Peer response: Decision Trees and k-means Clustering for Medical Use Cases

Within supervised learning, Craig identifies decision trees (DTs) as a widely used algorithm, capable of performing both classification and regression by employing non-parametric modelling. He highlights explainability as one of the main advantages of DTs, particularly when used in medical scenarios, given the high ethical standards involved and the potential life-altering impacts of AI model outcomes (Muller, Mayrhofer, Van Veen and Holzinger, 2021; Weidener and Fischer, 2024). Model explainability is especially important in this field since implementation of AI technologies based on “black-box” models may be jeopardised by lack of trust from either medical professionals or patients (Petch, Di and Nelson, 2022; Gombolay et al., 2024). Importantly, DTs mimic the algorithmic nature of many clinical decision support tools already in use, such as the Manchester triage system, facilitating their translation and adoption in clinical practice (Tschoellitsch et al., 2023). Conversely, Craig identifies poor performance with small datasets as one of the limitations of DTs. Other limitations include the potential for overfitting by creating overtly complex trees (and therefore the need for tree “pruning”), sensitivity to unbalanced classes, among others (Bell, 2020; Russel and Norvig, 2021).

K-means clustering is then suggested as an example of how unsupervised learning can be used to aggregate data into relevant groups, based on identifying underlying similarities between elements. Clustering techniques have found many applications within medicine, such as imaging processing and analysis (as suggested by Craig). Other examples include unravelling of phenotypical groupings within heart failure (Segar et al., 2020), identifying distinct cell groups from transcriptomic data (Kobak and Berens, 2019), and, interestingly, development of risk prediction tools (a task usually performed using supervised learning) (Baheti, Innani, Nasrallah and Bakas, 2024; Lamp et al., 2024). Besides the limitations mentioned by Craig (susceptibility to over-segmentation and noise sensitivity), k-means clustering models are also hindered by sensitivity to the initial choice of clusters, variability in approaches used to select an optimal k, and decreasing performance with high-dimensionality data (otherwise known as “curse of dimensionality”) (Russel and Norvig, 2021; Ikotun, Ezugwu, Abualigah, Abuhaija and Heming, 2023).

However, despite their limitations, DTs and k-means clustering can be extremely useful models for application of ML in medical scenarios, as long as the potential pitfalls of either approach are recognised and appropriately addressed.

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