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Intuition AI to Estimate Reservoir Fluid Properties in a More Definitive Way

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ABSTRACT

The complexities of reservoir fluid properties arise from the geological history of the field as well as diverse biochemical processes of the hydrocarbons once trapped. A unified geochemical, petrophysical, and biological model can be used to explain fluid properties found along a specific geographic trend or along depth. Previously an integrated model has been very computationally intensive and requires extensive, and therefore expensive, direct data calibration. Intuition AI is a promising tool to create this unified predictive model in a fraction of the time and cost than previous methods, yet still produce accurate fluid property predictions.

Intuition AI is an epistemic, causal artificial intelligence framework that can mine experts' experience and create a multi-view hypothesis set, which forms elements of situation-specific guardrails by vetting initial training data and ground truths. As more situational datasets are processed or more experts' hypotheses are added, this scientifically driven hybrid AI model is refined; the vetting process removes human opinion biases and fills gaps in the knowledge space by using translated or extended guardrails from one situation to its neighbor. Intuition AI takes the multi-view convergence approach to be more definitive in inferences. This multi-view approach enables intuition AI to create a reliable model with a few dozen data sets rather than the thousands typically needed by traditional machine learning.

This study showcases Intuition AI as applied to reservoir fluid property estimation and its ability to unify the geology, chemistry, and biological controls of the subsurface. Intuition AI uses C1–C5 gas views as reservoir fingerprints for training purposes. The trained AI uses mud gas logs from standard or advanced mud gas traps as its data source for estimates. An

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initial study designed to estimate gas-oil ratio (GOR) in the Gulf of Mexico shows great promise and scalability, providing a higher fidelity in fluid property estimation than attained with traditional machine learning. This measurable improvement is achieved with no additional investment in mudlogging operations or data collection.

INTRODUCTION

Mud-gas logging is the first taste of the hydrocarbon compositions in a well. Estimation of reservoir fluid properties from mud gas logging data, if reliable, can provide cheap and early assessment of fluid properties such as gas-oil ratio (GOR). This can greatly assist the front-end decision making in upstream operations by reducing cost, de-risking fluid-related decisions, providing a clear picture of field communication, and improving planning efficiency. However, computation of GOR, as well as other reservoir fluid properties that affect economic models, based on mud gas logs alone has not previously been possible. Efforts have been ongoing for decades to extract valuable reservoir insights by interpreting the mud-gas logging data in combination with drilling and other petrophysical parameters. Empirical formulae such as Wright Models using only the gas in mud values of C1–C4 and C1–C5 hydrocarbons to predict GOR have been in use for several decades but in many cases display high degree of errors in the estimation of GOR (Wright, 1996). There have been reports in the literature of better estimation techniques, some reporting better results than others, but none providing a consistently reliable method for quantitative prediction of the reservoir fluid properties from mud gas data (Anifowose et al., 2022).

The complexity of the problem lies in the gas extraction methodology, especially the type of gas trap used. Attempts to combine mud-gas data, drilling parameters, and other relevant operational conditions by Malik et al. (2021), has resulted in an integrated workflow to estimate net pay, GOR, bulk volume hydrocarbons, and oil typing. Yang et al. (2019) has used a machine learning approach to advanced mud-gas logging data with good success. Their approach has trained a model on a well-established reservoir fluid database with more than 2000 PVT samples. Though it is an excellent achievement, such machine learning models rely greatly on the availability of large volumes of pressure, volume, and temperature (PVT) data, which tend to be highly sensitive and proprietary to the exploration and production companies, as well as very expensive. For many basins, such a PVT database may not be available. It is in the context of this limited availability of PVT data that Intuition AI, a new genre of artificial intelligence, was first applied to estimate GOR, and it has produced very promising results in the initial set of blind tests (Chakraborty et al., 2023), but further development to other subbasins is necessary to prove its potential.

It is well known to industry experts that a major complexity of estimating GOR is in the uncertainty of fluid properties. These fluid properties can change significantly from one reservoir to another, from one well to another in the same reservoir, or even in the same well, from one depth to another. This happens because the subsurface situations can differ significantly depending upon the geographic location, geologic age, depositional environment, fluid migration history, reservoir connectivity, trapping, and fluid alteration histories that a region may undergo. The research presented here is an extension of the earlier application of Intuition AI but with expanded scope to estimate GOR within acceptable accuracy based on a model and translated situations from a known situational region, called its neighborhood, and relying solely on the mud gas data, drill data, and reservoir finger printing through geochemical data.

Intuition AI: Epistemic Causal AI.

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Intuition AI takes a use case-based practical approach and adds a new dimension to the recent trends of artificial intelligence by effectively mining experts' experience in building situationally adaptive rules (Chakraborty et al., 2018). This can be quite helpful in various industrial use cases especially where interpretation and estimation-based decision making is a must to reach the final goal. It is important to be as definitive as possible because millions of dollars can hinge on these decisions. Estimation of reservoir fluid properties, such as GOR, during drilling time is a great example of such applications.

Intuition AI believes in gaining knowledge from all forms of sources (Fig. 1). It also is built on a foundation assumption that in nature, everything happens gradually, and similar situations influence similar systems in similar ways. Therefore, experience from an analogous system behavior can be extended effectively to another system under similar situations. Moreover, ballpark estimation can give decently reliable results due to the nature of gradual transition in these systems. In fact, any time the system behaves exceptionally, an anomaly can be detected. For example, in case of sudden change in GOR, a hidden reservoir connectivity is likely to be found.

Intuition AI attempts to understand the science behind experts' ballparking method for estimation, critical decision making (especially in the wake of a rare event), and then refine and extend it towards unknown situations (Chakraborty et al., 2022). Ballparking involves the concept of reasonableness in the human mind and the mind's inherent ability to adjust expectations around an outcome from the same system depending upon situations. In Intuition AI these flexibilities, constraints, ballpark trends, and patterns are put together in the form of hypotheses which are then vetted against available observed ground truths to remove human bias and form or refine situational guardrails. Intuition AI has several unique features listed below, that are useful for reservoir evaluation (Chakraborty et al., 2023).

- Ability to create multiple views and track changes in system behavior in each view as situations change.
- Ability to model experts' hypotheses in a causal way that are broken down as constraints, unique patterns, and expected trends under different situations, thus forming guardrails.
- Understand consistency and situational stability by each view and dig from experience for a familiarity to mimic trajectory and estimate outcome.
- Correct situational bias, human bias, and generate interpretations from each view.

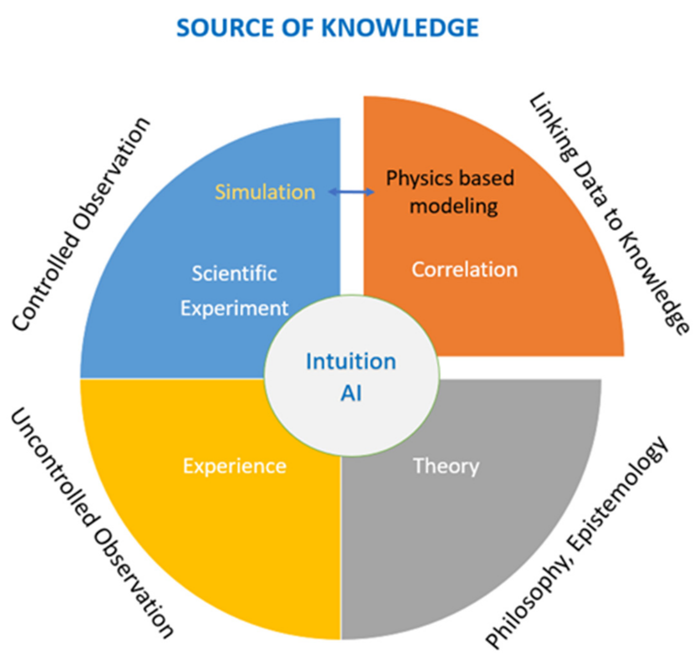

Figure 1. Sources of learning for intuition AI.

- Converge interpretations towards an inference, forming an overall dependability score based on each view's fidelity.
- Generate inference and explanation detailing each step with reference, so there is no surprise with the estimation results.

METHODS

Intuition AI identifies the current situation expressed in the data and maps it on the situational experiences it learned from any historical ground truths that are fed to it. This triggers the path and the process flow the AI chooses (Fig. 2).

Based on the situational proximity to its previous experiences, it uses one of the following three methodologies to estimate the target output:

- Ballparking methodology: This methodology is applied if the current situation is evaluated to be in the vicinity of a prior experience.
- Situational guardrail translation methodology: This methodology is applied when the current situation is not in the vicinity but in a zone that is situationally stable, the AI extends the guardrail using edge behavior.
- Situational guardrail extension methodology: This methodology is applied when the situational surface is moderately changing (linearly). The technique deploys the ballparking methodology repeatedly and iteratively, choosing the most gradual path and adapting to the situation at every iterative step.

Once the view interpretations/estimations are ready they are vetted against familiarity from previous experience. If the familiarity is high, the AI outputs an inference and explanation, if it is moderately familiar, it generates a guesstimate and explanation, if it finds an unfamiliar situation, the AI simply outputs an uninterpretable message. Significantly, it does not guesstimate uninterpretable situations. For the estimation of GOR reported in this paper, the intuition AI used the following datasets (Fig. 3) in addition to the experts' hypotheses. A total of 4 views were created, 3 of which were gas views and 1 of which was the reservoir geochemistry view against depth.

In the next phase, more information, including more views, will be added to further solidify the vetting process for inferencing. These can include historical data from other operations beyond mud gas logs which can greatly complement the situational map. For example, data from

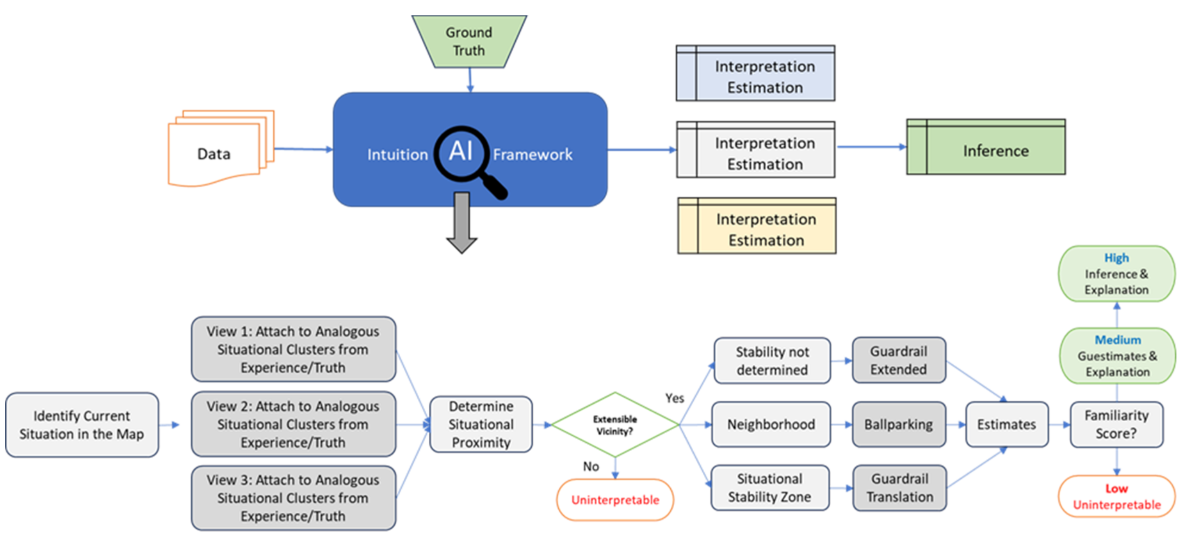

Figure 2. Intuition AI process flow.

Mud-gas Data
- Mud-gas: Gas in Air: C1-C5
- Gas trap type, Mud type

Drilling parameters:
- ROP, Bit Diameter, flow pump rate
- Mudflow, Suction Rate, Bit Diameter

Reservoir Familiarity
- Sub-basin information
- Gas-In-Mud: C1-C5 (Lab)
- Reservoir Pressure/Temp

Ground Truth (Lab measured) historical data
- GOR

Figure 3. Data needed for GOR estimation.

logging while drilling (LWD), wireline operations, and gamma ray measurements may be used to understand surprising lithology driven situations that can be missed by gas views alone. The intuition AI methodology can be extended to other fluid properties such as density, API gravity or viscosity.

RESULTS

Based on 18 blind tests from wells of 4 different subbasins and hydrocarbons obtained from an even mix of heated and non-heated gas traps, Intuition AI could estimate GOR within 20% accuracy 85% of the time. Close to 30% of the situations we faced in blind tests came out to be uninterpretable. A visual representation of Intuition AI output is shown (Fig. 4). The tracks highlight C1–C5 values in ppm; resistivity and gamma ray curves give an idea of the lithology; AI estimation of GOR generated from various hydrocarbon ratio-based analysis as well as subbasin by depth, and GOR generated from geochemical/lab-based fluid analysis. GOR inference is presented in a separate track along with the dependability score. With every interpretation of GOR intuition AI calculates the fidelity score and these fidelity scores are combined to obtain the overall dependability. When interpretation views converge the dependability increases making a consensus of views an extremely reliable inference. Dependability scale is broken into six categories, e.g., high (views in agreement), mid-high (views converging), medium (views apart), mid-low (views diverging), low (views in disagreement), and uninterpretable (situation unseen, best not to use this data point). Intuition AI believes in selective averaging and discrediting noisy estimates. For a particular depth of interest, the GOR can estimated by doing an average of the "truth-telling population" of the near-by rows that have dependability indicated as high, mid-high, or medium. If trustworthy estimations are stitched together for a well, the overall GOR estimation for a certain depth or a zone improves dramatically. This helps overall modeling of the well be more reliable.

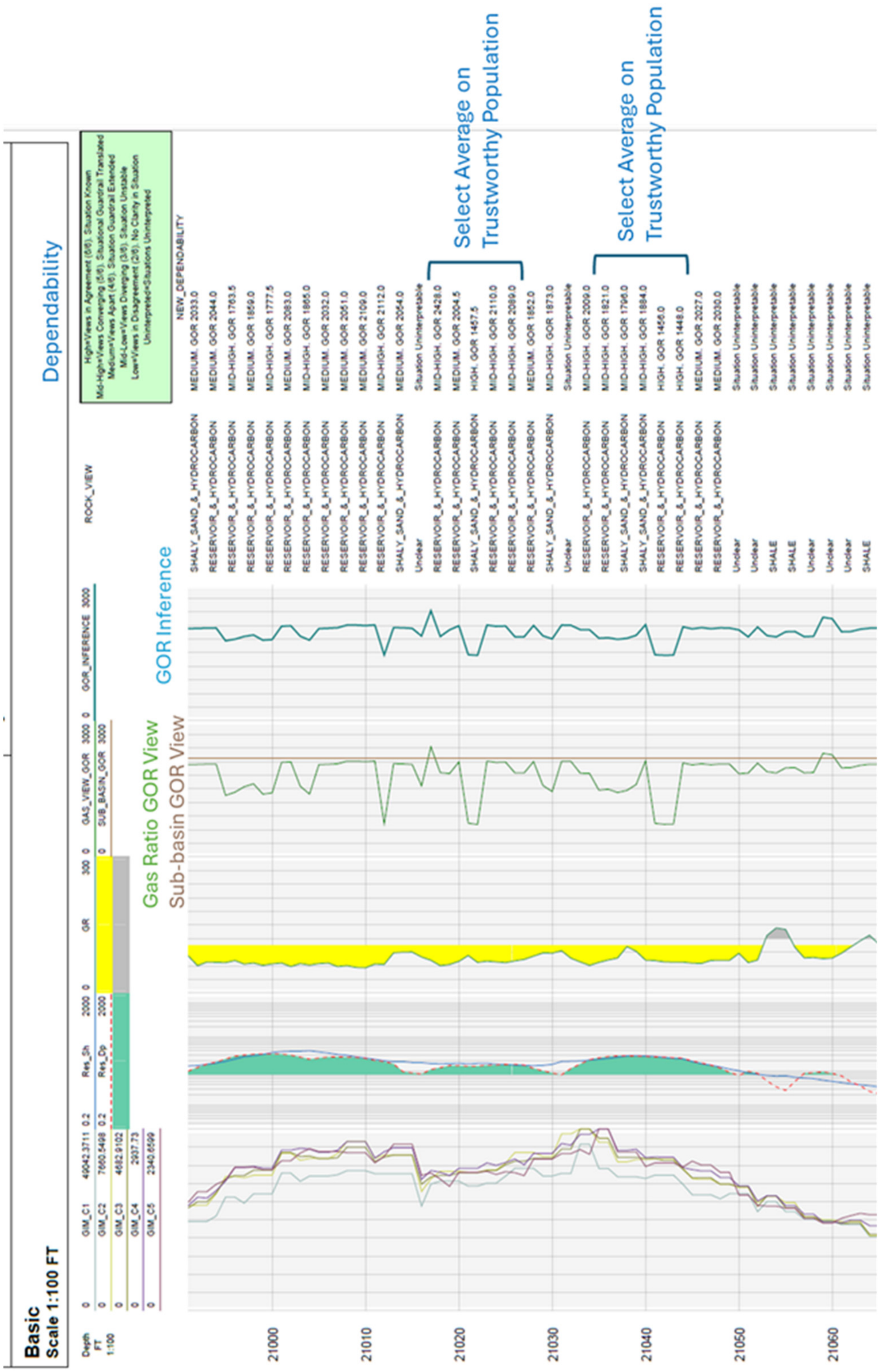

Figure 4. AI output on GOR interpretation views and inference.

SUMMARY AND CONCLUSIONS

This study effectively proves that intuition AI can translate the knowledge gathered from one subbasin to an adjacent subbasin in the Gulf of Mexico region. More work is planned by adding new views, truth points, and hypotheses. A reduction in uninterpretable counts is expected with more views. The next phase of study will attempt to estimate other fluid properties such as fluid density, API gravity, and viscosity.

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