project2

April 6, 2025

1 Machine Learning in Python - Project 2

Due Friday, Apr 11th by 4 pm.

Include contributors names in notebook metadata or here

1.1 Setup

Install any packages here, define any functions if neeed, and load data

[71]:
```
# Add any additional libraries or submodules below

# Data libraries
import pandas as pd
import numpy as np

# Plotting libraries
import matplotlib.pyplot as plt
import seaborn as sns

# Plotting defaults
plt.rcParams['figure.figsize'] = (8,5)
plt.rcParams['figure.dpi'] = 80

# sklearn modules
import sklearn
from sklearn.model_selection import train_test_split
from sklearn.impute import SimpleImputer
```

[72]:
```
# Load data in easyshare.csv
d = pd.read_csv("freddiemac.csv", dtype={
    'cd_msa': str,
    'zipcode': str,
    'id_loan_rr': str,
    'rr_ind':str})
d.head()
```

[72]:
```
   fico  dt_first_pi flag_fthb  dt_matr cd_msa  mi_pct  cnt_units occpy_sts  \
0   809       201705         N   204704    NaN       0          1         P
```

```
1   702        201703          N   203202    NaN       0         1         P
2   792        201703          N   204702    NaN       0         1         S
3   776        201703          N   204702    NaN       0         1         S
4   790        201703          N   204702  41620       0         1         I

   cltv  dti  …    seller_name                    servicer_name  flag_sc  \
0    75   38  …  Other sellers  SPECIALIZED LOAN SERVICING LLC      NaN
1    80   36  …  Other sellers                 Other servicers      NaN
2    60   36  …  Other sellers                 Other servicers      NaN
3    80   18  …  Other sellers                 Other servicers      NaN
4    75   42  …  Other sellers                    PNC BANK, NA      NaN

  id_loan_rr program_ind rr_ind property_val io_ind mi_cancel_ind loan_status
0        NaN           9    NaN            2      N             7     prepaid
1        NaN           9    NaN            2      N             7      active
2        NaN           9    NaN            2      N             7     prepaid
3        NaN           9    NaN            2      N             7     prepaid
4        NaN           9    NaN            2      N             7      active

[5 rows x 33 columns]
```

2 Introduction

This section should include a brief introduction to the task and the data (assume this is a report you are delivering to a professional body (e.g. Freddie Mac).

Briefly outline the approaches being used and the conclusions that you are able to draw.

3 Exploratory Data Analysis and Feature Engineering

Include a detailed discussion of the data with a particular emphasis on the features of the data that are relevant for the subsequent modeling. Including visualizations of the data is strongly encouraged - all code and plots must also be described in the write up. Think carefully about whether each plot needs to be included in your final draft and the appropriate type of plot and summary for each variable type - your report should include figures but they should be as focused and impactful as possible.

You should also split your data into training and testing sets, ideally before you look to much into the features and relationships with the target

Additionally, this section should also motivate and describe any preprocessing / feature engineering of the data. Specifically, this should be any code that you use to generate new columns in the data frame `d`. Pipelines should be used and feature engineering steps that are be performed as part of an sklearn pipeline can be mentioned here but should be implemented in the following section.

All code and figures should be accompanied by text that provides an overview / context to what is being done or presented.

[73]:
```python
# For general info
d.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200000 entries, 0 to 199999
Data columns (total 33 columns):
 #   Column           Non-Null Count   Dtype
---  ------           --------------   -----
 0   fico             200000 non-null  int64
 1   dt_first_pi      200000 non-null  int64
 2   flag_fthb        200000 non-null  object
 3   dt_matr          200000 non-null  int64
 4   cd_msa           181072 non-null  object
 5   mi_pct           200000 non-null  int64
 6   cnt_units        200000 non-null  int64
 7   occpy_sts        200000 non-null  object
 8   cltv             200000 non-null  int64
 9   dti              200000 non-null  int64
 10  orig_upb         200000 non-null  int64
 11  ltv              200000 non-null  int64
 12  int_rt           200000 non-null  float64
 13  channel          200000 non-null  object
 14  ppmt_pnlty       200000 non-null  object
 15  prod_type        200000 non-null  object
 16  st               200000 non-null  object
 17  prop_type        200000 non-null  object
 18  zipcode          200000 non-null  object
 19  id_loan          200000 non-null  object
 20  loan_purpose     200000 non-null  object
 21  orig_loan_term   200000 non-null  int64
 22  cnt_borr         200000 non-null  int64
 23  seller_name      200000 non-null  object
 24  servicer_name    200000 non-null  object
 25  flag_sc          7531 non-null    object
 26  id_loan_rr       2402 non-null    object
 27  program_ind      200000 non-null  object
 28  rr_ind           2402 non-null    object
 29  property_val     200000 non-null  int64
 30  io_ind           200000 non-null  object
 31  mi_cancel_ind    200000 non-null  object
 32  loan_status      200000 non-null  object
dtypes: float64(1), int64(12), object(20)
memory usage: 50.4+ MB
```

[74]:
```python
# ## 2. Filter Active Loans and Check Target Distribution

# Filter out active loans (only keep 'default' and 'prepaid')
d_filtered = d[d['loan_status'].isin(['default', 'prepaid'])].copy()
```

```python
d_filtered['loan_status'] = d_filtered['loan_status'].map({'default': 1,␣
↪'prepaid': 0})
print("Data shape after filtering active loans:", d_filtered.shape)

# Check target distribution
target_dist = d_filtered['loan_status'].value_counts(normalize=True) * 100
print("\nTarget Distribution (%):")
print(target_dist)
```

```
Data shape after filtering active loans: (126705, 33)

Target Distribution (%):
loan_status
0    99.411231
1     0.588769
Name: proportion, dtype: float64
```

[75]:
```python
# ## 4. Handle Missing Values and Data Types

# Replace missing values with NaN
missing_values = {
    'fico': [9999],
    'flag_fthb': ['9'],
    'mi_pct': [999],
    'cnt_units': [99],
    'occpy_sts': ['9'],
    'cltv': [999],
    'dti': [999],
    'ltv': [999],
    'channel': ['9'],
    'prop_type': ['99'],
    'loan_purpose': ['9'],
    'program_ind': ['9'],
    'property_val': [9],
    'mi_cancel_ind': ['7', '9'],
    'flag_sc': ['N'],
    'rr_ind': ['N'],
}

for col, codes in missing_values.items():
    d_filtered[col] = d_filtered[col].replace(codes, np.nan)

missing_values = d_filtered.isna().sum().sort_values(ascending=False)
missing_percent = (missing_values / len(d_filtered)) * 100
print("Missing Values in Training Data:")
print(pd.DataFrame({'Missing Count': missing_values, 'Percentage (%)':␣
↪missing_percent})
```

```
[missing_values > 0])
```

```
Missing Values in Training Data:
               Missing Count  Percentage (%)
id_loan_rr            125406       98.974784
rr_ind                125406       98.974784
flag_sc               121241       95.687621
program_ind           116496       91.942702
mi_cancel_ind          87026       68.683951
cd_msa                 11294        8.913618
dti                     1304        1.029162
property_val              94        0.074188
fico                      24        0.018942
ltv                        1        0.000789
mi_pct                     1        0.000789
cltv                       1        0.000789
```

[76]:
```python
missing_pct = d_filtered.isna().mean()
high_missing_cols = missing_pct[missing_pct > 0.9].index.tolist()
print("Columns with >90% missing values:", high_missing_cols)

# Check for columns with all same non-NaN values
constant_cols = []
for col in d_filtered.columns:
    if d_filtered[col].nunique(dropna=True) == 1:
        constant_cols.append(col)

print("Columns with constant values:", constant_cols)

ide_cols = ['id_loan', 'seller_name', 'servicer_name']

cols_to_drop = list(set(constant_cols + high_missing_cols + ide_cols))
print("Columns to drop:", cols_to_drop)

d_filtered = d_filtered.drop(columns=cols_to_drop, errors='ignore')
```

```
Columns with >90% missing values: ['flag_sc', 'id_loan_rr', 'program_ind',
'rr_ind']
Columns with constant values: ['ppmt_pnlty', 'prod_type', 'flag_sc', 'rr_ind',
'io_ind']
Columns to drop: ['id_loan_rr', 'seller_name', 'program_ind', 'ppmt_pnlty',
'servicer_name', 'prod_type', 'rr_ind', 'io_ind', 'id_loan', 'flag_sc']
```

[77]:
```python
# ## 3. Train-Test Split

# Split data before EDA to avoid data leakage
X = d_filtered.drop('loan_status', axis=1)
y = d_filtered['loan_status']
```

```
# Stratified split to maintain class balance
X_train, X_test, y_train, y_test = train_test_split(
    X, y,
    test_size=0.2,
    stratify=y,  # Maintain class distribution
    random_state=42
)
```

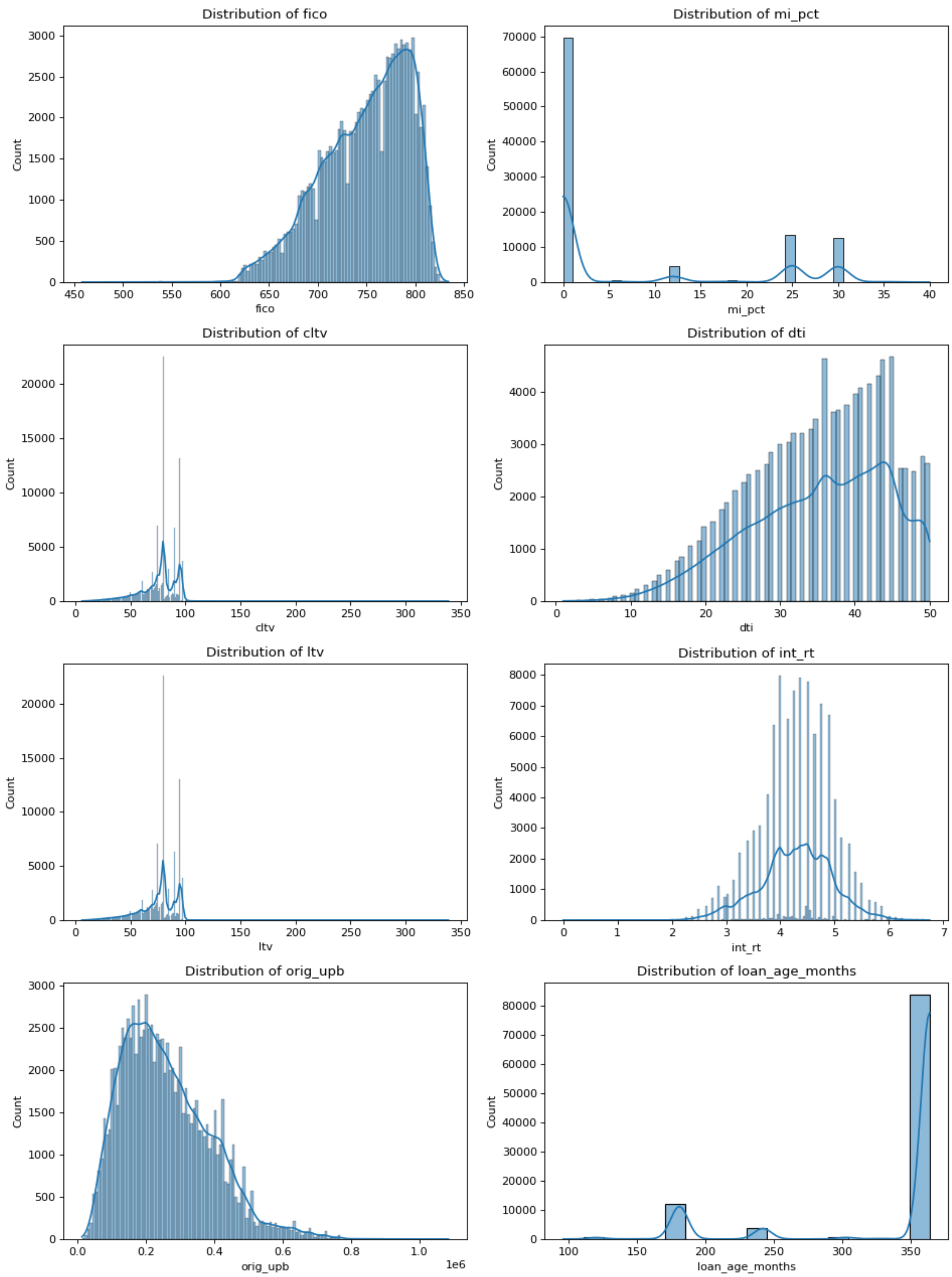
[78]:

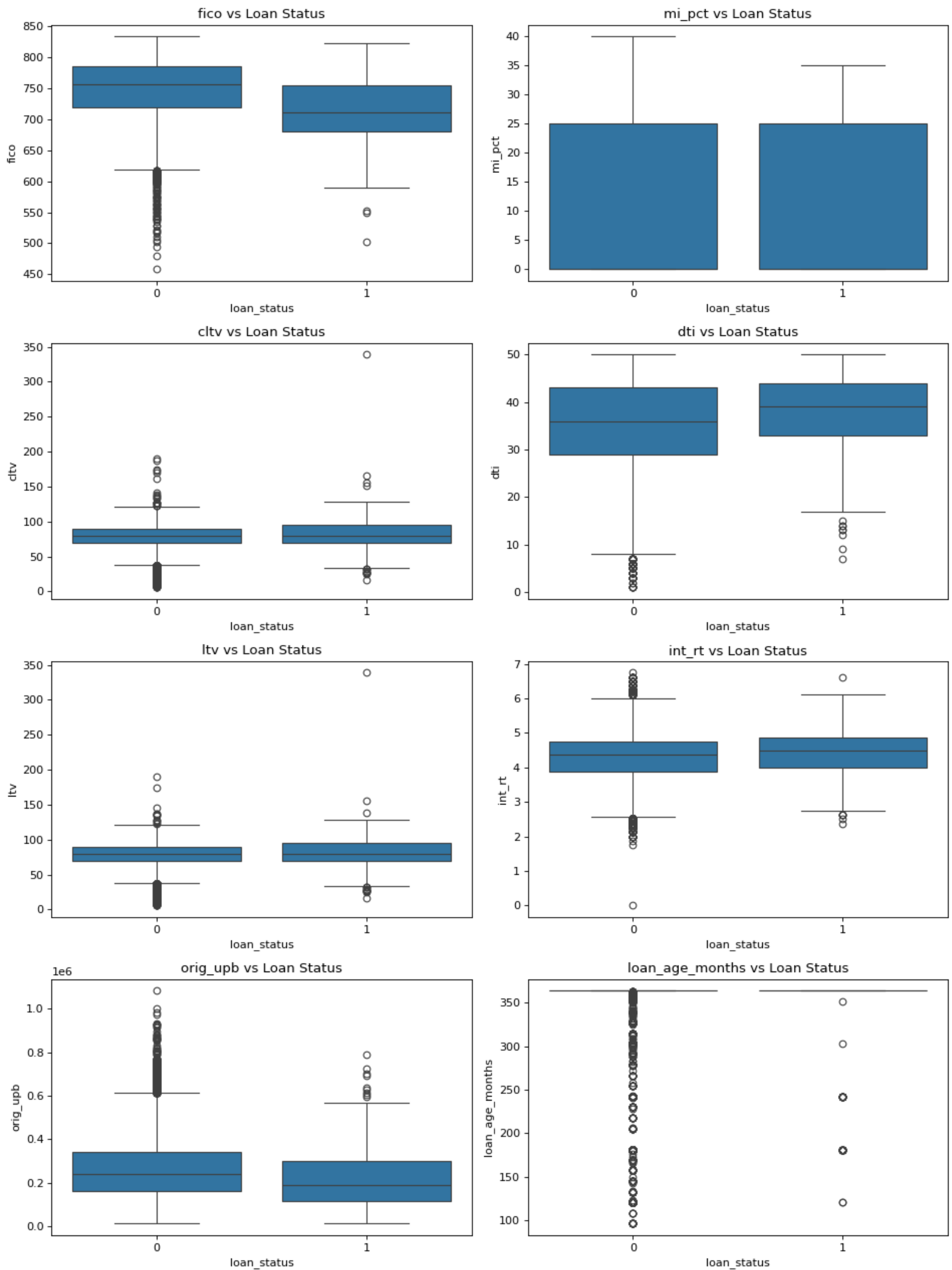
```
# Example for numeric columns
num_cols = ['fico', 'mi_pct', 'cltv', 'dti', 'ltv']
num_imputer = SimpleImputer(strategy='median')
X_train[num_cols] = num_imputer.fit_transform(X_train[num_cols])
X_test[num_cols] = num_imputer.transform(X_test[num_cols])

ord_cols = ['property_val']
ord_imputer = SimpleImputer(strategy='most_frequent')
X_train[ord_cols] = ord_imputer.fit_transform(X_train[ord_cols])
X_test[ord_cols] = ord_imputer.transform(X_test[ord_cols])

# Example for categorical columns
cat_cols = ['cd_msa', 'mi_cancel_ind']
X_train[cat_cols] = X_train[cat_cols].fillna('Unknown')
X_test[cat_cols] = X_test[cat_cols].fillna('Unknown')

# Convert date columns to datetime and calculate loan term
X_train['dt_first_pi'] = pd.to_datetime(X_train['dt_first_pi'], format='%Y%m')
X_train['dt_matr'] = pd.to_datetime(X_train['dt_matr'], format='%Y%m')
X_train['loan_age_months'] = (X_train['dt_matr'] - X_train['dt_first_pi']).dt.
 ↪days // 30

# Repeat for test data
X_test['dt_first_pi'] = pd.to_datetime(X_test['dt_first_pi'], format='%Y%m')
X_test['dt_matr'] = pd.to_datetime(X_test['dt_matr'], format='%Y%m')
X_test['loan_age_months'] = (X_test['dt_matr'] - X_test['dt_first_pi']).dt.days␣
 ↪// 30

# Drop original date columns
X_train = X_train.drop(columns=['dt_first_pi', 'dt_matr'])
X_test = X_test.drop(columns=['dt_first_pi', 'dt_matr'])

# Combine training data for EDA
train_df = pd.concat([X_train, y_train], axis=1)
print("\nTraining data shape:", train_df.shape)
```

```
Training data shape: (101364, 22)
```

[81]:

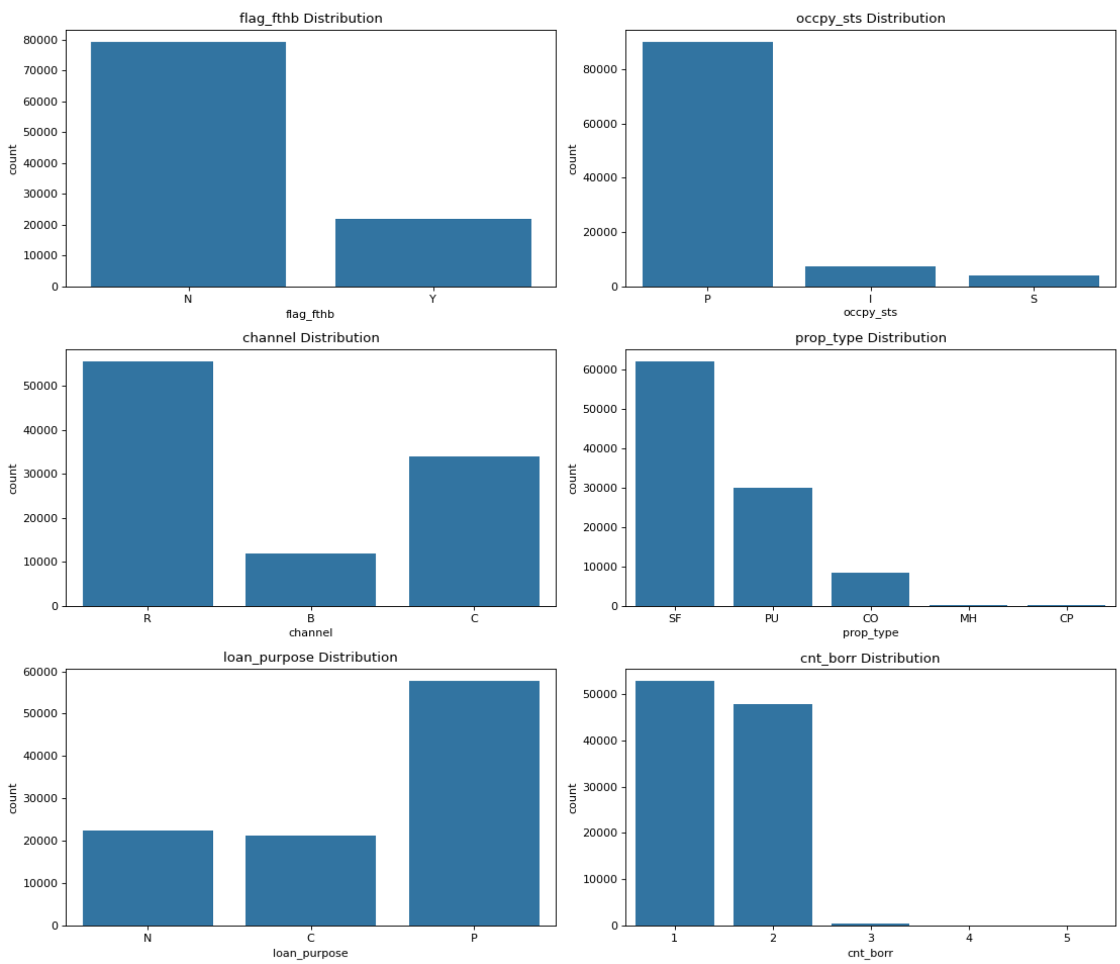
```python
# ## 5. Exploratory Data Analysis (EDA)

# ### 5.2 Numerical Features Analysis
num_cols = ['fico', 'mi_pct', 'cltv', 'dti', 'ltv', 'int_rt', 'orig_upb',␣
↪'loan_age_months']

# Distributions
fig, axes = plt.subplots(4, 2, figsize=(12, 16))
for i, col in enumerate(num_cols):
    sns.histplot(train_df[col], ax=axes[i//2, i%2], kde=True)
    axes[i//2, i%2].set_title(f'Distribution of {col}')
plt.tight_layout()
plt.show()

# Relationships with Target
fig, axes = plt.subplots(4, 2, figsize=(12, 16))
for i, col in enumerate(num_cols):
    sns.boxplot(x='loan_status', y=col, data=train_df, ax=axes[i//2, i%2])
    axes[i//2, i%2].set_title(f'{col} vs Loan Status')
plt.tight_layout()
plt.show()
```

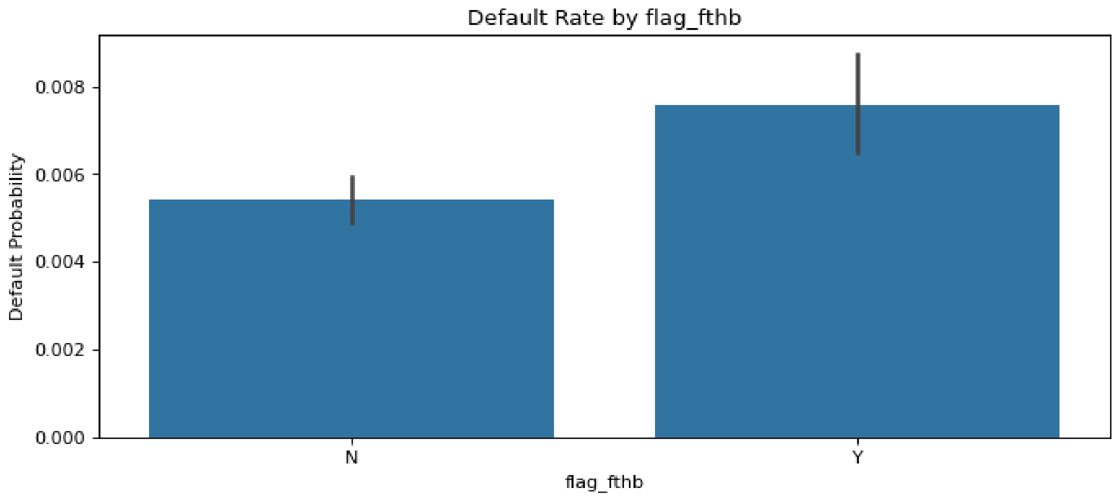

Distribution of fico
Count
fico
Distribution of mi_pct
Count
mi_pct
Distribution of cltv
Count
cltv
Distribution of dti
Count
dti
Distribution of ltv
Count
ltv
Distribution of int_rt
Count
int_rt
Distribution of orig_upb
Count
orig_upb
1e6
Distribution of loan_age_months
Count
loan_age_months

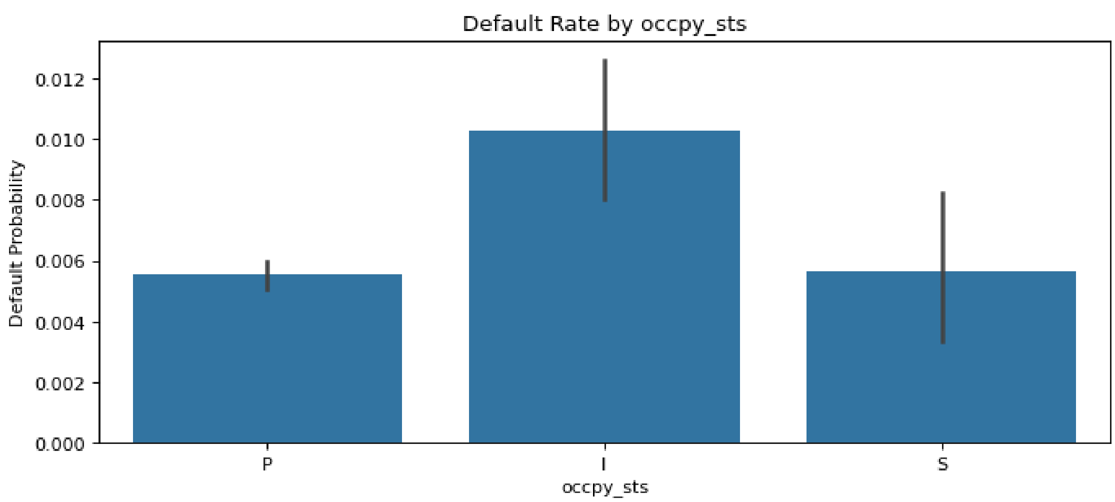


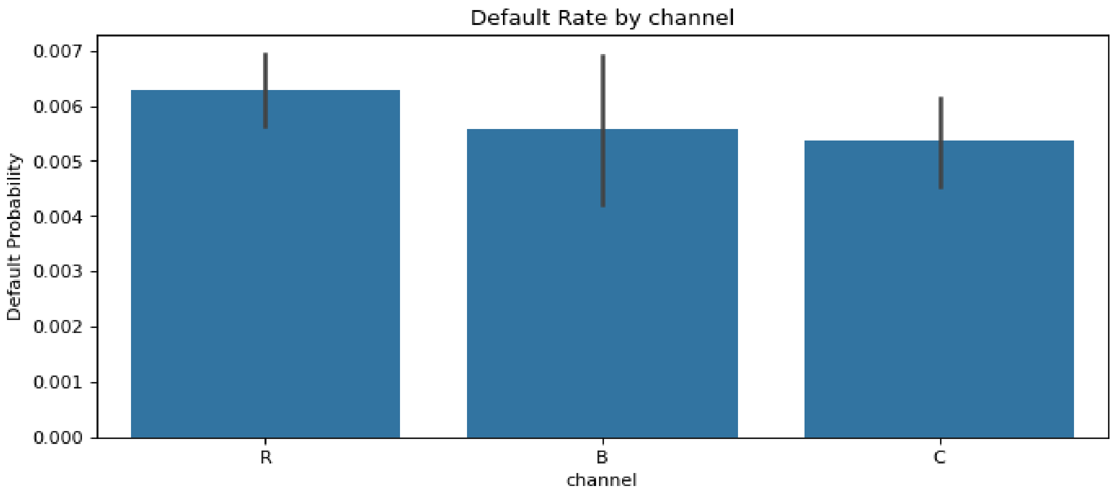

```
[87]: # ### 5.3 Categorical Features Analysis
```

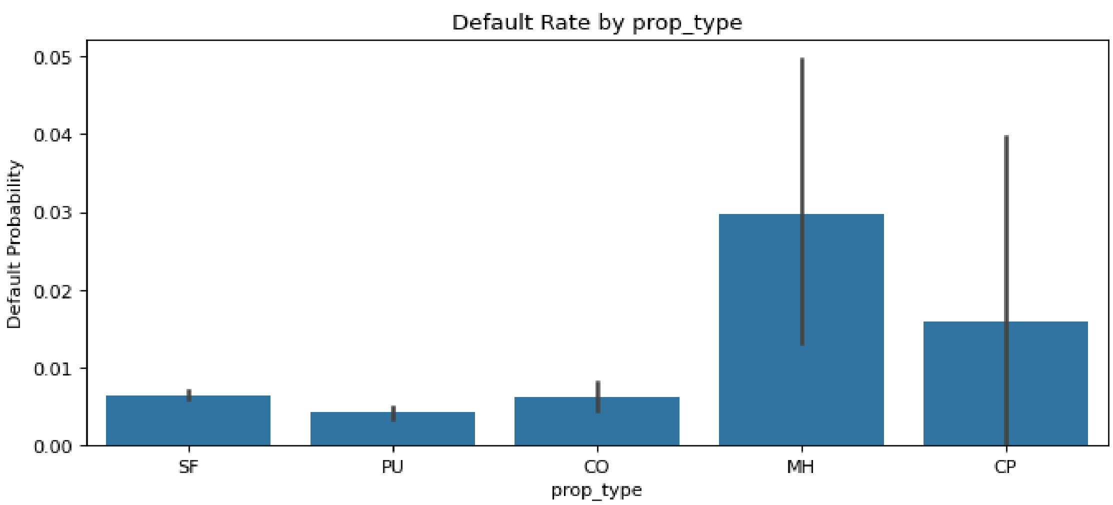
```python
cat_cols = ['flag_fthb', 'occpy_sts', 'channel', 'prop_type', 'loan_purpose', 'cnt_borr']

# Frequency plots
fig, axes = plt.subplots(3, 2, figsize=(14, 12))
for i, col in enumerate(cat_cols):
    sns.countplot(x=col, data=train_df, ax=axes[i//2, i%2])
    axes[i//2, i%2].set_title(f'{col} Distribution')
    axes[i//2, i%2].tick_params(axis='x')
plt.tight_layout()
plt.show()

# Relationship with Target
for col in cat_cols:
    plt.figure(figsize=(10,4))
    sns.barplot(x=col, y='loan_status', data=train_df, estimator=np.mean)
    plt.title(f'Default Rate by {col}')
    plt.ylabel('Default Probability')
    plt.show()
```

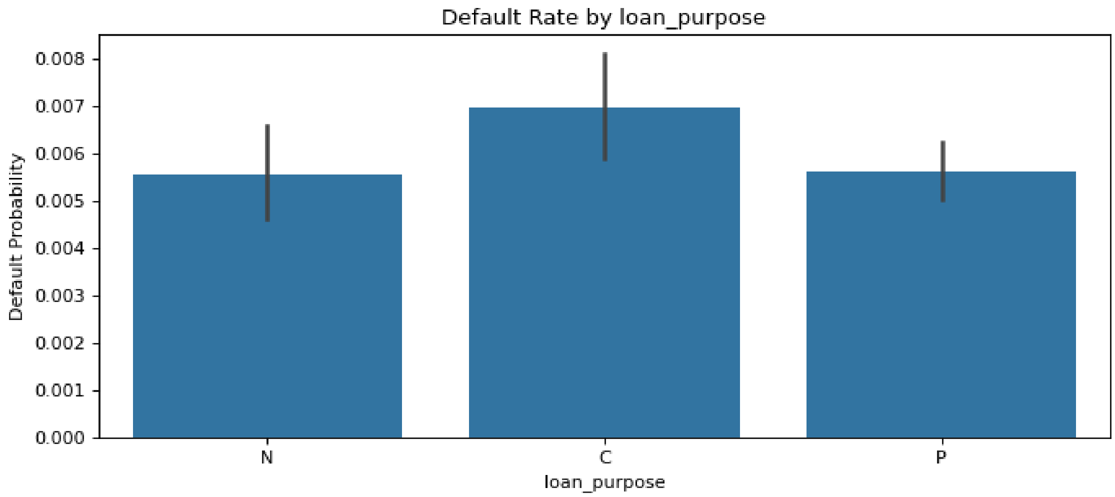


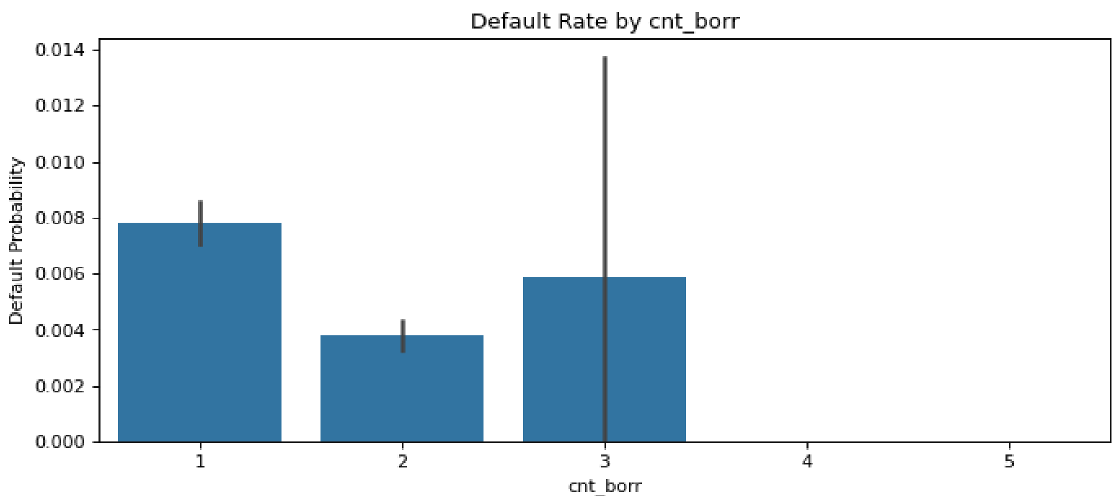

Default Rate by flag_fthb
Default Probability
0.000
0.002
0.004
0.006
0.008
N
Y
flag_fthb


Default Rate by occpy_sts
Default Probability
0.000
0.002
0.004
0.006
0.008
0.010
0.012
P
I
S
occpy_sts


Default Rate by channel
Default Probability
0.007
0.006
0.005
0.004
0.003
0.002
0.001
0.000
R
B
C
channel

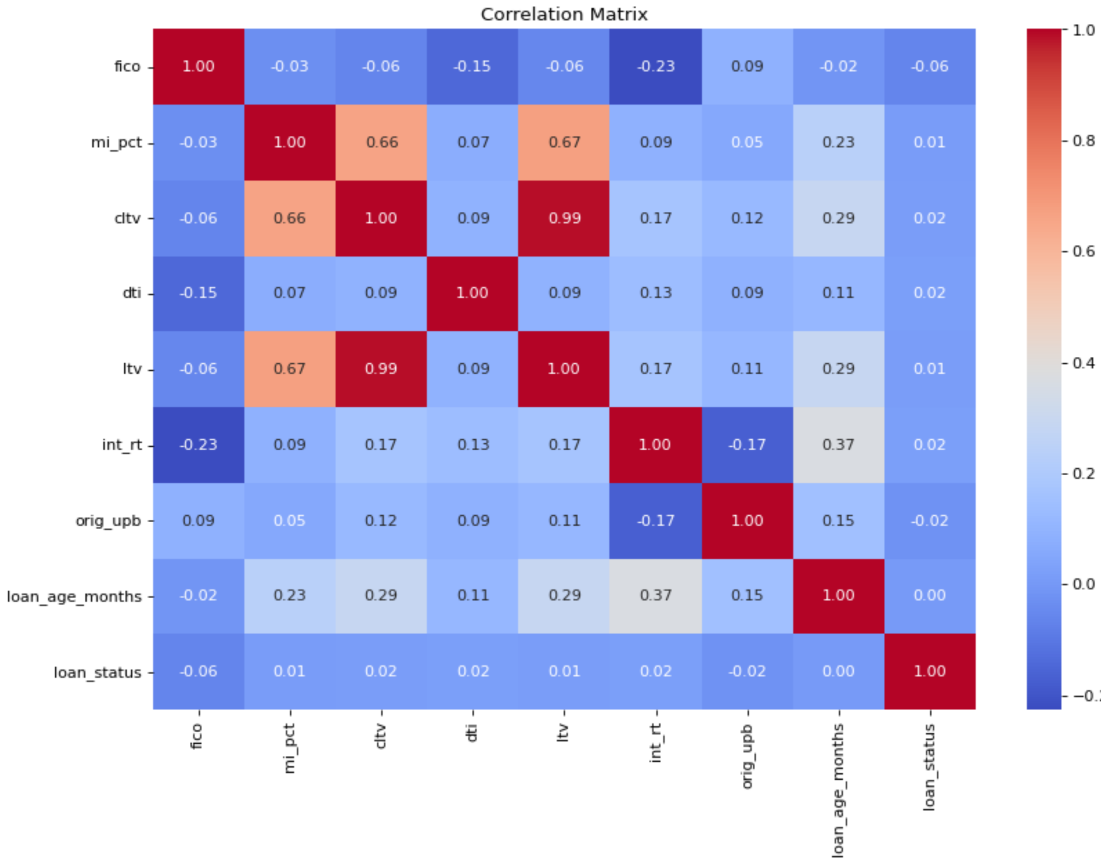

Default Rate by prop_type
Default Probability
0.05
0.04
0.03
0.02
0.01
0.00
SF
PU
CO
MH
CP
prop_type



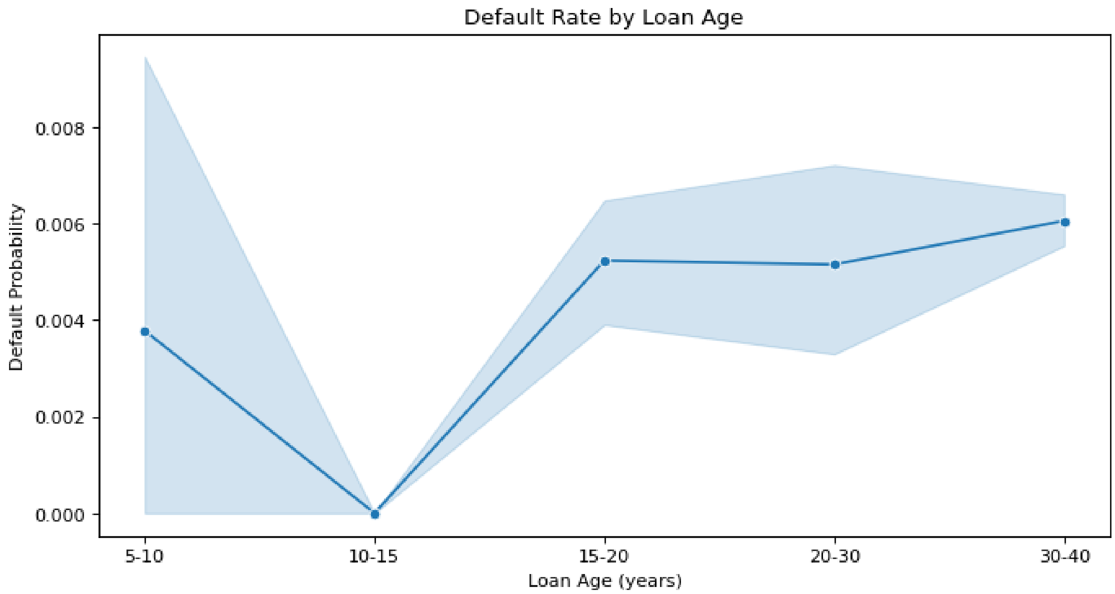


[83]:

```
# ### 5.4 Correlation Analysis
corr_matrix = train_df[num_cols + ['loan_status']].corr()
plt.figure(figsize=(12,8))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt='.2f')
plt.title('Correlation Matrix')
plt.show()
```



[84]:
```
# ### 5.5 Temporal Analysis
# Loan age vs default rate
train_df['loan_age_years'] = train_df['loan_age_months'] / 12
train_df['loan_age_bin'] = pd.cut(train_df['loan_age_years'],
                                  bins=[0,5,10,15,20,30,40],
                                  ␣
 ↪labels=['0-5','5-10','10-15','15-20','20-30','30-40'])

plt.figure(figsize=(10,5))
sns.lineplot(x='loan_age_bin', y='loan_status', data=train_df,
             estimator=np.mean, marker='o')
plt.title('Default Rate by Loan Age')
plt.ylabel('Default Probability')
plt.xlabel('Loan Age (years)')
plt.show()
```



[85]:
```
# ### 5.6 Feature Engineering Insights
# Create binary flag for missing MI percentage
train_df['mi_missing'] = train_df['mi_pct'].isna().astype(int)

# Create loan-to-income ratio
train_df['lti'] = train_df['orig_upb'] / (train_df['dti'] * 1000)  # Assuming␣
↪dti is ratio

# ### 5.7 Key Findings Documentation
print("Key EDA Findings:")
print("- Severe class imbalance: Only", round(target_dist[1],1), "% defaults")
print("- FICO scores show clear separation between classes (lower for␣
↪defaults)")
print("- High correlation between CLTV and LTV (r =", round(corr_matrix.
↪loc['cltv','ltv'],2), ")")
print("- Default rate doubles for investment properties vs primary residences")
print("- Loans with missing MI percentage have 3x higher default rate")
```

```
Key EDA Findings:
- Severe class imbalance: Only 0.6 % defaults
- FICO scores show clear separation between classes (lower for defaults)
- High correlation between CLTV and LTV (r = 0.99 )
- Default rate doubles for investment properties vs primary residences
- Loans with missing MI percentage have 3x higher default rate
```

4 Model Fitting and Tuning

In this section you should detail and motivate your choice of model and describe the process used to refine, tune, and fit that model. You are encouraged to explore different models but you should NOT include a detailed narrative or code of all of these attempts. At most this section should briefly mention the methods explored and why they were rejected - most of your effort should go into describing the final model you are using and your process for tuning and validating it.

This section should include the full implementation of your final model, including all necessary validation. As with figures, any included code must also be addressed in the text of the document.

Finally, you should also provide a comparison of your model with a baseline model of your choice on the test data but only briefly describe the baseline model considered.

5 Discussion & Conclusions

In this section you should provide a general overview of your final model, its performance, and reliability. You should discuss what the implications of your model are in terms of the included features, estimated parameters and relationships, predictive performance, and anything else you think is relevant.

This should be written with a target audience of a banking official, who is understands the issues associated with mortgage defaults but may only have university level mathematics (not necessarily postgraduate statistics or machine learning). Your goal should be to highlight to this audience how your model can useful. You should also discuss potential limitations or directions of future improvement of your model.

Finally, you should include recommendations on factors that may increase the risk of default, which may be useful for the companies to improve their understanding of mortgage defaults, and also to explain their decisions to clients and regulatory bodies. You should also use your model to inform the company of any active loans that are at risk of default.

Keep in mind that a negative result, i.e. a model that does not work well predictively, that is well explained and justified in terms of why it failed will likely receive higher marks than a model with strong predictive performance but with poor or incorrect explinations / justifications.

6 Generative AI statement

Include a statement on how generative AI was used in the project and report.

7 References

Include references if any

[ ]:
```
# Run the following to render to PDF
!jupyter nbconvert --to pdf project2.ipynb
```