Results with PCA clustering

			Scoring Schemes				
Measures	ARACNE	AWE	AWE w/o TF	CLR	ID	MRNET	
Dynamic Time Warping (Asymmetric constraint path)	2	2	2	2	2	2	
Dynamic Time Warping (Symmetric constraint path 1)	2	2	2	2	2	2	
Dynamic Time Warping (Symmetric constraint path 2)	2	2	2	2	2	2	
Euclidian distance	2	2	2	2	2	2	
L10Norm distance	2	2	2	2	2	2	
Manhattan distance	2	2	2	2	2	2	
Kendall correlation coefficient	1	3	3	3	1	3	
MI - Equal Frequency discretization through optimized maximum likelihood	1	1	1	3	1	3	
MI - Equal Frequency discretization through optimized maximum likelihood over coarse-grained variables (Kolmogorov-Sinai entropy)				3		3	
MI - Equal Frequency discretization through shrinkage	1	1	1	1	1	3	
MI - Equal Frequency discretization through shrinkage over coarse-grained variables (Kolmogorov-Sinai entropy)						3	
MI - Equal Width discretization through optimized maximum likelihood	1	1	1	1	1	1	
MI - Equal Width discretization through optimized maximum likelihood over coarse-grained variables (Kolmogorov-Sinai entropy)	2	3	3	2	3	2	
MI - Equal Width discretization through shrinkage	1	1	1	1	1	1	
MI - Equal Width discretization through shrinkage over coarse-grained variables (Kolmogorov-Sinai entropy)						3	
Pearson correlation coefficient	3	1	1	3	1	1	
Spearman correlation coefficient	1	3	3	3	1	3	
Mean between symbolic sequence similarity and MI on symbol vectors with Equal Frequency discretization through optimized maximum likelihood	1	1	1	1	1	3	
Mean between symbolic sequence similarity and MI on symbol vectors with Equal Width discretization through optimized maximum likelihood	1	1	1	1	1	3	
MI on symbol vectors with Equal Frequency discretization through optimized maximum likelihood	1	1	1	1	1	3	
MI on symbol vectors with Equal Width discretization through optimized maximum likelihood	3	3	3	1	3	3	
Qualitative distance measure	3	3	3	3	3	3	
Symbol sequence similarity	1	3	3	3	1	3	

Figure 1: Clustering (PCA) of base methods into 3 views (clusters) for the SynTReN *E. coli* dataset with 100 nodes and noise level 0.0. Each base method is a combination of a distance measure and a scoring scheme (cf. Supplementary File 1). The number (and the corresponding color) in a cell identifies the cluster to which a base method is assigned. Empty cells indicate that the corresponding base method has not been associated with any cluster. This can happen if the base method returns no interactions.

			Scoring Sch	nemes		
Measures	ARACNE	AWE	AWE w/o TF	CLR	ID	MRNET
Dynamic Time Warping (Asymmetric constraint path)	2	2	2	2	2	2
Dynamic Time Warping (Symmetric constraint path 1)	2	2	2	2	2	2
Dynamic Time Warping (Symmetric constraint path 2)	2	2	2	2	2	2
Euclidian distance	2	2	2	2	2	2
L10Norm distance	2	2	2	2	2	2
Manhattan distance	2	2	2	2	2	2
Kendall correlation coefficient	1	3	3	3	1	4
MI - Equal Frequency discretization through optimized maximum likelihood	1	1	1	3	1	3
MI - Equal Frequency discretization through optimized maximum likelihood over coarse-grained variables (Kolmogorov-Sinai entropy)				3		4
MI - Equal Frequency discretization through shrinkage	1	1	1	1	1	3
MI - Equal Frequency discretization through shrinkage over coarse-grained variables (Kolmogorov-Sinai entropy)						4
MI - Equal Width discretization through optimized maximum likelihood	4	4	4	4	4	4
MI - Equal Width discretization through optimized maximum likelihood over coarse-grained variables (Kolmogorov-Sinai entropy)	4	3	3	4	3	4
MI - Equal Width discretization through shrinkage	4	4	4	4	4	4
MI - Equal Width discretization through shrinkage over coarse-grained variables (Kolmogorov-Sinai entropy)						4
Pearson correlation coefficient	3	1	1	1	1	3
Spearman correlation coefficient	1	3	3	3	1	4
Mean between symbolic sequence similarity and MI on symbol vectors with Equal Frequency discretization through optimized maximum likelihood	1	1	1	1	1	4
Mean between symbolic sequence similarity and MI on symbol vectors with Equal Width discretization through optimized maximum likelihood	1	1	1	1	1	4
MI on symbol vectors with Equal Frequency discretization through optimized maximum likelihood	1	1	1	1	1	4
MI on symbol vectors with Equal Width discretization through optimized maximum likelihood	3	3	3	4	3	4
Qualitative distance measure	3	4	4	3	4	4
Symbol sequence similarity	1	3	3	3	1	3

Figure 2: Clustering (PCA) of base methods into 4 views (clusters) for the SynTReN *E. coli* dataset with 100 nodes and noise level 0.0. Each base method is a combination of a distance measure and a scoring scheme (cf. Supplementary File 1). The number (and the corresponding color) in a cell identifies the cluster to which a base method is assigned. Empty cells indicate that the corresponding base method has not been associated with any cluster. This can happen if the base method returns no interactions.

			Scoring Sch	nemes		
Measures	ARACNE	AWE	AWE w/o TF	CLR	ID	MRNET
Dynamic Time Warping (Asymmetric constraint path)	2	2	2	2	2	2
Dynamic Time Warping (Symmetric constraint path 1)	2	2	2	2	2	2
Dynamic Time Warping (Symmetric constraint path 2)	2	2	2	2	2	2
Euclidian distance	2	2	2	2	2	2
Kendall correlation coefficient	1	5	5	5	1	3
L10Norm distance	2	1	1	2	1	2
Manhattan distance	2	2	2	2	2	2
Mean between symbolic sequence similarity and MI on symbol vectors with Equal Frequency discretization through optimized maximum likelihood	1	1	1	5	1	3
Mean between symbolic sequence similarity and MI on symbol vectors with Equal Width discretization through optimized maximum likelihood	4	1	1	5	1	3
MI - Equal Frequency discretization through optimized maximum likelihood	1	1	1	5	1	3
MI - Equal Frequency discretization through optimized maximum likelihood over coarse-grained variables (Kolmogorov-Sinai entropy)				5		3
MI - Equal Frequency discretization through shrinkage	1	1	1	5	1	3
MI - Equal Frequency discretization through shrinkage over coarse-grained variables (Kolmogorov-Sinai entropy)						3
MI - Equal Width discretization through optimized maximum likelihood	5	4	4	4	4	5
MI - Equal Width discretization through optimized maximum likelihood over coarse-grained variables (Kolmogorov-Sinai entropy)	2	4	4	4	4	2
MI - Equal Width discretization through shrinkage	4	4	4	4	4	5
MI - Equal Width discretization through shrinkage over coarse-grained variables (Kolmogorov-Sinai entropy)						3
MI on symbol vectors with Equal Frequency discretization through optimized maximum likelihood	1	1	1	5	1	3
MI on symbol vectors with Equal Width discretization through optimized maximum likelihood	4	1	1	5	4	3
Pearson correlation coefficient	4	4	4	4	1	4
Qualitative distance measure	4	4	4	4	4	3
Spearman correlation coefficient	1	5	5	5	1	3
Symbol sequence similarity	4	5	5	5	1	3

Figure 3: Clustering (PCA) of base methods into 5 views (clusters) for the SynTReN *E. coli* dataset with 100 nodes and noise level 0.0. Each base method is a combination of a distance measure and a scoring scheme (cf. Supplementary File 1). The number (and the corresponding color) in a cell identifies the cluster to which a base method is assigned. Empty cells indicate that the corresponding base method has not been associated with any cluster. This can happen if the base method returns no interactions.

_			Scoring Sch	emes		
Measures	ARACNE	AWE	AWE w/o TF	CLR	ID	MRNET
Dynamic Time Warping (Asymmetric constraint path)	2	2	2	2	2	2
Dynamic Time Warping (Symmetric constraint path 1)	2	2	2	2	2	2
Dynamic Time Warping (Symmetric constraint path 2)	2	2	2	2	2	2
Euclidian distance	2	2	2	2	2	2
L10Norm distance	2	1	1	2	2	2
Manhattan distance	2	2	2	2	2	2
Kendall correlation coefficient	1	3	3	3	1	3
MI - Equal Frequency discretization through optimized maximum likelihood	1	1	1	1	1	3
MI - Equal Frequency discretization through optimized maximum likelihood over coarse-grained variables (Kolmogorov-Sinai entropy)				3		3
MI - Equal Frequency discretization through shrinkage	1	1	1	1	1	3
MI - Equal Frequency discretization through shrinkage over coarse-grained variables (Kolmogorov-Sinai entropy)						3
MI - Equal Width discretization through optimized maximum likelihood	3	1	1	1	3	1
MI - Equal Width discretization through optimized maximum likelihood over coarse-grained variables (Kolmogorov-Sinai entropy)	2	2	2	3	2	2
MI - Equal Width discretization through shrinkage	3	1	1	1	3	1
MI - Equal Width discretization through shrinkage over coarse-grained variables (Kolmogorov-Sinai entropy)						3
Pearson correlation coefficient	1	1	1	3	1	1
Spearman correlation coefficient	1	3	3	3	1	3
Mean between symbolic sequence similarity and MI on symbol vectors with Equal Frequency discretization through optimized maximum likelihood	1	1	1	3	1	3
Mean between symbolic sequence similarity and MI on symbol vectors with Equal Width discretization through optimized maximum likelihood	1	1	1	3	1	3
MI on symbol vectors with Equal Frequency discretization through optimized maximum likelihood	1	1	1	3	1	3
MI on symbol vectors with Equal Width discretization through optimized maximum likelihood	1	1	1	1	1	3
Qualitative distance measure	1	3	3	1	3	3
Symbol sequence similarity	1	3	3	3	1	3

Figure 4: Clustering (PCA) of base methods into 3 views (clusters) for the SynTReN Yeast dataset with 100 nodes and noise level 0.0. Each base method is a combination of a distance measure and a scoring scheme (cf. Supplementary File 1). The number (and the corresponding color) in a cell identifies the cluster to which a base method is assigned. Empty cells indicate that the corresponding base method has not been associated with any cluster. This can happen if the base method returns no interactions.

			Scoring Sc	hemes		
Measures	ARACNE	AWE	AWE w/o TF	CLR	ID	MRNET
Dynamic Time Warping (Asymmetric constraint path)	2	2	2	2	2	2
Dynamic Time Warping (Symmetric constraint path 1)	2	2	2	2	2	2
Dynamic Time Warping (Symmetric constraint path 2)	2	2	2	2	2	2
Euclidian distance	2	2	2	2	2	2
L10Norm distance	2	2	2	2	2	2
Manhattan distance	2	2	2	2	2	2
Kendall correlation coefficient	1	3	3	3	1	4
MI - Equal Frequency discretization through optimized maximum likelihood	1	1	1	3	1	3
MI - Equal Frequency discretization through optimized maximum likelihood over coarse-grained variables (Kolmogorov-Sinai entropy)				3		4
MI - Equal Frequency discretization through shrinkage	1	1	1	1	1	3
MI - Equal Frequency discretization through shrinkage over coarse-grained variables (Kolmogorov-Sinai entropy)						4
MI - Equal Width discretization through optimized maximum likelihood	4	4	4	4	4	4
MI - Equal Width discretization through optimized maximum likelihood over coarse-grained variables (Kolmogorov-Sinai entropy)	4	3	3	4	3	4
MI - Equal Width discretization through shrinkage	4	4	4	4	4	4
MI - Equal Width discretization through shrinkage over coarse-grained variables (Kolmogorov-Sinai entropy)						4
Pearson correlation coefficient	3	1	1	1	1	3
Spearman correlation coefficient	1	3	3	3	1	4
Mean between symbolic sequence similarity and MI on symbol vectors with Equal Frequency discretization through optimized maximum likelihood	1	1	1	1	1	4
Mean between symbolic sequence similarity and MI on symbol vectors with Equal Width discretization through optimized maximum likelihood	1	1	1	1	1	4
MI on symbol vectors with Equal Frequency discretization through optimized maximum likelihood	1	1	1	1	1	4
MI on symbol vectors with Equal Width discretization through optimized maximum likelihood	3	3	3	4	3	4
Qualitative distance measure	3	4	4	3	4	4
Symbol sequence similarity	1	3	3	3	1	3

Figure 5: Clustering (PCA) of base methods into 4 views (clusters) for the SynTReN Yeast dataset with 100 nodes and noise level 0.0. Each base method is a combination of a distance measure and a scoring scheme (cf. Supplementary File 1). The number (and the corresponding color) in a cell identifies the cluster to which a base method is assigned. Empty cells indicate that the corresponding base method has not been associated with any cluster. This can happen if the base method returns no interactions.

			Scoring Sc	hemes		
Measures	ARACNE	AWE	AWE w/o TF	CLR	ID	MRNE"
Oynamic Time Warping (Asymmetric constraint path)	2	2	2	2	2	2
Oynamic Time Warping (Symmetric constraint path 1)	2	2	2	2	2	2
Dynamic Time Warping (Symmetric constraint path 2)	2	2	2	2	2	2
uclidian distance	2	5	5	2	2	2
endall correlation coefficient	1	4	4	4	1	3
10Norm distance	2	5	5	2	1	2
Anhattan distance	2	2	2	2	2	2
Mean between symbolic sequence similarity and MI on symbol vectors with Equal Frequency discretization through optimized maximum likelihood	4	1	1	4	1	3
lean between symbolic sequence similarity and MI on symbol vectors with Equal Width discretization through optimized maximum likelihood	4	1	1	4	4	3
II - Equal Frequency discretization through optimized maximum likelihood	5	5	5	4	5	3
11 - Equal Frequency discretization through optimized maximum likelihood over coarse-grained variables (Kolmogorov-Sinai entropy)				2		4
/II - Equal Frequency discretization through shrinkage	5	5	5	4	5	3
11 - Equal Frequency discretization through shrinkage over coarse-grained variables (Kolmogorov-Sinai entropy)						4
1I - Equal Width discretization through optimized maximum likelihood	3	3	3	3	3	5
III - Equal Width discretization through optimized maximum likelihood over coarse-grained variables (Kolmogorov-Sinai entropy)	5	2	2	4	2	5
1I - Equal Width discretization through shrinkage	3	3	3	3	3	5
11 - Equal Width discretization through shrinkage over coarse-grained variables (Kolmogorov-Sinai entropy)						4
II on symbol vectors with Equal Frequency discretization through optimized maximum likelihood	4	1	1	4	4	3
II on symbol vectors with Equal Width discretization through optimized maximum likelihood	4	1	1	1	4	3
earson correlation coefficient	3	3	3	4	1	3
ualitative distance measure	4	5	5	4	5	3
pearman correlation coefficient	1	4	4	4	1	3
ymbol sequence similarity	5	4	4	4	5	3

Figure 6: Clustering (PCA) of base methods into 5 views (clusters) for the SynTReN Yeast dataset with 100 nodes and noise level 0.0. Each base method is a combination of a distance measure and a scoring scheme (cf. Supplementary File 1). The number (and the corresponding color) in a cell identifies the cluster to which a base method is assigned. Empty cells indicate that the corresponding base method has not been associated with any cluster. This can happen if the base method returns no interactions.

D5InSilico - 3 Views	_	D5InSilico - 4 Views	_	D5InSilico - 5 Views	_	D5EColi - 3 Views	_	D5EColi - 4 Views	_	D5EColi - 5 Views	_	D5Yeast - 3 Views	_	D5Yeast - 4 Views	_	D5Yeast - 5 Views	_
Methods		Methods		Methods]	Methods		Methods	1								
Regression1	1	Correlation1	1	Meta2	1	Correlation1	1	Regression1	1	Other3	1	Bayesian3	1	Bayesian3	1	MutualInformation5	1 /
Regression5	1	Meta2	1	Correlation1	1	Correlation2	1	Other1	1	Correlation1	1	Bayesian6	1	Correlation1	1	Other1	1 /
Other1	1	Meta4	1	Meta4	1	Correlation3	1	Other3	1	MutualInformation1	1	Correlation1	1	Correlation2	1	Correlation2	1 /
Other3	1	MutualInformation1	1	MutualInformation1	1	Meta1	1	Meta1	1	Correlation2	1	Correlation2	1	Meta2	1	Correlation1	1 /
Meta4	1	MutualInformation3	1	Other4	1	Meta2	1	Meta4	1	Meta2	1	Meta2	1	MutualInformation1	1	Other4	1 /
Regression3	1	Other1	1	Regression3	1	Meta4	1	MutualInformation1	1	Meta4	1	Meta4	1	MutualInformation5	1	MutualInformation1	1 /
Regression6	1	Other3	1	Other1	1	MutualInformation1	1	Correlation1	1	Regression1	1	MutualInformation1	1	Other1	1	Other3	1 /
Regression8	1	Other4	1	Other3	1	Other1	1	Correlation2	1	Correlation3	1	MutualInformation5	1	Other3	1	Meta2	1 /
MutualInformation1	1	Regression1	1	Regression5	1	Other3	1	Correlation3	1	Meta1	1	Other1	1	Other4	1	Bayesian3	1 /
MutualInformation3	1	Regression3	1	Regression1	1	Regression1	1	Meta2	1	Other1	1	Other3	1	Regression1	1	Regression1	1 /
Correlation1	1	Regression5	1	Bayesian5	2	Meta3	2	Regression5	2	Regression5	2	Other4	1	Correlation3	2	MutualInformation4	2
Other4	1	Regression6	1	Bayesian4	2	MutualInformation2	2	Other6	2	Regression4	2	Other6	1	Meta3	2	Regression4	2
Meta2	1	Regression8	1	Regression4	2	MutualInformation3	2	Regression2	2	MutualInformation5	2	Regression1	1	MutualInformation2	2	MutualInformation2	2
Meta3	1	Bayesian4	2	Other2	2	MutualInformation4	2	Regression3	2	Regression2	2	Correlation3	2	MutualInformation3	2	Regression3	2
Regression2	2	Bayesian5	2	Regression2	2	MutualInformation5	2	Regression4	2	Regression8	2	Meta3	2	MutualInformation4	2	Regression8	2
Regression4	2	MutualInformation2	2	Other8	3	Other4	2	Regression6	2	MutualInformation2	2	MutualInformation2	2	Other8	2	Regression5	2
Regression7	2	MutualInformation4	2	Other7	3	Other6	2	Regression8	2	MutualInformation4	2	MutualInformation3	2	Regression3	2	Regression6	2
MutualInformation2	2	Other2	2	Bayesian1	3	Other7	2	MutualInformation2	2	MutualInformation3	2	MutualInformation4	2	Regression4	2	Correlation3	2
MutualInformation4	2	Regression2	2	MutualInformation5	3	Other8	2	MutualInformation3	2	Regression6	2	Other5	2	Regression5	2	MutualInformation3	2
Bayesian4	2	Regression4	2	Bayesian2	3	Regression2	2	MutualInformation4	2	Other6	2	Other7	2	Regression6	2	Bayesian1	3
Bayesian5	2	Bayesian1	3	Meta5	3	Regression3	2	MutualInformation5	2	Bayesian4	3	Other8	2	Regression8	2	Bayesian2	3
Other2	2	Bayesian2	3	Other6	3	Regression4	2	Bayesian1	3	Bayesian5	3	Regression3	2	Bayesian1	3	Regression2	4
Other5	2	Bayesian3	3	Bayesian3	3	Regression5	2	Bayesian2	3	Bayesian6	3	Regression4	2	Bayesian2	3	Bayesian5	4
Other6	3	Correlation2	3	Meta1	3	Regression6	2	Bayesian3	3	Bayesian3	3	Regression5	2	Bayesian4	4	Meta1	4
Meta1	3	Correlation3	3	Bayesian6	4	Regression8	2	Bayesian4	3	Other4	4	Regression6	2	Bayesian5	4	Bayesian4	4
MutualInformation5	3	Meta1	3	Meta3	4	Bayesian1	3	Bayesian5	3	Other2	4	Regression7	2	Bayesian6	4	Bayesian6	4
Correlation2	3	Meta5	3	Other5	4	Bayesian2	3	Bayesian6	3	Other5	4	Regression8	2	Meta1	4	Other6	4
Correlation3	3	MutualInformation5	3	Regression7	4	Bayesian3	3	Regression7	4	Regression7	4	Bayesian1	3	Meta4	4	Other2	5
Other8	3	Other6	3	Regression8	5	Bayesian4	3	Other2	4	Other8	4	Bayesian2	3	Meta5	4	Meta3	5
Bayesian1	3	Other7	3	Correlation2	5	Bayesian5	3	Other4	4	Meta3	4	Bayesian4	3	Other2	4	Other8	5
Bayesian2	3	Other8	3	MutualInformation2	5	Bayesian6	3	Other5	4	Other7	4	Bayesian5	3	Other5	4	Regression7	5
Bayesian3	3	Bayesian6	4	Correlation3	5	Meta5	3	Other7	4	Meta5	4	Meta1	3	Other6	4	Meta4	5
Bayesian6	3	Meta3	4	MutualInformation3	5	Other2	3	Other8	4	Bayesian1	5	Meta5	3	Other7	4	Other7	5
Other7	3	Other5	4	Regression6	5	Other5	3	Meta3	4	Bayesian2	5	Other2	3	Regression2	4	Other5	5
Meta5	3	Regression7	4	MutualInformation4	5	Regression7	3	Meta5	4	Regression3	5	Regression2	3	Regression7	4	Meta5	5

Figure 7: Clustering (PCA) of base methods for the DREAM5 datasets into 3, 4 and 5 views (clusters). The number (and the corresponding color) in a cell identifies the cluster to which a base method is assigned.

Results with K-means clustering

		2 2 2 2 2 2 2 2 2 2 2 2 2 2 3 3 2 2 2 2				
Measures	ARACNE	AWE	AWE w/o TF	CLR	ID	MRNET
Dynamic Time Warping (Asymmetric constraint path)	2	2	2	2	2	2
Dynamic Time Warping (Symmetric constraint path 1)	2	2	2	2	2	2
Dynamic Time Warping (Symmetric constraint path 2)	2	2	2	2	2	2
Euclidian distance	2	2	2	2	2	2
Kendall correlation coefficient	3	2	2	2	3	2
L10Norm distance	2	2	2	2	2	2
Manhattan distance	2	2	2	2	2	2
Mean between symbolic sequence similarity and MI on symbol vectors with Equal Frequency discretization through optimized maximum likelihood	3	2	2	2	3	2
Mean between symbolic sequence similarity and MI on symbol vectors with Equal Width discretization through optimized maximum likelihood	3	2	2	2	3	2
MI - Equal Frequency discretization through optimized maximum likelihood	3	2	2	2	3	2
MI - Equal Frequency discretization through optimized maximum likelihood over coarse-grained variables (Kolmogorov-Sinai entropy)	1	2	2	2	1	2
MI - Equal Frequency discretization through shrinkage	3	2	2	2	3	2
MI - Equal Frequency discretization through shrinkage over coarse-grained variables (Kolmogorov-Sinai entropy)	1	2	2		1	2
MI - Equal Width discretization through optimized maximum likelihood	2	2	2	2	3	2
MI - Equal Width discretization through optimized maximum likelihood over coarse-grained variables (Kolmogorov-Sinai entropy)	2	2	2	2	1	2
MI - Equal Width discretization through shrinkage	2	2	2	2	3	2
MI - Equal Width discretization through shrinkage over coarse-grained variables (Kolmogorov-Sinai entropy)	1	2	2		1	2
MI on symbol vectors with Equal Frequency discretization through optimized maximum likelihood	3	2	2	2	3	2
MI on symbol vectors with Equal Width discretization through optimized maximum likelihood	3	2	2	2	3	2
Pearson correlation coefficient	2	2	2	2	2	2
Qualitative distance measure	3	2	2	3	1	2
Spearman correlation coefficient	3	2	2	2	3	2
Symbol sequence similarity	3	2	2	2	3	2

Figure 8: Clustering (K-means) of base methods into 3 views (clusters) for the SynTReN *E. coli* dataset with 100 nodes and noise level 0.0. Each base method is a combination of a distance measure and a scoring scheme (cf. Supplementary File 1). The number (and the corresponding color) in a cell identifies the cluster to which a base method is assigned. Empty cells indicate that the corresponding base method has not been associated with any cluster. This can happen if the base method returns no interactions.

			Scoring Sc	hemes		
Measures	ARACNE	AWE	AWE w/o TF	CLR	ID	MRNET
Dynamic Time Warping (Asymmetric constraint path)	4	2	2	2	4	4
Dynamic Time Warping (Symmetric constraint path 1)	4	2	2	4	4	4
Dynamic Time Warping (Symmetric constraint path 2)	4	2	2	2	4	4
Euclidian distance	4	2	2	4	4	4
Kendall correlation coefficient	3	2	2	2	3	2
.10Norm distance	4	2	2	2	4	4
Manhattan distance	4	2	2	4	4	4
Mean between symbolic sequence similarity and MI on symbol vectors with Equal Frequency discretization through optimized maximum likelihood	3	2	2	2	3	2
Mean between symbolic sequence similarity and MI on symbol vectors with Equal Width discretization through optimized maximum likelihood	3	2	2	2	3	2
MI - Equal Frequency discretization through optimized maximum likelihood	3	2	2	2	3	2
MI - Equal Frequency discretization through optimized maximum likelihood over coarse-grained variables (Kolmogorov-Sinai entropy)	1	2	2	2	1	2
MI - Equal Frequency discretization through shrinkage	3	2	2	2	3	2
MI - Equal Frequency discretization through shrinkage over coarse-grained variables (Kolmogorov-Sinai entropy)	1	2	2		1	2
MI - Equal Width discretization through optimized maximum likelihood	2	2	2	2	3	2
MI - Equal Width discretization through optimized maximum likelihood over coarse-grained variables (Kolmogorov-Sinai entropy)	2	2	2	2	1	2
MI - Equal Width discretization through shrinkage	2	2	2	2	3	2
MI - Equal Width discretization through shrinkage over coarse-grained variables (Kolmogorov-Sinai entropy)	1	2	2		1	2
MI on symbol vectors with Equal Frequency discretization through optimized maximum likelihood	3	2	2	2	3	2
MI on symbol vectors with Equal Width discretization through optimized maximum likelihood	3	2	2	2	3	2
Pearson correlation coefficient	2	2	2	2	2	2
Qualitative distance measure	3	2	2	3	1	2
spearman correlation coefficient	3	2	2	2	3	2
Symbol sequence similarity	3	2	2	2	3	2

Figure 9: Clustering (K-means) of base methods into 4 views (clusters) for the SynTReN *E. coli* dataset with 100 nodes and noise level 0.0. Each base method is a combination of a distance measure and a scoring scheme (cf. Supplementary File 1). The number (and the corresponding color) in a cell identifies the cluster to which a base method is assigned. Empty cells indicate that the corresponding base method has not been associated with any cluster. This can happen if the base method returns no interactions.

			Scoring Sc	hemes		
Measures	ARACNE	AWE	AWE w/o TF	CLR	ID	MRNET
Dynamic Time Warping (Asymmetric constraint path)	4	2	2	2	4	4
Oynamic Time Warping (Symmetric constraint path 1)	4	2	2	2	4	4
Dynamic Time Warping (Symmetric constraint path 2)	4	2	2	2	4	4
Euclidian distance	4	2	2	4	4	4
Kendall correlation coefficient	5	2	2	2	5	3
L10Norm distance	4	2	2	2	4	4
Manhattan distance	4	2	2	4	4	4
Mean between symbolic sequence similarity and MI on symbol vectors with Equal Frequency discretization through optimized maximum likelihood	5	2	2	2	5	3
Mean between symbolic sequence similarity and MI on symbol vectors with Equal Width discretization through optimized maximum likelihood	5	2	2	2	5	3
MI - Equal Frequency discretization through optimized maximum likelihood	5	2	2	2	5	3
MI - Equal Frequency discretization through optimized maximum likelihood over coarse-grained variables (Kolmogorov-Sinai entropy)	1	2	2	2	1	2
MI - Equal Frequency discretization through shrinkage	5	2	2	2	5	3
MI - Equal Frequency discretization through shrinkage over coarse-grained variables (Kolmogorov-Sinai entropy)	1	2	2		1	2
MI - Equal Width discretization through optimized maximum likelihood	3	2	2	2	3	2
MI - Equal Width discretization through optimized maximum likelihood over coarse-grained variables (Kolmogorov-Sinai entropy)	2	2	2	2	1	2
MI - Equal Width discretization through shrinkage	3	2	2	2	3	2
MI - Equal Width discretization through shrinkage over coarse-grained variables (Kolmogorov-Sinai entropy)	1	2	2		1	2
MI on symbol vectors with Equal Frequency discretization through optimized maximum likelihood	5	2	2	2	5	3
MI on symbol vectors with Equal Width discretization through optimized maximum likelihood	5	2	2	2	5	3
Pearson correlation coefficient	2	2	2	2	3	2
Qualitative distance measure	5	2	2	5	1	3
Spearman correlation coefficient	5	2	2	2	5	3
symbol sequence similarity	5	2	2	2	5	3

Figure 10: Clustering (K-means) of base methods into 5 views (clusters) for the SynTReN *E. coli* dataset with 100 nodes and noise level 0.0. Each base method is a combination of a distance measure and a scoring scheme (cf. Supplementary File 1). The number (and the corresponding color) in a cell identifies the cluster to which a base method is assigned. Empty cells indicate that the corresponding base method has not been associated with any cluster. This can happen if the base method returns no interactions.

			Scoring Sch	emes		
Measures	ARACNE	AWE	AWE w/o TF	CLR	ID	MRNET
Dynamic Time Warping (Asymmetric constraint path)	2	2	2	2	2	2
Dynamic Time Warping (Symmetric constraint path 1)	2	2	2	2	2	2
Dynamic Time Warping (Symmetric constraint path 2)	2	2	2	2	2	2
Euclidian distance	2	2	2	2	2	2
Kendall correlation coefficient	3	2	2	2	3	2
L10Norm distance	2	2	2	2	1	2
Manhattan distance	2	2	2	2	2	2
Mean between symbolic sequence similarity and MI on symbol vectors with Equal Frequency discretization through optimized maximum likelihood	3	2	2	2	3	2
Mean between symbolic sequence similarity and MI on symbol vectors with Equal Width discretization through optimized maximum likelihood	3	2	2	2	3	2
MI - Equal Frequency discretization through optimized maximum likelihood	3	2	2	2	3	2
MI - Equal Frequency discretization through optimized maximum likelihood over coarse-grained variables (Kolmogorov-Sinai entropy)	1	2	2	2	1	2
MI - Equal Frequency discretization through shrinkage	3	2	2	2	3	2
MI - Equal Frequency discretization through shrinkage over coarse-grained variables (Kolmogorov-Sinai entropy)	1	2	2		1	2
MI - Equal Width discretization through optimized maximum likelihood	2	2	2	2	3	2
MI - Equal Width discretization through optimized maximum likelihood over coarse-grained variables (Kolmogorov-Sinai entropy)	2	2	2	2	1	2
MI - Equal Width discretization through shrinkage	2	2	2	2	3	2
MI - Equal Width discretization through shrinkage over coarse-grained variables (Kolmogorov-Sinai entropy)	1	2	2		1	2
MI on symbol vectors with Equal Frequency discretization through optimized maximum likelihood	3	2	2	2	3	2
MI on symbol vectors with Equal Width discretization through optimized maximum likelihood	3	2	2	2	3	2
Pearson correlation coefficient	2	2	2	2	2	2
Qualitative distance measure	3	2	2	3	1	2
Spearman correlation coefficient	3	2	2	2	3	2
Symbol sequence similarity	3	2	2	2	3	2

Figure 11: Clustering (K-means) of base methods into 3 views (clusters) for the SynTReN Yeast dataset with 100 nodes and noise level 0.0. Each base method is a combination of a distance measure and a scoring scheme (cf. Supplementary File 1). The number (and the corresponding color) in a cell identifies the cluster to which a base method is assigned. Empty cells indicate that the corresponding base method has not been associated with any cluster. This can happen if the base method returns no interactions.

			Scoring Sc	hemes		
Measures	ARACNE	AWE	AWE w/o TF	CLR	ID	MRNET
Dynamic Time Warping (Asymmetric constraint path)	4	2	2	2	4	4
Dynamic Time Warping (Symmetric constraint path 1)	4	2	2	4	4	4
Dynamic Time Warping (Symmetric constraint path 2)	4	2	2	4	4	4
Euclidian distance	4	2	2	4	4	4
Kendall correlation coefficient	3	2	2	2	3	2
L10Norm distance	4	2	2	4	4	4
Manhattan distance	4	2	2	4	4	4
Mean between symbolic sequence similarity and MI on symbol vectors with Equal Frequency discretization through optimized maximum likelihood	3	2	2	2	3	2
Mean between symbolic sequence similarity and MI on symbol vectors with Equal Width discretization through optimized maximum likelihood	3	2	2	2	3	2
MI - Equal Frequency discretization through optimized maximum likelihood	3	2	2	2	3	2
MI - Equal Frequency discretization through optimized maximum likelihood over coarse-grained variables (Kolmogorov-Sinai entropy)	1	2	2	2	1	2
MI - Equal Frequency discretization through shrinkage	3	2	2	2	3	2
MI - Equal Frequency discretization through shrinkage over coarse-grained variables (Kolmogorov-Sinai entropy)	1	2	2		1	2
MI - Equal Width discretization through optimized maximum likelihood	2	2	2	2	3	2
MI - Equal Width discretization through optimized maximum likelihood over coarse-grained variables (Kolmogorov-Sinai entropy)	2	2	2	2	1	2
MI - Equal Width discretization through shrinkage	2	2	2	2	3	2
MI - Equal Width discretization through shrinkage over coarse-grained variables (Kolmogorov-Sinai entropy)	1	2	2		1	2
MI on symbol vectors with Equal Frequency discretization through optimized maximum likelihood	3	2	2	2	3	2
MI on symbol vectors with Equal Width discretization through optimized maximum likelihood	3	2	2	2	3	2
Pearson correlation coefficient	2	2	2	2	2	2
Qualitative distance measure	3	2	2	3	1	2
Spearman correlation coefficient	3	2	2	2	3	2
Symbol sequence similarity	3	2	2	2	3	2

Figure 12: Clustering (K-means) of base methods into 4 views (clusters) for the SynTReN Yeast dataset with 100 nodes and noise level 0.0. Each base method is a combination of a distance measure and a scoring scheme (cf. Supplementary File 1). The number (and the corresponding color) in a cell identifies the cluster to which a base method is assigned. Empty cells indicate that the corresponding base method has not been associated with any cluster. This can happen if the base method returns no interactions.

			Scoring Sc	hemes		
Measures	ARACNE	AWE	AWE w/o TF	CLR	ID	MRNET
Dynamic Time Warping (Asymmetric constraint path)	4	2	2	2	4	4
Dynamic Time Warping (Symmetric constraint path 1)	4	2	2	4	4	4
Dynamic Time Warping (Symmetric constraint path 2)	4	2	2	4	4	4
Euclidian distance	4	2	2	4	4	4
Kendall correlation coefficient	5	2	2	2	5	3
L10Norm distance	4	2	2	4	4	4
Manhattan distance	4	2	2	4	4	4
Mean between symbolic sequence similarity and MI on symbol vectors with Equal Frequency discretization through optimized maximum likelihood	5	2	2	2	5	3
Mean between symbolic sequence similarity and MI on symbol vectors with Equal Width discretization through optimized maximum likelihood	5	2	2	2	5	3
MI - Equal Frequency discretization through optimized maximum likelihood	5	2	2	2	5	3
MI - Equal Frequency discretization through optimized maximum likelihood over coarse-grained variables (Kolmogorov-Sinai entropy)	1	2	2	2	1	2
MI - Equal Frequency discretization through shrinkage	5	2	2	2	5	3
MI - Equal Frequency discretization through shrinkage over coarse-grained variables (Kolmogorov-Sinai entropy)	1	2	2		1	2
MI - Equal Width discretization through optimized maximum likelihood	2	2	2	2	5	2
MI - Equal Width discretization through optimized maximum likelihood over coarse-grained variables (Kolmogorov-Sinai entropy)	2	2	2	2	1	2
MI - Equal Width discretization through shrinkage	2	2	2	2	5	2
MI - Equal Width discretization through shrinkage over coarse-grained variables (Kolmogorov-Sinai entropy)	1	2	2		1	2
MI on symbol vectors with Equal Frequency discretization through optimized maximum likelihood	5	2	2	2	5	3
MI on symbol vectors with Equal Width discretization through optimized maximum likelihood	5	2	2	2	5	3
Pearson correlation coefficient	2	2	2	2	2	2
Qualitative distance measure	5	2	2	5	1	3
Spearman correlation coefficient	5	2	2	2	5	3
Symbol sequence similarity	5	2	2	2	5	3

Figure 13: Clustering (K-means) of base methods into 5 views (clusters) for the SynTReN Yeast dataset with 100 nodes and noise level 0.0. Each base method is a combination of a distance measure and a scoring scheme (cf. Supplementary File 1). The number (and the corresponding color) in a cell identifies the cluster to which a base method is assigned. Empty cells indicate that the corresponding base method has not been associated with any cluster. This can happen if the base method returns no interactions.

D5InSilico - 3 Views		D5InSilico - 4 Views		D5InSilico - 5 Views		D5EColi - 3 Views		D5EColi - 4 Views		D5EColi - 5 Views		D5Yeast - 3 Views		D5Yeast - 4 Views		D5Yeast - 5 Views	
Methods		Methods		Methods		Methods		Methods		Methods		Methods		Methods		Methods	
Other5	1	Other5	1	Other5	1	Other2	1	Other2	1	Other2	1	Regression2	1	Regression2	1	Regression2	1
Other2	1	Other2	1	Other2	1	Other5	1	Other5	1	Other5	1	Other2	1	Other2	1	Other2	1
Regression7	1	Regression7	1	Regression7	1	Other6	2	Other6	2	Other6	2	Meta3	1	Meta3	1	Meta3	1
Meta2	2	Meta2	2	Other6	2	Other3	3	Other3	3	Other3	3	Other6	2	Other6	2	Other6	2
Regression8	2	Correlation2	2	Meta2	3	Other4	3	Other4	3	Other4	3	Other8	3	Other8	3	Other8	3
Meta4	2	Correlation1	2	Other8	3	MutualInformation5	3	MutualInformation5	3	MutualInformation5	3	Meta1	3	Meta1	3	Meta1	3
Other4	2	Meta4	2	Other7	3	Other8	3	Other8	3	Other8	3	Meta2	3	Meta2	3	Meta2	3
Regression4	2	Other4	2	Regression8	3	Correlation1	3	Correlation1	3	Correlation1	3	Regression1	3	Regression1	3	Regression1	3
MutualInformation3	2	Regression4	2	Meta4	3	Meta3	3	Meta3	3	Meta3	3	Regression4	3	Regression4	3	Regression3	3
Regression5	2	Correlation3	2	Other4	3	Bayesian6	3	Bayesian6	3	Bayesian6	3	Regression3	3	Regression3	3	Regression8	3
Meta5	2	Bayesian6	3	Regression4	3	MutualInformation2	3	MutualInformation2	3	MutualInformation2	3	Regression8	3	Regression8	3	Bayesian5	3
Regression6	2	Other8	3	MutualInformation3	3	Meta4	3	Meta4	3	Meta4	3	Bayesian5	3	Bayesian5	3	Regression7	3
MutualInformation4	2	Bayesian5	3	Regression5	3	Other7	3	Other7	3	Other7	3	Regression7	3	Regression7	3	Bayesian6	3
Other6	2	Meta3	3	Regression6	3	MutualInformation4	3	MutualInformation4	3	MutualInformation4	3	Bayesian6	3	Bayesian6	3	Regression5	3
Correlation2	2	Other7	3	MutualInformation4	3	MutualInformation3	3	MutualInformation3	3	MutualInformation3	3	Regression5	3	Regression5	3	Regression6	3
MutualInformation2	2	Bayesian4	3	Bayesian6	3	Meta5	3	Bayesian1	3	Bayesian1	3	Regression6	3	Regression6	3	Bayesian1	3
Correlation1	2	MutualInformation1	3	Correlation2	3	Bayesian1	3	Bayesian2	3	Bayesian2	3	Bayesian1	3	Bayesian1	3	Bayesian4	3
Bayesian1	2	MutualInformation5	3	MutualInformation2	3	Bayesian2	3	Bayesian4	3	Bayesian4	3	Bayesian4	3	Bayesian4	3	Bayesian3	3
Regression3	2	Regression2	3	Correlation1	3	Bayesian4	3	Bayesian5	3	Bayesian5	3	Bayesian3	3	Bayesian3	3	Bayesian2	3
Other1	2	Bayesian3	3	Bayesian1	3	Bayesian5	3	Correlation2	3	Correlation2	3	Bayesian2	3	Bayesian2	3	Correlation3	3
Correlation3	2	Regression8	4	Regression3	3	Correlation2	3	Regression1	3	Regression1	3	Correlation3	3	Correlation3	3	MutualInformation5	3
Other3	2	MutualInformation3	4	Other1	3	Regression1	3	Bayesian3	3	Bayesian3	3	MutualInformation5	3	MutualInformation5	3	Other1	3
Bayesian2	2	Regression5	4	Regression2	3	Bayesian3	3	Correlation3	3	Correlation3	3	Other1	3	Other1	3	MutualInformation4	3
Regression1	2	Meta5	4	Correlation3	3	Correlation3	3	Regression5	3	Regression5	3	MutualInformation4	3	MutualInformation4	3	Correlation2	3
Meta1	2	Regression6	4	Other3	3	Regression5	3	Regression4	3	Regression2	3	Correlation2	3	Correlation2	3	MutualInformation2	3
Bayesian6	3	MutualInformation4	4	Bayesian2	3	Regression4	3	Regression2	3	Regression7	3	MutualInformation2	3	MutualInformation2	3	Correlation1	3
Other8	3	Other6	4	Regression1	3	Regression2	3	Regression7	3	Regression8	3	Correlation1	3	Correlation1	3	Other4	3
Bayesian5	3	MutualInformation2	4	Meta1	3	Regression7	3	Regression8	3	Regression3	3	Other4	3	Other4	3	MutualInformation1	3
Meta3	3	Bayesian1	4	Meta5	4	Regression8	3	Regression3	3	Regression6	3	MutualInformation1	3	MutualInformation1	3	Other3	3
Other7	3	Regression3	4	Bayesian5	5	Regression3	3	Regression6	3	MutualInformation1	3	Other3	3	Other3	3	Meta4	3
Bayesian4	3	Other1	4	Meta3	5	Regression6	3	MutualInformation1	3	Meta2	3	Meta4	3	Meta4	3	Other7	3
MutualInformation1	3	Other3	4	Bayesian4	5	MutualInformation1	3	Meta2	3	Meta1	3	Other7	3	Other7	3	Other5	3
MutualInformation5	3	Bayesian2	4	MutualInformation1	5	Meta2	3	Meta1	3	Other1	3	Other5	3	Other5	3	MutualInformation3	3
Regression2	3	Regression1	4	MutualInformation5	5	Meta1	3	Other1	3	Meta5	4	MutualInformation3	3	MutualInformation3	3	Meta5	4
Bayesian3	3	Meta1	4	Bayesian3	5	Other1	3	Meta5	4	Regression4	5	Meta5	3	Meta5	4	Regression4	5

Figure 14: Clustering (K-means) of base methods for the DREAM5 datasets into 3, 4 and 5 views (clusters). The number (and the corresponding color) in a cell identifies the cluster to which a base method is assigned.