SPE-198288-MS
Using Machine Learning to Identify Coal Pay Zones from Drilling and Logging-while-Drilling (LWD) Data

Ruizhi Zhong, The University of Queensland
Raymond L. Johnson Jr, The University of Queensland
Zhongwei Chen, The University of Queensland

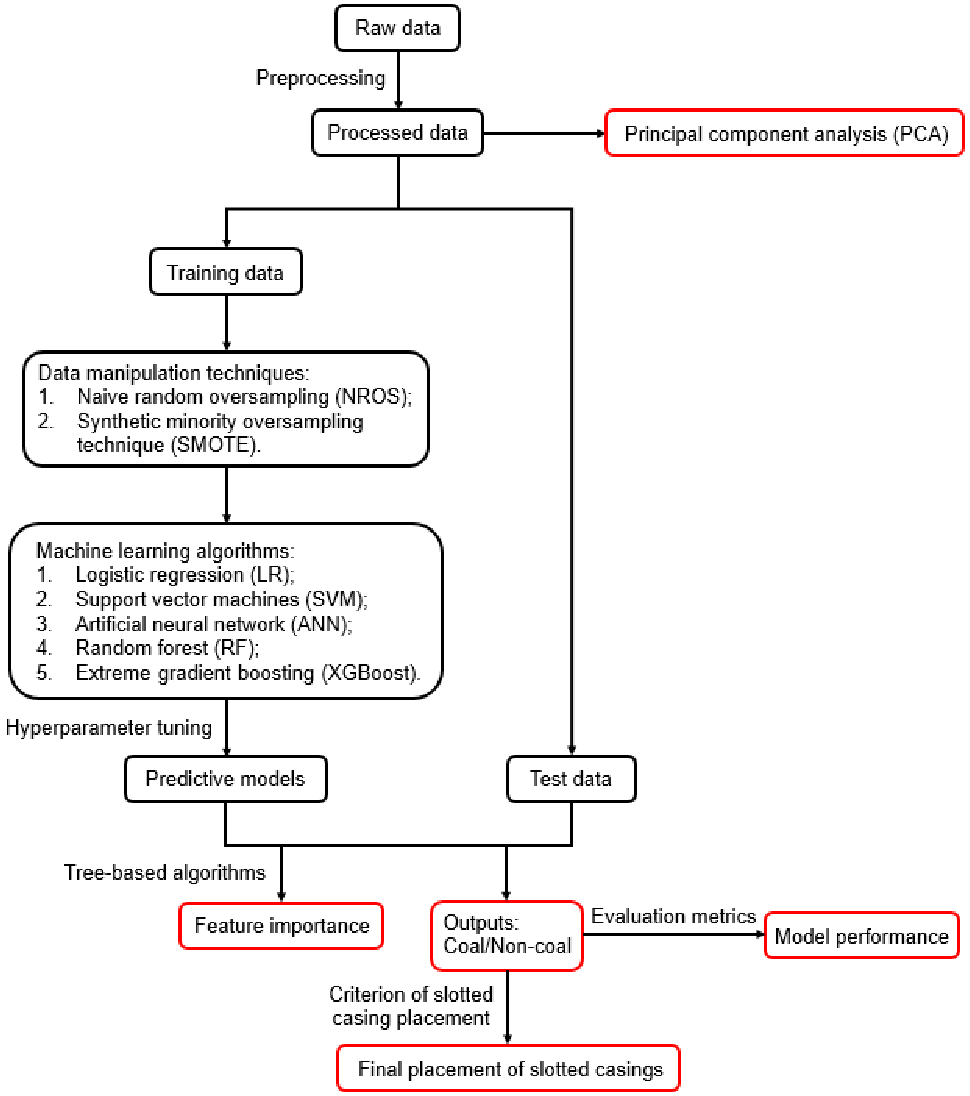
Research Challenge

Can we identify coal pay zones quickly and reduce costs?

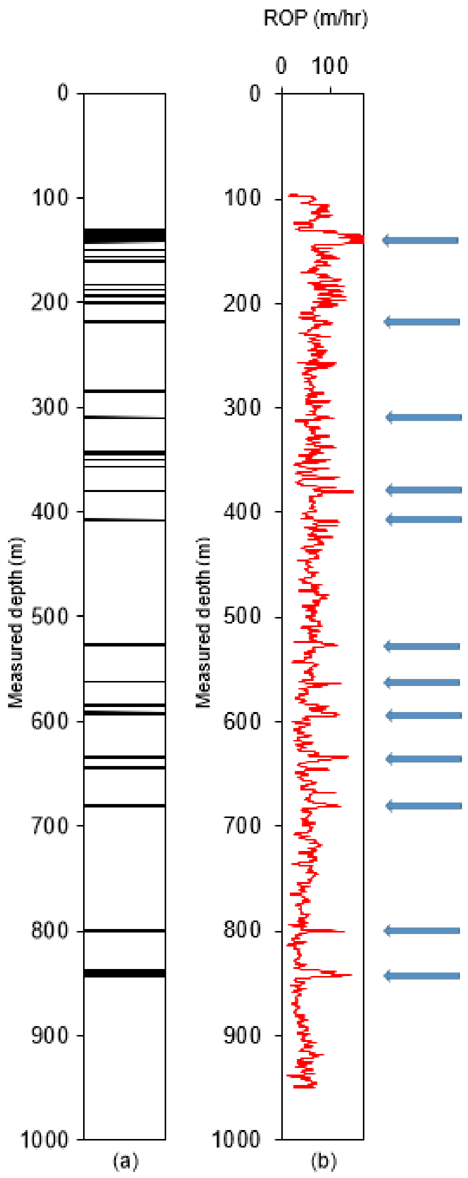
Method	Disadvantages
Well logging	Expensive (tool and rig time) Acquired on a few wells Potential logging failure (especially in deviated and horizontal sections)
Laboratory tests (or coring)	Scale effects Time/resource intensive Require lab & quality samples

Machine learning provides the opportunity to obtain rock properties using drilling data – fast, accurate, and low-cost.

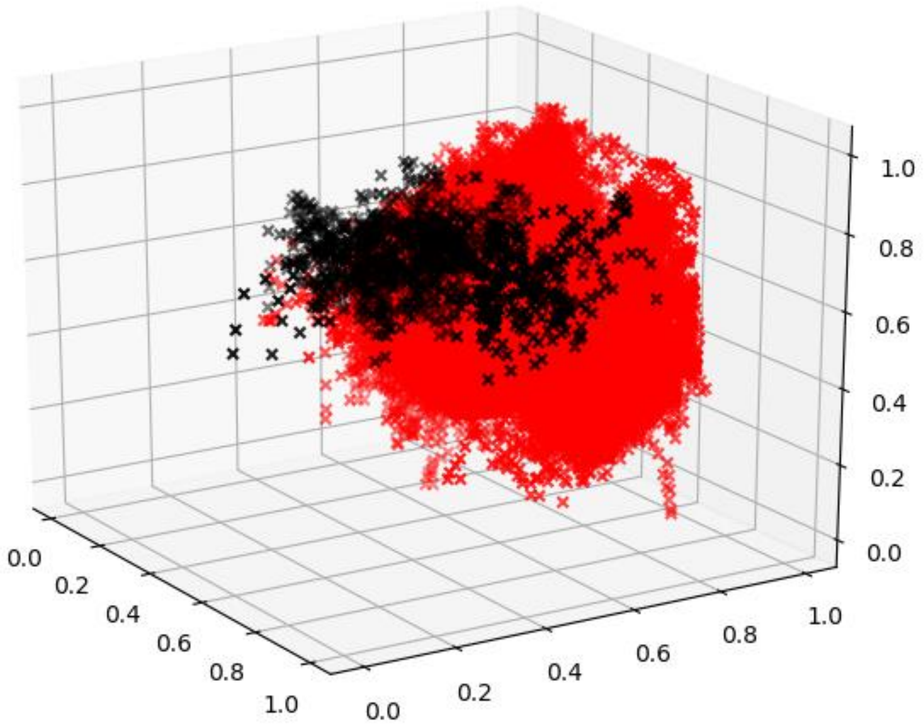
Project Workflow



Correlations Between Inputs and Output



(a) Coal zones based on the density log (bulk density<1.8 g/cc). Black sections are coal zones.
(b) ROP curve with noted peaks. (ROP: rate of penetration).



3D view of Principal Component Analysis.
Black dots: coal zone samples and
Red dots: non-coal zone samples.

Machine Learning Algorithms

Algorithm	Strengths	Weaknesses
LR	1. Robust to noise; 2. Good interpretability because the output is the probability.	1. Requires data preparation; 2. Handles only linear decision boundaries.
SVM	1. Works well in complicated domains; 2. Works well with outliers.	1. Requires data preparation; 2. Kernel selection can be hard; 3. Poor performance and long computation time if the dataset is large and noisy.
ANN	1. Robust to noise and missing values; 2. Good performance on some tasks such as image and text recognition.	1. Lack of interpretability; 2. Requires data preparation; 3. Computationally expensive.
RF	1. No effort for data preparation; 2. Able to rank feature importance; 3. Works well in high dimensional spaces.	1. Lack of interpretability if tree quantity is large; 2. May overfit if data is noisy.
XGBoost	1. No effort for data preparation; 2. Able to rank feature importance; 3. State-of-art accuracy in many regression and classification problems.	1. Lack of interpretability; 2. Poor performance on some tasks such as image and text recognition.

Strengths and weaknesses of used machine learning algorithms.

LR: logistic regression
SVM: support vector machines
ANN: artificial neural network
RF: random forest
XGBoost: extreme gradient boosting

Data Manipulation Techniques

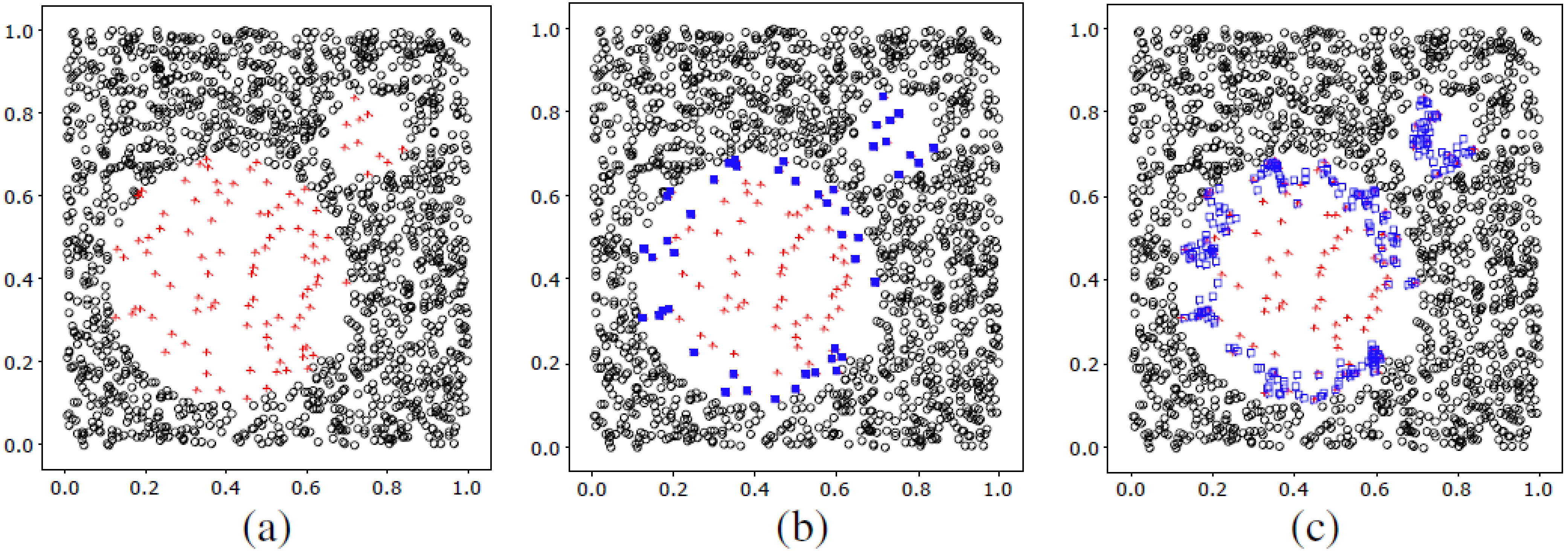
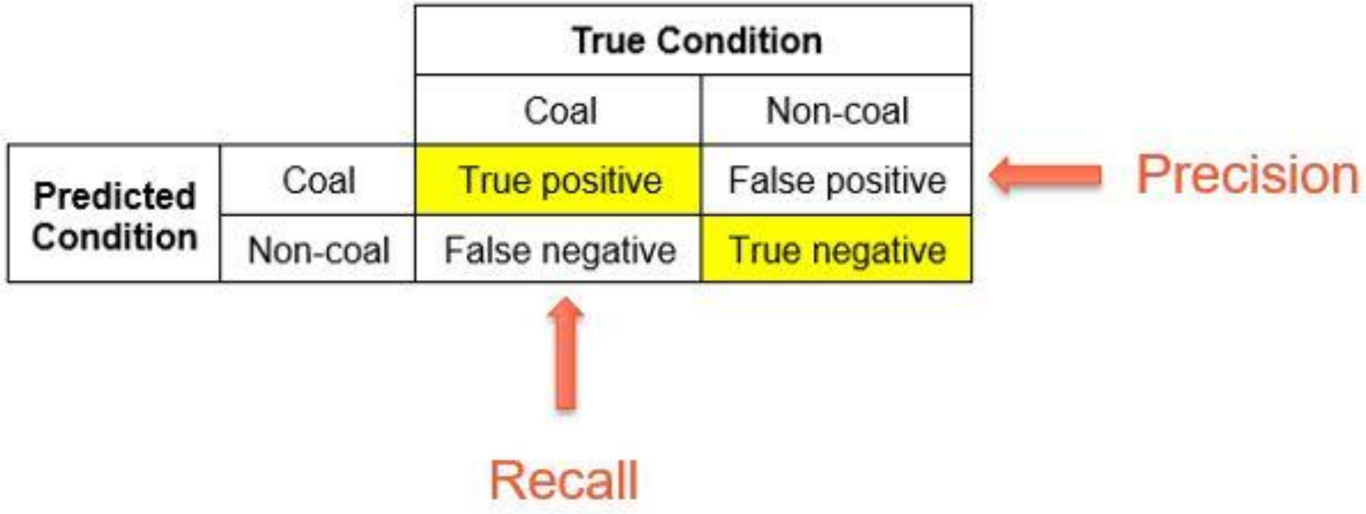


Diagram of borderline synthetic minority oversampling technique (SMOTE) (Han et al. 2005).
(a) The original distribution of circle data set.
(b) Selection of borderline minority samples (blue solid squares).
(c) Generation of borderline synthetic minority examples (blue hollow squares)

Evaluation Metrics



Precision = $\frac{\text{Ture positve}}{\text{True positive}+\text{False positive}}$

In all predicted coal sections, the percentage of true coal in these sections.

Recall = $\frac{\text{Ture positve}}{\text{True positive}+\text{False negative}}$

In all true coal sections, the percentage of predicted coal from the model.

F1 Score = 2 $\frac{\text{Precision}\cdot\text{Recall}}{\text{Precision}+\text{Recall}}$

Model accuracy that considers both the precision and recall.

Well Information

1. Dataset from six wells in the Surat Basin, Australia.
2. The measured depth (MD) of these wells is up to 1000 m and true vertical depth (TVD) is up to around 500 m.
3. These wells are drilled in the same pad with final inclinations about 70° .

Well No.	TVD (m)	MD (m)	Number of samples
1	95.9-478.0	96.1-950.5	8510
2	184.5-483.6	190.1-950.7	7607
3	97.7-495.0	98.0-949.9	8520
4	99.6-346.5	99.8-480.4	14159
5	363.3-510.2	544.4-1009.1	4523
6	274.1-444.5	290.0-744.7	4532

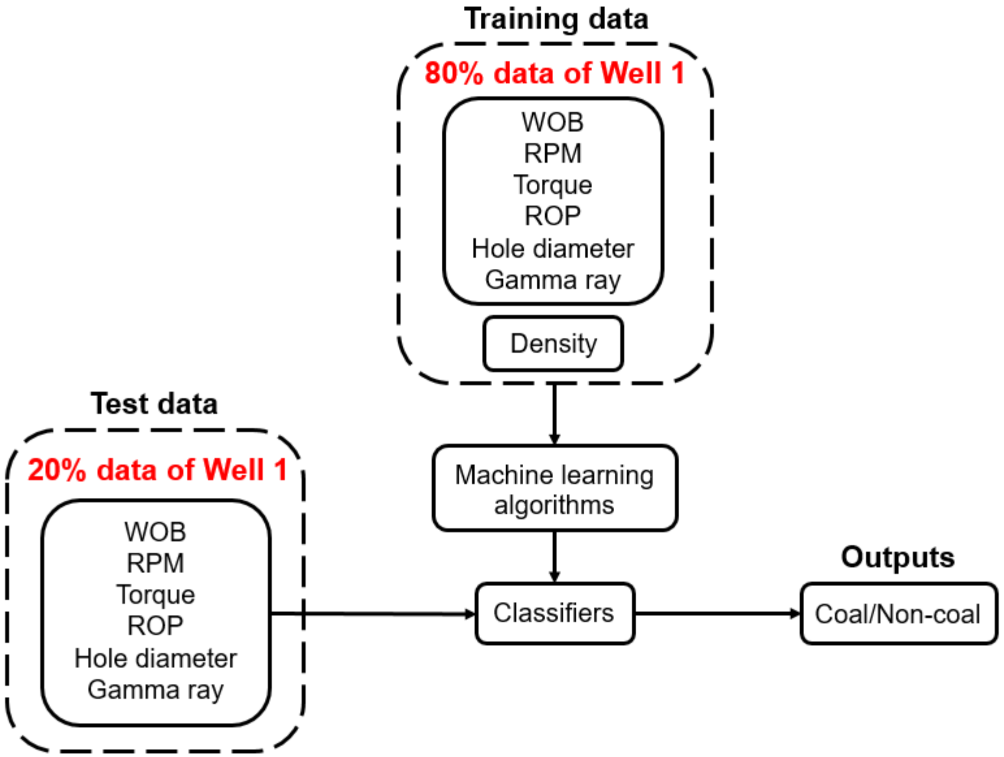
Summary of study wells

Parameter	Min	Max	Average
WOB (klbf)	-8.124	22.532	8.726
RPM (r/min)	-37.457	74.891	41.702
Torque (ft.lbf)	-966.072	13730.05	5682.719
ROP (m/hr)	11.618	233.478	61.795
Diameter (in.)	8.435	19.319	9.545
Gamma ray (API)	19.86	108.864	63.238

Summary of input data from Well 1

Single Well Experiments

Single well experiment suits for only one well is drilled and some drilled sections have poor or missing logs to identify coal pay zones.

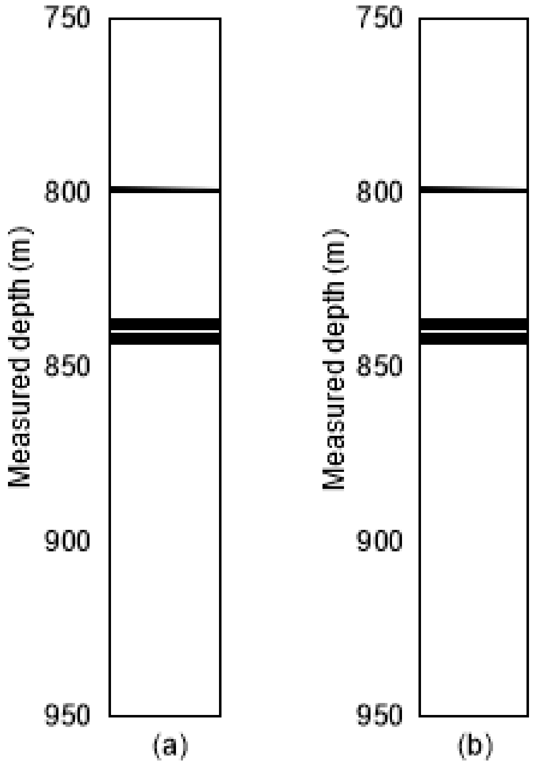


Flowchart of the numerical experiment for single well experiment.

Model	Precision	Recall	F1 Score
LR	0.78	0.48	0.59
LR+NROS	0.33	0.91	0.49
LR+SMOTE	0.35	0.9	0.5
SVM	0.82	0.56	0.66
SVM+NROS	0.43	0.96	0.6
SVM+SMOTE	0.44	0.94	0.6
ANN	0.83	0.58	0.67
ANN+NORS	0.53	0.95	0.68
ANN+SMOTE	0.5	0.94	0.65
RF	0.84	0.61	0.7
RF+NROS	0.42	0.91	0.58
RF+SMOTE	0.43	0.93	0.59
XGBoost	0.72	0.8	0.75

Results of coal prediction performance for single well experiments (Well 1).

Results of Single Well Experiments

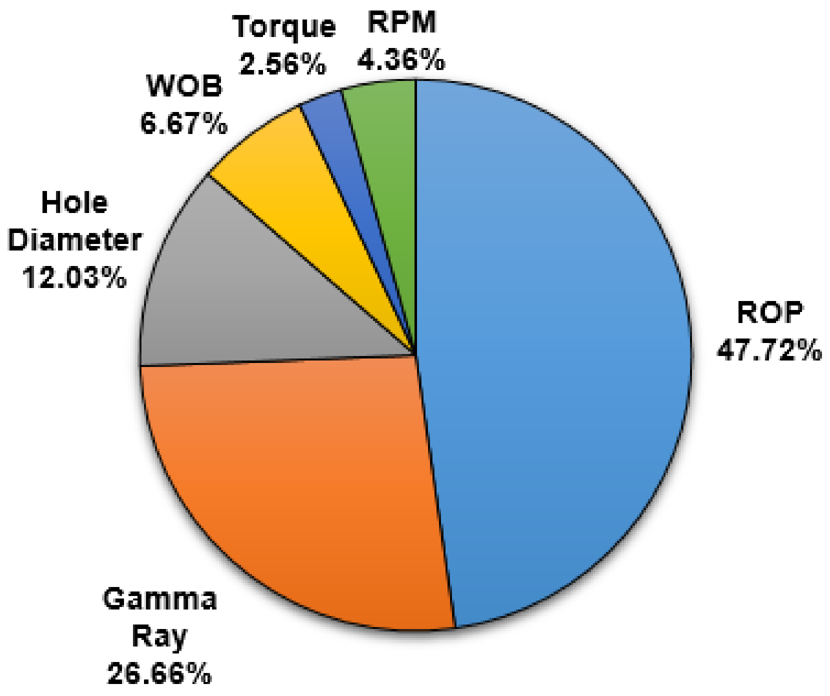


Results of the test section (780.4 m-950.5 m) in Well 1 using random forest.
(a) Coal zones determined by density log.
(b) Coal zones determined by random forest.

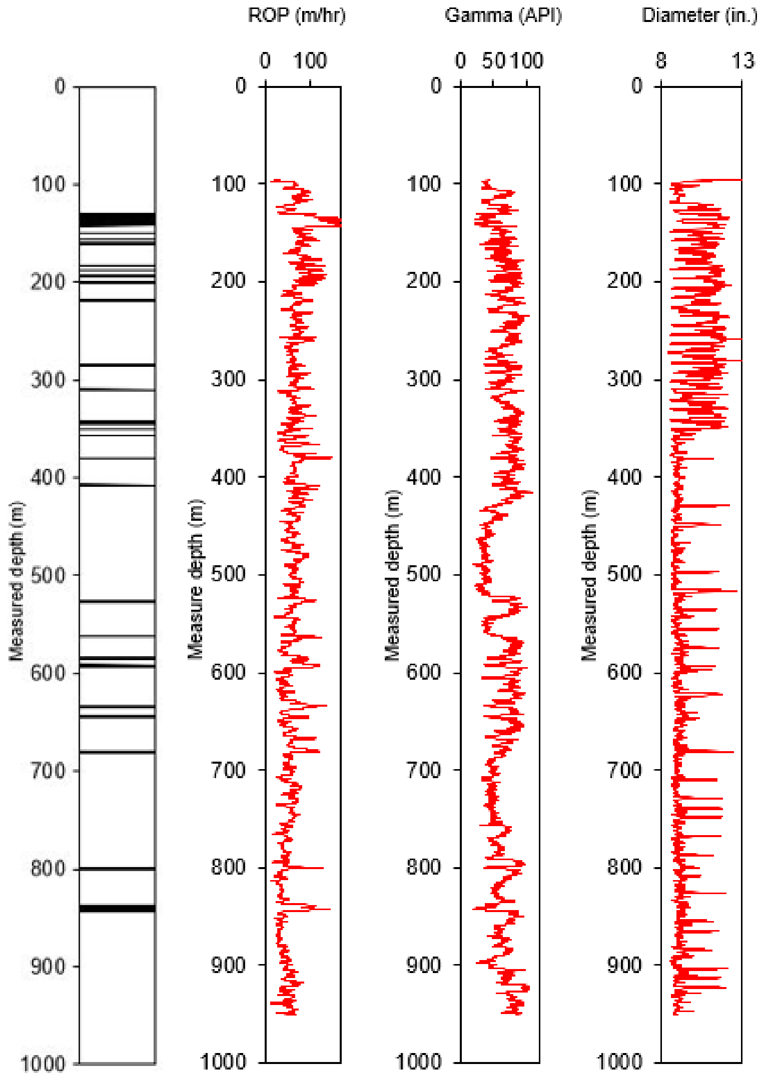
		True Condition	
		Coal	Non-coal
Predicted Condition	Coal	51	7
	Non-coal	13	1630

Confusion matrix of random forest experiment in Well 1.

Results of Single Well Experiments



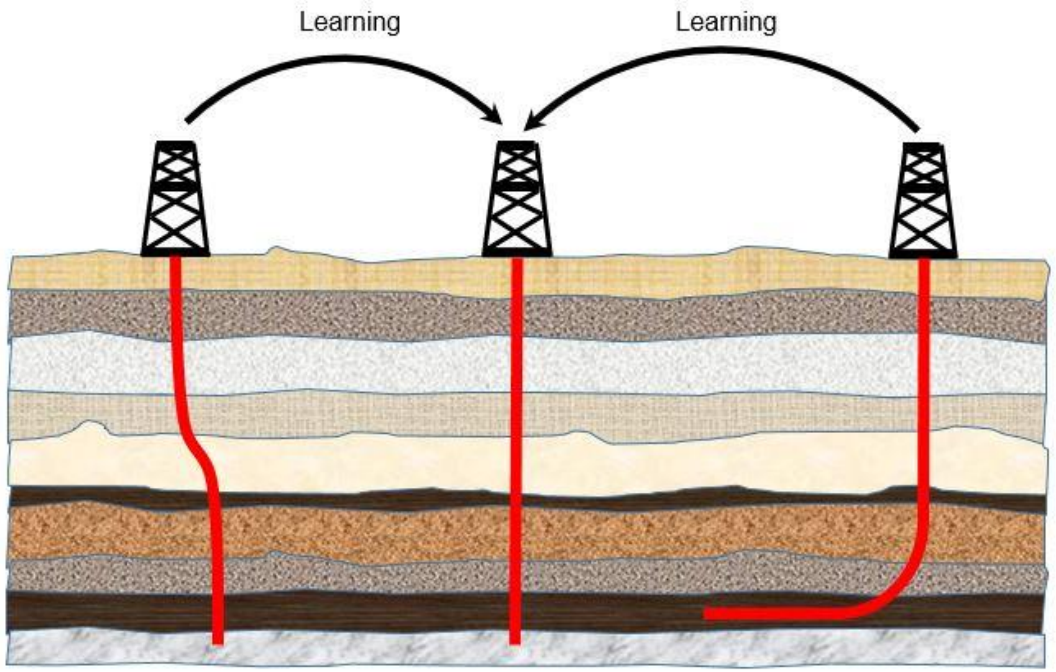
Feature importance of single well experiment in Well 1 based on random forests. (ROP: rate of penetration; RPM: rotations per minute; WOB: weight on bit).



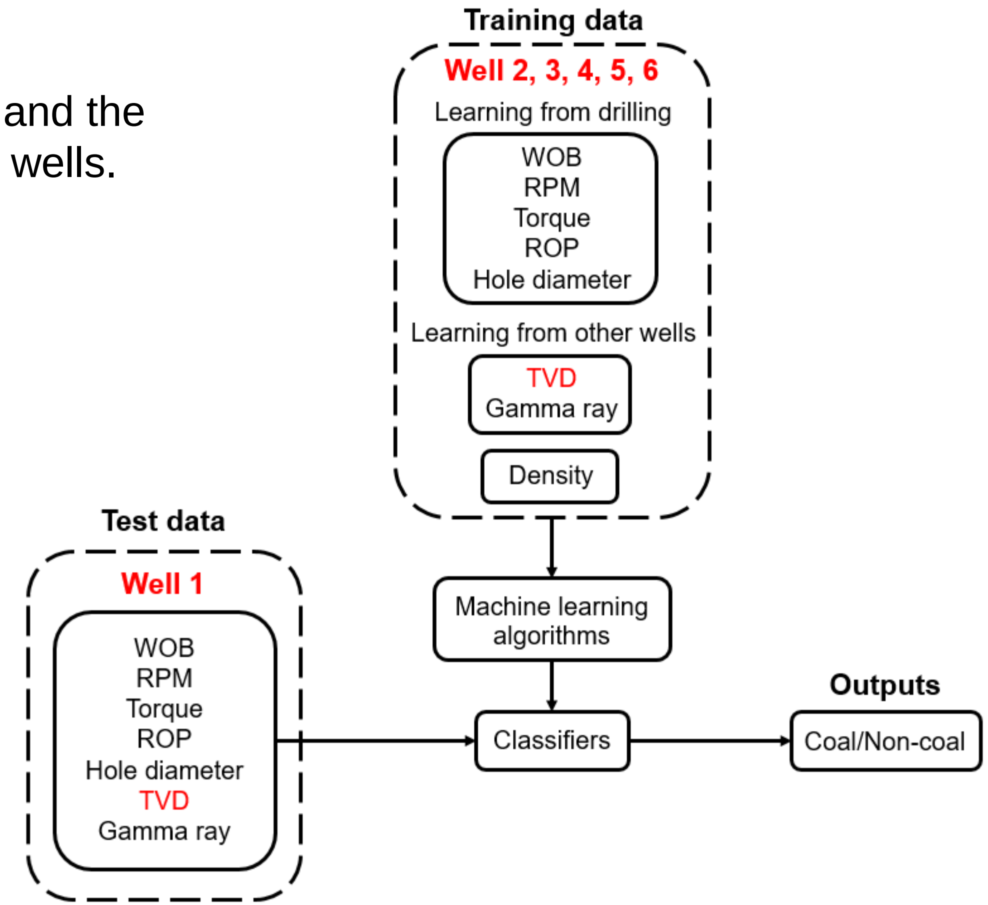
Comparison of coal zones and important input logs (ROP, gamma ray, and hole diameter) in Well 1.

Multiple Well Experiments

Multiple well experiment suits for some wells have already been drilled and the data from these old wells can be used to predict coal pay zones in new wells.

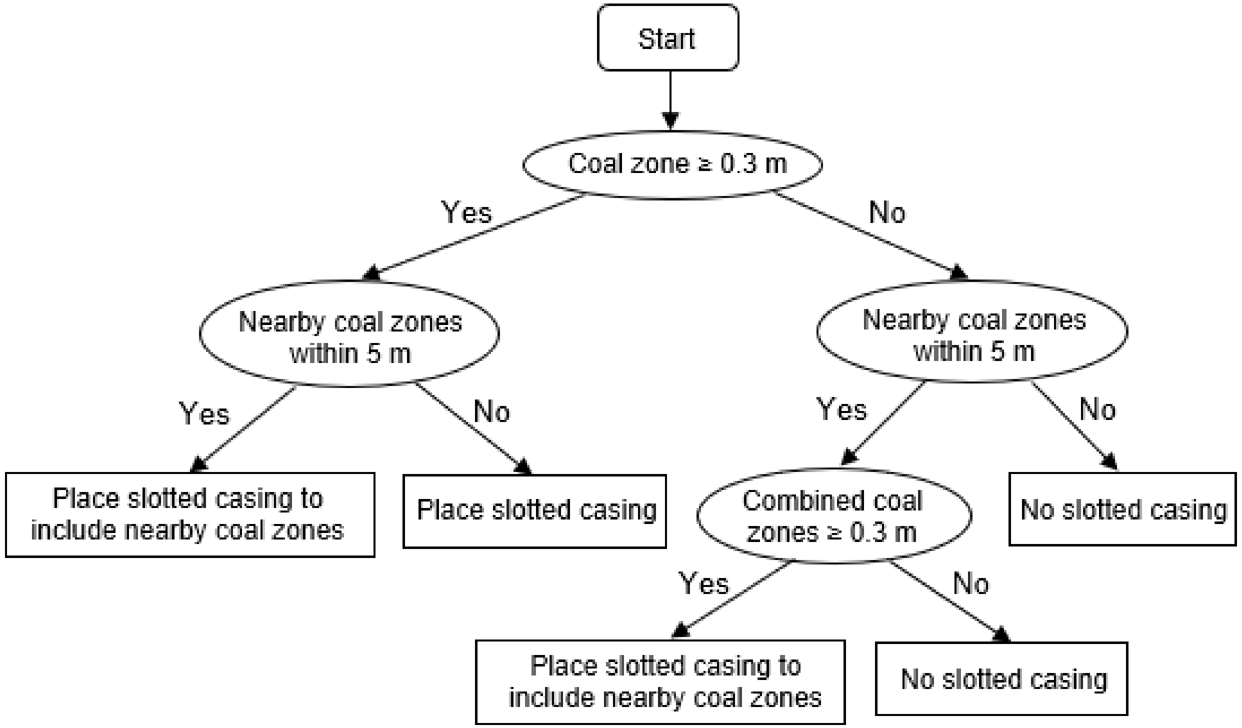


Schematic of learning from other wells



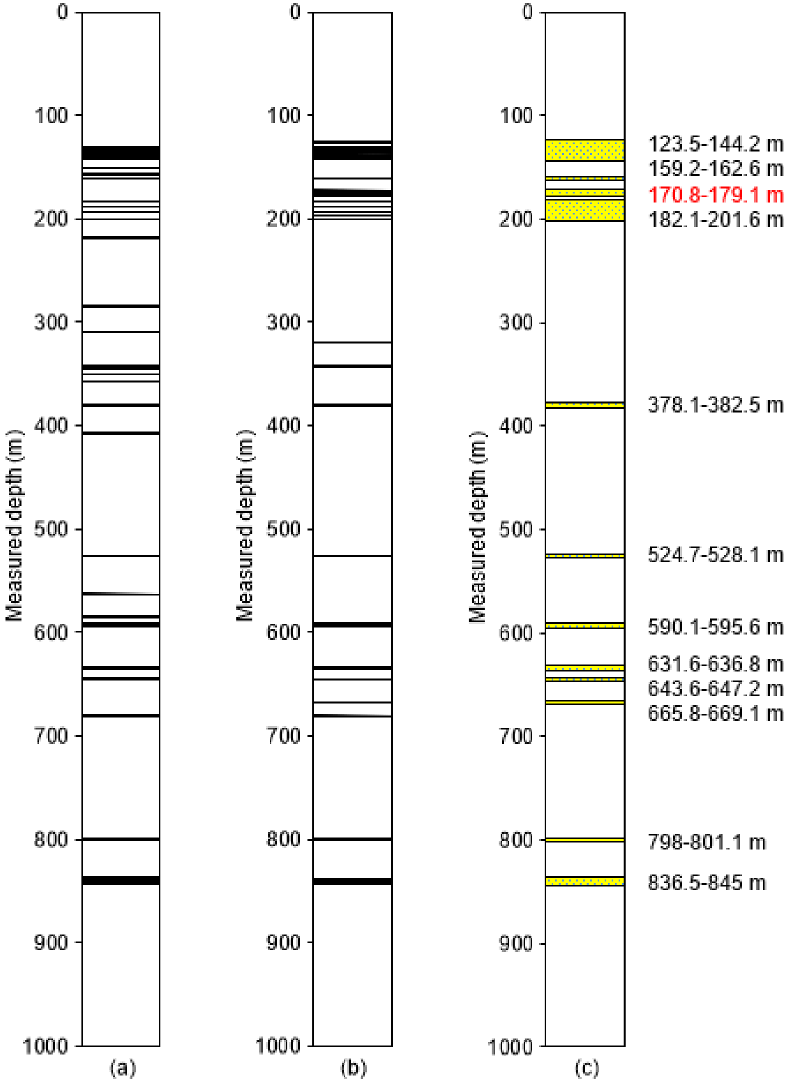
Flowchart of machine learning for coal identification in Well 1 using multiple wells

Flowchart of Slotted Casing Placement



$$\text{Coal identification rate} = \frac{\text{Predicted coals covered by slotted casing}}{\text{Coals from the density log}}$$

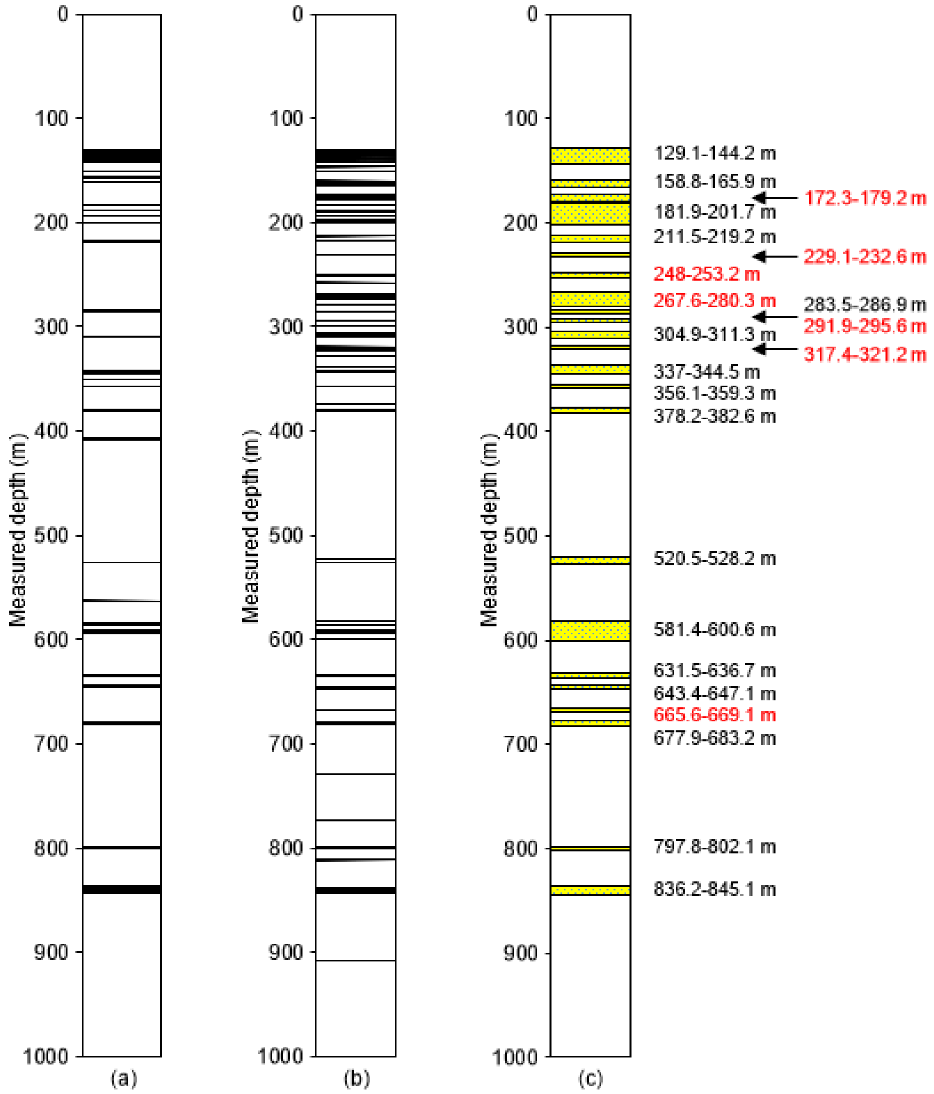
Results of Multiple Well Experiments



Coal zones and slotting casing placement for Well 1 using XGBoost (precision: 0.67, recall: 0.69, and F1 score: 0.68).

(a) Coal zones based on the density log.
(b) Coal zones determined by XGBoost.
(c) Slotted casing placement based on results of XGBoost. The coal identification rate after slotted casing placement is 83%.

Results of Multiple Well Experiments



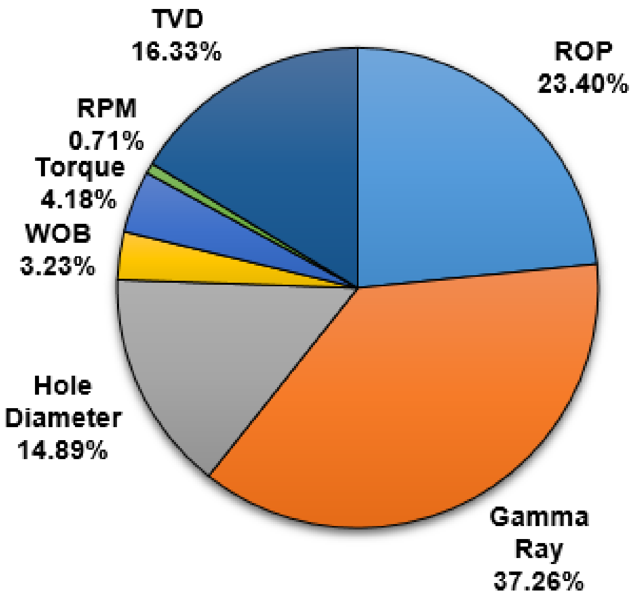
Coal zones and slotting casing placement for Well 1 using ANN with SMOTE (precision: 0.52, recall: 0.79, and F1 score: 0.63).

(a) Coal zones based on the density log.
(b) Coal zones determined by ANN with SMOTE.
(c) Slotted casing placement based on results of ANN with SMOTE. The coal identification rate is 94.7%.

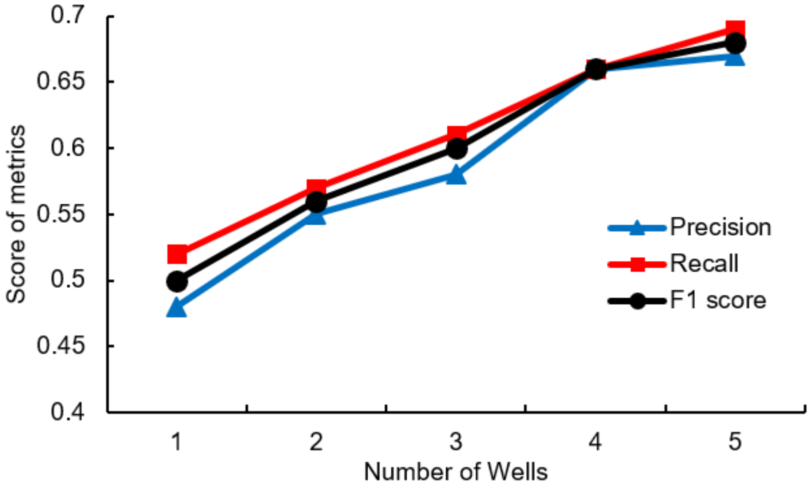
Results of Multiple Well Experiments

Well No.	Coal identification rate	Method
1	94.7%	ANN with SMOTE
2	100%	RF with NROS
3	97.7%	ANN with NROS
4	91.7%	ANN with SMOTE
5	99%	ANN with NROS
6	99.2%	ANN with NROS

The coal identification rate for all wells



Feature importance for multiple well experiments (Well 1) based on random forests with SMOTE.
ROP: rate of penetration;
RPM: rotations per minute;
TVD: true vertical depth;
WOB: weight on bit.



Scores of metrics vs. number of wells used in XGBoost training.

Conclusions

1. The 3D PCA using drilling and LWD data shows that coal zone samples can be separated from non-coal zone samples, serving as the basis of using machine learning to identify coal zones.

2. Experiments using original machine learning algorithms (LR, SVM, ANN, and RF) have high precision and low recall on coal prediction. When coupled with data manipulation techniques (NROS or SMOTE), results show low precision and high recall. XGBoost can adjust the scale-pos-weight to have balanced or unbalanced precision and recall.

3. A criterion of slotting casing placement is developed. For multiple well experiments, the coal identification rate for all six wells is over 90% with three wells over 99%.

Conclusions

4. High ROP, low gamma ray and large hole diameter are strong indicators of coal zones. TVD is another important feature for multiple well experiments.

5. Data quantity is very important to achieve good results from machine learning experiments.

6. For single well experiments, either XGBoost or SVM/ANN/RF with NROS/SMOTE works well. For multiple well experiments, ANN/RF with NROS/SMOTE is recommended.

Acknowledgements / Thank You / Questions

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