	raw data		representation			
	in-time-based	transform-based	shape-based	model-based	feature-based	iterative-based (embedded)
raw data	×	×	×	×	×	x
transformation		X 				
representation			X 	X 	X	
clustering	×	X	X	X	×	
example						Start Initial Values
			+	$Y_{t} = \alpha + \beta_{1} Y_{t-1} + \beta_{2} Y_{t-2} + \dots + \epsilon_{t}$	$ \begin{array}{c} \vec{x} \\ \sigma^2 \\ \hat{\rho}_k \\ \sum x_{t+1} - x_t \\ \beta_t \\ \vdots \end{array} $	Expectation Maximization No Converged Yes End
algorithm	LKMA	DTW	DFT	VAR	tsfresh	GBTM
notes	 low interpretability ignore temporal order sensitive to noise same interval [in-time] same length (no missing) [in-time] sensitive to offset [in-time] 		 poor fit with few observations poor fit if assumptions violated [model, embedded] dangerous if model fit is poor (e.g., over- or under fitting) [model, embedded] often assumes the same parametric distribution [embedded] slower with complex models [embedded] 			
	 no shape assumed fast modeling readily available software algotrithms established in the field 		 reduced dimensional space more acurate then raw fast modeling readily available software robust to missing data varying intervals varying lengths often scaleable performance (e.g., model fitted once) relatively few observations per trajectory high interpretability [model, feature, embedded] allows use of domain knowledge [model, feature, embedded] distinct cluster trajectories [embedded] good for prediction [embedded] 			