01_Data_Exploration

June 8, 2025

0.1 Dataset Understanding

The first phase of any data-centric project, particularly in the healthcare domain, requires a thorough understanding of the structure, semantics, and scope of the data sources involved. This notebook is dedicated to the initial exploration of the MIMIC-III clinical database, a publicly available dataset that includes de-identified health-related data associated with over 60,000 intensive care unit (ICU) admissions. The database encompasses a wide range of structured tables capturing demographic information, administrative details, diagnoses, laboratory results, vital signs, prescriptions, and more. The primary goal of this chapter is to provide a systematic overview of the core MIMIC-III tables that are fundamental to our modeling task. By performing an initial inspection of each dataset—examining their dimensionality, column names, data types, and representative records—we establish a foundational understanding that will inform downstream preprocessing, cohort definition, and feature engineering strategies.

To preserve computational feasibility during initial exploration, only a sample of rows is loaded for the largest tables. Full data ingestion will be deferred to the feature engineering phase, where filters based on cohort definitions and ICU stay windows will be applied. This initial exploration enables a critical appraisal of data completeness, granularity, and linkage keys across tables, and lays the groundwork for selecting an appropriate disease cohort and engineering predictive variables for ICU length of stay modeling.

[ ]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from IPython.display import display
```

[ ]:
```
PATH='../data/raw/'
EXPORT_PATH = '../data/processed/'
ASSETS_PATH='../assets/plots/data_exploration/'

patients = pd.read_csv(PATH + "PATIENTS.csv")
admissions = pd.read_csv(PATH + "ADMISSIONS.csv")
icustays = pd.read_csv(PATH + "ICUSTAYS.csv")
diagnoses = pd.read_csv(PATH + "DIAGNOSES_ICD.csv")
d_icd_diagnoses = pd.read_csv(PATH + "D_ICD_DIAGNOSES.csv")
chartevents = pd.read_csv(PATH + "CHARTEVENTS.csv", nrows=100)
labevents = pd.read_csv(PATH + "LABEVENTS.csv", nrows=5000)
inputevents_mv = pd.read_csv(PATH + "INPUTEVENTS_MV.csv", nrows=5000)
inputevents_cv = pd.read_csv(PATH + "INPUTEVENTS_CV.csv", nrows=5000)
```

```
outputevents = pd.read_csv(PATH + "OUTPUTEVENTS.csv", nrows=5000)
prescriptions = pd.read_csv(PATH + 'PRESCRIPTIONS.csv', usecols=['HADM_ID',␣
↪'DRUG'])
```

0.2 Demographic and Mortality Data of Patients

PATIENTS.csv provides demographic and survival information for each patient included in the MIMIC-III database. This dataset is essential for identifying individual patients and for understanding general demographic patterns, such as gender distribution, age-related trends, and mortality rates. The file allows the integration of demographic information with clinical and physiological data, enabling a comprehensive assessment of patient characteristics and long-term outcomes after critical care.

[ ]:
```
print(patients.shape)
display(patients.head())
```

```
(46520, 8)

   ROW_ID  SUBJECT_ID GENDER                  DOB                  DOD  \
0     234         249      F  2075-03-13 00:00:00                  NaN
1     235         250      F  2164-12-27 00:00:00  2188-11-22 00:00:00
2     236         251      M  2090-03-15 00:00:00                  NaN
3     237         252      M  2078-03-06 00:00:00                  NaN
4     238         253      F  2089-11-26 00:00:00                  NaN

              DOD_HOSP DOD_SSN  EXPIRE_FLAG
0                  NaN     NaN            0
1  2188-11-22 00:00:00     NaN            1
2                  NaN     NaN            0
3                  NaN     NaN            0
4                  NaN     NaN            0
```

0.3 Hospital Admission History and Patient Care Pathways

ADMISSIONS.csv documents each hospitalization event of patients registered in the MIMIC-III database. This dataset is critical for tracking the history of care, analyzing admission patterns, and studying the causes of hospitalization and clinical outcomes of critically ill patients. The table provides a comprehensive view of the patient pathway within the health care facility, allowing analyses on the impact of length of stay, frequency of hospitalizations, and key diagnostics associated with admission. It also allows linking different clinical episodes of the same patient, facilitating longitudinal studies.

[ ]:
```
print(admissions.shape)
display(admissions.head())
```

```
(58976, 19)

   ROW_ID  SUBJECT_ID  HADM_ID            ADMITTIME            DISCHTIME  \
0      21          22   165315  2196-04-09 12:26:00  2196-04-10 15:54:00
```

```
1      22          23   152223  2153-09-03 07:15:00  2153-09-08 19:10:00
2      23          23   124321  2157-10-18 19:34:00  2157-10-25 14:00:00
3      24          24   161859  2139-06-06 16:14:00  2139-06-09 12:48:00
4      25          25   129635  2160-11-02 02:06:00  2160-11-05 14:55:00

  DEATHTIME ADMISSION_TYPE         ADMISSION_LOCATION  \
0       NaN      EMERGENCY       EMERGENCY ROOM ADMIT
1       NaN       ELECTIVE  PHYS REFERRAL/NORMAL DELI
2       NaN      EMERGENCY  TRANSFER FROM HOSP/EXTRAM
3       NaN      EMERGENCY  TRANSFER FROM HOSP/EXTRAM
4       NaN      EMERGENCY       EMERGENCY ROOM ADMIT

          DISCHARGE_LOCATION INSURANCE LANGUAGE          RELIGION  \
0  DISC-TRAN CANCER/CHLDRN H   Private      NaN      UNOBTAINABLE
1           HOME HEALTH CARE  Medicare      NaN          CATHOLIC
2           HOME HEALTH CARE  Medicare     ENGL          CATHOLIC
3                       HOME   Private      NaN  PROTESTANT QUAKER
4                       HOME   Private      NaN      UNOBTAINABLE

  MARITAL_STATUS ETHNICITY            EDREGTIME            EDOUTTIME  \
0        MARRIED     WHITE  2196-04-09 10:06:00  2196-04-09 13:24:00
1        MARRIED     WHITE                  NaN                  NaN
2        MARRIED     WHITE                  NaN                  NaN
3         SINGLE     WHITE                  NaN                  NaN
4        MARRIED     WHITE  2160-11-02 01:01:00  2160-11-02 04:27:00

                                           DIAGNOSIS  HOSPITAL_EXPIRE_FLAG  \
0                             BENZODIAZEPINE OVERDOSE                     0
1  CORONARY ARTERY DISEASE\CORONARY ARTERY BYPASS…                     0
2                                          BRAIN MASS                     0
3                      INTERIOR MYOCARDIAL INFARCTION                     0
4                             ACUTE CORONARY SYNDROME                     0

   HAS_CHARTEVENTS_DATA
0                     1
1                     1
2                     1
3                     1
4                     1
```

0.4 ICU Stay Records and Critical Care Timeline

ICUSTAYS.csv describes all Intensive Care Unit (ICU) stays within a hospitalization event for each patient. It provides granular information on ICU admission and discharge times, type of care unit, and length of stay in ICU (LOS), which represents the primary target variable of this project. The dataset plays a central role in predicting patient outcomes and understanding care delivery within the ICU environment. The data can be linked with other clinical data sources to extract temporal trends and treatment patterns during the ICU stay.

```
[ ]: print(icustays.shape)
     display(icustays.head())
```

```
(61532, 12)

   ROW_ID  SUBJECT_ID  HADM_ID  ICUSTAY_ID DBSOURCE FIRST_CAREUNIT  \
0     365         268   110404      280836  carevue           MICU
1     366         269   106296      206613  carevue           MICU
2     367         270   188028      220345  carevue            CCU
3     368         271   173727      249196  carevue           MICU
4     369         272   164716      210407  carevue            CCU

  LAST_CAREUNIT  FIRST_WARDID  LAST_WARDID               INTIME  \
0          MICU            52           52  2198-02-14 23:27:38
1          MICU            52           52  2170-11-05 11:05:29
2           CCU            57           57  2128-06-24 15:05:20
3          SICU            52           23  2120-08-07 23:12:42
4           CCU            57           57  2186-12-25 21:08:04

              OUTTIME     LOS
0  2198-02-18 05:26:11  3.2490
1  2170-11-08 17:46:57  3.2788
2  2128-06-27 12:32:29  2.8939
3  2120-08-10 00:39:04  2.0600
4  2186-12-27 12:01:13  1.6202
```

0.5 Diagnosis Codes and Clinical Conditions Assigned During Admissions

DIAGNOSES_ICD.csv lists the diagnostic codes (ICD-9) assigned to each hospital admission, defining the clinical conditions for each patient encounter. D_ICD_DIAGNOSES.csv provides detailed descriptions of ICD-9 codes, offering the clinical context for each diagnosis. Together, these datasets are fundamental for identifying patient cohorts based on specific diseases, which is the starting point of the project pipeline. They enable comprehensive studies of comorbidity profiles and disease-specific clinical pathways of ICU patients.

```
[ ]: print(diagnoses.shape)
     display(diagnoses.head())
```

```
(651047, 5)

   ROW_ID  SUBJECT_ID  HADM_ID  SEQ_NUM ICD9_CODE
0    1297         109   172335      1.0     40301
1    1298         109   172335      2.0       486
2    1299         109   172335      3.0     58281
3    1300         109   172335      4.0      5855
4    1301         109   172335      5.0      4254
```

```
[ ]: print(d_icd_diagnoses.shape)
     display(d_icd_diagnoses.head())
```

```
(14567, 4)

   ROW_ID ICD9_CODE                SHORT_TITLE  \
0     174     01166     TB pneumonia-oth test
1     175     01170    TB pneumothorax-unspec
2     176     01171   TB pneumothorax-no exam
3     177     01172  TB pneumothorx-exam unkn
4     178     01173  TB pneumothorax-micro dx

                                          LONG_TITLE
0  Tuberculous pneumonia [any form], tubercle bac…
1              Tuberculous pneumothorax, unspecified
2  Tuberculous pneumothorax, bacteriological or h…
3  Tuberculous pneumothorax, bacteriological or h…
4  Tuberculous pneumothorax, tubercle bacilli fou…
```

0.6 Continuous Monitoring of Physiological and Clinical Parameters in ICU

CHARTEVENTS.csv records bedside clinical observations and vital signs collected continuously during ICU stays. This is the largest dataset in MIMIC-III and contains high-resolution data on physiological measurements (e.g., heart rate, blood pressure, respiratory rate). It provides crucial insights into the acute clinical state of patients and allows for detailed time-series analysis to model patient deterioration or recovery trends. Due to its large size, it may be useful to sample it for exploratory data analysis.

[ ]:
```python
print(chartevents.shape)
display(chartevents.head())
```

```
(100, 15)

   ROW_ID  SUBJECT_ID  HADM_ID  ICUSTAY_ID  ITEMID            CHARTTIME  \
0     788          36   165660      241249  223834  2134-05-12 12:00:00
1     789          36   165660      241249  223835  2134-05-12 12:00:00
2     790          36   165660      241249  224328  2134-05-12 12:00:00
3     791          36   165660      241249  224329  2134-05-12 12:00:00
4     792          36   165660      241249  224330  2134-05-12 12:00:00

             STORETIME   CGID   VALUE  VALUENUM VALUEUOM  WARNING  ERROR  \
0  2134-05-12 13:56:00  17525   15.00     15.00    L/min        0      0
1  2134-05-12 13:56:00  17525  100.00    100.00      NaN        0      0
2  2134-05-12 12:18:00  20823    0.37      0.37      NaN        0      0
3  2134-05-12 12:19:00  20823    6.00      6.00      min        0      0
4  2134-05-12 12:19:00  20823    2.50      2.50      NaN        0      0

   RESULTSTATUS  STOPPED
0           NaN      NaN
1           NaN      NaN
2           NaN      NaN
3           NaN      NaN
```

```
4           NaN      NaN
```

0.7 Laboratory Test Results and Biochemical Monitoring

LABEVENTS.csv documents the results of laboratory tests performed during hospital admissions. This dataset enables monitoring of biochemical and hematologic parameters over time, providing valuable information on organ function and systemic diseases. The data support the creation of predictive models based on the evolution of laboratory parameters in critically ill patients. As with CHARTEVENTS, sampling is recommended for initial exploration.

[ ]:
```python
print(labevents.shape)
display(labevents.head())
```

```
(5000, 9)

   ROW_ID  SUBJECT_ID  HADM_ID  ITEMID            CHARTTIME VALUE  VALUENUM  \
0     281           3      NaN   50820  2101-10-12 16:07:00  7.39      7.39
1     282           3      NaN   50800  2101-10-12 18:17:00   ART       NaN
2     283           3      NaN   50802  2101-10-12 18:17:00    -1     -1.00
3     284           3      NaN   50804  2101-10-12 18:17:00    22     22.00
4     285           3      NaN   50808  2101-10-12 18:17:00  0.93      0.93

  VALUEUOM      FLAG
0    units       NaN
1      NaN       NaN
2    mEq/L       NaN
3    mEq/L       NaN
4   mmol/L  abnormal
```

0.8 Drug Administration and Fluid Management in ICU

INPUTEVENTS_MV.csv and INPUTEVENTS_CV.csv contain detailed information on fluids, drugs, and nutritional substances administered to patients during their ICU stay. They are essential for understanding treatment strategies and analyzing the effect of medication and fluid balance on patient outcomes. These datasets allow modeling of dose-response relationships and exploring the relationship between therapeutic interventions and ICU length of stay.

[ ]:
```python
print(inputevents_mv.shape)
display(inputevents_mv.head())
```

```
(5000, 31)

   ROW_ID  SUBJECT_ID  HADM_ID  ICUSTAY_ID            STARTTIME  \
0     241       27063   139787      223259  2133-02-05 06:29:00
1     242       27063   139787      223259  2133-02-05 05:34:00
2     243       27063   139787      223259  2133-02-05 05:34:00
3     244       27063   139787      223259  2133-02-03 12:00:00
4     245       27063   139787      223259  2133-02-03 12:00:00

              ENDTIME  ITEMID      AMOUNT AMOUNTUOM       RATE  …  \
```

```
0  2133-02-05 08:45:00  225166    6.774532       mEq        NaN  …
1  2133-02-05 06:30:00  225944   28.132997        ml  30.142497  …
2  2133-02-05 06:30:00  225166    2.813300       mEq        NaN  …
3  2133-02-03 12:01:00  225893    1.000000      dose        NaN  …
4  2133-02-03 12:01:00  220949  100.000000        ml        NaN  …

  TOTALAMOUNTUOM ISOPENBAG  CONTINUEINNEXTDEPT  CANCELREASON  \
0             ml         0                   0             1
1             ml         0                   0             0
2             ml         0                   0             0
3             ml         0                   0             2
4             ml         0                   0             2

   STATUSDESCRIPTION COMMENTS_EDITEDBY COMMENTS_CANCELEDBY  \
0          Rewritten               NaN                  RN
1    FinishedRunning               NaN                 NaN
2    FinishedRunning               NaN                 NaN
3          Rewritten                RN                 NaN
4          Rewritten                RN                 NaN

         COMMENTS_DATE ORIGINALAMOUNT  ORIGINALRATE
0  2133-02-05 12:52:00      10.000000      0.050000
1                  NaN      28.132998     30.255817
2                  NaN       2.813300      0.050426
3  2133-02-03 17:06:00       1.000000      1.000000
4  2133-02-03 17:06:00     100.000000      0.000000

[5 rows x 31 columns]
```

[ ]:
```python
print(inputevents_cv.shape)
display(inputevents_cv.head())
```

```
(5000, 22)

   ROW_ID  SUBJECT_ID   HADM_ID  ICUSTAY_ID            CHARTTIME  ITEMID  \
0     592       24457  184834.0    205776.0  2193-09-11 09:00:00   30056
1     593       24457  184834.0    205776.0  2193-09-11 12:00:00   30056
2     594       24457  184834.0    205776.0  2193-09-11 16:00:00   30056
3     595       24457  184834.0    205776.0  2193-09-11 19:00:00   30056
4     596       24457  184834.0    205776.0  2193-09-11 21:00:00   30056

   AMOUNT AMOUNTUOM  RATE  RATEUOM  …  ORDERID  LINKORDERID  STOPPED  \
0   100.0        ml   NaN      NaN  …   756654      9359133      NaN
1   200.0        ml   NaN      NaN  …  3564075      9359133      NaN
2   160.0        ml   NaN      NaN  …   422646      9359133      NaN
3   240.0        ml   NaN      NaN  …  5137889      9359133      NaN
4    50.0        ml   NaN      NaN  …  8343792      9359133      NaN
```

```
   NEWBOTTLE ORIGINALAMOUNT  ORIGINALAMOUNTUOM  ORIGINALROUTE ORIGINALRATE  \
0        NaN            NaN                 ml           Oral          NaN
1        NaN            NaN                 ml           Oral          NaN
2        NaN            NaN                 ml           Oral          NaN
3        NaN            NaN                 ml           Oral          NaN
4        NaN            NaN                 ml           Oral          NaN

  ORIGINALRATEUOM  ORIGINALSITE
0             NaN           NaN
1             NaN           NaN
2             NaN           NaN
3             NaN           NaN
4             NaN           NaN

[5 rows x 22 columns]
```

0.9 Fluid Output and Balance Data for ICU Patients

OUTPUTEVENTS.csv captures all recorded patient outputs (e.g., urine volume, drainage fluids) during ICU stays. This dataset is important for calculating fluid balance, which is a key clinical parameter associated with mortality and ICU length of stay. The information helps in understanding renal function and the physiological response to treatments administered during critical care.

[ ]:
```
print(outputevents.shape)
display(outputevents.head())
```

```
(5000, 13)

   ROW_ID  SUBJECT_ID   HADM_ID  ICUSTAY_ID            CHARTTIME  ITEMID  \
0     344       21219  177991.0    225765.0  2142-09-08 10:00:00   40055
1     345       21219  177991.0    225765.0  2142-09-08 12:00:00   40055
2     346       21219  177991.0    225765.0  2142-09-08 13:00:00   40055
3     347       21219  177991.0    225765.0  2142-09-08 14:00:00   40055
4     348       21219  177991.0    225765.0  2142-09-08 16:00:00   40055

   VALUE VALUEUOM            STORETIME   CGID  STOPPED  NEWBOTTLE  ISERROR
0  200.0       ml  2142-09-08 12:08:00  17269      NaN        NaN      NaN
1  200.0       ml  2142-09-08 12:08:00  17269      NaN        NaN      NaN
2  120.0       ml  2142-09-08 13:39:00  17269      NaN        NaN      NaN
3  100.0       ml  2142-09-08 16:17:00  17269      NaN        NaN      NaN
4  200.0       ml  2142-09-08 16:17:00  17269      NaN        NaN      NaN
```

0.10 Disease Cohort Selection

At this stage, it is possible to define the target population for my study. Because MIMIC-III is a very large dataset covering several diseases and types of patients, the project requires the selection of a specific subset of patients with a clinically well-defined disease. This approach reflects real-world clinical research, where models are usually developed and validated on homogeneous patient cohorts. Steps to achieve this goal are as follows.

0.10.1 Creating a Category Column

Create the ICD9_CATEGORY column by extracting the first 3 digits of the ICD9_CODE code. The ICD-9 codes used in MIMIC-III are very detailed, sometimes with hundreds of subcategories for the same clinical condition. By considering only the first 3 digits in a new column called ICD9_CATEGORY, related codes can be grouped together and a broader, more clinically meaningful categorization of diseases can be obtained. This greatly simplifies the cohort selection process.

```
[ ]: diagnoses['ICD9_CATEGORY'] = diagnoses['ICD9_CODE'].astype(str).str[:3]
     diagnoses.head() # Useful for grouping similar clinical conditions
```

```
[ ]:    ROW_ID  SUBJECT_ID  HADM_ID  SEQ_NUM ICD9_CODE ICD9_CATEGORY
     0    1297         109   172335      1.0     40301           403
     1    1298         109   172335      2.0       486           486
     2    1299         109   172335      3.0     58281           582
     3    1300         109   172335      4.0      5855           585
     4    1301         109   172335      5.0      4254           425
```

0.10.2 Retrieving Long Medical Description of Each ICD9 Code

Numeric ICD9 codes are difficult to interpret on their own. By merging DIAGNOSES_ICD with D_ICD_DIAGNOSES, one can better understand the medical meaning of each code and accurately select the target disease category for my study.

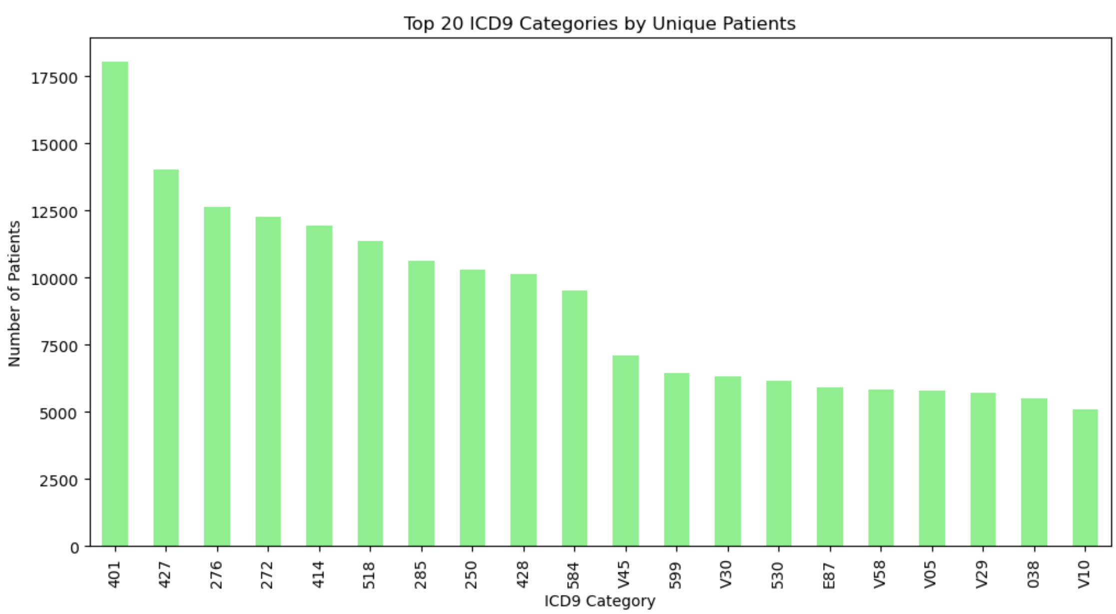
```
[ ]: # Create ICD9_CATEGORY in D_ICD_DIAGNOSES to simplify the merge, resulting in a
      ↪dataset having a title for every code.
     d_icd_diagnoses['ICD9_CATEGORY'] = d_icd_diagnoses['ICD9_CODE'].astype(str).
      ↪str[:3]
     category_titles = d_icd_diagnoses[['ICD9_CATEGORY', 'LONG_TITLE']].
      ↪drop_duplicates()
     diagnoses = diagnoses.merge(category_titles, on='ICD9_CATEGORY', how='left')

     diagnoses.head()
```

```
[ ]:    ROW_ID  SUBJECT_ID  HADM_ID  SEQ_NUM ICD9_CODE ICD9_CATEGORY  \
     0    1297         109   172335      1.0     40301           403
     1    1297         109   172335      1.0     40301           403
     2    1297         109   172335      1.0     40301           403
     3    1297         109   172335      1.0     40301           403
     4    1297         109   172335      1.0     40301           403

                                          LONG_TITLE
     0  Hypertensive chronic kidney disease, malignant…
     1  Hypertensive chronic kidney disease, malignant…
     2  Hypertensive chronic kidney disease, benign, w…
     3  Hypertensive chronic kidney disease, benign, w…
     4  Hypertensive chronic kidney disease, unspecifi…
```

0.10.3 Exploring and Selecting the Target Disease Cohort

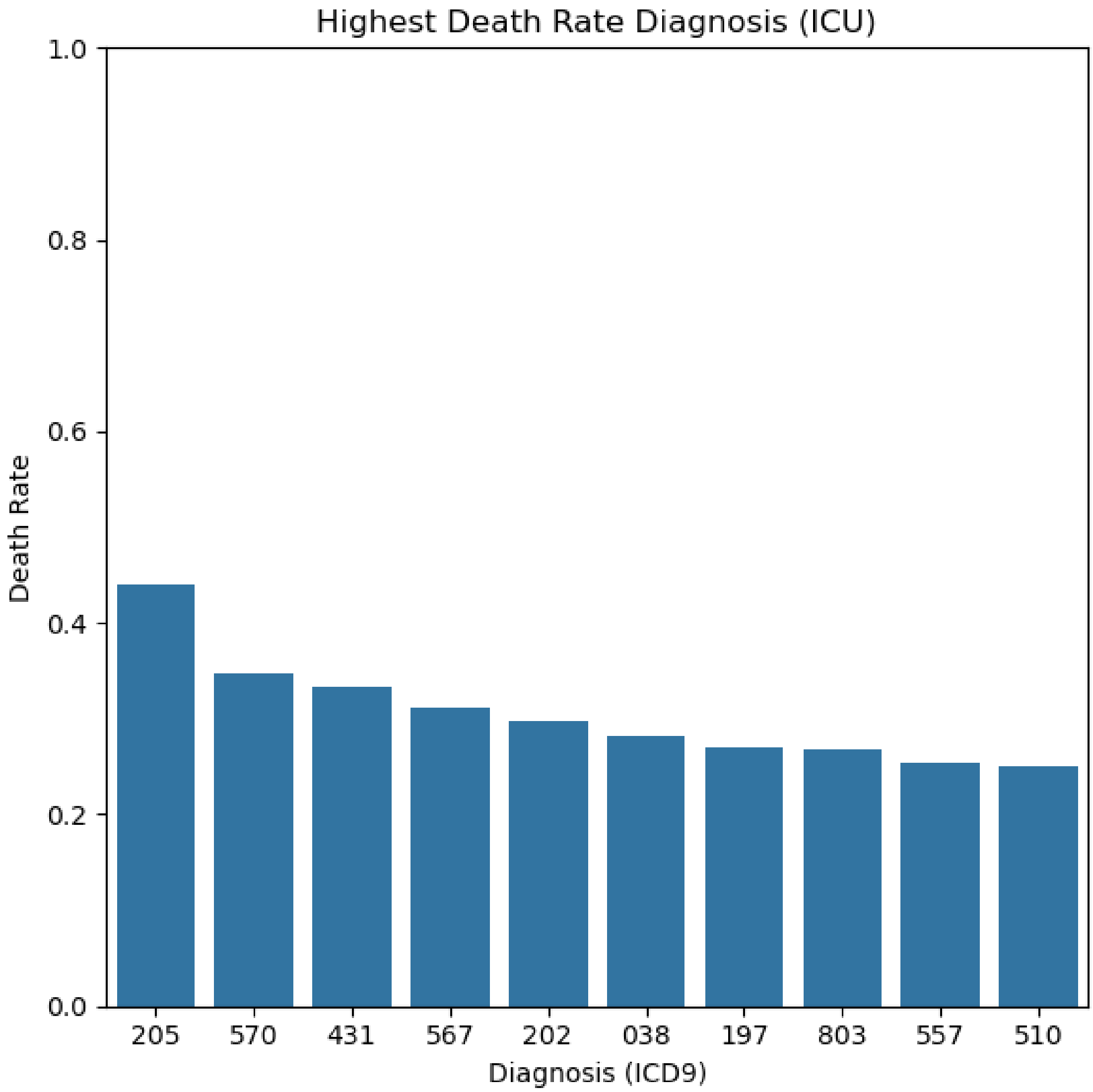
Patients Analysis In the plot showing the number of unique patients per ICD-9 category, code 038 (Sepsis) does not appear among the most prevalent overall—being surpassed, for example, by codes 250 (Diabetes Mellitus) and 414 (Coronary Artery Disease). Nonetheless, it stands out due to several clinically and epidemiologically relevant features. Specifically, code 038: it ranks among the top ten diagnoses in terms of ICU admissions and demonstrates a meaningful combination of clinical severity and cohort size By comparison: Code 250 is highly prevalent, but many associated admissions are non-critical or reflect secondary diagnoses; Code 414 is often managed outside of the ICU and more commonly appears as a comorbidity rather than the primary reason for admission. Conversely, code 038 represents a high-priority clinical condition in the ICU setting, being both sufficiently specific to avoid diagnostic ambiguity and statistically well-represented. These characteristics make it a strong candidate for developing predictive models of hospital length of stay.

```
[ ]: diagnoses['ICD9_CATEGORY'] = diagnoses['ICD9_CODE'].astype(str).str[:3]
     counts = diagnoses.groupby('ICD9_CATEGORY')['SUBJECT_ID'].nunique().
      ↪sort_values(ascending=False)

     counts.head(20).plot(kind='bar', figsize=(12,6), color=['lightgreen'])
     plt.title('Top 20 ICD9 Categories by Unique Patients')
     plt.xlabel('ICD9 Category')
     plt.ylabel('Number of Patients')
     plt.savefig(ASSETS_PATH + 'top20_icd9_categories_by_unique_patients.png',␣
      ↪dpi=300)
     plt.show()
```



Death Rate Analysis In the "Highest Death Rate Diagnosis (ICU)" plot, ICD-9 code 038 (Sepsis) exhibits a high mortality rate, surpassed only by codes 486 (Pneumonia) and 410 (Acute Myocardial Infarction). However, each of these alternatives presents specific limitations: Code 486 is marked by significant clinical heterogeneity and high variability in length of stay (LOS), which complicates the development of reliable predictive models. Code 410, despite its clinical severity, is generally associated with shorter and more variable LOS, often driven by rapid outcomes (either recovery or death), limiting the predictive utility of LOS-based models. In contrast, code 038 represents a high-risk condition with a more gradual clinical course and a sufficiently informative LOS distribution. This makes it particularly well-suited for predictive modeling focused on hospital length of stay estimation.

[ ]:
```python
main_diag = diagnoses.sort_values('SEQ_NUM').drop_duplicates('HADM_ID', keep='first')
main_diag['ICD9_CODE'] = main_diag['ICD9_CODE'].astype(str).str[:3]

diag_mortality = main_diag.merge(admissions, on='HADM_ID', how='left')

mortality_summary = diag_mortality.groupby('ICD9_CODE').agg(
    N_PATIENTS=('HADM_ID', 'count'),
    N_DEATHS=('HOSPITAL_EXPIRE_FLAG', 'sum')
).reset_index()

mortality_summary['DEATH_RATE'] = mortality_summary['N_DEATHS'] / mortality_summary['N_PATIENTS']

mortality_summary = mortality_summary[mortality_summary['N_PATIENTS'] >= 50] # Filter
top_mortalità = mortality_summary.sort_values('DEATH_RATE', ascending=False).head(10) # # Sort by death rate

# Plot
plt.figure(figsize=(6, 6))
sns.barplot(data=top_mortalità, x='ICD9_CODE', y='DEATH_RATE')
plt.title('Highest Death Rate Diagnosis (ICU)')
plt.xlabel('Diagnosis (ICD9)')
plt.ylabel('Death Rate')
plt.ylim(0, 1)
plt.tight_layout()
plt.savefig(ASSETS_PATH + 'death_rate_by_diagnosis.png', dpi=300)
plt.show()
```

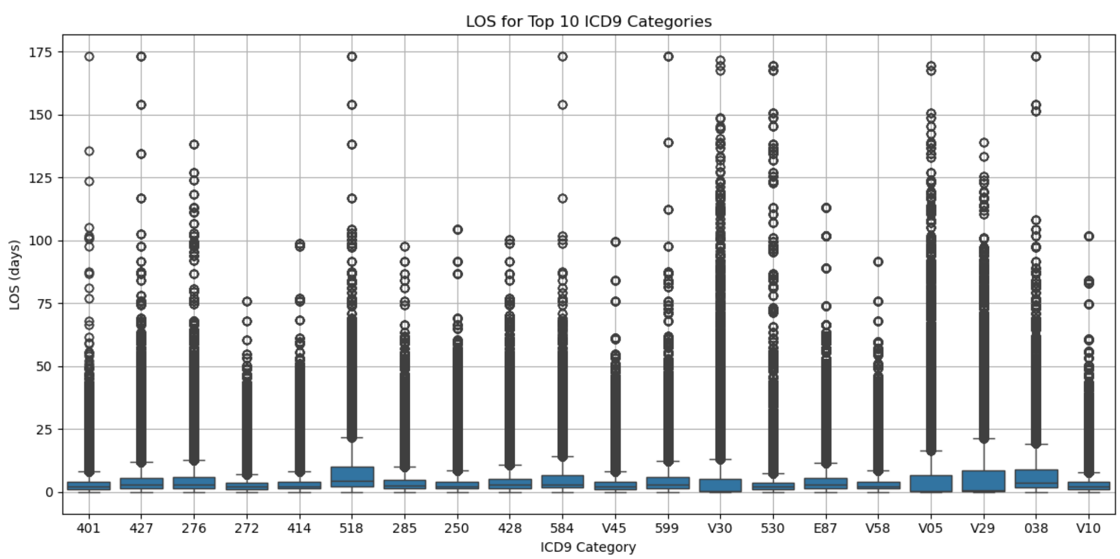


LOS Analysis The initial analysis focuses on intensive care unit (ICU) length of stay (LOS) across the most prevalent ICD-9 diagnostic categories and ICU admission diagnoses. Among these, category 038, corresponding to sepsis, stands out due to its moderate-to-high LOS distribution, with a substantial proportion of patients experiencing ICU stays longer than seven days. A particularly noteworthy feature is the relatively low dispersion in LOS for this group, especially when compared to other high-variability critical conditions such as acute respiratory failure (code 518) and acute hepatic failure (code 570). This reduced variability suggests that LOS in septic patients is more stable and predictable, which is a crucial property for the development of reliable predictive models, as it limits unexplained variance and enhances model robustness.

Overall, the findings indicate that septic patients: * Require considerable intensive care resources; * Represent a relatively homogeneous population with respect to LOS

This balance between a high median LOS and constrained variability makes sepsis an optimal clinical condition for training and validating predictive models aimed at forecasting ICU stay and optimizing critical care resource allocation.

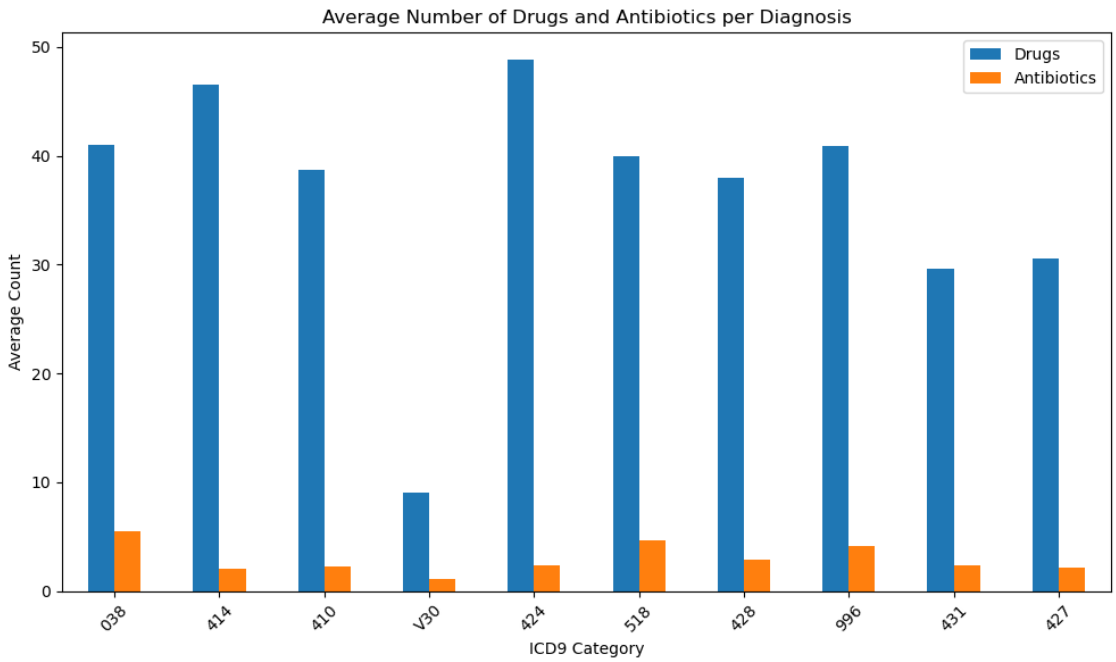
```
[ ]: counts = diagnoses.groupby('ICD9_CATEGORY')['SUBJECT_ID'].nunique().
     ↪sort_values(ascending=False).head(20).index

     # Filter
     diag_top = diagnoses[diagnoses['ICD9_CATEGORY'].isin(counts)]
     diag_top = diag_top.merge(icustays[['SUBJECT_ID', 'HADM_ID', 'ICUSTAY_ID',␣
     ↪'LOS']], on=['SUBJECT_ID', 'HADM_ID'], how='left')
     diag_top = diag_top.dropna(subset=['LOS'])

     # Plot
     plt.figure(figsize=(12, 6))
     sns.boxplot(x='ICD9_CATEGORY', y='LOS', data=diag_top, order=counts)
     plt.title('LOS for Top 10 ICD9 Categories')
     plt.xlabel('ICD9 Category')
     plt.ylabel('LOS (days)')
     plt.grid(True)
     plt.tight_layout()
     plt.savefig(ASSETS_PATH + 'top10_categories_los.png', dpi=300)
     plt.show()
```



Treatments Analysis Analysis of the drug and antibiotic usage table highlights ICD-9 code 038 (Sepsis) as notable for having one of the highest average numbers of medications administered per patient (~38.6), and an high rate of antibiotic usage (~5.2), second only to code 486. These indicators reflect a high level of therapeutic intensity and provide a rich source of information - in terms of drug types and dosage patterns - for predictive modeling. The clinical complexity associated with sepsis appears sufficient to justify advanced analysis of length of stay (LOS). Conversely, codes 518 and 571 were excluded despite an even greater drug burden, due to their frequent association with multi-organ failure and highly variable interventions, which reduce the reliability and predictive accuracy of modeling efforts.

[ ]:
```
# Antibiotics labels
antibiotic_pattern = 'cillin|mycin|cef|penem|cycline|azole|floxacin'

# Counts drugs per HADM_ID
drug_counts = prescriptions.groupby('HADM_ID')['DRUG'].nunique().
↪reset_index(name='N_DRUGS')

# Counts antibiotics per HADM_ID
abx_mask = prescriptions['DRUG'].str.contains(antibiotic_pattern, case=False,␣
↪na=False)
abx_counts = prescriptions[abx_mask].groupby('HADM_ID')['DRUG'].nunique().
↪reset_index(name='N_ANTIBIOTICS')

# Merge
drug_data = pd.merge(drug_counts, abx_counts, on='HADM_ID', how='left').
↪fillna(0)

# Add ICD9 Category
main_diagnoses = diagnoses.sort_values('SEQ_NUM').drop_duplicates('HADM_ID',␣
↪keep='first')
main_diagnoses['ICD9_CATEGORY'] = main_diagnoses['ICD9_CODE'].astype(str).str[:
↪3]

# Add drugs counter
drug_data = pd.merge(drug_data, main_diagnoses[['HADM_ID', 'ICD9_CATEGORY']],␣
↪on='HADM_ID', how='left')

# Summary
summary = drug_data.groupby('ICD9_CATEGORY').agg({
    'N_DRUGS': 'mean',
    'N_ANTIBIOTICS': 'mean',
    'HADM_ID': 'count'
}).rename(columns={'HADM_ID': 'Patients', 'N_DRUGS': 'Drugs', 'N_ANTIBIOTICS':␣
↪'Antibiotics'}).reset_index()

summary = summary.sort_values(by='Patients', ascending=False).head(10)
summary.plot(x='ICD9_CATEGORY', y=['Drugs', 'Antibiotics'], kind='bar',␣
↪figsize=(10,6))
plt.title('Average Number of Drugs and Antibiotics per Diagnosis')
plt.ylabel('Average Count')
plt.xlabel('ICD9 Category')
plt.xticks(rotation=45)
plt.tight_layout()
```

```
plt.savefig(ASSETS_PATH + 'drug_antibiotic_usage.png', dpi=300)
plt.show()
```



Final Justification for Selecting ICD-9 Code 038 – Sepsis The multidimensional analysis of the main ICD-9 diagnoses identifies 038 – Septicemia/Sepsis as the most robust, balanced, and clinically relevant cohort for the task of predicting ICU length of stay (LOS). Unlike other diagnoses that excel in isolated dimensions but fall short in others, code 038 demonstrates a well-rounded profile across all key criteria:

Representativeness: It consistently ranks among the top ten ICD-9 codes in terms of patient volume and ICU admissions, ensuring statistical power without being overly generic or ambiguous, as is the case with code 250 (Diabetes Mellitus). Clinical Severity: It is associated with high—but not extreme—mortality, indicating a complex and sufficiently prolonged clinical course suitable for predictive modeling (unlike 410 – Acute Myocardial Infarction, which often involves rapid outcomes). Length of Stay (LOS): It exhibits a relatively long median LOS with low variability, an ideal scenario for building reliable predictive models. In contrast, codes such as 518 or 570 show extreme dispersion, which hinders modeling precision. Informational Richness: Patients diagnosed with sepsis typically receive numerous medications, including antibiotics, resulting in a structured and informative dataset highly conducive to training machine learning models. No other ICD-9 category analyzed meets all four criteria with equivalent robustness. Diagnoses like 486 (Pneumonia) or 570 (Liver Failure) offer specific advantages but are limited by structural weaknesses (e.g., clinical heterogeneity, low prevalence, or excessive variability), which undermine their predictive reliability. Therefore, selecting code 038 as the primary cohort allows for an optimal balance between statistical robustness, clinical relevance, and data richness, positioning it as the most suitable candidate for developing effective, generalizable, and clinically meaningful predictive models.

Criterion	038 – Sepsis	250 – Diabetes	410 – MI	518 – Resp. Failure
Patient Volume	High	Very High	High	Moderate
Clinical Severity	High	Low	Very High	Very High
LOS Stability	Moderate & Stable	Low & Variable	Short LOS	Very Variable
Treatment Informativeness	High (drugs & abx)	Low	Low	High but heterogeneous
Overall Suitability	Optimal	Weak context	Limited	Too noisy

0.10.4 Exporting the Sepsis Cohort for Downstream Use

After selecting the target population based on ICD-9 code 038 (sepsis), it is crucial to persistently save the list of admissions (HADM_ID) and patients (SUBJECT_ID) associated with this diagnosis. This step enables reusability in the next phases of the project (clinical visualization and feature engineering), ensuring reproducibility and consistency. The export also includes ICUSTAY_ID, when available, to simplify the join with temporal clinical events.

[ ]:
```python
# Extract first diagnosis per admission
main_diagnoses = diagnoses.sort_values('SEQ_NUM').drop_duplicates('HADM_ID',␣
↪keep='first')

# Filter for Sepsis (ICD9_CATEGORY = '038')
sepsis = main_diagnoses[main_diagnoses['ICD9_CATEGORY'] == '038']

# Retain only identifiers
sepsis_ids = sepsis[['SUBJECT_ID', 'HADM_ID']].drop_duplicates()

# (Optional) Join with ICU stay IDs for completeness
icustays = pd.read_csv(PATH + "ICUSTAYS.csv", usecols=["SUBJECT_ID", "HADM_ID",␣
↪"ICUSTAY_ID"])
sepsis_ids = pd.merge(sepsis_ids, icustays, on=["SUBJECT_ID", "HADM_ID"],␣
↪how="left")

# Save to processed directory
sepsis_ids.to_csv("../data/processed/sepsis_cohort.csv", index=False)

# Confirm
print("[SUCCESS] Sepsis cohort exported:", sepsis_ids.shape)
sepsis_ids.head()
```

```
[SUCCESS] Sepsis cohort exported: (3686, 3)
```

[ ]:

	SUBJECT_ID	HADM_ID	ICUSTAY_ID
0	51797	104616	265369.0
1	44534	183659	204918.0

```
2         14828    144708     293475.0
3         14828    125239     288771.0
4         44500    101872     260996.0
```

The output indicates that 3686 hospital admissions (HADM_ID) were identified with a primary diagnosis of sepsis (ICD9 = 038), spanning multiple SUBJECT_ID values—some patients (e.g., 14828) appear more than once due to recurrent admissions. The ICUSTAY_ID column provides the corresponding ICU stay, confirming that the cohort has been successfully linked to intensive care episodes. This level of detail is essential for clinical time series analysis, as dynamic data in MIMIC-III (e.g., CHARTEVENTS, INPUTEVENTS_MV) are indexed by ICUSTAY_ID.

[ ]:
```
# Install needed packages
!apt-get install texlive texlive-xetex texlive-latex-extra pandoc &> /dev/null
!pip install pypandoc &> /dev/null

# Mount your google drive to get access to your ipynb files

from google.colab import drive
drive.mount('/content/drive')
# and copy your notebook to this colab machine. Note that I am using *MY*␣
↪notebook filename

!cp "/content/drive/MyDrive/Colab Notebooks/01_Data_Exploration.ipynb" ./ &> /
↪dev/null

# Then you can run the converter.

!jupyter nbconvert --to PDF "01_Data_Exploration.ipynb" &> /dev/null
```