# **Evaluation and Application of Nonlinear Dimensionality Reduction Methods** for Phylogenetic Inference

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# INTRODUCTION

Phylogenetic analyses of large and diverse data sets generally result in large sets of competing phylogenetic trees. Consensus tree methods used to summarize sets of competing trees discard important information regarding the similarity and distribution of competing trees. A more fine grain approach is to use a dimensionality reduction method to project tree-to-tree distances in low dimension Euclidean space [1]. Such an approach gives us a way to better understand the processes and patterns of evolution and well as how well suited our models and methods are performing. For example, analyses of different data partitions may support different phylogenies because reconstruction methods sometimes fail to adequately accommodate process heterogeneity underlying data partitions found within an alignment [2, 3, 4, 5] or because some data partitions simply do not share the same evolutionary history [6]. Furthermore, large data sets are typically more computationally challenging to analyze and often call for more extreme heuristic shortcuts, which may fail to converge to a global optimum [7].

In this study, first, we systematically evaluate the performance of several nonlinear dimensionality reduction (NLDR) methods on several tree-to-tree distances obtained from independent nonparametric bootstrap analyses of genes from three mid- to large-sized mitochondrial genome alignments. Second, we apply the most reliable NLDR method to visualize the consequences of removing potentially misleading characters from an alignment of 169 Elasmobranch protein coding sequences comprised of 1 mtDNA and 7 nuclear loci. Characters were removed from the alignment based on how well they fit a model of stationarity using a program called DRUIDS [8]. We expect that sets of trees favored by individual loci will be more difficult to distinguish in projections (i.e., landscapes) of phylogenetic trees obtained from analyses of an alignment after the DRUIDS filter is applied.

# **Study Goals**

- 1. Evaluate the performance and goodness of fit of several popular distance-based NLDR methods
- 2. Compare the tree projects of different mtDNA data sets
- 3. Evaluate different tree-to-tree metrics
- 4. Evaluate the effect of nonstationary characters on tree inference.

# Methods of NLDR

### Data

Taxa Number of Sequen				ces Reference				
Fishes 90				[9] Setiamarga et al., 2008				
Mammals 89				[10] Kjer and Honeycutt, 2007				
Salamande	irs	42	[11] Zhang et al., 2008					
TABLE 1. oublished	Aligned wh I studies rep	nole mitochon presenting a c	drial DNA (mt. liverse set of a	DNA) gen animal tax	omes we a.	re obtained	from three	
	Number of Trees				Number of Trees			
Gene	Fishes	Mammals	Salamanders	Gene	Fishes	Mammals	Salamanders	
12S	256	219	119	ND1	507	170	111	
16S	205	146	106	ND2	371	129	111	
ATP6	415	540	156	ND3	690	1559	355	
ATP8	939	362	783	ND4	219	150	108	
COI	386	228	106	ND4	1362	1056	378	
COII	444	433	196	ND4L	188	114	103	
COIII	643	554	149	ND5	162	146	108	
CHAR	225	105	100	TOTALS	7022	6001	2011	

TABLES 2. Rhotogenetic reast view distribution and of the theorem (MMA data (STR) / ) conparements lookings panalysis (100 replicates) on sets of the (5-mR)(L genes A tree-to-tree distance matrix was created for the Fish, Mammal, and Salamander data set by concatenating the bootstrap trees found for gene. First of all, let us concentrate on the unweighted Robinson-Foulds (RF) distance [12].

## Compare NLDR Methods Visual Inspection



FIGURE 1. Two-dimensional projections of 3011 non-parametric bootstrap trees from the salamander data set using four cost functions (x-axi) and three optimization algorithms (yaxis). The colors represent the underlying genes used to generate the trees (see Table 2). \*Kruskal-1 uses the linear iteration method instead of the stochastic gradient descent method used by the other cost functions in this row.

## **Goodness of Fit Measures**

Salamander		Majorization	Gauss Seidel	Stochastic	Linear Iteration
	1NN	0.631518	0.636533		0.656958
KRUSKAL-1	CON	0.867292	0.868435		0.883922
	TRU	0.889536	0.890508		0.904859
	1NN	0.631518	0.643607	0.692826	
VORMALIZED	CON	0.867292	0.872708	0.898833	
	TRU	0.889536	0.892184	0.96152	
	1NN	0.585785	0.62461	0.618765	
NLM	CON	0.852738	0.875596	0.871919	
	TRU	0.952199	0.96244	0.961883	
	1NN	0.629326	0.650017	0.897077	
CCA	CON	0.847438	0.8747	0.972035	
	TRU	0.819831	0.897908	0.965572	

TABLE 3. Three goodness of fit measures used to evaluate each combination of cost function and optimization algorithm: INN = 1 Nearest Neighbour [13], CON = Continuity [14] and TRU = Trustworthiness [14].

## Landscapes of mtDNA Gene Trees



FIGURE 2. Two-dimensional projections of 6001 Mammals (a) and 7022 Fishes (b)

## Plots of Tree-to-Tree distances Visual Inspection



#### salarmender data set using rour tra-to-tra- distance metines (Foomson Foulds [72], Math Distance [15, 10], Agd1 [17], and Agreament Subtes [17]). The color spresent the underlying geneo used to generate the trees. Projections were made using TreeScaper [18] with the cost function set to CCA and the optimization algorithm set to Stochastic Gradient Occant.

# Method of testing

Data

	Number of M	L Bootstrap Trees	Number of ML Bootstrap Trees		
Gene	Unfiltered	Filtered	Gene	Unfiltered	Filtered
RAG1	120	116	ND2	116	139
ACT	137	133	PROX1	112	110
KBTBD2	111	106	SCFD2	113	113
TOB101	161	145	RAG2	116	121
			TOTALS	986	983

TABLE 4. The number of ML (GTR+  $\Gamma$ +Pinvar) nonparametric bootstrap (100 replicates) trees and the number of characters in each gene partition before and after the DRUIDS filter.

## Results



FIGURE 4. Projections of bootstrap and Bayesian trees obtained from the analysis of unfiltered and DRUIDS filtered alignments. Each locus was analyzed independently. RFdistances were calculated on concatenated sets of trees obtained from each analysis and RF-distances were projected using CCA and Stochastic Gradient Decent (i.e., a dimensionality reduction method). The colored points in the left projections represent trees favored by different loci. The colors in the right plots represent trees obtained from unfiltered and DRUIDS filtered alignments. No characters were removed by the DRUIDS filter for the SCFD2 locus.

## **Quantitative Comparisons**

	11	NN	Random Index Method				
Measure	Original	2D	3D	Original	2D	3D	
Unfiltered	0.997972	0.998986	0.998986	0.1397	0.1482	0.1453	
DRUID Filtered	0.997965	0.997965	0.997965	0.1397	0.1456	0.1442	

TABLE 5. Two cluster-based methods were used to quantify whether the DRUID filtered data lessened the distinction among sets of trees favored by different loci. Both the 1NN [13] and Random Index Methods suggest that filtering the data does not lessen the distinction, which is consistent with our visualizations.

#### References



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