



Deep Learning Application in Well Production Problems

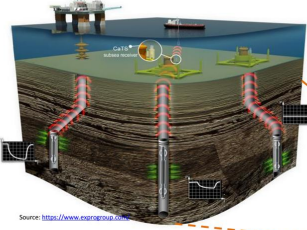
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Introduction

Goal: To build a deep learning model that describes the reservoir behavior using only well bottom hole pressure and flow rate data.

Why?

- Commonly used numerical reservoir simulator requires physical input data (e.g. rock properties and reservoir dimension). Some of them are expensive and difficult to obtain.
- Reduces manual work: less effort!



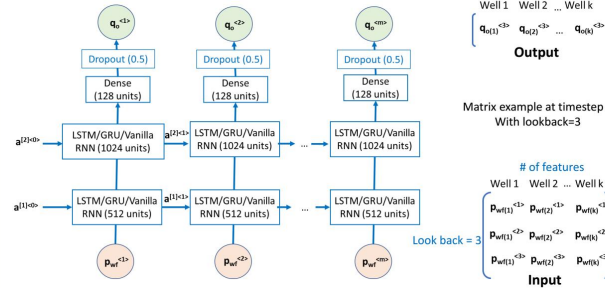
Deep Learning Model

Dataset

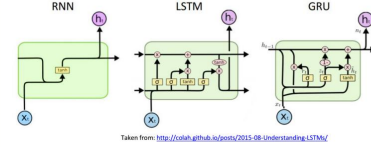
- Input: bottom hole pressure; prediction: flow rate.
- Generated from ECLIPSE, a numerical reservoir simulator.
- Three producing wells in a homogeneous reservoir.
- Training length: 1260 hours; development length: 270 hours; test length: 270 hours.
- Time interval: 1 hour
- Preprocessing: apply min-max scaling to the input and target (separately)

Model

- Sequence model architecture:



- The type of recurrent layers in this study:

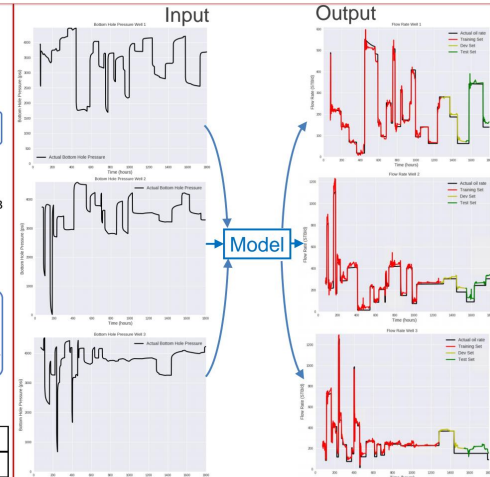
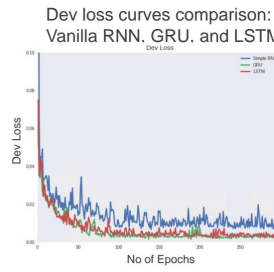
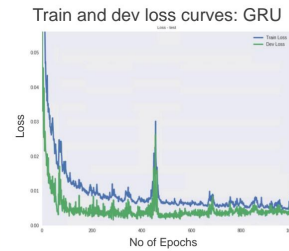


Setup:

Optimizer	Adam
Learning Rate	0.001
# of epochs	300
Batch size	300
Look back	25
Loss function	MSE

$$MSE = \frac{1}{N} \sum_{i=1}^N (\hat{y}_i - y_i)^2$$

Results



Model	Training Acc	Dev Acc	Test Acc
Vanilla RNN	0.58	0.55	0.56
LSTM	0.95	0.76	0.75
GRU	0.95	0.91	0.89

Discussion

- Vanilla RNN run faster than LSTM and GRU, but was not able to capture extreme variations in the pressure and rate data.
- Best performer: GRU.
- For the model to perform well, there should be enough data and variations in the training set

Future Work

- Reduce the noise in the prediction
- Build a model in more complex reservoir

References

Tian, C. and Horne, R.N., (2015a). "Applying Machine Learning and Data Mining Techniques to Interpret Flow Rate, Pressure, and Temperature Data from Permanent Downhole Gauges", SPE Western Regional Meeting, ECLIPSE Reference Manual 2015.1. Schlumberger, 2015.

F. Chollet et al. Keras. Gttps://keras.io, 2015