Cross-Oilfield Reservoir Classification via Multi-Scale Sensor Knowledge Transfer

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Abstract

Reservoir classification is an essential step for the exploration and production process in the oil and gas industry. An appropriate automatic reservoir classification will not only reduce the manual workloads of experts, but also help petroleum companies to make optimal decisions efficiently, which in turn will dramatically reduce the costs. Existing methods mainly focused on generating reservoir classification in a single geological block but failed to work well on a new oilfield block. Indeed, how to transfer the subsurface characteristics and make accurate reservoir classification across the geological oilfields is a very important but challenging problem. To that end, in this paper, we present a focused study on the cross-oilfield reservoir classification task. Specifically, we first propose a *Multi-scale Sensor Extraction (MSE)* module to extract the multi-scale feature representations of geological characteristics from multivariate well logs. Furthermore, we design an encoder-decoder module, i.e., *Specific Feature Learning (SFL)*, to take advantage of specific information of both oilfields. Then, we develop a *Knowledge-Attentive Transfer (KAT)* module to learn the feature-invariant representation and transfer the geological knowledge from a source oilfield to a target oilfield. Finally, we evaluate our approaches by conducting extensive experiments with real-world industrial datasets. The experimental results clearly demonstrate the effectiveness of our proposed approaches to transfer the geological knowledge and generate the cross-oilfield reservoir classifications.

Introduction

Reservoir classification, which aims at identifying hydrocarbon reservoir under subsurface, is one of the most essential steps for the exploration and development process in the oil and gas industry. Figure 1 demonstrates a sample workflow from logging the well to making the reservoir classifications. Specifically, engineers will first use various sensors during well logging to obtain a continuous record of the geological properties of the formation. Next, with simple

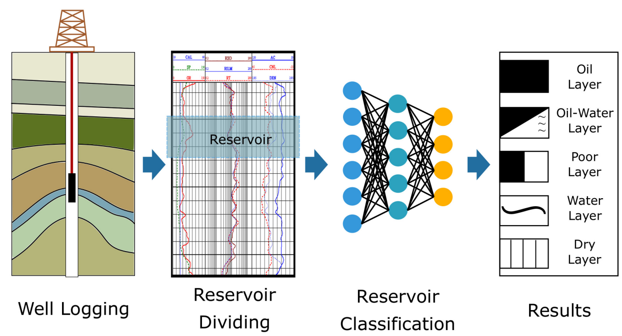

Figure 1: Workflow of the oil exploration process.

rules, such as shale baseline (Klusman 1980), experts can easily divide the reservoirs. Then, experts will analyze the well logs to identify the location and quantity of the hydrocarbon and determine the type of formation (e.g. oil, gas or water). This process is so-called the reservoir classification. Finally, based on the classification results of reservoirs, the engineers will make further drilling and production plan. In fact, in real industrial activities, the production of about 40% of shale wells underperform expectations (Scollard 2014) because of inaccurate reservoir classifications and inappropriate understanding of the subsurface. To that end, how to learn the subsurface characteristics and make accurate reservoir classification are the major concerning issues in both industry and academia.

Traditionally, researchers mainly use the reservoir modeling to explore the subsurface (Tong et al. 2017) or expert systems to assist the reservoir classification process (Einstein, Edwards et al. 1990). However, these methods largely rely on the experts' experiences and manual processes which are costly in time and money. Recently, thanks to the tremendous success of machine learning and data mining, automated methods have been emerging as promising tools to enhance the oil and gas exploration process (Holdaway 2014; Mohaghegh et al. 2011). Unfortunately, existing researches mostly apply supervised learning methods to generate the reservoir classification from well logs in a specific geological block. That makes it difficult for these methods to work well in a newly discovered oil field due to different geologi-

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cal conditions and diverse feature distributions. Considering the highly time and economic costs for experts' processing and labeling, it is not a good solution to retrain or fine-tune the model with new labeled data in a different oilfield. To that end, it is an urgent demand to explore the cross-oilfield reservoir classification approach and improve the availability of automated methods in real industrial scenarios.

However, it is still an open issue with great challenges to learn the subsurface characteristics and make accurate reservoir classifications across oilfields. First, understanding the subsurface from well logs is still an open issue. On the one hand, the geological characteristics are complex and affected by multivariate features. On the other hand, the different well log scales of depth interval have different effects on the representation of these geological characteristics. Second, in the real industry scenario, the experts will choose different sensors to log geological conditions according to the environmental demands in distinct geological blocks. For this reason, sensing data from different oilfields are always inconsistent, which makes it is hard to directly transfer the model from one oilfield to another oilfield. Last but not least, it is difficult to learn the invariant features and transfer the geological knowledge from a source oilfield to the target oilfield due to the various feature distributions.

To address these challenges, in this paper, we propose a novel solution, i.e., Multi-scale Sensor Knowledge Transfer (MSKT) model, to transfer the geological knowledge from a source oilfield to another target oilfield and automatically generate cross-oilfield reservoir classifications. More specifically, we first develop a Multi-scale Sensor Extraction (MSE) to extract the multi-scale feature representations of geological characteristics from multivariate well logs. Meanwhile, for addressing the inconsistent features between the source and target oilfield, we propose an encoder-decoder module, i.e., Specific Feature Learning (SFL), to learning the additional geological features from discriminative well logs in both oilfields. Then, we propose a Knowledge-Attentive Transfer (KAT) module to learn the oilfield-invariant representation and transfer the geological knowledge from a source oilfield to a target oilfield. Finally, we evaluate our approaches by conducting extensive experiments with a real-world industry dataset. The experimental results clearly demonstrate the effectiveness of our proposed approaches to transfer the geological knowledge and generate the cross-oilfield reservoir classifications.

Related Work

The related works can be grouped into three categories: the reservoir classification, the researches on time series classification, and the domain adaption.

Reservoir Classification. Reservoir classification aims at generating the oil and gas properties in a specific depth interval based on well log features. Accuracy reservoir classifications are vital to maximizing returns on dollar investments in a well (Baldwin et al. 1989). Actually, researchers have made lots of continuing efforts for improved accuracy in measuring and estimating reservoir properties from the well logs (Szucs and Civan 1996). For a long time, experts mainly use the reservoir modeling (Pyrcz and Deutsch 2014) to determine the formation parameters and generate the classification of reservoirs. These methods are largely relied on the experts' experiences and need much time for manually analyzing the well log data. These years, substantial increases in data availability and increasingly realistic characters of computer technologies make geoscience enter the era of artificial intelligence (Karpatne et al. 2018; Bergen et al. 2019). Along this line, some researchers focus on automated algorithms to generate lithofacies and reservoir properties (Holdaway 2014; Mohaghegh et al. 2011; Hall 2016). Unfortunately, existing researches mostly apply supervised learning methods to generate the reservoir classifications in a specific geological block. But in a new oilfield block, there is lack of training data. These supervised learning methods cannot work well due to the different feature distributions of distinct geological environments. To that end, in this paper, we present a novel study on the cross-oilfield transfer learning to address this problem.

Time Series Classification. As the well logs are a series of sensor data indicating chemical and physical characteristics of geology, the reservoir classification then is similar to the time series classification task. Existing researches related to the time series classification can be classified into two main groups: traditional methods and deep learning methods. For a long time, researchers mainly use feature-based approaches or methods to extract a set of features that represent time series patterns (Baydogan, Runger, and Tuv 2013; Schäfer and Leser 2017), such as Bag-of-features (Baydogan, Runger, and Tuv 2013). These methods mainly rely on the feature construction of the time series and required heavy feature engineering (Karim et al. 2018). Recently, more and more researchers begin to employ deep learning methods to address time series classification tasks (Zheng et al. 2014; Wang, Yan, and Oates 2017). Along this line, some studies propose a hybrid model incorporating CNN with Long Short-Term Memory (LSTM) networks (Karim et al. 2018; Karim, Majumdar, and Darabi 2019). These deep learning methods are efficient and do not require any heavy preprocessing on the data or feature engineering.

Domain Adaptation. Domain adaptation is another related research area, which mainly focus on a type of transfer learning scenario where two domains (source and target) share their feature space but have different distributions (Purushotham et al. 2017). Existing studies mainly attempt to solve the issue of enabling a model trained on a certain dataset to perform well on a differently distributed dataset, of which the labels are completely or partially unknown (Ben-David et al. 2006). Along this line, many researchers focus on reducing the discrepancy between the source and target domains, including alignments of the subspaces (Fernando et al. 2013), parameter augmentation (Watanabe, Hashimoto, and Tsuruoka 2016), and domain-invariant projection (Ganin et al. 2016; Baktashmotlagh et al. 2013). For example, *Ganin et al.* propose a Domain-Adversarial Neural Network (DANN) (Ganin et al. 2016) to address domain adaptation by learning domain-invariant features through a neural network architecture,

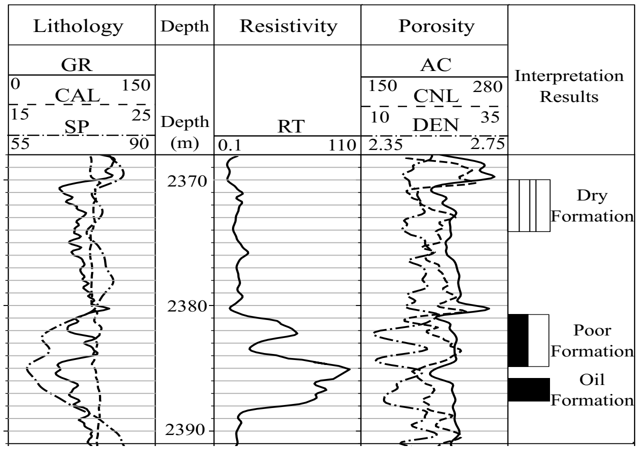

Figure 2: Example of multivariate well logs from various sensors.

which consists of three main components, i.e., a feature extractor, a discriminative classifier, and an adversarial domain classifier. In particular, DANN mainly focus on learning the domain-invariant features which could make the model appropriately classify samples from the target domain without having access to labels of the target's training set.

Preliminaries

In this section, we first give a brief overview of well logs. Then, we introduce the research problem of cross-block reservoir classification and overview of our proposed Multi-scale Sensor Knowledge Transfer (MSKT) model.

Well Log

A well log records continuous sensor values along with the depth, which indicates subsurface geological properties. It often consists of a number of measurements, such as gamma radiation and interval transit time, to detect and quantify oil and gas reserves. For example, the Gamma Ray (GR) log is recorded during a sonic shear test for detecting formation change and identifying the location of the shale formation. The Spontaneous Potential (SP) log is recorded as an electrode relative to a fixed reference electrode to reflect the electric potential difference. The CALiper (CAL) log provides the borehole diameter curves of open-hole and cased wells, and provide support for monitoring the quality of drilling, casing, and cementing. The ResisTivity (RT) and AcoustiC (AC) measure the formation resistivity and interval transit time, respectively. The values of well logs are often measured at every 0.125 meters. These well logs are the major features for the reservoir classification task. Figure 2 shows an example of multivariate well logs mainly used in this paper. The y-axis of this figure represents the measured depth, the four first plots on the left show the measured logs and the last plot demonstrates the reservoir classification results by experts.

Problem and Framework Overview

Problem Statement. In this paper, we propose a focused study on the cross-oilfield reservoir classification problem. Formally, given a set of labeled training well log data $\mathbf{D}_i^S = \{X_i^S, y_i^S\}_{i=1}^{N^S}$ from source oilfield and unlabeled training data $\mathbf{D}_i^T = \{X_j^T\}_{j=1}^{N^T}$ from the target oilfield, where N^S and N^T are the number of labeled data and unlabeled data, $X_i = [x_1, x_2, \cdots, x_N]$ are the well log series in a specific depth interval $[0 : N]$. For each depth point $x_t = [x_t^{l1}, x_t^{l2}, \cdots, x_t^{ln}]$, where x_t^{l1} is the measurement of well log $l1$, $|ln|$ is the number of input well logs. For each input sample X_i, our task is to predict the target reservoir class of X_i. As mentioned above, in the real industry scenario, the experts will choose different sensors to log geological conditions according to the environmental demands in distinct geological oilfields. We define these different well logs as specific features X_i'. Then, the goal of cross-oilfield reservoir classification is to train a robust model based on labeled data in the source oilfield and adapt it to predict the unlabeled data in the target oilfield.

Framework Overview. For tackling the above problem, we propose a knowledge-powered solution framework, i.e., Multi-scale Sensor Knowledge Transfer (MSKT) model, which is shown in Figure 3. There are three major components: (1) Multi-scale Sensor Extraction (MSE) module to generate geophysical features from well logs; (2) Specific Feature Learning (SFL) module to take advantages of the additional specific features from discriminative well logs across various oilfields; (3) Knowledge-Attentive Transfer (KAT) module to transfer the geophysical knowledge from a source block to a target block and generate oilfield-invariant feature representations.

Methodology

In this section, we introduce the details of our proposed method, i.e., Multi-scale Sensor Knowledge Transfer (MSKT) model.

Multi-scale Sensor Extraction

As mentioned above, the well logs are a series of sensor data. Thus, it is important to model the fluctuation of sensor signals. Moreover, the reservoir depth is not determined before well logging and the different scales of geophysical and geochemical signals may have different effects on the representation of geological characteristics. To that end, we propose a multi-scale sensor extraction module to generate the representation of geological characteristics at various depth interval. More specifically, considering the long-term dependencies and gradient vanishing and expansion problems in sequential learning tasks (Li et al. 2018; Wu et al. 2020), we firstly develop an LSTM (Hochreiter and Schmidhuber 1997) model to learn hidden states of the global series data. Formally, given the well log series $X_i = [x_1, x_2, \cdots, x_T]$ as the input, we essentially use the final hidden state $\widehat{E}_0 = LSTM(X_i)$ as the global representation of the well logs.

While LSTM has possessed the ability to learn long-term dependencies in sequences, it is still limited to explore

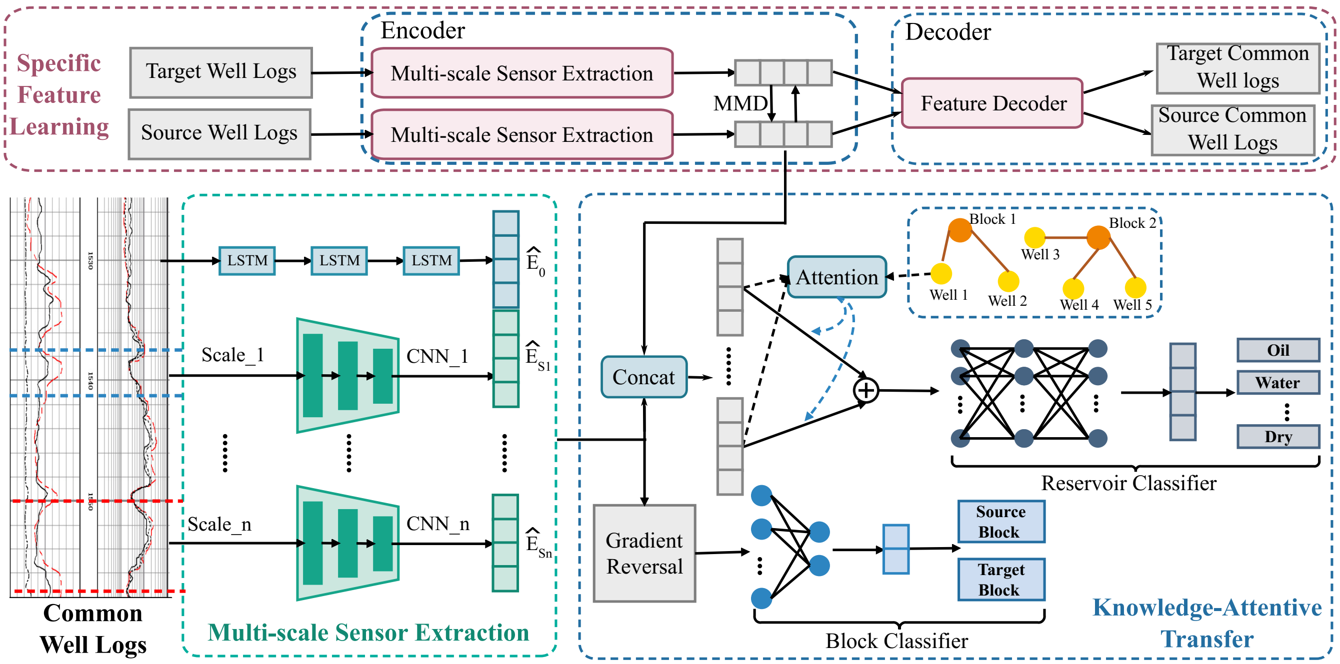

Figure 3: The overview of Multi-scale Sensor Knowledge Transfer (MSKT) model.

the feature relationships under multi-scale perspectives. As Temporal Convolutional Network (TCN) has been proved to successfully capture the local spatiotemporal relationships (Lea et al. 2016), we develop multiple convolutional networks to generate the multi-scale feature representations. Specifically, we apply a set of 1D filters on each of L convolutional layers that capture the fluctuation of input signals over different scales. For the l-th layer, the component of activation $E_s^{(l)}$ at s scale for each step t can be defined as:

$$E_{s,t}^{(l)} = f_s\left(\sum_{t'=1}^{s}\left\langle W_{t'}^{(l)}, E_{t+s-t'}^{(l-1)}\right\rangle + \hat{b}^{(l)}\right), \qquad (1)$$

where $l \in \{1, \ldots, L\}$ is the layer index, $W_{t'}^{(l)}$ is the weight matrix, $\hat{b}^{(l)}$ is the basis term, s is the filter duration, and $f_s(\cdot)$ is a Rectified Linear Unit. We perform a batch normalization layer (Ioffe and Szegedy 2015) after the convolutional output of each scale. Then, with a global average polling layer, we can generate the final representation of the target scale s as $\widehat{E_s} = GlobalAveragePooling\left(E_{s,t}^{(L)}\right)$.

Next, we have generate both of the global representation $\widehat{E}_0$ and multi-scale representations $\{\widehat{E}_{s1}, \ldots, \widehat{E}_{sn}\}$. We can simplify our Multi-scale Sensor Extraction module as $G(X_i) = [\widehat{E}_0, \widehat{E}_{s1}, \ldots, \widehat{E}_{sn}]$.

Specific Feature Learning

So far, we have generated multi-scale well log features from the common sensors in both the source and target oilfields, such as the gamma ray sensor and the acoustic wave sensor. However, in the real industry scenario, it is challenging to ensure that cross-oilfield sensing data can be consistent. For example, oilfield A may have three well logs, i.e., gamma ray, acoustic wave and spontaneous potential. Besides these three well logs, oilfield B may have another two well logs, i.e., compensating neutron well logging and resistivity well logging. There are mainly two reasons for this feature inconsistency. On the one hand, because of the various exploration and production time, the exploration techniques and sensors are different. On the other hand, with the consideration of cost and specific geological environments, the exploration and production sensors in different oilfields will also vary.

Actually, this feature inconsistency makes a great challenging to transfer the geological knowledge across various oilfields. Intuitively, we can only use the common sensor data to make reservoir classifications. However, it will lead to a lack of some important geological information. To this end, we propose a Specific Feature Learning (SFL) method to make use of the specific features from discriminative well logs in different oilfields. More specifically, we first develop an encoder-decoder model to discriminative learning the specific features from the source and target oilfield. We use X'^{S}_{i} and X'^{T}_{i} to denote the specific feature inputs from the source and target oilfield, respectively. Then, we can generate specific feature representations from two separate encoder networks. Here, we use two Multi-scale Sensor Extraction modules with different input settings as encoder networks, so we can generate the specific feature representations $G(X'^{S}_{i}), G(X'^{T}_{i})$ for both the source and target oilfields. Next, in order to train the decoder, we develop a three-layers MLP model as the shared encoder network to ensure specific feature representations are informative and available. Finally, we use mean square error to optimize the whole encoder-decoder module as follows.

$$L_e(\widehat{X_i}, X_i) = \frac{1}{|l^S|} \sum_{X^l \in X_i} \left(\widehat{X^l} - X^l\right)^2, \quad (2)$$

where $\widehat{X^l}$ is the decoder prediction of well log l and X^l is the ground-truth. Here, we use the common well log feature input X_i^S, X_i^T as the ground-truth of the source and target oilfields, respectively. Therefore, the final loss function of encoder-decoder is $L_{ed} = L_e(\widehat{X_i^S}, X_i^S) + L_e(\widehat{X_i^T}, X_i^T)$.

Moreover, considering the diverse distributions of specific features from the different oilfield, we use Maximum Mean Discrepancy (MMD) (Quadrianto, Petterson, and Smola 2009) to make the oilfield-invariant specific feature representations. More formally,

$$L_{MMD} = MMD\left[G({X'}_i^S), G({X'}_i^T)\right], \quad (3)$$

where $G({X'}_i^S), G({X'}_i^T)$ denote the representations of specific features from the source oilfield and the target oilfield, respectively.

Knowledge-Attentive Transfer

After we extract well log features from different scales, we have generated the well log representation of each depth interval. Next, we introduce how to transfer the geological knowledge from different oilfields and get the final forecasting for a given well e and well logs X_i. Actually, for transferring the geological knowledge from a source oilfield to a target oilfield, it is important to learning the invariant features which are effective for the task of reservoir classifications in both source and target oilfields. To that end, we propose the knowledge-Attentive Transfer (KAT) learning module to promote the emergence of features that are not only discriminative for the reservoir classification task on the source labeled oilfield but also indiscriminate to the shift between the source and target oilfields. In detail, we design two classifiers, i.e., the reservoir classifier and the domain classifier, to learn the cross-oilfield geological feature representations from source oilfield data and target oilfield data. Next, we introduce these two classifiers in details.

Oilfield Classifier. The domain classifier aims to learn cross-oilfield geological feature representations, where the inputs are the labeled data from the source oilfield and the unlabeled data from the target oilfield. Specifically, we propose the domain classification to predict the oilfield labels of the samples from the source and target oilfields. For learning the latent relationships between the features in labeled and unlabeled data, we mainly aim to encourage the feature extractor to generate the domain-invariant representations. Indeed, the traditional training strategy for the classifier is to minimize the classification error, i.e., to distinguish the two oilfields as accurately as possible. Differently, the domain classifier is to learn the invariant feature representations which are indiscriminate to the shift between the oilfields and make the domain classifier cannot discriminate the source and target oilfields. With this intention, we add the Gradient Reversal Layer (GRL) (Ganin et al. 2016) to reverse the gradient direction in the training process. More formally, we can describe the gradient reversal layer as a "pseudo-function" (Zhang et al. 2019), which is defined by two incompatible equations describing its forward and back-propagation processes:

$$G'(x) = x, \quad \frac{\partial G'(x)}{\partial x} = -\lambda I. \quad (4)$$

In our model, $G'(x) = G(X_i) = [\widehat{E}_0, \widehat{E}_{s1}, \ldots, \widehat{E}_{sn}]$ is the function of our Multi-scale Sensor Extraction process. Then, we can get the result of domain classifier as:

$$y_d = Softmax(\sum_{s' \in \mathbf{S}} W_{s'}^d \widehat{E}_{s'})), \quad (5)$$

where f_m^d is a one-layer MultiLayer Perceptron (MLP) model, and $S = \{0, s_1, \cdots, s_n\}$ is the scale collection of the feature extractor. After a softmax layer, we can obtain the domain classification scores y_d. Eventually, we can optimize the domain classifier by the cross-entropy loss functions:

$$L_{blo} = -\frac{1}{N_d} \sum_{i=1}^{N_d} y_d \ln y_d^{'} + (1 - y_d) \ln(1 - y_d^{'}), \quad (6)$$

where N_d is the number of all samples in the source and target oilfields, $y_d^{'}$ denotes the ground truth of the domain class. Therefore, in Eq. 4, during the forward pass, the input is left unchanged, while during backpropagation, the gradient is negated. The loss in Eq. 6 is thus maximised, thereby encouraging the feature extractor to find representations of the features which are oilfield-invariant.

Reservoir Classifier. The reservoir classifier is the main component, which aims at mining the subsurface geological condition and detecting the classes of underground oil and gas reserves. Actually, due to the action of plate tectonic forces, the subsurface geological conditions are complex and the stratifications are always uncertain even in the same oilfield. To that end, the geological characteristics may vary greatly from well to another well, especially when two wells are geographically far apart. In other words, the geographically closer wells will have more similar geological properties (such as lithology, mineral). For capturing the geographical relationships between two wells, we utilize a knowledge graph to jointly model the geographical and geological relationships of wells. More specifically, we develop an exploration knowledge graph. There are 60,406 entities from three categories, i.e., oilfields, wells and strata, and eight relationships (such as 'Adjacent Well', 'isIn oilfield' and 'Upper' or 'lower' strata) between them. Then, for learning the distributional representations of geographical and geological knowledge, we utilize an effective and efficient knowledge graph embedding method, i.e., TransR (Lin et al. 2015), to generate the entity embedding vectors v. Along this line, the well k can be represented as an entity vector v_k. As mentioned above, the closer wells may have more similar geological properties, then v_k contains this transferred knowledge related to other wells.

Indeed, the geological feature from each scale has a different influence on the representation of well logs. Then, how

Statistics	#9FAB2	#BF8A9
# of total wells	445	221
# of total samples	1,076,537	662,067
# of wells in training set	178	88
# of wells in test set	88	89
# of unlabeled wells	179	44
# of total well logs	21	12
# of common well logs	5	5

Table 1: The statistics of datasets.

Benchmarks	#9FAB2 →			#BF8A9 →		
	Prec.	Rec.	F1	Prec.	Rec.	F1
LSTM	0.61	0.33	0.36	0.59	0.43	0.48
ALSTM	0.65	0.37	0.40	0.57	0.46	0.49
FCN	0.66	0.35	0.38	0.57	0.45	0.50
LSTMFCN	0.65	0.42	0.46	0.57	0.59	0.57
ALSTMFCN	0.66	0.39	0.43	0.58	0.54	0.55
DANN	0.65	0.51	0.55	0.61	0.62	0.62
MSKT	**0.67**	**0.76**	**0.69**	**0.62**	**0.71**	**0.66**

Table 2: The performances of cross-oilfield reservoir classifications.

to qualify the contributions of each scale and learn the special representation for it is an open issue. Considering the different influence on the representation of well logs from the different wells and different feature extractor scales, we propose an attention mechanism to highlight different parts of the depth scale by assigning weights to encoding vectors in each scale of well log representation. More formally, we can generate the attention score α_s for each feature scale s in the target well k as:

$$U_s = V^T tanh(W_1 \widehat{E}_s + W_2 v_k), \quad \alpha_s = \frac{\exp(U_s)}{\sum_{s' \in \mathbf{S}} \exp(U_{s'})}, \tag{7}$$

where V^T, W_1, W_2 are weighted matrices, $\widehat{E}_s \in Concat(G(X_i), G({X'}_i^S))$ is the representation of both common and specific well logs in the source oilfield and e_k is the graph embedding vector of well k. Then, we can generate our prediction score of the reservoir classification incorporating the knowledge from well k as:

$$y_r = Softmax(f_m^r(W_S^r \sum_{s' \in \mathbf{S}} \alpha_s \widehat{E}_s)), \tag{8}$$

where f_m^r is a two-layer MultiLayer Perceptron (MLP) model, W_S^r are weighted matrices. After a softmax layer, we can obtain the reservoir classification scores. Eventually, we can optimize the reservoir classifier by the cross-entropy loss function as:

$$L_{res} = -\frac{1}{N_r} \sum_{i=1}^{N_r} \sum_{m=1}^{M} y'_{r,m} \ln(y_{r,m}), \tag{9}$$

where N_r denotes the number of labeled samples from source oilfield, M is the number of reservoir classes, $y'_{r,m}, y_{r,m}$ are the ground truth and prediction score for class m. Therefore, in training stage, our optimization function is $L = L_{ed} + L_{MMD} + L_{res} + L_{blo}$. Finally, we use Adam algorithm (Kingma and Ba 2015) in mini-batches to update our model parameters with the backpropagation.

Experiment

In this section, we will construct extensive experiments on a large-scale real-world data set. First, we make data analysis and explore the feature invariance of cross-oilfield well log data. Second, we describe the experimental setup in details. Finally, we demonstrate the results of compared experiments, ablation study and performance analysis of the source oilfield.

Dataset Description

The experimental data sets are collected from the real industry exploration and production process of a famous oil and gas company, i.e., PetroChina [1]. These data sets contain a large number of well logs in two main oilfield oilfields, i.e., #9FAB2 and #BF8A9. All the well information and oilfield information have been desensitized to protect data privacy. Table 1 shows the statistics of experimental datasets. For each oilfield, the wells have multiple types of sensor data in the Log ASCII Standard (LAS) format, and different oilfields have different sets of sensor types. As mentioned above, sensor data are always inconsistent with the consideration of the cost and different drilling technologies. As demonstrated in Table 1, we mainly used five common well logs, i.e., GR, RT, AC, CAL, SP. Actually, there are 21 well logs, which including 16 specific well logs in #9FAB2 oilfield. In addition to five common logs, there are 7 discriminative well logs in #BF8A9 oilfield. These specific well logs will be used in SFL module.

Experimental Setup

Hyperparameters Setting. We set the size of the max convolution window to 21 for well logs and designed three convolution scales, i.e. 11, 15 and 21. The number of filters for each convolution was set to 256, 256 and 128. The dimension of the state in the LSTM was set to 128. The dimension of well embedding V_k was set to 100. As a default setting, the activation functions used in the convolution layers and fully connected layer were set to Rectified Linear Unit (ReLU). All weight matrices are randomly initialized by a uniform distribution. Our model was trained with an initial learning rate of 0.01 and was exponentially decayed by a factor of 0.75. The batch size of samples was set to 30000. We stop the training process when the loss on the validation set stabilizes.

Comparison Methods. In order to demonstrate the effectiveness of MSKT, we compare it with several methods which are mainly grouped into two categories, i.e., the time series classification method and the domain adaption

[1]http://www.petrochina.com.cn/

Benchmarks	#9FAB2 →			#BF8A9 →		
	Prec.	Rec.	F1	Prec.	Rec.	F1
Only MSE	0.65	0.42	0.49	0.58	0.62	0.59
MSE+KA	0.67	0.50	0.54	0.58	0.63	0.60
MSE+KAT	0.68	0.53	0.56	0.62	0.70	0.63

Table 3: The ablation study of our proposed method.

method. Our compared methods include LSTM (Hochreiter and Schmidhuber 1997), ALSTM (Bahdanau, Cho, and Bengio 2014), FCN (Wang, Yan, and Oates 2017), LSTM-FCN (Karim et al. 2018; Karim, Majumdar, and Darabi 2019), ALSTMFCN (Karim et al. 2018; Karim, Majumdar, and Darabi 2019) and DANN (Ganin et al. 2016).

Evaluation Metrics. To evaluate the reservoir classification performances, here we select three widely used widely-used metrics (Zheng et al. 2014; Tonutti et al. 2019), i.e., Precision(Prec.), Recall(Rec.) (Liu et al. 2012), and F1 measure. Considering our task is a multi-class classification problem, we use the weighted average scores to evaluate the performances of our proposed MSKT and all compared methods. Specifically, we weight the metrics of each class by the number of samples from that class.

Experimental Results

Performance Comparison. To demonstrate the effectiveness of our proposed model, we compare MSKT with other state-of-the-art methods of both time series and domain adaption on the cross-oilfield reservoir classification task. We conduct the cross-oilfield experiments between two oilfields. Then, we have two reservoir classification tasks, i.e., "#9FAB2 → " and "#BF8A9 → ". We use the notation "#9FAB2 →" represents the task which transfers from the source oilfield #9FAB2 to the target oilfield #BF8A9.

Table 2 shows the performances of reservoir classifications of our proposed MSKT and all compared methods. Overview, our proposed MSKT achieves the best performance on both datasets. Specifically, MSKT outperforms all compared methods with the improvement by up to 1.6%, 14.5% and 6.1% in precision, recall and F1, respectively. That clearly demonstrates the effectiveness of our proposed method. When compared with the non-transfer model, our proposed MSKT achieves over 15.7% improvement in F1 score, which clearly demonstrates the importance of domain adaption for our cross-oilfield reservoir classification task. Moreover, we can also observe that the transfer learning method DANN achieves the second-best performance. That indicates the effectiveness of learning the oilfield-invariant features for the cross-oilfield reservoir classifications. Finally, we test the statistical significance between the MSKT and all compared methods. We find in recall and F1, our proposed MSKT has largely significant improvements ($p-value$<0.001) over the result set of all other compared methods. And in precision, MSKT achieve significant improvements ($p-value$<0.01).

Ablation Study. The strengths of MSKT model come from three novel components, i.e., the Multi-scale Sensor Extraction (MSE), Specific Feature Learning (SFL) and Knowledge-Attentive Transfer (KAT). To justify the designs of each module in MSKT, we investigate the influence of each important module. We study the performance of the following three variants, i.e., only MSE module, MSE module with the knowledge graph embedding (MSE+KG) and MSE with KAT module (MSE+KAT). Table 2 shows the performances of these variants. Moreover, we have the results of MSKT equipped all components (MSE+KAT+SFL) in Table 2. From Table 2 and Table 3, we have following observations: 1) The MSKT with SFL module outperform MSE+KAT model with a large margin, which indicates that taking advantage of the specific features is important for cross-oilfield reservoir classifications. 2) With KAT module, our proposed method MSE+KAT have achieved better performance than other variants and traditional method DANN. It indicates the effectiveness of our proposed knowledge-attentive transfer learning method. 3) Compare all the methods which do not have transfer learning strategy, we find our proposed MSE+KG model has achieved the best performance. One possible reason is that the knowledge graph brings the power of extensive geological information cross two different oilfields via the unified KG embedding.

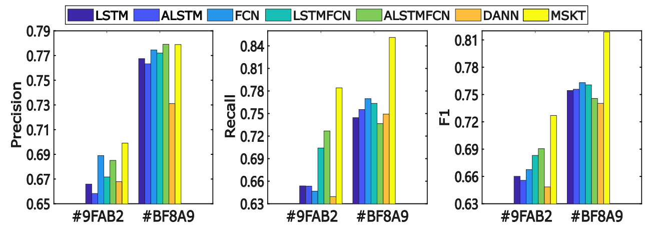

Figure 4: The illustration of reservoir classification performances on the source oilfield.

Analysis on Source Performances. In the exploration and production process of the petroleum company, experts care the method performances not only on the target oilfield but also the source oilfield. To that end, we further validate the effectiveness of our models on the source oilfield. Figure 4 shows reservoir classification performances on the source oilfield. From Figure 4, we have the following observations: 1) Our proposed MSKT outperforms all other compared methods with a large margin. One possible reason is that MSKT can take advantages of specific well log features. 2) We find DANN model achieves better performance than other non-transfer models on the target oilfield but fail to outperform sever models on the source oilfield. That indicates the transfer learning strategy may be negative to the performances on the source oilfield.

Conclusion and Future Work

In this paper, we presented a focused study on cross-oilfield reservoir classification problem. For transferring the geological knowledge from a source oilfield to a target oilfield, a novel Multi-scale Sensor Knowledge Transfer (MSKT) model was proposed. Specifically, we first proposed *Multi-scale Sensor Extraction (MSE)* to obtain the multi-scale feature representations of geological characteristics from multivariate well logs. Meanwhile, for addressing the inconsistent features between the source and target oilfield, we proposed an encoder-decoder module, i.e., *Specific Feature Learning (SFL)*, to learning the additional geological features from discriminative well logs in both oilfields. Then, we developed a *knowledge-Attentive Transfer (KAT)* module to learn the feature-invariant representations and transfer the geological knowledge from a source oilfield to a target oilfield. Finally, we evaluated our proposed method by conducting extensive experiments with real-world industrial datasets. The experimental results clearly demonstrated the effectiveness of our proposed solution to transfer the geological knowledge and generate the cross-oilfield reservoir classifications.

In the future, we would like to consider the characteristics and impact of different sensors (such as GR, AC) for the prediction. Moreover, we are also willing to integrate more geological domain knowledge and make our results more explainable. Last but not least, we will extend our proposed MSKT to much more sensor data mining scenarios, such as cross-domain anomaly detection. Although our work mainly focused on the cross-domain learning problem in the oil and gas industry, there are some similar problems in other real industrial scenarios. We hope our study can bring some new insights from the application view of sensor data mining and the technical view of exploiting transfer learning for cross-domain series modeling.

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