AADE-20-FTCE-014

Drilling Fluid Reporting: from Data to Insight

Yuan Yao and Zhibin Sun, Pegasus Vertex, Inc.; Chuck Light, Valence Drilling Fluids LLC

Abstract

The numerical data in daily mud reports has been fully used in reporting and monitoring well operation and even more in well summarizing. However, a large quantity of literal data from daily mud reports is not being taken full advantage of. Artificial Intelligent (AI) technologies are used in studying the literal data to extract critical and valuable information hidden in words.

In this study, a library containing a variety of incident key words frequently used in oil field is created. Then Natural Language Processing (NLP) is used to study a massive quantity of literal information that mud engineers commented in more than 6000 mud reports in 327 wells and search the key words related to the library, and then label the reports and the wells with the key words. In this process, NLP can take consideration of case sensitivity, stop words, abbreviations, different tenses and negations in the sentences.

Results show that the NLP methods can accurately identify those wells associated with certain types of incidents and on a specific date. The implementation to real-world data is also highly accurate in incident labeling. The data mining methods with NLP technology have proven effectiveness and accuracy in analyzing literal data in daily mud reports. They save human labors in identifying critical information from massive data. Users can apply the methods to find out the wells with a certain feature, further analyze and predict the trend of wells to support decision making.

Introduction

In computer science, AI sometimes called machine intelligence, is intelligence demonstrated by machines. It involves executing tasks based on intelligent behavior of humans in solving complex issues. Compared to other automations, AI facilitates reduction of human tasks and operational expenses.

The concept of AI was first proposed in 1940's. The first field of AI research was founded at a workshop in Dartmouth College in 1956. During the past 60 years, the development of AI experienced two golden times: from 1956 to 1974 and from 1980 to 1987. Since 2011, AI has become a hot topic again and is even more popular than any time before. People consider nowadays as the third booming time of AI.

The application of AI technologies promoted technological improvement of all industries. Apple Siri in iPhone uses speech recognition and NLP technologies to identify speaker's words and phrases, understand the meanings, and then respond to commands or answer questions. Tesla developed autopilot system that utilizes deep learning neural networks to assist drivers in lane centering, cruise control, self-parking and self-driving. In March 2016, the AlphaGo program developed by DeepMind beat top human professional Go player, which marked a significant milestone in the development of AI as numerical estimates show that the number of possible games of Go far exceeds the number of atoms in the observable universe.

The application of AI technologies in Oil and Gas industry started a little later than other industries, but its growing speed is rapid. In August 2015, Shell launched its Virtual AI Assistant system that provides customers the convenience of searching and discovering lubricant products using natural language. In March 2019, Aker Solutions applied machine-learning algorithms to their AI platform to analyze sensor data from more than 30 offshore structures, which enables the company to identify suboptimal operations and impending failures before they occur. In 2020, Baker Hughes launched an AI-based application that uses machine learning to compare real-time data with historical data across production operations to allow well operators to predict future production more accurately. AI technologies provide a level of efficiency and accuracy that humans can never achieve, saving time on the jobs and cutting cost.

The application of AI technologies in drilling operation is mainly used to predict and prevent incidents and then decrease or even eliminate non-production time (NPT). The most general method is using machine learning to analyze an enormous amount of historical data to discover the deep connections and patterns between drilling data and non-expected incidents. In this process, machine learning models are built, which can be used in monitoring real-time field data. Once it recognizes any data patterns which it predicts to foreshadow bad results, it will send alert before the hazard happens. Therefore, field engineers can take timely remedial action accordingly, or stop the ongoing operation to prevent the occurrence of incidents. More advanced AI systems can even provide optimal solutions to avoid the incidents or minimize the impact of them. Of course, it requires superior machine learning algorithms, more research and optimization.

In recent years, many researchers dedicated their time and efforts to the research and development of AI technologies, therefore, many excellent AI models were built. Three typical machine-learning algorithms were employed to analyze drilling data of earlier drilled wells including depth, mud density, filtration, pump pressure, flow rate and geostress, and then a risk prediction model of lost circulation while drilling was established. (Zejun Li et al., 2018). Key drilling parameters including mud weight, equivalent circulation density, plastic viscosity, yield point, flow rate, revolutions per minutes, weight on bit, and nozzles total flow area were used as inputs with an advanced AI technique to estimate mud losses prior to drilling. (Husam Alkinani et al., 2019). An Artificial Neutral Network (ANN) model was developed to predict ROP using 10 input drilling parameters. (Mohammed AI Dushaishi et al., 2019). ANN technique was also used to generate empirical models to predict the rheological parameters in real time based on more than 1200 real field measured points of mud weight and marsh funnel viscosity. (Ibrahim H. Gomaa et al., 2019). All the previous studies and researches focused on numerical data only, but underutilized the valuable literal data. Additionally, in order to analyze historical data about drilling incidents or the cause of NPT, we need to locate these incidents and NPT events first, and the literal data from drilling reports are the best resource for us to obtain this information.

Daily mud report is a sheet of data filled out by mud engineers at the well site on a daily basis. It records drilling information, mud test results, mud additive usage and inventory accounting, etc. A typical daily mud report is shown in Figure 1. The literal contents in the red boxes are recommended tour treatments and remarks. The recommended tour treatments section records all treatments that has been done to the mud system since the last report, while the remarks section records important drilling information, summary of the daily operations, events or incidents occurs, and concerns. The numerical data can be extracted and put into analysis easily, but the literal data is always ignored and is not fully exploited because it is difficult to extract information from it. The purpose of this study is to let AI technology scan the information among a large number of daily mud reports and recognize key words indicating happened incidents accurately.

Natural Language Processing

Natural language processing (NLP) is the most important AI technology we used in this study. It is a subfield of artificial intelligence and linguistics, which concerns with how to program computers to process and analyze large amounts of natural language data.

The development of NLP generally started in 1950s. The first application of NLP is Georgetown–IBM experiment, which involved completely automatic translation of more than sixty Russian sentences into English. Starting in the late 1980s, there was a revolution in NLP with the introduction of machine learning algorithms for language processing. Since 2010, representation learning and deep neural network-style machine learning methods became widespread in NLP.

NLP is frequently used to identify and extract valuable information from large amount of text data, especially in the era of information explosion. Google's Gmail can identify junk emails based on the text in the emails. News websites classify news and make suggestions based on the users' read history. NLP can also identify the sentiment within the tweets of Donald Trump's account and tell whether himself or his staff posted the tweets.

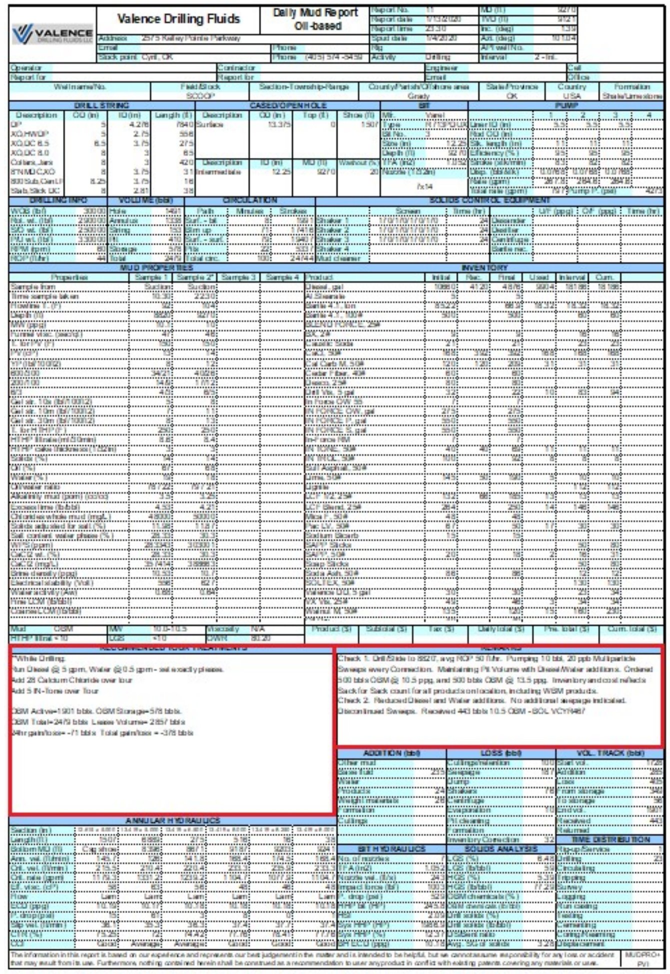
Valence Drilling Fluids
Daily Mud Report
Oil-based

Figure 1 – A daily mud report sample

Methods

Data Mining is the process of exploratory data analysis through unsupervised machine learning. In PVI's mud reporting software, we applied data mining techniques in NLP to analyze and extract key information from the mud report text.

Data Mining

We applied two approaches in NLP to discover the incidents information within the text of the daily mud reports by R, one of the mostly powerful computer languages in AI field.

First, we treat each text of the report as a collection of individual words. In this way, we treat every word or phrase in a document as a potentially important keyword and we can know how often each word or term appears in each report. After splitting sentences, stripping white spaces, removing numbers and punctuation, and converting to lower case, we get a list of simplified text for further analysis.

But the problem is, many of the most frequently used words in English are worthless in the analysis – these words are called stop words, such as the, of, and, to, etc. There are typically about 400 to 500 of them, and they are removed from our results.

Another problem that will lower the effectiveness of NLP is obvious: English has many words with different forms. A noun has its plural, such as “dog, dogs”. A verb has different tenses and voices, such as “buy, bought”, “mine, miner, mining”, and “continue, continuously”. They aren’t actually different. So, we must group these together as the same basic word. In fact, these similar words have a same root, or stem. When these words with the same stem appear in the text, we trim these words using the NLP corpus library in R. For example, by trimming “user, users, used, using” we get the stem of them as “us”. Next, because “us” is not what we want in our results, we use the most common word of “us” in the text to re-complete it. So here, for example, all the “user, users, used, using” become “used”.

Secondly, to make up for the limitation of NLP, which is not able to handle more complex semantic expression or extract specific words mud professionals care most, we defined keywords and phrase lists to reinforce the result. First, we use the common incident words to filter the results. The different forms of words, such as abbreviations, are also considered. For example, “shut in, shut-in, SIDP, SICP” are used to find out the keywords related to an incident of shut in. Second, from the sentences these incident keywords appear, eliminate those with any words of negation, such as “no, not, avoid, prevent, hardly, etc.” Third, because many specialized words are context-dependent, we include another filter-out list to remove the incidents we picked up that are actually not incidents. For example, the occurrence of the phrase “soap stick” doesn’t mean a pipe stuck incident; “lost circulation material” doesn’t mean a lost circulation incident happens; and kick out doesn’t relate to a kick incident at all. Finally, to ensure the accuracy of the incidents detected, we sampled and checked the results by human experts to correct errors and enhance the keyword lists.

Predictive Modeling

The data mining techniques we are applying above are used to “label” the text data, which seems like to label an answer “2” to an equation “1+1=?”. With the right answer, we can use the “questions” and the “answers” to “train” the computer to discover the relation between them. The computer can perform supervised machine learning to build predictive models to identify incidents in future mud report texts. The first step we are doing is to build classification predictive models. For example, we are trying to build models to decide what kind of incidents have happened to a certain well, in a certain day. After collecting and integrating more numerical data into our training data, we are building more regression predictive models. For example, we use the survey data and operational parameters to help train models to predict the possibilities of the incidents before drilling. Some of the mostly used machine learning algorithms can be applied to train the models, such as Logistic Regression, Classification Tree, and Random Forest. To improve the accuracy, we are planning to implement Artificial Neural Networks (ANN) to train our models.

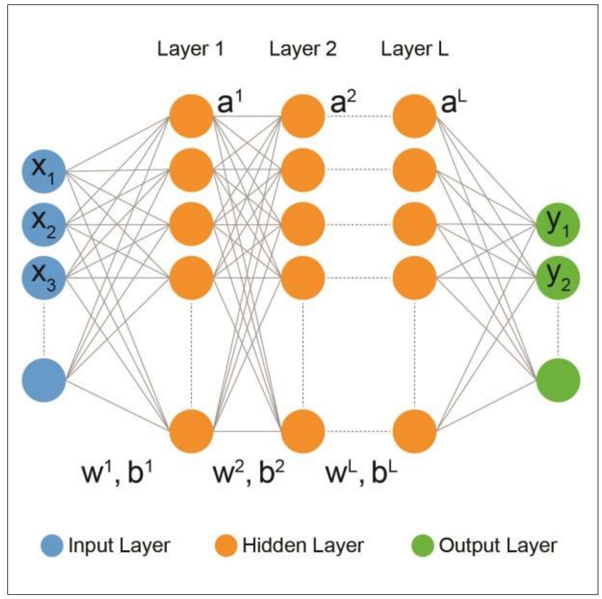

Figure 2 – Artificial Neural Network Architecture

The neural networks in our brains have numerous dendrites and axons to input and output information, they are interconnected within the network. The ANN is one of the most successful bionic implementations in AI field. It mimics the structure of neural networks, in which information is passed on from one node to another. As shown in the Figure 2, ANN has three types of layers: Input Layer, Hidden Layer and Output Layer. The data is processed in the network by Forward Propagation. First, each node in input layer passes one input data, such as each numeral or text data in a mud report, to every node of the first hidden layer. Every node in the first hidden layer then applies a combination function to the input data and passes the result to every node in the second hidden layer. The nodes in the second layer will do the same as the first layer. When the data is applied a combination function in the last hidden layer, it will be passed to the nodes in the output layer. The nodes of the output layer will provide the results we wish to see, such as the possibilities of each incidents, after applying similar combination functions. Although there are so many functions within the network, when training the model, the parameters of the functions in each node will be adjusted according to the difference between the output data and the true data. Therefore, the large scale of the network requires more computational power, but the accuracy of the results will be much higher.

Although the projected accuracy of the ANN will be higher, the ANN tends to overfit and variable selection is not possible. ANN is also a “black box” method: it provides no insight into relationships between input data and the outcome, so it would not inform much knowledge about how to decrease incident rates, for example.

Case Study

We have done two case studies for this research. In the first study, 57 wells were involved in the analysis. The purpose of this study is to improve the accuracy of the NLP model. At the first round of the analysis, the NLP model marked out 75 occurrences of incidents. Then we pulled out those reports and manually searched for the key words, to verify if the results from the NLP model are truly correct. The verification process helped us detect some incorrect search results caused by NLP misunderstanding the true meanings of the sentences. For instance, the sentence “For bit balling add 10 sacks walnut to sweeps” contains an incident key word “balling”, so the NLP model misidentified this situation as a happened balling incident. But in fact the sentence means adding walnut to prevent balling, and bit balling actually doesn’t happen. We upgraded the NLP model to correct the mistakes and then kept repeating the verification procedure until all search results were proven correct. After correction, the optimized NLP model cut down the occurrence number of incident to 62. Manual verification proved all 62 incidents were marked correctly. In summary, the first study corrected 13 errors in the NLP procedure. The comparison between before and after the correction is shown in Table 1.

Before Correction		After Correction	
Incident	**No of Wells**	**Incident**	**No of Wells**
Balling	13	Shut in	12
Shut in	12	Failure	10
Failure	10	Stuck	7
Stuck	9	Lost circulation	6
Lost circulation	7	Damage	6
Damage	6	Ballooning	5
Ballooning	5	Washout	4
Washout	4	Kick	4
Kick	4	Influx	3
Influx	3	Balling	3
Twist	1	Twist	1
Buckle	1	Buckle	1
Total	**75**	**Total**	**62**

Table 1 – Result comparison in Study 1

In the second study, we applied the optimized NLP model to 270 random wells. The incident ranking is shown in Table 2. We ran the NLP program in very low configured computer with a 2.4GHz CPU and 2GB memory. The program took 20 minutes to finish the whole analysis with an average processing speed about 5 reports per second. The successful execution on the low-configured computer indicates that this NLP model doesn’t require an expensive supercomputer. The speed can be boosted significantly if a better computer is used.

Incident	No of Wells
Failure	30
Shut in	29
Damage	27
Stuck	26
Balling	19
Lost circulation	16
Influx	13
Washout	12
Kick	12
Ballooning	8
Buckle	5
Well control	4
Twist	3
Wash over	1
Total	**205**

Table 2 – Result of Study 2

Problem

There are many facts making the NLP model very hard to achieve a desired accuracy. First, mud engineers have very different styles of writing, which brings difficulties to the AI system to understand. Second, some mud engineers may unintentionally avoid using those incident words directly. Instead they would like to use some alternative words to make the reports look better. This approach again increases the difficulties for the AI model to understand the written contents, and to identify happened incidents. Third, there is a small probability that the daily mud reports may include some uncommon abbreviations or codes to present some incidents. AI model is unable to recognize.

Conclusions

1. this research proves that the developed NLP model can successfully extract incident related information from a larger amount of literal data of daily mud reports.

2. the NLP model spent 20 minutes to finish the analysis of about 7000 daily mud reports from 270 wells within a low level computer. Considering the difficulties of the algorithms, the processing speed is acceptable. The process can be further accelerated by optimizing the algorithms or using a more powerful computer.

3. the accuracy of the NLP results increased greatly after supervised training was applied to the model repeatedly.

4. the results from the NLP model provide reliable data; they can be further used in real time data monitoring as comparison data to predict incidents.

Acknowledgments

We thank Valence Drilling Fluid for providing reliable data to us to do all the analysis and authorizing us to cite the daily mud report as a sample.

Nomenclature

AI	=	Artificial Intelligent
ANN	=	Artificial Neural Network
NLP	=	Natural Language Processing
NPT	=	Non-production Time

References

1. Husam Alkinani, Abo Al Hameedi and Shari Dunn-Norman 2019. "Using Artificial Intelligence Method to Estimate Lost Circulation Events Prior to Drilling" AADE-19-BTCE-022, AADE National Technical Conference and Exhibition, Denver, April 9-10, 2019. Available from www.aade.org
2. Mohammed Al Dushaishi, Ahmad Aladasani, Qutaiba Okasha, and Mortadha Al-saba 2019. "Neural Network Application to Manage Drill Stem Vibrations and Improve Drilling Performance" AADE-19-NTCE-068, AADE National Technical Conference and Exhibition, Denver, April 9-10, 2019. Available from www.aade.org
3. Ibrahim H. Gomaa, Salaheldin Elkatatny, Abdulazeez Abdulraheem and Mohamed A. Mahmoud 2019. "Real-Time determination of the rheological properties of High Over-Balanced Drilling Fluid Using Artificial intelligence" AADE-19-NTCE-070, Technical Conference and Exhibition, Denver, April 9-10, 2019. Available from www.aade.org
4. Zejun Li, Mian Chen, Yan Jin, Yunhu Lu, Hanqing Wang, Zhi Geng, Shiming Wei 2018 "Study on Intelligent Prediction for Risk Level of Lost Circulation While Drilling Based on Machine Learning" ARMA-2018-105 , 52nd U.S. Rock Mechanics/Geomechanics Symposium, Seattle, Washington, June 17-20, 2018.