Modeling and performance prediction of Lithium ion cells

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Space quality vs Commercial cells

Space quality

- Quality and reliability are assured.
- Performance, Life test data & support available.
- Very expensive (>100x) + long lead time
- Few manufacturers –availability of frozen design over long time

Commercially-Off-The-Shelf technology (COTS)

- Advanced technology SOA cells
- Available from Several manufacturers.
- Nil Procurement lead time
- Automated high volume production assures uniformity
- Inexpensive.
- No assurance on Quality & Reliability.

Reliability for COTS - fast and accurate

Challenge: Every battery ages differently, depending on its usage and conditions during manufacturing.

Key:

1. Accelerated testing to failure
2. ML to predict battery life

Article | Published: 25 March 2019

Data-driven prediction of battery cycle life before capacity degradation

Kristen A. Severson, Peter M. Attia, Norman Jin, Nicholas Perkins, Benben Jiang, Zi Yang, Michael H. Chen, Muratahan Aykol, Patrick K. Herring, Dimitrios Fraggedakis, Martin Z. Bazant, Stephen J. Harris, William C. Chueh & Richard D. Braatz

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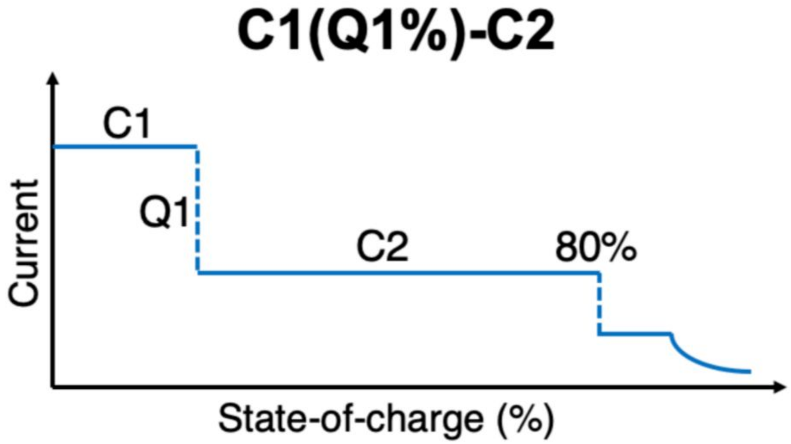
18k Accesses | **63** Citations | **163** Altmetric | Metrics

Severson et. al. Nature Energy ‘19

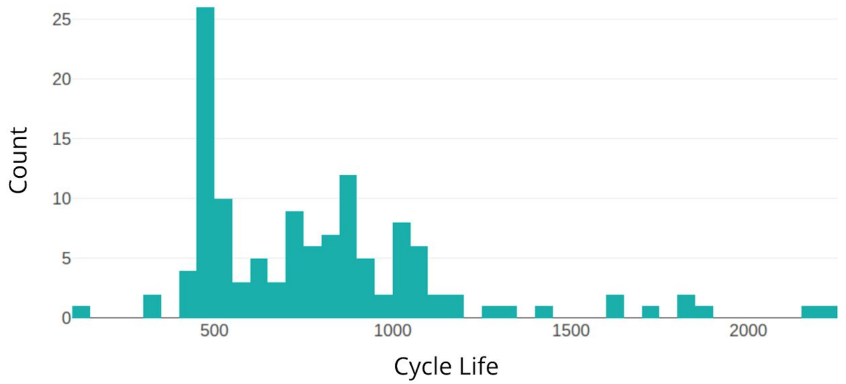
Attia, Grover et. al. Nature ‘20

Accelerated testing to failure

- 124 cells, different fast charging policies

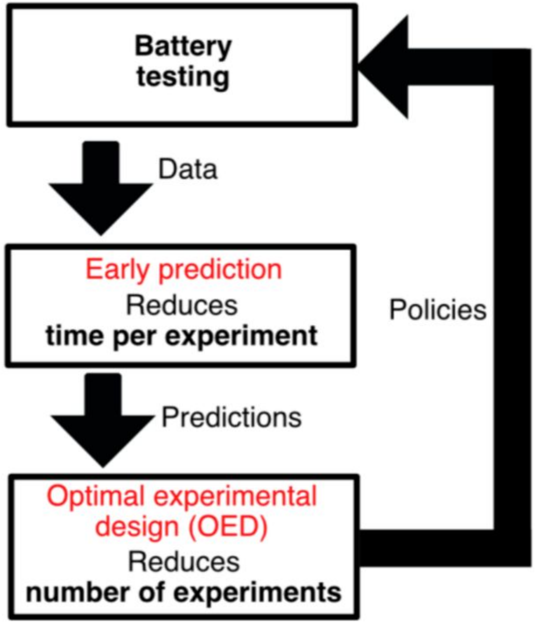


Fast charging policy. C1, Q1, C2 are different for each cell.



Different policies result in different cycle life. All cells tested to failure. Failure event : Capacity reduces to 80% (i.e. 20% loss)

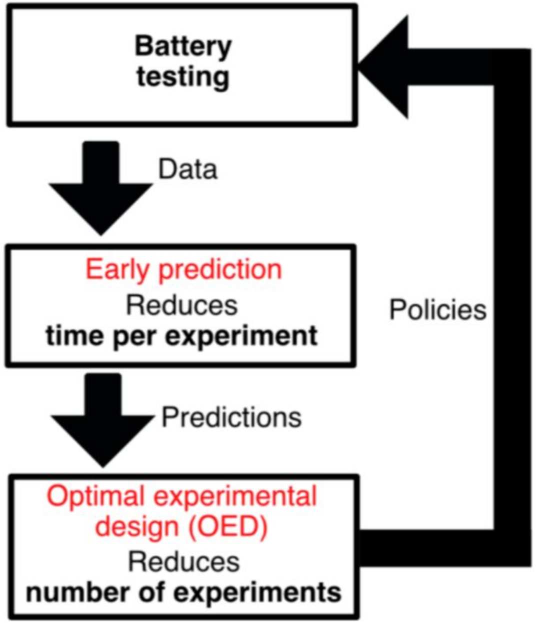
Choosing charging policies



Severson et. al. Nature Energy ‘19

Determines next policy to test for each cell.

Discovered new long-life fast-charging policy



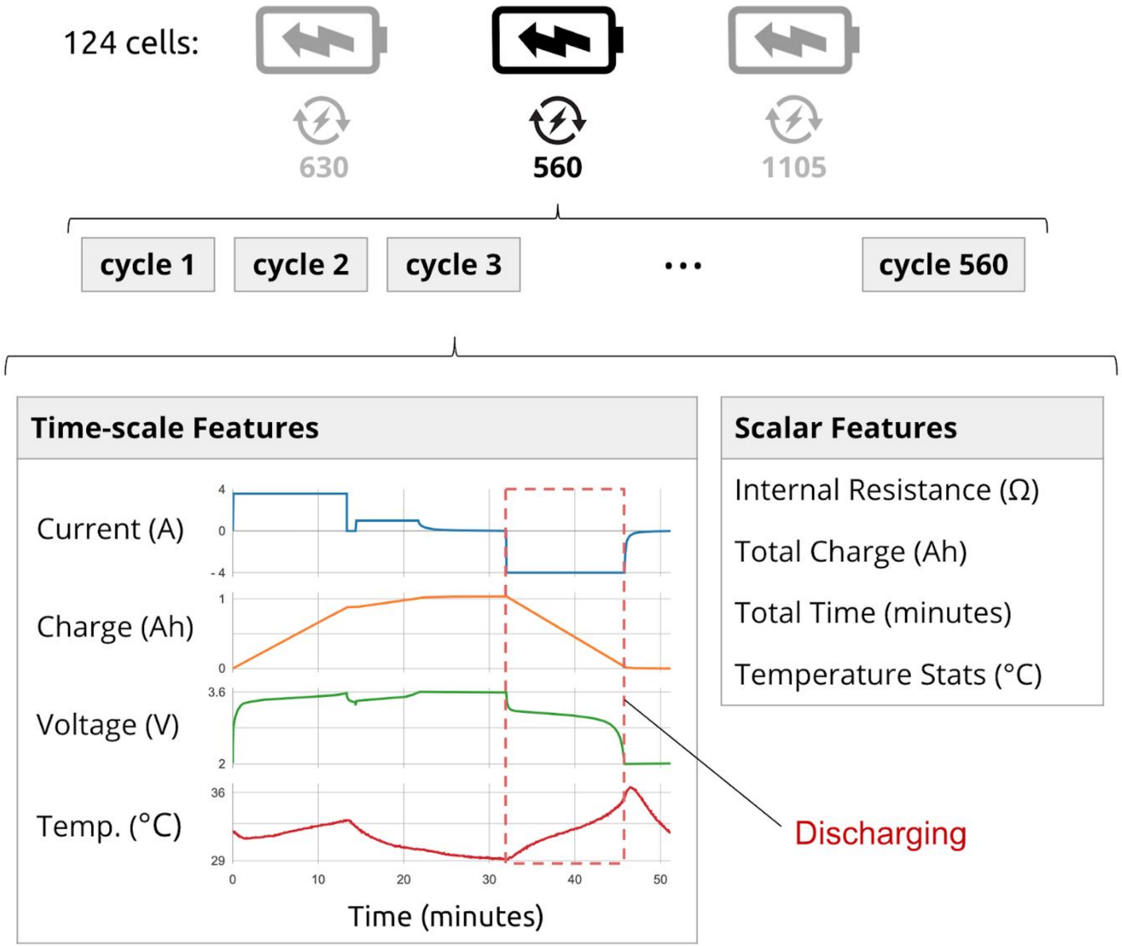
Attia, Grover et. al. Nature '20

Predicts the cycle life for each policy.

Identified a fast-charging policy that will provide long-life.

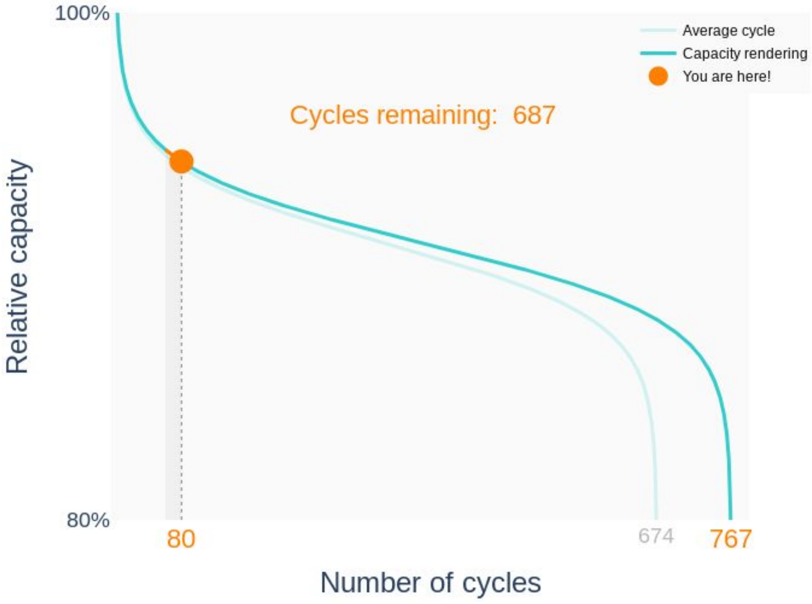
Data

The data consists of 124 battery cells, each has gone through a variable number of charging cycles, and for each cycle we have measurements over time and scalar measurements.



Predict: How many cycles {lived, remaining}?

- State of Health (**SoH**) : How many cycles has the cell lived through?
- Remaining Useful Life (**RUL**) : How many cycles will it last before it breaks?

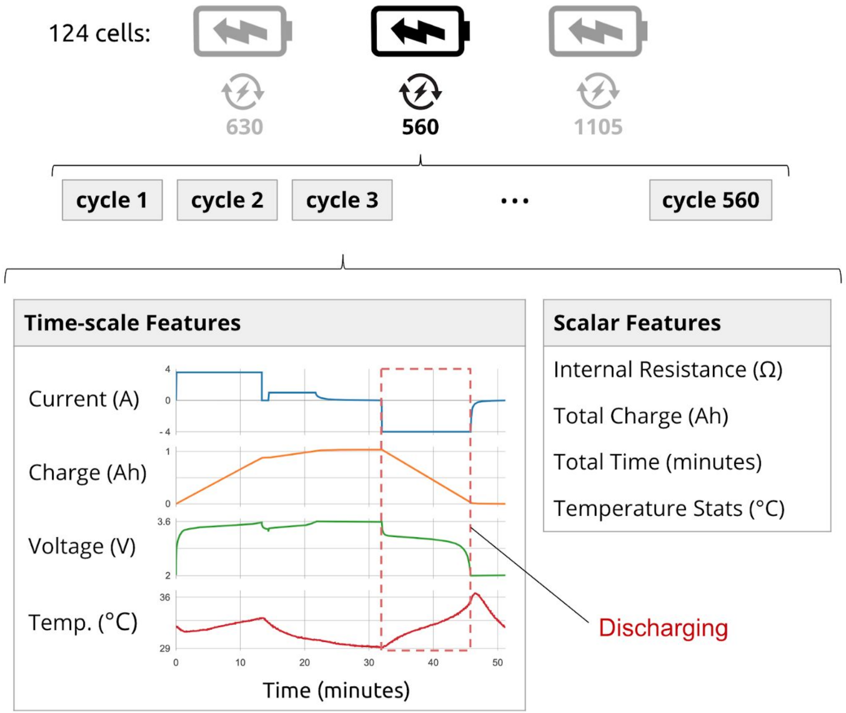


Data pre-processing

- Training machine learning models requires cleaning and processing data.
- Use the process in Severson et. al. '19

1: Discard unwanted data

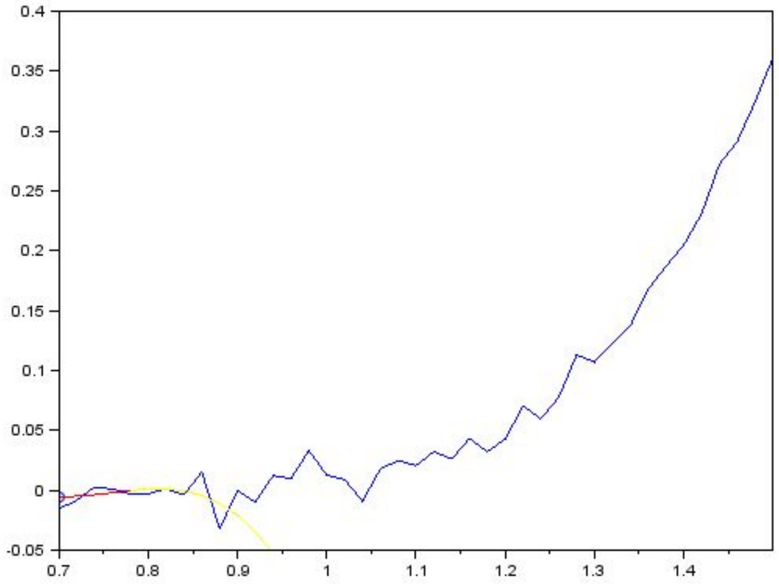
- Crop to the discharging cycle.
- Remove cycles that had time gaps, small outliers, or other inconsistencies.



2: Smooth out noise [optional]

Savitzky–Golay filter is used to smooth out the noise.

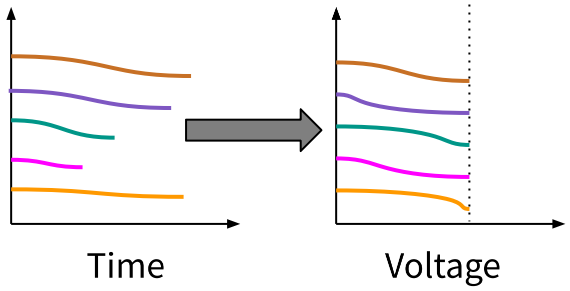
- Select sliding window of n data points. (n is odd)
- Fit a curve to the points in the window.
- Replace the point in the middle of the window to the smoothed one that is on the curve.



Animation showing smoothing being applied, passing through the data from left to right. The red line represents the local polynomial being used to fit a subset of the data. The smoothed values are shown as circles.

3: Voltage range as reference instead of time.

Issue with time as reference: Different charging policies mean that some cycles finish quicker than others and the time measurements of charge and temperature can't be compared as they were.



1. Take the voltage range during discharging as the reference instead of time.
   a. Range for fully charged and discharged voltage for a cell stays constant
2. Interpolate charge and temperature over voltage.
3. Resample charge and temperature at 1000 equidistant voltage steps.

All measurements now have the same length for every cell and cycle.

Data: Input and Output

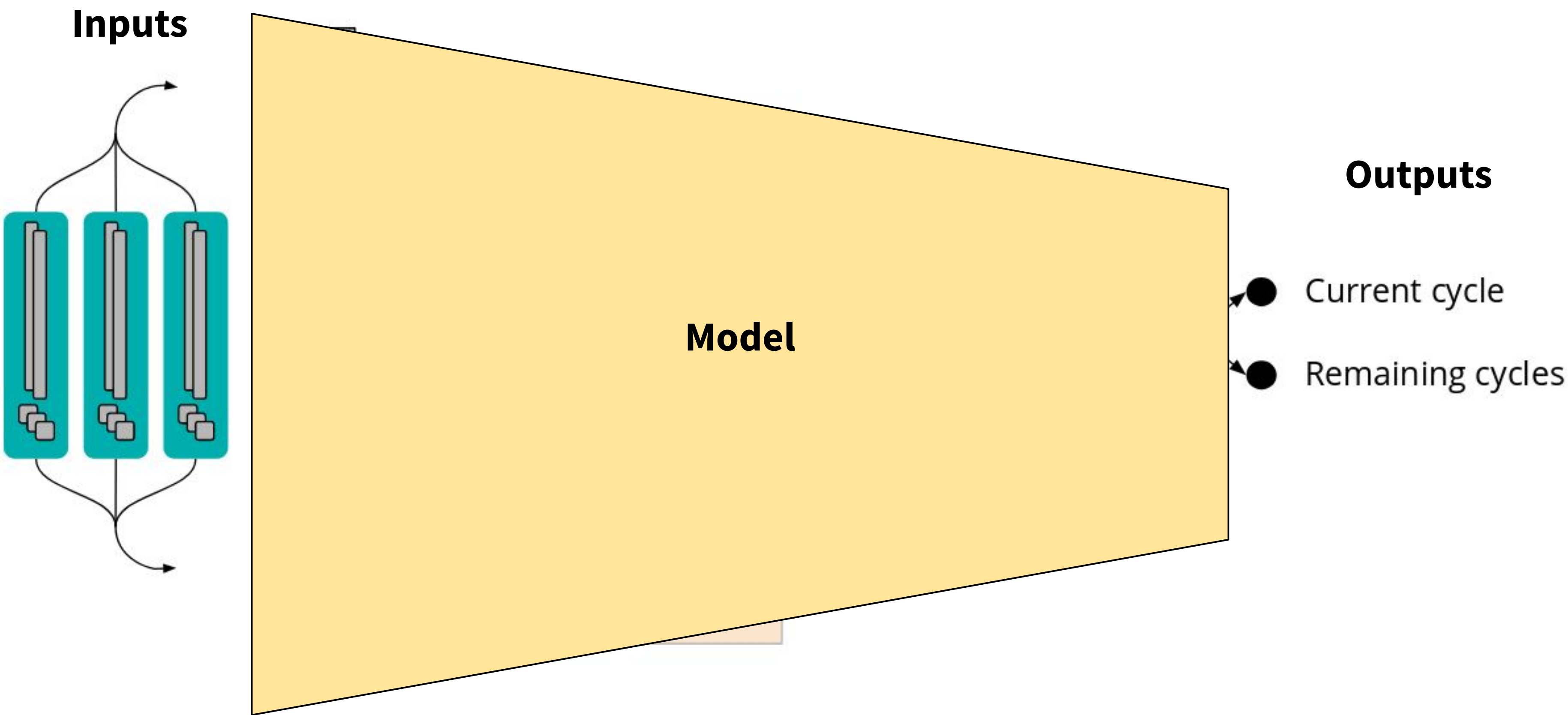
Inputs:

- Charge (20 cycles x 1000 points sampled over Voltage)
- Temperature (20 cycles x 1000 points sampled over Voltage)
- Internal Resistance (20 cycles x 1)
- Discharge Time (20 cycles x 1)
- Total Charge (20 cycles x 1)

Outputs:

- Current cycle
- Remaining cycles

Model



ML: Learn a function to fit data

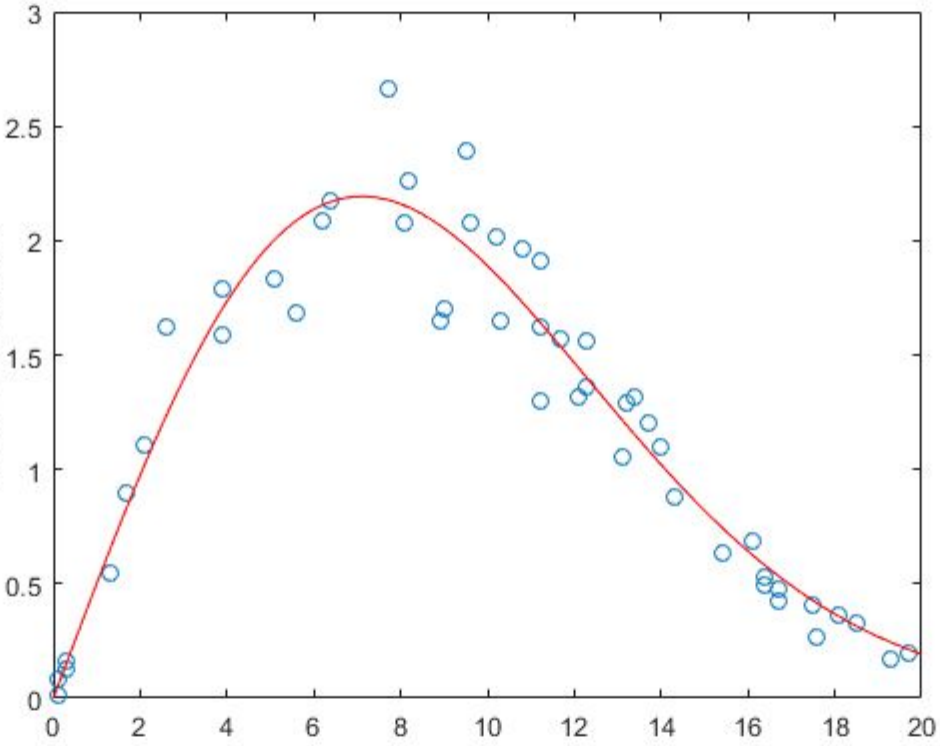
Input: x

Output: y

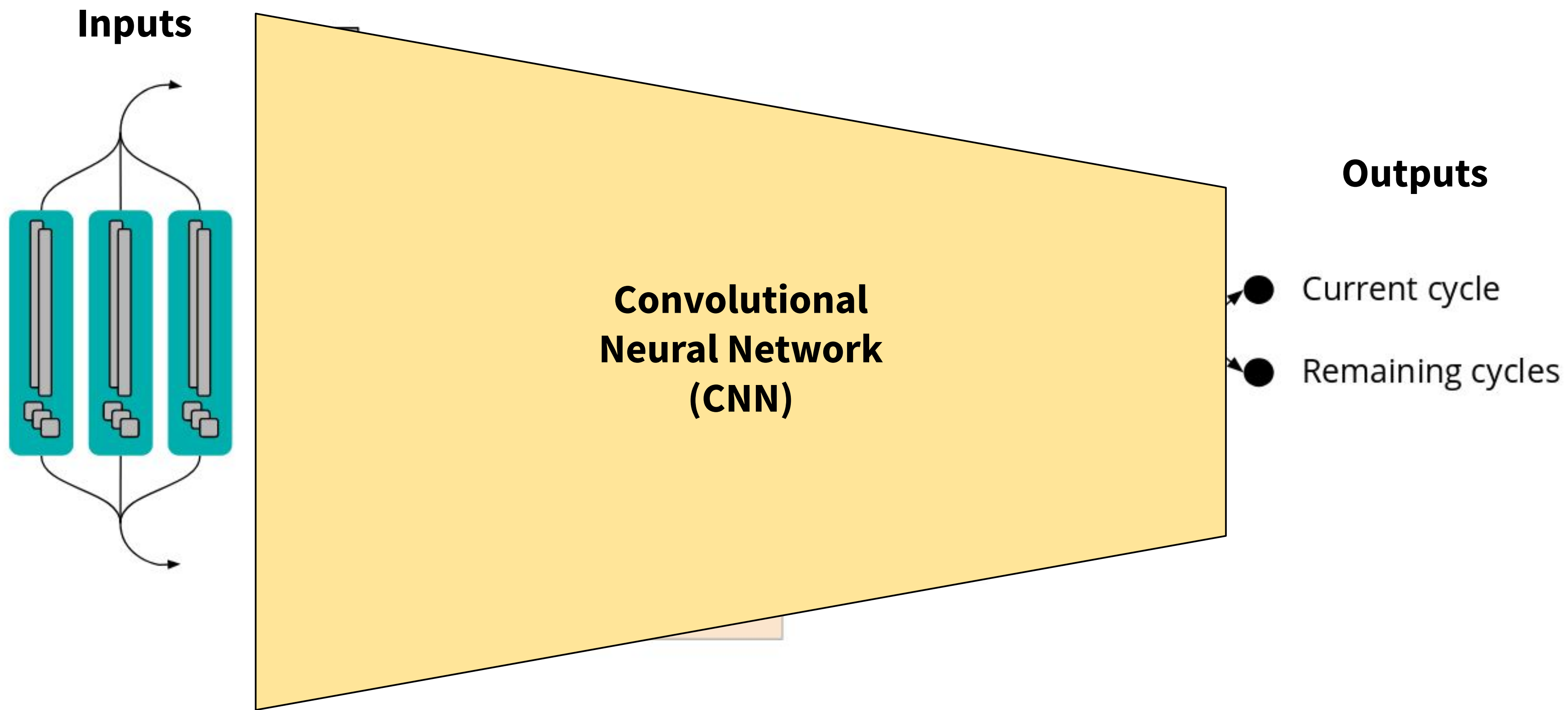
Model: f()

Optimize: y - f(x)

Learn **f** such that f(x) = y



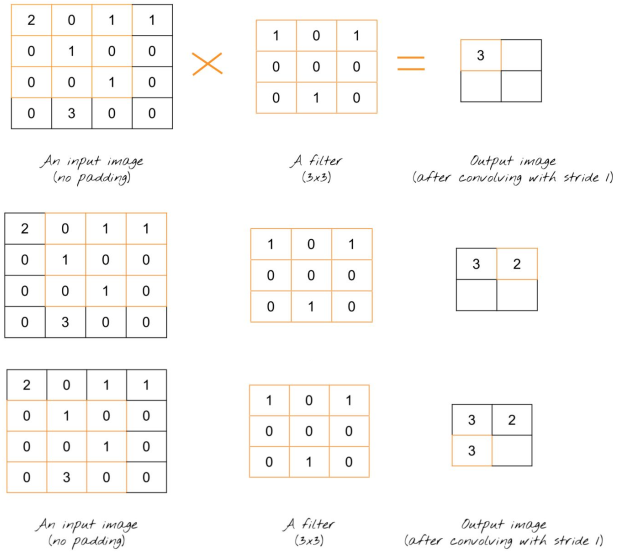
Our model is a Convolutional Neural Network

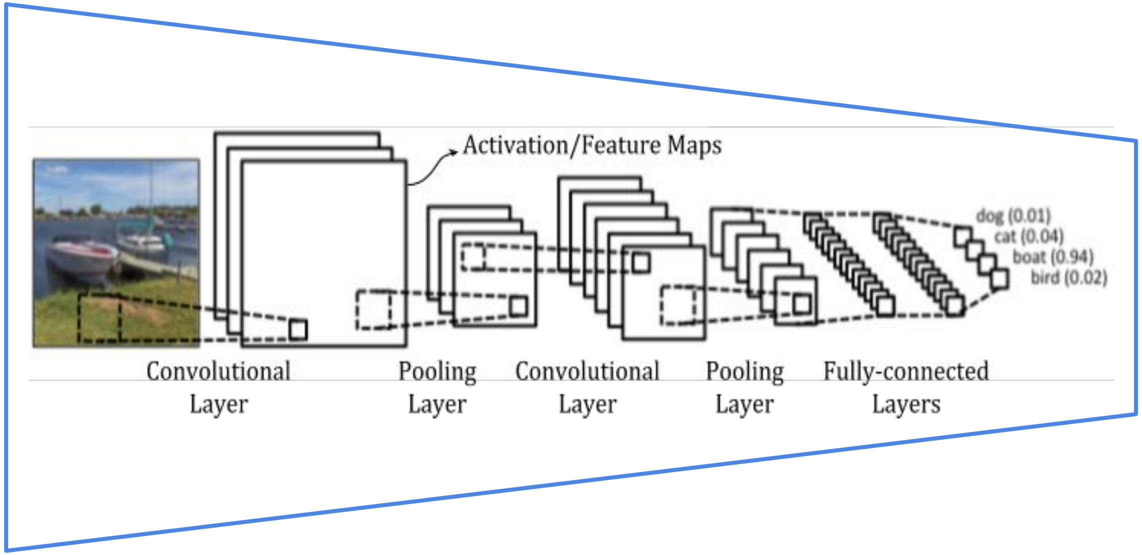


Convolutional Neural Network (CNN)

Convolution “filters” help identify pattern in raw data (e.g. image edges)

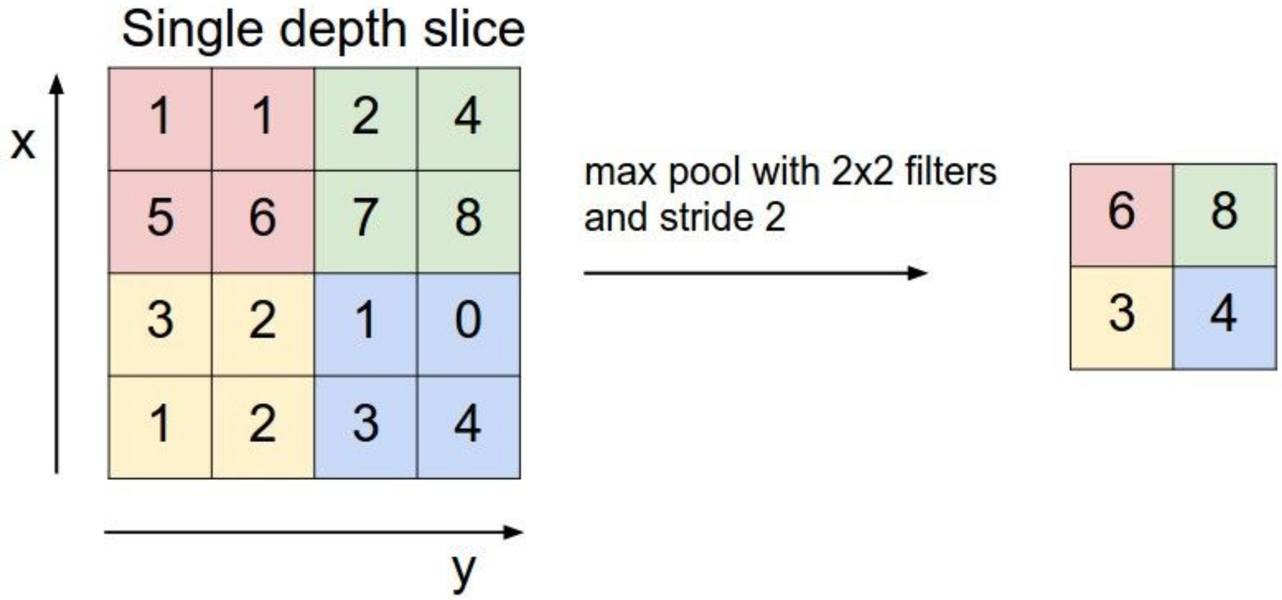
CNNs - automatically learn “filters” / weights.



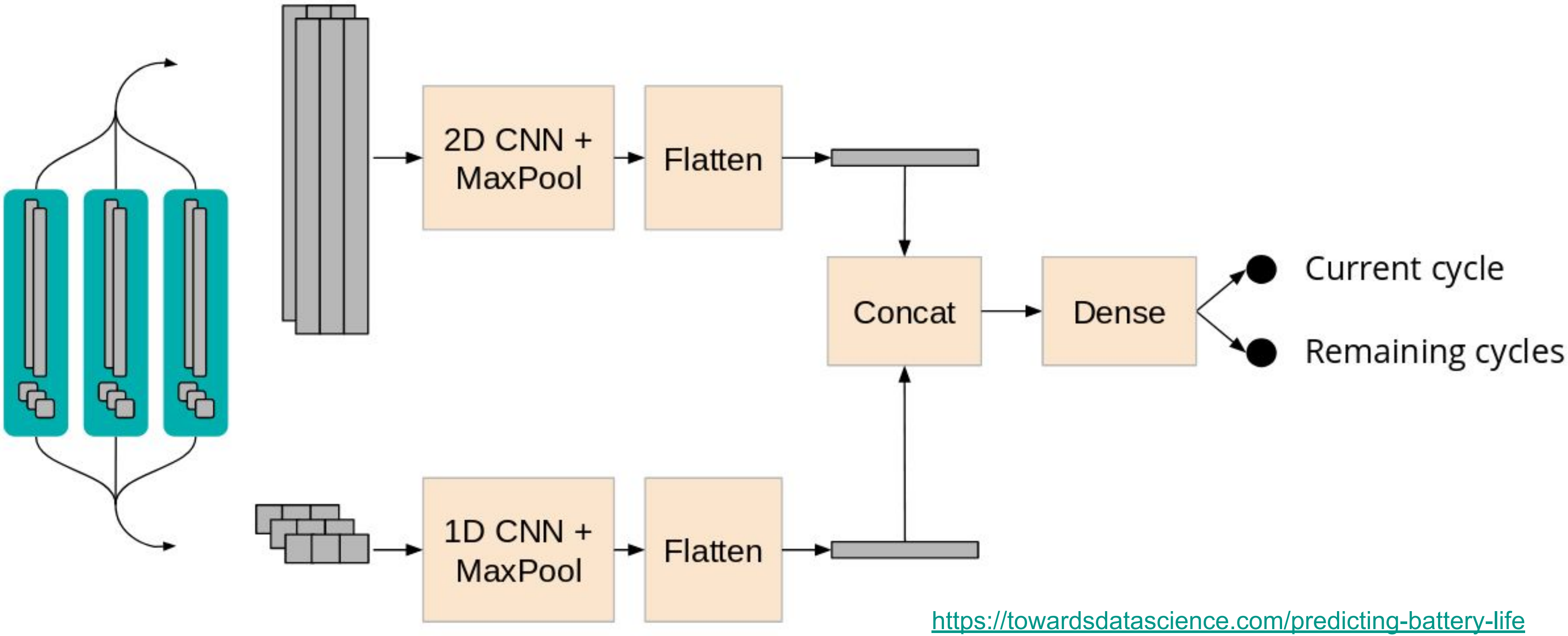


Max-pooling (down-sampling)

Convolution layer is followed by a max pooling (down sampling) operation.



Battery life prediction model



https://towardsdatascience.com/predicting-battery-lifetime-with-cnns-c5e1faeecc8f

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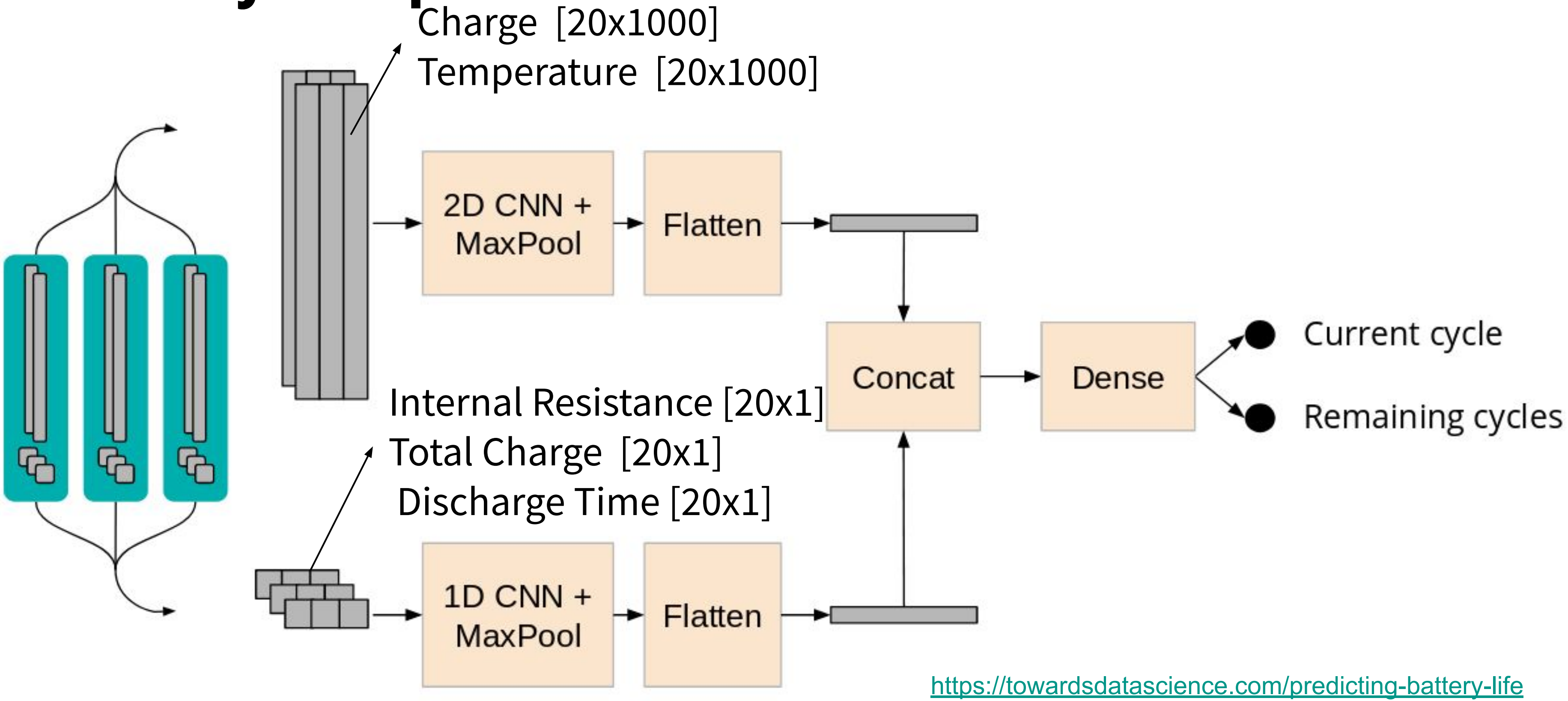

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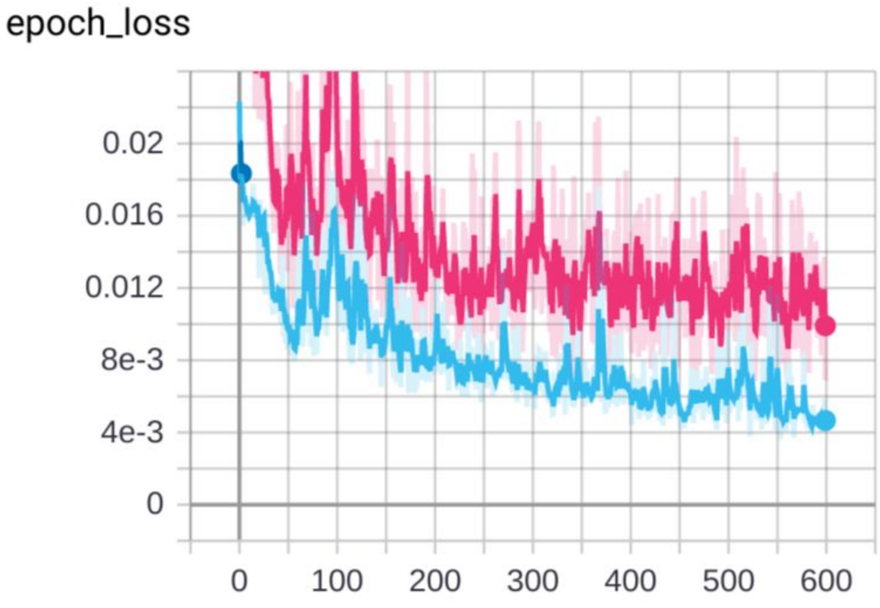
Training: Showing a model lots of examples

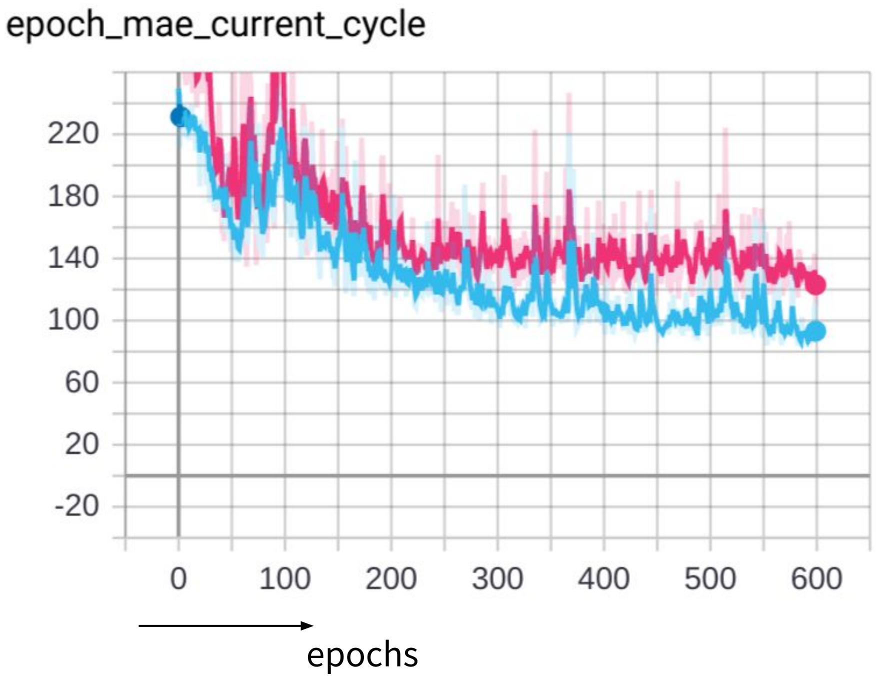
(Input, Output) pairs

Goal: Learn weights W to produce
correct output on any given input.

Model training

Looks at the entire dataset of input and output pairs several hundred times.





1 epoch → 1 full pass of the entire training data.

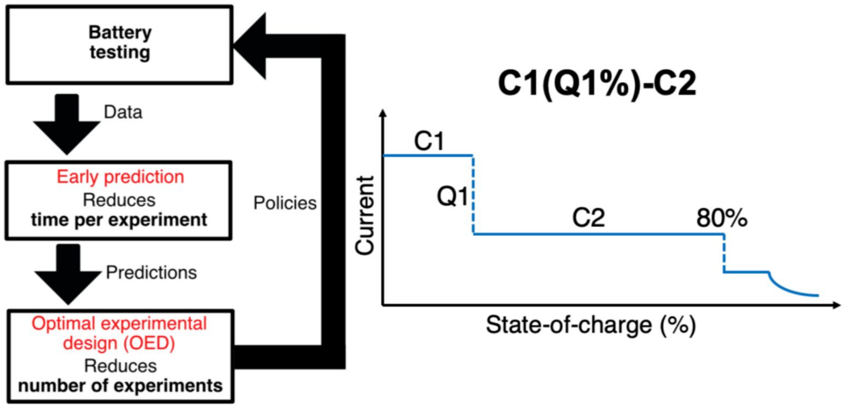
Prediction

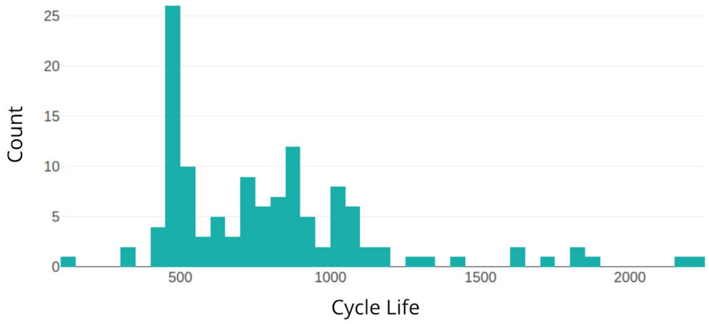
Error: 6.8%

Conclusion

- Policies for accelerated testing can be used to generate data for new types of cells.
- Once a model is trained, with just 20 cycles of data SoH and RUL can be predicted.

Choosing charging policies





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