Subject offered for a contract starting October 2018

SUBJECT TITLE: EARTHQUAKE HAZARD ESTIMATION: A COMBINED PHYSICS BASED AND MACHINE LEARNING APPROACH.

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Financing: Los Alamos National Lab and Laboratoire de Recherche Commun ENS-CEA

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Context:

As we have been reminded time and again, earthquakes are a devastating natural phenomenon that can have a huge societal and economic impact. In the last years, the Magnitude 7.8 Kaikoura earthquake in New Zealand, the Magnitude 8.1 Chiapas and 7.1 Central earthquakes in Mexico, and more recently the Magnitude 7.8 Kermanshah earthquake in Iran have highlighted many of the shortcomings in our current understanding of earthquake physics underscoring the fact that forecasting an event remains a remarkably challenging goal. Earthquake simulations play a fundamental role in our attempts to progress toward a more complete understanding of fault friction and ultimately addressing forecasting. A key shortcoming in modeling is the ability to account for a complex fault network and then predict the sequence of earthquakes that have historically occurred on such fault networks. The earthquake physics groups at ENS and Los Alamos have developed physics based computational models that can now potentially simulate these sequences, in tandem with conducting related laboratory studies and field observations.

However, such models involve unconstrained or poorly constrained parameters like frictional properties on the fault, small-scale fault geometric uncertainty, etc. Machine Learning (ML) algorithms can eliminate these uncertainties by systematically, and intelligently, identifying parameters that best reproduce these earthquake sequences by sequentially running forward physics-based models and adjusting parameters such that a given metric is satisfied (the past earthquake sequence in our case here). In particular, reinforcement learning has been applied in the past to other problems with the aim of estimating unknown parameters and exploring high dimensional spaces, while limiting the number of necessary iterations and drastically reducing computational costs - with high success. Coupling reinforcement learning and Bayesian optimization with physics-based computational models of faults could allow us to develop simulations accounting precisely for past earthquake sequences. Another main advantage of these methods is that they allow building predictive models: given a simulation's input parameters, they can estimate the simulation's result (without having to run the simulation itself). By using the physics-based computational model calibrated by machine learning and the associated predictive model, one could produce probabilistic estimates of seismic hazard for a given fault. We propose to develop this approach and apply it to an important test case—the Cascadia subduction zone.

Project:

In western North America, the Cascadia region is overdue for a Megaquake. Cascadia is where the fascinating phenomenon of episodic slow slip and tremor was first discovered about 15 years ago. This behavior takes place down dip on the fault, adjacent to the locked zone where the Megaquake is expected to nucleate. Slip events take place regularly at intervals of about 12 to 18 months. The fundamental question is how slow slips and stick slips are coupled—can simulating the slow slip behavior tell us how and when the coupling occurs? We will address this question by both simulating and analyzing the fault characteristics of slow slip by relying on existing geophysical datasets:

- We will simulate the fault with the aim of reaching a better understanding of the coupling between slow slip events and seismogenic events, and attempt to place probabilities on ground motions by using the associated models. The parameters of the simulation will be set through reinforcement learning and Bayesian optimization, through the methods described above.
- We will apply machine learning to geophysical datasets to try to uncover unidentified signals that could reveal new fault friction physics. In our previous work on laboratory data, we found that ML can be used to place tight bounds on failure times, and informs us of previously unidentified frictional physics by discovering a new signal. Preliminary results on Cascadia data from Vancouver Island, Canada, also suggest that continuous seismic waves contain rich information regarding the state of the fault (fault displacement, timing and duration of upcoming slow slips). We have some evidence that this method may provide real advances in characterizing friction in-situ.

These two approaches are complementary, as the analysis of geophysical datasets may help to enrich our physics-based computational model. In particular, information on the state of the fault inferred from continuous seismic waves could be used within the computational model and help to place better estimates on ground motion probabilities.

This PhD project would be a unique attempt to combine earthquake physics models, earthquake observations and machine learning in a systematic and integrated fashion.