RiceNet v2: an improved network prioritization server for rice genes

Tak Lee, Taeyun Oh, Sunmo Yang, Junha Shin, Sohyun Hwang, Chan Yeong Kim, Hyojin Kim, Hongseok Shim, Jung Eun Shim, Pamela C. Ronald, and Insuk Lee

Supplementary Online Methods

Defining a gene set for RiceNet v2

From 39,054 Non-TE locus from Os-Nipponbare-Reference-IRGSP-1.0 (1), we excluded 2,619 hypothetical proteins from the genes for RiceNet v2. We also excluded ChrSy and ChrUn genes because these genes were not mapped to any chromosomes. Including mitochondrial and chloroplast genes, total 36,736 genes were considered in constructing RiceNet v2. If either of two genes of a network link does not belong to these genes, the link was removed.

Gold standard gene pairs for training RiceNet v2

The Gene Ontology biological process (GO-BP) terms annotated by Biofuel Feedstock Genomics Resource (2), Kyoto Encyclopedia of Genes and Genomes (KEGG) metabolic pathways (3), MapMan metabolic pathways (4) and known/predicted biochemical pathways from RiceCyc (5) have been used to generate gold standard gene pairs to train the networks. The gold standard gene pairs were generated by pairing all the genes in each annotated terms. This method can give rise to training bias if a term has too many annotated genes because there will be too many gold standard gene pairs from a single term which may cause functional bias towards those terms. To minimize the training bias, ten biggest GO-BP terms were ignored during gold standard set construction. The gold standard set from GO-BP annotations was composed of 75,732 positive gene pairs and 4,937,629 negative gene pairs covering 3,167 *O. sativa* genes, ~9% of the 36,736 genes for network construction. For the same purpose of bias reduction during construction of a gold standard set based on KEGG, we ignored two biggest terms and five broad-concept terms of the KEGG pathways (release 72.0). Excluding the seven metabolic pathway terms resulted in a gold standard set of 290,809 positive and 8,384,886 negative gene pairs for 4,166 *O. sativa* genes, ~11% of the 36,736 genes. To generate gold standard from MapMan metabolic pathways, we generated gene pairs from pathways of third or fourth subBINs of hierarchy, because first and second BIN contains broad concept terms. We also ignored all the BINs starting with 35 because they are unknown. We ignored 11 pathways with vast number of annotated genes during gene pairing, resulted in a gold standard set of 201,359 positive and 22,29,3919 negative gene pairs for 6,708 genes, ~18% of the 36,736 genes. Lastly, for RiceCyc (version 3.3), we generated the gold standard pairs with ignoring three biggest pathways, resulted in 90,014 positive and 3,001,327 negative gene pairs for 2,487 genes, \sim 7% of the 36,736 genes. We combined all of the four sets of gold standard gene pairs to generate the integrated gold standard set, composing 591,664 positive and 58,416,152 negative gene pairs for 10,864 *O. sativa* genes, ~30% of the 36,736 genes. The excluded pathway terms during gold standard construction are listed at **Supplementary table 2**.

Benchmarking and integrating inferred functional links

Functional associations between genes from experimental, computational data were inferred by calculating the likelihood ratio (Log likelihood score, *LLS*) based on Bayesian statistics framework. *LLS* was calculated with the following equation;

$$
LLS = \ln\left(\frac{P(L|D)/P(\neg L|D)}{P(L)/P(\neg L)}\right)
$$

where $P(L|D)/P(\neg L|D)$ is the odds of gold standard positives $(P(L|D))$ and negatives $(P(\neg L|D))$ for a given data. $P(L)$ / $P(\neg L)$ is the odds of all gold standard positives ($P(L)$) and negatives $(P(\neg L))$. A network functional link can be supported by many multiple data types with different *LLS*s. Since not all of the data for integration are fully independent, naïve Bayesian integration is not a plausible approach. Hence, we used the weighted sum (*WS*) formula to integrate the data by modifying naïve Bayesian (6). The *WS* is defined as

$$
WS = S_0 + \sum_{i=1}^n \frac{S_i}{D \times i}, for all S \ge T,
$$

where *S* is the *LLS*. S_0 is the best *LLS*s and S_i is *LLS* of *i*th rank. *D* is a free parameter that is used to give weight. *T* is the minimum *LLS* threshold. Weighted sum takes full score of the top *LLS* and partial scores of the rest of the *LLS* by weight factor to alleviate the addition of redundant information.

Inferring links from genomic context: Phylogenetic profile similarity (PG) and Gene neighborhood (GN)

Similar evolutionary conservation pattern between two genes across species are sometimes due to their functional relatedness. This genomic context similarity enables us to infer co-functional links between genes. For constructing RiceNet v2, we used the two most widely used genomic context based network link inferring methods, Phylogenetic profile similarity (PG) (7-9) and gene neighborhood (GN) (10-12). A total of 2,144 sequenced genomes were used. (122 Archae, 1,626 Bacteria and 396 Eukarya genomes)

Phylogenetic profile similarity of two rice genes reflects their co-inheritance during speciation. Co-functionality of genes can be inferred from co-inheritance because genes that function together tend to be inherited together. To measure probability of co-inheritance of two genes, we first ran BLASTp for all *O. sativa* genes against the 2,144 genomes. With the best BLASTp scores for each of genomes, 36,736 (number of *O. sativa* genes) by 2,144 (number of genomes) phylogenetic profile matrix was constructed. The association between two genes based on phylogenetic profiles was measured by mutual information (MI) scores as described in *Date et al*. (13). We did not use the whole concatenated profile of the 2,144 genomes. Rather, sub-profiles for each of three domains of life (Archaea, Bacteria, Eukarya) were separately used which resulted in constructing three networks. These were subsequently integrated to construct a single network. We found that there was substantial increase in the network coverage and accuracy by using this divide-and-integrate approach based on domain-specific phylogenetic profiles.

Two distinct measures of genomic neighborhood exist: i) direct physical distance between neighboring genes (11,12,14), and ii) neighborhood probability (10). There have been evidences that these two measures are complementary (15). We reasoned that if the two methods give complementary information, both of the measurements can be useful. Thus, we inferred cofunctional links with both measures. They were subsequently integrated to generate a single GN co-functional network.

Inferring links from literature curated (LC) protein-protein interactions (PPI)

Observing protein-protein interactions (PPIs) in the cell is one of the most popular and certain way to discover the functional associations between genes. To infer the PPI interaction based functional associations for rice, we mined three PPI databases: DIP(16), IntAct (17), MINT (18).

Inferring links from co-expression (CX) patterns

Genes with similar biological functions tend to co-express in diverse biological contexts. High dimensional microarray and RNA-seq data can be used to infer co-functional links between coexpressed genes. We analyzed expression data sets based on four array platforms in GEO (Gene Expression Omnibus) database (19): GPL2025, GPL13160, GPL6864 and GPL8852. To infer co-functional linkages by co-expression patterns, we first created a vector for each gene that contains expression profiles across microarray experiments (GEO samples) in each GEO series. Then we calculated all pairwise Pearson correlation coefficients between vectors to address for co-expression patterns. GEO series with less than 12 samples were not used because measuring correlation with short vectors can generate many promiscuous co-expression patterns between genes. Each GEO series (see **Supplementary table 1**) generated a single co-functional network. Benchmarking with the gold standard set resulted in 39 co-functional networks. They were further integrated into a single CX network for rice.

Links transferred from other species' networks by orthology (Associalogs)

Many biological functions of genes are evolutionarily conserved across species by orthology. This allows transferring the functional information of genes from one species to another. We transferred co-functional linkages from networks of other organisms to RiceNet v2 using the associalog method (20). The links were transferred from three organisms with published genome scale functional gene networks: YeastNet v3 (21) for *Saccharomyces cerevisiae*, WormNet v3 (22) for *Caenorhabtitis elegans*, AraNet v2 (23) for *Arabidopsis thaliana*. In addition, unpublished network links were transferred from three other organisms: *Homo sapiens*, *Danio rerio,* and *Drosophila melanogaster*. Orthology between genes were mapped by using Inparanoid (24).

Supplementary table 1. Comparison between RiceNet v1 and RiceNet v2

Datasets described above are denoted by XX-YY. XX represents the names of the species: AT*: Arabidopsis thaliana*, CE: *Caenorhabtitis elegans*, DM: *Drosophila melanogaster*, DR: *Danio rerio*, HS: *Homo sapiens*, OS: *Oryza sativa*, SC: *Saccharomyces cerevisiae*. YY represents the type of data used to infer network links: CX: inferred from coexpression pattern of genes, CC: inferred from co-citation of genes across published papers, DC: inferred from protein domain co-occurrence pattern of the genes, GN: inferred from gene neighborhood, GT: inferred from genetic interactions, HT: inferred from high-throughput protein-protein interaction experiments, LC: inferred by curating protein-protein interactions from the literature, PG: inferred by measuring phylogenetic profile similarity, TS: inferred from protein tertiary structure based protein-protein interaction model.

Supplementary table 2. Ignored pathway terms during generation of gold standard gene pairs

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