The problem is to identify different patches in a dataset that have distinct statistical properties and to finding the boundary between them. I consider here a one-dimensional problem with two patches divided by a point.

Suppose a dataset $d(x)$ has left and right hand parts, $d_L(x)$ and $d_R(x)$, respectively, with each drawn from different pdfs, described by autocorrelation functions $C_L(r)$ and $C_R(r)$, respectively, with $r = |x_1 - x_2|$ and no correlation between left and right parts, and where the point dividing the parts is $x_0$. The problem is to estimate $x_0$.

Method. I use a grid search over $x_0$ to determine the $x_0^{est}$ that minimizes the generalized error $E(x_0)$, where the both the prediction error and the error in prior information contribute to $E$. The autocorrelation functions $C_L(r)$ and $C_R(r)$ are assumed to be known. The error in prior information is computed using an overall variance, $\frac{1}{2} \left( C_L^2(0) + C_R^2(0) \right)$ that does not vary between regions.
Gaussian processes regression is used to estimate $d^{pre}(x, x_0)$ using an overall covariance matrix

$$
\begin{bmatrix}
C_L & 0 \\
0 & C_R
\end{bmatrix}
$$

where $[C_L]_{ij} = C_L(r_{ij})$ for $i, j < x_0$ and $r = |x_i - x_j|$.

Although I hold $C_L$ and $C_R$ fixed in this work, I imagine that it would be possible to view them as functions of hyper-parameters and then augment the grid-search to search over their possible values.

In multidimensional cases, I imagine that it would be possible to parameterize the boundary as a curve with a curve whose shape is controlled by a few parameters, and then grid search over the parameter.
1. Experiment 1.

True data, $d^{\text{true}}(x)$ (black). Observed data, $d^{\text{obs}}(x)$ (red)

Left hand part drawn from data with autocorrelation $C_L(r)$ and right and from $C_R(r)$, (with $r = |x_1 - x_2|$) and no correlation between left and right parts

Dividing point $x_0$ shown by dotted vertical line.
2. True (black) and estimated (red) $C_L(r)$ (top) and true (black) and estimated (red) $C_R(r)$ (bottom). Estimates are from time series drawn from pdfs with these autocorrelation functions.
3. Generalized error for all possible $x_0$s, with minimum (red dotted vertical) line and true $x_0$ (black dotted vertical line)
4. Observed data, $d^{obs}(x)$ (black) and true $x_0$ (black dotted vertical line). Predicted data, $d^{pre}(x)$ (red) and estimated $x_0$ (black dotted vertical line).
Experiments with a different $x_0$
5.
Experiment 2

(Top) Generalized error for all possible choices of $x_0$.

(Bottom) True data, $d^{true}(x)$ and true $x_0$ (black). Estimated data, $d^{obs}(x)$ and estimated $x_0$ (red)
6.
Experiment 3

(Top) Generalized error for all possible choices of $x_0$.

(Bottom) True data, $d^{true}(x)$ and true $t_0$ (black). Estimated data, $d^{obs}(x)$ and estimated $x_0$ (red)
Results

The estimated $x_0$ is found to be close to the true value, as long as the $C_L(r)$ and $C_R(r)$ are sufficiently different that one leads to a poorer fit, when applied to data drawn from the other.