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Preliminary Report on Applications of Machine Learning Techniques to the Nevada Geothermal Play Fairway Analysis

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ABSTRACT

We are applying machine learning (ML) techniques, including training set augmentation and artificial neural networks, to mitigate key challenges in the Nevada play fairway project. The study area includes ~85 active geothermal systems as potential training sites and >12 geologic, geophysical, and geochemical features. The main goal is to develop an algorithmic approach to identify new geothermal systems in the Great Basin region. Major objectives include: 1) integrate ML techniques into the geothermal community; 2) develop open community datasets, whereby all play fairway and ML datasets and algorithms are publicly released and available for modification by various user groups; 3) identify data acquisition targets with high value for future work; 4) identify new signatures to detect blind geothermal systems; and 5) foster new capabilities for characterizing subsurface temperature and permeability. Initially, ML techniques are being applied to the same play fairway datasets and workflow. ML will then be applied to both enhanced and additional datasets, with modification of the PFA workflow to incorporate the new datasets. Finally, ML will be applied to define new workflows using the enhanced and additional datasets. An algorithmic approach that empirically learns to estimate weights of influence for diverse parameters can potentially scale and perform better than the play fairway analysis. Initial work on this project has involved 1) evaluating potential positive and negative training sites, 2) transformation of datasets into formats suitable for ML, and 3) initial development and testing of ML techniques.

1. INTRODUCTION

The Great Basin region is a world-class geothermal province with ~720 MWe of current gross generation from ~24 power plants. However, studies indicate far greater potential for both conventional hydrothermal and EGS systems in the region (Williams et al., 2009). Most systems, especially those ≥130°C, reside in normal fault terminations, fault intersections, step-overs in normal fault systems, and extensional accommodation zones, as opposed to the main fault segments (e.g., Curewitz and Karson, 1997; Faulds et al., 2006; Faulds and Hinz, 2015). These fault interaction zones contain higher fault and fracture densities, which enhance permeability.

Because most geothermal systems in the Great Basin are controlled by Quaternary normal faults, they generally reside near the margins of actively subsiding basins. Thus, upwelling fluids along faults commonly flow into permeable subsurface sediments in the basin and do not daylight directly along the fault. Outflow from these upwellings may emanate many kilometers away from the deeper source or remain blind with no surface manifestations (Richards and Blackwell, 2002). Blind systems are thought to comprise the majority of geothermal resources in the region (Coolbaugh et al., 2007). Thus, techniques are needed both to identify the structural settings enhancing permeability and to determine which areas may harbor subsurface hydrothermal fluid flow. The recent development in central Nevada of the highly productive geothermal system at McGinness Hills (Nordquist and Delwiche, 2013), a blind field directly northeast of Austin, Nevada, currently producing ~165 MW, suggests that many such systems are yet to be discovered in the Great Basin. The technical challenge is developing methodologies to locate such systems economically and with minimal risk.

Geothermal play fairway analysis (PFA) is a concept adapted from the petroleum industry (Doust, 2010) that aims to improve the efficiency and success rate of geothermal exploration and drilling. It involves integration of geologic, geophysical, and geochemical parameters indicative of geothermal activity (Faulds et al., 2017). The concept is applied to the evaluation of both known, undeveloped systems and potential undiscovered blind systems. PFA was successfully applied to 96,000 km^2 of the Great Basin region in Nevada (Figs. 1 and 2; Faulds et al., 2017, 2018), indicating great promise in PFA. The Nevada PFA project incorporated ~10 geologic, geophysical, and geochemical parameters indicative of geothermal activity. It led to discovery of two new geothermal systems. The PFA leveraged logistic regression, weights of evidence, and other statistical measures as a type of ML technique. A set of features, each gauged by a perceived weight of influence, were combined to estimate geothermal potential. However, PFA faces key challenges, including estimating weights of influence for various parameters, incomplete datasets, and a limited number of training sites. Compared to the petroleum industry, PFAs for geothermal systems are in their infancy. Also, geothermal PFA methodologies can vary widely between regions depending on geologic setting, quality of exposure, and effectiveness of geophysical techniques under local conditions. Thus, an important question is whether artificial intelligence (AI)/machine learning (ML) methods can enhance PFA and further reduce risks in geothermal exploration. Considering the success of the Nevada PFA project and rapidly emerging ML technology, it is timely to merge these efforts into a single project that applies ML techniques to PFA and evaluates the relative performance of both technologies.

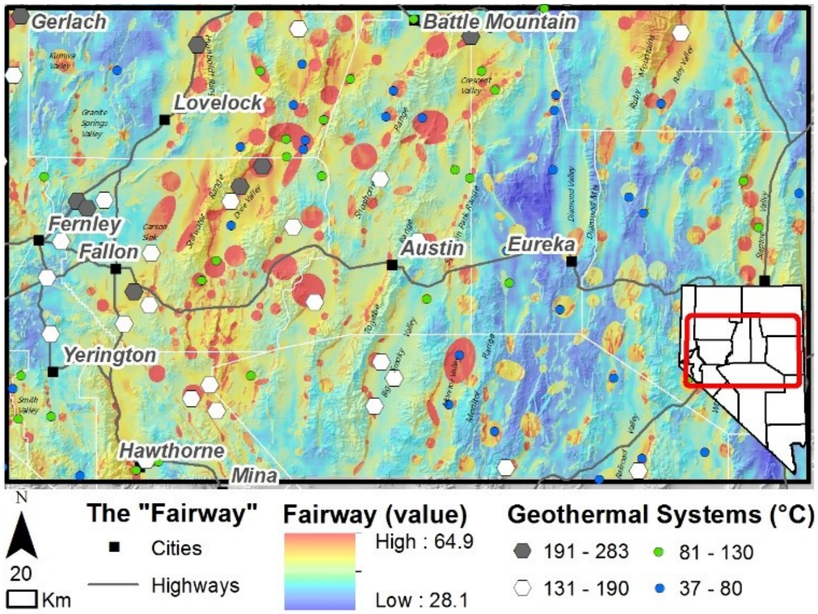

Figure 1: The play fairway model of the study area in west-central to eastern Nevada (modified from Faulds et al., 2018).

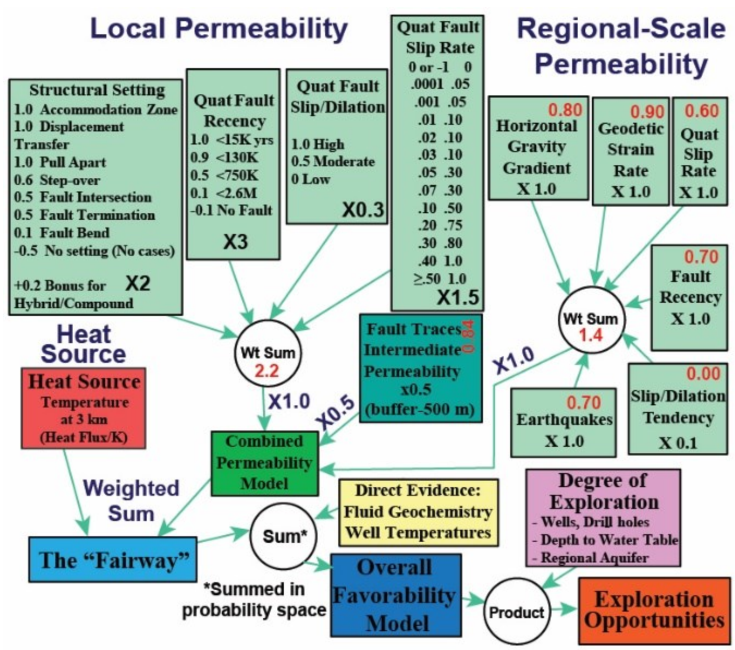

Figure 2: Nevada PFA workflow. Note the mixture of numerical, categorical, and ordinal features, each tied to geographic positions on a map with varying scales of resolution (modified from Faulds et al., 2017).

2. MACHINE LEARNING

Recent developments and successes in AI and ML, using artificial neural networks (ANN) and convolutional neural networks (Goodfellow et al., 2018), hold promise for improving the PFA. Initially, we are considering a supervised learning approach to be most directly applicable to our dataset and comparable to our past results. Supervised learning involves an algorithm that is optimized to associate pairs of measurable features and labels by providing it with many examples. Each piece of information included in the representation of the input to a problem is known as a feature, and each piece of information in the desired output of the problem is a target, or label. Specifically, an algorithm is provided with a set of examples whereby geological and geophysical features are known to be associated with a viable geothermal system or not (positive or negative labels). The distinction between supervised and unsupervised algorithms is not, however, formally and rigidly defined, because there is no objective test for distinguishing whether a value is a feature or a target provided by a supervisor (Goodfellow et al., 2018).

The data for many geoscience applications require customization to optimize applications of AI methods (Cracknell and Reading, 2014). First, geoscience problems commonly deal with multidimensional arrays (tensors) of features distributed on 2D and 3D maps. In addition, a general paucity of training sites with known labels generates challenges for conventional statistical approaches, but supervised ML methods can be adapted to address this. Another consideration is the nature of data. Input datasets carrying information for regression or classification are commonly a mix of numerical values (e.g. temperature, distance to a fault, or gravity anomalies), categorical variables (mineral assemblages or rock types), and ordinal variables (*this is bigger than that*; i.e. with ranking, but no scaling). Also, these datasets may not have the same resolution or same degree of certainty. Finally, variably understood physical principles indicate relations between features and labels. Incorporating expert knowledge into the learning algorithms can therefore be important.

Generally, supervised ML uses two sources of knowledge: 1) labeled data (X, Y pairs), and 2) hand-engineered features, network architecture, and other components. However, as problems dictate and as the availability of geoscience data grows, approaches that leverage *big data* are becoming necessary. Where possible, it is best to balance between feeding large numbers of features into a network and letting the algorithm determine the relations vs. engineering the complete hypothesis and algorithm by hand. The former, while unbiased and allowing data to guide results, can be prone to over-fitting. The latter runs the risk of extreme bias, leading to under-fitting such that important links among features may not be recognized. Also, the algorithms developed in the hand-engineered approach may not be appropriate for new data types or to new realms of application.

We are addressing these issues by revisiting the PFA workflow (Fig. 2) and re-analyzing accompanying data using ML methods in order of increasing complexity. We compare the weights used in the original workflow to those derived by the optimization of a variety of fully connected ANNs constrained by benchmark data. We are applying these principles specifically in regard to enhancing subsurface characterization, elucidating the prospectivity of geothermal resources, and addressing the challenges of incorporating and improving the interoperability of diverse 2D and 3D datasets. In later phases of the project, we will extend our approach to include anomaly/novelty detection methods and unsupervised clustering of the salient geological and geophysical features. In the end, we hope to provide maps of the probability of finding new geothermal systems from a variety of models including measures of confidence.

3. PROJECT OBJECTIVES AND WORK PLAN

The major objectives of this project include: 1) integrate ML techniques into the geothermal community; 2) develop open community datasets (especially labeled datasets, whereby all PFA and ML datasets and algorithms from this project are publicly released and available for modification by various user groups); 3) identify data acquisition targets with high value for future work by academic or industry groups; 4) identify new signatures to detect blind geothermal systems; and 5) foster new capabilities for characterizing subsurface temperature and permeability.

To accomplish the objectives, we are instituting a three-tiered approach (Fig. 3) that applies ML techniques to the Nevada PFA region. Initially (stage-1), we are applying ML techniques to the same datasets and workflow used in the PFA and comparing results. As in the PFA, the workflow (Fig. 2) will involve an overall framework of permeability at various scales, incorporating multiple geologic and geophysical geochemical parameters. These features will be weighted by perceived influence and relation to final resource probability (similar to that in the PFA project), utilizing known systems as positive training sites. The workflow is a type of computational graph representing steps of performed calculations to be placed in a ML framework. A ML-derived algorithmic approach that empirically learns to estimate weights of influence for diverse parameters can potentially scale and perform better than the qualitative expert opinions employed in the PFA. We have redrawn the original PFA diagram (Fig. 4) to show its similarity to a neural network with linear activation functions (Goodfellow et al., 2018). In stage-2, we will utilize enhanced and additional existing datasets in a similar workflow. A refined regional gravity dataset will be employed, and regional magnetics, paleo-geothermal features (e.g. sinter; Yap et al., 2018), and possibly magnetotelluric data (e.g., Wannamaker et al., 2019) may be added. This will necessitate modification of the workflow and relative weightings, which will be done using a ML algorithmic approach. We may use the PFA workflow again but will also explore a fully connected ANN. In stage-3, we will diverge from the PFA workflow and fully engage ML techniques to explore new workflows, combinations of datasets, and relative weightings of each parameter. We will explore options beyond ANN or perhaps enhancements to ANN.

Expected results and major accomplishments after completion of the first two stages include: 1) full incorporation and adaptation of the PFA methodology into the AI/ML system; 2) comparative analysis of the PFA and ML techniques; 3) initial insights from the ML approach into new links between various features; and 4) recognition of any challenges to adapting PFA to ML techniques. We expect to discover heretofore unrecognized links between various datasets that will lead to new insights into the signatures of geothermal activity, thereby facilitating discovery of blind systems. Results from all three stages will be compared to the original PFA outcomes, and the relative merits of the PFA and ML methodologies will be documented.

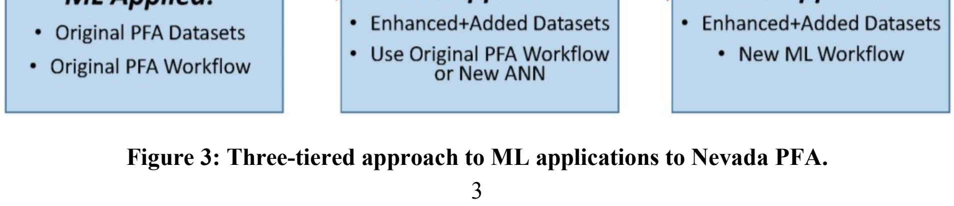

Figure 3: Three-tiered approach to ML applications to Nevada PFA.

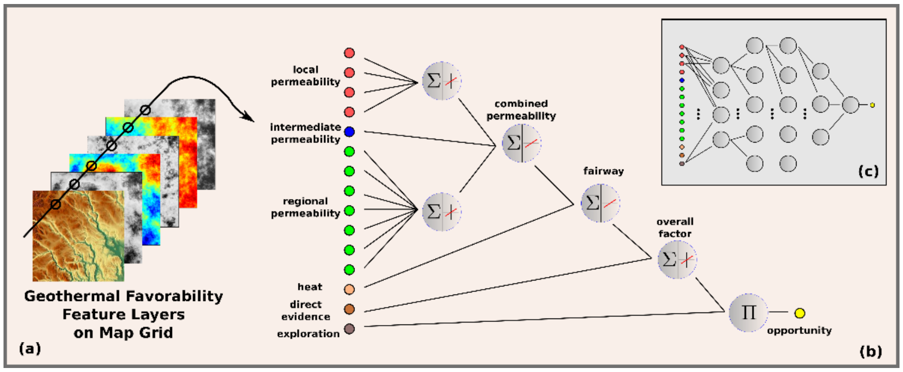

Figure 4: a) Geothermal potential features are mix of numerical, categorical, and ordinal types, each tied to geographic positions. b) PFA workflow is redrawn (from Fig. 2) as computation graph to show similarity to neural network with linear activation functions. At each location, the feature vector is fed to the PFA workflow and each grid associated with geothermal probability. c) Comparison of the PFA workflow to a typical fully connected neural network shows how the original computation graph has been hand-engineered to include a structure using expert knowledge. This illustrates how the neural network will begin by mimicking the workflow of the previous PFA analysis. The neural nets will then evolve in complexity, as nodes and functions increase, to evaluate more complex interactions among the data and the geothermal sites.

4. PRELIMINARY RESULTS

Initial work on this project has involved 1) delineation of positive and negative training sites, 2) transformation of datasets into formats suitable for ML, and 3) initial development and testing of ML techniques. The application of ML techniques requires a reasonable number of training sites. In the Nevada PFA, statistical methods were hindered by only 34 benchmarks of known relatively high-temperature (>130°C) systems. For this ML project, we are considering a broader temperature range (>37°C) if the site has an anomalously high temperature gradient. The reasoning is that anomalous temperature gradients require relatively high permeability. This could yield as many as ~86 positive training sites for development of ML algorithms (Fig. 5). We may use the lower-temperature sites in this group as negative sites instead of positive sites, or we might consider them as gradational between positive and negative sites. Geological, geophysical, and geochemical datasets are available from most of these sites. To test and develop our ML algorithms, we ultimately plan to evaluate existing more detailed datasets from many of these positive training sites, where available.

A challenge in the early stages of this project has been defining negative training sites. Choosing sites that yielded low play fairway values seemed circuitous, especially considering that a goal of our ML project is to test the PFA. We also reviewed prospective geothermal systems that had yielded poor results in terms of temperature and/or permeability. However, there were a limited number of such sites (~10) with readily available data. In contrast, there is a relatively large number (>250) of relatively deep (>1 km) oil and gas wells in the region that do not show any temperature anomalies (Fig. 5). These wells offer a relatively large number of potential negative training sites for the ML analysis. We plan to use a 3 to 5 km diameter around each of these wells as a buffer defining an individual negative training site, which will likely >100 potential negative training sites for the region. However, a regionally extensive, relatively cool carbonate aquifer occupies approximately the eastern third of the study area (e.g., Mifflin and Hess, 1979; Welch et al., 2007), where these wells are clustered. The carbonate aquifer may significantly bias this dataset. Thus, we are currently evaluating the potential effects of the carbonate aquifer on this dataset.

Transformation of original PFA datasets to suitable formats for application of ML algorithms is critical for this project. Transformation methods include conversion to and from high-resolution xyz files to ensure portability between map-based platforms (e.g. ArcGIS) and non-map-based statistical platforms (e.g., R). Once data are evaluated, a suitable SQL database such as Microsoft Access is chosen. The ML algorithms and code are then formatted, made available via Jupyter Notebook, and ultimately linked with a GitHub repository, which allows for storage and sharing of code and data. The early stages of database development include derivation of higher-level processed datasets that explore and identify portions of the data space most relevant for geothermal potential. Known systems, or labeled datasets, are being divided into groups for training, development, and testing. About 2/3 of labeled datasets will be assigned to the training group, with the rest reserved for development (hand tuning) and testing (evaluation). By maintaining distinct training and testing datasets, we avoid introducing a learned-data bias (i.e., ML algorithms must be evaluated on labeled datasets never seen before).

Development and testing of ML techniques has initially involved applying ML to the original PFA datasets. This includes utilizing the PFA preprocessed data sets from the entire region, as well as the training sites, to implement PFA workflow in TensorFlow within Jupyter Notebooks. The original model is being used to test and verify the previous results, as well as verify the previous results, as well as provide a baseline measure of performance by comparing the predictions and errors of neural nets against the pre-existing expert-driven PFA model. By relaxing the expert constraints built into the PFA model as we move toward a fully-connected ANN, we will learn how best to set the balance between the sources of information (i.e., between letting the data speak for themselves and inserting expert knowledge). Balanced data sets (nominally equal numbers of positive and negative outcomes or labels) are needed for this type of supervised learning classification problem. While awaiting final definition of negative training sites, we created sets of “synthetic” negative data to use for preliminary trials. The combined positive and negative data were split into the required training and testing or validation sets. Using Google TensorFlow and the Python scripting language within Jupyter Notebooks, the original PFA workflow computation graph was replicated such that the weights in the model can either be preset for direct prediction or determined from training of the network via back propagation. A general fully connected ANN was generated for comparison to the original workflow. Both networks (the PFA and the ANN) were tested for functionality by preliminary training trials on the PFA dataset with fake negatives. Both models train well and converge to a relatively high prediction accuracy.

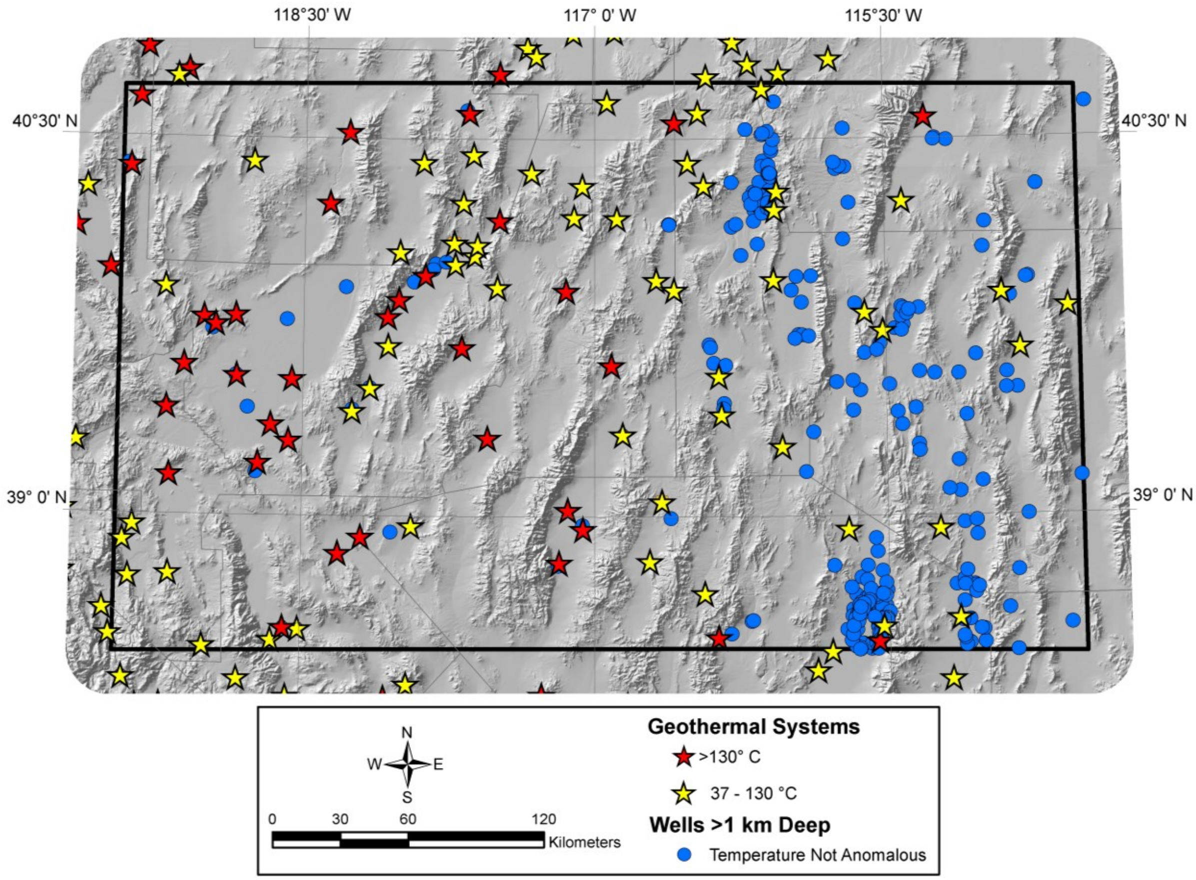

Figure 5: Map of the play fairway area showing 86 positive (red and yellow stars) and potential negative training sites (blue stars). Blue stars represent wells greater than 1 km in depth that do not have anomalously warm temperatures. Most of these wells were drilled for oil and gas exploration, but some were drilled for geothermal exploration. Due to the clustering of these wells, not all will be used for negative training sites. We are considering the appropriate diameter (~3 to 5 km) around such wells as a buffer of sorts for defining an individual negative training site.

5. CONCLUSIONS

This project builds on the Nevada play fairway project and aims to apply machine-learning techniques to reduce the risks in geothermal exploration, particularly for discovering blind geothermal systems. Although the Nevada play fairway project led to the discovery of at least two blind geothermal systems (Faulds et al., 2018; Craig, 2018; Faulds et al., 2019), challenges affected the PFA, including estimating weights of influence for parameters, incomplete datasets, and limited training sites. We hope to mitigate these challenges through innovative applications of ML techniques, including training set augmentation and artificial neural networks. The study area includes ~85 active geothermal systems as positive training sites and at least 100 negative training sites, primarily derived from cool oil and gas wells. The main goal is to develop an algorithmic approach to identify new geothermal systems in the Great Basin. The work plan is proceeding in three stages. Initially, ML techniques will be applied to the same PFA datasets and workflow. ML will then be applied to both enhanced and additional datasets, with modification of the PFA workflow to incorporate the new datasets. Finally, ML will be applied to define new workflows using the enhanced and additional datasets. An algorithmic approach that empirically learns to estimate weights of influence for diverse parameters can potentially scale and perform better than the PFA. This innovative project is likely to have significant impacts, given that evaluation of the interrelations of >12 parameters with a range of ML methods will provide novel insights into the application of ML concepts to assessment of geothermal potential and probably identify new signatures for detecting blind geothermal systems.

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