# Machine Learning Application to A Physical System

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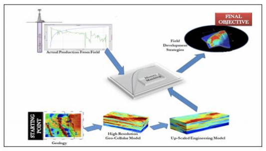
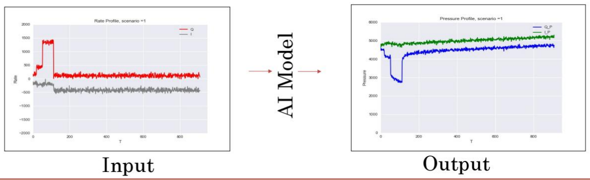
## 1- Problem Statement:

Predicting the behavior of subsurface fields is a challenging task that require accurate knowledge of the physical properties of the field in question, and the development of complex numerical simulation model that describe the behavior of the system.



## 2- Task:

Given rate profiles, and derivatives as a time series of $T\ time\ steps,$ from a specific reservoir as an input feature, represented by $\left\{Q, I, \frac{dQ}{dt}, \frac{dI}{dt}\right\} \epsilon\ R^{4\ X\ T}$ , with corresponding pressure profiles as an output, represented by $\{P\_Q, P\_I\} \epsilon\ R^{2\ X\ T}$ .



## 3- Data:

9 different rate and pressure profiles are generated randomly using fully-implicit solution of a simple reservoir under water injection, with only one producer. Every profile is considered one example. We start by one example for training, one for dev set, and the rest for testing.

## References:

- Dahaghi, A. K., & Mohaghegh, S. D. (2009, January 1). Intelligent Top-Down Reservoir Modeling of New Albany Shale. Society of Petroleum Engineers. SPE 125859-MS
- Enyioha, C., & Ertekin, T. (2017, October 9). Performance Prediction for Advanced Well Structures in Unconventional Oil and Gas Reservoirs Using Artificial Intelligent Expert Systems. Society of Petroleum Engineers. SPE 187037.
- Horn, J., De Jesus, O., & Hagan, M. (2009, April). Spurious Valleys in Error Surface of Recurrent Networks- Analysis and Avoidance. IEEE
- Mohaghegh, S. (2017). *Data-Driven Reservoir Modeling*. Richardson, TX: Society of Petroleum Engineers.
- Yeten, B., Castellini, A., Guyaguler, B., & Chen, W. H. (2005, January 1). A Comparison Study on Experimental Design and Response Surface Methodologies. Society of Petroleum Engineers. SPE 93347-MS

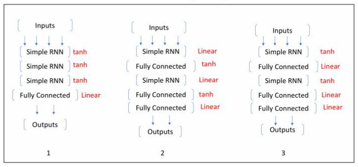
## 4- Model Architecture:

Number of nodes and learning rate is found through grid search.

**Cost Function:** MSE

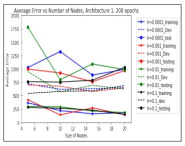
**Performance Metric:** Average sum of error in prediction where:

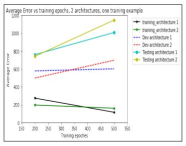
$$Error = |\hat{y} - y|$$



## 5- Initial Search:

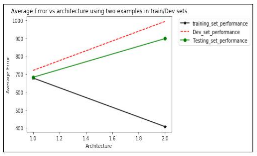
A grid search of
lr = [0.0001, 0.001, 0.01, 0.1, 1],
n = [ 5, 10, 15, 20, 25]





## 6- Switch Sequence:

every 5 epochs using 2 examples in training/ 2 in dev/ the rest for testing.



## 7- Regularization and SGD:

every 5 epochs using 2 examples in training/ 2 in dev/ the rest for testing.

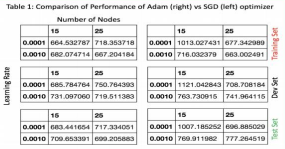


Table 1: Comparison of Performance of Adam (right) vs SGD (left) optimizer

Number of Nodes

Learning Rate

Training Set

|  | 15 | 25 |
|---|---|---|
| **0.0001** | 664.532787 | 718.353718 |
| **0.0010** | 682.074714 | 667.204184 |

|  | 15 | 25 |
|---|---|---|
| **0.0001** | 1013.027431 | 677.342989 |
| **0.0010** | 716.032379 | 663.002491 |

Dev Set

|  | 15 | 25 |
|---|---|---|
| **0.0001** | 685.784764 | 750.764393 |
| **0.0010** | 731.097060 | 719.511383 |

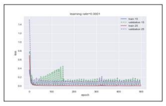
|  | 15 | 25 |
|---|---|---|
| **0.0001** | 1121.042843 | 708.708184 |
| **0.0010** | 763.730915 | 741.964115 |

Test Set

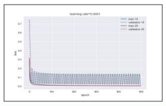
|  | 15 | 25 |
|---|---|---|
| **0.0001** | 683.441654 | 717.334051 |
| **0.0010** | 709.653391 | 699.205883 |

|  | 15 | 25 |
|---|---|---|
| **0.0001** | 1007.185252 | 696.885029 |
| **0.0010** | 769.911982 | 777.264519 |

## 8- Learning: SGD vs Adam

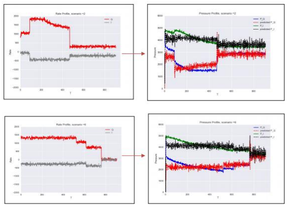


Adam



SGD

## 9- Examples of Prediction



## 10- Conclusions and Future Work:

- This work demonstrated the nature of iterative process to arrive at the right architecture and data. Grid search is helpful, but a random search should be more efficient and will be implemented as an improvement.
- Amount of data the network sees during training affect the performance. K- fold cross validation should be used to reach the best division of data that generate the best performance with matching data distributions.
- Optimizing using SGD with gradient clipping worked better than Adam in this case. This indicate the uniqueness of every problem and what works best in one case might not work in other. SGD will be explored further in the future.
- LSTM and GRU could be helpful and should be explored further.