Gaussian Process Regression in Laser Plasma Experiments

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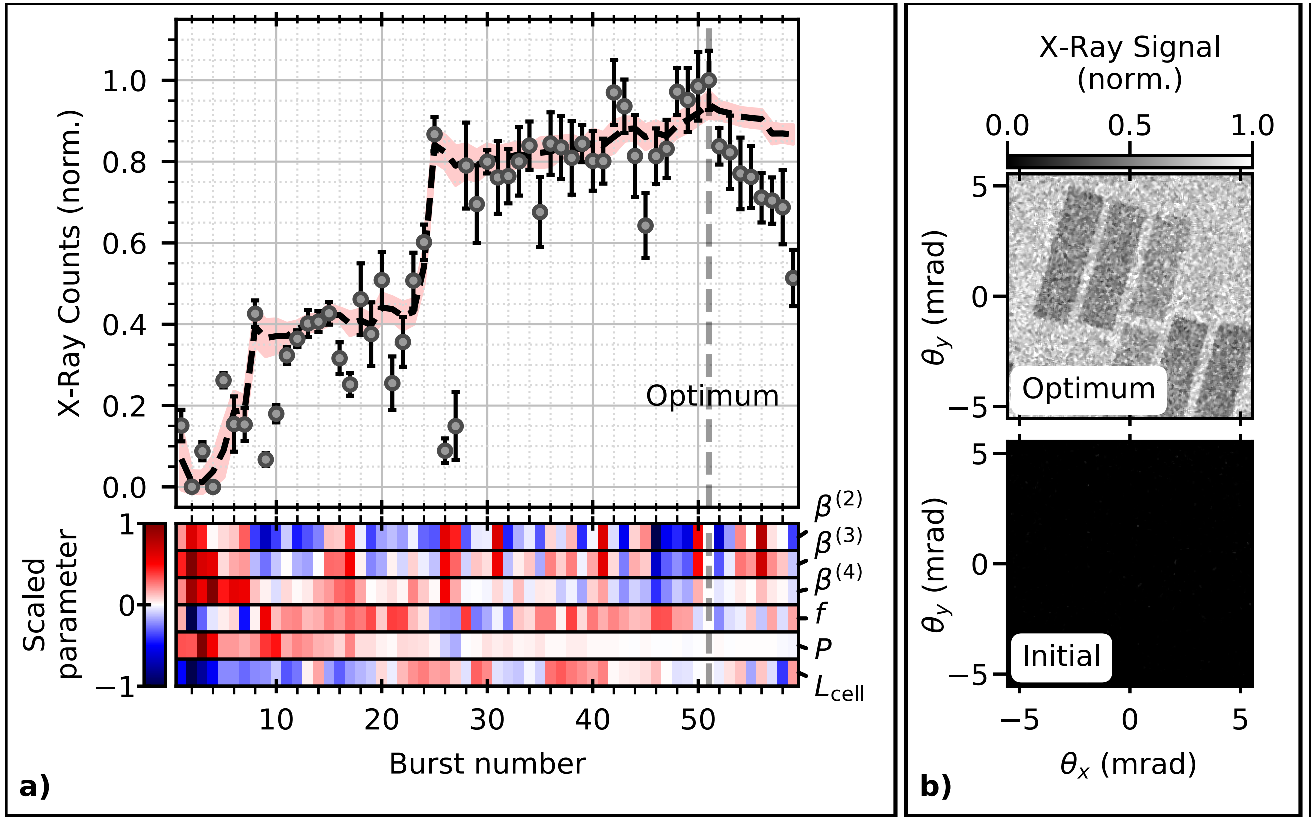
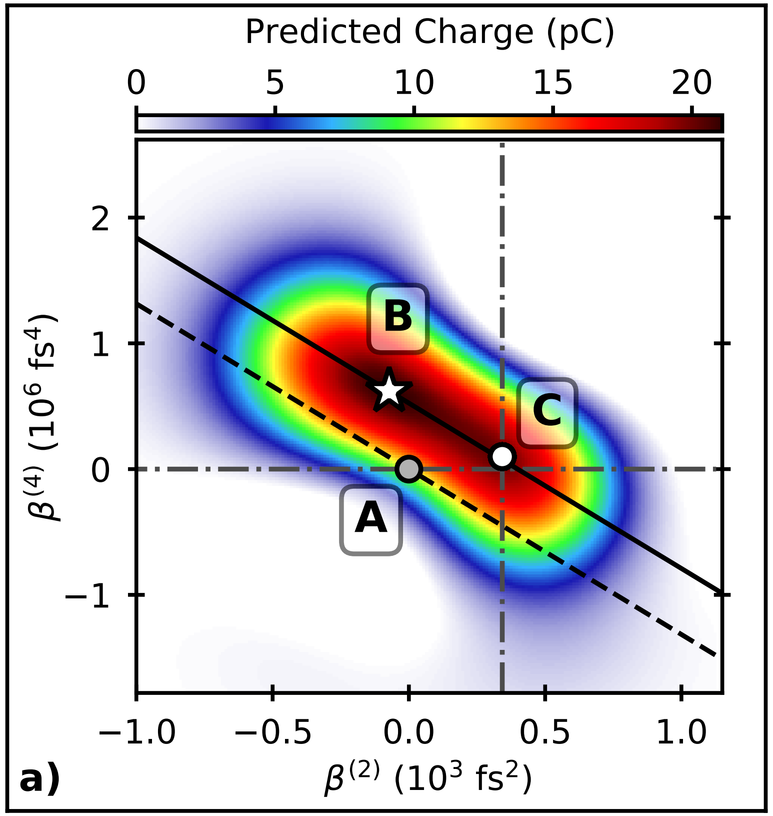
Artificially Intelligent Laser Plasma Accelerators

- Autonomous optimization of Laser Wakefield Acceleration using Machine Learning
- Used to optimize electron and x-ray beams in autonomous laser wakefield acceleration experiments

Optimisation of x-ray beams for imaging applications



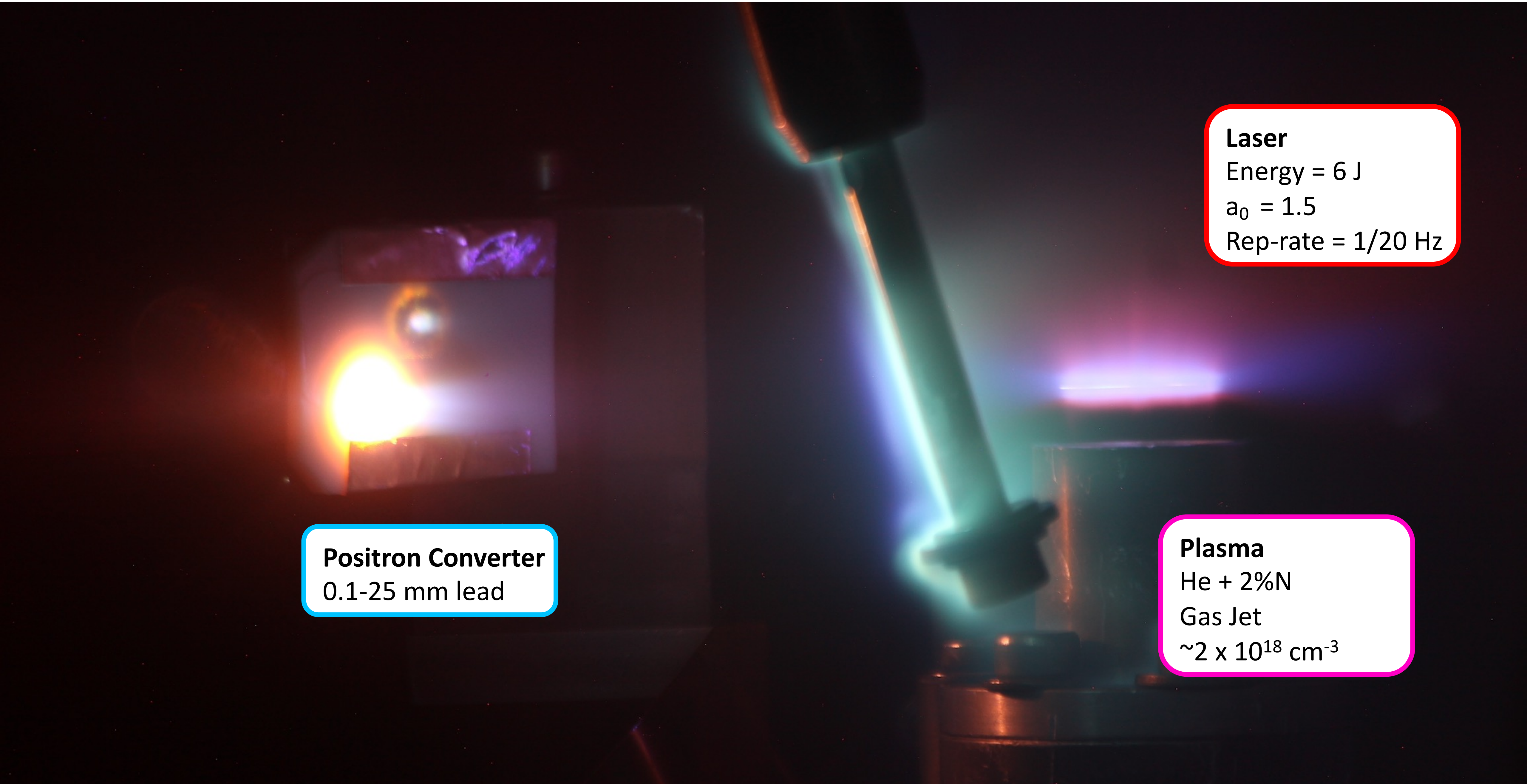
Builds statistical models for inferring physics



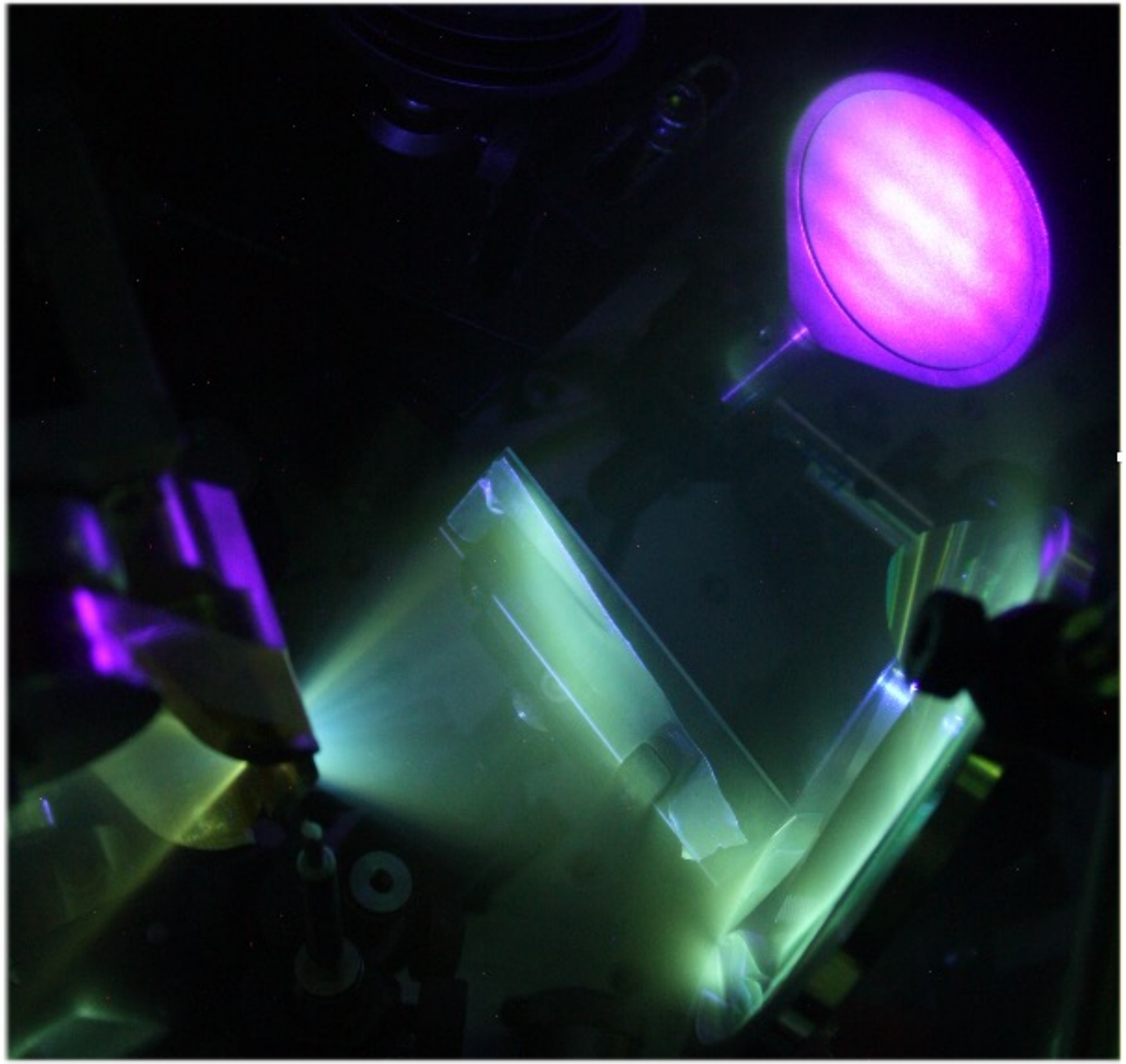
Automation and control of laser wakefield accelerators using Bayesian optimisation

R. J. Shalloo, *et al. Nature Comms.* **11,** 6355 (2020). https://doi.org/10.1038/s41467-020-20245-6

Experiment for Generation of Positrons with a LWFA electron beam

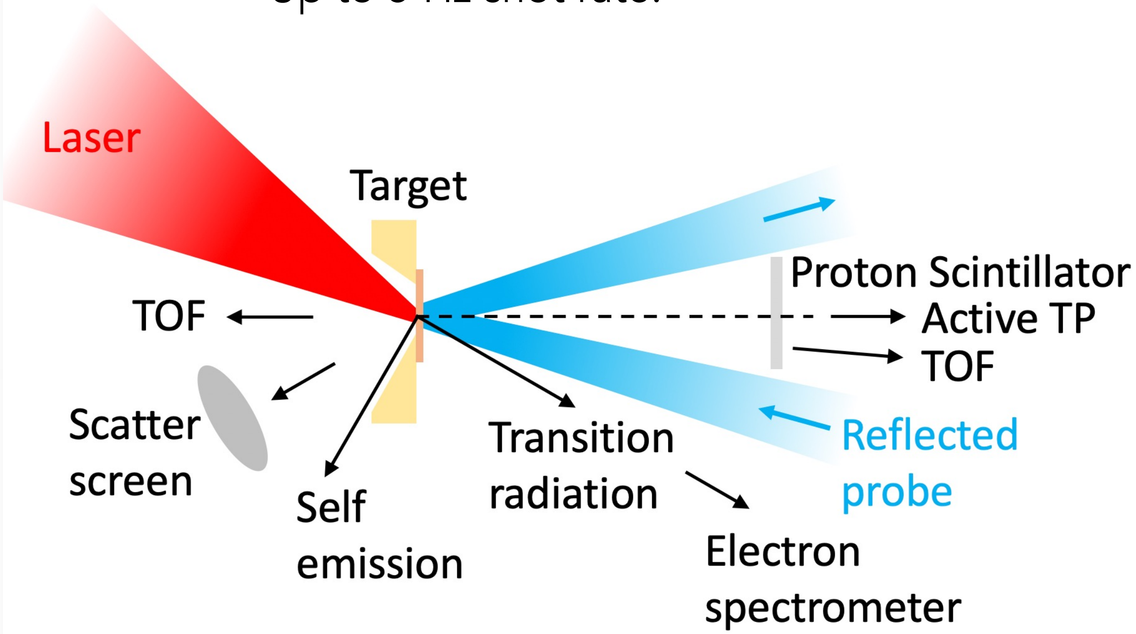


Automation of a Laser-driven ion accelerator



ASTRA TA2, Central Laser Facility U.K.

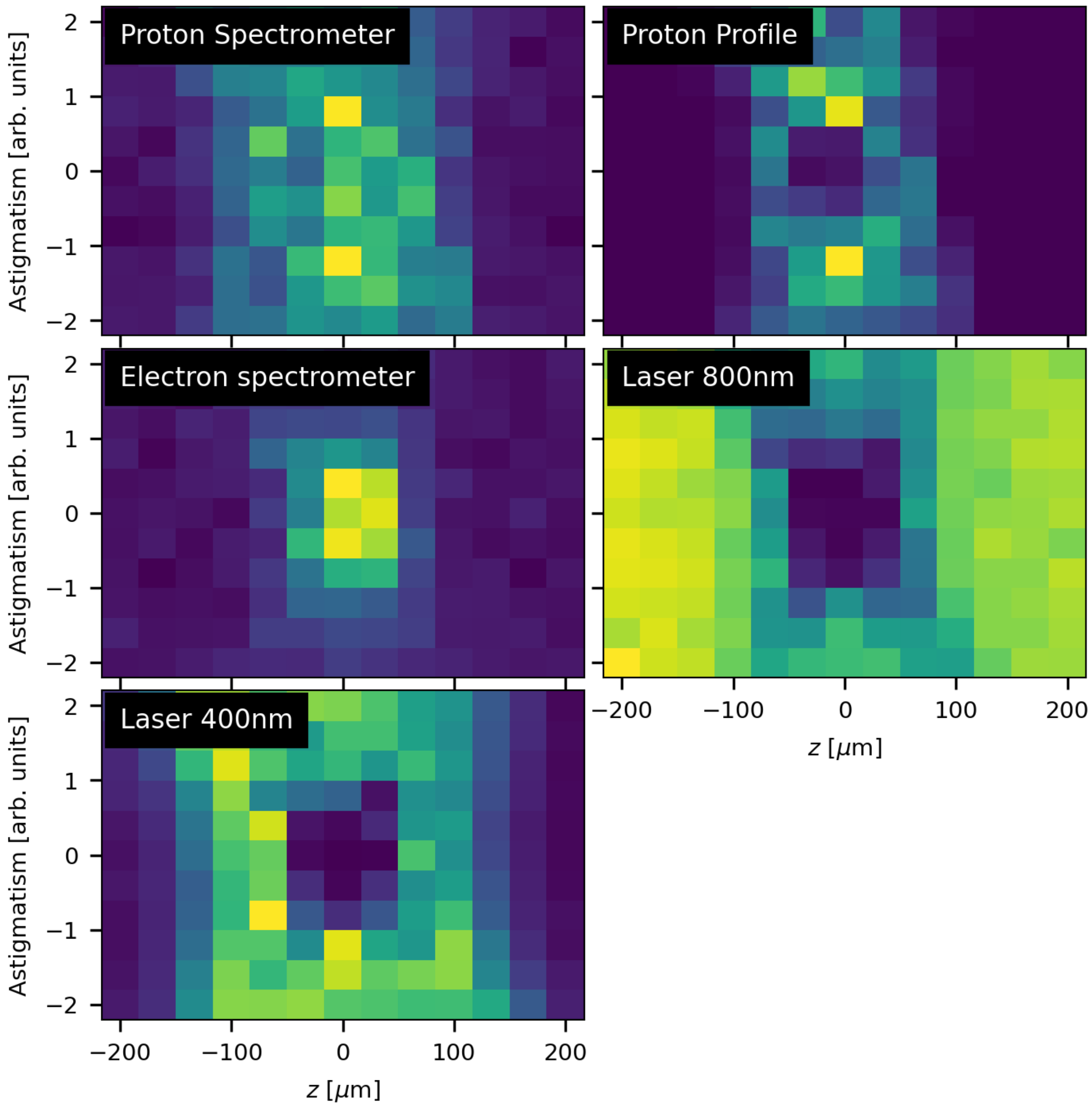
- Up to 500 mJ on target in 40 fs focused with F/2.5 OAP (Rayleigh length ~ 15 μm)
- Up to 5 Hz shot rate.

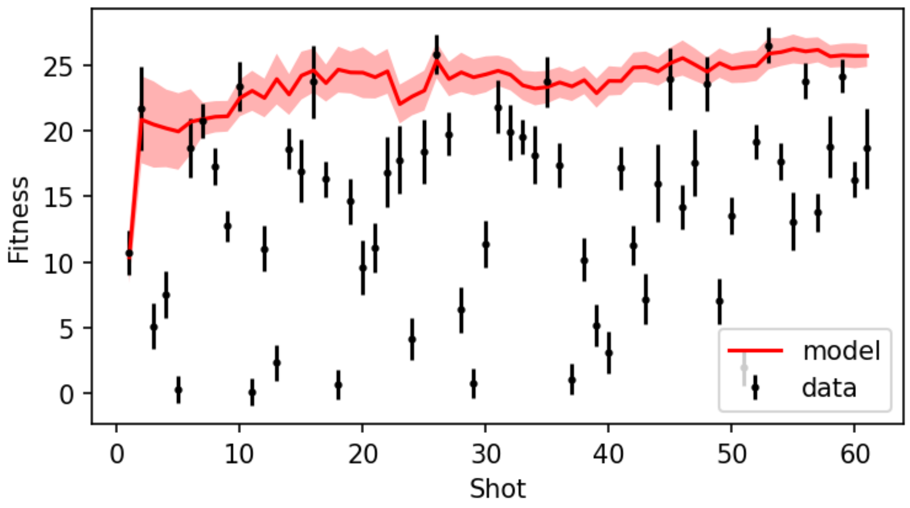


Targetry

- Tape drive (Imperial College London) primarily using 12.7 or 50 μm Kapton tape, but also 20 μm steel and 25 μm copper.
- Water sheet (SLAC).

Automated scans for exploring parameter dependence

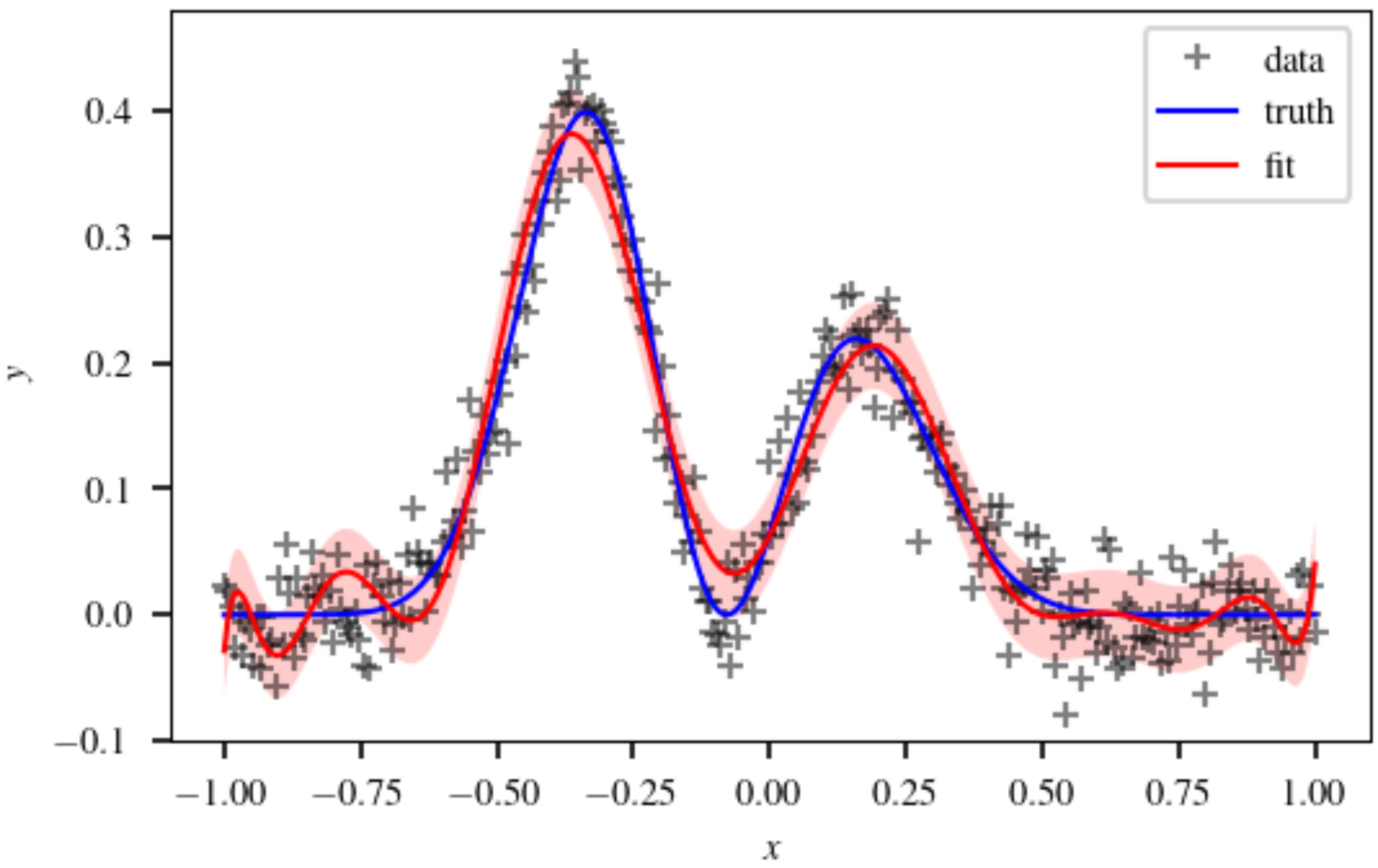




- 2D scans of target position and laser wavefront provide a slice of parameter space with 15 data points for each pixel
- Multiple scans taken of different parameters with different target types
- Aim to combine all data runs into single dataset which can be used to test models and develop algorithms

Challenges: Dealing with Heteroskedasticity

Homoskedastic, i.e. constant noise



True function + constant gaussian noise

$$y = f(x) + \epsilon$$

Normally linear regression assumes homoscedasticity as minimizes error function

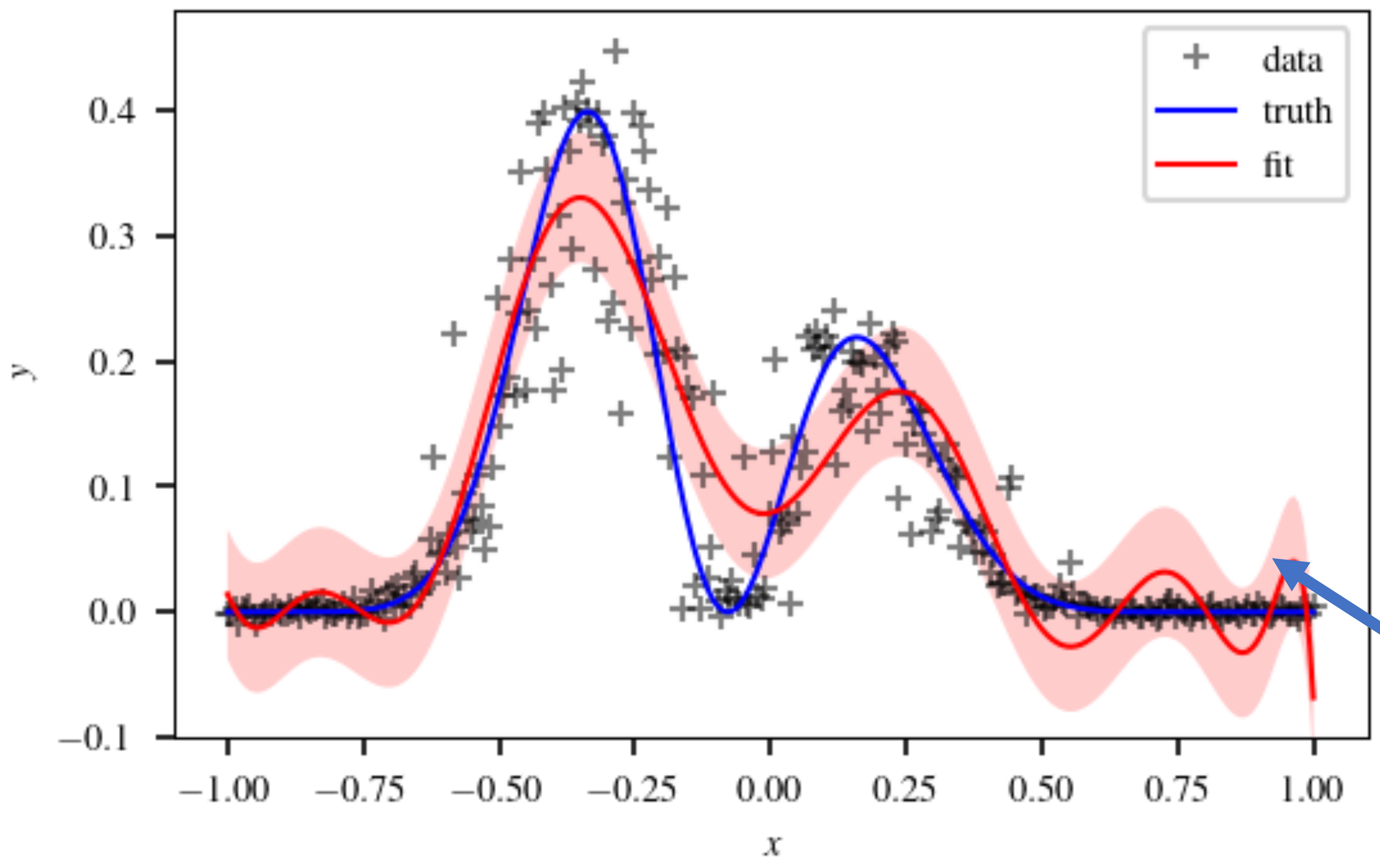
$$\eta = \sqrt{\left\langle \left(y(x) - y_f(x,p)\right)^2 \right\rangle}$$

Where $y_{\mathrm{f}}(x,p)$ is the model values at *x* for model parameters *p*.

Fitting a 15-order polynomial

Challenges: Dealing with Heteroskedasticity

Heteroskedastic, i.e. non-constant noise



True function + varying gaussian noise

$$y = f(x) + \epsilon(x)$$

$$y = (1 + \epsilon_y) f(x + \epsilon_x) + \epsilon_0$$

Signal dependent error

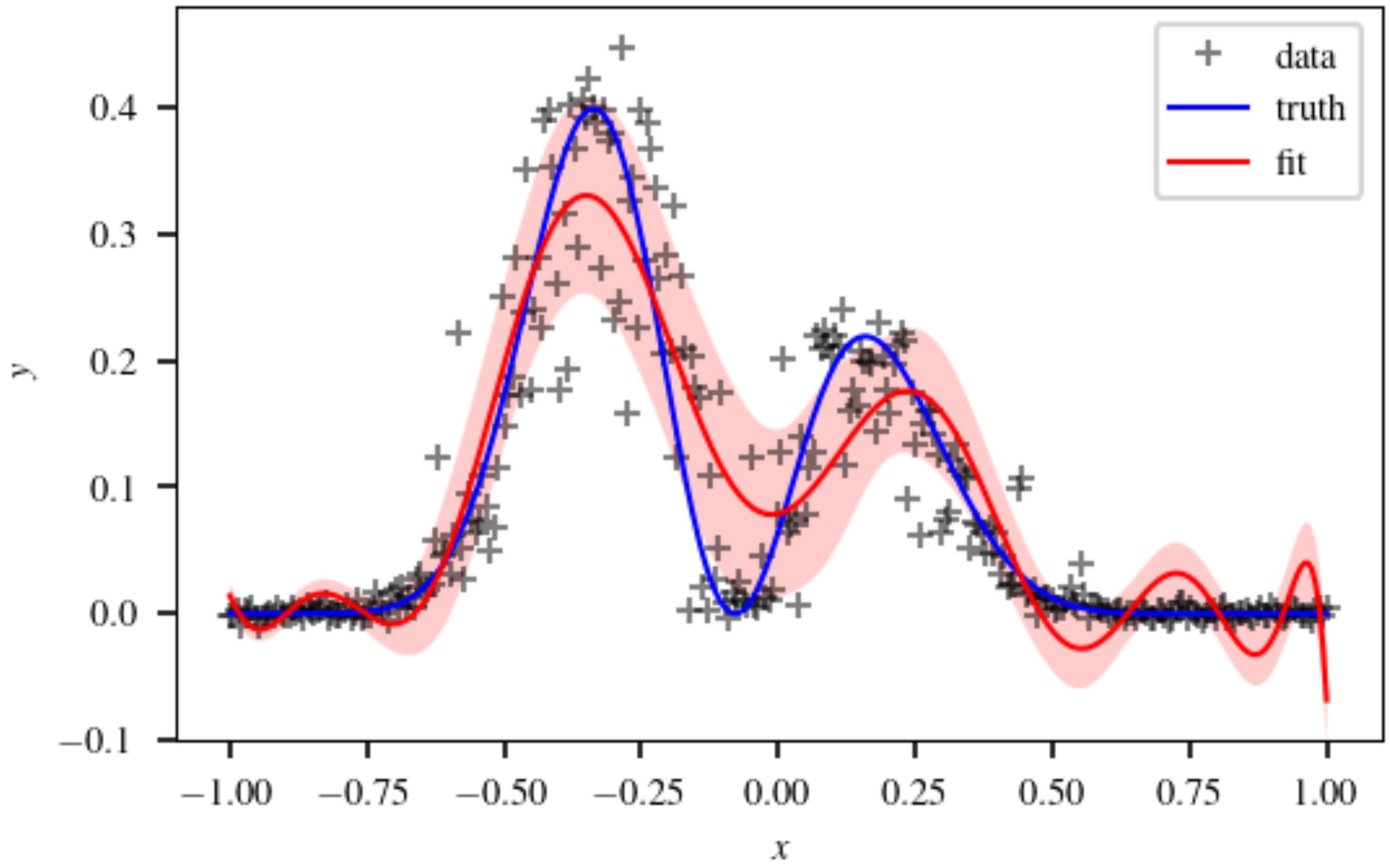
Input value error

Constant error

Constant noise not a good fit

Challenges: Dealing with Heteroskedasticity

Heteroscedastic, i.e. non-constant noise



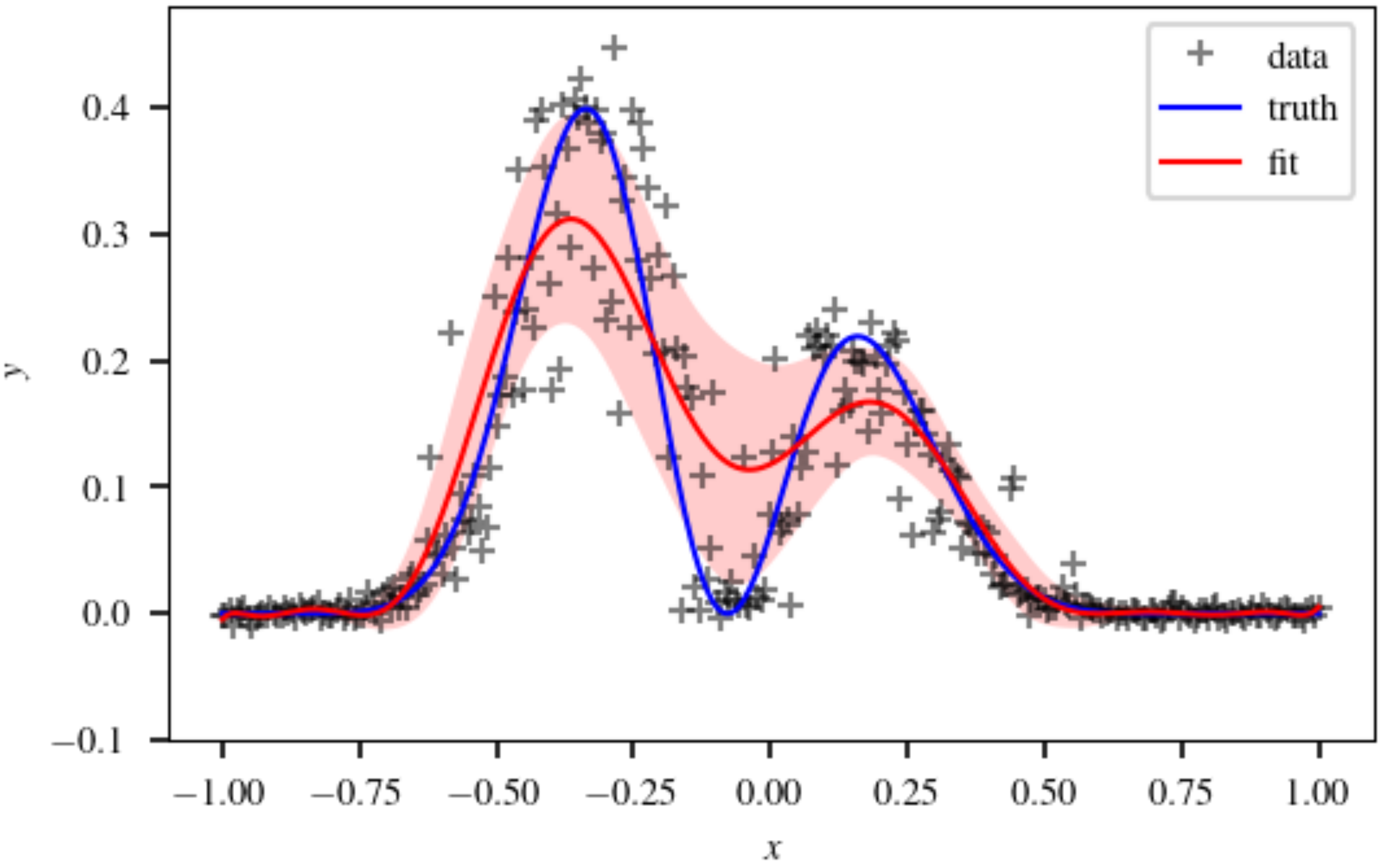
Can approximate noise. $\epsilon(x)$ by making local measurements of error, i.e. by gaussian smoothing

Function fit is still bad here as fitting still done assuming constant noise – what we might do is make an error function like

$$\eta = \sqrt{\left\langle \left(\frac{y(x) - y_f(x,p)}{\epsilon(x)} \right)^2 \right\rangle}$$

Challenges: Dealing with Heteroskedasticity

Heteroscedastic, i.e. non-constant noise



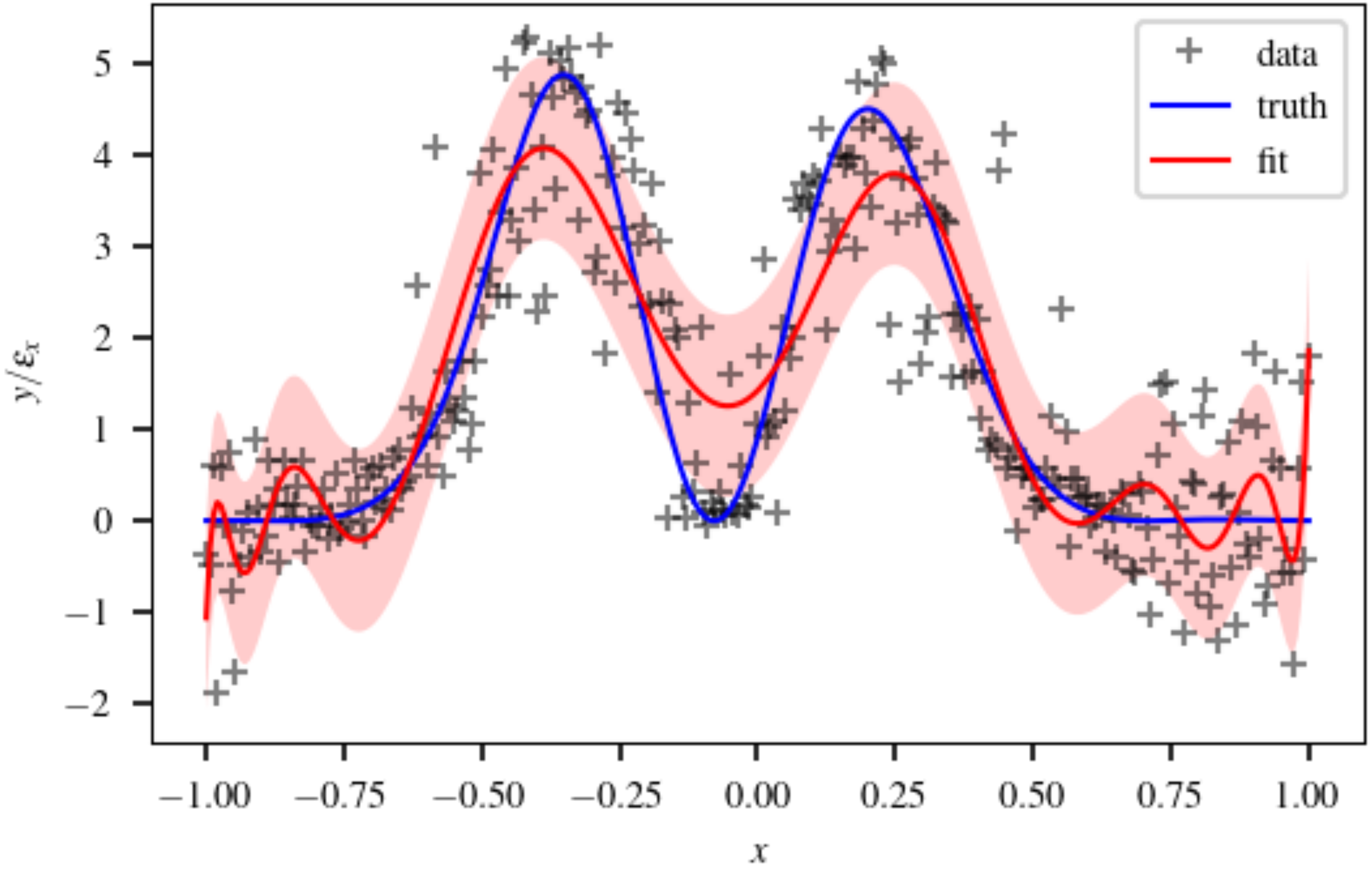
Re-fitting model with weighted regression

$$\eta = \sqrt{\left\langle \left(\frac{y(x) - y_f(x,p)}{\epsilon(x)} \right)^2 \right\rangle}$$

Model better constrained where the error is low.
Can iterate this process with updated $\epsilon(x)$

Challenges: Dealing with Heteroskedasticity

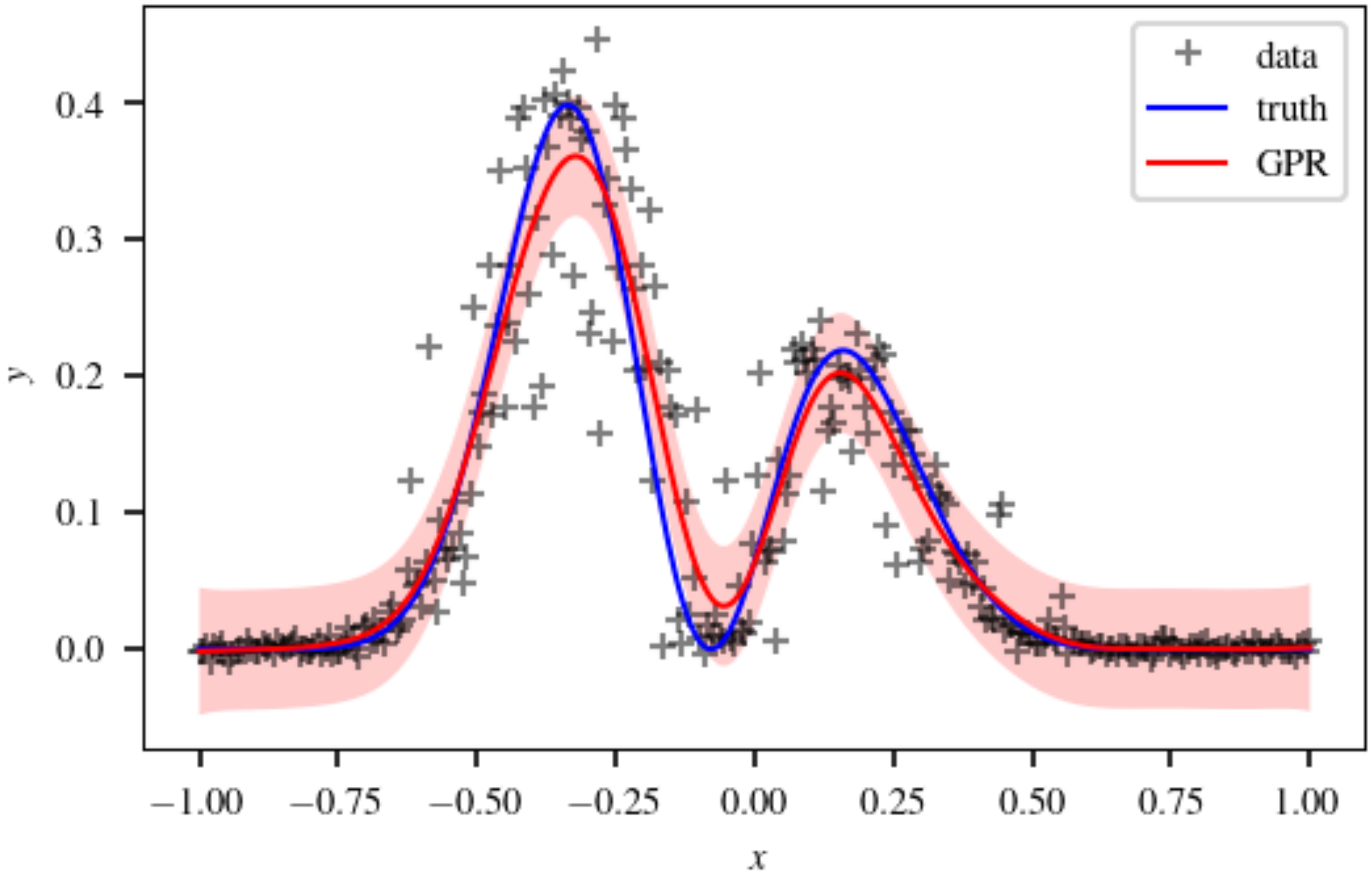
Scaling function by error recovers homoskedastic case



$$\eta = \sqrt{\left\langle \left(\frac{y(x) - y_f(x,p)}{\epsilon(x)} \right)^2 \right\rangle}$$

Challenges: Dealing with Heteroskedasticity

Now using gaussian process regression

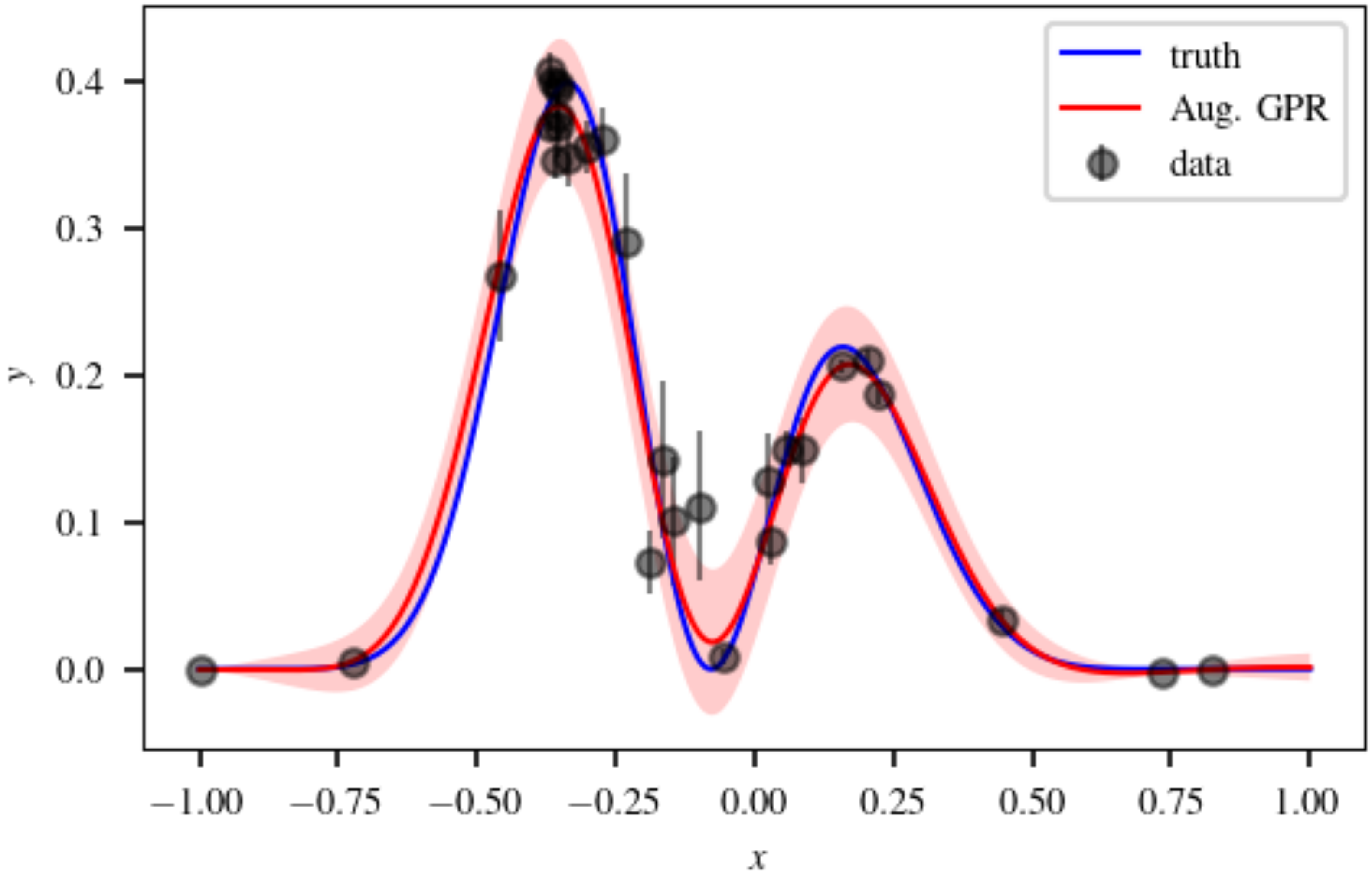


RBF + WhiteKernel

- GPR is able to fit the data much better than polynomial linear regression
- The model assumes constant noise which is not a good fit

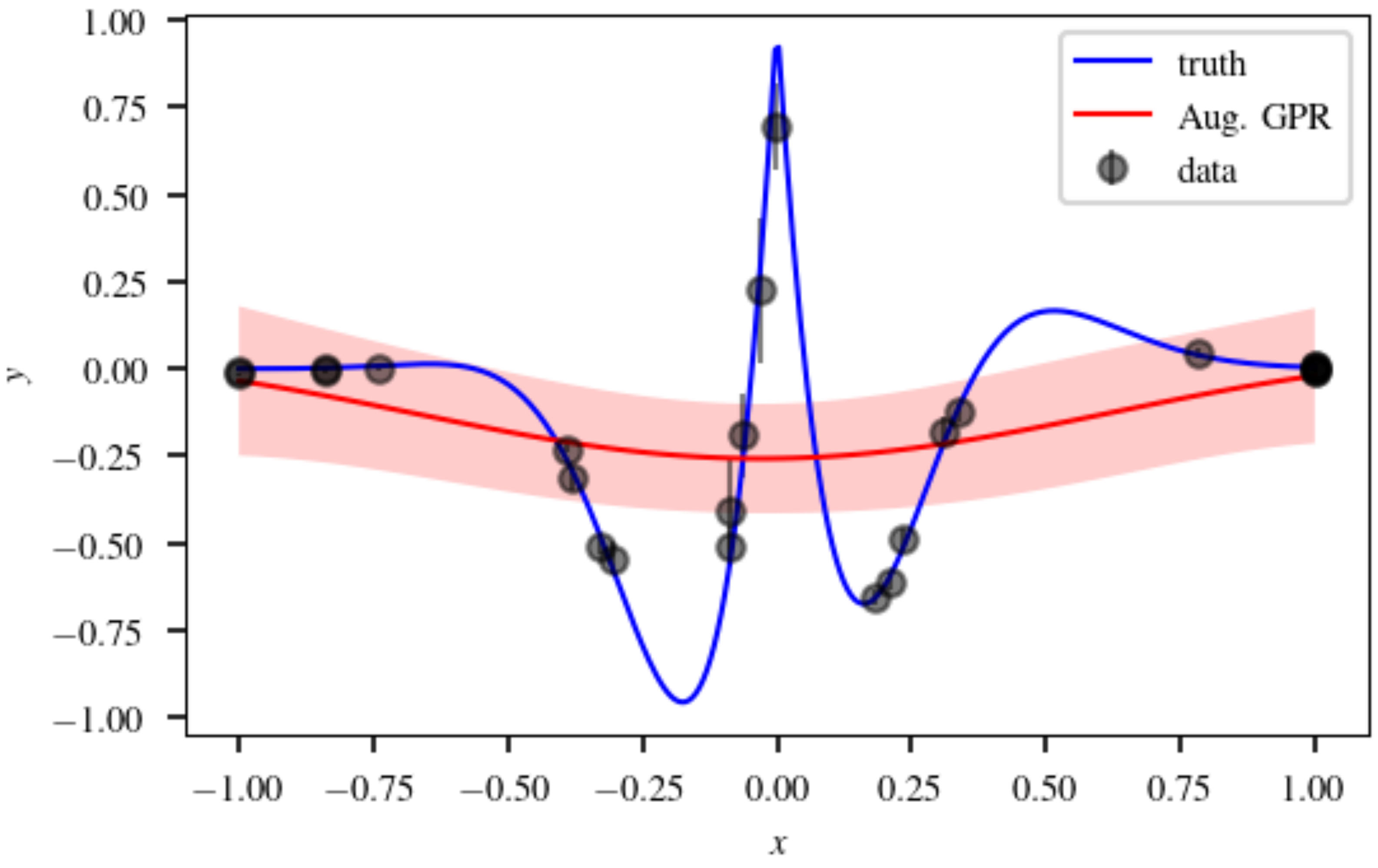
Challenges: Dealing with Heteroskedasticity

Augmented Gaussian Process Regression models fitted to signal and noise



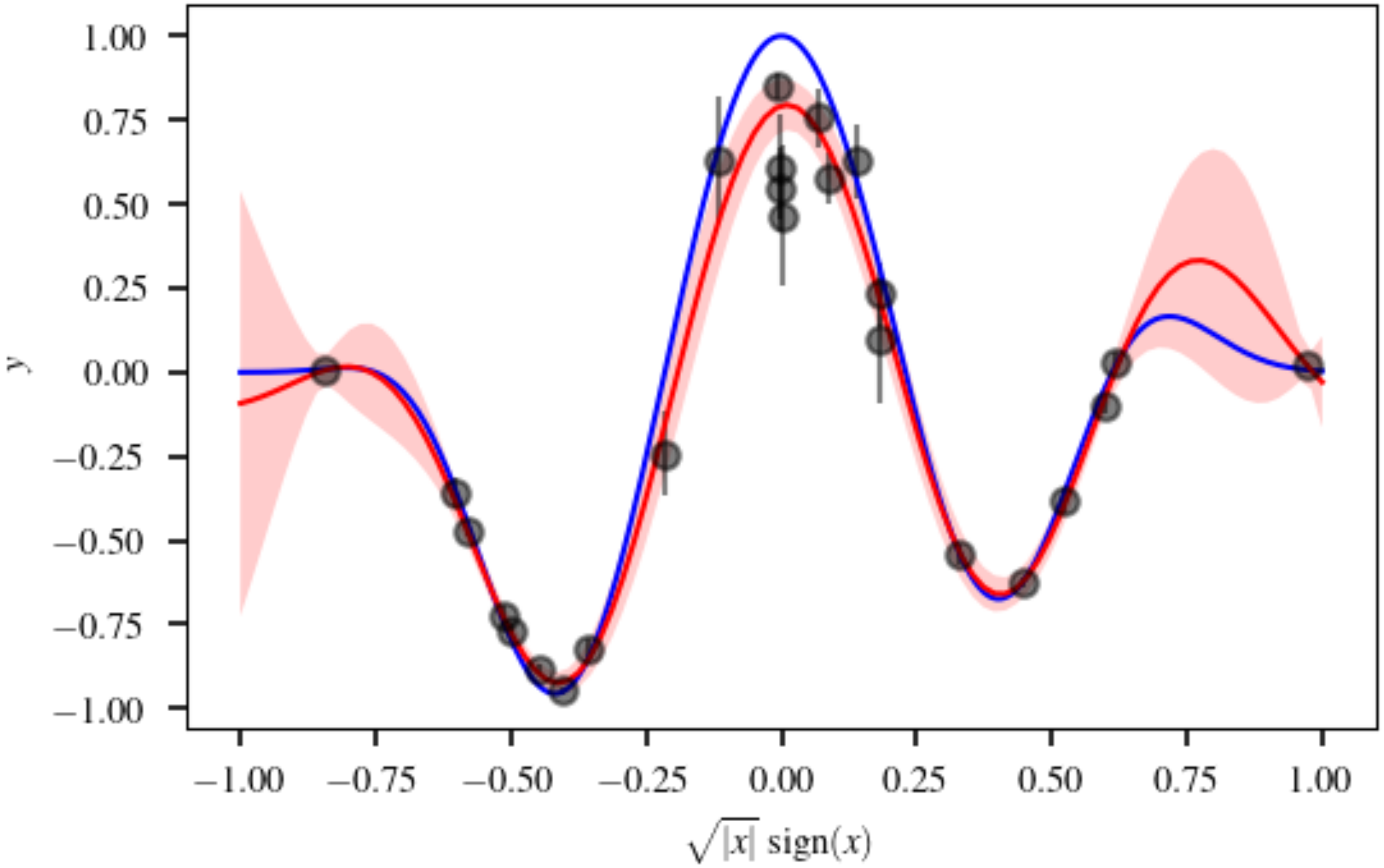
- Using 30 bursts of 5 shots and model guided optimization in last 10 bursts to find peak
- Each measurement now has an individual error
- Slightly better model agreement
- Are there better ways to handle this?

Challenges: Dealing with strange dimensions



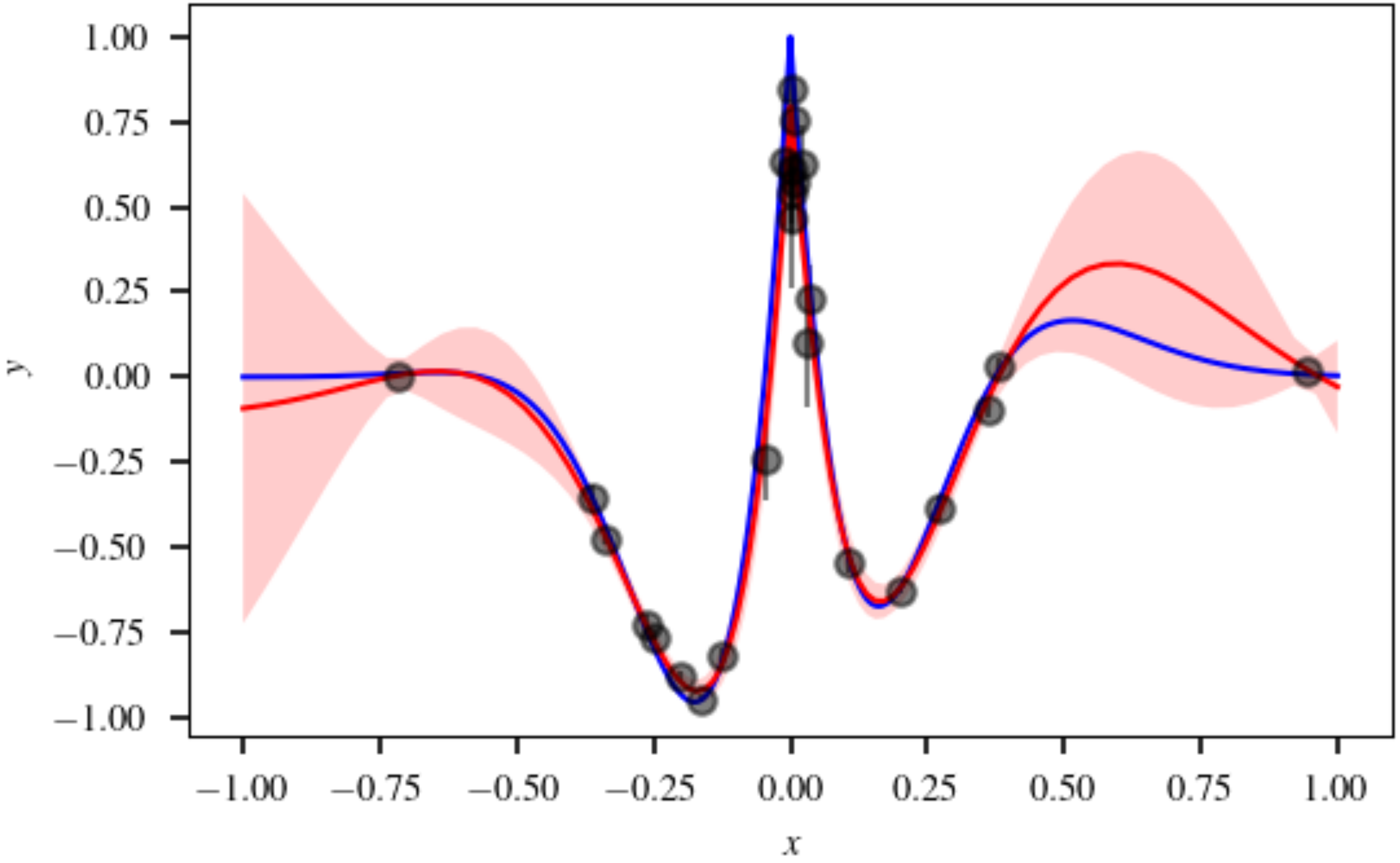
- Sometime signals vary much more quickly in some regions than others
- We have typically used stationary kernels that assume that the data is the same smoothness everywhere

Challenges: Dealing with strange dimensions



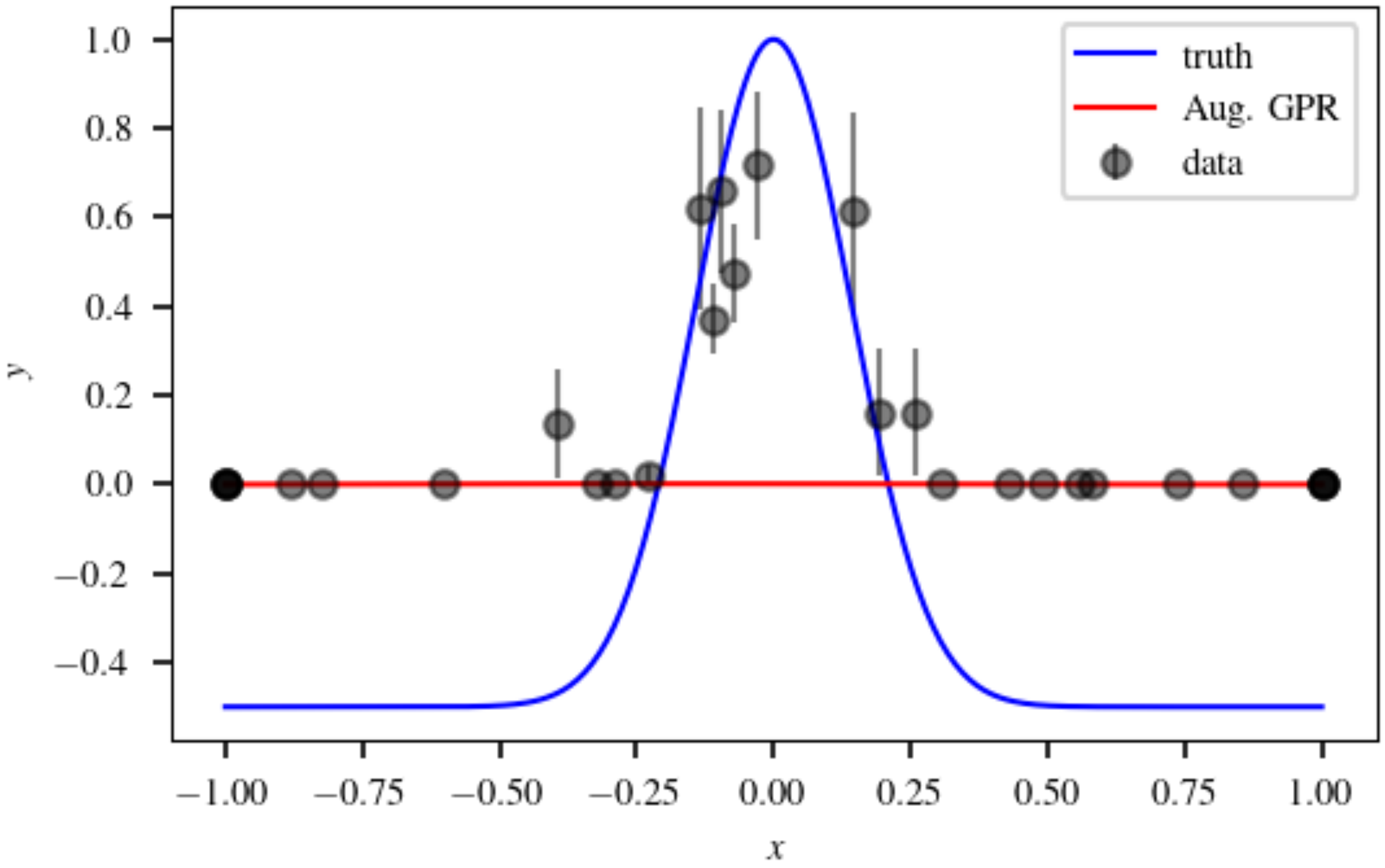
- One solution can be to find some coordinate mapping that makes the signal easier to model
- Can this mapping be found automatically?
- Or use non-stationary kernels
- Perhaps need to know the right mapping to start with
- Lots of papers around on this!

Challenges: Dealing with strange dimensions



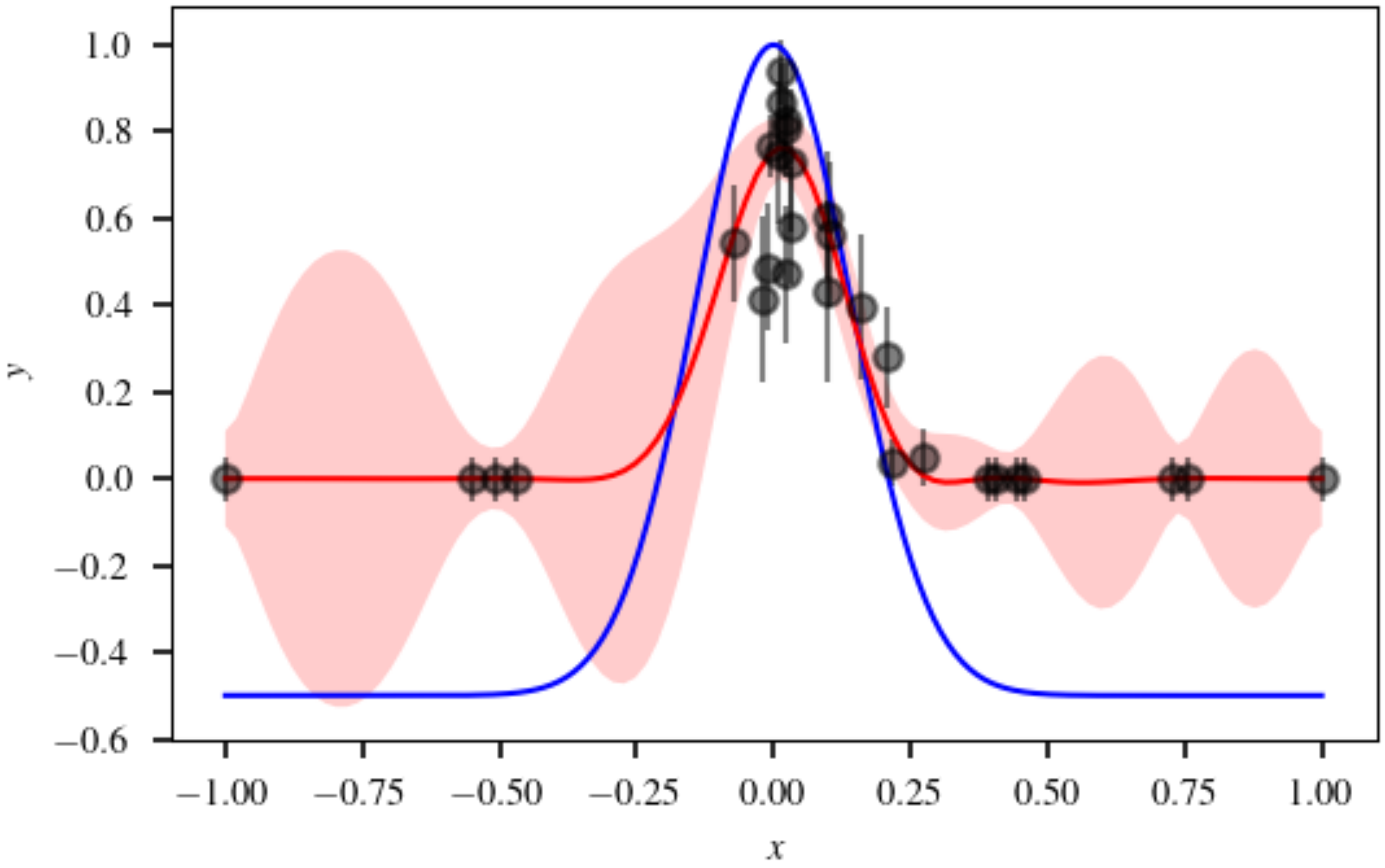
- Remapping data onto original coordinate recovers the sharp dependance on the input parameter

Challenges: Dealing with diagnostic thresholds



- When dealing with detector thresholds and low diagnostic noise there might be lots of zeros with no shot-to-shot variation
- This over constrains the model to fit the zeros and makes the non-zero data points look insignificant

Challenges: Dealing with diagnostic thresholds



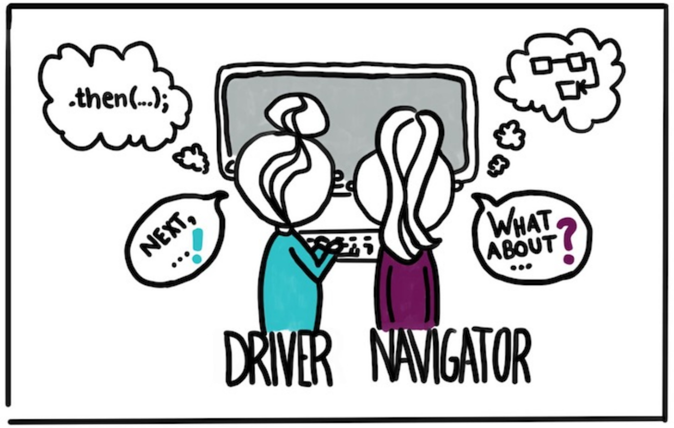
- Adding a small constant noise value to all values gives the model some more freedom and allows it to fit the data better
- Accurate modelling of diagnostics may be required to get better uncertainty of measured values
- Can we included uncertainty on each point may not be symmetric + - ?

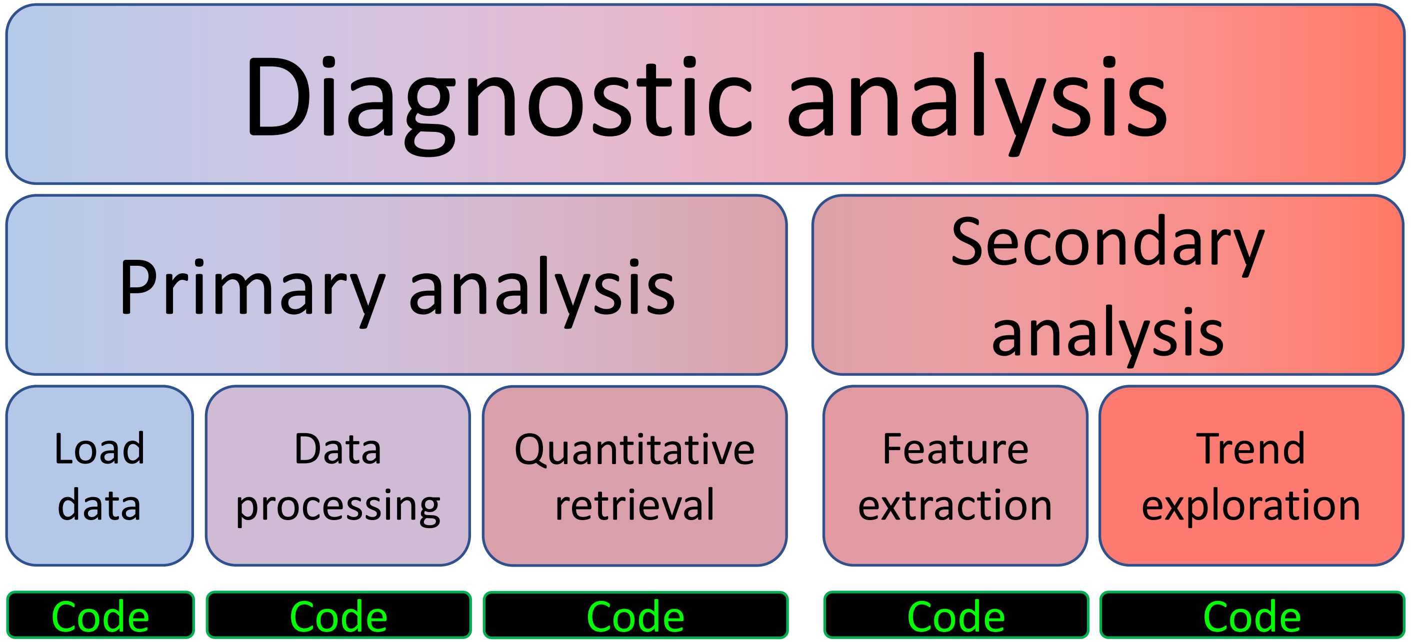
Question

"How do you factor in varied skill level in computing among your team? (Both to take advantage of skills on your team, and to not leave anyone behind?)"

- Experiment operation, primary analysis, secondary analysis
- Should we adopt professional programming practices?
    - Follow style guidelines, write minimum code to get the job done
    - https://www.python.org/dev/peps/pep-0008/
    - Separate into small testable units and design tests for each. Match each unit to some real world process.

Pair programming





https://martinfowler.com/articles/on-pair-programming.html

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