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ACSE-9

10th, SEP, 2019

Application of Machine Learning to Achieve Robust and Accurate Classification of Well Log Data

MASTER INDEPENDENT RESEARCH PROJECT

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▪ Acknowledgments

With many thanks to my supervisors, Dr. Gerard Gorman, Dr. Navjot Kukreja, and Dr. Peter Fitch, for their extensive support and guidance throughout this project.

Introduction

- Dataset
- Limitations

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▪ Introduction

▪ **Well log:**

(a form of geoscience recording data)

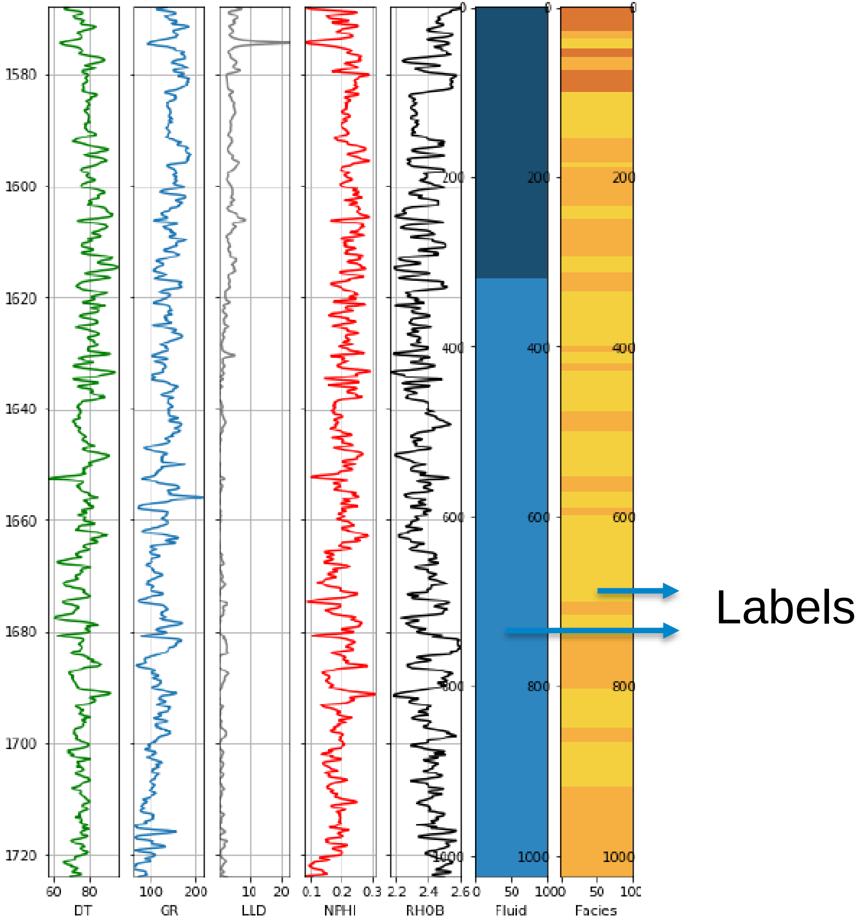

Figure 2: Example of well logs data from one well(1K-01) with three different label schemes (Fluid: Fluid scheme; Facies: Log_Facies scheme; MixLabel: MixedLabel scheme) (*Implementation Code*).

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Introduction (Input Features)

9 input features

Names	Units	Meanings
Depth	m	Depth down the borehole;
CALI	inches	How wide the borehole is;
DT	sec/ft	P-wave Transit Time (or sonic log);
GR	API	Gamma Ray;
LLD	ohm.m	Deep Resistivity;
LLS	ohm.m	Shallow Resistivity;
MSFL	ohm.m	Micro Resistivity;
NPHI	pu (porosity units)	Neutron Porosity;
RHOB	g/cm^3	Bulk Density;

Table 2: Nine input features with their meanings.

Introduction (Input Features)

6 common input features

Names	Units	Meanings
Depth	m	Depth down the borehole;
CALI	inches	How wide the borehole is;
~~DT~~	~~sec/ft~~	~~P-wave Transit Time (or sonic log);~~
GR	API	Gamma Ray;
LLD	ohm.m	Deep Resistivity;
~~LLS~~	~~ohm.m~~	~~Shallow Resistivity;~~
~~MSFL~~	~~ohm.m~~	~~Micro Resistivity;~~
NPHI	pu (porosity units)	Neutron Porosity;
RHOB	g/cm^3	Bulk Density;

Table 2: Nine input features with their meanings.

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▪ Introduction (Label Schemes)

Scheme Names	Meanings
Log_Facies (Scheme)	These exist for the five wells predicted by the geologist so that they can predict facies in the un-cored well based on the log signature; 3 categories; (1: channel sandstone) (2: floodplain mudstone) (3: lacustrine and paleosol mud)
Fluid (Scheme)	These exist for the five wells predicted by the geologist; 2 categories; (1: in the hydrocarbon-bearing zone) The mixture of hydrocarbon and formation water; (2: in the water-bearing zone) Only formation water;
MixedLabel (Scheme)	These exist for the five wells Mixed by the prediction of Log_Facies and Fluid by the geologist; 5 categories; (1: - Log_Facies 1 & Fluid 1) (2: - Log_Facies 1 & Fluid 2) (3: - Log_Facies 2 & Fluid 1) (4: - Log_Facies 2 & Fluid 2) (5: - Log_Facies 3 & Fluid 1) Noticeably, there is always 5 categories in this MixedLable scheme since there is no Log_Facies 3 & Fluid 2 categories throw all of our data;

Table 3: Original schemes and mixed label schemes.

- ❑ Focus more on Log_Facies
- ❑ Fluid is too easy to be classified
- ❑ MixedLabel (5 classes)

To check whether it could have good performance or not.

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Introduction (wells locations)

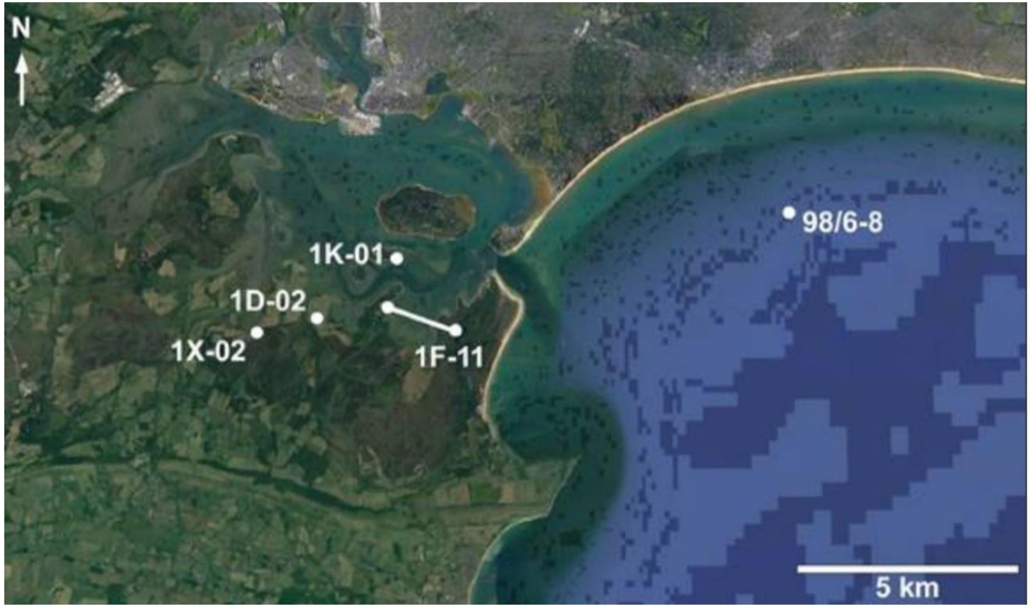

Figure 1: The locations of all five wells in Wytch Farm (Reference to Fitch, 2019).

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Introduction (Limitations)

- Five labelled wells with total 4695 data points.
- Different geologists might come up with different labelling schemes on well log data.
- Input features are different for different dataset.
- Cannot apply the same hyperparameters.
- Cannot simply compare the accuracy across data sets !

- Find **standard workflow** with basic machine learning methods.
- Find **solution** for companies with limited training data.

1. Supervised learning

Approach and evaluation

(1) Inputs Features Selection
(Logistic Regression)

(2) Training and Testing
(Logistic Regression)

(3) Our Proposed Data Augmentation Method
(Logistic Regression & Support Vector Machines)

(4) Setting Threshold Prediction Rate
(Logistic Regression)

2. Unsupervised Learning

Approaches and Evaluation

(1) Qualitative Evaluation by PCA and t-SNE

(2) Quantitative Evaluation with K-means Clustering

▪ 1. Supervised learning

(1) Inputs Features Selection

(2) Training and Testing

(3) Our Proposed Data Augmentation Method

(4) Setting Threshold Prediction Rate

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▪ 1. Supervised learning

(1) Inputs Features Selection (Logistic Regression)

Should we include all the input features?
Should we include Depth?

1. Supervised learning Approach and evaluation

- **(1) Inputs Features Selection (Control Variables)**

	Fluid	Log_Facies	MixedLabel
Accuracy with all features	0.95	0.82	0.78
Accuracy without 'DEPTH'	0.94	0.81	0.78
Accuracy without DT	0.94	0.81	0.79
Accuracy without GR	0.94	0.81	0.77
Accuracy without LLD	0.82	0.81	0.67
Accuracy without NPHI	0.95	0.75	0.73
Accuracy without RHOB	0.95	0.68	0.68

Table 5: Multi wells accuracy of logistic regression with cross validation method (*Implementation Code*).

- (Multi- wells)
- (All Labels)

1. Supervised learning Approach and evaluation

- **(1) Inputs Features Selection (Weights)**

	DEPTH	DT	GR	LLD	NPHI	RHOB
Class-1 weights	0.3626	-0.1178	-0.0185	-0.1905	-2.6303	-4.0262
Class-2 weights	-0.0963	-0.0890	-0.2362	-0.0651	1.2637	1.9491
Class-3 weights	-0.9516	0.1216	1.1952	0.6124	0.4884	1.4670
L1-norm	1.4105	0.3284	1.4499	0.8680	4.3824	7.4423

- (Multi- wells)
- (Log_Facies)

Table 8: The weights and its L1-norm of logistic regression for all the wells in our dataset with 6 common inputs features throughout our data set. The feature weights with the largest two L1-norm are marked as red (*Implementation Code*).

1. Supervised learning Approach and evaluation

- **(1) Inputs Features Selection (Weights)**

	DEPTH	DT	GR	LLD	NPHI	RHOB
Class-1 weights	-1.0054	0.2752	-0.3944	0.9254	-1.2766	-3.7828
Class-2 weights	0.7984	-0.4165	0.1919	-0.7669	0.1980	1.8236
Class-3 weights	-0.4231	1.203	0.5706	0.0095	0.4360	1.1768
L1-norm	2.2269	1.8947	1.1569	1.7018	1.9106	6.7832

- (Single- well)
- (Log_Facies)

Table 7: The weights and its L1-norm of logistic regression for well 1K-01 with 6 common inputs features throughout dataset 1. The feature weights with the largest two L1-norm are marked as red (*Implementation Code*).

1. Supervised learning Approach and evaluation

- **(1) Inputs Features Selection (Control Variables)**

	Log_Facies
Accuracy with All Features	0.06
Accuracy without 'DEPTH'	0.55
Accuracy without 'DT'	0.33
Accuracy without 'GR'	0.06
Accuracy without 'LLD'	0.06
Accuracy without 'NPHI'	0.07
Accuracy without 'RHOB'	0.06

- (one well for training one well for testing)
- (Log_Facies)

WHY? --- limited training data --- Depth is dominating

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1. Supervised learning Approach and evaluation

- **(1) Inputs Features Selection (Control Variables)**

Highest accuracy

More Robust

Depth is no longer dominating

	Fluid	Log_Facies	MixedLabel
Accuracy with all features	0.95	0.82	0.78
Accuracy without 'DEPTH'	0.94	0.81	0.78
Accuracy without DT	0.94	0.81	0.79
Accuracy without GR	0.94	0.81	0.77
Accuracy without LLD	0.82	0.81	0.67
Accuracy without NPHI	0.95	0.75	0.73
Accuracy without RHOB	0.95	0.68	0.68

Table 5: Multi wells accuracy of logistic regression with cross validation method (*Implementation Code*).

- **(Multi- wells)**
- (All Labels)

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▪ 1. Supervised learning

(2) Training and Testing (Logistic regression)

What data splitting method should we use?

- **(2) Training and Testing**

(1: Single well – Cross-validation)

The data from a single well in our data set are randomly split with 90 percent used as the training set and 10 percent used as the testing set. The accuracy is obtained from averaging results from 10 independent trials.

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1. Supervised learning Approach and evaluation

- ## (2) Training and Testing

(2: Multi wells – Cross-validation)

The data from all the wells in our data set are randomly split with 90 percent used as the training set and 10 percent used as the testing set. The accuracy is obtained from averaging results from 10 independent trials. We only used the 6 common inputs features for multi well testing.

Data from all the wells are mixed together.

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1. Supervised learning Approach and evaluation

- **(2) Training and Testing**

(3: Multi well – Cross-wells) Randomly splitting the wells

Select four wells in our data set as training data and use the remaining well in data set 1 as testing data. Run 5 independent trials, each with a different testing well, to make sure all the five wells have been used as a testing data once. Calculate the average accuracy. I only used the 6 common input features for multi well testing.

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(2) Training and Testing

Methods	Well/Wells	Fluid	Log_Facies	MixedLabel
Single well with cross validation method	1D-02	0.99	0.87	0.88
Single well with cross validation method	1F-11	0.98	0.90	0.88
Single well with cross validation method	1K-01	0.98	0.77	0.80
Single well with cross validation method	1X-02	0.99	0.86	0.84
Single well with cross validation method	98_6-8	0.99	0.82	0.79
Multi wells with cross validation method	all 5 wells	0.96	0.81	0.79
Multi wells with cross wells method	all 5 wells	0.89	0.80	0.71

Table 10: The accuracy of different data selection run throw logistic regression with different training and testing methods (*Implementation Code*).

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▪ 1. Supervised learning

(3) Our Proposed Data Augmentation Method

How to increase the accuracy with limited data?

1. Supervised learning Approach and evaluation

- **(3) Our Proposed Data Augmentation Method**

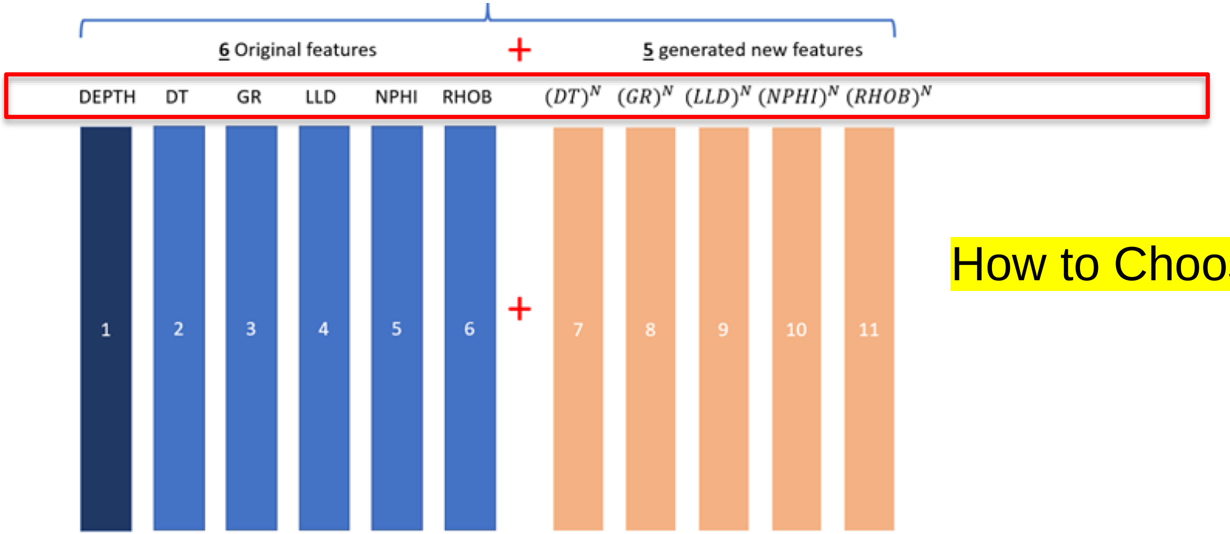


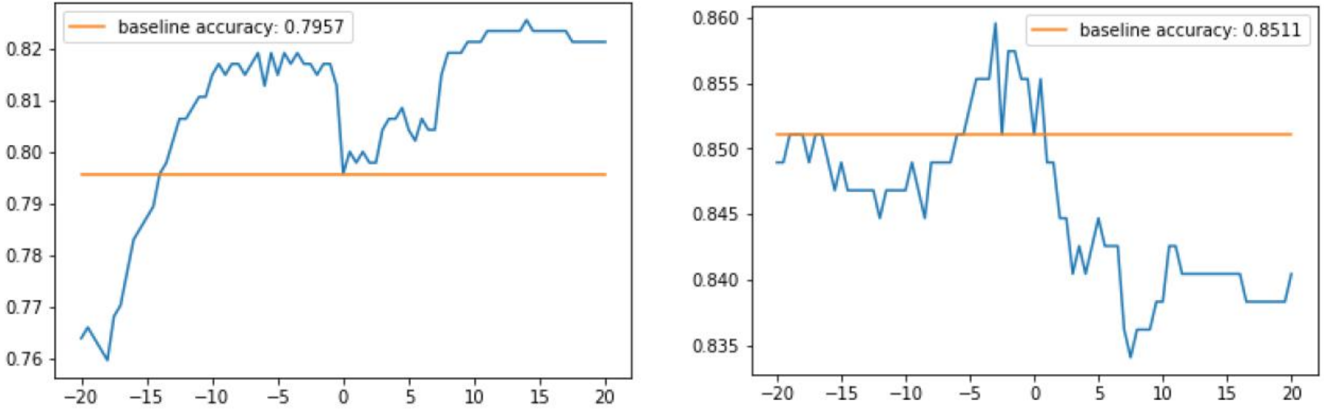
Figure 4: Workflow of our data augmentation method (creating new data sets with 11 features).

Total 11 Features

How to Choose the N(the power)?

1. Supervised learning Approach and evaluation

- **(3) Our Proposed Data Augmentation Method**



(a) Logistic Regression

(b) SVM

Figure 5: Accuracy changes test by logistic regression (left) and SVM (right). X-axis represents the values of power. Y-axis represents the corresponding testing accuracy. The orange line represents the baseline result with raw features. *Implementation Code*

▪ 1. Supervised learning

(4) Setting Threshold Prediction Rate

How can we help companies with limited training data?

(4) Setting Threshold Prediction Rate

Input pixels, $\mathbf{x}$

Shape: (3, 32, 32)

Forward propagation $\longrightarrow$

Feedforward output, $\mathbf{y}_i$

cat	dog	horse
5	4	2
4	2	8
4	4	1

Shape: (3,)

Softmax function $\longrightarrow$

Softmax output, $\mathbf{S}(\mathbf{y}_i)$

cat	dog	horse
0.71	0.26	0.04
0.02	0.00	0.98
0.49	0.49	0.02

Shape: (3,)

1. Supervised learning Approach and evaluation

- **(4) Setting Threshold Prediction Rate**

(1) Threshold Predicted Rate (TPR):

TPR: the percentage of tested data that have a prediction of classes

TPR = tested data that have a prediction of classes/ total tested data

(2) Threshold Predicted Accuracy (TPA):

TPA: The accuracy of all the tested data that have a prediction of classes

TPA = correct predicted tested data that have a prediction of classes/ total tested data that have a prediction of classes.

1. Supervised learning Approach and evaluation

(4) Setting Threshold Prediction Rate

Accuracy \ Threshold	Softmax	50%	60%	70%	80%	90%	95%
Fluid TPR	1	1	0.97	0.94	0.92	0.87	0.80
Fluid TPA	0.95	0.95	0.97	0.98	0.98	0.99	0.99
Log_Facies TPR	1	0.98	0.86	0.71	0.52	0.25	0.09
Log_Facies TPA	0.81	0.82	0.86	0.91	0.95	0.98	0.98
Mixedlabel TPR	1	0.87	0.70	0.53	0.32	0.05	0.01
Mixedlabel TPA	0.78	0.83	0.88	0.91	0.95	0.95	0.97

Table 11: Threshold predicted rate(TPR) and Threshold predicted accuracy(TPA) for three different labels schemes (*Implementation Code*).

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▪ 2. Unsupervised Learning

(1) Qualitative Evaluation by PCA and t-SNE

(2) Quantitative Evaluation with K-means Clustering

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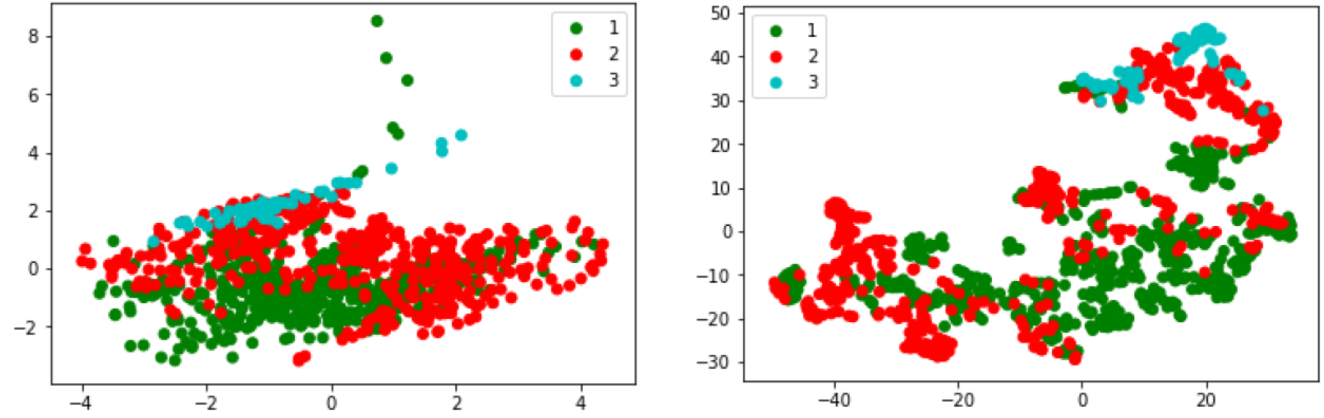
▪ 2. Unsupervised Learning

(1) Qualitative Evaluation by PCA and t-SNE

2. Unsupervised learning Approach and evaluation

- **(1) Qualitative Evaluation by PCA and t-SNE (Single well)**



(c) Log_Facies 1: green dot; Log_Facies 2: red dot; Log_Facies 3: light blue dot. (PCA)

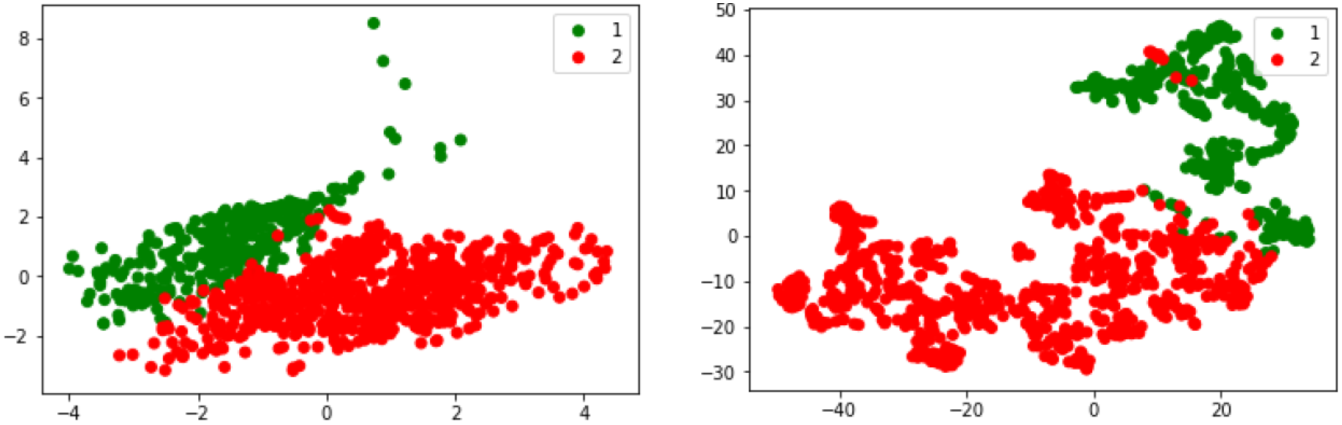
(d) Log_Facies 1: green dot; Log_Facies 2: red dot; Log_Facies 3: light blue dot. (t-SNE)

Figure 6: Visualization with PCA (left) and T-SNE (right) based on well log data from a single well(1K-01). 6 common features (e.g., Depth, DT, GR, LLD, NPHI, RHOB) are used as input

- Log_Facies
- No clear Clusters

2. Unsupervised learning Approach and evaluation

- **(1) Qualitative Evaluation by PCA and t-SNE (Single well)**



(a) Fluid 1: green dot; Fluid 2: red dot. (PCA) (b) Fluid 1: green dot; Fluid 2: red dot. (t-SNE)

Figure 6: Visualization with PCA (left) and T-SNE (right) based on well log data from a single well(1K-01). 6 common features (e.g., Depth, DT, GR, LLD, NPHI, RHOB) are used as input

- Fluid
- Clear Clusters

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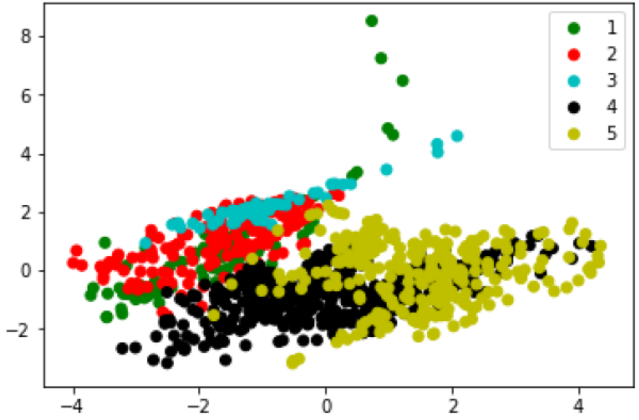
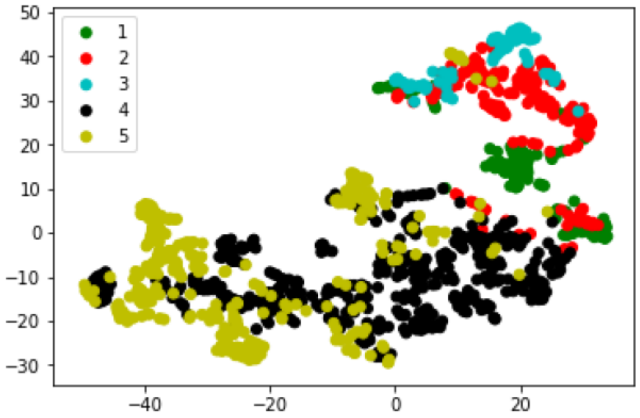
2. Unsupervised learning Approach and evaluation

- **(1) Qualitative Evaluation by PCA and t-SNE (Single well)**



(e) MixedLabel 1: green dot; MixedLabel 2: red dot; MixedLabel 3: light blue dot; MixedLabel 4: black dot; MixedLabel 5: yellow dot. (PCA)



(f) MixedLabel 1: green dot; MixedLabel 2: red dot; MixedLabel 3: light blue dot; MixedLabel 4: black dot; MixedLabel 5: yellow dot. (t-SNE)

Figure 6: Visualization with PCA (left) and T-SNE (right) based on well log data from a single well(1K-01). 6 common features (e.g., Depth, DT, GR, LLD, NPHI, RHOB) are used as input

- MixedLabel
- No clear clusters

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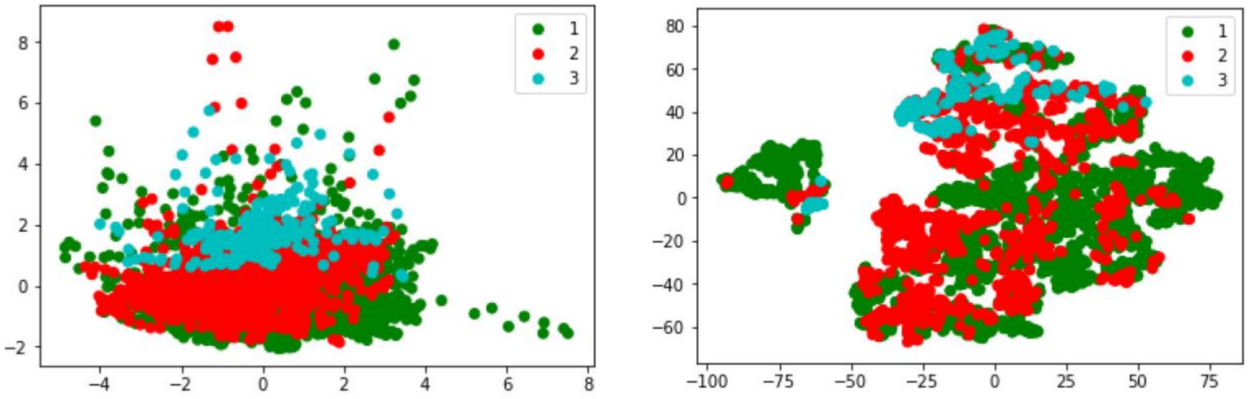
2. Unsupervised learning Approach and evaluation

- **(1) Qualitative Evaluation by PCA and t-SNE (Multi wells)**



(a) Log_Facies 1: green dot; Log_Facies 2: red dot; Log_Facies 3: light blue dot. (PCA)

(b) Log_Facies 1: green dot; Log_Facies 2: red dot; Log_Facies 3: light blue dot. (t-SNE)

Figure 7: Visualization with PCA (left) and T-SNE (right) based on well log data from multiple wells. 6 common features (i.e., Depth, DT, GR, LLD, NPHI, RHOB) are used as input for figures (a, b, c, d). 5 common features (i.e., DT, GR, LLD, NPHI, RHOB) are used as input for figures (e, f)

- Log_Facies
- Two clusters

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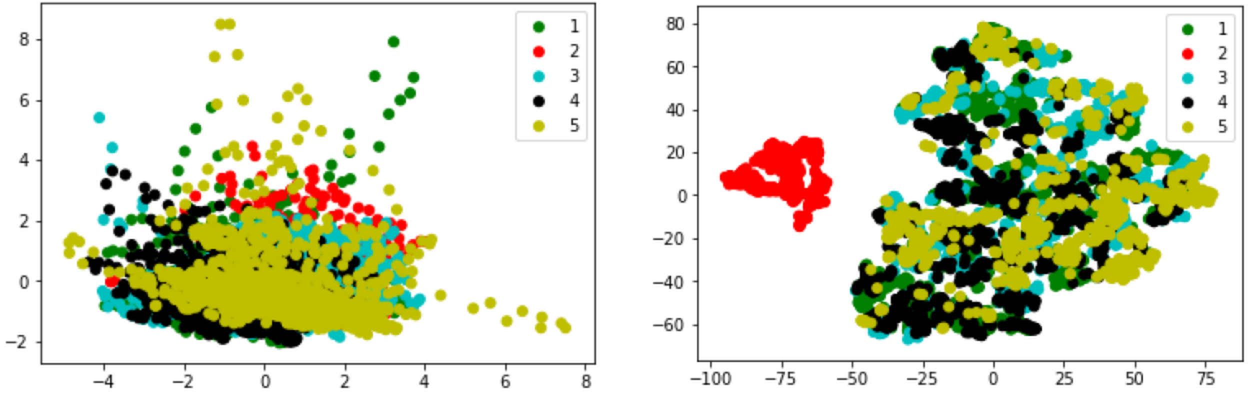
2. Unsupervised learning Approach and evaluation

- **(1) Qualitative Evaluation by PCA and t-SNE (Multi wells)**



(c) Well 1: green dot; Well 2: red dot; Well 3: light blue dot; Well 4: black dot; Well 5: yellow dot.(PCA)

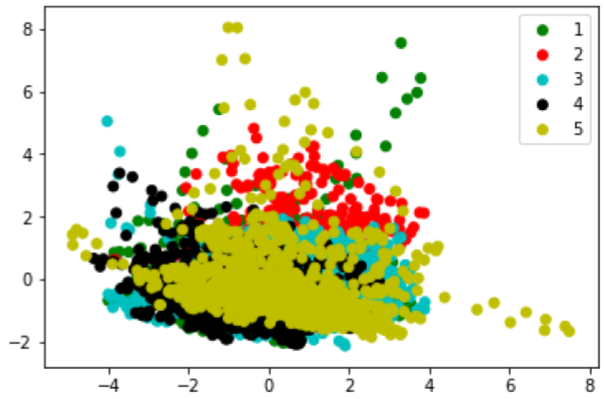
(d) Well 1:green dot; Well 2:red dot; Well 3:light blue dot; Well 4:black dot; Well 5:yellow dot.(t-SNE)

Figure 7: Visualization with PCA (left) and T-SNE (right) based on well log data from multiple wells. 6 common features (i.e., Depth, DT, GR, LLD, NPHI, RHOB) are used as input for figures (a, b, c, d). 5 common features (i.e., DT, GR, LLD, NPHI, RHOB) are used as input for figures (e, f)

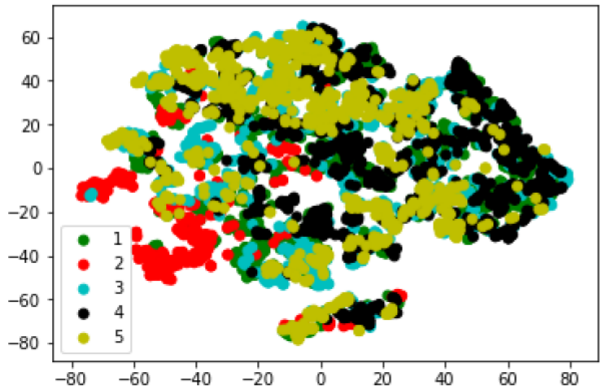
- Wells
- Separate one well

2. Unsupervised learning Approach and evaluation

- **(1) Qualitative Evaluation by PCA and t-SNE (Multi wells)**



(e) Well 1: green dot; Well 2: red dot; Well 3: light blue dot; Well 4: black dot; Well 5: yellow dot.(PCA)



(f) Well 1:green dot; Well 2:red dot; Well 3:light blue dot; Well 4:black dot; Well 5:yellow dot.(t-SNE)

Figure 7: Visualization with PCA (left) and T-SNE (right) based on well log data from multiple wells. 6 common features (i.e., Depth, DT, GR, LLD, NPHI, RHOB) are used as input for figures (a, b, c, d). 5 common features (i.e., DT, GR, LLD, NPHI, RHOB) are used as input for figures (e, f)

- Wells
- No clear clusters

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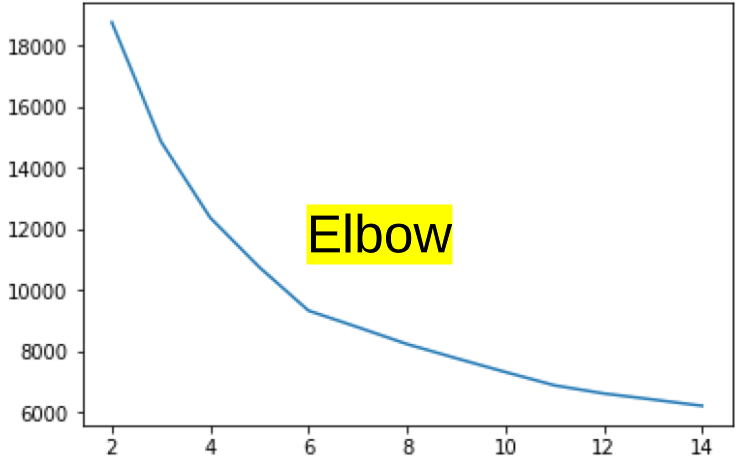
▪ 2. Unsupervised Learning

(2) Quantitative Evaluation with K-means Clustering

2. Unsupervised learning Approach and evaluation

- **(2) Quantitative Evaluation with K-means Clustering**



The sum of squared distances of samples to their closest cluster centre decreases dramatically until the number of clusters reaches to 6.

Figure 8: Sum of squared distances of samples to their closest cluster(Y-axis) center versus K value(X-axis) (*Implementation Code*).

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2. Unsupervised learning Approach and evaluation

- **(2) Quantitative Evaluation with K-means Clustering (K=6)**

Schemes	Classes	K	Cluster Labels	Labelled Clusters Accuracy	Total Accuracy
Fluid	2	6	Cluster1 (Fluid-1) Cluster2 (Fluid-1) Cluster3 (Fluid-1) Cluster4 (Fluid-1) Cluster5 (Fluid-2) Cluster6 (Fluid-1)	Cluster1 (0.93) Cluster2 (0.82) Cluster3 (0.63) Cluster4 (0.73) Cluster5 (0.99) Cluster6 (1.00)	0.85
Log_Facies	3	6	Cluster1 (Log_Facies-1) Cluster2 (Log_Facies-1) Cluster3 (Log_Facies-1) Cluster4 (Log_Facies-1) Cluster5 (Log_Facies-2) Cluster6 (Log_Facies-1)	Cluster1 (0.81) Cluster2 (0.47) Cluster3 (0.78) Cluster4 (0.78) Cluster5 (0.51) Cluster6 (0.67)	0.67
MixedLabel	5	6	Cluster1 (MixedLabel-1) Cluster2 (MixedLabel-4) Cluster3 (MixedLabel-1) Cluster4 (MixedLabel-4) Cluster5 (MixedLabel-4) Cluster6 (MixedLabel-2)	Cluster1 (0.67) Cluster2 (0.77) Cluster3 (0.54) Cluster4 (0.58) Cluster5 (0.46) Cluster6 (0.40)	0.58

Table 13: Unsupervised accuracy by sufficient K=6. Cluster labels represent the cluster index and the majority of true label in the corresponding clusters (*Implementation Code*).

Conclusion

(1) it is fundamental to keep all input features when developing a robust machine learning model;

(2) data splitting according to wells is more robust compared to directly random split the full data set;

(3) I proposed a MixedLabel approach for classification, which shows comparable performance.

Conclusion

(4) I proposed a data augmentation approach by generating more input features with specific powers can improve classification performance remarkably;

(5) it is easy for both supervised and unsupervised methods to achieve higher prediction accuracies on a small portion of the training samples;

(6) supervised learning models are generally more robust and give higher accuracies than unsupervised learning models;

- **Future Possible Implementations**

❑ Supervise learning

❑ Data augmentation

All Input Features

Cross-wells

THANK YOU !

(3) Our Proposed Data Augmentation Method

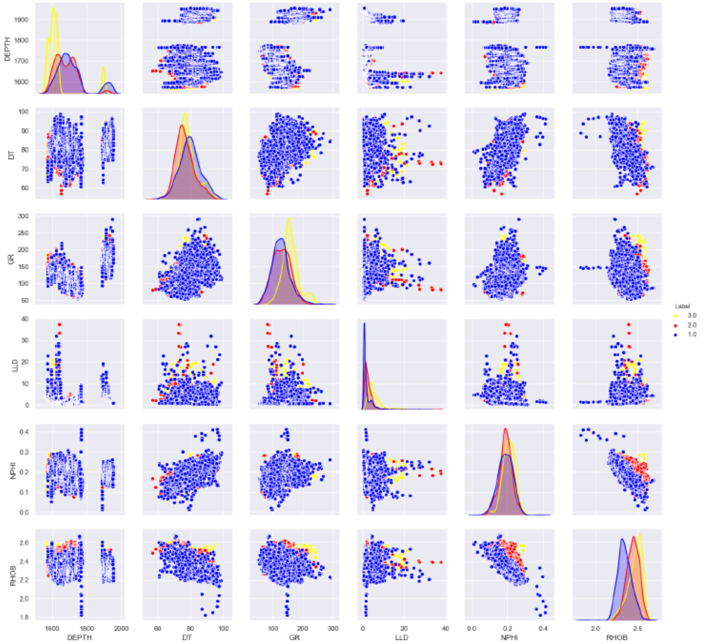

Figure 3: The correlations graphs between six common inputs features from data set 1 one by one (Log_Facies1:blue; Log_Facies2:red; Log_Facies3:yellow) (*Implementation Code*).