Multivariate Time Series Imputation

CATERPILLAR®

CAT Digital

Contributors

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Project Description

CAT Digital

- Caterpillar designs, manufactures, and sells construction and mining equipment
- The digital branch brings advanced analytics and AI capabilities to the famous yellow iron

CAT 797F Monitoring Service

- Over 70 channels of data sampled each second
- Common problem: missing critical data for a time period due to sensor glitches/anomalies

Data Imputation

- We aim to impute (assign values) to this missing data
- An analytics model in Python will be used to solve this problem



Project Purpose

- CAT provides machine condition monitoring services to aid dealers and customers
- Missing gaps of data are problematic for machine learning (ML) models
- Improved ML models will make the monitoring service more reliable

About The Data

Multivariate Time Series Data

- 78 channel sensors per asset
- Sampled Every Second (1Hz frequency)
- Roughly 20 million lines of data per asset

Obfuscated Data

- All channels and assets are given generic names and units to keep data secure
- Ex: Asset ABC00123, Sensor1A (Units C)

MICE Model

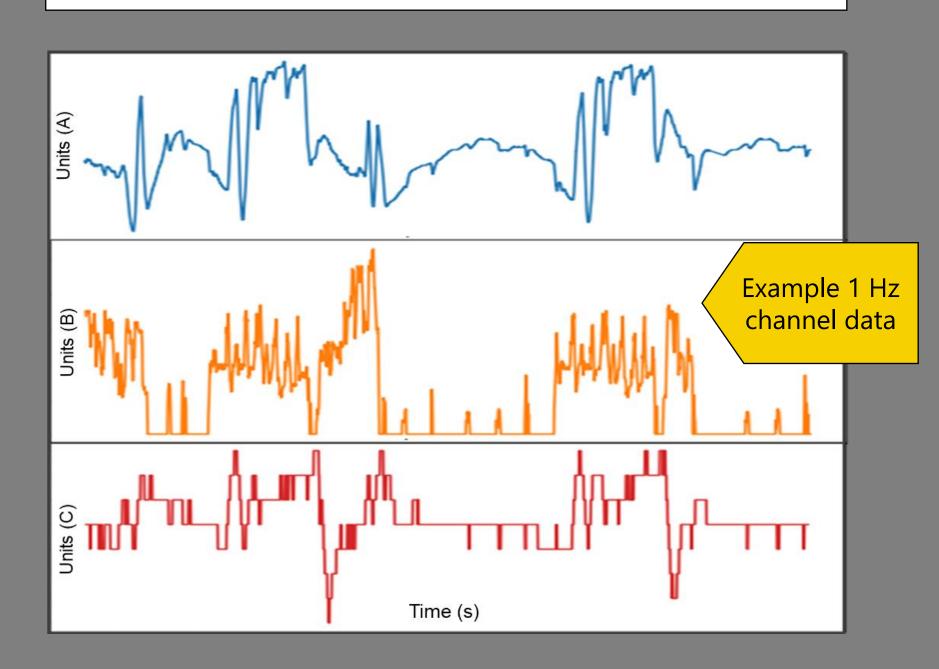
<u>Multiple Imputation by Chained Equations</u>

Iterative Process

- Initial prediction
- Regress on other variables to improve imputed value
- Repeat until convergence

Reasoning

- Works very well when other correlated channels are available
- Accounts for uncertainty due to missing data
- Used for most imputation when similar channels were available



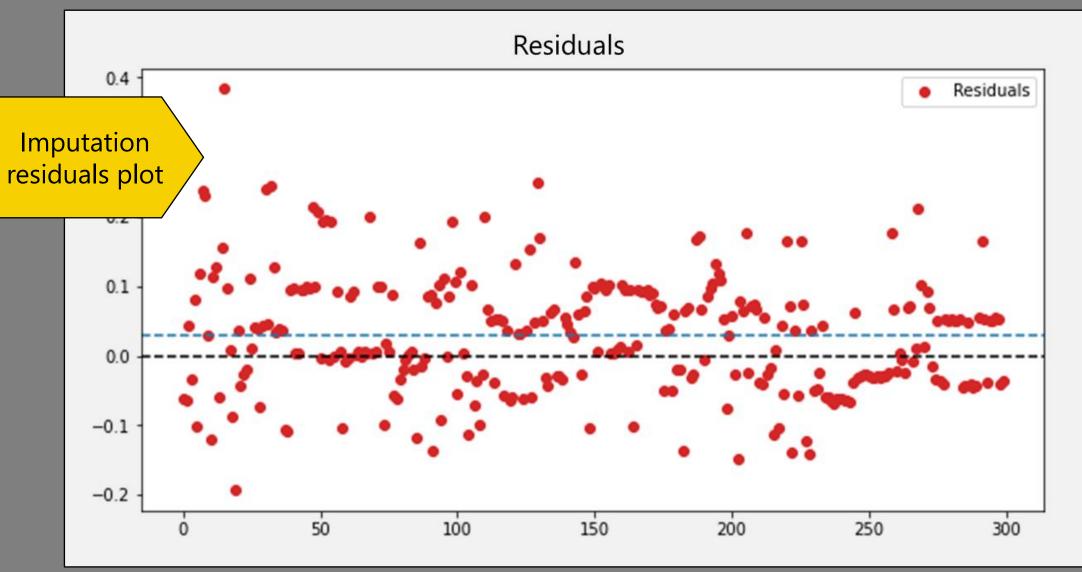
KNN Model

<u>K</u> <u>N</u>earest <u>N</u>eighbors

- Impute values based on Euclidean distance with other channels
- Projects values into high dimensional space
- This is an effective but memory hungry algorithm

Results & Conclusions

- MICE is a more optimal solution when considering its speed and flexibility
- MICE outperforms traditional imputation methods for over 80% of channels
- On average, MICE has a Mean Absolute Error of less than 10%
- This will solve a significant percentage of the problem



Cross Validation

Cross Validation

- Simulate missing data using existing data
- Used to compare error statistics across different models

Error Statistics

- Mean Absolute Error
- Bias

Baseline Comparison

- How much of an improvement is the model compared to...?
 - Mean/Median/Mode Fill
 - Linear Interpolation
- Allows us to determine if our complex approach is worthwhile



Future Goals

Python API

- Callable functions to impute data
- Select the best performing model based on the data characteristics
- Easy to use for CAT Data Scientists

Improve Efficiency

- Formal assessment of tradeoff between time and accuracy
- Allow different levels of precision to be specified in the API
- Improved recognition for channels that cannot be imputed well using our models



Acknowledgements

Data matrix



Speaker

Andy

Generative Adversarial Network

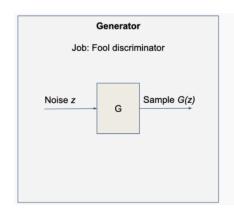
- Generator: generates imputation results from the given dataset
- Discriminator: takes output from Generator to determine which data was originally missing

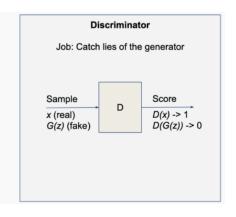
Tensorflow / Keras

- Neural network framework for developing the model
- tensorflow.keras.layers: LSTM, Conv1D, BatchNormalization, Dense

Results

- High accuracy for many channels
- Requires longer training time than other methods





Loss propagate (+) Generator (MSE) Hint Generator Imputed Matrix Hint Matrix x_{22} Discriminator propagate Loss p24 p25

Estimated mask matrix

Original data

Random matrix

Mask matrix

(Cross Entropy)