

# Machine vision for X-ray Imaging, Intelligent Search and AutoML

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# Imaging Facilities



Machine vision



Intelligent  
Search



Auto-ML



# DOE National User Facilities @LBNL

More than 10,000 researchers a year use these facilities.



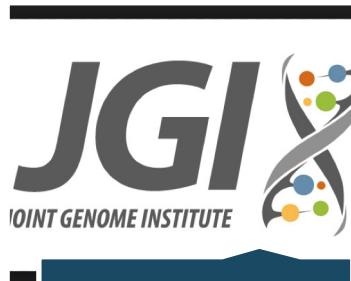
ESnet



Molecular  
Foundry



ALS



JGI



NERSC



CS enables 35 petabytes of data traffic each month, with expectation of ~7 exabytes of scientific data in 2021



# Machine Vision and Metrology for Materials



Analyze microstructure of materials to advance manufacturing

## Ceramic matrix composites



Robert Ritchie



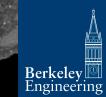
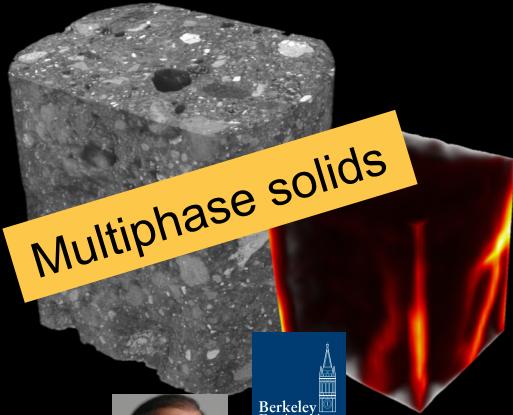
Yan Gao

## Carbon textiles



Francesco Panerai

## Roman concrete



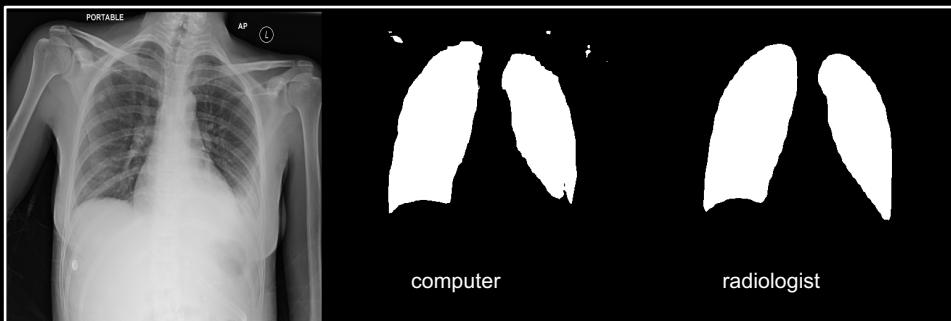
Paulo Monteiro



BERKELEY LAB



# LDRD ACTS: lung scans of Covid-19 patients



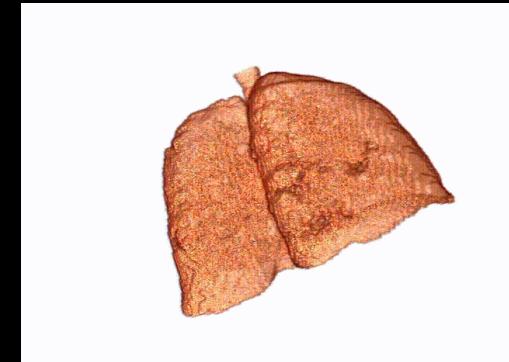
## Chest X-ray

2D

Broadly available

Projection of 3D

Bones muddle the image



## Computed tomography

3D

Restricted availability

Details at sub-mm scale

Bones are “erased” digitally

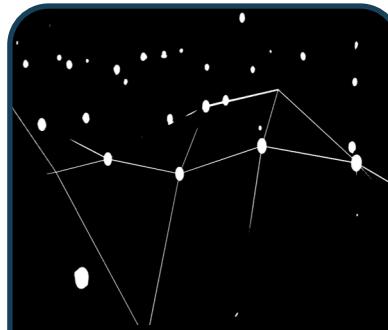
# Imaging Facilities



Machine vision

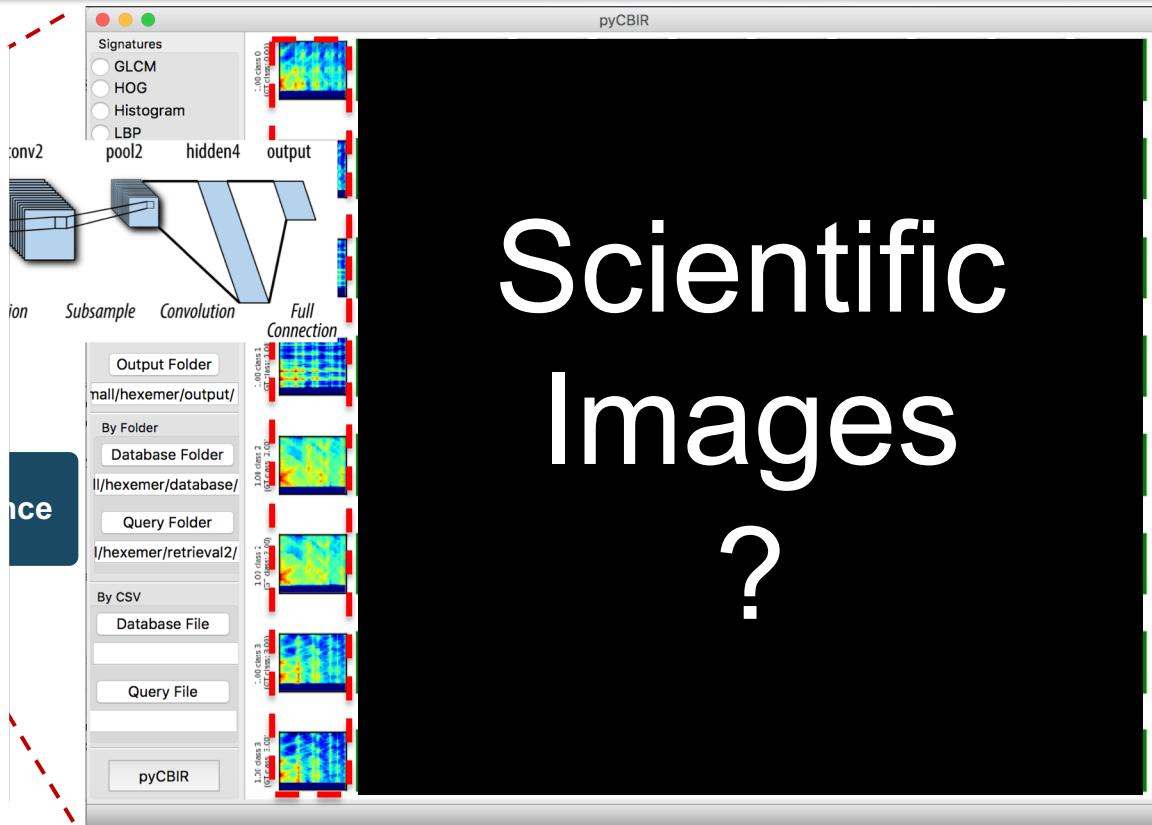
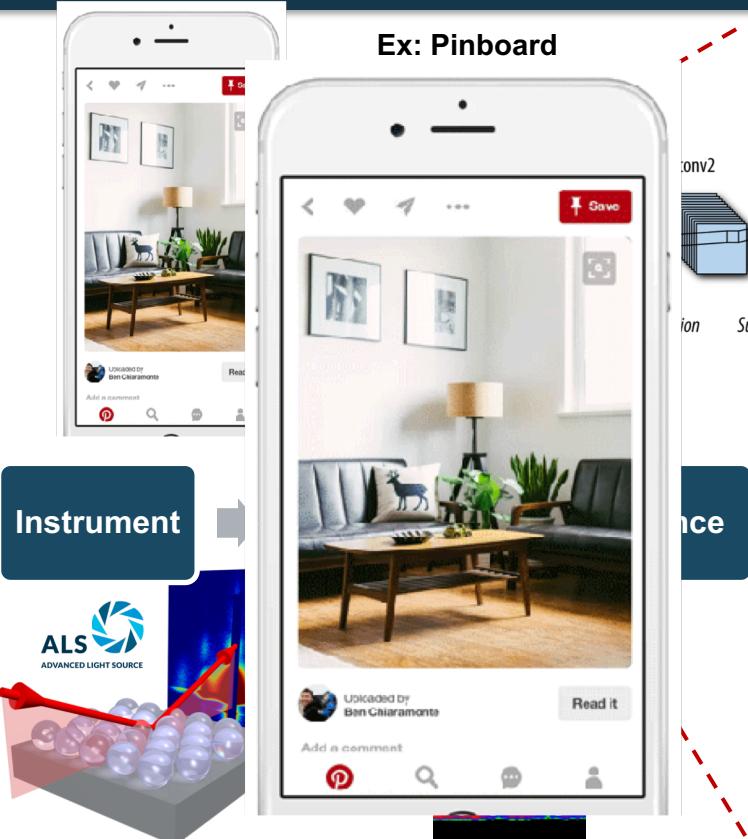


Intelligent  
Search



Auto-ML

# Deep learning to search patterns by similarity



Araujo, Silva, **Ushizima**, Medeiros, Hexemer, Parkinson, Carneiro, Bale, "Reverse Image Search for Scientific Data within and beyond the Visible Spectrum", **Expert Systems with Applications**, 2018.

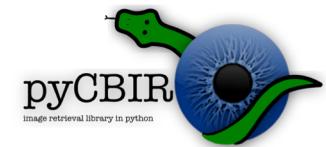
# GISAXS and CNN

- **Can we train a CNN to aid in the classification of new samples in real time?**
  - Fast classification and feedback at beamtime;
  - Disregard poor data if it doesn't hold useful information.
- **Focused on unit cell classification:**
  - 7 classes, ≠ resolutions and noise models;
  - Numerous ML architectures;
  - Simulated data.



# GISAXS, SAXS, WAXS, GIWAXS experimental data

- **Can we recover metadata from experimental data?**
  - Choice of instrument mode is dynamic;
  - Experimental data is “harder” than simulation;
  - Moving million samples.
- **Focused on fast similarity search:**
  - Efficient similarity search and clustering of dense vectors;
  - KDTree, BallTree and MongoDB;
  - Auto-ML.



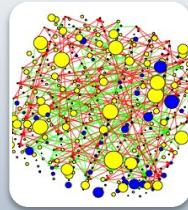
# Imaging Facilities





## Preprocessing

- cleaning
- encoding



## Optimization

- feature extraction
- model selection



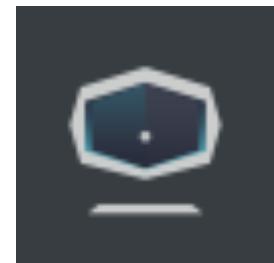
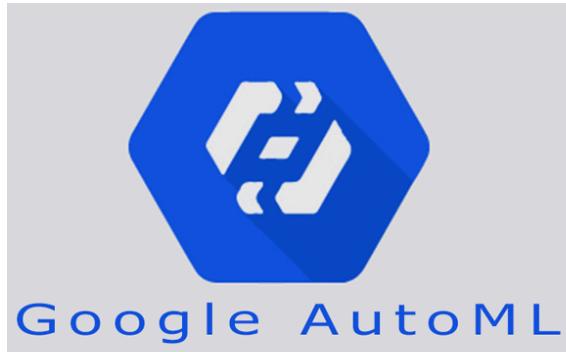
## Deployment

- prediction
- interpretation

- Process of automating ML tasks to solve real-world problems;
- Covers the complete pipeline from the raw dataset to the deployable ML model;
- ML pipeline automation made of reusable parts = FAIR\*.

\*FAIR = findable, accessible, interpretable and reproducible

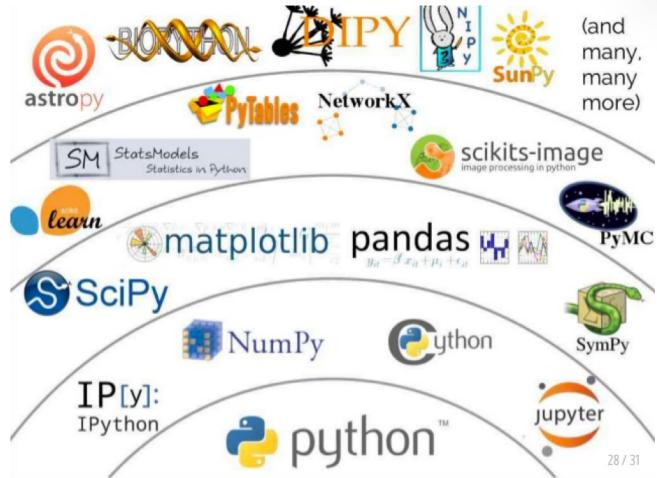
# Who owns Auto-ML?



# Hands-on with Python



1. Arrays with **numpy**
2. Picture with **skimage**
3. Volume with **itkwidgets**
4. ML with **sklearn**
5. Auto-ML

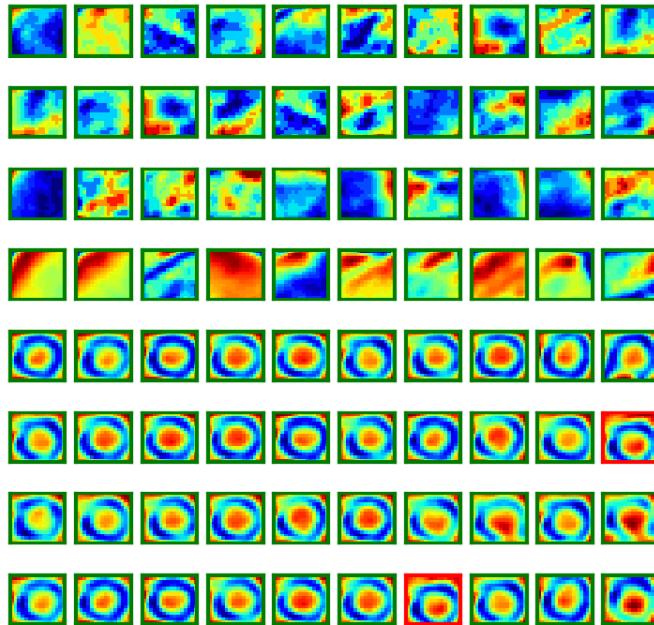


<https://bit.ly/AI4ALS>



# AUTO-ML

CNN featurization



### 3. Compare Baseline

```
[*]: best_model = compare_models()
```

Processing: 14:26:19  
Initiated 14:26:19  
Status Training Fold 1 of 10  
Estimator AdaBoost Classifier  
ETC 3.27 Minutes Remaining

	Model	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC	TT (Sec)
0	Quadratic Discriminant Analysis	0.709	0.0	0.9667	0.9767	0.9696	0.9553	0.9592	0.0362
1	Random Forest Classifier	0.9524	0.0	0.9444	0.9646	0.9487	0.9271	0.9351	2.1587
2	K Neighbors Classifier	0.9518	0.0	0.9444	0.9620	0.9498	0.9262	0.9325	0.0166
3	Gradient Boosting Classifier	0.9518	0.0	0.9472	0.9644	0.9482	0.9261	0.9342	0.2904
4	Naive Bayes	0.9427	0.0	0.9417	0.9583	0.9407	0.9136	0.9225	0.0159
5	Decision Tree Classifier	0.9427	0.0	0.9361	0.9571	0.9387	0.9122	0.9215	0.0205
6	Logistic Regression	0.9336	0.0	0.9333	0.9474	0.9320	0.9000	0.9078	0.0704
7	Ada Boost Classifier	0.9327	0.0	0.9250	0.9446	0.9287	0.8968	0.9048	0.2755
8	Extra Trees Classifier	0.9327	0.0	0.9250	0.9446	0.9287	0.8968	0.9048	1.1128
9	Extreme Gradient Boosting	0.9327	0.0	0.9250	0.9496	0.9284	0.8970	0.9076	0.0670
10	Light Gradient Boosting Machine	0.9327	0.0	0.9250	0.9446	0.9287	0.8968	0.9048	0.0665
11	Linear Discriminant Analysis	0.8873	0.0	0.8861	0.9076	0.8852	0.8300	0.8413	0.0191
12	Ridge Classifier	0.8582	0.0	0.8583	0.8843	0.8558	0.7871	0.8014	0.0244
13	SVM - Linear Kernel	0.8264	0.0	0.8167	0.7710	0.7832	0.7260	0.7506	0.0157

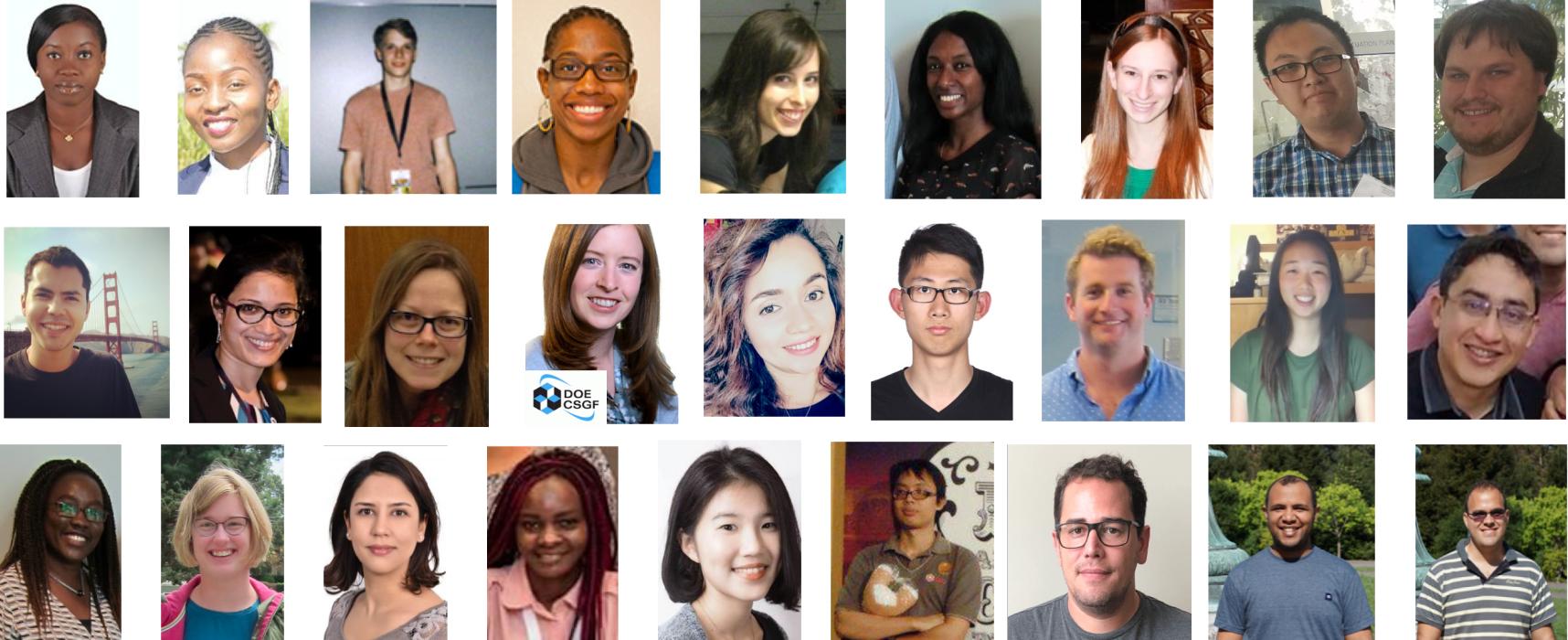
Data types inferred automatically  
Handles imputation  
Tune hyperparameters  
Individual ML  
Ensemble, Blend, Stack

# Conclusion



# Cultivating emerging scientists

Research and development through collaboration with and support to the next generation of scientists and engineers around the world



# Acknowledgements



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BNL	Xiaobiao Huang, Chris Tassone, Ryan Coffee
LANL	Kevin Yager, Tom Caswell
VA	Aric Hagberg
GE:	Duygu Tosun
IBM:	Yan Gao, Anjali Singhal
Intel:	Alexandre Andreopoulos
Microsoft:	David J. Michalak
NASA:	Vani Mandava
	Nagi Mansour, Francesco Panerai (now UIUC)



Thank you





# Thank you

**<https://bit.ly/AI4ALS>**



Instrument	Materials sample	Science discovery	New Analytics/ML
<b>microCT</b> 3D - $\mu\text{m}$	CMC, carbon fiber, concrete, rocks, soil, archeological assets	Material deformation, search of experiments by microCT similarity	Detection, segmentation, classification
<b>GISAXS</b> 2D - nm	Thin films - applications to gaseous sensors and piezoelectric devices	Categorization of million-scale databases	Classification
<b>Crystallography</b> 2D - $\mu\text{m}$	Protein structure	Screening of diffraction patterns containing Bragg peaks	Detection, Classification
<b>CT</b> 3D - $\mu\text{m}$	Human brain	Evaluation of biomarkers ( <i>locus ceruleous</i> ) - correlation to Alzheimer's	Detection, segmentation, characterization
<b>MRI</b> 3D - mm	Human brain	Data fusion with CT and histology for enhancement of clinical data	Detection, segmentation, classification
<b>SEM</b> 2D - nm	Nanocrystal frameworks for film design	Quantitative tools to drive architecture of colloidal nanocrystal films	Segmentation, classification
<b>STEM</b> 3D - nm	Microelectronics, concrete design	Lowest ever dielectric constant for PMO, new structure on cement shrinkage (foil)	Segmentation, characterization, classification



# Recent Accomplishments

X-ray

Electron

Instrument	Selected Publications
microCT 3D - $\mu\text{m}$	MacNeil, Ushizima, Panerai, Masour, Parkinson, <i>Interactive Volumetric Segmentation for Textile Microtomography Data using Wavelets and Non-local Means</i> , <b>Journal of Statistical Analysis and Data Mining</b> 2019.
GISAXS 2D - nm	. Araujo, Silva, Ushizima, Parkinson, Hexemer, Carneiro, Medeiros, <i>Reverse Image Search for Scientific Data within and beyond the Visible Spectrum</i> , <b>Expert Systems with Applications</b> , 2018 . Ushizima, Araujo, Romuere, "Searchable datasets in Python: images across domains, experiments, algorithms and learning – pyCBIR", pyData San Francisco 2016.
Crystallography 2D - $\mu\text{m}$	Ke, Brewster, Yu, Yang, Ushizima, Sauter, <i>A Convolutional Neural Network-Based Screening Tool for X-ray Serial Crystallography</i> , <b>Journal of Synchrotron Radiation</b> 2018.
CT 3D - $\mu\text{m}$	Alegro, Theofilas, Nguy, Castruita, Seeley, Ushizima, Grinberg, <i>Automating Cell Detection and Classification in Human Brain Fluorescent Microscopy Images Using Dictionary Learning and Sparse Coding</i> , <b>Journal of Neuroscience Methods</b> , 2017.
MRI 3D - mm	
SEM 2D - nm	Williams, Ushizima, Zhu, Anders, Milliron, Helms, <i>Nearest-Neighbour Nanocrystal Bonding Dictates Framework Stability or Collapse in Colloidal Nanocrystal Frameworks</i> , <b>Chemical Communications</b> , Royal Society of Chemistry, 2017.
STEM 3D - nm	Ushizima, Bale, Bethel, Ercius, Helms, Krishnam, Grinberg, Haranczyk, Macdowell, Odziomek, Perciano, Parkinson, Ritchie, Yang. <i>IDEAL: Images across Domains, Experiments, Algorithms and Learning</i> , <b>Journal of Minerals, Metals and Materials</b> , 2016.