



STAT 555 PROJECT REPORT

Analysis of RNA-seq data using DESeq2

Instructor

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PΙ

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Identification of differentially expressed genes in RNA-seq data from Drosophila knockdown models for 16p11.2 region and its functional analysis

<u>Abstract:</u> The 16p11.2 region has been a hotspot for various microdeletion and CNVs leading to various neurodevelopmental disorders in humans. *Drosophila melanogaster* knockdown models have been successfully used to study the effect of deletion of these orthologous genes in flies. We performed a RNA-seq analysis on six gene knockdown models in flies. Here, we suggest a workflow to perform a differential expression analysis of the RNA-seq data using the *DESeq2* package in *R*. We also perform a functional annotation study of the significant genes obtained from analysis using *DAVID*.

Introduction:

The data was obtained from RNA-seq analysis of fly models for the *16p11.2* microdeletion. This deletion is implicated in neurodevelopmental disorders of the CNV.

The 16p11.2 gene knockdown models in *Drosophila melanogaster* were constructed for studying the deletion. Ten human genes found in the 16p11.2 region have orthologous genes in *Drosophila*. Knockdown models were created for these orthologs using crosses and they were assessed for any abnormal phenotype in the progeny. RNA-seq analysis was performed for six models with an abnormal neurodevelopmental phenotype. The human genes with their orthologs in *Drosophila* are as follows:

- C16orf53 (Pa1)
- CDIPT (Pis)
- MAPK3 (rl)
- DOC2A (Rph)
- CORO1A (coro)
- KCTD13 (CG10465)

We had three biological replicates for each of these genes as well as for wild-type gene. The RNA-Seq data was recorded in a .csv file with the corresponding FlyBase Gene IDs for further analysis. A qPCR analysis of the fly heads was also performed to confirm the abnormal phenotype in these models. The objective of the analysis is to find if a mutation in any of these genes or a knockdown of the entire gene is responsible for neurodevelopmental disorders in Drosophila models and then find possible convergence in humans.

METHODS:

The overview of the basic process followed for the project is shown in Figure 1. The raw counts for the RNA-seq analysis were obtained for the biological replicates of the knockdown genes as well as the wild-type. The primary filtering, differential expression analysis and sorting the results was performed using R. Later, the significant genes were analysed for functional annotation and *Gene Ontology* using DAVID (Source: https://david.ncifcrf.gov/). The results obtained from the analysis were imported in R. An annotation of all the significant genes was performed by comparing it to the *org.Dm.eg.db* database. Further, convergence studies of the orthologous genes in humans will be performed using this data.

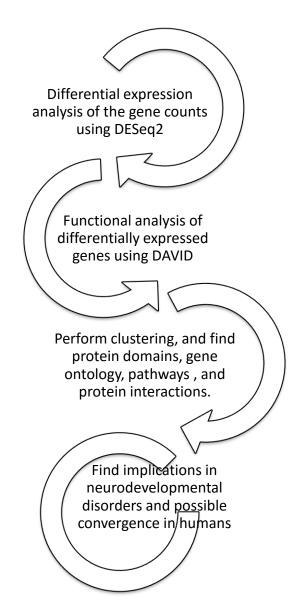


Fig. 1: An overview of the steps undertaken for the analysis

The chart of working pipeline below (Fig. 2) shows the overall working and computing flow for the analysis, right from the process of obtaining the data, the analysis performed, the functions used in R to importing the functional analysis results. A detailed R script with the significance of each chunk is provided in a .rmd format as a supplementary information file. Refer *Project_SHETTY.Rmd*.

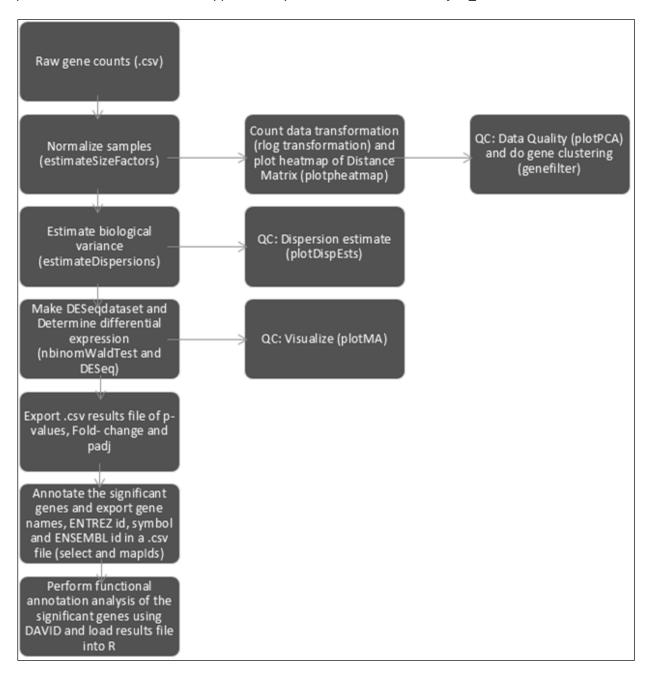


Fig.2: R pipeline for analysis

Results:

1. rlog transformation

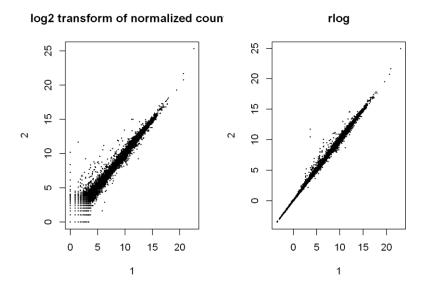


Fig. 3: Scatterplot of transformed counts from two samples. Shown are scatterplots using the log2 transform of normalized counts (left side) and using the rlog (right side).

We can see how genes with low counts (bottom left-hand corner) seem to be excessively variable on the ordinary logarithmic scale, while the rlog transform compresses differences for the low count genes for which the data provide little information about differential expression.

2. Heatmaps

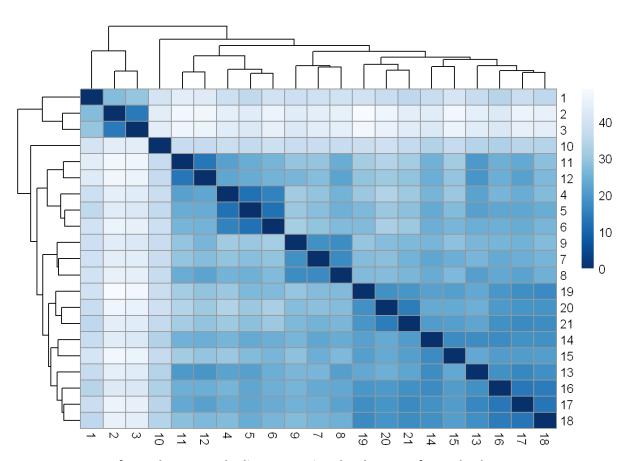


Fig.4: Heatmap of sample-to-sample distances using the rlog-transformed values.

This heatmap was plotted to assess overall similarity between samples and to see if it fit to the expectation from the experiment's design. The dist function was used to calculate the Euclidean distance between the samples and was used on the rlog-transformed data to ensure nearly equal contribution from all the samples.

3. MA plot

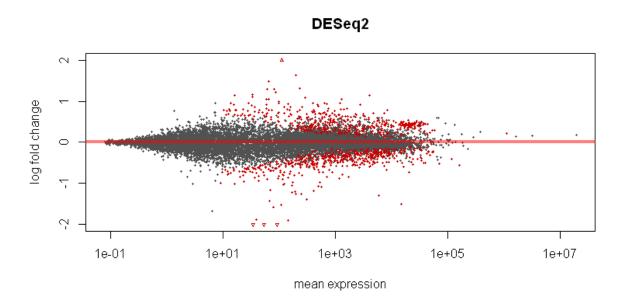


Fig. 5: MA plot of Differential expression analysis

This MA Plot was done for quality testing by plotting average of the counts normalized by size factor on the x-axis and log2 fold change on the y-axis representing each gene with a dot. Genes with an adjusted p value below a threshold (here 0.1, the default) are shown in red.

4. MA plot for log2FC

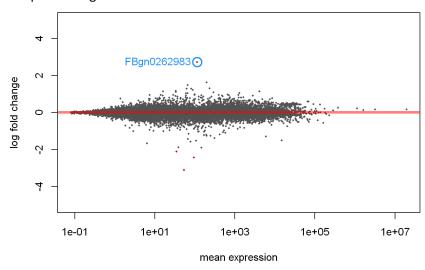
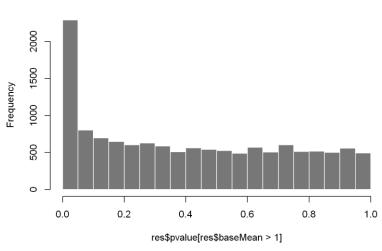


Fig. 6: An MA-plot of a test for large log2 fold changes.

The red points indicate genes for which the log2 fold change was significantly higher than 1 or less than -1 (treatment resulting in more than doubling or less than halving of the normalized counts). The point circled in blue indicates the gene with the lowest adjusted p value.

5. Histogram of pvalues



Histogram of res\$pvalue[res\$baseMean > 1]

Fig. 7: Histogram of p values for genes with mean normalized count larger than 1.

We observe the expected shape thus showing that the analysis was successful and FDR estimation can be done.

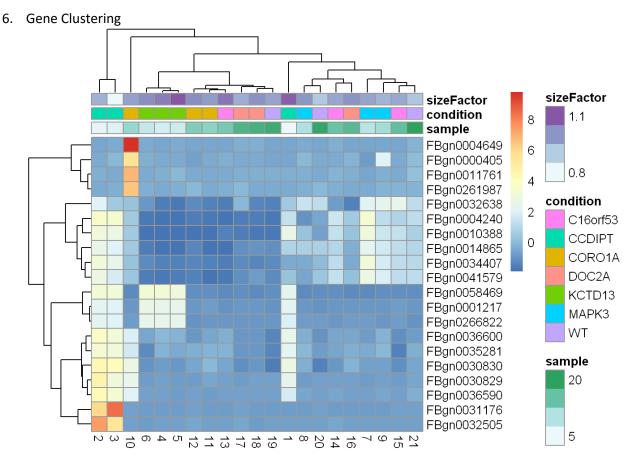
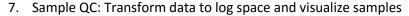


Fig. 8: Heatmap of relative rlog-transformed values across samples.

Treatment status and cell line information are shown with colored bars at the top of the heatmap and the key is given on the right of the figure. It shows the genes that covary.



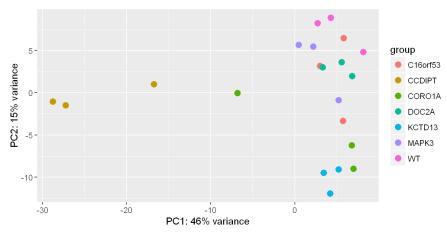


Fig. 9: PCA plot of biological variance

We can clearly see the different clusters being plotted as a result of the differential expression within these genes. CCDIPT shows most variance as compared to the rest of the samples.

8. Estimate biological variance and visualize

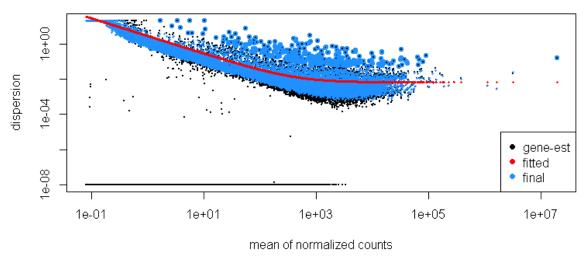


Fig. 10: Plot of mean of normalized counts vs dispersion

We can see that due to the normalization the biological variance was reduced in the sample.

9. Results of Differential expression analysis

```
results
log2 fold change (MAP): condition WT vs C16orf53
wald test p-value: condition WT vs C16orf53
DataFrame with 15526 rows and 6 columns
                            baseMean log2FoldChange
                                                          1fcse
                                                                                  pvalue
                                                                                         <numeric>
                           <numeric>
                                          <numeric>
                                                      <numeric>
                                                                  <numeric>
                                                                               <numeric>
FBqn0000003
                                       -0.028297941 0.09010026 -0.31407168 0.753466596
                        4.157232e-01
                                                                                                NΑ
                                       -0.097157915 0.11940750 -0.81366679
FBan0000008
                       1.373449e+03
                                                                            0.415835866 0.7294320
FBgn0000014
                        1.005504e+00
                                        0.009108037 0.14430764
                                                                 0.06311542
                                                                            0.949674596
                                                                                                NA
FBgn0000015
                                        0.227695475 0.14551510
                                                                 1.56475495 0.117640378
                        8.116016e-01
FBgn0000017
                        1.032277e+04
                                        -0.201885153 0.06257215
                                                                -3.22643792 0.001253414
                                                                                         0.0217338
FBgn0267794
FBgn0267795
                                                                  1.0637907 0.287423504
                        4.332910e+00
                                          0.2601586 0.24455810
                                          -0.1862581 0.06938935
                                                                 -2.6842455 0.007269371 0.0732219
                        2.882373e+03
 _no_feature
                                          0.1570121 0.16376547
                        3.179654e+06
                                                                  0.9587619 0.337678721 0.6632151
                        1.624583e+06
                                          0.1370420 0.06300241
                                                                  2.1751873 0.029616084 0.1777616
 _ambiguous
__aliqnment_not_unique 1.948180e+07
                                          0.1706467 0.26103655
                                                                  0.6537271 0.513287612 0.7934417
```

Fig. 11: Using the results() function of the DESeq2 analysis package

The above table containing the p-values, log2 fold change and adjusted p-values was obtained from the analysis. This was further filtered by only selecting the significant genes having padj<0.05 for GO analysis.

10. GO analysis

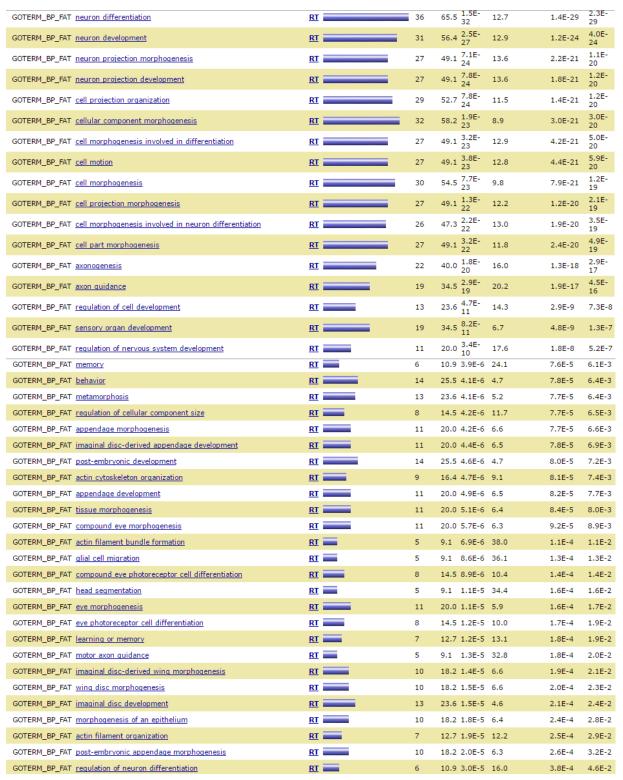


Fig. 12: GO analysis showing biological process involved in neurodevelopmental disorders

The GO analysis biological process (as shown in the .rmd file) using DAVID gave interesting results. The significant genes from the differential expression analysis can be seen here to be involved in a host of biological processes that contribute to neurodevelopmental health. Right from neuron development, differentiation, gliogenesis to memory these genes seem to play an important role in maintaining the health of the CNS. Any mutation in these could adversely affect the functioning of the nervous system.

Category ⇔ RT KEGG_PATHWAY 4.8E-2 4.2E-1 Wnt signaling pathway RT WNT SIGNALING PATHWAY Alzheimer's disease MAPK signaling pathway Canonical pathway ------TAK1 PS-1 NLK Notum FRP Idax Duplin c-myc Cer-1 CBP c-jun CKΙε GBP fra-1 Cell cycle Dvl cycD DNA CK2 Wif-1 PEDF ICAT SMAD3 Axam Groucho Xsox17 SOST CtBP Dkk +p Phosphorylation +p independence p53 signaling pathway TGF-β signaling pathway p53 Skp1 Ubiquitin medeated PAR-1 Nkd Cul1 Proteolysis Phosphorylation independence Planar cell polarity (PCP) pathway Focal adhesion Prickle Daami RhoA Cytoskeletal change Wnt11 Frizzled INVS Gene transcription MAPK signaling pathway Wnt/ Ca ²⁺pathway CaMKII

11. KEGG Pathway result for GO analysis

Fig. 13: The WNT Signaling pathway

Frizzled

G protein?

Wnt5

04310 3/4/16 (c) Kanehisa Laboratories

The KEGG pathway from the GO analysis of the subset of the significant genes playing a role in neurodevelopmental function gave the result as 'the WNT signalling pathway'. A closer look at the pathway interactions shows that it might play a role in Alzheimer's disease.

► CaN

₽KC

NFAT

DNA

12. Gene associations

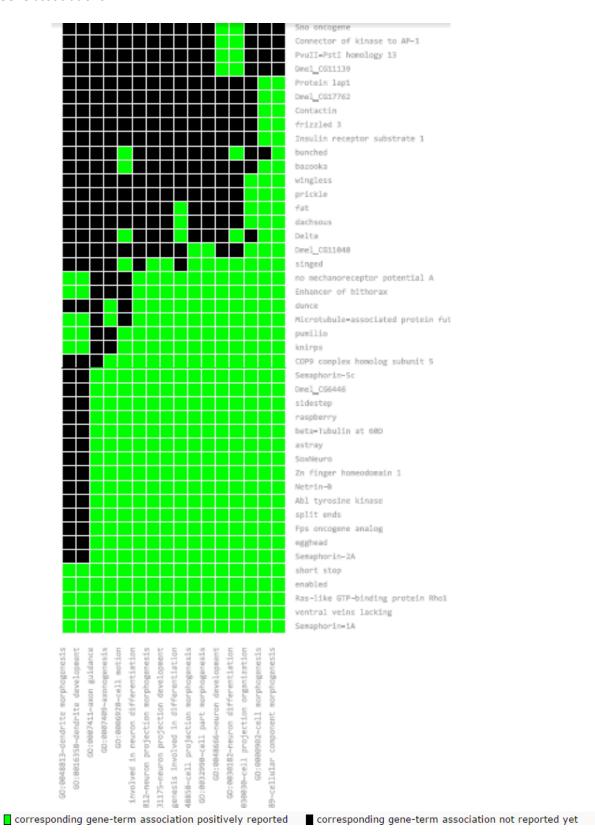


Fig. 14(a): Gene associations between the processes and significant genes

From the .rmd file we can see the various clusters that were formed according to the gene function and processes. The above cluster showing significance for neurodevelopmental disorders had a high enrichment score in the DAVID analysis. It gives a brief overview of each of the reported gene associations in the neurodevelopment processes.

13. Gene batch using kappa statistic

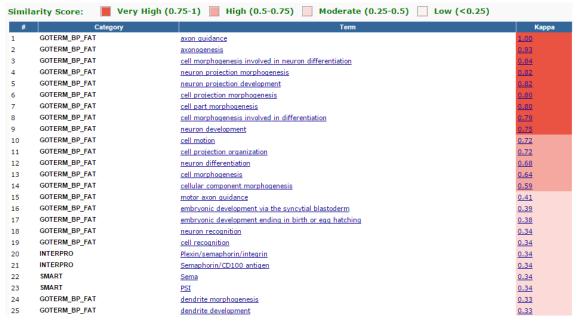


Fig. 15: Kappa statistic for the gene association

"Any given gene is associating with a set of annotation terms. If genes share similar set of those terms, they are most likely involved in similar biological mechanisms. The algorithm adopts kappa statistics to quantitatively measure the degree of the agreement how genes share the similar annotation terms. Kappa result ranges from 0 to 1. The higher the value of Kappa, the stronger the agreement. Kappa more than 0.7 typically indicates that agreement of two genes are strong. Kappa values greater than 0.9 are considered excellent."

(Source: DAVID website-Linear Search Algorithm in Gene Name Batch Viewer)

14. Annotation

> resannotated[1:10,] GENENAME ENTREZID ENSEMBL SYMBOL 1 FBgn0000003 <NA> <NA> <NA> 2 FBgn0000008 arc 43852 а abdominal A abd-A FBqn0000014 42037 FBgn0000015 Abdominal B Abd-B 47763 5 FBqn0000017 Ab1 Abl tyrosine kinase 45821 6 FBqn0000018 abo abnormal oocyte 44793 7 FBqn0000024 Ace Acetylcholine esterase 41625 abnormal chemosensory jump 6 8 47080 FBgn0000028 acj6 FBqn0000032 Acph-1 Acid phosphatase 1 48445 10 FBgn0000036 nAChRalpha1 nicotinic Acetylcholine Receptor alpha1 42918

Fig. 16: Annotation in R of the significant genes

Finally, an annotation of all the significant genes was performed using the packages *Annotation.Dbi* and *org.Dm.eg.db*. We can see the ENSEMBL, GENENAME, SYMBOL S and

ENTREZID stored for each gene. Some genes also had missing values. These annotations can be used to perform further functional analysis and convergence studies.

Discussion:

Using the DESeq2 package it was possible to perform a very detailed differential expression analysis of the genes. The significant genes obtained from the analysis were then analysed on DAVID for functional annotation which also gave promising results. It gave a lot of information about the biological processes, pathways, clustering and gene associations between the significant genes. To confirm the results of the analysis I also ran the significant genes on the *geneontology.org* website which uses *PANTHER*.

	-	-,	-											
motor neuron axon guidance								<u>61</u>	<u>15</u>	3.94		3.80	+	4.56E-02
single-organism developmental process								<u>3344</u>	<u>275</u>	216.18		1.27	+	1.25E-02
→developmental process								<u>3368</u>	<u>277</u>	217.73		1.27	+	1.12E-02
<u>→anatomical structure development</u>								<u>3213</u>	<u>264</u>	207.71		1.27	+	2.33E-02
<u> </u>								<u>2298</u>	<u>208</u>	148.56		1.40	+	5.63E-04
<u> </u>								<u>2865</u>	<u>238</u>	185.21		1.29	+	3.89E-02
⊌single-multicellular organism process								<u>3107</u>	<u>258</u>	200.85		1.28	+	1.41E-02
□ PLXI	ND1 Plexin-D1		branchiomotor neuron axon guidance		GO_Central	Homo sapiens	IBA	PANTHER:PTN001476654		plexin pthr22625		GO_REF:0000033		20150911
□ SLIT	SLIT1 Slit homolog 1 protein		motor neuron axon guidance		UniProt	Homo sapiens	IMP		family not named pthr24373			PMID:16162649		20100122
□ SEM	IA3A Semapho 3A	rin-	branchiomotor neuron axon guidance		Ensembl	Homo sapiens	IEA	Ensembl:ENSMUSP00000030714		semaphorin pthr11036		GO_REF:0000019		20160409
□ PLXI	XNA3 Plexin-A3		branchiomotor neuron axon guidance		GO_Central	Homo sapiens	IBA	PANTHER:PTN001476654	plexin pthr22625			GO_REF:0000033		20150911
□ ALC	AM CD166 at	tigen	motor neuron axon guidance		Ensembl	Homo sapiens	IEA	Ensembl:ENSMUSP00000023312	cell surface glycoprotein muc18-related pthr11973			GO_REF:0000	019	20160409
■ ERB	B2 Receptor tyrosine- protein ki erbB-2	ase	motor neuron axon guidance		Ensembl	Homo sapiens	IEA	Ensembl:ENSMUSP00000053897		ne-protein e receptor 4416		GO_REF:0000	019	20160409
SEM	IA3F Semapho 3F	rin-	branchiomotor neuron axon guidance		Ensembl	Homo sapiens	IEA	Ensembl:ENSMUSP00000141865	sema pthr1		GO_REF:0000019		019	20160409
■ NOG	G Noggin		motor neuron axon guidance		Ensembl	Homo sapiens	IEA	Ensembl:ENSMUSP00000061427	morp	hogenetic in inhibitor, in	GO_REF:000001\$		019	20160409
■ EGR	E3 SUMO protein lig		motor neuron axon guidance		Ensembl	Homo sapiens	IEA	Ensembl:ENSMUSP00000041053	early respo	growth		GO_REF:0000	019	20160409

Fig. 17 (a): GO analysis using *PANTHER* gave similar results and also returned a list of the orthologous genes in *Homo sapiens*.

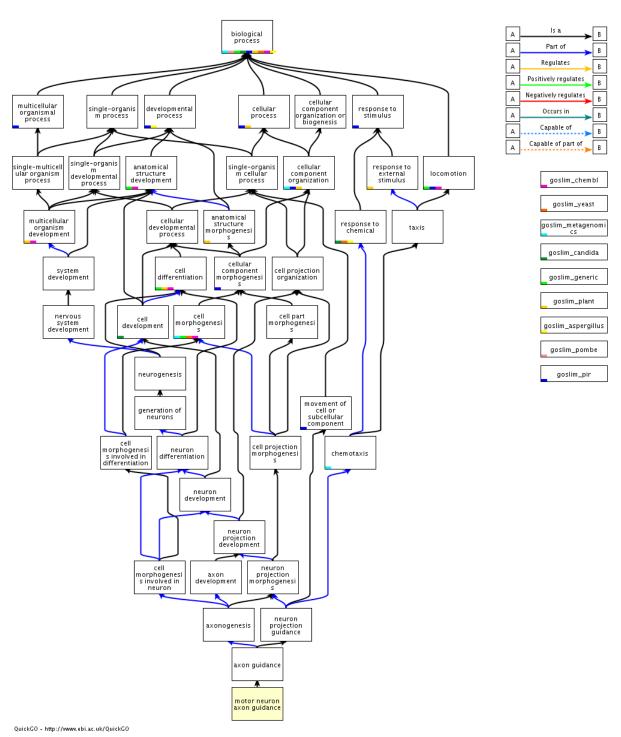


Fig. 17 (b): The graph view of the pathway and where the node 'motor neuron axon guidance' lies on it

This search gave similar results too though not exactly the same as the DAVID analysis. However, it also gave me a list of the orthologous genes that were affected in humans thus showing some kind of convergence between the two. The graph view of the process gave a detailed view of where the node lies in the pathway. This relation can be used to assess how the functioning of these genes might be affected due to mutations in any of these links.

The results obtained from the analysis showed that these genes played some role in neurodevelopment which needs to be assessed in detail further. Due to the scope of the report only a basic analysis of the RNA-seq data was possible. A detailed analysis by reproducing the experiment and refining the suggested steps will yield more significant and definite results into the role that these genes play in causing neurodevelopmental disorders.

References:

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