BLUE WATERS - GEO MAPPING AND MODELING THE WORLD

APPING AND MODELING THE WORLD

The Geometry of Data

Aaron D. Saxton, PhD, Data Scientist saxton@illinois.edu







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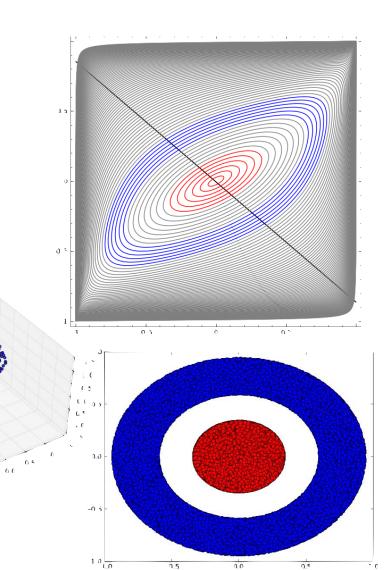


- Toy Example
 - Neural Network Basics
 - Model Training
 - Projections
- MNIST Data Set
 - Neural Network
 - Convolution Neural Network
- Outreach
- Current Work on Blue Waters



The Geometry of Data: Welcome!

- Inspired by Christopher Olah blog post
 - Neural Networks, Manifolds, and Topology (https://colah.github.io/posts/2014-03-NN-Manifolds-Topology/)



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Toy Example Problem Seven Segment Display



<u>Representations</u>

Seven Segment							6			
Arabic Numeral	0	1	2	3	4	5	6	7	8	9
Breadboard Voltage Vector (1-High, 0-Low)	$ \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 0 \end{bmatrix} $	$\begin{bmatrix} 0 \\ 1 \\ 1 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$	$ \begin{bmatrix} 1 \\ 1 \\ 0 \\ 1 \\ 1 \\ 0 \\ 1 \end{bmatrix} $	$ \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 0 \\ 0 \\ 1 \end{bmatrix} $	$\begin{bmatrix} 0\\1\\1\\0\\0\\1\\1\end{bmatrix}$	$ \begin{bmatrix} 1 \\ 0 \\ 1 \\ 1 \\ 0 \\ 1 \\ 1 \end{bmatrix} $	$ \begin{bmatrix} 1 \\ 0 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{bmatrix} $	$\begin{bmatrix} 1\\1\\1\\0\\0\\0\\0\\0\end{bmatrix}$	$ \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{bmatrix} $	$ \begin{bmatrix} 1 \\ 1 \\ 1 \\ 0 \\ 0 \\ 1 \\ 1 \end{bmatrix} $





Toy Example Problem Seven Segment Display



Malfunctioning: 2 or 8 ?

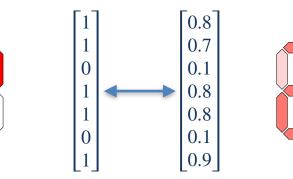
• Simple way to add noise

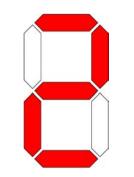
•
$$x + \mathcal{N}(\mu, \sigma^2)$$

Nonlinear way to add noise

• $x + \mathcal{N}(\mu_1, \sigma_1^2)$ if $x \in \{2, 3, 5\}$ else $x + \mathcal{N}(\mu_2, \sigma_2^2)$

- Selection Bias
 - $x + \mathcal{N}(\mu_1, \sigma_1^2)$ Model Training
 - $x + \mathcal{N}(\mu_2, \sigma_2^2)$ Model Validation/Deployed
- What can a neural network do for us?







[1]

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 $lpha_{0_1}, lpha_1$

Input

 $lpha_{0_2}, lpha_2$

Hidden

Hidden

 β_0, β

Output

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Neural Network, A Basic Exercise

$$\begin{array}{c} \text{Input: } X = \begin{bmatrix} 1 \\ 0 \\ 1 \\ 1 \\ 0 \\ 1 \end{bmatrix} \\ \text{Weights: } \alpha_{0_1}, \alpha_1 = \begin{bmatrix} \alpha_{01} \\ \alpha_{01} \\ \alpha_{01} \\ \alpha_{014} \\ \alpha_{014} \end{bmatrix}, \begin{bmatrix} \alpha_{1_{11}} & \alpha_{1_{12}} & \alpha_{1_{13}} & \alpha_{1_{14}} & \alpha_{1_{15}} & \alpha_{1_{16}} & \alpha_{1_{17}} \\ \alpha_{1_{21}} & \alpha_{1_{22}} & \alpha_{1_{23}} & \alpha_{1_{24}} & \alpha_{1_{25}} & \alpha_{1_{26}} \\ \alpha_{1_{31}} & \alpha_{1_{32}} & \alpha_{1_{31}} & \alpha_{1_{34}} & \alpha_{1_{33}} & \alpha_{1_{36}} & \alpha_{1_{37}} \\ \alpha_{1_{31}} & \alpha_{1_{32}} & \alpha_{1_{31}} & \alpha_{1_{44}} & \alpha_{1_{45}} & \alpha_{1_{46}} & \alpha_{1_{47}} \\ \alpha_{1_{51}} & \alpha_{1_{52}} & \alpha_{1_{53}} & \alpha_{1_{55}} & \alpha_{1_{55}} \\ \alpha_{1_{51}} & \alpha_{1_{52}} & \alpha_{1_{53}} & \alpha_{1_{55}} & \alpha_{1_{55}} \\ \alpha_{1_{51}} & \alpha_{1_{52}} & \alpha_{1_{53}} & \alpha_{1_{55}} & \alpha_{1_{55}} \\ \alpha_{1_{51}} & \alpha_{1_{52}} & \alpha_{1_{53}} & \alpha_{1_{55}} & \alpha_{1_{55}} \\ \alpha_{1_{55}} & \alpha_{1_{55}} & \alpha_{1_{55}} \\ \alpha_{1_{5}} & \alpha_{1_{5}} & \alpha_{1_{55}} & \alpha_{1_{55}} \\ \alpha_{1_{5}} & \alpha_{1_{5}} & \alpha_{1_{55}} & \alpha_{1_{55}} \\ \alpha_{1_{5}} & \alpha_{1_{5}} & \alpha_{1_{5}} & \alpha_{1_{5}} \\ \alpha_{2_{3}} & \alpha_{2_{3}} & \alpha_{2_{3}} \\ \alpha$$

• α_{0m}, α_m along with the choice of $\sigma(x)$ completely describe the *m*'th "Dense Layer"

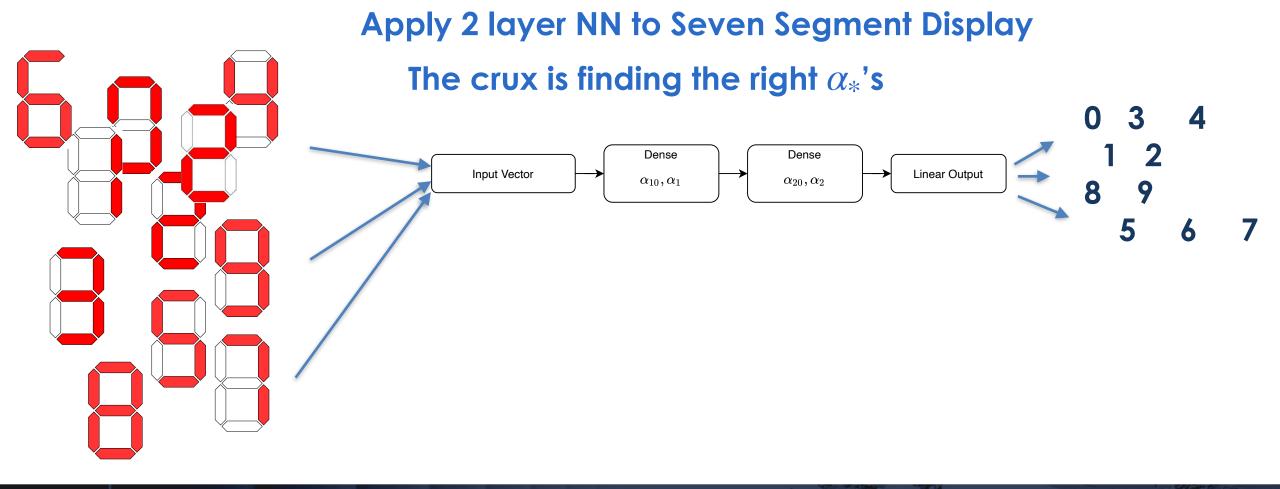
- 10 classifications, model output is a 10 dimensional vector
 - Final classification is read as "argmax" of output





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Neural Network, A Basic Exercise





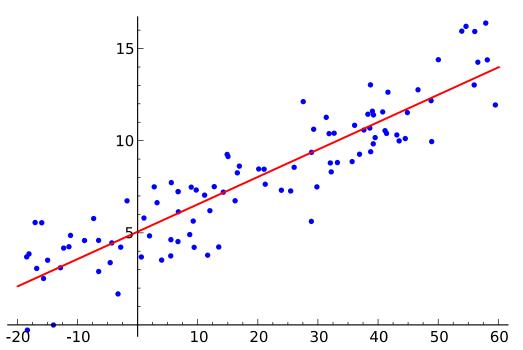


Machine Learning Is Just Curve Fitting

- Simple $y = m \cdot x + b$ regression
 - Goal: Find m,b
 - With data set $\{(x_i, y_i)\}_{i=1,..,n}$
 - Let the error be

•
$$R = \sum_{i=1}^{n} \left[(y_i - (m \cdot x_i + b)) \right]^2$$

- Minimize *R* with respect to *m* and *b*.
- In practice we consider more general y = f(x)
 - Many more α 's







Gradient Descent

- Searching for minimum of
- $R = \sum_{i} \left[y_{i} f_{\alpha_{i}}(x_{i}) \right]^{2}$ $\nabla R = \langle R_{\alpha_{1}}, R_{\alpha_{2}}, \dots, R_{\alpha_{n}} \rangle$
 - R and ∇R is a sum over i
- Update parameters

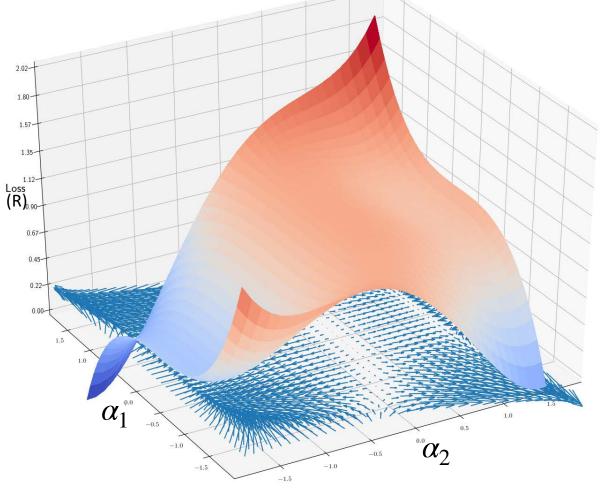
$$R\left(\overrightarrow{\alpha}_{t+1}\right) = R\left(\overrightarrow{\alpha}_t + \gamma \nabla R\right)$$

- γ : Learning Rate
- Some Other Loss Function

Root Mean Square,
$$R = \sqrt{\sum_{i}^{n} \left[(y_i - f_{\alpha_*}(x_i)) \right]^2}$$

Cross Entropy, $\tilde{R} = -\sum_{i}^{M} (y_i) \log \left(f_{\alpha_*}(x_i) \right)$

Fictitious Loss Surface With Gradient Field





Stochastic Gradient Decent

• Single training example, (x_i, y_i) , Sum over only one training example

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•
$$\nabla R_{(x_i, y_i)} = \left\langle R_{\alpha_1}, R_{\alpha_2}, \dots, R_{\alpha_n} \right\rangle_{(x_i, y_i)}$$

- $R_{(x_i,y_i)}\left(\overrightarrow{\alpha}_{t+1}\right) = R\left(\overrightarrow{\alpha}_t + \gamma \nabla R\right)_{(x_i,y_i)}$
- γ : Learning Rate
- Choose next (x_{i+1}, y_{i+1}) , (Shuffled training set)
- SGD with mini batches
- Many training example, (x_i, y_i) , Sum over many training example
 - Batch Size or Mini Batch Size (This gets ambiguous with distributed training)
- SGD often outperforms traditional GD, want small batches.
 - <u>https://arxiv.org/abs/1609.04836</u>, On Large-Batch Training ... Sharp Minima
 - https://arxiv.org/abs/1711.04325, Extremely Large ... in 15 Minutes

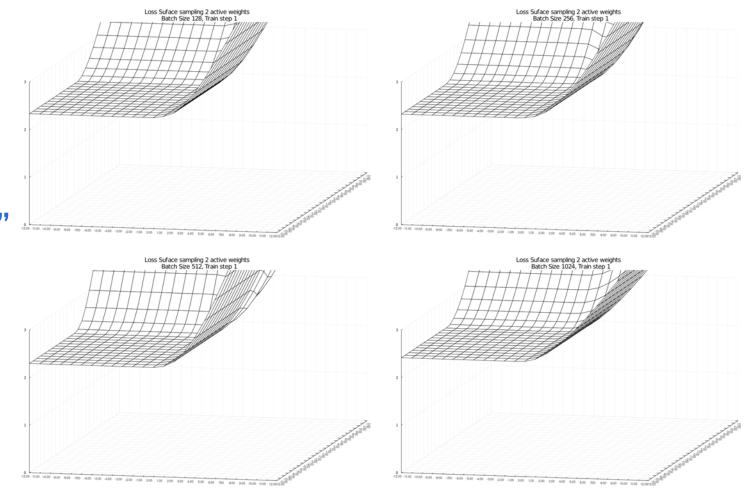




Neural Network, A Basic Exercise

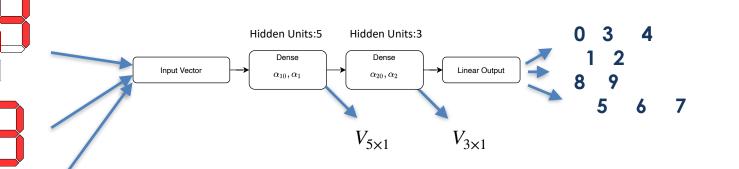
- Training the model yields a sequence of weights
- Investigate Batch Size: 128, 256, 512, 1024
- We choose the 2 "most active" α_* 's and sample them
- "most active" is the l^2 norm across training steps

Input Vector





Neural Network, A Basic Exercise

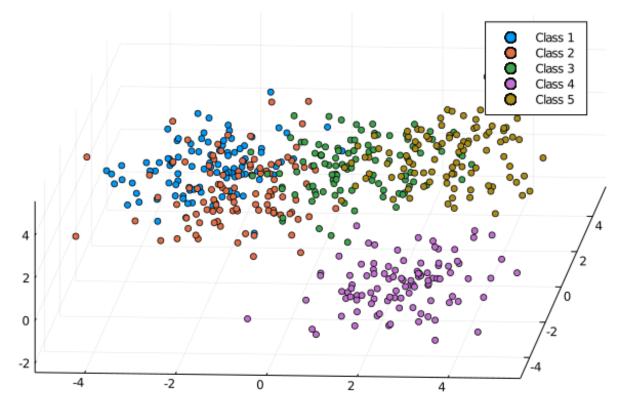


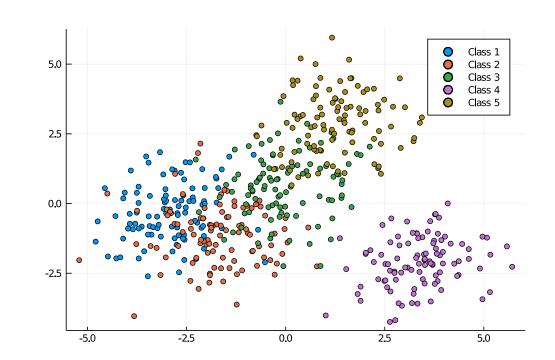
- Each layer has an output vector for each input
 - Input Vec: 7x1
 - Layer 1 Out Vec: 5x1
 - Layer 2 Out Vec: 3x1
- We need a way to visualize higher dimensional vectors



Projecting To Lower Dimension: Principle Component Analysis (PCA)

- Finds a basis which maximizes variance
 - Notice, this is a linear transformation



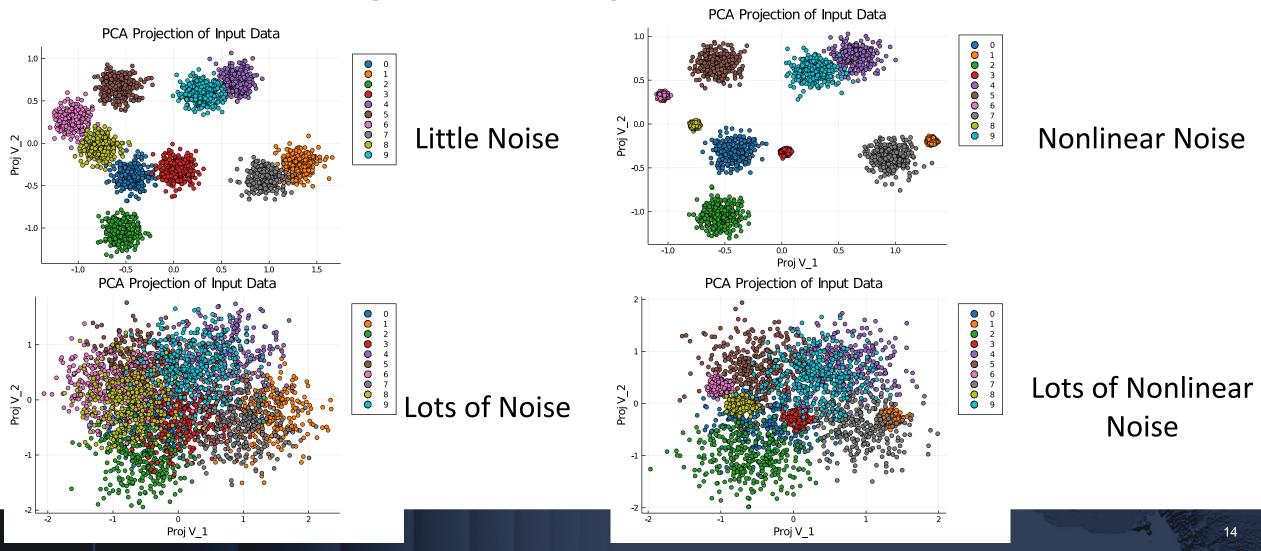


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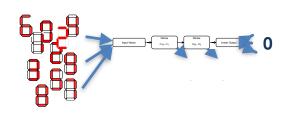
PCA on Seven Segment Voltage Vector

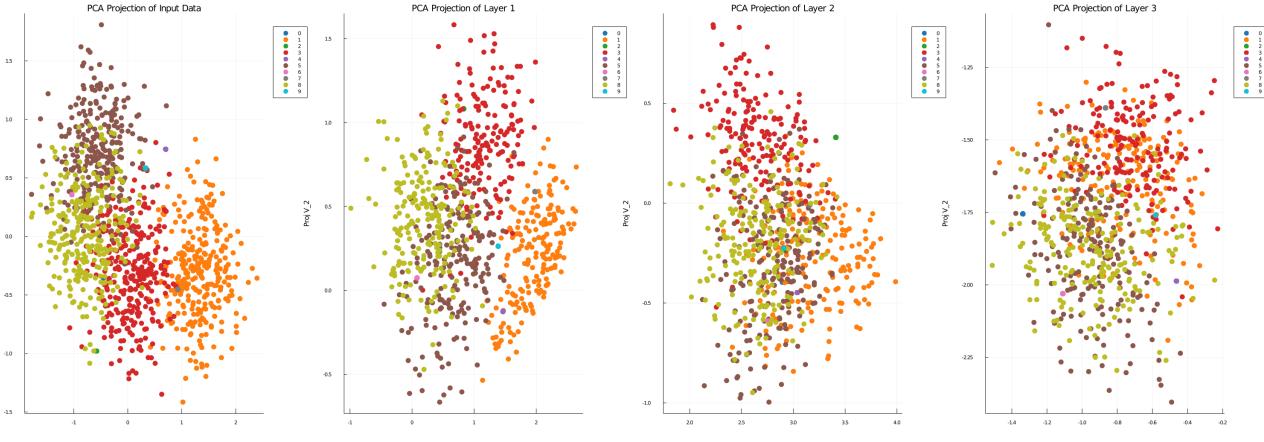




Neural Network, A Basic Exercise

- Hidden Units: 20,10
- Accuracy: Aprox 90% PCA Projection of Input Data



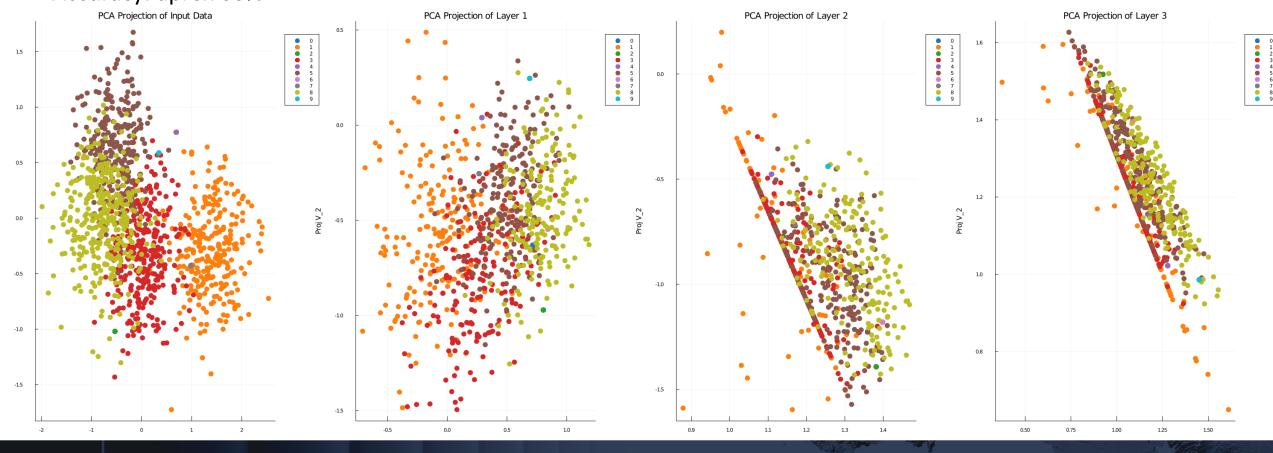






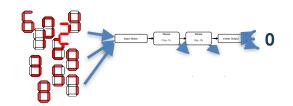
Neural Network, A Basic Exercise

Hidden Units: 5,3Accuracy: aprox 60%

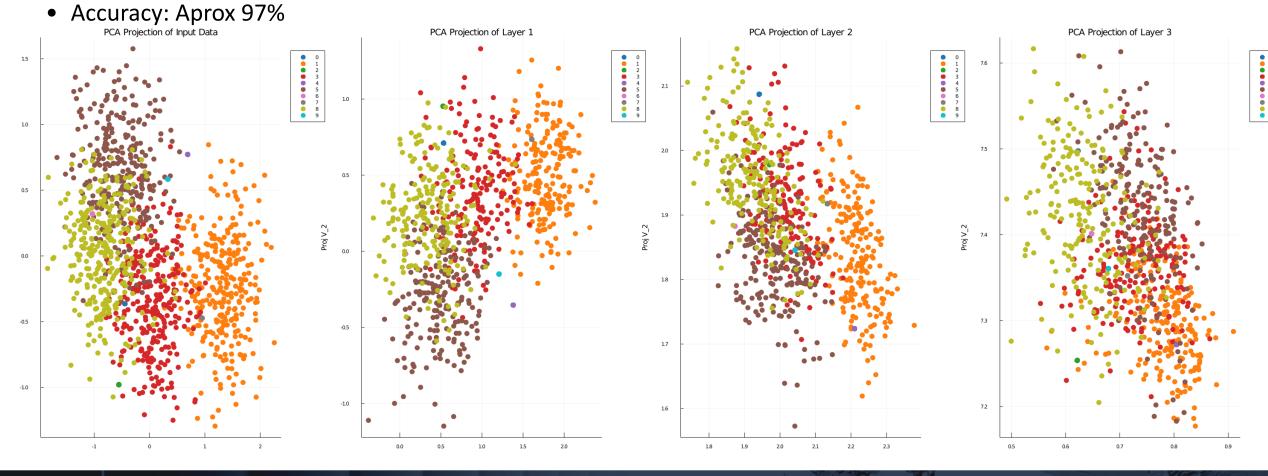




Neural Network, A Basic Exercise



• Hidden Units: 200,100





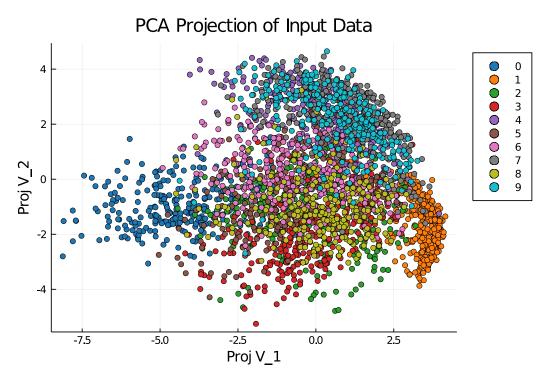


MNIST Data Set

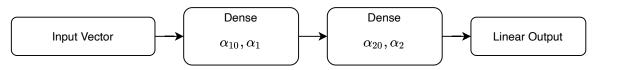
- Standard Dataset of Hand Written Arabic Numeral
- 28x28 Pixels
- 1 channel



• Lets try this NN again



PCA MNIST Flattened Image Vectors

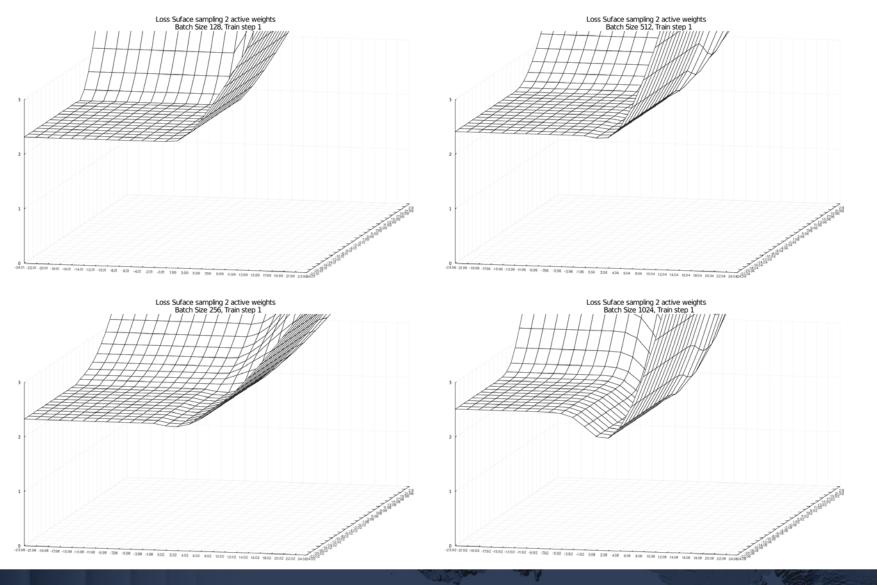






MNIST Example

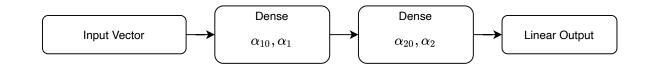
- MNIST is a dataset of hand written Arabic Numerals (Images)
- Same NN as Seven Segment Display



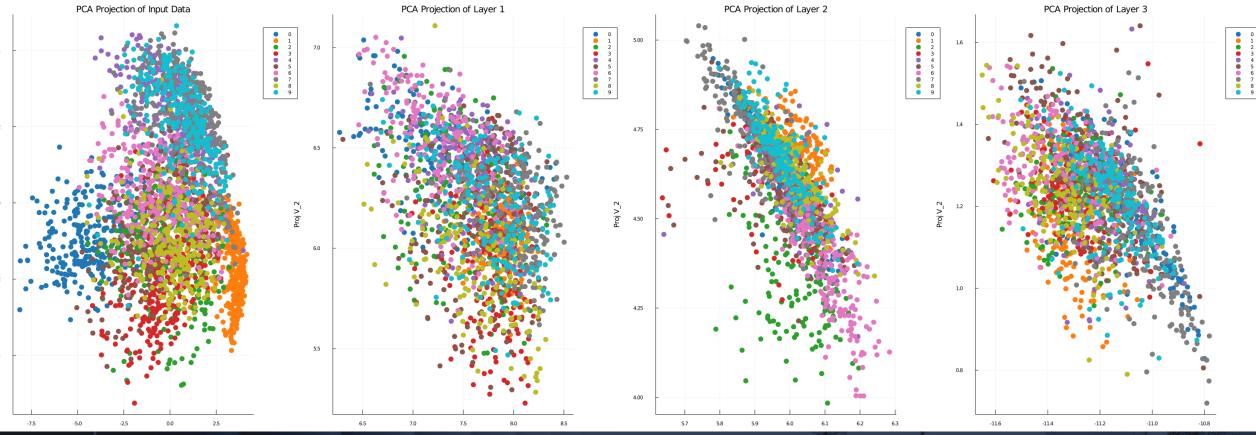




MNIST Example



- MNIST is a dataset of hand written Arabic Numerals (Images)
- Same NN as Seven Segment Display







MNIST Example: Convolutions!

Convolutions

- For two functions, f(x), g(x) $(f * g)(x) = \int_{-\infty}^{\infty} f(y)g(x - y) dy$ $-\infty$ Area under $f(\tau)g(t-\tau)$ f(1) 0.8 g(t-1) 0.6 (f+g)(t) 0.4 0.2 • g is the kernel to f-1.5 -2 -0.5 0.5 -1 Û. 1.5 2 z&t
 - Above is a rolling average





Demo

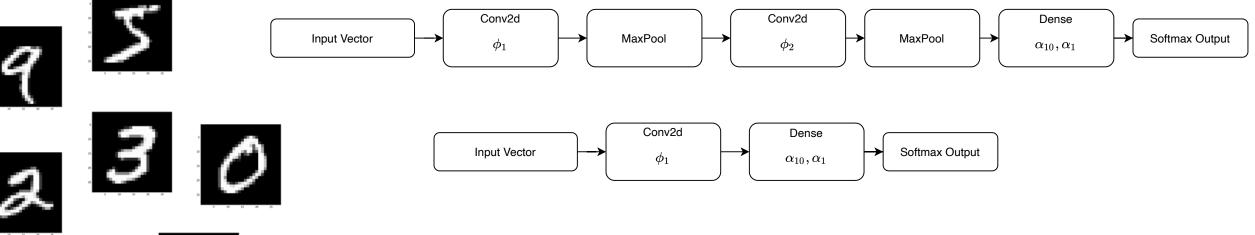
http://setosa.io/ev/image-kernels/

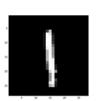




MNIST Example: Convolutional Neural Net (CNN)

- Let's Consider 2 model architectures and compare.
- ϕ_i are filters (or kernels)
 - Trainable Parameters



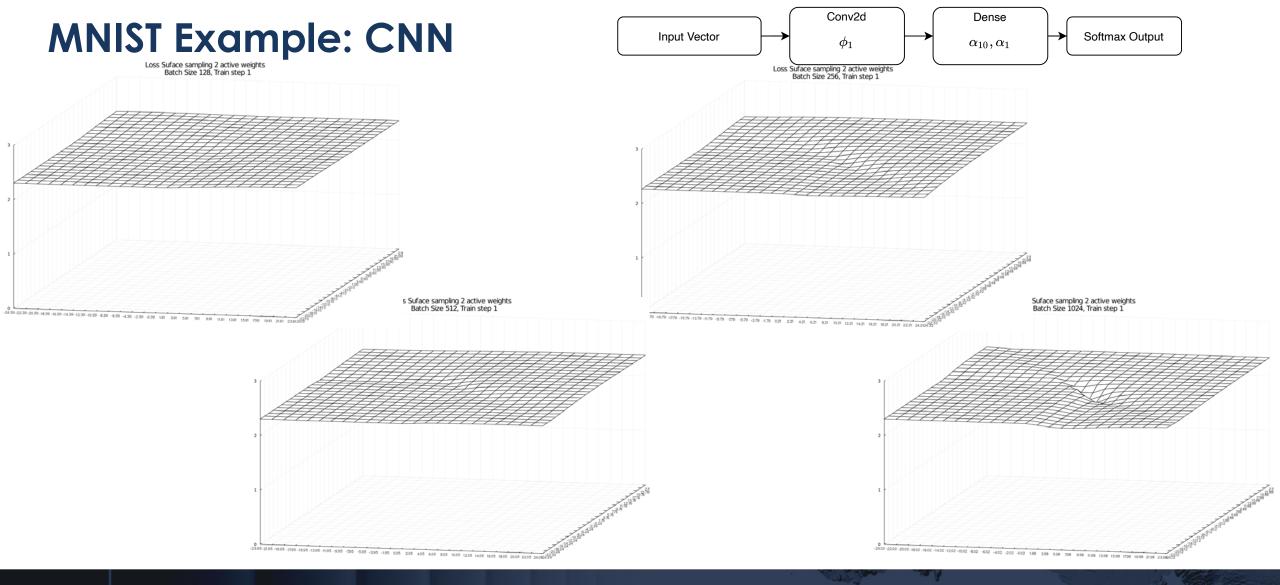






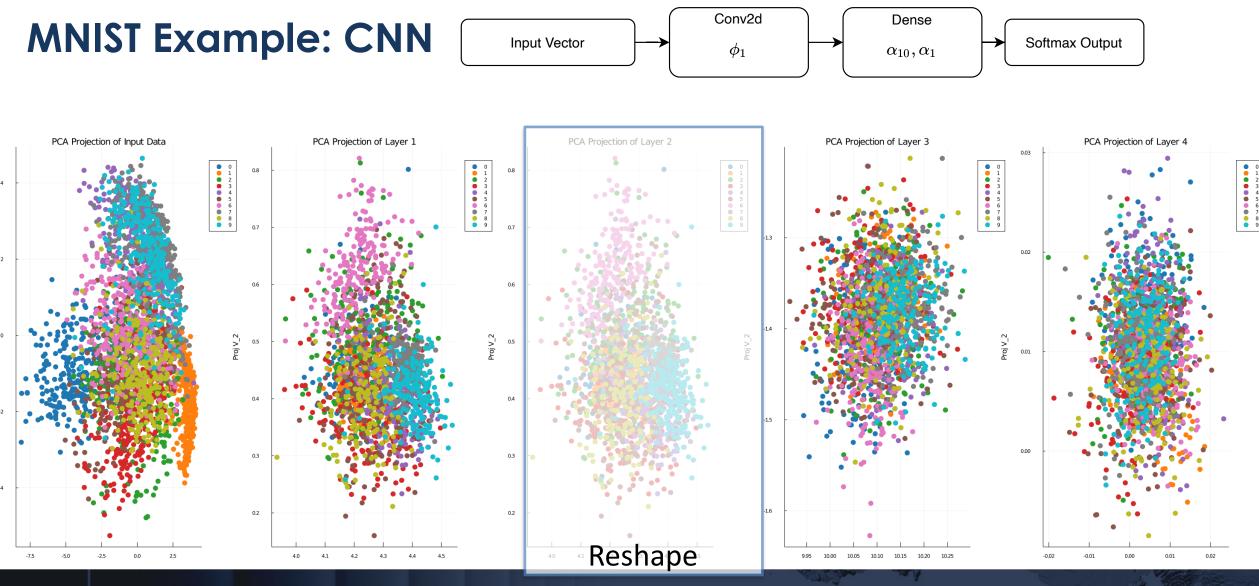














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Conv2d Conv2d Dense **MNIST Example: CNN** Input Vector MaxPool MaxPool Softmax Output ϕ_1 ϕ_2 $lpha_{10}, lpha_1$ PCA Projection of Layer 4 PCA Projection of Input Data PCA Projection of Layer 1 PCA Projection of Layer 2 PCA Projection of Layer 5 PCA Projection of Layer 6 PCA Projection of Layer 7 PCA Projection of Layer 3 -0.5 • 0 • 0 • 0 • 0 • 1 • 2 1
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 9 -1.0 0.06 -1.5 roj V_2 roj V 18.8 -2.5 18.6 2.5 -3.5 Reshape 17.0 17.5 18.0 -7.5 -5.0 -2.5 0.0 2.5 2 4 6 8 10 12 14 -21 -20 -19 16.5 -25.4 -25.3 -25.2 -25.1 -25.0 -24.9 -24.8 0.00 0.01 0.02 0.03 0.04 0.05



Take Aways

- Large Batch Size has affect on loss surface
 - Empirically: Large batch size results in poor SGD minimizer

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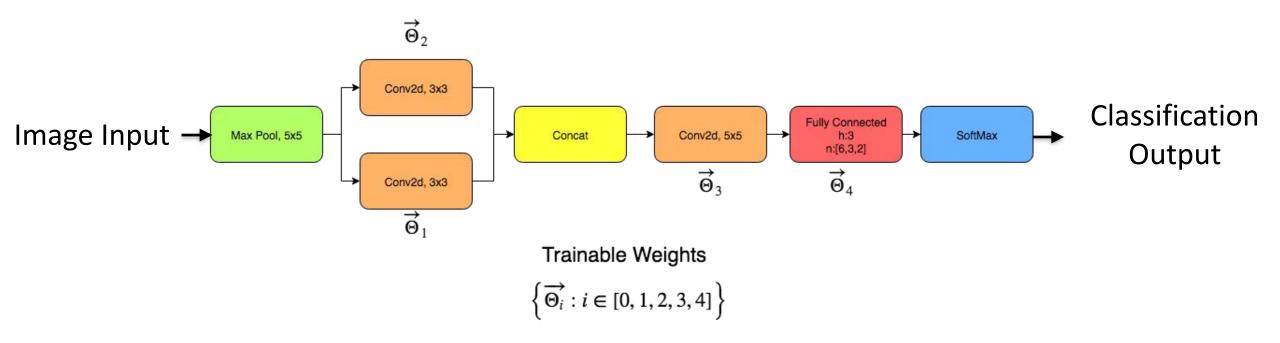
- Layers "Project" data between manifolds
 - SGD finds the weights that do this in a useful way
 - Good models "separate data"
- Finding "Goldilocks" models
 - Not too much transform Not enough dimensions to wiggle in
 - Not to little transform Danger of over fitting

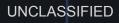
Now what!?



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Faux Model Example

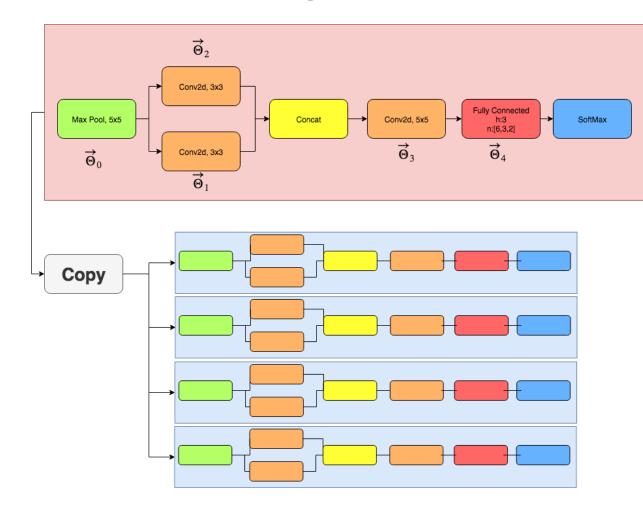


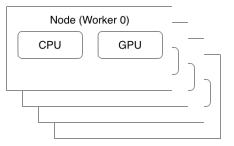






Distributed Training, Data Distributed

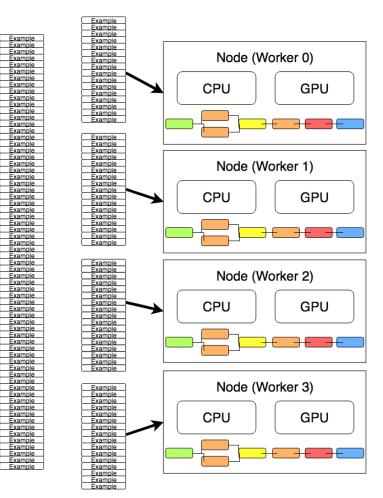








Distributed Training, Data Distributed



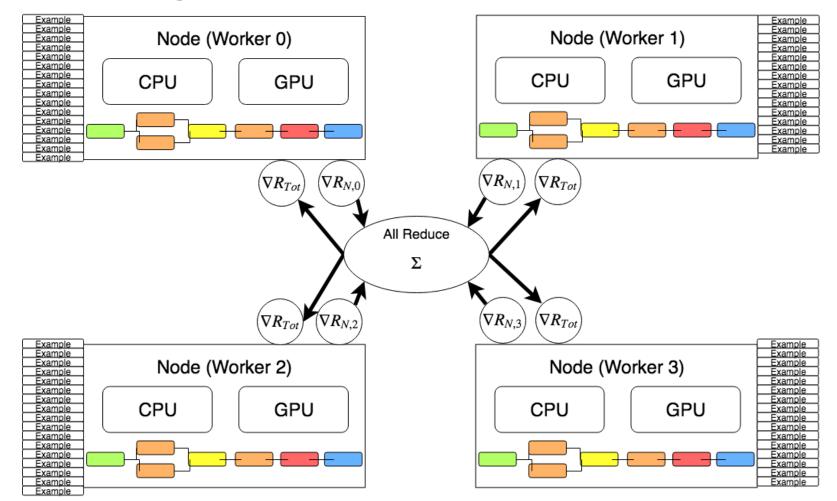
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CRA





Distributed Training, Data Distributed





Where do we go from here?

- This is a solicitation!
- Survey says NGA is interested (Future Topics)
 - CNN's, GANs
 - Transformers, Image Segmentation
- Looking for teams to deploy your ML training onto BW
 - What we learn from these methods is transferable to other architectures
- Contact
 - <u>help+bw@ncsa.illinois.edu</u>
 - Aaron Saxton, <u>saxton@illinois.edu</u>
 - Brett Bode, <u>brett@illinois.edu</u>
 - Greg Bauer, gbauer@illinois.edu
 - Bill Kramer, <u>wtkramer@illinois.edu</u>



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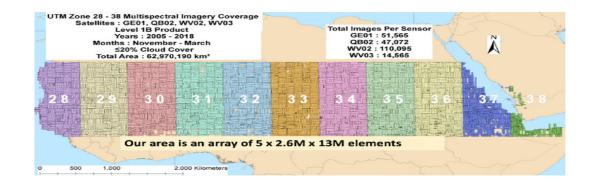
Requesting Access to Blue Waters

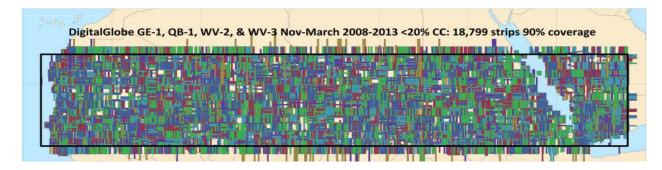
- Access to Blue Waters starts with the submission of a two-page request describing your project and its resource requirements.
 - Projects can be small (50,000 Node Hours (NH)) to extreme (many million NH)
 - If your project is new to HPC start with a small request, additional time can be quickly added later once the need is demonstrated.
 - Include the type and amount of support you may need from BWs staff to get your project running. The Blue Waters team is available to advise on these points.
- Questions
 - NCSA/Illinois: email <u>help+bw@ncsa.Illinois.edu</u>
 - NGA POCs:
 - Chuck Crittenden, Geomatics Source, Charles.D.Crittenden@nga.mil
 - Kevin Dobbs, Research, Kevin.E.Dobbs.ctr@nga.mil
 - Brain Bates, Automation, Brian.F.Bates@nga.mil
 - Victor Gonzales, Research, Victor.M.Gonzalez@nga.mil



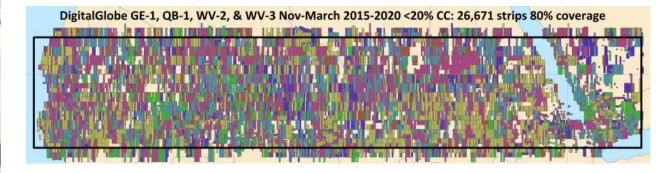
Showcase Current Work on BW

"Arid & semi-arid tree-crown enumeration at the 50 cm scale Compton Tucker and Colleagues" — Compton (Jim) Tucker, et. al.





Total trees count:10,291,286,733Total bush count:1,214,754,908Total crown area:283,546,878,649 m²Total area studied:11,675,817 km²Total processing time:57,688,256 core hoursVersion 1.0 @ 19-July=2020Version 1.1 will correct input data omissions (<5% of study area)</td>



BLUE WATERS - GEO MAPPING AND MODELING THE WORLD

QUESIONS?

The Geometry of Data Aaron D. Saxton, PhD, Data Scientist saxton@illinois.edu

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