Household Electric Power Consumption

Time Series Trends & Forecasts

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Household Power Consumption | Time Series : Agenda

- Background
- Daily Power Consumption Trends
- Weekly Power Consumption Trends
- Multi-Year Power Consumption Trends
- Model / Prediction / Forecasts
- Seasonality
- Recommendations

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Household Power Consumption | Time Series : Background

- Problem Statement:
  - IOT Analytics closing deal for new sub-metering devices in Smart Homes.
  - Smart Home owners need to understand and control their power usage from these devices
  - Pre-existing power usage data can be used to develop preliminary analytical tools & visualizations for customers.
- Data Set Analyzed:
  - "Individual Household Electric Power Consumption Data Set"
    - Repository: UC Irvine Machine Learning Repository
    - Source: G. Hebrail & A. Berard, EDF R&D, Clamart, France
  - 3 sub-meters:
    - #1: Kitchen (Dishwasher, oven, Microwave)
    - #2: Laundry Room (washing-machine, dryer, refrigerator, light)
    - #3: Heating + Cooling (Electric wafer heater, AC unit)

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UC IRVINE

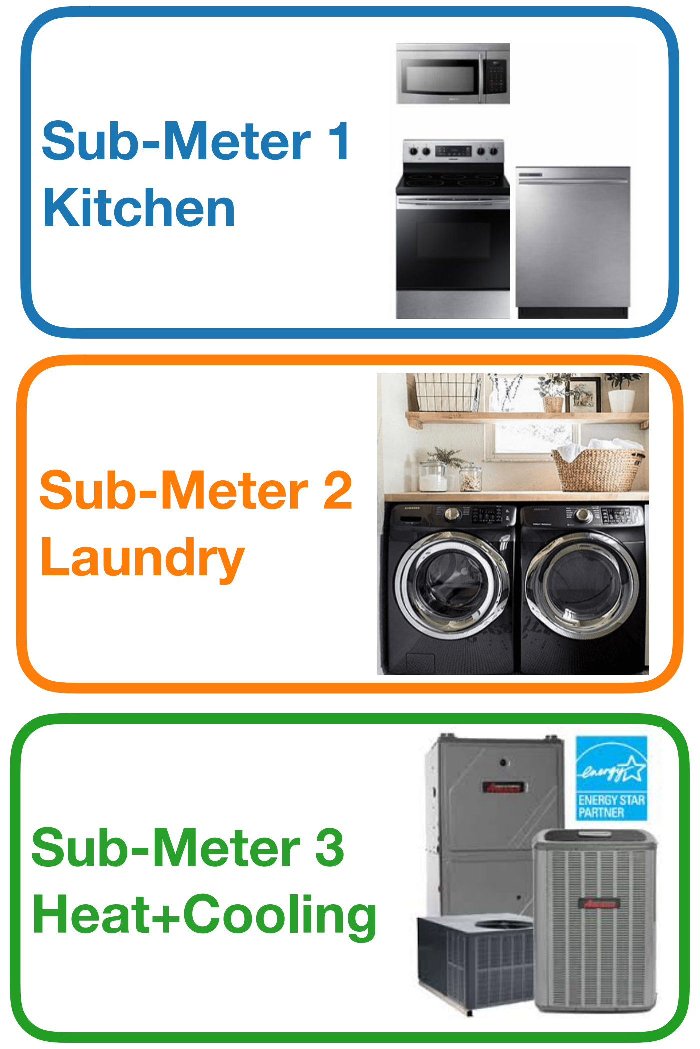
Sub-Meter 1
Kitchen

Sub-Meter 2
Laundry

Sub-Meter 3
Heat+Cooling

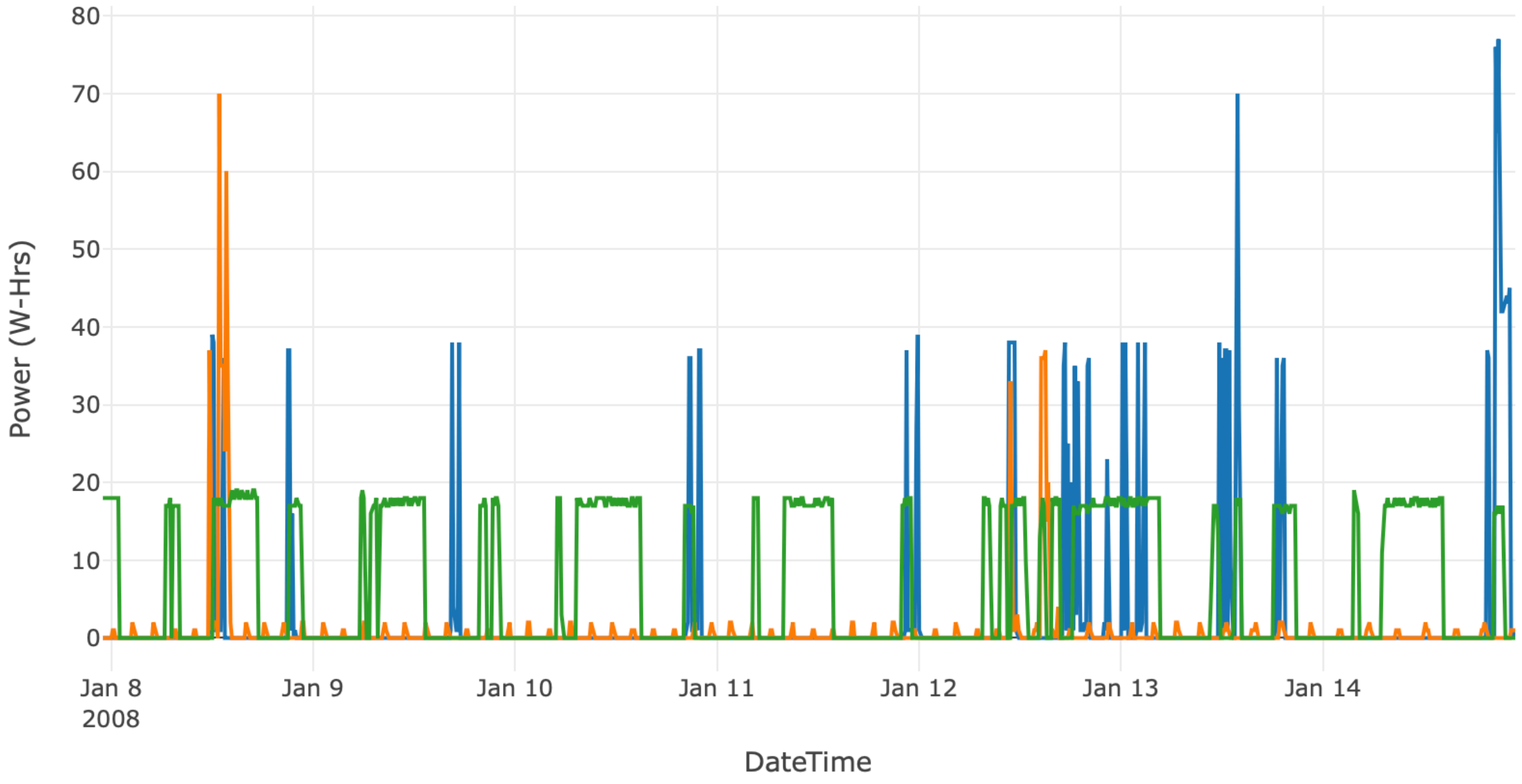
Household Power Consumption | Time Series : Daily Trends

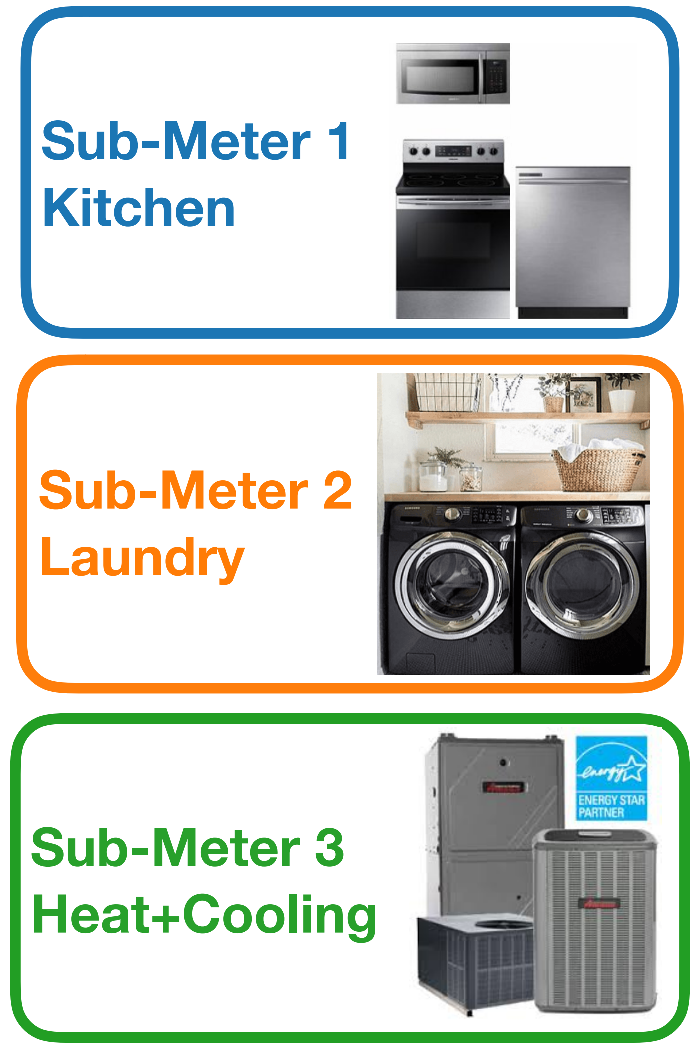
- Zoom in on single day
  - January 9, 2008, (10 minute interval)
- Key Insights
  1. Heat+Cooling (sub-meter 3) shows peaks in the morning and at night. Likely corresponds showering/bathing ⇒ heater consuming power.
     - Duration of peak could be valuable metric for customers to give insights to customers
  2. Laundry room (sub-meter 2) has small peaks roughly every 2 hrs. Could correspond the fridge turning on for cooling.
     - Tracking intensity of these peaks day to day could give customers insight on how efficient their fridge is or if the fridge is dying.



Household Power Consumption | Time Series : Weekly Trends

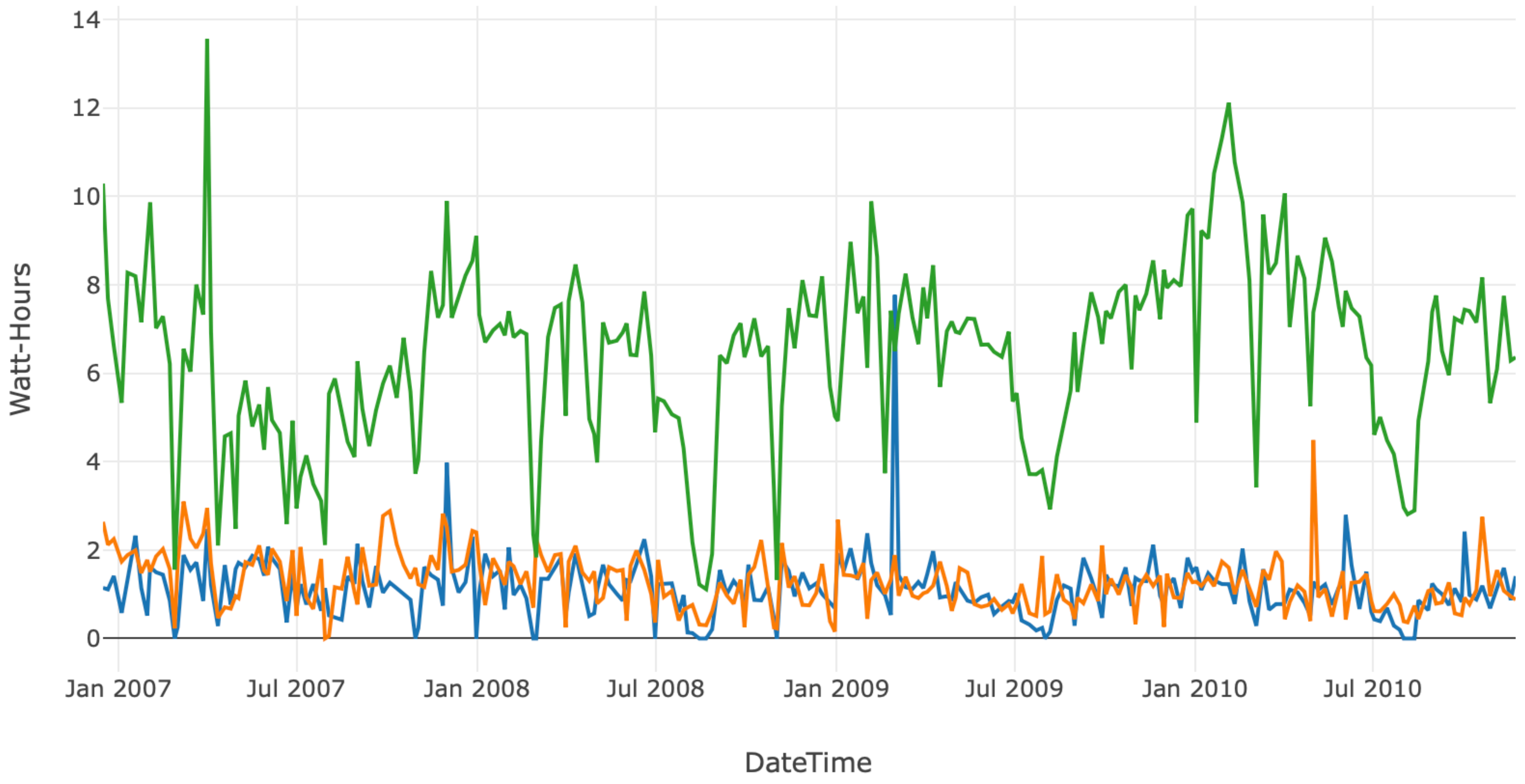
- Zoom out to single week
  - January 8-15 (2nd week of the month), 2008, (10 minute interval)
- Key Insights
  1. Spike in laundry power. Likely corresponds to washer-dryer use.
     - Could compare intensity of spike across customers to give users insight on the relative efficiency of their wash-dryer.
  2. Peaks for kitchen correlate w/ peak in heat+cooling
  3. Jan 13 (Sunday) shows irregular behavior relative to rest of the days.
     - Parsing weekend vs. weekday usage could allow users to more accurately understand how weekday vs. weekend behavior is affecting power.

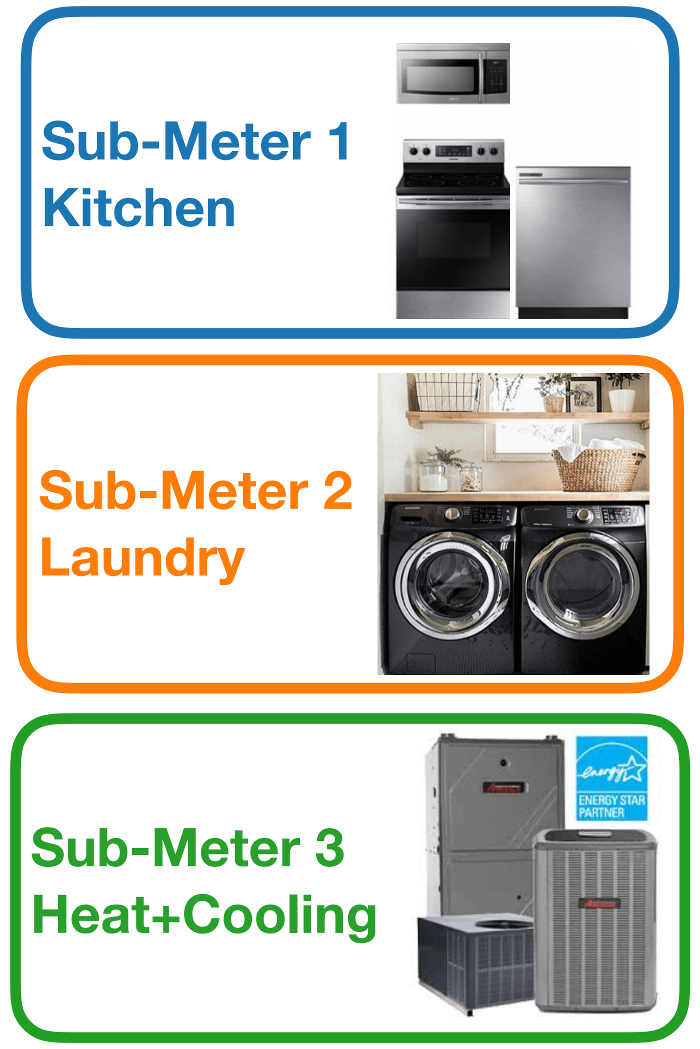




Household Power Consumption | Time Series : Multi-Year Trends

- Zoom out to all years
  - 2007-2010, mean power per week for each sub-meter (i.e. weekly interval)
- Key Insights
  1. Heat+cooling appears to have seasonal trend. Can we predict this? Do other sub-meters have seasonal trends as well?





- Models:
  1. SARIMA: Seasonal Autoregressive Integrated Moving Average Model
  2. Holt-Winters Simple Exponential Smoothing on Seasonally Adjusted Data

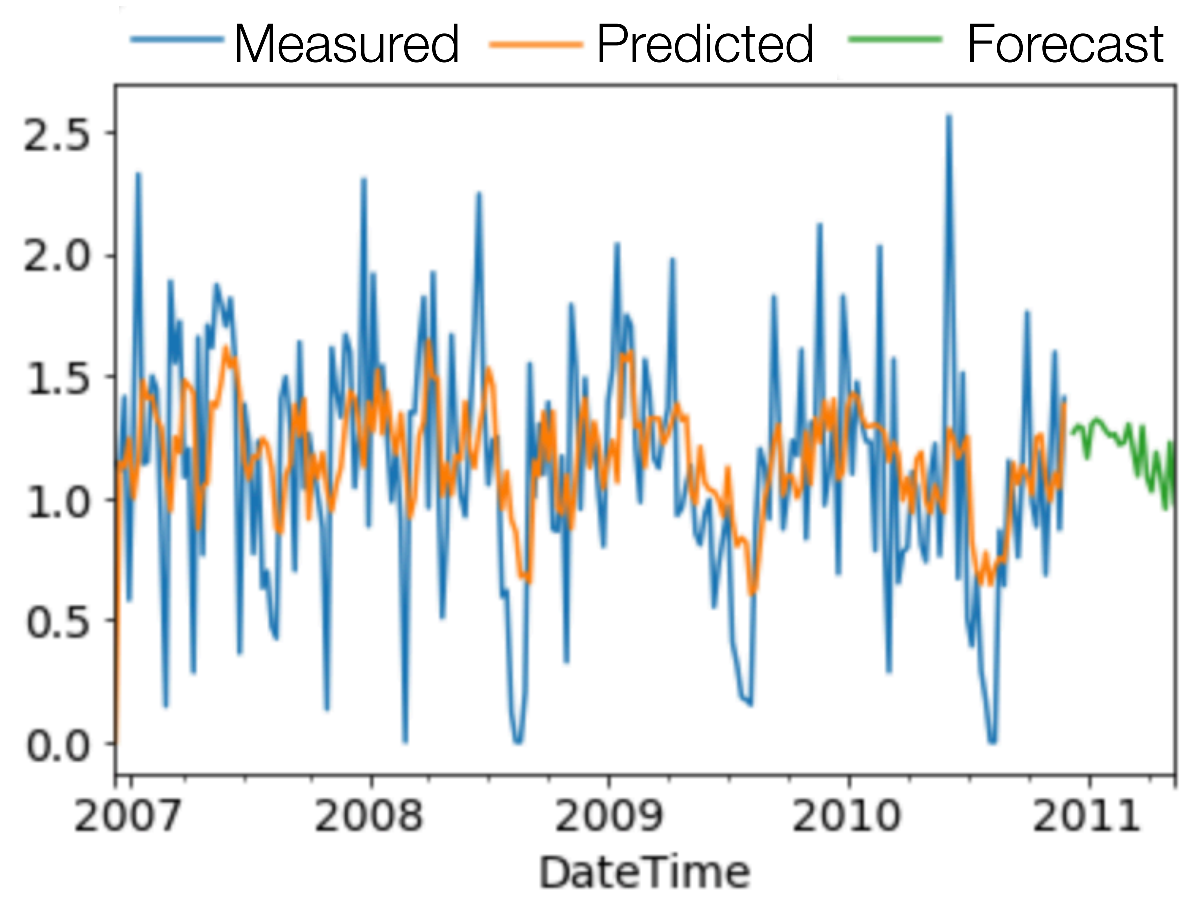
Household Power Consumption | Time Series : SARIMA Model

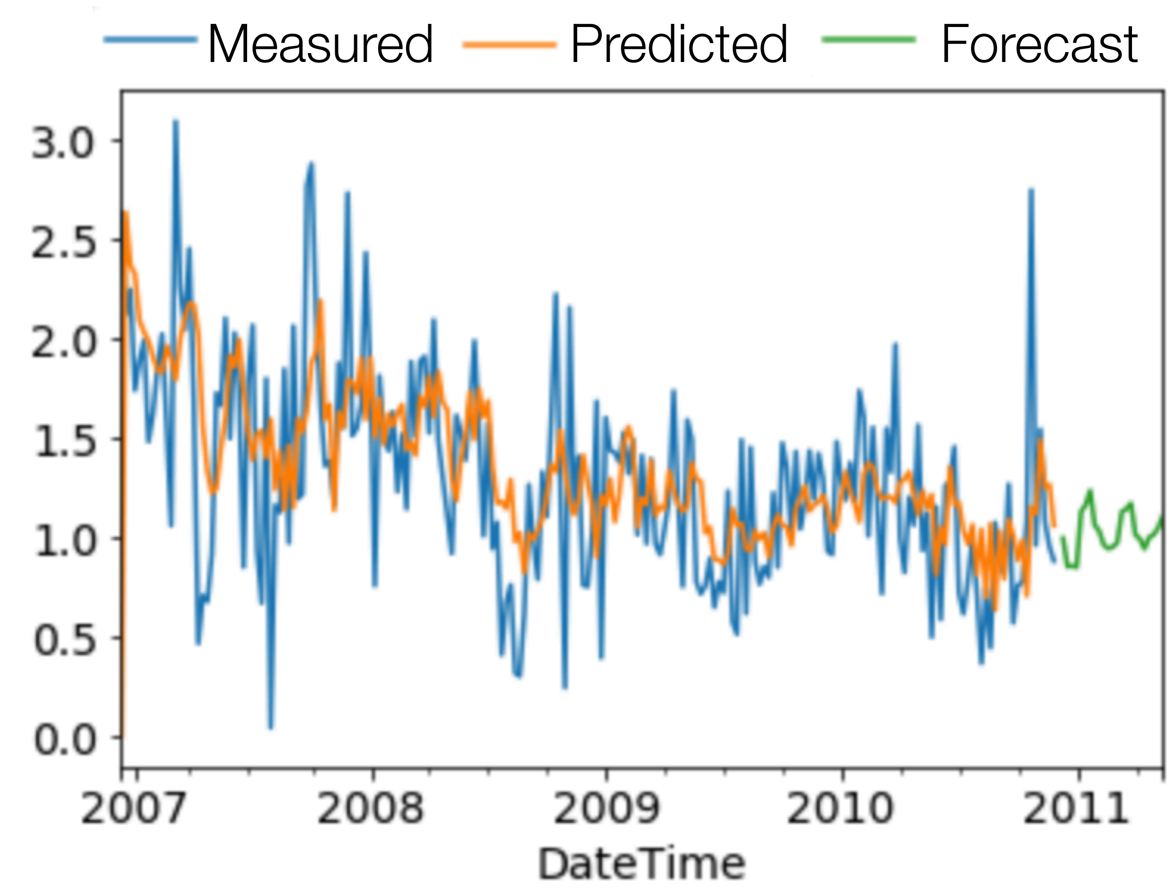
- SARIMA: Seasonal Autoregressive Integrated Moving Average Model
  - grid-search of model parameters performed to find best model for each sub-meter
- Best Models RMSE:
  - Represents average error expected from prediction
  - Higher error for sub-meter 3 prediction. Result of sub-meter 3 power consumption typically being ~3X meter 1 and 2
- Weekly Power: Measured vs. Predicted vs. Forecast
  - Model predicts granular & seasonal trends well, with more error in granular (week-to-week) trends for sub-meter 1 & 2.
  - 24 Week forecast seems reasonable based on historical data

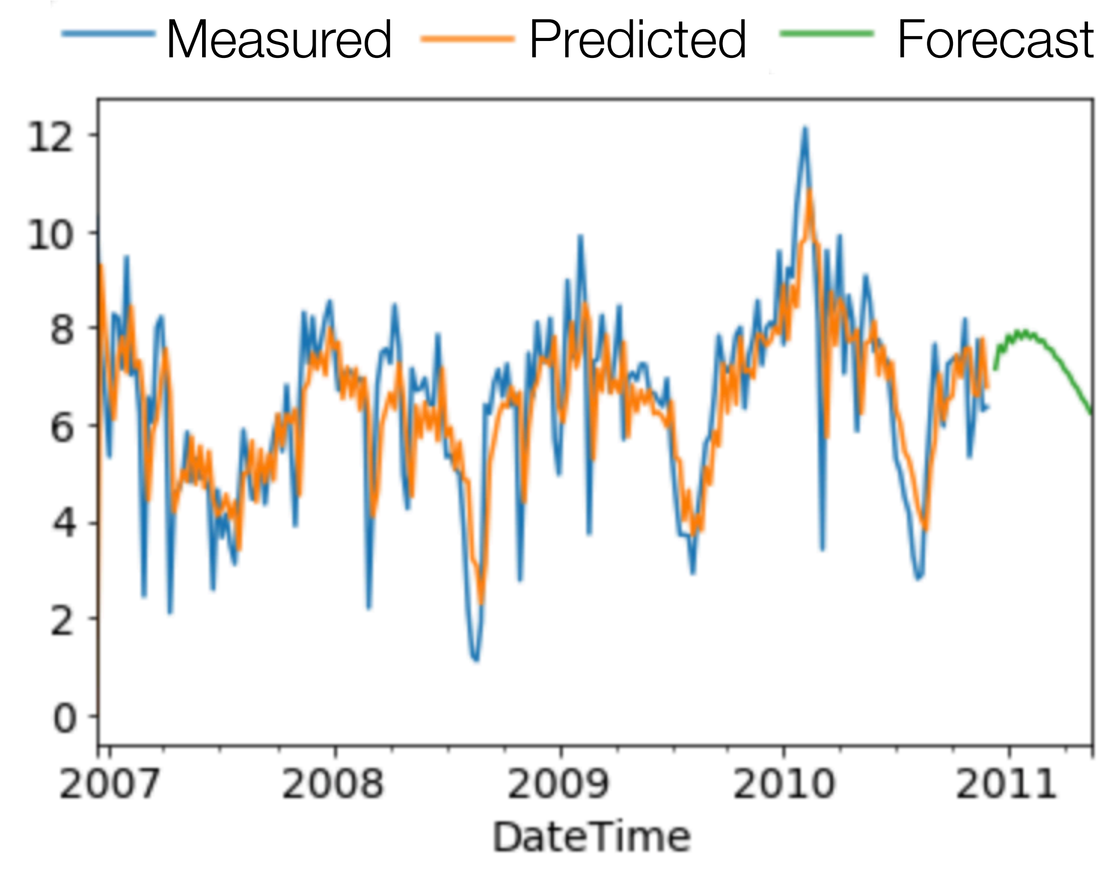
	Sub-Meter 1 Kitchen	Sub-Meter 2 Laundry	Sub-Meter 3 Heat + Cooling
Best Models RMSE	0.46	0.49	1.54

Weekly Power (W-Hr)

Measured
predicted
forecast



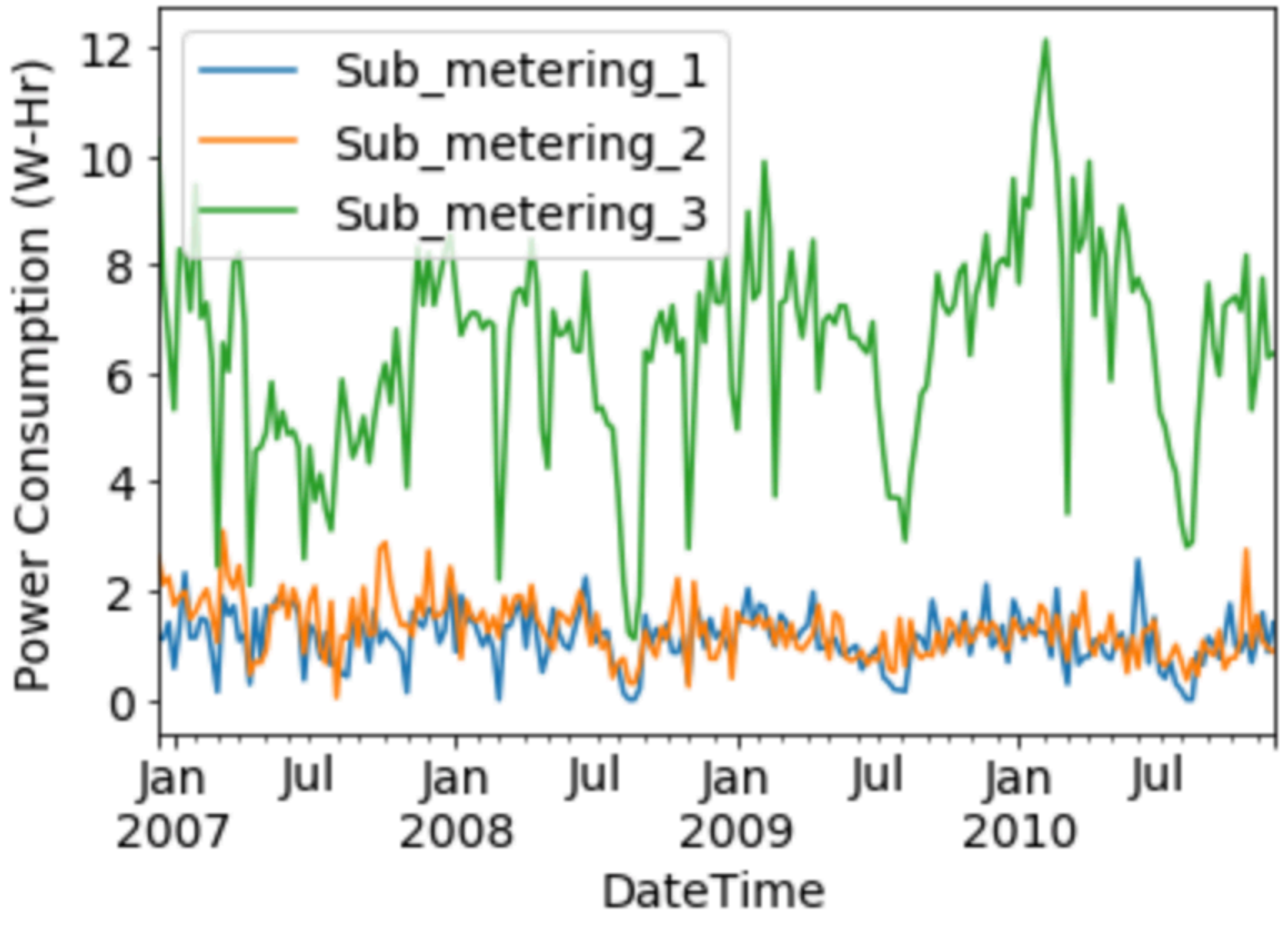




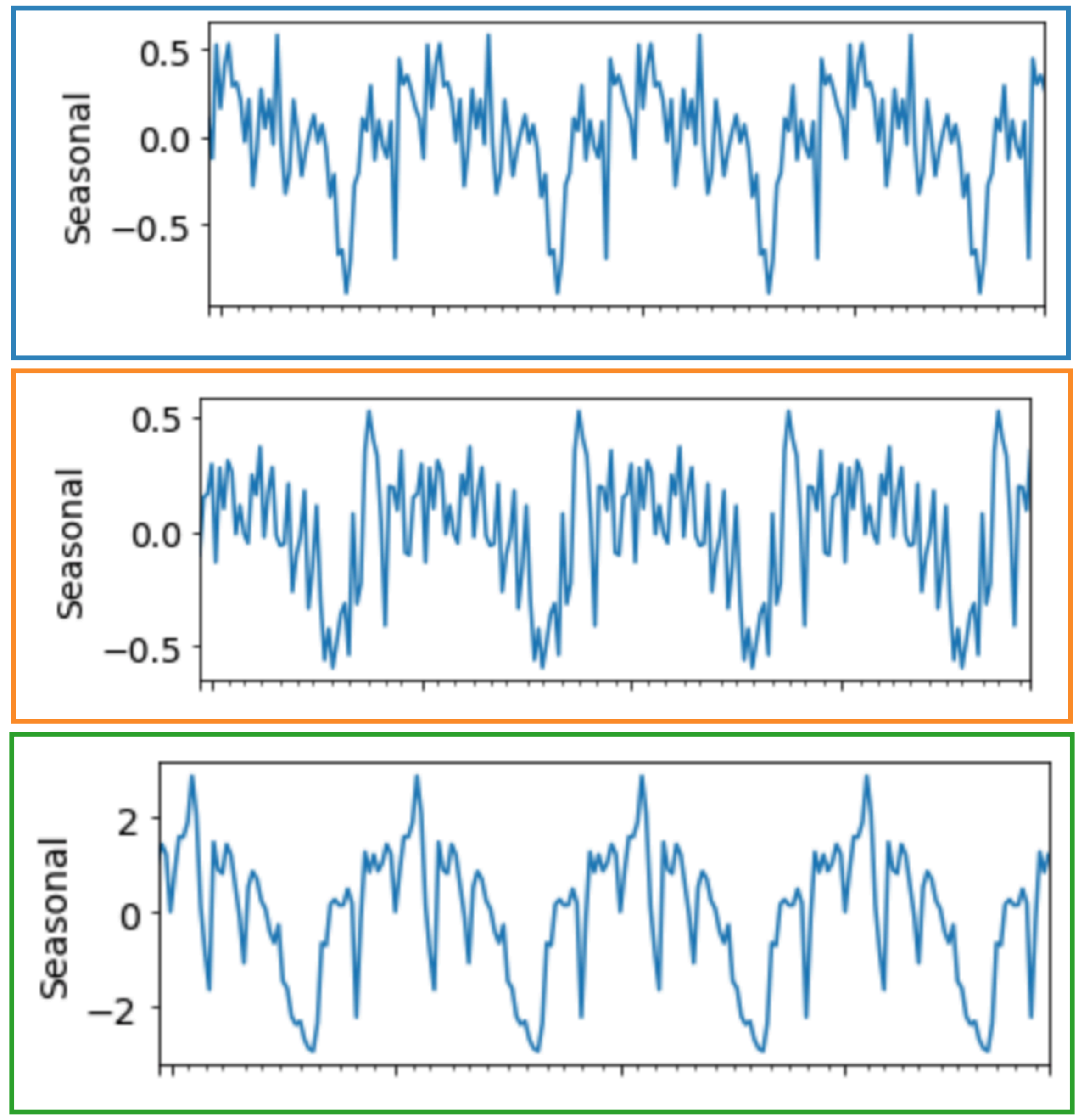
Household Power Consumption | Time Series : Seasonality

- Seasonality Decomposition:
  - Additive model used to decompose seasonality:
    - Raw Data = Non-Seasonal Trend + Seasonal Component + Random Noise
- Seasonal Component Observations:
  - All sub meters show significant season trends.
  - ~6 month cycle of rising power (sept-march) then falling power (march-sept).
  - Likely corresponds to seasonal temperature/weather changes. May also be related to the amount of daylight throughout the year

Raw Data

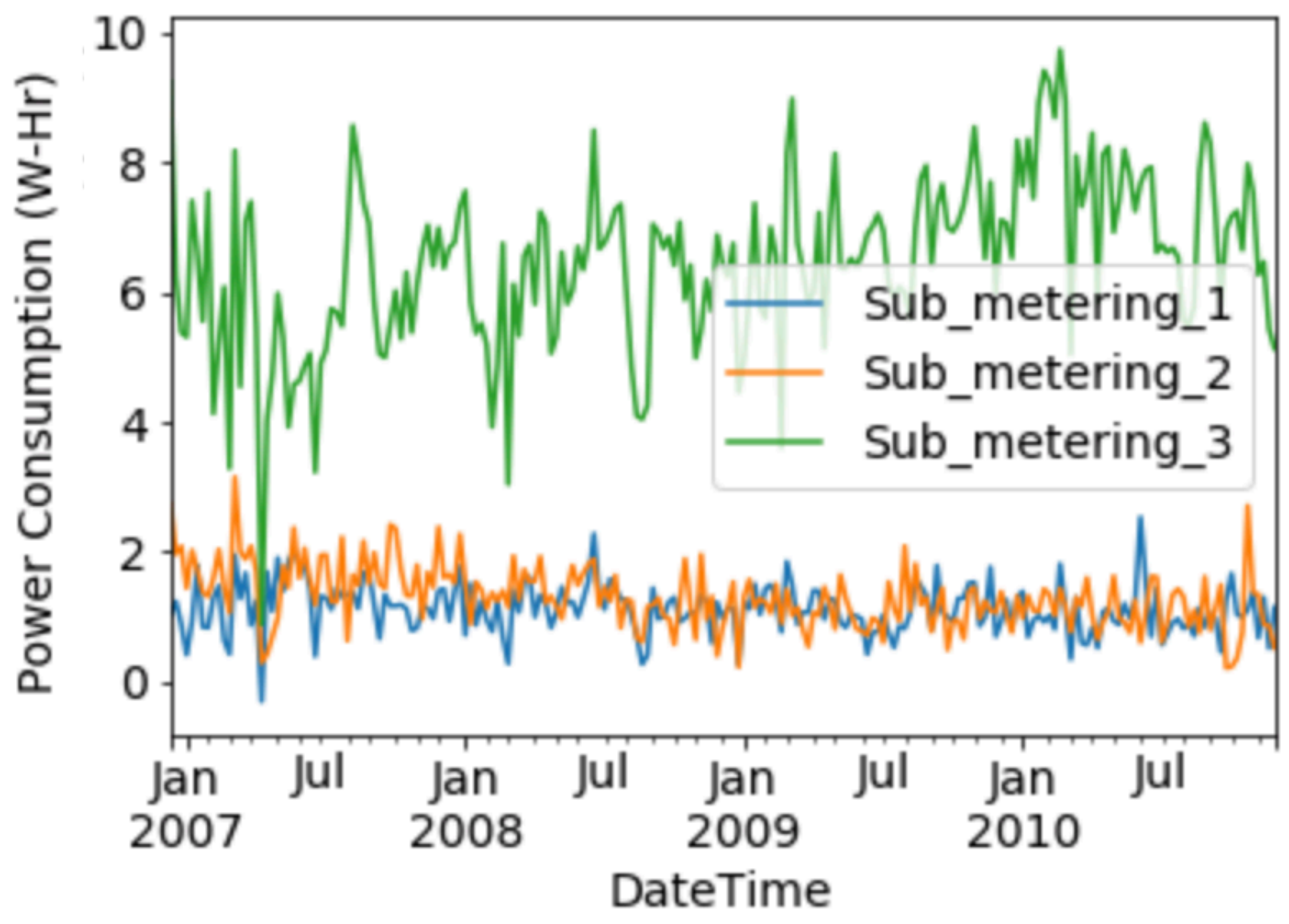


Seasonal Component



Seasonal Adjusted Power

(Non-Seasonal Trend + Random)



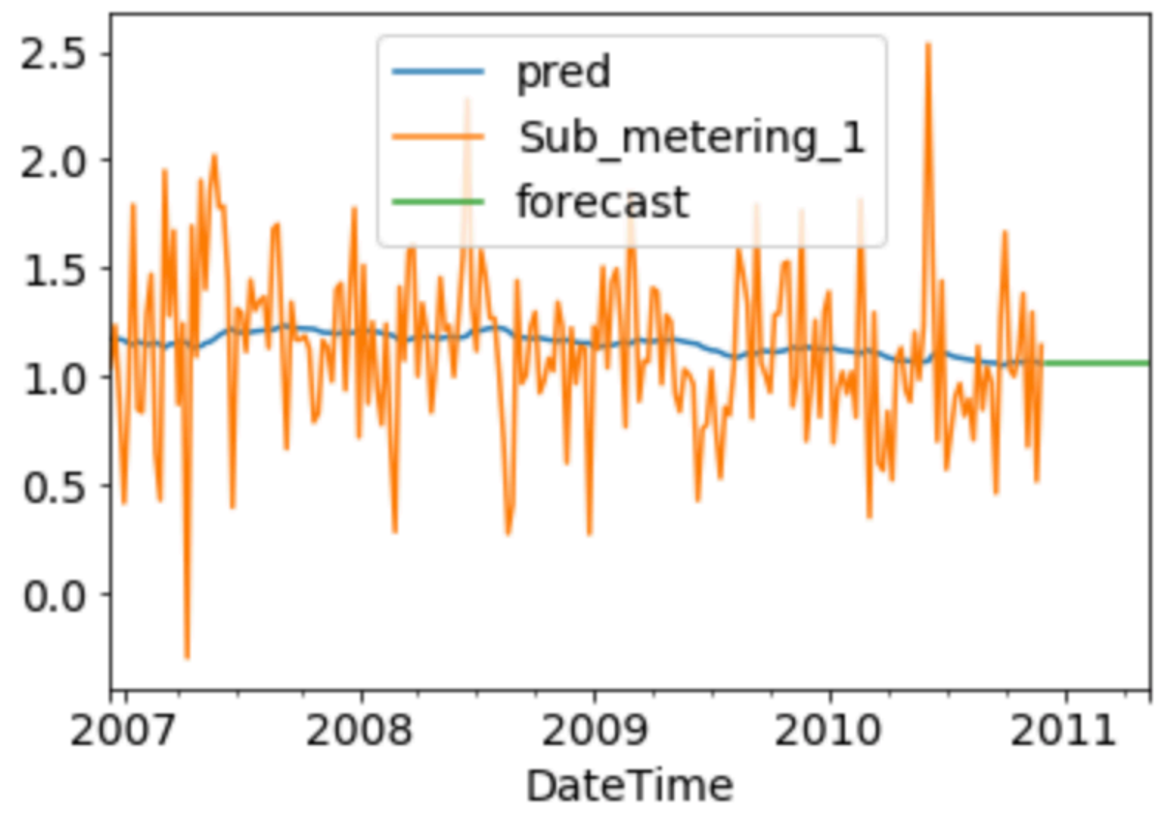
Household Power Consumption | Time Series : Non-Seasonal Trend

- Holt-Winters Simple Exponential Smoothing Model Fit to Non-Seasonal data
- Non-Seasonal Weekly Power: Measured vs. Predicted vs. Forecast
  - Fit prediction (pred) lines highlight non-seasonal trends
    - Sub-meter 1 shows no change in non-seasonal power over time
    - Sub-meter 2 power consumption is reducing over time
    - Sub-meter 3 shows slight upward trend, but may be part of longer term, multi-year, cycle which is beyond the length of this data set.
  - 24 week forecast shown in green

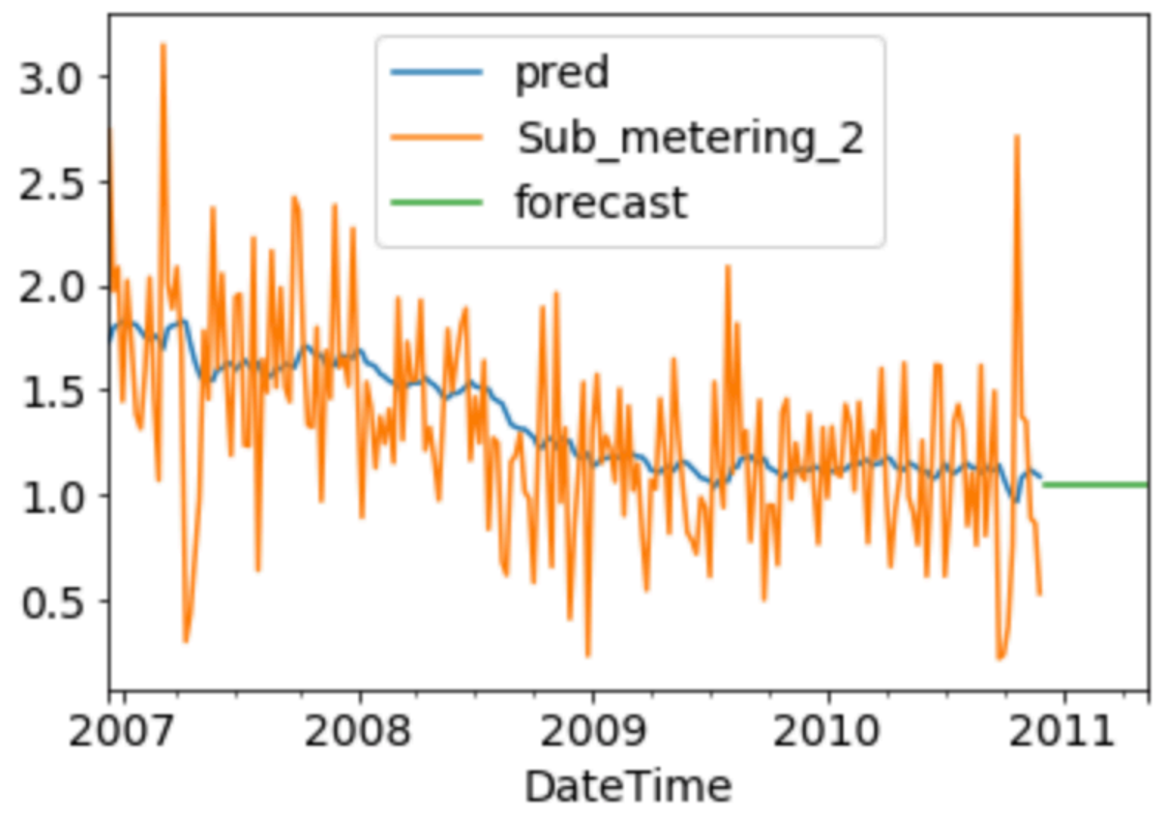
Non-Seasonal Weekly Power (W-Hr)

Measured
Predicted
Forecast

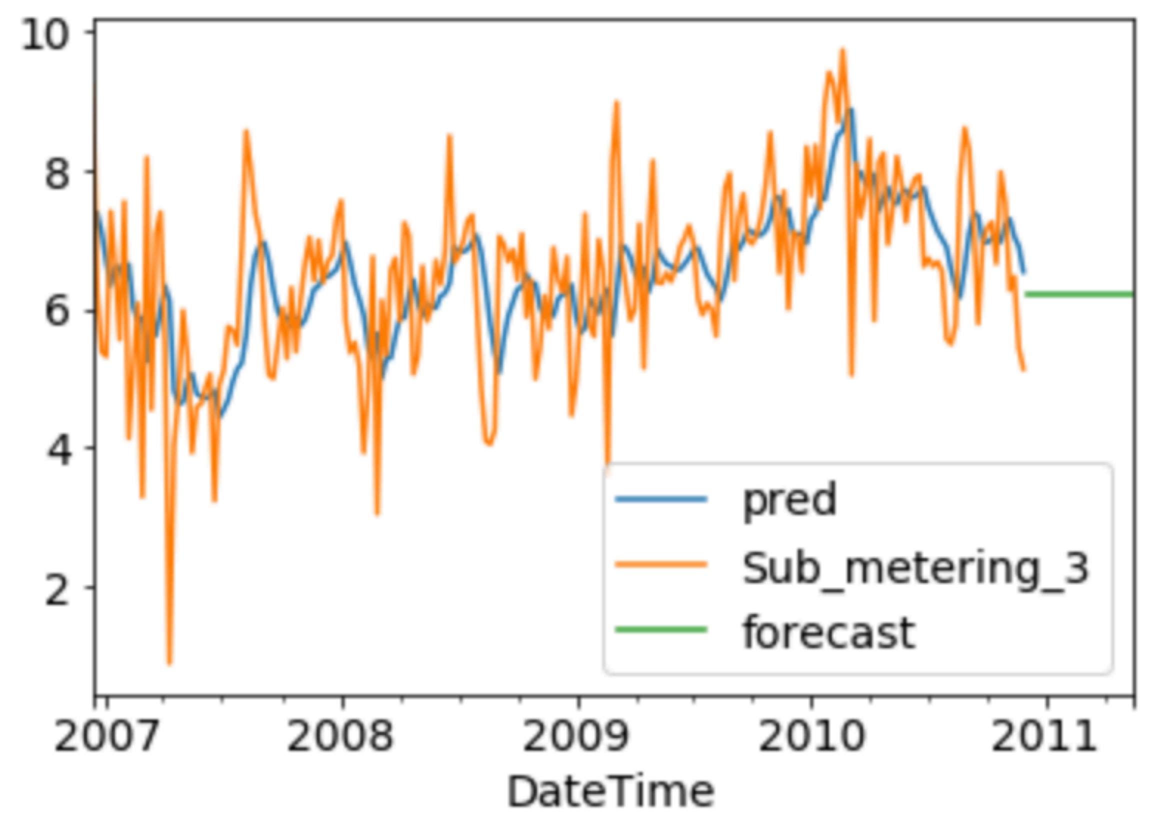
Sub-Meter 1: Kitchen



Sub-Meter 2: Laundry



Sub-Meter 3: Heat + Cooling



Household Power Consumption | Time Series : Summary

- Objectives Achieved:
  - Time series analysis resulted in key insights into daily, weekly, yearly, & seasonal trends for each sub-meter
  - Preliminary models show strong forecasting & prediction ability
- Top 5 Recommendations
  1. Develop daily, weekly, & yearly power consumption metrics. More granular (daily) metrics should focus on length & intensity of peak power consumption throughout the gradual time frame
  2. Weekly metrics should differentiate between weekend & weekday activity/usage to ensure the more spontaneous weekend behavior does not convolute the more routine weekday behavior, thus diluting the potential customer insights
  3. Implement SARIMA model optimized via grid-search to predict/forecast avg. power consumption per week
  4. Use seasonal decomposition via an additive model to show customers the non-seasonal trend in their power consumption
  5. Implement Holt-Winters Simple Exponential Smoothing model to further highlight non-seasonal trends & make forecasts in the non-seasonal power consumption
- Lessons Learned
  1. Plotly is effective graphing library when interactive graphs are required. Matplotlib is a more favorable library when running pipeline-style plotting routines.
  2. SARIMA encompasses ARIMA, so one should just run grid-search on SARIMA & skip ARIMA altogether.
  3. Grid search should be performed using parallel computing methods, since SARIMA has 7 hyperparameters, resulting in a large grid-search space
  4. Seasonal decomposition is a simple & effective method to extract & visualize seasonal frequency, while also allowing observation of non-seasonal trends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