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Commentary on Quantitative Comorbidity Risk Assessment of Dementia in Taiwan

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Machine Learning Algorithms in Medical Big Data [1,2]

Machine learning algorithms apply statistical technologies to obtain a clearer understanding of complex big data [3,4]. In order to apply machine learning algorithms to medical research, big enough related dataset must be collected first. For a massive amount of data to be of value for further applications or decision making, it must be analyzed to extract insights. Data analytics entails extracting information from dataset by machine learning algorithms. (Figure 1) illustrates the procedure of moving from big data collection to insight to decision (or prediction). Researchers in the field of machine learning believe that there exists a process that explains the data we observe, for example, the comorbidities of dementia. Although the details of the process underlying the generation of data is unknown, at least it must not be completely random. That is, there exist certain patterns in the data. Machine learning technologies may not be able to identify the process completely, but it can construct a good and useful approximation. This approximation may not explain everything, but may still be able to account for some part of the data. Althrough identifying the complete process may not be possible, certain patterns or regularities can still be detected.

This is the niche of machine learning. Such patterns may help us understand the process, or we can use those patterns to make predictions: If the future, at least the near future, will not be greatly different from the past in which a massive sample data was collected, then predictions can also be expected to be accurate. Machine learning algorithms are applied in many domains, but different performance metrics are appropriate for different domains. For example, the Receiver Operating Characteristic (ROC) curve area is preferred in medicine. Other extensively used metrics include accuracy, F-score, Lift, average precision, precision/recall break-even point, squared error, and cross-entropy. The performance metrics illustrate different trade-offs in the predictions made by a classifier. Therefore, a learning algorithm may perform well on one metric, but perform sub-optimally on other metrics. Accordingly, algorithms are evaluated using a broad set of performance metrics.

Evaluating Quantitative Comorbidity Risks of Senile Dementia in Taiwan

Dementia is one of the most dependent and disabling illnesses among older people [5,6]. Many potential risk factors for dementia such as socio-demographic status, lifestyle, medications, genetic characteristics, environmental phenomena, and comorbidities, have been identified [7-9]. Comorbidities can be easily checked out and treated by physicians. Elderly people with dementia have more than 1 chronic comorbidity [6,10,11]. However, the reports on evaluating quantitative comorbidity risks of dementia remain ignored. Lin et al. [6] first introduced a machine learning algorithm to assess quantitative comorbidity risks of dementia in Taiwan. (Figure 2) presents all adjusted Odds Ratios (ORs) observed for people with 1 to 6 comorbidities of dementia. In brief, the quantitative effects of 2 to 6 comorbidities and age difference on dementia slowly raised and the corresponding ORs were less than additive [6]. Notably, the highest adjusted ORs of dementia with 1 to 6 comorbidities were 4.938 (for depression), 6.726 (for depression and vascular disease), 6.841 (for depression, head injury, and vascular disease), 8.619 (for depression, head injury, vascular disease, and hearing loss), 8.767 (for depression, head injury, vascular disease, hearing loss, and diabetes mellitus), and 5.954 (for depression and the 5 other comorbidities), respectively. The data reveal that depression is one of significant comorbidity risk factors for dementia. Several hypotheses have been presented to address the relationship between depression and dementia [6,9,12,13]. First, depression is an early prodromal symptom/sign of dementia. A clinical trial by Muliyala et al. [12] illustrated that the prevalence of dementia reduced by 10% over 7 years when the cases with depression were treated [12]. Second, depression is an independent risk factor for dementia. Even if depression was controlled at early stages, it could not eliminate an attack of dementia or may only decline the incidence of disability [9]. A systematic review [13] demonstrated that people with no history of depression have a lower risk of subsequent dementia in later life than do those with depression. Moreover, depression and dementia may share a common etiology in the brain. Patients with dementia experience the negative biological effects which may be associated with the etiology of depression, such as inflammation, increased blood brain barrier permeability, white matter damage, and increased cortisol concentrations [9].

Figure 1: Big data collection and predictive analytics moving from data to insight to decision.

Summary

In clinical practice, machine learning algorithms provide insights for making predictions and decisions in the treatment of dementia. Future studies on dementia should involve additional heterogeneous variables, including socio-demographic status (e.g., family history, and education), lifestyle factors (e.g., unhealthy diet, drinking and smoking habits, and physical inactivity), medications, environmental

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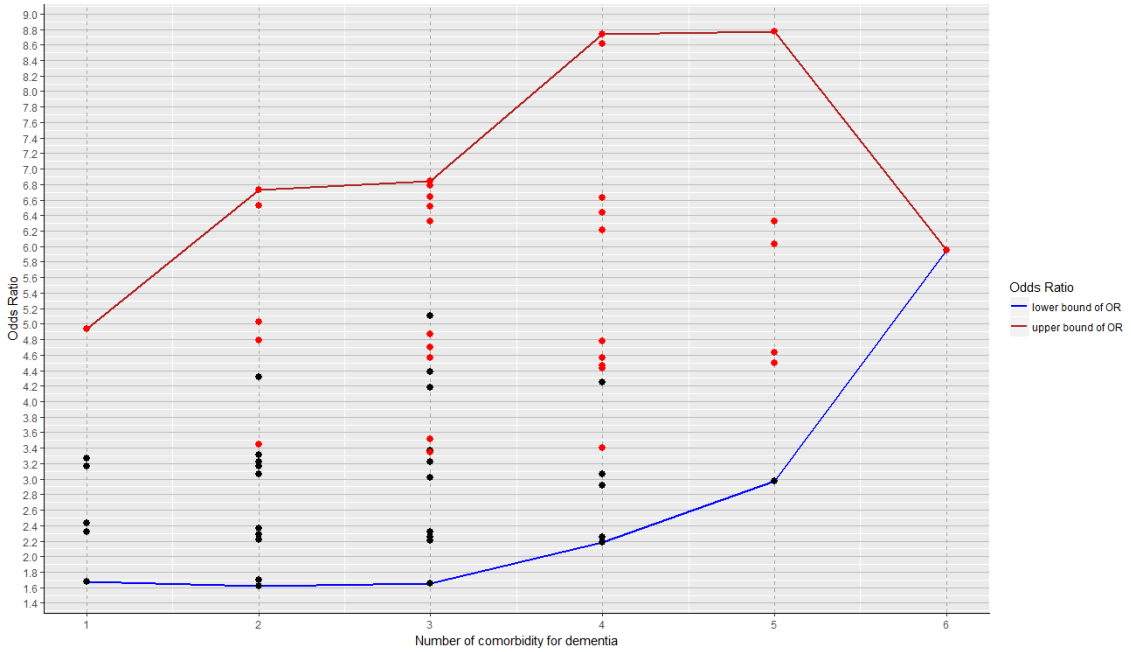

Figure 2: All odds ratios observed for patients with 1 to 6 comorbidities of dementia after adjustment for age, sex, urban residence, and income level. Red dot involved the comorbidity with depression; black dot did not involve depression.

phenomena, and genetic characteristics (e.g. Apolipoprotein (APOE)). In addition, this article suggests primary care physicians for early prevention of depression in dementia development.

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