

Lecture 12:

Long Short-Term Memory Networks (LSTMs) – Part II



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Machine Learning Algorithms

MSSE 277B, 3 Units

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<https://www.analyticsvidhya.com>



Outline

- LSTM for Classification
- Bidirectional LSTMs
- Stacked LSTMs
- LSTM + CNN

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Outline

- LSTM for Classification
- Bidirectional LSTMs
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minimal model:

```
[N_samples, LengthSeq, N_features] = X.shape  
[N_samples, N_classes] = Y.shape
```

Y is one-hot encoded

```
model = Sequential()
```

```
model.add(LSTM(n_neurons, activation = 'tanh',\  
               input_shape = (LengthSeq, N_features)))
```

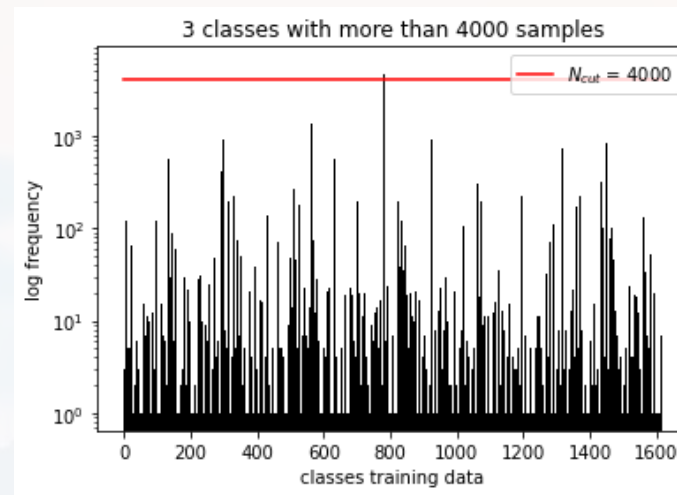
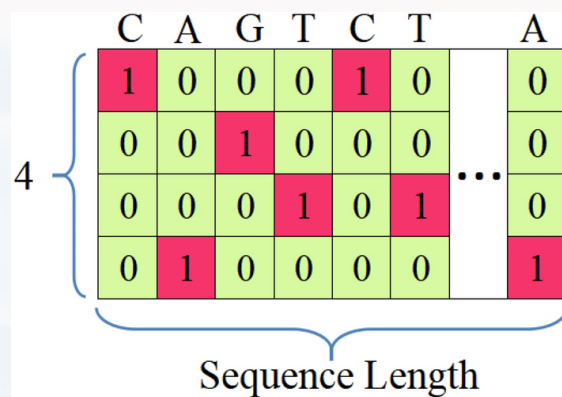
```
model.add(Dense(N_classes, activation = 'softmax'))
```

```
opt = optimizers.Adam()  
model.compile(loss = 'categorical_crossentropy', optimizer = opt,\  
              metrics = ['accuracy'])
```

```
model.summary()
```

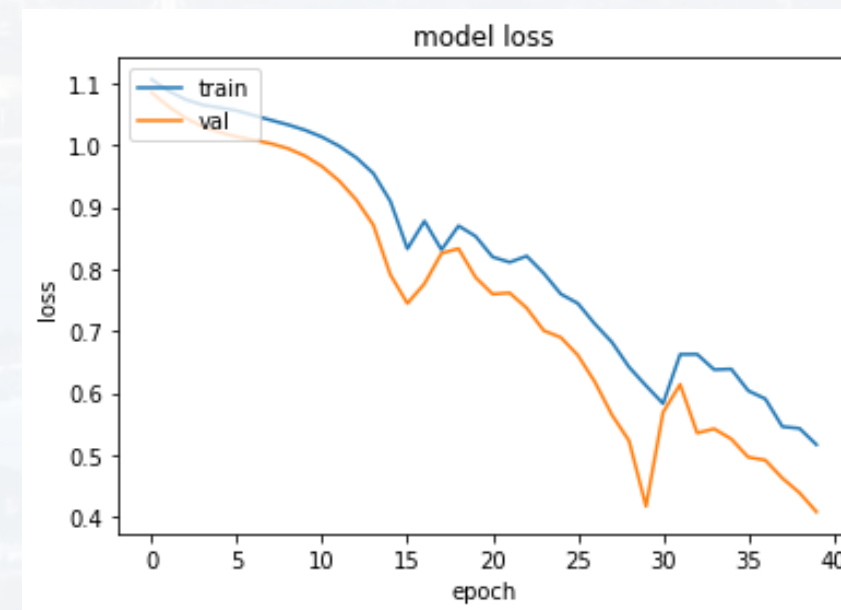
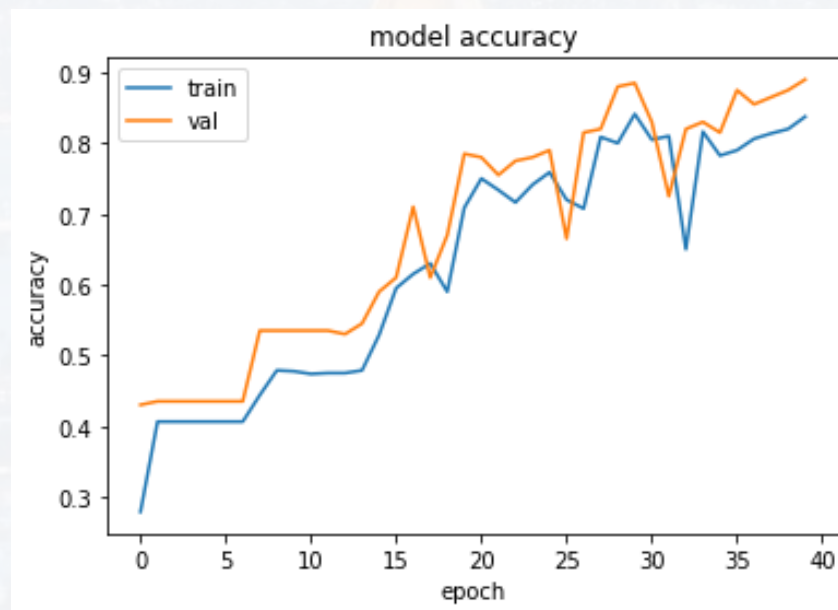


barcode example



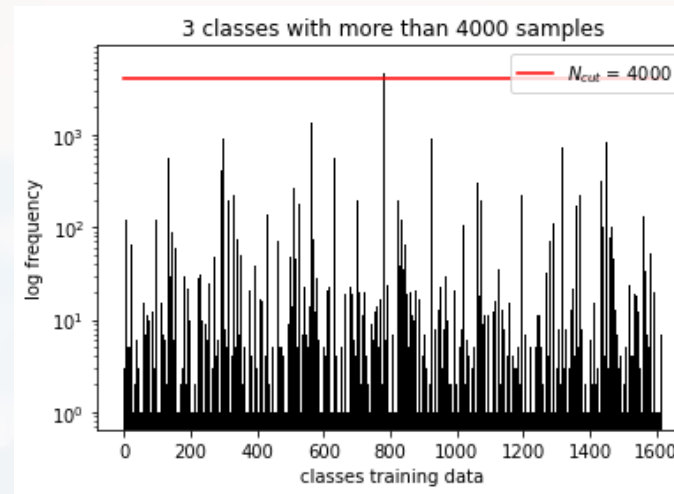
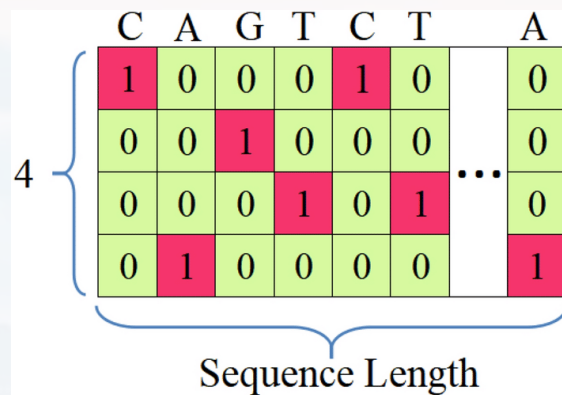
for computational reasons:

- **three** classes
- **1k** samples total
- sequences cut to length **500**



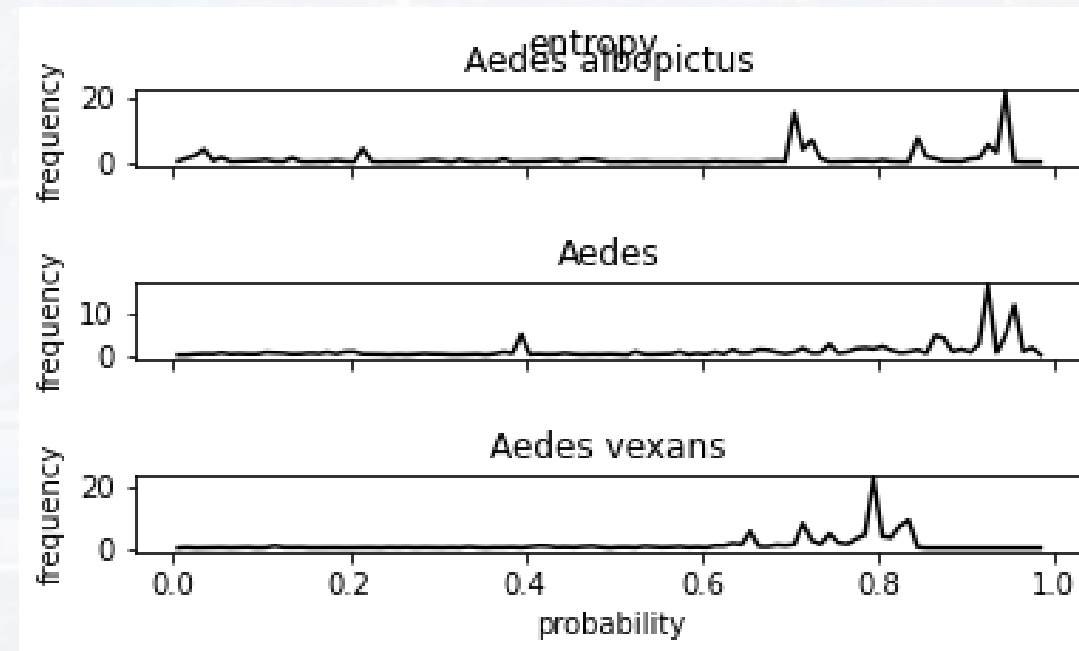
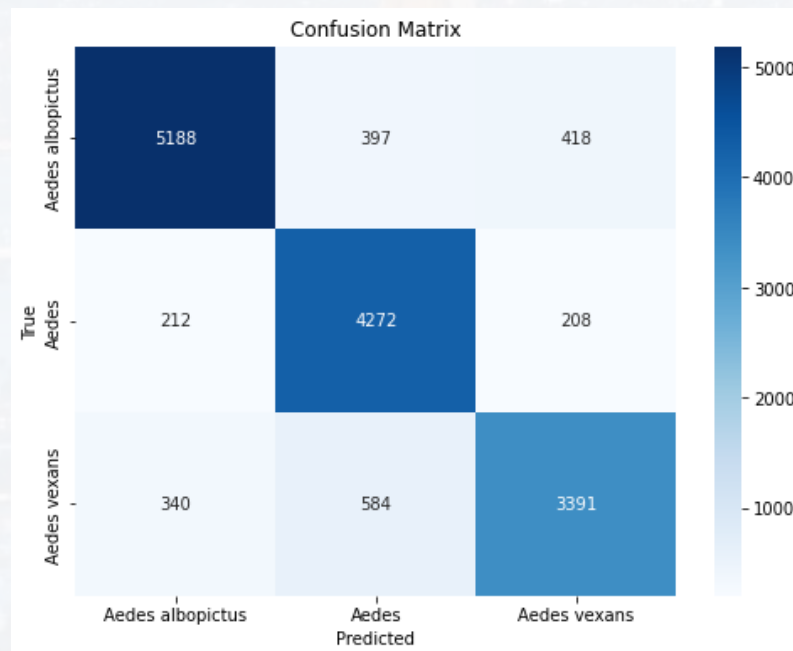


barcode example



for computational reasons:

- **three** classes
- **1k** samples total
- sequences cut to length **500**





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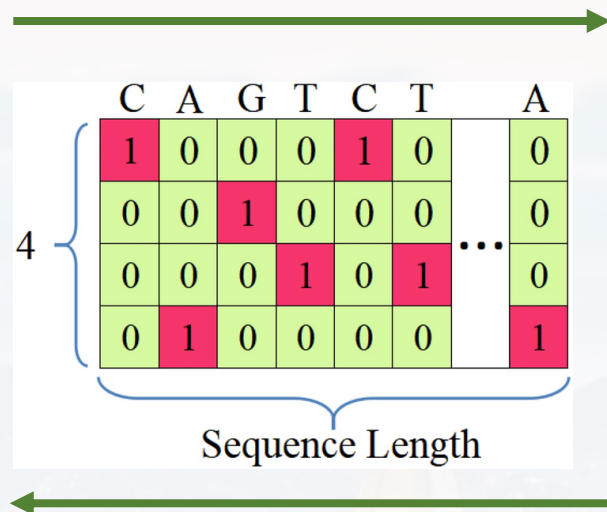


Outline

- LSTM for Classification
- **Bidirectional LSTMs**
- Stacked LSTMs
- LSTM + CNN



sometimes, sequences can be read from two directions :



```
from keras.layers import Bidirectional
```

```
model = Sequential()  
model.add(Bidirectional(LSTM(n_neurons, activation = 'tanh'),\  
                        input_shape = (dt_past, n_features)))  
model.add(Dense(dt_futu))
```

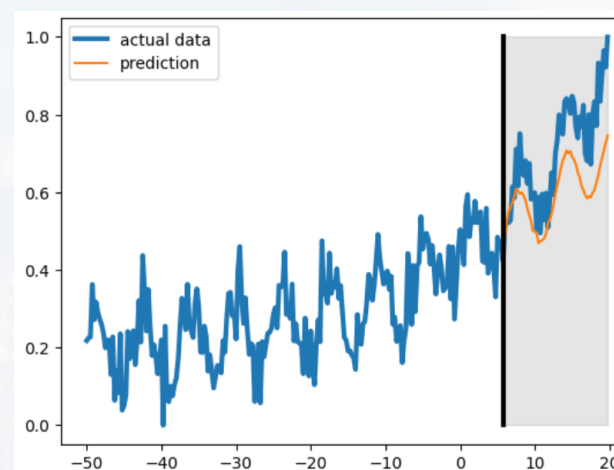
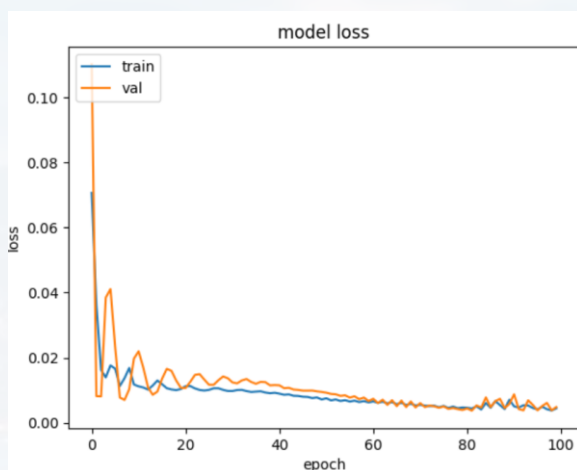
```
opt = optimizers.Adam()  
model.compile(loss = 'mean_squared_error', optimizer = opt)
```

```
model.summary()
```

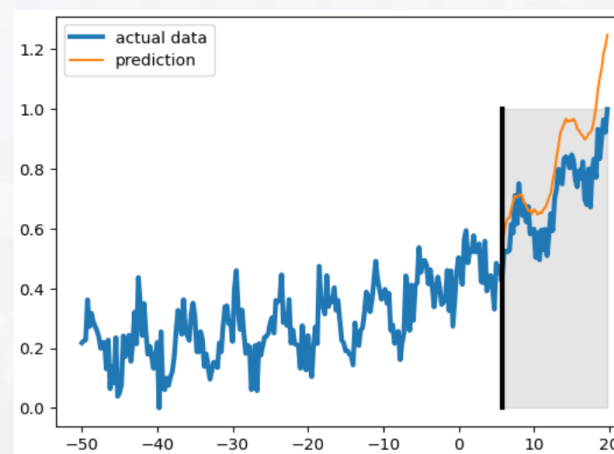
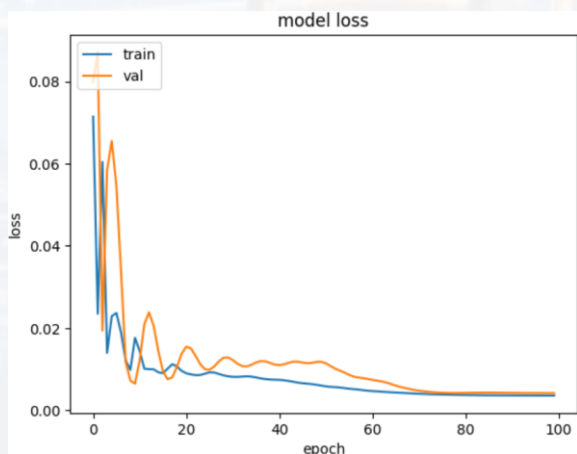



```
model = Sequential()  
model.add(Bidirectional(LSTM(n_neurons, activation = 'tanh'), input_shape = (dt_past, n_features)))  
model.add(Dense(dt_futu))  
opt = optimizers.Adam()  
model.compile(loss = 'mean_squared_error', optimizer = opt)  
model.summary()
```

vanilla



bidirectional



Layer (type)	Output Shape	Param #
bidirectional (Bidirectional)	(None, 800)	1286400
dense_1 (Dense)	(None, 8)	6408
Total params: 1292808 (4.93 MB)		
Trainable params: 1292808 (4.93 MB)		
Non-trainable params: 0 (0.00 Byte)		



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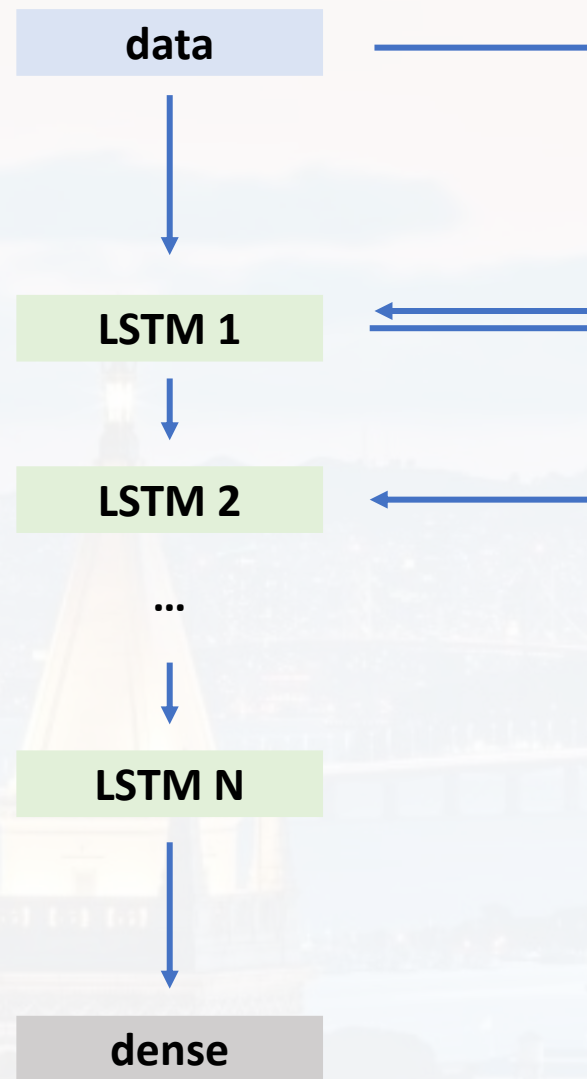


Outline

- LSTM for Classification
- Bidirectional LSTMs
- **Stacked LSTMs**
- LSTM + CNN



idea:



shape: ($\text{len}(y(t)) - dt_past - dt_futu + 1$)
x dt_past x features

shape: ($\text{len}(y(t)) - dt_past - dt_futu + 1$)
x dt_past x hidden state

return_sequences = True



```
model = Sequential()

model.add(LSTM(n_neurons, activation = 'tanh',\
               return_sequences = True, input_shape = (dt_past, n_features)))

model.add(LSTM(2*n_neurons, activation = 'relu',\
               return_sequences = True))

model.add(LSTM(n_neurons, activation = 'relu'))

model.add(Dense(dt_futu))

opt = optimizers.Adam()
model.compile(loss = 'mean_squared_error', optimizer = opt)

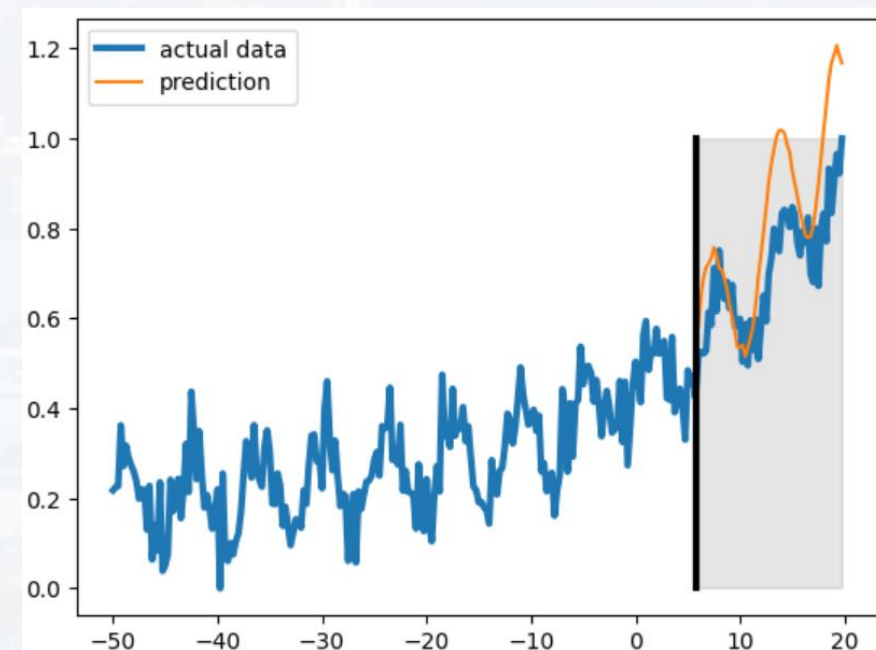
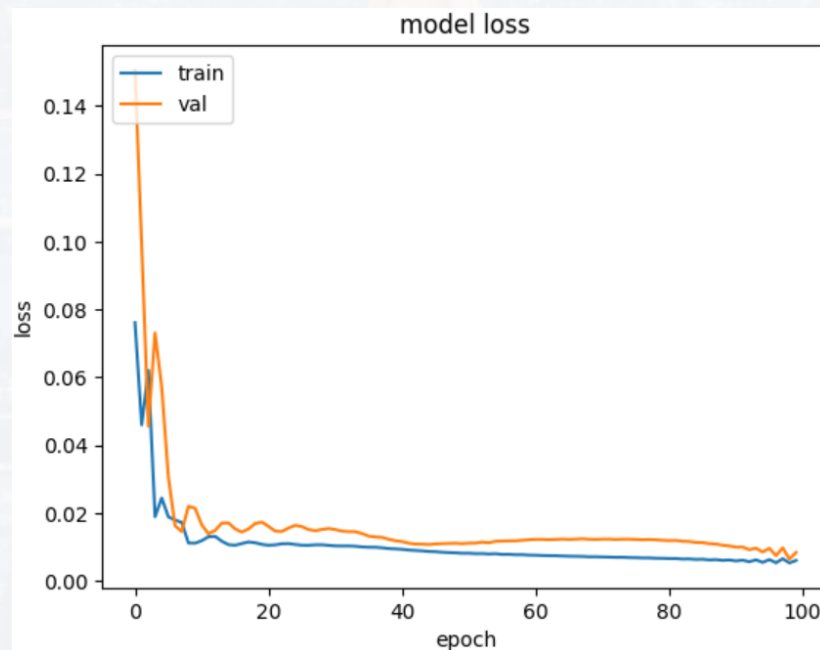
model.summary()
```

all LSTMs, **except the last** stack needs
return_sequences = True



Layer (type)	Output Shape	Param #
lstm_2 (LSTM)	(None, 20, 400)	643200
lstm_3 (LSTM)	(None, 20, 800)	3843200
lstm_4 (LSTM)	(None, 400)	1921600
dense_2 (Dense)	(None, 8)	3208

=====
Total params: 6411208 (24.46 MB)
Trainable params: 6411208 (24.46 MB)
Non-trainable params: 0 (0.00 Byte)



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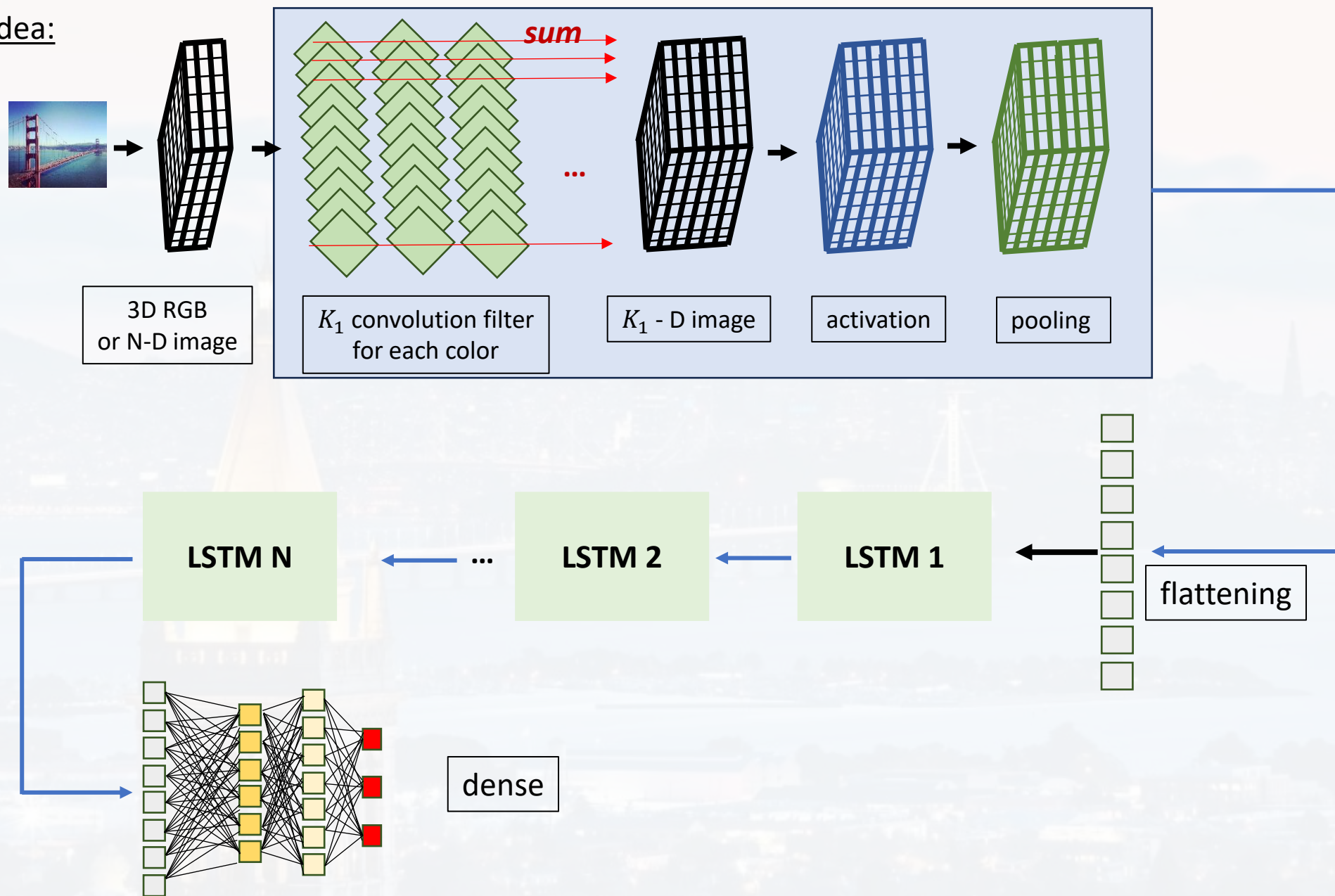


Outline

- LSTM for Classification
- Bidirectional LSTMs
- Stacked LSTMs
- **LSTM + CNN**



idea:





idea:

input expected by CNN (images):

$(N_images, N_x, N_y, N_color)$

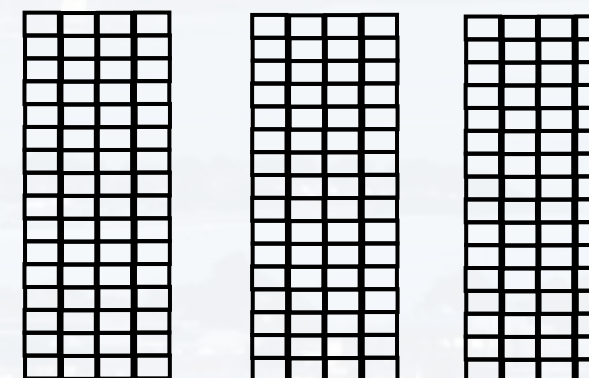
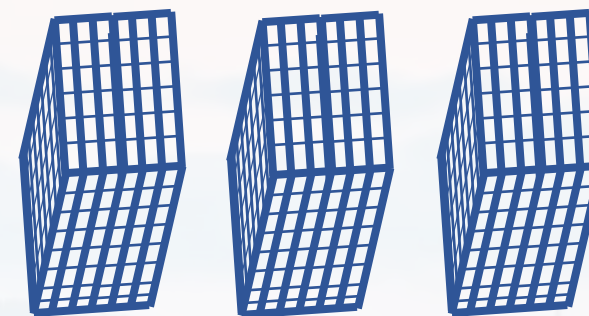
input expected by CNN (videos):

$(N_videos, N_t, N_x, N_y, N_color)$

input expected by LSTM (sequences):

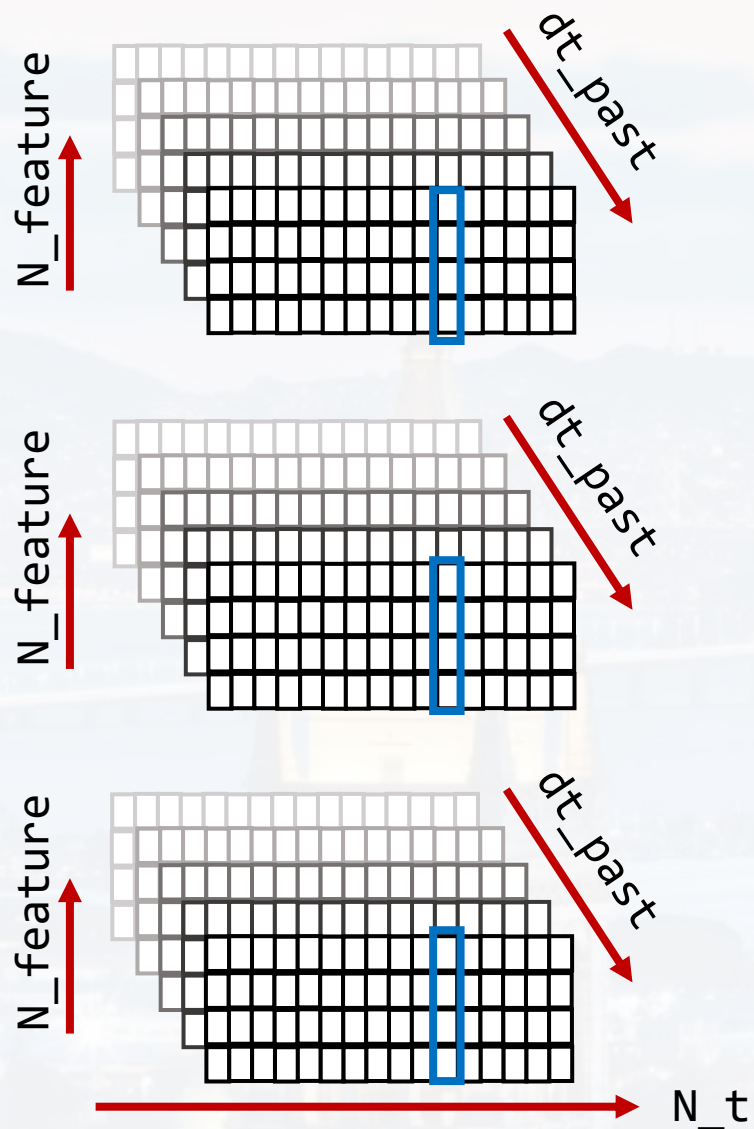
$(N_sequences, N_t, N_feature)$

None





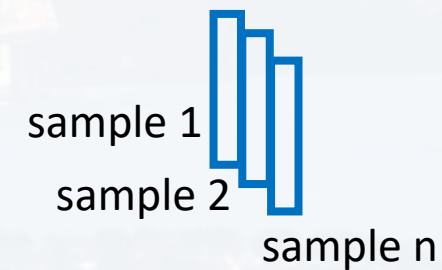
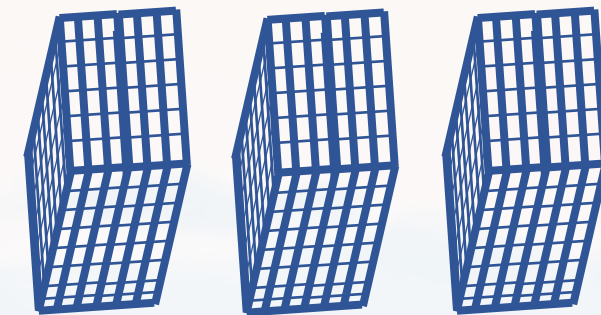
$(N_images, N_x, N_y, N_color)$



sample 1

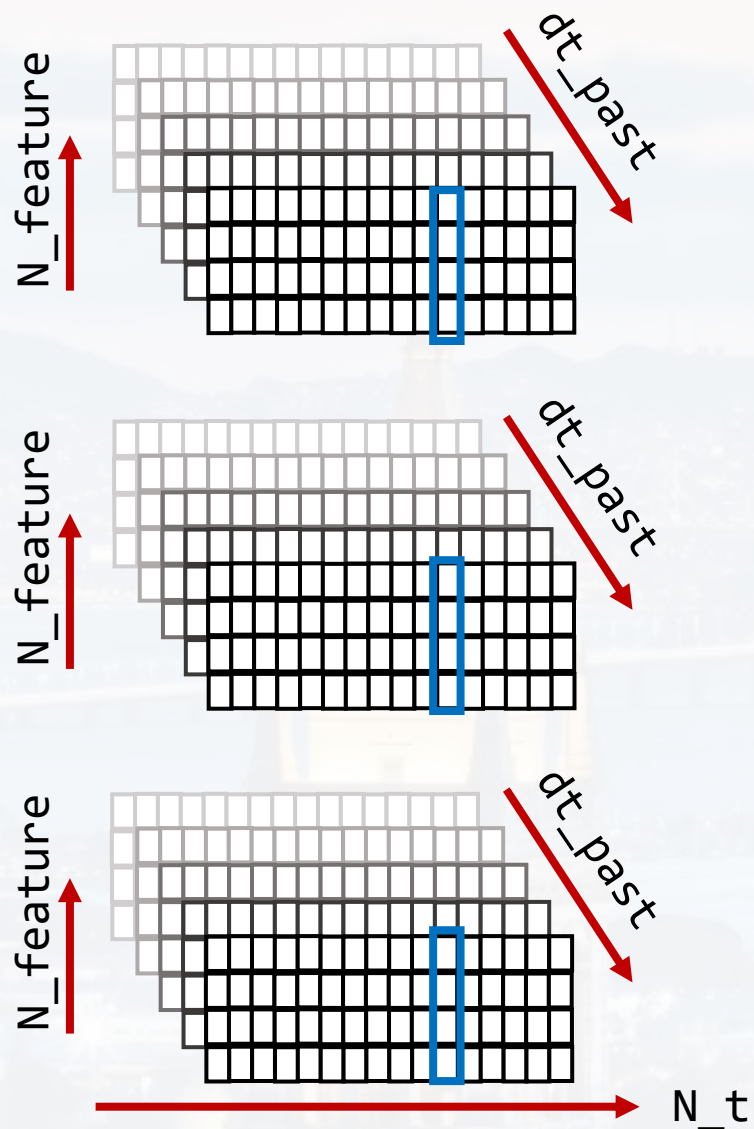
sample 2

sample n





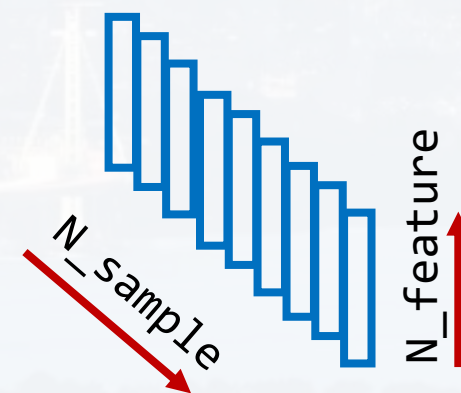
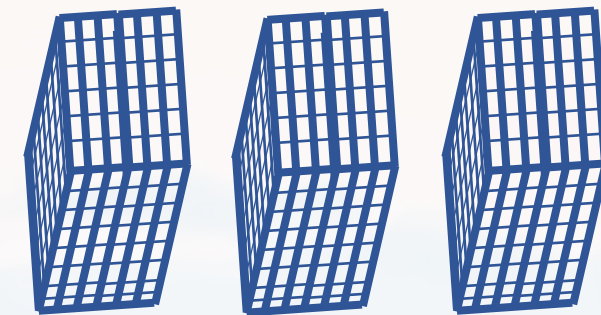
$(N_images, N_x, N_y, N_color)$



sample 1

sample 2

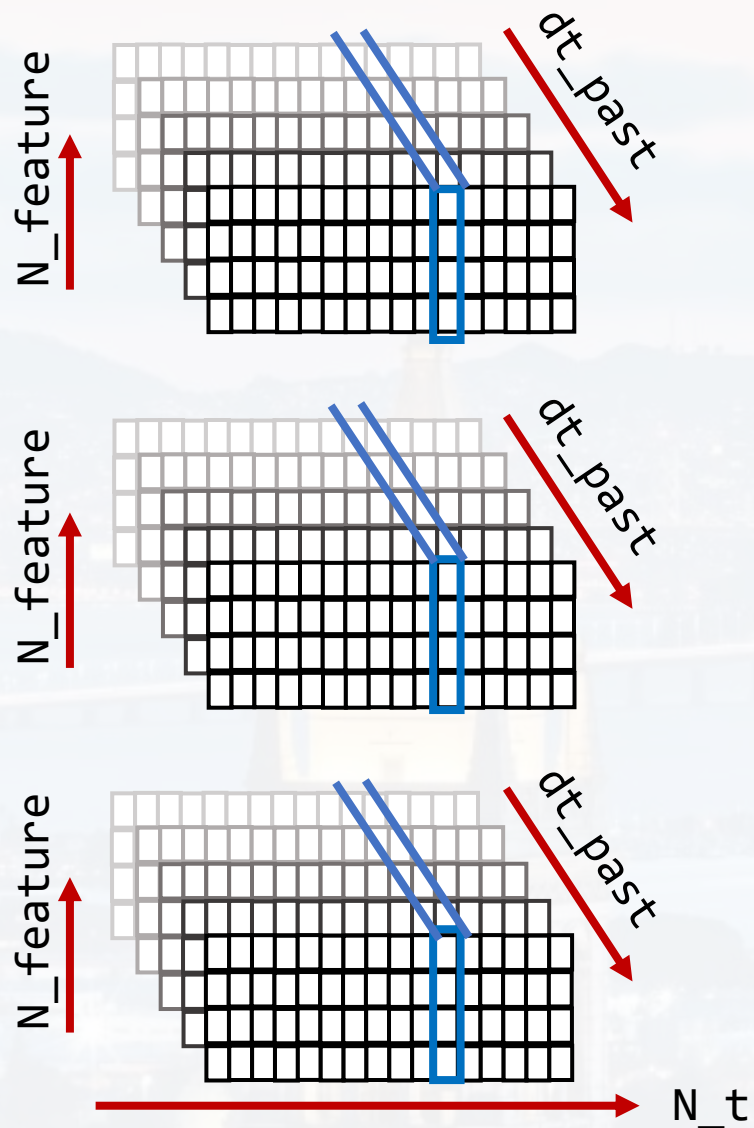
sample n



for **one** timepoint t



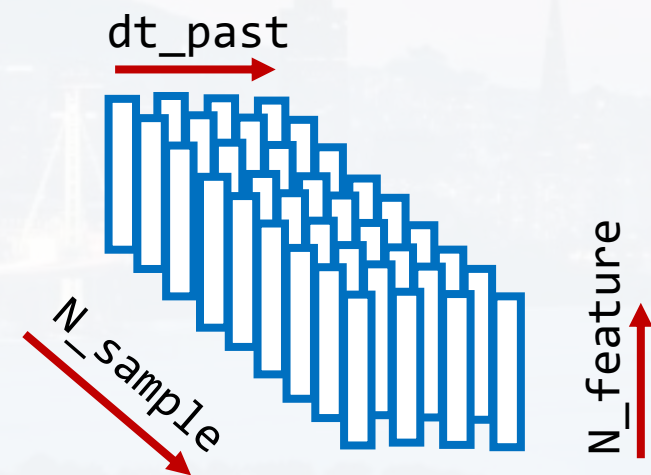
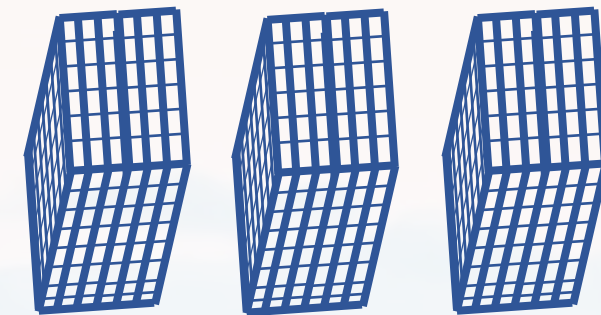
$(N_images, N_x, N_y, N_color)$



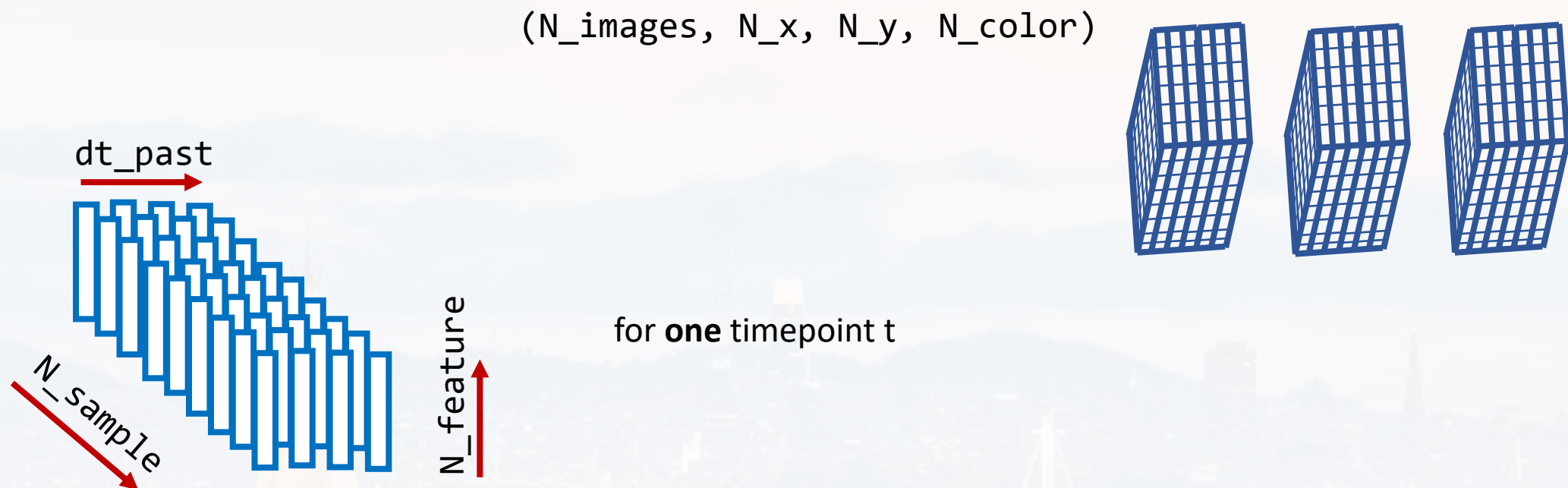
sample 1

sample 2

sample n



for **one** timepoint t



regression: **one** sample of N_features and dt_past

```
X = X.reshape((X.shape[0], N_samples, dt_past, n_features))
```




```
X = X.reshape((X.shape[0], N_samples, dt_past, n_features))
```

```
model = Sequential()  
model.add(TimeDistributed(Conv1D(filters = 64, kernel_size = 3,\br/>                                activation = 'relu'),\br/>                                input_shape = (None, dt_past, n_features)))
```

1D filter along time coordinate

```
model.add(TimeDistributed(MaxPooling1D(pool_size = 2)))
```

```
model.add(TimeDistributed(Flatten()))
```

takes care of
maintaining
matrix orientation

```
model.add(LSTM(n_neurons, input_shape = (dt_past, n_features),\br/>              activation = 'tanh'))
```

```
model.add(Dense(dt_futu))
```

```
opt = optimizers.Adam()  
model.compile(loss = 'mean_squared_error', optimizer = opt)
```

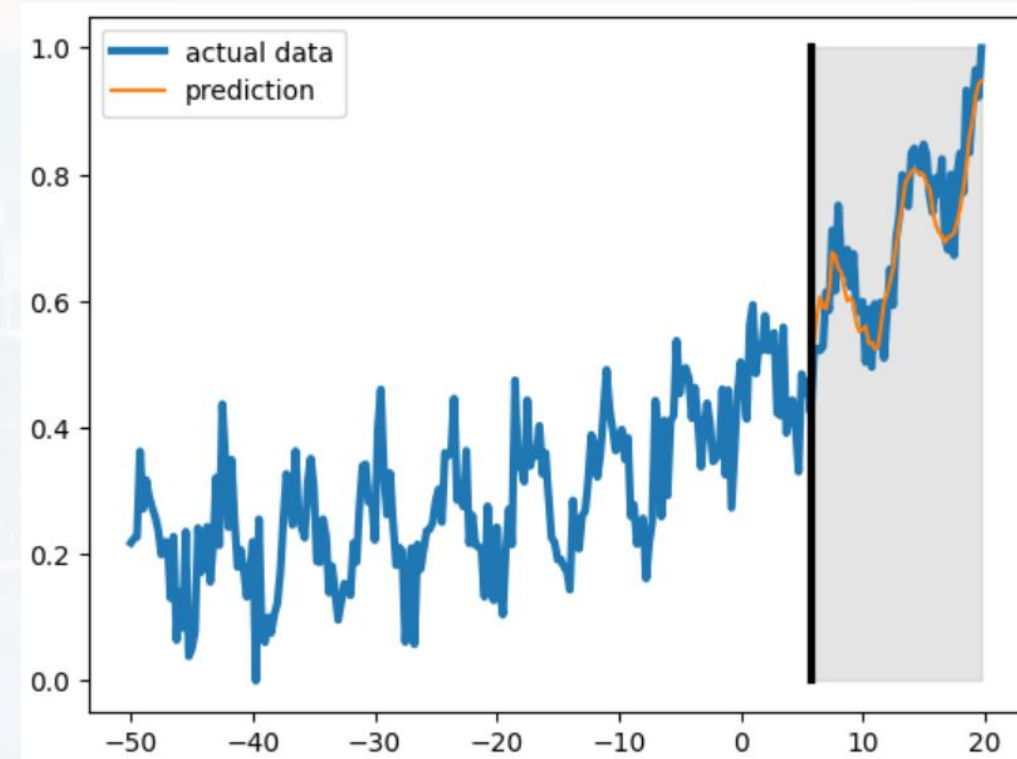
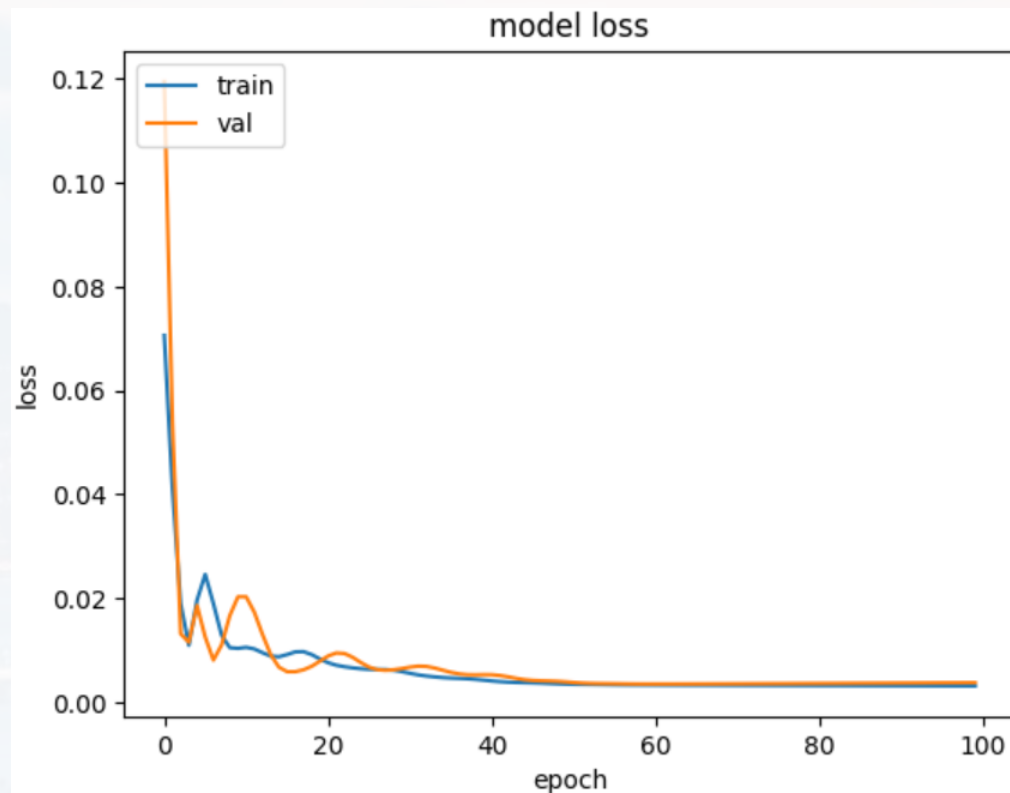
```
model.summary()
```

actual input is (None, None, dt_past, n_features)



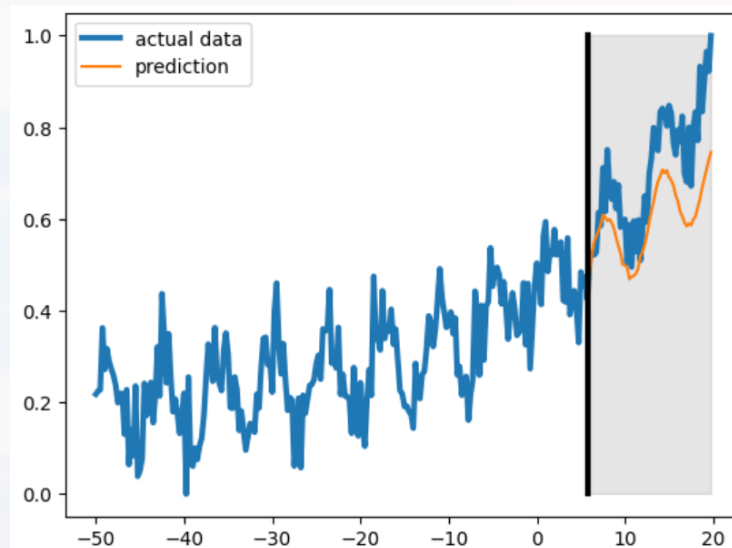
Layer (type)	Output Shape	Param #
=====		
time_distributed (TimeDistributed)	(None, None, 18, 64)	256
time_distributed_1 (TimeDistributed)	(None, None, 9, 64)	0
time_distributed_2 (TimeDistributed)	(None, None, 576)	0
lstm_5 (LSTM)	(None, 400)	1563200
dense_3 (Dense)	(None, 8)	3208
=====		
Total params: 1566664 (5.98 MB)		
Trainable params: 1566664 (5.98 MB)		
Non-trainable params: 0 (0.00 Byte)		

actual input is (None, None, dt_past, n_features)

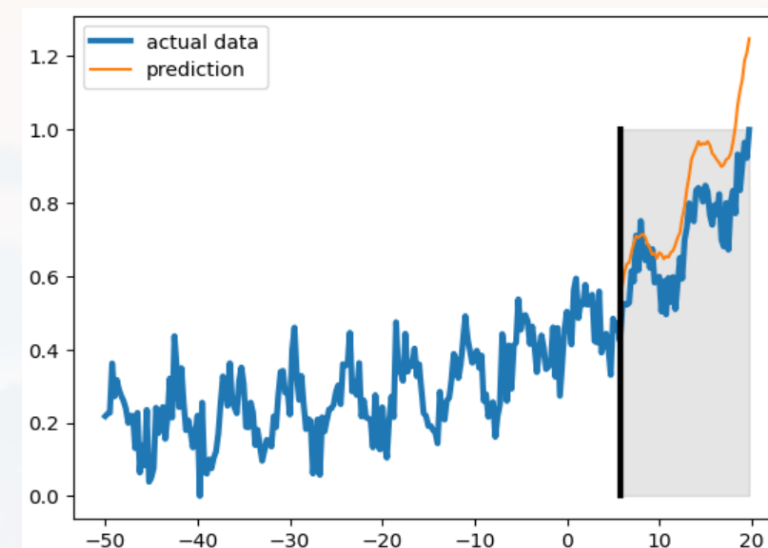




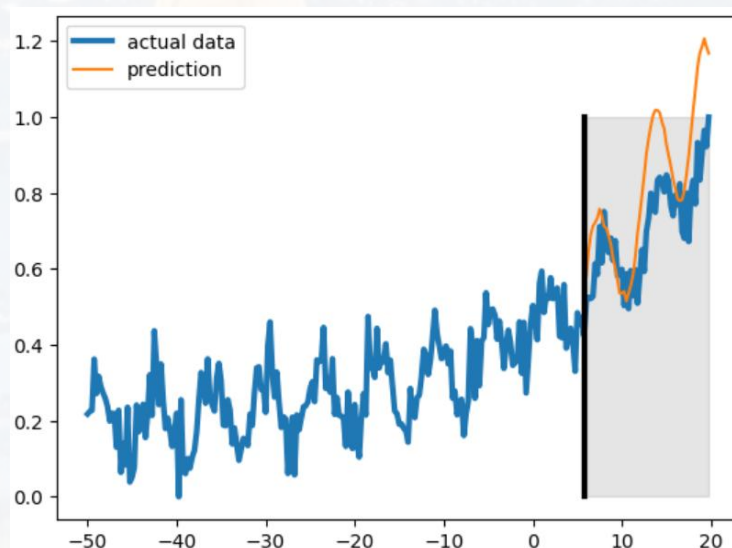
vanilla



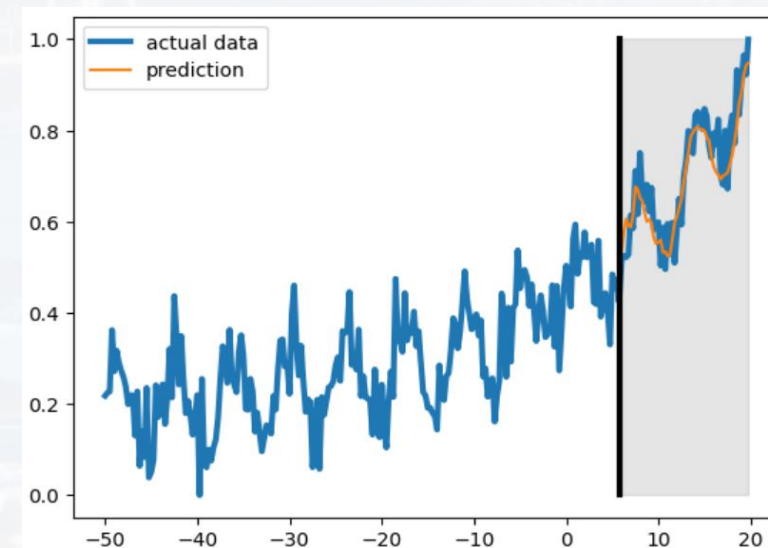
bidirectional



stacked



LSTM + CNN





classification: N samples of N_features and dt_past = Length_Seq

```
[N_sample, LengthSeq, N_features] = X.shape
```

1D filter along time coordinate
= LengthSeq

```
model = Sequential()
```

```
model.add(Conv1D(filters = 64, kernel_size = 3, activation = 'relu',\n                  input_shape = (LengthSeq, N_features)))
```

```
model.add(MaxPooling1D(pool_size = 2))
```

```
model.add(LSTM(n_neurons, activation = 'tanh'))
```

```
model.add(Dense(Nclass, activation = 'softmax'))
```

```
opt = optimizers.Adam()
```

```
model.compile(loss = 'categorical_crossentropy', optimizer = opt,\n              metrics = ['accuracy'])
```

```
model.summary()
```



classification: N samples of N_{features} and $\text{dt_past} = \text{Length_Seq}$

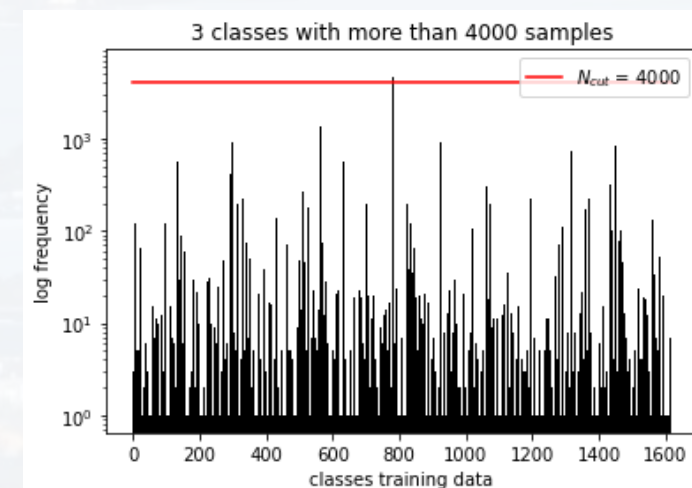
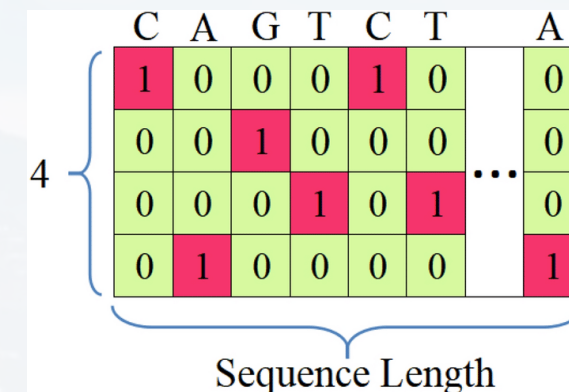
$[N_{\text{sample}}, \text{LengthSeq}, N_{\text{features}}] = X.\text{shape}$

Layer (type)	Output Shape	Param #
conv1d_8 (Conv1D)	(None, 498, 64)	832
max_pooling1d_7 (MaxPooling1D)	(None, 249, 64)	0
lstm_7 (LSTM)	(None, 100)	66000
dense_4 (Dense)	(None, 3)	303
Total params: 67135 (262.25 KB)		
Trainable params: 67135 (262.25 KB)		
Non-trainable params: 0 (0.00 Byte)		

for computational reasons:

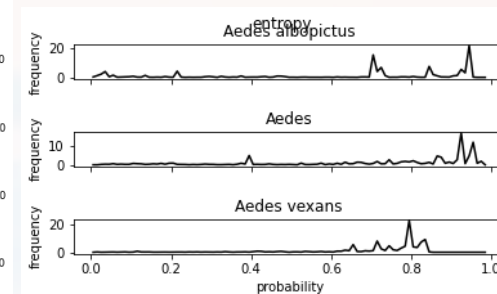
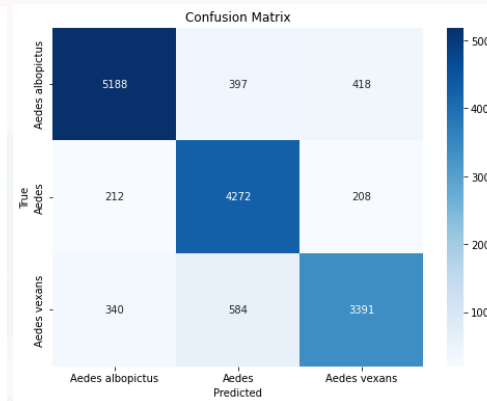
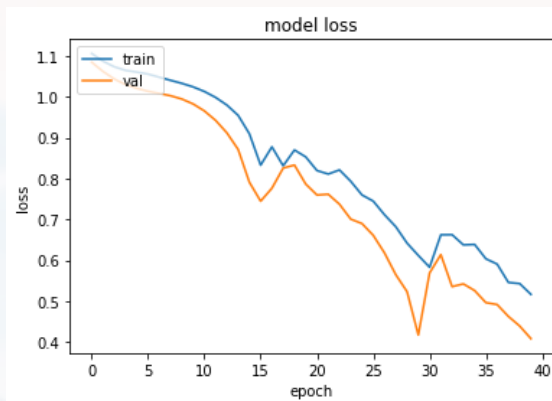
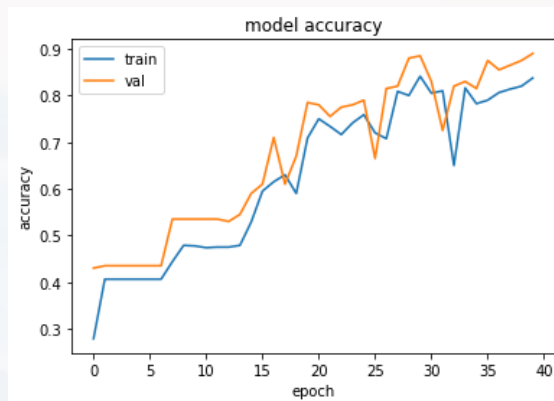
- **three** classes
- **1k** samples total
- sequences cut to length **500**

barcode example

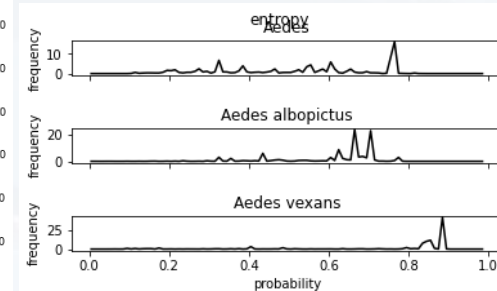
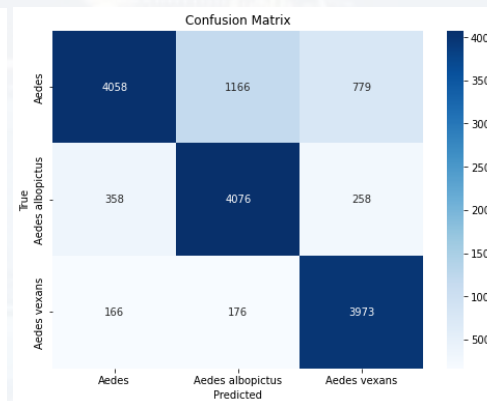
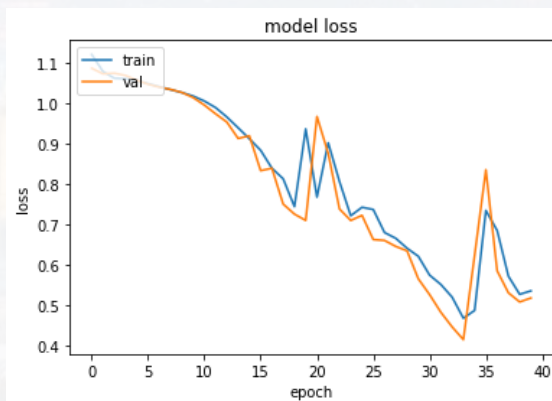
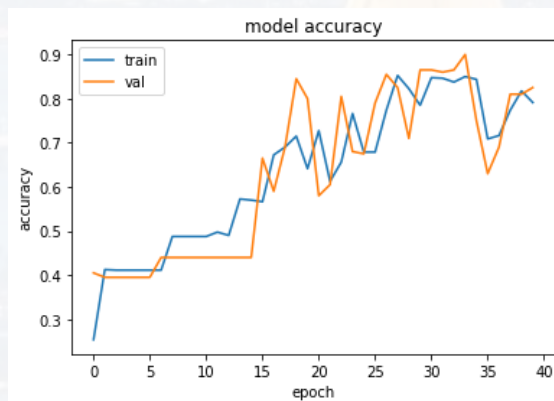




LSTM



LSTM+CNN



Thank you for your attention!

