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VSB - Partial Discharge Fault Detection in Covered Conductors

A Case Study in building Machine Learning Binary Classification Models for Unbalanced Classes

Jeffrey Egan / 13 March 2019

What are we covering here?

- This tech talk will cover the signal processing and machine learning modeling tasks completed to identify partial discharge faults present in covered conductors in real environments. Partial discharge faults are power line degradations that will eventually result in power outages or fires. Identifying them is key to reducing maintenance costs and preventing power outages.
- The discussion includes signal processing topics relevant to useful feature extraction from noisy signals and data - features used to train machine learning models.
- Machine Learning discussions cover binary classification models, evaluation criteria, and model tuning required to train effective models when the classes are heavily unbalanced.

First, what is Kaggle?

- Kaggle is an online community of data scientists and machine learners.
- Kaggle allows users to:
  - Find and publish data sets.
  - Explore and build models in a web-based data-science environment.
  - Work with other data scientists and machine learning engineers.
  - Enter competitions to solve data science challenges.
- Kaggle got its start by offering machine learning competitions and now also offers a public data platform, a cloud-based workbench for data science, and short form Artificial Intelligence education.
- Google acquired Kaggle on 8 March 2017.

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Challenge: Partial Discharge Fault Detection

- Overhead power lines run for hundreds of miles to supply power to cities. These great distances make it expensive to manually inspect the lines for damage that doesn't immediately lead to a power outage (like tree branches falling on lines).
- These modes of damage lead to a phenomenon known as partial discharge — an electrical discharge which does not bridge the electrodes between an insulation system completely.
- Partial discharges slowly damage the power line, so left unrepaired they will eventually lead to a power outage or start a fire.
- The challenge is to detect partial discharge patterns in signals acquired from these power lines with a new meter designed at the ENET Centre at VŠB. Effective classifiers using this data will make it possible to continuously monitor power lines for faults – helping to reduce maintenance costs and prevent power outages.

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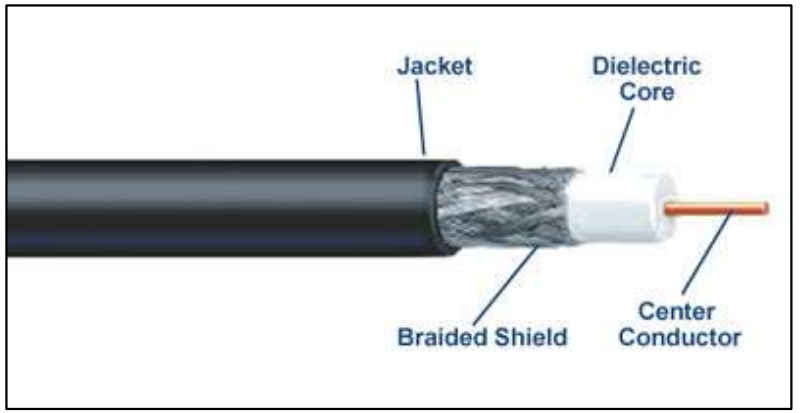
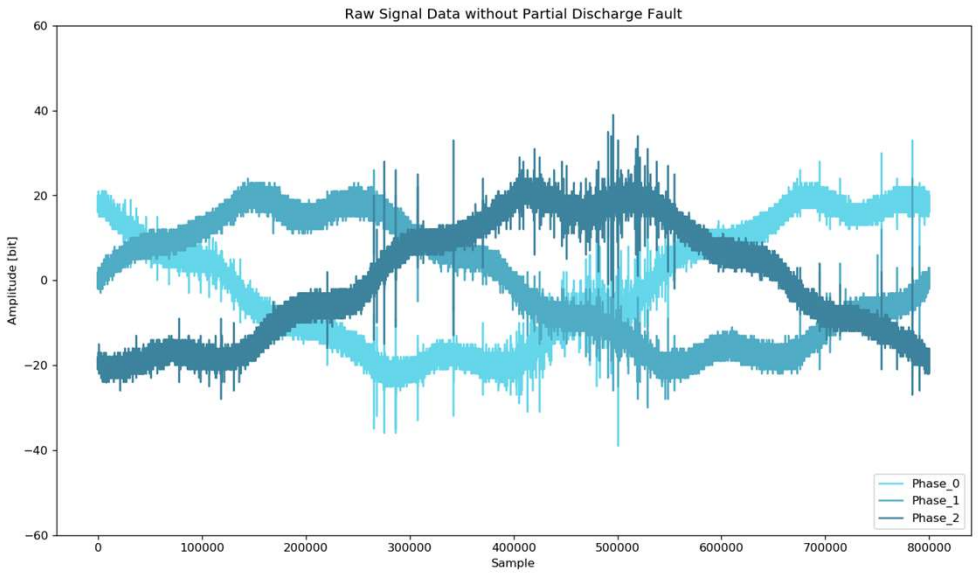
Visual Aides – Anatomy of a Covered Conductor

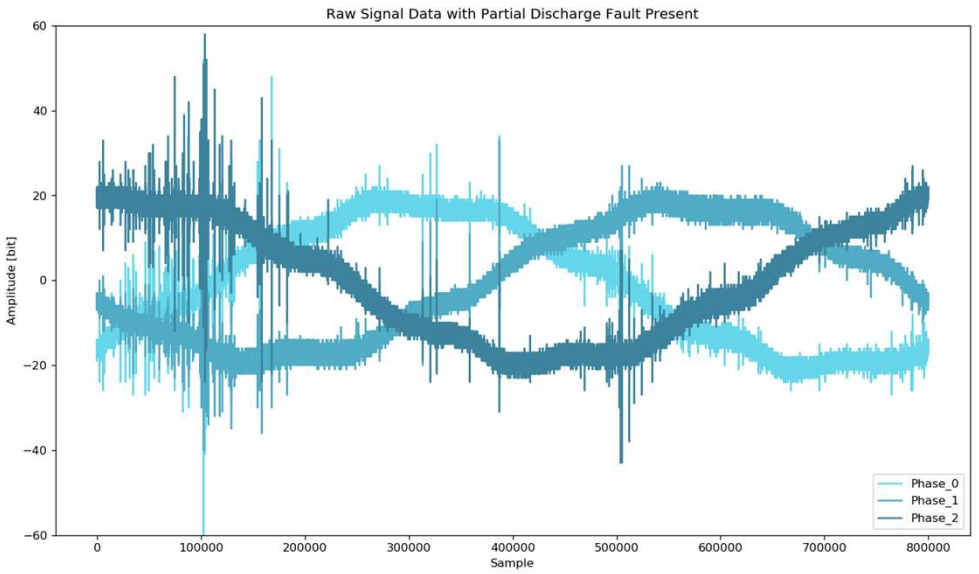


Examination Reveals Highly Unbalanced Data

- All Provided Data: Labeled & Unlabeled
  - Labeled Training Set: 2,904 Measurements = 8,712 Signals (only 30% of data is labeled)
  - Unlabeled Test Set: Perform Binary Classification: 6,779 Measurements = 20,337 Signals
- Occurrence of Faults and Non-Faults in Labeled Data
  - 8187 Signals without Fault, 213 Signals with Fault (only 2.5% of labeled signals have faults!)
- Grouping of Signal Faults per Measurement
  - Measurements with no faults present: 2710 (93.3% of measurements exhibit no fault)
  - Measurements with fault present in only 1 phase: 19 (9.7% of cases where faults present)
  - Measurements with faults present in 2 of 3 phases: 19 (9.7% of cases where faults present)
  - Measurements with faults present in all 3 phases: 156 (80.4% of cases where faults present)

Sample Measurements with 3 Phase Signals





Each signal (phase) contains 800,000 measurements of a power line's voltage, taken over 20 milliseconds.

For signal processing, that means each signal data set has a sample rate of 40 million samples per second.

The underlying electric grid operates at 50Hz, this means each signal covers a single complete grid cycle.

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Detecting Partial Discharges is Difficult

PD Pattern Observed alongside other Noise Sources

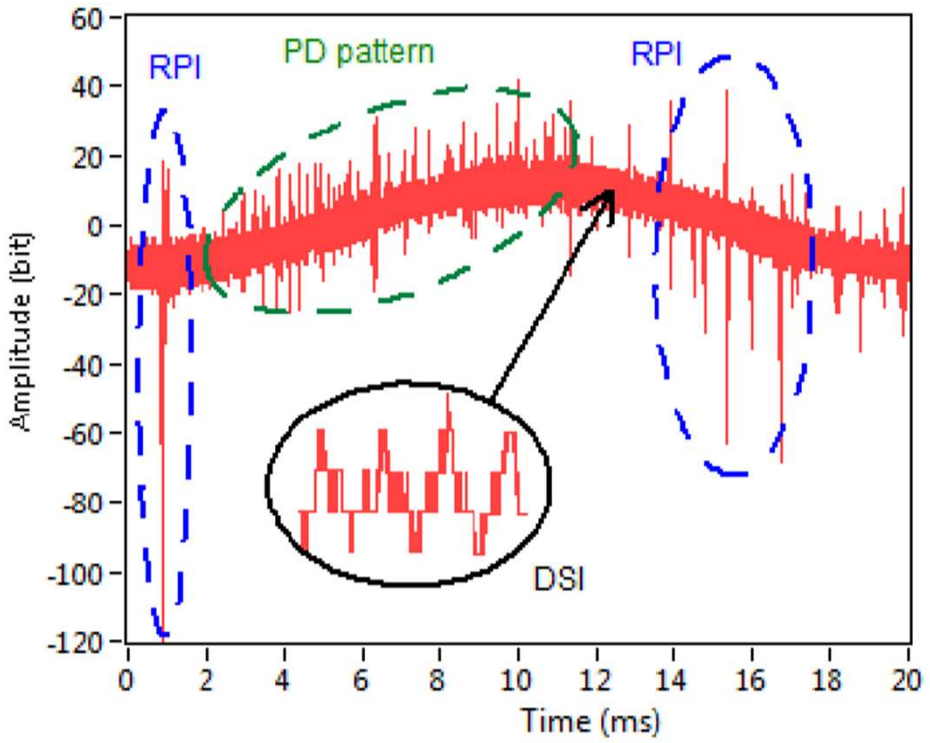

Figure from Reference [1]

Many other sources of noise could be falsely attributed to partial discharge.

- Ambient and Amplifier Noise
- PD: Partial Discharge Fault Pattern
- DSI: Discrete Spectral Interference
  - E.g. Radio Emissions, Power Electronics
- RPI: Random Pulses Interference
  - Lightning, Switching Operations, Carona

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Identify and Cancel Carona Discharge Peaks

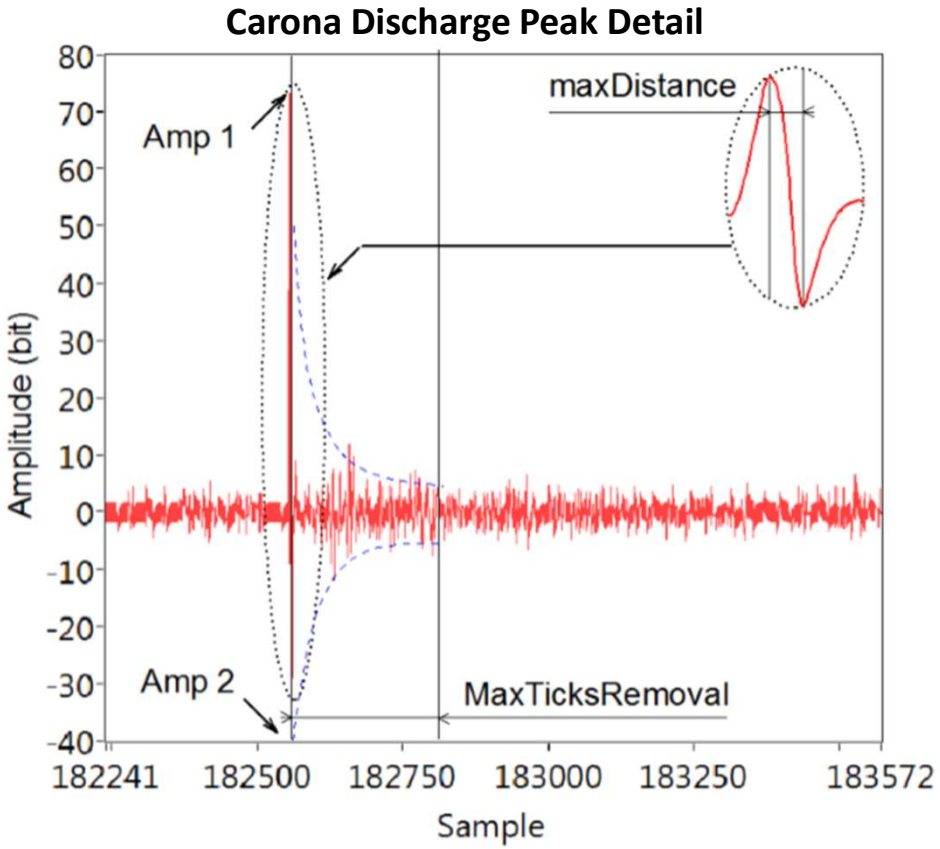

Figure from Reference [1]

- A corona discharge is an electrical discharge brought on by the ionization of a fluid such as air surrounding a conductor that is electrically charged.
- Spontaneous corona discharges occur naturally in high-voltage systems unless care is taken to limit the electric field strength.
- A corona will occur when the strength of the electric field (potential gradient) around a conductor is high enough to form a conductive region, but not high enough to cause electrical breakdown or arcing to nearby objects.

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Focus on Portions of the Sinusoid with Rising Amplitude for Improved PD Detection

Sections of Sinusoidal Shape (1,2) with the Statistically Highest Occurrence of PD pulses

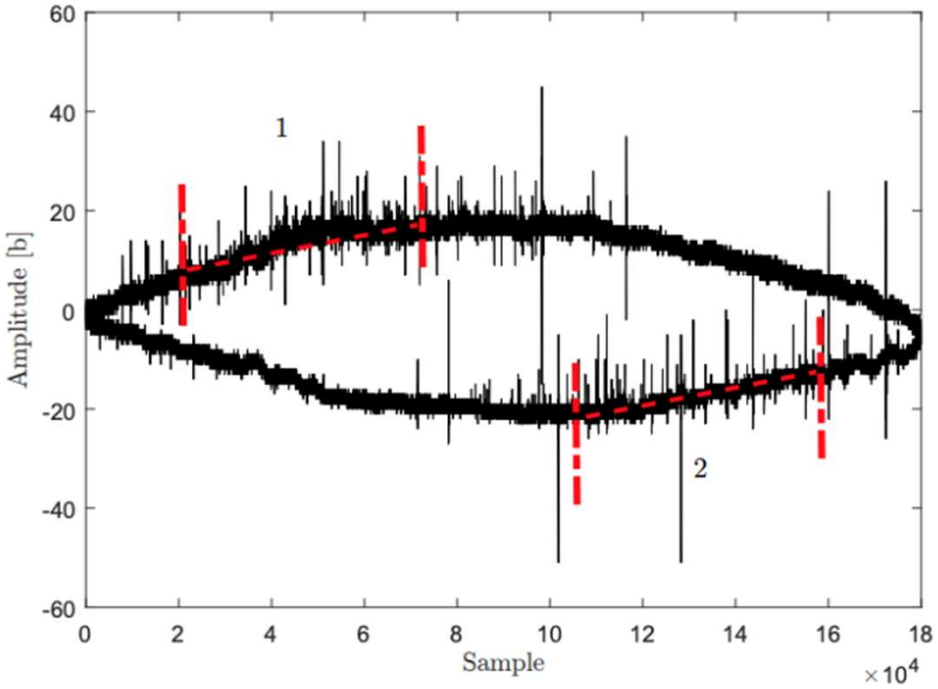

Figure from Reference [2]

- One of the most common fundamental features of the PD pattern is that it occurs on the rising amplitude edges of the sinusoidal curve.
- During feature extraction, this allows omission of half of the signal data points – increasing processing efficiency.
- Running feature extraction on the high-probable region also increases the model's ability to detect true faults and avoid false positives.

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Overview of the Signal Processing Approach

- Discrete Wavelet Transform to Remove Spectral Interference and Ambient Noise
  - Daubechies 4 Wavelet (db4)
- Fit a Sinusoidal Function to the DWT Signal and Detect the PD-Probable Region
- Use an Nth Discrete Difference to De-Trend the Function
  - First-order has proven sufficient
- Perform Peak Detection and Subsequently Cancel of False Peaks
  - Peak Detection using Fixed Amplitude Threshold
  - Cancel High Amplitude Peaks, and Peaks Attributed to Corona Discharge

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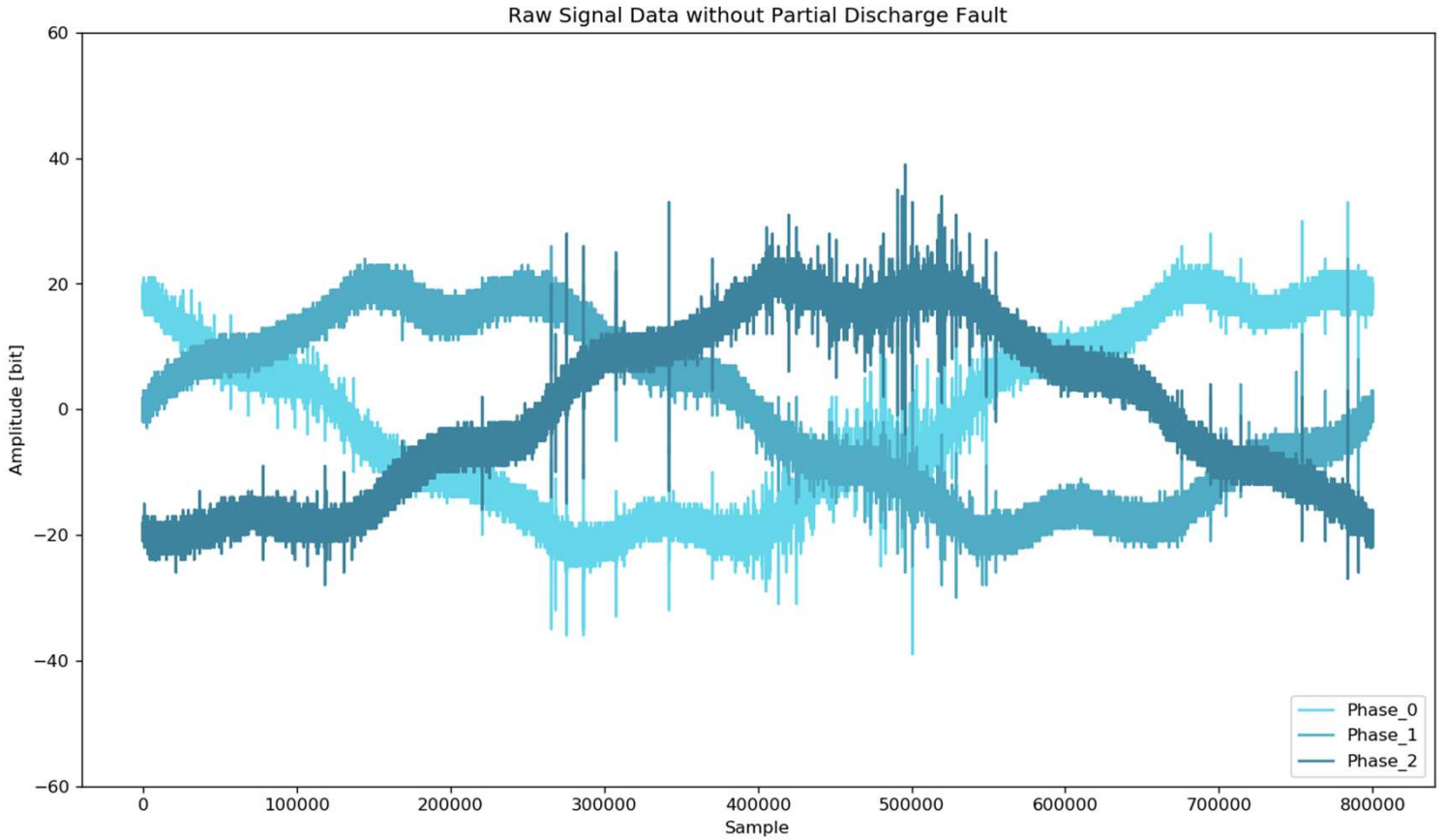
Examining the Raw Signal Data



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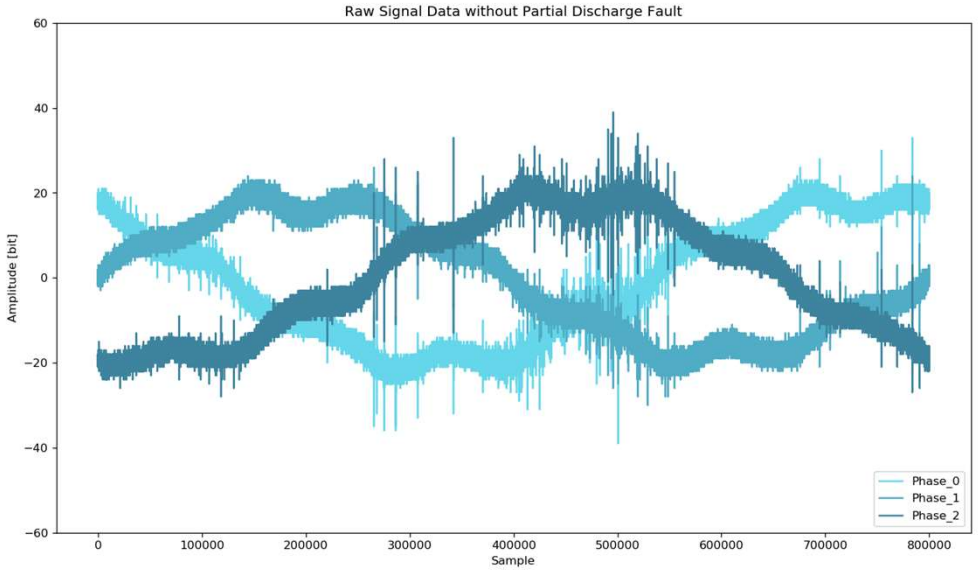
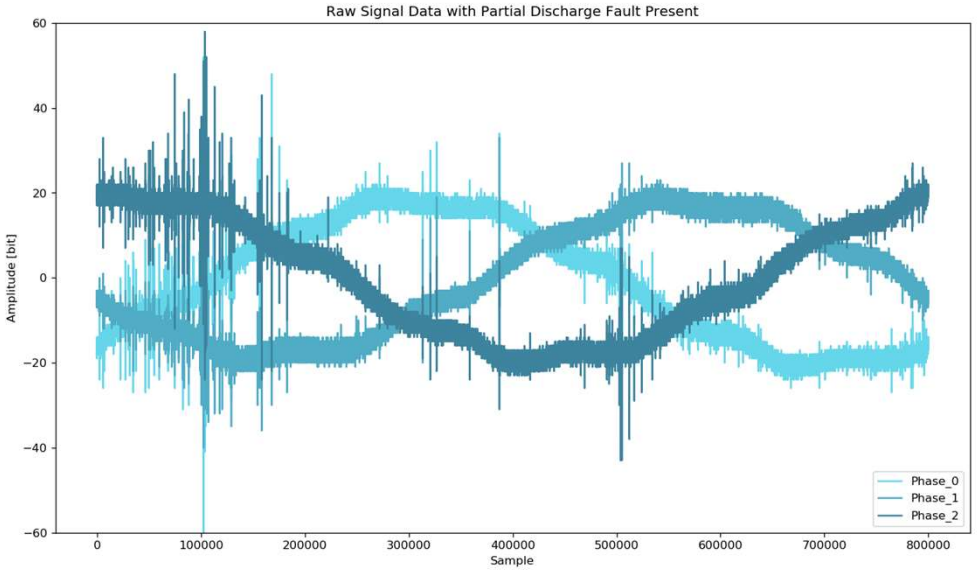
Examining the Raw Signal Data





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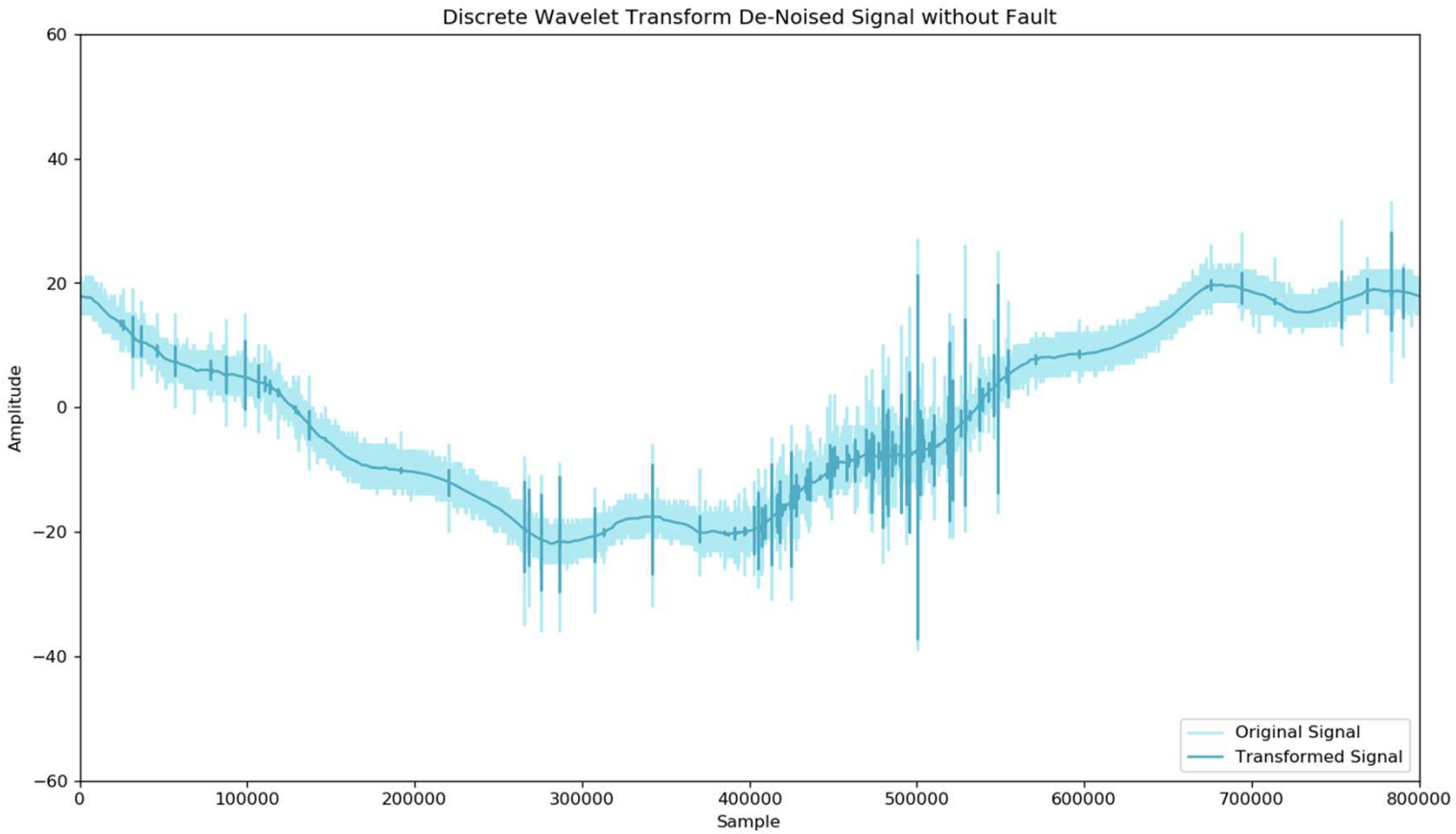
Remove DSI & Ambient Noise with DWT



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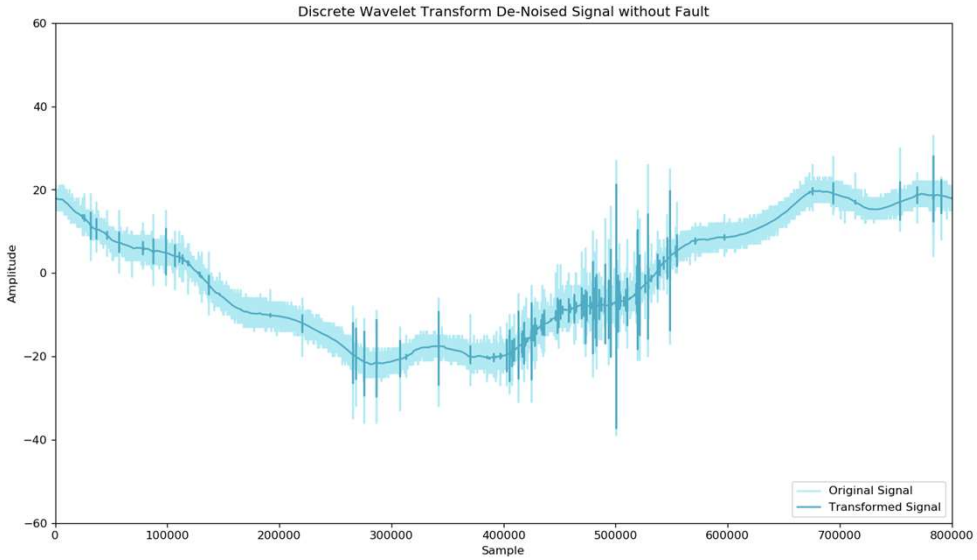

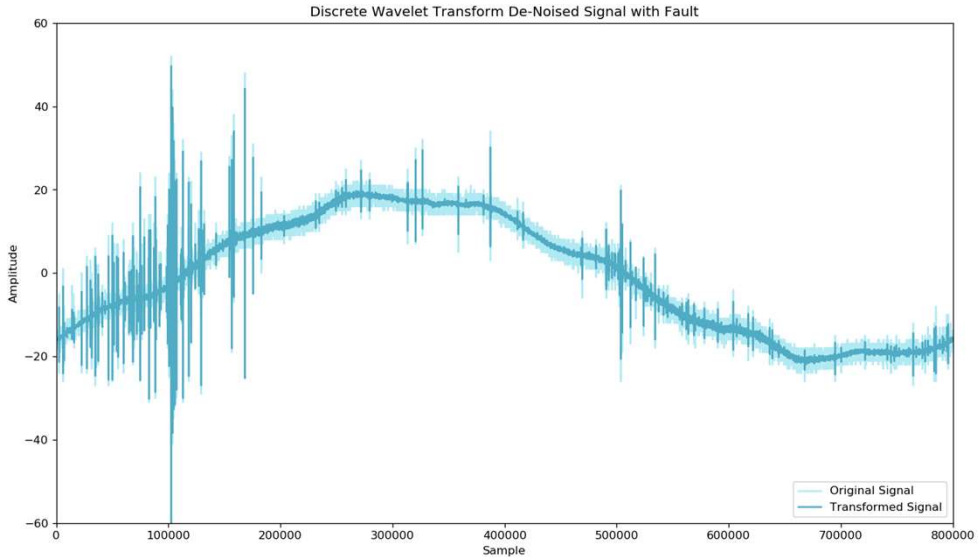

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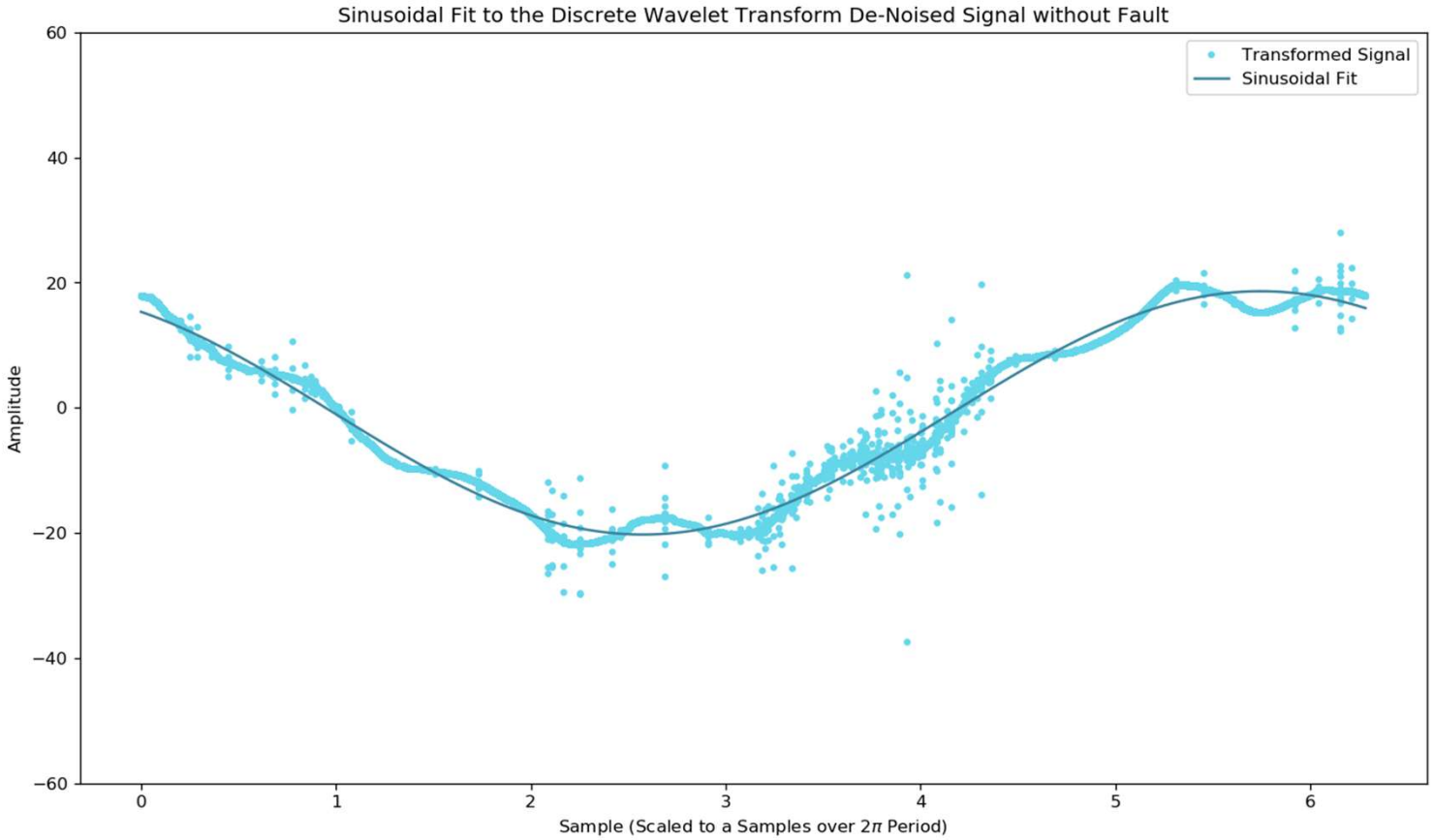
Fit a Sinusoidal Function to the DWT Signal



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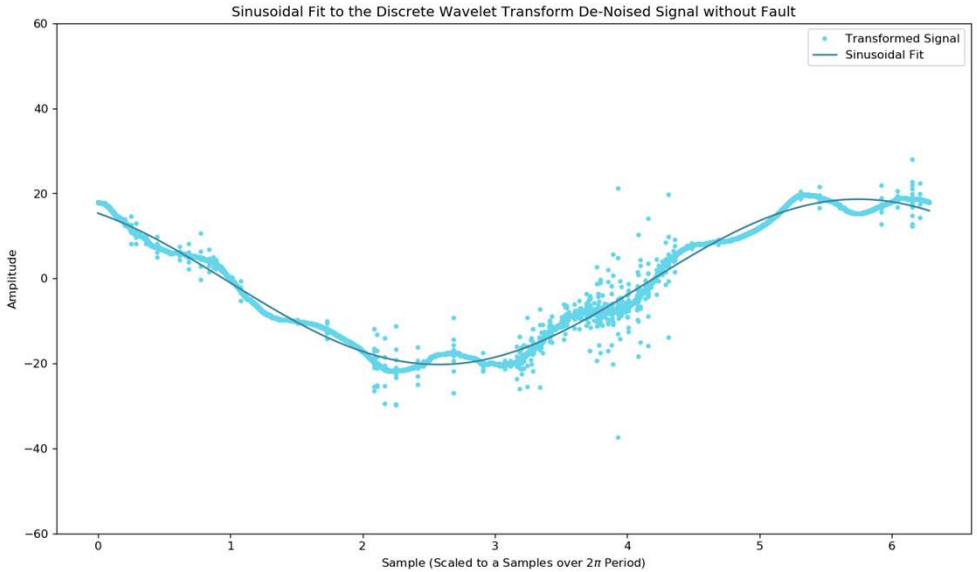

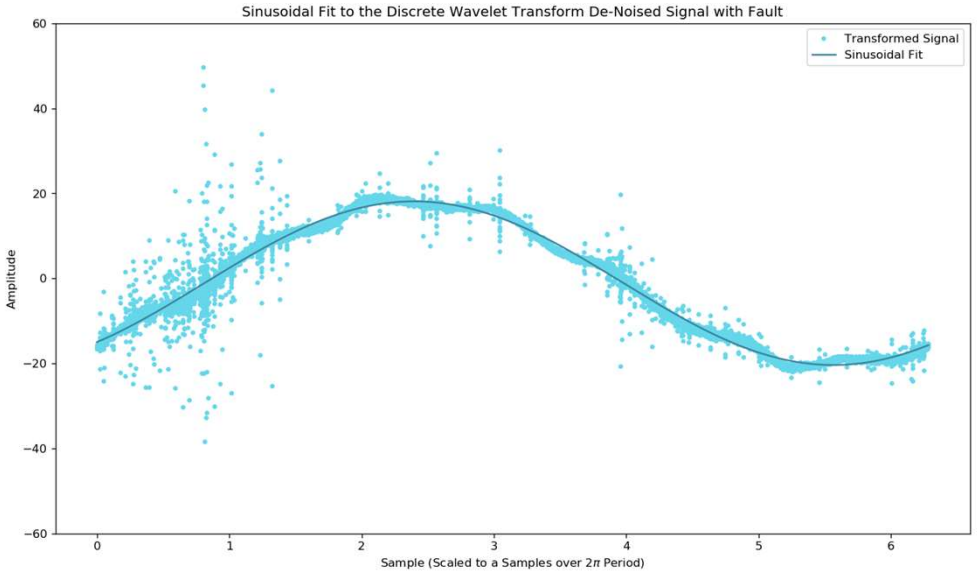

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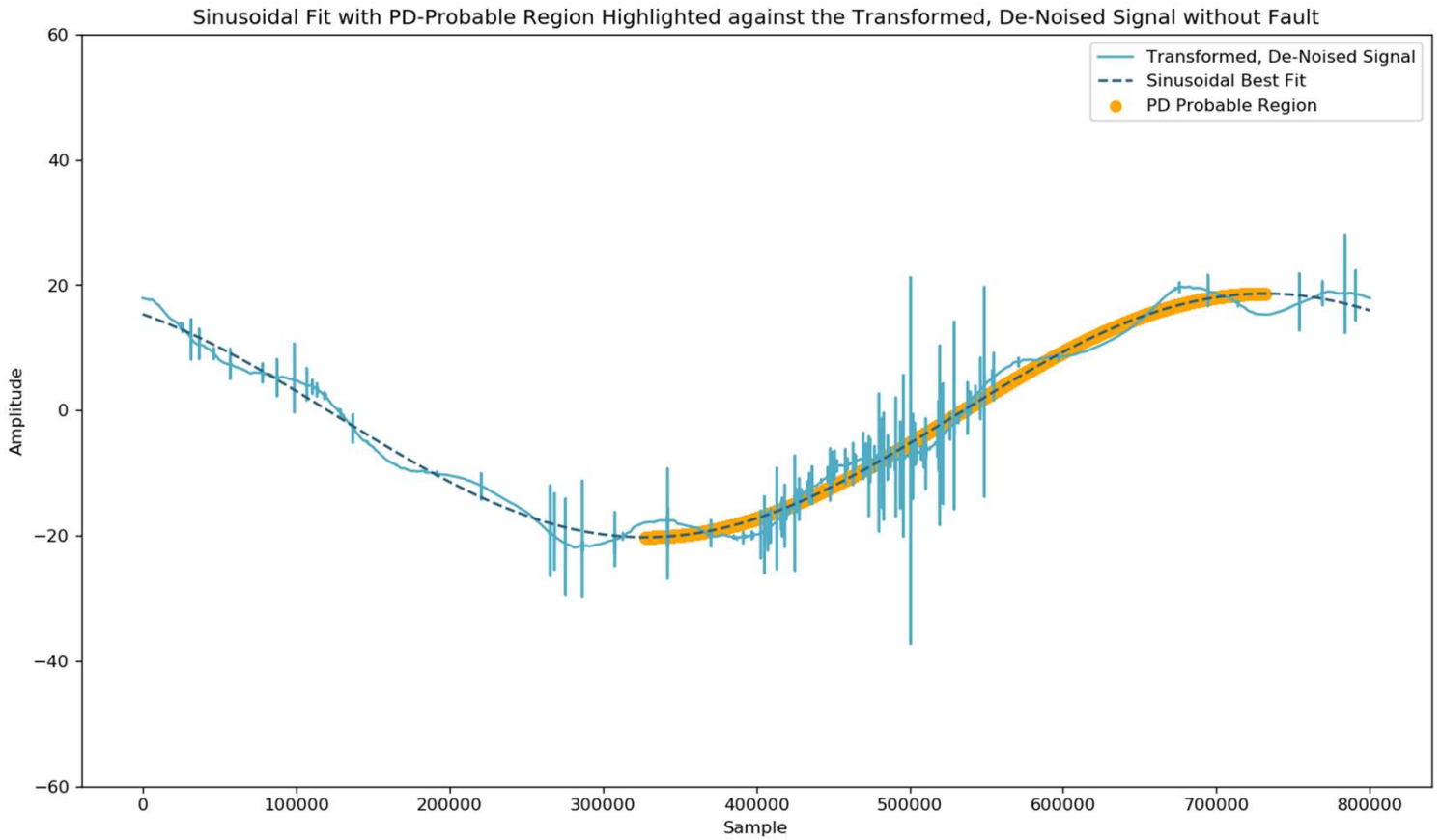
Use Sinusoid to Identify PD-Probable Region



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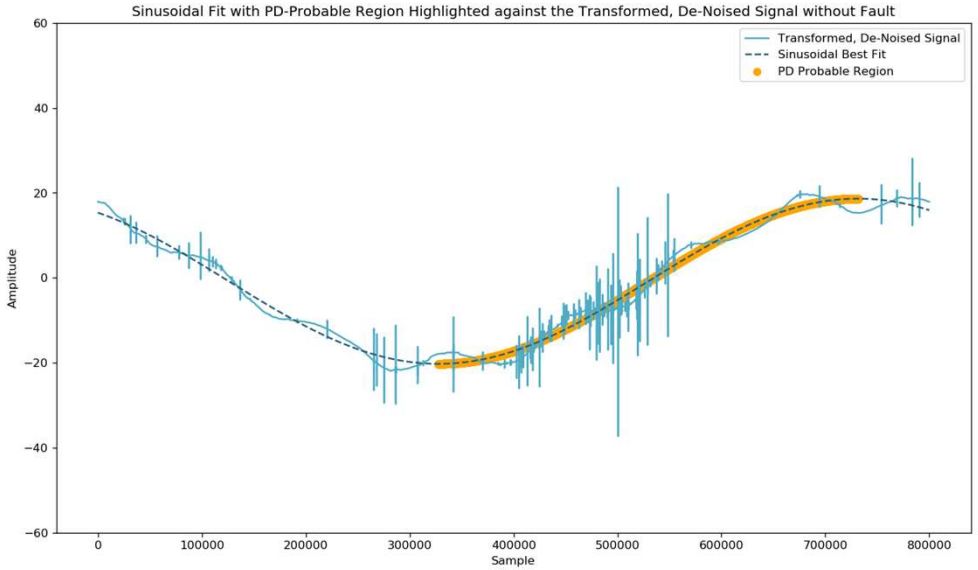

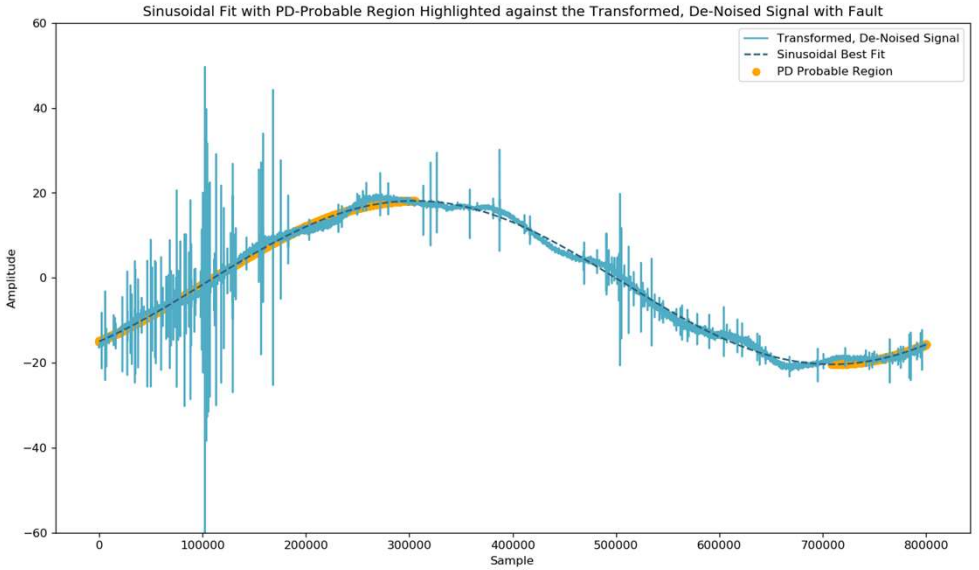

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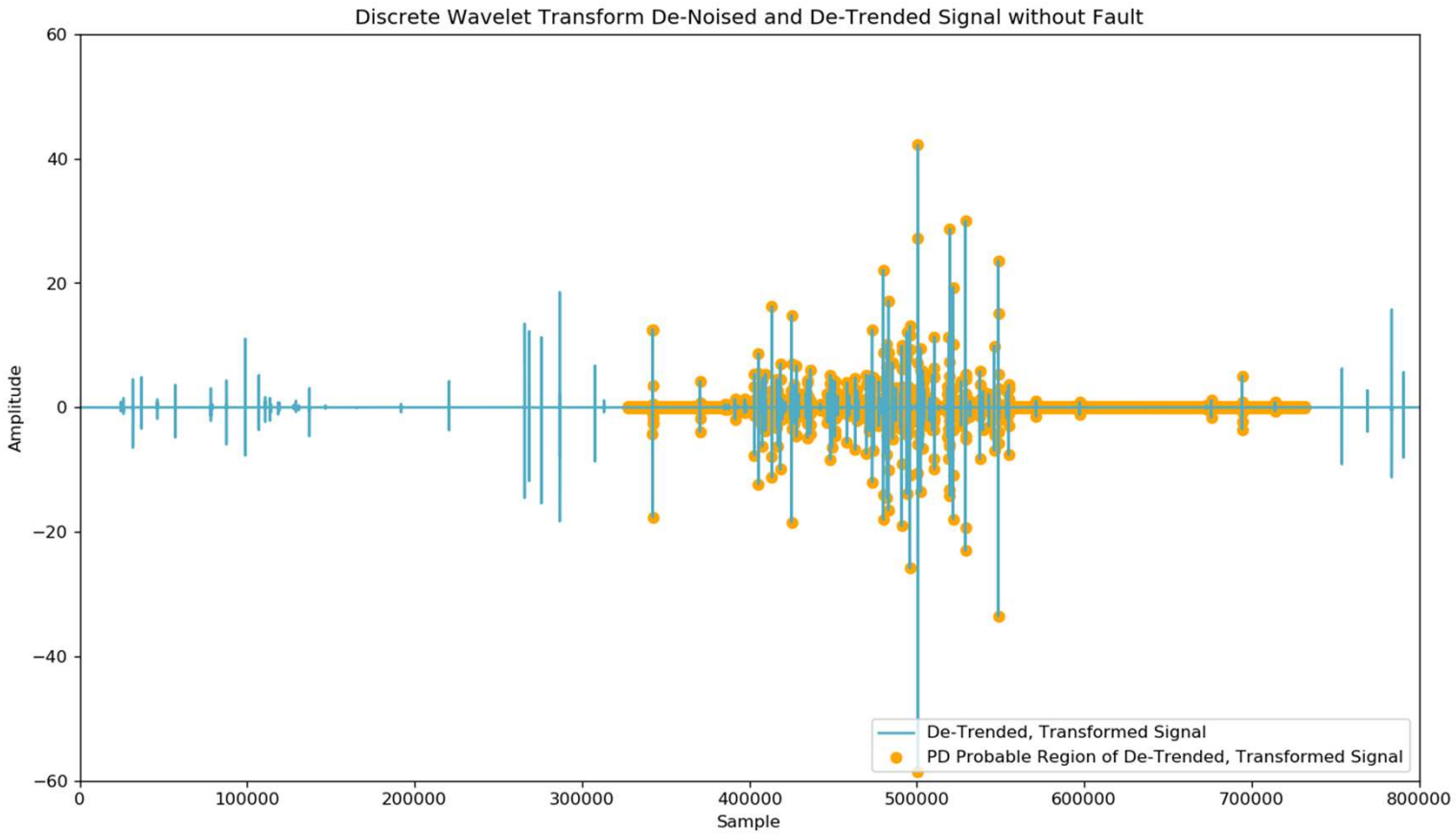
Detrend Signal to Remove Sinusoidal Element



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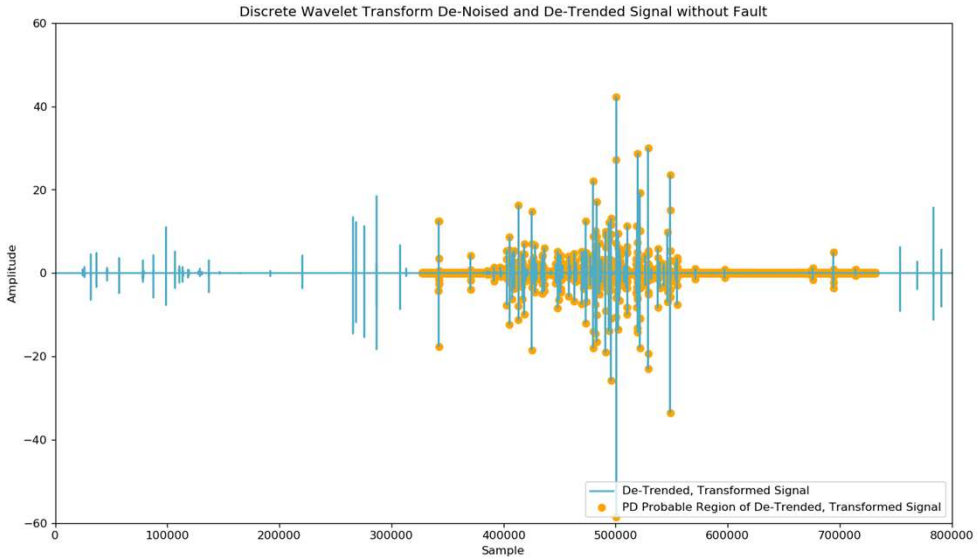

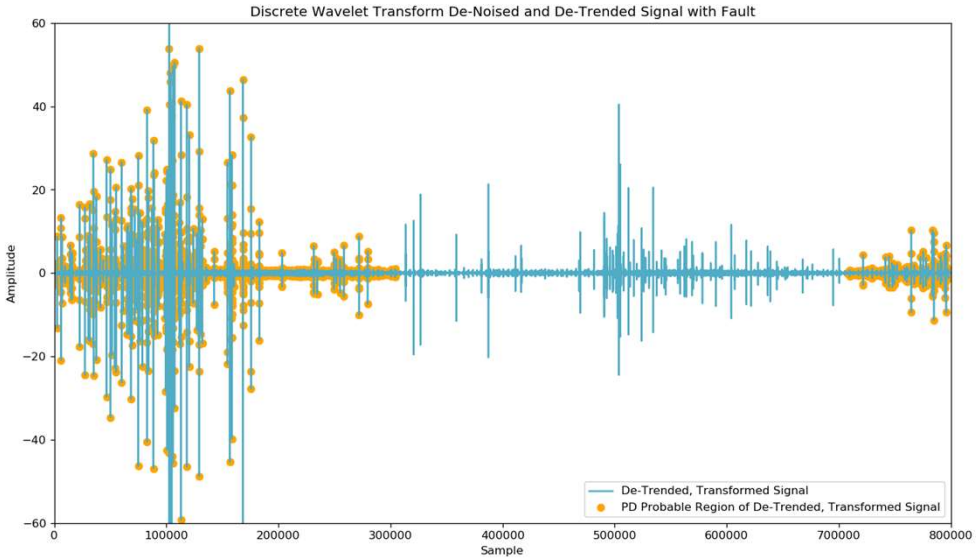

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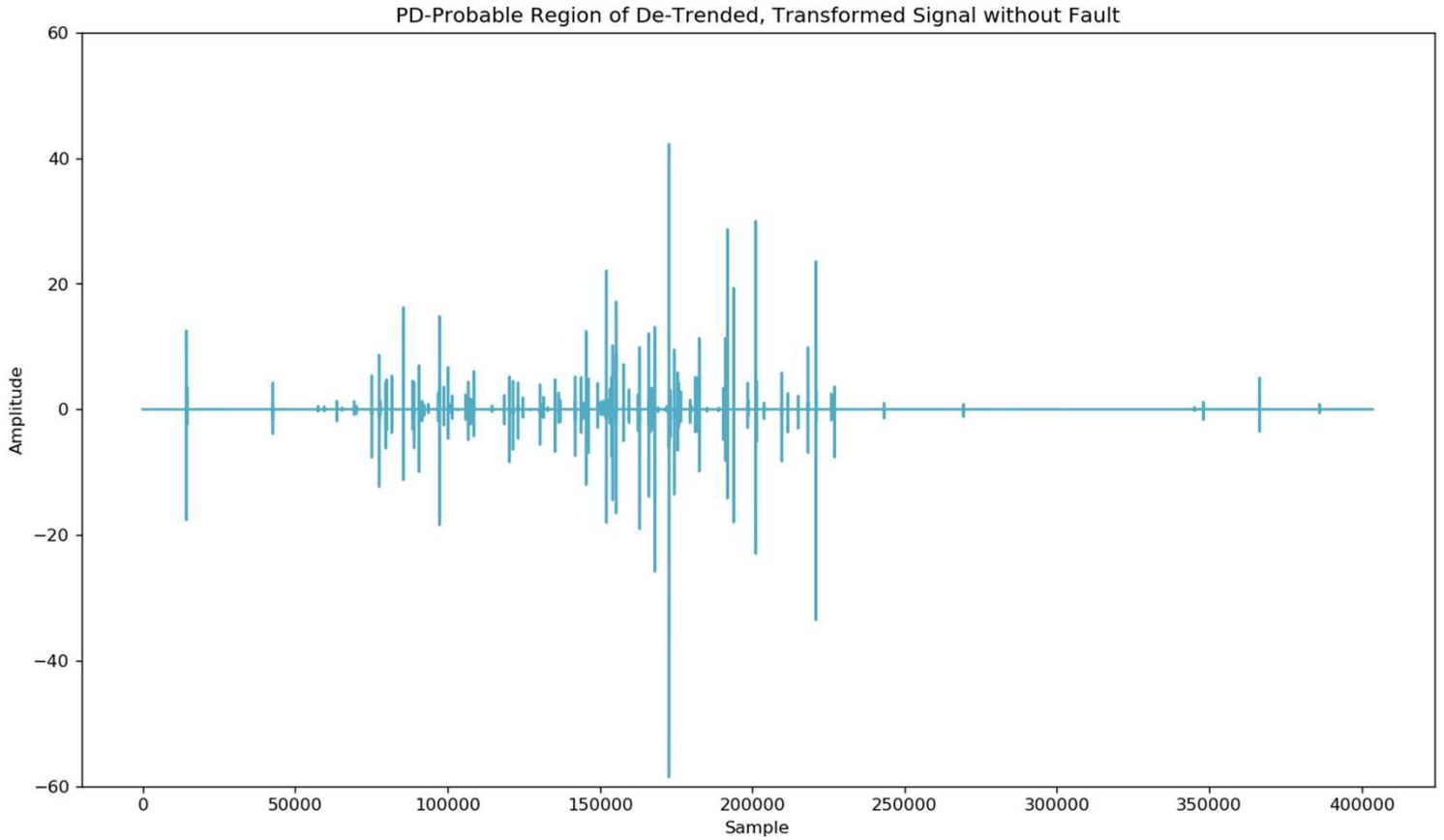
Trim to PD-Probable Region of Detrended Data



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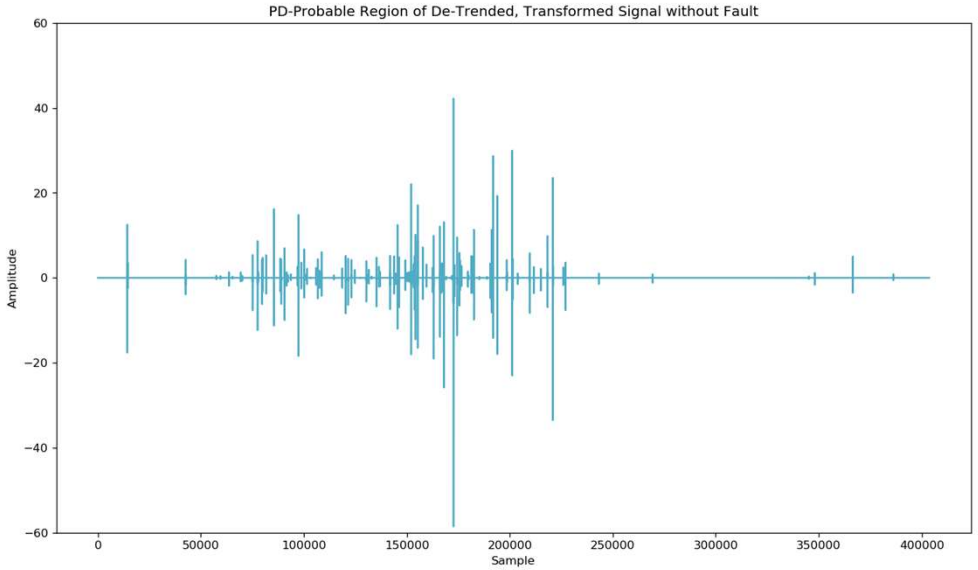

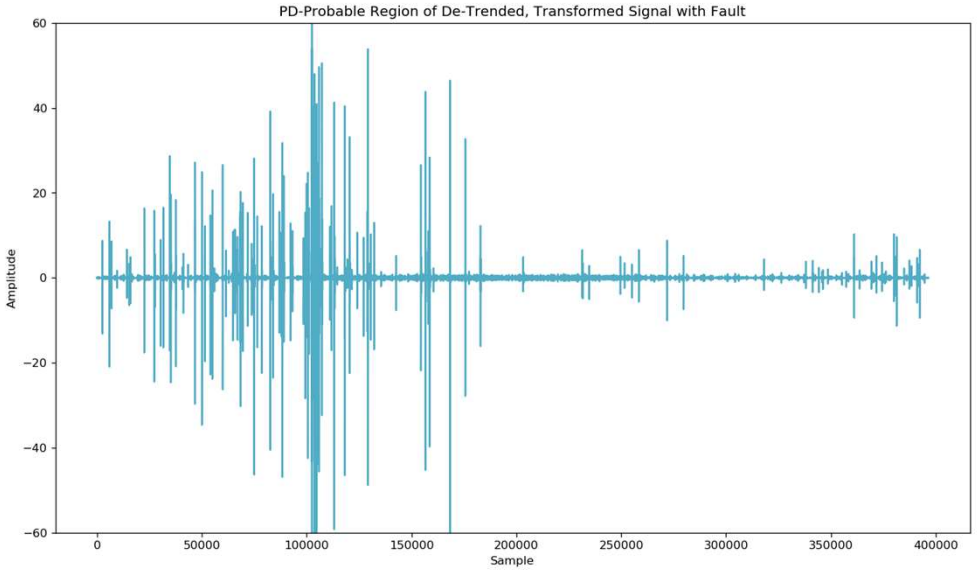

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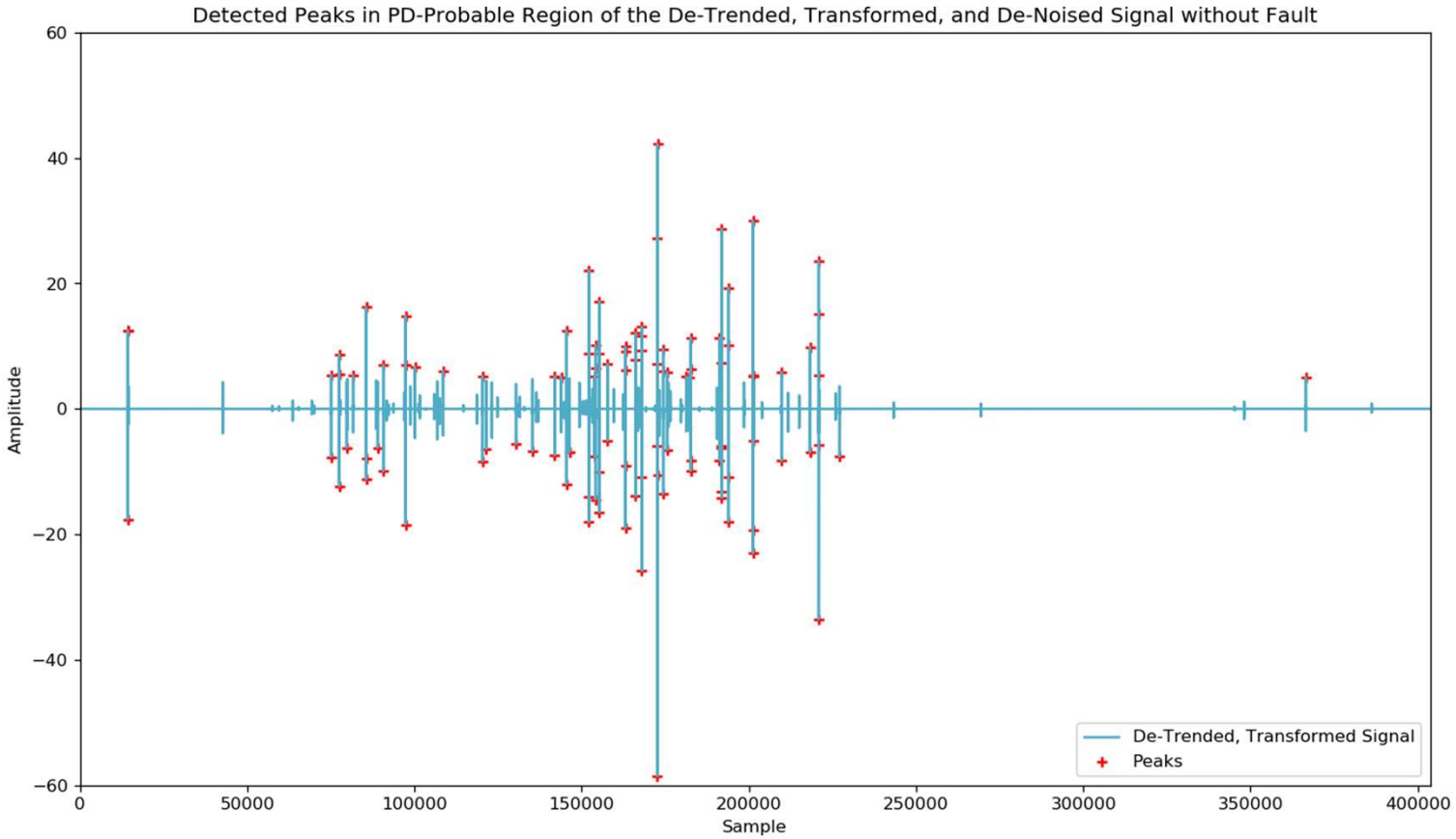
Run Peak Detection on PD-Probable Region



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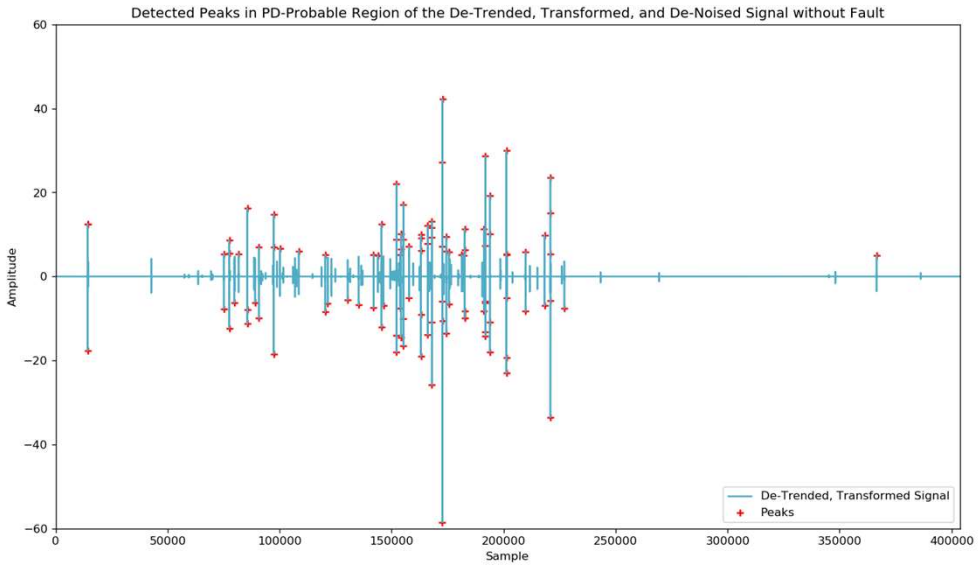

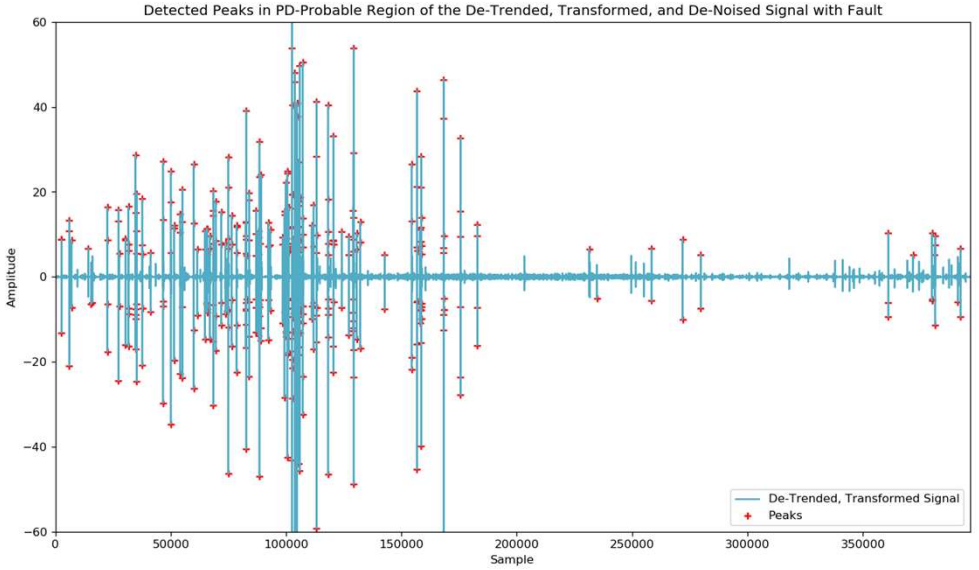

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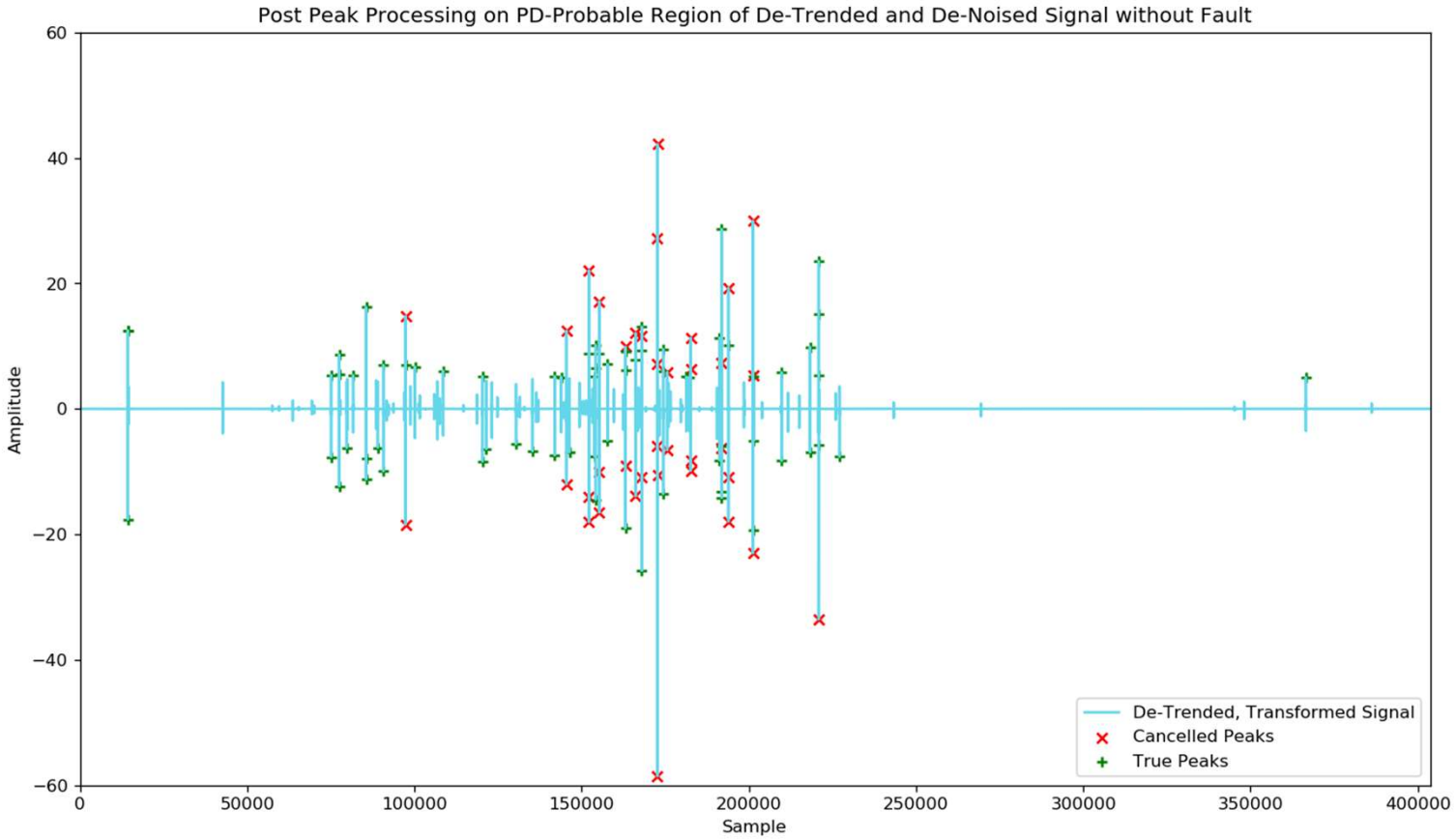
Cancel False Peaks Before Processing Signals



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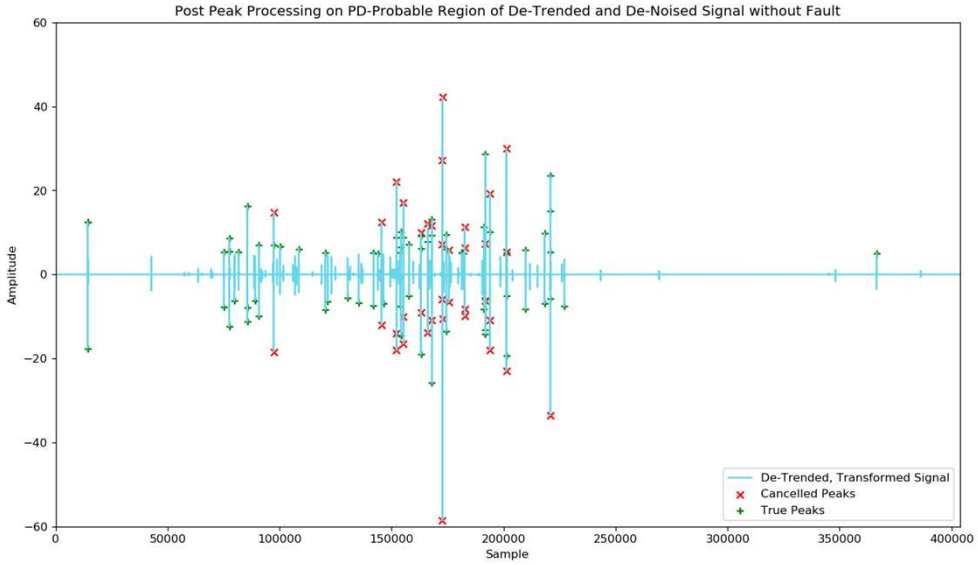

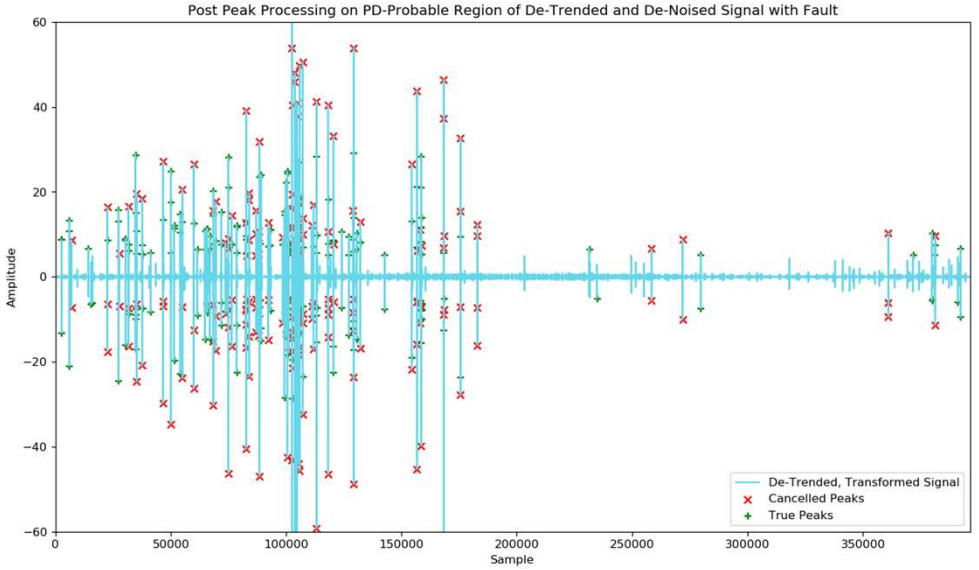

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Perform Feature Extraction on Signal

Process the PD-Probable Region of the De-Trended, De-Noised Signal and Build a Feature Table to be used as Input to Machine Learning Models.

- 5^{th} Percentile
- 25^{th} Percentile
- 75^{th} Percentile
- 95^{th} Percentile
- Median
- Mean
- Standard Deviation
- Variance
- Root Mean Square
- Entropy
- Number of Zero Crossings
- Number of Mean Crossings
- Minimum Peak Height
- Maximum Peak Height
- Minimum Peak Width
- Maximum Peak Width
- Number of Detected Peaks
- Number of True Peaks
- Number of True High Peaks
- Number of True Low Peaks (Valleys)

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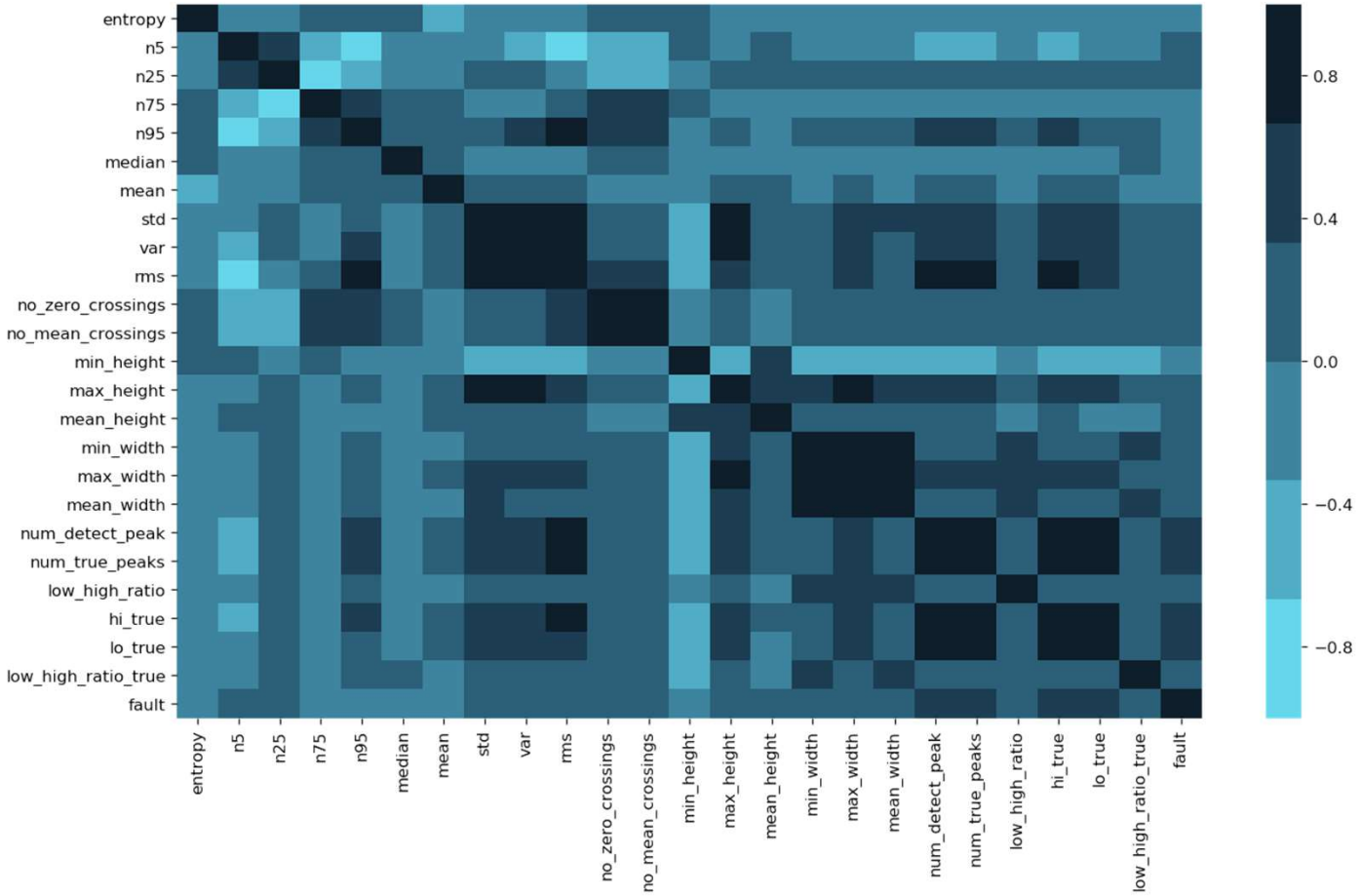
Feature Exploration – Correlation Heat Map



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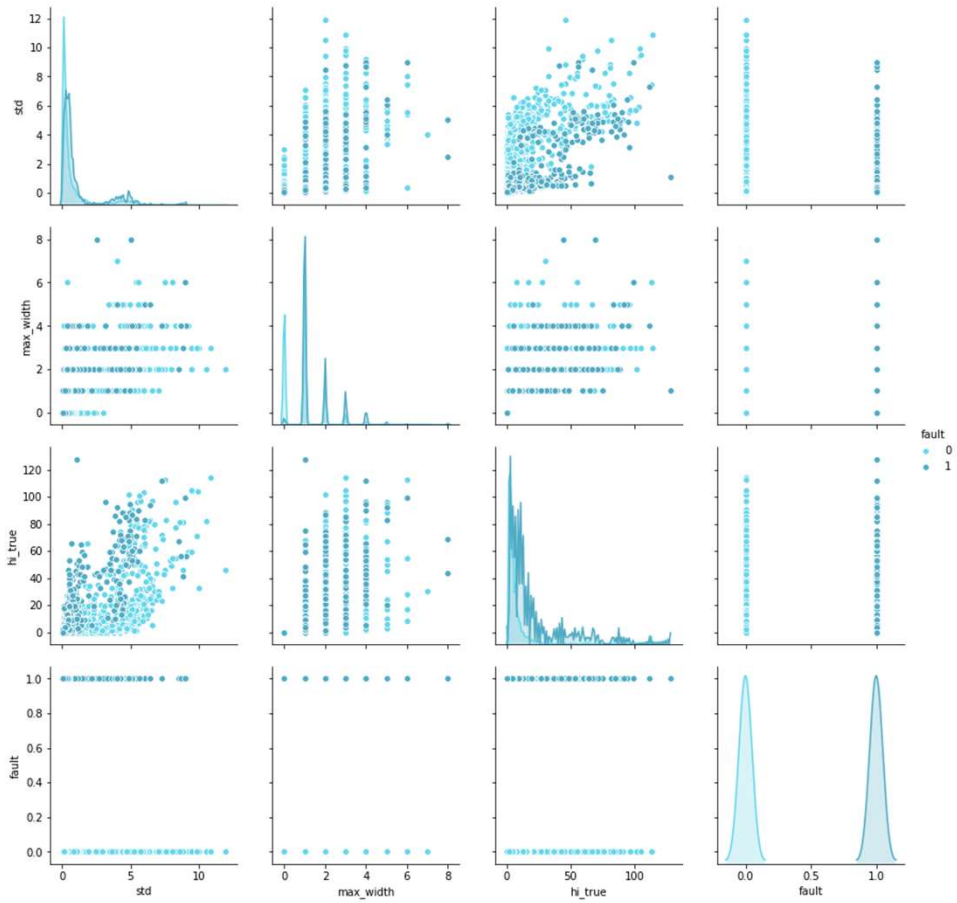
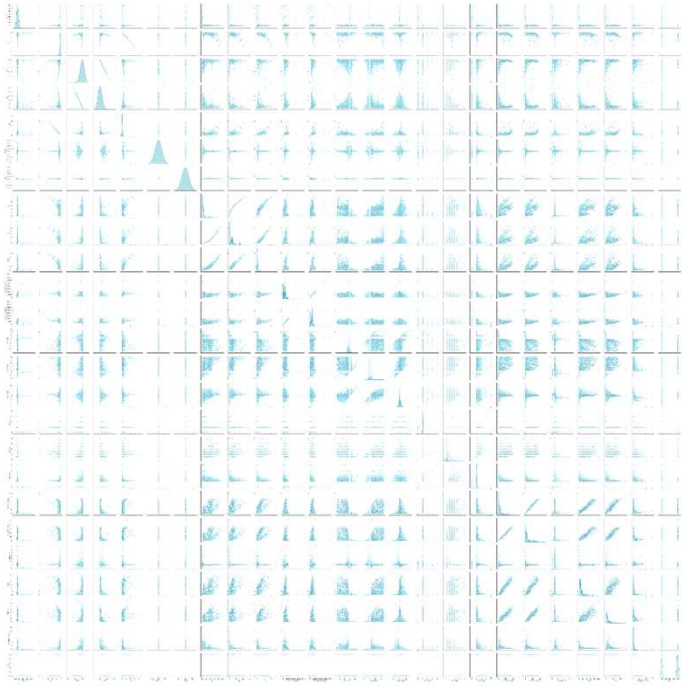
Feature Exploration – Pair Grid to Detect Trends



4x4 Pair Grid to Show Detail

Scatters and KDE

Full 25x25 Pair Grid



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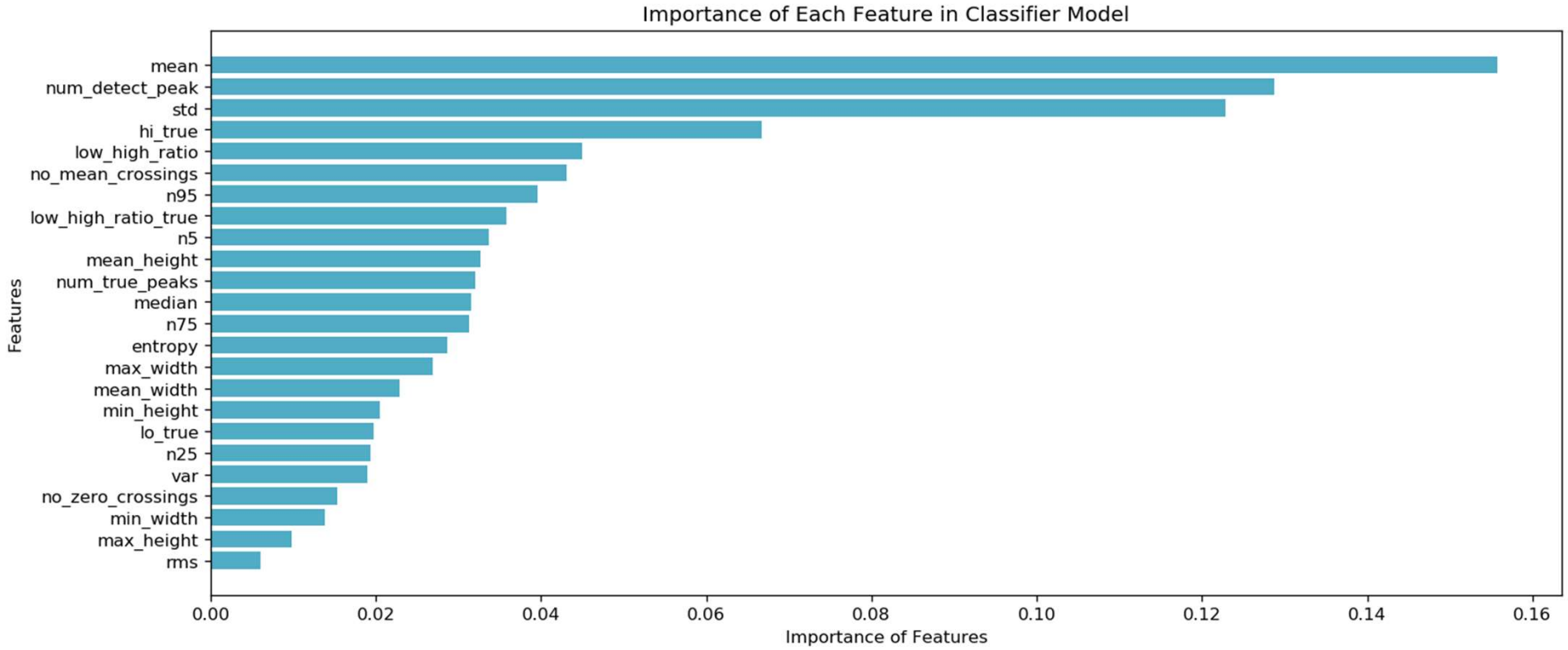
Not All Features are Equally Influential



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Prototype Binary Classification Models

At the root of the task is building a Machine Learning model capable of binary classification and this also equally adept at handling unbalanced classes.

- k-Nearest Neighbors (k-NN)
  - Monte Carlo over k parameter
- Support Vector Machines (SVM)
  - Radial Basis Function (rbf) kernel and Monte Carlo over gamma parameter.
- Random Forest Decision Trees (RF)
  - Regarded for handling unbalanced data when tuned properly.
- Light Gradient Boosting Framework (LightGBM)
  - Powerful, tree-based learning algorithm that grows vertically (leaf-wise)
  - Sensitive to overfitting on small data sets (<10,000 data points)
  - In binary classification, model returns probability that a sample belongs to the positive class.

Evaluate Model Performance with MCC

- Model performance is evaluated using Matthews Correlation Coefficient (MCC) between the predicted and observed response. The MCC is given by:

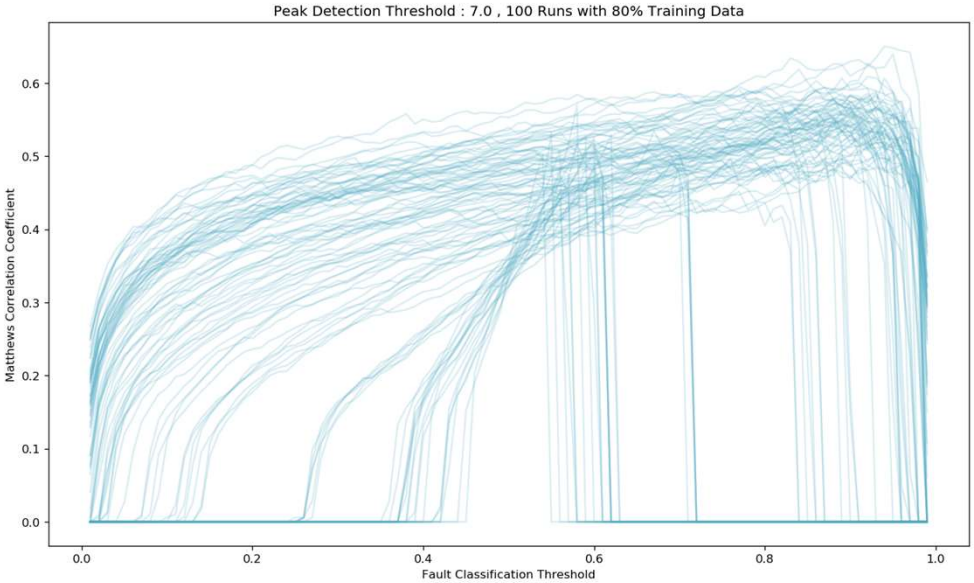
$$MCC = \frac{(TP * TN) - (FP * FN)}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}$$

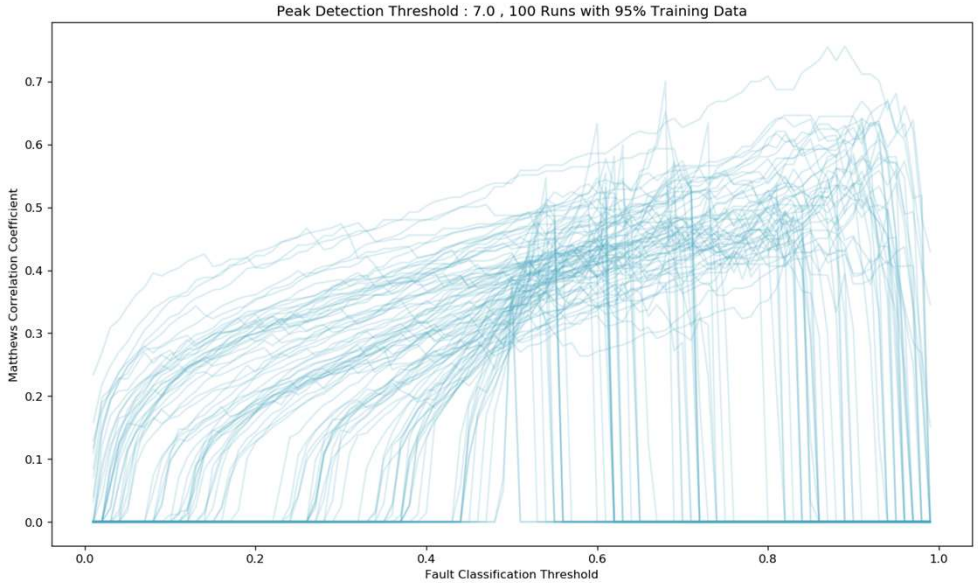
  where TP is the number of true positives, TN the number of true negatives, FP the number of false positives, and FN the number of false negatives.

- Matthews Correlation Coefficient is an apt metric to assess a binary classification model, especially one with a highly unbalanced class where metrics like accuracy, precision, and recall don't adequately capture the effectiveness of a model.

Concerns with Training/Test Splits on Unbalanced Data

Perform Monte Carlo trials that vary the `random_state` and `test_size` parameters in sklearn's `train_test_split` function and assess the impact of different thresholds on performance.





The goal is to find and set thresholds for Peak Detection and Fault Classification that routinely yield higher Matthews Correlation Coefficient scores and are robust to varied divisions of the training data.

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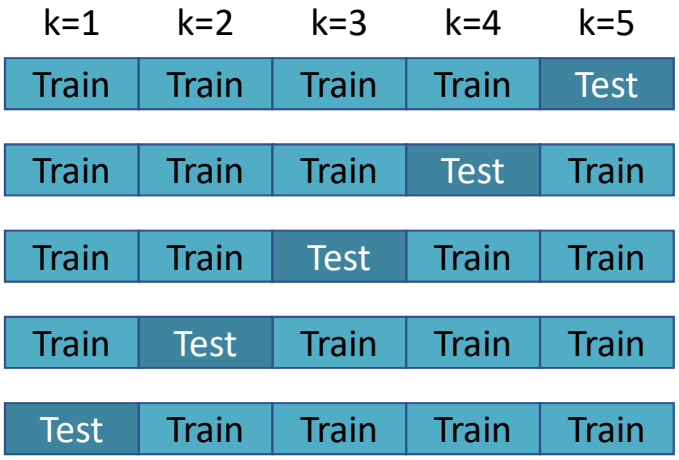
Revisiting Random Forest – Tuning for Unbalanced Classes

- Use Ensemble k-Fold Cross-Validation
  - Splits the data into k parts, Take k-1 parts as training data and 1 part for validation
  - Train and predict with the model k times over, holding out a different part each time.
  - Ensemble output produces probability of sample belonging to a class, not assignment
  - Average and use the prediction probabilities from the k scores to assign a class
- Set and Tune Class Weights
  - Enables cost-sensitive learning to remove a bias favoring the dominant class
  - Impose a costly penalty on minority class misclassification
  - Initially set weights based on ratios of data points in each class
  - Iterations on tailoring the weights can improve model performance
- Adjust Thresholds on Classification Probabilities to Over/Under Predict a Class
  - Another method to improve minority class performance
  - Adjust probability thresholds for making a classification

Use k-Fold CV to Ensure Model Robustness to Test/Train Splits

- Use Ensemble k-Fold Cross-Validation to Validate Model Robustness to Test-Train Splits
  - Splits the data into k parts, Take k-1 parts as training data and 1 part for validation
  - Train and predict with the model k times over, holding out a different part each time.
  - Ensemble output produces probability of sample belonging to a class, not assignment
  - Average and use the prediction probabilities from the k scores to assign a class



An example of 5-fold Cross Validation.

For each iteration, fit the model on the training folds and evaluate it using the test fold.

Retain the evaluation scores and probabilities between iterations but discard the trained model.

Modify Class Weights used in Model Training to Remove Bias

- Set and Tune Class Weights
  - Enables cost-sensitive learning to remove a bias favoring the dominant class
  - Impose a costly penalty on minority class misclassification
  - Initially set weights based on ratios of data points in each class
  - Iterations on tailoring the weights can improve model performance

- Example from this Project

  Default Weights are Uniform:

```
class_weight = dict({0:1.0, 1:1.0})  # default weights
```

  Initial set the weights based on ratio of samples in training data.

  Recall 213 / 8712 signals have faults present thus set fault weight 8499/2134 = 39.90

```
class_weight = dict({0:1.0, 1:39.9})  # initial, adjusted weights
```

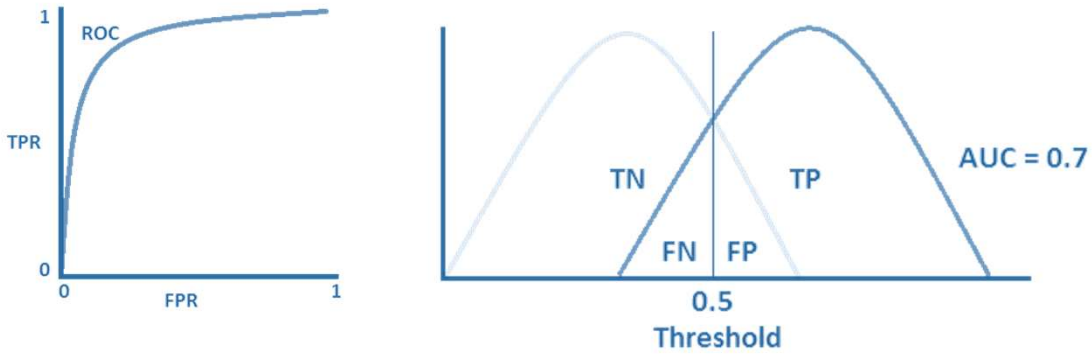
  Iterate and optimize weights through Monte Carlo analysis

```
class_weight = dict({0:0.5, 1:2.0})  # optimized, adjusted weights
```

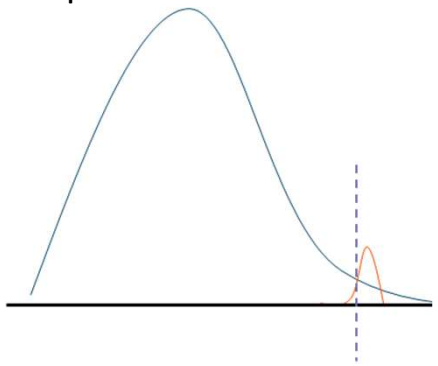
Adjust Probability Thresholds Used to Predict a Class

- Adjust Thresholds on Classification Probabilities to Over/Under Predict a Class
  - Another method to improve minority class performance
  - Default threshold is 0.5 for binary classification,
  - Use sklearn.metrics.roc_curve to find and set more appropriate thresholds
    - `fpr, tpr, thresholds = metrics.roc_curve(y, y_prob, pos_label=1)`
  - In the final Partial Discharge detection model, the threshold is set to 0.85

Example ROC & Threshold



Still Exaggerated but Curves More Representative of PD Data



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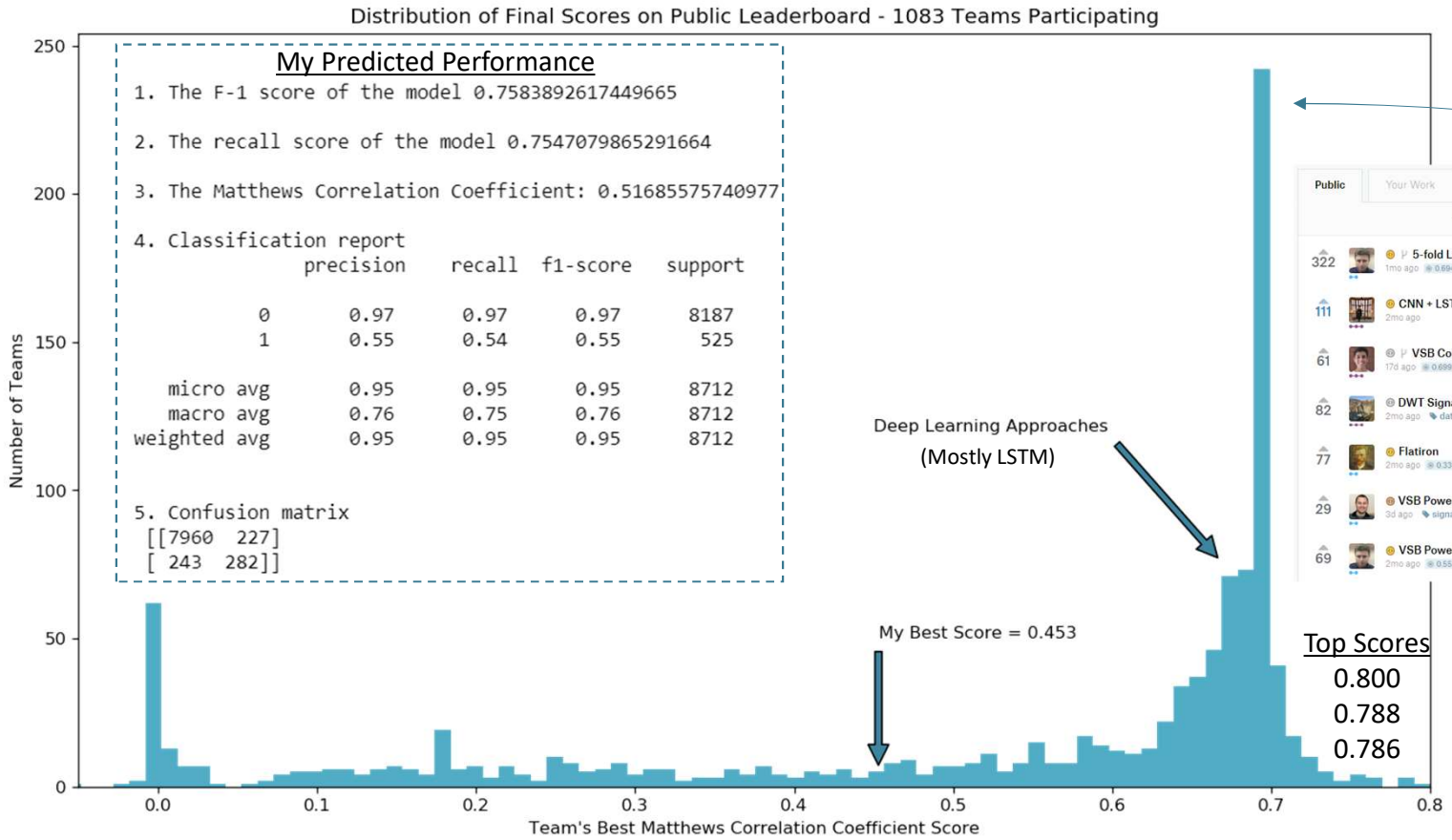
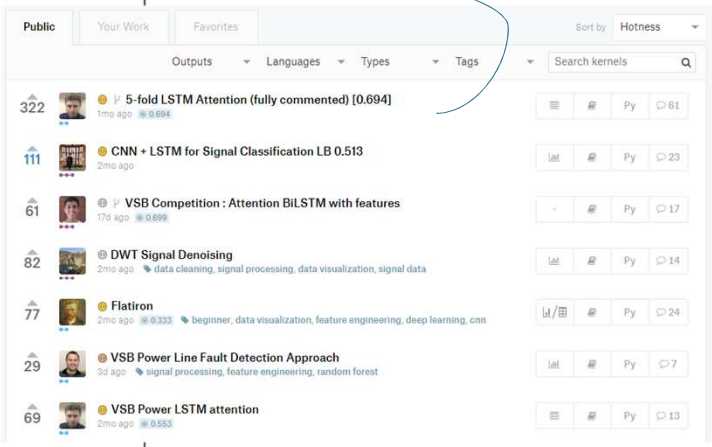
(Nearly) Final Results and Performance



Users replicating a successful approach



Trending Kernels for this Project

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Key Lessons for Dealing with Unbalanced Classes

- Use the right performance metric
  - Traditional metrics like accuracy, precision, recall, and F1 scores can be misleading
  - Matthews Correlation Coefficient – an effective binary classification performance measure - even for classes of very different sizes.
  - Pearson's Chi-Squared Test - a similar metric for higher order classification problems
- Account for the influence of test-train splits
  - With so few samples belonging to one of the classes, results can vary wildly
  - Rerun your analysis and testing while varying splits and random states to find robust performance predictions.
- Use a model or framework built for the task, and tune it properly
  - Some models are more adept at handling unbalanced classes than others
  - Modify and iterate on the impact of class weights, don't rely on defaults
  - Ensemble Cross-Validation – robust test-train splits, produces probabilities not classes
  - Use Probabilities of Class Assignment to Under or Over Predict a Class

Possible Paths to Improvement on this Project

- Move from Detection in Single Cycles to an Accumulator or N-Cycle Detection
  - Detect persistent faults while mitigating sporadic effects like corona
  - Data should already exist: signal data is device or location tagged

- While not globally true, when a fault is present in one phase, the likelihood of fault present in one or both or the other phases is also quite high.
  - Implement some logic that weights the probability of detection in the aggregate of the measurement?
  - How to use this data without introducing bias?

- Improved signal processing and feature extraction
- Further steps to mitigate mitigate suspected overfitting
- Avoid feature extraction, and evaluate deep learning methods like LTSM

References – Useful Academic Papers on the Subject

1. Misak, S., et al. “A Complex Classification Approach of Partial Discharges from Covered Conductors in Real Environment.” *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 24, no. 2, 2017, pp. 1097–1104., doi:10.1109/tdei.2017.006135.
2. Vantuch, Tomas. *Analysis of Time Series Data*, 2018, dspace.vsb.cz/bitstream/handle/10084/133114/VAN431_FEI_P1807_1801V001_2018.pdf.

My Kaggle kernel and GitHub repos have been set public:

Kaggle Kernel: https://www.kaggle.com/jeffreyegan/vsb-power-line-fault-detection-approach

GitHub: https://github.com/jeffreyegan/VSB_Power_Line_Fault_Detection

Forks & collaboration welcome!

Q: What's Next?
A: More DSP / ML challenges!

- Predicting Earthquakes for Los Alamos National Labs – Geophysics Group!

- Forecasting earthquakes is one of the most important problems in Earth science because of their devastating consequences. Current scientific studies related to earthquake forecasting focus on three key points: when the event will occur, where it will occur, and how large it will be.

- In this competition, you will address when the earthquake will take place. Specifically, you'll predict the time remaining before laboratory earthquakes occur from real-time seismic data.

- https://www.kaggle.com/c/LANL-Earthquake-Prediction

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