



Original article

Predicted *Drosophila* Interactome Resource and web tool for functional interpretation of differentially expressed genes

Xiao-Bao Ding¹, Jie Jin¹, Yu-Tian Tao¹, Wen-Ping Guo¹, Li Ruan¹, Qiao-lei Yang², Peng-Cheng Chen², Heng Yao², Hai-bo Zhang¹ and Xin Chen^{1,2,3,*}

¹Institute of Big Data and Artificial Intelligence in Medicine, School of Electronics and Information Engineering, Taizhou University, 1139 Shifu Avenue, Taizhou 318000, China, ²Institute of Pharmaceutical Biotechnology and the First Affiliated Hospital Department of Radiation Oncology, Zhejiang University School of Medicine, 866 Yuhantang Rd, Hangzhou 310058, China and ³Joint Institute for Genetics and Genome Medicine between Zhejiang University and University of Toronto, Zhejiang University, 866 Yuhantang Rd, Hangzhou 310058, China

*Corresponding author: Tel/Fax: +86-571-88208595; Email: xinchen@zju.edu.cn

Citation details: Ding,X.-B., Jin,J., Tao,Y.-T. *et al.* Predicted *Drosophila* Interactome Resource and web tool for functional interpretation of differentially expressed genes. *Database* (2020) Vol. 2020: article ID baaa005; doi:10.1093/database/baaa005

Received 21 October 2019; Revised 3 December 2019; Accepted 13 January 2020

Abstract

Drosophila melanogaster is a well-established model organism that is widely used in genetic studies. This species enjoys the availability of a wide range of research tools, well-annotated reference databases and highly similar gene circuitry to other insects. To facilitate molecular mechanism studies in *Drosophila*, we present the Predicted *Drosophila* Interactome Resource (PDIR), a database of high-quality predicted functional gene interactions. These interactions were inferred from evidence in 10 public databases providing information for functional gene interactions from diverse perspectives. The current version of PDIR includes 102 835 putative functional associations with balanced sensitivity and specificity, which are expected to cover 22.56% of all *Drosophila* protein interactions. This set of functional interactions is a good reference for hypothesis formulation in molecular mechanism studies. At the same time, these interactions also serve as a high-quality reference interactome for gene set linkage analysis (GSLA), which is a web tool for the interpretation of the potential functional impacts of a set of changed genes observed in transcriptomics analyses. In a case study, we show that the PDIR/GSLA system was able to produce a more comprehensive and concise interpretation of the collective functional impact of multiple simultaneously changed genes compared with the widely used gene set annotation tools, including PANTHER and David. PDIR and its associated GSLA service can be accessed at <http://drosophila.biomedtzc.cn>.

Introduction

Drosophila melanogaster, also known as the fruit fly, is one of the most commonly used model organisms and has been widely studied for more than a century (1, 2). The short life cycle of 12 days, ease of maintenance, low cost and abundance of genetic tools in *Drosophila* have made it a leading model in genetics research. In addition to insects, *Drosophila* shares many features, genes and pathways with mammalian systems (1). It has also been widely used for research in development (3), brain disease (4) and cancer treatment (5).

Today, the omics technology has been extensively used for molecular mechanism studies (6–8). The availability of abundant and complicated omics data brings both an unprecedented opportunity to comprehensively describe the physiological status of study subjects at the molecular level and, at the same time, an unparalleled challenge to elucidate the underlying design logic of the physiological processes from these comprehensive molecular-level descriptions.

To address this challenge, many approaches have been developed to derive high-level biological senses from the omics data. These approaches typically rely on the identification of a set of simultaneous changed genes (changed gene set, CGS) between two physiological statuses and then use an enrichment-based method to evaluate whether a CGS has an enriched representation of a gene set that defined a biological process. The widely used enrichment-based gene set annotation tools include PANTHER (9), KEGG (10) and DAVID (11).

In essence, this strategy summarizes the observed CGS into established biological concepts. This strategy is successful in many cases; however, in some cases where no established biological concepts can be found to accurately describe the change, enrichment-based approaches frequently report no annotation term or conceptually very general terms (such as GO:0008152, metabolic process) are found. Such results provide little value to elucidate the design logic of physiological processes and formulating further hypotheses to achieve effective control over desired traits.

On the other hand, when no established biological concepts may accurately describe the observed CGS, we still may use established concepts to describe the functional impacts of the CGS. For example, observed CGS may collectively lead to GO:0048867 (stem cell fate determination), even when the CGS genes are not enriched with these terms (for details, see ‘Discussion’). One way to implement this analysis strategy is to evaluate whether the observed CGS has strong functional associations with established biological process gene sets. If genes in the CGS have frequent functional associations with genes representing a biological function, the CGS is expected to interfere with this biolog-

ical function. We call this strategy gene set linkage analysis (GSLA), which has been successfully used in human and *Arabidopsis* transcriptome interpretation (12, 13). GSLA works for these two species because high-quality functional association gene networks exist (13, 14).

In this study, we present a high-quality functional association gene network for *Drosophila*, the Predicted *Drosophila* Interactome Resource (PDIR), and its associated GSLA web tool. PDIR integrates six types of evidence for functional gene association from public databases with timestamps before 2018. The accuracy of inferred functional associations in PDIR was assessed using protein interactions recently reported after 2018. The current version of PDIR includes 102 835 gene associations, which are expected to cover ~22.6% protein–protein interactions of *Drosophila*. ~50.5% of these functional associations are expected to represent protein–protein interactions. PDIR provides a web interface for users to query these functional associations between individual genes, as well as a GSLA web tool for users to interpret the collective functional impact of multiple simultaneously changed genes. We also present a case study to illustrate the use of PDIR/GSLA.

Materials and Methods

Source data

To train the prediction model, six types of evidence suggesting functional associations between genes were collected from seven public databases before 2018, which include 11 937 expression profiles (Coxpresdb), 97 220 gene annotations (Gene Ontology Consortium, GOC), 60 368 domain interactions (IDDI and Pfam), 31 278 subcellular gene localizations (Compartments), 17 737 phylogenetic profiles (DIOPT) and 5628 *Drosophila* proteins and proteins from *Arabidopsis thaliana*, *Caenorhabditis elegans*, *Homo sapiens*, *Mus musculus*, *Rattus norvegicus*, *Saccharomyces cerevisiae* and *Schizosaccharomyces pombe* to compute interologs.

Protein–protein interactions were considered to be a strong evidence of functional associations. In this study, we attempt to predict functional associations that are as strong as protein interactions (14). A total of 155 871 experimentally reported *Drosophila* protein–protein interactions were collected from three public databases, including BioGRID (15), IntAct (16) and FlyBase (17) (Supplementary Table S1). To ensure the reliability of example interactions, we removed those reported in less than two independent studies and those reported only in high-throughput experiments. This filtering resulted in 4434 high-confidence protein–protein interactions (Supplementary Table S1). For the prediction of functional gene associations with uniform gene ID, we used Uniprot

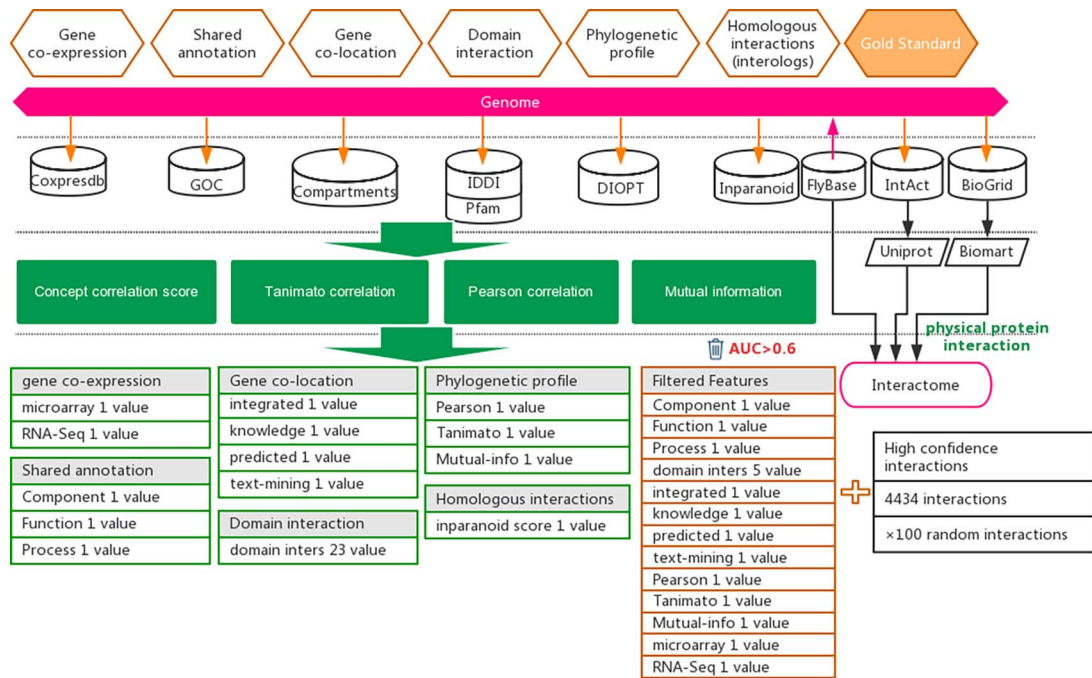


Figure 1. Workflow for the inference of functional interactions between *Drosophila* genes. High-quality experimental reported protein interactions were integrated from three databases and were used as positive examples. Six types of functional association evidence from 10 databases were collected to infer putative functional interactions. A total of 17 high-quality feature values were selected from 36 feature values that characterize this evidence with different mathematical representations. Random gene pairs after removing positive examples were used as negative examples. The number of negative examples was 100 times that of the positive examples.

(15) and BioMart (16) software to convert different gene IDs to FlyBase ID (Figure 1).

Feature value computation

Thirty-six mathematical characterizations were used to compute the feature values from the data collected above. The detailed equations can be found in the PDIR website. In total, 3 shared annotation features, 2 co-expression features, 4 subcellular co-localization features, 23 domain interaction features, 3 phylogenetic profile features and 1 homologous interaction feature resulted in Supplementary Table S3.

Evaluation of feature values

The area under the curve (AUC) of the receiver operating characteristic (ROC) test was used to evaluate the quality of feature values to suggest functional associations. By applying different cut-offs, each feature value produced a series of sensitivities and specificities when it was used to predict protein interactions, evaluated using our training dataset (data before 2018). The sensitivities and specificities corresponding to different cut-offs were plotted as the ROC curve (X-axis, 1-specificity; Y-axis, sensitivity). Feature values with AUC less than 0.6 were considered not informative

to indicate strong functional associations and were removed (Supplementary Figure S1).

Website construction

The PDIR database runs on LNMP, which is an integrated running environment, including Linux, Nginx, MySQL and PHP. The MySQL database is used for data storage, maintenance and operation. The interaction interface is developed with the Laravel framework based on PHP. The front-end of PDIR is a Vue.js-based single page application (SPA). Vue.js is an open-source JavaScript framework for interface creation and a web application framework compatible with SPA. The functional association network is visualized with Cytoscape (17).

Microarray data analysis

We retrieved the microarray dataset GSE99071 from the GEO database (18). The original research indicated that approximately 1000 genes showed differential expression (up- or down-regulated) in the *Apc1* mutant (*Apc1*Q8, also referred to as *Apc1*-/-) relative to the wild type (w1118). Three biological repeats were performed for both the *Apc1* mutant and the wild type. These expression profiles were re-analyzed using the online GEO2R tool with default param-

eters. The top 250 transcriptionally changed genes were selected based on adj.P. Val (P -value after the adjustment for multiple testing).

Results

Integration of data for the prediction of functional associations between *Drosophila* genes

Experimentally reported protein–protein interactions in *Drosophila* (*D. melanogaster*) were collected from three databases, i.e. BioGRID (19), IntAct (20) and FlyBase (21) (Figure 1 and Supplementary Table S1). These interactions were further filtered by supporting evidence provided in each database, keeping only experimentally confirmed interactions (Figure 1). The resulting dataset of high-confidence protein interactions was used as positive examples in training the prediction model (Supplementary Table S1).

In addition to protein–protein interactions, six types of other evidence suggesting functional associations between genes from different biological perspectives were collected from seven databases, which include CoXPRESDB (22), GOC (23), Compartments (24), IDDI (25), Pfam (26), DIOPT (27) and InParanoid (28) (Figure 1). Using different mathematical characterizations, 36 feature values were derived from these six types of evidence to characterize the strength of functional association suggested by each type of evidence (Supplementary Table S2).

Not all feature values are expected to provide equal amount of information to suggest functional associations between genes. To increase the signal-to-noise ratio in the later functional association prediction step, we removed features that did not show a strong correlation to functional associations. The ROC curve was used to assess the capability of a feature to indicate protein interactions. In this study, protein interactions were considered a strong type of functional association (13). Seventeen features with AUC greater than 0.6 were selected for use (Supplementary Table S3 and Supplementary Figure S1).

Prediction of functional associations between genes

The libSVM package was used to train and predict functional associations (29, 30) (Figure 1). Positive examples include 4434 protein interactions published before 2018, which represent examples of strong functional associations between genes. Negative examples were prepared by generating random pairs of genes that do not overlap with the positive examples. Considering the low probability of two random genes having functional associations, the

generated negative examples are expected to include few false negatives. The positive-to-negative ratio in the training dataset was set to 1:100 to reflect the expectation that only a small fraction of gene pairs has functional associations. This approach of predicting functional gene associations may be considered an implementation of transfer learning. Both protein interactions and functional gene associations may be predicted from the evidence of functional associations; furthermore, protein interactions may be considered a special form of strong functional gene interactions. Therefore, ‘knowledge’ (i.e. the classification model) gained from predicting protein interactions may be used for predicting functional gene associations. In practice, there are experimentally reported gold-standard protein interactions, but there is no well-established gold-standard dataset for strong functional gene associations. With the strategy of transfer learning, we may avoid the difficulty of lacking gold-standard dataset when predicting functional gene associations and use the knowledge gained in predicting protein interactions (i.e. a special form of strong functional interactions) to predict functional gene associations.

To train the prediction model, the soft-margin Gaussian kernel SVM algorithm was used. The kernel width parameter σ and soft-margin parameter C were optimized with a 5-fold cross-validation targeting an optimal harmonic mean of sensitivity and specificity. With optimized σ and C , a prediction model was trained with all training data. This model was validated with an external validation dataset consisting of 559 protein interactions published after 31 December 2017 and randomly generated negative examples. In validation, this model showed a sensitivity of 22.15% and a specificity of 99.95%. For comparison, we also evaluated how well the predicted interaction in DroID, MIST and STRING covered these new interactions. Results are shown in Supplementary Table S4.

Applying this model to all *Drosophila* gene pairs produced 98056 inferred functional associations. These inferred functional interactions together with the 4779 known protein interactions make the PDIR dataset, which consists of 102835 interactions. To estimate how much proportion of protein–protein interactions were covered by the predicted functional interactome, we solved the following equation:

$$N_{interactome} \times Sensitivity + (N_{all-pairs} - N_{interactome}) \times (1 - specificity) = N_{predict},$$

where $N_{interactome}$ is the expected number of all protein–protein interactions in *Drosophila*, $N_{all-pairs}$ is the number of all gene pairs in *Drosophila*, $N_{predict}$ is the number of predicted gene associations and sensitivity and specificity are

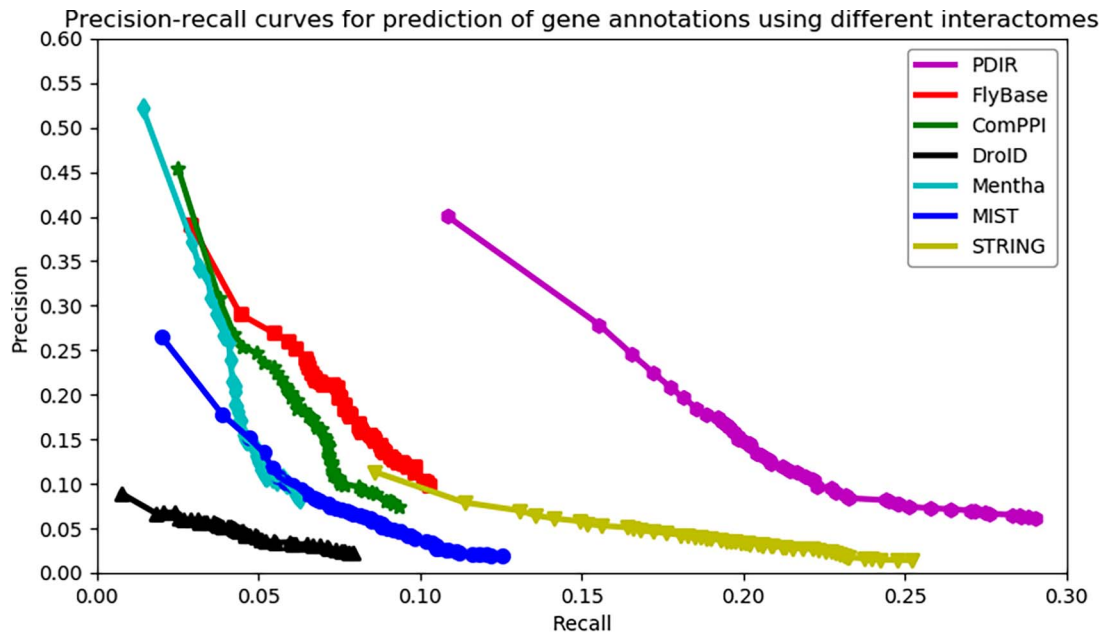


Figure 2. Assessment of the capabilities of seven interactomes to group functionally associated genes together. The precision-recall curves of gene function prediction using different interactomes are illustrated. Precision estimates the proportion of correct annotations identified by an interactome. Recall estimates the proportion of new annotations that is identified by an interactome.

the accuracy measures produced when the prediction model was validated with newly published protein interactions. Solving this equation gives an estimated size of *Drosophila* protein interactome 2.24×10^5 . This number corresponds to one protein interaction among 433 gene pairs, which is on the same order of magnitude as the reported fraction of protein interactions in yeast (1/775; (31)).

Evaluation of functional gene association network

One way to evaluate the quality of a functional association network is to evaluate how well it can group functionally associated genes together. This quality may be measured by the accuracy of using a gene's network neighbors to predict the gene's function with the 'guilt-by-association' strategy. In this study, the quality of the predicted functional associations was compared with six existing *Drosophila* interactomes, including FlyBase (21), ComPPI (32), DroID (33), mentha (34), MIST (35) and STRING (36). For each gene in each interactome, its GO biological process annotations were predicted as the terms enriched in the annotations of its first-degree network neighbors. In our evaluation, PANTHER term enrichment tool (9) was used to compute enriched terms.

We used the precision-recall curve to compare the overall accuracy of new annotation prediction across seven interactomes. The data used to infer PDIR gene associations were collected before 2018 (31 December 2017). We

collected 2833 genes from GO (37, 38) with new annotations dated up to 10 March 2019. These genes had a total of 104 795 annotations, of which 11 464 annotations were newly added (after 2018). Recall is measured as how much proportion of these new annotations may be successfully predicted. Precision is measured as how much proportion of the PANTHER predicted annotations are consistent with the known annotations (including both new and old annotations).

Each PANTHER-predicted annotation has an enrichment significance. The number of reported annotations will change when a cut-off on the significance value is applied. A higher cut-off will result in more reported annotations, leading to higher recall but also a higher false positive rate. In contrast, a lower cut-off will result in less reported annotations, leading to lower recall but also higher precision. The advantage of the precision-recall curve is that it shows precision and recall rates on different cut-offs, which gives a more comprehensive view of the quality of the interactome, independent of the selection of cut-offs. The higher the AUC, the better an interactome may support 'guilt-by-association' prediction of gene function.

As shown in Figure 2, the PDIR curve resides on top of others with the highest AUC, suggesting its superior quality to group functionally associated genes together. When the curve of PDIR reaches the high-recall region, it maintains the highest precision. The curves of the other six interactomes are below that of PDIR in all areas. Although FlyBase, ComPPI, DroID, mentha and MIST have similar

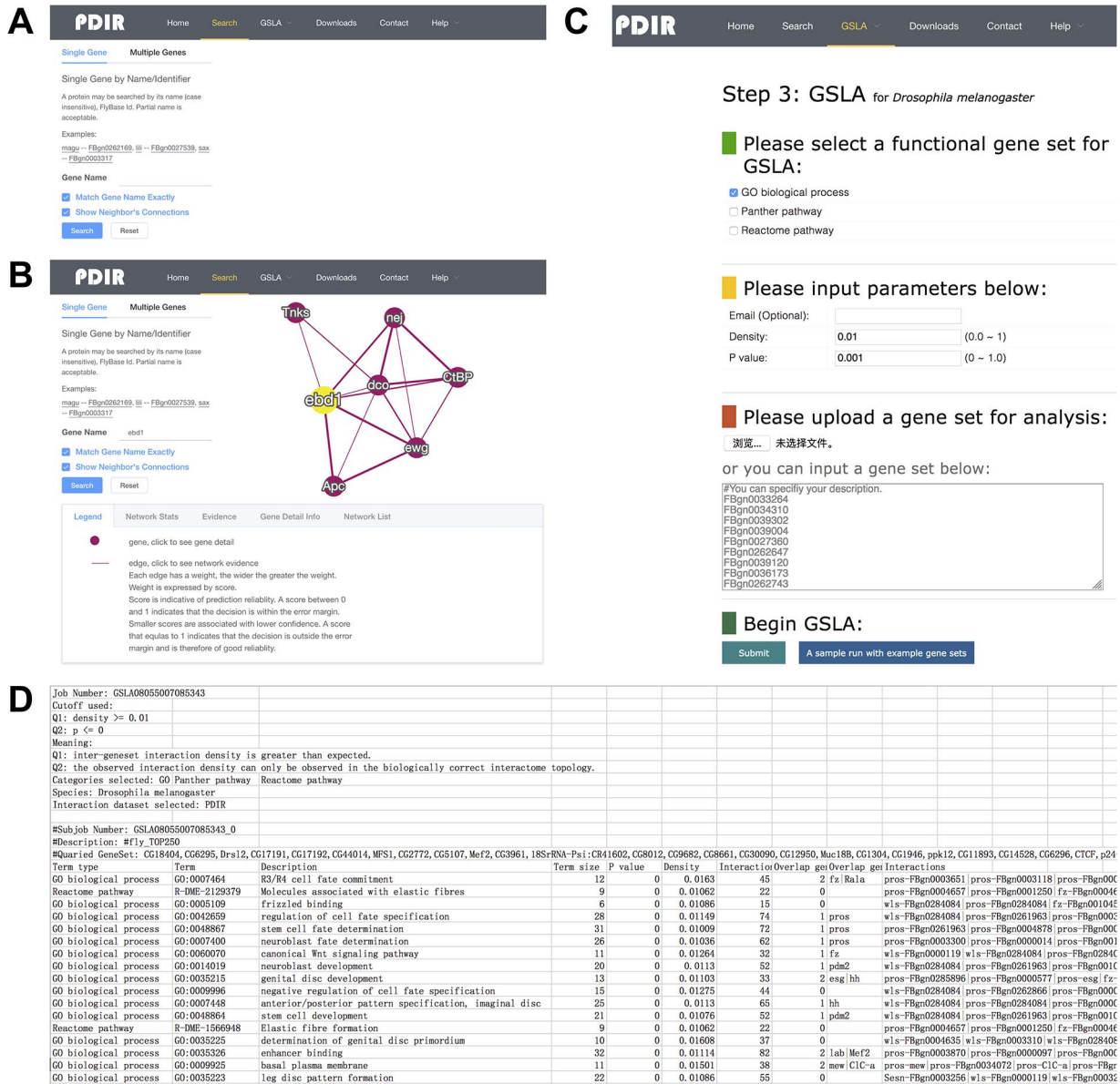


Figure 3. Interface of PDIR and GS LA. (A) Two search options in PDIR. (B) Search result page. A right click on the edge will show interaction details. (C) Interface of GS LA. (D) Results of a GS LA analysis job.

high-precision regions, these curves did not reach the high-recall regions. On the other hand, STRING reached the high-recall region, but its precision did not increase much in the low-recall region. This observation indicated that a high proportion of STRING interactions were weak functional gene associations, which may raise the false positive rates during function prediction. In general, PDIR showed a balance between coverage and accuracy. The overall quality of PDIR exceeds those of other compared interactomes.

PDIR/GS LA web interface

The interface of PDIR is user-friendly and easy to operate. PDIR provides two search options, a single gene search

and a multiple gene search (Figure 3A). Both search options offer access to PDIR with FlyBase ID or gene name. Single Gene mode reports putative functional associations involving the query gene, whereas Multiple Genes mode reports functional associations between the query genes. The resulting functional associations are provided in a tabular form (Figure 3B). A graphical view of the reported functional associations is provided at the right side of the query interface. The feature values that were used by our model to predict these interactions will be provided if a user correctly clicks the edges in the graphical view of the reported functional associations. In addition, users can also navigate to a gene information page that provides more detailed annotation of a gene by clicking the nodes

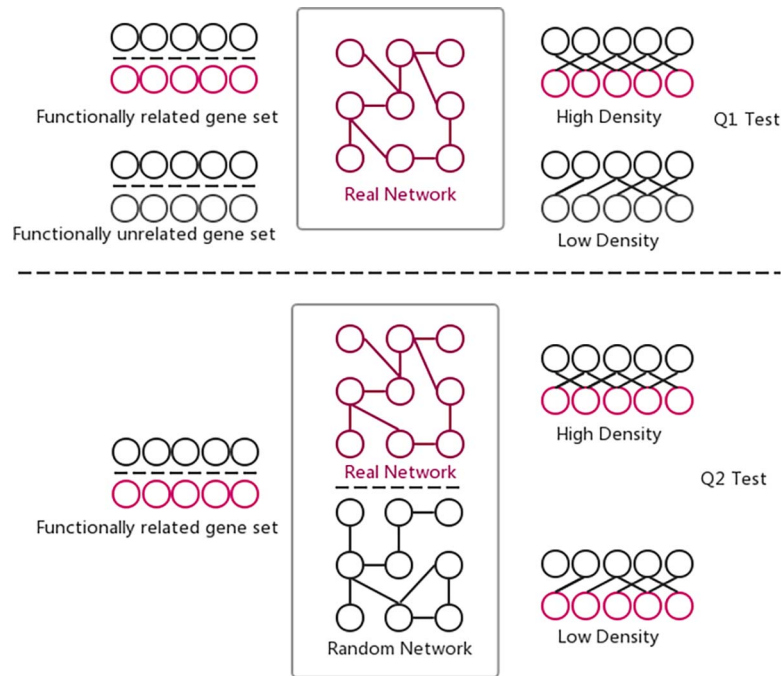


Figure 4. Two hypothesis tests that GSLA used to identify significant functional associations between two gene sets that are biologically meaningful. Q1 tests whether the density of functional associations between two biologically meaningful gene sets is higher than random gene pairs, while Q2 tests whether the strong functional associations observed between two gene sets can only be observed from the biologically correct network, rather than any random interactomes.

in the graphical view. Users can download all reported functional associations between genes. A full dump of the PDIR database is also available for download. More details about the PDIR/GSLA web tool can be found on the help section of the website.

The GSLA web tool was first developed with the predicted *Arabidopsis* interactome (13) for functional interpretation of CGS in *Arabidopsis*. GSLA relies on testing two hypotheses (Q1 and Q2) to ensure the significance of reported functional associations between two gene sets (Figure 4). The first test (Q1) examines whether the inter-gene-set gene association density between functionally associated gene sets is higher than the background gene association density between random gene sets. The second test (Q2) examines whether the observed high density between functionally associated gene sets can only be observed in the biologically correct functional gene association network. In other words, the density observed in PDIR is higher than the densities observed in random gene association networks consisting of the same genes with each gene having the same number of neighbors. In a biological sense, Q1 tests the strength of a functional association between two gene sets, while Q2 verifies that the observed strong functional association is the result of biologically correct network topology (i.e. our knowledge of the molecular mechanisms), rather than the result of the compositions of these two gene sets. Some genes, known as hubs, have considerably more

neighbors than other genes. Gene sets that include many hubs are therefore more likely to connect to other gene sets. Q2 is used to remove the confounding factor of gene set composition and to ensure the biological significance of the functional associations detected between gene sets. Q1 and Q2 are related but different tests that complement each other to increase the sensitivity and specificity of GSLA. The default criteria for GSLA to report a functional association between gene sets are density > 0.01 for Q1 and $P < 0.001$ for Q2.

The PDIR web interface provides a link to the GSLA online service that uses PDIR functional associations to interpret the functional impacts of observed CGS in *Drosophila*. The main interface of GSLA is illustrated in Figure 3C. To submit an observed CGS, users can submit a whitespace delimited list of gene IDs. GSLA accepts five types of *Drosophila* gene IDs, including FlyBase ID, gene name, UniprotKB ID, Ensembl gene and protein ID and NCBI Entrez ID. However, the internal server works only with FlyBase ID. The submitted IDs, if accepted, will be automatically mapped to FlyBase ID before further computation. To prevent information loss associated with ID mapping, it is suggested that submit CGS lists with FlyBase ID are used. The criteria to report significant functional associations (test Q1 and Q2 as described above) can be customized (Figure 3C). Before submitting an analysis job, users need to provide an email address

	GO Enrichment Analysis	David	GS LA
immune system process	Terms not in original publication	Terms not in original publication	No related terms
Wnt signaling pathway	No related terms	Consistent with original publication	Consistent with original publication
frizzled protein	No related terms	No related terms	Consistent with original publication
enhancer	No related terms	No related terms	Consistent with original publication
stem cell	No related terms	No related terms	Consistent with original publication
nervous systems	No related terms	No related terms	Terms not in original publication
genital disc	No related terms	No related terms	Terms not in original publication

Figure 5. Functional interpretations produced by PDIR/GSLA. Compared with GO enrichment analysis and DAVID, the annotations produced by GS LA are more comprehensive and more accurate.

to receive the results. We recommend using the top 50–200 changed genes as the query CGS to obtain optimal functional impact interpretations. In the result file, the top 10 lines show the analysis parameters (Figure 3D). Below is a table that shows the functionally associated biological processes and functional association between the genes in reported biological processes and the genes in the query CGS.

Using the PDIR/GSLA system to re-analyze the *Apc1* knockdown dataset

Wnt signaling pathways play an important role in cell fate determination and proliferation (39). Aberrant Wnt signaling often leads to diseases including birth defects and cancers (40). The canonical Wnt signaling pathways are well understood (41). The Wnt/ β -catenin pathway, a canonical Wnt pathway, is conserved between humans and *Drosophila*, which is known to regulate the proliferation of intestinal stem cells (ISCs) (18, 42). In the Wnt ‘off’ state, the transcription coactivator, β -catenin, is phosphorylated and degraded by proteasome (18). When Wnt is ‘on’, β -catenin becomes stable and translocates into the nucleus to interact with DNA-binding transcription factor (18). Hyperactivation of the Wnt pathway, which may be caused by truncating mutations of the tumor suppressor adenomatous polyposis coli (APC), can initiate the development of colorectal cancer (43, 44). Using the *Drosophila* model,

Tian *et al.* (18) demonstrated that *Apc1* loss leads to the overactivation of Wingless target genes, excessive number of ISCs, defects in adhesion and epithelial polarity and disorganization of the intestinal architecture. Two evolutionarily conserved transcription cofactors, Earthbound and Erect wing, are both essential for the hyperactivation of Wnt signaling. In addition, Hayden *et al.* (45) found that loss of *Apc1* results in severe defects in optic lobe development during the medullar development stage.

To investigate the pattern of gene regulation in the *Apc1* mutant, Tian *et al.* (18) measured the midgut transcriptomes of the wild-type and mutated lines using a microarray (GEO database, GSE99071). These researchers reported that over 1000 genes showed more than 2-fold expression changes (18). To assess whether the prediction tools can derive helpful biological insights from these changed genes, we performed PDIR/GSLA, DAVID (11) and GO enrichment (37, 38) analysis with the top 250 changed genes. As shown in Figure 5, GO enrichment analysis reported only one GO term, GO:0019731, antibacterial humoral response (Supplementary Table S5), which is not knowingly related to the main physiology of Wnt pathways. The DAVID tool, which relies on a term clustering technology, reported Wnt-related biological processes that are consistent with those reported by the original authors. However, DAVID reported a total of 176 terms in 20 clusters (Supplementary Table S6). Among them, there are 62 GO terms. The top 20 GO terms (ranked by *P*-value) included

many lipid metabolism and immune system processes. These metabolism terms are also not knowingly related to the main physiology of Wnt pathways. In contrast, PDIR/GSLA reported 17 terms (Supplementary Table S7). In addition to the Wnt pathway-related terms, PDIR/GSLA also found stem cell proliferation-related items, which are known to be the 'functional impact' of the Wnt hyperactivation. An excessive number of ISCs is also an observed phenotype of the *Apc1* mutant (18). Furthermore, GSLA also reported neuroblast development terms and elastic fiber formation terms, which are well-known functional impacts of the Wnt pathways. In this case study, the interpretation provided by PDIR/GSLA is broader and more accurate, which may better help experimental biologists explain the observation and formulate further hypotheses to elucidate the mechanisms of Wnt pathways.

Discussion

Before this study, there have been many efforts directed at building reference interactomes for *Drosophila*. To date, many related resources are available. For example, BioGRID (19), IntAct (20) and FlyBase (21) are dedicated to the curation of experimentally reported molecular interactions. DroID (33) and MIST (35) provide both experimentally reported interactions and interactions predicted by interologs. STRING (36) provides predicted molecular interactions. Experimentally reported interactions are more accurate than predicted interactions. However, the number of experimentally reported interactions is still small. According to the estimated size of the *Drosophila* protein interactome (2.24×10^5), a typical experimental interaction dataset, FlyBase, included 41 272 interactions, which represents 18.36% of protein interactome. This estimation does not consider false positive experimental interactions. Therefore, the actual coverages of these experimental interaction databases are expected to be lower. Although this coverage is comparable to PDIR, these interactions are mostly protein interactions, which are only one type of functional gene interaction. In contrast, PDIR is inferred from multiple types of evidence suggesting functional gene associations from different biological perspectives. Therefore, PDIR consists of functional interactions that are as strong as protein interactions, which provides a more comprehensive view of the true functional gene interaction network. On the other hand, databases that provide predicted interactions enjoy high coverage of the true protein interactome. For example, STRING provides 4 072 942 interactions and is estimated to cover 53.12% of protein interactions. However, databases providing predicted interactions often have very high false positive rates. STRING, as a typical example, is expected to have

a low reliability of 2.93% if considered as a protein interaction database. For these reasons, as demonstrated in our new gene annotation prediction assessment (Figure 2), both experimental reported interaction datasets and predicted interactomes did not perform, as well as PDIR, which enjoys a balanced sensitivity and reliability (22.6% coverage and 50.5% reliability if evaluated as protein interactome). Therefore, PDIR complements existing *Drosophila* interactomes as a high-quality reference for analyzing functional gene interactions.

The availability of PDIR enables the application of GSLA for *Drosophila* CGS interpretation. To report significant functional associations between two gene sets, GSLA assesses the density of functional gene associations between individual genes in two gene sets. Successful application of this strategy requires that the reference interactome has both high precision and high coverage of true functional interactome, which requires an interactome of balanced accuracy. Previous interactomes did not satisfy this requirement. In our assessments, using other interactomes, GSLA did not produce interpretations as useful as PDIR (data not shown). The same case was observed when we previously developed high-quality functional interactomes for humans and *Arabidopsis*.

As mentioned in the introduction, the availability of the PDIR/GSLA system enables the interpretation of *Drosophila* CGS for their potential functional impacts, which extends the capacity of current enrichment-based tools to summarize CGS into known biological processes. When there is no established biological concept that may accurately describe an observed CGS, PDIR/GSLA may still help researchers to understand the observed change in terms of how it connects to related physiologies. Meanwhile, the functional gene interactions provided in PDIR serve as a useful reference for investigators to focus on genes that likely mediate the mechanisms of interest.

Supplementary Data

Supplementary data are available at Database online

Author contributions

Xiao-Bao Ding developed the computational workflow and analyzed the data with the help of Heng Yao. Jie Jin developed the web database and tools. Yu-Tian Tao and Li Ruan wrote the manuscript. Wen-Ping Guo performed interaction prediction. Qiao-Lei Yang re-analyzed the microarray dataset. Peng-Cheng Chen and Heng Yao provided initial conceptualizations of the PDIR/GSLA system. Hai-Bo Zhang built the interaction model. Xin Chen designed and coordinated the project, and together with Yu-

Tian Tao wrote the first draft of this manuscript. All authors reviewed and edited the final manuscript.

Funding

National Natural Science Foundation of China (grant nos. 31571356 and 81830073); Breeding program of Taizhou University (grant no. 2018PY010).

Conflict of interest. None declared.

References

- Beckingham, K.M., Armstrong, J.D., Texada, M.J. *et al.* (2005) *Drosophila melanogaster*—the model organism of choice for the complex biology of multi-cellular organisms. *Grav. Space Biol. Bull.*, **18**, 17–29.
- Tolwinski, N.S. (2017) Introduction: *Drosophila*—a model system for developmental biology. *J Dev Biol*, **5**, 9.
- Rogoyski, O.M., Pueyo, J.I., Couso, J.P. *et al.* (2017) Functions of long non-coding RNAs in human disease and their conservation in *Drosophila* development. *Biochem. Soc. Trans.*, **45**, 895–904.
- Prüßing, K., Voigt, A. and Schulz, J.B. (2013) *Drosophila melanogaster* as a model organism for Alzheimer's disease. *Mol. Neurodegener.*, **8**, 35.
- Morata, G. and Calleja, M. (2019) Cell competition and tumorigenesis in the imaginal discs of *Drosophila*. *Semin. Cancer Biol.* doi: 10.1016/j.semcancer.2019.06.010
- Branson, K., Robie, A.A., Bender, J. *et al.* (2009) High-throughput ethomics in large groups of *Drosophila*. *Nat. Methods*, **6**, 451–457.
- Armknacht, S., Boutros, M., Kiger, A. *et al.* (2005) High-throughput RNA interference screens in *Drosophila* tissue culture cells. *Methods Enzymol.*, **392**, 55–73.
- Stanyon, C.A., Liu, G., Mangiola, B.A. *et al.* (2004) A *Drosophila* protein-interaction map centered on cell-cycle regulators. *Genome Biol.*, **5**, R96.
- Mi, H., Huang, X., Muruganujan, A. *et al.* (2017) PANTHER version 11: expanded annotation data from Gene Ontology and Reactome pathways, and data analysis tool enhancements. *Nucleic Acids Res.*, **45**, D183–D189.
- Kanehisa, M., Sato, Y., Furumichi, M. *et al.* (2019) New approach for understanding genome variations in KEGG. *Nucleic Acids Res.*, **47**, D590–D595.
- Huang, D.W., Sherman, B.T. and Lempicki, R.A. (2009) Systematic and integrative analysis of large gene lists using DAVID bioinformatics resources. *Nat. Protoc.*, **4**, 44–57.
- Shi, D., Zhang, J., Zhou, Q. *et al.* (2017) Quantitative evaluation of human bone mesenchymal stem cells rescuing fulminant hepatic failure in pigs. *Gut*, **66**, 955–964.
- Yao, H., Wang, X., Chen, P. *et al.* (2018) Predicted Arabidopsis interactome resource and gene set linkage analysis: a transcriptomic analysis resource. *Plant Physiol.*, **177**, 422–433.
- Zhou, X., Chen, P., Wei, Q. *et al.* (2013) Human interactome resource and gene set linkage analysis for the functional interpretation of biologically meaningful gene sets. *Bioinformatics*, **29**, 2024–2031.
- UniProt Consortium (2019) UniProt: a worldwide hub of protein knowledge. *Nucleic Acids Res.*, **47**, D506–D515.
- Smedley, D., Haider, S., Ballester, B. *et al.* (2009) BioMart—biological queries made easy. *BMC Genomics*, **10**, 22.
- Shannon, P., Markiel, A., Ozier, O. *et al.* (2003) Cytoscape: a software environment for integrated models of biomolecular interaction networks. *Genome Res.*, **13**, 2498–2504.
- Tian, A., Benchabane, H., Wang, Z. *et al.* (2017) Intestinal stem cell overproliferation resulting from inactivation of the APC tumor suppressor requires the transcription cofactors Earthbound and Erect wing. *PLoS Genet.*, **13**, e1006870.
- Oughtred, R., Stark, C., Breitkreutz, B.J. *et al.* (2019) The BioGRID interaction database: 2019 update. *Nucleic Acids Res.*, **47**, D529–D541.
- Orchard, S., Ammari, M., Aranda, B. *et al.* (2014) The MIntAct project—IntAct as a common curation platform for 11 molecular interaction databases. *Nucleic Acids Res.*, **42**, D358–D363.
- Thurmond, J., Goodman, J.L., Strelts, V.B. *et al.* (2019) FlyBase 2.0: the next generation. *Nucleic Acids Res.*, **47**, D759–D765.
- Obayashi, T., Kagaya, Y., Aoki, Y. *et al.* (2019) COXPRESdb v7: a gene coexpression database for 11 animal species supported by 23 coexpression platforms for technical evaluation and evolutionary inference. *Nucleic Acids Res.*, **47**, D55–D62.
- Gene Ontology Consortium (2015) Gene Ontology Consortium: going forward. *Nucleic Acids Res.*, **43**, D1049–D1056.
- Binder, J.X., Pletscher-Frankild, S., Tsafou, K. *et al.* (2014) COMPARTMENTS: unification and visualization of protein subcellular localization evidence. *Database (Oxford)*, **2014**, bau012.
- Kim, Y., Min, B. and Yi, G.S. (2012) IDDI: integrated domain-domain interaction and protein interaction analysis system. *Proteome Sci.*, **10**, S9.
- El-Gebali, S., Mistry, J., Bateman, A. *et al.* (2019) The Pfam protein families database in 2019. *Nucleic Acids Res.*, **47**, D427–D432.
- Hu, Y., Flockhart, J., Vinayagam, A. *et al.* (2011) An integrative approach to ortholog prediction for disease-focused and other functional studies. *BMC Bioinformatics*, **12**, 357.
- O'Brien, K.P., Remm, M. and Sonnhammer, E.L.L. (2005) Inparanoid: a comprehensive database of eukaryotic orthologs. *Nucleic Acids Res.*, **33**, D476–D480.
- Winters-Hilt, S., Yelundur, A., McChesney, C. *et al.* (2006) Support vector machine implementations for classification & clustering. *BMC Bioinformatics*, **7**, S4.
- Chang, C.C. and Lin, C.J. (2011) LIBSVM: a library for support vector machines. *ACM Trans. Intell. Syst. Technol.*, **2**, 1–27.
- Yu, H., Braun, P., Yildirim, M.A. *et al.* (2008) High-quality binary protein interaction map of the yeast interactome network. *Science*, **322**, 104–110.
- Veres, D.V., Gyurkó, D.M., Thaler, B. *et al.* (2015) CompPPI: a cellular compartment-specific database for protein-protein interaction network analysis. *Nucleic Acids Res.*, **43**, D485–D493.
- Murali, T., Pacifico, S., Yu, J. *et al.* (2011) DroID 2011: a comprehensive, integrated resource for protein, transcription factor, RNA and gene interactions for *Drosophila*. *Nucleic Acids Res.*, **39**, D736–D743.
- Calderone, A., Castagnoli, L. and Cesareni, G. (2013) mentha: a resource for browsing integrated protein-interaction networks. *Nat. Methods*, **10**, 690–691.

35. Hu,Y., Vinayagam,A., Nand,A. *et al.* (2018) Molecular Interaction Search Tool (MIST): an integrated resource for mining gene and protein interaction data. *Nucleic Acids Res.*, **46**, D567–D574.
36. Szklarczyk,D., Franceschini,A., Wyder,S. *et al.* (2015) STRING v10: protein–protein interaction networks, integrated over the tree of life. *Nucleic Acids Res.*, **43**, D447–D452.
37. Ashburner,M., Ball,C.A., Blake,J.A. *et al.* (2000) Gene ontology: tool for the unification of biology. The Gene Ontology Consortium. *Nat. Genet.*, **25**, 25–29.
38. The Gene Ontology Consortium (2019) The Gene Ontology Resource: 20 years and still GOing strong. *Nucleic Acids Res.*, **47**, D330–D338.
39. Gao,C. and Chen,Y.G. (2010) Dishevelled: the hub of Wnt signaling. *Cell. Signal.*, **22**, 717–727.
40. Clevers,H. (2006) Wnt/beta-catenin signaling in development and disease. *Cell*, **127**, 469–480.
41. MacDonald,B.T., Tamai,K. and He,X. (2009) Wnt/beta-catenin signaling: components, mechanisms, and diseases. *Dev. Cell*, **17**, 9–26.
42. Zhang,Z., Wang,X., Zhang,L. *et al.* (2017) Wnt/ β -catenin signaling pathway in trophoblasts and abnormal activation in preeclampsia (review). *Mol. Med. Rep.*, **16**, 1007–1013.
43. Schepers,A. and Clevers,H. (2012) Wnt signaling, stem cells, and cancer of the gastrointestinal tract. *Cold Spring Harb. Perspect. Biol.*, **4**, a007989.
44. Cancer Genome Atlas Network (2012) Comprehensive molecular characterization of human colon and rectal cancer. *Nature*, **487**, 330–337.
45. Hayden,M.A., Akong,K. and Peifer,M. (2007) Novel roles for APC family members and Wingless/Wnt signaling during *Drosophila* brain development. *Dev. Biol.*, **305**, 358–376.