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# GENES AND SITES UNDER ADAPTATION AT THE PHYLOGENETIC SCALE ALSO EXHIBIT ADAPTATION AT THE POPULATION-GENETIC SCALE

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## Abstract

1       Adaptation in protein-coding sequences can be detected from multiple sequence alignments  
2       across species, or alternatively by leveraging polymorphism data inside a population. Across  
3       species, quantification of the adaptive rate relies on phylogenetic codon models, classically  
4       formulated in terms of the ratio of non-synonymous over synonymous substitution rates.  
5       Evidence of an accelerated non-synonymous substitution rate is considered a signature of  
6       pervasive adaptation. However, because of the background of purifying selection, these  
7       models are potentially limited in their sensitivity. Recent developments have led to more  
8       sophisticated mutation-selection codon models aimed at making a more detailed quantitative  
9       assessment of the interplay between mutation, purifying and positive selection. In this  
10       study, we conducted a large-scale exome-wide analysis of placental mammals with mutation-  
11       selection models, assessing their performance at detecting proteins and sites under adaptation.  
12       Importantly, mutation-selection codon models are based on a population-genetic formalism  
13       and thus are directly comparable to McDonald & Kreitman tests at the population level  
14       to quantify adaptation. Taking advantage of this relationship between phylogenetic and  
15       population genetics, we integrated divergence and polymorphism data across the entire exome  
16       for 29 populations across 7 genera, and showed that proteins and sites detected to be under  
17       adaptation at the phylogenetic scale are also under adaptation at the population-genetic  
18       scale. Altogether, our exome-wide analysis shows that phylogenetic mutation-selection codon  
19       models and population-genetic test of adaptation can be reconciled and are congruent, paving  
20       the way for integrative models and analyses across individuals and populations.

21 **Keywords** Adaptation · phylogenetic · population genetics · codon models

## 22 Significance Statement

23 Detecting genes under adaptation represents a key step in the decoding of genomes. Several methods have been  
24 proposed, focussing either on the short time scale (population genetics, e.g. human populations), or on the  
25 long time scale (phylogenetics, e.g. across mammals). However, the accuracy of these methods is still under  
26 debate, and it is still unclear whether the signatures of adaptation are congruent across evolutionary scales. In  
27 this study, using novel phylogenetic methods and gathering genome data across and within species, we show  
28 that the signatures of adaptation at the phylogenetic and population-genetic scales can be reconciled. While  
29 providing a mutual confirmation of the two approaches, our work paves the way for further methodological  
30 integration between micro- and macro-evolutionary genomics.

## 31 Introduction

32 Present-day genetic sequences are informative of populations' past evolutionary history and can carry  
33 signatures of selection at different scales. One main goal of molecular evolution is to disentangle and quantify  
34 the intensity of neutral, adaptive and purifying evolution acting on sequences, leveraging variations in  
35 sequences between and within species. Theoretically, in order to detect adaptive evolution, one must have  
36 data where part of the sequence is known to be under a neutral regime, which can be used as a null model.  
37 In the case of protein-coding DNA sequences, synonymous sites are usually taken as proxies for neutral sites,  
38 although there are instance where they are indeed under selection[1–3]. Non-synonymous mutations, on the  
39 other hand, might be under a mixture of varying degrees of adaptive and purifying selection. Contrasting  
40 synonymous and non-synonymous changes, two different types of methods have emerged to quantify both  
41 positive and purifying selection acting on protein-coding sequences. One method, stemming from phylogeny,  
42 uses a multiple sequence alignment comprised of genes from different species and relies on codon models  
43 to deduce the selective regime from the patterns of non-synonymous versus synonymous substitutions[4, 5].  
44 Starting with the work of McDonald & Kreitman[6], another method, stemming from population genetics,  
45 contrasts polymorphism within a population and divergence to a closely related species.

46 At the population-genetic scale, one of the most widely used tests for adaptation relies on the substitutions  
47 between two closely related species and polymorphism within one population[6]. Under a strict neutral  
48 model (i.e. assuming non-synonymous mutations are either neutral or strongly selected), the ratios of non-  
49 synonymous polymorphisms over synonymous polymorphisms ( $\pi_N/\pi_S$ ) and of non-synonymous substitutions  
50 over synonymous substitutions ( $d_N/d_S$ ) are expected to be equal. If, in addition, strongly advantageous  
51 mutations occur, they are fixed rapidly in the population, thus contributing solely to divergence but not  
52 to polymorphism. As a result, the positive difference between  $d_N/d_S$  and  $\pi_N/\pi_S$  gives an estimate of  
53 the adaptive rate  $\omega_A = d_N/d_S - \pi_N/\pi_S$ [7]. This simple argument is not strictly valid in the presence of  
54 moderately deleterious non-synonymous mutations, which can segregate at substantial frequency in the  
55 population without reaching fixation, thus contributing solely to polymorphism, and not to divergence,  
56 potentially resulting on an underestimation of the rate of adaptive evolution[8]. Subsequent developments  
57 have tried to correct for this effect by relying on an explicit nearly-neutral model[9, 10], so as to estimate  
58 the rate of evolution expected in the absence of adaptation (called  $\omega_0$ ) based on polymorphism, and then to  
59 compare it with the rate of evolution,  $\omega = d_N/d_S$ , to get an estimate of the rate of adaptation as  $\omega_A = \omega - \omega_0$ .

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60 In their current formulation, phylogeny-based methods rely on the ratio of non-synonymous substitutions  
61 over synonymous substitutions, called  $\omega$ [4, 5]. Assuming synonymous mutations are neutral,  $\omega > 1$  signals an  
62 excess in the rate of non-synonymous substitutions compared to the neutral expectation, indicating that the  
63 protein is under adaptive evolution. Conversely, a deficit in non-synonymous substitutions, leading to  $\omega < 1$ ,  
64 means the protein is under purifying selection. In practice, proteins are typically under a mix of adaptive  
65 and purifying selection dominated by the latter, thus typically leading to an  $\omega < 1$  even in the presence of  
66 positive selection. At a finer scale, site models can detect a specific site ( $i$ ) of the sequence with a  $\omega^{(i)} > 1$ [11,  
67 12]. Site models have the advantage of greater sensitivity and the ability to pinpoint where positive selection  
68 acts on the protein. However, even at the level of a single site under recurrent adaptation, not all amino-acids  
69 are expected to be adaptive, leading to  $\omega^{(i)}$  capturing a mix of adaptive and purifying selection, reducing the  
70 sensitivity of test. An alternative approach to detect adaptation would be to rely on an explicit nearly-neutral  
71 model as the null against which to detect deviations, similarly to the McDonald & Kreitman test. Recent  
72 development in this direction, the so-called phylogenetic mutation-selection models provide a null model  
73 by estimating the fitness landscape over amino acid sequences, for each site of the sequence[13–15]. At the  
74 mutation-selection balance, the probability for a specific codon to be fixed in the population is proportional  
75 to its fitness, and a mutation from a high fitness amino acid towards a low fitness amino acid will have a  
76 small probability of fixation, genuinely accounting for purifying selection. Conversely, only nearly-neutral  
77 mutations between high fitness amino acids will tend to be permitted by the model, allowing for the explicit  
78 calculation of the nearly-neutral rate of non-synonymous substitutions at mutation-selection balance, called  
79  $\omega_0$ [16, 17]. By contrasting  $\omega$  estimated by  $\omega$ -based codon models and  $\omega_0$  calculated from mutation-selection  
80 models, one can hope to extract the rate of adaptation  $\omega_A^{\text{phy}} = \omega - \omega_0$ .

81 Interestingly, the rate of adaptation is directly comparable between phylogenetic and population-genetic  
82 methods since both seek a deviation of  $\omega$  from a nearly-neutral null model, estimated with mutation-selection  
83 models in phylogenetic context ( $\omega_0$ ) or from standing polymorphism in a population-genetic context ( $\pi_N/\pi_S$ ).  
84 This raises the question whether the two signals of adaptation are correlated, thus representing a unique  
85 opportunity to confront phylogeny-based and population-based methods. These two methods work over  
86 very different time scales, for that reason, they might be capturing different signals: long-term evolutionary  
87 Red-Queen for phylogeny-based methods versus events of adaptation in specific lineages for population-based  
88 methods. Nonetheless, we expect sites and proteins under long-term evolutionary Red-Queen regimes to  
89 maintain their signal of adaptation in several independent lineages for which the McDonald & Kreitman test  
90 is applied.

91 Accordingly, in this study, we first applied  $\omega$ -based and mutation-selection codon models to whole exome  
92 data from placental mammals, so as to quantify the rate  $\omega_A^{\text{phy}}$  for each site and protein and detect signatures  
93 of adaptive evolution at the phylogenetic scale. Then, we developed a pipeline integrating (and aligning)  
94 divergence and polymorphism data across the entire exome for 29 populations across 7 genera, namely *Equus*,  
95 *Canis*, *Bos*, *Capra*, *Ovis*, *Chlorocebus* and *Homo*. Finally, using this pipeline, we assessed the congruence  
96 between the phylogeny-based and population-based approaches, by testing if the group of sequences detected  
97 with a high rate of adaptation in the phylogeny-based method also displays a high rate of adaptation according  
98 to the population-based method.

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## 99 Results

### 100 Detecting genes and sites under adaptation

101 We derived a two-step approach (see methods), which we applied to a set of alignments of orthologous genes  
102 at the scale of placental mammals. The  $d_N/d_S$  estimated by the site model ( $\omega$ ) is plotted against the  $d_N/d_S$   
103 predicted by the nearly-neutral mutation-selection model ( $\omega_0$ ) for genes (scatter plot in fig. 1A) and sites  
104 (density plot in fig. 1B). An excess of  $\omega$  relative to  $\omega_0$  is a typical signature of ongoing positive selection[17,  
105 18]. Accordingly, genes, or sites, were considered to be under an adaptive regime (in red) if the value of their  
106  $\omega$  is higher than that of their  $\omega_0$ , with non-overlapping 95% posterior credibility intervals. This procedure  
107 retrieved 822 out of 14,509 genes, which are putatively under a long-term evolutionary Red-Queen regime. At  
108 the site level, the nearly-neutral assumption appears to be rejected for 104,129 out of 8,895,374 sites. Of note,  
109 this selection procedure is not meant as a routine statistical test, but only as an enrichment procedure, for  
110 the needs of the subsequent analysis shown below. In practice, this selection is likely to be conservative and  
111 to have a rate of false discovery of the order of 1% at the gene-level, and 5% at the site-level (see methods).

112 Of note, selection based on  $\omega > \omega_0$  is more sensitive than based on the commonly used criterion of  $\omega > 1$ ,  
113 since  $\omega_0$  is always lower than 1 by definition[16]. Thus, we can uncover sites under adaptation ( $\omega > \omega_0$ ) with  
114 a mean  $\omega$  lower than 1 (29,543 sites in fig. 1C). These sites could not have been detected by  $\omega$ -based codon  
115 models relying on the criterion that  $\omega > 1$ . At the gene level, only two genes have an estimated  $\omega > 1$ , such  
that this distinction is not relevant.

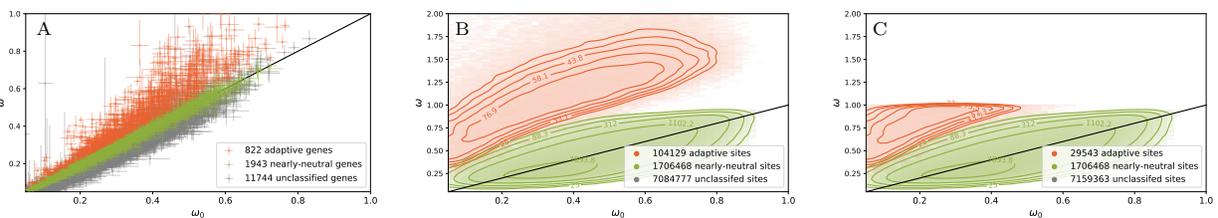


Figure 1: Detection of protein-coding sequences ongoing adaptation at the phylogenetic scale.  $\omega$  estimated by the site model against  $\omega_0$  calculated by the mutation-selection model. Scatter plot of 14,509 genes in panel A, with 95% bayesian credible interval ( $\alpha = 0.05$ ). Density plot of sites in panel B and C. Genes or sites are then classified whether they detected as adaptive ( $\omega > \omega_0$  in red) or nearly-neutral ( $\omega \simeq \omega_0$  in green). In panel C, the set of sites detected exclusively by mutation-selection codon models have a mean  $\omega < 1$ .

116

### 117 Ontology enrichment tests

118 Next, we investigated whether the genes classified as adaptive ( $\omega > \omega_0$ ) showed enrichment in specific ontology  
119 terms. Thus, we performed 775 instances of Fisher's exact test to estimate ontology enrichment by contrasting  
120 with genes in the control group, not classified as adaptive. 42 ontologies are observed with a p-value ( $p_v$ )  
121 corrected for multiple comparison (Holm-Bonferroni correction,  $p_v^{\text{adj}}$ ) lower than the risk  $\alpha = 0.05$  (see  
122 table S1). At a finer scale, we weighted genes by their proportion of sites considered under adaptation with  
123 a  $\omega$ -based site model ( $\omega > 1$ , see table S2) or with a mutation-selection model ( $\omega > \omega_0$ , see table S3). For  
124 each ontology, the proportion of sites under adaptation is compared between the set of genes sharing this  
125 given ontology and the rest of the genes (Mann-Whitney U test). The statistical test based on the the first

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126 criterion ( $\omega > 1$ ) is correlated with ontologies related to immune processes, while the statistical test based on  
 127 the the second criterion ( $\omega > \omega_0$ ) is also correlated with ontologies related to the external membrane and  
 128 cellular adhesion.

129 **Congruence between phylogeny- and population-based methods**

130 Finally, we investigated whether the phylogeny-based and the population-based methods give congruent  
 131 results in terms of detection of adaptive evolution (fig. 2). To do so, population genomic data were collected  
 132 for 29 populations across 7 genera. For each population,  $\omega_A$  as proposed by McDonald & Kreitman (MK)[6]  
 133 was computed on the concatenate of the 822 genes classified as adaptive by the phylogeny-based method  
 134 (red dots in fig. 2 and 3). This result was compared to a null distribution obtained by computing  $\omega_A$  over  
 135 sets of 822 genes that were randomly sampled (1,000 replicates) among the genes classified as nearly-neutral  
 136 according to the mutation-selection model (green violins in fig. 2 and 3). Importantly, the terminal lineages  
 137 over which the population-genetic method was applied were not included in the phylogenetic analysis. As a  
 138 result, the two methods are working on entirely non-overlapping compartments of the evolutionary history  
 139 across mammals. For all 29 populations, the  $\omega_A$  estimated by the population-genetic method was significantly  
 140 higher for the putatively adaptive gene-set than for the putatively nearly-neutral gene sets of the same size (at  
 141 a risk  $\alpha = 0.05$  corrected for multiple testing, Holm-Bonferroni correction). There is thus a good qualitative  
 142 agreement between the two methods as to what they capture and interpret as positive selection at the gene  
 143 level.

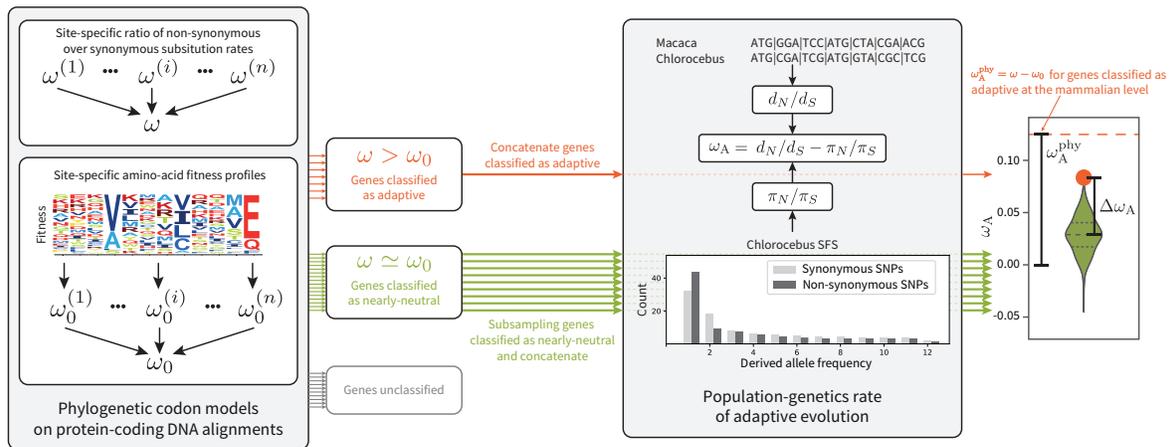


Figure 2: Integrating divergence and polymorphism for the detection of adaptation. At the phylogenetic level,  $\omega$  (classical codon models) and  $\omega_0$  (mutation-selection codon models) are computed from protein-coding DNA alignments, allowing to classify genes into adaptive (in red) and nearly-neutral (in green) regime. At the population-genetic level, for each population,  $\omega_A$  is computed on the concatenate of genes classified as under adaptation. The result is compared to the empirical null distribution of  $\omega_A$  in each population, obtained by randomly sampling (1,000 replicates) a subset under a nearly-neutral regime.

144 The same procedure was applied at a finer scale with sites instead of genes. For each population,  $\omega_A$  was  
 145 computed on the concatenate of the 104,129 sites classified as adaptive by the phylogeny-based method, and  
 146 compared to the empirical null distribution (fig. 3B) and table 1. Out of 29 populations, 24 have an  $\omega_A$   
 147 estimated by the population-genetic method significantly higher for the putatively adaptive site-set than

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148 for the putatively nearly-neutral site-sets of the same size taken at random (at a risk  $\alpha = 0.05$  corrected for  
 149 multiple testing, Holm-Bonferroni correction). Of note, the 5 populations for which the test is not significant  
 150 are the human populations.

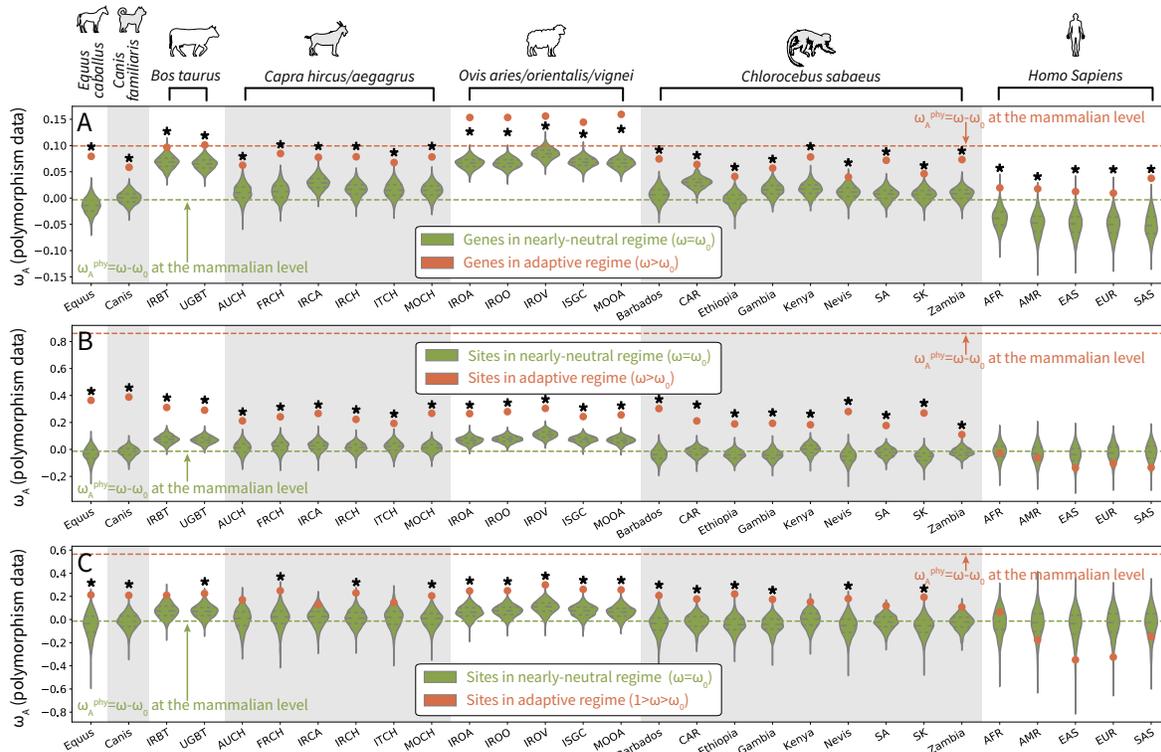


Figure 3: Enrichment of adaptation at the population-genetic scale for 29 populations across 7 genera at the gene (panel A) and site (panels B and C) level. For each population,  $\omega_A$  is computed on 822 genes (A) and 104,129 sites (B) having a high rate of adaptation at the phylogenetic scale ( $\omega > \omega_0$  in red). In panel C, the set of 29,543 sites are detected exclusively by mutation-selection codon models with a mean  $\omega < 1$ . The result is compared to the empirical null distribution of  $\omega_A$ , obtained by randomly sampling (1,000 replicates) a subset of genes and sites under a nearly-neutral regime (violin plot in green). \* signify that the  $p_v$  corrected for multiple comparison (Holm-Bonferroni correction) is lower than the risk  $\alpha = 0.05$ . The acronym of populations, and the quantitative value of  $\omega_A$  and  $p_v$  are shown in table 1

151 Except for *Equus* and *Humans*, on average, the  $\omega_A$  returned by MK is positive even for the putatively  
 152 nearly-neutral replicates, and significantly so for *Bos* ( $\omega_A$  in the range 0.65 – 0.68 for genes and site) and  
 153 *Ovis* ( $\omega_A$  in the range 0.66 – 0.84 for genes and sites). This suggests the presence of a background of positive  
 154 selection captured by MK methods but not by phylogenetic methods. This background signal could correspond  
 155 either to adaptation specifically present in the terminal lineages on which the MK method is applied and  
 156 absent over the rest of the mammalian tree, or to low-intensity recurrent positive selection, present over the  
 157 tree but nevertheless missed by phylogenetic methods, owing to a lack of sensitivity. Alternatively, part of it  
 158 could be an artifact of MK methods, due for example to a recent demographic expansion (*Bos* and *Ovis* are  
 159 the two among those analysed by the population-genetic approach showing the highest levels of synonymous  
 160 diversity), or to a more general mismatch between short- and long-term effective population size ( $N_e$ ) [19].

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161 Regardless of its exact cause, subtracting this background, so as to compare, not directly the  $\omega_A$  of the  
162 population-genetic method, but the  $\Delta\omega_A$  between the putatively adaptive set and the control replicates, to  
163 the  $\omega_A^{\text{phy}} = \omega - \omega_0$  returned by the phylogenetic method, may give a more meaningful basis for a quantitative  
164 comparison between phylogenetic and population-genetic approaches (fig. 2). Of note, across all analyses  
165 shown in fig. 3A and B, this population-genetic  $\Delta\omega_A$  is always smaller than the phylogenetic  $\omega_A^{\text{phy}}$ . This  
166 asymmetry is expected, as a result of a selection bias: the genes of the test set were selected precisely  
167 for their high phylogenetic signal, while keeping a blind eye to their population-genetic signal. From this  
168 perspective, the ratio  $\Delta\omega_A/\omega_A^{\text{phy}}$  can be interpreted as an estimate of the fraction of the total signal captured  
169 by the phylogenetic enrichment procedure that is confirmed by MK statistics. This ratio, hereafter called the  
170 confirmation rate, is indicated in table 1.

171 At the gene level, the confirmation rate is relatively high, ranging from 30% to up to 90%. At the site level,  
172 the confirmation rate is lower (30% on average), which could betray a higher rate of false discovery at the  
173 site level, or could be the result of subtle molecular evolutionary processes, such as intermittent adaptation  
174 (on some but not on all branches) or within-gene turnover (ongoing adaptation targeting different sites on  
175 different branches).

176 After discarding sites with a mean  $\omega > 1$ , the remaining 29,543 sites classified as being under an adaptive  
177 regime have  $1 > \omega > \omega_0$  and are specifically discovered by the mutation-selection approach. Since their  
178  $\omega$  is less than 1, they could not be detected by classical codon models. This raises the question of the  
179 empirical value of these findings. Indeed, while mutation-selection methods are more sophisticated and  
180 may therefore have a greater sensitivity, they may also be more prone to producing false positives. The  
181 phylogenetic/population-genetic confrontation developed here can be used to assess this important point.  
182 As shown in (fig. 3C) and table 1, out of 29 populations, for 17 out of the 29 populations that have been  
183 analysed, the confirmation rate is significantly positive ( $\alpha=0.05$ , Holm-Bonferroni correction), and of the  
184 order of 10% on average. This importantly suggests the presence of a background of low-intensity positive  
185 selection, which is missed by classical codon models, but partially detected by mutation-selection models. In  
186 other words, the approach can detect a long-term evolutionary Red-Queen even for a site with  $\omega < 1$  that is  
187 still under adaptation at the population-genetic scale.

188 Because genes and sites classified as adaptive have a higher  $\omega$  than genes/sites classified as nearly-neutral,  
189  $\omega_A$  could simply be higher for genes with higher  $\omega$  due to this confounding factor. Thus we performed  
190 additional experiments where  $\omega$  is controlled to be the same in the nearly-neutral replicate and the adaptive  
191 set of genes (fig. S2-6 and tables S5-9). Additionally, we performed the same experiments with a more  
192 stringent risk  $\alpha = 0.005$  (10 times greater) to classify genes and sites as adaptive (fig. S7-9 and tables S9-10).  
193 Our results are robust to both controlling for  $\omega$  and with a different threshold to classify genes and sites  
194 as adaptive. Finally, we computed  $\omega_A$  using the software polyDFE[20], which relies on the synonymous  
195 and non-synonymous unfolded site-frequency spectra (SFS) to estimate the distribution of fitness effects of  
196 mutations (DFE), and the rate of adaptation (fig. S10-17 and tables S11-18). Depending on the underlying  
197 assumptions for the shape of the DFE and the definition of  $\omega_A$ , we observed a wide range of  $\omega_A$  both for the  
198 set of adaptive and nearly-neutral genes/sites. However, the statistical test for the enrichment of  $\omega_A$  between  
199 the set of adaptive and nearly-neutral genes/sites gives results in the same direction whether computed by  
200 polyDFE or as McDonald & Kreitman [6] statistic, although the confirmation rate and the associated  $p_v$  are  
201 different.

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Population	Species	$\pi_S$	Genes (822)			Sites (104,129)			Sites ( $\omega < 1$ ) (29,543)		
			$\Delta\omega_A$	$p_v^{\text{adj}}$	$\frac{\Delta\omega_A}{\omega_{\text{phy}}}$	$\Delta\omega_A$	$p_v^{\text{adj}}$	$\frac{\Delta\omega_A}{\omega_{\text{phy}}}$	$\Delta\omega_A$	$p_v^{\text{adj}}$	$\frac{\Delta\omega_A}{\omega_{\text{phy}}}$
Diverse (Equus)	Equus caballus	0.002	0.094	<b>0.0*</b>	0.928	0.399	<b>0.0*</b>	0.459	0.258	<b>0.0*</b>	0.446
Diverse (Canis)	Canis familiaris	0.004	0.058	<b>0.0*</b>	0.557	0.406	<b>0.0*</b>	0.463	0.227	<b>0.0*</b>	0.392
Iran (IRBT)	Bos taurus	0.008	0.028	<b>0.020*</b>	0.278	0.237	<b>0.0*</b>	0.272	0.134	0.150	0.231
Uganda (UGBT)	Bos taurus	0.008	0.036	<b>0.0*</b>	0.355	0.222	<b>0.0*</b>	0.254	0.156	<b>0.017*</b>	0.270
Australia (AUCH)	Capra hircus	0.003	0.052	<b>0.0*</b>	0.506	0.202	<b>0.0*</b>	0.230	0.168	0.143	0.290
France (FRCH)	Capra hircus	0.003	0.073	<b>0.0*</b>	0.709	0.220	<b>0.0*</b>	0.250	0.236	<b>0.039*</b>	0.407
Iran (IRCA)	Capra aegagrus	0.004	0.049	<b>0.0*</b>	0.482	0.242	<b>0.0*</b>	0.275	0.108	0.396	0.186
Iran (IRCH)	Capra hircus	0.004	0.062	<b>0.0*</b>	0.610	0.210	<b>0.0*</b>	0.239	0.217	<b>0.017*</b>	0.375
Italy (ITCH)	Capra hircus	0.003	0.052	<b>0.0*</b>	0.511	0.174	<b>0.0*</b>	0.199	0.134	0.308	0.232
Morocco (MOCH)	Capra hircus	0.004	0.064	<b>0.0*</b>	0.626	0.256	<b>0.0*</b>	0.292	0.201	<b>0.0*</b>	0.347
Iran (IROA)	Ovis aries	0.007	0.087	<b>0.0*</b>	0.847	0.199	<b>0.0*</b>	0.228	0.183	<b>0.017*</b>	0.316
Iran (IROO)	Ovis orientalis	0.009	0.087	<b>0.0*</b>	0.848	0.204	<b>0.0*</b>	0.233	0.176	<b>0.0*</b>	0.304
Iran (IROV)	Ovis vignei	0.005	0.072	<b>0.0*</b>	0.697	0.194	<b>0.0*</b>	0.222	0.192	<b>0.0*</b>	0.332
Various (ISGC)	Ovis aries	0.008	0.076	<b>0.0*</b>	0.742	0.171	<b>0.0*</b>	0.195	0.189	<b>0.0*</b>	0.326
Morocco (MOOA)	Ovis aries	0.008	0.093	<b>0.0*</b>	0.905	0.189	<b>0.0*</b>	0.216	0.193	<b>0.0*</b>	0.333
Barbados	Chlorocebus sabaeus	0.003	0.068	<b>0.0*</b>	0.665	0.341	<b>0.0*</b>	0.390	0.248	<b>0.0*</b>	0.430
Central African Republic (CAR)	Chlorocebus sabaeus	0.006	0.034	<b>0.0*</b>	0.334	0.229	<b>0.0*</b>	0.262	0.195	<b>0.0*</b>	0.338
Ethiopia	Chlorocebus sabaeus	0.005	0.044	<b>0.0*</b>	0.425	0.231	<b>0.0*</b>	0.264	0.264	<b>0.0*</b>	0.457
Gambia	Chlorocebus sabaeus	0.005	0.041	<b>0.0*</b>	0.403	0.236	<b>0.0*</b>	0.270	0.217	<b>0.0*</b>	0.375
Kenya	Chlorocebus sabaeus	0.004	0.061	<b>0.0*</b>	0.598	0.181	<b>0.0*</b>	0.207	0.152	0.150	0.264
Nevis	Chlorocebus sabaeus	0.003	0.029	<b>0.020*</b>	0.279	0.332	<b>0.0*</b>	0.380	0.237	<b>0.017*</b>	0.410
South Africa (SA)	Chlorocebus sabaeus	0.006	0.065	<b>0.0*</b>	0.633	0.199	<b>0.0*</b>	0.228	0.142	0.108	0.246
Saint Kitts (SK)	Chlorocebus sabaeus	0.004	0.040	<b>0.0*</b>	0.388	0.324	<b>0.0*</b>	0.371	0.253	<b>0.0*</b>	0.439
Zambia	Chlorocebus sabaeus	0.006	0.066	<b>0.0*</b>	0.642	0.132	<b>0.0*</b>	0.151	0.131	0.150	0.227
African (AFR)	Homo sapiens	0.002	0.059	<b>0.012*</b>	0.568	-0.010	1.000	-0.012	0.089	1.000	0.155
Ad Mixed American (AMR)	Homo sapiens	0.002	0.067	<b>0.006*</b>	0.647	-0.029	1.000	-0.034	-0.141	1.000	-0.244
East Asian (EAS)	Homo sapiens	0.002	0.063	<b>0.006*</b>	0.610	-0.096	1.000	-0.111	-0.296	1.000	-0.513
European (EUR)	Homo sapiens	0.002	0.061	<b>0.015*</b>	0.590	-0.078	1.000	-0.089	-0.289	1.000	-0.500
South Asian (SAS)	Homo sapiens	0.002	0.089	<b>0.0*</b>	0.866	-0.113	1.000	-0.130	-0.111	1.000	-0.193

Table 1: Across 29 populations (rows), table of quantitative value of  $\Delta\omega_A$  between the set classified as adaptive and nearly-neutral shown in fig. 3.  $p_v^{\text{adj}}$  associated to the test are corrected for multiple comparison (Holm–Bonferroni correction, \* for  $p_v^{\text{adj}} < 0.05$ ).  $\frac{\Delta\omega_A}{\omega_{\text{phy}}}$  is the ratio of  $\Delta\omega_A$  at the population-genetic level and the phylogenetic level.  $\pi_S$  is the observed genetic diversity (number of SNPs per site) counted over synonymous sites.

## 202 Discussion

203 Quantifying the rate of adaptation assumes that we can measure the rate of evolution and more importantly  
204 its deviation from a null model of evolution disallowing adaptation. For phylogenetic codon models, this  
205 null model of evolution is usually assumed to be neutral evolution and the rate of evolution computed  
206 as the ratio of non-synonymous over synonymous substitution rates ( $\omega$ ) is thus compared to 1. We first  
207 showed that, at the phylogenetic scale,  $\omega$  can be compared to its expectation under the mutation-selection  
208 model ( $\omega_0$ ), a nearly-neutral model instead of a neutral model of evolution, giving a quantitative estimate  
209 of the rate of adaptation as  $\omega_A^{\text{phy}} = \omega - \omega_0$ . The application of this approach exome-wide across placental  
210 mammals suggests that 822 out of 14,509 proteins are under a long-term evolutionary Red-Queen, with  
211 ontology terms related to immune processes and the external membrane of cells. Enrichment of ontologies  
212 related to immune processes is expected, as found by many studies[12, 21, 22]. However, we also detect an  
213 enrichment with ontologies related to the external membrane and cell adhesion, which are the target of virus  
214 and parasites. Altogether, the mutation-selection method effectively detects adaptation regardless of the  
215 background of purifying selection, and returns reasonable candidates for adaptive evolution. Of note, in its  
216 current implementation, and unlike classical codon models[23, 24], the mutation-selection approach does not  
217 yet provide a proper and well-calibrated statistical test for calling genes or sites under adaptation with a  
218 well-controlled frequentist risk. This was not a problem in the enrichment analysis conducted in this article,  
219 which relies on downstream controls based on random permutations. Nevertheless, the encouraging results  
220 obtained here give a motivation for developing such a test, which should then have an increased power to  
221 detect adaptation, compared to classical codon models relying on the  $\omega > 1$  criterion.

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222 At the population-genetic scale, the availability of approaches to detect adaptation[6, 25] raises the  
223 question whether the rate of adaptation calculated at the phylogenetic scale as  $\omega_A^{\text{phy}}$  is congruent with the  
224 rate calculated at the population genetics scale by McDonald & Kreitman (MK)[6] as  $\omega_A = d_N/d_S - \pi_N/\pi_S$ .  
225 In this light, the set of genes and sites detected to be under adaptation at the phylogenetic scale showed  
226 a significant increase in  $\omega_A$  such as inferred by population-based method (29 populations across 7 genera).  
227 Quantitatively, about 30% to 90% of the signal detected by the phylogeny-based approach is confirmed by the  
228 population-based approach. This result is in stark contrast with studies comparing  $\omega$ -based codon models at  
229 the gene level with MK methods, which found that the set of genes detected at different scales does not seem  
230 to overlap beyond random expectations[26]. The reasons for this discrepancy are not totally clear. The use of  
231 different codon modeling strategies could play a role here. More fundamentally however, our study relies  
232 on a large and densely sampled phylogeny with  $\simeq 100$  taxa across placental mammals, versus 5 *Drosophila*  
233 and 5 *Brassicaceae* in Chen *et al.* [26]. As a result, the phylogenetic aspect of our analysis benefits from an  
234 increased power, while being also inherently more focussed on genes characterized by recurrent adaptation  
235 over a very large evolutionary scale (i.e. long-term evolutionary Red Queens), for which population-genetic  
236 signals of adaptation may be more easily recovered. We thus showed empirically that the mutation-selection  
237 codon model provides a null (nearly-neutral) model from which we can disentangle purifying and adaptive  
238 evolution. However, our procedure still has some limitations.

239 Mutation-selection codon models assume a constant effective population size while it has been established  
240 that its fluctuations has a major effect on selection dynamics[27, 28]. Estimating changes in effective  
241 population size in a mutation-selection framework is possible[29], although too computational intensive in its  
242 current implementation to be performed genome-wide. Second, epistasis is not modeled while it can have  
243 a large effect on the response of the rate of evolution with change in population size[30]. More generally,  
244 pervasive epistasis generates an entrenchment of the amino acids[31–33], resulting in a slowing down of the rate  
245 evolution[17, 34] or a standstill[35]. Consequently, our estimation of the predicted rate of evolution computed  
246 at mutation-selection balance ( $\omega_0$ ) is over-estimated given that epistasis is not taken into account, such that  
247  $\omega_A^{\text{phy}} = \omega - \omega_0$  is thus under-estimated. Altogether, we argue that our estimate of  $\omega_A^{\text{phy}}$  is conservative and  
248 could be increased by modeling epistasis (although indirectly) within the mutation-selection framework[33].

249 On the other hand, at the population-genetic scale, the greatest limitation to detecting adaptation is the  
250 lack of power determined by the genetic diversity since polymorphisms are rare and estimation of  $\pi_N/\pi_S$   
251 requires to pool many sites for which SNPs are available. Since the effects of mild purifying selection are  
252 more pronounced on longer time scales (i.e. mildly deleterious mutations contribute disproportionately to  
253 polymorphism, compared to divergence),  $\omega_A$  as computed by MK can be biased by moderately deleterious  
254 mutations[8, 36] and by the change in population size through time[37]. To overcome this bias, model-based  
255 approaches relying on the synonymous and non-synonymous site-frequency spectra (SFS) to estimate the  
256 distribution of fitness effects of mutations (DFE), so as to account for the contribution of mild selective  
257 effects to standing polymorphism, have been developed[9, 20] and are often used[10, 38]. However, the broad  
258 range of  $\omega_A$  estimated on sets of genes/sites classified as nearly-neutral suggests that these models are lacking  
259 power, even more than the MK statistic, because of the sparsity of the SFS. Beside changes in population  
260 size biasing the estimation[19], we argue that inferring  $\omega_A$  using an underlying DFE model is also highly  
261 sensitive to assumptions for the shape of the DFE and the definition of  $\omega_A$ . For example, the value of  $\omega_A$  is  
262 computed as an integral, where the bounds of this integral is debated by different authors[10, 39]. It is thus  
263 relatively easy to change the definition of  $\omega_A$  (fig. S12-15 and tables S13-16) or to constrain the underlying

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264 DFE (fig. S12-17 and tables S13-18) to obtain a wide range of  $\omega_A$  on the same dataset. Taken together,  
265 we argue that comparing  $\omega_A$  to 0 is not a robust test for adaptation. Instead,  $\omega_A$  for a particular genomic  
266 region of interest should be compared to other genomic regions for which the nearly-neutral evolution is not  
267 rejected, and the difference  $\Delta\omega_A$  should be compared to 0, as done in this study. More generally, our empirical  
268 analysis emphasizes the limitations of, and the difficulties raised by, the model-based population-genetic  
269 approaches. In this respect, further exploring the congruence (or lack thereof) between phylogenetic and  
270 population-genetic approaches will represent a useful asset to clarify those delicate problems, given that  
271 similar benefits are also expected on the side of phylogenetic approaches, which are far from immune from  
272 methodological limitations.

273 More broadly on a theoretical level, this work leverages a specific overlap between phylogenetic and  
274 population genetics, namely that the rate of adaptation  $\omega_A^{\text{phy}}$  in phylogenetic codon models and  $\omega_A$  in the MK  
275 test should theoretically be directly comparable. Based on this theoretical relationship, our study is paving  
276 the way for studies and methods augmenting molecular polymorphism data within species with information  
277 about divergence data between species[40], and by assessing empirically the relationship between phylogenetic  
278 and population genetics[41]. In this light, mutation-selection models at the phylogenetic scale can play a dual  
279 role: pinpointing genes and sites under adaptation ( $\omega_A^{\text{phy}} > 0$ ), and also seeking the genomic region for which  
280 the nearly-neutral theory is not rejected ( $\omega_A^{\text{phy}} \simeq 0$ ).

## 281 Methods

### 282 Phylogenetic dataset

283 Protein-coding DNA sequences alignments in placental mammals and their corresponding gene trees were  
284 extracted from the [OrthoMaM](#) database, containing 116 mammalian reference sequences in v10c[42–44].  
285 Genes located on the X, Y and mitochondrial chromosome were discarded from the analysis, since the number  
286 of polymorphism, necessary in population-based method, is expected to be different on these sequences.  
287 Additionally, sequences from the species for which polymorphism are available, as well as their sister species  
288 have been discarded from the analysis to ensure independence between the data used in the phylogenetic  
289 and population-genetic method. Altogether, we analyzed 14,509 protein-coding DNA sequences alignment  
290 containing at most 87 reference sequences of placental mammals.

### 291 Adaptation in phylogeny-based method

292 Classical codon models estimates a parameter  $\omega = d_N/d_S$ , namely the ratio of the non-synonymous over  
293 the synonymous substitution rates[4, 5]. In the so-called site models,  $\omega$  is allowed to vary across sites[11,  
294 45]. In *Bayescode*, site-specific  $\omega^{(i)}$  (fig. 1B, y-axis) are independent identically distributed from a gamma  
295 distribution[46]. In a second step, the average over sites is calculated, giving estimates of  $\omega$  for each  
296 protein-coding sequence (fig. 1A, y-axis).

297 In contrast, mutation-selection models assume that the protein-coding sequence is at mutation-selection  
298 balance under a fixed fitness landscape, which is itself characterized by a fitness vector over the 20 amino  
299 acid at each site[13–15]. Mathematically, the rate of non-synonymous substitution from codon  $a$  to codon  $b$   
300 ( $q_{a \rightarrow b}^{(i)}$ ) at site  $i$  of the sequence is equal to the rate of mutation from the underlying DNA change ( $\mu_{a \rightarrow b}$ )  
301 multiplied by the scaled probability of fixation of the mutation ( $\mathbb{P}_{a \rightarrow b}^{(i)}$ ). Crucially, the probability of fixation

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302 depends on the difference of scaled fitness between the amino acid encoded by the mutated codon ( $F_b^{(i)}$ ) and  
 303 the fitness of the amino acid encoded by the original codon ( $F_a^{(i)}$ ) of site  $i$ [47, 48]. Altogether, the rate of  
 304 substitution from codon  $a$  to  $b$  at a given site  $i$  is:

$$q_{a \rightarrow b}^{(i)} = \mu_{a \rightarrow b} P_{a \rightarrow b}^{(i)} = \mu_{a \rightarrow b} \frac{F_b^{(i)} - F_a^{(i)}}{1 - e^{F_a^{(i)} - F_b^{(i)}}}. \quad (1)$$

305 Fitting the mutation-selection model on a sequence alignment leads to an estimation of the mutation rate  
 306 matrix ( $\mu$ ) as well as the 20 amino acid fitness landscape ( $F^{(i)}$ ) at each site  $i$ . From these parameters, one  
 307 can compute  $\omega_0^{(i)}$  (fig. 1B, x-axis), the site-specific rate of non-synonymous over synonymous substitution at  
 308 the mutation-selection balance:

$$\omega_0^{(i)} = \frac{\sum_{a \in \mathcal{C}} \sum_{b \in \mathcal{N}_a} \pi_a^{(i)} q_{a \rightarrow b}^{(i)}}{\sum_{a \in \mathcal{C}} \sum_{b \in \mathcal{N}_a} \pi_a^{(i)} \mu_{a \rightarrow b}}, \quad (2)$$

where  $\mathcal{C}$  is the set all the possible codons (61 by discarding stop codons),  $\pi_a^{(i)}$  is the equilibrium frequency  
 of codon  $a$  at site  $i$ , and  $\mathcal{N}_a$  is the set of codons that are non-synonymous to  $a$ [16, 17]. The equilibrium  
 frequency of codon  $a$  at site  $i$  is the product of the nucleotide frequencies at its three positions and the scaled  
 Wrightian fitness of the amino acid ( $F_a^{(i)}$ ):

$$\pi_a^{(i)} = \frac{\sigma_{a[1]} \sigma_{a[2]} \sigma_{a[3]} e^{F_a^{(i)}}}{\sum_{b=1}^{61} \sigma_{b[1]} \sigma_{b[2]} \sigma_{b[3]} e^{F_b^{(i)}}}, \quad (3)$$

309 where  $\sigma_{a[j]} \in \{A, T, C, G\}$  is the equilibrium frequency (given by the mutational matrix) of the nucleotide  
 310 at position  $j \in \{1, 2, 3\}$  of codon  $a$ . In a second step, the average over sites is calculated, giving estimates  
 311 of  $\omega_0$  for each protein-coding sequences (fig. 1A, x-axis). Under the assumption that the protein is under a  
 312 nearly-neutral regime, the calculated  $\omega_0$  (mutation-selection model) and the estimated  $\omega$  (site model) should  
 313 be the same[16].

314 We ran the Bayesian software *BayesCode* (<https://github.com/ThibaultLatrille/bayescode>) on each  
 315 protein-coding DNA alignment[49]. Each Monte-Carlo Markov-Chain (MCMC) is run during 2,000 points,  
 316 with a burn-in of 1,000 points, to obtain the posterior mean of  $\omega$  and  $\omega_0$  across the MCMC, as well as the 95%  
 317 posterior credibility interval for genes and sites. Genes and sites classified under an adaptive regime (in red)  
 318 are rejecting the nearly-neutral assumption such that the lower bound for the credible interval of  $\omega$  ( $\alpha = 0.05$ )  
 319 is above the upper bound of the credible interval of  $\omega_0$  ( $\alpha = 0.05$ ), meaning that the value of their  $\omega$  is higher  
 320 than that of their  $\omega_0$ . Because this is a unilateral test ( $\omega > \omega_0$ ) and the two credible interval are independent,  
 321 the risk is  $(\alpha/2)^2 = 0.025^2 = 0.000625$  for each test. Empirically, the nearly-neutral assumption appears to  
 322 be rejected for 822 out 14,509 genes, while  $0.000625 \times 14,509 \simeq 9$  genes are expected due to the multiple  
 323 testing, suggesting a  $9/822 \simeq 1\%$  rate of false positive at the gene level. At the site level, the nearly-neutral  
 324 assumption appears to be rejected for 104,129 out of 8,895,374 sites, while  $0.000625 \times 8,895,374 \simeq 5,560$  are  
 325 expected due to the multiple testing, suggesting a  $5,560/104,129 \simeq 5\%$  rate of false positive at the site level.  
 326 Genes and sites are classified under a nearly-neutral regime (in green) if the average  $\omega$  is within the credible  
 327 interval of the  $\omega_0$ , and respectively the average  $\omega_0$  is also within the credible interval of  $\omega$ , meaning  $\omega = \omega_0$ .  
 328 Additionally, the set of sites detected exclusively by mutation-selection codon models have a mean  $\omega < 1$ .  
 329 Genes and sites that do not fall in any of these categories are considered unclassified.

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330 **Polymorphism dataset**

331 Each SNP (chromosome, position, strand) in the focal species was matched to its relative position (chromosome,  
332 position, strand) in the protein-coding DNA alignment by first converting the genomic positions to relative  
333 position in the coding sequence (CDS) using gene annotation files (GTF format) downloaded from Ensembl  
334 ([ensembl.org](https://ensembl.org)). We then verified that the SNP downloaded from Ensembl were matching the reference in the  
335 CDS (FASTA format). Second, the relative position in the CDS was converted to position in the multiple  
336 sequence alignment (containing gaps) from OrthoMaM database[42–44] by doing a global pairwise alignment,  
337 using the Biopython function pairwise2, between the CDS fasta and the sequence found in the alignment.  
338 This conversion from genomic position to position in the alignment is only possible if the assembly used for  
339 SNP calling is the same as the one used in the alignment, the GTF annotations and the FASTA sequences.

340 We retrieved the genetic variants representing the population level polymorphism from the following species  
341 and respective available datasets: *Equus caballus* (EquCab2 assembly in the EVA study PRJEB9799[50]),  
342 *Canis familiaris* (CanFam3.1 assembly in the EVA study PRJEB24066[51]), *Bos taurus* (UMD3.1 assembly  
343 in the NextGen project), *Ovis aries* (Oar\_v3.1 assembly in the NextGen project), *Capra Hircus* (CHIR1  
344 assembly in the NextGen project converted to ARS1 assembly with dbSNP identifiers[52]), *Chlorocebus*  
345 *sabaeus* (ChlSab1.1 assembly in the EVA project PRJEB22989[53]), *Homo sapiens* (GRCh38 assembly from  
346 the 1000-genome project[54, 55]).

347 Variants not inside genes are discarded at the beginning of the analysis. Insertions and deletions are not  
348 analyzed, and only Single Nucleotide Polymorphisms (SNPs) with only one mutant allele are considered.  
349 Stop codon mutants are also discarded. For populations containing more than 8 sampled individuals, the  
350 site-frequency spectrum (SFS) is subsampled down to 16 chromosomes (8 diploid individuals) without  
351 replacement (hyper-geometric distribution) to alleviate the effect of different sampling depth in the 29  
352 populations. Moreover, subsampling mitigate the impact of moderately deleterious mutations segregating at  
353 low frequency on  $\pi_N/\pi_S$ , since they are more likely to be discarded than polymorphism segregating at higher  
354 frequency. The Snakemake pipeline for integrating polymorphism and divergence data uses custom scripts  
355 written in python 3.9.

356 **Rate of adaption in population-based method**

357 The genes and sites classified as under adaptation are concatenated. For each population  $\pi_N/\pi_S$  is computed  
358 as the sum of non-synonymous over synonymous polymorphism on the concatenated SFS.  $d_N/d_S$  is computed  
359 on the concatenated pairwise alignment between focal and sister species extracted from OrthoMaM, the  
360  $d_N/d_S$  count is performed by *yn00*. We considered *Ceratotherium simum simum* as *Equus caballus* sister  
361 species; *Ursus maritimus* as *Canis familiaris* sister species; *Bison bison bison* as *Bos taurus* sister species;  
362 *Pantholops hodgsonii* as *Ovis aries* sister species; *Pantholops hodgsonii* as *Capra Hircus* sister species; *Macaca*  
363 *mulatta* as *Chlorocebus sabaeus* sister species and finally we considered *Pan troglodytes* as *Homo sapiens* sister  
364 species. Altogether,  $\omega_A = d_N/d_S - \pi_N/\pi_S$  is thus computed for each population on genes and sites classified  
365 as under adaptation. The result is compared to the empirical null distribution of  $\omega_A$ , obtained by randomly  
366 sampling (1,000 sampling replicates) a subset of genes/sites classified as nearly-neutral.

367 Other methods to compute  $\omega_A$  such as polyDFE[20] are also used (eq. 3-20 in supplementary materials),  
368 which relies on the synonymous and non-synonymous unfolded site-frequency spectra (SFS) to estimate the

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369 distribution of fitness effects of mutations (DFE), and the rate of adaptation. In polyDFE, GammaExpo  
370 models the fitness effect of weakly deleterious non-synonymous mutations as distributed according to a  
371 negative Gamma and the fitness effect of weakly advantageous mutations are distributed exponentially. This  
372 method is an extension of the methods introduced by Eyre-Walker and collaborators[9, 56]. Unfolded SFSs  
373 are obtained by polarizing SNPs using the 3 closest outgroups found in the OrthoMam alignment with est-usfs  
374 v2.04[57].

## 375 1 Data availability

376 The data underlying this article are available at [10.5281/zenodo.7107234](https://doi.org/10.5281/zenodo.7107234). Scripts and instructions necessary  
377 to reproduce the empirical experiments on the original dataset or with user-specified datasets is available at  
378 <https://github.com/ThibaultLatrille/AdaptaPop>.

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## 386 3 Author information

387 TL, NR and NL designed the study. TL gathered and formatted the data and conducted the analyses with  
388 BayesCode using scripts in Python and pipeline in Snakemake. TL, NR and NL contributed to the writing of  
389 the manuscript.

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