

System Identification

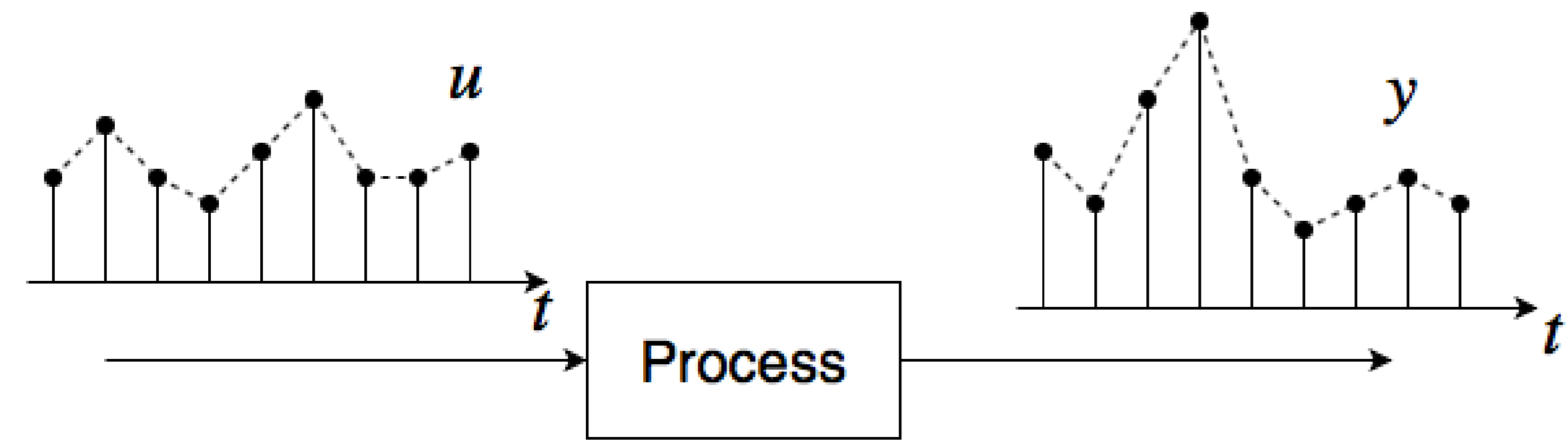


Figure 1: System identification problem.

Prediction Error Methods

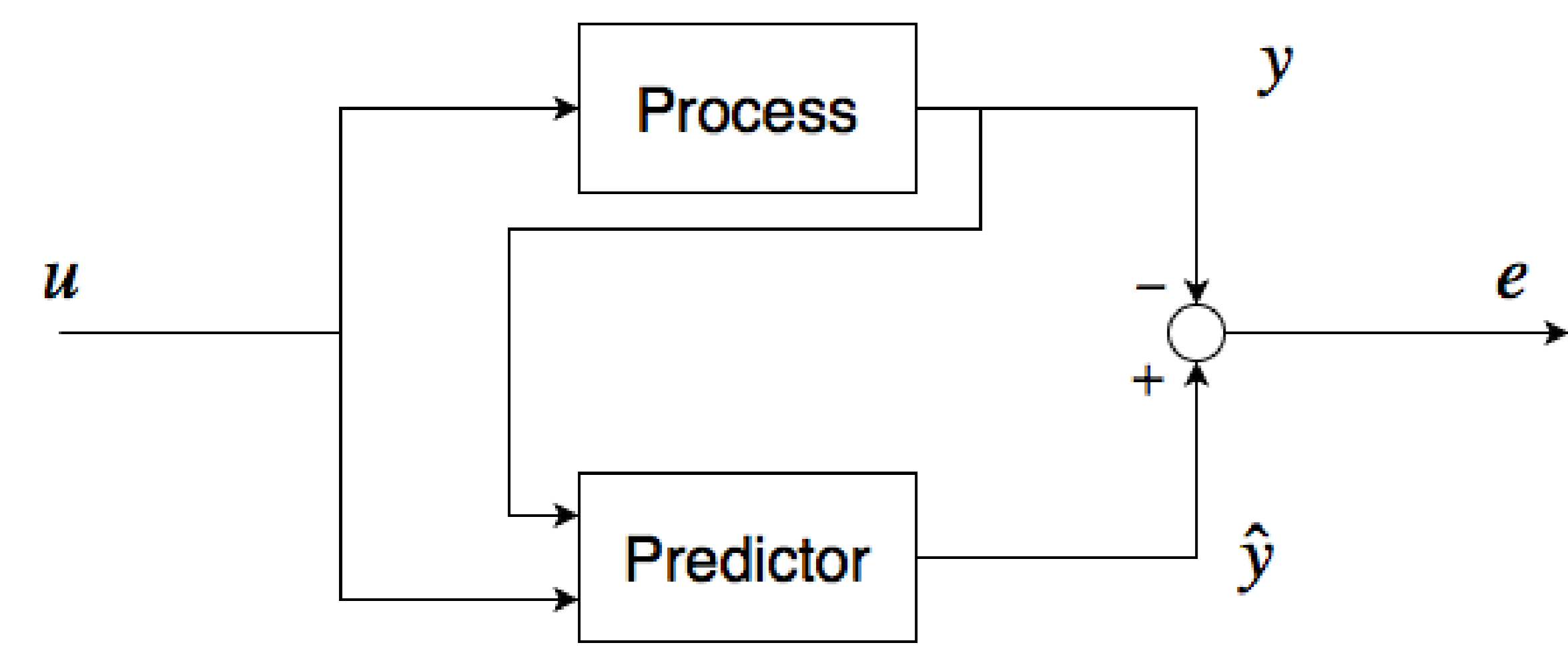


Figure 2: Prediction error methods. ⁱ

NARX

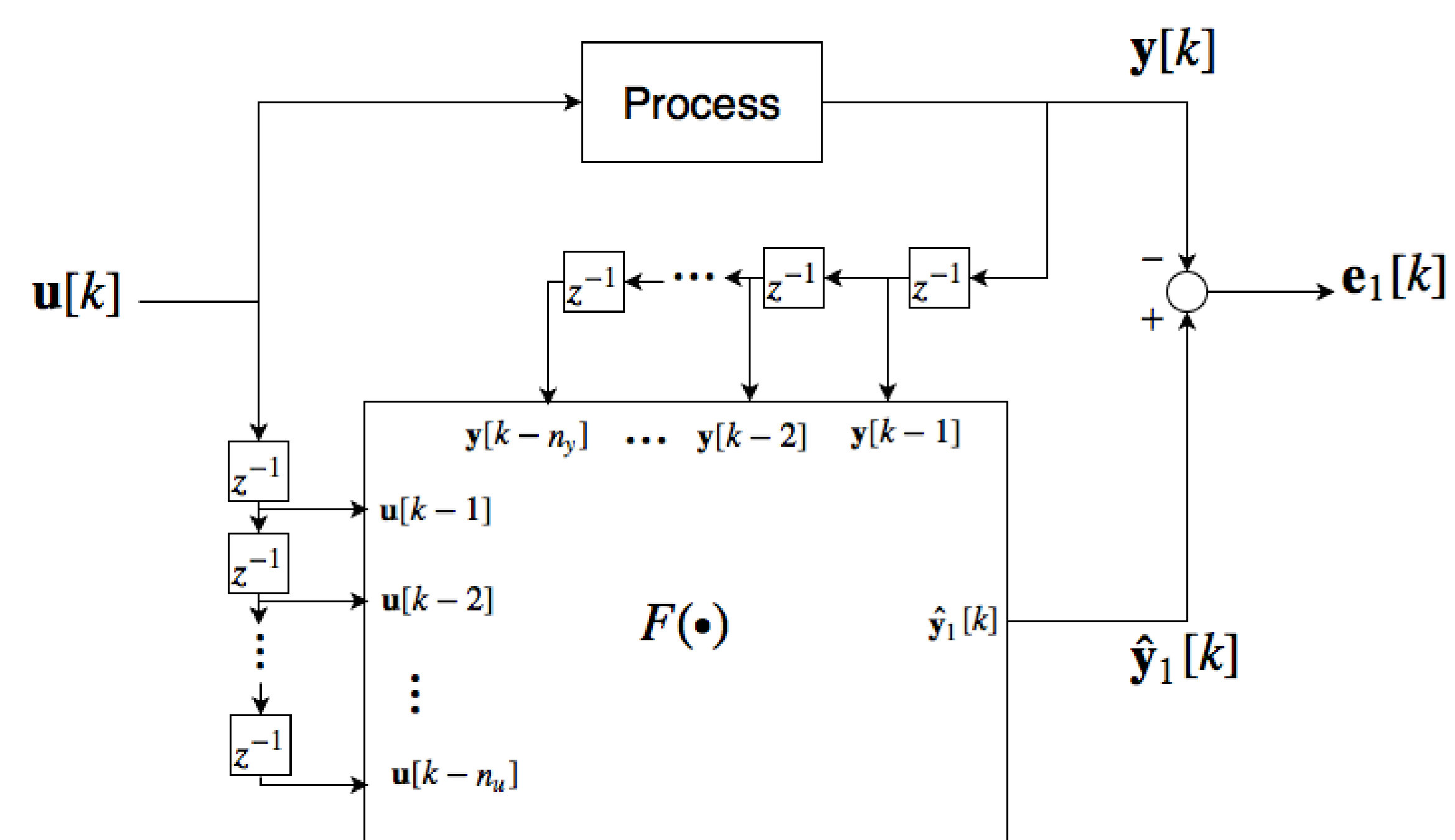


Figure 3: Nonlinear autoregressive with exogenous input (NARX) model. ⁱ

NOE

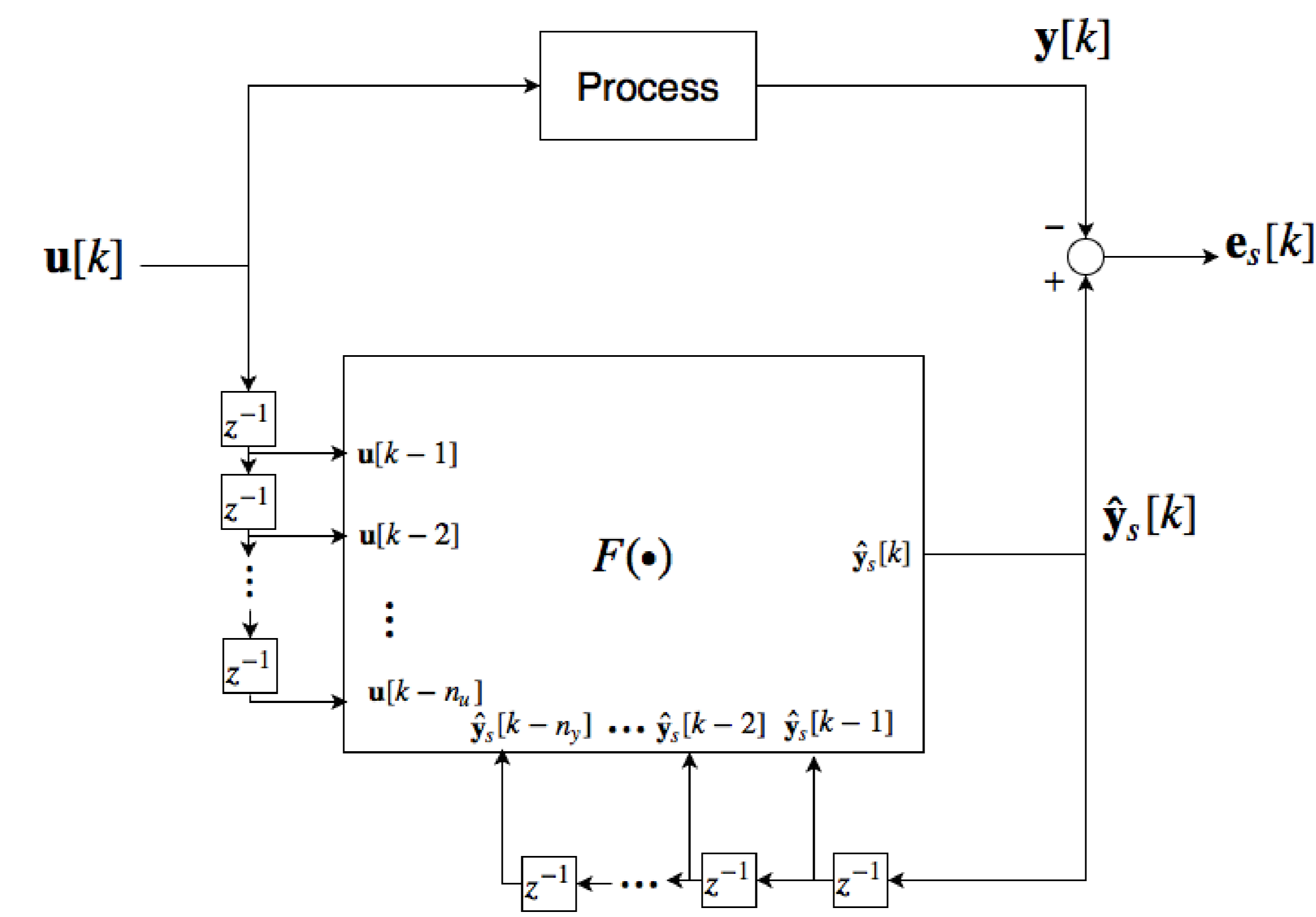


Figure 4: Nonlinear output error (NOE) model. ⁱ

Possible Advantages of NOE models

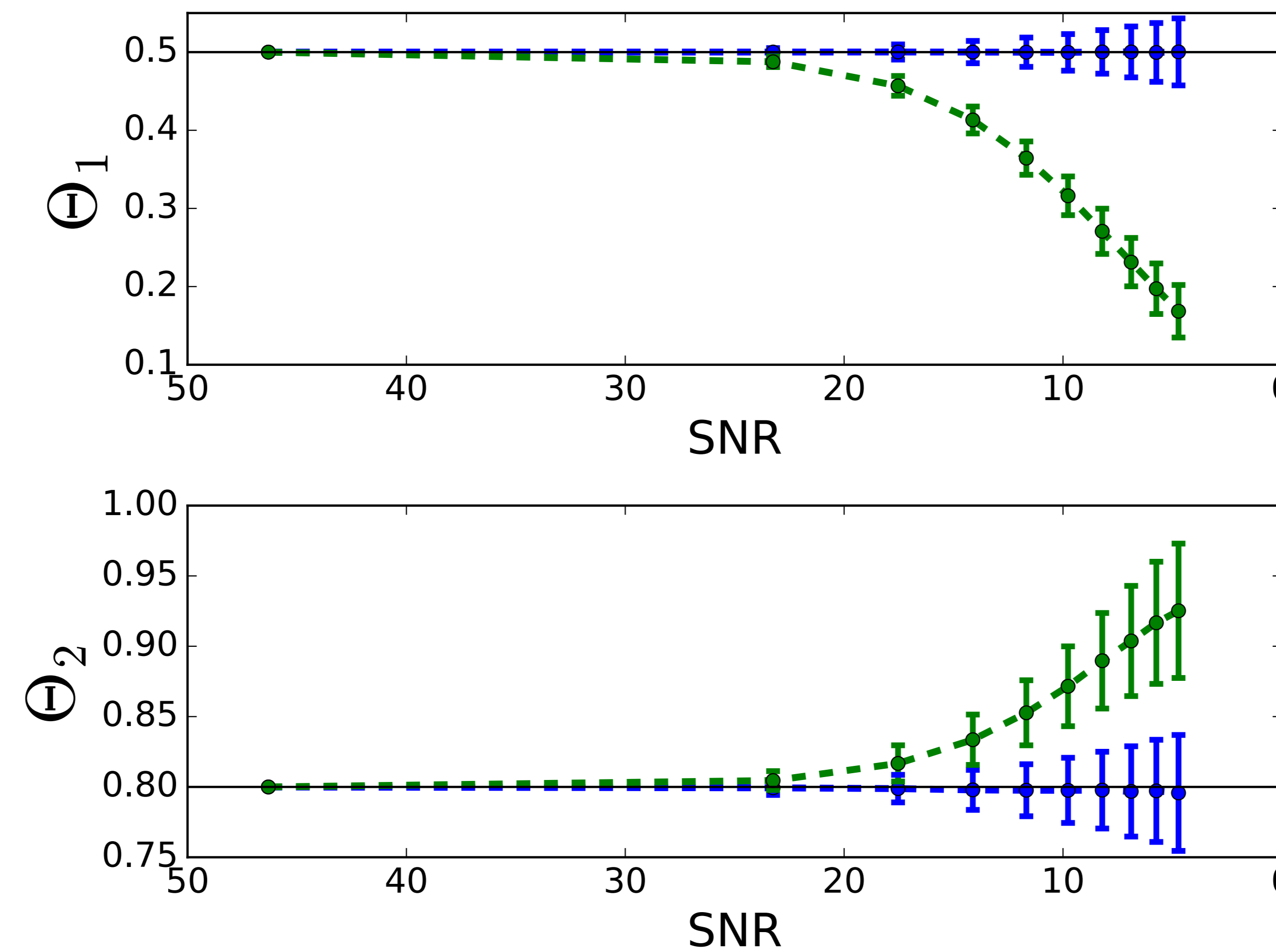


Figure 5: Expected values (dots) and standard deviation $\pm\sigma_{\hat{\theta}}$ (bars) of parameter. Estimated using an NOE model (in blue) and an NARX model (in green). The true value is represented as the horizontal line. ⁱ

Multiple Shooting

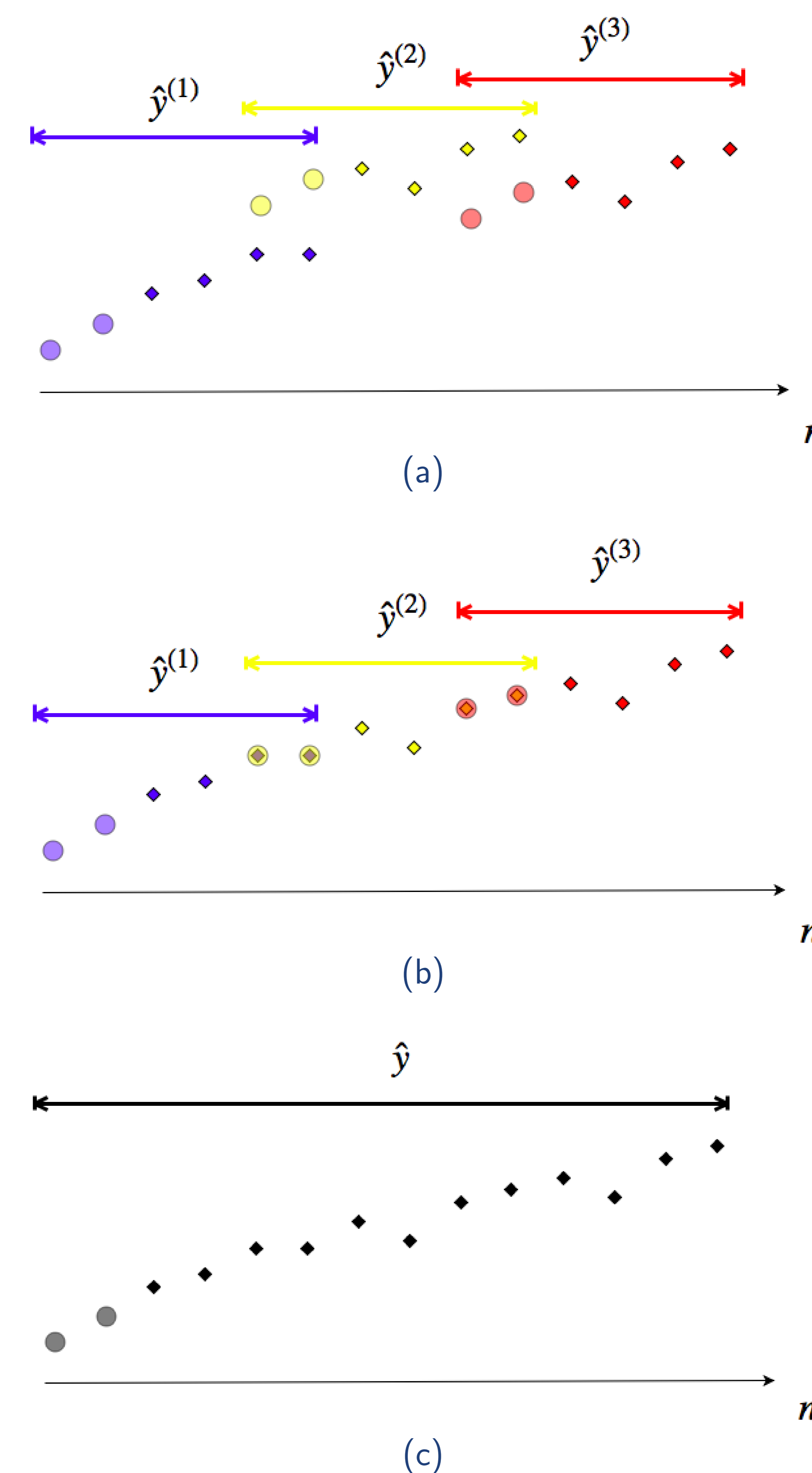


Figure 6: Three consecutive simulations $\hat{y}^{(i)}$, $i = 1, 2, 3$ are indicated with different colors. The initial conditions are represented with circles \circ and subsequent simulated values with diamonds \diamond . ⁱ

Multiple Minima Problem

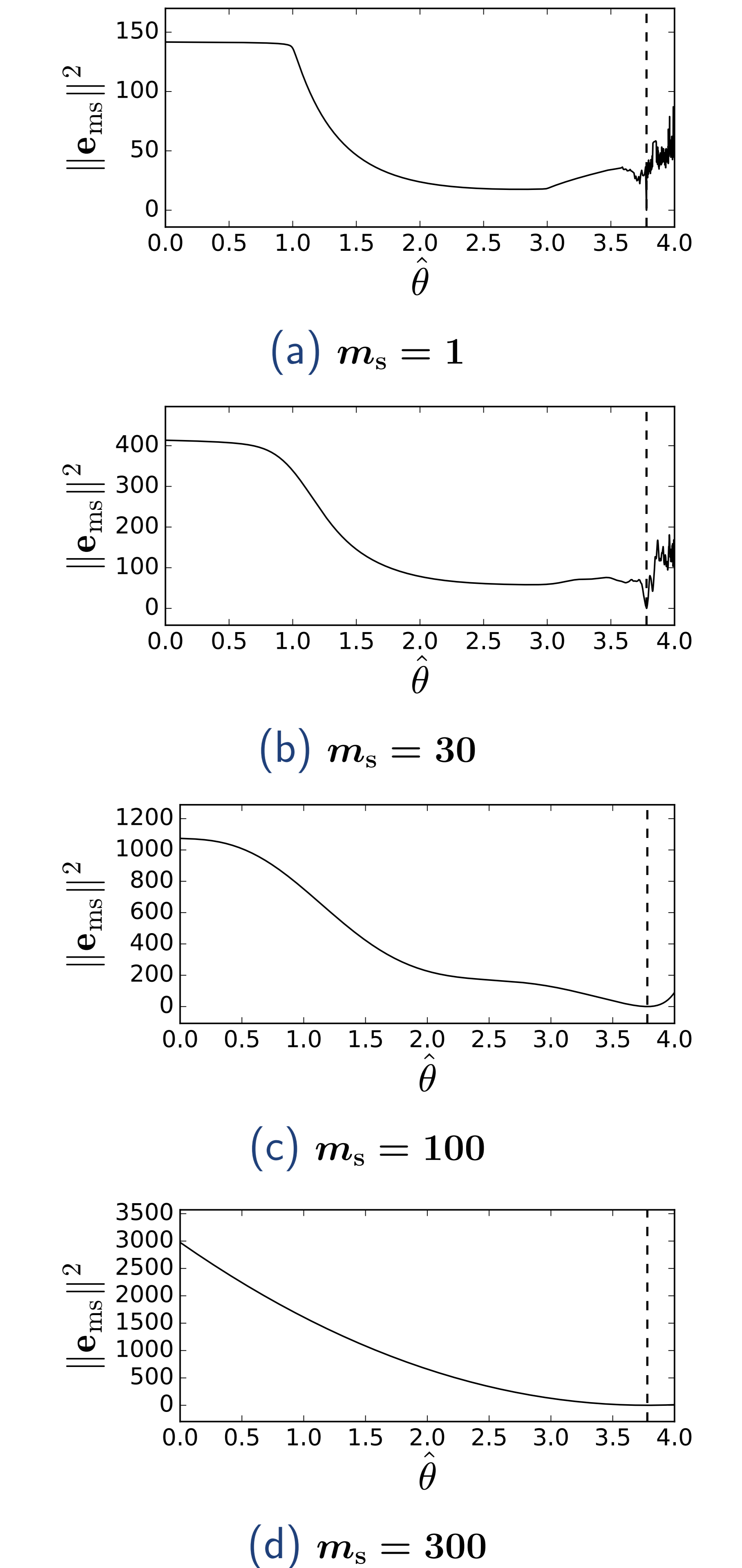


Figure 7: Shows $\|e_{ms}\|^2$ as a function of $\hat{\theta}$ for fixed initial conditions. The vertical dashed line (---) represents the true parameter value. ⁱ

Acknowledges

This work has been supported by the Brazilian agencies CAPES, CNPq and FAPEMIG.

Prediction Error Methods

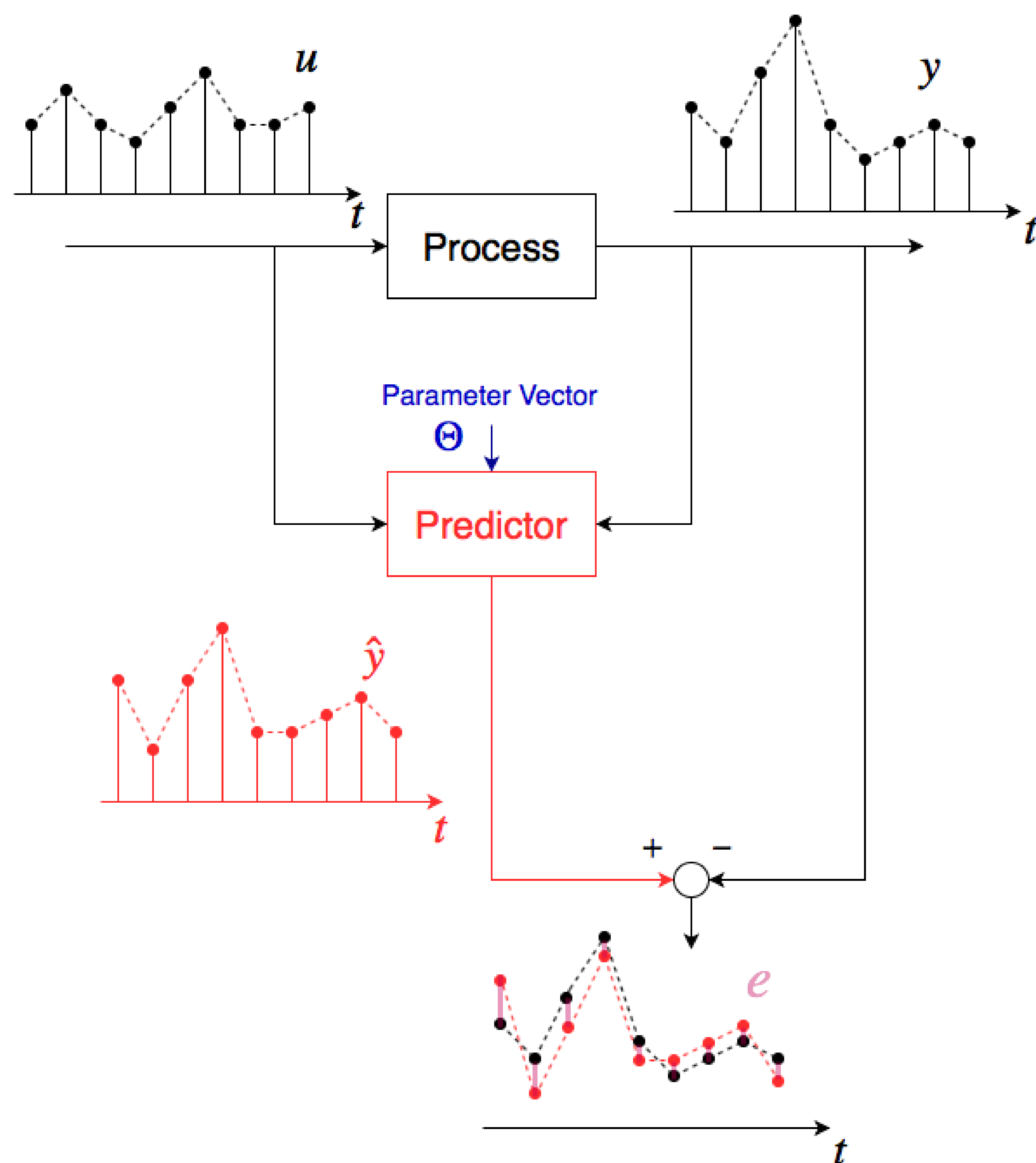


Figure 8: *Prediction error methods.* These methods estimate the parameters by minimizing the error between the optimal output prediction and the measured value

Difference Equation Models

Difference equations:

$$y[k] = F(y[k-1], y[k-2], y[k-3], u[k-1], u[k-2], u[k-3]; \Theta).$$

One-step-ahead Prediction

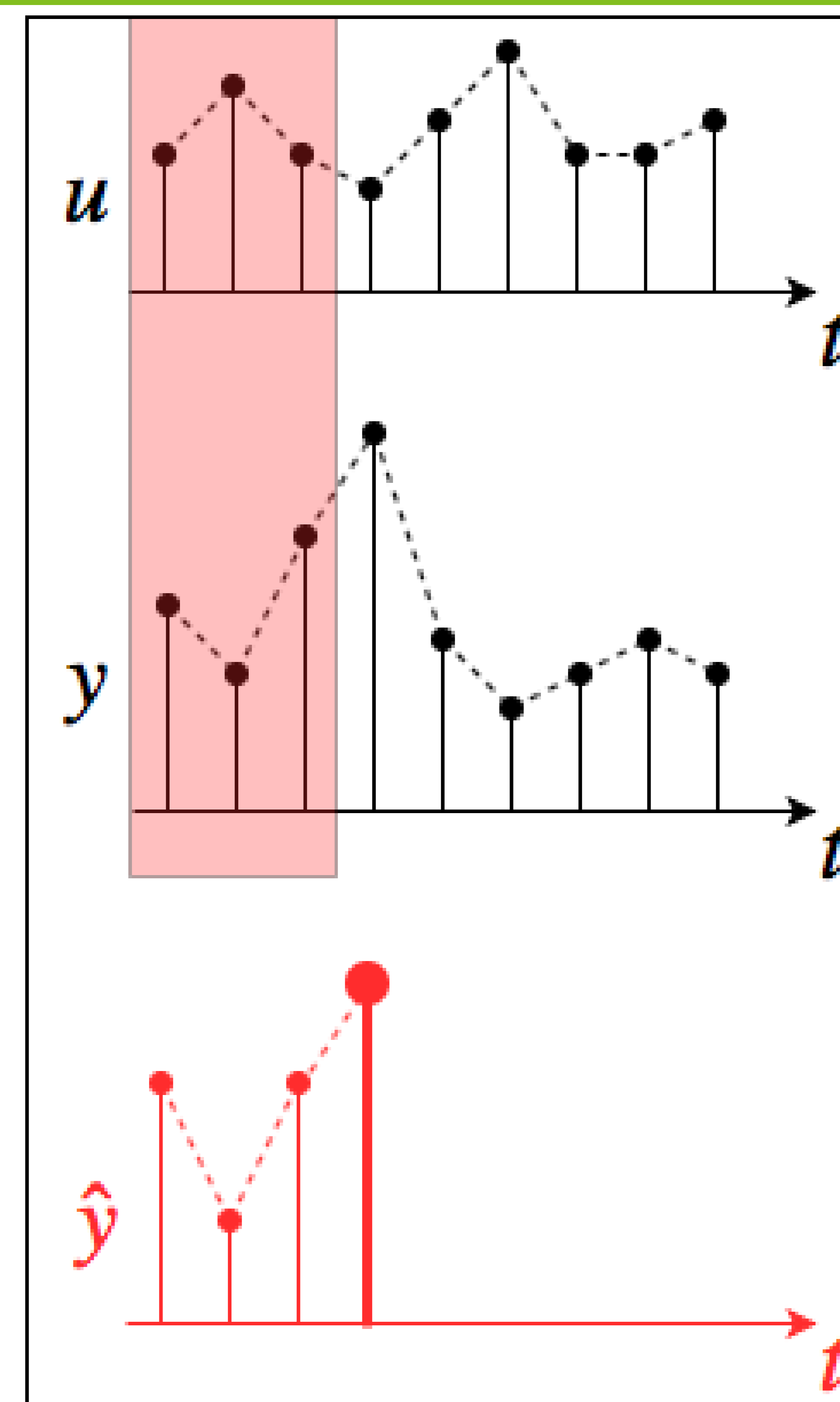


Figure 9: One-step-ahead prediction.

Free-run Simulation

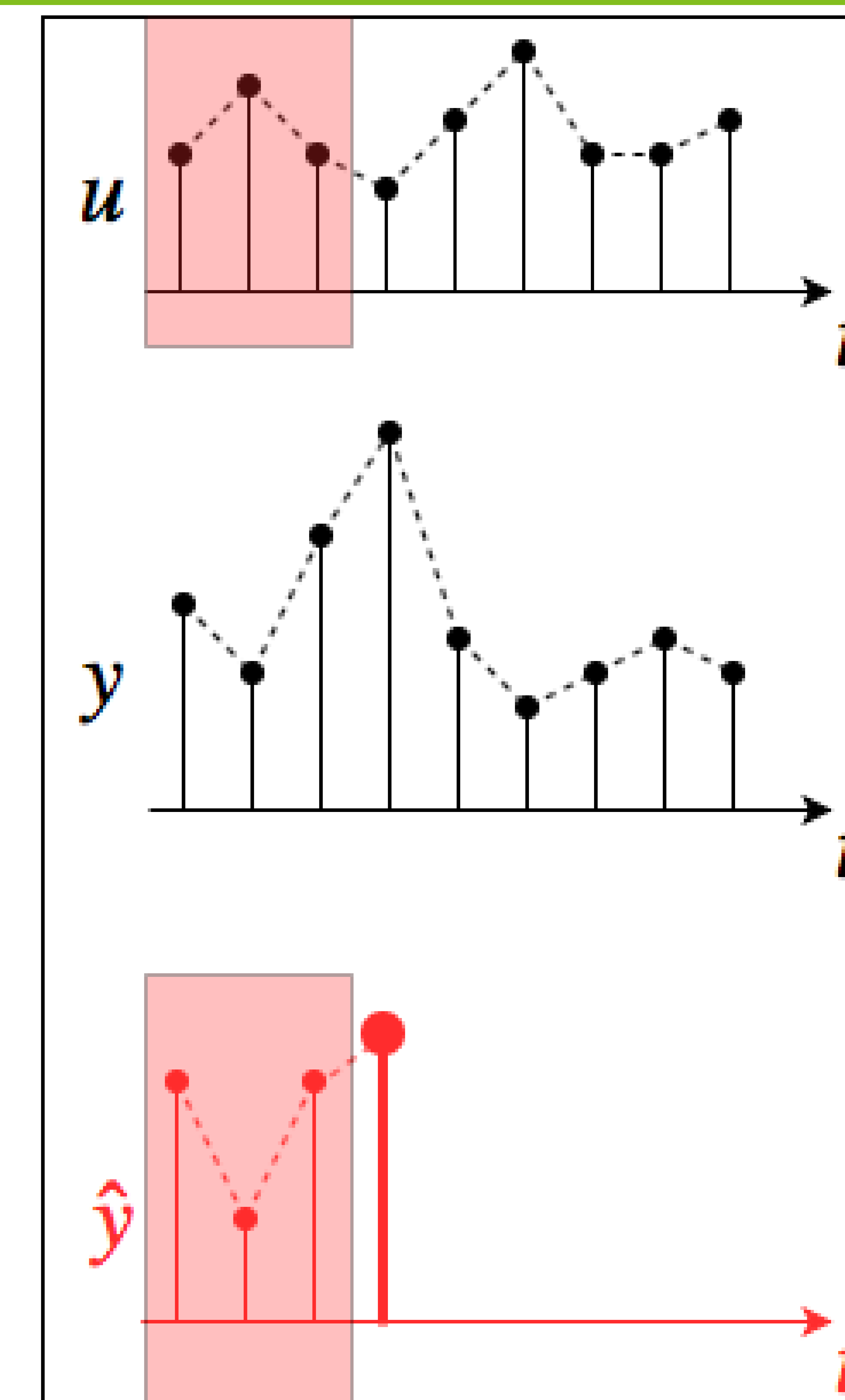


Figure 10: Free-run simulation.

Prediction Error Methods

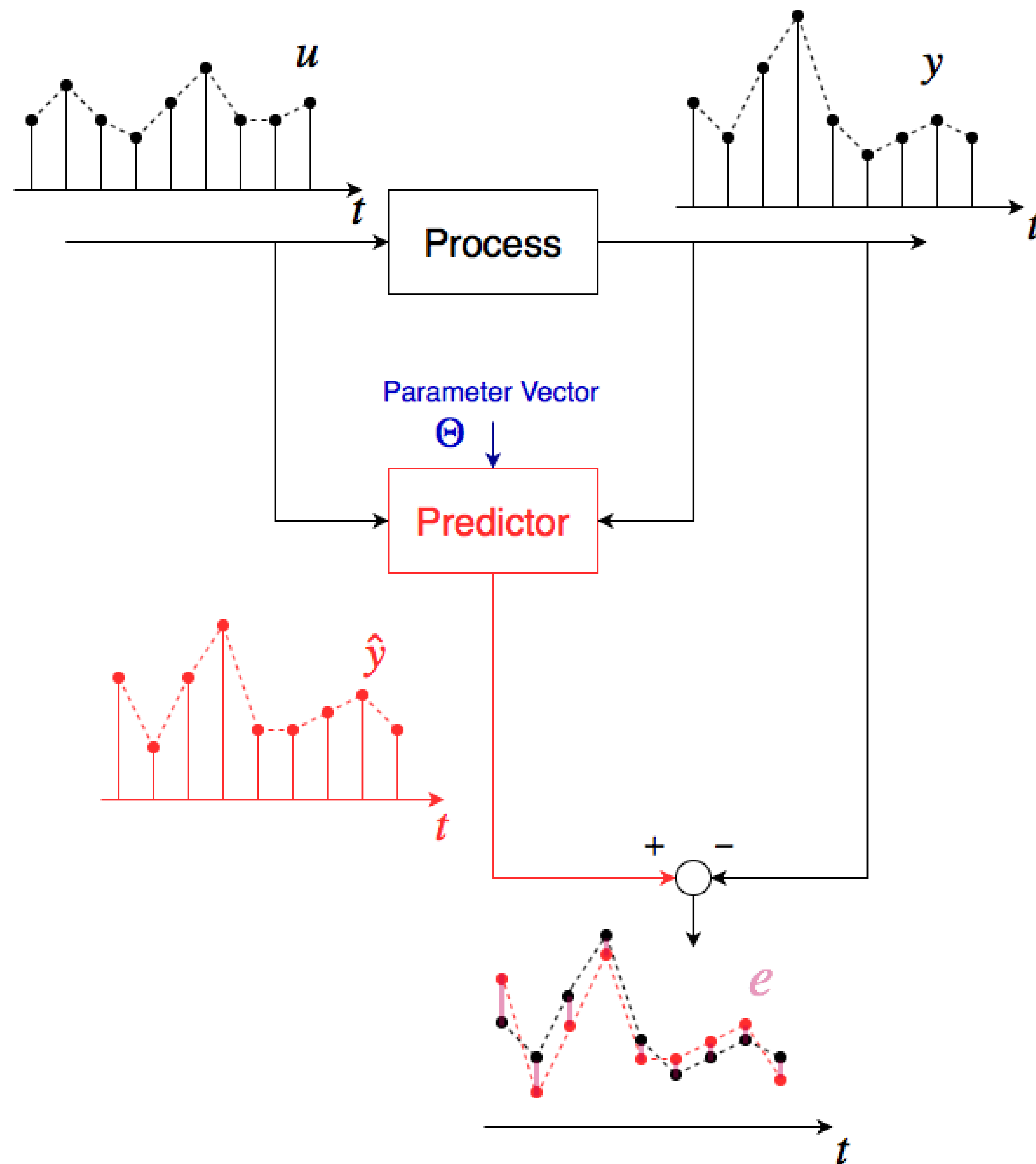


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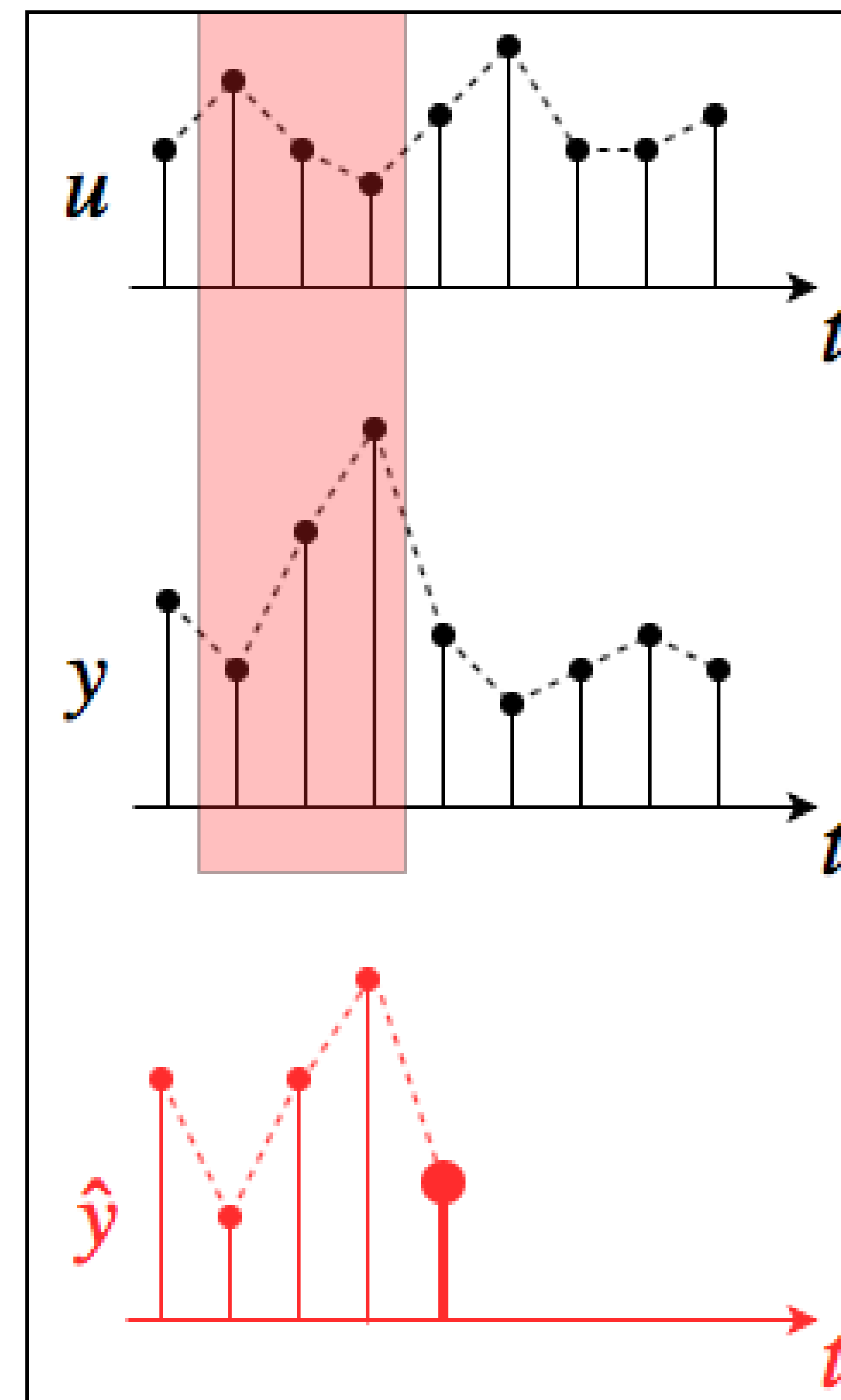


Figure 9: One-step-ahead prediction.

Free-run Simulation

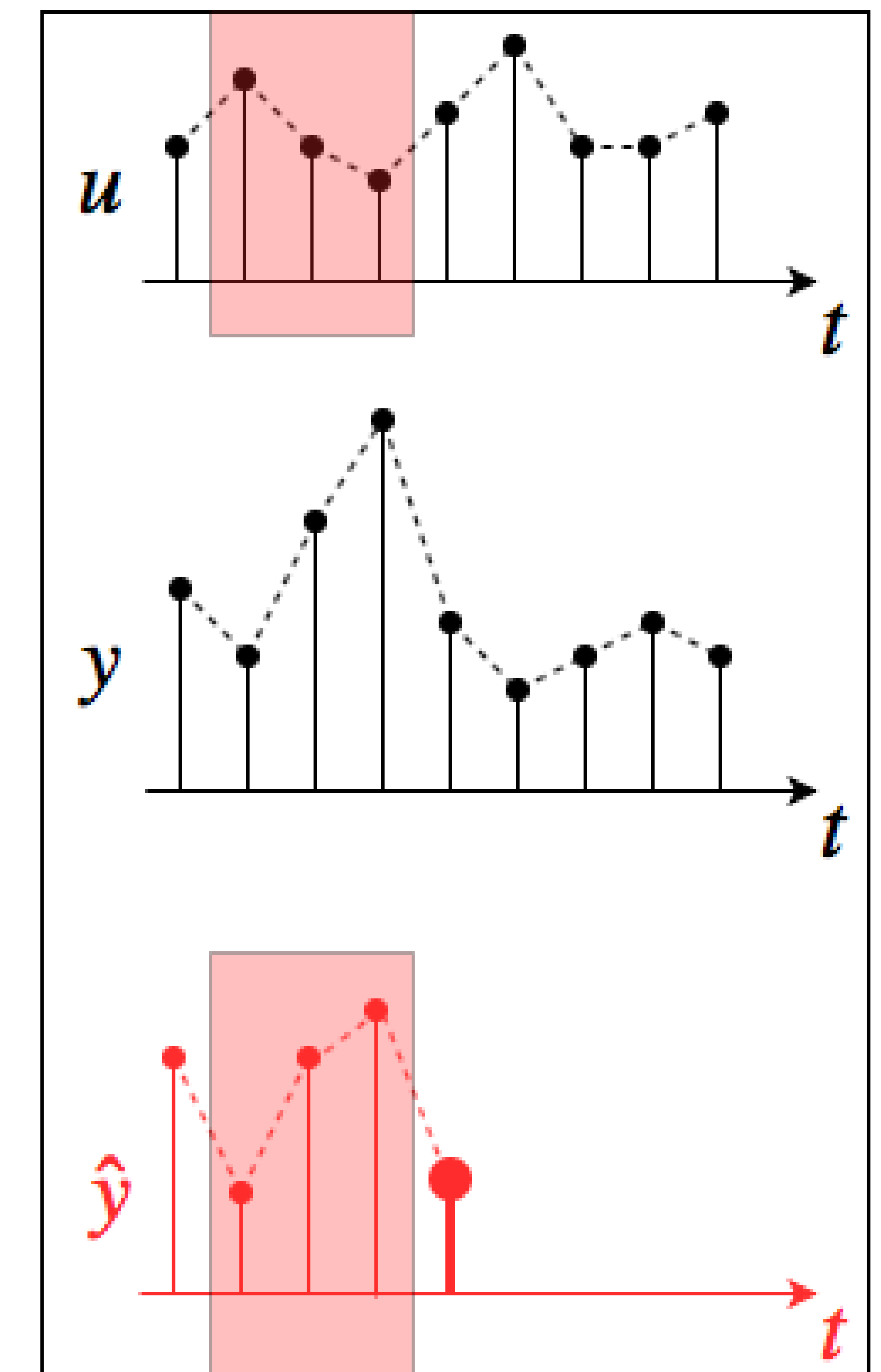


Figure 10: Free-run simulation.

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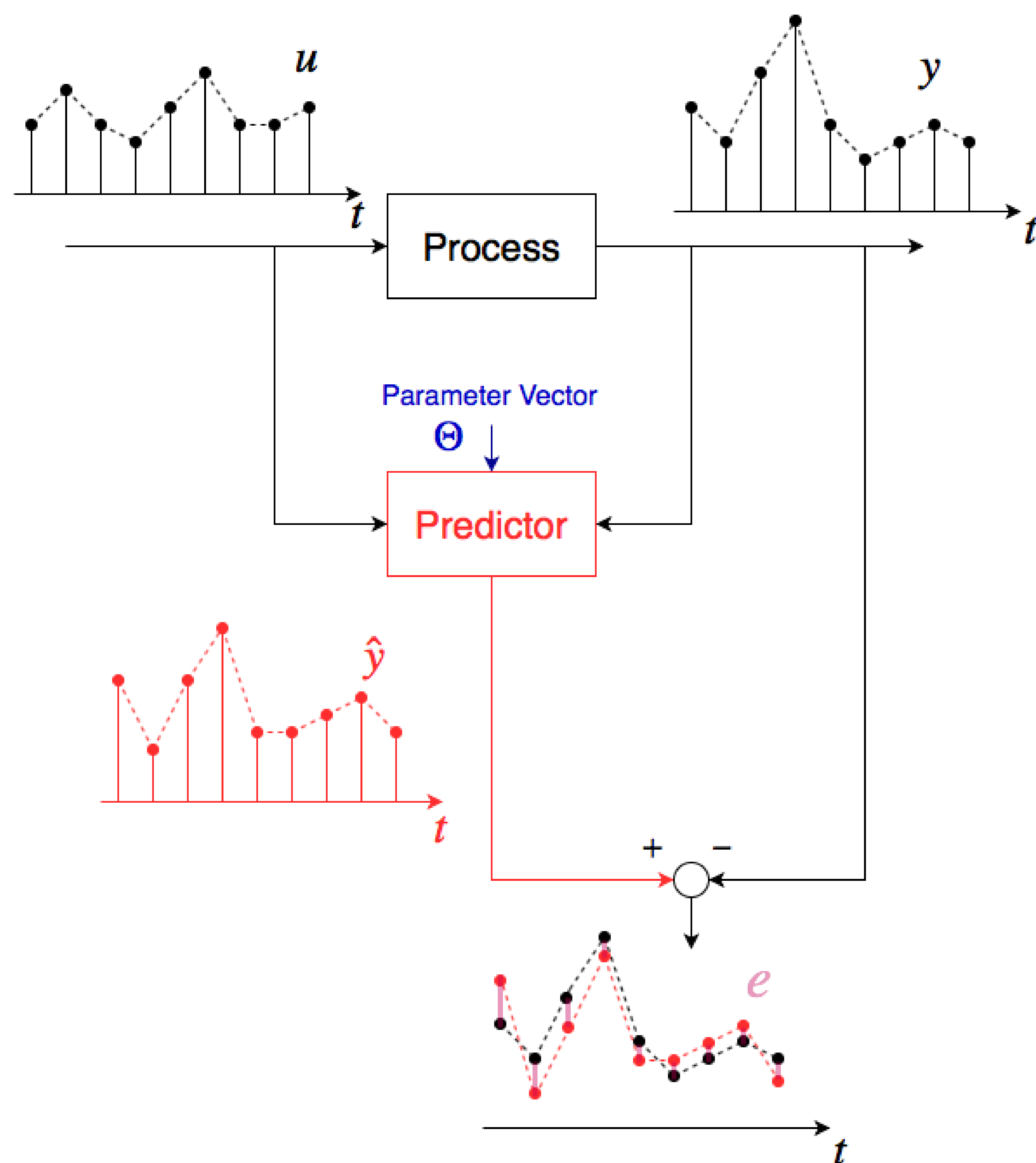


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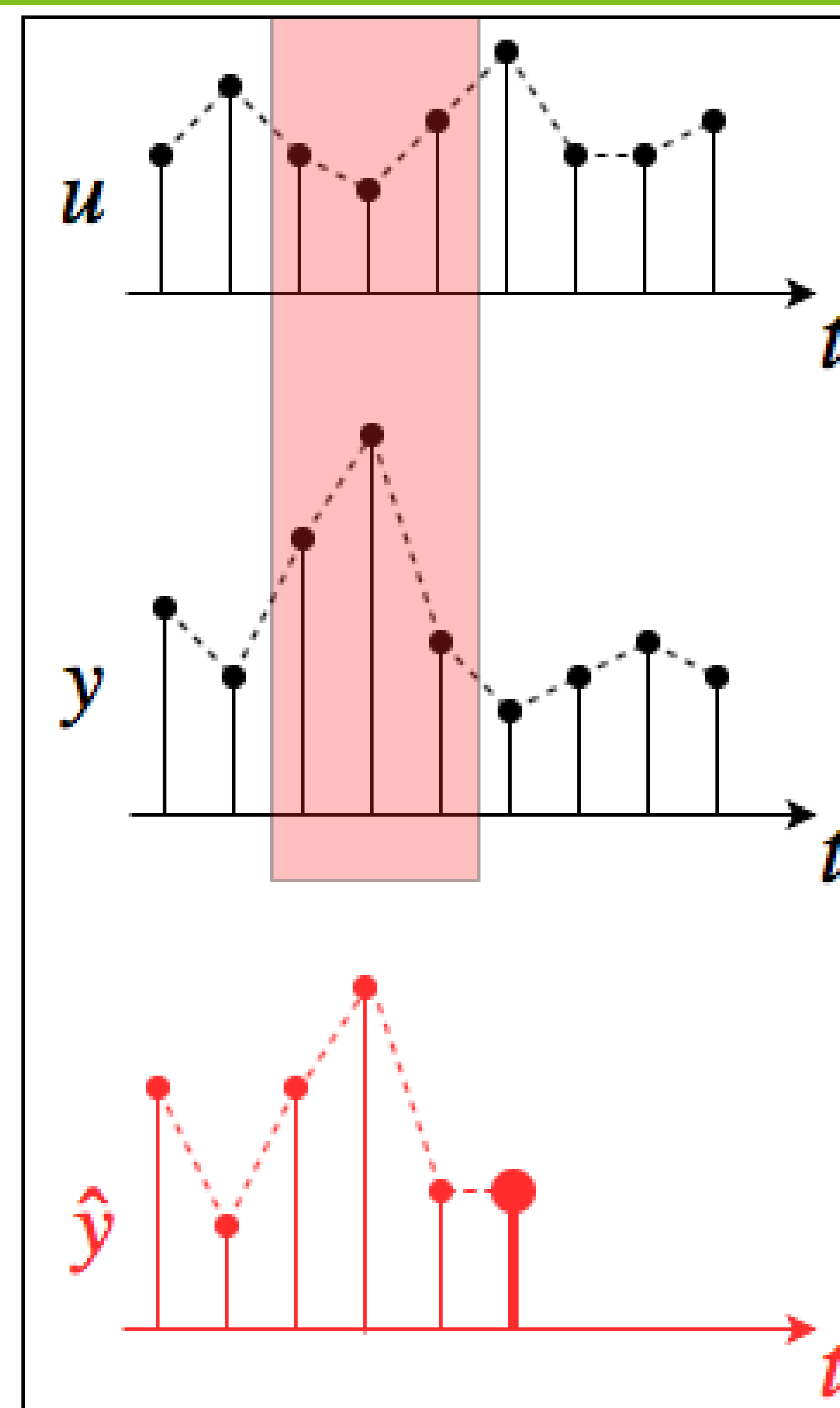


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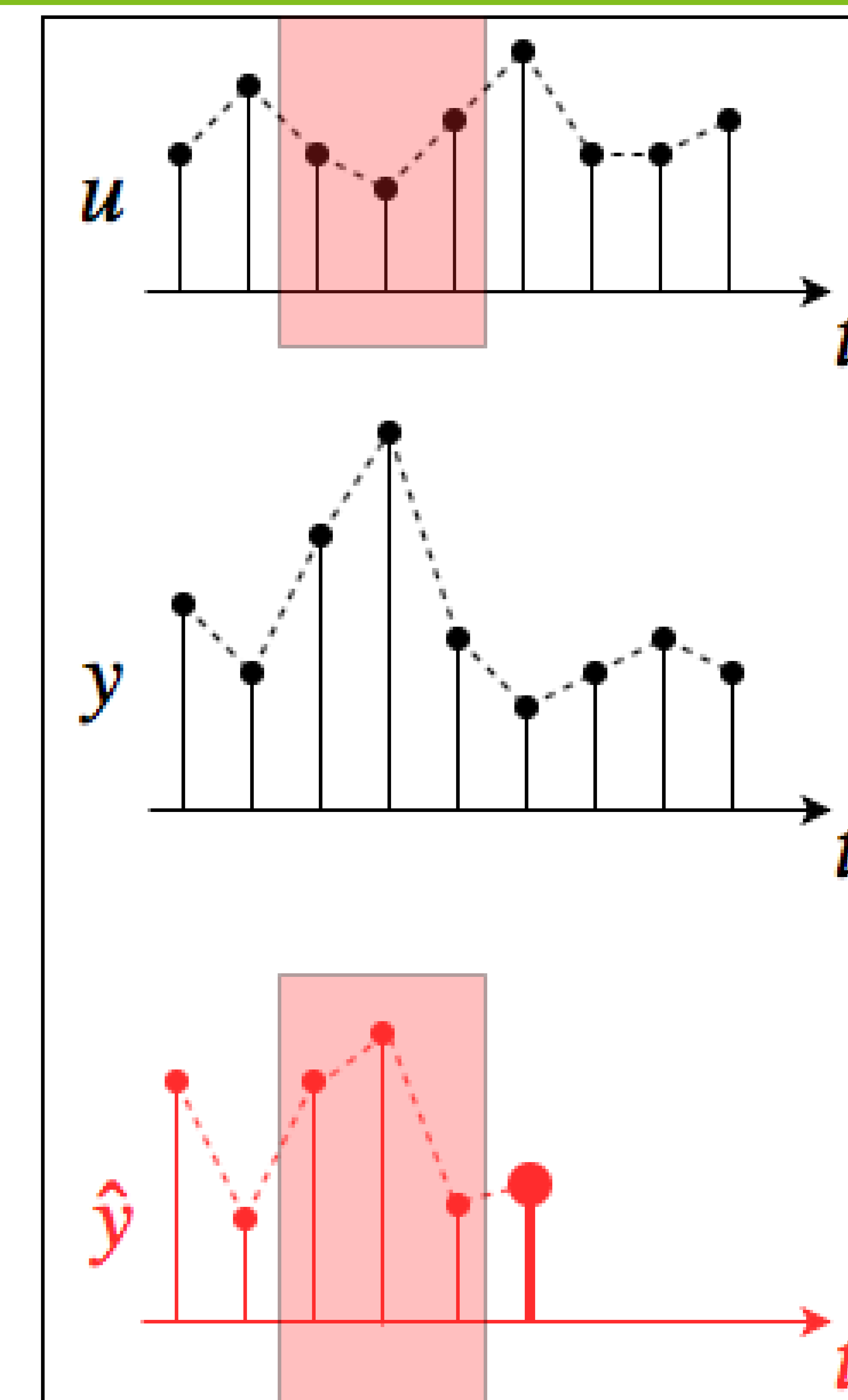


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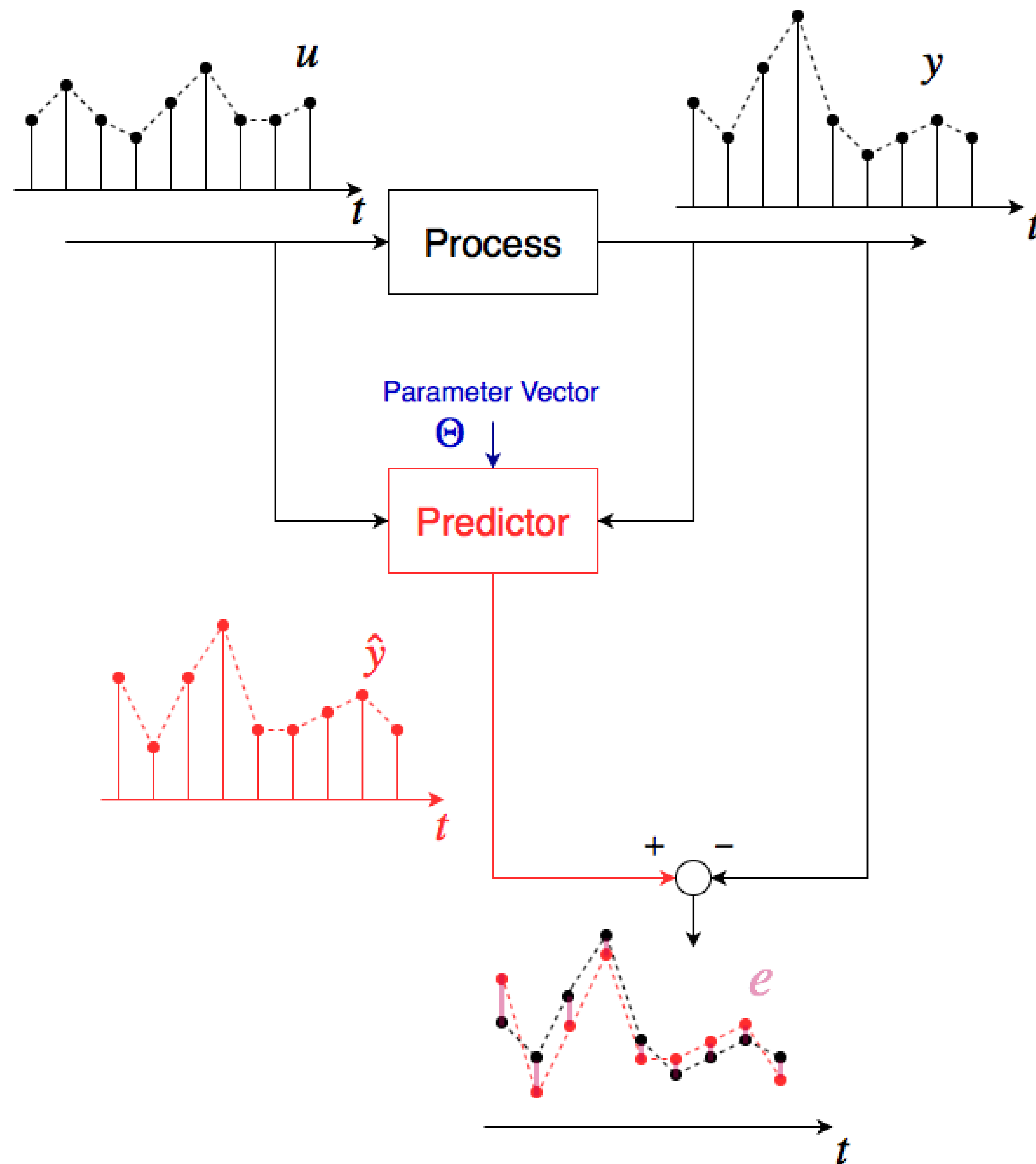


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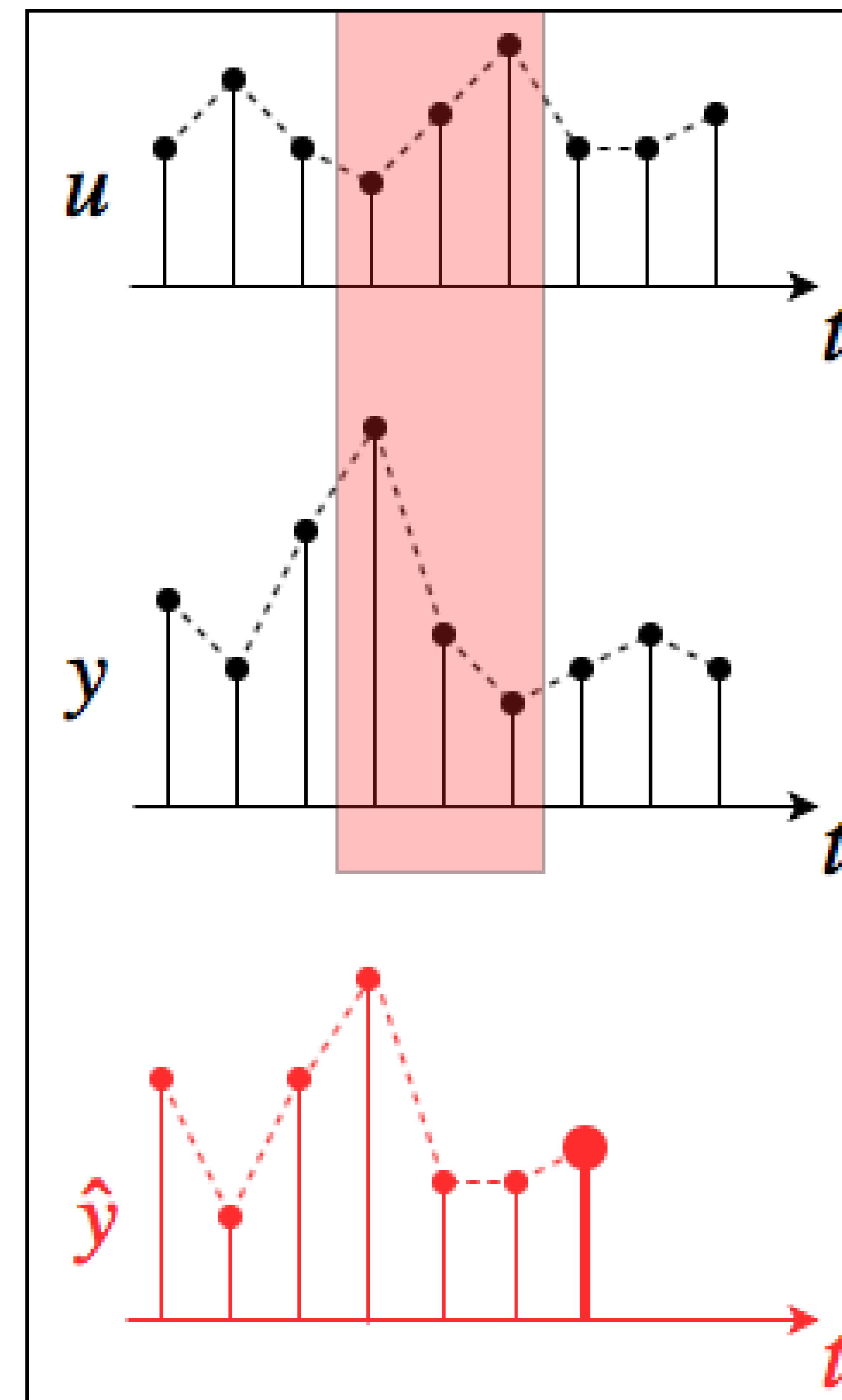


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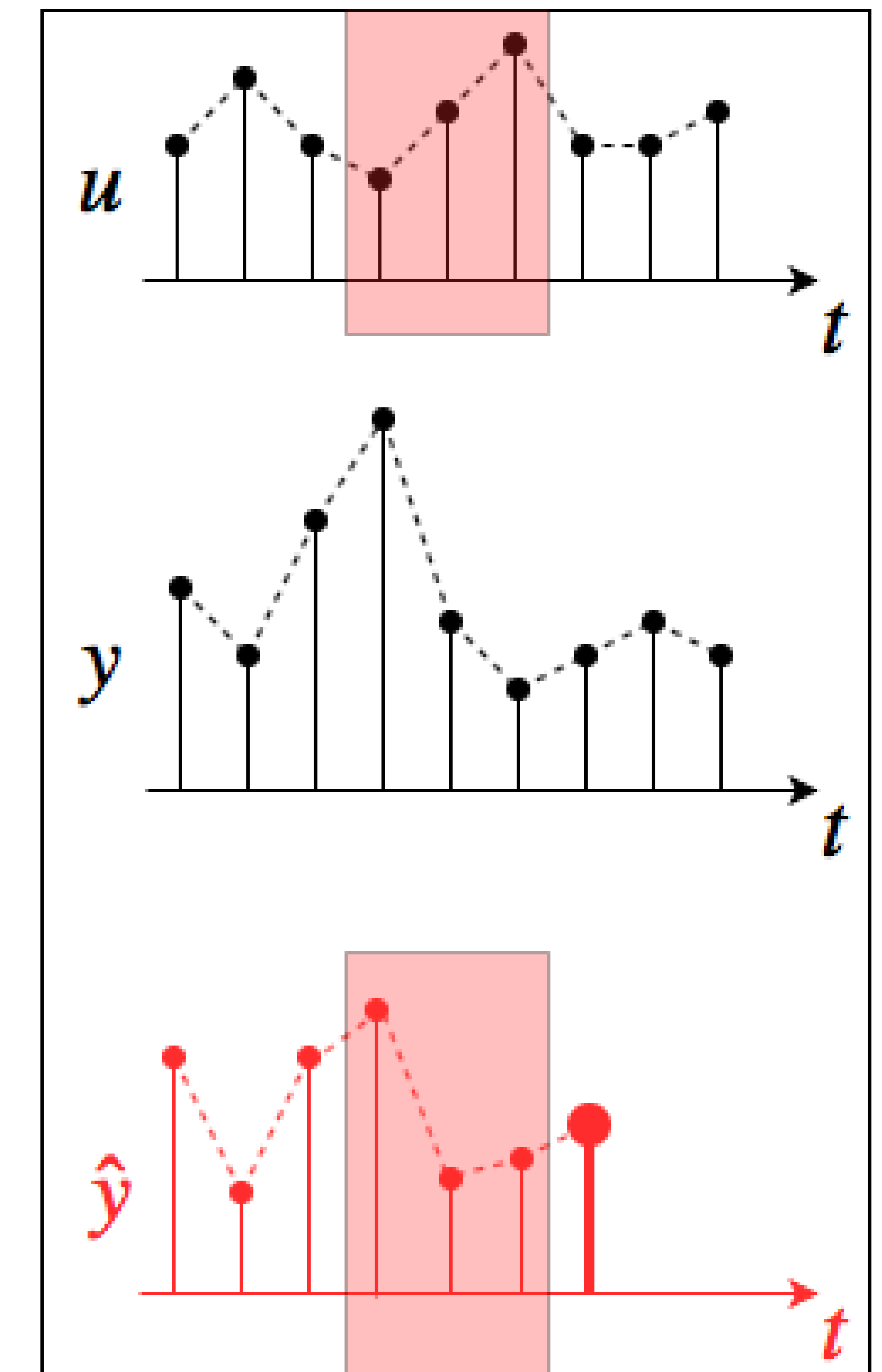


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Prediction Error Methods

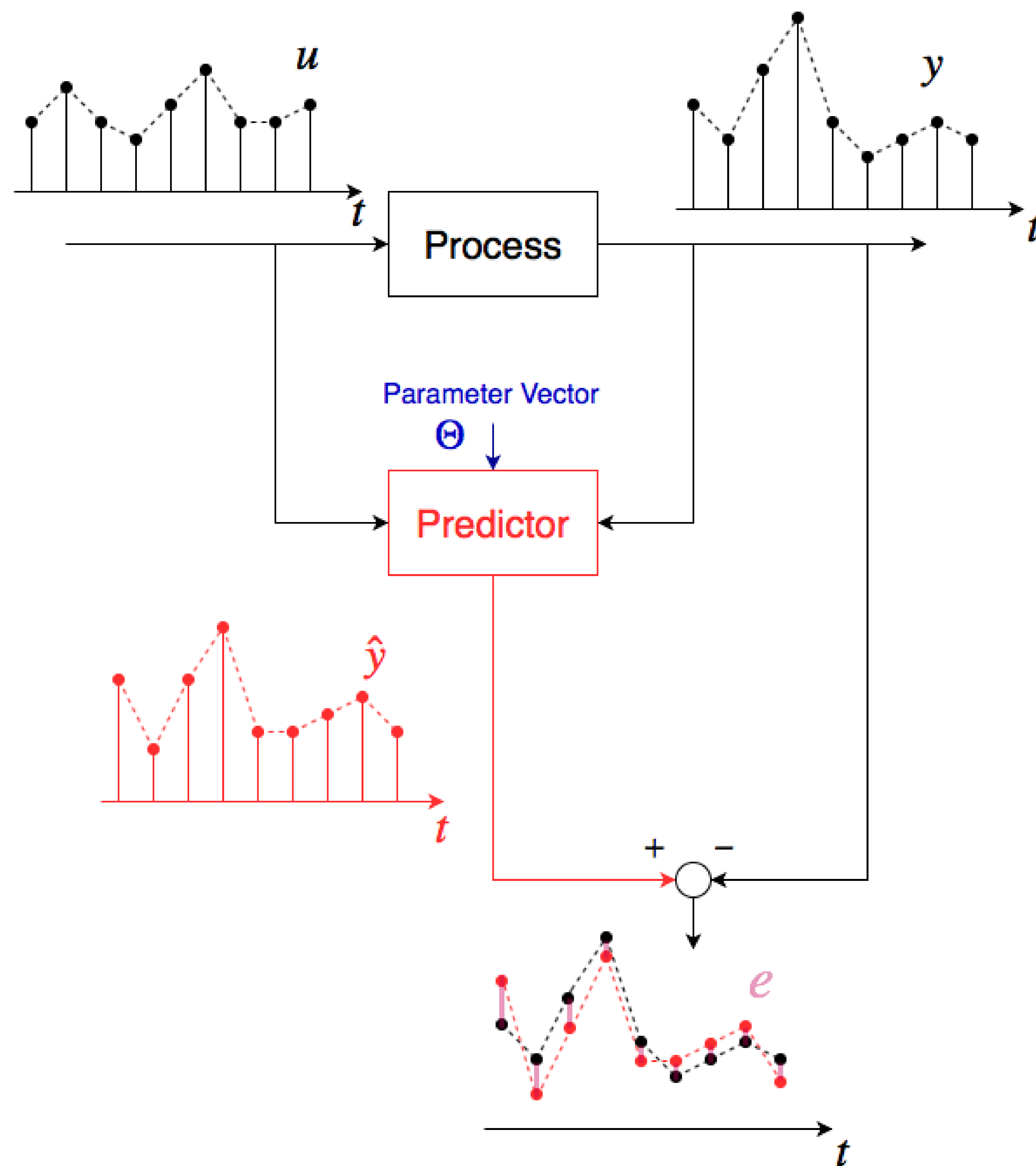


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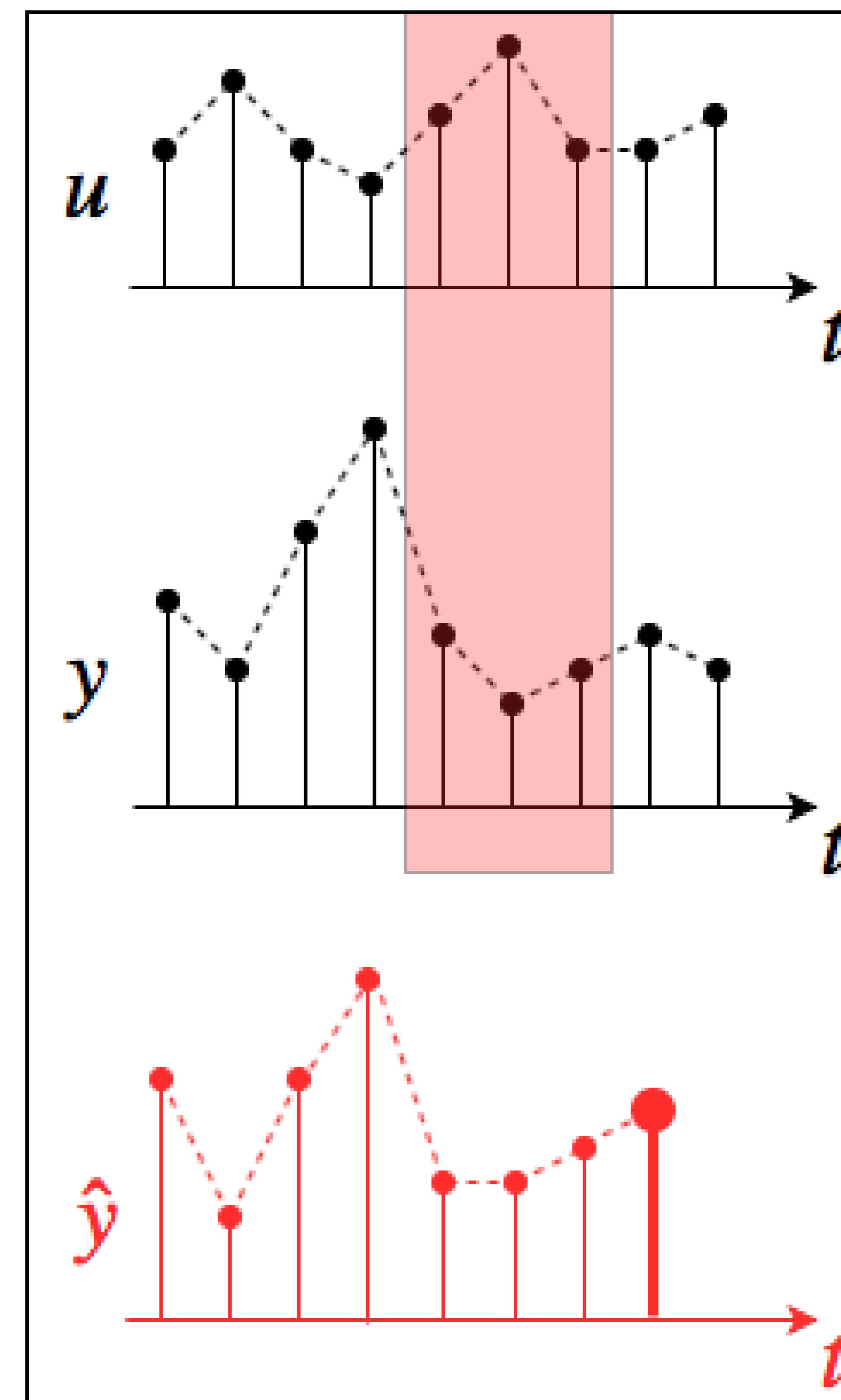


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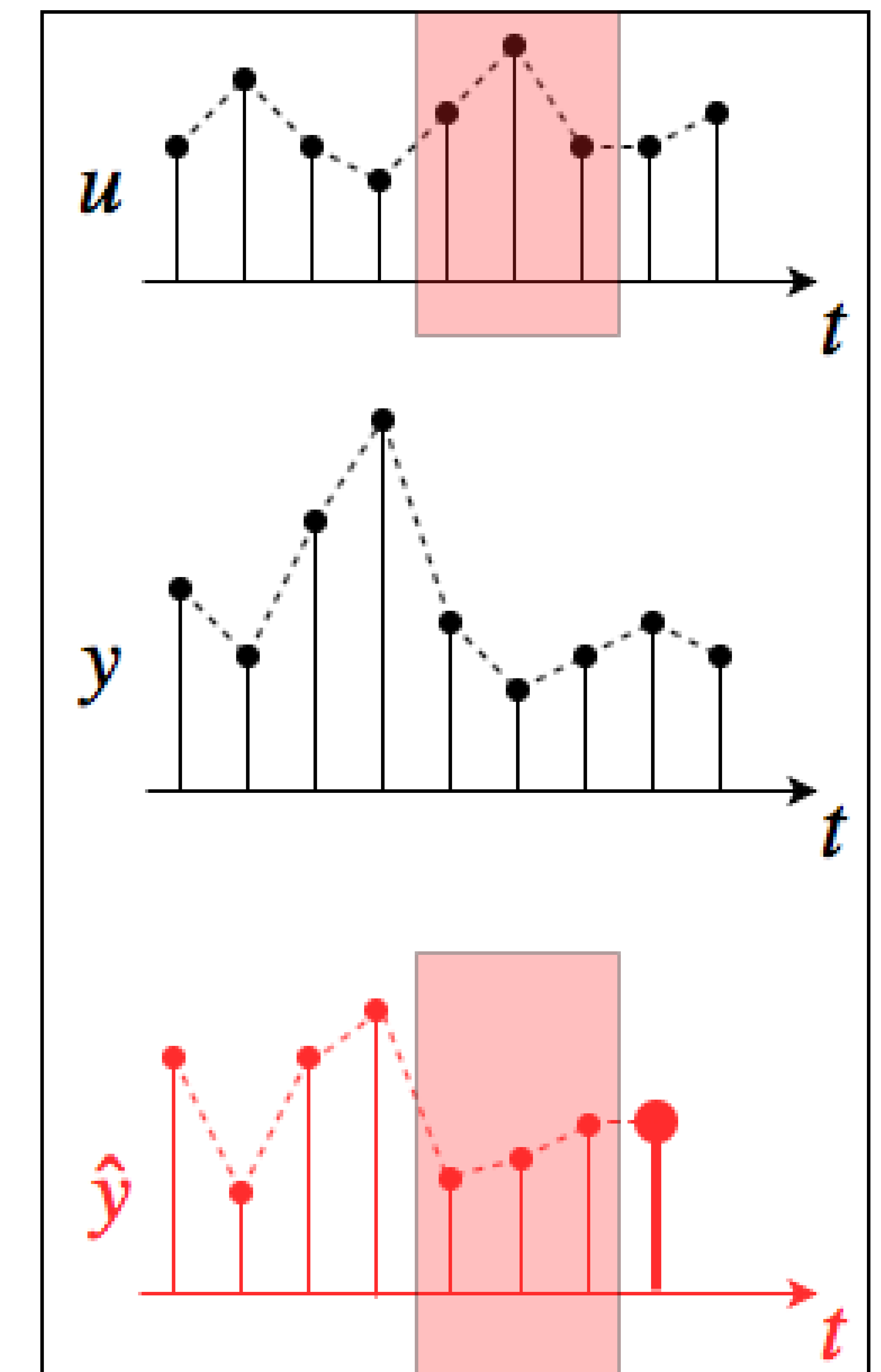


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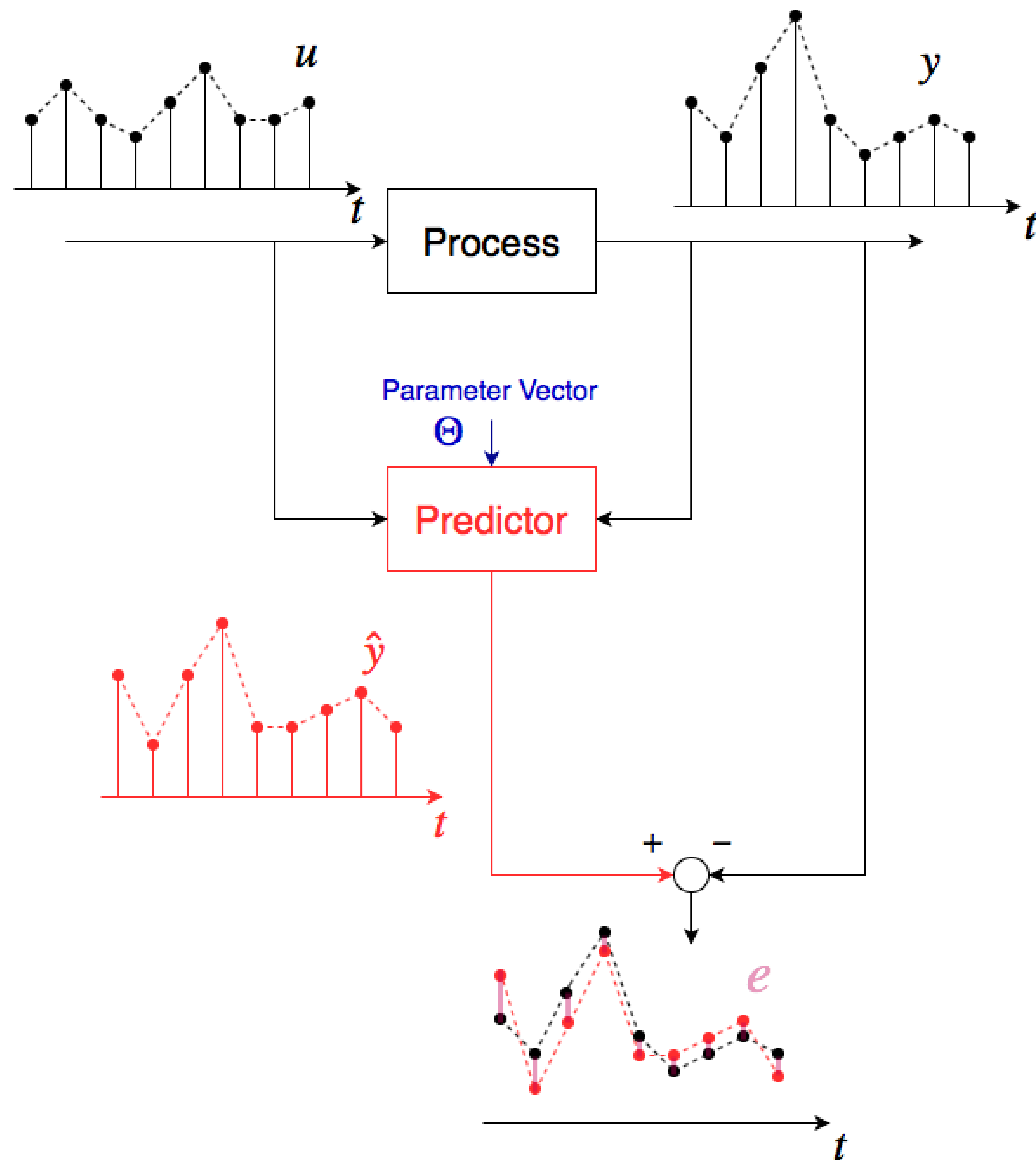


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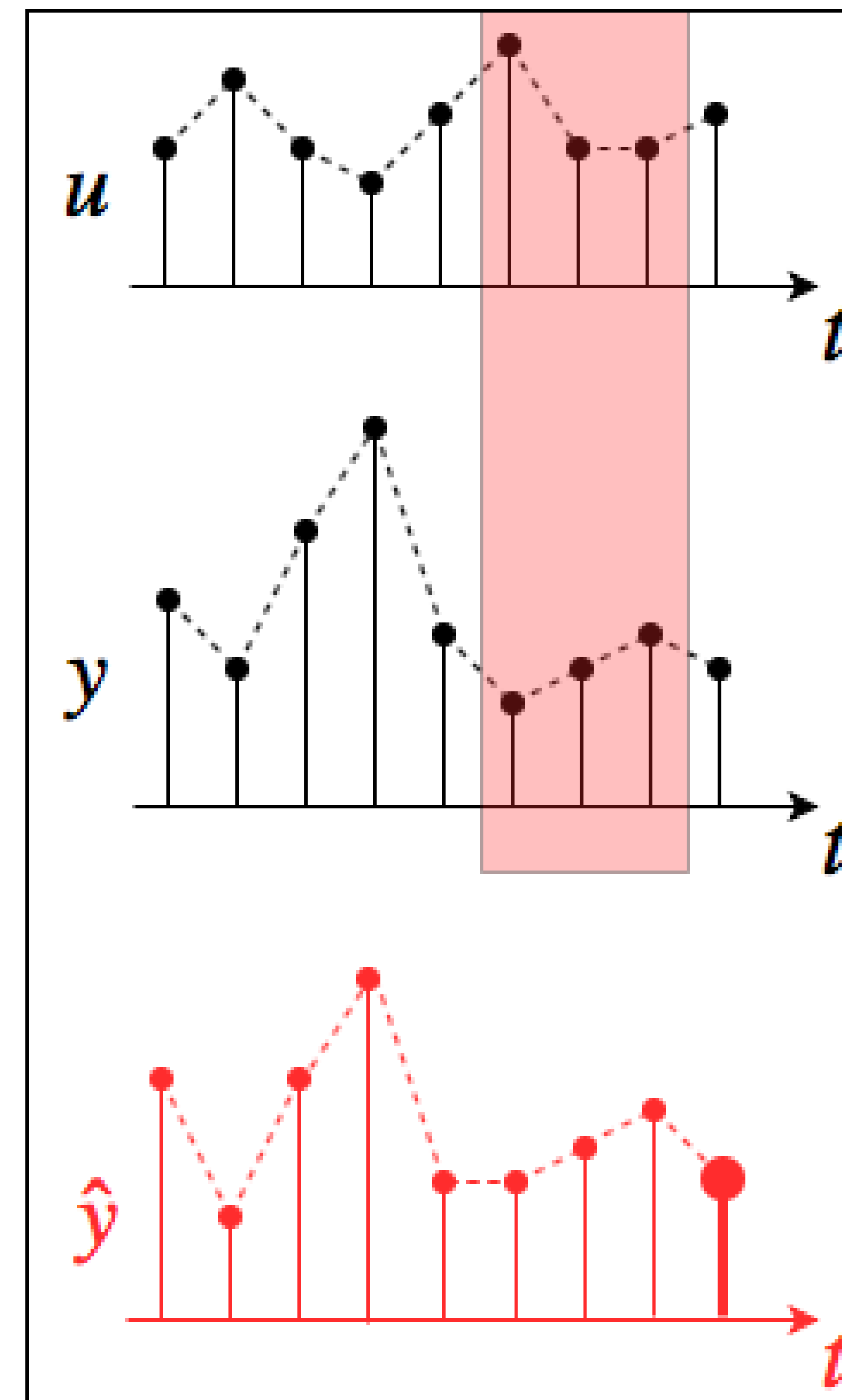


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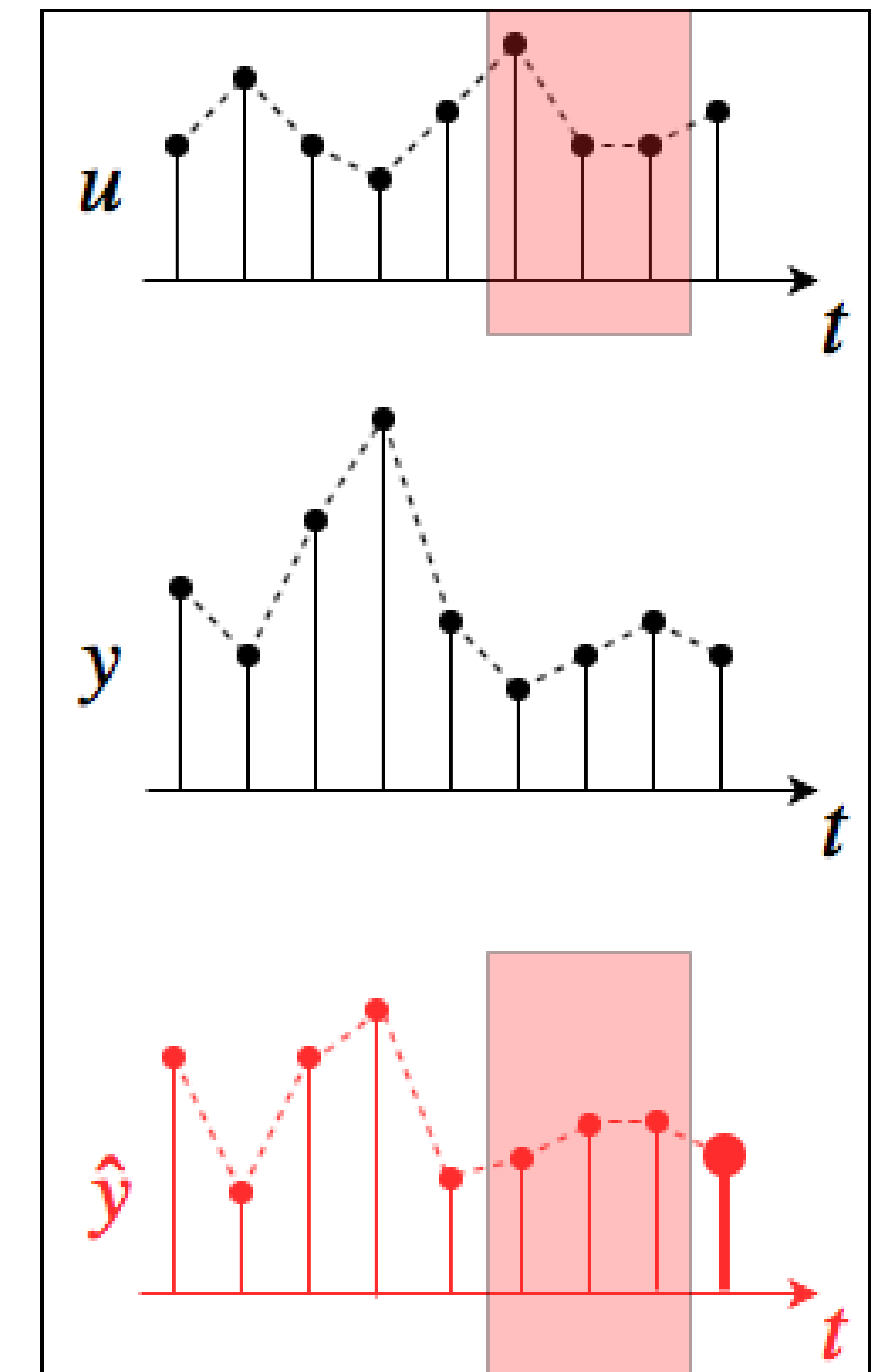


Figure 10: Free-run simulation.

Prediction Error Methods

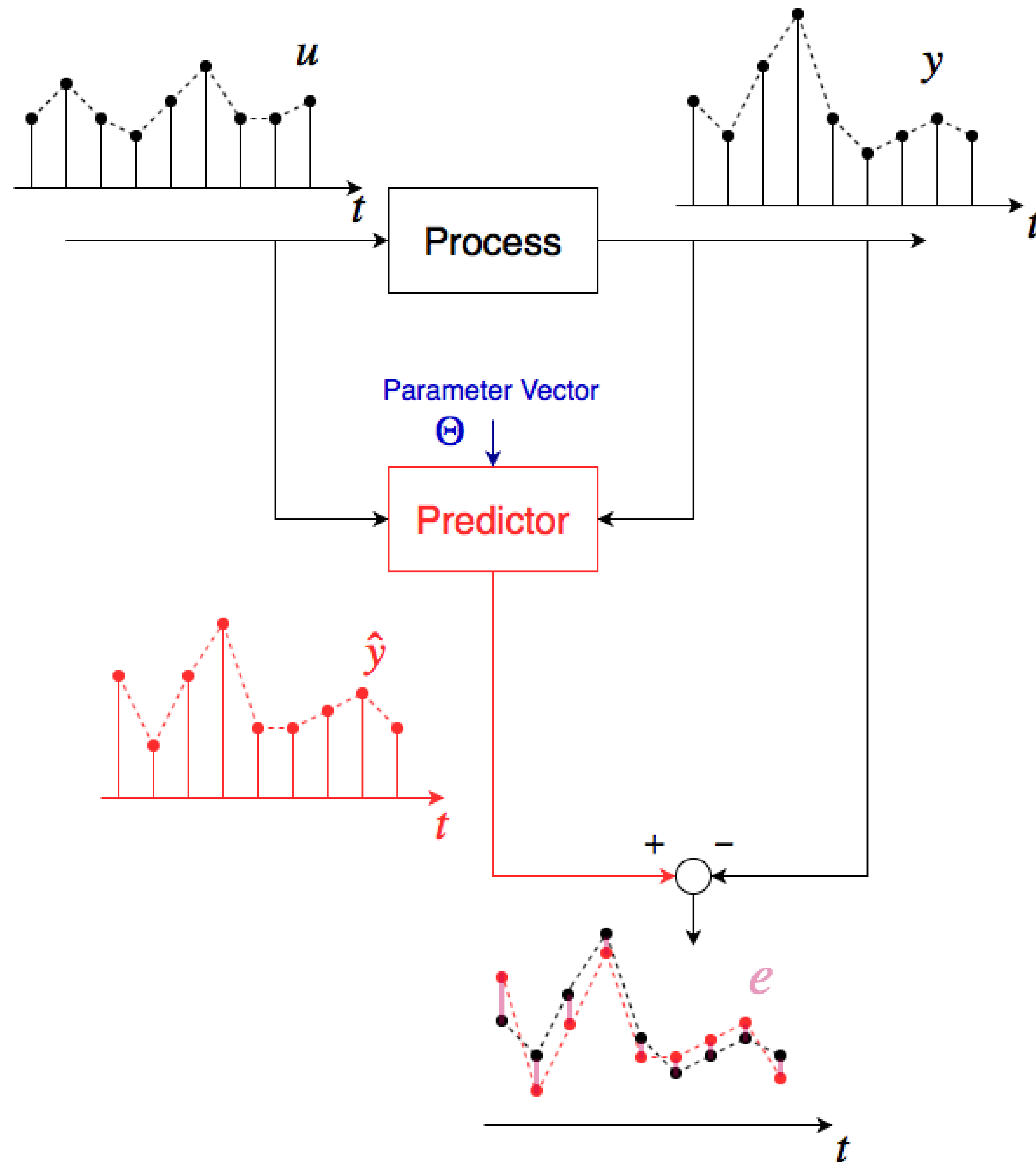


Figure 11: *Prediction error methods.* These methods estimate the parameters by minimizing the error between the optimal output prediction and the measured value

Difference Equation with Noise

$$y^*[k] = F(y[k-1], y[k-2], y[k-3], u[k-1], u[k-2], u[k-3]; \Theta^*) + v[k],$$

$$y[k] = y^*[k] + w[k].$$

NARX model

- ▶ NARX (nonlinear autoregressive with exogenous input) models follows from considering $w[k] = 0$ and $v[k]$ as white noise:

$$y^*[k] = F(\underline{y}_{[k]}, \underline{u}_{[k]}; \Theta^*) + v[k]$$

$$y[k] = y^*[k]. \quad (1)$$

- ▶ The optimal predictor for this situation is the **one-step-ahead prediction**.
- ▶ Parameters are estimated minimizing the sum of square errors between the **one-step-ahead prediction** and the measured values.

NOE model

- ▶ NOE (nonlinear output error) models follows from considering $v[k] = 0$ and $w[k]$ as white noise:

$$y^*[k] = F(\underline{y}_{[k]}, \underline{u}_{[k]}; \Theta^*)$$

$$y[k] = y^*[k] + w[k]. \quad (2)$$

- ▶ The optimal predictor for this situation is the **free-run simulation**.
- ▶ Parameters are estimated minimizing the sum of square errors between the **free-run simulation** and the measured values.

Problem Statement

Consider the nonlinear system:

$$\begin{aligned} y^*[k] &= \Theta_1 y^*[k-1] + \Theta_2 u[k-2] + \Theta_3 u^2[k-1] + \Theta_4 (y^*)^2[k-2] + \Theta_5 \\ y[k] &= y^*[k] + w[k]. \end{aligned} \quad (3)$$

for which $\Theta = [0.5, 0.8, 1, -0.05, 0.5]^T$ and $w[k]$ is a white Gaussian output error.

Simulation Results

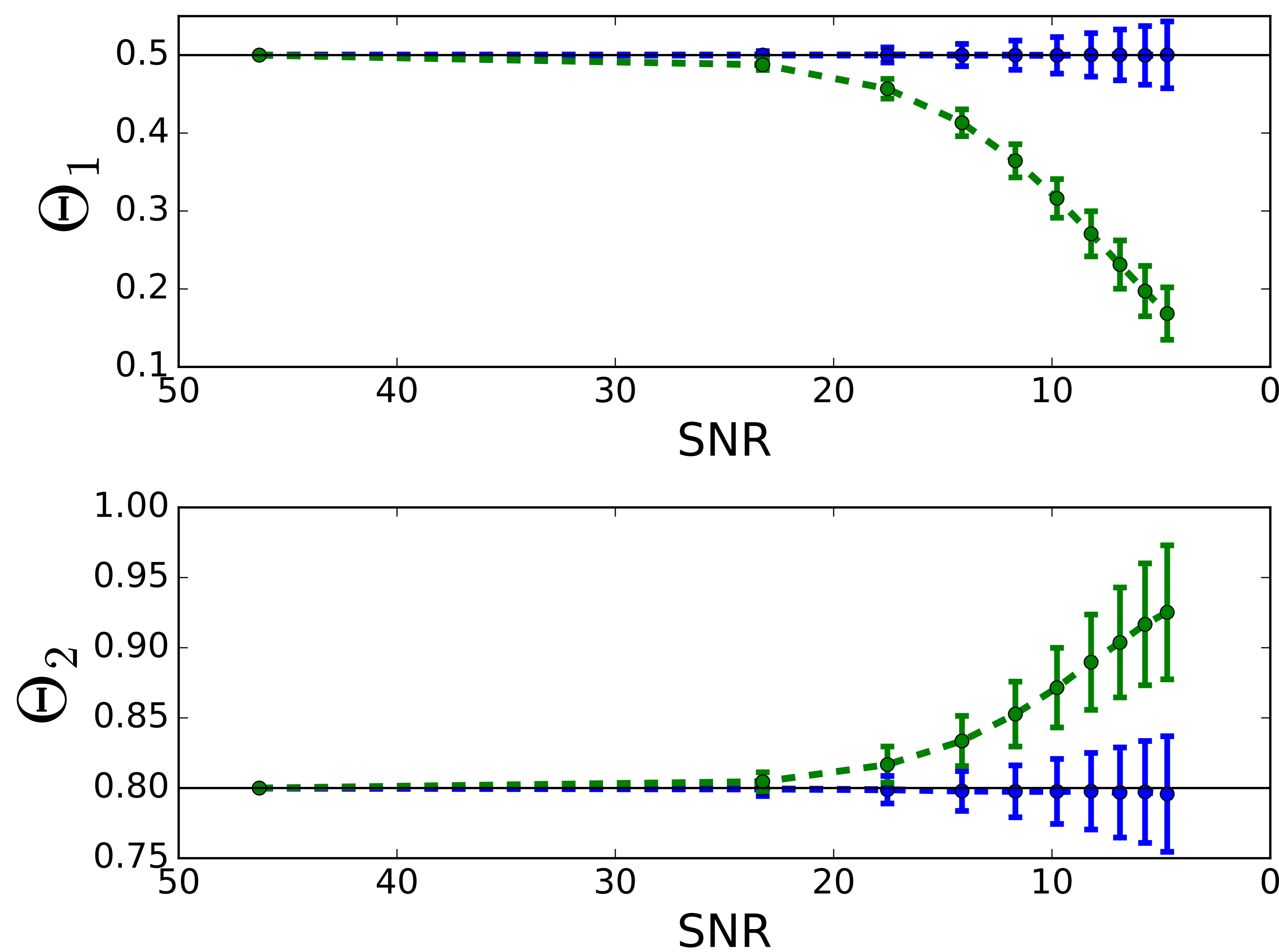


Figure 12: Expected values (dots) and standard deviation $\pm\sigma_{\hat{\Theta}}$ (bars) of parameter. Estimated using an NOE model (in blue) and an NARX model (in green). The true value, Θ_1 , is represented as the horizontal line.

Generated Input and Output

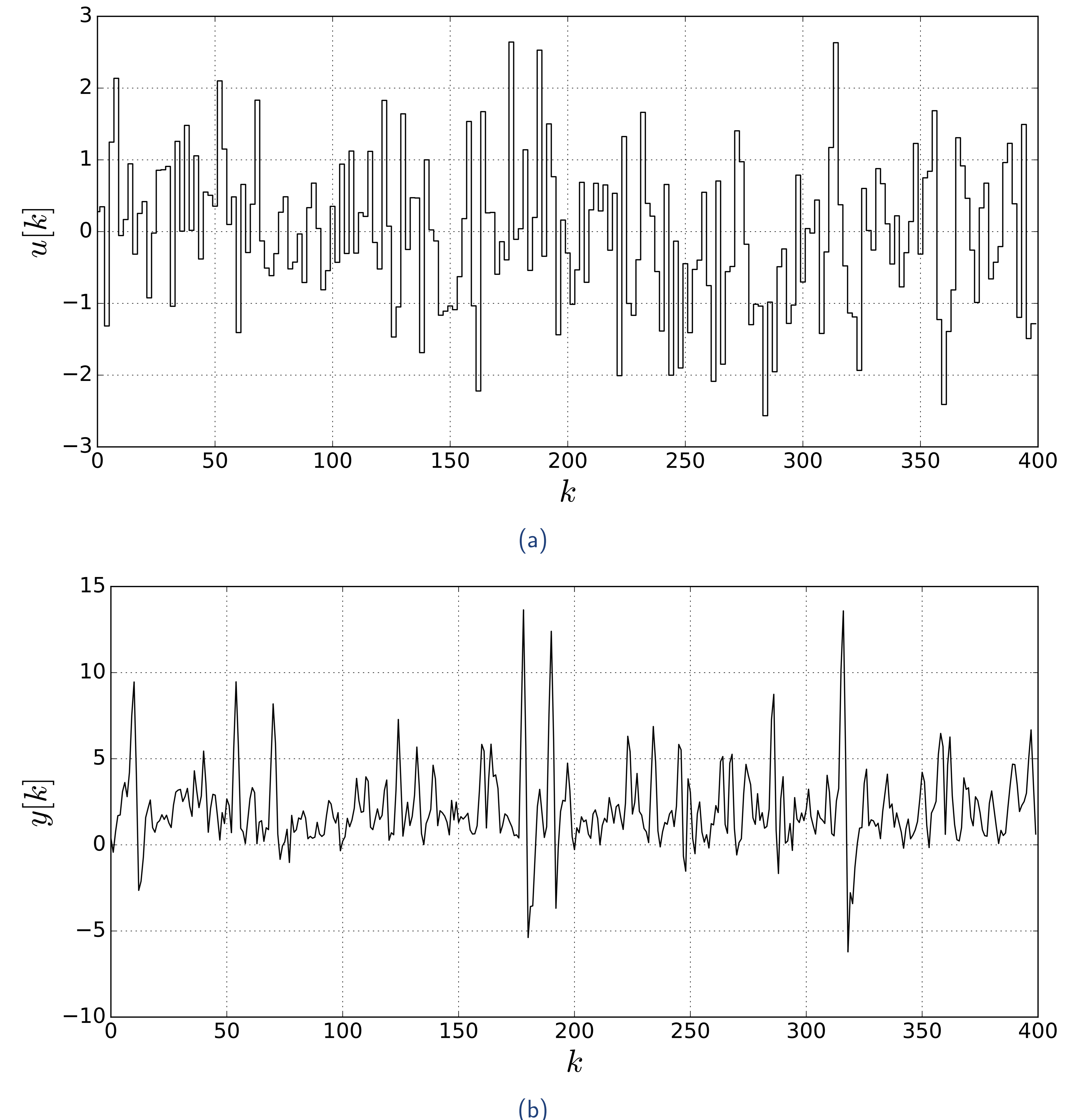


Figure 13: (a) Input; (b) Output.

Single Shooting

Minimize free-run simulation error:

$$\min_{\Theta} \frac{1}{2} \|\mathbf{e}_s\|^2.$$

Multiple Shooting

- ▶ Suppose the dataset is subdivided into m_s smaller datasets;
- ▶ Let $\mathbf{e}_s^{(i)}$ be the error between the free-run simulation $\hat{\mathbf{y}}^{(i)}$ and the correspondent measured output;
- ▶ $\mathbf{e}_{ms} = [(\mathbf{e}_s^{(1)})^T, \dots, (\mathbf{e}_s^{(m_s)})^T]^T$;
- ▶ When the initial conditions of one simulation coincide with the end of the previous, we have: $\mathbf{e}_{ms} = \mathbf{e}_s$;
- ▶ Estimate NOE model parameters by solving the following constrained optimization problem:

$$\begin{aligned} & \min_{\Phi} \frac{1}{2} \|\mathbf{e}_{ms}\|^2 \\ & \text{subject to: } \hat{\mathbf{y}}^{(i)}[\text{end}] = \mathbf{y}_0^{(i+1)}, \quad i = 1, \dots, m_s - 1. \end{aligned}$$

The variables for the optimization problem are both the parameter vector and the initial conditions:

$$\Phi = \left[\Theta^T \mathbf{y}_0^{(1)T} \dots \mathbf{y}_0^{(m_s)T} \right]^T.$$

- ▶ Name is an analogy with ODE parameter estimation methods.

Illustrative example

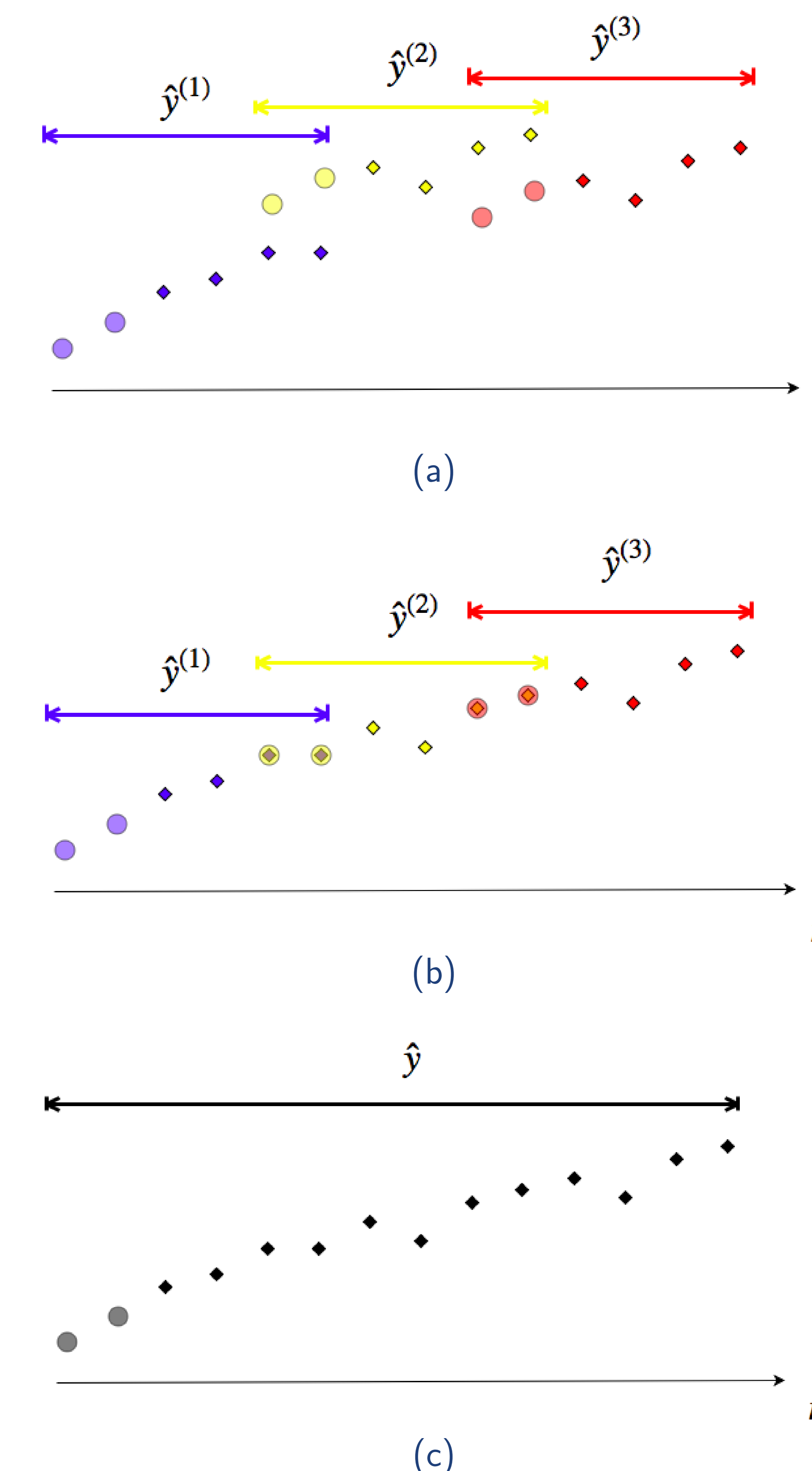


Figure 14: Three consecutive simulations $\hat{\mathbf{y}}^{(i)}$, $i = 1, 2, 3$ are indicated with different colors. The initial conditions are represented with circles ○ and subsequent simulated values with diamonds ◇.

Problem Statement

A dataset with 300 samples for $\theta = 3.78$ were generated using the logistic map:

$$y[k] = \theta y[k-1](1 - y[k-1]).$$

A twofold approach is adopted to illustrate the limitations of single shooting method for this example: i) For the generated dataset, a slice of the optimization objective function is obtained by varying $\hat{\theta}$; and, ii) for 100 initial guesses θ^0 chosen randomly (uniform) between 0 and 4 the parameter θ parameter was estimated and the results displayed on a histogram.

Objective Function Slice

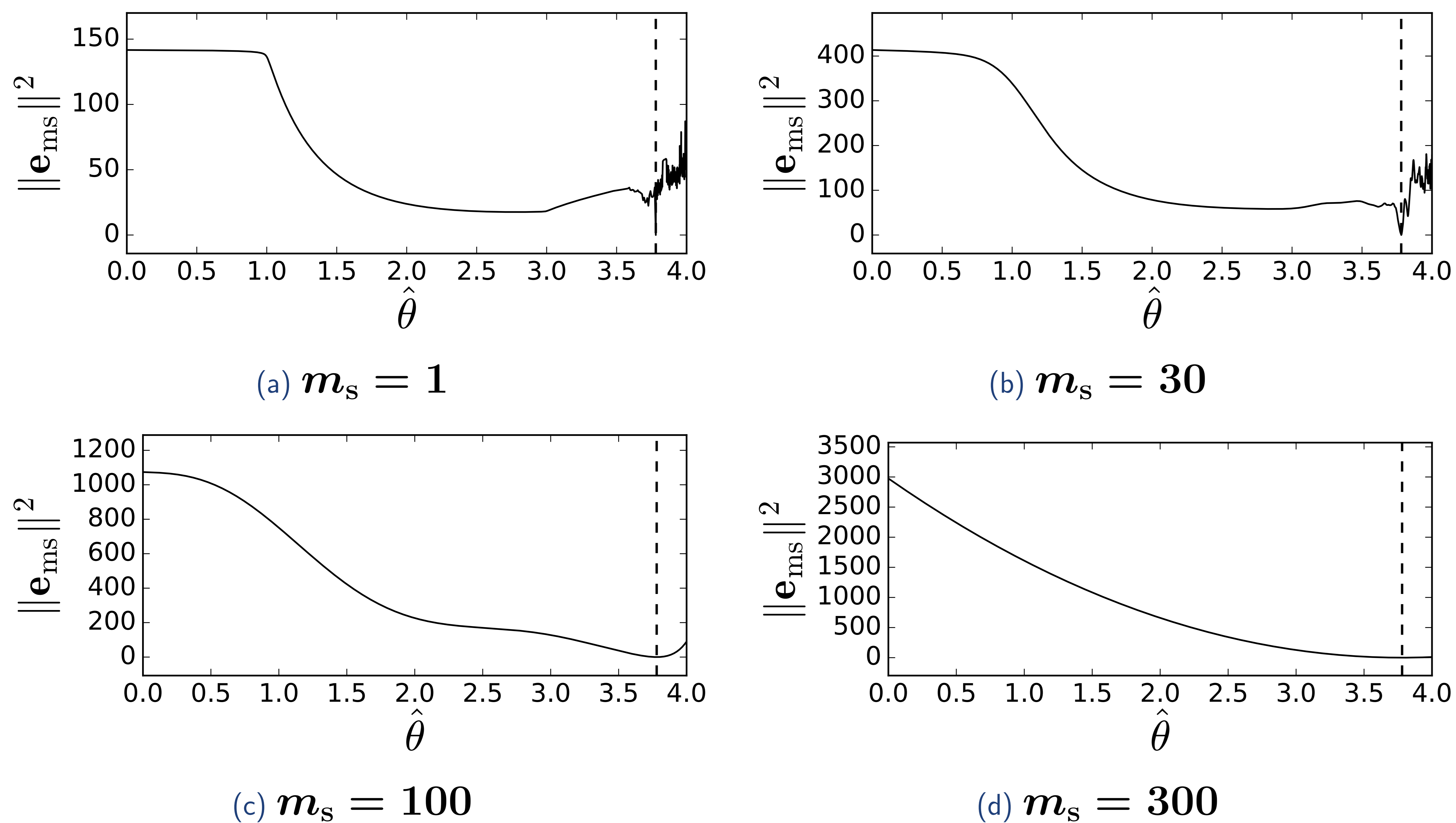


Figure 15: Shows $\|e_{ms}\|^2$ as a function of $\hat{\theta}$ for fixed initial conditions. The vertical dashed line (—) represents the true parameter value.

Convergence Histogram

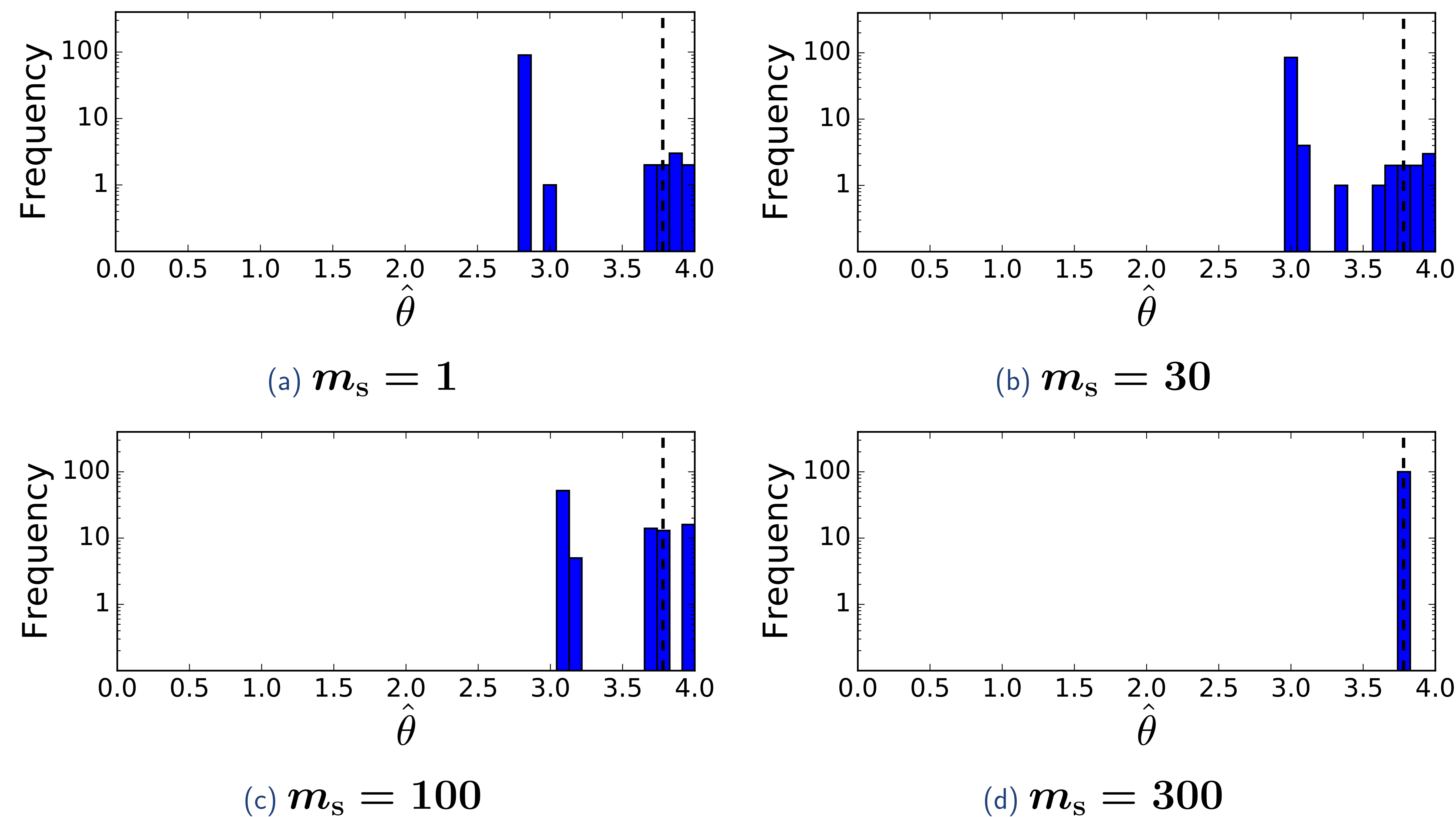


Figure 16: Histograms (in log scale) of the estimated parameter values to which the algorithm converged. The vertical dashed line (—) represents the true parameter value.