

AFRICAN CENTERS OF EXCELLENCE IN BIOINFORMATICS

KAMPALA, UGANDA

Gene Regulatory Networks 2



Yunhua Zhu,
Ph.D in stem cell biology

Computational Genomics
Specialist – Transcriptomics

Bachelor in biochemistry @NUS
Ph.D in stem cell biology @NUS
Postdoc in neurodegeneration, single cell
biology @JHU
Bioinformatician @ NIH

Recent projects

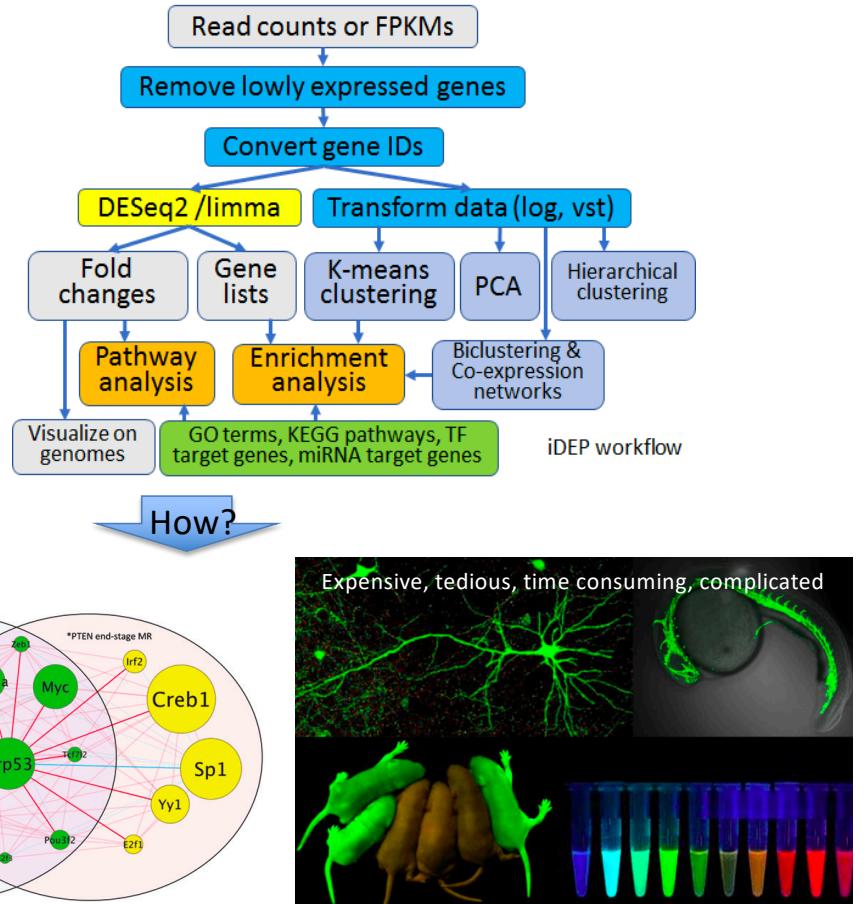
- Single cell analysis of cancer stem cells
- Single cell analysis of immune response in lung cancer
- Bulk RNA-seq on irradiation, HIV blood samples
- PLEASE JOIN THE DISCUSSION

Today's Instructor

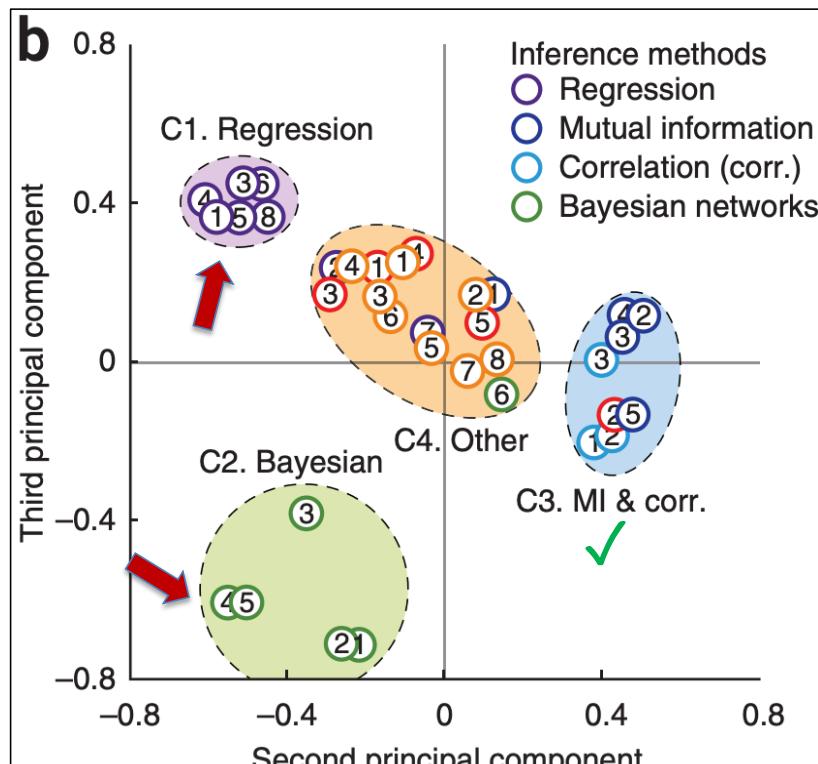
- Bioinformatics and Computational Biosciences Branch (BCBB), NIAID
- National Institutes of Health, Bethesda, MD USA.
- Contact our team via email:
 - Github: git clone https://github.com/niaid/Gene_Regulatory_Networks
 - Googledoc, <https://tinyurl.com/zhu-GRN>
 - Instructors: zhuy16@nih.gov
 - Server: ssh username@137.63.194.9:
 - **cp /home/bcbb_teaching_files/zhu/cisTarget_databases session_2/**
- Email: bioinformatics@niaid.nih.gov
- Linkedin: <https://tinyurl.com/zhu-linkedin>

Why study gene regulatory networks

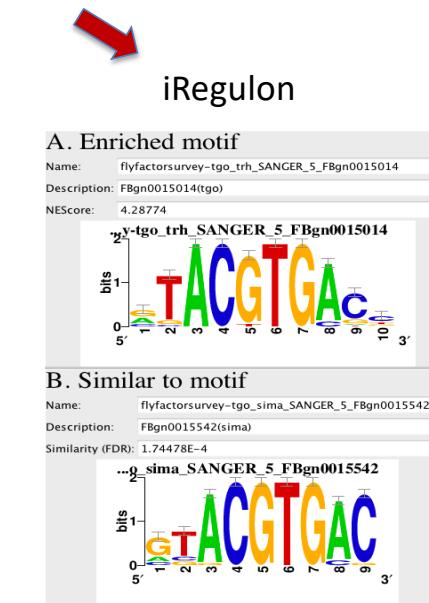
- Why
 - High throughput are just screening procedures
 - Gene lists do not inform relationship between genes
 - Regulatory information is hidden in the statistical relationships
 - Down-stream validation is costly, tediously and risky
- Aims
 - To find regulatory network, to inform finding of key candidate genes/master regulators for validation
- Challenges
 - Data are massive, and mostly static that do not reflect dynamic regulation
 - Relationships can take various forms, linear or non-linear



GENIE3-- GEne Network Inference with Ensemble of trees



Based on statistical relationship
between genes



Database based, prediction of
upstream transcriptional regulators

Overview of Tools in GRN inference

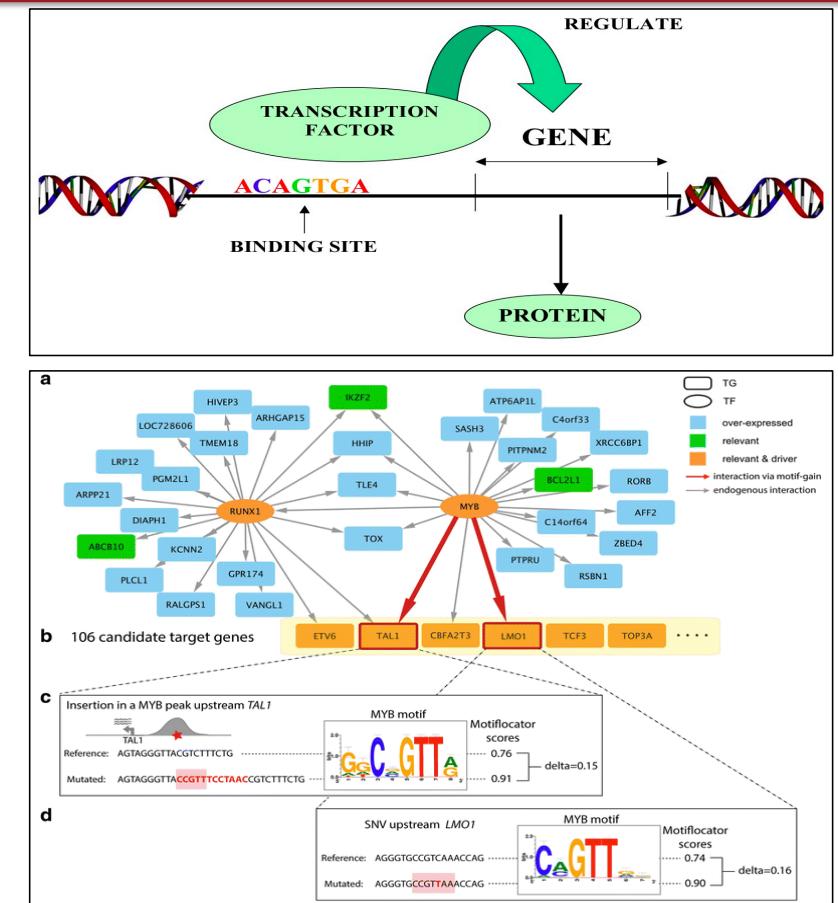
Software	ARACNE	NetworkInference/ PIDC	bnlearn	GENIE3	iRegulon	SCENIC
semantics	Mutual information	Partial Information Decomposition	Bayes theory	Random Forest, Regression tree	Promoter and TF binding sequence, database	Combination of regression and promoter sequence
years published	2006	2017	2009	2010	2014	2017
No. of cited	2179	82	894	658	337	265
FullName/explanation	Algorithm for the Reconstruction of Accurate Cellular Networks	Using proportional unique contribution (PUC) to a target gene	Bayes net structure and parameter learning, causality	GEne Network Inference with Ensemble of trees	reverse-engineer the transcriptional regulatory network with regulatory sequence analysis	single-cell regulatory network inference and clustering
Implementation	GUI (geWorkbench)	Julia	R	R	GUI (Cytoscape)	R, Python
type of experiment	Microarray, bulk RNA-seq	Single cell data	General	single cell data	a list of gene names	single cell data
input format	.exp and csv(ref)	csv, matrix	csv, matrix	csv	a list	csv/loom file
output	xgmml	network file	directed network file	network file	network file/binding sequences	network file/heatmap

Today

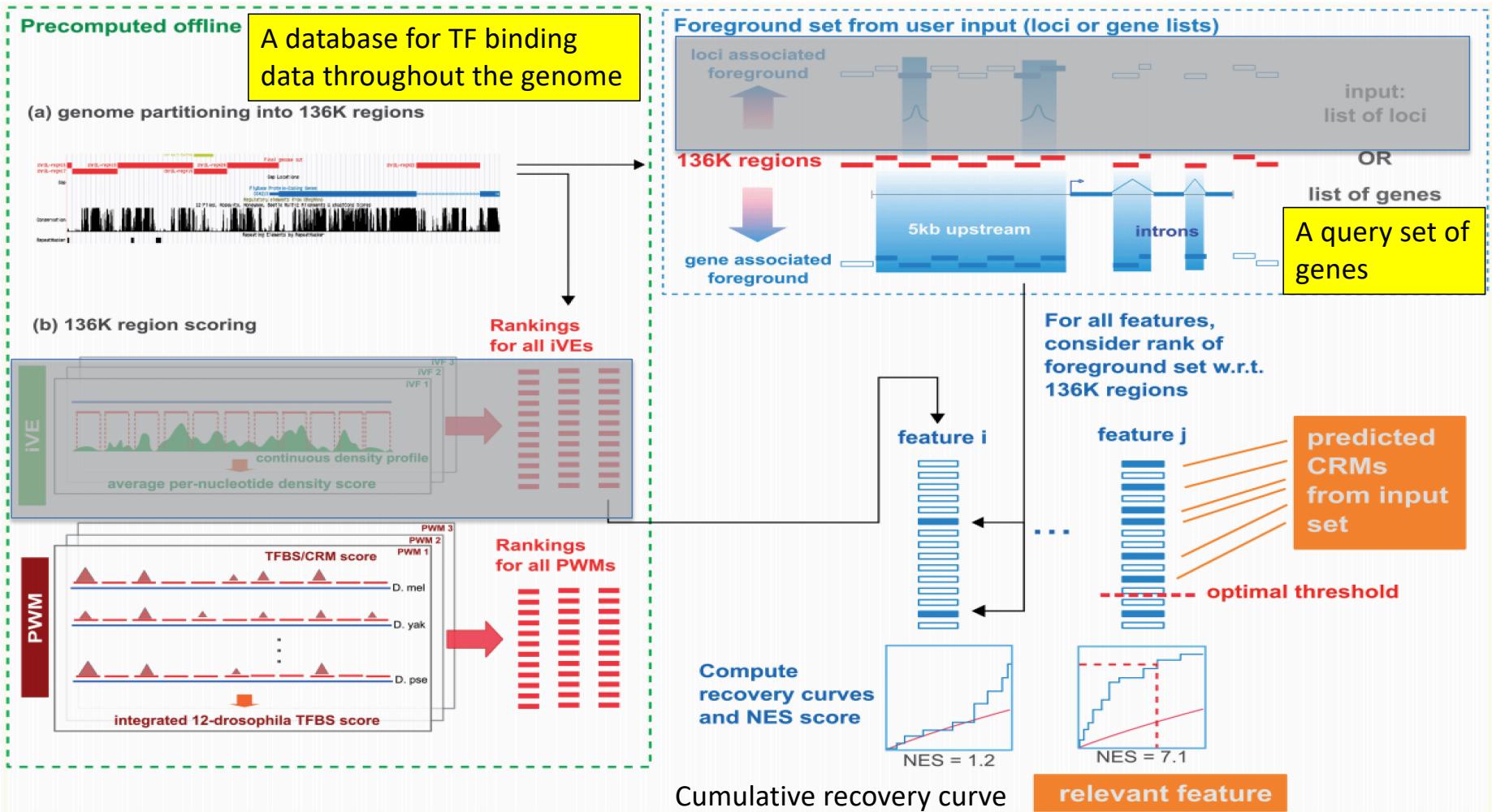
Next week

Introduction to iRegulon

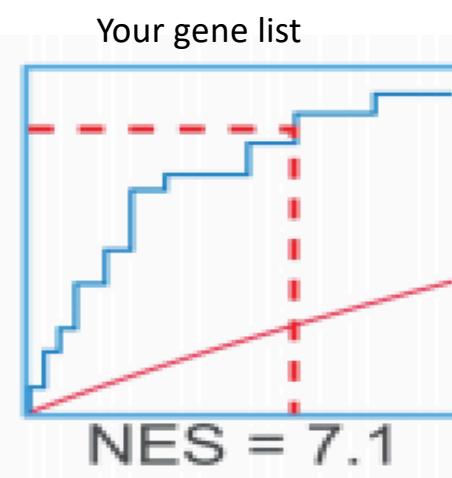
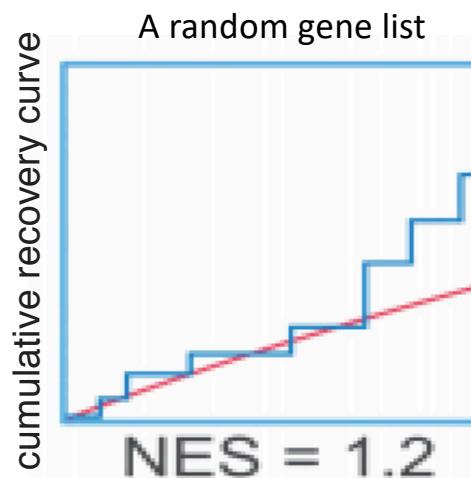
- Transcriptional activity correlates with TF binding on promoter of target genes.
- One transcriptional factor activate a group of genes to achieve a specific function.
- TF expression increases its activity.
- Transcriptional factor has conserved binding sequence/motif.
- Many of the binding sequences have been validated.



How iRegulon Work?



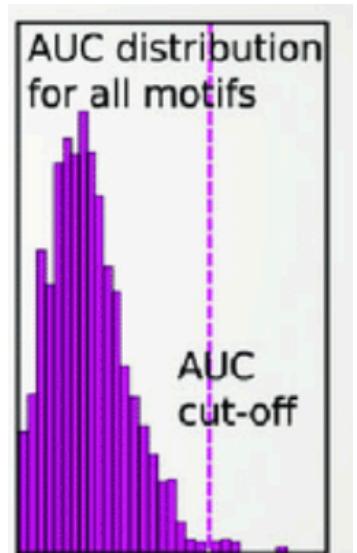
Normalized Enrichment Scores



Ranking of likelihood of all PWMs in all 137k loci, as a target for a TFBS.
(The ranking is based on a combination of motif clustering and comparative genomics.)

For all TBBS/CRMs, area under the curve (AUC) were calculated for top 1% of the rank. NES were calculated.

$$\text{NES} = \frac{AUC - AUC_{mean}}{AUC_{std}}$$



The TFBS/Motif information

Table 1. Description of the motif and track collections used.

Source	Organism(s)	Type of motif	# motifs "6K"	# motifs "10K"	# tracks "1K ChIP"
Elemento [73]	Drosophila	Predicted (conserved) ^a	371	371	-
FlyFactorSurvey [75]	Drosophila	B-1H, others (e.g., FlyReg)	614	652	-
hPDI [77]	Human	Experimental	437	437	-
Jaspar [21]	Multiple species	Curated	1315	1315	-
SelexConsensus [76]	Drosophila	Curated (FlyReg)	38	38	-
Stark [74]	Drosophila	Predicted (conserved) ^a	228	228	-
Tiffin [76]	Drosophila	Predicted (gene sets) ^a	120	120	-
TRANSFAC PUBLIC [5]	Multiple species	Curated, ChIP-chip	398	398	-
TRANSFAC PRO [5]	Multiple species	Curated, ChIP-chip	1153	1850	-
YetFasco [78]	Yeast	Uniprobe, Curated, ChIP-chip	1709	1709	-
ENCODE [79]	Human	Predicted (from DHS) ^a	-	683	-
Factorbook [46]	Human	ENCODE ChIP-Seq motifs	-	79	-
Taipale [132]	Human, Mouse	HT-Selex	-	820	-
iDMMPMM [133]	Human	footprints, Selex, b1h, peaks	-	39	-
SwissRegulon [134]	Human	Curated	-	190	-
Wolfe [135]	Drosophila	ZFP motifs	-	36	-
HOMER [116]	Multiple species	ChIP-Seq Motifs, others (e.g. ENCODE)	-	1865	-
Dimers [136]	Human	Predicted dimers	-	603	-
ENCODE ChIP-Seq [23]	Human	-	-	-	999
Taipale ChIP-Seq [24]	Human	-	-	-	117
p53 and control ChIP-Seq (this study)	Human	-	-	-	2
Total			6383	11611 (9713 nr)	1118

^aOrphan motifs (unknown TFs).

nr = non-redundant.

doi:10.1371/journal.pcbi.1003731.t001



Demo on iRegulon

- How to import the gene list to Cytoscape
- Set parameters for iRegulon to run
- Interpret the output and how to save a Cytoscape network.



Pro and cons

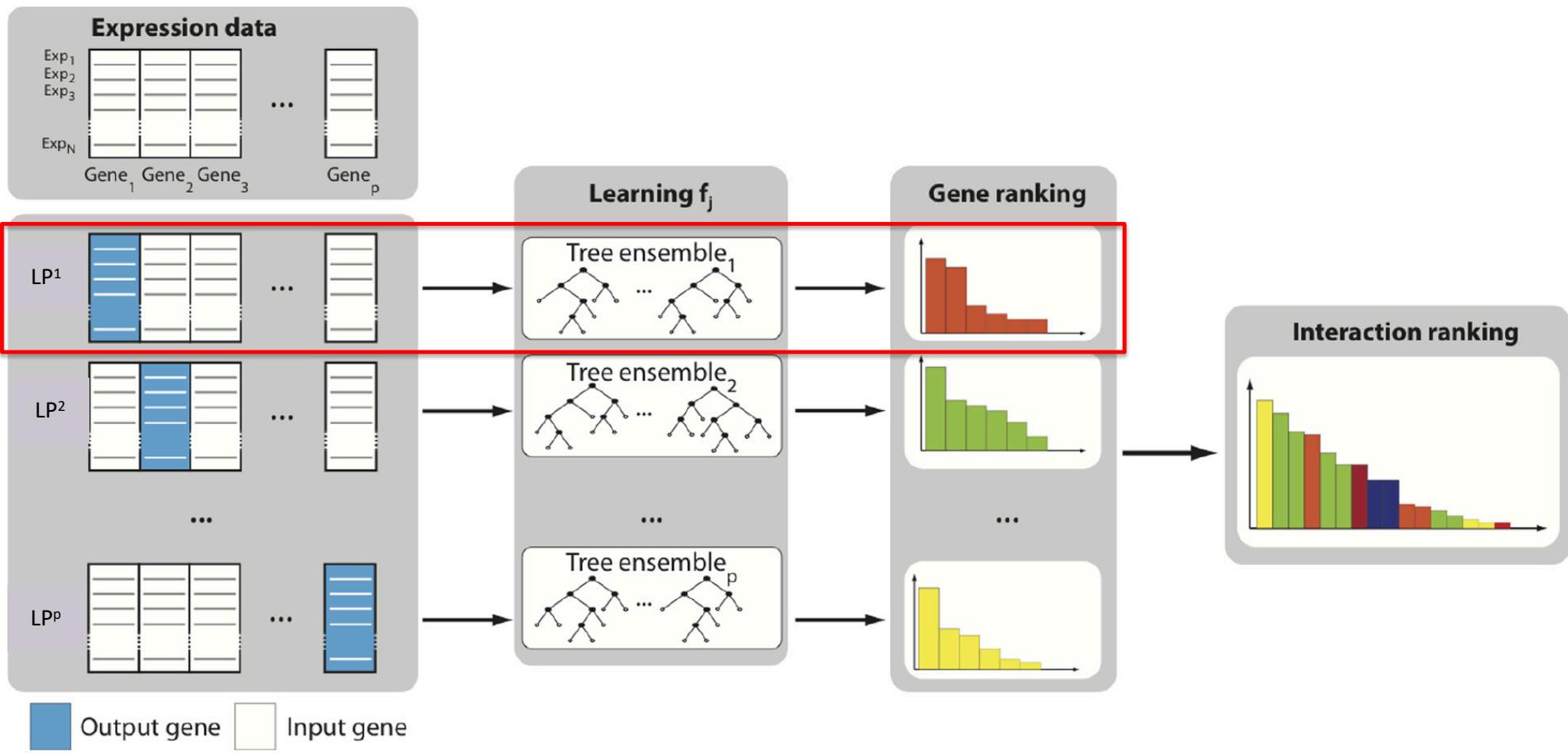
- Pros
 - Directly generate hypothesis
 - Based on prominent feature in your transcriptional data
 - More trustable than single gene
 - Allow generation of a richer hypothesis
 - Binding sequence ---mutagenesis to test the TF binding.
 - Using real-time PCR to test the set of gene regulation by the TF
 - Well informed on the biology
- Cons
 - The binding data is only by sequence enrichment, not guaranteed
 - Binding is dependent not only on sequence but also on DNA/histone modifications.
 - multiple TFs can bind to the same conserved sequence.



GENIE3-- GEne Network Inference with Ensemble of trees

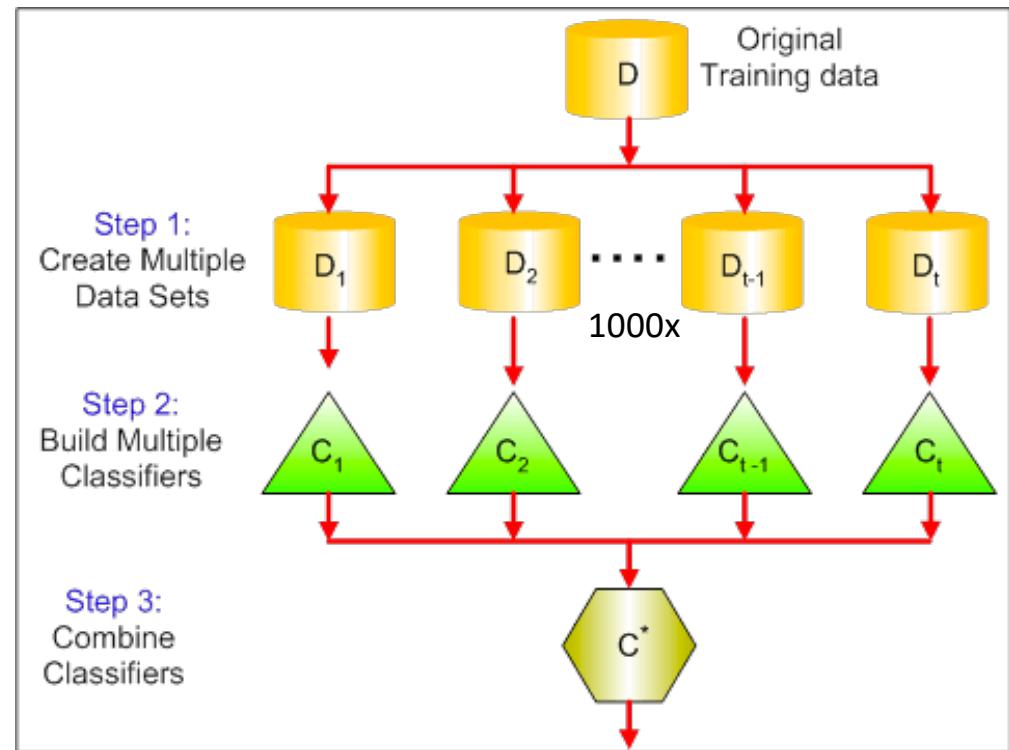
- Using bootstrapping/bagging to generate learning samples.
- Within each learning sample (LS), construct regression trees for each gene as a target.
- For each genes, average the ensemble of trees to have a combined rank of regulators of that gene.
- Combine all the interactions together. To have a rank of all gene—gene interaction throughout all genes in the list.

Bootstrapping/ ensemble of trees



Building many small trees by bootstrapping/Bagging

- Question: what are regressor/classifiers of a target gene j
- From training data D, Derive multiple data sets/Learning sample (LS)
- From each data sets, build a regression trees. To determine the importance of each other gene in determining gene j
- Combine all the classifiers to have a final one.

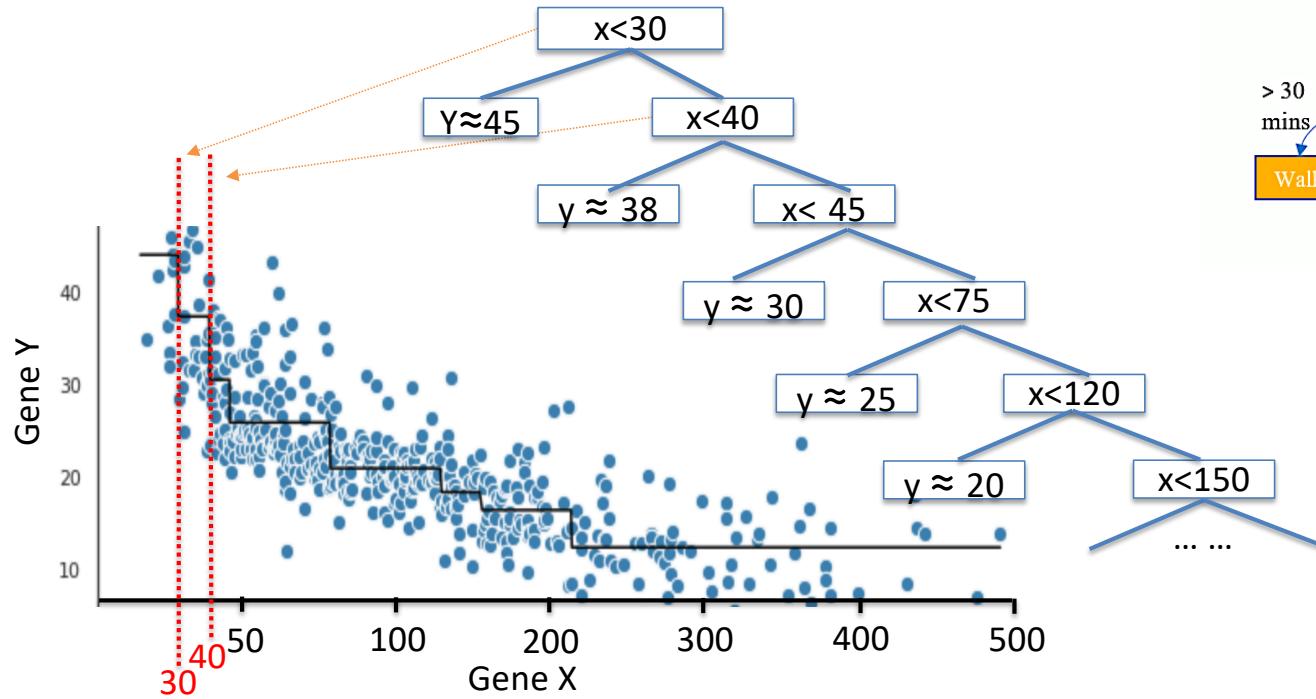


Bootstrapping/Bagging other genes

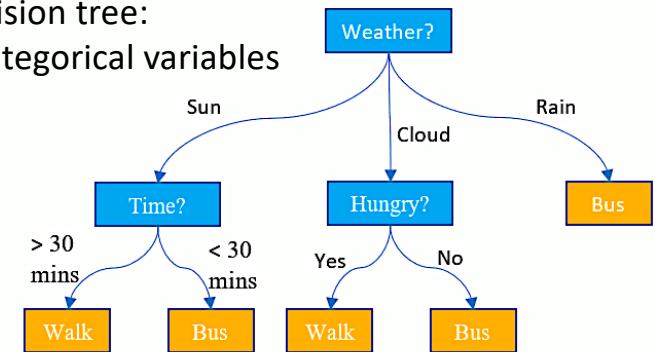
	Cst3	Ubb	Dbi	Malat1	Custom	Ppia	Fabp7	Aldoc	Rpl41	Actb	Tmsb4x	Col1a1	Wif1	Hmga2	Eef1a1	Anoe	Slc1a3	Tspan7	Gstm1	Rn45s	Tuba1a	Cox7c	Fth1	
C1	28972.58	2837.97	12868.7	6472.14	33810.79	11533.01	15985.54	6012.69	15835.42	2564.16	812.17	15324.53	5591.03	2196.97	3271.17	2154.78	3454.3	1304.16	2458.26	6484.96	5812.14	124.6	9864.46	861
C2	20355.72	6552.88	16688.47	3155.32	26170.54	9928.4	3058.52	4836.24	3215.21	2333.16	24.59	4523.57	18692.86	6497.76	3454.11	3064.79	3759.06	3422.24	5195.19	4184.75	2842.53	29.05	4654.4	2260
C3	19571.34	5010.84	9920.7	5195.99	25021.09	7369.39	13253.52	118.62	79.13	3131.61	38.12	11239.78	8476.72	9211.29	3274.66	3586.28	4818.08	621.52	3606.3	10173.67	5722.82	1862.53	0	1132
C4	22518.94	10976.37	9269.34	10577.01	24678.19	8392.77	2289.83	6145.14	2117.77	4600.66	1258.42	5053.78	12701.38	6489.99	1794.51	3676.78	11929.93	4394.81	2673.44	5003.65	3614.04	3366.39	3227.89	1791
C5	32946.08	18300.93	11012.57	7813.54	24664.25	9134.71	19037.38	15417.84	246.34	1785.77	1463.79	159.96	10998.27	2664.36	3211.03	3716.36	13208.09	5773.75	8841.08	6484.05	2821.56	992.69	633.44	2135
C6	45035.81	7503.7	15465.83	15742.18	24641.42	5876.89	2081.12	6127.73	3281.25	2311.31	11.09	7771.38	7110.98	5882.38	1202.19	1210.86	3441.37	8171.91	4565.17	3840.97	5687.78	128.69	0	155
C7	27325.95	17524.64	5079.66	1553.14	23388.84	9246.24	2494.55	7229.04	83.76	2555.33	26.9	0	11273.35	10688.7	17.29	5043.56	7190.25	4884.42	5645.77	6752.9	2046.3	1443.9	1549.61	1457
C8	28598.32	13294.21	15629.39	6255.72	23214.06	6377.92	9589.91	9727.12	7402.6	2194.46	419.92	3164.16	7883.68	6022.92	195.16	3218.22	5746.22	5754.6	7054.2	11326.48	2256.41	2280.83	1799.71	120
C9	11924.57	11957.49	4054.95	9665.19	22324.25	6628.45	15734.99	18610.21	81.03	1403.86	182.19	0	9571.93	1396.93	1033.34	1679.16	6459.22	9157.3	8784.53	4288	3014.09	2068.73	0	1e
C10	28773.24	7807.45	14077.06	18425.99	21404.47	4076.15	6706.01	20192.97	5111.03	1892.57	32.19	227.76	4856.78	4024.37	119.52	3164.64	6286.29	3667.08	13287.7	5719.8	4003.37	45.81	0	4140
C11	59296.6	11949.45	9850.14	10269.25	2022.98	4154.15	9846.89	10098.65	0	4282.25	1773.52	0	1944.25	1539.12	861.68	1181.9	2902.33	7176.5	2878.95	10153.42	847.52	1053.03	254.71	5767
C12	27066.48	16386.59	3933.27	6433	20005.32	13004.58	2766.45	3625.74	56.63	3310.38	618.79	0	4487.53	402.55	2205.37	5331.03	7636	8843.22	5563.64	4529.56	20.6.17	4312.5	169.88	3362
C13	5881.6	17473.04	21105.9	760.5	19240.64	14206.8	28989.2	6207.65	121.27	3797.25	29.71	0	4652.62	22621.97	821.94	5796.2	4897.41	5067.96	7508.47	12310.76	5385.59	2877.31	3880.52	116
C14	5885.47	26852.53	14423.57	896.2	19126.04	9406.04	14444.33	4939.8	432.48	3738.73	1757.23	0	6909.67	3075.26	5462.22	107.31	85.62	4861.73	13.34	1463.49	1944.83	4283.63	129.74	1761
C15	7057.19	20252.39	5966.61	3767.4	19081.58	10698.72	1528.02	7303.56	101.25	3895.1	2968.08	0	6234.44	928.49	8996.8	8059.14	3598.73	1623.47	3902.69	655.61	230.83	3472.68	0	3904
C16	63420.2	4939.71	11587.48	4647.81	18064.62	5407.58	453.2	13627.09	163.91	2154.97	1079.26	0	5863.84	2039.13	1679.57	20	8147.01	6295.86	8238.75	2861.48	2235.23	1570.56	229.47	4506
C17	37523.68	8154.25	14200.53	17441.93	17870.31	10431.63	23545.8	4755.24	0	3630.82	3726.88	0	4578.13	2784.5	1974.59	280.02	4905.36	2960.4	3751.65	702.2	6523.99	6095.61	712.16	41
C18	14011.98	19156.08	20259.12	897.12	16158.44	6337.53	26127.42	10284.31	5606.15	2382.28	10.72	0	2462.27	13237.35	2768.26	6047.12	4150.64	3041.51	3031.86	5925.61	2324.71	1754.76	4872.04	2529
C19	3615.53	17359.78	9660.94	11935.03	16108.91	11435.47	1527.87	18275.44	10522.98	3056.47	23.47	0	8784.84	5137.45	4205.51	34.93	2313	2907.4	5622.8	3812.92	1457.8	2883.32	1644.22	2726
C20	22492.38	6511.3	12661.18	6849.22	16079.16	4714.21	2352.97	3133.54	2299.98	2098.69	3206.18	5645.4	2114.37	7913.66	346.05	7296.65	2681.19	4031.66	6249.99	47.7.12	5771.25	859.92	4139.96	2667
C21	16016.61	26377.88	5224.08	7534.88	15632.02	11502.82	14505.76	14648.69	112.22	5178.27	1396.75	255.05	9384.81	179.5	1506.64	375.7	4166.95	6570.09	513.01	549.31	3528.25	10922.26	617.21	366
C22	9903.64	11213.86	14894.99	15219	9156.72	7092.46	8311.5	0	6559.12	39.87	12573.04	6743.61	5458.02	36.41	1389.21	6483.98	8833.23	5098.73	5663.7	5539.01	6130.76	0	1973	
C23	22133.84	7935.07	11468.22	12168.68	15078.11	6143.38	4138.59	587.87	0	3720.28	2720.53	9437.65	4004.74	9395.01	75.58	1610.1	1854.2	8120.99	4339.07	7106.98	6994.01	1989.87	4943.53	3378
C24	17477.16	7885.82	7263.56	14068.43	14758.02	5905.18	1290.67	5956.3	0	2355.03	2068.33	16292.5	6857.31	13291.3	585.08	361.65	3234.78	4153.96	926.63	2253.4	5652.71	6133.83	31.03	3750
C25	72284.97	12102.17	4635.61	18638.25	14671.26	108.22	115.78	3774.57	0	3426.27	1744.99	0	7204.42	2189.71	55.63	26.95	1221.59	16613.68	8117.34	8344.37	4950.34	1858.22	6159.55	35
C26	16586.81	27295.85	7285.31	5918.66	14386.26	841.24	995.03	8223.5	0	2593.93	18.05	0	6426.18	985.84	33.84	4700.35	3605.9	4285.93	4351.81	4562.32	1670.05	2238.96	299.65	1578
C27	87.24	49057.03	6585.44	861.27	14338.6	9305.77	8658.24	31.59	3032.34	4202.53	15.22	0	462.32	143.15	3933.56	3669.47	62.79	158.37	57.12	26.89	5556.5	3222.44	14451.02	15
C28	62085.93	15165.13	8871.78	13409.71	14108.55	4336.75	8448.68	3841.31	37.34	2343.19	395.8	169.73	7624.54	942.37	25.69	3426.99	2669.76	7219.47	5708.88	6583.29	3490.5	611.16	0	2565
C29	35420.6	22968.24	8470.86	17743.87	13944.7	6124.75	1028.09	10793.26	3585.06	1798.61	24.5	2773.74	6581.18	5070.13	108.46	2480.67	2483.42	4946.95	6794.18	5077.71	1926.72	1042.93	1906.95	2054
C30	3783.66	37109.78	15886.6	1308.36	13714.35	13128.89	7386.6	18323.63	4365.59	6459.07	10.58	9659.69	12422.87	6322.46	6210.84	7515.46	249.28	824.68	1577.94	12644.65	2631.18	3275.34	2026.29	10479
C31	30558.53	12173.08	13754.65	17744.06	13620.63	7650.73	5063.56	10401.22	7842.53	1830.7	43.94	0	4245.47	7584.95	4675.48	1615.78	12734.93	6238.07	5563.88	4134.05	3377.11	7875.11	3921.27	818
C32	11461.73	6633.12	3607.31	11347.65	13533.05	10151.59	31.21	5997.45	225.76	2084.78	1985.04	718.33	9031.11	1412.35	4527.81	5020.12	2841.33	4787.42	4512.45	842.57	2149.41	2072.1	632.13	3579
C33	34223.25	12952.5	11797.97	25484.37	13155.97	1026.11	2576.93	6079.7	0	4113.37	7.84	999.17	7815.9	3351.07	103.07	41.98	3273.68	2849.23	11026.25	6417.36	1403.61	2413.31	3126.28	28
C34	38934.12	10048.69	9551.77	14269.56	12956.65	5336.78	80.78	4318.62	2654.36	2086.82	32.17	4894.4	7071.33	4002.29	43.68	38.75	4827.64	6994.37	4098.74	5486.5	4282.69	1770.33	3856.33	2206
C35	16331.95	9416.24	3448.03	18729.2	12904.53	15833.47	3251.26	9681.75	0	4382.14	0	0	3802.04	1224.51	1190.64	4840.31	6224.22	4175.47	3306.31	3139.48	2322	1546.68	224.67	1966
C36	5536.46	8368.96	2233.67	4478.96	12720.47	8313.25	24.86	27.71	5275.43	5036.1	1791.07	5286.31	2158.07	1406.36	19275	5554.84	258	968.79	14.79	25.17	2662.81	1371.04	2701.5	19

Within each learning sample, grow a regression tree

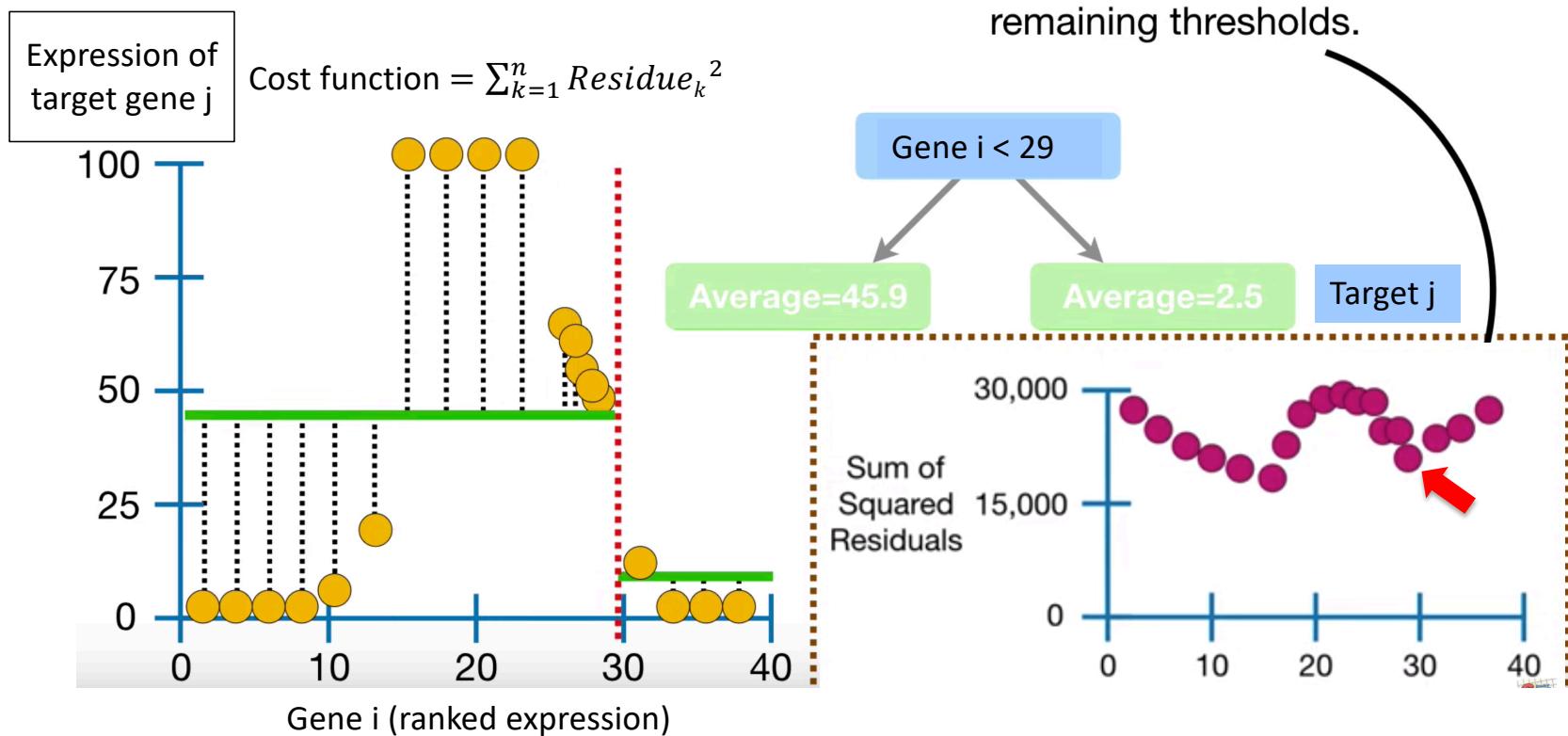
A regression tree:
For continuous variables



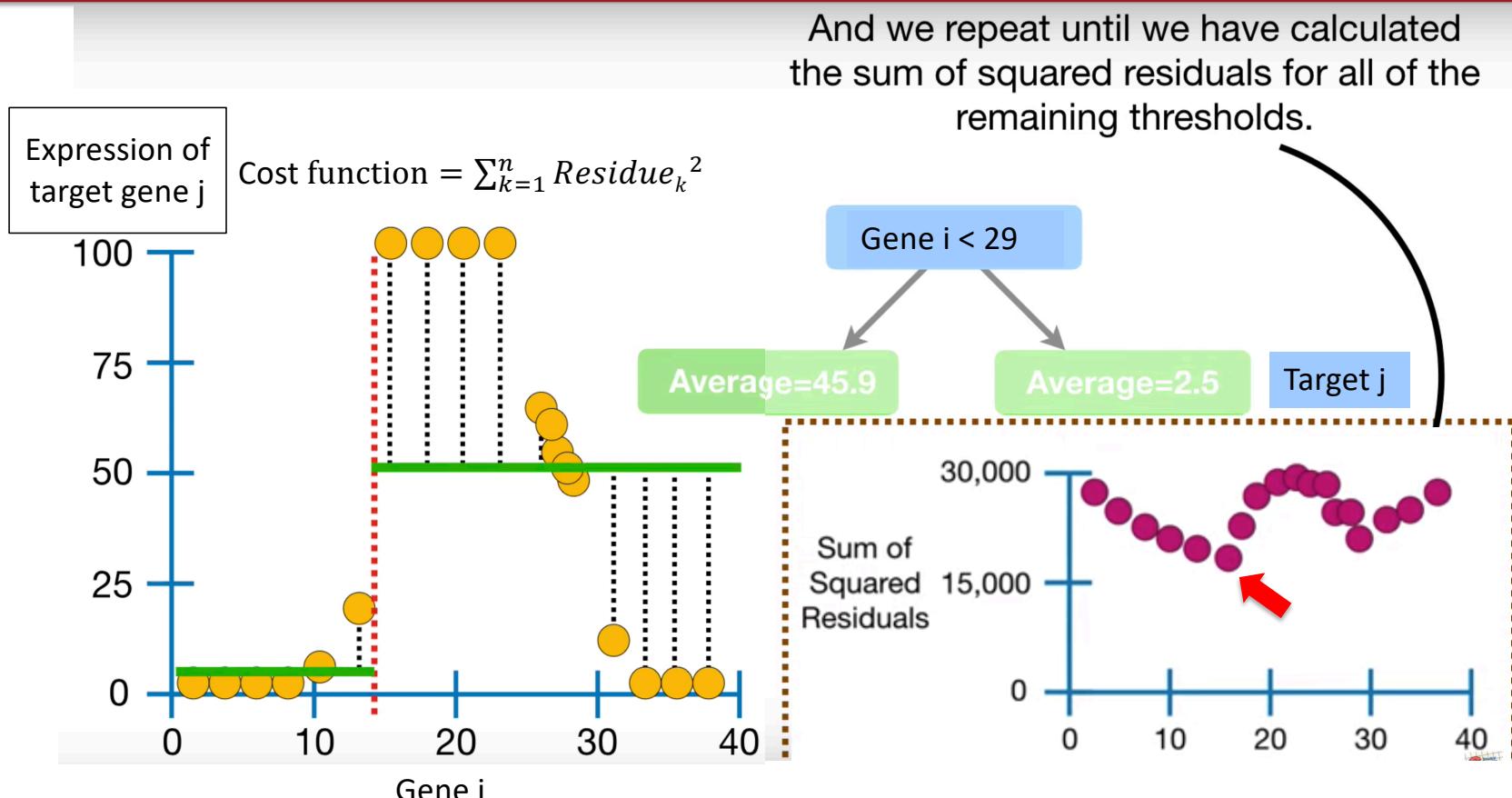
A decision tree:
For categorical variables



How a regression tree works



How a regression tree works





Build a tree from multiple variables

Grow a regression tree

1. For a given target gene j
2. For each of the feature gene i , determine the cost values for each possible split. Choose the lowest cost value as a potential split point.
3. Iterate through each of the rest gene as predictor, get the lowest cost value for each.
4. Choose the gene that provide the lowest cost to make a first split.

5. For each of the branch, do the same 2 → 4 and iterate, until all the branch reaches the minimal number of samples.

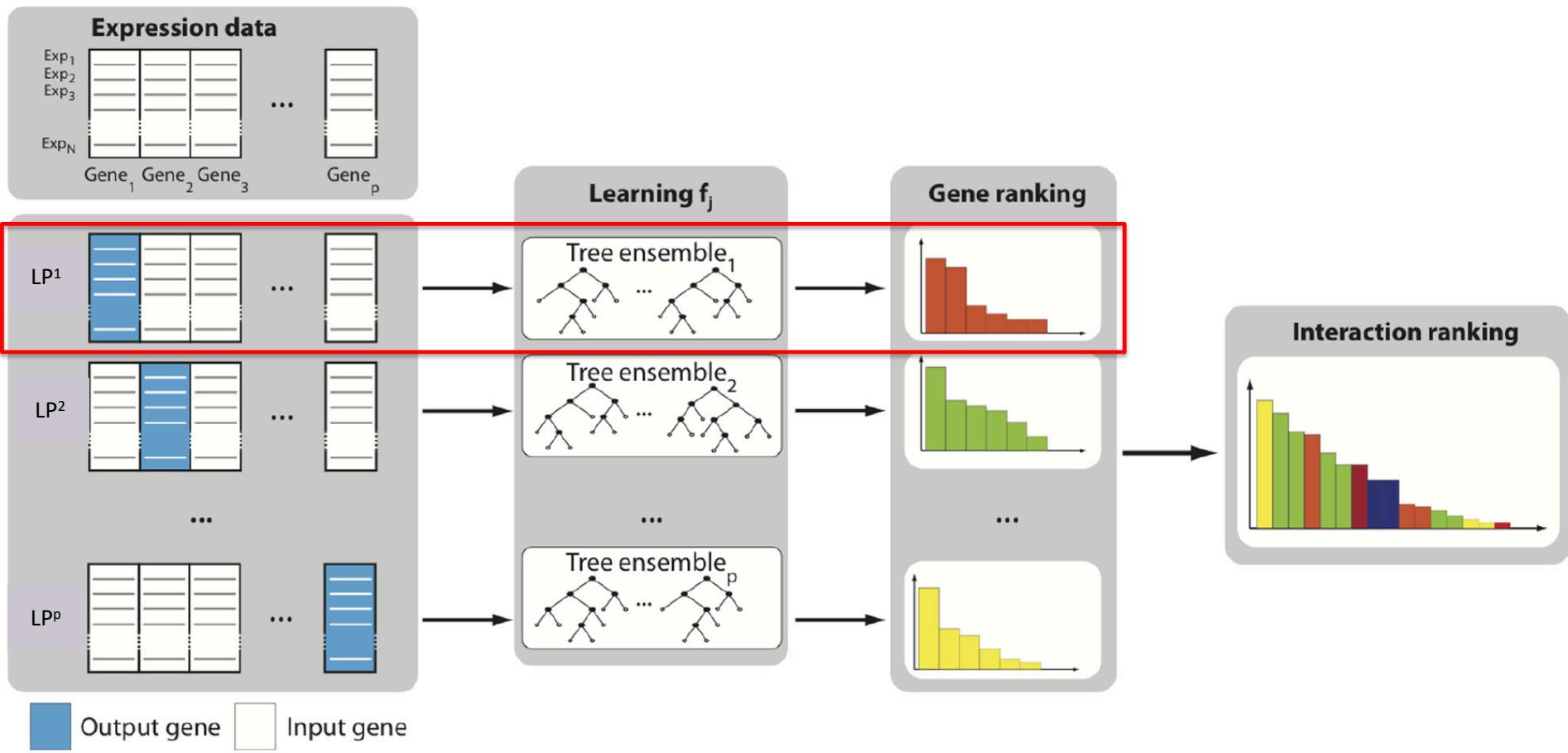
Determining feature importance

1. Sum up all the variances of Y explained by splitting by a specific gene in all the branches . That's the score for the feature importance.
2. Rank the genes by feature importance.

Combine feature importance for all the target genes as a rank of all interactions.

1. For each of the target gene, repeat through 1 → 7, until all the feature importance for all target genes are determined.
2. Combine all the ranks for all interactions within the transcriptome.

Bootstrapping/ ensemble of trees





Discussion on Genie3

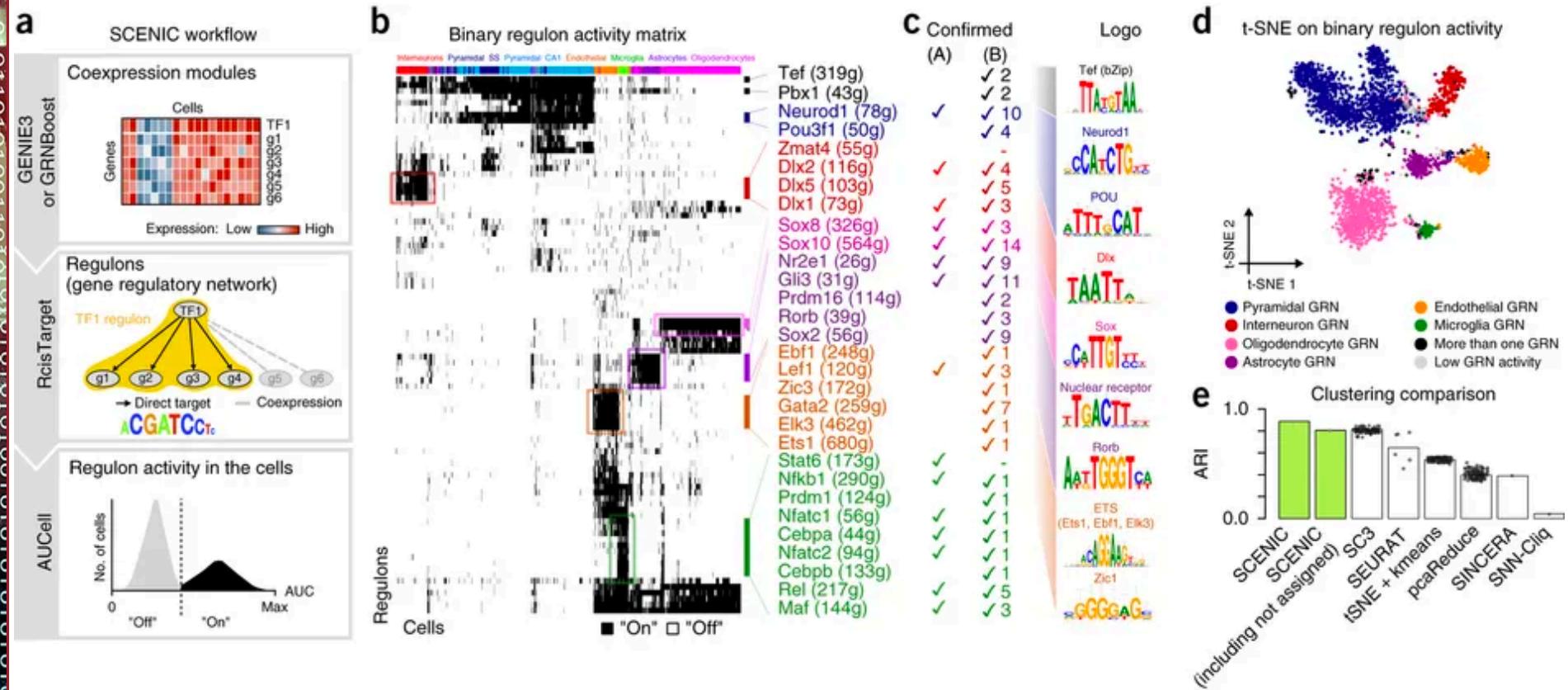
- Efficiently handle large dataset.
 - Parallel processing
 - Implemented in R and Python (even faster)
- Has been joined with cis-Target (**iRegulon**) to identify TF-target regulation in single cell data.



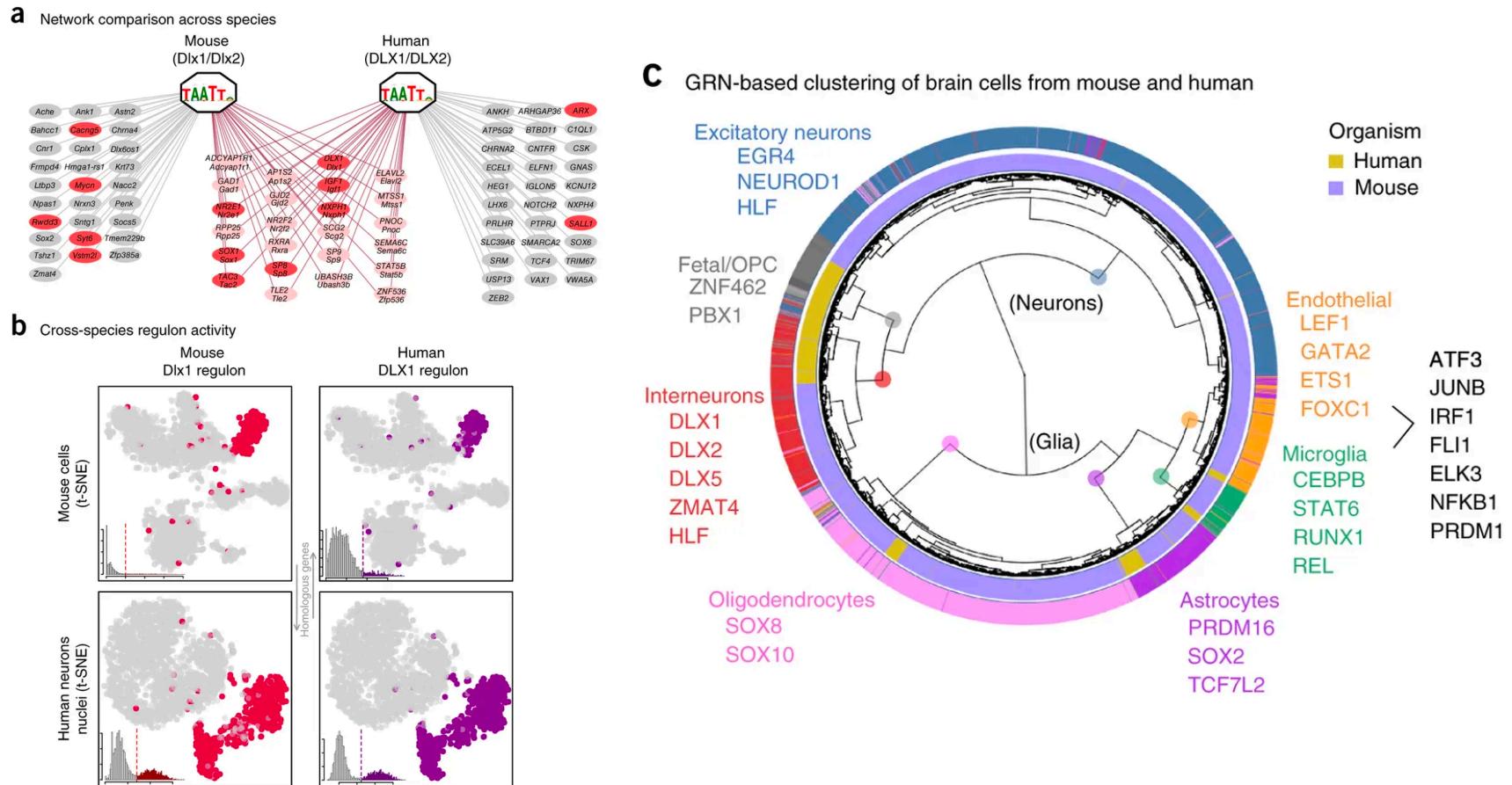
SCENIC

- A combinatory approach is preferred to reduce noise.
- Integrate GENIE3 co-expression module detection with iRegulon-detection of TF regulation.

SCENIC workflow and results



What do you achieve?





Running SCENIC

- Run the installation may spent 2 hrs.
- Convert files to loom files. Loom files are good
- Download the cis-target file may take a long time. And how to set up these files before hand?
 - 1.1 G for mm9 mouse. Take 30 minutes
- Which page to use for a dry run before your own data.

Object-oriented programming (OOP)– internal structure of an S4 object: scenicOptions

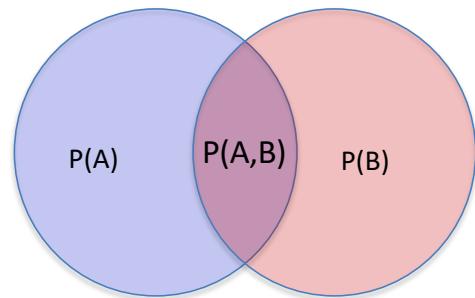
@inputDatabaseInfo	@settings	@filenames
<pre>getDatabaseInfo(scenicOptions, "org") \$org [1] "mgi" \$datasetTitle [1] "" \$cellInfo [1] "int/cellInfo.Rds" \$colVars [1] "int/colVars.Rds" NA \$int_01 [1] "int/cellColorNgenes.Rds" NA</pre>	<pre>getSettings(scenicOptions, "nCores") getDatabases(scenicOptions) getDbAnnotation(scenicOptions) \$dbs 10kb "mm9-tss-centered-10kb-7species.mc9nr.feather" \$dbDir [1] ".cisTarget_databases" \$db_mcVersion [1] "v9" \$verbose [1] TRUE \$nCores [1] 10 \$seed [1] 123 \$devType [1] "pdf" \$modules \$modules\$weightThreshold [1] 0.001 \$regulons list() \$aucell \$aucell\$smallestPopPercent [1] 0.25 \$defaultTsne \$defaultTsne\$dims [1] 50 \$defaultTsne\$perpl [1] 50 \$defaultTsne\$aucType [1] "AUC" \$tSNE_filePrefix [1] "int/tSNE"</pre>	<pre>getIntName(scenicOptions, "genesKept") loadInt(scenicOptions, "genie3ll", ifNotExists="null") \$int fileName genesKept "int/1.1_genesKept.Rds" corrMat "int/1.2_corrMat.Rds" genie3wm "int/1.3_GENIE3_weightMatrix.Rds" genie3ll "int/1.4_GENIE3_linkList.Rds" genie3weighPlot "int/1.5_weightPlot" tfModules_asDF "int/1.6_tfModules_asDF.Rds" tfModules_forEnrichment "int/2.1_tfModules_forMotifEnrichmet.Rds" motifs_AUC "int/2.2_motifs_AUC.Rds" motifEnrichment_full "int/2.3_motifEnrichment.Rds" motifEnrichment_selfMotifs_wGenes "int/2.4_motifEnrichment_selfMotifs_wGenes.Rds" regulonTargetsInfo "int/2.5_regulonTargetsInfo.Rds" regulons "int/2.6_regulons_asGeneSet.Rds" regulons_incidMat "int/2.6_regulons_asIncidMat.Rds" aucell_regulons "int/3.1_regulons_forAUCell.Rds" aucell_genesStatsPlot "int/3.2_aucellGenesStats" aucell_rankings "int/3.3_aucellRankings.Rds" aucell_regulonAUC "int/3.4_regulonAUC.Rds" aucell_thresholds "int/3.5_AUCellThresholds.Rds" aucell_thresholdsTxt "int/3.5_AUCellThresholds_Info.tsv" aucell_binary_full "int/4.1_binaryRegulonActivity.Rds" aucell_binary_nonDupl "int/4.2_binaryRegulonActivity_nonDupl.Rds" aucell_regulonSelection "int/4.3_regulonSelections.Rds" aucell_binaryRegulonOrder "int/4.4_binaryRegulonOrder.Rds" getOutName(scenicOptions, "s2_motifEnrichment") \$output fileName s2_motifEnrichment "output/Step2_MotifEnrichment.tsv" s2_motifEnrichmentHtml "output/Step2_MotifEnrichment_preview.html" s2_regulonTargetsInfo "output/Step2_regulonTargetsInfo.tsv" s3_AUCheatmap "output/Step3_RegulonActivity_heatmap" s3_AUCtSNE_colAct "output/Step3_RegulonActivity_tSNE_colByActivity" s3_AUCtSNE_colProps "output/Step3_RegulonActivity_tSNE_colByCellProps" s4_boxplotBinaryActivity "output/Step4_BoxplotActiveCellsRegulon" s4_binaryActivityHeatmap "output/Step4_BinaryRegulonActivity_Heatmap" s4_binarytSNE_colAct "output/Step4_BinaryRegulonActivity_tSNE_colByActivity" s4_binarytSNE_colProps "output/Step4_BinaryRegulonActivity_tSNE_colByCellProps" loomFile "output/scenic.loom"</pre>

OOP objects in R

- Commonly used in genomic analysis
- Classified to S3,S4, R5, R6 objects
- Customized names for class
- Structure of S4 objects
 - @ slots
 - \$ lists of items
 - Manually defined Methods that operation on the object



Method 5: Bayesian Network – conditional dependence



$$P(A, B) = P(A | B) * P(B) = P(B | A) * P(A)$$



Bayes rule:

$$P(A | B) = \frac{P(B | A)P(A)}{P(B)}$$

Bayesian network – the conditional probability

If A and B are independent
A= winter (yes 25%, no 75%)
B= happy (yes 50%, no 50%)



$$\begin{aligned}P(A) &= 25\% \\P(B) &= 50\% \\P(\text{winter, happy}) &= \\P(A,B) &= 25\% * 50\% = 12.5\%\end{aligned}$$

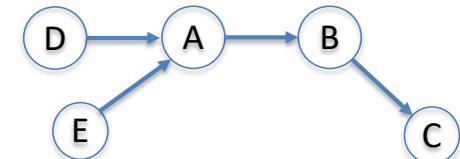
Correct

How about if B dependent on A:
A= winter (yes 25% or no 75%)
B= cold weather (overall yes 25%, no 75%)


$$\begin{aligned}P(A) &= 25\% \\P(B|A) &= 100\% \text{ on winter and } 0\% \text{ on other seasons.} \\&\text{Overall } 25\% \\&\text{The conditional probability of winter \& cold is} \\P(A=\text{winter}, B=\text{cold}) &= P(A)P(B) = 25\% * 25\% = 6.25\% \\&\text{wrong!}\end{aligned}$$

$$\begin{aligned}P(\text{winter, cold}) &= \\P(A=\text{winter}; B=\text{cold}) &= P(A)P(B|A) = 25\% * 100\% = 25\%\end{aligned}$$

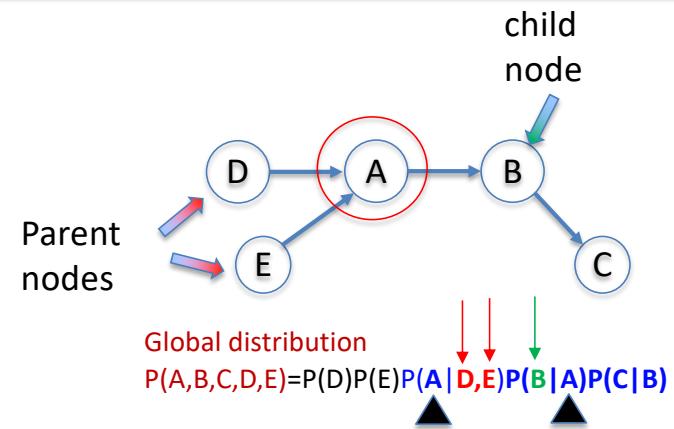
A= winter (yes or no 50% each)
B= cold weather (yes or no 100%)
C= wear sweater (yes or no, 50%)
D= month of a year
E= location on the earth



Global distribution
 $P(A,B,C,D,E) = P(D)P(E)P(A|D,E)P(B|A)P(C|B)$

Parent nodes and child node

- To a given node
 - Conditional nodes (reasons or contributing factors) are called parents.
 - The consequent nodes are child nodes.
- 2 components in Bayes Net,
 - 1. Graph structure: edges (arrows, can be defined by a list of nodes and parents of each node).
 - 2. Parameters (θ): $P(D)$, $P(E)$, $P(A|D,E)$, $P(B|A)$, $P(C|B)$



Learn the network structure and parameters

Divide the Bayes net into two components:

- Θ : the conditional probabilities
- G : the structure
 - Can be decomposed to each node with parents (X_i and Π_{x_i}).

The problem

$$P(M | \mathcal{D}) = P(\mathcal{G}, \Theta | \mathcal{D}) = \underbrace{P(\mathcal{G} | \mathcal{D})}_{\text{learning}} \cdot \underbrace{P(\Theta | \mathcal{G}, \mathcal{D})}_{\text{structure learning}} \cdot \underbrace{P(M | \mathcal{G}, \Theta)}_{\text{parameter learning}}$$

Step 1

Step 2

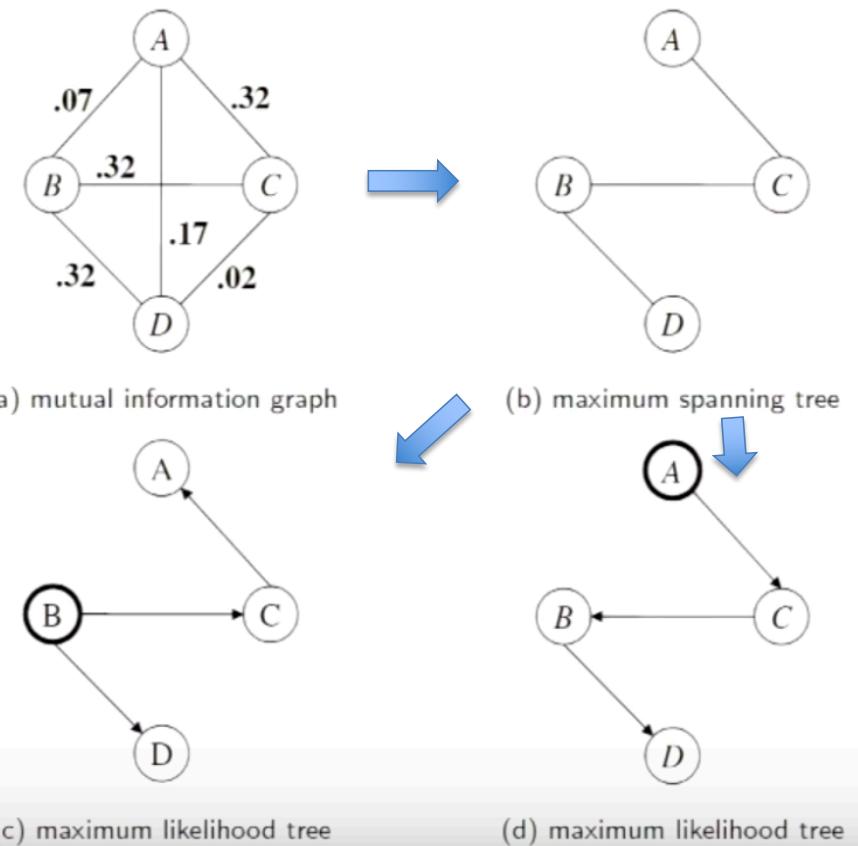
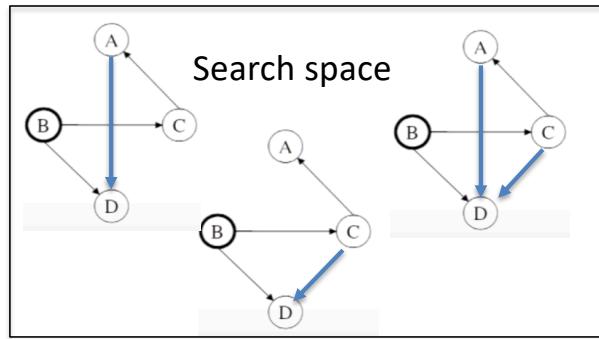
Probability of a model (M) given the data set (D).

Learning the skeleton of a graph

- Constructing Maximum Spanning Tree.
- Add direction through starting from a random node.

BIC score = Bayesian Information Criterion

$$\text{Score}(G|\mathcal{D}) \stackrel{\text{def}}{=} \text{LL}(G|\mathcal{D}) - \psi(N) \cdot ||G||$$



Assign directions: Induction of Causality algorithm

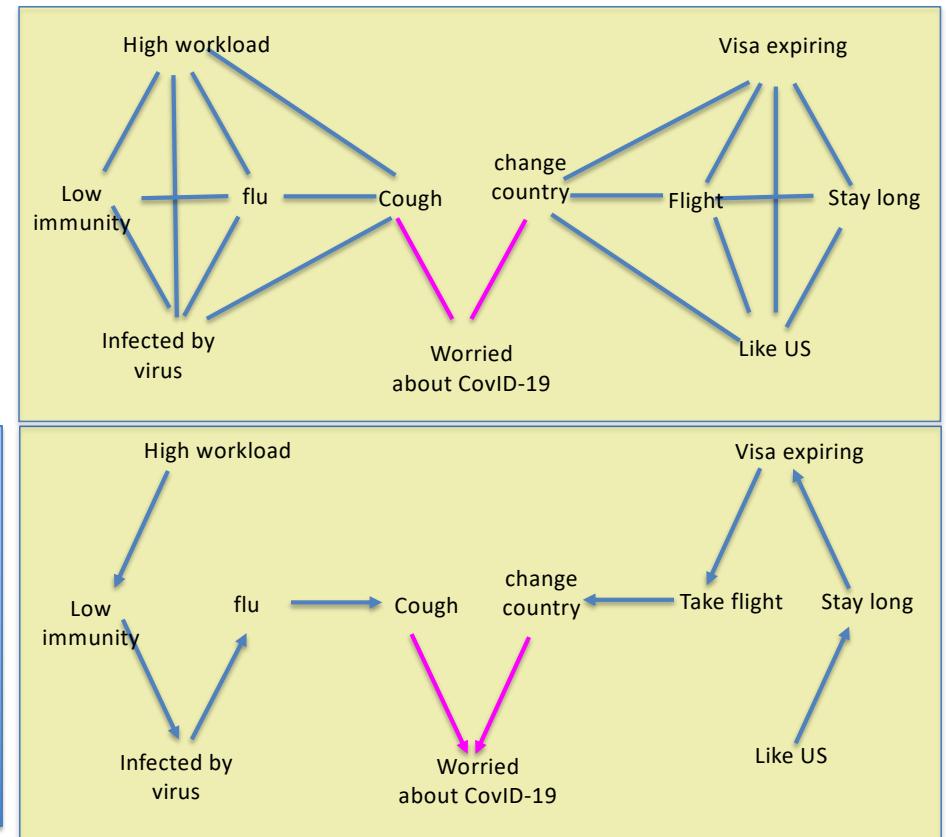
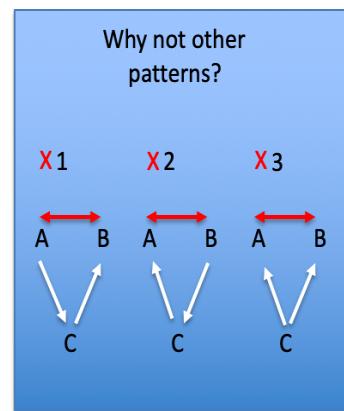
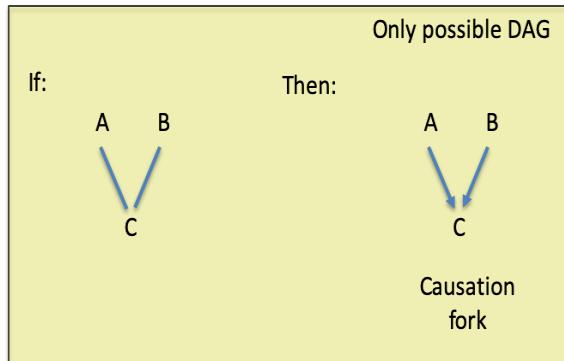
The Induction of Causality Algorithm:

If,

1. A, B are not connected through any other connection.
2. A and B have a common connection to C

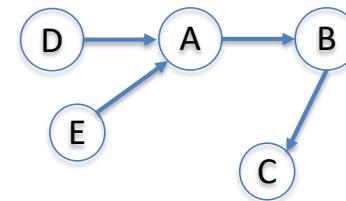
Then:

arrows point from A and B to C



Curse of the dimensionality

- Complexity increases exponentially with respect to:
 - Number of bins each node can take.
 - Number of parent nodes that a node can have.
- Solutions
 - Breaking a huge network into conditionally independent units



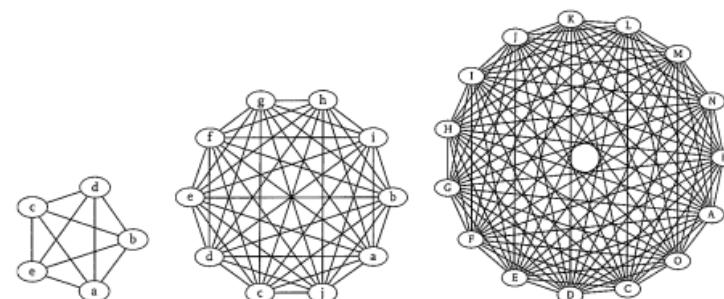
Global distribution

$$P(A, B, C, D, E) = P(D)P(E)P(A|D, E)P(B|A)P(C|B)$$

If each sample has 5 bins

Values to fully enumerate the distribution table: $5^5 = 1875$

Enumerate the Bayesian network: $5 + 5 + 125 + 25 + 25 = 185$



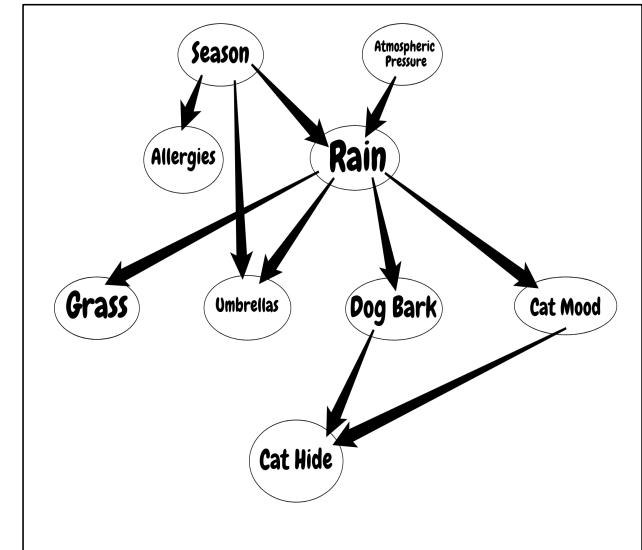
Discussion on Bayesian Network

Pros

- Easy interpretation

Cons

- Requires large computation
- Decomposition of Bayesian seems not efficient



$$P(A | B) = \frac{P(B | A)P(A)}{P(B)}$$



Demonstration on bnlearn in R

- bnlearn in R
 - Demonstrate the import of data
 - Data structure
 - Output structure
 - Demonstrate how the graph are calculated
 - Import in to Cytoscape for visualization



Thank you for your attention!

- Questions?
 - GitHub: https://github.com/niaid/Gene_Regulatory_Networks
 - Googledoc, <https://tinyurl.com/zhu-GRN>
 - My email: zhuy16@nih.gov
 - BCBB email: bioinformatics@niaid.nih.gov



The end



Other resources

- GraphPlot, <http://juliagraphs.github.io/GraphPlot.jl/>
- Gamma distribution, <https://towardsdatascience.com/gamma-distribution-intuition-derivation-and-examples-55f407423840>
- `install.packages("igraph")`
- `install.packages("bnlearn")`
- `BiocManager::install("Rgraphviz")`
- iGraph for network analysis
<https://www.bioss.ac.uk/people/helen/igraphIntro.html>
- <https://www.r-bloggers.com/interactive-network-visualization-with-r/>

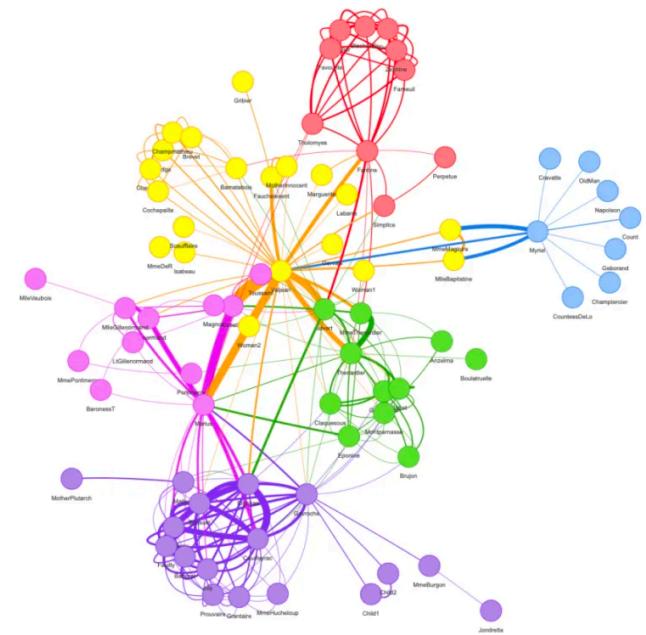


How to set up a tunel to server

- `install.packages('IRkernel') # Don't forget step 2/2!`
- `IRkernel::installspec()`
- `using Pkg`
- `Pkg.add("IJulia")`
- `user@local_machine$ ssh -N -L localhost:8888:localhost:8888
user@remote_mahcine`
- Paste this to the url to access the Julia – "localhost:1234"



- > tpm=read.table("S_GSE71485_Single TPM.txt",row.names=1,header=T)
 - > Tpm=tpm[rowMeans(tpm)>100,]
 - > write.table(Tpm,"S_GSE71485_Single TPM.txt")
 -



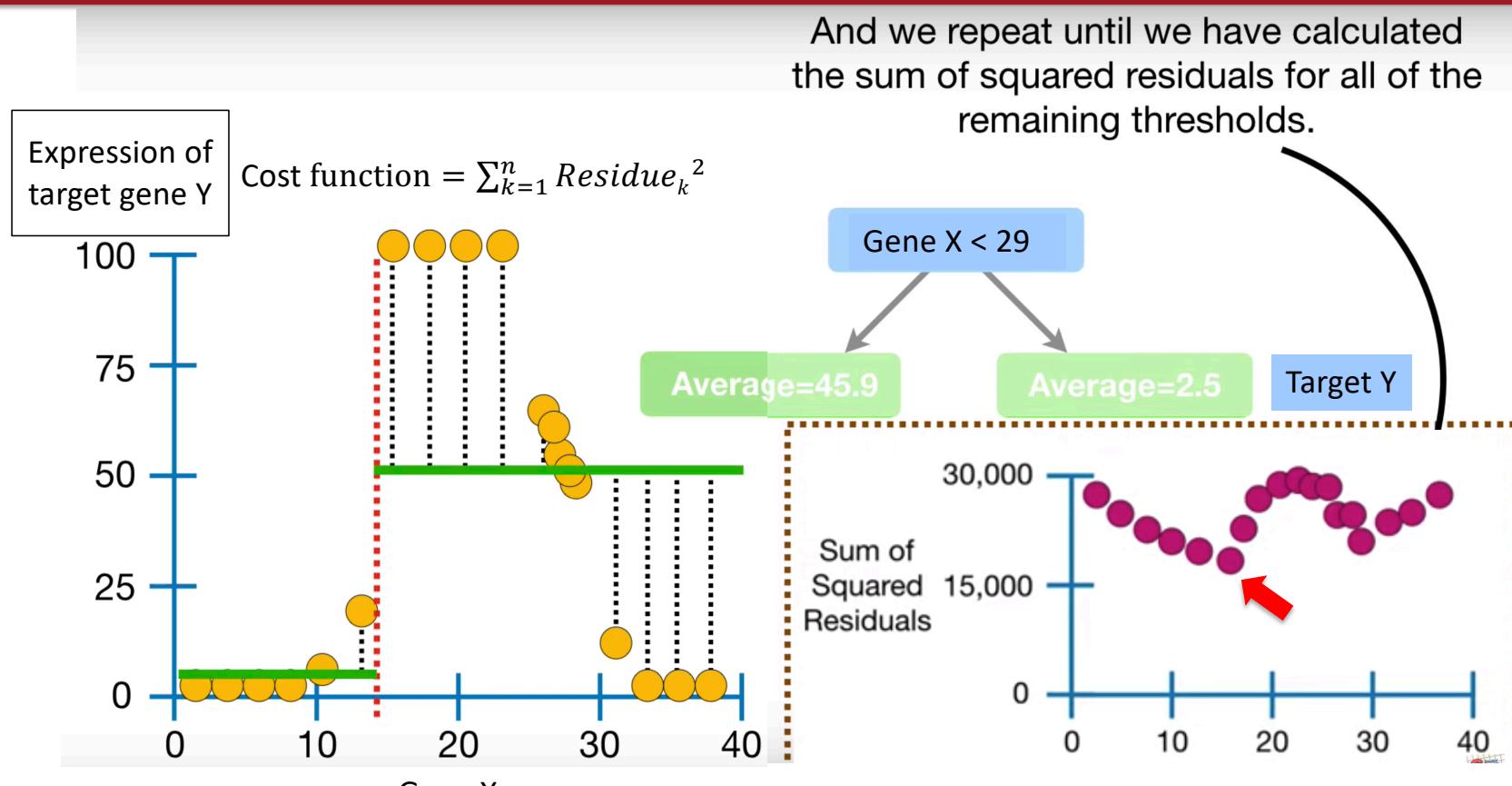
Parameters in Bayesian network

$$P(A | B) = \frac{\text{likelihood prior}}{\text{posterior Evidence}}$$
$$P(A | B) = \frac{P(B | A)P(A)}{P(B)}$$

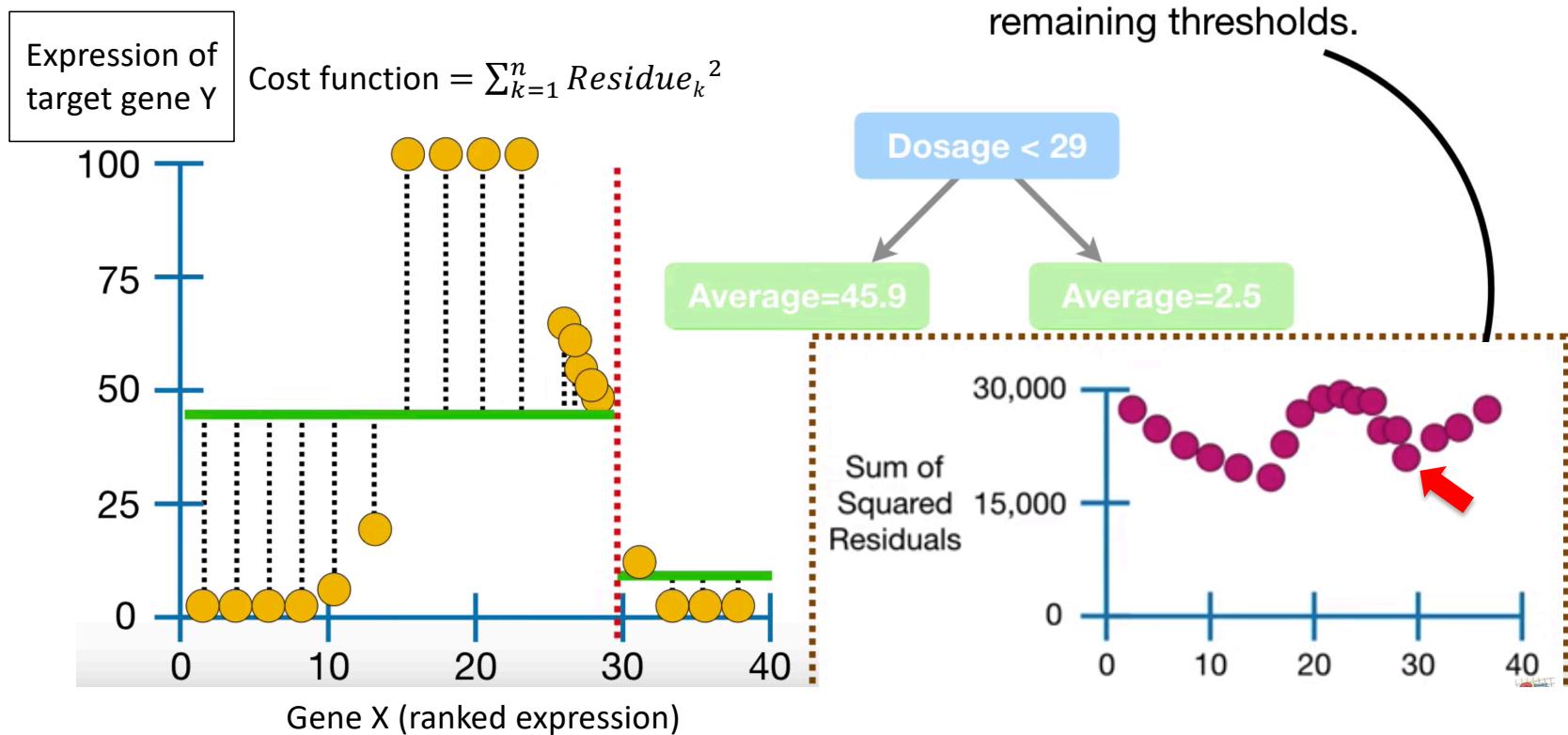
$$P(\text{cold} | \text{winter}) = \frac{\text{posterior likelihood prior}}{\text{Evidence}} = \frac{P(\text{winter} | \text{cold})P(\text{cold})}{P(\text{winter})} = \frac{P(\text{winter} | \text{cold})P(\text{cold})}{P(\text{winter})} = \frac{100\% * 25\%}{25\%} = 100\%$$



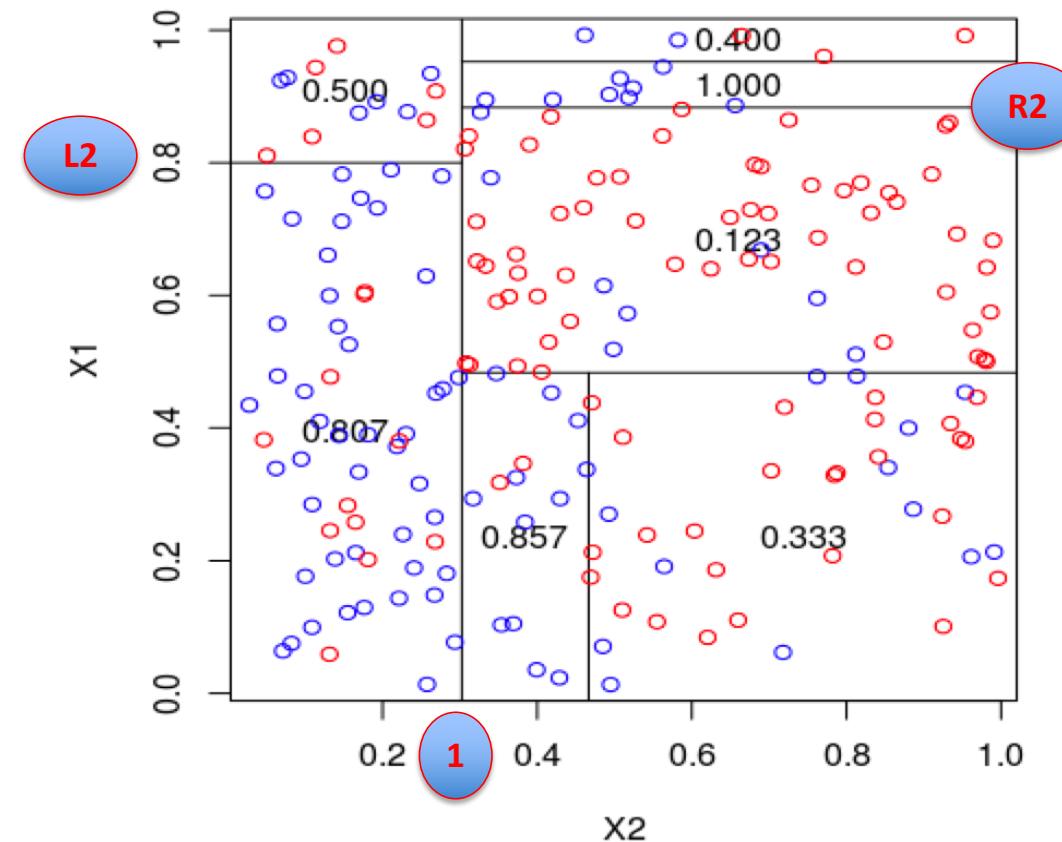
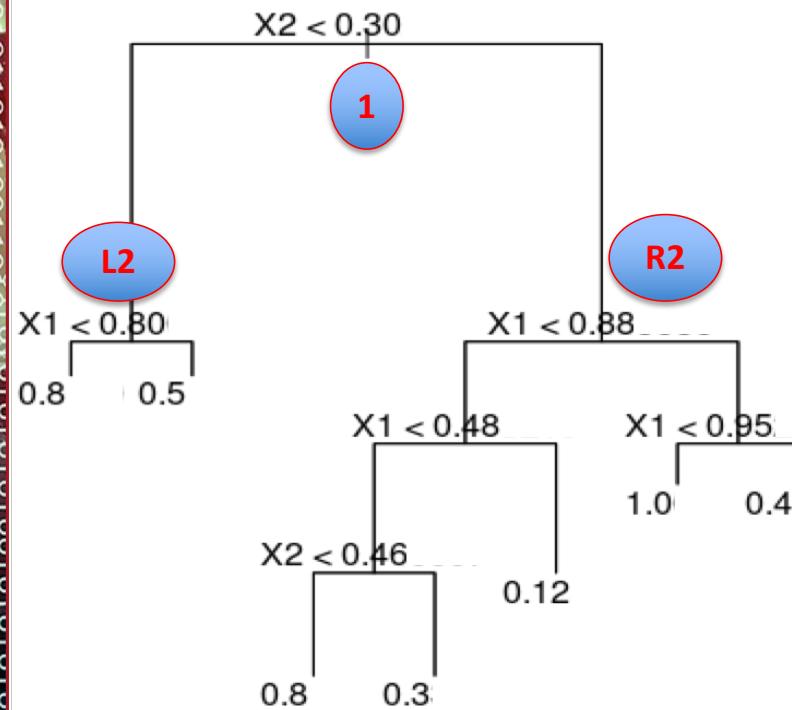
How regression tree works



How regression tree works



A regression tree by two variables



Target: The % of blue circles
Variables: X_1 and X_2

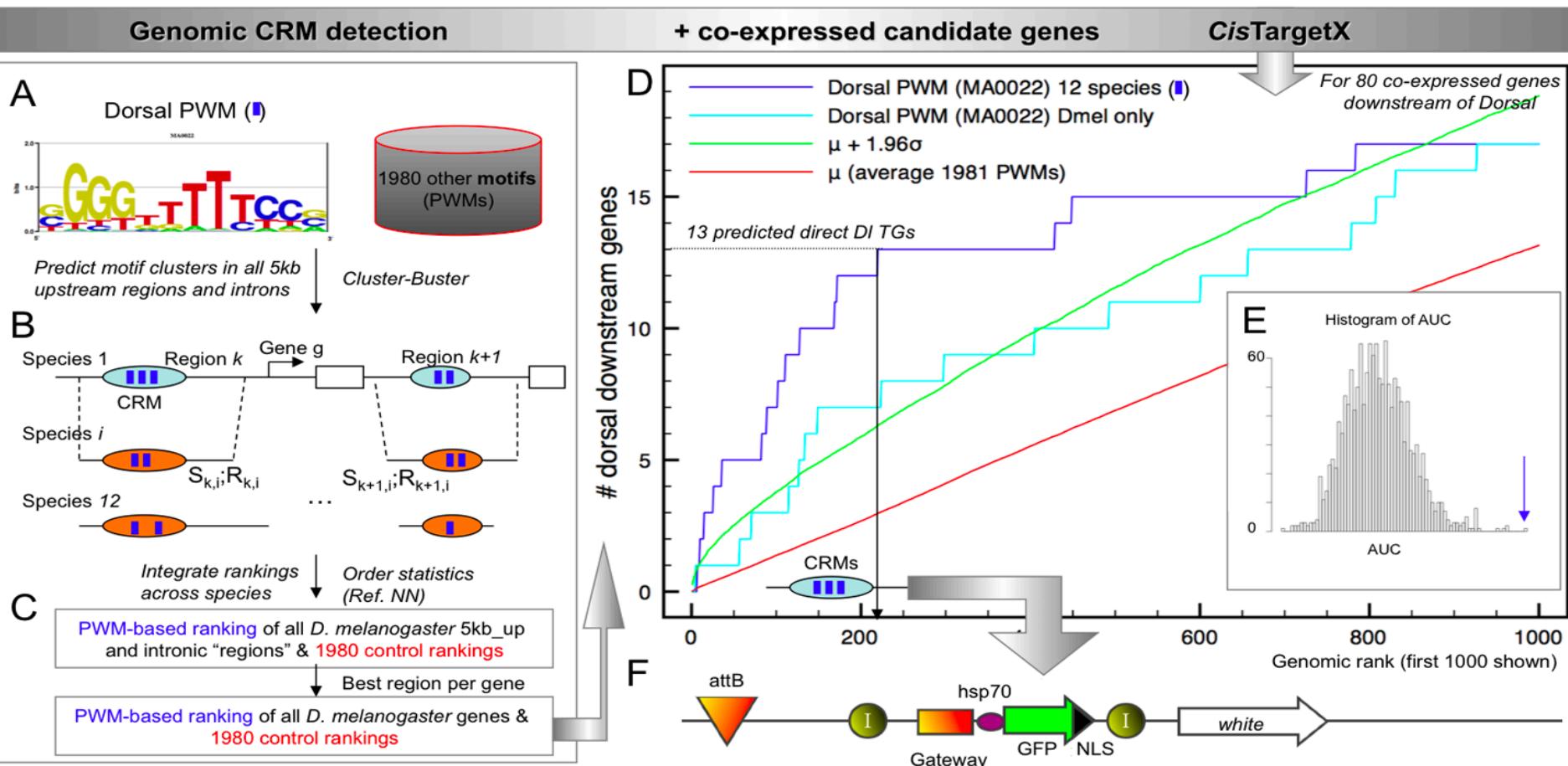


Build a tree from multiple variables

Procedures of using regression tree

1. Create 1000 learning samples using bagging/bootstrapping
2. Within each learning sample
3. With a given target gene Y
4. For each of the feature gene, determine the cost values for each possible split. Chose the lowest cost value as a potential split point.
5. Iterate through each of the gene as predictor, get the lowest cost value.
6. Choose the gene that provide the lowest cost to make that first decision.
7. For each of the branch, do the same $2 \rightarrow 4$ and iterate, until all the branch reaches the minimal number of samples.
8. Sum up all the variances of Y explained by splitting by a specific gene in all the branches . That's the score for the feature importance.
9. Rank the genes by feature importance.

10. For each of the target gene, repeat through 1 \rightarrow 7, until all the feature importance for all target genes are determined.
11. Combine all the ranks, and reranked all. That is the rank of all relationships within the transcriptome.



iRegulon

