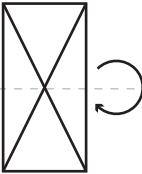
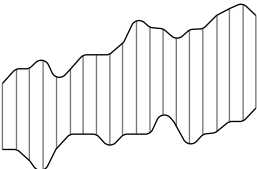
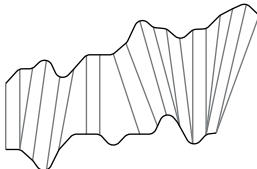
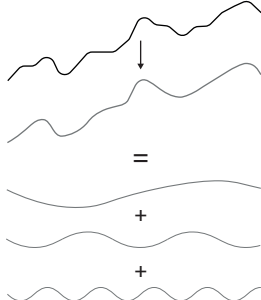
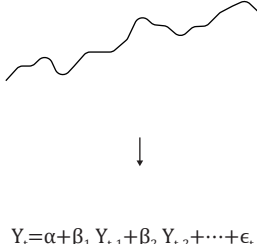
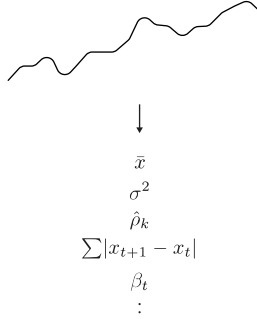
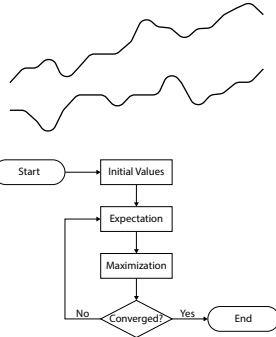


	raw data		representation			embedded
	in-time-based	transform-based	shape-based	model-based	feature-based	iterative-based
raw data	X	X	X	X	X	X
transformation		↓ X				
representation		↓ X	↓ X	↓ X	↓ X	↓ 
clustering	↓ X	↓ X	↓ X	↓ X	↓ X	
example						
algorithm	<i>LKMA</i>	<i>DTW</i>	<i>DFT</i>	<i>VAR</i>	<i>tsfresh</i>	<i>GBTM</i>
notes	<ul style="list-style-type: none"> ⊖ 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 		<ul style="list-style-type: none"> ⊖ dangerous if model fit is poor ⊖ assumptions violated (poor fit) ⊖ too few observations (poor fit) ⊕ reduced dimensional space ⊕ more accurate than raw ⊕ fast modeling ⊕ readily available software ⊕ robust to missing data (b/c calculated on multiple observations) ⊕ varying intervals ⊕ varying lengths ⊕ often scalable performance (e.g., model only needs to be fitted once) ⊕ relatively few observations per trajectory 			<ul style="list-style-type: none"> ⊕ high interpretability ⊕ use domain knowledge to choose summarize features) ⊖ 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 more complex models ⊕ robust to missing data (b/c calculated on multiple observations) ⊕ varying intervals ⊕ varying lengths ⊕ interpretable (e.g., distinct cluster trajectories) ⊕ good for prediction