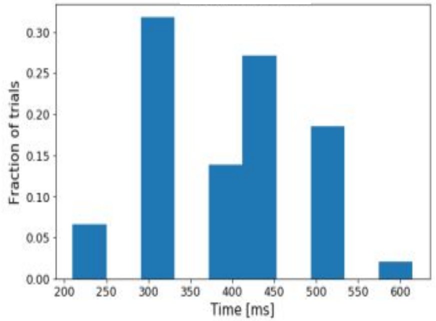
NS1 Mucca

Ramps from “snapshot, Dimensional reduction, Trial Prediction

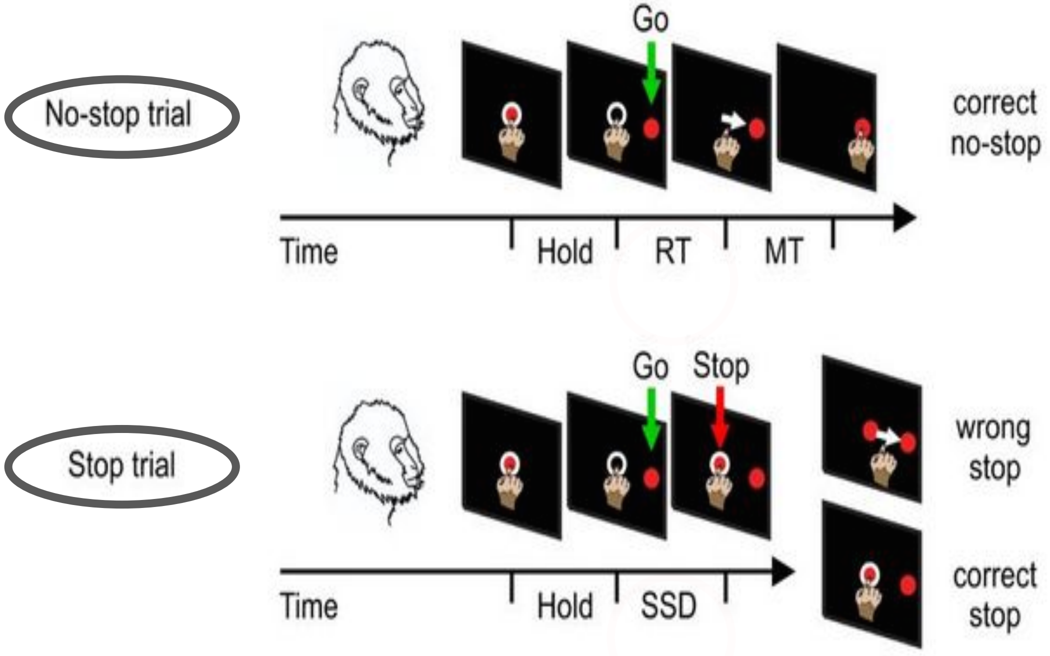
Experimental context: Stop task (movement inhibition)

- When you see the GO signal, touch the red dot on
  - The shorter your RT, the sooner you get the reward
- Yet, sometimes (randomly), there appears a STOP signal
  - Reward if you DON'T move!
  - Cancel planned movement
- SSD random



Easy STOP → Hard STOP

Reaction time (RT): time from GO to movement

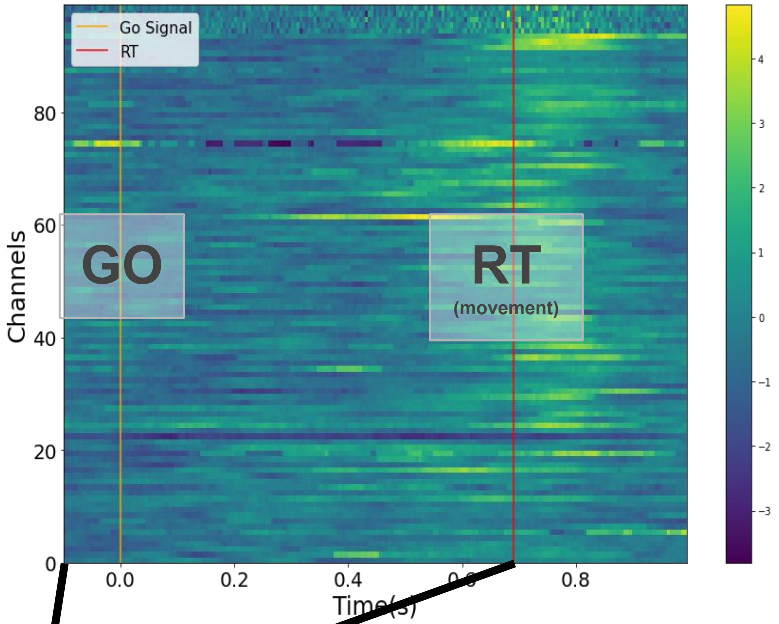


Stop signal delay (SSD): time from GO to STOP

Data and aim

- 10^3 No-stop trials
- 10^2 Stop trials:
  - wrong (movement)/correct (success inhibition)
- Behavior
  - RT (for no-stop and wrong stop trials)
  - SSD (for stop trials)
- Electrophysiology
  - Neural activity from 96 electrodes (channels) in dorsal Premotor Cortex (PMd)
- Can we "predict" behavior from multi-channel neural activity?

Sample 1100 ms neural recording from 96 channels (No-stop trial)



From neural recordings to RTs

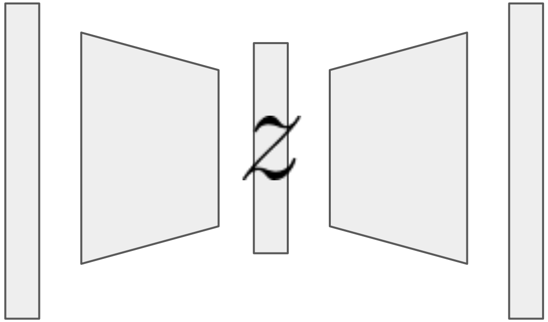
? **RT**

Ongoing effort to make data more "machine learning friendly"

Dimensional Reduction with VAE/VDE

A window W or a specific time X used interchangeably as x

$$W(t) = \{X(t-\tau), \ldots, X(t)\}$$



$$q_\phi(z|x)$$
$$p_\theta(z)$$

Posterior parameter (learned)

Prior parameter (fixed)

$$\underbrace{-\mathcal{L}(\theta, \phi; x^{(i)})}_{\text{negative ELBO}} = \underbrace{\omega \cdot D_{KL}(q_\phi(z|x^{(i)})||p_\theta(z))}_{\text{weighted KL divergence}} + \underbrace{\mathbb{E}_{q_\phi(z|x^{(i)})}[-\log p_\theta(x^{(i)}|z)]}_{\text{expected negative log-likelihood}}$$

$$D_{KL}(q_\phi(z|x)||p_\theta(x)) \approx \frac{1}{L}\sum_{l=1}^{L} \log \frac{q_\phi(z^{(l)}|x)}{p_\theta(x)}$$
$$z^{(l)} \sim q_\phi(z|x)$$

Prior : gaussian 6 dim with sigma = 1
q_\phi : gaussian 6 dim with full covariance matrix

$$VAE : E(x_i(t)) \rightarrow z_i(t), D(z_i(t)) \rightarrow \hat{x}_i(t)$$

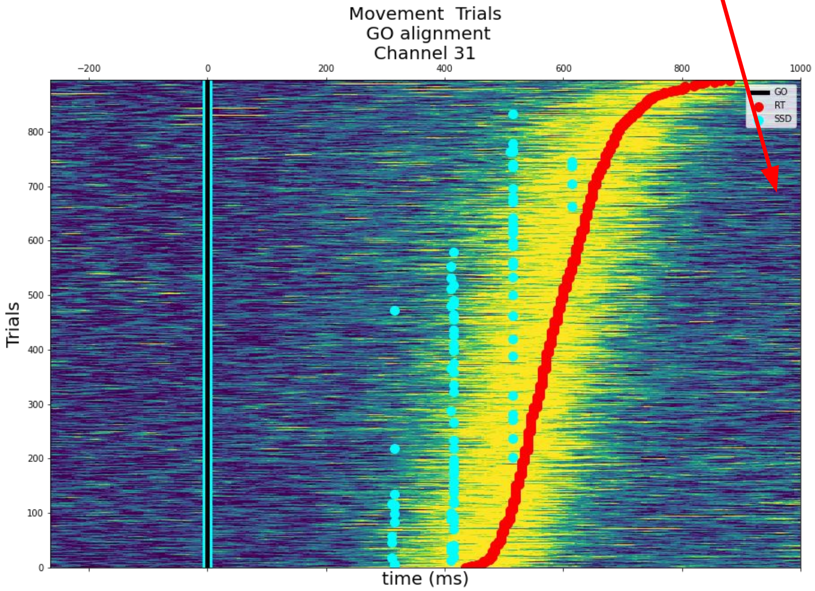
$$VDE : E(x_i(t)) \rightarrow z_i(t), U(z_i(t)) \rightarrow \hat{x}_i(t+1)$$

Test the reduction (A good channel)

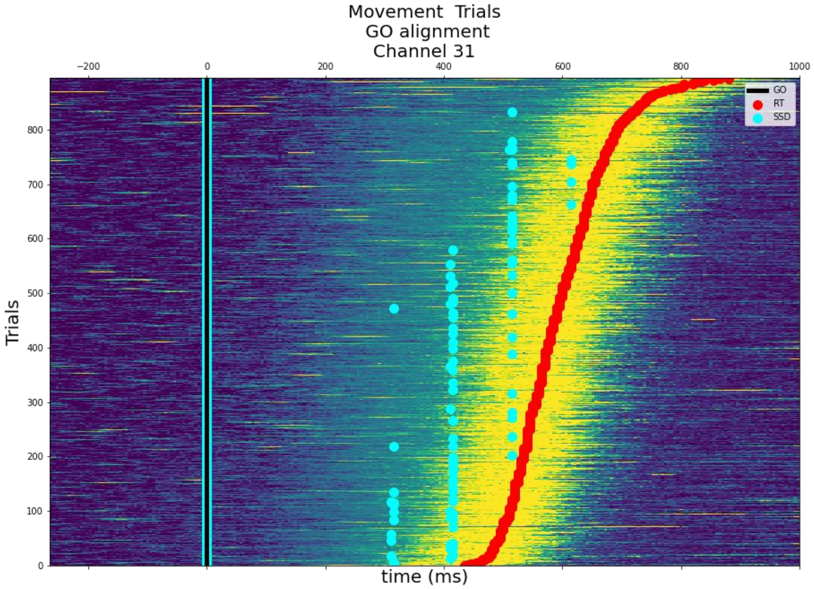
Trained on 06-06, 09-01, 02-12
Tested on 16-01

All trials sorted by
their reaction time.

Original data

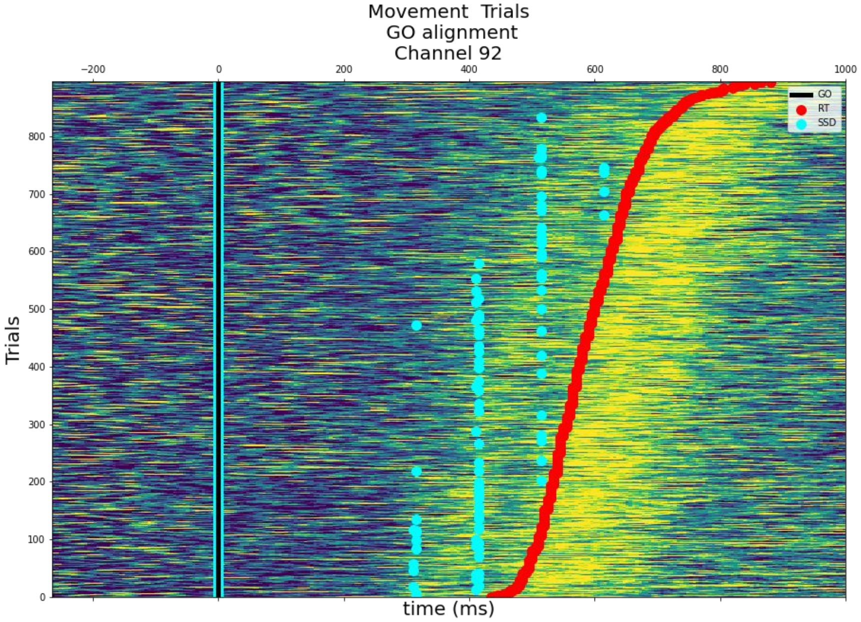


Decoded data

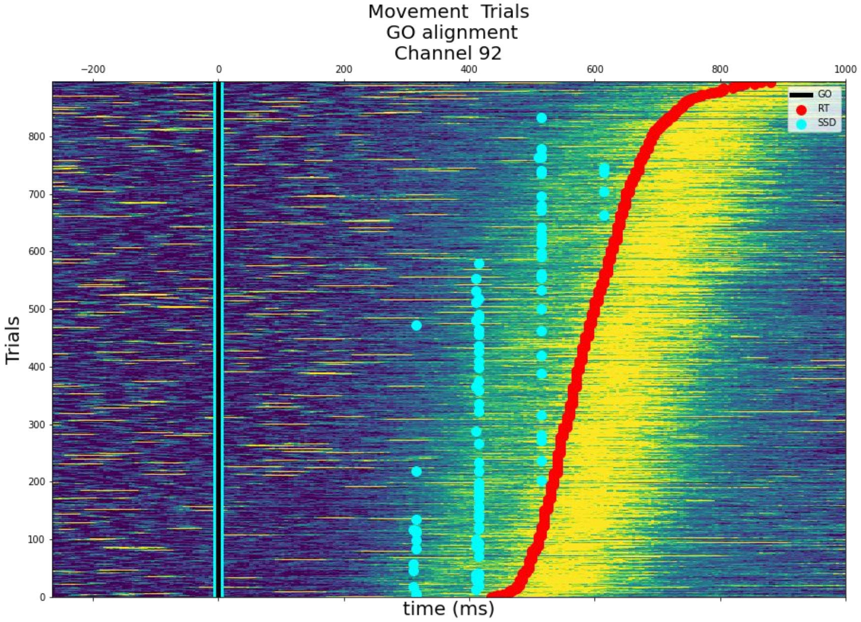


Test the reduction (A worse channel)

Original data

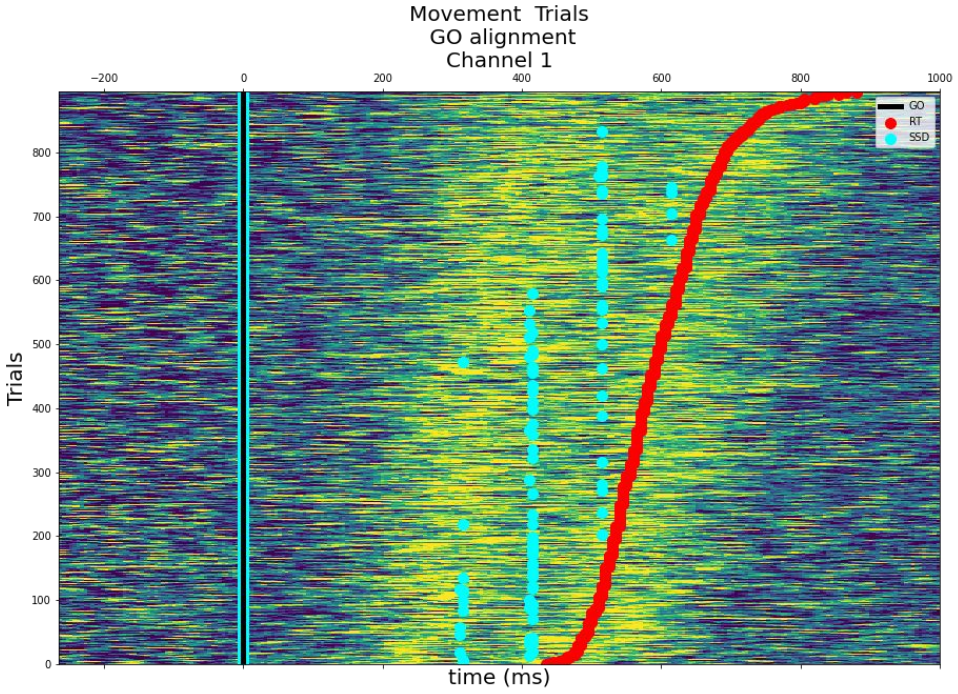


Decoded data

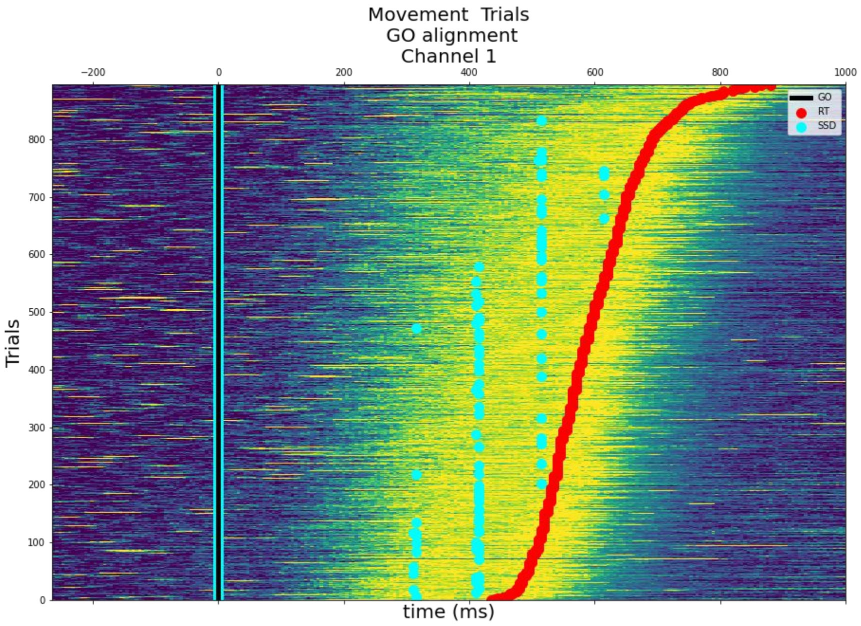


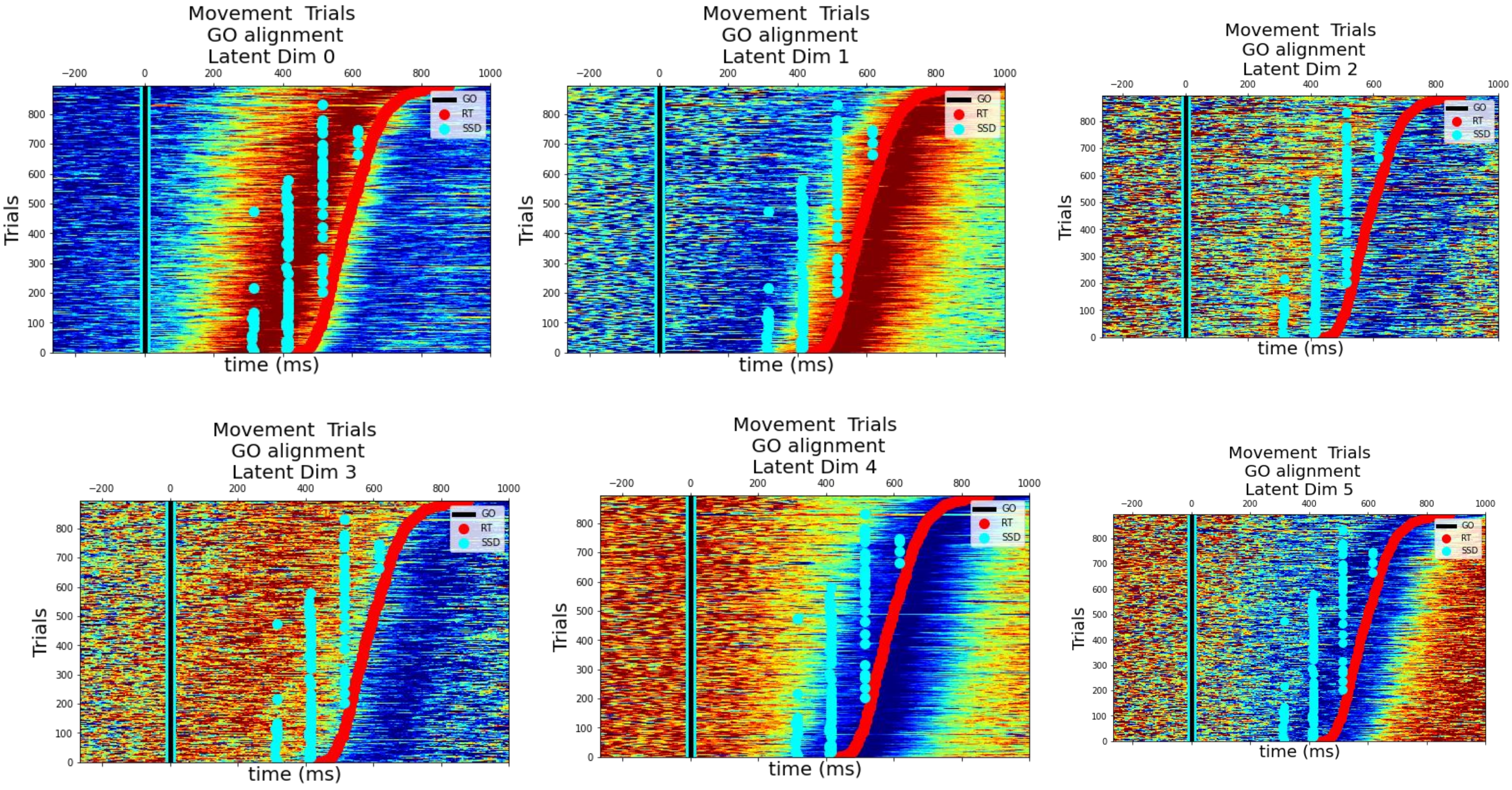
Test the reduction (A worse channel)

Original data

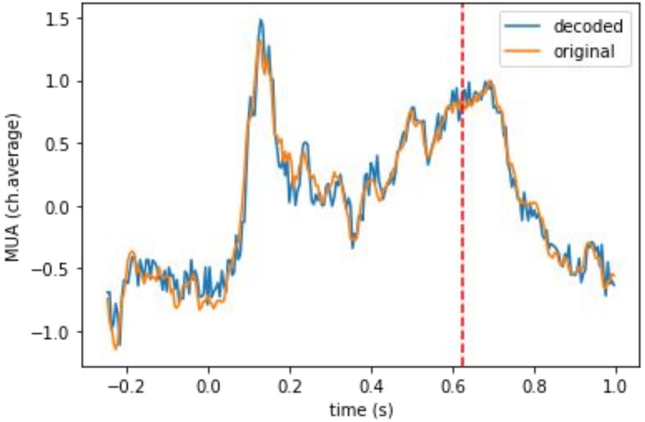


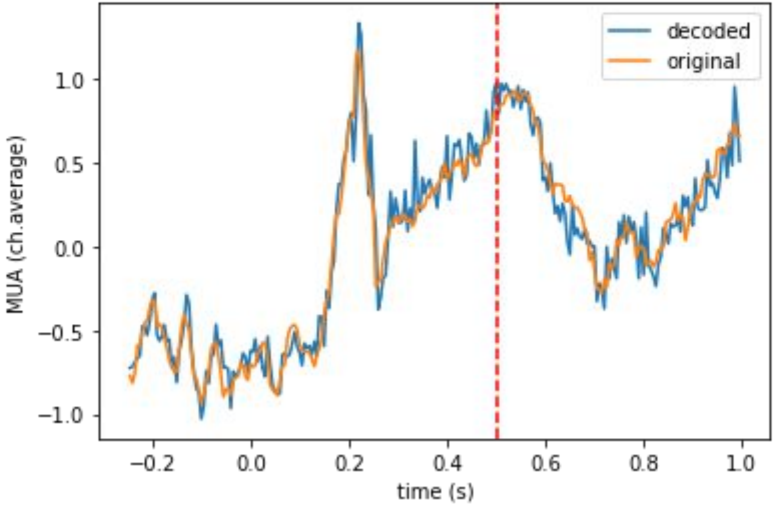
Decoded data

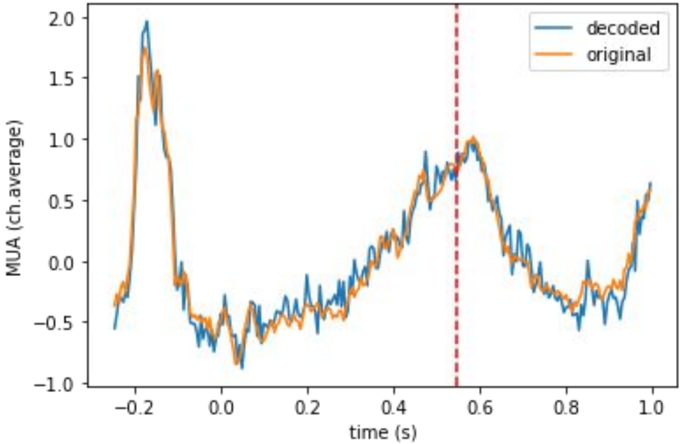


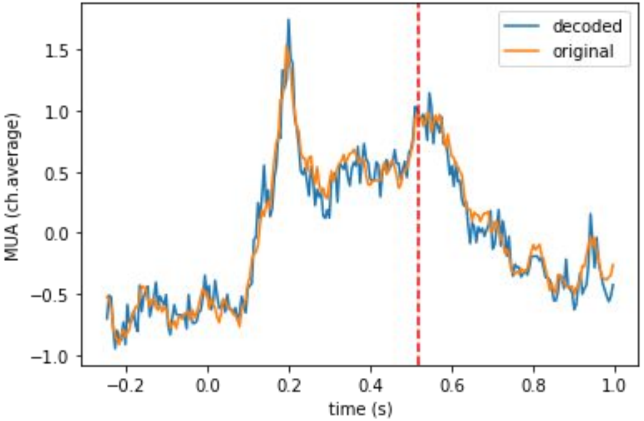

Movement Trials
GO alignment
Latent Dim 0
Movement Trials
GO alignment
Latent Dim 1
Movement Trials
GO alignment
Latent Dim 2
Movement Trials
GO alignment
Latent Dim 3
Movement Trials
GO alignment
Latent Dim 4
Movement Trials
GO alignment
Latent Dim 5
−200
0
200
400
600
800
1000
Trials
0
100
200
300
400
500
600
700
800
time (ms)
GO
RT
SSD

Single trial reconstruction

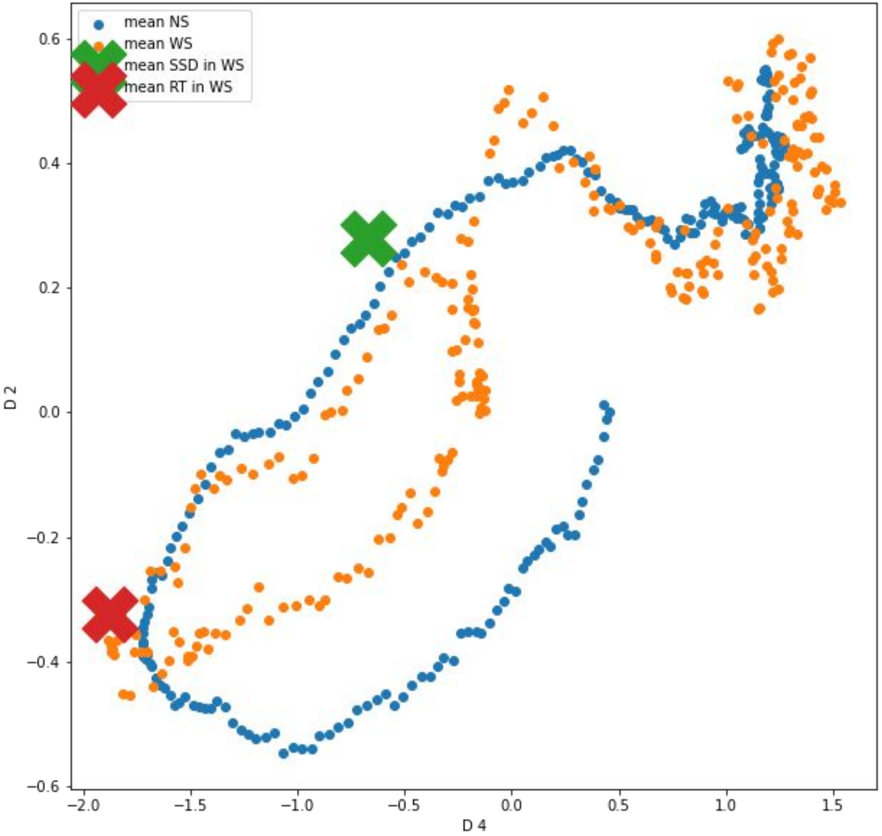




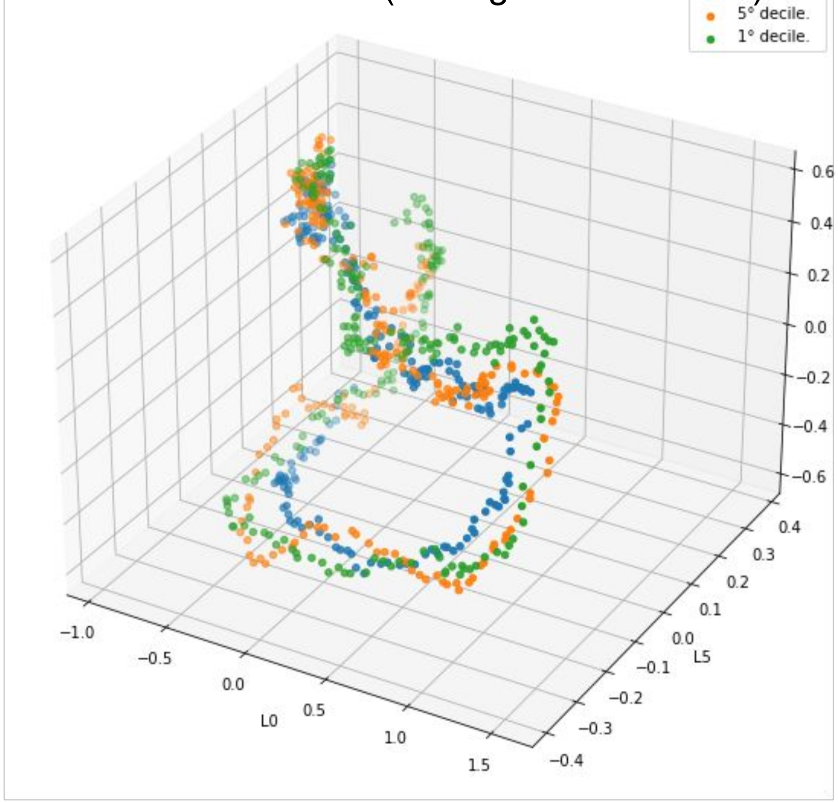




encoded dimensions



Fast and slow RT (average over a decile)



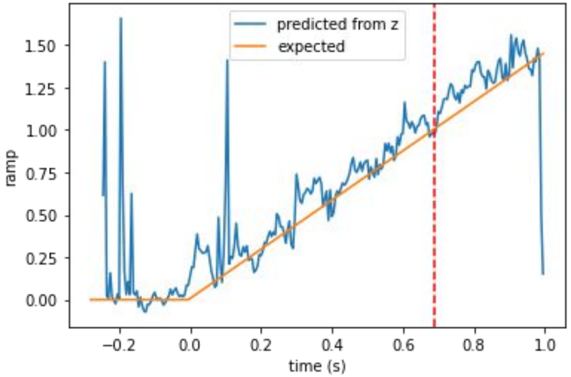
Additional conditioning on the latent space:

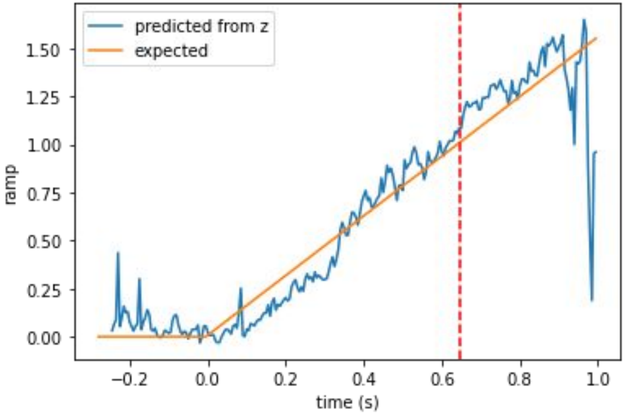
We can easily apply conditions to the latent space:

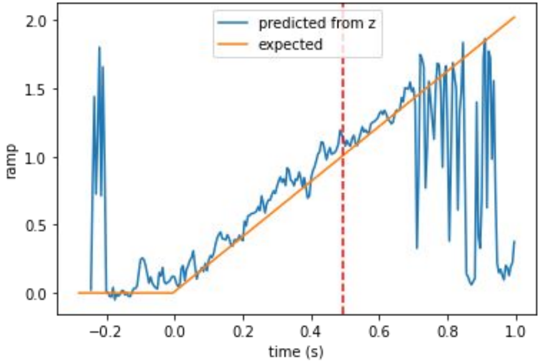
 In this case we choose to use “from z(t) we should be able to reconstruct the ramp rp(t) with a **linear regression**

Additional conditions may be:

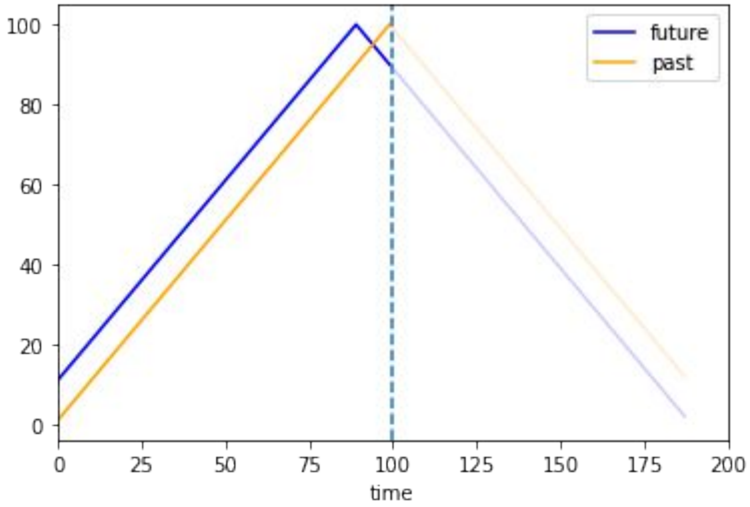
- Ability to detect left from right?
- A condition to the autocorrelation function of z(t)z(t+tau)

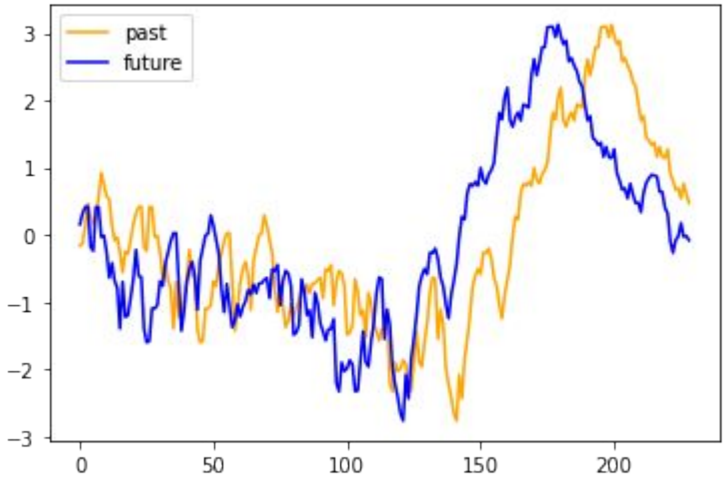




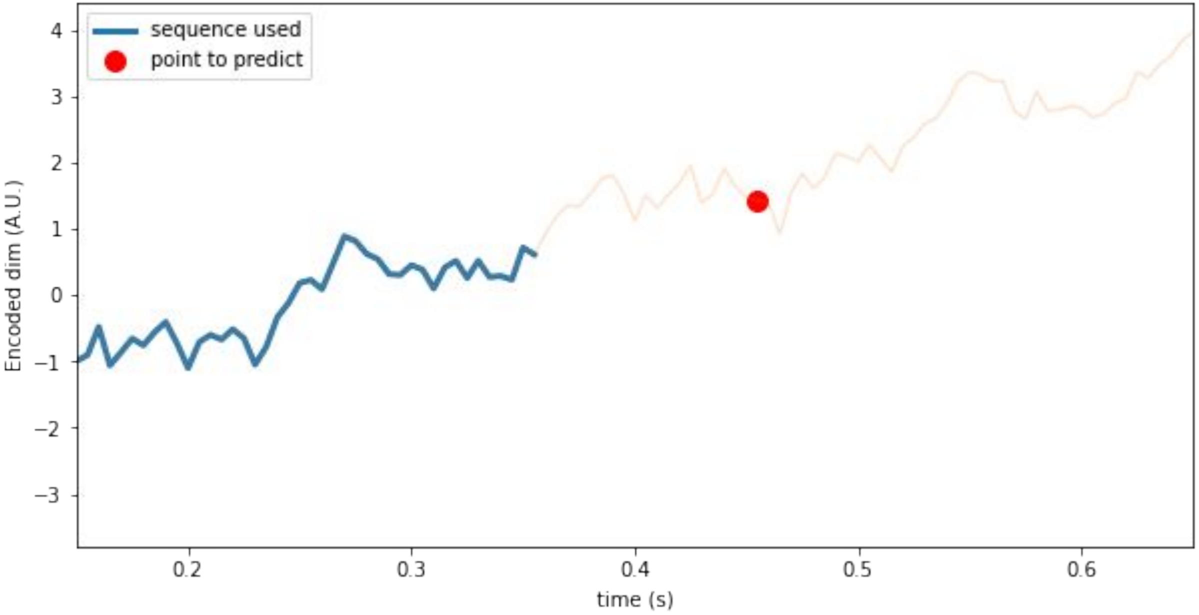


Predict the future in the encoded dimensions

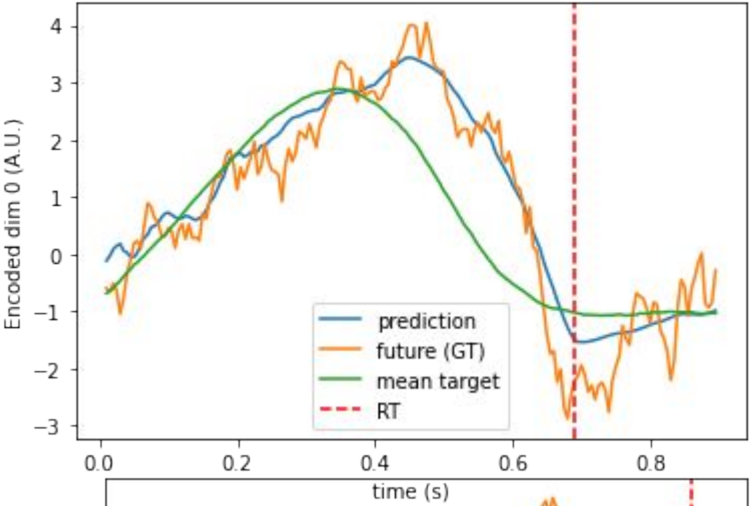


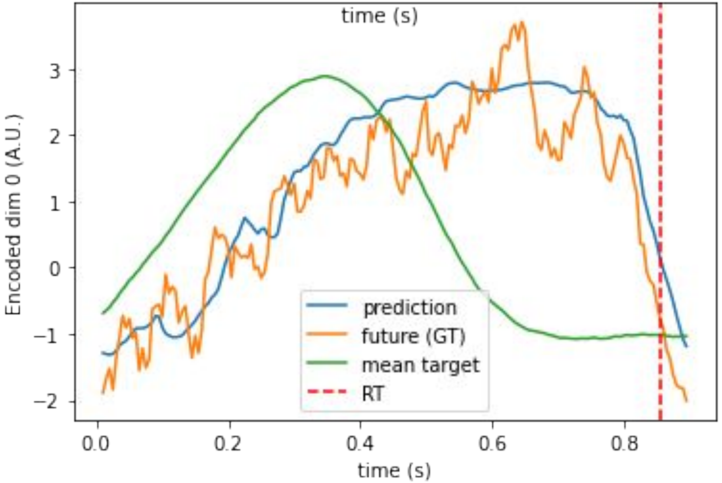


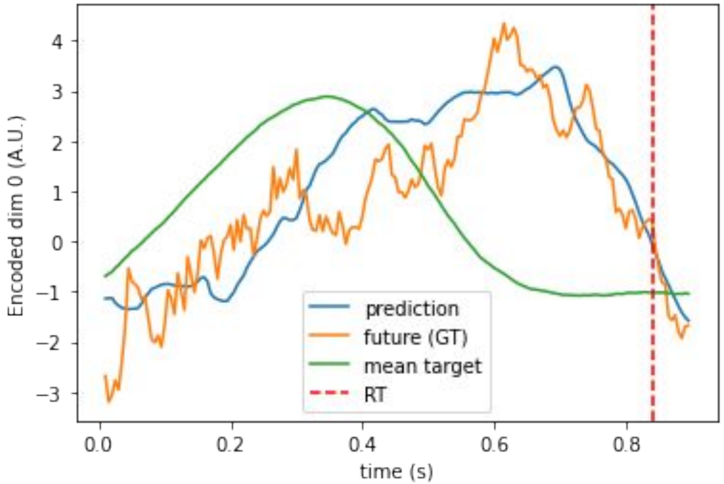
Lets try a 100 ms prediction (20 steps)

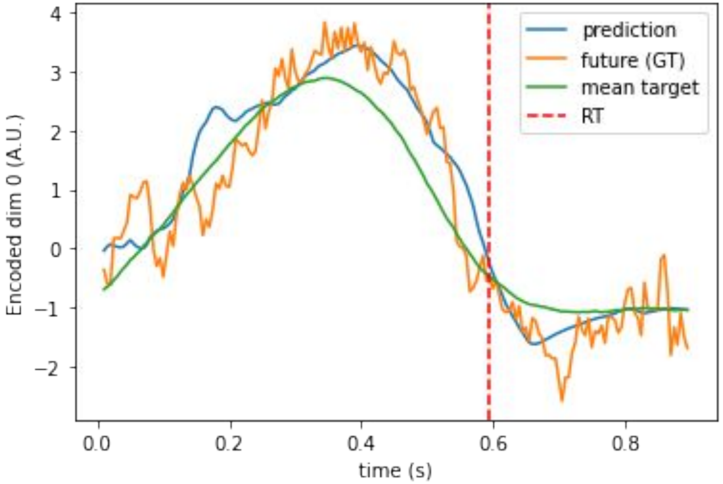


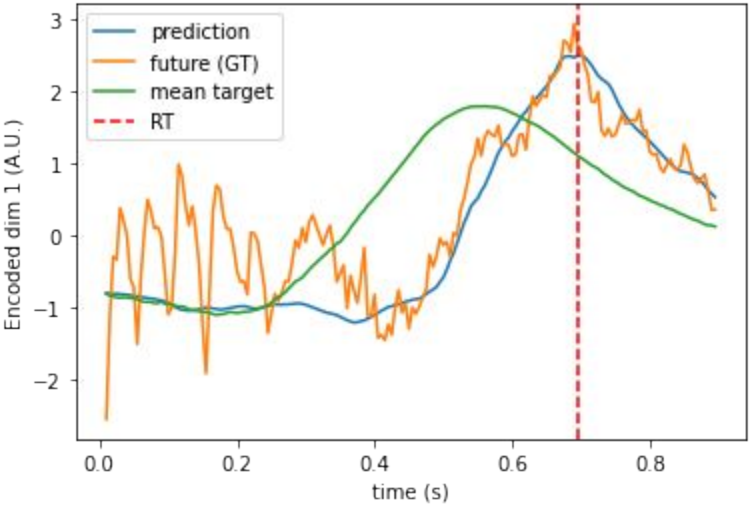
Single trials prediction



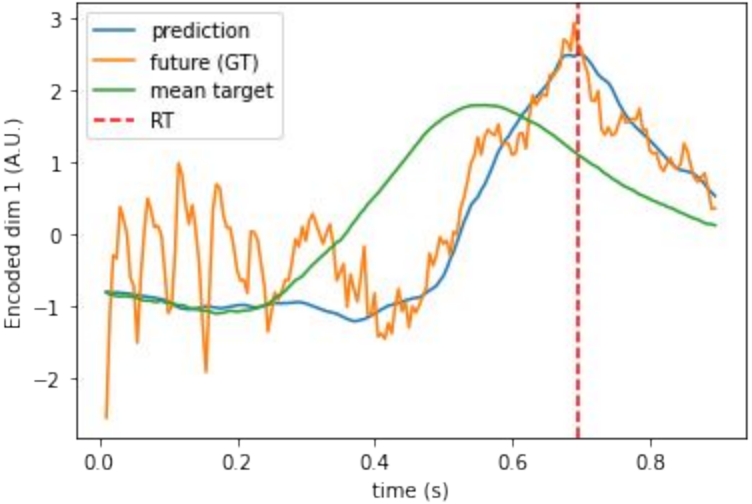




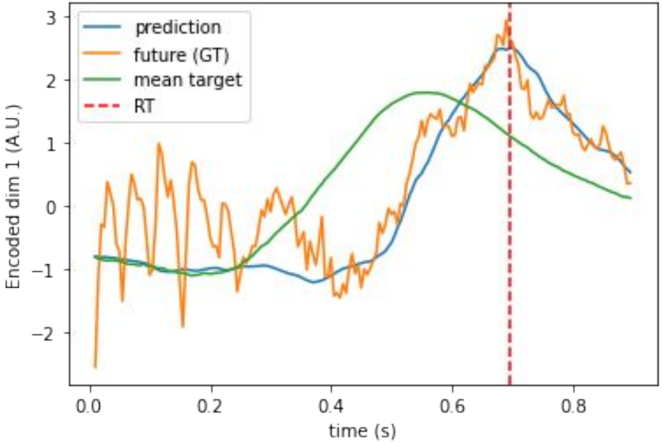




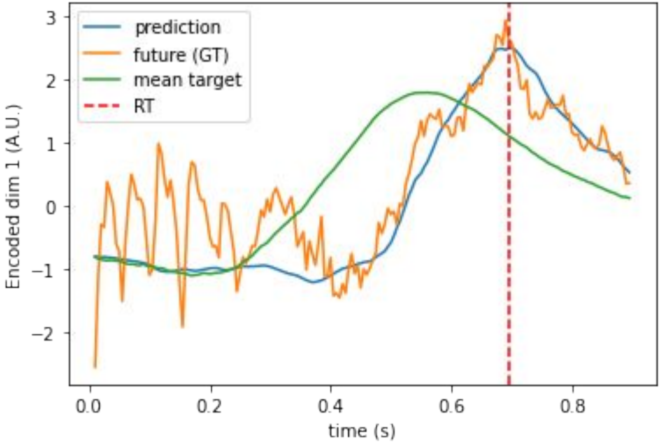
prediction
future (GT)
mean target
RT
Encoded dim 1 (A.U.)
time (s)



prediction
future (GT)
mean target
RT
Encoded dim 1 (A.U.)
time (s)



prediction
future (GT)
mean target
RT
Encoded dim 1 (A.U.)
time (s)



prediction
future (GT)
mean target
RT
Encoded dim 1 (A.U.)
time (s)

Ramps with MLP

Integrated Gradients