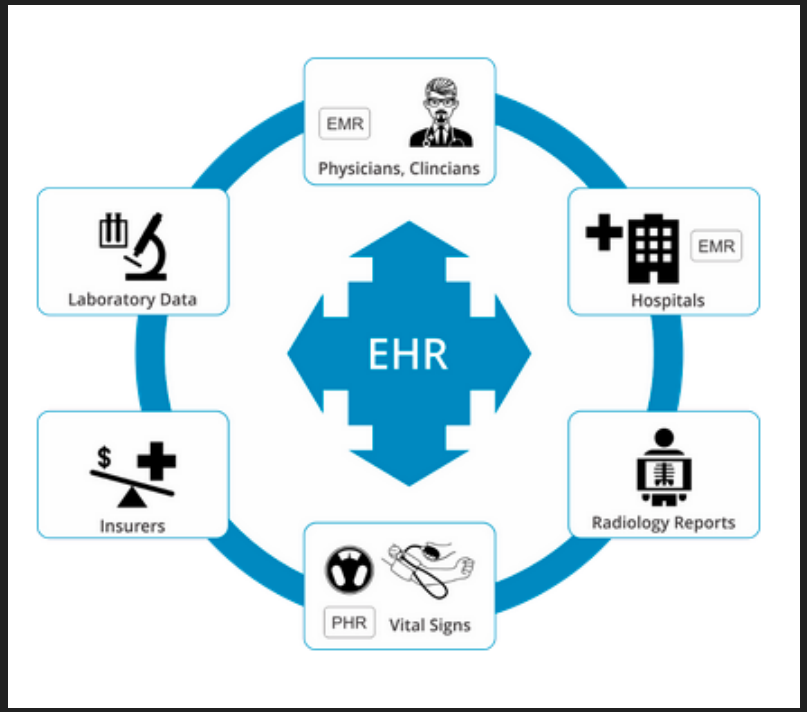
Python에서 EMR데이터 (생존)분석 따라하기

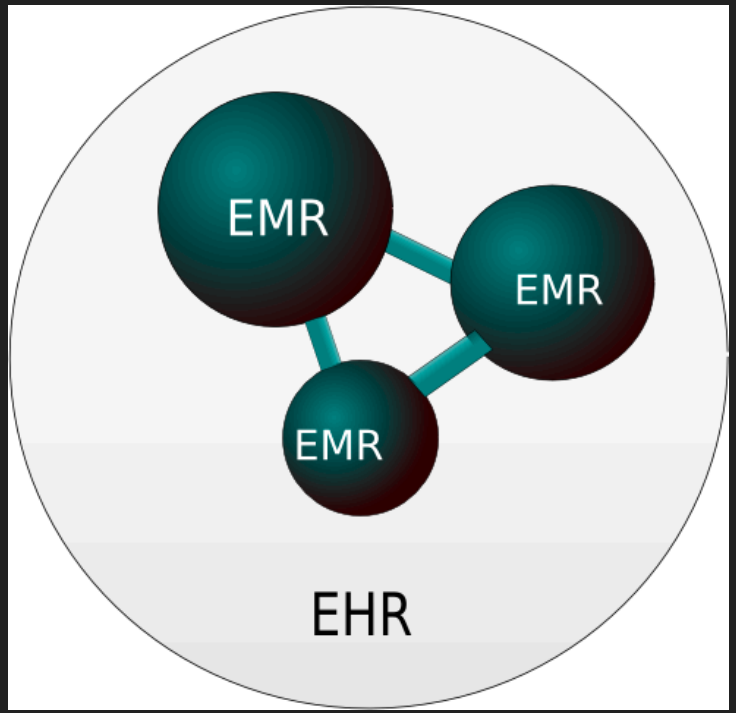
Soo-Heang Eo, Lead Data Scientist
HuToM

Background

EMR vs. EHR?

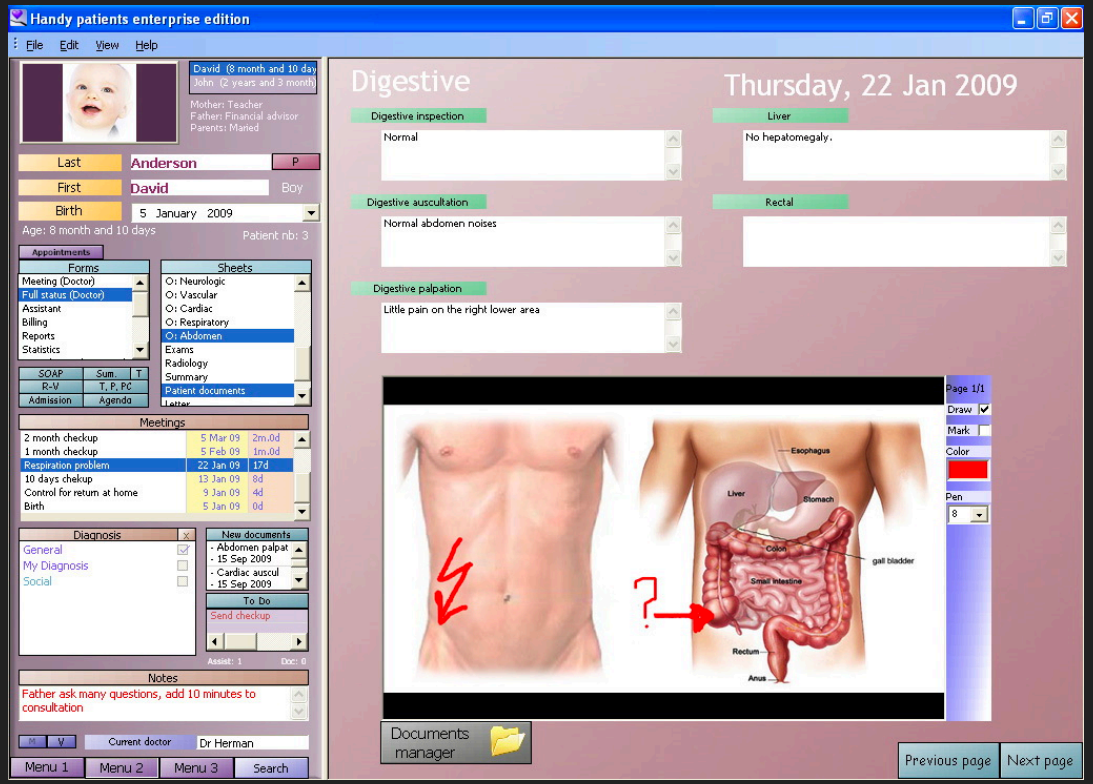


https://doctors.practo.com/emr-vs-ehr-whats-difference/



https://sooyongshin.wordpress.com/2017/05/14/healthcare-data-data-data-2-clinical-data-data-in-emr/

EMR (Electric Medical Records)



Systematized collection of patient and population electronically-stored health information in a digital format including

- Demographics
- medical history
- medication and allergies
- immunization status
- laboratory test results
- radiology images
- vital signs
- personal statistics like age and weight
- billing information

https://en.wikipedia.org/wiki/Electronic_health_record

Publicly Available EMR Dataset

3. Data derived from Electronic Health Records (EHRs)

Building the graph of medicine from millions of clinical narratives
Co-occurence statistics for medical terms extracted from 14 million clinical notes and 260,000 patients.
Paper: http://www.nature.com/articles/sdata201432
Data: http://datadryad.org/resource/doi:10.5061/dryad.jp917

Learning Low-Dimensional Representations of Medical Concept
Low-dimensional embeddings of medical concepts constructed using claims data. Note that this paper utilizes data from *Building the graph of medicine from millions of clinical narratives*
Paper: http://cs.nyu.edu/~dsontag/papers/ChoiChiuSontag_AMIA_CRI16.pdf
Data: https://github.com/clinicalml/embeddings

MIMIC-III, a freely accessible critical care database
Anonymized critical care EHR database on 38,597 patients and 53,423 ICU admissions. **Requires registration**.
Paper: http://www.nature.com/articles/sdata201635
Data: http://physionet.org/physiobank/database/mimic3cdb/

Clinical Concept Embeddings Learned from Massive Sources of Medical Data
Embeddings for 108,477 medical concepts learned from 60 million patients, 1.7 million journal articles, and clinical notes of 20 million patients
Paper: https://arxiv.org/abs/1804.01486
Embeddings: https://figshare.com/s/00d69861786cd0156d81
Interactive tool: http://cui2vec.dbmi.hms.harvard.edu

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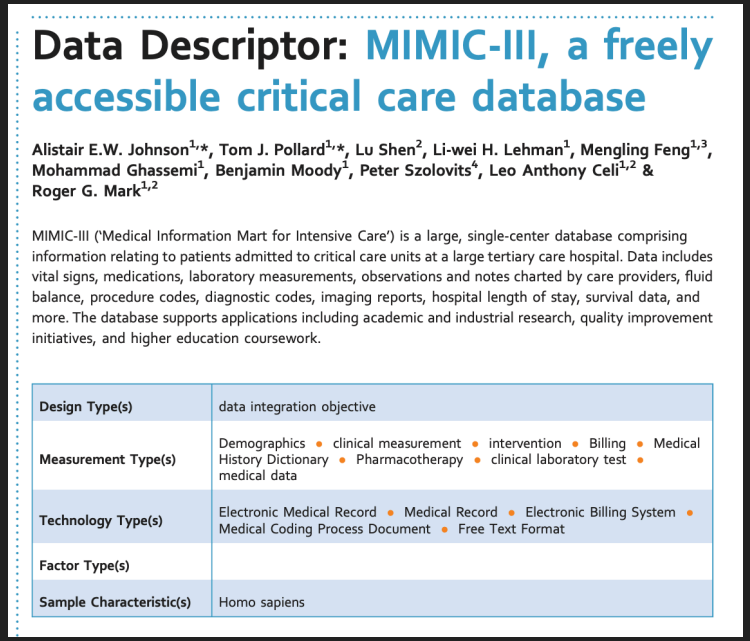
https://github.com/beamandrew/medical-data

Publicly Available EMR Dataset

MIMIC Critical Care Data



Data Descriptor: MIMIC-III, a freely accessible critical care database

Alistair E.W. Johnson[1,*], Tom J. Pollard[1,*], Lu Shen[2], Li-wei H. Lehman[1], Mengling Feng[1,3], Mohammad Ghassemi[1], Benjamin Moody[1], Peter Szolovits[4], Leo Anthony Celi[1,2] & Roger G. Mark[1,2]

MIMIC-III ('Medical Information Mart for Intensive Care') is a large, single-center database comprising information relating to patients admitted to critical care units at a large tertiary care hospital. Data includes vital signs, medications, laboratory measurements, observations and notes charted by care providers, fluid balance, procedure codes, diagnostic codes, imaging reports, hospital length of stay, survival data, and more. The database supports applications including academic and industrial research, quality improvement initiatives, and higher education coursework.

Design Type(s)	data integration objective
Measurement Type(s)	Demographics • clinical measurement • intervention • Billing • Medical History Dictionary • Pharmacotherapy • clinical laboratory test • medical data
Technology Type(s)	Electronic Medical Record • Medical Record • Electronic Billing System • Medical Coding Process Document • Free Text Format
Factor Type(s)	
Sample Characteristic(s)	Homo sapiens

https://www.nature.com/articles/sdata201635.pdf

I2B2 Clinical Notes (NLP) Data

i2b2

Informatics for Integrating Biology & the Bedside

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NLP Research Data Sets

Data Sets

- Home
- *User*
  - Register
  - Login
- *Data Use Agreement*
  - Academic
  - Commercial

i2b2 is a passionate advocate for the potential of exist
directly impact healthcare improvement. In our many
become increasingly obvious that the value locked in
mission. In order to enhance the ability of natural lang
fine grained information from clinical records, i2b2 has
notes from the Research Patient Data Repository at P
organized by Dr. Ozlem Uzuner. We are pleased to n
for general research purposes. At this time we are rele
Challenges as i2b2 NLP Research Data Sets. A simila
Challenge will be released on the one year anniversa
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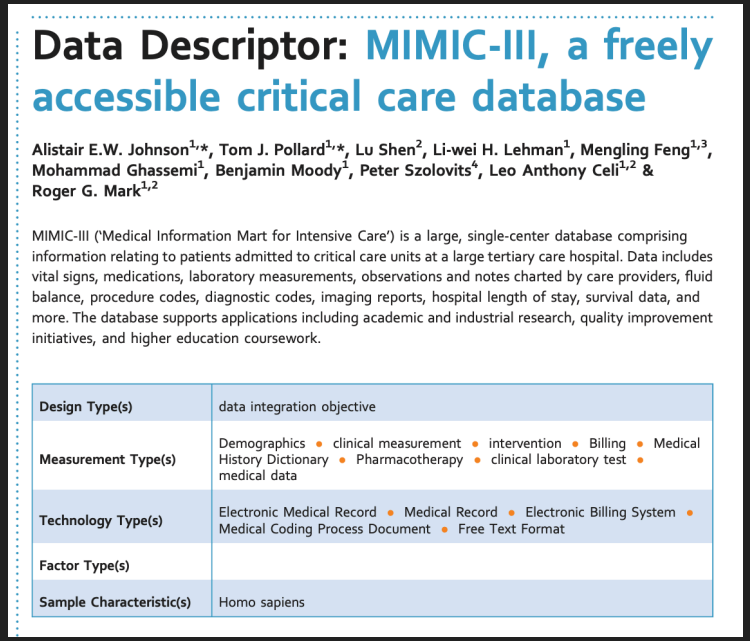
To access these notes, please use the Registration lir
your proposal and, if acceptable, will ask you to sign a
before releasing the notes to you. Given the goal of le
you share your annotations back to us following public
access, whichever comes first.

https://www.i2b2.org/NLP/DataSets/Main.php

Publicly Available EMR Dataset

MIMIC Critical Care Data



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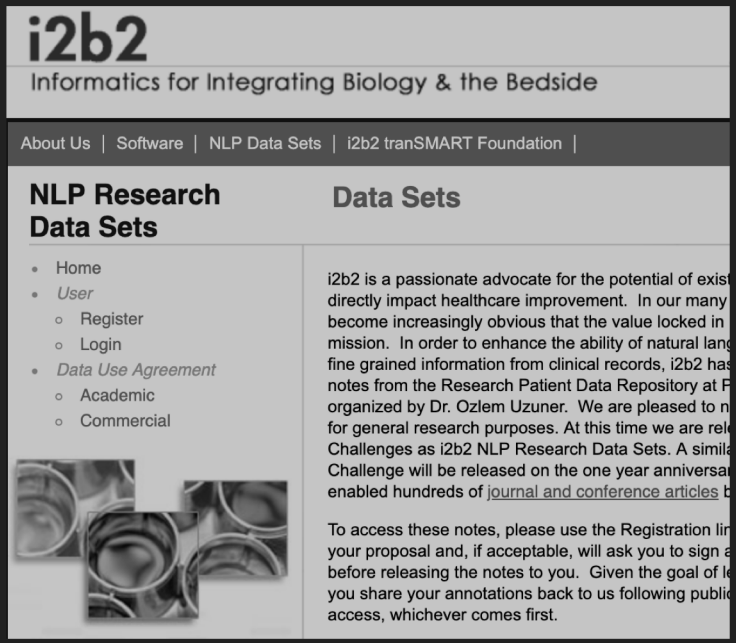
Sample Characteristic(s)	Homo sapiens

https://www.nature.com/articles/sdata201635.pdf

I2B2 Clinical Notes Data



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NLP Research Data Sets

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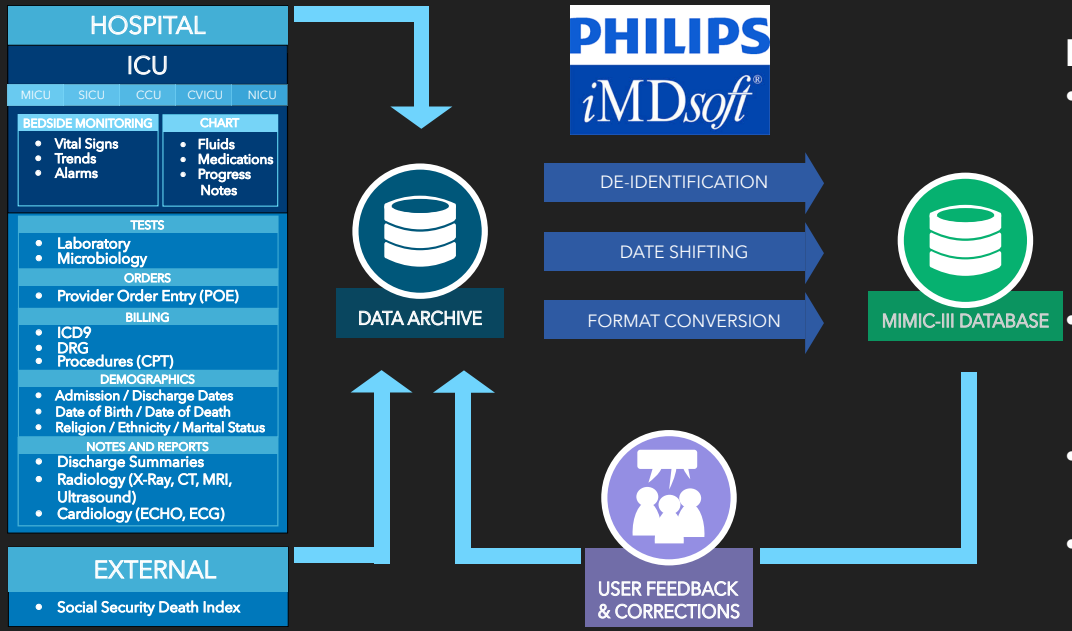
MIMIC

Data Analysis

MIMIC III Dataset



Medical Information Mart for Intensive Care

- **Single Centre**: Beth Israel Deaconess Medical Centre
  - U.S. Based (Boston, MA)
  - Has MICU, SICU, CCU, CSRU, TSICU, ...
- **Detailed in-ICU** information derived from: electronic medical records, critical care information systems, lab system,...
- **Limited out-of-ICU** information (social security death masterfile)
- >60,000 ICU stays, >40,000 patients (2002-2012)

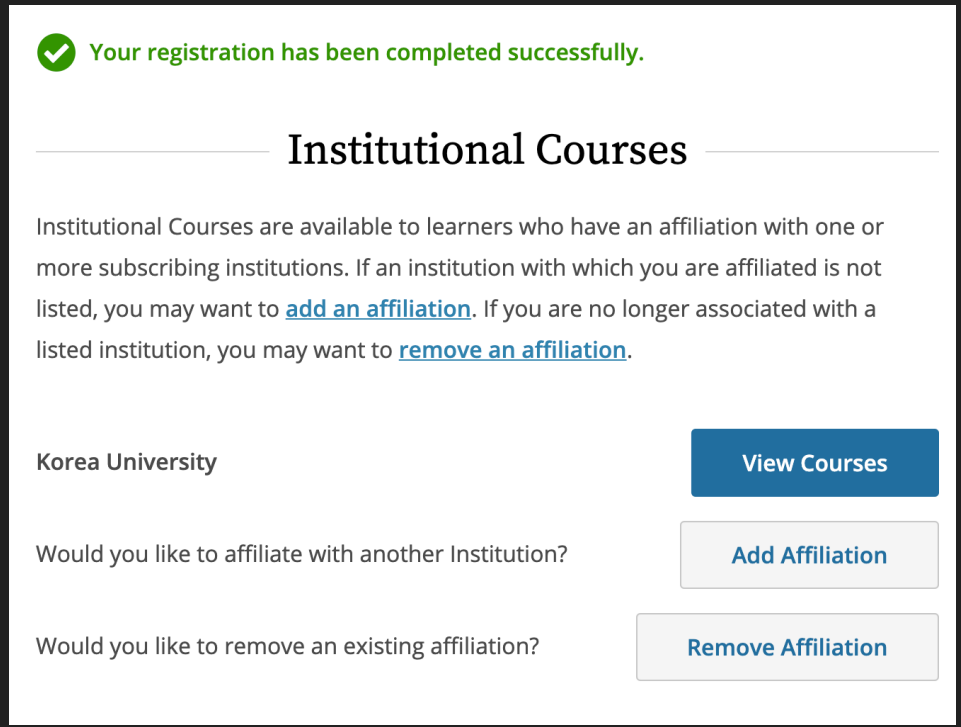
https://github.com/MIT-LCP/mimic-workshop/tree/master/intro_to_mimic

ACESS MIMIC Dataset

Complete the required training course

Prior to requesting access to MIMIC, you will need to complete the CITI "Data or Specimens Only Research" course:

- First register on the CITI program website, selecting "Massachusetts Institute of Technology Affiliates" as your affiliation (***not*** *"independent learner"*): https://www.citiprogram.org/index.cfm?pageID=154&icat=0&ac=0
- Follow the links to add a Massachusetts Institute of Technology Affiliates course. In the Human Subjects training category, select the "Data or Specimens Only Research" course
- Complete the course and save a copy of your completion report. The completion report lists all modules completed, with dates and scores.



https://mimic.physionet.org/gettingstarted/access/

ACESS MIMIC Dataset

Request access to MIMIC-III:

- Create an account on PhysioNet using the following link: https://physionet.org/pnw/login. If you already have a PhysioNetWorks account, log in to it.
- Follow the instructions on PhysioNet to apply for access to the MIMIC-III project, remembering to provide your CITI completion report: https://physionet.org/works/MIMICIIIClinicalDatabase/access.sht
- When your application has been approved you will receive emails containing instructions for downloading the database from PhysioNetWorks. Approval may take several business days, and will be delayed if your request is missing any required information.

https://mimic.physionet.org/gettingstarted/access/

PhysioNet Clinical Database Restricted Data Use Agreement

If I am granted access to PhysioNet Clinical Databases (MIMIC-II, MIMIC-III, eICU Collaborative Research Database, Deidentified Medical Text, MIMIC-CXR), I agree to the terms and conditions below:

1. I will not attempt to identify any individual or institution referenced in PhysioNet restricted data.
2. I will exercise all reasonable and prudent care to avoid disclosure of the identity of any individual or institution referenced in PhysioNet restricted data in any publication or other communication.
3. I will not share access to PhysioNet restricted data with anyone else.
4. I will exercise all reasonable and prudent care to maintain the physical and electronic security of PhysioNet restricted data.
5. If I find information within PhysioNet restricted data that I believe might permit identification of any individual or institution, I will report the location of this information promptly by email to PHI-report@physionet.org, citing the location of the specific information in question so that it can be investigated and removed if necessary.
6. I have requested access to PhysioNet restricted data for the sole purpose of lawful use in scientific research, and I will use my privilege of access, if it is granted, for this purpose and no other.
7. I have completed a training program in human research subject protections and HIPAA regulations, and I am submitting proof of having done so.
8. I will indicate the general purpose for which I intend to use the database in my application.
9. If I openly disseminate my results, I will also contribute the code used to produce those results to a repository that is open to the research community.
10. This agreement may be terminated by either party at any time, but my obligations with respect to restricted data from PhysioNet shall continue after termination.

I agree | I do not agree

DOWNLOAD MIMIC dataset

MIMIC3py

A Python library to load and analyze the MIMIC III Critical Care Database

"MIMIC-III (**M**edical **I**nformation **M**art for **I**ntensive **C**are III) is a large, freely-available database comprising deidentified health-related data associated with over forty thousand patients who stayed in critical care units of the Beth Israel Deaconess Medical Center between 2001 and 2012." It includes demographics, vital signs, laboratory tests, medications, clinical notes, and more.

More details are availible at:

- https://mimic.physionet.org/about/mimic/
- http://www.nature.com/articles/sdata201635

This repository contains Python 3 code that will help you:

- Download the data.
- Load the data into Pandas data frames.

The package is hosted on pypi at: https://pypi.python.org/pypi/MIMIC3py/0.11

You can install it using `pip install MIMIC3py`

https://github.com/SpiroGanas/MIMIC3py/tree/master/MIMIC3py

config.py

```
# This is the folder where the files will located
local_save_folder = "/data/ehr/mimic3"

# ENTER YOUR PHYSIONET USERNAME AND PASSWORD HERE ############################
physionet_USERNAME = "eo.sooheang@gmail.com"
physionet_PASSWORD = "******************"
##############################################################################

# You may need to update some of these variables if MIMIC III gets updated
physionet_BASE_URL = "https://physionet.org/works/MIMICIIIClinicalDatabase/files/ve

# Comment out any file you don't want to download.
# Note that some of the files are very, very big.
physionet_FILENAMES = [
    "ADMISSIONS.csv.gz",  # 12 MB
    "CALLOUT.csv.gz",  # 6.1 MB
    "CAREGIVERS.csv.gz",  # 199 KB
    "CHARTEVENTS.csv.gz",  # 33 GB ------BIG!!!
    "CPTEVENTS.csv.gz",  # 56 MB
    "DATETIMEEVENTS.csv.gz",  # 502 MB
    "D_CPT.csv.gz",  # 14 KB
    "DIAGNOSES_ICD.csv.gz",  # 19 MB
    "D_ICD_DIAGNOSES.csv.gz",  # 1.4 KB
    "D_ICD_PROCEDURES.csv.gz",  # 305 KB
    "D_ITEMS.csv.gz",  # 933 KB
    "D_LABITEMS.csv.gz",  # 43 KB
    "DRGCODES.csv.gz",  # 11 MB
    "ICUSTAYS.csv.gz",  # 6.1 MB
    "INPUTEVENTS_CV.csv.gz",  # 2.3 GB ------BIG!!!
    "INPUTEVENTS_MV.csv.gz",  # 931 MB
    "LABEVENTS.csv.gz",  # 1.8GB ------BIG!!!
    "MICROBIOLOGYEVENTS.csv.gz",  # 70 MB
    "NOTEEVENTS.csv.gz",  # 3.8 GB  ------BIG!!!
    "OUTPUTEVENTS.csv.gz",  # 379 MB
    "PATIENTS.csv.gz",  # 2.6 MB
    "PRESCRIPTIONS.csv.gz",  # 735 MB
    "PROCEDUREEVENTS_MV.csv.gz",  # 47 MB
    "PROCEDURES_ICD.csv.gz",  # 6.5 MB
    "SERVICES.csv.gz",  # 3.4 MB
```

ACESS MIMIC Dataset (EASY WAY)

MIMIC-III Clinical Database (Demo)

Our new website is in development. Try it out at: https://alpha.physionet.org and give us feedback

The MIMIC-III (Medical Information Mart for Intensive Care) Clinical Database contains comprehensive clinical data from tens of thousands of Intensive Care Unit (ICU) patients. This project is a demo version which has only 100 patients and excludes the noteevents table.

Tom Pollard
Massachusetts Institute of Technology
Institute for Medical Engineering & Science
Cambridge, Massachusetts
United States of America

If you wish to obtain the demo database, you must agree to the following conditions:

1. You agree not to attempt to identify any of the individual subjects of the file.
2. If you find information within the file that you believe might permit identification of any of the individual subjects of the file, you agree to report this promptly by email to phi-support@physionet.org, citing the specific information in question so that it can be investigated and removed if necessary.
3. You agree to exercise all reasonable and prudent care to avoid disclosure of the identity of any of the individual subjects of the file in any publication or other communication of your analysis of the file.
4. If you agree to all of these terms and conditions, access to this file will be granted to you as an individual. You may not share it with anyone else. Your colleagues can obtain access to this file as individuals via the same procedure you are following.

For access to this project, indicate your agreement with the terms and conditions above by clicking on the words "I agree" below:

I agree

Downloads:

The MIMIC-III demo dataset (v1.4) can be downloaded either as 25 comma-separated-value (CSV) files or as a single Postgres database backup file (Postgres 9.5). The Postgres backup file can be downloaded by clicking on the link below:

- mimiciii_demo-postgres_9_5.backup

On a unix based system, the CSV files can be downloaded in a shell using the following command:

```
wget --user YOURUSERNAME --ask-password -A csv.gz -m -p -E -k -K -np
https://physionet.org/works/MIMICIIIClinicalDatabaseDemo/files/
```

After download, the files can be decompressed using the command-line tool gzip ("`gzip -d *.gz`"). Alternatively, files can be kept compressed and imported directly into a database.

https://physionet.org/works/MIMICIIIClinicalDatabaseDemo/

Tools for MIMIC

MIMIC Code Repository

build passing | DOI 10.5281/zenodo.821872 | chat on gitter

This is a repository of code shared by the research community. The repository is intended to be a central hub for sharing, refining, and reusing code used for analysis of the MIMIC critical care database. To find out more about MIMIC, please see: https://mimic.physionet.org

You can read more about the code repository in the following open access paper: The MIMIC Code Repository: enabling reproducibility in critical care research.

Brief introduction

The repository is organized as follows:

- benchmark - Various speed tests for indices
- buildmimic - Scripts to build MIMIC-III in a relational database management system (RDMS), in particular postgres is our RDMS of choice
- concepts - Useful views/summaries of the data in MIMIC-III, e.g. demographics, organ failure scores, severity of illness scores, durations of treatment, easier to analyze views, etc. The paper above describes these in detail.
- notebooks - A collection of R markdown and Jupyter notebooks which give examples of how to extract and analyze data
- notebooks/aline - An entire study reproduced in the MIMIC-III database - from cohort generation to hypothesis testing
- tests - You should always have tests!
- tutorials - Similar to the notebooks folder, but focuses on explaining concepts to new users

MIMIC Critical Care Datathon

These are training materials for the MIMIC Critical Care Database. The package includes:

- a demo version of MIMIC which can be quickly installed in the Firefox web browser with the SQLite Plugin.
- some sample SQL queries which can be used to query the MIMIC data
- an IPython Notebook which connects to the demo MIMIC database and allows analysis to be carried out using Python.

What is MIMIC-III?

MIMIC-III is a widely-used, freely available dataset developed by the MIT Lab for Computational Physiology, comprising deidentified health data associated with >40,000 critical care patients. It includes demographics, vital signs, laboratory tests, medications, and more. Details are available on the MIMIC website: https://mimic.physionet.org/

Workshop overview

During the workshop, you will:

- Learn about MIMIC-III, the publicly accessible critical care database
- Create a local version of MIMIC-III with a small sample of patients using the Firefox SQLite Plugin
- Explore the patient data using SQL
- Plot and analyse the data using Python
- Get inspiration for future research projects

Downloading the materials

If you are familiar with git, please clone this repository. If not, click the 'Download ZIP' button on the right and then unzip the materials onto your computer.

https://github.com/MIT-LCP/mimic-workshop

Navigating MIMIC

Events tables

- `chartevents`: Charted observations for a patient
- `labevents`: Lab measurements both within hospital and (sometimes) outpatient clinics
- `inputevents`: Input fluids (e.g. intravenous medications)
- `microbiologyevents`: Microbiology measurements and sensitivities
- ~~`noteevents`~~: Deidentified patient notes

Other tables

- `diagnoses_icd`: Hospital assigned diagnosis codes.
- `procedures_icd`: Hospital assigned procedure codes
- `caregivers`: Caregivers who have recorded data
- `prescriptions`: Medications ordered for a patient
- ...

More tables and full documentation: https://mimic.physionet.org/

Connect to the database

- We can use the sqlite3 library to connect to the MIMIC database
- Once the connection is established, we'll run a simple SQL query.

In [2]:
```
# Connect to the MIMIC database
conn = sqlite3.connect('../data/mimicdata.sqlite')
```

In [3]:
```
# Create our test query
test_query = """
SELECT subject_id, hadm_id, admittime, dischtime, admission_type, diagnosis
FROM admissions
LIMIT 10;
"""
```

In [4]:
```
# Run the query and assign the results to a variable
test = pd.read_sql_query(test_query,conn)
```

In [5]:
```
# Display the first few rows
test.head()
```

Out[5]:

	SUBJECT_ID	HADM_ID	ADMITTIME	DISCHTIME	ADMISSION_TYPE	DIAGNOSIS
0	40036	198489	2141-08-01 23:46:00	2141-08-09 19:15:00	EMERGENCY	SEPSIS
1	40080	162107	2106-05-31 16:43:00	2106-06-05 01:18:00	EMERGENCY	CONGESTIVE HEART FAILURE
2	40084	195762	2173-01-31 22:11:00	2173-02-05 01:31:00	EMERGENCY	INTRACRANIAL HEMORRHAGE;OPEN FX
3	40116	157106	2150-02-19 00:12:00	2150-03-11 13:58:00	EMERGENCY	GASTROINTESTINAL BLEED
4	40120	146466	2120-01-27 20:41:00	2120-02-12 17:14:00	EMERGENCY	CONGESTIVE HEART FAILURE

Navigating MIMIC

In [6]:
```
query = """
SELECT de.icustay_id
  , (strftime('%s',de.charttime)-strftime('%s',ie.intime))/60.0/60.0 as HO
  , di.label
  , de.value
  , de.valuenum
  , de.uom
FROM chartevents de
INNER join d_items di
ON de.itemid = di.itemid
INNER join icustays ie
ON de.icustay_id = ie.icustay_id
WHERE de.subject_id = 40084
ORDER BY charttime;
"""

ce = pd.read_sql_query(query,conn)


# OPTION 2: load chartevents from a CSV file
# ce = pd.read_csv('data/example_chartevents.csv', index_col='HOURSSINCEAD
```

In [7]:
```
# Preview the data
# Use 'head' to limit the number of rows returned
ce.head()
```

Out[7]:

	ICUSTAY_ID	HOURS	LABEL	VALUE	VALUENUM	UOM
0	264630	0.201667	PH (dipstick)	5	5.00	units
1	264630	0.201667	Specific Gravity (urine)	1.02	1.02	
2	264630	1.801667	Temperature Fahrenheit	94.3	94.30	¿F
3	264630	2.668333	Heart Rate	84	84.00	bpm
4	264630	2.668333	Non Invasive Blood Pressure systolic	106	106.00	mmHg

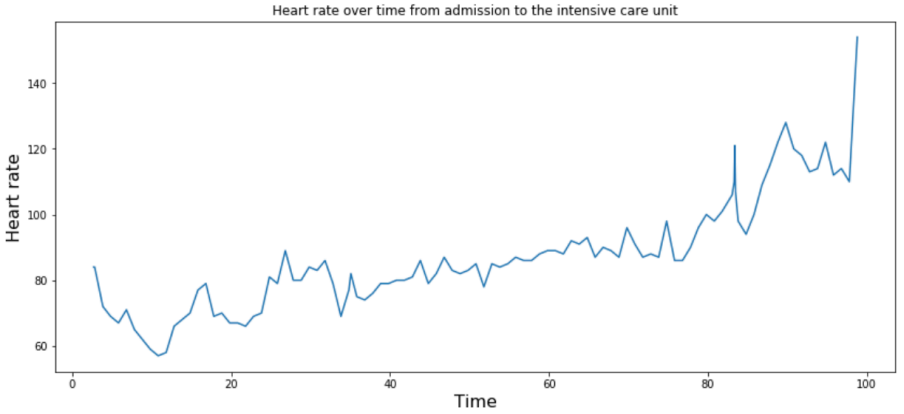
Plot 1: How did the patients heart rate change over time?

- Using the methods described above to select our data of interest, we can create our x and y axis values to create a time series plot of heart rate.

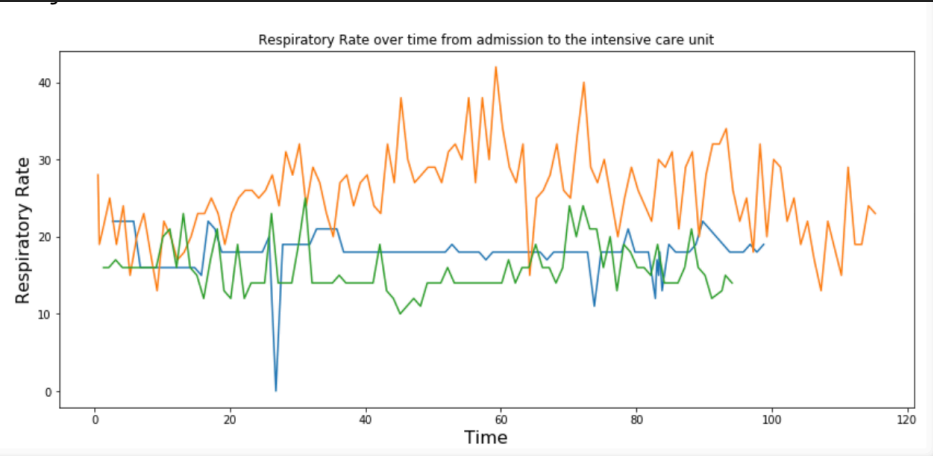
In [11]:
```
# Which time stamps have a corresponding heart rate measurement?
print(ce.index[ce.LABEL=='Heart Rate'])
```

```
Int64Index([   3,   18,   97,  101,  118,  161,  190,  198,  230,  285,
            ...
            2241, 2276, 2284, 2293, 2303, 2323, 2332, 2358, 2365, 2371],
           dtype='int64', length=103)
```

```
Text(0.5, 1.0, 'Heart rate over time from admission to the intensive care unit')
```



Navigating MIMIC




```
data = []
for subject_id in [40084, 40080, 40004]:
    query = """
    SELECT de.icustay_id
      , (strftime('%s',de.charttime)-strftime('%s',ie.intime))/60.0/60.0 a
      , di.label
      , de.value
      , de.valuenum
      , de.uom
    FROM chartevents de
    INNER join d_items di
    ON de.itemid = di.itemid
    INNER join icustays ie
    ON de.icustay_id = ie.icustay_id
    WHERE de.subject_id = """ + str(subject_id) + """
    ORDER BY charttime;
    """

    ce = pd.read_sql_query(query,conn)

    valueName = "Respiratory Rate";

    # Set x equal to the times
    x_hr = ce.HOURS[ce.LABEL==valueName]

    # Set y equal to the heart rates
    y_hr = ce.VALUENUM[ce.LABEL==valueName]

    # Plot time against heart rate
    plt.figure(figsize=(14, 6))
    data.append([x_hr,y_hr]);

for patient in data:
    plt.plot(patient[0], patient[1]);

plt.xlabel('Time',fontsize=16)
plt.ylabel(valueName,fontsize=16)
plt.title(valueName + ' over time from admission to the intensive care uni
```

Navigating MIMIC

Select data on the first hospital stay

In [4]:

```
# Run query and assign the results to a Pandas DataFrame
# Get first admission for each patient
query = \
"""
WITH admit AS (
    SELECT p.gender,
        ROUND( (CAST(EXTRACT(epoch FROM a.dischtime - a.admittime)/(60*60*24) AS numeric)), 4) AS
 los_hospital,
        ROUND( (CAST(EXTRACT(epoch FROM a.admittime - p.dob)/(60*60*24*365.242) AS numeric)), 4) A
S age,
        DENSE_RANK() OVER (PARTITION BY a.subject_id ORDER BY a.admittime) AS admission_seq,
        a.ethnicity, a.admission_type, a.insurance, a.religion, a.marital_status, a.hospital_expir
e_flag
    FROM patients p
    LEFT JOIN admissions a
    ON p.subject_id = a.subject_id)
SELECT *
FROM admit
WHERE admission_seq = 1;
"""

data = pd.read_sql_query(query,con)
```

https://github.com/MIT-LCP/mimic-code/blob/master/notebooks/tableone-demo.ipynb

Navigating MIMIC

```
# Columns to include in the summary table
columns = ['gender', 'los_hospital', 'age', 'ethnicity','admission_type', 'insurance',
           'religion', 'marital_status','hospital_expire_flag']

# List of categorical variables
categorical = ['gender', 'ethnicity', 'insurance', 'religion', 'marital_status',
           'hospital_expire_flag']

# Group the data
groupby = 'admission_type'

# Display the top n number of categorical variables
limit = 3

# Compute p values
pval = False

# Display a count of null values
isnull = False

t = TableOne(data, columns=columns, categorical=categorical,
         groupby=groupby, limit=limit, pval=pval, isnull=isnull)

t.tableone
```

		Grouped by admission_type		
		ELECTIVE	EMERGENCY	URGENT
variable	level			
n		8	90	2
age		74.23 (11.05)	90.01 (68.12)	75.66 (4.29)
ethnicity	WHITE	8 (100.0)	65 (72.22)	1 (50.0)
	UNKNOWN/NOT SPECIFIED		9 (10.0)	1 (50.0)
	BLACK/AFRICAN AMERICAN		6 (6.67)	
gender	F	5 (62.5)	48 (53.33)	2 (100.0)
	M	3 (37.5)	42 (46.67)	
hospital_expire_flag	0	8 (100.0)	58 (64.44)	1 (50.0)
	1		32 (35.56)	1 (50.0)
insurance	Medicare	5 (62.5)	70 (77.78)	1 (50.0)
	Private	3 (37.5)	15 (16.67)	1 (50.0)
	Medicaid		4 (4.44)	
los_hospital		11.67 (11.79)	9.86 (14.43)	6.26 (0.81)
marital_status	MARRIED	4 (50.0)	36 (48.0)	1 (50.0)
	SINGLE	2 (25.0)	18 (24.0)	
	WIDOWED	1 (12.5)	13 (17.33)	
religion	CATHOLIC	6 (75.0)	33 (37.08)	
	UNOBTAINABLE		16 (17.98)	
	NOT SPECIFIED	1 (12.5)	14 (15.73)	

Navigating MIMIC (T-SNE)

```
query = """
WITH firstvals as (
    SELECT rank() OVER (PARTITION BY vi.subject_id ORDER BY ic.intime ASC) as icuorder,
    vi.*, ic.intime, di.icd9_code, dd.short_title, ic.los_icu, ic.hospital_expire_flag,
    ic.los_hospital, ic.age, ic.gender, an.angus,
    el.congestive_heart_failure, el.cardiac_arrhythmias,el.valvular_disease,el.pulmonary_circulati
on,
    el.peripheral_vascular,el.hypertension,el.paralysis,el.other_neurological,el.chronic_pulmonar
y,
    el.diabetes_uncomplicated,el.diabetes_complicated,el.hypothyroidism,el.renal_failure,el.liver_
disease,
    el.peptic_ulcer,el.aids,el.lymphoma,el.metastatic_cancer,el.solid_tumor,el.rheumatoid_arthriti
s,
    el.coagulopathy,el.obesity,el.weight_loss,el.fluid_electrolyte,el.blood_loss_anemia,
    el.deficiency_anemias,el.alcohol_abuse,el.drug_abuse,el.psychoses,el.depression
    FROM vitalsfirstday vi
    INNER JOIN diagnoses_icd di
    ON vi.hadm_id = di.hadm_id
    INNER JOIN d_icd_diagnoses dd
    ON di.icd9_code = dd.icd9_code
    INNER JOIN icustay_detail ic
    ON vi.icustay_id = ic.icustay_id
    INNER JOIN elixhauser_ahrq el
    ON vi.hadm_id = el.hadm_id
    INNER JOIN angus_sepsis an
    ON vi.hadm_id = an.hadm_id
    WHERE di.seq_num = 1
    ORDER BY vi.subject_id)
SELECT *
FROM firstvals
WHERE age >=16
AND los_icu >=1
"""

phys = pd.read_sql_query(query,con)
```

Navigating MIMIC (T-SNE)

```
# Encode
# Encode gender
phys['gender'] = pd.factorize(phys['gender'])[0]
phys['icd9_code_enc'] = pd.factorize(phys['icd9_code'])[0]
```

```
# vars of interest

# physvars = ['heartrate_min', 'heartrate_max', 'sysbp_min', 'sysbp_max', 'diasbp_min', 'diasbp_ma
x', 'meanbp_min',
#             'meanbp_max', 'resprate_min', 'resprate_max', 'tempc_min', 'tempc_max', 'spo2_min',
 'spo2_max',
#             'glucose_min', 'glucose_max']

# physvars = ['heartrate_mean', 'sysbp_mean', 'diasbp_mean', 'meanbp_mean',
#             'resprate_mean', 'tempc_mean', 'spo2_mean', 'glucose_mean']

physvars = ['heartrate_min', 'heartrate_max', 'sysbp_min', 'sysbp_max', 'diasbp_min', 'diasbp_max'
, 'meanbp_min',
            'meanbp_max', 'resprate_min', 'resprate_max', 'tempc_min', 'tempc_max', 'spo2_min', 's
po2_max',
            'glucose_min', 'glucose_max', 'heartrate_mean', 'sysbp_mean', 'diasbp_mean', 'meanbp_m
ean',
            'resprate_mean', 'tempc_mean', 'spo2_mean', 'glucose_mean']
```

Navigating MIMIC (T-SNE)

In [8]:
```
# remove rows with nan
phys.dropna(inplace=True, subset=physvars)
```

In [9]:
```
# Limit the dataset for speed
if run_on_subset:
    n_to_compute=10000
    phys = phys[:n_to_compute]
    print('Running on limited subset.')
```

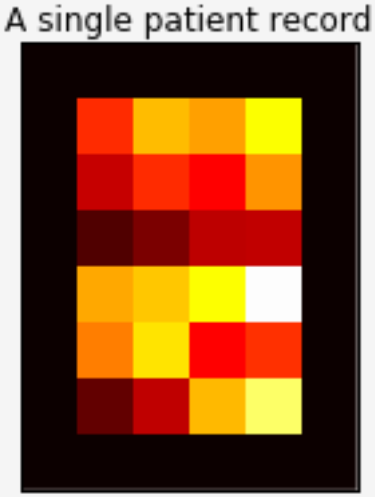
```
Running on limited subset.
```

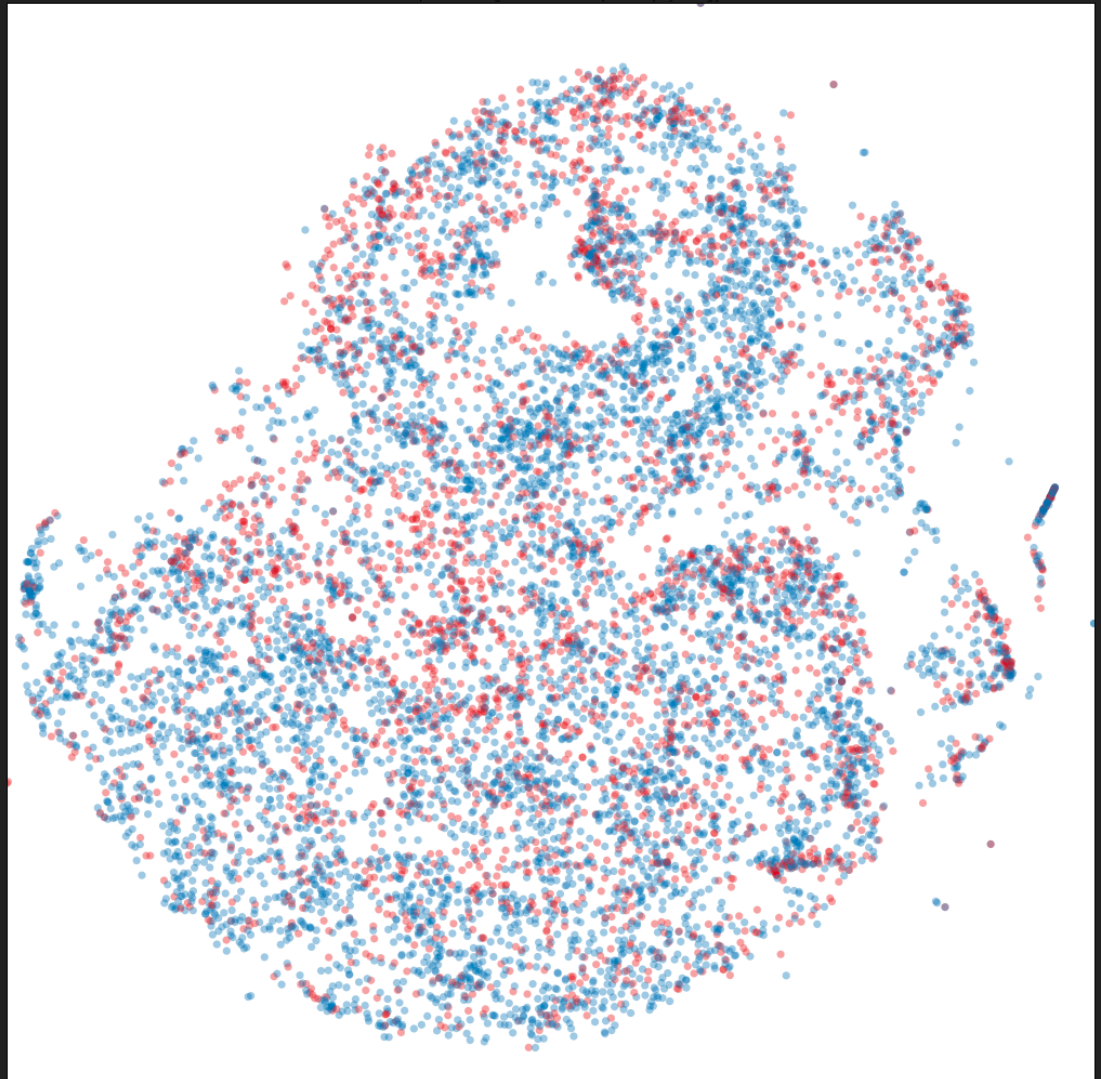
In [10]:
```
# Scale columns with zero mean and unit variance
if scaleinput:
    print('Columns scaled with with zero mean and unit variance.')
    phys[physvars] = MinMaxScaler().fit_transform(phys[physvars])
```

In [11]:
```
# run the tsne
X_tsne = TSNE(learning_rate=1000,random_state=randomstate).fit_transform(phys[physvars].values)
```

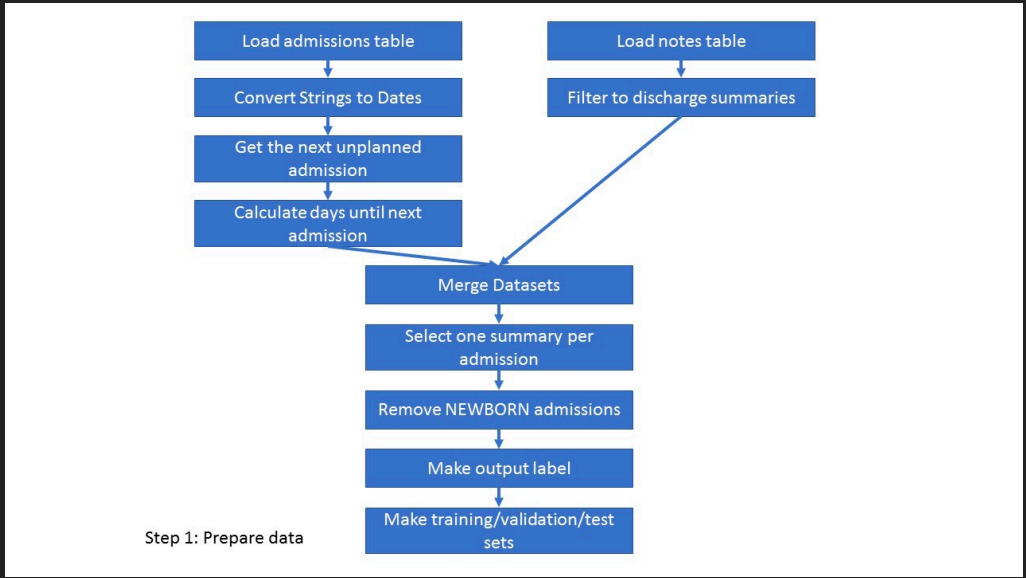
Navigating MIMIC (T-SNE)

```
# Plot image that represents a single patient
# These should be simple to interpret
# Once finalised, add these to the clustered plot
# Note: would be interesting to compare plots for different classes

# get dimension of image and add box around it
# cols=int(len(physvars)/rows)
patient_index = 4
cols=int(np.floor(np.sqrt(len(physvars))))
rows=int(np.ceil(len(physvars)/np.float(cols)))
dims=(rows+2,cols+2)
physbox=np.zeros([dims[0],dims[1]])
physvec=np.zeros(cols*rows)
physvec[:len(physvars)] = phys[physvars].iloc[patient_index].values
physbox[1:-1,1:-1]=physvec.reshape((dims[0]-2,dims[1]-2))

print physbox
plt.figure(figsize=(3, 3))
plt.imshow(physbox,cmap="hot",interpolation="none")
plt.xticks([])
plt.yticks([])
plt.title('A single patient record')
```



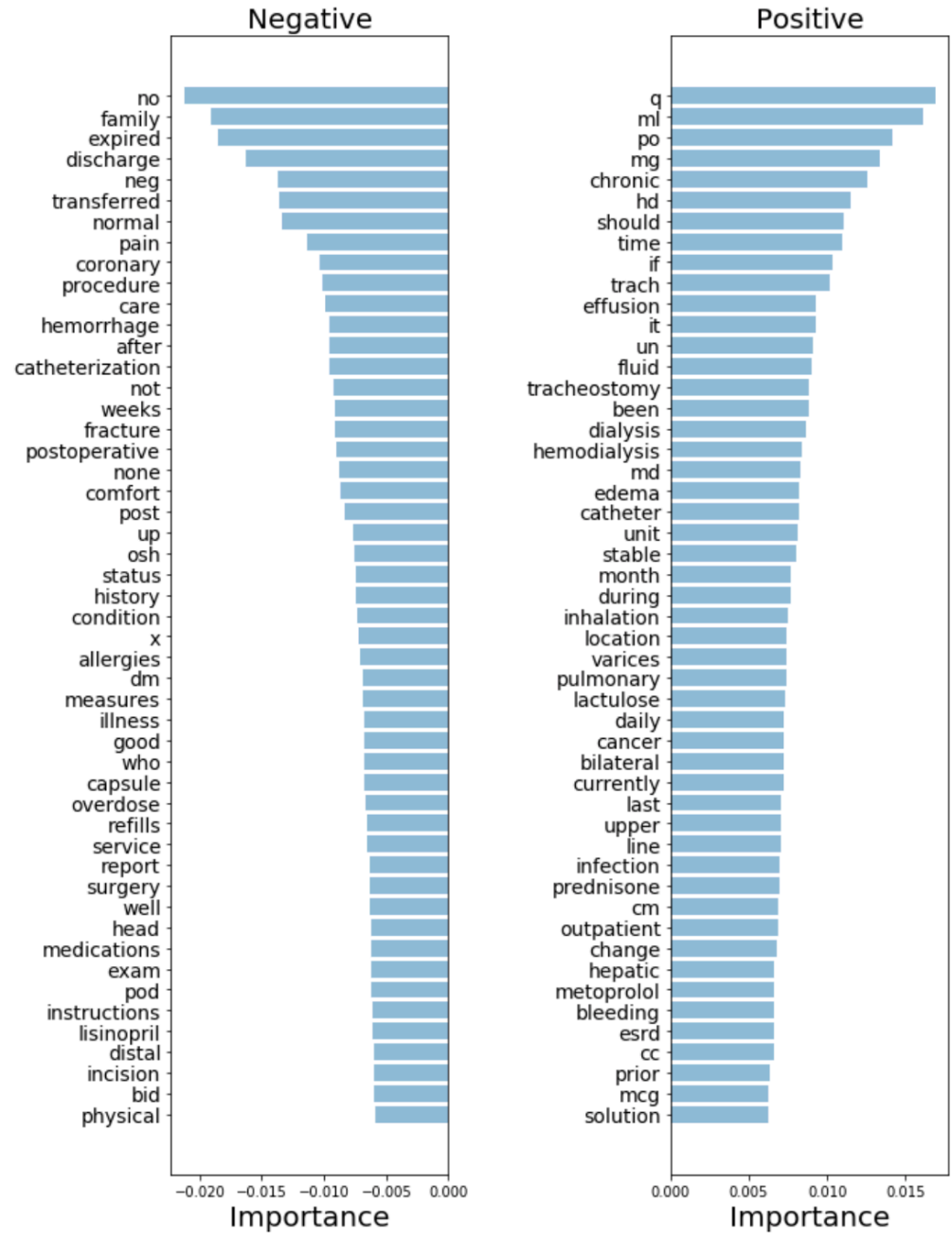


Clinical NLP using MIMIC



- **ADMISSIONS** — a table containing admission and discharge dates (has a unique identifier HADM_ID for each admission)
- **NOTEEVENTS** — contains all notes for each hospitalization (links with HADM_ID)

https://towardsdatascience.com/introduction-to-clinical-natural-language-processing-predicting-hospital-readmission-with-1736d52bc709


Negative
no
family
expired
discharge
neg
transferred
normal
pain
coronary
procedure
care
hemorrhage
after
catheterization
not
weeks
fracture
postoperative
none
comfort
post
up
osh
status
history
condition
x
allergies
dm
measures
illness
good
who
capsule
overdose
refills
service
report
surgery
well
head
medications
exam
pod
instructions
lisinopril
distal
incision
bid
physical
−0.020
−0.015
−0.010
−0.005
0.000
Importance
Positive
q
ml
po
mg
chronic
hd
should
time
if
trach
effusion
it
un
fluid
tracheostomy
been
dialysis
hemodialysis
md
edema
catheter
unit
stable
month
during
inhalation
location
varices
pulmonary
lactulose
daily
cancer
bilateral
currently
last
upper
line
infection
prednisone
cm
outpatient
change
hepatic
metoprolol
bleeding
esrd
cc
prior
mcg
solution
0.000
0.005
0.010
0.015
Importance

Clinical NLP using MIMIC

Publicly Available Clinical BERT Embeddings

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Model	MedNLI	i2b2 2006	i2b2 2010	i2b2 2012	i2b2 2014
BERT	77.6%	93.9	83.5	75.9	92.8
BioBERT	80.8%	**94.8**	86.5	78.9	**93.0**
Clinical BERT	80.8%	91.5	86.4	78.5	92.6
Discharge Summary BERT	80.6%	91.9	86.4	78.4	92.8
Bio+Clinical BERT	**82.7%**	94.7	87.2	**78.9**	92.5
Bio+Discharge Summary BERT	**82.7%**	94.8	**87.8**	78.9	92.7

Table 2: Accuracy (MedNLI) and Exact F1 score (i2b2) across various clinical NLP tasks.

Model	Disease			Operations			Generic		
	Glucose	Seizure	Pneumonia	Transfer	Admitted	Discharge	Beach	Newspaper	Table
BioBERT	insulin	episode	vaccine	drainage	admission	admission	coast	news	tables
	exhaustion	appetite	infection	division	sinking	wave	rock	official	row
	dioxide	attack	plague	transplant	hospital	sight	reef	industry	dinner
Clinical	potassium	headache	consolidation	transferred	admission	disposition	shore	publication	scenario
	sodium	stroke	tuberculosis	admitted	transferred	transfer	ocean	organization	compilation
	sugar	agitation	infection	arrival	admit	transferred	land	publicity	technology

https://arxiv.org/pdf/1904.03323.pdf

Clinical NLP using MIMIC

clinicalBERT

Repository for Publicly Available Clinical BERT Embeddings Paper (NAACL Clinical NLP Workshop 2019)

We are in the process of submitting Clinical BERT to PhysioNet.

In the interim, the models can be downloaded here, or via

```
wget -O pretrained_bert_tf.tar.gz https://www.dropbox.com/s/8armk04fu16algz/pretrained_bert_tf.tar.gz?dl=1
```

All models are finetuned from the Cased BERT-Base model.

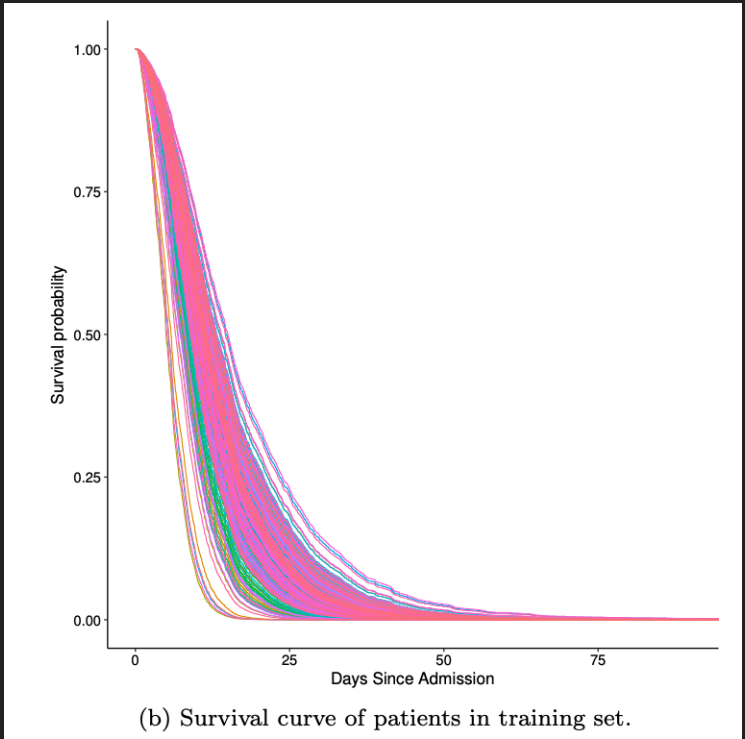
https://github.com/EmilyAlsentzer/clinicalBERT

Discussion

NLP

DE-Identification

Advanced Analysis (Survival Analysis)



(b) Survival curve of patients in training set.

Tanigawa and Pfhol (2017)

scikit-survival

scikit-survival is a Python module for survival analysis built on top of scikit-learn. It allows doing survival analysis while utilizing the power of scikit-learn, e.g., for pre-processing or doing cross-validation.

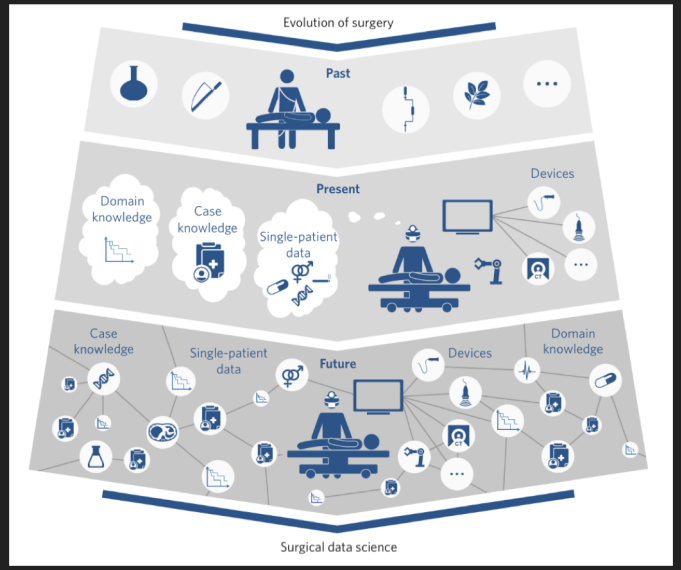
https://github.com/sebp/scikit-survival

LIFELINES

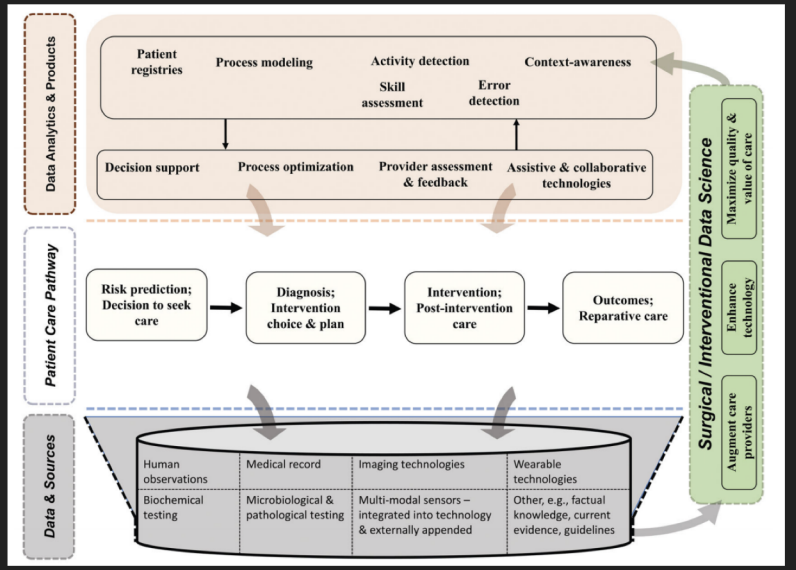
https://github.com/CamDavidsonPilon/lifelines

Surgical Data Science

The age of computer integrated surgery (CIS) with patient specific data



https://www.nature.com/articles/s41551-017-0132-7



Vedula and Hager (2017, Innov Surg Sci)