DeepWell-Application of Deep learning Techniques For Drilling Prediction

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Final Project – CS 230

Abstract

We applied deep learning techniques using a Recurrent Neural Network to the prediction of the well's drilling states (Drilling/non-Drilling time) based on the measurements collected down-hole and at the top of the well. We used an LSTM network and a softmax output layer. Our work aims to the automation of this identification that is still carried out manually by the drilling engineer during the drilling process.

Introduction

Access to hydrocarbon resources is made possible by the drilling of a well, this activity can became extremely challenging if the well's architecture is complex. The goal of my work is to automate the identification of the well's drilling states (Drilling/non-Drilling time) using sensors data collected during the drilling process. There is different types of sensors at the top and the bottom of the well. Improving the prediction using only the measurements at the top of the well will result in subsequent savings, the safety and integrity of the drilling operations will also be improved.

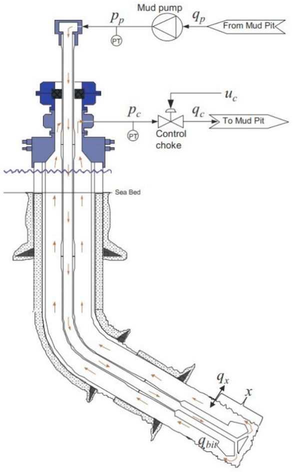

Figure: Schematic of an oil well drilling system [4]

Data

Raw Data:

- Sensors measurements for 25 wells.
- The frequency of the measurements is 100 HZ.
- For each well, the data is organized as a table, where the columns represent the feature and the rows represent time steps of the measurements, the table contains millions of rows due to the high frequency of the measurements.
- A total of 7 out of 25 wells have 130 features and the remaining 18 wells have 68 features

The input data is in the form of time series, they have been **smoothed** using a sliding window, then we**re-sampled** the new smooth data and applied **time to depth conversion**. we also **shuffled** the data and split it in Train/Dev/Test sets.

Input Data The statistics for the input data are:

Table: Model input data

Set	# of Samples
Train (90%)	3080448
Dev. (5%)	171008
Test. (5%)	171008

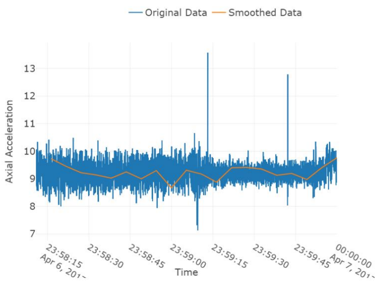

Figure: Comparison between the smoothed and Original data

Figure: Hierarchy of Predicted Properties

Model

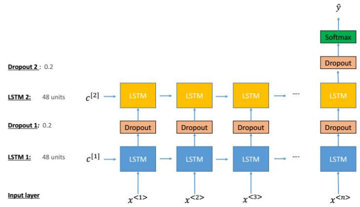

Figure: LSTM architecture

Table: Base Model

Property	Value
LSTM Network	Base Model
# Nodes layer 1	48
# Nodes layer 2	48
Dropout	0.2
Optimizer	Rmsprop
Model Type	LSTM Stateless
Batch Size	64
Test Split [%]	5
Dev. Split [%]	5
Sliding Window Width	2

Hyper Parameters Tuning

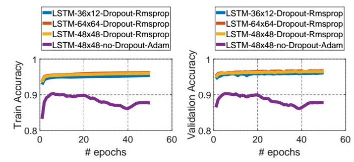

Figure: Hyper parameters Tuning Using different Models

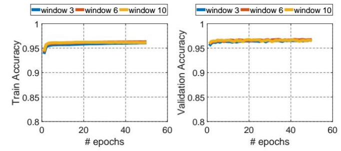

Figure: Hyper parameters Tuning Using different window width

Results

Compared Models:

- **Base Model:** LSTM - 2 Layers (48x48) , with dropout and Rmsprop optimizer
- **Model2:** LSTM - 2 Layers (36x12) , with dropout and Rmsprop optimizer (different parameters)
- **Model3:** LSTM - 2 Layers (64x64) , with dropout and Rmsprop optimizer (different parameters)
- **Model4:** LSTM - 2 Layers (48x48) , no-dropout and Adam optimizer.

Table: Metrics Comparison

	Train			Dev		
Model	**Loss**	**Acc.**	**F1**	**Loss**	**Acc.**	**F1**
Base Model	0.0929	0.9651	0.965	0.0781	0.97	0.9701
Model 2	0.1092	0.9585	0.9586	0.0946	0.9641	0.9641
Model 3	0.0886	0.9666	0.966	0.0748	0.9712	0.9713
Model 4	0.2711	0.8957	0.8959	0.2659	0.8978	0.8965

Best Model- Test Results:

Table: Test Metrics

	Test		
Model	**Loss**	**Acc.**	**F1**
Model 3	0.0781	0.9701	0.97

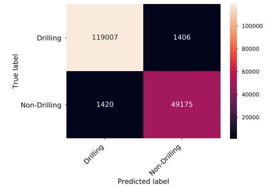

Figure: Confusion Matrix for 2 Class Classification - Test Results

Conclusions

- Very good results for the prediction of Drilling/ non-Drilling states
- Model 3 gives the best results despite requiring the longest time to train, there is a trade off in terms of Training time/ Accuracy to choose between the tow models Model 3 and 1.
- The multiclass classification (Drilling/ Pull out/ Decent/ Surface) has excellent accuracy but suffers from imbalanced data set, further exploration should be done to improve minority classes identification (Pull out/ Descent)
- We plan to use the results of this classification as an input to classify their sub-classes

Reference

[1] J. Hoffimann al, Sequence Mining and Pattern Analysis in Drilling, 2017

[2] G.V. Veres al. Data Analytics for Drilling Operational States Classifications, ESANN 2015

[3] S. Hochreiter, Long Short-Term Memory, Neural Computation 9(8):17351780, 1997.

[4] H. Agus, Infinite-Dimensional Observer for Process Monitoring in Managed Pressure Drilling, 2015