

Supplementary File S3. Weight peptide coexpression-network analysis of 20 mice cortical phosphopeptides

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Step 1.

- Import or install all required packages:

```
library(readxl)
library(WGCNA)
```

```
## Loading required package: dynamicTreeCut
```

```
## Loading required package: fastcluster
```

```
##
```

```
## Attaching package: 'fastcluster'
```

```
## The following object is masked from 'package:stats':
```

```
##
```

```
##      hclust
```

```
##
```

```
##
```

```
## Attaching package: 'WGCNA'
```

```
## The following object is masked from 'package:stats':
```

```
##
```

```
##      cor
```

```
library(textshape)
```

```
library(AnnotationDbi)
```

```
## Loading required package: stats4
```

```
## Loading required package: BiocGenerics
```

```
##
```

```
## Attaching package: 'BiocGenerics'
```

```

## The following object is masked from 'package:textshape':
##
##      combine

## The following objects are masked from 'package:stats':
##
##      IQR, mad, sd, var, xtabs

## The following objects are masked from 'package:base':
##
##      anyDuplicated, aperm, append, as.data.frame, basename, cbind,
##      colnames, dirname, do.call, duplicated, eval, evalq, Filter, Find,
##      get, grep, grepl, intersect, is.unsorted, lapply, Map, mapply,
##      match, mget, order, paste, pmax, pmax.int, pmin, pmin.int,
##      Position, rank, rbind, Reduce, rownames, sapply, setdiff, sort,
##      table, tapply, union, unique, unsplit, which.max, which.min

## Loading required package: Biobase

## Welcome to Bioconductor
##
##      Vignettes contain introductory material; view with
##      'browseVignettes()'. To cite Bioconductor, see
##      'citation("Biobase)", and for packages 'citation("pkgname)".

## Loading required package: IRanges

## Loading required package: S4Vectors

##
## Attaching package: 'S4Vectors'

## The following objects are masked from 'package:base':
##
##      expand.grid, I, unname

##
## Attaching package: 'IRanges'

## The following object is masked from 'package:grDevices':
##
##      windows

library(org.Mm.eg.db)

##

library(GO.db)
library(graphics)
library(cluster)

```

Step 2.

- Read in the proteomics expression data (Log2FC Intensities only!!!)
- Convert first column “PhosName” to rownames
- Check for genes and samples with too many missing values, if true move on.
- Note: In this dataset we will not remove outliers, they are biologically relevant

```
# The following setting is important, do not omit.
options(stringsAsFactors = FALSE);

df1_expr <- read_excel(path = "C:/Users/Marcu/OneDrive/Documents/Proteomic dataset and metadataset_Marcu/
                        sheet = "p-40DPI expression data");
df1_expr <- as.data.frame(df1_expr)

df1_expr <- column_to_rownames(df1_expr, "PhosName")

df1_test = goodSamplesGenes(df1_expr, verbose = 3);

## Flagging genes and samples with too many missing values...
## ..step 1

df1_test$allOK

## [1] TRUE

head(df1_expr)

##                               Blast rTg4510 3
## _QAS[Phospho (STY)]LDGLQQLR_.2             9.526490
## _GQSQLS[Phospho (STY)]NPTDDSWK_.2           9.851300
## _ERGS[Phospho (STY)]PVSGR_.2                4.013213
## _PQSPVIQATAGS[Phospho (STY)]PK_.2           6.751435
## _QSLs[Phospho (STY)]SADNLEPDVQGHQVAAR_.3    3.822566
## _ELEKPM[Oxidation (M)]QSKPQS[Phospho (STY)]PVIQAT[Phospho (STY)]AGSPK_.3 5.324073
##                               Blast rTg4510 4
## _QAS[Phospho (STY)]LDGLQQLR_.2             9.530376
## _GQSQLS[Phospho (STY)]NPTDDSWK_.2           9.539574
## _ERGS[Phospho (STY)]PVSGR_.2                9.209353
## _PQSPVIQATAGS[Phospho (STY)]PK_.2           5.927391
## _QSLs[Phospho (STY)]SADNLEPDVQGHQVAAR_.3    3.574952
## _ELEKPM[Oxidation (M)]QSKPQS[Phospho (STY)]PVIQAT[Phospho (STY)]AGSPK_.3 5.323749
##                               Blast rTg4510 1
## _QAS[Phospho (STY)]LDGLQQLR_.2             9.561561
## _GQSQLS[Phospho (STY)]NPTDDSWK_.2           9.405308
## _ERGS[Phospho (STY)]PVSGR_.2                8.782871
## _PQSPVIQATAGS[Phospho (STY)]PK_.2           6.760365
## _QSLs[Phospho (STY)]SADNLEPDVQGHQVAAR_.3    6.333914
## _ELEKPM[Oxidation (M)]QSKPQS[Phospho (STY)]PVIQAT[Phospho (STY)]AGSPK_.3 4.105218
##                               Blast rTg4510 2
## _QAS[Phospho (STY)]LDGLQQLR_.2             9.310794
## _GQSQLS[Phospho (STY)]NPTDDSWK_.2           9.712202
```

## _ERGS[Phospho (STY)]PVSGR_.2	8.880438
## _PQSPVIQATAGS[Phospho (STY)]PK_.2	6.777097
## _QSLS[Phospho (STY)]SADNLEPDVQGHQVAAR_.3	3.817567
## _ELEKPM[Oxidation (M)]QSKPQS[Phospho (STY)]PVIQAT[Phospho (STY)]AGSPK_.3	6.646825
##	Blast rTg4510 5
## _QAS[Phospho (STY)]LDGLQQLR_.2	3.115400
## _GQSLS[Phospho (STY)]NPTDDSWK_.2	8.281087
## _ERGS[Phospho (STY)]PVSGR_.2	8.729670
## _PQSPVIQATAGS[Phospho (STY)]PK_.2	5.821003
## _QSLS[Phospho (STY)]SADNLEPDVQGHQVAAR_.3	4.029503
## _ELEKPM[Oxidation (M)]QSKPQS[Phospho (STY)]PVIQAT[Phospho (STY)]AGSPK_.3	3.541612
##	Sham rTg4510 3
## _QAS[Phospho (STY)]LDGLQQLR_.2	9.128237
## _GQSLS[Phospho (STY)]NPTDDSWK_.2	8.488968
## _ERGS[Phospho (STY)]PVSGR_.2	8.712071
## _PQSPVIQATAGS[Phospho (STY)]PK_.2	6.335705
## _QSLS[Phospho (STY)]SADNLEPDVQGHQVAAR_.3	4.409535
## _ELEKPM[Oxidation (M)]QSKPQS[Phospho (STY)]PVIQAT[Phospho (STY)]AGSPK_.3	3.130726
##	Sham rTg4510 4
## _QAS[Phospho (STY)]LDGLQQLR_.2	8.832007
## _GQSLS[Phospho (STY)]NPTDDSWK_.2	9.166122
## _ERGS[Phospho (STY)]PVSGR_.2	9.143115
## _PQSPVIQATAGS[Phospho (STY)]PK_.2	5.972878
## _QSLS[Phospho (STY)]SADNLEPDVQGHQVAAR_.3	6.631398
## _ELEKPM[Oxidation (M)]QSKPQS[Phospho (STY)]PVIQAT[Phospho (STY)]AGSPK_.3	4.770406
##	Sham rTg4510 5
## _QAS[Phospho (STY)]LDGLQQLR_.2	8.754462
## _GQSLS[Phospho (STY)]NPTDDSWK_.2	8.739547
## _ERGS[Phospho (STY)]PVSGR_.2	9.223609
## _PQSPVIQATAGS[Phospho (STY)]PK_.2	6.107640
## _QSLS[Phospho (STY)]SADNLEPDVQGHQVAAR_.3	3.837163
## _ELEKPM[Oxidation (M)]QSKPQS[Phospho (STY)]PVIQAT[Phospho (STY)]AGSPK_.3	3.258363
##	Sham rTg4510 1
## _QAS[Phospho (STY)]LDGLQQLR_.2	8.803521
## _GQSLS[Phospho (STY)]NPTDDSWK_.2	8.562182
## _ERGS[Phospho (STY)]PVSGR_.2	9.012200
## _PQSPVIQATAGS[Phospho (STY)]PK_.2	6.324103
## _QSLS[Phospho (STY)]SADNLEPDVQGHQVAAR_.3	3.805728
## _ELEKPM[Oxidation (M)]QSKPQS[Phospho (STY)]PVIQAT[Phospho (STY)]AGSPK_.3	3.201110
##	Sham rTg4510 2
## _QAS[Phospho (STY)]LDGLQQLR_.2	9.436497
## _GQSLS[Phospho (STY)]NPTDDSWK_.2	9.636452
## _ERGS[Phospho (STY)]PVSGR_.2	8.581217
## _PQSPVIQATAGS[Phospho (STY)]PK_.2	6.498198
## _QSLS[Phospho (STY)]SADNLEPDVQGHQVAAR_.3	3.775299
## _ELEKPM[Oxidation (M)]QSKPQS[Phospho (STY)]PVIQAT[Phospho (STY)]AGSPK_.3	4.757065
##	Blast NC 3
## _QAS[Phospho (STY)]LDGLQQLR_.2	8.958440
## _GQSLS[Phospho (STY)]NPTDDSWK_.2	8.567541
## _ERGS[Phospho (STY)]PVSGR_.2	8.638906
## _PQSPVIQATAGS[Phospho (STY)]PK_.2	6.061009
## _QSLS[Phospho (STY)]SADNLEPDVQGHQVAAR_.3	6.410237
## _ELEKPM[Oxidation (M)]QSKPQS[Phospho (STY)]PVIQAT[Phospho (STY)]AGSPK_.3	5.728836
##	Blast NC 4

## _QAS[Phospho (STY)]LDGLQQLR_.2	8.959951
## _GQSLS[Phospho (STY)]NPTDDSWK_.2	8.494754
## _ERGS[Phospho (STY)]PVSGR_.2	8.497609
## _PQSPVIQATAGS[Phospho (STY)]PK_.2	5.481435
## _QSLS[Phospho (STY)]SADNLEPDVQGHQVAAR_.3	4.070464
## _ELEKPM[Oxidation (M)]QSKPQS[Phospho (STY)]PVIQAT[Phospho (STY)]AGSPK_.3	4.865707
##	Blast NC 5
## _QAS[Phospho (STY)]LDGLQQLR_.2	9.478251
## _GQSLS[Phospho (STY)]NPTDDSWK_.2	8.846596
## _ERGS[Phospho (STY)]PVSGR_.2	9.106709
## _PQSPVIQATAGS[Phospho (STY)]PK_.2	5.688370
## _QSLS[Phospho (STY)]SADNLEPDVQGHQVAAR_.3	3.950248
## _ELEKPM[Oxidation (M)]QSKPQS[Phospho (STY)]PVIQAT[Phospho (STY)]AGSPK_.3	5.152731
##	Blast NC 6
## _QAS[Phospho (STY)]LDGLQQLR_.2	9.231628
## _GQSLS[Phospho (STY)]NPTDDSWK_.2	8.337931
## _ERGS[Phospho (STY)]PVSGR_.2	8.130642
## _PQSPVIQATAGS[Phospho (STY)]PK_.2	5.878283
## _QSLS[Phospho (STY)]SADNLEPDVQGHQVAAR_.3	4.038407
## _ELEKPM[Oxidation (M)]QSKPQS[Phospho (STY)]PVIQAT[Phospho (STY)]AGSPK_.3	6.243723
##	Blast NC 1
## _QAS[Phospho (STY)]LDGLQQLR_.2	8.347308
## _GQSLS[Phospho (STY)]NPTDDSWK_.2	5.893559
## _ERGS[Phospho (STY)]PVSGR_.2	2.853323
## _PQSPVIQATAGS[Phospho (STY)]PK_.2	4.868358
## _QSLS[Phospho (STY)]SADNLEPDVQGHQVAAR_.3	3.891793
## _ELEKPM[Oxidation (M)]QSKPQS[Phospho (STY)]PVIQAT[Phospho (STY)]AGSPK_.3	3.830884
##	Blast NC 2
## _QAS[Phospho (STY)]LDGLQQLR_.2	9.066606
## _GQSLS[Phospho (STY)]NPTDDSWK_.2	8.568276
## _ERGS[Phospho (STY)]PVSGR_.2	7.917190
## _PQSPVIQATAGS[Phospho (STY)]PK_.2	5.660179
## _QSLS[Phospho (STY)]SADNLEPDVQGHQVAAR_.3	6.281934
## _ELEKPM[Oxidation (M)]QSKPQS[Phospho (STY)]PVIQAT[Phospho (STY)]AGSPK_.3	4.714183
##	Sham NC 3
## _QAS[Phospho (STY)]LDGLQQLR_.2	9.238355
## _GQSLS[Phospho (STY)]NPTDDSWK_.2	9.093485
## _ERGS[Phospho (STY)]PVSGR_.2	9.019227
## _PQSPVIQATAGS[Phospho (STY)]PK_.2	6.536391
## _QSLS[Phospho (STY)]SADNLEPDVQGHQVAAR_.3	3.999680
## _ELEKPM[Oxidation (M)]QSKPQS[Phospho (STY)]PVIQAT[Phospho (STY)]AGSPK_.3	6.865086
##	Sham NC 4
## _QAS[Phospho (STY)]LDGLQQLR_.2	8.851384
## _GQSLS[Phospho (STY)]NPTDDSWK_.2	8.686150
## _ERGS[Phospho (STY)]PVSGR_.2	9.052475
## _PQSPVIQATAGS[Phospho (STY)]PK_.2	5.935714
## _QSLS[Phospho (STY)]SADNLEPDVQGHQVAAR_.3	3.683997
## _ELEKPM[Oxidation (M)]QSKPQS[Phospho (STY)]PVIQAT[Phospho (STY)]AGSPK_.3	5.175933
##	Sham NC 1
## _QAS[Phospho (STY)]LDGLQQLR_.2	9.026282
## _GQSLS[Phospho (STY)]NPTDDSWK_.2	8.437126
## _ERGS[Phospho (STY)]PVSGR_.2	8.218046
## _PQSPVIQATAGS[Phospho (STY)]PK_.2	5.841424
## _QSLS[Phospho (STY)]SADNLEPDVQGHQVAAR_.3	3.765512

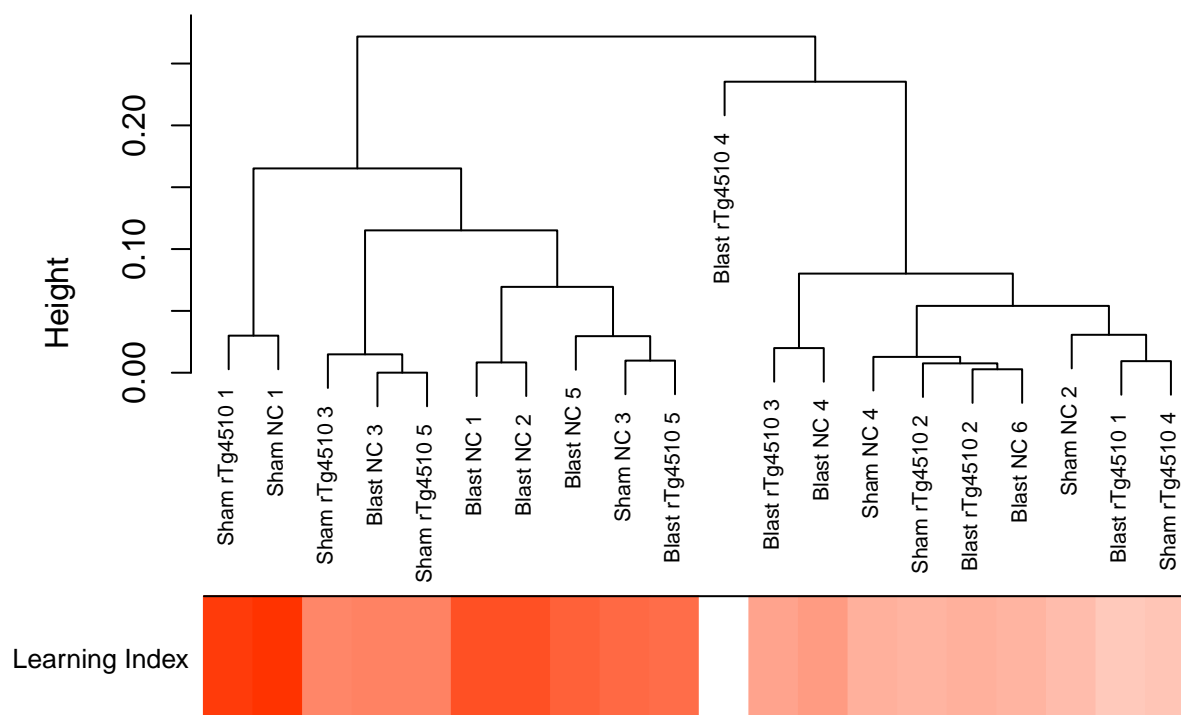
```
## _ELEKPM[Oxidation (M)]QSKPQS[Phospho (STY)]PVIQAT[Phospho (STY)]AGSPK_.3 4.804185
## Sham NC 2
## _QAS[Phospho (STY)]LDGLQQLR_.2 8.979440
## _GQSLS[Phospho (STY)]NPTDDSWK_.2 8.454514
## _ERGS[Phospho (STY)]PVSGR_.2 8.299261
## _PQSPVIQATAGS[Phospho (STY)]PK_.2 6.011762
## _QSLS[Phospho (STY)]SADNLEPDVQGHQVAAR_.3 3.809294
## _ELEKPM[Oxidation (M)]QSKPQS[Phospho (STY)]PVIQAT[Phospho (STY)]AGSPK_.3 4.582183
```

Step 3.

- Import trait/clinical/phenotype dataset
- In df2_trait convert first column to rownames
- visualize how the clinical traits relate to the sample dendrogram.
- Convert traits to a color representation (i.e., white means low, red means high, grey means missing entry)
- Plot the sample dendrogram and the colors underneath:

```
df2_trait <- as.data.frame(read_excel("C:/Users/Marcu/OneDrive/Documents/cogwall_df for WGCNA.xlsx", sheet = "Sheet1"))
df2_trait <- column_to_rownames(df2_trait, "Animal_ID");
sampleTree2 = hclust(dist(df2_trait), method = "average");
traitColors = numbers2colors(df2_trait$`Learning Index`, signed = FALSE);
dend_trait <- plotDendroAndColors(sampleTree2, traitColors,
                                groupLabels = names(df2_trait),
                                main = "Sample Dendrogram and Learning Index Heatmap", cex.dendroLabels = 0.8)
```

Sample Dendrogram and Learning Index Heatmap



Step 4.

- Standard peptide screening based on marginal correlation (i.e., Network terminology: GS1 will be referred to as signed peptide significance measure)

```
## Transpose proteomic/expression data to have genes in columns and samples as rows
df1_expr_transposed <- data.frame(t(df1_expr))

GS1= as.numeric(cor(df2_trait, df1_expr_transposed, use="p"));
p.Standard=corPvalueFisher(GS1, nSamples =length(df2_trait));

## Since the q-value function has problems with missing data, we use the following trick
p.Standard2=p.Standard
p.Standard2[is.na(p.Standard)]=1
q.Standard=qvalue(p.Standard2)$qvalues;

# Form a data frame to hold the results
PhosPepNames <- row.names(df1_expr)
StandardPeptideScreeningResults=data.frame(PhosPepNames,PearsonCorrelation=GS1,
                                           p.Standard, q.Standard)

head(StandardPeptideScreeningResults)
```

##

PhosPepNames

```
## 1 _QAS[Phospho (STY)]LDGLQQLR_.2
## 2 _GSQLS[Phospho (STY)]NPTDDSWK_.2
## 3 _ERGS[Phospho (STY)]PVSGR_.2
## 4 _PQSPVIQATAGS[Phospho (STY)]PK_.2
## 5 _QSLs[Phospho (STY)]SADNLEPDVQGHQVAAR_.3
## 6 _ELEKPM[Oxidation (M)]QSKPQS[Phospho (STY)]PVIQAT[Phospho (STY)]AGSPK_.3
## PearsonCorrelation p.Standard q.Standard
## 1 -0.43553296 NaN 1
## 2 -0.25315597 NaN 1
## 3 0.03173034 NaN 1
## 4 -0.05579011 NaN 1
## 5 0.26961245 NaN 1
## 6 -0.15698126 NaN 1
```

Step 5.

- Now export “StandardGeneScreeningResults” to filter in excel if $\text{abs}(r) < 0.5$.
- Import nw data frame (df3_expr)
- Transpose for network construction

```
# First we need to save the results as a csv
write.csv(StandardPeptideScreeningResults, "C:/Users/Marcu/OneDrive/Documents/WGCNA_StandardGeneScreeningResults.csv")
# Note: due to the small n number for the study, no pvalues were attributable, only pearson r therefore

## Import new filtered dataset
df3_expr <- read_excel("C:/Users/Marcu/OneDrive/Documents/Proteomic dataset and metadataset_Marcus.xlsx",
                      sheet = "p-4ODPI expression filtered df");

## Transpose proteomic/expression of filtered data to have genes in columns and samples as rows
df3_expr <- column_to_rownames(df3_expr, "PhosName");
df3_expr_transposed <- data.frame(t(df3_expr))

head(df3_expr)
```

```
## Blast rTg4510 3
## _RKPGAGGS[Phospho (STY)]PALAR_.3 8.238760
## _IVHSES[Phospho (STY)]QPEKESR_.2 6.232174
## _TDPGS[Phospho (STY)]IENLC[Carbamidomethyl (C)]PGK_.2 8.986573
## _TGGECS[Phospho (STY)]LDEEAEGSKK_.2 4.265219
## _S[Phospho (STY)]MDSLCL[Carbamidomethyl (C)]SVPVEGK_.2 4.289535
## _SNS[Phospho (STY)]QENVEASHPSQDGKR_.3 7.910812
## Blast rTg4510 4
## _RKPGAGGS[Phospho (STY)]PALAR_.3 8.928654
## _IVHSES[Phospho (STY)]QPEKESR_.2 6.598271
## _TDPGS[Phospho (STY)]IENLC[Carbamidomethyl (C)]PGK_.2 3.758421
## _TGGECS[Phospho (STY)]LDEEAEGSKK_.2 3.737585
## _S[Phospho (STY)]MDSLCL[Carbamidomethyl (C)]SVPVEGK_.2 4.530391
## _SNS[Phospho (STY)]QENVEASHPSQDGKR_.3 8.126560
## Blast rTg4510 1
## _RKPGAGGS[Phospho (STY)]PALAR_.3 7.615425
## _IVHSES[Phospho (STY)]QPEKESR_.2 5.575043
## _TDPGS[Phospho (STY)]IENLC[Carbamidomethyl (C)]PGK_.2 4.598085
## _TGGECS[Phospho (STY)]LDEEAEGSKK_.2 3.300677
```


## _S[Phospho (STY)]MDSLC[Carbamidomethyl (C)]SVPVEGK_.2	3.826115		
## _SNS[Phospho (STY)]QENVEASHPSQDGKR_.3	7.609041		
##		Blast	rTg4510 2
## _RKPGAGGS[Phospho (STY)]PALAR_.3	8.154468		
## _IVHSES[Phospho (STY)]QPEKESR_.2	3.822685		
## _TDPGS[Phospho (STY)]IENLC[Carbamidomethyl (C)]PGK_.2	4.023560		
## _TGGECS[Phospho (STY)]LDEEAEGSKK_.2	3.424170		
## _S[Phospho (STY)]MDSLC[Carbamidomethyl (C)]SVPVEGK_.2	3.294690		
## _SNS[Phospho (STY)]QENVEASHPSQDGKR_.3	7.948428		
##		Blast	rTg4510 5
## _RKPGAGGS[Phospho (STY)]PALAR_.3	7.255080		
## _IVHSES[Phospho (STY)]QPEKESR_.2	5.815416		
## _TDPGS[Phospho (STY)]IENLC[Carbamidomethyl (C)]PGK_.2	3.767603		
## _TGGECS[Phospho (STY)]LDEEAEGSKK_.2	3.602941		
## _S[Phospho (STY)]MDSLC[Carbamidomethyl (C)]SVPVEGK_.2	2.995633		
## _SNS[Phospho (STY)]QENVEASHPSQDGKR_.3	7.238229		
##		Sham	rTg4510 3
## _RKPGAGGS[Phospho (STY)]PALAR_.3	7.559636		
## _IVHSES[Phospho (STY)]QPEKESR_.2	4.509915		
## _TDPGS[Phospho (STY)]IENLC[Carbamidomethyl (C)]PGK_.2	3.800942		
## _TGGECS[Phospho (STY)]LDEEAEGSKK_.2	3.827025		
## _S[Phospho (STY)]MDSLC[Carbamidomethyl (C)]SVPVEGK_.2	3.028972		
## _SNS[Phospho (STY)]QENVEASHPSQDGKR_.3	7.742838		
##		Sham	rTg4510 4
## _RKPGAGGS[Phospho (STY)]PALAR_.3	8.641213		
## _IVHSES[Phospho (STY)]QPEKESR_.2	5.366398		
## _TDPGS[Phospho (STY)]IENLC[Carbamidomethyl (C)]PGK_.2	3.280498		
## _TGGECS[Phospho (STY)]LDEEAEGSKK_.2	3.938133		
## _S[Phospho (STY)]MDSLC[Carbamidomethyl (C)]SVPVEGK_.2	4.052468		
## _SNS[Phospho (STY)]QENVEASHPSQDGKR_.3	7.715931		
##		Sham	rTg4510 5
## _RKPGAGGS[Phospho (STY)]PALAR_.3	8.533593		
## _IVHSES[Phospho (STY)]QPEKESR_.2	5.639189		
## _TDPGS[Phospho (STY)]IENLC[Carbamidomethyl (C)]PGK_.2	3.786346		
## _TGGECS[Phospho (STY)]LDEEAEGSKK_.2	4.300083		
## _S[Phospho (STY)]MDSLC[Carbamidomethyl (C)]SVPVEGK_.2	4.515215		
## _SNS[Phospho (STY)]QENVEASHPSQDGKR_.3	7.794398		
##		Sham	rTg4510 1
## _RKPGAGGS[Phospho (STY)]PALAR_.3	7.604037		
## _IVHSES[Phospho (STY)]QPEKESR_.2	4.530955		
## _TDPGS[Phospho (STY)]IENLC[Carbamidomethyl (C)]PGK_.2	3.200704		
## _TGGECS[Phospho (STY)]LDEEAEGSKK_.2	4.169271		
## _S[Phospho (STY)]MDSLC[Carbamidomethyl (C)]SVPVEGK_.2	3.972674		
## _SNS[Phospho (STY)]QENVEASHPSQDGKR_.3	7.446234		
##		Sham	rTg4510 2 Blast NC 3
## _RKPGAGGS[Phospho (STY)]PALAR_.3	8.792485	7.930930	
## _IVHSES[Phospho (STY)]QPEKESR_.2	7.393740	5.324989	
## _TDPGS[Phospho (STY)]IENLC[Carbamidomethyl (C)]PGK_.2	9.014376	8.701669	
## _TGGECS[Phospho (STY)]LDEEAEGSKK_.2	4.471540	4.371601	
## _S[Phospho (STY)]MDSLC[Carbamidomethyl (C)]SVPVEGK_.2	4.100130	3.451314	
## _SNS[Phospho (STY)]QENVEASHPSQDGKR_.3	8.177623	7.695513	
##		Blast NC 4	Blast NC 5
## _RKPGAGGS[Phospho (STY)]PALAR_.3	8.294293	8.677245	
## _IVHSES[Phospho (STY)]QPEKESR_.2	5.432989	5.951327	

```
## _TDPGS[Phospho (STY)]IENLC[Carbamidomethyl (C)]PGK_.2 3.484541 3.591541
## _TGGECS[Phospho (STY)]LDEEAEGSKK_.2 3.627032 4.105278
## _S[Phospho (STY)]MDSLC[Carbamidomethyl (C)]SVPVEGK_.2 4.256511 4.138116
## _SNS[Phospho (STY)]QENVEASHPSQDGKR_.3 7.447561 8.318089
## Blast NC 6 Blast NC 1
## _RKPGAGGS[Phospho (STY)]PALAR_.3 8.674047 7.550161
## _IVHSES[Phospho (STY)]QPEKESR_.2 5.900654 4.160454
## _TDPGS[Phospho (STY)]IENLC[Carbamidomethyl (C)]PGK_.2 3.135309 3.305870
## _TGGECS[Phospho (STY)]LDEEAEGSKK_.2 3.649046 3.515330
## _S[Phospho (STY)]MDSLC[Carbamidomethyl (C)]SVPVEGK_.2 3.864178 4.077840
## _SNS[Phospho (STY)]QENVEASHPSQDGKR_.3 8.093542 7.609236
## Blast NC 2 Sham NC 3
## _RKPGAGGS[Phospho (STY)]PALAR_.3 7.970520 7.815962
## _IVHSES[Phospho (STY)]QPEKESR_.2 6.097862 5.464425
## _TDPGS[Phospho (STY)]IENLC[Carbamidomethyl (C)]PGK_.2 4.423620 3.283576
## _TGGECS[Phospho (STY)]LDEEAEGSKK_.2 3.109278 3.797314
## _S[Phospho (STY)]MDSLC[Carbamidomethyl (C)]SVPVEGK_.2 3.651650 4.012446
## _SNS[Phospho (STY)]QENVEASHPSQDGKR_.3 7.830169 7.668289
## Sham NC 4 Sham NC 1
## _RKPGAGGS[Phospho (STY)]PALAR_.3 8.554644 7.960728
## _IVHSES[Phospho (STY)]QPEKESR_.2 6.053357 5.689051
## _TDPGS[Phospho (STY)]IENLC[Carbamidomethyl (C)]PGK_.2 3.865864 4.164917
## _TGGECS[Phospho (STY)]LDEEAEGSKK_.2 3.352127 3.651180
## _S[Phospho (STY)]MDSLC[Carbamidomethyl (C)]SVPVEGK_.2 3.136995 3.436048
## _SNS[Phospho (STY)]QENVEASHPSQDGKR_.3 7.898524 8.032992
## Sham NC 2
## _RKPGAGGS[Phospho (STY)]PALAR_.3 7.693437
## _IVHSES[Phospho (STY)]QPEKESR_.2 5.986509
## _TDPGS[Phospho (STY)]IENLC[Carbamidomethyl (C)]PGK_.2 4.313431
## _TGGECS[Phospho (STY)]LDEEAEGSKK_.2 3.326329
## _S[Phospho (STY)]MDSLC[Carbamidomethyl (C)]SVPVEGK_.2 3.541460
## _SNS[Phospho (STY)]QENVEASHPSQDGKR_.3 7.835881
```

Step 6.

- Construction of a weighted peptide co-expression network and network modules. Note: The adjacency matrix, also called the connection matrix, is a matrix containing rows and columns which is used to represent a simple labelled graph, with 0 or 1 in the position of (V_i, V_j) according to the condition whether V_i and V_j are adjacent or not. Defining a weighted peptide co-expression network here we define the adjacency matrix using soft thresholding with $\beta=8$ (unsigned = 6, signed = 12).
- Define k-connectivity measure
- Test adjacency network set to $\beta = 8$ for scale free-topology
- Plot results (Histogram and Scatter plot with trend line)

```
ADJ1=abs(cor(df3_expr_transposed,use="p"))^8

# When you have relatively few genes (<5000) use the following code:
k=as.vector(apply(ADJ1,2,sum, na.rm=T))
# When you have a lot of genes use the following code: "k=softConnectivity(datE=datExpr,power=6); this

# Plot a histogram of k and a scale free topology plot
sizeGrWindow(10,5)
par(mfrow=c(1,2))
```

```
k_histogram <- hist(k)
scale_free_plot <- scaleFreePlot(k, main="Check scale free topology\n")
plot(scale_free_plot)
```

Note: k-Histogram and scale free topology explained: The approximate straight line relationship (r^2)

Figure. Histogram and scatter plot to assess network for scale-free topology Impression: Beta = 8 was the only beta that created scale free topology in data

Step 7.

- Convert adjacency similarity matrix to a dissimilarity matrix (dissADJ)
- Convert topological overlap matrix to a dissimilarity matrix (dissTOM)
- Define modules using topological overlap dissimilarity
- Plot results.

```
# Comparing various module detection methods
# Definition of clustering dissimilarity from adjacency
# Many clustering procedures require a dissimilarity matrix as input.
# We define a dissimilarity based on adjacency:
# Turn adjacency into a measure of dissimilarity:
dissADJ=1-ADJ1

# Use of topological overlap to define dissimilarity
# Adjacency can be used to define a separate measure of similarity,
# the Topological Overlap Matrix(TOM).
# We will convert the TOM matrix to a dissimilarity matrix as well (dissTOM)
dissTOM=TOMdist(ADJ1)
```

```
## ..connectivity..
## ..matrix multiplication (system BLAS)..
## ..normalization..
## ..done.
```

```
simTOM=1-(TOMdist(ADJ1))
```

```
## ..connectivity..
## ..matrix multiplication (system BLAS)..
## ..normalization..
## ..done.
```

```
collectGarbage()
```

```
# Module definition using the topological overlap based dissimilarity.
# We now use the topological overlap based dissimilarity as input to the
# clustering methods.
# Calculate the dendrogram:
hierTOM = hclust(as.dist(dissTOM),method="average");
```

```

# We will compare three different tree-cutting methods:
colorStaticTOM = as.character(cutreeStaticColor(hierTOM, cutHeight=.99, minSize=20))
colorDynamicTOM = labels2colors (cutreeDynamic(hierTOM,method="tree"))
colorDynamicHybridTOM = labels2colors(cutreeDynamic(hierTOM, distM= dissTOM , cutHeight = 0.998,
                                                    deepSplit=2, pamRespectsDendro = FALSE))

## ..done.

# Now we plot the results
sizeGrWindow(10,5)
plotDendroAndColors(hierTOM,
                    colors=data.frame(colorStaticTOM,
                                      colorDynamicTOM, colorDynamicHybridTOM),
                    dendroLabels = FALSE, marAll = c(1, 8, 3, 1),
                    main = "Gene dendrogram and module colors, TOM dissimilarity")

```

Gene dendrogram and module colors, TOM dissimilarity

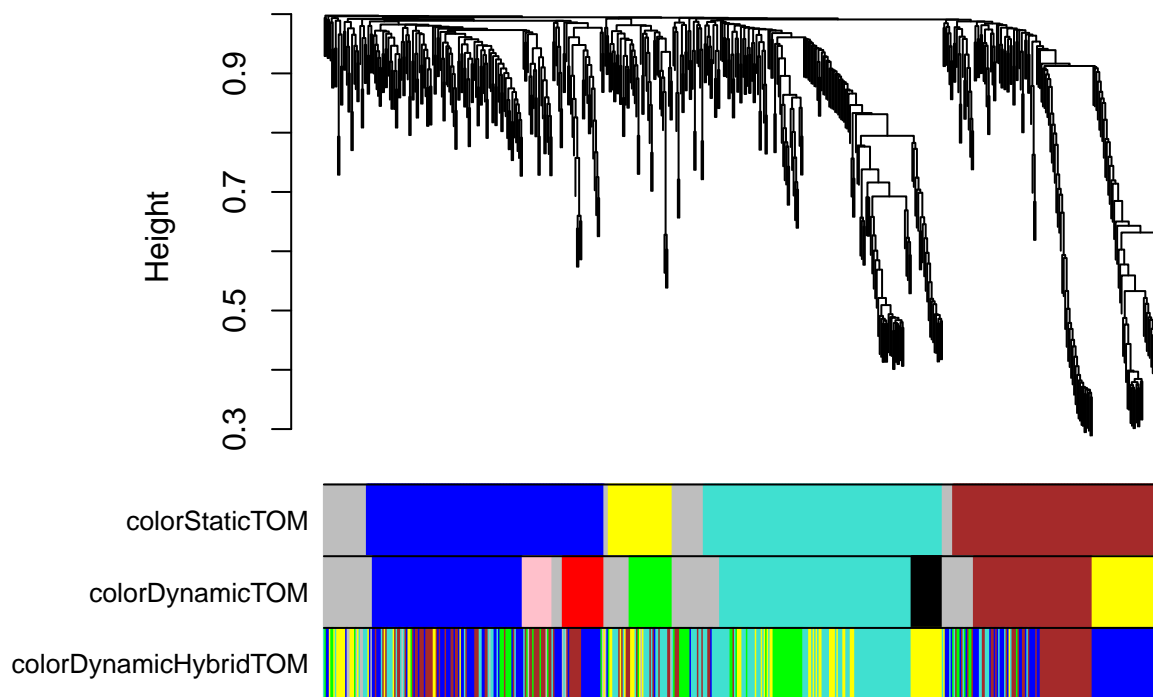


Figure. Weighted peptide coexpression-network

Step 8.

- Compile the module assignment (colors) into a single list (colorsh1)
- Compute module eigenpeptides for animal's phosphopeptidome
- Relating modules and module-eigenpeptides to learning index
- Calculate Peptide significance (i.e., analogous to gene significance)

```

# Since the "colorDynamicTOM" tree cutting method captures most of the data
# and has very similar results to other tree cutting methods,
# will use this method for defining modules (colors at bottom of dendrogram)
# We define a shorter name for the module assignment of choice,
# remove unneeded variables and save the results for use in subsequent
# sessions.
colorh1= colorDynamicTOM

# remove the dissimilarities, adjacency matrices etc to free up space
rm(ADJ1); rm(dissADJ);
collectGarbage()

# Representing modules by eigenpeptides and relating eigenpeptides to one another
# to get a sense of how related the modules are one can summarize each module by # its eigenpeptides (f
datME=moduleEigengenes(df3_expr_transposed, colorh1)$eigengenes
signif(cor(datME, use="p"), 2)

```

```

##           MEblack MEblue MEbrown MEgreen MEgrey MEpink MERed MEturquoise
## MEblack      1.00  0.34   0.55   0.47   0.60  0.23  0.20         0.86
## MEblue       0.34  1.00   0.70   0.58   0.81  0.83  0.68         0.55
## MEbrown      0.55  0.70   1.00   0.59   0.71  0.53  0.51         0.69
## MEgreen      0.47  0.58   0.59   1.00   0.71  0.48  0.43         0.55
## MEgrey       0.60  0.81   0.71   0.71   1.00  0.65  0.64         0.74
## MEpink       0.23  0.83   0.53   0.48   0.65  1.00  0.62         0.44
## MERed        0.20  0.68   0.51   0.43   0.64  0.62  1.00         0.37
## MEturquoise  0.86  0.55   0.69   0.55   0.74  0.44  0.37         1.00
## MEyellow     0.29  0.54   0.82   0.35   0.55  0.35  0.49         0.43
##           MEyellow
## MEblack      0.29
## MEblue       0.54
## MEbrown      0.82
## MEgreen      0.35
## MEgrey       0.55
## MEpink       0.35
## MERed        0.49
## MEturquoise  0.43
## MEyellow     1.00

```

```

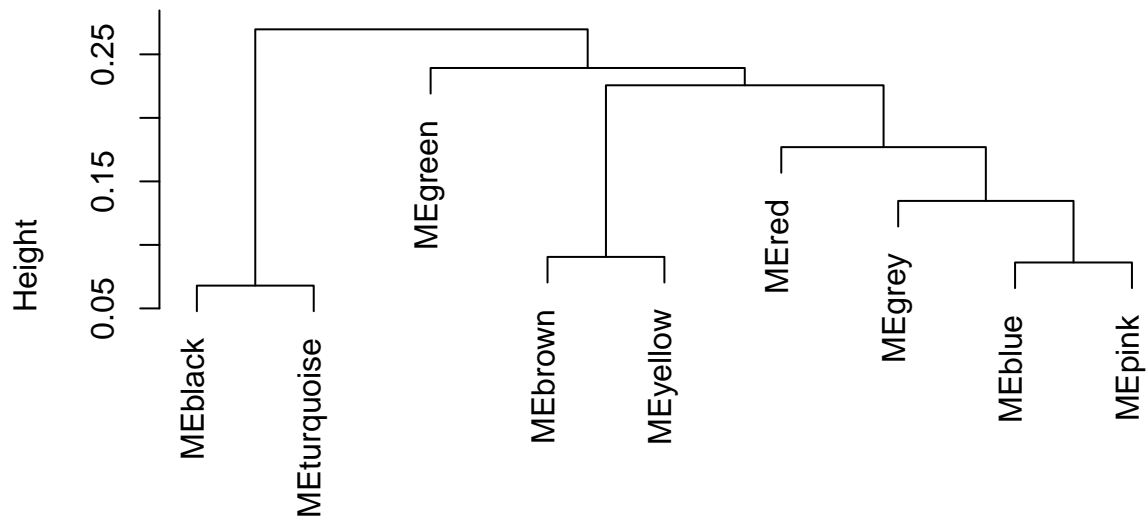
# We define a dissimilarity measure between the module eigenpeptides
# that keeps track of the sign of the correlation between the module
# eigenpeptides, and use # it to cluster the eigenpeptide:
dissimME=(1-t(cor(datME, method="p")))/2
hclustdatME=hclust(as.dist(dissimME), method="average" )

# Plot the eigenpeptide dendrogram
par(mfrow=c(1,1))
plot(hclustdatME, main="Clustering tree based of the module eigengenes")

```

Clustering tree based of the module

eigengenes

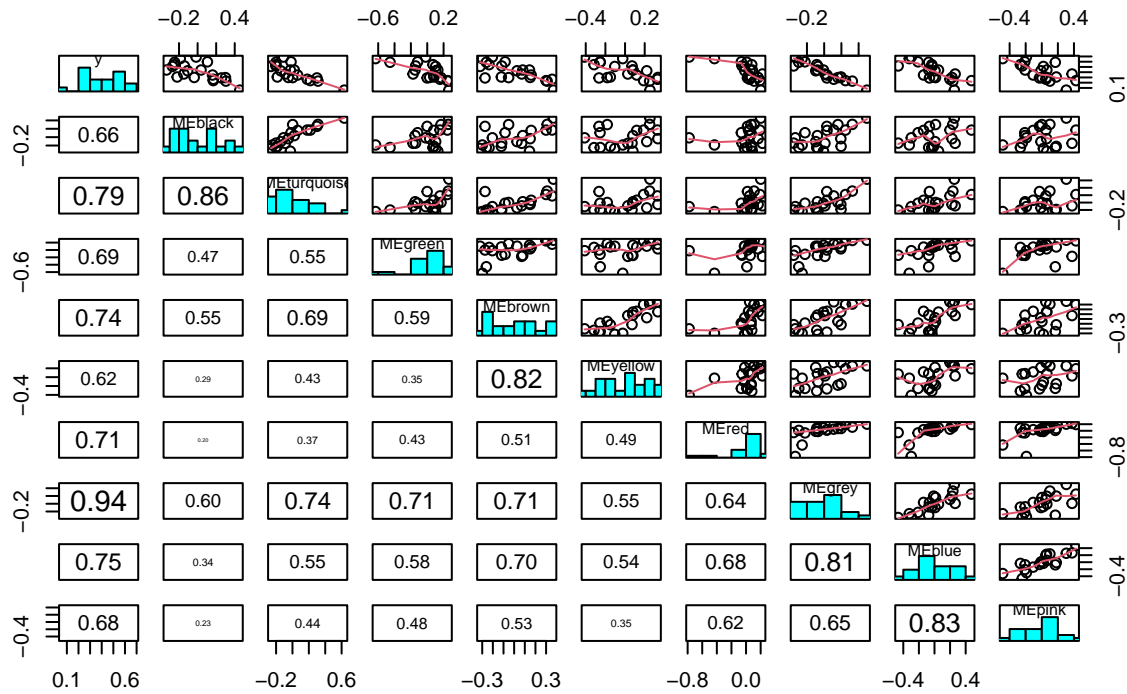


```
as.dist(dissimME)
hclust (*, "average")
```

*# Impression: The (I) blue and yellow eigengenes,
and the (II) brown and turquoise eigenpeptide are highly related, as
evidenced by their elevated merging height.*

Pairwise scatter plots of mice (n = 20) phenotypes (learning index) # and module eigenpeptides.
PW_scatt_initLL <- plotMEpairs(datME, y=df2_trait\$`Learning Index`,)

Relationship between module eigengenes

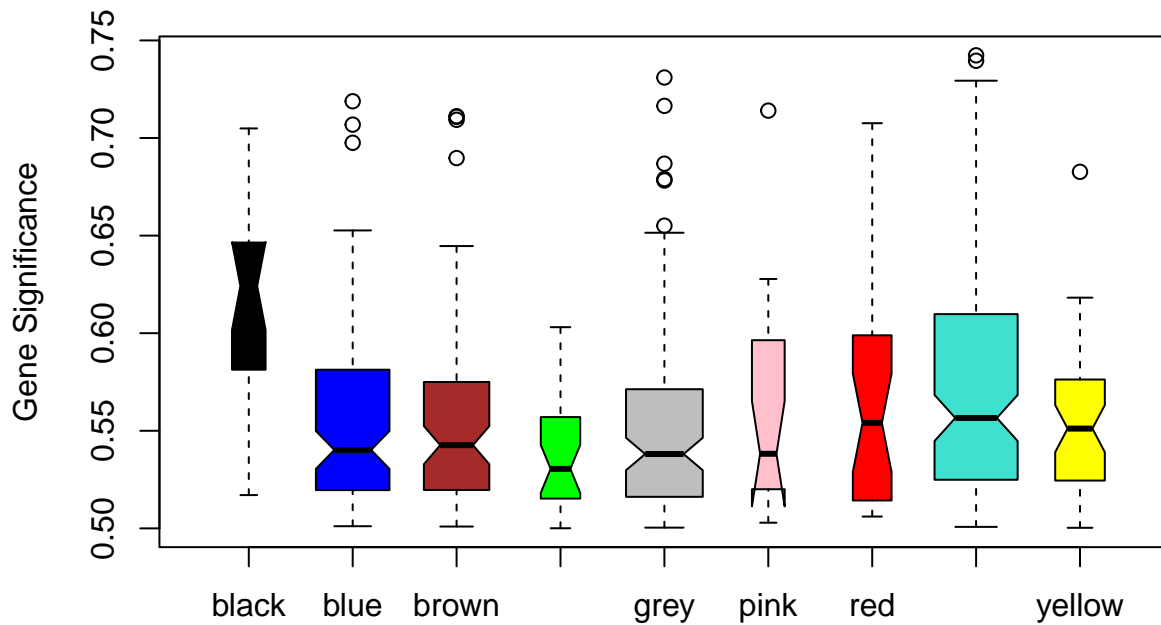


```
# The module eigenpeptides (first PC) of different modules may be
# highly correlated. WpCNA can be interpreted as a biologically
# motivated data reduction scheme that allows for dependency between
# the resulting components. In contrast, principal component analysis # imposes orthogonality between t
# Since modules may represent biological pathways there is no
# biological reason why modules should be orthogonal to each other.
GS1=as.numeric(cor(df2_trait$`Learning Index`,df3_expr_transposed, use="p"))
GeneSignificance=abs(GS1)
```

```
# Next module significance is defined as average gene significance.
ModuleSignificance=apply(GeneSignificance, colorh1, mean, na.rm=T)
```

```
# To plot module significance, one can use the following code:
par(mfrow = c(1,1))
plotModuleSignificance(GeneSignificance,colorh1, boxplot = TRUE)
```

Gene significance across modules, p-value=3.4e-05



Step 9.

- Compute intramodular connectivity
- Evaluate relationship between peptide significance and intramodular connectivity
- Compute module membership for each module
- Evaluate relationship between module membership and intramodular connectivity

```
# Module membership and intramodular connectivity: We begin by calculating the
# intramodular connectivity for each peptide. (In network literature,
# connectivity is often referred to as "degree".) The function
# intramodularConnectivity computes the whole network connectivity kTotal, the
# within module connectivity kWithin, kOut=kTotal-kWithin, and
# kDiff=kIn-kOut=2*kIn-kTotal.
ADJ1=abs(cor(df3_expr_transposed,use="p"))^6
Alldegrees1=intramodularConnectivity(ADJ1, colorh1)
head(Alldegrees1)
```

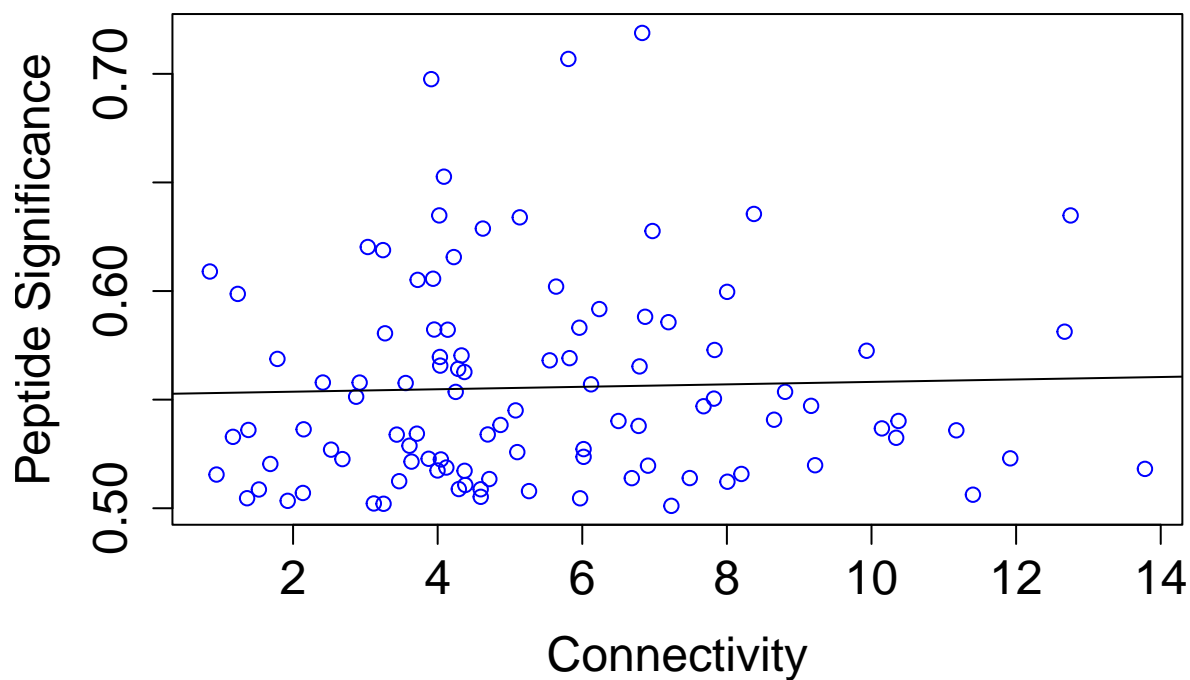
```
##
## kTotal kWithin
## X_RKPGAGGS.Phospho..STY..PALAR_.3 13.169946 7.829837
## X_IVHSES.Phospho..STY..QPEKESR_.2 5.157729 1.661596
## X_TDPGS.Phospho..STY..IENLC.Carbamidomethyl..C..PGK_.2 6.854629 4.934478
## X_TGGEYS.Phospho..STY..LDEEAEGSKK_.2 33.558267 23.776103
## X_S.Phospho..STY..MDSLC.Carbamidomethyl..C..SVPVEGK_.2 27.156917 22.248421
## X_SNS.Phospho..STY..QENVEASHPSQDGKR_.3 10.217091 5.959858
```



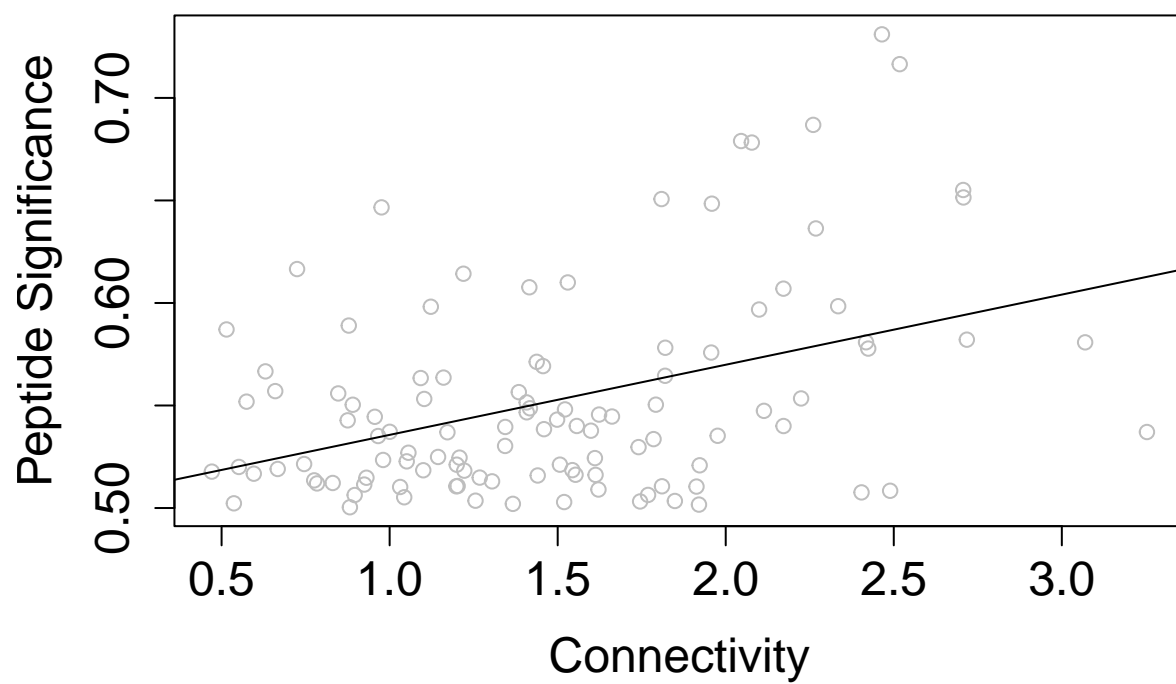
```
##
## X_RKPGAGGS.Phospho..STY..PALAR_.3      5.340109  2.489728
## X_IVHSES.Phospho..STY..QPEKESR_.2      3.496133 -1.834537
## X_TDPGS.Phospho..STY..IENLC.Carbamidomethyl..C..PGK_.2 1.920151  3.014327
## X_TGGEYS.Phospho..STY..LDEEAEGSKK_.2    9.782164 13.993940
## X_S.Phospho..STY..MDSL.C.Carbamidomethyl..C..SVPVEGK_.2 4.908496 17.339925
## X_SNS.Phospho..STY..QENVEASHPSQDGKR_.3  4.257233  1.702625
```

```
# Relationship between peptide significance and intramodular connectivity:
# We plot the peptide significance against intramodular connectivity.
colorlevels=unique(colorh1)
sizeGrWindow(9,6)
par(mfrow=c(2,as.integer(0.5+length(colorlevels)/2)))
par(mar = c(4,5,3,1))
for (i in c(1:length(colorlevels)))
{
  whichmodule=colorlevels[[i]];
  restrict1 = (colorh1==whichmodule);
  verboseScatterplot(Alldegrees1$kWithin[restrict1],
    GeneSignificance[restrict1], col=colorh1[restrict1],
    main=whichmodule,
    xlab = "Connectivity", ylab = "Peptide Significance", abline = TRUE)
}
```

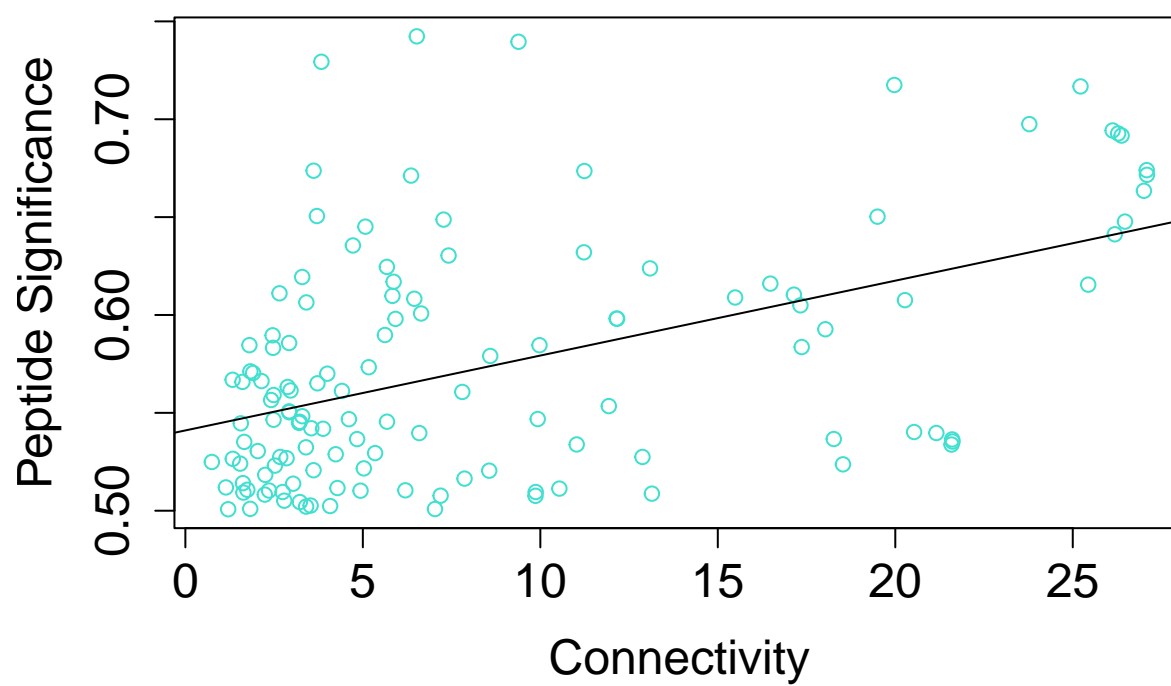
blue cor=0.034, p=0.74



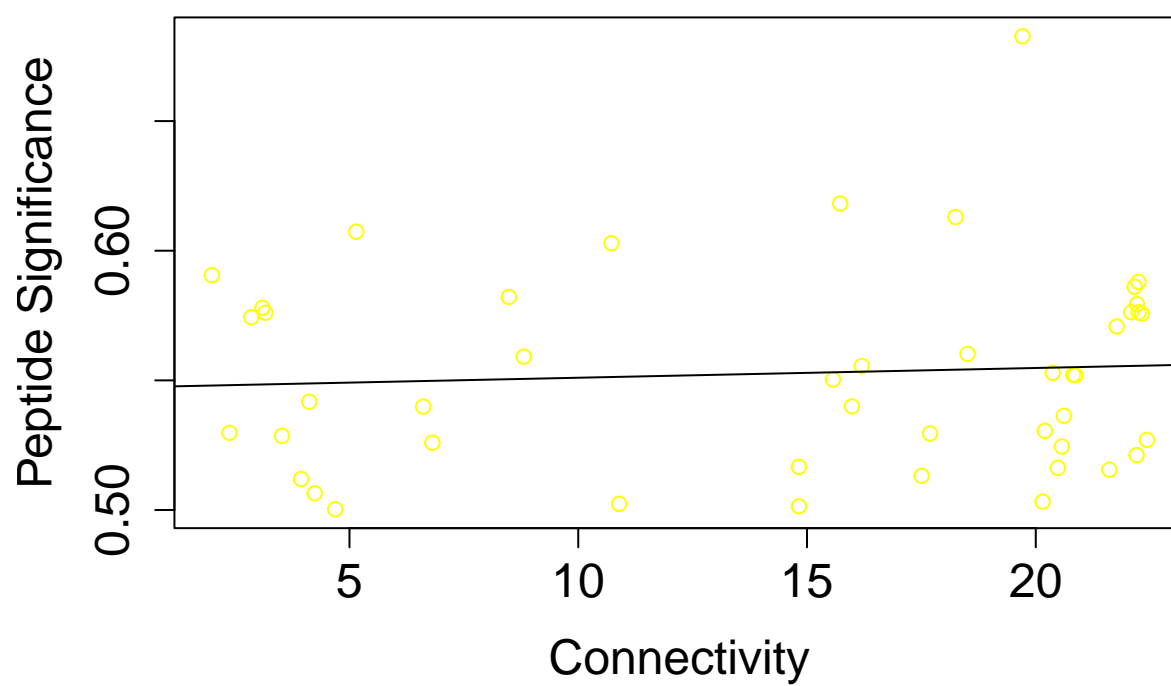
grey cor=0.41, p=8.7e-06



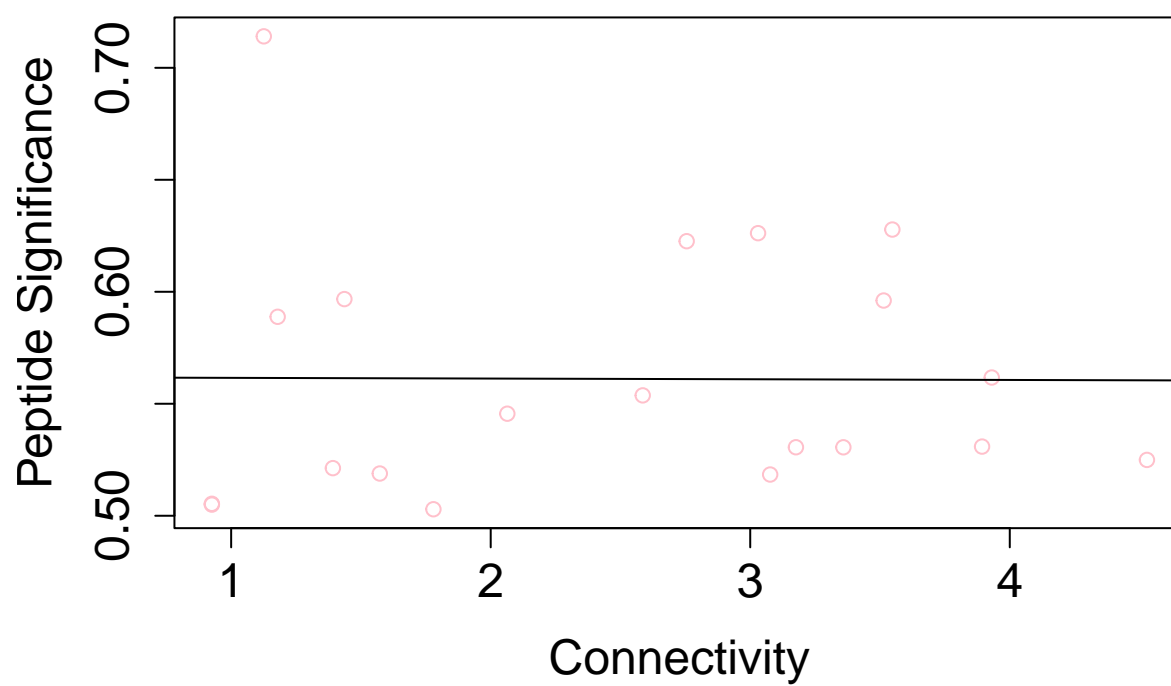
turquoise cor=0.48, p=8.6e-09



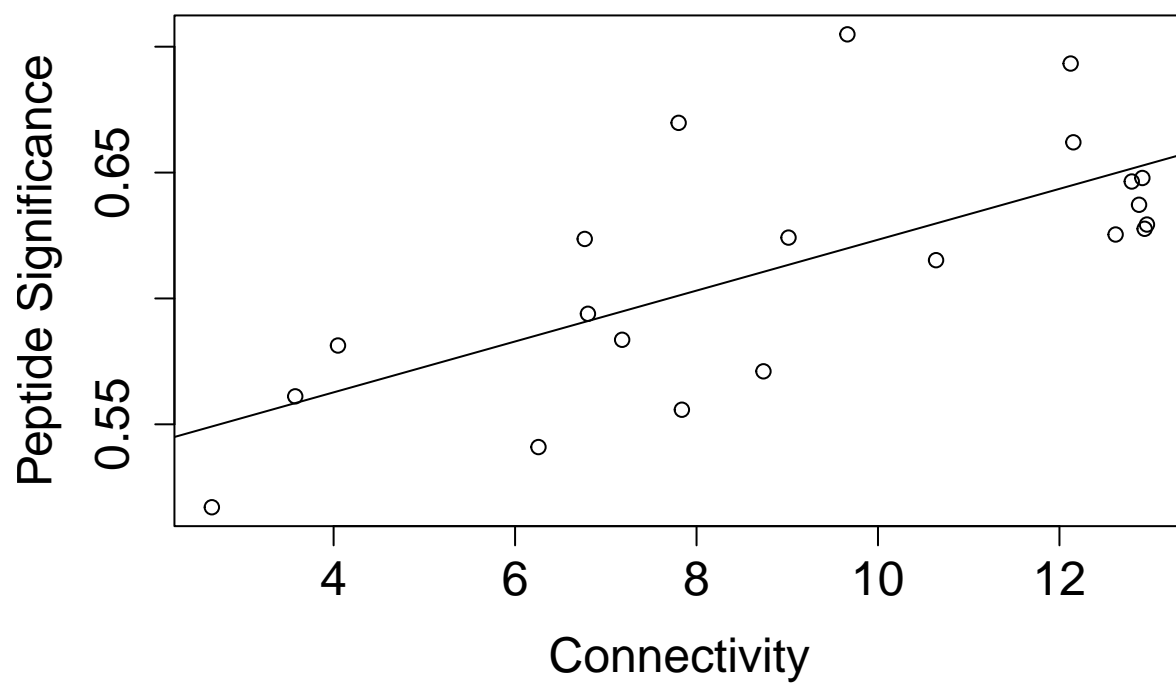
yellow cor=0.074, p=0.63

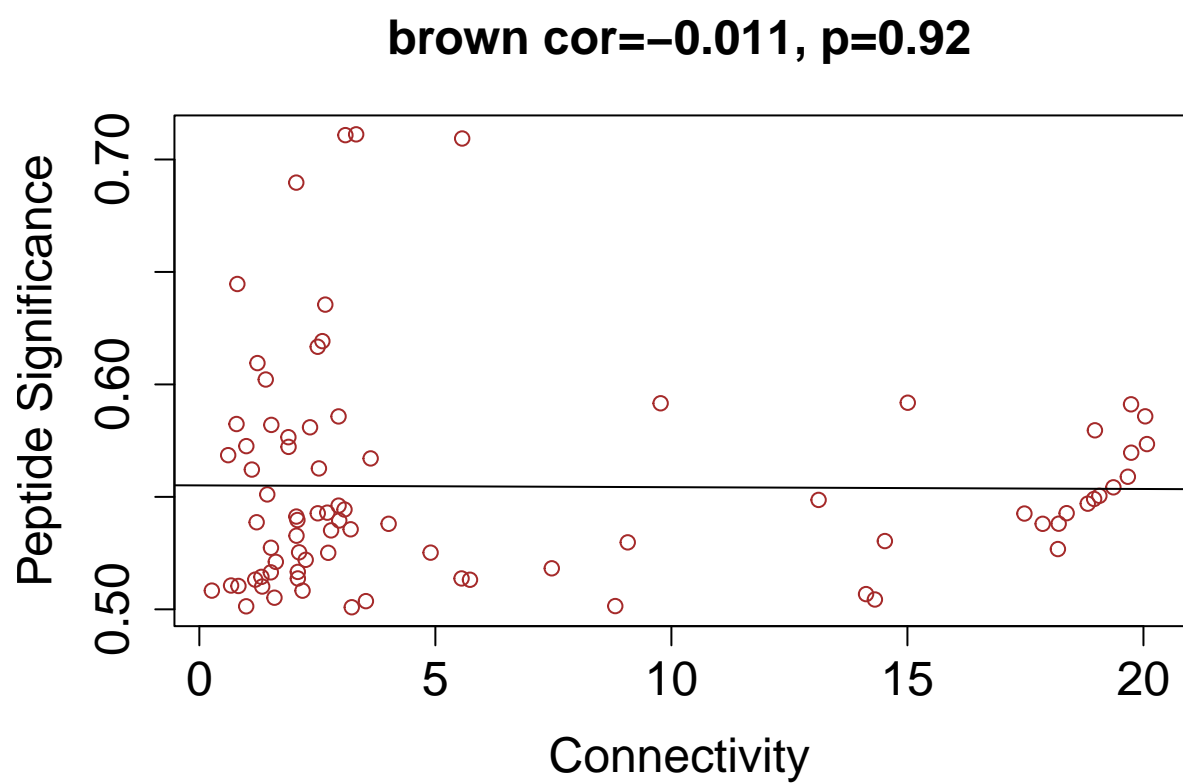


pink cor=-0.0064, p=0.98

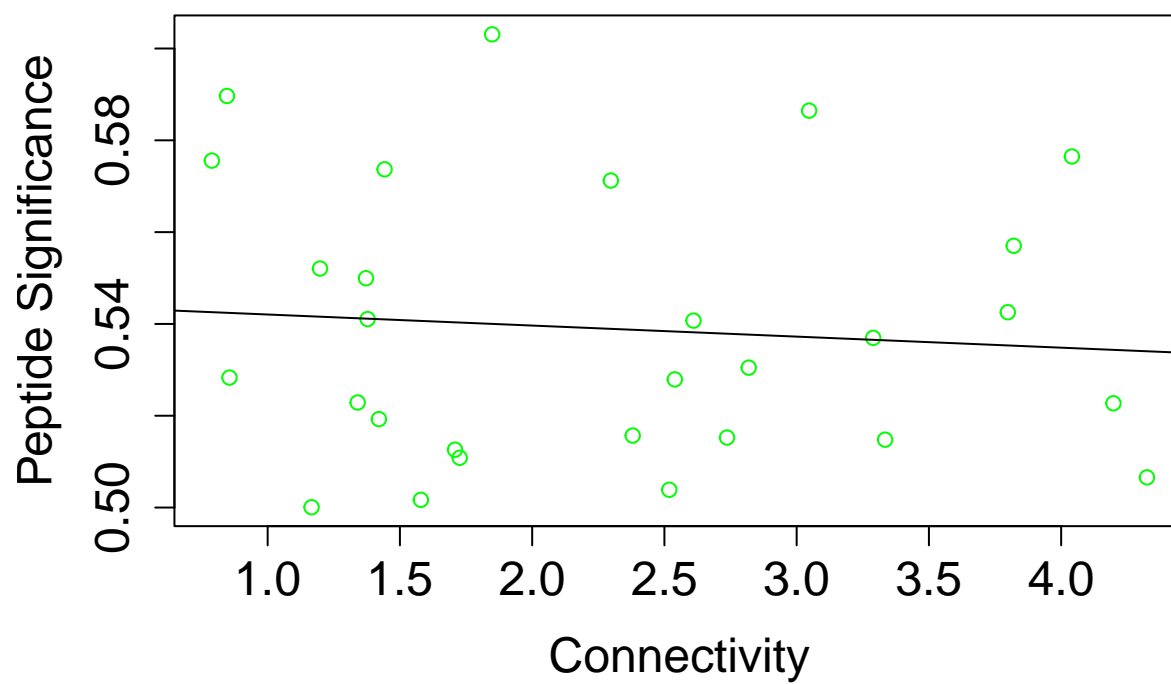


black cor=0.69, p=0.00054





green cor=-0.089, p=0.65



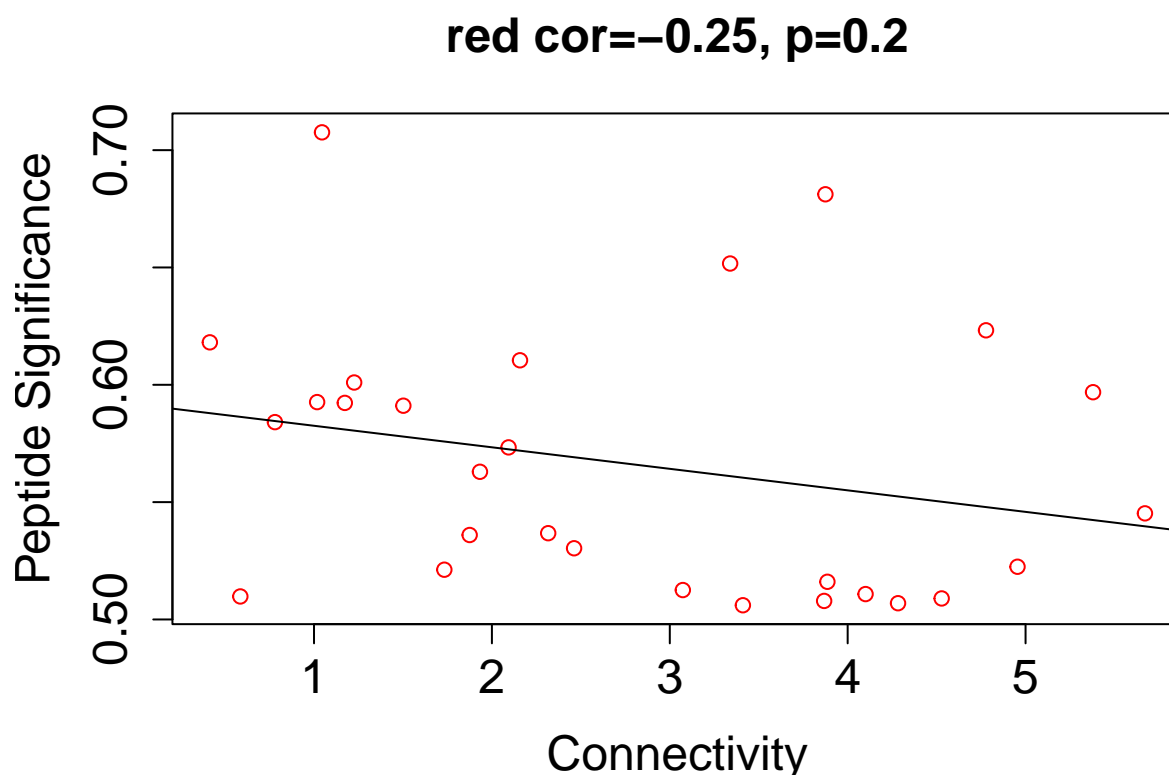


Figure. Peptide significance vs intramodular connectivity

```
# Define a module eigenpeptide-based connectivity measure for each peptide as the
# correlation between a the peptide expression and the module eigenpeptide.
# Specifically, kMEbrown(i) = cor(xi, MEbrown), where xi is the peptide
# expression profile of peptide i and MEbrown is the module eigenpeptide of the
# brown module. Note that the definition does not require that peptide i is a
# member of the brown module. We define a data frame containing the module
# membership (MM) values for each module. In the past, we called the module
# membership values kME.
```

```
datKME=signedKME(df3_expr_transposed, datME, outputColumnName="MM.")
head(datKME)
```

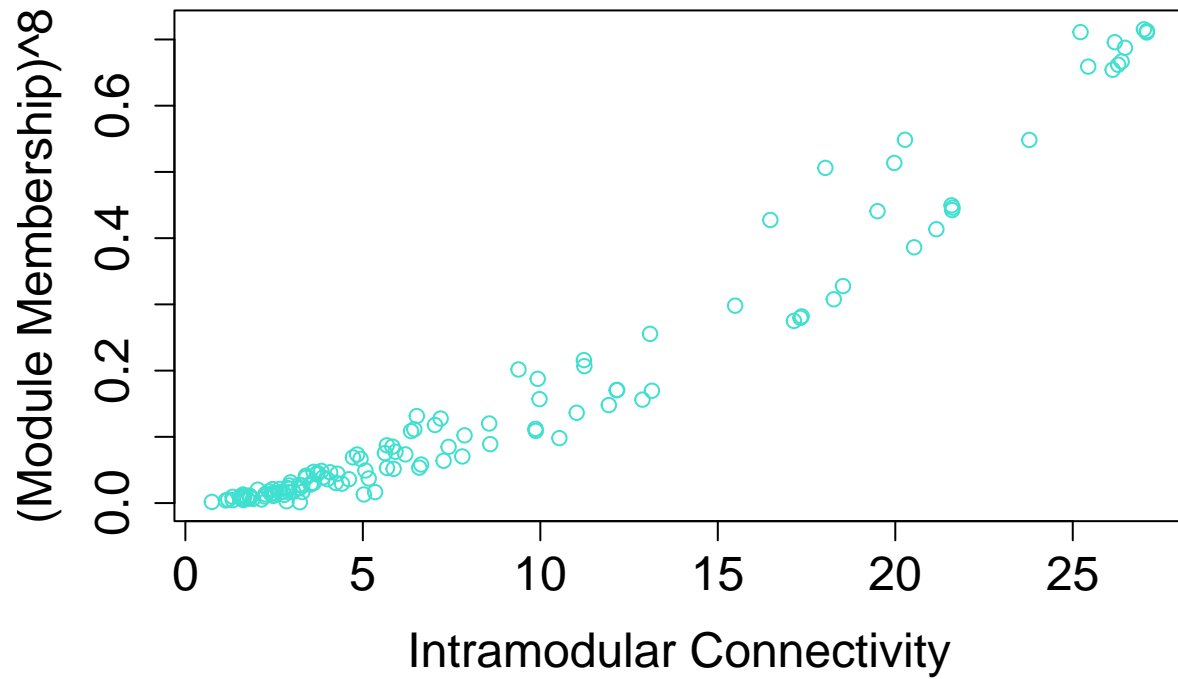
```
##                                     MM.black  MM.blue
## X_RKPGAGGS.Phospho..STY..PALAR_.3  0.2151763 0.7867407
## X_IVHSES.Phospho..STY..QPEKESR_.2  0.2829994 0.6062450
## X_TDPGS.Phospho..STY..IENLC.Carbamidomethyl..C..PGK_.2 0.5995808 0.2356841
## X_TGGEYS.Phospho..STY..LDEEAEGSKK_.2 0.8297820 0.4553535
## X_S.Phospho..STY..MDSLC.Carbamidomethyl..C..SVPVEGK_.2 0.2052835 0.4864796
## X_SNS.Phospho..STY..QENVEASHPSQDGKR_.3 0.2465135 0.7563672
##                                     MM.brown  MM.green
## X_RKPGAGGS.Phospho..STY..PALAR_.3  0.5416833 0.2871711
## X_IVHSES.Phospho..STY..QPEKESR_.2  0.3798168 0.5246010
## X_TDPGS.Phospho..STY..IENLC.Carbamidomethyl..C..PGK_.2 0.1569356 0.2775329
## X_TGGEYS.Phospho..STY..LDEEAEGSKK_.2 0.7307644 0.4792520
## X_S.Phospho..STY..MDSLC.Carbamidomethyl..C..SVPVEGK_.2 0.7296602 0.2922138
## X_SNS.Phospho..STY..QENVEASHPSQDGKR_.3 0.3785909 0.2517185
```

```
##
## X_RKPGAGGS.Phospho..STY..PALAR_.3      MM.grey  MM.pink
## X_IVHSES.Phospho..STY..QPEKESR_.2      0.5738522 0.5283085
## X_TDPGS.Phospho..STY..IENLC.Carbamidomethyl..C..PGK_.2 0.7160377 0.3604438
## X_TGGEYS.Phospho..STY..LDEEAEGSKK_.2 0.5290195 0.1945320
## X_TGGEYS.Phospho..STY..LDEEAEGSKK_.2 0.5858764 0.3272709
## X_S.Phospho..STY..MDSLC.Carbamidomethyl..C..SVPVEGK_.2 0.4818338 0.3001532
## X_SNS.Phospho..STY..QENVEASHPSQDGKR_.3 0.6404675 0.6769100
##
## MM.red MM.turquoise
## X_RKPGAGGS.Phospho..STY..PALAR_.3      0.6800069 0.3882324
## X_IVHSES.Phospho..STY..QPEKESR_.2      0.1919280 0.4315670
## X_TDPGS.Phospho..STY..IENLC.Carbamidomethyl..C..PGK_.2 0.1427152 0.7129611
## X_TGGEYS.Phospho..STY..LDEEAEGSKK_.2 0.3332141 0.9276358
## X_S.Phospho..STY..MDSLC.Carbamidomethyl..C..SVPVEGK_.2 0.4523361 0.3442287
## X_SNS.Phospho..STY..QENVEASHPSQDGKR_.3 0.7186990 0.3616790
##
## MM.yellow
## X_RKPGAGGS.Phospho..STY..PALAR_.3      0.55823609
## X_IVHSES.Phospho..STY..QPEKESR_.2      0.32494908
## X_TDPGS.Phospho..STY..IENLC.Carbamidomethyl..C..PGK_.2 0.08284898
## X_TGGEYS.Phospho..STY..LDEEAEGSKK_.2 0.47654669
## X_S.Phospho..STY..MDSLC.Carbamidomethyl..C..SVPVEGK_.2 0.97617547
## X_SNS.Phospho..STY..QENVEASHPSQDGKR_.3 0.29395250
```

```
# We now have a module membership value for each peptide in each module.
```

```
# Relationship between the module membership measures (e.g. MM.turquoise) and
# intramodular connectivity. We now explore the relationship between the module
# membership measures (e.g. MM.turquoise) and intramodular connectivity.
# We choose 2 modules to plot: turquoise, black
# For simplicity we write the code out explicitly for each module.
which.color="turquoise"
restrictGenes=which.h1==which.color
verboseScatterplot(Alldegrees1$kWithin[ restrictGenes],
  (datKME[restrictGenes, paste("MM.", which.color, sep="")])^8,
  col=which.color,
  xlab="Intramodular Connectivity",
  ylab="(Module Membership)^8")
```

cor=0.97, p=7.2e-80



```
which.color="black"
restrictGenes=colorh1==which.color
verboseScatterplot(Alldegrees1$kWithin[ restrictGenes],
  (datKME[restrictGenes, paste("MM.", which.color, sep="")])^8,
  col=which.color,
  xlab="Intramodular Connectivity",
  ylab="(Module Membership)^8")
```

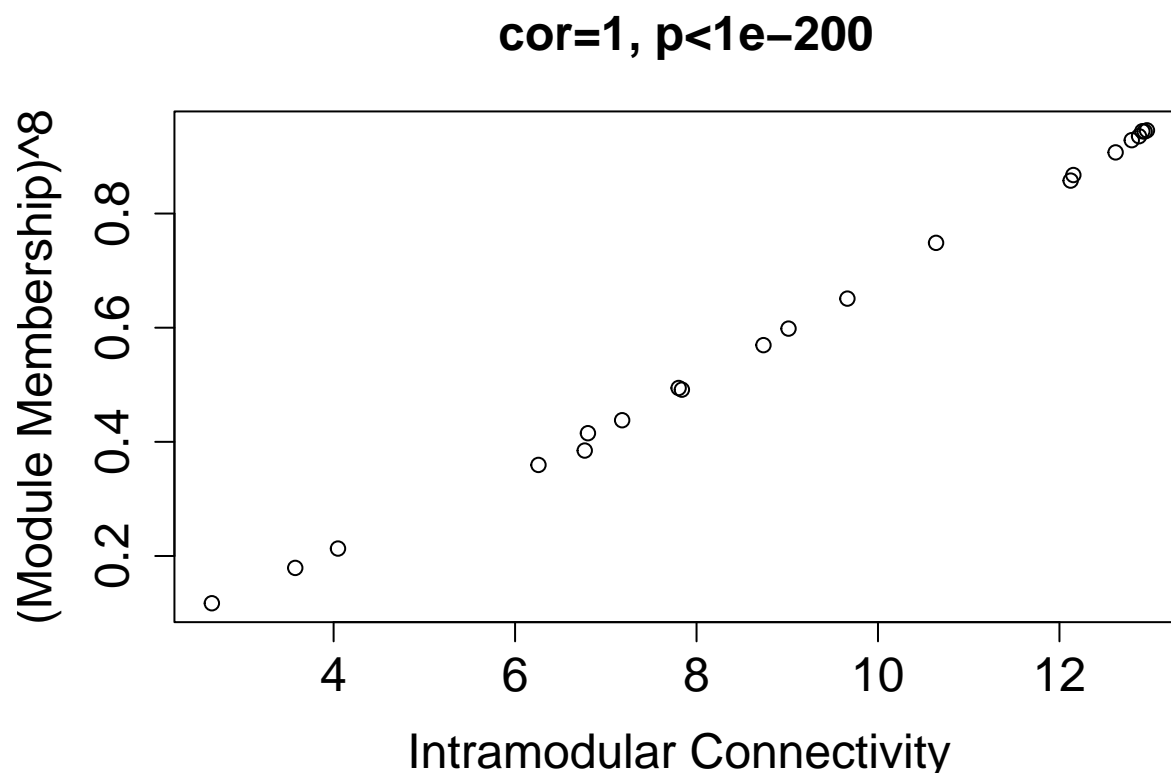


Figure. Intramodular Connectivity vs Module Membership for turquoise and black modules Impression: Module membership raised to Beta-power 8 (y-axis) vs. intramodular connectivity (x-axis) plotted separately for selected modules in the dataset. After raising the module membership to a power of 8, it is highly correlated with the intramodular connectivity (kWithin).

Step 10.

- Multi-dimensional scaling (MDS) plots
- Visualize topological overlap matrix

```
# In this section we visualize peptide co-expression networks. We begin with a multi-dimensional scaling.
cmd1=cmdscale(as.dist(dissTOM),2)
```

```
# We now create a TOM plot, a heatmap plot depicting the topological overlap
# matrix supplemented by hierarchical clustering dendrograms and the module
# colors. For large peptide sets, say more than 2000 peptides, this will take a
# long time. We will remove the "grey" module (un-clustered phosphopeptides) to
# save computation time.
```

```
power=8
color1=colorDynamicTOM
restGenes= (color1 != "grey")
diss1=1-TOMsimilarityFromExpr( df3_expr_transposed[, restGenes], power = 8)
```

```
## TOM calculation: adjacency..
```

```
## ..will not use multithreading.  
## Fraction of slow calculations: 0.000000  
## ..connectivity..  
## ..matrix multiplication (system BLAS)..  
## ..normalization..  
## ..done.
```

```
hier1=hclust(as.dist(diss1), method="average")  
diag(diss1) = NA
```

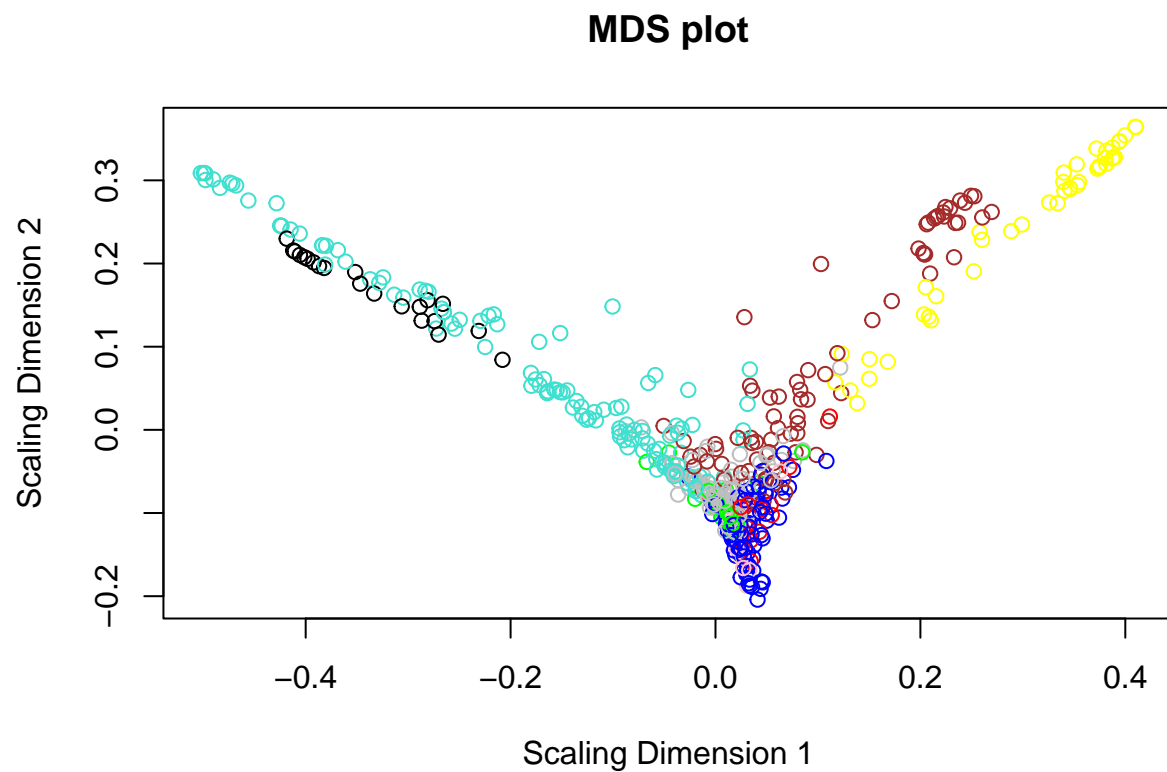


Figure. Multi-dimensional scaling plot

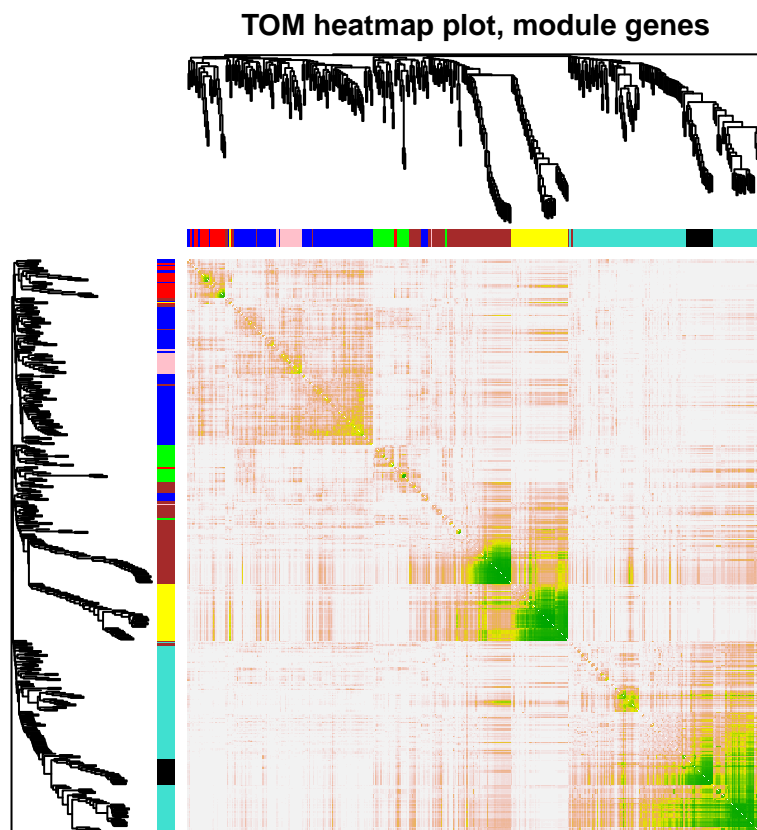


Figure. Topological overlap matrix