



Track patient recovery in real-time by processing streaming data

BIOMEDICAL DATA DESIGN

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The slide features a white background with a black border. In the corners, there are decorative blue circles: a large one in the top-left, a medium one in the top-right, and a small one in the bottom-left.

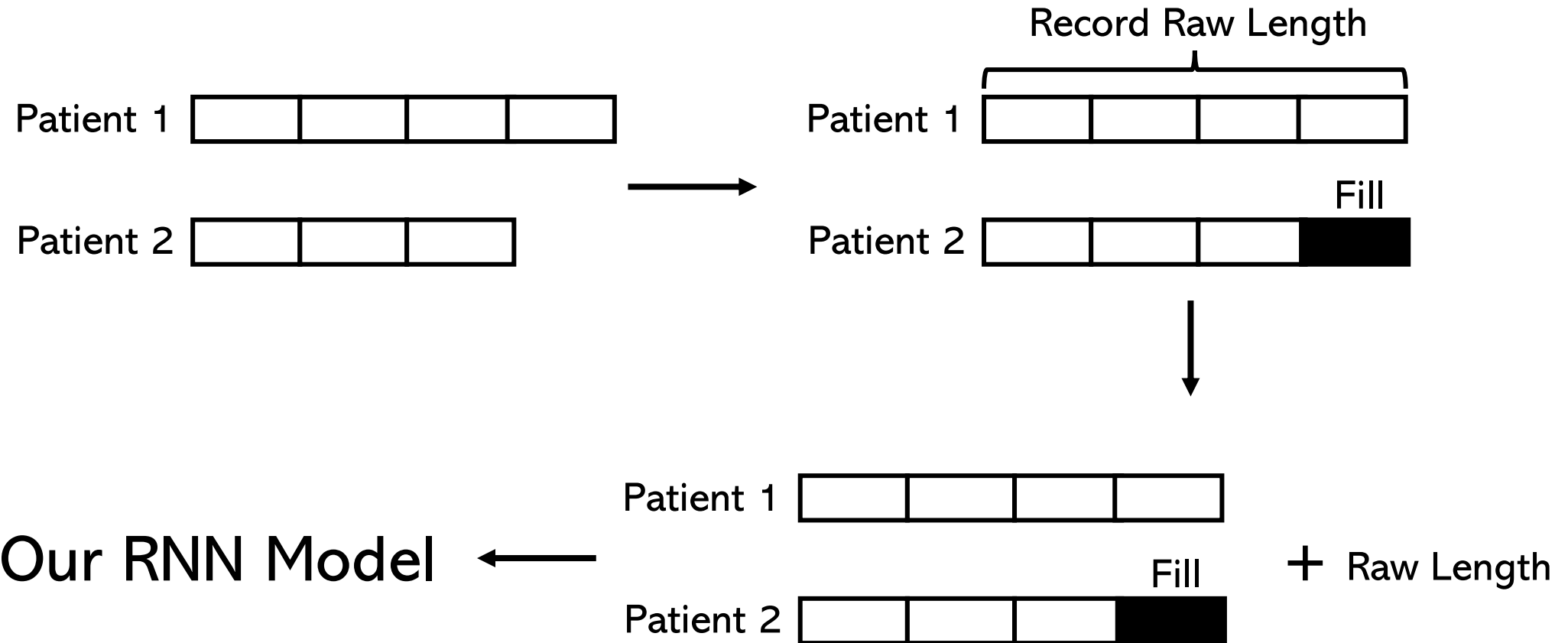
01

‘Real-time’ Prediction

01 'Real-time' Prediction

Last Week:

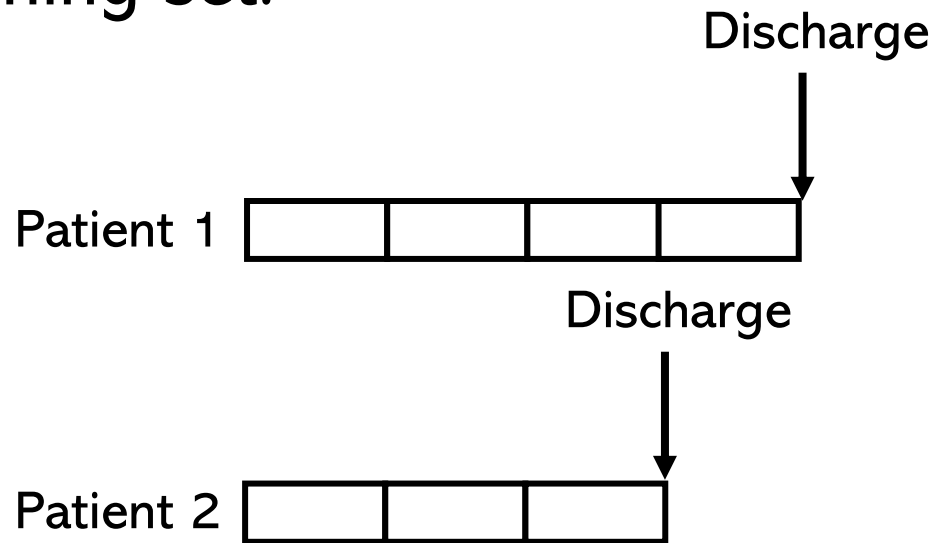
RNN model deal with time series of **different lengths**



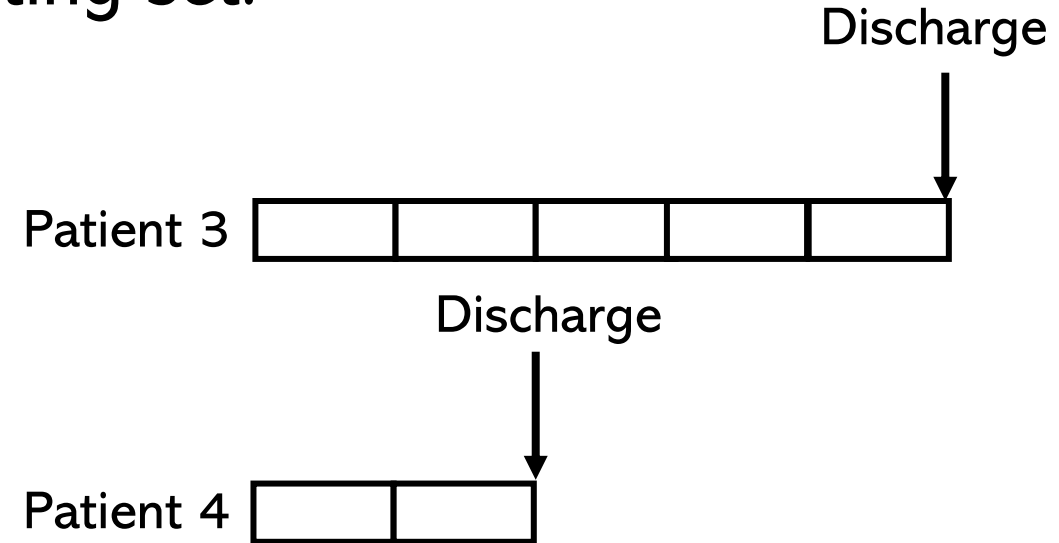
01 'Real-time' Prediction

Last Week:

Training set:



Testing set:



01 'Real-time' Prediction

Repeat for five times:

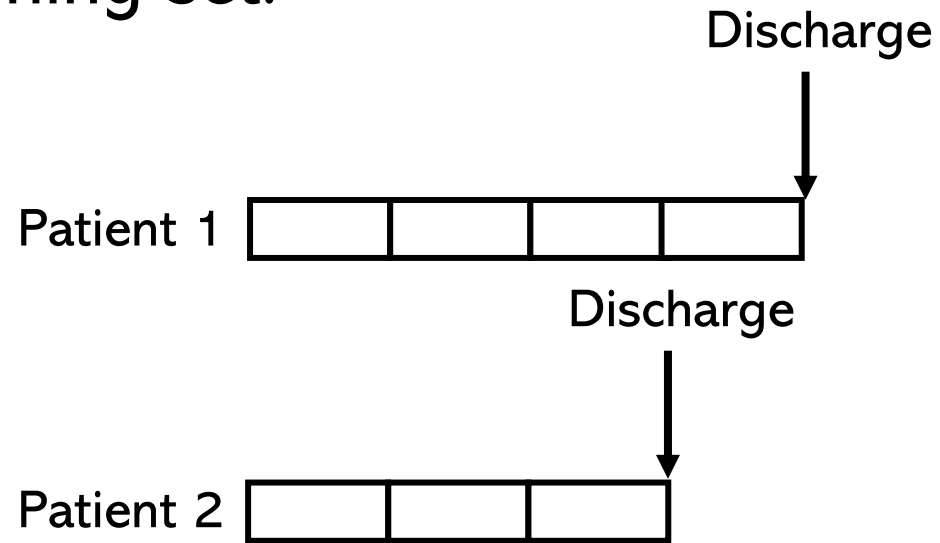
```
Epoch 8/20, Loss: 0.10321918874979019
Epoch 9/20, Loss: 0.0093935402110219
Epoch 10/20, Loss: 0.07064346969127655
Epoch 11/20, Loss: 0.09824777394533157
Epoch 12/20, Loss: 0.09720230847597122
Epoch 13/20, Loss: 0.023129863664507866
Epoch 14/20, Loss: 0.07097922265529633
Epoch 15/20, Loss: 0.5772714018821716
Epoch 16/20, Loss: 1.3697293996810913
Epoch 17/20, Loss: 0.0018030975479632616
Epoch 18/20, Loss: 0.28388893604278564
Epoch 19/20, Loss: 0.38625386357307434
Epoch 20/20, Loss: 0.011136839166283607
Accuracy: 0.9139784946236559
Precision: 0.8926553672316384
Recall: 0.9239766081871345
...
[ 13 169]]
Accuracy: [0.9139784946236559, 0.8924731182795699, 0.9274193548387096, 0.8978494623655914, 0.9327956989247311]
avg_Acc:0.9129032258064516
Time taken: 31197.8478 seconds
```

Accuracy: 91.3%

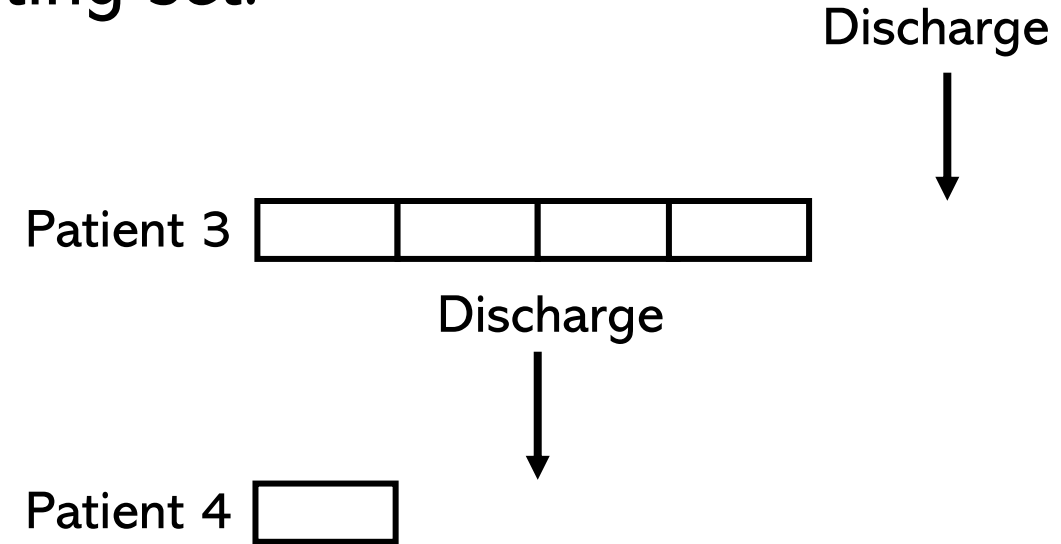
01 'Real-time' Prediction

This Week:

Training set:



Testing set:



For the testing part, we **don't give the last hour** to predict the final mortality

01 'Real-time' Prediction

Repeat for
four times:

```
Epoch 10/20, Loss: 0.31515413522720337
Epoch 11/20, Loss: 1.2940282821655273
Epoch 12/20, Loss: 0.6931993365287781
Epoch 13/20, Loss: 0.31462329626083374
Epoch 14/20, Loss: 0.3369888663291931
Epoch 15/20, Loss: 0.31822213530540466
Epoch 16/20, Loss: 0.3157409131526947
Epoch 17/20, Loss: 0.6965146064758301
Epoch 18/20, Loss: 0.6935627460479736
Epoch 19/20, Loss: 0.3151668310165405
Epoch 20/20, Loss: 0.6933030486106873
Accuracy: 0.806970509383378
Precision: 0.9243697478991597
Recall: 0.6358381502890174
F1 Score: 0.7534246575342467
Confusion Matrix:
[[191  9]
 [ 63 110]]
```

```
Epoch 10/20, Loss: 0.6931630969047546
Epoch 11/20, Loss: 0.3337962329387665
Epoch 12/20, Loss: 0.6931714415550232
Epoch 13/20, Loss: 0.6932192444801331
Epoch 14/20, Loss: 0.3200587034225464
Epoch 15/20, Loss: 0.3239499628543854
Epoch 16/20, Loss: 0.5084646940231323
Epoch 17/20, Loss: 0.6931554675102234
Epoch 18/20, Loss: 0.6961817741394043
Epoch 19/20, Loss: 0.693185031414032
Epoch 20/20, Loss: 0.693149983882904
Accuracy: 0.8579088471849866
Precision: 0.8520710059171598
Recall: 0.8372093023255814
F1 Score: 0.844574780058651
Confusion Matrix:
[[176  25]
 [ 28 144]]
```


```
Epoch 10/20, Loss: 0.6934880018234253
Epoch 11/20, Loss: 0.6932013630867004
Epoch 12/20, Loss: 0.6931668519973755
Epoch 13/20, Loss: 0.6941850781440735
Epoch 14/20, Loss: 0.31728488206863403
Epoch 15/20, Loss: 0.6931740045547485
Epoch 16/20, Loss: 0.693154513835907
Epoch 17/20, Loss: 0.6931524872779846
Epoch 18/20, Loss: 1.3090211153030396
Epoch 19/20, Loss: 0.6931576132774353
Epoch 20/20, Loss: 0.3151927590370178
Accuracy: 0.848404255319149
Precision: 0.8155339805825242
Recall: 0.8983957219251337
F1 Score: 0.8549618320610687
Confusion Matrix:
[[151  38]
 [ 19 168]]
```

```
Epoch 10/20, Loss: 0.3345186114311218
Epoch 11/20, Loss: 0.6931914687156677
Epoch 12/20, Loss: 0.31854328513145447
Epoch 13/20, Loss: 1.0125386714935303
Epoch 14/20, Loss: 0.4884851574897766
Epoch 15/20, Loss: 0.3698061406612396
Epoch 16/20, Loss: 0.8132229447364807
Epoch 17/20, Loss: 0.31506800651550293
Epoch 18/20, Loss: 0.3157444894313812
Epoch 19/20, Loss: 0.695896565914154
Epoch 20/20, Loss: 0.3164122700691223
Accuracy: 0.8679245283018868
Precision: 0.8315217391304348
Recall: 0.8947368421052632
F1 Score: 0.8619718309859156
Confusion Matrix:
[[169  31]
 [ 18 153]]
```

Accuracy: 84.5%

Recall: 84.3%

A significant drop!!

The slide features a white background with a black border. In the corners, there are blue circular shapes: a large one in the top-left, a medium one in the top-right, a small one in the bottom-left, and a small one in the bottom-right.

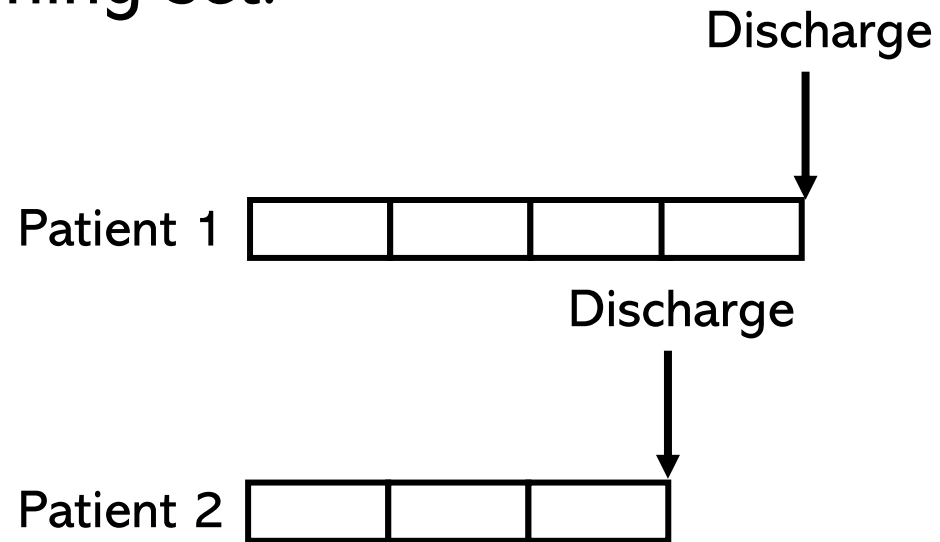
02

Next Step

02 Change the training set

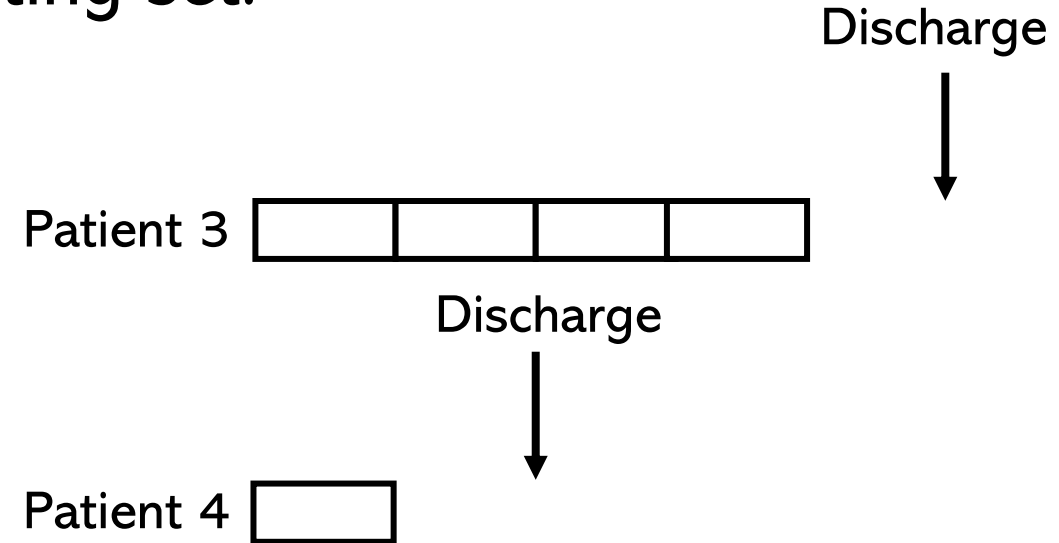
Now:

Training set:



Changes:

Testing set:



For the testing part, we **don't give the last hour** to predict the final mortality

02 Change the parameters

Learning rate

Loss

Drop out

...

The slide features a white background enclosed by a thick black rectangular border. Three large, solid blue circles are positioned at the corners: one in the top-left, one in the bottom-left, and one on the right side. The text "Thank you" is centered in the middle of the slide.

Thank you

01 LSTM

Last week: Machine learning



First day's flattened data



This week: LSTM



First two day's flattened data as two time stamps

Patient1
Patient2
Patient3

Time stamp1	Time stamp2
Patient1	Patient1
Patient2	Patient2
Patient3	Patient3

01 LSTM

LSTM: 2 days

	precision	recall	f1-score	support
0.0	0.48	1.00	0.65	154
1.0	0.00	0.00	0.00	165
accuracy			0.48	319
macro avg	0.24	0.50	0.33	319
weighted avg	0.23	0.48	0.31	319
[[154 0]				
[165 0]]				

All Zero



Too few time stamps

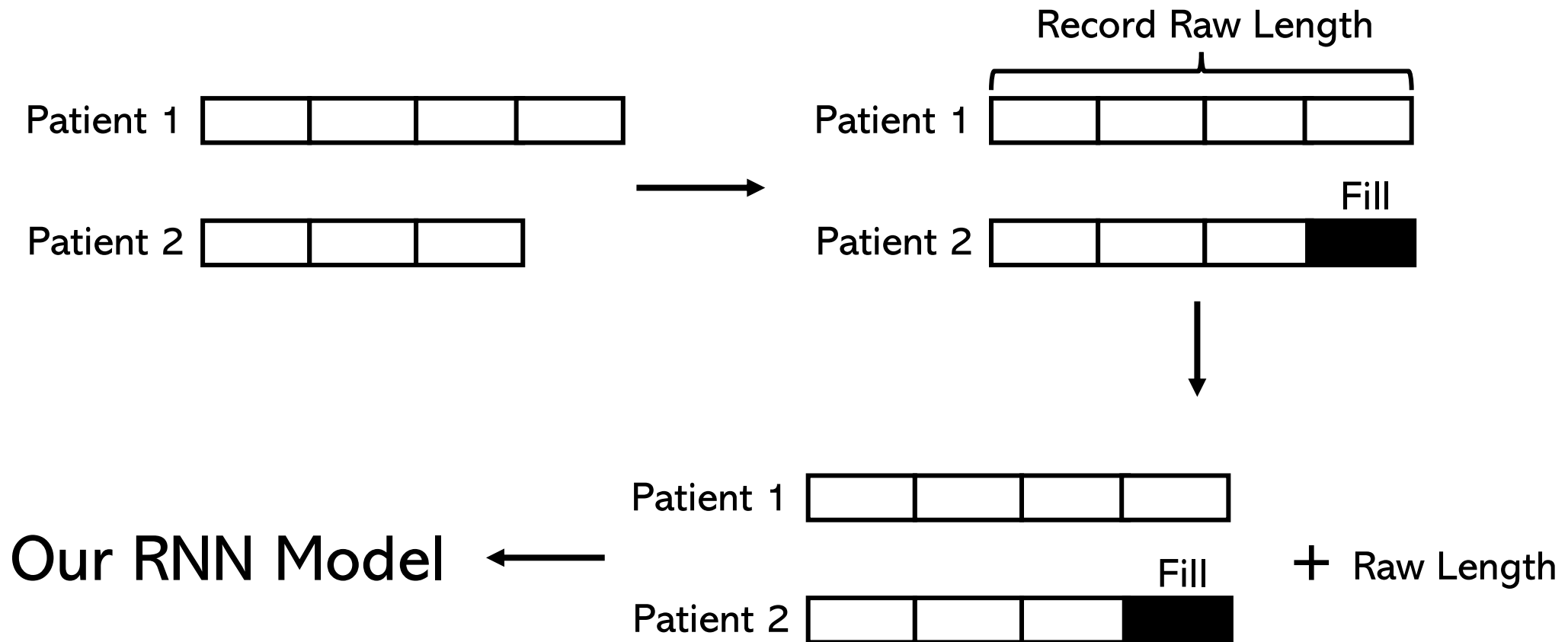
LSTM:48 hours
(with interpolation)

...				
weighted avg	0.73	0.73	0.73	342
[[119 54]				
[39 130]]				

Add more time stamps

02 'Real-time' Prediction

RNN model deal with time series of **different lengths**



02 'Real-time' Prediction

Fill the series and record the raw length

```
# load the data
data = pd.read_csv('balanced_LSTM_long.csv')

# Tagged feature columns and label columns
feature_columns = [col for col in data.columns if col not in ('patientunitstayid', 'observationoffset', 'actualicumorality')]
label_column = 'actualicumorality'

# Initialize the list of features and labels
sequences = []
labels = []

# Group and create sequences for each patient
for _, group in data.groupby('patientunitstayid'):
    # For each patient, the features are converted to a tensor
    sequence = torch.tensor(group[feature_columns].values, dtype=torch.float)
    sequences.append(sequence)

    # Assuming that each patient has the same label, so we only take the label of the first record
    labels.append(group[label_column].iloc[0])

lengths = torch.tensor([len(seq) for seq in sequences])
print(lengths.numpy())

# Fill the sequence
padded_sequences = pad_sequence(sequences, batch_first=True)
```

02 'Real-time' Prediction

RNN

How to use the inputs?

```
def forward(self, input_seq, input_length):
    #print(input_seq.size())
    batch_size, _, _ = input_seq.size()
    seq_len = int(input_length.item()) # Get the value of the length from the tensor
    #print(seq_len)
    # 初始化隐藏状态
    h0 = torch.zeros(1, batch_size, self.hidden_size)
    c0 = torch.zeros(1, batch_size, self.hidden_size)
    # Initialize the previous day's output
    prev_output = torch.zeros(batch_size, self.output_size)

    # Process the entire sequence recursively
    for t in range(seq_len):
        # Combining the day's input with the previous day's output
        combined_input = torch.cat((input_seq[:, t, :], prev_output), dim=1).unsqueeze(1)
        # Through LSTM
        if t == 0:
            lstm_out, (h, c) = self.lstm(combined_input, (h0, c0))
        else:
            lstm_out, (h, c) = self.lstm(combined_input, (h, c))
        # Use only the last output of the sequence
        final_output = self.fc(lstm_out[:, -1, :])
        # Updating the previous day's output
        prev_output = self.sigmoid(final_output)

    return prev_output
```

Results

```
Epoch 1/10, Loss: 0.3596692979335785
Epoch 2/10, Loss: 0.7099694013595581
Epoch 3/10, Loss: 0.3183300793170929
Epoch 4/10, Loss: 0.6963921189308167
Epoch 5/10, Loss: 0.35637760162353516
Epoch 6/10, Loss: 0.6995091438293457
Epoch 7/10, Loss: 0.7040725350379944
Epoch 8/10, Loss: 0.6934269070625305
Epoch 9/10, Loss: 0.5024394392967224
Epoch 10/10, Loss: 0.6532086133956909
```

Accuracy~85%

02 'Real-time' Prediction

Time-consuming

```
Epoch 17/100, Loss: 0.31905150413513184
Epoch 18/100, Loss: 0.6933485865592957
Epoch 19/100, Loss: 0.6933465003967285
Epoch 20/100, Loss: 0.3626611530780792
Epoch 21/100, Loss: 0.3548220694065094
Epoch 22/100, Loss: 0.6931563019752502
Epoch 23/100, Loss: 0.3166859745979309
Epoch 24/100, Loss: 0.3259027302265167
...
Epoch 71/100, Loss: 0.6931471824645996
Epoch 72/100, Loss: 0.3139694035053253
Epoch 73/100, Loss: 0.3144867420196533
Epoch 74/100, Loss: 0.31408748030662537
```

Whole night but failed!!

Check if there are mistakes

02 'Real-time' Prediction

Another easier method:

Use the last day of patients to train



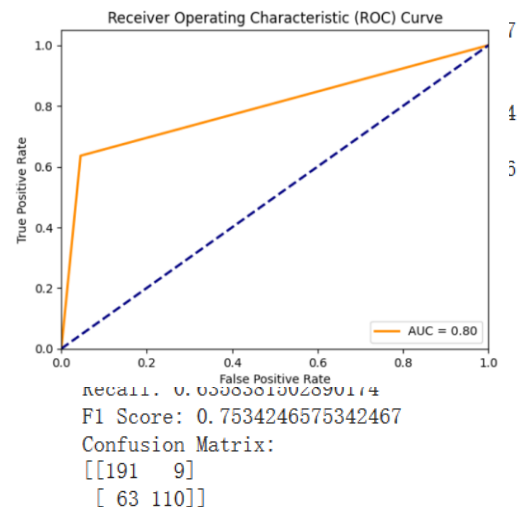
Use each single day's data as input to predict

We assume that different days' data are independent

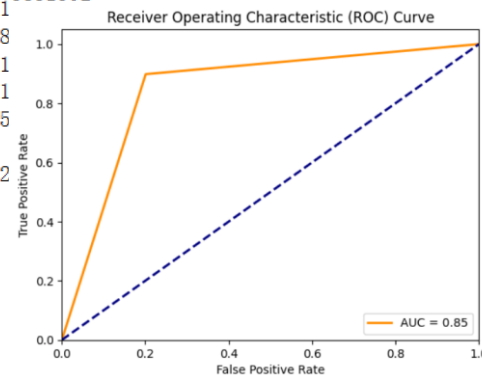
01 'Real-time' Prediction

Repeat for
four times:

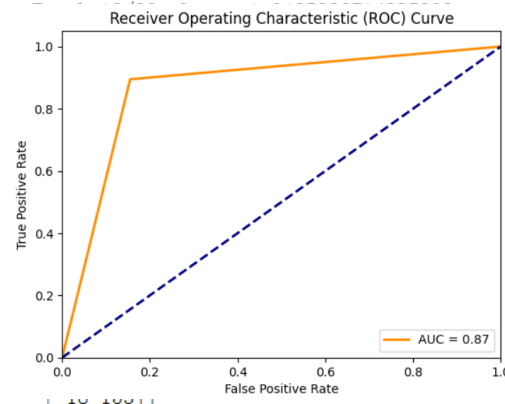
```
Epoch 10/20, Loss: 0.6931630969047546
Epoch 11/20, Loss: 0.3337962329387665
Epoch 12/20, Loss: 0.6931714415550232
Epoch 13/20, Loss: 0.6932192444801331
Epoch 14/20, Loss: 0.3200587034225464
Epoch 15/20, Loss: 0.3239499628543854
Epoch 16/20, Loss: 0.5084646940231323
Epoch 17/20, Loss: 0.6931554675102234
Epoch 18/20, Loss: 0.6961817741394043
Epoch 19/20, Loss: 0.693185031414032
Epoch 20/20, Loss: 0.693149983882904
Accuracy: 0.8579088471849866
Precision: 0.8520710059171598
Recall: 0.8372093023255814
F1 Score: 0.844574780058651
Confusion Matrix:
[[176 25]
 [ 28 144]]
```



```
Epoch 10/20, Loss: 0.6934880018234253
Epoch 11/20, Loss: 0.6932013630867004
Epoch 12/20, Loss: 0.6931668519973755
Epoch 13/20, Loss: 0.6941850781440735
Epoch 14/20, Loss: 0.31728488206863403
Epoch 15/20, Loss: 0.6931740045547485
Epoch 16/20, Loss: 0.69315451
Epoch 17/20, Loss: 0.69315248
Epoch 18/20, Loss: 1.30902111
Epoch 19/20, Loss: 0.69315761
Epoch 20/20, Loss: 0.31519275
Accuracy: 0.848404255319149
Precision: 0.8155339805825242
Recall: 0.8983957219251337
F1 Score: 0.8549618320610687
Confusion Matrix:
[[151 38]
 [ 19 168]]
```



```
Epoch 10/20, Loss: 0.3345186114311218
Epoch 11/20, Loss: 0.6931914687156677
Epoch 12/20, Loss: 0.31854328513145447
```



Accuracy: 84.0%

Recall: 85.2%

A significant drop!!

03 Next step

Epoch 1/10, Loss: 0.5323466062545776
Epoch 2/10, Loss: 0.7005636096000671
Epoch 3/10, Loss: 0.34396567940711975
Epoch 4/10, Loss: 0.3216598629951477
Epoch 5/10, Loss: 0.37011444568634033
Epoch 6/10, Loss: 1.1123342514038086
Epoch 7/10, Loss: 0.6933222413063049
Epoch 8/10, Loss: 0.6972675323486328
Epoch 9/10, Loss: 0.7365317940711975
Epoch 10/10, Loss: 0.6936031579971313

Accuracy: 0.8203753351206434

Precision: 0.7586206896551724

Recall: 0.8953488372093024

F1 Score: 0.8213333333333334

Confusion Matrix:

```
[[152  49]
 [ 18 154]]
```

Epoch 1/10, Loss: 0.6513708829879761
Epoch 2/10, Loss: 0.6125394105911255
Epoch 3/10, Loss: 0.7148727178573608
Epoch 4/10, Loss: 0.7017617225646973
Epoch 5/10, Loss: 0.33441460132598877
Epoch 6/10, Loss: 0.3995670676231384
Epoch 7/10, Loss: 0.6942034959793091
Epoch 8/10, Loss: 0.3185052275657654
Epoch 9/10, Loss: 0.6968369483947754
Epoch 10/10, Loss: 0.321229487657547

Accuracy: 0.7789757412398922

Precision: 0.6943231441048034

Recall: 0.9298245614035088

F1 Score: 0.7949999999999999

Confusion Matrix:

```
[[130  70]
 [ 12 159]]
```

Epoch 1/10, Loss: 0.9933973550796509
Epoch 2/10, Loss: 0.717208981513977
Epoch 3/10, Loss: 0.3334490954875946
Epoch 4/10, Loss: 0.5397564768791199
Epoch 5/10, Loss: 0.5919001698493958
Epoch 6/10, Loss: 0.6943417191505432
Epoch 7/10, Loss: 0.6934819221496582
Epoch 8/10, Loss: 0.31822171807289124
Epoch 9/10, Loss: 0.6941342949867249
Epoch 10/10, Loss: 0.31616759300231934

Accuracy: 0.8471849865951743

Precision: 0.8333333333333334

Recall: 0.838150289017341

F1 Score: 0.8357348703170029

Confusion Matrix:

```
[[171  29]
 [ 28 145]]
```

Epoch 1/10, Loss: 0.7399792075157166
Epoch 2/10, Loss: 0.8454279899597168
Epoch 3/10, Loss: 0.33754962682724
Epoch 4/10, Loss: 0.697210967540741
Epoch 5/10, Loss: 0.3270319104194641
Epoch 6/10, Loss: 0.32441461086273193
Epoch 7/10, Loss: 0.5552095174789429
Epoch 8/10, Loss: 0.32459592819213867
Epoch 9/10, Loss: 1.3068009614944458
Epoch 10/10, Loss: 0.32740145921707153

Accuracy: 0.8191489361702128

Precision: 0.7430167597765364

Recall: 0.8580645161290322

F1 Score: 0.7964071856287425

Confusion Matrix:

```
[[175  46]
 [ 22 133]]
```

Epoch 1/10, Loss: 0.7011728882789612
Epoch 2/10, Loss: 0.710917592048645
Epoch 3/10, Loss: 0.3280715346336365
Epoch 4/10, Loss: 0.6912604570388794
Epoch 5/10, Loss: 0.6948522925376892
Epoch 6/10, Loss: 1.030002236366272
Epoch 7/10, Loss: 0.6941815614700317
Epoch 8/10, Loss: 0.32503750920295715
Epoch 9/10, Loss: 0.693243145942688
Epoch 10/10, Loss: 0.6932666301727295

Accuracy: 0.848404255319149

Precision: 0.8421052631578947

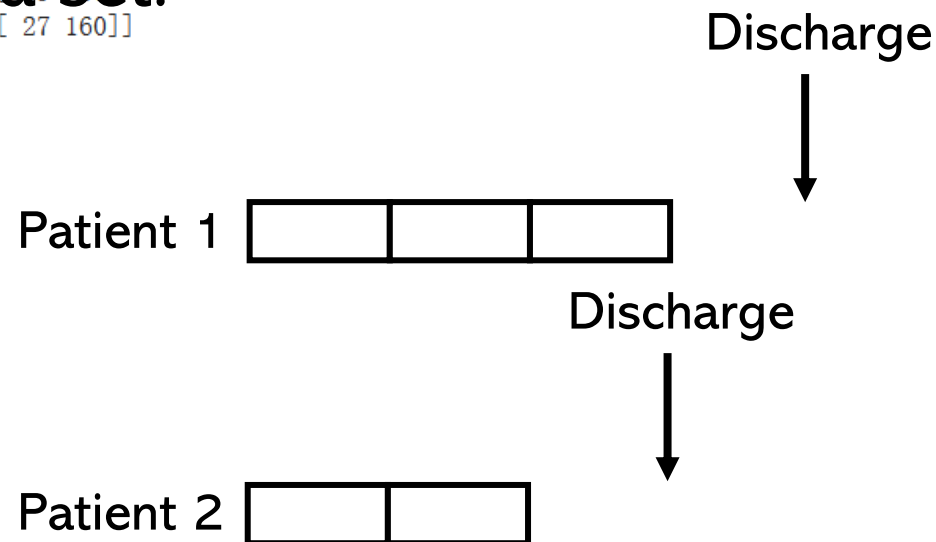
Recall: 0.8556149732620321

F1 Score: 0.8488063660477454

Confusion Matrix:

```
[[159  39]
 [ 27 160]]
```

Data set:



03 Next step

Data set:

