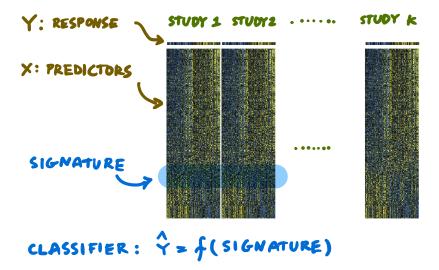
Validation and Replicability of Prediction Algorithms in Oncology

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NATIONAL CANCER POLICY FORUM WORKSHOP 2018

- Consultant: None Related to the Topic
- Speaker's Bureau: None
- Grant/Research support from: NIH-NCI; MIT-Harvard Bridge Project;
 Licensing of BayesMendel software for genetic counseling.
- Stockholder in: CRA Health
- Honoraria from: Academic Only
- co-Founder / Board Member: Phaeno
- Relevant patents: POSTN for debulking in OC
- Employee of: Dana Farber Cancer Institute

signatures, classifier, validation, replicability



Meta-analysis overview

Literature review

Prognostic models

101 candidate papers Five review papers

Inclusion Criteria

- √ Training sample size > 40
- Focus on late-stage serous
- ✓ Multivariate model
- ✓ Continuous risk scor
- ✓ Claims to predict surviva
- √ Possible to reproduce mode

14 prediction models implemented 100 pages documentation survHD Bioconductor package

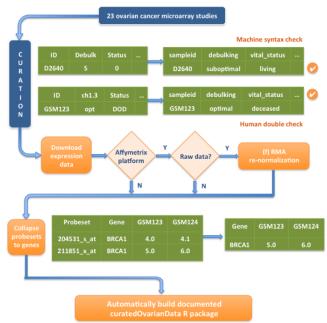
Database of curated gene expression

Standardized clinical annotation and gene ID 23 studies, 2,908 samples

Inclusion Criteria

- ✓ Sample size > 40
- ✓ Primary tumors
- ✓ Overall survival available
- ✓ Events (deaths) > 15
- ✓ Late stage, high grade tumors
- ✓ Serous subtype

10 datasets, 1455 samples curatedOvarianData Bioconductor package

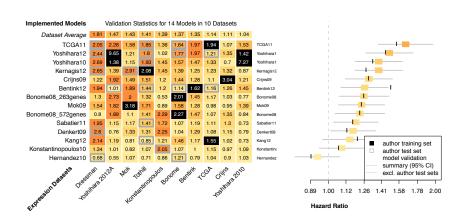


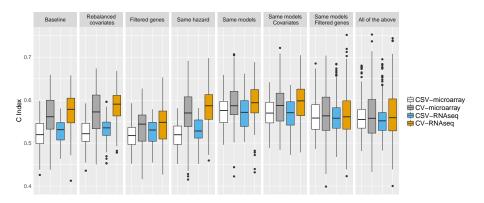
Model	Reproducibility†					
	Model	Training Data	Validation Data	Verified		
	Provided	Available	Available	Implementation		
TCGA11 [12]	YES	YES	YES	YES		
Denkert09 [13]	YES	YES	YES	YES		
Bonome08_263genes [14]	YES	YES	YES	YES		
Bonome08_572genes [14]	YES	YES	YES	YES		
Mok09 [15]	NO	YES	YES	PARTIALLY		
Yoshihara12 [16]	YES	-	YES	YES		
Yoshihara10 [17]	YES	=	YES	YES		
Bentink12 [18]	YES	=	YES	YES		
Kang12 [19]	YES	YES	YES	PARTIALLY		
Crijns09 [20]	NO	YES	NO	NO		
Kernagis12 [21]	PARTIALLY	YES	YES	PARTIALLY		
Sabatier11 [22]	PARTIALLY	NO	NO	NO		
Konstantinopoulos10 [23]	YES	-	YES	PARTIALLY		
Hernandez10 [24]	PARTIALLY	-	YES	PARTIALLY		

Compare to loannidis 08: "We reproduced two analyses in principle and six partially or with some discrepancies; ten could not be reproduced."

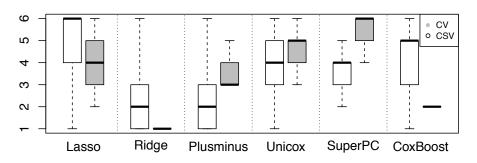
Implemented Models	Validation Statistics for 14 Models in 10 Datasets										
Dataset Average	1.81	1.47	1.43	1.41	1.39	1.37	1.35	1.14	1.11	1.04	
TCGA11	2.05	2.28	1.58	1.85	1.36	1.64	1.97	1.94	1.07	1.53	TCGA11
Yoshihara12	2.44	9.65	1.21	1.8	1.02	1.77	1.97	1.21	1.35	1.42	Yoshihara1
Yoshihara10	2.69	1.38	1.15	1.93	1.45	1.57	1.47	1.33	0.7	7.27	Yoshihara1
Kernagis12	2.65	1.39	2.91	2.08	1.45	1.39	1.25	1.23	1.32	0.87	Kernagis12
Crijns09	1.22	1.92	1.49	1.51	1.2	1.44	1.28	1.1	3.04	1.21	Crijns09
Bentink12	1.94	1.01	1.89	1.44	1.2	1.14	1.62	1.16	1.26	1.45	Bentink12
Bonome08_263genes	1.3	2.73	2	1.32	0.53	2.01	1.45	1.17	1.03	0.77	Bonome08
Mok09	1.54	1.82	3.18	1.71	0.89	1.58	1.28	0.98	0.95	1.39	Mok09
Bonome08_572genes	0.8	1.89	1.1	1.41	2.29	2.27	1.47	1.07	1.35	0.84	Bonome08
Sabatier11	1.95	1.15	1.17	1.41	1.72	1.07	1.19	1.11	1.3	0.73	Sabatier11
Denkert09	2.6	0.76	1.33	1.31	2.25	1.04	1.29	1.08	1.15	0.79	Denkert09
Kang12	2.14	1.19	0.81	0.85	1.21	1.46	1.17	1.55	1.02	0.73	Kang12
Konstantinopoulos10	1.34	1.01	0.82	1.07	2.05	1.07	1	1.15	0.97	1.09	Konstantin
Hernandez10	0.68	0.55	1.07	0.71	0.86	1.21	0.79	1.04	0.9	1.03	Hernandez
Let's the other than the thing one wing to the still the											

synthesis of validation matrix





Distribution of ranks



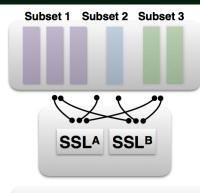
Attention to replicability requires rethinking existing machine learning principles.

Training Studies Subsets

Single Study Learners

Ensemble

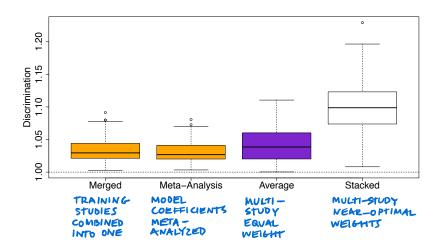
Cross-Study Learner





WA1 SSLA1 +....+WB3 SSLB3

Progress



lessons

- 1 Variability across studies is unavoidable; some of this variability genuinely contributes scientific insight.
- 2 To make progress in replicability, it is important to:
 - Work harder at educating the scientific community about how much cross-study variation to expect
 - Work harder at generating curated comprehensive data collections
 - Think harder about existing machine learning and prediction principles.

team credits



Ganzfried, B.F., Riester, M., Haibe-Kains, B., Risch, T., Tyekucheva, S., Jazic, I., Wang, X.V., Ahmadifar, M., **Birrer, M.J.**, Parmigiani, G., **Huttenhower, C., Waldron, L.**, 2013. curatedOvarianData: clinically annotated data for the ovarian cancer transcriptome. Database 2013, bat013–bat013.

Waldron, L., Haibe-Kains, B., Culhane, A.C., Riester, M., Ding, J., Wang, X.V., Ahmadifar, M., Tyekucheva, S., Bernau, C., Risch, T., Ganzfried, B.F., Huttenhower, C., Birrer, M., Parmigiani, G., 2014. Comparative meta-analysis of prognostic gene signatures for late-stage ovarian cancer. JNCI 106, dju049–dju049.

Zhao, S.D., Parmigiani, G., Huttenhower, C., Waldron, L., 2014. Más-o-menos: a simple sign averaging method for discrimination in genomic data analysis. Bioinformatics 30, 3062–3069.

Bernau, C., Riester, M., Boulesteix, A.-L., Parmigiani, G., Huttenhower, C., Waldron, L., **Trippa, L.**, 2014. Cross-study validation for the assessment of prediction algorithms. Bioinformatics 30, i105–12.

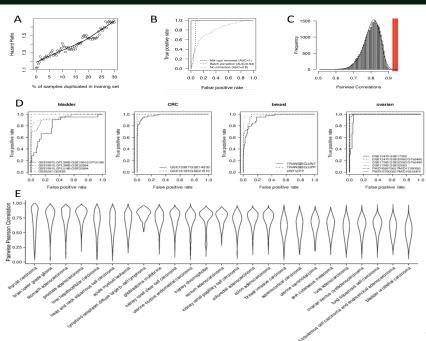
Trippa, L., Waldron, L., Huttenhower, C., Parmigiani, G., 2015. Bayesian nonparametric cross-study validation of prediction methods. Ann. Appl. Stat 9, 402–428.

Waldron, L., Riester, M., Ramos, M., Parmigiani, G., Birrer, M., 2016. The Doppelgänger Effect: Hidden Duplicates in Databases of Transcriptome Profiles. JNCI 108, djw146.

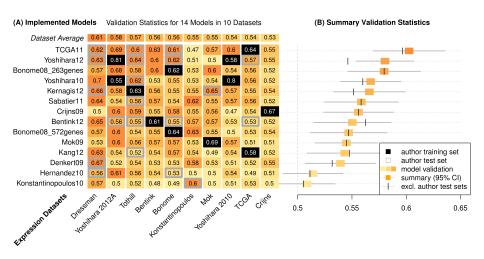
Zhang Y, Bernau C, Parmigiani G, Waldron L. The impact of different sources of heterogeneity on loss of accuracy from genomic prediction models. Biostatistics. 2018;6(e1002358):701.

Patil, P. Parmigiani, G. Building replicable predictors via ensembling.

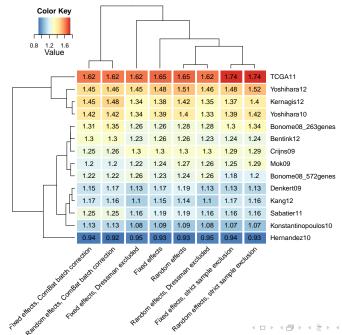




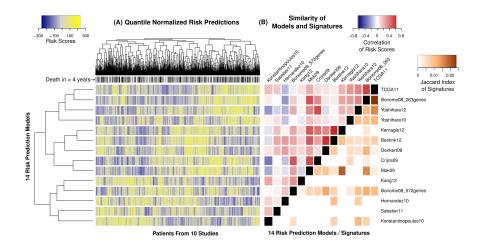
using c-stat instead



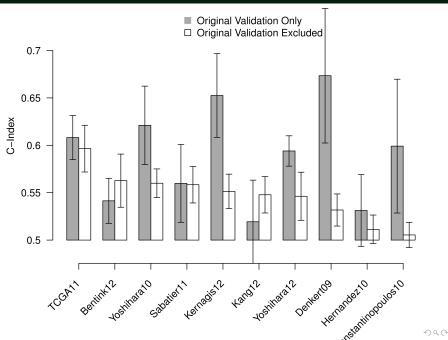
sensitivity analysis

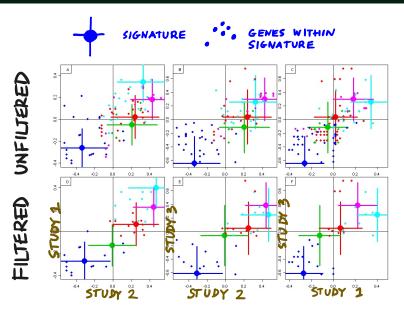


do predictors rank patients similarly?



selection bias in choice of validation study?

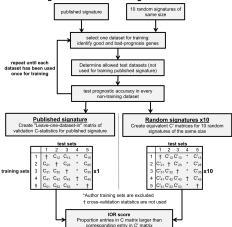




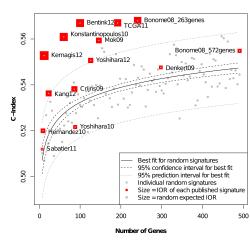
SCALE: PREDICTION STRENGTH (COX EFFECT SIZE)

signatures

A) Methodology for comparing prognostic quality of gene sets to random gene sets



B) Gene set Improvement over Random Signatures





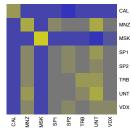


Cross-study performance evaluation: Evaluates Methodology

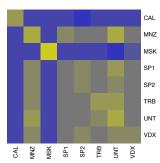


No.	Name	Adjuvant	# patients	# ER+	3Q survival	Median follow-up	Original	Reference
		therapy			[mo.]	[mo.]	identifiers ‡	
1	CAL	chemo, hormonal	118	75	42	82	CAL	Chin et al. (2006)
2	MNZ	none	200	162	120	94	MAINZ	Schmidt et al. (2008)
3	MSK	combination	99	57	76	82	MSK	Minn et al. (2005)
4	ST1	hormonal	512*	507*	114	106	MDA5, TAM, VDX3	Foekens et al. (2006)
5	ST2	hormonal	517	325	126	121	EXPO, TAM	Symmans et al. (2010)
6	TRB	none	198	134	143	171	TRANSBIG	Desmedt et al. (2007)
7	UNT	none	133	86	151	105	UNT	Sotiriou et al. (2006)
8	VDX	none	344	209	44	107	VDX	Minn et al. (2007)

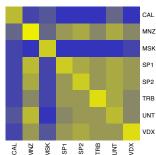


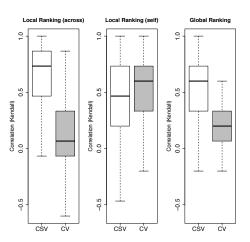


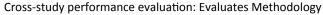


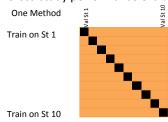




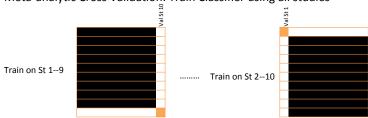






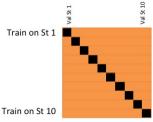


Meta-analytic Cross Validation: Train Classifier using all studies



training on many studies

Cross-study performance evaluation: Evaluates Methodology



Cross-study Training for Replicability: Trains new Predictors

Train on St 1—5 use Z Validate on 6-10

