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Learning Over Object Boundary Point Clouds

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SN 284
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Final Presentation for
COMP 775, taught by Dr. S. Pizer

BLUF

- We use transfer learning to generate features from boundary points on brain structures with few examples
- The transferred features are used as input to a single-layer neural network to estimate if an at-risk infant is autistic
- This method produces results that are on-par or better with competing techniques
- Further research is required to improve stability to variable network initialization
  - There is some concern that the dearth of testing data is hiding an overfitting problem
  - Additional data would likely assist with this difficulty

Problem Overview

Predict if an at-risk, six-month-old has autism using only brain scans of the bilateral hippocampi and the caudate nuclei

- At six months, it is not possible to make a diagnosis using behavior atypicalities because the child isn't sufficiently developed
- Early diagnosis and response may be able to minimize symptoms

Primary challenges:

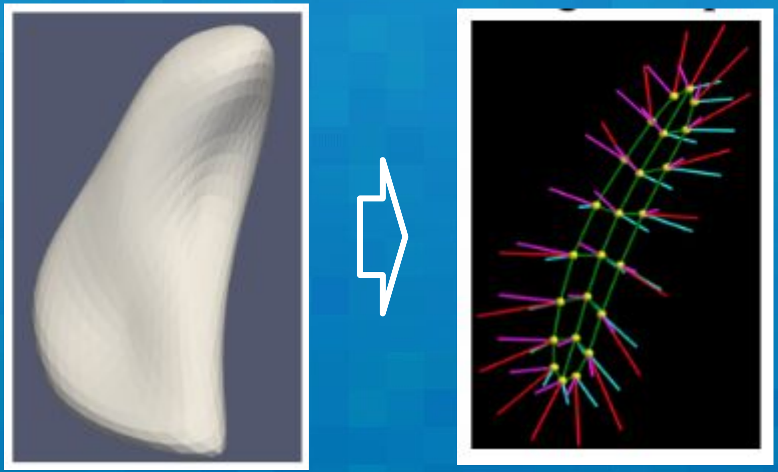
- Minimal data - the scarcity of data for this task makes it difficult to train a neural network
- Data modality - typical networks are not well-suited to unordered inputs

Data Set

- The data was collected as part of an NIH study referred to as the Infant Brain Imaging Study (IBIS)

- MRI scans of the bilateral hippocampi and the caudate nuclei were taken of at-risk infants during natural sleep

- A skeletal representation was fit to the data*
  - 143 total negative examples
  - 34 total positive examples
  - Split (randomly) 80/20, train/test



*Junpyo Hong "Classification of Neuroanatomical Structures Based on Non-Euclidean Geometric Object Properties," Dept. Computer Science, UNC 2018

Method

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1. Create a pair of hold-out classes from the ModelNet 40 point cloud dataset
   - The pair will take the place of the IBIS set for testing and proof of concept
2. Train a deep neural network on the remaining 38 classes
   - Use the Deep Set architecture to take advantage of permutation in-/equi-variance
3. Transfer the network to the held-out pair
4. Convert the IBIS s-rep data into boundary point cloud
   - The medical data must exist in the same format as the original data set
   - Yields ~70 points per example
5. Transfer the neural network to the IBIS point cloud data

Network Architecture

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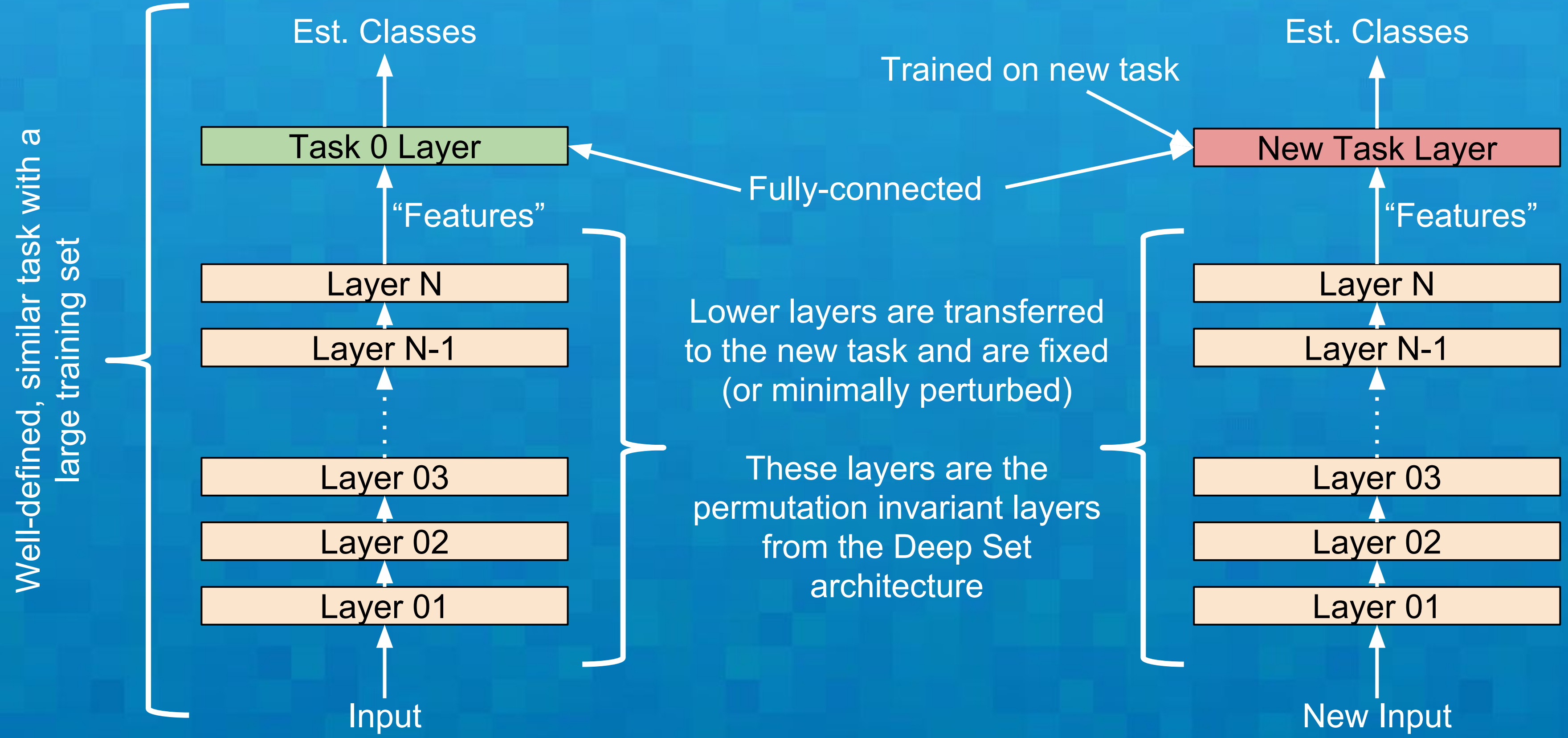
- Since our data modality is somewhat unusual, we cannot use a conventional CNN/DNN which exploit localized information through convolutions over a grid
  - Our data is composed of arbitrarily-ordered 3D points on the object boundary
- Deep Set* layers incorporates all the data and exploits permutation invariant and equivariant operations to overcome the lack of a regular grid
  - Permutation invariant: $f(\Gamma x) = f(x)$, where Γ is some reordering operation
  - Permutation equivariant: $f(\Gamma x) = \Gamma f(x)$
  - Deep Set also handles a variable number points input
- By stacking several Deep Set layers we can extract local and non-local object features to use in classification

*M. Zaheer, S. Kottur, S. Ravanbakhsh, B. Poczos, R. R. Salakhutdinov, and A. J. Smola. Deep sets. In Proc. NIPS, pages 3394–3404, 2017.

Transfer Learning



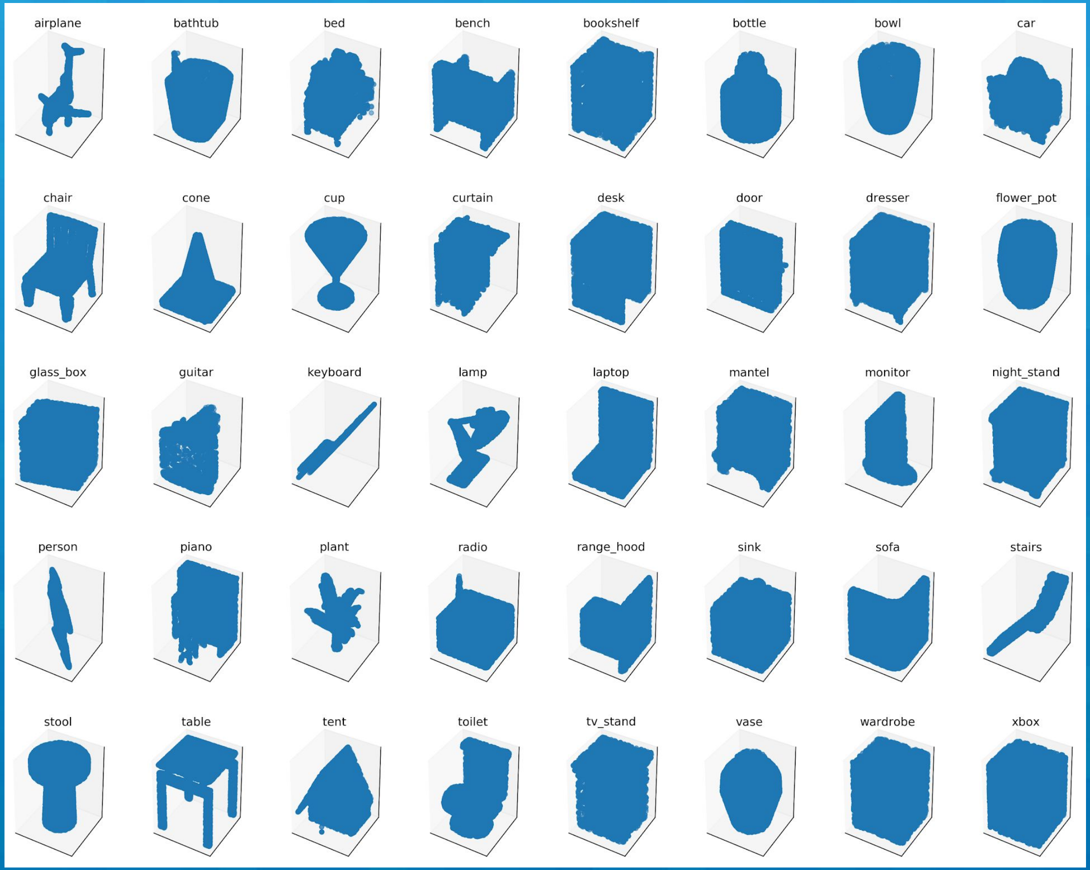
Model Net 40

- ModelNet is a collection of 3D CAD models maintained by Princeton*

- We will use points taken from the boundary of 40 different classes
    - 10,000 points per object

- These 40 classes have been standardized by Princeton

- The Deep Set model achieves ~87% classification accuracy on the full 40 classes



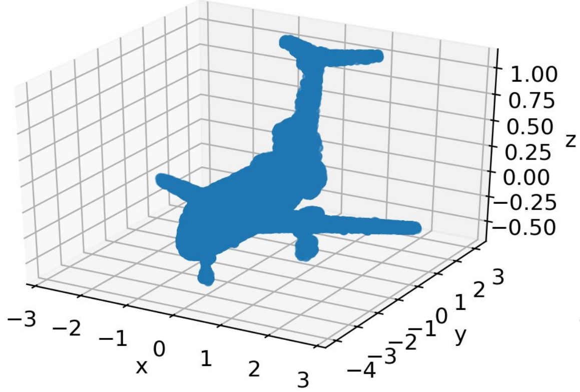
*http://modelnet.cs.princeton.edu

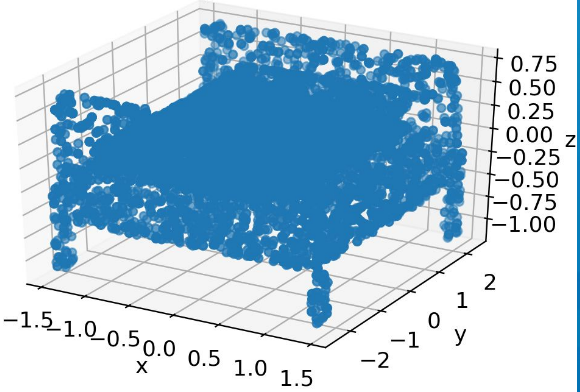
Stand-In Dataset

- Before transferring the trained model to the IBIS dataset we'll test how well the model transfers to two held-out classes
  - Train the Deep Set model to recognize 38 of the the 40 classes and transfer the model to the remaining two (for binary classification)

- This is a proof-of-concept test since we known the model can handle the two classes and since the new classes have exactly the same number of points as the original model

- We will hold out airplanes and beds
  - ~500 training examples per class
  - 100 testing examples per class





Results: ModelNet 10k Points

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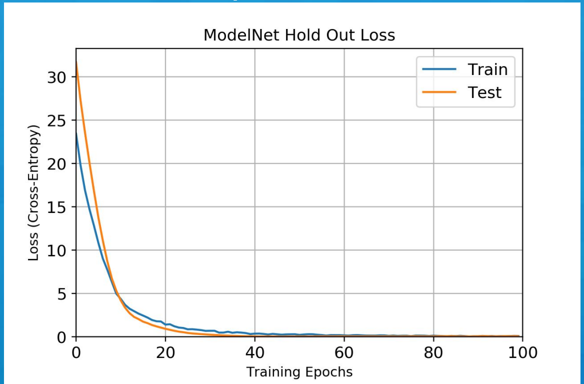
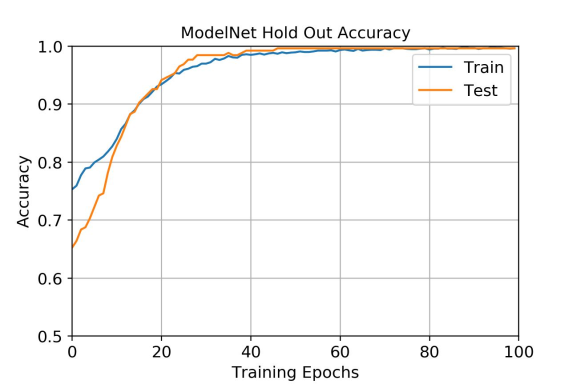
Airplane/Bed



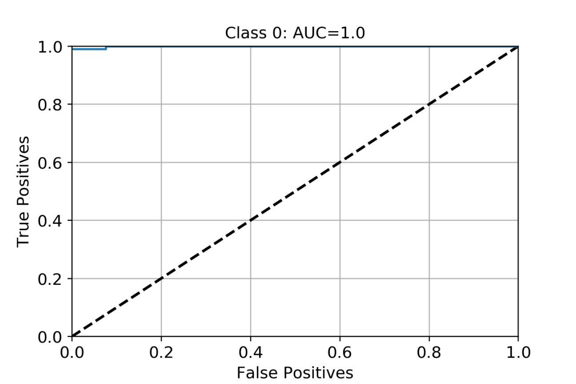


The transferred neural network easily learns to distinguish point clouds of airplanes from beds

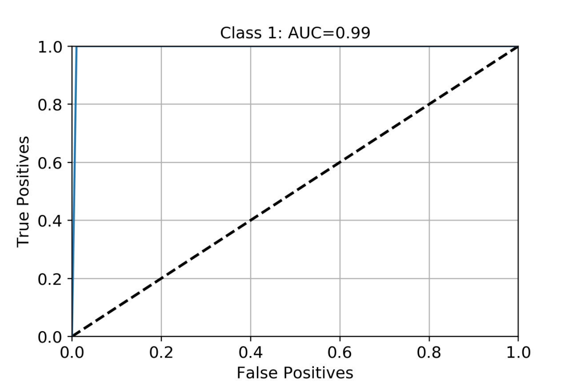
Airplane AUC: 1.00
Bed AUC: 0.99

This demonstrates that the overall method is sound

Airplane

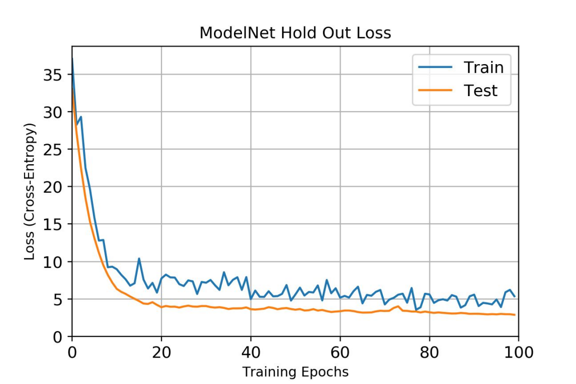


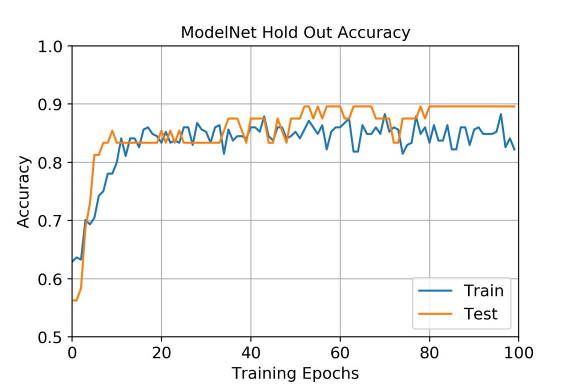
Bed



Results: IBIS 10k Points

IBIS



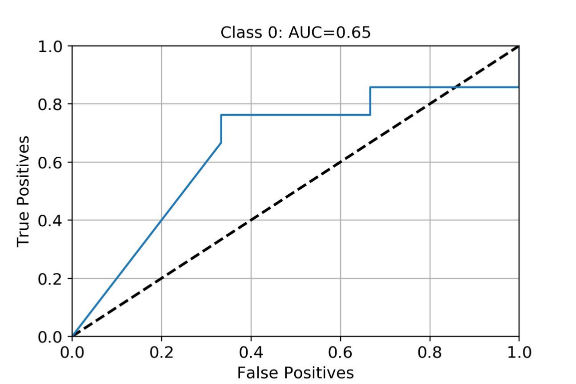


The transferred neural network does a reasonable job of distinguishing between autism and not-autism using s-rep derived point clouds

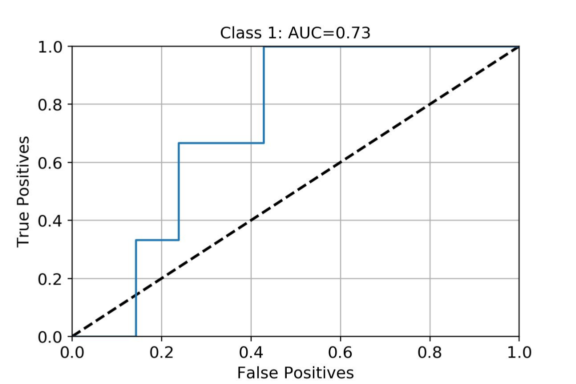
Negative: 0.65
Positive: 0.73

These results vary considerably with the initialization. The results shown here are among the best.

Not-Autism



Autism



Class Split/Similarity

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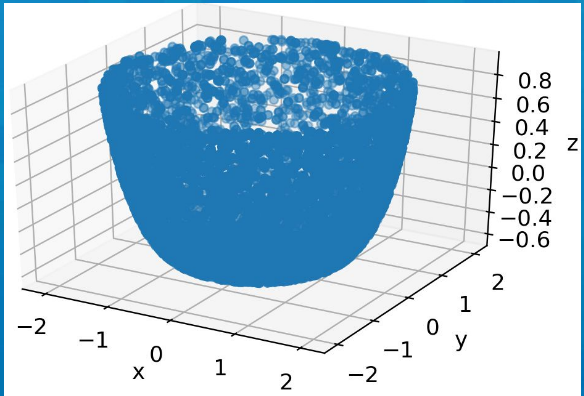
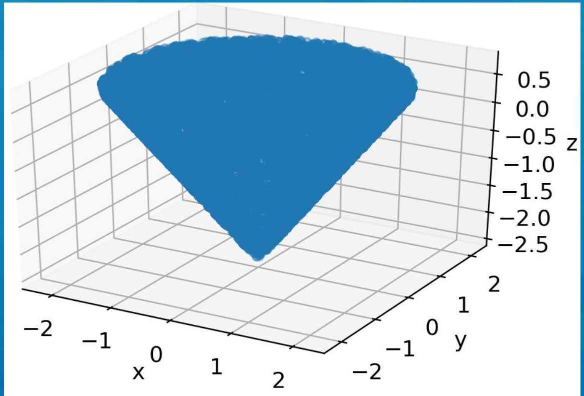
- The airplane/bed split was selected because it has a similar number of examples per class
- This is unlike the IBIS dataset where there are ~4x as many negative examples
- Additionally, the positive/negative examples are relatively similar in shape, whereas airplanes and beds are dissimilar
- To this end, bowls and cups were used as the held-out classes from ModelNet
    - 64 bowl training examples
    - 167 cone training examples
    - 20 testing examples per class

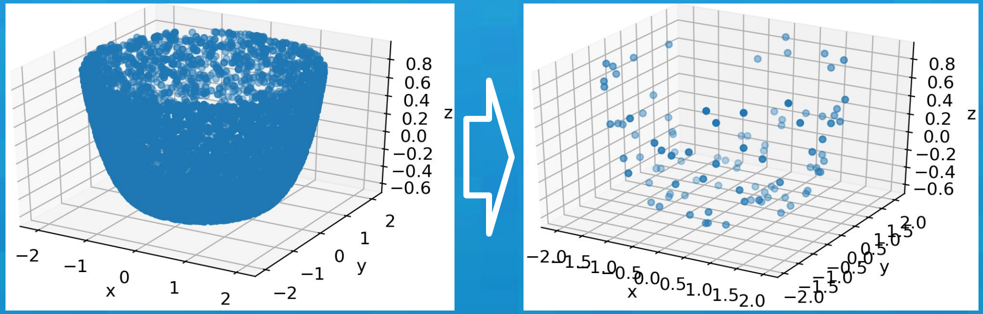


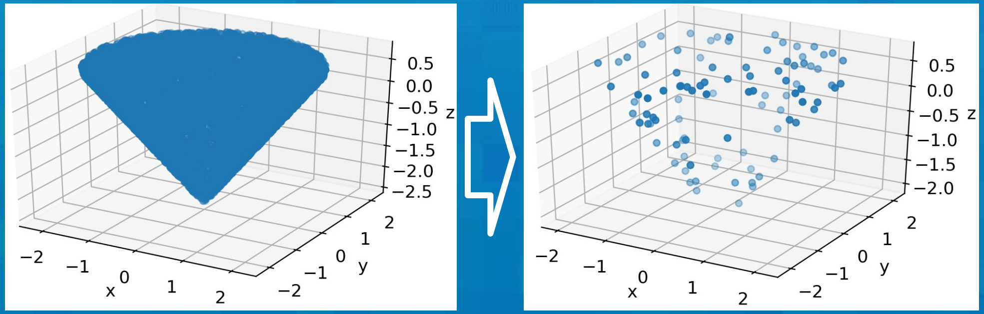


Number of Points

- A major concern for this method is the difference between the number of points in the original training set and the number of points in the fine-tuned set
    - There are more than 100x the number of points in ModelNet than in the s-rep extracted set
    - Note: I believe additional boundary points could be interpolated from the s-rep data

- To make sure that this is not a problem, randomly downsample the ModelNet data prior to training





Results: ModelNet 100 Points

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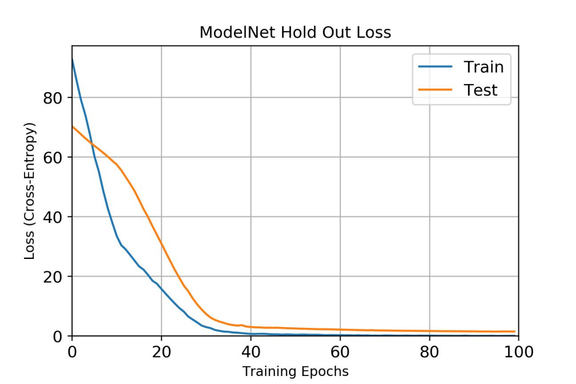
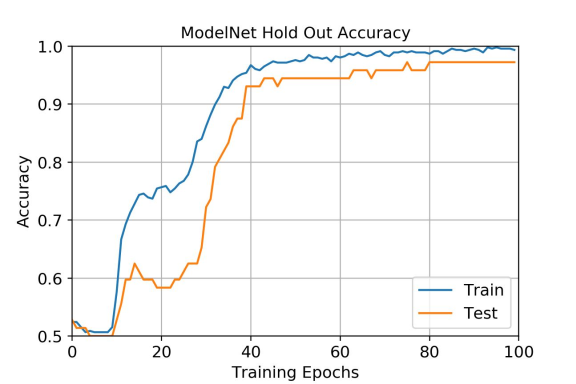
Bowl/Cone





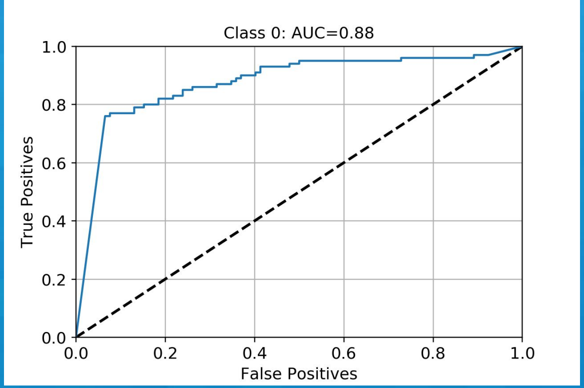
The transferred network does not achieve as high of accuracy when only 100 points are used

Bowl AUC: 0.88

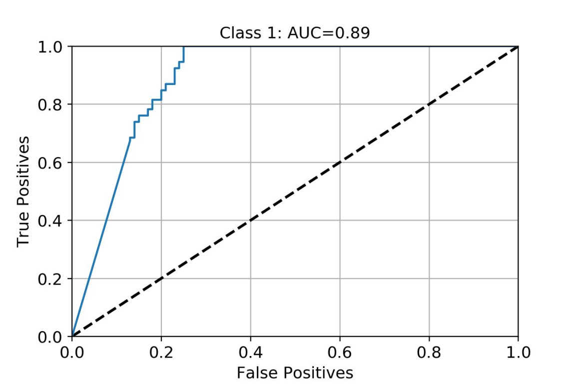
Cone AUC: 0.89

Note: the original network maintains ~87% accuracy on the original 38 classes

Bowl

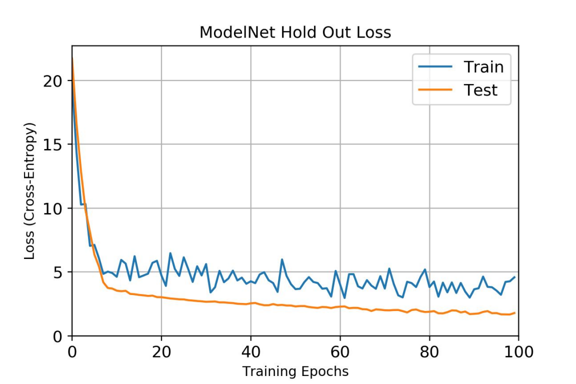


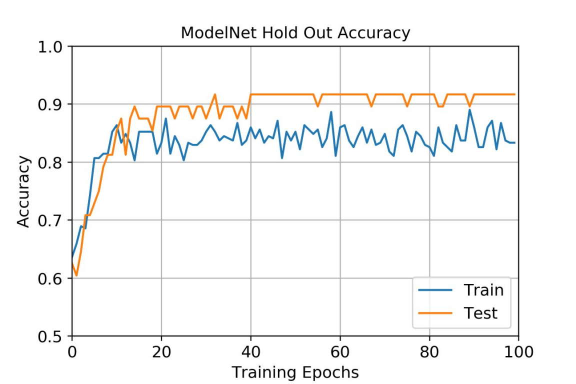
Cone



Results: IBIS 100 Points

IBIS



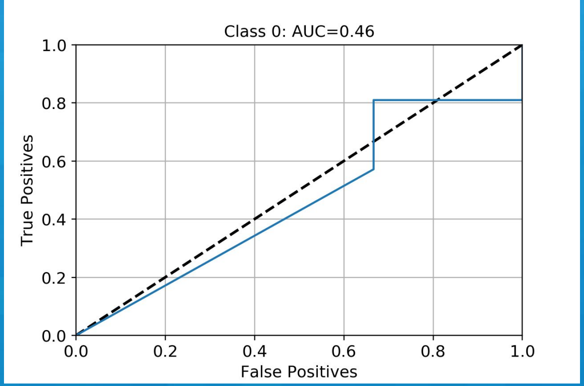


The overall accuracy is equitable to when used 10,000 points but the AUC is lower

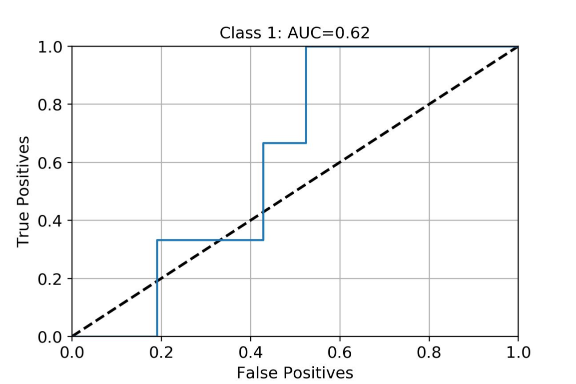
Negative AUC: 0.46
Positive AUC: 0.62

As before, the initialization has a large impact on the results, though they do not appear as extreme as before

Not-Autism



Autism



Takeaways

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- The transferred features are used as input to a single-layer neural network to estimate if an at-risk infant is autistic
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Acknowledgements

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Dr. J. Oliva for providing the ModelNet 40 dataset in point-cloud form, a Tensorflow implementation of the deepset architecture, and many helpful conversations and advice

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Questions?

- Template