Supporting the Training of Physics Informed Neural Networks for Seismic Inversion Using Provenance

Renan Souza, Andres Codas, Alberto Nogueira Junior, Joao Almeida, Miguel Quiñones, Leonardo Azevedo, Raphael Thiago, Elton Soares, Marcelo Costalonga Cardoso, Leonardo Martins
IBM Research

9.29.2020 - 10.1.2020 – AAPG Annual Convention and Exhibition 2020, Online/Virtual

Abstract

Seismic inversion is a procedure to infer properties of the earth's subsurface through seismic wave observations at the surface and sparse well core samples. It maps the rock distribution on the subsurface and, thus, enables the evaluation of the reservoir structure. The goal is to refine hypotheses on the earth's rock distribution by adjusting a velocity model of the seismic wave propagation, based on the mismatch of simulated results and observations. The consistency of the inversion process must be checked by a geoscientist. Reduced-order modeling and optimization regularization techniques, such as constraining the solution search space around a hypothesis, may speed up the process to find the solution but introduces bias that must be later assessed considering the hypotheses made, thus it is important to track the modeling decisions. Finding the solution of a seismic inversion problem is an exploratory, time-consuming computational experiment that demands collaborative work between geoscientists and numerical method engineers. They attempt to simplify the physics modeling aiming at efficient forecasting of seismic waves. Physics Informed Neural Networks (PINNs), which uses Deep Learning (DL) algorithms, help to construct efficient simulator proxies. Beyond the selection of the rock distribution and velocity model, PINNs require the selection and training of a DL model for the seismic wave displacement field. Then, training a PINN requires pondering these models for physics consistency, observed data matching, initial hypothesis deviation, and overall

modeling simplicity. Through the training process, the experts need to explore a wide variety of factors, such as modeling parameters, DL architectures, and physical equations. However, it is hard to analyze these factors to understand which are impacting the results. Therefore, it is necessary to track the hypotheses made, correlate them to all factors investigated, to allow an in-depth final assessment. Managing data lineage (i.e., provenance) has shown to be a good alternative to track scientific data in iterative computational methods, allowing for a detailed result analysis in large-scale scientific and engineering workflows. In this work, we investigate the use of provenance data to support the training of PINNs in the seismic inversion problem. We propose a method to track the data analyzed by the experts in the exploratory process to find the solution of the seismic inversion problem using PINNs. Our goal is to enable faster insights, supporting the decisions made during the training of PINNs. We show that the method allows for a broader and in-depth understanding of which and how specific factors in the exploratory process affected the inference process, helping the experts speed up their work.

AAPG Datapages/Search and Discovery Article # 91200 © 2020 AAPG Annual Convention & Exhibition Online, Sept. 29- Oct. 1.