# Lecture 6: Electronic Health Records Introduction

Serena Yeung

**BIODS 220: AI in Healthcare** 

# Announcements

- Upcoming deadlines:
  - A1 due Tue 10/6
  - Project proposal due Fri 10/9



Serena Yeung

**BIODS 220: AI in Healthcare** 

Patient Timeline

Patient chart in digital form, containing medical and treatment history

|                             | 00 0            | 0000    | 00 0 | 00          | 0.000   |                            | 00                      | 0 00   | 00  | 00                              | 000   | 00   | 0:000   | 0   | 000   | 00    |   | 1   |   |
|-----------------------------|-----------------|---------|------|-------------|---|----------------------------|-------------------------|--|---|---------------------------------|---|--|---|---|---|-------|---|---|---|
| Labs & Flowsheets           | 0               | 0       |      |             | 0   |                            | 0                       |  | 0 0   | )                               | 00  | 00   | 0   | 0   | 000   | Ø     |   |   |   |
| Orders                      |                 |         |      |             |   |                            |                         |  | 0 0   |                                 | 00  |  | ace   |   |   | 0     |   |   |   |
| Procedures                  |                 |         |      |             |   |                            |                         |  |   |                                 |   |  | 0.0   |   |   | 0     |   | 1   |   |
| Diagnoses                   |                 |         |      |             |   |                            |                         |  |   |                                 | D   |  |   |   |   | 0     |   |   |   |
| Notes                       |                 |         |      |             |   |                            |                         |  |   |                                 |   |  |   |   |   | 0     |   |   |   |
| Medication                  |                 |         |      |             |   |                            |                         |  | 20  |                                 |   |  | CIND  |   |   | 0     |   | 10  |   |
| Y                           | Month 1<br>Year | Month 2 |      | Month 3     | Month 4   |                            | Month 5                 | Monthi   | Mon   | th 7                            | Month 8   |  | Aonth 9   | Month 1   | 0   | Month |   | Month 12<br>Yeat  |   |
|                             |                 | /       |      |             |   |                            | mitted<br>iospital      |  |   |                                 |   |  |   |   |   | premo | 24 hours<br>dicted ris<br>rtality: 19<br>ient dies                          | sk of inp<br>9.9%.  |   |
|                             | -               |         |      | 0           |   | -                          |                         |  |   |                                 |   |  |   |   |   |       |   | -   |   |
| Encounters                  | 0               | 00      |      | 0           | 000000  | 0                          |                         |  | -   | 000                             | 0 0   |  | 0 00  | ~   | (20) (20)   |       | ~ ~~  | 1   |   |
| Labs & Flowsheets<br>Orders | 0 0             | 00      | 0    |             |   | 0:00                       |                         | 0 00   | 0   | 000                             | 00 0  |  | 00  | 0   |   | 0 0   | 000   |   |   |
| Procedures                  | 0               |         |      | 00          | 00  | wie                        | 0                       | 0 00   |   |                                 | 0   |  | 00  | 0   | 0   | 00    | ,   | 1   |   |
| Diagnoses                   | 2               |         | _    | 0           |   | 1                          |                         |  |   |                                 |   |  |   |   |   |       |   | 1   |   |
| Notes                       | <u> </u>        |         |      | ×           |   | 1                          | 0 00                    | 00 00  | 0000  | 0                               |   |  |   |   |   | -     | • 0   |   |   |
|                             | 0               |         |      |             | 0 0   | 0 10                       |                         |  | (   | 0                               |   |  |   |   |   | -     |   | 1   |   |
| Medication                  |                 |         |      |             |   |                            |                         |  |   |                                 |   |  |   |   |   |       |   |   |   |
| Medication                  |                 | 09.0    | 0    |             | 100 I I I I I I I I I I I I I I I I I I                         | 1                          |                         |  |   | 00.00                           |   | 14:00  |   | 0   |   |       | 0   | 1 16:00   |   |
| Medication                  | 04:00           | 08:0    | 0    |             | 200   | 1                          | 5:00                    | 20:00  |   | 00:00<br>Day 2                  |   | 34:00  | 08  | (Q)<br>8:00   |   | 12:00 | 0   | 16:00   |   |
|                             |                 | 08:0    | 0    | 12          | 2:00  | 16                         | 5:00                    | 20:00  |   | 00:00<br>Day 2                  |   | 04:00  | 08  |   |   |       | 0   | 16:00   |   |
|                             | 04:00           | 08:0    | 0    | 12          | 2:00  | 16                         |                         | 20:00  |   |                                 |   | 04:00  | 08  |   |   |       | 0   | 16:00   |   |
| c                           | 04:00           | 08:0    | 0    | 12          | 2:00  | 16                         | 5:00<br>JRS AFTER ADMIS | 20:00  |   |                                 |   | 04:00  | 06  |   |   |       |   | 16:00   |   |
| c                           | 04:00           | 08:0    | 0    | 12          | 2:00  |                            | 5:00<br>JRS AFTER ADMIS | 20:00  |   |                                 |   | 04:00  | 08  |   |   |       |   |   |   |
| 1:42 hours                  | 04:00           | 08:0    | 0    | 12          | 2:00  | 16<br>100 HOL<br>00:00 hrs | 5:00<br>JRS AFTER ADMIS | 20:00<br>500 →   |   |                                 | +7:38 ho  |  | 08  |   |   | 12:00 |   | 00 hrs  | l   |
| 1:42 hours                  | 04:00           | 08:0    | 0    | 12          | BEFORE ADMISS   | aon Hou<br>00:00 hrs       | 5:00<br>JRS AFTER ADMIS | 20:00<br>×→<br>+3:33 hours<br>Physician Not  |   | Day 2                           | +7:38 ho  | urs  |   | 8:00  |   | 12:00 | +24<br>+22:47 hou   | 00 hrs  | Note                                      |
| I1:42 hours                 | 04:00           | 08:0    | 0    | 12          | BEFORE ADMISS   | aon Hou<br>00:00 hrs       | 5:00<br>JRS AFTER ADMIS | 20:00<br>+3:33 hours<br>Physician Note<br>* PMH of me  | e<br>etastatic b  | Day 2                           | +7:38 ho<br>Radiolo   | urs<br>gy Repor  | t - CT CHEST  | ABDOME  |   | 12:00 | +24<br>+22:47 hou<br>Pulmonary  | oo hrs  |   |
| I1:42 hours                 | 04:00           | 08:0    | 0    | 12          | BEFORE ADMISS<br>-2:42 hour<br>Medicatio<br>Vancomy             | son Hou<br>00:00 hrs       | 5:00<br>JRS AFTER ADMIS | 20:00<br>+3:33 hours<br>Physician Not<br>* PMH of me<br>cancer, R lun  | e<br>etastatic b<br>ng maligna                              | Day 2                           | +7:38 ho<br>Radiolo<br>" FINE   | urs<br>gy Repor  | t - CT CHEST  | ABDOME  | IN PELVIS   | 12:00 | +24<br>+22:47 hou<br>Pulmonary  | coo hrs   | ted pleural                               |
| 1:42 hours                  | 04:00           | 08:0    | 0    | 12          | BEFORE ADMISS   | son Hou<br>00:00 hrs       | 5:00<br>JRS AFTER ADMIS | 20:00<br>+3:33 hours<br>Physician Not<br>* PMH of me<br>cancer, R lun<br>effusion, and F                                     | e<br>etastatic b<br>ng maligna<br>R lung em                 | Day 2<br>preast<br>ant<br>pyema | +7:38 ho<br>Radiolo<br>" FINE<br>Redemo   | gy Repor   | t - CT CHEST<br>HEST LUNGS<br>n of a modera   | ABDOME<br>AND PLE   | IN PELVIS<br>EURA:<br>Ieural  | 12:00 | +24<br>+22:47 hou<br>Pulmonary<br>" has a c<br>space tha                    | rs<br>y Consult<br>omplica<br>at require                          | <b>ted pleural</b><br>s IR guidance.      |
| 1:42 hours                  | 04:00           | 08.0    | 0    | 12          | BEFORE ADMISS<br>-2:42 hour<br>Medicatio<br>Vancomy             | son Hou<br>00:00 hrs       | 5:00<br>JRS AFTER ADMIS | 20:00<br>+3:33 hours<br>Physician Noto<br>" PMH of me<br>cancer, R lun<br>effusion, and R<br>who presents of                 | e<br>etastatic b<br>ng maligna<br>R lung em<br>with increas | Day 2<br>preast<br>ant<br>pyema | +7:38 ho<br>Radiolog<br>" FINE<br>Redemo<br>effusio   | urs<br>gy Repor<br>DINGS : C<br>Donstratio<br>on. inter  | t - CT CHEST<br>HEST LUNGS<br>n of a modera<br>val removal o  | ABDOME<br>AND PLE<br>te left pl<br>f a right c  | EN PELVIS<br>EURA:<br>Ieural<br>chest   | 12:00 | +24<br>+22:47 hou<br>Pulmonary<br>" has a C<br>space tha<br>CT scan si      | rs<br>y Consult<br>omplica<br>at require<br>howing in             | ted pleural<br>s IR guidance.<br>Icreased |
| I1:42 hours                 | 04:00           | 08:0    | 0    | 12          | BEFORE ADMISS<br>-2:42 hour<br>Medicatio<br>Vancomy             | son Hou<br>00:00 hrs       | 5:00<br>JRS AFTER ADMIS | 20:00<br>+3:33 hours<br>Physician Not<br>* PMH of me<br>cancer, R lun<br>effusion, and F                                     | e<br>etastatic b<br>ng maligna<br>R lung em<br>with increas | Day 2<br>preast<br>ant<br>pyema | +7:38 ho<br>Radiolo<br>" FINE<br>Redemo<br>effusio<br>tube wit                                    | urs<br>gy Repor<br>DINGS : C<br>onstratio<br>on. inter<br>thin a loc                             | t - CT CHEST<br>HEST LUNGS<br>n of a modera<br>val removal o<br>ulated right p                                      | ABDOME<br>AND PLE<br>te left pl<br>f a right o<br>bleural e                                       | EURA:<br>leural<br>chest  | 12:00 | +22:47 hou<br>Pulmonary<br>" has a C<br>space tha<br>CT scan si<br>loculted | rs<br>y Consult<br>omplica<br>at require<br>howing in<br>effusion | <b>ted pleural</b><br>s IR guidance.      |
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|                             | 04:00           | 08:0    |      | 4-HOURS     | BEFORE ADMISS<br>-2:42 hour<br>Medicatic<br>Vancomy<br>Metronid | son Hou<br>00:00 hrs       | 5:00<br>JRS AFTER ADMIS | 20:00<br>+3:33 hours<br>Physician Note<br>" PMH of me<br>cancer, R lum<br>effusion, and R<br>who presents I<br>drainage from | e<br>etastatic b<br>ng maligna<br>R lung em<br>with increas | Day 2<br>preast<br>ant<br>pyema | +7:38 ho<br>Radiolog<br>" FINE<br>Redemo<br>effusio<br>tube will<br>which c<br>Interval           | gy Repor<br>DINGS : Constratio<br>on. inter<br>thin a loc<br>ontains f<br>progress               | t - CT CHEST<br>HEST LUNGS<br>no f a modera<br>val removal o<br>ulated right p<br>oci of air. [].<br>ion of disease | ABDOME<br>AND PLE<br>te left pl<br>f a right o<br>bleural e<br>IMPRESS<br>e in the cl             | EV PELVIS<br>EURA:<br>leural<br>chest<br>effusion<br>iION: 1.<br>hest and           | 12:00 | +22:47 hou<br>Pulmonary<br>" has a C<br>space tha<br>CT scan si<br>loculted | rs<br>y Consult<br>omplica<br>at require<br>howing in<br>effusion | ted pleural<br>s IR guidance.<br>Icreased |
| I1:42 hours                 | 04:00           | 08:0    | F    | -3:23 hours | BEFORE ADMISS<br>-2:42 hour<br>Medicatic<br>Vancomy<br>Metronic | son Hou<br>00:00 hrs       | 5:00<br>JRS AFTER ADMIS | 20:00<br>+3:33 hours<br>Physician Note<br>" PMH of me<br>cancer, R lum<br>effusion, and R<br>who presents I<br>drainage from | e<br>etastatic b<br>ng maligna<br>R lung em<br>with increas | Day 2<br>preast<br>ant<br>pyema | +7:38 ho<br>Radiolog<br>" FINE<br>Redemo<br>effusio<br>tube will<br>which c<br>Interval<br>abdome | gy Repor<br>DINGS : Constration<br>on. inter<br>thin a loc<br>ontains f<br>progress<br>en includ | t - CT CHEST<br>HEST LUNGS<br>no fa modera<br>val removal o<br>ulated <b>right p</b><br>oci of air. [].             | ABDOME<br>AND PLE<br>te left pl<br>f a right o<br>pleural e<br>IMPRESS<br>e in the cl<br>d medias | IN PELVIS<br>EURA:<br>Ideural<br>Chest<br>Iffusion<br>GON: 1.<br>hest and<br>trinal | 12:00 | +22:47 hou<br>Pulmonary<br>" has a C<br>space tha<br>CT scan si<br>loculted | rs<br>y Consult<br>omplica<br>at require<br>howing in<br>effusion | ted pleural<br>s IR guidance.<br>Icreased |

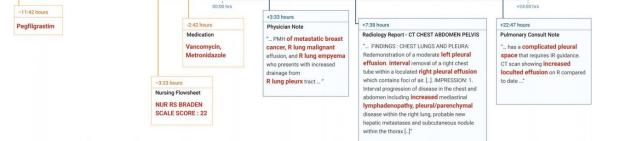
Figure credit: Rajkomar et al. 2018

## Serena Yeung

### **BIODS 220: AI in Healthcare**

Patient Timeline

Patient chart in digital form, Encounters Labs & Flowshee Orders containing medical and Procedures Diagnoses treatment history Notes Medication Month 5 Admitted to hospital Encounters Labs & Flowsheets 00 0000 Orders Procedures Diagnoses Notes 0 0 0 0 0 0 0 0 0 0 0 Medication 12:00 16:00 04-00 08-00 20.00 00-00 Day 1 Day 2 - HOURS BEFORE ADMISSION 00:00 hrs -11:42 hours



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04.00

(1997)

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Month 11

12:00

0 0000

08.00

At 24 hours after admission. predicted risk of inpatient

Patient dies 10 days later.

16:00

mortality: 19.9%

Stores patient information over time

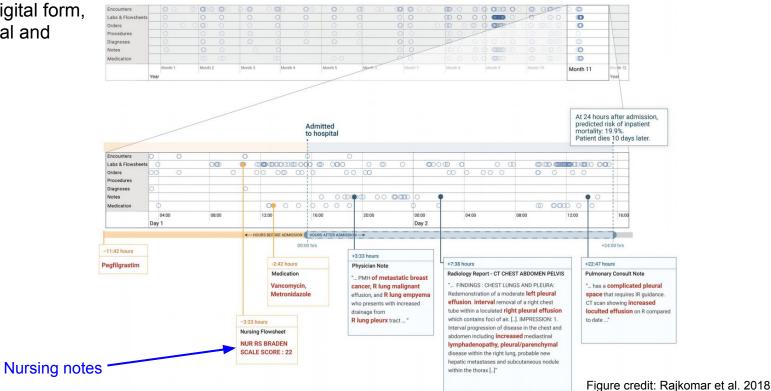
#### Figure credit: Rajkomar et al. 2018

### Serena Yeung

### **BIODS 220: AI in Healthcare**

Patient Timeline

Patient chart in digital form, containing medical and treatment history

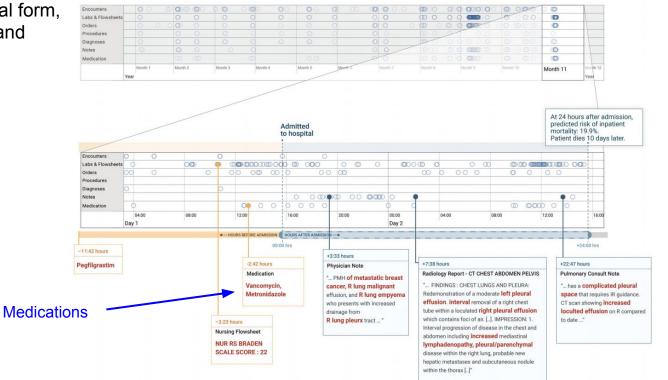


Serena Yeung

### **BIODS 220: AI in Healthcare**

Patient Timeline

Patient chart in digital form, containing medical and treatment history



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### **BIODS 220: AI in Healthcare**

Figure credit: Rajkomar et al. 2018

Patient Timeline

Patient chart in digital form, containing medical and treatment history

|                  |                 |         | 000       | 0.00           |                 | 00            | 0 00          | 000            |              |            |          | 0:000            | 0           | 000       | 00    |  |                   | 1                |
|------------------|-----------------|---------|-----------|----------------|-----------------|---------------|---------------|----------------|--------------|------------|----------|------------------|-------------|-----------|-------|--|-------------------|------------------|
| ibs & Flowsheets |                 |         |           |                |                 |               |               | 0 0            |              |            | 00       |                  | 0           | 000       | Ø     |  |                   |                  |
| orders           |                 | 0 00    |           |                |                 |               |               | 00             |              |            |          | QC               |             |           | 0     |  |                   |                  |
| Procedures       |                 |         |           |                |                 |               |               |                |              | 0 0        | 0        |                  |             |           | 0     |  |                   |                  |
| Diagnoses        |                 |         |           |                |                 |               |               |                |              | D          |          |                  |             |           | 0     |  |                   |                  |
| Notes            |                 |         |           |                |                 |               |               |                |              |            |          | ( <b>111)</b>    |             |           | 0     |  |                   |                  |
| Medication       |                 |         |           |                |                 |               |               | 00             |              |            |          | CIND             |             |           | 0     | 8  |                   | 1                |
|                  | Month 1<br>Year | Month 2 | Month 3   | Month          | 4               | Month 5       | Monttro       | Month 7        |              | Month 8    | M        | ionth 9          | Month       | 10        | Month | 1222   | Month 12<br>Year  |                  |
|                  |                 | /       |           |                | Admit<br>to hos | spital        |               |                |              |            |          |                  |             |           | pre   | 24 hours<br>dicted ris<br>ortality: 19<br>tient dies | sk of ir<br>9.9%. |                  |
|                  | 0 0             |         | 0         |                | ©               | 0             |               |                |              |            |          |                  |             |           |       |  | 1                 | -                |
| abs & Flowsheets |                 | OØ      |           |                | താറുറ്റത        |               | 0 0           | 0 (            | 0000         |            |          | 0 00             |             |           |       | 000 000  | )                 | -                |
| rders            | 00 0            |         | 0 00      | 0 00           | 0:0             |               | 0 00          |                |              | 0 00       | 00       | 0 0              | 0           | ) ()      |       |  | 1                 |                  |
| ocedures         |                 |         |           |                | -               |               |               |                |              |            |          |                  |             |           |       |  | 1                 |                  |
| agnoses          | 0               |         | 0         |                | 1               |               |               |                |              |            |          |                  |             |           |       |  | 1                 |                  |
| otes             |                 |         |           |                | : 0             |               | $\phi\phi$ oc | 0 0000 0       | •            |            |          |                  |             |           |       | • 0  | 1                 | _                |
| edication        | Φ               |         |           | 0 0            | 0 0             | 0 0 0         | 0             | φ              | C            |            |          |                  | 0           | 000       | o q   | 0  |                   |                  |
|                  | 04:00<br>Day 1  | 08:00   |           | 12:00          | 16:00           |               | 20:00         | 00:<br>Da      | ::00<br>ay 2 | 04         | 00       |                  | 08:00       |           | 12:00 |  | 16:00             | 1                |
|                  |                 |         | -HOU      | RS BEFORE ADMI | SSION HOURS     | AFTER ADMISSI |               |                |              |            |          |                  |             |           |       |  | 0                 |                  |
|                  |                 |         |           |                | 00:00 hrs       |               |               |                |              |            | -        |                  |             |           |       | +24  | 00 hrs            |                  |
| :42 hours        |                 |         |           |                | 00.00 ms        |               | 1             |                |              |            |          |                  |             |           |       | 724  | 001115            |                  |
|                  |                 |         |           |                |                 |               | +3:33 hours   |                |              |            |          |                  |             |           |       |  |                   |                  |
| filgrastim       |                 |         |           | -2:42 hou      |                 |               | Physician No  | .e             | 1            | +7:38 hour |          |                  |             |           |       | +22:47 hou   |                   |                  |
|                  |                 |         |           | Medicati       | .on             |               | PMH of m      | etastatic brea | ast          | Radiology  | Report   | - CT CHES        | T ABDOM     | EN PELVIS |       | Pulmonary  | Consu             | lt Note          |
|                  |                 |         |           | Vancom         | vcin.           |               |               | ng malignant   |              | FINDI      | IGS : CH | HEST LUNG        | S AND PL    | EURA:     |       | " has a c  | omplic            | cated pleural    |
|                  |                 |         |           | Metroni        |                 |               |               | R lung empye   |              | Redemon    | stration | of a mode        | rate left I | leural    |       |  |                   | res IR guidance. |
|                  |                 |         |           |                |                 |               |               | with increased |              |            |          | al removal       |             |           |       |  |                   | increased        |
|                  |                 |         |           |                |                 |               | drainage from |                |              |            |          | lated right      |             |           |       |  |                   | on on R compared |
|                  |                 |         |           |                |                 |               |               |                |              |            |          | oci of air. []   |             |           |       | to date"   | usit              | in on a compared |
|                  |                 |         | -3:23 hou |                |                 |               | R lung pleur  | A tract        |              |            |          | ion of disea     |             |           |       | to date  |                   |                  |
|                  |                 |         | Nursing F | Flowsheet      |                 |               |               |                |              |            |          | ng increas       |             |           |       |  |                   |                  |
|                  |                 |         |           |                |                 |               |               |                |              | abuomen    | menualin |                  |             | Sund      |       |  |                   |                  |
|                  |                 |         | NI ID DC  | BRADEN         |                 |               |               |                |              | lymphad    |          | About milesseeds |             |           |       |  |                   |                  |

# Serena Yeung

BIODS 220: AI in Healthcare

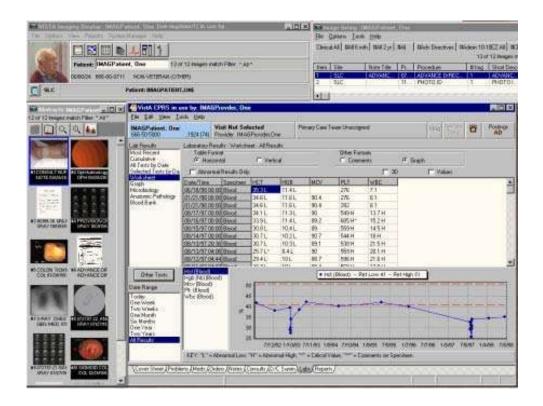
Patient Timeline

Patient chart in digital form, containing medical and treatment history

| Encounters       |         | 0000    | 00   | 00          | 0 0        |           |                 | 00           |           |                        | 00       |       | 000     |                       | 0.000                | 0 00      | 000                     | 00    |   |                   |                |
|------------------|---------|---------|------|-------------|------------|-----------|-----------------|--------------|-----------|------------------------|----------|-------|---------|-----------------------|----------------------|-----------|-------------------------|-------|---|-------------------|----------------|
| abs & Flowsheets |         |         |      |             |            |           |                 |              |           |                        |          |       | 000     |                       |                      |           | 000                     | Ø     |   |                   |                |
| ders             |         |         |      |             |            |           |                 |              |           |                        |          |       |         |                       | DIC                  | 5 00      |                         | 0     |   |                   |                |
| ocedures         |         |         |      |             |            |           |                 |              |           |                        |          |       |         |                       | 010                  |           |                         | 0     |   |                   |                |
| agnoses          |         |         |      |             |            |           |                 |              |           |                        |          |       | D       |                       |                      |           |                         | 0     |   |                   |                |
| otes             |         |         |      |             |            |           |                 |              |           |                        |          | /     |         |                       | ) (IIII) (I          |           |                         | 0     |   |                   |                |
| edication        |         |         |      |             |            |           |                 |              |           |                        | 20       |       |         |                       |                      |           |                         | 0     |   |                   |                |
| Ye               | Month 1 | Month 2 |      | Month 3     | 1          | Month 4   | 1               | Month 5      | Mont      | hō                     | Month    | h7    | Month 8 |                       | Month 9              | M         | inth 10                 | Month |   | Month 12<br>Year  |                |
|                  |         | _       | /    | _           | /          |           | Admit<br>to hos |              |           |                        |          |       |         |                       |                      |           |                         | prei  | 4 hours<br>dicted ris<br>rtality: 19<br>ient dies | k of inp<br>9.9%. |                |
| counters O       | 0       |         |      | 0           |            |           | 0               |              | 2         |                        |          |       |         |                       |                      | 1         |                         |       |   |                   |                |
|                  | 0       | 0       | 0    |             | 00000      |           |                 |              | 0         | 0                      | 0        | 00    | 000 0   |                       | 0 0                  | D         | 00000                   | 00000 | m 00  |                   |                |
|                  | 0 0     |         | 0    |             |            |           | 0:0             |              | 0 00      |                        | ~        |       |         |                       | 000                  | 1         | 0 0                     | 0 0   |   | 1                 |                |
| ocedures         |         |         |      |             |            |           | 1               |              |           |                        |          |       |         |                       |                      |           | -                       |       |   | 1                 |                |
| ignoses O        |         |         |      | 0           | -          |           | 1               |              |           |                        |          |       |         |                       |                      |           |                         |       |   | 1                 |                |
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| D                | ay 1    |         |      | _           |            |           |                 |              |           |                        |          | Day 2 |         |                       |                      |           |                         |       |   |                   |                |
|                  |         |         |      | <b>←</b> H0 | URS BEFORE | ADMISSION | HOURS           | AFTER ADMISS |           |                        |          |       |         |                       |                      |           |                         |       |   | 0                 | (              |
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| 42 hours         |         |         |      |             |            | 00.       | bolina          | - í          |           |                        |          |       |         |                       |                      |           |                         |       |   | 001113            |                |
| March 199        |         |         |      |             |            |           |                 |              | +3:33 ho  |                        |          |       |         |                       |                      |           |                         |       | 1   |                   |                |
| filgrastim       |         |         |      |             |            | 2 hours   |                 |              | Physicia  | n Note                 |          |       | +7:38   |                       |                      |           |                         |       | +22:47 hou  |                   |                |
|                  |         |         |      |             | Med        | dication  |                 |              | " PMH     | of metas               | static b | reast | Radio   | ogy Repo              | rt - CT CHE          | ST ABD    | MEN PELVIS              | 5     | Pulmonary   | Consult           | Note           |
|                  |         |         |      |             |            | comycin   |                 |              | cancer,   | R lung n<br>, and R lu | maligna  | int   |         |                       | CHEST LUN            |           |                         |       |   |                   | s IR guidance. |
|                  |         |         |      |             |            |           |                 |              |           | sents with             |          |       |         |                       | rval remova          |           | ht chest<br>al effusion |       | CT scan sl  | nowing in         | noreased       |
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|                  |         |         |      | Nursing     | g Flowshee | et        |                 | l            |           |                        |          |       |         |                       | ding increa          |           |                         |       |   |                   |                |
|                  |         |         |      | NUR R       | S BRADE    | EN        |                 |              |           |                        |          |       |         |                       | athy, pleu           |           |                         |       |   |                   |                |
|                  |         |         |      |             | SCORE      |           |                 |              |           |                        |          |       |         |                       | the right lun        | ig, proba | ble new                 |       |   |                   |                |
|                  |         |         |      |             |            |           |                 |              |           |                        | /        |       |         |                       | ases and su<br>x []* | ubcutane  | ous nodule              |       |   |                   |                |
| cal ima          |         |         |      |             |            |           |                 |              |           | -                      | /        | ~     |         | c metast<br>the thora |                      | ubcutane  | ous nodule              |       |   |                   |                |

Serena Yeung

BIODS 220: AI in Healthcare



1960s: invention 1980s: increased effort 2009: HITECH Act (Health Information Technology for Economic and Clinical Health Act) -- financial incentives for health care providers to adopt EHR

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# **BIODS 220: AI in Healthcare**

# EHR adoption in the US (hospitals)

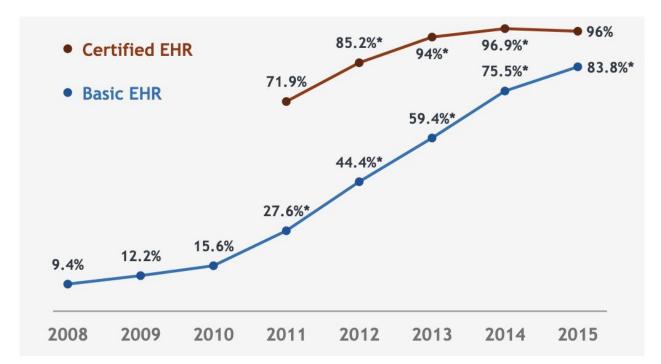


Figure credit: https://dashboard.healthit.gov/evaluations/images/db-35-figure1.svg

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## BIODS 220: AI in Healthcare

# EHR adoption in the US (hospitals)



Figure credit: https://dashboard.healthit.gov/evaluations/images/db-35-figure1.svg

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## BIODS 220: AI in Healthcare

# EHR adoption in the US (office-based physicians)

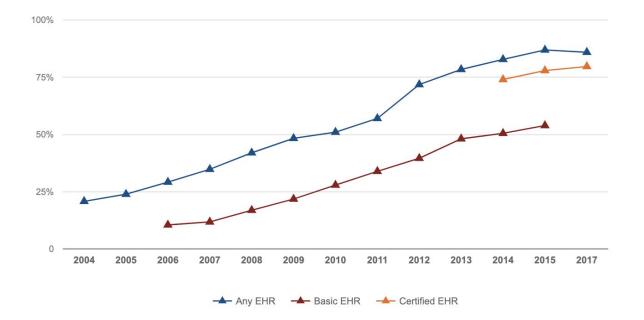


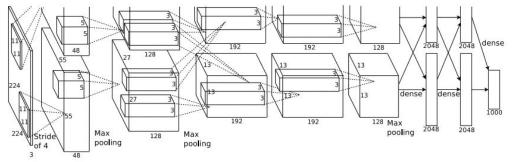
Figure credit: https://dashboard.healthit.gov/guickstats/pages/physician-ehr-adoption-trends.php

### Serena Yeung

# Convergence of key ingredients of deep learning

# Algorithms

Compute





Data



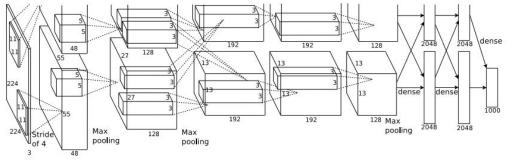
Serena Yeung

**BIODS 220: AI in Healthcare** 

# Convergence of key ingredients of deep learning

# Algorithms

Compute





Data



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### **BIODS 220: AI in Healthcare**

# A real example of EHR data: MIMIC-III dataset

- Open source database of de-identified data for 38,597 adult patients, corresponding to 49,785 hospital admissions
- All patients admitted to critical care units at Beth Israel Deaconess Medical Center (Boston, MA) between 2001 - 2012
- Also 7870 neonates admitted between 2001-2008
- Median hospital stay length: 6.9 days
- Median ICU stay length: 2.1 days
- In-hospital mortality: 11.5%
- Mean of 4579 charted observations and 380 laboratory measurements for each admission

Johnson et al. MIMIC-III, a freely accessible critical care database. 2016.

Lecture 6 - 16

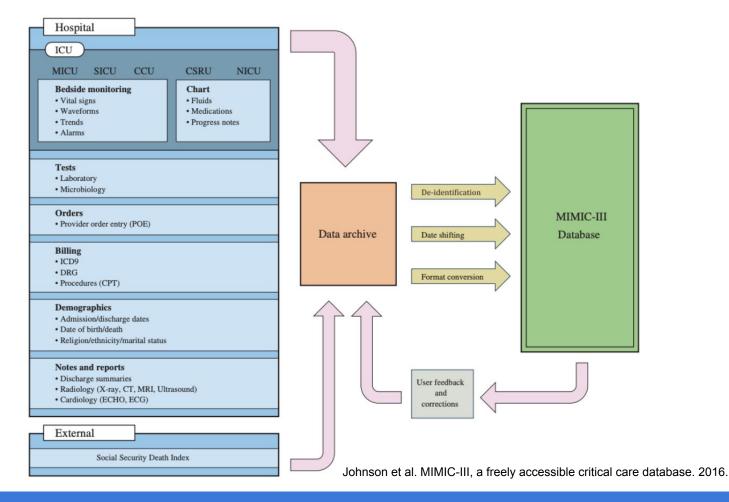
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# A real example of EHR data: MIMIC-III dataset

| Critical care unit                               | CCU              | CSRU             | MICU             | SICU             | TSICU            | Total            |
|--|------------------|------------------|------------------|------------------|------------------|------------------|
| Distinct patients, no. (% of total admissions)   | 5,674 (14.7%)    | 8,091 (20.9%)    | 13,649 (35.4%)   | 6,372 (16.5%)    | 4,811 (12.5%)    | 38,597 (100%)    |
| Hospital admissions, no. (% of total admissions) | 7,258 (14.6%)    | 9,156 (18.4%)    | 19,770 (39.7%)   | 8,110 (16.3%)    | 5,491 (11.0%)    | 49,785 (100%)    |
| Distinct ICU stays, no. (% of total admissions)  | 7,726 (14.5%)    | 9,854 (18.4%)    | 21,087 (39.5%)   | 8,891 (16.6%)    | 5,865 (11.0%)    | 53,423 (100%)    |
| Age, years, median (Q1-Q3)                       | 70.1 (58.4-80.5) | 67.6 (57.6–76.7) | 64.9 (51.7–78.2) | 63.6 (51.4–76.5) | 59.9 (42.9–75.7) | 65.8 (52.8–77.8) |
| Gender, male, % of unit stays                    | 4,203 (57.9%)    | 6,000 (65.5%)    | 10,193 (51.6%)   | 4,251 (52.4%)    | 3,336 (60.7%)    | 27,983 (55.9%)   |
| ICU length of stay, median days (Q1-Q3)          | 2.2 (1.2-4.1)    | 2.2 (1.2-4.0)    | 2.1 (1.2–4.1)    | 2.3 (1.3-4.9)    | 2.1 (1.2-4.6)    | 2.1 (1.2-4.6)    |
| Hospital length of stay, median days<br>(Q1-Q3)  | 5.8 (3.1-10.0)   | 7.4 (5.2–11.4)   | 6.4 (3.7–11.7)   | 7.9 (4.4–14.2)   | 7.4 (4.1–13.6)   | 6.9 (4.1–11.9)   |
| ICU mortality, percent of unit stays             | 685 (8.9%)       | 353 (3.6%)       | 2,222 (10.5%)    | 813 (9.1%)       | 492 (8.4%)       | 4,565 (8.5%)     |
| Hospital mortality, percent of unit stays        | 817 (11.3%)      | 424 (4.6%)       | 2,859 (14.5%)    | 1,020 (12.6%)    | 628 (11.4%)      | 5,748 (11.5%)    |

Johnson et al. MIMIC-III, a freely accessible critical care database. 2016.

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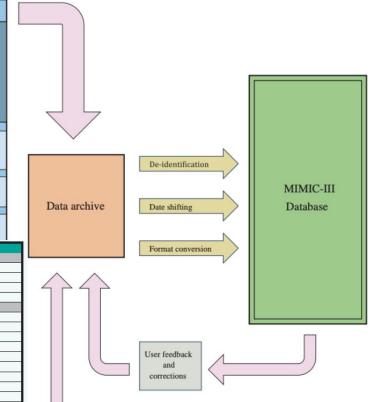


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### **BIODS 220: AI in Healthcare**

|   |   |   | ice   |  |  |     |
|---|---|---|---|--|--|-----|
|   |   | _   | MICU SICU CCU   | CSRU   | NICU                                       |     |
|   |   |   | Bedside monitoring<br>• Vital signs   | Chart<br>• Fluids  |  |     |
|   |   |   | Waveforms   | Medication   | 5  |     |
|   |   |   | Trends  | Progress no  | Sec. 1                                     |     |
|   |   |   | Alarms  | - i logicos inc  | 103  |     |
|   |   |   | 7 Harris  |  |  |     |
|   |   |   |   |  |  |     |
|   | D9 (International   |   | Tests   |  |  | 1   |
|   | •   |   | Laboratory  |  |  |     |
| cla   | ssification of  |   | Microbiology  |  |  |     |
|   |   |   |   |  |  |     |
| dis   | seases): 🔍 🔨  |   | Orders  |  |  |     |
|   | · · · · · · · · · · · · · · · · · · ·   |   | · Provider order entry (POE)  |  |  |     |
| Dia   | agnosis codes   |   |   |  |  | Dat |
|   |   |   |   |  |  |     |
|   | •   |   | Dilling   |  |  |     |
|   | -   |   | • ICD9  |  |  | ]   |
|   | DESCRIPTION   | 100-10  | • ICD9  | CRIPTION   |  |     |
|   | DESCRIPTION<br>Concentral Malformations at  | ICD-10<br>nd Chromosomal  | • ICD9 DES  | CRIPTION   |  |     |
| ICD-9   |   |   | • ICD9  | /ndrome)   | d urethra                                  |     |
| ICD-9<br>753.8<br>758.0   | Congenital Malformations a  | nd Chromosomal  | ICD9     DESi Abnormalities (including Down's Sy     Other congenital malform   | /ndrome)   | d urethra                                  |     |
| ICD-9<br>753.8<br>758.0<br>741.00   | Congenital Malformations an<br>Cystourethral anom NEC<br>Down's syndrome<br>Spin bif w hydroceph NOS  | nd Chromosomal<br>Q64.79<br>Q90.9<br>Q05.4  | ICD9     DESi     Abnormalities (including Down's Sy     Other congenital malform     Down syndr     Unspecified spina b  | <b>yndrome)</b><br>nations of bladder and<br>rome, unspecified<br>bifida with hydrocepha   | alus                                       |     |
| CD-9<br>753.8<br>758.0<br>41.00   | Congenital Malformations an<br>Cystourethral anom NEC<br>Down's syndrome<br>Spin bif w hydroceph NOS<br>Spina biffuda   | nd Chromosomal<br>Q64.79<br>Q90.9<br>Q05.4<br>Q05.8   | ICD9     DESi Abnormalities (including Down's Sy Other congenital malform     Down syndr     Unspecified spina b     Sacral spina bifida  | <b>(ndrome)</b><br>mations of bladder and<br>rome, unspecified   | alus                                       |     |
| 753.8<br>758.0<br>741.00<br>741.90  | Congenital Malformations au<br>Cystourethral anom NEC<br>Down's syndrome<br>Spin bif w hydroceph NOS<br>Spina bifida<br>Genitourinary S   | nd Chromosomal<br>Q64.79<br>Q90.9<br>Q05.4<br>Q05.8<br>ystem Diseases   | ICD9     DES     Abnormalities (Including Down's Sy     Other congenital malform     Down syndr     Unspecified spina b     Sacral spina bifda     (Including Incontinence and UTI)   | (ndrome)<br>mations of bladder and<br>rome, unspecified<br>bifida with hydrocepha<br>a without hydrocephal   | alus                                       |     |
| ICD-9<br>753.8<br>758.0<br>741.00<br>741.90<br>584.9  | Congenital Malformations au<br>Cystourethral anom NEC<br>Down's syndrome<br>Spin bif w hydroceph NOS<br>Spina bifida<br>Genitourinary S<br>Acute kidney failure NOS   | nd Chromosomal<br>Q64.79<br>Q90.9<br>Q05.4<br>Q05.8<br>ystem Diseases<br>N17.9  | ICD9     DESi     Abnormalities (including Down's Sy         Other congenital malforn         Down syndr         Unspecified spina b         Sacral spina biffda     (including Incontinence and UTI)         Acute kidney  | Indrome)<br>mations of bladder and<br>rome, unspecified<br>bifida with hydrocepha<br>a without hydrocephal<br>failure, unspecified   | alus                                       |     |
| CD-9<br>753.8<br>758.0<br>741.00<br>741.90<br>584.9<br>596.9  | Congenital Malformations au<br>Cystourethral anom NEC<br>Down's syndrome<br>Spin bif w hydroceph NOS<br>Spina bifida<br>Genitourinary S<br>Acute kidney failure NOS<br>Bladder disorder NOS   | nd Chromosomal<br>064.79<br>090.9<br>005.4<br>005.8<br>ystem Diseases<br>N17.9<br>N32.9   | ICD9     DES     Abnormalities (including Down's Sy     Other congenital maiform     Down syndr     Unspecified spina b     Sacral spina bifda     (including incontinence and UTI)     Acute kidney:     Bladder disc  | ndrome)<br>nations of bladder and<br>rome, unspecified<br>offida with hydrocepha<br>a without hydrocephal<br>failure, unspecified<br>order, unspecified  | alus<br>us                                 |     |
| CD-9<br>753.8<br>758.0<br>741.00<br>741.90<br>584.9<br>596.9<br>596.9<br>500.01   | Congenital Malformations au<br>Cystourethral anom NEC<br>Down's syndrome<br>Spin bif w hydroceph NOS<br>Spina bifida<br>Genitourinary S<br>Acute kidney failure NOS<br>Bladder disorder NOS<br>BPH w urinary obs/LUTS   | nd Chromosomal<br>064.79<br>090.9<br>005.4<br>005.8<br>ystem Diseases<br>N17.9<br>N32.9<br>N40.1  | ICD9     DESI     Abnormalities (including Down's Sy     Other congenital malform     Down syndr     Unspecified spina biflda     Sacral spina biflda     (including Incontinence and UTI)     Acute kidney     Bladder diss     Enlarged prostate with I   | ndrome)<br>nations of bladder and<br>rome, unspecified<br>offida with hydrocepha<br>a without hydrocephal<br>failure, unspecified<br>order, unspecified<br>lower urinary tract syn   | alus<br>us<br>mptoms                       |     |
| 753.8<br>758.0<br>741.00<br>741.90<br>584.9<br>596.9<br>596.9<br>500.01   | Congenital Malformations au<br>Cystourethral anom NEC<br>Down's syndrome<br>Spin bif w hydroceph NOS<br>Spina bifida<br>Genitourinary S<br>Acute kidney failure NOS<br>Bladder disorder NOS<br>BPH w urinary obs/LUTS<br>BPH w/o urinary obs/LUTS   | nd Chromosomal<br>064.79<br>090.9<br>005.4<br>005.8<br>vstem Diseases<br>N17.9<br>N32.9<br>N40.1<br>N40.0   | ICD9     DESt     Abnormalities (including Down's Sy     Other congenital malform     Down syndr     Unspecified spina b     Sacral spina biflda     (including Incontinence and UTI)     Acute kidney:     Bladder disc     Enlarged prostate with l     Enlarged prostate with  | ndtrome)<br>nations of bladder and<br>orome, unspecified<br>olifida with hydrocephal<br>a without hydrocephal<br>failure, unspecified<br>order, unspecified<br>lower urinary tract sy<br>ti lower urinary tract sy   | alus<br>us<br>mptoms                       |     |
| ICD-9<br>753.8<br>758.0<br>741.00<br>741.90<br>584.9<br>596.9<br>500.01<br>500.00<br>585.9  | Congenital Maiformations au<br>Cystourethral anom NEC<br>Down's syndrome<br>Spin bif w hydroceph NOS<br>Spina bifida<br>Genitourinary S<br>Acute kidney failure NOS<br>Bladder disorder NOS<br>BPH w urinary obs/LUTS<br>Chronic kidney dis NOS   | nd Chromosomal<br>064.79<br>090.9<br>005.4<br>005.8<br>ystem Diseases<br>N17.9<br>N32.9<br>N40.1<br>N40.0<br>N18.9  | ICD9     DESi     Abnormalities (including Down's Sy     Other congenital malform     Down syndr     Unspecified spina b     Sacral spina biffda     (including Incontinence and UTI)     Acute kidney     Bladder disc     Enlarged prostate with 1     Enlarged prostate with 0     Chronic kidney  | ndtrome)<br>nations of bladder and<br>rome, unspecified<br>olifida with hydrocephal<br>a without hydrocephal<br>failure, unspecified<br>order, unspecified<br>lower urinary tract sy<br>it lower urinary tract sy<br>olisease, unspecified   | alus<br>us<br>mptoms                       |     |
| ICD-9<br>753.8<br>758.0<br>741.00<br>741.90<br>584.9<br>596.9<br>500.01<br>500.00<br>585.9<br>753.19  | Congenital Maiformations au<br>Cystourethral anom NEC<br>Down's syndrome<br>Spin bif w hydroceph NOS<br>Spina bifida<br>Genitourinary S<br>Acute kidney failure NOS<br>Bladder disorder NOS<br>BPH wu urinary obs/LUTS<br>BPH w/o urinary obs/LUTS<br>Chronic kidney dis NOS<br>Cystic kidney diseas NEC  | Name         Chromosomal           064.79         090.9           005.4         005.8           ystem Diseases         N17.9           N32.9         N40.1           N40.0         N18.9           061.8         061.8  | ICD9     DES     Abnormalities (including Down's Sy     Other congenital malform     Down syndr     Unspecified spina b     Sacral spina bifda     (including incontinence and UTI)     Acute kidneys     Enlarged prostate withou     Chronic kidney     Other cysite  | ndrome)<br>mations of bladder ann<br>rome, unspecified<br>offida with hydrocephal<br>failure, unspecified<br>order, unspecified<br>lower urinary tract syn<br>it lower urinary tract syn<br>disease, unspecified<br>oldsease, unspecified  | alus<br>us<br>mptoms                       |     |
| ICD-9<br>753.8<br>758.0<br>741.00<br>741.90<br>584.9<br>596.9<br>500.01<br>585.9<br>585.9<br>585.9<br>585.6   | Congenital Maiformations au<br>Cystourethrai anom NEC<br>Down's syndrome<br>Spin bif w hydroceph NOS<br>Spina bifida<br>Genitourinary S<br>Acute kidney failure NOS<br>Bladder disorder NOS<br>BPH wu urinary obs/LUTS<br>BPH wu urinary obs/LUTS<br>Chronic kidney dis NOS<br>Cystic kidney diseas NEC<br>End stage renal disease  | nd Chromosomal<br>064.79<br>090.9<br>005.4<br>005.8<br>vstem Diseases<br>N17.9<br>N32.9<br>N40.1<br>N40.0<br>N18.9<br>061.8<br>N18.6  | ICD9     DES     Abnormalities (including Down's Sy     Other congenital malform     Down syndr     Unspecified spina biflda     Sacral spina biflda     (including incontinence and UTI)     Acute kidney:     Bladder disc     Enlarged prostate with I     Enlarged prostate withou     Chronic kidney     Other cystic     End stage     End stage     End stage  | ndtrome)<br>mations of bladder and<br>orome, unspecified<br>fifda with hydrocephal<br>a without hydrocephal<br>failure, unspecified<br>lower urinary tract sy<br>it lower urinary tract sy<br>disease, unspecified<br>clader urinary tract sy<br>diseases<br>e renai disease   | alus<br>us<br>mptoms                       |     |
| ICD-9<br>753.8<br>758.0<br>741.00<br>584.9<br>596.9<br>500.01<br>500.00<br>585.9<br>753.19<br>585.6<br>625.6  | Congenital Malformations au<br>Cystourethral anom NEC<br>Down's syndrome<br>Spin bif w hydroceph NOS<br>Spina bifida<br>Genitourinary S<br>Acute kidney falure NOS<br>Bladder disorder NOS<br>BPH w urinary obs/LUTS<br>Chronic kidney dis NOS<br>Cystic kidney diseas NEC<br>End stage renal disease<br>Fem stress incontinence  | nd Chromosomal<br>064.79<br>090.9<br>005.4<br>005.8<br>ystem Diseases<br>N17.9<br>N32.9<br>N40.1<br>N40.0<br>N18.9<br>061.8<br>N18.6<br>N39.3   | ICD9     DESI     Abnormalities (including Down's Sy         Other congenital maiforn         Down syndr         Unspecified spina b         Sacral spina biffda     (including Incontinence and UTI)         Acute kidney         Bladder disc         Enlarged prostate withou         Chronic kidney         Other cystic         End stage         End stage         Stress incontin                      | ndtrome)<br>nations of bladder and<br>rome, unspecified<br>olifida with hydrocephal<br>a without hydrocephal<br>failure, unspecified<br>lower urinary tract sy<br>it lower urinary tract sy<br>it lower urinary tract sy<br>idisease, unspecified<br>c kidney disease<br>ence (female) (male)  | alus<br>us<br>mptoms                       |     |
| 1CD-9<br>753.8<br>758.0<br>741.00<br>741.90<br>741.90<br>586.9<br>500.01<br>500.00<br>585.9<br>753.19<br>585.6<br>625.6<br>625.6<br>625.6<br>787.60 | Congenital Maiformations au<br>Cystourethral anom NEC<br>Down's syndrome<br>Spin bif w hydroceph NOS<br>Spina bifida<br>Genitourinary S<br>Acute kidney failure NOS<br>Bladder disorder NOS<br>BPH w/o urinary obs/LUTS<br>Chronic kidney dis NOS<br>Cystic kidney diseas NEC<br>End stage renal disease<br>Fem stress incontinence<br>Full incontinence -feces   | nd Chromosomal<br>064.79<br>090.9<br>005.4<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8<br>005.8 | ICD9     DESi     Abnormalities (including Down's Sy     Other congenital maiform     Down syndr     Unspecified spina b     Sacral spina biffda     (including Incontinence and UTI)         Acute kidney         Bladder disc         Enlarged prostate without         Chronic kidney         Other cystic         End stage         Stress incontini          Full incont         Full incont             | ndrome)<br>mations of bladder ann<br>rome, unspecified<br>jifida with hydrocephal<br>a without hydrocephal<br>failure, unspecified<br>order, unspecified<br>lower urinary tract sy<br>disease, unspecified<br>c kidney diseases<br>e renal disease<br>e rene disease (male)<br>tinence of fneces   | alus<br>us<br>mptoms                       |     |
| 100-9<br>753.8<br>758.0<br>741.00<br>741.90<br>584.9<br>596.9<br>500.01<br>585.9<br>585.9<br>585.9<br>585.6<br>625.6<br>877.60<br>596.51            | Congenital Maiformations au<br>Cystourethral anom NEC<br>Down's syndrome<br>Spin bif w hydroceph NOS<br>Spina bifida<br>Genitourinary S<br>Acute kidney failure NOS<br>Bladder disorder NOS<br>BPH wu urinary obs/LUTS<br>BPH w/o urinary obs/LUTS<br>Chronic kidney dis NOS<br>Cystic kidney diseas NEC<br>End stage renal disease<br>Fem stress incontinence<br>Full incontinence-feces<br>Hypertonicity of bladder                               | nd Chromosomal<br>064.79<br>090.9<br>005.4<br>005.8<br>N17.9<br>N40.1<br>N40.0<br>N18.9<br>061.8<br>N18.6<br>N39.3<br>R15.9<br>N32.81   | ICD9     DESI     Abnormalities (including Down's Sy     Other congenital malform     Down syndr     Unspecified spina b     Sacral spina bifda     (including Incontinence and UTI)     Acute Kidney     Bladder disc     Enlarged prostate withou     Chronic Kidney     Other cystic     End stage     Stress incontin     Fuil inconti      Overac     Overac   | ndrome)<br>mations of bladder ann<br>rome, unspecified<br>jifda with hydrocephal<br>a without hydrocephal<br>failure, unspecified<br>lower urinary tract syn<br>it lower urinary tract syn<br>disease, unspecified<br>skidney diseases<br>e renal disease<br>e renal disease<br>e renal disease<br>erence (female) (male)<br>tinence of feces<br>citve bladder   | alus<br>us<br>mptoms<br>ymptoms            |     |
| ICD-9<br>753.8<br>758.0<br>741.00<br>741.90<br>584.9<br>596.9<br>500.01<br>585.9<br>585.9<br>585.6<br>625.6<br>787.60<br>996.51<br>787.60           | Congenital Maiformations au<br>Cystourethral anom NEC<br>Down's syndrome<br>Spin bif w hydroceph NOS<br>Spina bifida<br>Genitourinary S<br>Acute kidney failure NOS<br>Bladder disorder NOS<br>BPH w/o urinary obs/LUTS<br>Chronic kidney dis NOS<br>Cystic kidney diseas NEC<br>End stage renal disease<br>Fem stress incontinence<br>Full incontinence -feces   | nd Chromosomal<br>064.79<br>090.9<br>005.4<br>005.8<br>ystem Diseases<br>N17.9<br>N32.9<br>N40.1<br>N40.0<br>N18.9<br>061.8<br>N18.6<br>N39.3<br>R15.9<br>N32.81<br>R39.14  | ICD9     DESI     Abnormalities (including Down's Sy     Other congenital maiform     Down syndr     Unspecified spina b     Sacral spina bifida     (including Incontinence and UTI)     Acute kidney     Bladder disc     Enlarged prostate withou     Chronic kidney     Other cystic     End srgg     Stress incontin     Fuil incont     Fuelin continence     Overac     Feeling of incomp              | ndrome)<br>mations of bladder and<br>orome, unspecified<br>jifda with hydrocephal<br>a without hydrocephal<br>failure, unspecified<br>lower urinary tract sy<br>it lower urinary tract sy<br>it lower urinary tract sy<br>disease, unspecified<br>c kidney diseases<br>e renai disease<br>ence (female) (male)<br>tinence of feces<br>zitve bladder<br>plete bladder emptyin                                   | alus<br>us<br>mptoms<br>ymptoms<br>g       |     |
| ICD-9<br>753.8<br>758.0<br>741.00<br>741.90<br>584.9<br>596.9<br>500.01<br>585.9<br>753.19<br>585.6<br>625.6<br>625.6<br>787.60<br>996.51<br>788.24 | Congenital Maiformations au<br>Cystourethrai anom NEC<br>Down's syndrome<br>Spin bif w hydroceph NOS<br>Spina bifda<br>Genitourinary S<br>Acute kidney failure NOS<br>Bladder disorder NOS<br>BPH wu urinary obs/LUTS<br>BPH w/ urinary obs/LUTS<br>Chronic kidney diseas NEC<br>End stage renal disease<br>Fem stress incontinence<br>Full incontinence-feces<br>Hypertonicity of bladder<br>lincmplet bidder emptying                             | nd Chromosomal<br>064.79<br>090.9<br>005.4<br>005.8<br>N17.9<br>N40.1<br>N40.0<br>N18.9<br>061.8<br>N18.6<br>N39.3<br>R15.9<br>N32.81   | ICD9     DESi     Abnormalities (including Down's Sy     Other congenital maiforn     Down syndr     Unspecified spina b     Sacral spina biffda     (including Incontinence and UTI)     Acute kidney i     Bladder disc     Enlarged prostate with I     Enlarged prostate withou     Chronic kidney     Other cystic     End Stress incontin     Full Incont     Feeling of Incomp     Incontinence withou | ndrome)<br>mations of bladder ann<br>rome, unspecified<br>jifda with hydrocephal<br>a without hydrocephal<br>failure, unspecified<br>lower urinary tract syn<br>it lower urinary tract syn<br>disease, unspecified<br>skidney diseases<br>e renal disease<br>e renal disease<br>e renal disease<br>erence (female) (male)<br>tinence of feces<br>citve bladder   | alus<br>us<br>mptoms<br>ymptoms<br>g       |     |
| ICD-9<br>753.8<br>758.0<br>741.00<br>741.90<br>584.9<br>596.9<br>500.01<br>585.9<br>585.9<br>585.9<br>585.6   | Congenital Maiformations au<br>Cystourethral anom NEC<br>Down's syndrome<br>Spin bif w hydroceph NOS<br>Spina bifida<br>Genitourinary S<br>Acute kidney failure NOS<br>Bladder disorder NOS<br>BPH w urinary obs/LUTS<br>Chronic kidney dis NOS<br>Cystic kidney diseas NEC<br>End stage renal disease<br>Fem stress incontinence<br>Full incontinence -feces<br>Hypertonicity of bladder<br>Incomplet bidder emptying<br>Incontince wo sensr aware | nd Chromosomal<br>064.79<br>090.9<br>005.4<br>005.8<br>005.8<br>005.8<br>017.9<br>N32.9<br>N40.1<br>N40.0<br>N18.9<br>061.8<br>N18.6<br>N18.6<br>N19.3<br>R15.9<br>N32.81<br>N39.14<br>N39.42   | ICD9     DESi     Abnormalities (including Down's Sy     Other congenital maiforn     Down syndr     Unspecified spina b     Sacral spina biffda     (including Incontinence and UTI)     Acute kidney i     Bladder disc     Enlarged prostate with I     Enlarged prostate withou     Chronic kidney     Other cystic     End Stress incontin     Full Incont     Feeling of Incomp     Incontinence withou | ndrome)<br>mations of bladder ann<br>rome, unspecified<br>jifda with hydrocephal<br>a without hydrocephal<br>failure, unspecified<br>order, unspecified<br>lower urinary tract sy<br>it lower urinary tract sy<br>disease, unspecified<br>c kidney diseases<br>e renal diseases<br>ence (female) (male)<br>tinence of feces<br>citive bladder<br>plete bladder emplyin<br>out sensory awarenes<br>incontinence | alus<br>us<br>mptoms<br>ymptoms<br>g<br>ss |     |

Hospital



Johnson et al. MIMIC-III, a freely accessible critical care database. 2016. Additional figure credit:

http://www.shieldhealthcare.com/community/wp-content/uploads/2015/08/ICD-9-to-ICD-10-Conversion-Guide-Page-1.jpg

# Serena Yeung

# **BIODS 220: AI in Healthcare**

DRG (diagnosis related group): Higher-level codes describing patient groups w/ similar hospital resource use

#### **DRG Code and Description**

079 Respiratory Infections & Inflammations Age >17 w CC 121 Circulatory Disorders w AMI & Major Comp Discharged Alive 387 Prematurity w Major Problems 389 Full Term Neonate w Major Problems 489 HIV w Major Related Condition HIV w Major Related Condition 489 080 Respiratory Infections & Inflammations Age >17 w/o CC

ICU

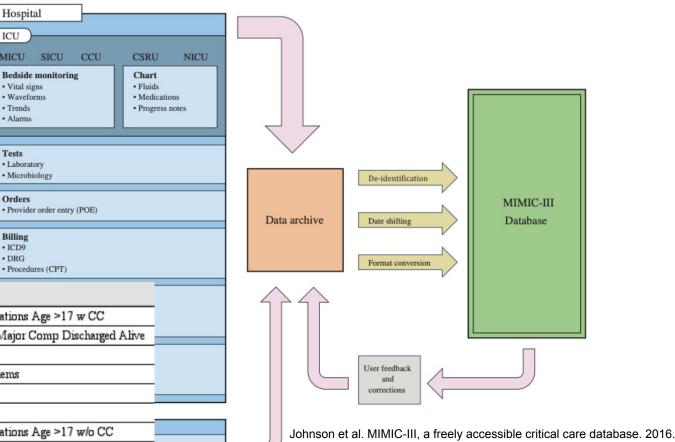
MICU

Tests

• ICD9

• DRG

081 Respiratory Infections & Inflammations Age 0-17



Additional figure credit: https://www.flashcode.com/help pages/drg from icd.html

## Serena Yeung

# **BIODS 220: AI in Healthcare**

### **CPT** (Current procedural terminology): procedures and services codes

#### BONE DENSITOMETRY/DEXA P-DEXA forearm 77081

#### CAT SCANS

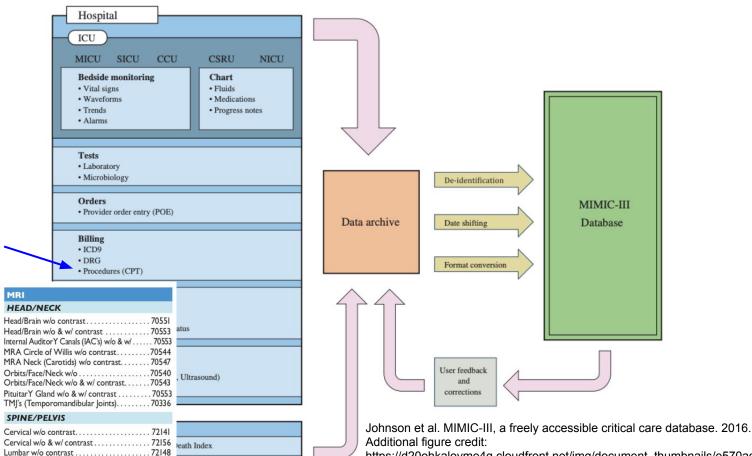
#### ABDOMEN

| Abdomen w/o contrast      | 74150 |
|---------------------------|-------|
| Abdomen w/ contrast       | 74160 |
| Abdomen w/o & w/ contrast | 74170 |

#### CHEST/THORAX

| Chest/Thorax w/o contrast      | 71250 |
|--------------------------------|-------|
| Chest/Thorax w/ contrast       | 74150 |
| Chest/Thorax w/o & w/ contrast | 71270 |
| EXTREMITIES                    |       |
| Upper w/o contrast             |       |

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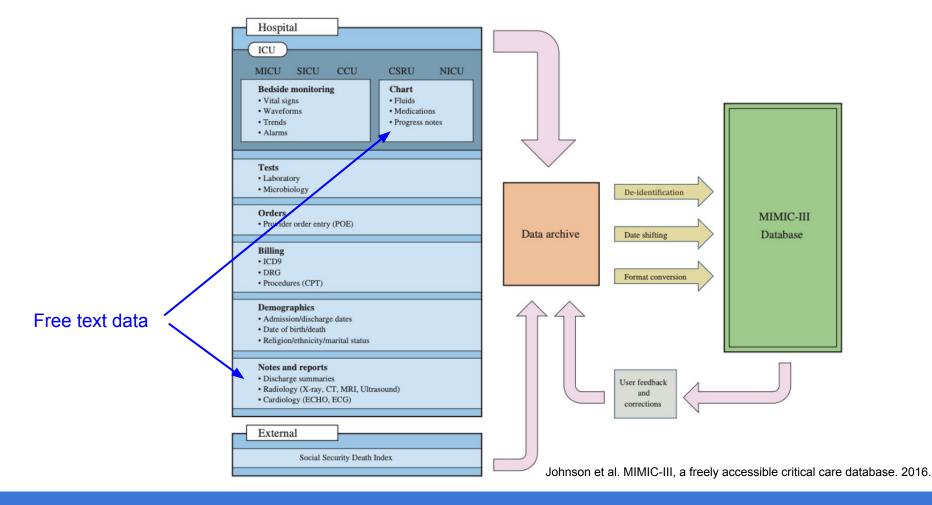


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Database

# Serena Yeung

# **BIODS 220: AI in Healthcare**



### Serena Yeung

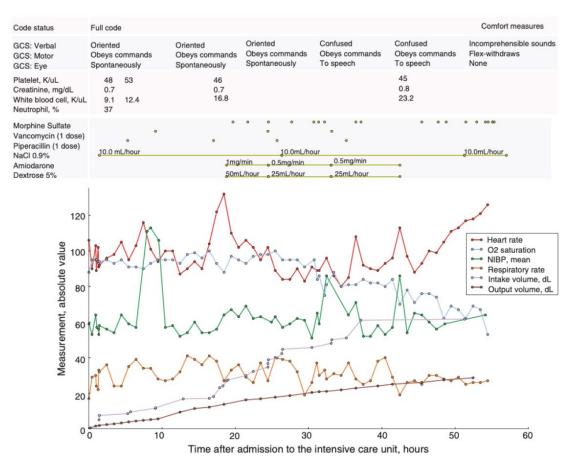
### **BIODS 220: AI in Healthcare**

| Critical care unit   | CCU stays, No.<br>(% by unit) | CSRU stays, No.<br>(% by unit) | MICU stays, No.<br>(% by unit) | SICU stays, No.<br>(% by unit) | TSICU stays, No.<br>(% by unit) | Total stays, No.<br>(% by unit) |
|--|-------------------------------|--------------------------------|--------------------------------|--------------------------------|---------------------------------|---------------------------------|
| Infectious and parasitic diseases, i.e.,<br>septicemia, other infectious and<br>parasitic diseases, etc., (001–139)  | 305 (4.2%)                    | 72 (0.8%)                      | 3,229 (16.7%)                  | 448 (5.6%)                     | 152 (2.8%)                      | 4,206 (8.6%)                    |
| Neoplasms of digestive organs and<br>intrathoracic organs, etc., (140–239)   | 126 (1.8%)                    | 287 (3.2%)                     | 1,415 (7.3%)                   | 1,225 (15.3%)                  | 466 (8.6%)                      | 3,519 (7.2%)                    |
| Endocrine, nutritional, metabolic, and immunity (240–279)  | 104 (1.4%)                    | 36 (0.4%)                      | 985 (5.1%)                     | 178 (2.2%)                     | 54 (1.0%)                       | 1,357 (2.8%)                    |
| Diseases of the circulatory system, i.e.,<br>ischemic heart diseases, diseases of<br>pulmonary circulation, dysrhythmias,<br>heart failure, cerebrovascular diseases,<br>etc., (390–459) | 5,131 (71.4%)                 | 7,138 (78.6%)                  | 2,638 (13.6%)                  | 2,356 (29.5%)                  | 684 (12.6%)                     | 17,947 (36.6%)                  |
| Pulmonary diseases, i.e., pneumonia<br>and influenza, chronic obstructive<br>pulmonary disease, etc., (460–519)  | 416 (5.8%)                    | 141 (1.6%)                     | 3,393 (17.5%)                  | 390 (4.9%)                     | 225 (4.1%)                      | 4,565 (9.3%)                    |
| Diseases of the digestive system (520-579)   | 264 (3.7%)                    | 157 (1.7%)                     | 3,046 (15.7%)                  | 1,193 (14.9%)                  | 440 (8.1%)                      | 5,100 (10.4%)                   |
| Diseases of the genitourinary system,<br>i.e., nephritis, nephrotic syndrome,<br>nephrosis, and other diseases of the<br>genitourinary system (580–629)                                  | 130 (1.8%)                    | 14 (0.2%)                      | 738 (3.8%)                     | 101 (1.3%)                     | 31 (0.6%)                       | 1,014 (2.1%)                    |
| Trauma (800–959)   | 97 (1.3%)                     | 494 (5.4%)                     | 480 (2.5%)                     | 836 (10.5%)                    | 2,809 (51.7%)                   | 4,716 (9.6%)                    |
| Poisoning by drugs and biological substances (960–979)   | 50 (0.7%)                     | 2 (0.0%)                       | 584 (3.0%)                     | 58 (0.7%)                      | 11 (0.2%)                       | 705 (1.4%)                      |
| Other  | 565 (7.9%)                    | 739 (8.1%)                     | 2,883 (14.9%)                  | 1,204 (15.1%)                  | 563 (10.4%)                     | 5,954 (12.1%)                   |
| Total  | 7,188 (14.6%)                 | 9,080 (18.5%)                  | 19,391 (39.5%)                 | 7,989 (16.3%)                  | 5,435 (11.1%)                   | 49,083 (100%)                   |

Johnson et al. MIMIC-III, a freely accessible critical care database. 2016.

# Serena Yeung

# BIODS 220: AI in Healthcare



Johnson et al. MIMIC-III, a freely accessible critical care database. 2016.

### Serena Yeung

**BIODS 220: AI in Healthcare** 

# Examples of prediction tasks: phenotypes

- What conditions a patient has
- Useful for patient treatment and risk monitoring



Figure credit: Harutyunyan et al. Multitask learning and benchmarking with clinical time series data. 2019.

### Serena Yeung

# Examples of prediction tasks: in-hospital mortality

- Whether patient will die in the hospital
- Early detection of at-risk patients can improve outcomes

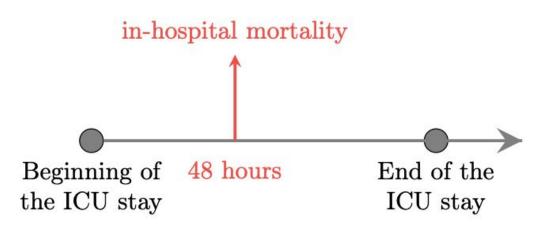


Figure credit: Harutyunyan et al. Multitask learning and benchmarking with clinical time series data. 2019.

### Serena Yeung

# Examples of prediction tasks: decompensation

- Whether patient will die in the next 24 hours
- Also for early detection, related to in-hospital mortality

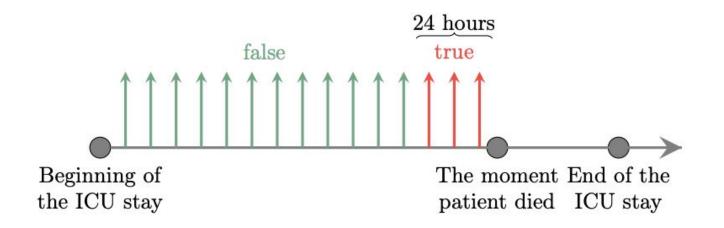


Figure credit: Harutyunyan et al. Multitask learning and benchmarking with clinical time series data. 2019.

# Serena Yeung

# Examples of prediction tasks: length-of-stay

- How much longer the patient is expected to stay in the ICU
- Useful for measuring patient acuity and resource management

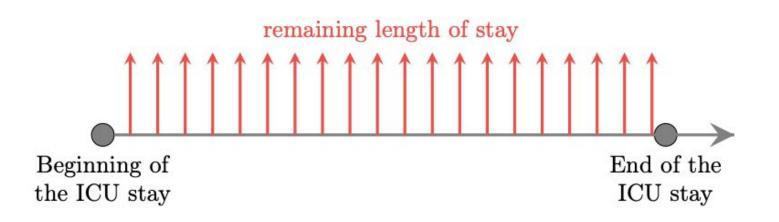


Figure credit: Harutyunyan et al. Multitask learning and benchmarking with clinical time series data. 2019.

### Serena Yeung

# Remember: "vanilla" neural networks for predictions from clinical variables

Let us consider the task of regression: predicting a single real-valued output from input data

Model input: data vector  $x = [x_1, x_2, ..., x_N]$ 

**Model output:** prediction (single number)  $\hat{y}$ 

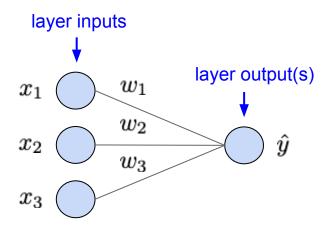
Example: predicting hospital length-of-stay from clinical variables in the electronic health record

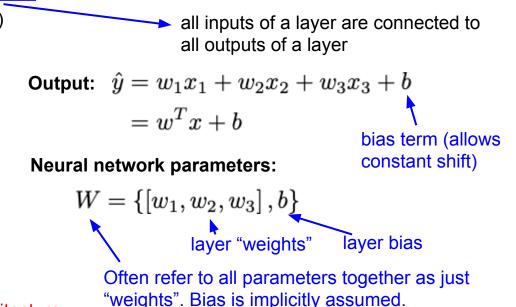
x = [age, weight, ..., temperature, oxygen saturation]  $\hat{y} = length-of-stay (days)$ 

# Remember: "vanilla" neural networks for predictions from clinical variables

Our first architecture: a single-layer, fully connected neural network

For simplicity, use a 3-dimensional input (N = 3)





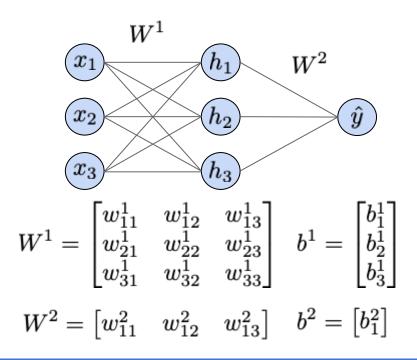
Caveats of our first (simple) neural network architecture:

- Single layer still "shallow", not yet a "deep" neural network. Will see soon how to stack multiple layers.
- Also equivalent to a linear regression model! But useful base case for deep learning.

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# Remember: "vanilla" neural networks for predictions from clinical variables $\sigma(a) = \frac{1}{1 + e^{-a}}$

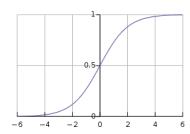
Two-layer fully-connected neural network



Output:  $h = \sigma(W^1x + b^1)$  $\hat{y} = W^2h + b^2$ 

Full function expression:  $\hat{y} = W^2(\sigma(W^1x + b^1)) + b^2$ 

Activation functions introduce non-linearity into the model -- allowing it to represent highly complex functions.



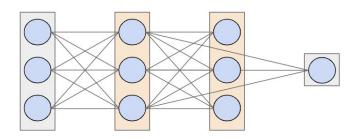
Sigmoid "activation function"

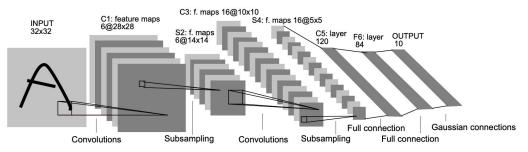
A **fully-connected neural network** (also known as multi-layer perceptron) is a stack of [affine transformation + activation function] layers. There is no activation function at the last layer.

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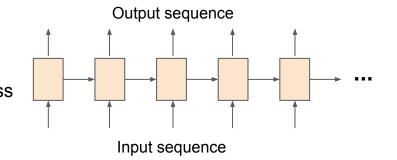
# Different classes of neural networks





Fully connected neural networks (linear layers, good for "feature vector" inputs)

**Convolutional neural networks** (convolutional layers, good for image inputs)



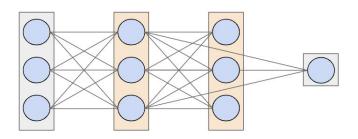
Recurrent neural networks

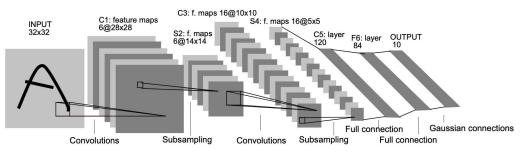
(linear layers modeling recurrence relation across sequence, good for sequence inputs)

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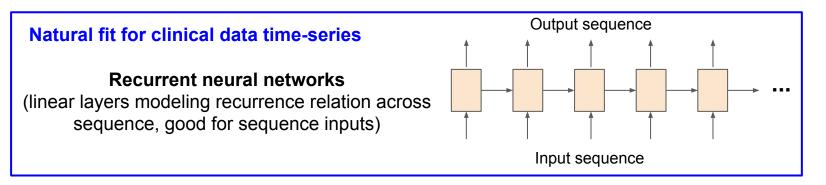
# Different classes of neural networks





**Fully connected neural networks** (linear layers, good for "feature vector" inputs)

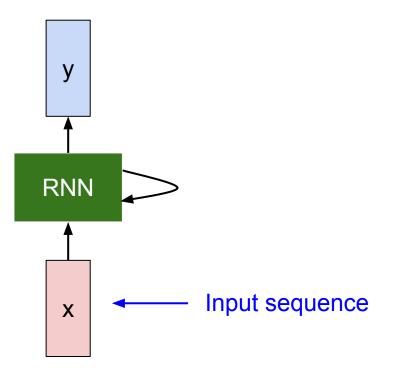
# **Convolutional neural networks** (convolutional layers, good for image inputs)



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# **Recurrent Neural Network**

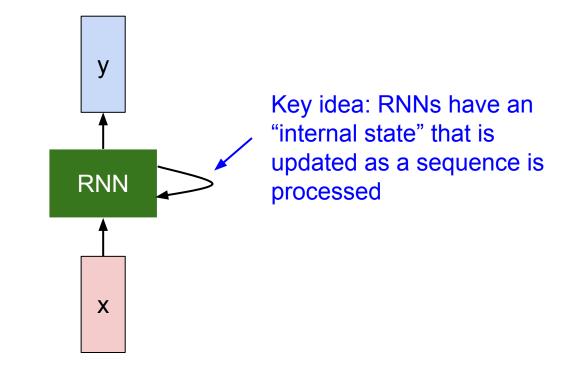


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# **Recurrent Neural Network**

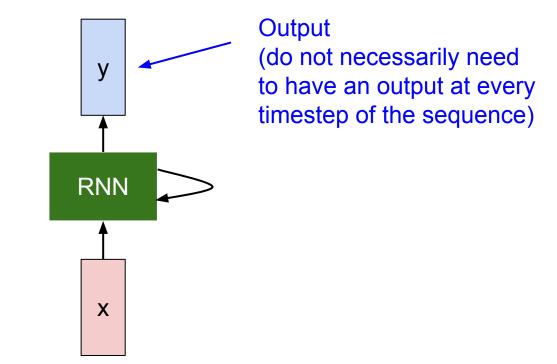


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# **Recurrent Neural Network**



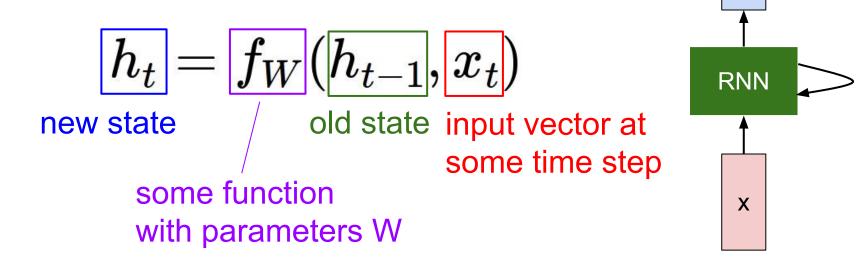
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# **Recurrent Neural Network**

We can process a sequence of vectors **x** by applying a **recurrence formula** at every time step:



Slide credit: CS231n

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Lecture 6 - 37

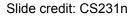
V

# **Recurrent Neural Network**

We can process a sequence of vectors **x** by applying a **recurrence formula** at every time step:

$$h_t = f_W(h_{t-1}, x_t)$$

# Notice: the same function and the same set of parameters are used at every time step.



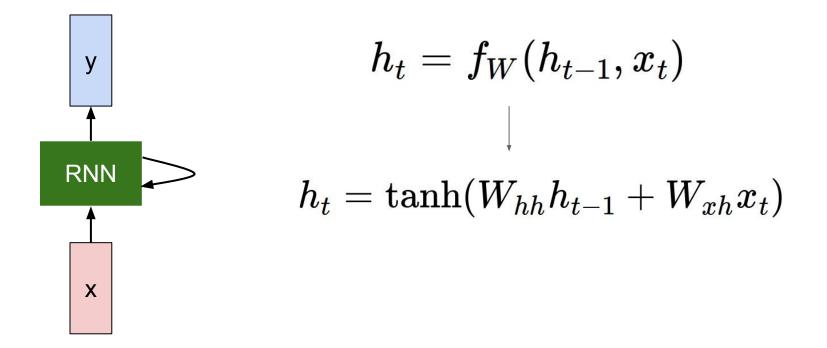
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V RNN Х

# (Vanilla) Recurrent Neural Network

The state consists of a single "hidden" vector h:



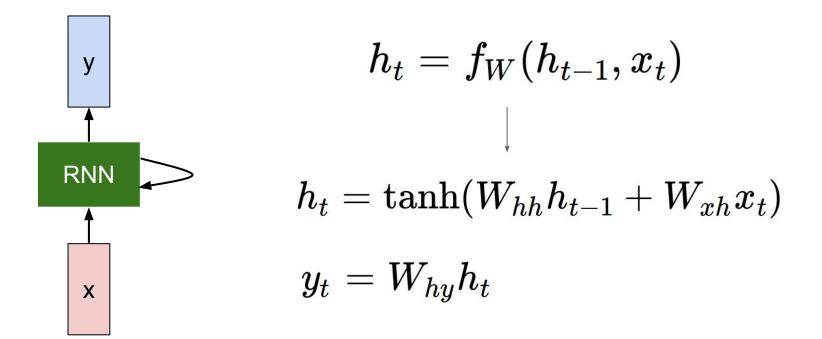
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# (Vanilla) Recurrent Neural Network

The state consists of a single *"hidden"* vector **h**:



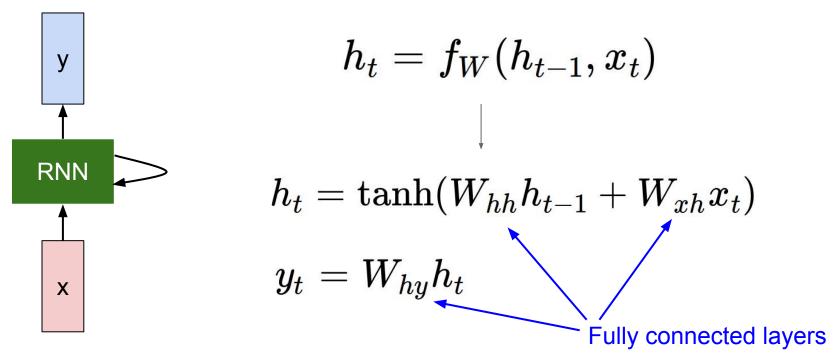
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# (Vanilla) Recurrent Neural Network

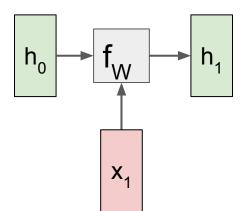
The state consists of a single *"hidden"* vector **h**:



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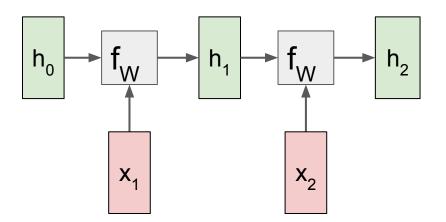
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#### Slide credit: CS231n

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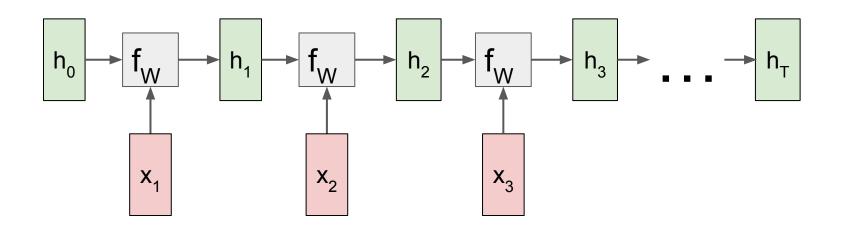
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#### Slide credit: CS231n

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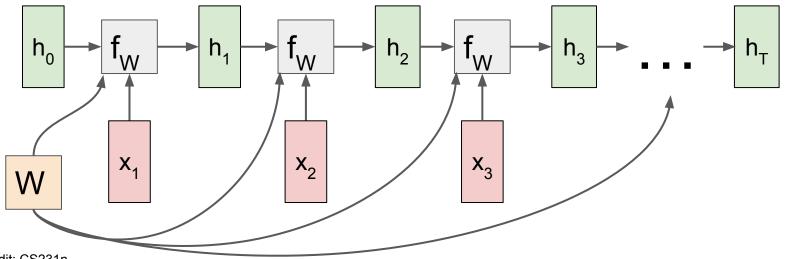


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Re-use the same weight matrix at every time-step

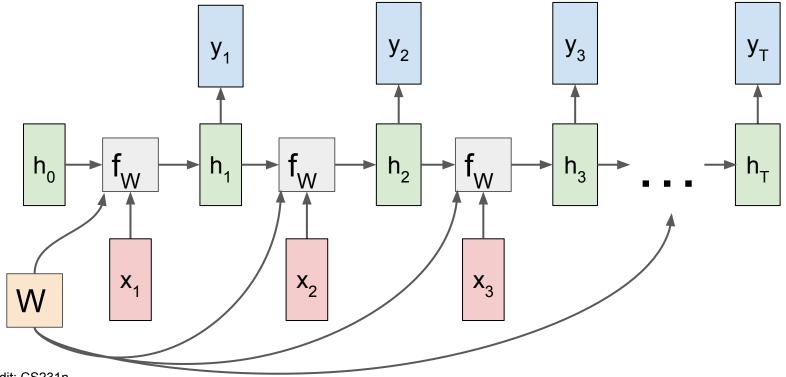


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### **RNN:** Computational Graph: Many to Many

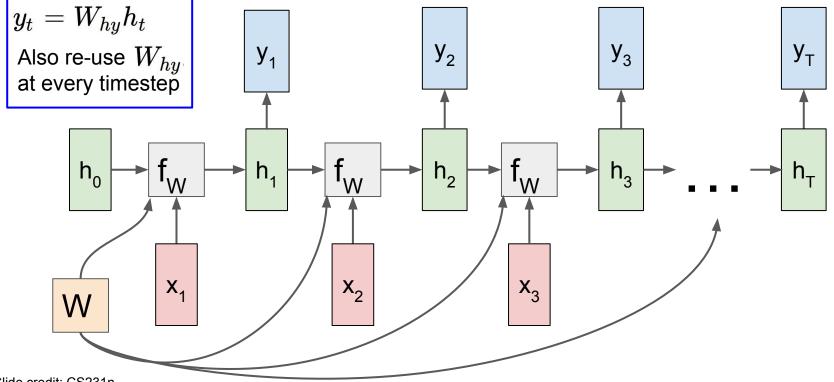


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### **RNN:** Computational Graph: Many to Many

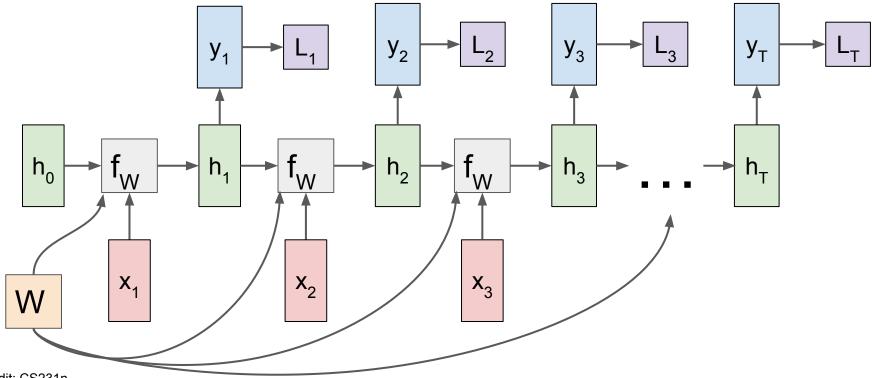


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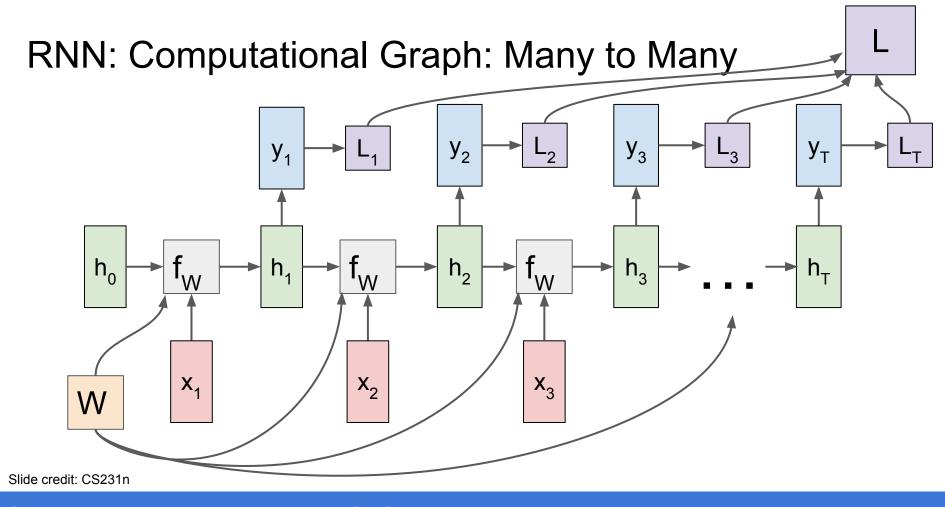
### **RNN:** Computational Graph: Many to Many



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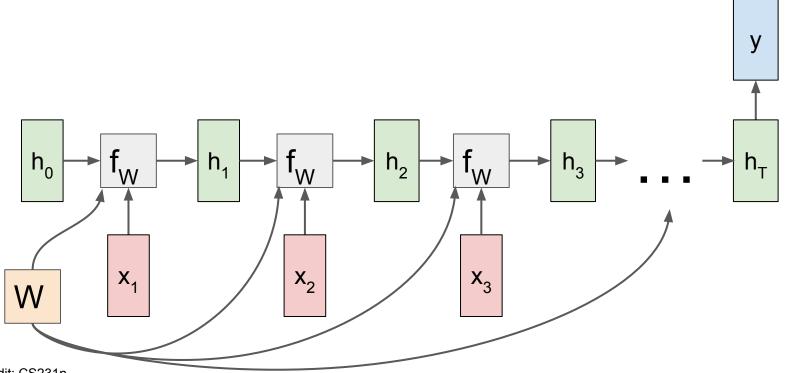
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### RNN: Computational Graph: Many to One

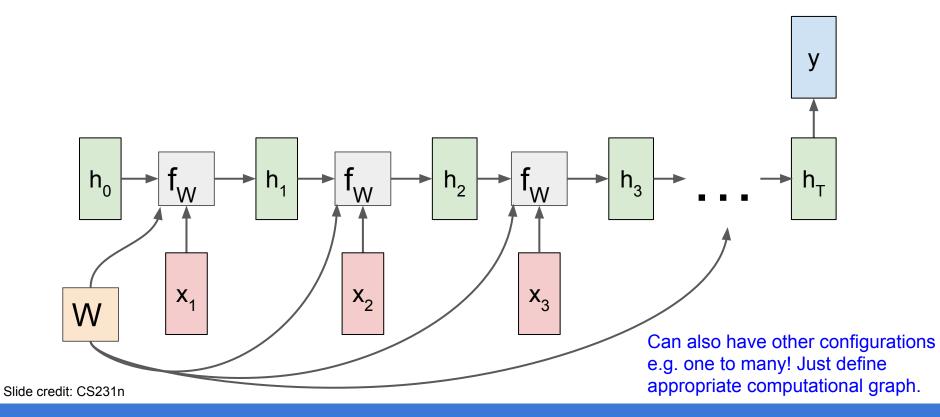


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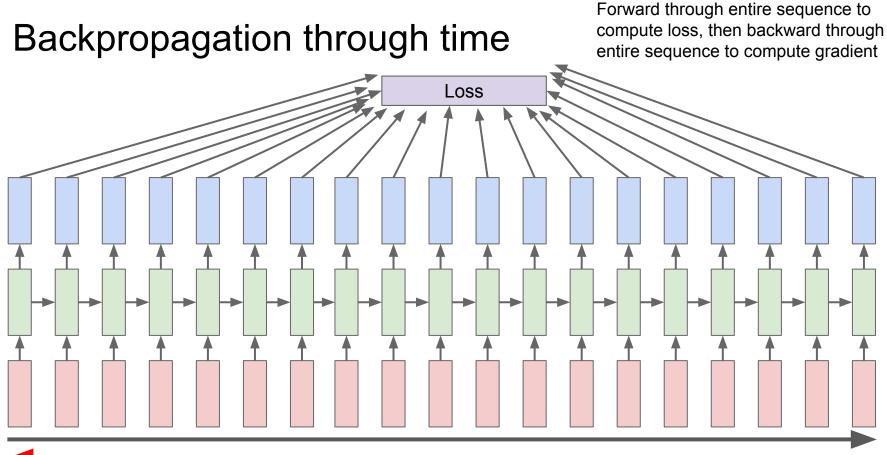
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### RNN: Computational Graph: Many to One



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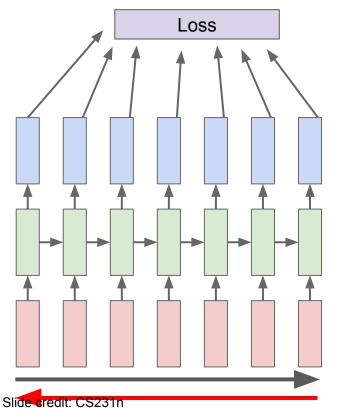


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### Truncated Backpropagation through time

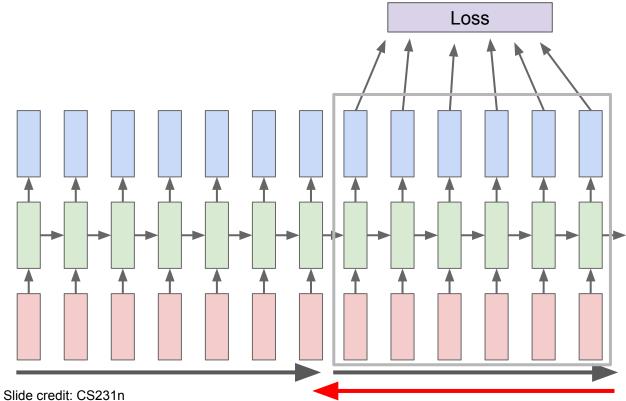


Run forward and backward through chunks of the sequence instead of whole sequence

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### **Truncated** Backpropagation through time

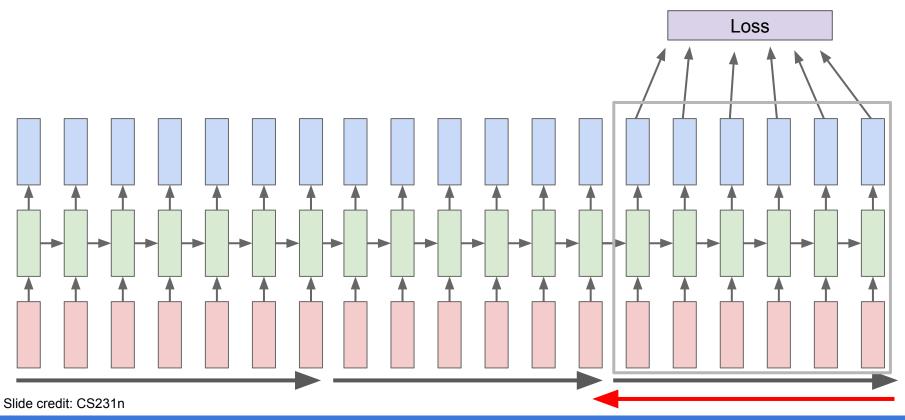


Carry hidden states forward in time forever, but only backpropagate for some smaller number of steps

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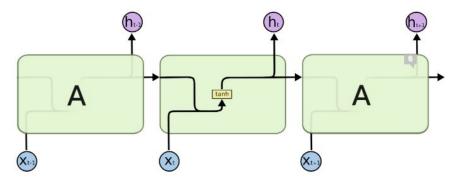
### **Truncated** Backpropagation through time



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Unrolled Vanilla RNN



$$h_t = anh(W_{hh}h_{t-1} + W_{xh}x_t)$$

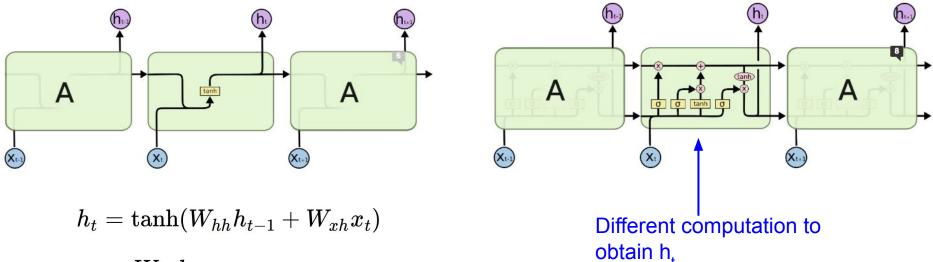
$$y_t = W_{hy}h_t$$

Figure credit: https://colah.github.io/posts/2015-08-Understanding-LSTMs/

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Unrolled Vanilla RNN

Unrolled LSTM



 $y_t = W_{hy}h_t$ 

Figure credit: https://colah.github.io/posts/2015-08-Understanding-LSTMs/

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"Cell state" flows through entire sequence. At each timestep, will be able to modify the cell state.

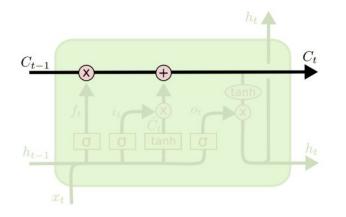
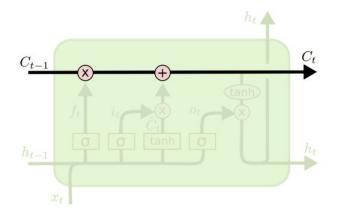


Figure credit: https://colah.github.io/posts/2015-08-Understanding-LSTMs/

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"Cell state" flows through entire sequence. At each timestep, will be able to modify the cell state.



Gates (sigmoid + elementwise multiplication) control passing of information. Sigmoid output of 1 = let everything through; output of 0 = let nothing through.

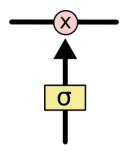


Figure credit: https://colah.github.io/posts/2015-08-Understanding-LSTMs/

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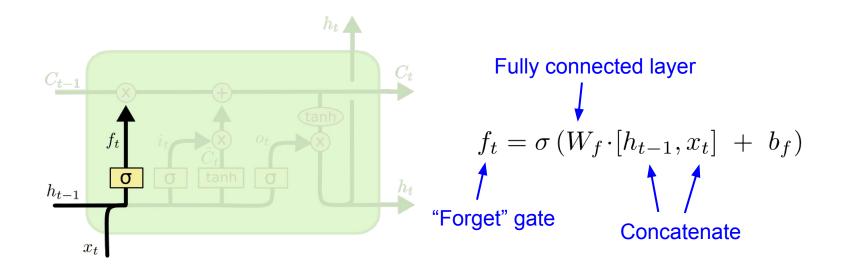
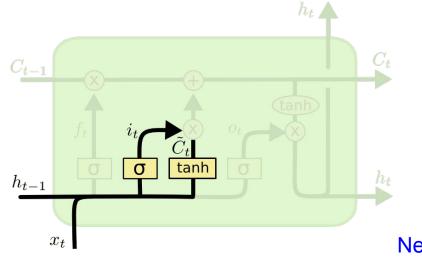


Figure credit: https://colah.github.io/posts/2015-08-Understanding-LSTMs/

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"Input" gate Fully connected layer  

$$i_t = \sigma \left( W_i \cdot [h_{t-1}, x_t] + b_i \right)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$

$$\uparrow$$
New "candidate" Fully connected layer  
values that could  
be added to modify  
cell state

Figure credit: https://colah.github.io/posts/2015-08-Understanding-LSTMs/

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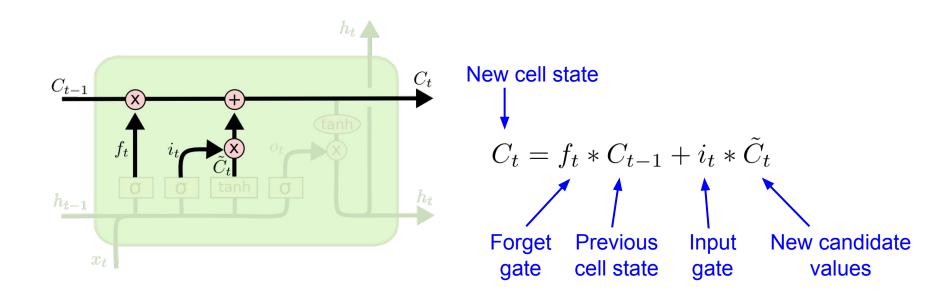
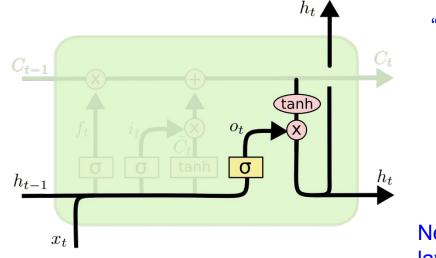


Figure credit: https://colah.github.io/posts/2015-08-Understanding-LSTMs/

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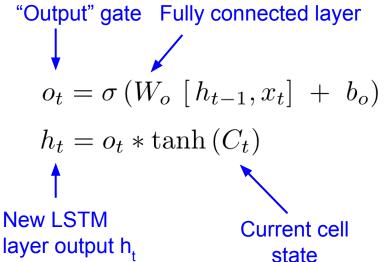


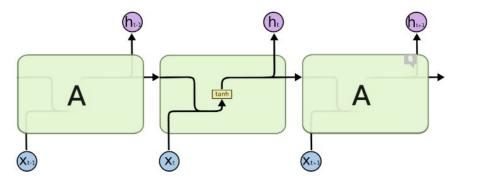
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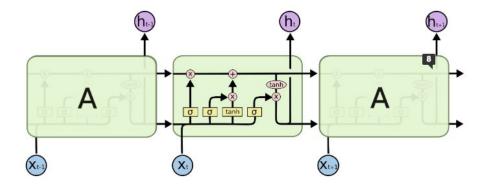
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Unrolled Vanilla RNN

Unrolled LSTM





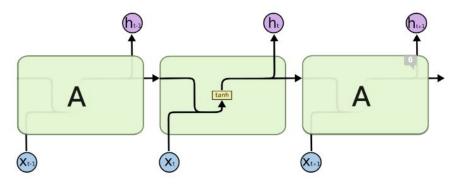
Lecture 6 - 64

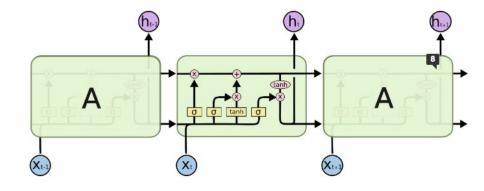
Figure credit: https://colah.github.io/posts/2015-08-Understanding-LSTMs/

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Unrolled Vanilla RNN

Unrolled LSTM





Usage of a "cell state" in the LSTM that is modified through addition allows improved gradient flow through longer sequences.

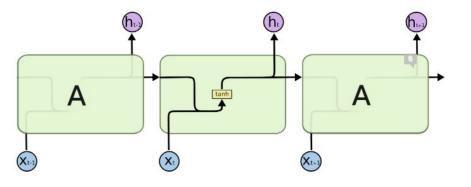
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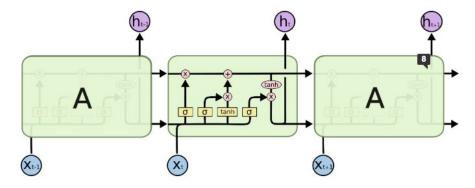
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Unrolled Vanilla RNN

Unrolled LSTM





LSTM often used over Vanilla RNN in practice.

Usage of a "cell state" in the LSTM that is modified through addition allows improved gradient flow through longer sequences.

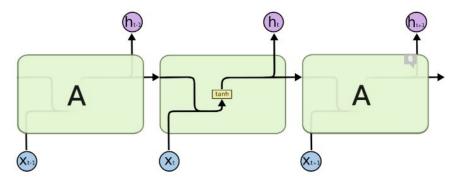
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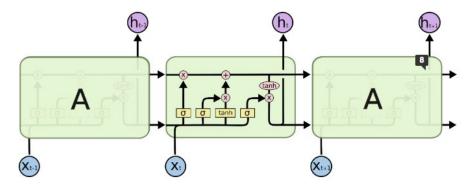
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Unrolled Vanilla RNN

Unrolled LSTM





LSTM often used over Vanilla RNN in practice.

Usage of a "cell state" in the LSTM that is modified through addition allows improved gradient flow through longer sequences.

Will also see other variants e.g. GRUs with different gating operations.

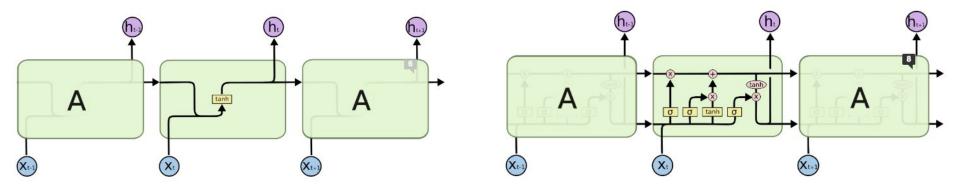
Figure credit: https://colah.github.io/posts/2015-08-Understanding-LSTMs/

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Unrolled Vanilla RNN

Unrolled LSTM



Can have multi-layer RNNs and LSTMs, where the {h} outputs of one layer form the input sequence for the next layer. One or two layers is common.

Figure credit: https://colah.github.io/posts/2015-08-Understanding-LSTMs/

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**BIODS 220: AI in Healthcare** 

# Harutyunyan et al.

- Benchmarked LSTMs vs logistic regression on common prediction tasks using MIMIC-III data
- In-hospital mortality, decompensation, length-of-stay, phenotype classification
- Used a subset of 17 clinical variables from MIMIC-III

| Variable                           | MIMIC-III table        | Impute value     | Modeled as  |
|------------------------------------|------------------------|------------------|-------------|
| Capillary refill rate              | chartevents            | 0.0              | categorical |
| Diastolic blood pressure           | chartevents            | 59.0             | continuous  |
| Fraction inspired oxygen           | chartevents            | 0.21             | continuous  |
| Glascow coma scale eye opening     | chartevents            | 4 spontaneously  | categorical |
| Glascow coma scale motor response  | chartevents            | 6 obeys commands | categorical |
| Glascow coma scale total           | chartevents            | 15               | categorical |
| Glascow coma scale verbal response | chartevents            | 5 oriented       | categorical |
| Glucose                            | chartevents, labevents | 128.0            | continuous  |
| Heart Rate                         | chartevents            | 86               | continuous  |
| Height                             | chartevents            | 170.0            | continuous  |
| Mean blood pressure                | chartevents            | 77.0             | continuous  |
| Oxygen saturation                  | chartevents, labevents | 98.0             | continuous  |
| Respiratory rate                   | chartevents            | 19               | continuous  |
| Systolic blood pressure            | chartevents            | 118.0            | continuous  |
| Temperature                        | chartevents            | 36.6             | continuous  |
| Weight                             | chartevents            | 81.0             | continuous  |
| рН                                 | chartevents, labevents | 7.4              | continuous  |

Harutyunyan et al. Multitask learning and benchmarking with clinical time series data. 2019.

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### Harutyunyan et al.

#### - Logistic regression models

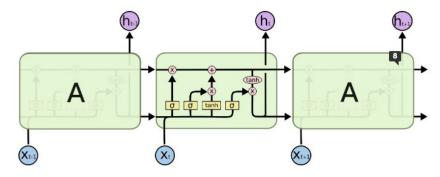
- Use hand-engineered feature vector to represent a time-series: min, max, mean, std dev, etc. of each feature in several subsequences (full series, first 10% of series, first 50%, last 10%, etc.)
- If feature does not occur in subsequence (<u>missing data</u>), impute with mean value from training set
- Categorical variables had meaningful numeric values -> no change
- Zero-mean unit-variance standardization of all features

Harutyunyan et al. Multitask learning and benchmarking with clinical time series data. 2019.

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# Harutyunyan et al.



Lecture 6 - 71

#### - LSTM models

- Bucket time series into regularly spaced intervals, take the value (or last value, if multiple) of each variable in the interval to create observation x<sub>t</sub>
- Encode categorical variables using a one-hot vector (vector of 0s with a 1 in the observed position).
- If variable is missing in a time bucket, impute using most recent observed measurement if it exists, and mean value from training set otherwise
- Concat the values of each clinical variable with a binary mask indicating presence or not (i.e., missing and needed to impute) to form full observation feature vector x<sub>t</sub>

Harutyunyan et al. Multitask learning and benchmarking with clinical time series data. 2019.

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# Harutyunyan et al.: in-hospital mortality

- Input: Time-series data for first 48 hours of ICU stay
- Output: binary classification of in-hospital mortality

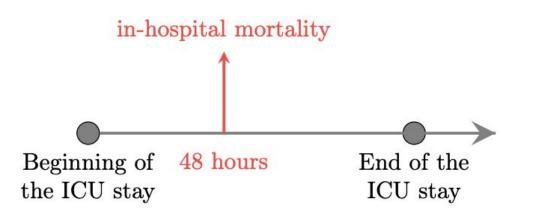


Figure credit: Harutyunyan et al. Multitask learning and benchmarking with clinical time series data. 2019.

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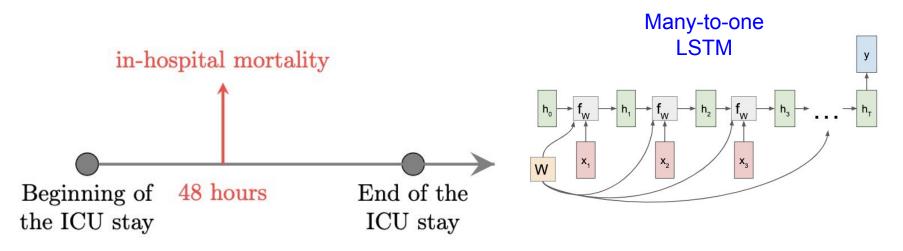


Figure credit: Harutyunyan et al. Multitask learning and benchmarking with clinical time series data. 2019.

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# Harutyunyan et al.: decompensation

- Input: Time-series data from beginning of stay until prediction time (every hour)
- Output: Binary classification of mortality in the next 24 hours

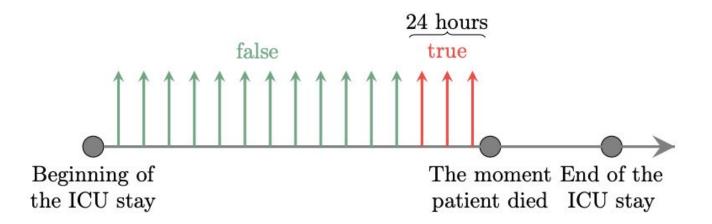


Figure credit: Harutyunyan et al. Multitask learning and benchmarking with clinical time series data. 2019.

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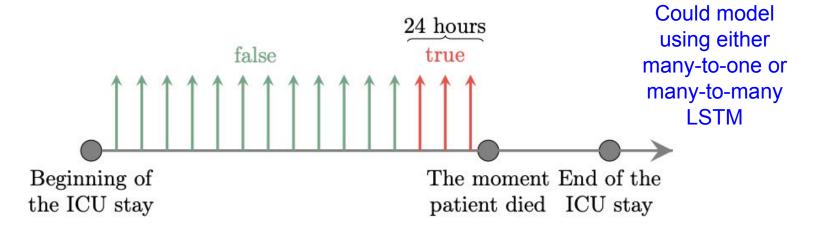
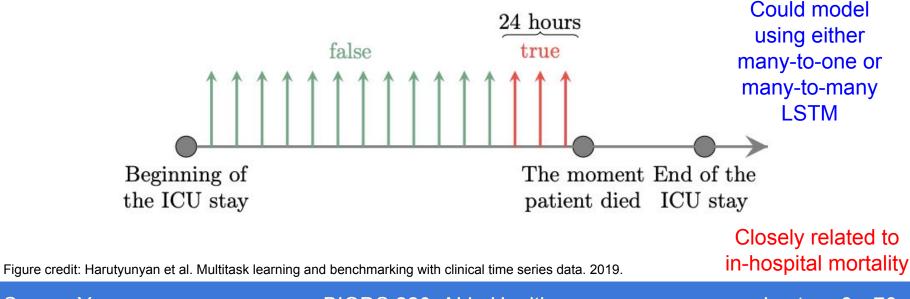


Figure credit: Harutyunyan et al. Multitask learning and benchmarking with clinical time series data. 2019.

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# Harutyunyan et al.: decompensation

- Input: Time-series data from beginning of stay until prediction time (every hour)
- Output: Binary classification of mortality in the next 24 hours



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# Harutyunyan et al.: length-of-stay

- Input: Time-series data from beginning of stay until prediction time (every hour)
- Output: remaining time spent in ICU. Model as classification problem: ICU stays < 1 day, each of 7 days, between 1-2 weeks, > 2 weeks

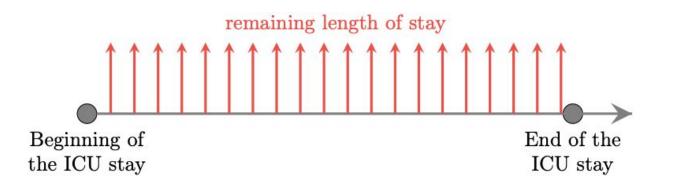


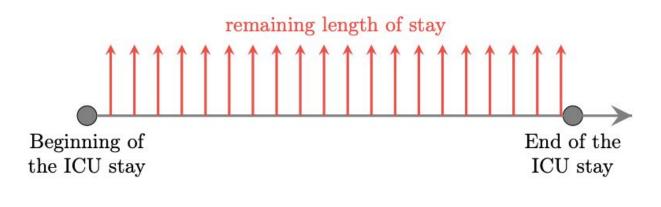
Figure credit: Harutyunyan et al. Multitask learning and benchmarking with clinical time series data. 2019.

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# Harutyunyan et al.: length-of-stay

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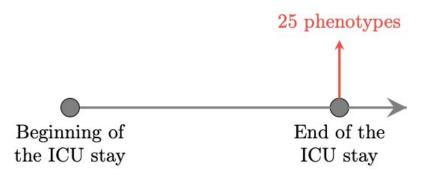
Can model problem in different ways, e.g. directly regress LOS value, or predict meaningful category of extended LOS (>7 days)

Figure credit: Harutyunyan et al. Multitask learning and benchmarking with clinical time series data. 2019.

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- Input: Time-series data corresponding to entire ICU stay
- Output: Multilabel classification of the presence of 25 acute care conditions (merged from ICD codes) in stay record



Phenotype

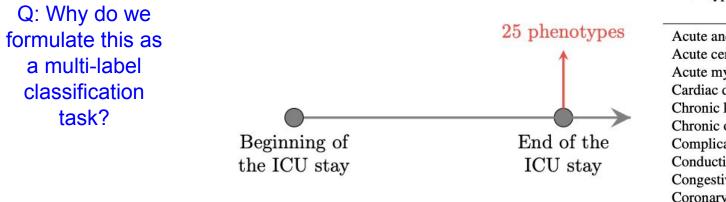
Acute and unspecified renal failure Acute cerebrovascular disease Acute myocardial infarction Cardiac dysrhythmias Chronic kidney disease Chronic obstructive pulmonary disease Complications of surgical/medical care Conduction disorders Congestive heart failure; nonhypertensive Coronary atherosclerosis and related Diabetes mellitus with complications Diabetes mellitus without complication Disorders of lipid metabolism

Figure credit: Harutyunyan et al. Multitask learning and benchmarking with clinical time series data. 2019.

#### Serena Yeung

### **BIODS 220: AI in Healthcare**

- Input: Time-series data corresponding to entire ICU stay
- Output: Multilabel classification of the presence of 25 acute care conditions (merged from ICD codes) in stay record



Phenotype

Acute and unspecified renal failure Acute cerebrovascular disease Acute myocardial infarction Cardiac dysrhythmias Chronic kidney disease Chronic obstructive pulmonary disease Complications of surgical/medical care Conduction disorders Congestive heart failure; nonhypertensive Coronary atherosclerosis and related Diabetes mellitus with complications Diabetes mellitus without complication Disorders of lipid metabolism

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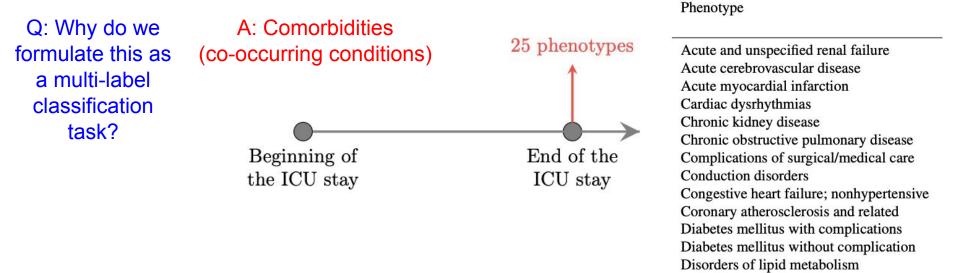


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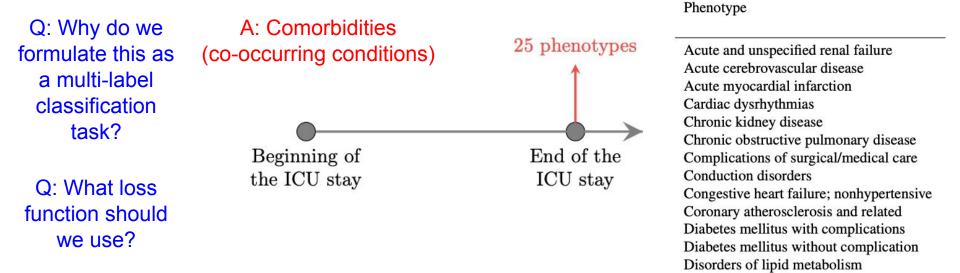


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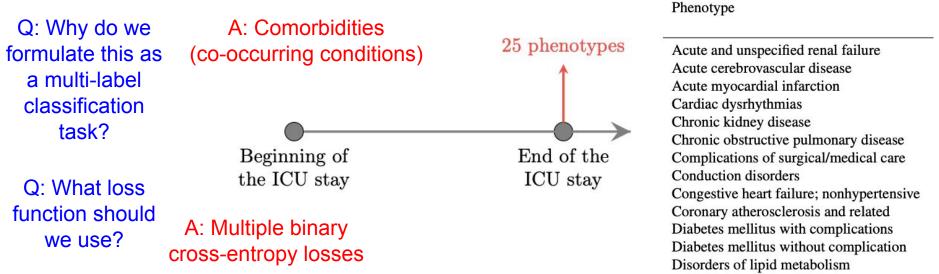


Figure credit: Harutyunyan et al. Multitask learning and benchmarking with clinical time series data. 2019.

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#### **BIODS 220: AI in Healthcare**

# Harutyunyan et al.: logistic regression vs LSTMs

Found better performance overall for LSTMs (S) vs logistic regression (LR). Also introduced more sophisticated variants and multi-task training (joint training of all tasks together).

| Model        | AUC-ROC              |       |        |                      |
|--------------|----------------------|-------|--------|----------------------|
| SAPS         | 0.720 (0.720, 0.720) | 1     | Model  | Macro AUC-ROC        |
| APS-III      | 0.750 (0.750, 0.750) | 50    | LR     | 0.739 (0.734, 0.743) |
| OASIS        | 0.760 (0.760, 0.761) | ping  | S      | 0.770 (0.766, 0.775) |
| SAPS-II      | 0.777 (0.776, 0.777) | 5     | S + DS | 0.774 (0.769, 0.778) |
| LR           | 0.848 (0.828, 0.868) | Pheno | С      | 0.776 (0.772, 0.781) |
|              |                      | her   | C + DS | 0.773 (0.769, 0.777) |
| S            |                      | P     | MS     | 0.768 (0.763, 0.772) |
| S + DS       | 0.856 (0.836, 0.875) |       | MC     | 0.774 (0.770, 0.778) |
| С            | 0.862 (0.844, 0.881) |       | wie    | 0.774 (0.770, 0.778) |
| C + DS<br>MS | 0.854 (0.834, 0.873) |       |        |                      |
|              | 0.861 (0.842, 0.878) |       |        |                      |

Figure credit: Harutyunyan et al. Multitask learning and benchmarking with clinical time series data. 2019.

0.870 (0.852, 0.887)

#### Serena Yeung

MC

# Harutyunyan et al.: logistic regression vs LSTMs

Found better performance overall for LSTMs (S) vs logistic regression (LR). Also introduced more sophisticated variants and multi-task training (joint training of all tasks together).

| 1                     | Model       | AUC-ROC                                      |                           |                              |  |  |
|-----------------------|-------------|--|---------------------------|------------------------------|--|--|
| In-hospital Mortality | SAPS        | 0.720 (0.720, 0.720)                         | Model                     | Macro AUC-ROC                |  |  |
|                       | APS-III     | 0.750 (0.750, 0.750)                         | bo LR                     | 0.739 (0.734, 0.743)         |  |  |
|                       | OASIS       | 0.760 (0.760, 0.761)                         | and R                     | 0.770 (0.766, 0.775)         |  |  |
|                       | SAPS-II     | 0.777 (0.776, 0.777)                         | 20+2                      | 0.774 (0.769, 0.778)         |  |  |
|                       |             | 0 949 (0 929 0 969)                          | Duend<br>C + DS<br>C + DS | 0.776 (0.772, 0.781)         |  |  |
|                       | LR          | 0.848 (0.828, 0.868)                         | C + DS                    | 0.773 (0.769, 0.777)         |  |  |
|                       | S<br>S · DS | 0.855 (0.835, 0.873)                         | A MS                      | 0.768 (0.763, 0.772)         |  |  |
|                       | S + DS<br>C | 0.856 (0.836, 0.875)<br>0.862 (0.844, 0.881) | MC                        | 0.774 (0.770, 0.778)         |  |  |
| <u> </u>              | C + DS      | 0.854 (0.834, 0.873)                         | -                         |                              |  |  |
| 2                     | MS          | 0.861 (0.842, 0.878)                         | Found bet                 | Found better performance for |  |  |
| 1                     | MC          | 0.870 (0.852, 0.887)                         | phenotypir                | henotyping acute vs chronic  |  |  |

conditions -- makes sense!

Figure credit: Harutyunyan et al. Multitask learning and benchmarking with clinical time series data. 2019.

#### Serena Yeung

# Summary:

- Introduction to EHRs
- EHR prediction tasks
- Recurrent neural networks and LSTMs

Next:

- More on EHR data
- More on feature representations and model interpretability