



# Bayesian Online Changepoint Detection

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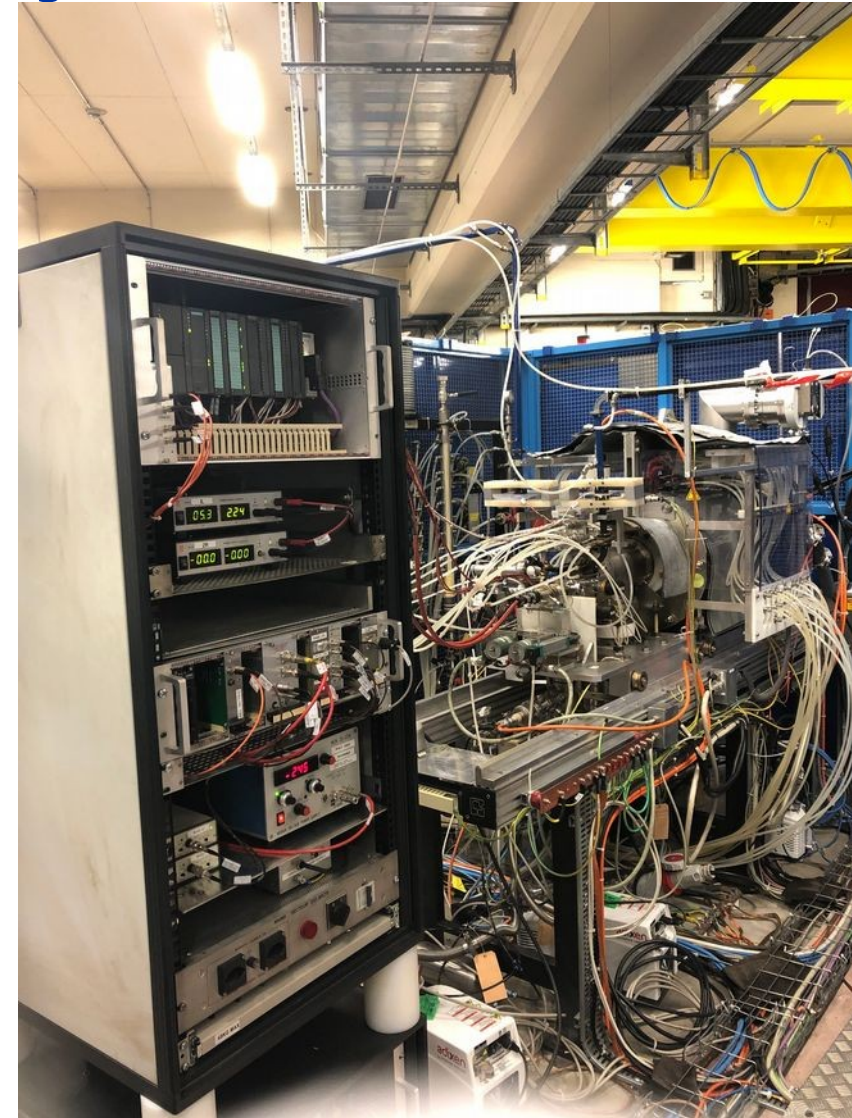
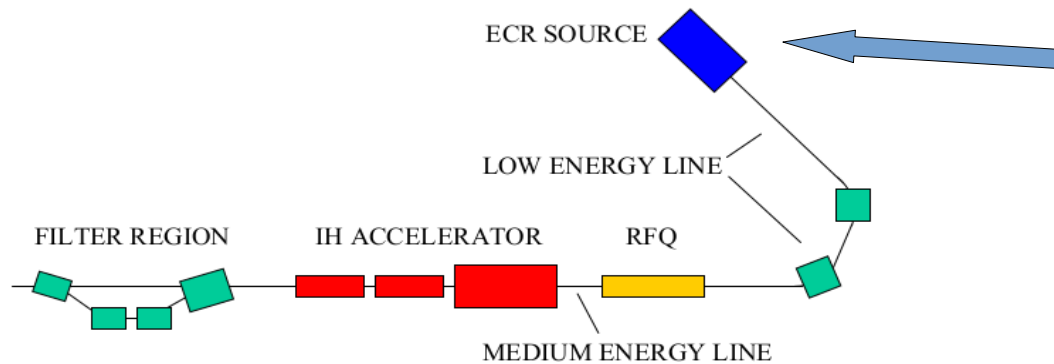


# Outlook

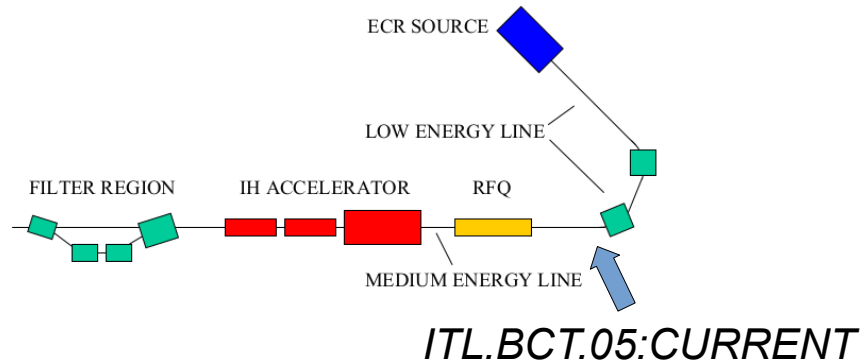
- Motivation at Linac3
- Presentation of the Algorithm
- Code example

# Layout of LINAC3 and the objective

Linac3 produces heavy ions, mainly Pb.

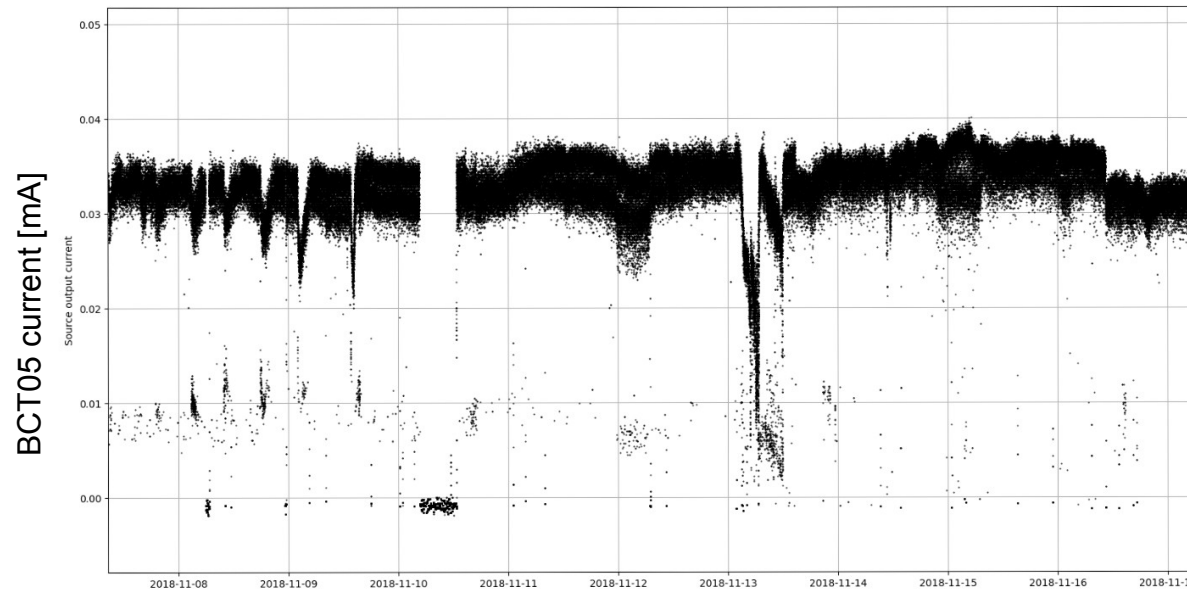


# Layout of LINAC3 and the objective



There is a lot to tweak at the source:  
Oven Power, RF, three solenoids, gas  
inflow, ...

This leads to a very complex system  
which can produce results that are very  
difficult to predict.



➡ The goal is to quickly  
identify regime changes in  
the output beam current

# Online Changepoint Detection

Given an ordered collection of data points (a time series)...

...change point detection is the task of detecting qualitative changes in the observed time series.

- Probabilistic models search for changes in distribution of data
- Other models minimize a cost function (e.g. piece wise linear regression)

...online change point detection performs analysis on streaming data.

- The full time series is typically not known
- Whenever new data is observed, decide if a change point occurred
- update model to include new knowledge (optional)

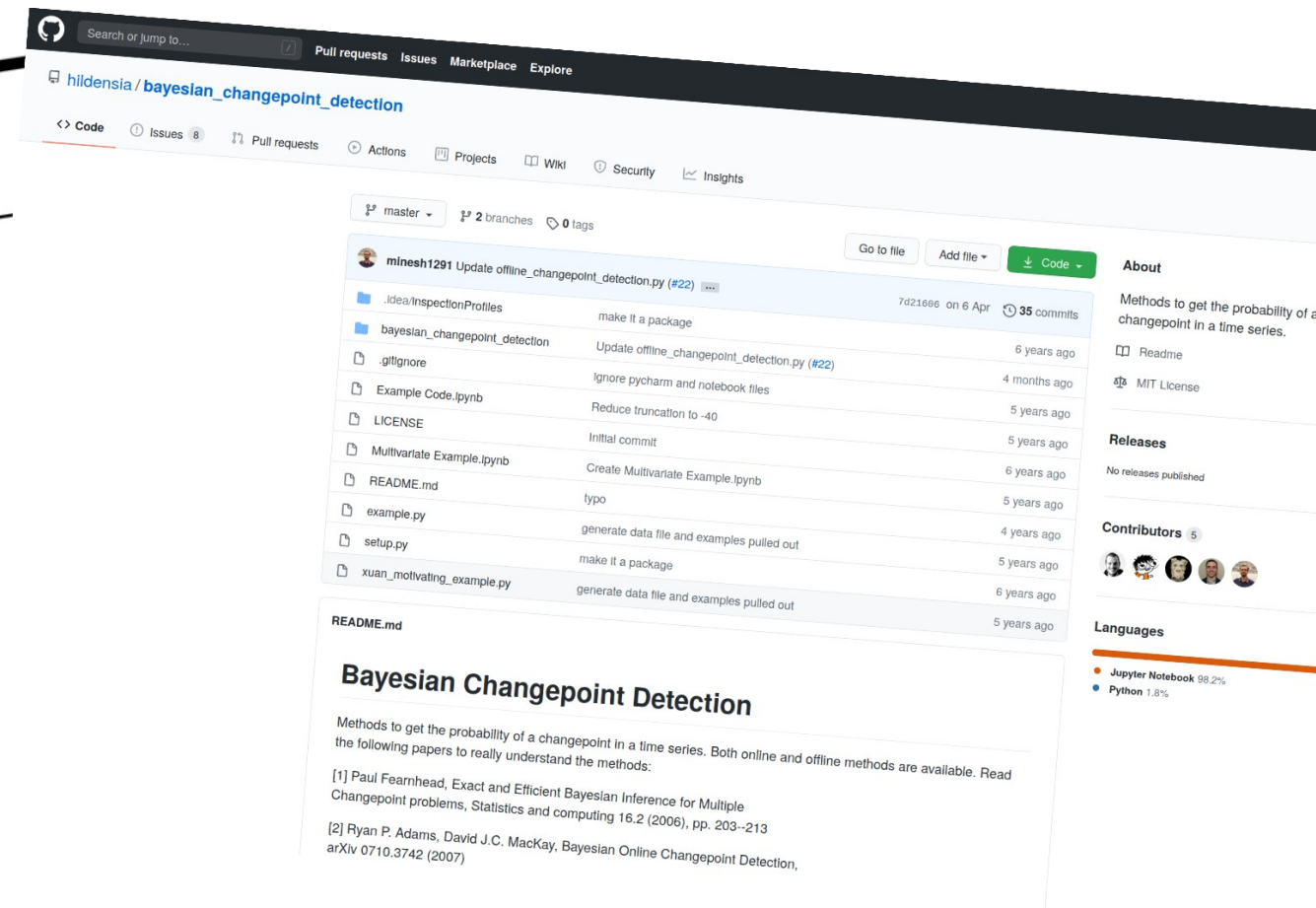
# Paper by Adams and MacKay (2007)

## Bayesian Online Changepoint Detection

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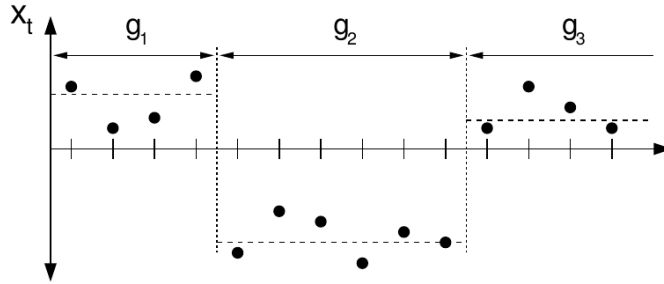
David J.C. MacKay  
Cavendish Laboratory  
Cambridge CB3 0HE  
United Kingdom

Published on arXiv: <https://arxiv.org/abs/0710.3742>  
Python implementation (MIT license):  
[https://github.com/hildensia/bayesian\\_changepoint\\_detection](https://github.com/hildensia/bayesian_changepoint_detection)



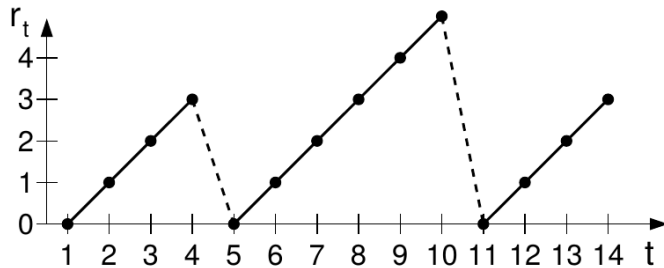


# The concept of run lengths



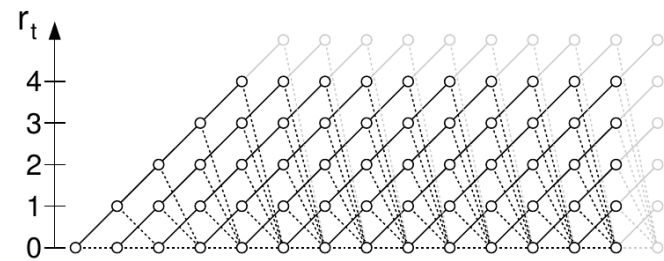
(a)

Consider an ordered series of points where the observations are drawn i.i.d. from different distributions.



(b)

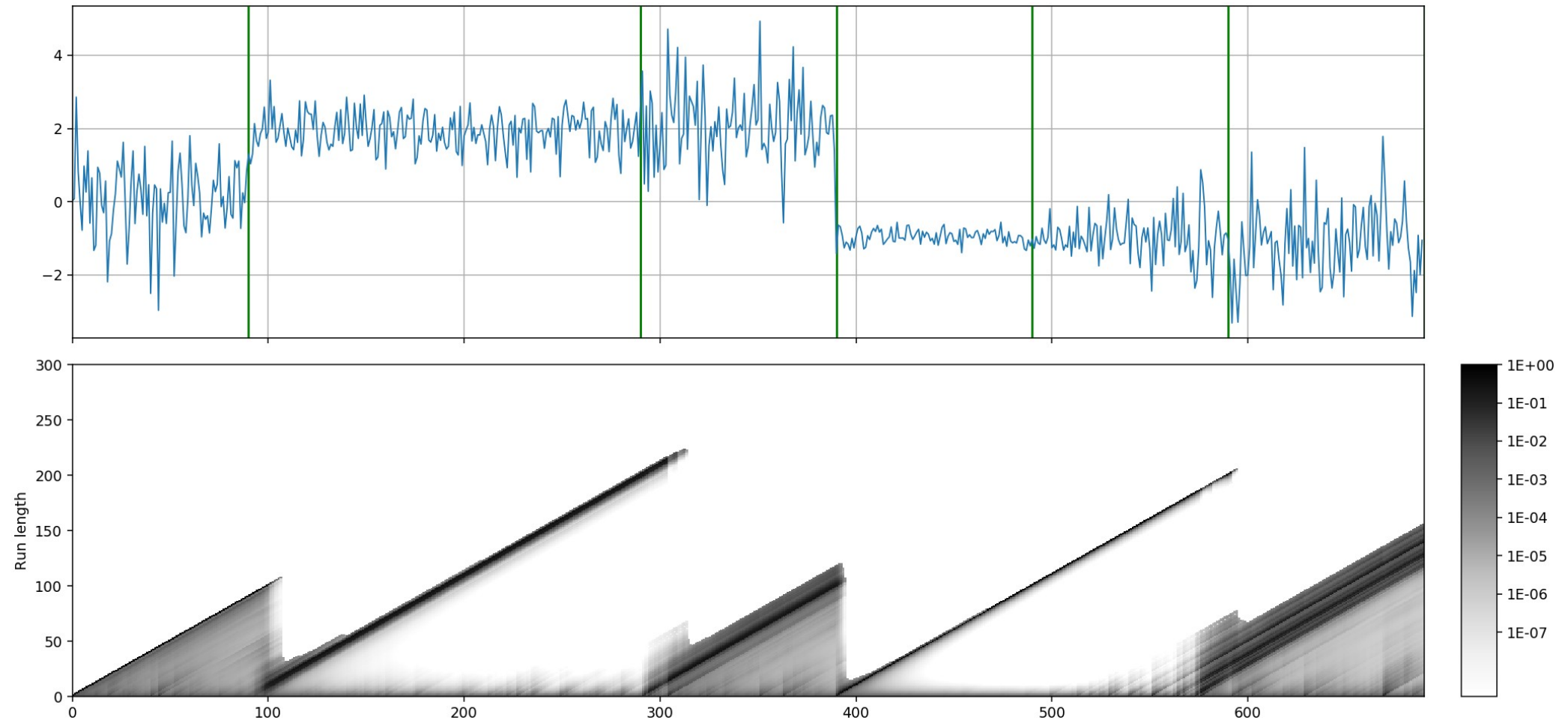
The run length  $r_t$  indicates how many time steps have passed since the last changepoint occurred.



(c)

Build a probabilistic model with probabilities for all possible run lengths at every time step.

# Example output on simulated data



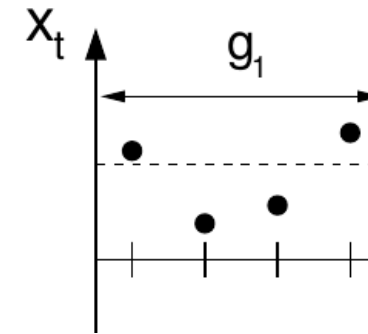
Simulated time series with true changepoints in green (top),  
Run length probabilities (bottom) – darker pixels mean represent higher probability



# Mathematical formulation of the model

We are interested in every time a new observation arrives

$$P(r_t \mid x_1, \dots, x_t) = \frac{P(r_t, x_1, \dots, x_t)}{P(x_1, \dots, x_t)}$$



Expansion leads to recursive term

$$P(r_t, x_1, \dots, x_t) = \sum_{r_{t-1}} P(r_t \mid r_{t-1}) P(x_t \mid r_{t-1}, x_1, \dots, x_{t-1}) P(r_{t-1}, x_1, \dots, x_{t-1})$$

Changepoint prior

Predictive probability  
of new observation

Previous run length  
probabilities

Afterwards update model parameters to reflect information gained from  $x_t$

Graphic from Bayesian Online Changepoint Detection, Adams & MacKay (2007)

# The Changepoint Prior

$$\sum_{r_{t-1}} \boxed{P(r_t \mid r_{t-1})} P(x_t \mid r_{t-1}, x_1, \dots, x_{t-1}) P(r_{t-1}, x_1, \dots, x_{t-1})$$

Given  $r_{t-1}$  there are only two possible outcomes for  $r_t$ :

- Changepoint happened:  $r_t = 0$
- No changepoint:  $r_t = r_{t-1} + 1$

$$P(r_t \mid r_{t-1}) = \begin{cases} H(r_{t-1} + 1) & \text{if } r_t = 0 \\ 1 - H(r_{t-1} + 1) & \text{if } r_t = r_{t-1} + 1 \\ 0 & \text{otherwise} \end{cases}$$

$H$  is called hazard function and encodes how the changepoint probability relates to the time passed since the last change  
e.g. a mechanic piece that is more likely to break as it gets older

If changepoints are equally likely at any time:  $H = 1/\lambda$  with  $\lambda \approx$  expected duration of segment

# A word on the predictive probability

$$\sum_{r_{t-1}} P(r_t \mid r_{t-1}) \boxed{P(x_t \mid r_{t-1}, x_1, \dots, x_{t-1})} P(r_{t-1}, x_1, \dots, x_{t-1})$$

Lets assume our data is in a segment follows a distribution  $\mathbf{D}$  with (unknown) parameters  $\boldsymbol{\theta}$ .  
Then, one could say

$$x_t \mid r_{t-1}, x_1, \dots, x_{t-1} \sim D(\bar{\theta})$$

With an estimate  $\bar{\theta}$  of the parameter.  
But, we are unsure about this estimate

$$\Rightarrow p(x_t \mid r_{t-1}, x_1, \dots, x_{t-1}) = \int_{\theta} p(x_t \mid \theta) * p(\theta \mid r_{t-1}, x_1, \dots, x_{t-1}) d\theta$$

Likelihood (how likely is  
the observation?)

Prior (how well does the  
parameter explain the  
previous observations)

➡ In general, this integral needs to be evaluated numerically (using MCMC methods)

# A word on the predictive probability

In our case we can make our lives easier using conjugate priors!

$$\int_{\mu, \sigma^2} N(x_t \mid \mu, \sigma^2) * p(\mu, \sigma^2 \mid r_{t-1}, x_1, \dots, x_{t-1}) d(\mu, \sigma^2)$$

↖  
This is a normal with  
unknown mean and  
variance

↖  
We can choose prior  
distribution to get an  
algebraic expression

The conjugate prior has four parameters that we update every time a new data point  $x$  is observed.

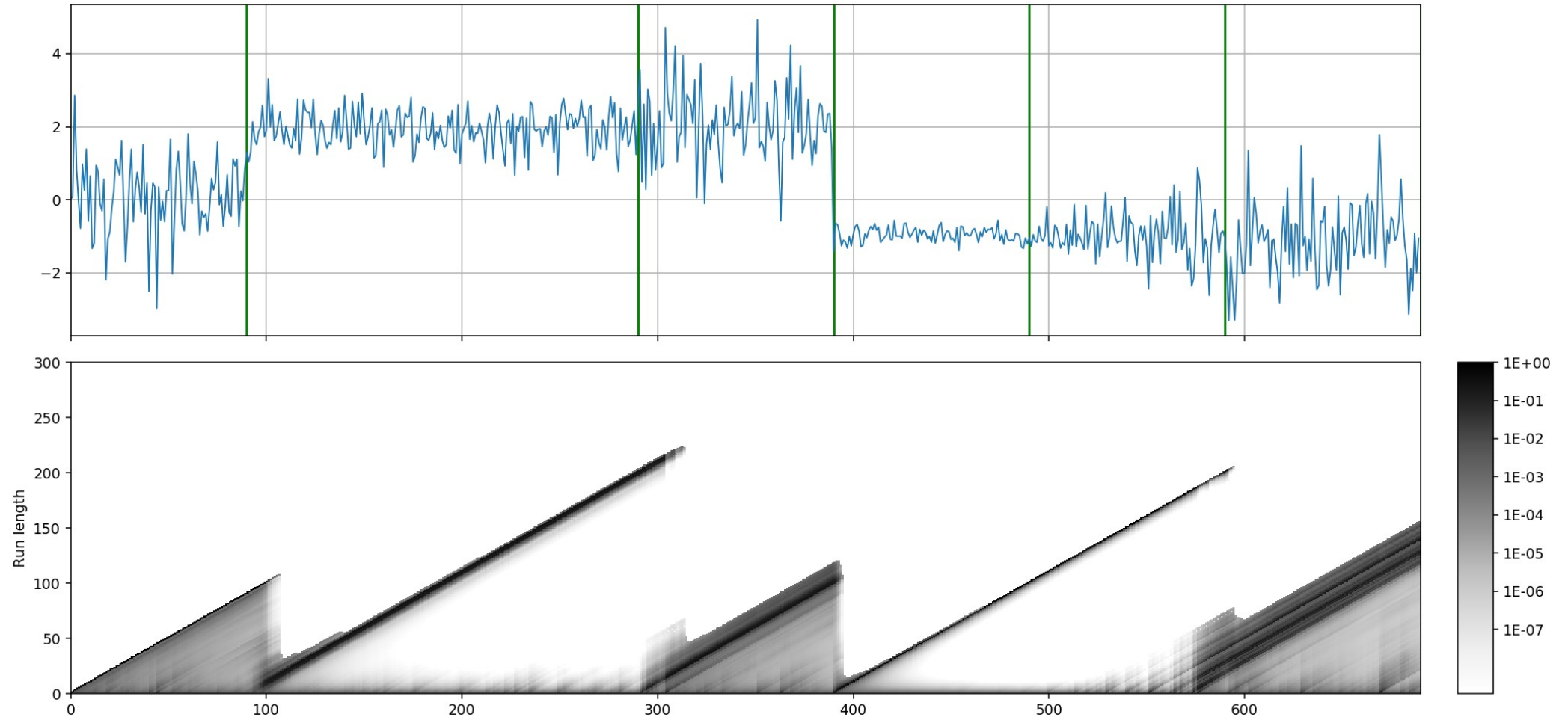
$$\begin{aligned} \kappa &\rightarrow \kappa + 1 \\ \hat{\mu} &\rightarrow \frac{\kappa \mu + x}{\kappa + 1} \end{aligned}$$

$$\begin{aligned} \alpha &\rightarrow \alpha + 0.5 \\ \beta &\rightarrow \beta + \frac{\kappa}{\kappa + 1} \frac{(x - \hat{\mu})^2}{2} \end{aligned}$$

Without going into detail, the integral equals the probability density of a Student-T distribution

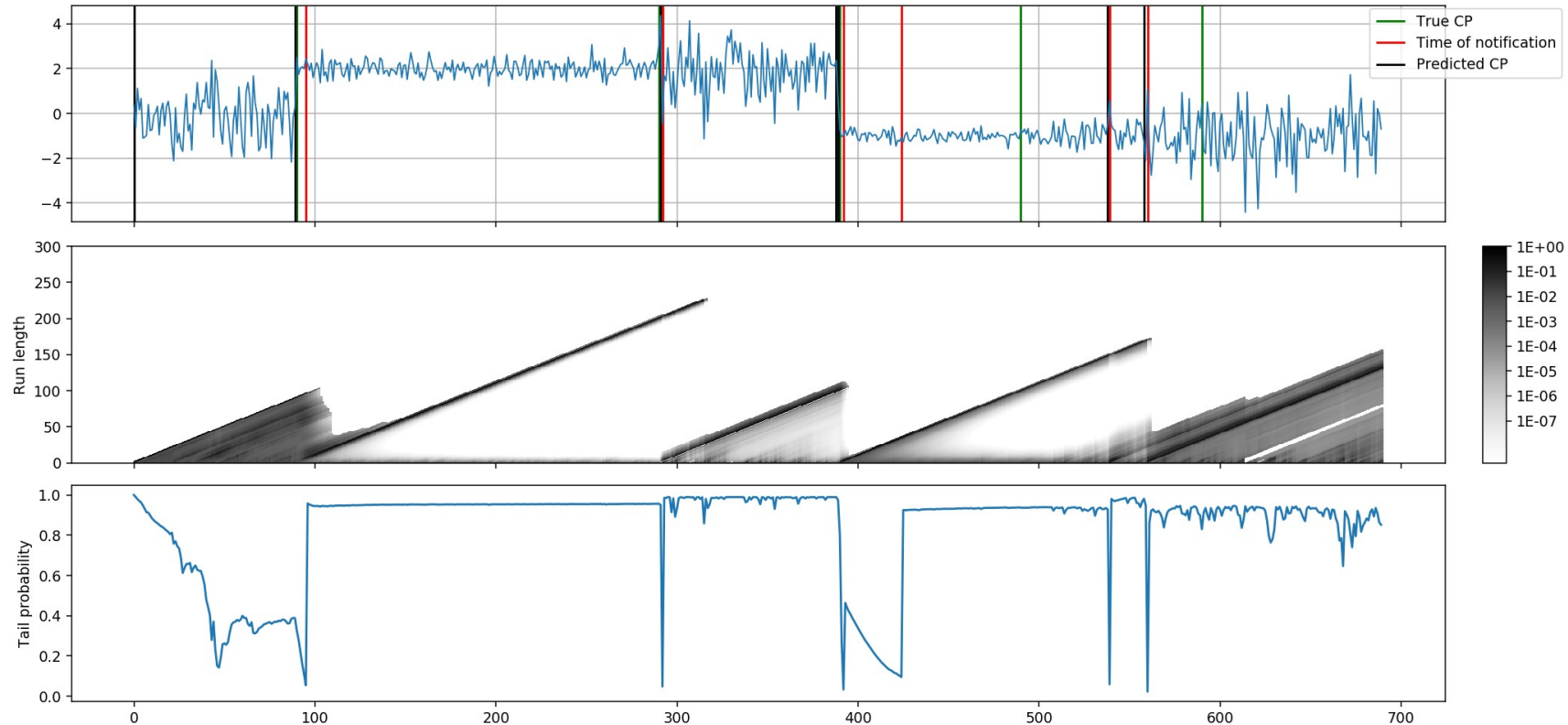
$$t_{2\alpha} \left( \hat{\mu}, \frac{\beta(\kappa + 1)}{\alpha \kappa} \right)$$

# And now?



Simulated time series with true changepoints in green (top),  
Run length probabilities (bottom) – darker pixels mean represent higher probability

# And now?



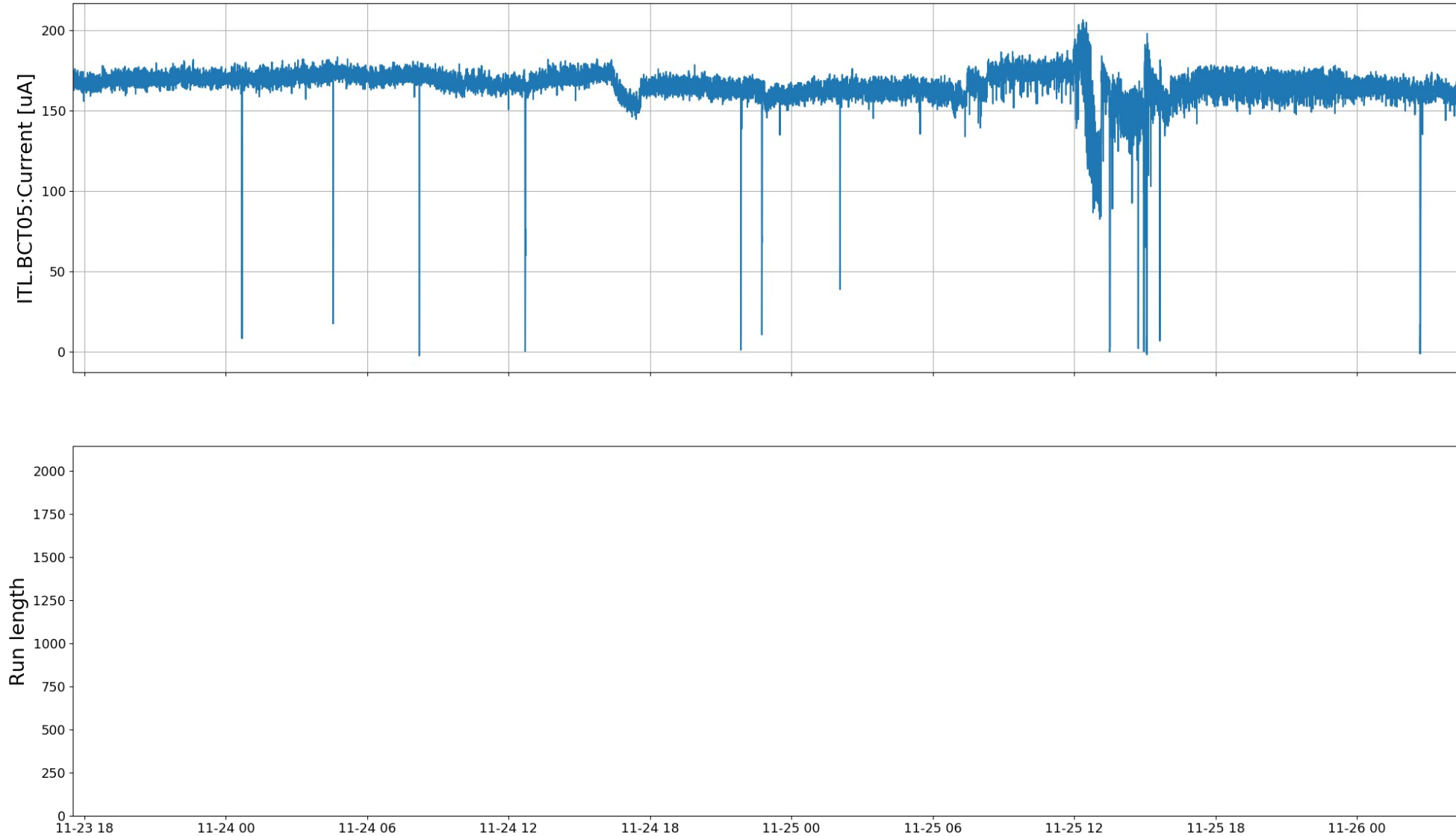
How to translate probabilities to actionable information?

Every time new data arrives, ask “Is it likely that the new data point is in the same segment?”

➡ Sum up the probability of the longest 20% run lengths and check if sum is smaller than 0.1



# First results on linac3 data



# First results on linac3 data

