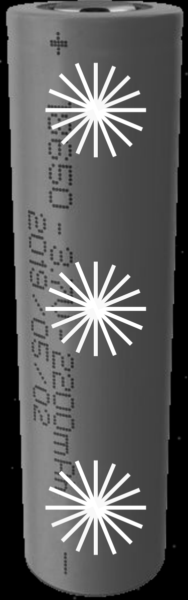
18650 Battery Life: Survival Analysis vs Machine Learning

A Comparative Study Using Data from the NASA Prognostics Data Repository



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Introduction

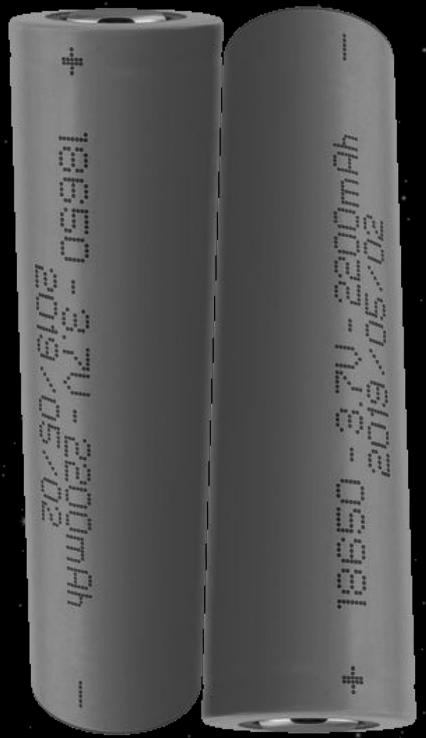
Batteries!

The Problem

- 18650 batteries are standard lithium-ion cells, also known as rechargeable batteries.
- They are used in a wide variety of applications.
- There is a need for accurate life-span predictions.
- Most models are purely data-driven or purely physics-driven.
- Need for models that integrate the two.

The Question

- Can we better predict battery survival time using survival analysis techniques or using a machine learning model?
- What kind of model is better at predicting how quickly a battery will die using data about how it is discharging?



The Goal

- Better Battery Life Prediction: Understanding and predicting battery life is essential for improving reliability and optimizing usage. It can also reduce costs and prevent unexpected failures.
- Comparison of Methods: This study compares two broad approaches — Survival Analysis and Machine Learning — to evaluate which method more accurately predicts the discharge time of 18650 batteries.

02
Background

What are 18650 Batteries?

- 18650 batteries are cylindrical lithium-ion cells.
  - Standard size rechargeable batteries.
- The performance and longevity of 18650 batteries are critical in these applications, as they directly affect the device’s overall efficiency and reliability.

Used in high-drain devices due to their high energy density and long cycle life. Examples of Applications:

- Electric Vehicles
- Laptops
- Flashlights
- Power Tools
- Drones
- Portable Power Banks

Understanding the 18650

- High Energy Density: 18650 batteries offer a high energy-to-weight ratio, making them ideal for devices requiring a lot of power in a small form factor.
- Long Cycle Life: These batteries can undergo hundreds to thousands of charge/discharge cycles, depending on usage, before significant capacity loss occurs.
- Safety Features: Often equipped with built-in protection circuits to prevent overcharging, overheating, and short circuits.

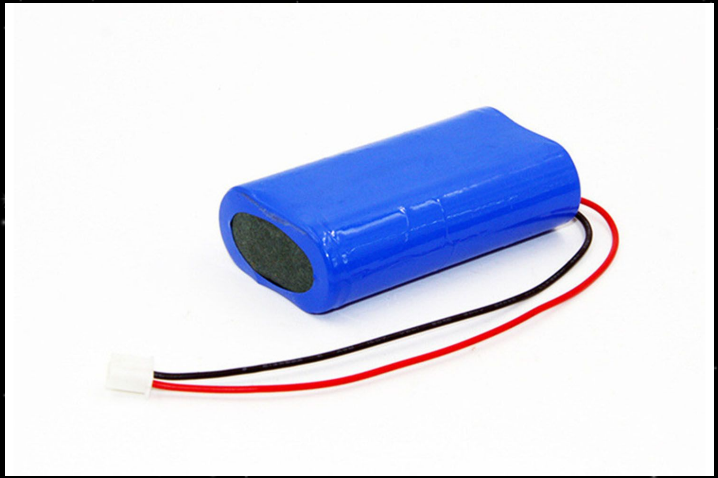
Accelerated Life Testing

- Subjecting a product to extreme conditions in order to find problems or faults at a faster rate than normal use
- Conditions in excess of standard operating conditions
  - Stress
  - Strain
  - **Voltage**
  - **Temperature**
  - Pressure
  - Vibration

03
Data

Battery Pack Data

- Data acquired from NASA's Prognostics Center of Excellence Data Set Repository
  - Consists of 21 data sets for a variety of prognostic tasks
- Accelerated life testing for 18650 lithium-ion batteries in packs of 2
- 26 battery packs in total
  - 18 regular life
  - 3 second life (packs that survived the initial testing)
  - 5 recommissioned (packs formerly subjected to varying current levels)
- 3 modes: charge, rest, and **discharge**

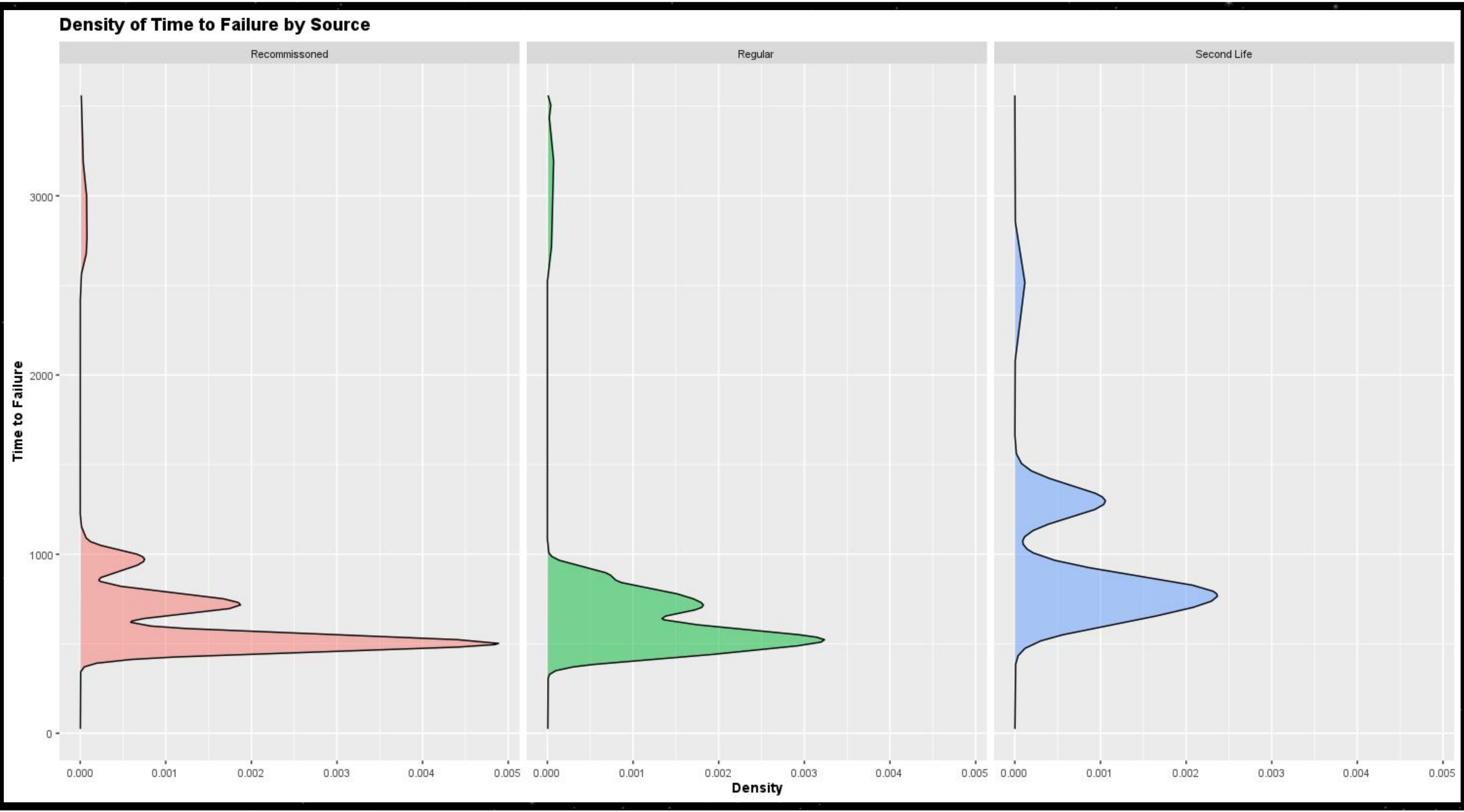


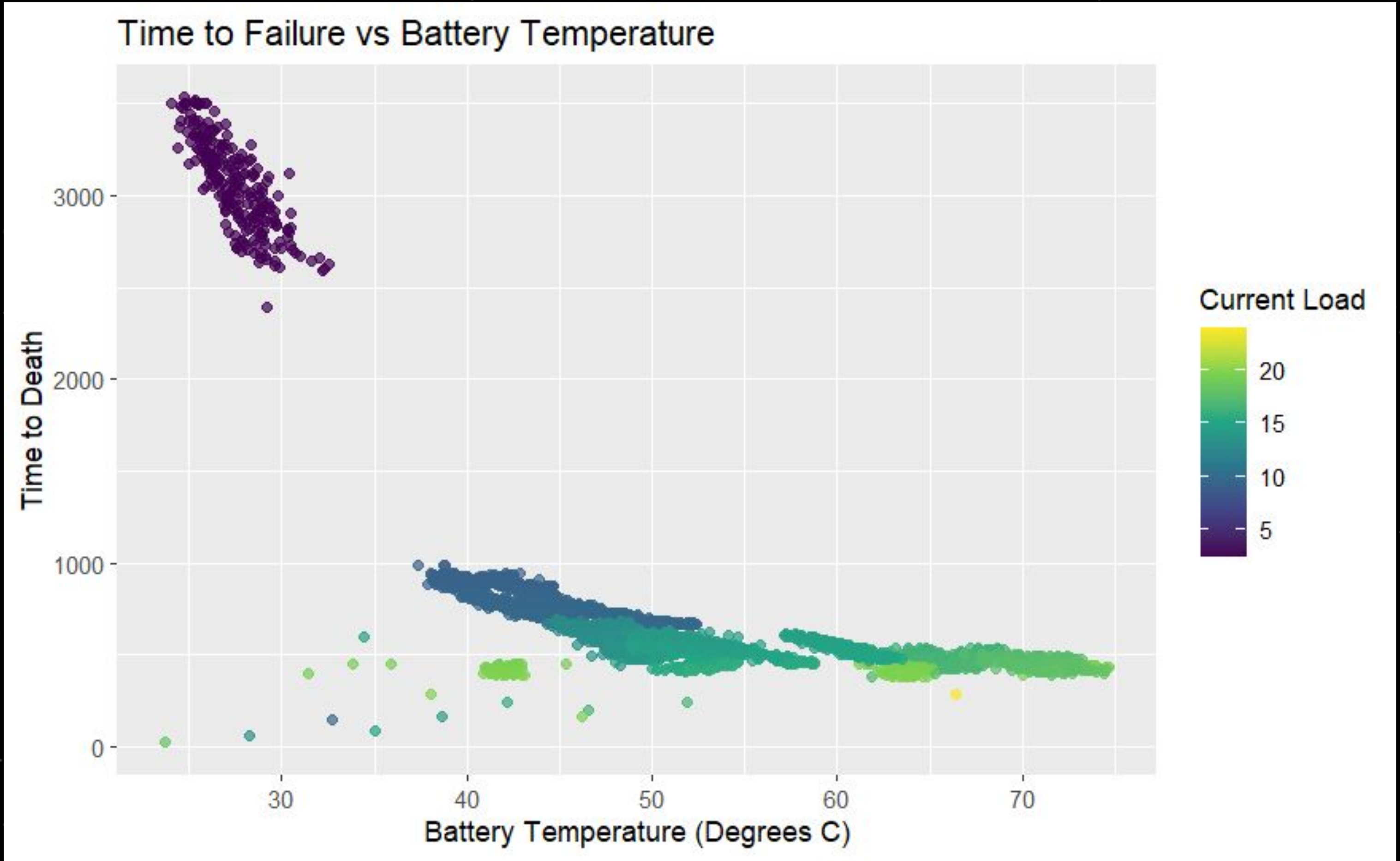
Battery Pack Data

- Each battery pack is measured once a second from start to finish
  - Measure load voltage and surface temperature
  - For discharge, output current is also measured
- Focusing only on the **discharge** phases
  - Battery packs are connected to circuits of varying current intensity
  - Battery packs discharge power until they are dead, and then they are charged
  - Want to predict the discharge time based on voltage, temperature, and current

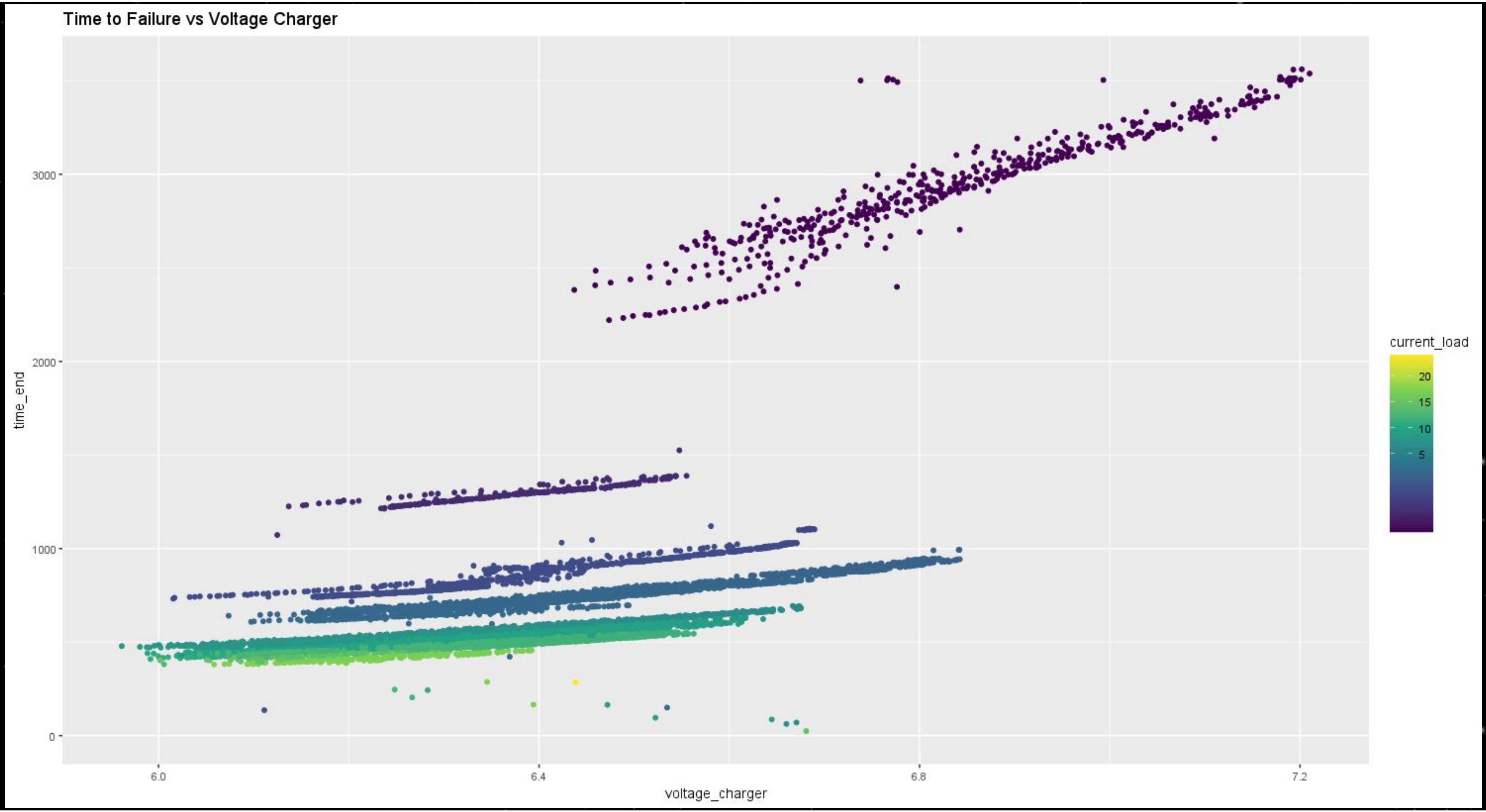
Battery Pack Data

- Each battery pack is measured during each of the three phases
- Split each life cycle into just the discharge phases, ignoring the charge and rest
    - Treating each discharge phase as its own miniature life cycle
- **Features**: surface temperature, loading voltage, output current,
    - Each phase is reduced to a single row consisting of averages of these three features
- **Response**: time to death (from full charge to no charge)


Density of Time to Failure by Source
Recommissoned
Regular
Second Life
Time to Failure
3000
2000
1000
0
0.000
0.001
0.002
0.003
0.004
0.005
Density



Time to Failure vs Battery Temperature
Time to Death
3000
2000
1000
0
30
40
50
60
70
Battery Temperature (Degrees C)
Current Load
20
15
10
5


Time to Failure vs Voltage Charger
time_end
3000
2000
1000
0
6.0
6.4
6.8
7.2
voltage_charger
current_load
20
15
10
5

04

Methodology

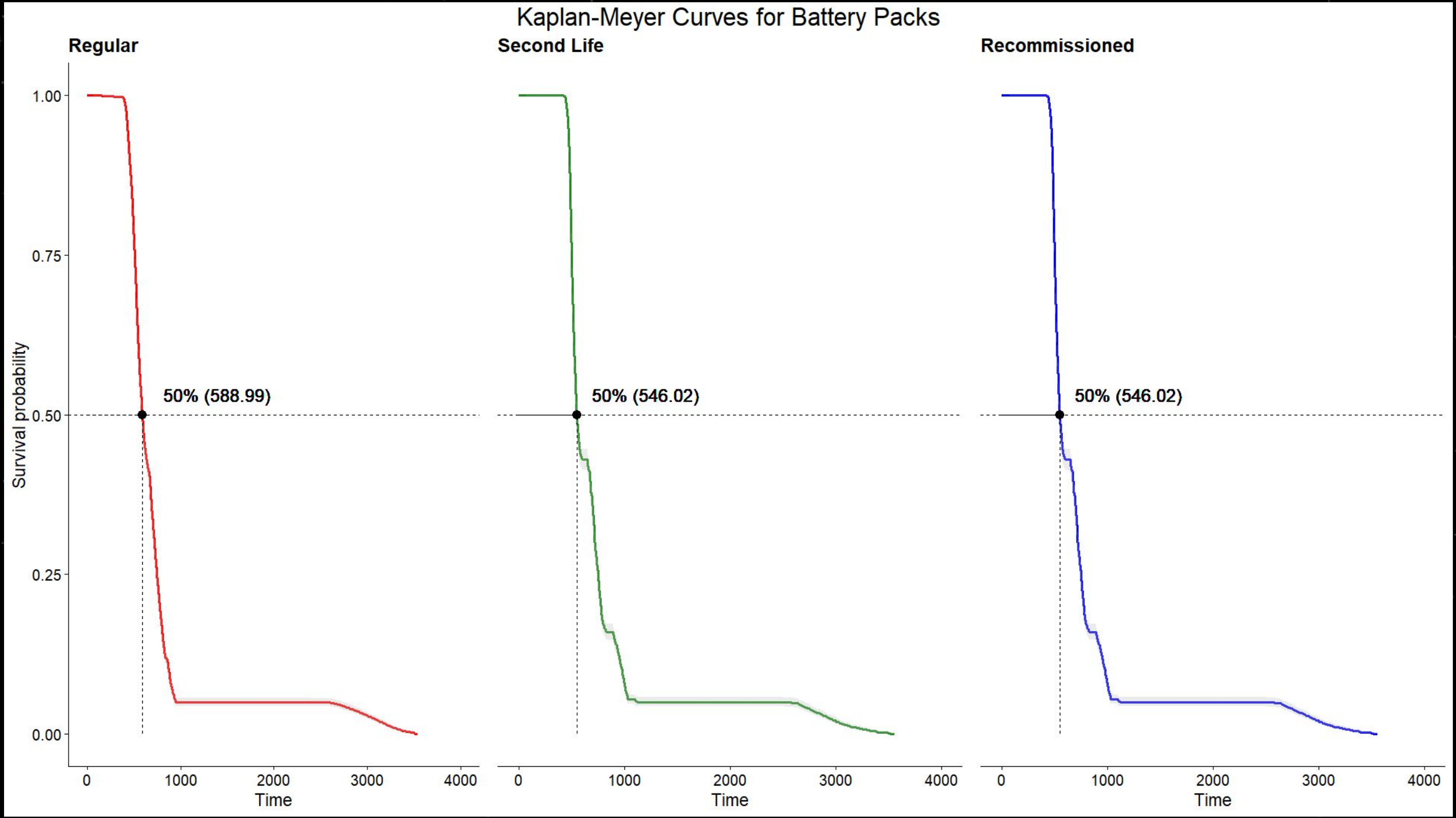
Survival Analysis - Weibull Regression

- Survival analysis measures the time to an event
- The event in question is the death of the battery
- Death in this case meaning the complete discharge of the battery cell. Not failure.
- $\texttt{TTF} \sim \texttt{Weibull}(M = b_0 + b_1\texttt{temp}^\diamond + b_2\texttt{voltage}^\diamond + b_3\texttt{current} + b_4\texttt{temp}^\diamond * \texttt{voltage}^\diamond * \texttt{current}, \sigma = 1/\beta)$
    - $\texttt{temp}^\diamond = 11605/(\texttt{TempC} + 273.15)$
    - $\texttt{voltage}^\diamond = log(\texttt{voltage})$
- Using R's survival and survminer libraries

Survival Analysis - Arrhenius Model

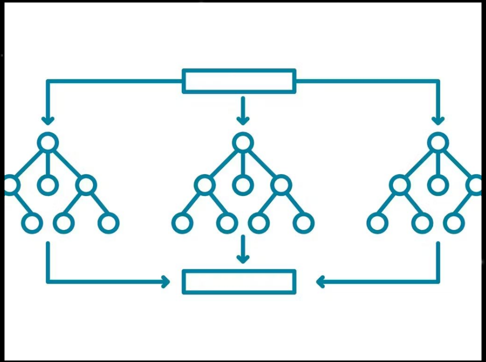
- Devised by Svante Arrhenius, a physicist and physical chemist
- In ALT, products are put under intense conditions
- Temperature has an effect on the rate of reaction
  - Temperature affects degradation rate
  - Temperature affects time to failure
- Arrhenius determined time to failure was proportional to the activation energy divided by the temperature in Kelvin
- Equation to the right is what we are using instead of standard temperature

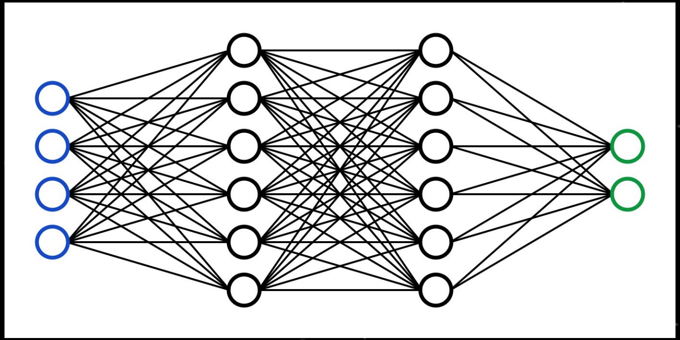
$$\mathtt{temp}^{\diamond} = 11605/(\mathtt{TempC} + 273.15)$$


Kaplan-Meyer Curves for Battery Packs
Regular
Second Life
Recommissioned
Survival probability
1.00
0.75
0.50
0.25
0.00
50% (588.99)
50% (546.02)
50% (546.02)
0
1000
2000
3000
4000
Time

Machine Learning - Models

- Wanted a range of models
- Increasing in complexity
- Using Python's sklearn package
- Three machine learning algorithms:
  - Linear regression
  - Random forest
  - Neural network (FNN)

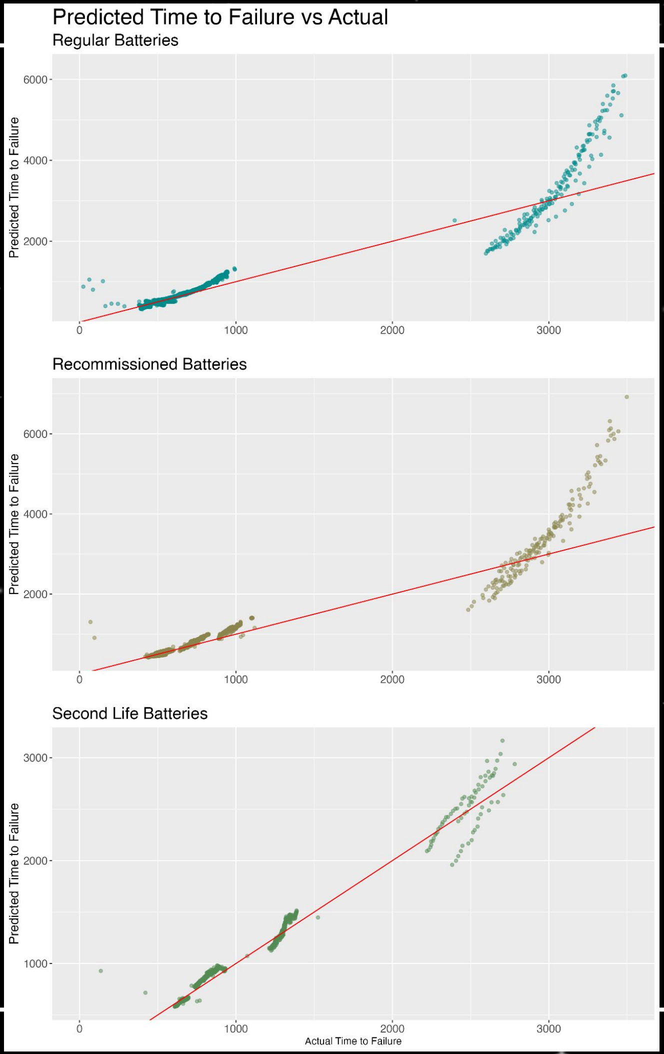




05
Results

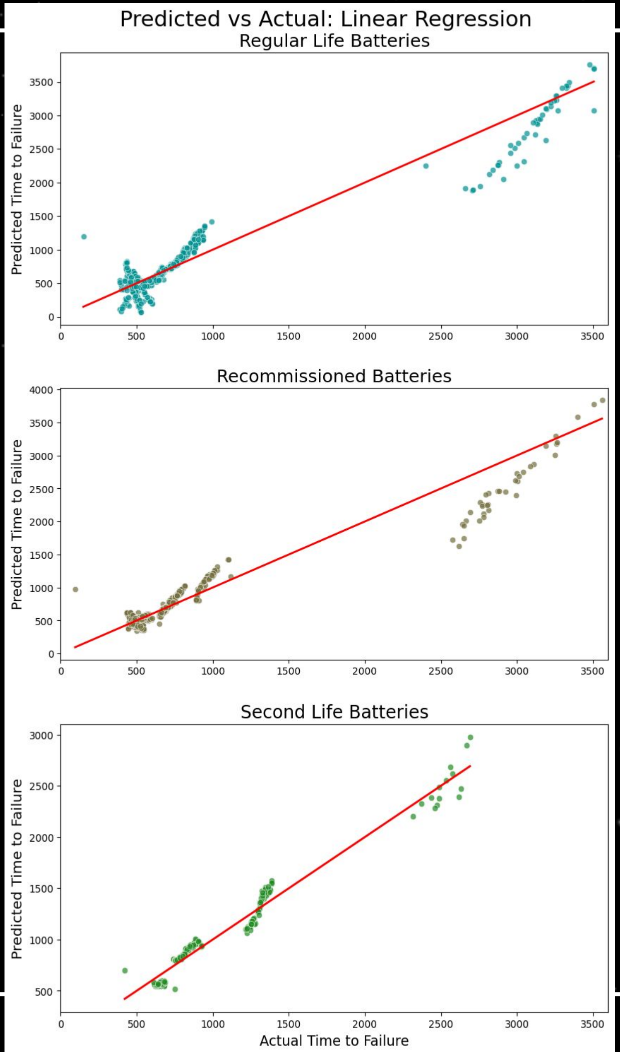
Weibull Regression

- **Regular battery packs:**
  - **MSE:** **55730.98**
  - **AIC:** 43722.1
  - **R^2:** 81.08%
- **Recommissioned battery packs:**
  - **MSE:** **70364.29**
  - **AIC:** 39455.26
  - **R^2:** 75.71%
- **Second life battery packs:**
  - **MSE:** **4971.93**
  - **AIC:** 15201.04
  - **R^2:** 97.23%



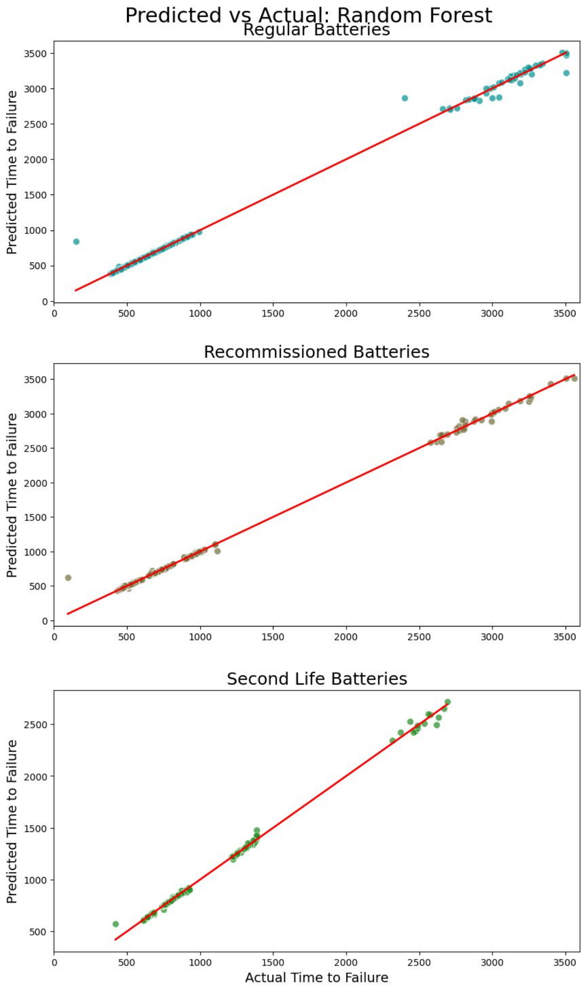
Linear Regression

- **Regular battery packs:**
  - **MSE:** **33084.63**
  - **AIC:** 7804.71
  - **R^2:** 91%
- **Recommissioned battery packs:**
  - **MSE:** **22612.53**
  - **AIC:** 7108.59
  - **R^2:** 92.31%
- **Second life battery packs:**
  - **MSE:** **7373.97**
  - **AIC:** 2494.69
  - **R^2:** 96.06%



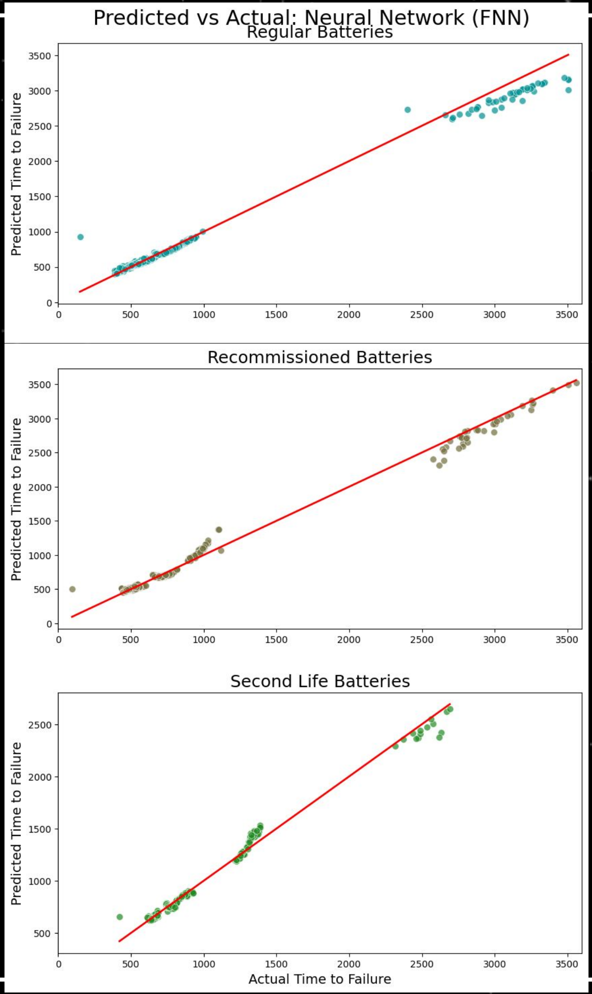
Random Forest

- **Regular battery packs:**
  - **MSE:** **927.07**
  - **AIC:** 5127.19
  - **R^2:** 99.7%
- **Recommissioned battery packs:**
  - **MSE:** **75.72**
  - **AIC:** 3151.49
  - **R^2:** 99.8%
- **Second life battery packs:**
  - **MSE:** **298.81**
  - **AIC:** 1600.24
  - **R^2:** 99.8%



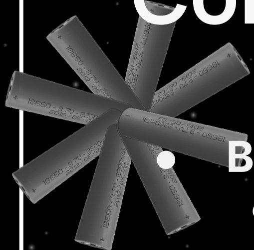
Neural Network (FNN)

- **Regular battery packs:**
  - **MSE:** **1726.28**
  - **MAE:** 21.14
  - **AIC:** 5600.84
  - **R^2:** 99.45%
- **Recommissioned battery packs:**
  - **MSE:** **1524.88**
  - **MAE:** 23.36
  - **AIC:** 5207.41
  - **R^2:** 99.48%
- **Second life battery packs:**
  - **MSE:** **2385.52**
  - **MAE:** 34.25
  - **AIC:** 2187.83
  - **R^2:** 98.72%

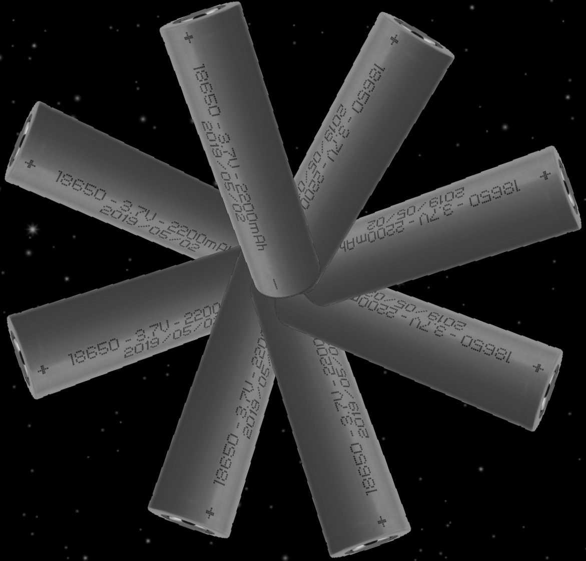


06
Conclusions

Comparison



- **Best**: Random Forest
    - Lowest error across the board
    - Highest R^2 across the board
    - Potentially risking overfitting
- **Worst**:
    - Regular and recommissioned: Weibull regression
        - Highest error and lowest R^2
    - Second life: Linear regression
        - Highest error and lowest R^2



Future Work

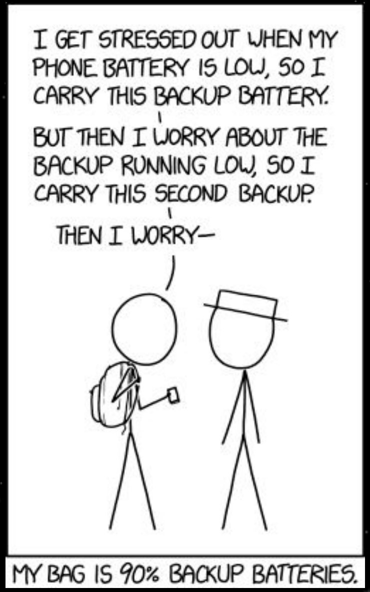
- Future work can be done with ALT testing on larger battery packs
- Incorporating other features
- Building a monitoring system for 18650 battery packs
- Generalize to other battery types
- Build more specific models
  - Clustering around different features

Citations

- **Data Set Citation:** Fricke, K., Nascimento, R., Corbetta, M., Kulkarni, C., & Viana, F. "Accelerated Battery Life Testing Dataset", NASA Prognostics Data Repository, Probabilistic Mechanics Lab, University of Central Florida, and NASA Ames Research Center, Moffett Field, CA

- **Publication Citation:** Fricke, K., Nascimento, R., Corbetta, M., Kulkarni, C., & Viana, F. (2023). Prognosis of Li-ion Batteries Under Large Load Variations Using Hybrid Physics-Informed Neural Networks. Annual Conference of the PHM Society, 15(1). https://doi.org/10.36001/phmconf.2023.v15i1.3463

Questions?


I GET STRESSED OUT WHEN MY PHONE BATTERY IS LOW, SO I CARRY THIS BACKUP BATTERY.
BUT THEN I WORRY ABOUT THE BACKUP RUNNING LOW, SO I CARRY THIS SECOND BACKUP.
THEN I WORRY—
MY BAG IS 90% BACKUP BATTERIES.