CS230

Early Cycle Life Prediction For Lithium Ion Batteries

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Abstract

In this work, we developed fully-connected neural network (FCNN) and recurrent neural network (RNN) to predict the cycle life of lithium-ion batteries using early-cycle data. Over 94% of test set accuracy was achieved in both of the models. Besides, we demonstrated that only the first 5 cycle is needed to achieve >95% training accuracy. We also set to predict the actual battery life in FCNN and <16% error of test set was obtained. These results were found to have comparable performances to current state of the art machine learning models, and demonstrated that deep learning can be a powerful tool in the battery field.

1 Introduction

Lithium-ion batteries is widely used in many fields, such as communications, navigation, aviation, and outer space technologies, for their high energy density, high output voltage, low self-discharge rate, long lifetime, high reliability and safety, and other advantages. However, development of battery with long lifetime requires tedious development cycles ranging months to years. Thus, accurate prediction of battery lifetime using early-cycle data could greatly accelerate advances in battery production, use and optimization. For instances, new manufacturing methods can be quickly tested and validated without lengthy data collection processes. Expedited iteration processes therefore could enhance efficiency (e.g. labor, cost) for high performing battery development. Consequently, the prediction of lithium-ion battery lifetime is critically important. However, the task is challenging since the degradation is nonlinear with cycling and has wide variability. Therefore, we hope to develop deep learning models that accurately predict the cycle life of commercial lithium ion batteries using early-cycle data.

2 Related Work

Many approaches have modeled lithium-ion battery life. Most predictions of remaining useful cycle life are done by mechanistic and semi-empirical method, summarized in these review [1,2]. Specialized diagnostic measurement such as coulombic efficiency [3] and impedance spectroscopy [4] can also be used for lifetime estimation. While these chemistry or mechanism-specific models have shown predictive success, it is hard to generalize well under varying operation condition (for example, fast charging), given the degradation mode may be different (for example, degradation may come from thermal and mechanical heterogeneity within a cell). Data-driven model has emerged in recent years. Richard et al. has demonstrated early cycle life prediction through machine learning approach [5] and found out specific feature (capacity as a function of voltage) has strong correlation with the cycle life. While the feature may fit in specific battery condition, it may not generalize well to other operating condition. Hence, we aim to construct a general and flexible model by using deep learning approach for early prediction of cycle life.

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3 Dataset and Features

We used publicly available data set from Toyota research institute [6]. Each battery cycle life data takes months to be completed, which makes the data generation process long and endless. Due to this reason, we currently have limited number of battery cells (124 cells). However, to the best of our knowledge, this data set is the largest publicly available for nominally identical commercial lithium-ion batteries cycled under controlled condition [5]. We allocated 60% of our total to the train set, 20% to the development set, and 20% to the test set. An overview of the whole dataset is shown in Figure 1. On the right side of Figure 1, it is shown that 8 parameters were recorded in each cycle, including cycle number (CN), discharge capacity (QC), charge capacity (CC), internal resistance (R), maximum temperature (T_{max}), mean temperature (T_{mean}), minimum temperature (T_{min}), and charging time (t). The cycle life ranges from 150 to 2300 using 72 different charging conditions, with cycle life (end of life) defined as the number of cycles when 80% capacity is consumed [5]. We preprocessed our dataset by normalizing and shuffling and removing battery cells that does not reach 80% capacity and has noisy channels resulted from instrument noises. The battery data from the first 5, 10, 50, 100 cycles was used in the training process. For example, to use the first 100 cycles as input data, we create 800 features in total. Two types of prediction are generated: (1) to predict the actual cycle life and (2) to determine the battery is good or not. Here, for the binary classification, we classified cells into "low-lifetime" (y = 0 when cycle life < 550) and "high-lifetime" (y = 1 when cycle life ≥ 550) with "550" generally considered as a common threshold for long battery operation [5].

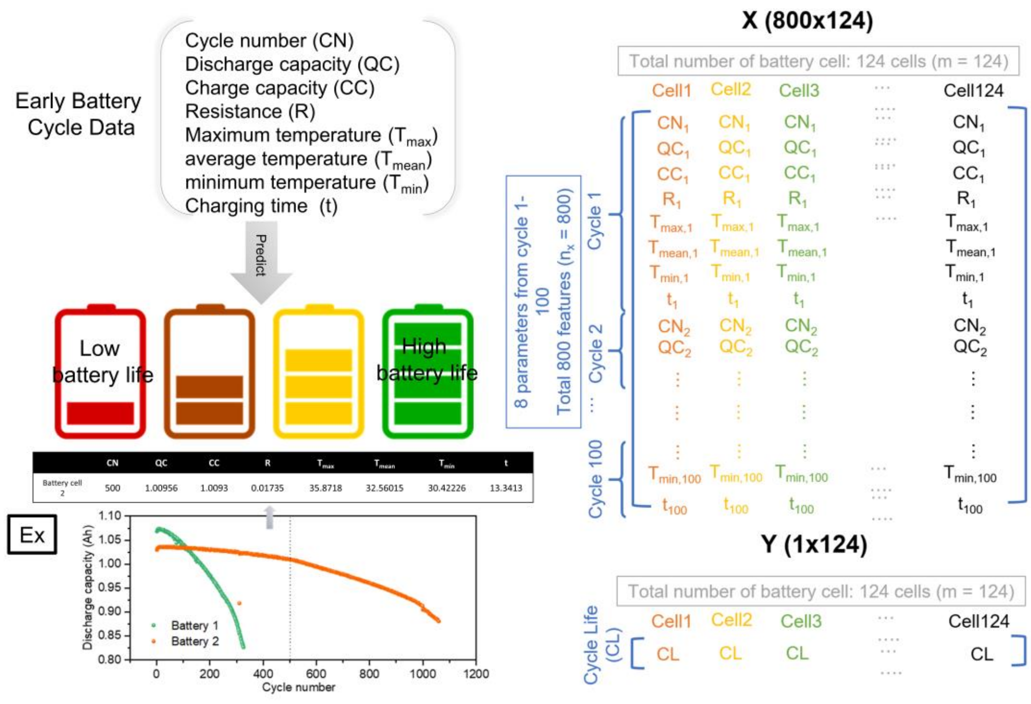

Figure 1: Overview of dataset and the arrangement of features.

4 Methods

Figure 2 shows the scheme for our FCNN model. Four hidden layers were created and ReLU was chosen to be our activation function for them. For the output layer, sigmoid and ReLU were selected to be the activation functions for binary classification and actual cycle life prediction, respectively. And based on different output, Binary Cross-Entropy Loss (Eq. (1)) and Root Mean Square Error (Eq. (2)) were used as our loss functions for binary classification and actual cycle life prediction, respectively. Adam was determined as our optimizer in the training process.

$$J_{BCE} = \frac{1}{m}\sum L(\hat{y}, y) = \frac{1}{m}\sum(-y\log\hat{y} - (1-y)\log(1-\hat{y})) \quad \text{Eq. (1)}$$

$$J_{RMSE} = \sqrt{\frac{1}{m}\sum L(\hat{y}, y)} = \sqrt{\frac{1}{m}\sum(\frac{\hat{y}-y}{y})^2} \quad \text{Eq. (2)}$$

Figure 3 shows our design for RNN model. In each neuron, tanh and sigmoid were used as the activation functions. Adam was determined as our optimizer in the training process. Since we plan to do binary classification, Binary Cross-Entropy Loss (eq. (1)) was used again as our loss function.

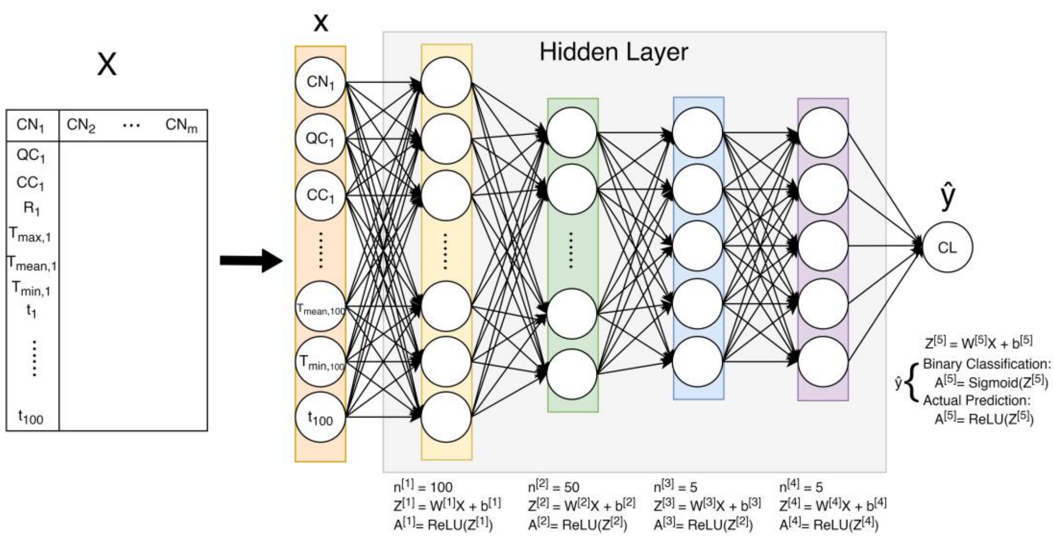

Figure 2: Scheme of fully-connected neural network (FCNN) model.

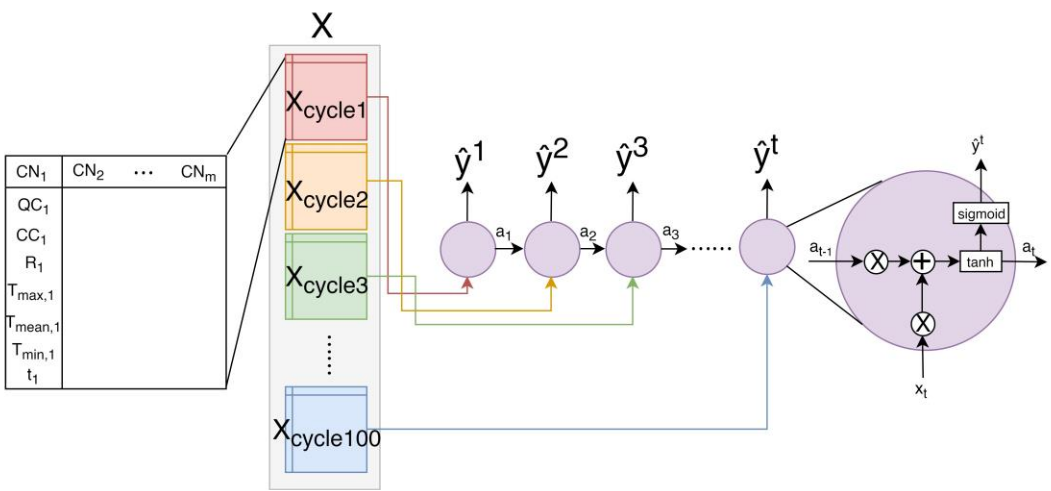

Figure 3: Scheme of recurrent neural network (RNN) model.

5 Results and Discussion

Results for binary classification of battery life - FCNN and RNN. Both of the FCNN and RNN models were used for the classification of battery cycle life. Parameters collected from first 5, 10, 50 and 100 cycles were used in model training, verification and testing, and the corresponding performances were compared to find the smallest cycles needed for accurate prediction. Table 1 summarizes the training, dev and test set accuracy of these four types of datasets using a FCNN with the optimized learning rate. The results suggest that using more cycles may provide us better prediction accuracy. But, only 5 cycles are needed to achieve acceptable accuracy (83%).

To prevent overfitting which may impact the performance of our model due to our small dataset size, early stopping was implemented in FCNN. Figure 4a shows a typical training and dev cost over 10000 iterations without early stopping. An increase in the dev cost after certain numbers of iterations may indicate a potential overfitting issue. Table 2 shows the training, dev and test set accuracy using the FCNN model with early stopping. However, no significant improvement was observed, which may again result from the small dataset problem.

Considering the fact that our dataset is sequential that we get same features in each cycle, RNN was also used to classify battery cycle life. Table 3 shows the training, dev and test accuracy using RNN. The test accuracy using only the first 5 cycles with RNN shows better performance than FCNN.

Table 1: The accuracy of training, dev and test sets from our FCNN model.

First n cycles with best learning rate (LR)	5 cycles	10 cycles	50 cycles	100 cycles
	LR=0.001	LR=0.001	LR=0.001	LR=0.001
Training accuracy (%)	100	100	100	100
Dev accuracy (%)	92	100	100	93
Test accuracy (%)	83	88	87	94

Table 2: The accuracy of training, dev and test sets from our FCNN model with early stopping.

First n cycles with best learning rate (LR)	5 cycles	10 cycles	50 cycles	100 cycles
	LR=0.001	LR=0.001	LR=0.001	LR=0.01
Training accuracy (%)	99	97	99	99
Dev accuracy (%)	100	90	100	100
Test accuracy (%)	85	90	85	87

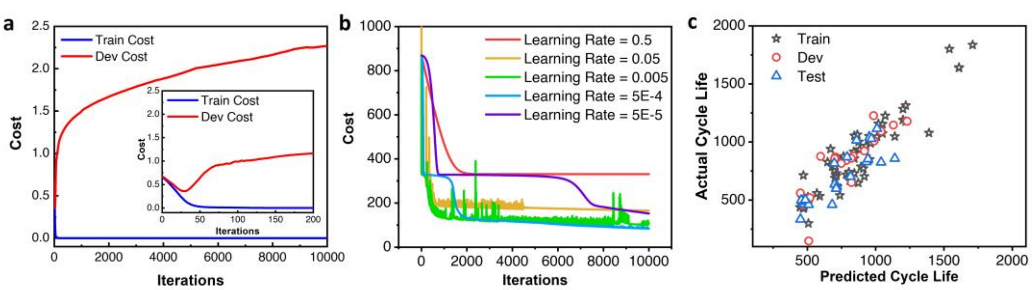

Figure 4: (a) Training and dev cost over iterations for binary classification. The increase of dev cost may indicate a possible overfitting issue. (b) Training and dev cost over iterations for actual life prediction with different learning rates. (c) Comparison of observed cycle life and predicted cycle life in training, dev and test sets.

Table 3: The accuracy of training, dev and test sets from our RNN model.

First n cycles with best learning rate (LR)	5 cycles	10 cycles	50 cycles	100 cycles
	LR=0.0005	LR=0.0005	LR=0.0005	LR=0.0005
Training accuracy (%)	96	97	98	98
Dev accuracy (%)	100	91	95	91
Test accuracy (%)	95	87	87	95

Results for predicting actual cycle life – FCNN. Using a limited number of datasets, the results are quite satisfying especially given how challenging the problem is. For quantitatively predicting cycle life, our model can achieve prediction errors of 14.8 % using only data from 100 cycles, at which point most batteries have yet to exhibit capacity degradation (Table 4). We explored different learning rate found the learning rate (LR) has significant effect on the training/development/test mean percentage error as the LR is tuned from 0.5 to 0.05. When LR= 0.5, it's too large so that the loss diverges (Figure 4b). Finally, we picked LR= 0.005 as the best model performance based on the lowest test accuracy (14.8%). Figure 4c shows our predicted cycle life versus observed cycle life.

Table 4: The error of training, dev and test sets from our FCNN model for actual battery life prediction.

Learning Rate	0.5	0.05	0.005	0.0005
Training error (%)	37	13	10	9
Dev error (%)	51	20	19	19
Test error (%)	39	15	15	15

6 Conclusion and Future Works

In conclusion, we demonstrated that deep learning can be a powerful tool to predict the battery life for lithium-ion batteries using early-cycle data. FCNN and RNN models were developed to classify a battery is good (cycle life ≥ 550) or not (cycle life < 550). Both of the models achieved over 94% accuracy, and suggested that only 5 cycles are required to obtain 95% test set accuracy. We also trained our FCNN to determine the actual battery life where appropriate activation and loss function were used. Our predicted values show a reasonable match to the actual battery life which suggests that deep learning does a great job in battery life prediction.

For the future, we can create an universal model for different battery cell type. We think that it would be very interesting to see how the model can be generalized well to other operating condition which may involve different degradation mechanism. For example, our current battery cells use lithium ion phosphate as cathode and graphite as anode. It is possible that our model can have promising performance on other anode/cathode type with similar materials such as lithium metal as anode or lithium cobalt oxide as cathode.

7 Contributions

Every team member contributed tangibly to the project, having some part in every experiment, research and analysis. Tzu-ling Liu performed data preprocessing for FCNN and RNN, baseline model for FCNN-BN and RNN-BN, tested models and performed hyperparameter searches, plots and figures, final report and poster. Yuchi Tsao assisted with model development, data preprocessing for RNN, tested models and performed hyperparameter searches, plots and figures, final report and poster. An-Chih Yang assisted with model development, plots and figures, final report and poster, finalize and re-organize the report and poster.

8 Github Repository

https://github.com/yctsao/CS230.git

9 References

[1] Ramadesigan, V. et al. Modeling and simulation of lithium-ion batteries from a systems engineering perspective. J. Electrochem. Soc. 159, R31–R45 (2012).

[2] Waag, W., Fleischer, C. Sauer, D. U. Critical review of the methods for monitoring of lithium-ion batteries in electric and hybrid vehicles. J. Power Sources 258, 321–339 (2014).

[3] Burns, J. C. et al. Evaluation of effects of additives in wound Li-ion cells through high precision coulometry. J. Electrochem. Soc. 158, A255–A261 (2011).

[4] Chen, C. H., Liu, J. Amine, K. Symmetric cell approach and impedance spectroscopy of high power lithium-ion batteries. J. Power Sources 96, 321–328 (2001).

[5] Braatz, R. D. et al. Data-driven prediction of battery cycle life before capacity degradation. Nature Energy 4, 383-391 (2019)

[6] https://data.matr.io/1/