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Data Driven Modelling of Plasma in Tokamaks

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What is Fusion ?

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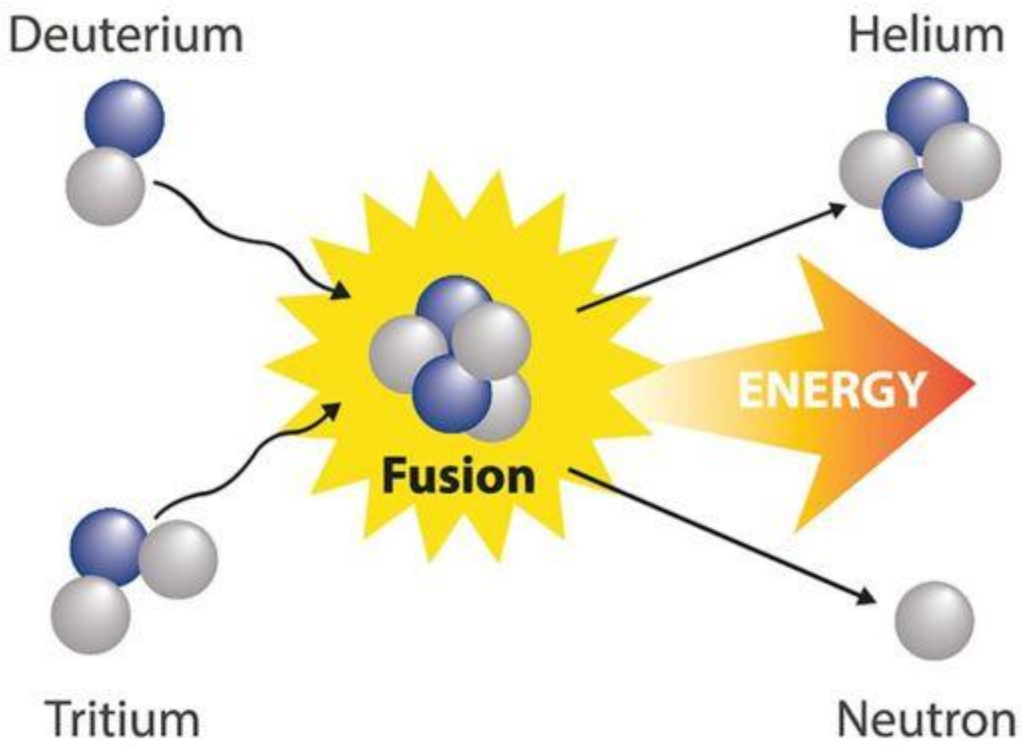
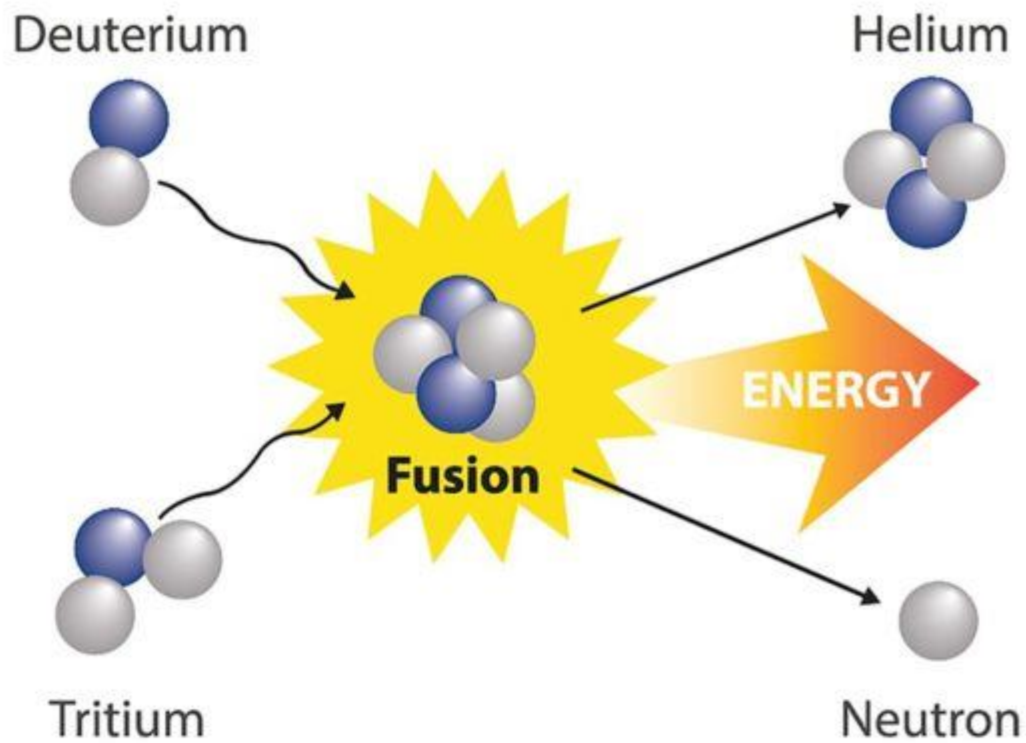
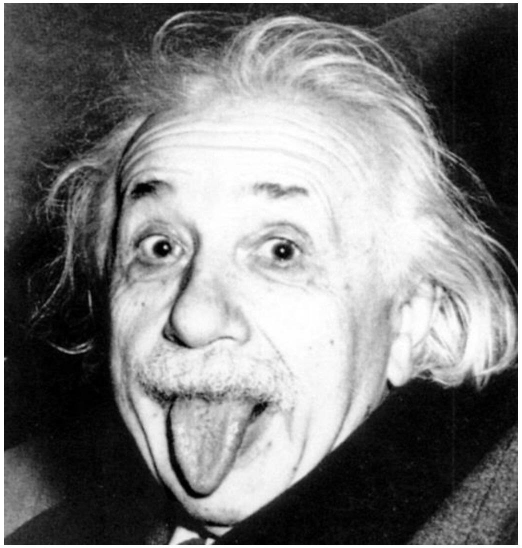


Source: Getty Images

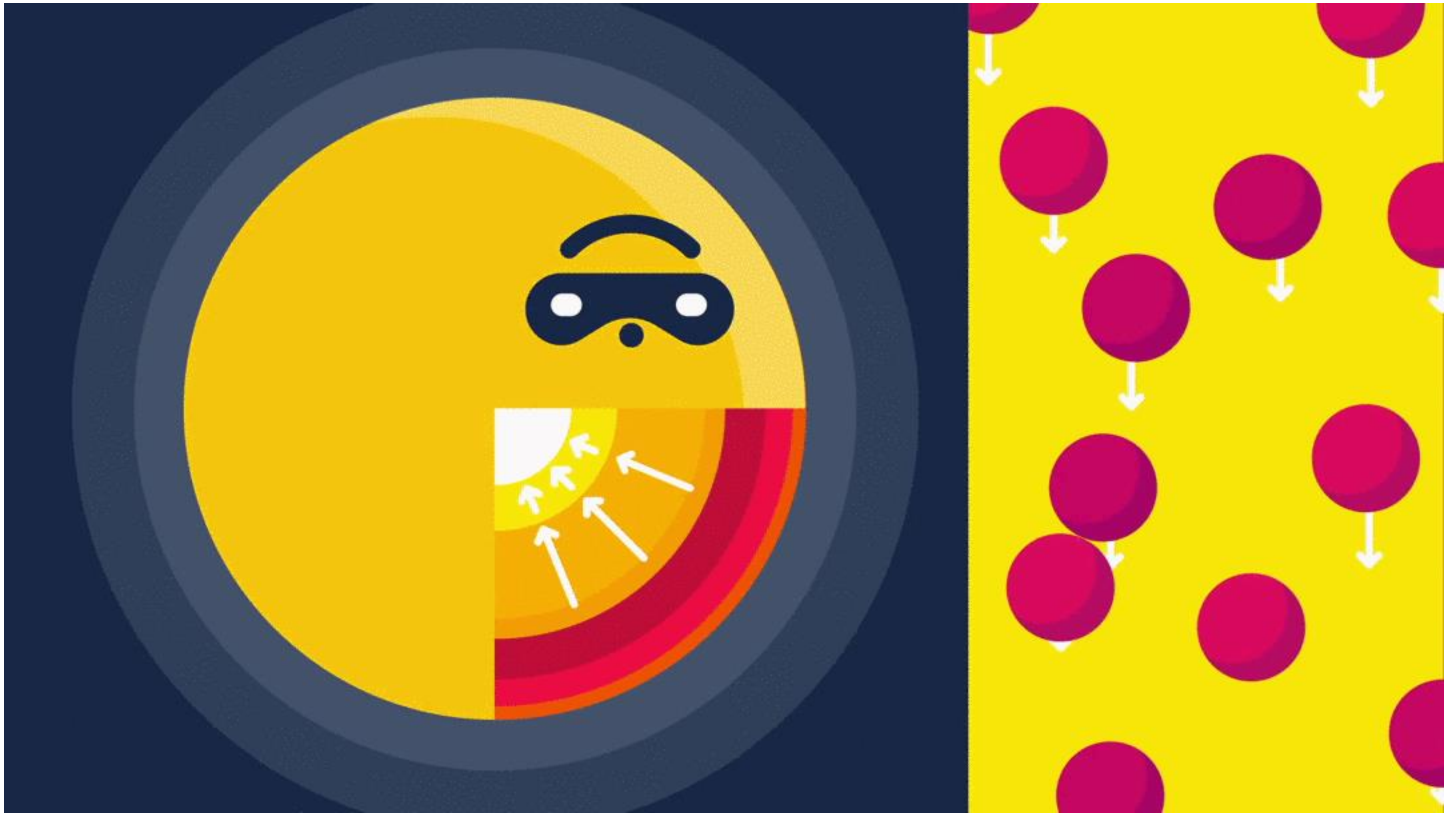
What is Fusion ?





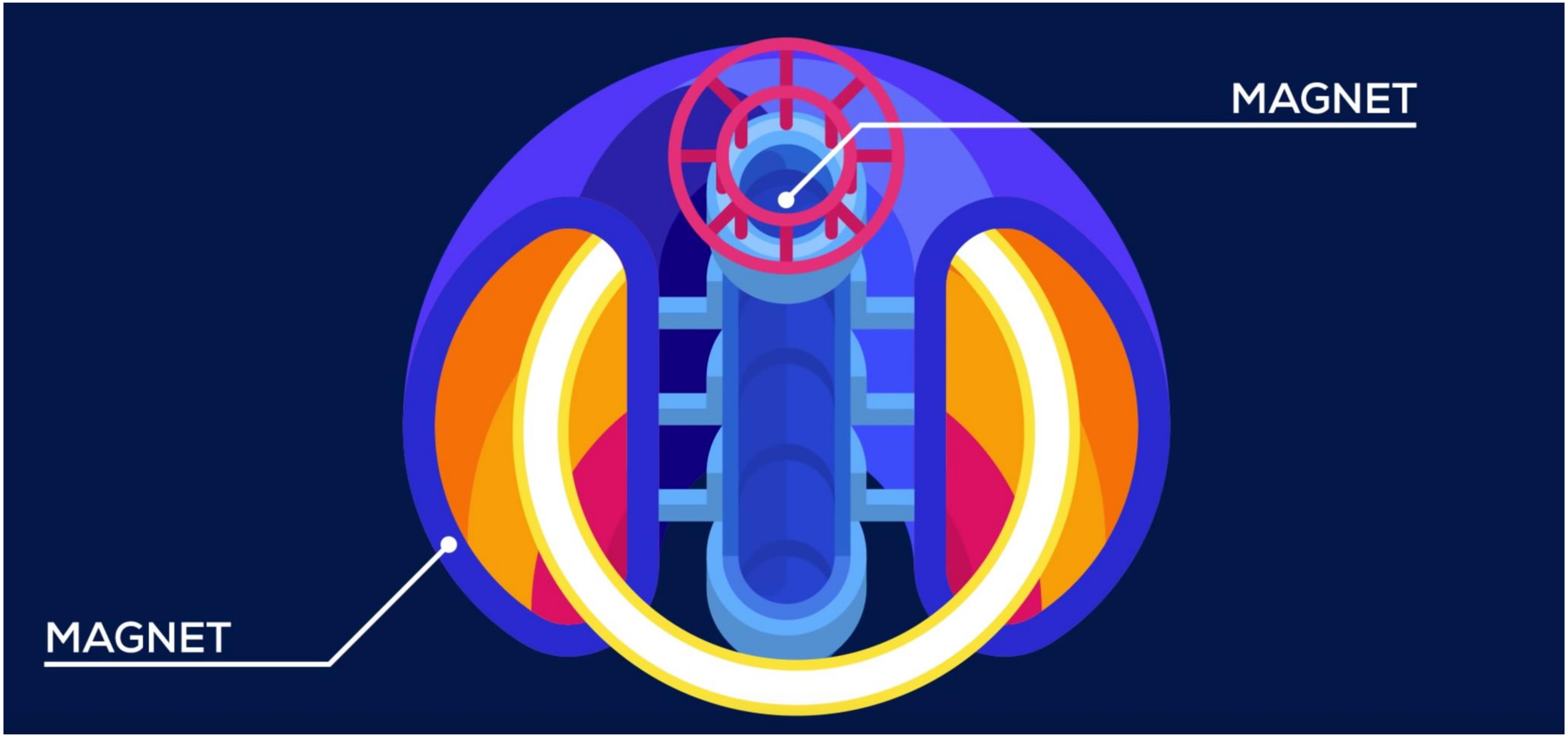
Energy = Mass x c^2

Source: Getty Images



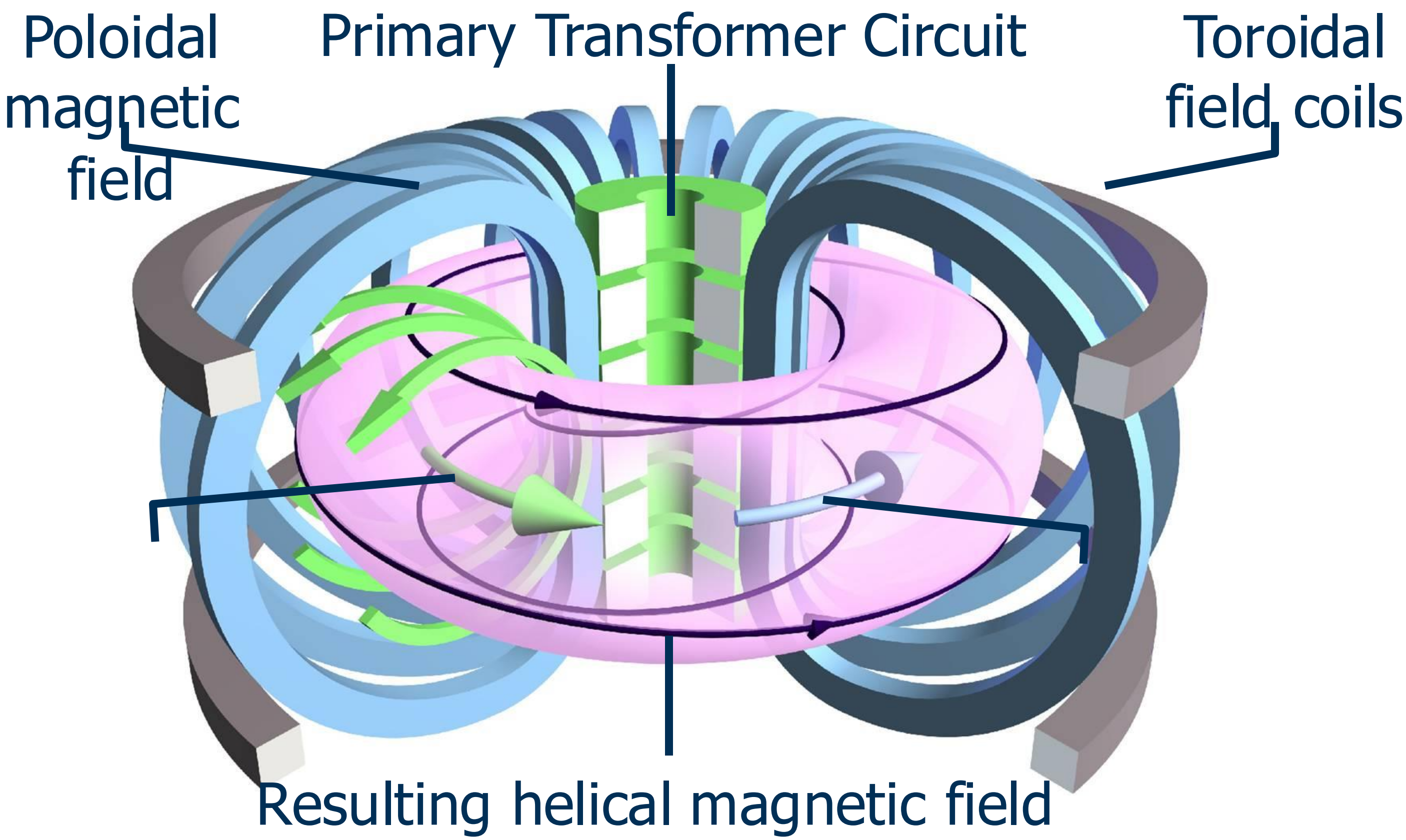
Source: Kurzgesagt – In a Nutshell

Magnetic Confinement

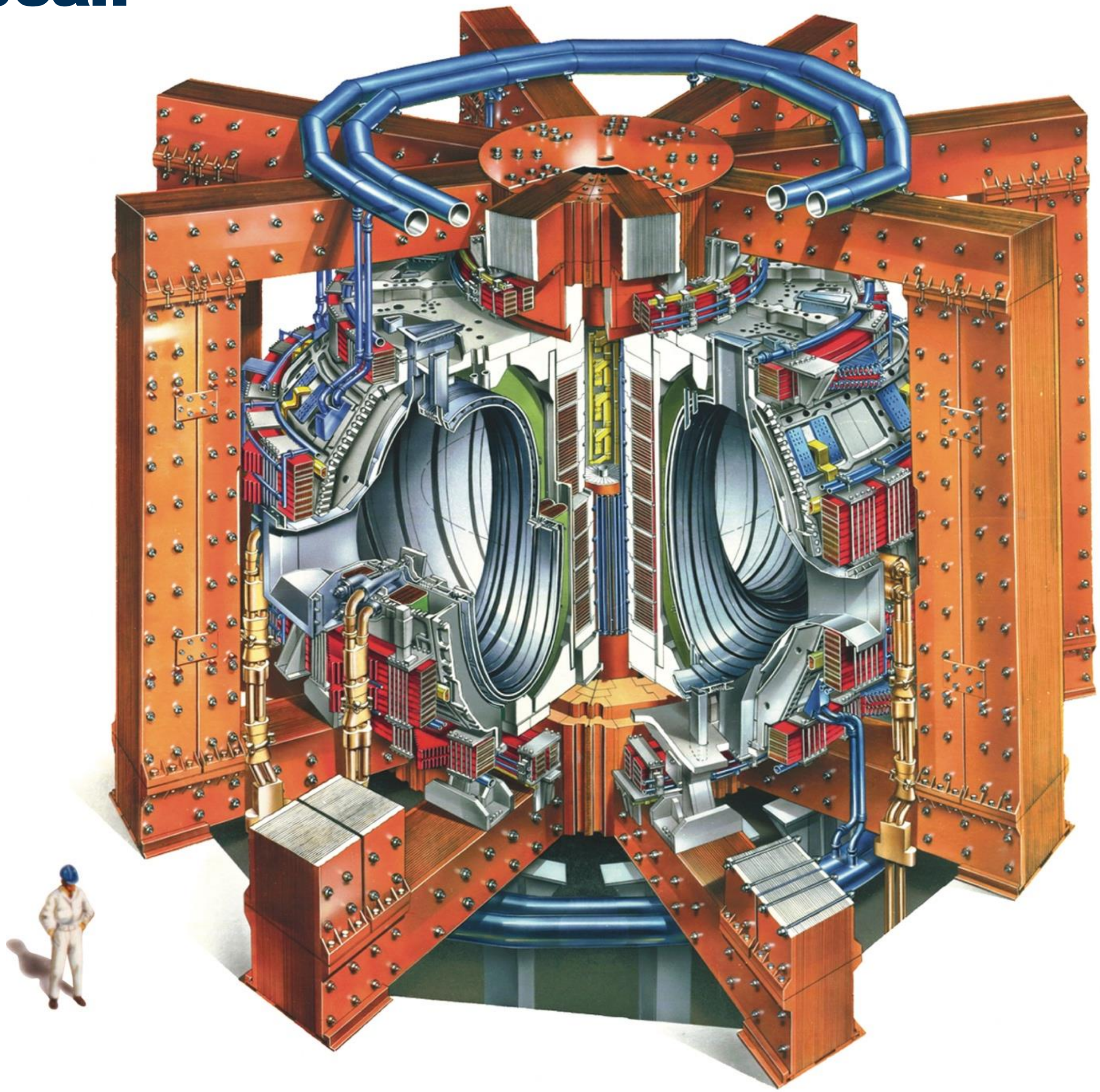


Source: Kurzgesagt – In a Nutshell

Tokamak – Structure



Joint European Torus (JET)



Source: EUROfusion

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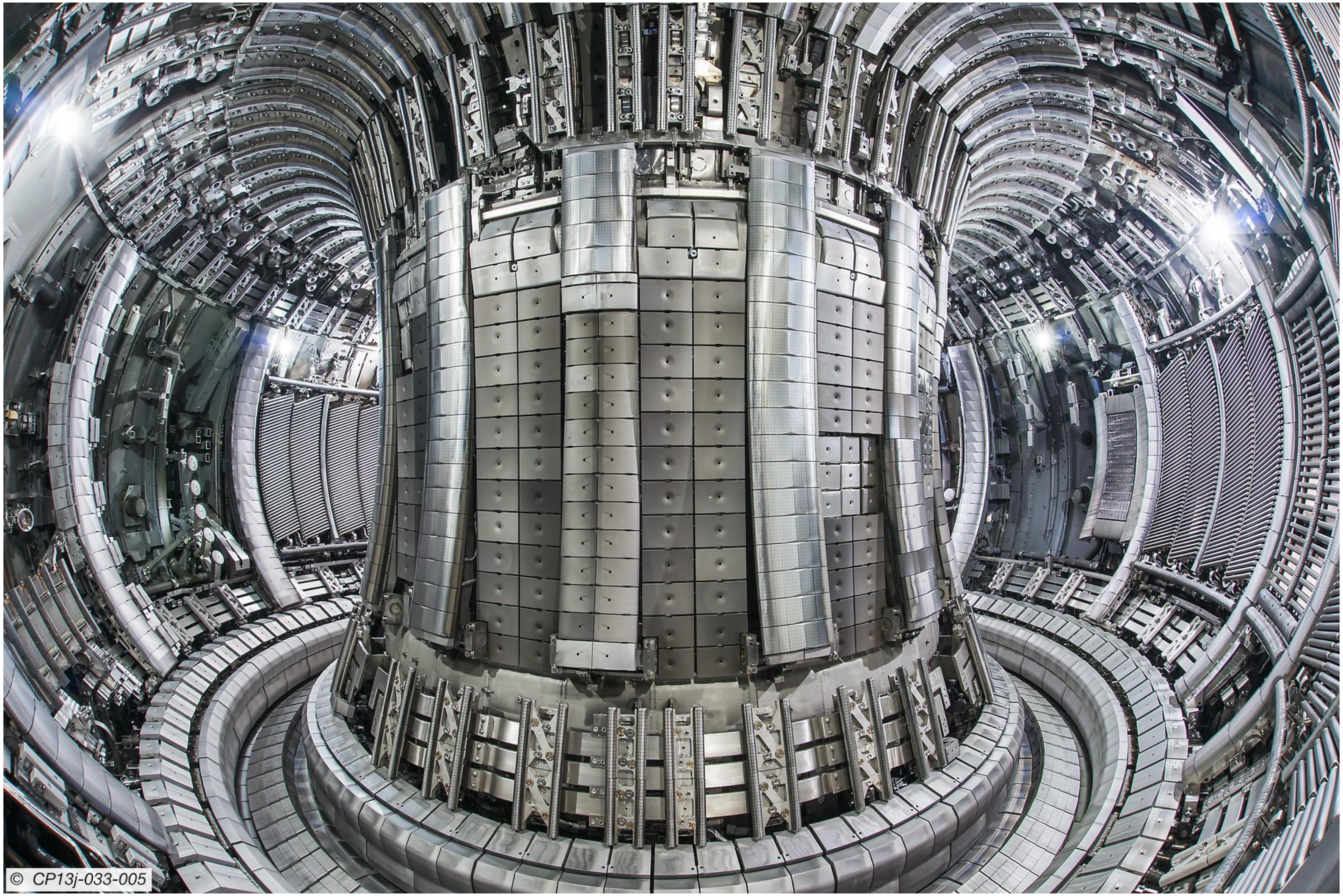
Tokamak – Internal View of JET



Source: EUROfusion

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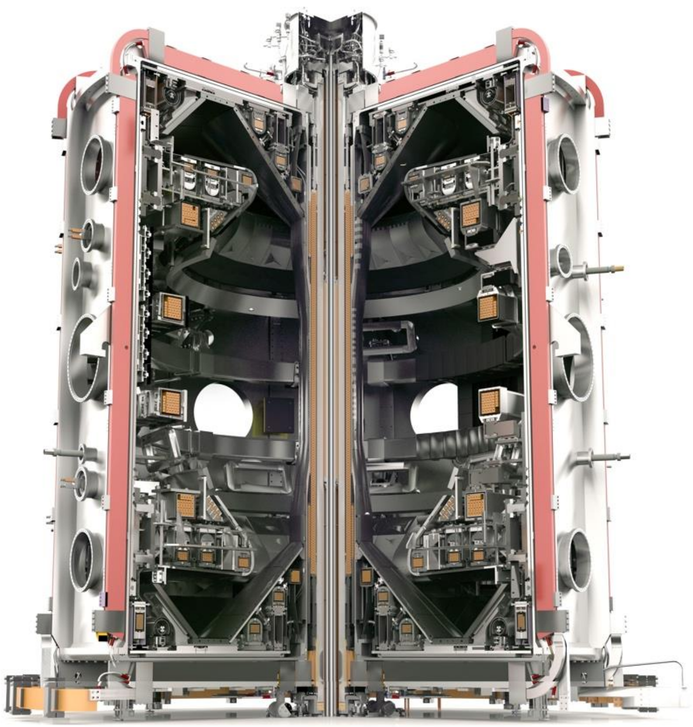
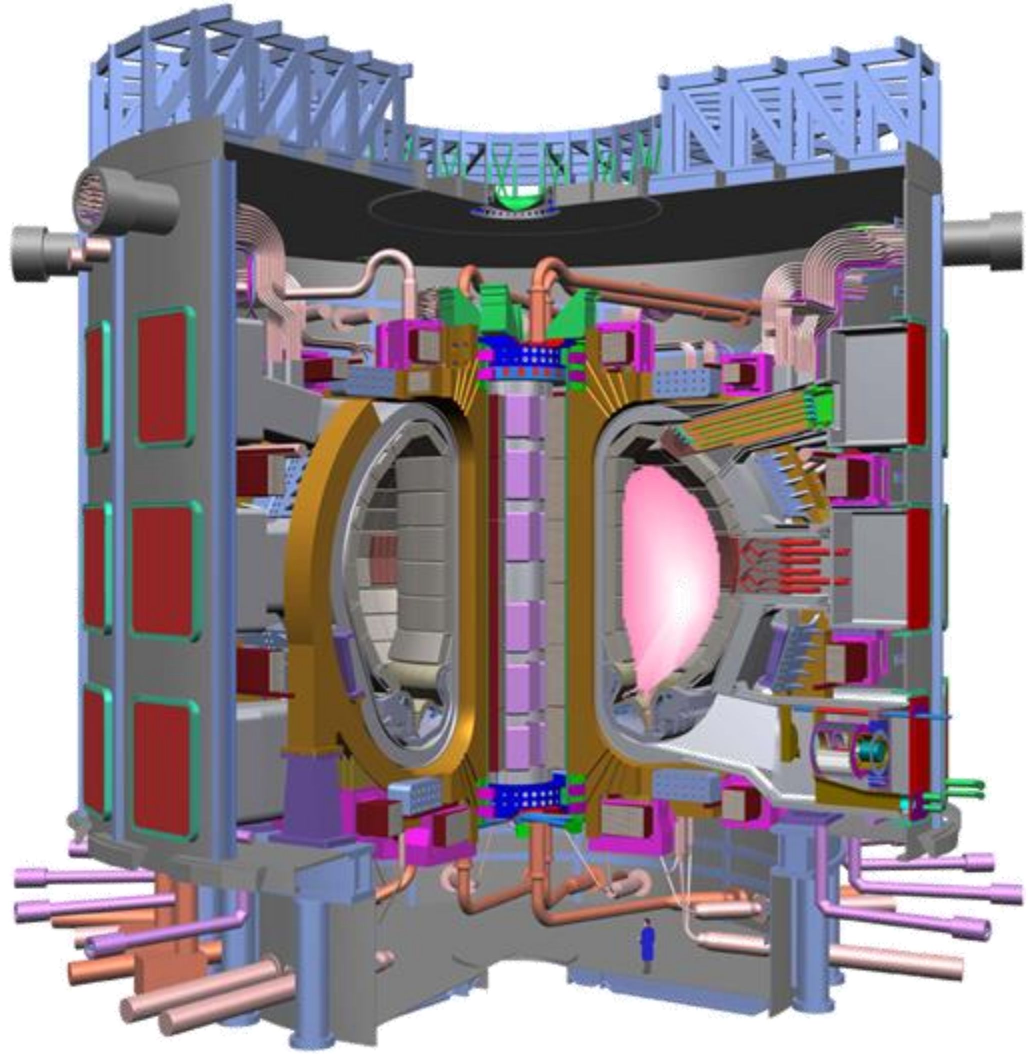
MAST-U



ITER



Data Driven Plasma Modelling

Fusion Research : Conundrum

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- Physical Experiments are Expensive, Complex and Time Intensive
- Physicists have to rely on developing vast code packages that can extensively perform simulations to understand plasma behavior under various conditions
- Complexity of the problems involved makes simulations often difficult to execute even on vast super clusters.

Plasma Modelling

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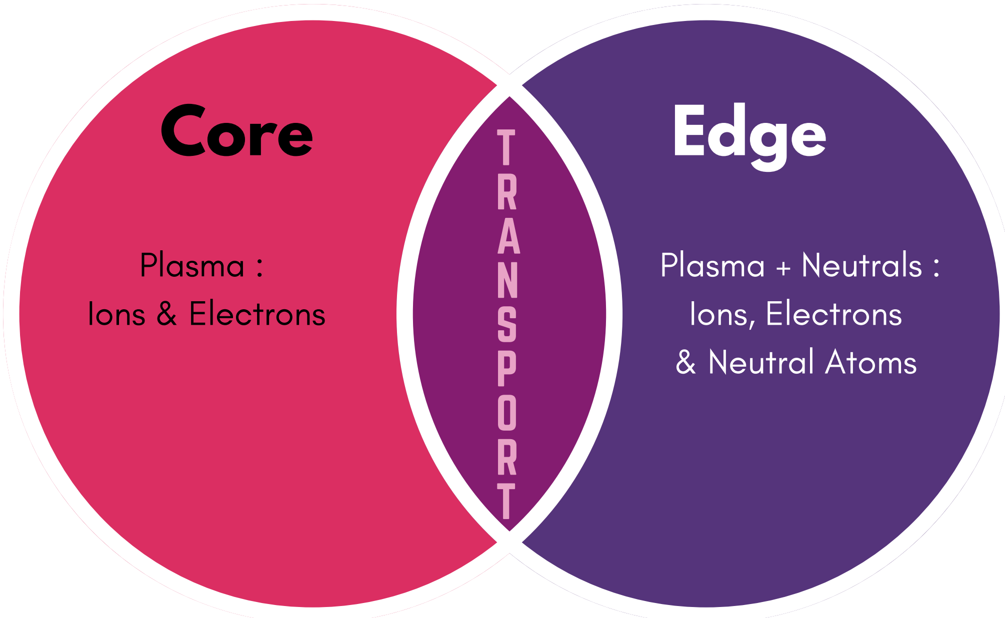
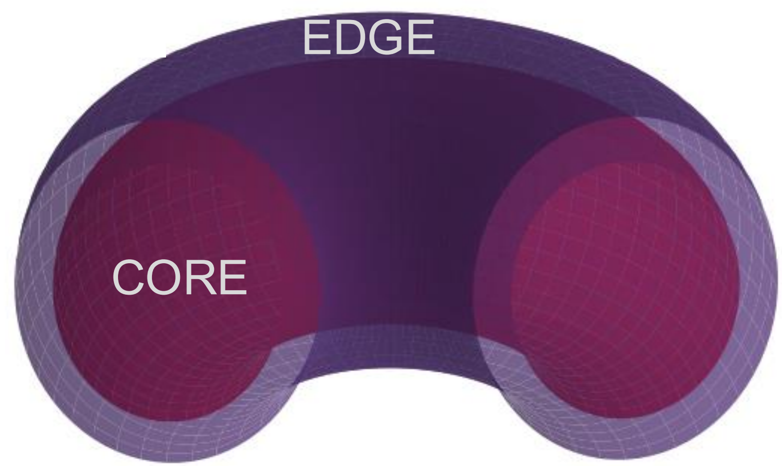
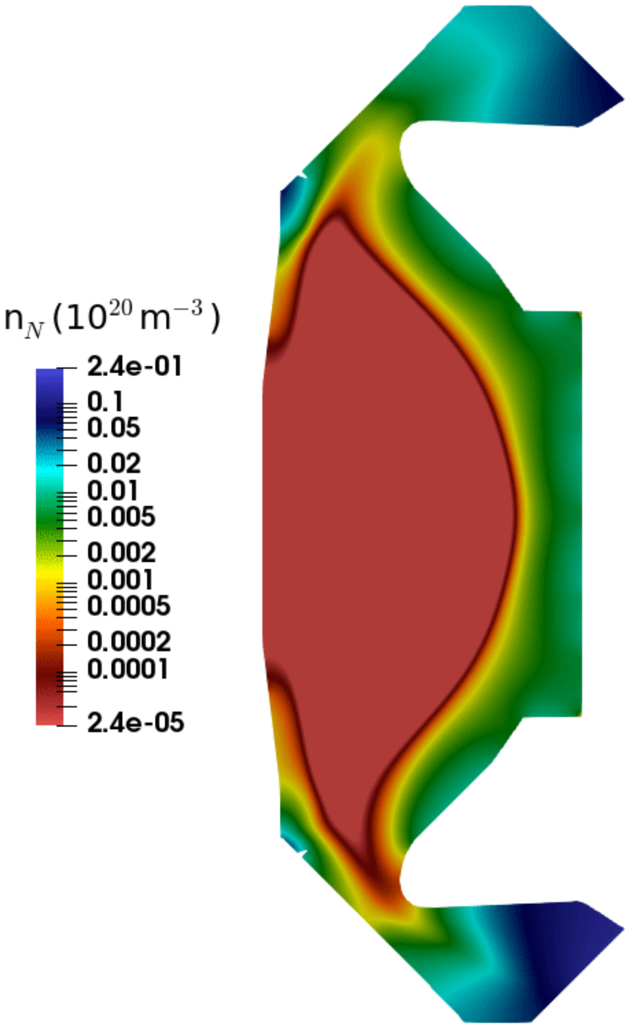




Edge Modelling



Evolution of the Neutral Density in 3D (2D cross section shown here) using the code suite JOREK.

Source:
ELM Instabilities in MAST-U.
S.F.Smith, S.J.P. Pamela,
M. Hölzl, G.T.A. Huijsmans.
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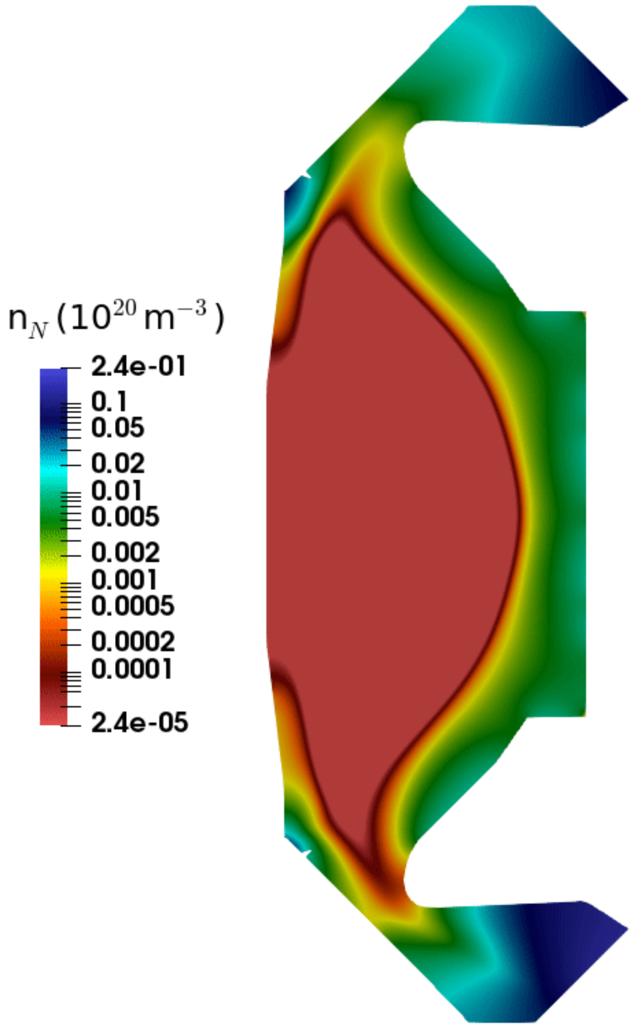
Edge Modelling



Evolution of the Neutral Density in 3D (2D cross section shown here) using the code suite JOREK.

To simulate the time evolution by 14 ms took over two months on 44 nodes, with each node consisting of 48 cores clocking 2.3GHz each.

Source:
ELM Instabilities in MAST-U.
S.F.Smith, S.J.P. Pamela,
M. Hölzl, G.T.A. Huijsmans.
UKAEA.

Universal Function Approximation Theorem of Neural Networks

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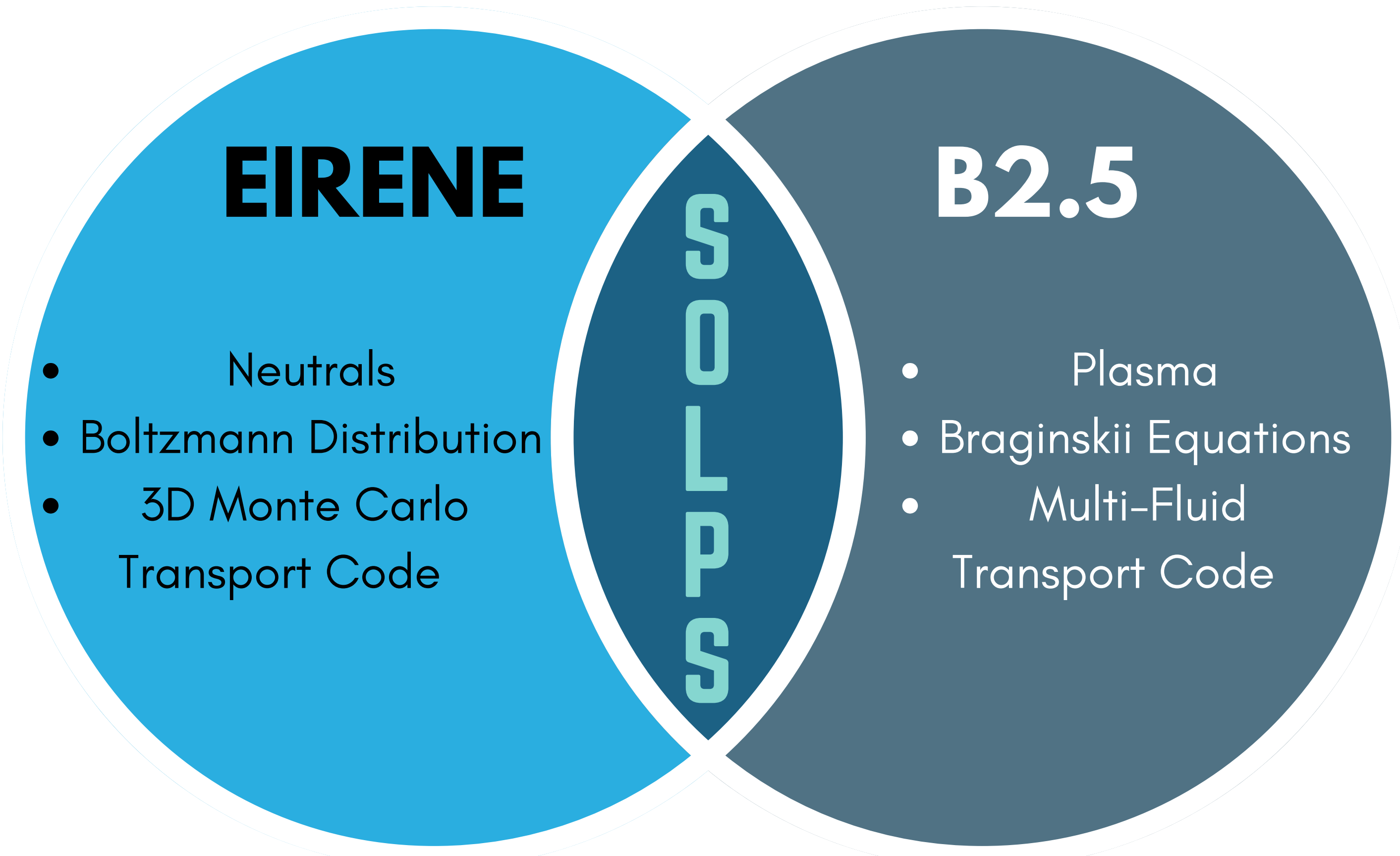
States that “a feed-forward network with finite hidden layers each consisting of finite number of nodes can approximate continuous functions on compact subsets of R^n ”.

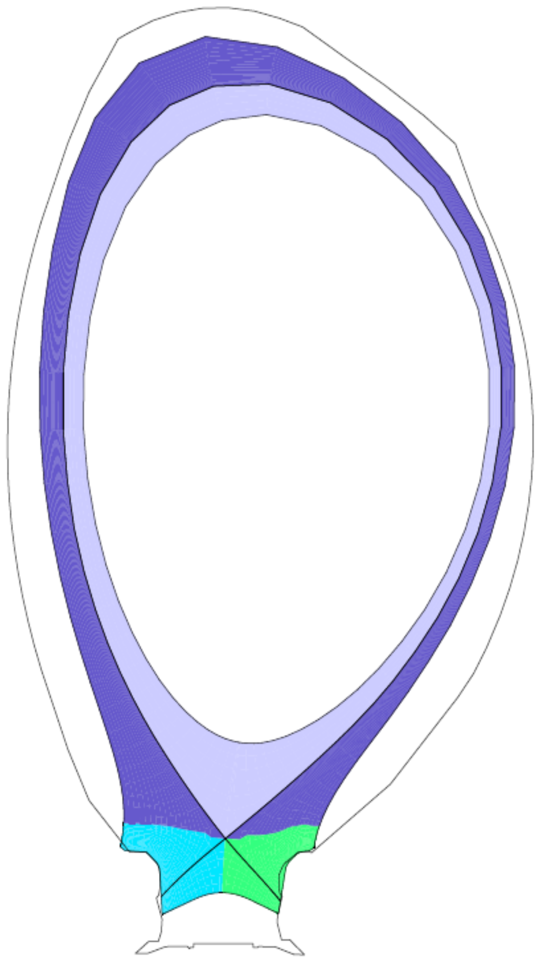
- Kurt Hornik, Maxwell Stinchcombe, and Halbert White. Multilayer feedforward networks are universal approximators. Neural Networks, 2(5):359 – 366, 1989.

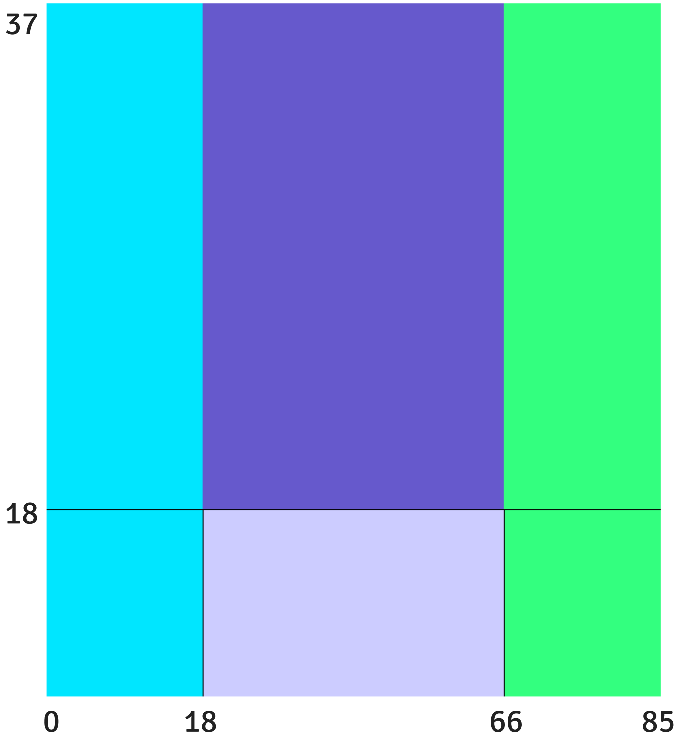
- G. Cybenko. Approximation by superpositions of a sigmoidal function. Mathematics of Control, Signals and Systems, 2(4):303–314, Dec 1989.

Scrape Off Layer Plasma Simulator



Grid Representation

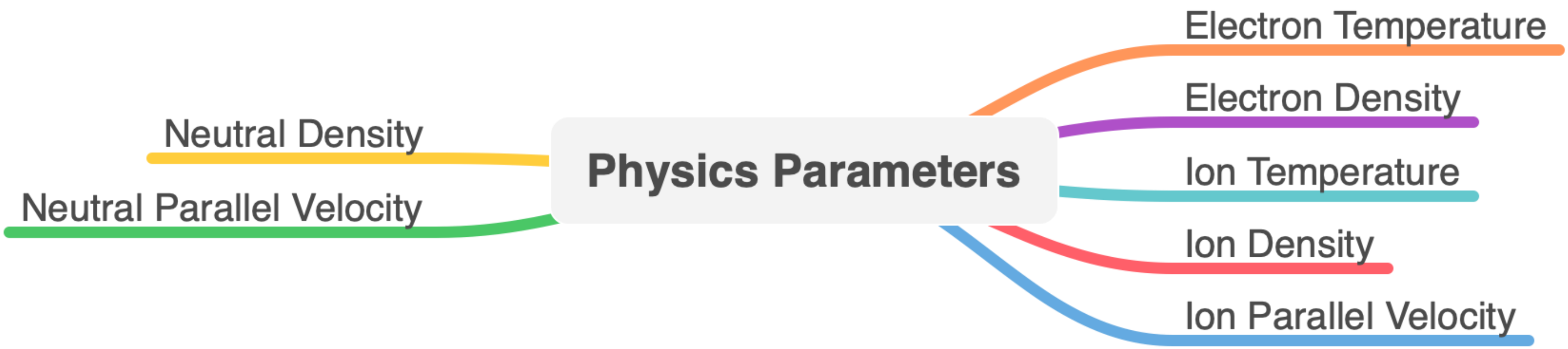




M. Stanojevic X. Bonnin D.P Coster, A. Kukushkin et al. Solps manual.

Parameters under Study

Training Data Gathered from previous SOLPS simulations



Parameters under Study

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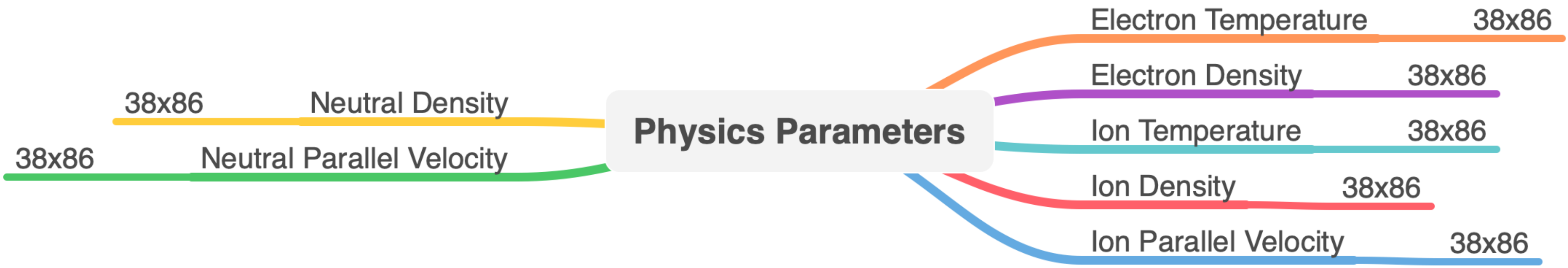
Training Data Gathered from previous SOLPS simulations



7 x (38x86) grids characterising Plasma Behaviour across the quadrangular representation of the Poloidal Cross-Section.

Data Generation

Phase I : Perturb the steady state by changing one or more of the modelling parameters

- Heating Power
- Puffing Rate
- Pump Intensity

Phase I simulations will help create the input datasets characterising the initial state of the edge.

Phase II : The outputs of the Phase I simulations are run with a fixed value of the three modelling parameters to run back to steady state.

Phase II simulations will help create the output datasets characterising the final state of the edge.

Data Generation

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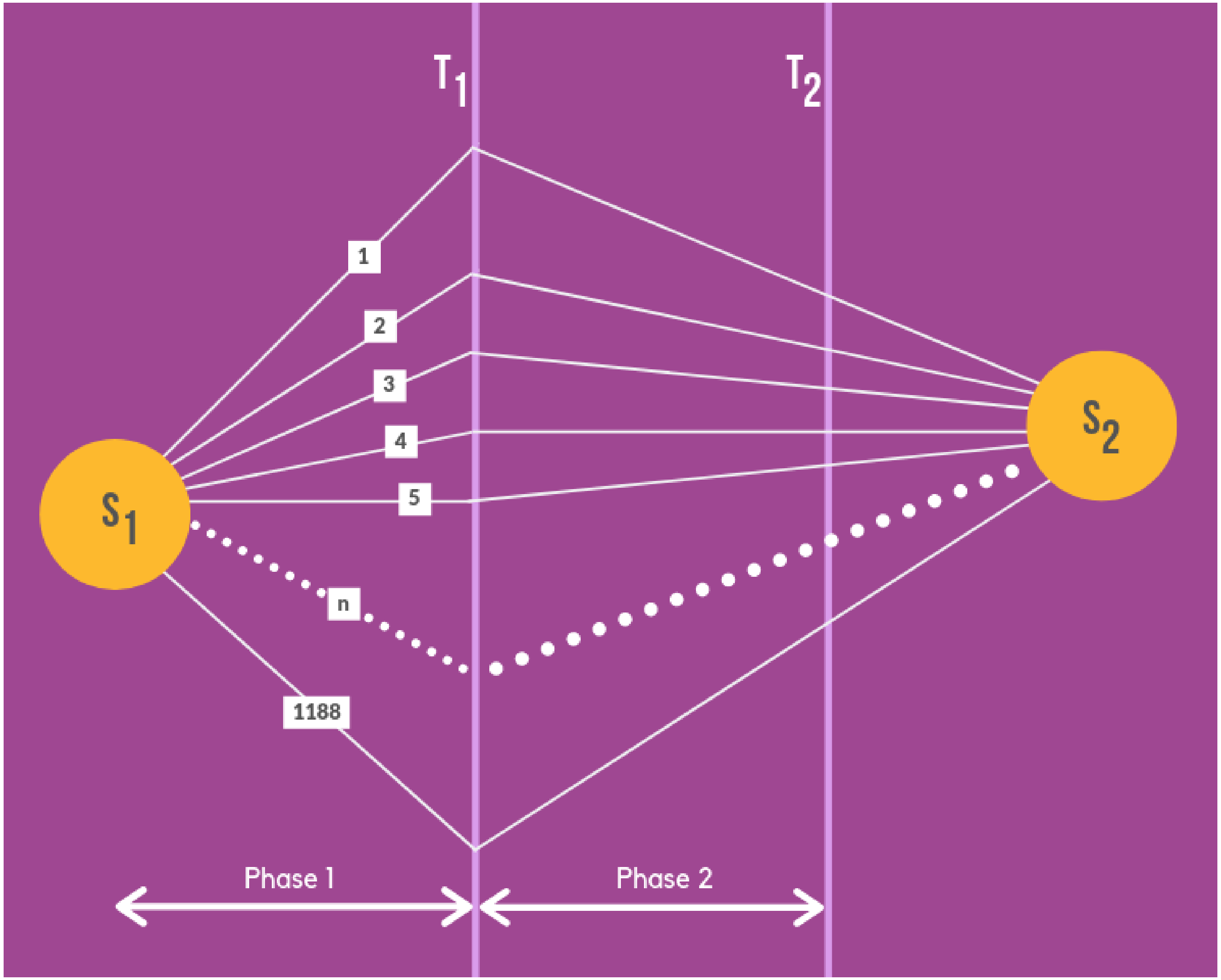
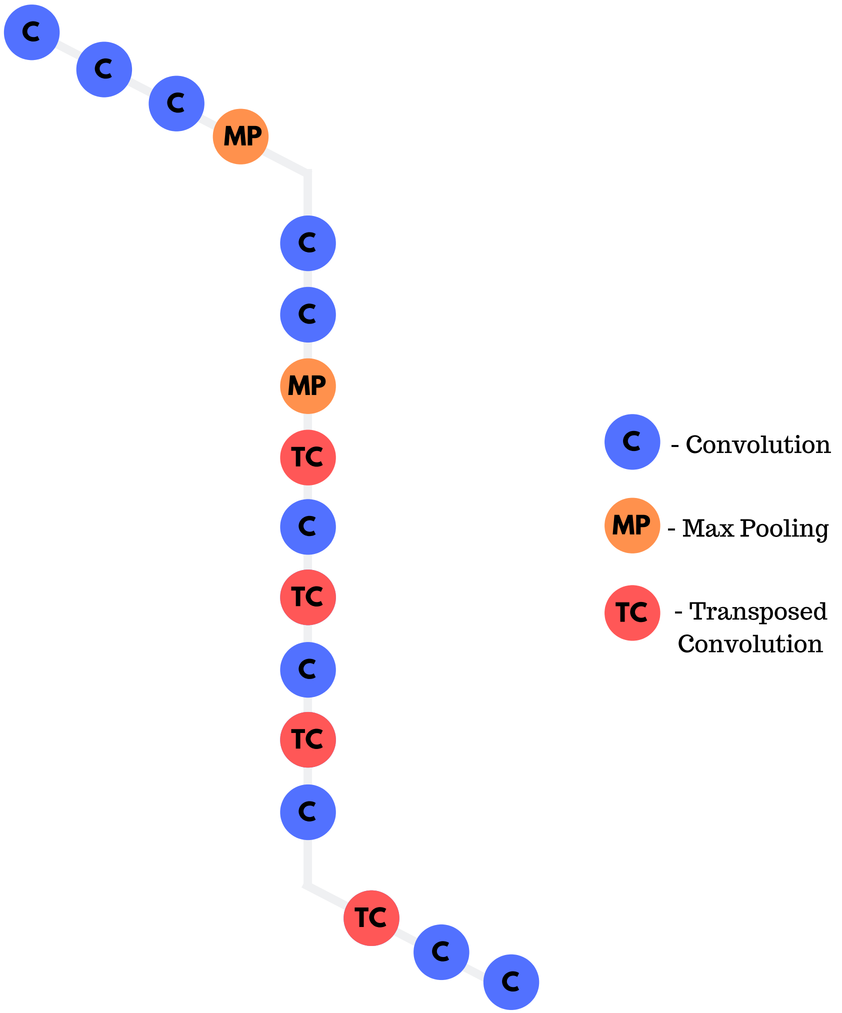


Initial Network



Results: Initial Network

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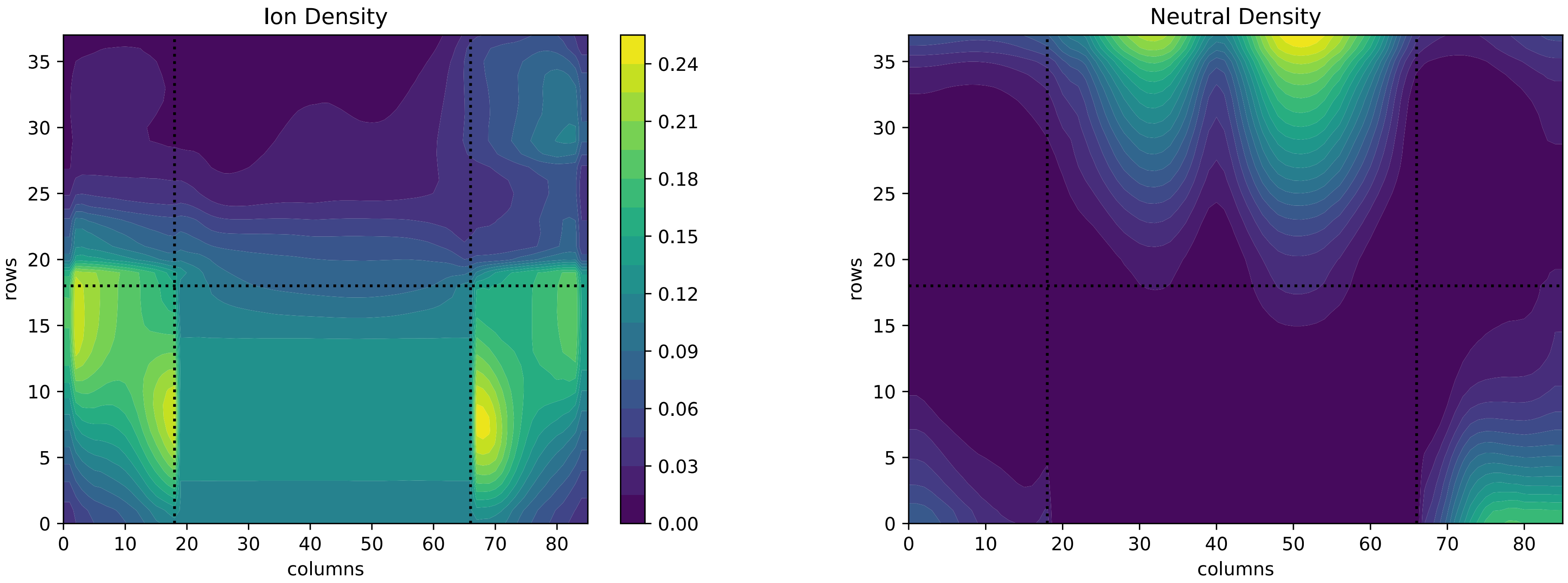
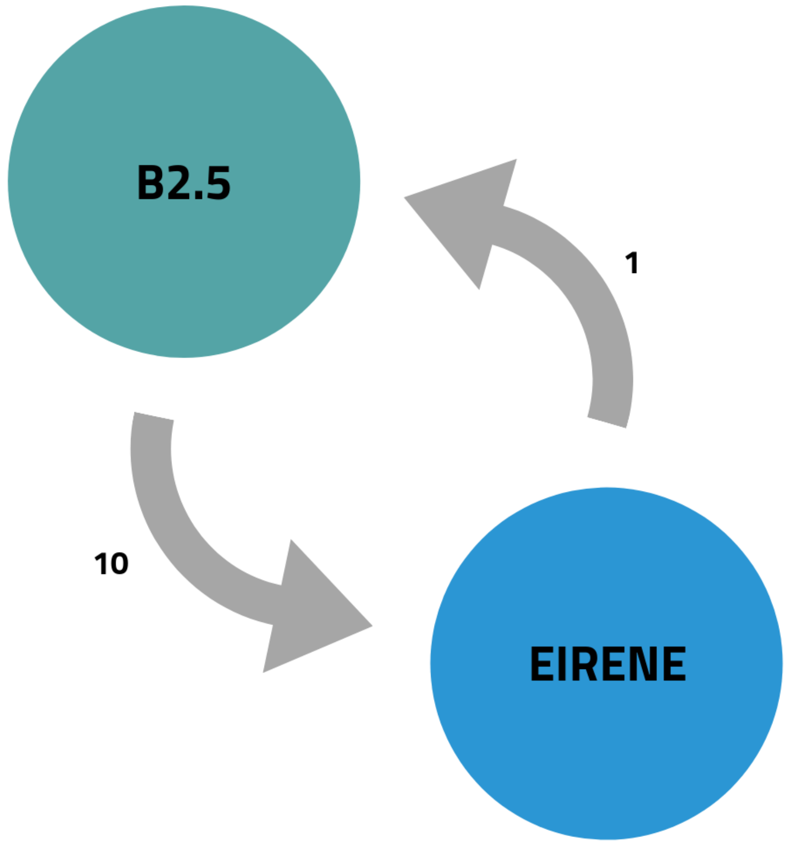
SOLPS Solution - Filled Contour Plots in Green and Blue
NN Solution – Line Contour Plots in Red and Orange



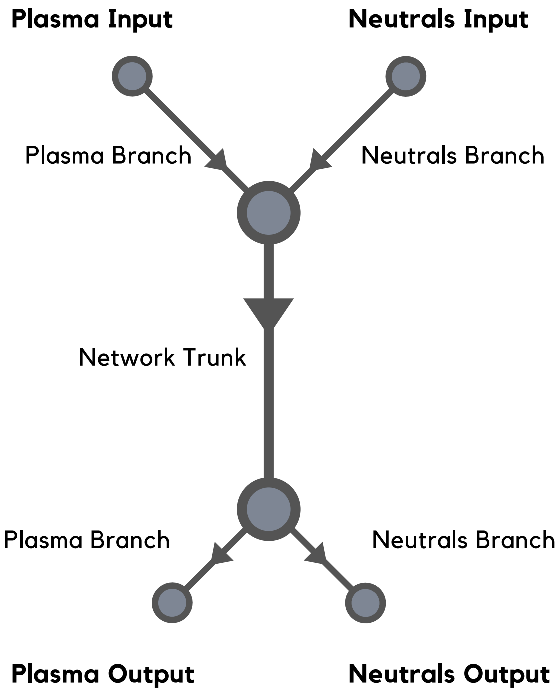
Now what could be messing up from getting a solid fit ?

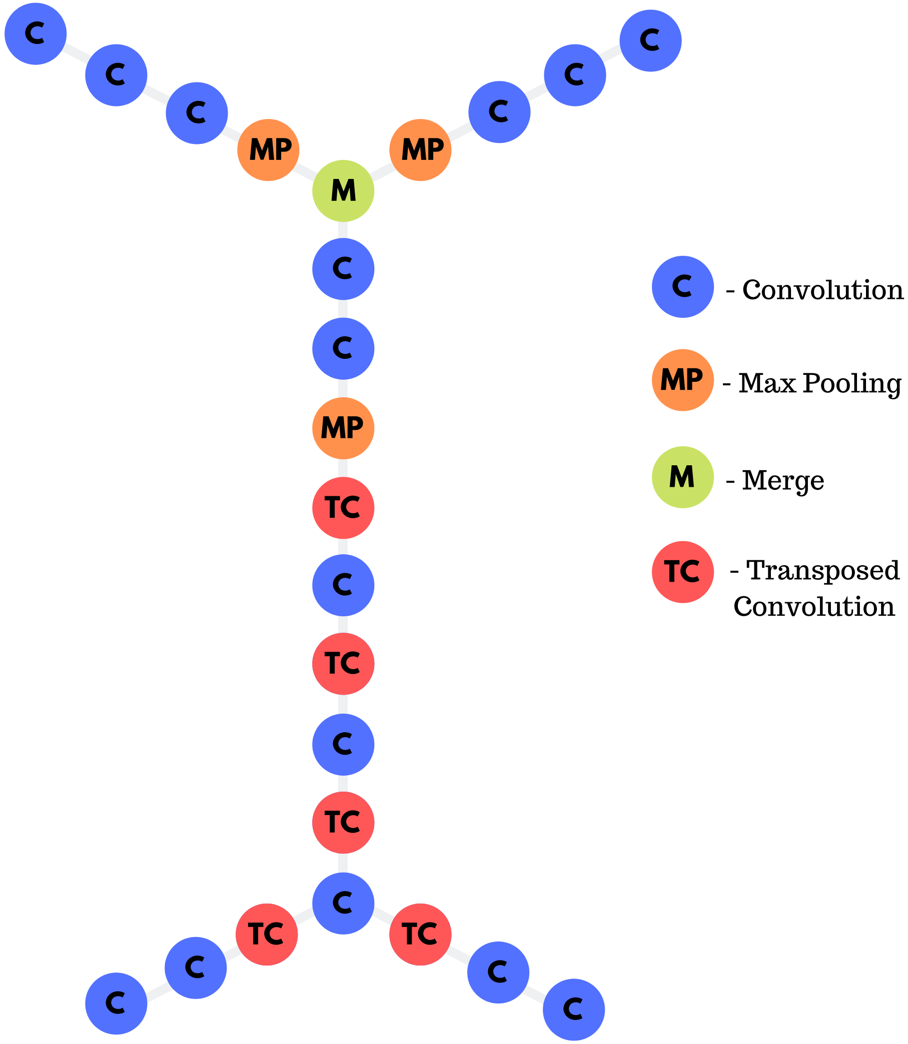
- EIRENE introducing random noise ?
- Imbalanced Dataset ?
- Lack of dedicated layers to pick up differing non-linearities ?

Information Exchange within SOLPS



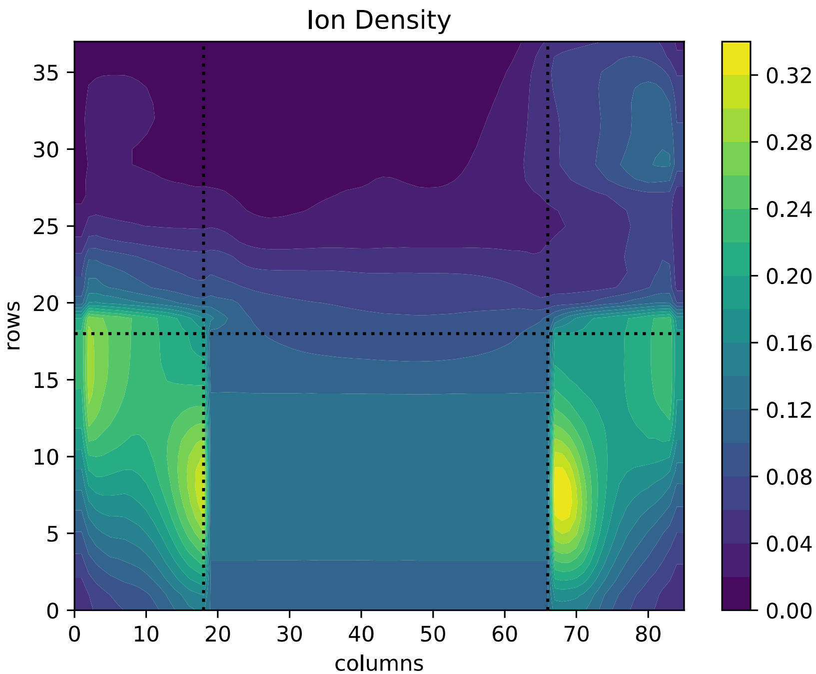
Bifurcated Network

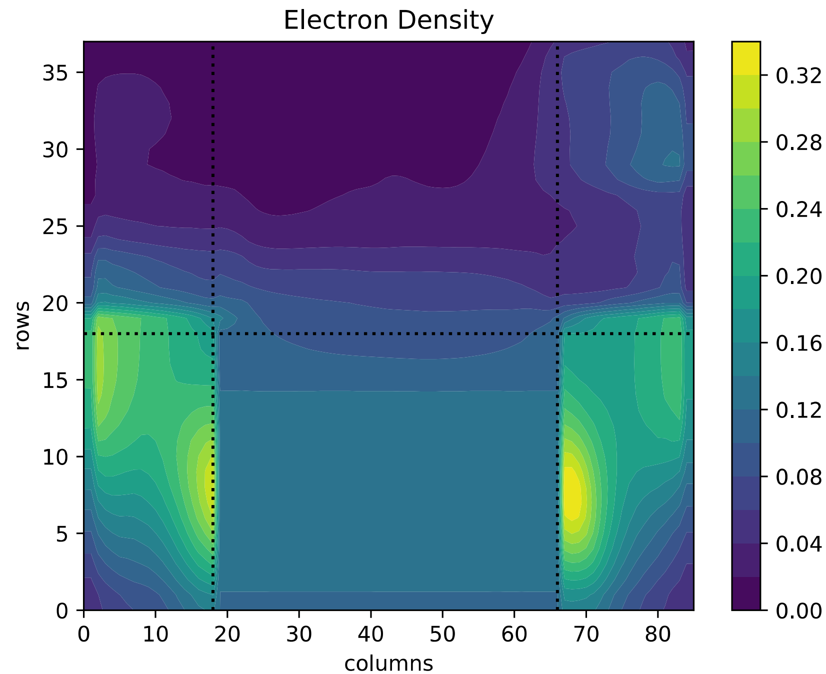




Results: Bifurcated Network

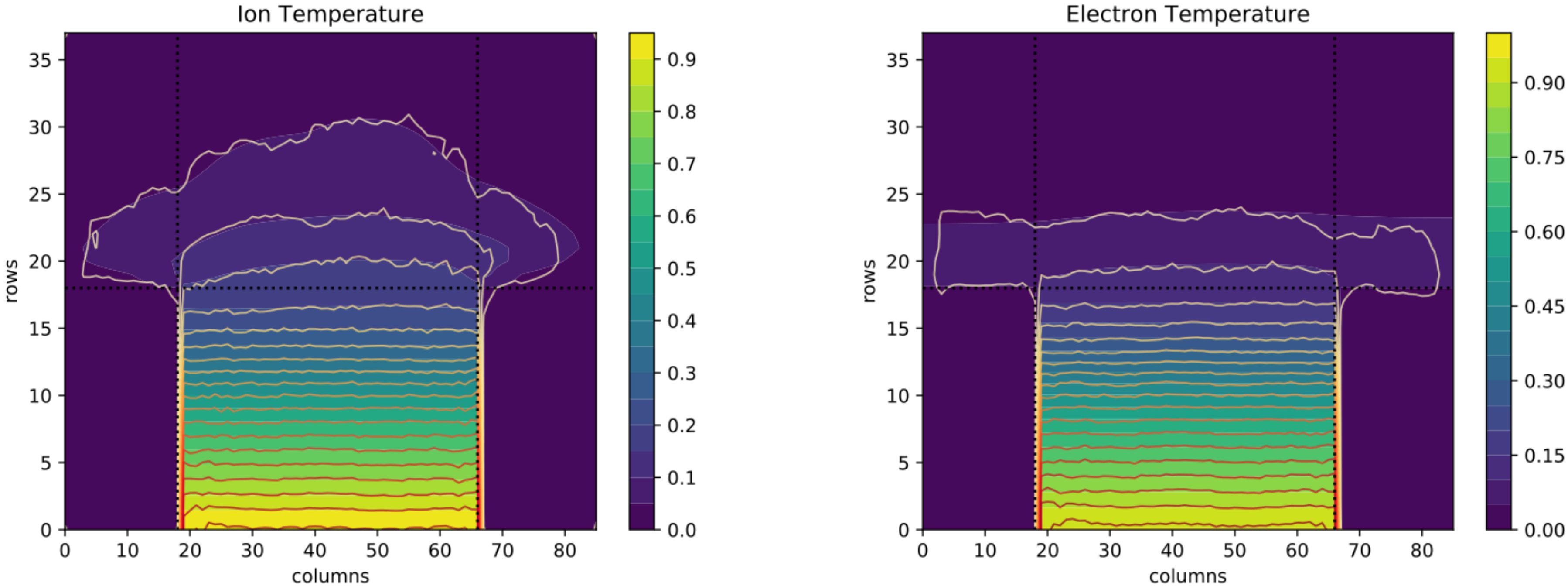
SOLPS Solution - Filled Contour Plots in Green and Blue
NN Solution – Line Contour Plots in Red and Orange





Results: Bifurcated Network

SOLPS Solution - Filled Contour Plots in Green and Blue
NN Solution – Line Contour Plots in Red and Orange



Results: Bifurcated Network

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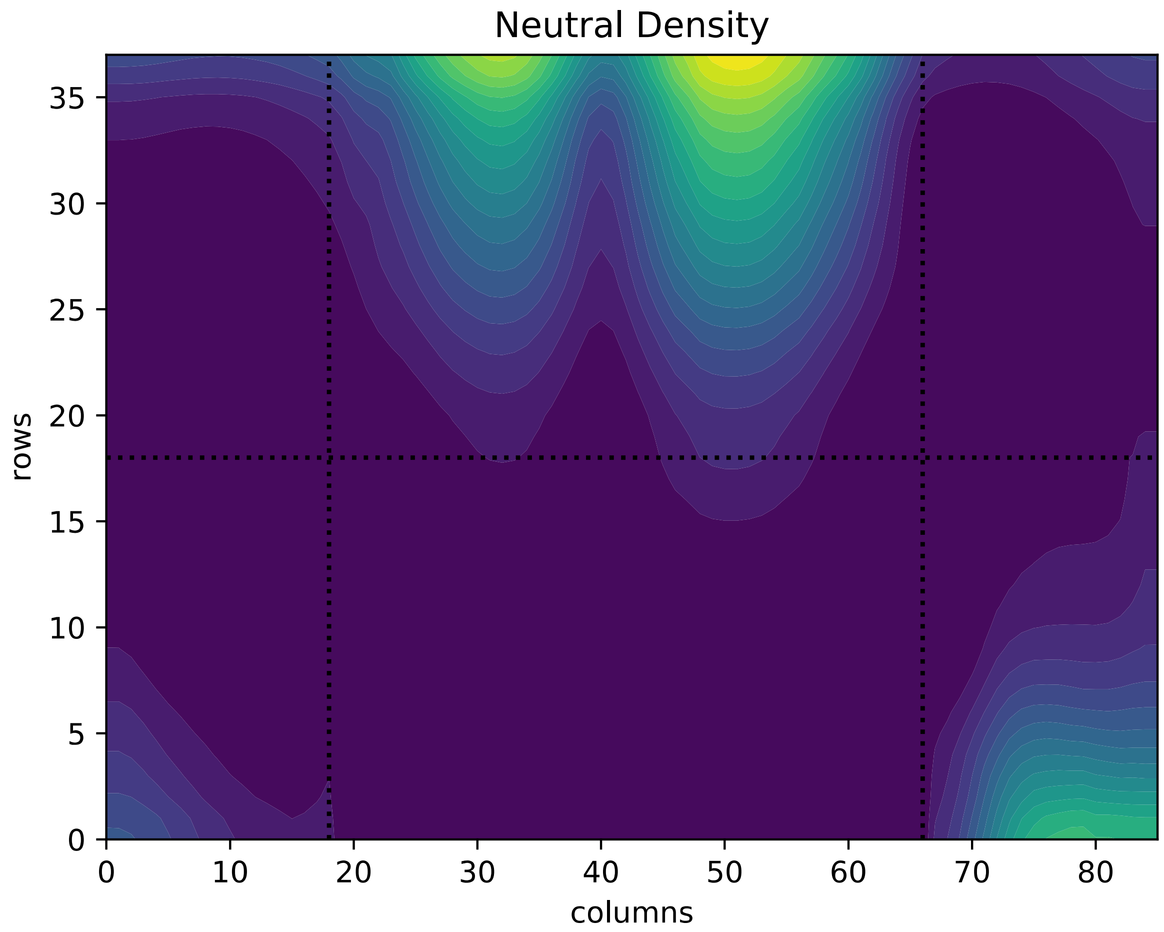
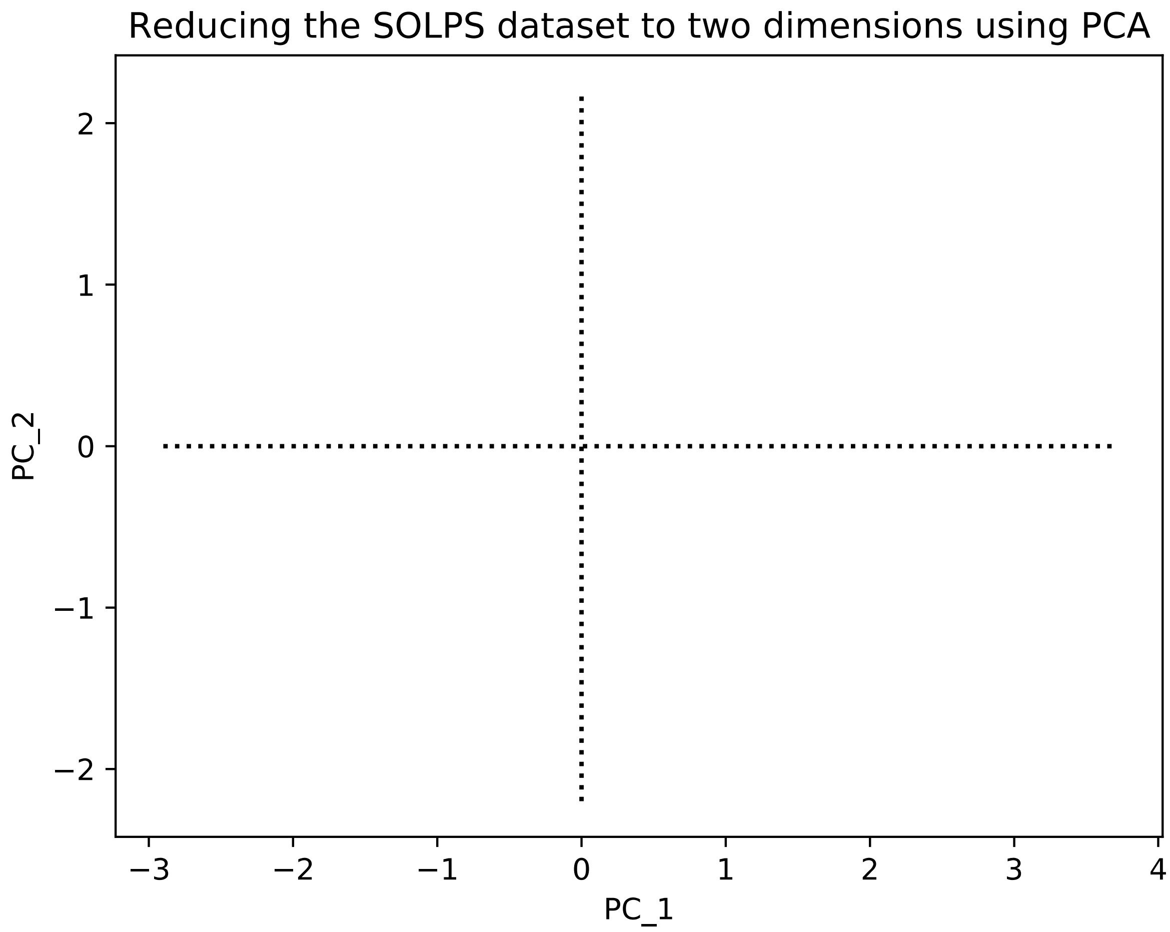
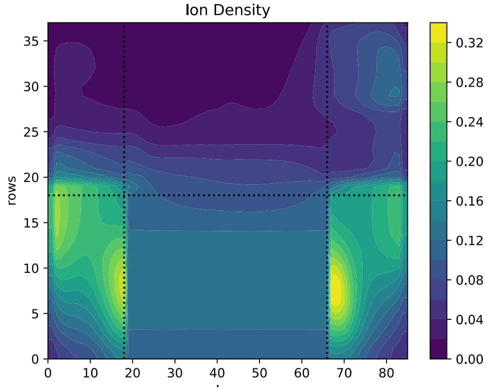
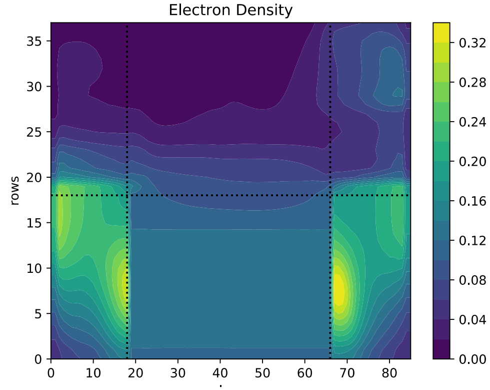


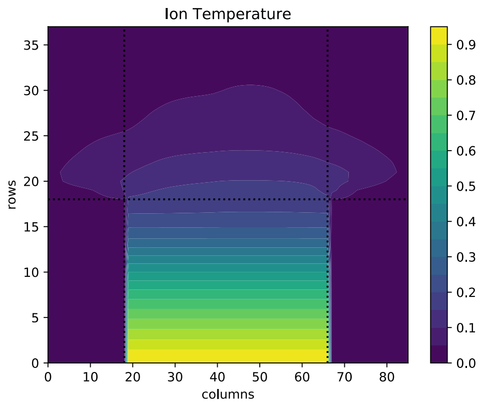
SOLPS Solution - Filled Contour Plots in Green and Blue
NN Solution – Line Contour Plots in Red and Orange

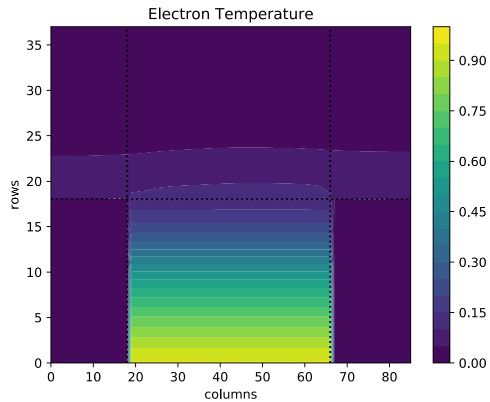
Data Diversity : Principal Component Analysis

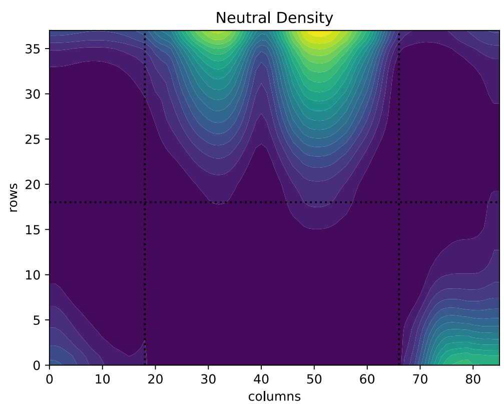


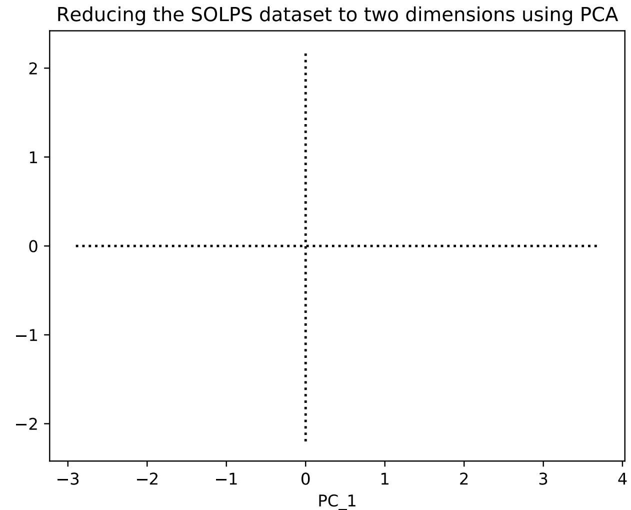

Ion Density
rows
0.32
0.28
0.24
0.20
0.16
0.12
0.08
0.04
0.00


Electron Density
rows
0.32
0.28
0.24
0.20
0.16
0.12
0.08
0.04
0.00


Ion Temperature
rows
columns
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0


Electron Temperature
rows
columns
0.90
0.75
0.60
0.45
0.30
0.15
0.00


Neutral Density
rows
columns


Reducing the SOLPS dataset to two dimensions using PCA
PC_1

Time Gain

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Edge Solution	Configuration	Time Taken	Training Time
SOLPS on ITM	2 x 18 @ 2.3 GHz	2 – 3 hours	N/A
SOLPS_FCN on FREIA	1 x 16 @ 2.6 GHz	0.033 seconds	117 minutes

Time Gain of more than 5 orders of Magnitude
Without much compromise on Accuracy.

Can be employed in a Predictor-Corrector Fashion.

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But still a Black Box !

Neural PDEs

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Convection-Diffusion Equation:

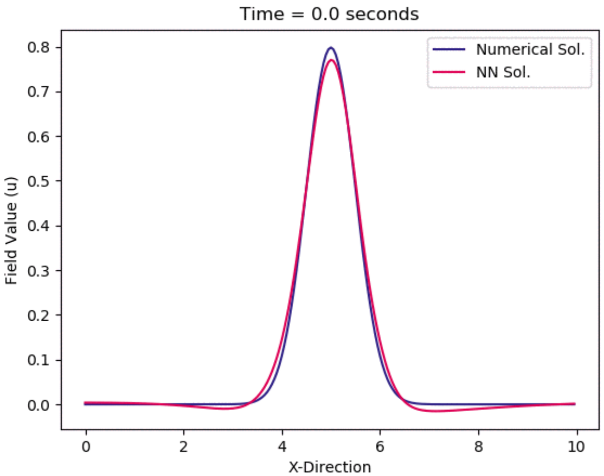
$$\frac{\partial u}{\partial t} + c\,\frac{\partial u}{\partial x} = D\,\frac{\partial^2 u}{\partial x^2}$$

Hybrid Loss Function = Functional Loss + Reconstruction Loss

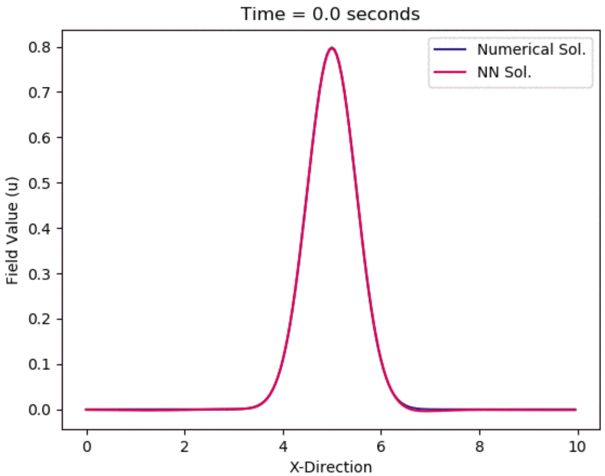
$$\text{Functional Loss} = \frac{\partial u'}{\partial t} + c\,\frac{\partial u'}{\partial x} - D\,\frac{\partial^2 u'}{\partial x^2}$$

$$\text{Reconstruction Loss} = \Sigma(u - u')^2$$

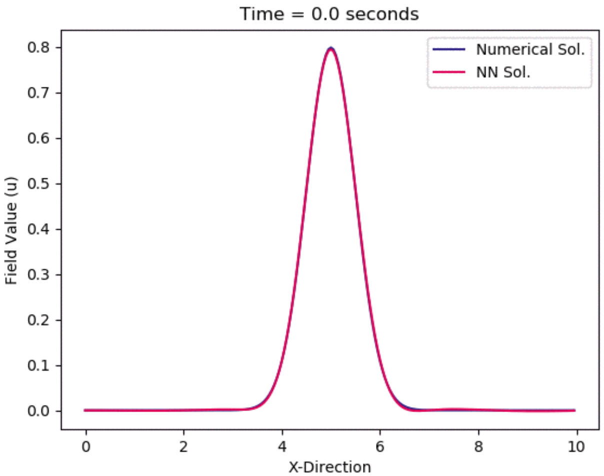
Neural PDEs



Reconstruction



Functional



Hybrid

Trained up to 1 second
Tested up to 2 seconds

Operation Tokamak

Made for EUROfusion by Mark Film

Tokamak Operation

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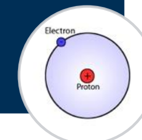
Magnetics 

Heating 

Fuel 

Exhaust 

Control 1000s of parameters that influence the confinement of the plasma.

All the while dealing with instabilities and avoiding disruptions

Extended Stable Plasma control requires a prophetic knowledge of how the Plasma would evolve in time.

Operation Cycle

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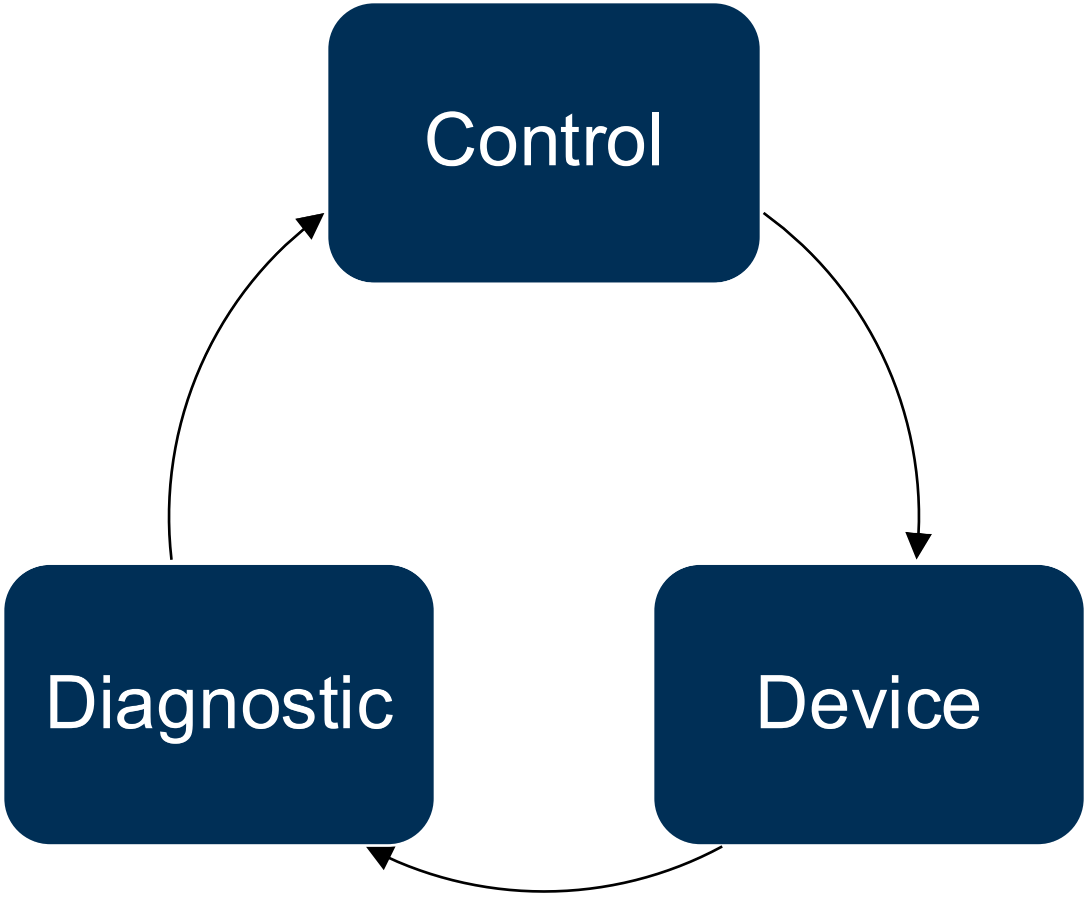
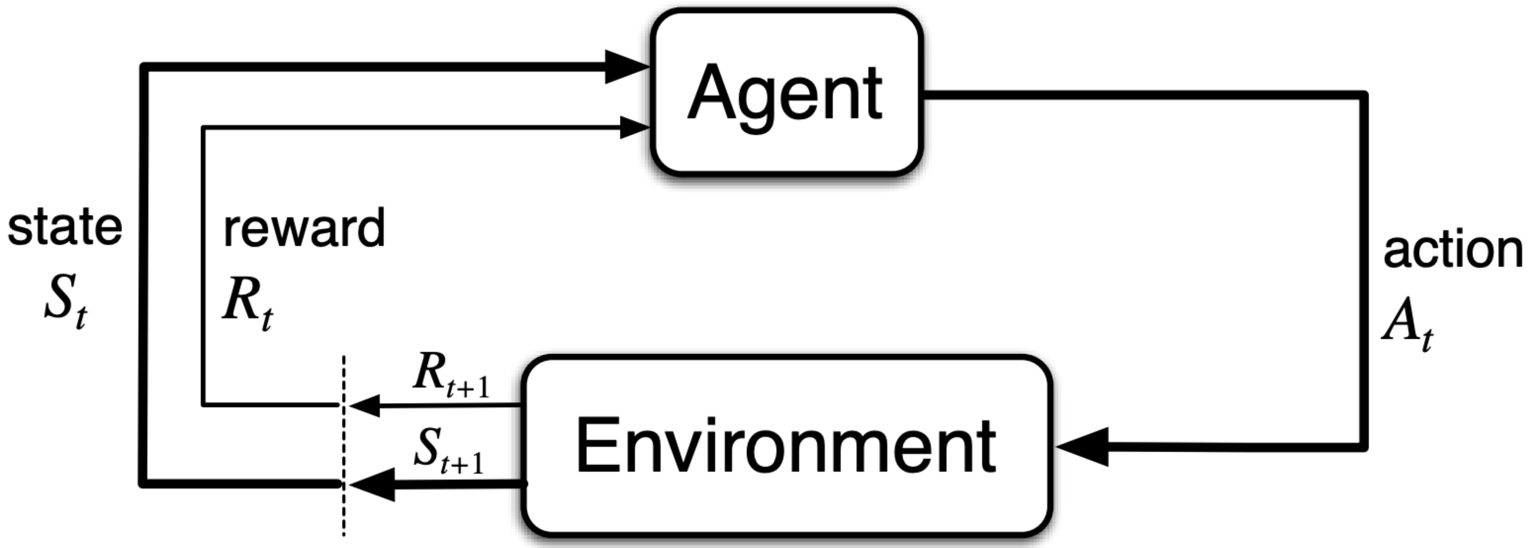


Exploring the Configuration Space of the operation cycle via Deep Reinforcement Learning



Source: R. Sutton – Reinforcement Learning: An Introduction

Conclusion

Barely Scratched the Surface …

Extract the complex nonlinear nature of Fusion Plasma effectively using deterministic AI approaches. Use ML based exploratory techniques to improve our control and performance of Fusion Devices.

Vast amounts of Experimental + Simulation Data

Building a team that is currently working with :

Rutherford Appleton Laboratory
University College London
Imperial College London
University of Oxford

And looking for collaborations from ML experts within the industry.

Thanks. Questions ?

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@littlevgkumar

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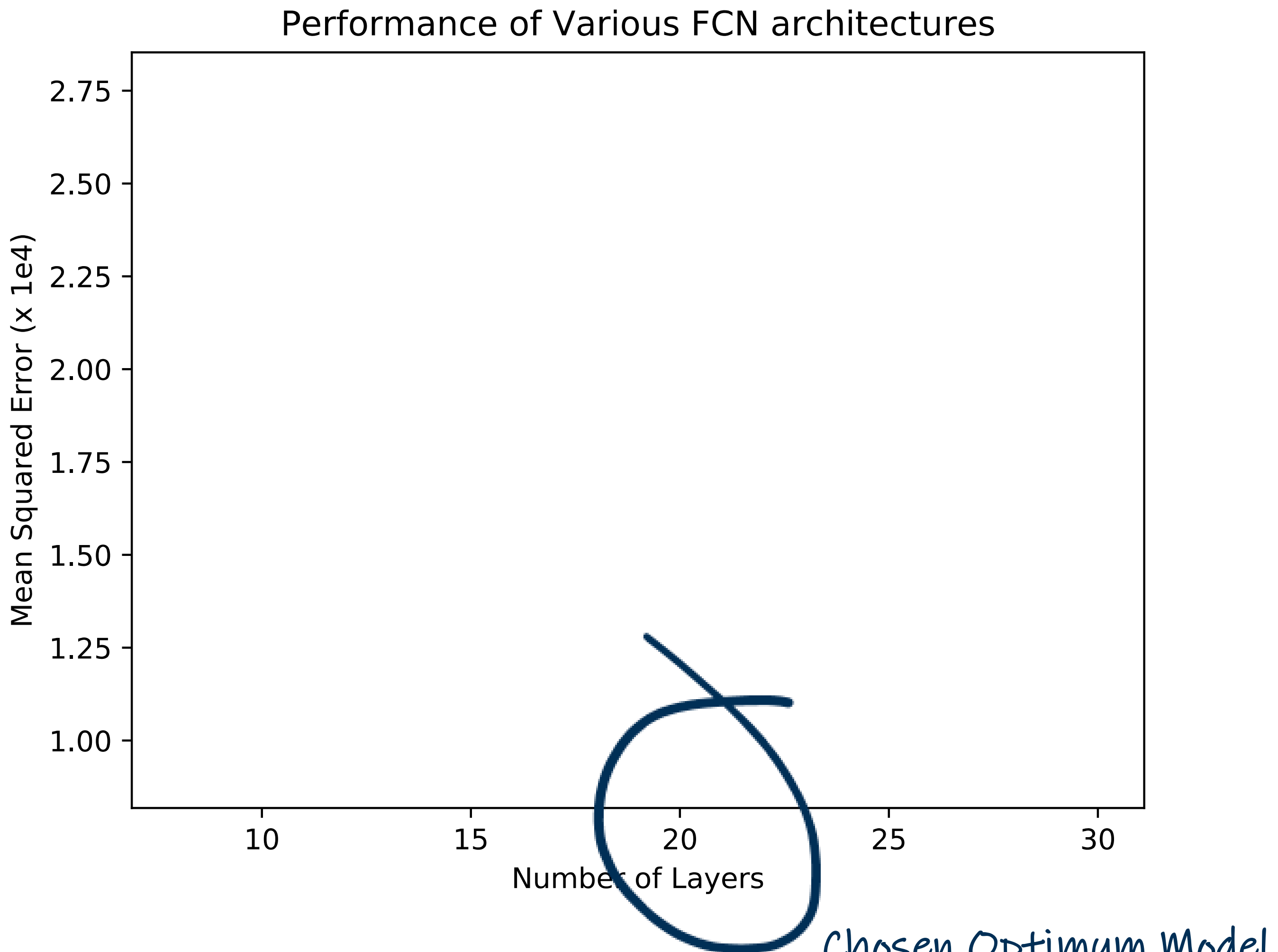
Appendix Slides

Depth Variation



Data Generation

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Phase I :

Initial Steady State Config :

Heating Power	4.080 MW
Puffing Rate	10^{21} s^{-1}
Pump Intensity	94 %

Parameter Scan :

Parameter	Min.	Max.	Step	Number
Heating Power	3.0 MW	8.5 MW	+ 0.5 MW	12
Puffing Rate	10^{17} s^{-1}	10^{21} s^{-1}	x 5.0	9
Pump Intensity	48 %	98 %	+ 5 %	11

Total Number of Simulations : 12 x 9 x 11 = 1188

Data Generation

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Phase II :

Final push towards Steady State Config :

Heating Power	3.0 MW
Puffing Rate	10^{18} s^{-1}
Pump Intensity	94 %

Output of Phase I → Input Data
Output of Phase II → Output Data

Labelled, Matching Dataset

Convolutional Strategies

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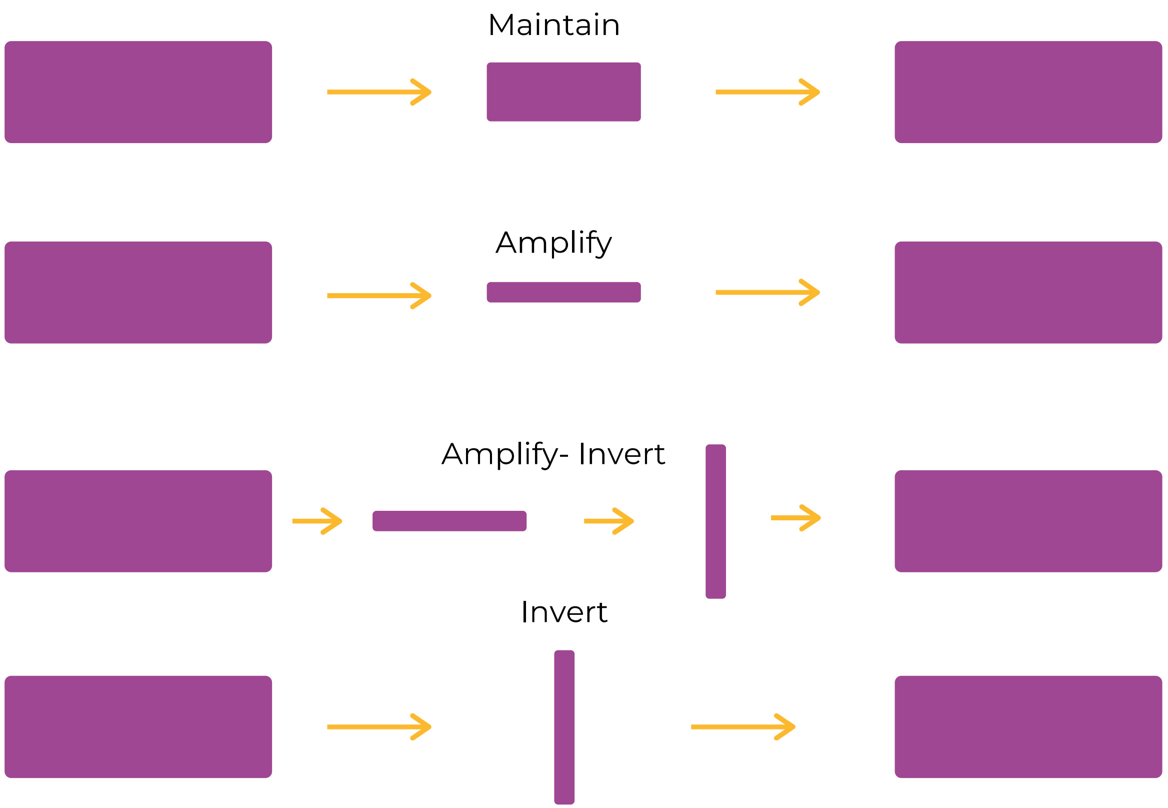

Convolutional Strategies