

Network analyses unveil ageing-associated pathways evolutionarily conserved from fungi to animals

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Abstract

The genetic roots of the diverse paces and shapes of ageing and of the large variations in longevity observed across the Tree of Life are poorly understood. Indeed, pathways associated with ageing/longevity are incompletely known, both in terms of their constitutive genes/proteins and of their molecular interactions. Moreover, there is limited overlap between the genes constituting these pathways across mammals. Yet, dedicated comparative analyses might still unravel evolutionarily conserved, important pathways associated with longevity or ageing. Here, we used an original strategy with a double evolutionary and systemic focus to analyse protein interactions associated with ageing or longevity during the evolution of five species of Opisthokonta. We ranked these proteins and interactions based on their evolutionary conservation and centrality in past and present protein-protein interaction networks (PPI), providing a big systemic picture of the evolution of ageing and longevity pathways, that identified which pathways emerged in which Opisthokonta lineages, were conserved and/or central. We confirmed that longevity/ageing associated proteins (LAPs), be they pro- or anti-longevity, are highly central in extant PPI, consistently with the Antagonistic Pleiotropy theory of ageing, and identified key antagonistic regulators of ageing/longevity, 52 of which with homologs in humans. While some highly central LAPs were evolutionarily conserved for over a billion years, we report a clear transition in the functionally important components of ageing/longevity within Bilaterians. We also predicted 487 novel evolutionarily conserved LAPs in humans, 54% of which are more central than mTOR, and 138 of which are druggable, defining new potential targets for anti-ageing treatments in humans.

Introduction

Ageing and longevity are critical components of organismal fitness, both characterised by their remarkable heterogeneity between, and sometimes even within, species across the Tree of Life. For instance, there is a 100-fold variation of longevity across mammals (Tacutu et al. 2018), and studies have revealed a diversity of paces and shapes of ageing across metazoans, even though all these taxa come from a last common ancestor (Baudisch and Vaupel 2012; Jones et al. 2014; Treaster et al. 2021; da Silva et al. 2022). Importantly, the genetic mechanisms that contribute to this heterogeneity are still poorly understood. While there is no doubt that ageing and longevity are in part genetically determined (Kenyon 2010), the pathways associated with ageing and longevity are incompletely known, both in terms of their constitutive genes/proteins and of their molecular

interactions. Indeed, genomic and transcriptomic analyses of organisms with high quality genomes, informed by careful considerations of molecular evolution, have uncovered sets of genes associated with ageing or longevity (Li and de Magalhães 2013; Gorbunova et al. 2014; Keane et al. 2015; Doherty and de Magalhães 2016; Foley et al. 2018; Sahm et al. 2018; Huang et al. 2019; Toren et al. 2020; Farré et al. 2021; Irving et al. 2021; Kacprzyk et al. 2021; Kolora et al. 2021; Orkin et al. 2021; Lu et al. 2022; Tejada-Martinez et al. 2022) with little overlap, even across mammalian species (Farré et al. 2021). This observation of a diversity of genetic bases of longevity and ageing across species is consistent with Darwinian theory, which predicts that longevity can be selected for, yet does not imply that homologous genes should be involved in longevity in different populations or species. Like extant organismal lineages, whose members thrive in very diverse environments and niches, members from ancestral organismal lineages from different clades and from different populations were not all exposed to the same ecological challenges during the course of evolution. For example, some organisms belong to lineages that can fly, while others can live in caves, or must face their predators on the ground (Lunghi and Bilandžija 2022). Similarly, some organisms are solitary, whereas others live in societies (Keller and Genoud 1997), and evolution of their longevities and ageing can thus be affected by social organisation and kin selection, etc. Such differences in past and present selective pressures likely explain the considerable variations in ageing and longevity observed throughout the Tree of Life, and since the effect of each gene variant on the longevity in individual species can be small, as is the case for humans (Singh et al. 2019) different combinations of different genes are possibly associated with the variability of lifespan within and between species.

More precisely, mainstream evolutionary theories of ageing, namely the Mutation Accumulation theory (MA) (Medawar 1952), the Antagonistic Pleiotropy theory (AP) (Williams 1957) and the Disposable Soma theory (DS) (Kirkwood and Holliday 1979), hold that ageing is not genetically programmed *per se* but occurs as a side-effect due to the existence of a selection shadow (Johnson et al. 2019). As a result, AP and MA do not make strong predictions regarding whether the same genes should be collaterally associated with ageing across populations and species, while DS predicts that the functions of the genes associated with ageing are likely related with repair/maintenance and energy allocation to trade-offs between reproduction and survival, mediated by a network of interacting, possibly synergistic processes, rather than by a single mechanism (Kirkwood 1997). In addition, reknown experts on aging consider that aging is a programmed process (Rando and Chang 2012). While more aging-associated genes or proteins than appreciated could be conserved (consistent with either AP theory or programmed theory), this is

not necessarily the case for longevity. Thus, although theoretically plausible, the limited overlap in genes associated with ageing and longevity across species nonetheless raises important conceptual and practical challenges (Farré et al. 2021). On the one hand, this limited overlap may reflect some limits of current methods of detection of longevity- and ageing-associated genes. On the other hand, this genetic heterogeneity does not preclude a form of functional unity at a higher level than genes: even though different gene families are associated with longevity or ageing across species, some belong to pathways (e.g. proteostasis, immune and inflammatory response, hemostasis, development, metabolism) that appear to be shared across species (Muntané et al. 2018; Farré et al. 2021; Treaster et al. 2021). Therefore, updated or enhanced comparative analyses may still unravel evolutionarily conserved pathways associated with longevity or ageing. To reach this goal, however, technical developments that enhance the predictive power of genomics and comparative genomics to detect longevity- and ageing- associated genes appear warranted.

Around twenty years ago, several pioneering ageing studies focusing on interactome data (e.g. (Promislow 2004; Ferrarini et al. 2005; Witten and Bonchev 2007; Fortney et al. 2010)) seeded an original path in this direction. They sought to identify not only the molecular components of pathways associated with ageing and longevity, but also the molecular interactions that compose these pathways. In brief, these approaches relied upon prior experimental evidence defining sets of genes associated with longevity or ageing, hereafter called longevity-associated genes (LAGs), such as those forming the mTOR nutrient-sensing signalling network (Kenyon 2010; Templeman and Murphy 2018; Papadopoli et al. 2019). mTOR is noteworthy because it has been shown to regulate many ageing-associated processes (including cellular senescence, immune responses, stem cell regulation, autophagy, mitochondrial function, and proteostasis) and to mediate caloric restriction-induced lifespan extension in model organisms. For some species, LAGs were further classified as pro- or anti-longevity (pro-LAG, anti-LAG), according to the altered lifespan phenotypes resulting from their genetic loss or gain of function in model organisms (Kenyon 2010; Tacutu et al. 2018). These phenotypic labels were then conjugated with additional, independent information from interactome databases (Szklarczyk et al. 2019) to perform protein-protein interaction networks (PPI) analyses with a focus on ageing and longevity associated pathways. Specifically, the topology of PPI of a few extant species was analysed to track the interactions between longevity-associated proteins (LAPs) (e.g. proteins encoded by LAGs) in order to determine the pathways to which these LAPs connected, and whether the patterns of connection of these LAPs presented distinctive topological features that could be exploited to predict additional components of longevity/ageing associated pathways using PPI. Owing to the paucity of the data,

these pioneering studies were generally conducted on one or two species, with a limited number of network metrics (Promislow 2004; Ferrarini et al. 2005; Budovsky et al. 2007; Bell et al. 2009; Wang et al. 2009; Zhang et al. 2016). Nonetheless, they made for stimulating findings. LAPs from model organisms (*Saccharomyces cerevisiae*, *Sc* and *Drosophila melanogaster*, *Dm*) were shown to be central, connected nodes in PPI networks. In particular, LAPs displayed higher node degree (the number of connections per node in the network) than other proteins not proposed to be associated with ageing or longevity (non-LAPs). Such a high connectivity was interpreted as a proxy for the functional pleiotropy of LAPs, in support of the AP theory (Promislow 2004), considering that, as more highly connected proteins tend to be more pleiotropic than expected by chance, these proteins will also be most likely to evolve an association with senescence. Indeed, by chance alone, more pleiotropic proteins are more likely to have some of their effects found at different ages, and that some of these hold opposite consequences on fitness. This idea that AP is a general principle of ageing was also brought forward in (Yanai et al. 2017). Moreover, the high centrality of LAPs in PPI was proposed as evidence that LAPs regulate fundamental biological processes (Fernandes et al. 2016; Tacutu et al. 2018). In addition, pro- and anti-longevity proteins were shown to be intertwined in the interactome of the worm *Caenorhabditis elegans* (*Ce*), with only few significant topological differences between their subnetworks, which represented two sets of interactions with opposing effects on longevity (Fernandes et al. 2016). The interactions between LAPs and non-LAPs in PPI were also a source of important findings. Interactions between LAPs and proteins encoded by age-related diseases (ARD) genes (Tacutu et al. 2011) and cancer genes (Budovsky et al. 2007; Bell et al. 2009; Budovsky et al. 2009; Wang et al. 2009; Zhang et al. 2016) unraveled connections between their respective pathways, hinting at mechanistical connections between some aspects of ageing and some diseases. Furthermore, using LAPs as reference nodes and mining PPI of a few extant species for non-LAP nodes with comparable topological properties than LAPs, allowed some authors to propose subsets of noteworthy non-LAP proteins that may contribute to presently unidentified ageing- or longevity-associated pathways in *Hs*, *Sc*, *Ce* and *Dm* (de Magalhães and Toussaint 2004; Managbanag et al. 2008; Tacutu et al. 2012; Wuttke et al. 2012; Avelar et al. 2020).

While powerful, the predictive approaches mentioned above did not systematically determine how critical for ageing/longevity their predicted candidate LAPs are, and did not fully exploit their comparative potential. Here, we developed evosystemics analyses of PPI (Watson et al. 2020) to uncover important, evolutionary conserved ageing associated pathways, i.e. pathways made of proteins with significant possible effects on ageing/longevity. We relied upon two non-

mutually exclusive criteria to rank proteins and protein interactions as critical to understanding ageing/longevity: their high evolutionary conservation across Opisthokonta, a one-billion-year-old clade, encompassing fungi and animals, and their high centrality in extant and/or ancestral protein interaction networks. Through systematic analyses of the topological properties of LAPs within such networks and through guilt-by-association analyses, we characterised central evolutionarily conserved pathways associated with ageing/longevity and predicted novel central, evolutionarily conserved LAPs in five Opisthokonta species (*Dm*, *Ce*, *Sc*, with *Mus musculus*, *Mm*, and *Homo sapiens*, *Hs*), some of these non-LAPs that we here proposed as new LAPs were supported by independent bibliographical validation. Promisingly, 265 of these 487 predicted additional LAPs are more central than mTOR in the human interactome and dominated by ribosomal proteins and ubiquitination pathways. Moreover, 28.3 % of the proteins predicted to hold important roles in longevity or ageing-associated pathways in humans are druggable, defining targets for potential novel anti-ageing treatments in humans in the short-term.

Results and Discussion

Theoretical pay-offs of evosystemic PPI analyses

Evosystemics jointly analyses evolutionary and topological signals (Watson et al. 2020). High evolutionary conservation across five species of Opisthokonta and high centrality in PPI (as defined in Figure S1A-D) provide two non-mutually exclusive criteria to rank proteins and protein interactions as critical to understanding ageing/longevity. On the one hand, highly conserved proteins and proteins interactions indicate homologous mechanisms, deeply rooted in the biology of Opisthokonta, which can therefore be experimentally studied in non-human species with potential translational payoffs. Likewise, highly central proteins contribute to interactions across many pathways and/or within large molecular machineries. Thus, changes in the genes coding such central proteins (or changes in their regulations) are likely to have strong impacts on many interconnected processes. Because evolutionarily conserved proteins are encoded by gene families with long time of residency within lineages, evolutionarily conserved proteins have had more opportunities to get involved into diverse functional partnerships, and are often expected to be more central in PPI than proteins from more recently evolved gene families (Baptiste and Huneman 2018). Consequently, uncovering i) highly central proteins and ii) evolutionarily conserved proteins

and interactions associated with ageing/longevity in PPI could identify critical pathways associated with longevity or ageing and suggest important targets to medically interfere with the ageing/longevity process, which could be validated across a broad range of species.

LAPs are highly central across PPI of five extant species of Opisthokonta

Our study used multiple stringency thresholds for PPI networks based on interaction confidence scores, a broader selection of Opisthokonta (*Sc*, *Ce*, *Dm*; *Mm* and *Hs*) and more network metrics (e.g. betweenness, closeness, degree, PageRank, Fig. S1A-D) than former PPI analysis on ageing/longevity (Promislow 2004; Ferrarini et al. 2005; Budovsky et al. 2007; Bell et al. 2009; Wang et al. 2009; Zhang et al. 2016). We used these different metrics, as, although often correlated in real networks, they could have captured slightly different aspects of network centrality. In our study, it turned out that irrespective of what specific network centrality was measured, the general conclusion regarding the centrality of LAPs is the same and generalises two previous findings derived from single species longevity networks. First, across the five tested species of Opisthokonta, LAPs are significantly more central in PPI than non-LAPs. This higher centrality was observed at various stringency thresholds, but limited by network size and the number of identified LAPs at high stringency for *Dm*, *Mm* and *Ce* (Fig. 1). This result, compatible with the AP theory (Promislow 2004; Ferrarini et al. 2005), is true for both pro-LAPs and for anti-LAPs (Fig. S2), with the same dependence on stringency, network size and number of identified LAPs; however, the imbalance between pro- and anti-longevity annotations in *Sc* (13% and 87% of the 400 *Sc* annotated ageing-associated proteins, respectively) may lead to a less robust signal of centrality for pro-longevity proteins. Accordingly, pro- and anti-longevity proteins appeared equally central in longevity networks across these five species of Opisthokonta (Fig S2). A few notable exceptions were found for experimental networks of *Sc*, possibly due to the imbalance mentioned above, and for *Ce*, where pro-longevity proteins displayed significantly higher centrality than anti-longevity proteins. The *Ce* observation is consistent with previously described higher clustering coefficient of pro-longevity proteins in the BioGrid PPI network (Fernandes et al. 2016).

Interestingly, pro-LAPs tend to interact significantly more with pro-LAPs whereas anti-LAPs tend to interact significantly more with anti-LAPs, both in entire interactomes (featuring both LAP and non-LAP nodes) and in longevity networks (featuring only LAPs as nodes) (Fig. 2, S3A), as determined by assortativity analyses and network permutation tests (Fig. S4). But this observation does not mean that there is a neat partition between pro-LAPs and anti-LAPs in the

PPI, since overall, the assortativity (Fig. S1E) values are only slightly positive (Fig. 2). In other words, interacting LAPs with antagonistic effects are widespread in PPI, suggesting that ageing and longevity associated pathways are commonly regulated by a diversity of checks and balances with opposite effects. However, remarkably, some pro-longevity and anti-longevity proteins entertain, in all analysed species, significantly more interactions with one another than expected by chance. It is interesting that our results identified differential correlations between pro-LAP and anti-LAP proteins, because this suggests that these two classes might indeed be biologically distinct, which was not necessarily obvious. Indeed, many of these pro-LAP and anti-LAP were identified by experiments that knock out genes and observe the effect on aging, whereas in nature more subtle variations in expression than a complete turn-off are likely to affect these genes, with effects that can both increase and decrease lifespan, depending on the specific expression changes for a given gene. Bearing this note of caution in mind, we propose that such LAPs, significantly strongly involved in interactions with proteins with opposite effects on longevity, correspond to key regulators in antagonistic regulatory mechanisms of longevity (ARMLs).

Three species harbor key antagonistic regulators of ageing/longevity

Using network permutation tests (Fig. S4), we found that three species displayed significantly stronger connections between pro-LAP and anti-LAP than what would be expected by chance, suggesting that such LAPs may be critically involved in the regulation of ageing/longevity (Fig. 3). Namely, we identified 13 LAPs involved in ARMLs in *Dm*; 38 in *Ce* and 40 in *Sc*. Several of these LAPs are homologs found in all three species and contribute to the mTOR signalling network, including mTOR itself (*Dm* Tor/*Ce* LET-363/*Sc* TOR1), but also the AGC kinases Akt (mTORC1 upstream activator and mTORC2 target: *Dm* Akt1, *Ce* AKT-1) and S6k (mTOR substrate: *Dm* S6k, *Sc* SCH9). As these LAPs are well-characterised for their key role in regulating ageing (Kenyon 2010; Templeman and Murphy 2018; Papadopoli et al. 2019), this observation provides proofs of concept that our approach can identify key antagonistic regulators. *Dm* and *Ce* also share the insulin/mTOR signalling network members PTEN phosphatase (*Dm* Pten/*Ce* DAF-18), Insulin receptor (*Dm* InR/*Ce* DAF-2), FOXO transcriptional regulator (*Dm* foxo/*Ce* DAF-16) and the NAD⁺-dependent protein acetylase sirtuin Sir2 (*Dm* Sir2/*Ce* SIR-2.1), whereas *Ce* and *Sc* share NAD⁺-reducing enzymes of the TCA cycle malate dehydrogenase and isocitrate dehydrogenase (*Ce* MDH-2/*Sc* MDH1/MDH2; *Ce* IDH-1/*Sc* IDH1). The existence of homologous key antagonistic regulators across Opisthokonta species supports the idea that

modulating lifespan has been evolutionarily important for at least a billion year and has occasionally relied on the same players, from fungi to animals.

In addition, we identified some LAPs (*Dm*: 3/13; *Ce*: 20/38; *Sc*: 23/40) involved in species-specific ARMLs with a comparable number of antagonistic interactions as emblematic mTOR network members, including, for example, the oxidative stress response protein Keap1, the cardiac-restricted actin-binding protein Vinc and the JNK phosphatase puc in *Dm* (Fig. 3A), which suggests that regulation by these LAPs may deserve careful investigations.

Overall, functions enriched in ARMLs in *Ce* and *Dm* correspond to functions described for proteins in the mTOR/Insulin network, such as stress response, regulation of translation, of regulated cell death and of growth and development (Fig. S5). Functions related to respiration were also enriched among *Ce* and *Sc* ARMLs: TCA cycle in *Ce* and *Sc*, ATP synthesis and mitochondrial electron transport chain in *Sc*. Finally, *Sc* ARMLs also displayed enrichment for chromatin regulation and DNA integrity checkpoint functions.

Strikingly, 52 ARML nodes and their associated interactions appear evolutionarily conserved at the taxonomic scale of Opisthokonta and can be found in humans, corresponding to 58% of these antagonistic regulators found either in *Ce*, *Dm* and *Sc*. These candidate antagonistic regulators of ageing/longevity in humans are associated with 5-14% of evolutionarily conserved interactions (depending on PPI stringency). Although genes are only seldom annotated as pro- or anti-longevity in humans, association with longevity can be inferred by genome-wide association studies (GWAS) as recorded in the LongevityMap database. Thus, among the 52 human homologs of ARMLs identified in *Dm*, *Ce* and *Sc*, we found 4 proteins (3 mTOR network members: AKT3, MTOR, RPS6KB1, and SOD2) that are significantly associated with long life in our species. Therefore, 48 other human genes may act as critical, evolutionarily conserved regulators of longevity/ageing in our species. Interestingly, 3 proteins (SOD2, ALDH2, PRKAA2) are also associated with ageing-related diseases (ARD) and can be targeted by drugs (Table 1).

Functional analyses of highly central LAPs

Unveiling highly central LAPs in ‘longevity PPI’, exclusively composed of LAPs, can point to especially critical components of ageing/longevity pathways. Indeed, by knowing these most central LAPs amongst the LAPs, one can focus on some ageing phenotypes that point to (the

expression of) important (central) proteins, at high risk of negatively affecting organismal or cellular homeostasy, or point to adaptations to longevity involving extremely deep structural components, i.e., the most highly central proteins of the interactome.

We analysed the functions of those LAPS by ranking LAPS by their centrality and by identifying high centrality outliers amongst LAPS in each extant longevity network, using network permutation tests (Fig. S4). Such high centrality outliers were found at all stringency thresholds, including in experimental networks, and their numbers unsurprisingly decreased with stringency (Fig. 4). As expected, many functions enriched among most central LAPS correspond to mTOR/Insulin signalling network-associated functions (Fig. S6), including maintenance/repair mechanisms, oxidative stress response, cell growth or autophagy (although Tor itself did not contribute to the top 20 most enriched functions among *Dm* centrality outliers).

In Bilateria, other signalling pathways involved in development and homeostasis, crosstalking with the mTOR network, were also found within centrality outliers, including MAPK (*Ce*: LET-23, LET-60, SEM-5, MPK-1, JNK-1; *Dm*: p38b, bsk; *Hs*: ERBB2, EGFR, GRB2, HRAS, MAPK3, MAPK14 and various growth factors), TGFbeta (*Dm*: dpp), Wnt (*Ce*: BAR-1, *Hs*: GSK3B, CTNNB1), Notch (*Ce*: GLP-1), JAK/STAT (*Hs*: JAK2, STAT5B, STAT3, NFkB (*Hs*: RELA, NFKB1), AR (*Hs*: AR) and TP53 (*Hs*: TP53, MDM2, TP53BP1; *Mm*: Trp53, Trp53bp1) signalling pathways. Highly central proteins from these signalling pathways contributed to the enrichment in the same functions as the mTOR network, e.g. MAPK signalling through p38 and JNK was associated with response to stress functions. The above results are compatible with the idea that aspects of ageing and longevity are connected to developmental programs, as well as with claims that some developmental processes can provoke ageing when they are active late in life, executing detrimental quasi-programs due to selection shadow (Blagosklonny 2006; Gems 2022). Besides signalling-associated functions, most central LAPS also displayed enrichment for ribosome biogenesis/protein translation, cellular respiration (ATP synthesis/ mitochondrial electron transport chain/TCA cycle functions) in *Ce* and *Sc*, telomere regulation in *Hs* and *Sc*, and regulated cell death in *Mm* and *Hs* (Fig. S6).

Interestingly, some highly central LAPS belonged to the same orthology family and were consistently recovered as highly central across 3 or 4 different Opisthokonta species (Fig. 4). These conserved centrality outliers were less frequently found in experimental networks, which is likely explained by their small size compared to the thresholded networks (with the exception of *Sc*).

These highly central, evolutionarily conserved LAPs were mTOR, AKT/S6K AGC kinases and PTEN homologs, all acting in the mTOR/Insulin signalling network, as well as the homologs for the oxidative stress regulators superoxide dismutase 2 and catalase, and for the protein acetylase sirtuin2.

Progressive changes in enriched ageing/longevity associated functions during Opisthokonta history

We next turn towards a more systematic analysis of the evolutionary conservation of LAPs and their pathways by analysing ancestral PPI of five species of Opisthokonta. We inferred ancestral PPI networks throughout the phylogeny of these Opisthokonta (Fig. S7) to identify which pathways, implementing which functions, had emerged in which lineages. These ancestral longevity networks are comprised only of nodes corresponding to orthogroups (Fig. S3B) and edges associated with ageing or longevity in at least two extant species. Such edges are important, either because they represent convergences in longevity networks (hinting at their possible functional importance) or because they were inherited from a common ancestor. Considering that possibility, we could infer the ancestral longevity networks composed by such edges by comparing extant longevity networks featuring only orthoproteins as nodes (obtained for increasing levels of stringencies, from PPI edge score ≥ 500 to the use of experimental edges only) (M&M). Given the small number of species, and the very large number of potential protein-protein interactions, one might worry that the likelihood of both false-positive and false-negative claims for deep evolutionary conservation of PPIs (i.e., both presence of and absence of conserved interactions) could be elevated. We verify this was not the case: using resampling of input PPI networks with networks from sister species of *Ce*, *Dm* or *Sc*, we found that this approach had a false positive rate of 0 for all resampled species, and a false negative rate, depending on PPI score thresholds, comprised between 0 and 3.7 % for *Ce* or *Dm* replacement, and between 8 and 16% for *Sc* replacement, indicating that our inferences of ancestral edges are conservative and that *Sc* networks have the most weight on the inference of the common ancestral network (M&M).

Consequently, we first used these ancestral networks to estimate the proportion of LAPs and their interactions from extant longevity networks that had already evolved in the past. These numbers reflect the proportion of LAPs and their interactions inherited in extant interactomes. Thus, a third of human LAPs and 7 % of their interactions date from ancestral interactomes of

Opisthokonta (Fig. 5). Moreover, extant ARMLs, e. g. 8 to 43% of the human ARML orthologs (Table 1) and 1 to 10 % of their extant interactions, depending on PPI stringency thresholds, can also be found in ancestral networks. Therefore, a phylogenetically broad range of organisms could still be used to experimentally highlight numerous mechanistic aspects associated with human ageing and longevity.

Second, we assigned a GO-term to each node in these ancestral networks by using the most GO-annotated species for each lineage for ancestral networks (i.e. human proteins for the common, bilaterian and euarchontoglires ancestors, and *Ce* proteins for the ecdisozoan ancestor). We identified functionally enriched GO-terms (top 20) for each network with Metascape (M&M) (Fig. 6). To assess whether different GO-terms (and below different functions) had been associated with ageing or longevity as Opisthokonta diverged from their last common ancestor, we compared these top 20 GO functional annotations for ancestral longevity networks. 40 % of the enriched GO-terms were shared between the common and the bilaterian ancestral networks, but only 5% were shared between the bilaterian and the ecdisozoan ancestral networks and 5% were shared between the bilaterian and the euarchontoglires ancestral networks. Thus, functionally enriched GO-terms associated with ageing/longevity shifted over time, with some evolutionary conservation outside bilaterians. Next, we compared which gene families contributed to GO-terms enrichment between ancestral networks (Table S8): for each of the evolutionarily conserved GO-terms, we further checked whether they involved similar or different gene families in the successive ancestral networks, using a Jaccard index between pairs of sequential ancestral networks (M&M). We concluded that a significant proportion of both genes and pathways had been conserved between the common and the bilaterian ancestral networks (Jaccard indices ranging from 0.53 to 0.89), whereas there were less shared gene families between the bilaterian and the ecdisozoan ancestral networks (Jaccard index = 0.21 for their unique shared GO-term) and between the bilaterian and the euarchontoglires ancestral networks (Jaccard index = 0.29 for their unique shared GO-term). These results show a limited overlap between gene families from functionally enriched GO-terms associated with ageing/longevity, reinforcing the notion that important LAPs differ within lineages of Opisthokonta, especially since the last common ancestor of bilaterians, i.e., there are many lineage specific evolutionary roads to ageing and longevity.

Although gene families and functionally enriched GO-terms associated with ageing and longevity showed limited overlap between Opisthokonta, we still wanted to verify whether some convergence in their even more general functions could not be detected for these enriched GO-

terms. For this, we grouped functionally enriched GO-terms into common functions, e.g. autophagy, stress response, or protein translation, etc. Functions enriched in the common ancestral network are linked to protein translation, stress response, energy production, autophagy and apoptosis. Consistent with the above results, the bilaterian ancestral network shared most of these enriched functions found in the common ancestral network, to the exception of apoptosis and with the addition of response to nutrient levels, a function linked to the mTOR signalling network. Interestingly however, ecdisozoan and euarchontoglire ancestral networks that displayed different enrichment of GO terms were also functionally divergent. The ecdisozoan network was enriched in autophagy and cell death, whereas the euarchontoglire network was enriched in DNA repair, telomere, response to nutrient levels, glucose homeostasis, apoptosis, cell cycle regulation and cell senescence-related functions. This distinction may reflect genuine differences in biological processes, i.e. lineage-specific evolution of longevity/ageing processes, or reflect an experimental bias in the functions investigated by researchers for these different clades. Consistently, a Pubmed search for "cellular senescence" in combination with species names and ageing/longevity/lifespan as keywords returns 28 times more abstracts for euarchontoglire species (*Hs*: 1302; *Mm*: 346) than for ecdisozoan species (*Ce*: 41, *Dm*: 18), even though cellular senescence can occur in ecdisozoan at least in *Dm* (Ito and Igaki 2016), but a similar search for "autophagy/mitophagy" returns only 2.5 times more abstracts for euarchontoglire species (*Hs*: 899; *Mm*: 440) than ecdisozoan species (*Ce*: 313, *Dm*: 229). These patterns are indeed in accordance with the imbalance in numbers of studies on cellular senescence performed in humans and mice versus flies and nematodes (~40 times more studies in humans and mice), rather than reflecting a preferential link with ageing and longevity.

Overall, these results suggest a progressive transition in enriched functions associated with ageing/longevity along the Opisthokonta phylogeny, although this interpretation could still be dependent on experimental biases, and the limited species sampling that was available for our study. Indeed, this sampling included four highly lab-adapted species (for which labels relative to ageing/longevity had previously been gathered from experiments) and humans, which have an unusual longevity; and therefore future studies with a broader taxonomic sampling covering even more of the diversity of Opisthokonta will be useful to assess the generality of our conclusions across animals and fungi. Still, resampling-based estimations of false negative and positive rates suggest low rates of type I and moderate rates of type II errors and thus a good representativity of the results even with a limited number of input species.

Inferring new evolutionarily conserved LAPs

Finally, we expanded our analysis of ageing and longevity associated pathways beyond the borders of extant and ancestral longevity networks (composed only of LAPs) by connecting these networks to the rest of the PPI networks from which they constitute a subset (the global interactomes, also featuring non-LAPs). We mined the global PPI networks (comprised of all orthologous proteins from a given organism, or all the conserved orthologous protein families for a clade) and all significantly supported edges (for various stringency thresholds), both for extant interactomes and for inferred ancestral interactomes (Fig. S9), to identify non-LAPs with significantly similar sets of neighbours to LAPs (Fig. S10). We reasoned that when a non-LAP (or a non-LAP family) significantly interacts with the same sets of proteins than a LAP (or a LAP family), this non-LAP may perform biological functions closely related to that of the LAP with which it plays the same structural role in the PPI network.

In extant networks, depending on which species was investigated, hundreds to thousands of non-LAPs shared significantly similar sets of neighbours than LAPs. Achieving phenotypic assays for so many candidate components of longevity or ageing-associated pathways would be overwhelming. Fortunately, analyses of ancestral PPI networks returned a much more manageable number of candidates, which in addition are evolutionarily conserved. Predicted proteins from ancestral networks were enriched for functions such as translation/ribosomal biogenesis in all 5 species, ubiquitination/proteasomal degradation in bilaterians, neddylation, cell cycle progression and DNA repair in euarchontoglires.

Our strategy makes an asymmetric use of LAPs, as these proteins have been known for a long time to have some direct or indirect connections with ageing, and of non-LAPs, which are proteins that were not reported to have direct or indirect connections with ageing in GenAge. Therefore, an analysis of the scientific literature to validate our predicted for novel LAPs from non-LAPs should not capture information that was used, in the first place, to define longevity-associated proteins. Consistently, we validated a subset of these non-LAPs that we predicted to be associated with ageing or longevity by querying either publication records in PubMed database or phenotypic annotations in species-specific databases (M&M). Predictions with such external support amounted to 24% in *Ce*, 9% in *Dm*, 10% in *Hs*, 5% in *Mm* and 8% in *Sc* (Table S11). Although selecting *Dm* genes at random (1321 genes with ageing-related annotations among 13986 protein-coding genes:

9.4%) would lead to a similar number of ageing-related annotations as evosystemic predictions (9 out of 119 predictions: 7.5%, $P > 0.05$), we saw an enrichment for ageing-annotated *Ce* genes (17 out of 74 predictions: 23%) compared to random sampling (1171 genes with ageing-related annotations in Wormbase among 19886 protein-coding genes: 5.9%, $P < 0.05$), suggesting that evosystemic analysis can be used to predict new ageing-associated genes.

Remarkably, 265 non-LAPs that we predicted to be associated with ageing/longevity are more central than MTOR in the human interactome (Table S12), forming a list of novel evolutionarily conserved super-central candidate proteins associated with ageing or longevity, dominated by ribosomal proteins and ubiquitination pathways. This list also includes KEAP1, a candidate regulator of ageing or longevity, since KEAP1 is also homologous to a key antagonistic regulator that we identified in *Dm*. Consistently with our prediction, KEAP1 has been suggested to regulate the ageing of human aortic endothelial cells (EC) in culture, as a repressor of Nrf2 transcription factor, the critical modulator of cellular stress-response (Kopacz et al. 2020). In addition, 138 out of the 487 new LAPs we predicted are potentially druggable, based on documented drug-protein interactions (M&M), and KEAP1 is one of those (Fig. 7, Table S11). Most interestingly for translational purposes, 28/138 of these druggable proteins are more central than MTOR (Table S12) and 1 amongst those is associated with ageing-related diseases (the proto-oncogene small GTPase superfamily member KRAS). Consequently, these candidate LAPs figure as possible targets for potential novel anti-ageing treatments in humans.

Conclusion

We presented a network-based approach to make some progresses in the analysis of ageing and longevity genes. This approach is surely not the only strategy to reach this goal, given that protein interaction networks lack direct information on mutations associated with longevity located in non-coding/regulatory regions of the genomes, however, we showed that evosystemics has some potential for ageing studies and for proposing novel candidate ageing or longevity related genes. Namely, we tracked the evolutionary history of protein interactions associated with ageing or longevity throughout the phylogeny of five species of Opisthokonta, to identify which pathways known to be associated with ageing or longevity had emerged in which lineages, were conserved and central. To do this, we conjugated two non-mutually exclusive criteria to rank proteins and protein interactions by their high evolutionary conservation across these Opisthokonta and their high centrality in extant and in inferred ancestral PPI. We applied our approach to five species of Opisthokonta, a broader taxonomic selection than used thus far in any previous PPI analyses on

ageing and longevity, mapped extant and ancestral networks with LAP, pro- and anti-longevity labels, and analysed their connections with a large range of network metrics. We confirmed that LAPs, be they pro- or anti-longevity, are highly central in extant PPI, and identified key antagonistic regulators of ageing/longevity. While some highly central proteins are evolutionarily conserved, we observed a transition in functionally important components of ageing or longevity along these different Opisthokonta lineages. Still, a third of the human LAPs and 7 % of their interactions date from ancestral interactomes of Opisthokonta, indicating that a phylogenetically broad range of model organisms could be investigated to understand central mechanistic aspects associated with human ageing and longevity. We also predicted new central, evolutionarily conserved LAPs, of which some could be validated by published independent experimental support. Importantly, we propose that a set of 487 LAPs should be included in the human longevity network. About half of them, largely associated with ribosomal proteins and ubiquitination pathways, are more central than mTOR in the human PPI. In addition, 28.3% of the proteins we predict to hold important roles in longevity or ageing-associated pathways in humans are druggable, defining potential targets for novel anti-ageing treatments in humans. While we feel this approach is promising, it is worth keeping in mind that our analysis could at the time being only rely upon five species for which *a priori* knowledge on ageing- and longevity-associated proteins were already available. Although this was the most phylogenetically diverse set of species we could currently analyze by this approach, two of the five species (mice and humans) have diverged less than a hundred million years ago, and as such represent a fraction of the genetic diversity of animals. Consequently, we hope that future evosystemic studies, benefiting from an enlarged taxonomic dataset from fungi to animals, will determine to what extent our conclusions generalize to all Opisthokonta species, beyond the five species carefully investigated here.

Materials and Methods

Protein-protein interaction stringency

Protein-protein interaction (PPI) networks were built from the STRING database (<https://string-db.org/>)(Szkłarczyk et al. 2019) for five species with longevity-related annotations in the GenAge database (<http://genomics.senescence.info/genes/>, Build 20)(Tacutu et al. 2018): *S. cerevisiae* (*Sc*, txid4932), *C. elegans* (*Ce*, txid6239), *D. melanogaster* (*Dm*, txid7227), *M. musculus* (*Mm*, txid10090) and *H. sapiens* (*Hs*, txid9606). STRING-recorded interactions between pairs of

proteins are weighted by confidence scores ranked from 0 to 1000. STRING PPI networks were filtered at different PPI stringencies either based on interaction score thresholds (scores above 500, 600, 700, 800 or 900), or solely based on interactions experimentally supported (hereafter referred to as experimental networks).

Label-based subnetwork induction

Nodes in PPI networks were labelled as longevity/ageing-associated proteins (LAPs) in accordance with the annotations in the GenAge database. Pro- (genes whose decreased expression by knockout, mutations or RNA interference reduces lifespan and/or whose overexpression extends lifespan) or anti-longevity (genes whose decreased expression extends lifespan and/or whose overexpression decreases it) labelling was also used for *Ce*, *Dm*, *Mm* and *Sc* proteins; genes associated with ‘unclear’ or ‘unannotated’ effects on longevity were labelled as ‘unclear’ in our dataset. LAPs, subdivided into pro-longevity, anti-longevity and ‘unclear’ labelled nodes and the edges connecting them (at the indicated PPI network threshold) defined the species-specific longevity networks used in this study (Fig S3A).

Orthology relationships

Orthology criteria were those of the Alliance of Genome Resources Portal (Alliance Database Version: 4.1.0, <http://www.alliancegenome.org>), which focuses on aggregating and curating orthology relationships between model organisms from a diversity of databases (The Alliance of Genome Resources Consortium et al. 2020) to annotate homologs among ARML and centrality outliers (using a ‘--HH + number’ arbitrary code (Table S13). For ancestral PPI network inference, orthology relationships were based on the more stringent OMA orthogroups from the OMA database (Orthologous MAtrix, <https://omabrowser.org/oma/home/>, OMA All.Jan2020 release)(Altenhoff et al. 2018). Orthology-labelled nodes were used to derive networks of orthologs, sharing the same OMA orthogroup identifiers (Fig. S3B), for each species and at each PPI stringency threshold.

Centrality analysis and outlier detection

Four metrics distributions were computed to determine the centrality of LAPs in PPI networks (Figure S2A-D). Three metrics (betweenness, closeness, and degree) were calculated using the NetworkAnalyser plugin in Cytoscape (Doncheva et al. 2012) and the PageRank (Page

et al. 1999) of each node was calculated using the algorithm implemented in the networkx Python package (<https://networkx.org>) with default parameters. Metrics distribution for pro-, anti-longevity proteins (model organisms) or only LAPs (for all five species), were compared to proteins not associated with longevity (non-LAPs) using the Mann-Whitney U-test (unilateral or bilateral, as indicated). P-values were adjusted for multiple testing using the Bonferroni method. To detect centrality outliers with statistically significant high values for centrality metrics in longevity networks (Figure S2A-D), normalized betweenness, degree, PageRank and closeness were computed using the networkx Python package at all PPI stringency thresholds. Statistically significant high values were determined by node rewiring permutation tests (see Network permutation tests Methods section). Because network permutation tests scale poorly with increasing network size, we compared node centrality in entire PPI networks by their average degree rank across all PPI stringency threshold.

Homophily analysis and candidate ARML detection

Homophily between labelled nodes in networks, i.e. the preferential connection with the same labels, was measured by computing assortativity coefficients (Figure S2E) as defined in equation II from Newman, 2003 (Newman 2003), in order to quantify the extent to which nodes with the same label connect with each other rather than with differently labelled nodes. Assortativity coefficients were calculated using the `attribute_assortativity_coefficient` function from the networkx Python package either for LAPs in entire networks or for pro- and anti-longevity labelled nodes in entire networks and longevity networks. Statistically significant assortativity coefficient values were determined by label permutation tests (see Network permutation tests Methods section). To detect candidate key regulators of ARMLs among pro- or anti-longevity labelled nodes in longevity networks, statistically significant high numbers of neighbors with the opposite label were determined by node rewiring permutation tests (see Network permutation tests Methods section).

Inference of ancestral PPI networks

To infer ancestral PPI networks, species-specific networks of orthologs (Fig. S3B) derived from longevity networks (Fig. S3A) at all PPI stringency thresholds and the reference phylogenetic tree associated with these taxa (in the bracketed format: (*Sc*, (*Ce*, *Dm*), (*Mm*, *Hs*))) were used as input for an in-house script (available on GitHub:

https://github.com/TeamAIRE/ancestral_interactome_inference), to detect conserved protein-protein interaction (edges between the same pair of orthologous proteins, present in different species) and map these edges on the phylogeny of five species of Opisthokonta. For any given edge, all mapped extant taxa in which the protein-protein interaction is observed were given as input to the 'get_common_ancestor' function of the ete3 Python package version 3.1.1 (Huerta-Cepas et al. 2016) to conduct a parsimony analysis and identify the last common ancestor (returned as an intermediate node of the phylogenetic tree) in which the protein-protein interaction was likely present (Fig. S7). Next, this last common ancestor was used to define the root of a subtree, subsequently explored to define which of its children intermediate nodes have likely conserved the edge (at least one descendant extant taxon possessing the edge) or lost the edge (none of its descendant extant taxa possessing the edge). For each intermediate node of the phylogeny, all the edges inferred to be present were then used to reconstruct the corresponding ancestral PPI network. To estimate the false negative/positive rates associated to ancestral edge inferences, we used a resampling approach to construct alternative ancestral networks from thresholded entire networks, by replacing the input of either *Sc*, *Ce* and *Dm* networks by the PPI network of a species with the same taxonomic rank (family) in the NCBI reference phylogeny, with more than 85% of protein sequences being 100% identical between the OMA and STRING databases. Alternative species were, for *Ce*: *C. briggsae* (txid6238), *C. remanei* (txid31234); for *Dm*: *D. ananassae* (txid7217), *D. erecta* (txid7220), *D. grimshawi* (txid7222), *D. persimilis* (txid7234), *D. sechellia* (txid7238), *D. simulans* (txid7240), *D. virilis* (txid7244), *D. yakuba* (txid7245), *D. willistoni* (txid7260); for *Sc*: *K. lactis* (txid284590), *C. glabrata* (txid284593), *E. gossypii* (txid284811), *V. polyspora* (txid436907), *L. thermotolerans* (txid559295), *K. naganishii* (txid1071383). False negatives were defined as edges present in all alternative but absent from reference ancestral networks, and false positives as edges present in reference and absent in all alternative ancestral networks. False positive rates were 0 for all three resampled species, and false negative rates were comprised between *Sc*: 12 and 20%; *Ce*: 0.5 and 4%; *Dm*: 0 and 1.5%.

LAP prediction based on ancestral networks

To predict ancestral proteins with similar topological properties as inferred ancestral LAPs, inferred ancestral PPI networks were mined for orthogroups with similar roles. This prediction is of course a first step. We do not consider that when a non-LAP shares the centrality and conservation properties of one or several ageing- or longevity- associated proteins, this topological proximity is in itself a sufficient evidence that the non-LAP is also an ageing- or longevity-

associated protein, e.g. it may not be sufficient to share topological properties with an ageing-associated protein to be another, undetected, ageing-associated protein. Further validation of the prediction is also necessary. However, it is worth noting here that our predictions were very stringent.

Precisely, node label permutation tests were used to identify significantly high Jaccard indices combined with significantly high numbers of common direct neighbors, with a Jaccard index minimal threshold of 0.5 and at least 1 common neighbor. Species-specific LAP predictions were obtained from the non-LAPs with significant LAP neighborhood in at least one of the ancestral networks from the lineage of the focal species. As expected, this approach identified non-LAPs in a species that are homologous to LAPs in another species and figured by construction as non-LAPs in the ancestral networks, which reassuringly supported our guilt-by-association approach. These already documented LAPs, representing from 0 to 28 % of all predictions, depending on the species, were filtered out.

To further validate our approach of functional prediction by guilt-by-association within a PPI network, independently of the ageing-associated labels, we verified that the functional distributions of these protein families and that of the protein families to which they were structurally equivalent matched with one another. To compute the functional similarity between predicting and predicted proteins, each predicting and associated predicted orthogroups were translated to species-specific representative Ensembl identifiers, and the biomaRt R package was used to retrieve species-specific associated GO-terms from the Ensembl database. Semantic similarity analysis was performed using GOGO on pairs of proteins (predictor-predicted) and semantic similarity scores for each GO category were computed as described (Zhao and Wang 2018). Median semantic similarity for molecular function was found superior to 0.5, indicating good functional correspondence between predictors and predicted proteins and supporting the potential involvement of predicted proteins in regulating ageing and longevity (Figs. S14, S15).

Supporting information for a role as a novel candidate LAP in extant species was gathered using systematic queries to the Pubmed database, following the template: {*symbol of the predicted LAG*} AND {*species-specific keywords*} AND (ageing OR aging OR longevity OR lifespan OR "life span" OR senescence). Species-specific keywords were 'elegans' for *Ce*, 'drosophila' for *Dm*, 'human OR sapiens' for *Hs*, 'mouse OR musculus' for *Mm* and 'yeast OR cerevisiae' for *Sc*. Curated abstracts with mention of a potential link between the predicted LAP and longevity were

retained as supporting data. Further, predicted LAPs for the three species *Sc*, *Dm* and *Ce* were compared with the list of genes associated to lifespan and ageing alterations in genetic experiments recorded in the corresponding species-specific databases *Saccharomyces* Genome Database (yeastgenome.org), Flybase (flybase.org) and Wormbase (wormbase.org). *Sc* phenotypes queried were ‘aging’, ‘lifespan decreased’ and ‘lifespan increased’; *Dm* phenotypes queried were ‘aging’, ‘lifespan’, ‘abnormal aging’, ‘delayed aging’, ‘premature aging’, ‘short lived’ and ‘long lived’; *Ce* phenotypes queried were ‘dauer lifespan variant’ (WBPhenotype:0001540), ‘extended life span’ (WBPhenotype:0000061), ‘shortened life span’ (WBPhenotype:0001171) and ‘aging variant’ (WBPhenotype:0001739). To calculate enrichments in ageing-related annotations in our predictions relative to random sampling, the number of all known protein-coding genes was derived from the number of genes associated with and Uniprot reference identifier in Wormbase for *Ce*, and from Flybase statistics for *Dm*, and a chi-square test was used. *Hs* predicted LAPs were additionally probed for genes associated with human cell senescence in the CellAge database (<https://genomics.senescence.info/cells/>, (Avelar et al. 2020)), genes with alleles associated with exceptional human longevity in the LongevityMap database (<https://genomics.senescence.info/longevity/>, (Budovsky et al. 2013)), Aging-Related Disease (ARD) genes (Fernandes et al. 2016) and druggable proteins recorded in the DGIdb database (Griffith et al. 2013). We also determined from DGIdb the number of drugs, the number of US Food and Drug Administration (FDA)-approved drugs, and the maximum DGIdb interaction score associated with each predicted LAP in human.

Network permutation tests

To detect centrality outlier nodes or candidate key antagonistic regulators, node rewiring permutation tests (Fig. S4) were performed by 1000 random network permutations rewiring the nodes but preserving the total number of edges, without preserving the degree distribution. To detect statistically significant high values of assortativity, and significantly high values of Jaccard index and numbers of common direct neighbors, node label permutation tests (Fig. S4) were performed by randomly shuffling node labels 1000 times. For each node and each metric, a counter was incremented each time the random value was greater than the reference value. P-values were then calculated by the ratio counter/number of permutations, and adjusted for multiple testing using the Bonferroni method.

Functional enrichment analysis

Functional enrichment analysis was performed using the Metascape online tool (<https://metascape.org/gp/index.html>) (Zhou et al. 2019) with customized Enrichment tab settings to retrieve enriched Biological Processes GO terms only. For inferred ancestral networks, orthogroups were translated to their extant protein representative in the most annotated species for each lineage, according to the Gene Ontology statistics (<http://current.geneontology.org/products/pages/downloads.html>): *Hs* proteins for the common, bilaterian and euarchontoglires ancestors, and *Ce* proteins for the excudisozoan ancestor. Metascape analysis files were parsed to retrieve the genes annotated with the top 20 enriched GO terms and a Jaccard index was computed to compare gene sets for shared GO terms between networks.

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Data Availability Statement

The data underlying this article are available in the article and in its online supplementary material.

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Figure legends

Figure 1. Analysis of the centrality of LAPs in PPI networks.

Matrix displaying pairwise comparisons (LAPs VS non-LAPs) of node centrality metrics distributions in the PPI networks from five Opisthokonta species (*S. cerevisiae*, *D. melanogaster*, *C. elegans*, *M. musculus* and *H. sapiens*) for six PPI stringency thresholds (from 500: less stringent networks to exp: more stringent networks). Stars in red cells indicate significantly higher centrality values for LAPs. Significance was determined using the unilateral Mann-Whitney U-test: **: $P < 0.001$; *: $P < 0.05$; NS: not significant (blue cells). P-values were adjusted for multiple testing using the Bonferroni method. This analysis shows that LAPs are more central than non-LAPs in PPI networks.

Figure 2. Homophily of LAPs in entire PPI networks and in longevity networks.

Homophily represents preferential interactions between similar kinds of nodes, and is estimated by assortativity coefficients. The distributions of assortativity coefficients were computed at six PPI stringency thresholds: (A) for LAPs and non-LAPs in the entire PPI networks of *S. cerevisiae*, *D. melanogaster*, *C. elegans*, *M. musculus* and *H. sapiens*; (B) for pro-longevity LAPs (pro-LAPs) and anti-longevity LAPs (anti-LAPs) in the entire PPI networks of *S. cerevisiae*, *D. melanogaster*, *C. elegans* and *M. musculus*; (C) for pro-LAPs and anti-LAPs in the longevity networks of *S. cerevisiae*, *D. melanogaster*, *C. elegans* and *M. musculus*. Assortativity coefficients were all significantly positive in node label permutation tests ($P < 0.05$), except in the *C. elegans* experimental longevity network (NS: not significant), indicating that proteins belonging to the same kind of LAPs (hence with the same effects on longevity) preferentially interact together.

Figure 3. Identification of candidate antagonistic regulatory mechanisms of longevity in longevity networks.

In longevity networks, some LAPs display a significantly high proportion of direct neighbours with an opposite effect on longevity (e.g. a pro-LAP being connected to significantly more anti-LAPs than expected by chance) and are therefore candidate regulators of longevity. Matrices of nodes with such a property for one or more PPI stringencies are indicated for three species: (A) *D. melanogaster*, (B) *C. elegans* and (C) *S. cerevisiae*. For each protein, the proportion of its neighbours with opposite effect on longevity is color-coded in cells, from blue: 0% to red: 100%.

Black cells indicate that the corresponding protein is absent from the network at the corresponding PPI stringency thresholds. The numbers of neighbors with opposite effects are indicated in the relevant cells only when significantly higher than by chance according to a node rewiring permutation test. Homolog outlier LAPs, i.e. LAPs found in multiple species, are indicated by a ‘-H + number’ homology code (as defined in Table S13) to the right of the protein names, highlighted in blue (when shared by two species) or yellow (when shared by three species), whereas species-specific outlier LAPs are indicated in bold. A star labels LAPs which were not found among centrality outliers in Fig. 4, indicating candidate regulators of longevity that are not highly central in the network. The white, light grey and dark grey bars on the left of each matrix further classify proteins depending on their outlier status, respectively, in both thresholded and experimentally-supported (exp) networks, in thresholded networks only, or in exp networks only. This figure shows that several species host evolutionary conserved LAPs highly connected to proteins with opposite effects on longevity/ageing.

Figure 4. Identification of the most central LAPs in longevity networks.

Some LAPs display a significantly high centrality in longevity networks, defined as possessing a significantly high value for at least two centrality metrics among betweenness, closeness, degree and PageRank. Matrices of nodes with such a property for one or more PPI stringencies are indicated for five species: (A) *S. cerevisiae*, (B) *C. elegans*, (C) *D. melanogaster*, (D) *M. musculus* and (E) *H. sapiens*. For each protein, the number of significantly high centrality metrics is color-coded in cells, from blue: 0-1 to red: 4. Homolog outlier LAPs found in multiple species are indicated by a ‘--H + number’ homology code (as defined in Table S13) to the right of the protein names, highlighted in blue (when present in four species) or yellow (when present in five species), whereas species-specific outlier LAPs are indicated in bold. The white, light grey and dark grey bars on the left of each matrix further classify proteins depending on their outlier status, respectively, in both thresholded and experimentally-supported (exp) networks, in thresholded networks only, or in exp networks only. This figure shows that several species host evolutionary conserved highly central LAPs in their longevity networks.

Figure 5. Inference of ancestral interactions based on shared LAP-LAP interactions between longevity networks.

The longevity networks of orthologs from *S. cerevisiae* (*Sc*), *C. elegans* (*Ce*), *D. melanogaster* (*Dm*), *M. musculus* (*Mm*) and *H. sapiens* (*Hs*) were used to infer ancestral networks at inner branches of the species phylogeny (as described in Figure S7) from ortholog-ortholog interactions shared between species. The resulting ancestral networks are shown here for PPI stringency threshold = 500. In these ancestral networks, node and edge colours indicate inferred presence in the last common ancestor of all 5 species (blue, in the last common ancestor of Opisthokonta), of all 4 bilaterian species (pink, in the bilaterian ancestor), of *Hs* and *Mm* (yellow, in the euarchontoglires ancestor) or of *Dm* and *Ce* (green, in the ecdisozoan ancestor). Extant longevity networks and proportions of ancestral nodes and edges in these networks are displayed to the right of the species phylogeny. These extant networks represent the interactions between LAPs belonging to shared orthogroups for each species. Nodes and edges in extant networks are coloured based on their inferred phylogenetic date of appearance, or grey if only present in the corresponding species. This figure shows that each extant longevity network contains evolutionarily conserved interactions, some of which as old as the last common ancestor of Opisthokonta.

Figure 6. Functional enrichment analysis of ancestral longevity networks.

To perform functional enrichment analysis of the proteic interactions inferred to be present in ancestral networks, ancestral orthogroups identified at each PPI stringency were analyzed using Metascape. *H. sapiens* protein identifiers were used as Metascape input to represent the functions of orthogroups found in common, bilaterian and euarchontoglires ancestral networks, and *C. elegans* protein identifiers were used as Metascape input to represent the functions of orthogroups found in ecdisozoan ancestral networks. On the species phylogeny, the top 20 enriched GO-terms identified by Metascape for ancestral proteins are positioned at the inner branches, and the top 20 enriched GO-terms for extant proteins (orthogroups found in extant longevity networks) are positioned at the leaves. Identical enriched GO-terms between ancestors or between ancestor and extant species are highlighted with the color corresponding to the oldest ancestor implementing the function (blue: for the last common ancestor of Opisthokonta; pink: for the bilaterian ancestor; yellow: for the euarchontoglires ancestor; green: for the ecdisozoan ancestor). Colored boxes surround GO-terms absent from ancestral networks but identical between sister species, suggesting that the same functions are used by closely related species to regulate longevity. This figure shows that the main enriched functions associated with longevity/ageing regulation have changed with the history of species.

Figure 7. Druggable human predicted LAPs.

We predicted 138 novel human LAPs, most with known drug interactions recorded in the DGIdb database. Predicted LAPs are ordered from left to right by their inferred age of first appearance (as old as the last common ancestor of Opisthokonta, as old as the Bilaterian ancestor, as old as the euarchontoglires ancestor) and by decreasing average centrality (average degree rank) in the corresponding ancestral longevity networks. A bar plot indicates the number of drugs linked to each of the 138 predicted human LAPs, with the number of FDA-approved drugs, when available, on top of each bar. Below the bar plot, a matrix displays support (purple cells) for a LAP function from (P) the literature in Pubmed abstracts, (C) the cellular senescence database CellAge or (L) GWAS data providing an association with longevity from the LongevityMap database. (A) indicates whether the LAP is associated to an Aging-Related Disease (ARD). This figure reports predicted evolutionary conserved human longevity-associated proteins, currently known to be targeted by drugs.

Figure 1

		LAPs compared to non-LAPs					
		PPI stringency					
		500	600	700	800	900	exp
<i>S. cerevisiae</i>	Betweenness	**	**	**	**	**	**
	Closeness	**	**	**	**	**	**
	Degree	**	**	**	**	**	**
	PageRank	**	**	**	**	**	**
<i>D. melanogaster</i>	Betweenness	**	**	**	**	**	NS
	Closeness	**	**	**	**	NS	NS
	Degree	**	**	**	**	NS	NS
	PageRank	**	**	**	*	NS	NS
<i>C. elegans</i>	Betweenness	**	**	**	**	**	**
	Closeness	**	**	**	**	*	NS
	Degree	**	**	**	**	**	NS
	PageRank	**	**	**	**	**	**
<i>M. musculus</i>	Betweenness	**	**	**	**	**	**
	Closeness	**	**	**	**	**	**
	Degree	**	**	**	**	*	**
	PageRank	**	**	**	**	**	**
<i>H. sapiens</i>	Betweenness	**	**	**	**	**	**
	Closeness	**	**	**	**	**	**
	Degree	**	**	**	**	**	**
	PageRank	**	**	**	**	**	**

Figure 2

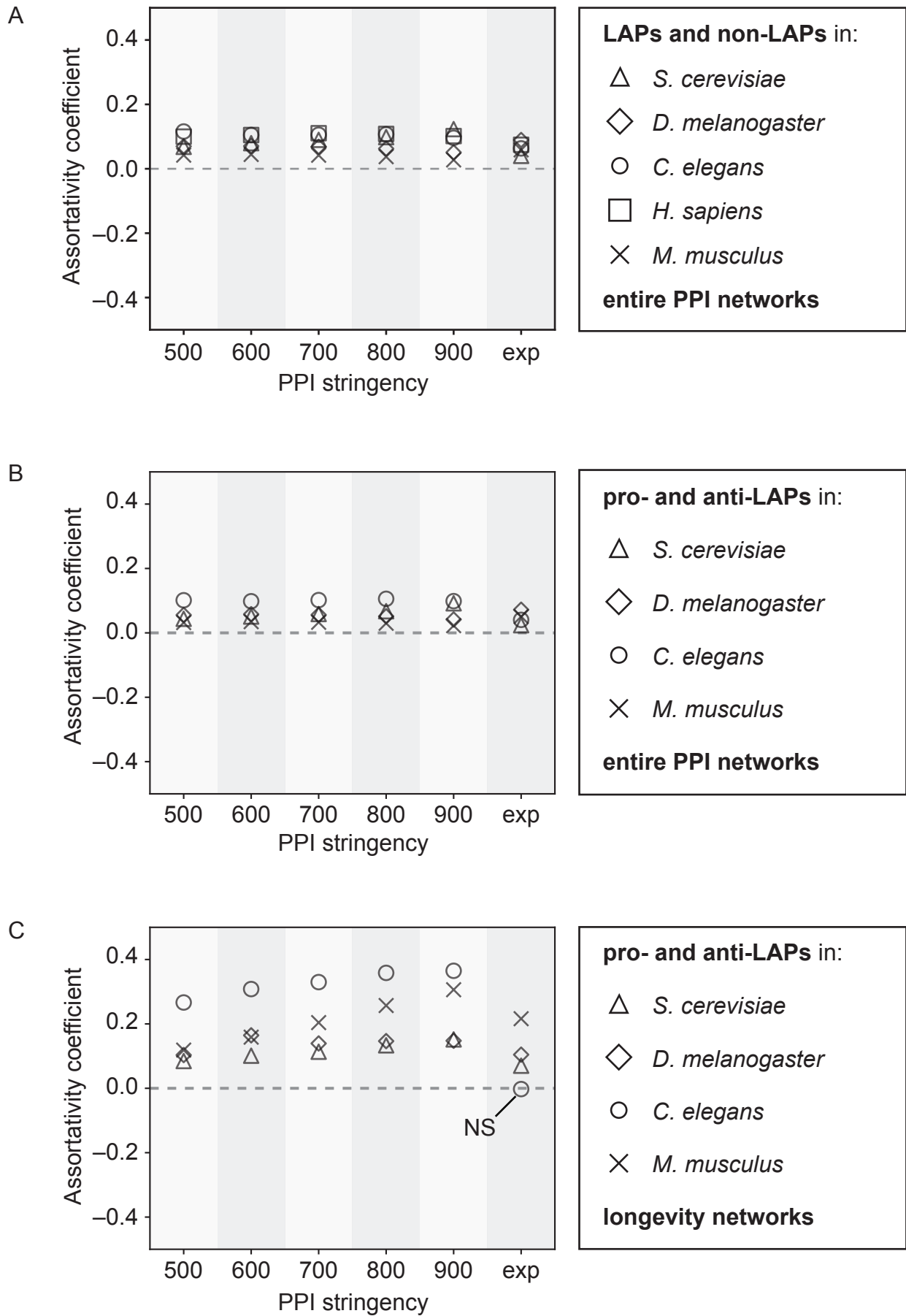
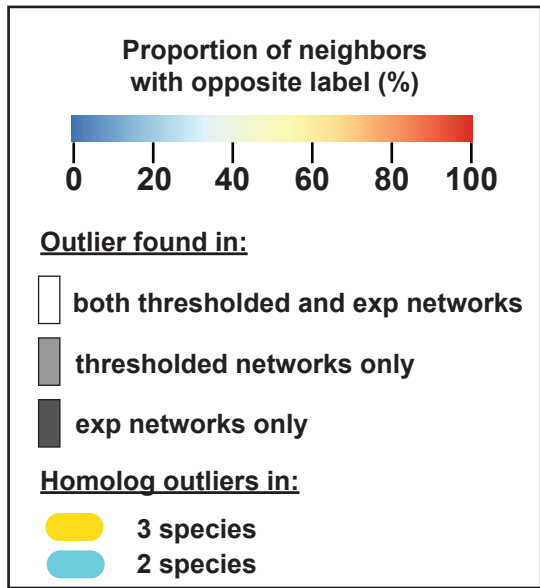
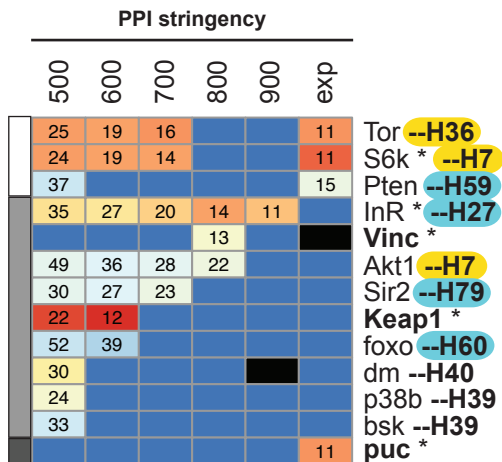


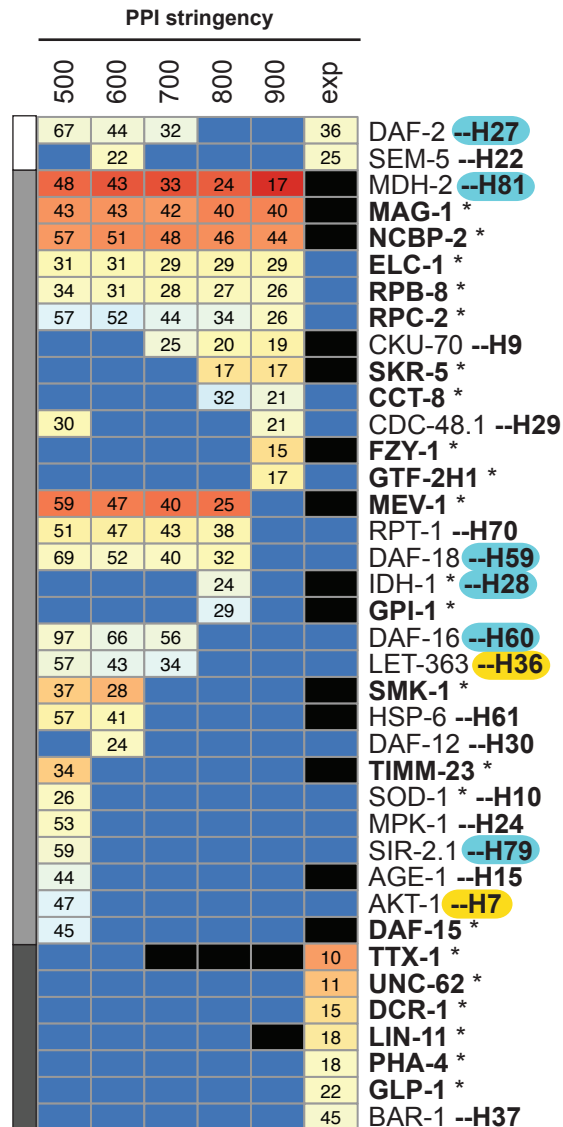
Figure 3



A



B



C

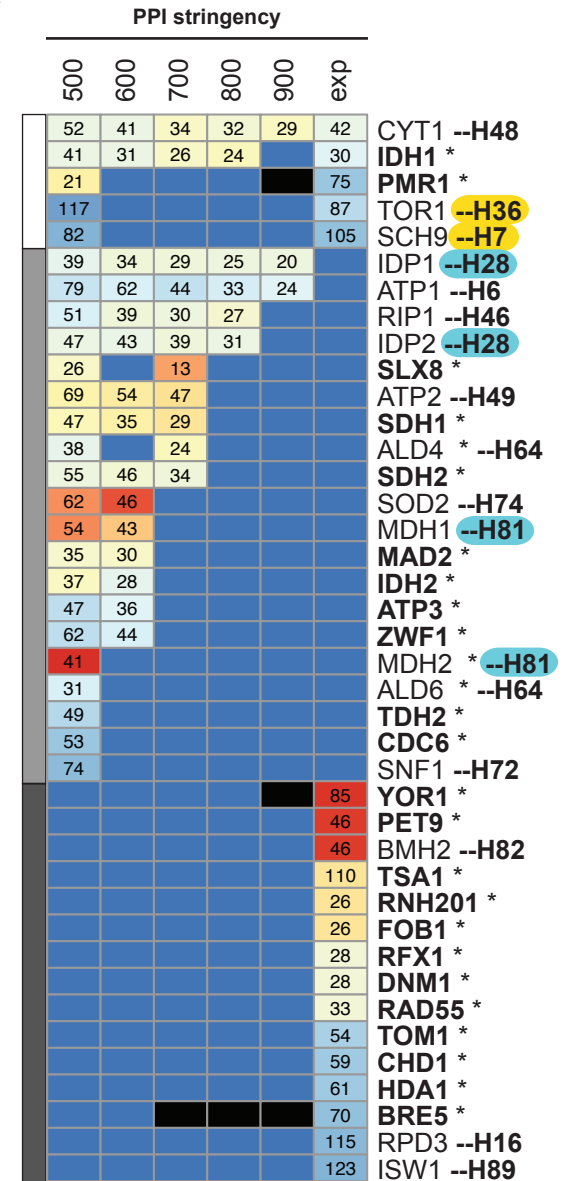
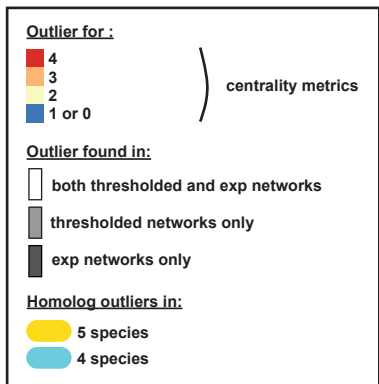
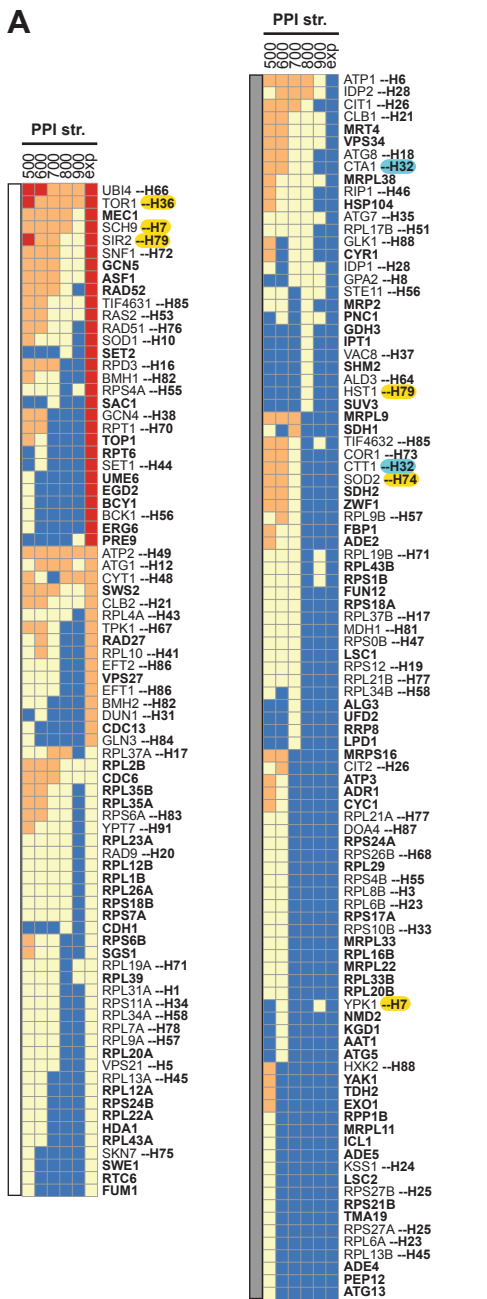


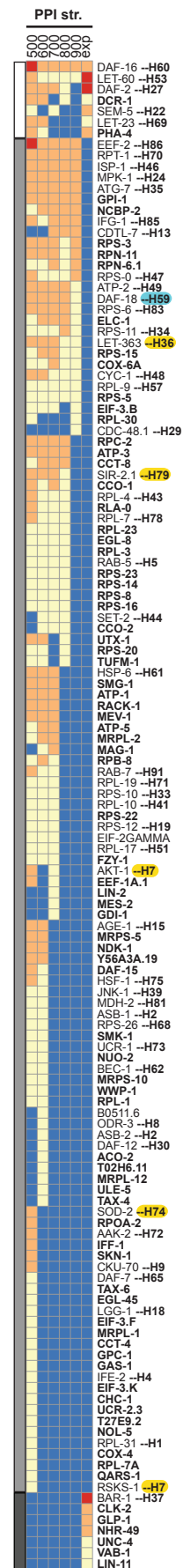
Figure 4



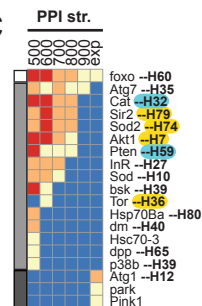
A



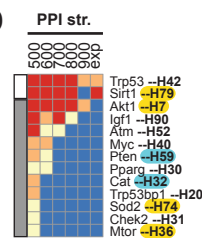
B



C



D



E

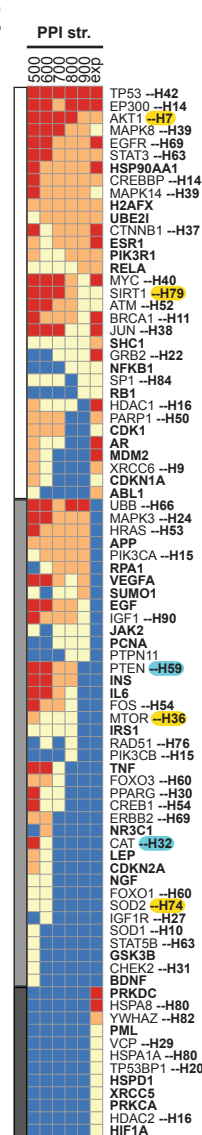


Figure 5

Proportion of ancestral
nodes / edges

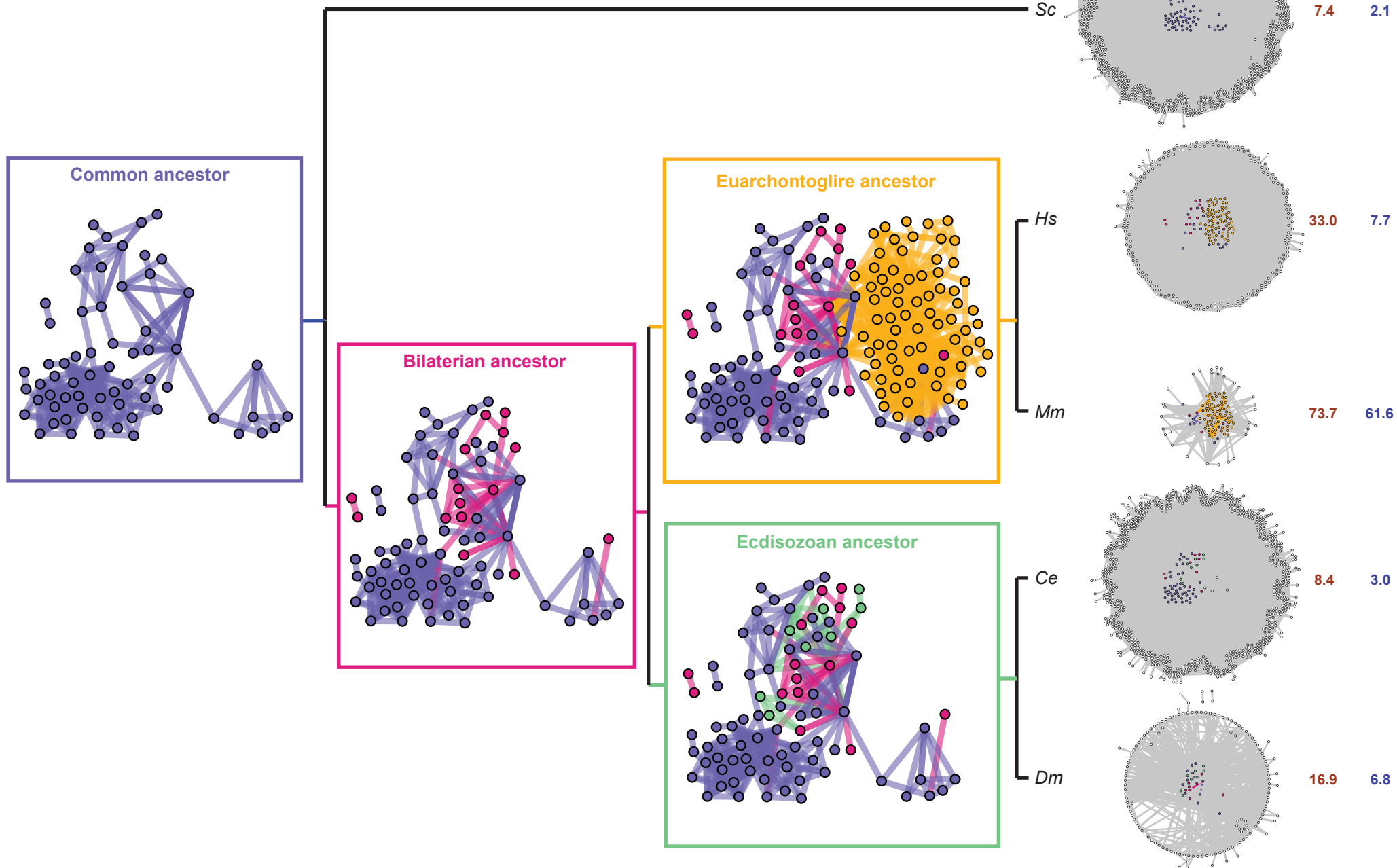


Figure 6

- Common ancestor**
- GO:0006091: generation of precursor metabolites and energy
 - GO:0043603: cellular amide metabolic process
 - GO:0062197: cellular response to chemical stress
 - GO:0007005: mitochondrion organization
 - GO:0006790: sulfur compound metabolic process
 - GO:0042743: hydrogen peroxide metabolic process
 - GO:0005975: carbohydrate metabolic process
 - GO:0002262: myeloid cell homeostasis
 - GO:0010506: regulation of autophagy
 - GO:0010332: response to gamma radiation
 - GO:0016570: histone modification
 - GO:0009725: response to hormone
 - GO:0001649: osteoblast differentiation
 - GO:0002639: positive regulation of immunoglobulin production
 - GO:0097190: apoptotic signaling pathway
 - GO:1901699: cellular response to nitrogen compound
 - GO:0021766: hippocampus development
 - GO:0019216: regulation of lipid metabolic process
 - GO:0048660: regulation of smooth muscle cell proliferation
 - GO:1903169: regulation of calcium ion transmembrane transport

- Bilaterian ancestor**
- GO:0015980: energy derivation by oxidation of organic compounds
 - GO:0062197: cellular response to chemical stress
 - GO:0043603: cellular amide metabolic process
 - GO:0006099: tricarboxylic acid cycle
 - GO:0009725: response to hormone
 - GO:0031667: response to nutrient levels
 - GO:0006790: sulfur compound metabolic process
 - GO:0007005: mitochondrion organization
 - GO:0010212: response to ionizing radiation
 - GO:0018105: peptidyl-serine phosphorylation
 - GO:0019725: cellular homeostasis
 - GO:2000377: regulation of reactive oxygen species metabolic process
 - GO:0010506: regulation of autophagy
 - GO:0055093: response to hyperoxia
 - GO:0005975: carbohydrate metabolic process
 - GO:0009408: response to heat
 - GO:0001775: cell activation
 - GO:0009896: positive regulation of catabolic process
 - GO:0031400: negative regulation of protein modification process
 - GO:0016570: histone modification

- Euarchoptoglires ancestor**
- GO:0006974: cellular response to DNA damage stimulus
 - GO:0071417: cellular response to organonitrogen compound
 - GO:0031667: response to nutrient levels
 - GO:2001233: regulation of apoptotic signaling pathway
 - GO:0010564: regulation of cell cycle process
 - GO:0006979: response to oxidative stress
 - GO:0043549: regulation of kinase activity
 - GO:1901214: regulation of neuron death
 - GO:0009411: response to UV
 - GO:0031331: positive regulation of cellular catabolic process
 - GO:0040008: regulation of growth
 - GO:0090398: cellular senescence
 - GO:0048732: gland development
 - GO:0097193: intrinsic apoptotic signaling pathway
 - GO:0046324: regulation of glucose import
 - GO:0006468: protein phosphorylation
 - GO:0042593: glucose homeostasis
 - GO:0032200: telomere organization
 - GO:0019216: regulation of lipid metabolic process
 - GO:0010821: regulation of mitochondrion organization

- Ecdisozoan ancestor**
- GO:0008340: determination of adult lifespan
 - GO:0009060: aerobic respiration
 - GO:0044271: cellular nitrogen compound biosynthetic process
 - GO:0000422: autophagy of mitochondrion
 - GO:0046034: ATP metabolic process
 - GO:0006979: response to oxidative stress
 - GO:0002119: nematode larval development
 - GO:0009792: embryo development ending in birth or egg hatching
 - GO:0050793: regulation of developmental process
 - GO:0051128: regulation of cellular component organization
 - GO:0009605: response to external stimulus
 - GO:0033554: cellular response to stress
 - GO:0032879: regulation of localization
 - GO:0019725: cellular homeostasis
 - GO:0009893: positive regulation of metabolic process
 - GO:0010942: positive regulation of cell death

- Sc**
- GO:0034727: piecemeal microautophagy of the nucleus
 - GO:0048519: negative regulation of biological process
 - GO:0031497: chromatin assembly
 - GO:0006099: tricarboxylic acid cycle
 - GO:0006464: cellular protein modification process
 - GO:0051128: regulation of cellular component organization
 - GO:0007154: cell communication
 - GO:1901293: nucleoside phosphate biosynthetic process
 - GO:0051728: regulation of cell cycle
 - GO:0002181: cytoplasmic translation
 - GO:0010737: protein kinase A signaling
 - GO:0072350: tricarboxylic acid metabolic process
 - GO:0031399: regulation of protein modification process
 - GO:0044087: regulation of cellular component biogenesis
 - GO:0051053: negative regulation of DNA metabolic process
 - GO:0051090: regulation of DNA-binding transcription factor activity
 - GO:0010906: regulation of glucose metabolic process
 - GO:0140053: mitochondrial gene expression
 - GO:0090033: positive regulation of filamentous growth
 - GO:0007005: mitochondrion organization

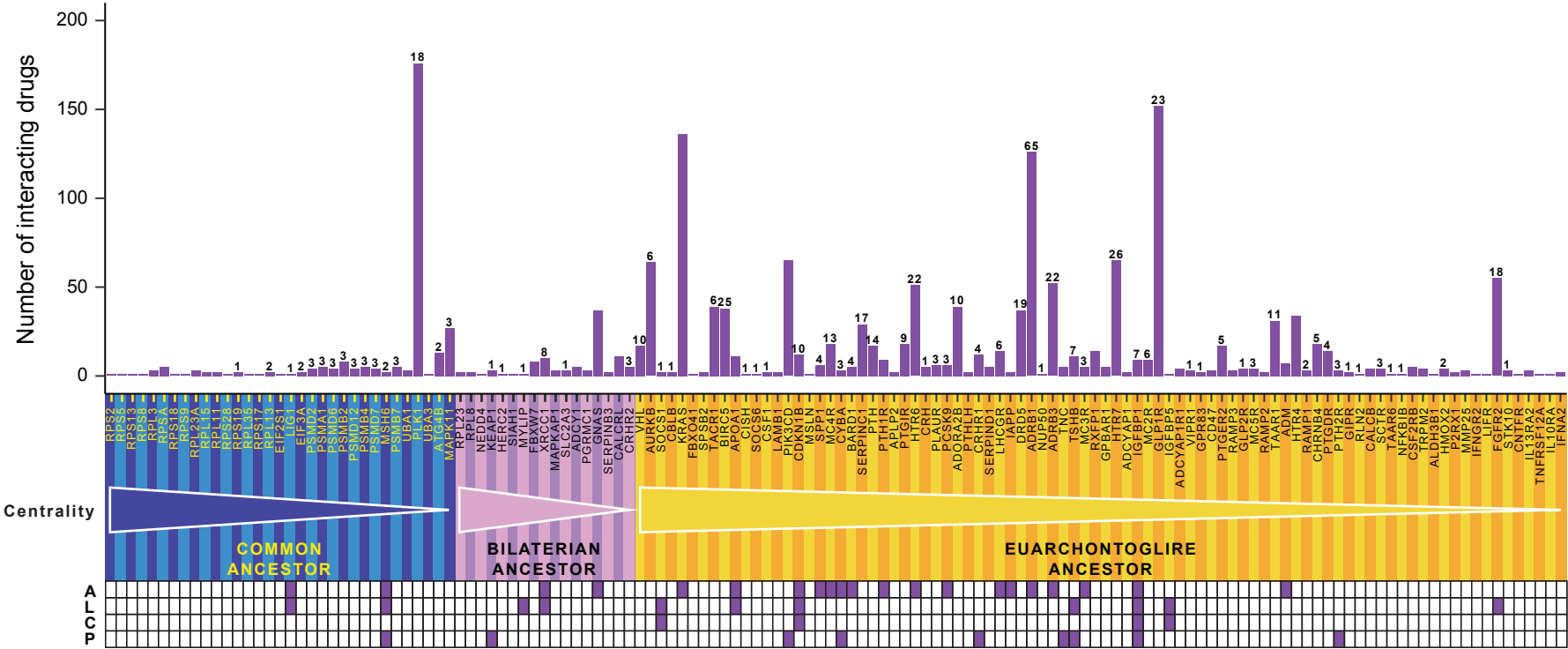
- Hs**
- GO:0006979: response to oxidative stress
 - GO:0009725: response to hormone
 - GO:0006974: cellular response to DNA damage stimulus
 - GO:0080135: regulation of cellular response to stress
 - GO:0009314: response to radiation
 - GO:2001233: regulation of apoptotic signaling pathway
 - GO:0010035: response to inorganic substance
 - GO:0001934: positive regulation of protein phosphorylation
 - GO:0002520: immune system development
 - GO:0009991: response to extracellular stimulus
 - GO:0010942: positive regulation of cell death
 - GO:0007167: enzyme-linked receptor protein signaling pathway
 - GO:0097190: apoptotic signaling pathway
 - GO:0048732: gland development
 - GO:0040008: regulation of growth
 - GO:1901214: regulation of neuron death
 - GO:0010564: regulation of cell cycle process
 - GO:0006468: protein phosphorylation
 - GO:0031331: positive regulation of cellular catabolic process
 - GO:0051098: regulation of binding

- Mm**
- GO:0006974: cellular response to DNA damage stimulus
 - GO:1901653: cellular response to peptide
 - GO:0008630: intrinsic apoptotic signaling pathway in response to DNA damage
 - GO:0048638: regulation of developmental growth
 - GO:0062012: regulation of small molecule metabolic process
 - GO:2001233: regulation of apoptotic signaling pathway
 - GO:0048660: regulation of smooth muscle cell proliferation
 - GO:0007568: aging
 - GO:0007346: regulation of mitotic cell cycle
 - GO:0001934: positive regulation of protein phosphorylation
 - GO:0043086: negative regulation of catalytic activity
 - GO:0006979: response to oxidative stress
 - GO:0010942: positive regulation of cell death
 - GO:0010817: regulation of hormone levels
 - GO:0048145: regulation of fibroblast proliferation
 - GO:0010638: positive regulation of organelle organization
 - GO:0014070: response to organic cyclic compound
 - GO:0071363: cellular response to growth factor stimulus
 - GO:0048732: gland development
 - GO:0032204: regulation of telomere maintenance

- Ce**
- GO:0008340: determination of adult lifespan
 - GO:0050793: regulation of developmental process
 - GO:0002119: nematode larval development
 - GO:0009893: positive regulation of metabolic process
 - GO:0044271: cellular nitrogen compound biosynthetic process
 - GO:0051128: regulation of cellular component organization
 - GO:0061062: regulation of nematode larval development
 - GO:0009628: response to abiotic stimulus
 - GO:0048609: multicellular organismal reproductive process
 - GO:0022611: dormancy process
 - GO:0070887: cellular response to chemical stimulus
 - GO:0009792: embryo development ending in birth or egg hatching
 - GO:0009605: response to external stimulus
 - GO:0046034: ATP metabolic process
 - GO:0048583: regulation of response to stimulus
 - GO:0048523: negative regulation of cellular process
 - GO:0010506: regulation of autophagy
 - GO:0061063: positive regulation of nematode larval development
 - GO:0065008: regulation of biological quality
 - GO:0071495: cellular response to endogenous stimulus

- Dm**
- GO:0008340: determination of adult lifespan
 - GO:0006979: response to oxidative stress
 - GO:1901700: response to oxygen-containing compound
 - GO:0031667: response to nutrient levels
 - GO:0010506: regulation of autophagy
 - GO:0051128: regulation of cellular component organization
 - GO:0034539: cellular response to oxidative stress
 - GO:0043467: regulation of generation of precursor metabolites and energy
 - GO:0009628: response to abiotic stimulus
 - GO:0033500: carbohydrate homeostasis
 - GO:0007610: behavior
 - GO:0007552: metamorphosis
 - GO:0031175: neuron projection development
 - GO:0031399: regulation of protein modification process
 - GO:0006091: generation of precursor metabolites and energy
 - GO:0002682: regulation of immune system process
 - GO:0042981: regulation of apoptotic process
 - GO:006796: phosphate-containing compound metabolic process
 - GO:1902531: regulation of intracellular signal transduction
 - GO:0040007: growth

Figure 7



Supplementary figure legends

Supplementary figure 1: Centrality and homophily metrics.

The centrality of nodes in networks was estimated using four centrality metrics: (A) the degree, that is the number of direct connections to this node; (B) the closeness, the reciprocal of the sum of the shortest path distances from a node to all the other nodes, normalised by the sum of all shortest paths, measuring how close a node is from all the others; (C) the betweenness, the sum of the fraction of shortest paths between all pairs of nodes that pass through a node, measuring the ‘hubness’ of a node; (D) the PageRank, originally designed as an algorithm to rank web pages (Page et al. 1999), that ranks all nodes based on the structure of the incoming links. Homophily between labelled nodes in a network was estimated using (E) the assortativity coefficient of the network, i.e. the Pearson correlation coefficient of degree between pairs of linked nodes (Newman 2003), taking a value between -1 (completely disassortative network) and 1 (completely assortative network).

Supplementary figure 2: Analysis of the centrality of pro-LAPs and anti-LAPs in PPI networks.

Pairwise comparisons of node centrality metrics distributions were performed between (left panel) pro-LAPs and non-LAPs; (centre panel) anti-LAPs and non-LAPs; (right panel) pro-LAPs and anti-LAPs for PPI networks from five Opisthokonta species for each PPI stringency threshold. Stars indicate significantly higher values for LAPs in red cells (left and centre panels), or significant differences between LAPs in yellow cells (right panel). Significance was determined using the unilateral (left and centre panels) or bilateral (right panel) Mann-Whitney U-test: **: $P < 0.001$; *: $P < 0.05$; NS: not significant (blue cells). P-values were adjusted for multiple testing using the Bonferroni method.

Supplementary figure 3: Derivation of subnetworks from node labels.

Nodes in PPI networks were labelled to derive subnetworks: (A) using LAGs annotations in the GenAge database (<http://genomics.senescence.info/genes/>, Build 20), defining longevity networks constituted by LAP-LAP interactions, either connecting nodes with identical labels (blue edges) or with opposite labels (orange edges); (B) using orthogroup labels from the OMA database (<https://omabrowser.org/oma/home/>, OMA All.Jan2020 release), defining networks of homologs/orthologs, allowing comparative analysis of interactions between conserved proteins between species (purple edges), or aggregation of subnetworks from different species.

Supplementary figure 4: Network permutation tests.

To detect outlier nodes with statistically significant values of degree, closeness, betweenness and PageRank, as well as nodes with statistically significant numbers of neighbors with opposite label, node rewiring permutation tests were performed by 1000 random network permutations rewiring the nodes but preserving the total number of edges. To detect statistically significant high values of assortativity, and to detect

significantly high values of Jaccard index and numbers of common direct neighbors, node label permutation tests were performed by 1000 random shufflings of the node labels.

Supplementary figure 5: Functional enrichment analysis of candidate ARMLs.

Metascape top 20 enriched GO-terms for (A) *Ce*, (B) *Dm* and (C) *Sc* candidate ARMLs.

Supplementary figure 6: Functional enrichment analysis of the most central LAPs.

Metascape top 20 enriched GO-terms for (A) *Ce*, (B) *Dm*, (C) *Hs*, (D) *Mm* and (E) *Sc* centrality outliers.

Supplementary figure 7: Inference of ancestral networks of orthologs.

Extant species-specific networks of orthologs (node colours indicate orthogroup labels) and a reference phylogenetic tree associated with these species were used to detect conserved protein-protein interaction (edges between the same pair of orthologous proteins, present in different species) and map these edges on the phylogeny (edge colours correspond to their inferred last common ancestor's colour). See M&M for methodological details.

Supplementary figure 8: Inference of ancestral interactions based on conserved LAP-LAP interactions from entire PPI networks.

The entire PPI networks of orthologs from five extant Opisthokonta species were used to infer ancestral networks at inner branches of the phylogeny (Figure S7), shown here for networks at PPI stringency threshold 500. Node and edge colours indicate inferred presence in the common ancestor of all 5 species (blue, common ancestor), of all 4 bilaterian species (pink, bilaterian ancestor), of *Hs* and *Mm* (yellow, euarchontoglires ancestor) or of *Dm* and *Ce* (green, ecdysozoan ancestor). The proportions of ancestral nodes and edges in extant networks of orthologs is indicated at the leaves.

Supplementary figure 9: Guilt-by-association approach for ancestral LAP prediction.

To detect non-LAP ancestral node with similar neighbours than LAP ancestral nodes in inferred ancestral networks, we used the Jaccard index and the absolute number of direct common neighbors (red) between LAP (yellow) and non-LAP (blue) nodes. Significant values of Jaccard index (the ratio between the intersection of the two neighborhoods for a pair of nodes to the union of these two neighborhoods) and of number of common neighbours were determined by network permutation tests (Fig. S4).

Supplementary figure 10: Semantic similarity between GO-terms associated with predicting and predicted proteins

Distribution box plots of GOGO semantic similarity scores (Molecular Function Ontology) using all pairs of GO-term sets associated with predicting and predicted proteins as inputs, for the five species analysed in this study.

Supplementary figure 11: Functional enrichment analysis of predicted LAPs.

Metascape top 20 enriched GO-terms for (A) *Ce*, (B) *Dm*, (C) *Hs*, (D) *Mm* and (E) *Sc* predicted LAPs.

Supplementary table 1: Proteins contributing to the functional enrichment in ancestral networks.

Protein hits for each Metascape top20 enriched GO-terms in ancestral networks.

Supplementary table 2: LAP prediction in five species of Opisthokonta.

For each species, the ancestral network (either common, bilaterian, ecdisozoan or euarchontoglires) where they were predicted is indicated with a number code: non-predicted (0), predicted in thresholded and experimental networks (1), predicted in thresholded networks only (2), predicted in experimental networks only (3). The average degree rank (ADR) in each ancestral network for each predicted LAP is indicated, as well as the number of unique predictors across all ancestral networks (ancestral LAPs with a significant similarity with the predicted ancestral LAP). The Pubmed column contains PMID for abstracts which support a LAP role for the predicted LAP (0 if there is no support). The other columns contain other species-specific sources of support: phenotypic annotations in databases (*Ce*: Wormbase; *Dm*: Flybase; *Sc*: Saccharomyces Genome Database) or presence in aging and longevity-related gene sets (*Hs*: CellAge, ARD, LongevityMap, see M&M). Support is indicated by 1, no support is indicated by 0. Human-specific annotations on druggability comprise the columns Druggable (yes: 1, no: 0), nb_drugs (number of drugs targeting the predicted LAP in DGIdb), FDA_approved_drugs (number of FDA-approved drugs targeting the predicted LAP in DGIdb, when there is only one its name is indicated), max_interaction_score (highest DGIdb drug-target interaction score).

Supplementary table 3: Super-central predicted human LAPs.

The 265 human predicted LAPs with an average degree rank (ADR) over all PPI stringency thresholds lower than MTOR (232.3). Associations with cellular senescence (from the CellAge gene set), with longevity (from the LongevityMap database), or with Ageing-Related Diseases (ARD gene set from Fernandes et al. 2016) and druggability according to the DGIdb database are indicated.

Supplementary table 4: Homology codes used to annotate outliers in extant longevity networks.

Annotations based on orthology relationships from the Alliance of Genome Resources Portal (Alliance Database Version: 4.1.0, <http://www.alliancegenome.org>). Arbitrary --H codes have been attributed to ARMLs and centrality outliers to compare extant species. The STRING, Alliance and gene symbol identifiers are indicated for the members of each --H group.

Figure S1

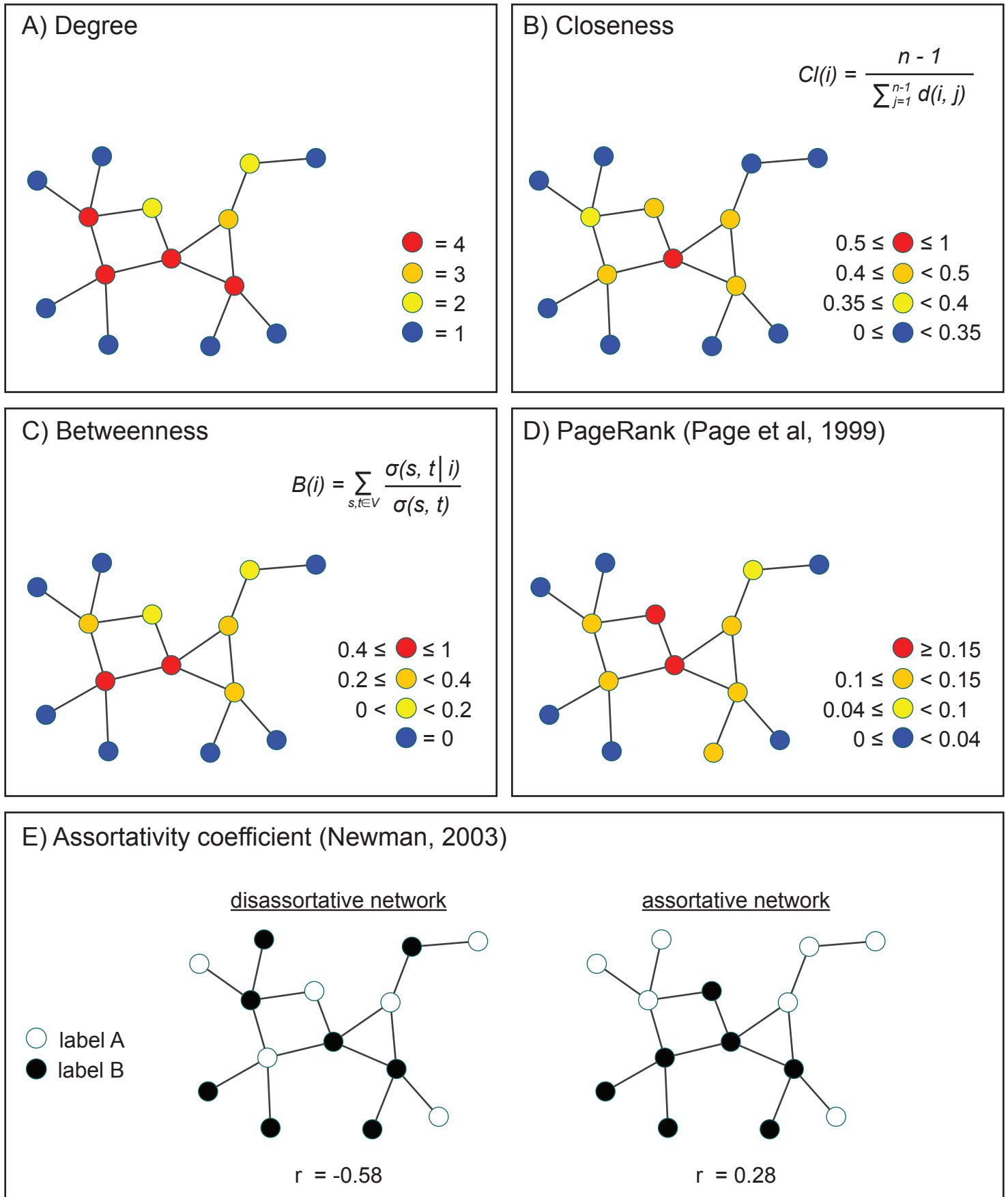


Figure S2



Figure S3

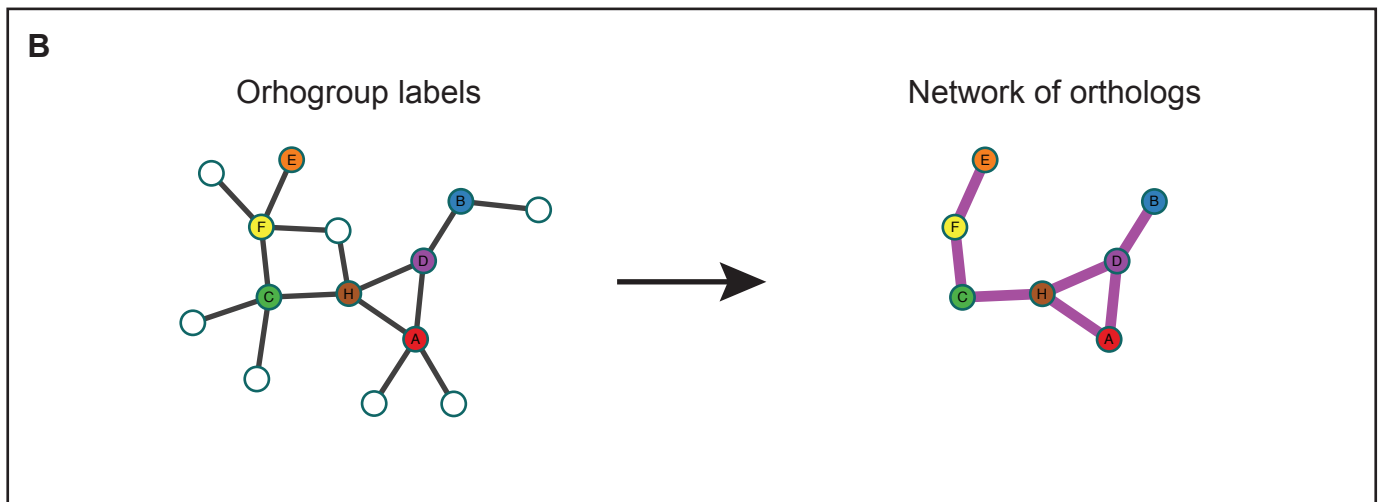
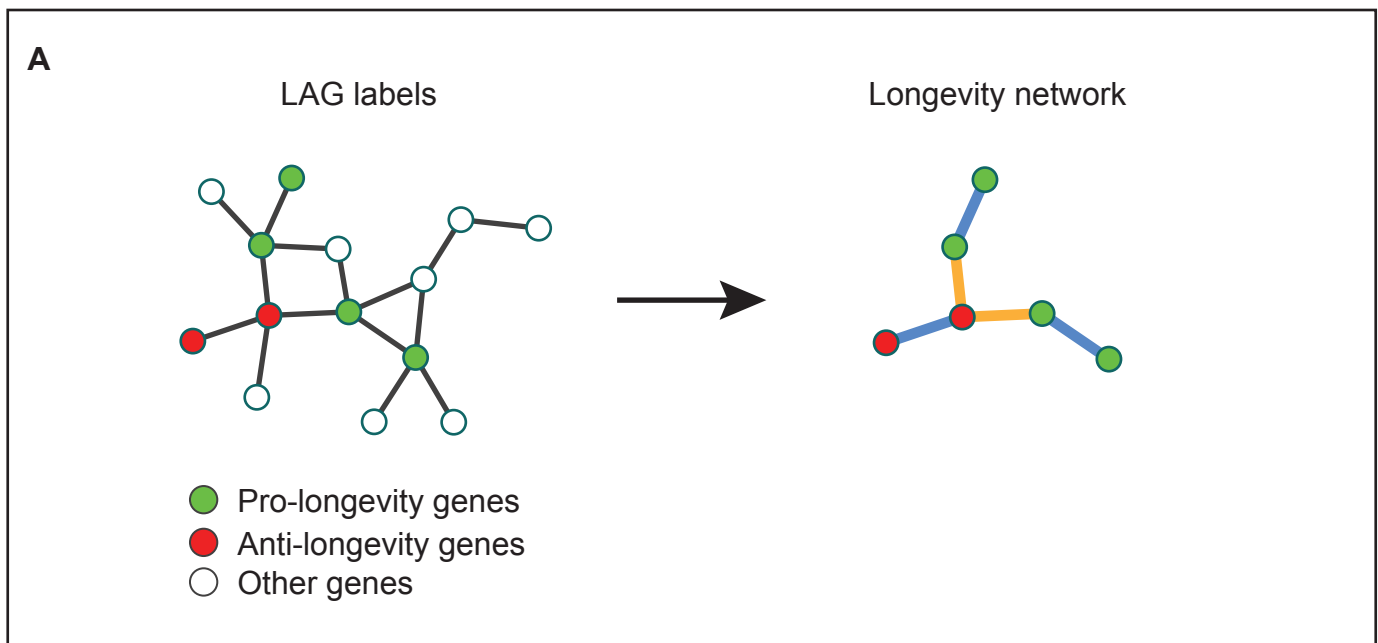


Figure S4

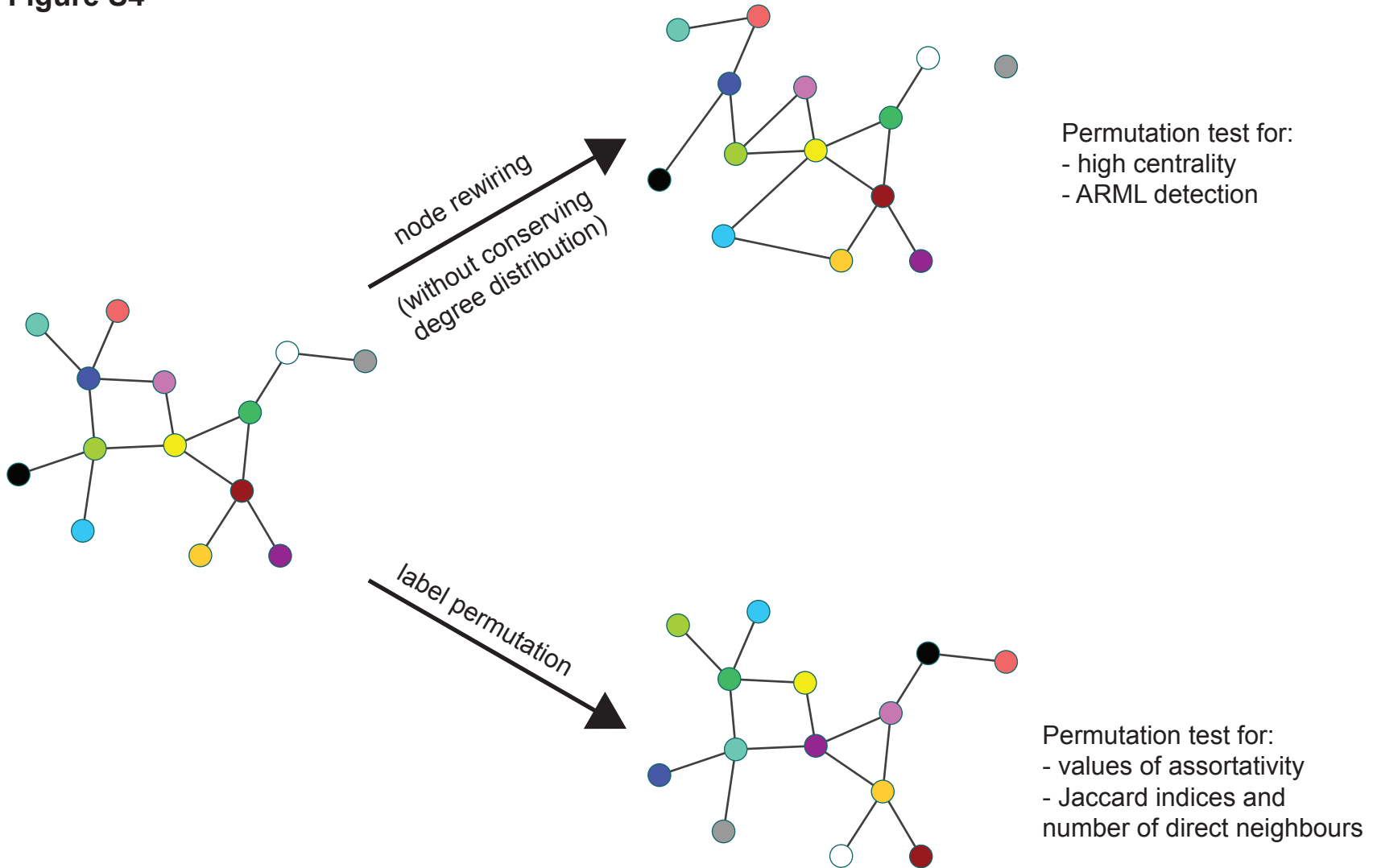
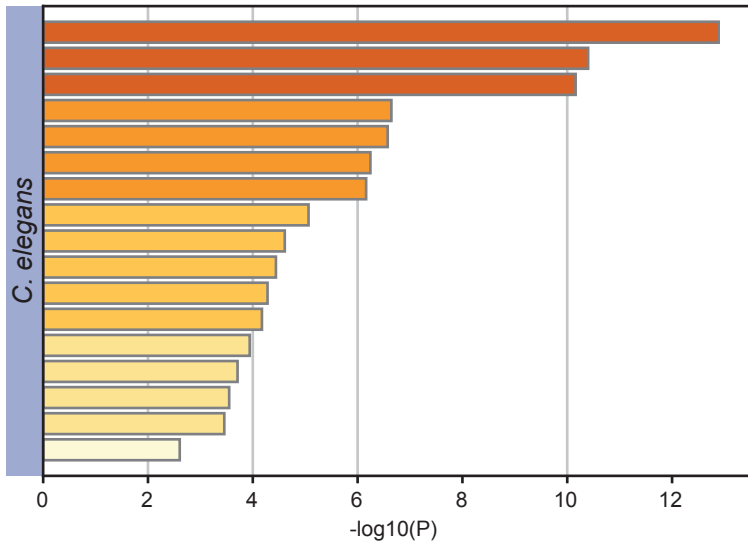


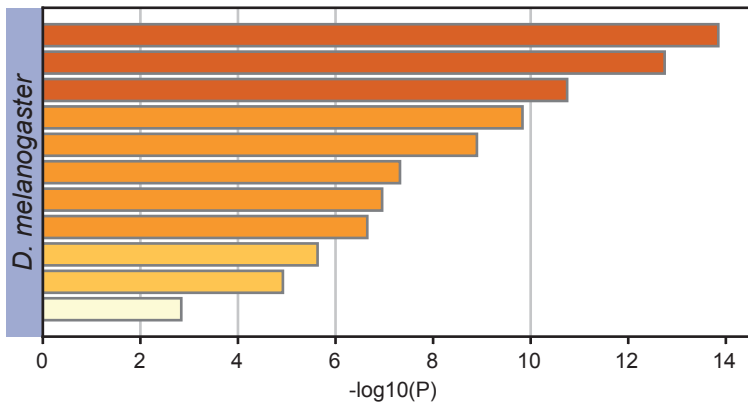
Figure S5

A



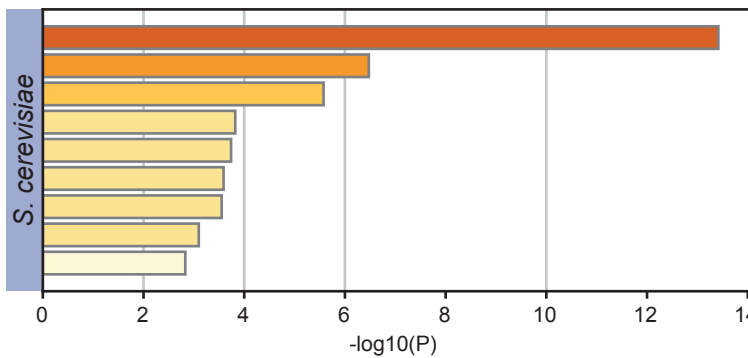
GO:0008340: determination of adult lifespan
GO:1902074: response to salt
GO:0051173: positive regulation of nitrogen compound metabolic process
GO:0008582: regulation of synaptic assembly at neuromuscular junction
GO:0010557: positive regulation of macromolecule biosynthetic process
GO:0006979: response to oxidative stress
GO:0009617: response to bacterium
GO:0022414: reproductive process
GO:0033554: cellular response to stress
GO:0007389: pattern specification process
GO:0045727: positive regulation of translation
GO:0006099: tricarboxylic acid cycle
GO:0040034: regulation of development, heterochronic
GO:1902115: regulation of organelle assembly
GO:0006351: transcription, DNA-templated
GO:0040028: regulation of vulval development
GO:0061061: muscle structure development

B



GO:0040014: regulation of multicellular organism growth
GO:0006979: response to oxidative stress
GO:0051239: regulation of multicellular organismal process
GO:0046620: regulation of organ growth
GO:0040012: regulation of locomotion
GO:0034599: cellular response to oxidative stress
GO:0006468: protein phosphorylation
GO:0010941: regulation of cell death
GO:0060259: regulation of feeding behavior
GO:0042325: regulation of phosphorylation
GO:0031399: regulation of protein modification process

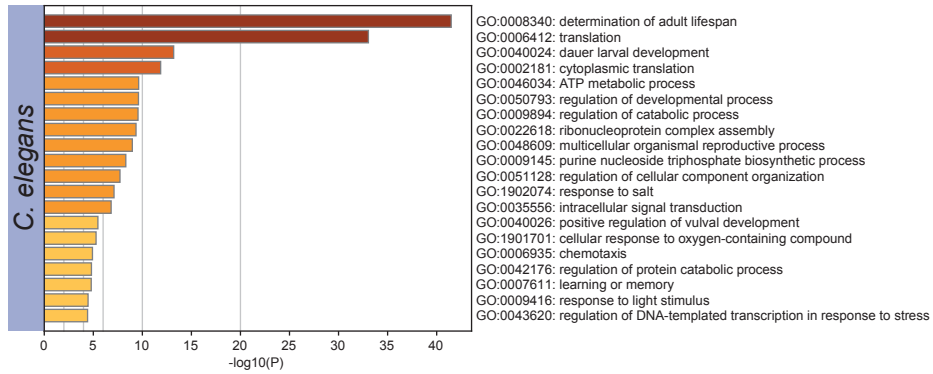
C



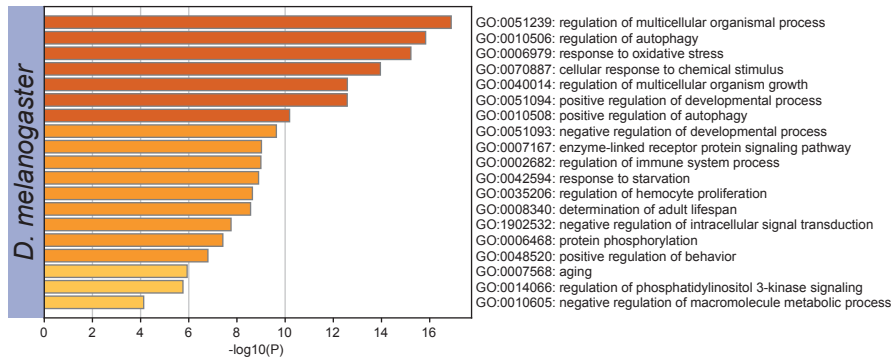
GO:0006091: generation of precursor metabolites and energy
GO:0006739: NADP metabolic process
GO:0046034: ATP metabolic process
GO:1905268: negative regulation of chromatin organization
GO:0022904: respiratory electron transport chain
GO:0072593: reactive oxygen species metabolic process
GO:0031570: DNA integrity checkpoint signaling
GO:0000041: transition metal ion transport
GO:0006006: glucose metabolic process

Figure S6

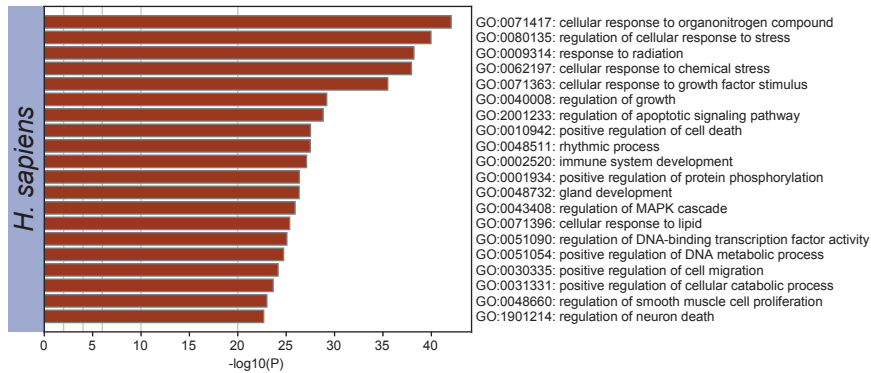
A



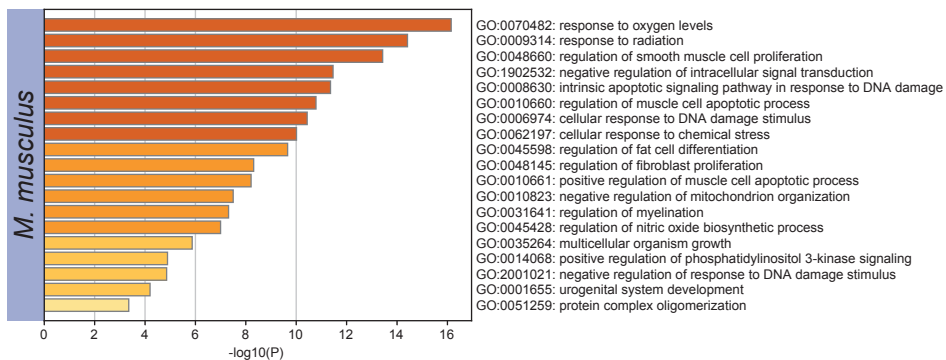
B



C



D



E

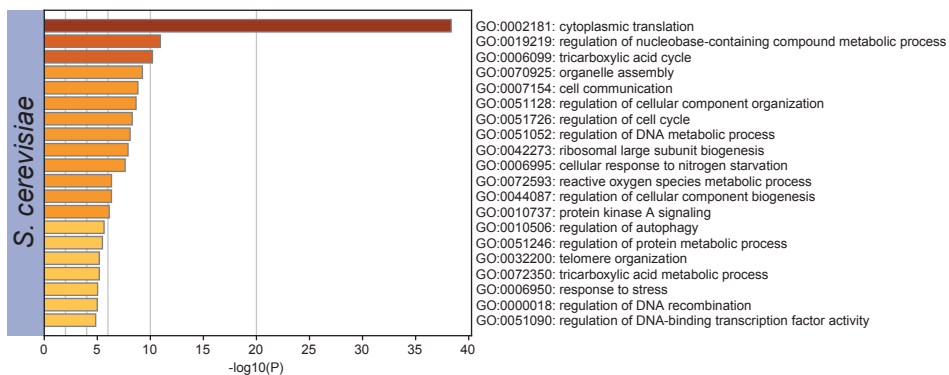


Figure S7

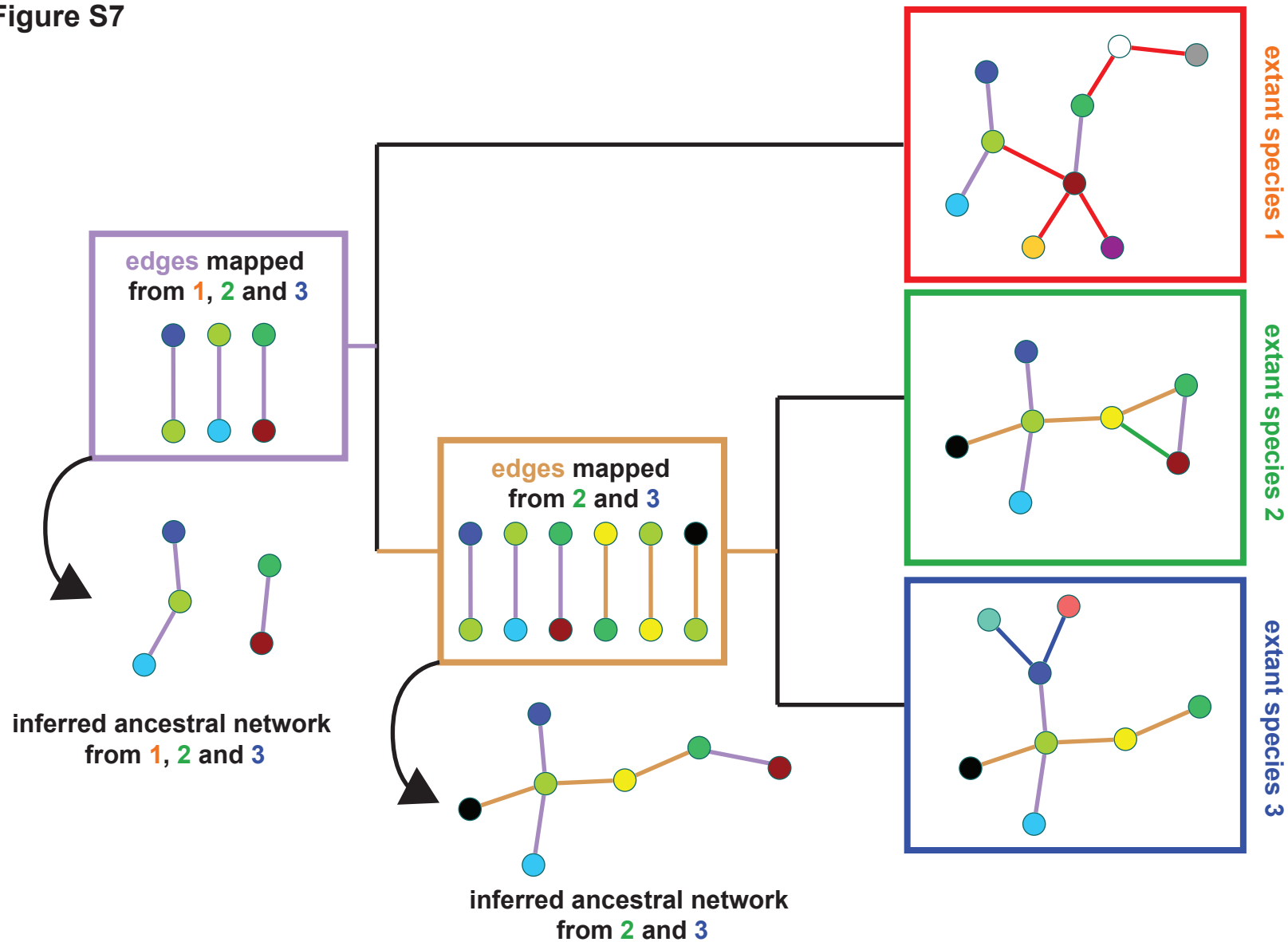


Figure S8

Proportion of ancestral
nodes / edges

Sc 29.7 19.9

Euarchontoglires ancestor

Hs 84.7 65.6

Mm 81.5 69.6

Ecdisozoan ancestor

Ce 26.9 17.3

Dm 36.8 31.4

Common ancestor

Bilaterian ancestor

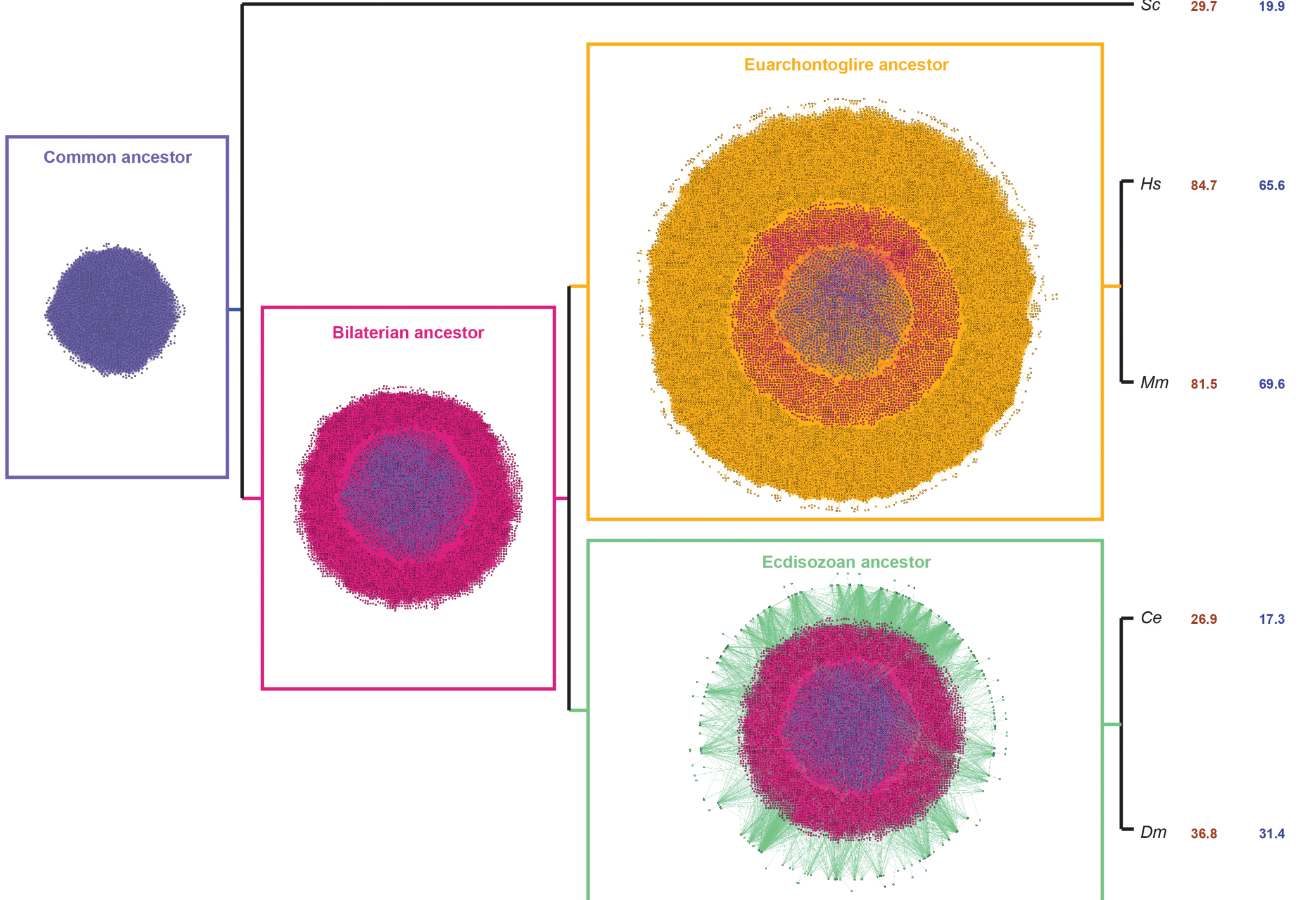
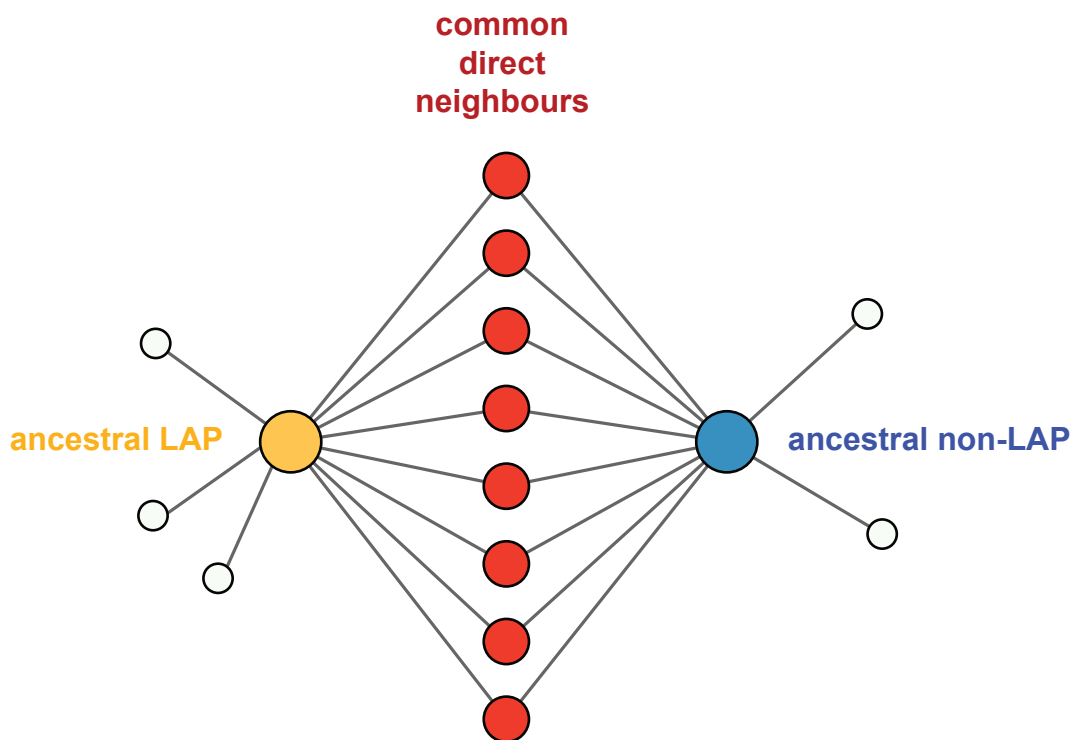


Figure S9



Number of common neighbours: 8
Total number of direct neighbours: 13

Jaccard index = 0.61 (8/13)

Figure S10

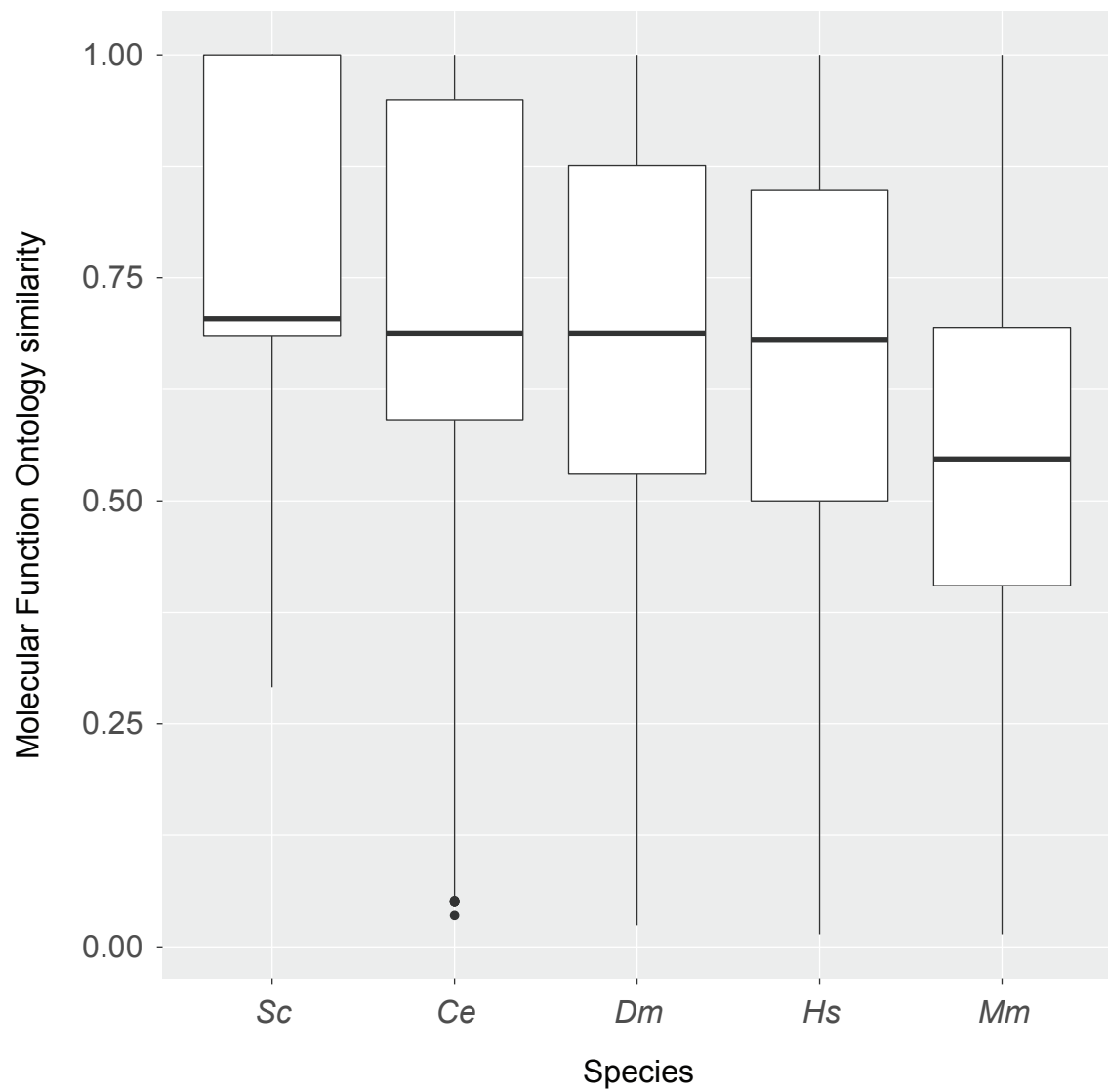
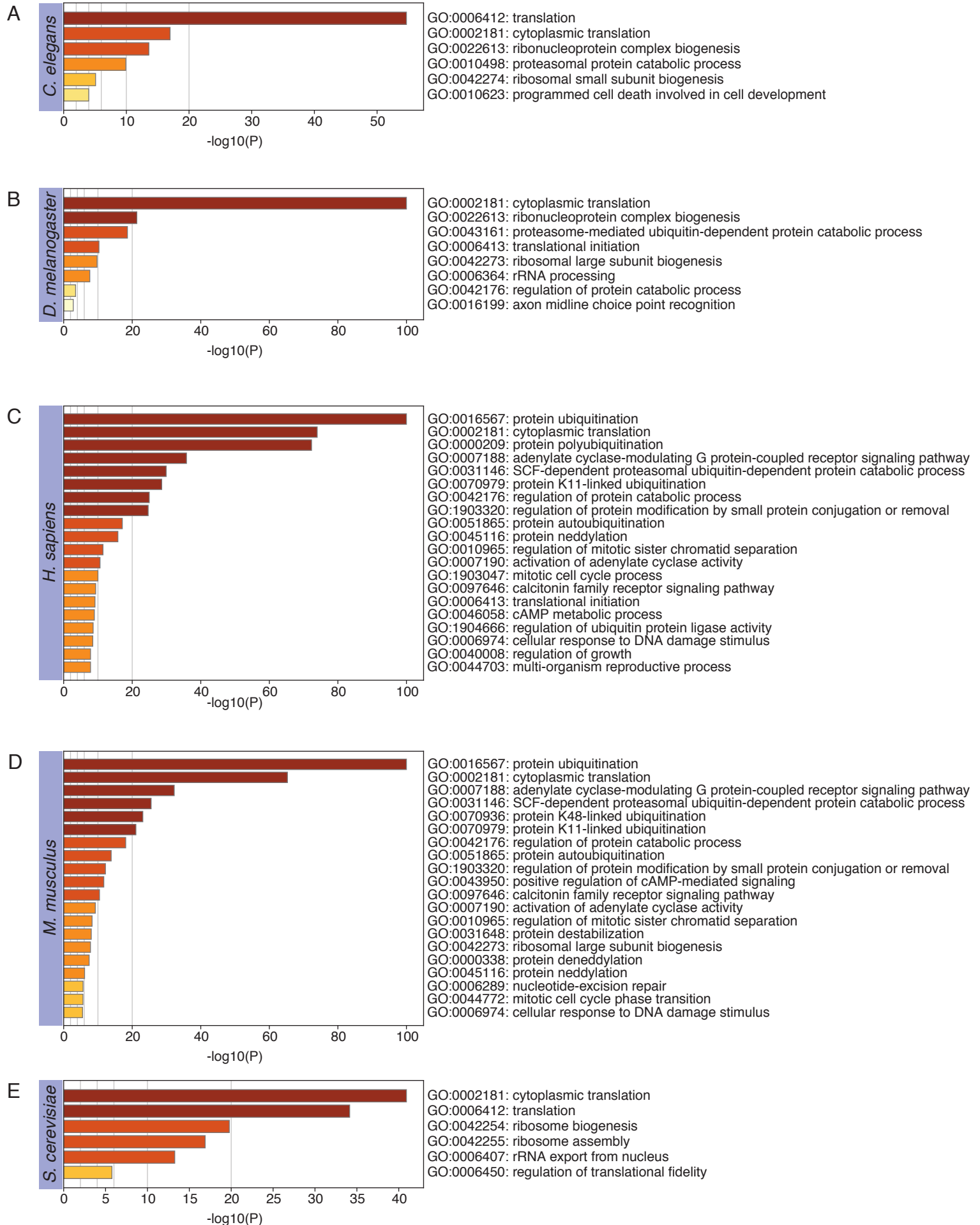


Figure S11



Hs_predictions

NFKBIE *	0	0	2	NA	NA	280.5	1	0	0	0	0	0	0	NA	NA	NA
GIP *	0	0	2	NA	NA	264.6	1	0	0	0	0	0	0	NA	NA	NA
HERC6 *	0	0	2	NA	NA	141.4	1	0	0	0	0	0	0	NA	NA	NA
CUL5 *	0	0	2	NA	NA	84.3	1	0	0	0	0	0	0	NA	NA	NA
TULP4	0	0	2	NA		236	1	0	0	0	0	0	0	NA	NA	NA
RLN2 *	0	0	2	NA	NA	273.2	1	0	0	0	0	0	0	1	1	NEOMYCIN (unknown)
MATN3 *	0	0	2	NA	NA	270.4	1	0	0	0	0	0	0	0	NA	NA
MKRN1 *	0	0	2	NA	NA	144	1	31476350	0	0	0	0	0	0	NA	NA
P2RX1 *	0	0	2	NA	NA	289.4	1	0	0	0	0	0	0	1	2	NA
STK10 *	0	0	2	NA	NA	302.6	1	0	0	0	0	0	0	1	3	BOSUTINIB (inhibitor)
MAPKAP1	0	0	3	NA	NA	308.8	1	0	0	0	0	0	0	0	3	NA
CCDC88A	0	0	3	NA	NA	325.2	1	0	0	0	0	0	0	0	NA	NA

Ce_predictions

Protein	Com	Bilate	Ecdis	ADR_common	ADR_bilaterian	ADR_ecdisozd	Predictors	Pubmed_ID	Wormbase
RPS-18	2	2	2	17,8	14,3	14	8	0	0
RPS-1	2	2	2	30,5	27,5	24,5	7	0	0
RPL-32 *	2	2	2	34,8	43,5	44,5	8	0	0
RPS-2 *	2	2	2	6	12,5	12,5	8	0	0
RPS-24	2	2	2	26,8	54,5	42	8	0	0
RPL-25.2 *	2	2	2	26,3	60	104,8	5	0	0
Y37E3.8 *	2	2	2	28,3	39,5	38,7	8	0	0
RPL-5 *	2	2	2	11,8	23,7	27,2	8	0	0
RLA-2	2	2	2	70,3	88,3	91	8	0	0
RPS-28 *	2	2	2	35,3	30,5	28,7	8	0	0
RPL-33 *	2	2	2	44,2	52,7	51,8	9	0	0
RPL-21	2	2	2	46	58	58	9	0	0
RPL-12	2	2	2	39,3	43,8	42,8	8	0	0
RPL-26	2	2	2	52	115,3	75	7	0	0
RPS-19 *	2	2	2	36,3	29	27,8	8	0	0
RPL-35	2	2	2	39,8	41,3	40,2	10	0	0
W01D2.1	2	2	2	58,7	96,3	89,2	6	0	0
RPL-41 *	2	2	2	48,2	64,5	56,7	8	0	0
RPL-15 *	2	2	2	29,7	40,3	41,3	8	0	0
RPS-13 *	2	2	2	9,3	14	14,8	8	0	0
RPL-34	2	2	2	64	68	64,2	8	0	0
RPS-7 *	2	2	2	30,2	90,3	51,5	7	0	0
RPS-9 *	2	2	2	20,2	17,2	16,3	8	0	1
RPL-43	2	2	2	44,3	48	48	8	0	0
RPL-11.2 *	2	2	2	29,8	31,7	30,5	8	0	0
RPL-20	2	2	2	35,2	47,3	49,3	9	0	0
RPS-29 *	2	2	2	45,7	30,2	26,8	8	0	1
RPS-27	2	2	2	64,3	128,3	83,3	3	0	1
RPL-13	2	2	2	58,7	59,5	54,2	9	0	0
RPS-17 *	2	2	2	48,3	69,8	68,2	6	0	0
RPL-18 *	2	2	2	49,8	77,8	66	7	0	0
ERFA-3 *	2	2	2	64,5	110,7	111,6	4	0	0
RPL-6	2	2	2	60,8	74,2	73,2	8	0	1
IFFB-1	0	2	2	58	88,3	90	8	0	0
RPL-16 *	0	2	2	48,5	111,5	66	7	0	0
RPN-8 *	0	2	2	112,3	134	88,2	1	0	1
RPL-29	0	2	2	53,7	98,3	78,8	6	0	0
UBC-16 *	0	2	2 NA		164,8	159	1	0	0
RPS-21	0	2	2	69,2	41,2	35,7	7	0	1
RPL-2 *	0	2	2 NA		58,5	41,8	8	0	0
RPN-1 *	0	2	2	102,7	124,3	84,7	1	0	1
C37C3.2 *	0	2	2	111,8	136,2	129,2	1	0	0
RPL-24.1 *	0	2	2	66,3	130,3	89,5	8	0	0
RPL-36 *	0	2	2	65,5	101,3	115	6	0	0
MRPL-11 *	0	2	2	102,7	99,2	93,8	2	0	0
RPL-11.1 *	0	2	2	71,6	147,4	144,8	3	15687263	1
EIF-3.I *	0	2	2	66,7	99,5	94,3	6	0	0
EIF-3.L *	0	2	2 NA		145,5	123,3	2	27690135	1
RPL-14 *	0	2	2	84,4	160,4	157,8	2	0	0
EIF-2ALPHA *	0	2	2	68,8	92,3	87	2	33723245	0
PAS-6 *	0	2	0	108,5	131,8	122	1	0	1
UBC-7 *	0	2	0 NA		157	150,6	1	0	0
W09C5.1 *	0	2	0	26,8	48,7	44	1	0	0
Y92H12A.2	0	2	0 NA		138,5	126,8	1	0	0
LIG-1 *	0	2	0	94,7	127	133	1	0	0
SPSB-2	0	2	0 NA		138	129,2	1	0	0
UBC-14 *	0	2	0	135,2	132,2	124	1	0	0
RPN-7 *	0	2	0	110	133,5	125,2	1	25093668	1

Ce_predictions

PBS-7 *	0	2	0	111,7	131,2	120,7	1	0	1
UBA-1	0	2	0	117,8	117,7	109	1	23354069	1
RPN-5 *	0	2	0	111	131,5	90	1	0	0
RPS-25 *	0	2	0	79,8	155,4	152,8	1	0	0
WDFY-3	0	3	3 NA		217,5	205,3	1	0	0
PBS-6 *	0	0	2	110,5	134	88,7	1	25093668	1
PAS-5 *	0	0	2	104,3	123,2	80,8	1	0	1
RPN-3 *	0	0	2	111,5	132,3	90,2	1	0	1
C48B6.2 *	0	0	2	35,2	40,2	32,7	1	0	0
F21D5.7 *	0	0	2	80,5	109,2	110	3	0	0
EIF-3.E *	0	0	2 NA		129,7	106,5	6	0	1
RPL-27 *	0	0	2 NA		NA	128	2	0	0
RPL-38 *	0	0	2 NA		NA	128	3	0	0
PAS-2 *	0	0	2	107,2	128,5	85,3	1	0	0
EIF-3.C *	0	0	2	80,8	97,2	82	1	0	0
TRX-2	0	0	3 NA		217,8	209	1	0	0

Dm_predictions

Protein	Com	Bilate	Ecdis	ADR_common	ADR_bilaterian	ADR_ecdisozc	Predictors	Pubmed_IL	Flybase
RpS23	2	2	2	17,2	20	19,5	8	0	0
RpS18	2	2	2	17,8	14,3	14	8	0	0
RpS3A	2	2	2	30,5	27,5	24,5	7	0	0
RpL32 *	2	2	2	34,8	43,5	44,5	8	0	0
RpS2 *	2	2	2	6	12,5	12,5	8	0	0
RpS24	2	2	2	26,8	54,5	42	8	0	0
RpL27A *	2	2	2	28,3	39,5	38,7	8	0	0
RpL30	2	2	2	34	42,2	45	8	0	0
RpL5 *	2	2	2	11,8	23,7	27,2	8	0	0
RpLP2	2	2	2	70,3	88,3	91	8	0	0
RpS28b *	2	2	2	35,3	30,5	28,7	8	0	0
RpL35A *	2	2	2	44,2	52,7	51,8	9	0	0
RpL21	2	2	2	46	58	58	9	0	0
RpL12	2	2	2	39,3	43,8	42,8	8	0	0
sta *	2	2	2	17,7	27,3	34,2	8	0	0
RpS5a	2	2	2	7	11,2	14,7	8	0	0
RpL26	2	2	2	52	115,3	75	7	0	0
RpS19a *	2	2	2	36,3	29	27,8	8	0	0
RpL35	2	2	2	39,8	41,3	40,2	10	0	0
RpL37a	2	2	2	58,7	96,3	89,2	6	0	0
RpL36A *	2	2	2	48,2	64,5	56,7	8	0	0
RpL31 *	2	2	2	66,3	68	75,8	7	0	0
RpL15 *	2	2	2	29,7	40,3	41,3	8	0	0
RpS15	2	2	2	25,8	22,2	19,2	8	0	0
RpS13 *	2	2	2	9,3	14	14,8	8	0	0
RpL34a	2	2	2	64	68	64,2	8	0	0
RpS7 *	2	2	2	30,2	90,3	51,5	7	0	0
RpS9 *	2	2	2	20,2	17,2	16,3	8	0	0
RpS16 *	2	2	2	17,7	26,7	34,8	8	0	0
RpL7A	2	2	2	34,8	53,5	57,3	8	0	0
RpS15Aa	2	2	2	19,5	34,2	42,7	8	0	0
RpL37A	2	2	2	44,3	48	48	8	0	0
RpS20	2	2	2	25	19,2	18	8	0	0
RpS8	2	2	2	11,5	19,3	21	7	0	0
RpL11 *	2	2	2	29,8	31,7	30,5	8	0	0
RpS14a	2	2	2	12,3	24,2	36,2	7	0	0
RpS11	2	2	2	12,5	11,3	13	6	0	0
RpS25 *	2	2	2	45	38	44	7	0	0
RpL18A	2	2	2	35,2	47,3	49,3	9	0	0
RpS29 *	2	2	2	45,7	30,2	26,8	8	0	0
RpS27	2	2	2	64,3	128,3	83,3	3	0	0
RpLP0	2	2	2	26,5	37,7	40,2	9	0	0
RpL13	2	2	2	58,7	59,5	54,2	9	0	0
RpS17 *	2	2	2	48,3	69,8	68,2	6	0	0
RpL3	2	2	2	16	29,7	28,2	8	0	0
RpL18 *	2	2	2	49,8	77,8	66	7	0	0
Elf *	2	2	2	64,5	110,7	111,6	4	0	0
RpL6	2	2	2	60,8	74,2	73,2	8	0	0
RpS3	2	2	2	5,8	8	8,2	8	30947023	0
eRF1 *	2	2	0	56	97,2	103,5	4	0	0
Atg4a	3	3	3	148,8	210,8	202,8	1	0	0
eIF5B	0	2	2	58	88,3	90	8	0	0
RpS10a	0	2	2	57,7	121,5	86,5	7	0	0
RpS10b *	0	2	2	NA	84,8	75,3	2	0	0
RpL13A *	0	2	2	48,5	111,5	66	7	0	0
RpL23	0	2	2	NA	57,3	39,3	8	0	0
Rpn8 *	0	2	2	112,3	134	88,2	1	0	0

Dm_predictions

RpL29	0	2	2	53,7	98,3	78,8	6	0	0
CG7220 *	0	2	2 NA		164,8	159	1	0	0
RpS26	0	2	2	52,3	115,8	78,3	7	0	0
RpS21	0	2	2	69,2	41,2	35,7	7	0	1
RpL7	0	2	2 NA		75,3	55,8	7	0	0
RpL8 *	0	2	2 NA		58,5	41,8	8	0	0
Rpn1 *	0	2	2	102,7	124,3	84,7	1	29615416	0
eIF5 *	0	2	2	111,8	136,2	129,2	1	0	1
RpL24 *	0	2	2	66,3	130,3	89,5	8	0	0
Rack1	0	2	2	20,7	49,8	52,7	9	24277934	1
mRpL11 *	0	2	2	102,7	99,2	93,8	2	0	1
Trip1 *	0	2	2	66,7	99,5	94,3	6	0	0
eIF3I *	0	2	2 NA		145,5	123,3	2	0	0
RpL28 *	0	2	2 NA		113,3	105,7	6	0	0
eIF-2alpha *	0	2	2	68,8	92,3	87	2	0	0
Prosalph6 *	0	2	0	108,5	131,8	122	1	0	0
CG40045 *	0	2	0 NA		157	150,6	1	0	0
Ip259 *	0	2	0	26,8	48,7	44	1	0	0
eIF3g1 *	0	2	0	79,5	115,5	123,3	2	0	0
Ube3a *	0	2	0 NA		149,8	141,7	1	0	0
Nedd4	0	2	0 NA		138,5	126,8	1	0	0
DNA-ligl *	0	2	0	94,7	127	133	1	0	0
CG17754 *	0	2	0 NA		166	163,4	1	0	0
gus	0	2	0 NA		138	129,2	1	0	0
CG3356 *	0	2	0 NA		160,2	157,6	1	0	0
Trim9	0	2	0 NA		159	152	1	0	0
CG33981 *	0	2	0 NA		167	164,4	1	0	0
Ubc7 *	0	2	0	135,2	132,2	124	1	0	0
RpS19b *	0	2	0	70,8	146	143,4	1	0	0
Rpn7 *	0	2	0	110	133,5	125,2	1	0	1
RpS28a *	0	2	0	50,6	125,2	122,6	1	0	0
RpL36 *	0	2	0	73,3	137,8	132,2	2	0	0
poe *	0	2	0 NA		133,6	131	1	0	0
Kpc1 *	0	2	0 NA		164,6	162	1	0	0
eIF3-S10 *	0	2	0	97	122,8	122,3	1	0	0
jet *	0	2	0 NA		135,3	127,2	1	0	0
Ppa *	0	2	0 NA		137,2	129	1	0	0
Prosbeta4 *	0	2	0	110,3	137,7	139	1	0	0
Prosbeta7 *	0	2	0	111,7	131,2	120,7	1	0	1
Uba1	0	2	0	117,8	117,7	109	1	23382794	1
CG32085 *	0	2	0 NA		148,8	146,2	1	0	0
Ubr1 *	0	2	0 NA		162,8	160,2	1	0	0
Prosbeta2 *	0	2	0	117	145,3	143,3	1	0	0
Ubc4 *	0	2	0	131,3	139,3	137	1	0	0
Rpn5 *	0	2	0	111	131,5	90	1	0	0
eIF-2beta *	0	2	0	101,5	127	126,2	2	0	0
RpS4	0	2	0	33,7	96,7	91	1	0	0
Iru *	0	2	0 NA		170,2	167,6	1	0	0
Prosbeta6 *	0	0	2	110,5	134	88,7	1	0	0
Prosalph5 *	0	0	2	104,3	123,2	80,8	1	0	0
Rpn3 *	0	0	2	111,5	132,3	90,2	1	0	1
CG4866 *	0	0	2	35,2	40,2	32,7	1	0	0
Srp54k *	0	0	2	80,5	109,2	110	3	0	0
Int6 *	0	0	2 NA		129,7	106,5	6	0	0
RpL27 *	0	0	2 NA	NA		128	2	0	0
RpL38 *	0	0	2 NA	NA		128	3	0	0
Prosalph2 *	0	0	2	107,2	128,5	85,3	1	0	0
eIF3-S8 *	0	0	2	80,8	97,2	82	1	0	0

				Dm_predictions					
eIF3-S9	0	0	2	63,5	86,3	74,5	1	0	0
Srp14 *	0	0	2 NA		178	175,4	1	0	0
Glo1	0	0	3 NA		217,8	209,7	1	34734976	1
CG8993	0	0	3 NA		217,8	209	1	0	0

Mm_predictions

Protein	Coml	Bilate	Euar	ADR_common	ADR_bilaterian	ADR_euarchol	Predictors	Pubmed_ID
Rpl21	2	2	2	46	58	160,5	9	0
Rpl6	2	2	2	60,8	74,2	166,2	9	0
Etf1 *	2	2	0	56	97,2	175,7	4	0
Rps23	2	2	0	17,2	20	78,5	7	0
Rps18	2	2	0	17,8	14,3	76,8	8	0
Rps3a1	2	2	0	30,5	27,5	90,2	7	0
Rpl32 *	2	2	0	34,8	43,5	132,2	8	0
Rps2 *	2	2	0	6	12,5	74,5	5	34103648
Rps24	2	2	0	26,8	54,5	190,5	6	0
Rpl23a *	2	2	0	26,3	60	145,3	5	0
Rpl27a *	2	2	0	28,3	39,5	126,2	8	0
Rpl30	2	2	0	34	42,2	123	8	0
Rpl5 *	2	2	0	11,8	23,7	100	8	0
Rplp2	2	2	0	70,3	88,3	185	8	0
Rps28 *	2	2	0	35,3	30,5	101,7	5	0
Rpl35a *	2	2	0	44,2	52,7	140,3	9	0
Rpl12	2	2	0	39,3	43,8	144,2	8	0
Rpsa *	2	2	0	17,7	27,3	105	8	0
Rps5	2	2	0	7	11,2	65,7	7	0
Rps19 *	2	2	0	36,3	29	100,8	8	0
Rpl35	2	2	0	39,8	41,3	145,5	7	0
Rpl37	2	2	0	58,7	96,3	220,5	5	0
Rpl36al *	2	2	0	48,2	64,5	174,5	8	0
Rpl31 *	2	2	0	66,3	68	148,3	7	0
Rps7	2	2	0	22,2	82,3	110,5	2	0
Rpl15 *	2	2	0	29,7	40,3	132,8	8	0
Rps15	2	2	0	25,8	22,2	99,2	8	31921849
Rps13 *	2	2	0	9,3	14	71,3	6	0
Rpl34	2	2	0	64	68	161	8	0
Rps9 *	2	2	0	20,2	17,2	68,3	7	0
Rps16 *	2	2	0	17,7	26,7	94,7	6	0
Rpl7a	2	2	0	34,8	53,5	160,7	8	0
Rps15a	2	2	0	19,5	34,2	89,2	3	0
Rpl37a	2	2	0	44,3	48	128,2	6	0
Rps20	2	2	0	25	19,2	88,5	7	0
Rps8	2	2	0	11,5	19,3	82,8	6	0
Rpl11 *	2	2	0	29,8	31,7	106,3	8	0
Rps14	2	2	0	12,3	24,2	70,5	7	0
Rps11	2	2	0	12,5	11,3	67,8	6	0
Rps25 *	2	2	0	45	38	106,7	7	0
Rpl18a	2	2	0	35,2	47,3	136	9	0
Rps29 *	2	2	0	45,7	30,2	112,3	8	0
Rplp0	2	2	0	26,5	37,7	129,2	9	0
Rpl13	2	2	0	58,7	59,5	150,8	8	0
Rps17 *	2	2	0	48,3	69,8	166	5	0
Rpl3	2	2	0	16	29,7	116	8	0
Rpl18 *	2	2	0	49,8	77,8	204,7	6	0
Rps3	2	2	0	5,8	8	59,3	7	0
Atg4b	3	3	0	148,8	210,8	308,3	1	0
Ube2g1 *	0	2	2 nan		157	127,5	2	0
Ube3a *	0	2	2 nan		149,8	111,2	2	0
Nedd4 *	0	2	2 nan		138,5	105	2	0
Keap1	0	2	2 nan		147,8	81,3	2	32590331;32487458;33318486
Klh5 *	0	2	2 nan		166	108	2	0
Spsb4 *	0	2	2 nan		138	104,2	2	0
Ube3c *	0	2	2 nan		160,2	131,2	2	0
Trim9	0	2	2 nan		159	128,5	2	0
Anapc13 *	0	2	2 nan		167	119,2	2	0
Ube2g2 *	0	2	2	135,2	132,2	116,5	2	0
Ubr4 *	0	2	2 nan		133,6	57,8	2	0
Rnf123 *	0	2	2 nan		164,6	124,8	2	0

Mm_predictions

Fbxl15 *	0	2	2	nan	135,3	97,5	2	0
Fbxl14 *	0	2	2	nan	137,2	103	2	0
Uba1 *	0	2	2	117,8	117,7	106,7	2	0
Ubr2 *	0	2	2	nan	162,8	135,8	2	0
Ube2k *	0	2	2	131,3	139,3	116,7	2	0
Eif5b	0	2	0	58	88,3	198,3	4	0
Psm1 *	0	2	0	108,5	131,8	223	1	0
Rps10 *	0	2	0	nan	84,8	148,7	2	0
Nsa2 *	0	2	0	26,8	48,7	134,7	1	0
Rpl38 *	0	2	0	58,7	122,3	162,5	1	0
Eif3g *	0	2	0	79,5	115,5	209,8	2	0
Rpl23	0	2	0	nan	57,3	111,8	6	0
Psm7 *	0	2	0	112,3	134	154	1	0
Lig1 *	0	2	0	94,7	127	206,3	1	0
Rpl29	0	2	0	53,7	98,3	274	5	0
Rps21	0	2	0	69,2	41,2	117,3	6	0
Rpl7	0	2	0	nan	75,3	147,8	2	0
Rpl8 *	0	2	0	nan	58,5	107,8	5	0
Psm2 *	0	2	0	102,7	124,3	144,2	1	0
Eif5 *	0	2	0	111,8	136,2	241,8	1	0
Gnb2l1	0	2	0	20,7	49,8	128,7	6	0
Rpl36 *	0	2	0	65,5	101,3	180,2	6	0
Mrpl11 *	0	2	0	102,7	99,2	187	1	0
Psm6 *	0	2	0	110	133,5	150,5	1	0
Eif3a *	0	2	0	97	122,8	221,5	1	0
Eif3i *	0	2	0	66,7	99,5	206	5	0
Eif3l *	0	2	0	nan	145,5	239,8	1	0
Psmb2 *	0	2	0	110,3	137,7	149,3	1	0
Rpl28 *	0	2	0	nan	113,3	192,7	2	0
Psmb4 *	0	2	0	111,7	131,2	146,8	1	0
Fbxl16 *	0	2	0	nan	148,8	103,3	1	0
Psmb7 *	0	2	0	117	145,3	162,8	1	0
Eif2s1 *	0	2	0	68,8	92,3	191	1	0
Psm12 *	0	2	0	111	131,5	150,8	1	0
Eif2s2 *	0	2	0	101,5	127	226,2	2	0
Rnf126	0	2	0	nan	170,2	292,8	1	0
Rpl27 *	0	2	0	59,5	123	182,3	1	0
Wdfy3	0	3	0	nan	217,5	312,2	1	0
Blm	0	0	1	nan	nan	236,8	2	0
Bard1 *	0	0	1	nan	nan	233,5	2	0
Rnf19a *	0	0	2	nan	nan	139,2	1	0
Mepe *	0	0	2	nan	nan	274,2	1	0
Fem1b	0	0	2	nan	215,8	213,5	1	0
Commd2 *	0	0	2	nan	184	186,2	1	0
Fbxo40 *	0	0	2	nan	nan	111,5	1	0
Wsb1 *	0	0	2	nan	nan	111	1	0
Fbxl18 *	0	0	2	nan	nan	116,4	1	0
Spsb2 *	0	0	2	nan	nan	117,4	1	0
Ube2o *	0	0	2	nan	164,4	133	1	0
Gan *	0	0	2	nan	nan	110,5	1	0
Asb14 *	0	0	2	nan	nan	116,6	1	0
Hrc *	0	0	2	nan	nan	277	1	0
Commd9 *	0	0	2	nan	nan	210,8	1	0
Fbxl3 *	0	0	2	nan	nan	102,3	1	0
Lrsam1 *	0	0	2	nan	nan	147,8	1	0
Ercc3	0	0	2	107	123,5	179,7	2	0
Rnf182 *	0	0	2	nan	nan	150,4	1	0
Dcun1d2	0	0	2	nan	nan	214,4	1	0
Serpinb3a *	0	0	2	nan	264	303,6	1	0
Cdca8 *	0	0	2	nan	nan	183	1	0
Kctd6 *	0	0	2	nan	nan	115	1	0
Adm *	0	0	2	nan	nan	272,2	3	29187812

Mm_predictions

Klhl3 *	0	0	2	nan	nan	114,4	1	0
Adam8 *	0	0	2	nan	nan	278,4	1	0
Asb18 *	0	0	2	nan	nan	117,6	1	0
Gpr20 *	0	0	2	nan	nan	272,6	1	0
Mib2 *	0	0	2	nan	147,3	125	1	0
Mapk11	0	0	2	155,2	203,5	223,2	1	0
Asb1 *	0	0	2	nan	nan	113,8	1	0
Fbxo4 *	0	0	2	nan	nan	107	1	0
Kras *	0	0	2	nan	nan	114,7	1	0
Chrn4 *	0	0	2	nan	nan	272,6	1	0
Asb4 *	0	0	2	nan	nan	111	1	0
Ube2j2 *	0	0	2	137,8	182,5	129,7	1	0
Trim37 *	0	0	2	nan	nan	149,8	1	0
Asb9 *	0	0	2	nan	nan	116	1	0
Uba7 *	0	0	2	nan	nan	128	1	0
Slc15a4 *	0	0	2	164,8	245	300,6	1	0
Trim71 *	0	0	2	nan	nan	138,2	1	0
Itch *	0	0	2	nan	nan	84,7	1	0
Hectd2 *	0	0	2	nan	nan	141,8	1	0
Commd3 *	0	0	2	nan	219,8	190,3	1	0
Trip12 *	0	0	2	142	222,2	103,8	1	0
Rnf41 *	0	0	2	nan	165	121,5	1	0
Gpr45 *	0	0	2	nan	nan	273,2	1	0
Fbxo10 *	0	0	2	nan	nan	115,6	1	0
Klhl21 *	0	0	2	nan	nan	116,8	1	0
Rnf144b *	0	0	2	nan	nan	146,8	1	0
Asb7 *	0	0	2	nan	nan	114,6	1	0
Gpr25 *	0	0	2	nan	nan	272,6	2	0
Mex3c *	0	0	2	nan	nan	148,4	1	0
Htr7 *	0	0	2	nan	nan	267,2	2	0
Klhl11 *	0	0	2	nan	nan	110,8	1	0
Cops3	0	0	2	nan	161	153	1	0
Asb17 *	0	0	2	nan	nan	116,8	1	0
lapp *	0	0	2	nan	nan	264	3	0
Cd53 *	0	0	2	nan	nan	278,2	1	0
Klhl2 *	0	0	2	nan	146,2	101,5	1	0
Are1 *	0	0	2	nan	165,6	138,2	1	0
Asb10 *	0	0	2	nan	nan	115,8	1	0
Calcrl *	0	0	2	nan	285	271,8	2	0
Fbxw7 *	0	0	2	nan	189,8	87,7	1	0
Ube2h	0	0	2	136,2	145,2	126,5	1	0
Ube2z *	0	0	2	nan	nan	147,2	1	0
Klhl42 *	0	0	2	nan	nan	115	1	0
Adcyap1r1 *	0	0	2	nan	nan	269,4	2	0
Dtx3l *	0	0	2	nan	nan	145,2	1	0
Adcy6 *	0	0	2	nan	nan	217,6	1	0
Asb2 *	0	0	2	nan	nan	108,8	1	0
Cblb *	0	0	2	nan	nan	110,5	1	0
Uba5 *	0	0	2	nan	141,5	122,7	1	0
Adcy3 *	0	0	2	nan	230	189,5	1	0
Mmp25	0	0	2	nan	nan	296,6	1	0
Taar2 *	0	0	2	nan	nan	273,8	3	0
Gpr176 *	0	0	2	nan	nan	273,6	3	0
Crhr1 *	0	0	2	nan	nan	258,8	2	0
Rnf34 *	0	0	2	nan	nan	148,4	1	0
Ifna2 *	0	0	2	nan	nan	340,2	1	0
Myip *	0	0	2	nan	164,8	127,2	1	0
Asb16 *	0	0	2	nan	nan	117,8	1	0
Mc4r *	0	0	2	nan	nan	229,2	2	0
Klhl9 *	0	0	2	nan	nan	116,2	1	0
Fbxo11 *	0	0	2	nan	129,7	95,2	1	0
Pth1r *	0	0	2	nan	nan	240,2	2	0

Mm_predictions

Adcyap1 *	0	0	2	nan	nan	267,6	1	29774542;16505386	
Traf7 *	0	0	2	nan	nan	151	1		0
Ube2l6 *	0	0	2	nan	nan	117,2	1		0
Cops7b *	0	0	2	nan	163,8	160,2	1		0
Commd1 *	0	0	2	nan	nan	206,6	1		0
Tacr1 *	0	0	2	nan	nan	133,2	1		0
Kctd7 *	0	0	2	nan	nan	111,6	1		0
Fbxo9	0	0	2	154,2	135	97,8	1		0
Fbxw2 *	0	0	2	nan	nan	109,5	1		0
Adcy8 *	0	0	2	nan	247	190,7	2		0
Anapc1 *	0	0	2	nan	117	70,2	1		0
Kbtbd13 *	0	0	2	nan	nan	111,4	1		0
Pja1 *	0	0	2	nan	nan	138,2	1		0
Fbxl8 *	0	0	2	nan	nan	118	1		0
Igfbp4 *	0	0	2	nan	nan	273,2	1	32223893	
Klhl20 *	0	0	2	nan	146,8	103,8	1		0
Adcy1	0	0	2	nan	229	213,8	2		0
Btbd6 *	0	0	2	nan	nan	113	1		0
Pthlh *	0	0	2	nan	nan	258,4	1		0
Calca *	0	0	2	nan	nan	273,6	2		0
Hectd3 *	0	0	2	nan	nan	151,2	1		0
Rap2b *	0	0	2	nan	nan	282,8	1		0
Asb5 *	0	0	2	nan	nan	116,2	1		0
Il13ra2 *	0	0	2	nan	nan	309,3	1		0
Fam20c *	0	0	2	nan	nan	245	1		0
Fbxl5 *	0	0	2	nan	nan	107,2	1		0
Trim50 *	0	0	2	nan	nan	150,6	1		0
Klhl25 *	0	0	2	nan	nan	117	1		0
Fbxw9 *	0	0	2	nan	213	113,6	1		0
Mnat1 *	0	0	2	nan	133,3	170,5	2		0
Ccnh *	0	0	2	116,5	134	171	2		0
Ramp1 *	0	0	2	nan	nan	272,2	2		0
Cul7 *	0	0	2	nan	nan	135,7	1		0
Rxfp1 *	0	0	2	nan	nan	267	2		0
Ube2q2 *	0	0	2	nan	nan	149,2	1		0
Taar5 *	0	0	2	nan	nan	271,6	1		0
Trim69 *	0	0	2	nan	nan	150,2	1		0
Trpm2	0	0	2	nan	nan	281,8	1	30999030	
Rchy1 *	0	0	2	nan	nan	126,2	1		0
Ube2e2 *	0	0	2	nan	nan	147,6	1		0
Pth2r *	0	0	2	nan	nan	272,8	1		0
Rnf19b *	0	0	2	nan	nan	148,2	1		0
Htr4 *	0	0	2	nan	nan	272,2	2		0
Huwe1 *	0	0	2	nan	162,4	119,7	1	22187431	
Fbxw8 *	0	0	2	nan	nan	110,3	1		0
Asb11 *	0	0	2	nan	nan	116,8	1		0
Mc2r *	0	0	2	nan	nan	267,6	1		0
Fbxo21 *	0	0	2	nan	nan	116,8	1		0
Siah1a *	0	0	2	nan	150,2	123,7	1		0
Wsb2 *	0	0	2	nan	nan	216,2	1		0
Vipr1 *	0	0	2	nan	nan	269,4	2		0
Aurkb *	0	0	2	nan	nan	92,8	2		0
Mc3r *	0	0	2	nan	nan	267	3		0
Gpr150	0	0	2	nan	nan	272,2	2		0
Cdc26 *	0	0	2	nan	nan	85,8	1	34590680	
Rlim *	0	0	2	nan	nan	136,3	1		0
Kbtbd7 *	0	0	2	nan	nan	114,8	1		0
Znrf2 *	0	0	2	nan	nan	143,4	1		0
Ptger2 *	0	0	2	nan	nan	271,4	2		0
Rnf25 *	0	0	2	nan	nan	141,3	1		0
Ubox5 *	0	0	2	nan	162,2	120,2	1		0
Nuf2 *	0	0	2	nan	nan	214,6	1		0

Mm_predictions

Wwp1 *	0	0	2	nan	nan	113,7	1	0
Glp1r *	0	0	2	nan	nan	268,4	2	0
Ube2d2a *	0	0	2	126,8	195	66	1	0
Lrr1 *	0	0	2	nan	147,8	98,6	1	0
Smurf2 *	0	0	2	nan	nan	85,2	1	28387615;24494704
Ptges2 *	0	0	2	nan	249,8	260,2	1	0
Nup214 *	0	0	2	nan	179,8	243,2	1	0
Vprbp *	0	0	2	nan	144,7	113,3	1	32730228
Gtf2h1 *	0	0	2	nan	142,5	194,3	2	0
Vhl *	0	0	2	nan	nan	67,2	1	23999831
Taar8b *	0	0	2	nan	nan	274,2	2	0
Ube2cbp *	0	0	2	nan	nan	145,8	1	0
Rnf130 *	0	0	2	nan	nan	146,6	1	0
Trim36 *	0	0	2	nan	nan	147,4	1	0
Commd7 *	0	0	2	nan	nan	211	1	0
Gtf2h2	0	0	2	108,7	128,5	189,3	2	0
Bub1 *	0	0	2	nan	181,7	139,8	1	0
Ube2e3 *	0	0	2	nan	150,2	124,7	1	0
Man2b1 *	0	0	2	nan	250,8	302	1	0
Pik3cd *	0	0	2	nan	nan	219,8	1	0
Fbxo17 *	0	0	2	nan	nan	113,2	1	0
Chrdl1 *	0	0	2	nan	nan	275,8	1	0
Trim63 *	0	0	2	nan	nan	137	1	29717119
Clec5a *	0	0	2	nan	nan	251,3	1	0
Ramp3 *	0	0	2	nan	nan	271,8	3	0
Cdkn1b *	0	0	2	nan	nan	222,5	1	0
Ramp2 *	0	0	2	nan	nan	272	1	0
Asb15 *	0	0	2	nan	nan	111,4	1	0
Fbxw5 *	0	0	2	nan	132,5	85,5	1	0
Park2	0	0	2	nan	131,7	93,5	1	0
Cul2 *	0	0	2	nan	96,3	62,8	1	0
Uba3 *	0	0	2	131,7	130	111,8	1	0
Ercc5	0	0	2	118,5	168	253,8	2	0
Nhlrc3 *	0	0	2	nan	nan	305	1	0
Fbxo27 *	0	0	2	nan	nan	113,2	1	0
Gtf2h3 *	0	0	2	113,8	137,3	190,8	2	0
Ube4a	0	0	2	133	137,2	117,8	1	0
Socs5 *	0	0	2	nan	nan	208,8	1	0
Ubac1 *	0	0	2	nan	nan	135,7	1	0
Ltn1 *	0	0	2	nan	152	118,8	1	0
Fem1a *	0	0	2	nan	nan	241,8	1	0
Smurf1 *	0	0	2	nan	141,3	103	1	0
Rnf115 *	0	0	2	nan	nan	139,5	1	0
Atp11a *	0	0	2	nan	nan	281,2	1	0
Klhl13 *	0	0	2	nan	nan	115	1	0
Lhcgr *	0	0	2	nan	nan	263,8	2	0
Fbxo7 *	0	0	2	nan	nan	109,4	1	0
Anapc10 *	0	0	2	nan	117,8	73	1	0
Adcy4 *	0	0	2	nan	245,8	214,4	2	0
Det1 *	0	0	2	nan	161,8	120,6	1	0
Rnf6 *	0	0	2	nan	nan	149,6	1	0
Htr6 *	0	0	2	nan	nan	243,7	1	0
Fbxl4 *	0	0	2	nan	147,4	103,2	1	0
Xrcc1 *	0	0	2	nan	194,6	276,2	2	0
Ano8 *	0	0	2	nan	nan	277,8	1	0
Atp8b4 *	0	0	2	nan	nan	284	2	0
Crhr2 *	0	0	2	nan	295	238,8	1	0
Dcun1d3 *	0	0	2	nan	nan	240,8	1	0
Ube3b *	0	0	2	nan	152,7	131,2	1	0
Cyba *	0	0	2	nan	nan	233,2	1	0
Ube2v2 *	0	0	2	nan	nan	106,5	1	0
Csf1 *	0	0	2	nan	nan	212,7	1	0

Mm_predictions

Pth *	0	0	2	nan	nan	239,8	1	0
Nup93 *	0	0	2	141,7	180,7	253,5	1	0
Scamp1 *	0	0	2	nan	nan	302,6	1	0
Trim21 *	0	0	2	nan	nan	135	1	0
Traip *	0	0	2	nan	nan	137,3	1	0
Ccnf *	0	0	2	nan	nan	85,8	1	0
Cops4	0	0	2	nan	157,2	152,5	1	0
Adcy7 *	0	0	2	nan	nan	216,6	2	0
Fzr1 *	0	0	2	nan	110,5	66	1	19160489
Bpifb2 *	0	0	2	nan	nan	275,8	2	0
Mc5r *	0	0	2	nan	nan	272	2	0
Fstl1 *	0	0	2	nan	nan	271,6	2	27426744
Gpr83 *	0	0	2	nan	nan	270,6	2	0
Fbxo15 *	0	0	2	nan	nan	109,5	1	0
Cntfr *	0	0	2	nan	nan	303,8	1	0
Gpbar1 *	0	0	2	nan	nan	267,2	2	0
Adrb1 *	0	0	2	nan	nan	265,6	2	0
Herc2 *	0	0	2	nan	148,8	105	1	0
Msh6	0	0	2	116,7	172,2	248,8	1	0
Aldh3b1 *	0	0	2	nan	nan	282	1	0
Sct *	0	0	2	nan	nan	267,4	2	0
Fbxl12 *	0	0	2	nan	nan	114,8	1	0
Herc3 *	0	0	2	nan	217,6	148	1	33565151
Tnc	0	0	2	nan	nan	266,8	2	33217999
Fshb *	0	0	2	nan	nan	260,4	2	0
Anapc7 *	0	0	2	nan	117,2	70,2	1	0
Anapc5 *	0	0	2	nan	118,8	74,3	1	0
Igfbp3	0	0	2	nan	nan	257,6	1	0
Arih2	0	0	2	138,5	143,5	131	1	0
Rbbp6 *	0	0	2	nan	209,8	131	1	0
Ankrd9 *	0	0	2	nan	nan	235,4	1	0
Ptgdr *	0	0	2	nan	nan	272,8	2	0
Gtf2h4 *	0	0	2	109,5	132,3	183,7	2	0
Adrb3 *	0	0	2	nan	nan	266,8	2	0
Anapc4 *	0	0	2	nan	124,4	69,4	1	0
Pth2 *	0	0	2	nan	nan	272,4	1	0
Shisa5 *	0	0	2	nan	nan	275,6	1	0
Olr1 *	0	0	2	nan	nan	276,4	2	0
Ufl1 *	0	0	2	nan	144	126,7	1	0
Fbxo2 *	0	0	2	nan	nan	107,3	1	0
Pgrmc1 *	0	0	2	nan	229,2	288,4	1	28005395
Pja2 *	0	0	2	nan	nan	140,8	1	0
Asb12 *	0	0	2	nan	nan	115	1	0
Btbd1 *	0	0	2	nan	nan	112,4	1	0
Fbxo31 *	0	0	2	nan	nan	112,8	1	0
Uba6 *	0	0	2	nan	nan	137,8	1	0
Adora2b *	0	0	2	nan	nan	256	2	34138843
Ncor1	0	0	2	nan	nan	204,8	1	0
Ube2f *	0	0	2	nan	nan	121,4	1	0
Nup50	0	0	2	nan	nan	266,2	1	0
Fbxl19 *	0	0	2	nan	nan	95,8	1	0
Mgrn1 *	0	0	2	nan	nan	134,5	1	0
Sparcl1 *	0	0	2	nan	nan	245,3	1	0
Trim32 *	0	0	2	nan	nan	132,5	1	0
Fgfr2 *	0	0	2	nan	nan	301,8	1	0
Lamtor2 *	0	0	2	nan	196,4	210,3	1	0
Trim41 *	0	0	2	nan	nan	150,6	1	0
Gpr27 *	0	0	2	nan	nan	273	2	0
Taar1 *	0	0	2	nan	nan	272	1	0
Asb13 *	0	0	2	nan	nan	117,6	1	0
Pcsk9 *	0	0	2	nan	nan	254	1	0
Lifr *	0	0	2	nan	nan	299,7	1	0

Mm_predictions

Taar9 *	0	0	2	nan	nan	274,4	2	0
Cish *	0	0	2	nan	nan	204,2	1	0
Ccnb2 *	0	0	2	nan	nan	141,8	1	0
Fbxw11 *	0	0	2	nan	nan	92,2	1	0
Fbxl13 *	0	0	2	nan	nan	114,6	1	0
Serpib6a *	0	0	2	nan	nan	316,6	1	0
Crh *	0	0	2	nan	nan	245,6	2	0
Fbxo41 *	0	0	2	nan	nan	116,4	1	0
Csf2rb *	0	0	2	nan	nan	281,3	1	0
Klhl22 *	0	0	2	nan	nan	112,8	1	0
Esp1 *	0	0	2	nan	nan	184,8	1	0
Taar6 *	0	0	2	nan	nan	273,6	2	0
Socs1 *	0	0	2	nan	nan	102,5	1	0
Serpind1 *	0	0	2	nan	nan	261,2	1	0
Siah2 *	0	0	2	nan	nan	131,3	1	0
Spsb3 *	0	0	2	nan	nan	240,8	1	0
Rbck1 *	0	0	2	nan	nan	120,2	1	0
Rnf138 *	0	0	2	nan	nan	141,5	1	0
Kbtbd8 *	0	0	2	nan	nan	115,2	1	0
Dzip3 *	0	0	2	nan	nan	137,3	1	0
Fbxl20 *	0	0	2	nan	141,8	101,5	1	0
Hmox2 *	0	0	2	nan	nan	289,4	2	0
Cand1 *	0	0	2	nan	185	203	1	0
Rnf114 *	0	0	2	nan	nan	149,8	1	0
Stc2 *	0	0	2	nan	nan	277,6	2	0
Socs3 *	0	0	2	nan	nan	69,3	1	0
Rnf4 *	0	0	2	nan	nan	134,2	1	0
Ifngr2 *	0	0	2	nan	nan	297,5	1	0
Gps1 *	0	0	2	nan	180	157,8	1	0
Sctr *	0	0	2	nan	nan	273,6	2	0
Tmem132a *	0	0	2	nan	nan	277,2	2	0
Znrf1 *	0	0	2	nan	nan	141,2	1	0
Ormdl3 *	0	0	2	163	223,8	290,6	1	0
Aplp2 *	0	0	2	nan	nan	240,3	1	0
Slc2a3 *	0	0	2	nan	226,4	275,6	1	0
Scg2 *	0	0	2	nan	nan	273	1	0
Il10ra *	0	0	2	nan	nan	336,6	1	0
Plaur *	0	0	2	nan	nan	248	1	0
Asb6 *	0	0	2	nan	nan	112	1	0
Clec4d *	0	0	2	nan	nan	284,6	1	0
Tmc6 *	0	0	2	nan	nan	284,4	2	0
Ube2r2 *	0	0	2	nan	159,4	130,8	1	0
Ube2a *	0	0	2	120	119,2	108,2	1	0
Commd10 *	0	0	2	nan	nan	210,6	1	0
Gpr15 *	0	0	2	nan	nan	273,6	1	0
Tnfrsf12a *	0	0	2	nan	nan	317,8	1	0
Socs6 *	0	0	2	nan	nan	210,3	1	0
Dcun1d4 *	0	0	2	nan	nan	211,8	1	0
Cops7a *	0	0	2	nan	nan	161,7	1	0
Spsb1 *	0	0	2	nan	nan	114,6	1	0
Pdia6 *	0	0	2	nan	197,5	226,5	1	0
Birc5 *	0	0	2	nan	nan	183,8	1	0
Maged2 *	0	0	2	nan	nan	315,2	1	0
Cd47 *	0	0	2	nan	nan	270,8	1	32679764;29042481
Nfkbb1 *	0	0	2	nan	nan	274,2	1	0
Serpinc1 *	0	0	2	nan	nan	235,2	1	0
Tspan14 *	0	0	2	nan	nan	283,2	1	0
Gpha2 *	0	0	2	nan	nan	273,6	1	0
Anapc2 *	0	0	2	nan	116,7	71,3	1	0
Wfs1 *	0	0	2	nan	237	236,3	1	0
Commd6 *	0	0	2	nan	nan	192,2	1	0
Glmn *	0	0	2	nan	nan	130,2	1	0

Mm_predictions

Vgf *	0	0	2	nan	nan		274,6	1		0
Hecw2 *	0	0	2	nan	nan		151,2	1		0
Mcemp1	0	0	2	nan	nan		281,2	1		0
Tmbim1 *	0	0	2	nan	nan		299,6	1		0
Spp1 *	0	0	2	nan	nan		224,2	1	29500246;28254837	
Relb *	0	0	2	nan	nan		267	1		0
Tarm1 *	0	0	2	nan	nan		285	1		0
Cdc23 *	0	0	2		147,8	111	66,8	1		0
Dmp1 *	0	0	2	nan	nan		271,8	1		0
Ambn *	0	0	2	nan	nan		271	1		0
Hvcn1 *	0	0	2	nan	nan		301,8	1		0
Fbxw4 *	0	0	2	nan		263,3	107,2	1		0
Golm1 *	0	0	2	nan	nan		276,8	2		0
Igfbp1 *	0	0	2	nan	nan		267,6	2		0
Drd5 *	0	0	2	nan	nan		265,4	1		0
Cdc27 *	0	0	2	nan		110,5	61,8	1		0
Apoa1 *	0	0	2	nan	nan		196,8	1		0
Fam20a *	0	0	2	nan	nan		243,8	1		0
Ltbp1 *	0	0	2	nan	nan		273	1		0
Scg3 *	0	0	2	nan	nan		275	1		0
Rnf7 *	0	0	2	nan		128,5	88,2	1		0
Gnas	0	0	2	nan		234,8	207	2		0
Gtf2h5 *	0	0	2	nan		137	187	2		0
Notum *	0	0	2	nan	nan		260,8	1		0
Cops8 *	0	0	2	nan	nan		161	1		0
Plk1	0	0	2		126,8	118	45,5	1		0
Glp2r *	0	0	2	nan	nan		272	2		0
Prkdc	0	0	2	nan	nan		260,8	1	24740260;17072335;15105825	
Ptgir *	0	0	2	nan	nan		242,7	2		0
Prkcsh *	0	0	2	nan		203,7	234,5	1		0
Mxra8 *	0	0	2	nan	nan		275,8	1		0
Fstl3 *	0	0	2	nan	nan		272	2		0
Trim39 *	0	0	2	nan	nan		152	1		0
Nup62 *	0	0	2		139	177,5	250,3	1		0
Adm2 *	0	0	2	nan	nan		273,2	1	32229709	
Lamb1 *	0	0	2	nan	nan		218,8	1		0
Gipr *	0	0	2	nan	nan		273	1	31003779	
Ube2b *	0	0	2	nan	nan		102	1		0
Fbxo30 *	0	0	2	nan	nan		116,8	1		0
Serpina10 *	0	0	2	nan	nan		265,8	1		0
Fbxo32 *	0	0	2	nan	nan		98,8	1		0
Igfbp5 *	0	0	2	nan	nan		268,8	1		0
Tshb *	0	0	2	nan	nan		266,8	1		0
Gphb5 *	0	0	2	nan	nan		274	1		0
Kcnab2 *	0	0	2	nan	nan		218,2	1		0
Ndc1	0	0	2	nan	nan		302,4	1		0
Lnx1 *	0	0	2	nan	nan		133,3	1		0
Msln *	0	0	2	nan	nan		223,8	1		0
Herc1 *	0	0	2	nan	nan		140,3	1		0
Trim11 *	0	0	2	nan	nan		139,8	1		0
Agpat2	0	0	2		159	239,2	264,6	1		0
Gpr97 *	0	0	2	nan	nan		303,4	1		0
Eva1a *	0	0	2	nan	nan		276,2	1		0
Nfkbie *	0	0	2	nan	nan		280,5	1		0
Gip *	0	0	2	nan	nan		264,6	1	31977316	
Herc6 *	0	0	2	nan	nan		141,4	1		0
Cul5 *	0	0	2	nan		125,7	84,3	1		0
Tulp4	0	0	2	nan		215	236	1		0
Rln1 *	0	0	2	nan	nan		273,2	1		0
Matn3 *	0	0	2	nan	nan		270,4	1		0
Mkrn1 *	0	0	2	nan	nan		144	1		0
P2rx1 *	0	0	2	nan	nan		289,4	1		0

					Mm_predictions			
Stk10 *	0	0	2	nan	nan	302,6	1	0
Mapkap1	0	0	3	nan	216,3	308,8	1	0
Ccdc88a	0	0	3	nan	nan	325,2	1	0
Terf1	0	0	3	nan	nan	286	1	30452555

Sc_predictions

Protein	Com	ADR_common	Predictors	Pubmed	Database
RPS9B *	2	20,2	3	0	0
RPS15	2	25,8	5	0	0
RPS18A	2	17,8	3	17174052	0
RPL32 *	2	34,8	4	0	0
RPS2 *	2	6	2	0	0
RPL25 *	2	26,3	2	0	0
RPL28 *	2	28,3	6	0	0
RPL30	2	34	5	0	0
RPL5 *	2	11,8	5	0	0
RPS28B *	2	35,3	4	0	0
RPL33A *	2	44,2	4	0	0
RPS0A *	2	17,7	1	0	0
RPS5	2	7	2	0	0
RPS19A *	2	36,3	2	0	0
RPL42B *	2	48,2	2	0	0
RPL31B *	2	66,3	3	0	0
RPS13 *	2	9,3	2	0	0
SUP45 *	2	56	1	0	0
RPS7B *	2	30,2	1	0	0
RPS3	2	5,8	2	0	0
RPS11B	2	12,5	2	0	0
RPS16A *	2	17,7	3	0	0
RPL8A	2	34,8	5	0	0
RPS22A	2	19,5	1	0	0
RPS20	2	25	5	0	0
RPS8A	2	11,5	3	0	0
RPL11A *	2	29,8	6	0	0
RPL15A *	2	29,7	4	0	0
RPS14B	2	12,3	6	0	0
RPS23A	2	17,2	5	0	0
RPS29B *	2	45,7	3	0	0
RPP0	2	26,5	6	0	0
RPS17B *	2	48,3	2	0	0
RPL3	2	16	3	0	0
RPL18A *	2	49,8	5	0	0
SUP35 *	2	64,5	1	28910422	0
RPS25A *	2	45	3	0	0
ATG4	3	148,8	1	0	0

Table_S11

Predicted LAP	ADR	Cellular senescence-association	Longevity-association	ARD-association	Druggability
PLK1	61,2	-	-	-	druggable
UBE2D2	92,2	-	-	-	-
RPS2	101,3	-	-	-	druggable
RPS3	102,2	-	-	-	-
VHL	105,3	-	-	-	druggable
RPS14	109,3	-	-	-	-
CDC27	114,8	-	-	-	-
SOCS3	117,3	-	-	-	-
RPS18	118	-	-	-	druggable
RPS9	119	-	-	-	druggable
KRAS	121,7	-	-	associated	-
FBXW7	123	-	-	-	-
RPS5	123,8	-	-	-	-
ITCH	124	-	-	-	-
RPS11	124,3	-	-	-	-
CUL2	124,5	-	-	-	-
FZR1	126	-	-	-	-
UBR4	127,3	-	-	-	-
RPS13	128,2	-	-	-	druggable
CDC23	128,8	-	-	-	-
AURKB	129	-	-	-	druggable
RPSA	129,2	-	-	-	-
RPS8	130,2	-	-	-	druggable
RPL11	131,5	-	-	-	druggable
RPS7	132,5	-	-	-	-
FBXW11	133	-	-	-	-
ADCY3	133	-	-	-	-
UBE2V2	133,3	-	-	-	-
RPL5	135,2	-	-	-	-
RPS20	135,2	-	-	-	-
RPS15A	135,2	-	-	-	-
ADCY8	135,8	-	-	-	-
SMURF2	136,5	associated	-	-	-
RPS3A	137,3	-	-	-	-
RPS16	137,5	-	-	-	-
ANAPC1	138,3	-	-	-	-
ADCY7	140,2	-	-	-	-
PARK2	140,2	-	-	-	-
ADCY1	140,2	-	-	-	druggable
ADCY6	140,8	-	associated	-	-
RPL8	141	-	-	-	-
ANAPC7	142,3	-	-	-	-
ADCY4	142,5	-	-	-	-
RPS15	143,2	-	-	-	-
ANAPC4	144,3	-	-	-	-
RPS23	144,3	-	-	-	-
ANAPC2	144,8	-	-	-	-
ANAPC10	146	-	-	-	-
RPL23A	146,3	-	-	-	-
ANAPC5	147,7	-	-	-	-
KEAP1	148,5	-	-	-	druggable
CUL5	150,2	-	-	-	-
RPL23	151,7	-	-	-	-
SMURF1	151,8	-	-	-	-
WWP1	152,3	associated	-	-	-
UBE3A	152,7	-	-	-	-
RPLP0	154,5	-	-	-	-
CDC26	155,3	-	-	-	-
FBXL19	155,7	-	-	-	-
RPS19	157,2	-	-	-	druggable
RPS28	157,3	-	-	-	druggable
SOCS1	158,2	associated	associated	-	druggable
FBXW5	159,7	-	-	-	-
FBXO7	160,7	-	-	-	-
NEDD4	163,2	-	-	-	-
UBA1	164,3	-	-	-	-
HUWE1	165,2	-	-	-	-
UBE2B	165,3	-	-	-	-

Table_S11

HERC2	165,5	-	-	-	druggable
CCNF	165,5	-	-	-	-
UBE2A	166	-	-	-	-
TRIM21	166,8	-	-	-	-
RPL30	167,2	-	-	-	-
GNB2L1	168	-	-	-	-
UBA3	168,8	-	-	-	druggable
RPL15	169	-	-	-	druggable
RPS29	169,2	-	-	-	-
RNF7	169,2	-	-	-	-
RPL3	170,3	-	-	-	druggable
RPS25	170,3	-	-	-	-
RPL37A	171,5	-	-	-	-
CBLB	172	-	-	-	druggable
RPL12	173	-	-	-	-
RPL18A	173,7	-	-	-	-
FBXO32	174,3	-	-	-	-
RPL27A	176,3	-	-	-	-
FBXL3	177	-	-	-	-
RPS21	177,2	-	-	-	-
RNF4	178	-	-	-	-
FBXL5	178,2	-	-	-	-
RPL35	178,5	-	-	-	druggable
FBXW4	178,7	-	-	-	-
UBE2L6	180,5	-	-	-	-
RPL7	180,8	-	-	-	-
RPL6	180,8	-	-	-	-
RPL32	181,7	-	-	-	-
FBXO4	182,7	-	-	-	-
FBXW2	183	-	-	-	-
TRIP12	183,5	-	-	-	-
KLHL2	185	-	-	-	-
RPS17	185,8	-	-	-	-
FBXO11	186	-	-	-	-
RPS10	186,2	-	-	-	-
RPL27	186,7	-	-	-	-
ASB6	186,8	-	-	-	-
RPL31	187	-	-	-	-
FBXO2	187,2	-	-	-	-
FBXW8	187,3	-	-	-	-
RPL13	188	-	-	-	druggable
GAN	188,3	-	-	-	-
FBXL15	188,8	-	-	-	-
UBE2K	189,2	-	-	-	-
RPL38	189,8	-	-	-	-
LRR1	190,2	-	-	-	-
ASB7	190,2	-	-	-	-
KLHL22	190,5	-	-	-	-
CUL7	191,2	-	-	-	-
BTBD1	191,2	-	-	-	-
FBXO9	191,3	-	-	-	-
VPRBP	191,5	-	-	-	-
RPL7A	191,7	-	-	-	-
FBXL13	191,7	-	-	-	-
ASB4	192,2	-	-	-	-
LNK1	192,2	-	-	-	-
ASB2	192,3	-	-	-	-
SIAH1	193,2	-	-	-	druggable
KLHL13	193,2	-	-	-	-
KCTD6	193,3	-	-	-	-
FBXO31	193,5	associated	-	-	-
KCTD7	193,5	-	-	-	-
KBTBD7	193,5	-	-	-	-
FBXL12	194	-	-	-	-
FBXO17	194	-	-	-	-
FBXW9	194	-	-	-	-
KLHL3	194,2	-	-	-	-
KLHL9	194,7	-	-	-	-
KLHL42	194,8	-	-	-	-

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ASB15	195	-	-	-	-
WSB1	195,3	-	-	-	-
KLHL20	195,3	-	-	-	-
ASB9	195,3	-	-	-	-
LTN1	195,5	-	-	-	-
ASB1	195,5	-	-	-	-
FBXO27	195,8	-	-	-	-
FBXL4	196	-	-	-	-
FBXL14	196,2	-	-	-	-
SPSB1	196,2	-	-	-	-
FBXO15	196,3	-	-	-	-
ASB11	196,3	-	-	-	-
ASB10	196,3	-	-	-	-
RBCK1	196,3	-	-	-	-
ASB12	196,5	-	-	-	-
KBTBD13	196,7	-	-	-	-
BTBD6	197,2	-	-	-	-
FBXL18	197,3	-	-	-	-
FBXO40	197,5	-	-	-	-
KBTBD8	197,5	-	-	-	-
FBXO10	198	-	-	-	-
FBXL20	198,2	-	-	-	-
FBXO21	198,3	-	-	-	-
FBXL16	198,5	-	-	-	-
DET1	198,5	-	-	-	-
FBXO30	198,5	-	-	-	-
KLHL11	198,7	-	-	-	-
KLHL21	198,8	-	-	-	-
ASB14	199,3	-	-	-	-
ASB5	199,5	-	-	-	-
SPSB2	199,5	-	-	-	-
ASB16	199,7	-	-	-	-
RPL21	200	-	-	-	-
SPSB4	200,2	-	-	-	-
ASB13	200,5	-	-	-	-
ASB17	200,5	-	-	-	-
ASB18	200,7	-	-	-	-
FBXO41	200,7	-	-	-	-
KLHL25	200,7	-	-	-	-
FBXL8	201	-	-	-	-
PSMD2	201,8	-	-	-	druggable
KLHL5	202	-	-	-	-
ANAPC13	202	-	-	-	-
UBE2F	202	-	-	-	-
CCNB2	202	-	-	-	-
RCHY1	202,2	-	-	-	-
RPL35A	202,5	-	-	-	-
UBE2E3	203,8	-	-	-	-
RPL36	204	-	-	-	-
SIAH2	204,7	-	-	-	-
RBBP6	204,7	-	-	-	-
UBA7	206,5	-	-	-	-
TRIM32	206,7	-	-	-	-
TRIM63	207,2	-	-	-	-
UBA6	207,8	-	-	-	-
UBE4A	208	-	-	-	-
TACR1	208,8	-	-	-	druggable
UBE2H	209	-	associated	-	-
RPL34	209,3	-	-	-	-
UBE2G2	209,7	-	-	-	-
UBE2E2	209,7	-	-	-	-
GLMN	211	-	-	-	-
RNF41	211,2	-	-	-	-
HECW2	212	-	associated	-	-
UBA5	212,3	-	-	-	-
UBE2O	212,7	-	-	-	-
PSMA1	212,8	-	-	-	druggable
UBAC1	214,8	-	-	-	-
BUB1	214,8	-	-	-	-

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PJA1	215,2	-	-	-	-
MIB2	215,3	-	-	-	-
HERC6	215,3	-	-	-	-
MEX3C	216	-	-	-	-
DTX3L	216,7	-	-	-	-
UBOX5	217	-	-	-	-
RPLP2	217,2	-	-	-	-
UBE3C	217,5	-	-	-	-
UBE2W	218,3	-	-	-	-
LRSAM1	218,5	-	-	-	-
MGRN1	218,7	-	-	-	-
TRIM37	219,2	-	-	-	-
RLIM	219,5	-	-	-	-
UBE2J2	219,8	-	-	-	-
RNF123	220	-	-	-	-
TRAIP	220	-	-	-	-
DZIP3	220,7	-	associated	-	-
TRIM39	220,8	-	-	-	-
RNF115	221	-	-	-	-
MKRN1	221,3	-	-	-	-
UBE2G1	221,5	-	-	-	-
ZNRF2	221,8	-	-	-	-
UBE2Z	222,2	-	-	-	-
RNF114	222,7	-	-	-	-
TRIM41	222,7	-	-	-	-
UBR2	222,7	-	-	-	-
MYLIP	223,7	-	associated	-	druggable
TRIM69	223,8	-	-	-	-
UBE2R2	224,3	-	-	-	-
TRIM11	224,3	-	-	-	-
RNF19B	224,5	-	-	-	-
TRIM50	224,5	-	-	-	-
HERC1	224,7	-	-	-	-
UBE3D	225,2	-	-	-	-
ARIH2	225,2	-	-	-	-
TRIM9	225,3	-	-	-	-
TRIM36	225,3	-	-	-	-
RNF144B	225,5	-	-	-	-
RNF130	225,7	-	-	-	-
RNF34	225,8	-	-	-	-
HERC3	226	-	-	-	-
UFL1	226,3	-	-	-	-
TRAF7	226,7	-	-	-	-
RNF19A	226,8	-	-	-	-
AREL1	227	-	-	-	-
TRIM71	227,2	-	-	-	-
UBE2Q2	227,2	-	-	-	-
RNF6	227,7	-	-	-	-
PJA2	227,8	-	-	-	-
HECTD3	228,3	-	-	-	-
BIRC5	228,7	-	-	-	druggable
RNF138	229,2	-	-	-	-
ZNRF1	229,8	-	-	-	-
UBE3B	229,8	-	-	-	-
RNF25	230,5	-	-	-	-
RNF182	231,2	-	-	-	-
PSMD12	231,7	-	-	-	druggable
RPL28	231,8	-	-	-	-
NSA2	231,8	-	-	-	-

TableS11

Homology code	STRING identifier	Alliance identifier	Protein symbol
--H1	4932.YDL075W	SGD:S000002233	RPL31A
--H1	6239.W09C5.6a	WB:WBGene00004445	RPL-31
--H2	6239.F35G12.10.1	WB:WBGene00000206	ASB-1
--H2	6239.F02E8.1.3	WB:WBGene00000207	ASB-2
--H3	6239.Y24D9A.4a	WB:WBGene00004419	RPL-7A
--H3	4932.YLL045C	SGD:S000003968	RPL8B
--H4	6239.R04A9.4	WB:WBGene00002060	IFE-2
--H4	6239.F53A2.6a	WB:WBGene00002059	IFE-1
--H5	4932.YOR089C	SGD:S000005615	VPS21
--H5	6239.F26H9.6	WB:WBGene00004268	RAB-5
--H6	6239.H28O16.1a	WB:WBGene00010419	H28O16.1
--H6	4932.YBL099W	SGD:S000000195	ATP1
--H7	7227.FBpp0082682	FB:FBgn0010379	Akt1
--H7	4932.YKL126W	SGD:S000001609	YPK1
--H7	4932.YHR205W	SGD:S000001248	SCH9
--H7	6239.C12D8.10b	WB:WBGene00000102	AKT-1
--H7	6239.Y47D3A.16	WB:WBGene00012929	RSKS-1
--H7	10090.ENSMUSP00000001780	MGI:87986	Akt1
--H7	7227.FBpp0305462	FB:FBgn0283472	S6k
--H7	9606.ENSP00000451828	HGNC:391	AKT1
--H8	4932.YER020W	SGD:S000000822	GPA2
--H8	6239.C34D1.3	WB:WBGene00003850	ODR-3
--H9	6239.Y47D3A.4	WB:WBGene00000519	CKU-70
--H9	9606.ENSP00000352257	HGNC:4055	XRCC6
--H10	6239.C15F1.7a	WB:WBGene00004930	SOD-1
--H10	7227.FBpp0305736	WB:WBGene00004930	Sod
--H10	4932.YJR104C	SGD:S000003865	SOD1
--H10	9606.ENSP00000270142	HGNC:11179	SOD1
--H11	10090.ENSMUSP00000017290	MGI:104537	Brca1
--H11	9606.ENSP00000418960	HGNC:1100	BRCA1
--H12	4932.YGL180W	SGD:S000003148	ATG1
--H12	7227.FBpp0289788	FB:FBgn0260945	Atg1
--H13	6239.B0285.1b	WB:WBGene00007135	CDTL-7
--H13	4932.YKL139W	SGD:S000001622	CTK1
--H14	9606.ENSP00000263253	HGNC:3373	EP300
--H14	9606.ENSP00000262367	HGNC:2348	CREBBP
--H15	9606.ENSP00000289153	HGNC:8976	PIK3CB
--H15	6239.B0334.8	WB:WBGene00000090	AGE-1
--H15	9606.ENSP00000263967	HGNC:8975	PIK3CA
--H16	9606.ENSP00000362649	HGNC:4852	HDAC1
--H16	9606.ENSP00000430432	HGNC:4853	HDAC2
--H16	4932.YNL330C	SGD:S000005274	RPD3
--H17	4932.YDR500C	SGD:S000002908	RPL37B
--H17	4932.YLR185W	SGD:S000004175	RPL37A
--H18	6239.C32D5.9	WB:WBGene00002980	LGG-1
--H18	4932.YBL078C	SGD:S000000174	ATG8
--H19	4932.YOR369C	SGD:S000005896	RPS12
--H19	6239.F54E7.2.3	WB:WBGene00004481	RPS-12
--H20	10090.ENSMUSP00000106278	MGI:1351320	Trp53bp1
--H20	4932.YDR217C	SGD:S000002625	RAD9
--H20	9606.ENSP00000371475	HGNC:11999	TP53BP1
--H21	4932.YGR108W	SGD:S000003340	CLB1
--H21	4932.YPR119W	SGD:S000006323	CLB2
--H22	9606.ENSP00000376345	HGNC:4566	GRB2
--H22	6239.C14F5.5	WB:WBGene00004774	SEM-5

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--H23	4932.YML073C	SGD:S000004538	RPL6A
--H23	4932.YLR448W	SGD:S000004440	RPL6B
--H24	6239.F43C1.2b	WB:WBGene00003401	MPK-1
--H24	4932.YGR040W	SGD:S000003272	KSS1
--H24	9606.ENSP00000263025	HGNC:6877	MAPK3
--H25	4932.YHR021C	SGD:S000001063	RPS27B
--H25	4932.YKL156W	SGD:S000001639	RPS27A
--H26	4932.YCR005C	SGD:S000000598	CIT2
--H26	4932.YNR001C	SGD:S000005284	CIT1
--H27	7227.FBpp0288669	FB:FBgn0283499	InR
--H27	6239.Y55D5A.5a	WB:WBGene00000898	DAF-2
--H27	9606.ENSP00000268035	WB:WBGene00000898	IGF1R
--H28	4932.YDL066W	SGD:S000002224	IDP1
--H28	4932.YLR174W	SGD:S000004164	IDP2
--H28	6239.F59B8.2b	WB:WBGene00010317	IDH-1
--H29	9606.ENSP00000351777	HGNC:12666	VCP
--H29	6239.C06A1.1	WB:WBGene00007352	CDC-48.1
--H30	9606.ENSP00000287820	HGNC:9236	PPARG
--H30	6239.F11A1.3a	WB:WBGene00000908	DAF-12
--H30	10090.ENSMUSP00000000450	MGI:97747	Pparg
--H31	9606.ENSP00000372023	HGNC:16627	CHEK2
--H31	10090.ENSMUSP00000066679	MGI:1355321	Chek2
--H31	4932.YDL101C	SGD:S000002259	DUN1
--H32	10090.ENSMUSP00000028610	MGI:88271	Cat
--H32	4932.YGR088W	SGD:S000003320	CTT1
--H32	4932.YDR256C	SGD:S000002664	CTA1
--H32	7227.FBpp0074825	FB:FBgn0000261	Cat
--H32	9606.ENSP00000241052	HGNC:1516	CAT
--H33	6239.D1007.6.2	WB:WBGene00004479	RPS-10
--H33	4932.YMR230W	SGD:S000004843	RPS10B
--H34	6239.F40F11.1.2	WB:WBGene00004480	RPS-11
--H34	4932.YDR025W	SGD:S000002432	RPS11A
--H35	4932.YHR171W	SGD:S000001214	ATG7
--H35	7227.FBpp0085891	FB:FBgn0034366	Atg7
--H35	6239.M7.5	WB:WBGene00010882	ATG-7
--H36	7227.FBpp0080003	FB:FBgn0021796	Tor
--H36	6239.B0261.2a	WB:WBGene00002583	LET-363
--H36	10090.ENSMUSP00000099510	MGI:1928394	Mtor
--H36	9606.ENSP00000354558	HGNC:3942	MTOR
--H36	4932.YJR066W	SGD:S000003827	TOR1
--H37	9606.ENSP00000344456	HGNC:2514	CTNNB1
--H37	6239.C54D1.6	WB:WBGene00000238	BAR-1
--H37	4932.YEL013W	SGD:S000000739	VAC8
--H38	9606.ENSP00000360266	HGNC:6204	JUN
--H38	4932.YEL009C	SGD:S000000735	GCN4
--H39	9606.ENSP00000378974	HGNC:6881	MAPK8
--H39	6239.B0478.1a	WB:WBGene00002178	JNK-1
--H39	7227.FBpp0079676	FB:FBgn0000229	bsk
--H39	7227.FBpp0080111	FB:FBgn0024846	p38b
--H39	9606.ENSP00000229795	HGNC:6876	MAPK14
--H40	10090.ENSMUSP00000022971	MGI:97250	Myc
--H40	9606.ENSP00000479618	MGI:97250	MYC
--H40	7227.FBpp0303995	FB:FBgn0262656	dm
--H41	6239.F10B5.1.2	WB:WBGene00004421	RPL-10
--H41	4932.YLR075W	SGD:S000004065	RPL10
--H42	10090.ENSMUSP00000104298	MGI:98834	Trp53

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--H42	9606.ENSP00000269305	HGNC:11998	TP53
--H43	6239.B0041.4	WB:WBGene00004415	RPL-4
--H43	4932.YBR031W	SGD:S00000235	RPL4A
--H44	6239.C26E6.9c	WB:WBGene00004782	SET-2
--H44	4932.YHR119W	SGD:S000001161	SET1
--H45	4932.YDL082W	SGD:S000002240	RPL13A
--H45	4932.YMR142C	SGD:S000004750	RPL13B
--H46	4932.YEL024W	SGD:S000000750	RIP1
--H46	6239.F42G8.12	WB:WBGene00002162	ISP-1
--H47	4932.YLR048W	SGD:S000004038	RPS0B
--H47	6239.B0393.1.1	WB:WBGene00004469	RPS-0
--H48	4932.YOR065W	SGD:S000005591	CYT1
--H48	6239.C54G4.8	WB:WBGene00000869	CYC-1
--H49	4932.YJR121W	SGD:S000003882	ATP2
--H49	6239.C34E10.6.1	WB:WBGene00000229	ATP-2
--H50	9606.ENSP00000355759	HGNC:270	PARP1
--H50	10090.ENSMUSP00000027777	MGI:1340806	Parp1
--H51	6239.Y48G8AL.8a	WB:WBGene00004429	RPL-17
--H51	4932.YJL177W	SGD:S000003713	RPL17B
--H52	10090.ENSMUSP00000113388	MGI:107202	Atm
--H52	9606.ENSP00000278616	HGNC:795	ATM
--H53	9606.ENSP00000407586	HGNC:5173	HRAS
--H53	6239.ZK792.6	WB:WBGene00002335	LET-60
--H53	4932.YNL098C	SGD:S000005042	RAS2
--H54	9606.ENSP00000306245	HGNC:3796	FOS
--H54	9606.ENSP00000387699	HGNC:2345	CREB1
--H55	4932.YHR203C	SGD:S000001246	RPS4B
--H55	4932.YJR145C	SGD:S000003906	RPS4A
--H56	4932.YLR362W	SGD:S000004354	STE11
--H56	4932.YJL095W	SGD:S000003631	BCK1
--H57	6239.R13A5.8	WB:WBGene00004420	RPL-9
--H57	4932.YGL147C	SGD:S000003115	RPL9A
--H57	4932.YNL067W	SGD:S000005011	RPL9B
--H58	4932.YIL052C	SGD:S000001314	RPL34B
--H58	4932.YER056C-A	SGD:S000002135	RPL34A
--H59	9606.ENSP00000361021	HGNC:9588	PTEN
--H59	7227.FBpp0088843	FB:FBgn0026379	Pten
--H59	10090.ENSMUSP00000013807	MGI:109583	Pten
--H59	6239.T07A9.6	WB:WBGene00000913	DAF-18
--H60	9606.ENSP00000385824	HGNC:3821	FOXO3
--H60	7227.FBpp0293589	FB:FBgn0038197	foxo
--H60	6239.R13H8.1h	WB:WBGene00000912	DAF-16
--H60	9606.ENSP00000368880	HGNC:3819	FOXO1
--H61	4932.YJR045C	SGD:S000003806	SSC1
--H61	6239.C37H5.8	WB:WBGene00002010	HSP-6
--H62	4932.YPL120W	SGD:S000006041	VPS30
--H62	6239.T19E7.3	WB:WBGene00000247	BEC-1
--H63	9606.ENSP00000293328	HGNC:11367	STAT5B
--H63	9606.ENSP00000264657	HGNC:11364	STAT3
--H64	4932.YOR374W	SGD:S000005901	ALD4
--H64	4932.YMR169C	SGD:S000004779	ALD3
--H64	4932.YPL061W	SGD:S000005982	ALD6
--H65	7227.FBpp0077451	FB:FBgn0000490	dpp
--H65	6239.B0412.2	WB:WBGene00000903	DAF-7
--H66	4932.YLL039C	SGD:S000003962	UBI4
--H66	9606.ENSP00000304697	HGNC:12463	UBB

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--H67	4932.YKL166C	SGD:S000001649	TPK3
--H67	4932.YPL203W	SGD:S000006124	TPK2
--H67	4932.YJL164C	SGD:S000003700	TPK1
--H68	6239.F39B2.6.2	WB:WBGene00004495	RPS-26
--H68	4932.YER131W	SGD:S000000933	RPS26B
--H69	9606.ENSP00000269571	HGNC:3430	ERBB2
--H69	6239.ZK1067.1c	WB:WBGene00002299	LET-23
--H69	9606.ENSP00000275493	HGNC:3236	EGFR
--H70	6239.C52E4.4.1	WB:WBGene00004501	RPT-1
--H70	4932.YKL145W	SGD:S000001628	RPT1
--H71	4932.YBL027W	SGD:S000000123	RPL19B
--H71	6239.C09D4.5.1	WB:WBGene00004431	RPL-19
--H71	4932.YBR084C-A	SGD:S000002156	RPL19A
--H72	4932.YDR477W	SGD:S000002885	SNF1
--H72	6239.T01C8.1b	WB:WBGene00020142	AAK-2
--H73	4932.YBL045C	SGD:S000000141	COR1
--H73	6239.F56D2.1	WB:WBGene00018963	UCR-1
--H74	10090.ENSMUSP00000007012	MGI:98352	Sod2
--H74	6239.F10D11.1.2	WB:WBGene00004931	SOD-2
--H74	7227.FBpp0086226	FB:FBgn0010213	Sod2
--H74	9606.ENSP00000446252	HGNC:11180	SOD2
--H74	4932.YHR008C	SGD:S000001050	SOD2
--H75	6239.Y53C10A.12	WB:WBGene00002004	HSF-1
--H75	4932.YHR206W	SGD:S000001249	SKN7
--H76	9606.ENSP00000372088	HGNC:9817	RAD51
--H76	4932.YER095W	SGD:S000000897	RAD51
--H77	4932.YPL079W	SGD:S000006000	RPL21B
--H77	4932.YBR191W	SGD:S000000395	RPL21A
--H78	6239.F53G12.10.1	WB:WBGene00004418	RPL-7
--H78	4932.YGL076C	SGD:S000003044	RPL7A
--H79	7227.FBpp0080015	FB:FBgn0024291	Sir2
--H79	6239.R11A8.4a	WB:WBGene00004800	SIR-2.1
--H79	9606.ENSP00000212015	HGNC:14929	SIRT1
--H79	4932.YDL042C	SGD:S000002200	SIR2
--H79	10090.ENSMUSP00000101082	MGI:2135607	Sirt1
--H79	4932.YOL068C	SGD:S000005429	HST1
--H80	7227.FBpp0082147	FB:FBgn0013277	Hsp70Ba
--H80	9606.ENSP00000364802	HGNC:5232	HSPA1A
--H80	9606.ENSP00000432083	HGNC:5241	HSPA8
--H81	4932.YKL085W	SGD:S000001568	MDH1
--H81	4932.YOL126C	SGD:S000005486	MDH2
--H81	6239.F20H11.3	WB:WBGene00003162	MDH-2
--H82	4932.YDR099W	SGD:S000002506	BMH2
--H82	4932.YER177W	SGD:S000000979	BMH1
--H82	9606.ENSP00000379287	HGNC:12855	YWHAZ
--H83	4932.YPL090C	SGD:S000006011	RPS6A
--H83	6239.Y71A12B.1a	WB:WBGene00004475	RPS-6
--H84	4932.YER040W	SGD:S000000842	GLN3
--H84	9606.ENSP00000329357	HGNC:11205	SP1
--H84	4932.YDR146C	SGD:S000002553	SWI5
--H85	4932.YGL049C	SGD:S000003017	TIF4632
--H85	4932.YGR162W	SGD:S000003394	TIF4631
--H85	6239.M110.4a	WB:WBGene00002066	IFG-1
--H86	6239.F25H5.4a.1	WB:WBGene00001167	EEF-2
--H86	4932.YOR133W	SGD:S000005659	EFT1
--H86	4932.YDR385W	SGD:S000002793	EFT2

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--H87	4932.YDR069C	SGD:S000002476	DOA4
--H87	4932.YMR223W	SGD:S000004836	UBP8
--H88	4932.YCL040W	SGD:S000000545	GLK1
--H88	4932.YGL253W	SGD:S000003222	HXK2
--H89	4932.YBR245C	SGD:S000000449	ISW1
--H89	4932.YOR304W	SGD:S000005831	ISW2
--H90	9606.ENSP00000302665	HGNC:5464	IGF1
--H90	10090.ENSMUSP00000056668	MGI:96432	Igf1
--H91	4932.YML001W	SGD:S000004460	YPT7
--H91	6239.W03C9.3.2	WB:WBGene00004271	RAB-7