

FunGraph-vignette

library(FunGraph)

take a look at genotypic data used in example

View(geno)

		Linkage	Genetic_Distances(cM)	2	4	6	9	11	12	15	17	
nn_np_9292	lg1			0.00	0	1	9	0	0	1	1	0
lm_ll_11315	lg1			1.71	0	1	1	1	0	0	1	1
lm_ll_4392	lg1			2.34	0	1	1	1	0	1	9	1
nn_np_8171	lg1			2.55	0	1	9	0	0	1	9	0
lm_ll_12452	lg1			2.89	1	0	0	0	1	1	0	0
lm_ll_7926	lg1			3.63	0	1	1	1	0	0	1	9

take a look at phenotypic data used in example

View(pheno)

	N1.x	N2.x	N3.x	N4.x	N5.x	N6.x	N7.x	N8.x	N9.x	N10.x
2	2.000000	3.000000	8.000000	12.000000	16.000000	18.000000	18.000000	21.000000	21.000000	23.000000
3	3.666667	4.333333	5.000000	5.666667	6.666667	8.333333	11.000000	13.666667	17.333333	24.333333
2	2.000000	2.666667	2.666667	2.666667	2.666667	3.333333	6.666667	10.66667	17.000000	20.333333
6	0.000000	1.000000	2.500000	5.000000	7.000000	13.000000	16.66667	23.500000	25.500000	26.000000
11	1.000000	1.000000	6.000000	19.000000	38.000000	43.000000	56.000000	74.000000	82.000000	85.000000
12	5.000000	6.000000	5.000000	6.000000	13.000000	18.000000	31.000000	41.000000	42.000000	52.000000

1.biFunMap examples

first plot mean curve to check initial parameters is OK

get_mean_curve_plot(pheno_df = pheno, times = 1:14)



notice wrong given initial parameters results in incorrect mean curve(blue line)

get_mean_curve_plot(pheno_df = pheno, times = 1:14, init_sd_par = c(2,0.1,2,0.1))



calculate LR value for a SNP

#geno[,1:-2] remove redundant information for calculation
get_LR_effect(marker = 1,
 geno_df = geno[,1:-2],
 pheno_df = pheno,
 times = 1:14)
#> \$LR
#> [1] 2.987023
#>
#> \$genetic_effect
#> [1] 0.201284440 0.264772200 0.346411882 0.456347711 0.610781174 0.830782203
#> [7] 1.133018240 1.516061350 1.952992338 2.399895761 2.813927481 3.167246698
#> [13] 3.45041293 3.665821955 0.29562724 0.176137079 0.123056444 0.684406580
#> [19] 0.855016280 0.031268774 0.611947813 0.006439401 0.820641806 0.831812650
#> [25] 0.835465411 0.832963884 0.822421353 0.80431180
#>
#> \$SWD_pars
#> [1] 38.7015809 17.3447288 0.4061965 -2.6845421 10.4652100 31.1062723
#> [7] 8.9873842 0.2296382 3.8482288 0.1321409 0.8847419 13.1424489
#> [13] 1.0636326 6.6143222
#>
#> \$SWL_pars
#> [1] 42.2212696 18.9548114 0.4060741 1.0666182 11.6341456 35.8311259
#> [7] 10.4193945 0.2290326 3.7232069 0.2276818 33.7781211 17.6666255
#> [13] 0.4254191 -7.0663826 8.8127371 36.7754624 10.0386477 0.2210782
#> [19] 3.2022828 0.1627884 0.8758515 18.0793325 1.0659165 6.5823555

calculate all biFunMap result

get_biFunMap_result(geno_df = geno[,1:-2],
 pheno_df = pheno,
 times = 1:14)

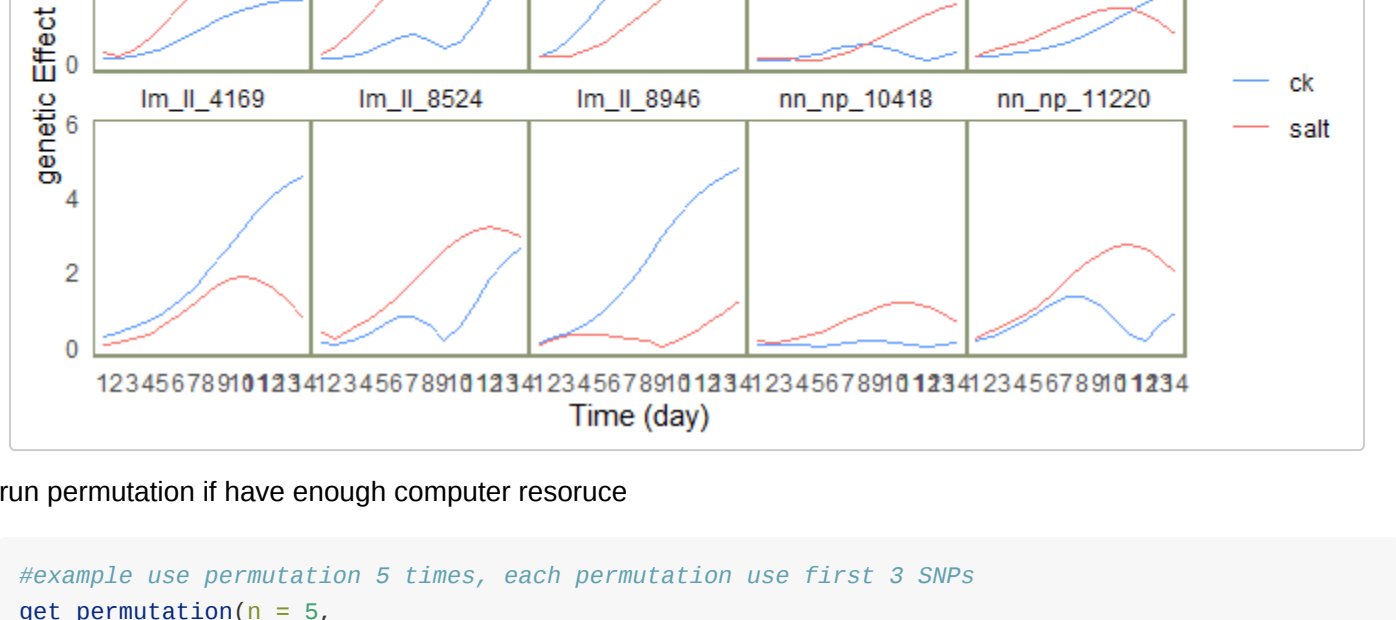
manhattan plot using calculate LR values

get_manh_plot(geno_df = geno, LR = LR)



choose 10 SNPs to show their genetic effect

get_genetic_effect_plot(genetic_effect = genetic_effect, number = 10)
#> Using rownames(df_ck) as id variables
#> Using rownames(df_salt) as id variables



run permutation if have enough computer resource

#example use permutation 5 times, each permutation use first 3 SNPs
get_permutation(n = 5,
 geno_df = geno[,1:3,-1:-2],
 pheno_df = pheno,
 times = 1:14)

see more about how FunMap work on [funmap2](#).

2.biFunClu examples

prepare initial parameters for biFunClu (may need to change init_sd_par manually) in this example only use first 100 rows to cluster, larger data set took more time

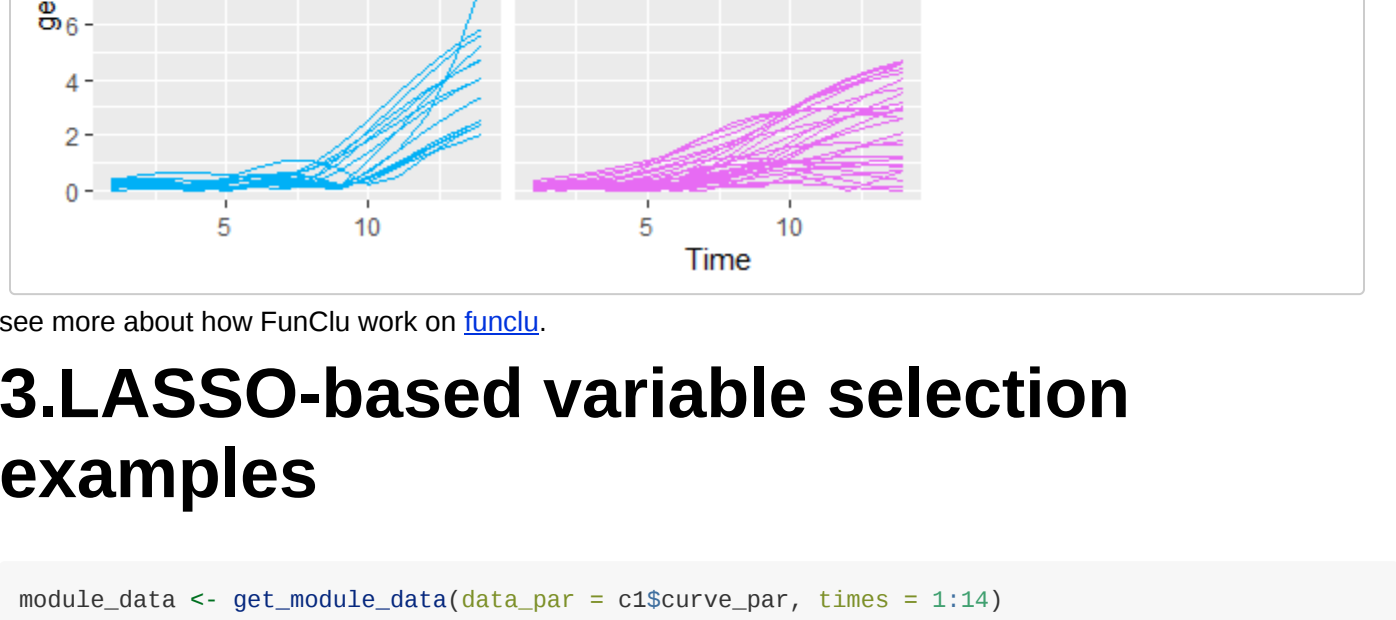
set.seed(2021) #use same initial value

input <- get_init_par(data = genetic_effect[1:100,],
 k = 5,
 legendre_order = 3,
 times = 1:14)
#> Loading required package: polynom

c1 <- get_cluster(input = input, itermax = 10)
#> Start biFunClu Calculation
#> Cluster numbers Legendre_order=3
#> Iter= 1 LL= -1079.353
#> Iter= 2 LL= -1119.84
#> Iter= 3 LL= -1128.265
#> Iter= 4 LL= -1133.143
#> Iter= 5 LL= -1138.125
#> Iter= 6 LL= -1141.217
#> Iter= 7 LL= -1143.213
#> Iter= 8 LL= -1144.979
#> Iter= 9 LL= -1146.217
#> Iter= 10 LL= -1146.848
#> Finish biFunClu Calculationcluster result data written

plot the result

get_cluster_base_plot(c1\$clustered_data[[1]])
#> Warning: Use of 'long_dftime' is discouraged. Use 'time' instead.
#> Warning: Use of 'long_dSeffect' is discouraged. Use 'effect' instead.
#> Warning: Use of 'long_dfMarker' is discouraged. Use 'marker' instead.
#> Warning: Use of 'long_dfCluster' is discouraged. Use 'cluster' instead.



see more about how FunClu work on [funclu](#).

3.LASSO-based variable selection examples

module_data <- get_module_data(data_par = c1\$curve_par, times = 1:14)

#select ck data for variable selection
get_interaction(data = module_data[[1]], col = 1)
#> [[1]]
#> [1] "Module1"
#>
#> [[2]]
#> [1] "Module3"
#>
#> [[3]]
#> [1] 3.785921

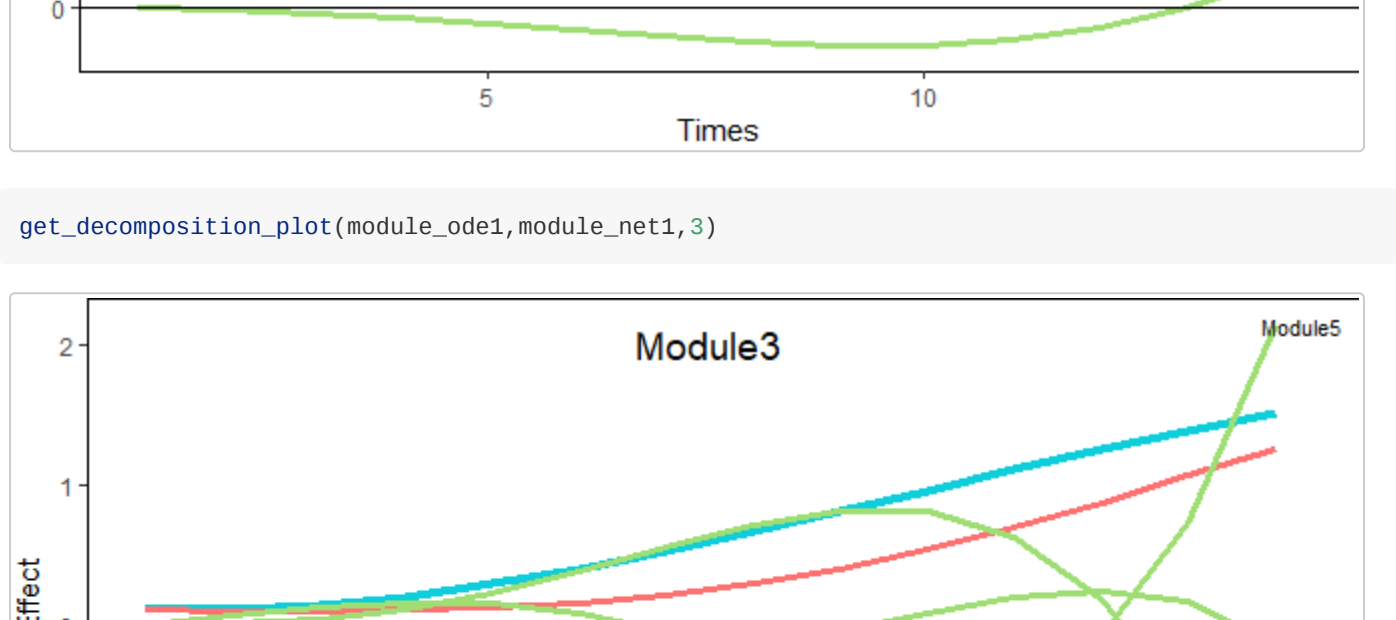
#alternatively, use a cluster data(ck) for variable selection
get_interaction(data = c1\$clustered_data[[1]][,ncol(c1\$clustered_data[[1]])],
 col = 1,
 reduction = TRUE)
#> [[1]]
#> [1] "nn_np_9292"
#> [[2]]
#> [1] "lm_ll_2416"
#>
#> [[3]]
#> [1] 2.981482

4.ODE solving examples

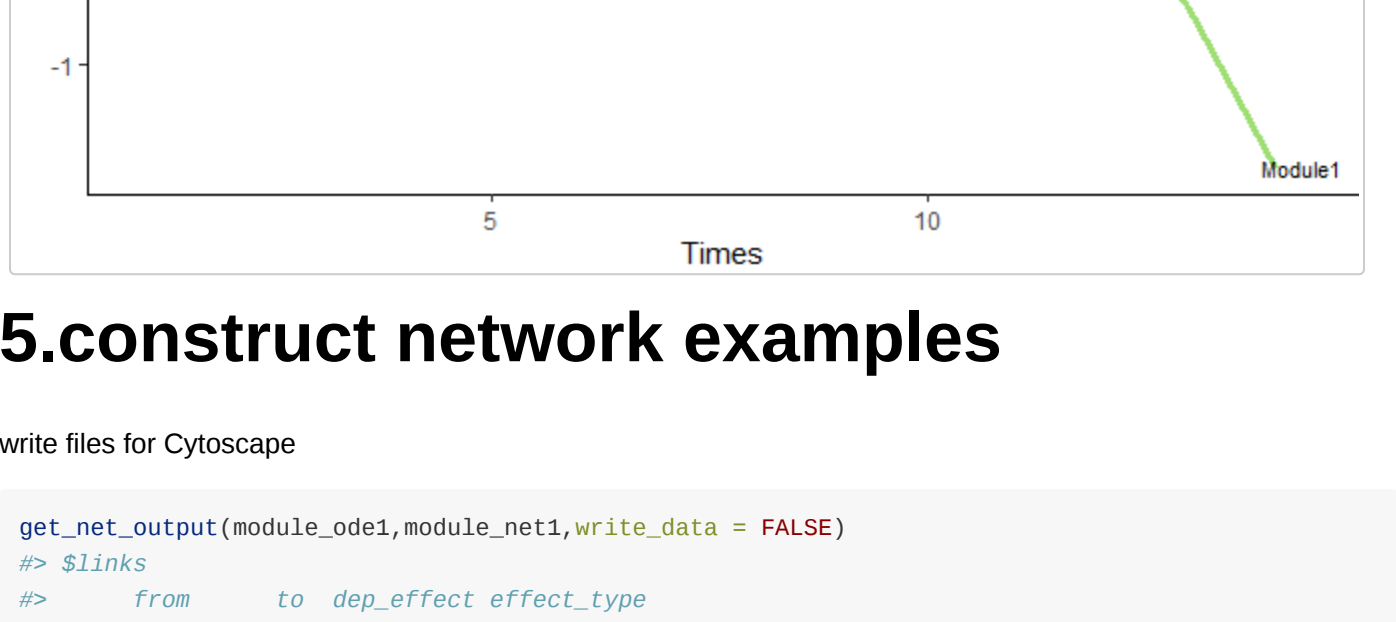
module_data <- get_module_data(data_par = c1\$curve_par, times = 1:14)
#for module just input module data
module_ode1 <- get_ode_par(data = module_data[[1]],
 times = 1:14,
 order = 3,
 reduction = FALSE,
 parallel = FALSE)
#> Start variable selection
#> Finish variable selection
#> Start ODE solving
#> Initial value 231.282946
#> Iter 10 value 0.884505
#> Iter 20 value 0.884431
#> Iter 30 value 0.884232
#> Iter 40 value 0.884145
#> Iter 50 value 0.884096
#> Iter 60 value 0.884079
#> Iter 70 value 0.884072
#> Iter 80 value 0.884063
#> Final value 0.884062
#> converged
#> Initial value 3.134045
#> Iter 10 value 0.880805
#> Iter 20 value 0.880684
#> Iter 30 value 0.880683
#> Iter 40 value 0.880683
#> Iter 50 value 0.880683
#> Iter 60 value 0.880683
#> Iter 70 value 0.880683
#> Iter 80 value 0.880683
#> Final value 0.880683
#> converged
#> Initial value 0.391978
#> Iter 10 value 0.008187
#> Iter 20 value 0.008119
#> Iter 30 value 0.008118
#> Iter 40 value 0.008117
#> Iter 50 value 0.008117
#> Iter 60 value 0.008117
#> Iter 70 value 0.008117
#> Iter 80 value 0.008117
#> Final value 0.008117
#> converged
#> Initial value 3.782728
#> Iter 10 value 0.880805
#> Iter 20 value 0.880684
#> Iter 30 value 0.880683
#> Iter 40 value 0.880683
#> Iter 50 value 0.880683
#> Iter 60 value 0.880683
#> Iter 70 value 0.880683
#> Iter 80 value 0.880683
#> Final value 0.880683
#> converged
#> Finish ODE solving
#the result should be further processed
module_net1 <- get_all_net(module_ode1)

take a look at whats going on with 1st and 3rd module(=1, =3) of CK data

get_decomposition_plot(module_ode1,module_net1,1)



get_decomposition_plot(module_ode1,module_net1,3)



5.construct network examples

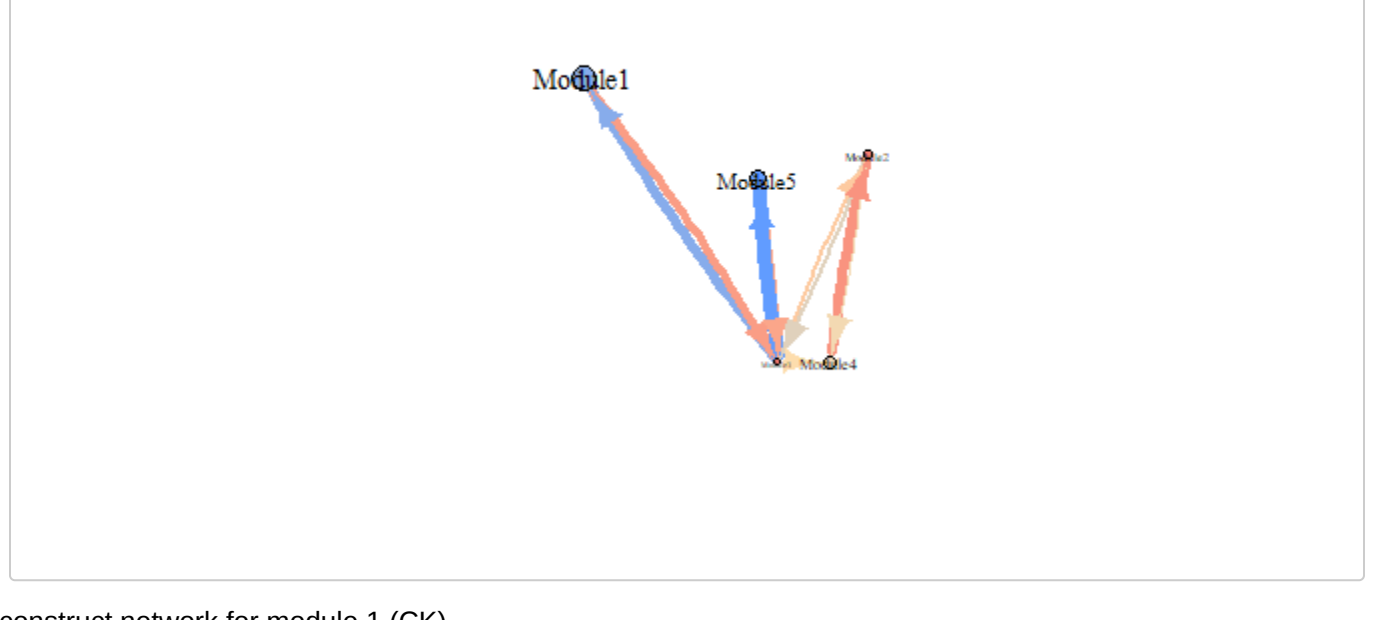
write files for Cytoscape

get_net_output(module_ode1,module_net1,write_data = FALSE)
#> \$links
#> from to dep_effect effect_type
#> 1 Module3 Module1 0.193903577 +
#> 2 Module3 Module2 0.047658701 +
#> 3 Module4 Module2 0.181438366 +
#> 4 Module1 Module3 0.157234797 +
#> 5 Module5 Module3 0.046536828 -
#> 6 Module5 Module2 0.135060370 -
#> 7 Module2 Module4 0.017624990 -
#> 8 Module3 Module4 0.095945851 -
#> 9 Module3 Module5 0.256124592 -
#>
#> \$nodes
#> id name received_effect influence
#> 1 Module1 Module1 3.1164808 -0.19390358
#> 2 Module2 Module2 0.9334943 -0.22807787
#> 3 Module3 Module3 0.4328814 -0.24570754
#> 4 Module4 Module4 1.4578692 -0.82287864
#> 5 Module5 Module5 2.1528598 -0.25612459

see more on how to use [Cytoscape](#).

or use igraph package for [cytoscape](#)

#acquire max_effect to control color
max_effect <- cbind(get_max_effect(module_net1),get_max_effect(module_net1))
network_plot(k = module_net1,
 title = 'CK',
 max_effect = max_effect,
 save_plot = FALSE)



construct network for module 1 (CK)

m1_ck <- get_subset_data(data = c1\$clustered_data[[1]], cluster = 1)
m1_ck_ode <- get_ode_par(data = m1_ck, times = 1:14, order = 3, reduction = TRUE, parallel = FALSE)
#> Start variable selection
#> Finish variable selection
#> Start ODE solving
#> Initial value 38.570698
#> Iter 10 value 0.083212
#> Iter 20 value 0.081157
#> Iter 30 value 0.080925
#> Iter 40 value 0.081156
#> Iter 50 value 0.081156
#> Iter 60 value 0.081156
#> Iter 70 value 0.081156
#> Iter 80 value 0.081156
#> Final value 0.081156
#> converged
#> Initial value 643.124332
#> Iter 10 value 0.009925
#> Iter 20 value 0.009601
#> Iter 30 value 0.009649
#> Iter 40 value 0.009646
#> Iter 50 value 0.009646
#> Iter 60 value 0.009646
#> Iter 70 value 0.009646
#> Iter 80 value 0.009646
#> Final value 0.009646
#> converged
#> Initial value 25.839055
#> Iter 10 value 0.001087
#> Iter 20 value 0.000994
#> Iter 30 value 0.000994
#> Iter 40 value 0.000994
#> Iter 50 value 0.000994
#> Iter 60 value 0.000994
#> Iter 70 value 0.000994
#> Iter 80 value 0.000994
#> Final value 0.000994
#> converged
#> Initial value 105.024243
#> Iter 10 value 0.082151
#> Iter 20 value 0.080863
#> Iter 30 value 0.080862
#> Iter 40 value 0.080862
#> Iter 50 value 0.080862
#> Iter 60 value 0.080862
#> Iter 70 value 0.080862
#> Iter 80 value 0.080862
#> Final value 0.080862
#> converged
#> Initial value 297.599609
#> Iter 10 value 0.006147
#> Iter 20 value 0.006081
#> Iter 30 value 0.006081
#> Iter 40 value 0.006079
#> Iter 50 value 0.006079
#> Iter 60 value 0.006079
#> Iter 70 value 0.006079
#> Iter 80 value 0.006079
#> Final value 0.006079
#> converged
#> Initial value 15.484284
#> Iter 10 value 0.080233
#> Iter 20 value 0.080137
#> Iter 30 value 0.080129
#> Iter 40 value 0.080129
#> Iter 50 value 0.080129
#> Iter 60 value 0.080129
#> Iter 70 value 0.080129
#> Iter 80 value 0.080129
#> Final value 0.080129
#> converged
#> Initial value 5.519125
#> Iter 10 value 0.002997
#> Iter 20 value 0.002789
#> Iter 30 value 0.002789
#> Iter 40 value 0.002789
#> Iter 50 value 0.002789
#> Iter 60 value 0.002789
#> Iter 70 value 0.002789
#> Iter 80 value 0.002789
#> Final value 0.002789
#> converged
#> Finish ODE solving
m1_ck_net <- get_all_net(m1_ck_ode)

max_effect <- cbind(get_max_effect(m1_ck_net),get_max_effect(m1_ck_net))
network_plot(k = m1_ck_net, title = 'Module1_CK', max_effect = max_effect, save_plot = FALSE)

