CSC108_HarmonyHealthcare_Data_Cleaning_and_Visualizations,_and_Lo
1

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0.0.1 Beyond the Emergency Department: Predictive Analytics for 6-Month Patient Admission in Harmony Healthcare

0.0.2 Problem Statement

Our goal is to build a predictive model that identifies whether a patient will experience at least one ED admission within the next six months. Based on instructor feedback, we removed columns directly tied to emergency department data, forcing the model to learn broader risk signals rather than simply reproducing ED activity. This notebook documents data cleaning, exploratory visualization, and an initial predictive model using forward feature selection with logistic regression.

[25]:
```
# from google.colab import drive
# drive.mount('/content/drive')

import pandas as pd
df = pd.read_excel('HarmonyHealthcareOneWeek_9_2025.xlsx')

# We want to keep the 'ED Episode Admit Last-6-Mths' column and remove all␣
↪other columns with ED in the name
ed_columns = [col for col in df.columns if 'ED' in col and col != 'ED Episode␣
↪Admit Last-6-Mths']
df = df.drop(columns=ed_columns)

# Assuming NaN in 'ED Episode Admit Last-6-Mths' means no admission, fill with␣
↪0 early
target = 'ED Episode Admit Last-6-Mths'
df[target] = df[target].fillna(0)

# Now we can remove any columns that are just empty to shrink the data further
df = df.dropna(axis=1, how='all')
df.head()
```

[25]:
```
   Age EHR Sex  ED Episode Admit Last-6-Mths Most Recent Encounter Type  \
0   26    male                           0.0                 TeleBHTher
1   14  female                           0.0                  Nutrition
2   11    male                           0.0                        F/U
3   49    male                           0.0                 BH Therapy
4   39  female                           0.0                    Telemed

   UDS Qualifying Encounter Count UDS Homelessness Status  \
0                            21.0            Not Homeless
1                             4.0            Not Homeless
2                             5.0            Not Homeless
3                            48.0            Not Homeless
4                             4.0            Not Homeless

  IP Episode Admit Date IP Episode Admit Location  IP Episode Admit Readmit  \
0                   NaT                       NaN                       NaN
1                   NaT                       NaN                       NaN
2                   NaT                       NaN                       NaN
3                   NaT                       NaN                       NaN
4                   NaT                       NaN                       NaN

   IP Episode Admit Past-6-Mths  … Urine Creatinine Date  \
0                           NaN  …                   NaT
1                           NaN  …                   NaT
2                           NaN  …                   NaT
3                           NaN  …                   NaT
4                           NaN  …                   NaT

  Urine Creatinine Code Urine Creatinine Result Varicella Titer Date  \
0                   NaN                     NaN                  NaT
1                   NaN                     NaN                  NaT
2                   NaN                     NaN                  NaT
3                   NaN                     NaN                  NaT
4                   NaN                     NaN                  NaT

  Varicella Titer Code Varicella Titer Result Violence Screening Date  \
0                  NaN                    NaN              2025-02-10
1                  NaN                    NaN                     NaT
2                  NaN                    NaN                     NaT
3                  NaN                    NaN              2025-08-26
4                  NaN                    NaN              2025-07-26

     Violence Screening Type Vision Screening Date Vision Screening Code
0  Domestic Violence PRAPARE            2024-11-08                 99173
1                        NaN            2025-01-02                 99173
2                        NaN            2024-11-09                 99173
3  Domestic Violence PRAPARE            2024-09-25                 99173
```

```
4  Domestic Violence PRAPARE             2025-06-24                 99173

[5 rows x 583 columns]
```

[26]:
```
target = 'ED Episode Admit Last-6-Mths' # Store our target var so we can use it␣
 ↪later

# Check target distribution
print(df[target].value_counts())
print(df[target].value_counts(normalize=True) * 100)

# Check missing percentages
missing_pct = (df.isna().mean() * 100).sort_values(ascending=False)
print(missing_pct[missing_pct > 0])
```

```
ED Episode Admit Last-6-Mths
0.0     2442
1.0      170
2.0       39
3.0       10
4.0        4
5.0        4
6.0        1
34.0       1
7.0        1
Name: count, dtype: int64
ED Episode Admit Last-6-Mths
0.0     91.392216
1.0      6.362275
2.0      1.459581
3.0      0.374251
4.0      0.149701
5.0      0.149701
6.0      0.037425
34.0     0.037425
7.0      0.037425
Name: proportion, dtype: float64
Material Security Food-Insecurity-ICD10-Date    99.962575
Opioid Dependence Dx Name                       99.962575
Transportation ICD10-Insecurity-Code            99.962575
Transportation ICD10-Insecurity-Date            99.962575
Cerebral Palsy Date                             99.962575
                                                  …
SDOH Triggers                                    0.898204
Patient Appointment No-Show Rate %               0.149701
Patient Appointment No-Show Count                0.149701
Patient Medicaid Risk Total Risk                 0.074850
Patient Medicaid Risk Risk Gap                   0.074850
```

```
Length: 561, dtype: float64
```

[27]:
```python
# Drop columns with >70% missing, except target
columns_to_drop = [c for c in df.columns if c != target and df[c].isna().mean()␣
    ↪* 100 > 70]
print("Number of columns to drop:", len(columns_to_drop))
df = df.drop(columns=columns_to_drop)
df.head()
```

```
Number of columns to drop: 417
```

[27]:
```
   Age EHR Sex  ED Episode Admit Last-6-Mths Most Recent Encounter Type  \
0   26    male                           0.0                 TeleBHTher
1   14  female                           0.0                  Nutrition
2   11    male                           0.0                        F/U
3   49    male                           0.0                 BH Therapy
4   39  female                           0.0                    Telemed

   UDS Qualifying Encounter Count UDS Homelessness Status  Active Medications  \
0                            21.0            Not Homeless                  13
1                             4.0            Not Homeless                  11
2                             5.0            Not Homeless                  23
3                            48.0            Not Homeless                  23
4                             4.0            Not Homeless                   4

  Alcohol Assessment Date Alcohol Assessment Code  Alcohol Assessment Result  \
0              2024-12-06                  AUDIT-C                        0.0
1              2025-09-17                  AUDIT-C                        0.0
2                     NaT                      NaN                        NaN
3              2024-06-05                  AUDIT-C                        3.0
4              2024-10-30                  AUDIT-C                        0.0

   … Stress Response Transportation Trigger  Transportation NonMed-Date  \
0  …      Not at all                    NaN                         NaN
1  …             NaN                    NaN                         NaN
2  …             NaN                    NaN                         NaN
3  …      Not at all                      N       8/26/2025 12:00:00 AM
4  …    A little bit                      N       7/26/2025 12:00:00 AM

   Transportation NonMed-Reponse       UDS SDOH Triggers  UDS SDOH Tally  \
0                            NaN       FINANCIAL STRAIN             1.0
1                            NaN       FINANCIAL STRAIN             1.0
2                            NaN       FINANCIAL STRAIN             1.0
3                              N  FINANCIAL STRAIN FOOD             2.0
4                              N       FINANCIAL STRAIN             1.0

  Violence Screening Date    Violence Screening Type  Vision Screening Date  \
0              2025-02-10  Domestic Violence PRAPARE             2024-11-08
```

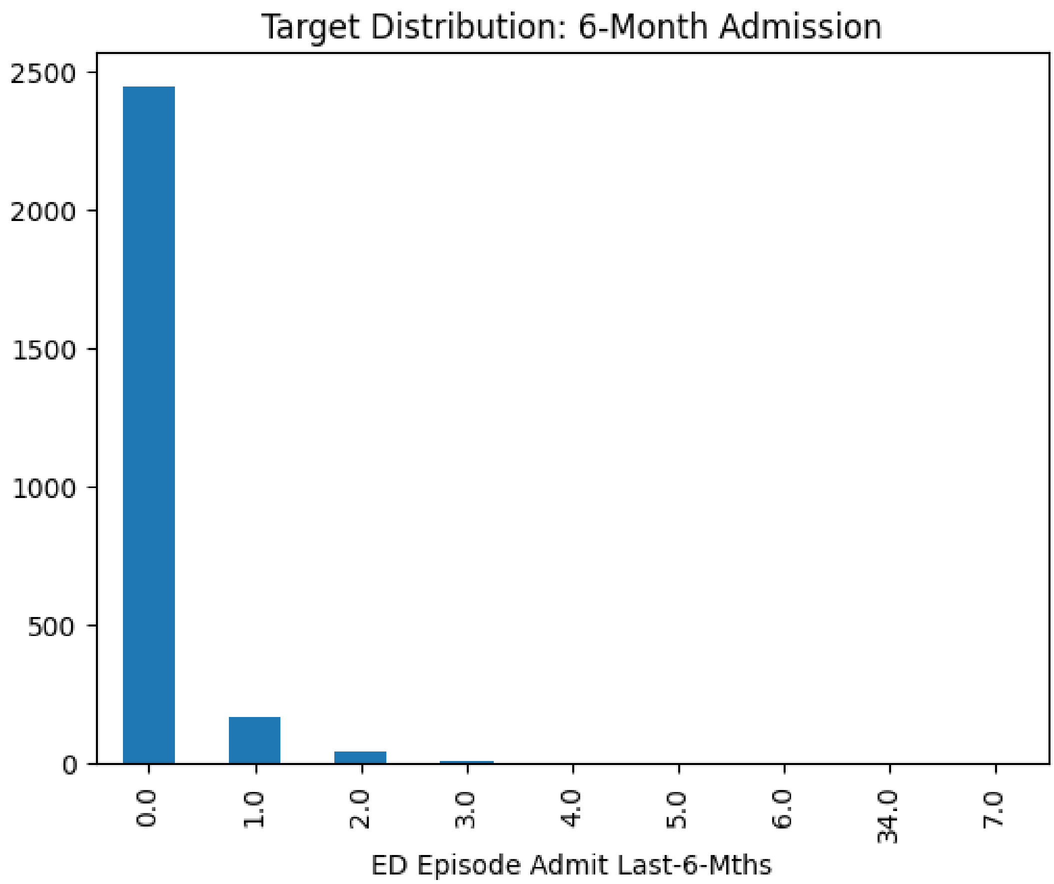
```
1                  NaT                          NaN            2025-01-02
2                  NaT                          NaN            2024-11-09
3           2025-08-26  Domestic Violence PRAPARE            2024-09-25
4           2025-07-26  Domestic Violence PRAPARE            2025-06-24

   Vision Screening Code
0                  99173
1                  99173
2                  99173
3                  99173
4                  99173

[5 rows x 166 columns]
```

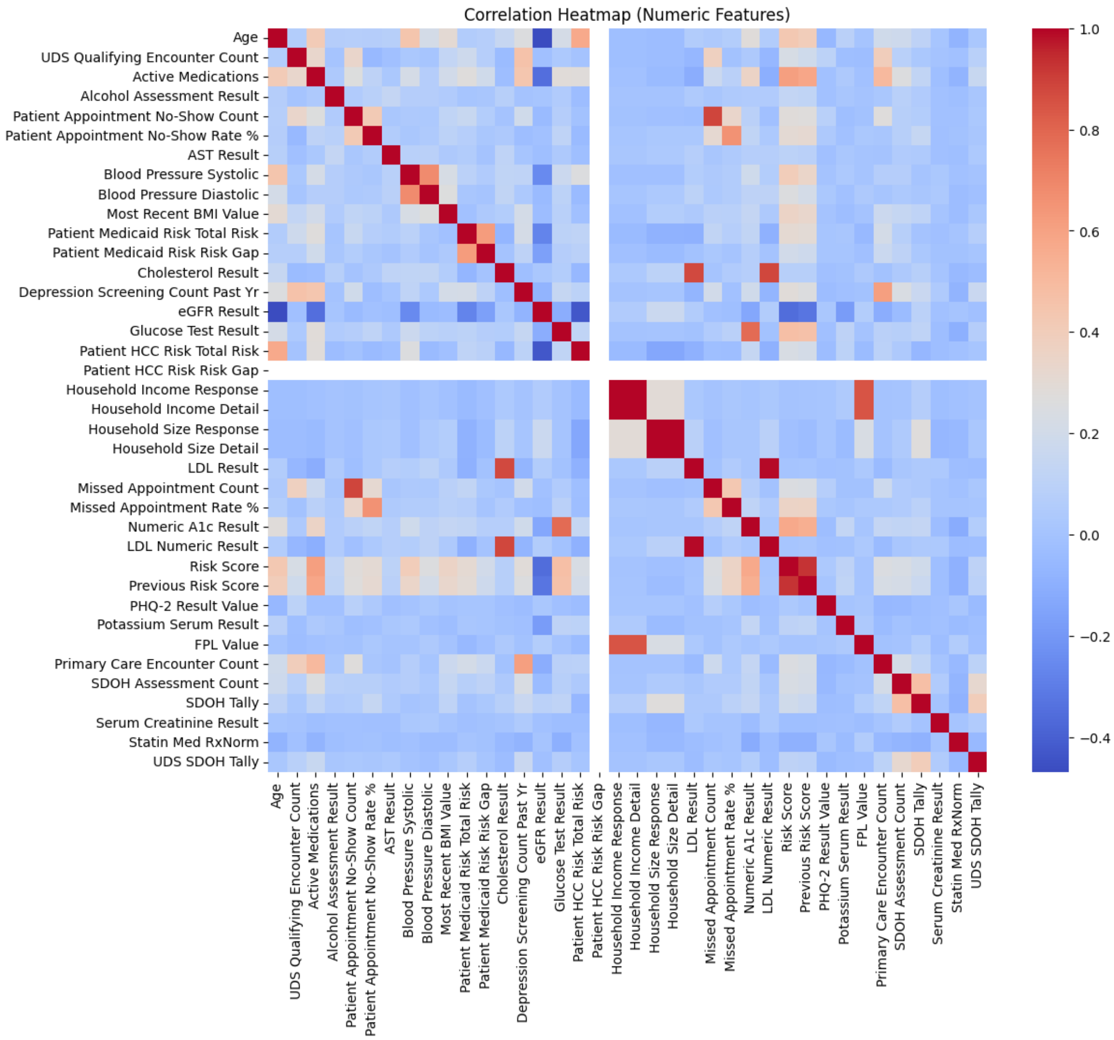
[28]:
```
# Impute missing values + encode categoricals

from sklearn.impute import SimpleImputer

target_col = 'ED Episode Admit Last-6-Mths' # Define target here too for␣
↪consistency

# Separate numerical + categorical
numeric_cols = df.select_dtypes(include='number').columns.tolist()
# Exclude the target column from numeric imputation
if target_col in numeric_cols:
    numeric_cols.remove(target_col)

cat_cols = df.select_dtypes(include=['object', 'category']).columns.tolist()

# Impute numerics with median
num_imputer = SimpleImputer(strategy='median')
df[numeric_cols] = num_imputer.fit_transform(df[numeric_cols])

# Impute categoricals with most frequent
cat_imputer = SimpleImputer(strategy='most_frequent')
df[cat_cols] = cat_imputer.fit_transform(df[cat_cols])

# One-hot encode categoricals
df = pd.get_dummies(df, columns=cat_cols, drop_first=True)

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2672 entries, 0 to 2671
Columns: 7049 entries, Age to Vision Screening Code_Z01.01
dtypes: bool(6970), datetime64[ns](40), float64(39)
memory usage: 19.4 MB
```

[29]:

```
# Visualizations!

import matplotlib.pyplot as plt
import seaborn as sns

# 1. Target distribution
df[target].value_counts().plot(kind='bar')
plt.title("Target Distribution: 6-Month Admission")
plt.show()

# 2. Histogram of top numeric features
# df[numeric_cols].hist(figsize=(12,10))
# plt.tight_layout()
# plt.show()

# 3. Correlation heatmap
plt.figure(figsize=(12,10))
sns.heatmap(df[numeric_cols].corr(), cmap='coolwarm')
plt.title("Correlation Heatmap (Numeric Features)")
plt.show()
```





[30]:
```python
# Convert target to binary (admitted = 1 if >0)
y = (df[target] > 0).astype(int)
X = df.drop(columns=[target])
```

[31]:
```python
# Clean and prepare data

# Make a copy of the dataframe to avoid modifying the original `df` from the␣
↪previous cell.
df_processed = df.copy()

# Target column name
target_col_name = "ED Episode Admit Last-6-Mths"
```

```
# Isolate the target variable BEFORE any potentially destructive␣
↪transformations.
# Apply fillna(0) and >0 to ensure binary classification, and then convert to␣
↪int.
y = (df_processed[target_col_name].fillna(0) > 0).astype(int)

# Drop the target column from the feature set X
X = df_processed.drop(columns=[target_col_name])

# Identify columns that are actual datetime objects in X.
# These are the columns from `df.info()` with dtypes `datetime64[ns]` from the␣
↪previous step.
datetime_cols_in_X = X.select_dtypes(include=['datetime64[ns]']).columns.
↪tolist()

# Convert identified datetime columns in X to numeric days since epoch.
# This avoids incorrectly converting other numeric columns.
for col in datetime_cols_in_X:
    X[col] = (X[col] - pd.Timestamp("1970-01-01")).dt.days

# Replace remaining missing numerical values in X with column medians.
# This imputation step is for the features (X) after date conversion.
X = X.fillna(X.median(numeric_only=True))

# Train/test split
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.3, random_state=42, stratify=y
)

# Standardize numerical data
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

[32]:
```
# Logistic Regression + evaluation function
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import roc_auc_score

def evaluate(feature_list):
    idxs = [X.columns.get_loc(f) for f in feature_list]

    model = LogisticRegression(
        max_iter=500,
```

```
        class_weight="balanced"
    )

    model.fit(X_train_scaled[:, idxs], y_train)

    preds = model.predict_proba(X_test_scaled[:, idxs])[:, 1]

    return roc_auc_score(y_test, preds)
```

[33]:

```
# Greedy forward feature selection

# Initialize lists: 'remaining' holds features not yet selected, 'selected'␣
↪holds chosen features,
# and 'scores' stores the AUC for the selected feature set at each step.
remaining = list(X.columns)
selected = []
scores = []

# Perform 10 steps of forward feature selection.
# In each step, we find the single best feature to add to our 'selected' set.
for step in range(10):
    best_feature = None
    best_auc = -1 # Initialize with a low AUC score to ensure the first valid␣
↪AUC is higher

    # Iterate through all features not yet selected to find the one that␣
↪maximizes AUC when added.
    for feat in remaining:
        # Create a temporary list of features that includes currently selected␣
↪features plus one 'candidate' feature.
        try_features = selected + [feat]
        # Evaluate the performance (AUC) of the model using this candidate set␣
↪of features.
        auc = evaluate(try_features)

        # If this candidate set yields a better AUC than the current best,␣
↪update best_auc and best_feature.
        if auc > best_auc:
            best_auc = auc
            best_feature = feat

    # Add the best performing feature from this step to the 'selected' list.
    selected.append(best_feature)
    # Record the AUC achieved with this new set of selected features.
    scores.append(best_auc)
    # Remove the selected feature from the 'remaining' list so it's not␣
↪considered again.
```

```python
    remaining.remove(best_feature)

    # Print the result for the current step.
    # print(f"Step {step+1}: Selected {best_feature} - AUC {best_auc:.4f}")

# After all steps are complete, print the final list of top 10 selected
 ↪features and their corresponding AUC scores.
print("\nTop 10 selected features:")
for i, (feat, auc) in enumerate(zip(selected, scores), 1):
    print(f"{i}. {feat} - AUC {auc:.4f}")
```

```
Top 10 selected features:
1. Patient Medicaid Risk Total Risk - AUC 0.6063
2. Insurance Primary Payer_HealthFirst MCD - AUC 0.6410
3. Most Recent Encounter Type_EOB - AUC 0.6611
4. Domestic Violence Reponse_I choose not to answer this question - AUC 0.6789
5. Sexually Active Code_43305-2 - AUC 0.6964
6. HCV Antibody Test Date - AUC 0.7141
7. Flu Date - AUC 0.7279
8. Last Well Care Visit Code_Z02.1 - AUC 0.7394
9. AST Result - AUC 0.7505
10. FPL Date_11/19/2024 12:00:00 AM - AUC 0.7591
```

0.0.3 Discussion of Early Results and Moving Forward

- The greedy selection approach identified a ranked set of features contributing incremental predictive value.
- The AUC values supply an interpretable measure of classification.
- Further improvements planned include:
  1. Cross validate the model with testing data
  2. Plot the AUC for more than 10 features
  3. Check correlation of selected features to make sure we are not selecting highly correlated features
  4. Attempt to compare to Lasso if enough time

The project was a collaborative effort between Mike and Spencer with both of us working on the data cleaning step and Mike taking charge of the algorithm and Spencer doing the write up and github steps. What remains is a little of a first come first serve effort with communication being key to make sure we don't step on each others toes.

Github link: https://github.com/99x5zbrvgj-droid/CSC108HHCFinal