Pathway based personalized analysis of gene expression data: method and applications

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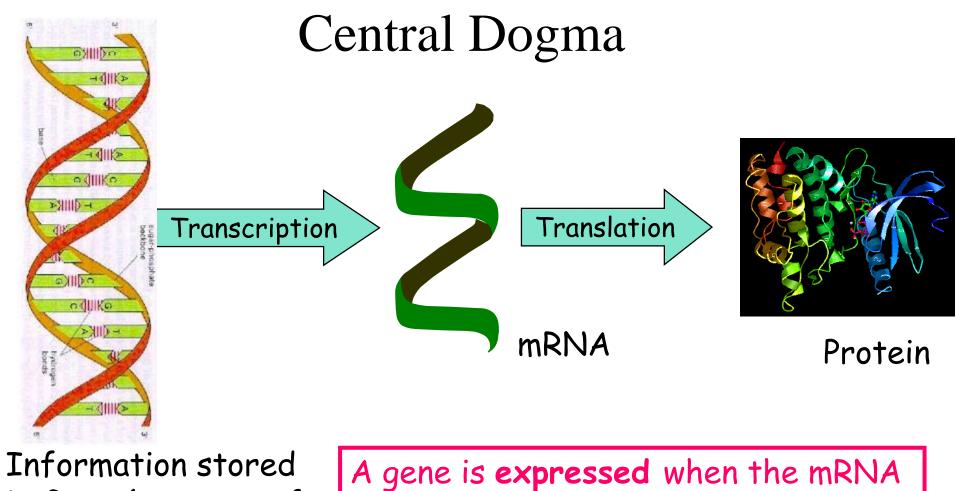
Carlos Caldas







Bari Dec 2017

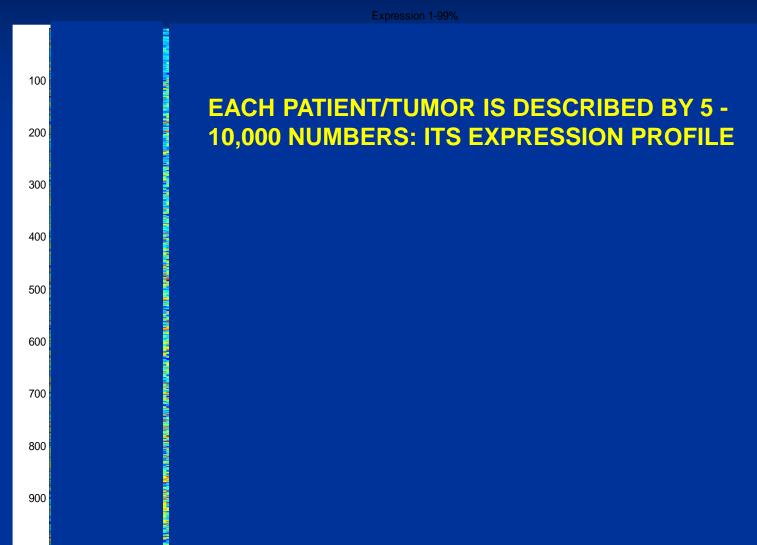


in Gene (segment of DNA)

A gene is **expressed** when the mRNA it codes for is transcribed

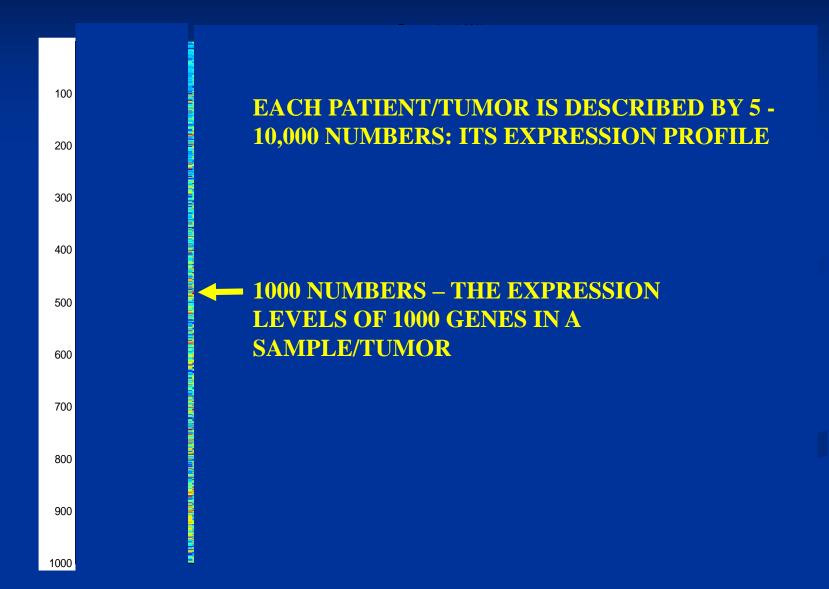
Cells express different subset of the genes (~5-10,000) in different tissues and under different conditions

MEASURE THE EXPRESSION LEVEL (mRNA) OF ~ 10,000 GENES

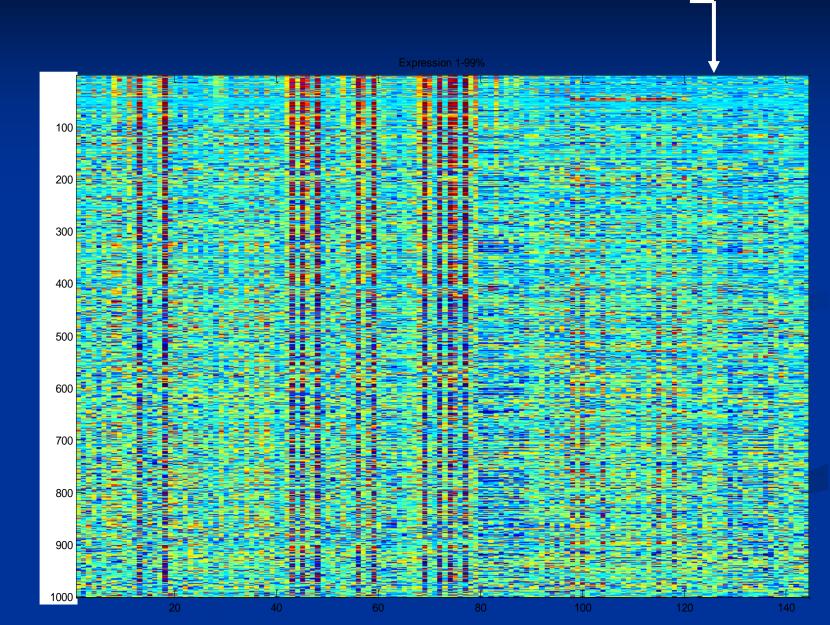


1000

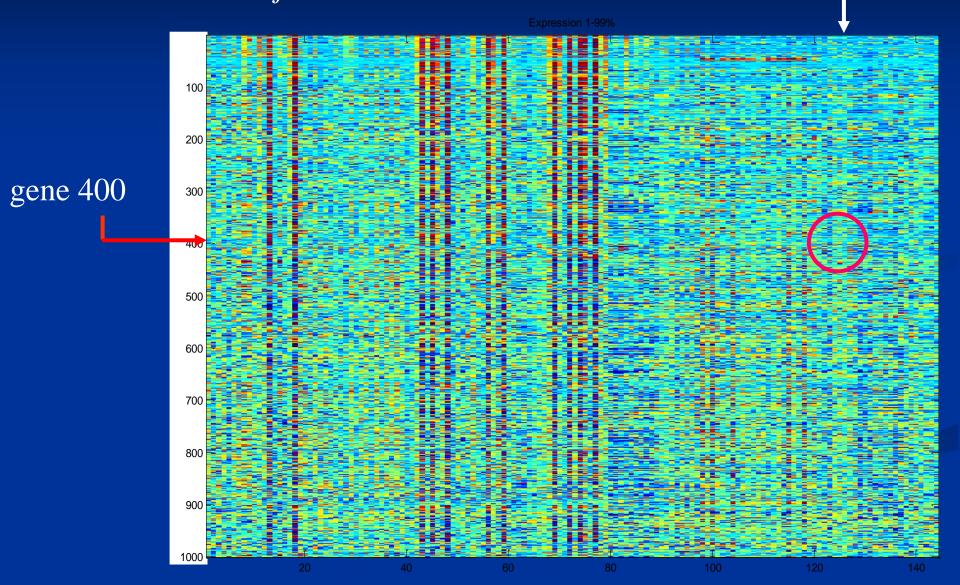
THE STANDARD METHOD: EXPRESSION – BASED ANALYSIS



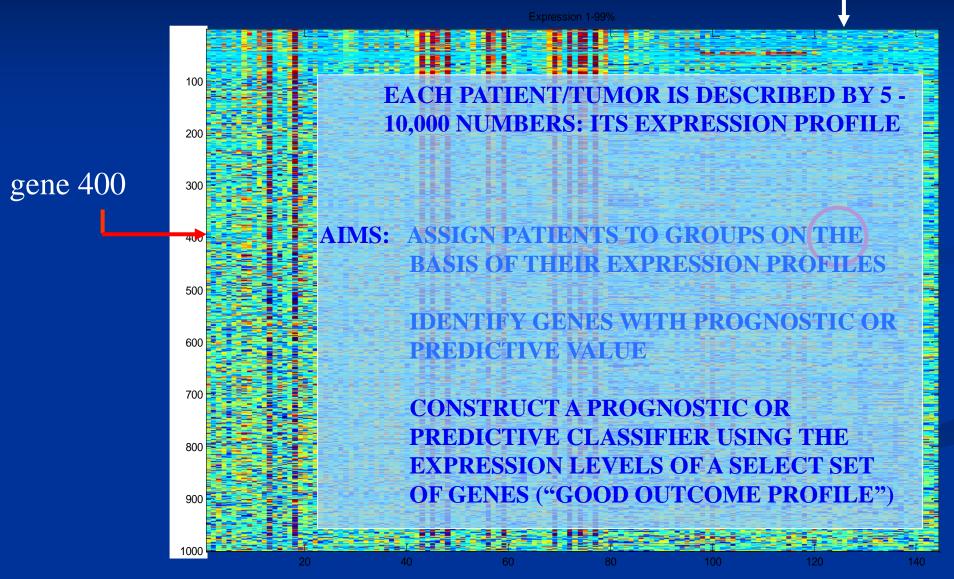
THE STANDARD METHOD: EXPRESSION – BASED ANALYSIS



THE STANDARD METHOD: EXPRESSION – BASED ANALYSIS $E_{ij} =$ EXPRESSION LEVEL OF GENE iSample # 127-IN SAMPLE jSample # 127-



THE STANDARD METHOD: EXPRESSION – BASED ANALYSIS $E_{ij} =$ EXPRESSION LEVEL OF GENE iSample # 127-IN SAMPLE jSample # 127-





PERSONALIZED PROGNOSTIC PREDICTIVE MEDICINE -

FOR BETTER TREATMENT OF CANCER

MEASURE (IN SAMPLE FROM TUMOR) GENOME- WIDE HIGH-THROUGHPUT DATA (MUTATIONS, GENE EXPRESSION, METHYLATION, SNP, DNA COPY NUMBER, ETC), AND USE FOR

- 1. PROGNOSIS (PREDICT OUTCOME, AGGRESSIVENESS)
- 2. PREDICT RESPONSE TO THERAPY

OF INDIVIDUAL PATIENTS/TUMORS

DESPITE OF GREAT IMPORTANCE AND 1000s of PAPERS, SO FAR – VERY LIMITED SUCCESS

FAILURES - WHY?:

SOME OF THE REASONS (1. CULTURAL AND 2. TECHNICAL):

1. THE FIELD WAS DOMINATED BY TWO EXTREMES:

a. USE **NO** BIOLOGICAL/CLINICAL EXISTING KNOWLEDGE, (turn ignorance into a virtue)

or

b. DEMAND/ASSUME FULL DETAILED MECHANISTIC KNOWLEDGE (don't dare talk to me unless you know and use all details)

2. FEW POINTS (TUMORS, 100 - 1000) IN HIGH DIMENSIONAL

SPACES (GENES: 1000 – 10,000): "CURSE OF DIMENSIONALITY"

"ATOMISTIC" APPROACH

WHAT'S WRONG WITH THIS CAR?:



"ATOMISTIC" APPROACH:

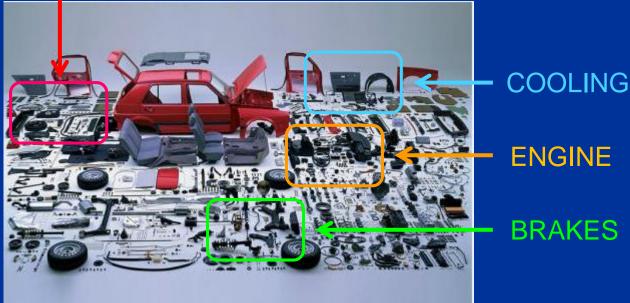
MEASURE SOME PROPERTY (e.g. TEMPERATURE) OF EVERY SINGLE COMPONENT – 12,000 NUMBERS CHARACTERIZE THE "STATE " OF EACH CAR

TRY TO DETERMINE THE FEATURES THAT CAN BE USED TO TELL HEALTHY CARS FROM SICK ONES.

NO EXISTING KNOWLEDGE ABOUT CARS IS USED

A "PHENOMENOLOGICAL" "SYSTEMS" APPROACH

TRANSMISSION



MEASURE FOR EACH **SYSTEM ONE** NUMBER, THAT INDICATES THE DEVIATION OF *THIS SYSTEM'S* FUNCTIONING FROM NORMAL.

EACH CAR IS CHARACTERIZED BY A SET OF SUCH "SYSTEM-LEVEL INDICATORS" (ABOUT 100) - USE *THESE* TO SEPARATE HEALTHY FROM SICK CARS

A "PHENOMENOLOGICAL" "SYSTEMS" APPROACH

TRANSMISSION



CARScellsCOOLINGheat shock proteinsENGINEmetabolism, growthBRAKESgrowth arrest, apoptosis

MEASURE FOR EACH **SYSTEM ONE** NUMBER, THAT INDICATES THE DEVIATION OF *THIS SYSTEM'S* FUNCTIONING FROM NORMAL.

EACH CAR IS CHARACTERIZED BY A SET OF SUCH **"SYSTEM-LEVEL** INDICATORS" (ABOUT 100) - USE *THESE* TO SEPARATE HEALTHY FROM SICK CARS

PATHWAY (OR - BIOLOGICAL PROCESS) – BASED ANALYSIS: THE IDEA

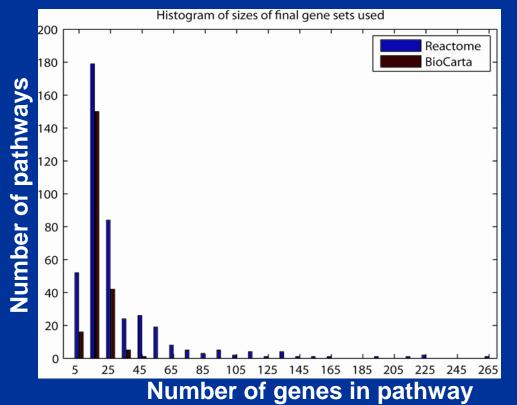
a. USE EXPRESSION (OR ANY OTHER) HIGH-THROUGHPUT DATA FROM A LARGE NUMBER OF SAMPLES.

b. USE BIOLOGICAL KNOWLEDGE – LISTS OF (10 - 100) GENES THAT BELONG TO A BIOLOGICAL PROCESS OR PATHWAY *P*

Drier, Sheffer & Domany PNAS 2013

b. USE EXISTING KNOWLEDGE - ASSIGNMENT OF GENES TO PATHWAYS *P*

USE *KEGG, BioCarta* FROM *MSigDB*, AND *NCI-Nature Pathway Interaction* DATABASES



TYPICALLY – TENS OF GENES IN A PATHWAY; HUNDREDS OF SAMPLES "CURSE OF DIMENSIONALITY" IS ELIMINATED

PATHWAY (OR - BIOLOGICAL PROCESS) – BASED ANALYSIS: THE IDEA

a. USE EXPRESSION (OR ANY OTHER) HIGH-THROUGHPUT DATA FROM A LARGE NUMBER OF SAMPLES.

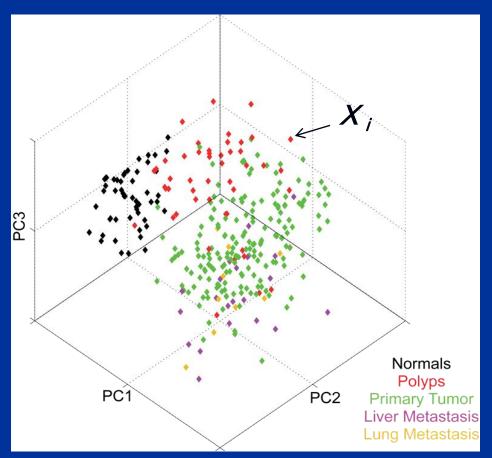
b. USE BIOLOGICAL KNOWLEDGE – LISTS OF (10 - 100) GENES THAT BELONG TO A BIOLOGICAL PROCESS OR PATHWAY *P*

c. DERIVE FOR EACH SAMPLE *i* AND PATHWAY *P* A "PATHWAY DEREGULATION SCORE" *D*(*i*,*P*)

Drier, Sheffer & Domany PNAS 2013

c. FOR EACH SAMPLE *i* AND PATHWAY *P* - CALCULATING THE PATHWAY DEREGULATION SCORE (PDS)

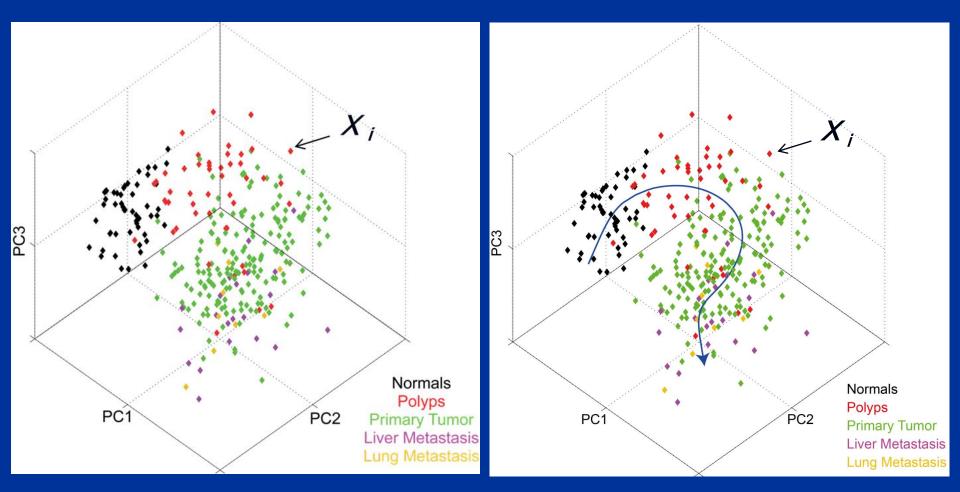
1. Consider pathway *P*; *identify* d_P genes that belong to it. Sample *i* is represented by a point X_i in the space of the expression values of these genes



KEGG APOPTOSIS PATHWAY, $d_P = 33$ GENES, COLON DATA

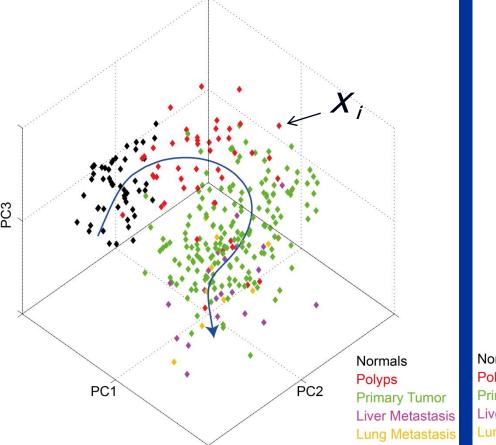
c. PATHWAY DEREGULATION SCORE (PDS)

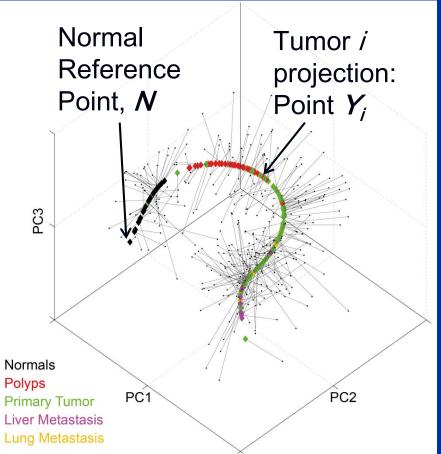
2. Calculate the *Principal Curve (Hastie & Stuezle 1989)* of the cloud of points formed by the full sample set



c. PATHWAY DEREGULATION SCORE (PDS)

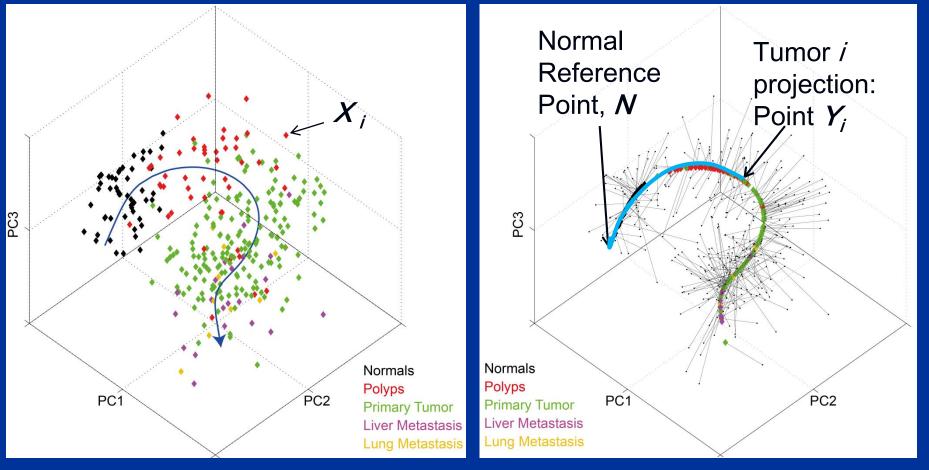
3. Project every sample onto the principal curve; projection of sample *i* is Y_i . The projection to the extremal point near the Normal samples is the Reference Point **N**





c. PATHWAY DEREGULATION SCORE (PDS)

4. The distance of Y_i from N, measured along the principal curve, is D_i (P), the Deregulation Score of pathway P in sample i.



PATHWAY (OR - BIOLOGICAL PROCESS) – BASED ANALYSIS: THE IDEA

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c. DERIVE FOR EACH SAMPLE *i* AND PATHWAY *P* A "PATHWAY DEREGULATION SCORE" D(i, P)

d. DO THIS FOR N_{P} ~ FEW HUNDRED PATHWAYS

e. A SAMPLE IS REPRESENTED IN TERMS OF ITS N_{ρ} PATHWAY DEREGULATION SCORES => DESCRIBED BY N_{ρ} PARAMETERS

f. PERFORM ALL ANALYSIS USING THESE "SYSTEM-LEVEL" VARIABLES WITH CLEAR BIOLOGICAL MEANING.

Drier, Sheffer & Domany PNAS 2013

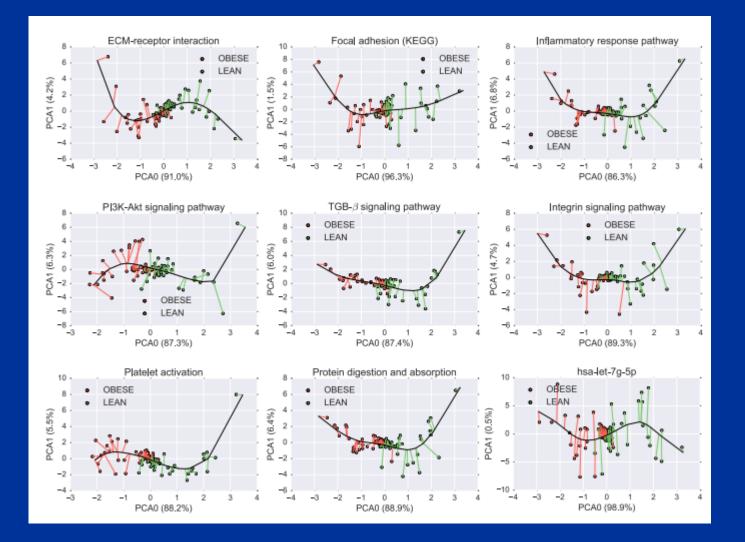
PATHWAY DEREGULATION IN OBESITY*

EXPRESSION DATA FROM 39 LEAN & 49 OBESE SUBJECTS

- 1. IDENTIFY 38 DIFFERENTIALLY EXPRESSED GENES
- 2. ENRICHMENT ANALYSIS: 16 PATHWAYS HAVE >2 OF THEIR GENES AMONG THE 38
- 3. PATHIFIER ANALYSIS OF THE 16 PATHWAYS SHOWS CLEAR SEPARATION IN DEREGULATION OF LEAN vs OBESE SUBJECTS

*Font-Clos, Zapperi, La Porta Sys Bio & App 2017

PATHWAY DEREGULATION IN OBESITY* - NEW OBESITY RELATED PATHWAYS



*Font-Clos, Zapperi, La Porta Sys Bio & App 2017

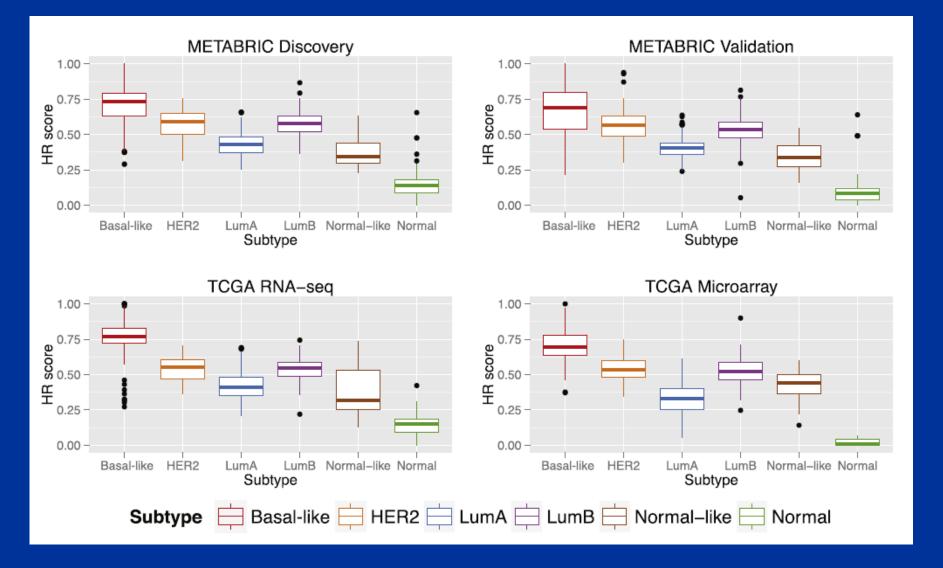
DNA REPAIR PATHWAY DEREGULATION IN BREAST CANCER*

EXPRESSION DATA ~ 4000 BREAST CANCER PATIENTS (4 DATASETS)

- MANUALLY CURATED LIST OF 82 GENES ASSOCIATED WITH HOMOLOGOUS RECOMBINATION (*HR*) - CRUCIAL FOR REPAIR OF DOUBLE STRANDED DNA BREAK
- 2. PATHIFIER ANALYSIS OF THE **HR** PATHWAY => HR SCORE FOR EACH SAMPLE, **ROBUST** ACROSS FOUR DATASETS!

*Liu et al Mol Onc 2016

HOMOLOGOUS RECOMBINATION (HR) SCORE - ROBUST



DNA REPAIR PATHWAY DEREGULATION IN BREAST CANCER*

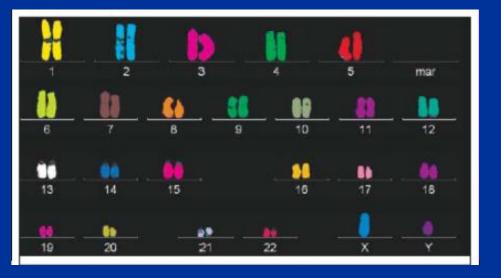
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- 3. FINDINGS: a. HR SCORE REFLECTS HR REPAIR DEFICIENCY b. HR SCORE IS ASSOCIATED WITH CHROMOSOMAL INSTABILITY

*Liu et al Mol Onc 2016

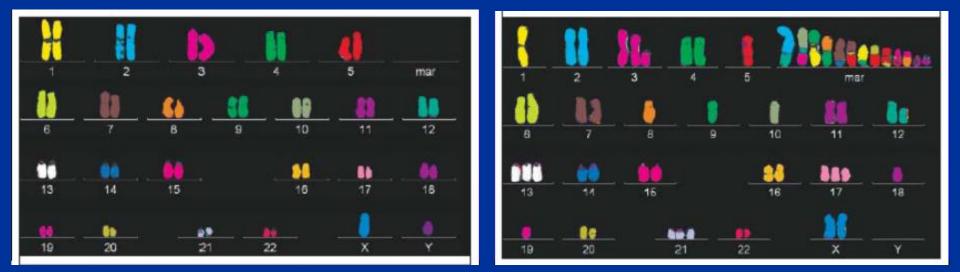
CHROMOSOMAL INSTABILITY

NORMAL CELLS MAINTAIN A VERY STABLE KARYOTYPE (SET OF CHROMOSOMES)



CHROMOSOMAL INSTABILITY

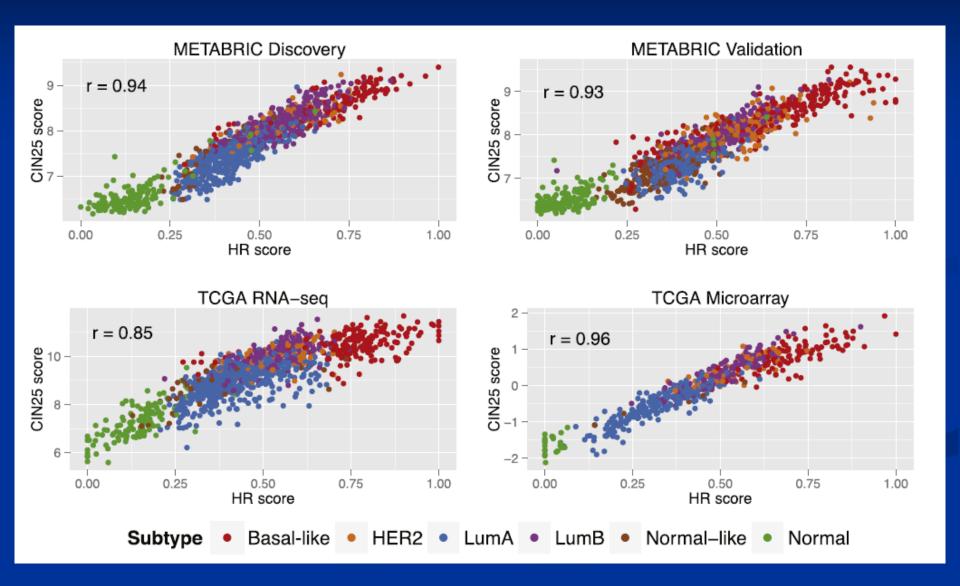
NORMAL CELLS MAINTAIN A VERY STABLE KARYOTYPE (SET OF CHROMOSOMES)



CANCER CELLS EXHIBIT ABNORMAL CHROMOSOME COPY NUMBERS (*ANEUPLOIDY*, *von Hansemann 1890*)

CHROMOSOMAL INSTABILITY (CIN)

HR SCORE - ASSOCIATED WITH CHROMOSOMAL INSTABILITY



DNA REPAIR PATHWAY DEREGULATION IN BREAST CANCER*

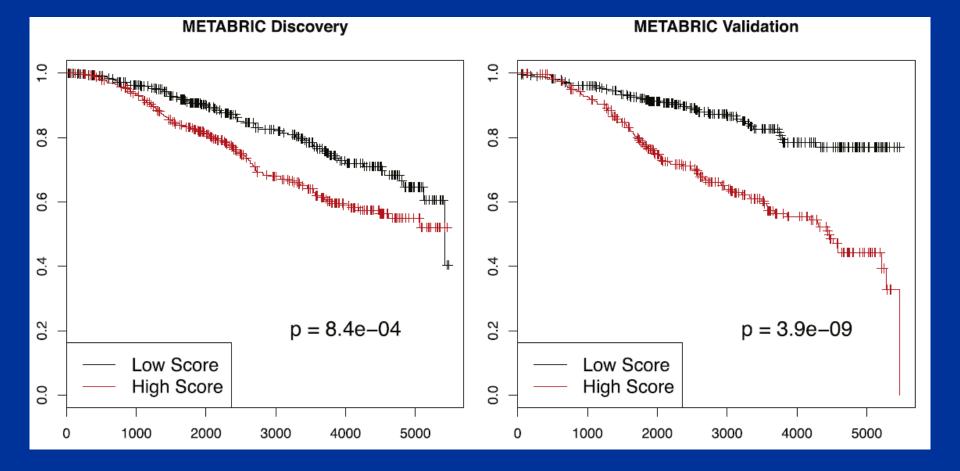
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 FINDINGS: a. HR SCORE REFLECTS HR REPAIR DEFICIENCY
 b. ASSOCIATION OF HR SCORE WITH CHROMOSOMAL INSTABILITY
 c. HIGH HR SCORE => WORSE SURVIVAL

*Liu et al Mol Onc 2016

HIGHER HR SCORE => WORSE SURVIVAL



- "CLASSSICAL" MACHINE LEARNING APPROACH TRAINING SET, FIT KNOWN RECURRENCE TIME y_i OF PATIENTS i=1,2,...N, AS A FUNCTION OF KNOWN VARIABLES $X_{i,k}$, k=1,2...K (GENE EXPRESSION, CLINICAL, etc)
- OUTCOME (GOOD/BAD) = THRESHOLD ON y
- USED 236 PATIENTS AS TRAINING SET & HAD 3 TEST SETS (606 PATIENTS
- STANDARD METHOD USES THE EXPRESSION VALUES OF K GENES
- Huang et al* CALCULATE PATHWAY DEREGULATION SCORES AND USE THESE AS THE VARIABLES $X_{i,k}$. 15 PATHWAYS ARE SELECTED (L1 LASSO)
- THE PATHWAY-BASED **PROGNOSTIC** PREDICTOR OUTPERFORMS THE STANDARD GENE-BASED PREDICTORS (PAM 50, Mammaprint 70)

*Huang et al PLoS Comp Bio 2014

DIAGNOSIS IN BREAST CANCER*

- AT DIAGMOSIS MOST BREAST TUMORS HAVE SPREAD TO LYMPH NODES
- SENSITIVITY (DISCOVERY RATE) OF MAMMOGRAPHY 54 77%

EARLY DISCOVERY => GOOD PROGNOSIS: NEED ACCURATE, LOW COST, NON-INVASIVE DIAGNOSTIC METHOD

PATHWAY BASED DIAGNOSIS, USING METABOLIC PATHWAYS

- 1. USE PLASMA & SERUM TO PROFILE BLOOD METABOLITES (MS) AND RNAseq EXPRESSION DATA FROM RESECTED TUMORS
- 2. CALCULATE PATHWAY DEREGULATION SCORES FOR ~300 METABOLIC PATHWAYS,

3. CONSTRUCT DIAGNOSTIC CLASSIFIER (3 - 8 PATHWAYS SELECTED)

*Huang et al Genome Medicine 2016

DIAGNOSIS IN BREAST CANCER*

THE RESULTING DIAGNOSTIC MODELS HAD OUTSTANDING PERFORMANCE, ROBUSTNESS (TRAINED ON MASS-SPEC METABOLOMIC DATA FROM PLASMA, TESTED ON SIMILAR DATA ON SERUM AND EXPRESSION DATA FROM TISSUE) AUC > 0.9, SENSITIVITY & SPECIFICITY > 0.9

DISCOVERED NEW DIAGNOSTIC METABOLIC PATHWAYS FOR EARLY STAGE BREAST CANCER DIAGNOSIS:

TAURINE & HYPOTAURINE METABOLIC PATHWAYS MOST PREDICTIVE ALANINE, ASPARTATE & GLUTAMINE METABOLISM PROTEIN DIGESTION AND ABSORPTION

*Huang et al Genome Medicine 2016

Using expression data from 1992 TUMOR and 144 NORMAL samples

(997 in "Discovery set", 995 in "Validation")

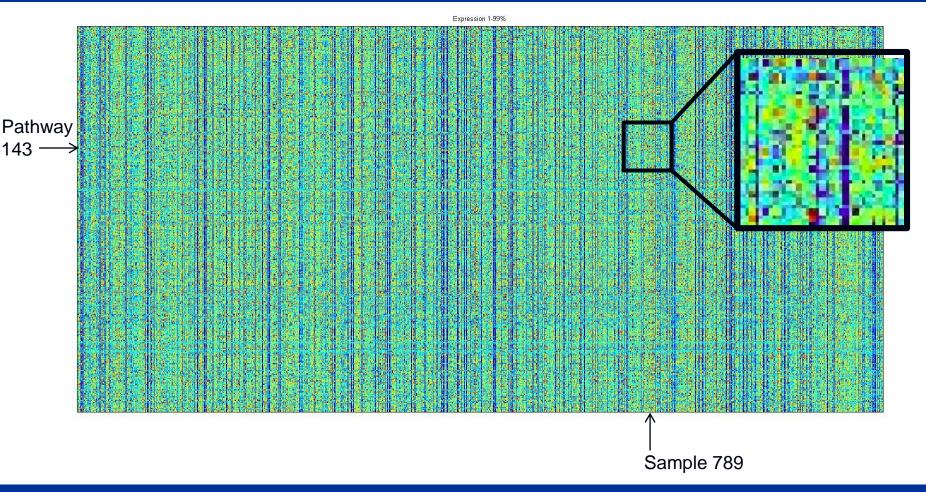
Calculate (using "Pathifier" analysis*) a Pathway Deregulation Score (PDS)

for 552 pathways/biological processes, for each sample (Discovery + Normal)

D(P,i) = PDS of pathway P in sample i – represent the extent to which pathway P is deregulated in sample i

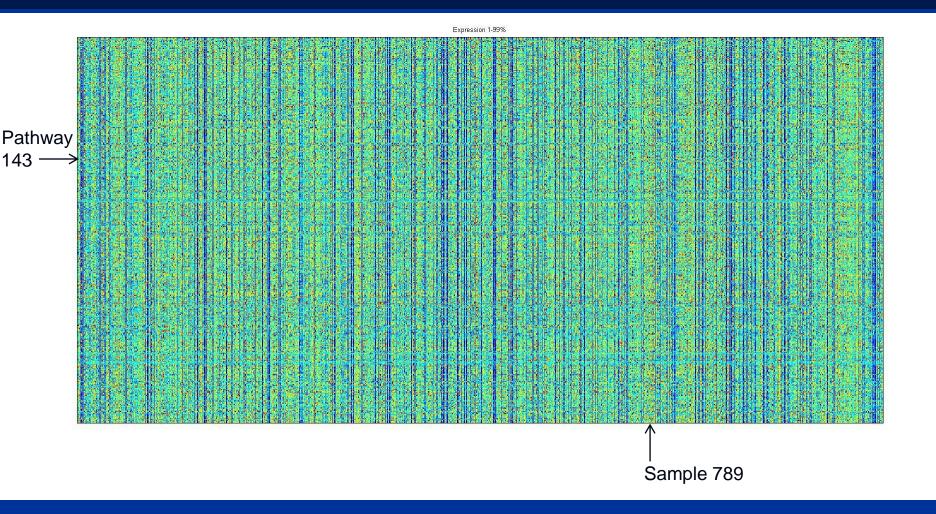
*Drier, Sheffer & Domany PNAS 2013

PDS OF 552 PATHWAYS: EACH SAMPLE (144 NORMAL, 997 BREAST TUMOR) IS REPRESENTED BY 552 SUCH PATHWAY–BASED SCORES**



**Livshits et al Mol Onc (2015)

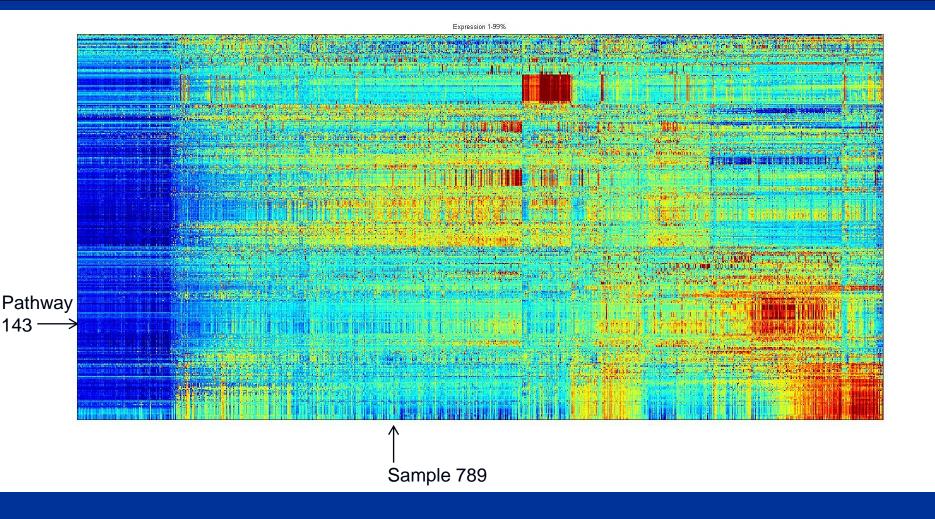
PERFORM ANALYSIS IN THIS SPACE: REORDERING* SAMPLES (**AND** PATHWAYS) REVEALS STRUCTURE IN DATA**



*Tsafrir et al *Bioinformatics* (2005)

**Livshits et al *Mol Onc* (2015)

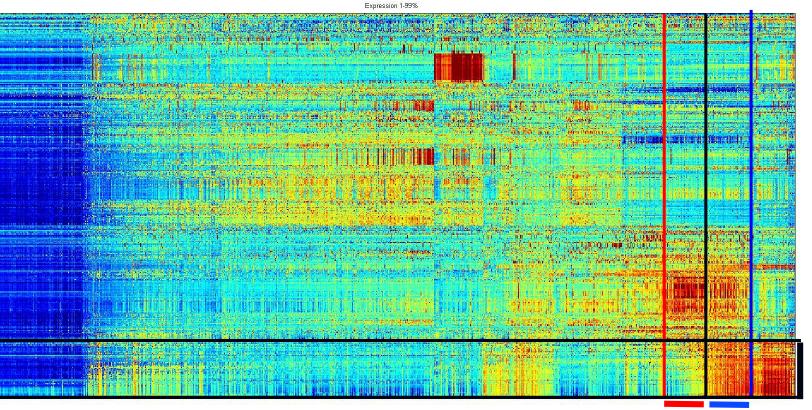
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FOCUS ON "TRIPLE NEGATIVE" TUMORS: TWO DISTINCT GROUPS

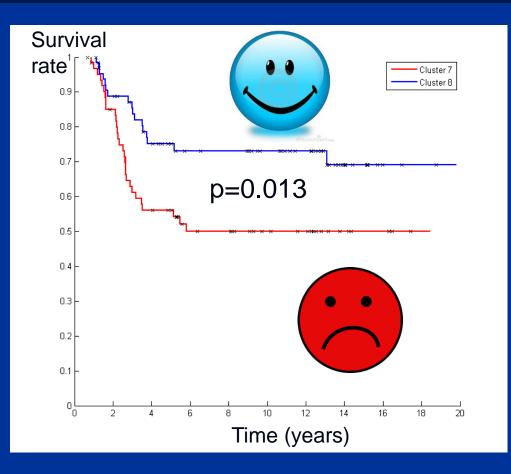


Immune pathways

"TRIPLE NEGATIVE" (TN) SUBTYPE – 2 GROUPS: HIGH AND LOW IMMUNE INVOLVEMENT

DIFFERENT OUTCOME/SURVIVAL FOR THE TWO GROUPS!

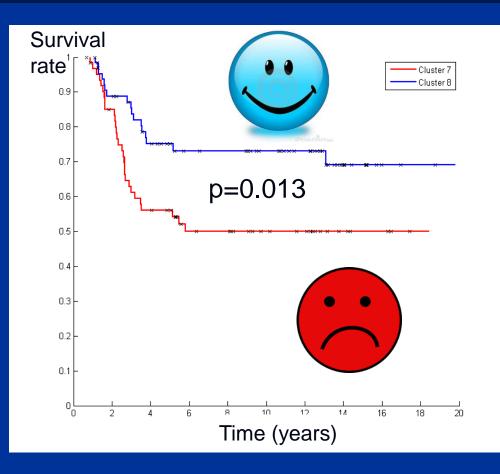
CLINICAL SIGNIFICANCE: FOR TN SUBTYPE, HIGH IMMUNE INVOLVEMENT → BETTER SURVIVAL



CLINICAL SIGNIFICANCE:

TN tumors with HIGH IMMUNE system involvement – better survival TN tumors with LOW IMMUNE system involvement -- worse

BIOLOGICAL INTERPRETATION: HIGH IMMUNE INVOLVEMENT (PDS) ⇔ HIGH *TIL* LEVEL



BIOLOGICAL INTERPRETATION:

HIGH IMMUNE PDS ⇔ high level of *T*umor *I*nfiltrating *L*ymphocytes

Highest correlation with *TIL* levels
for T-CELL related PATHWAYS
cell-specific signatures => Tcells
→ *BIOMARKER!*

PROGNOSTIC BIOMARKER?

Alexe et al (2007): no difference in survival between TN tumors with high/low immune involvement

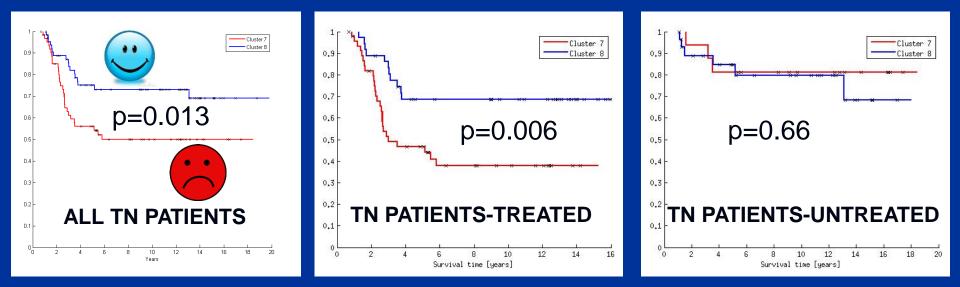
CLINICAL SIGNIFICANCE:

Basal tumors with HIGH IMMUNE system involvement – better survival Basal tumors with LOW IMMUNE system involvement -- worse

PREDICTIVE BIOMARKER: FOR TN SUBTYPE, IMMUNE INVOLVEMENT → BETTER RESPONSE TO THERAPY

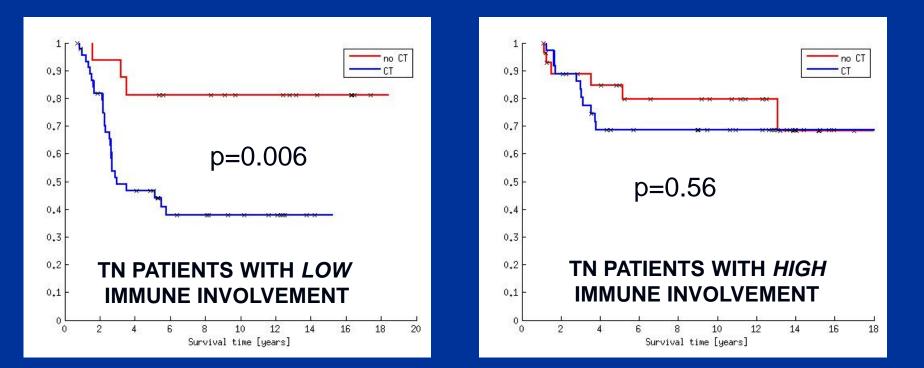
Alexe et al (2007): TN PATIENTS DID NOT RECEIVE CHEMOTHERAPY

METABRIC (2012): MAJORITY OF TN WERE TREATED (anthracyclins).



DIFFERENCE IN SURVIVAL BETWEEN BASAL PATIENTS WITH HIGH vs LOW IMMUNE INVOLVEMENT IS OBSERVED ONLY FOR PATIENTS WHO RECEIVED CHEMOTHERAPY. **PREDICTIVE BIOMARKER?**

PREDICTIVE BIOMARKER: FOR TN SUBTYPES, IMMUNE INVOLVEMENT -> BETTER RESPONSE TO THERAPY



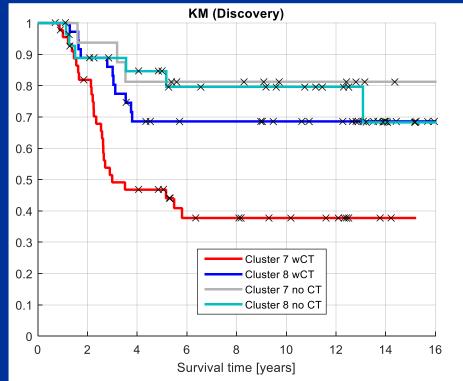
POSSIBLE INTERPRETATION 1: ANTHRACYCLINS ARE KILLING TN PATIENTS WITH *LOW* IMMUNE INVOLVEMENT, AND HAVE NO EFFECT ON PATIENTS WITH *HIGH* IMMUNE INVOLVEMENT.

INTERPRETATION 2: HIGH RISK PATIENTS (BAD *CLINICAL* INDICATORS) WERE SENT TO CHEMO. IF LOW IMMUNE – CHEMO DID NOT HELP. HIGH IMMUNE – CHEMO DID HELP!

PREDICTIVE BIOMARKER: FOR TN SUBTYPES, IMMUNE INVOLVEMENT → BETTER RESPONSE TO THERAPY

	СТ	No CT	Total
Cluster 7	46	16	62
(Low Imm)			
Cluster 8	36	29	65
(High Imm)			
Total	82	45	127

Anthracyclins & immune system: Zitvogel Cell Deat & Differ. (2014) Nat. Med. (2014) Oncoimmunology (2014)



WE USED CT/NO CT AS A PROXY FOR (CLASSICAL) HIGH/LOW RISK. HIGH IMMUNE INVOLVEMENT/TIL INDICATES GOOD RESPONSE OF HIGH-RISK TN PATIENTS TO ANTHRACYCLINS. **DO NOT TREAT (WITH ANTHRACYCLINS) HIGH RISK TN PATIENTS WITH LOW TIL.** *PREDICTIVE BIOMARKER!*

SUGGESTED DECISION PIPELINE:

- 1. IDENTIFY TRIPLE NEGATIVE (TN) PATIENTS (HISTOCHEMISTRY)
- 2. USE CLINICAL (OR OTHER) INDICATORS TO IDENTIFY HIGH RISK TN PATIENTS, CANDIDATES FOR CHEMOTHERAPY
- 3. FOR HIGH-RISK TN PATIENTS: MEASURE T – CELL INFILTRATE LEVEL IN TUMOR
- 4. IF LOW TIL DO NOT TREAT WITH ANTHRACYCLINES

TAKE – HOME LESSONS*:

- 1. DO NOT USE IGNORANCE-BASED "TOP RANKED" SINGLE GENE LISTS: THEY ARE UNSTABLE**, MOSTLY DEVOID OF BIOLOGICAL MEANING***.
- 2. CHARACTERIZE TUMORS BY KNOWLEDGE-BASED, SYSTEM-LEVEL VARIABLES[#] (Pathway Deregulation Scores).
- 3. LOWER AIMS: NO SILVER BULLET[&] THAT WORKS FOR ALL BREAST CANCER SUBTYPES AND ALL CHEMOTHERAPIES.
- 4. GENOMIC BIOMARKERS SHOULD COMPLEMENT CLASSICAL CLINICAL RISK INDICATORS (NOT REPLACE THEM).
- * Domany Cancer Res (2014)
 ** Ein-Dor et al Bioinformatics (2005); PNAS (2006)
 *** Drier et al PLoS ONE (2011)
 # Drier et al PNAS (2013)
 & Livshits et al Oncotarget (2015)

THANKS FOR LISTENING



APOLOGIES FOR RUNNING OVER TIME