Identification and classification of protein subfamilies using top-down phylogenetic tree reconstruction

Eduardo P Costa – Celine Vens – Hendrik Blockeel Dept. of Computer Science, Katholieke Universiteit Leuven

Proteins in a subfamily usually share a specific function that is not common to the entire family. We investigate the use of clustering trees to identify such subfamilies.

Protein function prediction	Top-down phylogenetic tree reconstruction	
Several computational methods have been designed to assist scientists in the context of protein function prediction: • Homology-based methods	Divisive clustering algorithm : Clus-φ • Start with one cluster containing all sequences	
End prone. end propagation, proteins can change functions	• Repeat	





Clus-φ uses the **minimum evolution hypothesis**, namely, constructing a tree with minimal total branch length, to choose the best split.

• Until there is only one sequence per cluster

Applying Clus- ϕ to protein subfamily identification

Problem: how to extract clusters?

- Stop criterion (e.g. entropy reduction, f-test)
- Post-processing pruning (e.g. category utility)

• Use subfamily information (semi-supervised learning) • Functional information may be available for some of the sequences Future work

ADVANTAGES over existing phylogenomic methods

- No need to build the complete tree if stop criterion is used
- Produces evolutionary trace
- Allows to identify functional sites

- Amino acids that are discriminating among different subfamilies

• Allows to directly classify new sequences into subfamilies

Experiments

Scenario 1

Goal: check if trees that have splits based on polymorphic positions are useful for protein subfamily identification

Setting: we added the subfamily information to the data and induced a classification tree using CLUS (supervised classification task)

Table 1. Number of leaves in the classification tree					
	# Subfamilies	Classification tree (# leaves)			
Enolase	8	8			
Crotonase	10	11			
Secretin	15	15			
Amine level 1	7	14			
Amine level 2	31	34			
NHR level 1	8	11			
NHR level 2	27	30			
NHR level 3	77	79			

Table 1 Number of leaves in the election tree



Results: Subfamilies can be perfectly separated from one another using compact trees. The results show that the solution we are looking for is part of the search space.

Scenario 2

Goal: evaluate the quality of the trees being produced, regardless of the stop criterion

Setting: we grew the tree completely until each node was a singleton, and then cut the tree in a way that all clusters were pure and that the tree was as compact as possible. We did the same for Neighbor Joining (NJ) and SCI-PHY.

Table 2. Number of leaves in the post-processed phylogenetic tree

	Clus-φ	NJ	SCI-PHY
Enolase	12	38	28
Crotonase	33	35	70
Secretin	19	20	22
Amine level 1	30	27	36
Amine level 2	49	52	52
NHR level 1	22	12	30
NHR level 2	43	31	38
NHR level 3	90	97	105



Results: Clus- ϕ produced more compact trees than NJ for 5 datasets, and more compact trees than SCI-PHY for 7 datasets. This shows that our method can yield good results if an adequate stop criterion is used.

Scenario 3

Goal: test the whole procedure

Setting: We defined as stop criterion the point where the entropy reduction given by best test, according to the total branch length heuristic, is less than 5%.

Evaluation measure: rand index (cfr. accuracy) rand index = 1 - [probability that 2 random proteins are in the same predicted cluster but have different subfamilies, or the other way around].

	Clus-φ	SCI-PHY
Enolase	0.98	0.86
Crotonase	0.57	0.80
Secretin	0.61	0.96
Amine level 1	0.17	0.87
Amine level 2	0.06	0.96
NHR level 1	0.64	0.81
NHR level 2	0.65	0.99
NHR level 3	0.62	0.96

Table 3. Rand index for the subfamily prediction task

Results: for most of the cases the Clus-φ tree stopped growing to soon, what explains the bad results.





Contact: <Eduardo.Costa@cs.kuleuven.be> <Celine.Vens@cs.kuleuven.be> <Hendrik.Blockeel@cs.kuleuven.be>

