**Network Applications in Earthquake Prediction (1994–2019): Meta-Analytic and Statistical Insights on Their Limitations**

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Abstract

In the last few years, deep learning has solved seemingly intractable problems, boosting the hope to find approximate solutions to problems that now are considered unsolvable.

近幾年，深度學習已經解決表面上棘手的問題，提振希望找到解決現在被認為無法解決的問題的近似解決方案

Earthquake prediction, the Grail of Seismology, is, in this context of continuous exciting discoveries, an obvious choice for deep learning exploration.

地震預測，地震學的聖杯，是在連續興奮發現的景況，對深度學習探勘是一個明顯的選擇

We reviewed the literature of artificial neural network (ANN) applications for earthquake prediction (77 articles, 1994–2019 period) and found two emerging trends: an increasing interest in this domain over time and a complexification of ANN models toward deep learning.

我們複習有關地震預測的人工神經網路應用的文章(77篇，在1944~2019間)然後找到2種新興趨勢:隨著時間推移，在這個領域有逐漸增加的利益和人工神經網路的複雜性朝向深度學習

Despite the relatively positive results claimed in those studies, we verified that far simpler (and traditional) models seem to offer similar predictive powers, if not better ones.

儘管相關正面的結果在這些文章已公布，我們以驗證較簡單的模型似乎提供相似的預測力量，如果不是較好的一個

Those include an exponential law for magnitude prediction and a power law (approximated by a logistic regression or one artificial neuron) for aftershock prediction in space.

那些包含大小預測的指數分布和空間中餘震預測的冪定律

Because of the structured, tabulated nature of earthquake catalogs, and the limited number of features so far considered, simpler and more transparent machine-learning models than ANNs seem preferable at the present stage of research.

因為地震目錄自然列表的結構和到目前為止考慮的功能數量有限，比ANN更簡單透明的機器學習模型似乎在現階段的研究更受喜愛

Those baseline models follow first physical principles and are consistent with the known empirical laws of statistical seismology (e.g., the Gutenberg–Richter law), which are already known to have minimal abilities to predict large earthquakes.

那些基準模型遵守第一原理和統計地震學的已知經驗定律(例如 GR Law)一致，已經知道有最小能力預測大地震

Introduction

Deep learning is rapidly rising as one of the most powerful go to techniques not only in data science(Jordan and Mitchell,2015；Lecun et al,2015) but also for solving hard and intractable problems of physics(Carleo and Troyer,2017；Hen et al, 2018；Pathak et al,2018)

深度學習快速成為一種強力的科技，不只是資料科學還有解決困難棘手的物理問題

This is explained by the greater performance of such techniques to discover hidden patterns in very large data sets. One of the main advantages of artificial neural networks(ANNS), which encompass both shallow and deep neural networks(DNNs), is that they do not require feature extraction and feature engineering, as relatively unprocessed data can be used directly to train the network with potentially very good results.

被這類科技較好的表現解釋，發現大量數據的隱藏模式最主要的優勢之一為ANNs，包含淺層和深度神經網路，他們不需特徵提取和特徵工程，作為相對未處理的檔案可以直接被用於訓練潛在網絡非常好的結果

It is not surprising that machine learning at large-including deep learning has become popular in statistical seismology(Bergen et al,2019; Kong et al,2019) and gives fresh hope for earthquake prediction ,or, more generally, probabilistic forecasts(Rouet-Leduc et al,2017; DeVries et al,2018; Hulbert et al,2019)

機器學習大範圍包含深度學習已經在統計地震學非常熱門和給予地震預測新興的希望，或是更普遍地概率預報

This challenge has long been considered impossible(Geller et al 1997) , although the seismological community has already gone through several cycles of optimism and pessimism over the past decades.

這個挑戰已經長期考慮可能，雖然地震共同體已經走過樂觀與悲觀好幾個周期在過去數十年

It appears that we have now entered a new phase of enthusiasm with machine-learning-based earthquake forecasting, which is reflected by the associated media euphoria.

看來我們現在已經進入了以機器學習為主的地震預報熱情的新階段，體現在媒體的欣喜中

Another boost of activity comes from the generation of improved earthquake catalogs based on convolutional neural network, although the potential use of those “Big Data catalogs” to improver earthquake predictability has yet to be investigated.

另一個活動的促進來自卷積神經網絡的改進地震目錄生成，雖然使用大數據目錄改善地震預測的潛力還有待調查

Given the current rapid expansion of the field, there is a real risk of inflation. It is , therefore, essential to invest a concrete and sober effort to discipline this research sector with technical rigor and baseline model benchmarks.

鑒於該領域的快速發展，有通貨膨脹的實際風險，因此最重要的是必須投入具體而合理的努力，以嚴格的技術和基準模型基準來規範該研究部門

In fact, designing a suitable ANN architecture can be a highly iterative process based on extensive hyper parameterization tuning and some filtering procedures.

事實上，基於廣泛的超參數化調整和一些過濾過程，設計合適的ANN體系結構可能是一個高度迭代的過程

How do such choices affect, not only the model performance, but the way the model is physically interpreted? Linked to the flexibility of ANNs and their black-box nature, can we miss critical scientific insights in the modeling process?

這些如何影響?不僅影響模型性能，還影響模型的物理解釋方式與人工神經網絡的靈活性及其黑盒性質有關，我們可以在建模過程中錯過重要的科學見解嗎?

Mignan and Broccardo recently demonstrated that a far simpler model can do as well as, if not better than a DNN, thus providing a preliminary answer to those questions.

Mignan和Broccardo 最近證明，如果不是DNN更好的模型，那麼簡單得多的模型也可以做到，從而為這些問題提供初步答案

That study was, however , limited to the forcasting of aftershocks in space, following up on the study of DeVries.

但是該研究僅限於對空間餘震的預測，對DeVries研究的後續

In the present article, we aim to answer the aforementioned questions by going beyond the study of Mignan and Broccardo, first by providing a comprehensive survey of the ANN-based earthquake prediction literature and second by investigating how simpler models, which can be related to first physical principles, compare to the prediction performances of published neural networks.

在現今的文章，我們為了回答先前所提到的問題，藉由超越Mignan 和Broccardo 的研究，首先對通過基於ANN的地震預測進行全面的調查，其次，研究與第一物理原理相關的更簡單的模型與已發布的神經網絡的預測性能相比如何

We will finally conclude with some recommendations for future uses of a neural network in earthquake predictability research.

最後，我們將對神經網絡在地震可預測性研究中的未來使用提出一些建議

ANN-Based Earthquake Prediction: A Literature Survey (1994–2019)

“The subject of Statistical Seismology aims to bridge the gap between physics-based models without statistics, and statistics-based models without physics” (Vere-Jones et al., 2005, p. 1023) and can then be divided into two categories, with earthquakes as point sources (i.e., seismicity) modeled as stochastic point processes, or earthquakes as seismic waves radiating from finite sources.

“統計地震學的目的是彌合差距在沒有統計學的基於物理學的模型和沒有物理學的基於統計學的模型之間進行比較”(Vere-Jones等，2005年p。 1023)，然後可以分為兩類，將地震作為點源（即地震性）建模為隨機點過程，或者將地震作為從有限源輻射的地震波建模。

We are here concerned with the applicability of ANNs in seismicity analyses that pertain to earthquake forecasting and prediction; we will only briefly comment on ANN applications in seismic-waveform analysis, in which case deep learning is far more pertinent due to the

data being unstructured in contrast to tabulated in earthquake catalogs.

在這裡，我們關注人工神經網絡在與地震預報和預測有關的地震活動性分析中的適用性； 我們將僅簡要評論ANN在地震波形分析中的應用，在這種情況下，由於

與地震目錄中的列表相反，數據是非結構化的。

Decision-tree approaches (e.g., Rouet-Leduc et al., 2017; Hulbert et al., 2019) are not considered in our review and subsequent analysis.

在我們的審查和後續分析中未考慮決策樹方法（例如Rouet-Leduc等，2017; Hulbert等，2019）。

We developed a comprehensive corpus of 77 articles, spanning from 1994 to 2019, on the topic of ANN-based earthquake prediction.

我們針對基於人工神經網絡的地震預測，從1994年到2019年開發了77篇文章的綜合語料庫。

Our screening method started with review articles (Florido et al., 2016) and the most recent and most cited studies found on Google Scholar for two sets of keyword searches (“earthquake prediction neural network” and “earthquake forecasting neural network”).

我們的篩選方法始於評論文章（Florido等，2016）以及Google學術搜索中針對兩組關鍵詞搜索（“地震預測神經網絡”和“地震預測神經網絡”）的最新和引用最多的研究。

All references cited in those articles were systematically assessed and the relevant ones added to the corpus. We repeated the reference list search for all added papers until no more relevant articles could be found. We scanned through Google Scholar a final time to find any potential noncited article.

系統地評估了那些文章中引用的所有參考文獻，並將相關參考文獻添加到語料庫中。 我們對所有添加的論文重複參考列表搜索，直到找不到更多相關文章。我們最後一次通過Google學術搜索進行了掃描，以查找任何可能的非引文。

Although a few references may have been missed, the survey should be considered complete enough to investigate emerging trends using a meta-analysis (Mignan, 2011, 2014, 2015, 2019a). The information on the full database, DB\_EQpred\_NeuralNets\_v1.json is available in Data and Resources.

儘管可能遺漏了一些參考文獻，但應該認為該調查足夠完整，可以使用薈萃分析調查新興趨勢（Mignan，2011、2014、2015、2019a）。 有關完整數據庫DB\_EQpred\_NeuralNets\_v1.json的信息，可在“數據和資源”中找到。

Figure 1 shows the annual rate of publications over time, which indicates a progressive increase in the number of studies on this topic. Only in the past 10 yr did important articles emerge in terms of number of citations and journal impact factor (Adeli and Panakkat, 2009; Reyes et al., 2013; DeVries et al., 2018).

圖1顯示了隨時間推移的年出版率，這表明該主題的研究數量正在逐步增加。 僅在過去十年中，有關引文數量和期刊影響因子的重要文章才出現（Adeli和Panakkat，2009； Reyes等，2013； DeVries等，2018）。

We will divide this survey into two sections:

(1) the classical ANN literature, with few hidden layers (see the

Classical ANN-Based Earthquake Prediction Literature section) and

(2) the very recent highly parameterized deep learning trend, up to six hidden layer DNN (DeVries et al., 2018) and three-convolutional-layer CNN (Huang et al., 2018; see the Highly Parameterized Deep Learning Trend section).

我們將調查分為兩部分：

古典的ANN文學，隱藏層很少（請參閱古典基於ANN的地震預測文獻部分）和(2)最近高度參數化的深度學習趨勢，多達六個隱藏層DNN（DeVries等人，2018）和三卷積層CNN（Huang等人，2018） ；請參閱高度參數化的深度學習趨勢部分）。

It should be noted that our survey differs from previous reviews (Florido et al., 2016) by being more systematic and analytical, but less descriptive. Those studies are thus complementary to each other.

請注意，我們的調查與之前的評論有所不同（Florido et al。，2016）通過更系統和更具分析性，但描述性較差。 因此，這些研究是對彼此。

Classical ANN-based earthquake prediction literature

ANNs were introduced in Seismology as early as 1990 (Dowla et al., 1990), only 4 yr after the seminal backpropagation article of Rumelhart et al. (1986). Few studies followed in the next years (Brodi, 2001).

據我們所知，最早用ANN模型測試地震預測的嘗試可以追溯到1994年（Aminzadeh等，1994； Lakkos等，1994）。在接下來的幾年中很少進行研究（Brodi，2001）。

The first DNN, with two hidden layers, was proposed in 2002 (Negarestaniet al., 2002) and the first recurrent neural network (RNN) in 2007 (Panakkat and Adeli, 2007).

第一個具有兩個隱藏層的DNN在2002年（Negarestaniet等人，2002年）提出，第一個遞歸神經網絡（RNN）在2007年提出（Panakkat和Adeli，2007年）。

Panakkat and Adeli (2007) provided the first comprehensive work on ANN applications to earthquake prediction, comparing three types of neural networks: a radial basis function neural network, a DNN, and an

RNN. The diversity of ANN architectures used for earthquake prediction is shown in Table 1.

Panakkat和Adeli（2007）比較了三種類型的神經網絡：徑向基函數神經網絡，DNN和神經網絡RNN。 表1顯示了用於地震預測的ANN體系結構的多樣性。

Most applications use time-series data, with seismicity indicators estimated from discretized bins and used as ANN input units (a same approach can be used in space, with data discretized in geographic cells).

大多數應用程序使用時間序列數據，並從離散化的信箱中估計地震活動性指標，並將其用作ANN輸入單位（可以在空間中使用相同的方法，而在地理單元中離散化數據）。

The size of the input layer varies from 2 to 94 neurons with a median of 6 and mean of 11 (excluding the CNN case, see the Highly Parameterized Deep Learning Trend section).

輸入層的大小從2到94個神經元不等，中位數為6，平均值為11（不包括CNN案例，請參見“高度參數化的深度學習趨勢”部分）。

Although 75% of the corpus studies use seismicity as input, others use geoelectric (4%), ionospheric (4%), or other signals (such as radon or stress); we here focus on seismicity-based analyses in which primary data consist of occurrence time, magnitude, longitude, latitude, and depth vectors.

儘管有75％的語料庫研究使用地震作為輸入，但其他研究使用地電（4％），電離層（4％）或其他信號（例如ra或壓力）。 在這裡，我們集中於基於地震活動的分析，其中主要數據包括發生時間，震級，經度，緯度和深度矢量。

The output units predict future mainshock characteristics, most often related to the event magnitude in a time or spacetime window (mainshock occurrence time and location are more seldom predicted; Panakkat and Adeli, 2009).

輸出單位可預測未來的主震特徵，通常與時間或時空窗口中的事件大小有關（很少預測主震的發生時間和位置； Panakkat和Adeli，2009）。

Their number is most often 1 (minimum, median, and mean obtained from the corpus), corresponding to a binary classification (e.g., mainshock above threshold mth or not) or a regression (e.g., mainshock magnitude m estimate). A list of the main features and outputs used in the corpus is also given in Table 1.

它們的數量通常為1（從語料庫中獲得的最小值，中位數和均值），對應於二元分類（例如主震是否高於閾值mth）或回歸（例如主震幅度m估計）。表1還列出了語料庫中使用的主要功能和輸出。

Features are standard statistical metrics, such as nth-order moments or quantiles, seismicity-based metrics (e.g., Panakkat and Adeli, 2007; Martínez-Álvarez et al., 2013; Asencio-Cortés et al., 2016, 2017) or, rarely, metrics used in financial analysis

(Alves, 2006).

功能是標準統計指標，例如n階 矩或分位數，基於地震烈度的指標（例如Panakkat和阿德利（Adeli），2007年； Martínez-Álvarez等，2013； Asencio-Cortés等人（2016年，2017年）或財務分析中使用的指標很少（Alves，2006）。

The so-called seismicity indicators are often the parameters of the Gutenberg–Richter (GR) law (equation 1a; Gutenberg and Richter, 1944) and/or of the modified Omori law (MOL; equation 1b; Omori, 1894; Utsu, 1961), which are the main empirical laws of statistical seismology:

所謂的地震活動度指標通常是古騰堡-里希特（GR）法（方程1a;古騰堡和里希特，1944年）和/或修改後的大森律（MOL;方程1b;大森，1894年;宇津，1961年）的參數 ），這是統計地震學的主要經驗定律：