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Ludwig-Maximilians-Universität München

OS 13.12.2019

OS 25.11.2019

OS 18.11.2019





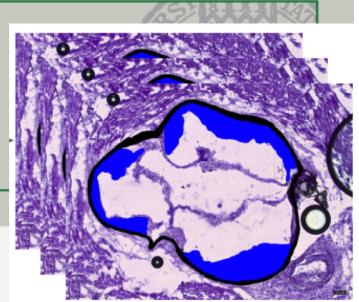
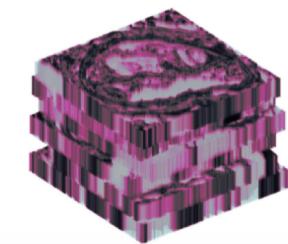
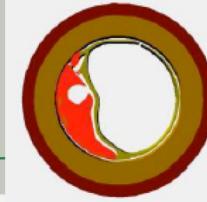
- Fuzzy discretization, values & logic for HT data analysis
- Confidence Intervals
 - in particular for GSEA/GNEA
- Robust GSEA
- Splicing
 - tool: MS data set => splicing candidates with estimation graphics
 - Splicing landscape in Cancer (CPTAC)
 - splicing for protein production (miRNA blocking of BP)
- (MS)-EmpireS
- 3D Reconstruction
 - 3D index of heterogeneous HT and annotation data
- Context based text mining
 - miRExplore
 - time-line, recommendation systems, IF
- ConceptMaker
 - SVD, MOFA, umap
- Systems Modeling of Expression (Yeast)
- Internet of Facts (IoF)
- Internet of Claims (IoC)

- DNA computing
- Brainbook

- Drug side effects and interactions (App)
- NGS/HT core center

- Cloud
- KI
- Climate Change

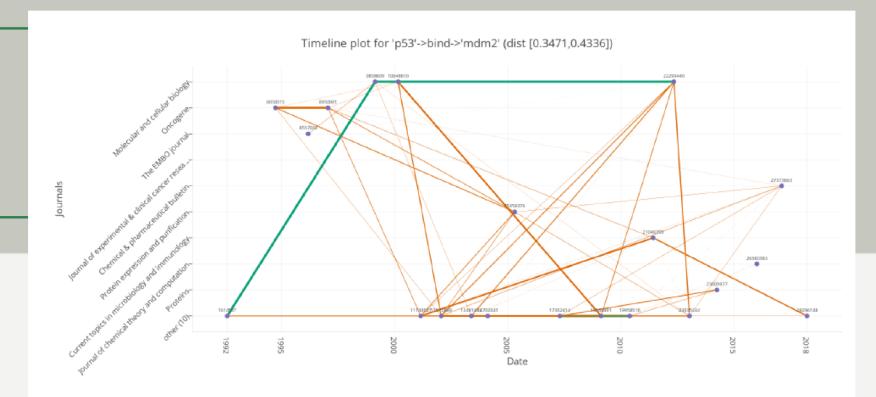




- **3D Reconstruction**
 - **3D index of heterogeneous HT and annotation data**
- **SFB1123 (Prof. Söhnlein, Celia Borja, Yue Wang)**
- **Kooperation in Z2 (Imhof, MSI)**
 - **MS => Constantin ?**
 - **NGS data**
 - **single cell data**
- **Bachelorarbeit Margaryta Olenchuk**
- **Vision:**
 - **Integration of heterogeneous data**
 - **Spatio-temporal model**
 - **„Superresolution“: Inference/imputation**

Visions and Projects

- **Context-based text mining**
 - miRexplore
 - Time-line
- **SFB1123: AtheMir**
- **Lehre: NEAP Master**
- **Resource for „contextual miRNA regulations“**
 - simple benchmark for context search
 - ... and recommendation/document similarity
 - as complete and accurate as possible
- **Time-line as „Killer-app“**
 - should be right !
 - new measure of scientific impact
 - find facts in contexts !





Increased expression of miR-330-3p: a novel independent indicator of poor prognosis in human breast cancer

H. Wang, S.-H. Chen, P. Kong, L.-Y. Zhang, L.-L. Zhang, N.-Q. Zhang, H. Gu

Hospital of Clinical Medicine, Binzhou Medical University, Binzhou, Shandong, China. gg4646mm369@126.com

ONCOLOGY

OBJECTIVE: Previous study has reported that miR-330-3p was highly expressed in breast cancer (BC) patients. However, the effect of miR-330-3p in BC progression remains largely unclear. The purpose of this study was to investigate the clinical significance of miR-330-3p expression in BC.

PATIENTS AND METHODS: The expression of miR-330-3p was detected by quantitative Real-time PCR in BC tissues and matched normal breast tissues. The association of miR-330-3p expression with clinicopathological factors of BC patients was also analyzed by χ^2 -test. Prognosis value of patients with BC was assessed by Kaplan-Meier method and Cox proportional hazards model, respectively.

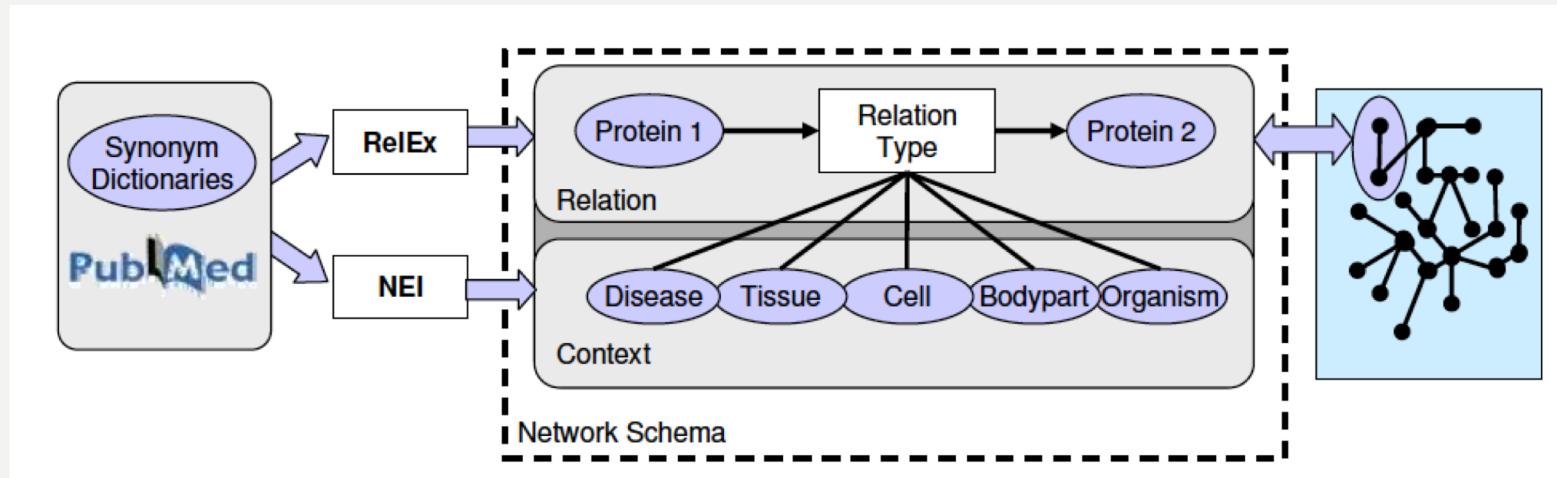
RESULTS: Quantitative real-time PCR analysis showed that the expression level of miR-330-3p was significantly higher in BC specimens than that in corresponding noncancerous tissues ($p < 0.01$). The levels of miR-330-3p were positively correlated with the status of TNM stage ($p = 0.011$) and lymph node metastasis ($p = 0.006$). Kaplan-Meier analysis revealed that 5-year overall survival of BC patients with high miR-330-3p expression was shorter compared to those patients with low miR-330-3p expression ($p < 0.0001$). Moreover, univariate and multivariate regression analysis demonstrated that miR-330-3p was an independent prognostic factor in BC.

CONCLUSIONS: Our data suggest that miR-330-3p upregulation maybe concurrently associated with prognosis in patients with BC, suggesting that miR-330-3p may be a potential prognostic biomarker and therapeutic target for patients with BC.



- **False Positive in miRExPlore:**
- „The levels of miR-330-3p were positively correlated with the status of TNM stage ($p = 0.011$) and lymph node metastasis ($p = 0.006$).“
- **But Context is very clear !**

- Diss Katrin Fundel (2007)



Increased expression of miR-330-3p “biomarker-of” poor prognosis in human breast cancer.

The context information from the sentence and the abstract which supports this relation is as follows:

Evidence: expression, increased expression, rtPCR

Objects: miR-330-3p

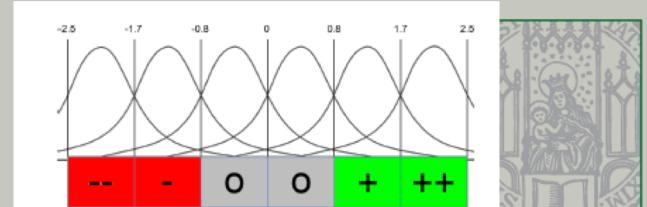
Disease: (human) breast cancer, TNM stage

Species: human

Tissue: breast cancer tissue, normal breast tissues

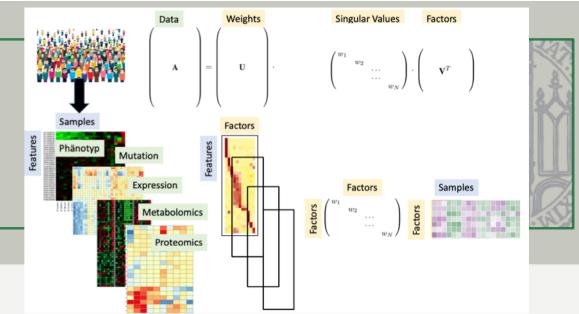
Experimental technique: prognosis, Kaplan-Meier method, Cox proportional hazards model, regression, x²-test

Year: Eur Rev Med Pharmacol Sci. (IF= 2.7)

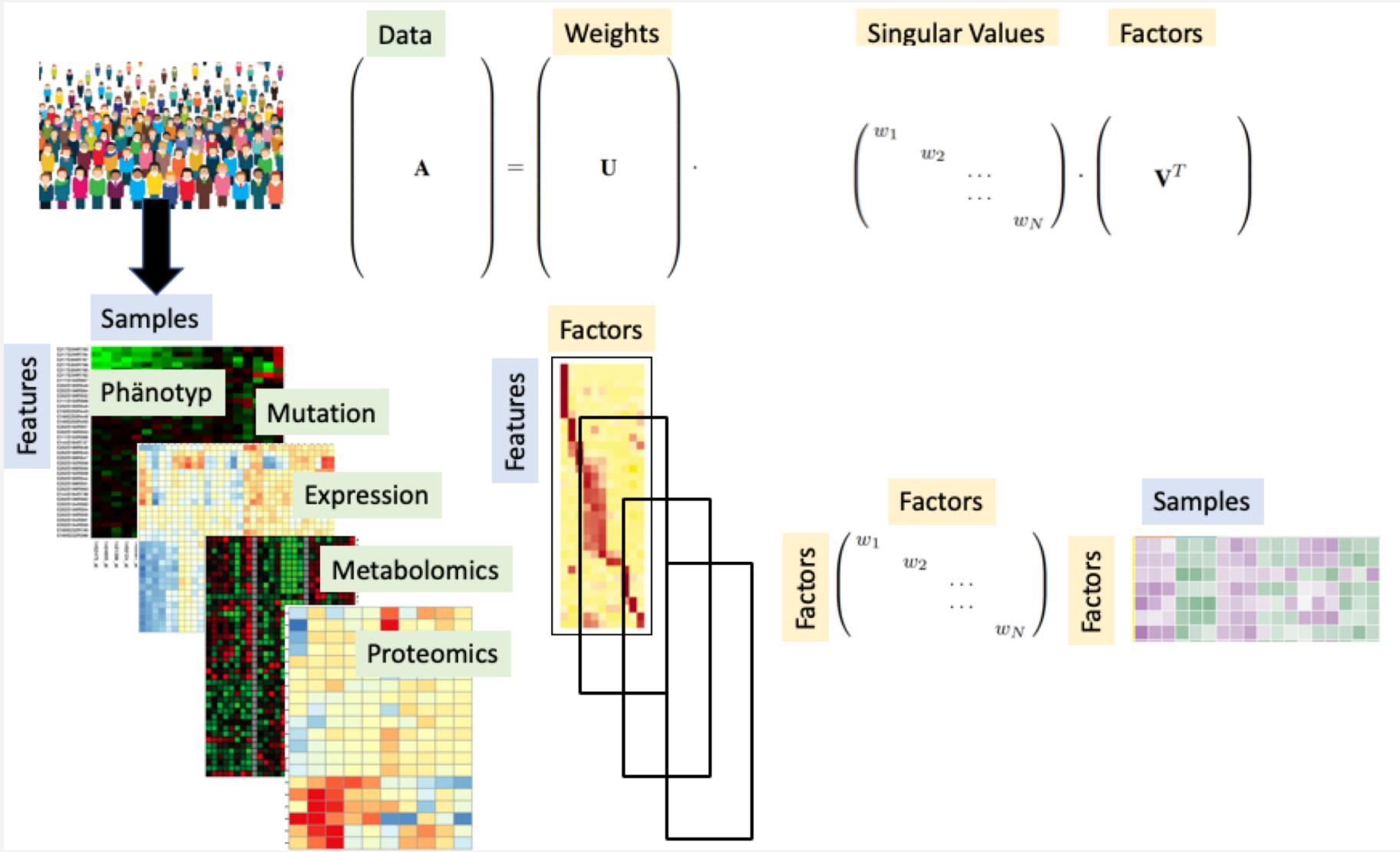


- **Fuzzy discretization, values & logic for HT data analysis (Lukas Diss)**
 - HT data description
 - Differential analysis
 - GSE analysis
- **SFB1123, Heatshock, NGS core**
- **Lehre: NEAP Master**
- **(MS)-Empire**
- **Combine Fuzzy Logic with context-dependent background distributions and local fold changes**
- **Combine Fuzzy Logic with confidence intervalsl and estimation graphics**
- **Extend to GSE, GPE (Evi Diss)**

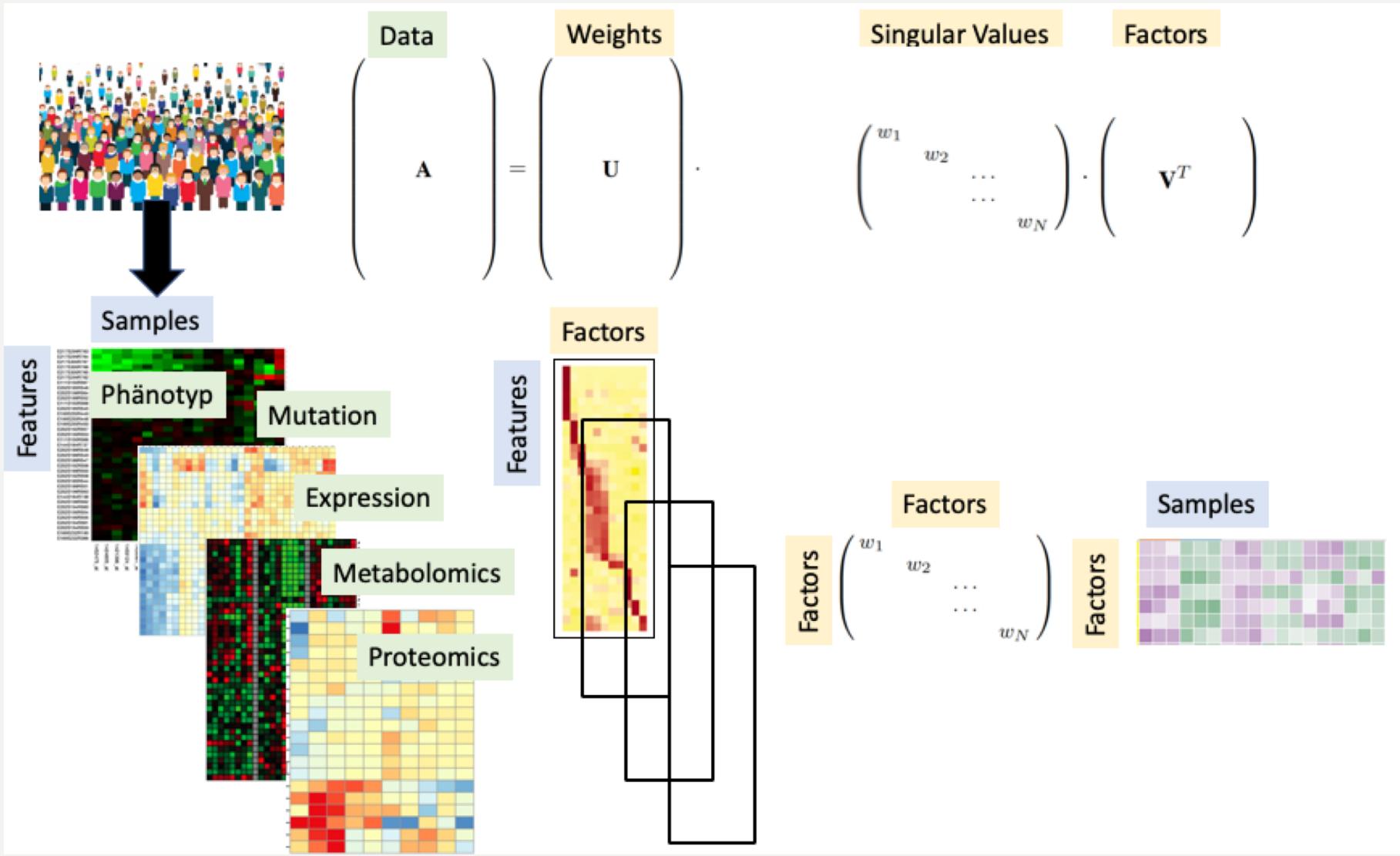
Visions and Projects



- HT data analysis and heterogeneous data integration
- SFB1123 Athernetwork, Atheroindex
- Cancer Inadscape (TCGA)
- Encode: reproducibilty ChipSeq, Atacseq etc
- Yeast Heatshock: Integration of data
- Can „classical“ integration methods work („latent“ methods)
 - t-SNE, umap
 - MOFA
 - ConceptMaker
- What about Bayesian Networks? Network Inference ?



SVD approach



2018

Multi-Omics Factor Analysis—a framework for unsupervised integration of multi-omics data sets

Ricard Argelaguet^{1,†} , Britta Velten^{2,†} , Damien Arnol¹ , Sascha Dietrich³ , Thorsten Zenz^{3,4,5} , John C Marioni^{1,6,7} , Florian Buettner^{1,8,*} , Wolfgang Huber^{2,**}  & Oliver Stegle^{1,2,***} 



Multi-omics studies promise the improved characterization of biological processes across molecular layers. However, methods for the unsupervised integration of the resulting heterogeneous data sets are lacking. We present Multi-Omics Factor Analysis (MOFA), a computational method for discovering the principal sources of variation in multi-omics data sets. MOFA infers a set of (hidden) factors that capture biological and technical sources of variability. It disentangles axes of heterogeneity that are shared across multiple modalities and those specific to individual data modalities. The learnt factors enable a variety of downstream analyses, including identification of sample subgroups, data imputation and the detection of outlier samples. We applied MOFA to a cohort of 200 patient samples of chronic lymphocytic leukaemia, profiled for somatic mutations, RNA expression, DNA methylation and *ex vivo* drug responses. MOFA identified major dimensions of disease heterogeneity, including immunoglobulin heavy-chain variable region status, trisomy of chromosome 12 and previously underappreciated drivers, such as response to oxidative stress. In a second application, we used MOFA to analyse single-cell multi-omics data, identifying coordinated transcriptional and epigenetic changes along cell differentiation.





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doi:10.1093/bioinformatics/bti1143

Text Mining

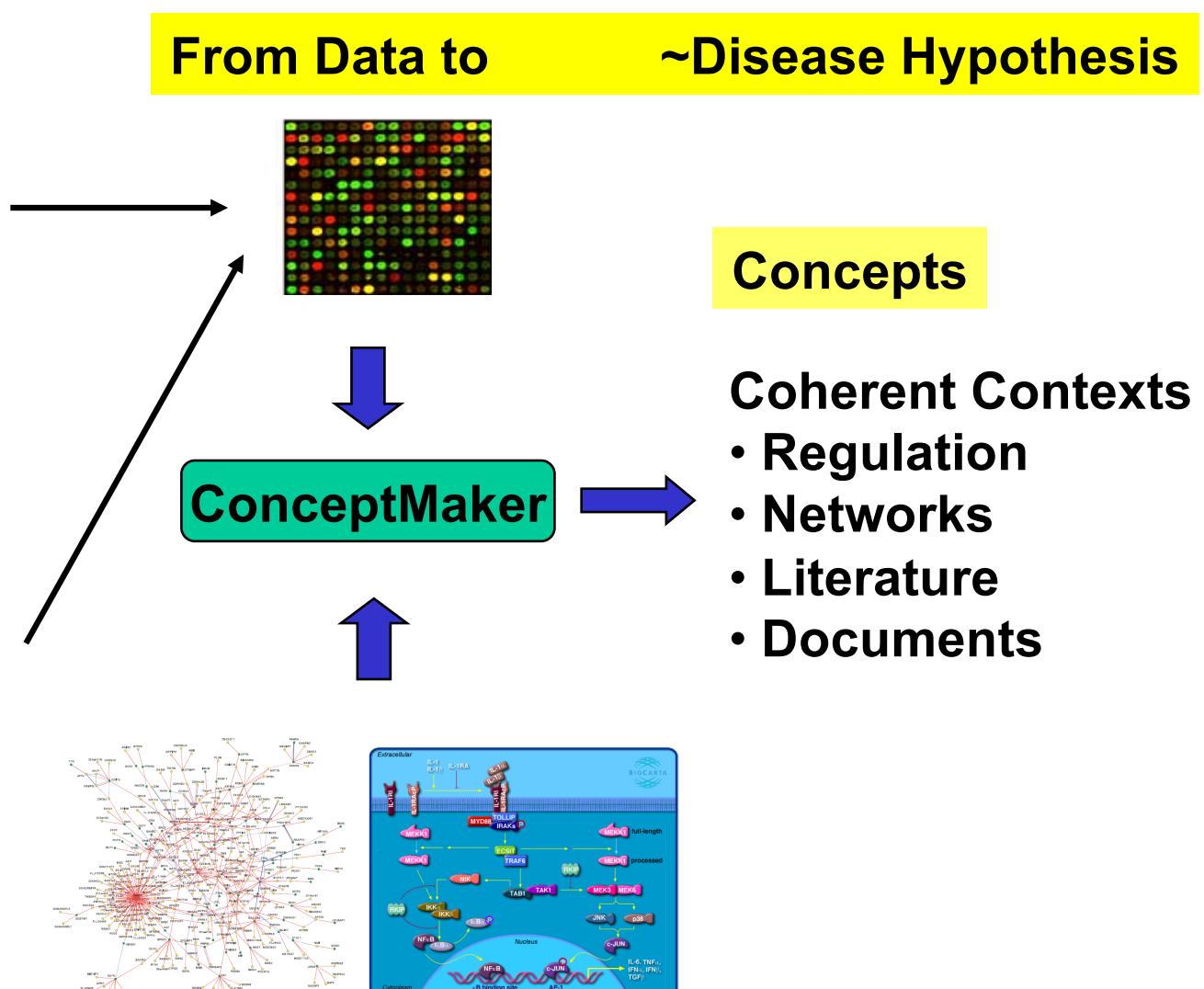
Expert knowledge without the expert: integrated analysis of gene expression and literature to derive active functional contexts

Robert Küffner*, Katrin Fundel and Ralf Zimmer

Department of Informatics, Ludwig-Maximilians-Universität München,
Amalienstrasse 17 80333 München, Germany



Understanding Complex Phenotypes and Diseases: e.g. Osteoarthritis



Küffner, Fundel et al.
2005-2006

PubMed

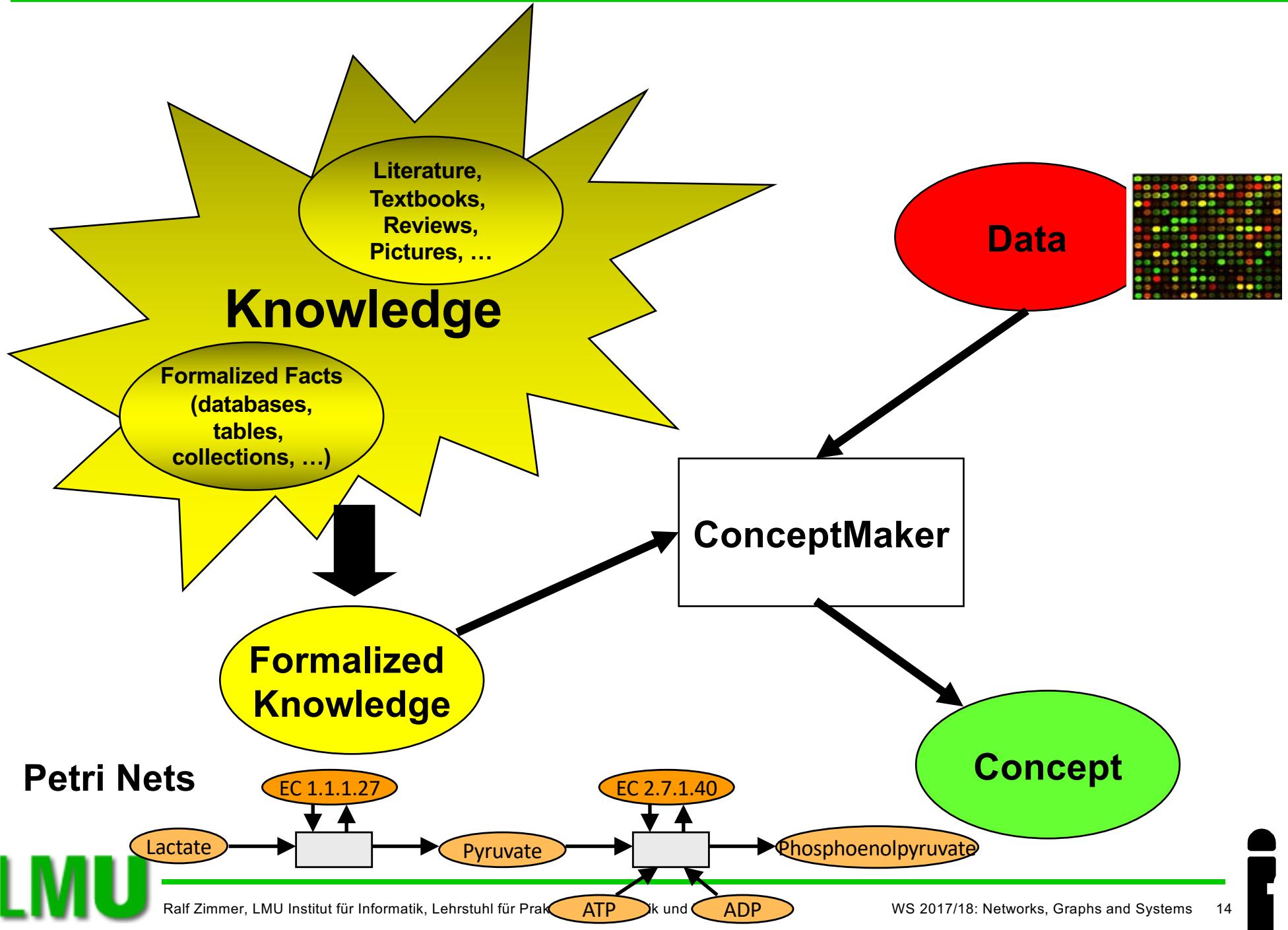
LMU

Ralf Zimmer, LMU Institut für Informatik, Lehrstuhl für Praktische Informatik und Bioinformatik,

WS 2017/18: Networks, Graphs and Systems

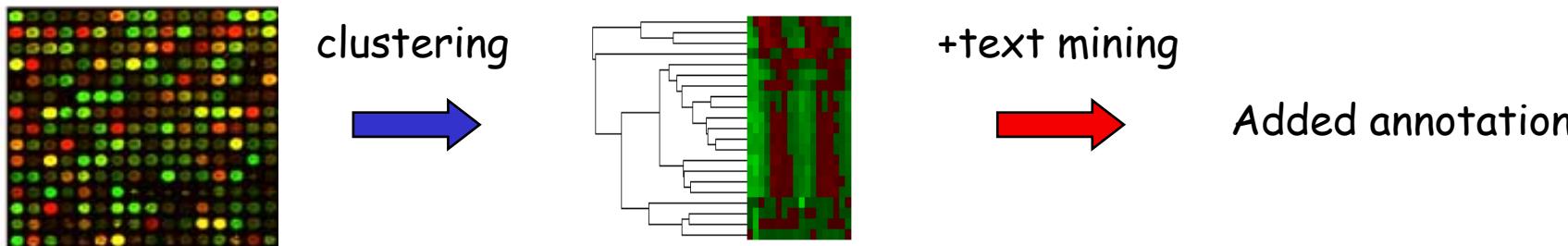


ConceptMaker: Concept



Augmenting expression analysis with text mining

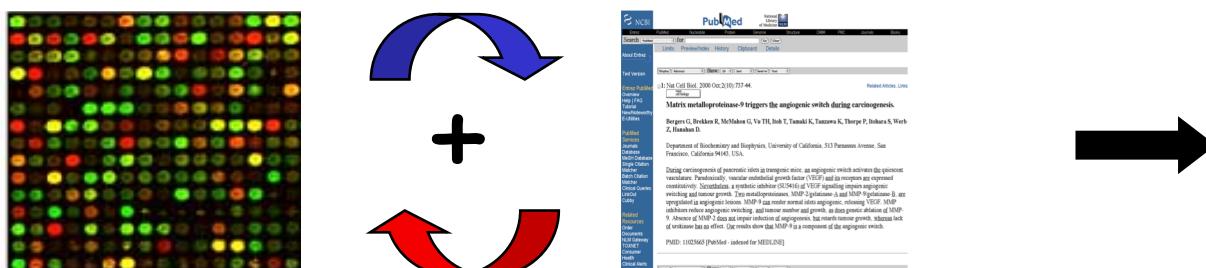
Approach 1, e.g. Masys et al, 2001:



Approach 2, e.g. Chaussabel&Cher, 2002 (Variant: GO-ORA):



ConceptMaker approach:



Queries optimized to select
functionally related and
significantly regulated genes
=active functional contexts

```

54 sc=11.0 sim=0.17 #= 3 neuroendocrin_peptid
55 sc=10.8 sim=0.40 #= 4 growth hormone
56 sc=10.8 sim=0.48 #= 3 tubulin
57 sc=10.3 sim=0.36 #= 3 gadd45
58 sc=10.0 sim=0.32 #= 3 antiprolif
59 sc= 5.2 sim=0.41 #= 3 fibronectin iii

```

Tree of clusters

```

7 3 secretas complex
45 3 melanoma, experimental
50 3 antizym
57 3 gadd45
56 3 tubulin
17 14 metallothionein
55 4 growth hormone
15 16 igfbp
21 5 serum
47 4 antigens, cd98
28 8 antigens, cd20
49 5 groucho
40 5 high mobility group p
58 3 antiprolif
38 5 oxygenator
48 6 proap
37 12 reti
33 12 alco
18 24 cyto
27 13 circ
5 59 wnt
23 17 rec
54 3 neu
35 7 plat
41 9 maci
46 4 rece
31 4 ccaaat-enhanc
43 9 interleuki
8 4 urinary r
2 3 s100 pr
53 8 heat-shock proteins 7
42 3 intergen
52 10 cofilin
19 18 wasp
6 6 erm protein
39 7 complement
16 15 cl inhibitor
12 6 hla-dr antigen
34 11 nadph oxidase
3 22 sialyltransferase
59 3 fibronectin iii
51 5 roundabout
1 51 leucin repeat
26 21 angiopoietin
22 10 receptors, fibroblast
10 46 activin
44 7 immediate-early prote
24 17 tetraspanin
11 33 integrin
30 6 tenascin
25 22 hyaluronan
13 25 sulfotransferase
29 11 protein-lysine 6-oxid
32 21 thrombospondin
4 29 matrix metalloprotein
14 15 muscular dystrophie
20 14 microfibril
36 6 extracellular matrix
9 21 laminin
0 30 collagen

```

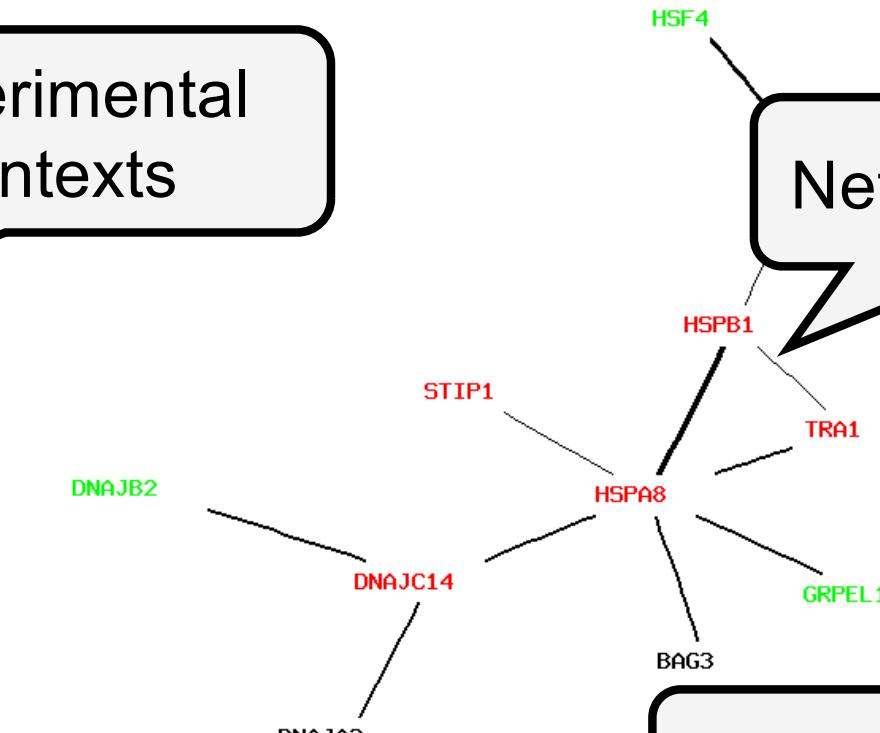
Cluster links

Gene tree

6	3.3	2.0	L-H-S	TRAL	tumor			
10	4.5	3.6	L-H-S	HSPB1	heat			
9	4.0	-2.6	L-H-S	HSF1	heat			
4	2.7	1.8	L-H-S	HSPB1	heat			
4	1.9	-2.0	L-H-S	HSF4	heat			
5	1.1	-1.3	L-H-S	DNAJA3	DnaJ			
5	0.8	-1.2	L-H-S	STCH	stress			
12	0.6	1.2	L-H-S	HSPALL	heat			
6	5.5	2.8	L-H-S	STIP1	stress-induced			
15	5.7	3.0	L-H-S	HSPA8	heat shock	70		
10	3.3	-2.1	L-H-S	GRPEL1	GrpE-like	1		
12	3.3	2.1	L-H-S	DNAJB4	DnaJ homolog, subfamily B, member 4			
12	4.2	-2.6	L-H-S	DNAJB2	DnaJ homolog, subfamily B, member 2			
15	5.8	3.2	L-H-S	DNAJC14	DnaJ homolog, subfamily C, member 14			
8	2.5	-2.0	L-H-S	BAG3	BCL2-associated athanogene 3			
8	0.7	1.1	L-H-S	BAG5	BCL2-associated athanogene 5			
7	3.9	2.6	L-H-S	BAG2	BCL2-associated athanogene 2			

Experimental contexts

Gene links



Coherent set of genes

Network context

1: HSPA8 heat shock 70kDa protein 8 [*Homo sapiens*]

GeneID: 3312

Summary

Official Symbol HSPA8

Official Full Name heat shock 70kDa protein 8

Annotations

provided by HGNC

Home Table Of Contents

Summary Genomic regions, transcripts...
Genomic context
Bibliography

Understanding Complex Phenotypes and Diseases: Data Analysis

```
54 sc=11.0 sim=0.17 #= 3 neuroendocrin peptide
55 sc=10.8 sim=0.16 #= 4 growth hormone
56 sc=10.3 sim=0.14 #= 3 gadd45
57 sc=10.3 sim=0.36 #= 3 antiprolif
58 sc=10.0 sim=0.32 #= 3 antiprolif
59 sc= 5.2 sim=0.41 #= 3 fibronectin 111
```

Tree of clusters

```
7 3 secretase complex
45 3 melanoma, experimental
50 3 antivir
53 3 gadd45
56 3 antiprolif
17 14 metallochaperone
53 4 growth hormone
15 3 actin
23 5 actin
47 4 anticens, cd98
48 5 anticens
49 5 high mobility group
53 5 antiprolif
58 5 proapopt
37 12 retinoid
16 24 cytochrome p-450 end
27 13 circadian rhythm
28 13 circadian rhythm
23 17 receptors, calcitonin
54 3 neuroendocrin peptide
34 9 macrophage colony-stim
41 4 receptors, tumor necr
31 4 receptors, tumor-necr
43 9 interleukin-6
8 4 urinary plasminogen a
3 8 heat-shock proteins ?
43 3 intercen
53 18 cofillin
18 6 egr protein
37 7 complement
39 18 integrin
12 6 hla-dc antigen
34 11 nadph oxidase
32 12 integrin
59 3 fibronectin 111
51 5 roundabout
1 5 integrin
26 21 angiopoietin
22 18 receptors, fibroblast
1 1 integrin
45 7 intermediate-early prote
24 17 tetraspanin
31 6 integrin
25 22 hyaluronan
33 22 sulfatoglycan
12 21 laminin, laminin-oxid
34 21 thrombopondin
29 29 matrix metalloproteinase
20 14 macrofibrillins
36 6 extracellular matrix
1 31 laminin
0 39 collagen
```

Cluster links

Literature contexts

Gene tree

```
6 J.J. 2.0 L-H-S TRA1
10 4.5 J.6 L-H-S HSPB1
9 4.1 -2.8 L-H-S HSPB1
4 1.8 -2.0 L-H-S HSF4
5 1.5 -1.0 L-H-S DNAJB3
5 0.5 1.0 L-H-S HSPB1
12 0.5 1.0 L-H-S HSPB1
6 0.5 2.8 L-H-S STIP1
15 5.7 2.1 L-H-S GRPEL1
10 3.7 2.1 L-H-S DNAJB4
12 3.3 2.1 L-H-S DNAJB4
13 3.7 2.1 L-H-S DNAJB4
15 5.0 3.2 L-H-S DNAJB4
8 2.5 -2.0 L-H-S BAG3
6 3.9 2.6 L-H-S BAG3
7 3.9 2.6 L-H-S BAG3
```

Coherent set of genes

Experimental contexts

Tree of clusters

Annotations

1	1	4560	18026	30100
1	10	303		
1	11	190		
1	111	1		
1	118	2		
1	12	165		
1	121	1		



639	20	104	1	68
640	20	21	1	
641	20	25	1	
642	20	30	1	
643	20	31	2	
644	20	32	1	

- Alternative Splicing
 - Detection (reliable, protein level, ... & transcript level)
 - Landscape (is splicing important?)
 - Tool
- SFB1123 MassSpec!
- Diss Constantin (MS-Empire, splicing project),
Diss Markus (EmpireS)
- Use CPTAC proteomics data:
 - tool: MS (TMT?) data set => all reliable splicing candidates (with estimation graphics)
 - Apply to CPTAC and identify some relevant cases, check for known and unknown
 - Apply for landscape: => IoF
 - Atheroindex (SFB1123) as a (simple) application



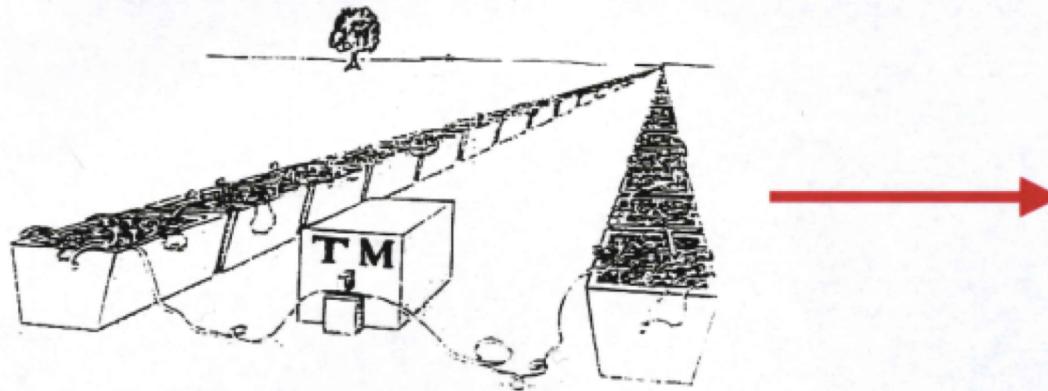
- **IoF & IoC**
 - Internet of Facts => time-lines with evidences, facts = relations in contexts
 - Internet of Claims => facts which could be True, i.e. in related contexts, in generalized contexts, but are not (yet) established/validated
 - Resource
- **SFB1123: AtheroNet, AtheroIndex**
- **NEAP recommendation systems**
- **NEAP relations, NEAP data search**
- **Context-based TextMining**
- **Robust data analysis: Transcriptomics (input), regulations (mechanism), mass spec (effect?)**



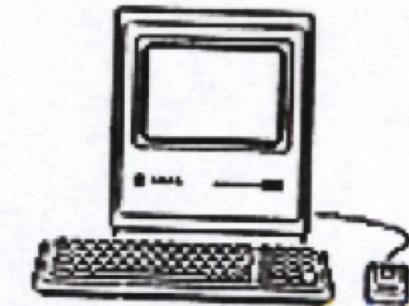
- **DNA Computing**
- **Lambda calculus:** $E = x \mid @ E E \mid \lambda x. E$
- **Semantic / meaning function = computation = string reduction**
- $m (@ \lambda x. E \ A) = E [x \leq A]$



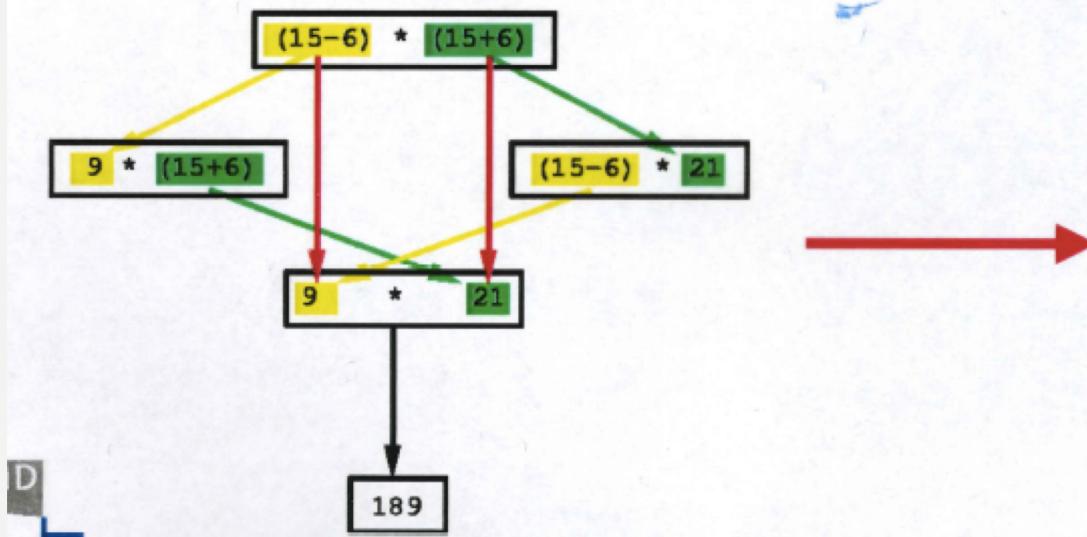
Zustandstransformation



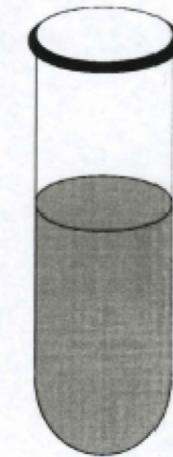
Computer



Ausdruckstransformation

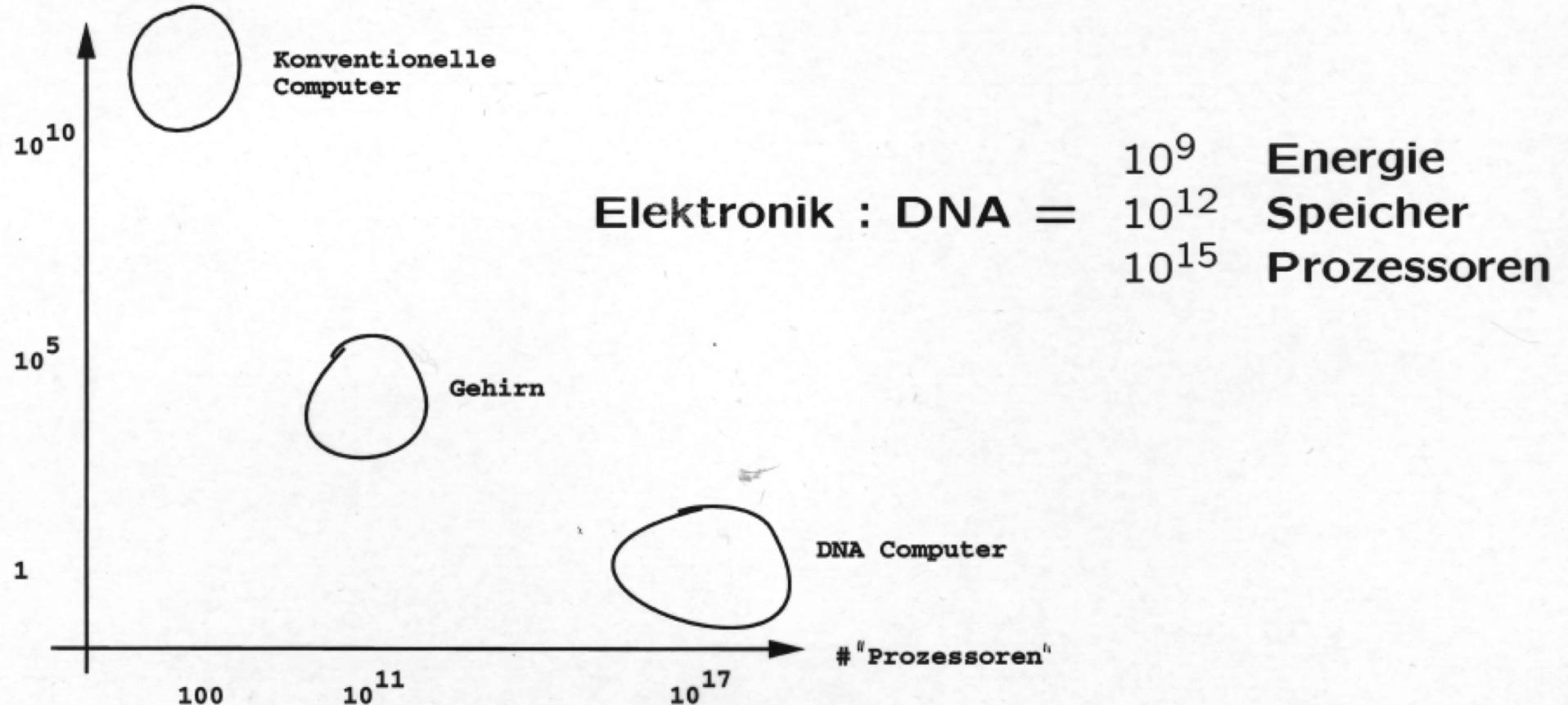


DNS Computer





Operationen/Stunde



DNA Lösung 6g/l: $6 * 10^{19}$ Moleküle à 200 bp $\approx 3 * 10^9$ TeraByte/l
PCR Zyklus 1min: $6 * 10^{19}$ Ops/min ≈ 1 Mio TeraOps/sec



- DNA Computing

Article

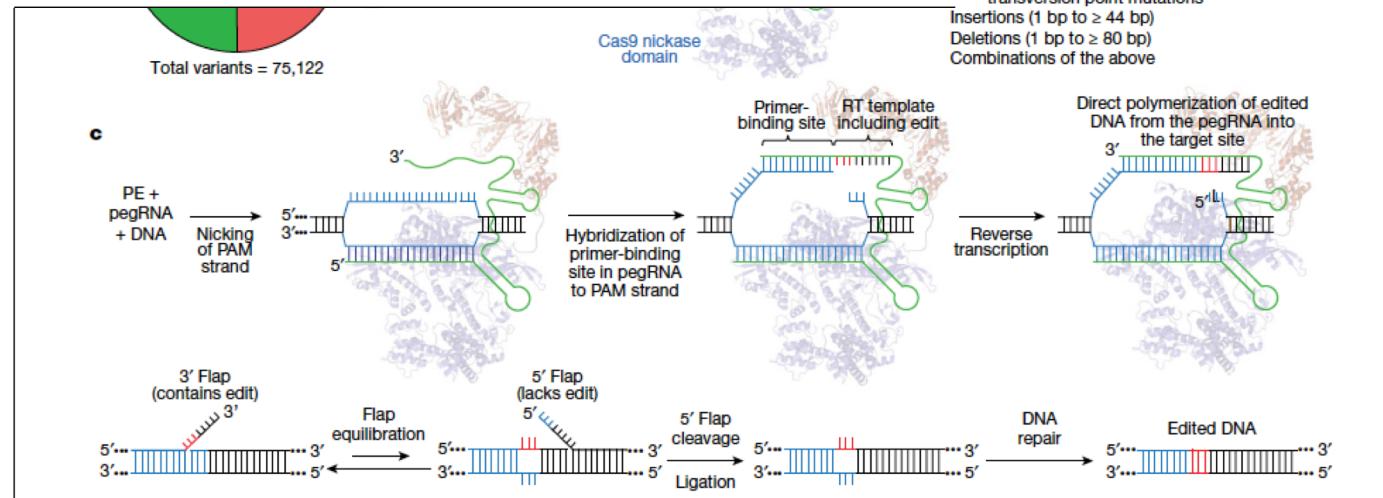
Search-and-replace genome editing without double-strand breaks or donor DNA

<https://doi.org/10.1038/s41586-019-1711-4>

Received: 26 August 2019

Accepted: 10 October 2019

Andrew V. Anzalone^{1,2,3}, Peyton B. Randolph^{1,2,3}, Jessie R. Davis^{1,2,3}, Alexander A. Sousa^{1,2,3}, Luke W. Koblan^{1,2,3}, Jonathan M. Levy^{1,2,3}, Peter J. Chen^{1,2,3}, Christopher Wilson^{1,2,3}, Gregory A. Newby^{1,2,3}, Aditya Raguram^{1,2,3} & David R. Liu^{1,2,3*}





- DNA Computing

Article | Published: 13 November 2019

High-resolution lineage tracking reveals travelling wave of adaptation in laboratory yeast

Alex N. Nguyen Ba, Ivana Cvijović, José I. Rojas Echenique, Katherine R. Artur Rego-Costa, Xianan Liu, Sasha F. Levy & Michael M. Desai

Nature 575, 494–499(2019) | Cite this article

8552 Accesses | 213 Altmetric | Metrics

nature

Letter | Published: 16 August 2017

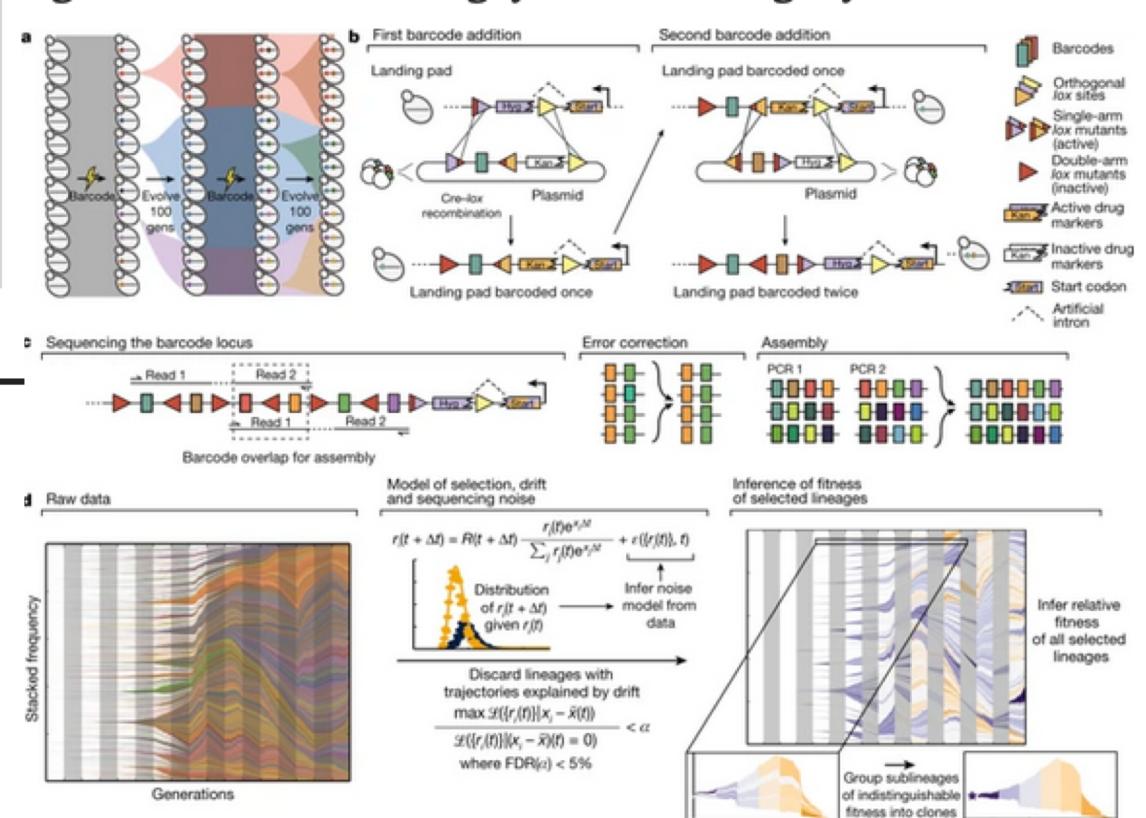
Polylox barcoding reveals haematopoietic stem cell fates realized *in vivo*

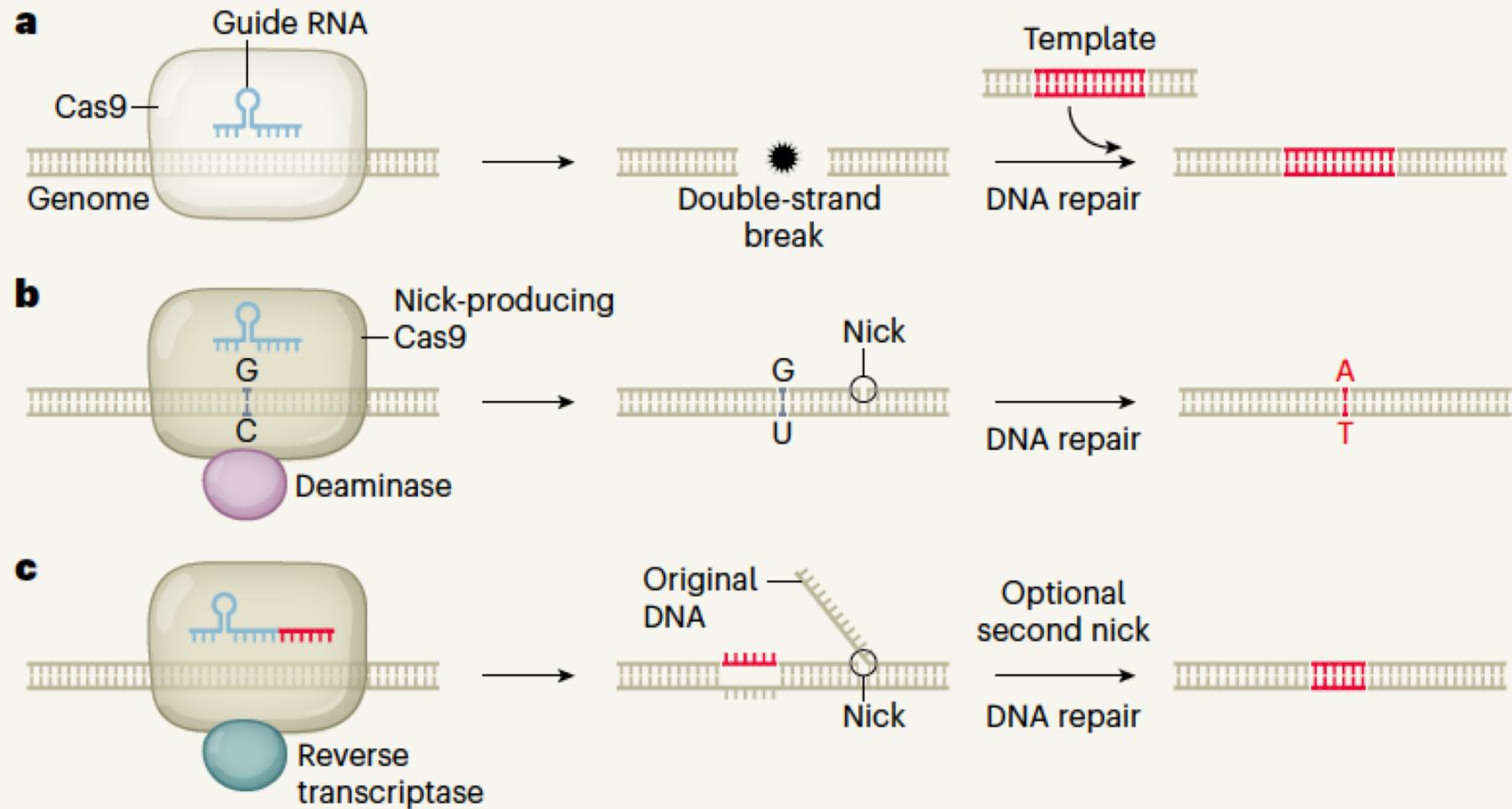
Weike Pei, Thorsten B. Feyerabend, Jens Rössler, Xi Wang, Daniel Postrach, Katrin Busch, Immanuel Rode, Kay Klapproth, Nikolaus Dietlein, Claudia Quedenau, Wei Chen, Sascha Sauer, Stephan Wolf, Thomas Höfer & Hans-Reimer Rodewald

Nature 548, 456–460(2017) | Cite this article

3900 Accesses | 90 Citations | 123 Altmetric | Metrics

Fig. 1: Renewable barcoding system and lineage dynamics.





Visions and Projects

- Climate neutral bioinformatics institute
- (First) Climate neutral university department





27.08.2019