Generating Synthetic Well Logs from Real-time Drilling Data

Stanford SCHOOL OF EARTH, ENERGY & ENVIRONMENTAL SCIENCES

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1. WHAT ARE WE PREDICTING?

Output: Wireline Logs:

- An expensive operation, performed by lowering a 'logging tool' into a well, to "log" petrophysical properties of rocks.
- **$2.6 billion** is annually spent on wireline logging.

Inputs: Drilling Data:

- The response of the drill bit is recorded in real-time and comes at no cost.
- We trained a model that can generate wireline logs from drilling response.

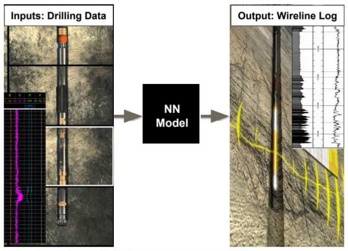


Figure 1. Acquisition of input features and output predictions

2. DATA SET & FEATURES

- 24 wells have been drilled in the Volve field in North Sea
- Data Examples:
  - Inputs: Rate of Penetration (ROP), Revolutions Per Minute (RPM)
  - Outputs: Bulk Density (RHOB), Neutron Porosity (NPHI)

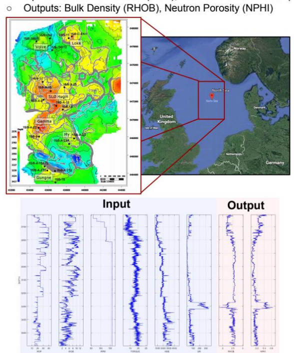
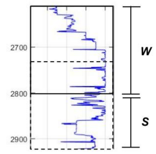


Figure 2. Volve structure map and well log example (Well A).

3. DATA PROCESSING & AUGMENTATION



Data Processing:

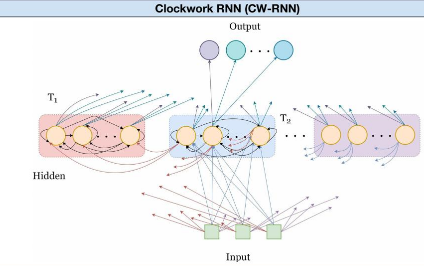
- Conversion to readable ASCII files.
- Interpolating missing and bad data.
- Extracting desired logs from different source files.

Data Augmentation:

- Sliding a window of fixed length and stride.
- Window= 32 and Stride= 4, yields 29040 training examples

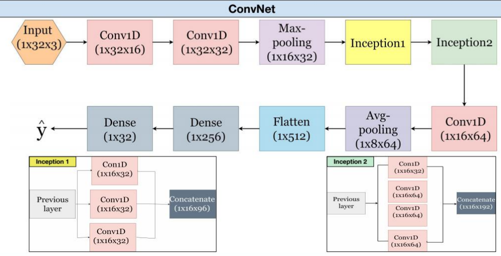
3. MODEL ARCHITECTURE

Clockwork RNN (CW-RNN)



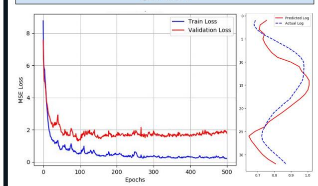
4. BASELINE MODEL ARCHITECTURE

ConvNet

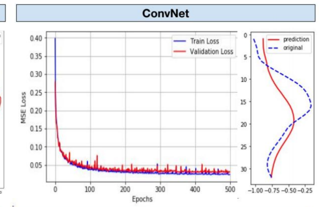


5. RESULTS AND VALIDATION

CW-RNN



ConvNet



Data Split	
Training	27588
Test	1452
Total	29040

Training Parameters	
Optimizer	ADAM
Learning Rate	0.001
Cost Function	Mean Squared Error

Trainable Parameters	
Model	**No. of Parameters**
CW-RNN	131,328
ConvNet	204,272

6. SUMMARY & HYPERPARAMETER TUNING OF CW-RNN

Sensitivity to Hidden Units

Hidden Units	Clocking Periods	Train MSE	Test MSE
64	**[1, 2, 3, 5, 8, 12, 18, 24]**	**4.90**	**7.63**
128	**[1, 2, 3, 5, 8, 12, 18, 24]**	**2.73**	**5.15**
256	**[1, 2, 3, 5, 8, 12, 18, 24]**	**1.76**	**3.04**
512	**[1, 2, 3, 5, 8, 12, 18, 24]**	**0.66**	**2.14**

Sensitivity to Clocking Periods

Hidden Units	Clocking Periods	Train MSE	Test MSE
256	**[1, 2]**	**1.67**	**2.89**
256	**[1, 2, 3, 5]**	**1.31**	**3.23**
256	**[1, 2, 3, 5, 8, 12]**	**1.29**	**2.99**
256	**[1, 2, 3, 5, 8, 12, 18, 24]**	**1.14**	**2.69**

7. DISCUSSION & CONCLUSION

- For the first time a model has been proposed to predict well logs from real-time drilling data.
- CW-RNN outperforms the baseline inception model for predicting wireline logs from drilling data.
- The choice of clocking periods for CW-RNN is data dependent.
- CW-RNN is faster than an equivalent RNN, since not all modules are evaluated at each time step.
- Other variations of RNN (LSTM and Bi-LSTM) suffer from representing the mean of Sequence.
- When using inception to multi channel sequence problems, 1D convolutions are less expensive and less prone to bias from padding than 2D convolutions.

8. FUTURE WORK

- Incorporate more logs in the training
- Use seismic data along with the drilling data
- Combine 1D CNN with CWRNN or other sequence methods
- Denoise the drilling data using wavelet transform and train a model on approximated wavelets
- The CW-RNN model should be tested and improved on other field datasets before deployment.

9. REFRENCES

1. Koutnik, Jan, et al. "A clockwork rnn." *arXiv preprint arXiv:1402.3511* (2014).
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4. Moazzeni, Alireza, and Mohammad Ali Haffar. "Artificial Intelligence for Lithology Identification through Real-Time Drilling Data." *Journal of Earth Science & Climatic Change* 6.3 (2015): 1-4.