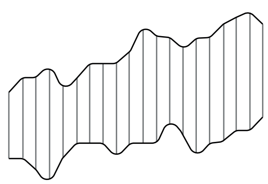
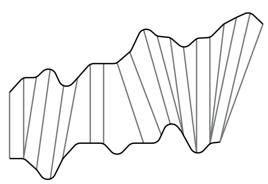
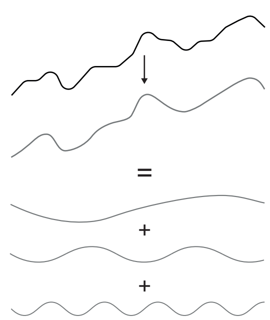
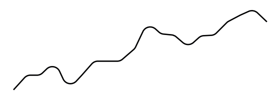
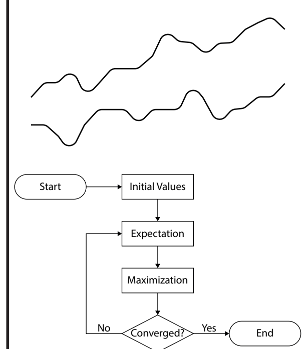
	raw		feature			embedded
	in-time-based	distance-based	shape-based	model-based	characteristic-based	iterative-based
raw data	X	X	X	X	X	X
transformation		X				
representation			X	X	X	
clustering	X	X	X	X	X	
example				 ↓ $Y_t=\alpha+\beta_1 Y_{t-1}+\beta_2 Y_{t-2}+\cdots+\epsilon_t$	 ↓ $\bar{x}$ σ^2 $\hat{\rho}_k$ $\sum\lvert x_{t+1}-x_t\rvert$ β_t $\vdots$	
algorithm	*LKMA*	*DTW*	*DFT*	*VAR*	*tsfresh*	*GBTM*
notes	− low interpretability − same interval (if not transformed) − same length (no missing) − no parameter dependence (ignore temporal order) − sensitive to offset (if not transformed) − sensitive to noise + no shape assumed (incl. sudden changes) + fast modeling + readily available software + cluster interpretation established in the field		− dangerous if model fit is poor − assumptions violated (poor fit) − too few observations (poor fit) + high interpretability + reduced dimensional space + use domain knowledge to choose summarize features) + more acurate then raw + fast modeling + readily available software + robust to missing data (b/c calculated on multiple observations) + varying intervals + varying lengths + often scaleable performance (e.g., model only needs to be fitted once) + relatively few observations per trajectory			− often assume the same parametric distribution − dangerous if model fit is poor (e.g., over- or under fitting) − assumptions violated (fit) − too few observations (fit) − slower with mode complex models + robust to missing data (b/c calculated on multiple observations) + varying intervals + varying lengths + interpretatble (e.g., distinct cluster trajectories) + good for prediction

based on: Aghabozorgi et al., 2015; den Teuling et al., 2021; and Liao, 2005