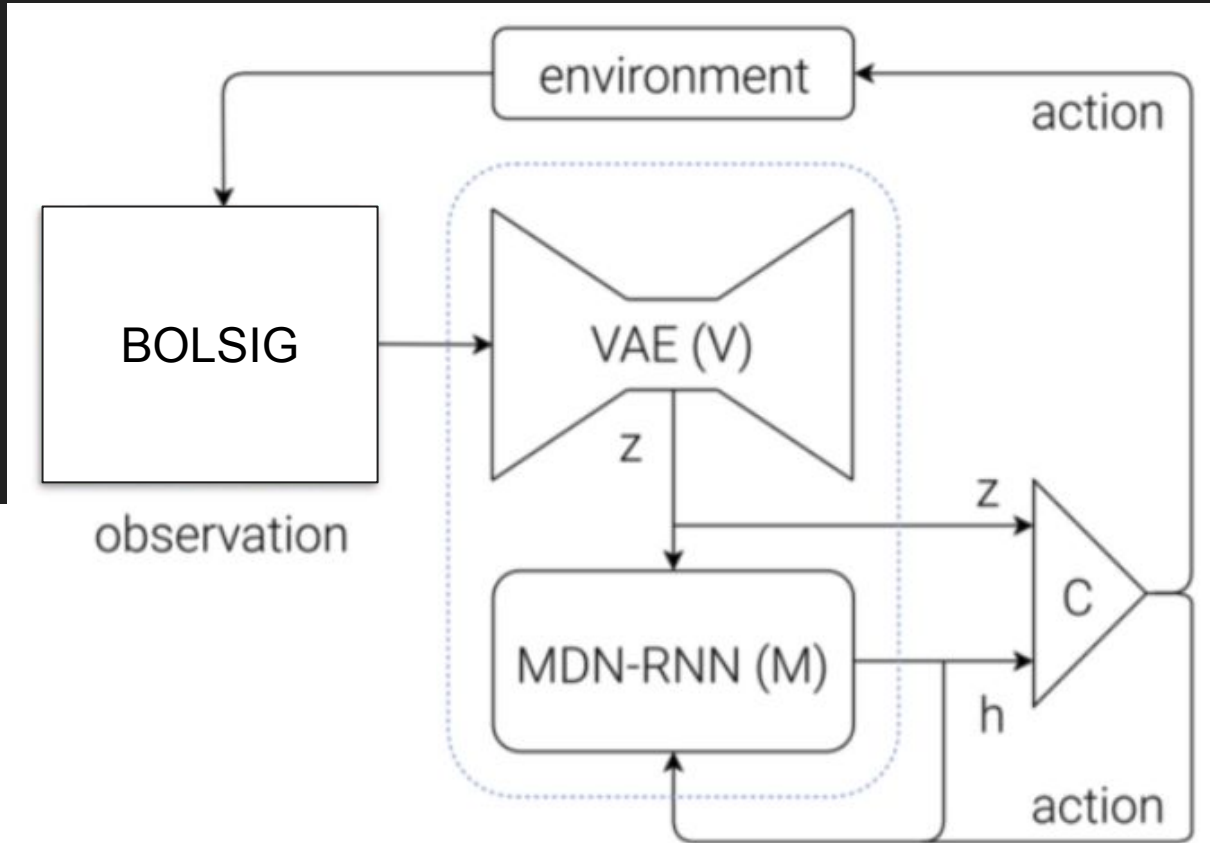
# Challenges

- **Is the transformation Invertible?** There is a chance that the transform is many to one. That is a number of different cross-sections can give rise to very similar transport quantities.
- **Function to function mapping** where the basis changes. A trivial mapping with same basis can be simply predicted using one neural network layer. (or if we have some special relations between the bases: Ex. Discrete Fourier Transform.)
- **Finite number** of grid points is insufficient to completely specify a function.
- **Transport quantities are functionals** and require integral over all possible energy values.
- Capturing the **Ramsauer Minima** and the peak of cross-section.
- Transport coefficient run-offs due to steep-decay of cross-section at high energies.
- **Computation Time** required by RNNs is long.
- **Memory** occupied by datasets is huge.

# Applications

- HV Circuit Breakers
- Plasma Research
- PET Scans

# Further Exploration: Reinforcement Learning



# Questions?

**Thank You**