Model-BasedML Project 42186

Markus Olsen(s184073), Stefan Jensen(s184058), Victoria Ipsen(s184048), Amalie Roark (s184227)

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1 What we wanna do

In a video of a heart beating is it possible to predict frame I_{t+n}, $n \in \{1, ..., N\}$. This system has temporal properties and temporal model will be created and used to generate future frames of the video.

2 Data

Specifically, we will use a GIF of a heart in one beat. This cycle is repeatedly played if the GIF is replicated. First we will investigate a binary image created by a threshold (see fig. 1). Each frame of the GIF will constitute one column in the input matrix. The total number of frames are 7. The frames are 500×700 given a input vector of K = 35000 pixels a frame. It is not clear to us yet what the processing time will be. Therefore, the frames have been compressed by binning of factor 10. First, the images where binning has been applied will be used and afterwards, we will explore the frames which have not been compressed.

This is the data that will be used initially to build the model. More data will be found or created with data augmentation after the initial model.

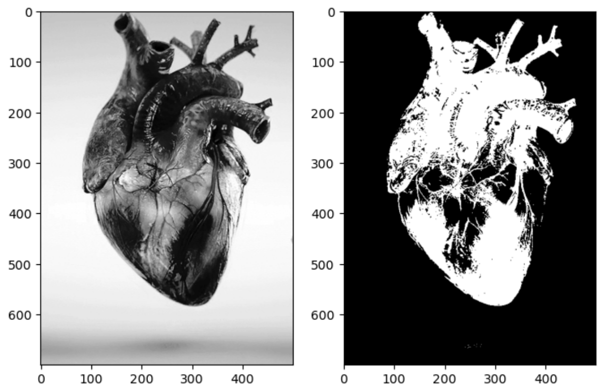

Figure 1: Single frame from data set

3 The model

Assuming that there is a temporal relationship between the frames in the video, multiple models can be used to generate new frames. Because each pixel will be presented as a variable see fig 2. Furthermore, Hidden Markov Model is a specific instance of the state space model where the latent variables are discrete, that also would be suitable.

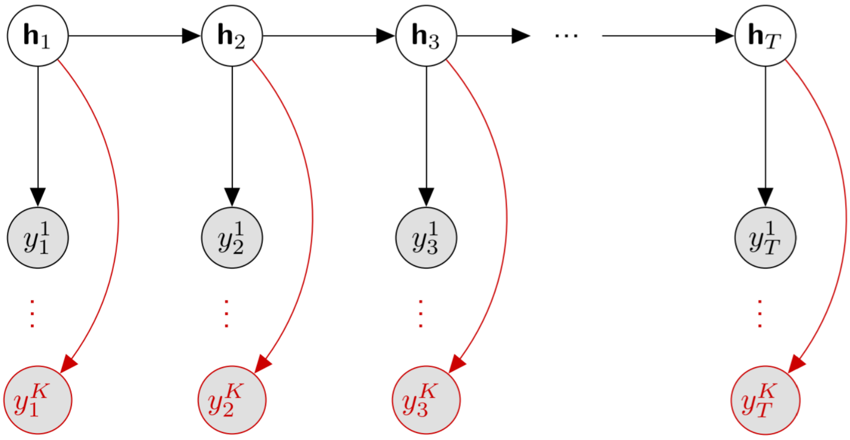

Figure 2: Multivariate state-space model from lecture slides. An observed node y_t^k corresponds to the pixel value k of the unraveled video frame t.

3.1 State Space Model (SSM)

Algorithm 1 Generative process

`Define priors`
$\Sigma = I\sigma$
$R =??$
`Draw first hidden state` $h_0 \sim \mathcal{N}(h_0|??)$
for $t \in \{1, ..., T\}$ **do**
  for $k \in \{1, ..., K\}$ **do**
    `Draw transition probabilities` $b_k \sim \mathcal{N}(b_k|\alpha)$
    `Draw emmision probabilities` $c_k \sim \mathcal{N}(c_k|\gamma)$
    `Draw new hidden state` $h_t \sim \mathcal{N}(h_t|bh_{t-1}, R)$
    `Draw continuous observation` $y_t \sim \mathcal{N}(y_t|ch_t, \Sigma)$
    `Draw binary observation` $p(yc_t = 1), y_t = \text{Sigmoid}(yc_t)$
for $t \in \{T+1, ..., T+T_{forecast}\}$ **do**
  for $k \in \{1, ..., K\}$ **do**
    `Draw transition probabilities` $b_k \sim \mathcal{N}(b_k|\alpha)$
    `Draw emmision probabilities` $c_k \sim \mathcal{N}(c_k|\gamma)$
    `Draw new hidden state` $h_{T+t} \sim \mathcal{N}(h_{T+t}|bh_t, R)$
    `Draw continuous observation for` $yc_{T+t} \sim \mathcal{N}(yc_{T+t}|ch_{T+t}, \Sigma)$
    `Draw binary observation` $p(yc_{T+t} = 1), y_{T+t} = \text{Sigmoid}(yc_{T+t})$

The observations will be continuous when drawing from a continuous latent space. But the Sigmoid function provides probabilities from $[0, 1]$ for $p(yc = 1)$ and will be the

main

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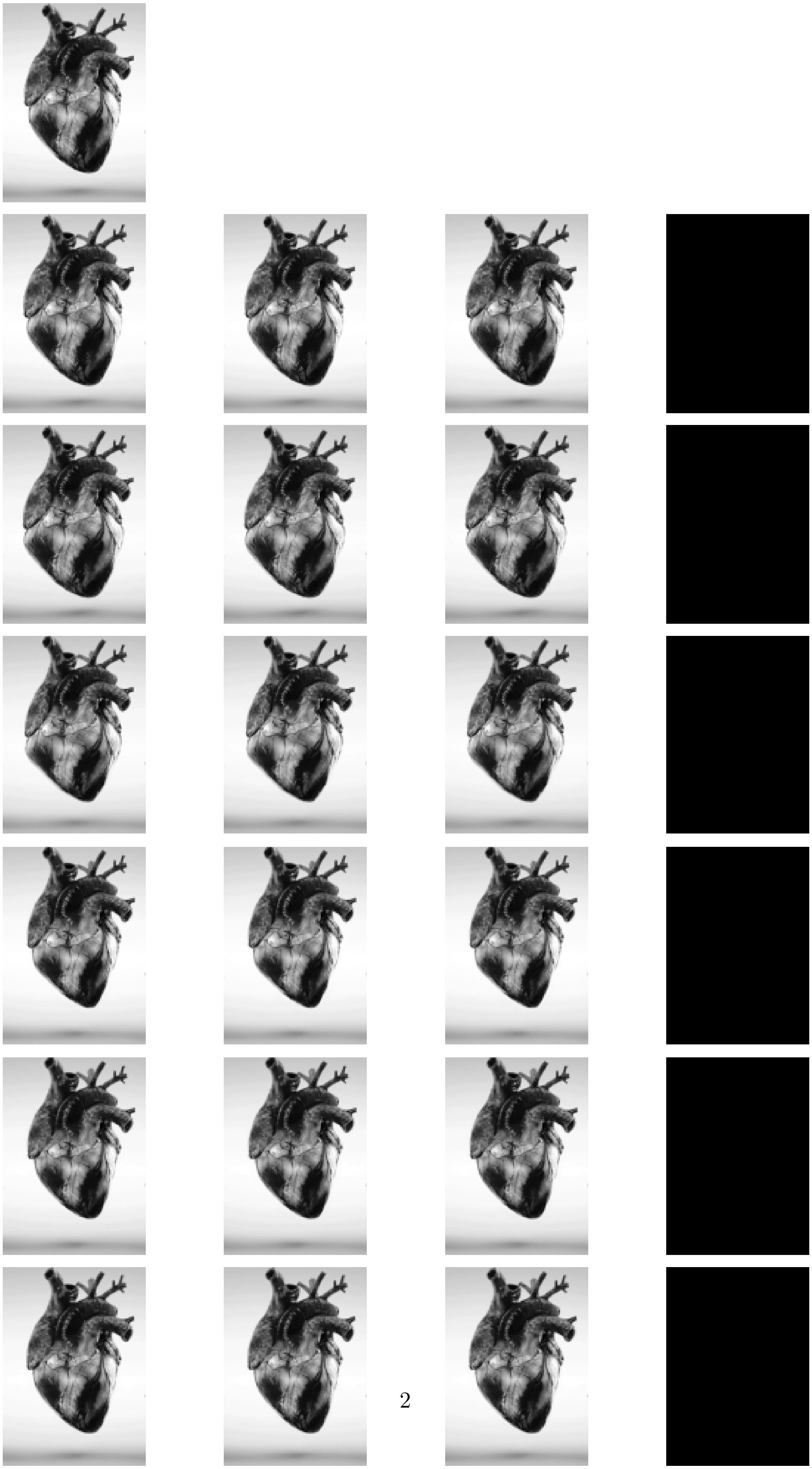
[47]:
```
import imageio
import torch
from IPython.display import clear_output
import matplotlib.pyplot as plt
import numpy as np
import cv2
%matplotlib inline
```

[48]:
```
# Load gif:
gif = imageio.mimread('data/1kWp.gif')

for i in range(len(gif)):
    print(gif[i].shape)
```

```
(700, 500)
(700, 500, 4)
(700, 500, 4)
(700, 500, 4)
(700, 500, 4)
(700, 500, 4)
(700, 500, 4)
```

Something weird seems to be going on with the frames, so we check with a subplot, where each row corresponds to the element in the `img` list

[49]:
```
fig,ax=plt.subplots(7,4,figsize=(6,10),constrained_layout=True)
ax[0,0].imshow(gif[0],cmap='gray')
ax[0,0].axis('off')

ax[0,1].set_visible(False)
ax[0,2].set_visible(False)
ax[0,3].set_visible(False)

for i in range(1,len(gif)):
    for j in range(4):
        ax[i,j].imshow(gif[i][:,:,j],cmap='gray')
        ax[i,j].axis('off')
plt.show()
```



First three images within each element of the list seems to be identical, let's verify..

[50]:
```
for i in range(1,len(gif)):
    print(f'List element {i}')
    print(np.all(gif[i][:,:,0]==gif[i][:,:,1]))
    print(np.all(gif[i][:,:,0]==gif[i][:,:,2]))
    print(np.all(gif[i][:,:,1]==gif[i][:,:,2]),'\n')
```

```
List element 1
True
True
True

List element 2
True
True
True

List element 3
True
True
True

List element 4
True
True
True

List element 5
True
True
True

List element 6
True
True
True
```

That is indeed true. We then convert to a 3D array

[51]:
```
im=[]
im.append(gif[0])
for i in range(1,len(gif)):
    im.append(gif[i][:,:,0].astype(float))
```

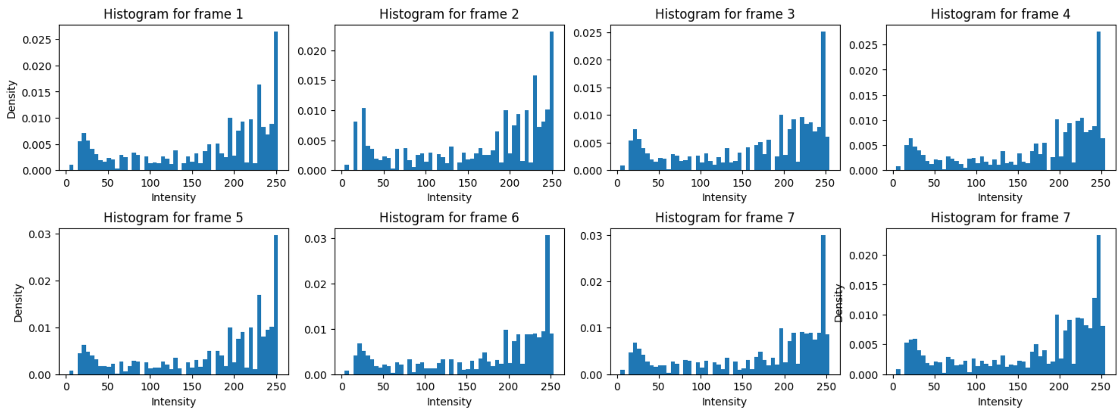
```
# Convert list to numpy array
im=np.asarray(im)

print(im.shape)
```

```
(7, 700, 500)
```

For some descriptive statistics, let's look at the mean and median per frame and overall as well as a per-frame and overall histogram:

[52]:
```
print('Per-frame mean and median value:\n')
print('Mean:',im.mean(axis=(1,2)).round(3))
print('Median:',np.median(im,axis=(1,2)))

print('overall mean and median value:\n')
print('Mean',im.mean().round(3))
print('Median',np.median(im))


fig,ax=plt.subplots(2,4,figsize=(18,6))
ax=ax.ravel()
for i in range(len(im)):
    _ = ax[i].hist(im[i].ravel(),bins=50,density=True)
    ax[i].set_title(f'Histogram for frame {i+1}')
    ax[i].set_xlabel('Intensity')
    if (i==0) or (i==4):
        ax[i].set_ylabel('Density')

_ = ax[-1].hist(im.ravel(),bins=50,density=True)
ax[-1].set_title(f'Histogram for frame {i+1}')
ax[-1].set_xlabel('Intensity')
ax[-1].set_ylabel('Density')

plt.subplots_adjust(hspace=0.4)
```

```
Per-frame mean and median value:

Mean: [167.501 165.938 165.29  170.584 173.547 172.881 171.086]
Median: [197. 197. 197. 202. 205. 205. 202.]
overall mean and median value:

Mean 169.547
Median 202.0
```

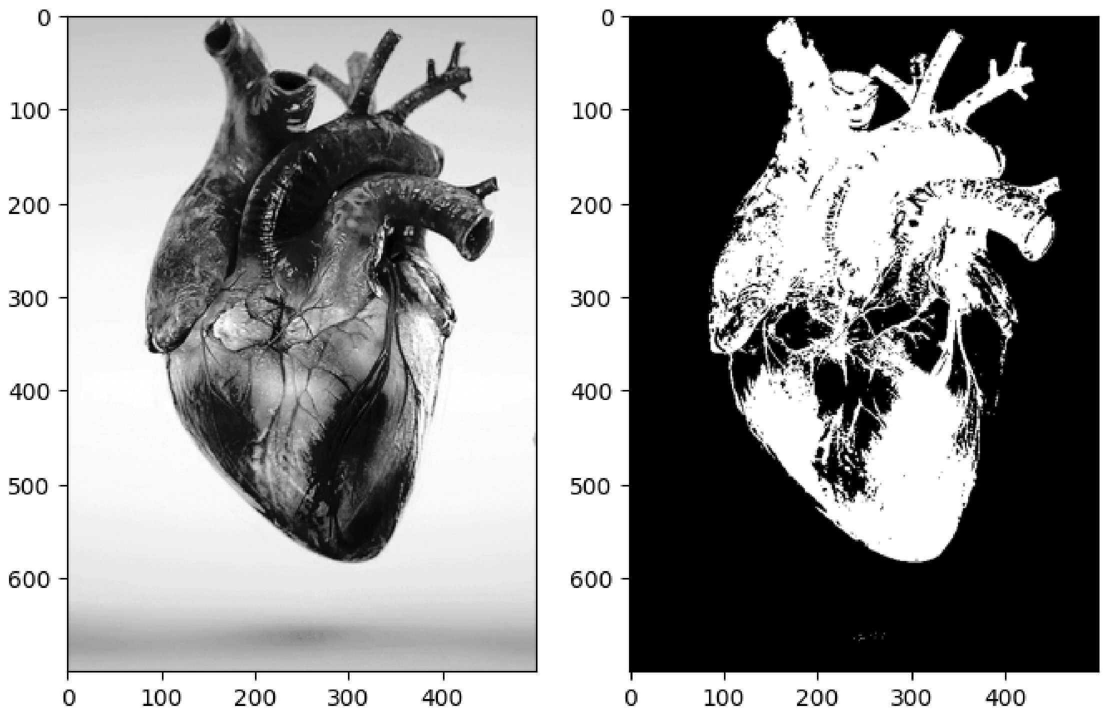


We then create the corresponding binary image. For now we simply threshold at the middle intensity

[53]:
```
imBin = (im < int(np.max(im)/2)).astype(float)
```

We then visualize both the grayscale gif and the binary gif for 5 cycles

[54]:
```
for t in range(5):
    for i in range(im.shape[0]):
        clear_output(wait=True)
        fig,ax=plt.subplots(1,2,figsize=(8,6))
        ax[0].imshow(im[i],cmap='gray')
        ax[1].imshow(imBin[i],cmap='gray')
        plt.show()
```



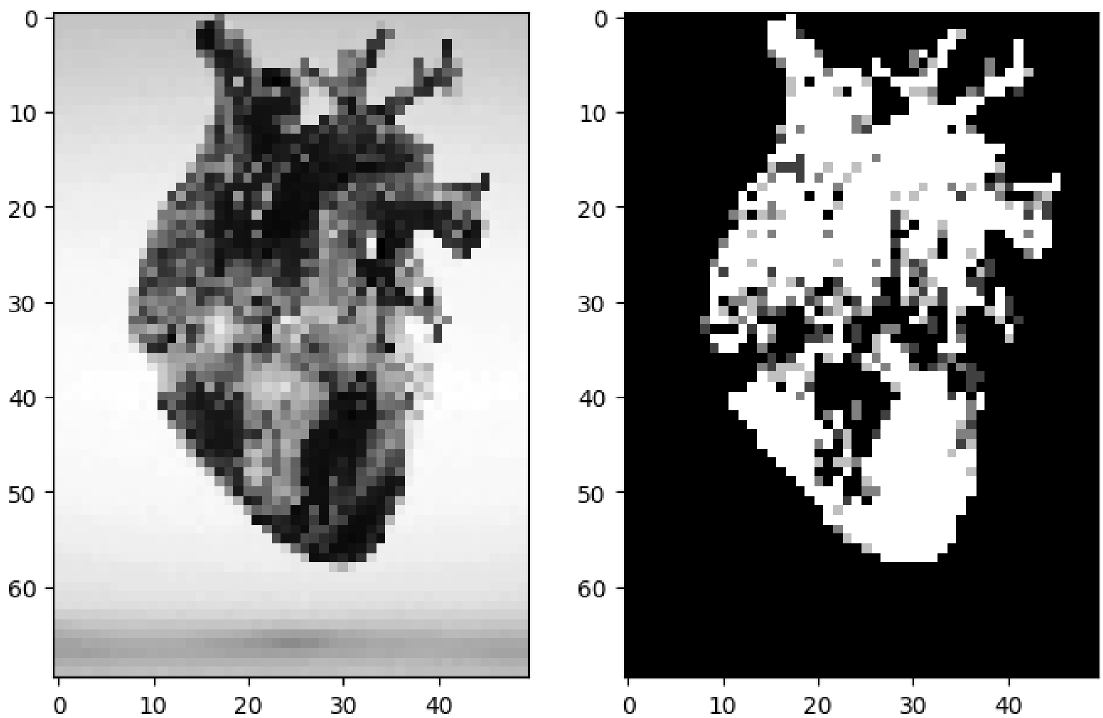
Next, we will downsample the image as it currently contains $700 \cdot 500 = 3.5 \cdot 10^5$ pixels per frame, which (at least for initial experiments) is way too much

[55]:
```
scaleFactor=10
new_dim=(int(im.shape[2]/scaleFactor),int(im.shape[1]/scaleFactor)) # For some
 ↪reason it should be opposite

imScaled=[]
imBinScaled=[]
for i in range(im.shape[0]):
    tmp = cv2.resize(im[i],new_dim)
    imScaled.append(tmp)

    tmp = cv2.resize(imBin[i],new_dim)
    imBinScaled.append(tmp)

imScaled = np.array(imScaled)
imBinScaled = np.array(imBinScaled)
```

We then visualize again

[56]:
```
for t in range(5):
    for i in range(im.shape[0]):
        clear_output(wait=True)
```

```
    fig,ax=plt.subplots(1,2,figsize=(8,6))
    ax[0].imshow(imScaled[i],cmap='gray')
    ax[1].imshow(imBinScaled[i],cmap='gray')
    plt.show()
```



With a scale factor of 10 we now have 3500 pixels per frame

Finally, we unravel image frames such that we have them in the format used for temporal models, i.e. we are reshaping from (7,H,W) to (7,H*W)

[57]:
```
vecLen=imScaled.shape[1]*imScaled.shape[2]
imScaledVec = imScaled.reshape(7,vecLen)
imBinScaledVec = imBinScaled.reshape(7,vecLen)
```

[58]:
```
print(imScaledVec.shape)
```

```
(7, 3500)
```