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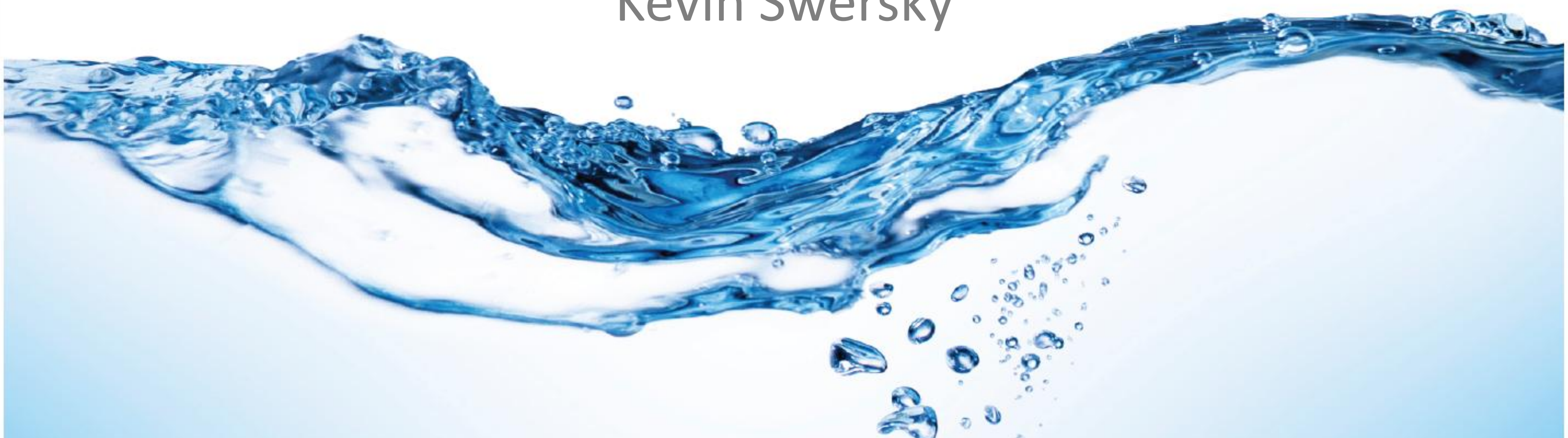
Machine learning for water monitoring, hydrology and sustainability

Kevin Swersky



Joint work with Touraj Farahmand, Nando de Freitas, Michael Osborne, Roman Garnett, Ryan Turner and others

Outline

- Why is water monitoring important?
- How is it done?
- How can machine learning help?
- What have we done so far?

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The water industry

- Fresh water is a limited resource
- Estimates of Canadian economic impact range from $7.3B-$23B
- Industries directly tied to water include:
  - Agriculture
  - Mining
  - Forestry
  - Hydro power
  - Waste management
- Essential to the health and well-being of both people and the environment

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Effects of climate

- Changing climates are creating water shortages and changing flood patterns
- Extreme weather is becoming the new norm
  - Urban supplies are under stress
- From 1994 to 1999 26% of Canadian municipalities reported water shortages due to increased consumption, drought, or infrastructure problems

Water Monitoring

- It is rare to find one level of government with sole jurisdiction over water monitoring. Typically shared by many levels.
- Data is needed for:
  - Allocation, engineering design, prediction and forecasting, environmental impact assessments, transportation, fisheries and ecosystems management, resource extraction, industrial use, recreation
- Monitoring is needed because water is not distributed evenly in space and time
  - Understanding its distribution can lead to solutions when water is temporarily unavailable

The linkage between water and the economy is so compelling that decisions about water are rarely deferred. Decisions that are uninformed almost always have unintended consequences, with impacts on the environment, health, and society.

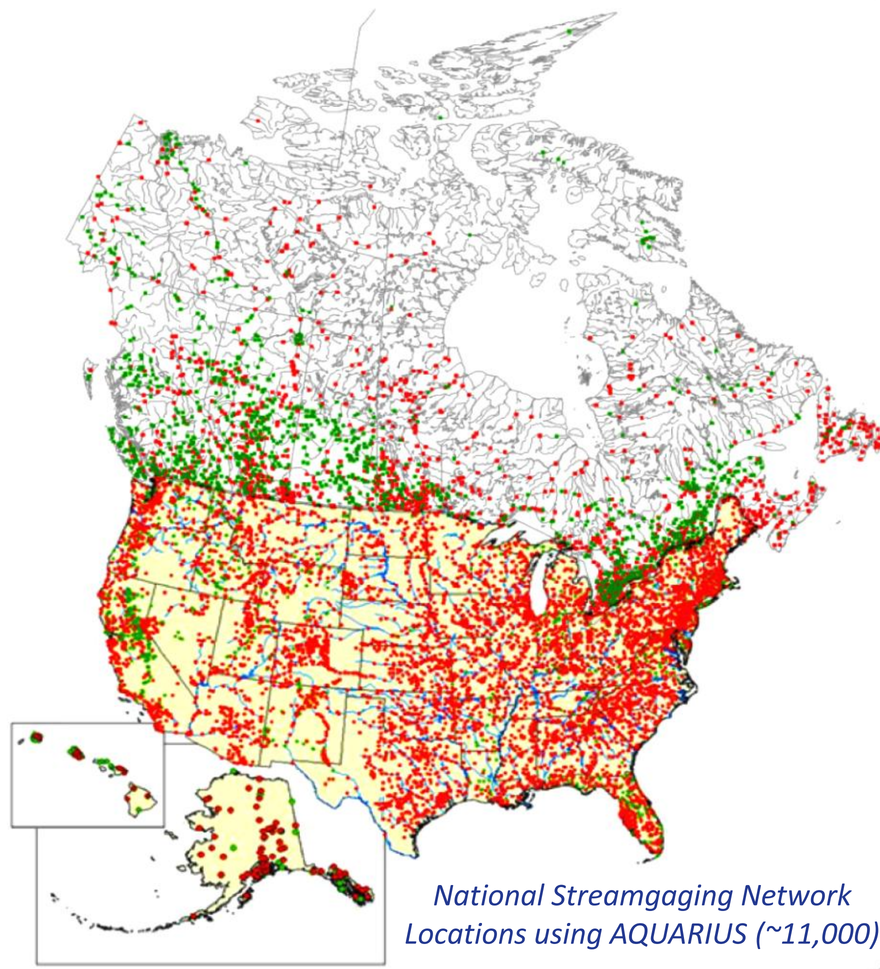
Water monitoring in North America

Survey of Canada

- 2400 stream gage stations
- 28 regional offices
- 200+ end users

US Geological Survey

- 7500 stream gage stations
- 500+ staff using AQUARIUS Rating Curve (GRSAT)



National Streamgaging Network Locations using AQUARIUS (~11,000)

Aquatic Informatics

- Vancouver based software development company
- 200+ customers in North America, Australia, Asia and Europe
  - Federal/State/Municipal Government Agencies
  - Engineering Consultants / Hydropower
  - Any organization responsible for managing water

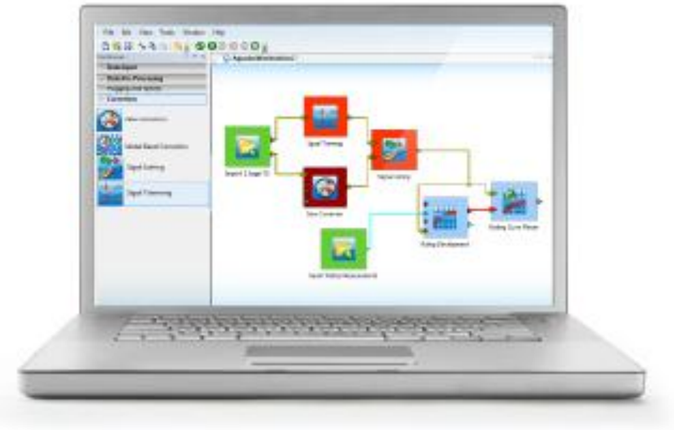
Aquarius

Aquatic Informatics

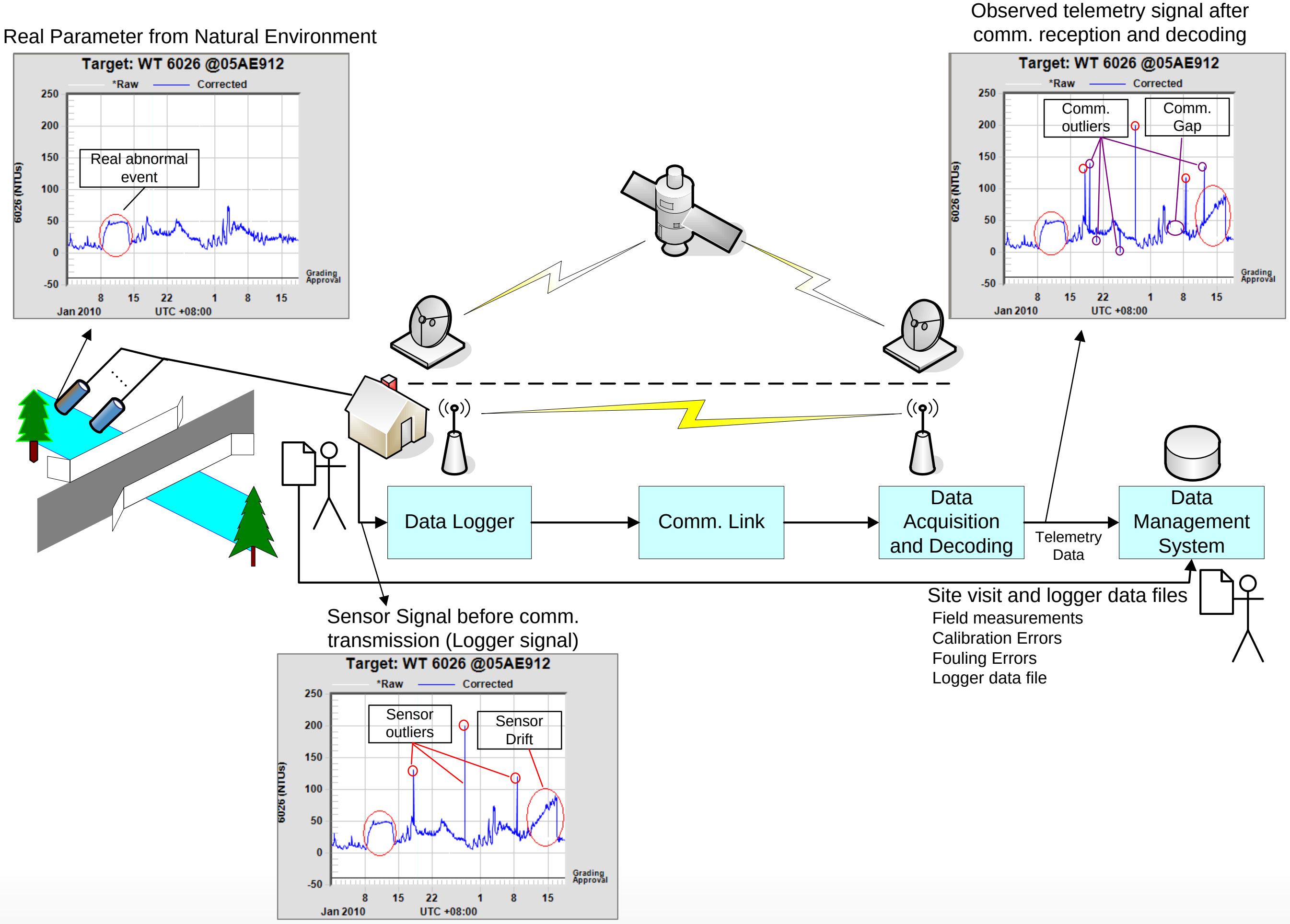
- Provides Customer Support, Customer Service, Training and Product Development

AQUARIUS

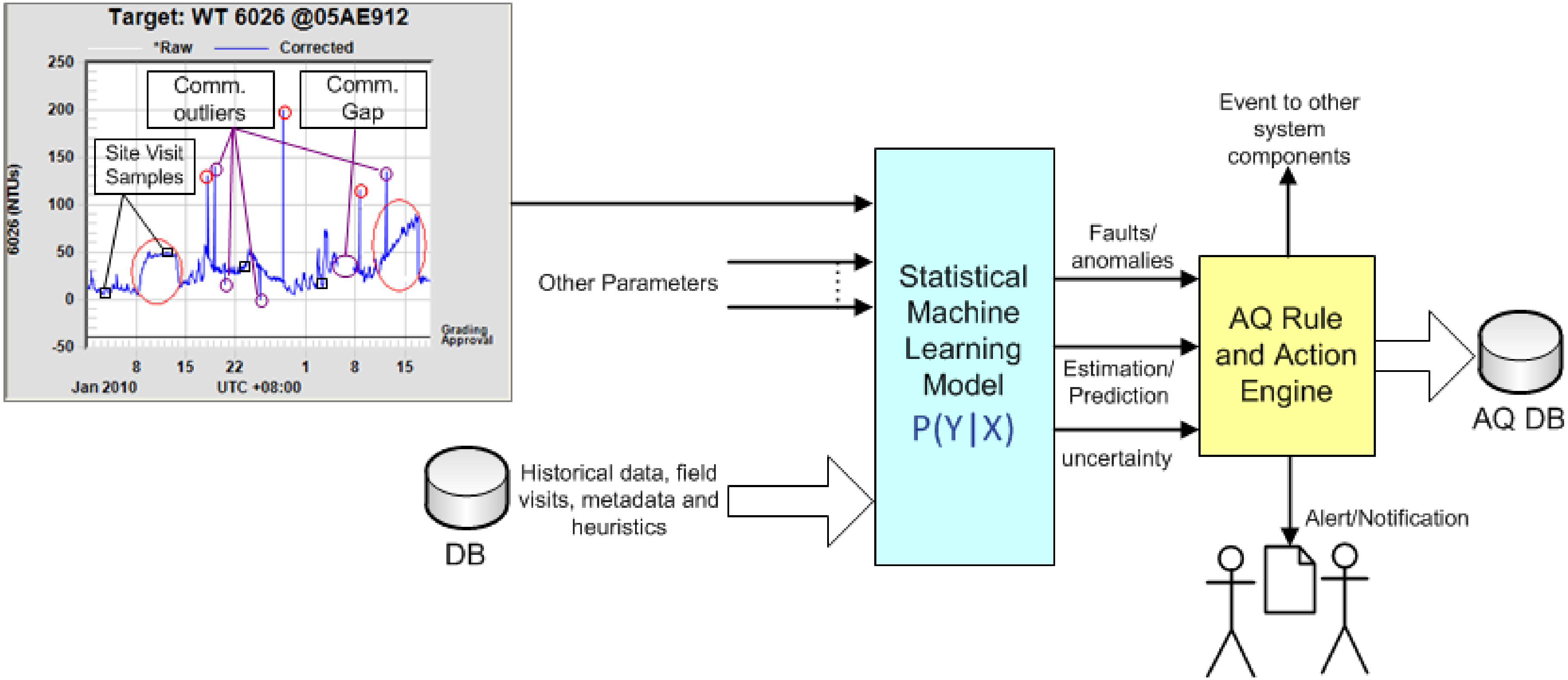
- Is software for hydrologists and water resource managers
- Is the *de facto* standard in North America for hydrometric Time Series data management and Rating Curve development.



Data acquisition and management



Data processing pipeline



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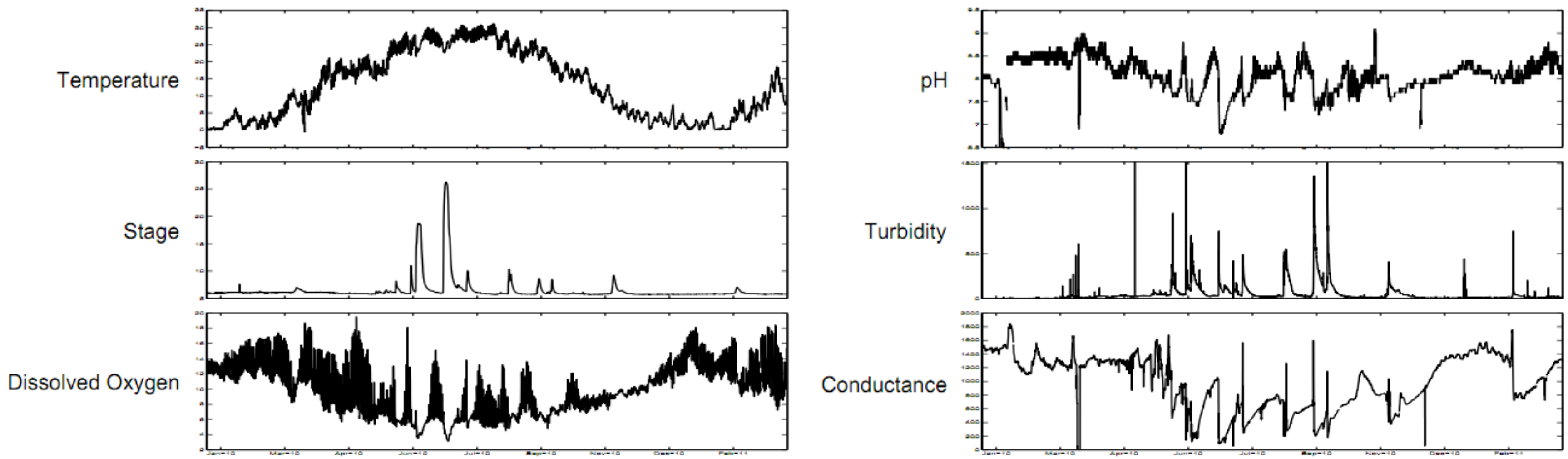
How can machine learning help?

Machine learning can automate, simplify and improve many aspects of water monitoring including:

1) Improving modeling and analysis
2) Detecting and correcting equipment malfunctions
3) Detecting environmental anomalies
4) Predicting the effects of policy decisions
5) Automating and controlling allocation and distribution

Common water quality indicators



For each signal: 1 point every ~5-15 minutes
= 30,000-100,000 points per year per signal

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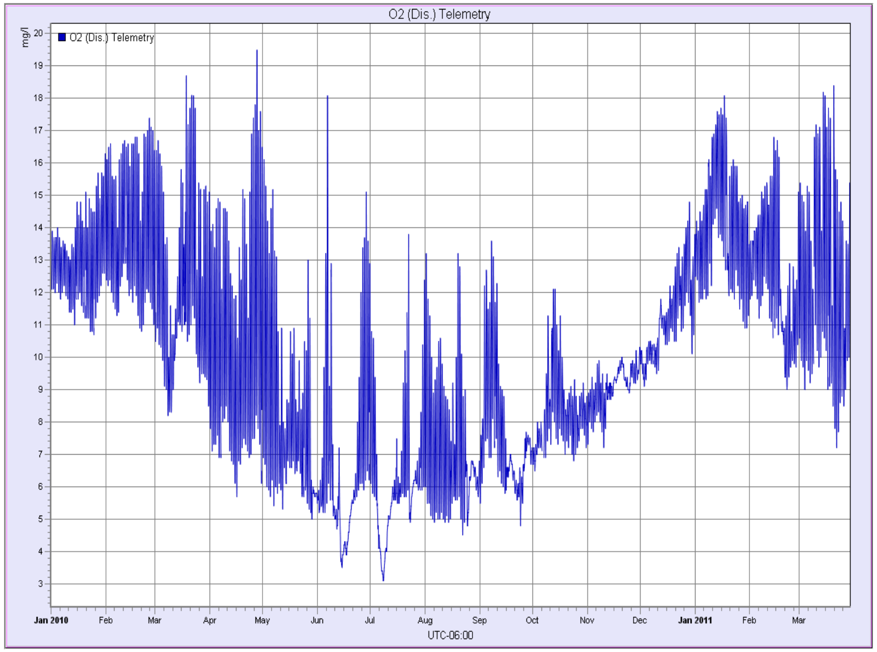
Challenges

Environmental time series in general are complex and hard to model

Problems:

- Highly non-stationary
- Highly non-linear
- Many changes in dynamics
- Can contain outliers, anomalies, gaps, etc.



Our models need to be:

- General
- Flexible
- Robust
- Interpretable
- Fast and efficient for real-time applications
- Easy to setup and use

Our first approach is develop good probabilistic models for several basic problems

- Gap filling/forecasting
- Fault detection
- Anomaly/outlier detection

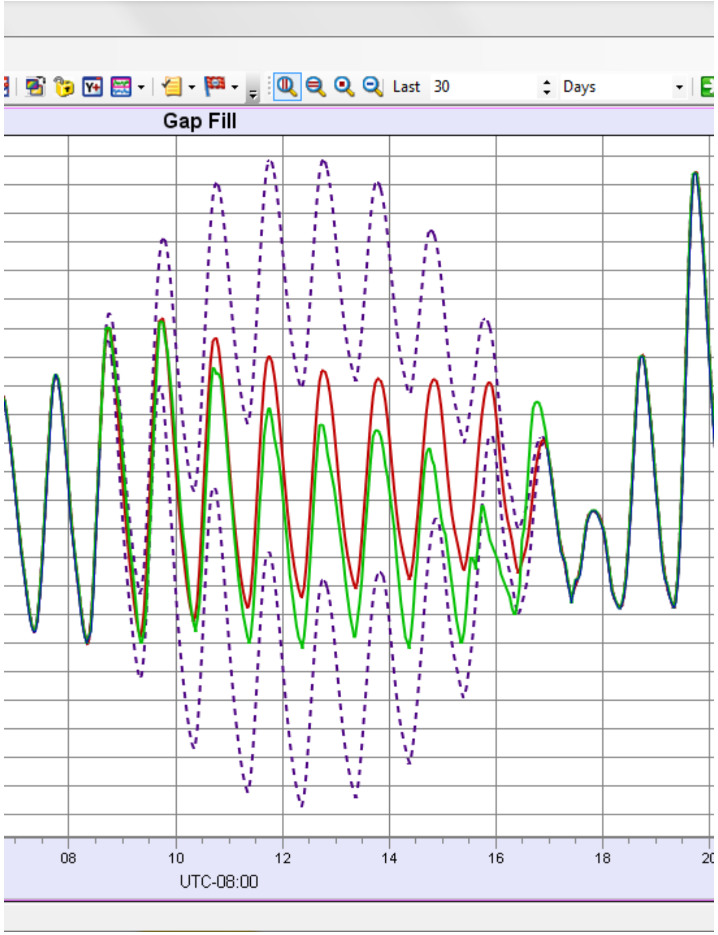
Probabilistic models provide many beneficial properties that are important in an industrial setting

- Consistent, unified framework
- Provides uncertainty in results
- Suggests natural extensions to deal with many kinds of issues

Univariate models

We use Gaussian processes to model univariate series

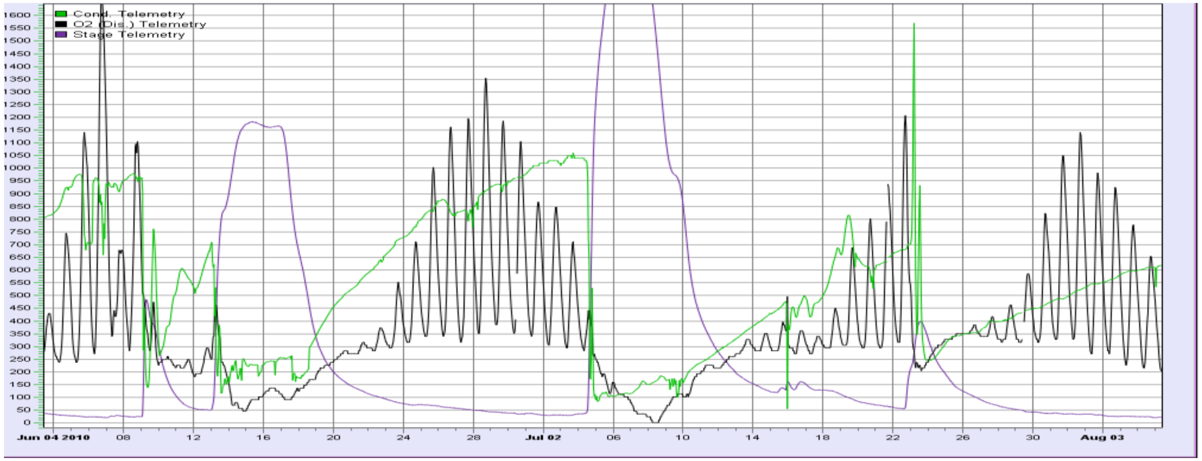
- Flexible, easy to use, tunable parameters are intuitive (choosing kernels)
- Sparse Gaussian processes can help with speed (Snelson 2006, Titsias 2009)
- Issues: heteroscedasticity, nonstationarity, spike noise, changepoints



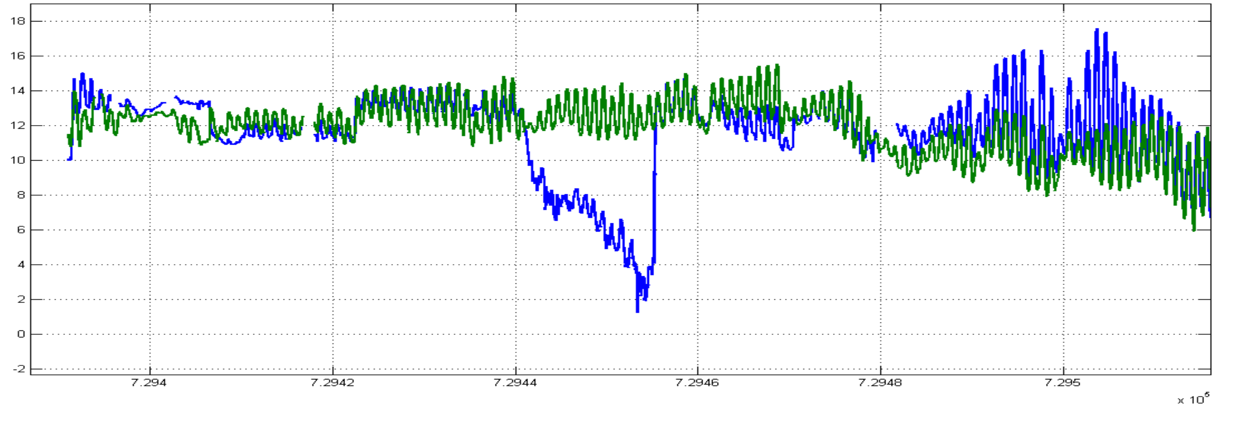
The power of redundancy

We can exploit correlated signals to build more robust models. Even simple linear methods work well under this regime.

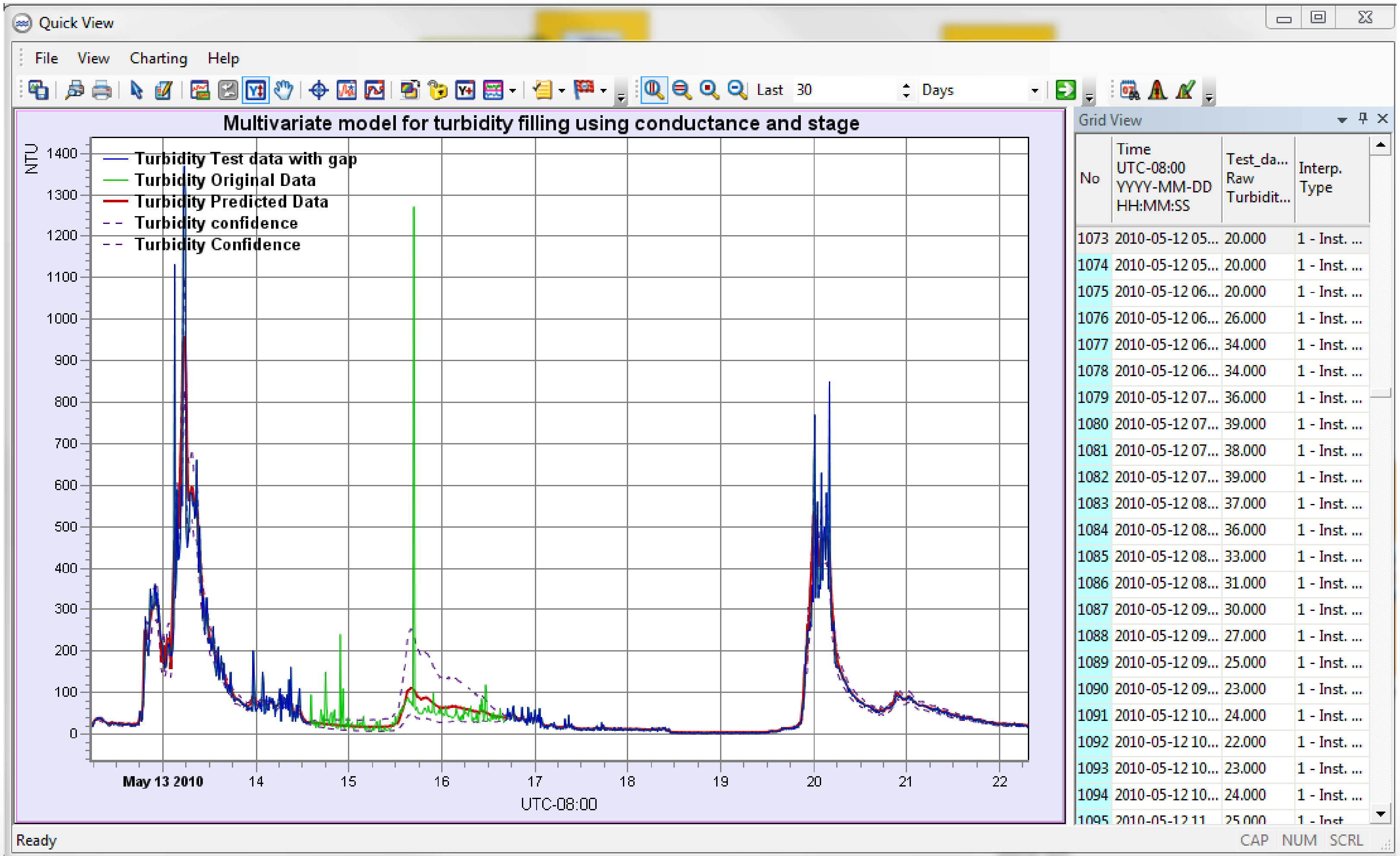
Nonlinearly correlated signals from same sensor



Linearly correlated signals from different sensors



The power of redundancy



The power of redundancy

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Handling sensor faults

- The Gaussian distribution is closed under affine transformations
- We make the assumption that a fault can be represented as an affine transformation of the observation
- We can model a variety of faults by modelling the observations y with time input t as (Garnett 2009):

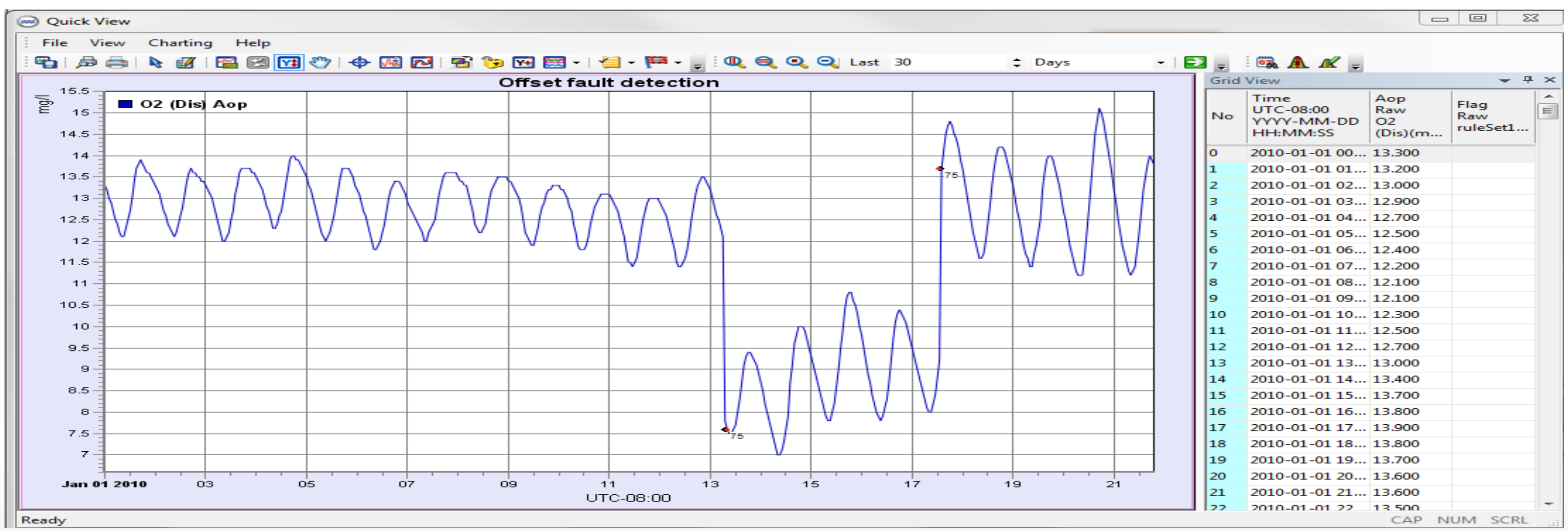
$$P(y|t) = N(y|A\mu(t) + b(t), \Sigma_m + \Sigma_n)$$

  - Where $\mu(t)$ is the model prediction, Σ_m is measurement noise.
  - A, b specify the contribution of the fault, A is a diagonal matrix
  - Σ_n is the noise contribution from the fault

Sensor offset

For example, a sensor that undergoes a constant offset c in a faulty region F:

- $A(i_t, i_t) = 1$
- $b(t) = \begin{cases} c & \text{if } t \in F \\ 0 & \text{else} \end{cases}$
- $\Sigma_\text{n} = 0$



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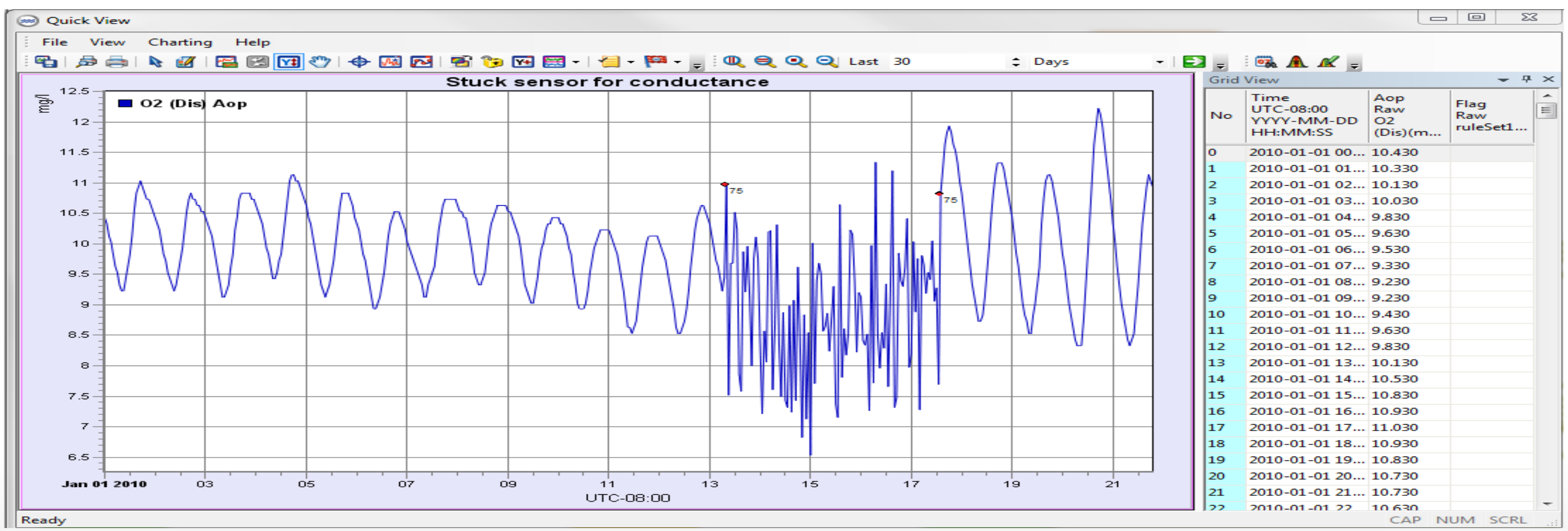
Stuck sensor

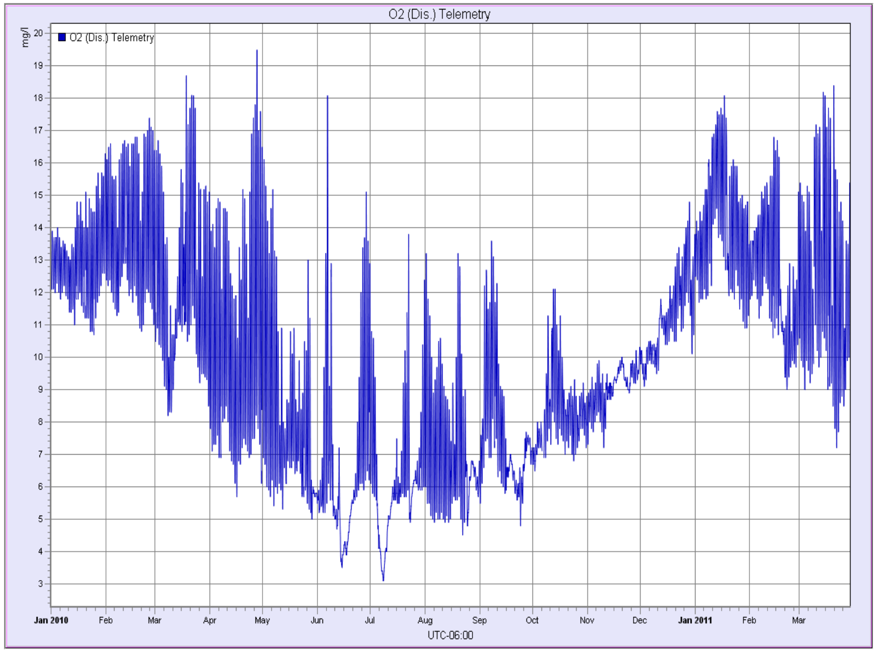
A stuck sensor that outputs some constant reading c plus noise:

- $A(i_t, i_t) = \begin{cases} 0 & \text{if } t \in F \\ 1 & \text{else} \end{cases}$
- $b(t) = \begin{cases} c & \text{if } t \in F \\ 0 & \text{else} \end{cases}$
- $\Sigma_n(i_t, i_t) = \sigma_n^2$



Sensor drift

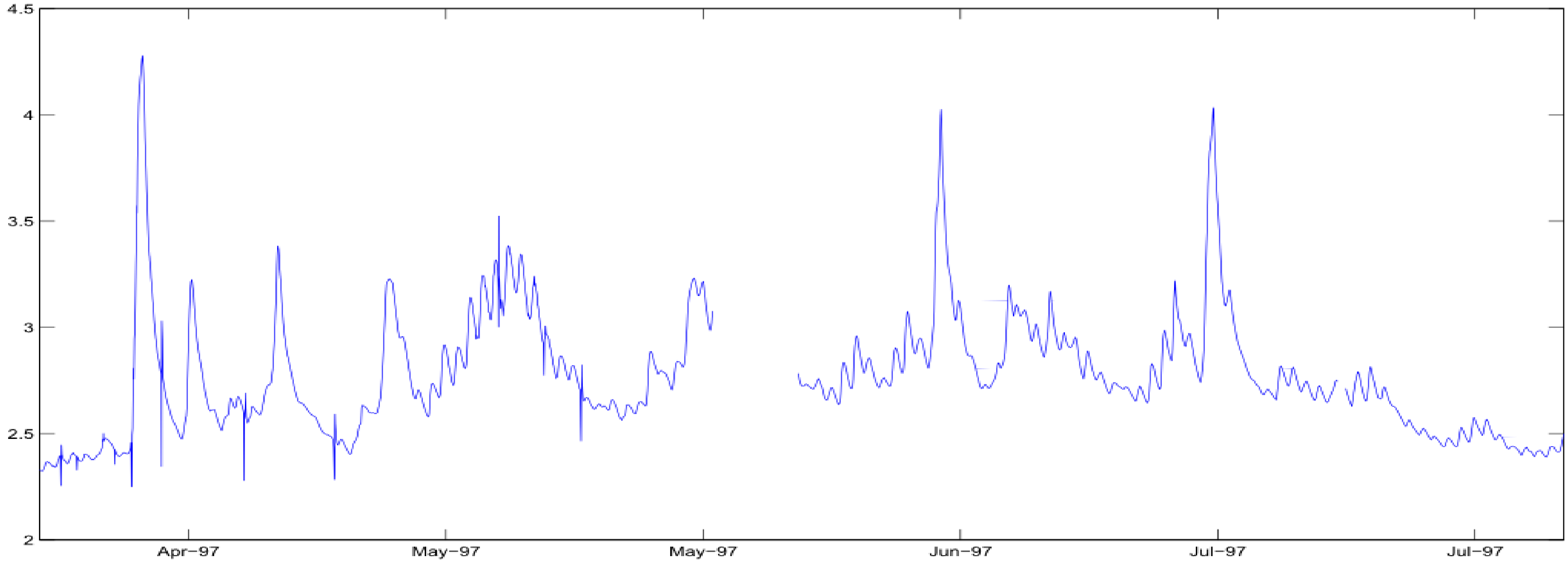
- Dealing with sensor drift is much harder!
- Drifts are often nonlinear due to sensor design
- In univariate signals, it is often difficult to even “eyeball” sensor drifts
  - Sensors are usually recalibrated every few weeks before drift becomes too severe
- Either we need to develop <u>really good</u> univariate drift models, or utilize sensor networks



Case study: fishkiller

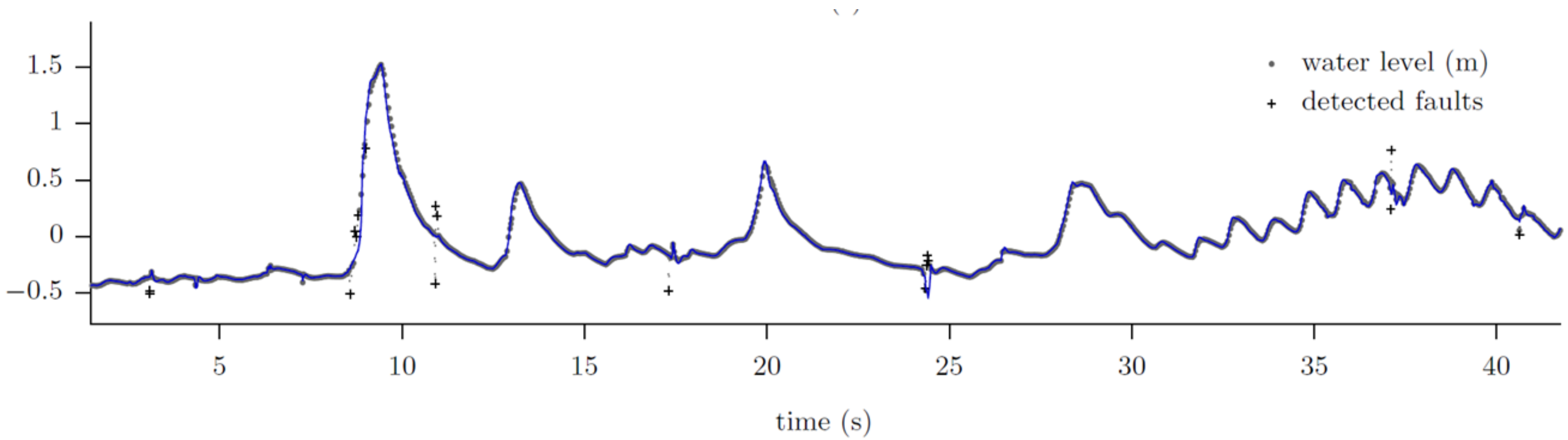
This is a time-series for a river in British Columbia measuring water level in meters

- Water level is determined by a nearby dam upstream
- When “jitters” occur, salmon get trapped and drown
- Detecting and preventing these events will save thousands of fish



Dealing with anomalies: the fault bucket (Osborne 2011)

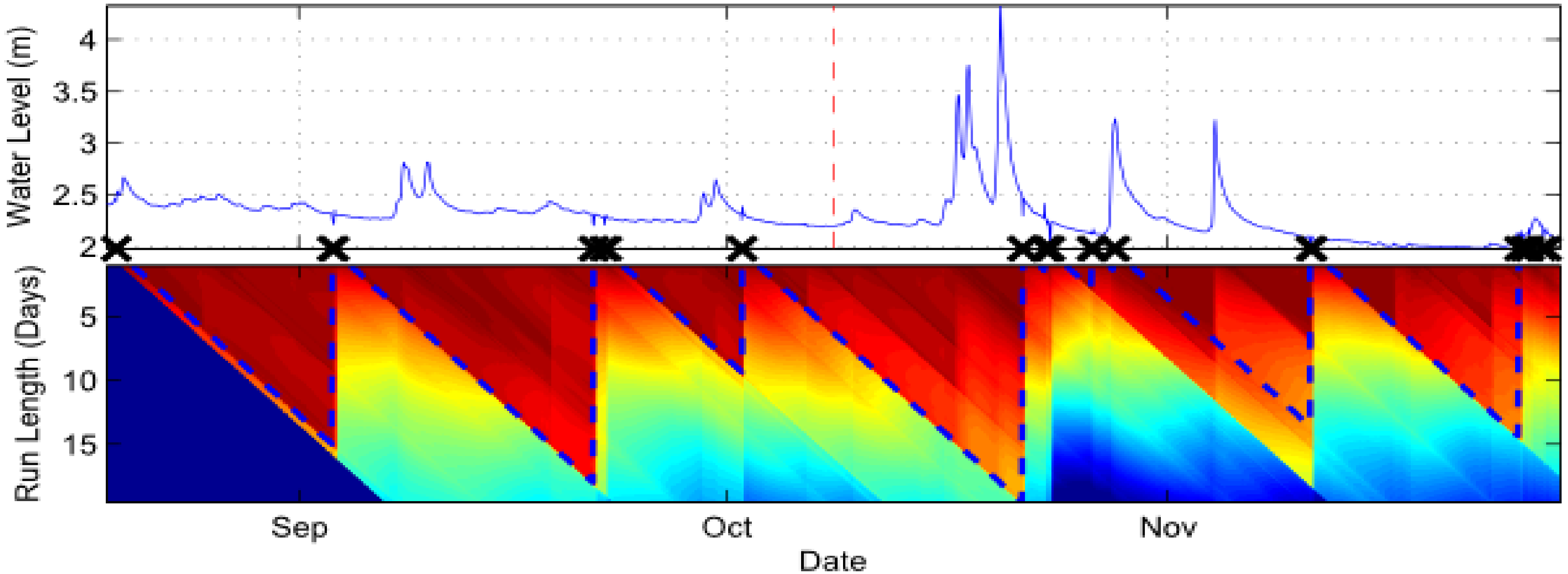
- Model faults as being a Gaussian with large variance
  - Each point can be faulty or not faulty
  - 2^n ways of classifying every point
- We make several approximations to get the posterior probability of faultiness for a current point
  - The 2^{n-1} posterior probability of past faults can be approximated by a single Gaussian
  - The present faultiness is independent of past faultiness



The supervised approach (Turner 2011)

Supervised extension to Bayesian Online Changepoint Detection (Turner 2010) algorithm.

- BOCPD trains a predictive distribution using data since the last changepoint which is a latent variable
- The supervised extension trains the conditional over run lengths directly



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Future Work

- Need <u>fast</u> nonlinear regression models for nonstationary data with multiple correlated outputs and side information that don't require much hand-tuning
- Consider supervised approaches for modelling sensor failures and anomalies
- How do we elegantly combine these models into a cohesive system?
- Long term work: lots of problems in e.g. time-series classification/motif detection, optimal control, multitask learning, etc.
- Really long term work: models to predict spatiotemporal changes for different decisions, models for automated control systems
- Will likely need to combine machine learning models with physical models

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Thank you!