

“Walking pathways” and how promoters can help to find new drugs.

(Practical guide to multi-omics and multi-
scale data integration)

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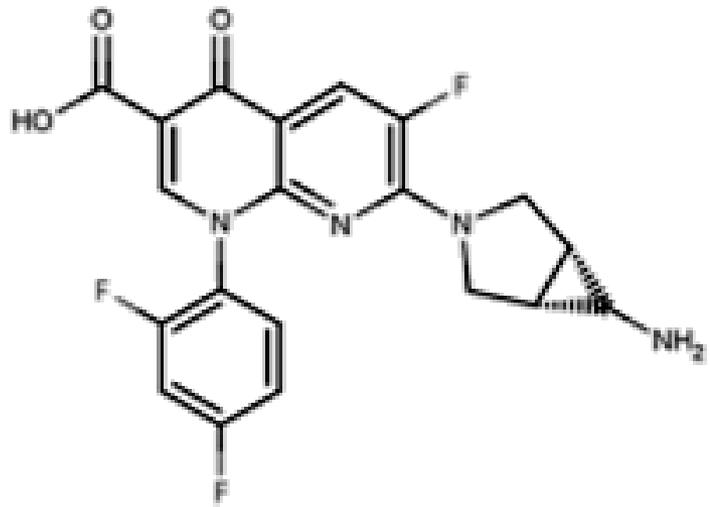
alexander.kel@genexplain.com



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Institute of Systems Biology

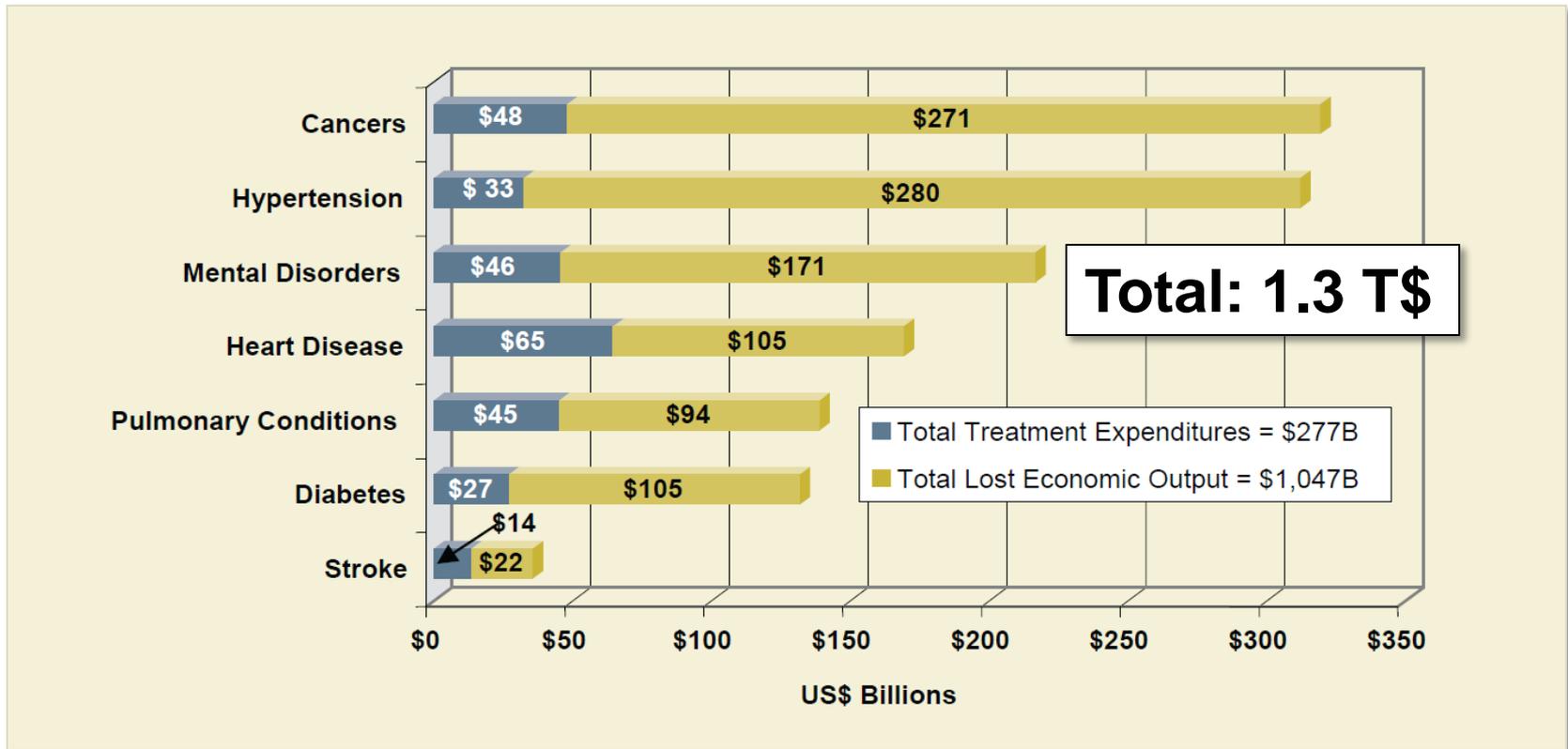
Novosibirsk

Trovafloxacin - antibiotic



Withdrawn from market due to risk of idiosyncratic hepatotoxicity in 2001.

Failure Affects National Economies: Medicines & Equitable Distribution

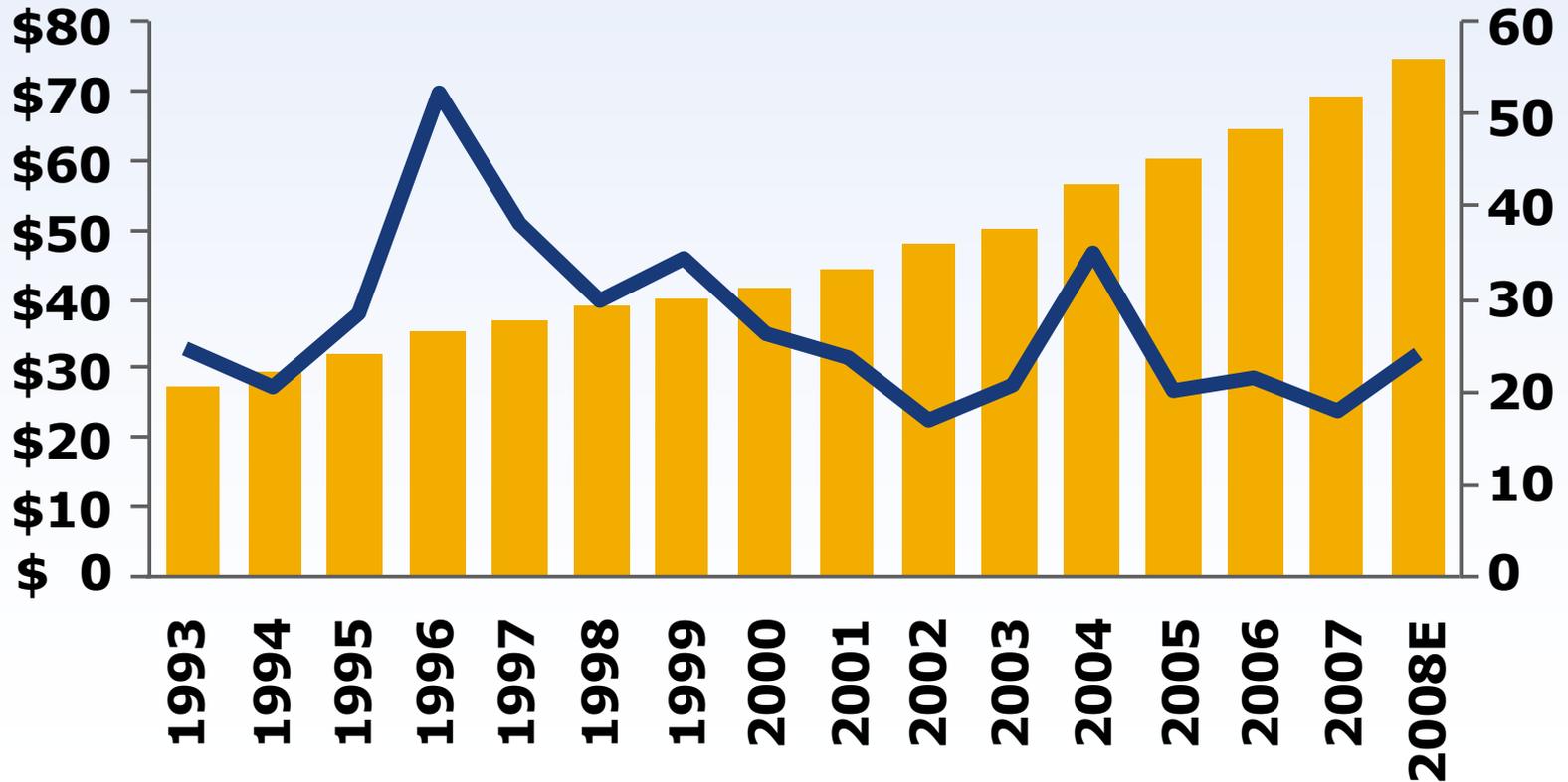


Combined treatment and productivity costs for US in 2007

Milken Institute 2008

R&D Pipeline

■ Global R&D Spending — Drug approvals: NMEs/BLAs

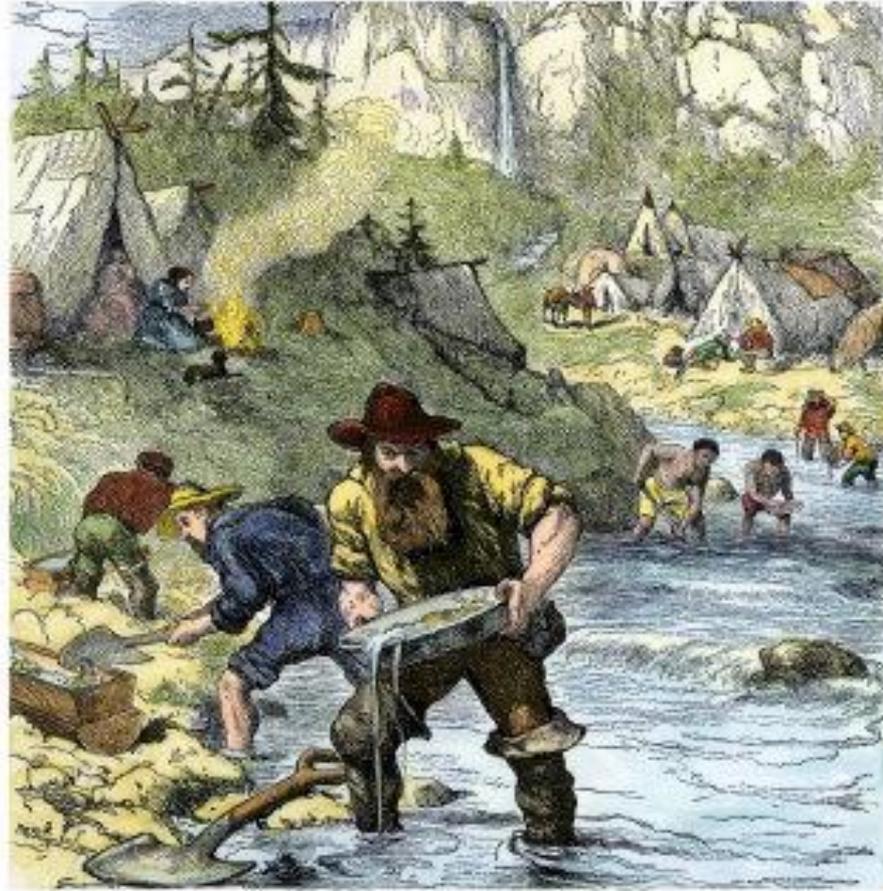


One of the main causes of high death rate for such diseases is the unsatisfactory quality of treatment, which in the first place is brought by low efficiency and insufficient safety of today's drugs and therapies.

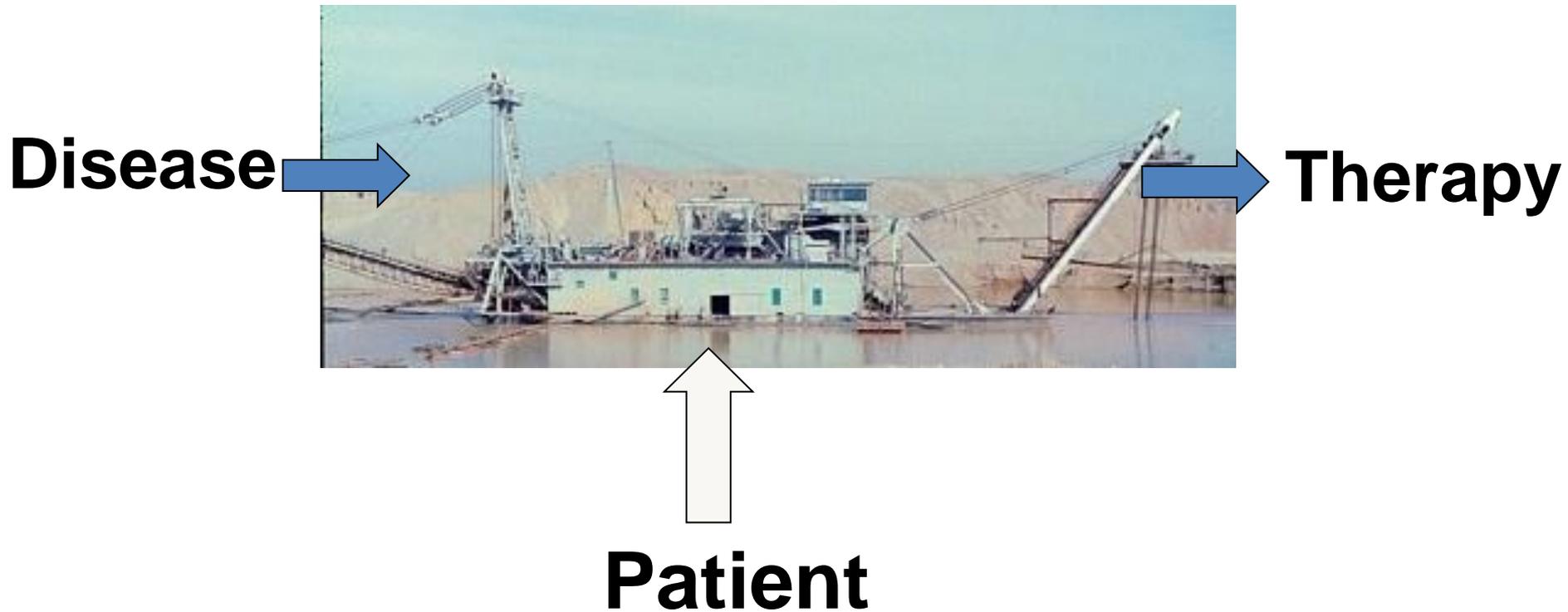
About 50% of prescribed medicine doesn't have any therapeutic effect at all. Moreover, 125 thousand deaths annually (in USA) are caused by the drugs' side effects.

It becomes more and more obvious that the main cause of this crisis is **the insufficient understanding of deep biological mechanisms** of initiation and flowing of pathological conditions and toxicity mechanisms used in drugs.

Drug discovery – the Gold Rush



Drug discovery – should become a technology



Systems medicine

Systems approaches will transform the way drugs are developed ... that will target multiple components of networks and pathways perturbed in diseases.

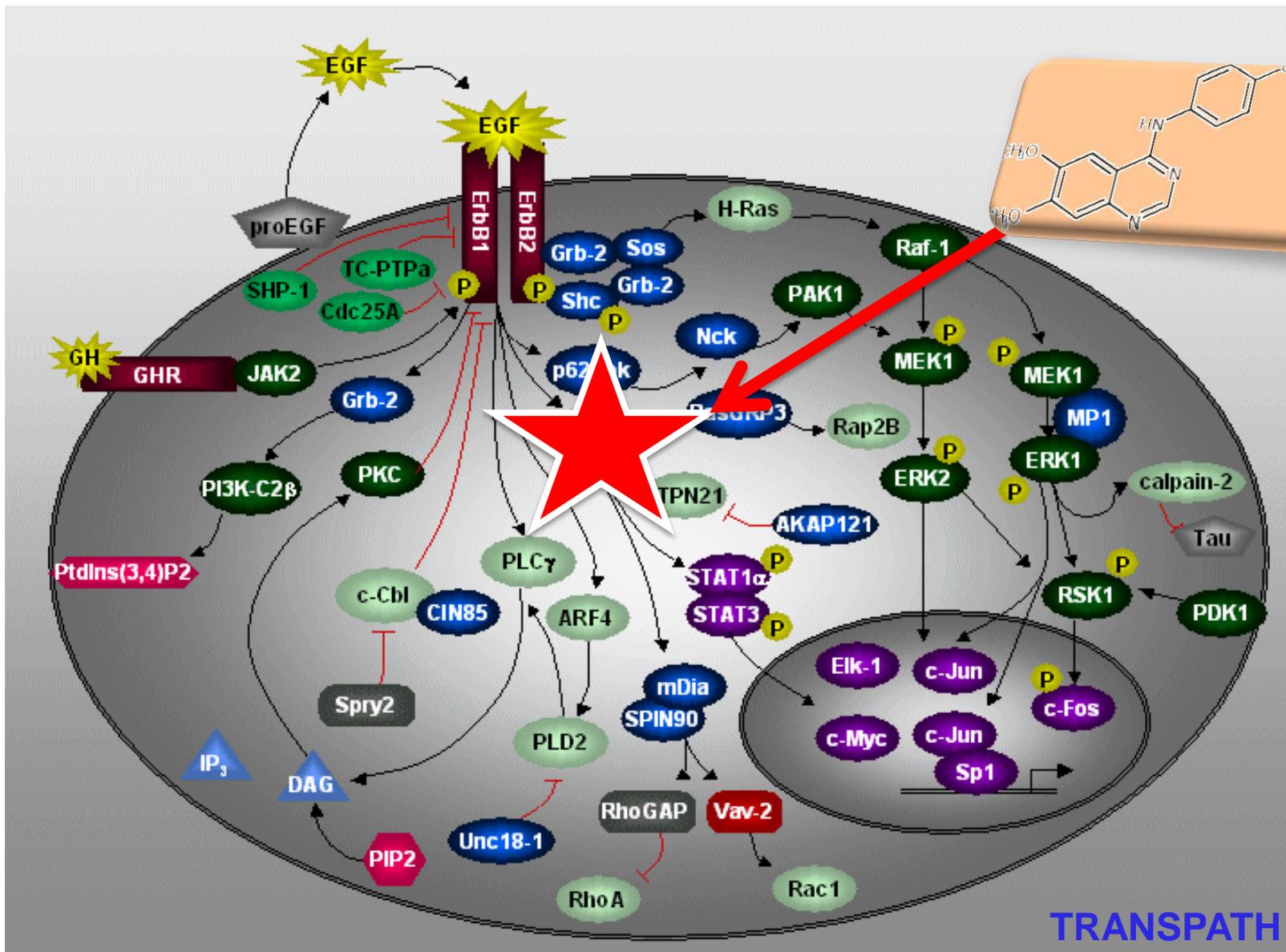
They will enable medicine to become predictive, personalized, preventive and participatory

Systems medicine: the future of medical genomics and healthcare

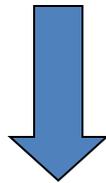
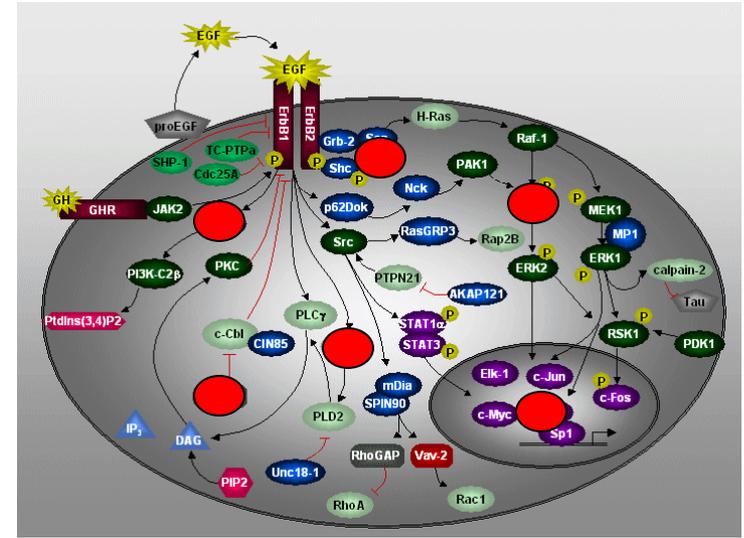
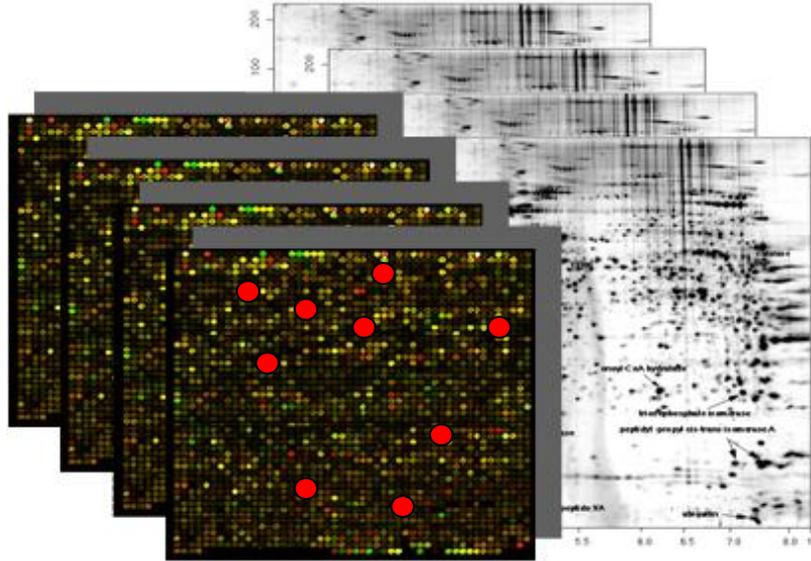
Charles Auffray^{1*}, Zhu Chen² and Leroy Hood³

Genome Med 2009, 1:2

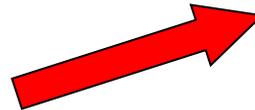
We should find a key pathway of a disease, select a good target and inhibit it.



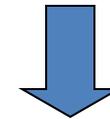
Pathway mapping



Differentially expressed genes/proteins



Mapping on pathways



Cause of disease ??

Transcriptional profiling of IKK2/NF- κ B- and p38 MAP kinase-dependent gene expression in TNF- α -stimulated primary human endothelial cells

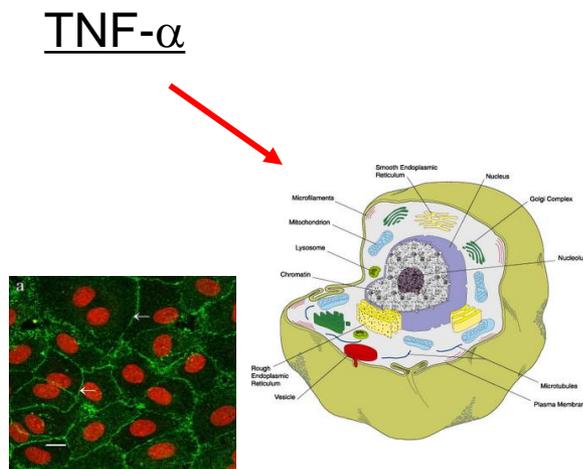
Dorothee Viemann, Matthias Goebeler, Sybille Schmid, Kerstin Klimmek, Clemens Sorg, Stephan Ludwig, and Johannes Roth

Inflammatory stimulation of endothelial cells by tumor necrosis factor α (TNF- α) involves activation of nuclear factor κ B (NF- κ B) and p38 mitogen-activated protein (MAP) kinase signaling pathways. A reliable analysis of the gene expression program elicited by TNF- α and its assignment to distinct signaling pathways is not available. A sophisticated analysis of oligonucleotide microarrays covering more

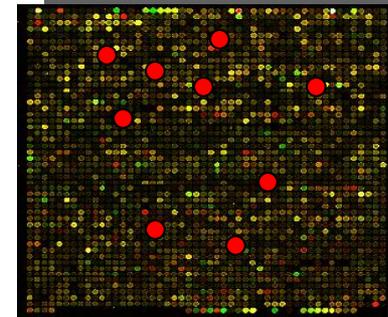
than 13 000 genes allowed definition of the TNF- α -regulated endothelial gene expression profile and novel TNF- α -induced genes. Virtually all TNF- α -inducible genes were dependent on κ B kinase 2 (IKK2)/NF- κ B activation, whereas a minor number was additionally modulated by p38. Furthermore, genes suppressed by IKK2/NF- κ B were newly identified. Real-time reverse transcriptase-polymer-

ase chain reaction (RT-PCR) and flow cytometry confirmed reliability of data. Thus, these results define a list of primary candidates for targeted modulation of endothelial functions during inflammation. (Blood. 2004;103:3365-3373)

© 2004 by The American Society of Hematology

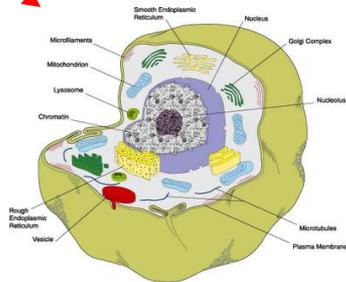
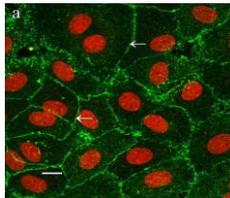


117 differentially expressed genes

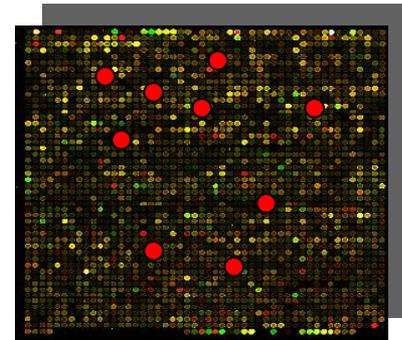


Can we predict TNF pathway?

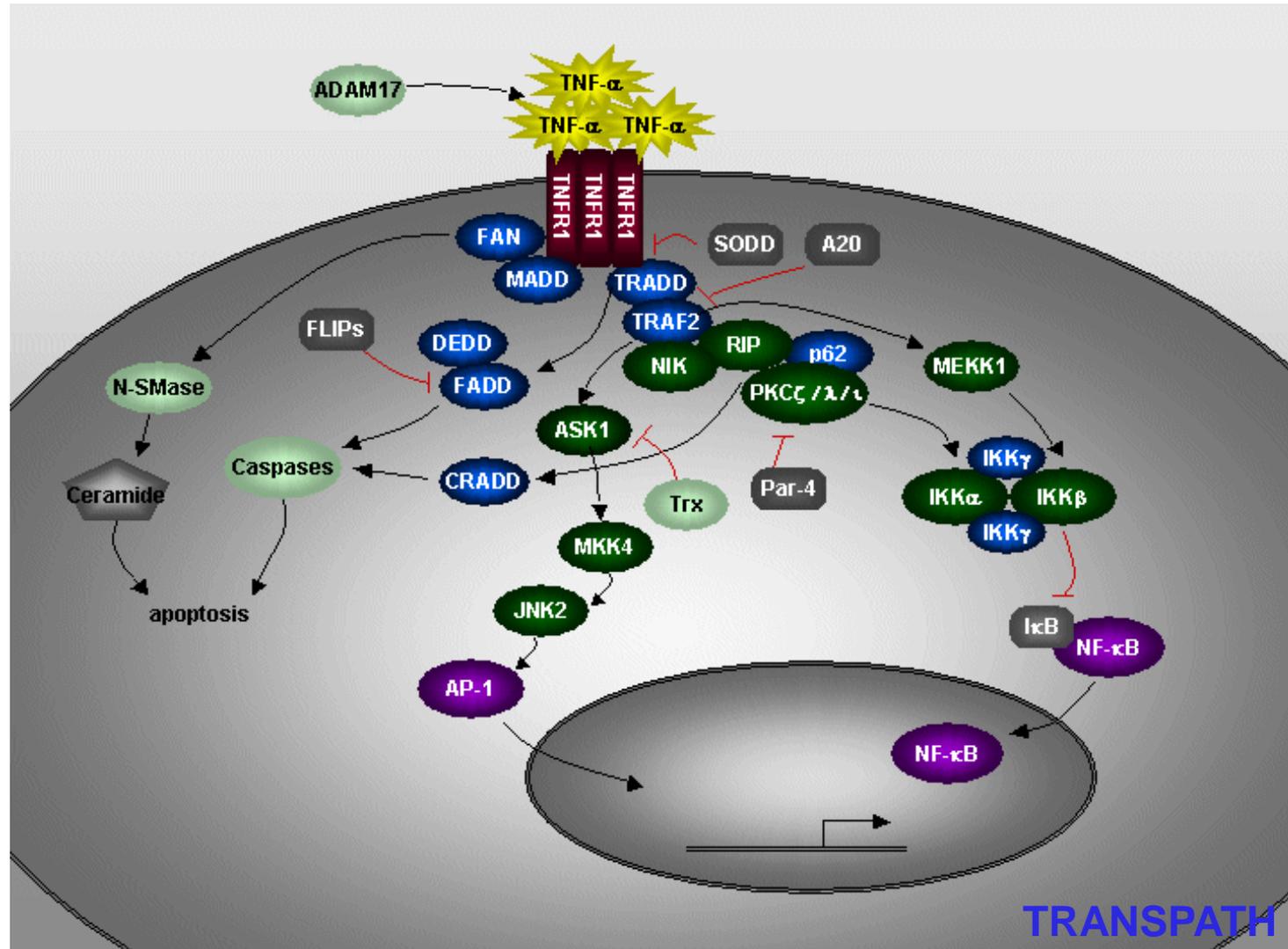
?



117 differentially expressed genes



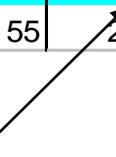
Canonical TNF pathway



Lets do mapping the differentially expressed genes on canonical pathways.

Pathway name	Hits	Pathway_id	Hit names	Pathway size	p-value
M-CSF ---> c-Ets-2	2	CH000000060	ETS2; CSF1	5	3.07E-03
IFNalpha, IFNbeta, IFNgamma ---> Rap1	3	CH000000595	IFNGR1; TYK2; IFNGR2	19	4.34E-03
Epo ---Lyn---> STAT5A	2	CH000000524	STAT5A; LYN	6	4.56E-03
activin A ---> Smad3	2	CH000000680	INHBA; SMAD3	10	1.31E-02
IFN pathway	3	CH000000740	IFNGR1; TYK2; IFNGR2	29	1.44E-02
Sonic Hedgehog pathway	2	CH000001022	MTSS1; PTCH	19	4.48E-02
hypoxia pathways	2	CH000000987	CDKN1B; NRIP1	21	5.38E-02
EDAR pathway	2	CH000000759	NFKBIA; CYLD	27	8.40E-02
Epo pathway	2	CH000000741	STAT5A; LYN	32	1.12E-01
TGFbeta pathway	3	CH000000711	BMP2; INHBA; SMAD3	72	1.39E-01
IL-22 pathway	1	CH000000762	TYK2	9	1.51E-01
IL-10 pathway	1	CH000000761	TYK2	9	1.51E-01
VEGF-A pathway	2	CH000000723	NOS3; VEGFA	42	1.75E-01
TLR3 pathway	2	CH000000820	TANK; IKBKE	44	1.88E-01
IL-8 pathway	2	CH000000786	CXCL1; IL8	46	2.01E-01
TNF-alpha pathway	2	CH000000772	NFKBIA; OSIL	53	2.48E-01
p38 pathway	2	CH000000849	MAP2K3; DUSP8	55	2.61E-01

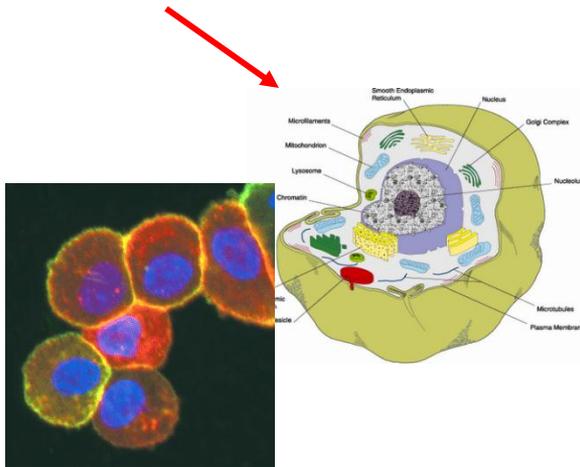
Not significant



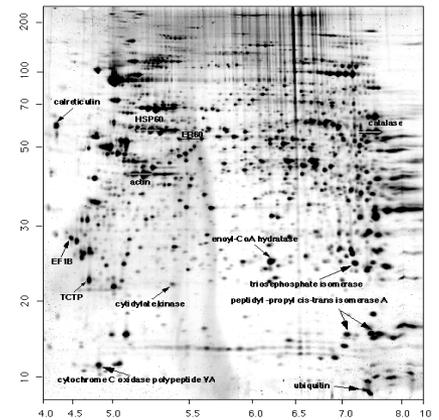
TNF pathway can not be found by direct mapping on canonical pathways....

Human epidermoid carcinoma A431 cells treated by epidermal growth factor (EGF)

EGF



320 differentially expressed proteins



Mapping differentially expressed proteins to canonical signal transduction pathways

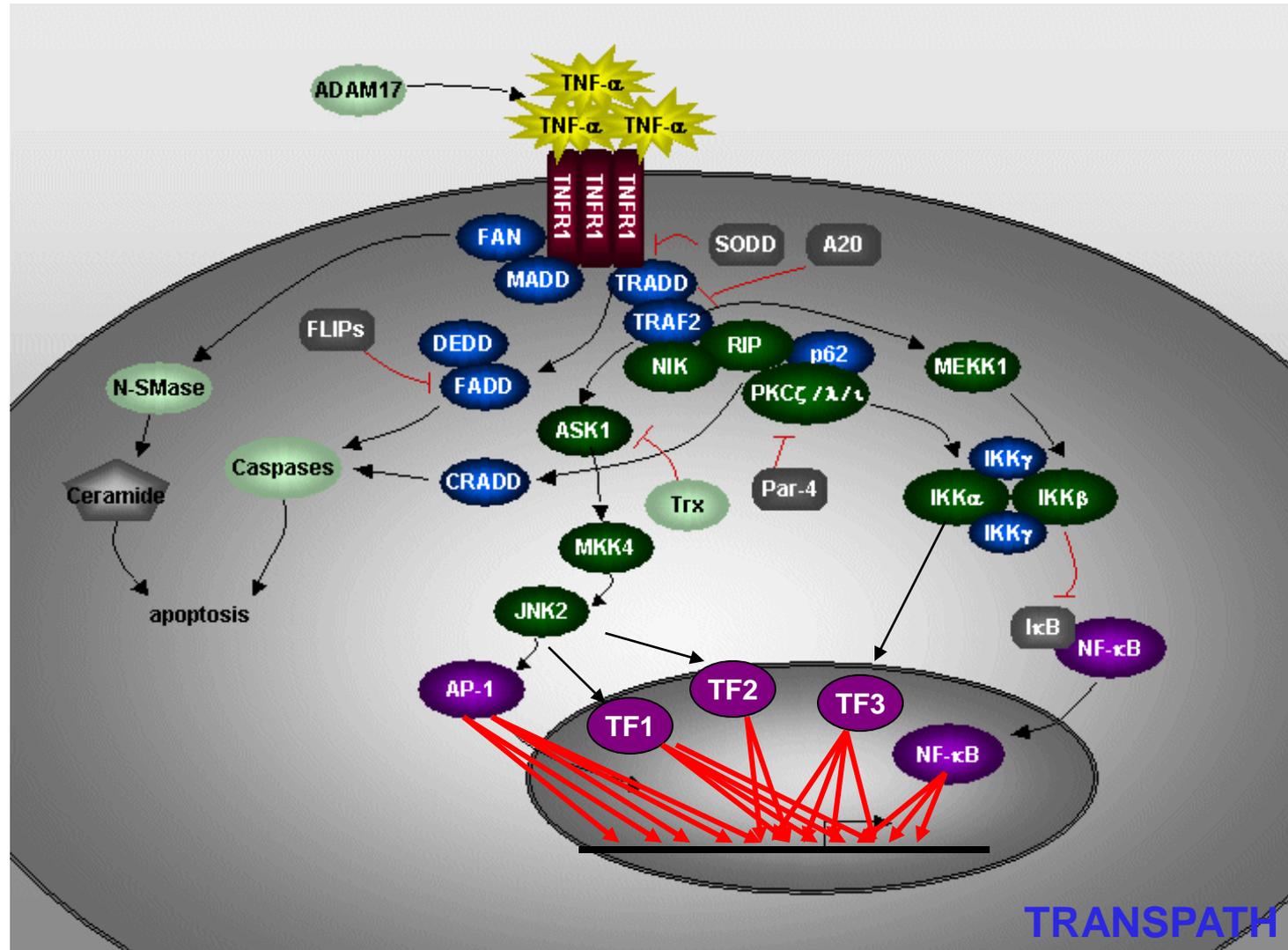
Pathway name	#Hits in group	Hit names	Group size	p-value
Caspase network	6	K18; E1; Cytochrome C; Hsp10; Ku70; Cdc42	104	0.00201348
CHIP ---/ Pael-R	2	E1; Hsc70	12	0.01177937
p53 pathway	4	E1; L23; Cytochrome C; Ku70	79	0.02072214
beta-catenin ---/ KAI1	1	Reptin52	5	0.06701759
Aurora-A cell cycle regulation	2	Ubc5B; E1	34	0.07924485
JNK pathway	3	E1; 14-3-3zeta; Trx1	75	0.0813304
parkin associated pathways	2	E1; Hsc70	40	0.10447487
beta-catenin:E-cadherin complex phosphorylation and dissociation	1	alpha-catenin	9	0.11739049
stress-associated pathways	3	E1; 14-3-3zeta; Trx1	100	0.15476
hypoxia pathways	1	Trx1	24	0.2849595
TNF-alpha pathway	1	Trx1	36	0.39594524
EGF pathway	1	E1	103	0.57615756

**Mapping on pathways does
not work
(even in such a simple cases)**

Why ?

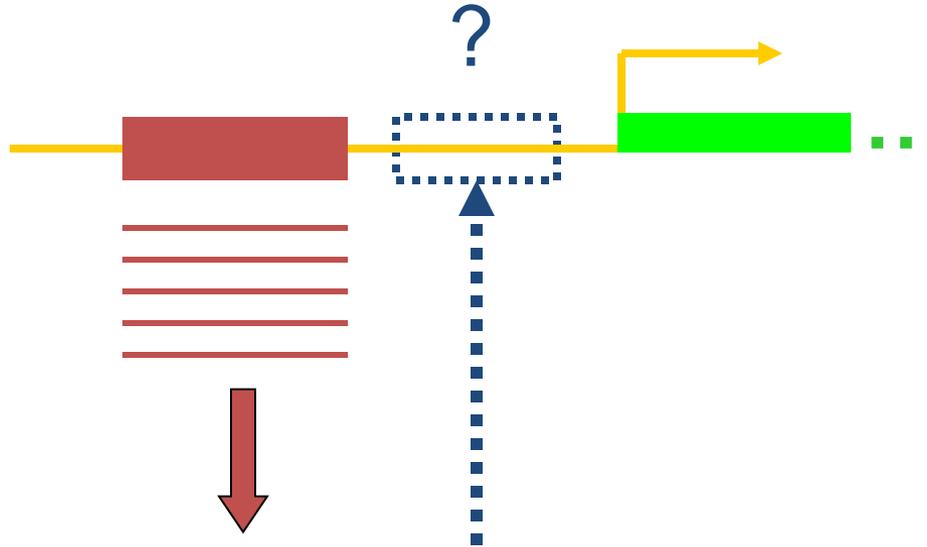
Pathways are
far from being
fully understood.

BIG gap of knowledge on interactions between TF and their target sites in DNA



TRANSPATH

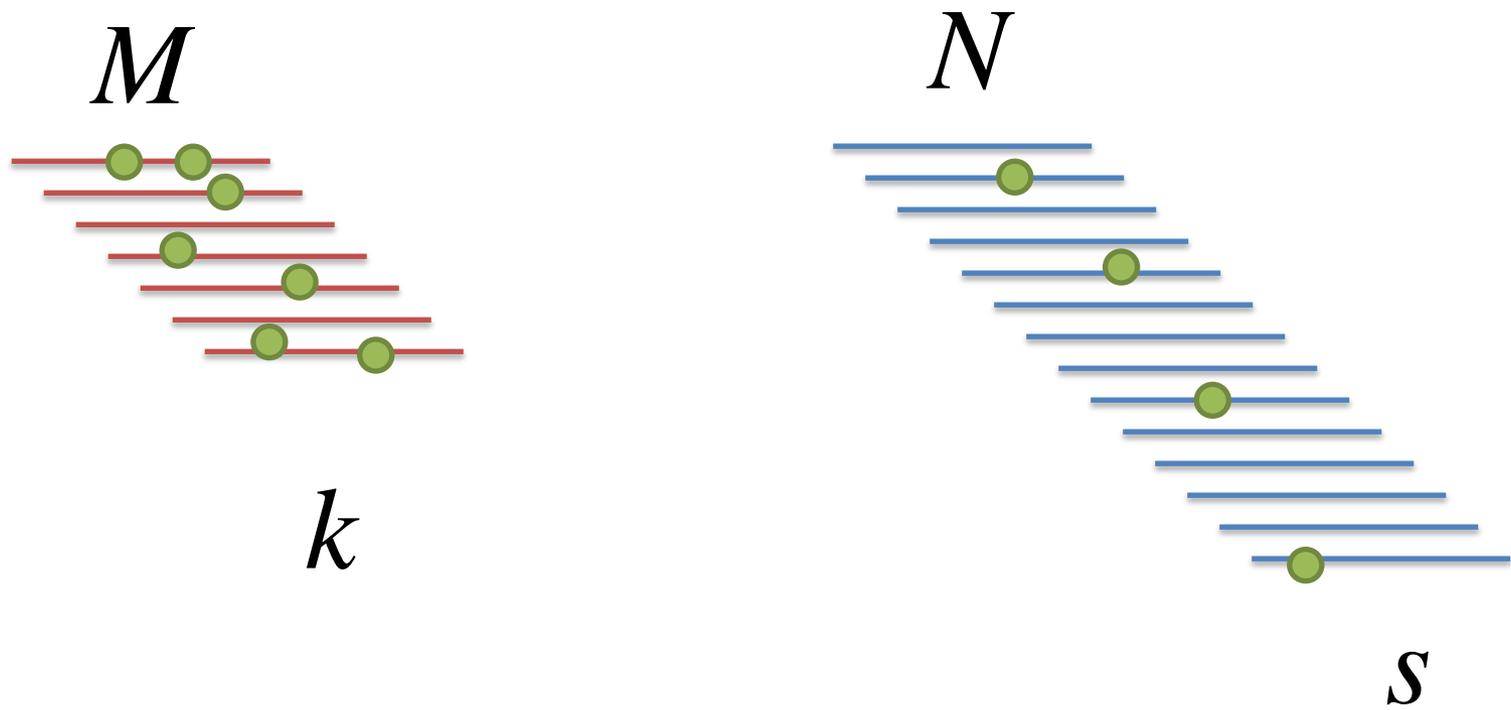
Search for new TF binding sites with PWMs (Match algorithm)



A	9	2	1	0	1	0	0	0	0	1	15	13	13	7
C	8	3	1	1	13	3	29	0	22	8	9	1	4	8
G	4	2	2	2	15	26	0	29	7	17	3	7	9	8
T	8	22	25	26	0	0	0	0	0	3	2	8	3	6
N	T	T	T	S	G	C	G	C	S	M	D	R		N

$$q = \frac{\sum_{i=1}^l I(i) f(b_i, i) - \sum_{i=1}^l I(i) f^{\min}(i)}{\sum_{i=1}^l I(i) f^{\max}(i)} \quad (1)$$

$$I(i) = \sum_{b \in \{A, T, G, C\}} f(b, i) \ln(4 f(b, i)) \quad (2)$$



$$p = M/N$$

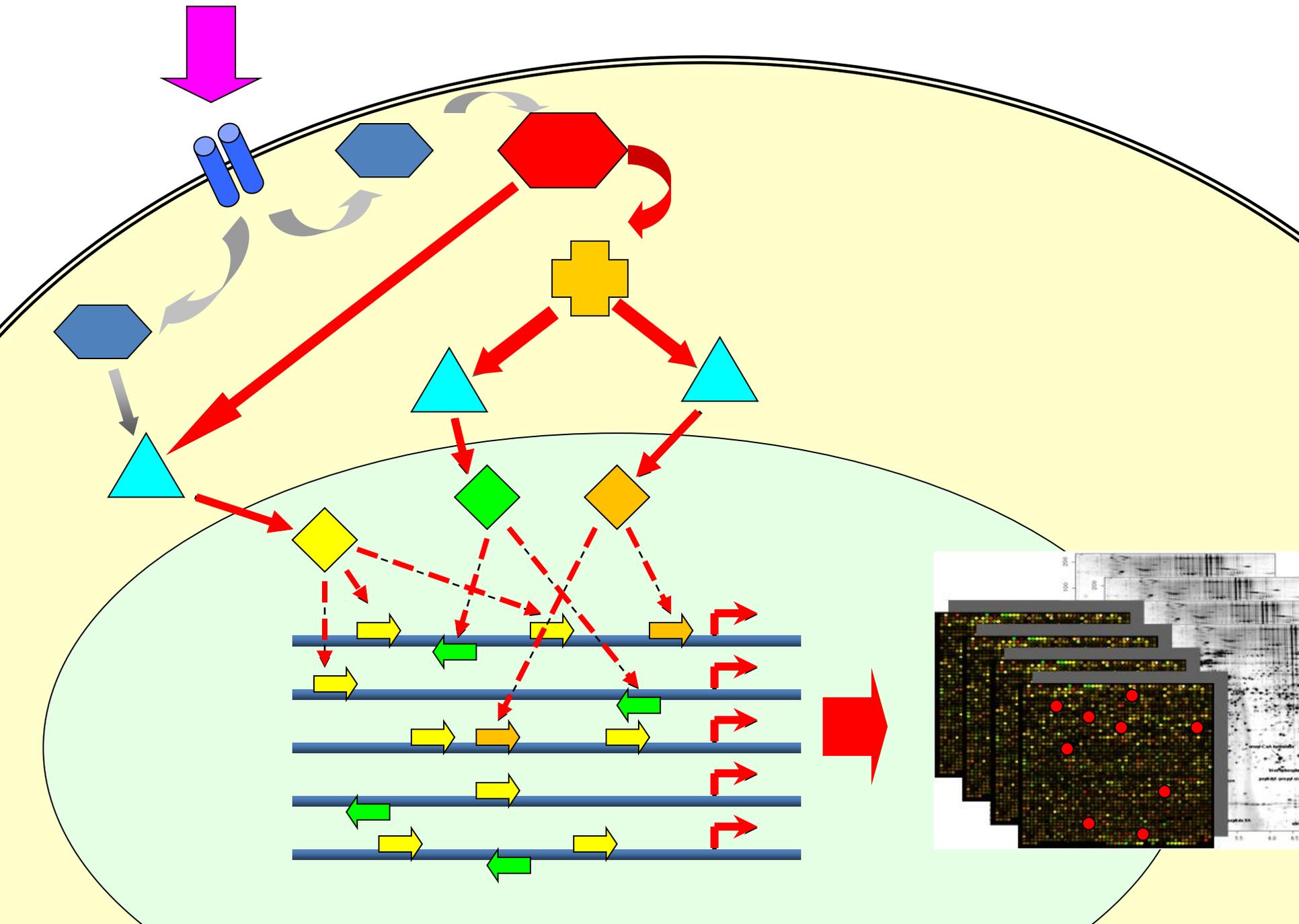
$$n = k + s$$

$$\text{p-value} = \sum_{i=k}^n \binom{n}{i} p^i (1-p)^{n-i}$$

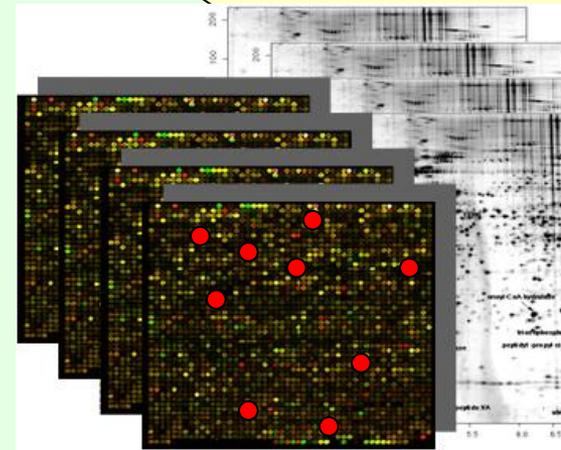
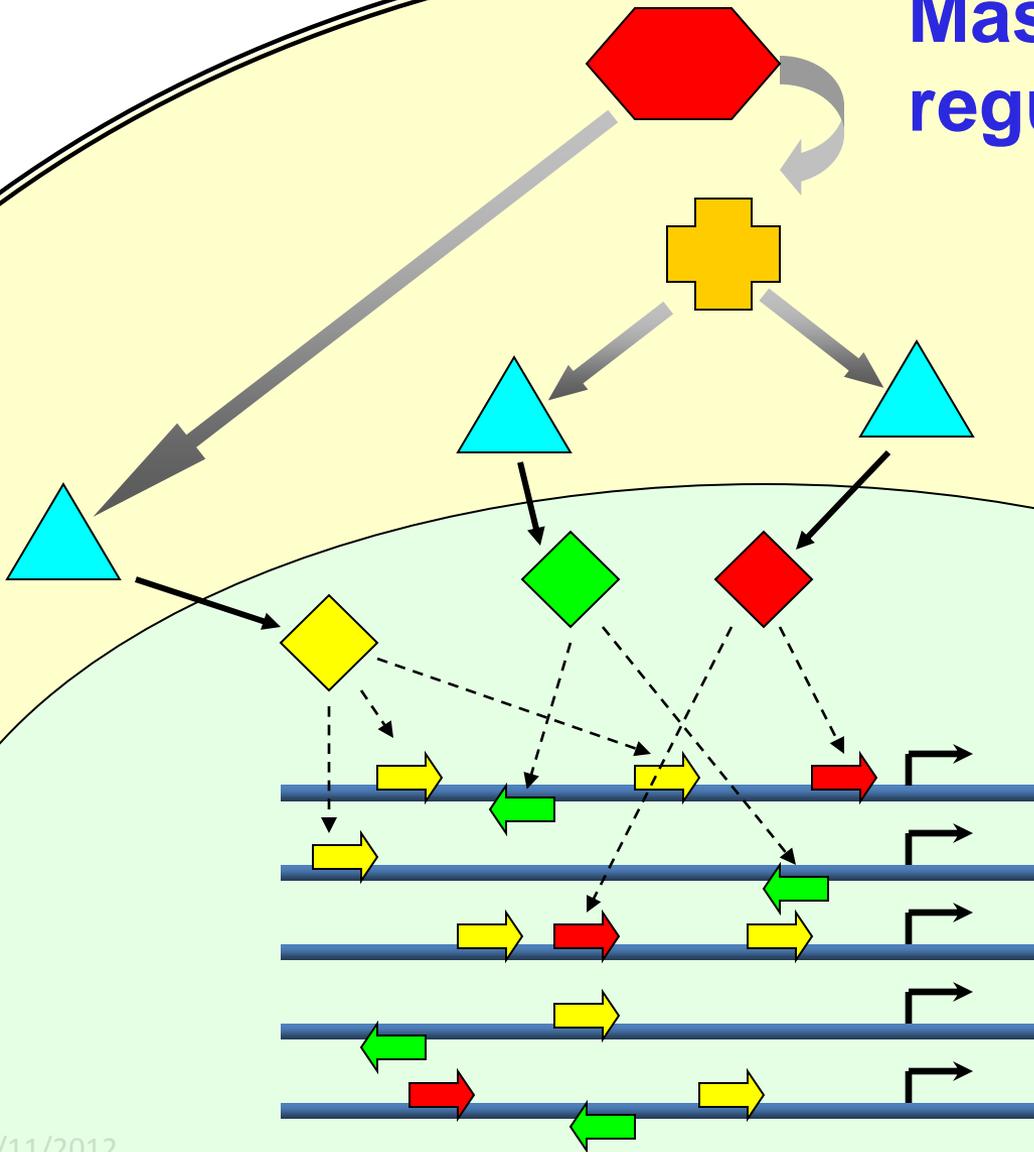
Overrepresented TFs in TNF-alpha regulated promoters

[First](#)
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[Last](#)
Showing 1 to 27 of 27 entries
Show entries

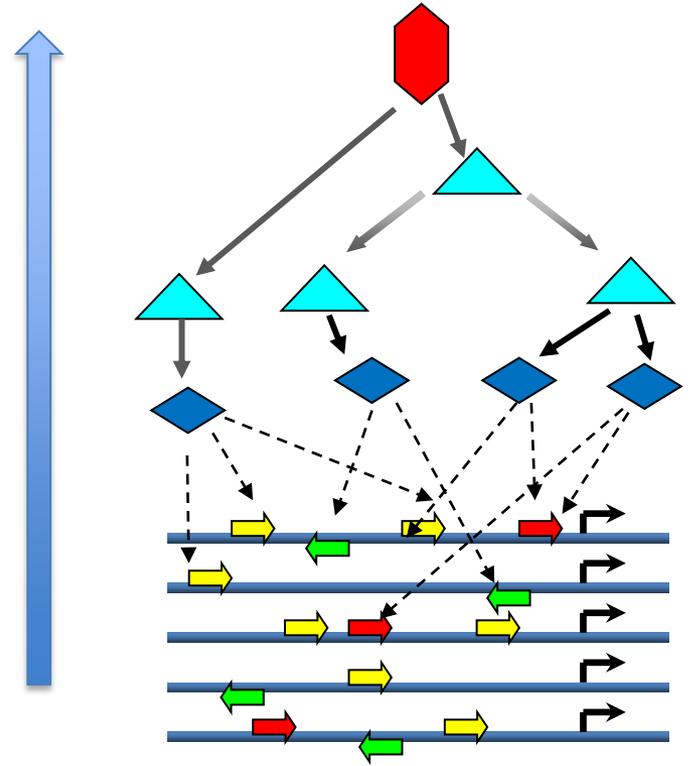
ID	Yes density per 1000bp	No density per 1000bp	Yes-no ratio	Matrix cutoff	P-value
V\$NFKB_Q6_01	0.30962	0.06917	4.47619	0.9337	1.3743E-5
V\$PPARG_01	0.36891	0.12846	2.87179	0.7339	1.4549E-4
V\$NKX3A_01	0.38208	0.13834	2.7619	0.9106	1.6526E-4
V\$PAX4_03	0.55336	0.2668	2.07407	0.9848	3.7636E-4
V\$XVENT1_01	0.14493	0.01976	7.33333	0.9328	6.6179E-4
V\$CP2_02	0.39526	0.16798	2.35294	0.9243	6.855E-4
V\$ZF5_B	0.21739	0.05929	3.66667	0.9211	8.5009E-4
V\$NKX22_01	0.47431	0.22727	2.08696	0.8995	8.9216E-4
V\$OCT1_07	0.49407	0.24704	2	0.8372	0.00119
V\$COREBINDINGFACTOR_Q6	0.11199	0.00988	11.33333	1	0.00132
V\$CEBPDELTA_Q6	0.21739	0.06917	3.14286	0.9615	0.00205
V\$IRF2_01	0.1054	0.00988	10.66667	0.909	0.00209
V\$POU3F2_02	0.16469	0.03953	4.16667	0.8875	0.0022
V\$PAX_Q6	0.19104	0.05929	3.22222	0.8706	0.0034
V\$AREB6_03	0.34256	0.16798	2.03922	0.9617	0.00546
V\$POU1F1_Q6	0.2108	0.07905	2.66667	0.9594	0.00606
V\$IRF_Q6	0.18445	0.06917	2.66667	0.9707	0.01017
V\$AP2_Q6	0.07246	0.00988	7.33333	0.9678	0.01959
V\$PBX_Q3	0.20422	0.09881	2.06667	0.9151	0.02736
V\$DMRT3_01	0.06588	0.00988	6.66667	0.9238	0.03023
V\$TTF1_Q6	0.1581	0.06917	2.28571	0.9881	0.03299
V\$AR_Q2	0.07905	0.01976	4	0.8671	0.03979
V\$HAND1E47_01	0.07905	0.01976	4	0.9652	0.03979
V\$AHR_Q5	0.05929	0.00988	6	0.9959	0.04636
V\$HOXA7_01	0.13175	0.05929	2.22222	1	0.05588



Master regulator

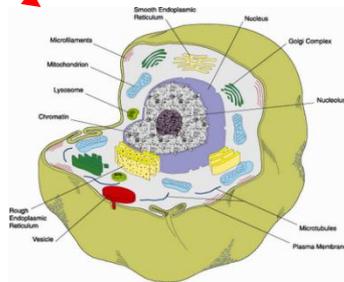
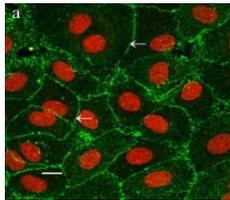


Search for the reason by the analysis of the ripples

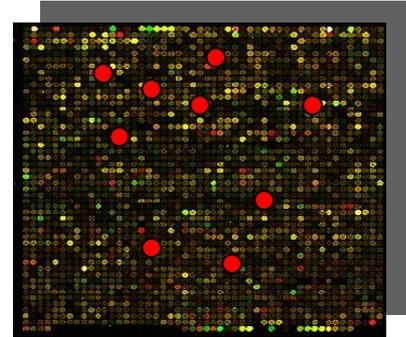


Can we predict TNF pathway?

?



117 differentially expressed genes



GeneXplain platform – target discovery pipeline

The screenshot displays the GeneXplain platform interface. At the top, a window titled 'nutlin3_UP_personalized' shows a table of gene expression data. Below this, a workflow diagram illustrates the analysis pipeline: 'Background set' leads to 'Sites on gene set', which then branches into 'summary' and 'Gene set Transpath'. 'summary' leads to 'Matrices to molecules', which then leads to 'Molecules' and 'Regulator search'. 'Gene set Transpath' also leads to 'Regulator search'. A 'Save hits' step leads to 'Molecules Upstream 8' and 'Molecules Instream 8 hits 2'. At the bottom, a network diagram shows a central node 'TRAF6' connected to 'Src-isoform1' and 'RIP1-isoform1', which are further connected to various other nodes like 'SIRT1alpha', 'SIRT1beta', 'SIRT1B', 'p75alpha', 'SIRT3-isoform1', 'NF-ATp43', 'Raf-1', 'ERK1', and 'ERK2'.

ID	name	title	SUM-p-value
A_32_P190809	ENSG00000111052	LIN7A	-93.26118912
A_24_P99145	ENSG00000140015	KCNH5	-63.58408057
A_23_P150053	ENSG00000107796	ACTA2	-60.69025229
A_24_P43810	ENSG00000147689	FAM83A	-59.39619785
A_23_P5392	ENSG00000115129	TP53I3	-57.06599393
A_32_P48397	ENSG00000196576	PLXNB2	-55.16124928
A_24_P865226	ENSG00000214725	AC120114.2	-54.60359943
A_23_P84219	ENSG00000163898	LIPH	-53.89717457
A_23_P52986	ENSG00000167992	VWCE	-53.62099399
A_24_P70888	ENSG00000196576	PLXNB2	-53.10577650

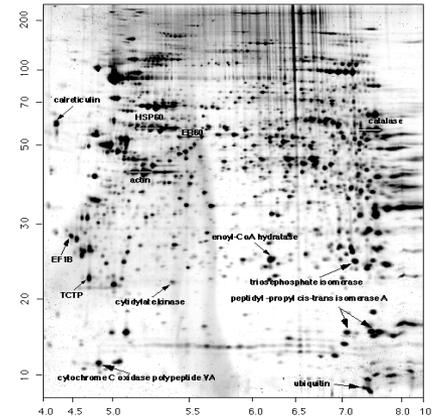
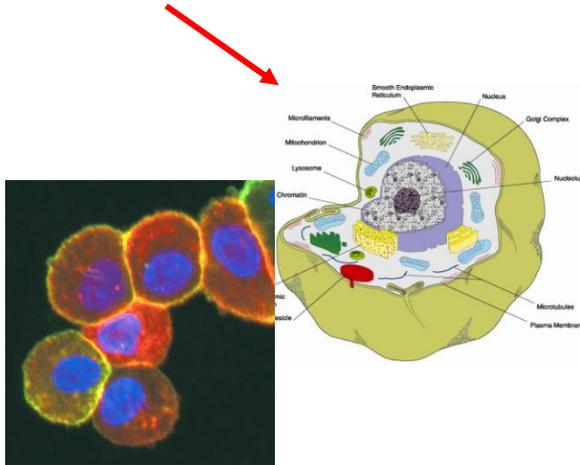
In this analysis, gene expression data from psoriasis lesion skin and uninvolved skin of the same 20 patients was analyzed. The following were the steps of analysis shown here.

1. CEL file normalization. This step resulted in two files, Experiment normalized (MAS5) and Control normalized (MAS5).

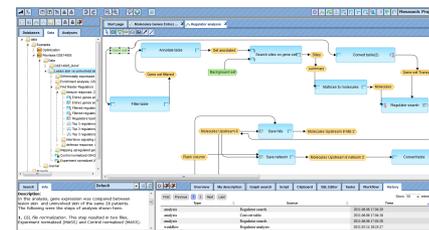
Human epidermoid carcinoma A431 cells treated by epidermal growth factor (EGF)

EGF ?

320 differentially expressed proteins



Master regulator analysis



EGF was still not in the list !



Pathways are
farfar....far
from being fully
undersood!

Combinatorial regulation

„Fuzzy puzzle“

AP-1

Consensus: TGA_gTCA

Human collagenase (-2013) * * * * *
TGA_gTCA

Mouse IL-2 (-143) * * * * *
TGTGTAA

Mouse IL-2 (-82) * * *
TGTAA_TA

Mouse c-fos promoter (Matrix search for TF binding sites)

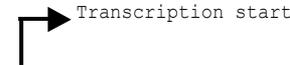
```

1          <-----V$IK1_01(0.86)   -----...V$CREBP1CJUN_01(0.85)
2          <-----V$IK2_01(0.90)   -----...V$CREB_01(0.96)
3          ----->V$AP2_Q6(0.87)   <-----V$GKLF_01(0.87)
4-->V$ATF_01(0.89)   <-----V$MZF1_01(0.99)   -----...V$ELK1_01(0.87)
5          <-----V$AP2_Q6(0.92)   <-----V$SP1_Q6(0.88)
6>V$AP1FJ_Q2(0.89)   <-----V$GKLF_01(0.85)
7>V$AP1_Q2(0.87)   <-----V$GKLF_01(0.86)
8->V$CREB_Q2(0.86)   <-----V$CTS1F54_01(0.90)
9->V$CREB_Q4(0.90)   <-----V$NRF2_01(0.90)
10         <-----V$GC_01(0.88)
11         ----->V$CAAT_01(0.87)
12         <-----V$TCF11_01(0.87)
13         ----->V$AP2_Q6(0.87)
14         <-----V$USF_Q6(0.93)
16         -----...V$ATF_01(0.94)
17         -----...V$AP1FJ_Q2(0.95)
20         -----...V$CREBP1_Q2(0.93)
21         -----...V$CREB_Q2(0.95)
23         -----...V$IK2_01(0.85)
MMCFOF_1  GAGCGCCCGCAGAGGGCCTTGGGGCGCGCTTCCCCCCTTCCAGTTCGCCCAGTGAGC  420

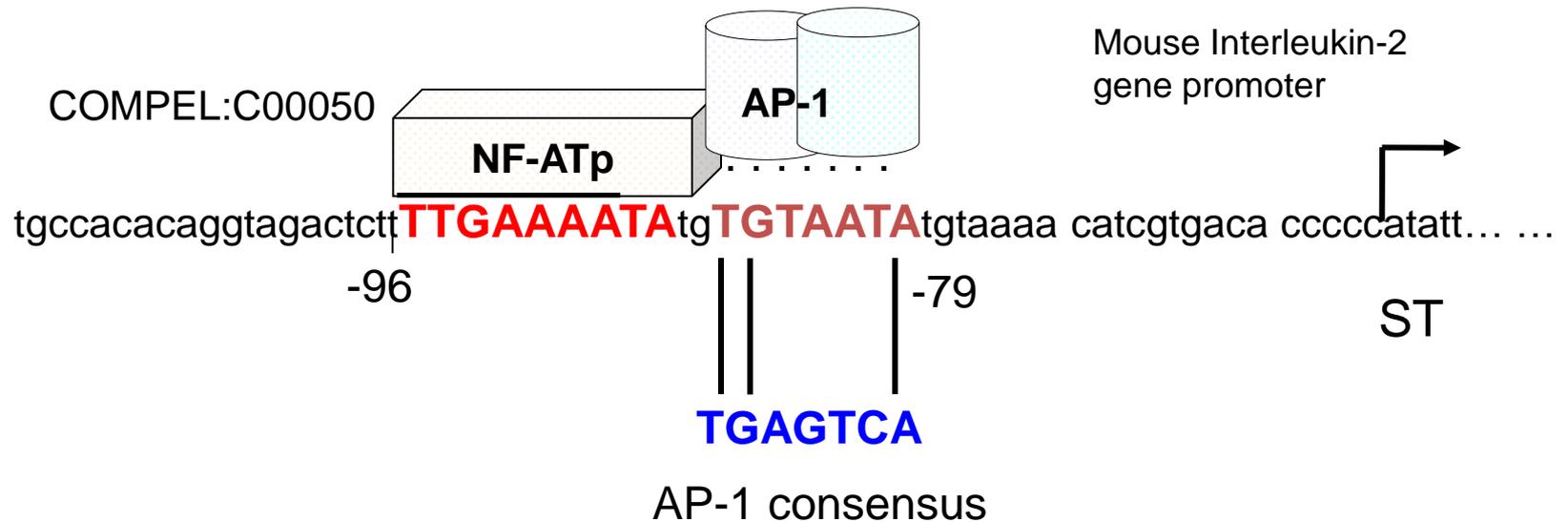
1-->V$CREBP1CJUN_01(0.85)   ----->V$BARBIE_01(0.86)
2-->V$CREB_01(0.96)   ----->V$TATA_01(0.95)
3          ----->V$CAAT_01(0.91)   ----->V$AP4_Q5(0.95)
4----->V$ELK1_01(0.87)   ----->V$HEN1_01(0.87)
5          ----->V$AP4_Q5(0.88)   <-----...V$CMYB_01(0.93)
6          <-----V$DPCR3HD_01(0.93)   -----...V$VMYB_02(0.89)
7          <-----V$TATA_01(0.88)
8          ----->V$HEN1_02(0.87)
9          <-----V$HEN1_02(0.86)
10         <-----V$AP4_Q1(0.88)
11         ----->V$LMO2COM_01(0.93)
12         <-----V$LMO2COM_01(0.93)
13         <-----V$MYOD_01(0.88)
17---->V$AP1FJ_Q2(0.95)   <-----V$AP4_Q6(0.99)
20---->V$CREBF1_Q2(0.93)   <-----V$MYOD_Q6(0.96)
21---->V$CREB_Q2(0.95)
23----->V$IK2_01(0.85)
24         <===== E2F (0.80)
MMCFOF_1  TAGGAAGTCCATCCATTACAGCGCTTCTATAAAGCGCCAGCTGAGGCGCCTACTACT  480

1          <-----V$CMYB_01(0.91)   -----...V$ER_Q6(0.86)
2          <-----V$LMO2COM_01(0.90)   <-----...V$TCF11_01(0.87)
3          ----->V$MYOD_Q6(0.90)   ----->V$STAT_01(0.93)
4          ----->V$VMYB_01(0.89)   <-----V$STAT_01(0.89)
5----->V$CMYB_01(0.93)   ----->V$LMO2COM_02(0.93)
6----->V$VMYB_02(0.89)   <-----V$CAAT_01(0.85)
7          ----->V$VMYB_02(0.88)
8          ----->V$EV11_04(0.86)
9          ----->V$GATA1_02(0.93)
12         <-----V$ZID_01(0.85)
13         <-----V$CP2_01(0.97)
14         ----->V$GATA_C(0.92)
15         ----->V$CMYB_01(0.86)
16         ----->V$CREL_01(0.91)
24         <===== E2F (0.82)
MMCFOF_1  CAACCGGACTGCAGCGAGCAACTGAGAAGACTGGATAGAGCCGGCGGTTCCCGGAACGA  540

```



One of the TF binding sites in a composite elements can be rather weak.
Weak DNA-protein interactions are stabilized by protein-protein interactions.



Composite Modules (CM)

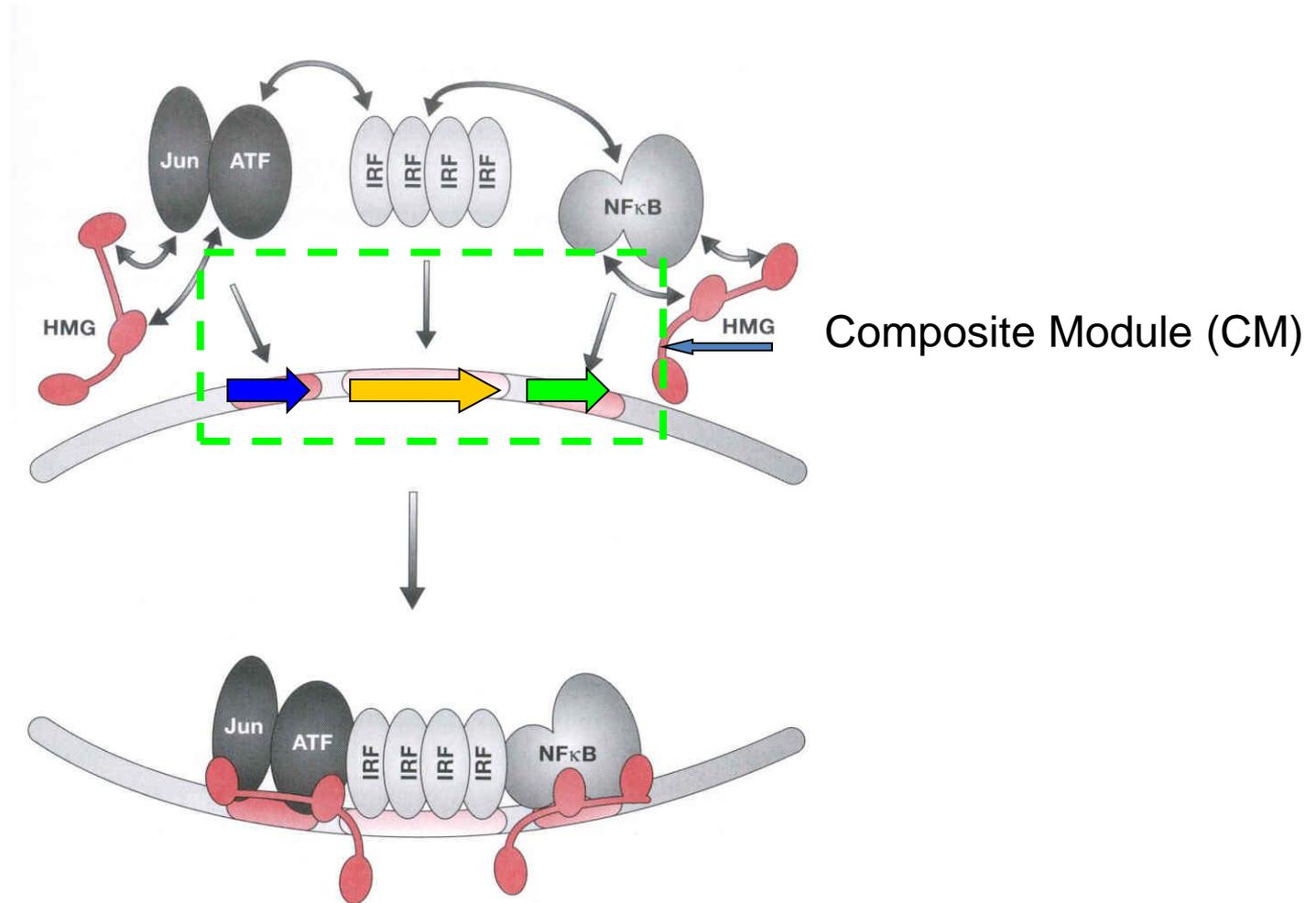
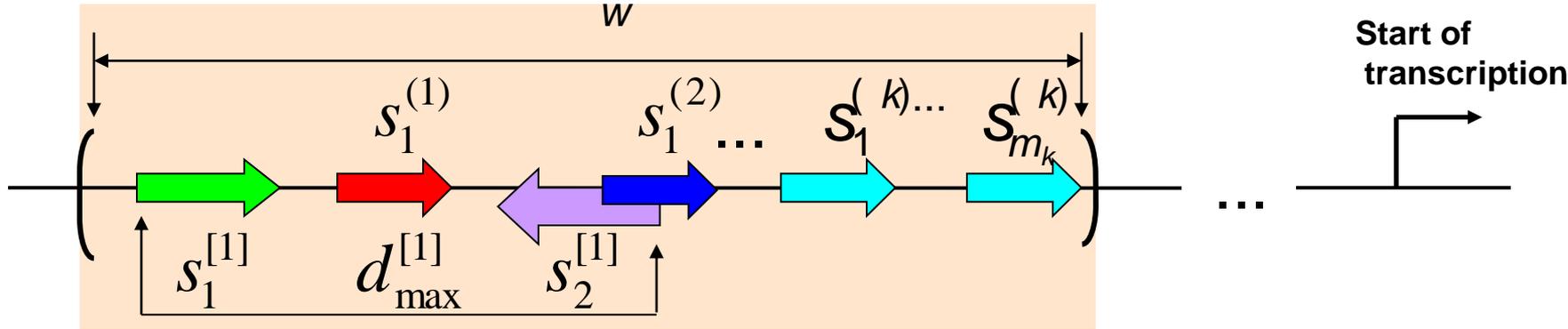


FIGURE 3.3. The human interferon- β enhanceosome. HMG represents HMGI/Y, a ubiquitous protein that binds cooperatively with the three activators. HMGI/Y both bends the DNA and contacts the activators. Each of the transcription factors shown is a member of a family of related activators (Mark Ptashne, Alexander Gann *Genes and Signals*, 2002)

Composite Modules (CM)



$d_{\max}^{[1]}$	$d_{\max}^{[1]}$...	$d_{\max}^{[R]}$	} Parameters of the model to be estimated by GA
$q_{cut-off}^{(1)}$	$q_{cut-off}^{(2)}$...	$q_{cut-off}^{(k)}$	
$\phi^{(1)}$	$\phi^{(2)}$...	$\phi^{(k)}$	

We created a genetic algorithm to find site combinations

Composite Modules (CM)

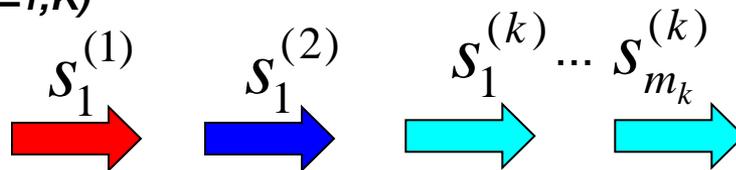
Composite Module Score (*cms*)

K, the number of individual PWMs in the module, ($k=1, K$)

Matrix cut-off values: $q_{cut-off}^{(k)}$

Relative impact values: $\phi^{(k)}$

Maximal number of best matches: m_k



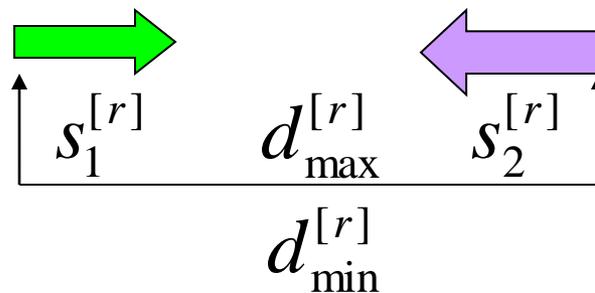
R, the number of pairs of PWMs

($r=1, R$)

Matrix cut-off values: $q_{1,cut-off}^{[r]}$ $q_{2,cut-off}^{[r]}$

Relative impact values: $\phi^{[r]}$

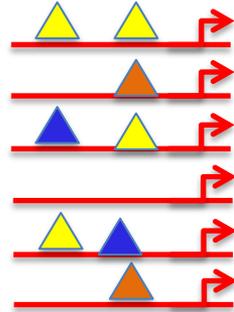
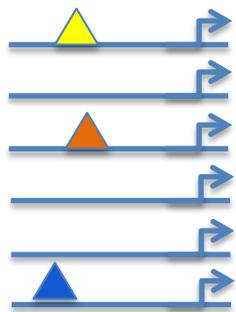
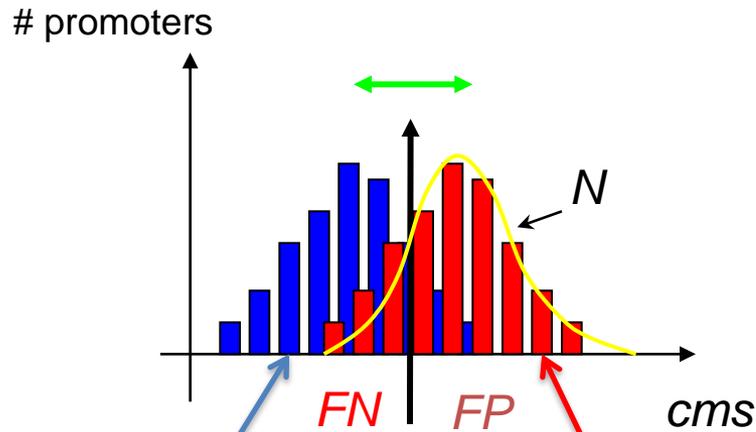
Maximal and minimal distances: $d_{max}^{[r]}$ $d_{min}^{[r]}$



$$cms = \sum_{k=1, K} \phi^{(k)} \times \sum_{i=1}^{m_k} q_i^{(k)} + \sum_{r=1, R} \phi^{[r]} \times (q_1^{[r]} + q_2^{[r]}) / MAX$$

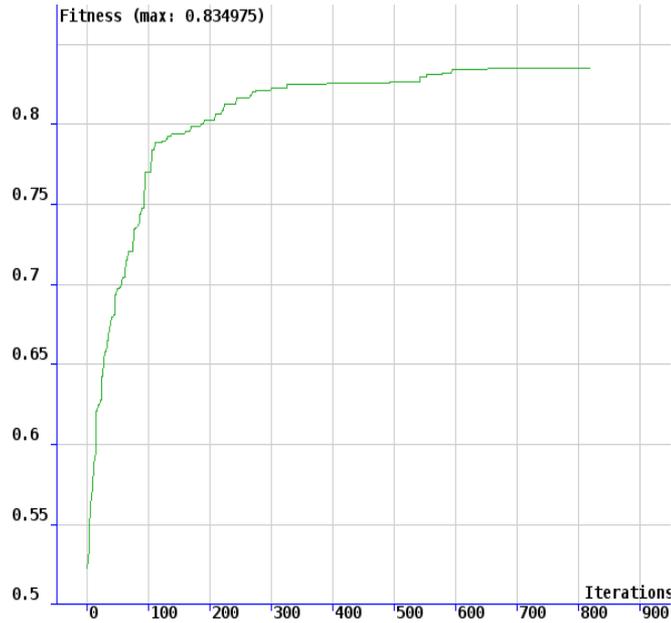
Fitness function of the Genetic-Regression Algorithm (GRA)

$$F = \alpha \cdot R + \beta \cdot (1 - FN) + (1 - \beta) \cdot (1 - FP) + \gamma \cdot T + \delta \cdot N - \mu \cdot k$$



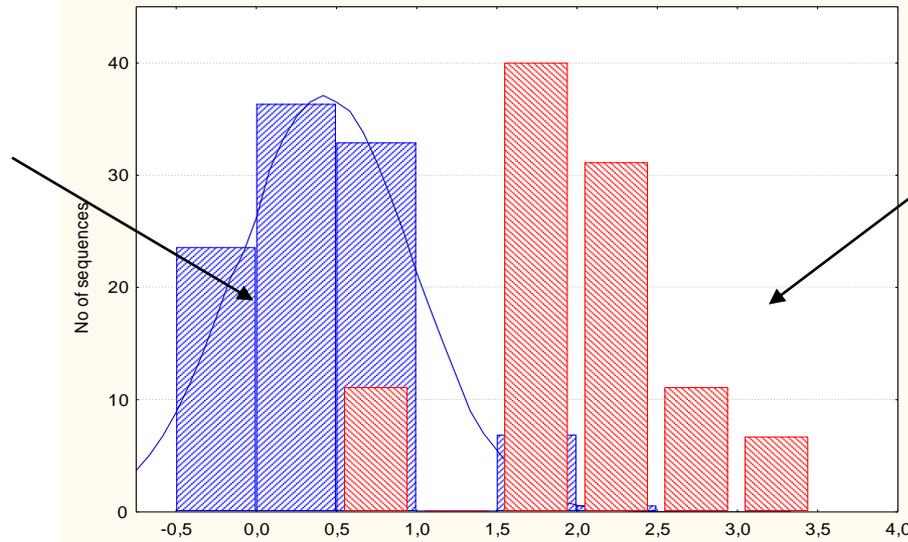
- R – linear regression
- FN – false negatives
- FP – false positives
- T – T-test (difference between mean values)
- N – normal likeness
- k – number of free parameters

Composite module in promoters of cell cycle-related genes



Weight: ϕ	$q_{cut-off}$	TF matrix
1.000000	0.840072	V\$E2F_19
0.954483	0.737637	V\$TATA_01
0.888064	0.939687	V\$CREB_01
0.816179	0.941583	V\$SP1_Q6
0.039746	0.839702	V\$TAL1BETAE47_01

Background sequences



Cell cycle-related promoters

Mouse c-fos promoter

```

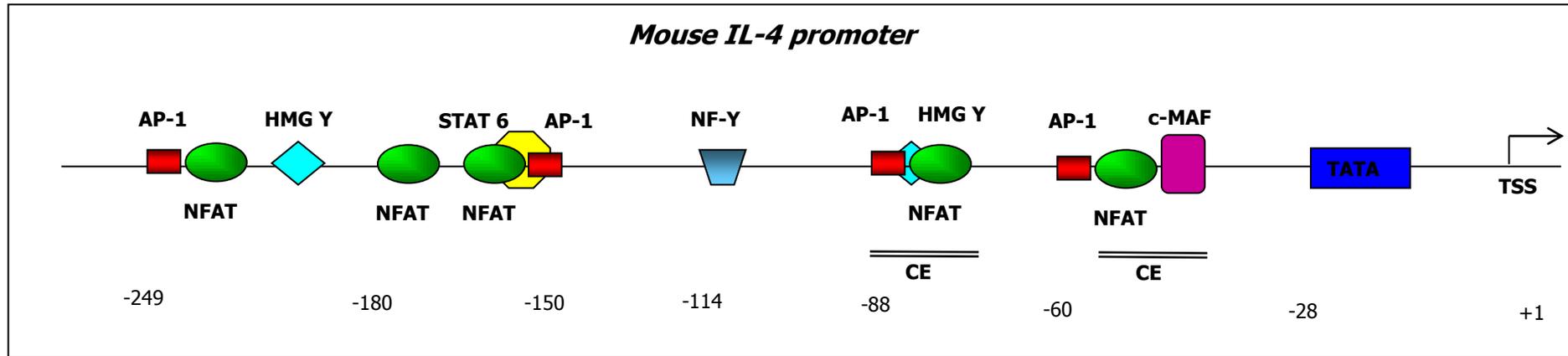
1          <-----V$IK1_01(0.86) -----..V$CREBP1CJUN_01(0.85)
2          <-----V$IK2_01(0.90) -----..V$CREB_01(0.96)
3          ----->V$AP2_Q6(0.87) <-----V$GKLF_01(0.87)
4-->V$ATF_01(0.89) <-----V$MZF1_01(0.99) -----..V$ELK1_01(0.87)
5          <-----V$AP2_Q6(0.92) <-----V$SP1_Q6(0.88)
6>V$AP1FJ_Q2(0.89) <-----V$GKLF_01(0.85)
7>V$AP1_Q2(0.87) <-----V$GKLF_01(0.86)
8->V$CREB_Q2(0.86) <-----V$CTSLF54_01(0.90)
9->V$CREB_Q4(0.90) <-----V$NRF2_01(0.90)
10         <-----V$GC_01(0.88)
11         ----->V$CAAT_01(0.87)
12         <-----V$TCF11_01(0.87)
13         ----->V$AP2_Q6(0.87)
14         <-----V$USF_Q6(0.93)
16         -----..V$ATF_01(0.94)
17         -----..V$AP1FJ_Q2(0.95)
20         -----..V$CREBP1_Q2(0.93)
21         -----..V$CREB_Q2(0.95)
23         -----..V$IK2_01(0.85)
MMCFOS_1  GAGCGCCCGCAGAGGGCCTTGGGGCGCGCTTCCCCCCCCTTCCAGTTCGCCCCAGTGAGC 420
1-->V$CREBP1CJUN_01(0.85) ----->V$BARBIE_01(0.86)
2-->V$CREB_01(0.96) ----->V$TATA_01(0.95)
3          ----->V$CAAT_01(0.91) ----->V$AP4_Q5(0.95)
4----->V$ELK1_01(0.87) ----->V$HEN1_01(0.87)
5          ----->V$AP4_Q5(0.88) <-----..V$CMYB_01(0.93)
6          <-----V$CDPCR3HD_01(0.93) -----..V$VMYB_02(0.89)
7          <-----V$TATA_01(0.88)
8          ----->V$HEN1_02(0.87)
9          <-----V$HEN1_02(0.86)
10         <-----V$AP4_01(0.88)
11         ----->V$LMO2COM_01(0.93)
12         <-----V$LMO2COM_01(0.93)
13         <-----V$MYOD_01(0.88)
17---->V$AP1FJ_Q2(0.95) <-----V$AP4_Q6(0.99)
20---->V$CREBP1_Q2(0.93) <-----V$MYOD_Q6(0.96)
21---->V$CREB_Q2(0.95)
23----->V$IK2_01(0.85)
24         <-----E2F(0.80)
MMCFOS_1  TAGGAAGTCCATCCATTACAGCGCTTCTATAAAGGCGCCAGCTGAGGCGCCTACTACTC 480
1          <-----V$CMYB_01(0.91) -----..V$ER_Q6(0.86)
2          <-----V$LMO2COM_01(0.90) <-----..V$TCF11_01(0.87)
3          ----->V$MYOD_Q6(0.90) ----->V$STAT_01(0.93)
4          ----->V$VMYB_01(0.89) <-----V$STAT_01(0.89)
5-----V$CMYB_01(0.93) ----->V$LMO2COM_02(0.93)
6----->V$VMYB_02(0.89) <-----V$CAAT_01(0.85)
7          ----->V$VMYB_02(0.88)
8          ----->V$EVI1_04(0.86)
9          ----->V$GATA1_02(0.93)
12         <-----V$ZID_01(0.85)
13         <-----V$CP2_01(0.97)
14         ----->V$GATA_C(0.92)
15         ----->V$CMYB_01(0.86)
16         ----->V$REL_01(0.91)
24         <-----E2F(0.82)
MMCFOS_1  CAACCGGACTGCAGCGAGCAACTGAGAAGACTGGATAGAGCCGGGTTCCGCGAACGA 540
1----->V$ER_Q6(0.86)
2-----V$TCF11_01(0.87)
3          ----->V$AP4_Q5(0.91)
4          ----->V$AP4_Q6(0.87)
5          ----->V$AP1FJ_Q2(0.93)
6          ----->V$AP1_Q2(0.90)
7          ----->V$AP1_Q4(0.87)
8          <-----V$IK2_01(0.94)
MMCFOS_1  GCAGTGACCGCGCTCCCACCCAGCTCTCTGCAGCTCC 580

```

Transcription start



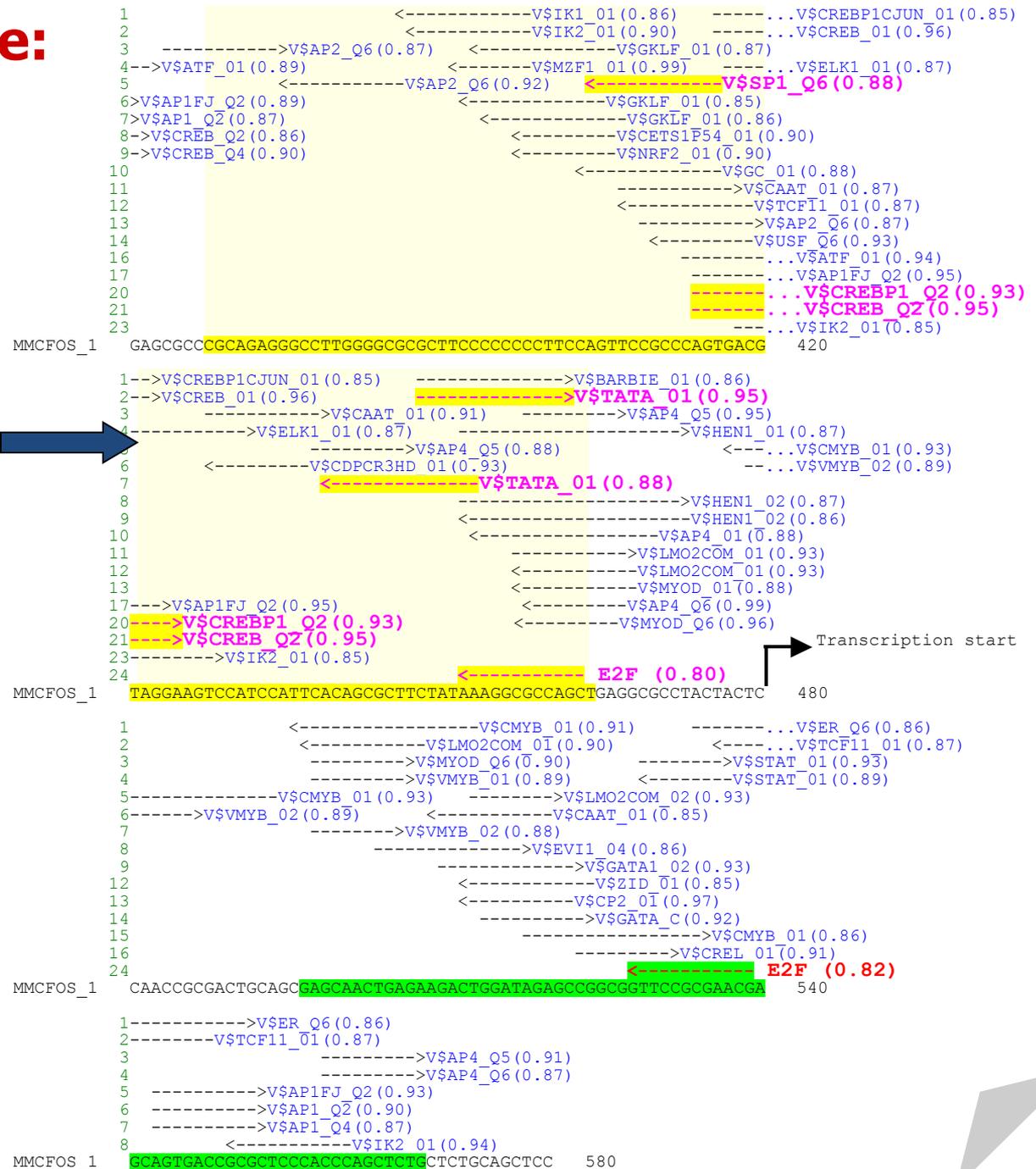
Promoter structure: current paradigm



Promoter is a parking place



Promoter structure: reality



Mouse c-fos promoter



Transcription start



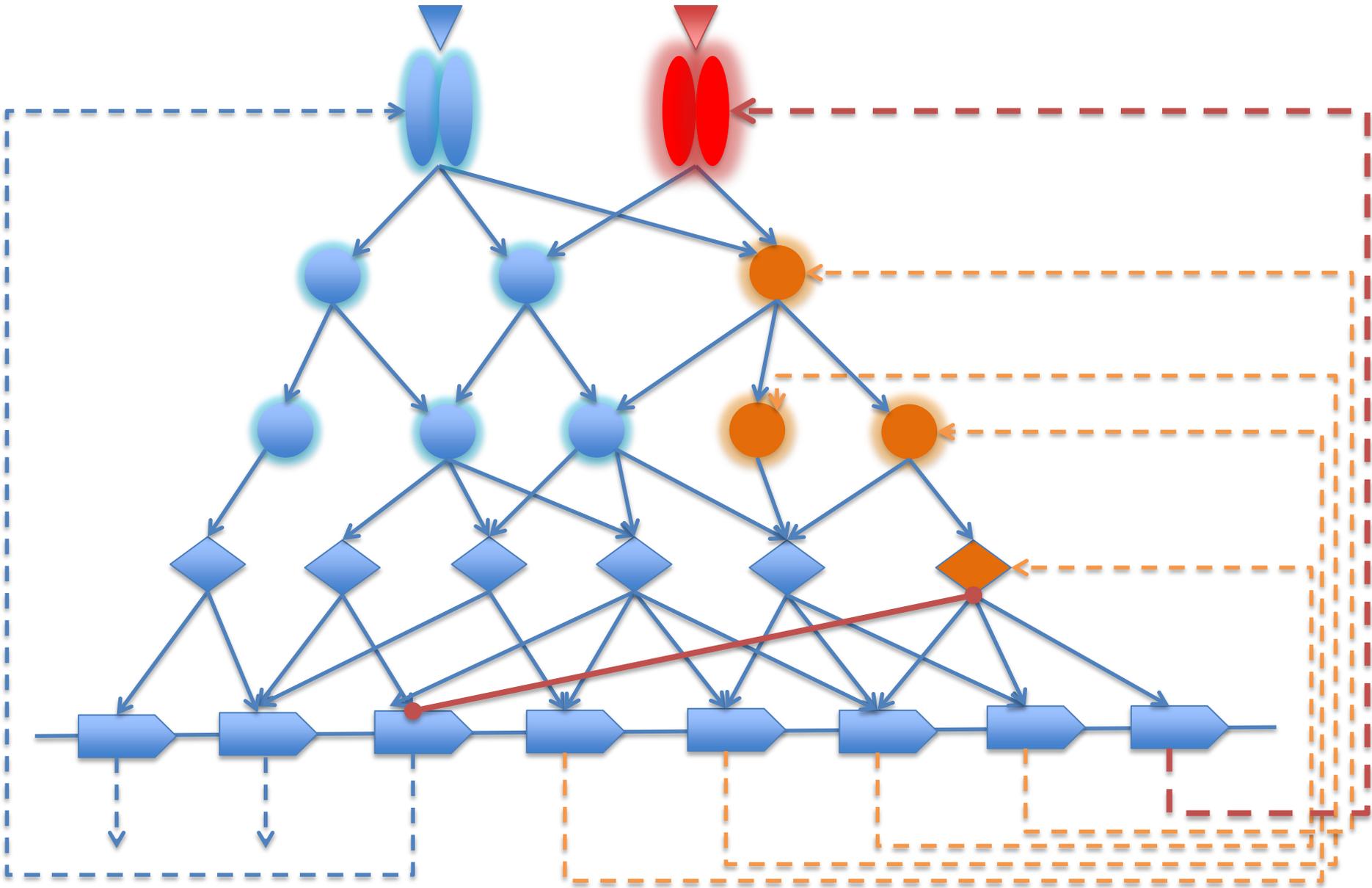
Parking in Italy

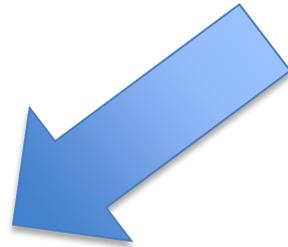




Network plasticity

„Walking pathways“





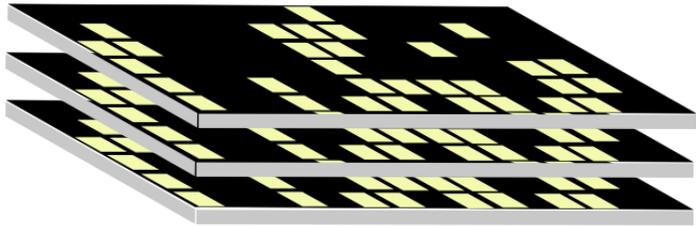
Epidermal Growth Factor induced Carcinogenicity

Philip Stegmaier¹, Alexander Kel¹, Edgar Wingender^{1,2}, and Jürgen Borlak³

Hepatocellular transcriptome data of IgEGF-overexpressing mice



transgenic

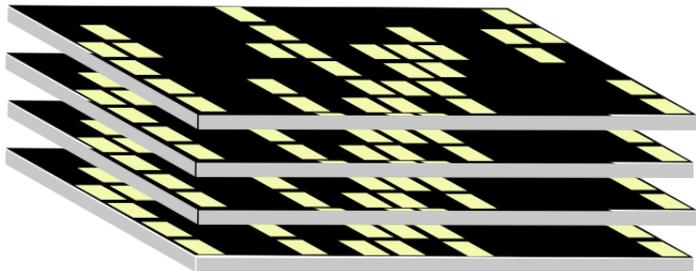


transgenic/normal

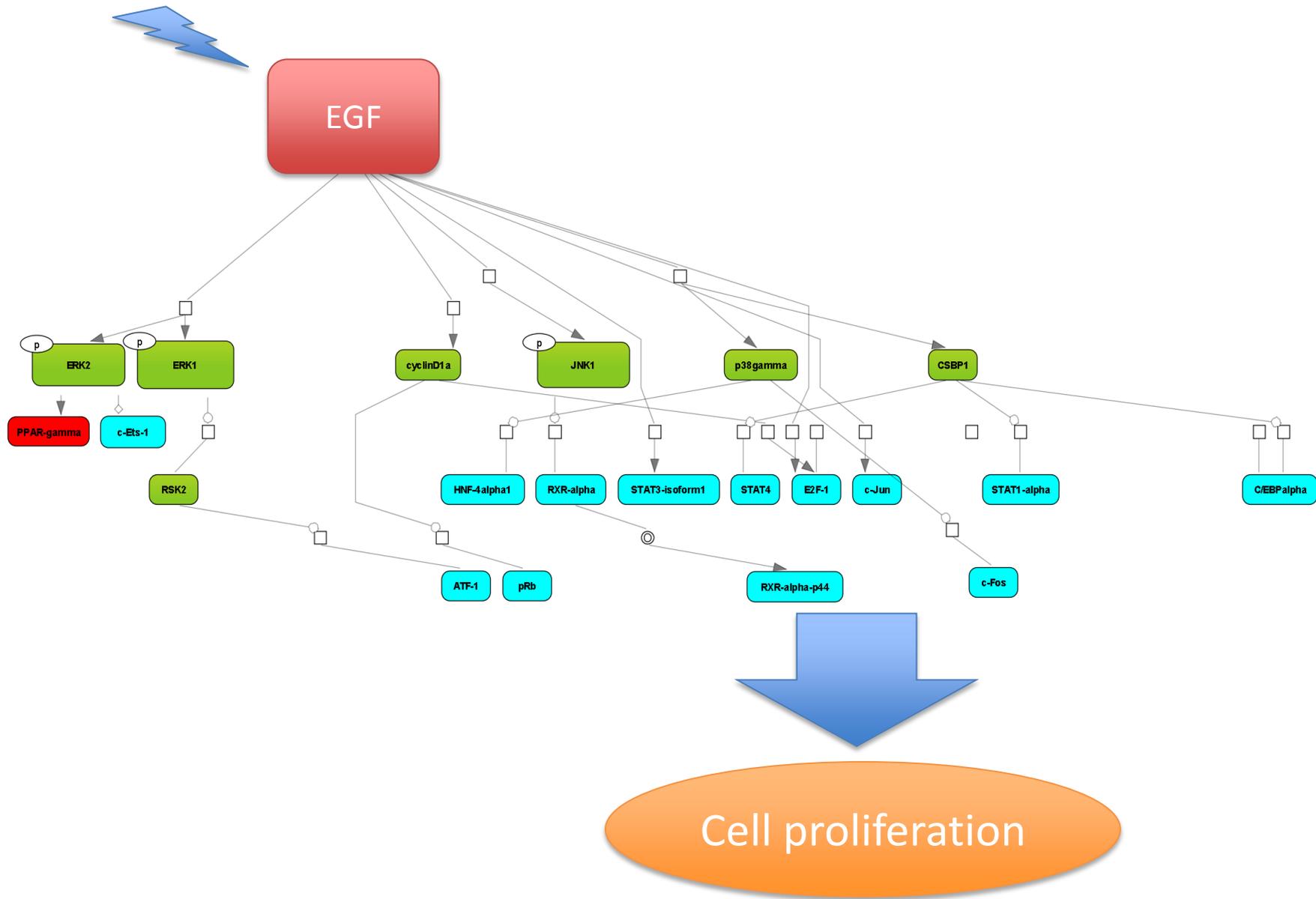
Tumoregenic
switch

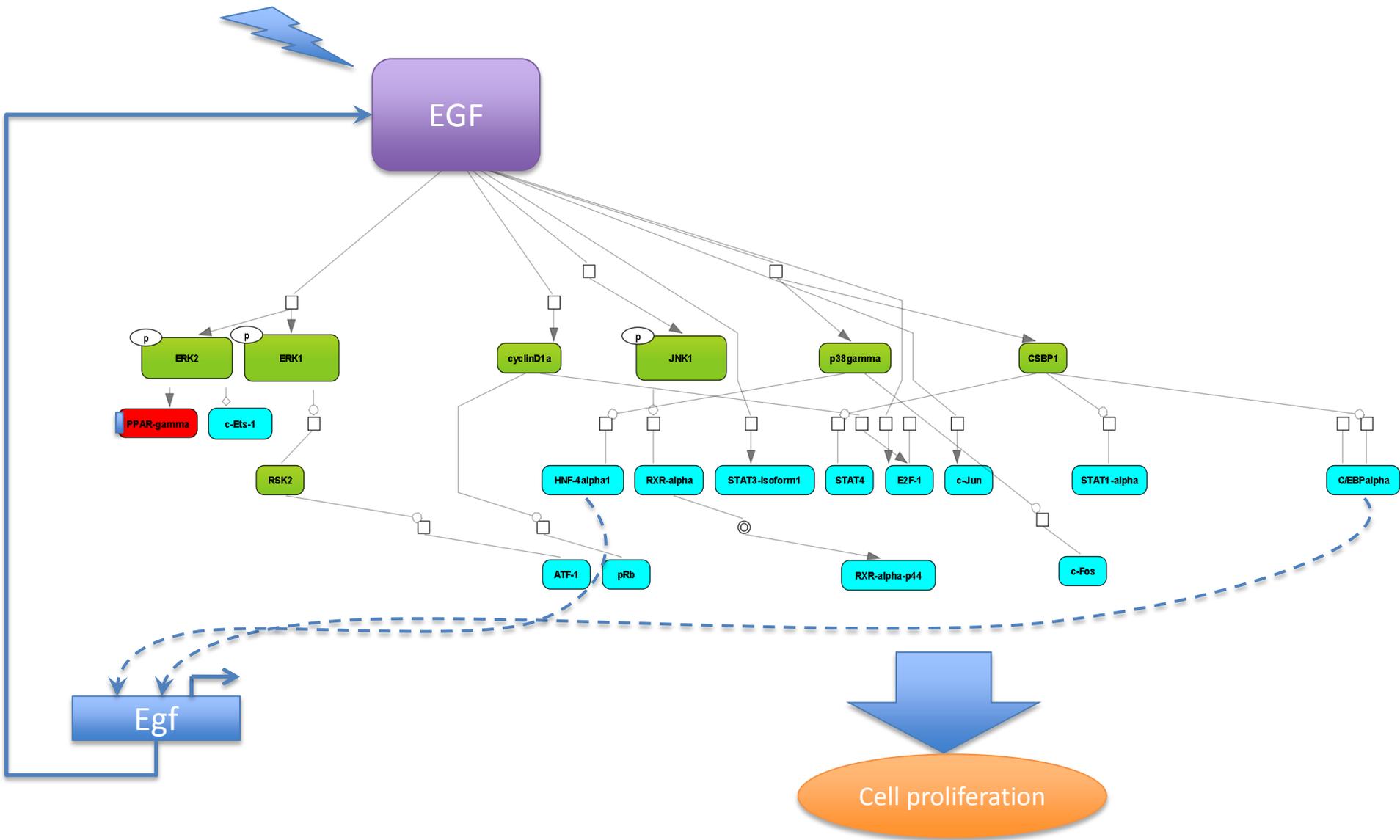


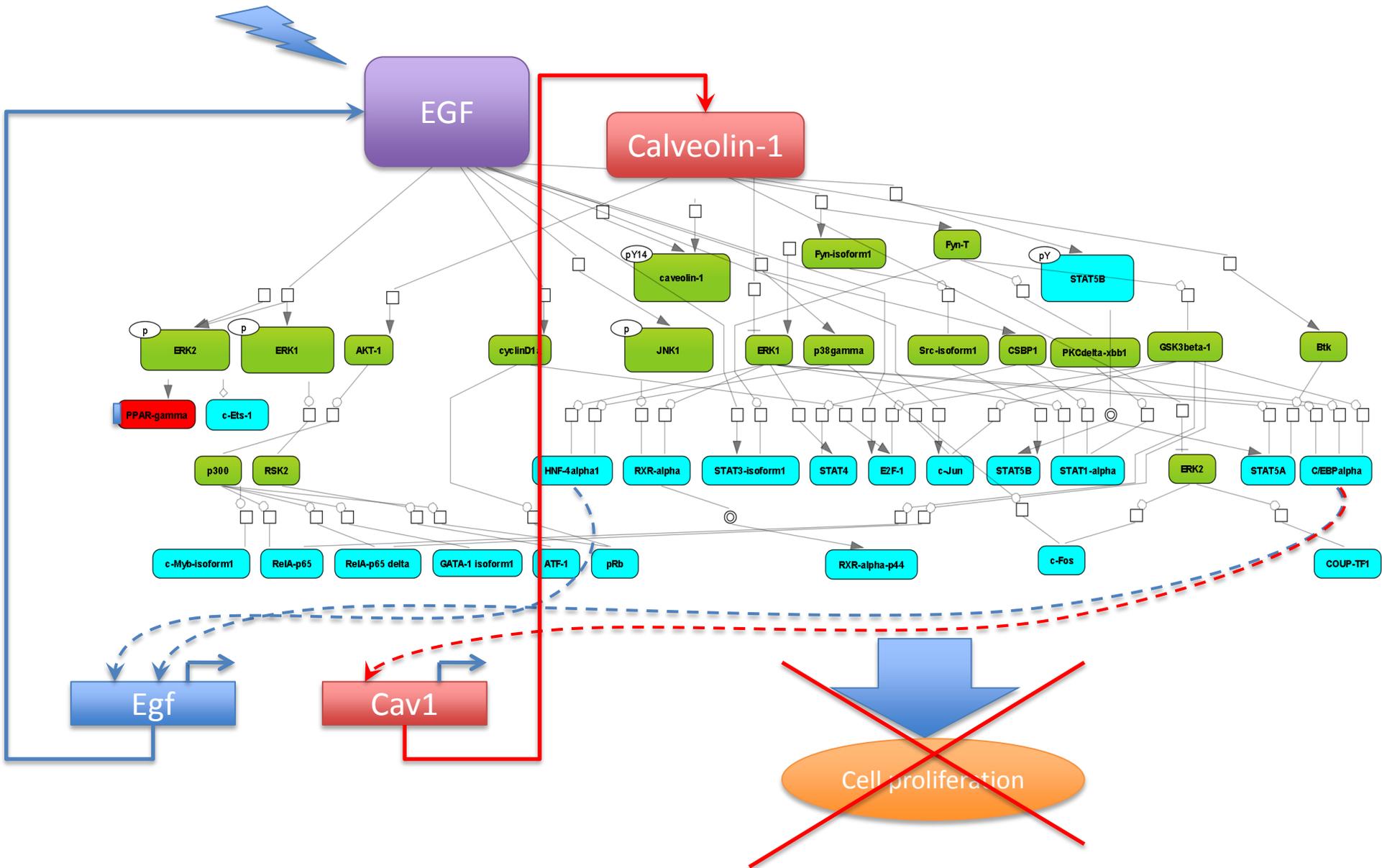
small tumor

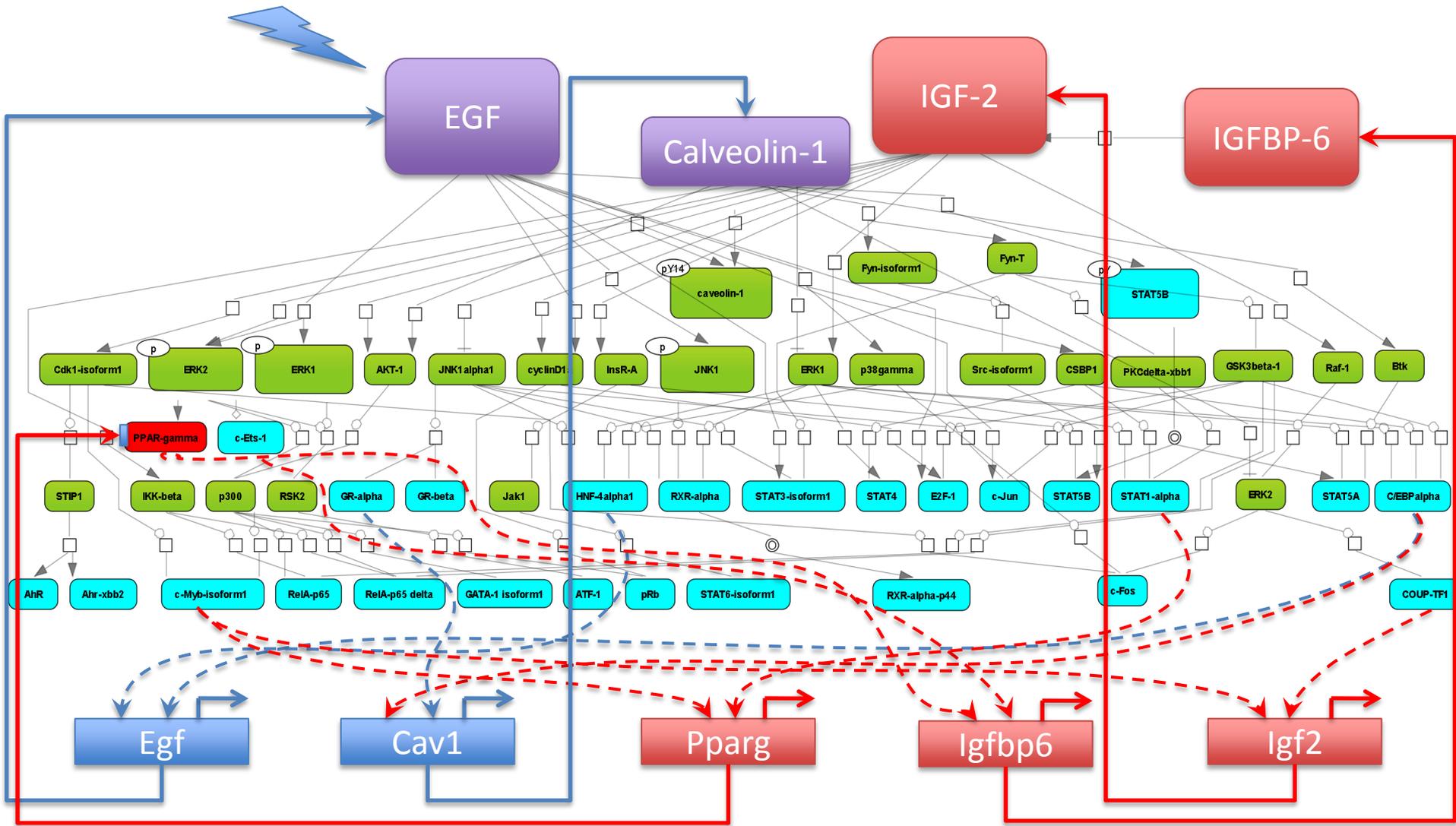


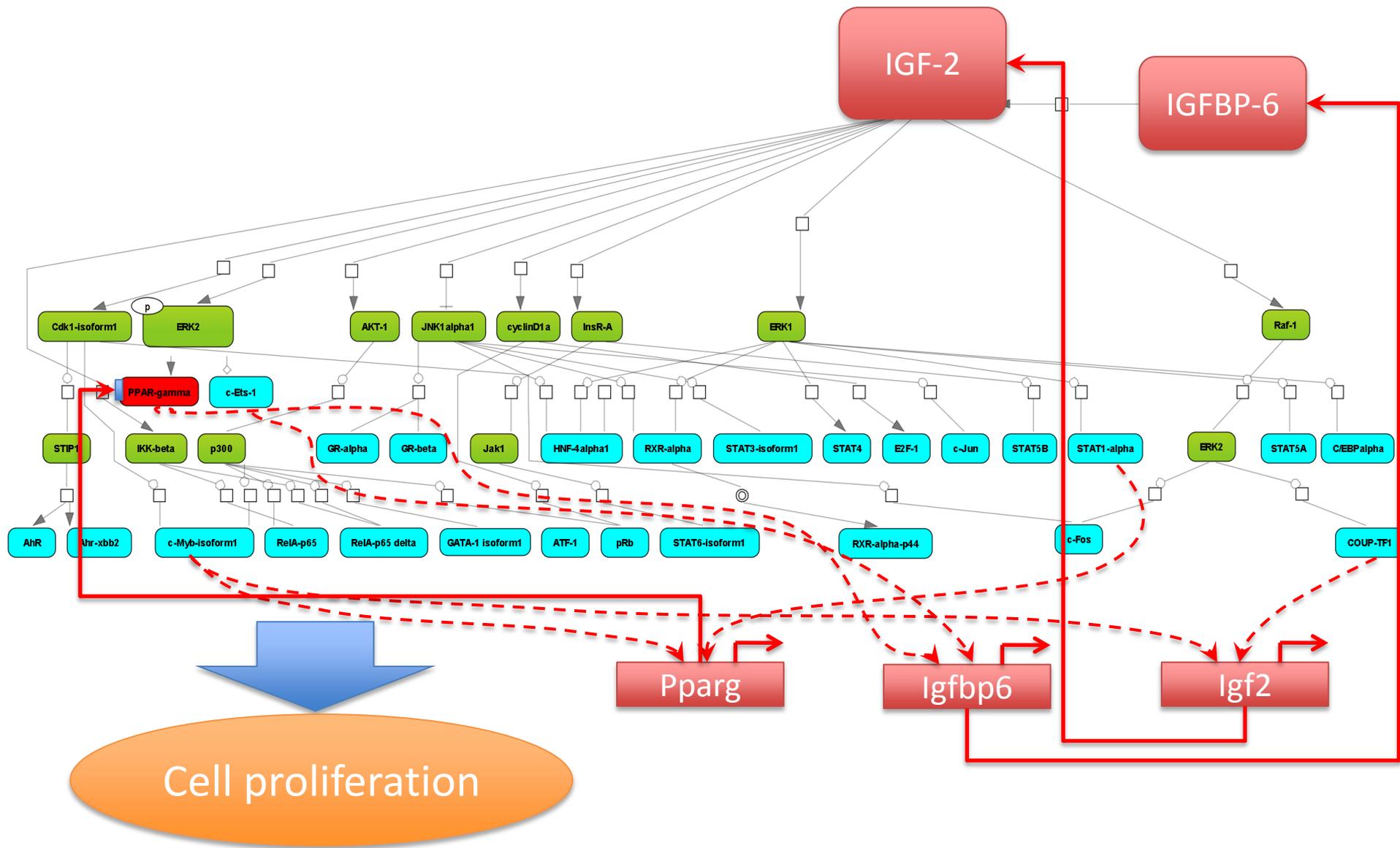
small tumor/normal







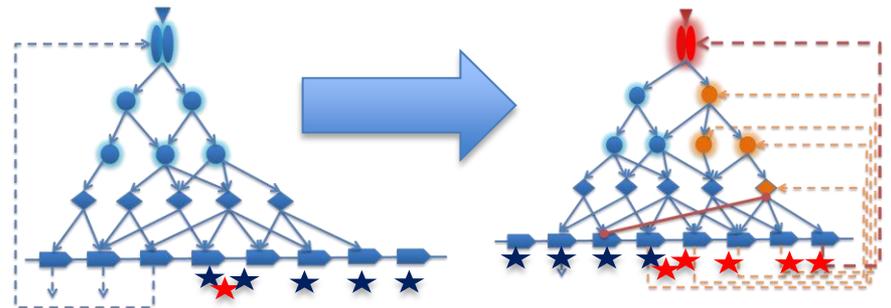




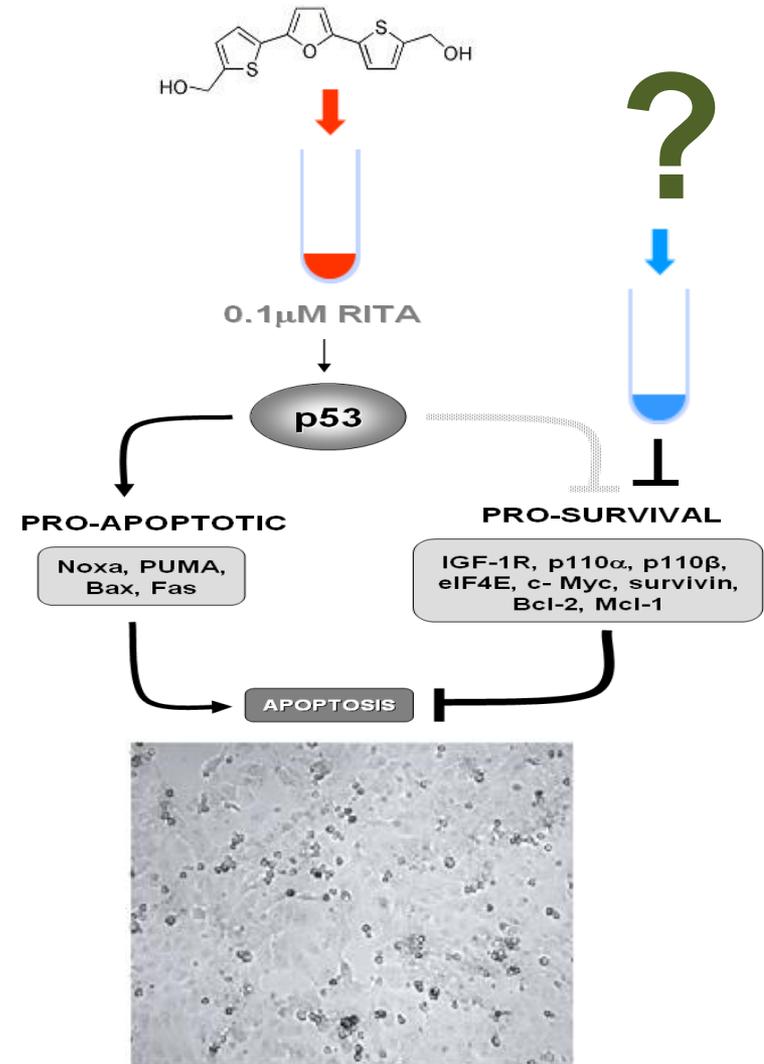
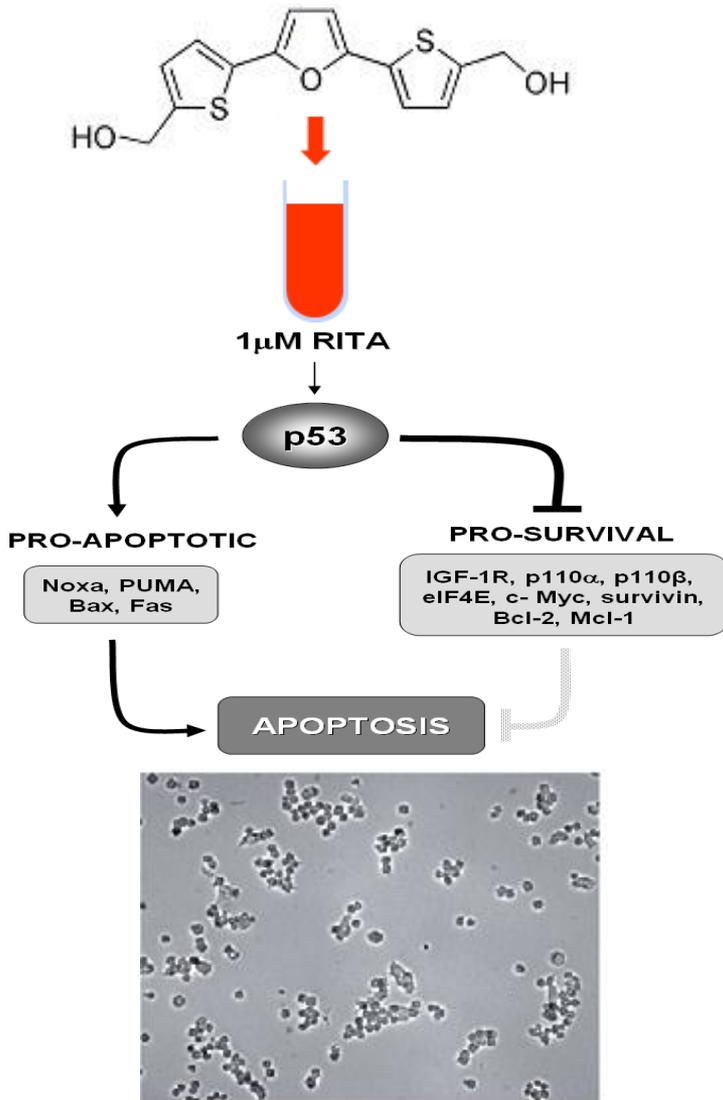
DNA is an active component
of biochemical networks.

Network plasticity is a result
of epigenetic evolution
in the cells.

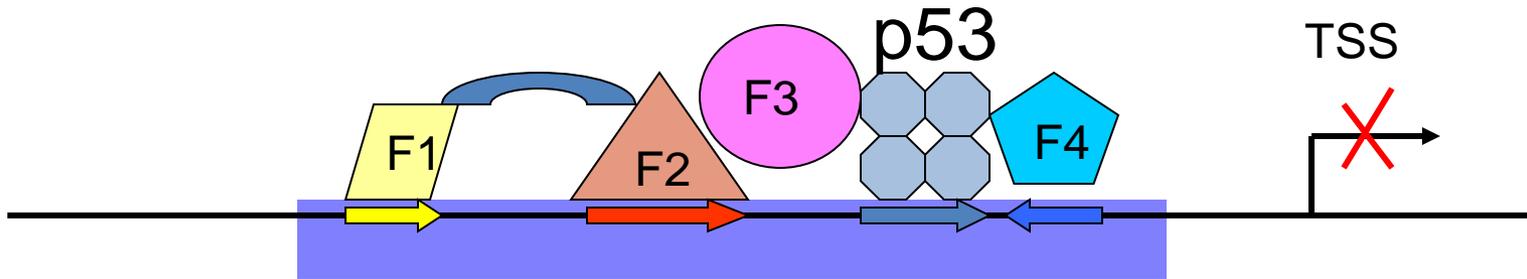
Cancer is cracking the combinatorial regulatory code



Net2Drug

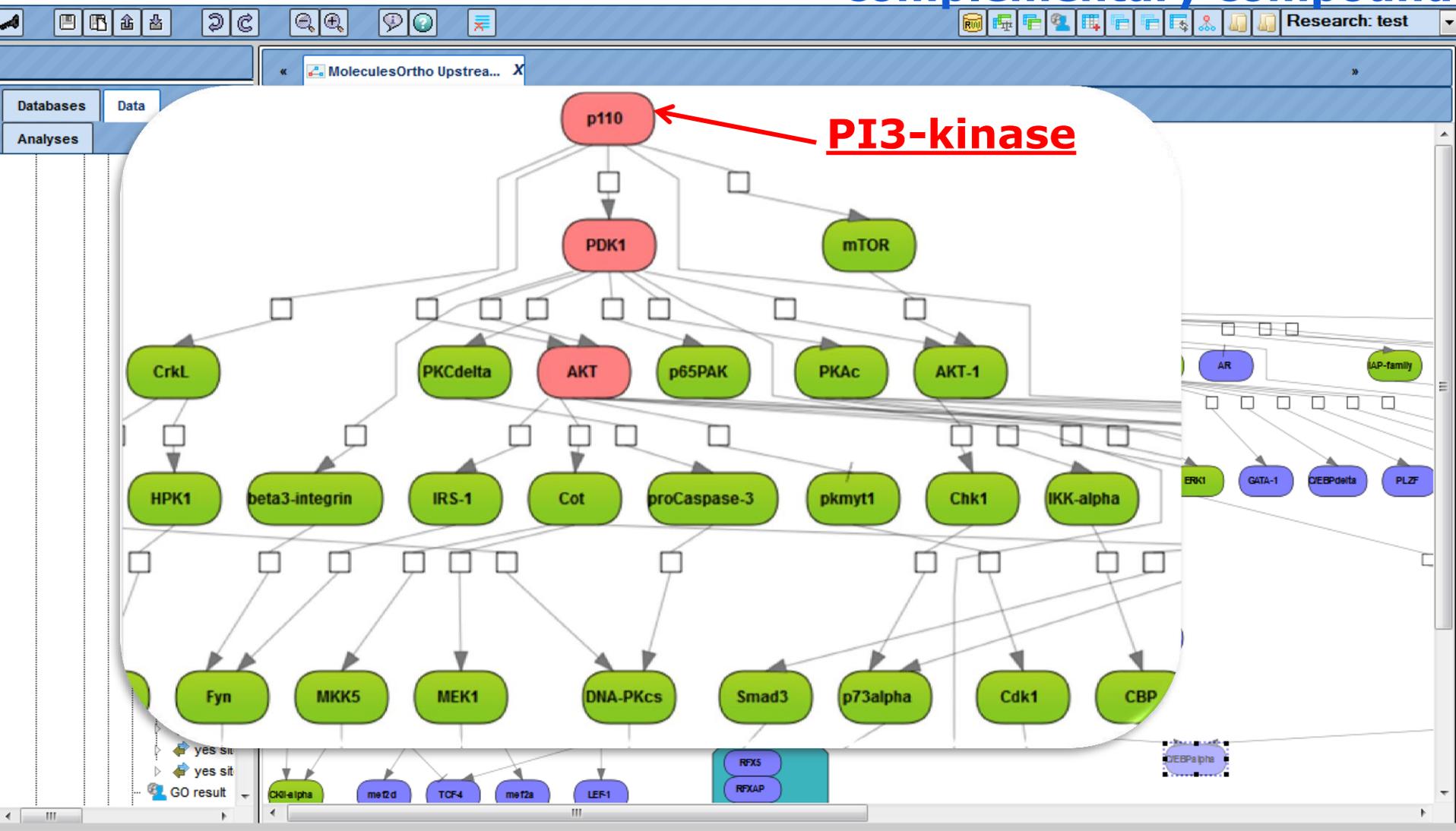


Enhanceosome binding area

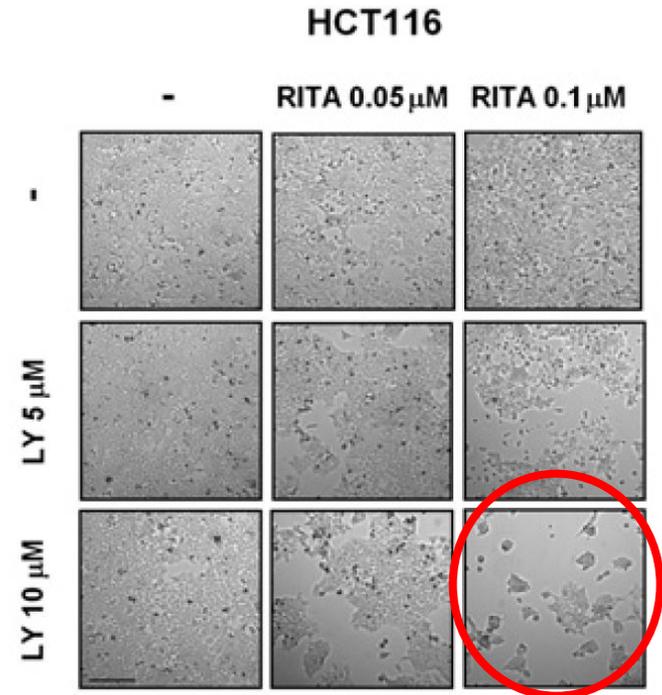
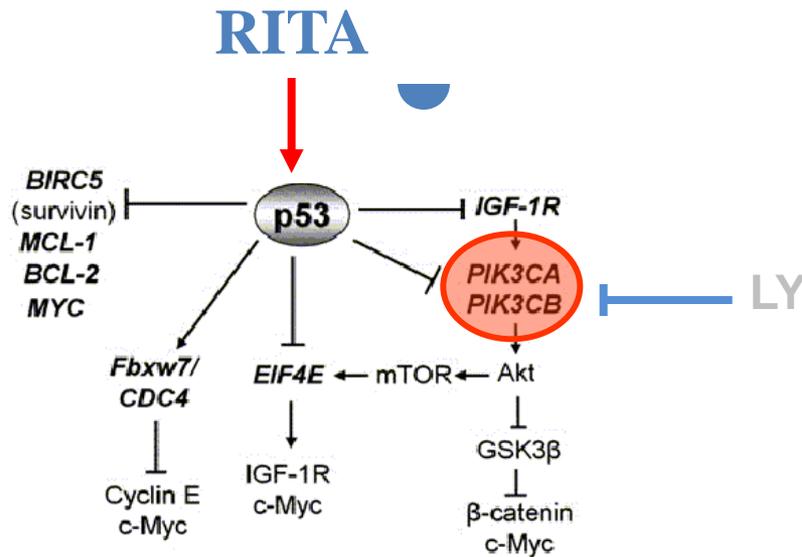


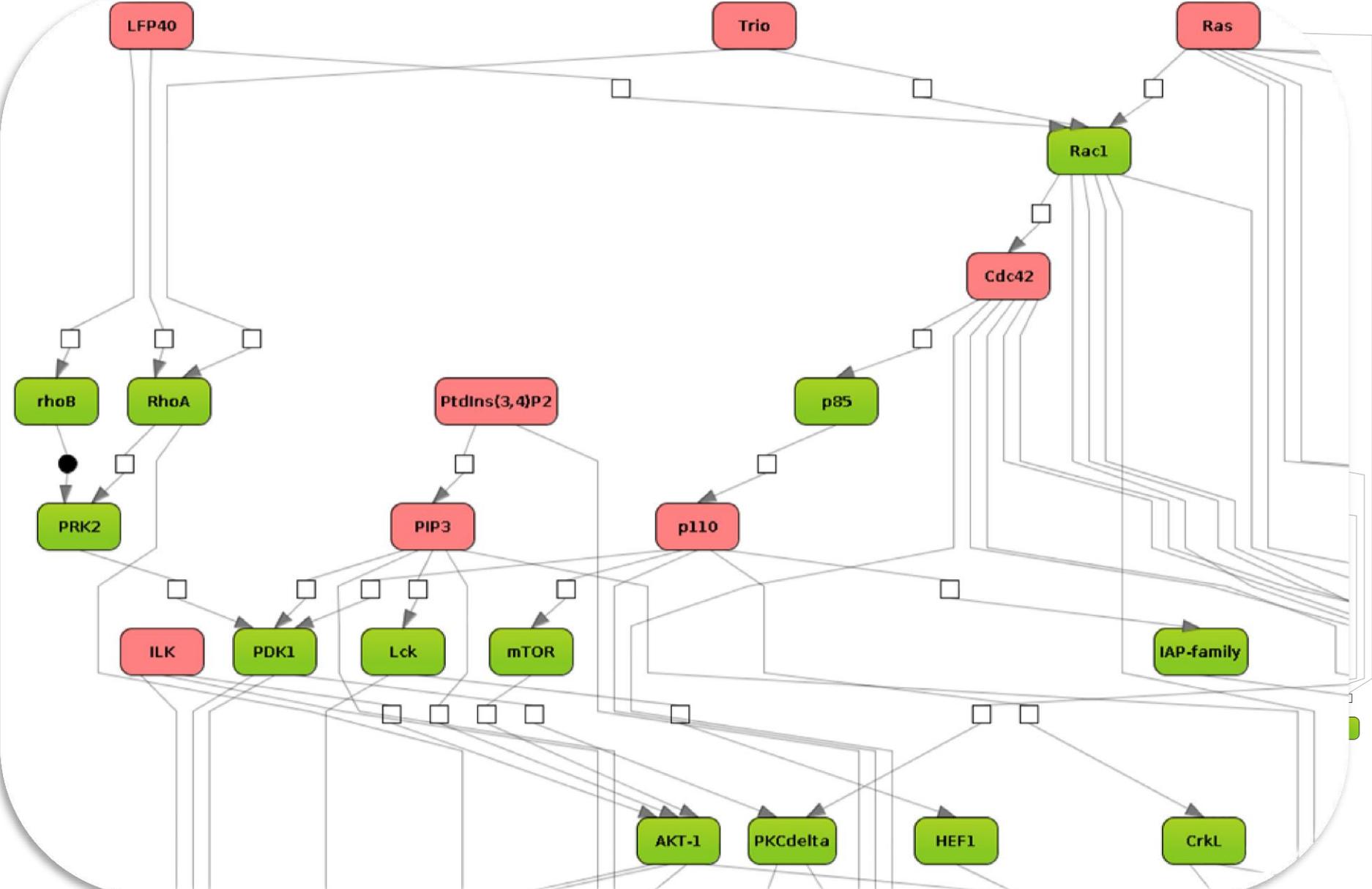
Repression of genes

Survival mechanisms of cancer cells upon RITA treatment and potential target proteins for a complementary compound

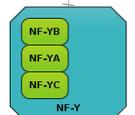


Death of Cancer cells treated with 0.1 μM RITA and PI3-kinase inhibitor LY294002





13/11/201



Systems Medicine

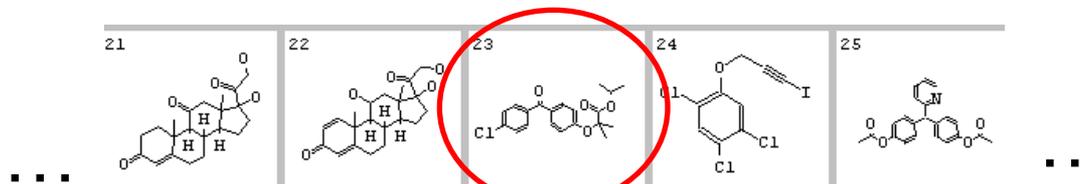


search ID: rmc92

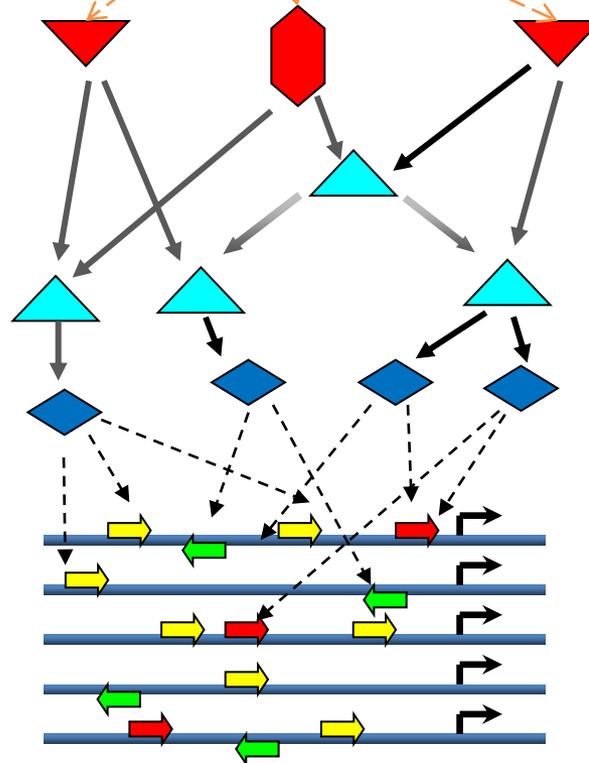
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Identified 16 novel compounds

ChemNavigator Library
24 million
compounds



SAR/QSAR



PA:SS Prediction of Activity Spectra for Substances Professional
Version 9.1
Copyright © 2009
V. Poroikov, D. Filimonov & Associates
<http://www.ibmc.msk.ru/PASS/>

48 Substructure
There are 6 kno
Druid ikeness

Tested 16 compounds in a panel of several cancer cell lines.

Found active: Compound N15

Hypoxia inducible factor 1 alpha inhibitor	Phosphatidylinositol 3-kinase beta inhibitor
---	---

Targets

Showed growth suppression in 3 different breast cancer cell lines. The effect appears to be p53-independent (kills p53-null colon cancer cells) and it does not affect the growth of non-transformed mammary epithelial cells

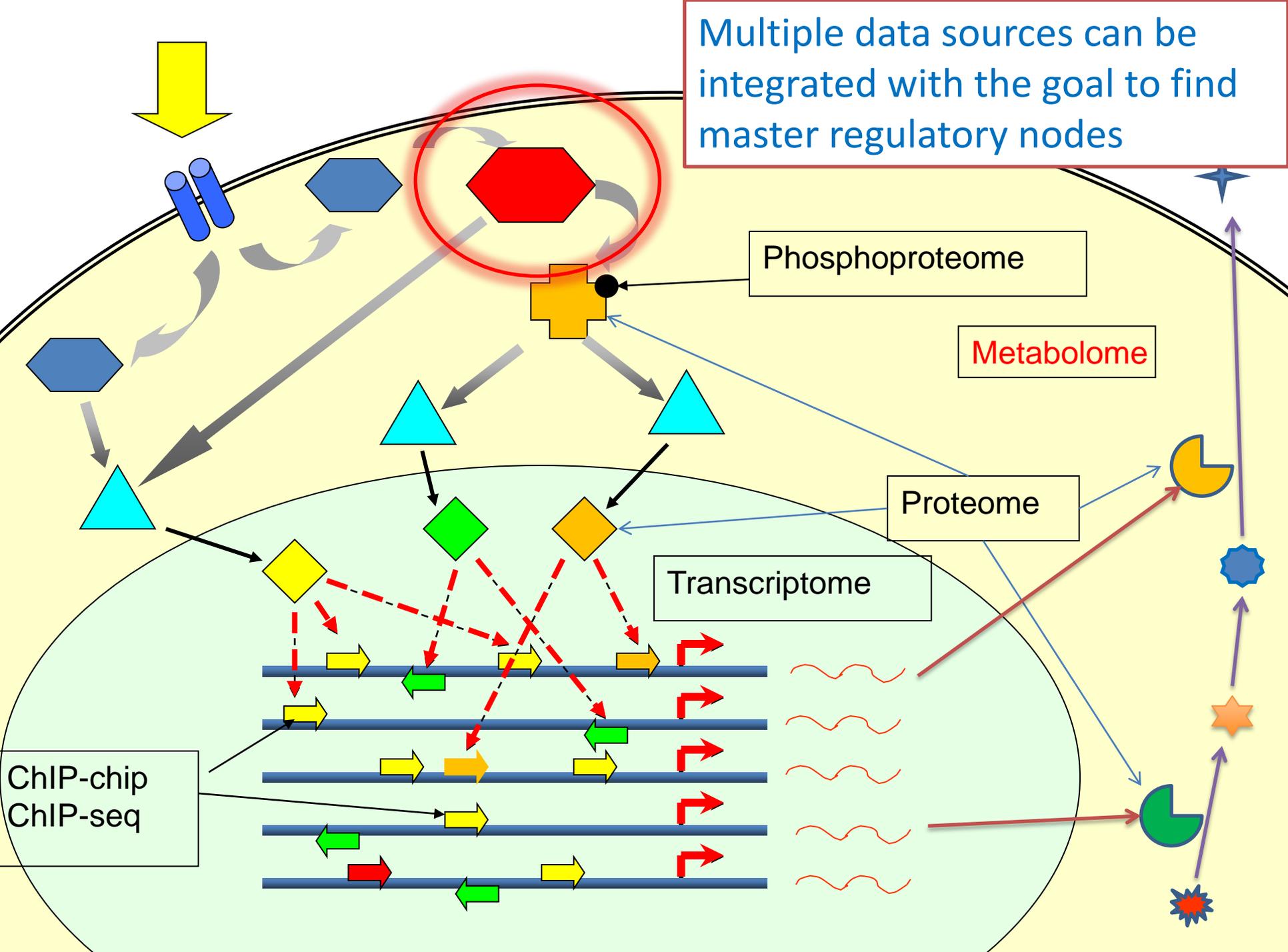
Found active: Compound N6

Cyclin-dependent kinase 2 inhibitor	Myc inhibitor
--	----------------------

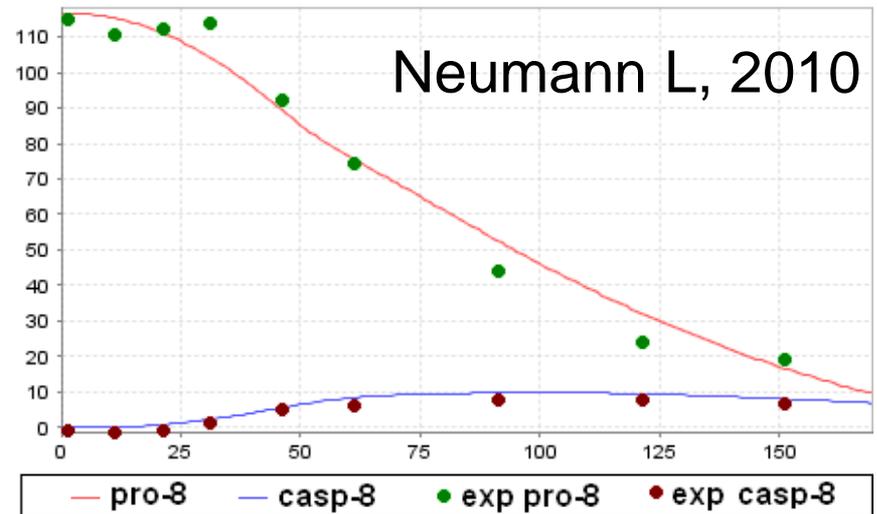
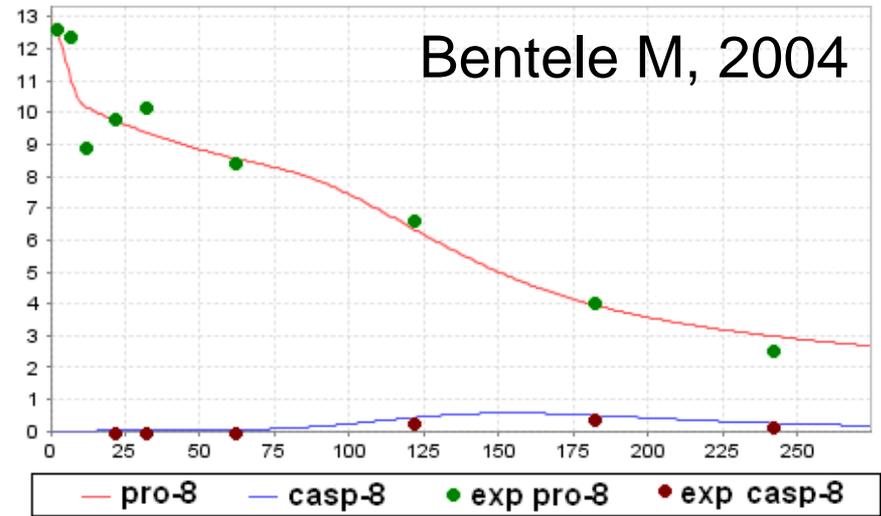
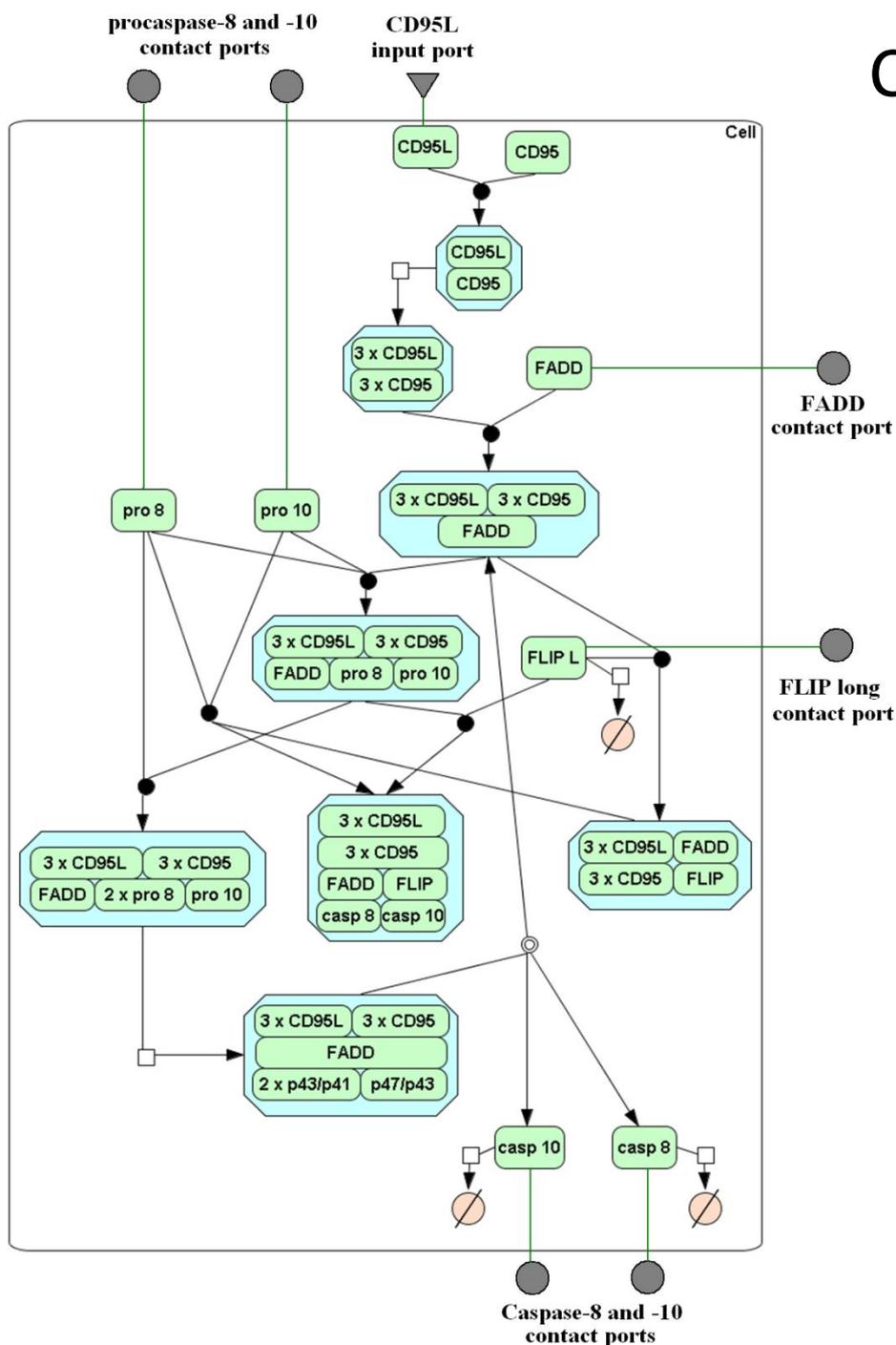
Targets

Out of panel of 7 different cancer lines it killed only melanoma cells without any effects in other cell lines and on control non-transformed mammary epithelial cells.

Multiple data sources can be integrated with the goal to find master regulatory nodes

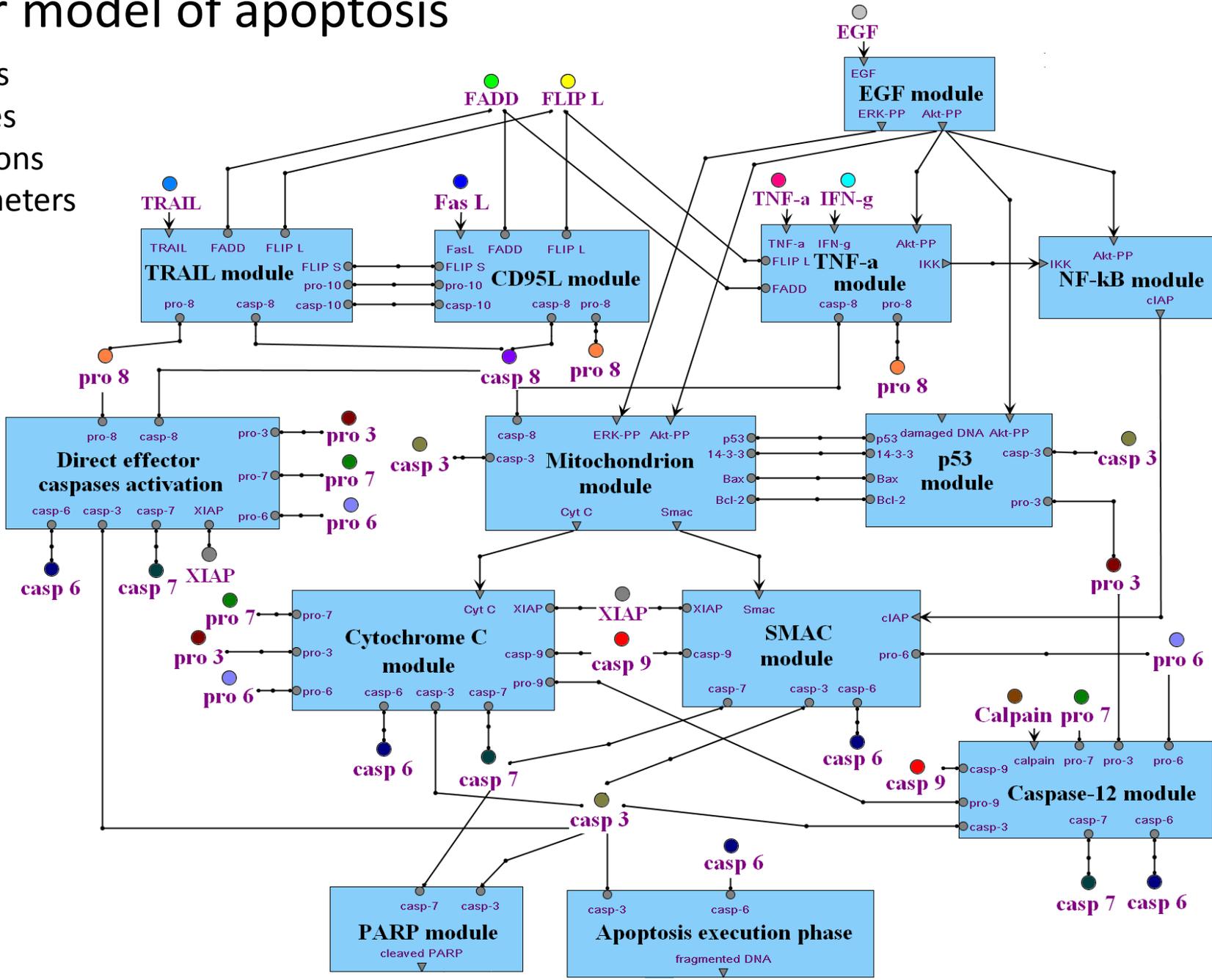


CD95L module and results of fitting its dynamics to experimental data



Modular model of apoptosis

- 13 modules
- 286 species
- 684 reactions
- 719 parameters



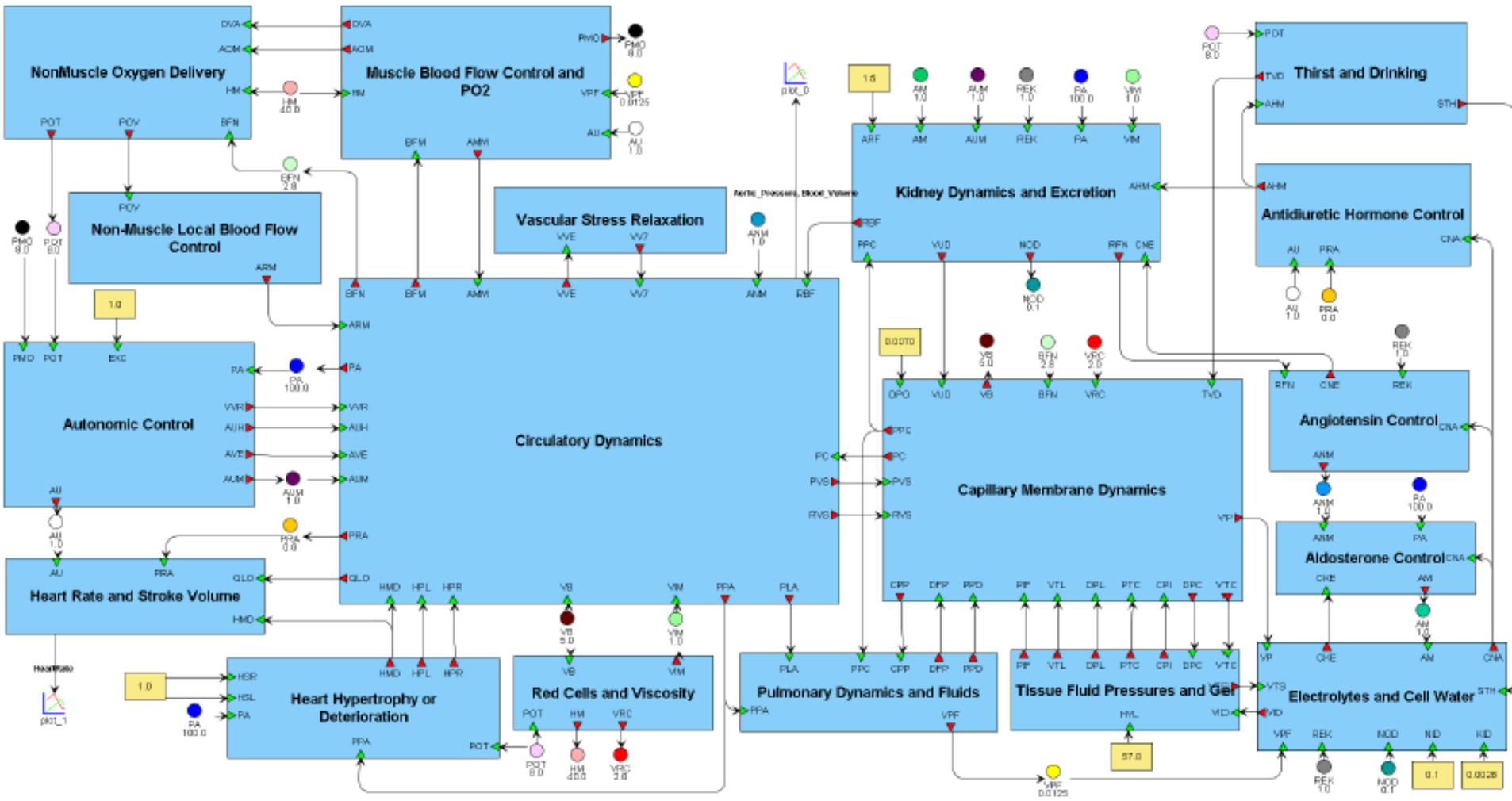
Modular Overall Circulation model

18 modules

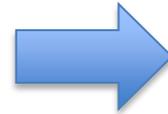
234 parameters

39 ordinary differential equations

172 assignments



From virtual cell to virtual human



www.genexplain.com

13/11/2012

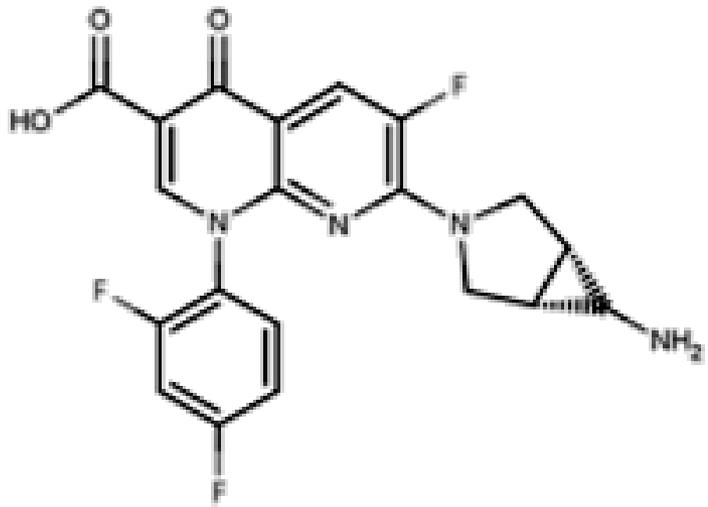
www.biouml.org

Build virtual human to find novel drugs



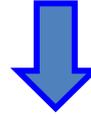
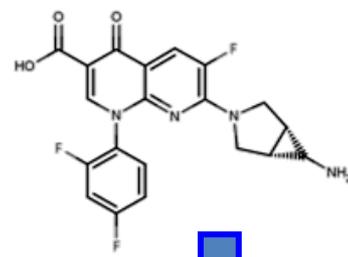
www.genexplain.com

Trovafloxacin - antibiotic



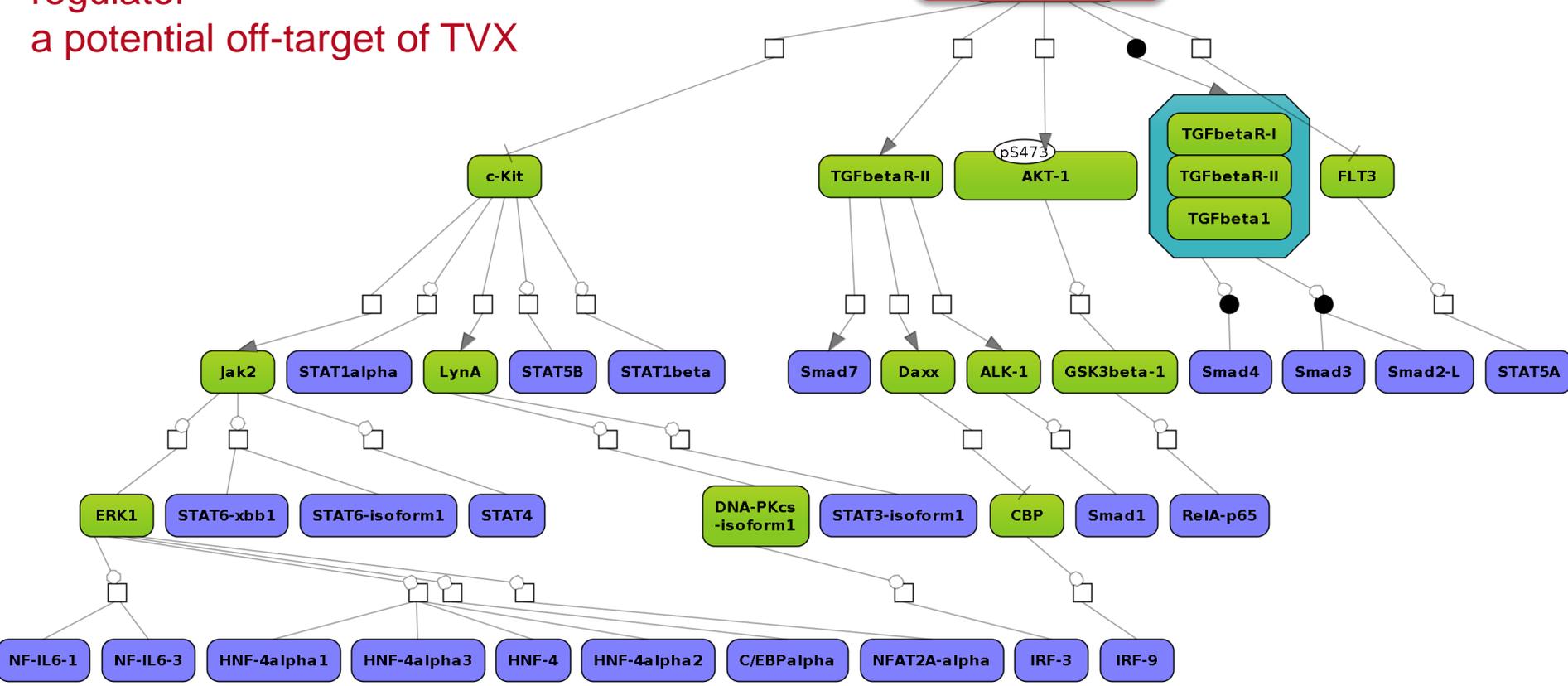
Withdrawn from market due to risk of idiosyncratic hepatotoxicity in 2001.

Trovafloxacin (TVX)

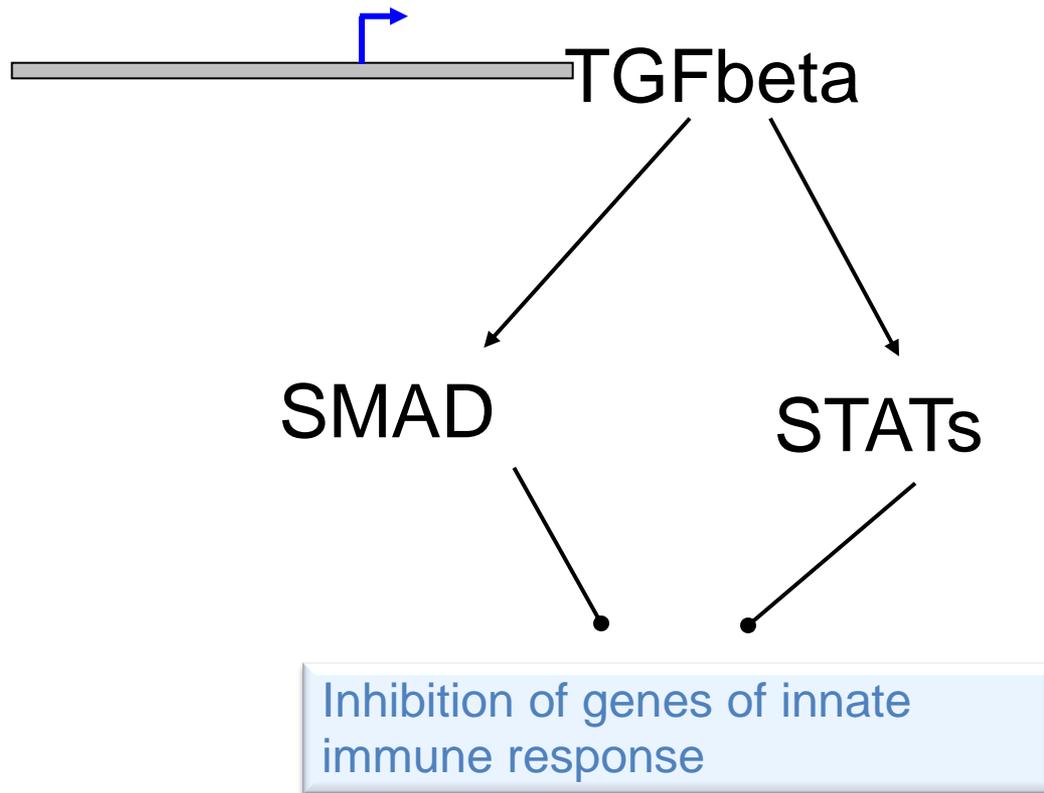


TGF-beta1

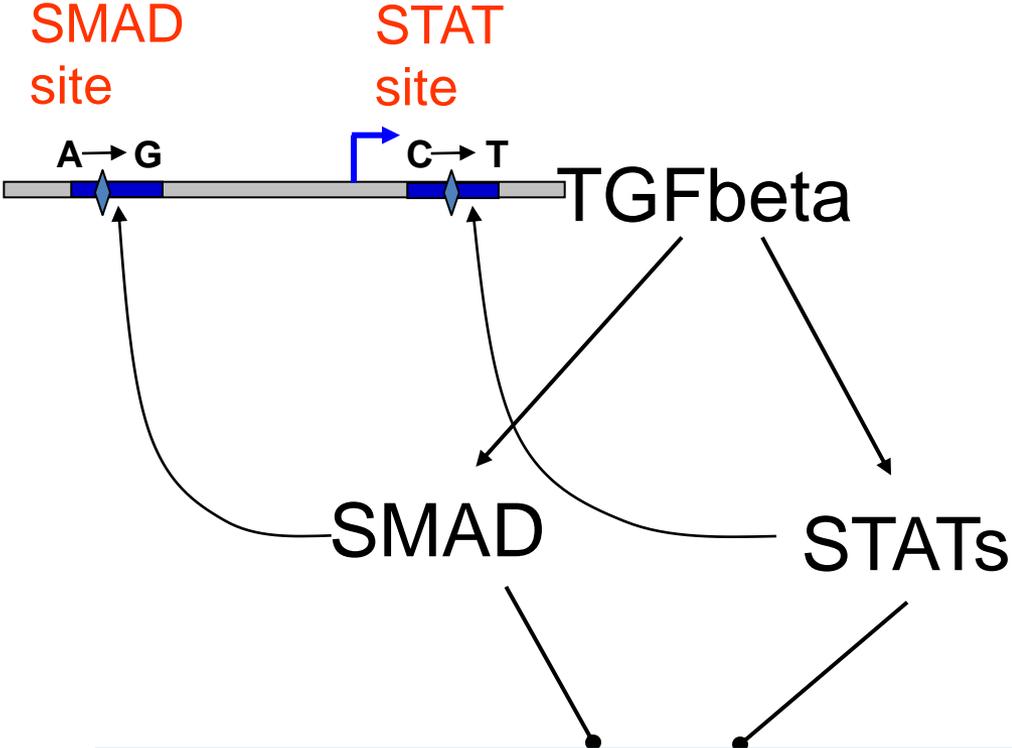
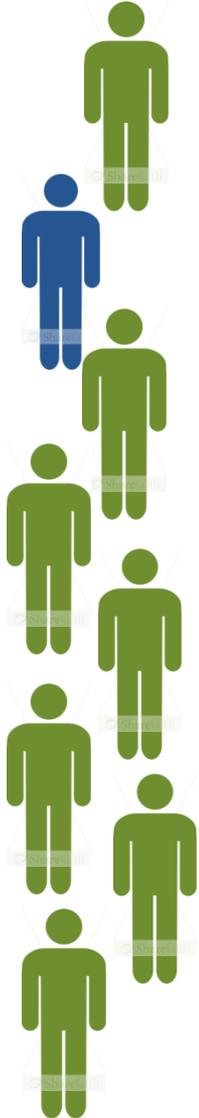
- We found TGF-beta1 as a master regulator – a potential off-target of TVX



TGF-beta dependent positive feedback



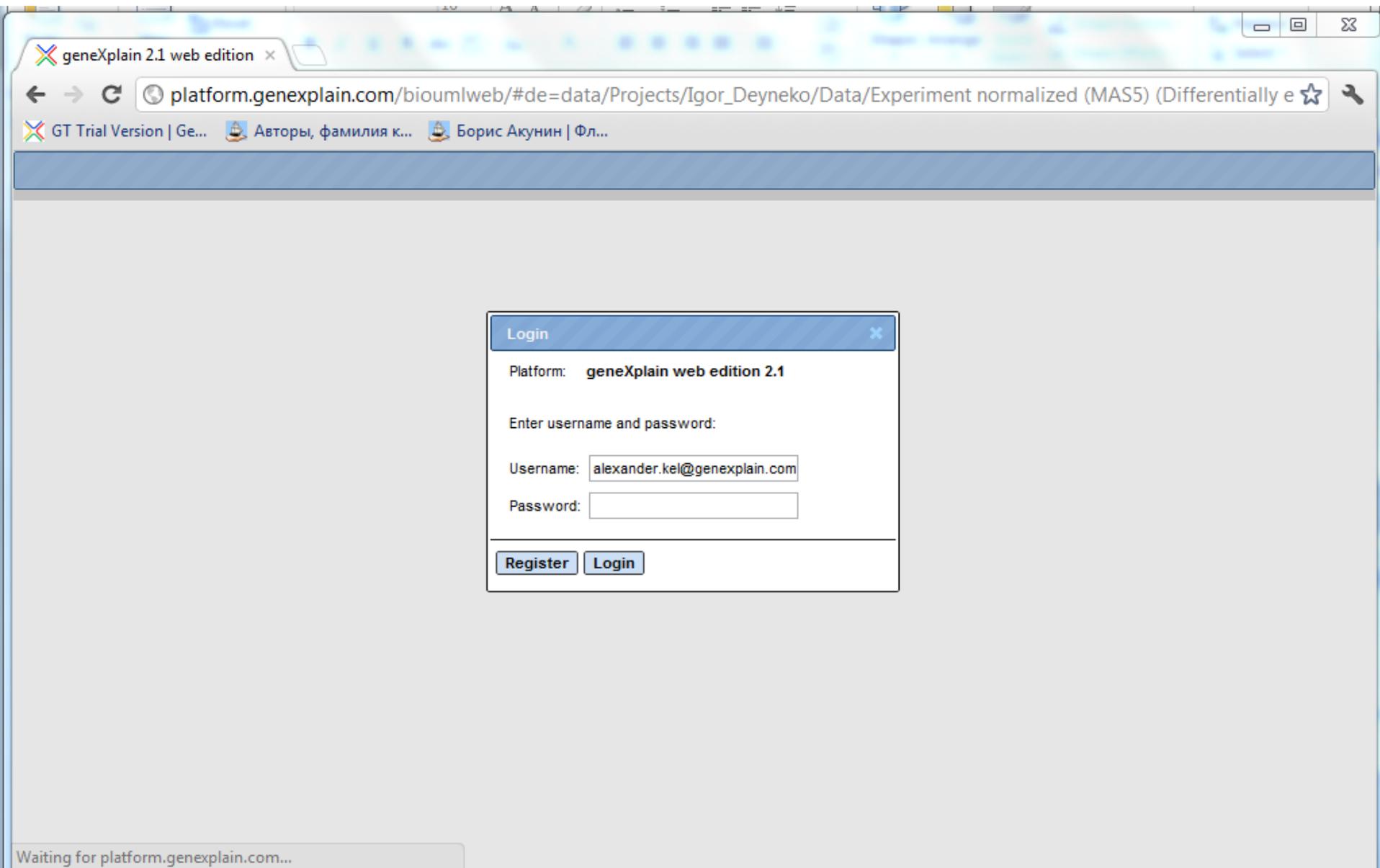
TGF-beta dependent positive feedback



Inhibition of genes of innate immune response

From virtual human to virtual patients





Databases **Data** **Analyses** **Users**

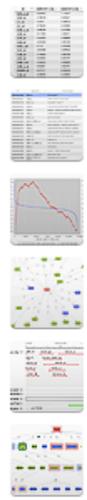
- analyses
 - Galaxy
 - JavaScript
 - Methods
 - Admin
 - Data manipulation
 - Data normalization
 - Functional classification
 - Import
 - Molecular networks**
 - Add expression values
 - Cluster by shortest path
 - Effector search
 - Extend network
 - Join diagrams
 - Regulator search
 - Save hits
 - Save network
 - Visualize results
 - NGS
 - Optimization
 - Simulation
 - Site analysis

Start page

Routes to explain gene regulation and functions

[User Guide](#) Examples:

-  [Load data](#)
-  [Normalize data](#)
-  [Detect differentially expressed genes](#)
-  [Discover functional enrichment](#)
-  [Identify master regulators in networks](#)
-  [Analyze regulatory genome regions](#)
-  [Find potential targets](#)



Search **Info**

Select database to search in...

 **My description** **Graph search** **Script** **Clipboard** **Tasks**

User description is not available

Scope: Format: Amount: GEO accession:

Series GSE11440

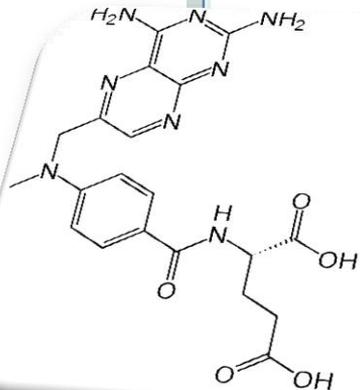
[Query DataSets for GSE11440](#)

Status Public on Sep 08, 2008
 Title Role of Caveolin 1, E-Cadherin, Enolase 2 and PKCa on resistance to methotrexate in human HT29 colon cancer cells
 Organism [Homo sapiens](#)
 Experiment type Expression profiling by array
 Summary A summary of the work associated to these microarrays is the following:

Methotrexate (MTX) is one of the earliest cytotoxic drugs used in cancer therapy, and despite the isolation of multiple other folate antagonists, methotrexate maintains its significant role as a treatment for different types of cancer and other disorders. The usefulness of treatment with methotrexate is limited by the development of drug resistance, which may be acquired through different ways. To get insights into the mechanisms associated with drug resistance and sensitization we have performed a functional analysis of genes deregulated in methotrexate resistant cells, either due to its co-amplification with the DHFR gene or as a result of a transcriptome screening using microarrays. Genes adjacent to dhfr locus and included in the 5q14 amplicon were overexpressed in HT29 MTX-resistant cells. Treatment with siRNAs against those genes caused a slight reduction in cell viability in both HT29 sensitive and resistant cells. On the other hand, microarray analysis of HT29 and HT29 MTX resistant cells unveiled overexpression of caveolin 1, enolase 2 and PKCa genes in treated cells without concomitant copy number gain. siRNAs against these three genes effectively reduced cell viability and caused a decreased MTX resistance capacity. Moreover, overexpression of E-cadherin, which was found underexpressed in MTX-resistant cells, also sensitized the cells toward the chemotherapeutic agent. We provide functional evidences indicating that caveolin 1 and E-cadherin may play a critical role in cell survival and may constitute potential targets for coadjuvant therapy.
 Keywords: DHFR, Methotrexate, drug resistance

Overall design

Two cell lines are compared in the study, which are HT29 colon cancer cells sensitive to methotrexate and HT29 cells resistant to 10e-5M MTX. Six



Research: alexand

Start page Normalize Affymetrix exp... X

Databases Data Analyses

data

- Examples
- Projects
 - alexander.ke2@googlemail.com
 - Data
 - Colon_cancer
 - GSE11440_RAW
 - Workflows
 - Net2Drug
 - Journal
 - tmp
 - Public

Experiment files	[3] GSM288501.CEL;GSM288502.CEL;GSM288536.C
Control files	[3] GSM288491.CEL;GSM288497.CEL;GSM288499.C
Method	MAS5
Background correction	MAS
Normalization method	quantiles
PM correction	pmonly
Summarization	mas
CDF version	<input type="checkbox"/> (select element)
Output table test data	.../Colon_cancer/Experiment normalized (MAS5) Auto
Output table control data	...ata/Colon_cancer/Control normalized (MAS5) Auto

Cancel

3%

```

INFO - Normalize files...
INFO - Generating R command...
INFO - Platform detected: HG-U133_Plus_2
INFO - Connecting to R...
INFO - Invoking R command (that will take some time)...
  
```

Databases | **Data** | **Analyses**

- Projects
 - alexander.kel2@googlemail.com
 - Data
 - Colon_cancer
 - GSE11440_RAW
 - Control normalized (MASS)

Start page | 1 X | Net2Drug X

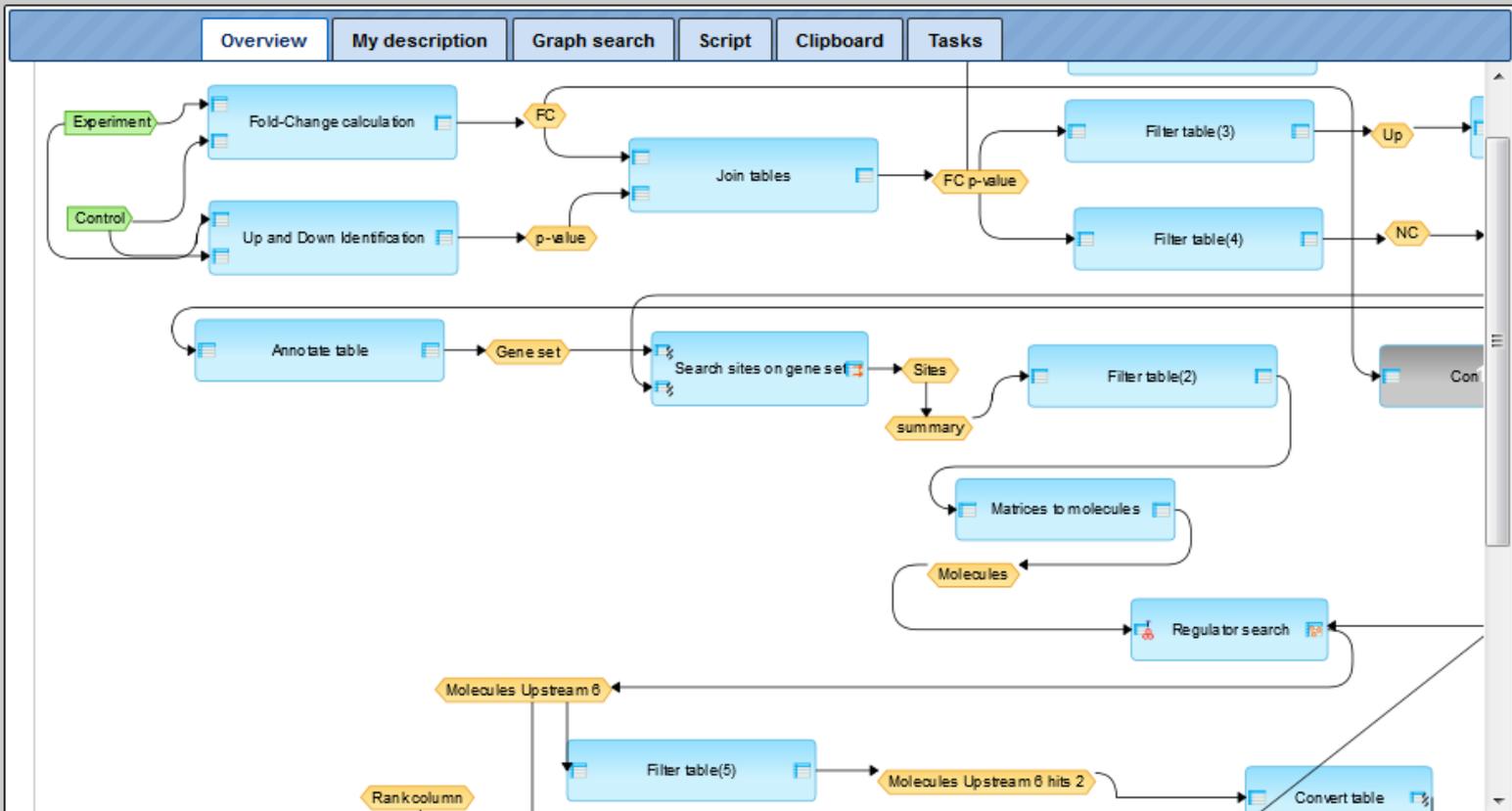
Net2Drug

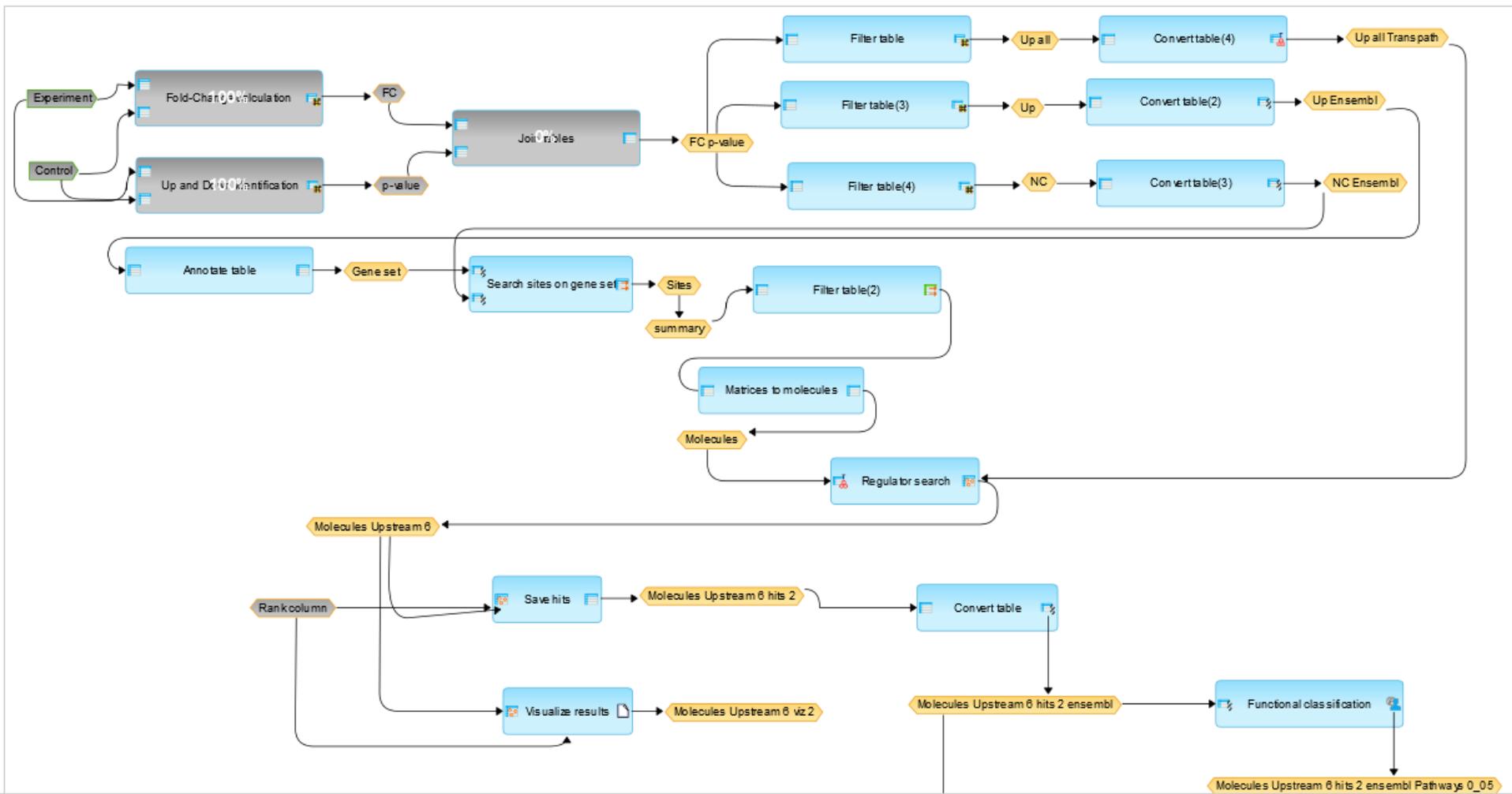
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Control	data/Projects/alexander.kel2@googlemail.com

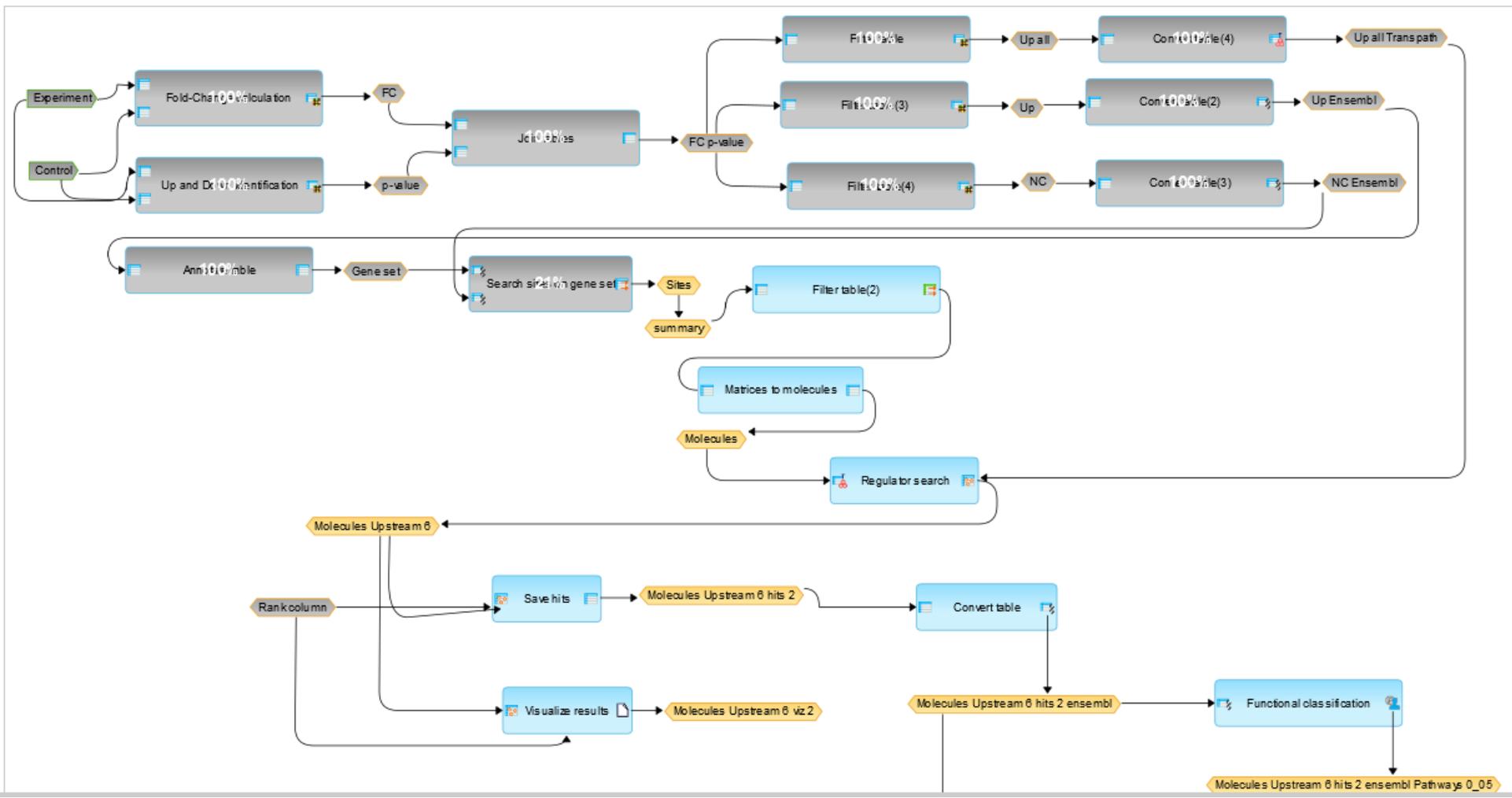
Run workflow | Edit workflow

Search | Info | Default

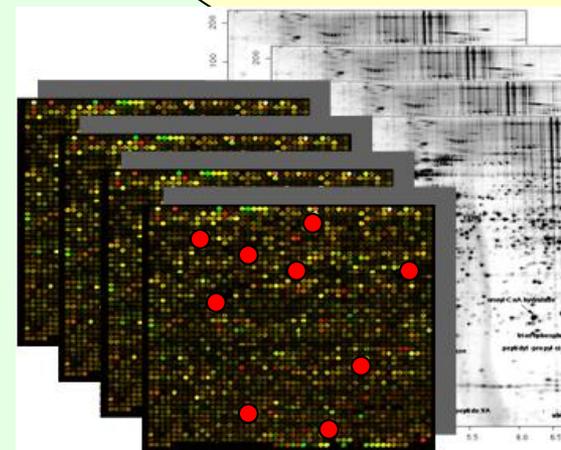
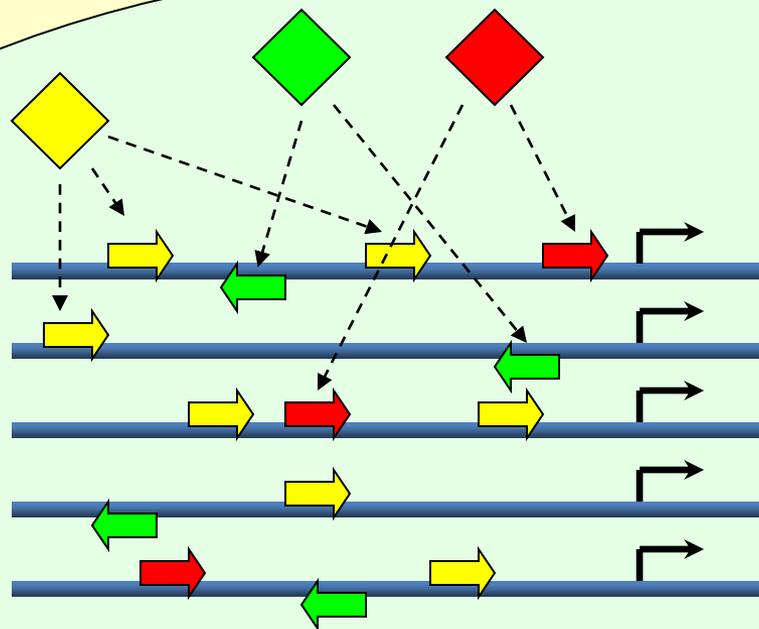
ID: Net2Drug
Title: Regulator analysis
Size: 94
Complete name: data/Projects/alexander.kel2@googlemail.com/Data/Workflows/Net2Drug







On the first step the workflow identified the differentially expressed genes in the resistant versus sensitive patients and identified transcription factors involved.



Here is the list of transcription factors predicted to be involved

Research: alexand

Start page | Molecules Upstream 6 PA... | Experiment normalized (... X

First Previous Page 1 of 1 Next Last Showing 1 to 21 of 21 entries Show 50 entries

ID	Yes density per 1000bp	No density per 1000bp	Yes-no ratio	Matrix cutoff	P-value
V\$CDPCR3_01	0.11552	0.01724	6.70061	0.8716	0.00428
V\$NKX3A_01	0.24755	0.04023	6.15362	0.9372	3.7523E-5
V\$STAT_Q6	0.19804	0.03448	5.74338	0.9909	3.2222E-4
V\$PPARA_02	0.28055	0.0862	3.25458	0.8253	8.984E-4
V\$KAI1_01	0.19804	0.06321	3.13275	0.9929	0.00618
V\$PAX2_01	0.21454	0.07471	2.87169	0.8644	0.00701
V\$SOX1_07	0.39607	0.15516	2.55261	0.8629	8.7635E-4
V\$SREBF1_Q3	0.5281	0.22987	2.29735	0.9162	4.7791E-4
V\$CMAF_01	1.18822	0.74708	1.59047	0.8444	0.00129
V\$AR_02	0.95717	0.61491	1.55662	0.777	0.005
V\$GATA4_Q3	1.6668	1.10338	1.51063	0.8533	6.3511E-4
V\$TST1_01	4.60434	3.64922	1.26173	0.8217	8.0258E-4
V\$TAL1BETAE47_01	3.8617	3.09178	1.24902	0.7841	0.00286
V\$XFD2_01	4.71986	3.86759	1.22036	0.7827	0.00296
V\$NFX1_01	4.3733	3.59175	1.2176	0.8539	0.00443
V\$CEBPB_GAMMA_Q6	4.96741	4.13769	1.20053	0.7778	0.00467
V\$PAX4_Q3	5.84207	4.95949	1.17796	0.8931	0.00558
V\$HMGY1_Q6	11.25505	9.93621	1.13273	0.8558	0.00335
V\$PAX2_Q2	16.05743	14.40147	1.11499	0.963	0.00224
V\$PAX6_Q1	18.38436	16.51629	1.1131	0.6045	0.00136
V\$DBP_Q6	17.79025	16.26918	1.09349	0.8364	0.00685

Search Info Default

Filters Columns My description Graph search Script Clipboard Tasks

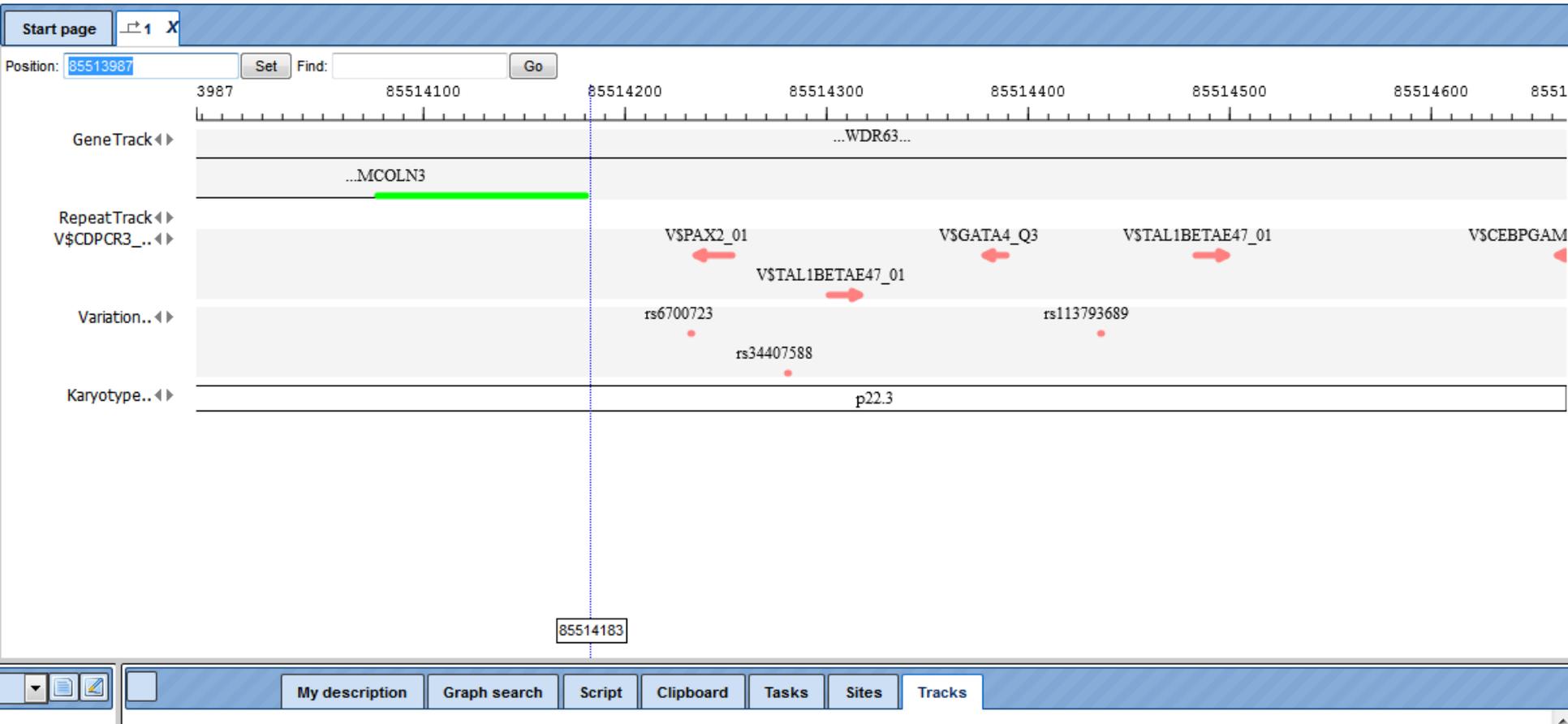
Template to construct the filtering expression:
 - Select template -

Columns (double-click to paste):
 ID
 Yes_density_per_1000bp
 No_density_per_1000bp
 Yes_no_ratio
 Matrix_cutoff
 P_value

Expression in JavaScript language:

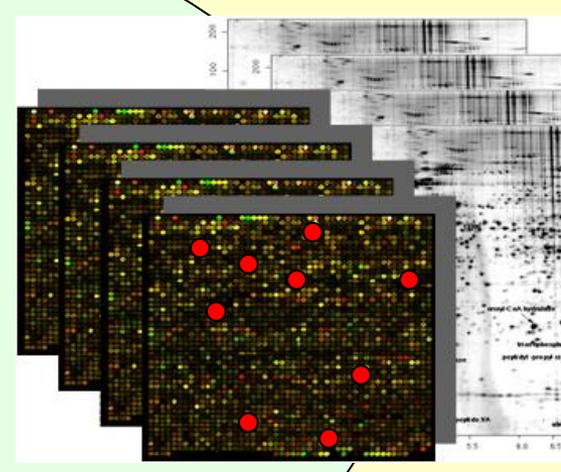
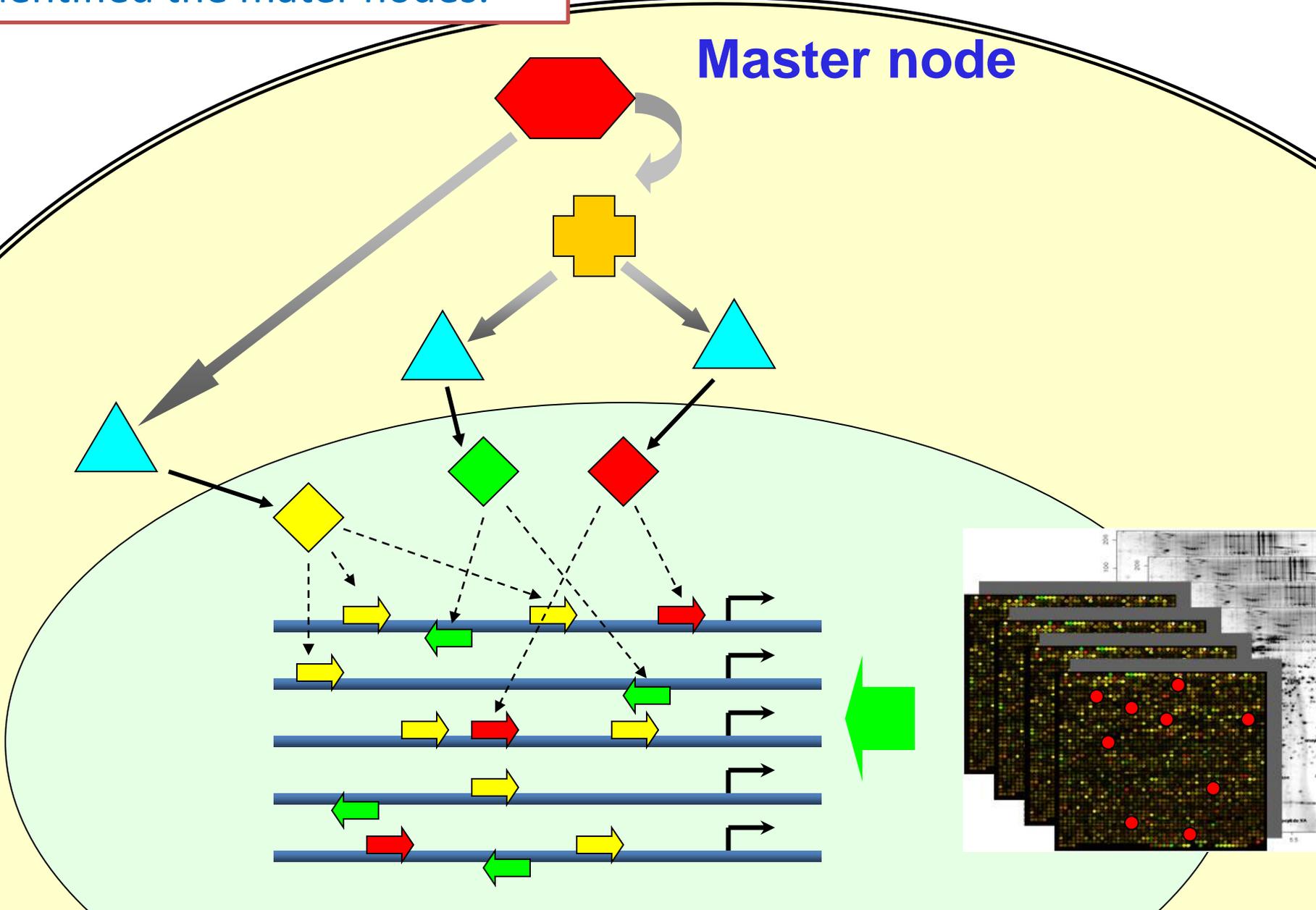
ID: summary
Size: 21
Complete name: data/Projects/alexander.kel2@googlemail.com/Data/Colon_cancer/Experiment normalized (MASS) FC p-value UP annotated_sites -500..100/summary

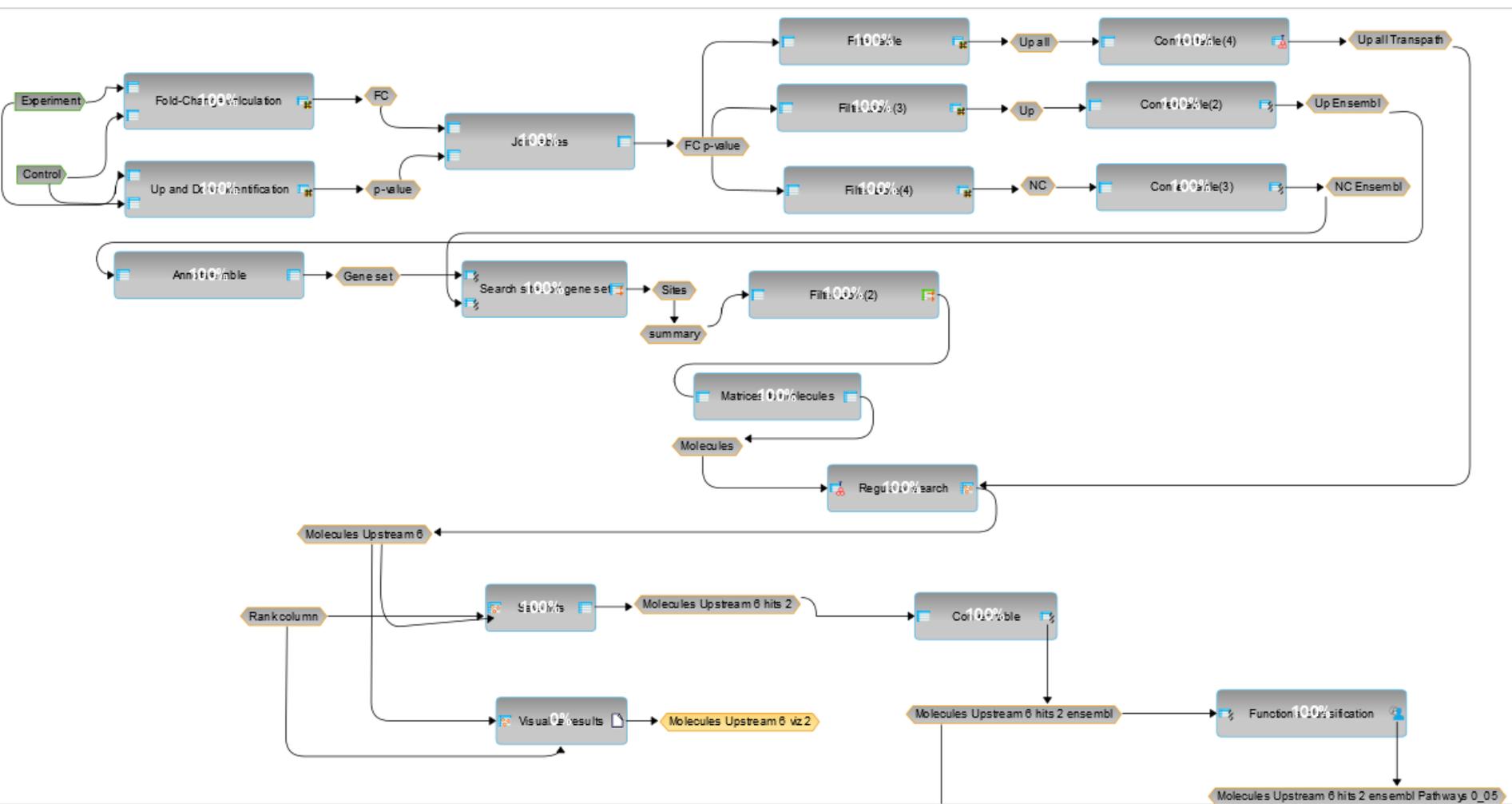
Here are the predicted sites for these transcription factors.



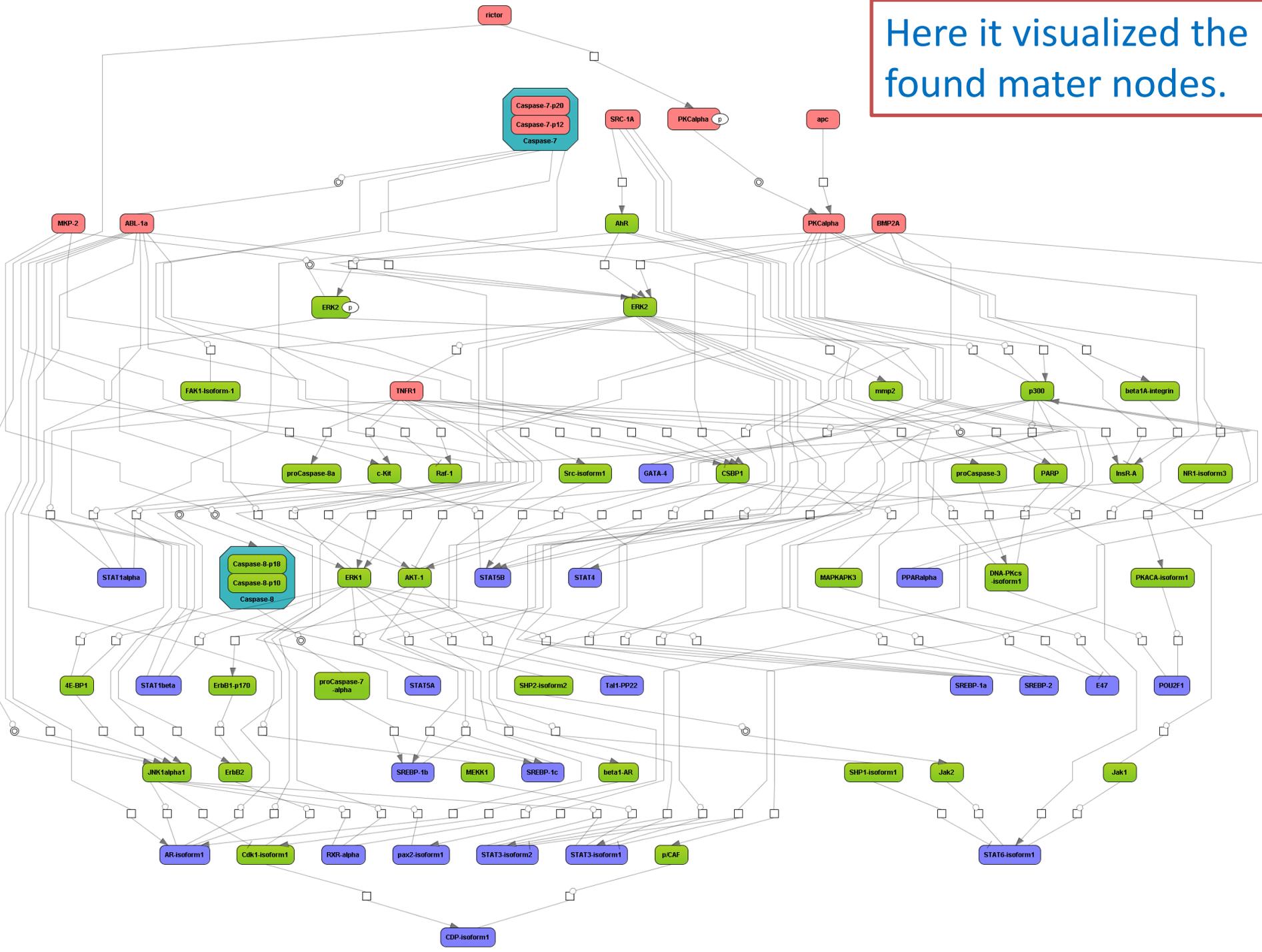
On the next step the workflow identified the mater nodes.

Master node





Here it visualized the found mater nodes.



Some of the master nodes have information in PASS about inhibitors or agonists

The screenshot displays a web-based interface for a bioinformatics database. The main content area shows a table of molecules with the following columns: ID, Hits names, Master molecule name, Reachable total, Reached from set, Score, Description, Molecule type, and PASS activity. The table contains 9 entries, with the first three rows highlighted in grey. The sidebar on the left shows a hierarchical tree view of the database structure, with 'Molecules Upstream 6 PASS activity' selected. The top navigation bar includes 'Start page' and 'Molecules Upstream 6 PA...'. The bottom status bar shows the search criteria: 'ID: Molecules Upstream 6 PASS activity filtered 3 hits' and 'Size: 9'. The bottom right corner contains a 'Template to construct the filtering expression:' field with the text 'Columns (double-click to paste):'.

ID	Hits names	Master molecule name	Reachable total	Reached from set	Score	Description	Molecule type	PASS activity
MO000107848	AR-isoform1(h), CDP-isoform1(h), E47(h), GATA-4(h), POU2F1(h), ...	Cdk1-isoform2(h)	21317	21	0.58876	cell division cycle 2, G1 to S and G2 to M	basic	Cyclin-dependent kinase 1 inhibitor; Cyclin-dependent kinase inhibitor
MO000023154	AR-isoform1(h), CDP-isoform1(h), E47(h), GATA-4(h), POU2F1(h), ...	PKCbeta2(h)	16078	21	0.45328	protein kinase C, beta	basic	Protein kinase C inhibitor; Protein kinase C stimulant
MO000082228	AR-isoform1(h), CDP-isoform1(h), E47(h), GATA-4(h), POU2F1(h), ...	ErbB1-p60(h)	13125	18	0.29716	epidermal growth factor receptor (erythroblastic leukemia viral (v-erb-b) oncogene homolog, avian)	basic	Epidermal growth factor antagonist; Epidermal growth factor receptor kinase inhibitor; ErbB-1 antagonist
MO000082230	AR-isoform1(h), CDP-isoform1(h), E47(h), GATA-4(h), POU2F1(h), ...	ErbB1-p110(h)	13125	18	0.29716	epidermal growth factor receptor (erythroblastic leukemia viral (v-erb-b) oncogene homolog, avian)	basic	Epidermal growth factor antagonist; Epidermal growth factor receptor kinase inhibitor; ErbB-1 antagonist
MO000087397	AR-isoform1(h), CDP-isoform1(h), E47(h),	ErbB1-4(h)	13125	18	0.29716	epidermal growth factor receptor (erythroblastic leukemia viral	basic	Epidermal growth factor antagonist; Epidermal growth factor

PASS / PharmaExpert multi-target search

Searching in a library of known drugs for compounds with potential of multi-target activity against selected targets

Multitargeted actions

Effects: Vascular (periferal) disease treatment

Number of targets: 4

Run Load Save

Cyclin-dependent kinase 1 inhibitor
Epidermal growth factor antagonist
Interferon agonist
MAP kinase inhibitor
Protein kinase C inhibitor

No	Pa	Number	Activity type	Activity type	Activity type
1	0.371	9	Cyclin-dependent kinase 1 inhibitor	Epidermal growth factor antagonist	
2	0.534	4	Cyclin-dependent kinase 1 inhibitor	Interferon agonist	
3	0.295	4	Cyclin-dependent kinase 1 inhibitor	MAP kinase inhibitor	
4	0.534	2	Epidermal growth factor antagonist	Interferon agonist	
5	0.110	5	Epidermal growth factor antagonist	MAP kinase inhibitor	
6	0.182	3	Interferon agonist	MAP kinase inhibitor	
7	0.534	2	Cyclin-dependent kinase 1 inhibitor	Epidermal growth factor antagonist	Interferon agonist
8	0.103	3	Cyclin-dependent kinase 1 inhibitor	Epidermal growth factor antagonist	MAP kinase inhibitor
9	0.100	1	Cyclin-dependent kinase 1 inhibitor	Interferon agonist	MAP kinase inhibitor
10	0.100	1	Epidermal growth factor antagonist	Interferon agonist	MAP kinase inhibitor
11	0.100	1	Cyclin-dependent kinase 1 inhibitor	Epidermal growth factor antagonist	Interferon agonist

Found a drug— **imiquimod**, with potential of activity for three targets

Prediction & Interpretation - C:\KEL\PASS\prestwick_chemical_library_cured-antineoplastic0.5.sdf. 98/108

Flunixin meglumine Acitretin Cortisone 2-Chloropyrazine Equilin **imiquimod** Clotrimazole

Save TXT Save SD Clipboard Exclude

Pa > Pi > Sort

Pa	Pi	<chemical_name>
0.534	0.001	imiquimod
0.144	0.036	Aminopurine, 6-benzyl

Types of Activities: Pa-Pi descending

Pa	Pi	Types of Activities
0.137	0.122	Homoserine dehydrogenase inhibitor
0.044	0.030	2-Amino-4-hydroxy-6-hydroxymethylidihydropteridine diphosphokir
0.042	0.028	Purinergic P2Y1 antagonist
0.077	0.063	Inositol 1,4,5-triphosphate receptor antagonist
0.234	0.220	Growth hormone antagonist
0.062	0.048	NMN nucleosidase inhibitor
0.263	0.250	Phosphatidylcholine-retinol O-acyltransferase inhibitor
0.262	0.249	Antimycopathies
0.226	0.213	Histamine release inhibitor
0.113	0.100	D-Octopine dehydrogenase inhibitor
0.194	0.182	Antimycobacterial
0.075	0.063	Cysteine-tRNA ligase inhibitor
0.078	0.066	Glycerol dehydrogenase inhibitor
0.309	0.297	Retinal oxidase inhibitor
0.171	0.160	Nardilysin inhibitor
0.116	0.105	D-lactate dehydrogenase inhibitor
0.094	0.083	Constipation treatment
0.173	0.162	Glycine amidinotransferase inhibitor
0.205	0.195	Antiprotozoal (Trypanosoma)
0.095	0.085	CMP-N-acetylneuraminatase inhibitor
0.055	0.045	Cyclin-dependent kinase 1 inhibitor
0.183	0.174	Transactivator transcription protein inhibitor
Substance inhibits cyclin-dependent kinase 1. EC 2.7.1.37.CDK		

Effect Mechanisms Toxicity Metabolism Transport Gene Expression

<input checked="" type="checkbox"/>	Cyclin-dependent kinase 1 inhibitor	0.055	0.045
<input checked="" type="checkbox"/>	Heat shock protein 90 antagonist	0.054	0.029
<input checked="" type="checkbox"/>	Purine nucleoside phosphorylase inhibitor	0.017	0.010
<input type="checkbox"/>	Antineoplastic (basal cell carcinoma)	0.750	0.001
<input type="checkbox"/>	Antineoplastic (bladder cancer)	0.490	0.073
<input type="checkbox"/>	Antineoplastic (brain cancer)	0.393	0.177
<input type="checkbox"/>	Antineoplastic (cervical cancer)	0.431	0.070
<input checked="" type="checkbox"/>	Antineoplastic (gastric cancer)	0.376	0.308
<input type="checkbox"/>	Antineoplastic (hematological cancer)	0.488	0.059
<input checked="" type="checkbox"/>	Antineoplastic (lung cancer)	0.406	0.182
<input type="checkbox"/>	Antineoplastic (lymphocytic leukemia)	0.465	0.070
<input checked="" type="checkbox"/>	Antineoplastic (lymphoma)	0.385	0.263
<input type="checkbox"/>	Antineoplastic (melanoma)	0.451	0.024
<input checked="" type="checkbox"/>	Antineoplastic (myeloid leukemia)	0.354	0.248
<input checked="" type="checkbox"/>	Antineoplastic (non-Hodgkin's lymphoma)	0.334	0.139
<input checked="" type="checkbox"/>	Antineoplastic (solid tumors)	0.211	0.203
<input checked="" type="checkbox"/>	Tumour necrosis factor agonist	0.799	0.001
<input checked="" type="checkbox"/>	Nucleotide metabolism regulator	0.549	0.028
<input checked="" type="checkbox"/>	Interferon agonist	0.534	0.001

N/A

Pa > Pi > (-)-limonene 6-monoxygenase inhibitor Drug-likeness >0 New Descriptors >= 0

Pa	Pi	Activity	Action	
Pa	>	Pi	Cyclin-dependent kinase 1 inhibitor	Delete
Pa	>	Pi	Epidermal growth factor antagonist	Clear
Pa	>	Pi	Interferon agonist	Load
				Include
				Save

Number of selected compounds: 2

<chemical_name> imiquimod; > <DRUG_LIKENESS> 0.952; 35 Substructure descriptors, 0 new; 672 Possible activities.



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Imiquimod

From Wikipedia, the free encyclopedia

Imiquimod (INN) is a prescription medication that acts as an immune response modifier. It is marketed by MEDA AB, Graceway Pharmaceuticals and iNova Pharmaceuticals under the trade names **Aldara** and **Zyclara**, and by Mochida as **Beselna**.

Contents [hide]

- History
- Uses
- Mechanism of action
- Disadvantages
- Chemistry
- See also
- References
- External links

History

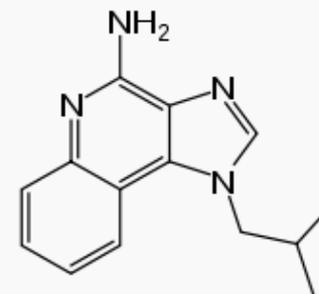
The original FDA approval was on February 27, 1997, FDA Application No. (NDA) 020723, by 3M. Imiquimod is approved to treat actinic keratosis, superficial basal cell carcinoma, and external genital warts. Adverse side effects have been reported, in some cases serious and systemic, resulting in the revision of warning labels.

Uses

Imiquimod is a patient-applied cream used to treat certain diseases of the skin, including skin cancers (basal cell carcinoma, Bowen's disease,^[1] superficial squamous cell carcinoma, some superficial malignant melanomas, and actinic keratosis) as well as genital warts (*condylomata acuminata*). It has also been tested for treatment of molluscum contagiosum, vulvar intraepithelial neoplasia, common warts that have proven difficult to treat,^[2] and vaginal intraepithelial neoplasia.^[3] Outstanding cosmetic result has resulted from the treatment of both

We predict that Imiquimod can be used as a second drug to overcome the resistance to methotrexate

Imiquimod



Systematic (IUPAC) name

3-(2-methylpropyl)-3,5,8-triazatricyclo[7.4.0.0^{2,6}]trideca-1(9),2(6),4,7,10,12-hexaen-7-amine

Clinical data

Licence data [EMA:Link](#), [US FDA:link](#)

Pregnancy cat. B1(AU) C(US)

Legal status POM (UK) B-only (US)

Routes Topical

Pharmacokinetic data

Half-life 30 hours (topical dose), 2 hours (subcutaneous dose)

Identifiers

CAS number 99011-02-6

ATC code D06BB10

PubChem CID 57469

DrugBank [ADBD01030](#)

Net
2
Drug



geneXplain



BIODATABASE
BIOLOGICAL DATABASES



0100100010011101
Institute of Systems Biology

PharmaExpert
RESEARCH LABORATORY

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ITEM



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