

A Deep Learning Approach to Sign Language Recognition using Stacked Sparse Autoencoders

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The Problem

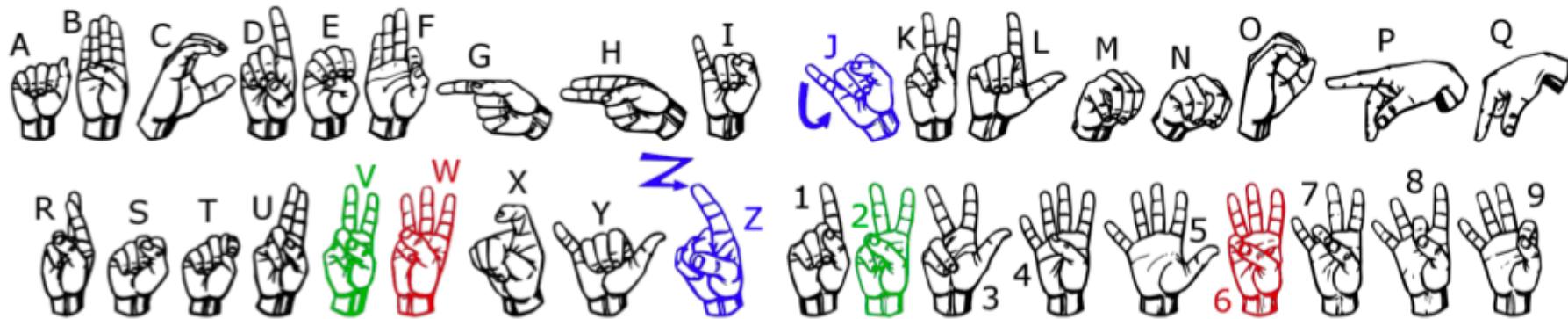
- American Sign Language (ASL)



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The Data

- *Learning the American Sign Language (ASL)*



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The Data

- *Learning* the American Sign Language (ASL)



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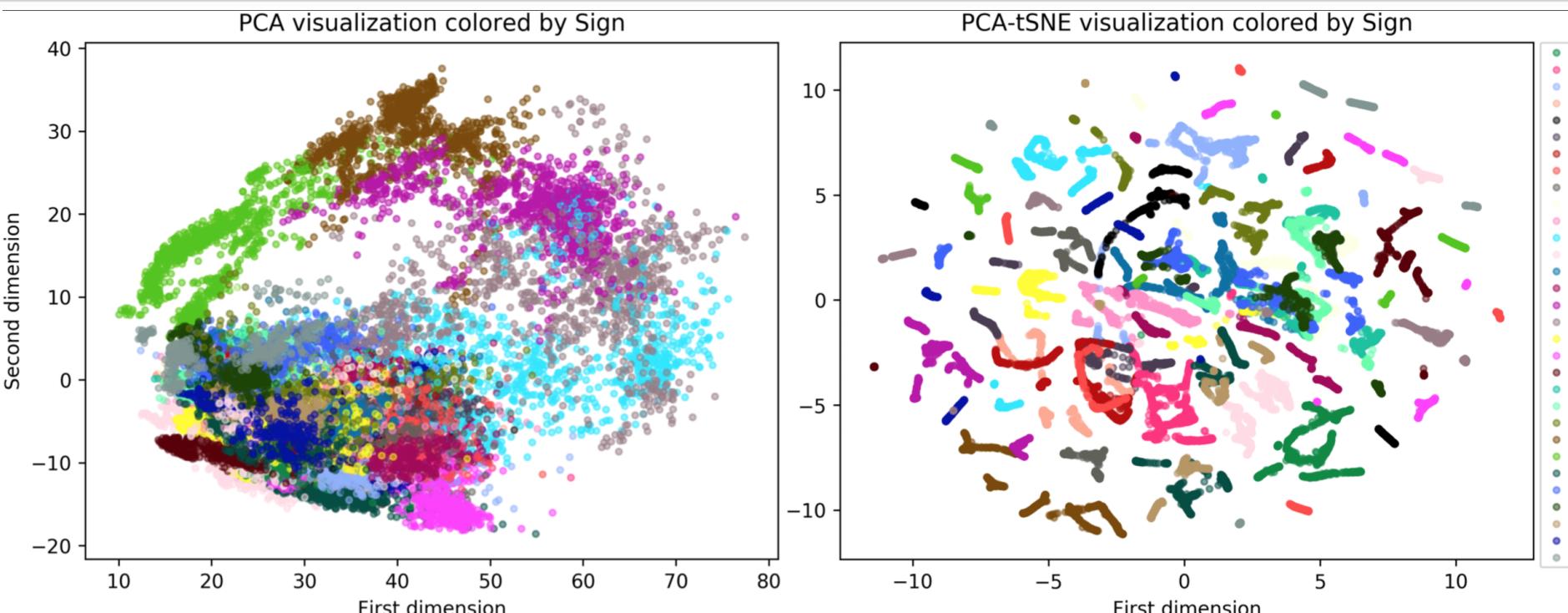
The Data

- *Learning* the American Sign Language (ASL)



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The Data



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Existing Approaches

Method	Class type	# of class	# of subj.	Test w/ diff.	Input	Accur.(%)
Nagi <i>et al.</i> [8]	Gesture	6	-	No	Color	96
Van den Bergh <i>et al.</i> [14]	Gesture	6	-	No	Color & Depth	99.54
Isaacs <i>et al.</i> [3]	Alphabets	24	-	-	Color	99.9
Pugeault <i>et al.</i> [10]	Alphabets	24	5	-	Color	73
Pugeault <i>et al.</i> [10]	Alphabets	24	5	-	Depth	69
Pugeault <i>et al.</i> [10]	Alphabets	24	5	-	Color & Depth	75
Kuznetsova <i>et al.</i> [6] (50/50)%	Alphabets	24	5	No	Depth	87
Kuznetsova <i>et al.</i> [6] (4/1)	Alphabets	24	5	Yes	Depth	57
Dong <i>et al.</i> [2] (50/50)%	Alphabets	24	5	No	Depth	90
Dong <i>et al.</i> [2] (4/1)	Alphabets	24	5	Yes	Depth	70
Ours (re-training) (50/25/25)%	Alph. & Digit	31	5	No	Depth	99.99
Ours (re-training) (3/1/1)	Alph. & Digit	31	5	Yes	Depth	75.18
Ours (re-training) (4/1)	Alph. & Digit	31	5	Yes	Depth	78.39
Ours (fine-tuning) (3/1/1)	Alph. & Digit	31	5	Yes	Depth	83.58
Ours (fine-tuning) (4/1)	Alph. & Digit	31	5	Yes	Depth	85.49

- Kang, B., Tripathi, S., Nguyen, T.Q.: Real-time sign language fingerspelling recognition using convolutional neural networks from depth map. In: Pattern Recognition (ACPR), 2015 3rd IAPR Asian Conference on, pp. 136–140. IEEE (2015)

Existing Solutions

- Learning the American Sign Language (ASL) **with CNNs**



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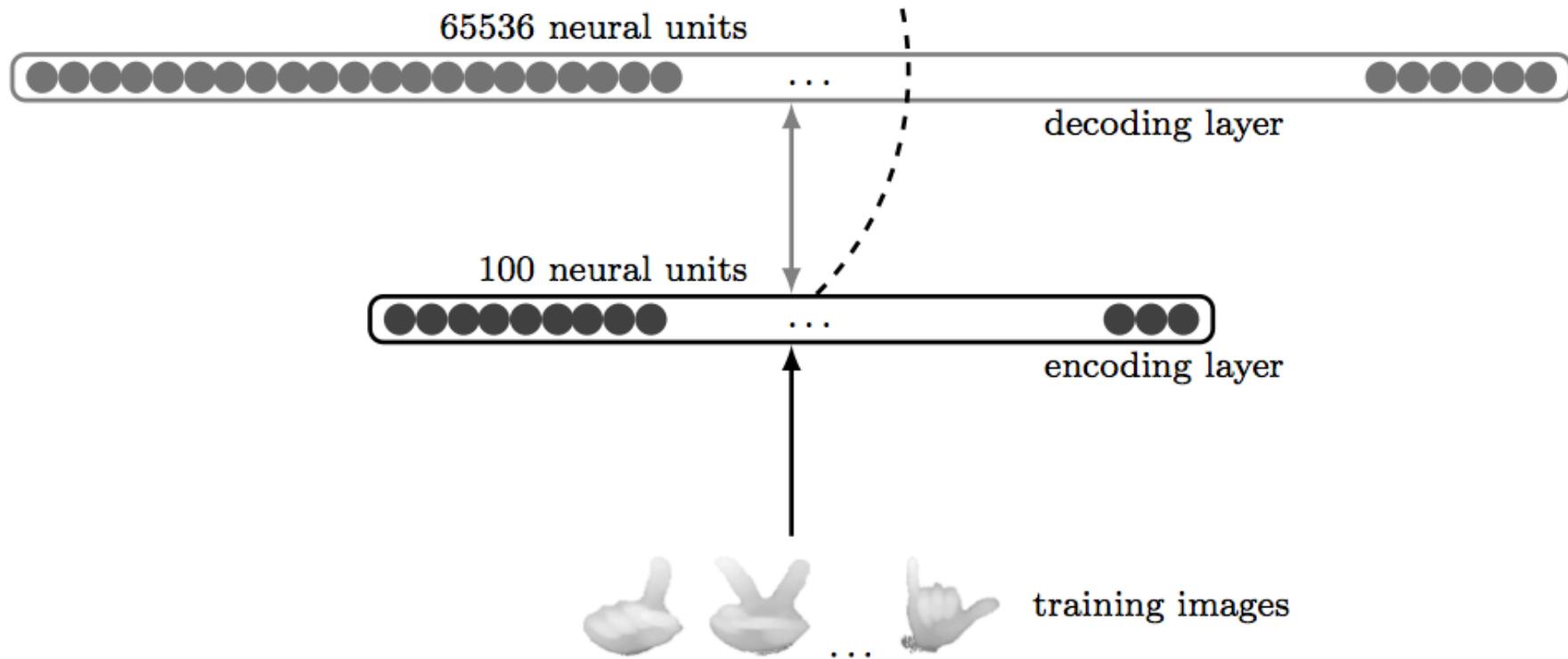
The Proposal

- Learning the American Sign Language (ASL)
with Auto-encoders
 - *Simpler than CNN*
 - *More efficient than CNN (deployed)*
 - *Faster to train than CNN (for a similar number of layers)*
 - *Similar performance to a CNN*
 - *CNNs are not the panacea in pattern recognition on images or computer vision*

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The Proposal

- *Lets talk about Auto-encoders*



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The Proposal

- *Lets talk about Auto-encoders*

$$L = \frac{1}{N} \|\mathbf{x}_n - \hat{\mathbf{x}}_n\|_2^2 + \theta_w \frac{1}{2} \sum_{l=1}^L \|\mathbf{w}^l\|_2^2 + \theta_s \sum_{m=1}^M KL(\theta_\alpha \| \bar{\alpha}_m)$$



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The Proposal

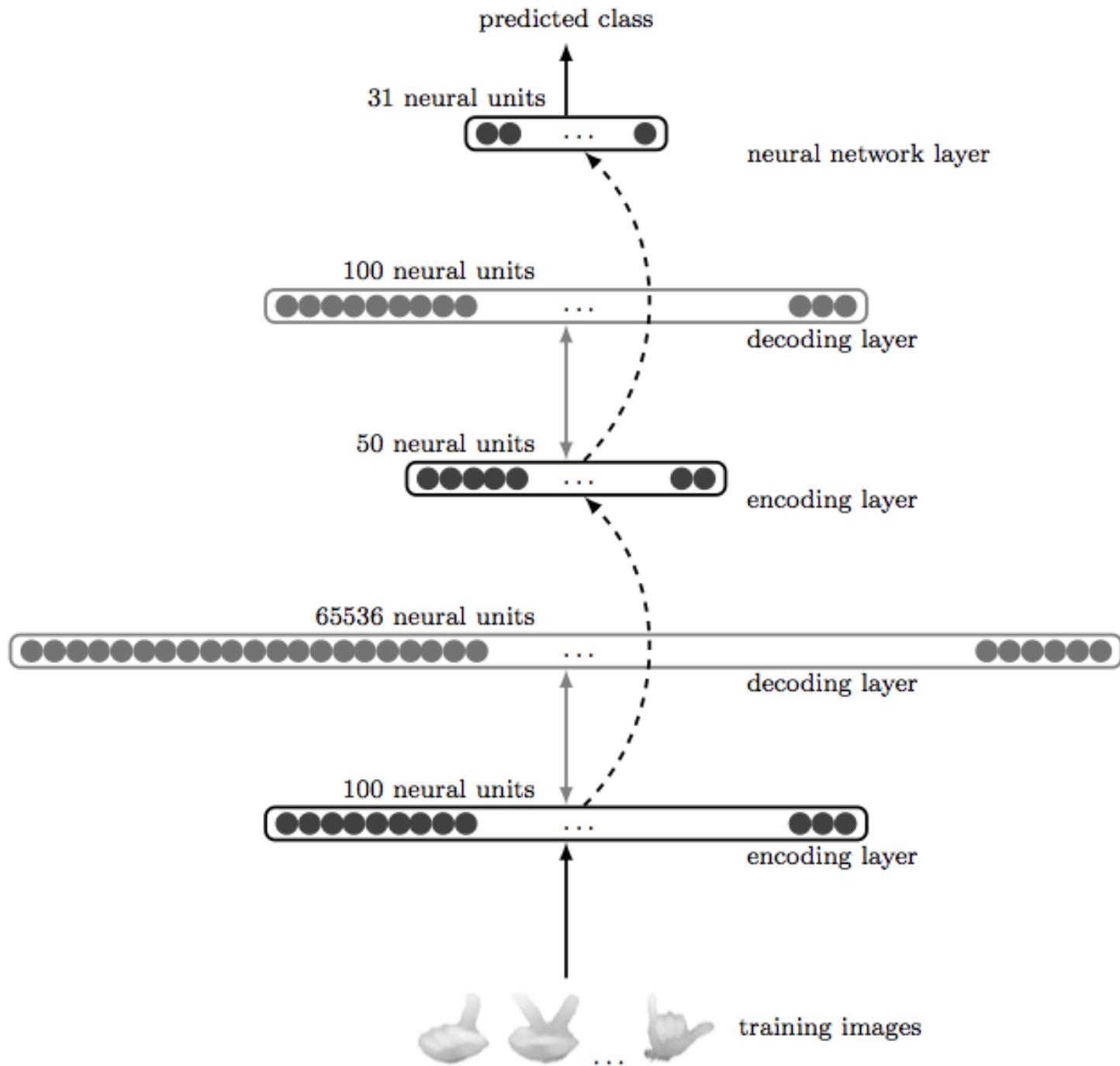
- *Lets talk about Auto-encoders*

$$L = \frac{1}{N} \|\mathbf{x}_n - \hat{\mathbf{x}}_n\|_2^2 + \theta_w \frac{1}{2} \sum_{l=1}^L \|\mathbf{w}^l\|_2^2 + \theta_s \sum_{m=1}^M KL(\theta_\alpha \| \bar{\alpha}_m)$$

$$\sum_{m=1}^M KL(\theta_\alpha \| \bar{\alpha}_m) = \sum_{m=1}^M \theta_\alpha \log \left(\frac{\theta_\alpha}{\bar{\alpha}_m} \right) + (1 - \theta_\alpha) \log \left(\frac{1 - \theta_\alpha}{1 - \bar{\alpha}_m} \right)$$

$$\bar{\alpha}_m = \frac{1}{N} \sum_{n=1}^N \psi \left(\mathbf{w}_m^{(l)T} \mathbf{x}_n + b_m^{(l)} \right)$$

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output $\mathbf{d}_n \in \mathbb{R}_+^{31}$

softmax activations



$\tilde{\mathbf{x}}_n \in \mathbb{R}_+^{50}$

logistic activations



$\hat{\mathbf{x}}_n \in \mathbb{R}_+^{100}$

logistic activations



$\mathbf{x}_n \in \mathbb{N}_+^{65536}$

sparse encoding layer

$$E = \frac{1}{N} \sum_{n=1}^N \sum_{c \in C} \hat{d}_{cn} \ln d_{cn} + (1 - \hat{d}_{cn}) \ln(1 - d_{cn})$$

neural network layer



input image

RIST

Results

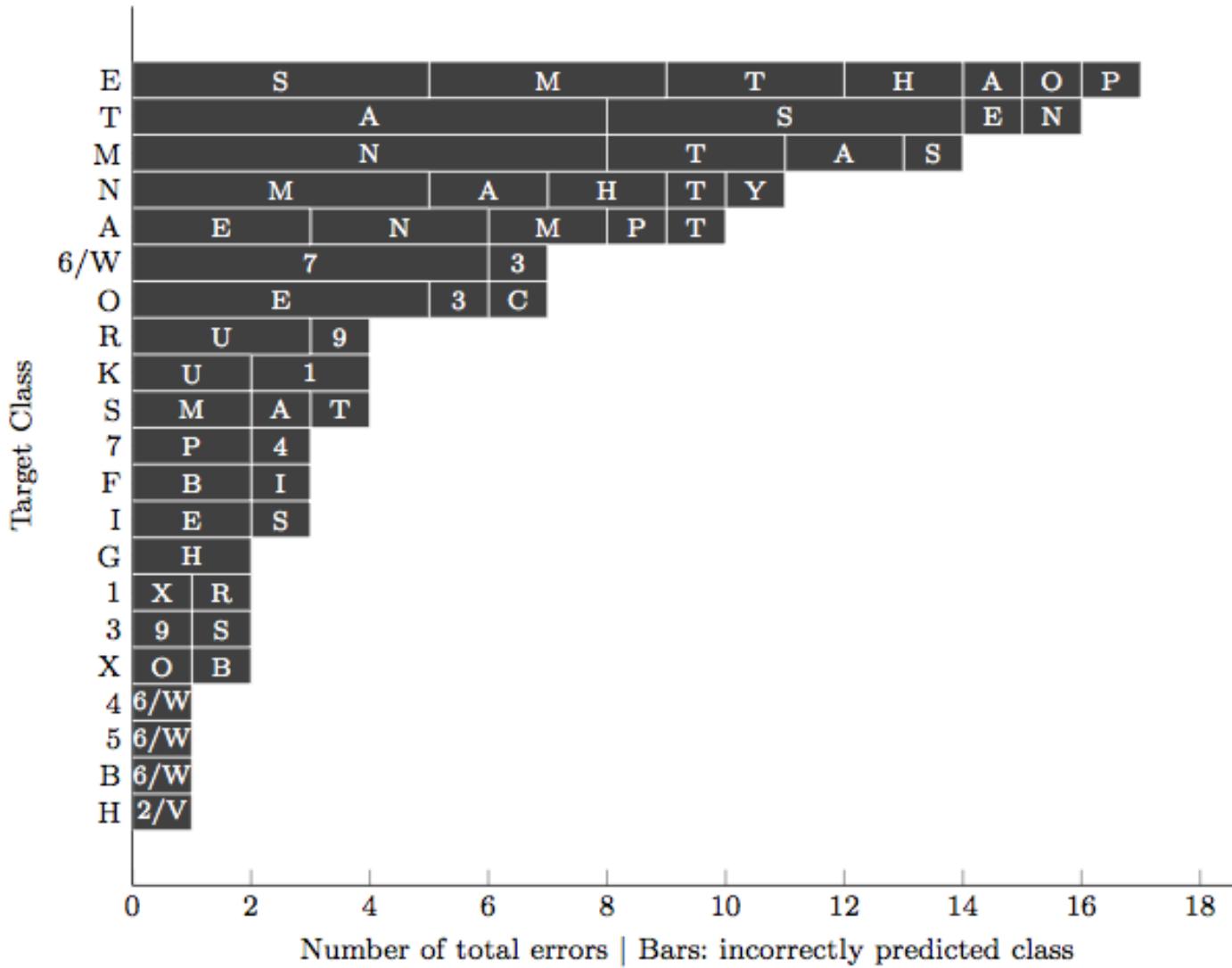
- *of the Auto-encoders*

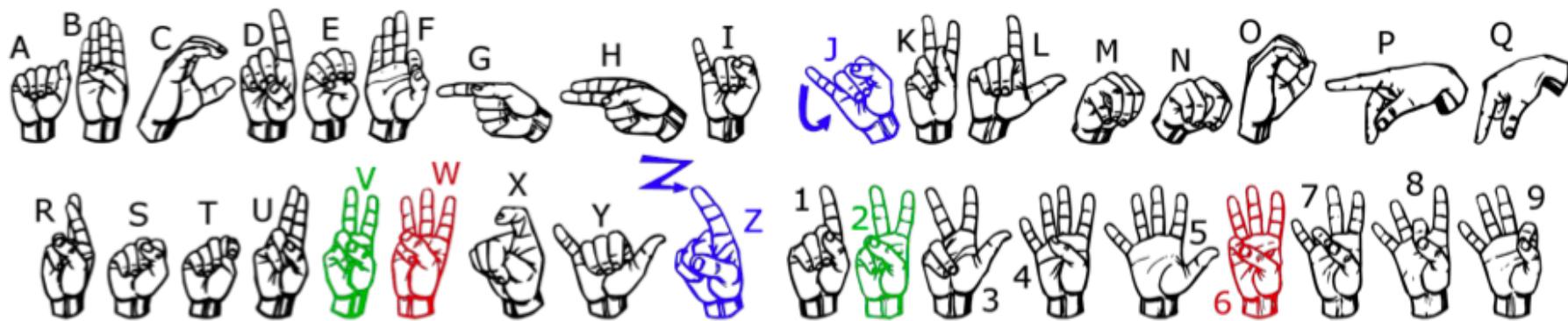
	S1	S2	S3	S4	S5	Avg.
ACC	0.9748	0.9923	0.9935	0.9929	0.9910	0.9889
SPC	0.9991	0.9997	0.9998	0.9998	0.9997	0.9996
MAE	0.1483	0.0640	0.0373	0.0347	0.0494	0.0667



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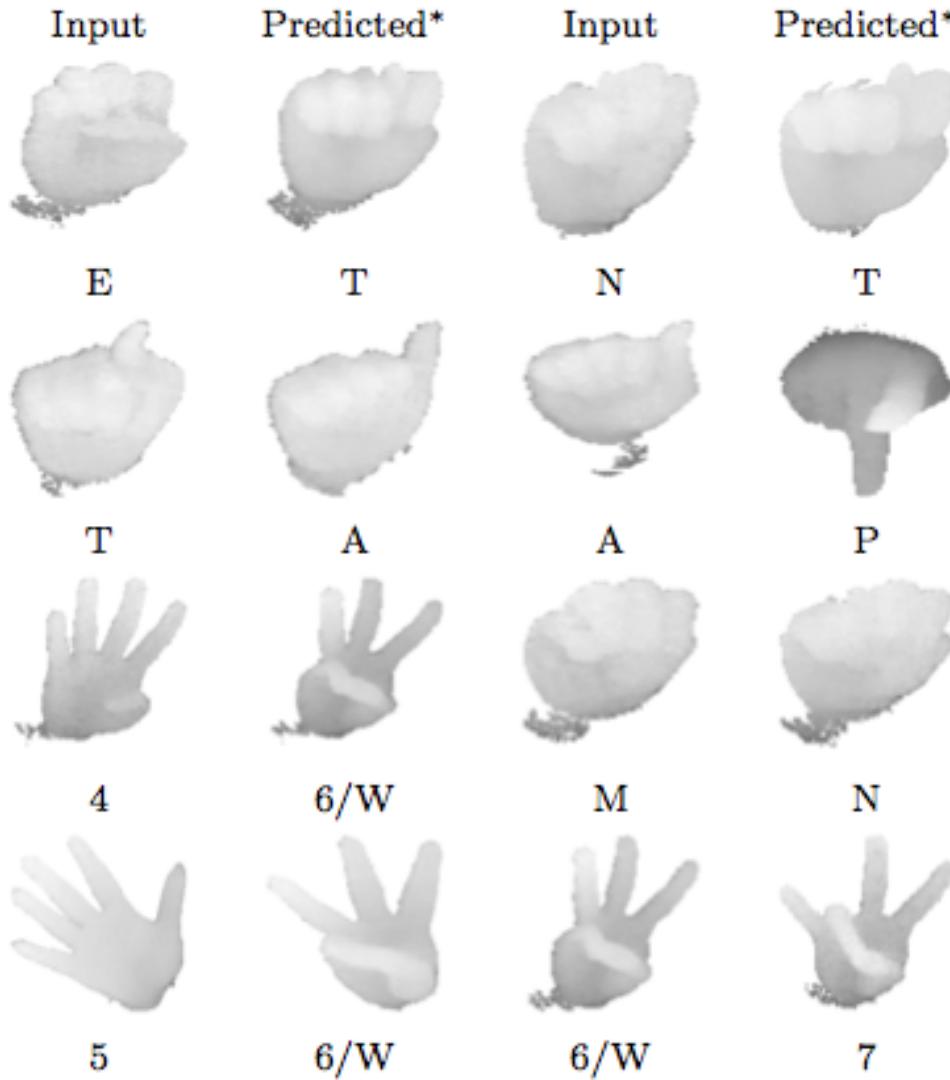
Results





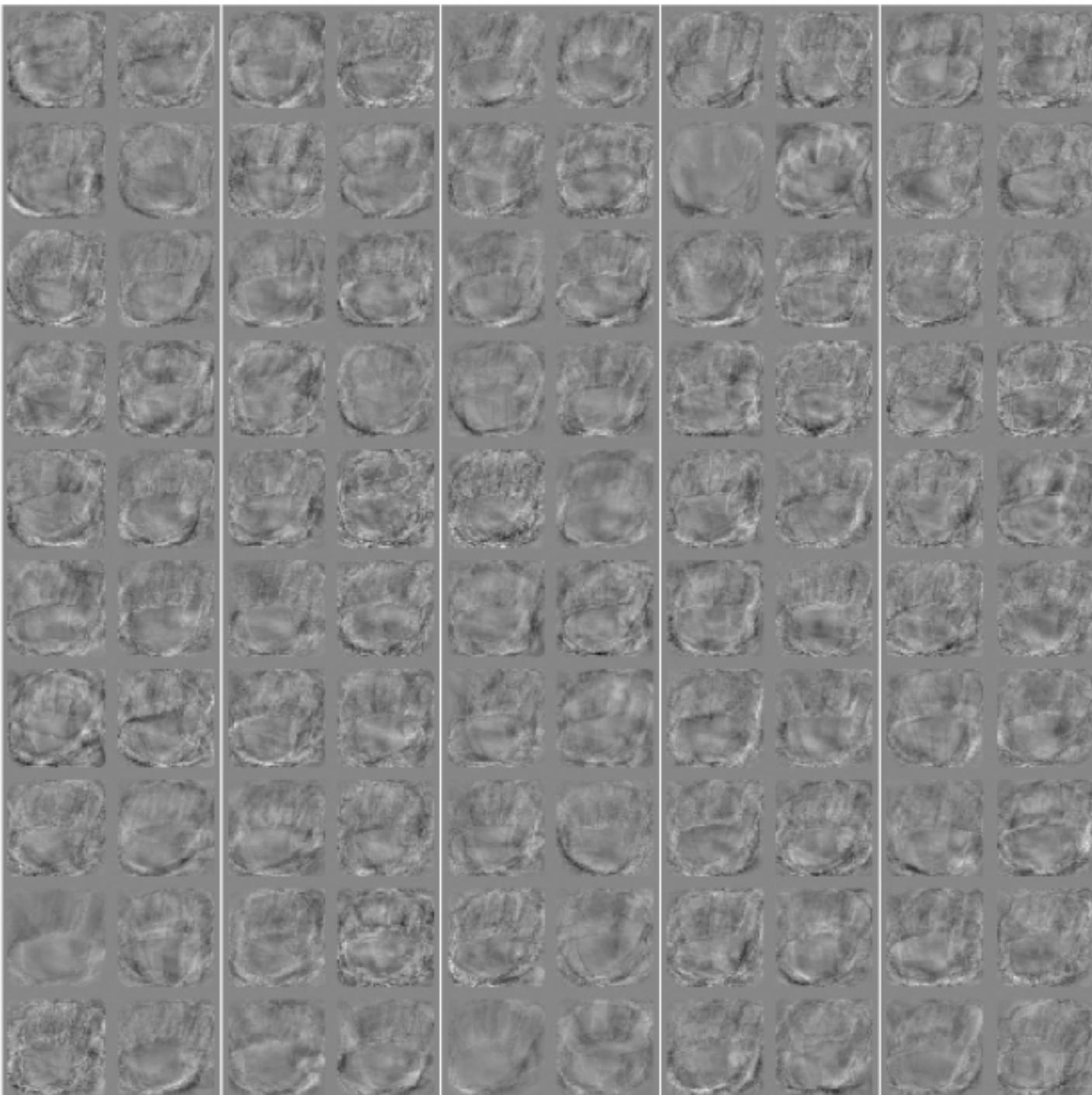
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Results



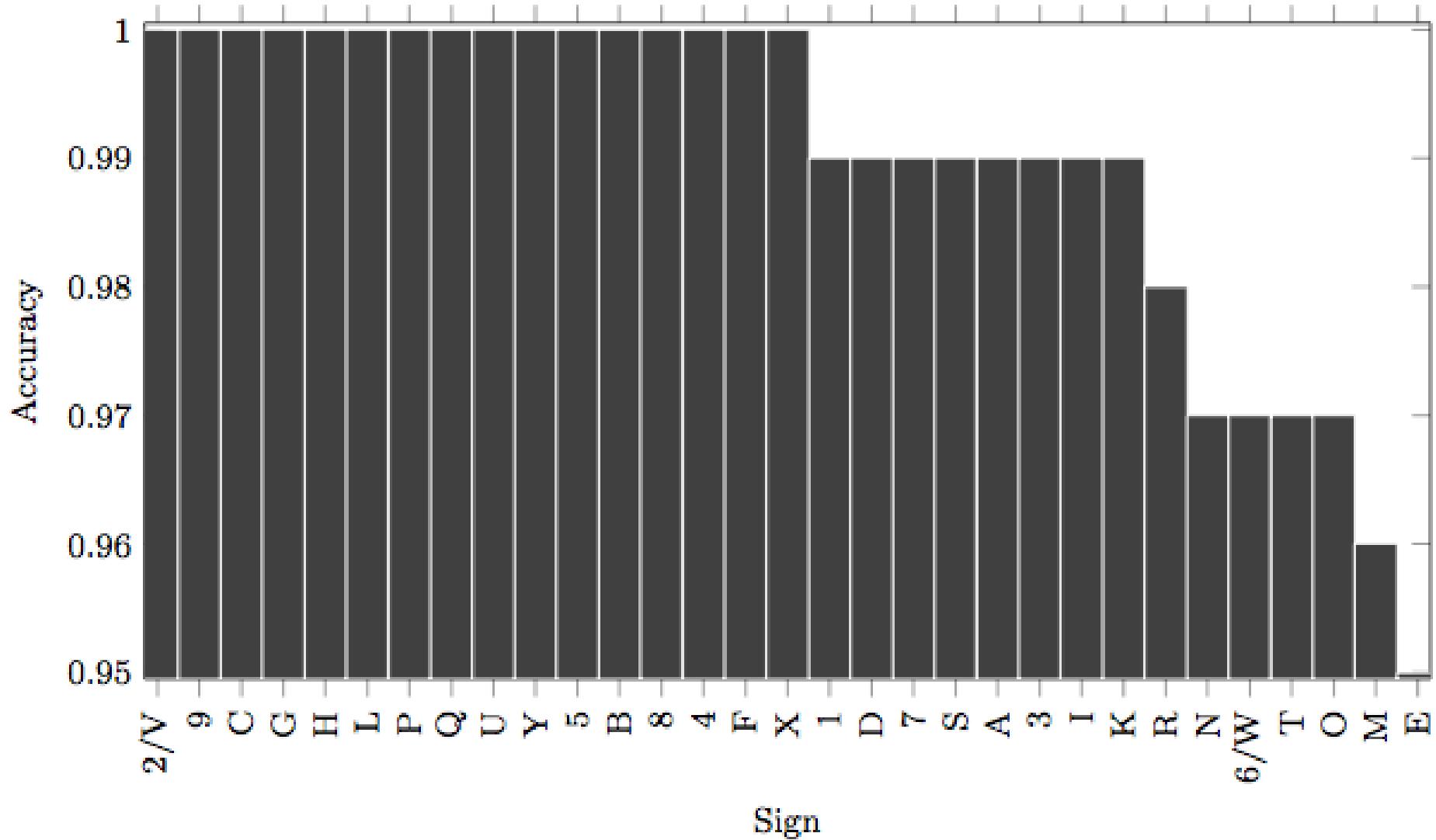
RIST

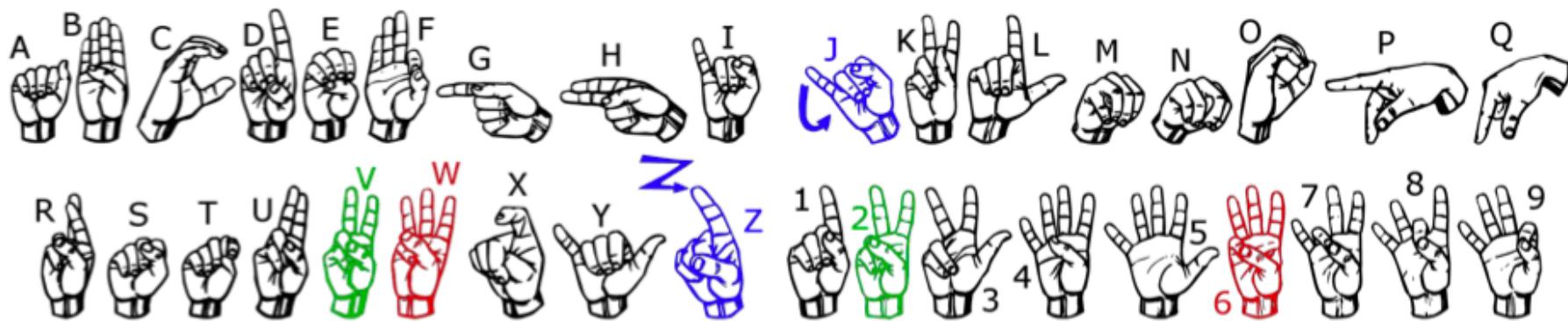
MAN



ST

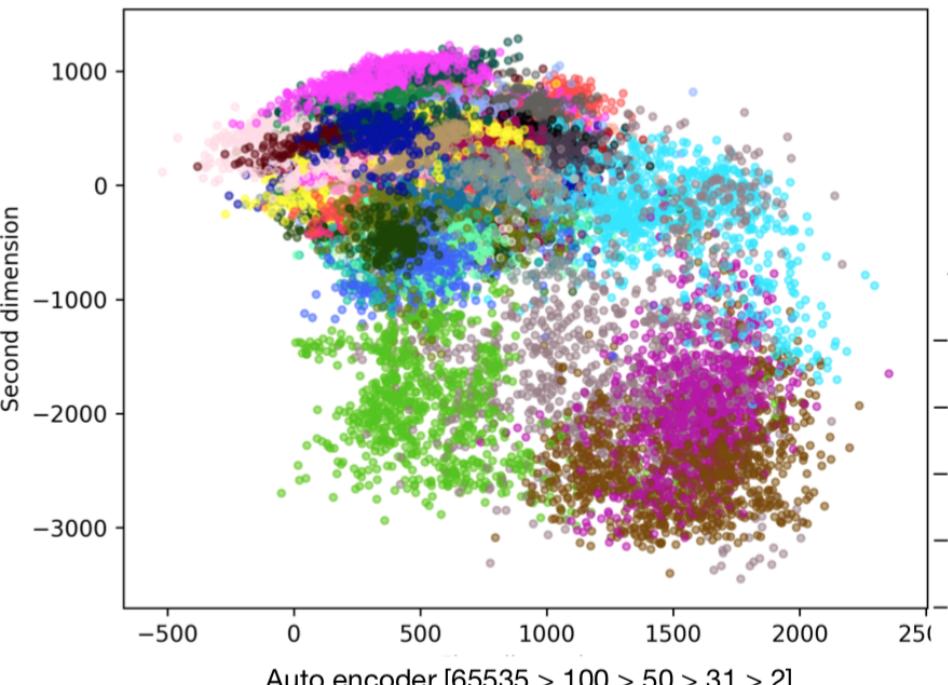
Results



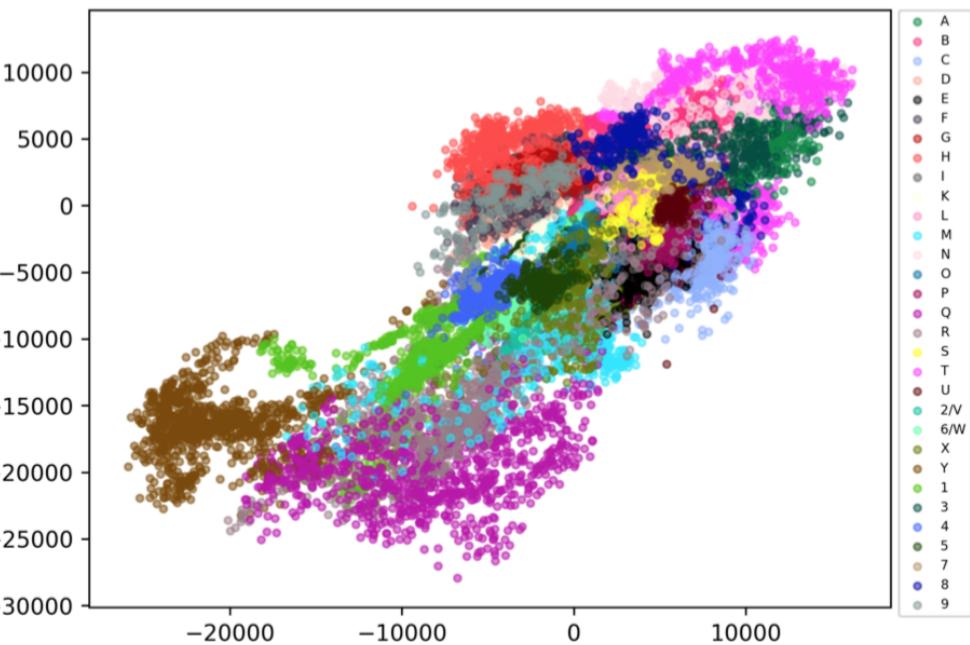


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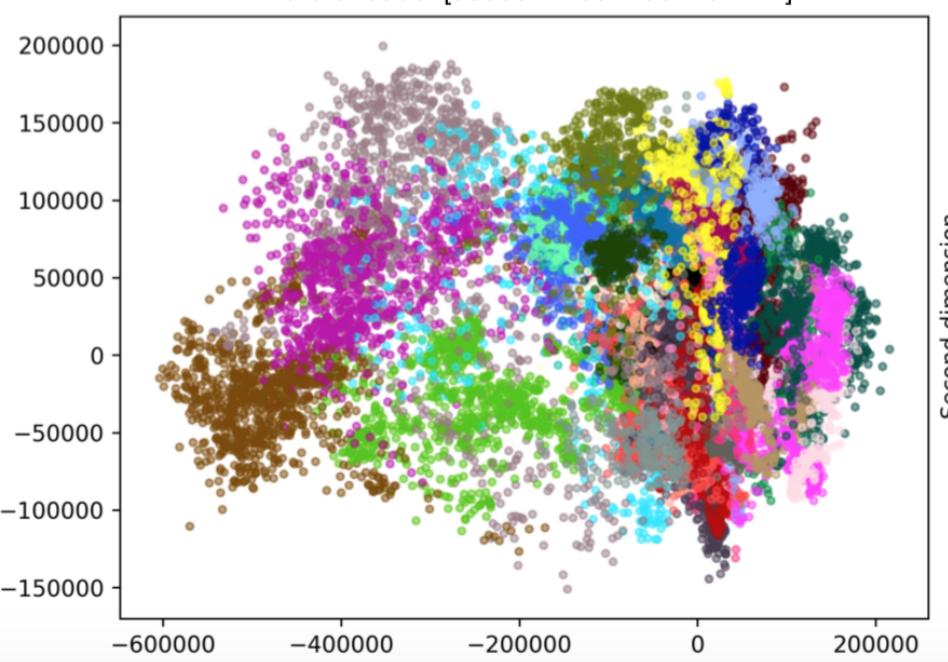
Auto encoder [65535 > 31 > 2]



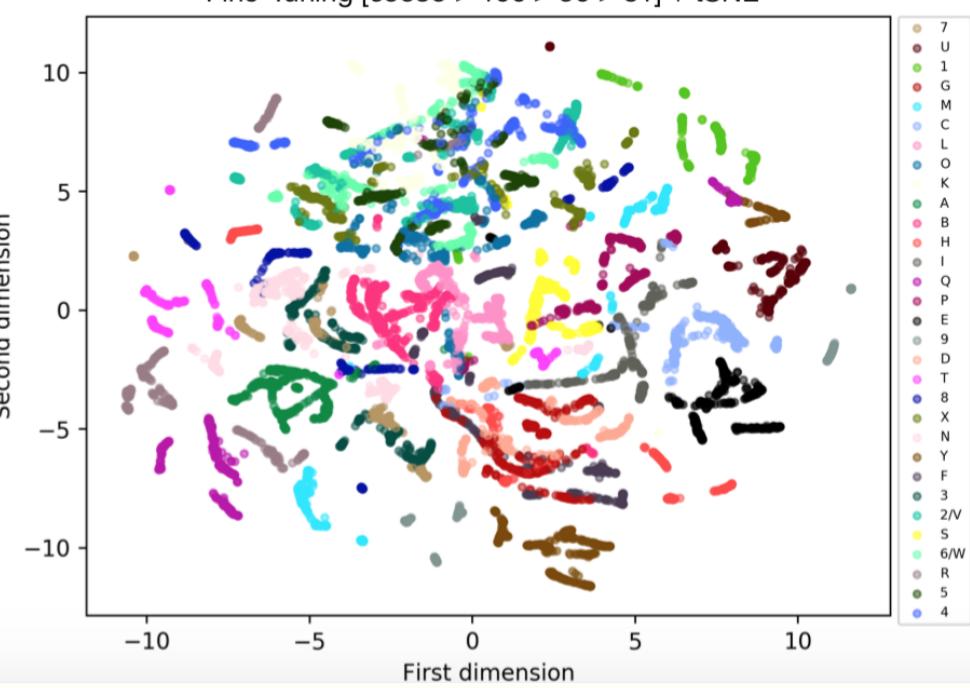
Auto encoder [65535 > 50 > 31 > 2]



Auto encoder [65535 > 100 > 50 > 31 > 2]



Fine-Tuning [65535 > 100 > 50 > 31] + tSNE



Chameleon Setup

- **Resource type:** bare metal/CHI@TACC
- **Lease:** GPU P100
- **Image:** CC-Ubuntu16.04-CUDA8
- **Libraries:**
 - cuDNN
 - libatlas-dev



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Libraries: cuDNN

```
Connection closed by 129.114.109.140
Pablos-MacBook-Air:~ ssh rivas_perea$ ssh cc@129.114.109.140
Welcome to Ubuntu 16.04.2 LTS (GNU/Linux 4.4.0-72-generic x86_64)

 * Documentation:  https://help.ubuntu.com
 * Management:     https://landscape.canonical.com
 * Support:        https://ubuntu.com/advantage

Get cloud support with Ubuntu Advantage Cloud Guest:
 http://www.ubuntu.com/business/services/cloud

0 packages can be updated.
0 updates are security updates.

Last login: Tue Sep 12 16:35:00 2017 from 204.210.149.122
cc@Fox:~$ sudo cp cuda/include/cudnn.h /usr/local/cuda/include
cc@Fox:~$ sudo cp cuda/lib64/libcudnn* /usr/local/cuda/lib64
cc@Fox:~$ sudo chmod a+r /usr/local/cuda/include/cudnn.h /usr/local/cuda/lib64/libcudnn*
cc@Fox:~$
```

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Chameleon Setup

- *Resource type*: bare metal/CHI@TACC
- *Lease*: GPU P100
- *Image*: CC-Ubuntu16.04-CUDA8
- *Packages*:
 - `gcc`, `gfortran`
 - `python-{numpy scipy matplotlib}`
 - `tensorflow`
 - `glances`, `nvidia-ml-py`, `screen`



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Conclusions

- Learning the American Sign Language (ASL)
with Auto-encoders
 - *Simpler than CNN*
 - *More efficient than CNN*
 - *Faster to train than CNN*
 - *Similar performance to a CNN*
 - *CNNs are not the panacea in pattern recognition on images or computer vision* (no free lunch theorem)

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Interested in code? Check Deep's repo:

<https://github.com/DeepDand/research>

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