Data Considerations for ML in Distribution System Model Calibration

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Presentation Overview

How do we leverage data processing and physical system characteristics to improve the machine learning results, while navigating common data quality issues? Using distribution system model calibration applications as an motivating example.

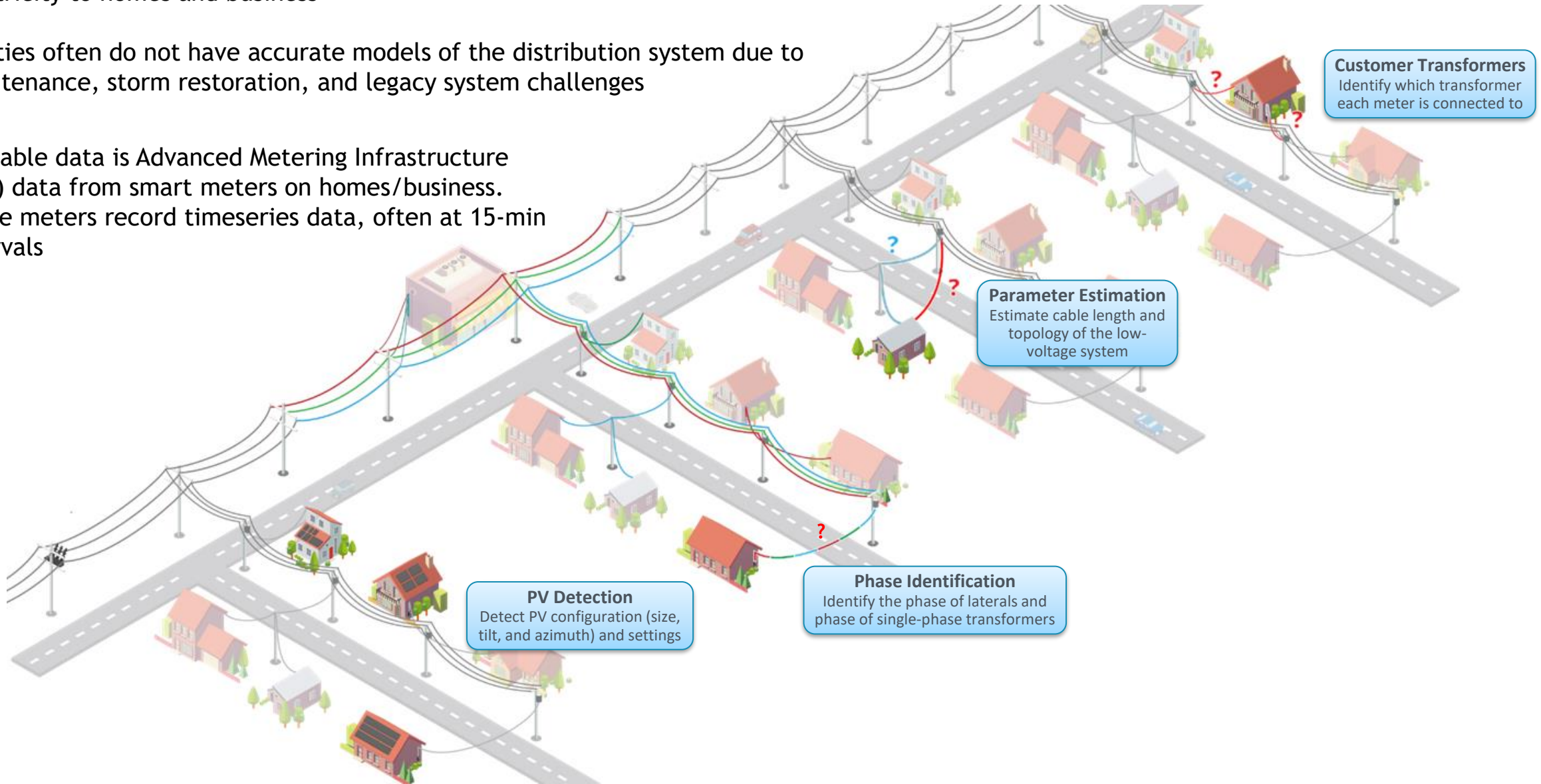
Motivating Point: Even after a ML model was selected, performance and robustness in real-world usage depended on data processing improvements. Without the problem-specific data pre-processing steps, the algorithm would not have been accurate or reliable enough to use outside of the lab

Presentation Agenda:

- Application Overview – What is distribution system model calibration, and why do we care?
- Phase Identification
  - Problem Characteristics
  - Data Considerations – Application Specific
  - Data Consideration – Data Quality
- Key Takeaways

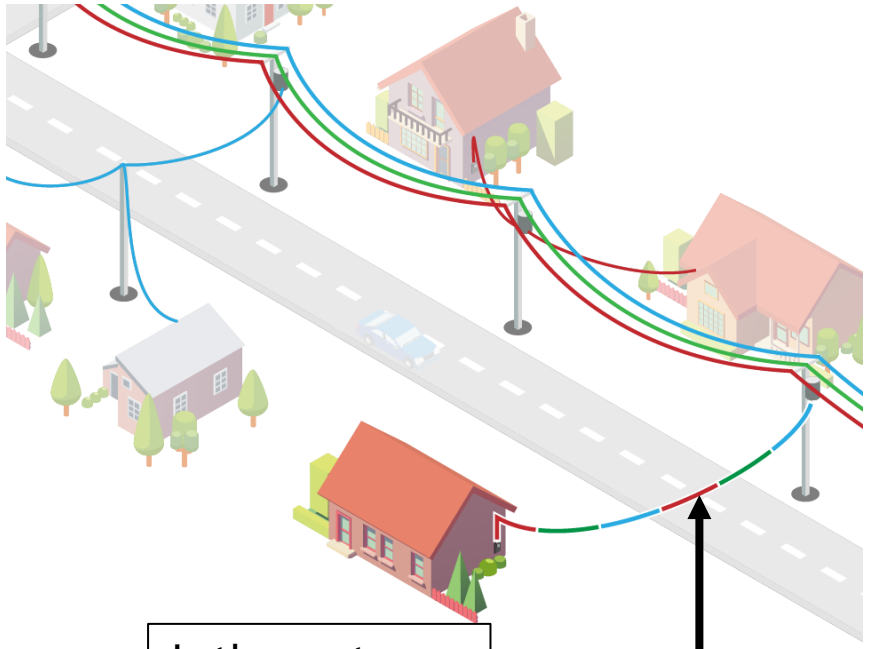
Application Overview

- The distribution system is the low voltage section of the power grid which serves electricity to homes and business
- Utilities often do not have accurate models of the distribution system due to maintenance, storm restoration, and legacy system challenges
- Available data is Advanced Metering Infrastructure (AMI) data from smart meters on homes/business. These meters record timeseries data, often at 15-min intervals

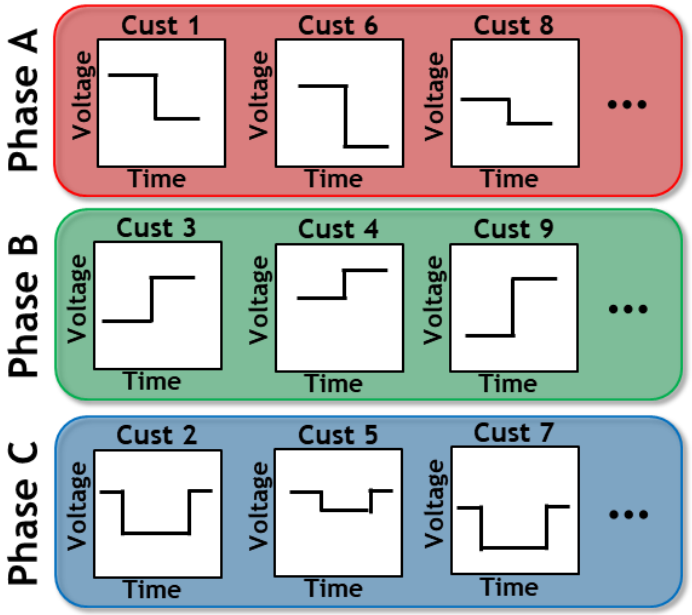


Phase Identification Problem Characteristics

- Customers connected to the same phase are electrically connected to all other customers on that phase. Thus, their voltages will be more highly correlated than customers on other phases
- Inherently lends itself to a clustering approach
- Customers will each have distinct energy usage characteristics



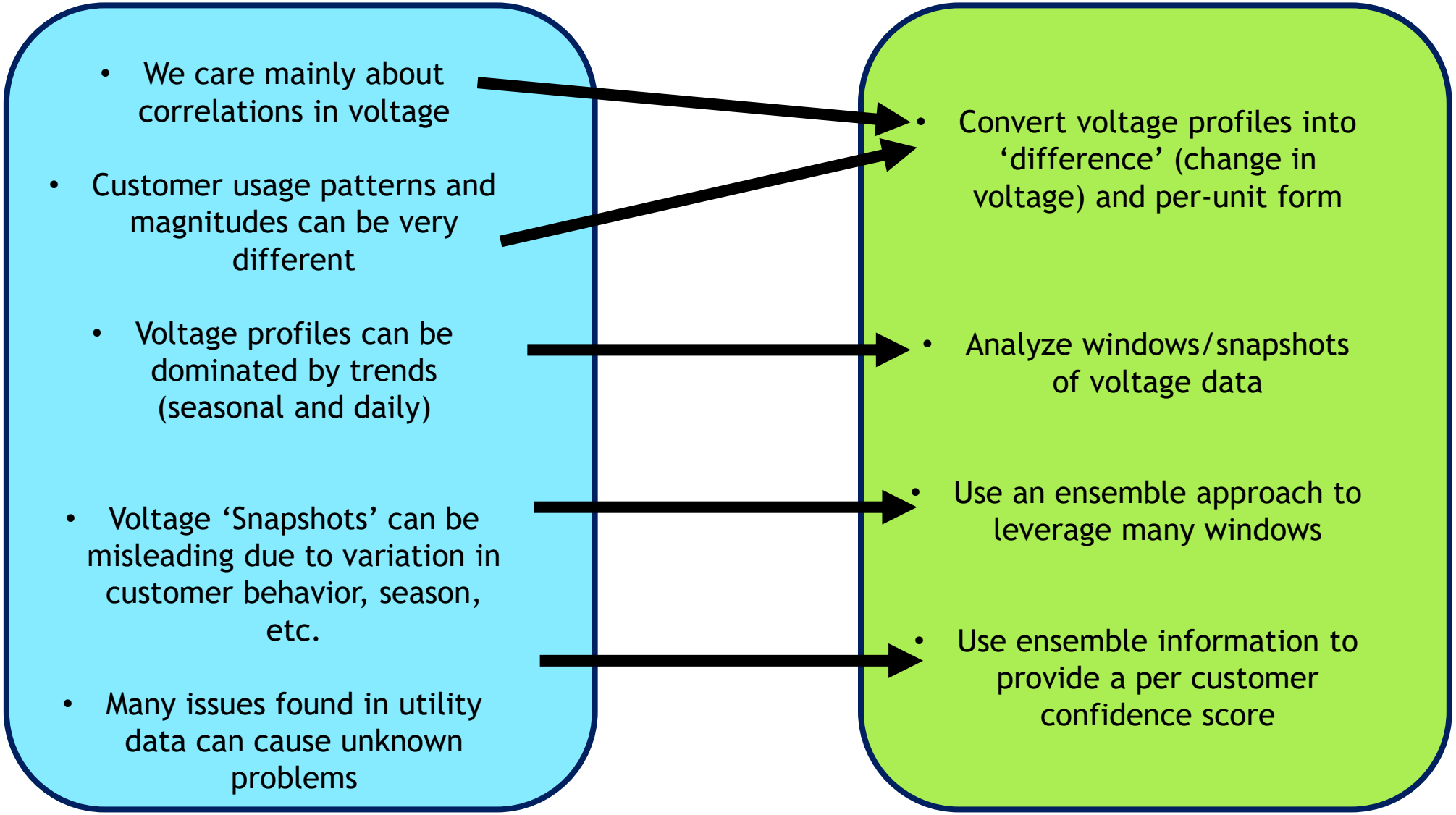
Is the customer connected to A, B, or C?



Even after deciding on an appropriate ML approach (Spectral Clustering), many of the improvements which made the overall algorithm work in the real world came from data processing changes

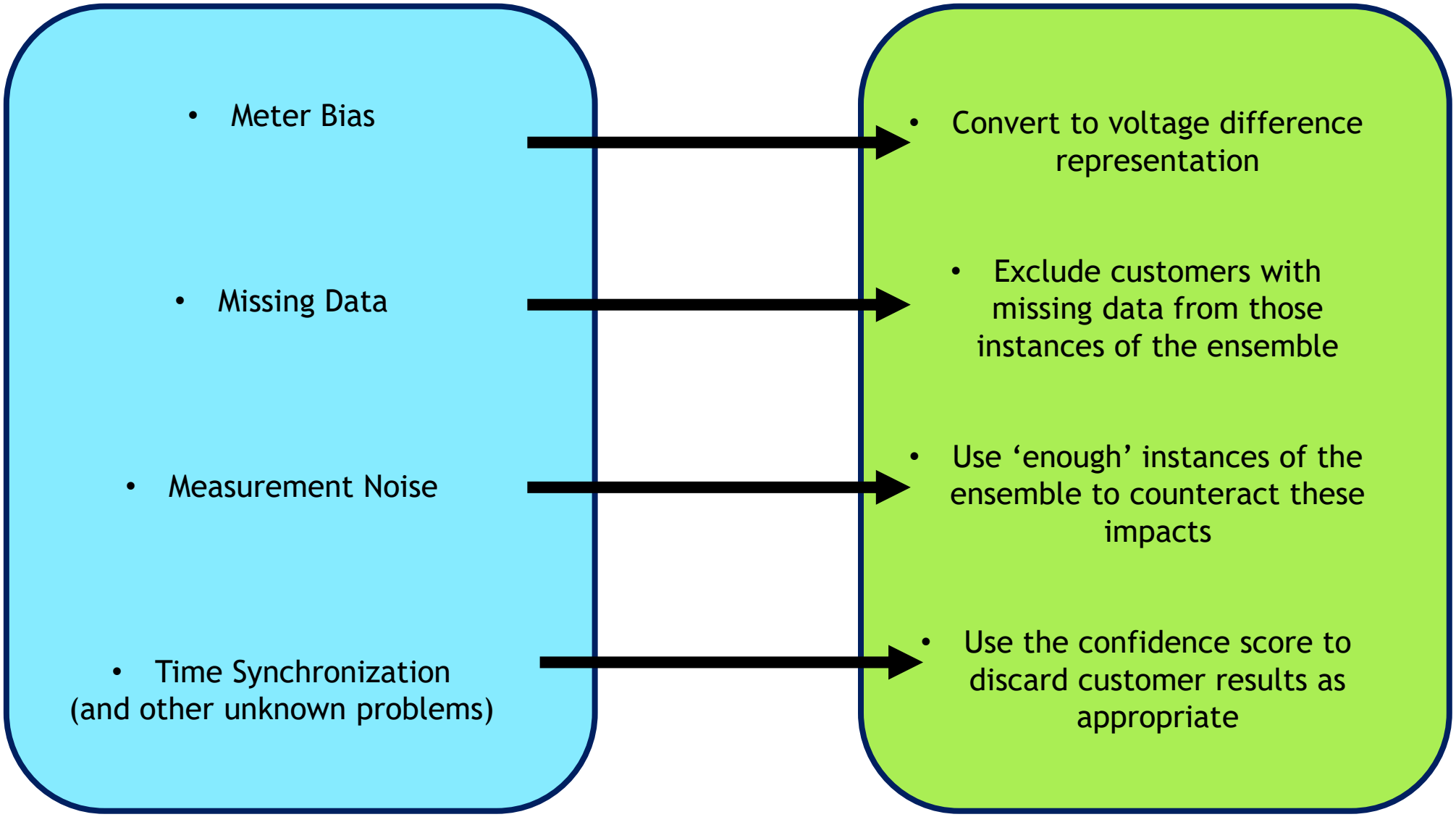
Phase Identification – Data Processing Solutions

Application specific considerations



Phase Identification – Data Processing Solutions

Data quality considerations



Key Takeaways

- Choosing a ML approach is just one step in the process

Questions to ask:

- What data processing can I apply based on the characteristics on my specific application?
- What data processing can I apply to resolve, or mitigate, data quality issues?
- Is there data processing I can use to increase algorithm robustness for unknown issues?