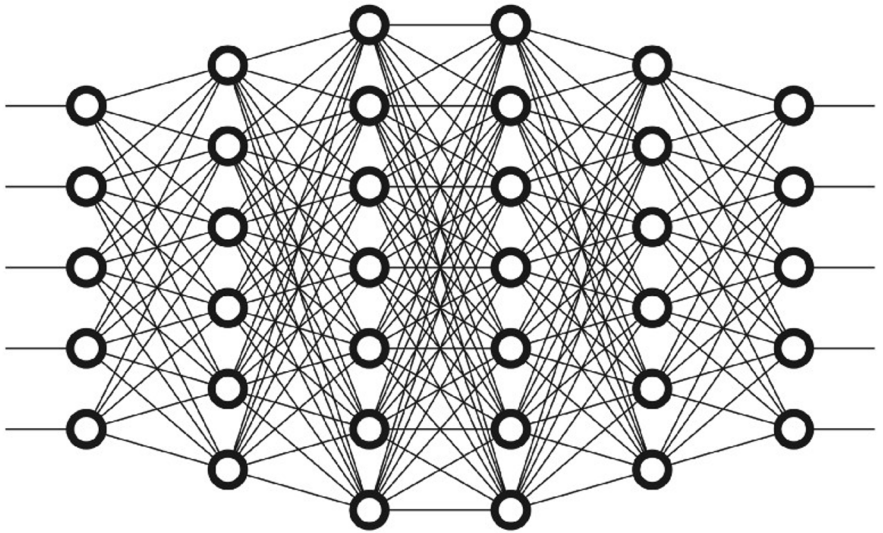
Massive Computational Experiments, Painlessly

STATS 285
Stanford University

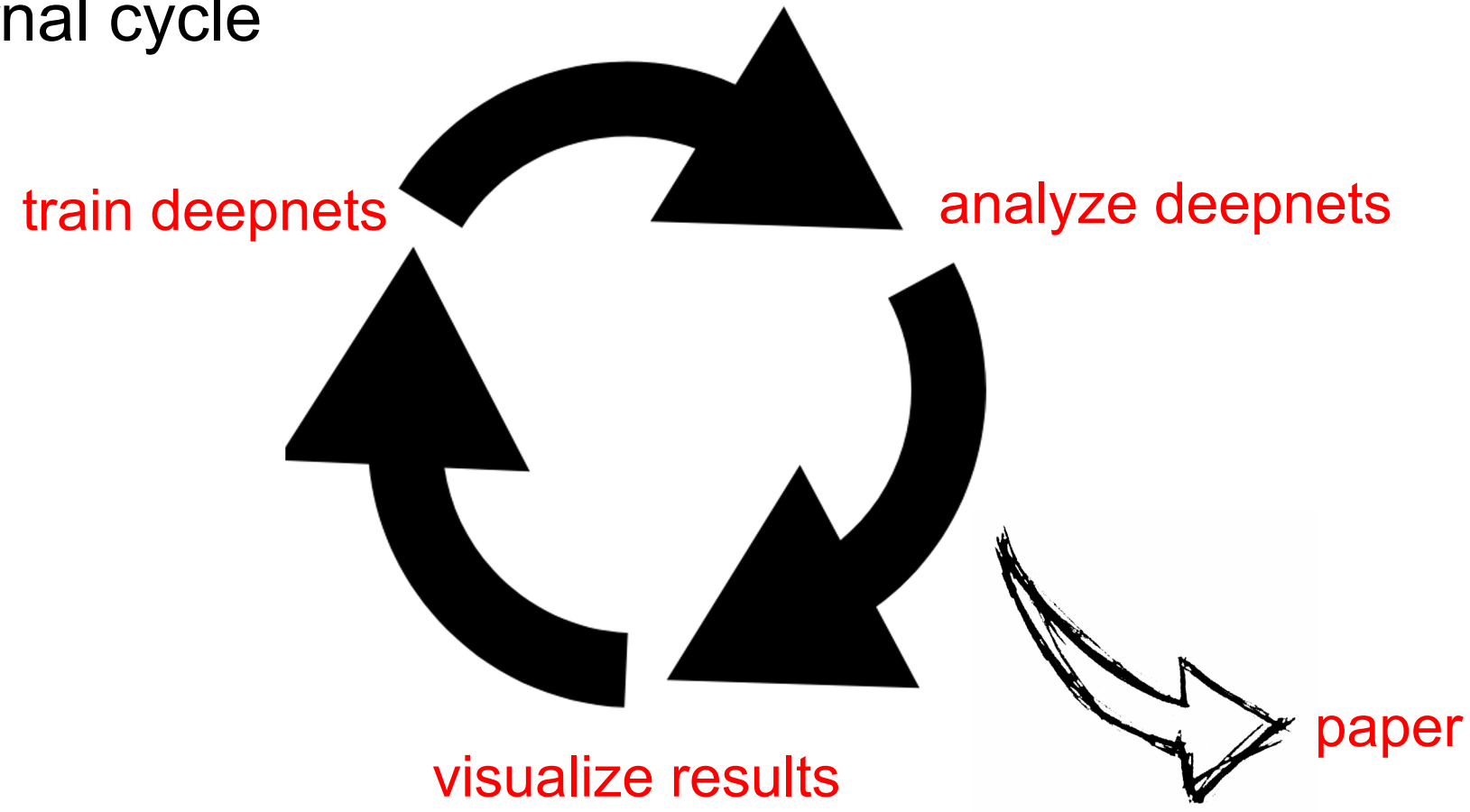
My research

Study of deep net:

- Features
- Weights
- Backpropagated errors
- Gradients
- Fisher information matrix
- Hessian
- …



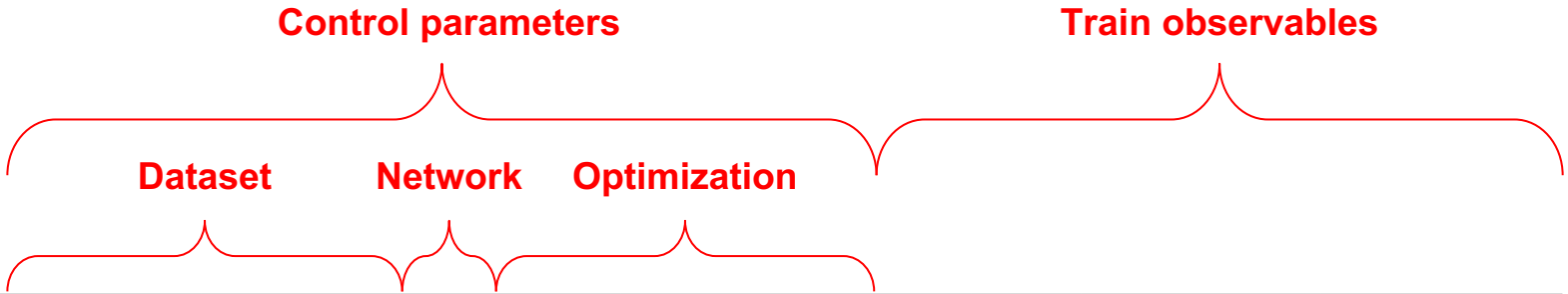
Eternal cycle



Training deepnets: experiment specification

- Dataset:
  - MNIST, FashionMNIST, CIFAR10, CIFAR100, ImageNet
- Network:
  - MLP, LeNet, VGG, ResNet
- Control parameters:
  - Dataset: sample size, number of classes
  - Network: width, depth
  - Optimization: algorithm, learning rate, learning rate scheduler, batch size
- Observables:
  - Top1 error, loss

Training deepnets: experiment results

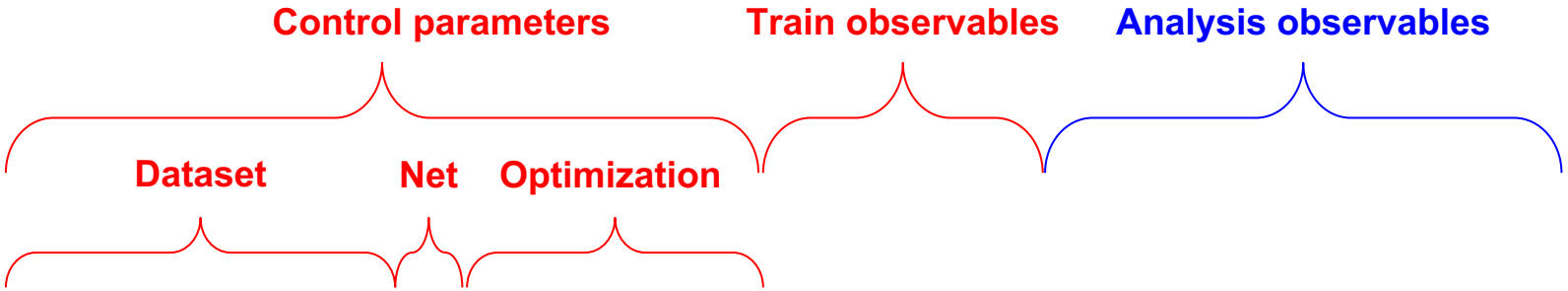


	Dataset	Network	Number of Classes	Examples per class	Depth	Optimizer	Learning rate	Batch size	Phase	Epoch	Top-1 error	Cross-entropy Loss
0006d21e9a	MNIST	VGG	10	5000	11	SGD	0.25	128	test	250	99.38322368421052	0.028507341263129524
000e518c8d	MNIST	VGG	10	5000	11	SGD	0.25	128	train	196	99.81637286324786	0.007986395810850156
01003dd1ea	MNIST	VGG	10	5000	11	SGD	0.25	128	test	30	98.41694078947368	0.057988858144534264
01421e353c	MNIST	VGG	10	5000	11	SGD	0.25	128	test	143	99.22902960526316	0.029485975980366532
0215d9cc00	MNIST	VGG	10	5000	11	SGD	0.25	128	train	129	99.8046875	0.0081629870324117
0216427c78	MNIST	VGG	10	5000	11	SGD	0.25	128	train	187	99.86812232905983	0.0058947943158957185
022684ea96	MNIST	VGG	10	5000	11	SGD	0.25	128	test	25	98.4888980263158	0.05374518193696674
027314b8b3	MNIST	VGG	10	5000	11	SGD	0.25	128	test	234	99.34210526315789	0.027728269660943432
02a513b57a	MNIST	VGG	10	5000	11	SGD	0.25	128	test	349	99.44490131578948	0.028374243527650833
031de9266f	MNIST	VGG	10	5000	11	SGD	0.25	128	test	44	98.01603618421052	0.07326431356762585
03585ce035	MNIST	VGG	10	5000	11	SGD	0.25	128	train	77	98.5844017094017	0.05233209439688641
362668092	MNIST	VGG	10	5000	11	SGD	0.25	128	train	292	100	0.001758613106277254
03672e776e	MNIST	VGG	10	5000	11	SGD	0.25	128	train	317	100	0.001763534063521104

Analyzing deepnets: analysis specification

- Dataset:
  - MNIST, FashionMNIST, CIFAR10, CIFAR100, ImageNet
- Network:
  - MLP, LeNet, VGG, ResNet
- Control parameters:
  - Dataset: sample size, number of classes
  - Network: width, depth
  - Optimization: find control parameters leading to best top-1 error
- Observables:
  - Spectra of deepnets features, backpropagated errors, gradients, Fisher information matrix, Hessian, …

Analyzing deepnets: analysis results



	Dataset	Network	Number of classes	Examples per class	Depth	Optimizer	Learning rate	Batch	Top-1 error	Path to model	Matrix type	Layer	Index of eigenvalue	Eigenvalue
00008c3007	MNIST	MLP	10	5000	8	SGD	[0.0678604404	128	98.97203947	/scratch/users/p	features	0	240	0.095884531
0003bb8fa2	MNIST	MLP	10	5000	8	SGD	[0.0678604404	128	98.97203947	/scratch/users/p	backprop errors	0	1562	6.224693205
0009cbc2ee	MNIST	MLP	10	5000	8	SGD	[0.0678604404	128	98.97203947	/scratch/users/p	backprop errors	0	228	4.193413758
000c50127e	MNIST	MLP	10	5000	8	SGD	[0.0678604404	128	98.97203947	/scratch/users/p	features	0	148	0.263989627
000d56712f	MNIST	MLP	10	5000	8	SGD	[0.0678604404	128	98.97203947	/scratch/users/p	backprop errors	0	1084	3.365795819
001039f911	MNIST	MLP	10	5000	8	SGD	[0.0678604404	128	98.97203947	/scratch/users/p	features	0	274	0.086070373
0015db9977	MNIST	MLP	10	5000	8	SGD	[0.0678604404	128	98.97203947	/scratch/users/p	backprop errors	0	699	1.015973296
001d99a2ed	MNIST	MLP	10	5000	8	SGD	[0.0678604404	128	98.97203947	/scratch/users/p	backprop errors	0	496	1.637548194
00224a8725	MNIST	MLP	10	5000	8	SGD	[0.0678604404	128	98.97203947	/scratch/users/p	backprop errors	0	975	5.148281800
00254c969b	MNIST	MLP	10	5000	8	SGD	[0.0678604404	128	98.97203947	/scratch/users/p	backprop errors	0	1986	-4.590460750
0027ad40da	MNIST	MLP	10	5000	8	SGD	[0.0678604404	128	98.97203947	/scratch/users/p	backprop errors	0	1477	7.881029162
002b584223	MNIST	MLP	10	5000	8	SGD	[0.0678604404	128	98.97203947	/scratch/users/p	backprop errors	0	1794	9.020487135
002fdcbd3a	MNIST	MLP	10	5000	8	SGD	[0.0678604404	128	98.97203947	/scratch/users/p	backprop errors	0	103	8.312590580

In practice slightly more complicated...

Phase
Dataset_path
Test_trans_only
Drop_last
Sampler
Corrupt_prob
Load_epoch
Train_batch_size
Test_batch_size
Training_results_path
Anals_results_path
Layers_func
Seed
Absorb_bn
Filter_bn
Milestones_perc
Gamma
Train_batch_size
Training_results_path
Save_middle

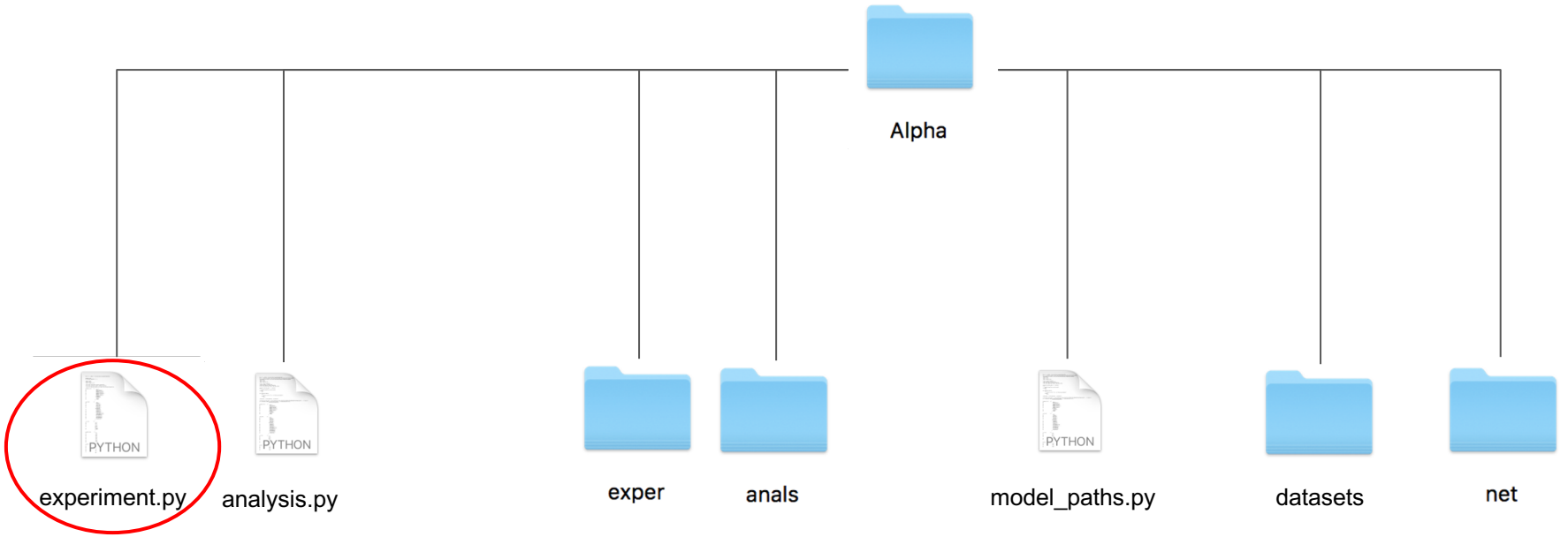
K_Normalization
Damping
Ignore_bias
save_K
Hessian_layer
All_params
Hessian_type
Init_poly_degpoly_deg
Poly_points
Spectrum_margin
Kappa
Log_hessian
Start_eig_range
Stop_eig_range
Power_method_iters
Test_batch_size
Device
Seed
Train_dump_file
Epoch_list

Repeat_idx
N_vec
Mult_num_classes
Trace_est_iters
Perplexity_list
Double
Rand_model
Bidiag
Cpu_eigvec
G_decomp_cpu
Train_dataset
Test_dataset
Loader_type
Pytorch_dataset
Dataset_path
Concat_loader
Switch_relu_pool
Scattering
Save_init_epoch
One_batch

Dataset_kwargs
Im_size
Padded_im_size
Num_classes
Input_ch
Threads
Limited_dataset
Examples_per_class
Epc_seed
Train_seed
Size_list
Pretrained
Retrain_last
Multilabel
Corrupt_prob
Reset_classifier
Resnet_type
Test_trans_only
Garbage_collect
Epochs

Double
Loader_constructor
Sampler
Pin_memory
normalized_Fashion
Momentum
Weight_decay
GAN
Forward_class
Classification
Forward_func
Critnet
Optim
Optim_kwargs
Epochs
Lr
Net_width
Num_layers

Alpha



specification of experiment and analysis

implementation of experiment and analysis

locations of trained models

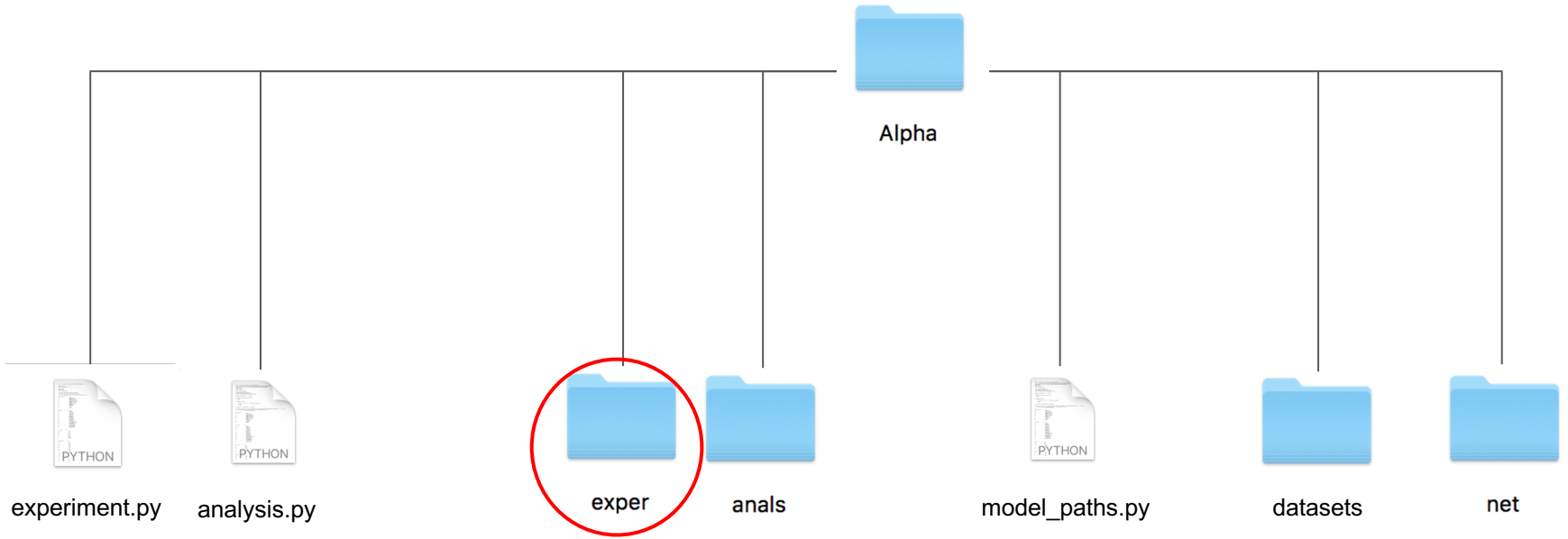
datasets

networks

experiment.py -- experiment specification

```python
from exper import Experiment

dataset_list = ['MNIST', 'FashionMNIST', 'CIFAR10']
net_list = ['VGG11_bn', 'ResNet18']
lr_list = [0.1,0.05,0.001]
size_list = [13, 26, 51, 98, 189, 365, 702, 1351, 2599, 5000]

for dataset_idx in range(3):
    for net_idx in range(2):
        for size_idx in range(10):
            for lr_idx in range(3):

                dataset_opts = {'dataset'           : dataset_list[dataset_idx]
                                'examples_per_class': size_list[size_idx],
                                }

                network_opts = {'depth'          : 8,
                                }

                optimization_opts = {'net'          : net_list[net_idx],
                                     'optim'        : 'SGD',
                                     'momentum'     : 0.9,
                                     'weight_decay': 5e-4,
                                     'epochs'       : 350,
                                     'lr'           : lr_list[lr_idx],
                                     'batch_size'   : 2**7,
                                     }

                opts = dict(dataset_opts, **optimization_opts)
                opts = dict(opts, **network_opts)

                Experiment(opts).run()
```

Alpha



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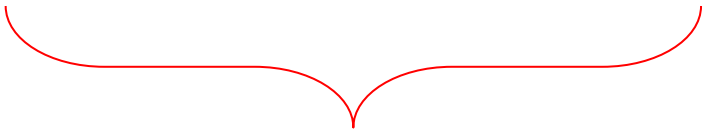
Experiment class -- experiment implementation

```
class Experiment:

    def __init__(self, opts):

        for key, value in opts.items():
            setattr(self, key, value)
```



Save all experiment specification in self

Experiment class -- experiment implementation

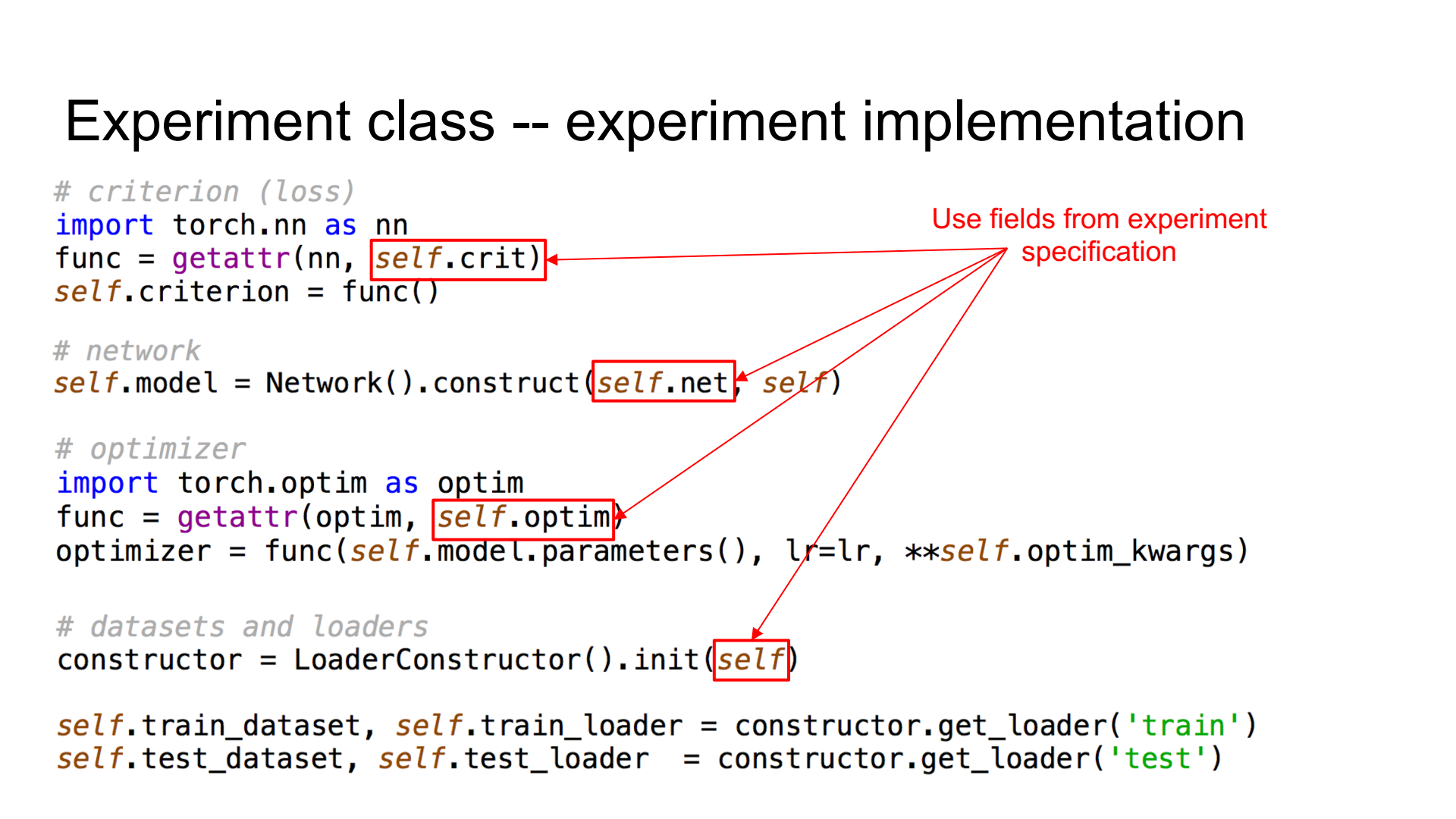
```
# criterion (loss)
import torch.nn as nn
func = getattr(nn, self.crit)
self.criterion = func()

# network
self.model = Network().construct(self.net, self)

# optimizer
import torch.optim as optim
func = getattr(optim, self.optim)
optimizer = func(self.model.parameters(), lr=lr, **self.optim_kwargs)

# datasets and loaders
constructor = LoaderConstructor().init(self)

self.train_dataset, self.train_loader = constructor.get_loader('train')
self.test_dataset, self.test_loader  = constructor.get_loader('test')
```



Experiment class -- experiment implementation

```
# iterate over batches
for input,label in self.loader:
    input = input.to(self.device)
    label = label.to(self.device)

    # run model
    prediction = self.model

    # compute loss
    loss = self.crit(prediction, label)

    # backpropagate
    self.optimizer.zero_grad()
    loss.backward()
    self.optimizer.step()
```

Experiment class -- experiment implementation

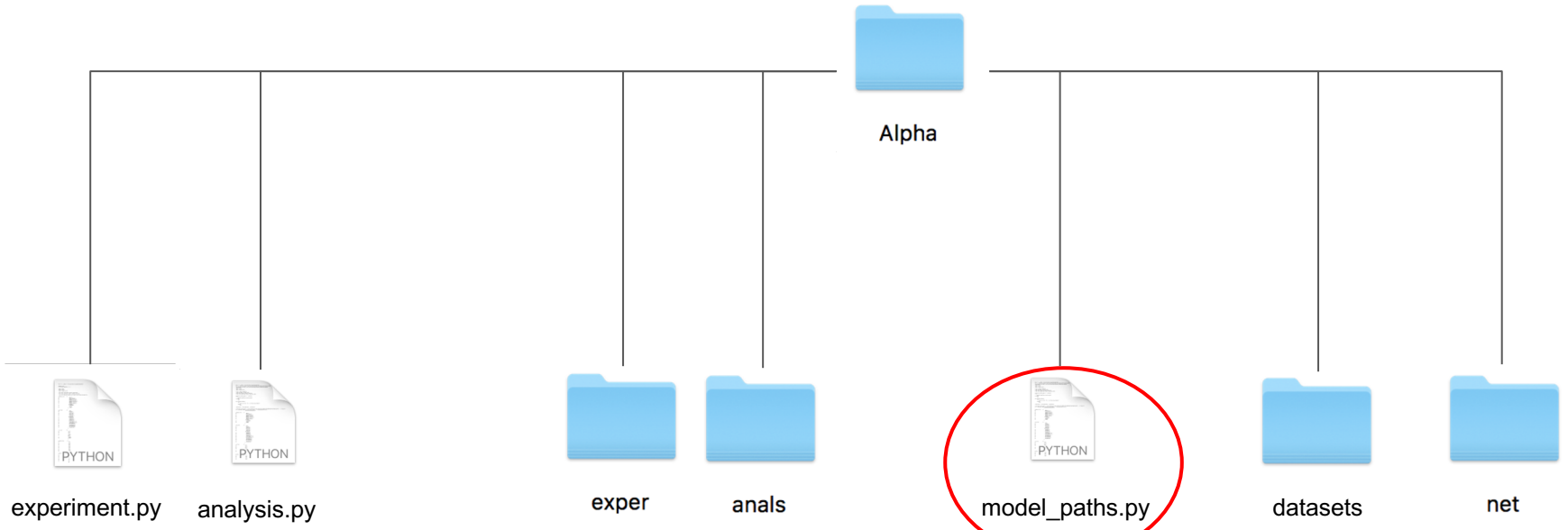
```
stats = {'phase'              : phase,
         'dataset'            : dataset,
         'epoch'              : epoch,
         'iter'               : iter,
         'iters'              : len(loader),
         'iter_batch_time'    : batch_time.val,
         'avg_batch_time'     : batch_time.avg,
         'iter_data_time'     : data_time.val,
         'avg_data_time'      : data_time.avg}

results.append(dict(self.__getstate__(), **stats))
```

experiment specification observables

Concatenate experiment specification to observables and as row to csv

Alpha



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model_paths.py

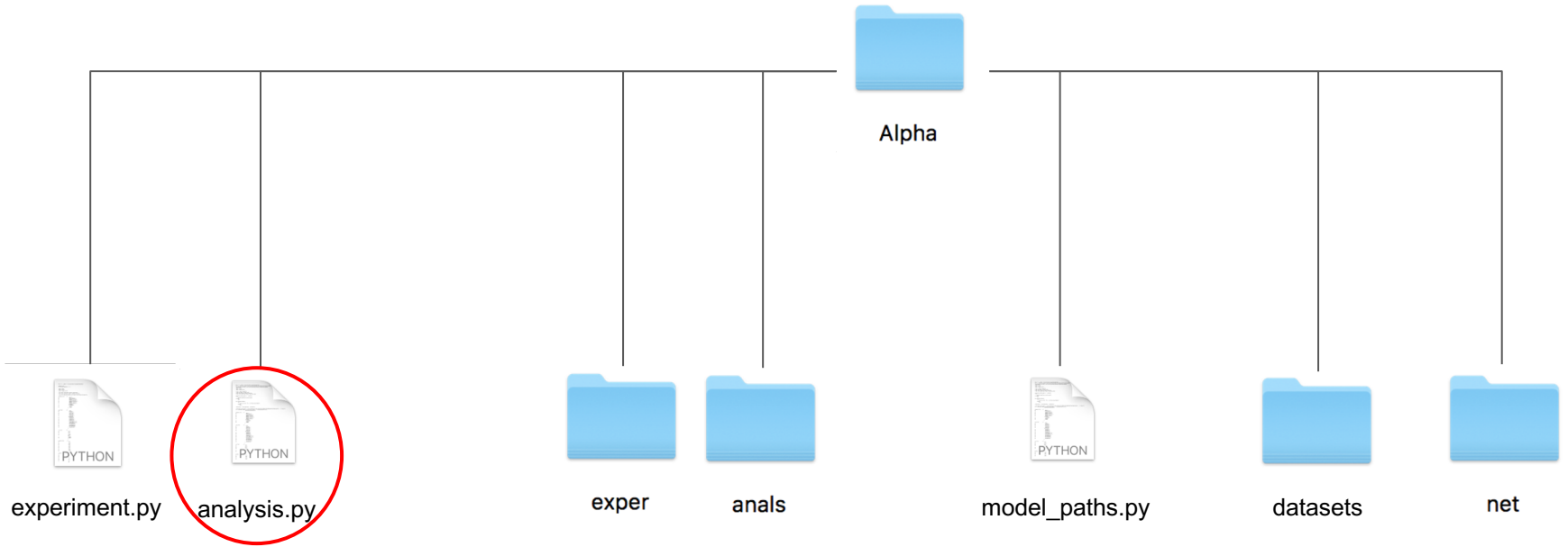
dictionary of trained model paths

```python
def get_model_path(dataset, network):
    return paths[dataset+'.'+network]

paths = {'MNIST.VGG11_bn'        : '/scratch/users/papyan/trained_models/3ad186bbfe8d7f6a6dfc1b116463956e72cd8b6b/',
         'FashionMNIST.VGG11_bn' : '/scratch/users/papyan/trained_models/8dd94ceaea2fe0a49f9b2f369ae12ccb35323056/',
         'CIFAR10.VGG11_bn'      : '/scratch/users/papyan/trained_models/43a7a251e5f0377cc0d59cd0bd15b94e87cc5f15/',
         'MNIST.ResNet18'        : '/scratch/users/papyan/trained_models/eafc959c4215e81a053b9823832cee8f42db760f/',
         'FashionMNIST.ResNet18' : '/scratch/users/papyan/trained_models/5dc2d5768e4dae39739b13a0ebcafbe57bd92cae/',
         'CIFAR10.ResNet18'      : '/scratch/users/papyan/trained_models/8d8c31045a4252a1b9a7b6aa6d3e041321b063f7/',
         }
```

* Each of this paths corresponds to all the models trained for a certain dataset and a certain network

Alpha



specification of experiment and analysis

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analysis.py -- analysis specification

```python
from model_paths import get_path
from anals.analysis import Analysis
from misc import get_csv
from misc import find_best_model

dataset_list = ['MNIST', 'FashionMNIST', 'CIFAR10']
net_list = ['VGG11_bn', 'ResNet18']
size_list = [13, 26, 51, 98, 189, 365, 702, 1351, 2599, 5000]
epoch_list = [10, 100]

for dataset_idx in range(3):
    for net_idx in range(2):
        for size_idx in range(10):
            for epoch_idx in range(2):

                path = get_path(dataset_list[dataset_idx], net_list[net_idx])

                df = get_csv(path)

                best_df, _ = find_best_model(size_list[size_idx])

                analysis_opts = {'load_epoch' : epoch_list[epoch_idx],
                                 }

                opts = dict(df, **analysis_opts)

                Analysis(opts).run()
```

Sherlock

- Cluster at Stanford
- Has many computational resources
  - CPUs
  - GPUs
- Useful for storing data
  - Laptop very limited in terms of memory
  - Data can get deleted if not touched for too long
  - Cloud costs money
- Interactive IPython notebook (Sherlock on demand)

ClusterJob: goal

```python
from model_paths import get_path
from anals.analysis import Analysis
from misc import get_csv
from misc import find_best_model

dataset_list = ['MNIST', 'FashionMNIST', 'CIFAR10']
net_list = ['VGG11_bn', 'ResNet18']
size_list = [13, 26, 51, 98, 189, 365, 702, 1351, 2599, 5000]
epoch_list = [10, 100]

for dataset_idx in range(3):
    for net_idx in range(2):
        for size_idx in range(10):
            for epoch_idx in range(2):

                path = get_path(dataset_list[dataset_idx], net_list[net_idx])

                df = get_csv(path)

                best_df, _ = find_best_model(size_list[size_idx])

                analysis_opts = {'load_epoch' : epoch_list[epoch_idx],
                                 }

                opts = dict(df, **analysis_opts)

                Analysis(opts).run()
```

Easily parallelizable!

dataset_idx=0, net_idx=0, size_idx=0, epoch_idx=0

dataset_idx=0, net_idx=0, size_idx=0, epoch_idx=1

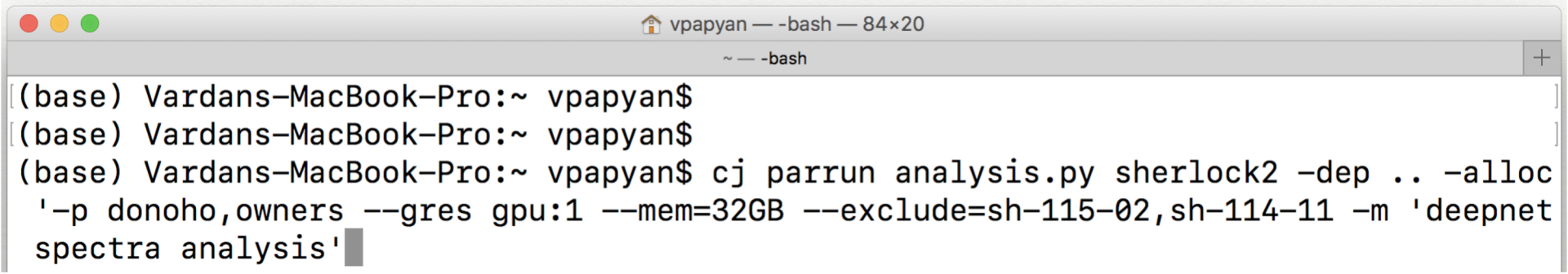
…

dataset_idx=2, net_idx=1, size_idx=3, epoch_idx=0

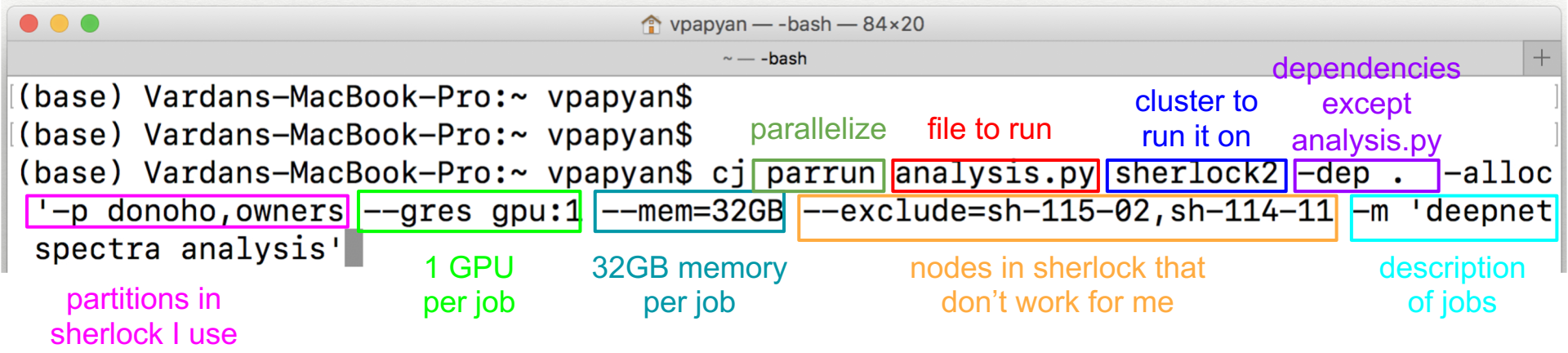
…

dataset_idx=2, net_idx=1, size_idx=9, epoch_idx=1

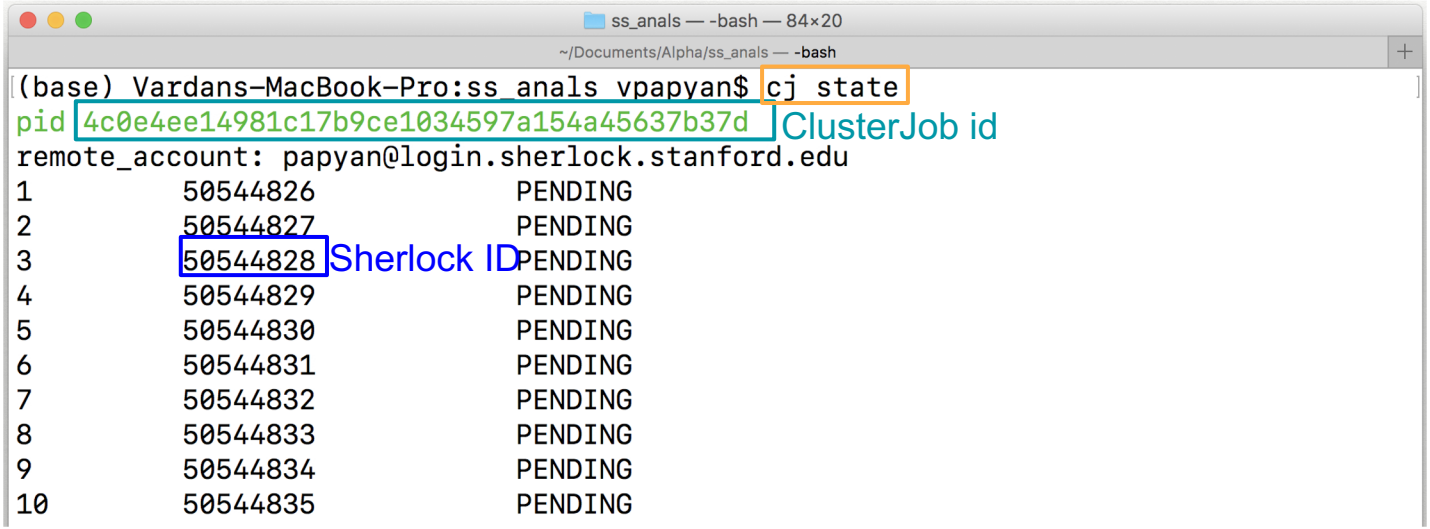
ClusterJob: jobs submission



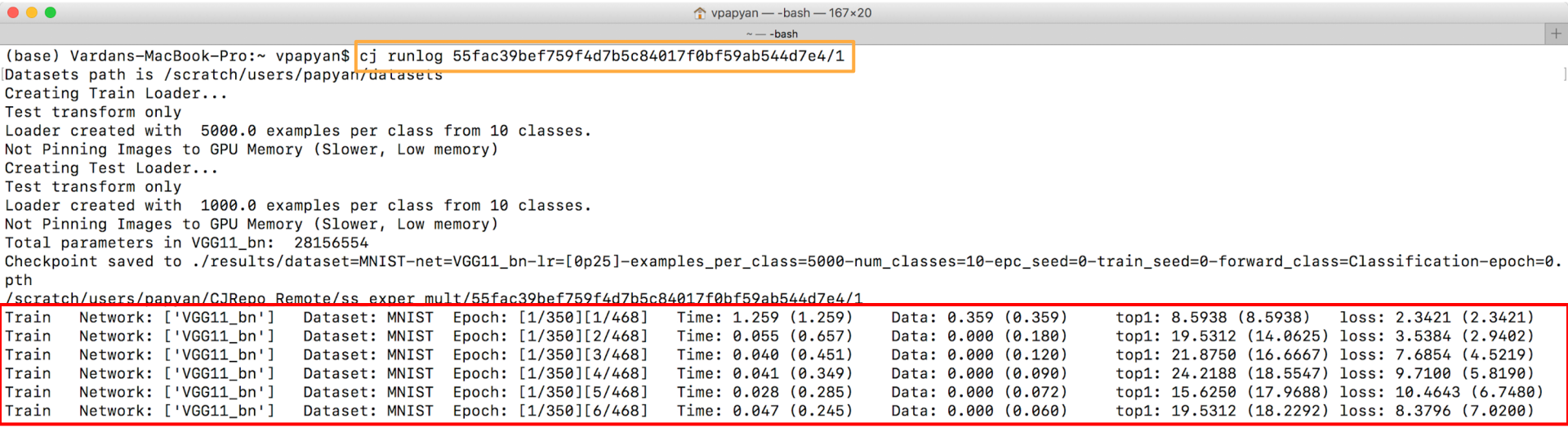
ClusterJob: jobs submission



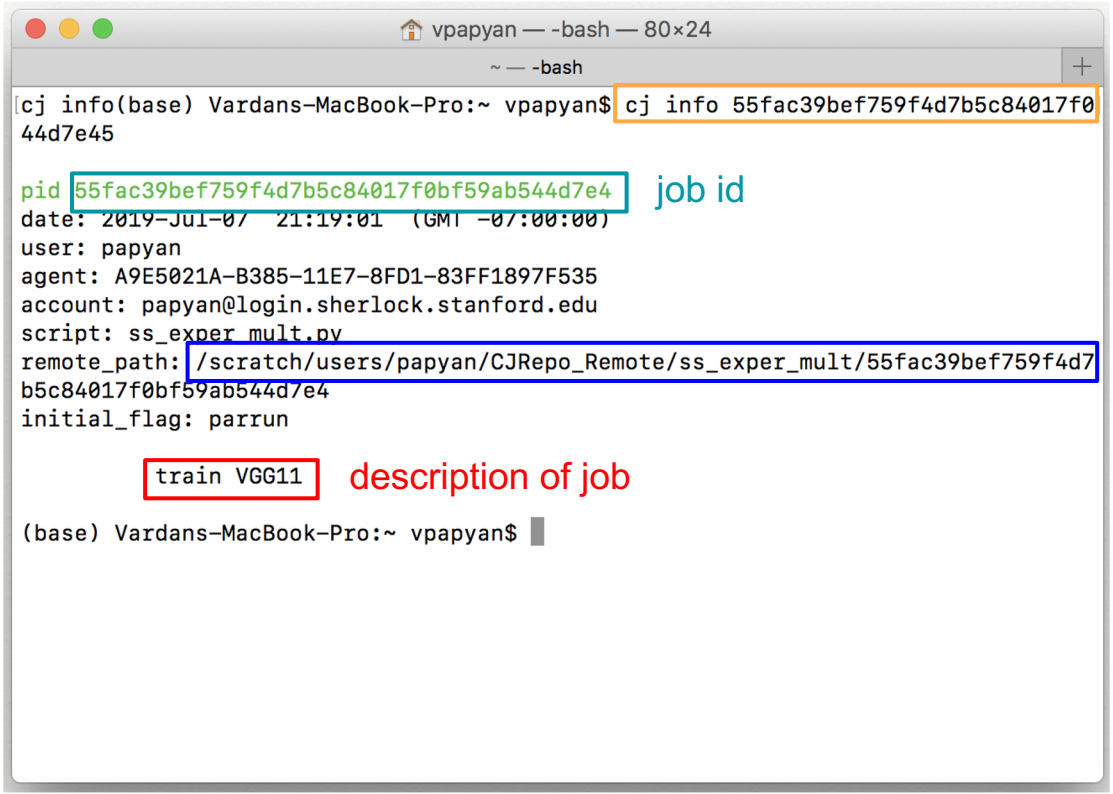
ClusterJob: check state of jobs



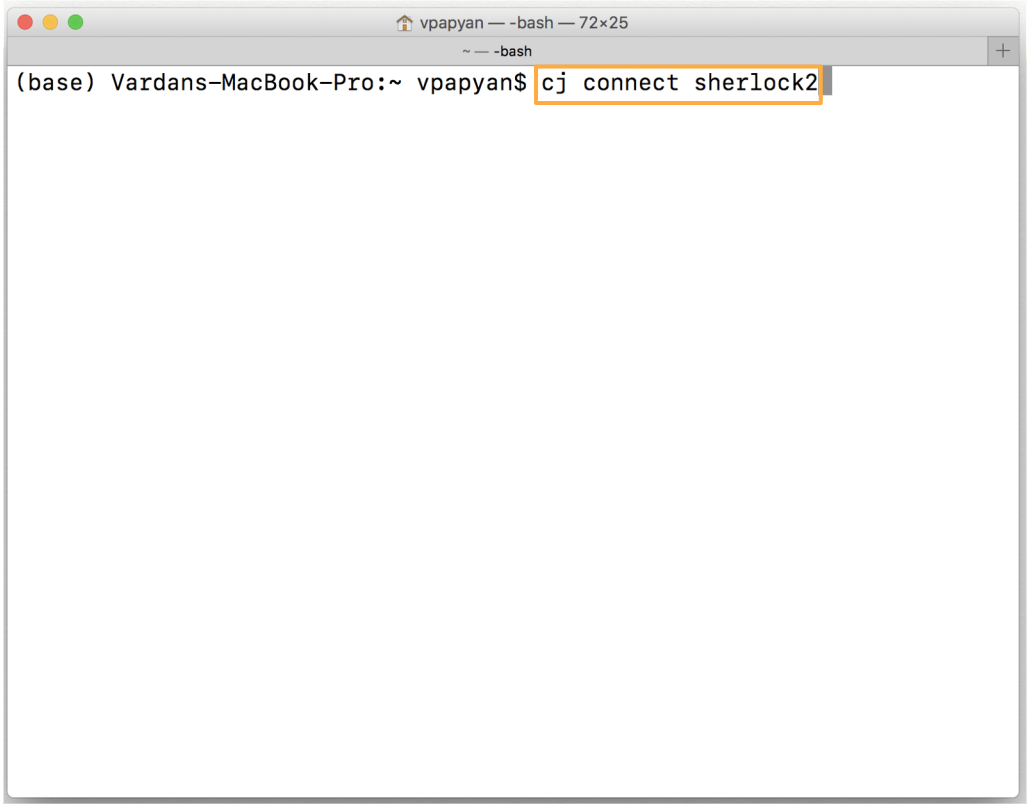
ClusterJob: check progress of jobs



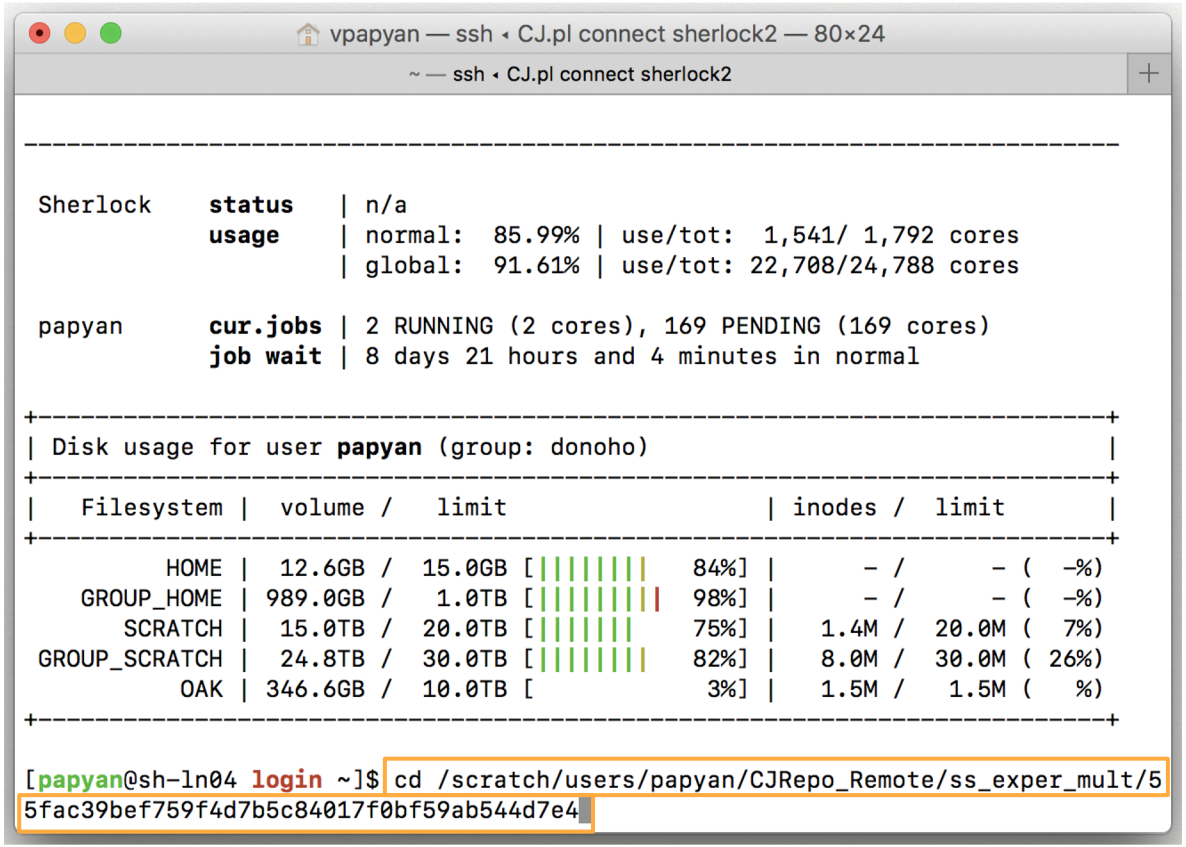
ClusterJob: find location of jobs on cluster



ClusterJob: connecting to cluster

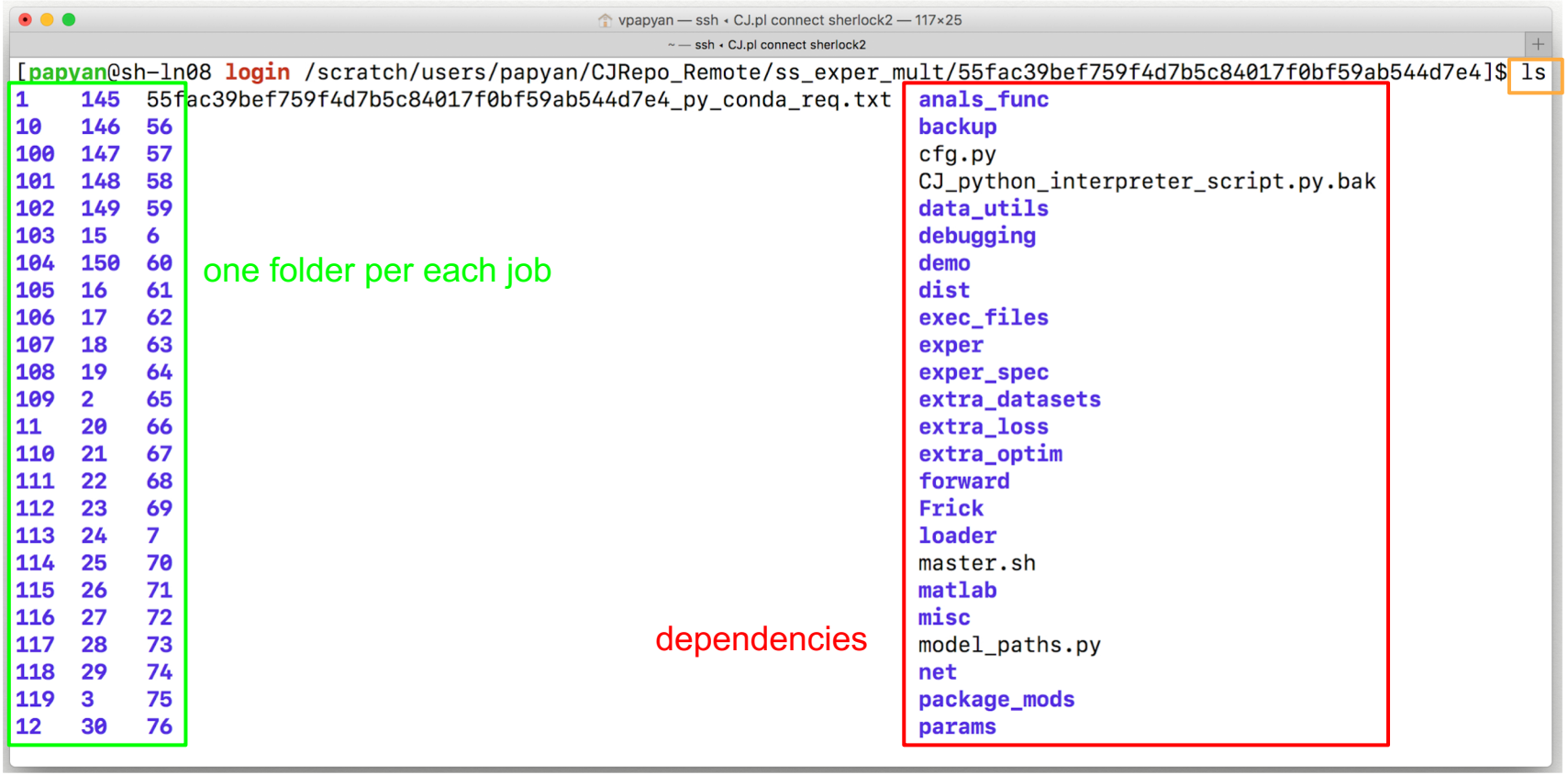


ClusterJob: changing directory to folder of jobs

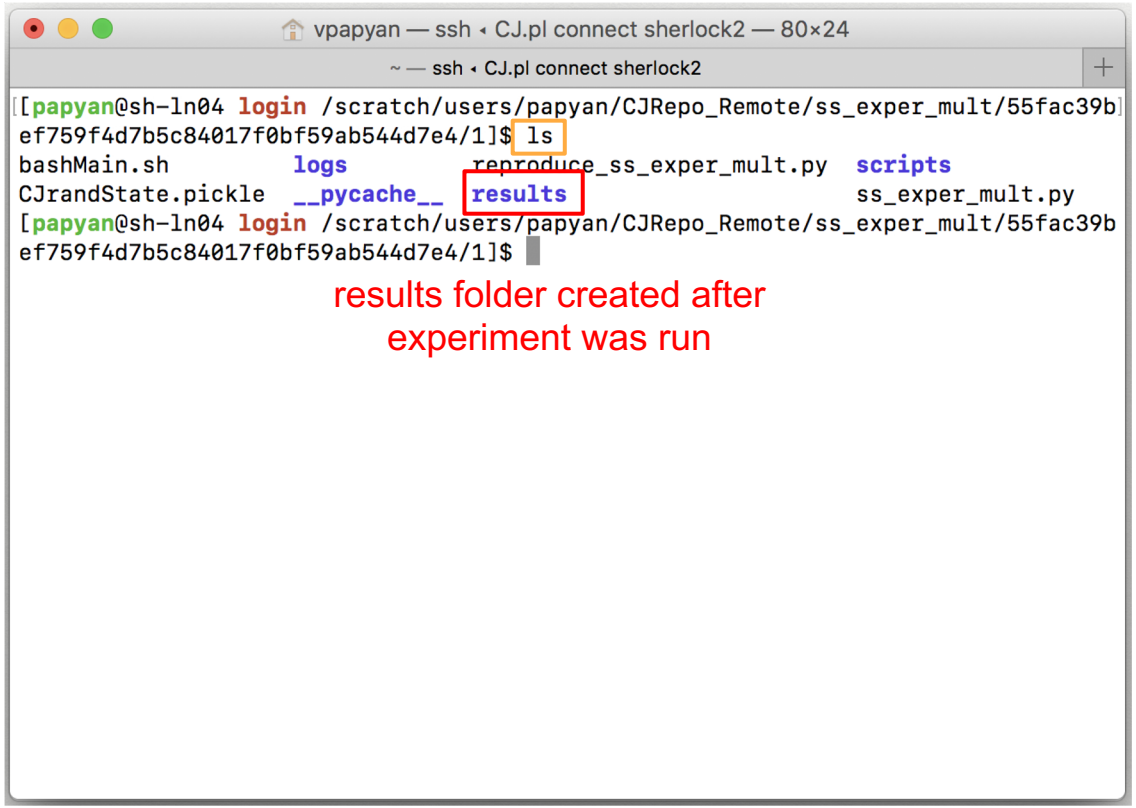


path on cluster to job

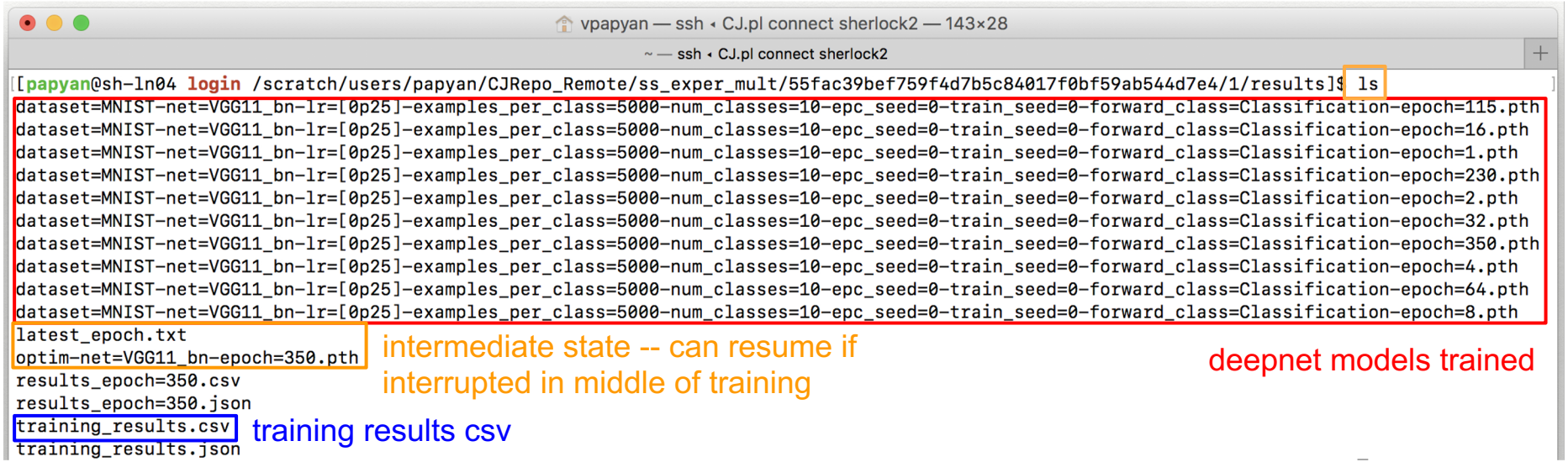
ClusterJob: folder of jobs



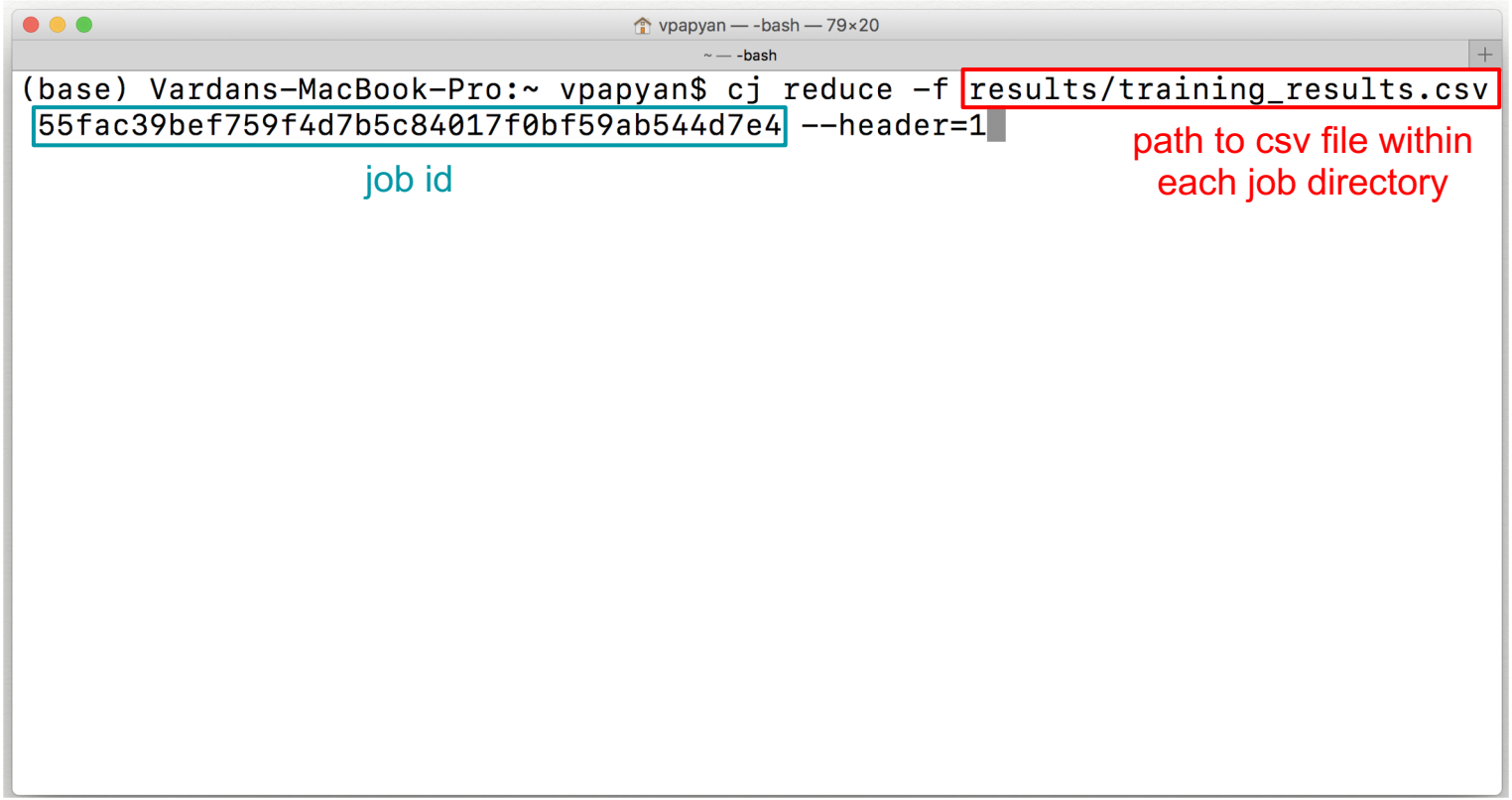
ClusterJob: folder of a single job



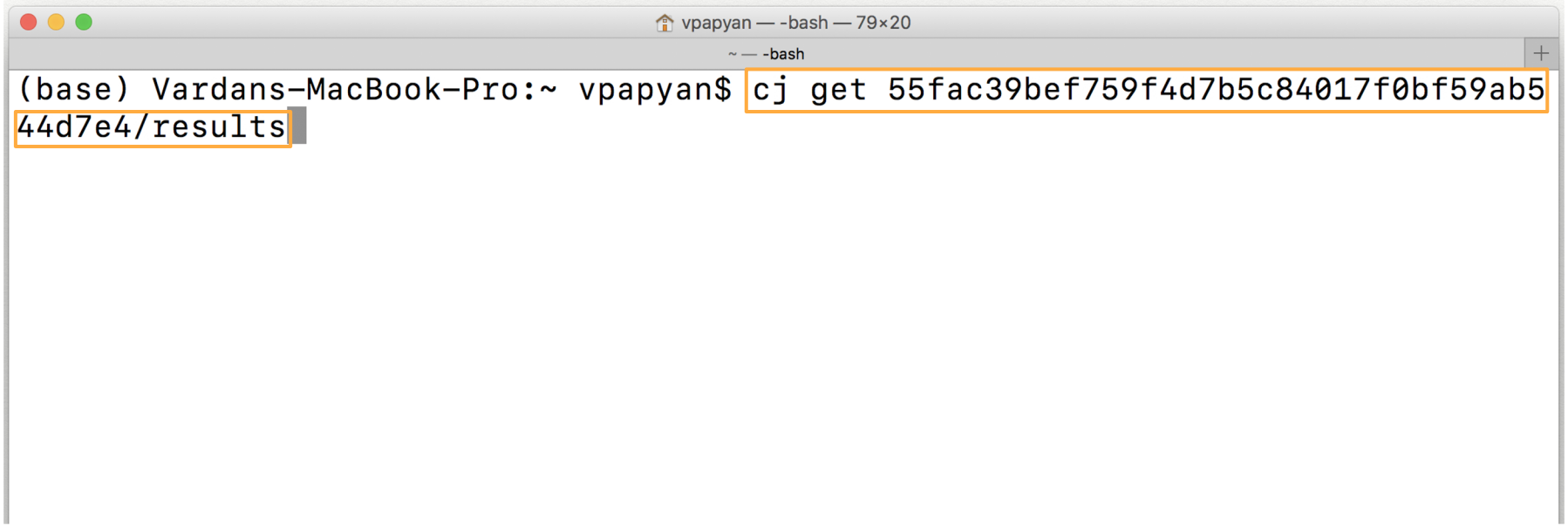
ClusterJob: results folder



ClusterJob: reducing all results into a single csv file



ClusterJob: downloading results to local machine



Good way of keeping track of running jobs:

- reduce
- get
- plot locally

Elasticluster

- During quarter Sherlock can get busy
- Two options:
  - Work nights / weekends / holidays
  - Cloud computing
- Elasticluster allows to easily set up clusters on GCP/AWS/Azure/…
- Works seamlessly with ClusterJob

Tableau

test_results.csv

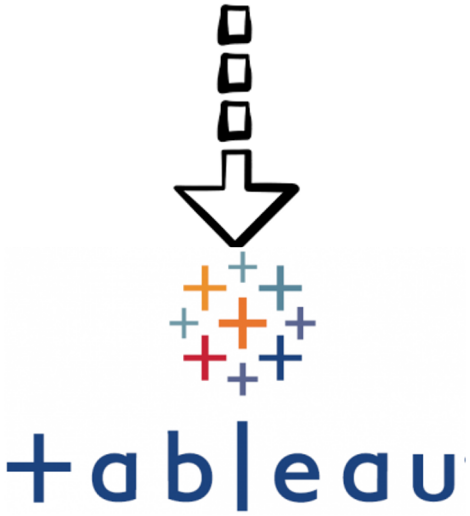


Tableau in a nutshell

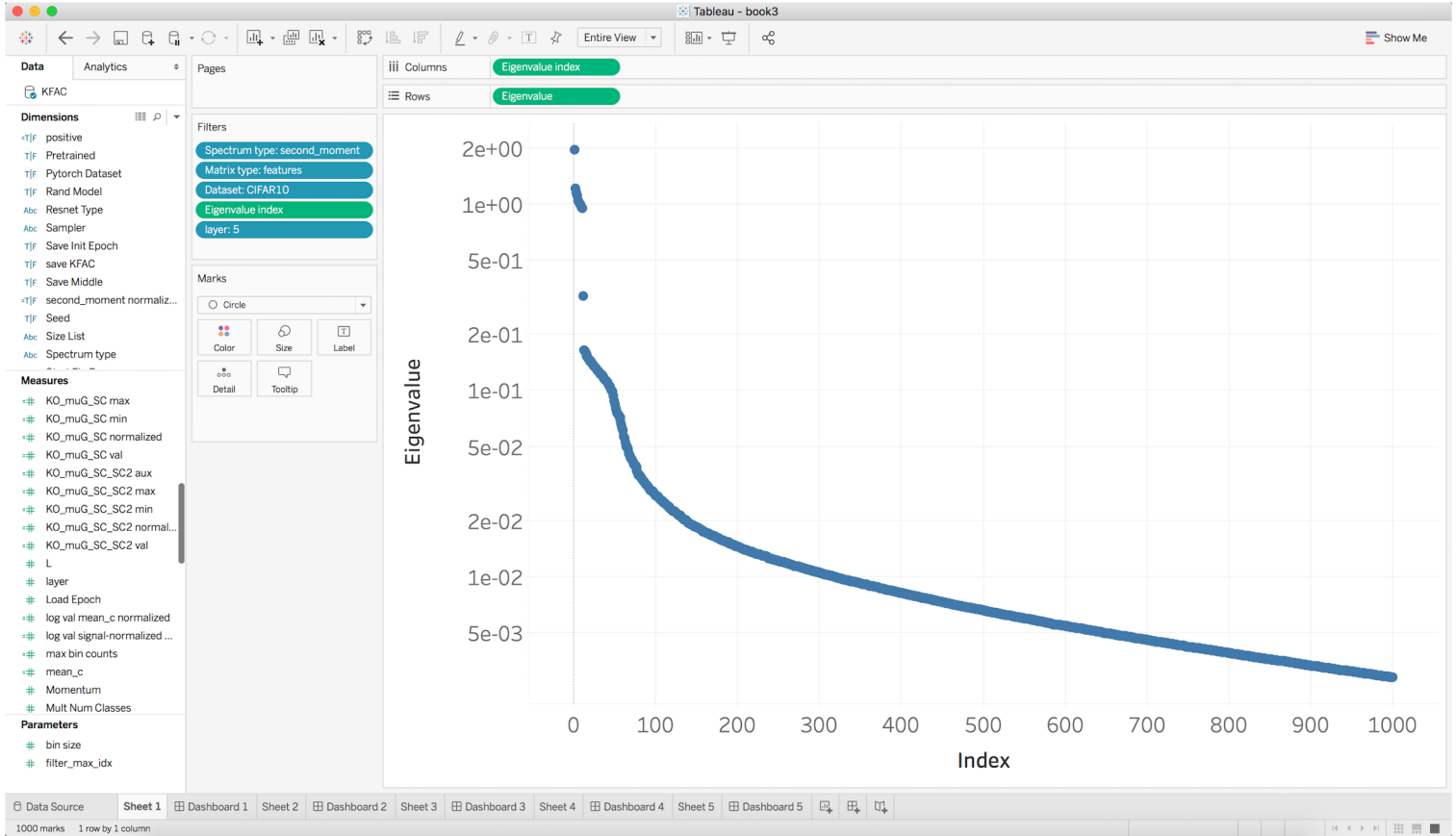
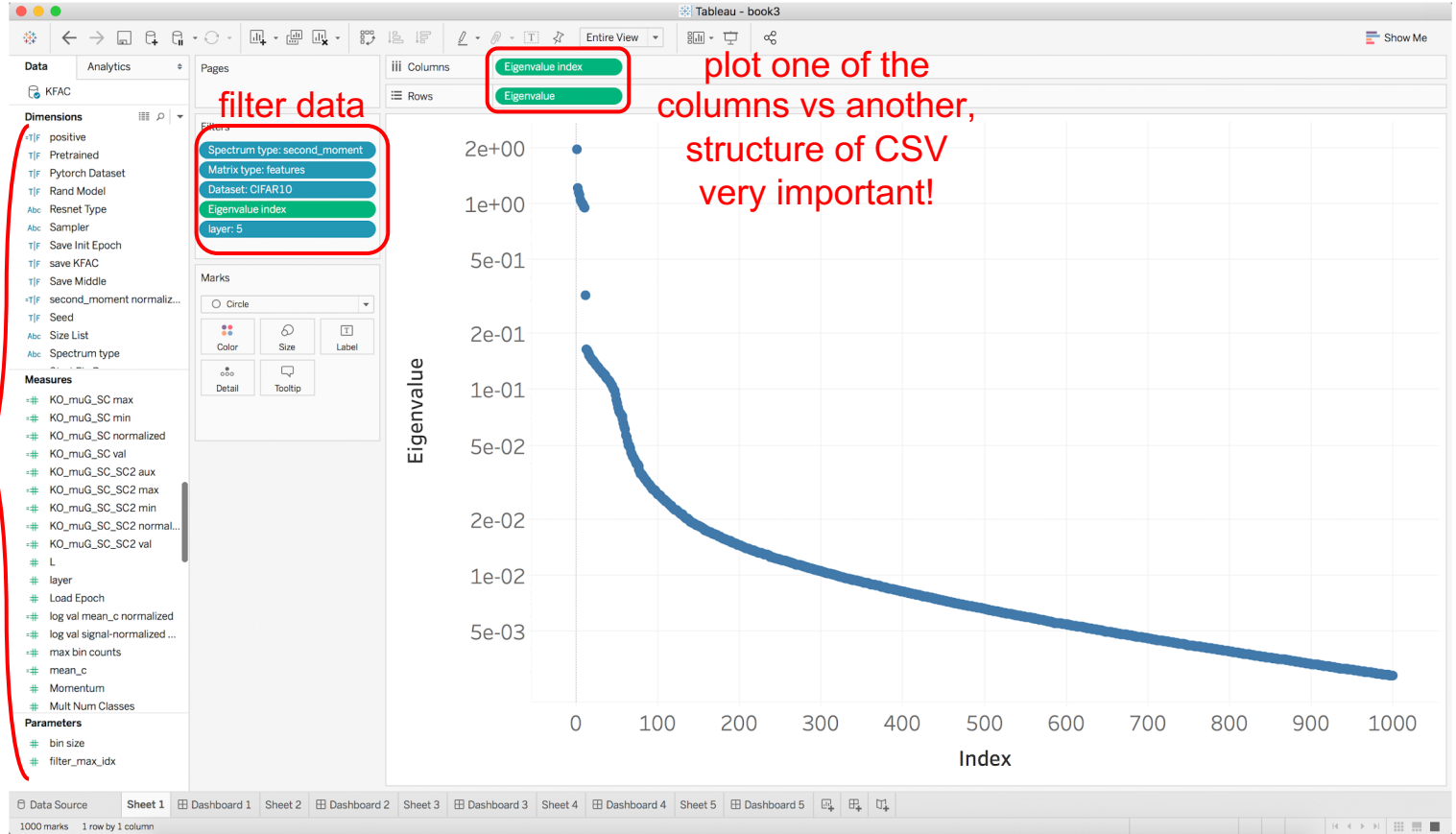


Tableau in a nutshell



columns in csv file

Tableau: XYZ grid

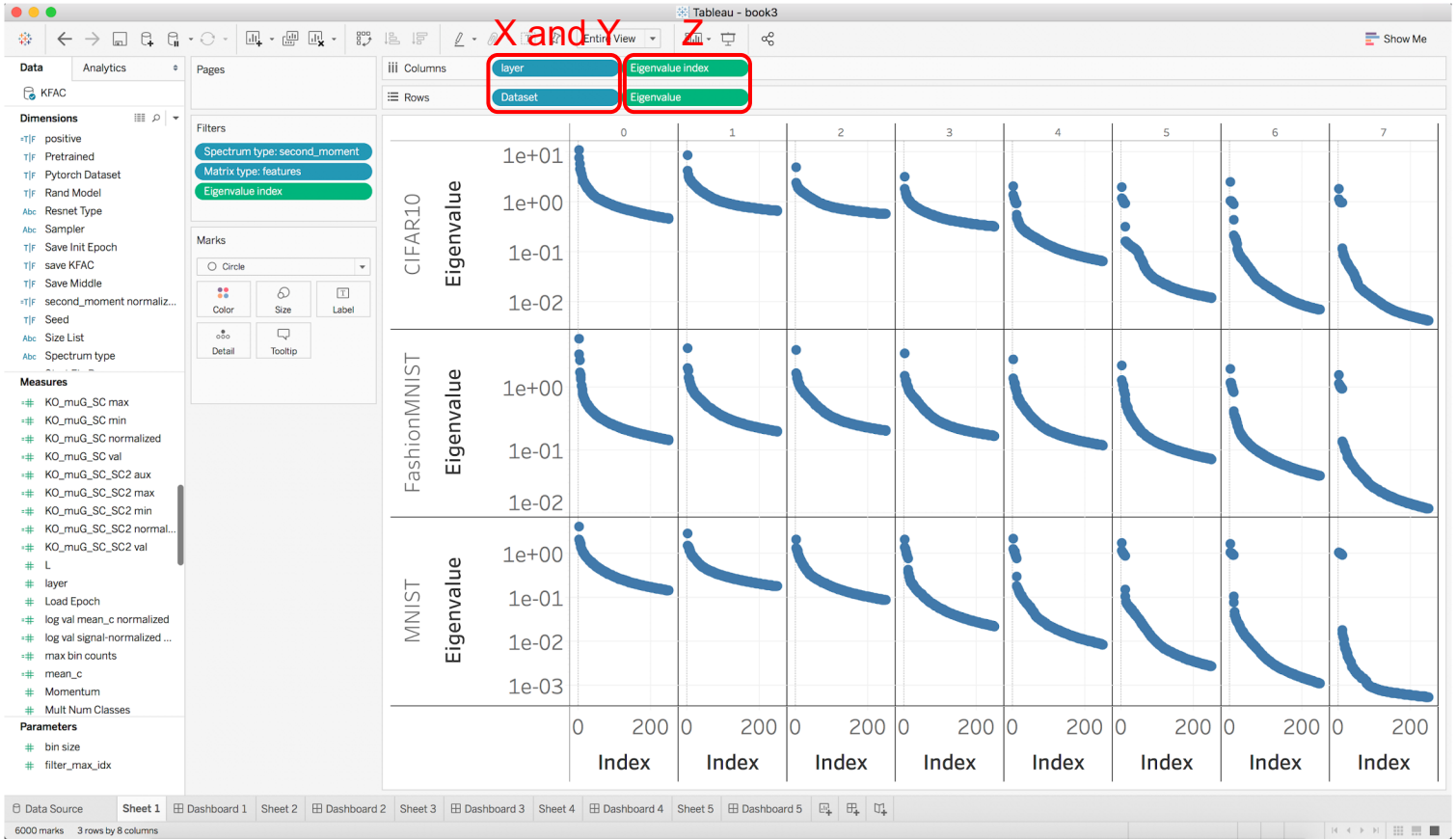
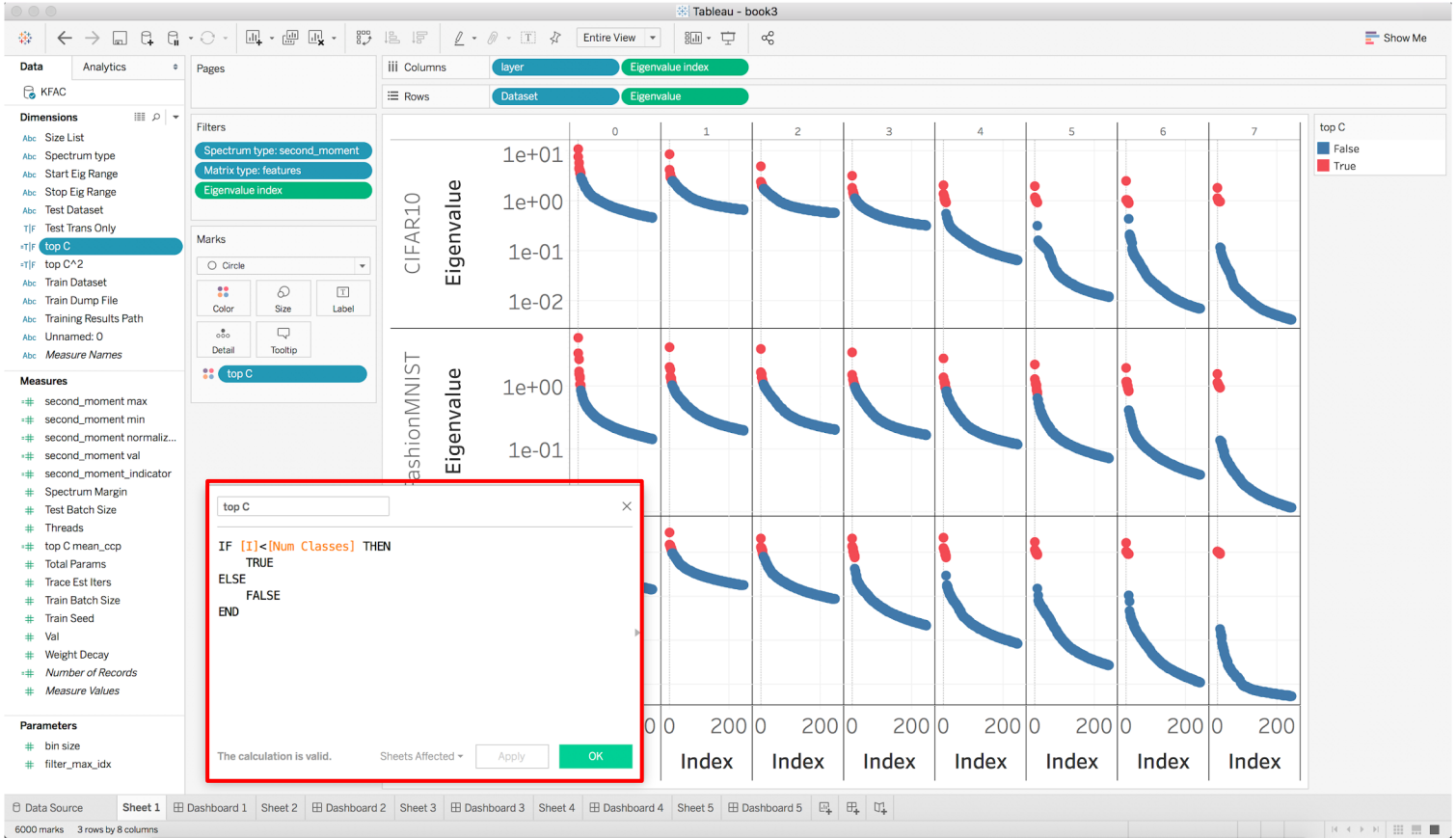


Tableau: simple functions of existing variables



Tableau

- Easy to analyze data -- drag and drop
- Easy to reproduce plots:
  - Delete results locally and keep only tableau sheet
  - Keep results on Sherlock2 / GCP
  - When need to recreate plot, download from cluster and open tableau sheet
- Easy to work with very large csv files using integration of tableau with the cloud
- Easy to calculate simple functions of existing columns

Summary

- **Alpha:** facilitates massive experiments by organizing code correctly
- **ClusterJob:** allows easy job parallelization
- **Sherlock2:** provides computational resources, storage, IPython notebooks
- **Elasticluster:** creates cluster on cloud, when sherlock is not enough
- **Tableau:** easy visualization of massive data