Video Activity Recognition for tic disorders

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Motivation

Conditions that induces motor and/or vocal spasms

Pretty common, especially for young people

Behavioral therapy is first-line treatment for all Tourette-like conditions:

- Help them understand how and when it happens
- Help them prevent tic from happening

Previous Work

Model the time serie with linear dynamical systems:

$$Y = (y_1, y_2, ..., y_n), Y \in \mathbb{R}^{P \times N}$$

$$X \in \mathbb{R}^{R \times N}, C \in \mathbb{R}^{R \times P}, A \in \mathbb{R}^{R \times R}$$

$$x_t = C y_t$$

$$x_{t+1} = A x_t$$

Issues with this method:

- Compression and dynamical system learning are separated
- Difficult to use an adaptive method for the compression

Our approach

Map the frames to a latent space using a neural network

- Model for compression can be any network
- Frame prediction is learned jointly with the compression

$$x_t = \Phi^E(y_t)$$
$$y_t = \Phi^D(x_t)$$
$$x_{t+1} = Ax_t$$

- Models used are all autoencoders:

Our approach

PCA-like autoencoder:

```
PCAAutoEncoder(
  (to_lower_rep): Linear(in_features=65536, out_features=10, bias=True)
  (from_lower_rep): Linear(in_features=10, out_features=65536, bias=True)
)
```

Our approach

One hidden layer autoencoder:

```
OneHAutoEncoder(
  (to_lower_rep): Sequential(
    (0): Linear(in_features=65536, out_features=200, bias=True)
    (1): ReLU()
    (2): Linear(in_features=200, out_features=10, bias=True)
  )
  (from_lower_rep): Sequential(
    (0): Linear(in_features=10, out_features=200, bias=True)
    (1): ReLU()
    (2): Linear(in_features=200, out_features=65536, bias=True)
  )
)
```

Our approach

Spatio-temporal convolutional autoencoder:

```
TemporalConvAE(
  (encoder_convs): Sequential(
    (0): Conv3d(1, 32, kernel_size=(8, 8, 8), stride=(2, 2, 2))
    (1): ReLU()
    (2): Conv3d(32, 32, kernel_size=(5, 7, 7), stride=(1, 2, 2))
    (3): ReLU()
  )
  (low_dim_mapping): Sequential(
    (0): Linear(in_features=115200, out_features=10, bias=True)
    (1): Linear(in_features=10, out_features=115200, bias=True)
  )
  (decoder_convs): Sequential(
    (0): ConvTranspose3d(32, 32, kernel_size=(5, 7, 7), stride=(1, 2, 2))
    (1): ReLU()
    (2): ConvTranspose3d(32, 1, kernel_size=(8, 8, 8), stride=(2, 2, 2))
    (3): ReLU()
  )
)
```

Compression models

Video used was recorded by the team at John Hopkins:

- Last 30 seconds
- Scaled to 256x256
- Converted to grayscale
- Around 30 fps

Each frame is mapped to 10 dimensions. For now we try to reconstruct the original frames as best as possible to show that information is preserved.

Compression models

Minimize the MSE of the reconstruction of frames:

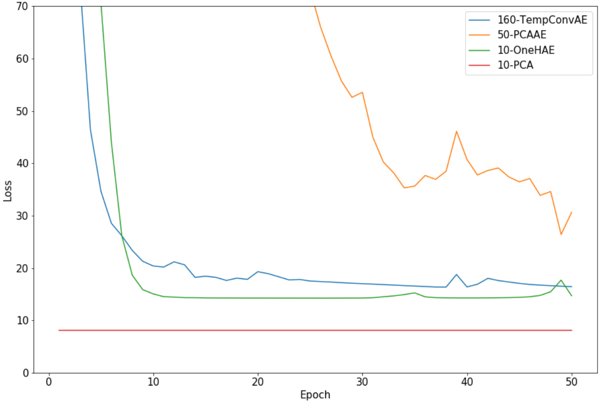
$$\mathscr{L}_1 = \|Y - \widehat{Y}\|_F^2 = \frac{1}{NP}\sum_{i=1}^{P}\sum_{j=1}^{N}(Y_{i,j} - \widehat{Y}_{i,j})^2$$

Notes on the embeddings' dimensions

- For the convolutional autoencoder, each encoded vectors is made from 16 frames, because we use convolutions over time. Hence from this vector 16 frames are being extrapolated. Thus to have a fair comparison its dimension is $16 * 10 = 160$.
- The PCA autoencoder is clearly worse than the others and harder to train. To be able to show that it still is learning, its latent dimension is of 50.

Compression models: Results

Harder than anticipated to compete with PCA:



Evolution of the loss during training

Time serie modelling

Fit a linear mapping A that predict the next frame's latent representation:

$$x_{t+1} = Ax_t$$

With the compression model fixed:

$$X \in \mathbb{R}^{R \times N}$$

$$X_- = (x_1, x_2, ..., x_{N-1})$$

$$X_+ = (x_2, x_3, ..., x_N)$$

$$AX_- = X_+ \rightarrow A = X_+ X_-^\dagger$$

Time serie modelling

To learn the matrix A jointly with the compression model we minimize the loss of reconstruction error of the prediction:

$$\mathscr{L}_2 = \frac{1}{N-1}\sum_{t=2}^{N}\|y_t - \Phi^D(A\Phi^E(y_{t-1}))\|$$

Time serie modelling's training

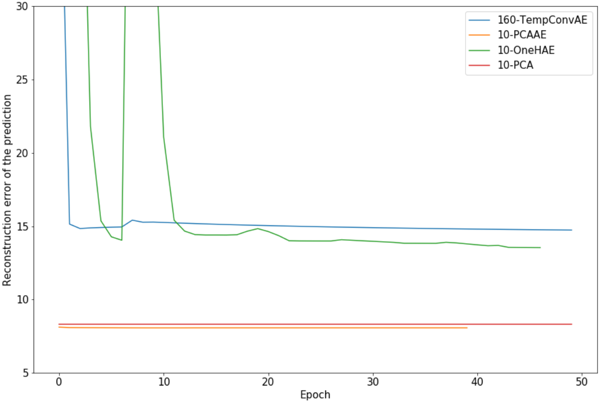
PCA-like autoencoder:

- Initialize the weights as in PCA model
- Optimize both models jointly

One hidden layer and convolutional autoencoder

- Initialize the compression model as at the end of last figure
- Optimize the transition matrix until it saturates
- Optimize both models in an alternating manner, 5 epochs each

Time serie modelling: Results



Evolution of the loss during training for frame prediction

Time serie modelling

A few comments:

- Loss may still not be representative of the quality of the embeddings
- PCA is very good at being *mostly accurate* but that's not what matters

One missing ingredient: the classification

- Will be based on the latent representation
- Could be deduced from the distance between them or any other more complicated model

Next steps

Once the dataset is ready and classification integrated, we will be able to better evaluate each models. In particular, we will see if the joint optimization indeed helps.

If the data takes too much time to arrive, we'll apply this to another common dataset and see how our method compare.