Is Machine Learning taking productivity in petroleum geoscience on a Moore's Law trajectory?

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Is Machine Learning taking productivity in petroleum geoscience on a Moore's Law trajectory?

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Introduction

During the last three decades Wolf and Pelissier-Combescure (1982), Delfiner et al. (1987), Baldwin et al. (1990), Wong et al. (1995), Helle et al. (2001) Bhatt and Helle (2002a,b), Dubois et al. (2007), Li and Anderson-Sprecher (2006), Zhang and Zhan (2017) have shown that neural networks such as multi-layer perceptrons (MLP) can be trained to infer lithology, sedimentary facies, porosity, and fluid saturation as functions of wireline logs. Machine Learning (ML) has been used to classify the seismic waveform (Anderson and Boyd 2004), solve AVO problems (Russell et al. 2002), and to segment seismic facies in 3D volumes (Meldahl et al., 2001; Zhao et al., 2015; Qi et al., 2016). Now, the next generation of ML techniques are transforming the subsurface workflow beyond these applications. This transformation is being enabled by multiple developments from outside the geoscience domain, namely:

- Algorithmic development, driven by AI researchers and tech companies, has given us; i) convolutional neural networks (CNN) (leCun et al., 1990; Krizhevsky et al., 2012) that have transformed the quality of image classification and segmentation tasks, ii) recurrent neural networks (RNN, LSTM) (Hochreiter and Schmidhuber, 1997a,b; Graves et al., 2006; Graves 2013; Sutskever et al., 2014) that have dramatically improved sequence-to-sequence learning, and generative adversarial networks (GAN) (Goodfellow et al., 2014; Zhu et al., 2017) which enable generation of realistic synthetic data and provide a powerful new class of architecture applicable to a wide range of problems.
- Open source libraries such as scipy, tensorflow, pytorch, sklearn, as well as open source geoscience specific libraries such as gempy (de la Varga et al., 2018), and devito (Luporini et al., 2018) are emerging and facilitating application of ML in geoscience.
- Increasing availability and democratization of sub-surface data in national data repositories (NDR) and other sources is enabling the geoscience community to experiment with novel data-analytics techniques, building data science into their problem-solving repertoire.
- GPU enabled high-performance computing, and cloud computing and storage have given a wider audience access to the supercomputing needed to drive the often memory- and compute-hungry algorithms.
- Emergence of data analytics platforms make the application of ML methods more practical for the generalist geoscientist who wants to focus on solving geoscience problems rather than writing bespoke code for each use case. Such platforms integrate data analytics with structured databases and enable users and organizations to apply ML on a large scale while maintaining order, data management, and provenance so that workflows are reproducible.

These enabling factors are changing how geoscientists interact with data. Interpretation is changing, workflows are changing, data management is changing, the way we deal with uncertainty is changing. These changes will have an impact on productivity in petroleum geoscience.

The value proposition of ML

The workflows typically used in geoscience today often require a lot of manual labour and experts to apply their experience-based knowledge. Any such manual, expert-driven, approach will naturally be prone to error and human bias, since subjective judgment is frequently used in the interpretation process and is inefficient, since the interpreter needs to make a long series of decisions. Costs are high, and owing to lack of time and technology limitations we are not able to make use of all relevant data using these traditional workflows and software.

So, can ML and data science mitigate these problems? Can we envisage data-driven analytics that are both more accurate, more precise, and more efficient than we can achieve with current workflows and software? ML models, such as neural networks, can approximate any continuous function on compact subsets (Hornik, 1991), a fact that continues to hold true for modern deep neural network architectures (Hanin, 2017). Individual machine-learning models essentially learn and perform an A to B mapping. They learn functions that describe the relationship (the transfer function) between some input (the features) and the desired output that is the target of our prediction (the label). In combination models, they can be used to learn and master tasks that require sophisticated decision-making capabilities (Mnih et al., 2015; Silver et al., 2017).

Traditional workflows rely on expert-driven manual model tuning using empirical (physics) equations and a string of

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experience-based expert decisions in the process. We can apply ML methods to encode these relationships. If we can make ML models that have the ability to generalize across data from various measurement tools and environmental conditions, human interpreters can save time, which can be spent on the more creative aspects of interpretation.

ML models should also have the potential to be more accurate and precise than we are used to as human interpreters since models can be trained using larger and richer data sets than we have capacity to use as humans. Quality of predictions can also increase since we can reduce human bias in a data-driven process.

Although the potential and benefit of ML in geoscience is promising, there are some practical challenges. While datasets we use can be large, the labels needed to train supervised regression and classification models are scarce and expensive to produce. Data scarcity and variability poses challenges to making models that generalize beyond the datasets they were trained on. Many problems in geoscience are also ambiguous and ill posed.

The changing face of sub-surface work

More and more geoscientists are now using ML in their work. Can ML make significant changes in interpretational aspects of that work? What are the use cases for ML in geoscience today, and what can we envisage for tomorrow?

Well data

At well scale, the geoscientist can now make reliable predictions of rock and fluid properties derived directly from data, quickly and repeatably without needing to rely on approximate models or inefficient and error-prone manual interpretation. Progress can be made rapidly at well scale as datasets are compact but rich in measurement and close to ground truth.

Transfer functions needed to infer porosity, lithology or fluid saturation from wireline logs can be learnt directly from the data. A porosity prediction model can for example be trained on wireline logs and on core-plug porosity data (Figure 1). With access to the right data we can quickly infer a rich set of property curves that can rival those that petrophysicists routinely provide

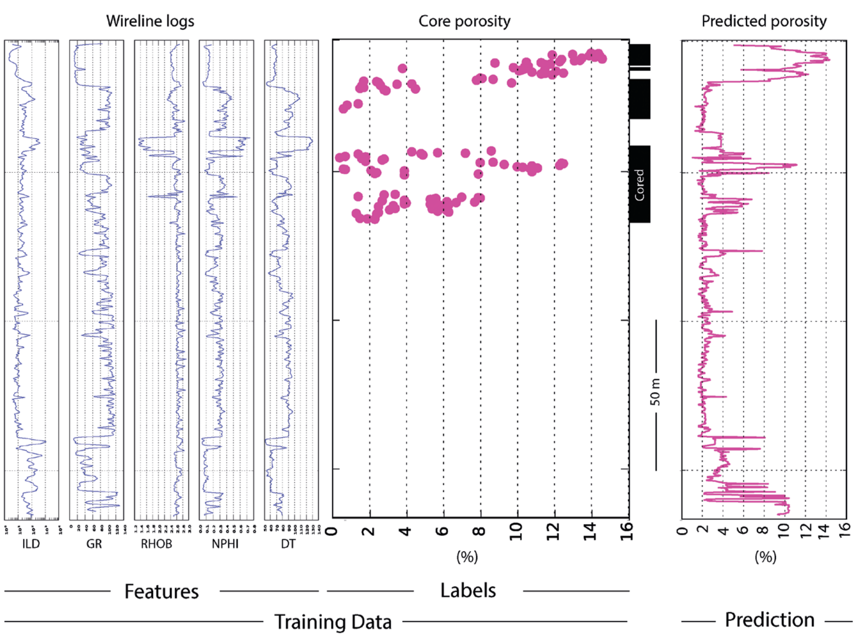

Figure 1 Porosity prediction from core data. From the left, wireline logs as a feature set, core plug measurements as labels, predicted porosity log to the right.

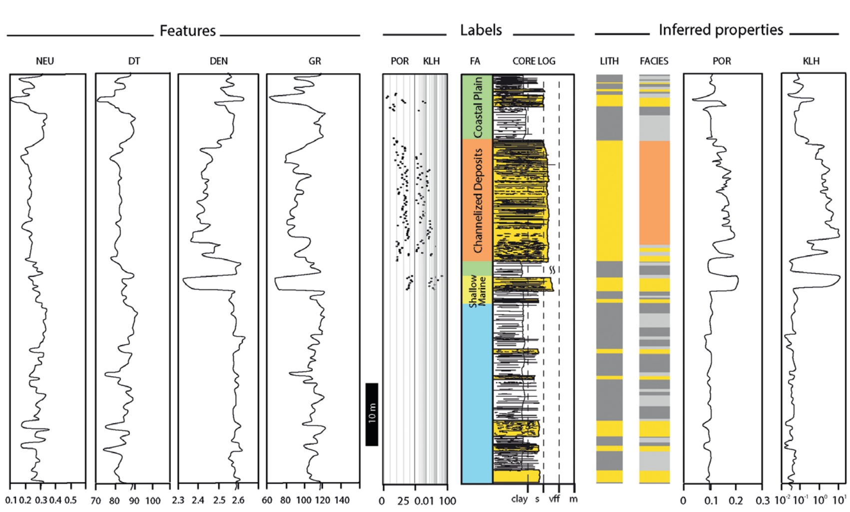

Figure 2 Multiple properties (lithology, sedimentary facies and porosity) inferred by ML models as functions of wireline logs. Models were trained on combinations of wireline logs (the features) and; i) lithology from core, ii) sedimentary facies from core description, iii) porosity from core plugs, and iv) permeability from core plugs (the labels) (core description courtesy of Tore Klausen).

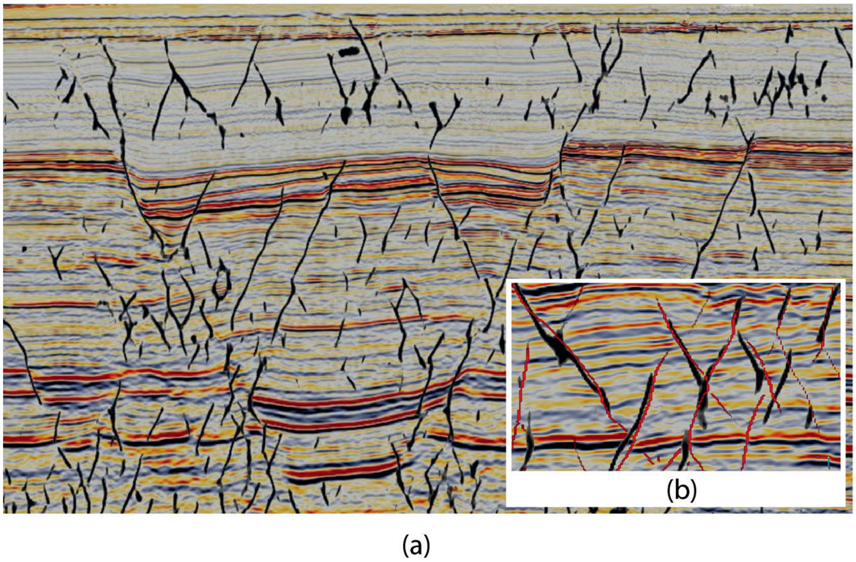

Figure 3 (a) Results of fault prediction on an inline slice not seen during training (black) from a Barents Sea 3D seismic dataset using a deep encoder-decoder network. Black pixels are fault probabilities over 0.5. This type of fault prediction is challenging using convolutional networks owing to the inherent class imbalance. (b) an example of detected faults (black) and supplied training labels (red). Training labels are derived from high probability values in fault attributes gathered on a small number of inline slices.

in their CPIs (Figure 2). With easy access to these property curves for an area of interest, we can explore the spatial distribution of rock and fluid properties efficiently, at scale. We can make data queries such as: 'show me the frequency-distribution of effective porosity from stratigraphic formation A, from area B, from depth interval C, and from lithology D'. Similar queries can be made for the other properties required for volumetric calculation and thus we can obtain data-driven property distributions required for probabilistic volume estimation. As geoscientists, we now have tools that we can seed with our expertise and creativity and use to interrogate data and answer questions.

Although well data often comes with a rich set of labels, e.g. from core, the efficiency increase we can achieve through supervised learning is still limited by the scarcity of labels, and the cost of obtaining them. Unsupervised learning methods may in the future be able to mitigate this problem. Currently, clustering methods applied to well data simply enable us to discover inherent patterns in the measurements. We need to find ways to understand how these patterns relate to the properties we need to quantify and predict as geoscientists and unlock the full potential of unsupervised methods.

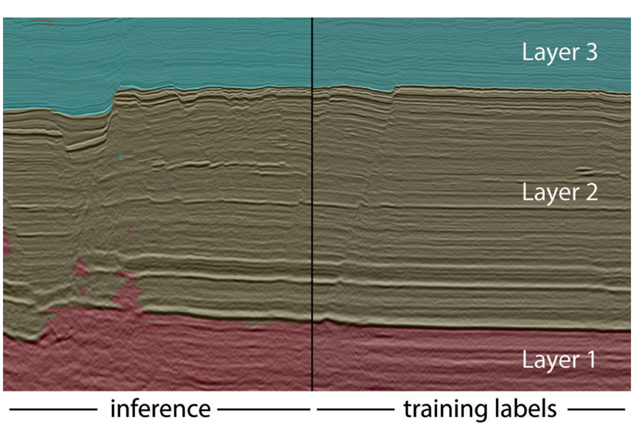

Figure 4 Stratigraphic classification on a 3D seismic dataset from the Barents Sea. A deep neural network was trained on labels highlighting three main stratigraphic intervals. Training labels are shown on the right hand side of the inline slice, and the prediction after training on a single labelled inline is shown to the left. Predictions can be improved by training on additional labelled inlines.

Seismic data

At seismic scale, we see the beginnings of modern ML being used for prediction of geological structure, stratigraphy and of rock and fluid properties. Initially, this is happening through ML-based approaches to seismic interpretation and inversion.

ML methods, such as fully convolutional deep networks (Long et al., 2015), have produced promising results for fault interpretation (Figure 3). Fully convolutional architectures provide more flexibility in how they can be trained and applied than conventional CNNs and are particularly suited to processing of large datasets such as seismic data, as they can be dynamically sized.

3D CNNs (Waldeland et al., 2018) and deep encoder-decoder networks such as SegNet (Badrinarayanan et al., 2015) have produced promising results for stratigraphic interpretation (Figure 4). These techniques classify a 3D seismic post stack dataset based on either 3D sub cubes or 2D sections, achieving a high level of consistency across a dataset based on a relatively small number of expert labelled examples. When applied to stratigraphic classification tasks, the boundaries of the extracted stratigraphic units are stable and consistent enough to produce good quality horizon surfaces (Figure 5).

In rock and fluid property prediction and inversion a host of ML methods are applicable and we have an extended toolset

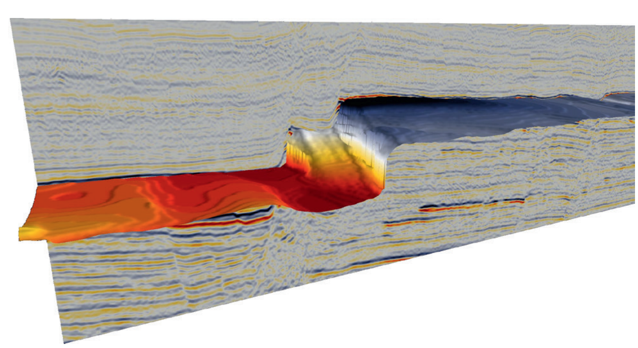

Figure 5 Boundaries of predicted stratigraphic units provide interfaces for extraction of key horizons. Even though the stratigraphic classifier was trained on a single inline section it produced an interface that behaved well from inline to inline, which was extracted over the entire 3D volume, and correctly captures details such as the fault relay ramp shown.

available for making such predictions. These range from manual feature engineering with classical ML models such as support vector machines (Figure 6) through to use of generative adversarial models (Mosser et al., 2018a) trained on synthetic data for elastic property inversion.

The changing role of the subsurface expert

Machine learning algorithms need appropriate data to learn from and environments to learn within. Successful application stems from construction of well posed problems or experiments with clean, balanced, and well-constructed data feeds. In subsurface work, well posed problems and clean, organized, and plentiful data is hard to come by and diminishes the further we head away from core scale measurements. We need to rely on domain expertise to bridge the gap.

Labelling and embedding knowledge

Undoubtedly supervised learning has been the area with most significant recent progress in ML across many fields. In subsurface work this provides us with a conundrum because of limited availability of reliable labels and the cost of producing those labels. Here we refer to 'label' meaning the target of a particular prediction task.

Taking seismic interpretation as an example, labels representing faults, horizons and geobodies are certainly costly to produce. Those that are available from traditional interpretation are often

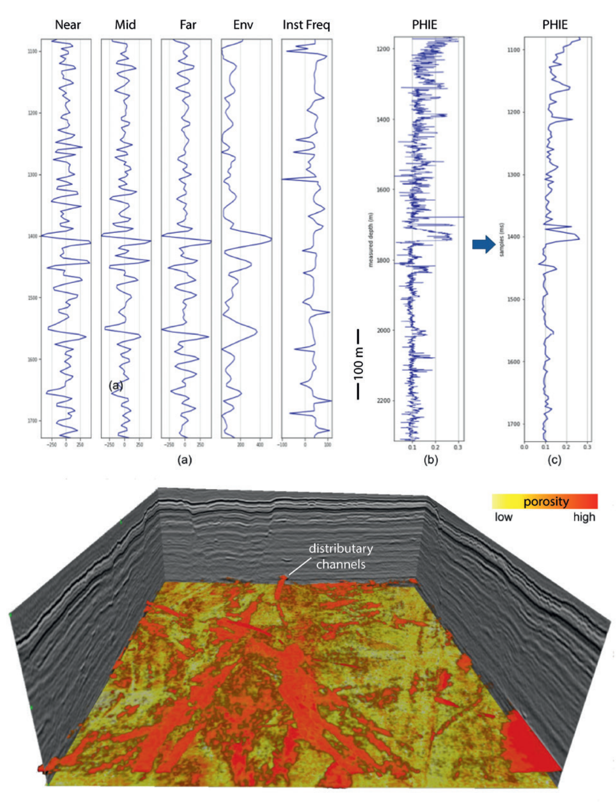

Figure 6 Porosity prediction on a 3D seismic dataset from the Barents Sea, showing (a) partial stack amplitudes and example features on on trace nearest well (b) porosity log predicted from core measurements (c) smoothed porosity log at seismic sampling rate (d) 3D rendering of predicted porosity volume. High porosity Triassic channels are rendered above a depth slice through the same volume (d).

highly subjective and produced for specific reasons, on a large scale to capture and promote understanding of an area, and at close scale to tightly define a static subsurface model for volumetric calculation and reservoir simulation. Because of the costs, usually only sufficient work is done to meet the criteria for each output, we do just enough regional interpretation to be certain of the basin-wide context we are working in and at reservoir scale we develop the static model, so it has just the right information for our simulations.

In applying supervised learning, we find that we need to approach label generation, and so seismic interpretation, differently. We are now producing interpretations (Figure 7) that are not immediately useful for model building but are instead geared towards training and enabling ML algorithms to do useful and precise work.

Types of labels can range from tags on individual data patches, through to bounding boxes (Figure 7a) for object detection to dense class labels for segmentation (Figure 7b, c) to precise picks of subsurface features (Figure 7d). Each type of label has a different role and can be used to answer a different question. The type of algorithm used will also place constraints on the labelling and conversely availability of labels limits choices of algorithms.

Some of these labels will seem strange in light of traditional seismic interpretation practices but their form and quality are very important in applying ML. Bounding box labels for example seem extreme and poorly suited for use with geological structures. However, they are relatively cheap to provide and allow localization of features for analysis on a large scale where precisely identifying the volume of an element is not of immediate importance. They also can provide an important supporting role in more advanced composite ML architectures (He et al., 2017).

How much of this type of interpretation will we need to do? In supervised learning our aim is to only need to label small portions of a dataset and allow the machine to automate the rest. We already see what is achievable with CNNs alone for some use cases (Waldeland et al., 2018; Mosser et al., 2018a). Basic labels on one to a few seismic slices can be sufficient to train a model to do inference for a full seismic cube. When we can achieve satisfactory results with such limited training across multiple interpretation tasks we can expect to be a lot more productive for smaller investments in manual picking work.

So manual interpretation work will still remain prevalent but may change its focus to feed information and expert knowledge into these new tools, collecting the right type of labels for a task and striving to maintain balanced training sets. The dynamics of this process are likely to be very different than that surrounding interpretation work that is done for our current task masters, the reservoir model and flow simulators. The payback could well be richer and more frequent feedback on the impact of expert decisions during the interpretation process and the extents to which our data supports them.

In the future, as capabilities such as transfer learning and generative models mature in our domain, we will maybe see less and less of a need for labelling of this type. If we can develop seismic models that generalize well, we can build useful pretrained models, so that this style of interpretation (labelling) may turn into a process of fine tuning for new structures and new forms of seismic data.

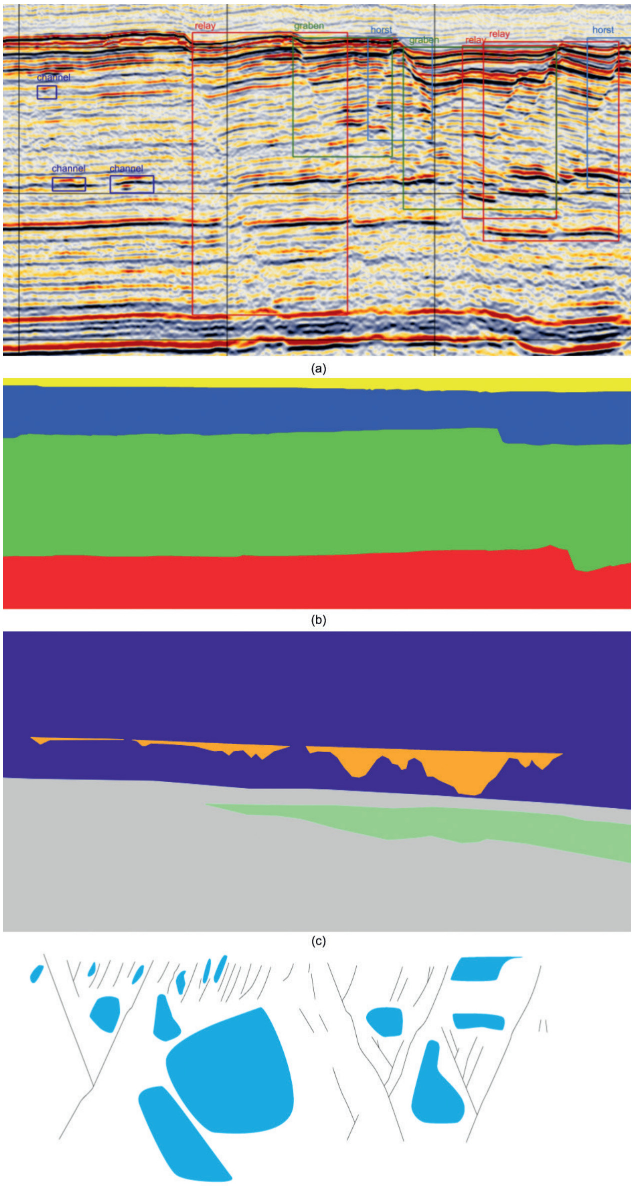

Figure 7 Labelling seismic for machine learning tasks; (a) bounding box labels for subsurface object detection, (b) dense labels over an entire inline for stratigraphic unit segmentation, (c) dense labels for geobody isolation as part of work to identify stratigraphic traps, (d) sparse label sets on an inline section for use in automated fault interpretation.

To supplement expert-driven labelling, we can generate labels with various physics simulators. Models can be trained on combinations of synthetic and measured data in a form of hybrid learning. Synthetic data, embodying the domain knowledge of the physics simulators, e.g. rock physics templates, petrophysics models or diagenetic models, can be used to capture knowledge that is not embedded in the locally available 'ground truth' training data.

Changing our relationship with subsurface uncertainty

Geological interpretation is typically based on sparse and low-resolution data and is thus inherently uncertain. Although we know this, and aim to account for uncertainty, e.g. for probabilistic volumetric estimates, our interpretation of seismic horizons rarely comes with an associated measure of uncertainty.

Scenario analysis can be done very efficiently using ML to construct multiple models based on variations of the input data. Practitioners are also exploring the use of Bayesian neural networks (Kendall and Gal, 2017) to determine model uncertainty and can show favourable performance for seismic interpretation tasks (Mosser et al., 2018b) (Figure 8). Stochastic reservoir modelling is now commonly used to create heterogeneous facies models, but in the future GANs are likely to play a key role in generating realistic sedimentary architectures for our reservoir models (Dupont et al., 2018). We need to progress beyond treating uncertainty as an afterthought in our workflows and use the opportunity that a data-driven approach provides to make uncertainty analysis fundamental to everything that we do.

Realizing the potential

Over the last few years we have seen a change of pace in development of ML applications for geoscience. For the most part this is fuelled by rapid development of ML in other domains but it is also the beginning of successful technology transfer into our own. In the above, we have talked about the advances already made and the further transformation of subsurface workflows that adopting the latest generation of ML capabilities may bring.

ML applications for specific use cases have matured sufficiently to be deployed for use in the daily business of E&P teams. Data analytics platforms, such as EarthNET, *earthnet.ai*, make the use of ML methods more practical for the generalist geoscientist, integrating data analytics with cleaned, ML-ready

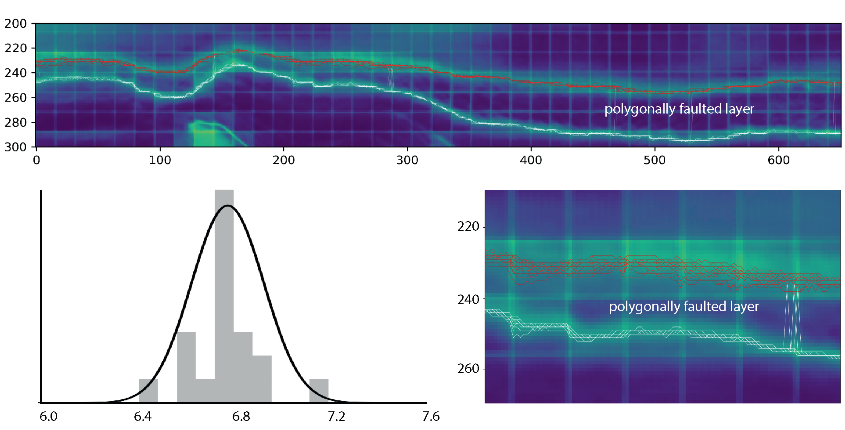

Figure 8 Uncertainty in volumetric estimates. Using bayesian deep networks, it is possible to integrate uncertainty estimates analysis within predictions made by deep neural networks. This allows multiple realizations to be generated and variation in positional and volumetric estimates to be quantified (figure reproduced with permission of Mosser et al., 2018b).

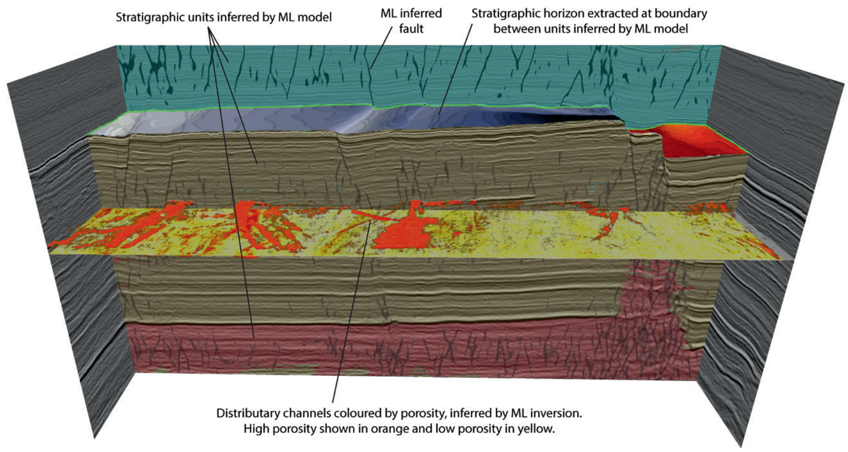

Figure 9 Multiple inferred properties from multiple ML models can provide the components required to build static geomodels for volumetric estimates and flow simulation.

databases, and thus enable users and organizations to readily apply ML workflows.

Integrated platforms facilitate semi-automated data management, quality-control and even improvement of the datasets used to train ML models, and enable tracking of data and model provenance (storing rich metadata and metrics that document how models were built, with which data they were built, and how well the models were able to match ground truth in blind tests), so that the scientific workflows can be made reproducible.

Using these integrated platforms for repeated model training and inference, across large datasets of wells and seismic, results in a growing machine-readable database of inferred rock and fluid property data, stratigraphic data, and structural geology data.

As these integrated data assets grow, we have at our disposal a rich database containing the properties we really care about as geoscientists. We can then perform queries for the information and insight which we need to inform the decisions we have to make in our search for oil and gas.

For example, with methods available today and quickly improving, we are able to obtain i) ML-derived lithology and fluid property curves for our wells, ii) ML-derived structural and stratigraphic interpretation of seismic data, and iii) rock and fluid property cubes from ML-assisted seismic inversion. With this data we can start to ask complex questions related to the distribution and nature of hydrocarbon accumulations. Instead of spending most of our time computing curves and picking seismic reflections, we, as geoscientists, can now apply our knowledge and creativity to ask the right questions (Figure 9).

In this article, we have briefly discussed some of the most significant factors that we see in adopting of this technology now. The base ML technologies and platforms exist and are there for us to exploit. Their development is continuing to accelerate in other industries taking value creation on a trajectory of exponential growth. Our task is to successfully adapt this technology to our data and our domain and take advantage of the tremendous opportunities it offers.

The breakthroughs that we are working towards will enable us to exploit all the relevant data available to us, to leverage true integration across data types and disciplines, to make data-driven uncertainty analysis a central part of our workflows. These changes will have an impact on the productivity of petroleum geoscience. Machine learning may now be taking productivity in petroleum geoscience on a Moore's Law trajectory.

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