

Artificial Intelligence in Medicine

Learning (2)

Nir Friedman and Tommy Kaplan 21/11/22

"I hate to generalize, but..."

Gloria Steinem



Generalization in medicine

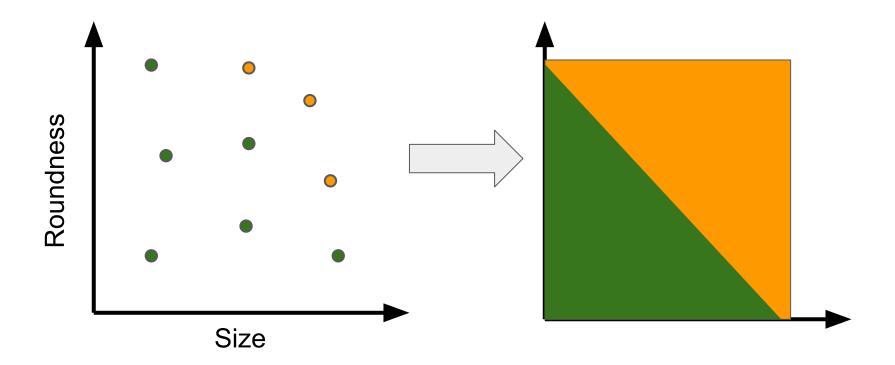
- Family medicine clinic, Jerusalem, yesterday:
- Physician examines 30 patients
- First 28 with cough / runny nose / headaches
 Upper respiratory viral infection
- A young pregnant woman with runny nose:

Allergy? Virus?

An elderly man, presenting stomach ache
 Colon cancer? Virus?

What is learning?





Generalization

Examples Classifier Test

Performance on heretofore unseen cases.

Why should it work?

Generalization

"Though this be madness, yet there is method in't"

Hamlet

Assumptions about the nature of examples:

- Samples are from the same "population"
- Actual concept has some regularity
 - Smoothness
 - Simplicity
 - O ...

Concepts

Train error - error on the training set (seen)

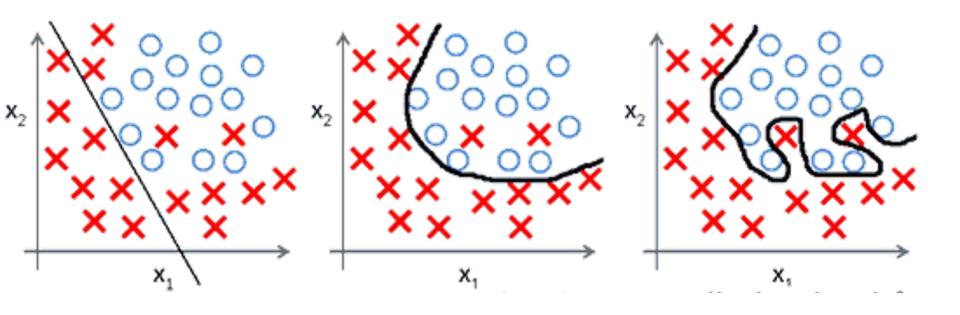
Test error - error on test set (yet unseen)

Are these related?

Implicit assumption:

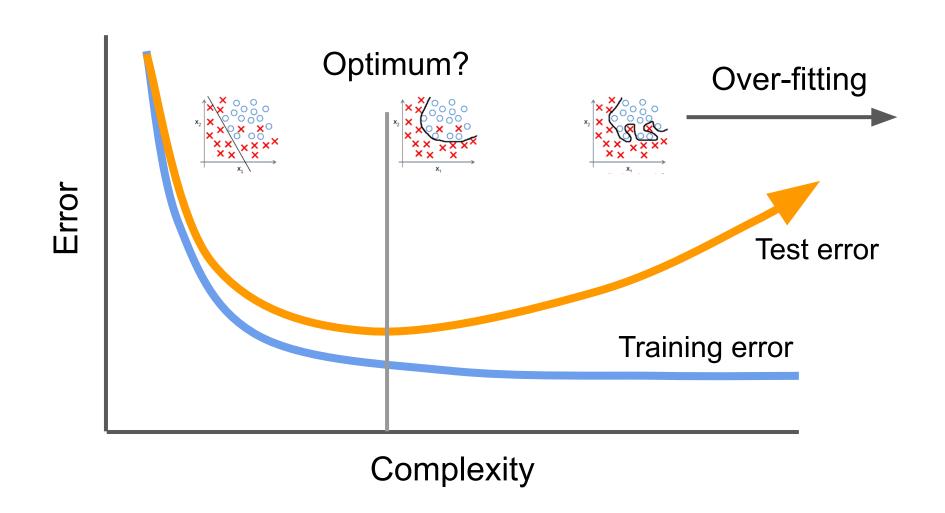
- Reducing training error will reduce also test error
- Is this reasonable?

Different classifiers



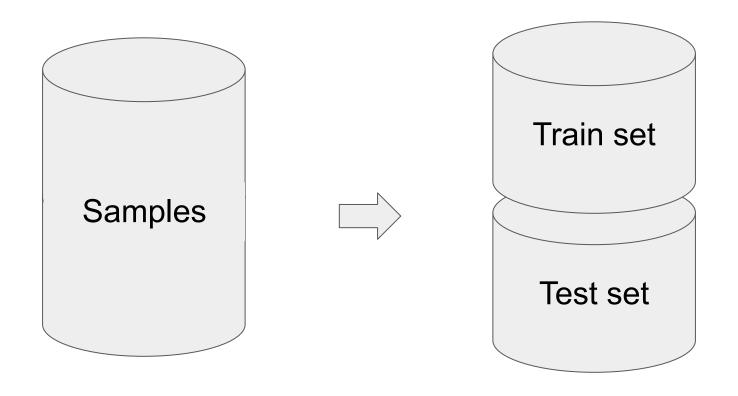
Complexity

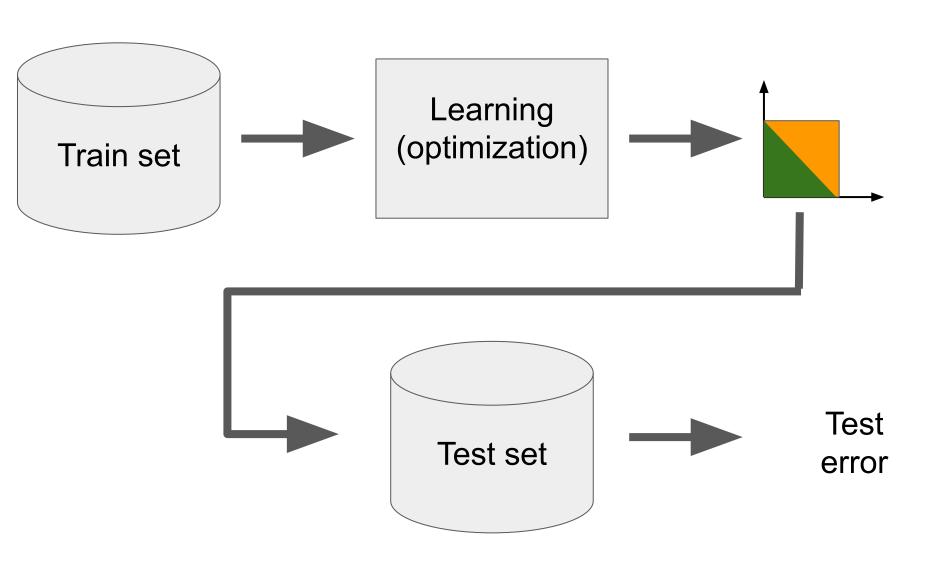
Train vs. test errors



Measures of complexity

- Degree of polynomial
- Number of questions in decision tree
- Number of free parameters
- Magnitude of parameters
- Curvature of decision surface
- Neighborhood size in K-nearest neighbors
- ...

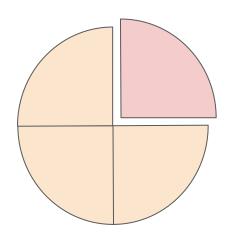


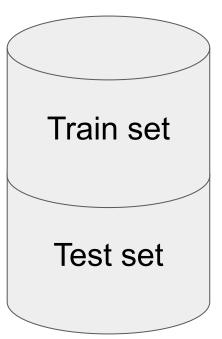


Issues:

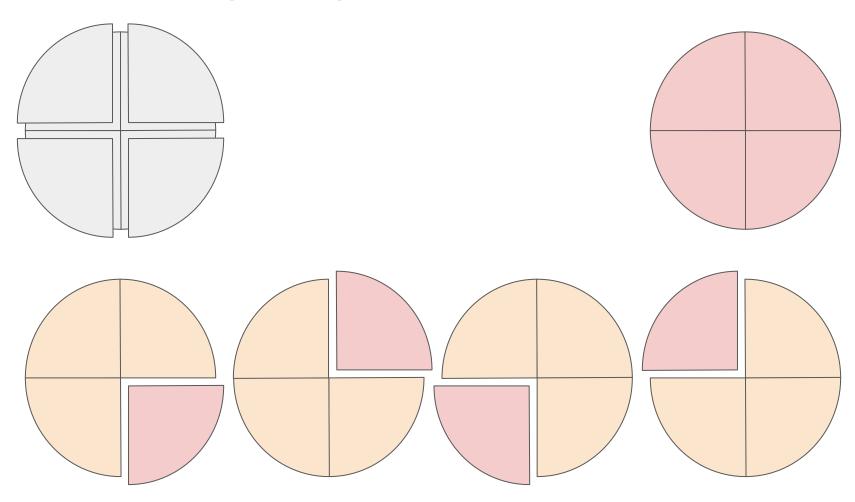
Train/Test allocation

- Small train set → not enough for learning
- Small test set → noisy error estimation



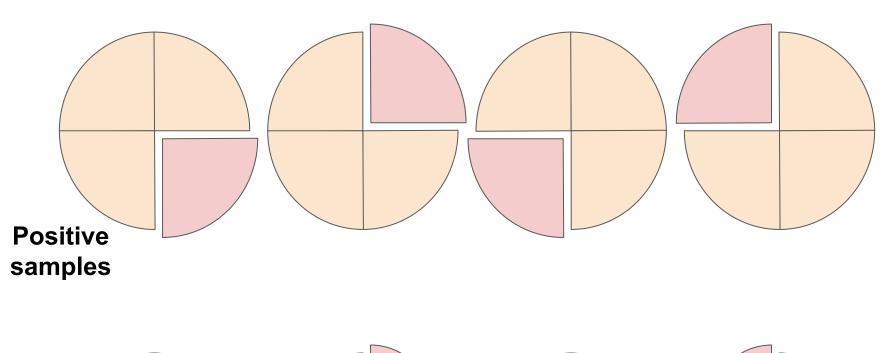


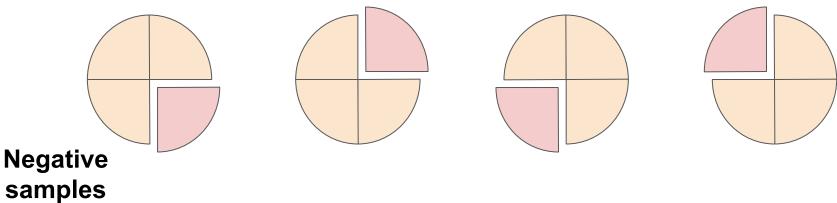
(4-fold) cross validation



Train Test

Stratified cross validation



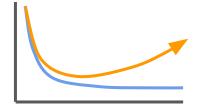


Issues:

Train/Test allocation

- Small train set → not enough for learning
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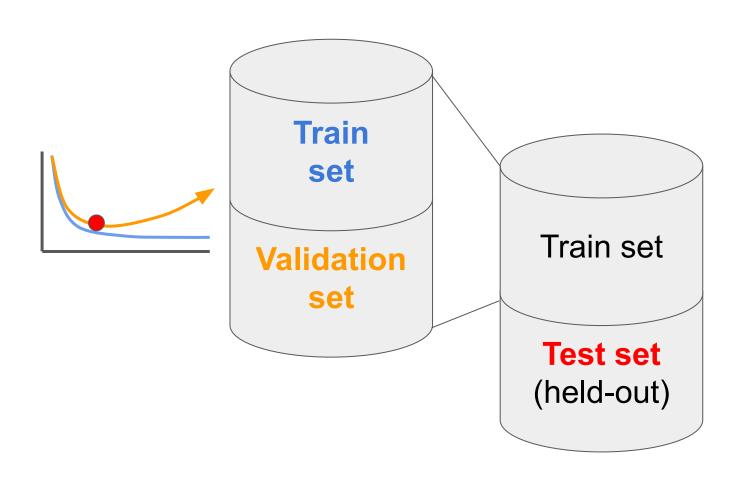
Use of Test set



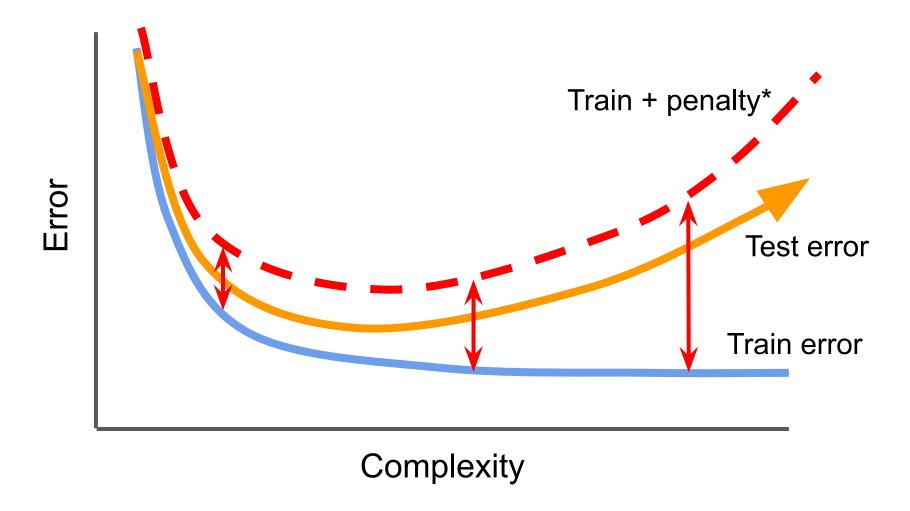
- Multiple evaluations (of classifiers)
- Test samples used for learning
- Over-fitting the test data!!

Train set

Test set



Theoretical bound of test error



Penalty* = function of model complexity

Summary so far

Choose complexity (hyper-parameters)

Estimate generalization performance

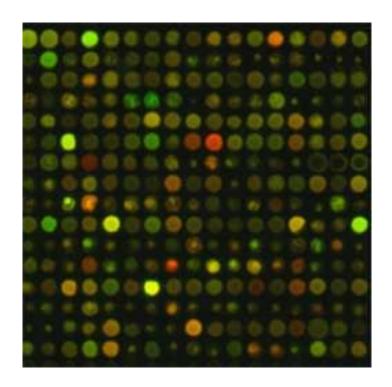
- Train/test split
- Cross-validation
- Theoretical limits

Learn model with chosen hyper-parameter value

Case study



June 2000, the human genome sequenced



Microarrays measure mRNA levels of 23K genes

Gene expression classifications and predictions of human cancers

Gene expression patterns of breast carcinomas distinguish tumor subclasses with clinical implications

Therese Sørlie^{a,b,c}, Charles M. Perou^{a,d}, Robert Tibshirani^e, Turid Aas^f, Stephanie Geisler^g, Hilde Johnsen^b, Trevor Hastie^e, Michael B. Eisen^h, Matt van de Rijnⁱ, Stefanie S. Jeffrey^j, Thor Thorsen^k, Hanne Quist^l, John C. Matese^c, Patrick O. Brown^m, David Botstein^c, Per Eystein Lønning^g, and Anne-Lise Børresen-Dale^{b,n}

Departments of ^bGenetics and ^lSurgery, The Norwegian Radium Hospital, Montebello, N-0310 Oslo, Norway; ^dDepartment of Genetics and Lineberger Comprehensive Cancer Center, University of North Carolina, Chapel Hill, NC 27599; Departments of ^eHealth Research and Policy and Statistics, ^cGenetics, ⁱPathology, ⁱSurgery, and ^mBiochemistry and Howard Hughes Medical Institute, Stanford University School of Medicine, Stanford, CA 94305; Departments of ^gMedicine (Section of Oncology), ^fSurgery, and ^kBiochemical Endocrinology, Haukeland University Hospital, N-5021 Bergen, Norway; and ^hLife Sciences Division, Lawrence Orlando Berkeley National Laboratories, and Department of Molecular and Cellular Biology, University of California, Berkeley, CA 94720

Contributed by David Botstein, July 17, 2001

Distinct types of diffuse large B-cell lymphoma identified by gene expression profiling

Ash A. Alizadeh^{1,2}, Michael B. Eisen^{2,3,4}, R. Eric Davis⁵, Chi Ma⁵, Izidore S. Lossos⁶, Andreas Rosenwald⁶, Jennifer C. Boldrick¹, Hajeer Sabet⁵, Truc Tran⁵, Xin Yu⁵, John I. Powell⁷, Liming Yang⁷, Gerald E. Marti⁸, Troy Moore⁹, James Hudson Jr⁸, Lisheng Lu¹⁰, David B. Lewis¹⁰, Robert Tibshirani¹¹, Gavin Sherlock⁴, Wing C. Chan¹², Timothy C. Greiner¹², Dennis D. Weisenburger¹², James O. Armitage¹³, Roger Warnke¹⁴, Ronald Levy⁶, Wyndham Wilson¹⁵, Michael R. Grever¹⁶, John C. Byrd¹⁷, David Botstein⁴, Patrick O. Brown^{1,18} & Louis M. Staudt⁵

Departments of Biochemistry, ³Genetics, ¹⁴Pathology, ⁶Medicine, ¹⁰Pediatrics and ¹¹Health Research & Policy and Statistics, and ¹⁸Howard Hughes Medical Institute, Stanford University School of Medicine, Stanford, California 94305, USA

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- ⁷ Bioinformatics and Molecular Analysis Section, CBEL, CIT, NIH, Bethesda, Maryland 20892, USA
- CBER, FDA, Bethesda, Maryland 20892, USA
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- ¹⁵ Medicine Branch, Division of Clinical Sciences, National Cancer Institute, National Institutes of Health, Bethesda, Maryland 20892, USA
- ¹⁶ Johns Hopkins Oncology Center, Johns Hopkins School of Medicine, Baltimore, Maryland 21287, USA
- 17 Walter Reed Army Medical Center, Washington, DC 20307, USA

Gene expression profiling predicts clinical outcome of breast cancer

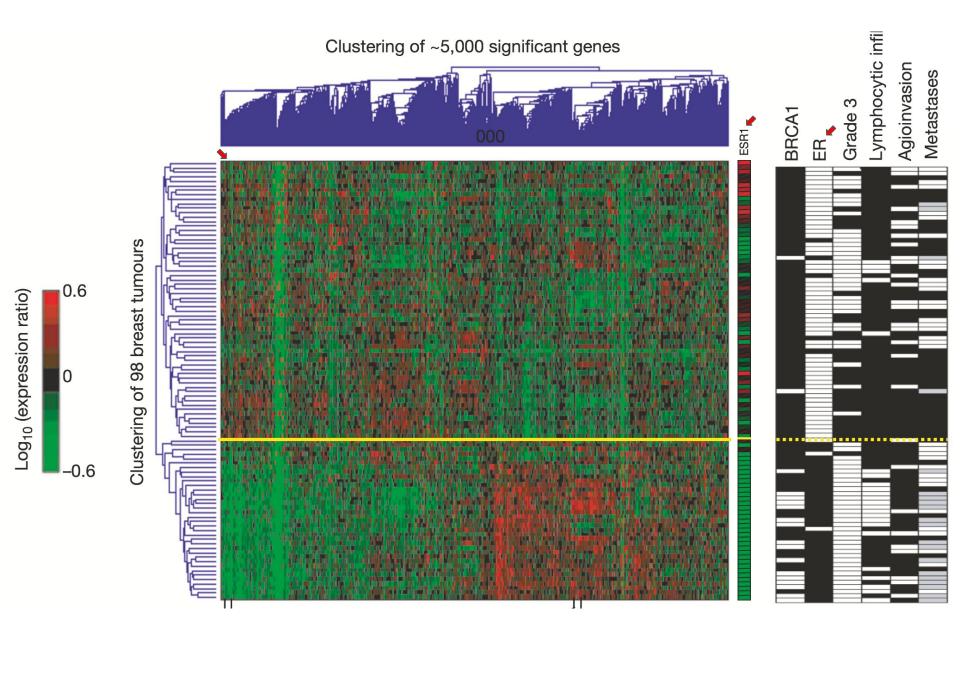
Laura J. van 't Veer*†, Hongyue Dai†‡, Marc J. van de Vijver*†, Yudong D. He‡, Augustinus A. M. Hart*, Mao Mao‡, Hans L. Peterse*, Karin van der Kooy*, Matthew J. Marton‡, Anke T. Witteveen*, George J. Schreiber‡, Ron M. Kerkhoven*, Chris Roberts‡, Peter S. Linsley‡, René Bernards* & Stephen H. Friend‡

* Divisions of Diagnostic Oncology, Radiotherapy and Molecular Carcinogenesis and Center for Biomedical Genetics, The Netherlands Cancer Institute, 121 Plesmanlaan, 1066 CX Amsterdam, The Netherlands ‡ Rosetta Inpharmatics, 12040 115th Avenue NE, Kirkland, Washington 98034,

Could gene expression predict clinical outcout?

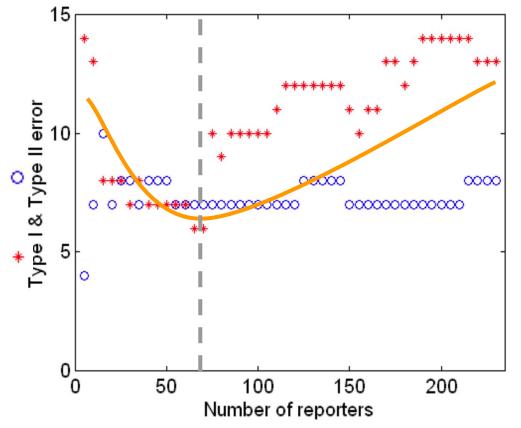
- Early breast cancer, at young patients.
- Chemotherapy reduces risk of metastases by ½
- 70-80% patients receiving it, would have survived without.
- How to identify which patients would likely need chemo, and which won't?

- 34 patients developed distant metastases within 5 years
- 44 were disease-free after 5 years
- (18 with BRCA1, 2 BRCA2 mutations)



How they learned a classification model?

- 34 "poor prognosis", 44 "good prognosis" samples
- From 23K genes, found top 231 correlated genes ("features")



- Leave-one-out CV
- Correlation-based classifier ("poor" or "good" prognosis)
- "Optimal set" of 70 genes



15 years later...

The NEW ENGLAND JOURNAL of MEDICINE

ESTABLISHED IN 1812

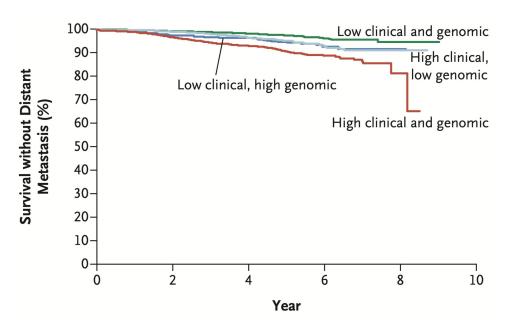
AUGUST 25, 2016

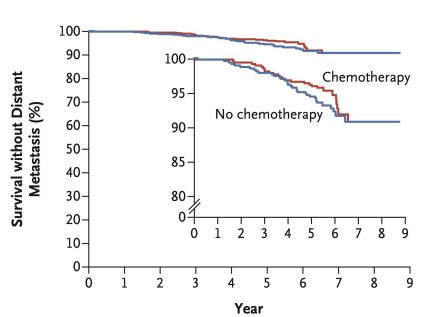
VOL. 375 NO. 8

- 6693 women
- 1550: high clinical risk, low genomic risk

70-Gene Signature as an Aid to Treatment Decisions in Early-Stage Breast Cancer

F. Cardoso, L.J. van't Veer, J. Bogaerts, L. Slaets, G. Viale, S. Delaloge, J.-Y. Pierga, E. Brain, S. Causeret, M. DeLorenzi, A.M. Glas, V. Golfinopoulos, T. Goulioti, S. Knox, E. Matos, B. Meulemans, P.A. Neijenhuis, U. Nitz, R. Passalacqua, P. Ravdin, I.T. Rubio, M. Saghatchian, T.J. Smilde, C. Sotiriou, L. Stork, C. Straehle, G. Thomas, A.M. Thompson, J.M. van der Hoeven, P. Vuylsteke, R. Bernards, K. Tryfonidis, E. Rutgers, and M. Piccart, for the MINDACT Investigators*





Is this a special set of genes?

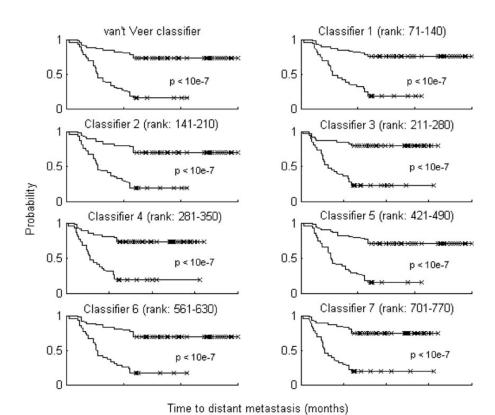


Outcome signature genes in breast cancer: is there a unique set?

Liat Ein-Dor^{1,†}, Itai Kela^{1,3,†}, Gad Getz^{1,†}, David Givol² and Eytan Domany^{1,*}

¹Department of Physics of Complex Systems, ²Department of Molecular Cell Biology and ³Department of Immunology, Weizmann Institute of Science, Rehovot 76100, Israel

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Syllabus

- 1. Introduction
- 2. Classification
- 3. Learning 1
- 4. Al in ophthalmology (Prof. Itay Chowers)
- 5. Learning 2
- 6. Regression
- 7. Clustering
- 8. Visualization (and dimensionality reduction)
- 9. Deep learning in image analysis (Prof. Leo Joskowicz)
- 10. Missing data, statistical dependencies
- 11. Natural language in medicine (Dr. Gabi Stanovsky)
- 12. Decisions (utility)
- 13. Longitudinal Data / Project