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Malignant Mesothelioma: a study on the interactome

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Starting from existing knowledge about a pathological condition we explore the related information sources (DisGeNet datasets), collect the list of human genes of interest and get protein-protein interaction data. After getting the data of interest we will build: seed genes interactome - interactions that involve seed genes only; union interactome -all proteins interacting with at least one seed gene; intersection interactome - all proteins interacting with at least one seed gene confirmed by both Dbs used in the protein-protein interaction data acquisition phase. Using the service Enrichr, we find and report in tables charts of the overrepresented GO categories limiting to the first 10 for each main category, BP, MF, CL) and the the overrepresented pathways (KEGG 2019 Human) for the seed genes and the union interactome genes.

The disease

Malignant mesothelioma is a cancer of the thin tissue (mesothelium) that lines the lung, chest wall, and abdomen. The major risk factor for mesothelioma is asbestos exposure.

In the section below we will see the genes involved in the disease (the so called seed genes) and the interactions between seed genes and non seed genes in the human organism. We collected the interaction data from two different PPI (Protein-Protein Interaction) sources and integrated together to build the seed genes interactome, the union interactome and the intersection interactome. Furthemore, we analyzed the network graph obtained by different interactomes using a Python library, NetworkX. We applied clustering methods for disease modules discovery. Finally, we found putative disease genes using DIAMOnD tool.

Seed genes

To get the list of the seed genes involved in the disease, we explored the **DisGeNet** website which has a search engine that helps users to find gene-disease associations

(GDAs). The gene-disease associations in **DisGeNET** is organized according to the types of source databases: for example, we get our GDAs from the CURATED dataset, which contains GDAs from UniProt, PsyGeNET, Orphanet, the CGI, CTD (human data), ClinGen, and the Genomics England PanelApp. From the browser we specified our disease of interest (Malignant Mesothelioma) and downloaded the dataset as tab separated text file.

Then, all of our data analysis is perfomed using a Python Library, Pandas, all configured under the Jupyter Lab framework. In Table 1 we show an example of the tab separated text file obtained from the procedure explained above. Of course, for the demonstration purpose we omitted some informations.

Table 1. List of seed genes for the Malignant Mesothelioma disease obtained from the CURATED dataset of the DisGeNet database.

Gene	Gene_id	UniProt	Gene_Full_Name	Protein_Class
NAT2	10	P11245	N-acetyltransferase 2	transferase
PARP1	142	P09874	poly(ADP-ribose) polymerase 1	NaN
ANXA2	302	P07355	Annexin A2	NaN
APOA1	335	P02647	Apolipoprotein A1	NaN

For all genes in the seed gene list, we have checked if the symbols were updated and approved on the HGNC website. All of the gene symbols were approved.

Then, we have collected the following information from Uniprot:

1. Official gene symbol.
2. Uniprot AC (a.k.a. 'Uniprot entry').
3. Protein name.
4. Entrez Gene ID (a.k.a 'GeneID),
5. and a very brief description of its function
   Every information was collected from Uniprot's section Reviewed (Swiss-Prot). Anyway, for the last point, we had to clean the string of function's description and truncate the string to keep it shorter and more readable.

In Table 2 we show an example of the tab separated csv file obtained from the procedure written above. Of course, for the demonstration purpose we omitted some informations.

We noticed that every gene has a function description in Uniprot Swiss Reviewed, except for the protein transducin beta like 1 X-linked receptor 1.

Symbol	Name	GeneID	UniprotAC	Function
NAT2	N-acetyltransferase 2	10	P11245	Participates in the detoxification of a plethora of hydrazine and arylamine drug
PARP1	poly(ADP-ribose) polymerase 1	142	Q6N069	Auxillary subunit of the N-terminal acetyl-transferase A (NatA) complex which dis-

				plays alpha (N-terminal) acetyltransferase activit
ANXA2	annexin A2	302	Q9H2H9	Functions as a sodium-dependent amino acid transporte
APOA1	apolipoprotein A1	335	P09874	Poly-ADP-ribosyltransferase that mediates poly-ADP-ribosylation of proteins and plays a key role in DNA repair

Summary on interaction data

For each seed gene, we collected all binary protein interactions from two different PPI sources:
- Biogrid Human, latest release available
- IID Integrated Interactions Database (experimental data only)

Table 3 Summarize the main results reporting:
no. of seed genes found in each different Dbs; total no. of interacting proteins, including seed genes, for each DB; total no. of interactions found in each DB.

Source Database	No. of seed genes	No. of interacting proteins	No. of interactions
Biogrid	104 of 109	17899	485380
IID	104 of 109	17278	270230

We have retrieved some informations from Uniprot about missing genes. These are the genes missing in Biogrid: **CCL27**, which has full name C-C motif chemokine 27 and is a Chemotactic factor that attracts skin-associated memory T-lymphocytes; **MIR125A, MIR126, MIR484, PWAR6** haven't any Uniprot corrispondence.
These are the genes missing from IID: **GPR27** which is an Orphan receptor and possible candidate for amine-like G-protein coupled receptor. **MIR125A, MIR126, MIR484, PWAR6** haven't any Uniprot corrispondence.

Interactome data

We have Build and stored three tables from all Dbs:
1. seed genes interactome: interactions that involve seed genes only
2. union interactome: all proteins interacting with at least one seed gene.
3. intersection interactome: all proteins interacting with at least one seed gene confirmed by both DBs

In the format:
interactor A gene symbol, interactor B gene symbol, interactor A Uniprot AC, interactor B Uniprot AC, database source

Seed genes interactome

We iteratively build a Pandas dataframe that contains the seed genes that interact in both Biogrid and IID, indicating the source db from which the interaction originates. We then saved the interactome as a tab-separated csv file. After eliminating the redundancies, we obtained a total number of 480 seed genes that interact on both databases.

Union Interactome

The construction of the union interactome was more cumbersome. We had to consider all the interactions in which one of the interactor is a seed gene. A nonseed gene interacts at least once with a seed gene; then, in the union interactome we also considered interactions between nonseeds.

In the Python implementation, we first built the dataframe containing seed-nonseed interactions for both databases.

Then for the nonseed-nonseed interactions we first built a list containing the gene symbols of the nonseeds.

Iterating on both dataframes we memorized the positions where both interactors are nonseeds, and at the end of the cycle we took the rows positioned in those indexes and we built a new dataframe, one for each database.

Finally, we merged all the tables obtained in the previous steps (the table with the seed-nonseed interactions and the two tables with the nonseed-nonseed interactions) and saved in the usual tabular csv format.

Intersection Interactome

The construction of the intersection interactome was pretty straightforward.

We splitted the table with all proteins interacting with at least one seed gene confirmed
by both DBs by the 'source_db' column. We dropped the 'source_db' column and merged again the two tables. In pandas, the default type of merge will use all columns and is inner, so it returns a new dataframe with values present in both dataframes.

Enrichment analysis

To perform the analysis on Enrichr, one must pass a list of genes, one for each row, both for the union and for the seed interactome.

But first, we had to clean up the symbols: many symbols were separated by a ";". It was necessary to create an ad-hoc function that would separate those symbols, one for each line. Other symbols were the full name of the protein and therefore had to be deleted. After this preliminary cleaning phase we passed the list of symbols to HGNC which returned the list of approved symbols which were also good for Enrichr. Finally, we have collected the tables of interest from Enrichr -KEGG HUMAN 2019 and the Ontologies tables of the GO categories overrepresented-. The tables are shown below. For simplicity purpose, not all columns are listed in this report: the complete version of the tables can be consulted among the documents attached to the report.

Kegg Human

Table 4 – Kegg Human for Union Interactome

Term	Overlap	P-Value	Adjusted P-value	Odds Ratio	Combined Score
Pathways in cancer	332/530	2.3160184215191657e-68	7.133336738279031e-66	2.3304132973944296	362.9290980239513
Proteoglycans in cancer	148/201	1.1968845263714163e-43	1.8432021706119808e-41	2.7392797915185976	270.7269582669007
MAPK signal-ing pathway	190/295	6.589420977602359e-42	6.765138870338424e-40	2.396085552865214	227.20428017464832
Neurotrophin signaling path-way	100/119	6.681108708752214e-39	5.144453705739206e-37	3.12625050020008	274.8022167574134
Human T-cell leukemia virus 1 infection	151/219	7.713025893092007e-39	4.751223950144676e-37	2.5650956729723857	225.10743021521782

Cellular senescence	122/160	7.740662923139611e-39	3.973540300545002e-37	2.8366815476190474	248.9310923049112
Chronic myeloid leukemia	72/76	2.212717327939685e-36	9.735956242934615e-35	3.524436090225564	289.35212180706884
MicroRNAs in cancer	183/299	5.378868699539398e-36	2.0708644493226677e-34	2.2769350215002397	184.91122572831318
Cell cycle	100/124	7.722340351336125e-36	2.6427564757905847e-34	3.000192012288786	242.56236161726193
FoxO signaling pathway	104/132	1.5456864924884733e-35	4.7607143968644975e-34	2.9310966810966814	234.9420841108548

Table 5 – Kegg Human for Seed genes

Term	Overlap	P-value	Adjusted P-value	Odds Ratio	Combined Score
Pathways in cancer	28/530	3.897228444575711e-20	1.200346360929319e-17	9.693612601696383	433.22146927792573
Cytokine-cytokine receptor interaction	22/294	4.2162985923687685e-19	6.493099832247902e-17	13.730262747300756	580.9296017973247
PI3K-Akt signaling pathway	21/354	3.3004782409568536e-16	3.388490994049037e-14	10.884776862074327	388.01284210700084
Gastric cancer	14/149	7.624401769285048e-14	5.870789362349487e-12	17.240317714426453	520.7409939607603
Melanoma	10/72	6.135713154692977e-12	3.7795993032908735e-10	25.484199796126408	657.9229052213992
Hepatocellular carcinoma	13/168	7.547315642500119e-12	3.8742886964833937e-10	14.198339886413278	363.61705884563713
MicroRNAs in cancer	15/299	8.435036230126662e-11	3.711415941255731e-09	9.204995244085788	213.5194563996091
Proteoglycans in cancer	12/201	1.02050112873949e-09	3.928929345647037e-08	10.954402300424485	226.7886844049197
JAK-STAT signaling pathway	11/162	1.3552588265201067e-09	4.6379968729799205e-08	12.458942122550685	254.40254528793014
Rheumatoid arthritis	9/91	1.6385277794983662e-09	5.046665560854968e-08	18.146990624054844	367.10396056733885

Table 6 – GO Biological Process 2018 for Seed Genes

Term	Overlap	P-value	Adjusted P-value	Odds Ratio	Combined Score
cytokine-mediated signaling pathway	33/633	1.3250962069344388e-23	6.761965943986441e-20	9.565633288403843	503.89816322760987
regulation of cell proliferation	33/740	1.728056361838507e-21	4.4091358072309494e-18	8.182494421026531	391.18288097824717
negative regulation of cell proliferation	22/363	3.806861592803352e-17	6.475471569358503e-14	11.120378092855155	420.42970764675295
negative regulation of cellular process	25/534	9.212689193067938e-17	1.1753088238056418e-13	8.590179706559463	317.17833889146505
cellular response to cytokine stimulus	23/456	3.725153514596662e-16	3.801891676997353e-13	9.254788347014324	328.78795621030633
positive regulation of intracellular signal transduction	21/479	1.3000676570450667e-13	1.1057075423168293e-10	8.044281856313804	238.6834145833249
positive regulation of MAPK cascade	17/289	3.2266561954769925e-13	2.352232366502728e-10	10.793308148947652	310.43885419871435
positive regulation of protein phosphorylation	18/412	9.256557917538748e-12	5.904526881650029e-09	8.01638906208248	203.66188622417422

| positive regulation of cell migration | 14/221 | 1.700397687971899e-11 | 9.641254890800668e-09 | 11.623562621943623 | 288.2361526936057 |
| positive regulation of leukocyte chemotaxis | 9/61 | 4.1505804953766564e-11 | 2.1180412267907072e-08 | 27.07174011129493 | 647.1550319766269 |

Table 7 – GO Biological Process 2018 for union interactome

Term	Overlap	P-value	Adjusted P-value	Odds Ratio	Combined Score
focal adhesion	246/356	2.0307521217463597E-63	9.057154462988762e-61	2.582736819118132	372.82956497885874
nuclear body	312/618	2.8626122970109088E-37	6.383625422334327e-35	1.8869533505215432	158.7756401506712
nuclear chromosome part	223/392	6.3003903982783755E-37	9.366580392107184e-35	2.1262476210816974	177.23344878903697
chromatin	182/296	1.7710370351351232E-36	1.9747062941756622e-34	2.298130685348028	189.18556079506217
nucleolus	329/676	3.2856822475828046E-35	2.930828564843861e-33	1.819048366782076	144.43408463071447
cytosolic part	114/159	2.5530499276119735E-32	1.8977671128582333e-30	2.67980239983357	194.9433893639449
cytosolic ribosome	89/124	1.3972500602057802E-25	8.902478955025399e-24	2.682645993212001	153.52815549613666
cytoskeleton	244/520	1.6517829255469964E-23	9.208689809924503e-22	1.753805902563144	92.00045179987413
chromosome	telomeric region (GO:0000781) 86/124	4.106995466029021e-23	0.0		2.592219723777889
nuclear speck	159/296	4.484949237649398E-23	2.000287359991632e-21	2.0077075767600903	103.31408203448869

Table 8 – GO Cellular Component 2018 for Seed Genes

Term	Overlap	P-value	Adjusted P-value	Odds Ratio	Combined Score
endoplasmic reticulum lumen	10/270	2.243366742502301E-6	0.0010005415671560263	6.795786612300374	88.39641733225105
secretory granule lumen	10/317	9.260444955473252E-6	0.0020650799225070535	5.788209417416722	67.08394905862652
Golgi lumen	5/98	1.9905230370730948E-4	0.029592442484486673	9.361542782250515	79.77853337459462
membrane raft	5/119	4.890641338098951E-4	0.0545306509198033	7.709505820676895	58.76969334749621
micro-ribonucleopro-tein complex	2/7	6.07108833817942E-4	0.05415410797656043	52.42463958060288	388.2989507254963
cytoplasmic vesicle lumen	5/129	7.060183179056919E-4	0.052480694964323095	7.111869710546903	51.60279763008014
RISC-loading complex	2/9	0.001033366784759019	0.06584022657178892	40.77471967380224	280.32346928993604
RISC complex	2/9	0.001033366784759019	0.05761019825031531	40.77471967380224	280.32346928993604
RNAi effector complex	2/9	0.00103336678475901	0.05120906511139139	40.77471967380224	280.32346928993604

		9			
endoribonuclease complex	2/13	0.0022073067613513895	0.09844588155627197	28.228652081863093	172.64593272108507
integral component of plasma membrane	17/1463	0.002352100148907491	0.09536696967388555	2.1321025666752367	12.904437078779413

Table 9 – GO Cellular Component 2018 for union interactome

Term	Overlap	P-value	Adjusted P-value	Odds Ratio	Combined Score
focal adhesion	251/356	4.5346082209039613E-67	2.022435266523167E-64	2.6229768592830394	400.68978123491956
nuclear body	318/618	1.1458242188789406E-39	2.5551880081000377E-37	1.914297272306981	171.64487992538255
nuclear chromosome part	225/392	9.696848035164027E-38	1.441598074561052E-35	2.1353407434402336	181.98747404685267
chromatin	184/296	1.6808370213764038E-37	1.8741332788346904E-35	2.3125804375804377	195.82088567023192
nucleolus	335/676	2.0728760143590152E-37	1.8490054048082416E-35	1.8436091152437306	155.72359910650673
cytosolic part	118/159	1.3052605504227113E-35	9.702436758142153E-34	2.7609314165917938	221.7692637732338
cytosolic ribosome	92/124	4.867179530715983E-28	3.101088672427612E-26	2.7601766513056836	173.5871452195253
cytoskeleton	247/520	2.07532927998706E-24	1.156996073592786E-22	1.7671130952380953	96.36407418439946
nuclear speck	161/296	6.989001469895008E-24	3.4634385061924156E-22	2.023507882882883	107.88879542793433

Table 10 – GO Molecular Function 2018 for Seed Genes

Term	Overlap	P-value	Adjusted P-value	Odds Ratio	Combined Score
cytokine activity	16/155	2.4729931254453526E-16	2.846415087387601E-13	18.940514945250072	680.6450624059376
chemokine activity	8/46	1.3174298501626127E-10	7.581808787685836E-8	31.910650179497406	725.9726581438525
chemokine receptor binding	8/49	2.2464562489679202E-10	8.618903808540254E-8	29.956936903201644	665.5381975150697
cytokine receptor binding	11/137	2.2491254011031932E-10	6.471858341674439E-8	14.732471706957744	327.2864186687703
growth factor activity	8/69	3.806975911266136E-9	8.763658547734645E-7	21.273766786331606	412.42240525569827
CCR chemokine receptor binding	6/38	5.46275429125203E-8	1.0479383648718477E-5	28.971511347175277	484.48269335895384
growth factor receptor binding	7/92	7.036776737660981E-7	1.1570471464353985E-4	13.960909453530117	197.78344245668825
CXCR chemokine receptor binding	4/17	1.8808008431372562E-6	2.706002213063727E-4	43.17323259579061	569.1878204612692

phosphatidylinositol-4,5-bisphosphate 3-kinase activity	6/68	1.8972531588132644E-6	2.4263759842156304E-4	16.189962223421478	213.304426719709
phosphatidylinositol bis-phosphate kinase activity	6/71	2.449916455653453E-6	2.8198538404571245E-4	15.505879312572684	200.32753534651505
phosphatidylinositol 3-kinase activity	6/76	3.6581738178341934E-6	3.8277800584792334E-4	14.485755673587638	181.3406058707963

Table 11 – GO Molecular Function 2018 for Union interactome

Term	Overlap	P-value	Adjusted P-value	Odds Ratio	Combined Score
RNA binding	784/1387	2.1033101487881945e-129	2.420909981255212e-126	2.102859889449652	623.056282269345
ubiquitin-like protein ligase binding	218/297	1.9553527383479043e-63	1.125305500919219e-60	2.7306798140131474	394.2891122920125
cadherin binding	223/313	5.7003348126335006e-61	2.1870284564470527e-58	2.650521071048228	367.67277076419657
ubiquitin protein ligase binding	208/284	2.7866643968572264e-60	8.01862680195667e-58	2.724681421864521	373.63627249426
protein kinase binding	289/495	2.377291220000058e-50	5.4725243884401337e-48	2.172017797017797	248.18190583988815
kinase binding	247/418	2.137297724191196e-44	4.1000494675734443e-42	2.198322510822511	221.0505653886766
protein kinase activity	286/513	2.2513515012897213e-44	3.701865111406383e-42	2.074050867910517	208.44670290557488
transcription regulatory region DNA binding	223/37	4.872974981030829e-41	7.010992753958106e-39	2.2182168321874207	205.89995317705942
transcription coactivator activity	183/291	2.683954168284042e-38	3.43247916410548e-36	2.33953117329406	202.39504655411312
DNA binding	408/893	4.7041898858607056e-35	5.4145225586256724e-33	1.6997280435130382	134.3499459614465

NETWORK MEASURES

Interactomes data

	UNION	INTERSECTION	SEED
No. of Nodes	5612	2521	74
No. of Edges	204691	3261	175
Average Path Length	2.4101	3.9022	2.7512
Average clustering coeff.	0.1553	0.0083	0.2319
Average degree	72.9416	2.6070	4.7297
No. of isolated nodes	0	0	15
Network diameter	5	10	6
Network radius	2.5	5	3
Centralization	0.291	0.215	0.279

# Connected Components	1	17	17

Global: I, U, SIG

In this paragraph we focus on the analysis of the data retrieved in the previous points. In order to do that for that kind of biological data we build up graphs. We have used two main tools to overcome that problem: the Python library *networkx* and *Cytoscape,* which attempts the most hard-computationally tasks. The graphical results can be seen in Figure 1, Figure2, Figure3. Respectively of Union-interactome, Intersection-Interactome and Seed Genes-Interactome.
The results of the global measures are stored in the table above. Isolating the Largest Connected Components for I and U we have noticed that, since there is only one connected components with no. of nodes >20, some measures coincides between global networks and those one with the LCC. For those networks I-LCC and U-LCC we have computed local measures.

Largest Connected Component

	U-LCC	**I-LCC**
No. of Nodes	5612	2481
No. of Edges	204691	3234
Average Path Length	2.4101	3.9022
Average cluste coeff.	0.1553	0.0083
Average degree	72.9416	0.2070
Diameter	5	10
Radius	2.5	5
Centralization	0.291	0.215

ID	**Degree**	**Betweennes**	**Closeness**	**Eigenvector**
APLP1	299	0.01245	0.532	0.064
CITED2	387	0.01131	0.498	0.073
EP300	421	0.00851	0.377	0.031
APOB	200	0.00844	0.446	0.042
CSF1R	182	0.00812	0.361	0.039
PRRC2A	223	0.00786	0.374	0.078
LSM1	168	0.00723	0.446	0.066
SLC4A1	182	0.00443	0.461	0.063
BCL3	255	0.00415	0.403	0.054
ADRB1	123	0.00411	0.38	0.046

Local I-LCC

CLUSTERING

We used MCL cluster algorithm implemented in Cytoscape in order to perform community detection both on I-LCC and U-LCC. We set inflation value = 2.0 and ran over 18 iterations. From the clusters obtained we selected those one which have more than 10 nodes, which appeared to be 4 for I-LCC and 19 for U-LCC. Finally we performed hypergeometric test on such communities via the module *scipy.stats* in order to select the significant ones which excludes the under-representation of seed genes. In the table below are reported the total number of genes and the seed-genes for each clusters.

Putative Disease Modules

I_LCC

	Clus1	Clus2	Clus3	Clus4
nodes	2271.0	24.00000	16.000000	13.000000
seed nodes	46.0	1.00000	1.000000	1.000000
pvalue	1.0	0.16875	0.085731	0.059125

U_LCC

	Clus1	Clus2	Clus3	Clus4	Clus5	Clus6	Clus7	Clus8	Clus9	Clus10	Clus11	Clus12	Clus13	Clus14
nodes	4390	70	65	63	58	57	56	27	27	27	26	20	17	15
seed nodes	16	2	1	1	0	2	1	2	1	1	1	1	0	1
pvalue	1	0.07293	0.228273	0.217994	0.557787	0.0442333	0.182448	0.0059431	0.0535119	0.0535119	0.0499883	0.0308231	0.212017	0.0178118

Clus15	Clus16	Clus17	Clus18
15	14	14	13
1	1	1	0
0.0178118	0.0155759	0.0155759	0.166522

From that we found out that statistically relevant clusters where just 8, all from the U-LCC network: IDs: 'Clus6','Clus8','Clus11','Clus12','Clus14','Clus15','Clus16','Clus17'. We classify them as Putative Disease Modules.

DIAMOnD 30 genes

DIAMOnD tool implemented by Barbasi group allows to detect the full disease module given a number of known proteins. We ran that algorithm over the whole BIOgrid_interactome and our seed_file. Here is reported the output of the first 30 genes found by the algorithm.

1. GLIS2
2. MAP2K5
3. ERBB2
4. CDKN2B
5. EPHA2
6. FGFR4
7. CBLC
8. LATS2
9. MDM4
10. STK11
11. PDGFRA
12. MAP2K3
13. CDK4
14. CD44
15. CCND2
16. BECN1
17. GRM1
18. KDELR2
19. TERT
20. AKT1
21. CDKN2C
22. ARNT
23. FZR1
24. RASSF1
25. CCNE1
26. TEAD2
27. MAP3K5
28. MAP2K6
29. HIF1A
30. MYC

Finally we have uploaded the whole set of 200 genes to enrichr to find the over-represented GO categories. Results of the enrichr analysis are showed below, limited to the first 10 categories.

| Biological process	Cellular Component	Molecular Function
thyroid hormone mediated signaling pathway	HSP90-CDC37 chaperone complex	RNA-directed 5'-3' RNA polymerase activity
cellular hyperosmotic salinity response	TEAD-2-YAP complex	RNA polymerase II transcription coactivator binding
N-terminal peptidyl-lysine acetylation	Rb-E2F complex	
positive regulation of transforming growth factor beta3 production	Ku70:Ku80 complex	Krueppel-associated box domain binding
rRNA export from nucleus	heteromeric SMAD protein complex	DNA-dependent protein kinase activity
N-terminal peptidyl-lysine acetylation	Ku70:Ku80 complex	HLH domain binding
regulation of response to gamma radiation	cyclin E1-CDK2 complex	IkappaB kinase activity
response to metformin	activin responsive factor complex	TFIIB-class transcription factor binding
regulation of secretion of lysosomal enzymes	brahma complex	primary miRNA binding

Gene Ontology DIAMOnD

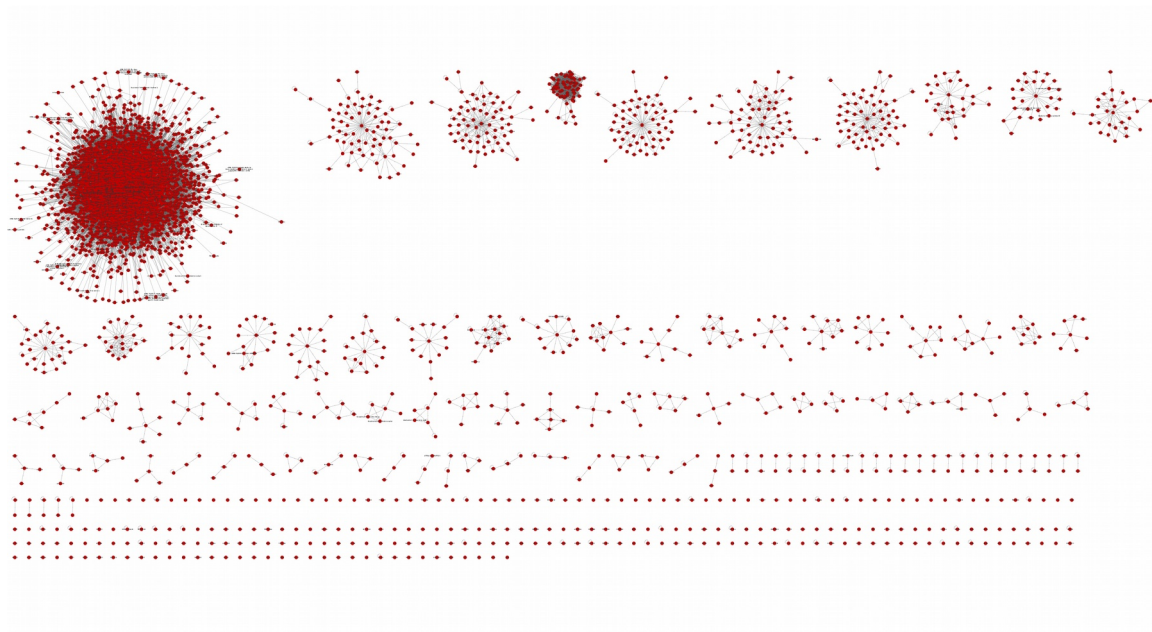| Kegg Pathways |
|---|
| P53 pathway feedback loops 1 |
| nsulin/IGF pathway-protein kinase B signaling cascade |
| p53 pathway feedback loops 2 |
| JAK/STAT signaling pathway |
| p53 pathway by glucose deprivation |
| Hypoxia response via HIF activation |
| P53 pathway |
| Ras Pathway |
| Interferon-gamma signaling pathway |
| Interleukin signaling pathway |

Kegg Pathway DIAMOnD

GRAPHS IMAGES
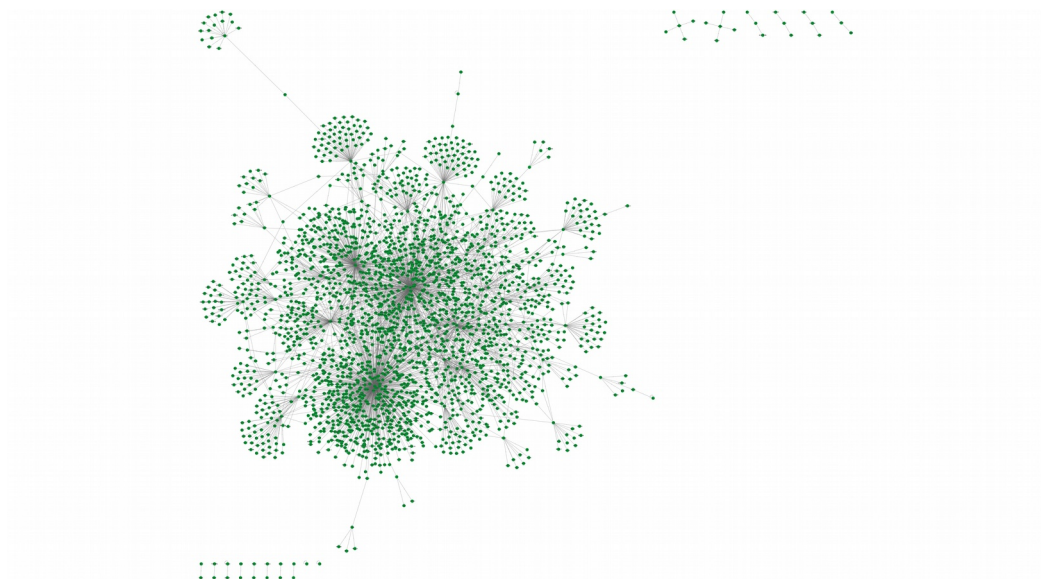
Intersection Interactome
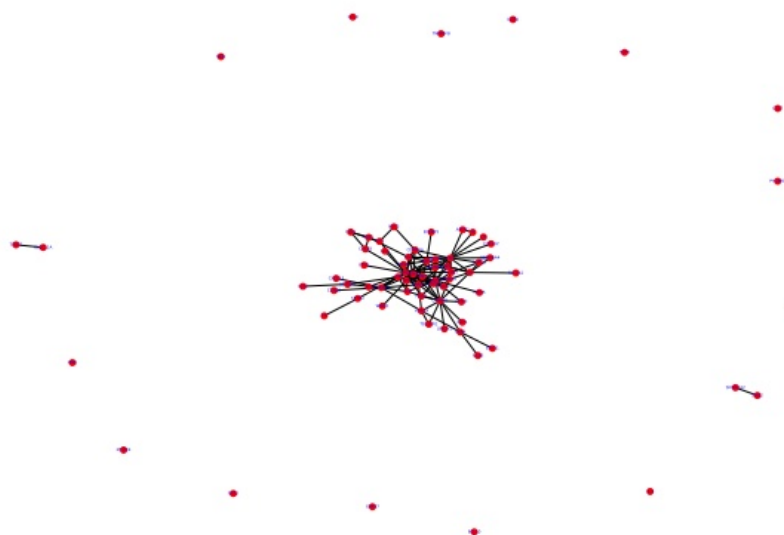
SGI

Union Interactome Clustered