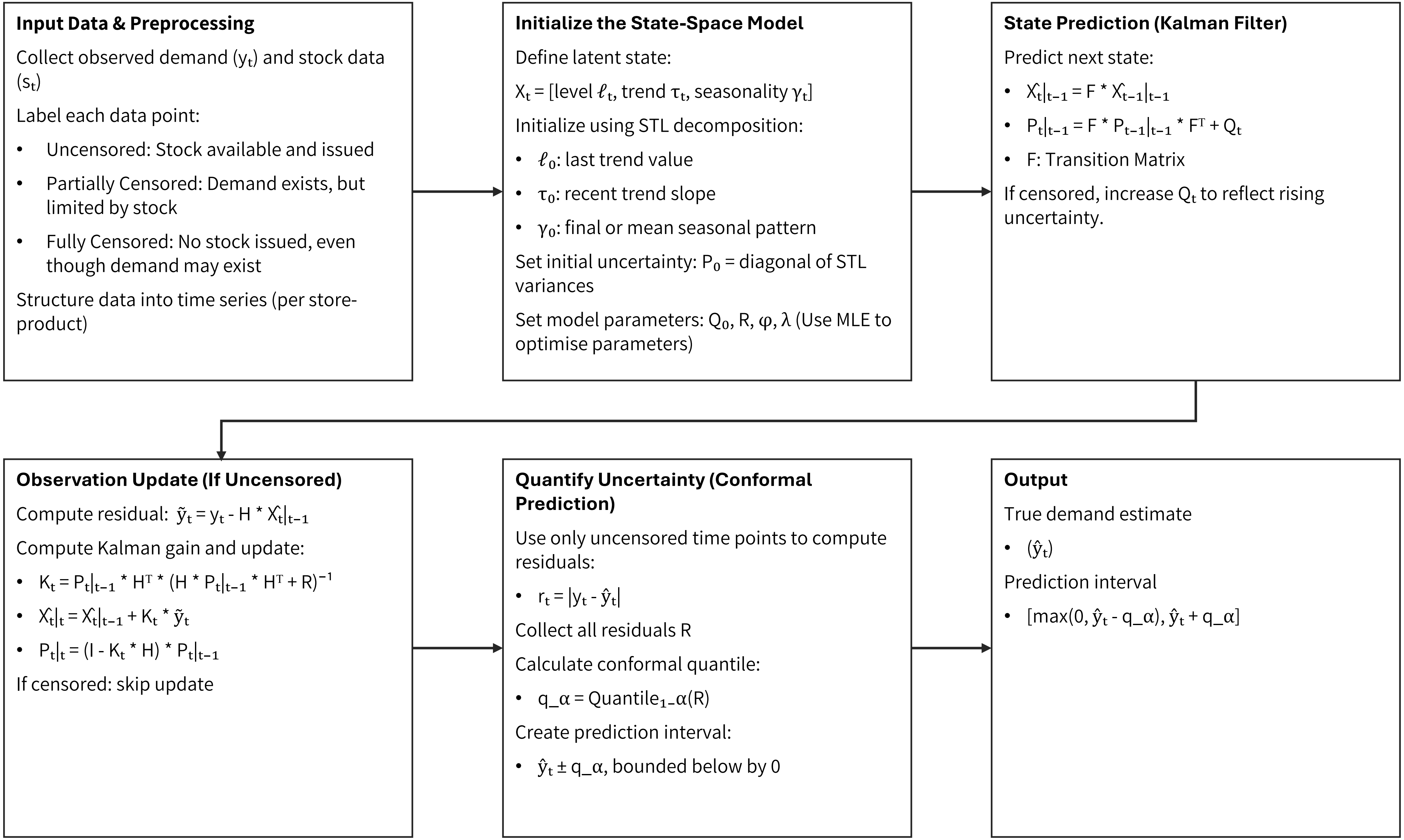

Input Data & Preprocessing
Collect observed demand (y_t) and stock data (s_t)
Label each data point:
• Uncensored: Stock available and issued
• Partially Censored: Demand exists, but limited by stock
• Fully Censored: No stock issued, even though demand may exist
Structure data into time series (per store-product)
Initialize the State-Space Model
Define latent state:
X_t = [level ℓ_t, trend τ_t, seasonality γ_t]
Initialize using STL decomposition:
• ℓ_0: last trend value
• τ_0: recent trend slope
• γ_0: final or mean seasonal pattern
Set initial uncertainty: P_0 = diagonal of STL variances
Set model parameters: Q_0, R, φ, λ (Use MLE to optimise parameters)
State Prediction (Kalman Filter)
Predict next state:
• $\hat{X}_t|_{t-1} = F * \hat{X}_{t-1}|_{t-1}$
• $P_t|_{t-1} = F * P_{t-1}|_{t-1} * F^T + Q_t$
• F: Transition Matrix
If censored, increase Q_t to reflect rising uncertainty.
Observation Update (If Uncensored)
Compute residual: $\tilde{y}_t = y_t - H * \hat{X}_t|_{t-1}$
Compute Kalman gain and update:
• $K_t = P_t|_{t-1} * H^T * (H * P_t|_{t-1} * H^T + R)^{-1}$
• $\hat{X}_t|_t = \hat{X}_t|_{t-1} + K_t * \tilde{y}_t$
• $P_t|_t = (I - K_t * H) * P_t|_{t-1}$
If censored: skip update
Quantify Uncertainty (Conformal Prediction)
Use only uncensored time points to compute residuals:
• $r_t = |y_t - \hat{y}_t|$
Collect all residuals R
Calculate conformal quantile:
• $q\_\alpha = \text{Quantile}_{1-}\alpha(R)$
Create prediction interval:
• $\hat{y}_t \pm q\_\alpha$, bounded below by 0
Output
True demand estimate
• ($\hat{y}_t$)
Prediction interval
• $[\max(0, \hat{y}_t - q\_\alpha), \hat{y}_t + q\_\alpha]$