Sensor Fault Detection with a Weighted Ensemble of ARMAX Forecasting Models

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LEC Data Challenge
26 September 2019

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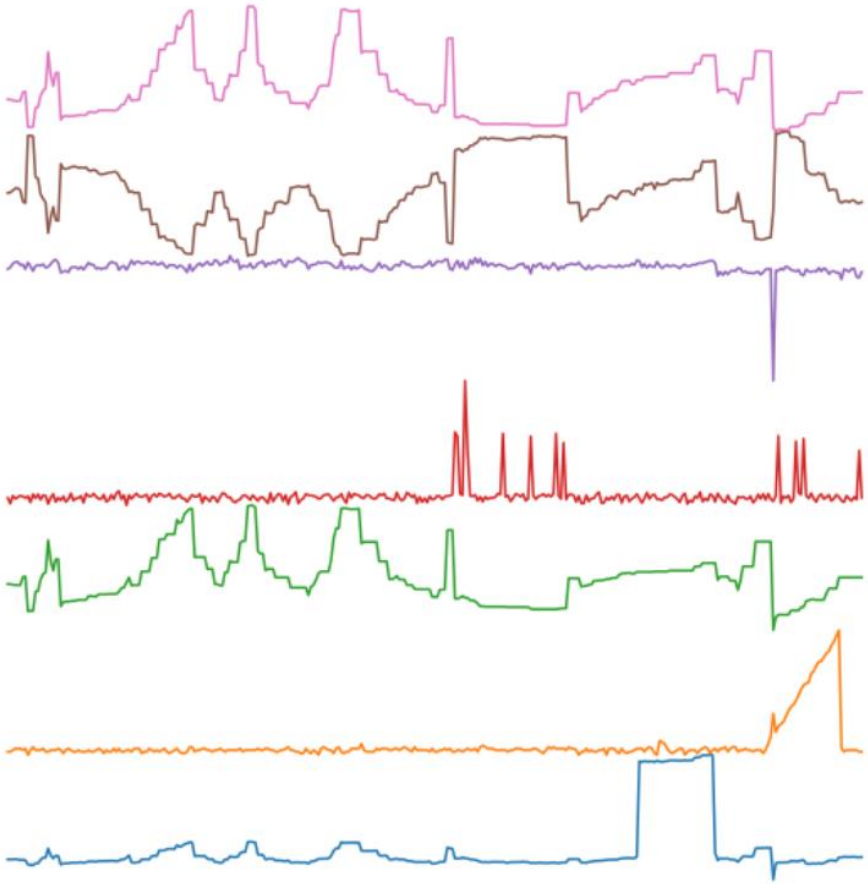
The Challenge

15 sensor measurements

339 points per sensor



The illustration to the right only shows the first 7 sensors.

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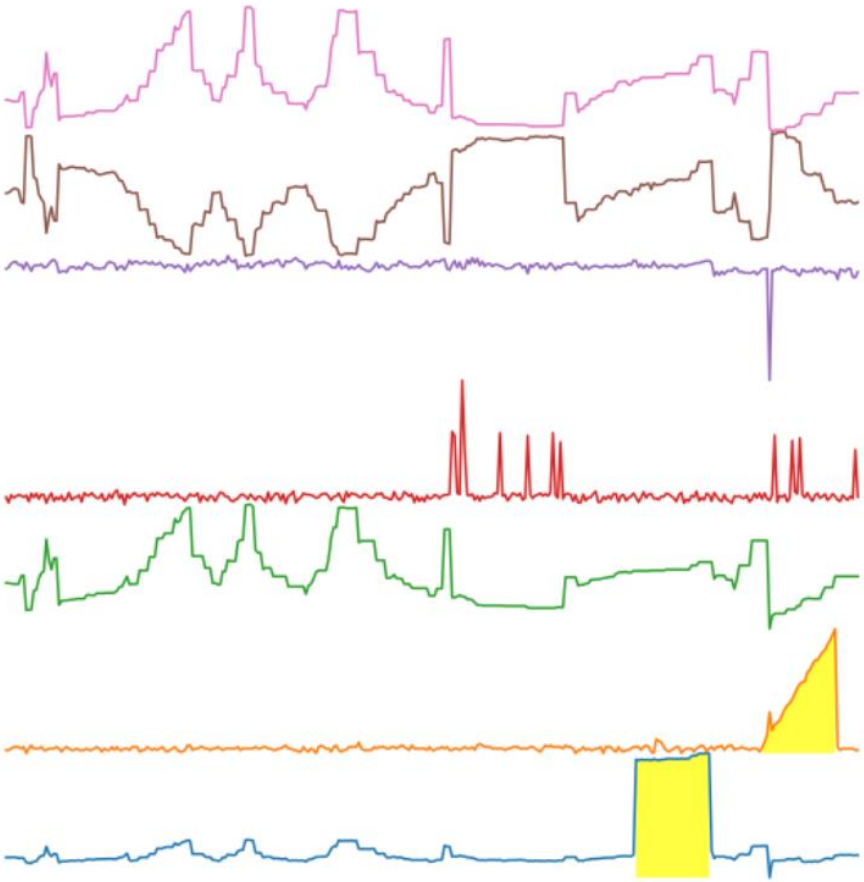
The Challenge (cont.)

15 sensor measurements

339 points per sensor

Only two regions are annotated as faulty!



The illustration to the right only shows the first 7 sensors.

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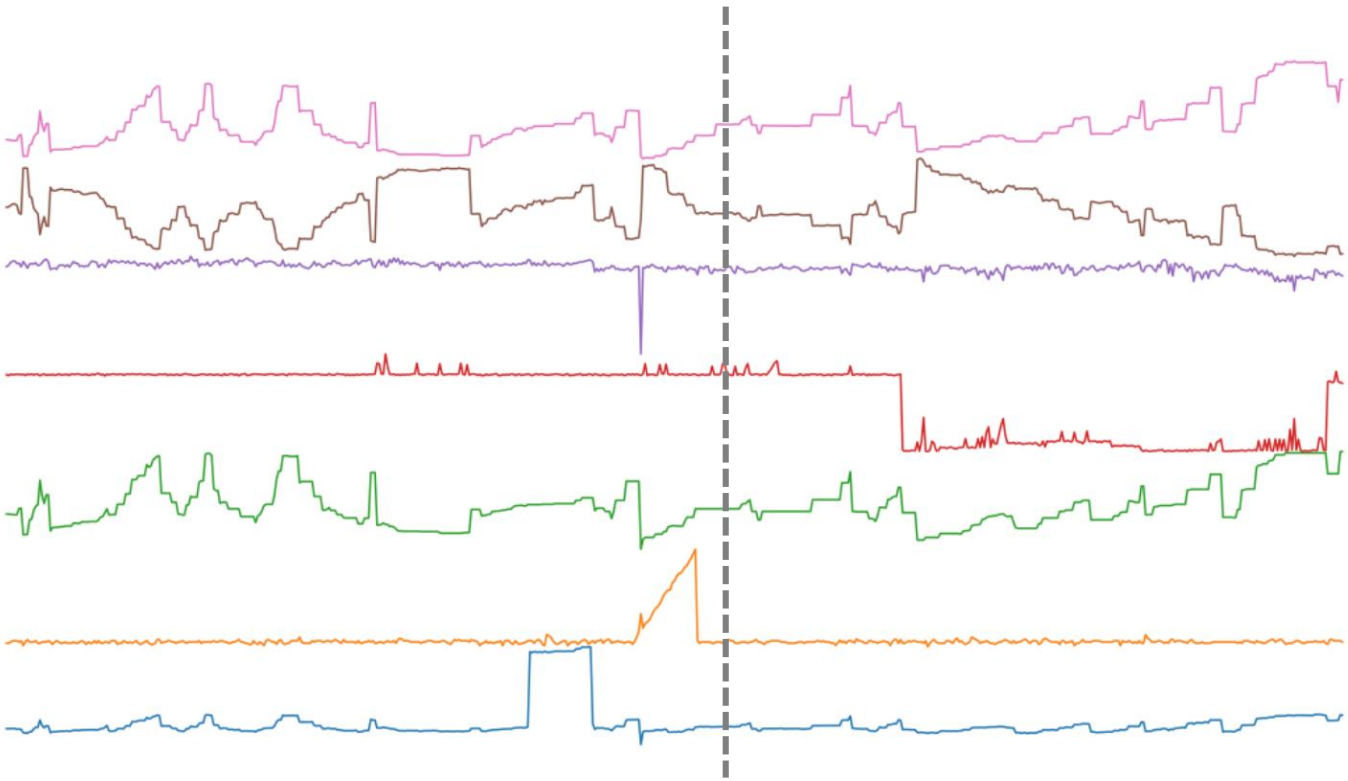
The Challenge (cont.)

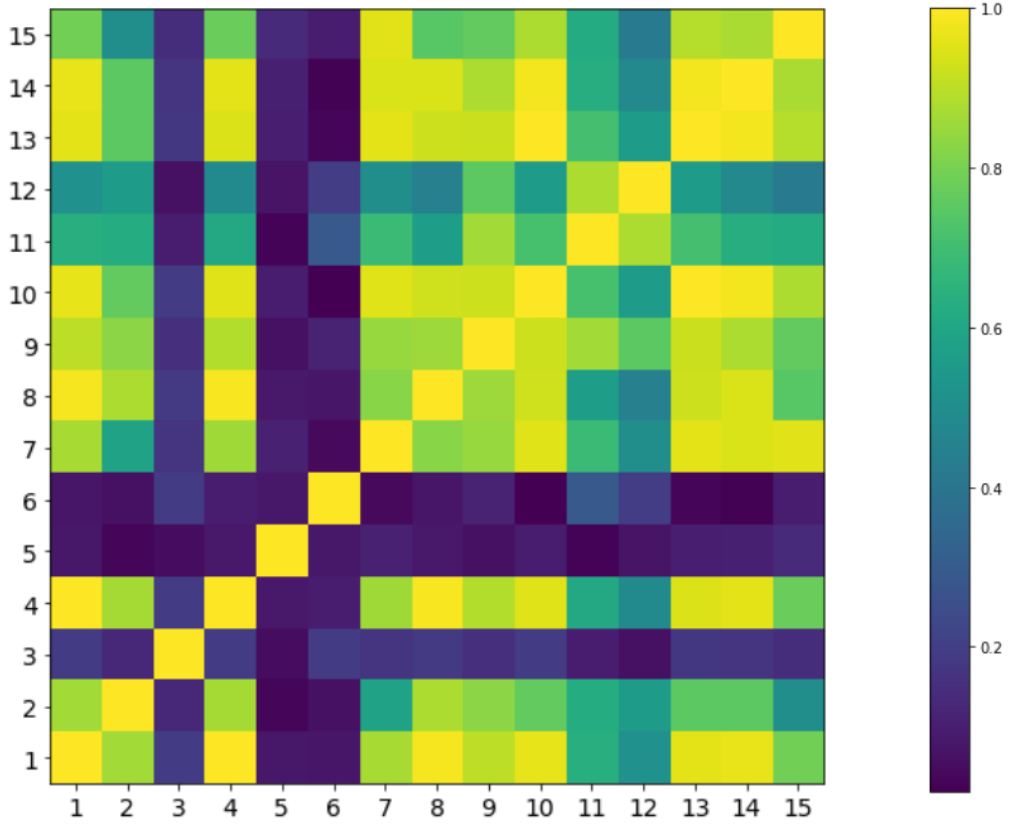
Detect the remaining faults in the test set!



Explorative Data Analysis

Spearman Correlation of sensor measurements

Why?
Be resistant to outliers!



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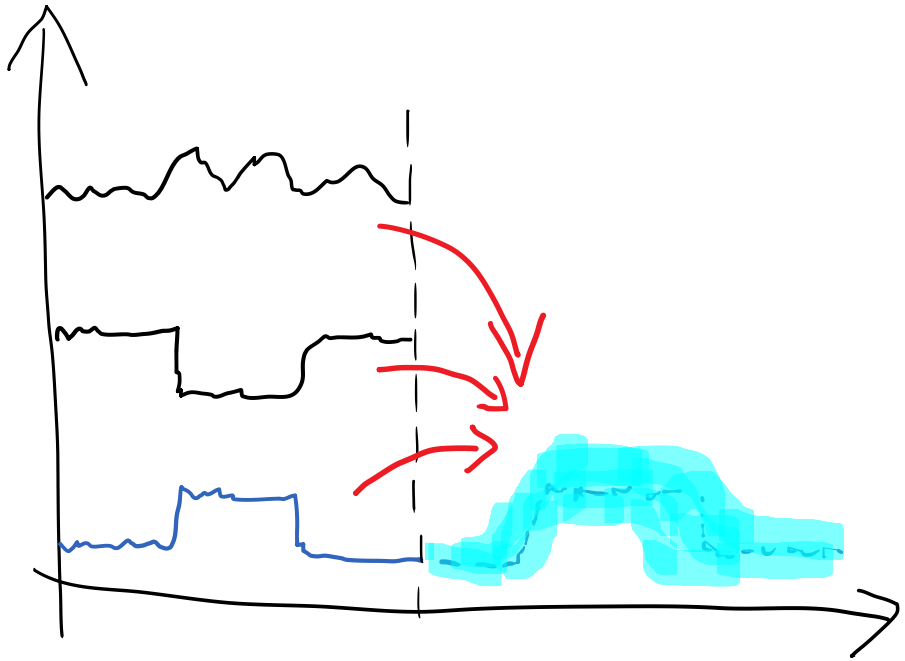
Approach

1. Per sensor, use ***entire past*** to forecast the future



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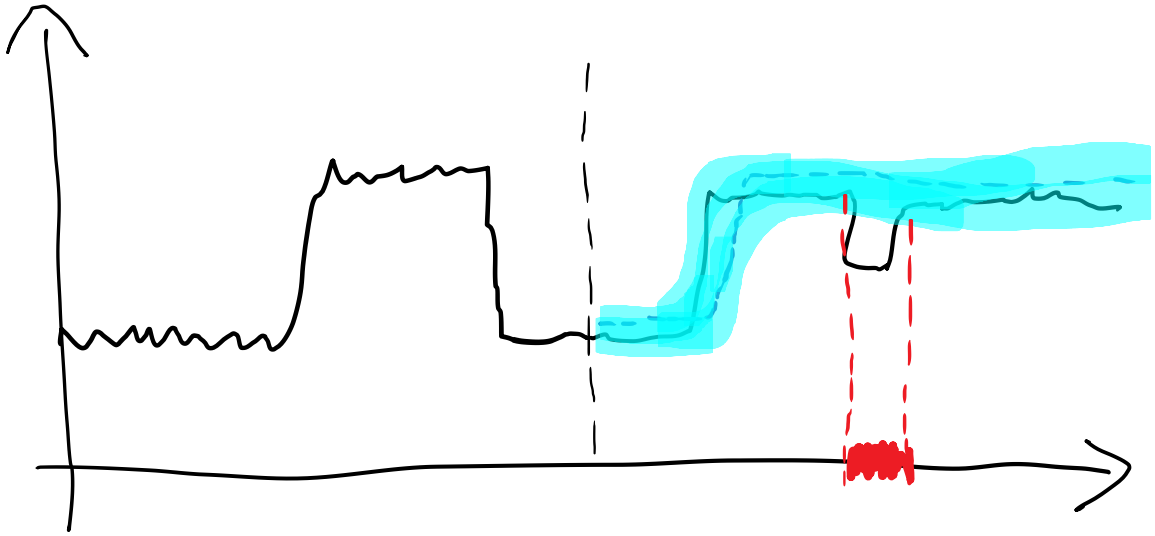
Approach (cont.)

2. Compare the real measurements with the forecast and alert on significant deviations



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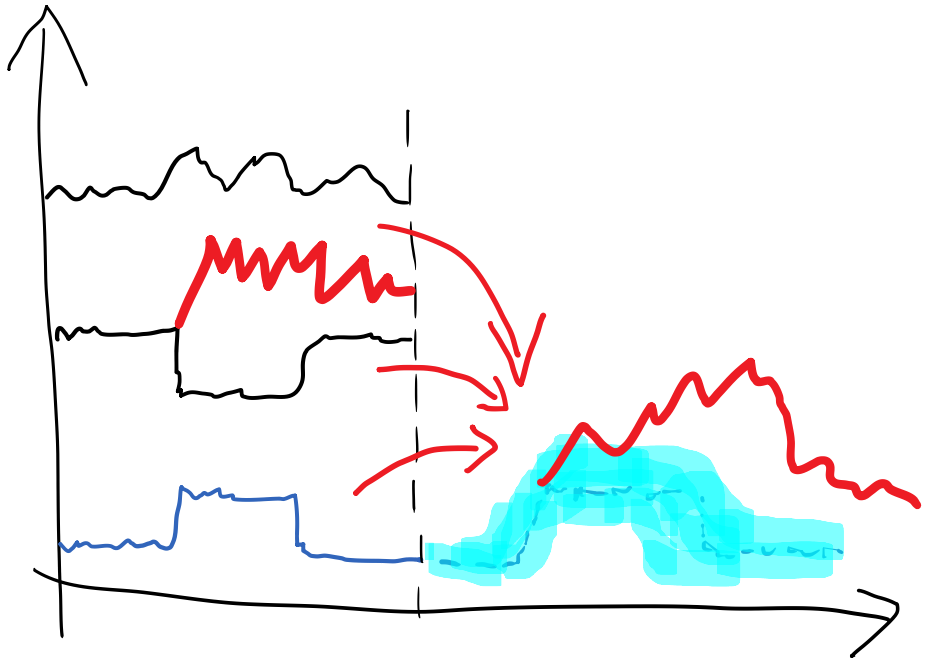
Approach (cont.)

There's a catch!

We can't trust the other sensors, because the could be faulty as well



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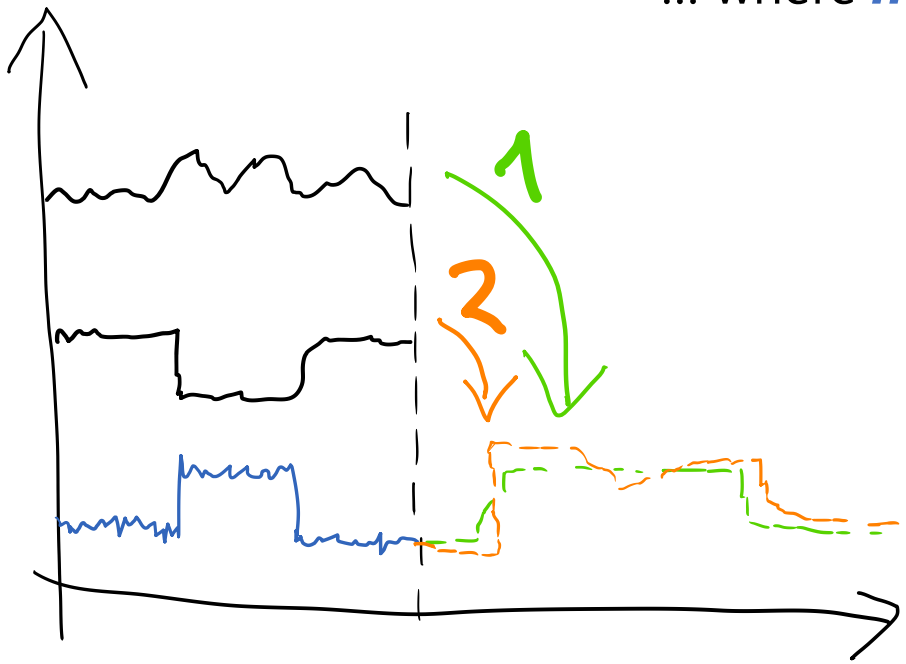
Revised Approach

Use an ensemble of models (feature bagging):
Per sensors, make ***n – 1*** forecasts, and combine them

… where ***n*** is the number of sensors



Why?
A smart combination should somehow neglect faulty predictions

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Method

1. For each sensors, train ***n – 1 ARMAX models***
   - ***AR*** Autoregression *(this sensor's past)*
   - ***MA*** Moving Average *(this sensor's past)*
   - ***X*** Exogenous Factors *(another sensor's past)*

$$X_t = \varepsilon_t + \sum_{i=1}^{p} \varphi_i X_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \sum_{i=1}^{b} \eta_i d_{t-i}$$

c ***AR*** ***MA*** ***X***

Why?
Because we can use the entire history to model the future

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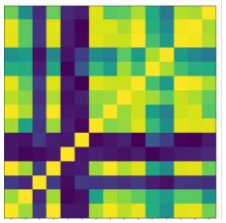
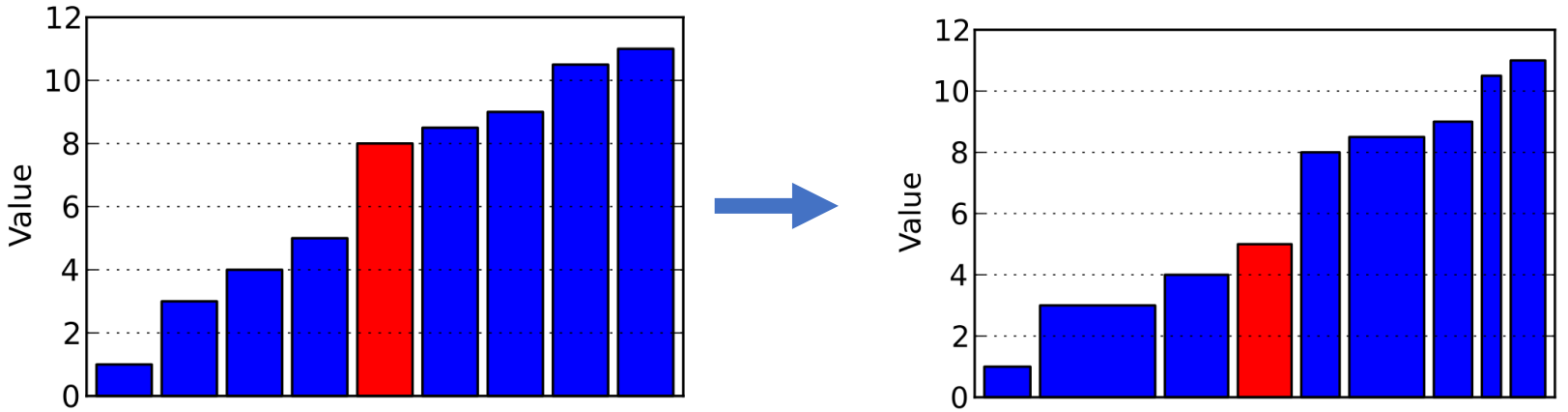
Method (cont.)

2. Combine the forecasts and error bands by taking their ***weighted median***



Remember the correlation matrix from before?
These are our weights!



User Bscan, Wikimedia Commons. 2016.
URL: https://commons.wikimedia.org/wiki/File:Weighted_median.svg

Why? Neglect predictions with weak correlation

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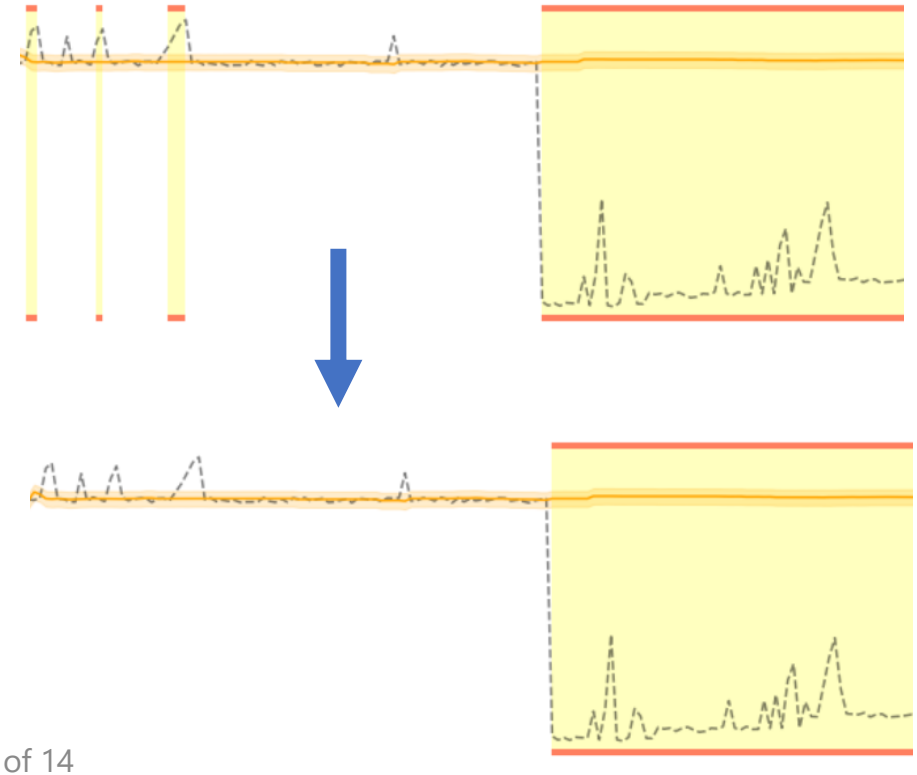
Method (cont.)

There's one more thing: Smooth the final predictions!

*E.g., with a **1D convolution** with window size ~ 5-10*



Why?
Remove uncommon temporal outliers

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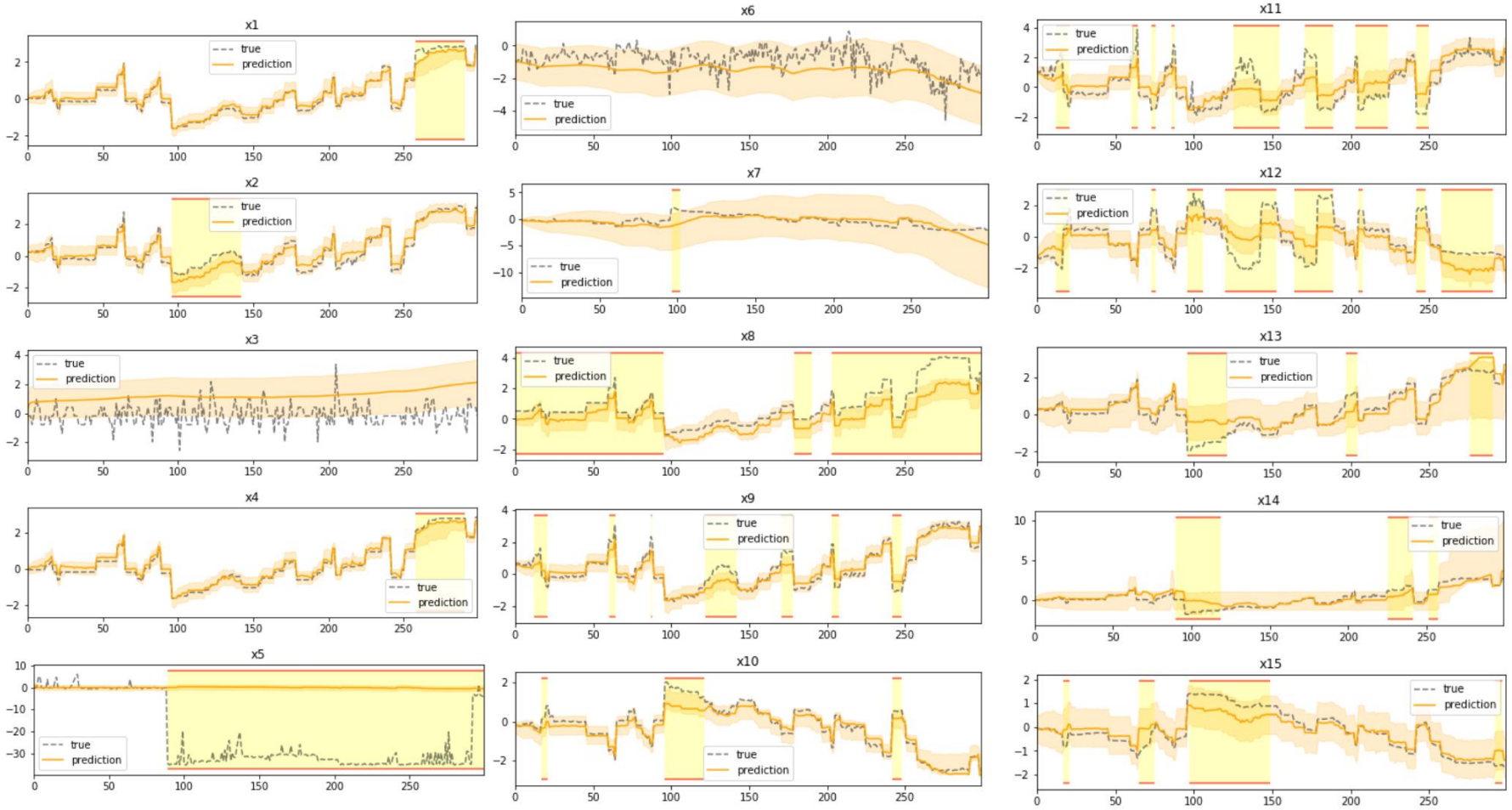
Final Results on Test Dataset



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Conclusion

- Per sensor, train an ensemble of ***n – 1 ARMAX forecasting models*** and combine the predictions with a ***weighted median***, based on their ***Spearman correlation*** coefficient
- **Future Work:** Adjustable sensitivity by computing different quantiles of the error bars

- Check out the Python source code on GitHub

github.com/blu3r4y/lec-data-challenge-2019

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