Stopping rules

Contents

1 Stopping rules

On-line references:

When Has Estimation Reached A Steady State [2] interactive

Stopping Rules in Estimation and Simulation (interactive Guide chapter)

Processing examples follow.

1.1 Stopping Rules in Estimation

Aim:

Experiments with stopping rules in estimation.

Description:

Quasi-Bayes estimation is done with and without stopping rules and results are compared (prediction-error norm).

Specification:

System: realization of *ndat* two-dimensional data generated by normal static mixture with *ncom* components determined by *seed*.

The components have common diagonal covariance with the diagonal filled by *diac*. Their centers are uniformly positioned on unit circle. Component weights are linearly decreasing. View details in code.

Decision: when to stop experiments.

Experience: *ndat* two-dimensional data records (collected on two channels); correct system structure.

Ignorance: model parameters; future system outputs; quality of compared estimation algorithms.

Loss function: negative *v*-log-likelihood normalized by number of processed data; prediction-errors norm; contour plots of the posterior pdf on estimated parameters.

Recommended experiments:

Observe stop time for different values of *threshold*= 0.001, 0.01, 0.1

Run example | description | view code

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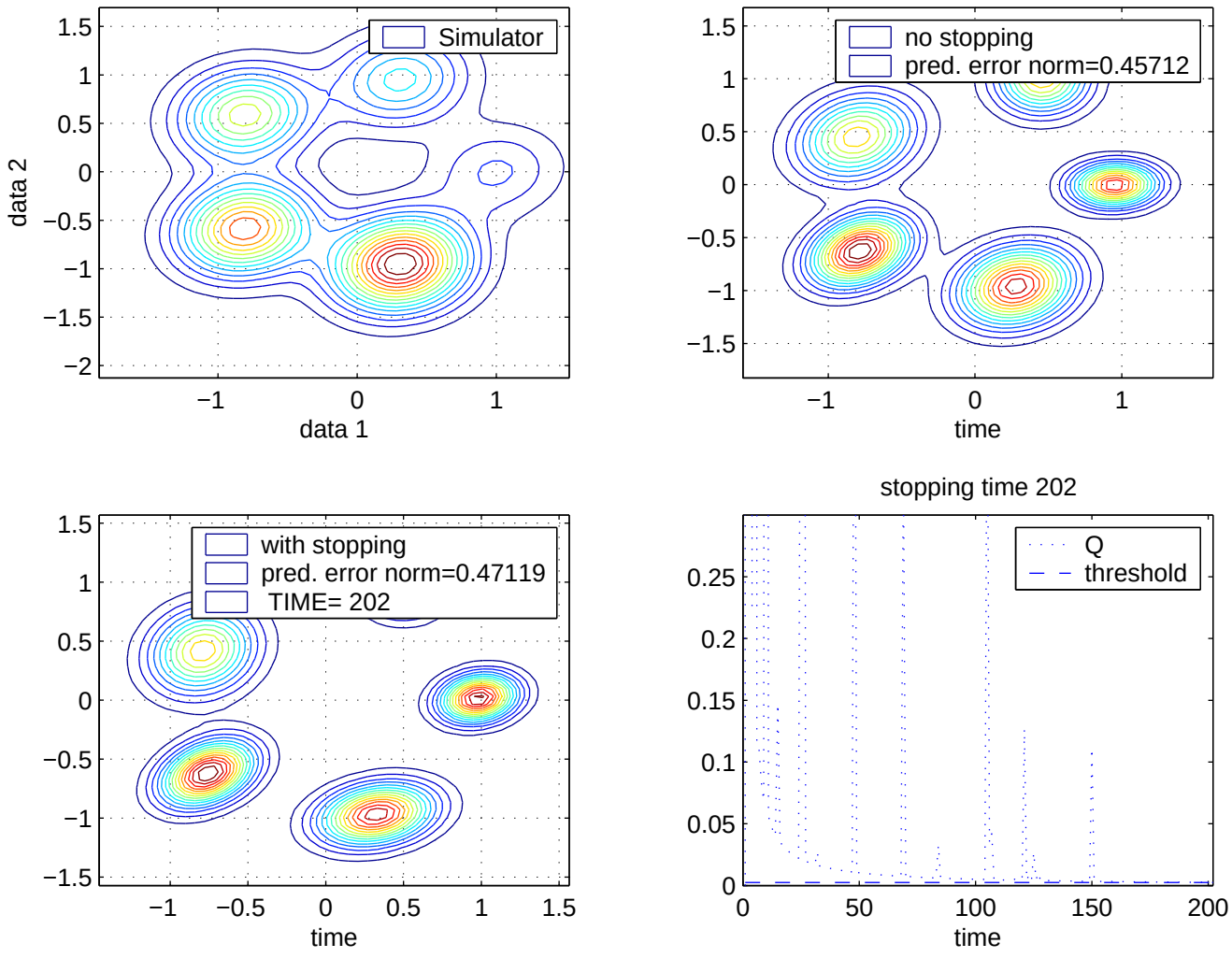

Figure 1: Results with defaults

1.2 Stopping Rules in Simulation

Aim:

Experiments with stopping rules in simulation.

Description:

Quasi-Bayes estimation is done with and without stopping rules and results are compared (prediction-error norm).

Specification:

System: realization of *ndat* two-dimensional data generated by normal static mixture with *ncom* components determined by *seed*.

The components have common diagonal covariance with the diagonal filled by *diac*. Their centers are uniformly positioned on unit circle. Component weights are linearly decreasing. View details in code.

Decision: when to stop experiments.

Experience: *ndat* two-dimensional data records (collected on two channels); correct system structure.

Ignorance: model parameters; future system outputs; quality of compared estimation algorithms.

Loss function: negative *v*-log-likelihood normalized by number of processed data; prediction-errors norm; contour plots of the posterior pdf on estimated parameters.

Recommended experiments:

Observe stop time for different values of *threshold*= 0.001, 0.01, 0.1

Run example | description | help on simeval | view code

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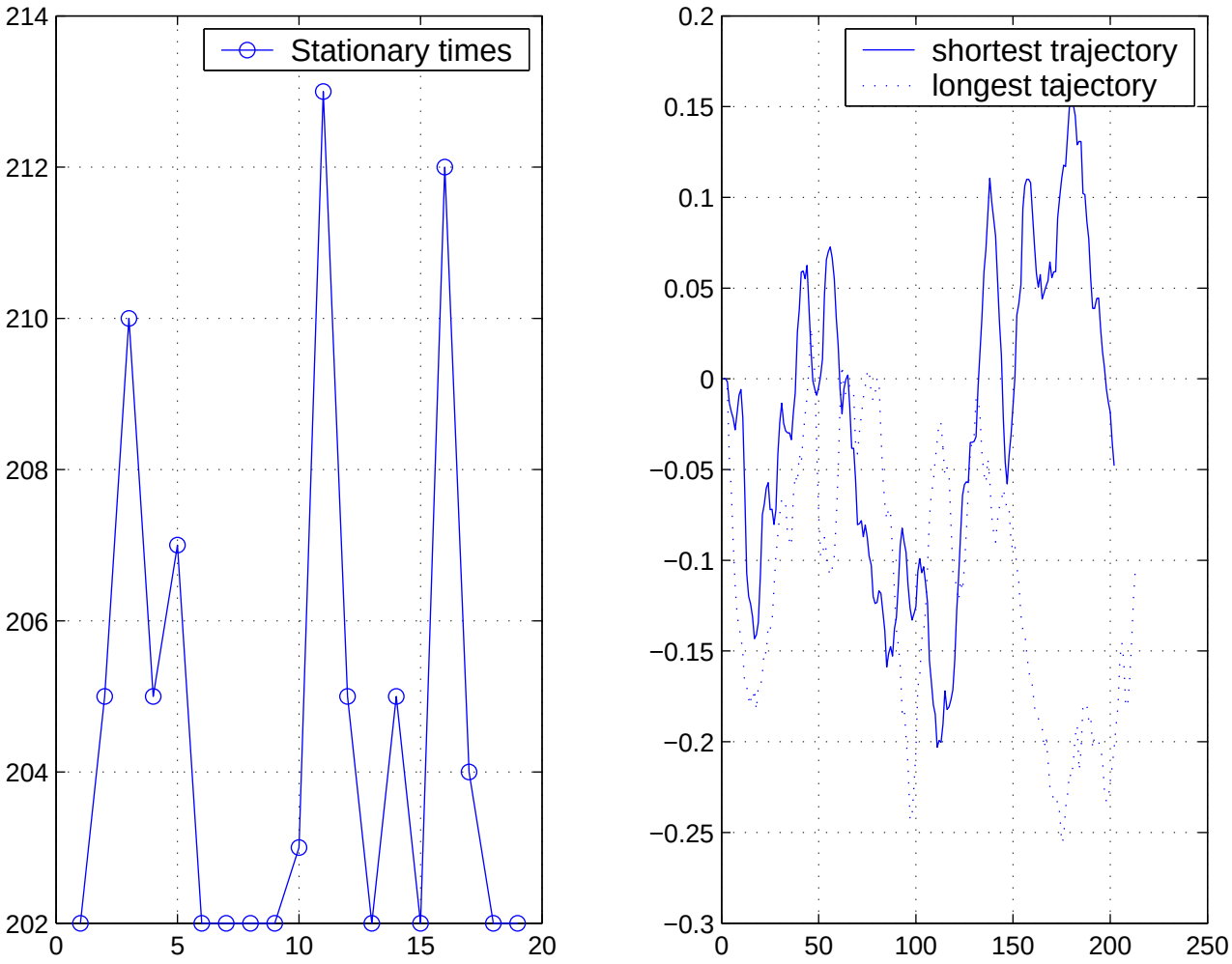

Figure 2: Results with defaults

1.3 Comparison of Mixture Estimation Algorithms

Aim:

To choose a learning algorithm and its tuning knobs adequate to the considered system. The algorithms compared are projection method (PB), quasi-Bayes, see Section 6.5.1{158} (QB), batch quasi-Bayes, see section 6.5.12{165} (BQB) and forgetting branching, see Algorithm 6.4.31{141} (BFRG), each of which approximately estimates mixture of a fixed known structure. Two functions designed using stopping rules are added: PX (projection method) and QX (qusi-Bayes with stopping rules.

Description:

Observed data are generated by a static simulated mixture. They are used for estimation of mixture models via the learning algorithms compared. Their performance is influenced by the number of iterations *niter* and forgetting rate frg. The forgetting branching uses additionally an alternative small forgetting rate $frga$.

Specification:

System: realization of *ndat* two-dimensional data generated by normal static mixture with *ncom* components determined by *seed*.

The components have common diagonal covariance with the diagonal filled by *diac*. Their centers are uniformly positioned on unit circle. Component weights are linearly decreasing. View details in code.

Decision: one-step-ahead output predictions, generalized Bayesian estimation of mixture parameters.

Experience: *ndat* two-dimensional data records (collected on two channels); correct system structure.

Ignorance: model parameters; future system outputs; quality of compared estimation algorithms.

Loss function: negative *v*-log-likelihood normalized by number of processed data; prediction-errors norm; contour plots of the posterior pdf on estimated parameters.

Recommended experiments:

Performance of the inspected heuristic algorithms vary with extent of data, noise level, system complexity, behavior realization and optional knobs of algorithms. It is worth inspecting the influence of

- extent of learning data, say *ndat* = 500, 300, 200
- system-noise variance, *diac* = 0.5, 1
- estimated system complexity, *ncom* = 10, 20
- behavior realization, *seed* = any positive integer
- number of iterations, *niter* = 10, 30, 100 (computational time increases linearly)
- involved forgetting factors on quality of branching-by-forgetting, frg = 0.99, 0.999 $frga$ = 0.5, 0.9

Run example | help on mixest | view code

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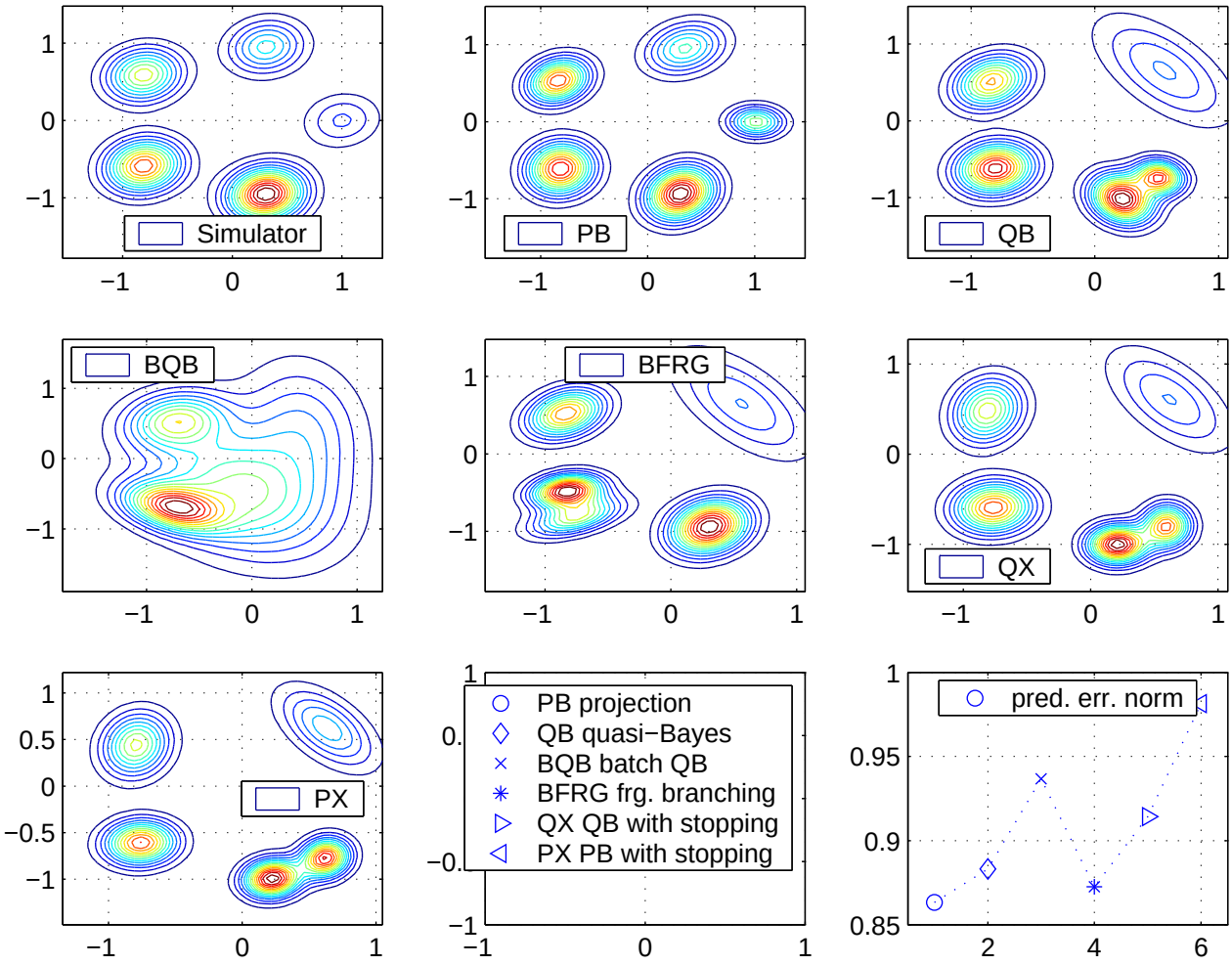

Figure 3: Results with defaults

1.4 Stopping Rules in Initialization

Aim:

Experiments with stopping rules in initialization.

Description:

An estimation method is selected specifying *opt*:

'p'	iterative projection based estimation (QB)
'q'	iterative quasi-Bayes mixture estimation (QB)
'b'	iterative batch quasi-Bayes mixture estimation (BQB)
'f'	iterative mixture estimation based on forgetting branching (BFRG)
'P'	iterative projection with stopping rules (PX)
'Q'	iterative projection with stopping rules (QX)
'n'	without iterative estimation (default) (single path of QB)

Then *mixinit* is called and individual iterations are displayed. As a measure of quality, prediction-error norm is displayed.

Specification:

System: realization of *ndat* two-dimensional data generated by normal static mixture with *ncom* components determined by *seed*.

The components have common diagonal covariance with the diagonal filled by *diac*. Their centers are uniformly positioned on unit circle. Component weights are linearly decreasing. View details in code.

Decision: when to stop estimation internally called by *mixinit*.

Experience: *ndat* two-dimensional data records.

Ignorance: model structure.

Loss function: negative *v*-log-likelihood

Recommended experiments:

Observe stop time for different values of *threshold*= 0.001, 0.01, 0.1

Run example | description | view code

Contents

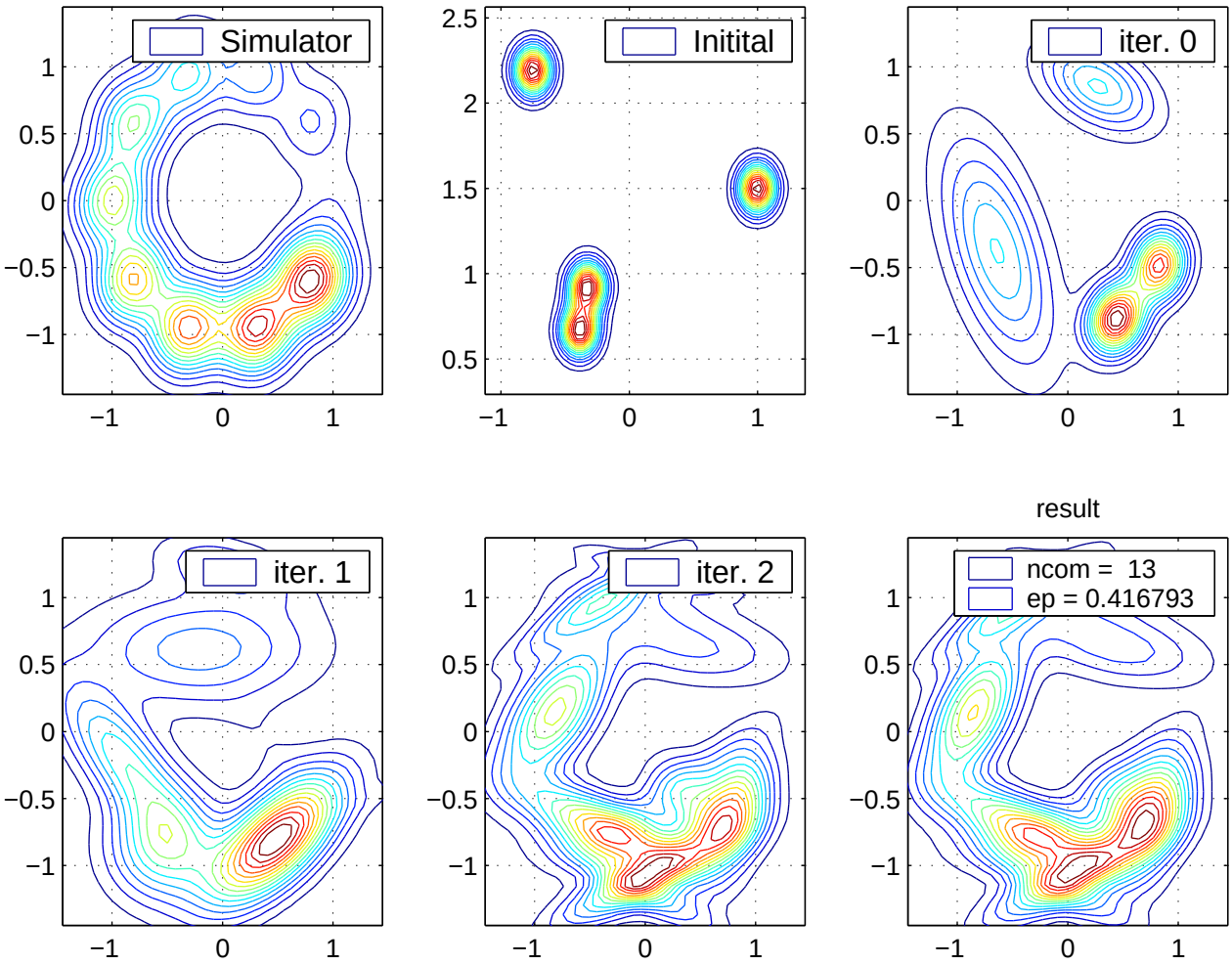

Figure 4: Results with defaults

References

[1] M. Kárný, J. Böhm, T.V. Guy, L. Jirsa, I. Nagy, P. Nedoma, and L. Tesař, *Optimized Bayesian Dynamic Advising: Theory and Algorithms*, Springer, London, 2004, to appear.

[2] M. Kárný, J. Kracík, I. Nagy, and P. Nedoma, "When Has Estimation Reached A Steady State? The Bayesian Sequential Test", *International Journal of Adaptive Control and Signal Processing*, 2004, accepted.