Applied Machine Learning for Design Optimization in Cosmology, Neuroscience, and Drug Discovery

Barnabas Poczos

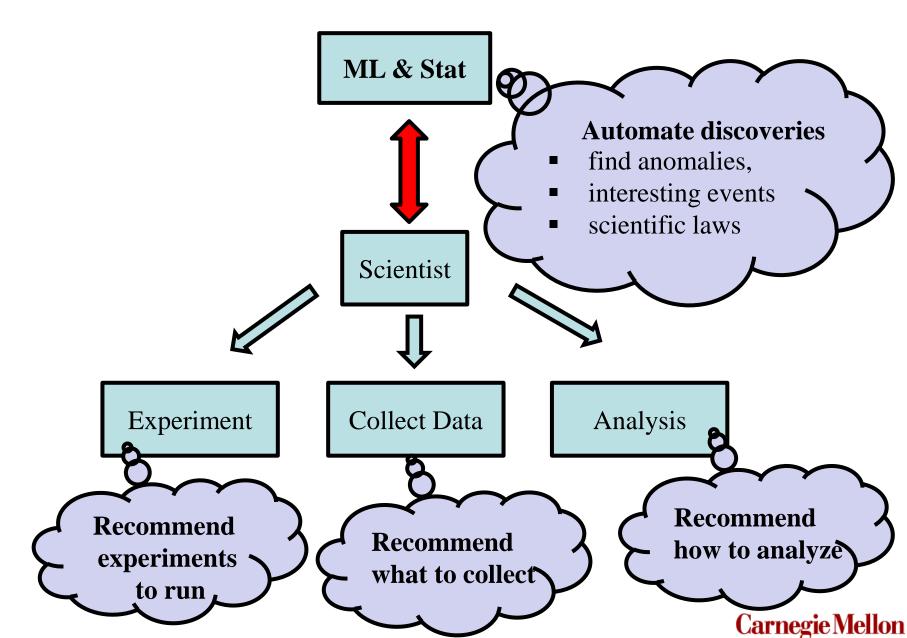
Machine Learning Department

Carnegie Mellon University

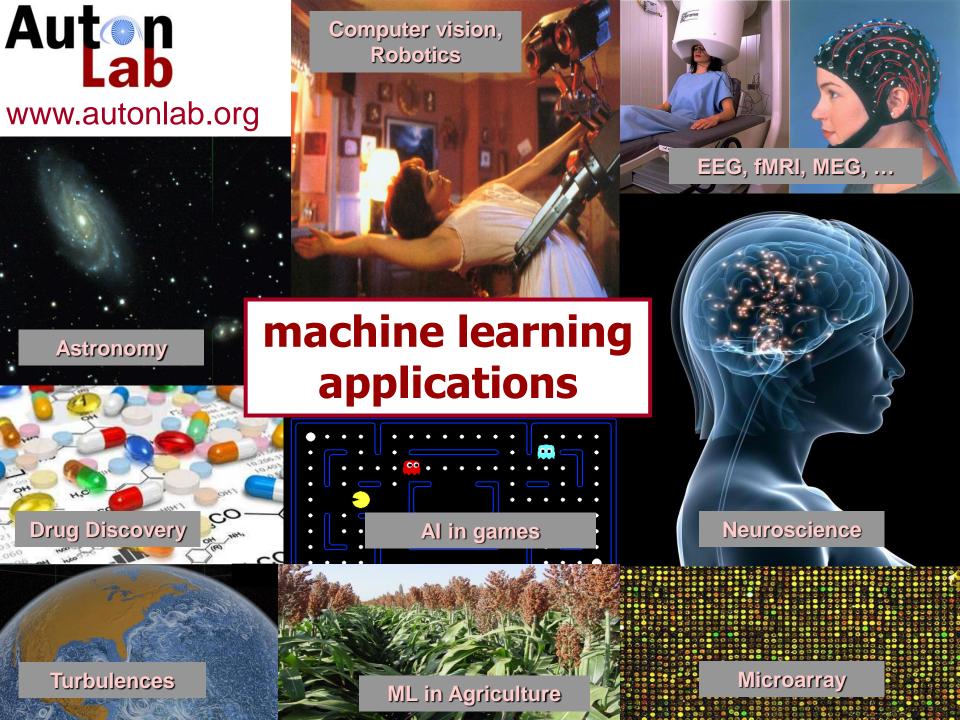
Machine Learning Technologies and their Applications for Scientific and Engineering Domains Workshop

NASA Langley Research Center

Goal: Create a Scientific Assistant

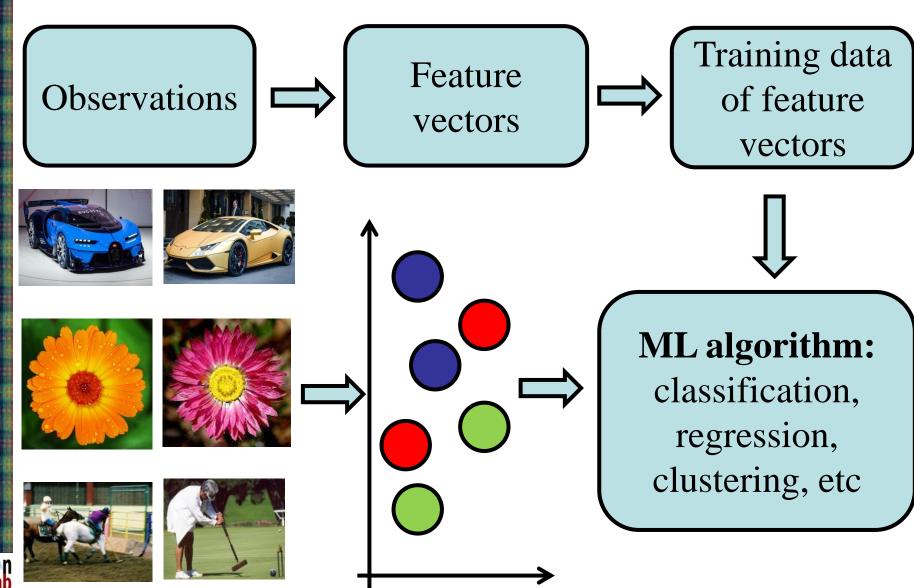


Auton Lab



Machine Learning on Complex Objects

Traditional Machine Learning

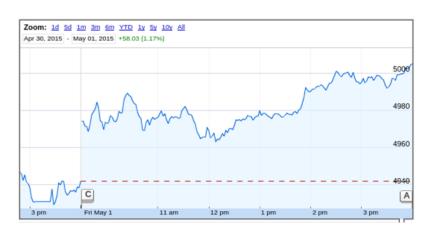


Auton Lab

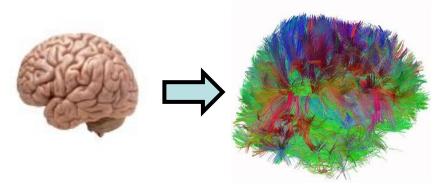
Carnegie Mellon

Complex Data is Everywhere

Finance

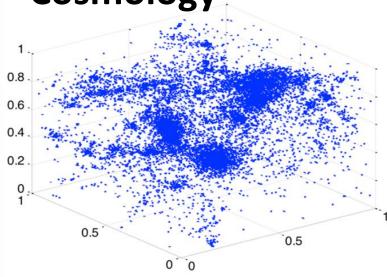


Neuroscience



Diffusion Weighted Imaging

Cosmology



Images

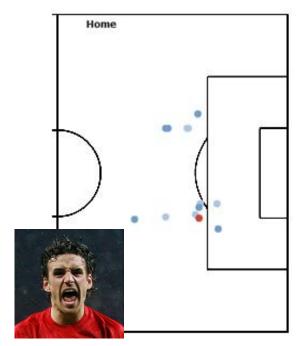


Auton ab

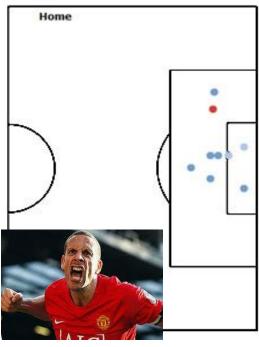
Carnegie Mellon

Distributional Data

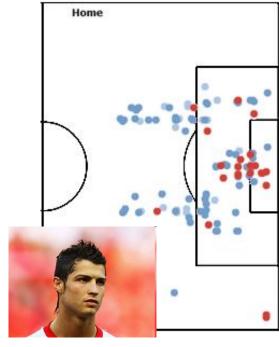
Manchester United 07/08



Owen Hargreaves



Rio Ferdinand



Cristiano Ronaldo

Shot Type

- Goals
- Shots on Goal
- Shots



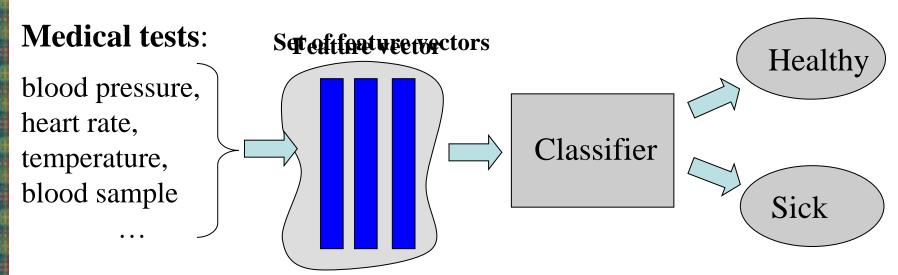


www.juhokim.com/projects.php

ML on Distributions



SMALdardens/dhinthleaiming



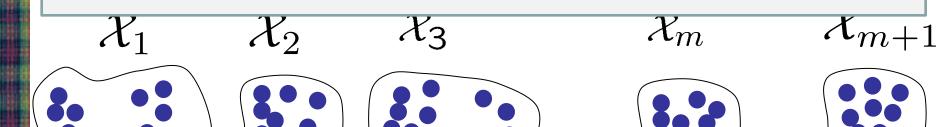
What happens if we repeat the medical tests?

Distribution Regression / Classification

$$Y_1=1$$
 $Y_2=0$ $Y_3=1$ $Y_m=0$?

Differences compared to standard methods on vectors

- ☐ The inputs are distributions, density functions (not vectors)
- ☐ We don't know these distributions, only sample sets are available (error in variables model)



Distribution Classification

We have T sample sets, $(\mathbf{X}_1, \dots, \mathbf{X}_T)$. [Training data] $\{X_{t,1}, \dots, X_{t,m_t}\} = \mathbf{X}_t \sim p_t$. \mathbf{X}_t has class $Y_t \in \{-1, +1\}$.

What is the class label Y of $\mathbf{X} = \{X_1, \dots, X_m\} \sim p$?

Solution: Use RKHS based SVM!

Calculate the Gram matrix $K_{ij} \doteq \langle \phi(p_i), \phi(p_j) \rangle_{\mathcal{K}} = K(p_i, p_j)$ $\doteq \exp(-\frac{D(p_i, p_j)}{\sigma^2})$

Dual form of \mathbf{SVM} :

$$\widehat{\alpha} = \arg\max_{\alpha \in \mathbb{R}^T} \sum_{i=1}^T \alpha_i - \frac{1}{2} \sum_{i,j}^T \alpha_i \alpha_j y_i y_j K_{ij}, \quad \text{subject to } \sum_i \alpha_i y_i = 0,$$

$$V = \operatorname{sign}(\sum_i \widehat{\alpha}_i \times K(x, x)) \in \{-1, +1\}.$$

 $Y = \operatorname{sign}(\sum_{i=1} \hat{\alpha}_i y_i K(p_i, p)) \in \{-1, +1\}$

Problems: We do not know p_i , p, $K(p_i, p_j)$, or $K(p_i, p)$... Carnegie Mellon



Distances / Divegences between Distributions

Euclidean: $D(p,q) = (\int (p(x) - q(x))^2 dx)^{1/2}$

Kullback-Leibler: $D(p,q) = KL(p,q) = \int p(x) \log \frac{p(x)}{q(x)} dx$

Renyi: $D(p,q) = R_{\alpha}(p||q) = \frac{1}{\alpha-1}\log\int p^{\alpha}q^{1-\alpha}$

RÉNYI DIVERGENCE ESTIMATION

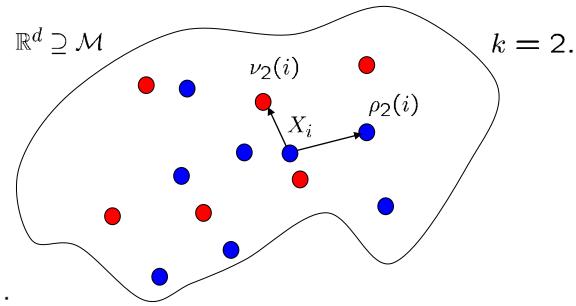
without density estimation



Estimate divergence
$$R_{\alpha}(p\|q) \doteq \frac{1}{\alpha-1} \log \int p^{\alpha}q^{1-\alpha}$$



The Estimator



 $k \geq 1$, fixed.

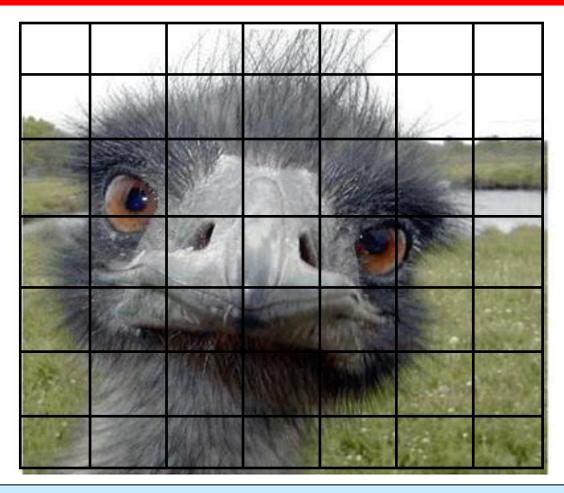
 $ho_k(i)$: the distance of the k-th nearest neighbor of X_i in $X_{1:n}$

 $\nu_k(i)$: the distance of the k-th nearest neighbor of X_i in $Y_{1:m}$

$$D_{\alpha}(p||q) \doteq \int p^{\alpha}q^{1-\alpha}$$

$$\widehat{D}_{\alpha}(X_{1:n}||Y_{1:m}) = \frac{1}{n} \sum_{i=1}^{n} \left(\frac{(n-1)\rho_{k}^{d}(i)}{m\nu_{k}^{d}(i)} \right)^{1-\alpha} \frac{\Gamma(k)^{2}}{\Gamma(k-\alpha+1)\Gamma(k+\alpha-1)}$$

ML on Distributions



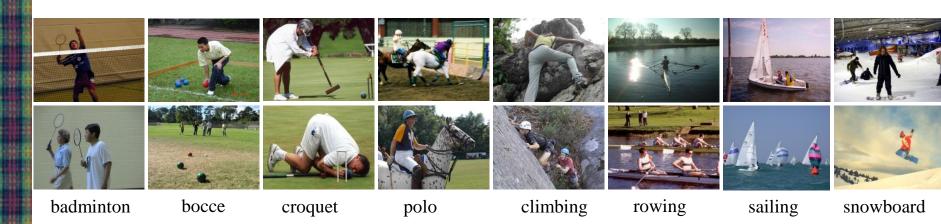
Dealing with complex objects

- □ break into smaller parts, represent the input as a **set** of smaller parts
- ☐ treat the set elements as sample points from some unknown distribution
- □ do *ML on these unknown distributions* represented by sets

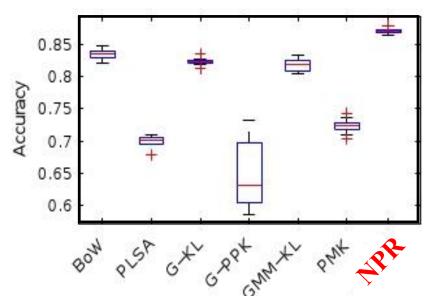
Auton Lab

carnegie vieno

Sport Events Classification [Li and Fei Fei, 2007]



8 categories, 1040 images, each represented by 295 to 1542 57 dim points.



- ☐ Best published: **86.7**% (Zhang et al, CVPR 2011)
- □ NPR: **87.1**%

Detecting Anomalous Images

50 highway images













/\



1

5 anomalies



















 Δ

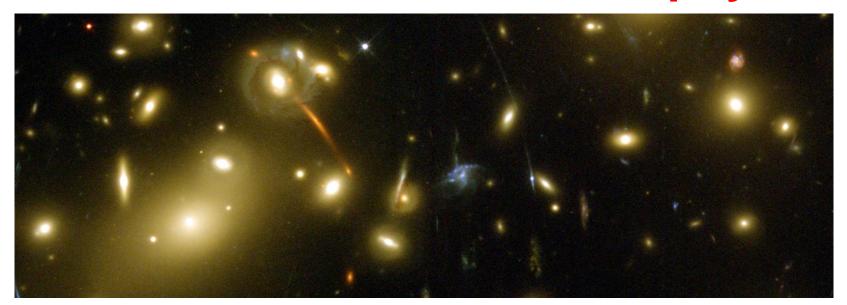
2-dimensional sample set representation of images (128 dim SIFT \Rightarrow 2 dim)

Anomaly score: divergences between the distributions of these sample sets

Carnegie Mellon

Cosmology Applications

Find new scientific laws in physics



Goal: Estimate dynamical mass of galaxy clusters.

Importance: Galaxy clusters are being the largest gravitationally bound systems in the Universe. Dynamical mass measurements are important to understand the behavior of dark matter and normal matter.

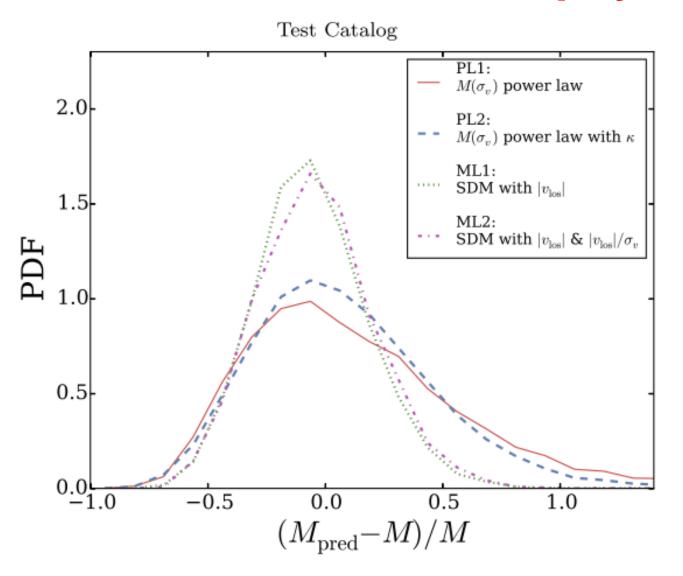
Difficulty: We can only measure the velocity of galaxies not the mass of their cluster Physicists estimate dynamical cluster mass from single velocity dispersion.

Our method: Estimate the cluster mass from the whole distribution of velocities rather than just a simple velocity distribution.

Carnegie Mellon

Auton Lab

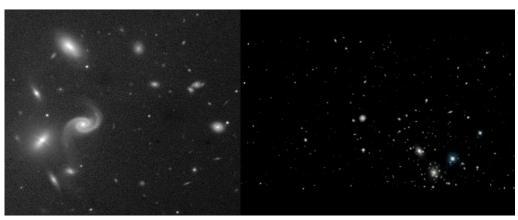
Find new scientific laws in physics



Carnegie Mellon

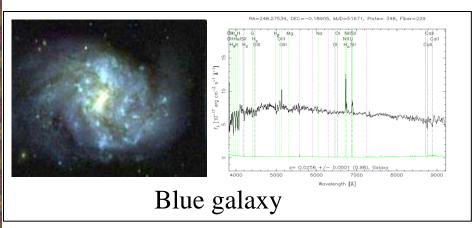


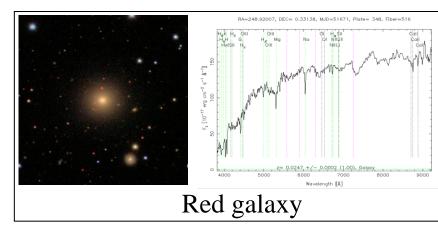
Find interesting Galaxy Clusters



Sloan Digital Sky Survey (SDSS)

- ☐ continuum spectrum
- □505 galaxy clusters (10-50 galaxies in each)
- □7530 galaxies





What are the most anomalous galaxy clusters?

The most anomalous galaxy cluster contains mostly

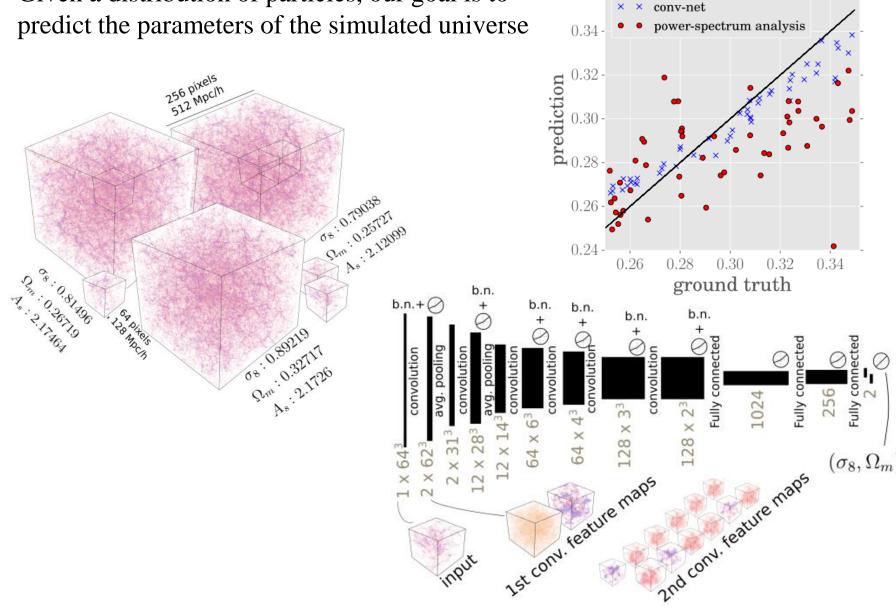
- □ star forming blue galaxies
- ☐ irregular galaxies

B. Póczos, L. Xiong & J. Schneider, UAI, 2011. Credits: ESA, NASA Carnegie Mellon



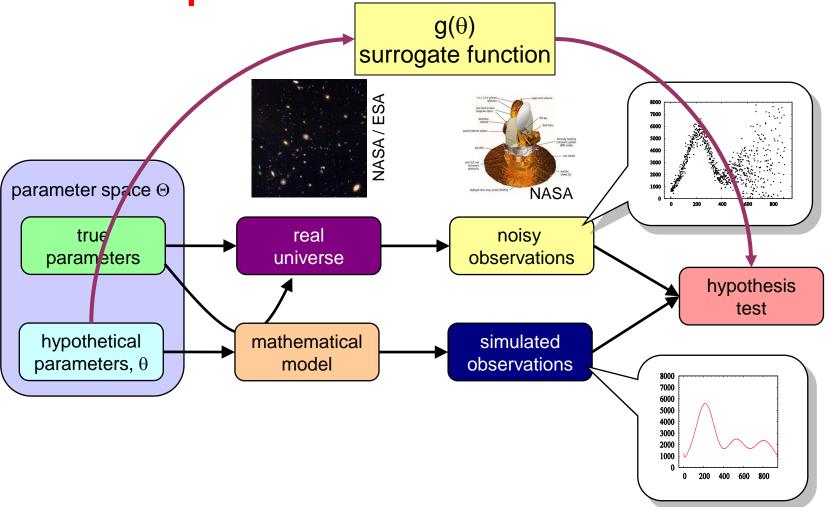
Find the parameters of Universe Ω_m

Given a distribution of particles, our goal is to



Active Learning & Design Optimization

Recommend experiments to find the true parameters of the universe



Computation problem: How to search parameter space

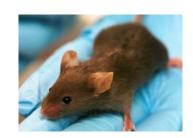
Solution: Learn a surrogate function and make experiment decisions using it

Carnegie Mellon

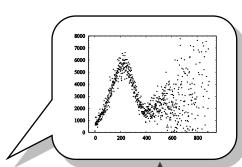


Recommend experiments for drug discovery









parameter space Θ

Parameters of Drugs:

- Compounds
- Quantities
- etc.

Drug effects on the Lab mouse



Expensive Observations (\$, time)

- Real Observations
- Simulated Observations
- Expert predictions
 (Bias, Variance, Fidelity, Cost)

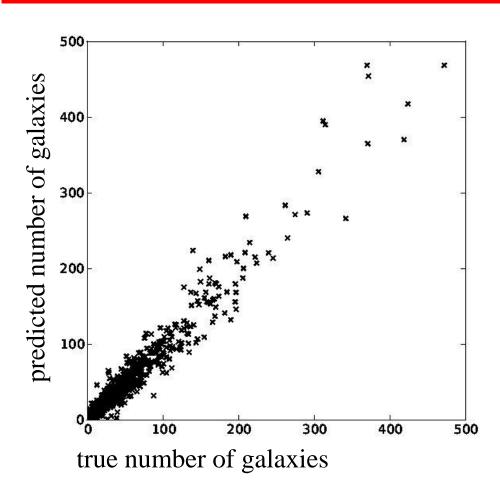
Observations:

- Blood samples
- Camera images
- EEG,
- etc.

g(θ) surrogate function to optimize



Learning Relationships from Simulations



Goal: predict the number of galaxies in a halo from a half dozen dark matter halo parameters

(#particles in a halo, velocity dispersion, max circular velocity, half mass radius,...)

data: Millenium simulation 395,832 halos

method: support vector regression

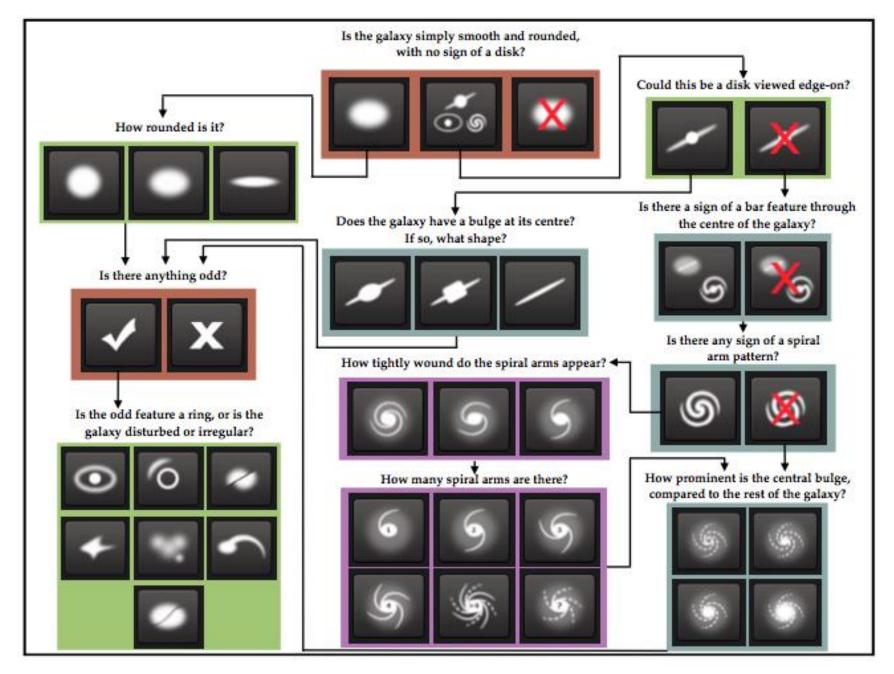
[Xiaoying Xu, 2012]



The Galaxy Zoo challenge

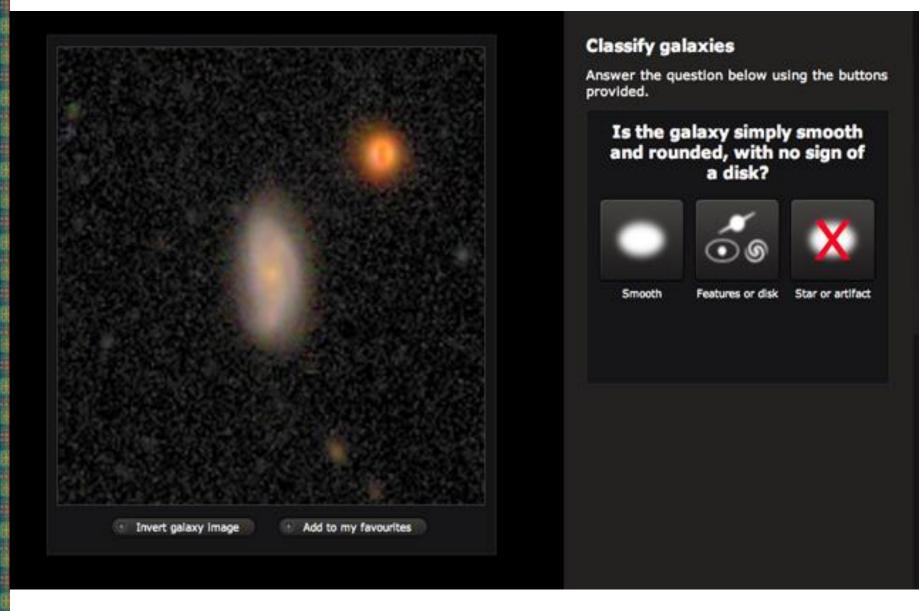
- ☐ Crowdsourcing project
- ☐ Users are asked to describe the morphology of galaxies based on images.
- ☐ They are asked questions such as "How rounded is the galaxy" and "Does it have a central bulge"...
- ☐ 37 different categories in a decision tree
- ☐ Training set: JPG images of 61578 galaxies.
- ☐ Test set: JPG images of 79975 galaxies
- ☐ Image resolution: 424x424 color JPEG images





Auton Lab

Willett et al. 2013.





The Large Synoptic Survey Telescope

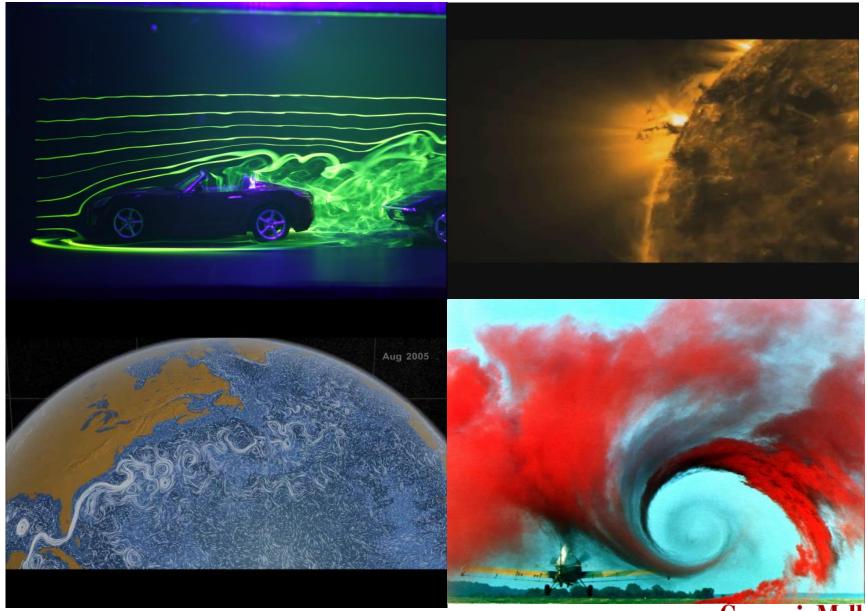


Big data questions

☐ 15 Terabytes of data ... every night

Other Examples in Physics

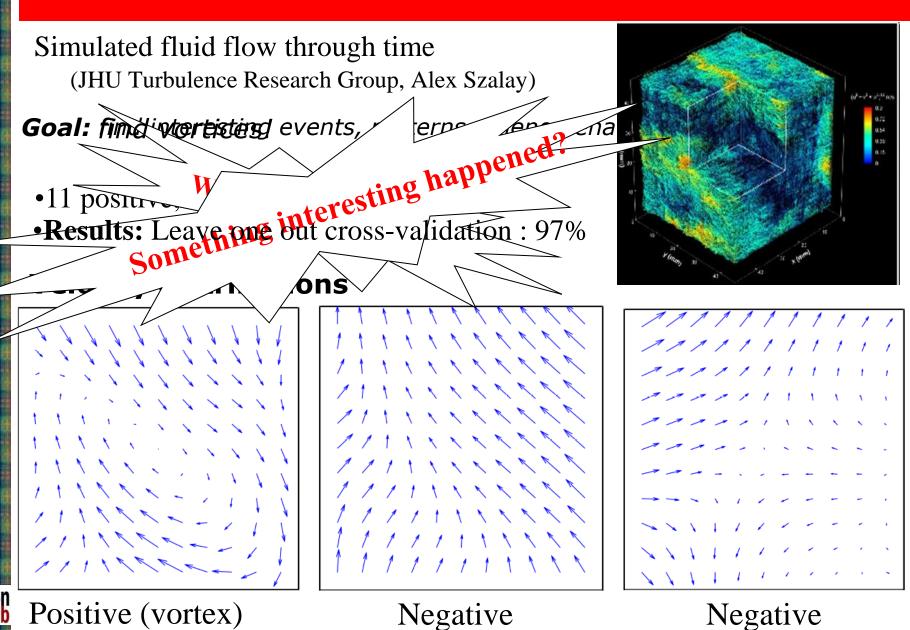
ML to Help Understanding Turbulences



Auton Lab

Carnegie Mellon

Turbulence Data Classification

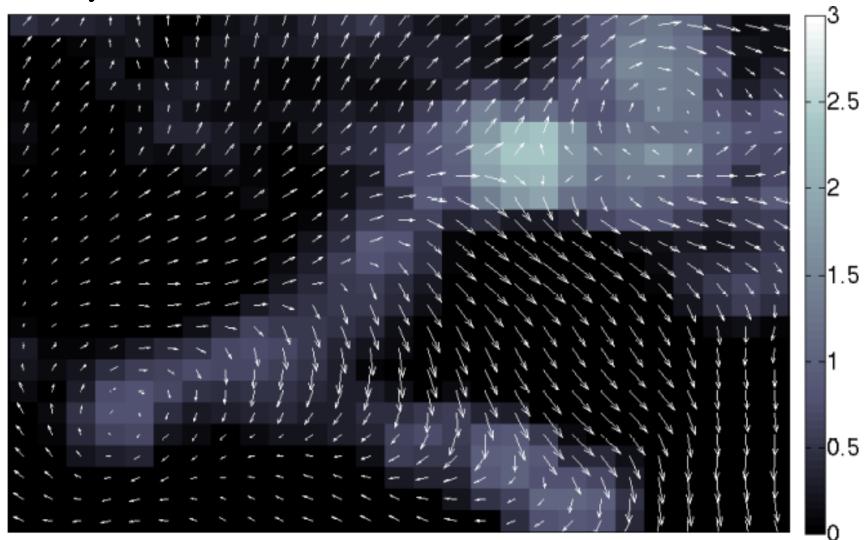


Carnegie Mellon

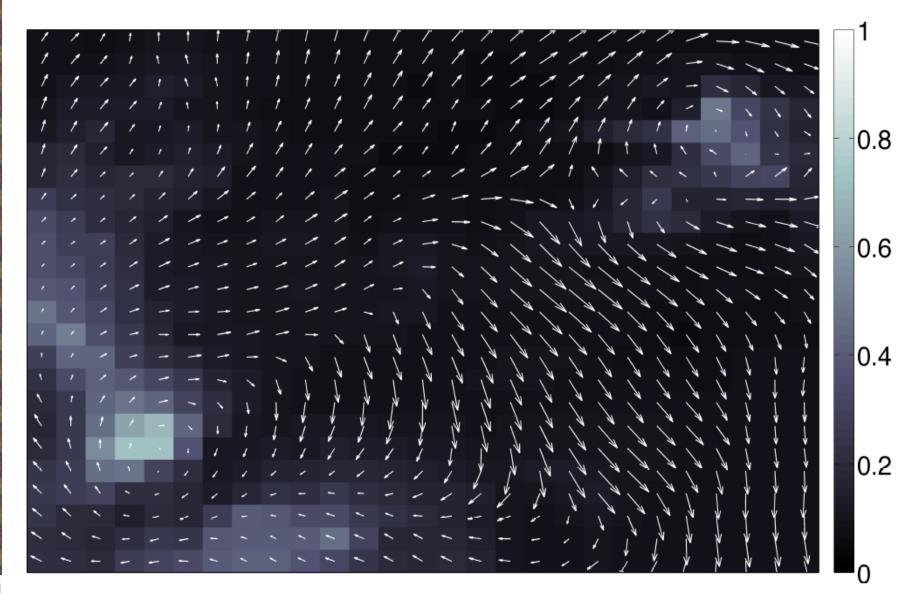
31

Find Interesting Phenomena in Turbulence Data

Anomaly detection



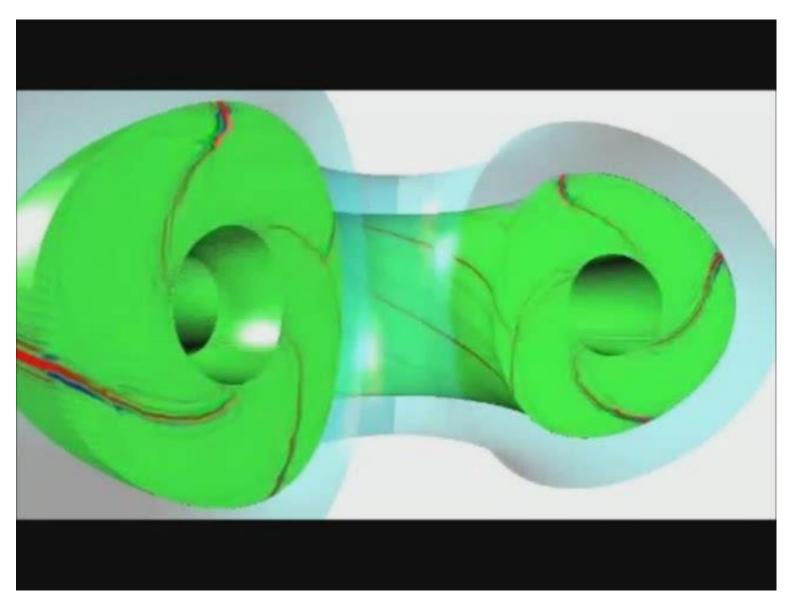
Finding Vortices





Classification probabilities

Fusion power plants



Auton Lab

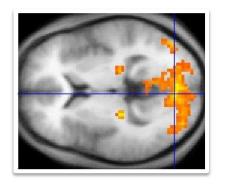
34

Neuroscience

Auton Lab

ML in Action: Neuroimaging

- MEG/fMRI mind reading contest
- MRI lie detector
- Decoding thoughts from brain scans





Rob a bank ...



Home » Health & Wellness

Brain Scans: Are You a Criminal?



Adjust font-size: + -

More:

36

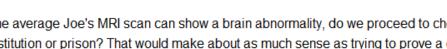
Brain Scans

Brain Scan

Disposition Defendant Criminal Behavior

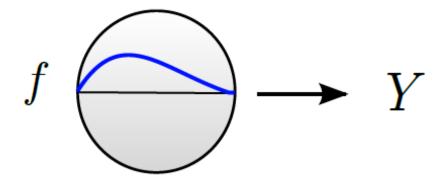
MRI Scans as Courtroom Evidence

The average Joe's MRI scan can show a brain abnormality, do we proceed to check him into the nearest mental institution or prison? That would make about as much sense as trying to prove a defendant innocent of a violent



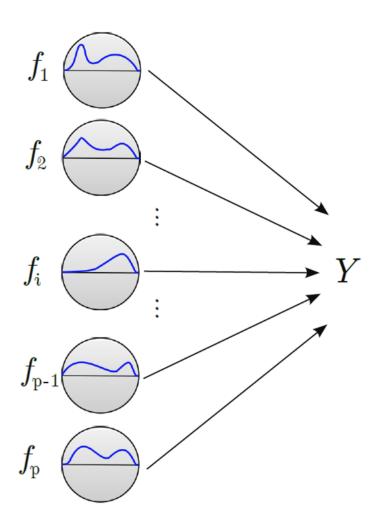
Fusso = Functional Shrinkage and Selection Operator (Functional Lasso)

Function-to-Real regression



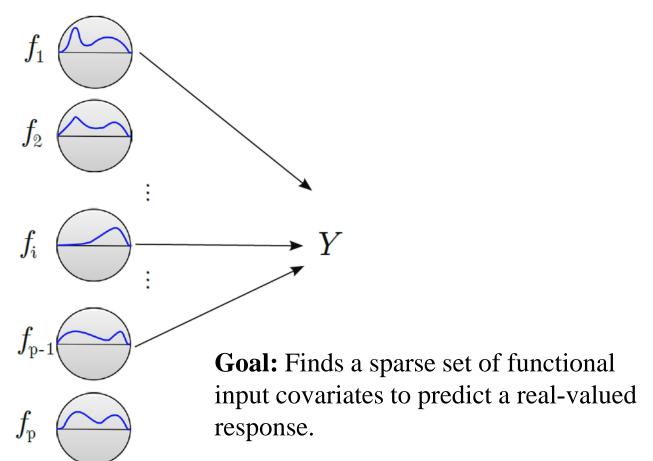
Many Functions-to-Real regression

Similarly, one may consider a mapping that takes in multiple functions:



Sparse Functions-to-Real regression

When the number of functional input covariates may be very large, a sparse model that depends only on a few of the functional covariates may be preferred:

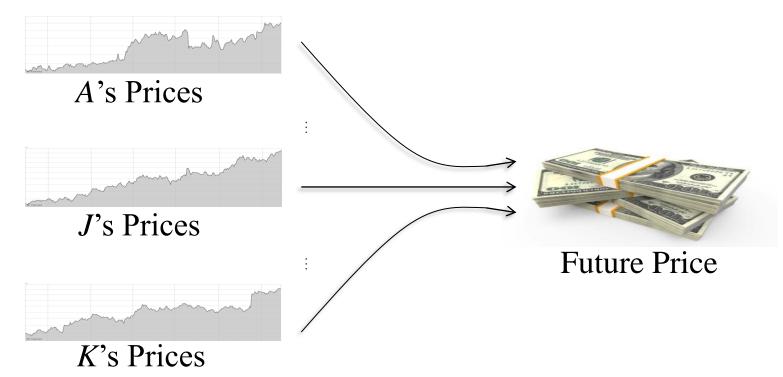


FuSSO Example Applications

Finance:

Inputs: Time-series of several product prices in the past

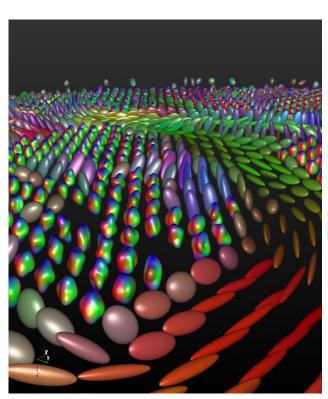
Output: Price of a particular product in the nearby future

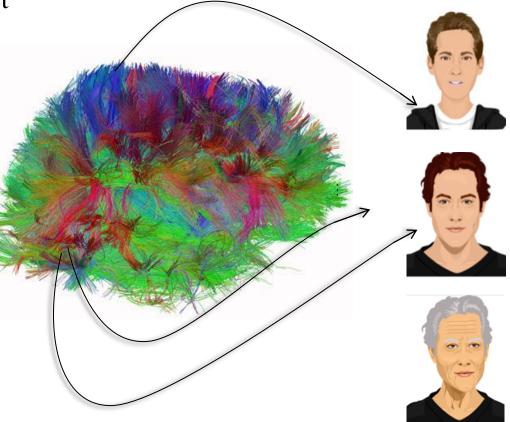


FuSSO Applications in Neuroimaging

Inputs: Functions at each voxel (e.g. orientation distribution functions)

Output: The age of the subject





Voxels' ODFs

Age

Image credit: http://bmia.bmt.tue.nl/software/viste/

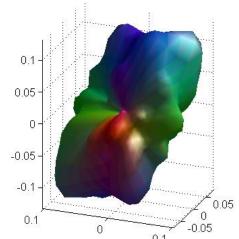
42

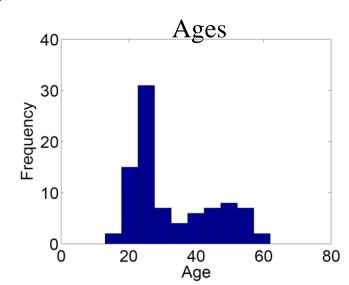
Carnegie Melløn

Results: Neuroimaging dataset

- ☐ Dataset with over 25K functions per subject for 89 total subjects (18 to 60 years old)
- ☐ Orientation distribution functions (ODF) at white matter voxels
- ☐ Goal: Predict the subject's age, given ODFs
- ☐ We compared to LASSO with peak ODF (quantitative anisotropy, QA) values. Finite dim non-functional data set.

Example Voxel ODF





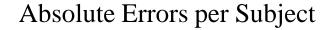
Auton Lab

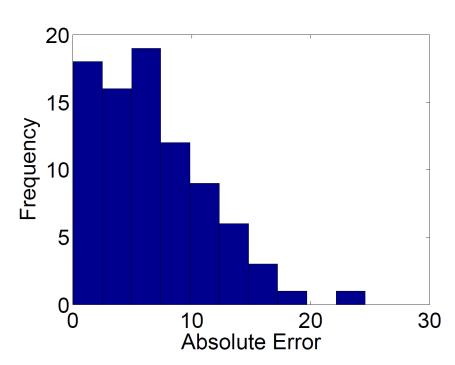
Image Sources: http://www.aging2.com/wp-content/uploads/2013/05/Screen-Shot-2013-05-28-at-9.48.49-PM.png; http://media.salon.com/2013/02/money1.jpg; http://3278as3udzze1hdk0f2th5nf18c1.wpengine.netdna-cdn.com/wp-content/uploads/2010/10/connectome-brain-diffusion-spectrum-imaging.jpg

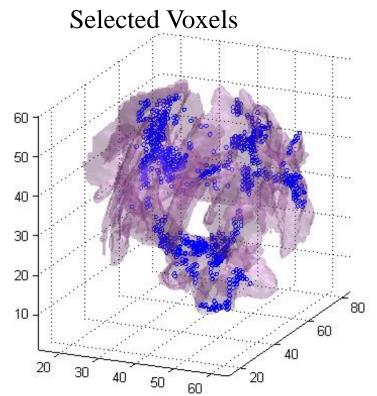
Results: Neuroimaging dataset

Results:

Method:	FuSSO	LASSO	Mean
	(ODFs)	(QAs)	Predict
MSE:	70.85	77.13	156.43







Mean error: 8.3 years, Naïve approach error: 12.5 years



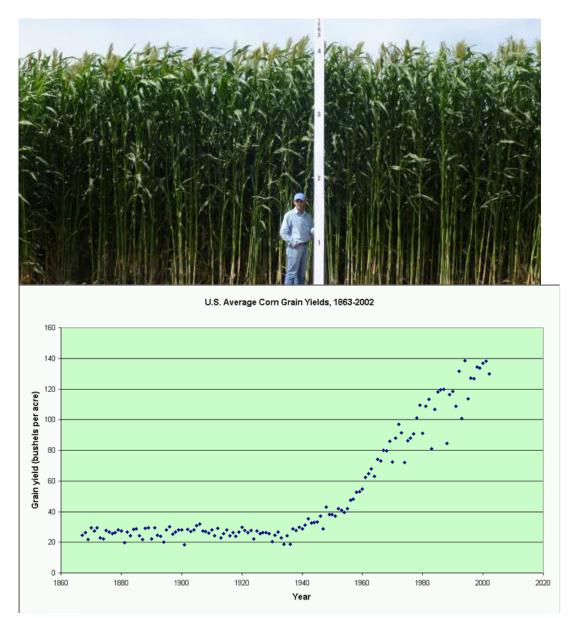
Agriculture



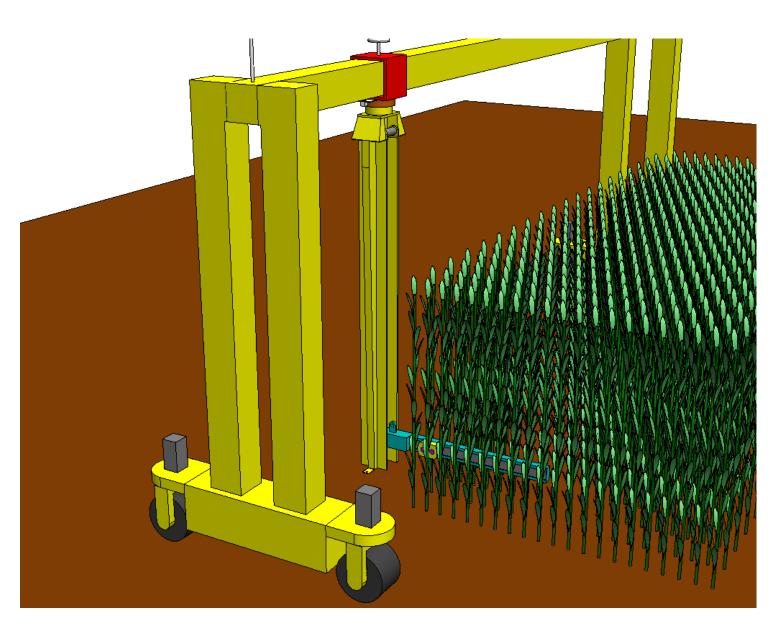
Agriculture

Recommend experiments (which plants to cross) to sorghum breeders.



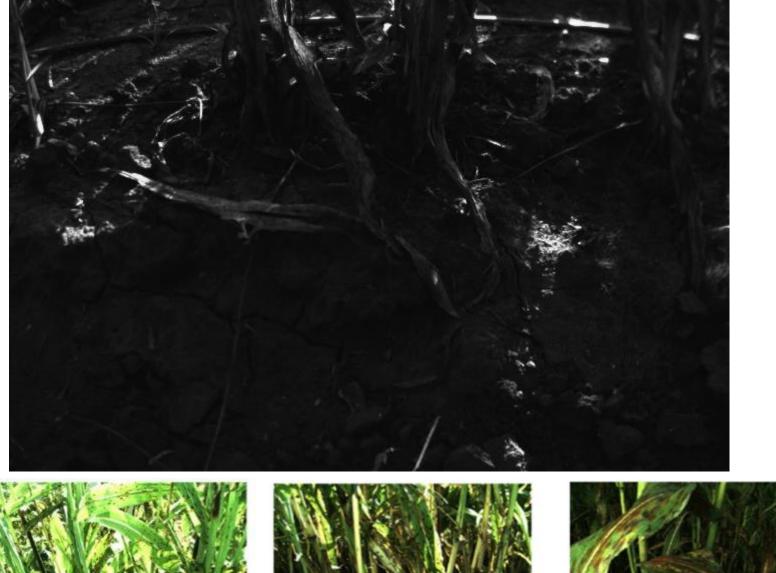


CMU Robot

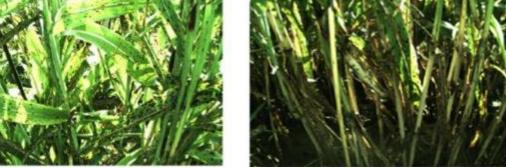


Auton Lab

■1 PB data ...

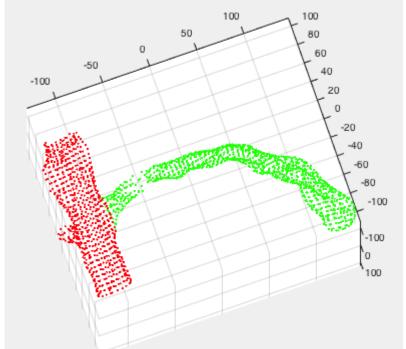


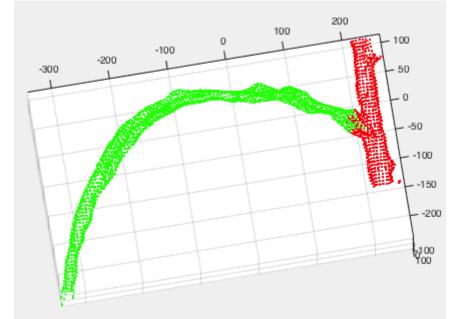






Carnegie Mellon





Name	Range	RMSE error
Leaf angle*	75.94	3.30 (4.35%)
Leaf radiation angle*	120.66	4.34 (3.60%)
Leaf length*	35.00	0.87 (2.49%)
Leaf width [max]	3.61	0.27 (7.48%)
Leaf width [average]	2.99	0.21 (7.02%)
Leaf area*	133.45	8.11 (6.08%)

Auton Lab 49

Carnegie Mellon

Grapes datasets





Take me home!

- **□ML** on Complex Objects
 - o ML on distributions
 - Lasso on functions
- ☐ Active learning and design optimization
- **□** Applications:
 - □ Cosmology
 - ☐ Drug Design
 - ☐ Agriculture
 - Neuroscience



Thanks for your attention! ©

If interested, please contact me! ©

bapoczos@cs.cmu.edu, GHC-8231



Linear Functional Regression

Functional analogues to finite dim linear regression models: for $Y_i \in \mathbb{R}$, $\epsilon_i \sim \mathcal{N}(0, \sigma)$, and $\Psi \subseteq \mathbb{R}^k$, a compact set:

One Real Vector vs. Functional Covariate:

Real Vector Covariate

Functional Covariate

$$Y_i = \langle X_i, w \rangle + \epsilon_i \mid Y_i = \langle f^{(i)}, g \rangle + \epsilon_i$$
where
$$X_i, w \in \mathbb{R}^d \text{ and } \begin{cases} f^{(i)}, g \in L_2(\Psi) \text{ and } \\ \langle X_i, w \rangle = \sum_{i=1}^d X_{ij} w_j \end{cases} \quad \langle f^{(i)}, g \rangle = \int_{\Psi} f^{(i)}(t) g(t) dt$$