```
Start coding or generate with AI.
```

Homework 1 - Ally Hayden

Task 1

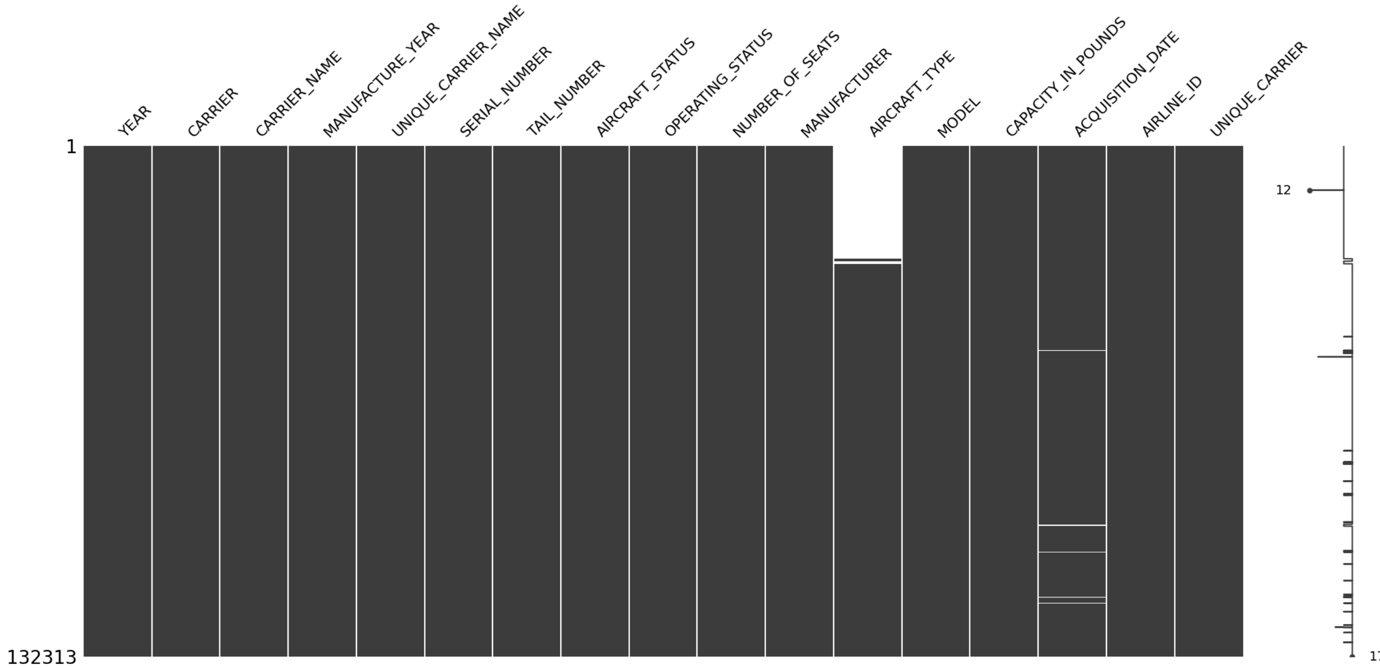
Investigate missing data in aircraft inventory dataset.

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from google.colab import drive
import numpy as np

# Mount Google Drive
drive.mount('/content/drive')
pd.set_option('display.precision', 3)

df = pd.read_csv("/content/drive/MyDrive/DATA 300/T_F41SCHEDULE_B43.csv", keep_default_na=False, na_values=[""])
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=Tr
<ipython-input-59-beb8561f7e4c>:11: DtypeWarning: Columns (11) have mixed types. Specify dtype option on import or set low_m
  df = pd.read_csv("/content/drive/MyDrive/DATA 300/T_F41SCHEDULE_B43.csv", keep_default_na=False, na_values=[""])
```

```
import missingno as msno

msno.matrix(df)
```

```
<Axes: >
```




```python
# columns to investigate
cols_to_check = ['CARRIER', 'CARRIER_NAME', 'MANUFACTURE_YEAR',
                 'NUMBER_OF_SEATS', 'CAPACITY_IN_POUNDS', 'AIRLINE_ID']

# summary
missing_summary = df[cols_to_check].isnull().sum().to_frame(name='Missing Count')
missing_summary['Missing %'] = (missing_summary['Missing Count'] / len(df)) * 100
print("Missing Data Summary:\n", missing_summary)
```

```
Missing Data Summary:
                     Missing Count  Missing %
CARRIER                          0      0.000
CARRIER_NAME                   105      0.079
MANUFACTURE_YEAR                 3      0.002
NUMBER_OF_SEATS                  7      0.005
CAPACITY_IN_POUNDS             101      0.076
AIRLINE_ID                     105      0.079
```

CARRIER column

After changing the pd.read_csv line to only count blank cells as missing the carrier column has 0 missing values so we do not need to impute it.

CARRIER_NAME column

```
# see if carrier_name and unique_care_name are missing in the same place
missing_carrier_name = df[df['CARRIER_NAME'].isna()]
print(missing_carrier_name[['CARRIER', 'UNIQUE_CARRIER_NAME']].drop_duplicates())

```

```
      CARRIER UNIQUE_CARRIER_NAME
11465      L4                 NaN
54610      OH                 NaN
```

These rows have missing values in both CARRIER_NAME and UNIQUE_CARRIER_NAME. Therefore, they cannot be imputed from UNIQUE_CARRIER_NAME. I believe it is safer to leave these rows unimputed because there are so few.

AIRLINE_ID Column

```
# check how many unique AIRLINE_IDs exist
carrier_id_check = df.groupby('CARRIER')['AIRLINE_ID'].nunique().sort_values(ascending=False)
print(carrier_id_check.head(10))  # shows if some carriers always map to one ID

```

```
CARRIER
PT     2
OH     2
YX     2
0WQ    1
16     1
1BQ    1
1EQ    1
16     1
20Q    1
23Q    1
Name: AIRLINE_ID, dtype: int64
```

Some CARRIERs map to only one AIRLINE_ID:

0WQ, 16, 1BQ, 1EQ, 20Q, 23Q

It is safe to impute these but ONLY these.

```
# put it the carriers that map to only ONE airline_id
unique_mappings = df.groupby('CARRIER')['AIRLINE_ID'].nunique()
single_id_carriers = unique_mappings[unique_mappings == 1].index

carrier_to_id = df[df['CARRIER'].isin(single_id_carriers)].dropna(subset=['AIRLINE_ID']).drop_duplicates('CARRIER')[['CARRIE

df['AIRLINE_ID'] = df.apply(
    lambda row: carrier_to_id[row['CARRIER']] if pd.isna(row['AIRLINE_ID']) and row['CARRIER'] in carrier_to_id else row['AI
    axis=1
)

```

CAPACITY_IN_POUNDS

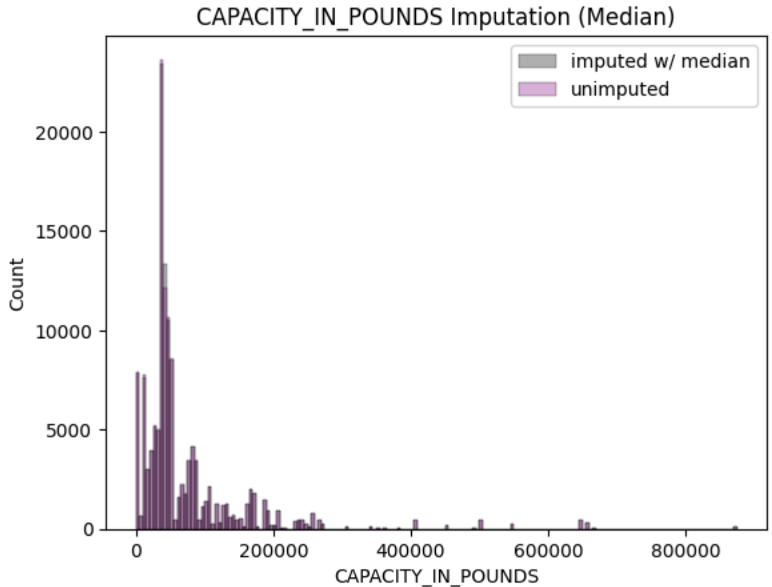
We can impute CAPACITY_IN_POUNDS becuase its a numeric continuous variable and the data is structured.

I chose Median becuase it is less influenced by extreme values, KNN on its own operated the same as Median but KNN with features captures inter-variable patterns.

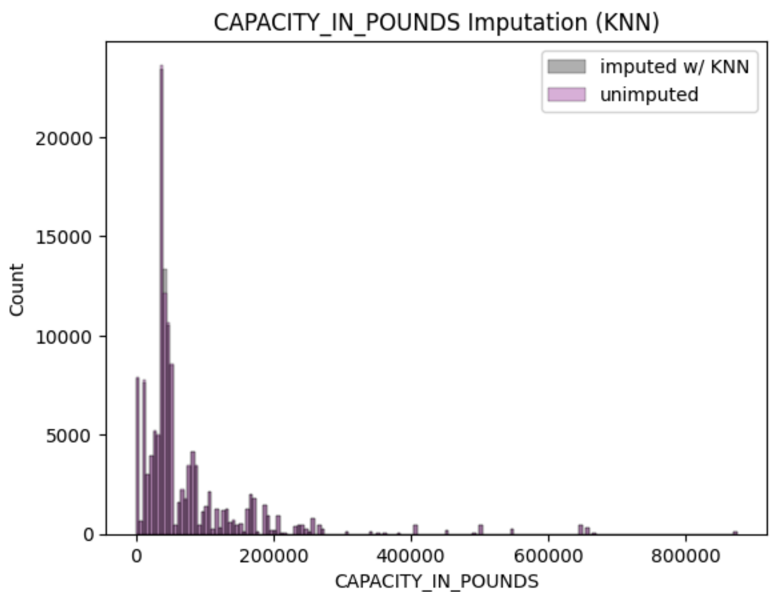
```
from sklearn.impute import SimpleImputer, KNNImputer
from sklearn.metrics import mean_squared_error

# random missing
df_temp = df[['CAPACITY_IN_POUNDS']].dropna().copy()
df_temp.loc[df_temp.sample(frac=0.01, random_state=0).index, 'CAPACITY_IN_POUNDS'] = np.nan

true_vals_cap = df[['CAPACITY_IN_POUNDS']].dropna().loc[df_temp[df_temp['CAPACITY_IN_POUNDS'].isna()].index]

# Median
```

```
median_imputer_cap = SimpleImputer(strategy='median')
df_temp['CAPACITY_IN_POUNDS'] = median_imputer_cap.fit_transform(df_temp[['CAPACITY_IN_POUNDS']])

# RMSE
rmse_cap = np.sqrt(mean_squared_error(true_vals_cap, df_temp.loc[true_vals_cap.index]))
print(f"RMSE (Median - CAPACITY_IN_POUNDS): {rmse_cap:.2f}")

# Plot
fig, ax = plt.subplots(1, 1)
sns.histplot(df_temp['CAPACITY_IN_POUNDS'], binwidth=5000, alpha=0.3, color='k', label='imputed w/ median')
sns.histplot(df['CAPACITY_IN_POUNDS'], binwidth=5000, alpha=0.3, color='purple', label='unimputed')
ax.set_title('CAPACITY_IN_POUNDS Imputation (Median)')
ax.legend()
plt.show()


# KNN
knn_imputer_cap = KNNImputer(n_neighbors=5)
df_temp['CAPACITY_IN_POUNDS'] = knn_imputer_cap.fit_transform(df_temp[['CAPACITY_IN_POUNDS']])

# RMSE
rmse_cap_knn = np.sqrt(mean_squared_error(true_vals_cap, df_temp.loc[true_vals_cap.index]))
print(f"RMSE (KNN - CAPACITY_IN_POUNDS): {rmse_cap_knn:.2f}")

# Plot
fig, ax = plt.subplots(1, 1)
sns.histplot(df_temp['CAPACITY_IN_POUNDS'], binwidth=5000, alpha=0.3, color='k', label='imputed w/ KNN')
sns.histplot(df['CAPACITY_IN_POUNDS'], binwidth=5000, alpha=0.3, color='purple', label='unimputed')
ax.set_title('CAPACITY_IN_POUNDS Imputation (KNN)')
ax.legend()
plt.show()

# KNN with features
knn_df = df[['CAPACITY_IN_POUNDS', 'NUMBER_OF_SEATS', 'MANUFACTURE_YEAR']].dropna().reset_index(drop=True)

missing_idx = knn_df.sample(frac=0.01, random_state=0).index
true_vals = knn_df.loc[missing_idx, 'CAPACITY_IN_POUNDS'].copy()
knn_df.loc[missing_idx, 'CAPACITY_IN_POUNDS'] = np.nan

knn_imputer = KNNImputer(n_neighbors=5)
knn_imputed = pd.DataFrame(knn_imputer.fit_transform(knn_df), columns=knn_df.columns)

# RMSE
rmse_better = np.sqrt(mean_squared_error(true_vals, knn_imputed.loc[missing_idx, 'CAPACITY_IN_POUNDS']))
print(f"RMSE (KNN with features - CAPACITY_IN_POUNDS): {rmse_better:.2f}")

# Plot
fig, ax = plt.subplots(1, 1)
sns.histplot(knn_df['CAPACITY_IN_POUNDS'], binwidth=5000, alpha=0.3, color='k', label='imputed w/ KNN with features')
sns.histplot(df['CAPACITY_IN_POUNDS'], binwidth=5000, alpha=0.3, color='purple', label='unimputed')
ax.set_title('CAPACITY_IN_POUNDS Imputation (KNN with features)')
ax.legend()
plt.show()
```

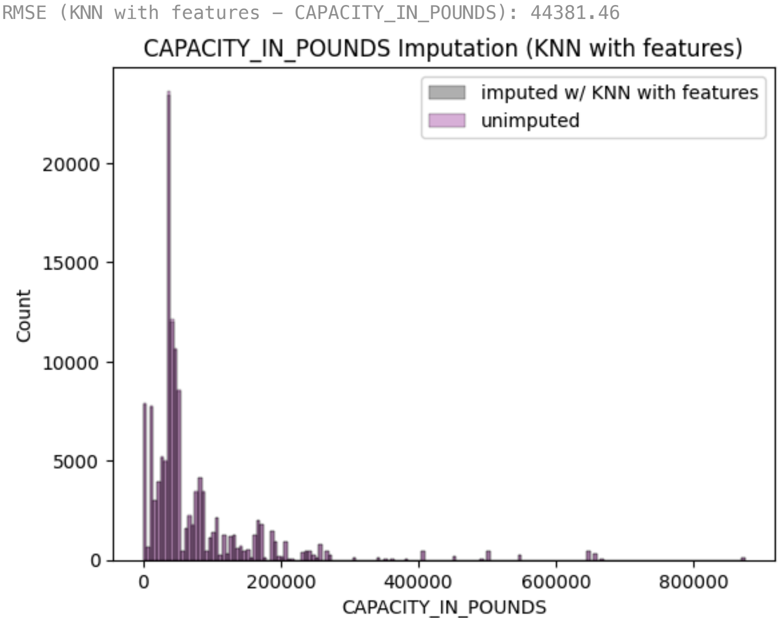
RMSE (Median - CAPACITY_IN_POUNDS): 92646.40



RMSE (KNN - CAPACITY_IN_POUNDS): 92646.40



RMSE (KNN with features - CAPACITY_IN_POUNDS): 44381.46



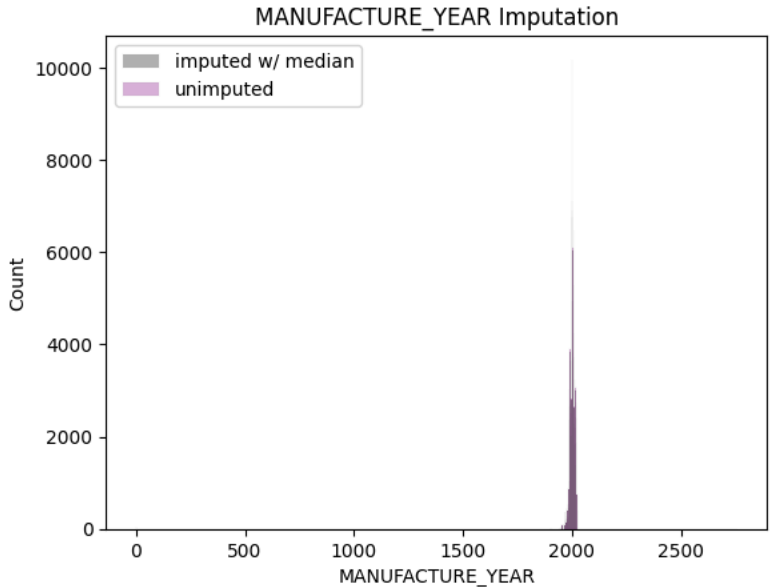
MANUFACTURE_YEAR:

We can impute MANUFACTURE_YEAR because it is a numeric, discrete variable, the missing values are relatively rare and likely missing at rando, and there's a clear association with other variables like MODEL or AIRLINE_ID.

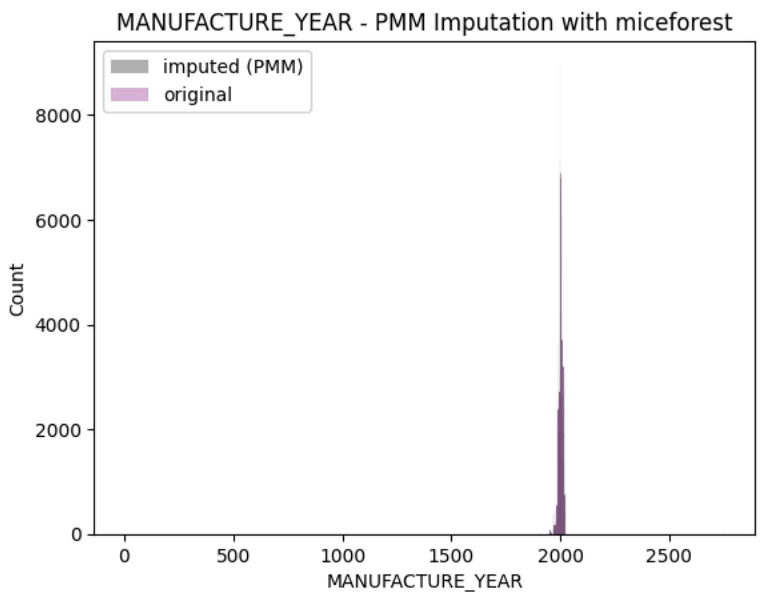
I chose to use Median because it works well when data is clustered and I chose PMM becuase it guarantees realistic values and avoids artificial midpoints.

```
# random missing
df_temp = df[['MANUFACTURE_YEAR']].dropna().copy()
df_temp.loc[df_temp.sample(frac=0.01, random_state=0).index, 'MANUFACTURE_YEAR'] = np.nan

true_vals_year = df[['MANUFACTURE_YEAR']].dropna().loc[df_temp[df_temp['MANUFACTURE_YEAR'].isna()].index]

# Median
median_imputer_year = SimpleImputer(strategy='median')
df_temp['MANUFACTURE_YEAR'] = median_imputer_year.fit_transform(df_temp[['MANUFACTURE_YEAR']])

# RMSE
rmse_year = np.sqrt(mean_squared_error(true_vals_year, df_temp.loc[true_vals_year.index]))
print(f"RMSE (MANUFACTURE_YEAR): {rmse_year:.2f}")

# Plot
fig, ax = plt.subplots(1, 1)
sns.histplot(df_temp['MANUFACTURE_YEAR'], binwidth=1, alpha=0.3, color='k', label='imputed w/ median')
sns.histplot(df['MANUFACTURE_YEAR'], binwidth=1, alpha=0.3, color='purple', label='unimputed')
ax.set_title('MANUFACTURE_YEAR Imputation')
ax.legend()
plt.show()

import miceforest as mf

# PMM
df_pmm = df[['MANUFACTURE_YEAR', 'CAPACITY_IN_POUNDS', 'NUMBER_OF_SEATS']].dropna().reset_index(drop=True)

missing_idx = df_pmm.sample(frac=0.01, random_state=0).index
true_vals = df_pmm.loc[missing_idx, 'MANUFACTURE_YEAR'].copy()
df_pmm.loc[missing_idx, 'MANUFACTURE_YEAR'] = np.nan

num_datasets = 4
kernel = mf.ImputationKernel(
    data=df_pmm,
    num_datasets=num_datasets,
    save_all_iterations_data=False,
    random_state=1
)

kernel.mice(1)

df_completed = kernel.complete_data(dataset=0)

# RMSE
rmse_pmm = np.sqrt(mean_squared_error(true_vals, df_completed.loc[missing_idx, 'MANUFACTURE_YEAR']))
print(f"RMSE (PMM - MANUFACTURE_YEAR): {rmse_pmm:.2f}")

# Plot
fig, ax = plt.subplots(1, 1)
sns.histplot(df_completed['MANUFACTURE_YEAR'], binwidth=1, alpha=0.3, color='k', label='imputed (PMM)')
sns.histplot(df_pmm['MANUFACTURE_YEAR'].dropna(), binwidth=1, alpha=0.3, color='purple', label='original')
ax.set_title('MANUFACTURE_YEAR - PMM Imputation with miceforest')
ax.legend()
plt.show()
```

```
RMSE (MANUFACTURE_YEAR): 10.16
```




```
RMSE (PMM - MANUFACTURE_YEAR): 7.06
```



NUMBER_OF_SEATS:

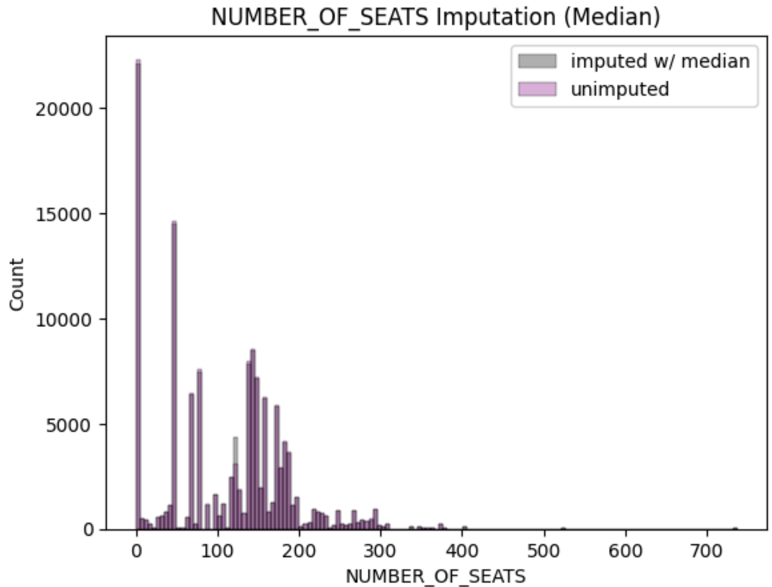
We can impute NUMBER_OF_SEATS because it's a discrete, positive integer tied to the MODEL of the aircraft and there's low variation within the model.

I chose to use Median beause it's simple and most aircrafts of the same model have the same seat amount. Same as with CAPACITY_IN_POUNDS I found that KNN alone was similar to Median but KNN with features improved accuracy by taking into account multiple features.

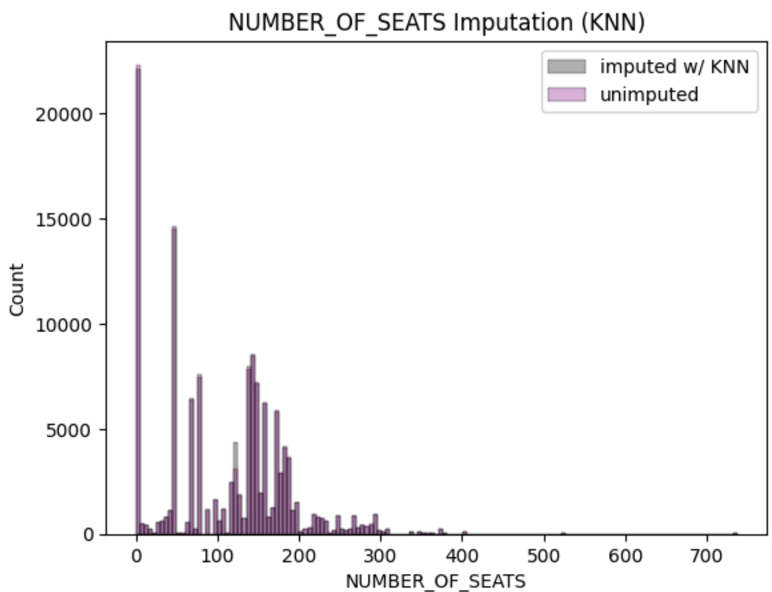
```python
# random missing
df_temp = df[['NUMBER_OF_SEATS']].dropna().copy()
df_temp.loc[df_temp.sample(frac=0.01, random_state=0).index, 'NUMBER_OF_SEATS'] = np.nan

true_vals_seats = df[['NUMBER_OF_SEATS']].dropna().loc[df_temp[df_temp['NUMBER_OF_SEATS'].isna()].index]

# Median
median_imputer_seats = SimpleImputer(strategy='median')
df_temp['NUMBER_OF_SEATS'] = median_imputer_seats.fit_transform(df_temp[['NUMBER_OF_SEATS']])

# RMSE
rmse_seats = np.sqrt(mean_squared_error(true_vals_seats, df_temp.loc[true_vals_seats.index]))
print(f"RMSE (Median - NUMBER_OF_SEATS): {rmse_seats:.2f}")

# Plot
```

```
fig, ax = plt.subplots(1, 1)
sns.histplot(df_temp['NUMBER_OF_SEATS'], binwidth=5, alpha=0.3, color='k', label='imputed w/ median')
sns.histplot(df['NUMBER_OF_SEATS'], binwidth=5, alpha=0.3, color='purple', label='unimputed')
ax.set_title('NUMBER_OF_SEATS Imputation (Median)')
ax.legend()
plt.show()

# KNN
knn_imputer_seats = KNNImputer(n_neighbors=5)
df_temp['NUMBER_OF_SEATS'] = knn_imputer_seats.fit_transform(df_temp[['NUMBER_OF_SEATS']])

# RMSE
rmse_seats_knn = np.sqrt(mean_squared_error(true_vals_seats, df_temp.loc[true_vals_seats.index]))
print(f"RMSE (KNN - NUMBER_OF_SEATS): {rmse_seats_knn:.2f}")

# Plot
fig, ax = plt.subplots(1, 1)
sns.histplot(df_temp['NUMBER_OF_SEATS'], binwidth=5, alpha=0.3, color='k', label='imputed w/ KNN')
sns.histplot(df['NUMBER_OF_SEATS'], binwidth=5, alpha=0.3, color='purple', label='unimputed')
ax.set_title('NUMBER_OF_SEATS Imputation (KNN)')
ax.legend()
plt.show()

# KNN with features
knn_df = df[['NUMBER_OF_SEATS', 'CAPACITY_IN_POUNDS', 'MANUFACTURE_YEAR']].dropna().reset_index(drop=True)

missing_idx = knn_df.sample(frac=0.01, random_state=0).index
true_vals = knn_df.loc[missing_idx, 'NUMBER_OF_SEATS'].copy()
knn_df.loc[missing_idx, 'NUMBER_OF_SEATS'] = np.nan

knn_imputer = KNNImputer(n_neighbors=5)
knn_imputed = pd.DataFrame(knn_imputer.fit_transform(knn_df), columns=knn_df.columns)

# RMSE
rmse_seats_knn_features = np.sqrt(mean_squared_error(true_vals, knn_imputed.loc[missing_idx, 'NUMBER_OF_SEATS']))
print(f"RMSE (KNN with features - NUMBER_OF_SEATS): {rmse_seats_knn_features:.2f}")

# Plot
fig, ax = plt.subplots(1, 1)
sns.histplot(knn_imputed['NUMBER_OF_SEATS'], binwidth=5, alpha=0.3, color='k', label='imputed w/ KNN with features')
sns.histplot(knn_df['NUMBER_OF_SEATS'], binwidth=5, alpha=0.3, color='purple', label='original')
ax.set_title('NUMBER_OF_SEATS Imputation (KNN with features)')
ax.legend()
plt.show()
```

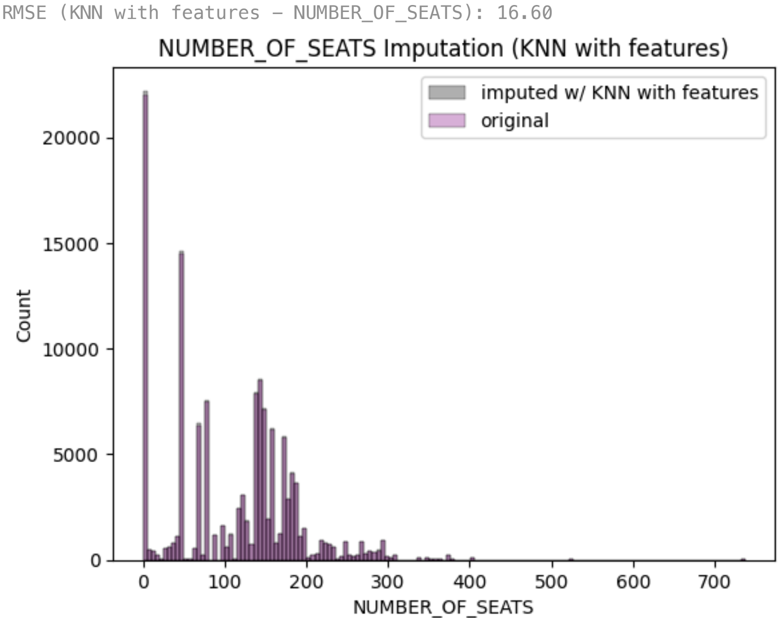
```
RMSE (Median - NUMBER_OF_SEATS): 77.11
```




```
RMSE (KNN - NUMBER_OF_SEATS): 77.11
```




```
RMSE (KNN with features - NUMBER_OF_SEATS): 16.60
```



```
# Adding numerical imputed columns to the df
df_extended = df.copy()

df_extended.loc[df_completed.index, 'MANUFACTURE_YEAR_PMM'] = df_completed['MANUFACTURE_YEAR'].round()
df_extended.loc[knn_df.index, 'NUMBER_OF_SEATS_KNN_FEATURES'] = knn_imputed['NUMBER_OF_SEATS'].round()
df_extended.loc[knn_df.index, 'CAPACITY_IN_POUNDS_KNN_FEATURES'] = knn_imputed['CAPACITY_IN_POUNDS'].round()

```

Task 2

Inspect the columns MANUFACTURER, MODEL, AIRCRAFT_STATUS, and OPERATING_STATUS and decide if transformation or standardization of data are required.

MANUFACTURER column

```
# convert to upper and get rid of spaces
df_extended['MANUFACTURER_CLEAN'] = df_extended['MANUFACTURER'].str.upper().str.strip()

manufacturer_map = {
    "BOEING": "BOEING",
    "THEBOEINGCO": "BOEING",
    "BOEING COMPANY": "BOEING",
    "BOEINGCO": "BOEING",
    "AIRBUS INDUSTRIE": "AIRBUS",
    "AIRBUS": "AIRBUS",
    "BOMBARDIER INC": "BOMBARDIER",
    "EMBRAER S.A.": "EMBRAER",
    "EMBRAER": "EMBRAER",
    "GULFSTREAM AEROSPACE": "GULFSTREAM",
    "CESSNA AIRCRAFT COMPANY": "CESSNA",
    "CESSNA": "CESSNA"
}

df_extended['MANUFACTURER_STD'] = df_extended['MANUFACTURER_CLEAN'].replace(manufacturer_map)

print(df_extended['MANUFACTURER_STD'].value_counts().head(20))
```

```
MANUFACTURER_STD
BOEING                44191
EMBRAER               15554
AIRBUS                13440
BOMBARDIER            11834
AIRBUSINDUSTRIES       7053
BOEINGCOMPANY          6767
CESSNA                 4514
MCDONNELLDOUGLAS       4306
MCDONNELL-DOUGLAS      4159
THEBOEINGCOMPANY       3975
CANADAIR               3861
AIRBUSINDUSTRIE        2666
ATR                    1181
DOUGLAS                1137
GE                     1110
DEHAVILLAND            1084
MCDONNELDOUGLAS         736
BOMBARDIERAEROSPACE     649
BOEINGCO.               584
GULFSTREAM              441
Name: count, dtype: int64
```

MODEL column

```
# convert to upper and get rid of spaces
df_extended['MODEL_CLEAN'] = df_extended['MODEL'].str.upper().str.strip()

print(df_extended['MODEL_CLEAN'].value_counts().head(30))

model_map = {
    "737-800": "BOEING 737-800",
    "737": "BOEING 737",
    "B737": "BOEING 737",
    "B737-800": "BOEING 737-800",
    "A320": "AIRBUS A320",
```

```
    "A320-200": "AIRBUS A320",
    "BOMBARDIER CRJ200": "CRJ200",
    "CRJ-200": "CRJ200",
    "EMBRAER 170": "EMBRAER E170",
    "EMB-170": "EMBRAER E170"
}

df_extended['MODEL_STD'] = df_extended['MODEL_CLEAN'].replace(model_map)

print(df_extended['MODEL_STD'].value_counts().head(10))

```

```
MODEL_CLEAN
EMB-145                 2976
B-737-7H4               2470
B737-823                2370
A320-232                2333
A321-231                2259
737-700PASSENGERONLY    2027
C-208B                  1872
B757-2                  1775
CRJ-2/4                 1761
B737-800PAX             1621
MD-80                   1610
A320-1/2                1466
ERJ-170-200LR           1379
B737-7/L                1349
757-200                 1345
CRJ200-2B19             1342
A319                    1267
B-737-8H4               1256
CRJ-200                 1148
ERJ-175                 1132
SUPER80PASSENGER        1108
MD-11                   1107
757-24APF               1039
B737-3                  1036
MD-88-PSGR              1028
C-208B/3                1017
757-232-PSGR             988
CRJ-900LR-PSGR           976
B737-823PASSENGER        956
B737-8                   951
Name: count, dtype: int64
MODEL_STD
EMB-145                 2976
B-737-7H4               2470
B737-823                2370
A320-232                2333
A321-231                2259
737-700PASSENGERONLY    2027
CRJ200                  1929
C-208B                  1872
B757-2                  1775
CRJ-2/4                 1761
Name: count, dtype: int64
```

AIRCRAFT_STATUS column

```
# convert to lower and get rid of spaces
df_extended['AIRCRAFT_STATUS_CLEAN'] = df_extended['AIRCRAFT_STATUS'].str.lower().str.strip()

print(df_extended['AIRCRAFT_STATUS_CLEAN'].value_counts())

aircraft_status_map = {
    "active": "active",
    "inactive": "inactive",
    "retired": "retired",
    "destroyed": "retired",
    "decommissioned": "retired",
    "in service": "active",
    "not in service": "inactive"
}

df_extended['AIRCRAFT_STATUS_STD'] = df_extended['AIRCRAFT_STATUS_CLEAN'].replace(aircraft_status_map)

print(df_extended['AIRCRAFT_STATUS_STD'].value_counts())
```

```
AIRCRAFT_STATUS_CLEAN
o    79506
```

```
b    43551
a     9134
l      122
Name: count, dtype: int64
AIRCRAFT_STATUS_STD
o    79506
b    43551
a     9134
l      122
Name: count, dtype: int64
```

OPERATING_STATUS column

```python
# convert to lower and get rid of spaces
df_extended['OPERATING_STATUS_CLEAN'] = df_extended['OPERATING_STATUS'].str.lower().str.strip()

print(df_extended['OPERATING_STATUS_CLEAN'].value_counts())

operating_status_map = {
    "operating": "operating",
    "not operating": "not operating",
    "inactive": "not operating",
    "active": "operating",
    "temporarily inactive": "not operating",
    "unknown": "unknown"
}

df_extended['OPERATING_STATUS_STD'] = df_extended['OPERATING_STATUS_CLEAN'].replace(operating_status_map)

print(df_extended['OPERATING_STATUS_STD'].value_counts())


```

```
OPERATING_STATUS_CLEAN
y    126648
n      5664
          1
Name: count, dtype: int64
OPERATING_STATUS_STD
y    126648
n      5664
          1
Name: count, dtype: int64
```

Task 3

Remove data rows with missing values.

```python
cleaned_aircraft_inventory = df_extended.dropna()
print(f"Remaining rows after dropping missing values: {len(cleaned_aircraft_inventory)}")
```

```
Remaining rows after dropping missing values: 101096
```

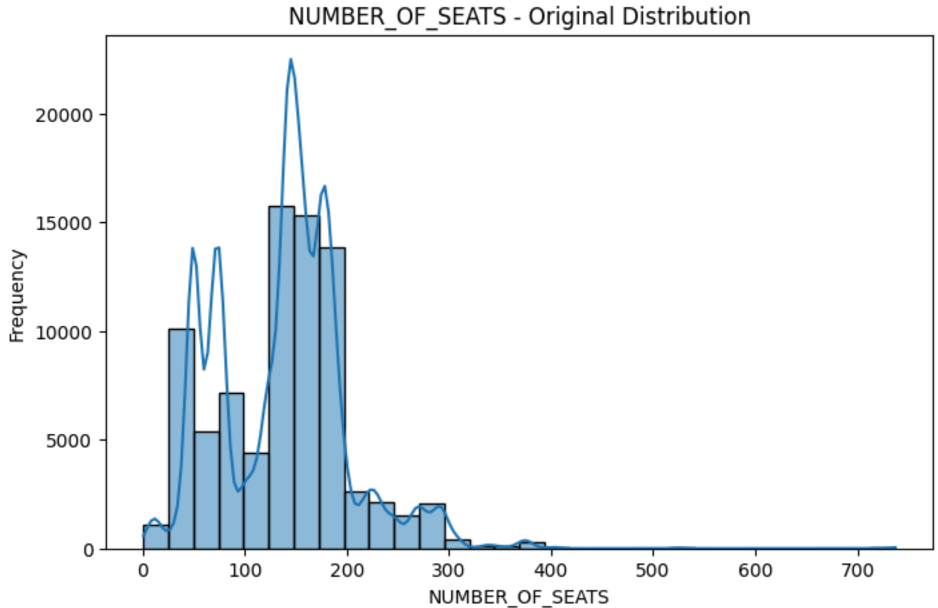
Task 4

Transformation and derivative variables with NUMBER_OF_SEATS and CAPACITY_IN_POUNDS

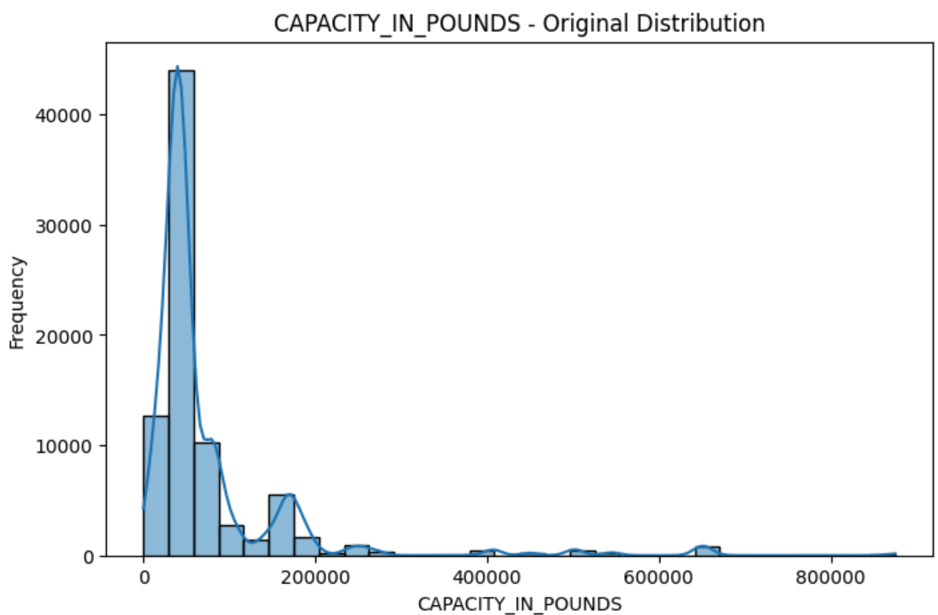
```python
from scipy.stats import boxcox

filtered_data = cleaned_aircraft_inventory[(cleaned_aircraft_inventory['NUMBER_OF_SEATS'] > 0) &
                                           (cleaned_aircraft_inventory['CAPACITY_IN_POUNDS'] > 0)].copy()

# check skewness and plot original histograms
for col in ['NUMBER_OF_SEATS', 'CAPACITY_IN_POUNDS']:
    skewness = filtered_data[col].skew()
    print(f"{col} skewness before Box-Cox: {skewness:.2f}")

    plt.figure(figsize=(8, 5))
    sns.histplot(filtered_data[col], bins=30, kde=True)
    plt.title(f'{col} - Original Distribution')
    plt.xlabel(col)
```

```
    plt.ylabel('Frequency')
    plt.show()

# apply Box-Cox transformation
filtered_data['NUMBER_OF_SEATS_BOXCOX'], _ = boxcox(filtered_data['NUMBER_OF_SEATS'])
filtered_data['CAPACITY_IN_POUNDS_BOXCOX'], _ = boxcox(filtered_data['CAPACITY_IN_POUNDS'])

# check skewness and plot new histograms
for col in ['NUMBER_OF_SEATS_BOXCOX', 'CAPACITY_IN_POUNDS_BOXCOX']:
    skewness = filtered_data[col].skew()
    print(f"{col} skewness after Box-Cox: {skewness:.2f}")

    plt.figure(figsize=(8, 5))
    sns.histplot(filtered_data[col], bins=30, kde=True)
    plt.title(f'{col} - After Box-Cox Transformation')
    plt.xlabel(col)
    plt.ylabel('Frequency')
    plt.show()

```

```
NUMBER_OF_SEATS skewness before Box-Cox: 0.78
```




```
CAPACITY_IN_POUNDS skewness before Box-Cox: 4.18
```




```
NUMBER_OF_SEATS_BOXCOX skewness after Box-Cox: 0.01
```