Data Science for Neuroscience

The Brain as Inspiration, Model and Data Source

Doctoral Thesis Defence

by

Chris Häusler

Machine Learning and Neuroscience
A Two Part & Two way relationship

1. Neuroscientists use Machine Learning

2. Cross Pollination

- Neuroscience to ML:
  - ANNs
  - Neuromorphic Hardware
  - Brain inspired computation (eg: Honeybee olfaction)
- ML to Neuroscience:
  - Hopfield for Associative memory
  - Slow Feature Analysis for Complex Cell organisation and Place cells
  - RBMs as a generalised representation learning framework and model for perceptual bistability

The Brain as

- *Inspiration*

  Advance the state-of-the-art through a novel training method for unsupervised Artificial Neural Networks called *Temporal Autoencoding*

- *Model*

  Hypothesise learning in visual cortex by applying *Temporal Autoencoding* to learn dynamic representations of natural image sequences.

- *Data Source*

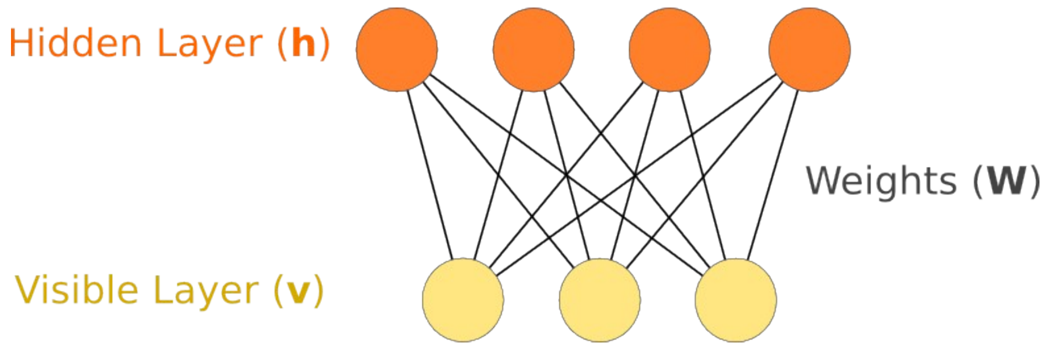
  Apply statistical and machine learning techniques to help better understand neural representation of movement in the human basal ganglia.

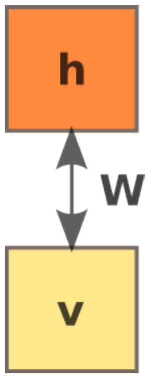
The Brain as Inspiration

Temporal Autoencoding
Improves Generative Models of Time Series

[Chris Häusler, Alex Susemihl, Martin Nawrot, Manfred Opper]
Submitted to *Neurocomputing*

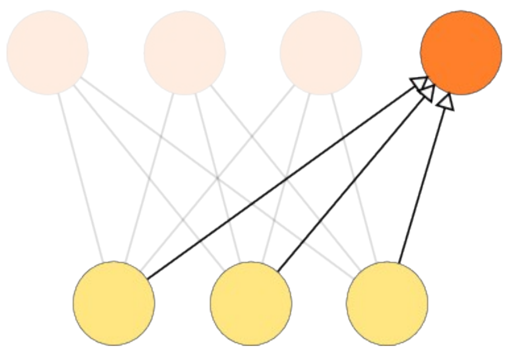
Restricted Boltzmann Machine (RBM)





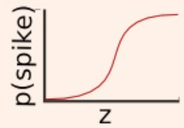
[Hinton, et al. 2006]

Propogate Up



$$\mathbf{z} = \mathbf{v}\mathbf{W}^T + \mathbf{b}$$

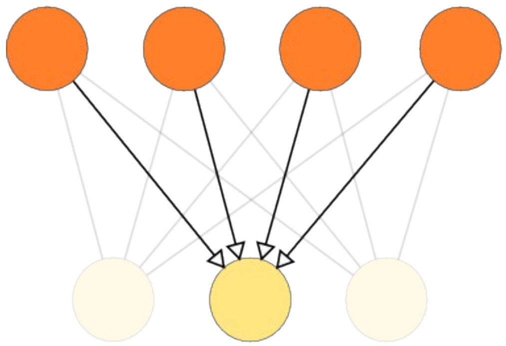
$\mathbf{h} =$



$\rightarrow$

$\rightarrow$ **[0, 1]**

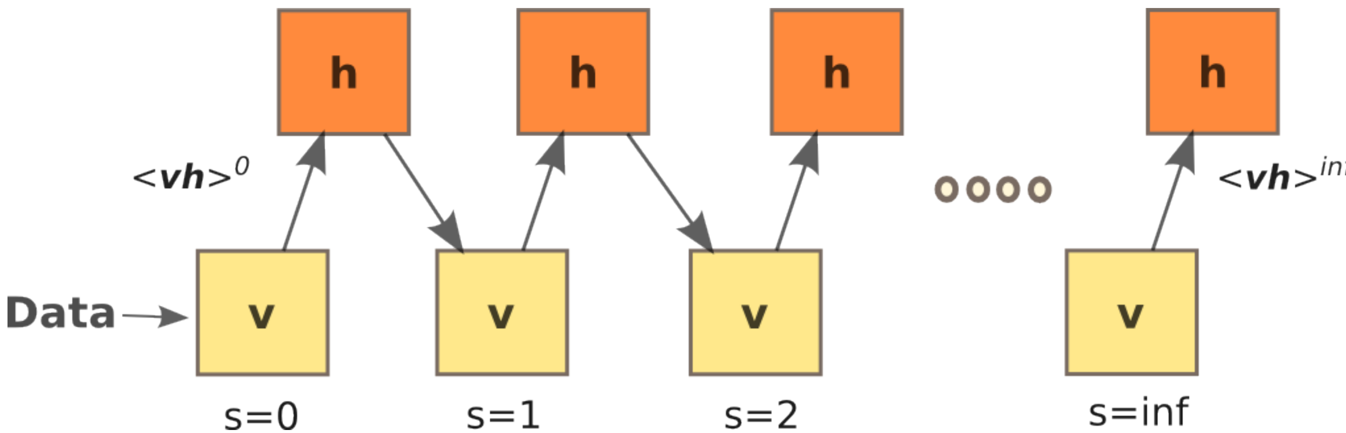
Propogate Down



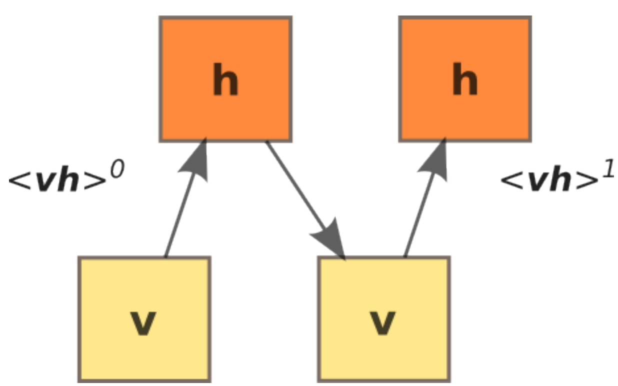
$$\mathbf{v} = \mathbf{W}^T\mathbf{h} + \mathbf{b}$$

Training RBMs

To Infinity?

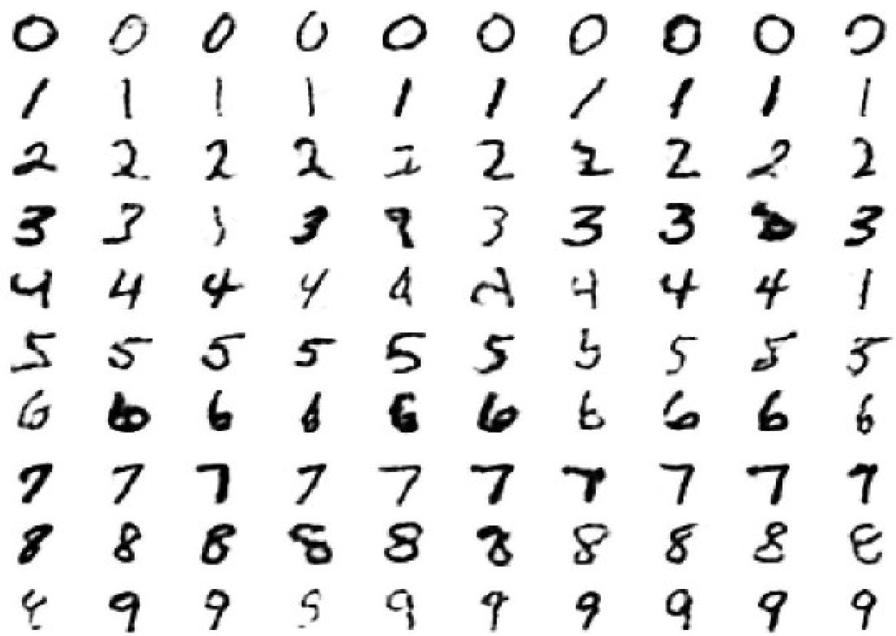


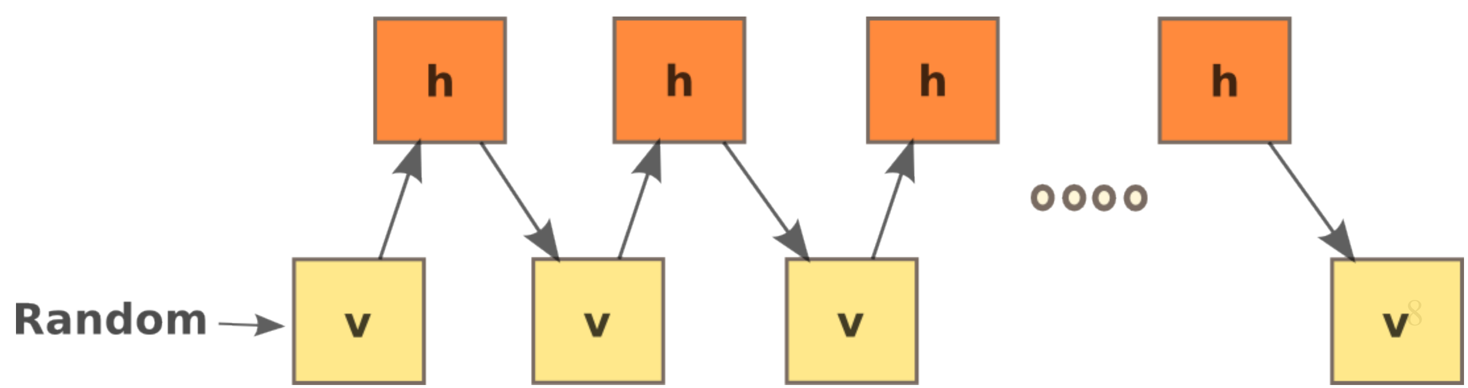
Or just once?



$$\Delta \mathbf{w} = \varepsilon \, (\langle \mathbf{vh} \rangle^0 - \langle \mathbf{vh} \rangle^1)$$

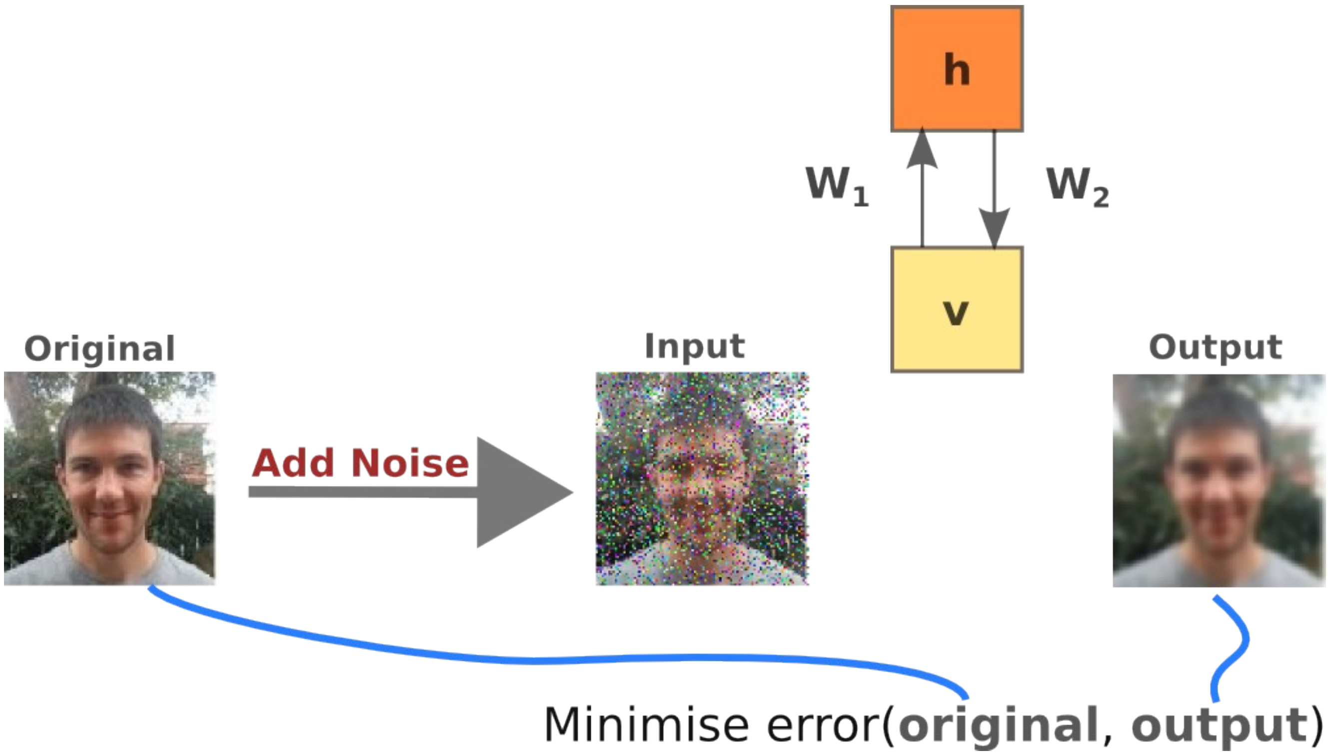
Generating with an RBM





[Hinton, et al. 2006]

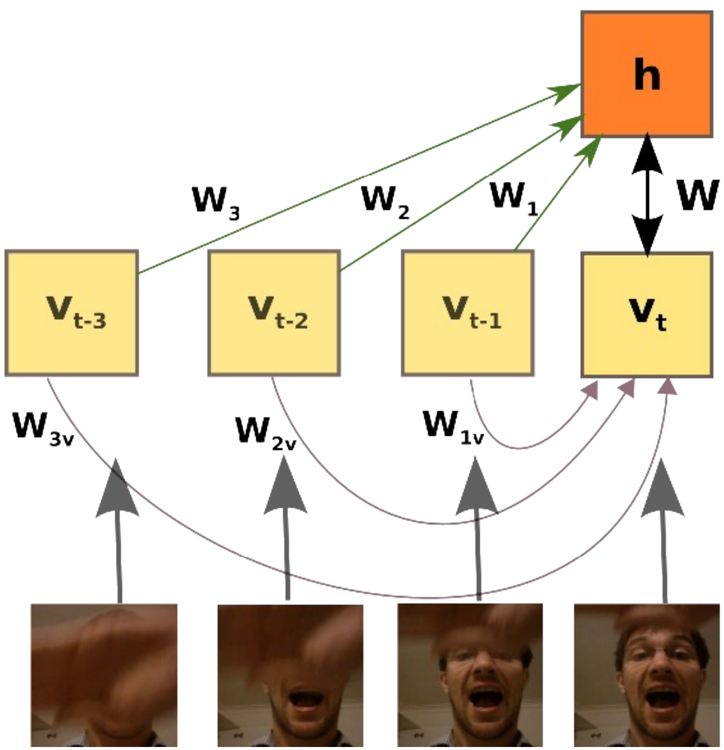
Denoising Autoencoders



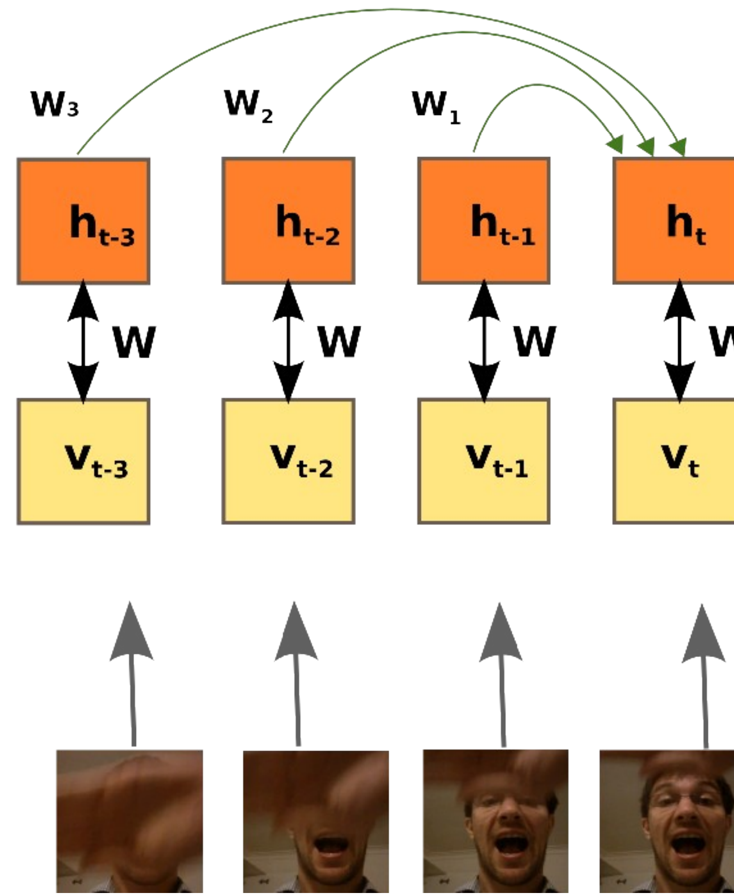
[Vincent, et al. 2008]

RBMs Through Time

Conditional RBM (CRBM)



Temporal RBM (TRBM)

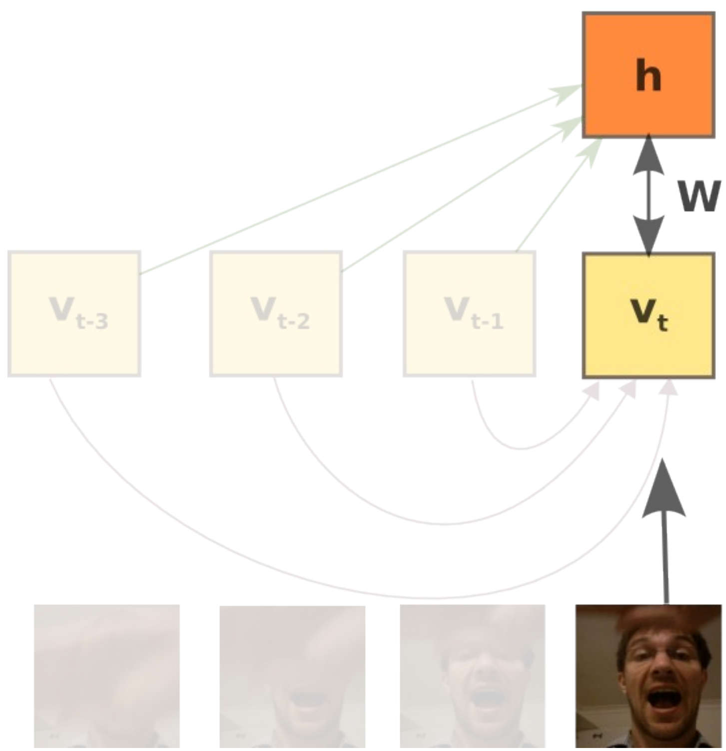


[Taylor, et al. 2007]

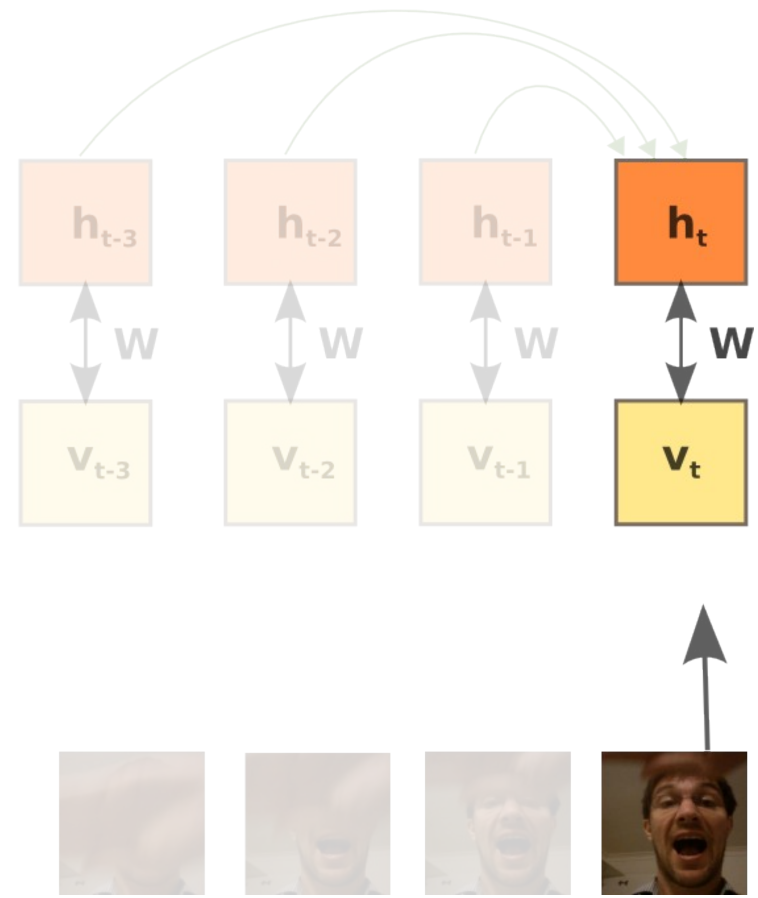
[Sutskever, et al. 2007]

Training. Step 1

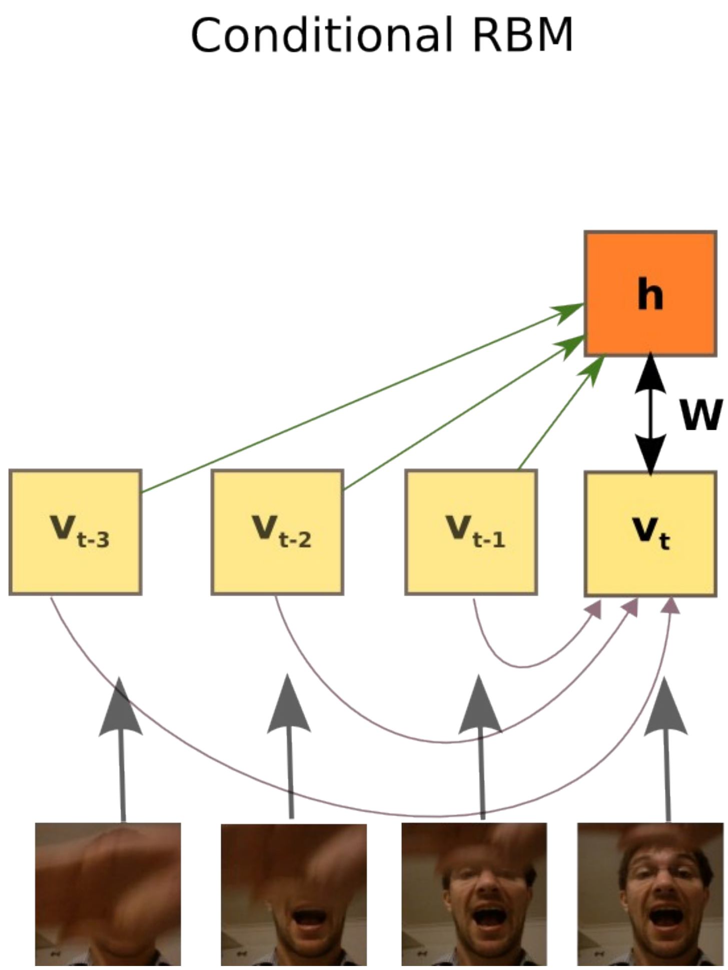
Conditional RBM

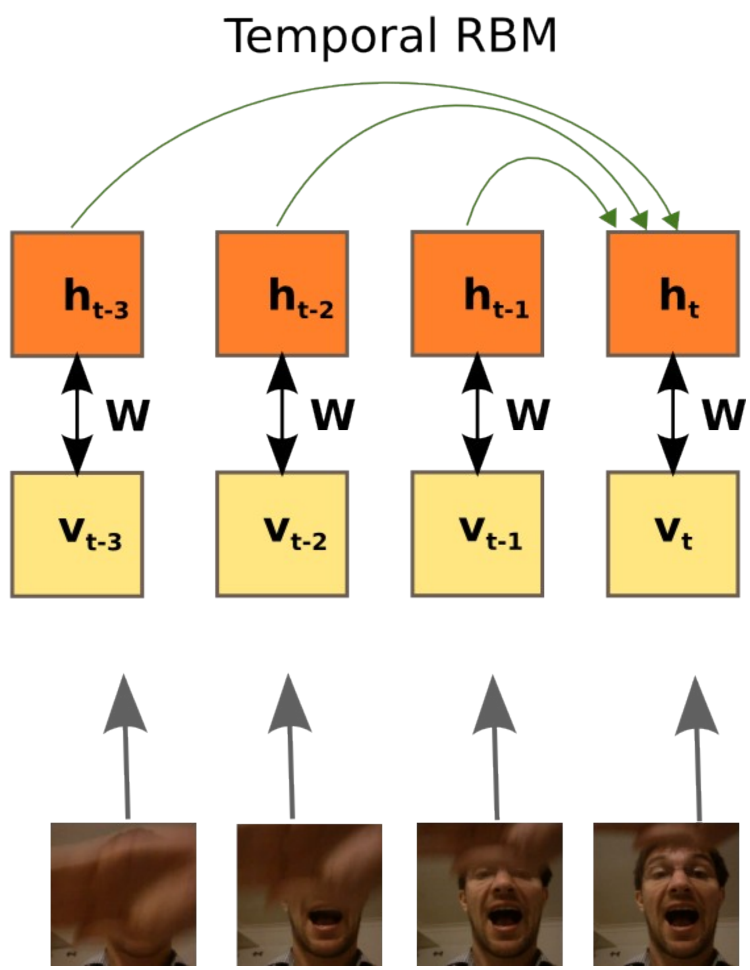


Temporal RBM

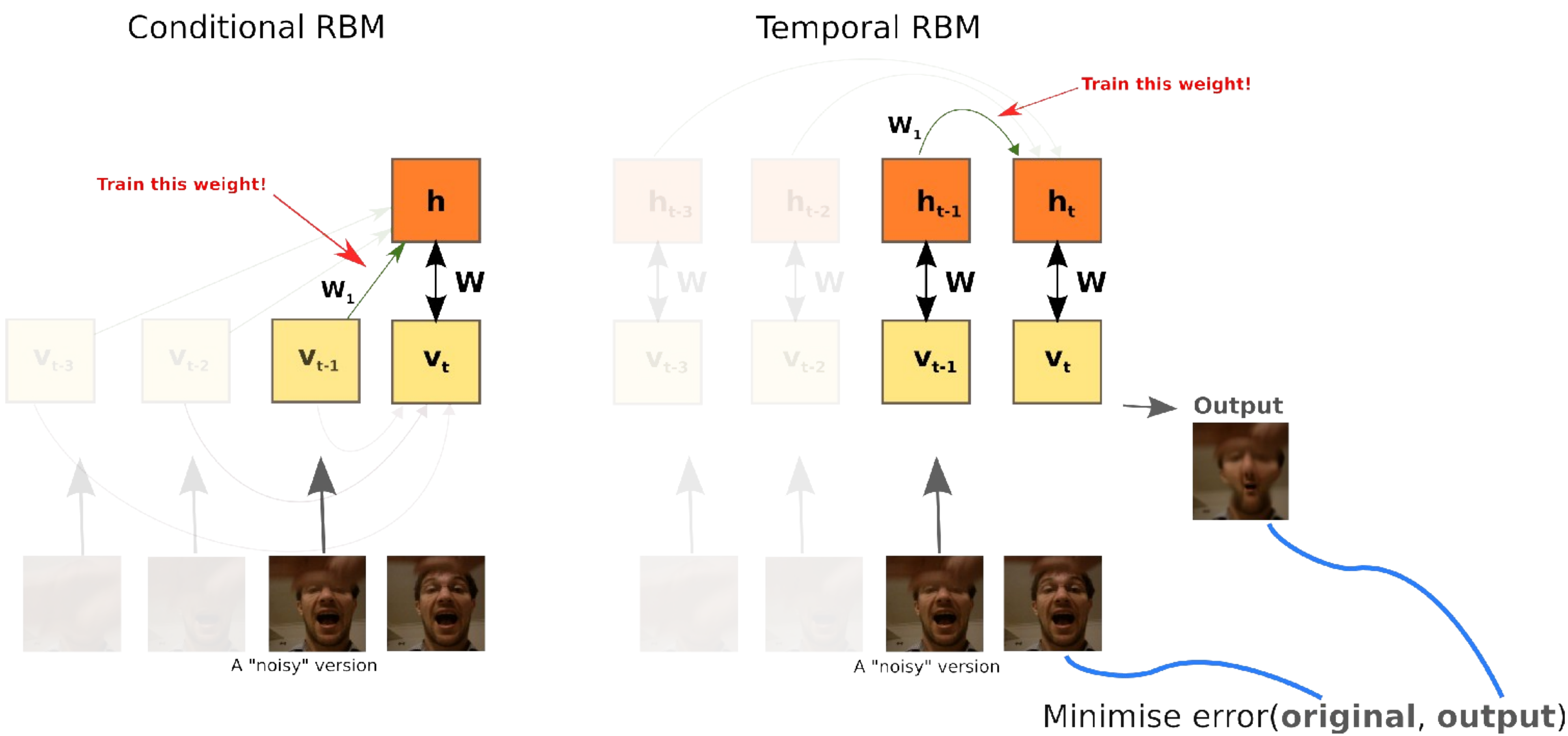


Training. Step 3

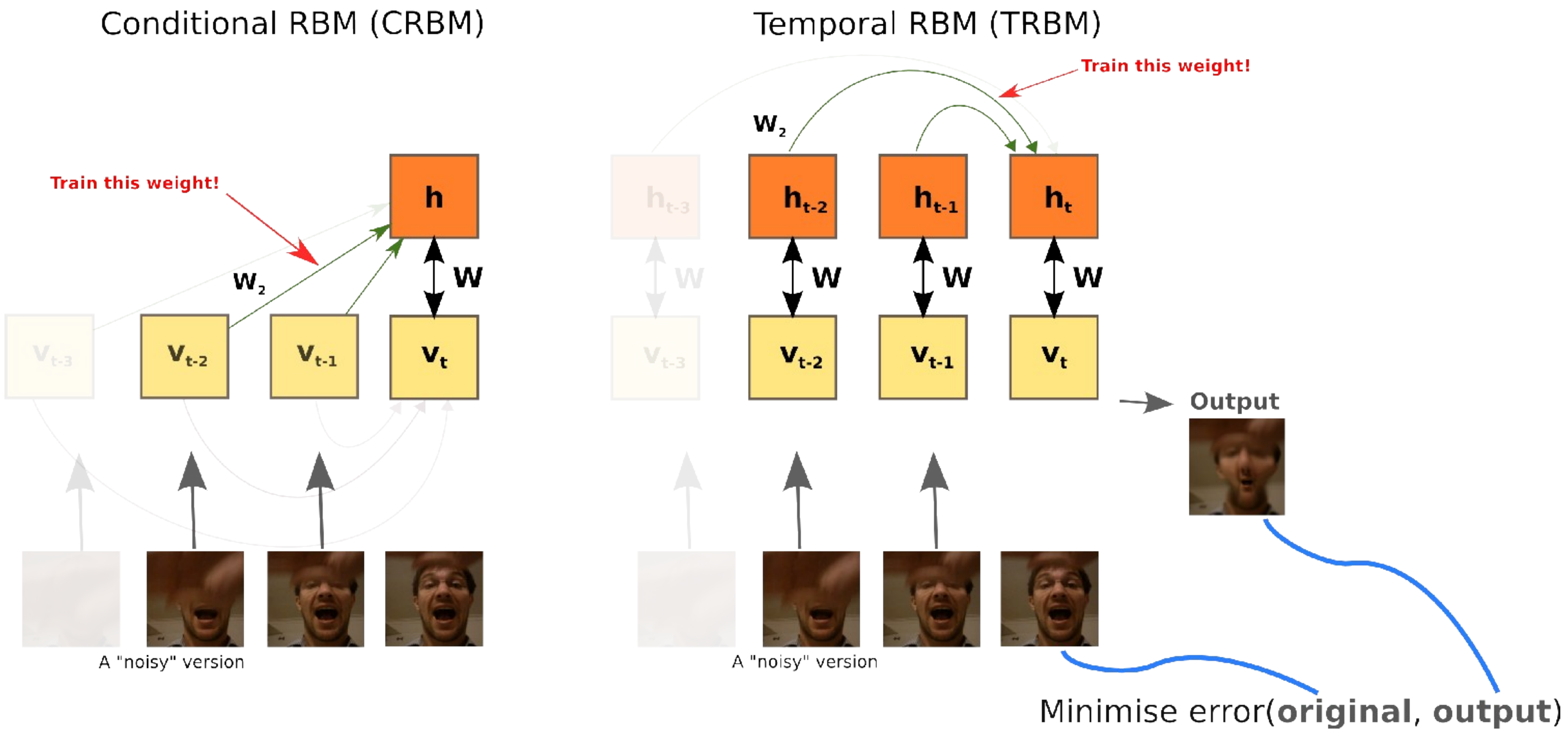




Training. Step 2: Temporal Autoencoding (NEW)

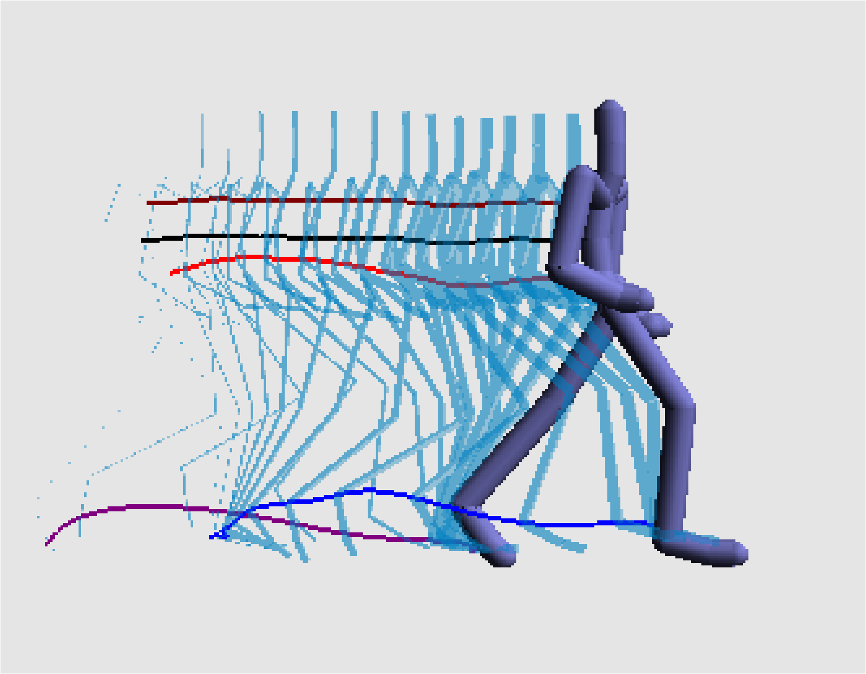


Training. Step 2: Temporal Autoencoding (NEW)



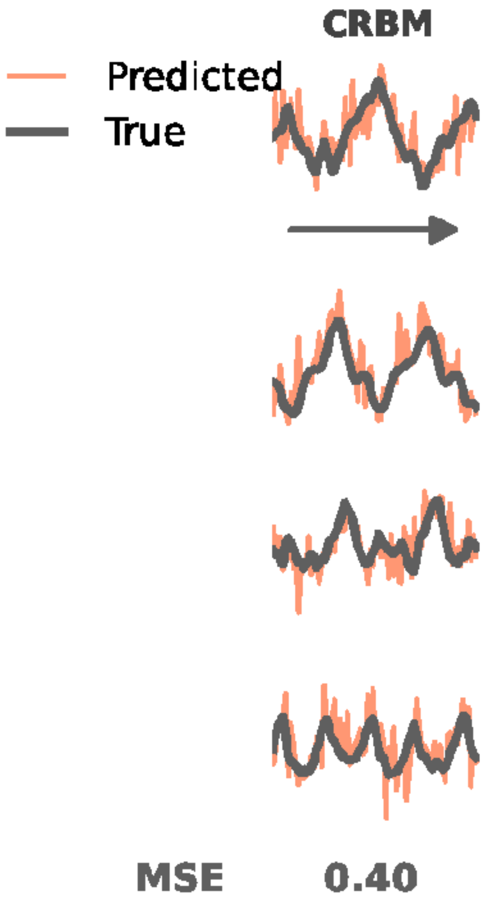
Step	**Action**
1. Static RBM Training	Constrain the static weights $\mathbf{w}$ using CD on single frame samples of the training data
2. Temporal Autoencoding	Constrain the temporal weights $\mathbf{w}_1$ to $\mathbf{w}_d$ using a denoising autoencoder on multi-frame samples of the data
3. Model Finalisation	Train all model weights together using CD on multi-frame samples of the data

Modelling Human Motion

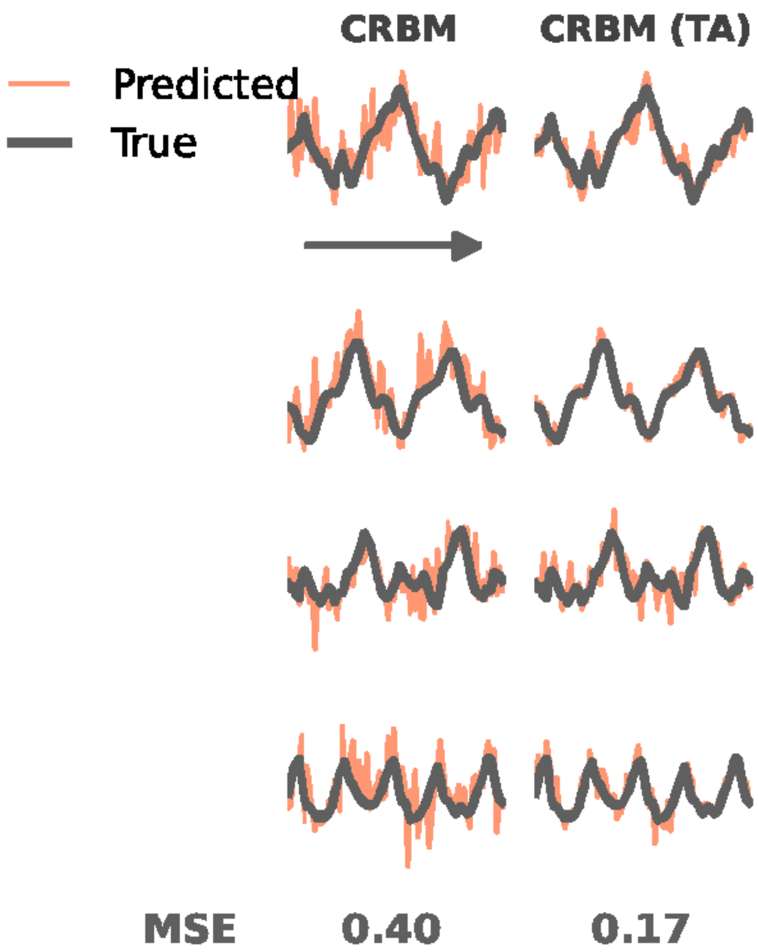


[Taylor, et al. 2007]

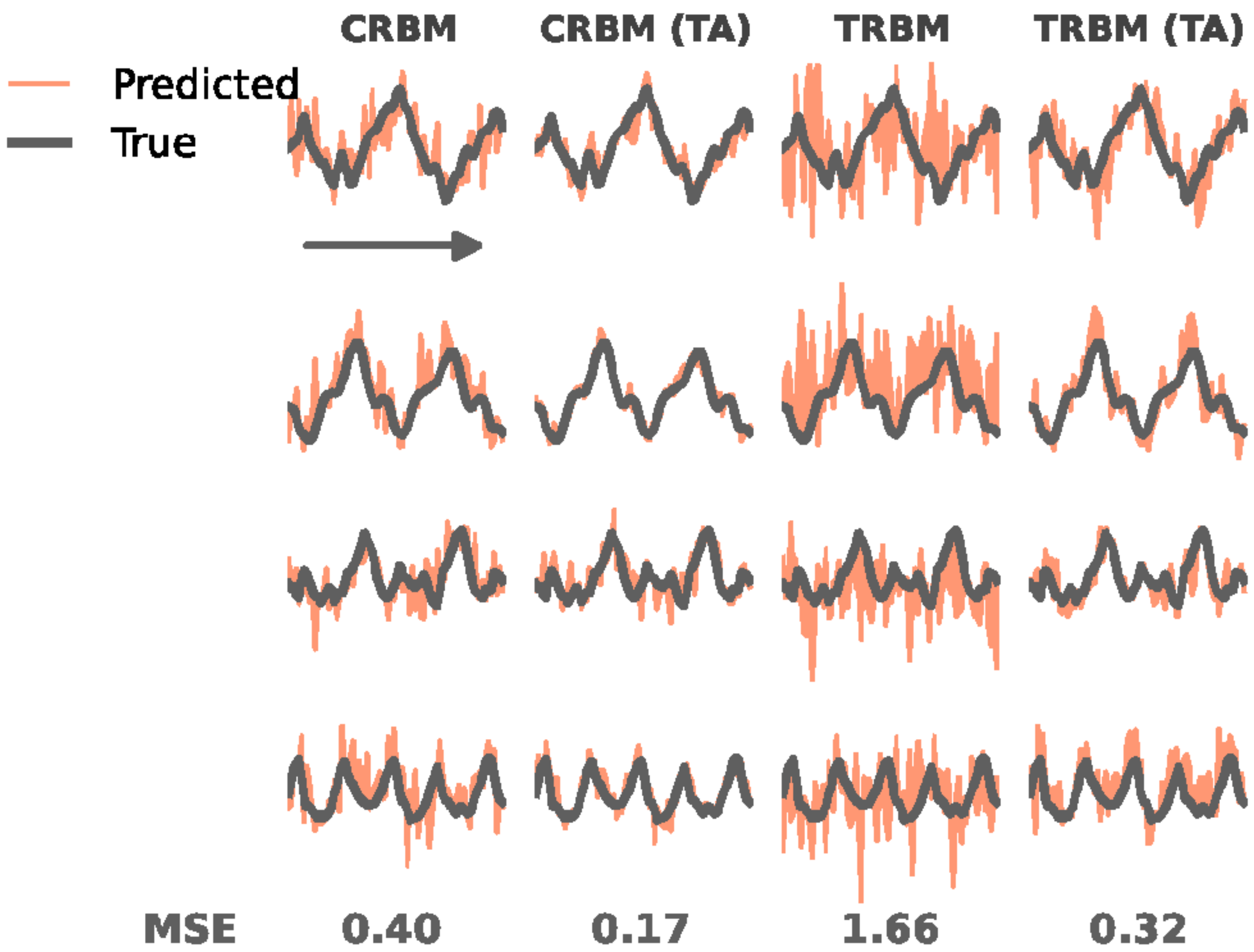
Learning to Walk



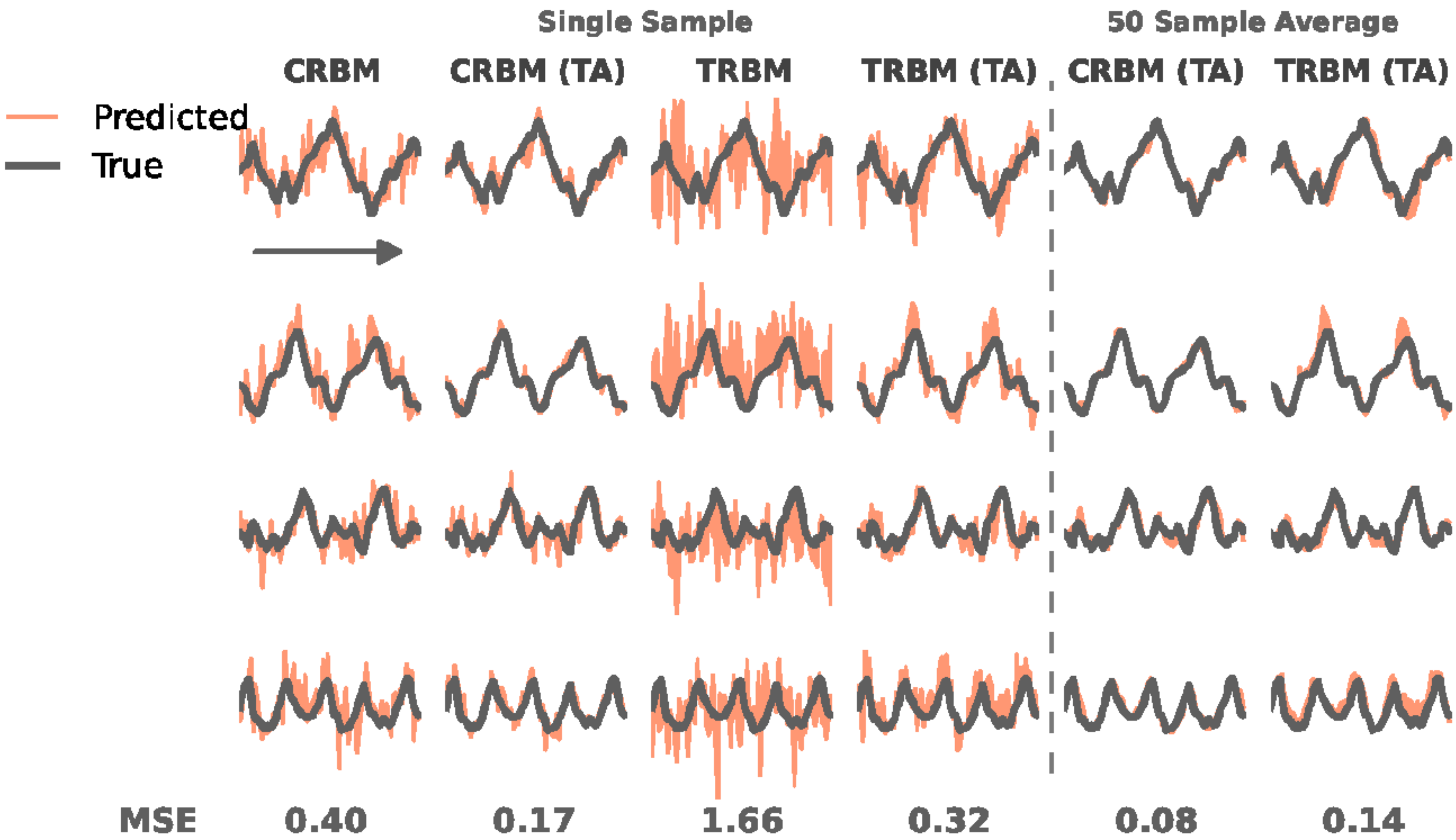
Learning to Walk



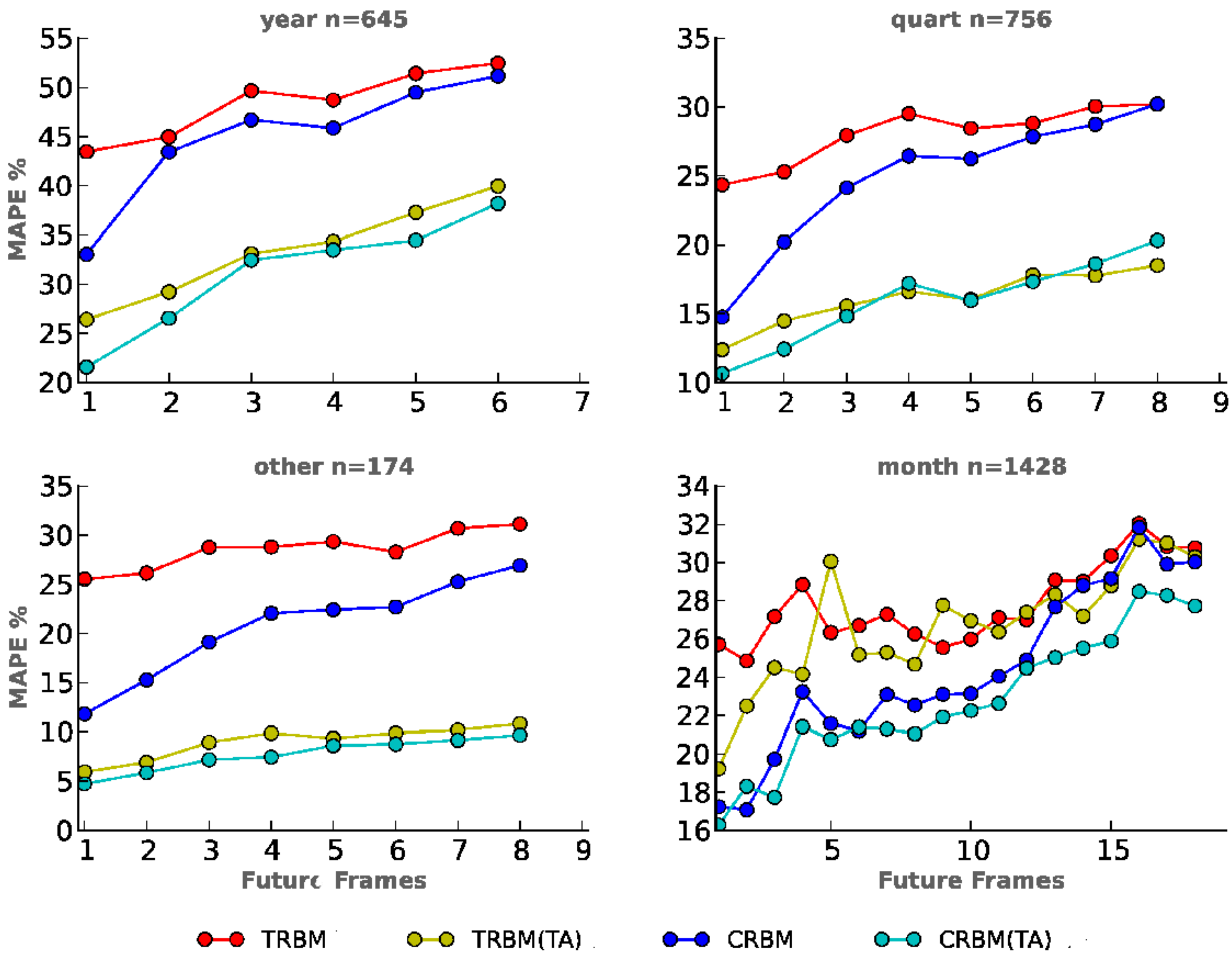
Learning to Walk



Learning to Walk



M3 forecasting competition



[Makridakis, et al. 2000]

The Brain as Model

Natural image sequences constrain dynamic receptive fields and imply a sparse code

[Chris Häusler, Alex Susemihl, Martin Nawrot]
Published in Brain Research, 2013

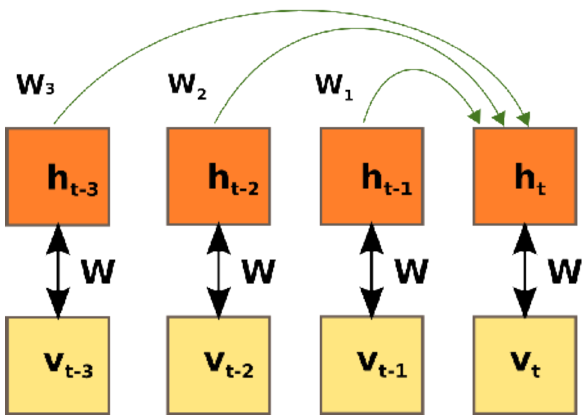
Learning from Natural Movies





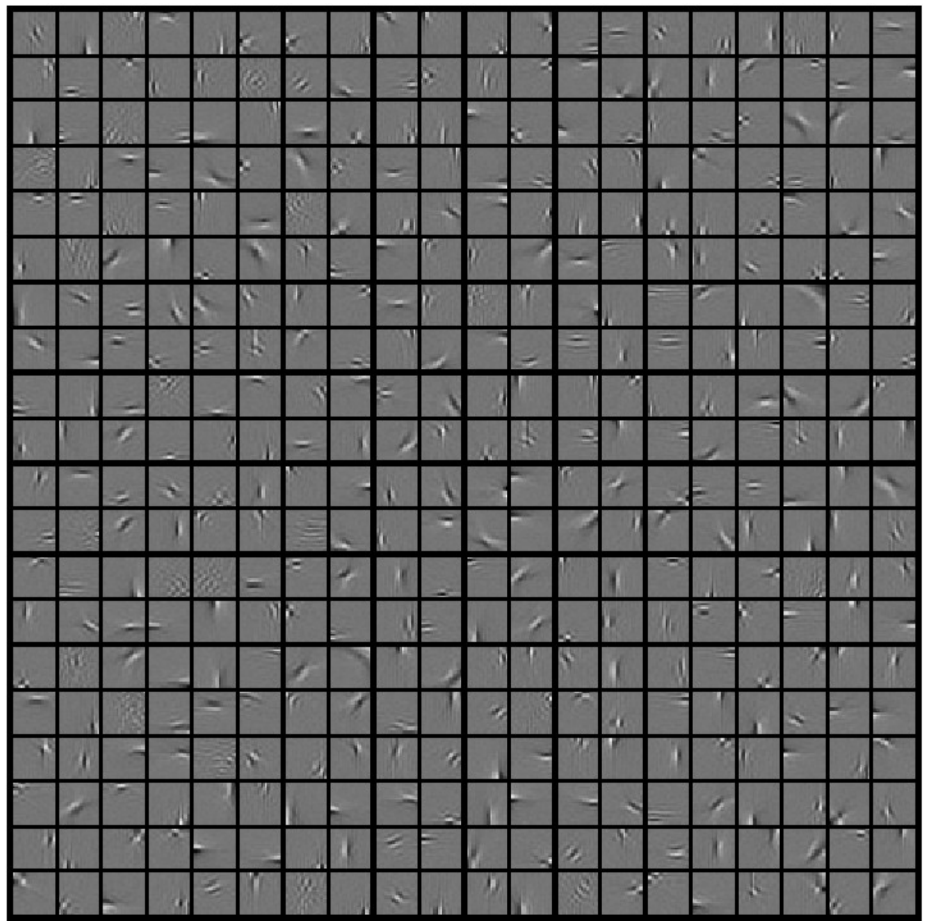
~15000 20x20 Pixel Patches for 30 frames each

Temporal RBM (TRBM)

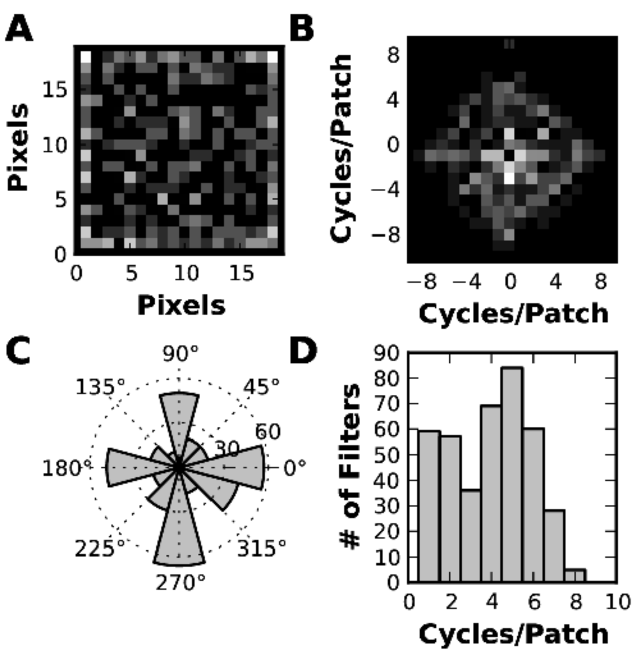


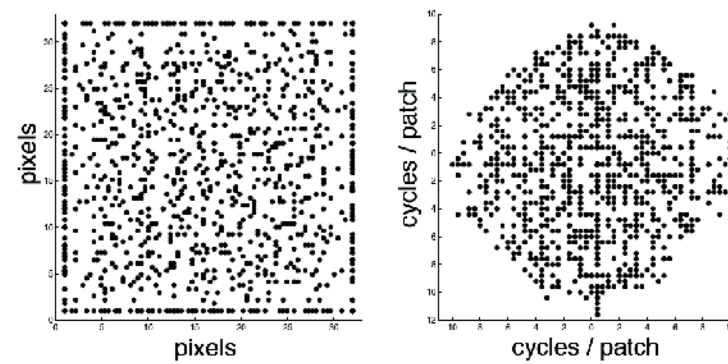
[Marszalek et al. 2009]

Static Receptive Fields

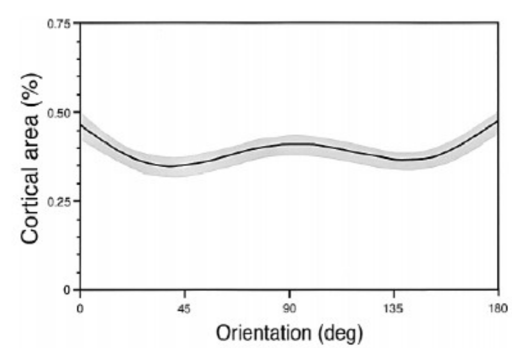


Receptive Field Statistics



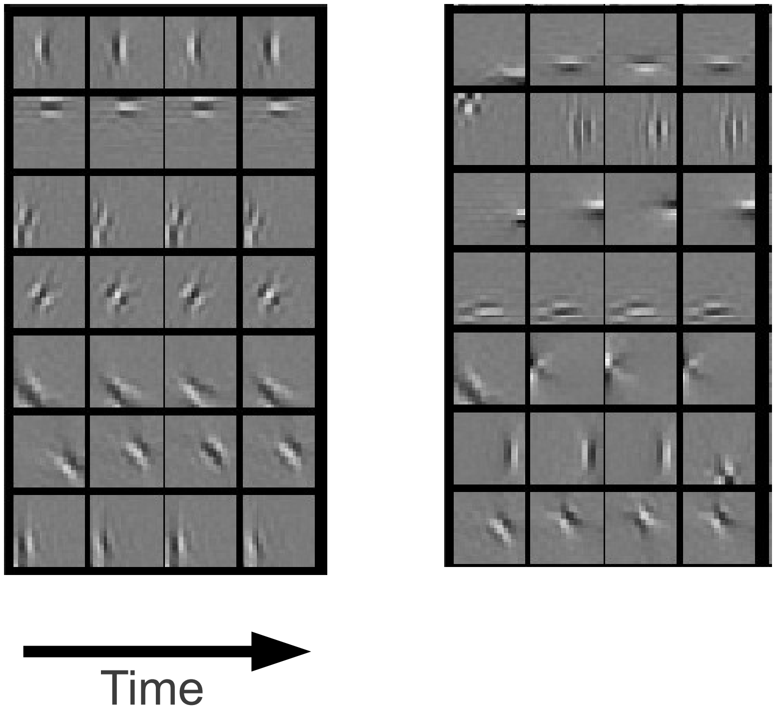


[Cadieu et al. 2012]



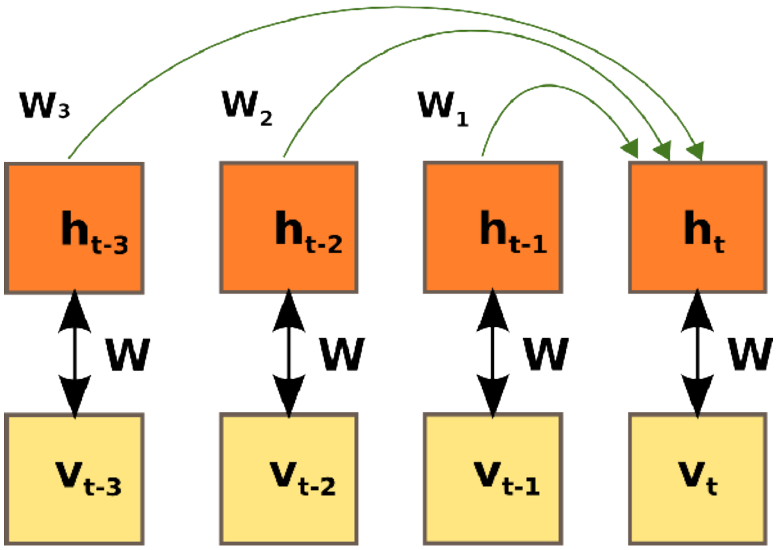
[Coppola et al. 1998]

Dynamic Receptive Fields

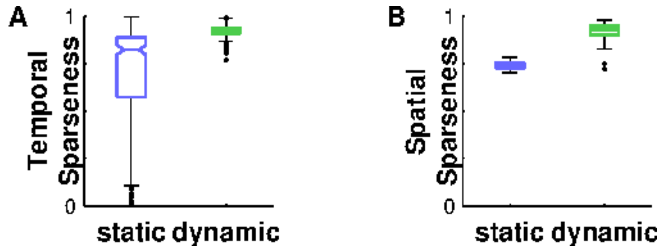


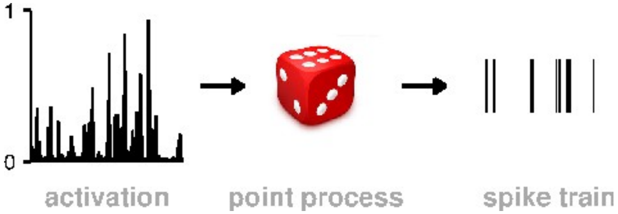
Form and Motion

Temporal RBM (TRBM)

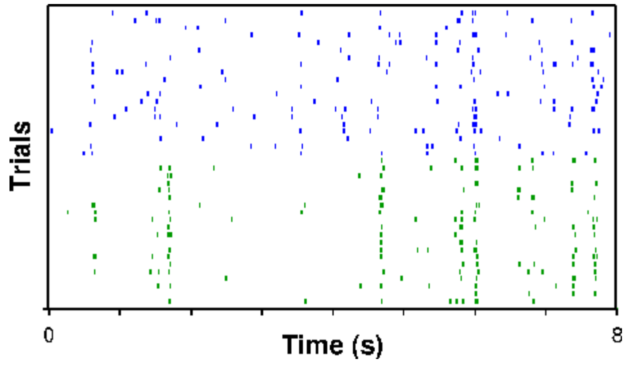


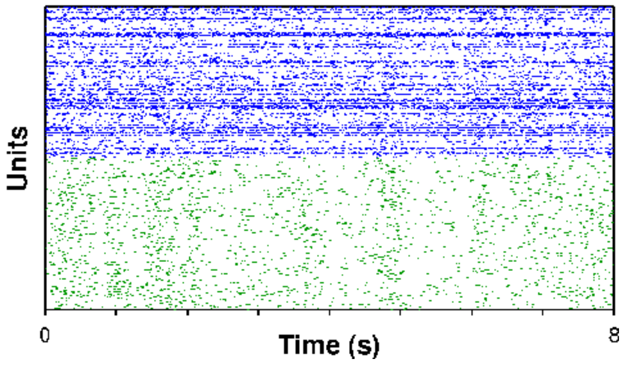
A Sparse Encoding





Static
Dynamic





A Round Up

Temporal Autoencoding

A new method for training temporal RBMs

Better performance for Generation & Prediction

TRBMs for Dynamic Stimulus Encoding

Propose how neural dynamic RFs may emerge naturally from smooth image sequences

Learns a Temporally and Spatially Sparse Code

Testament to Python

Data acquisition and Processing:

- numpy, pandas

Statistical Analysis:

- scipy, statsmodels

Modelling and Machine Learning:

- theano, scikit-learn, ipython parallel, scikitCVcluster

Data Visualisation and Story Telling:

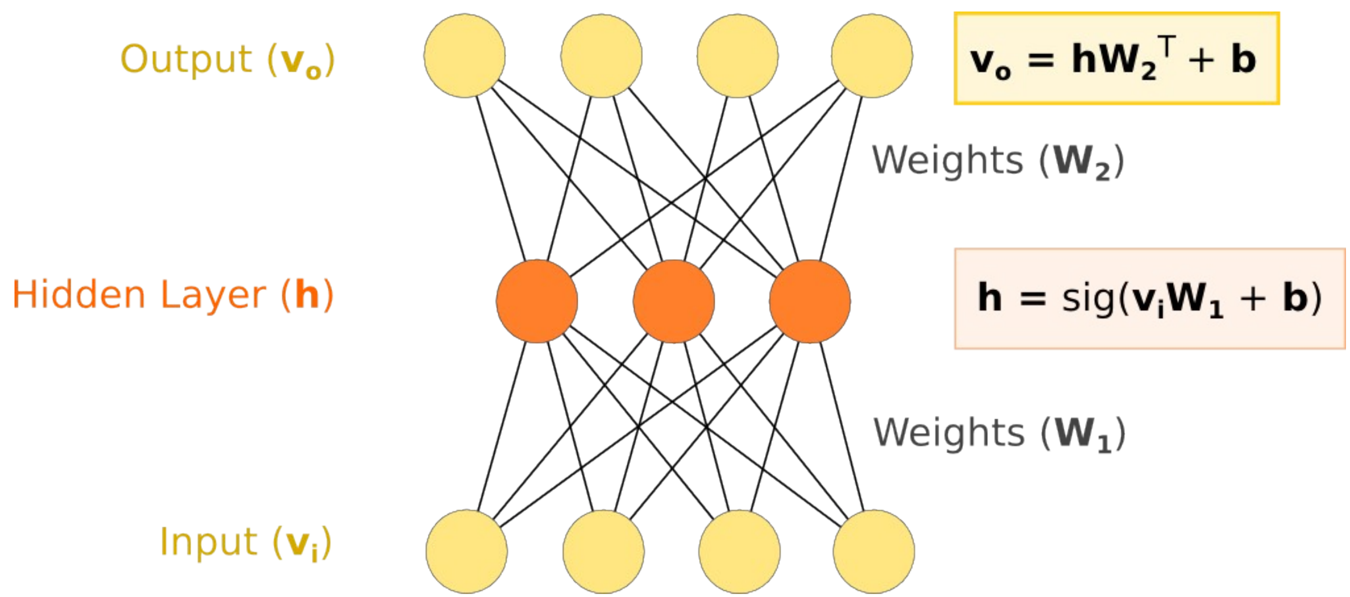
- matplotlib, prettyplotlib

Thank You!

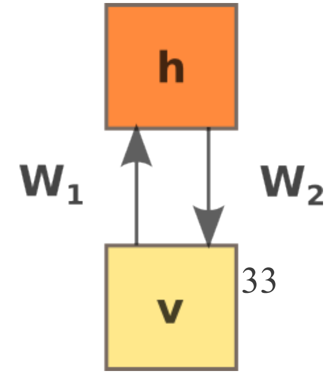
- Martin
- Manfred
- Alex
- Thomas + Jan for Kaggling and explaining things to me
- Michael – Keeping the servers up and bringing me to Neuroinf
- Neuroinf
- Vanessa, Margret & Julia – Unbelievable support
- Family for coming all the way from Australia and Austria to be here

Questions?

Autoencoders

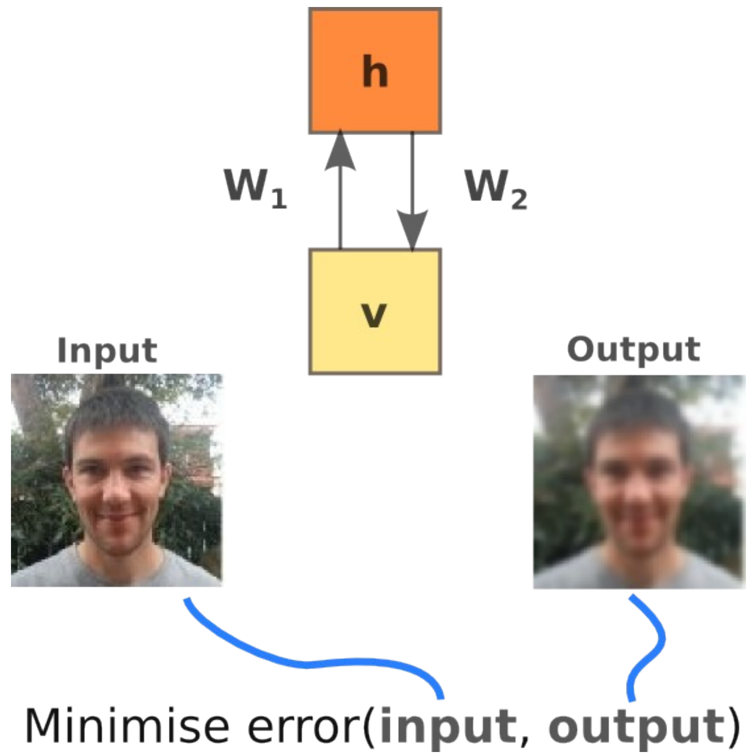


Alternate View

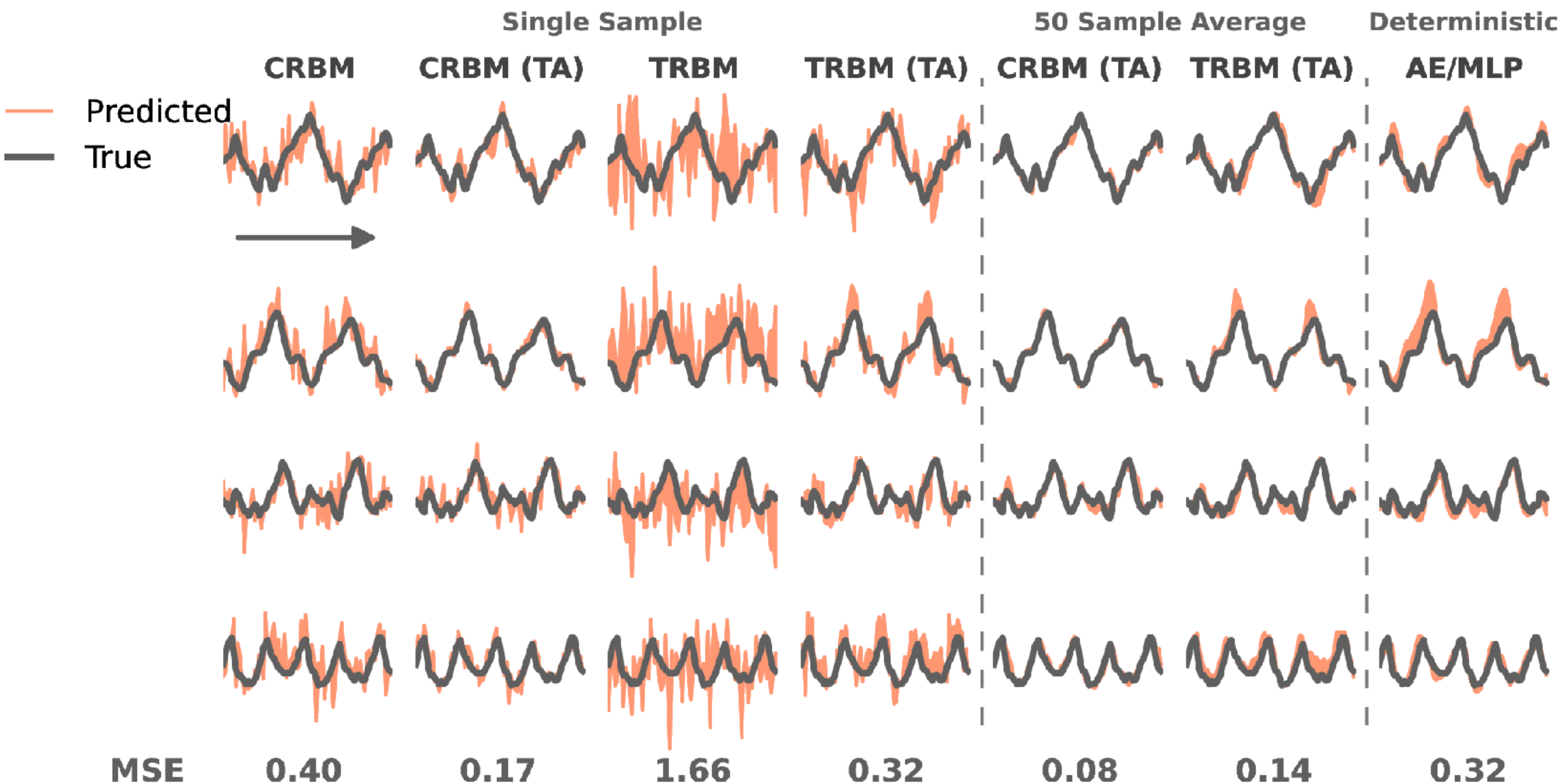


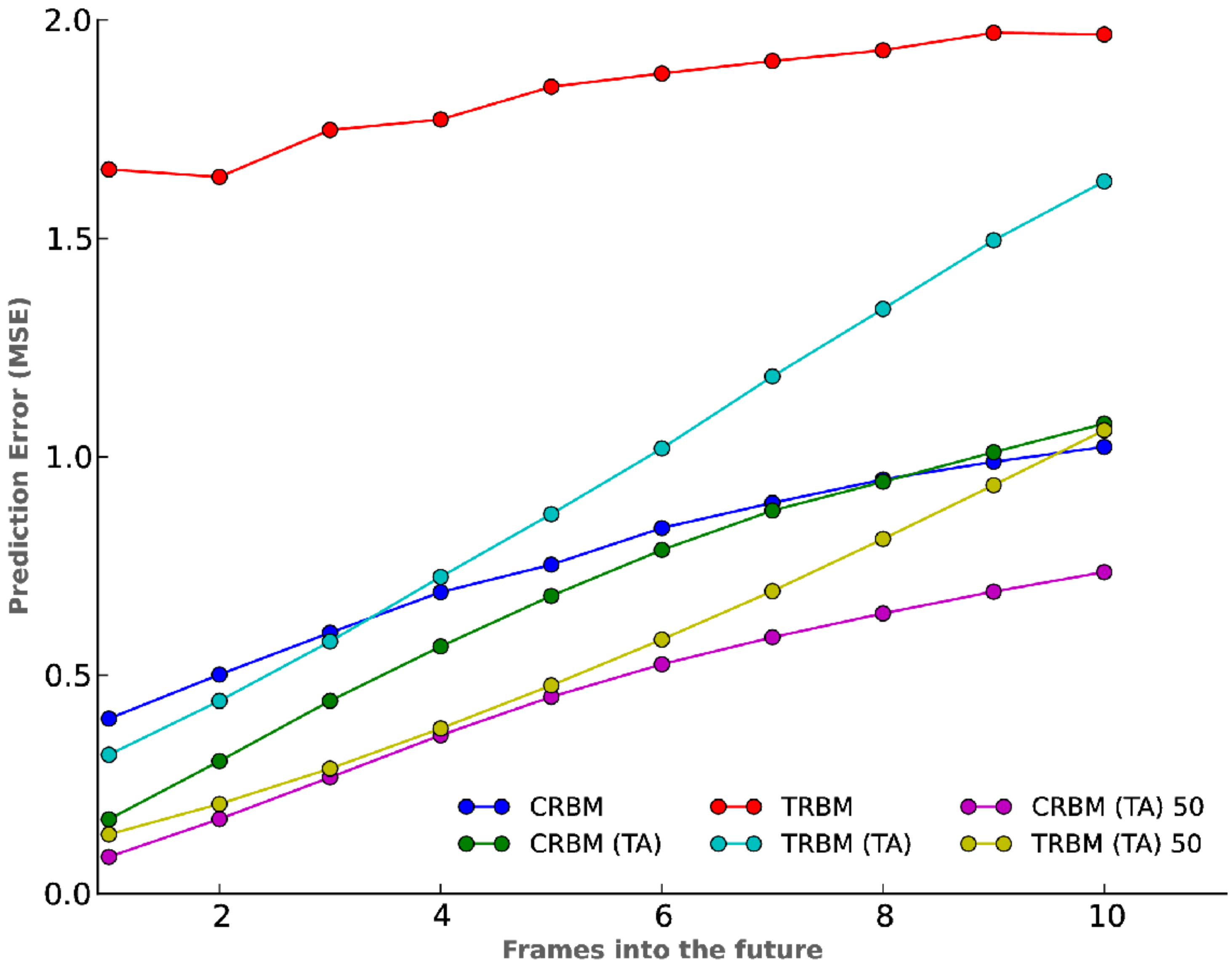
[Bengio, et al. 2007]

Autoencoders



Learning to Walk





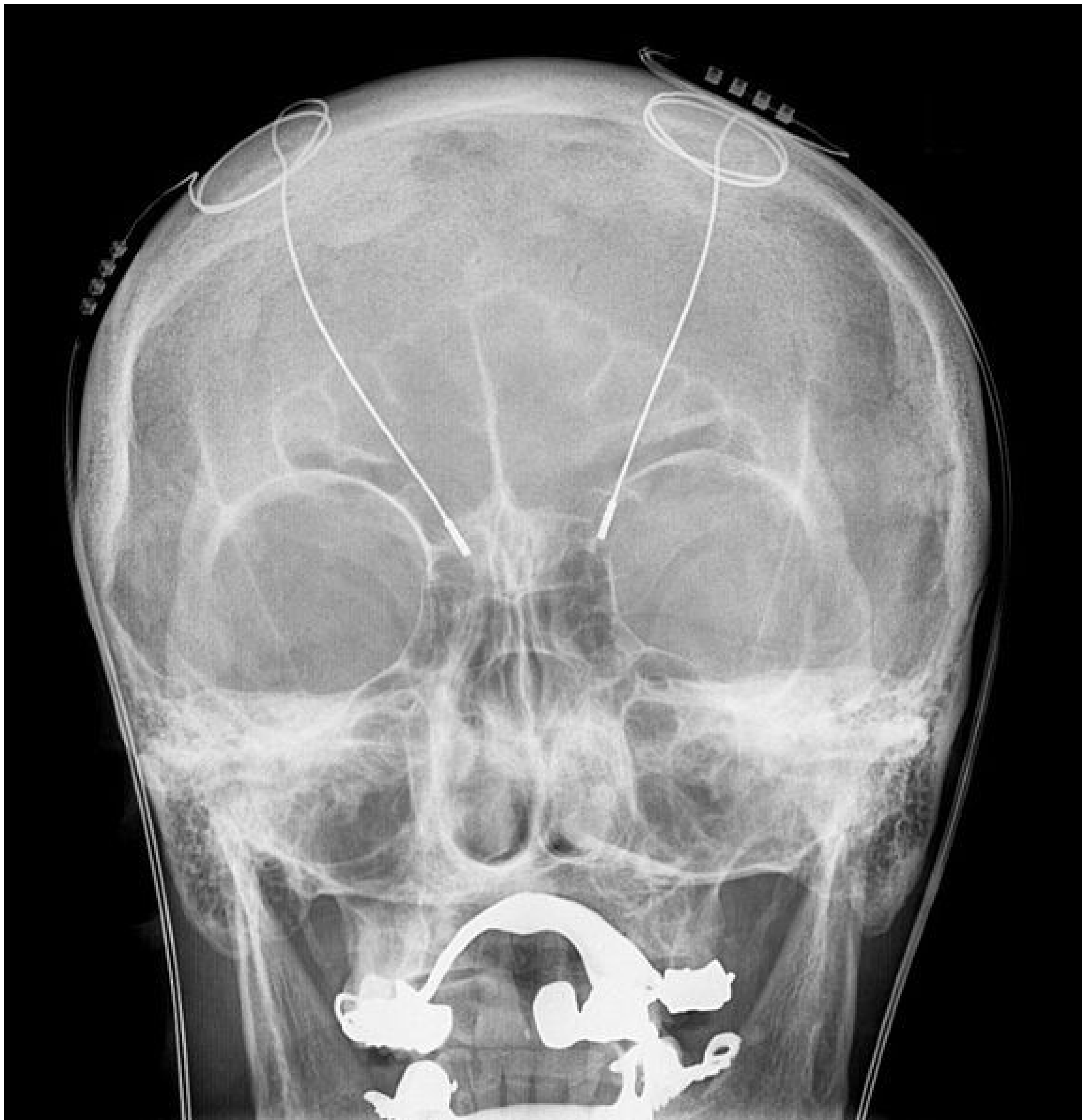
Prediction Error (MSE)
2.0
1.5
1.0
0.5
0.0
2
4
6
8
10
Frames into the future
CRBM
CRBM (TA)
TRBM
TRBM (TA)
CRBM (TA) 50
TRBM (TA) 50

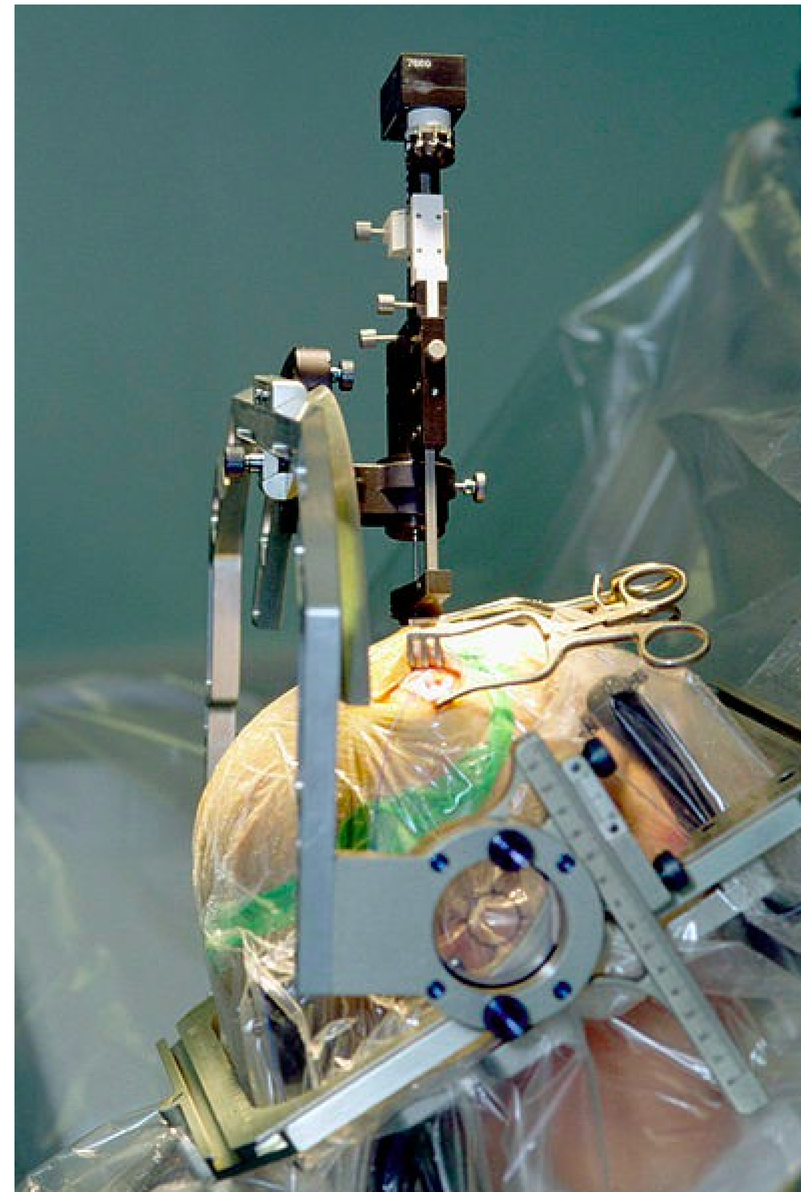
The Brain as Data Source

Investigating Movement Parameters in the Human Basal Ganglia

[Chris Häusler, Julius Hübl, Andrea Kühn, Martin Nawrot]

Deep Brain Stimulation



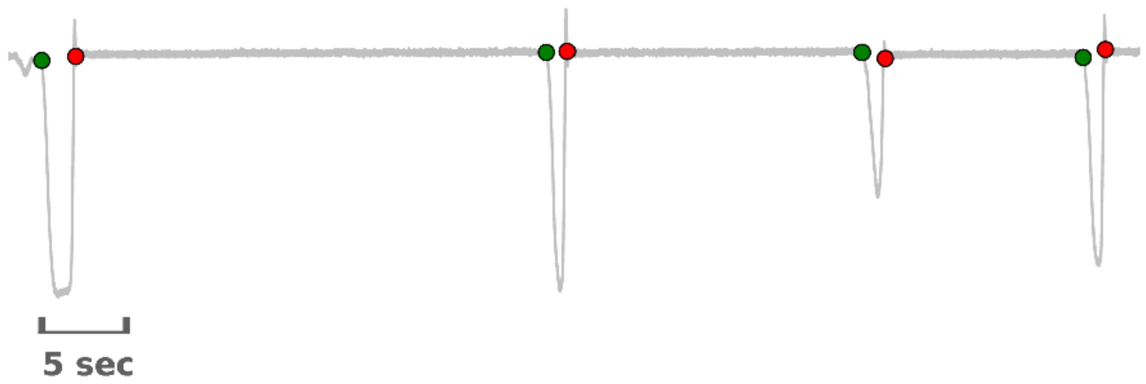


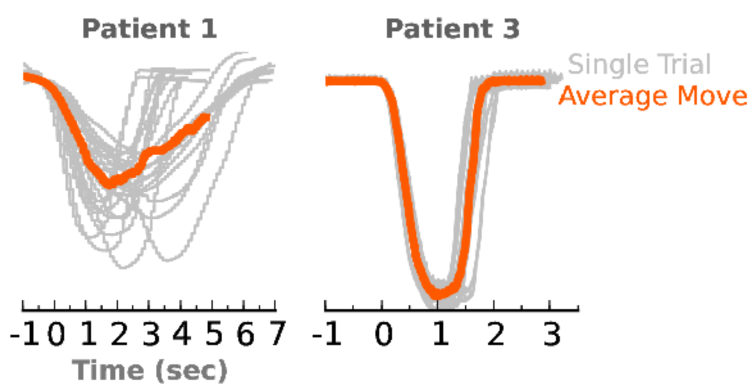
[Wikipedia]

The Data

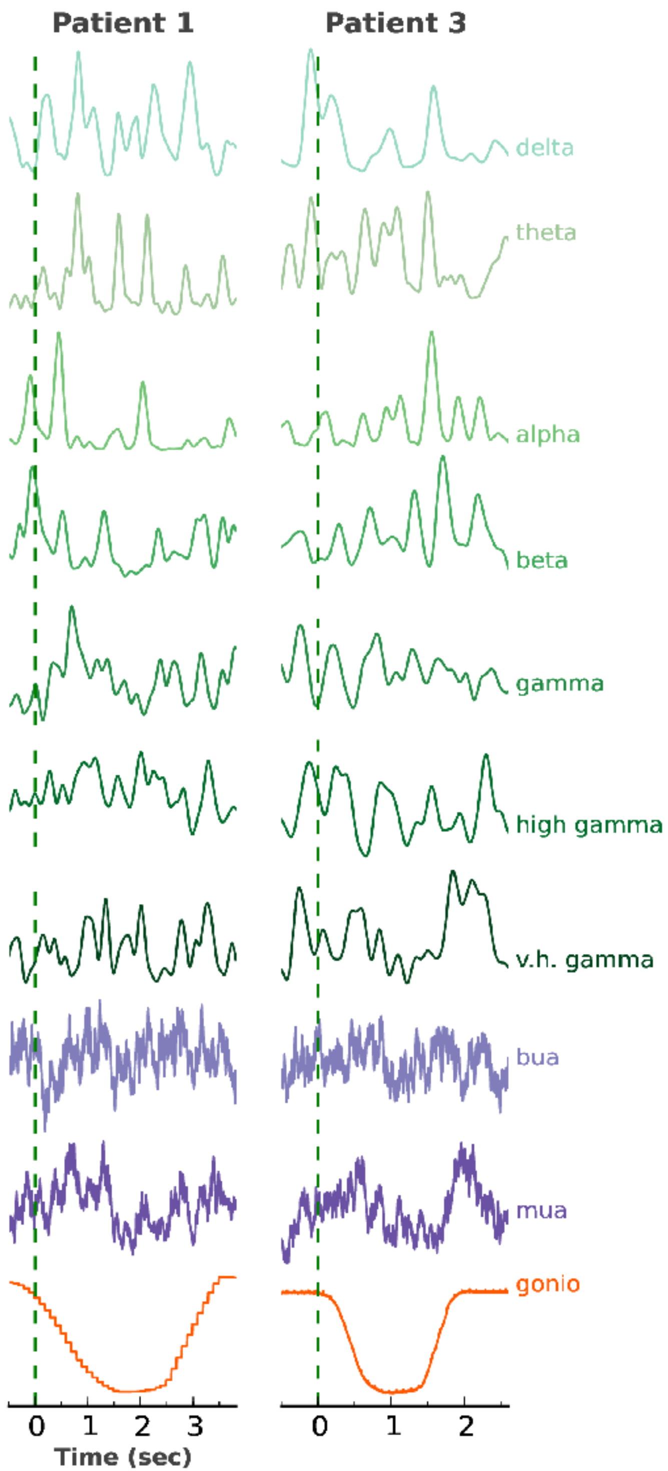
- 4 Patients
- Recordings from Stimulator electrode
- Neural Signals
  - 4 Extracellular electrodes
  - LFP
- Movement Signals
  - Hand position (approximate, recorded with a Goniometer)

Movements

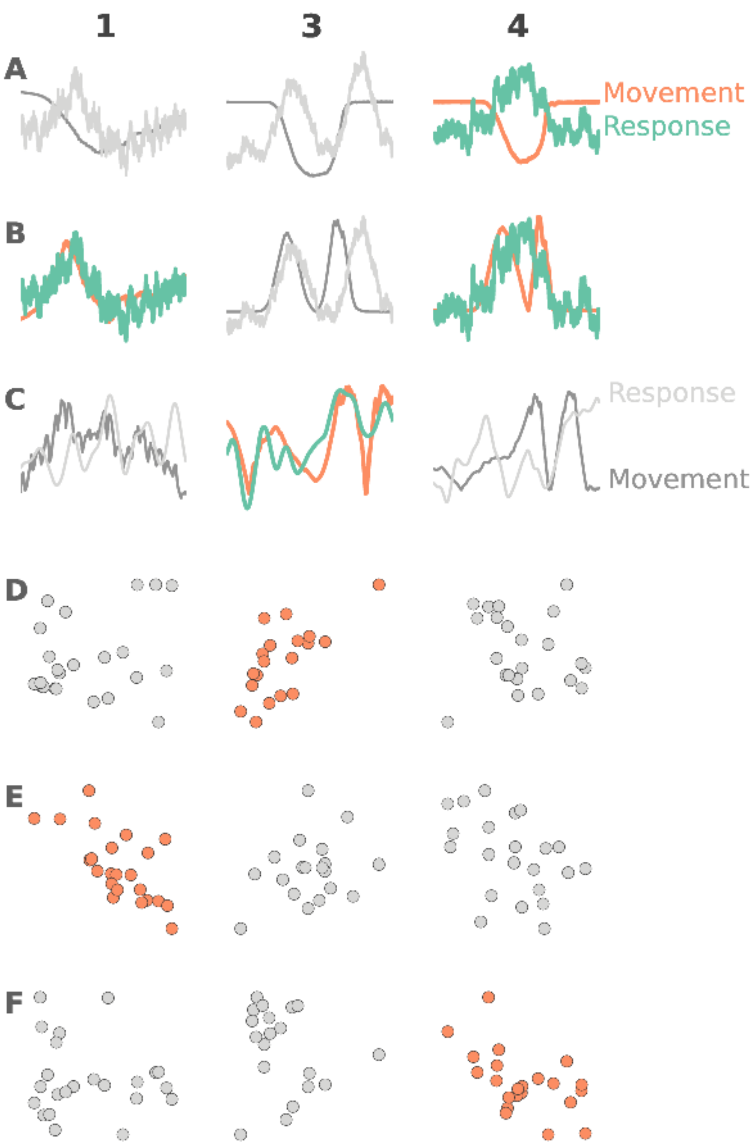

5 sec


Patient 1
Patient 3
Single Trial
Average Move
-1 0 1 2 3 4 5 6 7
-1 0 1 2 3
Time (sec)

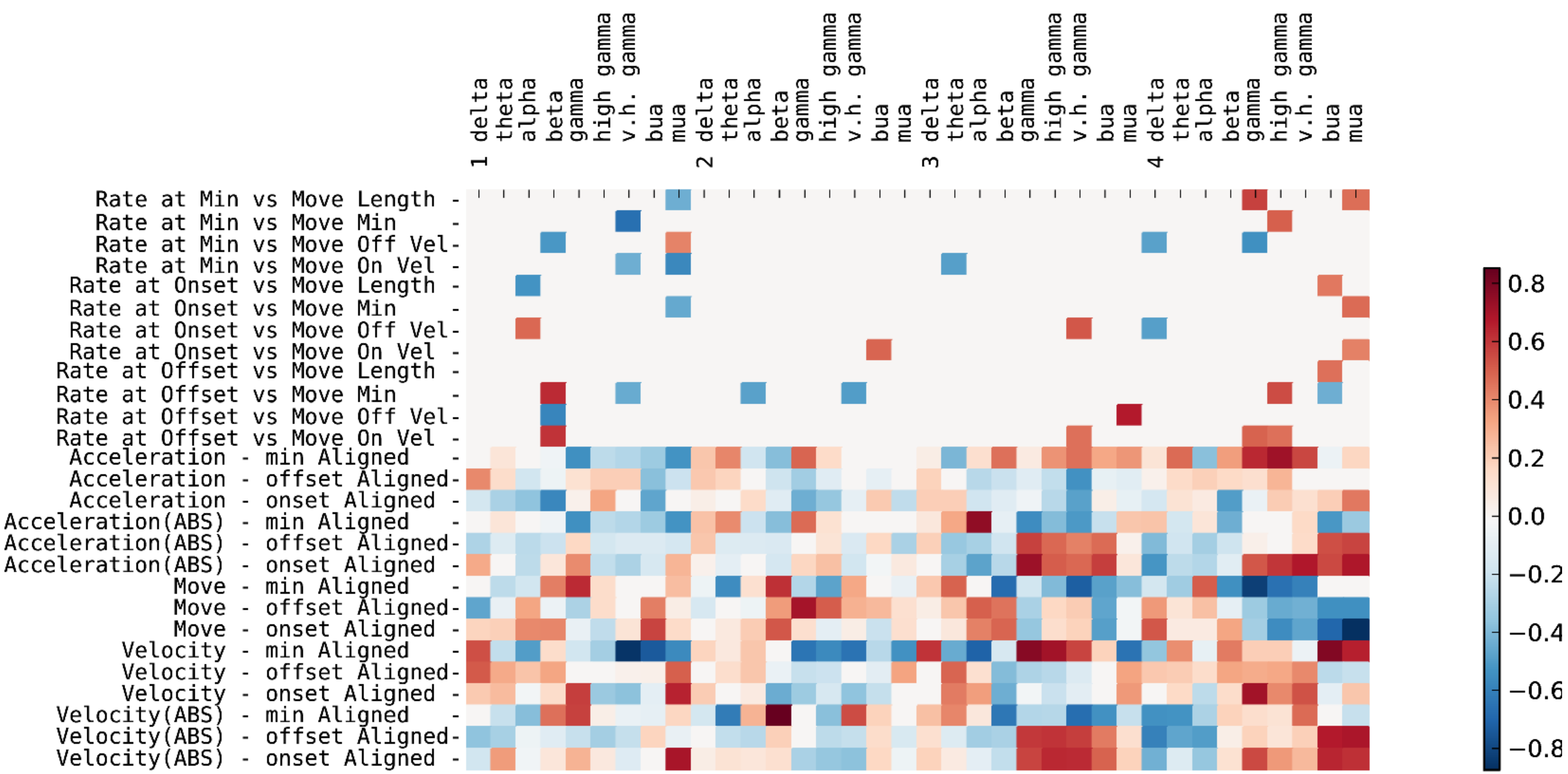
Neural Signals



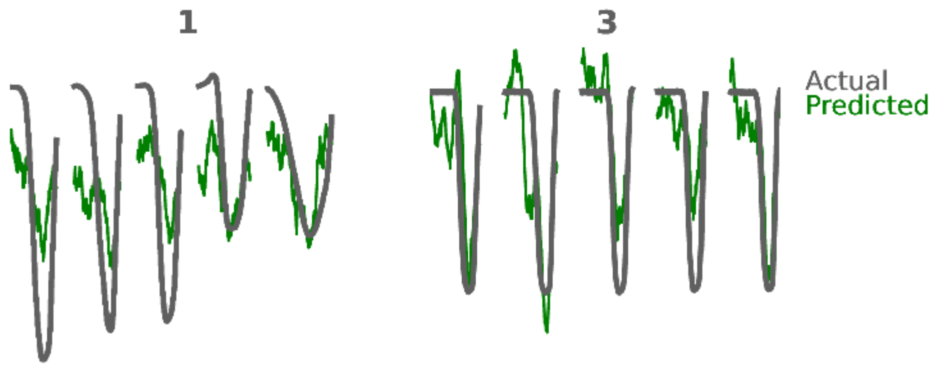
Neural vs Kinematic

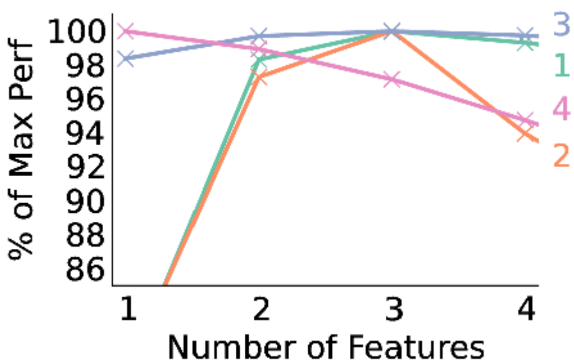


Correlation: Neural vs Kinematic



Predicting Movement





Predictive Features

Patient	Single Feature	Performance	Multiple Features	Performance
1	Bua	0.48	Bua, Beta, Gamma	0.61
2	Theta	0.21	Theta, Beta, Alpha	0.27
3	Mua	0.84	Mua, Very High Gamma, Gamma	0.86
4	Mua	0.64	Mua	0.64