

1 Introduction

There is a historic basis for using HLA gene frequencies in population studies. Mainly, there are six highly polymorphic loci to choose between that have different frequencies between individuals and different populations. Class II genes appear to be older than the class I genes[citation needed]. Although there is some trans-species HLA gene flow between human and apes, trans speciation is relatively minor and loci dependent. Thus, most human HLA alleles, although old, have probably evolved by genetic drift, selection and mutation with gene flow and admixture contributing to the polymorphisms in the MHC region since the split between apes and humans.

It is also claimed that HLA is under selection, which raise concerns

Nonetheless, hyperpolymorphic genes such as HLA class I and II are frequently used in anthropological and population genetic studies. HLA typing has its roots in serology and thus experimentally, large body of data is available. Because of their enormous polymorphism and differences between individuals and populations, the phylogenies of HLA genes are in theory highly informative for population genetics and anthropology. From an information theoretic perspective they are a promising research target, as the amount of all possible outcomes However, current methods are based on allele frequencies alone and do not leverage the information theoretic richness during bootstrapping: Bootstrapping is based on random sampling with replacement from the original input. To the best of our knowledge, all phylogenetic toolkits that are capable of dealing with allele frequencies sample gene-wise. I.e, either a gene is sampled and all its allele frequencies (in the case of HLA genes, this can be as high as ...) are considered or the gene is discarded in a bootstrap and then none of its allele frequencies are taken into account. This all-or-nothing approach works well when many loci are considered (e.g. microsatellites) but for few genes, it leads to a very coarse grained information entropy resolution.

Rich databases describing Therein, populations are described in terms of allele frequencies (see allelefrequenciens.net paper) Unfortunately, the low number of genes as biomarkers in combination with phylogenetic tools that expect high numbers of loci for bootstrapping have led to numerous works with incorrect bootstrapping. They providing false confidence into produced phylogenetic trees. The ramifications of such practices have caused severe controversies: In 2002, Piazza, Risch and Cavalli-Sforza have already criticized the works of Hajjej/Arnaiz-Villena and noted that phylogenetic analysis "Using results from the analysis of a single marker, particularly one likely to have undergone selection, for the purpose of reconstructing genealogies is unreliable and unacceptable practice in population genetics"

Nonetheless, a large number of HLA-based phylogeny reconstruction publications have since been published based on one or very few marker genes []. It is worth noting that HLA genes are hyperpolymorphic, and as such many columns in respective MSAs would carry information entropy for population genetics studies. Most tree reconstruction methods assume locus independence ([1]), which yet requires a rigorous examination. The problem is not necessarily

the low number of gene markers as long as they are hyperpolymorphic (i.e., respectively contain multiple polymorphic nucleotide loci) and representative enough for a species’ genome or population’s genepool.

Most phylogenetic tools used for tree reconstruction from allele frequencies are not suitable for low numbers of marker genes (Phylip, DISPAN, check GenPop), since they perform bootstrapping with loci (i.e., here: genes) as units. If only allele frequencies from a single gene are used, conventional bootstrapping performs resampling with replacement, draws repeatedly from only a single locus. Trivially, this single locus is in agreement with itself, and the tools report 100% branch support for all clades in the tree. False confidence Respected journals have failed to critically review this misuse of bootstrapping [?, 2]. For two genes A and B, resampling leads the combinations AA (25%), AB (50%) and BB (25%). If both A and B agree on the branch split 100% branch split support will be reported by the software. branch split is supported by both A and B, 100 as for example is the case in [2].

We here propose a method that constructs population phylogenies for HLA allele frequencies in combination with well structured databases with deep sequencing data for those genes.

Rich databases such as AlleleFrequencies.net help to obtain population specific descriptions in terms of allele frequencies. Subsequently, mapping of alleles to probabilistic sequence representations enable the expression of equivalent information as position specific weight matrices or classic multiple sequence alignments. This mapping is facilitated by comprehensive and wellstructured databases such as IMGT. With the algorithmic transition of gene markers to nucleotide markers the number of informative loci increases by orders of magnitude. This in turn constitutes an important prerequisite for the application of classic consensus tree construction and bootstrapping, as resampling from this much larger pool of loci is statistically more meaningful.

2 Methods

We download complete multiple sequence alignments from IPD-IMGT/HLA release 3.31.0. For all genes for which multiple sequence alignments are available, we parse the respective alignment file as obtained from IMGT (ref). The Python script is available at the github repository <https://github.com/HenschelLab/FreqRT>.

As we are aiming to capture the entirety of genetic variability associated with HLA genes/alleles, we parse for each HLA gene g its respective multiple sequence alignment into Position Weight Matrices (PWM, [3]) by associating each sequence to the allele identified by the first two digits of the sequence identifier. This yields one PWM for each allele A , which we denote W_A .

In turn, given m selected genes, we describe a population P as a set of m

PWMs W_g^P , which are the weighted sum of the respective allele PWMs

$$W_g^P = \sum_{A \in \mathcal{A}(g)} f_A^P W_A \quad (1)$$

where f_A^P is the frequency of allele A in population P and $\mathcal{A}(g)$ denotes the set of all alleles for g .

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input : Selected genes:  $G_1 \dots G_m$ , Allele frequencies  $f_{A_j}^{P_i}$  for  $n$ 
        populations  $P_1 \dots P_n$ 
output: Phylogenetic tree  $T$  for  $P_1 \dots P_n$  with bootstrap values
1 Preprocessing: Download MSAs from IMGT,  $\forall j$  generate  $W_{A_j}$ 
2 for  $P \in P_1 \dots P_n$  do
3   for  $g \in G_1 \dots G_m$  do
4      $W_g^P \leftarrow \sum_{A \in \mathcal{A}(g)} f_A^P W_A$ 
5   end
6 end
7 for  $bootstrap \leftarrow 1$  to 1000 do
8   for  $g \in G_1 \dots G_m$  do
9      $\overline{W_g^P} = \text{RandomResamplingColumns}(W_g^P)$  such that  $|\overline{W_g^P}| = |W_g^P|$ 
10  end
11  Calculate distance Matrix DM, performing pairwise Nei distance
    calculations between populations
12  for  $P_i \in P_1 \dots P_n$  do
13    for  $P_j \in P_{i+1} \dots P_n$  do
14       $DM_{ij} = \text{Nei}(\overline{W_g^{P_i}}, \overline{W_g^{P_j}})$ 
15    end
16  end
17   $T_{bootstrap} = \text{TreeConstruction}(DM)$ 
18 end
19 Combine bootstrap trees  $T_{bootstrap}$  to majority tree  $T$  with bootstrap
    values

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97	A	C				
99	B	C				
222	A	DRB1				
224	B	DRB1				
242	A	B				
89	A	DQB1	DRB1			
91	A	B	DQB1			
93	B	DQB1	DRB1			
96	A	B	C			
218	A	B	DRB1			
58	A	C	DQB1	DRB1		
60	B	C	DQB1	DRB1		
61	A	B	C	DQB1		
80	A	B	C	DRB1		
88	A	B	DQB1	DRB1		
13	A	B	C	DPB1	DRB1	
13	B	C	DPB1	DQB1	DRB1	
14	A	B	DPB1	DQB1	DRB1	
18	A	B	DQA1	DQB1	DRB1	
58	A	B	C	DQB1	DRB1	
6	B	C	DPB1	DQA1	DQB1	DRB1
7	A	B	C	DPB1	DQA1	DRB1
7	A	B	C	DQA1	DQB1	DRB1
7	A	B	DPB1	DQA1	DQB1	DRB1
12	A	B	C	DPB1	DQB1	DRB1

3 Conclusions

The wrong practice of bootstrapping seems to be relatively common place in the HLA community. We would hereby like to raise awareness during three time points of the publication cycle. First, software tools like Phylip, DISPAN etc ought to generate warnings, when the number of provided loci is too low to subject allele frequencies to bootstrapping. Secondly, naturally scientists creating phylogenies should know what they are doing. Finally, journals like PLoS ONE need to improve review procedures for population phylogenys built with allele frequencies, in particular those with just one or few loci.

References

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- [3] G. D. Stormo, T. D. Schneider, L. Gold, and A. Ehrenfeucht, “Use of the perceptron algorithm to distinguish translational initiation sites in e. coli,” *Nucleic acids research*, vol. 10, no. 9, pp. 2997–3011, 1982.