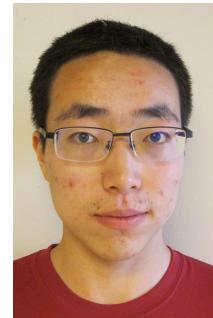


studies

a paradigm for research in data science

Vardan Papyan

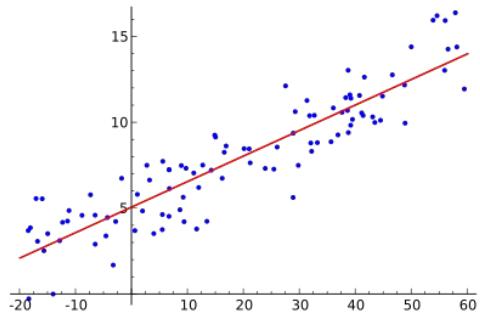
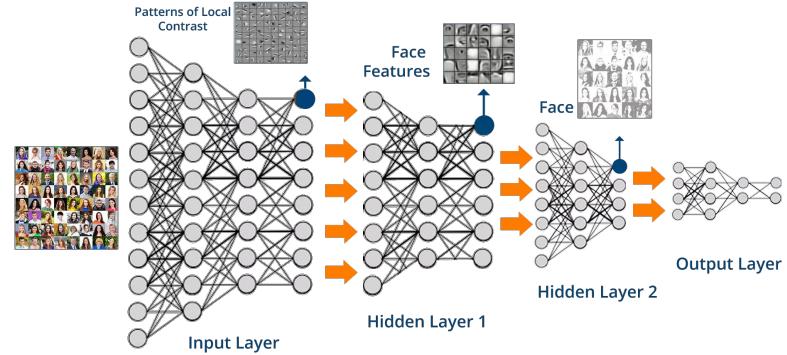


Nobody knows what data science is

Statistics:

A collage of mathematical formulas and diagrams related to statistics and probability theory. It includes:
1. A diagram of a circle with a radius r and a central angle θ , with formulas for area and circumference.
2. A formula for the expected value of a function $u(x)$: $E[u(x)] = \int u(x) p(x) dx$.
3. A formula for the variance $V = \lim_{n \rightarrow \infty} \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2$.
4. A diagram of a bell-shaped curve with mean μ and standard deviation σ , with the formula $f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$.
5. A formula for the moment generating function $M(t) = E[e^{tX}] = \int e^{tx} p(x) dx$.
6. A formula for the characteristic function $\phi(t) = E[e^{itX}] = \int e^{itx} p(x) dx$.
7. A formula for the cumulative distribution function $F(x) = P(X \leq x) = \int_{-\infty}^x p(x) dx$.
8. A formula for the probability density function $p(x) = f(x)/F(x)$.

Machine learning:



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





— datasets considered canonical for certain task



— all relevant methods



— control parameters



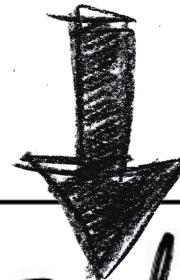
— observables of interest

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
8 end
```



Finding

Navigating in the XYZ space

- Python



- Dedicated software: Tableau (more on this later)



- Online website: D3



Change plot size: [±](#)

Change circle size: [±](#)

Choose control parameters Z or observables W:

V1:

- K
- log_K
- path_sparsity
- log_path_sparsity
- noise_std
- log_noise_std
- mse_noisy
- log_mse_noisy
- mse_clean
- log_mse_clean
- mse_clean_div_noise
- log_DF_mc_tr
- clean_sub_noisy
- log_clean_sub_noisy
- bias
- log_bias
- SURE
- log_SURE
- SURE_div_noise

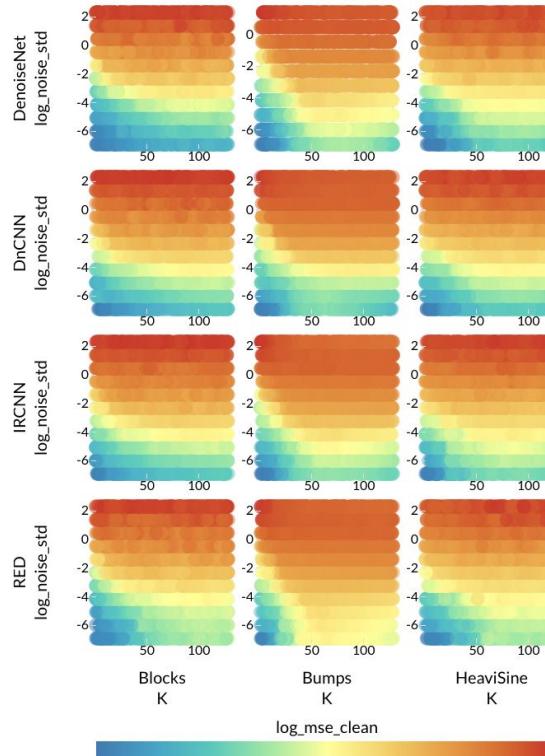
V2:

- K
- log_K
- path_sparsity
- log_path_sparsity
- noise_std
- log_noise_std
- mse_noisy
- log_mse_noisy
- mse_clean
- log_mse_clean
- mse_clean_div_noise
- log_DF_mc_tr
- clean_sub_noisy
- log_clean_sub_noisy
- bias
- log_bias
- SURE
- log_SURE
- SURE_div_noise

V3:

- K
- log_K
- path_sparsity
- log_path_sparsity
- noise_std
- log_noise_std
- mse_noisy
- log_mse_noisy
- mse_clean
- log_mse_clean
- mse_clean_div_noise
- log_DF_mc_tr
- clean_sub_noisy
- log_clean_sub_noisy
- bias
- log_bias
- SURE
- log_SURE
- SURE_div_noise

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



[to pdf](#)

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reproducible code](#)

[download models](#)

[download xyz array](#)

[add data](#)

Hypothesis



theory



SANDBOX

If you want to be a data scientist...

Follow the paradigm

Work that way

Create tools that work that way

Evaluate other people's work that way

This is what data science is about

Data science v.s STATS and ML

Statistics:

- Too much math
- Over simplified generative models
- Evading the truth

}

Staying true to phenomena seen in practice

Machine learning:

- Uninformative predictive models
- Too quick to jump to conclusions
- Too much reliance on poetry
- Sees the truth through the pinhole of a single method-dataset

}

Comprehensive experimentation

People are groping for this

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

Levi Waldron, Benjamin Haibe-Kains, Aedín C. Culhane, Markus Riester, Jie Ding, Xin Victoria Wang, Mahnaz 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.

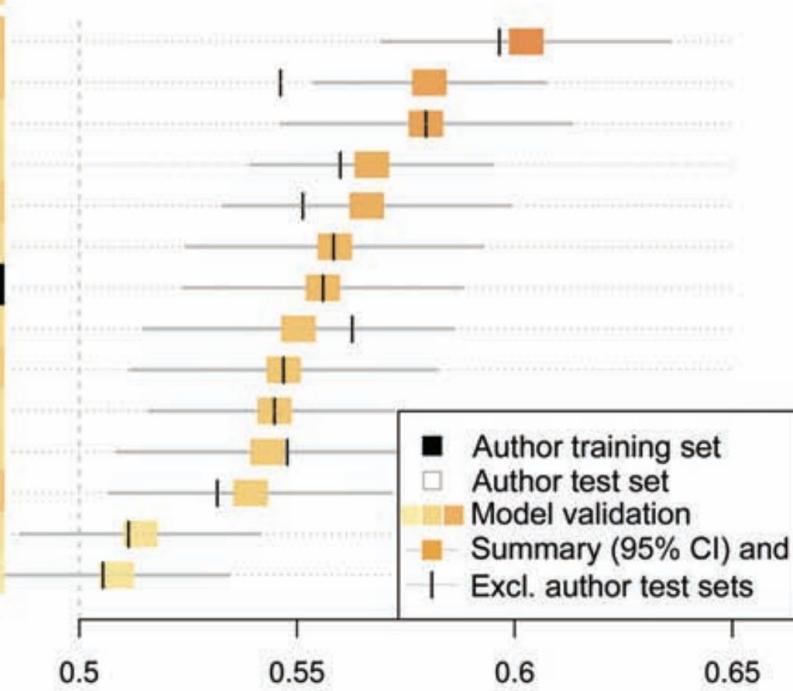
Results Twelve published models had 95% confidence intervals of the C-index that did not include the null value of 0.5; eight outperformed 97.5% of signatures including the same number of randomly selected genes and trained on the same data. The four top-ranked models achieved overall validation C-indices 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.

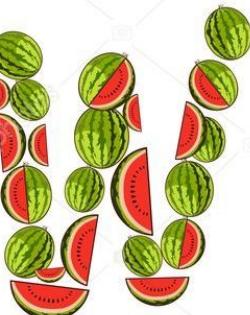
A

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, Tothill, Bentink, Bonome, Konstantinopoulos, Mok, Yoshihara 2010, TCGA, Crijns

B

					
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

Understanding deep learning requires rethinking generalization

<https://arxiv.org> › cs ▾

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

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





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Caffe

Chainer

DL4J
DeepLearning4j

K
KERAS

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MatConvNet

MINERVA

mxnet

Purine

TensorFlow

theano

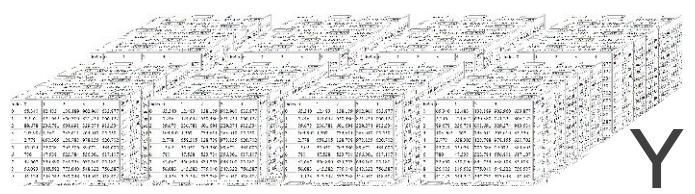
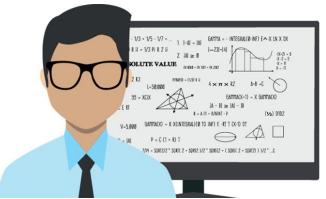
torch



ElastiCluster

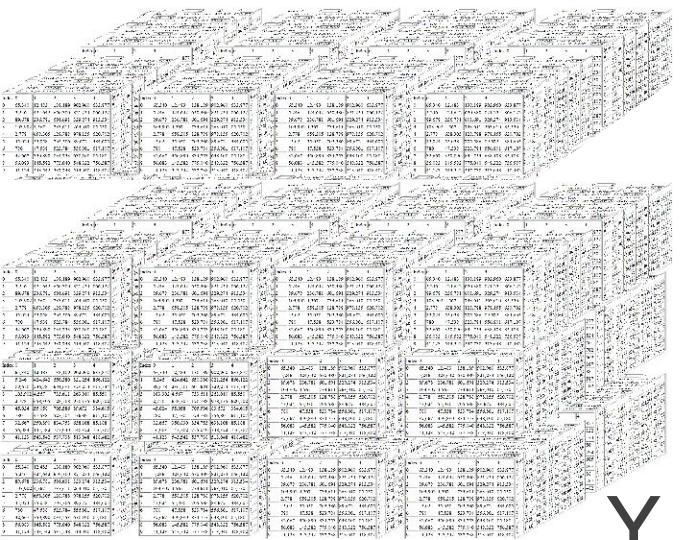
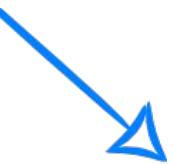


Pywren



Z

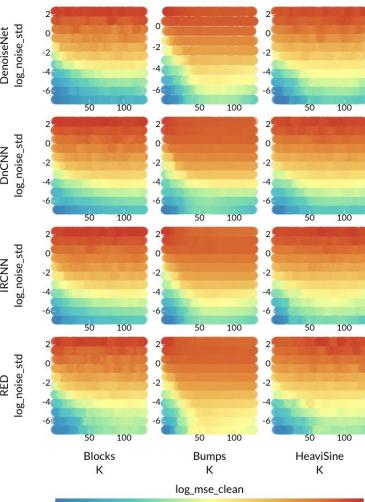
X



Z

Y

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



A Bibliometric Model for Journal Discarding Policy at Academic Libraries

Example: Jiménez-Contreras, Mercedes De La Moreda, and Elena Ruiz de Gopea
Facultad de Documentación, Campus de Cartuja, Universidad de Granada, 18071-Granada, Spain
E-mail: eruiz@ugr.es

Natalia Buitrago-Morales
Departamento de Ingeniería Química, Facultad de Ciencias, Campus de Fuentenueva, Universidad de Granada, 18071-Granada, Spain. E-mail: buitrago@ugr.es

Ramón Ruiz-Rodríguez
Facultad de Documentación, Campus de Cartuja, Universidad de Granada, 18071-Granada, Spain.
E-mail: RuizRodr@ugr.es

The authors propose a bibliometric model for determining the discarding policy of journals in academic libraries. This model uses data mining techniques to analyze the characteristics of the library's collection and its users' needs. The model takes into account various factors such as journal impact factor, age, and popularity. The results show that the model can predict the discarding policy with a high degree of accuracy. The proposed model can help academic libraries to make informed decisions about their collections, which can lead to better resource allocation and improved user satisfaction.

Introduction
Discarding policies refer to the set of rules used by the shelves of journal libraries to remove old or less frequently used journals. These policies are usually based on a combination of qualitative and quantitative criteria. In this paper, we propose a model to predict the discarding policy of journals in academic libraries. The model uses data mining techniques to analyze the characteristics of the library's collection and its users' needs. The results show that the model can predict the discarding policy with a high degree of accuracy. The proposed model can help academic libraries to make informed decisions about their collections, which can lead to better resource allocation and improved user satisfaction.

Materials and Methods
The data used in this study was obtained from the library of the University of Granada. It consists of information about the collection of journals, including their titles, publication dates, and impact factors. The data also includes information about the users' needs, such as the frequency of use and the importance of the journals. The data was processed using data mining techniques to identify patterns and trends. The results were then used to develop a model that can predict the discarding policy of journals.

Results and Discussion
The results of the model show that it is able to predict the discarding policy of journals with a high degree of accuracy. The model can correctly predict the discarding policy for approximately 85% of the journals in the collection.

Conclusion
The proposed model for determining the discarding policy of journals in academic libraries is a useful tool for managing library collections. It can help libraries to make informed decisions about their collections, which can lead to better resource allocation and improved user satisfaction.

ACKNOWLEDGMENTS
The authors would like to thank the library of the University of Granada for providing the data used in this study.

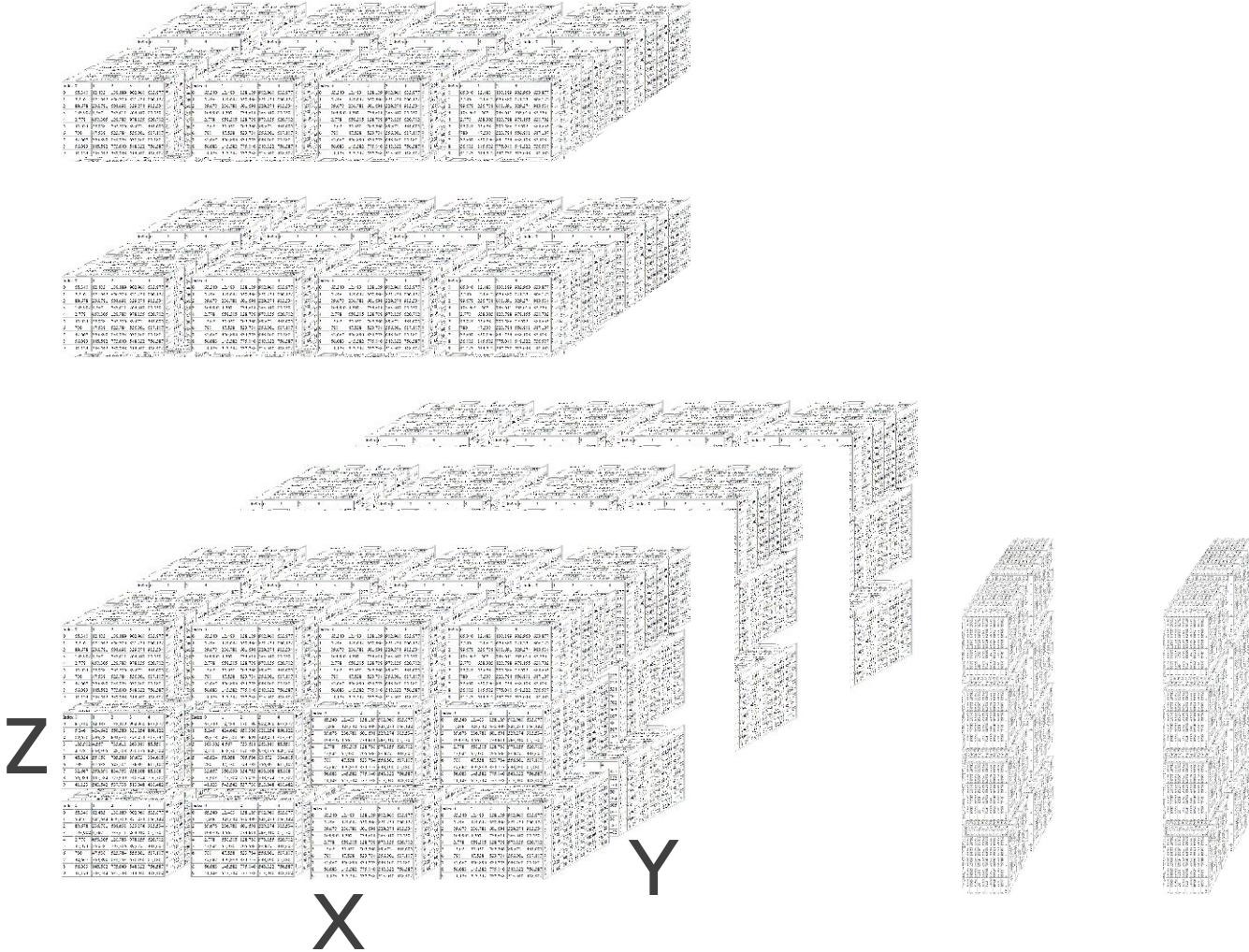
REFERENCES
1. Jiménez-Contreras, M., De la Moreda, E., & Ruiz de Gopea, E. (2017). A bibliometric model for journal discarding policy at academic libraries. *Journal of the American Society for Information Science and Technology*, 68(1), 148-158.

APPENDIX
The following table shows the number of issues discarded per year for each journal in the collection. The table also includes the total number of issues in the collection and the percentage of issues discarded.

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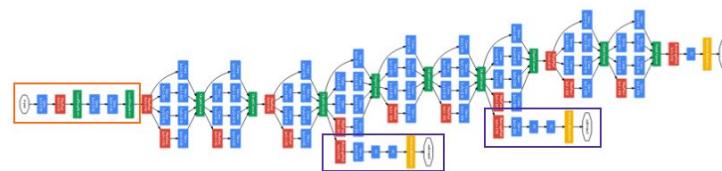
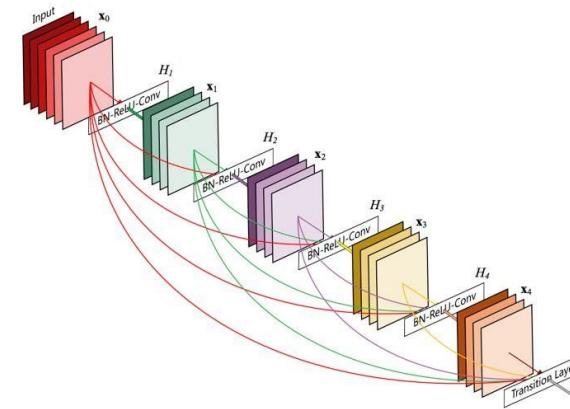
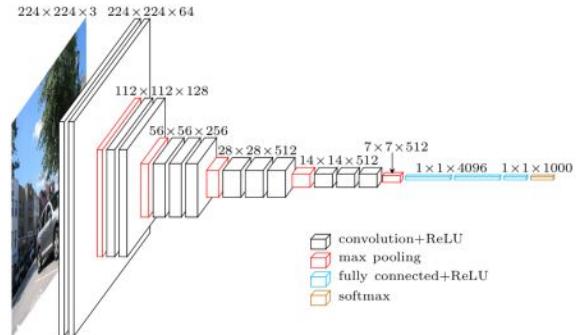


Personal
XYZ



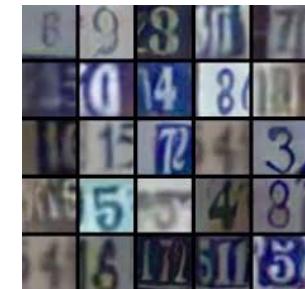
net_list

```
= [  
    'CNN',  
    'AlexNet',  
    'VGG11_bn',  
    'VGG13_bn',  
    'VGG16_bn',  
    'VGG19_bn',  
    'ResNet18',  
    'ResNet34',  
    'ResNet50',  
    'ResNet101',  
    'ResNet152',  
    'SqueezeNet_1_0',  
    'SqueezeNet_1_1',  
    'DenseNet121',  
    'DenseNet161',  
    'DenseNet169',  
    'DenseNet201',  
    'Inception3'  
]
```



Y

```
dataset_list = [  
    'MNIST',  
    'FashionMNIST',  
    'EMNIST_byclass',  
    'EMNIST_bymerge',  
    'EMNIST_balanced',  
    'EMNIST_letters',  
    'EMNIST_digits',  
    'CIFAR10',  
    'CIFAR100',  
    'STL10',  
    'SVHN',  
]
```



Z

```
lr_list = [  
    0.5,  
    0.25,  
    0.1,  
    0.075,  
    0.05,  
    0.025,  
    0.01,  
    0.0075,  
    0.0050,  
    0.0025,  
    0.001,  
    0.00075,  
    0.0005,  
    0.00025,  
    0.0001,  
]
```

XYZ experiment

```
for model_name in [...]:  
    for dataset_name in [...]:  
        for learning_rate in [...]:  
  
            network = create_model(model_name)  
            dataset = create_dataset(dataset_name)  
  
            for epoch in range(num_epochs):  
                for image, target in dataset:  
  
                    # forward pass  
                    output = network(image)  
  
                    # backward pass  
                    loss(output, target).backward()  
  
                    # update model  
                    optimizer.step(learning_rate)  
  
                    # compute accuracy  
                    acc = compute_accuracy()  
  
                    # save to csv  
                    save_results(acc)
```



save **EVERYTHING** about
the experiment in the CSV

XYZ experiment in practice

```

loader_opts = {'train_dataset' : str(row['train_dataset']),
    'test_dataset' : row['test_dataset'],
    'phase' : None,
    'loader_type' : str(row['loader_type']),
    'pytorch_dataset' : bool(row['pytorch_dataset']),
    'dataset_path' : '../..../data',
    'dataset_path' : '/scratch/users/payan/datasets',
    'dataset_kwargs' : {},
    'im_size' : int(row['im_size']),
    'padded_im_size' : int(row['padded_im_size']),
    'num_classes' : int(row['num_classes']),
    'input_ch' : int(row['input_ch']),
    'threads' : 0,
    'limited_dataset' : bool(row['limited_dataset']),
    'examples_per_class' : int(row['examples_per_class']),
    'epc_seed' : epc_seed_idx,
    'train_seed' : train_seed_idx,
    'size_list' : str(row['size_list']),
    'pretrained' : bool(row['pretrained']),
    'multilabel' : bool(row['multilabel']),
    'corrupt_prob' : 0,
    'test_trans_only' : True,
    'concat_loader' : False,
    'loader_constructor' : Constructor,
    'drop_last' : False,
}

train_opts = {'crit' : str(row['crit']),
    'net' : str(row['net']),
    'optim' : str(row['optim']),
    'epochs' : int(row['epochs']),
    'lr' : float(row['lr']),
    'milestones_perc' : str(row['milestones_perc']),
    'gamma' : float(row['gamma']),
    'train_batch_size' : 128,
    'test_batch_size' : 128,
    'cuda' : torch.cuda.is_available(),
    'seed' : int(row['seed']),
    'eps' : float(row['seed']),
}

```

```

results_opts = {'training_results_path': training_results_path,
    'train_dump_file' : str(row['train_dump_file']),
    'save_init_epoch' : bool(row['save_init_epoch']),
    'garbage_collect' : bool(row['garbage_collect']),
    'save_middle' : bool(row['save_middle']),
}

cpu_opts = {'one_batch' : bool(row['one_batch'])}

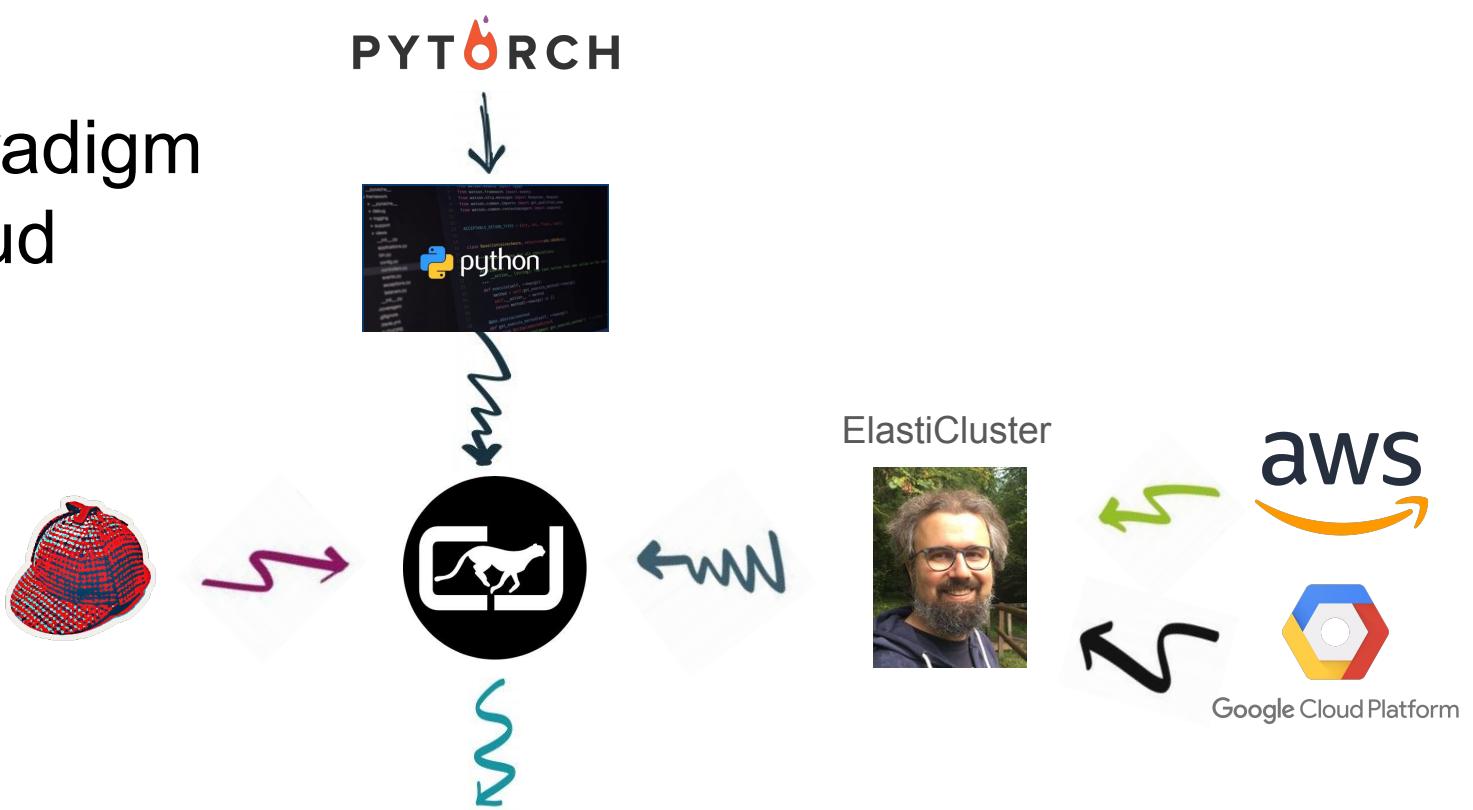
analys_opts = {'k' : float('inf'),
    'project_last' : False,
    'analys_results_path' : analysis_results_path,
    'do_visual' : False,
    'embedded_max_examples' : 512,
    'stats_max_examples' : float('inf'),
    'save_Sigma_wc' : True,
    'vgg_remove_last_dropout' : True,
    'reset_classifier' : True,
    'analyze_last_only' : True,
    'l_analysis' : l,
    'layers_func' : 'get_imp_layers',
    'hook_type' : 'output',
    'activations_per_example' : 10,
    'distribution' : 'norm',
    'coeff_max_examples' : 1000,
    'single_coeff_model' : True,
    'record_activation' : False,
    'compute_norm_mean' : False,
    'compute_Sigma_b_w' : False,
    'compute_w_norm_mean' : True,
    'compute_t_norm_mean' : True,
    'power' : 0.75,
    'seed' : False,
}

spectral_opts = {'hessian_type' : hessian_type_list[hessian_type_i],
    'init_poly_deg' : 64,
    'poly_deg' : 256, # paper suggests M=100
    'mat_vec_iters' : float('inf'),
    'poly_points' : 2**9,
    'spectrum_margin' : 0.05,
    'log_hessian' : False,
    'start_eig_range' : -float('inf'),
    'stop_eig_range' : float('inf'),
    'power_method_iters' : 256,
    'repeat_idx' : repeat_idx,
}

```



Stack paradigm & the cloud



```
pid 8dee32690f1fadf3ad36770d66874d6bb29a8bef
remote_account: papyan@login.sherlock.stanford.edu
1          28560970      COMPLETED
2          28560972      COMPLETED
3          28560973      COMPLETED
•
```

Me coding plots on python:



```
import pandas as pd
import matplotlib.pyplot as plt

df = get_data_frame(path_to_csv)

colors = cm.rainbow(np.linspace(0, 1, num_learning_rates))

for dataset in [...]:
    for net in [...]:
        for learning_rate in [...]:

            df = df[(df['dataset'] == dataset)
                      & (df['net'] == net)
                      & (df['learning_rate'] == learning_rate)]

            plt.plot(df.epoch, df.accuracy, color=colors[learning_rate])
            plt.title('dataset: {}, net: {}, learning_rate: {}'.format(
                dataset,
                net,
                learning_rate))
```

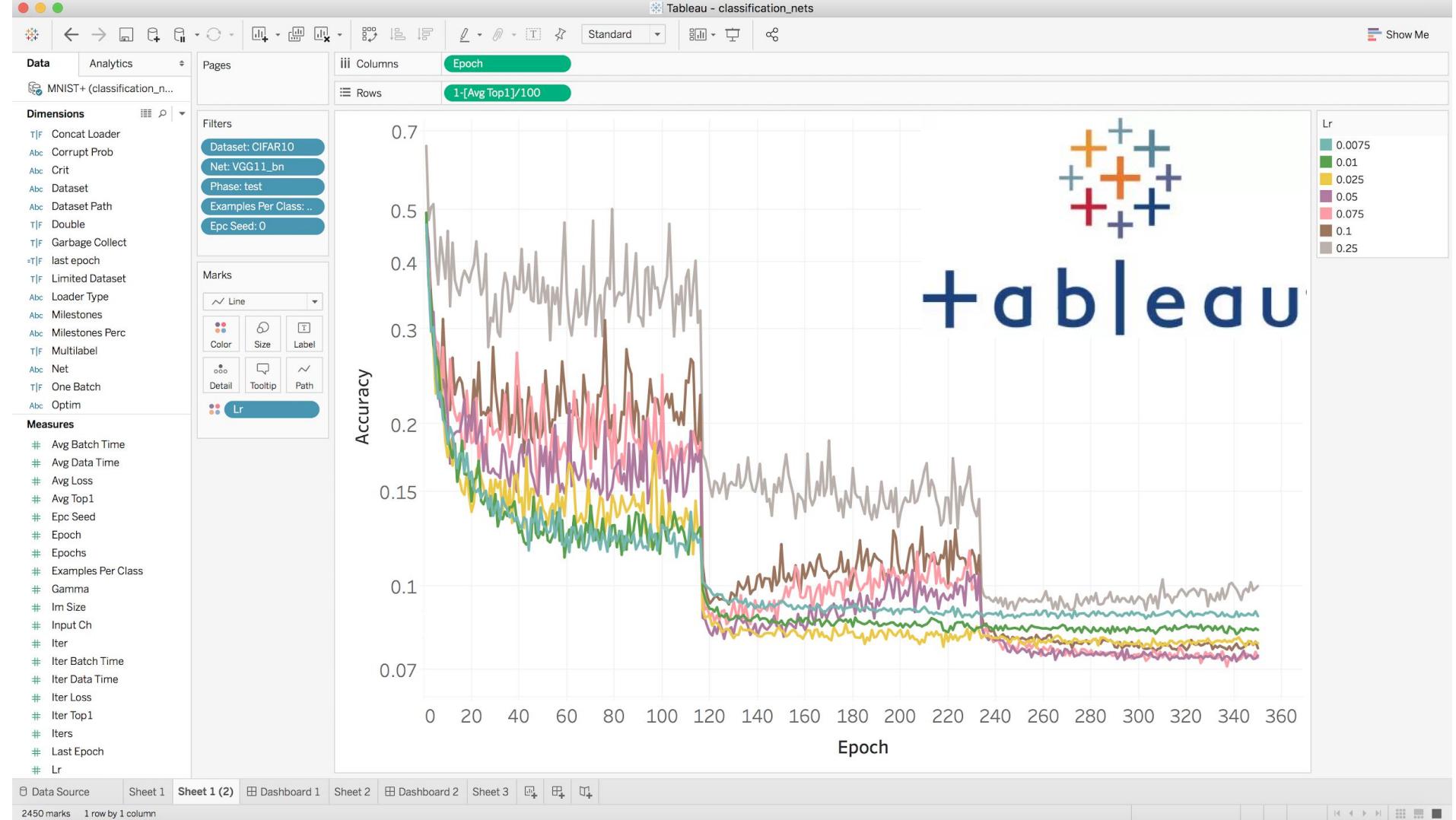


Tableau is...

- **P**owerful: can compute mathematical expressions
- **E**fficient: can handle tens of GB easily
- **R**: you write R scripts (can do regression!)
- **F**ast: few clicks to create plot
- **E**asy: drag and drop
- **C**loud: data sits on cloud
- **T**ime: spent on more useful things

CJ > GCP > Tableau > Laptop

The screenshot shows the Google Cloud Platform Storage interface. The left sidebar has a 'Storage' tab selected, followed by 'Browser', 'Transfer', 'Transfer Appliance', and 'Settings'. The main area shows 'Bucket details' for 'hs-deep-lab-donoho-papyan-bucket'. The 'Objects' tab is active, showing a list of objects. The list includes:

Name	Size	Type	Storage class	Last modified	Public access	Encryption
.DS_Store	6 KB	application/octet-stream	Multi-Regional	10/3/18, 5:50 PM	Not public	Google-managed key
02c408210011e5d44ac849a40e85515f2866862c/	–	Folder	–	–	Per object	–
51503e5b3ba9270616ceef8de3a2ef9b6ad4ccc/	–	Folder	–	–	Per object	–
5a1fd69df03dc72f46cd3733f94bb9da00b76a3f/	–	Folder	–	–	Per object	–
7daa5ee19c4d52cd9807477424d7d1707ce86ec4/	–	Folder	–	–	Per object	–

Final thoughts

Data science is XYZ studies

This is the field done properly

This is what there is to do

There is no other way

Join before it's too late

Science In The Cloud

Monajemi/Donoho/Murri

Cloud is inevitable

Modern Data Science:

- Computationally demanding
- Varied in scale and scope

Campus-resident resources:

- Limited resources (e.g., GPUs, TPUs)
- Fixed policies

Cloud in inevitable

- Scalable and Fast
- Flexible (individual resources)
- Reliable

Google Cloud Platform	Amazon Web Services ^[7]	Microsoft Azure ^[8]
Google Compute Engine	Amazon EC2	Azure Virtual Machines
Google App Engine	AWS Elastic Beanstalk	Azure Cloud Services
Google Container Engine	Amazon EC2 Container Service	Azure Container Service
Google Cloud Bigtable	Amazon DynamoDB	Azure Cosmos DB
Google BigQuery	Amazon Redshift	Microsoft Azure SQL Database
Google Cloud Functions	Amazon Lambda	Azure Functions
Google Cloud Datastore	Amazon DynamoDB	Cosmos DB
Google Storage	Amazon S3	Azure Blob Storage

Existing Cloud Computing Models for DS

- Computing by provisioning a server
 - ElastiCluster-ClusterJob Model (Stanford-UZH)
 - CodaLab Worksheets Model (Stanford-Microsoft)
- Serverless Computing
 - PyWren (UC-Berkeley)
- Third Party Products
 - Databricks
 - Domino DataLabs
 - Civis Analytics
 - SageMaker (AWS)
 - Cloud ML (Google)

ElastiCluster-ClusterJob Model



+ ElastiCluster +



ElastiCluster-ClusterJob Model

```
$ elasticcluster start gce
```

```
$ cj parrun experiment.py gce
```

ElastiCluster

- Open-source software (GPL License) started at UZH
- Python API to setup and resize clusters
- Uses Ansible (Infrastructure as Code)
- Cloud-agnostic (AWS, GCE, AZURE)
- Offers many Operating Systems and Job Schedulers
- Offers many add-ons (JupyterHub, Cuda, etc.)

ElastiCluster Config

[setup/slurm]

```
provider=ansible  
frontend_groups=slurm_master  
compute_groups=slurm_worker,cuda
```

[cloud/google]

```
provider=google  
gce_client_id=***  
gce_client_secret=***  
gce_project_id=***
```

[login/gmail]

```
image_user=hatefmonajemi
```

[cluster/gce]

```
setup=slurm  
cloud=google  
login =gmail  
frontend_nodes=1  
compute_nodes=4  
flavor=n1-standard-4
```



You choose!

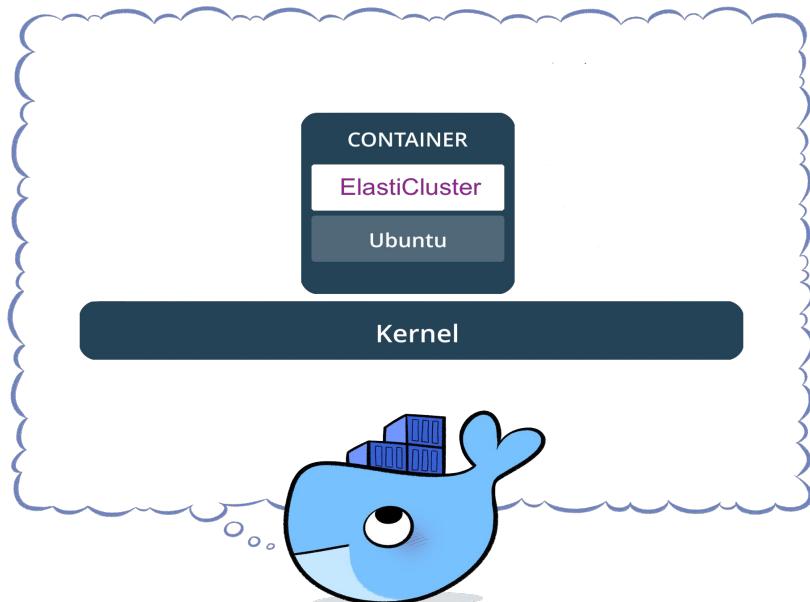
ElastiCluster 0-Install Script

- Uses Docker containers to facilitate installation

`elasticcluster.sh:`

```
exec docker run murri/elasticcluster "$@"
```

[Link to Dockerfile](#)



Using ElastiCluster

- Use the script directly

```
$ ./elasticcluster.sh start gce
```

- Define an alias for convenience (inside `~/.bash_profile`)

```
alias elasticcluster='/Users/hatef./elasticcluster.sh'
```

```
$ elasticcluster start gce
```

Give info of your cluster to CJ

- Extract the front-node IP address

```
$ elasticcluster list-nodes gce
```

- Provide CJ with necessary config

```
$ cj config gce --update
```

Run and manage experiments!

```
$ cj parrun experiments.py gce
```

```
$ cj state
```

```
$ cj runlog $/1
```

```
$ cj error $/1
```

```
$ cj sanity (exists|lines) PID
```

```
$ cj reduce results.txt PID
```