Tackling Black Box Learning using Neural Networks

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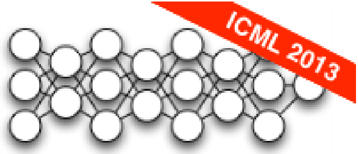
Introduction

ICML Black Box Challenge



- Train a classifier on a dataset that is not human readable
  - Without the knowledge of what the data consists of
- Designed to reduce the usefulness of having a human researcher working in loop with the training algorithm
- Organized by Yoshua Bengio, Ian Goodfellow and Dumitru Erhan as part of **ICML 2013 - Challenges in Representation Learning** [1]

Dataset

- Problem of Semi-supervised Deep Learning

Dataset is divided as

- *Supervised data* - 1000 labeled examples with 1875 features classified into 9 classes
- *Unsupervised data* - 135,735 unlabeled examples again with 1875 features
- *Test data* - 10,000 examples split into
  - 5000 public set examples
  - 5000 private set examples

Baselines

- Random Baseline - **11.1 %**
- Logistic Regression - **21.1 %**
- ZCA + 1 layer net - **41 %**
- ZCA + 3 layer net - **51.5 %**

Benchmark Results

First Position

Sparse Filtering + Feature Selection + SVM with linear kernel - **70.22 %**

Second Position

Pseudo Labels + Denoising Autoencoder + Dropout - **69.58 %** [2]

Third Position

Horizontal and Vertical Ensemble for Classification - **69.14 %**

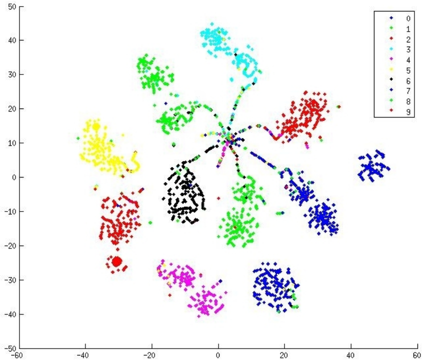
Pseudo Labels

- Generate pseudo labels for unlabeled data

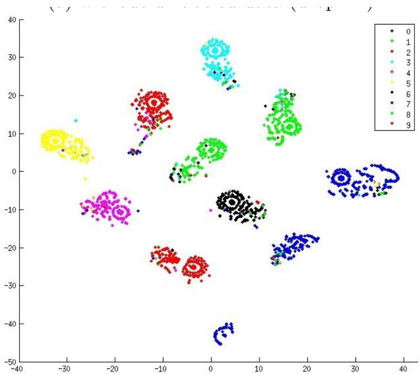
Method

- run a classifier on labeled examples
- determine probable labels for the unlabeled data
- use both sets of data together for training
- recalculate pseudo labels every weight update

- minimizes conditional entropy of class labels for unlabeled data [3]
- prefers low density separation between classes



(a) without unlabeled data (dropNN)



(b) with unlabeled data and Pseudo-Label (+PL)

Figure: t-SNE 2-D embedding of the network output of MNIST test data

Sparse Filtering Approach

- **Unsupervised feature learning**
- A major performance constraint of sparse RBMs or autoencoders is hyperparameter tuning
- Optimizes a simple cost function - **sparsity of L2-normalized features** [4]
- Learn sparsely activated features by
  - **Population Sparsity**
  - **Lifetime Sparsity**
  - **High dispersal**

Sparse Filtering + Supervised Training

- Break the large unsupervised data into **5000** example chunks
- Train a **feedforward Sparse Filter** on these chunks
  - each chunk will be pulled in for training in **data batches** of given count
  - produce 10 feature sets having revised weights
- Picked out the top performing **120 features** out of 1875 initially

Implementation

- Find the **revised representation** for the training and test data
- Train a **feedforward** Neural Network on the supervised data using these revised weights
- Experiments with neural net architecture

Architectural experiments

Num	N	L	Act	D	Opt	Epoch	Batch Size	Acc
Best	**1500**	**2**	**sigmoid**	**0.4**	**adam**	**200**	**128**	**64.74**
1	1000	1	relu	0.4	adam	20	128	60.12
2	200	2	sigmoid	0.4	adam	20	128	51.22
3	1000	2	sigmoid	0.4	adam	100	128	64.02
4	1000	3	sigmoid	0.4	adam	100	128	63.86
5	1000	2	sigmoid	0.4	adam	1000	128	63.80
6	1500	2	sigmoid	0.5	adam	200	128	64.50
7	2000	2	sigmoid	0.4	adam	200	128	64.66
8	1500	2	sigmoid	0.3	adam	200	128	64.66
9	1500	2	sigmoid	0.4	adam	200	256	64.42
10	1500	2	sigmoid	0.4	sgd	200	128	39.50
11	1500	2	relu	0.4	adam	200	128	61.72

Table: Neural Network Experiments on sparsed features
(N = neurons, L = layers, Act = activation, D = dropout, Opt = Optimizer)

Validation Plots on data in original dimensions

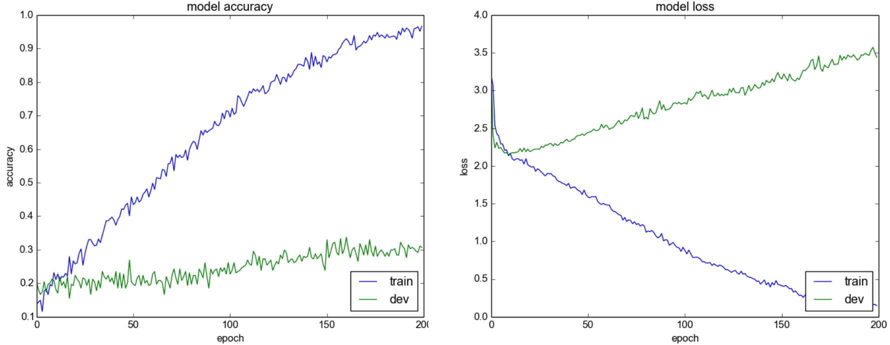


Figure: Validation plots for original data - 1875 dimensions

Validation Plots on data in reduced dimensions

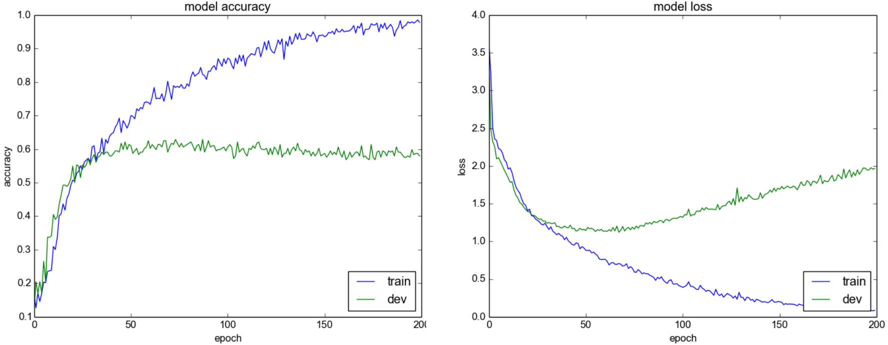


Figure: Validation plots for sparse filtered and ensembled data - 1200 dimensions

Computation of Pseudo Labels

- Train a feedforward neural net on the supervised examples
- Find probable labels of the unsupervised data
- Retrain the neural network with the **combined** data
- At this point, the network might not have learnt the pseudo labels properly or might be **overfitted**
- Retrain the network until **convergence** (till there are no significant changes in predicted labels)

Pseudo Labels Method: Results

Iterations	1 hidden + 1000 neurons	2 hidden + 1500 neurons each
1	56.04	47.86
3	55.48	47.98
6	55.26	48.16
10	55.00	48.10
17	56.08	48.74

Table: Pseudo Labels training after specific iterations of the algorithm

Irregularities

- Giving same weights to both supervised and unsupervised data
- Need to change weight coefficients of unsupervised data in a time dependent manner
- In some cases, maybe the system is actually moving away from true labels
- The code for both the implementations is available on **https://github.com/TitasNandi/ICML-BlackBox-Challenge**

Future Work

Future Work

- Address irregularities in Pseudo Label training
- The success of these methods is **powerful**
  - Reduces annotation overload massively
  - **Black Box** Learning in true sense
- Extend it to data from cQA sites

References

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