Bayesian deep learning and uncertainty quantification applied to induced seismicity locations at the Groningen gas field in the Netherlands – What do we need for safe AI?

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SUMMARY

Recently, with the increase of dense seismic monitoring networks and the resultant massive seismic data all over the world (e.g., Groningen gas reservoir), the traditional geophysical algorithms have faced the “big data” and high dimensionality issues and become inefficient and costly. Deep learning, as a candidate to mitigate the “big data” and high dimensionality problems, has started to be applied to many geophysical problems; however, previous deep learning studies seldom consider the model uncertainty, which may seriously impair reservoir production estimates, ground motion predictions, and seismic early warnings. Bayesian neural networks provide a practical solution to solve the uncertainty quantification problems in deep learning, i.e., to make AI safe. In this paper, we construct a Bayesian convolutional neural network and implement a stochastic regularized technique – dropout – to quantify the uncertainty of seismic location. This method has been applied to induced seismicities in the Groningen gas field in the Netherlands.

INTRODUCTION

Induced seismicity occurs in many oil and gas fields due to fluid injection and/or extraction all over the world, including America, Canada, China, Europe and the Middle East. Many countries have employed dense seismic networks to monitor induced seismicity and to obtain information about the seismic source physics, reservoir structures and ground motions. The massive seismic data make the traditional geophysical methods inefficient and costly.

Historically, Groningen has low local seismicity; however, in recent years, the gas production in the Groningen field has caused an increase of induced seismicity. To monitor the induced seismicity at Groningen gas field, more than 70 boreholes (each borehole has one 3-component accelerometer and four 3-component geophones) and 17 surface accelerometers were deployed to monitor induced seismicity (Figure 1(b)). Since 2009, the Royal Netherlands Meteorological Institute (KINM) has recorded more than 1000 earthquakes (M<5). These events are generally smaller than M 5; however, these events, occurring in the reservoirs, are very shallow with focal depths less than about 4 km. As a result, in Groningen, where oil fields are close to populated areas, these induced earthquakes could produce ground accelerations high enough to cause damage to local structures.

To better estimate the seismic impacts on infrastructures and mitigate seismic hazards, Shell instrumented 17 local houses and continuously monitored house motions from 09/2017 to 10/2018 (Figure 1(b)). Figure 1(b) shows the location of induced seismicity during the house monitoring period on a Groningen map based on the KNMI catalog. The location of the induced seismicity correlated well with pre-existing faults.

The induced seismicity and subsurface structure in Groningen was intensively studied and well documented by many research groups. Spica et al. (2018) gave an overview of structures from surface to reservoir depth in the Groningen gas field. van Thienen-Visser and Breunese (2015) published a detailed report about the seismicity and the fault map in Groningen field. Willacy et al. (2018, 2019) applied a full-waveform-based event location algorithm to the Groningen induced seismicity. However, little research has applied AI methods to the Groningen induced seismicity. With the recent tremendous increase of seismic data in the Groningen gas field, we are able to apply deep learning methods to study the Groningen induced seismicity.

Deep learning has been successfully used in many areas, e.g., image classification, natural language processing, etc. (LeCun et al., 2015; Goodfellow et al., 2016). In recent years, more and more deep learning algorithms have been applied to geoscience problems (Beroza, 2018; Kong et al., 2018; Bergen et al., 2019). Fully connected neural networks have been used to solve traditional location and tomography problems (Araya-Polo et al., 2018; DeVries et al., 2018; Gu et al., 2018). Many studies have applied convolutional neural networks to automatically locate earthquakes without manual phase-arrival picking (Huang et al., 2018; Zhang et al., 2018; Kriegerowski et al., 2018). Deep convolutional neural networks have also been used to obtain fast approximate simulation of seismic waves (Moseley et al., 2018). Richardson (2018) has proposed a new full waveform inversion algorithm with recurrent neural networks.

These previous deep learning studies seldom consider uncertainty quantification of weights of neural net, choice of architecture, choice of hidden layers, etc, which may result in serious problems (e.g., automatic driving). Bayesian neural networks provide a way to understand uncertainties of deep learning system and make AI safe (Ghahramani, 2016). The complexity of deep neural networks makes it difficult to derive an analytical expression of the probability distribution of parameters in Bayesian neural nets, as well as the probability distribution of the prediction. Gal (2016); Gal and Ghahramani (2016a,b) have proposed practical tools – Bayesian deep neural nets with stochastic regularization techniques (SRTs) – to quantify uncertainties in deep learning. These tools can be scaled to big data and complex neural nets.

We implement a Bayesian convolutional neural network with a stochastic regularization technique (SRT), MC dropout, to locate induced seismicity in the Groningen gas field and quantify the location uncertainties. The neural networks were first trained with synthetic waveform data and then applied to real seismic data.
Bayesian deep neural networks and uncertainty quantification applied to induced seismicity

The probability distribution of the prediction \( y^* \) giving testing inputs \( x^* \) with Bayesian neural networks can be represented as

\[
p(y^*|x^*, X, Y) = \int p(y^*|x^*, \omega)p(\omega|X, Y)d\omega.
\]  

(1)

where \( X \) and \( Y \) are training inputs and outputs. \( \omega \) is a general representation of random variables in deep neural networks, e.g., weights and bias (fully connected neural layers), kernels (convolutional neural networks), and gates (recurrent neural networks), depending on neural network structures. \( p(\omega|X, Y) \) is hard to derive analytically. An approximation variational distribution \( q_\theta(\omega) \) is always used instead. \( q_\theta(\omega) \) can be evaluated by minimizing the Kullback-Leibler (KL) divergence (Kullback and Leibler, 1951)

\[
KL(q_\theta(\omega)||p(\omega|X, Y)) = \int q_\theta(\omega) \log \frac{q_\theta(\omega)}{p(\omega|X, Y)}d\omega.
\]  

(2)

Then, Equation 1 can be approximated as

\[
p(y^*|x^*, X, Y) \approx \int p(y^*|x^*, \omega)q_\theta(\omega)d\omega = q_\theta(y^*|x^*).
\]  

(3)

For complex deep neural networks, the approximated distribution \( q_\theta(\omega) \) are always evaluated by stochastic regularization tools during training, e.g., dropout, multiplicative Gaussian noise, and dropConnect (Gal, 2016).

Given the approximated distribution \( q_\theta(\omega) \), we can generate \( T \) realizations of model parameters, i.e., stochastic forward passes, according to the posterior model distribution

\[
\{\omega^i\}_{i=1,\ldots,T} \sim q_\theta(\omega).
\]  

(4)

Assuming a Gaussian likelihood of the prediction \( y \)

\[
p(y^*|f^\omega(x^*)) = N\left(y^*; f^\omega(x^*), \tau^{-1}I\right).
\]  

(5)

where \( \tau \) is the precision of the measurement, the mean and variance of the prediction of Bayesian neural networks can be written as (Gal, 2016)

\[
\mathbb{E}[y^*] \approx \frac{1}{T} \sum_{i=1}^{T} \hat{y}_i^*(x^*),
\]  

(6)

\[
\text{Var}[y^*] \approx \tau^{-1} \frac{1}{T} \sum_{i=1}^{T} \hat{y}_i^*(x^*)^T \hat{y}_i^*(x^*) - \mathbb{E}[y^*]^{T} \mathbb{E}[y^*].
\]  

(7)

In this study, we construct a Bayesian convolutional neural network to map the 2D seismic wave field to seismic locations (Figure 2). To stochastically inject noise to model during training, we added one dropout layer after the last convolutional layer and before the fully connected layer. The output of the dropout layer is passed to the fully connected layer and output a three-dimensional location vector \( y \). A regression loss function is used to measure the mean-square-error during training.
Bayesian deep neural networks and uncertainty quantification applied to induced seismicity

Figure 2: Architecture of Bayesian convolutional neural network.

Figure 3: (a) Location of 8775 synthetic sources (red dots) and cross-sections of 3-D velocity model. (b) Location of 8775 synthetic sources (red dots) and 64 stations (green triangles) in a map view. (c) Normalized seismic time series at 64 stations.

TRAINING OF THE BAYESIAN NEURAL NETWORK

To train the Bayesian neural network, we first generate synthetic waveforms at trial earthquake locations \((39 \times 45 \times 5 = 8775)\) (Figure 3(a)). Figure 3(b) shows the locations of 64 stations with the synthetic earthquake locations in a map view. One example of a 2D wavefield due to one synthetic event at \(y = (245.6, 598.4, 3)\) km is shown in Figure 3(c). The 2D wavefields, i.e., 2D images, are inputs of the network. The 3-D location vectors \(y\) are outputs of the network. We use synthetic waveform fields observed at 64 stations and location \((y)\) pairs to train our convolutional neural network.

During the training, the dropout layer at the end of convolutional layers and before the fully connected layer stochastically injects noise at each iteration.

TESTING AND UNCERTAINTY QUANTIFICATION

We test the Bayesian neural network with noise-perturbed synthetic wave fields. The testing data are generated by adding 10\% Gaussian random noise to the “clean” synthetic wavefields.

To quantify the uncertainty of testing outputs, we apply the MC dropout method by generating \(T = 1000\) realizations of the Bayesian neural network for each testing input, i.e., stochastic forward passes. At each realization, the dropout layer is between the last convolutional layer and the fully connected layer and the dropout probability is 0.2. The posterior mean and variations of locations can be calculated by Equation 7. We show the posterior mean of locations of 1775 events at depth of 3 km in a map view in Figure 4. The posterior standard deviations in X, Y, and Z directions of 1775 events are shown in Figure 5(a), 5(b), and 5(c).

The location uncertainties are significantly affected by the station coverage. The synthetic sources away from the region with dense stations have larger bias and variance. Another interesting finding is the small variance in the Z direction. This waveform-based neural network location method provides good resolution in the Z direction. Accurate location in depth is very important in reservoir characterization.
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Figure 4: Posterior mean of the locations of 1775 synthetic sources (red dots) at depth of 3km. Black dots show the ground truth locations. Blue lines link the posterior mean locations and the ground truth.

CONCLUSIONS

Local earthquakes in Groningen are generally smaller than M 5; however, these events, occurring in the reservoirs, are very shallow with focal depths less than about 4 km. As a result, in Groningen, where oil fields are close to populated areas, these induced earthquakes could produce ground accelerations high enough to cause damage to local structures. Accurate and fast location and uncertainty quantification for big volumes of seismic data can help to better predict ground motions and generate more reliable building codes to mitigate seismic hazards.

We apply the Bayesian convolutional neural network, with the MC dropout technique, to locate the induced seismicities in Groningen and quantify the location uncertainty. The Bayesian deep neural network-based algorithms work efficiently to quantify model uncertainty in deep learning, e.g., weights in neural networks. However, the uncertainty due to data distribution, noise (errors in labels and measurements, etc.), and model structures (architectures, hidden layers, activation functions, etc.) of deep neural networks still need to be further studied.

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Figure 5: Posterior standard deviation in X, Y, and Z directions.
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