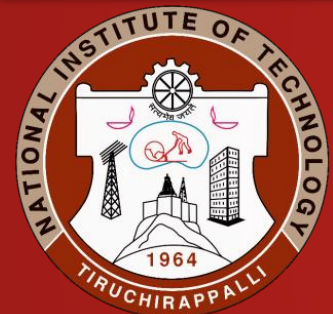


# VIBRATION ANALYSIS OF TAPERED TRUNCATED CANTILEVER BEAMS USING DEEP LEARNING



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# OVERVIEW

- Motivation
- Deep Learning Model
- Data Generation
- Model Training
  - Training parameters and results
  - Percent deviations of predicted values
  - Graphical comparison with actual values
- Extrapolation Analysis
  - Prediction ability over unseen data range
- Conclusion
- Future Research

# OVERVIEW

➤ Motivation

# MOTIVATION

- ✓ Some problems are really difficult or impossible to solve theoretically.
- ✓ In some cases these can be solved by fitting curve to some data-points generated for special cases.
- ✓ Data driven approach:
  1. Removes necessity of field specific knowledge.
  2. There is a large amount of data present.
    - Highly optimized algorithms are there to process this data.
  3. Tremendous computational power available.

# OVERVIEW

- Motivation
- Deep Learning Model



# DEEP LEARNING MODEL

1. Training data was generated using MATLAB.
2. Neural network features:
  1. Activation function: PReLU
  2. Loss function: Mean squared percent error
  3. Optimizer: Adam optimizer
3. Training of Neural network was done on Python using PyTorch.

# INPUT VARIABLES

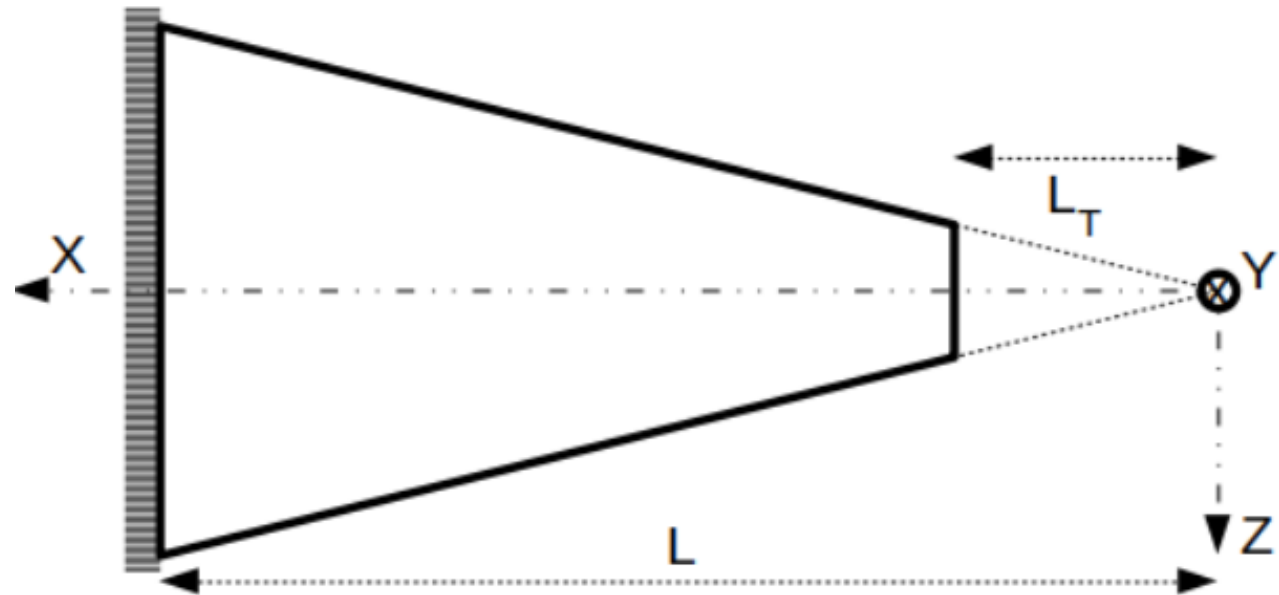
- Variation in cross-sectional properties:

$$A = A_C \delta^\eta$$

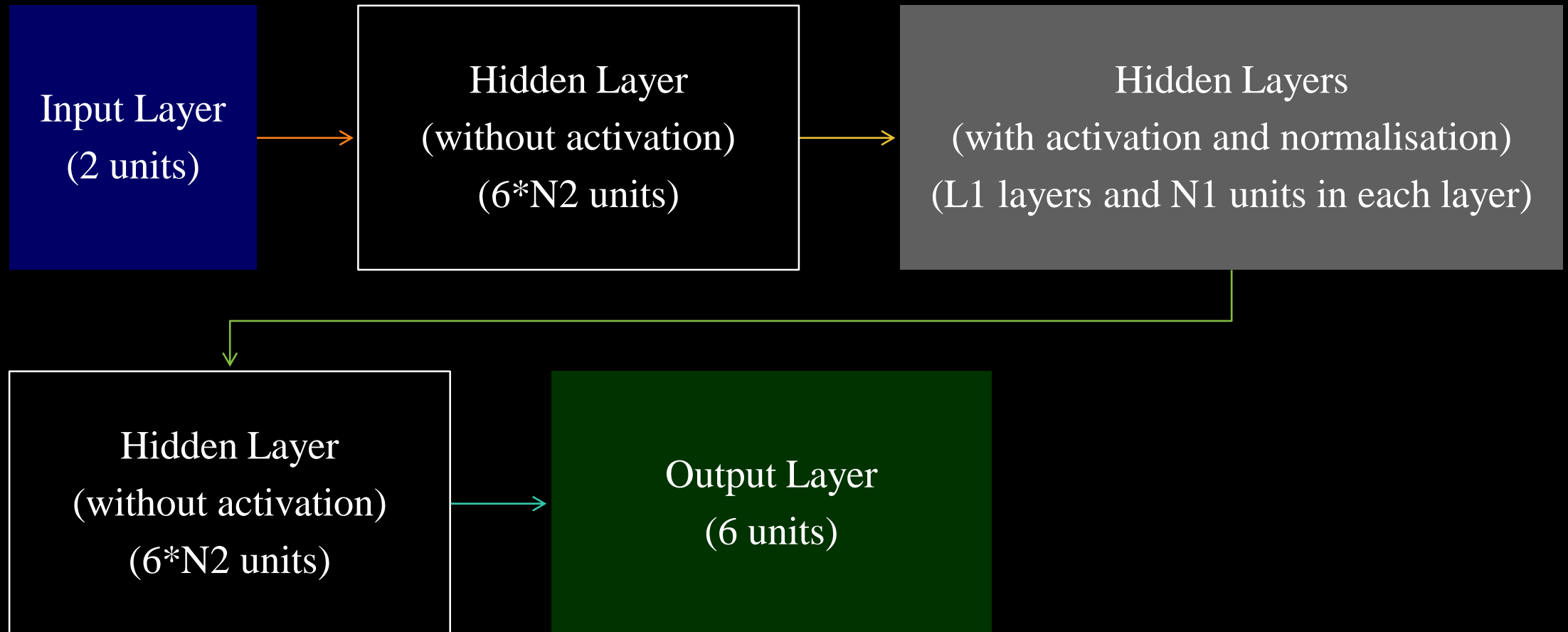
$$I = I_C \delta^{\eta+2}$$

(where,  $\delta = \frac{x}{L}$ ,  $\delta \in [\delta_0, 1]$  and  $\eta$  is a non-negative real number)

- $\eta$  and  $\delta_0$  are inputs to the neural network.



# NEURAL NETWORK ARCHITECTURE

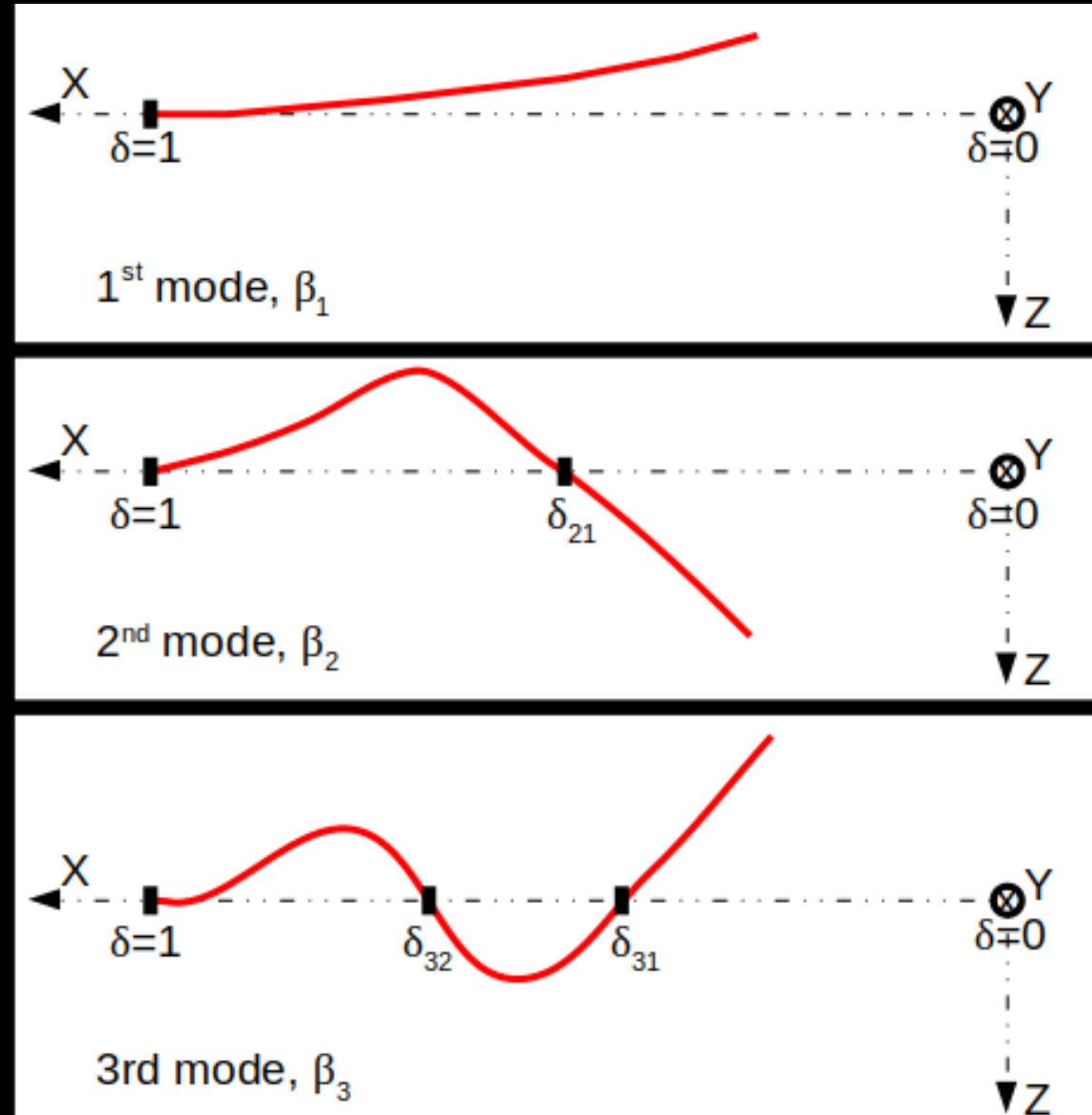




# OUTPUT VARIABLES

➤  $\beta_1, \beta_2, \beta_3, \delta_{21}, \delta_{31}, \delta_{32}$   
(6 variables)

- $\beta_1, \beta_2, \beta_3$  are the natural frequency parameters
- $\delta_{21}, \delta_{31}, \delta_{32}$  are the node locations



# ACTUAL VARIATION OF OUTPUT VARIABLES

1. Euler-Bernoulli equation

$$\frac{\partial^2}{\partial x^2} \left( EI(x) \frac{\partial^2 y(x, t)}{\partial x^2} \right) + \rho A(x) \frac{\partial^2 y(x, t)}{\partial t^2} = 0$$

2. Using variable separation

$$y(x, t) = W(x) e^{i\omega t}$$

3. General solution of  $W(x)$

$$W(\delta) = (L\delta)^{-\eta/2} [c_1 J_\eta(z) + c_2 Y_\eta(z) + c_3 I_\eta(z) + c_4 K_\eta(z)]$$

where,  $z = 2\beta\delta^{1/2}$ ,  $\beta = \omega^2 L^4 \left( \frac{\rho A_C}{EI_C} \right)$ ,  $\delta = \frac{x}{L}$

$J_\eta$  and  $Y_\eta$  are  $\eta^{\text{th}}$  order Bessel Functions of first and second kind, respectively.

$I_\eta$  and  $K_\eta$  are modified  $\eta^{\text{th}}$  order Bessel Function of first and second kind, respectively.

4. Boundary conditions

$$\frac{\partial}{\partial \delta} \left( EI(\delta) \frac{\partial^2 W(\delta)}{\partial \delta^2} \right) = \frac{\partial^2 W(\delta)}{\partial \delta^2} = 0, \text{ at } \delta = \delta_0$$
$$W(\delta) = \frac{\partial W(\delta)}{\partial \delta} = 0, \text{ at } \delta = \delta_1 = 1$$

# ACTUAL VARIATION OF OUTPUT VARIABLES

6. After applying boundary conditions we will get 4 linear equations:

$$\Delta = \begin{vmatrix} J_{\eta+1}(z_0) & Y_{\eta+1}(z_0) & I_{\eta+1}(z_0) & -K_{\eta+1}(z_0) \\ J_{\eta+2}(z_0) & Y_{\eta+2}(z_0) & I_{\eta+2}(z_0) & K_{\eta+2}(z_0) \\ J_{\eta}(z_1) & Y_{\eta}(z_1) & I_{\eta}(z_1) & K_{\eta}(z_1) \\ J_{\eta+1}(z_1) & Y_{\eta+1}(z_1) & -I_{\eta+1}(z_1) & K_{\eta+1}(z_1) \end{vmatrix} = 0$$

7. After solving  $\Delta = 0$ , we can get values of  $\beta = \beta_r$ , where,  $r$  is the mode number. From which, we can compute  $\omega_r$  and  $z_r$  using following relations,

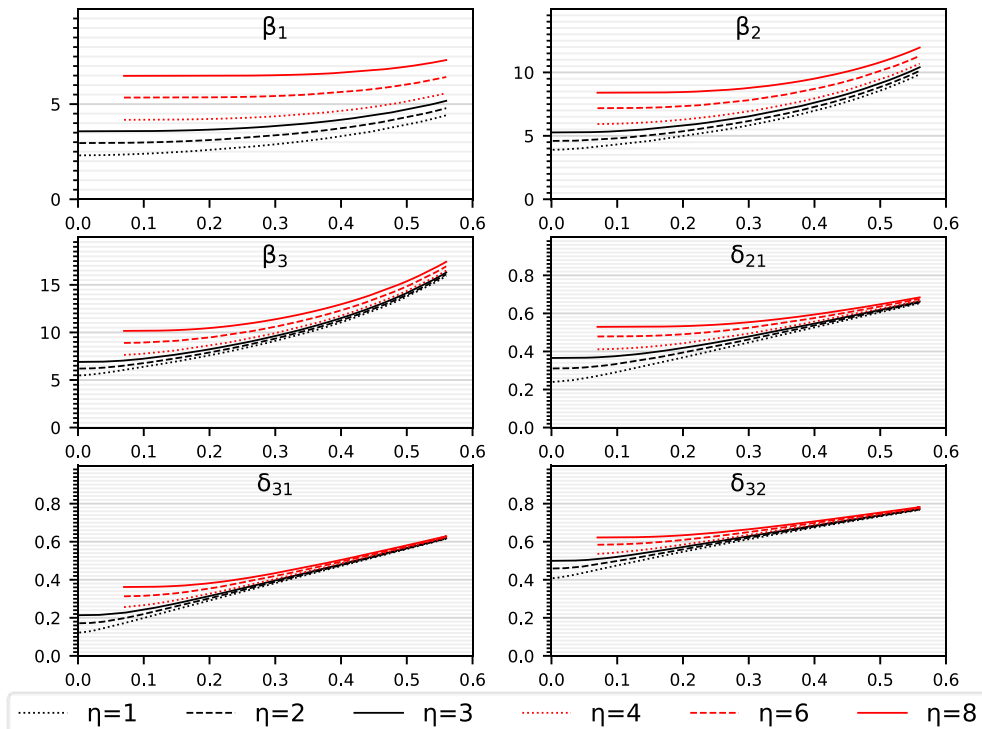
$$\omega_r = \left(\frac{\beta_r}{L}\right)^2 \sqrt{\frac{EI_C}{\rho A_C}}, \quad z_r = 2\beta_r \delta^{1/2}$$

8. Finally, mode shapes can be obtained as follows,

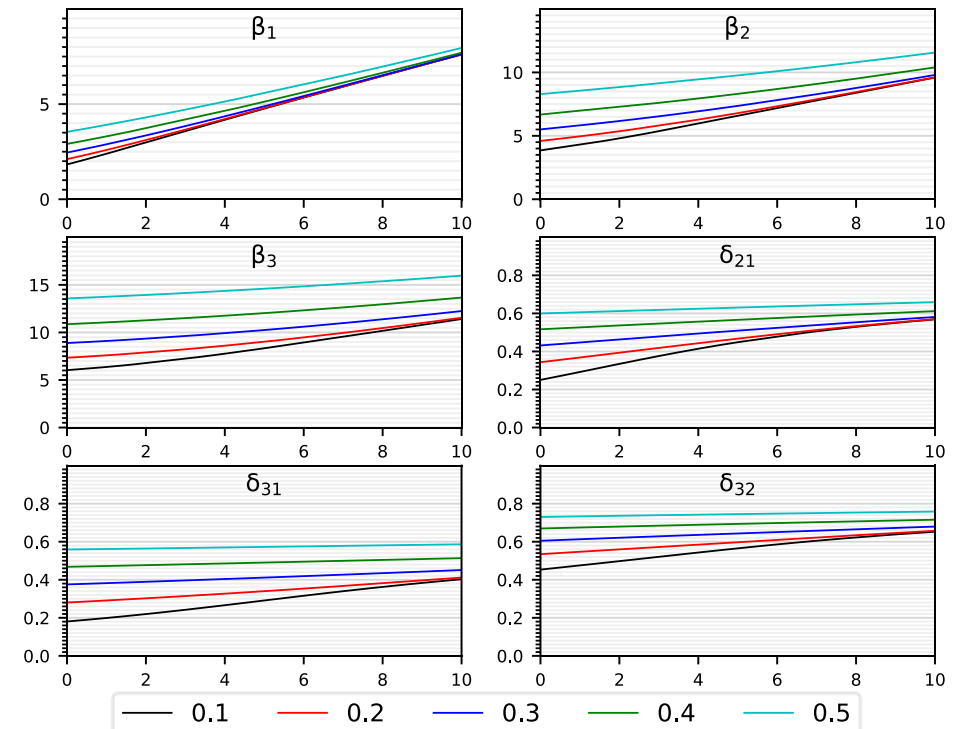
$$W(\delta) = (L\delta)^{-\eta/2} [c_1 J_{\eta}(z_r) + c_2 Y_{\eta}(z_r) + c_3 I_{\eta}(z_r) + c_4 K_{\eta}(z_r)]$$

# ACTUAL VARIATION OF OUTPUT VARIABLES

Output Values vs  $\delta_0$  for different values of  $\eta$



Output Values vs  $\eta$  for different values of  $\delta_0$



# OVERVIEW

- Motivation
- Deep Learning Model
- Data Generation

# DATA GENERATION

1.  $\eta \in [0, 3], \delta_0 \in [2e-3, 0.56] \Rightarrow 301 * 15,000$  datapoints.
2.  $\eta \in [3, 10], \delta_0 \in [7e-2, 0.56] \Rightarrow 701 * 15,000$  datapoints.
3. For  $\eta \in [0, 10]$ , data from the two cases was merged:
  - $\eta \in [0, 3], \delta_0 \in [2e-3, 0.56] \Rightarrow 301 * 15,000 = 4,515,000$ .
  - $\eta \in (3, 10], \delta_0 \in [7e-2, 0.56] \Rightarrow 700 * 15,000 = 10,500,000$ .

➤ In total 15,015,000 datapoints were generated.

➤ But only a fraction was used for training.

# OVERVIEW

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# MODEL TRAINING

- Training and validation data
  - Generated data was shuffled.
  - Few data points were sampled from shuffled data to train the neural network.
  - Some datapoints for validation were also selected.
- Test data
  - A separate data set was created by randomly sampling points.
- Results
  - Trained model was evaluated over the unseen test dataset to report the results.



# OVERVIEW

- Motivation
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  - Training parameters and results

# TRAINING PARAMETERS

**Table 1: Deep Learning model training parameters**

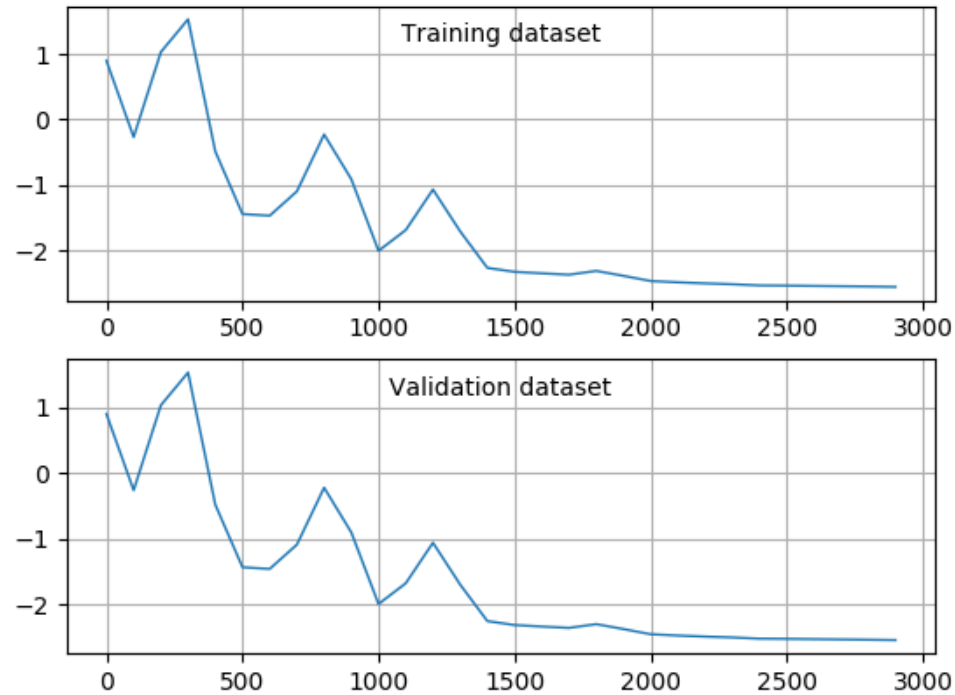
	<b>SD (Small Dataset)</b>	<b>BD (Big Dataset)</b>
<b># Training datapoints</b>	$2*2^{11}$	$20*2^{11}$
<b># Validation datapoints</b>	1,000	
<b># Iterations</b>	30,000	
<b>Initial Learning Rate</b>	0.01	
<b>Update period</b>	5,000	
<b>Update factor</b>	5	

# TRAINING RESULTS

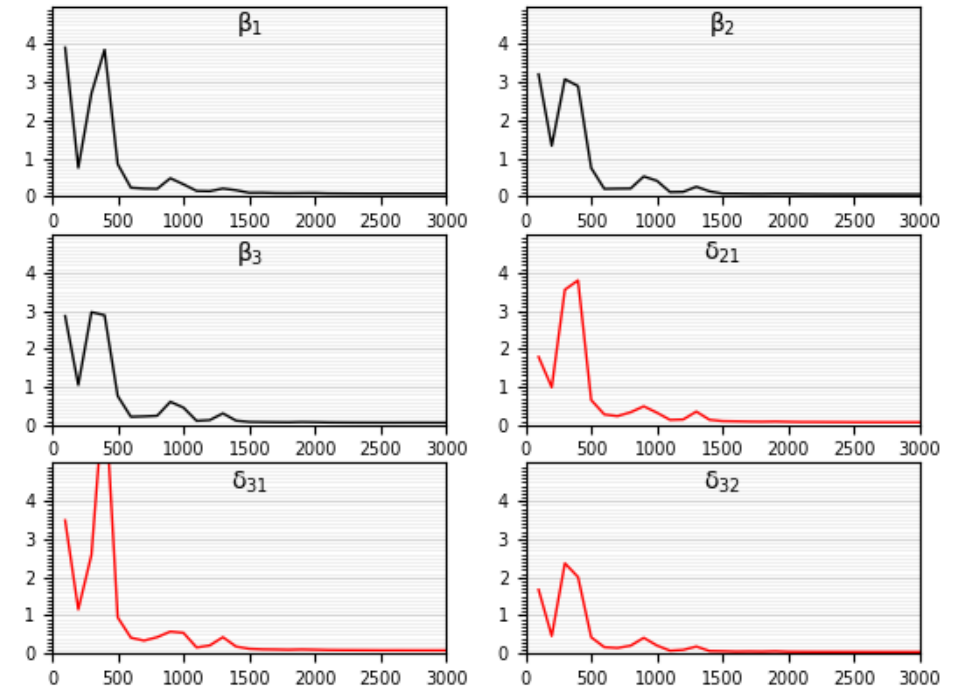
	SD (Small Dataset)	BD (Big Dataset)
# Training datapoints	$2 \cdot 2^{11}$	$20 \cdot 2^{11}$
L1	3	7
N1	173	207
N2	3	3
	SN (Small Network)	BN (Big Network)

# TRAINING RESULTS

Mean squared percent error vs number of iterations on  $\log_{10}$  scale



Training set- 99<sup>th</sup> percentile percent deviation vs number of iterations



# OVERVIEW

- Motivation
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  - Training parameters and results
  - Percent deviations of predicted values

# PERCENT DEVIATIONS

Table 2: For  $\eta \in [0, 3]$ ,  $\delta_0 \in [2e-3, 0.56]$

Output	Mean Percent dev.		Max. Percent dev.	
	SD-SN	BD-BN	SD-SN	BD-BN
$\beta_1$	0.022	0.011	0.115	0.106
$\beta_2$	0.020	0.008	0.110	0.071
$\beta_3$	0.021	0.009	0.111	0.052
$\delta_{21}$	0.016	0.012	0.172	0.101
$\delta_{31}$	0.024	0.013	0.317	0.255
$\delta_{32}$	0.012	0.007	0.159	0.083

Table 3: For  $\eta \in [3, 10]$ ,  $\delta_0 \in [7e-2, 0.56]$

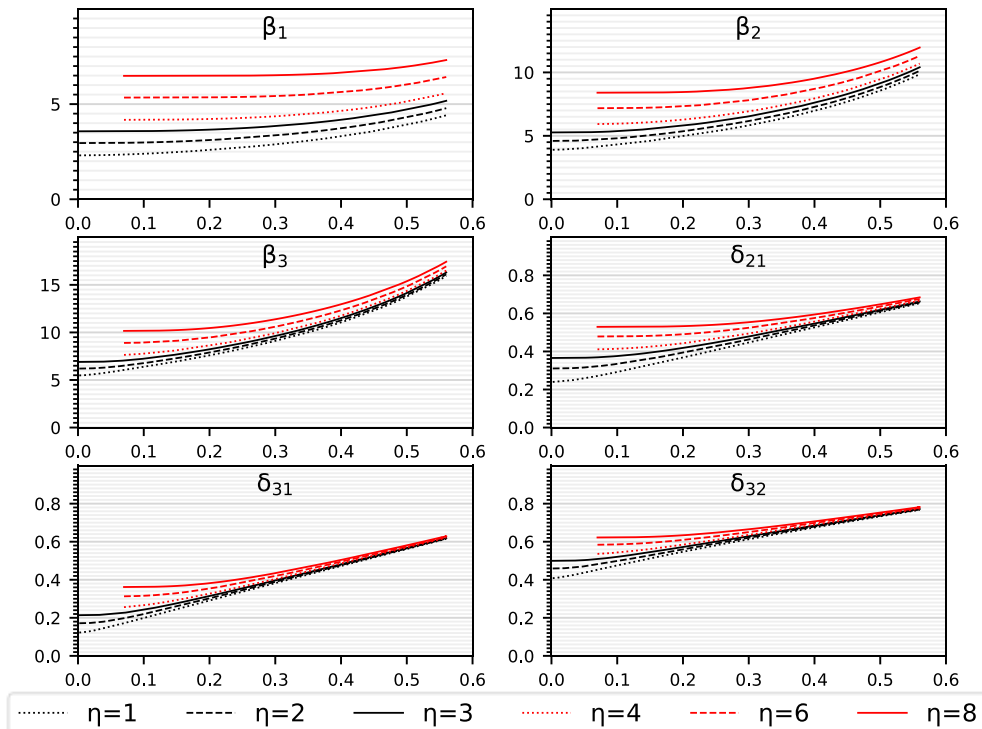
Output	Mean Percent dev.		Max. Percent dev.	
	SD-SN	BD-BN	SD-SN	BD-BN
$\beta_1$	0.019	0.011	0.130	0.079
$\beta_2$	0.018	0.010	0.130	0.046
$\beta_3$	0.019	0.010	0.123	0.054
$\delta_{21}$	0.013	0.009	0.090	0.050
$\delta_{31}$	0.019	0.009	0.169	0.051
$\delta_{32}$	0.010	0.005	0.055	0.037

# OVERVIEW

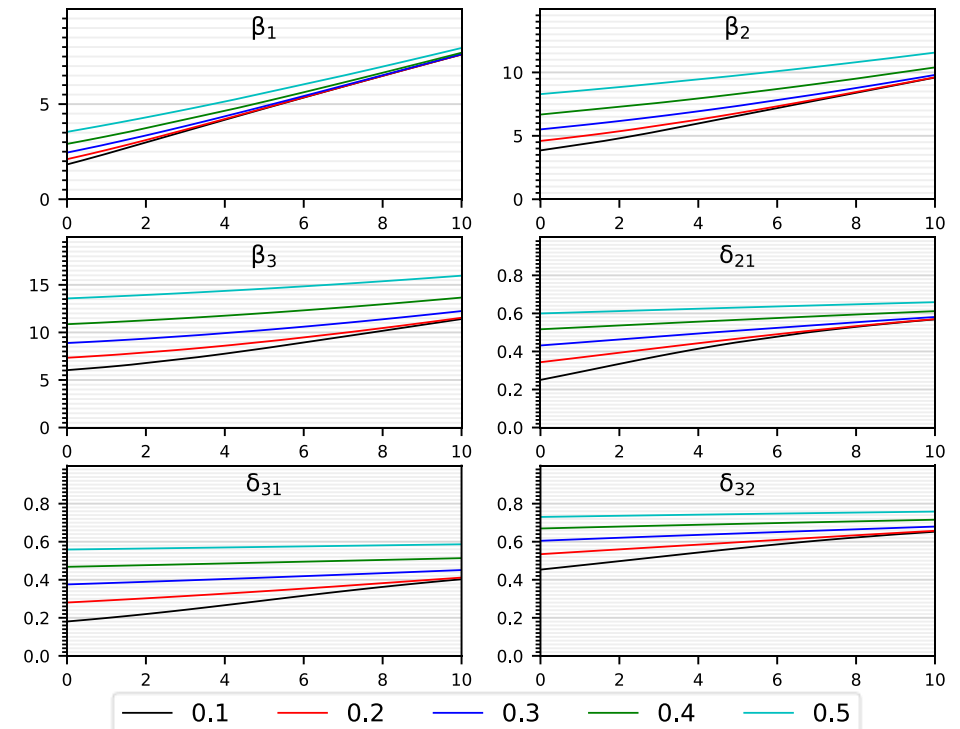
- Motivation
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  - Graphical comparison with actual values

# COMPARISON BETWEEN ACTUAL AND PREDICTED VALUES

Output Values vs  $\delta_0$  for different values of  $\eta$



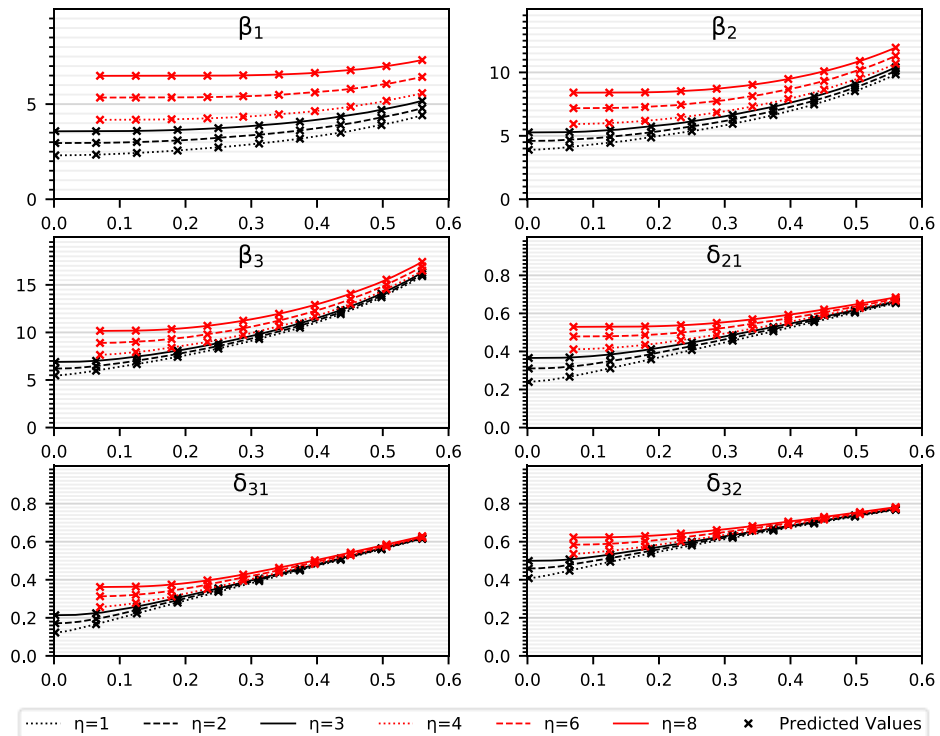
Output Values vs  $\eta$  for different values of  $\delta_0$



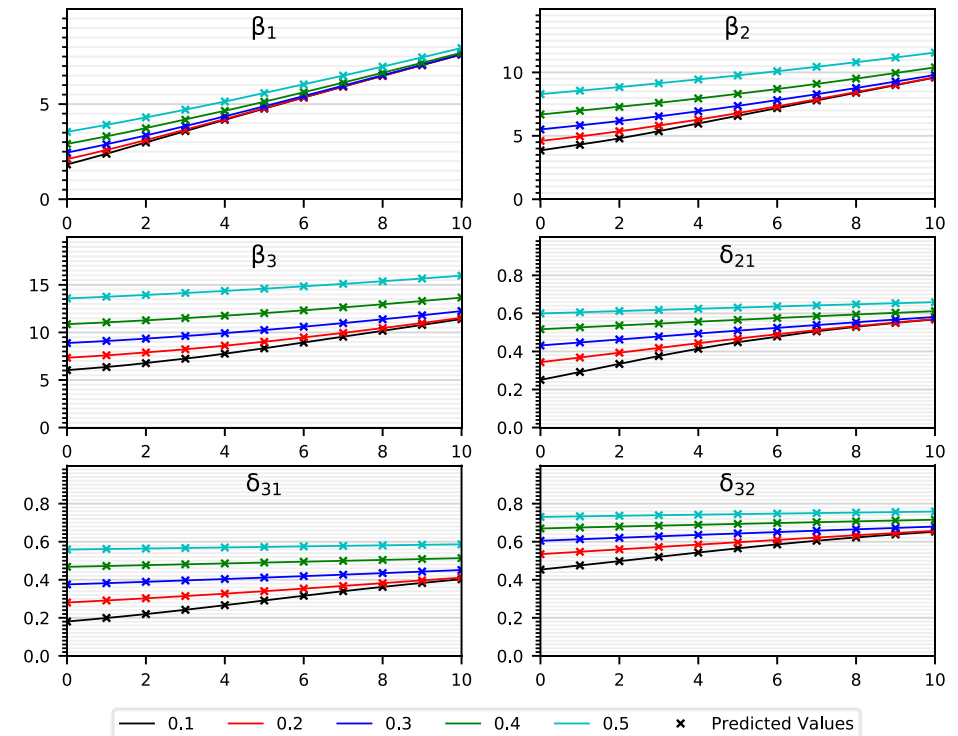


# COMPARISON BETWEEN ACTUAL AND PREDICTED VALUES

Output Values vs  $\delta_0$  for different values of  $\eta$



Output Values vs  $\eta$  for different values of  $\delta_0$



# OVERVIEW

- Motivation
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  - Percent deviations of predicted values
  - Graphical comparison with actual values
- Extrapolation Analysis



# EXTRAPOLATION ANALYSIS

- Data was then split back into two parts as generated:  
**Part 1:**  $\eta \in [0, 3], \delta_0 \in [2e-3, 0.56]$   
**Part 2:**  $\eta \in [3, 10], \delta_0 \in [7e-2, 0.56]$
- Models corresponding to SD and BD mentioned earlier were trained on one part and then evaluated on the other to see its extrapolation capabilities.

# OVERVIEW

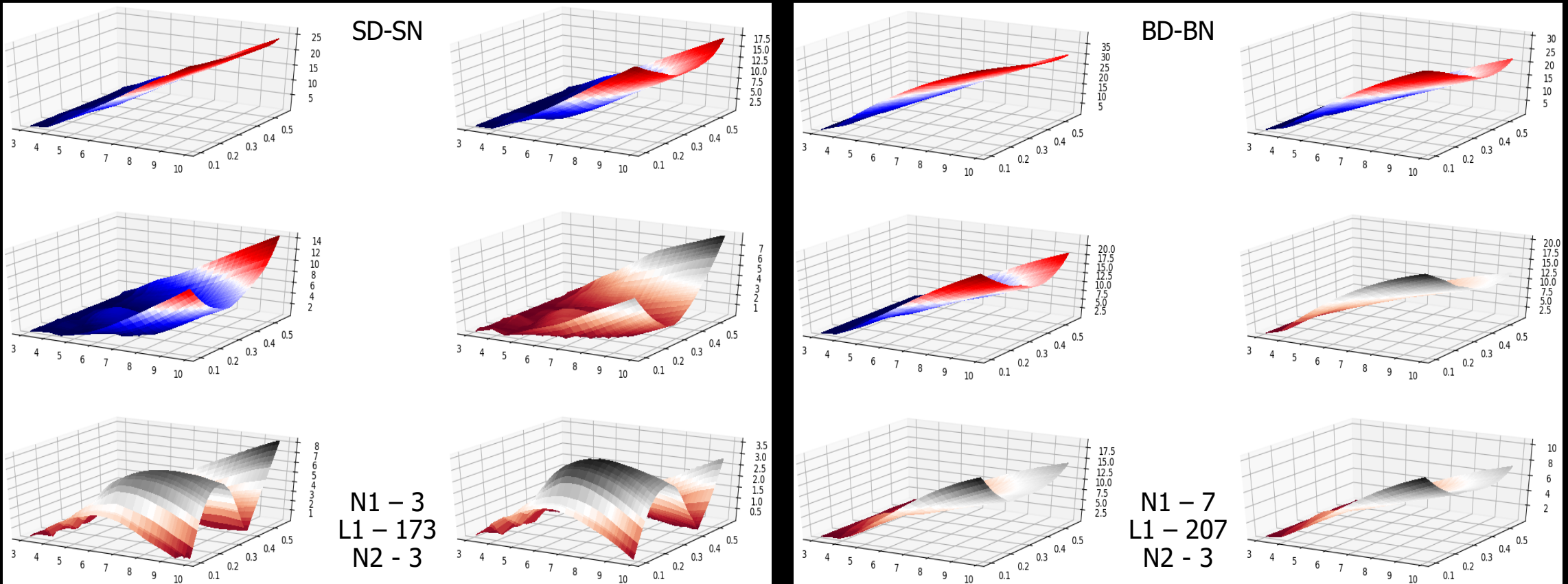
- Motivation
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# TRAINED ON PART 1 EVALUATED OVER PART 2

Table 4: Trained over  $\eta \in [0, 3]$  and evaluated over  $\eta \in [3, 10]$

Output	Mean Percent dev.		Max. Percent dev.	
	SD-SN	BD-BN	SD-SN	BD-BN
$\beta_1$	12.922	19.327	26.671	40.068
$\beta_2$	7.082	12.582	19.416	31.156
$\beta_3$	3.737	8.609	13.828	23.150
$\delta_{21}$	1.866	8.318	7.643	21.166
$\delta_{31}$	2.919	7.453	7.816	20.621
$\delta_{32}$	1.331	4.310	3.593	11.100

# PERCENT DEVIATION VARIATION



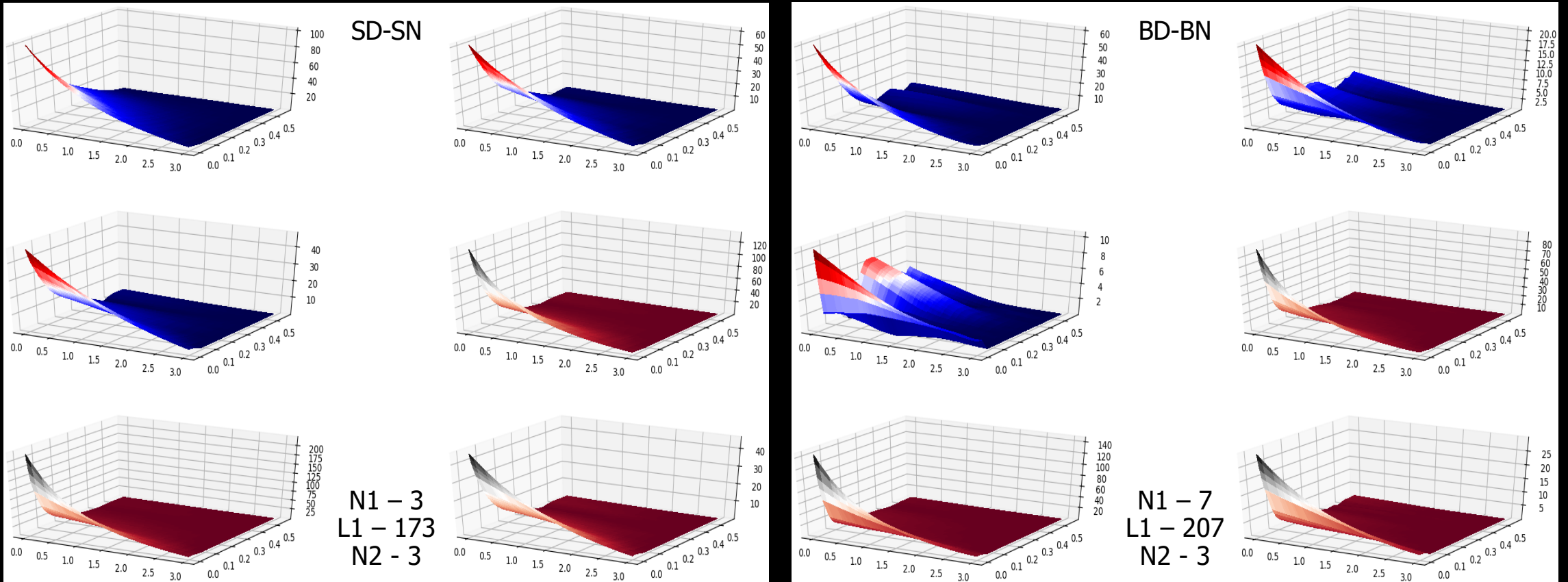
# TRAINED ON PART 2 EVALUATED OVER PART 1

Table 5: Trained over  $\eta \in [3, 10]$  and evaluated over  $\eta \in [0, 3]$

Output	Mean Percent dev.		Max. Percent dev.	
	SD-SN	BD-BN	SD-SN	BD-BN
$\beta_1$	10.620	4.630	94.813	57.242
$\beta_2$	6.181	1.808	58.538	19.544
$\beta_3$	4.826	1.361	45.678	10.128
$\delta_{21}$	7.060	3.664	121.945	80.435
$\delta_{31}$	9.475	4.975	202.181	134.401
$\delta_{32}$	3.174	1.408	43.375	27.963



# PERCENT DEVIATION VARIATION





# OVERVIEW

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# CONCLUSION

	Small Neural Network	Large Neural Network
Simple trend in Training Data compared to evaluation data	Not Recommended	Recommended
Complex trend in Training Data compared to evaluation data	Recommended	Not Recommended

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# FUTURE RESEARCH

- These models can also be trained on data for beams subjected to other boundary conditions.
  - Due to similar underlying equations, we can expect reasonably high accuracy in predictions.
- Other better models could be developed to improve the extrapolation accuracy of the neural network far away from trained range.
  - Challenging part in doing this is the complex nature of Bessel functions, which contain integrations of factorial, factorials in denominator, etc.



THANK YOU

Questions ?