# **Battery Lifetime Prediction**

Given a few cycles

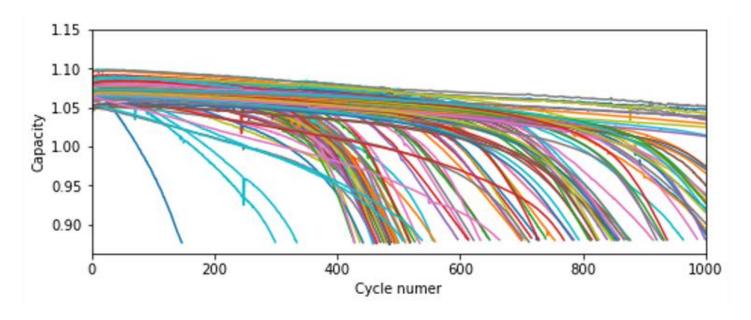
Jinpu Cao, Solomon Kim, Zewen Zhang

#### Battery Life Prediction Is Important



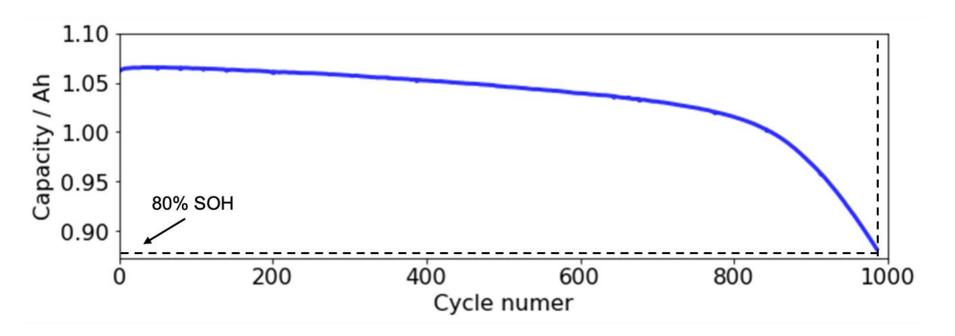
**Battery life prediction** 

#### Non-linearity in Battery Degradation Modes

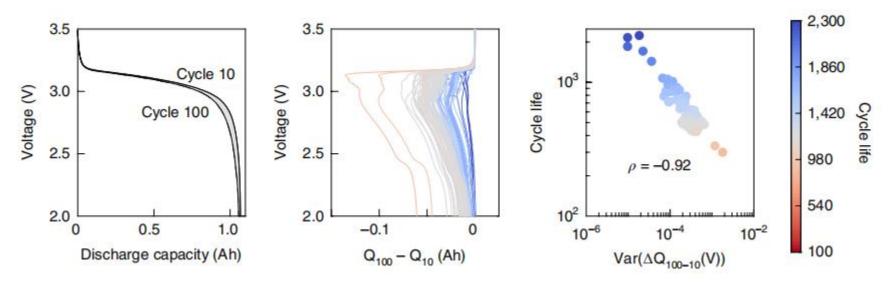


Mechanical / Chemical / Electrochemical Heterogeneities

#### **Battery Lifetime Definition**



#### Data-driven Methods For Battery Life Prediction



- Limited dataset size (124 cells)
- Feature extraction based on 100 cycles data

Severson, Kristen A., et al. Nature Energy 4.5 (2019): 383-391.

### Target Area #1: Battery R&D Companies

- Interviewed many different Battery R&D Companies
  - Finding: Many don't use ML
- Respectfully, PhD's without strong CS/data science background
- Case Studies: Proterra, Gridtential





#### Target Area #2: EV Customers

- Create used EV car market
  - Customer's can determine lifetime on their batteries.
- 3rd Party Certification Agency
- Accelerate EV adoption





#### Target Area #3: Second Use Battery Companies

- Partner with companies like B2U Storage Solutions
  - Interview Finding: No effective way to determine lifetime





#### What are potential competitors?

- Voltaiq is more focused on management not prediction
  - Called Sales Representative
  - Interviewed Yen T. Yeh
    - Battery Engineer



#### Long-term vision Part 1

- Scale Al for Climate
- Alternative to C3AI
  - Don't work with oil companies
  - Focus on Climate Change



#### Long-term vision Part 2

- Work at intersection of AI and Climate Change
  - Agriculture
    - Crop detection
  - Green Buildings
    - Demand Response
  - Transportation
  - Smart Grids
  - Energy
    - Cloud Forecasting



#### **Mentors**

- Professor Simona Onori
  - Energy Resources Engineering Department
- Professor Adam Brandt
  - Energy Resources Engineering Department
- Brian Bartholomeusz
  - Executive Director of Innovation Transfer, TomKat Center for Sustainable Energy







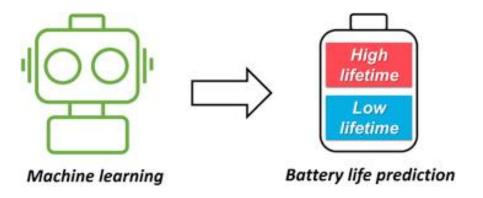
#### **Potential Challenges**

- Communicating the Effectiveness of Al
  - Use of Metaphors
  - Learn from Different Experts
- Learn from Alumni Community in Stanford Climate Ventures

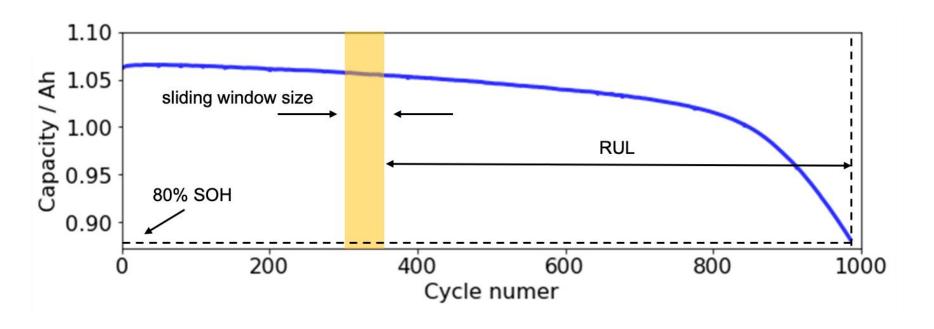


# What's going on under the hood?

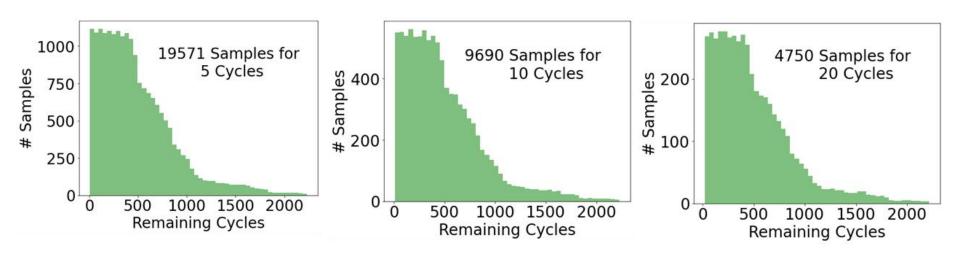
- Feel free to stop me/interrupt me :)
- Explaining the Machine Learning demonstrates uniqueness



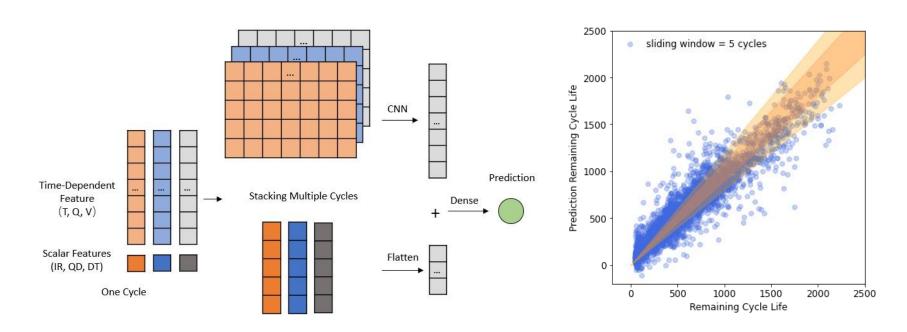
#### Sliding Window for Data Augmentation



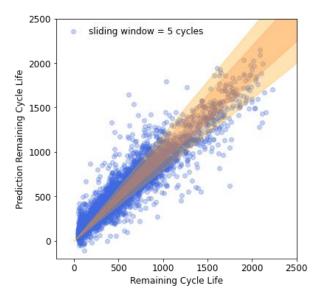
#### **Augmented Dataset For Prediction**

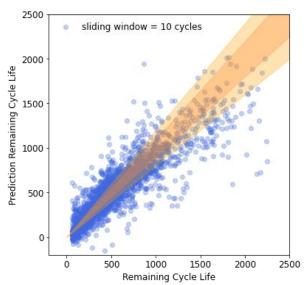


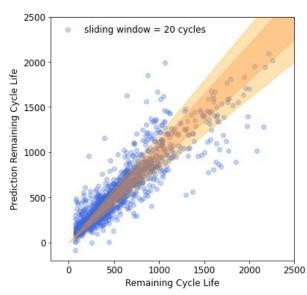
#### Convolutional Neural Network Based Models



#### Results from CNN models







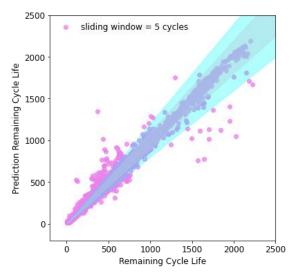
**MAPE: 23.6%** 

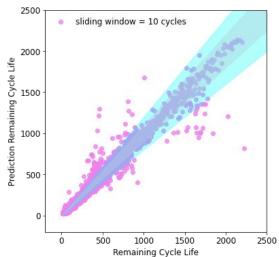
10%-BAND: 38.2% 20%-BAND: 63.8% **MAPE: 26.5%** 

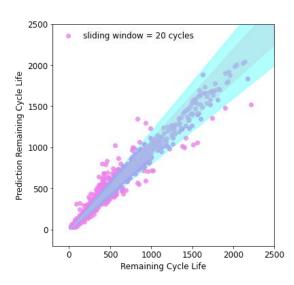
10%-BAND: 32.6% 20%-BAND: 57.3% **MAPE: 24.3%** 

10%-BAND: 38.2% 20%-BAND: 62.6%

#### Results from RNN models







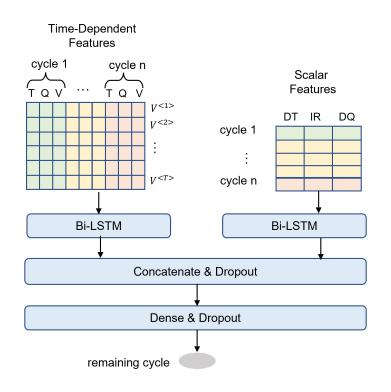
**MAPE: 7.5%** 

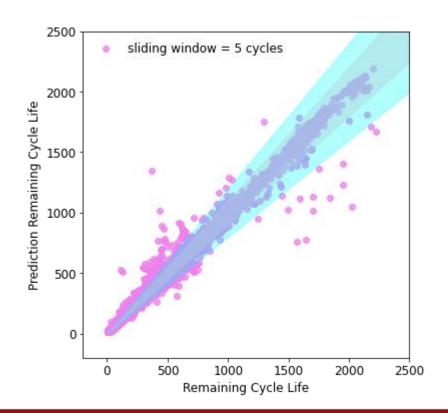
10%-BAND: 81.5% 20%-BAND: 92.7% **MAPE: 11.6%** 

10%-BAND: 61.8% 20%-BAND: 84,6% **MAPE: 11.9%** 

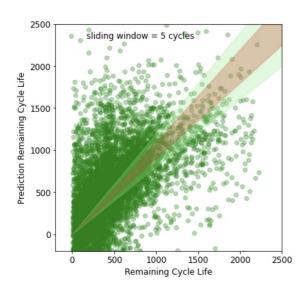
10%-BAND: 59.1% 20%-BAND: 83.1%

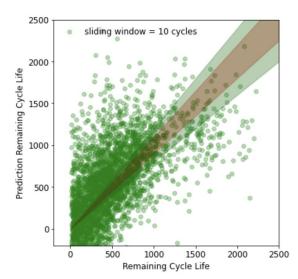
#### Recurrent Neural Network Based Models

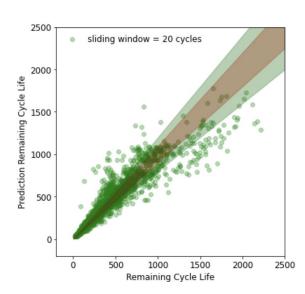




#### Results for Linear Regression







**MAPE: 456%** 

10%-BAND: 10.5%

20%-BAND: 20.1%

**MAPE: 254%** 

10%-BAND: 10.4%

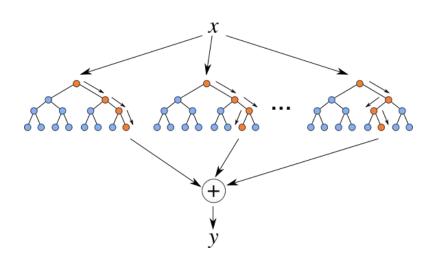
20%-BAND: 21.0%

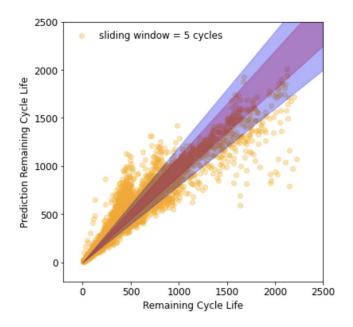
**MAPE: 258%** 

10%-BAND: 10.5%

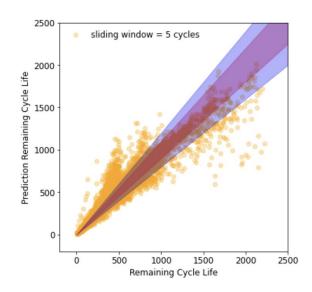
20%-BAND: 25.1%

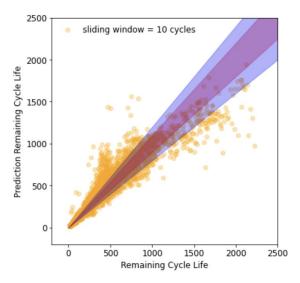
# Random Forest Regression Models

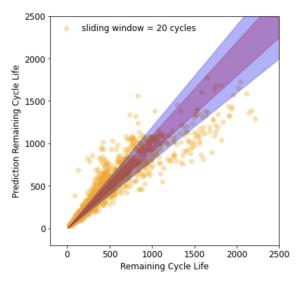




#### Results from Random Forest Regression







**MAPE: 14.0%** 

10%-BAND: 50.4% 20%-BAND: 74.4% **MAPE: 16.1%** 

10%-BAND: 40.0%

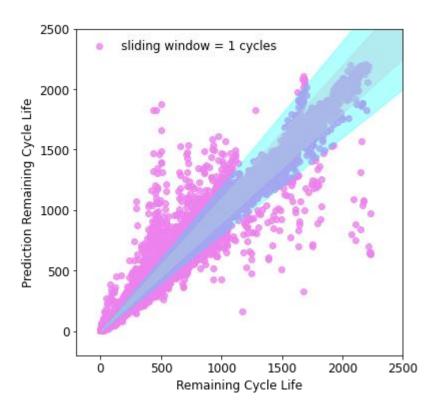
20%-BAND: 53.1%

**MAPE: 17.9%** 

10%-BAND: 39.4%

20%-BAND: 52.6%

## What about only 1 Cycle?



MAPE:12.1 %!

# Challenges/Future Work

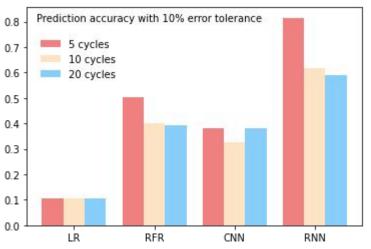


#### Summary

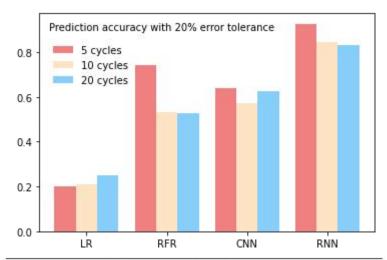
- Data augmentation
  - 124 batteries → ~13k samples
- Remaining cycles prediction model
  - Linear regression
  - Random Forest regression
  - Convolutional neural network (CNN)
  - Recurrent neural network (RNN)
- Discuss # cycles ~ prediction accuracy
- Develop confidence intervals for prediction

# Thank you!

#### Prediction Accuracy with Given Acceptable Interval



#Cycles	Linear Regression	Random Forest	CNN	RNN
5	0.105	0.504	0.382	0.815
10	0.104	0.400	0.326	0.618
20	0.105	0.394	0.382	0.591



#Cycles	Linear Regression	Random Forest	CNN	RNN
10	0.210	0.531	0.573	0.846
20	0.251	0.526	0.626	0.831