Achieving Optimal Horizontal Drill Operations

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Abstract. In this paper, we present a novel method of predicting the onset of a slide event in horizontal drilling operations. Horizontal drilling operations attempt to create a well through a subsurface as quickly as possible by rotating a drill through the subsurface. A slide event occurs when the drill begins to inefficiently rotate through the subsurface, resulting in a significantly reduced rate of penetration. Slide events can be prevented, or significantly reduced in their impact, when their onset is accurately predicted. We present a method of accurately predicting the onset of slide events with a time-series based predictive model that operates on real-time drilling data. We identify controllable features that allow drill operators to mitigate or prevent slide events.

1 Introduction

Drilling a well involves many moving parts to reach its total depth. Total depth is the total length of a well measured by the length of pipe to reach the bottom of the well. Total depth is reached fastest when a drill is in a state of rotation, providing the greatest rate of penetration. However, there are many factors that can put a drill into a sliding state, reducing the rate of penetration through the subsurface. The goal is to reduce the amount of sliding a drill experiences while reaching total depth. This provides a stable and higher rate of penetration through the subsurface, allowing drilling operations to reach total depth faster.

The model that we present in this paper predicts the onset of a slide event within a specified time frame. The model identifies controllable features that allow drill operators to take actions in order to prevent or mitigate an impending slide event.

If drill operators are provided a ten minute prediction window for an impending slide event, they have sufficient time to adjust pumping rates, torque, drill pressure, etc. to prevent said slide event. Thus, our model is focused on providing accurate predictions for the ten minute prediction window as a minimum. If drill operators are provided a thirty minute prediction window, they have additional time to discuss optimal drill parameters with an onsite geologist. Since this could ultimately increase drilling efficiency, we look at a thirty minute prediction window as an upper bound for our model.

The rate of penetration is reduced slightly when slide event mitigation measures are introduced. However, the rate of penetration is greatly reduced during an actual slide event. Thus, the costs of false positives with our model are small compared to the cost of missing a slide event prediction.

We employ data resampling techniques as part of our analysis to allow for quick run times of our models. We found a one-minute resampling rate had little impact on model performance and was our chosen resampling rate for all analysis. The machine used for analysis consisted of 6 CPU cores with thirty two gigabytes of memory.

The models created for this project consist of three well known classification models: Logistic regression, Random Forest, and Support Vector Machine. The Logistic Regression model accomplishes the identification of the binary response variable at the same accuracy as the Support Vector Machine model (98%) with only one percent decrease in F1 score (97%) when compared to Support Vector Machine. The Logistic Regression model trains faster than the Support Vector Machine model, saving time on iterations and tuning of hyperparameters. The Random Forest model performed the worst of all three models and was not chosen as a recommendation due to low accuracy and F1 scores. Ultimately, we decided on the Logistic Regression model as our optimal model choice. It performed almost as well as Support Vector Machine but ran significantly faster.

Through our analysis, we were able to conclude that not only is slide event prediction feasible, but prevention and mitigation of slide events is also practical. The features we identified as important to our classification model include features that are controllable by drill operators on site. Through the manipulation of drill parameters identified by our model, drill operators can mitigate or possibly prevent an impending slide event.

The feature selection process identifies both controllable (prescriptive) and non-controllable (predictive) features that are relevant to the classification problem. Controllable features indicate drilling parameters drill operators can modify in real time to prevent or mitigate slide events. For example, pump pressure was identified as a controllable feature relevant to the classification problem. This value can be controlled by drill operators to prevent an impending slide event. Conversely, depth hole true vertical is a feature relevant to the classification problem but is more predictive in nature as drill operators cannot modify this value.

We are not the first to be interested in optimizing drill operations. Understandably, there is prior work related to our problem domain. US Patent 6,152,246 describes a database application designed to measure drilling parameters, apply operating limits, and alert operators when specified events occur [1]. While this work is related to our problem, this invention is geared towards real time event monitoring and alerts. Our slide event prediction model achieves additional benefit by being able to alert operators of an upcoming slide event. This allows operators to take preventative measures before the slide event ever occurs.

The remainder of this paper is organized as follows. In Section 2 we present an overview of drilling operations and slide events. In Section 3 we review the data that is obtained during a drilling operation. We identify the primary features utilized by our model in Section 4. In Section 5 we give a brief overview of some of the terms and metrics we will use when discussing our model selections and results. Sections 6, 7, and 8 discuss our application of Support Vector Machine, Random Forest, and Logistic Regression models to the data. We discuss our results in Section 9. We point out ethical considerations in Section 10. We draw relevant conclusions in Section 11.

2 Drilling and Slide Events

The ongoing advances in drilling technology are designed to meet the need to optimize drill operations to prevent slide events. While optimal drilling parameters have always been a concern, slide events are less prevalent in vertical drilling operations. As horizontal drilling operations became more popular, the focus on preventing slide events increased.

During drilling operations, slide events are identified by monitoring the rate of penetration, bit inclination, and pipe consumption. When a slide event is detected, drill operators use the ROCKit system for adjustments. With this system, the drill pipe is rocked back and forth in an effort to return the drill back to a rotating state[1]. Using our predictive model, drill operators can employ the ROCKit system or other methods prior to a slide event occurring in order to prevent the drill from ever entering a sliding state.

Triple Crown Resources's budget for capital expenditures is dominated by the expenses associated with drilling and hydrocarbon production. Reduction of capital spend in this area would allow Triple Crown Resources to obtain larger investments and expand their drilling operations to surrounding areas. Furthermore, by reducing the time needed to reach total depth, Triple Crown Resources would be signalling to equity partners that they have mastered advanced analytic techniques allowing them to perform better than their competitors.

2.1 Slide Events

A slide event occurs when the rate of penetration of the rotary drill decreases and the drill bit no longer rotates at optimal capacity. Rotation is the desired state of a drill bit; however, when a drill is sliding it is pushing through the rock formation instead of efficiently rotating. Conditions that contribute to slide events include the type of rock formation encountered by the drill bit, the bit condition, and the amount of formation pressure encountered.

2.2 Horizontal Drilling

A horizontal well is constructed such that it can make a turn in the subsurface usually at 75 or 85 degrees. In Fig. 1, well paths in the left image are considered vertical wells whereas the well path in the right image is considered a horizontal

[1] Nabors. "ROCKit System", https://www.nabors.com/software/performance-drilling-software/rockit-system [Accessed 13 July 2019]

well. The key difference among these wells is well paths on the left never reach an inclination of 75 degrees or greater, and as such are not considered a horizontal well. Horizontal drills operate in order to maximize reservoir extraction by allowing the lateral portion of the well to stay within the producing rock formation longer.

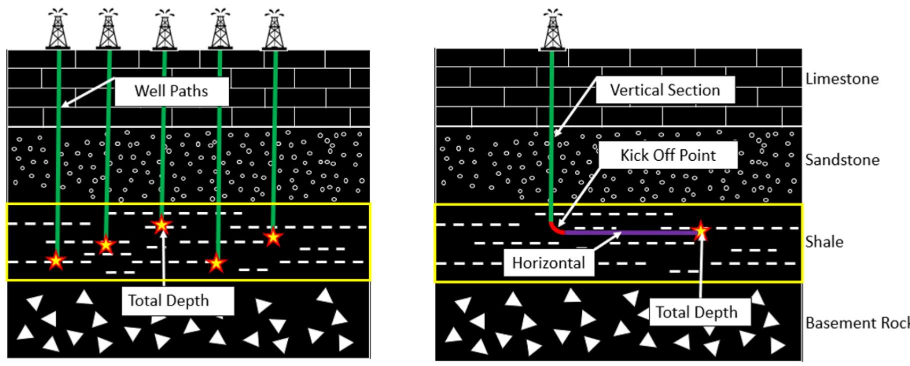

Fig. 1. Types of Well Paths: Vertical wells were the dominant type early in the industry as technology and understanding of reservoirs were not as advanced as they are today. Horizontal wells gained acceptance in the early 2000's and are now a standard type for drilling operations.

2.3 Drilling Advances

A traditional vertical well contains a bore hole that extends vertically below the derrick. In a true horizontal well, the bore hole goes from vertical to horizontal at a point in the well path (see Fig. 1). The first vertical well was drilled in 1895 using a percussion drilling method and reached a depth of sixty five feet. For comparison, modern day deep water wells have reached depths of 24,000 feet. Technology advancements led to a new type of drilling technique called rotary drilling. The basic concepts for rotary drilling initiated in the late 1800's can still be seen in today's operations, as drill pipes spin drilling down into the subsurface. This type of drilling operation is a necessity for energy companies to reach deep target depths.

Directional drilling was initiated to fish tools lost in a bore hole [3]. Intentional directional drilling methods were first used in 1930 on the shores of Huntington Beach, California. In 1934, directional drilling was used to kill a well blowout by pumping heavy mud into a deviated borehole.

2.4 Permian Basin

The Permian Basin stretches from the lower Southern portion of New Mexico and extends to much of West Texas (see Fig. 2). This basin was formed during the Paleozoic era. From the geological timeline, much of the structures which ultimately formed the traps for hydrocarbon were created during the late Paleozoic Era (251 million years ago) [9].

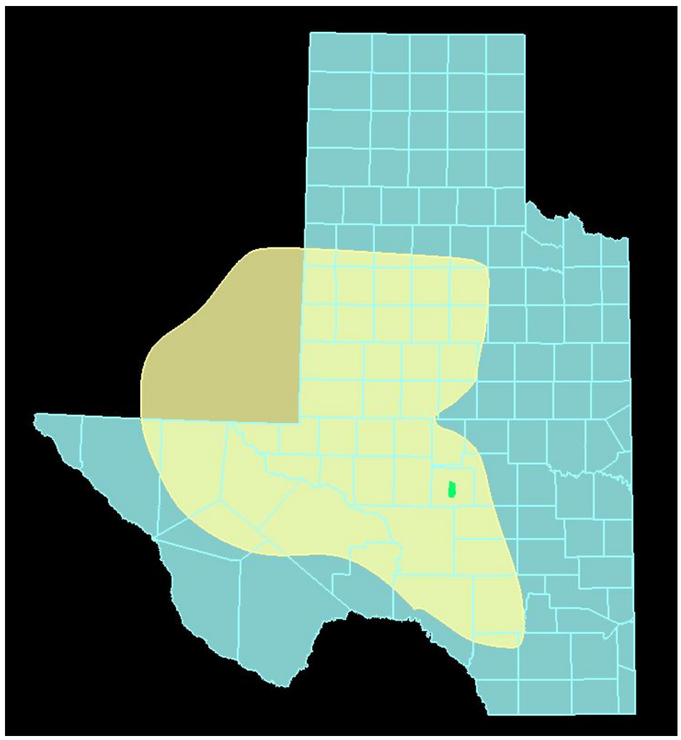

Fig. 2. Permian Basin: The Permian Basin is roughly 86,000 square miles and split into multiple sub basins. Midland, Delware, and Val Verde make up the larger Permian Basin. Each basin comes with its own unique challenges such as shale thickness, mineralogy, pressure, and access to drill sites. Formation water is an operational challenge that affects all companies in the basin. Water that is produced from a well cannot be pumped back down and requires transportation and treatment. Up to 15,000 barrels of formation water can be produced daily from a producing well. The green area in the image represents the drilling area that sourced our data for analysis.

The basin is divided into three structural development phases. This paper concentrates on the tectonic activity of the Hercynian Orogeny which occurs when the North America plate collides with the South American plate. This tectonic activity is one of the major factors that contributed to the conventional traps exploited by early gas and oil exploration. Eventually, as tectonic activity slowed and mountains eroded, sediment consisting of limestone, shale, and fine-grained sandstone layered the basin [7].

Oil was first produced from the basin in the middle of the 1920's, and major activity started during the 1950s. Much of the data from these early periods is still used today to deliver control points of the basin. These control points help geologists map different formations in the subsurface layers [5].

In modern development, companies now have higher quality data available and are able to divide previous grouped formations into sub-formations. The Wolfcamp formation is one such sub-formation that resulted from higher quality data. This formation is a target for most companies involved in the Permian Basin. Using today's mapping technology, this formation has been divided into three benches - upper, middle, and lower Wolfcamp.

Though the Permian Basin has been producing for more than five decades, new technology emerged that brought additional life to the basin in recent years. Hydraulic fracturing ("fracking") has been around since 1949, but it was not until the early 2000's that fracking was combined with horizontal drilling techniques. The ability to drill in a horizontal direction to stay within a formation gave an unprecedented way to drain reservoirs that were once thought to be on the decline for producing hydrocarbons (see Fig. 3).

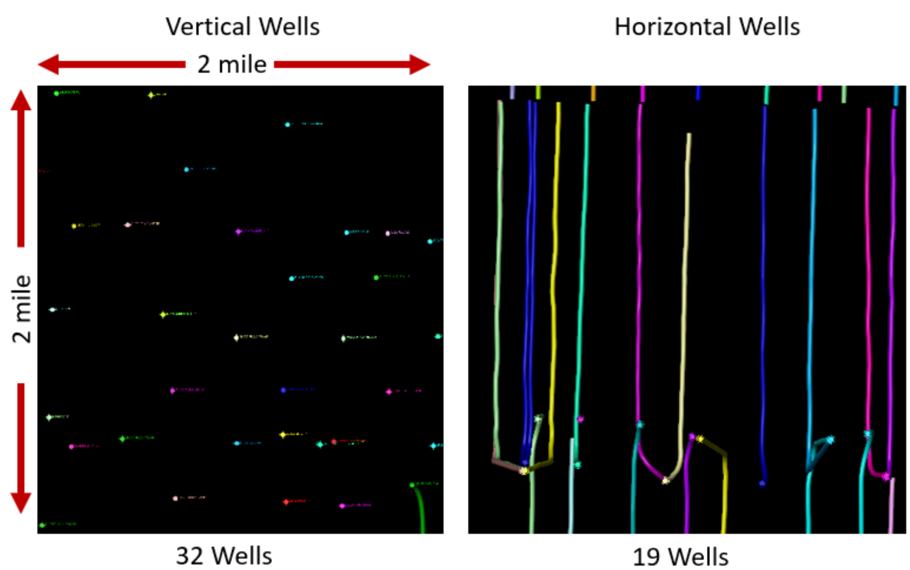

Fig. 3. Vertical versus Horizontal Drilling: Horizontal drilling programs bring a lesser environmental impact than traditional vertical wells. Draining a reservoir with vertical wells requires a much bigger environmental footprint, requires more drills, and costs more. A single pad can hold as many as eight horizontal wells.

Recently, it has been reported that the Permian Basin is the world's top oil producer. Saudi Aramco's Ghawar field produced 3.8 million barrels per day in 2018. Comparatively, the Energy Information Administration reports that the Permian Basin is now producing 4.2 million barrels per day compared to an average of 3.4 million barrels per day for 2018 [6]. Thus, oil production in the Permian Basin is increasing and companies are investing more capital.

3 Data

A leap in technology and computing power thrust many industries, including Energy, into Big Data Analytics. However, the velocity of the data captured proved to complicate analysis for the Energy industry [4]. Specifically, real time drilling sensors capture data every second. Many in the industry were not experienced in how to analyze and make the best use of this data. With the market drop in 2014, Energy companies began to realize this data was a valuable asset. Efforts were put forth to recruit talent that could make use of these large datasets that had been sitting idle in 3rd party vendor databases

The data provided to us originates from drilling operations conducted by Nabors Industries. This data is streamed real-time to data stores and exposed for analysis through the MyWells portal. The data provided covers twenty one wells. Most importantly, the data set contains a feature "Rockit-OnOff" which indicates if a drill is in a sliding or rotating state. This feature is used as our prediction variable. The Nabors system allows for monitoring of drill operations which can be used to validate the success of our model (see Fig. 4).

The data is collected from sensors located anywhere from thirty to fifty feet behind the drill bit. The sensors record features such as inclination, rate of penetration, pressure, resistivity and many others. The data is captured every second and is sent directly from the drill string to the drillers cabin.

An example of sensor data collected is pressure tracking sensor data. These sensors are used to monitor the surface pressure being applied downhole. This data is used to identify potential downhole problems regarding washouts, kicks, or loss of pressure. Another example of sensor data is the torque sensor. This sensor is positioned around the main power cable connected to the top drive system. As torque increases, a greater current is drawn by the top drive system that is recorded by the torque sensor.

The data is represented in WITSML (wellsite information transfer standard markup language) which can be read from the vendor's propriety application known as MyWells or can be read directly utilizing a programming language such as Python or C#. The WITSML data feeds allow developers to consume the data in many different ways and can be used to feed a model data in real time.

Data for our analysis was was produced from twenty-one previous wells drilled by Triple Crown Resources. The data consist of 512 features and 2.9 million rows of data. These features include four date time features, one categorical feature, thirty-eight binary features, and 469 continuous features.

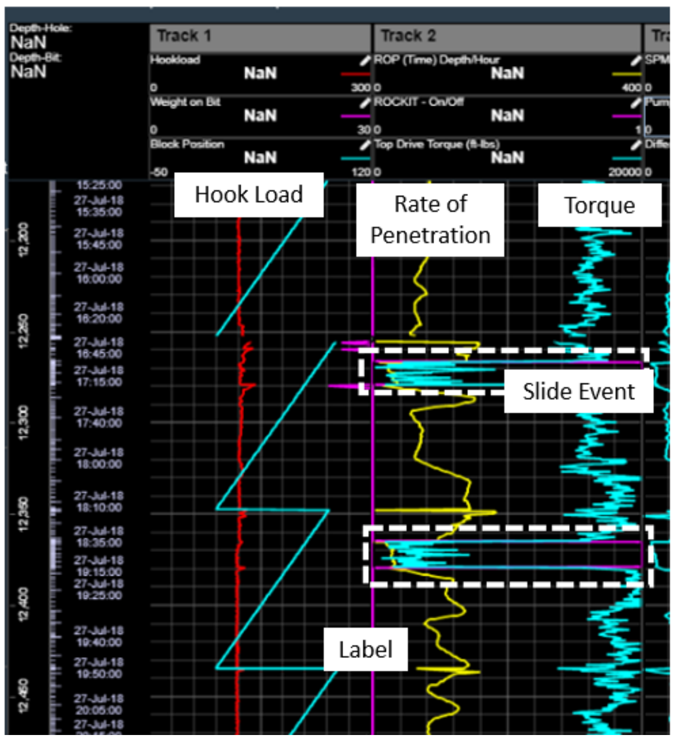

Fig. 4. MyWells Interface: A real time operational dashboard used while drilling. Drill operators use this information to control drilling operations and maintain optimal drilling parameters. The highlighted areas above shows how the rate of penetration drops significantly during a slide event.

4 Feature Selection

We applied a Decision Tree feature selection process to select the most relevant features. Ultimately our chosen features explained 97% of the variance. Table 1 describes features we used for analysis in our model.

A significant finding resulting from our feature selection process was the identification of relevant features that are controllable by drill operators. The concept of prescriptive versus predictive features is important for our problem at hand. Prescriptive features indicate features that can be used to change the classification outcome, whereas predictive features only indicate a possible classification. By identifying controllable (prescriptive) features that are relevant to the classification of slide events, we have identified a means to prevent or mitigate slide events.

We identified the following controllable features as relevant to our classification problem: TorqueDelta, TopDriveTorqueft_lbs, ADROPSetpointValue, RotaryRPM, PumpPressure, ROCKIT_RPMRW. These feature values all correspond to drill parameters that can be controlled by drill operators. Providing insight into these feature values allows drill operators to take preventative measures when an impending slide event is predicted. Thus, using insights from our model, drill operators can take actions to prevent or mitigate a slide event.

Table 1. Chosen Features for Analysis: Using decision tree feature selection combined with business domain knowledge, we were able to focus on ten features for analysis.

Variable	**Calculation/Description**
ROPMinuteDepth	Rate of penetration.
TorqueDelta	The twisting force that causes rotation.
Hookload	Total force pulling down on the hook. Includes the weight of the drillstring, drill collars, and any ancillary equipment.
BitRPM	Current rate of bit penetration.
TopDriveTorqueft_lb	Amount of torque generated from the top drive.
ADROPSetpointValue	The setpoint value entered on the HMI for ROP.
DepthHoleTVD	Position of the bit in terms of true vertical depth.
RotaryRPM	Rotation rate per minute.
PumpPressure	The pressure sensor is used to monitor mud pump pressure.
ROCKIT_RPMRW	RPM set point RockIT uses when correcting the quill position.

5 Metrics

Prior to discussing our model selection and results, a brief overview of the metrics we utilized is warranted. For our models, we focused on accuracy, precision, recall, and F1 scores as metrics to gauge the effectiveness of our models.

It is important to understand some key terms when describing the above metrics. All of the above metrics are measures of proportion when looking at true positives, true negatives, false positives, and false negatives. A true positive occurs when the predicted value is positive and the actual value is positive. Similarly, a true negative occurs when the predicted value is negative and the actual value is negative. Conversely, a false positive occurs when the predicted value is positive and the actual value is negative. A false negative occurs when the predicted value is negative and the actual value is positive. see Fig. 5 for an overview of these terms. A relevant result is a result where the actual value is positive (true positive or false negative).

Accuracy is the proportion of correctly predicted true outcomes in the dataset. Accuracy works well as a measure of model effectiveness when the dataset is well balanced. Accuracy be explained by the formula:

$Accuracy = (TruePositive + TrueNegative)/(TruePositive + FalsePositive + FalseNegative + TrueNegative)$

Precision is the proportion of true positives compared to all positive results returned by the model. This metric is useful for determining the percentage of your model prediction that is relevant. Precision is explained by the formula:

$Precision = (TruePositive)/(TruePositive + FalsePositive)$

Recall is the proportion of actual positives that are predicted correctly by the model. This metric indicates the percentage of total relevant results that are correctly predicted by the model. Recall is explained by the formula:

$Recall = (TruePositive)/(TruePositive + FalseNegative)$

F1 score takes both precision and recall into account (using their harmonic mean) and is another measure used to determine the effectiveness of a model. F1 score is explained by the formula:

$F1 = 2 * ((Precision * Recall)/(Precision + Recall))$

6 Support Vector Machine

Support Vector Machines are supervised learning models that are useful for classification and regression problems. A Support Vector Machine model assigns data points to one of two categories by training an optimal hyperplane, which is in essence a decision boundary [2].

We applied a Support Vector Machine model against the data using a Radial Basis Function kernel. With the Support Vector Machine model, we achieved an accuracy of 0.98966, precision of 0.97791, recall of 0.98811, and an F1 score of 0.98298.

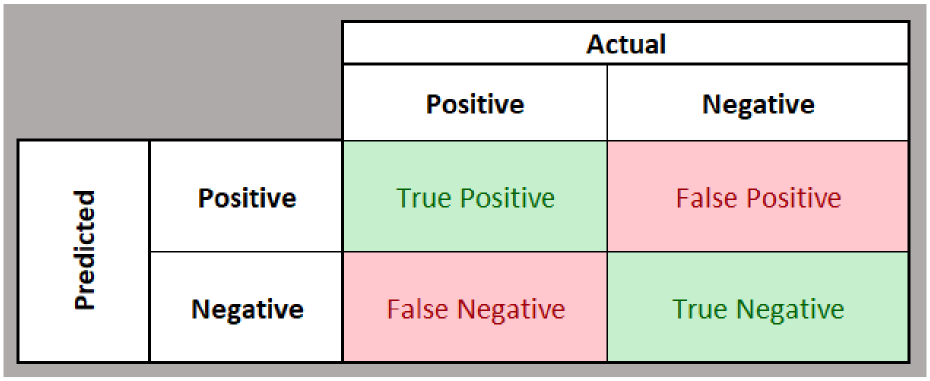

Fig. 5. Metric Terms: True Positives, True Negatives, False Positives, and False Negatives are all used when calculating accuracy, precision, recall, and F1 scores.

7 Random Forest

Random forest models employ an ensemble approach by using a collection of decision trees for classification [10]. The mean or mode classification result from the individual trees results in the overall classification for the model.

We applied Random Forest against the data using ten estimators. With the Random Forest model, we achieved an accuracy of 0.97823, precision of 0.97612, recall of 0.95127, and an F1 score of 0.96353.

8 Logistic Regression

A logistic regression model is useful when predicting a binary event such as true/false, 1/0, pass/fail, etc. [8]. This fit well with our problem at hand as we were predicting a binary outcome - sliding or not sliding.

We applied Logistic Regression against the data using a limited memory Broyden-Fletcher-Goldfarb-Shanno solver. With the Logistic Regression model, we achieved an accuracy of 0.98639, precision of 0.97685, recall of 0.97816, and an F1 score of 0.97751.

9 Analysis and Results

We used a combination of domain knowledge and data resampling techniques to optimize the size of our data for analysis. We struck a balance between accuracy and speed of analysis which is explained in the analysis subsection. Our results follow with a comparison of model performance metrics.

9.1 Analysis

Due to the size of the dataset, it is our decision to take samples of the data every ten seconds. This decision resulted in a dataset of 2.98 million records initially.

We decided to reduce the number of features to reduce the size of the dataset. We removed columns only containing NULL values or single values. In addition, we removed columns that contained less than 90% of filled values. These decisions reduced the feature count for initial analysis down to 122.

In addition, by utilizing industry specific business insight, we were able to further reduce the size of our dataset. Triple Crown Resources indicates records with an inclination value greater than or equal to 85 degrees are relevant to our problem domain. This inclination value indicates the record is related to the horizontal section of the well which is the focus of our problem statement. Removing records not meeting this criteria reduced our initial dataset to 725,000 records.

We additionally chose to experiment with data re-sampling to decrease the time required to run analysis. We attempted re-sampling rates of one minute, five minutes, and ten minutes. The results of this analysis are seen in Table 2. We experienced only minor drops in model performance at the one minute re-sampling rate. Across all the metrics used to gauge model performance, one-minute re-sampling only resulted in drops of 0.01 to 0.02. Re-sampling rates of five minutes and ten minutes resulted in significant decrease of model performance. As such, we decided to proceed with re-sampling of the data using a one minute re-sampling rate. This struck a good balance between speed and accuracy.

We performed exploratory data analysis on the original dataset as well as the reduced feature dataset. Fortunately, the data is populated well. Only two features have notable NA percentages. MWDContinuousInclination has an NA percentage of 3.25% and MWDGammaAPI has an NA percentage of 1.66%. These features turn out not to be a concern as they were excluded from our reduced feature dataset used for analysis.

With our reduced feature dataset, none of our features have NA values. However, we do have some issues with the feature distribution. ROPMinuteDepth, Depth_Bit, ADROPSetpointValue, and DepthHoleTVD are all right-skewed. Also, TopDriveTorqueCommand shows significant deviation from normality. Since we have a large sample size, the central limit theorem should come into play and the deviations from normality are not a concern.

9.2 Results

For predicting the very next data point, we achieved the best model performance (as determined by F1 score) with the Support Vector Machine model (see Table 3).

Using the Support Vector Machine model, our model only misclassified five events (see Fig. 6). It appears the model is misclassifying the beginning and end

Table 2. Re-sampling Metrics: Re-sampling rates of one minute, five minutes, and ten minutes were attempted. Notable decreases in model performance were experienced with five minute and ten minute re-sampling rates. However, a one minute re-sampling rate resulted in only minor decreases in model performance.

	Raw			
Model Type	**Accuracy**	**Precision**	**Recall**	**F1 Score**
Support Vector Machine	0.98966	0.97791	0.98811	0.98298
Logistic Regression	0.98639	0.97685	0.97816	0.97751
Random Forest	0.97823	0.97612	0.95127	0.96353
	1 Minute			
Support Vector Machine	0.98004	0.95853	0.96932	0.96389
Logistic Regression	0.97578	0.95408	0.95776	0.95591
Random Forest	0.95285	0.91211	0.91675	0.91443
	5 min			
Support Vector Machine	0.9241	0.86704	0.85674	0.86186
Logistic Regression	0.92081	0.86647	0.84346	0.85481
Random Forest	0.89532	0.86584	0.73515	0.79516
	10 min			
Logistic Regression	0.8622	0.7765	0.71409	0.74399
Random Forest	0.82009	0.75185	0.53491	0.62509
Support Vector Machine	0.86183	0.78947	0.69169	0.73735

Table 3. Model Results: The Support Vector Machine model performed the best as determined by F1 score. Logistic Regression was a close second while Random Forest performed the worst.

	Raw			
Model Type	**Accuracy**	**Precision**	**Recall**	**F1 Score**
Support Vector Machine	0.98966	0.97791	0.98811	0.98298
Logistic Regression	0.98639	0.97685	0.97816	0.97751
Random Forest	0.97823	0.97612	0.95127	0.96353

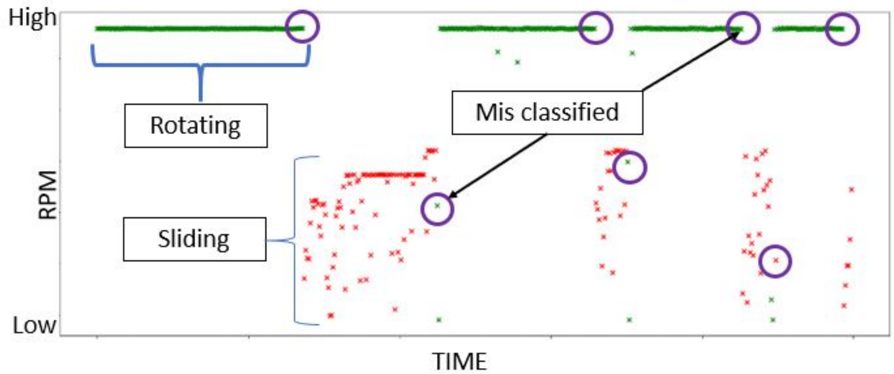

Fig. 6. Classification Results: Five events were misclassified using the Support Vector Machine model. It appears the model is misclassifying the beginning and end of a slide event.

of a slide event. Fortunately, this is not a major concern as we are interested in the overall duration of a slide event, not just the beginning or end.

When incorporating our future time-window predictions, we achieved 82% and 83% accuracy with Logistic Regression and Support Vector Machine models respectively at the ten-minute window. These accuracy scores dropped to 73% for both Logistic Regression and Support Vector Machine at the thirty-minute prediction as seen in Table 4. The Random Forest model performed the worst for all prediction time windows and thus was not a candidate for optimal model choice.

The most impactful result from our analysis is related to the features identified as relevant to our classification problem. In addition to determining predictive features, we were fortunate to have determined prescriptive features. Meaning, some of the relevant features for our model are attributes controllable by drill operators. In addition to being able to predict when a slide event will occur, our model gives drill operators the necessary information to modify drill parameters in order to mitigate or prevent a slide event.

10 Ethics

Creating a more efficient drilling program does allow for monetary gains for the industry, however the environmental impact cannot be ignored. Byproducts of drilling include large amounts of formation water that require treatment and cannot be used for irrigation due to chemical contamination. In addition, earthquakes have been on the increase in areas where fracking operations are conducted. Weighing the environmental costs against shareholder return is an ethical issue that must be discussed. The improved drilling efficiency our model brings could result in expanded drilling operations, and thus more environmental concerns.

Table 4. Future Prediction: Support Vector Machine performed the best at predicting future events with Logistic Regression a close second. Random Forest performed the worst at all time windows.

	30 minute future prediction			
Model Type	**Accuracy**	**Precision**	**Recall**	**F1 Score**
Support Vector Machine	0.725670466	0.528301887	0.0172653	0.033437827
Logistic Regression	0.725924671	0.569230769	0.01140743	0.022366631
Random Forest	0.674532898	0.296422487	0.134114383	0.184674167
	25 minute future prediction			
Support Vector Machine	0.726614133	0.53046595	0.045629721	0.084031228
Logistic Regression	0.724538214	0.492370295	0.07461076	0.129585007
Random Forest	0.669505169	0.345919325	0.227377833	0.27439308
	20 minute future prediction			
Support Vector Machine	0.74403728	0.622185612	0.174657006	0.272749157
Logistic Regression	0.738487609	0.552298468	0.255588099	0.349457266
Random Forest	0.720398221	0.481850305	0.231231694	0.3125
	15 minute future prediction			
Support Vector Machine	0.779547573	0.657037944	0.413750578	0.507756337
Logistic Regression	0.772049479	0.617860188	0.446893788	0.518651042
Random Forest	0.724646276	0.498332906	0.299522121	0.37415752
	10 minute future prediction			
Support Vector Machine	0.831871902	0.717820069	0.639586866	0.67644901
Logistic Regression	0.824713009	0.700940975	0.631570834	0.664450211
Random Forest	0.749565807	0.549339283	0.493448435	0.519896053

Additionally, our model brings the possibility of workforce displacement. The model we propose can potentially automate aspects of drilling operations that have traditionally been handled by field personnel. These field personnel currently bring their expertise and many years of experience to drill sites. They advise drill operators on the best way to set drill parameters based on formation conditions. Our model can be used by drill operators in real-time to optimally adjust drill parameters. Thus, the need for field personnel could be reduced by our model. This certainly results in ethical issues for consideration. Workforce re-training programs could be used to lessen the displacement impact.

11 Conclusion

Ultimately, we decided the Logistic Regression model was the optimal choice for our problem at hand. Although the Support Vector Machine model performed slightly better (2% greater accuracy), the Logistic Regression model ran much quicker making it easier to deploy in a business setting.

By identifying controllable features as part of the classification model, we have demonstrated a viable means for mitigating slide events.

References

1. Charles H. King, Mitchell D. Pinckard, D.P.S.A.O.D.W.: Method of and system for monitoring drilling parameters. (11 2000), http://patft.uspto.gov, patent Number - 6,152,246
2. Gandhi, R.: Support vector machine — introduction to machine learning algorithms. Towards Data Science (6 2018), https://towardsdatascience.com/support-vector-machine-introduction-to-machine-learning-algorithms-934a444fca47, accessed 10 December 2019
3. Ma, T., Chen, P., Zhao, J.: Overview on vertical and directional drilling technologies for the exploration and exploitation of deep petroleum resources. Geomechanics and Geophysics for Geo-Energy and Geo-Resources **2**(4), 365–395 (Dec 2016). https://doi.org/10.1007/s40948-016-0038-y, https://doi.org/10.1007/s40948-016-0038-y
4. Mohammadpoor, M., Torabi, F.: Big data analytics in oil and gas industry: An emerging trend. Petroleum (2018). https://doi.org/https://doi.org/10.1016/j.petlm.2018.11.001, http://www.sciencedirect.com/science/article/pii/S2405656118301421
5. Rapier, R.: Fracking has been around since 1949, why the recent controversy? Global Energy Initiative (12 2014), globalenergyinitiative.org/insights/58-fracking-has-been-around-since-1949-why, accessed 3 June 2019
6. Rapier, R.: The permian basin is now the world's top oil producer. Forbes (4 2019), https://www.forbes.com/sites/rrapier/2019/04/05/the-permian-basin-is-now-the-worlds-top-oil-producer/#6534487d3eff, accessed 8 July 2019
7. Sepmstrata.org: Permian basin tectonics - SEPM strata. SEPM Strata (2019), http://www.sepmstrata.org/page.aspx?pageid=137, accessed 8 July 2019
8. Swaminathan, S.: Logistic regression — detailed overview. Towards Data Science (3 2018), https://towardsdatascience.com/logistic-regression-detailed-overview-46c4da4303bc, accessed 10 December 2019

9. Tang, C.M.: Permian basin. Encyclopedia Britannica (5 2015), www.britannica.com/place/Permian-Basin, accessed 3 June 2019
10. Yiu, T.: Understanding random forest. Towards Data Science (6 2019), https://towardsdatascience.com/understanding-random-forest-58381e0602d2, accessed 10 December 2019