# Dask_Pipeline

July 1, 2025

## 1 Configuration and Imports

[2]:
```
from google.colab import auth
auth.authenticate_user()
```

[62]:
```
import dask.dataframe as dd
from dask_ml.preprocessing import StandardScaler, OneHotEncoder
from dask_ml.model_selection import train_test_split
from google.cloud import bigquery
import bigframes as bf
import bigframes.pandas as bpd
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
import numpy as np
import time
from sklearn.utils.class_weight import compute_sample_weight
from sklearn.utils.multiclass import type_of_target
from sklearn.preprocessing import StandardScaler, OneHotEncoder,␣
↪FunctionTransformer
from sklearn.feature_extraction import FeatureHasher
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.metrics import accuracy_score, classification_report,␣
↪confusion_matrix, cohen_kappa_score
from sklearn.base import BaseEstimator, TransformerMixin, clone
from collections import Counter
from xgboost import XGBClassifier
```

[4]:
```
project_id = "my-first-gcp-project-452814"
client = bigquery.Client(project=project_id)

print("Project ID:", client.project)
```

```
Project ID: my-first-gcp-project-452814
```

## 2 Datasets

The datasets used in these project were the ones we considered most relevant for the task at hand.

They were uploaded to the BigQuery project `my-first-gcp-project-452814` via Google Cloud Storage.

Below we perform some queries to vizualize and ensure data quality in all of these the datasets.

### 2.1 Chartevents Reduced

Contains time-stamped clinical data and measurements recorded for patients during their hospital stay.

- `ROW_ID`: Unique identifier for the row.
- `SUBJECT_ID`: Foreign key to the PATIENTS table.
- `HADM_ID`: Foreign key to the ADMISSIONS table.
- `ITEMID`: Foreign key to the D_ITEMS table, indicating the type of measurement.
- `CHARTTIME`: Timestamp when the measurement was recorded.
- `STORETIME`: Timestamp when the measurement was stored.
- `VALUE`: The value of the measurement (can be numeric or text).
- `VALUENUM`: Numeric value of the measurement, if applicable.
- `VALUEUOM`: Unit of measurement.
- `WARNING`: Flags indicating potential issues with the data.

#### 2.1.1 Reducing the original Chartevents dataset

We decided to create a more small and acessible table using the original `chartevents`. This new table, `chartevents_reduced`, that will be used from now on, only contains the measurements of the most common disease in the original table.

[ ]:
```
start_time = time.time()

query = """
-- Step 1: Create a new table for disease-related data
CREATE OR REPLACE TABLE `my-first-gcp-project-452814.cdle_project_dataset.
 ↪chartevents_reduced` AS

-- Step 2: Identify and select only disease-related measurements
WITH disease_measurements AS (
  SELECT *
  FROM `my-first-gcp-project-452814.cdle_project_dataset.chartevents`
  WHERE ITEMID IN (
    -- Cardiovascular
    220045,  -- Heart Rate
    220050,  -- Blood Pressure Systolic
    220051,  -- Blood Pressure Diastolic

    -- Metabolic/Endocrine
    220179,  -- Glucose
```

```
    50912,   -- Creatinine
    50809,   -- Glucose (serum)

    -- Respiratory
    220277,  -- SpO2
    224690,  -- Respiratory Rate

    -- Infection/Inflammation
    50813,   -- Lactate (sepsis marker)

    -- Liver
    50821    -- Bilirubin
  )
),

-- Step 3: Find the top 3 most common disease measurements
top_disease_measurements AS (
  SELECT
    ITEMID,
    COUNT(*) AS measurement_count
  FROM disease_measurements
  GROUP BY ITEMID
  ORDER BY measurement_count DESC
  LIMIT 3
)

-- Step 4: Create final table with only top disease measurements
SELECT d.*
FROM disease_measurements d
JOIN top_disease_measurements t ON d.ITEMID = t.ITEMID;
"""

query_job = client.query(query)
print("Dataset reduced sucessfully")

end_time = time.time()
execution_time = end_time - start_time
print(f"Query Execution Time: {execution_time:.2f} seconds")
```

```
Dataset reduced sucessfully
Query Execution Time: 0.70 seconds
```

### 2.1.2 Visualization

[ ]:
```
start_time = time.time()

dataset_id = "cdle_project_dataset"
```

```
table_id = "chartevents_reduced"

table_ref = client.dataset(dataset_id).table(table_id)

chartevents = client.list_rows(table_ref).to_dataframe()

end_time = time.time()
execution_time = end_time - start_time
print(f"Query Execution Time: {execution_time:.2f} seconds")

chartevents.head()
```

```
Query Execution Time: 7.32 seconds
```

[ ]:

```
     ROW_ID  SUBJECT_ID  HADM_ID  ICUSTAY_ID  ITEMID  \
0  19184847       66298   152072      200105  220045
1  24904858       79894   106711      201234  220045
2    759709        9002   120994      203667  220045
3  30895546       91558   119749      204020  220045
4  34071445       99469   179324      204842  220179

                  CHARTTIME                 STORETIME   CGID VALUE  VALUENUM  \
0 2104-10-24 00:05:00+00:00                       NaT   <NA>     0       0.0
1 2104-05-01 02:00:00+00:00 2104-05-01 02:10:00+00:00  16037     0       0.0
2 2177-05-05 01:40:00+00:00 2177-05-05 01:48:00+00:00  18784     0       0.0
3 2183-09-01 09:10:00+00:00 2183-09-01 09:18:00+00:00  16526     0       0.0
4 2183-05-13 16:20:00+00:00 2183-05-13 17:10:00+00:00  19589     0       0.0

  VALUEUOM  WARNING  ERROR RESULTSTATUS STOPPED
0      bpm        0      0         None    None
1      bpm        0      0         None    None
2      bpm        0      0         None    None
3      bpm        0      0         None    None
4     mmHg        0      0         None    None
```

### 2.1.3 Data quality check

[ ]:

```
start_time = time.time()

query = """
-- Data Quality Assessment for chartevents_reduced
WITH stats AS (
  SELECT
    COUNT(*) AS total_records,
    COUNT(DISTINCT SUBJECT_ID) AS unique_patients,
    COUNT(DISTINCT HADM_ID) AS unique_admissions,
    COUNT(DISTINCT ITEMID) AS unique_measurement_types
```

```
  FROM `my-first-gcp-project-452814.cdle_project_dataset.chartevents_reduced`
),

measurement_analysis AS (
  SELECT
    ITEMID,
    COUNT(*) AS record_count,
    ROUND(COUNT(*)*100/(SELECT total_records FROM stats), 2) AS␣
 ↪percentage_of_total,
    MIN(VALUENUM) AS min_value,
    MAX(VALUENUM) AS max_value,
    AVG(VALUENUM) AS avg_value,
    COUNT(CASE WHEN VALUENUM IS NULL THEN 1 END) AS null_value_counts,
    COUNT(CASE WHEN VALUE = '' THEN 1 END) AS empty_string_counts,
    MIN(CHARTTIME) AS earliest_measurement,
    MAX(CHARTTIME) AS latest_measurement
  FROM `my-first-gcp-project-452814.cdle_project_dataset.chartevents_reduced`
  GROUP BY ITEMID
),

temporal_analysis AS (
  SELECT
    EXTRACT(YEAR FROM CHARTTIME) AS year,
    EXTRACT(MONTH FROM CHARTTIME) AS month,
    COUNT(*) AS measurements_count
  FROM `my-first-gcp-project-452814.cdle_project_dataset.chartevents_reduced`
  GROUP BY year, month
  ORDER BY year, month
)

SELECT
  -- Basic Statistics
  s.total_records,
  s.unique_patients,
  s.unique_admissions,
  s.unique_measurement_types,

  -- Measurement-specific quality metrics
  ARRAY(
    SELECT AS STRUCT * FROM measurement_analysis
    ORDER BY record_count DESC
  ) AS measurement_quality,

  -- Temporal distribution
  (SELECT COUNT(*) FROM temporal_analysis) AS months_with_data,
  (SELECT MIN(year) FROM temporal_analysis) AS first_year,
  (SELECT MAX(year) FROM temporal_analysis) AS last_year,
```

```
   -- Data completeness
   (SELECT COUNT(*) FROM `my-first-gcp-project-452814.cdle_project_dataset.
 ↪chartevents_reduced` WHERE CHARTTIME IS NULL) AS null_timestamps,
   (SELECT COUNT(*) FROM `my-first-gcp-project-452814.cdle_project_dataset.
 ↪chartevents_reduced` WHERE SUBJECT_ID IS NULL) AS null_patient_ids,

   -- Clinical validity checks
   (SELECT COUNT(*) FROM `my-first-gcp-project-452814.cdle_project_dataset.
 ↪chartevents_reduced`
    WHERE ITEMID = 220045 AND (VALUENUM < 20 OR VALUENUM > 250)) AS␣
 ↪abnormal_heart_rates,

   (SELECT COUNT(*) FROM `my-first-gcp-project-452814.cdle_project_dataset.
 ↪chartevents_reduced`
    WHERE ITEMID = 220050 AND (VALUENUM < 50 OR VALUENUM > 300)) AS␣
 ↪abnormal_bp_readings
FROM stats s
"""

query_job = client.query(query)
data_quality = query_job.to_dataframe()

end_time = time.time()
execution_time = end_time - start_time
print(f"Query Execution Time: {execution_time:.2f} seconds")

data_quality
```

```
Query Execution Time: 3.49 seconds
```

[ ]:
```
   total_records  unique_patients  unique_admissions  \
0        6724529            17717              21927

   unique_measurement_types  \
0                         3

                              measurement_quality  months_with_data  \
0  [{'ITEMID': 220045, 'record_count': 2762225, '…              1289

   first_year  last_year  null_timestamps  null_patient_ids  \
0        2100       2209                0                 0

   abnormal_heart_rates  abnormal_bp_readings
0                  1177                     0
```

## 2.2 Admissions

Contains information about patient admissions to the hospital, such as admission and discharge times, admission type, and insurance information.

- `ROW_ID`: Unique identifier for each row
- `SUBJECT_ID`: Foreign key to the PATIENTS table.
- `HADM_ID`: Unique identifier for the hospital admission
- `ADMITTIME`: Timestamp for hospital admission.
- `DISCHTIME`: Timestamp for hospital discharge.
- `DEATHTIME`: Timestamp for patient death, if applicable.
- `ADMISSION_TYPE`: Type of admission, e.g., EMERGENCY, ELECTIVE, URGENT.
- `ADMISSION_LOCATION`: Location of the patient prior to admission.
- `DISCHARGE_LOCATION`: Location to which the patient was discharged.
- `INSURANCE`: The patient's insurance provider.
- `LANGUAGE`: The patient's primary language.
- `RELIGION`: The patient's religious affiliation.
- `MARITAL_STATUS`: The patient's marital status.
- `ETHNICITY`: The patient's ethnicity.
- `EDREGTIME`: Emergency Department registration time
- `EDOUTTIME`: Emergency Department departure time
- `DIAGNOSIS`: The patient's primary diagnosis.
- `HOSPITAL_EXPIRE_FLAG`: Indicates if the patient died in the hospital.
- `HAS_CHARTEVENTS_DATA`: Flag indicating if there is chart event data.

### 2.2.1 Visualization

[ ]:
```python
dataset_id = "cdle_project_dataset"
table_id = "Admissions"

table_ref = client.dataset(dataset_id).table(table_id)

admissions = client.list_rows(table_ref).to_dataframe()

admissions.head()
```

[ ]:
```
   ROW_ID  SUBJECT_ID  HADM_ID                  ADMITTIME  \
0    4060        3369   126808 2111-01-24 11:53:00+00:00
1   50952       74869   123152 2150-09-05 17:49:00+00:00
2   12812       10484   113233 2190-09-18 22:39:00+00:00
3   13573       11091   164694 2101-06-07 13:57:00+00:00
4   33654       27527   155091 2131-08-27 18:01:00+00:00

                  DISCHTIME                  DEATHTIME ADMISSION_TYPE  \
0 2111-01-25 22:40:00+00:00 2111-01-25 22:40:00+00:00      EMERGENCY
1 2150-09-12 18:30:00+00:00 2150-09-12 18:30:00+00:00      EMERGENCY
2 2190-09-24 20:40:00+00:00 2190-09-24 20:40:00+00:00      EMERGENCY
3 2101-09-18 07:20:00+00:00 2101-09-18 07:20:00+00:00      EMERGENCY
```

```
4 2131-10-03 05:30:00+00:00 2131-10-03 05:30:00+00:00      EMERGENCY

          ADMISSION_LOCATION DISCHARGE_LOCATION INSURANCE LANGUAGE  \
0  PHYS REFERRAL/NORMAL DELI       DEAD/EXPIRED   Private     None
1  TRANSFER FROM HOSP/EXTRAM       DEAD/EXPIRED  Medicare     ENGL
2  TRANSFER FROM HOSP/EXTRAM       DEAD/EXPIRED  Medicaid     None
3  CLINIC REFERRAL/PREMATURE       DEAD/EXPIRED   Private     None
4  CLINIC REFERRAL/PREMATURE       DEAD/EXPIRED   Private     PTUN

        RELIGION MARITAL_STATUS         ETHNICITY EDREGTIME EDOUTTIME  \
0   UNOBTAINABLE         SINGLE             WHITE       NaT       NaT
1       CATHOLIC        WIDOWED  ASIAN - JAPANESE       NaT       NaT
2       CATHOLIC        MARRIED             WHITE       NaT       NaT
3       CATHOLIC      SEPARATED             WHITE       NaT       NaT
4  NOT SPECIFIED        MARRIED             WHITE       NaT       NaT

                           DIAGNOSIS  HOSPITAL_EXPIRE_FLAG  \
0                               None                     1
1                ? SEROTONIN SYNDROME                     1
2  (AML) ACUTE MYELOGENOUS LEUKEMIA                     1
3  (AML) ACUTE MYELOGENOUS LEUKEMIA                     1
4  (AML) ACUTE MYELOGENOUS LEUKEMIA                     1

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

### 2.2.2 Data quality check

[ ]:
```
query = """
-- Data Quality Assessment for admissions
SELECT
    COUNT(*) AS total_records,
    COUNT(DISTINCT HADM_ID) AS unique_admissions,
    COUNT(DISTINCT SUBJECT_ID) AS unique_patients,
    COUNT(CASE WHEN ADMITTIME IS NULL THEN 1 END) AS null_admit_times,
    COUNT(CASE WHEN DISCHTIME IS NULL THEN 1 END) AS null_discharge_times,
    COUNT(CASE WHEN ADMISSION_TYPE IS NULL THEN 1 END) AS null_admission_types,
    COUNT(CASE WHEN ADMISSION_LOCATION IS NULL THEN 1 END) AS␣
↪null_admission_locations,
    COUNT(CASE WHEN INSURANCE IS NULL THEN 1 END) AS null_insurance_info,
    MIN(ADMITTIME) AS first_admission,
    MAX(ADMITTIME) AS last_admission
FROM `my-first-gcp-project-452814.cdle_project_dataset.Admissions`;
```

```
"""

query_job = client.query(query)
data_quality = query_job.to_dataframe()
data_quality
```

```
[ ]:   total_records  unique_admissions  unique_patients  null_admit_times  \
0          58976              58976            46520                 0

   null_discharge_times  null_admission_types  null_admission_locations  \
0                     0                     0                         0

   null_insurance_info            first_admission            last_admission
0                    0 2100-06-07 19:59:00+00:00 2210-08-17 17:13:00+00:00
```

### 2.3 Callout

Contains information about requests for services or consultations for patients.

- ROW_ID: Unique identifier for the row.
- SUBJECT_ID: Foreign key to the PATIENTS table.
- HADM_ID: Foreign key to the ADMISSIONS table.
- CALLOUT_ID: Unique identifier for the callout request.
- CALLOUTTIME: Timestamp for the callout request.
- SERVICE_ID: ID of the service requested.
- LOCATION: Location of the patient when the callout was placed.
- STATUS: Status of the callout request.
- OUTCOME: Outcome of the callout request.
- ACKNOWLEDGE_TIME: Timestamp when the callout was acknowledged.
- OUTCOMETIME: Timestamp when the callout outcome was recorded.
- FIRSTRESERVATIONTIME: of the first reservation.
- CURRENTRESERVATIONTIME: Timestamp of the current reservation.
- CREATETIME: Timestamp when the row was created.
- UPDATETIME: Timestamp when the row was updated.
- CALLOUT_WARDID: Ward ID of the callout.
- CALLOUT_SERVICEREQUEST: Service requested.
- CALLOUT_TELEPHONE: Telephone number for the callout.
- REQUEST_TELE: Telephone request.
- REQUEST_RESP: Respiratory reqTimestampuest.
- REQUEST_CDIFF: C. difficile request.
- REQUEST_MRSA: MRSA request.
- REQUEST_VRE: VRE request.
- DISCHARGE_WARDID: Discharge ward ID.
- ACKNOWLEDGE_STATUS: Acknowledge status.

### 2.3.1 Visualization

[ ]:
```
dataset_id = "cdle_project_dataset"
table_id = "Callout"

table_ref = client.dataset(dataset_id).table(table_id)

callout = client.list_rows(table_ref).to_dataframe()

callout.head()
```

[ ]:
```
   ROW_ID  SUBJECT_ID  HADM_ID  SUBMIT_WARDID SUBMIT_CAREUNIT  CURR_WARDID  \
0   15115       31974   144780           <NA>            None         <NA>
1     161         309   162308              7            None            2
2     169         333   160548              7            None            2
3     197         383   173723              7            None            2
4     136         253   176189              7            None            2

  CURR_CAREUNIT  CALLOUT_WARDID CALLOUT_SERVICE  REQUEST_TELE  …  \
0          None               1             MED             1  …
1           CCU               2             CCU             1  …
2           CCU               2             CCU             1  …
3           CCU               2             CCU             1  …
4           CCU               2             CCU             1  …

  CALLOUT_STATUS CALLOUT_OUTCOME  DISCHARGE_WARDID ACKNOWLEDGE_STATUS  \
0       Inactive      Discharged                 0     Unacknowledged
1       Inactive      Discharged                 2       Acknowledged
2       Inactive      Discharged                 2       Acknowledged
3       Inactive      Discharged                 2     Unacknowledged
4       Inactive      Discharged                 2       Acknowledged

                 CREATETIME                UPDATETIME  \
0 2191-01-26 13:55:10+00:00 2191-01-26 13:55:10+00:00
1 2160-06-05 10:22:04+00:00 2160-06-05 10:22:04+00:00
2 2137-09-30 09:42:12+00:00 2137-09-30 09:42:12+00:00
3 2143-09-08 10:53:04+00:00 2143-09-08 10:53:04+00:00
4 2174-01-23 09:57:24+00:00 2174-01-23 10:44:12+00:00

             ACKNOWLEDGETIME               OUTCOMETIME FIRSTRESERVATIONTIME  \
0                        NaT 2191-01-26 14:10:04+00:00                  NaT
1 2160-06-05 11:20:06+00:00 2160-06-05 19:25:01+00:00                  NaT
2 2137-09-30 09:45:08+00:00 2137-10-01 14:40:02+00:00                  NaT
3                        NaT 2143-09-08 11:55:02+00:00                  NaT
4 2174-01-23 11:10:50+00:00 2174-01-23 13:40:02+00:00                  NaT

  CURRENTRESERVATIONTIME
```

```
0                    NaT
1                    NaT
2                    NaT
3                    NaT
4                    NaT

[5 rows x 24 columns]
```

### 2.3.2 Data quality check

```
[ ]: query = """
-- Data Quality Assessment for callout
WITH basic_stats AS (
    SELECT
        COUNT(*) AS total_records,
        COUNT(DISTINCT SUBJECT_ID) AS unique_patients,
        COUNT(DISTINCT HADM_ID) AS unique_admissions,
        COUNT(DISTINCT ROW_ID) AS unique_row_ids,
        COUNT(DISTINCT SUBMIT_WARDID) AS unique_submit_ward_ids,
        COUNT(DISTINCT SUBMIT_CAREUNIT) AS unique_submit_care_units,
        COUNT(DISTINCT CURR_WARDID) AS unique_current_ward_ids,
        COUNT(DISTINCT CURR_CAREUNIT) AS unique_current_care_units,
        COUNT(DISTINCT CALLOUT_WARDID) AS unique_callout_ward_ids,
        COUNT(DISTINCT CALLOUT_SERVICE) AS unique_callout_service,
        COUNT(DISTINCT REQUEST_TELE) AS unique_request_telephones,
        COUNT(DISTINCT REQUEST_RESP) AS unique_request_resp,
        COUNT(DISTINCT REQUEST_CDIFF) AS unique_request_cdiff,
        COUNT(DISTINCT REQUEST_MRSA) AS unique_request_mrsa,
        COUNT(DISTINCT REQUEST_VRE) AS unique_request_vre,
        COUNT(DISTINCT CALLOUT_STATUS) AS unique_callout_statuses,
        COUNT(DISTINCT CALLOUT_OUTCOME) AS unique_callout_outcomes,
        COUNT(DISTINCT DISCHARGE_WARDID) AS unique_discharge_ward_ids,
        COUNT(DISTINCT ACKNOWLEDGE_STATUS) AS unique_acknowledge_statuses
    FROM `my-first-gcp-project-452814.cdle_project_dataset.Callout`
),
completeness AS (
    SELECT
        COUNT(CASE WHEN SUBJECT_ID IS NULL THEN 1 END) AS null_subject_ids,
        COUNT(CASE WHEN HADM_ID IS NULL THEN 1 END) AS null_hadm_ids,
        COUNT(CASE WHEN SUBMIT_WARDID IS NULL THEN 1 END) AS␣
 ↪null_submit_ward_ids,
        COUNT(CASE WHEN SUBMIT_CAREUNIT IS NULL THEN 1 END) AS␣
 ↪null_submit_care_units,
        COUNT(CASE WHEN SUBMIT_CAREUNIT = '' THEN 1 END) AS␣
 ↪empty_submit_care_units,
        COUNT(CASE WHEN CURR_WARDID IS NULL THEN 1 END) AS null_curr_ward_ids,
```

```
        COUNT(CASE WHEN CURR_CAREUNIT IS NULL THEN 1 END) AS null_curr_care_units,
        COUNT(CASE WHEN CURR_CAREUNIT = '' THEN 1 END) AS empty_curr_care_units,
        COUNT(CASE WHEN CALLOUT_WARDID IS NULL THEN 1 END) AS null_callout_ward_ids,
        COUNT(CASE WHEN CALLOUT_SERVICE IS NULL THEN 1 END) AS null_callout_service,
        COUNT(CASE WHEN CALLOUT_SERVICE = '' THEN 1 END) AS empty_callout_service,
        COUNT(CASE WHEN REQUEST_TELE IS NULL THEN 1 END) AS null_request_telephones,
        COUNT(CASE WHEN REQUEST_RESP IS NULL THEN 1 END) AS null_request_resp,
        COUNT(CASE WHEN REQUEST_CDIFF IS NULL THEN 1 END) AS null_request_cdiff,
        COUNT(CASE WHEN REQUEST_MRSA IS NULL THEN 1 END) AS null_request_mrsa,
        COUNT(CASE WHEN REQUEST_VRE IS NULL THEN 1 END) AS null_request_vre,
        COUNT(CASE WHEN CALLOUT_STATUS IS NULL THEN 1 END) AS null_callout_statuses,
        COUNT(CASE WHEN CALLOUT_STATUS = '' THEN 1 END) AS empty_callout_statuses,
        COUNT(CASE WHEN CALLOUT_OUTCOME IS NULL THEN 1 END) AS null_callout_outcomes,
        COUNT(CASE WHEN CALLOUT_OUTCOME = '' THEN 1 END) AS empty_callout_outcomes,
        COUNT(CASE WHEN DISCHARGE_WARDID IS NULL THEN 1 END) AS null_discharge_ward_ids,
        COUNT(CASE WHEN ACKNOWLEDGE_STATUS IS NULL THEN 1 END) AS null_acknowledge_statuses,
        COUNT(CASE WHEN ACKNOWLEDGE_STATUS = '' THEN 1 END) AS empty_acknowledge_statuses,
        COUNT(CASE WHEN CREATETIME IS NULL THEN 1 END) AS null_createtimes,
        COUNT(CASE WHEN UPDATETIME IS NULL THEN 1 END) AS null_updatetimes,
        COUNT(CASE WHEN ACKNOWLEDGETIME IS NULL THEN 1 END) AS null_acknowledgetimes,
        COUNT(CASE WHEN OUTCOMETIME IS NULL THEN 1 END) AS null_outcometimes,
        COUNT(CASE WHEN FIRSTRESERVATIONTIME IS NULL THEN 1 END) AS null_firstreservationtimes,
        COUNT(CASE WHEN CURRENTRESERVATIONTIME IS NULL THEN 1 END) AS null_currentreservationtimes
    FROM `my-first-gcp-project-452814.cdle_project_dataset.Callout`
),
temporal_analysis AS (
    SELECT
        MIN(CREATETIME) AS first_creation_time,
        MAX(CREATETIME) AS last_creation_time,
        MIN(UPDATETIME) AS first_update_time,
        MAX(UPDATETIME) AS last_update_time,
```

```
        MIN(ACKNOWLEDGETIME) AS first_acknowledge_time,
        MAX(ACKNOWLEDGETIME) AS last_acknowledge_time,
        MIN(OUTCOMETIME) AS first_outcome_time,
        MAX(OUTCOMETIME) AS last_outcome_time,
        MIN(FIRSTRESERVATIONTIME) AS first_reservation_time,
        MAX(FIRSTRESERVATIONTIME) AS last_reservation_time,
        MIN(CURRENTRESERVATIONTIME) AS first_current_reservation_time,
        MAX(CURRENTRESERVATIONTIME) AS last_current_reservation_time
    FROM `my-first-gcp-project-452814.cdle_project_dataset.Callout`
)
SELECT
    bs.*,
    c.*,
    t.*
FROM basic_stats bs
CROSS JOIN completeness c
CROSS JOIN temporal_analysis t;
"""

query_job = client.query(query)
data_quality = query_job.to_dataframe()
data_quality
```

[ ]:
```
   total_records  unique_patients  unique_admissions  unique_row_ids  \
0          34499            22871              28732           34499

   unique_submit_ward_ids  unique_submit_care_units  unique_current_ward_ids  \
0                       9                         5                       35

   unique_current_care_units  unique_callout_ward_ids  unique_callout_service  \
0                          5                       37                      21

   …          first_update_time          last_update_time  \
0  … 2100-06-08 12:58:29+00:00 2210-08-20 16:05:16+00:00

     first_acknowledge_time     last_acknowledge_time  \
0 2100-06-08 12:58:32+00:00 2210-08-20 16:05:27+00:00

         first_outcome_time         last_outcome_time  \
0 2100-06-08 15:10:26+00:00 2210-08-20 18:55:15+00:00

     first_reservation_time     last_reservation_time  \
0 2100-06-08 11:55:26+00:00 2210-08-20 16:25:16+00:00

   first_current_reservation_time  last_current_reservation_time
0       2100-08-09 14:42:25+00:00      2209-08-05 14:01:23+00:00
```

```
[1 rows x 60 columns]
```

## 2.4 ICD Diagnoses Description

Contains descriptions for ICD-9 diagnosis codes.

- `ROW_ID`: Unique identifier for the row.
- `ICD9_CODE`: The ICD-9 diagnosis code.
- `SHORT_TITLE`: Short description of the diagnosis.
- `LONG_TITLE`: Long description of the diagnosis.

### 2.4.1 Visualization

[ ]:
```
dataset_id = "cdle_project_dataset"
table_id = "D_ICD_Diagnoses"

table_ref = client.dataset(dataset_id).table(table_id)

d_icd_diagnoses = client.list_rows(table_ref).to_dataframe()

d_icd_diagnoses.head()
```

[ ]:
```
   ROW_ID ICD9_CODE               SHORT_TITLE  \
0    5120      4957   "ventilation" pneumonit
1   11159     94416   1 deg burn back of hand
2   11157     94414  1 deg burn fingr w thumb
3    3658     36911   1 eye-sev/oth-blind NOS
4   12505     94811  10-19% bdy brn/10-19% 3d

                                          LONG_TITLE
0                           "Ventilation" pneumonitis
1              Erythema [first degree] of back of hand
2  Erythema [first degree] of two or more digits …
3  Better eye: severe vision impairment; lesser e…
4  Burn [any degree] involving 10-19 percent of b…
```

### 2.4.2 Data quality check

[ ]:
```
query = """
-- Data Quality Assessment for d_icd_diagnoses
SELECT
    COUNT(*) AS total_records,
    COUNT(DISTINCT ROW_ID) AS unique_row_ids,
    COUNT(DISTINCT ICD9_CODE) AS unique_icd9_codes,
    COUNT(DISTINCT SHORT_TITLE) AS unique_short_titles,
    COUNT(DISTINCT LONG_TITLE) AS unique_long_titles,
```

```
    -- Completeness checks
    COUNT(CASE WHEN ROW_ID IS NULL THEN 1 END) AS null_row_ids,
    COUNT(CASE WHEN ICD9_CODE IS NULL THEN 1 END) AS null_icd9_codes,
    COUNT(CASE WHEN SHORT_TITLE IS NULL THEN 1 END) AS null_short_titles,
    COUNT(CASE WHEN LONG_TITLE IS NULL THEN 1 END) AS null_long_titles,

    COUNT(CASE WHEN ICD9_CODE = '' THEN 1 END) AS empty_icd9_codes,
    COUNT(CASE WHEN SHORT_TITLE = '' THEN 1 END) AS empty_short_titles,
    COUNT(CASE WHEN LONG_TITLE = '' THEN 1 END) AS empty_long_titles,

    -- Basic Analysis of ICD9 Code Length
    AVG(LENGTH(ICD9_CODE)) AS avg_icd9_code_length,
    MIN(LENGTH(ICD9_CODE)) AS min_icd9_code_length,
    MAX(LENGTH(ICD9_CODE)) AS max_icd9_code_length,
    COUNT(CASE WHEN LENGTH(ICD9_CODE) NOT BETWEEN 3 AND 5 THEN 1 END) AS␣
↪potential_invalid_icd9_length_count,

    -- Potential data inconsistencies
    COUNT(CASE WHEN SHORT_TITLE LIKE '%NOS%' AND LONG_TITLE NOT LIKE '%not␣
↪otherwise specified%' THEN 1 END) AS short_title_nos_long_title_mismatch,
    COUNT(CASE WHEN SHORT_TITLE LIKE '%NEC%' AND LONG_TITLE NOT LIKE '%not␣
↪elsewhere classified%' THEN 1 END) AS short_title_nec_long_title_mismatch

FROM
    `my-first-gcp-project-452814.cdle_project_dataset.D_ICD_Diagnoses`;
"""
query_job = client.query(query)
data_quality = query_job.to_dataframe()
data_quality
```

[ ]:

```
   total_records  unique_row_ids  unique_icd9_codes  unique_short_titles  \
0          14567           14567              14567                14328

   unique_long_titles  null_row_ids  null_icd9_codes  null_short_titles  \
0               14562             0                0                  0

   null_long_titles  empty_icd9_codes  empty_short_titles  empty_long_titles  \
0                 0                 0                   0                  0

   avg_icd9_code_length  min_icd9_code_length  max_icd9_code_length  \
0              4.686483                     3                     5

   potential_invalid_icd9_length_count  short_title_nos_long_title_mismatch  \
0                                    0                                 2195

   short_title_nec_long_title_mismatch
0                                 2138
```

### 2.5 D Items

Contains metadata about different medical items (measurements, procedures, medications) recorded in the database.

- ROW_ID: Unique identifier for the row.
- ITEMID: Unique identifier for the item.
- LABEL: Label or name of the item.
- ABBREVIATION: Abbreviation for the item.
- DBSOURCE: Source database for the item.
- LINKSTO: Table linked to.
- CATEGORY: Category of the item.
- UNITNAME: Unit of measurement for the item.
- PARAM_TYPE: Parameter type.
- CONCEPTID: Identifier for the concept.

#### 2.5.1 Visualization

[ ]:
```
dataset_id = "cdle_project_dataset"
table_id = "D_Items"

table_ref = client.dataset(dataset_id).table(table_id)

d_items = client.list_rows(table_ref).to_dataframe()

d_items.head()
```

[ ]:
```
   ROW_ID  ITEMID                                          LABEL ABBREVIATION  \
0     457     497  Patient controlled analgesia (PCA) [Inject]         None
1     458     498                               PCA Lockout (Min)         None
2     459     499                                  PCA Medication         None
3     460     500                                  PCA Total Dose         None
4     461     501                              PCV Exh Vt (Obser)         None

  DBSOURCE      LINKSTO CATEGORY UNITNAME PARAM_TYPE CONCEPTID
0  carevue  chartevents     None     None       None      None
1  carevue  chartevents     None     None       None      None
2  carevue  chartevents     None     None       None      None
3  carevue  chartevents     None     None       None      None
4  carevue  chartevents     None     None       None      None
```

#### 2.5.2 Data quality check

[ ]:
```
query = """
-- Data Quality Assessment for d_items
SELECT
    COUNT(*) AS total_records,
    COUNT(DISTINCT ROW_ID) AS unique_row_ids,
```

```
    COUNT(DISTINCT ITEMID) AS unique_itemids,
    COUNT(DISTINCT LABEL) AS unique_labels,
    COUNT(DISTINCT ABBREVIATION) AS unique_abbreviations,
    COUNT(DISTINCT DBSOURCE) AS unique_dbsources,
    COUNT(DISTINCT LINKSTO) AS unique_linkstos,
    COUNT(DISTINCT CATEGORY) AS unique_categories,
    COUNT(DISTINCT UNITNAME) AS unique_unitnames,
    COUNT(DISTINCT PARAM_TYPE) AS unique_param_types,
    COUNT(DISTINCT CONCEPTID) AS unique_conceptids,

    -- Completeness checks (NULL values)
    COUNT(CASE WHEN ROW_ID IS NULL THEN 1 END) AS null_row_ids,
    COUNT(CASE WHEN ITEMID IS NULL THEN 1 END) AS null_itemids,
    COUNT(CASE WHEN LABEL IS NULL THEN 1 END) AS null_labels,
    COUNT(CASE WHEN ABBREVIATION IS NULL THEN 1 END) AS null_abbreviations,
    COUNT(CASE WHEN DBSOURCE IS NULL THEN 1 END) AS null_dbsources,
    COUNT(CASE WHEN LINKSTO IS NULL THEN 1 END) AS null_linkstos,
    COUNT(CASE WHEN CATEGORY IS NULL THEN 1 END) AS null_categories,
    COUNT(CASE WHEN UNITNAME IS NULL THEN 1 END) AS null_unitnames,
    COUNT(CASE WHEN PARAM_TYPE IS NULL THEN 1 END) AS null_param_types,
    COUNT(CASE WHEN CONCEPTID IS NULL THEN 1 END) AS null_conceptids,

    -- Completeness checks (Empty strings)
    COUNT(CASE WHEN LABEL = '' THEN 1 END) AS empty_labels,
    COUNT(CASE WHEN ABBREVIATION = '' THEN 1 END) AS empty_abbreviations,
    COUNT(CASE WHEN DBSOURCE = '' THEN 1 END) AS empty_dbsources,
    COUNT(CASE WHEN LINKSTO = '' THEN 1 END) AS empty_linkstos,
    COUNT(CASE WHEN CATEGORY = '' THEN 1 END) AS empty_categories,
    COUNT(CASE WHEN UNITNAME = '' THEN 1 END) AS empty_unitnames,
    COUNT(CASE WHEN PARAM_TYPE = '' THEN 1 END) AS empty_param_types,
    COUNT(CASE WHEN CONCEPTID = '' THEN 1 END) AS empty_conceptids

FROM
    `my-first-gcp-project-452814.cdle_project_dataset.D_Items`;
"""
query_job = client.query(query)
data_quality = query_job.to_dataframe()
data_quality
```

[ ]:

```
   total_records  unique_row_ids  unique_itemids  unique_labels  \
0          12487           12487           12487          11847

   unique_abbreviations  unique_dbsources  unique_linkstos  unique_categories  \
0                  2907                 3                7                 94

   unique_unitnames  unique_param_types  …  null_param_types  \
0                53                   7  …              9495
```

```
   null_conceptids  empty_labels  empty_abbreviations  empty_dbsources  \
0            12487             0                    0                0

   empty_linkstos  empty_categories  empty_unitnames  empty_param_types  \
0               0                 0                0                  0

   empty_conceptids
0                 0

[1 rows x 29 columns]
```

### 2.6 ICD Diagnoses

Contains ICD-9 diagnosis codes assigned to patients during their hospital admissions.

- `ROW_ID`: Unique identifier for the row.
- `SUBJECT_ID`: Foreign key to the PATIENTS table.
- `HADM_ID`: Foreign key to the ADMISSIONS table.
- `SEQ_NUM`: Sequence number for the diagnosis within the admission.
- `ICD9_CODE`: The ICD-9 diagnosis code.

#### 2.6.1 Visualization

[ ]:
```
dataset_id = "cdle_project_dataset"
table_id = "Diagnoses_ICD"

table_ref = client.dataset(dataset_id).table(table_id)

diagnoses_icd = client.list_rows(table_ref).to_dataframe()

diagnoses_icd.head()
```

[ ]:

| | ROW_ID | SUBJECT_ID | HADM_ID | SEQ_NUM | ICD9_CODE |
|---|---|---|---|---|---|
| 0 | 1297 | 109 | 172335 | 1 | 40301 |
| 1 | 1298 | 109 | 172335 | 2 | 486 |
| 2 | 1299 | 109 | 172335 | 3 | 58281 |
| 3 | 1300 | 109 | 172335 | 4 | 5855 |
| 4 | 1301 | 109 | 172335 | 5 | 4254 |

#### 2.6.2 Data quality check

[ ]:
```
query = """
-- Data Quality Assessment for diagnoses_icd
SELECT
    COUNT(*) AS total_records,
    COUNT(DISTINCT ROW_ID) AS unique_row_ids,
```

```
    COUNT(DISTINCT SUBJECT_ID) AS unique_patients,
    COUNT(DISTINCT HADM_ID) AS unique_admissions,
    COUNT(DISTINCT SEQ_NUM) AS unique_sequence_numbers,
    COUNT(DISTINCT ICD9_CODE) AS unique_icd9_codes,

    -- Completeness checks (NULL values)
    COUNT(CASE WHEN ROW_ID IS NULL THEN 1 END) AS null_row_ids,
    COUNT(CASE WHEN SUBJECT_ID IS NULL THEN 1 END) AS null_subject_ids,
    COUNT(CASE WHEN HADM_ID IS NULL THEN 1 END) AS null_hadm_ids,
    COUNT(CASE WHEN SEQ_NUM IS NULL THEN 1 END) AS null_sequence_numbers,
    COUNT(CASE WHEN ICD9_CODE IS NULL THEN 1 END) AS null_icd9_codes,

    -- Completeness checks (Empty strings)
    COUNT(CASE WHEN ICD9_CODE = '' THEN 1 END) AS empty_icd9_codes,

    -- Analysis of ICD9 Code Length
    AVG(LENGTH(ICD9_CODE)) AS avg_icd9_code_length,
    MIN(LENGTH(ICD9_CODE)) AS min_icd9_code_length,
    MAX(LENGTH(ICD9_CODE)) AS max_icd9_code_length,
    COUNT(CASE WHEN LENGTH(ICD9_CODE) NOT BETWEEN 3 AND 5 THEN 1 END) AS␣
  ↪potential_invalid_icd9_length_count

FROM
    `my-first-gcp-project-452814.cdle_project_dataset.Diagnoses_ICD`;
"""
query_job = client.query(query)
data_quality = query_job.to_dataframe()
data_quality
```

[ ]:

```
   total_records  unique_row_ids  unique_patients  unique_admissions  \
0         651047          651047            46520              58976

   unique_sequence_numbers  unique_icd9_codes  null_row_ids  null_subject_ids  \
0                       39               6984             0                 0

   null_hadm_ids  null_sequence_numbers  null_icd9_codes  empty_icd9_codes  \
0              0                     47               47                 0

   avg_icd9_code_length  min_icd9_code_length  max_icd9_code_length  \
0              4.448883                     3                     5

   potential_invalid_icd9_length_count
0                                    0
```

## 2.7 Icustays

Contains information about patient stays in the intensive care unit (ICU).

- ROW_ID: Unique identifier for the row.
- SUBJECT_ID: Foreign key to the PATIENTS table.
- HADM_ID: Foreign key to the ADMISSIONS table.
- ICUSTAY_ID: Unique identifier for the ICU stay.
- DBSOURCE: Source database.
- FIRST_CAREUNIT: First care unit the patient was in.
- LAST_CAREUNIT: Last care unit the patient was in.
- FIRST_WARDID: First ward ID.
- LAST_WARDID: Last ward ID.
- INTIME: Timestamp for ICU admission.
- OUTTIME: Timestamp for ICU discharge.
- LOS: Length of ICU stay.

### 2.7.1 Visualization

[ ]:
```
dataset_id = "cdle_project_dataset"
table_id = "ICUStays"

table_ref = client.dataset(dataset_id).table(table_id)

icustays = client.list_rows(table_ref).to_dataframe()

icustays.head()
```

[ ]:
```
   ROW_ID  SUBJECT_ID  HADM_ID  ICUSTAY_ID    DBSOURCE FIRST_CAREUNIT  \
0     372         275   129886      219649     carevue            CCU
1     389         291   113649      256641     carevue            CCU
2     390         291   125726      275109  metavision            CCU
3     394         294   152578      222074     carevue            CCU
4     401         301   160332      288401     carevue            CCU

  LAST_CAREUNIT  FIRST_WARDID  LAST_WARDID                    INTIME  \
0           CCU             7            7 2170-10-07 11:28:53+00:00
1           CCU             7            7 2102-04-08 23:05:28+00:00
2           CCU             7            7 2106-04-17 12:26:17+00:00
3           CCU             7            7 2118-01-17 21:45:05+00:00
4           CCU             7            7 2189-11-11 12:12:33+00:00

                    OUTTIME     LOS
0 2170-10-14 14:38:07+00:00  7.1314
1 2102-04-09 11:20:11+00:00  0.5102
2 2106-04-18 22:05:39+00:00  1.4023
3 2118-01-20 11:12:45+00:00  2.5609
4 2189-11-13 22:11:28+00:00  2.4159
```

### 2.7.2 Data quality check

[ ]:
```
query = """
-- Data Quality Assessment for icustays
SELECT
    COUNT(*) AS total_records,
    COUNT(DISTINCT ROW_ID) AS unique_row_ids,
    COUNT(DISTINCT SUBJECT_ID) AS unique_patients,
    COUNT(DISTINCT HADM_ID) AS unique_admissions,
    COUNT(DISTINCT ICUSTAY_ID) AS unique_icustay_ids,
    COUNT(DISTINCT DBSOURCE) AS unique_dbsources,
    COUNT(DISTINCT FIRST_CAREUNIT) AS unique_first_careunits,
    COUNT(DISTINCT LAST_CAREUNIT) AS unique_last_careunits,
    COUNT(DISTINCT FIRST_WARDID) AS unique_first_wardids,
    COUNT(DISTINCT LAST_WARDID) AS unique_last_wardids,

    -- Completeness checks (NULL values)
    COUNT(CASE WHEN ROW_ID IS NULL THEN 1 END) AS null_row_ids,
    COUNT(CASE WHEN SUBJECT_ID IS NULL THEN 1 END) AS null_subject_ids,
    COUNT(CASE WHEN HADM_ID IS NULL THEN 1 END) AS null_hadm_ids,
    COUNT(CASE WHEN ICUSTAY_ID IS NULL THEN 1 END) AS null_icustay_ids,
    COUNT(CASE WHEN DBSOURCE IS NULL THEN 1 END) AS null_dbsources,
    COUNT(CASE WHEN FIRST_CAREUNIT IS NULL THEN 1 END) AS null_first_careunits,
    COUNT(CASE WHEN LAST_CAREUNIT IS NULL THEN 1 END) AS null_last_careunits,
    COUNT(CASE WHEN FIRST_WARDID IS NULL THEN 1 END) AS null_first_wardids,
    COUNT(CASE WHEN LAST_WARDID IS NULL THEN 1 END) AS null_last_wardids,
    COUNT(CASE WHEN INTIME IS NULL THEN 1 END) AS null_intimes,
    COUNT(CASE WHEN OUTTIME IS NULL THEN 1 END) AS null_outtimes,
    COUNT(CASE WHEN LOS IS NULL THEN 1 END) AS null_los,

    -- Completeness checks (Empty strings)
    COUNT(CASE WHEN FIRST_CAREUNIT = '' THEN 1 END) AS empty_first_careunits,
    COUNT(CASE WHEN LAST_CAREUNIT = '' THEN 1 END) AS empty_last_careunits,
    COUNT(CASE WHEN DBSOURCE = '' THEN 1 END) AS empty_dbsources,

    -- Basic Analysis of LOS (Length of ICU Stay)
    AVG(LOS) AS avg_los,
    MIN(LOS) AS min_los,
    MAX(LOS) AS max_los,
    COUNT(CASE WHEN LOS < 0 THEN 1 END) AS negative_los_count -- Potential data␣
 ↪issue

FROM
    `my-first-gcp-project-452814.cdle_project_dataset.ICUStays`;
"""
query_job = client.query(query)
data_quality = query_job.to_dataframe()
```

```
data_quality
```

```
[ ]:    total_records  unique_row_ids  unique_patients  unique_admissions  \
0           61532           61532            46476              57786

   unique_icustay_ids  unique_dbsources  unique_first_careunits  \
0               61532                 3                       6

   unique_last_careunits  unique_first_wardids  unique_last_wardids  …  \
0                      6                    16                   17  …

   null_intimes  null_outtimes  null_los  empty_first_careunits  \
0             0             10        10                      0

   empty_last_careunits  empty_dbsources   avg_los  min_los   max_los  \
0                     0                0  4.917972   0.0001  173.0725

   negative_los_count
0                   0

[1 rows x 29 columns]
```

## 2.8 Patients

Contains demographic information about the patients in the database.

- ROW_ID: Unique identifier for the row.
- SUBJECT_ID: Unique identifier for the patient.
- GENDER: Patient's gender.
- DOB: Patient's date of birth.
- DOD: Patient's date of death, if applicable.
- DOD_HOSP: Date of death in hospital.
- DOD_SSN: Date of death according to Social Security records.
- EXPIRE_FLAG: Flag indicating if the patient expired.

### 2.8.1 Visualization

```
[ ]: dataset_id = "cdle_project_dataset"
table_id = "Patients"

table_ref = client.dataset(dataset_id).table(table_id)

patients = client.list_rows(table_ref).to_dataframe()

patients.head()
```

```
[ ]:    ROW_ID  SUBJECT_ID GENDER                       DOB DOD DOD_HOSP DOD_SSN  \
     0     234         249      F 2075-03-13 00:00:00+00:00 NaT      NaT     NaT
     1     238         253      F 2089-11-26 00:00:00+00:00 NaT      NaT     NaT
     2     242         258      F 2124-09-19 00:00:00+00:00 NaT      NaT     NaT
     3     243         260      F 2105-03-23 00:00:00+00:00 NaT      NaT     NaT
     4     247         264      F 2162-11-30 00:00:00+00:00 NaT      NaT     NaT

        EXPIRE_FLAG
     0            0
     1            0
     2            0
     3            0
     4            0
```

#### 2.8.2 Data quality check

```
[ ]: query = """
-- Data Quality Assessment for patients
SELECT
    COUNT(*) AS total_records,
    COUNT(DISTINCT ROW_ID) AS unique_row_ids,
    COUNT(DISTINCT SUBJECT_ID) AS unique_patients,
    COUNT(DISTINCT GENDER) AS unique_genders,
    COUNT(DISTINCT DOB) AS unique_dates_of_birth,
    COUNT(DISTINCT DOD) AS unique_dates_of_death,
    COUNT(DISTINCT DOD_HOSP) AS unique_dates_of_death_hospital,
    COUNT(DISTINCT DOD_SSN) AS unique_dates_of_death_ssn,
    COUNT(DISTINCT EXPIRE_FLAG) AS unique_expire_flags,

    -- Completeness checks (NULL values)
    COUNT(CASE WHEN ROW_ID IS NULL THEN 1 END) AS null_row_ids,
    COUNT(CASE WHEN SUBJECT_ID IS NULL THEN 1 END) AS null_subject_ids,
    COUNT(CASE WHEN GENDER IS NULL THEN 1 END) AS null_genders,
    COUNT(CASE WHEN DOB IS NULL THEN 1 END) AS null_dates_of_birth,
    COUNT(CASE WHEN DOD IS NULL THEN 1 END) AS null_dates_of_death,
    COUNT(CASE WHEN DOD_HOSP IS NULL THEN 1 END) AS␣
 ↪null_dates_of_death_hospital,
    COUNT(CASE WHEN DOD_SSN IS NULL THEN 1 END) AS null_dates_of_death_ssn,
    COUNT(CASE WHEN EXPIRE_FLAG IS NULL THEN 1 END) AS null_expire_flags,

    -- Completeness checks (Empty strings)
    COUNT(CASE WHEN GENDER = '' THEN 1 END) AS empty_genders,

    -- Basic Analysis of Dates
    MIN(DOB) AS first_dob,
    MAX(DOB) AS last_dob,
    MIN(DOD) AS first_dod,
```

```
    MAX(DOD) AS last_dod,

    -- Potential Data Inconsistencies
    COUNT(CASE WHEN DOD IS NOT NULL AND EXPIRE_FLAG = 0 THEN 1 END) AS␣
↪died_but_not_expired_flag,
    COUNT(CASE WHEN DOD IS NULL AND EXPIRE_FLAG = 1 THEN 1 END) AS␣
↪expired_flag_but_no_dod

FROM
    `my-first-gcp-project-452814.cdle_project_dataset.Patients`;
"""
query_job = client.query(query)
data_quality = query_job.to_dataframe()
data_quality
```

[ ]:

```
   total_records  unique_row_ids  unique_patients  unique_genders  \
0          46520           46520            46520               2

   unique_dates_of_birth  unique_dates_of_death  \
0                  32540                  12911

   unique_dates_of_death_hospital  unique_dates_of_death_ssn  \
0                            8747                      11301

   unique_expire_flags  null_row_ids  …  null_dates_of_death_hospital  \
0                    2             0  …                         36546

   null_dates_of_death_ssn  null_expire_flags  empty_genders  \
0                    33142                  0              0

                  first_dob                  last_dob  \
0 1800-07-02 00:00:00+00:00 2201-07-24 00:00:00+00:00

                  first_dod                  last_dod  \
0 2100-06-19 00:00:00+00:00 2211-06-10 00:00:00+00:00

  died_but_not_expired_flag expired_flag_but_no_dod
0                         0                       0

[1 rows x 24 columns]
```

# 3 Junction of tables

To make the pre-processing and Length of ICU Stay prediction more efficient we decided to create a table, using a querie, that contain the most relevant columns of each of the datasets.

The most relevant columns choosen were: - Patient Info: `SUBJECT_ID`, `GENDER`, `DOB`, `EXPIRE_FLAG`, AGE_AT_ADMISSION - Admission Info: HADM_ID, ADMITTIME, DISCHTIME, ADMISSION_TYPE, ADMISSION_LOCATION, INSURANCE, ETHNICITY, ADMISSION_DIAGNOSIS_TEXT, ADMISSION_HOUR - ICU Stay Info: ICUSTAY_ID, ICU_INTIME, ICU_OUTTIME, ICU_LOS (Target), FIRST_CAREUNIT - Diagnosis Info: PRIMARY_ICD9_CODE, PRIMARY_ICD9_TITLE - Callout Info: NUM_CALLOUTS

[ ]:
```
query = """
-- Creating a junction table with aggregated diagnoses, callouts and engineered␣
 ↪features

CREATE OR REPLACE TABLE `my-first-gcp-project-452814.cdle_project_dataset.
 ↪junction_table` AS

-- Define CTEs within the AS clause
WITH
  -- CTE to select only the primary diagnosis for each hospital admission
  PrimaryDiagnosis AS (
    SELECT
      di.HADM_ID,
      di.ICD9_CODE,
      dd.SHORT_TITLE AS ICD9_SHORT_TITLE
    FROM
      `my-first-gcp-project-452814.cdle_project_dataset.Diagnoses_ICD` AS di
    LEFT JOIN
      `my-first-gcp-project-452814.cdle_project_dataset.D_ICD_Diagnoses` AS dd␣
 ↪ON di.ICD9_CODE = dd.ICD9_CODE
    WHERE
      di.SEQ_NUM = 1 -- Filter for primary diagnosis only
  ),

  -- CTE to count the number of callouts for each hospital admission
  CalloutCount AS (
    SELECT
      HADM_ID,
      COUNT(*) AS NUM_CALLOUTS -- Count callouts per admission
    FROM
      `my-first-gcp-project-452814.cdle_project_dataset.Callout`
    GROUP BY
      HADM_ID
  )

-- Main SELECT statement that uses the CTEs
SELECT
    -- Patient demographics & calculated age
    p.SUBJECT_ID,
    p.GENDER,
    p.DOB,
    p.EXPIRE_FLAG,
```

```
    DATE_DIFF(DATE(a.ADMITTIME), DATE(p.DOB), YEAR) AS AGE_AT_ADMISSION, --␣
↪Calculate age

    -- Admission details & extracted features
    a.HADM_ID,
    a.ADMITTIME,
    a.DISCHTIME,
    a.ADMISSION_TYPE,
    a.ADMISSION_LOCATION,
    a.INSURANCE,
    a.ETHNICITY,
    a.DIAGNOSIS AS ADMISSION_DIAGNOSIS_TEXT,
    EXTRACT(HOUR FROM a.ADMITTIME) AS ADMISSION_HOUR,

    -- ICU stay details (TARGET VARIABLE HERE)
    icu.ICUSTAY_ID,
    icu.INTIME AS ICU_INTIME,
    icu.OUTTIME AS ICU_OUTTIME,
    icu.LOS AS ICU_LOS,           -- TARGET VARIABLE
    icu.FIRST_CAREUNIT,

    -- Primary Diagnosis details (from CTE)
    pd.ICD9_CODE AS PRIMARY_ICD9_CODE,
    pd.ICD9_SHORT_TITLE AS PRIMARY_ICD9_TITLE,

    -- Aggregated Callout details (from CTE)
    cc.NUM_CALLOUTS

FROM
    -- Start with patients table
    `my-first-gcp-project-452814.cdle_project_dataset.Patients` AS p
LEFT JOIN
    -- Join with admissions using SUBJECT_ID
    `my-first-gcp-project-452814.cdle_project_dataset.Admissions` AS a ON p.
↪SUBJECT_ID = a.SUBJECT_ID
LEFT JOIN
    -- Join with ICU stays using HADM_ID
    `my-first-gcp-project-452814.cdle_project_dataset.ICUStays` AS icu ON a.
↪HADM_ID = icu.HADM_ID
LEFT JOIN
    -- Join with pre-filtered primary diagnosis using HADM_ID
    PrimaryDiagnosis AS pd ON a.HADM_ID = pd.HADM_ID
LEFT JOIN
    -- Join with pre-aggregated callout counts using HADM_ID
    CalloutCount AS cc ON a.HADM_ID = cc.HADM_ID
```

```
"""

query_job = client.query(query)
query_job.result()
```

[ ]: <google.cloud.bigquery.table._EmptyRowIterator at 0x79c9620a6dd0>

### 3.0.1 Visualization

[ ]:
```
dataset_id = "cdle_project_dataset"
table_id = "junction_table"

table_ref = client.dataset(dataset_id).table(table_id)

junction_table = client.list_rows(table_ref).to_dataframe()

junction_table.head()
```

[ ]:
```
   SUBJECT_ID GENDER                        DOB  EXPIRE_FLAG  AGE_AT_ADMISSION  \
0       21852      M 2079-10-15 00:00:00+00:00            1                54
1       19082      F 1869-10-30 00:00:00+00:00            1               300
2       23493      M 2103-04-03 00:00:00+00:00            0                 0
3       20778      F 2105-09-02 00:00:00+00:00            1                75
4       13647      M 2081-12-22 00:00:00+00:00            0                27

   HADM_ID                 ADMITTIME                 DISCHTIME ADMISSION_TYPE  \
0   144317 2133-06-02 05:09:00+00:00 2133-06-02 03:14:00+00:00      EMERGENCY
1   187326 2169-10-30 04:28:00+00:00 2169-11-06 19:45:00+00:00      EMERGENCY
2   127281 2103-04-03 09:25:00+00:00 2103-04-08 12:17:00+00:00        NEWBORN
3   113683 2180-12-02 17:46:00+00:00 2180-12-11 19:21:00+00:00      EMERGENCY
4   143439 2108-12-17 01:53:00+00:00 2108-12-23 13:00:00+00:00      EMERGENCY

         ADMISSION_LOCATION  …       ADMISSION_DIAGNOSIS_TEXT  \
0  ** INFO NOT AVAILABLE **  …                 CARDIAC ARREST
1  ** INFO NOT AVAILABLE **  …  RESPIRATORY FAILURE,UROSEPSIS
2  ** INFO NOT AVAILABLE **  …                        NEWBORN
3  ** INFO NOT AVAILABLE **  …                 ANKLE FRACTURE
4  ** INFO NOT AVAILABLE **  …                 GUN SHOT WOUND

  ADMISSION_HOUR ICUSTAY_ID                ICU_INTIME  \
0              5     251228 2133-06-02 05:10:11+00:00
1              4     263042 2169-10-30 04:29:22+00:00
2              9     252466 2103-04-03 09:36:42+00:00
3             17     260515 2180-12-05 16:40:35+00:00
4              1     292926 2108-12-17 02:40:14+00:00

                ICU_OUTTIME ICU_LOS FIRST_CAREUNIT  PRIMARY_ICD9_CODE  \
```

```
0 2133-06-02 05:10:27+00:00  0.0002          CSRU                4271
1 2169-11-03 15:29:54+00:00  4.4587          MICU               51881
2 2103-04-03 22:29:06+00:00  0.5364          NICU               76519
3 2180-12-06 17:48:37+00:00  1.0472          MICU                8244
4 2108-12-18 18:06:51+00:00  1.6435         TSICU               86349

         PRIMARY_ICD9_TITLE NUM_CALLOUTS
0   Parox ventric tachycard         <NA>
1  Acute respiratry failure            1
2         Preterm NEC 2500+g        <NA>
3      Fx bimalleolar-closed           1
4   Colon injury NEC-closed         <NA>

[5 rows x 22 columns]
```

# 4 Data Pre-Processing - Dask

In this section of the project, we will use **Dask** to perform some pre-processing on the `junction_table`, to deal with repeated rows and null values

## 4.1 Duplicate Rows Analysis

[5]:
```
dtype = {
    "SUBJECT_ID": "float64",
    "GENDER": "object",
    "DOB": "object",
    "EXPIRE_FLAG": "float64",
    "AGE_AT_ADMISSION": "float64",
    "HADM_ID": "float64",
    "ADMITTIME": "object",
    "DISCHTIME": "object",
    "ADMISSION_TYPE": "object",
    "ADMISSION_LOCATION": "object",
    "INSURANCE": "object",
    "ETHNICITY": "object",
    "ADMISSION_DIAGNOSIS_TEXT": "object",
    "ADMISSION_HOUR": "float64",
    "ICUSTAY_ID": "float64",
    "ICU_INTIME": "object",
    "ICU_OUTTIME": "object",
    "ICU_LOS": "float64",
    "FIRST_CAREUNIT": "object",
    "PRIMARY_ICD9_CODE": "object",
    "PRIMARY_ICD9_TITLE": "object",
    "NUM_CALLOUTS": "float64"
}
```

```
ddf = dd.read_csv('gs://n_cdle_project/junction_table', dtype=dtype)
```

[6]:
```
print(ddf.dtypes)
```

```
SUBJECT_ID                          float64
GENDER                      string[pyarrow]
DOB                         string[pyarrow]
EXPIRE_FLAG                         float64
AGE_AT_ADMISSION                    float64
HADM_ID                             float64
ADMITTIME                   string[pyarrow]
DISCHTIME                   string[pyarrow]
ADMISSION_TYPE              string[pyarrow]
ADMISSION_LOCATION          string[pyarrow]
INSURANCE                   string[pyarrow]
ETHNICITY                   string[pyarrow]
ADMISSION_DIAGNOSIS_TEXT    string[pyarrow]
ADMISSION_HOUR                      float64
ICUSTAY_ID                          float64
ICU_INTIME                  string[pyarrow]
ICU_OUTTIME                 string[pyarrow]
ICU_LOS                             float64
FIRST_CAREUNIT              string[pyarrow]
PRIMARY_ICD9_CODE           string[pyarrow]
PRIMARY_ICD9_TITLE          string[pyarrow]
NUM_CALLOUTS                        float64
dtype: object
```

[8]:
```
start_time = time.time()

# Group by ICUSTAY_ID and count number of rows
result_ddf = (
    ddf.groupby("ICUSTAY_ID")
       .size()
       .to_frame("number_of_rows")      # convert to DataFrame and name the␣
 ↪count column
       .reset_index()                   # reset index to make ICUSTAY_ID a␣
 ↪column again
       .query("number_of_rows > 1")
       .sort_values("number_of_rows", ascending=False)
)

# Compute the result
results = result_ddf.compute()

# Print results
```

```
print("ICUSTAY_ID | number_of_rows")
print("-----------------------------")
for _, row in results.iterrows():
    print(f"{row['ICUSTAY_ID']} | {row['number_of_rows']}")

end_time = time.time()
execution_time = end_time - start_time
print(f"Query Execution Time: {execution_time:.2f} seconds")
```

```
ICUSTAY_ID | number_of_rows
-----------------------------
Query Execution Time: 0.90 seconds
```

### 4.1.1 Conclusion

Based on the results of the query, we can conclude that besides the rows that contain the value `None` that are not any duplicate rows.

## 4.2 Null Values Analysis

[10]:
```
start_time = time.time()

# Total number of rows
total_rows = ddf.shape[0].compute()

# Count of nulls per column
null_counts = ddf.isna().sum().compute()

# Percentage of nulls per column
null_percentages = (null_counts / total_rows * 100).round(2)

# Combine into a single transposed DataFrame for display
null_analysis_df = pd.DataFrame({
    'null_count': null_counts,
    'null_percentage': null_percentages
}).T

print(f"Total number of rows: {total_rows}")
print("  Null Value Analysis (Transposed View):")
print(null_analysis_df)

end_time = time.time()
execution_time = end_time - start_time
print(f"Query Execution Time: {execution_time:.2f} seconds")
```

```
Total number of rows: 62722
  Null Value Analysis (Transposed View):
                 SUBJECT_ID  GENDER  DOB  EXPIRE_FLAG  AGE_AT_ADMISSION  \
```

```
null_count             0.0     0.0  0.0          0.0               0.0
null_percentage        0.0     0.0  0.0          0.0               0.0

                 HADM_ID  ADMITTIME  DISCHTIME  ADMISSION_TYPE  \
null_count           0.0        0.0        0.0             0.0
null_percentage      0.0        0.0        0.0             0.0

                 ADMISSION_LOCATION  …  ADMISSION_DIAGNOSIS_TEXT  \
null_count                      0.0  …                     25.00
null_percentage                 0.0  …                      0.04

                 ADMISSION_HOUR  ICUSTAY_ID  ICU_INTIME  ICU_OUTTIME  ICU_LOS  \
null_count                  0.0      1190.0      1190.0      1200.00  1200.00
null_percentage             0.0         1.9         1.9         1.91     1.91

                 FIRST_CAREUNIT  PRIMARY_ICD9_CODE  PRIMARY_ICD9_TITLE  \
null_count               1190.0              47.00              839.00
null_percentage             1.9               0.07                1.34

                 NUM_CALLOUTS
null_count           31366.00
null_percentage         50.01

[2 rows x 22 columns]
Query Execution Time: 2.34 seconds
```

### 4.2.1 Conclusion

There are 62722 rows. The core patient and admission data is complete. However, approximately 1.9% of rows have nulls for ICU-related features, including the target variable `ICU_LOS`, primarily representing non-ICU admissions or missing discharge times. The primary diagnosis title has minor missingness (~1.3%). The biggest problem is the `NUM_CALLOUTS` feature, that has a high null rate (50%), requiring specific handling.

### 4.2.2 Approach to Missing Values in `NUM_CALLOUTS`

Knowing that the feature `NUM_CALLOUTS` is not too essential to predict the lenght of stay, we will remove this column from the table to avoid future processing problems.

[11]:
```python
ddf = ddf.drop(columns=["NUM_CALLOUTS"])
```

### 4.2.3 Approach to other Missing Values

Knowing that the rows with missing values in other columns, including the target column `ICU_LOS` represent a very small percentage of the dataset, we decided the simplest and most effective solution would be to remove these rows.

[12]:
```python
ddf = ddf.dropna()
```

### 4.2.4 Running the Null Values Query again

In order to assess if our changes were sucessful, we decided to run the Null Values query again.

[14]:
```
start_time = time.time()

# Total number of rows
total_rows = ddf.shape[0].compute()

# Count of nulls per column
null_counts = ddf.isna().sum().compute()

# Percentage of nulls per column
null_percentages = (null_counts / total_rows * 100).round(2)

# Combine into a single transposed DataFrame for display
null_analysis_df = pd.DataFrame({
    'null_count': null_counts,
    'null_percentage': null_percentages
}).T

print(f"Total number of rows: {total_rows}")
print("  Null Value Analysis (Transposed View):")
print(null_analysis_df)

end_time = time.time()
execution_time = end_time - start_time
print(f"Query Execution Time: {execution_time:.2f} seconds")
```

```
Total number of rows: 60748
  Null Value Analysis (Transposed View):
                 SUBJECT_ID  GENDER  DOB  EXPIRE_FLAG  AGE_AT_ADMISSION  \
null_count              0.0     0.0  0.0          0.0               0.0
null_percentage         0.0     0.0  0.0          0.0               0.0

                 HADM_ID  ADMITTIME  DISCHTIME  ADMISSION_TYPE  \
null_count           0.0        0.0        0.0             0.0
null_percentage      0.0        0.0        0.0             0.0

                 ADMISSION_LOCATION  …  ETHNICITY  ADMISSION_DIAGNOSIS_TEXT  \
null_count                      0.0  …        0.0                       0.0
null_percentage                 0.0  …        0.0                       0.0

                 ADMISSION_HOUR  ICUSTAY_ID  ICU_INTIME  ICU_OUTTIME  ICU_LOS  \
null_count                  0.0         0.0         0.0          0.0      0.0
null_percentage             0.0         0.0         0.0          0.0      0.0

                 FIRST_CAREUNIT  PRIMARY_ICD9_CODE  PRIMARY_ICD9_TITLE
```

```
null_count                  0.0              0.0              0.0
null_percentage             0.0              0.0              0.0

[2 rows x 21 columns]
Query Execution Time: 2.56 seconds
```

#### 4.2.5 Conclusion

There are 60748 rows (~96.8% of the original table) and there are no missing values, as expected.

**Fixing Column Types**

[15]:
```
timestamp_cols = ["DOB", "ADMITTIME", "DISCHTIME", "ICU_INTIME", "ICU_OUTTIME"]

for col in timestamp_cols:
    ddf[col] = dd.to_datetime(ddf[col], errors="coerce")

int_cols = ["SUBJECT_ID", "EXPIRE_FLAG", "AGE_AT_ADMISSION", "HADM_ID",␣
 ↪"ADMISSION_HOUR", "ICUSTAY_ID"]

for col in int_cols:
    ddf[col] = ddf[col].astype("int64")

cat_cols = ["GENDER", "ADMISSION_TYPE", "ADMISSION_LOCATION", "INSURANCE",
            "ETHNICITY", "ADMISSION_DIAGNOSIS_TEXT", "FIRST_CAREUNIT",␣
 ↪"PRIMARY_ICD9_CODE", "PRIMARY_ICD9_TITLE"]

for col in cat_cols:
    ddf[col] = ddf[col].astype("category")
```

# 5 Dataset Analysis - Dask

In this section, we use **Dask** to perform a dataset analysis on three different topics, **Patients**, **Medical Data** and **Correlations**.

In **Patients** and **Medical Data** we will analyse the distribution of several features and try to find connections between them and the target feature (**Length of ICU Stay**), to get a better understanding of what features will be more relevant to our ML model.

In **Correlations** we will try to find connections between different features of the dataset, to gain an even better insight of the data.

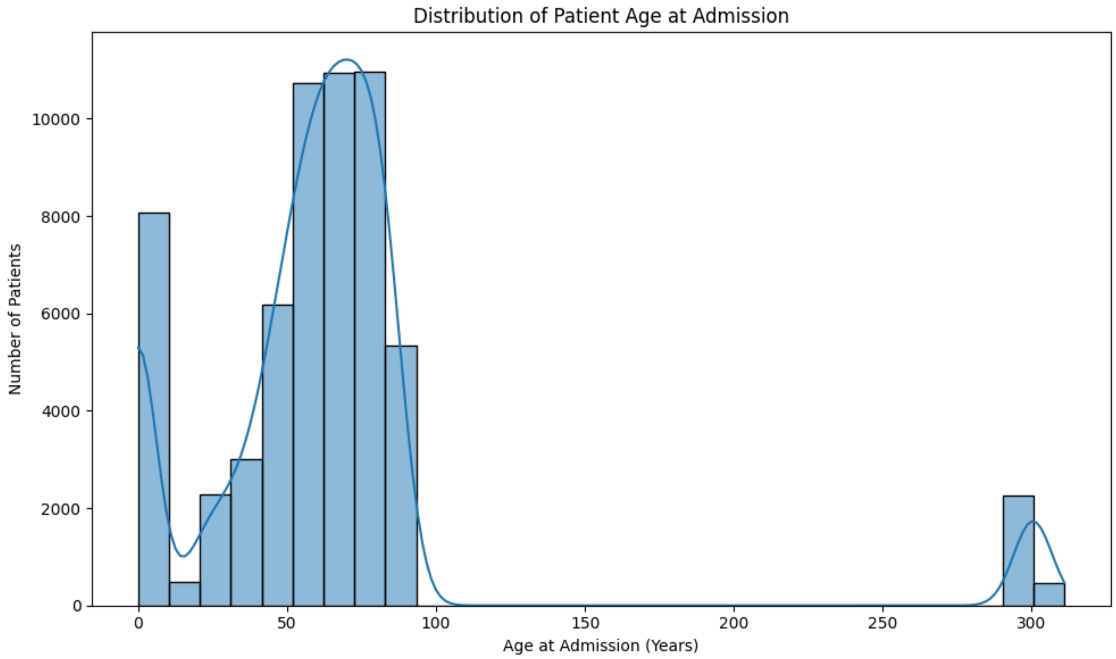
## 5.1 Patients

We will start this analysis with an in-depth analysis of the features regarding patients characteristics, which include:

- `Age`
- `Insurance`

### 5.1.1 Age Analysis

[19]:
```python
start_time = time.time()

# 1. Filter Dask DataFrame for non-null AGE_AT_ADMISSION
age_ddf = ddf["AGE_AT_ADMISSION"]

# 2. Compute to Pandas
age_series = age_ddf.compute()
age_df = age_series.to_frame(name="AGE_AT_ADMISSION")  # <- Convert to DataFrame

# 3. Plot histogram + KDE
if not age_df.empty:
    plt.figure(figsize=(10, 6))
    sns.histplot(data=age_df, x='AGE_AT_ADMISSION', kde=True, bins=30)
    plt.xlabel("Age at Admission (Years)")
    plt.ylabel("Number of Patients")
    plt.title("Distribution of Patient Age at Admission")
    plt.tight_layout()
    plt.show()
else:
    print("No non-null AGE_AT_ADMISSION values to plot.")

# 4. Print summary statistics
print("\nAge at Admission Statistics:")
print(age_df["AGE_AT_ADMISSION"].describe())

end_time = time.time()
execution_time = end_time - start_time
print(f"Query Execution Time: {execution_time:.2f} seconds")
```



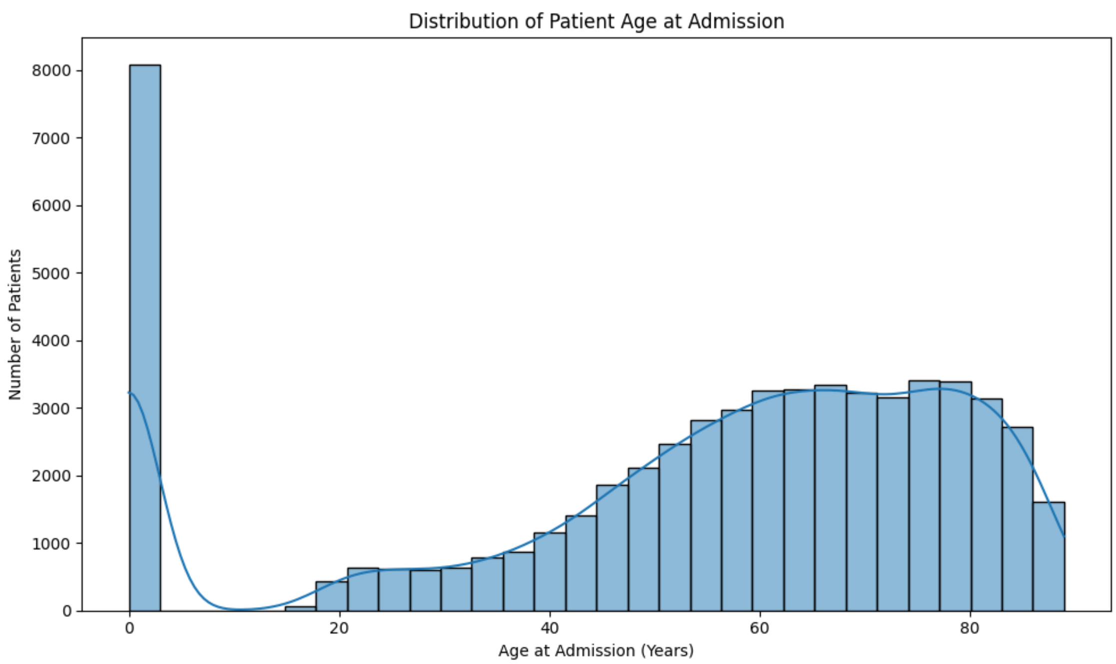

```
Age at Admission Statistics:
count    60748.000000
mean        64.939998
std         57.138132
min          0.000000
25%         44.000000
50%         62.000000
75%         76.000000
max        311.000000
Name: AGE_AT_ADMISSION, dtype: float64
Query Execution Time: 2.38 seconds
```

#### 5.1.2 Eliminating rows with Age bigger then 120 years

Given the histogram results, we decided to eliminate the rows with outliers that most definitely represent input errors, given that there are no people near 300 years old.

[21]:
```
start_time = time.time()

age_df_filtered = age_df[age_df["AGE_AT_ADMISSION"] <= 120]

# 3. Plot histogram + KDE
if not age_df_filtered.empty:
    plt.figure(figsize=(10, 6))
    sns.histplot(data=age_df_filtered, x='AGE_AT_ADMISSION', kde=True, bins=30)
```

```
    plt.xlabel("Age at Admission (Years)")
    plt.ylabel("Number of Patients")
    plt.title("Distribution of Patient Age at Admission")
    plt.tight_layout()
    plt.show()
else:
    print("No non-null AGE_AT_ADMISSION values to plot.")

# 4. Print summary statistics
print("\nAge at Admission Statistics:")
print(age_df_filtered["AGE_AT_ADMISSION"].describe())

end_time = time.time()
execution_time = end_time - start_time
print(f"Query Execution Time: {execution_time:.2f} seconds")
```



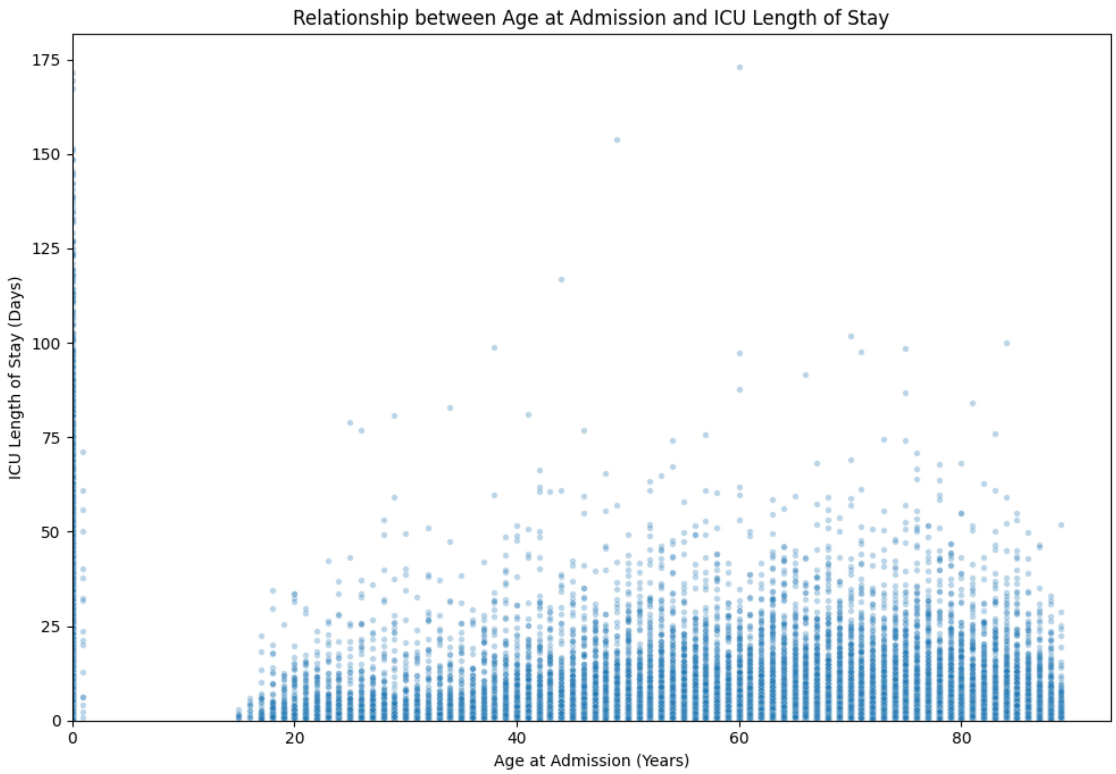

```
Age at Admission Statistics:
count    58039.000000
mean        53.943693
std         26.560400
min          0.000000
25%         43.000000
50%         61.000000
75%         74.000000
max         89.000000
```

```
Name: AGE_AT_ADMISSION, dtype: float64
Query Execution Time: 0.78 seconds
```

After eliminating these input error mistakes, we ended up with a table containing 58039 rows (~95.5% of the previous table).

### 5.1.3 Age & Length of ICU Stay

[28]:
```python
start_time = time.time()

# 1. Filter AGE_AT_ADMISSION to remove outliers
filtered_ddf = ddf[ddf["AGE_AT_ADMISSION"] <= 100]

# 2. Select relevant columns and bring to memory
age_los_df = filtered_ddf[["AGE_AT_ADMISSION", "ICU_LOS"]].compute()

# 3. Plot and correlation
if not age_los_df.empty:
    plt.figure(figsize=(10, 7))
    sns.scatterplot(x="AGE_AT_ADMISSION", y="ICU_LOS", data=age_los_df, alpha=0.
 ↪3, s=15)
    plt.xlabel("Age at Admission (Years)")
    plt.ylabel("ICU Length of Stay (Days)")
    plt.title("Relationship between Age at Admission and ICU Length of Stay")
    plt.ylim(bottom=0)
    plt.xlim(left=0)
    plt.tight_layout()
    plt.show()

    # Correlation
    correlation = age_los_df["AGE_AT_ADMISSION"].corr(age_los_df["ICU_LOS"])
    print(f"\nCorrelation between Age at Admission and ICU LOS: {correlation:.
 ↪3f}")
else:
    print("No data to plot.")

end_time = time.time()
execution_time = end_time - start_time
print(f"Query Execution Time: {execution_time:.2f} seconds")
```




```
Correlation between Age at Admission and ICU LOS: -0.161
Query Execution Time: 6.84 seconds
```

### 5.1.4 Conclusion

By analysing the histogram of `Age`, we can see that the most common age intervals in the dataset are `0` and `50-80`. The dataset proposely ommits data from minor patients with the excpetion of newborns.

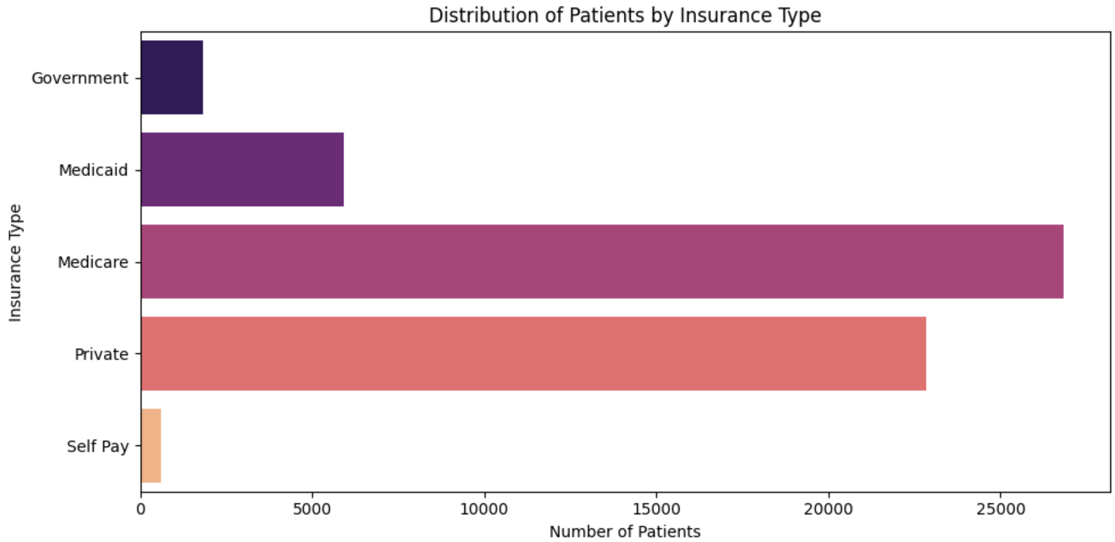
Regarding the connection between `Age` and `Length of ICU Stay`, we can conclude that: 1. The vast majority of ICU stays are relatively short (concentrated roughly below 25 days) across all adult age groups. 2. While short stays are common for all ages, the spread of the values of `Length of ICU Stay` appears to widen slightly for older patients, which means that very long stays seem slightly more prevalent among older age groups.

### 5.1.5 Insurance Analysis

[34]:
```
start_time = time.time()

# 1. Group by insurance and count occurrences
insurance_counts = (
    filtered_ddf.groupby("INSURANCE")
```

```
        .size()
        .compute()
        .sort_values(ascending=False)
        .reset_index(name="count")
        .rename(columns={0: "INSURANCE"})
)

# 2. Plot horizontal bar chart
if not insurance_counts.empty:
    plt.figure(figsize=(10, 5))
    sns.barplot(x='count', y='INSURANCE', data=insurance_counts,␣
↪palette='magma', orient='h')
    plt.xlabel("Number of Patients")
    plt.ylabel("Insurance Type")
    plt.title("Distribution of Patients by Insurance Type")
    plt.tight_layout()
    plt.show()
else:
    print("No data to plot.")

end_time = time.time()
execution_time = end_time - start_time
print(f"Query Execution Time: {execution_time:.2f} seconds")
```

```
/usr/local/lib/python3.11/dist-
packages/dask/dataframe/dask_expr/_groupby.py:1562: FutureWarning: The default
of observed=False is deprecated and will be changed to True in a future version
of pandas. Pass observed=False to retain current behavior or observed=True to
adopt the future default and silence this warning.
  self._meta = self.obj._meta.groupby(
<ipython-input-34-7ff799173bd5>:16: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same
effect.

  sns.barplot(x='count', y='INSURANCE', data=insurance_counts, palette='magma',
orient='h')
```



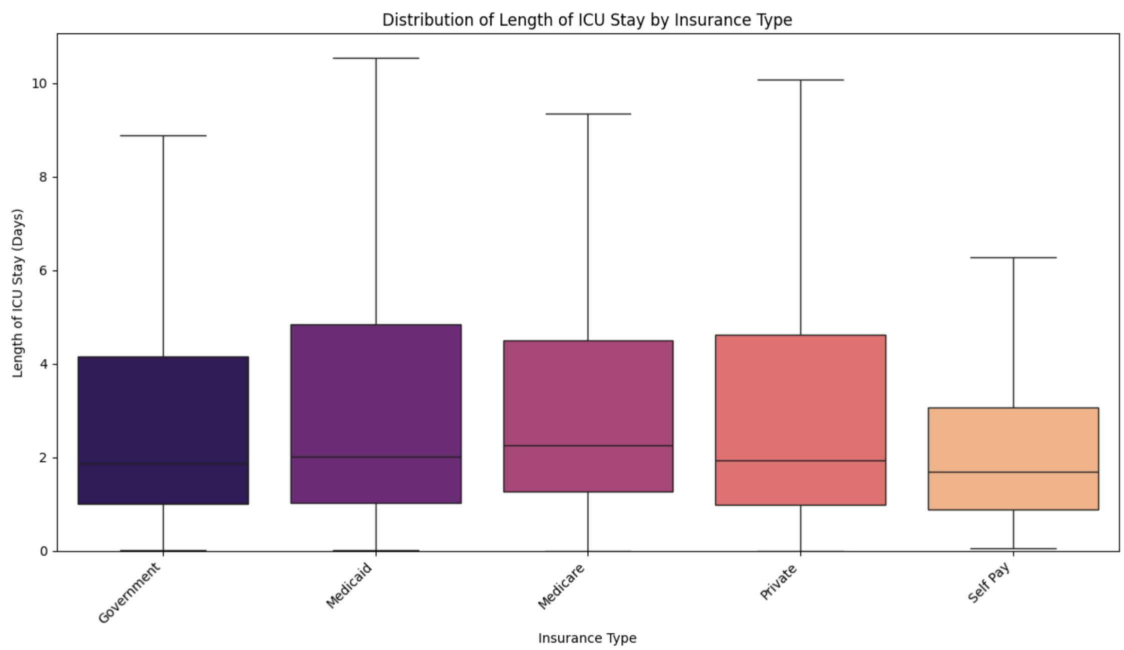

```
Query Execution Time: 2.77 seconds
```

#### 5.1.6 Insurance & Length of ICU Stay

[36]:
```
start_time = time.time()

# 1. Select relevant columns
insurance_los_ddf = filtered_ddf[["INSURANCE", "ICU_LOS"]]

# 2. Bring to memory for plotting/stats
insurance_los_df = insurance_los_ddf.compute()

# 3. Plot and summarize
if not insurance_los_df.empty:
    plt.figure(figsize=(12, 7))
    sns.boxplot(x='INSURANCE', y='ICU_LOS', data=insurance_los_df,␣
 ↪palette='magma', showfliers=False)
    plt.xlabel("Insurance Type")
    plt.ylabel("Length of ICU Stay (Days)")
    plt.title("Distribution of Length of ICU Stay by Insurance Type")
    plt.xticks(rotation=45, ha='right')
    plt.ylim(bottom=0)
    plt.tight_layout()
    plt.show()

    # Summary statistics
    print("\nSummary Statistics for ICU LOS by Insurance Type:")
    print(insurance_los_df.groupby("INSURANCE")["ICU_LOS"].describe())
else:
```

```
    print("No data returned for insurance vs. LOS analysis.")

end_time = time.time()
execution_time = end_time - start_time
print(f"Query Execution Time: {execution_time:.2f} seconds")
```

```
<ipython-input-36-e7db03b38274>:12: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.boxplot(x='INSURANCE', y='ICU_LOS', data=insurance_los_df,
palette='magma', showfliers=False)
```




```
Summary Statistics for ICU LOS by Insurance Type:
              count      mean        std     min       25%      50%       75%  \
INSURANCE
Government   1822.0  4.895602   9.793321  0.0057  0.998850  1.87805  4.167150
Medicaid     5919.0  5.900825  12.800130  0.0036  1.025900  2.02050  4.835200
Medicare    26843.0  4.306665   6.252719  0.0001  1.260800  2.26430  4.501300
Private     22845.0  5.611555  12.140707  0.0002  0.982100  1.92950  4.625200
Self Pay      610.0  3.062356   4.486948  0.0614  0.888425  1.68900  3.057675

                 max
```

```
INSURANCE
Government  101.8397
Medicaid    169.4202
Medicare    173.0725
Private     171.6227
Self Pay     43.1465
Query Execution Time: 7.77 seconds
```

```
<ipython-input-36-e7db03b38274>:23: FutureWarning: The default of observed=False
is deprecated and will be changed to True in a future version of pandas. Pass
observed=False to retain current behavior or observed=True to adopt the future
default and silence this warning.
  print(insurance_los_df.groupby("INSURANCE")["ICU_LOS"].describe())
```

#### 5.1.7 Conclusion

By analysing the bar chart of `Insurance`, we can see that the most common insurance systems are `Medicare` followed by `Private`, and that there is a significantly lower number of patients using other systems.

Regarding the connection between `Insurance` and `Length of ICU Stay`, we can conclude that all systems have a similar distribution and mean in the comparison of the two metrics, with the exception of `Self Pay`, whose average value for `Length of ICU Stay` is significantly lower.

### 5.2 Medical Data

We will continue the dataset analysis with an in-depth analysis of the features regarding patients medical records while they were hositalized, which include:

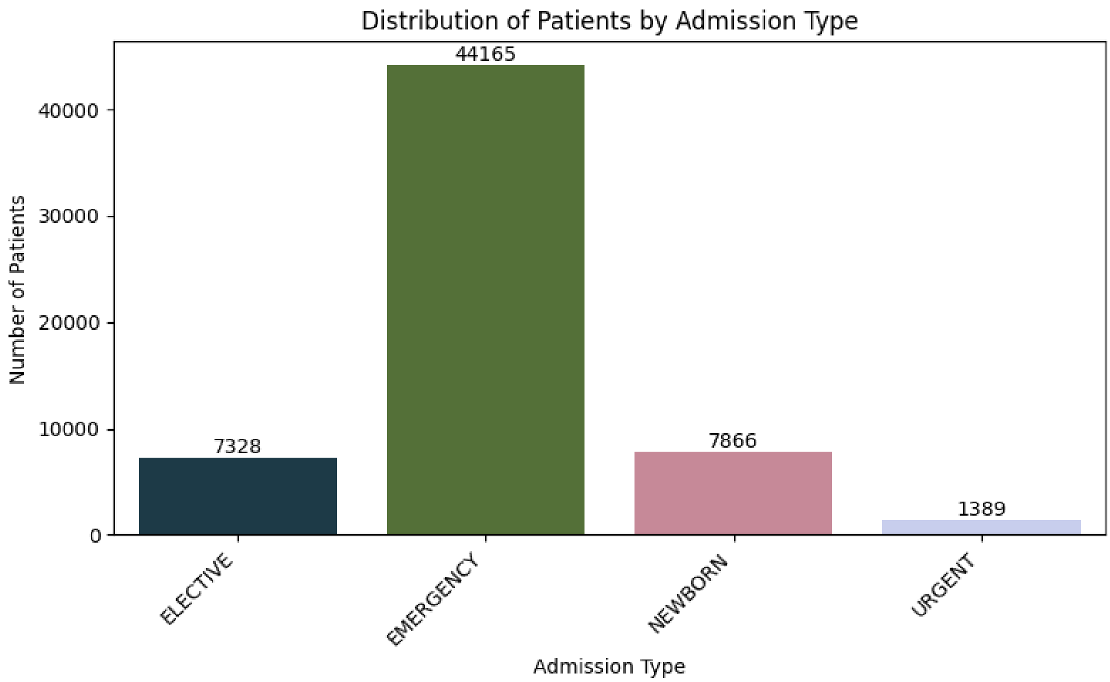
- `Type of Admission`
- `Diagnostic Code`
- `First Care Unit`
- `Length of ICU Stay (Target)`

#### 5.2.1 Type of Admission Analysis

[33]:
```
start_time = time.time()

# 1. Group by ADMISSION_TYPE and count
adm_type_counts = (
    filtered_ddf.groupby("ADMISSION_TYPE")
        .size()
        .compute()
        .sort_values(ascending=False)
        .reset_index(name="count")
)

# 2. Plot bar chart
if not adm_type_counts.empty:
    plt.figure(figsize=(8, 5))
```

```python
    ax = sns.barplot(x='ADMISSION_TYPE', y='count', data=adm_type_counts,␣
↪palette='cubehelix')
    plt.xlabel("Admission Type")
    plt.ylabel("Number of Patients")
    plt.title("Distribution of Patients by Admission Type")
    plt.xticks(rotation=45, ha='right')

    # Add value labels to bars
    for container in ax.containers:
        ax.bar_label(container)

    plt.tight_layout()
    plt.show()
else:
    print("No data returned for admission type distribution.")

end_time = time.time()
execution_time = end_time - start_time
print(f"Query Execution Time: {execution_time:.2f} seconds")
```

```
/usr/local/lib/python3.11/dist-
packages/dask/dataframe/dask_expr/_groupby.py:1562: FutureWarning: The default
of observed=False is deprecated and will be changed to True in a future version
of pandas. Pass observed=False to retain current behavior or observed=True to
adopt the future default and silence this warning.
  self._meta = self.obj._meta.groupby(
<ipython-input-33-6ba51112c5e1>:15: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  ax = sns.barplot(x='ADMISSION_TYPE', y='count', data=adm_type_counts,
palette='cubehelix')
```



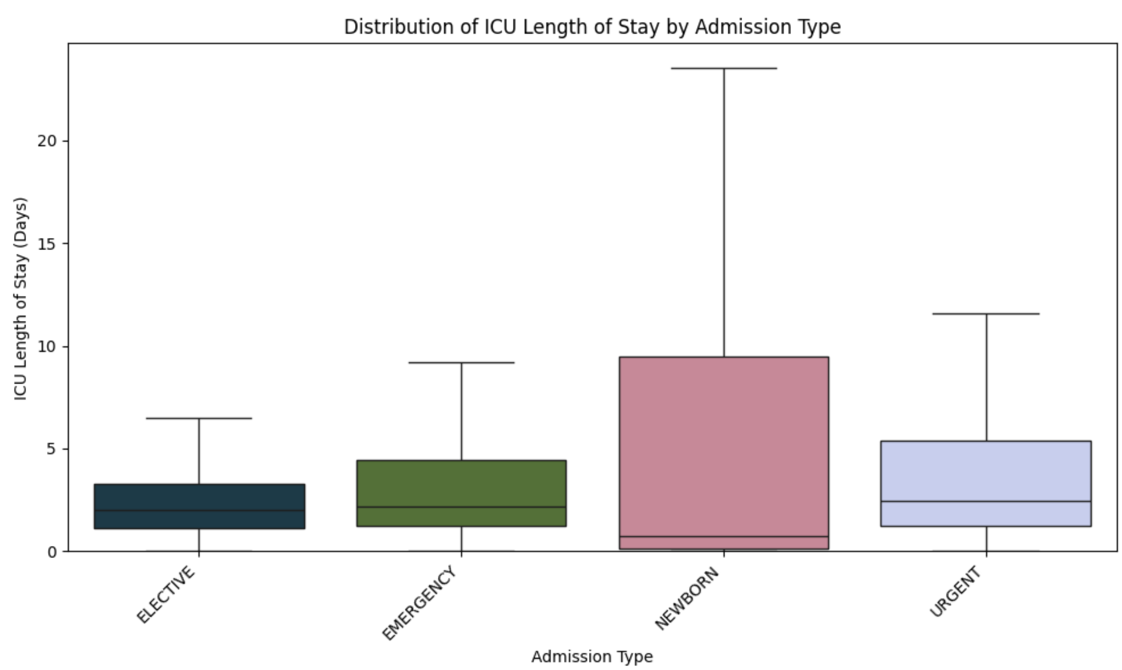

```
Query Execution Time: 2.66 seconds
```

### 5.2.2 Type of Admission & Length of ICU Stay

[37]:
```
start_time = time.time()

# 1. Select relevant columns from the cleaned DataFrame
adm_type_los_ddf = filtered_ddf[["ADMISSION_TYPE", "ICU_LOS"]]

# 2. Compute to Pandas
adm_type_los_df = adm_type_los_ddf.compute()

# 3. Plot and describe
if not adm_type_los_df.empty:
    plt.figure(figsize=(10, 6))
    sns.boxplot(x='ADMISSION_TYPE', y='ICU_LOS', data=adm_type_los_df,␣
 ↪palette='cubehelix', showfliers=False)
    plt.xlabel("Admission Type")
    plt.ylabel("ICU Length of Stay (Days)")
    plt.title("Distribution of ICU Length of Stay by Admission Type")
    plt.xticks(rotation=45, ha='right')
    plt.ylim(bottom=0)
    plt.tight_layout()
    plt.show()
```

```python
    # Summary statistics
    print("\nSummary Statistics for ICU LOS by Admission Type:")
    print(adm_type_los_df.groupby("ADMISSION_TYPE")["ICU_LOS"].describe())
else:
    print("No data returned for admission type vs. LOS analysis.")

end_time = time.time()
execution_time = end_time - start_time
print(f"Query Execution Time: {execution_time:.2f} seconds")
```

```
<ipython-input-37-1121dcee2c5f>:12: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.boxplot(x='ADMISSION_TYPE', y='ICU_LOS', data=adm_type_los_df,
palette='cubehelix', showfliers=False)
```




```
Summary Statistics for ICU LOS by Admission Type:
                  count      mean        std     min       25%     50%  \
ADMISSION_TYPE
ELECTIVE         7226.0  3.503513   6.008552  0.0004  1.140675  1.9895
EMERGENCY       41601.0  4.309662   6.436865  0.0001  1.229700  2.1897
NEWBORN          7866.0  9.878190  20.483139  0.0008  0.137675  0.7253
```

```
URGENT          1346.0  5.356694   8.359788  0.0025  1.241075  2.4351

                     75%       max
ADMISSION_TYPE
ELECTIVE        3.283750  173.0725
EMERGENCY       4.420000  169.4202
NEWBORN         9.500975  171.6227
URGENT          5.380250   97.4897
Query Execution Time: 8.09 seconds
```

```
<ipython-input-37-1121dcee2c5f>:23: FutureWarning: The default of observed=False
is deprecated and will be changed to True in a future version of pandas. Pass
observed=False to retain current behavior or observed=True to adopt the future
default and silence this warning.
  print(adm_type_los_df.groupby("ADMISSION_TYPE")["ICU_LOS"].describe())
```

### 5.2.3 Conclusion

The distributions of patients by `Type of Admission` is uneven, with most admissions being classified as `EMERGENCY`. The least recurrent type of admissions is `Urgent`.

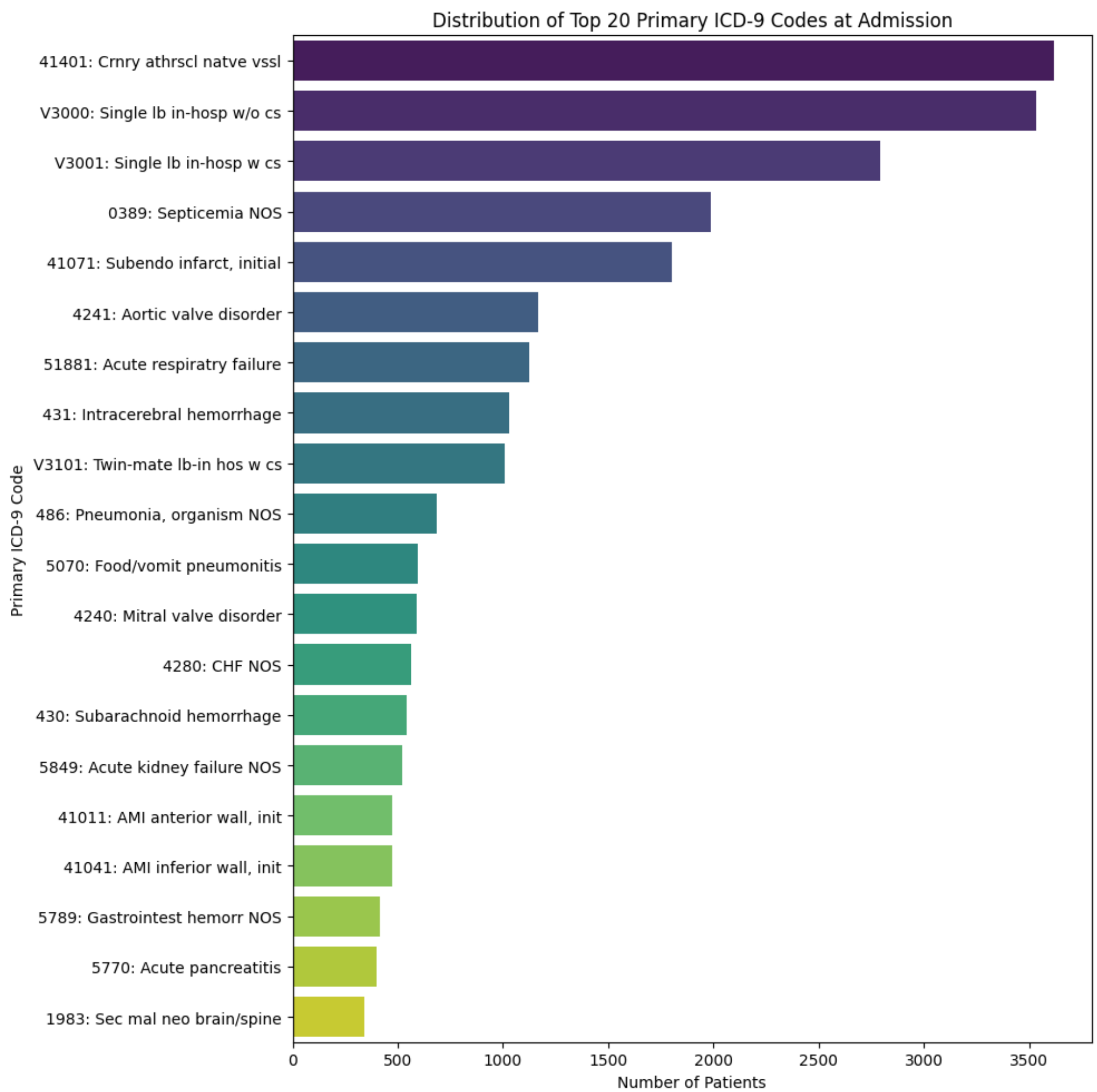
There is an evident connection between `Type of Admission` and `Length of ICU Stay`, with `NEWBORN` having the highest mean values (close to 10 days) while the other types of admission have mean values between 3 to 5 days.

### 5.2.4 Diagnosis Analysis

[51]:
```
start_time = time.time()

# Ensure PRIMARY_ICD9_CODE is string
filtered_ddf = filtered_ddf.
 ↪assign(PRIMARY_ICD9_CODE=filtered_ddf["PRIMARY_ICD9_CODE"].astype(str))

# 1. Count top 20 ICD-9 codes (and fix column names properly)
icd_counts = (
    filtered_ddf["PRIMARY_ICD9_CODE"]
    .value_counts()
    .compute()
    .nlargest(20)
    .reset_index()
    .rename(columns={"index": "PRIMARY_ICD9_CODE", 0: "count"})
)

# 2. Get titles
icd_titles = (
    filtered_ddf[["PRIMARY_ICD9_CODE", "PRIMARY_ICD9_TITLE"]]
    .drop_duplicates(subset=["PRIMARY_ICD9_CODE"])
    .compute()
    .dropna(subset=["PRIMARY_ICD9_TITLE"])
```

```
)

# 3. Merge counts with titles
icd9_distribution_df = icd_counts.merge(icd_titles, on="PRIMARY_ICD9_CODE",␣
↪how="left")

# 4. Plot
if not icd9_distribution_df.empty:
    plt.figure(figsize=(10, 10))
    icd9_distribution_df["PRIMARY_ICD9_TITLE"] =␣
↪icd9_distribution_df["PRIMARY_ICD9_TITLE"].astype(str)
    icd9_distribution_df["CODE_TITLE"] = (
        icd9_distribution_df["PRIMARY_ICD9_CODE"] + ": " +
        icd9_distribution_df["PRIMARY_ICD9_TITLE"].replace("nan", "N/A")
    )

    sns.barplot(
        x="count",
        y="CODE_TITLE",
        data=icd9_distribution_df,
        palette="viridis",
        orient="h"
    )

    plt.xlabel("Number of Patients")
    plt.ylabel("Primary ICD-9 Code")
    plt.title("Distribution of Top 20 Primary ICD-9 Codes at Admission")
    plt.tight_layout()
    plt.show()

    print("\nTop ICD-9 Code Distribution:")
    print(icd9_distribution_df[["PRIMARY_ICD9_CODE", "count",␣
↪"PRIMARY_ICD9_TITLE"]])
else:
    print("No data returned for primary ICD-9 code distribution.")

end_time = time.time()
execution_time = end_time - start_time
print(f"Query Execution Time: {execution_time:.2f} seconds")
```

```
<ipython-input-51-bd3e9e7b3720>:36: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same
effect.

  sns.barplot(
```




```
Top ICD-9 Code Distribution:
   PRIMARY_ICD9_CODE  count        PRIMARY_ICD9_TITLE
0              41401   3617  Crnry athrscl natve vssl
1              V3000   3534  Single lb in-hosp w/o cs
2              V3001   2792    Single lb in-hosp w cs
3               0389   1988            Septicemia NOS
4              41071   1803  Subendo infarct, initial
5               4241   1168     Aortic valve disorder
6              51881   1124  Acute respiratry failure
7                431   1031  Intracerebral hemorrhage
8              V3101   1008  Twin-mate lb-in hos w cs
9                486    684   Pneumonia, organism NOS
```

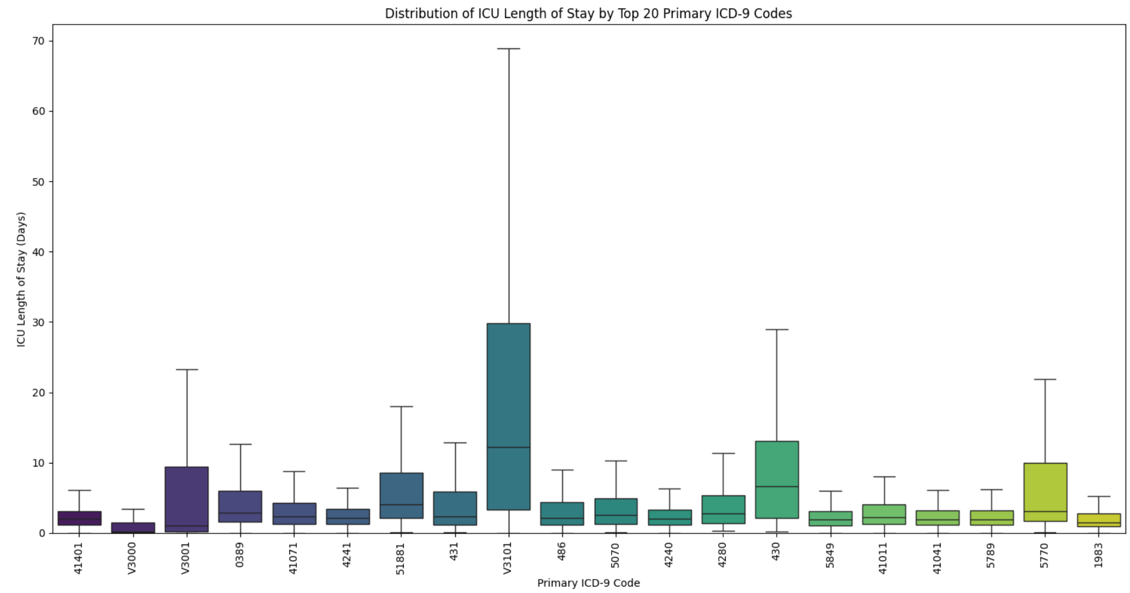
```
10              5070    596    Food/vomit pneumonitis
11              4240    592     Mitral valve disorder
12              4280    562                   CHF NOS
13               430    542   Subarachnoid hemorrhage
14              5849    523  Acute kidney failure NOS
15             41011    473   AMI anterior wall, init
16             41041    471   AMI inferior wall, init
17              5789    415   Gastrointest hemorr NOS
18              5770    399        Acute pancreatitis
19              1983    343   Sec mal neo brain/spine
Query Execution Time: 12.88 seconds
```

### 5.2.5 Diagnosis & Length of ICU Stay

[52]:
```
start_time = time.time()

# Ensure PRIMARY_ICD9_CODE is as string
filtered_ddf = filtered_ddf.
↪assign(PRIMARY_ICD9_CODE=filtered_ddf["PRIMARY_ICD9_CODE"].astype(str))

# 1. Get top 20 most frequent ICD-9 codes (as strings)
top_codes_list = (
    filtered_ddf["PRIMARY_ICD9_CODE"]
    .value_counts()
    .compute()
    .nlargest(20)
    .index
    .tolist()
)

# 2. Filter and select necessary columns
if top_codes_list:
    icd9_los_ddf = filtered_ddf[
        filtered_ddf["PRIMARY_ICD9_CODE"].isin(top_codes_list)
    ][["PRIMARY_ICD9_CODE", "ICU_LOS"]]

    # 3. Compute to pandas
    icd9_los_df = icd9_los_ddf.compute()

    # 4. Plot
    if not icd9_los_df.empty:
        plt.figure(figsize=(15, 8))
        sns.boxplot(
            x="PRIMARY_ICD9_CODE",
            y="ICU_LOS",
            data=icd9_los_df,
            palette="viridis",
```

```
            order=top_codes_list,
            showfliers=False
        )
        plt.xlabel("Primary ICD-9 Code")
        plt.ylabel("ICU Length of Stay (Days)")
        plt.title("Distribution of ICU Length of Stay by Top 20 Primary ICD-9␣
↪Codes")
        plt.xticks(rotation=90)
        plt.ylim(bottom=0)
        plt.tight_layout()
        plt.show()

        print("\nSummary Statistics for ICU LOS by Top 20 Primary ICD-9 Codes:")
        print(icd9_los_df.groupby("PRIMARY_ICD9_CODE")["ICU_LOS"].describe())

    else:
        print("No data returned for top ICD-9 codes vs. LOS analysis.")
else:
    print("Cannot proceed with LOS analysis as no top ICD-9 codes were␣
↪identified.")

end_time = time.time()
execution_time = end_time - start_time
print(f"Query Execution Time: {execution_time:.2f} seconds")
```

```
<ipython-input-52-3bf58f3a6526>:28: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.boxplot(
```




Summary Statistics for ICU LOS by Top 20 Primary ICD-9 Codes:

| PRIMARY_ICD9_CODE | count | mean | std | min | 25% | 50% |
|---|---|---|---|---|---|---|
| 0389 | 1988.0 | 5.329782 | 7.084884 | 0.0079 | 1.614200 | 2.87470 |
| 1983 | 343.0 | 2.509505 | 3.203271 | 0.0079 | 1.005550 | 1.51880 |
| 41011 | 473.0 | 3.895759 | 5.718157 | 0.0435 | 1.314000 | 2.20950 |
| 41041 | 471.0 | 3.449264 | 4.951962 | 0.0033 | 1.230300 | 1.94030 |
| 41071 | 1803.0 | 4.026161 | 5.369919 | 0.0016 | 1.288900 | 2.35840 |
| 41401 | 3617.0 | 2.876750 | 3.885769 | 0.0048 | 1.154600 | 1.99070 |
| 4240 | 592.0 | 3.466497 | 5.780785 | 0.0077 | 1.159450 | 2.02135 |
| 4241 | 1168.0 | 3.624112 | 5.788327 | 0.0014 | 1.233175 | 2.14675 |
| 4280 | 562.0 | 4.949970 | 6.628354 | 0.3021 | 1.387300 | 2.73745 |
| 430 | 542.0 | 9.060081 | 8.904613 | 0.1733 | 2.170775 | 6.62515 |
| 431 | 1031.0 | 4.795295 | 5.835963 | 0.1118 | 1.213400 | 2.30710 |
| 486 | 684.0 | 3.930527 | 4.905842 | 0.0280 | 1.196175 | 2.15545 |
| 5070 | 596.0 | 4.541065 | 5.972763 | 0.1101 | 1.334350 | 2.55865 |
| 51881 | 1124.0 | 6.957914 | 7.858505 | 0.1524 | 2.096675 | 4.12695 |
| 5770 | 399.0 | 8.341084 | 12.501480 | 0.0566 | 1.757150 | 3.08880 |
| 5789 | 415.0 | 2.812222 | 3.300042 | 0.0214 | 1.149050 | 1.96770 |
| 5849 | 523.0 | 3.024175 | 4.131413 | 0.0012 | 1.110750 | 1.90300 |
| V3000 | 3534.0 | 4.589990 | 14.277310 | 0.0037 | 0.104725 | 0.20955 |
| V3001 | 2792.0 | 10.340239 | 21.146993 | 0.0008 | 0.162275 | 1.02360 |
| V3101 | 1008.0 | 21.719032 | 26.430318 | 0.0098 | 3.314175 | 12.19845 |

| PRIMARY_ICD9_CODE | 75% | max |
|---|---|---|
| 0389 | 6.028650 | 91.5726 |

```
1983                 2.743500   30.7172
41011                4.038900   76.9211
41041                3.198900   40.9936
41071                4.309700   53.0333
41401                3.134600   68.2052
4240                 3.360900   75.9919
4241                 3.437825   98.6446
4280                 5.372050   68.9517
430                 13.097175   54.5119
431                  5.869350   51.7955
486                  4.354575   41.5576
5070                 4.938750   59.4319
51881                8.548500   71.0056
5770                 9.929350  101.7390
5789                 3.202750   36.3250
5849                 3.082300   43.2606
V3000                1.457850  167.5077
V3001                9.443825  171.6227
V3101               29.786825  142.3605
Query Execution Time: 15.99 seconds
```

### 5.2.6 Conclusion

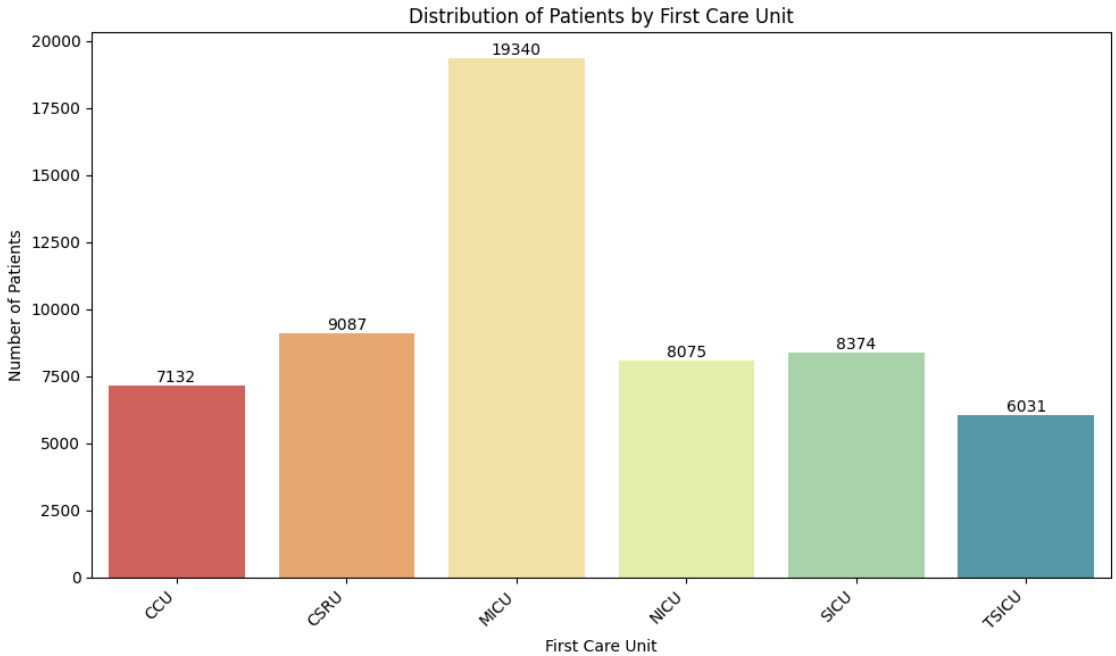
There is a very unsymmetric distribution of Diagnosis. In the top-20 most common diagnosis, with the most common being `41401 (Coronary atherosclerosis of native vessel)`. The correlation between some `Diagnosis` and `ICU Length of Stay` is evident, with `V3101 (Twin mate, liveborn, delivered in hospital, with cesarean section)` having a mean value very high compared to other types of Diagnosis. There are also diagnosis who have an average of `ICU Length of Stay` very low in comparison, like `V3000 (Single liveborn, delivered in hospital, without cesarean section)`.

### 5.2.7 First Care Unit Analysis

[53]:
```python
start_time = time.time()

# 1. Group by FIRST_CAREUNIT and count
careunit_counts = (
    filtered_ddf.groupby("FIRST_CAREUNIT")
    .size()
    .compute()
    .sort_values(ascending=False)
    .reset_index(name="count")
)

# 2. Plot
if not careunit_counts.empty:
    plt.figure(figsize=(10, 6))
```

```python
    ax = sns.barplot(x="FIRST_CAREUNIT", y="count", data=careunit_counts,␣
↪palette="Spectral")
    plt.xlabel("First Care Unit")
    plt.ylabel("Number of Patients")
    plt.title("Distribution of Patients by First Care Unit")
    plt.xticks(rotation=45, ha="right")

    # Add count labels
    for container in ax.containers:
        ax.bar_label(container)

    plt.tight_layout()
    plt.show()
else:
    print("No data returned for first care unit distribution.")

end_time = time.time()
execution_time = end_time - start_time
print(f"Query Execution Time: {execution_time:.2f} seconds")
```

```
/usr/local/lib/python3.11/dist-
packages/dask/dataframe/dask_expr/_groupby.py:1562: FutureWarning: The default
of observed=False is deprecated and will be changed to True in a future version
of pandas. Pass observed=False to retain current behavior or observed=True to
adopt the future default and silence this warning.
  self._meta = self.obj._meta.groupby(
<ipython-input-53-9eb78ae8727a>:15: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  ax = sns.barplot(x="FIRST_CAREUNIT", y="count", data=careunit_counts,
palette="Spectral")
```



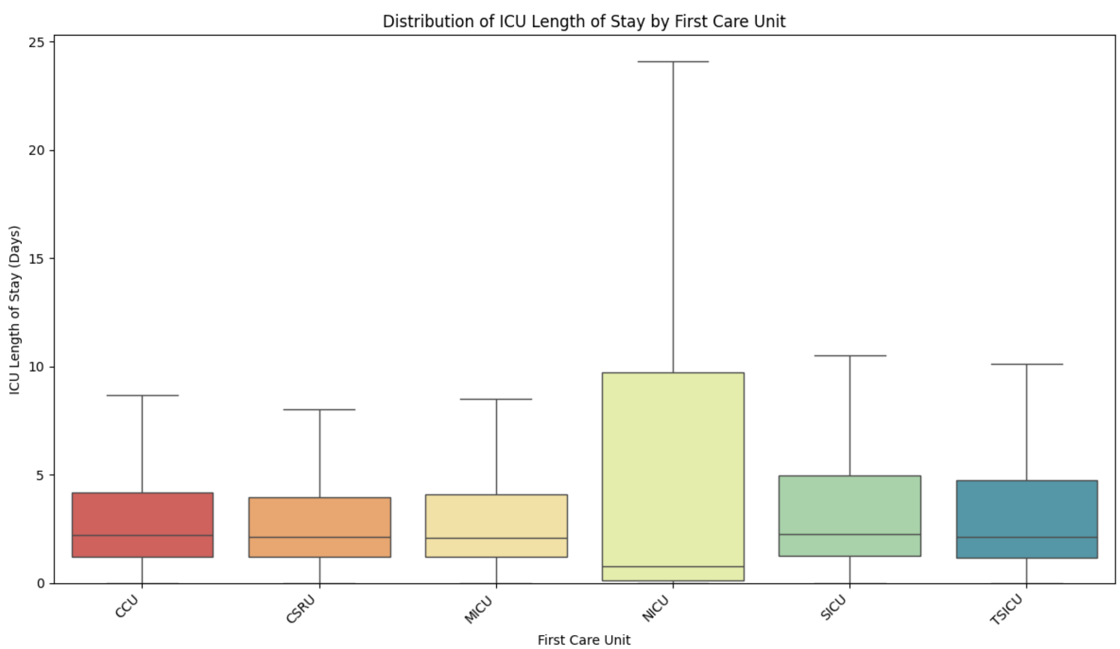

```
Query Execution Time: 3.80 seconds
```

### 5.2.8 First Care of Unit & Length of ICU Stay

[54]:
```python
start_time = time.time()

# 1. Select relevant columns from the cleaned DataFrame
careunit_los_ddf = filtered_ddf[["FIRST_CAREUNIT", "ICU_LOS"]]

# 2. Compute to Pandas
careunit_los_df = careunit_los_ddf.compute()

# 3. Plot and describe
if not careunit_los_df.empty:
    plt.figure(figsize=(12, 7))
    sns.boxplot(
        x="FIRST_CAREUNIT",
        y="ICU_LOS",
        data=careunit_los_df,
        palette="Spectral",
        showfliers=False
    )
    plt.xlabel("First Care Unit")
    plt.ylabel("ICU Length of Stay (Days)")
    plt.title("Distribution of ICU Length of Stay by First Care Unit")
    plt.xticks(rotation=45, ha="right")
```

```
    plt.ylim(bottom=0)
    plt.tight_layout()
    plt.show()

    # Summary statistics
    print("\nSummary Statistics for ICU LOS by First Care Unit:")
    print(careunit_los_df.groupby("FIRST_CAREUNIT")["ICU_LOS"].describe())
else:
    print("No data returned for first care unit vs. LOS analysis.")

end_time = time.time()
execution_time = end_time - start_time
print(f"Query Execution Time: {execution_time:.2f} seconds")
```

```
<ipython-input-54-e2d327078eaf>:12: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.boxplot(
```




```
Summary Statistics for ICU LOS by First Care Unit:
                    count        mean         std      min        25%       50%  \
FIRST_CAREUNIT
```

```
CCU               7132.0    3.953257    5.619626  0.0012  1.213125  2.19915
CSRU              9087.0    3.888229    6.097731  0.0001  1.213850  2.14770
MICU             19340.0    4.042175    5.890149  0.0004  1.189600  2.09700
NICU              8075.0   10.004395   20.644582  0.0008  0.140500  0.78470
SICU              8374.0    4.749462    6.997957  0.0003  1.258775  2.26470
TSICU             6031.0    4.519062    6.760158  0.0016  1.174100  2.12800

                     75%       max
FIRST_CAREUNIT
CCU             4.200700  100.1225
CSRU            3.943200  153.9280
MICU            4.109775  116.8327
NICU            9.723350  171.6227
SICU            4.964775  101.7390
TSICU           4.755900  173.0725
Query Execution Time: 8.19 seconds
```

```
<ipython-input-54-e2d327078eaf>:29: FutureWarning: The default of observed=False
is deprecated and will be changed to True in a future version of pandas. Pass
observed=False to retain current behavior or observed=True to adopt the future
default and silence this warning.
  print(careunit_los_df.groupby("FIRST_CAREUNIT")["ICU_LOS"].describe())
```

### 5.2.9 Conclusion

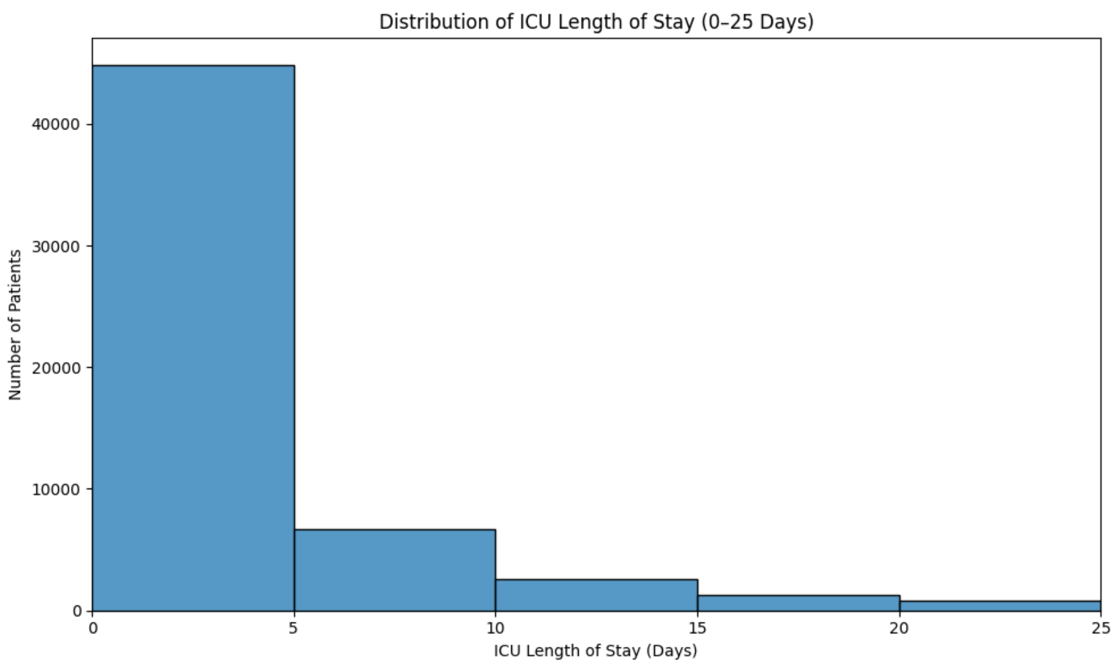
There is a relative uniform distribution in the number of patients by `First Care Unit` with the exception being `MICU (Medical Intensive Care Unit)`, that has a count of patients that is more than double of each other type of `First Care Unit`.

The correlation between `Type of Care Unit`and `ICU Length of Stay`is also relatively uniform with an exception, `NICU (Neonatal Intensive Care Unit)`.

### 5.2.10 Length of ICU Stay Analysis

[55]:
```
start_time = time.time()

# 1. Select ICU_LOS column from the filtered dataframe
icu_los_series = filtered_ddf["ICU_LOS"]

# 2. Compute to Pandas for plotting
icu_los_df = icu_los_series.compute().to_frame(name="ICU_LOS")

# 3. Filter for LOS within 0-25 days
plot_data = icu_los_df[(icu_los_df["ICU_LOS"] >= 0) & (icu_los_df["ICU_LOS"] <=␣
↪25)]

# 4. Plot
if not plot_data.empty:
    plt.figure(figsize=(10, 6))
```

```
    sns.histplot(data=plot_data, x="ICU_LOS", kde=False, bins=5)
    plt.xlabel("ICU Length of Stay (Days)")
    plt.ylabel("Number of Patients")
    plt.title("Distribution of ICU Length of Stay (0-25 Days)")
    plt.xlim(left=0, right=25)
    plt.tight_layout()
    plt.show()

    # Descriptive stats
    print("\nICU Length of Stay Statistics:")
    print(icu_los_df["ICU_LOS"].describe())
else:
    print("No data returned for ICU LOS distribution (0-25 days).")

end_time = time.time()
execution_time = end_time - start_time
print(f"Query Execution Time: {execution_time:.2f} seconds")
```




```
ICU Length of Stay Statistics:
count    58039.000000
mean         4.988276
std          9.824303
min          0.000100
25%          1.103350
50%          2.091800
```

```
75%          4.550800
max        173.072500
Name: ICU_LOS, dtype: float64
Query Execution Time: 6.30 seconds
```

### 5.2.11 Conclusion

By analysing the distribution of `ICU Length of Stay` we can see clearly that most of patients only stay for `5 days or less`, with a decreasing trend of the number of patients as the number of days increases.

## 5.3 Correlations

To finish this analysis we will attemp to find connectios between the following set of features:

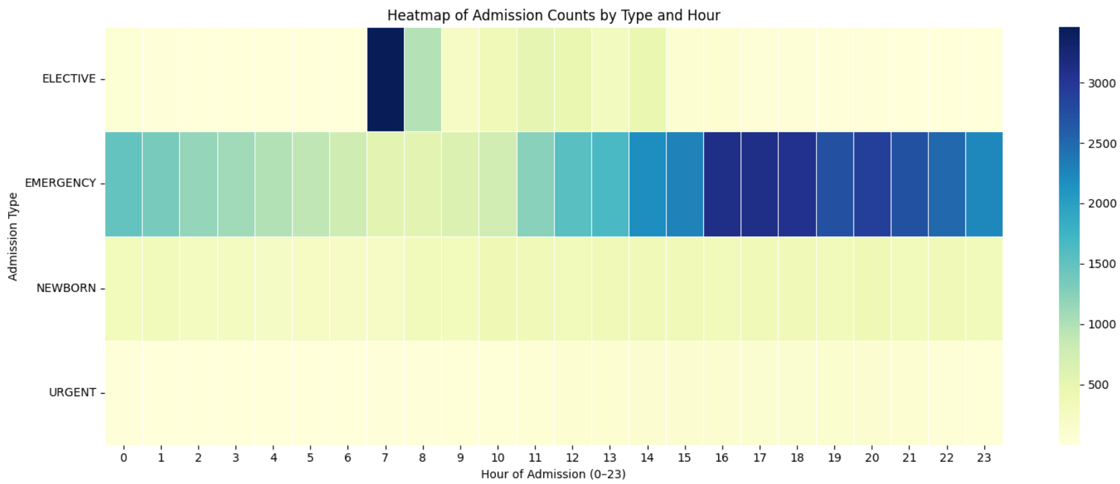
- `Type of Admission & Hour of Admission`
- `Type of Admission and Death`
- `Diagnosis & First Care Unit`
- `First Care Unit & Death`

### 5.3.1 Type of Admission & Hour of Admission

[60]:
```
start_time = time.time()

# 1. Group by ADMISSION_TYPE and ADMISSION_HOUR and count occurrences
adm_type_hour_df = (
    filtered_ddf.groupby(["ADMISSION_TYPE", "ADMISSION_HOUR"])
    .size()
    .compute()
    .reset_index(name="count")
)

# 2. Ensure numeric types
adm_type_hour_df["count"] = pd.to_numeric(adm_type_hour_df["count"],␣
 ↪errors="coerce")
adm_type_hour_df["ADMISSION_HOUR"] = pd.
 ↪to_numeric(adm_type_hour_df["ADMISSION_HOUR"], errors="coerce")
adm_type_hour_df.dropna(subset=["count", "ADMISSION_HOUR"], inplace=True)

# 3. Plot heatmap
if not adm_type_hour_df.empty:
    try:
        heatmap_data = (
            adm_type_hour_df
            .pivot(index="ADMISSION_TYPE", columns="ADMISSION_HOUR",␣
 ↪values="count")
            .fillna(0)
            .astype(float)
```

```
        )

        plt.figure(figsize=(15, 6))
        sns.heatmap(heatmap_data, annot=False, fmt=".0f", linewidths=.5,␣
↪cmap="YlGnBu")
        plt.xlabel("Hour of Admission (0-23)")
        plt.ylabel("Admission Type")
        plt.title("Heatmap of Admission Counts by Type and Hour")
        plt.yticks(rotation=0)
        plt.tight_layout()
        plt.show()

        # Print the table
        print("\nPivoted Data for Heatmap:")
        print(heatmap_data)
        print("\nPivoted Data Types:")
        print(heatmap_data.dtypes)

    except Exception as e:
        print(f"An error occurred during plotting: {e}")
        print("\nOriginal DataFrame dtypes before pivot:")
        print(adm_type_hour_df.dtypes)
        if "heatmap_data" in locals():
            print("\nPivoted DataFrame dtypes before plotting:")
            print(heatmap_data.dtypes)

else:
    print("No data returned from the grouped admission type/hour analysis.")

end_time = time.time()
execution_time = end_time - start_time
print(f"Query Execution Time: {execution_time:.2f} seconds")
```

```
/usr/local/lib/python3.11/dist-
packages/dask/dataframe/dask_expr/_groupby.py:1562: FutureWarning: The default
of observed=False is deprecated and will be changed to True in a future version
of pandas. Pass observed=False to retain current behavior or observed=True to
adopt the future default and silence this warning.
  self._meta = self.obj._meta.groupby(
```




```
Pivoted Data for Heatmap:
ADMISSION_HOUR       0       1       2       3      4      5      6       7  \
ADMISSION_TYPE
ELECTIVE          70.0    20.0    12.0     9.0    2.0    4.0    6.0  3457.0
EMERGENCY       1474.0  1348.0  1169.0  1095.0  989.0  917.0  778.0   552.0
NEWBORN          324.0   330.0   265.0   282.0  236.0  245.0  226.0   229.0
URGENT            23.0    14.0    12.0    10.0    4.0    8.0   13.0    23.0

ADMISSION_HOUR     8      9  …      14      15      16      17      18  \
ADMISSION_TYPE               …
ELECTIVE        986.0  222.0  …   461.0    84.0    87.0    51.0    42.0
EMERGENCY       554.0  643.0  …  2184.0  2292.0  3111.0  3111.0  3077.0
NEWBORN         347.0  320.0  …   356.0   356.0   337.0   353.0   378.0
URGENT           19.0   30.0  …    98.0   101.0   104.0   111.0   111.0

ADMISSION_HOUR      19      20      21      22      23
ADMISSION_TYPE
ELECTIVE          21.0    15.0    11.0     1.0     8.0
EMERGENCY       2733.0  2907.0  2722.0  2500.0  2238.0
NEWBORN          347.0   403.0   348.0   378.0   349.0
URGENT           123.0    96.0    84.0    53.0    36.0

[4 rows x 24 columns]

Pivoted Data Types:
ADMISSION_HOUR
0     float64
1     float64
2     float64
3     float64
```

```
4     float64
5     float64
6     float64
7     float64
8     float64
9     float64
10    float64
11    float64
12    float64
13    float64
14    float64
15    float64
16    float64
17    float64
18    float64
19    float64
20    float64
21    float64
22    float64
23    float64
dtype: object
Query Execution Time: 3.44 seconds
```

### 5.3.2 Conclusion

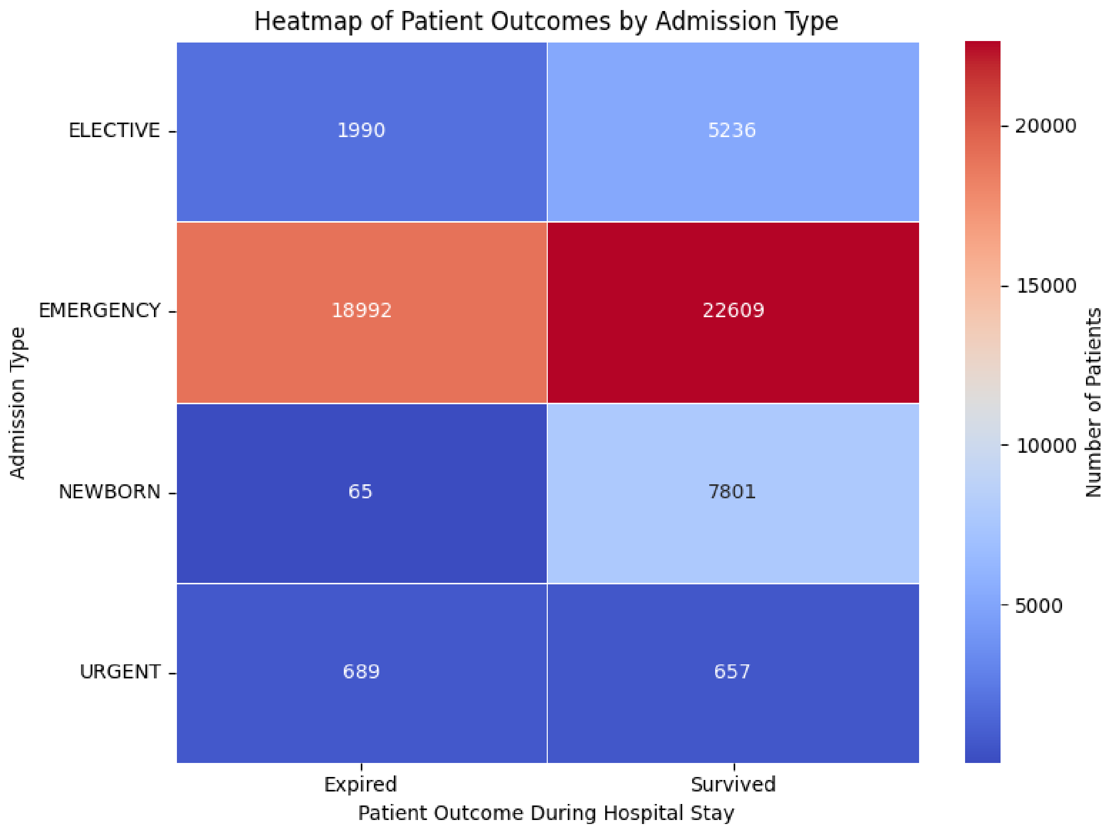
By visualizing the heatmap, we can see that the `EMERGENCY` `Type of Admission` is very correlated with `Hour of Admission`, being much more common in the evening/night `16PM - 23PM`. The `Type of Admission` `ELECTIVE` is also correlated with `Hour of Admission`, being very common at `7AM`.

### 5.3.3 Type of Admission & Death

[57]:
```
start_time = time.time()

# 1. Group by ADMISSION_TYPE and EXPIRE_FLAG
adm_type_expire_df = (
    filtered_ddf.groupby(["ADMISSION_TYPE", "EXPIRE_FLAG"])
    .size()
    .compute()
    .reset_index(name="count")
)

# 2. Map EXPIRE_FLAG to readable outcome labels
adm_type_expire_df["Outcome"] = adm_type_expire_df["EXPIRE_FLAG"].map({0:
 ↪"Survived", 1: "Expired"})

# 3. Pivot for heatmap
if not adm_type_expire_df.empty:
    heatmap_data = (
```

```python
        adm_type_expire_df
        .pivot(index="ADMISSION_TYPE", columns="Outcome", values="count")
        .fillna(0)
        .astype(float)
    )

    # 4. Plot
    plt.figure(figsize=(8, 6))
    sns.heatmap(
        heatmap_data,
        annot=True,
        fmt=".0f",
        linewidths=.5,
        cmap="coolwarm",
        cbar_kws={"label": "Number of Patients"}
    )
    plt.xlabel("Patient Outcome During Hospital Stay")
    plt.ylabel("Admission Type")
    plt.title("Heatmap of Patient Outcomes by Admission Type")
    plt.yticks(rotation=0)
    plt.tight_layout()
    plt.show()

    # 5. Print pivoted table
    print("\nPivoted Data for Heatmap:")
    print(heatmap_data)
else:
    print("No data returned for outcome heatmap analysis.")

end_time = time.time()
execution_time = end_time - start_time
print(f"Query Execution Time: {execution_time:.2f} seconds")
```

```
/usr/local/lib/python3.11/dist-
packages/dask/dataframe/dask_expr/_groupby.py:1562: FutureWarning: The default
of observed=False is deprecated and will be changed to True in a future version
of pandas. Pass observed=False to retain current behavior or observed=True to
adopt the future default and silence this warning.
  self._meta = self.obj._meta.groupby(
```




```
Pivoted Data for Heatmap:
Outcome          Expired  Survived
ADMISSION_TYPE
ELECTIVE          1990.0    5236.0
EMERGENCY        18992.0   22609.0
NEWBORN             65.0    7801.0
URGENT             689.0     657.0
Query Execution Time: 3.20 seconds
```

### 5.3.4 Conclusion

The clearest conclusion from this HeatMap is that patients who have `EMERGENCY` as their `Type of Admission` tend to `EXPIRE` much more frequently.

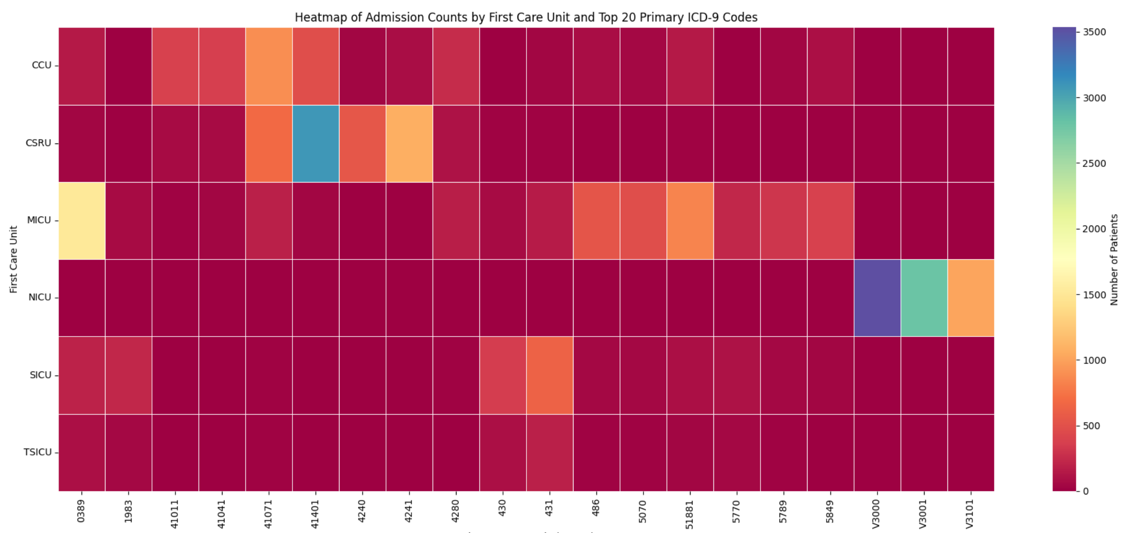
### 5.3.5 First Care Unit & Diagnosis

[58]:
```
start_time = time.time()

# 1. Force PRIMARY_ICD9_CODE to string
```

```
filtered_ddf = filtered_ddf.
 ↪assign(PRIMARY_ICD9_CODE=filtered_ddf["PRIMARY_ICD9_CODE"].astype(str))

# 2. Get top 20 ICD-9 codes as strings
top_icd9_codes = (
    filtered_ddf["PRIMARY_ICD9_CODE"]
    .value_counts()
    .compute()
    .nlargest(20)
    .index
    .tolist()
)

# 3. Filter rows where ICD-9 is in top list and FIRST_CAREUNIT is not null
careunit_icd9_ddf = filtered_ddf[
    (filtered_ddf["PRIMARY_ICD9_CODE"].isin(top_icd9_codes)) &
    (filtered_ddf["FIRST_CAREUNIT"].notnull())
][["FIRST_CAREUNIT", "PRIMARY_ICD9_CODE"]]

# 4. Group and count
careunit_icd9_df = (
    careunit_icd9_ddf
    .groupby(["FIRST_CAREUNIT", "PRIMARY_ICD9_CODE"])
    .size()
    .compute()
    .reset_index(name="count")
)

# 5. Pivot and plot
if not careunit_icd9_df.empty:
    heatmap_data = (
        careunit_icd9_df
        .pivot(index="FIRST_CAREUNIT", columns="PRIMARY_ICD9_CODE",␣
 ↪values="count")
        .fillna(0)
        .astype(float)
    )

    plt.figure(figsize=(18, 8))
    sns.heatmap(
        heatmap_data,
        annot=False,
        fmt=".0f",
        linewidths=.5,
        cmap="Spectral",
        cbar_kws={'label': 'Number of Patients'}
    )
```

```python
    plt.xlabel("Primary ICD-9 Code (Top 20)")
    plt.ylabel("First Care Unit")
    plt.title("Heatmap of Admission Counts by First Care Unit and Top 20␣
↪Primary ICD-9 Codes")
    plt.xticks(rotation=90)
    plt.yticks(rotation=0)
    plt.tight_layout()
    plt.show()

    print("\nPivoted Data for Heatmap:")
    print(heatmap_data)
else:
    print("No data returned for First Care Unit vs Top ICD-9 Code heatmap.")

end_time = time.time()
execution_time = end_time - start_time
print(f"Query Execution Time: {execution_time:.2f} seconds")
```

```
/usr/local/lib/python3.11/dist-
packages/dask/dataframe/dask_expr/_groupby.py:1562: FutureWarning: The default
of observed=False is deprecated and will be changed to True in a future version
of pandas. Pass observed=False to retain current behavior or observed=True to
adopt the future default and silence this warning.
  self._meta = self.obj._meta.groupby(
```




```
Pivoted Data for Heatmap:
PRIMARY_ICD9_CODE    0389    1983   41011   41041   41071    41401    4240    4241  \
FIRST_CAREUNIT
```

```
CCU                 150.0    4.0  379.0  371.0  885.0   476.0   37.0    80.0
CSRU                 31.0    4.0   62.0   67.0  684.0  3092.0  550.0  1075.0
MICU               1509.0   59.0   27.0   28.0  187.0    38.0    4.0     9.0
NICU                  0.0    0.0    0.0    0.0    0.0     0.0    0.0     0.0
SICU                207.0  226.0    1.0    2.0   27.0     6.0    1.0     3.0
TSICU                91.0   50.0    4.0    3.0   20.0     5.0    0.0     1.0

PRIMARY_ICD9_CODE   4280    430    431    486   5070  51881   5770   5789  \
FIRST_CAREUNIT
CCU                251.0   13.0   39.0   74.0   45.0  141.0   13.0   29.0
CSRU               107.0   18.0   14.0   11.0   12.0   22.0    7.0    9.0
MICU               173.0   64.0  163.0  535.0  474.0  835.0  231.0  317.0
NICU                 0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0
SICU                23.0  351.0  627.0   50.0   43.0   86.0   99.0   43.0
TSICU                8.0   96.0  188.0   14.0   22.0   40.0   49.0   17.0

PRIMARY_ICD9_CODE   5849   V3000   V3001   V3101
FIRST_CAREUNIT
CCU                 85.0     0.0     0.0     0.0
CSRU                 7.0     0.0     0.0     0.0
MICU               384.0     0.0     0.0     0.0
NICU                 0.0  3534.0  2792.0  1008.0
SICU                34.0     0.0     0.0     0.0
TSICU               13.0     0.0     0.0     0.0
Query Execution Time: 6.32 seconds
```

### 5.3.6 Conclusion

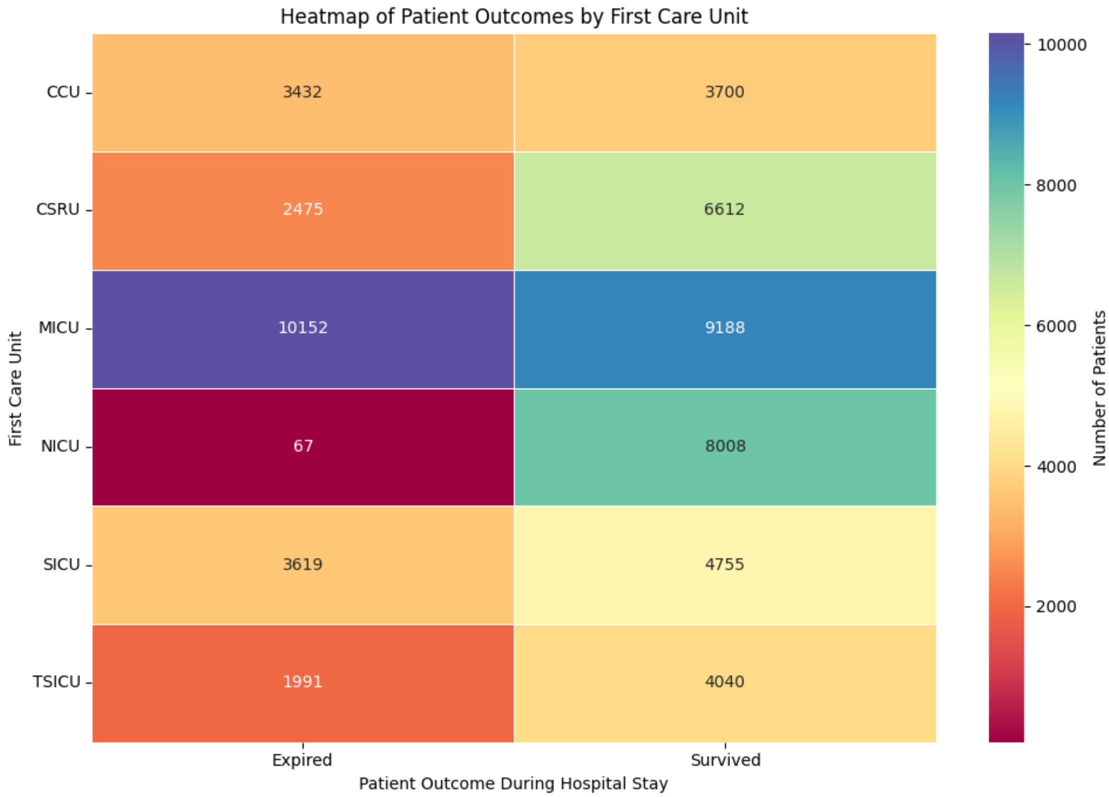
The strongest connections between First Care Unit and Diagnosis are V3000 (Single liveborn, delivered in hospital, without cesarean section) and NICU (Neonatal Intensive Care Unit) and 41401 (Coronary atherosclerosis of native coronary artery) and CSRU (Cardiac Surgery Recovery Unit).

### 5.3.7 First Care Unit & Death

[61]:
```python
start_time = time.time()

# 1. Group by FIRST_CAREUNIT and EXPIRE_FLAG
careunit_expire_df = (
    filtered_ddf.groupby(["FIRST_CAREUNIT", "EXPIRE_FLAG"])
    .size()
    .compute()
    .reset_index(name="count")
)

# 2. Map EXPIRE_FLAG to readable labels
careunit_expire_df["Outcome"] = careunit_expire_df["EXPIRE_FLAG"].map({0:␣
↪"Survived", 1: "Expired"})
```

```python
# 3. Pivot for heatmap
if not careunit_expire_df.empty:
    heatmap_data = (
        careunit_expire_df
        .pivot(index="FIRST_CAREUNIT", columns="Outcome", values="count")
        .fillna(0)
        .astype(float)
    )

    # 4. Plot
    plt.figure(figsize=(10, 7))
    sns.heatmap(
        heatmap_data,
        annot=True,
        fmt=".0f",
        linewidths=.5,
        cmap="Spectral",
        cbar_kws={'label': 'Number of Patients'}
    )
    plt.xlabel("Patient Outcome During Hospital Stay")
    plt.ylabel("First Care Unit")
    plt.title("Heatmap of Patient Outcomes by First Care Unit")
    plt.yticks(rotation=0)
    plt.tight_layout()
    plt.show()

    # 5. Print pivot table
    print("\nPivoted Data for Heatmap:")
    print(heatmap_data)
else:
    print("No data returned for First Care Unit vs Outcome heatmap.")

end_time = time.time()
execution_time = end_time - start_time
print(f"Query Execution Time: {execution_time:.2f} seconds")
```

```
/usr/local/lib/python3.11/dist-
packages/dask/dataframe/dask_expr/_groupby.py:1562: FutureWarning: The default
of observed=False is deprecated and will be changed to True in a future version
of pandas. Pass observed=False to retain current behavior or observed=True to
adopt the future default and silence this warning.
  self._meta = self.obj._meta.groupby(
```




```
Pivoted Data for Heatmap:
Outcome          Expired  Survived
FIRST_CAREUNIT
CCU               3432.0    3700.0
CSRU              2475.0    6612.0
MICU             10152.0    9188.0
NICU                67.0    8008.0
SICU              3619.0    4755.0
TSICU             1991.0    4040.0
Query Execution Time: 4.98 seconds
```

### 5.3.8 Conclusion

In half of the `First Care Units`, the ratio between patients that `expired` and `survived` is fairly equal (and close to 1). In the other half, which include the units `NICU`, `TSICU` and `CSRU`, the number of patients that `survived` is much higher than the number of patients that `expired`.

# 6 XGBoost Classifier Predictor Model

In this section we use a `XGBoost Classifier` model to predict the `ICU Length of Stay`, that we divide in bins of two days ([1-3] days, [3-5] days, ...). The `window size` we chose was `1 day` (24 hours), given that most data is collected in that window and most records have a value of `ICU Length of Stay` lower than 3 days, which means a bigger window size would exclude most of the data. We divided this section of the work in 2 parts: 1. Dividing the dataset, Categorizing the Target and Implementing Custom Sample Weights 2. Pre-Processing the features 3. Applying the model 4. Visualizing the results

The discussion of results was done in the final conclusions.

### 6.1 Dividing the Dataset, Categorizing the Target and Implementing Custom Sample Weights

Here we will divide the dataset in Train, Test and Validation. We will do this by: 1. Eliminating the features that are only collected after the first 24 hours (our `window size`) or are not relevant 2. Removing the records whose value for `ICU Length of Stay` is lower than 24 hours 3. Using the library `scikit-learn` to perform the division 4. Converting the target feature from `continuous values` to `bins` 5. Calculating the custom sample weights to ensure a less biased prediction towards the majority class 6. Normalizing the sample weights

[64]:
```python
# --- Configuration ---
TARGET_VARIABLE = 'ICU_LOS'
WINDOW_DAYS = 1.0
MAX_ICU_LOS_DAYS = 25.0
BIN_WIDTH = 2.0
TEST_SIZE = 0.10
VALIDATION_SIZE = 0.10
CUSTOM_WEIGHT_ALPHA = 0.8

print("--- Block 1: Dividing Dataset, Target Categorization & CUSTOM Sample␣
↪Weights ---")
start_time = time.time()

try:
    ddf = filtered_ddf
    original_row_count = ddf.shape[0].compute()
    print(f"Original row count: {original_row_count}")

    ddf = ddf[ddf[TARGET_VARIABLE] >= WINDOW_DAYS]
    rows_after_min_los_filter = ddf.shape[0].compute()
    print(f"Rows remaining after MIN LOS filter (>= {WINDOW_DAYS} days):␣
↪{rows_after_min_los_filter}")

    ddf = ddf[ddf[TARGET_VARIABLE] <= MAX_ICU_LOS_DAYS]
    rows_after_max_los_filter = ddf.shape[0].compute()
    print(f"Rows remaining after MAX LOS filter (<= {MAX_ICU_LOS_DAYS} days):␣
↪{rows_after_max_los_filter}")

    if rows_after_max_los_filter > 0:
        features_to_exclude = [
```

```
            'SUBJECT_ID', 'HADM_ID', 'ICUSTAY_ID', 'DOB',
            'ADMITTIME', 'DISCHTIME', 'ICU_INTIME', 'ICU_OUTTIME',
            'PRIMARY_ICD9_TITLE', 'EXPIRE_FLAG'
        ]

        all_columns = ddf.columns
        features_for_training_initial = [
            col for col in all_columns
            if col not in features_to_exclude and col != TARGET_VARIABLE
        ]

        print(f"Initial features considered for training:␣
↪{features_for_training_initial}")

        X = ddf[features_for_training_initial]
        y_continuous = ddf[TARGET_VARIABLE]

        X_pd = X.compute()
        y_continuous_pd = y_continuous.compute()

        if len(X_pd) < 3:
            raise ValueError("Not enough data to split.")

        train_val_size = 1.0 - TEST_SIZE
        X_train_val, X_test, y_train_val_cont, y_test_cont = train_test_split(
            X_pd, y_continuous_pd, test_size=TEST_SIZE, random_state=42,␣
↪shuffle=True
        )

        val_split_ratio = VALIDATION_SIZE / train_val_size if train_val_size >␣
↪0 else 0

        if len(X_train_val) < 2 or val_split_ratio == 0:
            X_train, X_val = X_train_val, pd.DataFrame()
            y_train_cont, y_val_cont = y_train_val_cont, pd.Series(dtype=float)
        else:
            X_train, X_val, y_train_cont, y_val_cont = train_test_split(
                X_train_val, y_train_val_cont, test_size=val_split_ratio,␣
↪random_state=42, shuffle=True
            )

        def convert_los_to_categories(los_series, bin_width, min_los):
            adjusted_los = los_series - min_los
            categories = np.floor(adjusted_los / bin_width).astype(int)
            return np.maximum(0, categories)
```

```
        y_train_cat = convert_los_to_categories(y_train_cont, BIN_WIDTH,␣
↪WINDOW_DAYS)
        y_val_cat = convert_los_to_categories(y_val_cont, BIN_WIDTH,␣
↪WINDOW_DAYS)
        y_test_cat = convert_los_to_categories(y_test_cont, BIN_WIDTH,␣
↪WINDOW_DAYS)

        all_cats = pd.concat([
            pd.Series(y_train_cat),
            pd.Series(y_val_cat),
            pd.Series(y_test_cat)
        ]).dropna().astype(int)

        if all_cats.empty:
            num_classes = 1
            max_cat_overall = 0
            train_sample_weights = np.array([])
        else:
            max_cat_overall = all_cats.max()
            num_classes = max_cat_overall + 1

            if len(y_train_cat) > 0:
                print(f"\n--- Calculating CUSTOM Sample Weights␣
↪(alpha={CUSTOM_WEIGHT_ALPHA}) ---")
                class_counts = Counter(y_train_cat)
                total_samples = len(y_train_cat)

                class_weights_map = {
                    cls: 1.0 / (count ** CUSTOM_WEIGHT_ALPHA) if count > 0 else␣
↪1.0
                    for cls, count in class_counts.items()
                }

                train_sample_weights = np.array([class_weights_map.get(cls, 1.
↪0) for cls in y_train_cat])
                train_sample_weights = (train_sample_weights / np.
↪sum(train_sample_weights)) * total_samples

                print(f"Custom class weights map: {class_weights_map}")
                print(f"Computed CUSTOM sample weights. Shape:␣
↪{train_sample_weights.shape}")
            else:
                train_sample_weights = np.array([])

        print(f"\nTarget variable converted to {num_classes} categories (0 to␣
↪{max_cat_overall}).")
```

```python
        print("\nDataset shapes:")
        print(f"X_train: {X_train.shape}, y_train_cat: {y_train_cat.shape}")
        if not X_val.empty:
            print(f"X_val: {X_val.shape}, y_val_cat: {y_val_cat.shape}")
        else:
            print("X_val is empty.")
        print(f"X_test: {X_test.shape}, y_test_cat: {y_test_cat.shape}")

        if original_row_count > 0:
            percentage_kept = (rows_after_max_los_filter / original_row_count)␣
↪* 100
            print(f"\nPercentage of original records kept after ALL filtering:␣
↪{percentage_kept:.2f}%")
    else:
        raise ValueError("No data left after filtering.")

except Exception as e:
    print(f"Error: {e}")
    X_train, X_val, X_test = pd.DataFrame(), pd.DataFrame(), pd.DataFrame()
    y_train_cat = y_val_cat = y_test_cat = pd.Series(dtype=int)
    train_sample_weights = np.array([])
    num_classes = 1
    features_for_training_initial = []

end_time = time.time()
print(f"\nExecution time: {end_time - start_time:.2f} seconds")
```

```
--- Block 1: Dividing Dataset, Target Categorization & CUSTOM Sample Weights ---
Original row count: 58039
Rows remaining after MIN LOS filter (>= 1.0 days): 46321
Rows remaining after MAX LOS filter (<= 25.0 days): 44439
Initial features considered for training: ['GENDER', 'AGE_AT_ADMISSION',
'ADMISSION_TYPE', 'ADMISSION_LOCATION', 'INSURANCE', 'ETHNICITY',
'ADMISSION_DIAGNOSIS_TEXT', 'ADMISSION_HOUR', 'FIRST_CAREUNIT',
'PRIMARY_ICD9_CODE']

--- Calculating CUSTOM Sample Weights (alpha=0.8) ---
Custom class weights map: {0: 0.0003634369074874825, 4: 0.003567379116988738, 1:
0.0008840502035876041, 3: 0.0025809482616361177, 2: 0.0016579799257901674, 8:
0.008045657161370626, 6: 0.005605339521480853, 9: 0.00995539059449496, 10:
0.012264988137738082, 5: 0.004555275341602907, 7: 0.0068874041958582035, 11:
0.012945881104681681}
Computed CUSTOM sample weights. Shape: (35551,)

Target variable converted to 12 categories (0 to 11).

Dataset shapes:
```

```
X_train: (35551, 10), y_train_cat: (35551,)
X_val: (4444, 10), y_val_cat: (4444,)
X_test: (4444, 10), y_test_cat: (4444,)

Percentage of original records kept after ALL filtering: 76.57%

Execution time: 36.40 seconds
```

### 6.2 Pre-Processing the Features

Here we will pre-process the features before applying the predictor model. We will do this by: 1. Defining the features to be used in training and their respective category 2. Feature enginner the features based on their category: - `Scale` for `Continuous Numerical` features - `Encode using sin and cos` for `Cyclical Numerical` features - `One-hot Encode` for `Low/Medium Cardinality Categorical` Features - `Dictifier Transformation` followed by a `FeatureHasher Transformation` for `High Cardinality Categorical` features

[65]:
```
# --- Record Start Time ---
start_time = time.time()
print("\n--- Block 2: Pre-Processing the Features ---")

# If X_train is empty, skip preprocessing
if 'X_train' in globals() and not X_train.empty:

    # --- 1. Define Feature Lists (based on X_train columns) ---

    _features_for_training = [
        'AGE_AT_ADMISSION',      # Numerical continuous
        'ADMISSION_TYPE',        # Categorical low cardinality
        'INSURANCE',             # Categorical low cardinality
        'PRIMARY_ICD9_CODE',     # Categorical high cardinality
        'FIRST_CAREUNIT',        # Categorical low cardinality
        'ADMISSION_HOUR'         # Numerical cyclical
    ]
    # Filter features to only those present in the training data from Block 1
    features_for_training_final = [f for f in _features_for_training if f in␣
↪X_train.columns]
    print(f"Features selected for preprocessing: {features_for_training_final}")


    numerical_cont_features = [f for f in ['AGE_AT_ADMISSION'] if f in␣
↪features_for_training_final]
    numerical_cycl_features = [f for f in ['ADMISSION_HOUR'] if f in␣
↪features_for_training_final] # e.g., 0-23
    categorical_low_card_features = [f for f in ['ADMISSION_TYPE', 'INSURANCE',␣
↪'FIRST_CAREUNIT'] if f in features_for_training_final]
```

```
    categorical_high_card_features = [f for f in ['PRIMARY_ICD9_CODE'] if f in␣
↪features_for_training_final]

    print(f"Continuous numerical features: {numerical_cont_features}")
    print(f"Cyclical numerical features: {numerical_cycl_features}")
    print(f"Low/Medium cardinality categorical features:␣
↪{categorical_low_card_features}")
    print(f"High cardinality categorical features:␣
↪{categorical_high_card_features}")

    # --- 2. Feature Engineering & Preprocessing Pipeline Components ---

    # a) Continuous Numerical Features: Scale
    numerical_cont_transformer = Pipeline(steps=[
        ('scaler', StandardScaler())
    ])

    # b) Cyclical Numerical Features: Encode hour using sine and cosine
    def sin_transformer(X_in):
        # Ensure input is 2D for FunctionTransformer
        X_proc = X_in.copy()
        if isinstance(X_proc, pd.Series): X_proc = X_proc.to_frame()
        elif X_proc.ndim == 1: X_proc = X_proc.reshape(-1, 1)
        return np.sin(2 * np.pi * X_proc / 24.0)

    def cos_transformer(X_in):
        X_proc = X_in.copy()
        if isinstance(X_proc, pd.Series): X_proc = X_proc.to_frame()
        elif X_proc.ndim == 1: X_proc = X_proc.reshape(-1, 1)
        return np.cos(2 * np.pi * X_proc / 24.0)

    # c) Low/Medium Cardinality Categorical Features: One-hot encode
    categorical_low_card_transformer = Pipeline(steps=[
        ('onehot', OneHotEncoder(handle_unknown='ignore', sparse_output=False))
    ])

    # d) High Cardinality Categorical Features: Feature Hashing
    # Custom Transformer for FeatureHasher Input
    class Dictifier(BaseEstimator, TransformerMixin):
        def __init__(self, col_name):
            self.col_name = col_name
        def fit(self, X, y=None):
            return self
        def transform(self, X_in):
            # X_in is expected to be a DataFrame/Series for the specific column
            if isinstance(X_in, pd.DataFrame): series = X_in.iloc[:, 0]
            elif isinstance(X_in, pd.Series): series = X_in
```

```
            else: series = pd.Series(X_in.flatten()) # Fallback for numpy array
            return [{self.col_name: str(val)} for val in series]

    # --- Create the list of transformers for ColumnTransformer ---
    transformers_list = []

    if numerical_cont_features:
        transformers_list.append(('num_cont', numerical_cont_transformer,␣
↪numerical_cont_features))
    if numerical_cycl_features: # Assuming only one cyclical feature␣
↪'ADMISSION_HOUR' for this example
        transformers_list.append(('hour_sin',␣
↪FunctionTransformer(sin_transformer, validate=False),␣
↪numerical_cycl_features))
        transformers_list.append(('hour_cos',␣
↪FunctionTransformer(cos_transformer, validate=False),␣
↪numerical_cycl_features))
    if categorical_low_card_features:
        transformers_list.append(('cat_low', categorical_low_card_transformer,␣
↪categorical_low_card_features))

    if categorical_high_card_features:
        n_hash_features = 50 # Number of features for the hasher, adjust as␣
↪needed
        for i, col_name in enumerate(categorical_high_card_features):
            print(f"  - Adding hasher for high-cardinality feature: {col_name}")
            transformer_name = f'cat_high_{col_name.replace(" ", "_").lower()}'␣
↪# Unique name
            high_card_pipeline = Pipeline(steps=[
                ('dictifier', Dictifier(col_name=col_name)),
                ('hasher', FeatureHasher(n_features=n_hash_features,␣
↪input_type='dict'))
            ])
            transformers_list.append((transformer_name, high_card_pipeline,␣
↪[col_name])) # Pass as list
    else:
        print("No high cardinality features specified or found for hashing.")

    # --- Define the main ColumnTransformer ---
    if transformers_list:
        preprocessor = ColumnTransformer(
            transformers=transformers_list,
            remainder='drop', # Drop any columns not specified in␣
↪features_for_training_final
            n_jobs=-1
        )
```

```
        print("Preprocessor defined.")
    else:
        print("No features to preprocess. Preprocessor not created.")
        preprocessor = 'passthrough' # Or handle as an error/empty pipeline

else:
    print("X_train is empty or not defined. Skipping feature preprocessing.")
    features_for_training_final = []
    preprocessor = 'passthrough' # To avoid error in next block

# --- Record End Time ---
end_time = time.time()
execution_time = end_time - start_time
print(f"\nExecution time: {execution_time:.2f} seconds")
```

```
--- Block 2: Pre-Processing the Features ---
Features selected for preprocessing: ['AGE_AT_ADMISSION', 'ADMISSION_TYPE',
'INSURANCE', 'PRIMARY_ICD9_CODE', 'FIRST_CAREUNIT', 'ADMISSION_HOUR']
Continuous numerical features: ['AGE_AT_ADMISSION']
Cyclical numerical features: ['ADMISSION_HOUR']
Low/Medium cardinality categorical features: ['ADMISSION_TYPE', 'INSURANCE',
'FIRST_CAREUNIT']
High cardinality categorical features: ['PRIMARY_ICD9_CODE']
  - Adding hasher for high-cardinality feature: PRIMARY_ICD9_CODE
Preprocessor defined.

Execution time: 0.00 seconds
```

### 6.3 Applying the XGBoost Classifier Model

Here we will apply the `XGBoost` model to the dataset. We will do this by:

1. Defining the model pipeline
2. Training the model
3. Making predictions using the trained model
4. Post-Process predictions

[67]:
```
# --- Record Start Time ---
start_time_block3_weighted = time.time()
print("\n--- Block 3: Applying the XGBoost Model (Classification) - MANUAL␣
↪PREDICTION FALLBACK & SAMPLE WEIGHTS ---")

# Ensure necessary variables are available
if ('X_train' not in globals() or X_train.empty or
    'y_train_cat' not in globals() or y_train_cat.empty or
    'preprocessor' not in globals() or
    'features_for_training_final' not in globals() or
```

```
    'num_classes' not in globals() or
    'train_sample_weights' not in globals()):
    print("Necessary data (X_train, y_train_cat, preprocessor, features,␣
↪num_classes, train_sample_weights) not available or y_train_cat is empty.␣
↪Skipping model training.")
    y_pred_val_final = pd.Series(dtype=int)
    y_pred_test_final = pd.Series(dtype=int)
    xgb_model_pipeline = None
    fitted_pipeline_preprocessor = None
    fitted_pipeline_classifier = None
else:
    if y_train_cat.empty:
        print("  y_train_cat is EMPTY. Cannot proceed with model training.")
        xgb_model_pipeline = None
        fitted_pipeline_preprocessor = None
        fitted_pipeline_classifier = None
    elif train_sample_weights is None or train_sample_weights.size == 0:
        print("  train_sample_weights is None or empty. Cannot proceed with␣
↪weighted training.")
        xgb_model_pipeline = None
        fitted_pipeline_preprocessor = None
        fitted_pipeline_classifier = None
    else:
        print(f"  y_train_cat.shape: {y_train_cat.shape}, dtype: {y_train_cat.
↪dtype}")
        if y_train_cat.isnull().any():
            print(f"  WARNING: y_train_cat contains NaNs! Count: {y_train_cat.
↪isnull().sum()}")
        y_train_cat = y_train_cat.astype(int) # Ensure it's int
        print(f"  Type of target (y_train_cat): {type_of_target(y_train_cat)}")
        print(f"  y_train_cat.min(): {y_train_cat.min()}, y_train_cat.max():␣
↪{y_train_cat.max()}")

        current_X_train_cols = X_train.columns.tolist()
        valid_features_for_model = [f for f in features_for_training_final if f␣
↪in current_X_train_cols]
        if not valid_features_for_model:
            print("WARNING: No valid features for model found in X_train.␣
↪Preprocessing might be incorrect or use no features.")

        X_train_processed_standalone = None
        try:
            if preprocessor == 'passthrough':
                X_train_processed_standalone =␣
↪X_train[valid_features_for_model].copy() if valid_features_for_model else␣
↪X_train.copy()
```

```
            elif hasattr(preprocessor, 'fit_transform'):
                temp_preprocessor_standalone = clone(preprocessor)
                print("  Fitting and transforming X_train with a cloned␣
↪preprocessor for standalone test...")
                X_train_processed_standalone = temp_preprocessor_standalone.
↪fit_transform(X_train[valid_features_for_model])
                print(f"  X_train_processed_standalone shape:␣
↪{X_train_processed_standalone.shape}")
            else:
                 print("  Preprocessor is not 'passthrough' and does not have␣
↪'fit_transform'. Cannot preprocess for standalone test.")
        except Exception as e_preprocess_standalone:
            print(f"  ERROR during X_train preprocessing for standalone test:␣
↪{e_preprocess_standalone}")

        if X_train_processed_standalone is not None:
            standalone_xgb = XGBClassifier(objective='multi:softmax',␣
↪num_class=num_classes, n_estimators=50, learning_rate=0.1, max_depth=3,␣
↪random_state=42, n_jobs=-1, eval_metric='mlogloss')
            try:
                # Pass sample_weight to standalone fit
                standalone_xgb.fit(X_train_processed_standalone, y_train_cat,␣
↪sample_weight=train_sample_weights)
                print("  Standalone XGBClassifier fitted successfully with␣
↪sample_weight!")
            except Exception as e_standalone:
                print(f"  ERROR fitting standalone XGBClassifier with␣
↪sample_weight: {e_standalone}")
        else:
            print("  Skipping Standalone XGBClassifier test as X_train could␣
↪not be processed for it.")

        # preprocessor is the definition from Block 2. Pipeline will fit it.
        xgb_model_pipeline = Pipeline(steps=[
            ('preprocessor', preprocessor),
            ('classifier', XGBClassifier(objective='multi:softmax',␣
↪num_class=num_classes, n_estimators=100, learning_rate=0.1, max_depth=5,␣
↪subsample=0.8, colsample_bytree=0.8, random_state=42, n_jobs=-1,␣
↪eval_metric='mlogloss'))
        ])

        fitted_pipeline_preprocessor = None
        fitted_pipeline_classifier = None
        pipeline_fit_successful = False

        try:
```

```
            print(f"  Attempting to fit the pipeline on␣
↪X_train[valid_features_for_model] (shape: {X_train[valid_features_for_model].
↪shape if valid_features_for_model else X_train.shape}) and y_train_cat...")
            fit_params = {'classifier__sample_weight': train_sample_weights}
            xgb_model_pipeline.fit(X_train, y_train_cat, **fit_params)
            print("  Pipeline fitted successfully with sample_weight!")
            pipeline_fit_successful = True
            fitted_pipeline_preprocessor = xgb_model_pipeline.
↪named_steps['preprocessor']
            fitted_pipeline_classifier = xgb_model_pipeline.
↪named_steps['classifier']

        except Exception as e_pipeline_fit:
            print(f"  ERROR during pipeline.fit() with sample_weight:␣
↪{e_pipeline_fit}")
            xgb_model_pipeline = None # Ensure pipeline is None if fit fails

        # Initialize prediction variables
        y_pred_val_final = pd.Series(dtype=int)
        y_pred_test_final = pd.Series(dtype=int)

        if pipeline_fit_successful and fitted_pipeline_preprocessor and␣
↪fitted_pipeline_classifier:
            # Validation set predictions
            if 'X_val' in globals() and not X_val.empty:
                if 'y_val_cat' in globals() and not y_val_cat.empty: # Check if␣
↪there's a target to compare
                    try:
                        # Use the same features for transform as were used for␣
↪training the preprocessor
                        X_val_to_transform = X_val # Pass the X_val with all␣
↪original features
                        X_val_processed = fitted_pipeline_preprocessor.
↪transform(X_val_to_transform)
                        print(f"    X_val_processed shape: {X_val_processed.
↪shape}")
                        y_pred_val_cat_manual = fitted_pipeline_classifier.
↪predict(X_val_processed)
                        y_pred_val_final = pd.Series(y_pred_val_cat_manual,␣
↪index=X_val.index)
                        print(f"    Manual predictions on validation set␣
↪successful. Shape: {y_pred_val_final.shape}")
                    except Exception as e_manual_pred_val:
                        print(f"    ERROR during manual prediction on␣
↪validation set: {e_manual_pred_val}")
                else:
```

```
                    print("  Validation set target (y_val_cat) is empty.␣
↪Skipping manual validation predictions.")
            else:
                print("  Validation set (X_val) is empty or not available.␣
↪Skipping manual validation predictions.")

            # Test set predictions
            if 'X_test' in globals() and not X_test.empty:
                if 'y_test_cat' in globals() and not y_test_cat.empty: # Check␣
↪if there's a target to compare
                    try:
                        X_test_to_transform = X_test # Pass the X_test with all␣
↪original features
                        X_test_processed = fitted_pipeline_preprocessor.
↪transform(X_test_to_transform)
                        print(f"    X_test_processed shape: {X_test_processed.
↪shape}")
                        y_pred_test_cat_manual = fitted_pipeline_classifier.
↪predict(X_test_processed)
                        y_pred_test_final = pd.Series(y_pred_test_cat_manual,␣
↪index=X_test.index)
                        print(f"    Manual predictions on test set successful.␣
↪Shape: {y_pred_test_final.shape}")
                    except Exception as e_manual_pred_test:
                        print(f"    ERROR during manual prediction on test set:␣
↪{e_manual_pred_test}")
                else:
                    print("  Test set target (y_test_cat) is empty. Skipping␣
↪manual test predictions.")
            else:
                print("  Test set (X_test) is empty or not available. Skipping␣
↪manual test predictions.")

        elif xgb_model_pipeline is not None:
            try:
                if 'X_val' in globals() and not X_val.empty and 'y_val_cat' in␣
↪globals() and not y_val_cat.empty:
                    y_pred_val_cat_pipeline = xgb_model_pipeline.predict(X_val)␣
↪# Use full X_val
                    y_pred_val_final = pd.Series(y_pred_val_cat_pipeline,␣
↪index=X_val.index)
                    print(f"  Pipeline predictions on validation set successful.
↪ Shape: {y_pred_val_final.shape}")
                if 'X_test' in globals() and not X_test.empty and 'y_test_cat'␣
↪in globals() and not y_test_cat.empty:
```

```
                    y_pred_test_cat_pipeline = xgb_model_pipeline.
↪predict(X_test) # Use full X_test
                    y_pred_test_final = pd.Series(y_pred_test_cat_pipeline,␣
↪index=X_test.index)
                    print(f"  Pipeline predictions on test set successful.␣
↪Shape: {y_pred_test_final.shape}")
            except Exception as e_pipeline_predict:
                print(f"  ERROR during pipeline.predict() fallback:␣
↪{e_pipeline_predict}")
        else:
            print("\nPipeline did not fit successfully. No predictions will be␣
↪made.")

# --- Record End Time ---
end_time = time.time()
execution_time = end_time - start_time
print(f"\nXGBoost training & prediction execution time (MANUAL PREDICTION␣
↪FALLBACK & SAMPLE WEIGHTS block): {execution_time:.2f} seconds")
```

```
--- Block 3: Applying the XGBoost Model (Classification) - MANUAL PREDICTION
FALLBACK & SAMPLE WEIGHTS ---
  y_train_cat.shape: (35551,), dtype: int64
  Type of target (y_train_cat): multiclass
  y_train_cat.min(): 0, y_train_cat.max(): 11
  Fitting and transforming X_train with a cloned preprocessor for standalone
test…
  X_train_processed_standalone shape: (35551, 68)
  Standalone XGBClassifier fitted successfully with sample_weight!
  Attempting to fit the pipeline on X_train[valid_features_for_model] (shape:
(35551, 6)) and y_train_cat…
  Pipeline fitted successfully with sample_weight!
    X_val_processed shape: (4444, 68)
    Manual predictions on validation set successful. Shape: (4444,)
    X_test_processed shape: (4444, 68)
    Manual predictions on test set successful. Shape: (4444,)

XGBoost training & prediction execution time (MANUAL PREDICTION FALLBACK &
SAMPLE WEIGHTS block): 283.36 seconds
```

### 6.4 Vizualizating the Results

To end we use statistical measures and adequate plots to visualize the prediction results.

[68]:
```
# --- Record Start Time ---
start_time = time.time()
print("\n--- Block 4: Evaluating and Visualizing Results ---")
```

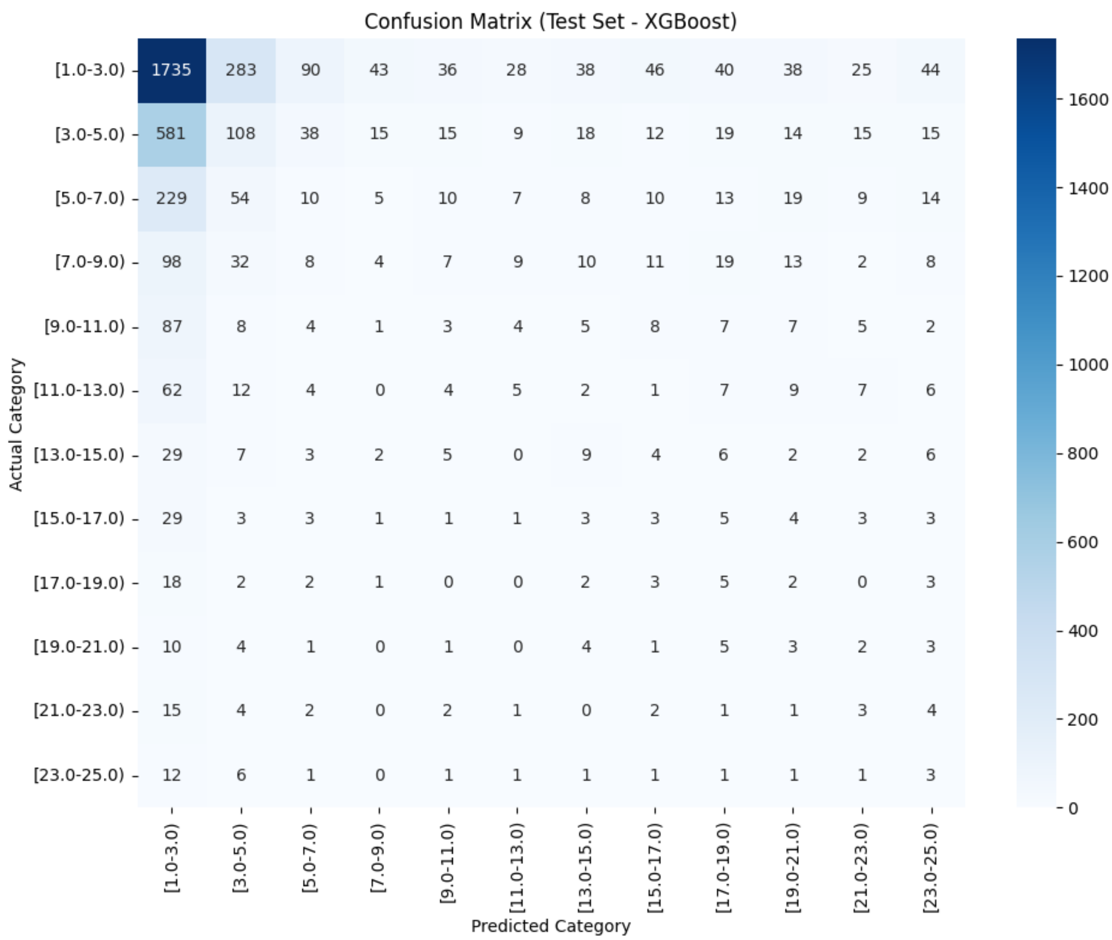
```
# Check if necessary data for evaluation is available
if ('y_val_cat' not in globals() or
    'y_test_cat' not in globals() or
    'y_pred_val_final' not in globals() or
    'y_pred_test_final' not in globals() or
    'num_classes' not in globals()):
    print("Necessary data for evaluation/visualization is missing. Skipping.")
else:
    # Define descriptive labels for your bins for plotting
    bin_labels_for_plots = []
    if 'WINDOW_DAYS' in globals() and 'BIN_WIDTH' in globals() and num_classes␣
↪> 0 :
         for i in range(num_classes):
            lower_bound = WINDOW_DAYS + i * BIN_WIDTH
            upper_bound = WINDOW_DAYS + (i + 1) * BIN_WIDTH
            bin_labels_for_plots.append(f"[{lower_bound:.1f}-{upper_bound:.
↪1f})")
    else: # Fallback labels
        bin_labels_for_plots = [f"Cat {i}" for i in range(num_classes)]

    print(f"Using bin labels for plots: {bin_labels_for_plots}")


    # --- 1. Evaluate the Model ---
    # Validation Set Metrics (if y_val_cat and y_pred_val_final are not empty)
    if not y_val_cat.empty and not y_pred_val_final.empty:
        # Ensure labels in classification report and confusion matrix cover all␣
↪possible classes
        unique_labels_present_val = np.union1d(y_val_cat.unique(),␣
↪y_pred_val_final.unique())
        # Ensure all labels from 0 to num_classes-1 are considered for␣
↪consistency if some classes have 0 instances
        report_labels_val = list(range(num_classes))

        accuracy_val = accuracy_score(y_val_cat, y_pred_val_final)
        kappa_val = cohen_kappa_score(y_val_cat, y_pred_val_final,␣
↪labels=report_labels_val if report_labels_val else None)
        report_val = classification_report(y_val_cat, y_pred_val_final,␣
↪labels=report_labels_val, target_names=bin_labels_for_plots, zero_division=0)

        print("\n--- Validation Set Metrics (XGBoost - Categorical) ---")
        print(f"Accuracy: {accuracy_val:.3f}")
        print(f"Cohen's Kappa: {kappa_val:.3f}")
        print("Classification Report (Validation):\n", report_val)
    else:
```

```
        print("\nValidation data (actual or predicted) is empty. Skipping␣
↪validation metrics.")

    # Test Set Metrics (if y_test_cat and y_pred_test_final are not empty)
    if not y_test_cat.empty and not y_pred_test_final.empty:
        unique_labels_present_test = np.union1d(y_test_cat.unique(),␣
↪y_pred_test_final.unique())
        report_labels_test = list(range(num_classes))

        accuracy_test = accuracy_score(y_test_cat, y_pred_test_final)
        kappa_test = cohen_kappa_score(y_test_cat, y_pred_test_final,␣
↪labels=report_labels_test if report_labels_test else None)
        report_test = classification_report(y_test_cat, y_pred_test_final,␣
↪labels=report_labels_test, target_names=bin_labels_for_plots,␣
↪zero_division=0)
        cm_test = confusion_matrix(y_test_cat, y_pred_test_final,␣
↪labels=report_labels_test)

        print("\n--- Test Set Metrics (XGBoost - Categorical) ---")
        print(f"Accuracy: {accuracy_test:.3f}")
        print(f"Cohen's Kappa: {kappa_test:.3f}")
        print("Classification Report (Test):\n", report_test)
        # print("Confusion Matrix (Test):\n", cm_test)

        # --- 2. Visualize Results (Test Set) ---
        # a) Confusion Matrix Heatmap
        if num_classes > 0:
            plt.figure(figsize=(min(10, num_classes + 2), min(8, num_classes +␣
↪1)))
            sns.heatmap(cm_test, annot=True, fmt='d', cmap='Blues',
                        xticklabels=bin_labels_for_plots,
                        yticklabels=bin_labels_for_plots)
            plt.xlabel("Predicted Category")
            plt.ylabel("Actual Category")
            plt.title("Confusion Matrix (Test Set - XGBoost)")
            plt.tight_layout()
            plt.show()

            # b) Actual vs. Predicted Class Distribution
            plt.figure(figsize=(max(8, num_classes * 0.8), 6))
            actual_counts = y_test_cat.value_counts().
↪reindex(range(num_classes), fill_value=0).sort_index()
            predicted_counts = y_pred_test_final.value_counts().
↪reindex(range(num_classes), fill_value=0).sort_index()
```

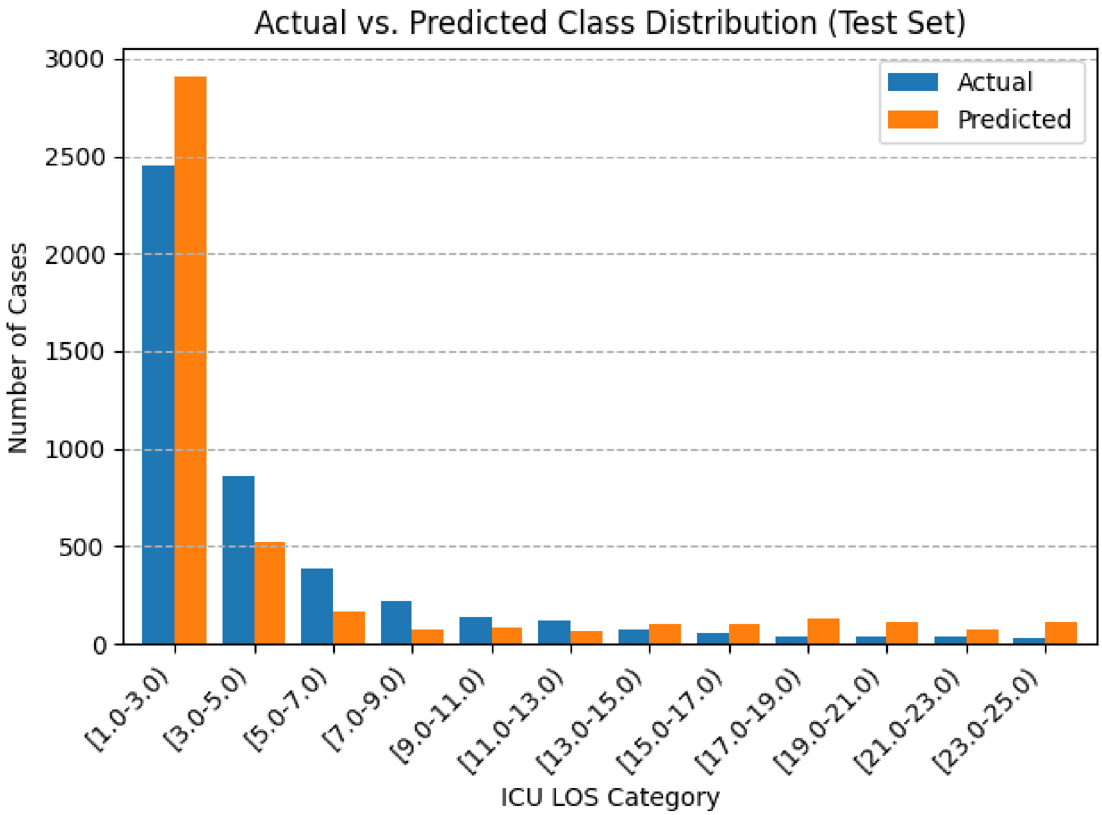
```python
            df_counts = pd.DataFrame({'Actual': actual_counts, 'Predicted':␣
↪predicted_counts})
            if not df_counts.empty:
                # Use the generated bin_labels_for_plots for the x-axis ticks
                df_counts.index = [bin_labels_for_plots[i] for i in df_counts.
↪index if i < len(bin_labels_for_plots)]

                df_counts.plot(kind='bar', width=0.8)
                plt.title("Actual vs. Predicted Class Distribution (Test Set)")
                plt.xlabel("ICU LOS Category")
                plt.ylabel("Number of Cases")
                plt.xticks(rotation=45, ha="right")
                plt.legend()
                plt.grid(axis='y', linestyle='--')
                plt.tight_layout()
                plt.show()
            else:
                print("Cannot plot class distribution: Counts data is empty.")
        else:
            print("Number of classes is 0, cannot generate plots.")
    else:
        print("\nTest data (actual or predicted) is empty. Skipping test␣
↪metrics and visualization.")


# --- Record End Time ---
end_time = time.time()
execution_time = end_time - start_time
print(f"\nExecution time: {execution_time:.2f} seconds")
```

```
--- Block 4: Evaluating and Visualizing Results ---
Using bin labels for plots: ['[1.0-3.0)', '[3.0-5.0)', '[5.0-7.0)', '[7.0-9.0)',
'[9.0-11.0)', '[11.0-13.0)', '[13.0-15.0)', '[15.0-17.0)', '[17.0-19.0)',
'[19.0-21.0)', '[21.0-23.0)', '[23.0-25.0)']

--- Validation Set Metrics (XGBoost - Categorical) ---
Accuracy: 0.438
Cohen's Kappa: 0.083
Classification Report (Validation):
               precision    recall  f1-score   support

   [1.0-3.0)       0.61      0.71      0.66      2478
   [3.0-5.0)       0.25      0.16      0.20       815
   [5.0-7.0)       0.12      0.05      0.07       378
   [7.0-9.0)       0.09      0.03      0.05       238
  [9.0-11.0)       0.05      0.03      0.03       156
```

```
 [11.0-13.0)       0.03      0.02      0.02        95
 [13.0-15.0)       0.04      0.04      0.04        96
 [15.0-17.0)       0.05      0.09      0.07        64
 [17.0-19.0)       0.01      0.03      0.01        38
 [19.0-21.0)       0.05      0.17      0.08        35
 [21.0-23.0)       0.03      0.13      0.05        23
 [23.0-25.0)       0.04      0.14      0.06        28

    accuracy                           0.44      4444
   macro avg       0.11      0.13      0.11      4444
weighted avg       0.41      0.44      0.42      4444


--- Test Set Metrics (XGBoost - Categorical) ---
Accuracy: 0.426
Cohen's Kappa: 0.060
Classification Report (Test):
               precision    recall  f1-score   support

   [1.0-3.0)       0.60      0.71      0.65      2446
   [3.0-5.0)       0.21      0.13      0.16       859
   [5.0-7.0)       0.06      0.03      0.04       388
   [7.0-9.0)       0.06      0.02      0.03       221
  [9.0-11.0)       0.04      0.02      0.03       141
 [11.0-13.0)       0.08      0.04      0.05       119
 [13.0-15.0)       0.09      0.12      0.10        75
 [15.0-17.0)       0.03      0.05      0.04        59
 [17.0-19.0)       0.04      0.13      0.06        38
 [19.0-21.0)       0.03      0.09      0.04        34
 [21.0-23.0)       0.04      0.09      0.06        35
 [23.0-25.0)       0.03      0.10      0.04        29

    accuracy                           0.43      4444
   macro avg       0.11      0.13      0.11      4444
weighted avg       0.38      0.43      0.40      4444
```




<Figure size 960x600 with 0 Axes>




```
Execution time: 2.44 seconds
```

# 7 Final Conclusions

### 7.0.1 Features Distribution

We were able to get some interesting conclusions from the distribution analysis for each feature, namely: - Most of patients only stay in ICU for `5 days or less`, with a decreasing trend of the number of patients as the number of days increases.

### 7.0.2 Features Correlation

We were also able to draw interesting conclusions from the correlation between different features, namely: - The correlation between `Diagnosis` and `ICU Length of Stay` is evident, with `Twin mate, liveborn, delivered in hospital, with cesarean section` having a much higher mean value compared to other types of Diagnosis - Regarding the connection between `Age` and `Length of ICU Stay`, we can conclude that the vast majority of ICU stays are relatively short across all adult age groups, although the spread of the values of `Length of ICU Stay` appears to widen slightly for older patients - All `Insurance` systems have a similar distribution and mean for `ICU Length of Stay`, with a clear exception of `Self Pay`, whose average value is significantly lower. - Patients who have `EMERGENCY` as their `Type of Admission` tend to `EXPIRE`(die) much more frequently. - `NICU (Neonatal Intensive Care Unit)` has the lowest number of deaths and `MICU (Medical Intensive Care Unit)` has the highest number of deaths.

#### 7.0.3 Predictor Model

- The `accuracy` value in the `Validation` and in `Testing` set are similar and have medium-low values, which mean the model wasn't very sucessful at predicting the patients `ICU Length of Stay` during the validation phase
- The `Cohen's Kappa` value for both `Validation` and `Testing` is very low, which indicates the model is not much better than a random chance model at predicting the correct classes
- The `heatmap` shows that the model is very good at predicting correctly the majority class [1-3] days, but mostly fails at predicting other classes correctly
- The `bar plot` shows that the model predictions distribution is pretty similar to the actual data distribution, which is a good sign for possible future improvements
- In summary, the predictions for the majority class are accurate but for minority classes are not, which is a very common problem in Machine Learning prediction models.
- In future works, we could try to improve these bad results by performing better `feature engineering`, performing `fine-tuning` in the parameters of the predictor model, choose more wisely the features to use and possibly choose a more adequate model for the dataset.

#### 7.0.4 BigQuery and Execution Time

- The BigQuery proved to be a reliable and intuitive platform to perform `Machine Learning` projects
- The queries that were timed (not all were because all the results would be very similar) executed almost instantly (range from < 1 second to ~3/4 seconds)
- All the steps for executing the `XGBoost Classifier` model were also (and surprisingly!) very fast, with all executions running almost instantly

#### 7.0.5 Dask and Execution Time

- Dask can support very large datasets while maintaining very quick and efficient processing speeds.
- However, because of the way we treated the data, we weren't able to see many improvements when compared to other libraries like Pandas, with most executions ranging from 2~40 seconds.

#### 7.0.6 Project Developed by:


- Francisco Macieira → up202207166@edu.fc.up.pt
- Manuel Silva → up202108874@edu.fe.up.pt
- Nuno Gomes → up202206195@edu.fc.up.pt