

201954 Deep Learning & SNOMED CT

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Summary

Deep learning has started to make a significant impact in medicine, due to the explosion in healthcare data and advances in computational power. To realise the full potential, it is vital that SNOMED CT is adopted internationally. We discuss the advantages, opportunities and practical challenges.

Audience

Clinical, Research/academic, Technical

Learning Objectives

1. Importance of SNOMED to support advanced machine learning with EHRs;
2. Advantages of SNOMED in providing an evidence-base for clinical algorithms;
3. Opportunities SNOMED provides for international collaboration and local implementation; Practical challenges of clinical research with SNOMED

Abstract

There have been many recent advances with the application of machine learning to healthcare [1]. Most significantly, deep learning - a subfield of machine learning – has started to make an impact in many different areas of medicine. For example, deep learning in imaging diagnostics has led to impressive results in radiology [2], oncology [3], and ophthalmology [4].

Deep learning uses multiple layers of neural networks – along with extremely large quantities of data - to produce algorithms which are optimised for a task. Deep learning is well suited to healthcare applications, due to the volume of data the industry is now generating – in the United States alone, it is estimated that there are 1018 bytes of data, and that this is growing at a rate of almost 50% per year [5].

Alongside image-level diagnostic algorithms, there is substantial interest in using deep learning techniques with electronic health record (EHR) data [6]. This presents new opportunities for advanced population health applications - for example, risk stratification for non-communicable disease, predicting future hospital admissions, and deriving personalised targets to minimise disease complications [7,8,9].

The global progress in introducing SNOMED CT as a standard across digital healthcare systems is an extremely important component of any EHR deep-learning programme. It is essential for the scientific development of new algorithms and for providing the supporting evidence base. This includes training models, testing, internal and external validation, ensuring national and international reproducibility, reflecting local epidemiology, and reducing iatrogenic risk. There remain, however, several challenges when using SNOMED-coded EHR data for deep learning. Many of these challenges are centred on the use of the underlying clinical terminology in the real-world – for example, variance in coding standards between organisations and individual clinicians; high dimensionality introduced by the large number concepts; granularity of pre-coordinated terms; multiple hierarchy searches for extracting potential predictor variables; missing data; inconsistent coding of laboratory observations.



The author, Dr Chris Bates, is actively involved in deep-learning projects using EHR data. He will present several applications that he has helped develop, using one of the world's largest SNOMED CT coded research databases, covering millions of EHRs. These applications include deep neural networks for early cancer detection, for diabetic complications, and for sepsis alerting. He will discuss the advantages, techniques, challenges and practical considerations for working with SNOMED CT at scale for machine-learning research.

Reference Documentation

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