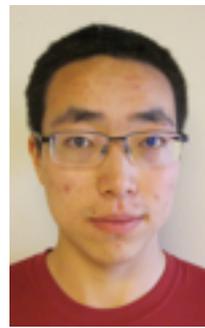


# studies

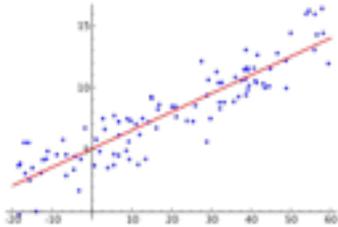
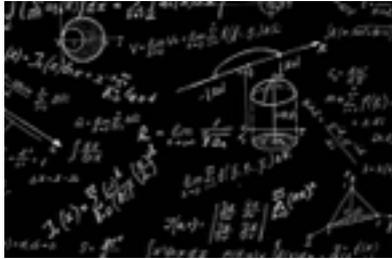
a paradigm for research in data science

Vardan Papyan

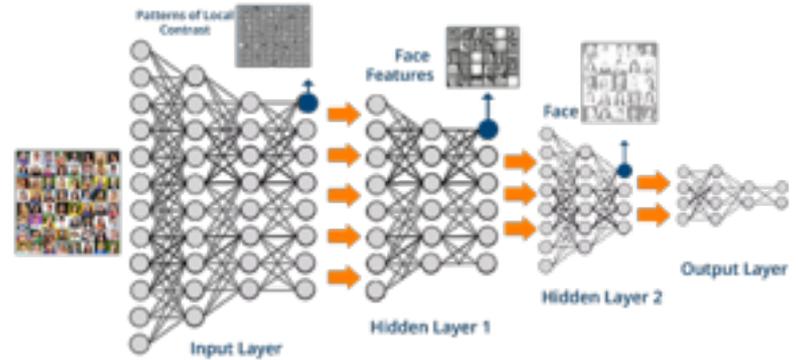


# Nobody knows what data science is

Statistics:



Machine learning:



We are proposing to show you what data science is...

**XYZ** studies

A stylized, hand-drawn letter 'X' in blue with a black shadow effect.

— all relevant methods

A stylized, hand-drawn letter 'Y' in blue with a black shadow effect.

— datasets considered canonical for certain task

A stylized, hand-drawn letter 'Z' in blue with a black shadow effect.

— control parameters

A stylized, hand-drawn letter 'W' in blue with a black shadow effect.

— observables of interest

## Algorithm 1: Description of XYZ experiment

---

**Input** : methods  $X$ , datasets  $Y$ , control parameters  $Z$

**Output**: observables  $W$

```
1 foreach method  $x \in X$  do  
2   | foreach dataset  $y \in Y$  do  
3   |   | foreach control parameter  $z \in Z$  do  
4   |   |   | /* run experiment and collect observables          */  
5   |   |   |  $W(x, y, z) = \text{Experiment}(x, y, z)$   
6   |   | end  
7 end
```



Finding

# Navigating the space of finding

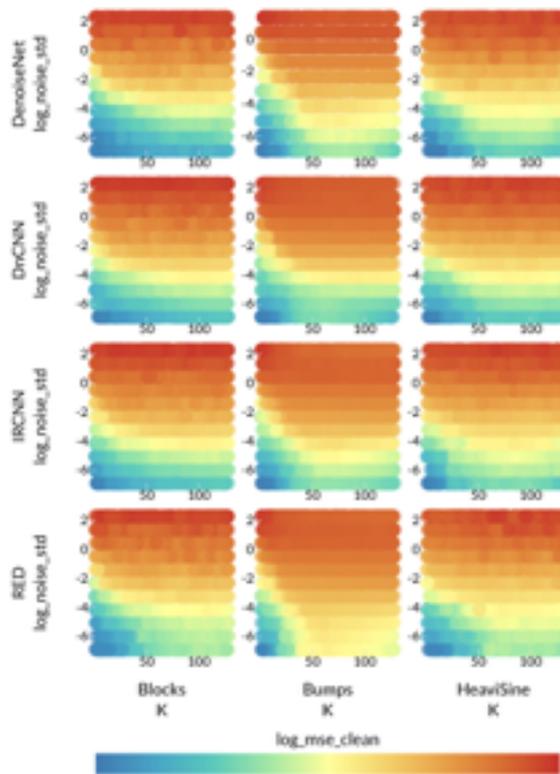
Change plot size: [-](#) [+](#)

Change circle size: [-](#) [+](#)

Choose control parameters Z or observables W:

- | V1:  | V2:                                       | V3:  |
|--|---|--|
| <input type="radio"/> K                        | <input checked="" type="radio"/> K        | <input type="radio"/> K                        |
| <input type="radio"/> log_K                    | <input type="radio"/> log_K               | <input type="radio"/> log_K                    |
| <input type="radio"/> path_sparsity            | <input type="radio"/> path_sparsity       | <input type="radio"/> path_sparsity            |
| <input type="radio"/> log_path_sparsity        | <input type="radio"/> log_path_sparsity   | <input type="radio"/> log_path_sparsity        |
| <input type="radio"/> noise_std                | <input type="radio"/> noise_std           | <input type="radio"/> noise_std                |
| <input checked="" type="radio"/> log_noise_std | <input type="radio"/> log_noise_std       | <input type="radio"/> log_noise_std            |
| <input type="radio"/> mse_noisy                | <input type="radio"/> mse_noisy           | <input type="radio"/> mse_noisy                |
| <input type="radio"/> log_mse_noisy            | <input type="radio"/> log_mse_noisy       | <input type="radio"/> log_mse_noisy            |
| <input type="radio"/> mse_clean                | <input type="radio"/> mse_clean           | <input type="radio"/> mse_clean                |
| <input type="radio"/> log_mse_clean            | <input type="radio"/> log_mse_clean       | <input checked="" type="radio"/> log_mse_clean |
| <input type="radio"/> mse_clean_div_noise      | <input type="radio"/> mse_clean_div_noise | <input type="radio"/> mse_clean_div_noise      |
| <input type="radio"/> DF_mc_tr                 | <input type="radio"/> DF_mc_tr            | <input type="radio"/> DF_mc_tr                 |
| <input type="radio"/> log_DF_mc_tr             | <input type="radio"/> log_DF_mc_tr        | <input type="radio"/> log_DF_mc_tr             |
| <input type="radio"/> clean_sub_noisy          | <input type="radio"/> clean_sub_noisy     | <input type="radio"/> clean_sub_noisy          |
| <input type="radio"/> log_clean_sub_noisy      | <input type="radio"/> log_clean_sub_noisy | <input type="radio"/> log_clean_sub_noisy      |
| <input type="radio"/> bias                     | <input type="radio"/> bias                | <input type="radio"/> bias                     |
| <input type="radio"/> log_bias                 | <input type="radio"/> log_bias            | <input type="radio"/> log_bias                 |
| <input type="radio"/> SURE                     | <input type="radio"/> SURE                | <input type="radio"/> SURE                     |
| <input type="radio"/> log_SURE                 | <input type="radio"/> log_SURE            | <input type="radio"/> log_SURE                 |
| <input type="radio"/> SURE_div_noise           | <input type="radio"/> SURE_div_noise      | <input type="radio"/> SURE_div_noise           |

For each method X and dataset Y, V1 is plotted against V2 and colored with V3.



to pdf

download  
reproducible code

download models

download xyz array

add data

Hypothesis



theory



SANDBOX

# Data science **needs** to be...

- Practical **findings** that explain reality,  
**NOT** theorems!
- Reliable comprehensive **insights**,  
**NOT** poetry,  
**NOT** cherry picking,  
**NOT** inadequate experimentation.

Data science **needs**  
to be **XYZ!**

**Theorem 1** (Pythagoras).  $a^2 + b^2 = c^2$ .

Nam dui ligula, fringilla a, euismod sodales, sollicitudin vel, wisi. Morbi auctor lorem non justo. Nam lacus libero, pretium at, lobortis vitae, ultricies et, tellus. Donec aliquet, tortor sed accumsan bibendum, erat ligula aliquet magna, vitae ornare odio metus a mi. Morbi ac orci et nisl hendrerit mollis. Suspendisse ut massa. Cras nec ante. Pellentesque a nulla. Cum sociis natoque penatibus et magnis dis parturient montes, nascetur ridiculus mus. Aliquam tincidunt urna. Nulla ullamcorper vestibulum turpis. Pellentesque cursus luctus mauris.

*Proof of Theorem 1.* (state your proof here)

□



People are groping for this

## Comparative Meta-analysis of Prognostic Gene Signatures for Late-Stage Ovarian Cancer

Levi Waldron, Benjamin Haibe-Kains, Aedin C. Culhane, Markus Riester, Jie Ding, Xin Victoria Wang, Mehrnaz Ahmadifar, Svitlana Tyekucheva, Christoph Bernau, Thomas Risch, Benjamin Frederick Ganzfried, Curtis Huttenhower, Michael Birrer, Giovanni Parmigiani

Manuscript received February 24, 2013; revised January 13, 2014; accepted January 29, 2014.

**Correspondence to:** Giovanni Parmigiani, PhD, Department of Biostatistics and Computational Biology, Dana-Farber Cancer Institute, 450 Brookline Ave, Boston, MA 02115 (e-mail: gp@jimmy.harvard.edu).

**Background** Ovarian cancer is the fifth most common cause of cancer deaths in women in the United States. Numerous gene signatures of patient prognosis have been proposed, but diverse data and methods make these difficult to compare or use in a clinically meaningful way. We sought to identify successful published prognostic gene signatures through systematic validation using public data.

**Methods** A systematic review identified 14 prognostic models for late-stage ovarian cancer. For each, we evaluated its 1) reimplementation as described by the original study, 2) performance for prognosis of overall survival in independent data, and 3) performance compared with random gene signatures. We compared and ranked models by validation in 10 published datasets comprising 1251 primarily high-grade, late-stage serous ovarian cancer patients. All tests of statistical significance were two-sided.

**Results** Twelve published models had 95% confidence intervals of the C-index that did not include the null value of 0.5; eight outperformed 97.5% of signatures including the same number of randomly selected genes and trained on the same data. The four top-ranked models achieved overall validation C-indices of 0.56 to 0.60 and shared anti-correlation with expression of immune response pathways. Most models demonstrated lower accuracy in new datasets than in validation sets presented in their publication.

Validation Statistics for 14 Models in 10 Datasets

Dataset average	0.61	0.58	0.57	0.56	0.56	0.55	0.55	0.54	0.54	0.53
TCGA11	0.62	0.69	0.6	0.63	0.61	0.47	0.57	0.6	0.64	0.55
Yoshihara12	0.63	0.81	0.64	0.6	0.62	0.51	0.5	0.58	0.57	0.55
Bonome08_263genes	0.57	0.68	0.58	0.6	0.62	0.53	0.6	0.54	0.56	0.52
Yoshihara10	0.7	0.55	0.62	0.53	0.55	0.53	0.54	0.8	0.56	0.52
Kernagis12	0.66	0.58	0.63	0.56	0.55	0.55	0.65	0.57	0.55	0.54
Sabatier11	0.64	0.54	0.56	0.57	0.54	0.62	0.55	0.57	0.56	0.52
Crijns09	0.5	0.6	0.59	0.55	0.58	0.55	0.56	0.47	0.54	0.67
Bentink12	0.65	0.56	0.55	0.61	0.55	0.57	0.57	0.53	0.53	0.52
Bonome08_572genes	0.57	0.6	0.54	0.55	0.64	0.63	0.55	0.5	0.53	0.54
Mok09	0.53	0.6	0.56	0.57	0.57	0.53	0.69	0.57	0.51	0.51
Kang12	0.63	0.54	0.52	0.54	0.57	0.54	0.49	0.54	0.58	0.52
Denkert09	0.67	0.52	0.54	0.53	0.53	0.58	0.53	0.51	0.52	0.55
Hernandez10	0.56	0.61	0.56	0.54	0.53	0.5	0.5	0.54	0.49	0.51
Konstantinopoulos10	0.57	0.5	0.52	0.48	0.49	0.6	0.5	0.51	0.53	0.5

Expression datasets

Dressman

Yoshihara 2012A

Tothhill

Bentink

Bonome

Konstantinopoulos

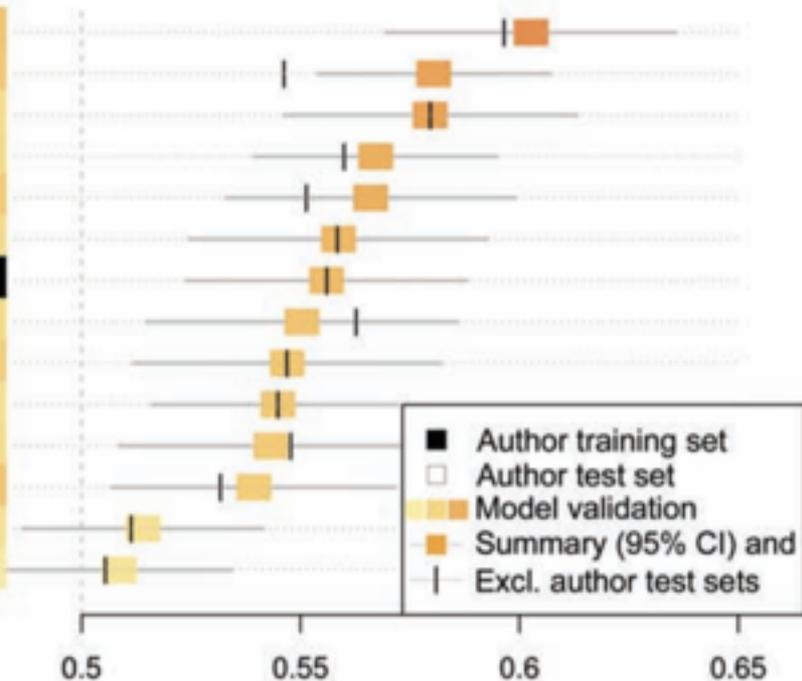
Mok

Yoshihara 2010

TCGA

Crijns

B



# Deep Learning



# Understanding deep learning requires rethinking generalization

<https://arxiv.org> › cs ▼

by C Zhang - 2016 - Cited by 303 - Related articles

Perfect score on the ICLR reviews

ICLR 2017 best paper award

OCT 13, 2017 @ 01:23 PM 7,420

2 Free Issues of Forbes

## What You Need To Know About One Of The Most Talked-About Papers On Deep Learning To Date





## Rethinking Generalization

by Zhang et. al

CIFAR10,  
ImageNet

MLP, AlexNet,  
Inception

% randomized  
labels

number of epochs  
until perfect fit,  
test error at epoch  
of perfect fit

Could be done  
on more  
datasets and  
methods



## Rethinking Generalization

by Zhang et. al

CIFAR10,  
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% randomized  
labels

number of epochs  
until perfect fit,  
test error at epoch  
of perfect fit

Could be done  
on more  
datasets and  
methods

## Importance of Single Direction Generalization

Morcos et. al

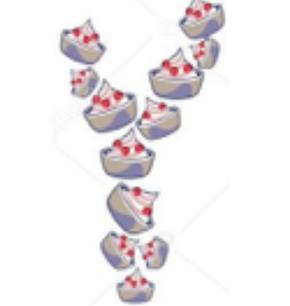
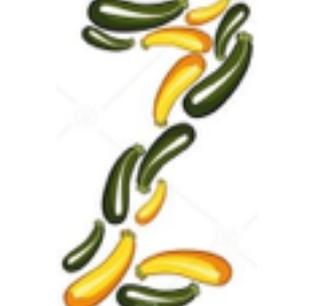
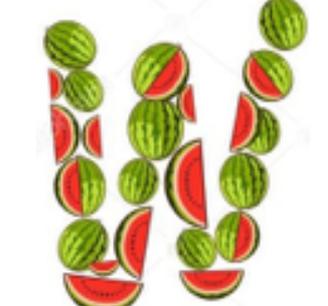
MNIST,  
CIFAR10,  
ImageNet

MLP, 11-layer  
CNN, ResNet

dropout, batch  
normalization,  
% randomized  
labels

reliance on single  
neuron,  
class specificity

Relied on  
control  
parameters in  
previous work

					
<p><b>Rethinking Generalization</b> by Zhang et. al</p>	<p>CIFAR10, ImageNet</p>	<p>MLP, AlexNet, Inception</p>	<p>% randomized labels</p>	<p>number of epochs until perfect fit, test error at epoch of perfect fit</p>	<p>Could be done on more datasets and methods</p>
<p><b>Importance of Single Direction Generalization</b> Morcos et. al</p>	<p>MNIST, CIFAR10, ImageNet</p>	<p>MLP, 11-layer CNN, ResNet</p>	<p>dropout, batch normalization, % randomized labels</p>	<p>reliance on single neuron, class specificity</p>	<p>Relied on control parameters in previous work</p>
<p><b>Are GANs Created Equal?</b> Lucic et. al</p>	<p>MNIST, FASHION - MNIST, CIFAR10, CELEBA</p>	<p>MM GAN, NS GAN, LSGAN, WGAN, WGAN GP, DRAGAN, BEGAN, VAE</p>	<p>seed, computational budget</p>	<p>precision, recall, F1</p>	<p>Great example!</p>

If you want to be a data scientist...

You **must** do research this way

You **must** evaluate others this way

And...

You **must** accept this is the only way,  
otherwise your work will be irrelevant



Z



X

Y



ElastiCluster

Pywren



CodaLab



Caffe



DL4J  
Deeplearning4j



Microsoft  
CNTK

MatConvNet

MINERVA

mxnet



theano





Z



X

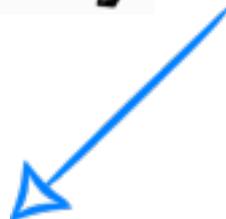
Y



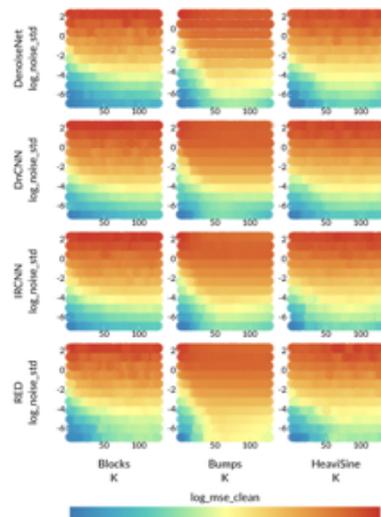
Z

X

Y



For each method X and dataset Y, V1 is plotted against V2 and colored with V3.



### A Bibliometric Model for Journal Descending Policy at Academic Libraries

Journal of Academic Librarianship, November 2014, Volume 14, Number 6, Pages 345-354

Journal of Academic Librarianship

Volume 14, Number 6, November 2014, Pages 345-354

Journal of Academic Librarianship

Volume 14, Number 6, November 2014, Pages 345-354

Abstract: This article presents a bibliometric model for journal descending policy at academic libraries. The model is based on a combination of journal impact factors and journal descending policies. The model is used to identify the most important journals in a library's collection. The model is used to identify the most important journals in a library's collection. The model is used to identify the most important journals in a library's collection.

