Artificial Intelligence for Medical Data with Python

10 SAMPLE SLIDES

1th session

Health Data Management

UNIVERSITY OF THE
AEGEAN
SCHOOL OF ENGINEERING
DEPARTMENT OF INFORMATION
AND COMMUNICATION
SYSTEMS ENGINEERING

Presenter: Panagiotis Symeonidis

Associate Professor

http://panagiotissymeonidis.com

psymeon@aegean.gr

Problem Definition

- Can we use lab tests, health interventions, and the medicines of a patient to make predictions about her health?

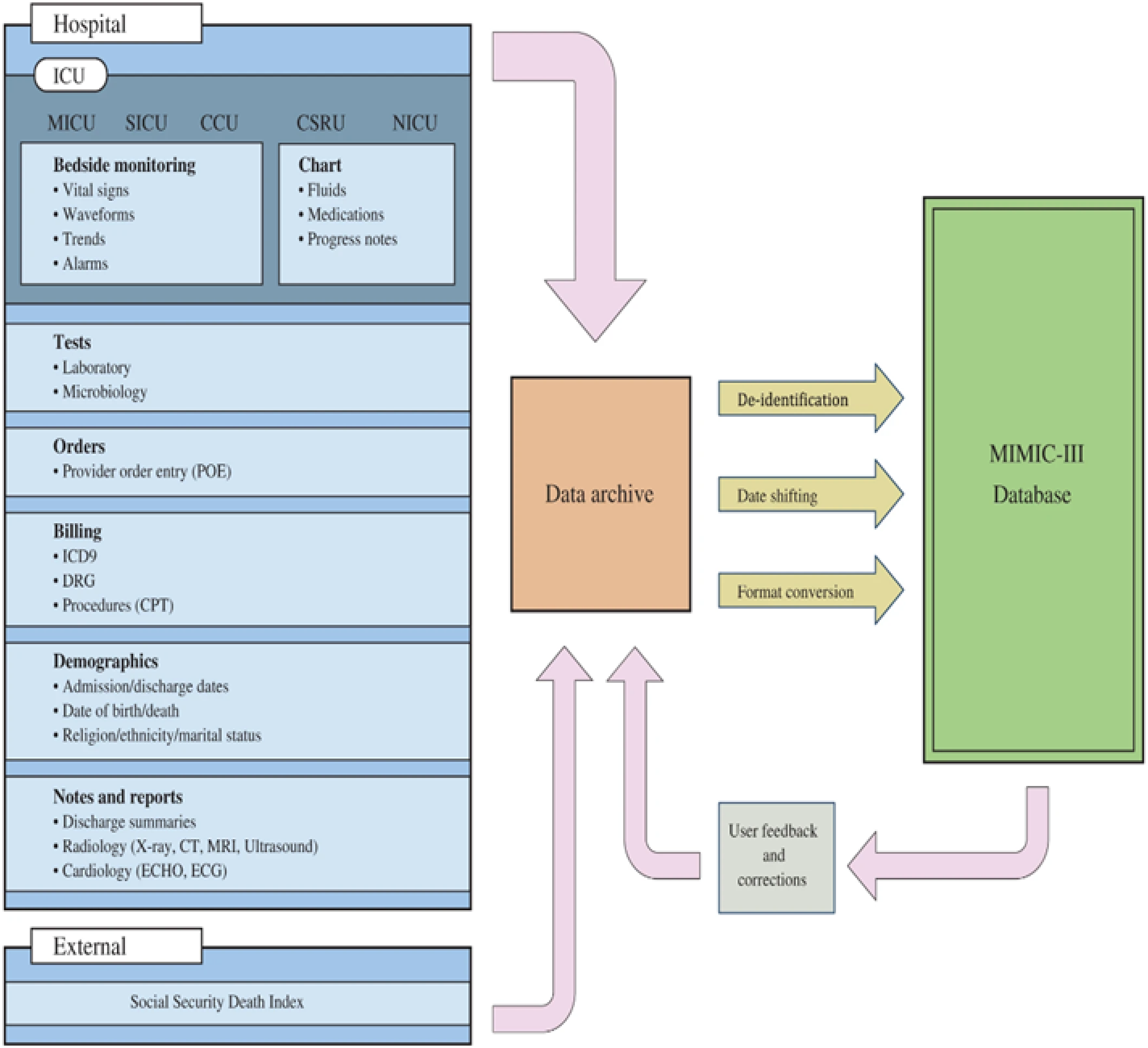
- Can we use Reinforcement learning to provide drug combinations to Medical Doctors for their patients?

- Can we minimize the unwanted side effects among the drugs of a recommended treatment to have less toxicity?

- Can we maximize the synergistic effect of drugs for faster or more effective patient's recovery?

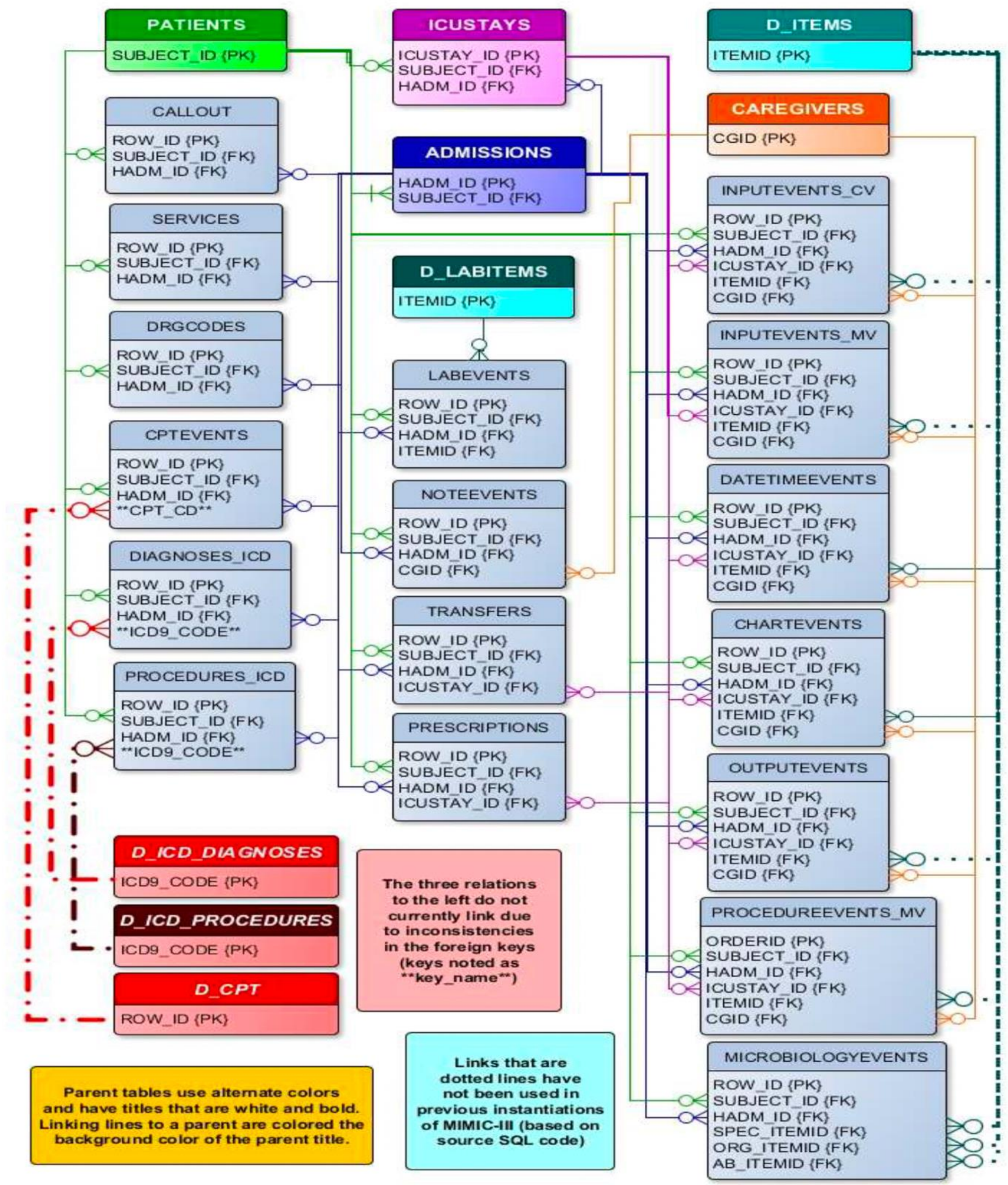
MIMIC III Data set

- Beth Israel Deaconess Medical Center in Boston, Massachusetts
- 38,597 distinct adult patients
- 4,579 charted observations ('chartevents')
- 380 laboratory measurements ('labevents & inputevents')
- Demographic, Procedures/Interventions, Medications
- Patient follow-up after discharge
- 44 GB of medical data!



Johnson, Alistair EW, et al. "MIMIC-III, a freely accessible critical care database." *Scientific data* 3.1 (2016): 1-9.

Figure 2: MIMIC-III Entity Relationship Class Diagram

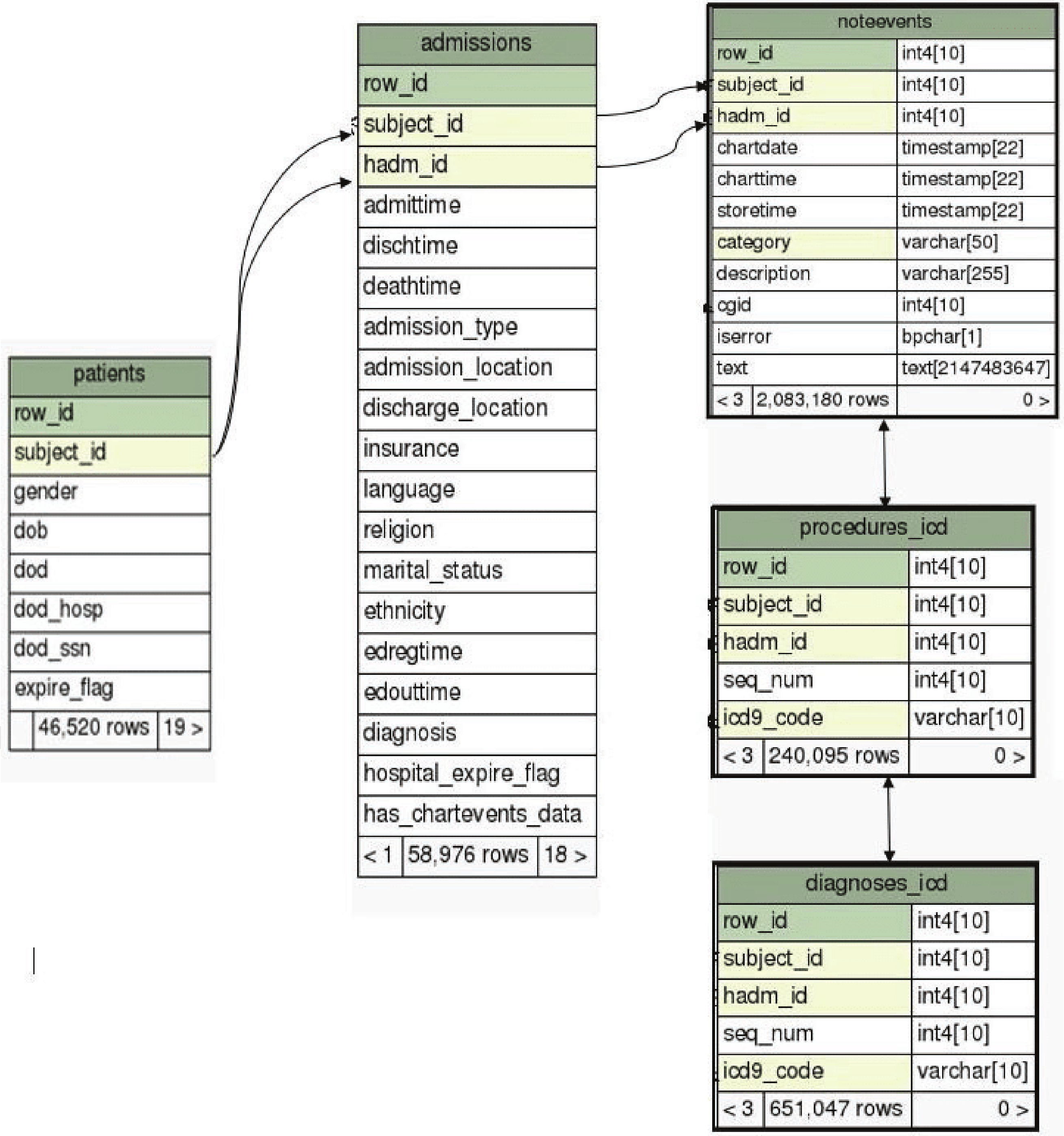


E-R Diagram of MIMIC III

Important considerations from the ER diagram (Figure 2):

- Only the attributes used as primary key and foreign key are listed in the ER diagram.
  - For a complete list of attributes, consult the Data Dictionary.
- Finally, since the dataset is so large, it was impossible to refine the cardinality to know which one-to-many relationships are "zero or more" or "one or more" on the "many" side of the relationship. For purposes of the ER diagram, it was known that all patients have at least one admission, so the "one or more" relationship was used. For all other relationships, there is an assumption that there may be individual ICU stays that may not have data represented in some of the other tables even though, realistically, there are probably many more "one or more" notations that should have been used in the ER diagram.
  - As always, any errors in the above interpretations are the fault of this document's author alone.

Creation of the Data Dictionary was an important part of the conceptual understanding of the MIMIC-III database. With 324 different attributes in the 26 tables, much care was exercised for understanding the structure of the MIMIC-III database.



patients
row_id
subject_id
gender
dob
dod
dod_hosp
dod_ssn
expire_flag
46,520 rows
19 >
admissions
row_id
subject_id
hadm_id
admittime
dischtime
deathtime
admission_type
admission_location
discharge_location
insurance
language
religion
marital_status
ethnicity
edregtime
edouttime
diagnosis
hospital_expire_flag
has_chartevents_data
< 1
58,976 rows
18 >
noteevents
row_id int4[10]
subject_id int4[10]
hadm_id int4[10]
chartdate timestamp[22]
charttime timestamp[22]
storetime timestamp[22]
category varchar[50]
description varchar[255]
cgid int4[10]
iserror bpchar[1]
text text[2147483647]
< 3
2,083,180 rows
0 >
procedures_icd
row_id int4[10]
subject_id int4[10]
hadm_id int4[10]
seq_num int4[10]
icd9_code varchar[10]
< 3
240,095 rows
0 >
diagnoses_icd
row_id int4[10]
subject_id int4[10]
hadm_id int4[10]
seq_num int4[10]
icd9_code varchar[10]
< 3
651,047 rows
0 >

Parameters' Selection Lists of our Application

Groups of Subject IDs

- All Subject IDs
- Subject IDs Diagnosed with Diabetes
- Rest Subject IDs

Subject IDs

- 10017
- 10264
- 10424
- 10629
- 10633
- 10731
- 10806
- 10967
- 10976
- 11003

Chart Events Labels

- Glucose
- Glucose (70-105)
- Art.pH
- Arterial BP Mean
- Arterial BP [Diastolic]
- Arterial BP [Systolic]
- Arterial Base Excess
- Arterial CO2(Calc)
- Arterial PaCO2
- Arterial PaO2

Location

- HOSPITAL
- ICU_24H
- ICU_AFTER_24H

Age Range 5.0

Patient's Info

PATIENT INFORMATION

Gender	Female
Age	74 (hosp. entry)
Diabet.	YES
Death	AFTER ICU, 1199 days after ICU discharge

Diseases

DIAGNOSES

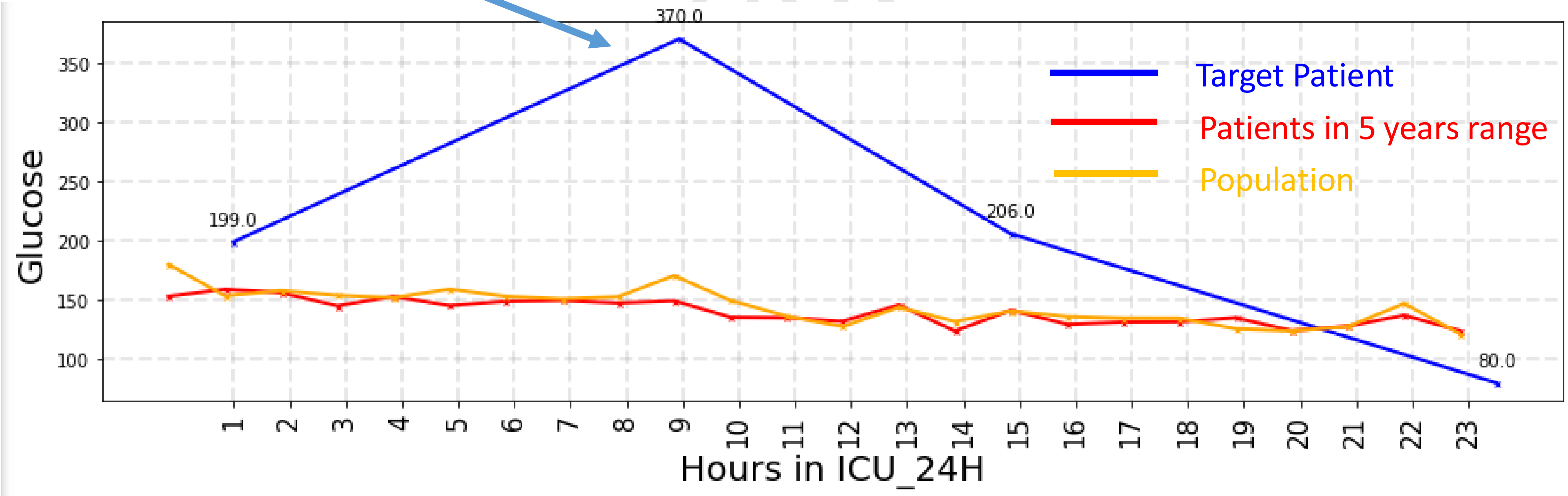
ICD9	DESCRIPTION
0380	Streptococcal septicemia
78552	Septic shock
5070	Pneumonitis due to inhalation of food or vomitus
5849	Acute kidney failure, unspecified
42731	Atrial fibrillation
1977	Malignant neoplasm of liver, secondary
1578	Malignant neoplasm of other specified sites of pancreas
2866	Defibrination syndrome
29590	Unspecified schizophrenia, unspecified
2764	Mixed acid-base balance disorder
99592	Severe sepsis
25070	Diabetes with peripheral circulatory disorders, type II or unspecified type, not stated as uncontrolled

PATIENT INFORMATION

Gender	Female
Age	74 (hosp. entry)
Diabet.	YES
Death	AFTER ICU, 1199 days after ICU discharge

Alerting doctors

Glucose measurements



PATIENT INFORMATION

```
Gender   Female
Age      74 (hosp. entry)
Diabet.  YES
Death    AFTER ICU, 1199 days after ICU discharge
```

Insulin doses

INPUTEVENTS

TIME	ITEM	AMOUNT	AMOUNT UNITS	RATE	RATE UNITS
9.3 Hours after ICU entry	Insulin			6	U/hr
9.3 Hours after ICU entry	Insulin	0	U		
9.8 Hours after ICU entry	Insulin	3	U		
9.8 Hours after ICU entry	Insulin			10	U/hr
10.8 Hours after ICU entry	Insulin	10	U		
10.8 Hours after ICU entry	Insulin			12	U/hr
11.8 Hours after ICU entry	Insulin			10	U/hr
11.8 Hours after ICU entry	Insulin	12	U		
12.8 Hours after ICU entry	Insulin			12	U/hr
12.8 Hours after ICU entry	Insulin	10	U		
13.8 Hours after ICU entry	Insulin	12	U		

Another Example : Patient 83607

PATIENT INFORMATION

Gender Female
Age 49 (hosp. entry)
Diabet. YES
Death AFTER ICU, 92 days after ICU discharge

Diagnoses

40391	Hypertensive chronic kidney disease, unspecified, with chronic kidney disease stage V or end stage renal disease
7907	Bacteremia
5531	Umbilical hernia without mention of obstruction or gangrene
25042	Diabetes with renal manifestations, type II or unspecified type, uncontrolled
V4511	Renal dialysis status
0417	Pseudomonas infection in conditions classified elsewhere and of unspecified site