Accelerating battery development by early prediction of cell lifetime
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Motivation & objective
• Battery testing typically takes months to years
• Electrochemical models fail to capture dynamics during fast charging
• Early prediction of cycle life would accelerate R&D, manufacturing, and optimization
• Goal: Predict final cycle life (~1000s of cycles) using <100 cycles

Dataset: n=124; Cycle lives range from 150 to 2300

Features
1. Elastic net
Regularized linear regression
\[ \theta = \arg\min_{\theta} (|y - X\theta| + \alpha(1 - \lambda)|\theta|^2 + \lambda|\theta|_1) \]
Simultaneously performs feature selection and regularized coefficient fitting

2. Random forest regression
Bagging of decision trees, with subset of features selected to decorrelate trees
Optimize over number of trees (B) & max depth (d)

3. Adaboost regression
Sequential tree growing; learns slowly using information from previously grown trees
Optimize over number of trees (B) & learning rate (\lambda)

We use 5-fold cross validation given small dataset
Training set = 84 cells, test set = 40 cells

Techniques

Results and Discussion
We developed models for 20 – 100 cycles, in increments of 10 cycles:
Elastic net
Random forest
Adaboost

Future work, contributions, references
Most information-rich data source: voltage curves
Develop voltage visualizations for feature extraction
Slices show linear trend → good for prediction!
Other features: capacity, temperature, resistance

Cycle life
We can reduce # cycles required!
As expected, error generally increases with decreasing cycle number; some overfitting
Random forest performs best
Elastic net feature selection
Low cycle numbers (20–40): Charge time, surface fits, capacity, internal resistance (primarily time-independent features)
High cycle numbers (60–100): Line cuts, change in capacity (primarily degradation features)

Future work:
• Incorporate features from other components of dataset (rest periods, charging)
• Apply CNNs to X-ray images taken before cycling (manufacturing defects?)
• Classify cells into high/low lifetimes (preliminary screening applications)
• Using reinforcement learning to find optimal fast charging policies

Contributions: All authors contributed to data exploration, feature generation, model development, and poster/report creation.

References:
S. J. Harris, D. J. Harris, C. Li. J. Power Sources 342, 589-597 (2017).