

The *GOSim* package

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1 Introduction

The Gene Ontology (GO) has become one of the most widespread systems for systematically annotating gene products within the bioinformatics community and is developed by the Gene Ontology Consortium (The Gene Ontology Consortium, 2004). It is specifically intended for describing gene products with a controlled and structured vocabulary. GO terms are part of a Directed Acyclic Graph (DAG), covering three orthogonal taxonomies or "aspects": *molecular function*, *biological process* and *cellular component*. Two different kinds of relationship between GO terms exist: the "is-a" relationship and the "part-of" relationship. Providing a standard vocabulary across any biological resources, the GO enables researchers to use this information for automated data analysis.

The *GOSim* package (Fröhlich et al., 2007) provides the researcher with various information theoretic similarity concepts for GO terms (Resnik, 1995, 1999; Lin, 1998; Jiang and Conrath, 1998; Lord et al., 2003; Couto et al., 2003, 2005). Moreover, since version 1.1.5 *GOSim* contains several new similarity concepts, which are based on so-called diffusion kernel techniques (Lerman and Shakhnovich, 2007). Additionally *GOSim* implements different methods for computing functional similarities between gene products based on the similarities between the associated GO terms (Speer et al., 2005; Fröhlich et al., 2006; Schlicker et al., 2006; Lerman and Shakhnovich, 2007; del Pozo et al., 2008). This can, for instances, be used for clustering genes according to their biological function (Speer et al., 2005; Fröhlich et al., 2006) and thus may help to get a better understanding of the biological aspects covered by a set of genes.

Since version 1.1 *GOSim* additionally offers the possibility of a GO enrichment analysis using the topGO package (Alexa et al., 2006). Hence, *GOSim* acts now as an umbrella for different analysis methods employing the GO structure.

2 Usage of *GOSim*

To elucidate the usage of *GOSim* we show an example workflow and explain the employed similarity concepts. We create a character vector of Entrez gene IDs, which we assume to be from human:

```

> library(GOSim)
> genes=c("207", "208", "596", "901", "780", "3169", "9518", "2852", "26353", "8614", "7494")

```

Next we investigate the GO annotation within the current ontology (which is *biological process* by default):

```

> getGOInfo(genes)

      207       208       596       901       780
go_id Character,101 Character,29 Character,111 Character,3 Character,17
Term     Character,101 Character,29 Character,111 Character,3 Character,17
Definition Character,101 Character,29 Character,111 Character,3 Character,17
IC       Numeric,101 Numeric,29 Numeric,111 Numeric,3 Numeric,17
            3169       9518       2852       26353       8614
go_id     Character,22 Character,3 Character,39 Character,3 Character,13
Term      Character,22 Character,3 Character,39 Character,3 Character,13
Definition Character,22 Character,3 Character,39 Character,3 Character,13
IC       Numeric,22 Numeric,3 Numeric,39 Numeric,3 Numeric,13
            7494
go_id     Character,11
Term      Character,11
Definition Character,11
IC       Numeric,11

```

2.1 Term Similarities

Let us examine the similarity of the GO terms for genes "8614" and "2852" in greater detail:

```

> getTermSim(c("GO:0007166", "GO:0007267", "GO:0007584", "GO:0007165", "GO:0007186"), m)

```

	GO:0007166	GO:0007267	GO:0007584	GO:0007165	GO:0007186
GO:0007166	0.2628131	0.1806383	0.1266641	0.1945233	0.2628131
GO:0007267	0.1806383	0.3551639	0.0000000	0.1806383	0.1806383
GO:0007584	0.1266641	0.0000000	0.5128961	0.1266641	0.1266641
GO:0007165	0.1945233	0.1806383	0.1266641	0.1945233	0.1945233
GO:0007186	0.2628131	0.1806383	0.1266641	0.1945233	0.4016432

This calculates Resnik's pairwise similarity between GO terms (Resnik, 1995, 1999):

$$sim(t, t') = IC_{ms}(t, t') := \max_{\hat{t} \in Pa(t, t')} IC(\hat{t}) \quad (1)$$

Here $Pa(t, t')$ denotes the set of all common ancestors of GO terms t and t' , while $IC(t)$ denotes the information content of term t . It is defined as (e.g. Lord et al. (2003))

$$IC(\hat{t}) = -\log P(\hat{t}) \quad (2)$$

i.e. as the negative logarithm of the probability of observing \hat{t} . The information content of each GO term is already precomputed for each ontology based on the empirical observation, how many times a specific GO term or any of its direct or indirect offsprings appear in the annotation of the GO with gene products. GOSim provides a normalized version of Resnik's similarity measure, which divides the information content of the minimum subsumer by the maximum information content of all GO terms, hence obtaining a number between 0 and 1.

```
> data("ICsBPhumanall")
> IC[c("GO:0007166", "GO:0007267", "GO:0007584", "GO:0007165", "GO:0007186")]

GO:0007166 GO:0007267 GO:0007584 GO:0007165 GO:0007186
3.006413   4.062846   5.867200   2.225221   4.594539
```

This loads the information contents of all GO terms within "biological process". Likewise, the data files `ICsMFhumanall` and `ICsCChumanall` contain the information contents of all GO terms within "molecular function" and "cellular component" for human. Since GOSim version 1.1.4.0 the information content of GO terms relies on the mapping of primary gene IDs (mainly Entrez) to GO terms provided by the libraries `org.Dm.eg.db` (fly), `org.Hs.eg.db` (human), `org.Mm.eg.db` (mouse), etc. Additionally, it is possible to pass a user provided mapping via the function `setEvidenceLevel`. Please refer to the manual pages for details. If only GO terms having certain evidence codes should be considered, one must explicitly calculate the corresponding information contents in the function `calcICs`. Again, more information on this function can be found in the manual pages.

To continue our example from above, let us also calculate Jiang and Conrath's pairwise similarity between GO terms, which is the default, for comparison reasons (Jiang and Conrath, 1998):

```
> getTermSim(c("GO:0007166", "GO:0007267", "GO:0007584", "GO:0007165", "GO:0007186"), v
               GO:0007166 GO:0007267 GO:0007584 GO:0007165 GO:0007186
GO:0007166  0.9505312  0.5105747  0.2498911  0.7587689  0.7519293
GO:0007267  0.5105747  0.9828000  0.0000000  0.5740054  0.4169139
GO:0007584  0.2498911  0.0000000  0.9971692  0.2740140  0.2119568
GO:0007165  0.7587689  0.5740054  0.2740140  0.8919565  0.5820734
GO:0007186  0.7519293  0.4169139  0.2119568  0.5820734  0.9898931
```

Jiang and Conrath's similarity measure is defined as

$$sim(t, t') = 1 - \min(1, IC(t) - 2IC_{ms}(t, t') + IC(t')) \quad (3)$$

i.e. the similarity between t and t' is 0, if their normalized distance is at least 1.

Likewise, we can also compute Lin's pairwise similarity between GO terms (Lin, 1998):

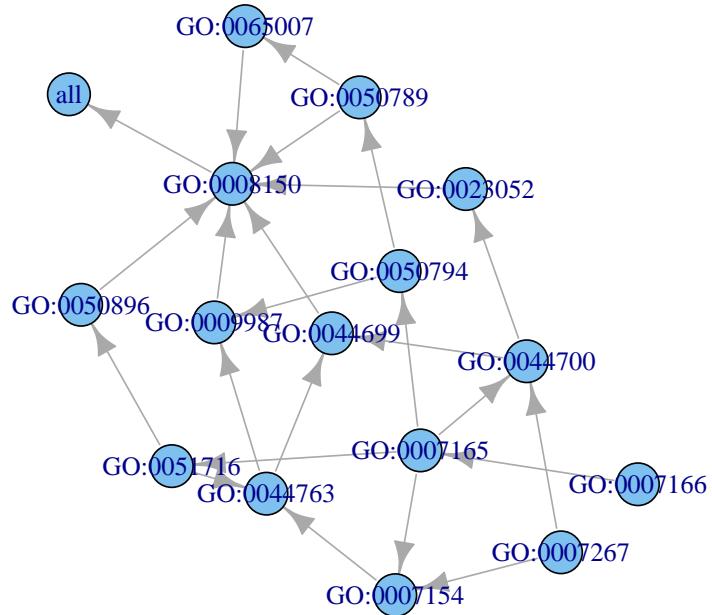
```
> getTermSim(c("GO:0007166", "GO:0007267", "GO:0007584", "GO:0007165", "GO:0007186"), m)
GO:0007166 GO:0007267 GO:0007584 GO:0007165 GO:0007186
GO:0007166 1.0000000 0.5846115 0.3265762 0.8506792 0.7910622
GO:0007267 0.5846115 1.0000000 0.0000000 0.6572401 0.4773693
GO:0007584 0.3265762 0.0000000 1.0000000 0.3581018 0.2770009
GO:0007165 0.8506792 0.6572401 0.3581018 1.0000000 0.6525805
GO:0007186 0.7910622 0.4773693 0.2770009 0.6525805 1.0000000
```

It is defined as:

$$sim(t, t') = \frac{2IC_{ms}(t, t')}{IC(t) + IC(t')} \quad (4)$$

Resnik's, Jiang-Conraths's and Lin's term similarities all refer to $IC_{ms}(t, t')$, the information content of the minimum subsumer of t and t' , i.e. of the lowest common ancestor in the hierarchy. For illustration let us plot the GO graph with leaves GO:0007166 and GO:0007267 and let us compute their minimum subsumer (see Fig. ??):

```
> library(igraph)
> G = getGOGraph(c("GO:0007166", "GO:0007267"))
> G2 = igraph.from.graphNEL(G)
> plot(G2, vertex.label=V(G2)$name)
```



```
> getMinimumSubsumer("GO:0007166", "GO:0007267")
```

```
[1] "GO:0023052"
```

In contrast to the above defined similarity measures Couto et al. (Couto et al., 2005) introduced a concept, which is not based on the minimum subsumer, but on the set of all disjunctive common ancestors. Roughly speaking, the idea is not to consider the common ancestor having the highest information content only, but also others, if they are somehow "separate" from each other, i.e. there exists a path to t or to t' not passing any other of the disjunctive common ancestors.

```
> getDisjCommAnc("GO:0007166", "GO:0007267")
```

```
[1] "GO:0007154" "GO:0009987" "GO:0023052" "GO:0044699" "GO:0044700"
[6] "GO:0044763"
```

In this case the set of disjunctive common ancestors consists of the minimum subsumer, GO:0007154, and its parent, GO:0009987, because from both there exists a path to GO:0007166 not passing any other disjunctive common ancestor(see Fig. ??).

Based on the notion of disjunctive common ancestors Resnik's similarity concept can be extended by defining:

$$sim(t, t') = IC_{share}(t, t') = \frac{1}{|DisjCommAnc|} \sum_{t \in DisjCommAnc} IC(t) \quad (5)$$

Likewise, Jiang-Conraths's and Lin's measures can be extended as well by replacing $IC_{ms}(t, t')$ by $IC_{share}(t, t')$.

```
> getTermSim(c("GO:0007166", "GO:0007267", "GO:0007584", "GO:0007165", "GO:0007186"), m)
```

	GO:0007166	GO:0007267	GO:0007584	GO:0007165	GO:0007186
GO:0007166	3.006413	1.507568	1.448955	1.545332	2.225221
GO:0007267	1.507568	4.062846	0.000000	1.507568	1.507568
GO:0007584	1.448955	0.000000	5.867200	1.448955	1.448955
GO:0007165	1.545332	1.507568	1.448955	2.225221	1.545332
GO:0007186	2.225221	1.507568	1.448955	1.545332	4.594539

Finally, it should be mentioned that also the depth and density enriched term similarity by Couto et al. (Couto et al., 2003) has been integrated into *GOSim*:

```
> setEnrichmentFactors(alpha=0.5, beta=0.3)
> getTermSim(c("GO:0007166", "GO:0007267", "GO:0007584", "GO:0007165", "GO:0007186"), m)
```

	GO:0007166	GO:0007267	GO:0007584	GO:0007165	GO:0007186
GO:0007166	9.038517	0.00000	0.00000	4.456869	3.732446
GO:0007267	0.000000	16.50672	0.00000	0.000000	0.000000
GO:0007584	0.000000	0.00000	34.42404	0.000000	0.000000
GO:0007165	4.456869	0.00000	0.00000	4.951609	0.000000
GO:0007186	3.732446	0.00000	0.00000	0.000000	21.109787

Since version 1.1.5 *GOSim* contains several new similarity concepts, which are based on so-called diffusion kernel techniques (Lerman and Shakhnovich, 2007) rather than on the information theoretic ideas presented before. For using these similarity measures it is necessary to pre-compute a diffusion kernel on the Gene Ontology graph via `calc.diffusion.kernel`. This will take some time and result in a kernel/similarity matrix that is stored in a file called e.g. 'diffKernelpowerBPhumanall.rda' (meaning matrix power diffusion kernel for ontology BP in human using all evidence codes) in the current working directory. Once the kernel is created, it has to be loaded into the environment first `load.diffusion.kernel`. Afterwards GO term similarities can be computed via function `getTermSim`. Please check the manual pages for details.

Since version 1.2 *GOSim* also contains Schlicker et al.'s GO term similarity measure (Schlicker et al., 2006), which is an adaption of Lin's similarity measure. Moreover, the graph information content similarity by Pesquita et al. has been implemented (Pesquita et al., 2007).

```
> getTermSim(c("GO:0007166", "GO:0007267", "GO:0007584", "GO:0007165", "GO:0007186"), m)
   GO:0007166 GO:0007267 GO:0007584 GO:0007165 GO:0007186
GO:0007166  0.9505312  0.5105747  0.2498911  0.7587689  0.7519293
GO:0007267  0.5105747  0.9828000  0.0000000  0.5740054  0.4169139
GO:0007584  0.2498911  0.0000000  0.9971692  0.2740140  0.2119568
GO:0007165  0.7587689  0.5740054  0.2740140  0.8919565  0.5820734
GO:0007186  0.7519293  0.4169139  0.2119568  0.5820734  0.9898931
```

2.2 Functional Gene Similarities

The special strength of *GOSim* lies in the possibility not only to calculate similarities for individual GO terms, but also for genes based on their complete GO annotation. Since *GOSim* version 1.1.5 for this purpose the following ideas have been implemented:

1. Maximum (Couto et al., 2003) and average pairwise GO term similarity
2. Average of best matching GO term similarities (Schlicker et al., 2006).
3. Computation of a so-called *optimal assignment* of terms from one gene to those of another one (Fröhlich et al., 2006).
4. Similarity derived from Hausdorff distances between sets (del Pozo et al., 2008).
5. Embedding of each gene into a feature space: (Speer et al., 2005; Fröhlich et al., 2006) proposed to define feature vectors by a gene's maximum GO term similarity to certain prototype genes. More simple (but probably also less accurate), (Mistry and Pavlidis, 2008) recently proposed to represent each gene by a feature vector describing the presence/absence of all GO terms. The absence of each GO term is additionally weighted by its information content. Within a feature space gene functional similarities naturally arise as dot products between feature vectors. These dot products can be understood as so-called *kernel functions* (Schölkopf and Smola, 2002), as used in e.g. Support Vector Machines (Cortes and Vapnik, 1995). Depending on the choice of later normalization (see below) one can arrive at the cosine similarity (Eq. 6), at the Tanimoto coefficient (Eq. 7) or at a measure similar to Lin's one (Eq. 8, Eq. 4).

2.2.1 Normalization of Similarities

Often, people want to normalize similarities, e.g. on the interval [0, 1], for better interpretation. To do so, we can perform the transformation

$$sim_{gene}(g, g') \leftarrow \frac{sim_{gene}(g, g')}{\sqrt{sim_{gene}(g, g)sim_{gene}(g', g')}} \quad (6)$$

Provided $sim_{gene} \geq 0$, the consequence will be a similarity of 1 for g with itself and between 0 and 1 for g with any other gene. In case of a feature space embedding this transformation is equivalent to computing the cosine similarity between two feature vectors.

Another possibility is to use Lin's normalization (see Eq. 4):

$$sim_{gene}(g, g') \leftarrow \frac{2sim_{gene}(g, g')}{sim_{gene}(g, g) + sim_{gene}(g', g')} \quad (7)$$

Furthermore, one can use a normalization in the spirit of the Tanimoto coefficient:

$$sim_{gene}(g, g') \leftarrow \frac{sim_{gene}(g, g')}{sim_{gene}(g, g) + sim_{gene}(g', g') - sim_{gene}(g, g')} \quad (8)$$

In case of a feature space embedding the transformation corresponds exactly to the Tanimoto coefficient between two feature vectors.

We now give a more detailed overview over the different similarity concepts mentioned above.

2.2.2 Maximum and Average Pairwise GO Term Similarity

The idea of the maximum pairwise GO term similarity is straight forward. Given two genes g and g' annotated with GO terms t_1, \dots, t_n and t'_1, \dots, t'_m we define the functional similarity between g and g' as

$$sim_{gene}(g, g') = \max_{\substack{i=1, \dots, n \\ j=1, \dots, m}} sim(t_i, t'_j) \quad (9)$$

where sim is some similarity measure to compare GO terms t_i and t'_j . This idea is, for instance, realized in FuSSiMeg (Couto et al., 2003). Instead of computing the maximum pairwise GO term similarity one may also take the average here.

2.2.3 Average of Best Matching GO Term Similarities

The idea of this approach (Schlicker et al., 2006) is to assign each GO term t_i occurring in gene g to its best matching partner $t'_{\pi i}$ in gene g' . Hence multiple GO terms from gene g can be assigned to one GO term from gene g' . A similarity score is computed by taking the average similarity of assigned GO terms. Since, however, genes can have an unequal number of GO terms the result depends on whether GO terms of gene g are assigned to those of gene g' or vice versa. Hence, in Schlicker et al. (2006) it was proposed to either take the maximum or the average of both similarity scores. Both strategies are implemented in *GOSim*.

2.2.4 Optimal Assignment Gene Similarities

To elucidate the idea of the optimal assignment (Fröhlich et al., 2006), consider the GO terms associated with gene "8614" on one hand and gene "2852" on the other hand:

```
> getGOInfo(c("8614", "2852"))
```

8614	2852	
go_id	Character, 13	Character, 39
Term	Character, 13	Character, 39
Definition	Character, 13	Character, 39
IC	Numeric, 13	Numeric, 39

Given a similarity concept sim to compare individual GO terms, the idea is now to assign each term of the gene having fewer annotation to exactly one term of the other gene such that the overall similarity is maximized. More formally the optimal assignment problem can be stated as follows: Let π be some permutation of either an n -subset of natural numbers $\{1, \dots, m\}$ or an m -subset of natural numbers $\{1, \dots, n\}$ (this will be clear from context). Then we are looking for the quantity

$$sim_{gene}(g, g') = \begin{cases} \max_{\pi} \sum_{i=1}^n sim(t_i, t'_{\pi(i)}) & \text{if } m > n \\ \max_{\pi} \sum_{j=1}^m sim(t_{\pi(j)}, t'_j) & \text{otherwise} \end{cases} \quad (10)$$

The computation of (10) corresponds to the solution of the classical maximum weighted bipartite matching (optimal assignment) problem in graph theory and can be carried out in $O(\max(n, m)^3)$ time (Mehlhorn and Näher, 1999). To prevent that larger lists of terms automatically achieve a higher similarity we may further sim_{gene} divide 10 by $\max(m, n)$.

In our example, using Lin's GO term similarity measure the following assignments yielding a corresponding similarity matrix are found:

```
> getGeneSim(c("8614", "2852"), similarity="OA", similarityTerm="Lin", avg=FALSE, verbose=TRUE)
filtering out genes not mapping to the currently set GO category ... ==> list of 2
term similarity matrix:
GO:0006874 GO:0006979 GO:0007166 GO:0007267 GO:0007566 GO:0007584
GO:0006874 1.00000000 0.00000000 0.2274750 0.08408554 0.0000000 0.0000000
GO:0006979 0.00000000 1.00000000 0.3275458 0.00000000 0.0000000 0.2475126
GO:0007166 0.22747501 0.3275458 1.0000000 0.58461150 0.0000000 0.3265762
GO:0007267 0.08408554 0.0000000 0.5846115 1.00000000 0.0000000 0.0000000
GO:0007566 0.00000000 0.0000000 0.0000000 0.00000000 1.0000000 0.0000000
GO:0007584 0.00000000 0.2475126 0.3265762 0.00000000 0.0000000 1.0000000
GO:0030968 0.16376373 0.4414432 0.4733334 0.39514856 0.0000000 0.4434258
GO:0033280 0.00000000 0.2092914 0.2631646 0.00000000 0.0000000 0.8458709
```

GO:0040015	0.13039013	0.0000000	0.1739665	0.00000000	0.1860972	0.0000000
GO:0043434	0.00000000	0.2605260	0.3496181	0.00000000	0.0000000	0.4877125
GO:0046697	0.00000000	0.0000000	0.0000000	0.00000000	0.7783503	0.0000000
GO:0071456	0.06225648	0.4052713	0.3727105	0.07111270	0.0000000	0.4071629
GO:2001256	0.12046150	0.0000000	0.1581194	0.00000000	0.0000000	0.0000000
	GO:0030968	GO:0033280	GO:0040015	GO:0043434	GO:0046697	GO:0071456
GO:0006874	0.1637637	0.0000000	0.1303901	0.0000000	0.0000000	0.06225648
GO:0006979	0.4414432	0.2092914	0.0000000	0.2605260	0.0000000	0.40527132
GO:0007166	0.4733334	0.2631646	0.1739665	0.3496181	0.0000000	0.37271054
GO:0007267	0.3951486	0.0000000	0.0000000	0.0000000	0.0000000	0.07111270
GO:0007566	0.0000000	0.0000000	0.1860972	0.0000000	0.7783503	0.00000000
GO:0007584	0.4434258	0.8458709	0.0000000	0.4877125	0.0000000	0.40716293
GO:0030968	1.0000000	0.4483505	0.1368560	0.5528910	0.0000000	0.54474045
GO:0033280	0.4483505	1.0000000	0.0000000	0.4859237	0.0000000	0.35097269
GO:0040015	0.1368560	0.0000000	1.0000000	0.0000000	0.1781009	0.00000000
GO:0043434	0.5528910	0.4859237	0.0000000	1.0000000	0.0000000	0.42580898
GO:0046697	0.0000000	0.0000000	0.1781009	0.0000000	1.0000000	0.00000000
GO:0071456	0.5447404	0.3509727	0.0000000	0.4258090	0.0000000	1.00000000
GO:2001256	0.1268545	0.0000000	0.1074404	0.0000000	0.0000000	0.00000000
	GO:2001256					
GO:0006874	0.1204615					
GO:0006979	0.0000000					
GO:0007166	0.1581194					
GO:0007267	0.0000000					
GO:0007566	0.0000000					
GO:0007584	0.0000000					
GO:0030968	0.1268545					
GO:0033280	0.0000000					
GO:0040015	0.1074404					
GO:0043434	0.0000000					
GO:0046697	0.0000000					
GO:0071456	0.0000000					
GO:2001256	1.0000000					
optimal assignment:						
	GO:0006874	GO:0006979	GO:0007166	GO:0007267	GO:0007566	GO:0007584
GO:0006874	1	0	0	0	0	0
GO:0006979	0	1	0	0	0	0
GO:0007166	0	0	1	0	0	0
GO:0007267	0	0	0	1	0	0
GO:0007566	0	0	0	0	1	0
GO:0007584	0	0	0	0	0	1
GO:0030968	0	0	0	0	0	0

GO:0033280	0	0	0	0	0	0
GO:0040015	0	0	0	0	0	0
GO:0043434	0	0	0	0	0	0
GO:0046697	0	0	0	0	0	0
GO:0071456	0	0	0	0	0	0
GO:2001256	0	0	0	0	0	0
	GO:0030968	GO:0033280	GO:0040015	GO:0043434	GO:0046697	GO:0071456
GO:0006874	0	0	0	0	0	0
GO:0006979	0	0	0	0	0	0
GO:0007166	0	0	0	0	0	0
GO:0007267	0	0	0	0	0	0
GO:0007566	0	0	0	0	0	0
GO:0007584	0	0	0	0	0	0
GO:0030968	1	0	0	0	0	0
GO:0033280	0	1	0	0	0	0
GO:0040015	0	0	1	0	0	0
GO:0043434	0	0	0	1	0	0
GO:0046697	0	0	0	0	1	0
GO:0071456	0	0	0	0	0	1
GO:2001256	0	0	0	0	0	0
	GO:2001256					
GO:0006874	0					
GO:0006979	0					
GO:0007166	0					
GO:0007267	0					
GO:0007566	0					
GO:0007584	0					
GO:0030968	0					
GO:0033280	0					
GO:0040015	0					
GO:0043434	0					
GO:0046697	0					
GO:0071456	0					
GO:2001256	1					
=====						
term similarity matrix:						
	GO:0001934	GO:0002695	GO:0007186	GO:0007204	GO:0008284	GO:0008285
GO:0001934	1.00000000	0.22007801	0.26720333	0.18199644	0.52148479	0.25414486
GO:0002695	0.22007801	1.00000000	0.22310634	0.15560831	0.22053153	0.47416475
GO:0007186	0.26720333	0.22310634	1.00000000	0.18460669	0.26787217	0.25819191
GO:0007204	0.18199644	0.15560831	0.18460669	1.00000000	0.18238716	0.17670495
GO:0008284	0.52148479	0.22053153	0.26787217	0.18238716	1.00000000	0.83460599

GO:0008285 0.25414486 0.47416475 0.25819191 0.17670495 0.83460599 1.00000000
 GO:0045909 0.32808696 0.14359053 0.16544703 0.41038426 0.32866354 0.15961704
 GO:0010579 0.60758037 0.14396173 0.59899810 0.11735835 0.31932412 0.15779813
 GO:0010628 0.90656841 0.20142197 0.24723804 0.19163405 0.48876477 0.23444188
 GO:0010629 0.88341800 0.46988842 0.24081684 0.18738474 0.23738239 0.54501949
 GO:0014068 0.39446408 0.17371799 0.35976742 0.14240737 0.39520019 0.19427372
 GO:0030263 0.53768169 0.04850166 0.05499861 0.04983805 0.05452169 0.05328585
 GO:0030264 0.05301288 0.04736763 0.05354497 0.04864143 0.05309282 0.05192021
 GO:0030335 0.47047325 0.20218546 0.24127903 0.16663498 0.47152076 0.23058080
 GO:0030518 0.22184371 0.19057139 0.40096172 0.15671929 0.22230455 0.21559634
 GO:0030819 0.78464087 0.18031913 0.21077711 0.14800225 0.41256254 0.20256677
 GO:0032024 0.39756345 0.17490633 0.33674516 0.43624498 0.39831119 0.19576113
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 GO:0043065 0.51862086 0.21951705 0.26637688 0.18151326 0.51989403 0.25339710
 GO:0043280 0.39856694 0.18926695 0.22310634 0.15560831 0.22053153 0.21392831
 GO:0045742 0.37722034 0.16706246 0.46456731 0.13678042 0.37789345 0.18598749
 GO:0045745 0.36650265 0.16288774 0.68956821 0.13325805 0.36713802 0.18082797
 GO:0045944 0.84089759 0.21718211 0.26294644 0.17950313 0.51328965 0.25029088
 GO:0050728 0.18169213 0.37518069 0.24528662 0.14833294 0.18204697 0.42158261
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 GO:0070374 0.42187574 0.18414548 0.38510107 0.15125169 0.42271783 0.20740823
 GO:0070474 0.30304961 0.13387850 0.15268474 0.12552444 0.30354148 0.14770597
 GO:0071333 0.15791354 0.13765840 0.31553102 0.68149839 0.15820761 0.15391441
 GO:0071356 0.06965070 0.06022107 0.33604865 0.06229511 0.06978875 0.06777665
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 GO:0071392 0.05871209 0.05186616 0.28268505 0.05339731 0.05881015 0.05737480
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 GO:0090200 0.37850501 0.16756089 0.34503835 0.13720133 0.37918272 0.18660546
 GO:2000353 0.33377457 0.14995556 0.17043710 0.12238158 0.33430145 0.16502841
 GO:2001238 0.36826583 0.16357655 0.45341130 0.13383884 0.36890733 0.18167726
 GO:0045909 GO:0010579 GO:0010628 GO:0010629 GO:0014068 GO:0030263
 GO:0001934 0.3280870 0.60758037 0.9065684 0.8834180 0.39446408 0.53768169
 GO:0002695 0.1435905 0.14396173 0.2014220 0.4698884 0.17371799 0.04850166
 GO:0007186 0.1654470 0.59899810 0.2472380 0.2408168 0.35976742 0.05499861
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 GO:0008284 0.3286635 0.31932412 0.4887648 0.2373824 0.39520019 0.05452169
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 GO:0010628 0.3421795 0.54279659 1.0000000 0.9394387 0.36427001 0.55793145

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GO:0043280	0.1435905	0.49791837	0.4187852	0.4098813	0.17371799	0.41372555
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	GO:0030264	GO:0030335	GO:0030518	GO:0030819	GO:0032024	GO:0032962
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 GO:0045745 0.04217273 0.34110028 0.29209690 0.30914130 0.44530823 0.25903819
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GO:0043280	0.70063704	1.00000000	0.16706246	0.16288774	0.39332239	0.1574053
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GO:0050728	0.18125313	0.15740531	0.37705728	0.36800401	0.17942456	1.0000000
GO:0050769	0.43318996	0.18880885	0.32989845	0.32167182	0.42859502	0.1570415
GO:0051053	0.20859120	0.32795640	0.16065814	0.15679366	0.89993969	0.3596719
GO:0051281	0.36385788	0.16215778	0.28809266	0.28179904	0.36061057	0.3235381
GO:0070374	0.42083403	0.18414548	0.58659183	0.57227618	0.41649616	0.4139151
GO:0070474	0.30244062	0.13387850	0.24242927	0.23737736	0.29989865	0.1289204
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GO:0090200	0.60911953	0.53480750	0.43881764	0.42895194	0.37416899	0.3781370
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GO:0002695	0.18880885	0.40137701	0.33666581	0.18414548	0.1338785	0.13765840
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GO:0008284	0.43518626	0.20950699	0.36526526	0.42271783	0.3035415	0.15820761
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GO:0070374	0.36355289	0.17639483	0.31343039	1.00000000	0.2626632	0.26493336
GO:0070474	0.39315259	0.12914229	0.23648960	0.26266324	1.0000000	0.11357774
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GO:0090200	0.33088061	0.16111904	0.28884138	0.47866667	0.2430296	0.24286041
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GO:2001238	0.32302924	0.15743179	0.28284025	0.57463937	0.2382139	0.23750866
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GO:0002695	0.06022107	0.06733108	0.05186616	0.16055023	0.1675609	0.14995556
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GO:0030263	0.04724700	0.05151490	0.04194583	0.26105619	0.3758095	0.34357588
GO:0030264	0.04617023	0.05023743	0.04109495	0.53455768	0.3678107	0.33687814
GO:0030335	0.06418704	0.07232767	0.05478137	0.51304937	0.3514730	0.31257520
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GO:0045745	0.24793151	0.27284186	0.21762227	0.24668075	0.4289519	0.26300535
GO:0045944	0.06876871	0.07819834	0.05808412	0.31490302	0.3741690	0.33039825
GO:0050728	0.20315185	0.22596869	0.17603662	0.13444522	0.3781370	0.12589407
GO:0050769	0.06008011	0.06715492	0.05176156	0.27999240	0.3308806	0.29618227

GO:0051053	0.05770114	0.06419648	0.04998602	0.15462663	0.1611190	0.14477534
GO:0051281	0.05184028	0.05702387	0.04552712	0.53976174	0.2888414	0.26204290
GO:0070374	0.27924902	0.31125615	0.24138385	0.27410197	0.4786667	0.29035356
GO:0070474	0.00000000	0.00000000	0.00000000	0.23452986	0.2430296	0.22145124
GO:0071333	0.51560532	0.57100148	0.44913575	0.11827606	0.2428604	0.11099850
GO:0071356	1.00000000	0.60516659	0.47000721	0.05134081	0.2548361	0.04804196
GO:0071375	0.60516659	1.00000000	0.69984532	0.05642010	0.2812271	0.05246140
GO:0071392	0.47000721	0.69984532	1.00000000	0.04514144	0.2229238	0.04257122
GO:0090004	0.05134081	0.05642010	0.04514144	1.00000000	0.5860990	0.22952691
GO:0090200	0.25483610	0.28122706	0.22292384	0.58609898	1.0000000	0.43406582
GO:2000353	0.04804196	0.05246140	0.04257122	0.22952691	0.4340658	1.00000000
GO:2001238	0.24894993	0.27407573	0.21840651	0.24758423	0.8919121	0.42565095
	GO:2001238					
GO:0001934	0.3682658					
GO:0002695	0.1635765					
GO:0007186	0.4534113					
GO:0007204	0.1338388					
GO:0008284	0.3689073					
GO:0008285	0.1816773					
GO:0045909	0.2534153					
GO:0010579	0.3097323					
GO:0010628	0.3390474					
GO:0010629	0.1659695					
GO:0014068	0.5461993					
GO:0030263	0.3686343					
GO:0030264	0.3609348					
GO:0030335	0.3426270					
GO:0030518	0.2933394					
GO:0030819	0.3103948					
GO:0032024	0.4470665					
GO:0032962	0.2599177					
GO:0043065	0.5926774					
GO:0043280	0.5220906					
GO:0045742	0.5278209					
GO:0045745	0.5162018					
GO:0045944	0.3641599					
GO:0050728	0.3694990					
GO:0050769	0.3230292					
GO:0051053	0.1574318					
GO:0051281	0.2828402					
GO:0070374	0.5746394					
GO:0070474	0.2382139					

GO:0071333 0.2375087
 GO:0071356 0.2489499
 GO:0071375 0.2740757
 GO:0071392 0.2184065
 GO:0090004 0.2475842
 GO:0090200 0.8919121
 GO:2000353 0.4256510
 GO:2001238 1.0000000

optimal assignment:

	GO:0001934	GO:0002695	GO:0007186	GO:0007204	GO:0008284	GO:0008285
GO:0001934	1	0	0	0	0	0
GO:0002695	0	1	0	0	0	0
GO:0007186	0	0	1	0	0	0
GO:0007204	0	0	0	1	0	0
GO:0008284	0	0	0	0	1	0
GO:0008285	0	0	0	0	0	1
GO:0045909	0	0	0	0	0	0
GO:0010579	0	0	0	0	0	0
GO:0010628	0	0	0	0	0	0
GO:0010629	0	0	0	0	0	0
GO:0014068	0	0	0	0	0	0
GO:0030263	0	0	0	0	0	0
GO:0030264	0	0	0	0	0	0
GO:0030335	0	0	0	0	0	0
GO:0030518	0	0	0	0	0	0
GO:0030819	0	0	0	0	0	0
GO:0032024	0	0	0	0	0	0
GO:0032962	0	0	0	0	0	0
GO:0043065	0	0	0	0	0	0
GO:0043280	0	0	0	0	0	0
GO:0045742	0	0	0	0	0	0
GO:0045745	0	0	0	0	0	0
GO:0045944	0	0	0	0	0	0
GO:0050728	0	0	0	0	0	0
GO:0050769	0	0	0	0	0	0
GO:0051053	0	0	0	0	0	0
GO:0051281	0	0	0	0	0	0
GO:0070374	0	0	0	0	0	0
GO:0070474	0	0	0	0	0	0
GO:0071333	0	0	0	0	0	0
GO:0071356	0	0	0	0	0	0
GO:0071375	0	0	0	0	0	0

GO:0071392	0	0	0	0	0	0
GO:0090004	0	0	0	0	0	0
GO:0090200	0	0	0	0	0	0
GO:2000353	0	0	0	0	0	0
GO:2001238	0	0	0	0	0	0
	GO:0045909	GO:0010579	GO:0010628	GO:0010629	GO:0014068	GO:0030263
GO:0001934	0	0	0	0	0	0
GO:0002695	0	0	0	0	0	0
GO:0007186	0	0	0	0	0	0
GO:0007204	0	0	0	0	0	0
GO:0008284	0	0	0	0	0	0
GO:0008285	0	0	0	0	0	0
GO:0045909	1	0	0	0	0	0
GO:0010579	0	1	0	0	0	0
GO:0010628	0	0	1	0	0	0
GO:0010629	0	0	0	1	0	0
GO:0014068	0	0	0	0	1	0
GO:0030263	0	0	0	0	0	1
GO:0030264	0	0	0	0	0	0
GO:0030335	0	0	0	0	0	0
GO:0030518	0	0	0	0	0	0
GO:0030819	0	0	0	0	0	0
GO:0032024	0	0	0	0	0	0
GO:0032962	0	0	0	0	0	0
GO:0043065	0	0	0	0	0	0
GO:0043280	0	0	0	0	0	0
GO:0045742	0	0	0	0	0	0
GO:0045745	0	0	0	0	0	0
GO:0045944	0	0	0	0	0	0
GO:0050728	0	0	0	0	0	0
GO:0050769	0	0	0	0	0	0
GO:0051053	0	0	0	0	0	0
GO:0051281	0	0	0	0	0	0
GO:0070374	0	0	0	0	0	0
GO:0070474	0	0	0	0	0	0
GO:0071333	0	0	0	0	0	0
GO:0071356	0	0	0	0	0	0
GO:0071375	0	0	0	0	0	0
GO:0071392	0	0	0	0	0	0
GO:0090004	0	0	0	0	0	0
GO:0090200	0	0	0	0	0	0
GO:2000353	0	0	0	0	0	0

GO:2001238	0	0	0	0	0	0	0
	GO:0030264	GO:0030335	GO:0030518	GO:0030819	GO:0032024	GO:0032962	
GO:0001934	0	0	0	0	0	0	0
GO:0002695	0	0	0	0	0	0	0
GO:0007186	0	0	0	0	0	0	0
GO:0007204	0	0	0	0	0	0	0
GO:0008284	0	0	0	0	0	0	0
GO:0008285	0	0	0	0	0	0	0
GO:0045909	0	0	0	0	0	0	0
GO:0010579	0	0	0	0	0	0	0
GO:0010628	0	0	0	0	0	0	0
GO:0010629	0	0	0	0	0	0	0
GO:0014068	0	0	0	0	0	0	0
GO:0030263	0	0	0	0	0	0	0
GO:0030264	1	0	0	0	0	0	0
GO:0030335	0	1	0	0	0	0	0
GO:0030518	0	0	1	0	0	0	0
GO:0030819	0	0	0	0	0	0	0
GO:0032024	0	0	0	0	0	1	0
GO:0032962	0	0	0	0	0	0	1
GO:0043065	0	0	0	0	0	0	0
GO:0043280	0	0	0	0	0	0	0
GO:0045742	0	0	0	0	0	0	0
GO:0045745	0	0	0	0	0	0	0
GO:0045944	0	0	0	1	0	0	0
GO:0050728	0	0	0	0	0	0	0
GO:0050769	0	0	0	0	0	0	0
GO:0051053	0	0	0	0	0	0	0
GO:0051281	0	0	0	0	0	0	0
GO:0070374	0	0	0	0	0	0	0
GO:0070474	0	0	0	0	0	0	0
GO:0071333	0	0	0	0	0	0	0
GO:0071356	0	0	0	0	0	0	0
GO:0071375	0	0	0	0	0	0	0
GO:0071392	0	0	0	0	0	0	0
GO:0090004	0	0	0	0	0	0	0
GO:0090200	0	0	0	0	0	0	0
GO:2000353	0	0	0	0	0	0	0
GO:2001238	0	0	0	0	0	0	0
	GO:0043065	GO:0043280	GO:0045742	GO:0045745	GO:0045944	GO:0050728	
GO:0001934	0	0	0	0	0	0	0
GO:0002695	0	0	0	0	0	0	0

GO:0007186	0	0	0	0	0	0
GO:0007204	0	0	0	0	0	0
GO:0008284	0	0	0	0	0	0
GO:0008285	0	0	0	0	0	0
GO:0045909	0	0	0	0	0	0
GO:0010579	0	0	0	0	0	0
GO:0010628	0	0	0	0	0	0
GO:0010629	0	0	0	0	0	0
GO:0014068	0	0	0	0	0	0
GO:0030263	0	0	0	0	0	0
GO:0030264	0	0	0	0	0	0
GO:0030335	0	0	0	0	0	0
GO:0030518	0	0	0	0	0	0
GO:0030819	0	0	0	0	1	0
GO:0032024	0	0	0	0	0	0
GO:0032962	0	0	0	0	0	0
GO:0043065	1	0	0	0	0	0
GO:0043280	0	1	0	0	0	0
GO:0045742	0	0	1	0	0	0
GO:0045745	0	0	0	1	0	0
GO:0045944	0	0	0	0	0	0
GO:0050728	0	0	0	0	0	1
GO:0050769	0	0	0	0	0	0
GO:0051053	0	0	0	0	0	0
GO:0051281	0	0	0	0	0	0
GO:0070374	0	0	0	0	0	0
GO:0070474	0	0	0	0	0	0
GO:0071333	0	0	0	0	0	0
GO:0071356	0	0	0	0	0	0
GO:0071375	0	0	0	0	0	0
GO:0071392	0	0	0	0	0	0
GO:0090004	0	0	0	0	0	0
GO:0090200	0	0	0	0	0	0
GO:2000353	0	0	0	0	0	0
GO:2001238	0	0	0	0	0	0
	GO:0050769	GO:0051053	GO:0051281	GO:0070374	GO:0070474	GO:0071333
GO:0001934	0	0	0	0	0	0
GO:0002695	0	0	0	0	0	0
GO:0007186	0	0	0	0	0	0
GO:0007204	0	0	0	0	0	0
GO:0008284	0	0	0	0	0	0
GO:0008285	0	0	0	0	0	0

GO:0045909	0	0	0	0	0	0
GO:0010579	0	0	0	0	0	0
GO:0010628	0	0	0	0	0	0
GO:0010629	0	0	0	0	0	0
GO:0014068	0	0	0	0	0	0
GO:0030263	0	0	0	0	0	0
GO:0030264	0	0	0	0	0	0
GO:0030335	0	0	0	0	0	0
GO:0030518	0	0	0	0	0	0
GO:0030819	0	0	0	0	0	0
GO:0032024	0	0	0	0	0	0
GO:0032962	0	0	0	0	0	0
GO:0043065	0	0	0	0	0	0
GO:0043280	0	0	0	0	0	0
GO:0045742	0	0	0	0	0	0
GO:0045745	0	0	0	0	0	0
GO:0045944	0	0	0	0	0	0
GO:0050728	0	0	0	0	0	0
GO:0050769	1	0	0	0	0	0
GO:0051053	0	1	0	0	0	0
GO:0051281	0	0	1	0	0	0
GO:0070374	0	0	0	1	0	0
GO:0070474	0	0	0	0	1	0
GO:0071333	0	0	0	0	0	1
GO:0071356	0	0	0	0	0	0
GO:0071375	0	0	0	0	0	0
GO:0071392	0	0	0	0	0	0
GO:0090004	0	0	0	0	0	0
GO:0090200	0	0	0	0	0	0
GO:2000353	0	0	0	0	0	0
GO:2001238	0	0	0	0	0	0
	GO:0071356	GO:0071375	GO:0071392	GO:0090004	GO:0090200	GO:2000353
GO:0001934	0	0	0	0	0	0
GO:0002695	0	0	0	0	0	0
GO:0007186	0	0	0	0	0	0
GO:0007204	0	0	0	0	0	0
GO:0008284	0	0	0	0	0	0
GO:0008285	0	0	0	0	0	0
GO:0045909	0	0	0	0	0	0
GO:0010579	0	0	0	0	0	0
GO:0010628	0	0	0	0	0	0
GO:0010629	0	0	0	0	0	0

GO:0014068	0	0	0	0	0	0
GO:0030263	0	0	0	0	0	0
GO:0030264	0	0	0	0	0	0
GO:0030335	0	0	0	0	0	0
GO:0030518	0	0	0	0	0	0
GO:0030819	0	0	0	0	0	0
GO:0032024	0	0	0	0	0	0
GO:0032962	0	0	0	0	0	0
GO:0043065	0	0	0	0	0	0
GO:0043280	0	0	0	0	0	0
GO:0045742	0	0	0	0	0	0
GO:0045745	0	0	0	0	0	0
GO:0045944	0	0	0	0	0	0
GO:0050728	0	0	0	0	0	0
GO:0050769	0	0	0	0	0	0
GO:0051053	0	0	0	0	0	0
GO:0051281	0	0	0	0	0	0
GO:0070374	0	0	0	0	0	0
GO:0070474	0	0	0	0	0	0
GO:0071333	0	0	0	0	0	0
GO:0071356	1	0	0	0	0	0
GO:0071375	0	1	0	0	0	0
GO:0071392	0	0	1	0	0	0
GO:0090004	0	0	0	1	0	0
GO:0090200	0	0	0	0	1	0
GO:2000353	0	0	0	0	0	1
GO:2001238	0	0	0	0	0	0
GO:2001238						
GO:0001934	0					
GO:0002695	0					
GO:0007186	0					
GO:0007204	0					
GO:0008284	0					
GO:0008285	0					
GO:0045909	0					
GO:0010579	0					
GO:0010628	0					
GO:0010629	0					
GO:0014068	0					
GO:0030263	0					
GO:0030264	0					
GO:0030335	0					

GO:0030518	0
GO:0030819	0
GO:0032024	0
GO:0032962	0
GO:0043065	0
GO:0043280	0
GO:0045742	0
GO:0045745	0
GO:0045944	0
GO:0050728	0
GO:0050769	0
GO:0051053	0
GO:0051281	0
GO:0070374	0
GO:0070474	0
GO:0071333	0
GO:0071356	0
GO:0071375	0
GO:0071392	0
GO:0090004	0
GO:0090200	0
GO:2000353	0
GO:2001238	1

=====

term similarity matrix:

	GO:0001934	GO:0002695	GO:0007186	GO:0007204	GO:0008284	GO:0008285
GO:0006874	0.18956951	0.16111130	0.1924032	0.96327998	0.1899935	0.18383542
GO:0006979	0.00000000	0.00000000	0.2776981	0.00000000	0.0000000	0.00000000
GO:0007166	0.32192373	0.26000870	0.7910622	0.21665702	0.3228951	0.30893321
GO:0007267	0.09322283	0.07707063	0.4773693	0.08050070	0.0934703	0.08989595
GO:0007566	0.00000000	0.00000000	0.0000000	0.00000000	0.0000000	0.00000000
GO:0007584	0.00000000	0.00000000	0.2770009	0.00000000	0.0000000	0.00000000
GO:0030968	0.22401252	0.19216964	0.4049366	0.15808124	0.2244824	0.21764415
GO:0033280	0.00000000	0.00000000	0.2299946	0.00000000	0.0000000	0.00000000
GO:0040015	0.15268665	0.32216121	0.1543554	0.12676207	0.1529372	0.35578731
GO:0043434	0.00000000	0.00000000	0.2934024	0.00000000	0.0000000	0.00000000
GO:0046697	0.00000000	0.00000000	0.0000000	0.00000000	0.0000000	0.00000000
GO:0071456	0.06712798	0.05832589	0.3237220	0.06026934	0.0672562	0.06538553
GO:2001256	0.14034178	0.12539701	0.1417504	0.11735835	0.1405534	0.13744912
	GO:0045909	GO:0010579	GO:0010628	GO:0010629	GO:0014068	GO:0030263
GO:0006874	0.4229081	0.1204615	0.2000490	0.1954228	0.1470025	0.05118915
GO:0006979	0.0000000	0.1747083	0.0000000	0.0000000	0.2128199	0.00000000

GO:0007166	0.1881854	0.4372131	0.3017171	0.2922087	0.4127581	0.06154269
GO:0007267	0.0000000	0.2790705	0.0000000	0.0000000	0.3490917	0.05702883
GO:0007566	0.1968291	0.0000000	0.0000000	0.0000000	0.0000000	0.00000000
GO:0007584	0.0000000	0.1744320	0.0000000	0.0000000	0.2124102	0.00000000
GO:0030968	0.1455048	0.2596200	0.2052091	0.2007658	0.3140368	0.04907904
GO:0033280	0.0000000	0.1545423	0.0000000	0.0000000	0.1836310	0.00000000
GO:0040015	0.3546344	0.1074404	0.1587928	0.3721151	0.1259208	0.00000000
GO:0043434	0.0000000	0.1807964	0.0000000	0.0000000	0.2219232	0.00000000
GO:0046697	0.1879061	0.0000000	0.0000000	0.0000000	0.0000000	0.00000000
GO:0071456	0.0000000	0.2145087	0.0000000	0.0000000	0.2562529	0.04607250
GO:2001256	0.1126994	0.1011779	0.1454839	0.1432364	0.1174040	0.00000000
	GO:0030264	GO:0030335	GO:0030518	GO:0030819	GO:0032024	GO:0032962
GO:0006874	0.04992759	0.17296137	0.1623026	0.15297184	0.45042420	0.12350529
GO:0006979	0.00000000	0.00000000	0.2347282	0.00000000	0.00000000	0.00000000
GO:0007166	0.05972824	0.28502725	0.4679114	0.24341527	0.38679808	0.18704318
GO:0007267	0.05546740	0.08368833	0.3910747	0.07261140	0.69207836	0.05702883
GO:0007566	0.00000000	0.00000000	0.0000000	0.00000000	0.00000000	0.00000000
GO:0007584	0.00000000	0.00000000	0.2342299	0.00000000	0.00000000	0.00000000
GO:0030968	0.04791817	0.20550140	0.3449739	0.18295194	0.29364399	0.14916313
GO:0033280	0.00000000	0.00000000	0.1997148	0.00000000	0.00000000	0.00000000
GO:0040015	0.00000000	0.14263294	0.1359240	0.12987743	0.12663682	0.10963679
GO:0043434	0.00000000	0.00000000	0.2458512	0.00000000	0.00000000	0.00000000
GO:0046697	0.00000000	0.00000000	0.0000000	0.00000000	0.00000000	0.00000000
GO:0071456	0.04504801	0.06203847	0.2795270	0.05573554	0.05416098	0.04607250
GO:2001256	0.00000000	0.45733181	0.1260533	0.12083618	0.45377292	0.10312334
	GO:0043065	GO:0043280	GO:0045742	GO:0045745	GO:0045944	GO:0050728
GO:0006874	0.18904533	0.16111130	0.1410142	0.1372734	0.18686592	0.1533251
GO:0006979	0.00000000	0.00000000	0.2042329	0.1988652	0.00000000	0.4135955
GO:0007166	0.32072488	0.26000870	0.5295439	0.5122653	0.31576488	0.2833794
GO:0007267	0.09291715	0.07707063	0.3329883	0.3230203	0.09164957	0.0000000
GO:0007566	0.00000000	0.00000000	0.0000000	0.0000000	0.00000000	0.0000000
GO:0007584	0.00000000	0.00000000	0.2038555	0.1985074	0.00000000	0.6009321
GO:0030968	0.22343135	0.19216964	0.3018427	0.2942007	0.22101285	0.3967368
GO:0033280	0.00000000	0.00000000	0.1772024	0.1731474	0.00000000	0.5165396
GO:0040015	0.15237651	0.13516123	0.1218802	0.1193189	0.15108208	0.3101200
GO:0043434	0.00000000	0.00000000	0.2126020	0.2067916	0.00000000	0.2317917
GO:0046697	0.00000000	0.00000000	0.0000000	0.0000000	0.00000000	0.0000000
GO:0071456	0.06696934	0.05832589	0.2469888	0.2411566	0.06630835	0.3672759
GO:2001256	0.14007972	0.12539701	0.1138838	0.1116445	0.13898504	0.1210370
	GO:0050769	GO:0051053	GO:0051281	GO:0070374	GO:0070474	GO:0071333
GO:0006874	0.16069324	0.15366975	0.78669393	0.1564457	0.1290810	0.70344634
GO:0006979	0.00000000	0.00000000	0.00000000	0.2263471	0.0000000	0.21241474

GO:0007166	0.25914495	0.24481983	0.21144708	0.4464537	0.1718473	0.36189434
GO:0007267	0.07683990	0.07299105	0.06385840	0.3748591	0.0000000	0.06923274
GO:0007566	0.28241049	0.00000000	0.00000000	0.0000000	0.1844556	0.00000000
GO:0007584	0.00000000	0.00000000	0.00000000	0.2258837	0.0000000	0.39781989
GO:0030968	0.19169741	0.18374426	0.16428383	0.3331681	0.1355411	0.53917361
GO:0033280	0.00000000	0.00000000	0.00000000	0.1936150	0.0000000	0.40847560
GO:0040015	0.39691205	0.31065885	0.28332785	0.1321480	0.3342800	0.11459004
GO:0043434	0.00000000	0.00000000	0.00000000	0.2366725	0.0000000	0.49348504
GO:0046697	0.29190372	0.00000000	0.00000000	0.0000000	0.1765969	0.00000000
GO:0071456	0.05819365	0.05595895	0.05042972	0.2706841	0.0000000	0.45733281
GO:2001256	0.12516602	0.12123256	0.63522824	0.1227992	0.1066283	0.10685043
	GO:0071356	GO:0071375	GO:0071392	GO:0090004	GO:0090200	GO:2000353
GO:0006874	0.06442044	0.07262417	0.05495129	0.13518396	0.1414616	0.12575988
GO:0006979	0.22489114	0.25319268	0.19213013	0.00000000	0.2048747	0.00000000
GO:0007166	0.38914493	0.45423752	0.31933754	0.20872197	0.3934867	0.19116349
GO:0007267	0.07395014	0.08496810	0.06173779	0.06310219	0.3341852	0.05819108
GO:0007566	0.00000000	0.00000000	0.00000000	0.00000000	0.0000000	0.00000000
GO:0007584	0.42113872	0.47401578	0.35989601	0.00000000	0.2044950	0.00000000
GO:0030968	0.56953487	0.63789352	0.48951240	0.16263407	0.3027555	0.15177190
GO:0033280	0.42901743	0.47442112	0.82129547	0.00000000	0.1776853	0.00000000
GO:0040015	0.00000000	0.00000000	0.00000000	0.11787561	0.1221846	0.11125041
GO:0043434	0.52378374	0.97040777	0.62086240	0.00000000	0.2132975	0.00000000
GO:0046697	0.00000000	0.00000000	0.00000000	0.00000000	0.0000000	0.00000000
GO:0071456	0.48115018	0.53408293	0.41795952	0.04995693	0.2476841	0.04682810
GO:2001256	0.00000000	0.00000000	0.00000000	0.38299885	0.1141495	0.10454967
	GO:2001238					
GO:0006874	0.1378898					
GO:0006979	0.1997499					
GO:0007166	0.5150975					
GO:0007267	0.3246580					
GO:0007566	0.0000000					
GO:0007584	0.1993888					
GO:0030968	0.2954612					
GO:0033280	0.1738176					
GO:0040015	0.1197429					
GO:0043434	0.2077483					
GO:0046697	0.0000000					
GO:0071456	0.2421200					
GO:2001256	0.1120156					
optimal assignment:						
GO:0006874	GO:0006979	GO:0007166	GO:0007267	GO:0007566	GO:0007584	
GO:0001934	0	0	0	1	0	0

GO:0002695	0	0	0	0	0	0
GO:0007186	0	0	1	0	0	0
GO:0007204	0	0	0	0	0	0
GO:0008284	0	0	0	0	0	0
GO:0008285	0	0	0	0	0	0
GO:0045909	0	0	0	0	0	0
GO:0010579	0	0	0	0	0	0
GO:0010628	0	0	0	0	0	0
GO:0010629	0	0	0	0	0	0
GO:0014068	0	0	0	0	0	0
GO:0030263	0	0	0	0	0	0
GO:0030264	0	0	0	0	0	0
GO:0030335	0	0	0	0	0	0
GO:0030518	0	0	0	0	0	0
GO:0030819	0	0	0	0	0	0
GO:0032024	0	0	0	0	0	0
GO:0032962	0	0	0	0	0	0
GO:0043065	0	0	0	0	0	0
GO:0043280	0	0	0	0	0	0
GO:0045742	0	0	0	0	0	0
GO:0045745	0	0	0	0	0	0
GO:0045944	0	0	0	0	0	0
GO:0050728	1	0	0	0	0	0
GO:0050769	0	1	0	0	0	0
GO:0051053	0	0	0	0	1	0
GO:0051281	0	0	0	0	0	1
GO:0070374	0	0	0	0	0	0
GO:0070474	0	0	0	0	0	0
GO:0071333	0	0	0	0	0	0
GO:0071356	0	0	0	0	0	0
GO:0071375	0	0	0	0	0	0
GO:0071392	0	0	0	0	0	0
GO:0090004	0	0	0	0	0	0
GO:0090200	0	0	0	0	0	0
GO:2000353	0	0	0	0	0	0
GO:2001238	0	0	0	0	0	0
	GO:0030968	GO:0033280	GO:0040015	GO:0043434	GO:0046697	GO:0071456
GO:0001934	0	0	0	0	0	0
GO:0002695	0	0	0	0	0	0
GO:0007186	0	0	0	0	0	0
GO:0007204	0	0	0	0	0	0
GO:0008284	1	0	0	0	0	0

GO:0008285	0	0	0	0	0	0
GO:0045909	0	0	0	0	0	0
GO:0010579	0	0	0	0	0	0
GO:0010628	0	0	0	1	0	0
GO:0010629	0	0	0	0	0	0
GO:0014068	0	0	0	0	0	0
GO:0030263	0	0	0	0	0	0
GO:0030264	0	0	0	0	0	0
GO:0030335	0	0	0	0	0	1
GO:0030518	0	0	0	0	0	0
GO:0030819	0	0	0	0	0	0
GO:0032024	0	0	0	0	0	0
GO:0032962	0	0	0	0	0	0
GO:0043065	0	0	0	0	0	0
GO:0043280	0	0	1	0	0	0
GO:0045742	0	0	0	0	0	0
GO:0045745	0	0	0	0	0	0
GO:0045944	0	0	0	0	0	0
GO:0050728	0	0	0	0	0	0
GO:0050769	0	0	0	0	0	0
GO:0051053	0	0	0	0	0	0
GO:0051281	0	0	0	0	0	0
GO:0070374	0	0	0	0	0	0
GO:0070474	0	0	0	0	0	0
GO:0071333	0	0	0	0	0	0
GO:0071356	0	1	0	0	0	0
GO:0071375	0	0	0	0	1	0
GO:0071392	0	0	0	0	0	0
GO:0090004	0	0	0	0	0	0
GO:0090200	0	0	0	0	0	0
GO:2000353	0	0	0	0	0	0
GO:2001238	0	0	0	0	0	0
GO:2001256						
GO:0001934	0					
GO:0002695	0					
GO:0007186	0					
GO:0007204	0					
GO:0008284	0					
GO:0008285	0					
GO:0045909	0					
GO:0010579	0					
GO:0010628	0					

GO:0010629	0
GO:0014068	0
GO:0030263	0
GO:0030264	0
GO:0030335	0
GO:0030518	0
GO:0030819	1
GO:0032024	0
GO:0032962	0
GO:0043065	0
GO:0043280	0
GO:0045742	0
GO:0045745	0
GO:0045944	0
GO:0050728	0
GO:0050769	0
GO:0051053	0
GO:0051281	0
GO:0070374	0
GO:0070474	0
GO:0071333	0
GO:0071356	0
GO:0071375	0
GO:0071392	0
GO:0090004	0
GO:0090200	0
GO:2000353	0
GO:2001238	0
<hr/>	
8614	2852
8614	1.000000 0.344252
2852	0.344252 1.000000

Note the difference to a gene similarity that is just based on the maximum GO term similarity and to a gene similarity that is based on the average of best matching GO terms:

```
> getGeneSim(c("8614", "2852"), similarity="max", similarityTerm="Lin", verbose=FALSE)

filtering out genes not mapping to the currently set GO category ... ==> list of 2
  8614      2852
8614 1.0000000 0.8751547
2852 0.8751547 1.0000000
```

```
> getGeneSim(c("8614", "2852"), similarity="funSimMax", similarityTerm="Lin", verbose=1)
filtering out genes not mapping to the currently set GO category ... ==> list of 2
  8614      2852
8614 1.0000000 0.6139785
2852 0.6139785 1.0000000
```

2.2.5 Gene Similarities In the Spirit of Hausdorff Metrics

Hausdorff metrics are a general concept for measuring distances between compact subsets of a metric space. Let X and Y be the two sets of GO terms associated to genes g and g' , and let $d(t, t')$ denote the distance between GO terms t and t' . Then the Hausdorff distance X and Y is defined as

$$d_{Hausdorff}(X, Y) = \max\{\sup_{t \in X} \inf_{t' \in Y} d(t, t'), \sup_{t' \in Y} \inf_{t \in X} d(t, t')\} \quad (11)$$

Using Hausdorff metrics for measuring gene functional distances was proposed in del Pozo et al. (2008). We translate the idea to define a similarity measure between g and g' (see the difference to previous GOSim versions):

$$sim_{gene}(g, g') = \exp(-d_{Hausdorff}(g, g')) \quad (12)$$

```
> getGeneSim(c("8614", "2852"), similarity="hausdorff", similarityTerm="Lin", verbose=1)
filtering out genes not mapping to the currently set GO category ... ==> list of 2
  8614 2852
8614    1    1
2852    1    1
```

2.2.6 Feature Space Embedding of Gene Products

The Simple Approach Mistry and Pavlidis (2008) proposed to represent each gene by a feature vector describing the presence/absence of all GO terms. The absence of each GO term is additionally weighted by its information content. In the feature space similarities arise as dot products. Hence, the similarity between two GO terms t and t' is implicitly defined as the product of their information content values, hence ignoring the exact DAG structure of the Gene Ontology as employed by the GO term similarity measures explained in the beginning of this document.

```
> getGeneSim(c("8614", "2852"), similarity="dot", method="Tanimoto", verbose=FALSE)
filtering out genes not mapping to the currently set GO category ... ==> list of 2
  8614 2852
8614    1  NaN
2852  NaN    1
```

This will calculate the Tanimoto coefficient between feature vectors as a similarity measure. It is possible to retrieve the feature vectors via:

```
> features = getGeneFeatures(c("8614", "2852"))

filtering out genes not mapping to the currently set GO category ... ==> list of 2
```

Embeddings via GO Term Similarities to Prototype Genes This approach is due to Speer et al. (2005); Fröhlich et al. (2006). The idea is to define a feature vector for each gene by its pairwise GO term similarity to certain prototype genes, i.e. the prototype genes form a (nonorthogonal) basis, and each gene is defined relative to this basis. The prototype genes can either be defined a priori or one can use one of the heuristics implemented in the function `selectPrototypes`. The default behavior is to select the 250 best annotated genes, i.e. which have been annotated with GO terms most often, but here we just use 5 for computational reasons:

```
> proto = selectPrototypes(n=5, verbose=FALSE)
```

We now calculate for each gene g feature vectors $\phi(g)$ by using their similarity to all prototypes p_1, \dots, p_n :

$$\phi(g) = (\text{sim}'(g, p_1), \dots, \text{sim}'(g, p_n))^T \quad (13)$$

Here sim' by default is the maximum pairwise GO term similarity. Alternatively, one can use other similarity measures for sim' as well. These similarity measures can by itself again be combined with arbitrary GO term similarity concepts. The default is the Jiang-Conrath term similarity.

Because the feature vectors are very high-dimensional we usually perform a principal component analysis (PCA) to project the data into a lower dimensional subspace:

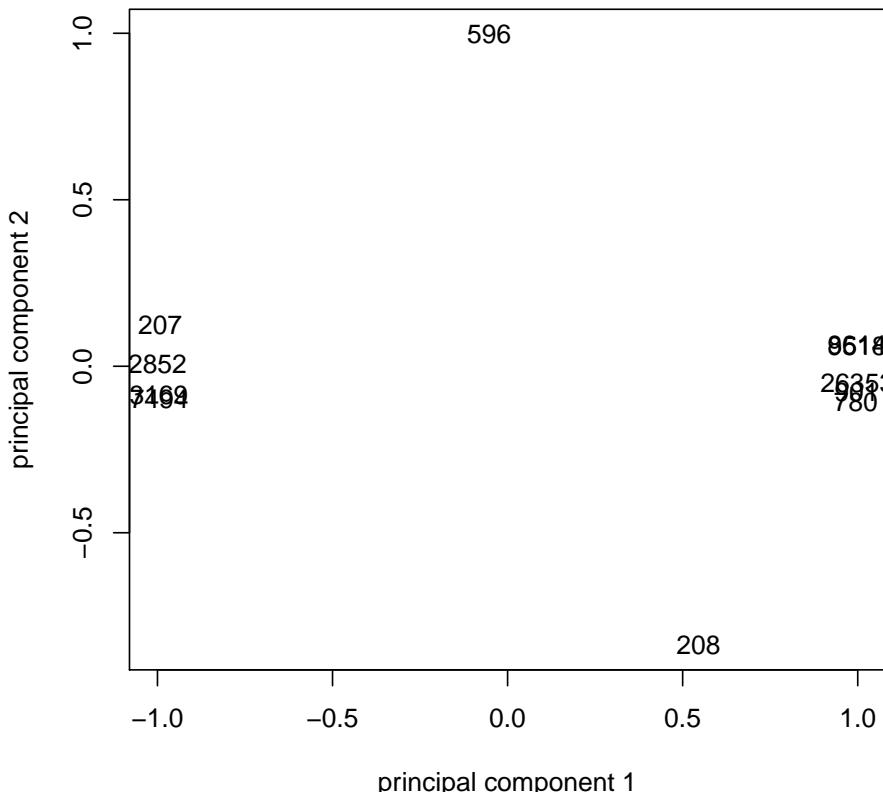
```
> PHI = getGeneFeaturesPrototypes(genes, prototypes=proto, verbose=FALSE)

filtering out genes not mapping to the currently set GO category ... ==> list of 1
filtering out genes not mapping to the currently set GO category ... ==> list of 5
```

This uses the above defined prototypes to calculate feature vectors and performs a PCA afterwards. The number of principal components is chosen such that at least 95% of the total variance in feature space can be explained (this is a relatively conservative criterion).

We can now plot our genes in the space spanned by the first 2 principal components to get an impression of the relative "position" of the genes to each other in the feature space (see Fig. ??). The feature vectors are normalized to Euclidian norm 1 by default:

```
> x=seq(min(PHI$features[,1]),max(PHI$features[,1]),length.out=100)
> y=seq(min(PHI$features[,2]),max(PHI$features[,2]),length.out=100)
> plot(x,y,xlab="principal component 1",ylab="principal component 2",type="n")
> text(PHI$features[,1],PHI$features[,2],labels=genes)
```



Finally, we can directly calculate the similarities of the genes to each other, this time using the Resnik's GO term similarity concept. These similarities may then be used to cluster genes with respect to their function:

```
> sim = getGeneSimPrototypes(genes, prototypes=proto, similarityTerm="Resnik", verbose=TRUE)
> h=hclust(as.dist(1-sim$similarity), "ward")
> plot(h,xlab="")
```

This produces a hierarchical clustering of all genes using Ward's method (see Fig. 1).

2.2.7 Combination of Similarities from Different Ontologies

It should be mentioned that up to now all similarity computations were performed within the ontology "biological process". One could imagine to combine functional similarities between gene products with regard to different taxonomies. An obvious way for doing so would be to consider the sum of the respective similarities:

$$sim_{total}(g, g') = sim_{Ontology1}(g, g') + sim_{Ontology2}(g, g') \quad (14)$$

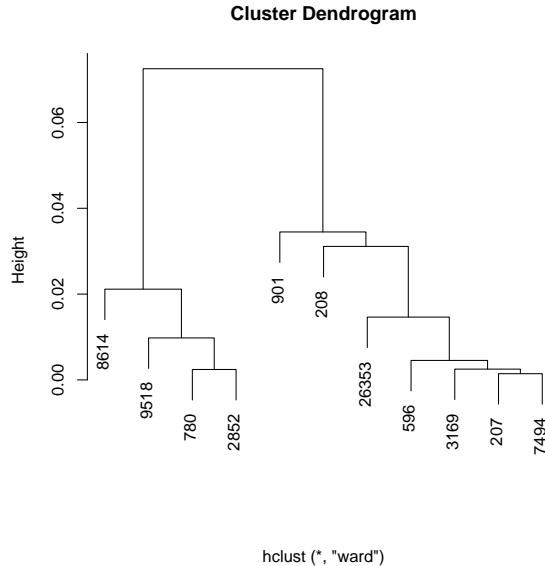


Figure 1: Possible functional clustering of the genes using Ward’s method.

Of course, one could also use a weighted averaging scheme here, if desired.

2.3 Cluster Evaluations

GOSim has the possibility to evaluate a given clustering of genes or terms by means of their GO similarities. Supposed, based on other experiments (e.g. microarray), we have decided to put genes "8614", "9518", "780", "2852" in one group, genes "3169", "207", "7494", "596" in a second and the rest in a third group. Then we can ask ourselves, how similar these groups are with respect to their GO annotations:

```
> ev = evaluateClustering(c(2,3,2,3,1,2,1,1,3,1,2), sim$similarity)
> plot(ev$clustersil, main="")
```

A good indication of the clustering quality can be obtained by looking at the cluster silhouettes (Rousseeuw, 1987) (see Fig. 2). This shows that clusters 1 and 2 are relatively homogenous with respect to the functional similarity of the genes contained in it, while the genes in cluster 3 are more dissimilar.

2.4 GO Enrichment Analysis

Since version 1.1 *GOSim* also offers the possibility of a GO enrichment analysis. Suppose, we may now want to get a clearer picture of the genes involved in cluster 1. For this purpose we use the topGO tool (Alexa et al., 2006).

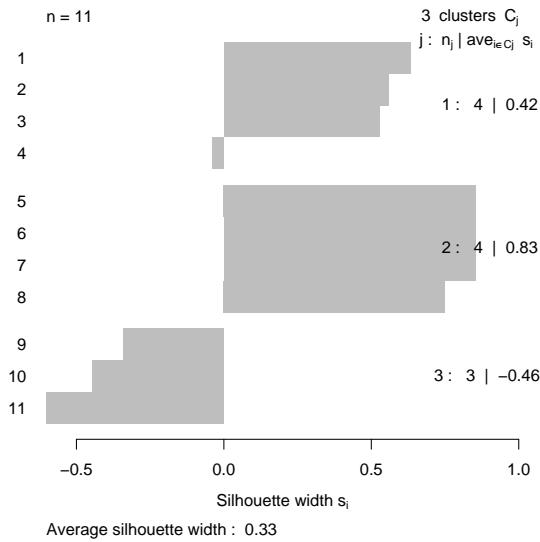


Figure 2: Silhouette plot of a possible given grouping of genes.

```

> library(org.Hs.eg.db)
> library(topGO)

groupGOTerms:           GOBPTerm, GOMFTerm, GOCCTerm environments built.

> allgenes = union(c("8614", "9518", "780", "2852"), sample(keys(org.Hs.egGO), 1000)
> GOenrichment(c("8614", "9518", "780", "2852"), allgenes) # print out what cluster

Building most specific GOs .....      ( 1467 GO terms found. )

Build GO DAG topology .....          ( 3862 GO terms and 8396 relations. )

Annotating nodes .....            ( 346 genes annotated to the GO terms. )

-- Elim Algorithm --
the algorithm is scoring 624 nontrivial nodes
parameters:
test statistic: fisher
cutOff: 0.01

Level 16:      2 nodes to be scored      (0 eliminated genes)

```

Level 15:	4 nodes to be scored	(0 eliminated genes)
Level 14:	4 nodes to be scored	(0 eliminated genes)
Level 13:	5 nodes to be scored	(0 eliminated genes)
Level 12:	12 nodes to be scored	(0 eliminated genes)
Level 11:	28 nodes to be scored	(0 eliminated genes)
Level 10:	42 nodes to be scored	(7 eliminated genes)
Level 9:	57 nodes to be scored	(10 eliminated genes)
Level 8:	71 nodes to be scored	(10 eliminated genes)
Level 7:	91 nodes to be scored	(10 eliminated genes)
Level 6:	95 nodes to be scored	(39 eliminated genes)
Level 5:	102 nodes to be scored	(57 eliminated genes)
Level 4:	66 nodes to be scored	(72 eliminated genes)
Level 3:	28 nodes to be scored	(82 eliminated genes)
Level 2:	16 nodes to be scored	(82 eliminated genes)
Level 1:	1 nodes to be scored	(82 eliminated genes)
\$GOTerms		
	go_id	Term
16505	GO:0006874	cellular calcium ion homeostasis
16996	GO:0007167	enzyme linked receptor protein signaling pathway
17259	GO:0007267	cell-cell signalling
17671	GO:0007566	embryo implantation
33138	GO:0022411	cellular component disassembly
50942	GO:0043434	response to peptide hormone stimulus
64631	GO:0048609	multicellular organismal reproductive process
71264	GO:0051924	regulation of calcium ion transport
78481	GO:0071310	cellular response to organic substance
82851	GO:0097305	response to alcohol

```

16505
16996      Any series of molecular signals initiated by the binding of an extra
17259
17671
33138
50942 Any process that results in a change in state or activity of a cell or an organ
64631
71264
78481
82851

$p.values
  GO:0097305  GO:0071310  GO:0007566  GO:0051924  GO:0007167  GO:0022411
0.0027496755 0.0049209533 0.0003004144 0.0020703496 0.0024663179 0.0043845519
  GO:0048609  GO:0043434  GO:0007267  GO:0006874
0.0075105079 0.0043845519 0.0011286353 0.0014846147

$genes
$genes$`GO:0097305`
[1] "1032"   "113"    "2255"   "225689" "2852"   "387"    "58189"  "8614"

$genes$`GO:0071310`
[1] "1027"   "10402"  "113"    "124857" "1440"   "2245"   "2254"   "2255"
[9] "23405"  "23545"  "23643"  "27018"  "2852"   "3717"   "3839"   "387"
[17] "3875"   "3973"   "4005"   "4057"   "4282"   "4314"   "4644"   "4654"
[25] "5058"   "57142"  "5771"   "581"    "5978"   "6376"   "7029"   "79753"
[33] "835"    "8519"   "8575"   "8614"   "9138"   "9518"   "9826"

$genes$`GO:0007566`
[1] "6159"   "780"    "8614"

$genes$`GO:0051924`
[1] "2852"   "387"   "4644"   "5023"   "581"    "781"    "8614"

$genes$`GO:0007167`
[1] "1027"   "113"    "124857" "1464"   "1942"   "200958" "2046"   "2152"
[9] "2245"   "2254"   "2255"   "23545"  "27018"  "2852"   "29760"  "347"
[17] "3717"   "387"    "55914"  "57142"  "5771"   "613"    "7029"   "780"
[25] "7879"   "835"    "9138"   "920"    "926"    "9518"   "9826"

$genes$`GO:0022411`
[1] "2852"   "3146"   "4314"   "581"    "6142"   "6159"   "6597"   "780"    "8775"   "8915"

```

```

$genes$`GO:0048609`
[1] "139886" "190"      "221656"  "26330"   "268"      "3301"     "3973"     "4201"
[9] "5023"    "581"      "780"      "835"     "8614"

$genes$`GO:0043434`
[1] "113"     "2254"    "2255"    "23545"   "2852"    "3717"    "4644"    "5058"    "5771"
[10] "8614"

$genes$`GO:0007267`
[1] "10368"   "113"     "148"     "1942"    "2254"    "2255"    "268"     "283849"
[9] "2852"    "3717"   "4644"    "5023"    "51222"   "5376"    "54472"   "5978"
[17] "64284"   "6495"   "8614"    "8775"    "88"      "9248"    "9518"    "9787"

$genes$`GO:0006874`
[1] "148"     "2852"   "3717"   "581"     "59340"   "8614"

```

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