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Proposal Clustering Methods

Clustering the Battery State of Health that Used on the Electric Vehicle

Final Project

NYCU

The rapid growth of electric vehicles (EVs) is revolutionizing the automotive industry, driven by the urgent need for sustainable transportation solutions that cut greenhouse gas emissions and reduce our dependence on fossil fuels [1]. With the utilization of EVs, there is a critical challenge for the battery. These power sources are not only costly but also demand regular maintenance to ensure they remain in peak condition. Furthermore, the flammability and potential explosiveness of some EV batteries underscore the importance of monitoring and predicting their state of health (SoH) [2].

The prediction of their SoH is also could predict when a battery might fail or require maintenance, thus preventing potential hazards and extending its lifespan. One promising method to achieve this is clustering SoH based on various battery characteristics and conditions. The critical factor affecting battery SoH is the charging cycle. When the SoH decreases, the charging times will increase despite the battery's power capacity staying the same[3].

By employing advanced clustering techniques, the SoH of EV batteries can be analyzed and predicted with remarkable precision. This not only enhances safety by preventing failures and accidents but also optimizes performance, making EVs even more reliable and efficient. With these insights, we can propel the EV industry forward, ensuring a sustainable and safe future for transportation. Some benefit that can be achieved from this solution is to create:

- Predictive Maintenance: It can predict which batteries are likely to fail sooner based on their charging time patterns. This allows for proactive maintenance and replacement, reducing the risk of unexpected downtime and extending the overall lifespan of battery-operated systems.
- Optimized Charging Protocols: There are opportunities to gain optimized charging protocols on the battery based on the cluster.
- Enhanced Battery Management Systems (BMS): Clustering provides valuable data for Battery Management Systems to monitor and control charging processes more effectively. BMS can adjust charging rates and schedules based on the clustered SoH data to maintain optimal battery health. So the battery lifetime can be increased.

The good cluster will provide more accurate information about the condition of the battery. So, to achieve that, there is a need to choose a method that can create the best cluster of the batteries SoH. The achievement of this condition is required to compare results from some clustering methods with different hyperparameters. The clustering methods that will be used are K-Medoid, Agglomerative, Mean Shift, DBSCAN, and Spectral Clustering. The chosen method is chosen because it has special benefits like:

- K-Medoid: Robustness to outliers (this makes it suitable for data with noise or outliers, which is common in real-world battery datasets) and interpretability (the clusters are more interpretable and meaningful in the context of battery health analysis) [4].

- Agglomerative: Hierarchical structure (allowing to visualize different levels of granularity in the data. This can provide insights into the hierarchy of battery health conditions, from broader categories to specific clusters) and flexibility in cluster shape (agglomerative clustering does not assume clusters to be spherical) [5].
- Mean Shift: Adaptive bandwidth (this method can automatically adapt the bandwidth parameter based on the density of data points. This makes it effective in identifying clusters of varying densities, which can be beneficial in detecting different levels of battery degradation) and has no assumptions on cluster number (this method does not require specifying the number of clusters beforehand, making it suitable for datasets where the number of battery health states is not known a prior) [6].
- DBSCAN: noise handling (it will be effective in handling noise and outliers, which are common in battery datasets due to sensor inaccuracies or sporadic anomalies in battery behavior) [7].
- Spectral Clustering: non-linear reparability (this method can capture non-linear relationships in the data) and graph-based approach (it can transform the data into a graph representation, allowing it to handle complex relationships) [8].

Reference:

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