hw2

April 29, 2024

[ ]:
```
import pandas as pd
import numpy as np
from sklearn.model_selection import KFold, train_test_split, GridSearchCV
from sklearn.svm import SVC
from sklearn.preprocessing import StandardScaler, LabelEncoder
import matplotlib.pyplot as plt
import matplotlib.patches as mpatches
from ISLP.svm import plot as plot_svm
```

0.1 Data Preparation

[ ]:
```
df = pd.read_csv("Housing.csv")
```

[ ]:
```
# retrieve labels from https://usa.ipums.org/usa-action/variables/live_search␣
↪for exploration purposes
col_labels = {
    "SERIAL": "Household serial number",
    "DENSITY": "Population-weighted density of PUMA",  # PUMA is Public Use␣
↪Microdata Area
    "OWNERSHP": "Ownership of dwelling (tenure) [general version]",  # owned/
↪being bought vs rented
    "OWNERSHPD": "Ownership of dwelling (tenure) [detailed version]",  # e.g.␣
↪rented vs no cash rent vs cash rent
    "COSTELEC": "Annual electricity cost",
    "COSTGAS": "Annual gas cost",
    "COSTWATR": "Annual water cost",
    "COSTFUEL": "Annual home heating fuel cost",
    "HHINCOME": "Total household income",
    "VALUEH": "House value",
    "ROOMS": "Number of rooms",
    "BUILTYR2": "Age of structure, decade",
    "BEDROOMS": "Number of bedrooms",
    "VEHICLES": "Vehicles available",
    "NFAMS": "Number of families in household",
    "NCOUPLES": "Number of couples in household",
    "PERNUM": "Person number in sample unit",
```

```
    "PERWT": "Person weight",  # sampling weight, indicates how many persons in␣
 ↪the U.S. population are represented by a given person
    "AGE": "Age",
    "MARST": "Marital status",
    "BIRTHYR": "Year of birth",
    "EDUC": "Educational attainment [general version]",
    "EDUCD": "Educational attainment [detailed version]",
    "INCTOT": "Total personal income",
}

df_readable = df.rename(columns=col_labels)
```

[ ]:
```
# filter by columns of interest and replace special missing values with NaN
cols_of_interest = [
    "Household serial number",
    "Population-weighted density of PUMA",
    "Ownership of dwelling (tenure) [general version]",
    "Number of rooms",
    "Age of structure, decade",
    "Number of bedrooms",
    "Number of families in household",
    "Number of couples in household",
    "Age",
    "Marital status",
    "Educational attainment [general version]",
    "Total personal income",
]

missing_values_per_col = {
    "Total personal income": [9999999],
}

df_filtered = df_readable[cols_of_interest].replace(missing_values_per_col, np.
 ↪nan)
```

[ ]:
```
# rename some long column names
cols_rename_map = {
    "Population-weighted density of PUMA": "Population-weighted density",
    "Ownership of dwelling (tenure) [general version]": "Ownership of dwelling",
    "Educational attainment [general version]": "Educational attainment",
}

df_filtered = df_filtered.rename(columns=cols_rename_map)
```

[ ]:
```
# filter to single family households with 0 or 1 couples -- 2 or 3 couples of␣
 ↪the same family living in the same household is an outlier.
df_single_family = df_filtered[
```

```
    (df_filtered["Number of families in household"] == 1)
    & (
        (df_filtered["Number of couples in household"] == 1)
        | (df_filtered["Number of couples in household"] == 0)
    )
]

# remove all rows with missing values
initial_length = len(df_single_family)
df_single_family = df_single_family.dropna()
new_length = len(df_single_family)
rows_dropped = initial_length - new_length
print(f"Removed {rows_dropped} rows with missing values out of {initial_length}␣
 ↪({(rows_dropped / initial_length)*100:.2f}%)")

# aggregate per head of household, defined as a person 18 or older with highest␣
 ↪personal income
index = (
    df_single_family[df_single_family["Age"] >= 18]
    .groupby("Household serial number")["Total personal income"]
    .idxmax()
)
df_single_family = df_single_family.loc[index]

# we can also aggregate by sorting, but seems like a bad approach
# df_single_family = df_single_family.sort_values("Total personal income",␣
 ↪ascending=False).drop_duplicates("Household serial number")

# drop Number of families in household since it's always 1
# drop Household serial number since we've already aggregated, and it's not␣
 ↪useful as a predictor
df_single_family = df_single_family.drop(columns=["Number of families in␣
 ↪household", "Household serial number"])
```

```
Removed 11840 rows with missing values out of 68131 (17.38%)
```

[ ]:
```
# group education into 5 categories: less than high school, high school, some␣
 ↪college, bachelor's, graduate
# by default is (], left-exclusive and right-inclusive
bins = [0, 5, 6, 9, 10, 11]
labels = [
    "Less than high school",
    "High school",
    "Some college",
    "Bachelor's",
    "Graduate",
]
```

```
df_single_family["Educational attainment"] = pd.cut(
    df_single_family["Educational attainment"],
    bins=bins,
    labels=labels,
    include_lowest=True,  # so 0 is included in 0-5
)
```

[ ]:
```
# group marital status into 3 categories: married (spouse present/absent),␣
↪previously married (separated/divorced/widowed), never married
bins = [1, 2, 5, 6]
labels = [
    "Married",
    "Previously married",
    "Never married",
]
df_single_family["Marital status"] = pd.cut(
    df_single_family["Marital status"],
    bins=bins,
    labels=labels,
    include_lowest=True,
)
```

[ ]:
```
# rename ownership of dwelling categories, 1 is Owned or being bought, 2 is␣
↪Rented
df_single_family = df_single_family.replace(
    {"Ownership of dwelling": {1: "Owned", 2: "Rented"}}
)
```

[ ]:
```
# encode categorical predictors as nominal, the distance betweeen our␣
↪categories is hard to quantify and may not be equal
# e.g. would distance between "Less than high school" and "High school" be the␣
↪same as "High school" and "Some college"?
nominal_cols = [
    "Educational attainment",
    "Marital status",
]

# one-hot encode (which is different to dummy encode) - doesn't drop first␣
↪category, easier to interpret and SVM can handle it
df_onehot = pd.get_dummies(df_single_family[nominal_cols], drop_first=False)
df_single_family = pd.concat([df_single_family, df_onehot], axis=1)
df_single_family = df_single_family.drop(columns=nominal_cols)
```

[ ]:
```
# group age into 3 categories: 18-34 (young adults), 35-64 (middle-aged␣
↪adults), 65+ (older adults)
bins = [18, 34, 64, float('inf')]
labels = ["Young adults", "Middle-aged adults", "Older adults"]
```

```python
# keep age as original data for later
age_groups = pd.cut(
    df_single_family["Age"],
    bins=bins,
    labels=labels,
    include_lowest=True
)

# create 3 separate dataframes for each age group
df_young_adults = df_single_family[age_groups == "Young adults"]
df_middle_aged_adults = df_single_family[age_groups == "Middle-aged adults"]
df_older_adults = df_single_family[age_groups == "Older adults"]
```

[ ]:
```python
# scaler for later use
scaler = StandardScaler()
```

0.2 Modeling

0.2.1 Young Adults

[ ]:
```python
X = df_young_adults.drop(columns=['Ownership of dwelling'])
y = df_young_adults['Ownership of dwelling']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
  ↪random_state=1)
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

Radial

[ ]:
```python
svm_rbf = SVC(kernel="rbf", tol=0.1)

kFold = KFold(n_splits=5, shuffle=True, random_state=1)
params = {"C": [0.001, 0.01, 0.1, 1, 10], "gamma": [0.0001, 0.001, 0.01, 1, 10,␣
  ↪100]}
cv = GridSearchCV(
    svm_rbf,
    param_grid=params,
    cv=kFold,
    refit=True,
    n_jobs=-1,
    scoring="accuracy",
    verbose=1,
)
cv.fit(X_train_scaled, y_train)

train_accuracy = cv.best_estimator_.score(X_train_scaled, y_train)
test_accuracy = cv.best_estimator_.score(X_test_scaled, y_test)
```

```
best_C_rbf = cv.best_params_["C"]
best_gamma = cv.best_params_["gamma"]
print(f"Radial CV results: C={best_C_rbf}, gamma={best_gamma}")
print(f"Train accuracy: {train_accuracy*100:.2f}%")
print(f"Test accuracy: {test_accuracy*100:.2f}%")
```

```
Fitting 5 folds for each of 30 candidates, totalling 150 fits
Radial CV results: C=10, gamma=0.01
Train accuracy: 80.52%
Test accuracy: 79.76%
```

Poly

[ ]:
```
svm_poly = SVC(kernel="poly", tol=0.1)

kFold = KFold(n_splits=5, shuffle=True, random_state=1)
params = {
    "C": [0.001, 0.01, 0.1, 1, 10],
    "degree": np.arange(2, 5, 1),
    "coef0": np.arange(0, 3, 0.5),
}
cv = GridSearchCV(
    svm_poly,
    param_grid=params,
    cv=kFold,
    refit=True,
    n_jobs=-1,
    scoring="accuracy",
    verbose=1,
)
cv.fit(X_train_scaled, y_train)

train_accuracy = cv.best_estimator_.score(X_train_scaled, y_train)
test_accuracy = cv.best_estimator_.score(X_test_scaled, y_test)

best_C_poly = cv.best_params_["C"]
best_degree = cv.best_params_["degree"]
best_coef0 = cv.best_params_["coef0"]

print(f"Poly CV results: C={best_C_poly}, degree={best_degree},␣
 ↪coef0={best_coef0}")
print(f"Train accuracy: {train_accuracy*100:.2f}%")
print(f"Test accuracy: {test_accuracy*100:.2f}%")
```

```
Fitting 5 folds for each of 90 candidates, totalling 450 fits
Poly CV results: C=0.1, degree=2, coef0=1.5
Train accuracy: 80.19%
Test accuracy: 79.69%
```

Linear

```
[ ]: svm_linear = SVC(kernel="linear", tol=0.1)

kFold = KFold(n_splits=5, shuffle=True, random_state=1)
params = {"C": [0.001, 0.01, 0.1, 1, 10]}
cv = GridSearchCV(
    svm_linear,
    param_grid=params,
    cv=kFold,
    refit=True,
    n_jobs=-1,
    scoring="accuracy",
    verbose=1,
)
cv.fit(X_train_scaled, y_train)

train_accuracy = cv.best_estimator_.score(X_train_scaled, y_train)
test_accuracy = cv.best_estimator_.score(X_test_scaled, y_test)

best_C_linear = cv.best_params_["C"]

print(f"Linear CV results: C={best_C_linear}")
print(f"Train accuracy: {train_accuracy*100:.2f}%")
print(f"Test accuracy: {test_accuracy*100:.2f}%")
```

```
Fitting 5 folds for each of 5 candidates, totalling 25 fits
Linear CV results: C=0.1
Train accuracy: 78.96%
Test accuracy: 79.20%
```

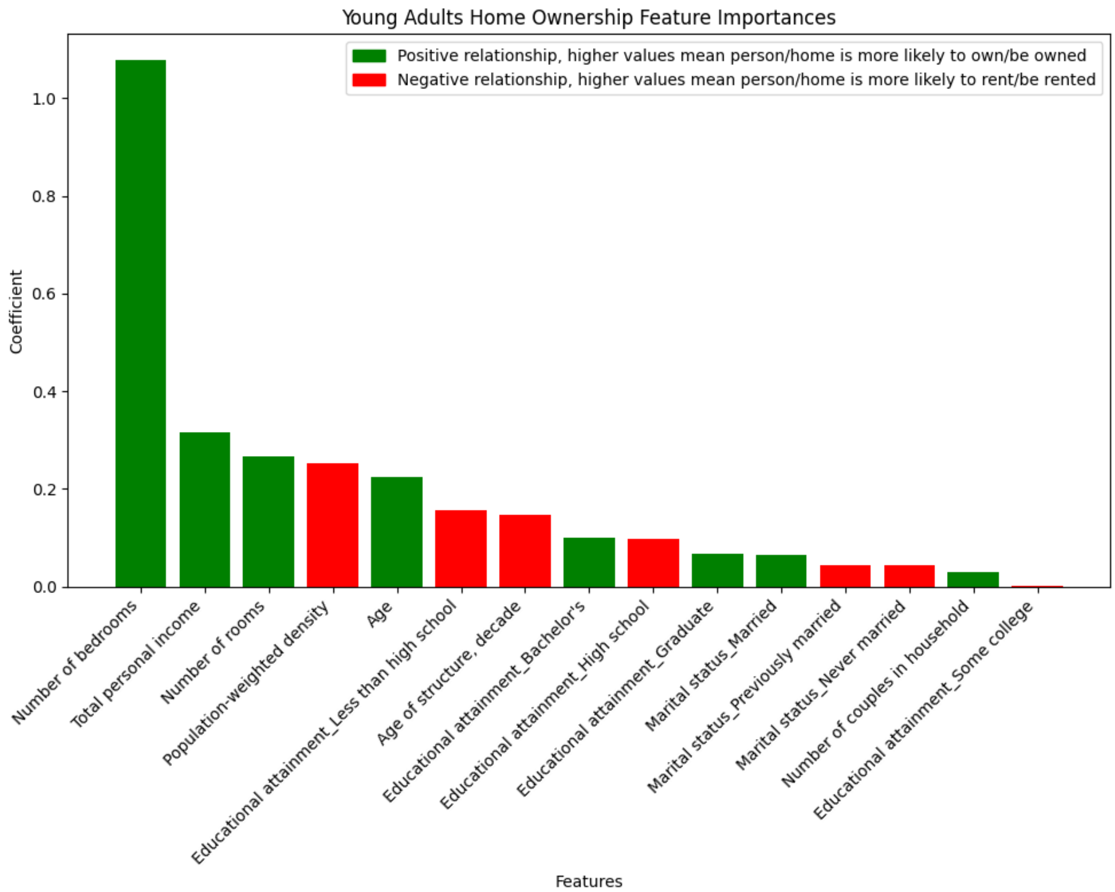
Feature Importance

```
[ ]: coef = cv.best_estimator_.coef_[0]  # using linear kernel
feature_importances = pd.DataFrame({"Feature": X.columns, "Coefficient": coef,␣
 ↪"AbsCoefficient": abs(coef)})
sorted_importances = feature_importances.sort_values(by="AbsCoefficient",␣
 ↪ascending=False)

# sum up importances of onehot encoded features
grouped_importances = feature_importances.groupby(
    feature_importances["Feature"].str.split("_").str[0]
).sum()
sorted_grouped_importances = grouped_importances.
 ↪sort_values(by="AbsCoefficient", ascending=False)
```

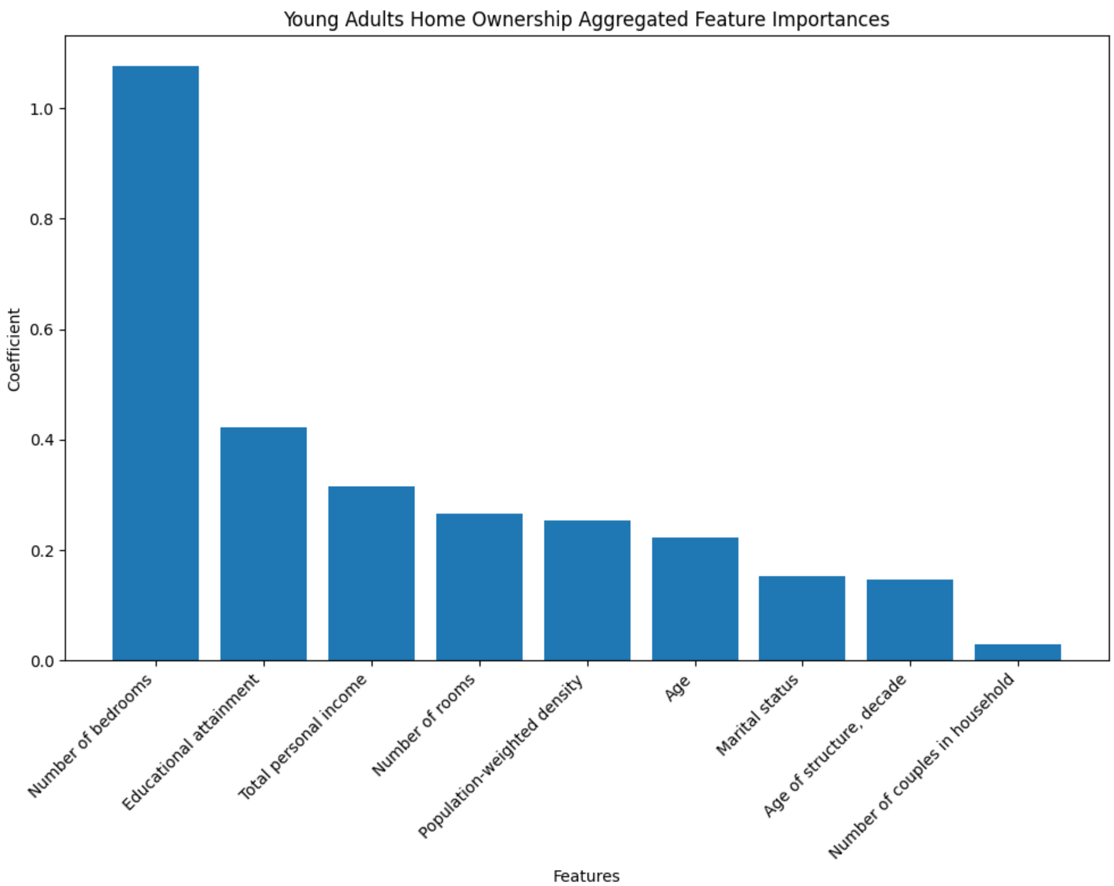
```
/var/folders/jy/pdgtcrw968d_3_tqfzr3w6y00000gn/T/ipykernel_84534/2379649311.py:6
: FutureWarning: The default value of numeric_only in DataFrameGroupBy.sum is
deprecated. In a future version, numeric_only will default to False. Either
specify numeric_only or select only columns which should be valid for the
```

function.
  grouped_importances = feature_importances.groupby(

[ ]:
```
# color the bars based on coefficient sign
colors = ['green' if coef < 0 else 'red' for coef in␣
 ↪sorted_importances["Coefficient"]]
green_patch = mpatches.Patch(color='green', label='Positive relationship,␣
 ↪higher values mean person/home is more likely to own/be owned')
red_patch = mpatches.Patch(color='red', label='Negative relationship, higher␣
 ↪values mean person/home is more likely to rent/be rented')

plt.figure(figsize=(10, 8))
plt.bar(sorted_importances['Feature'], sorted_importances["AbsCoefficient"],␣
 ↪color=colors)
plt.legend(handles=[green_patch, red_patch])
plt.xlabel("Features")
plt.ylabel("Coefficient")
plt.title("Young Adults Home Ownership Feature Importances")
plt.xticks(rotation=45, ha="right")
plt.tight_layout()
plt.show()
```



```
[ ]: plt.figure(figsize=(10, 8))
     plt.bar(sorted_grouped_importances.index,␣
      ↪sorted_grouped_importances["AbsCoefficient"])
     plt.xlabel("Features")
     plt.ylabel("Coefficient")
     plt.title("Young Adults Home Ownership Aggregated Feature Importances")
     plt.xticks(rotation=45, ha="right")
     plt.tight_layout()
     plt.show()
```



0.2.2 Middle-Aged Adults

```
[ ]: X = df_middle_aged_adults.drop(columns=['Ownership of dwelling'])
     y = df_middle_aged_adults['Ownership of dwelling']
     X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
      ↪random_state=1)
```

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

Radial

[ ]:
```
svm_rbf = SVC(kernel="rbf", tol=0.1)

kFold = KFold(n_splits=5, shuffle=True, random_state=1)
params = {"C": [0.001, 0.01, 0.1, 1, 10], "gamma": [0.0001, 0.001, 0.01, 1, 10,␣
 ↪100]}
cv = GridSearchCV(
    svm_rbf,
    param_grid=params,
    cv=kFold,
    refit=True,
    n_jobs=-1,
    scoring="accuracy",
    verbose=1,
)
cv.fit(X_train_scaled, y_train)

train_accuracy = cv.best_estimator_.score(X_train_scaled, y_train)
test_accuracy = cv.best_estimator_.score(X_test_scaled, y_test)

best_C_rbf = cv.best_params_["C"]
best_gamma = cv.best_params_["gamma"]
print(f"Radial CV results: C={best_C_rbf}, gamma={best_gamma}")
print(f"Train accuracy: {train_accuracy*100:.2f}%")
print(f"Test accuracy: {test_accuracy*100:.2f}%")
```

```
Fitting 5 folds for each of 30 candidates, totalling 150 fits
```

```
/opt/homebrew/anaconda3/envs/py39/lib/python3.9/site-
packages/joblib/externals/loky/process_executor.py:752: UserWarning: A worker
stopped while some jobs were given to the executor. This can be caused by a too
short worker timeout or by a memory leak.
  warnings.warn(
```

```
Radial CV results: C=10, gamma=0.001
Train accuracy: 82.09%
Test accuracy: 82.59%
```

Poly

[ ]:
```
svm_poly = SVC(kernel="poly", tol=0.1)

kFold = KFold(n_splits=5, shuffle=True, random_state=1)
params = {
    "C": [0.001, 0.01, 0.1, 1, 10],
    "degree": np.arange(2, 5, 1),
```

```
    "coef0": np.arange(0, 3, 0.5),
}
cv = GridSearchCV(
    svm_poly,
    param_grid=params,
    cv=kFold,
    refit=True,
    n_jobs=-1,
    scoring="accuracy",
    verbose=1,
)
cv.fit(X_train_scaled, y_train)

train_accuracy = cv.best_estimator_.score(X_train_scaled, y_train)
test_accuracy = cv.best_estimator_.score(X_test_scaled, y_test)

best_C_poly = cv.best_params_["C"]
best_degree = cv.best_params_["degree"]
best_coef0 = cv.best_params_["coef0"]

print(f"Poly CV results: C={best_C_poly}, degree={best_degree},␣
 ↪coef0={best_coef0}")
print(f"Train accuracy: {train_accuracy*100:.2f}%")
print(f"Test accuracy: {test_accuracy*100:.2f}%")
```

```
Fitting 5 folds for each of 90 candidates, totalling 450 fits
```

```
/opt/homebrew/anaconda3/envs/py39/lib/python3.9/site-
packages/joblib/externals/loky/process_executor.py:752: UserWarning: A worker
stopped while some jobs were given to the executor. This can be caused by a too
short worker timeout or by a memory leak.
  warnings.warn(
```

```
Poly CV results: C=10, degree=2, coef0=0.5
Train accuracy: 82.31%
Test accuracy: 82.87%
```

Linear

[ ]:
```
svm_linear = SVC(kernel="linear", tol=0.1)

kFold = KFold(n_splits=5, shuffle=True, random_state=1)
params = {"C": [0.001, 0.01, 0.1, 1, 10]}
cv = GridSearchCV(
    svm_linear,
    param_grid=params,
    cv=kFold,
    refit=True,
    n_jobs=-1,
```

```
    scoring="accuracy",
    verbose=1,
)
cv.fit(X_train_scaled, y_train)

train_accuracy = cv.best_estimator_.score(X_train_scaled, y_train)
test_accuracy = cv.best_estimator_.score(X_test_scaled, y_test)

best_C_linear = cv.best_params_["C"]

print(f"Linear CV results: C={best_C_linear}")
print(f"Train accuracy: {train_accuracy*100:.2f}%")
print(f"Test accuracy: {test_accuracy*100:.2f}%")
```

```
Fitting 5 folds for each of 5 candidates, totalling 25 fits
```

```
/opt/homebrew/anaconda3/envs/py39/lib/python3.9/site-
packages/joblib/externals/loky/process_executor.py:752: UserWarning: A worker
stopped while some jobs were given to the executor. This can be caused by a too
short worker timeout or by a memory leak.
  warnings.warn(
```

```
Linear CV results: C=1
Train accuracy: 82.22%
Test accuracy: 82.61%
```

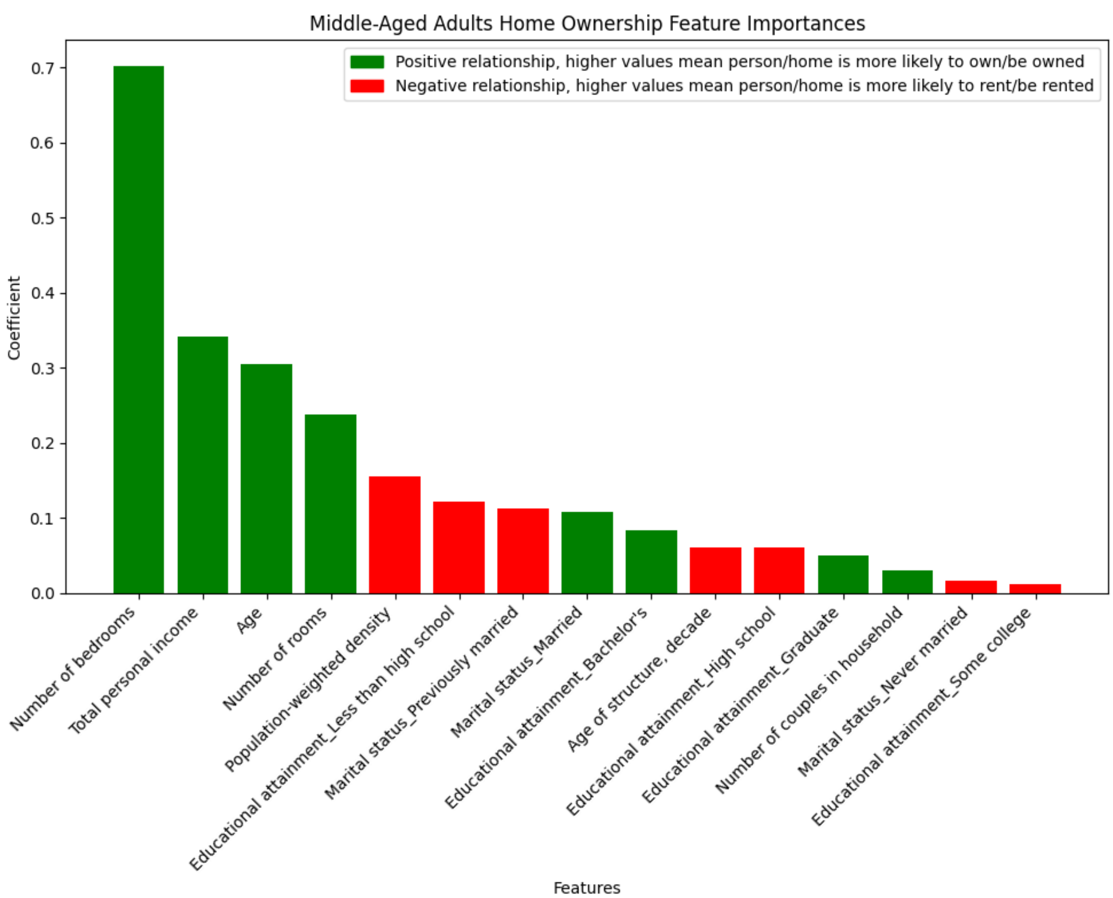
Feature Importance

[ ]:
```
coef = cv.best_estimator_.coef_[0]  # using linear kernel
feature_importances = pd.DataFrame({"Feature": X.columns, "Coefficient": coef,␣
↪"AbsCoefficient": abs(coef)})
sorted_importances = feature_importances.sort_values(by="AbsCoefficient",␣
↪ascending=False)

# sum up importances of onehot encoded features
grouped_importances = feature_importances.groupby(
    feature_importances["Feature"].str.split("_").str[0]
).sum()
sorted_grouped_importances = grouped_importances.
↪sort_values(by="AbsCoefficient", ascending=False)
```

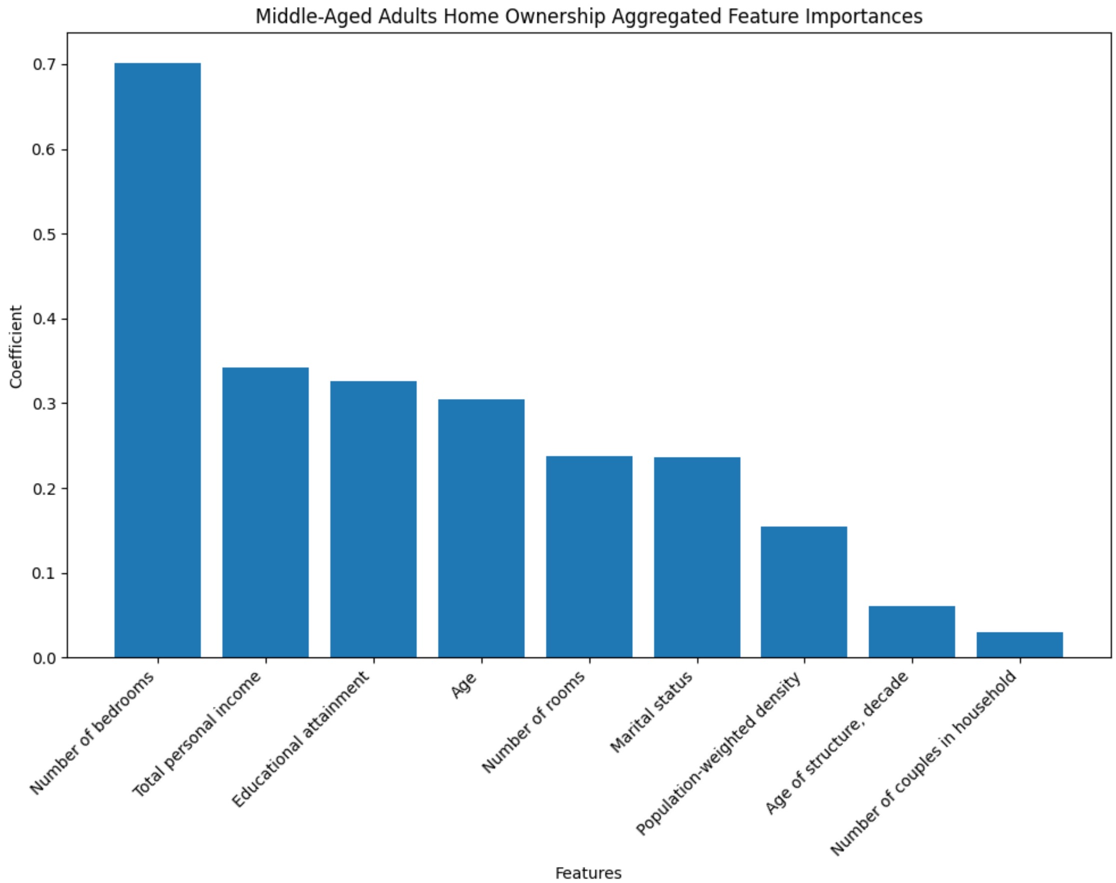
```
/var/folders/jy/pdgtcrw968d_3_tqfzr3w6y00000gn/T/ipykernel_84534/2379649311.py:6
: FutureWarning: The default value of numeric_only in DataFrameGroupBy.sum is
deprecated. In a future version, numeric_only will default to False. Either
specify numeric_only or select only columns which should be valid for the
function.
  grouped_importances = feature_importances.groupby(
```

[ ]:

```
# color the bars based on coefficient sign
colors = ['green' if coef < 0 else 'red' for coef in␣
 ↪sorted_importances["Coefficient"]]
green_patch = mpatches.Patch(color='green', label='Positive relationship,␣
 ↪higher values mean person/home is more likely to own/be owned')
red_patch = mpatches.Patch(color='red', label='Negative relationship, higher␣
 ↪values mean person/home is more likely to rent/be rented')

plt.figure(figsize=(10, 8))
plt.bar(sorted_importances['Feature'], sorted_importances["AbsCoefficient"],␣
 ↪color=colors)
plt.legend(handles=[green_patch, red_patch])
plt.xlabel("Features")
plt.ylabel("Coefficient")
plt.title("Middle-Aged Adults Home Ownership Feature Importances")
plt.xticks(rotation=45, ha="right")
plt.tight_layout()
plt.show()
```



```
[ ]: plt.figure(figsize=(10, 8))
     plt.bar(sorted_grouped_importances.index,␣
      ↪sorted_grouped_importances["AbsCoefficient"])
     plt.xlabel("Features")
     plt.ylabel("Coefficient")
     plt.title("Middle-Aged Adults Home Ownership Aggregated Feature Importances")
     plt.xticks(rotation=45, ha="right")
     plt.tight_layout()
     plt.show()
```



0.2.3 Older Adults

```
[ ]: X = df_older_adults.drop(columns=['Ownership of dwelling'])
     y = df_older_adults['Ownership of dwelling']
     X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
      ↪random_state=1)
     X_train_scaled = scaler.fit_transform(X_train)
     X_test_scaled = scaler.transform(X_test)
```

Radial

```
[ ]: svm_rbf = SVC(kernel="rbf", tol=0.1)

kFold = KFold(n_splits=5, shuffle=True, random_state=1)
params = {"C": [0.001, 0.01, 0.1, 1, 10], "gamma": [0.0001, 0.001, 0.01, 1, 10,␣
 ↪100]}
cv = GridSearchCV(
    svm_rbf,
    param_grid=params,
    cv=kFold,
    refit=True,
    n_jobs=-1,
    scoring="accuracy",
    verbose=1,
)
cv.fit(X_train_scaled, y_train)

train_accuracy = cv.best_estimator_.score(X_train_scaled, y_train)
test_accuracy = cv.best_estimator_.score(X_test_scaled, y_test)

best_C_rbf = cv.best_params_["C"]
best_gamma = cv.best_params_["gamma"]
print(f"Radial CV results: C={best_C_rbf}, gamma={best_gamma}")
print(f"Train accuracy: {train_accuracy*100:.2f}%")
print(f"Test accuracy: {test_accuracy*100:.2f}%")
```

```
Fitting 5 folds for each of 30 candidates, totalling 150 fits

/opt/homebrew/anaconda3/envs/py39/lib/python3.9/site-
packages/joblib/externals/loky/process_executor.py:752: UserWarning: A worker
stopped while some jobs were given to the executor. This can be caused by a too
short worker timeout or by a memory leak.
  warnings.warn(

Radial CV results: C=10, gamma=0.01
Train accuracy: 88.07%
Test accuracy: 87.06%
```

Poly

```
[ ]: svm_poly = SVC(kernel="poly", tol=0.1)

kFold = KFold(n_splits=5, shuffle=True, random_state=1)
params = {
    "C": [0.001, 0.01, 0.1, 1, 10],
    "degree": np.arange(2, 5, 1),
    "coef0": np.arange(0, 3, 0.5),
}
cv = GridSearchCV(
```

```
    svm_poly,
    param_grid=params,
    cv=kFold,
    refit=True,
    n_jobs=-1,
    scoring="accuracy",
    verbose=1,
)
cv.fit(X_train_scaled, y_train)

train_accuracy = cv.best_estimator_.score(X_train_scaled, y_train)
test_accuracy = cv.best_estimator_.score(X_test_scaled, y_test)

best_C_poly = cv.best_params_["C"]
best_degree = cv.best_params_["degree"]
best_coef0 = cv.best_params_["coef0"]

print(f"Poly CV results: C={best_C_poly}, degree={best_degree},␣
 ↪coef0={best_coef0}")
print(f"Train accuracy: {train_accuracy*100:.2f}%")
print(f"Test accuracy: {test_accuracy*100:.2f}%")
```

```
Fitting 5 folds for each of 90 candidates, totalling 450 fits
Poly CV results: C=1, degree=3, coef0=1.0
Train accuracy: 88.58%
Test accuracy: 87.06%
```

Linear

[ ]:
```
svm_linear = SVC(kernel="linear", tol=0.1)

kFold = KFold(n_splits=5, shuffle=True, random_state=1)
params = {"C": [0.001, 0.01, 0.1, 1, 10]}
cv = GridSearchCV(
    svm_linear,
    param_grid=params,
    cv=kFold,
    refit=True,
    n_jobs=-1,
    scoring="accuracy",
    verbose=1,
)
cv.fit(X_train_scaled, y_train)

train_accuracy = cv.best_estimator_.score(X_train_scaled, y_train)
test_accuracy = cv.best_estimator_.score(X_test_scaled, y_test)

best_C_linear = cv.best_params_["C"]
```

```
print(f"Linear CV results: C={best_C_linear}")
print(f"Train accuracy: {train_accuracy*100:.2f}%")
print(f"Test accuracy: {test_accuracy*100:.2f}%")
```

```
Fitting 5 folds for each of 5 candidates, totalling 25 fits
Linear CV results: C=10
Train accuracy: 87.58%
Test accuracy: 87.10%
```

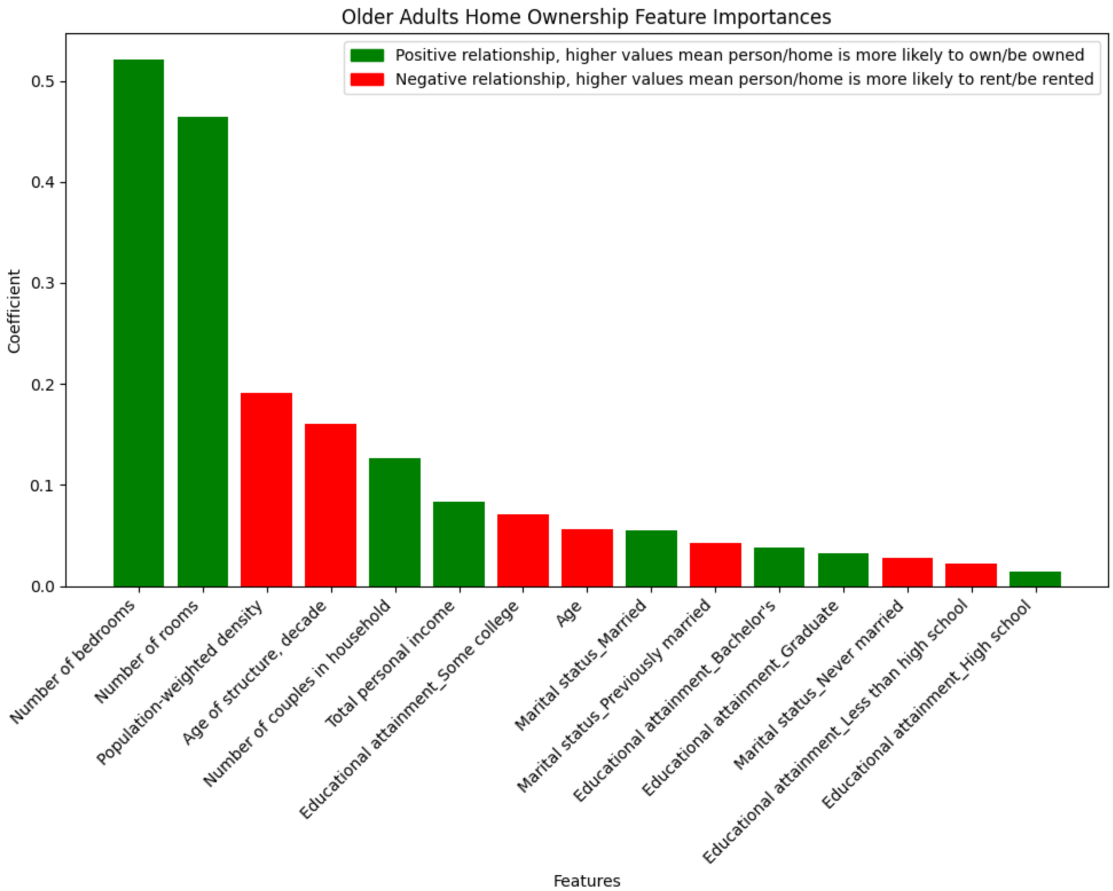
Feature Importance

[ ]:
```
coef = cv.best_estimator_.coef_[0]  # using linear kernel
feature_importances = pd.DataFrame({"Feature": X.columns, "Coefficient": coef,␣
↪"AbsCoefficient": abs(coef)})
sorted_importances = feature_importances.sort_values(by="AbsCoefficient",␣
↪ascending=False)

# sum up importances of onehot encoded features
grouped_importances = feature_importances.groupby(
    feature_importances["Feature"].str.split("_").str[0]
).sum()
sorted_grouped_importances = grouped_importances.
↪sort_values(by="AbsCoefficient", ascending=False)
```

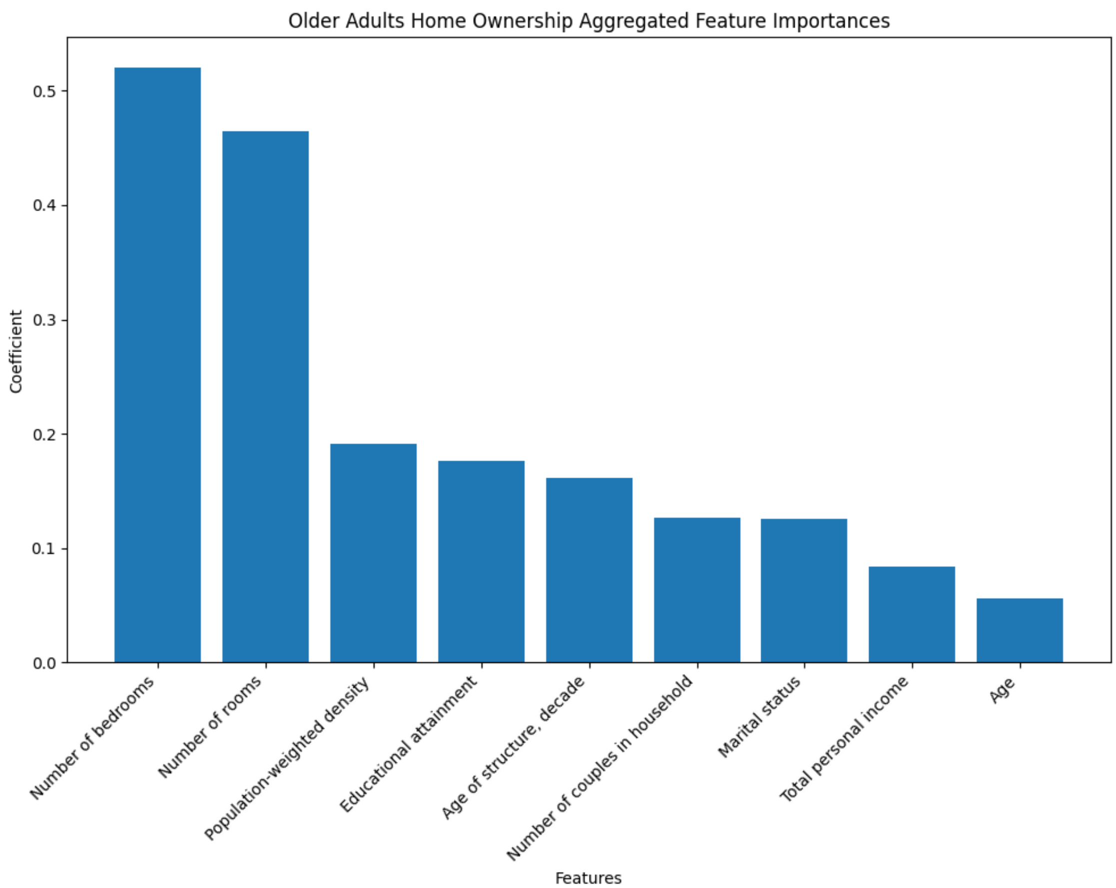
```
/var/folders/jy/pdgtcrw968d_3_tqfzr3w6y00000gn/T/ipykernel_84534/2379649311.py:6
: FutureWarning: The default value of numeric_only in DataFrameGroupBy.sum is
deprecated. In a future version, numeric_only will default to False. Either
specify numeric_only or select only columns which should be valid for the
function.
  grouped_importances = feature_importances.groupby(
```

[ ]:
```
# color the bars based on coefficient sign
colors = ['green' if coef < 0 else 'red' for coef in␣
↪sorted_importances["Coefficient"]]
green_patch = mpatches.Patch(color='green', label='Positive relationship,␣
↪higher values mean person/home is more likely to own/be owned')
red_patch = mpatches.Patch(color='red', label='Negative relationship, higher␣
↪values mean person/home is more likely to rent/be rented')

plt.figure(figsize=(10, 8))
plt.bar(sorted_importances['Feature'], sorted_importances["AbsCoefficient"],␣
↪color=colors)
plt.legend(handles=[green_patch, red_patch])
plt.xlabel("Features")
plt.ylabel("Coefficient")
plt.title("Older Adults Home Ownership Feature Importances")
plt.xticks(rotation=45, ha="right")
```

```
plt.tight_layout()
plt.show()
```




```
[ ]: plt.figure(figsize=(10, 8))
     plt.bar(sorted_grouped_importances.index,␣
      ↪sorted_grouped_importances["AbsCoefficient"])
     plt.xlabel("Features")
     plt.ylabel("Coefficient")
     plt.title("Older Adults Home Ownership Aggregated Feature Importances")
     plt.xticks(rotation=45, ha="right")
     plt.tight_layout()
     plt.show()
```



0.3 Misc

0.3.1 Prove 'Owned' was encoded as class 0 (to determine direction of relationship, i.e. negative coef == more likely to own)

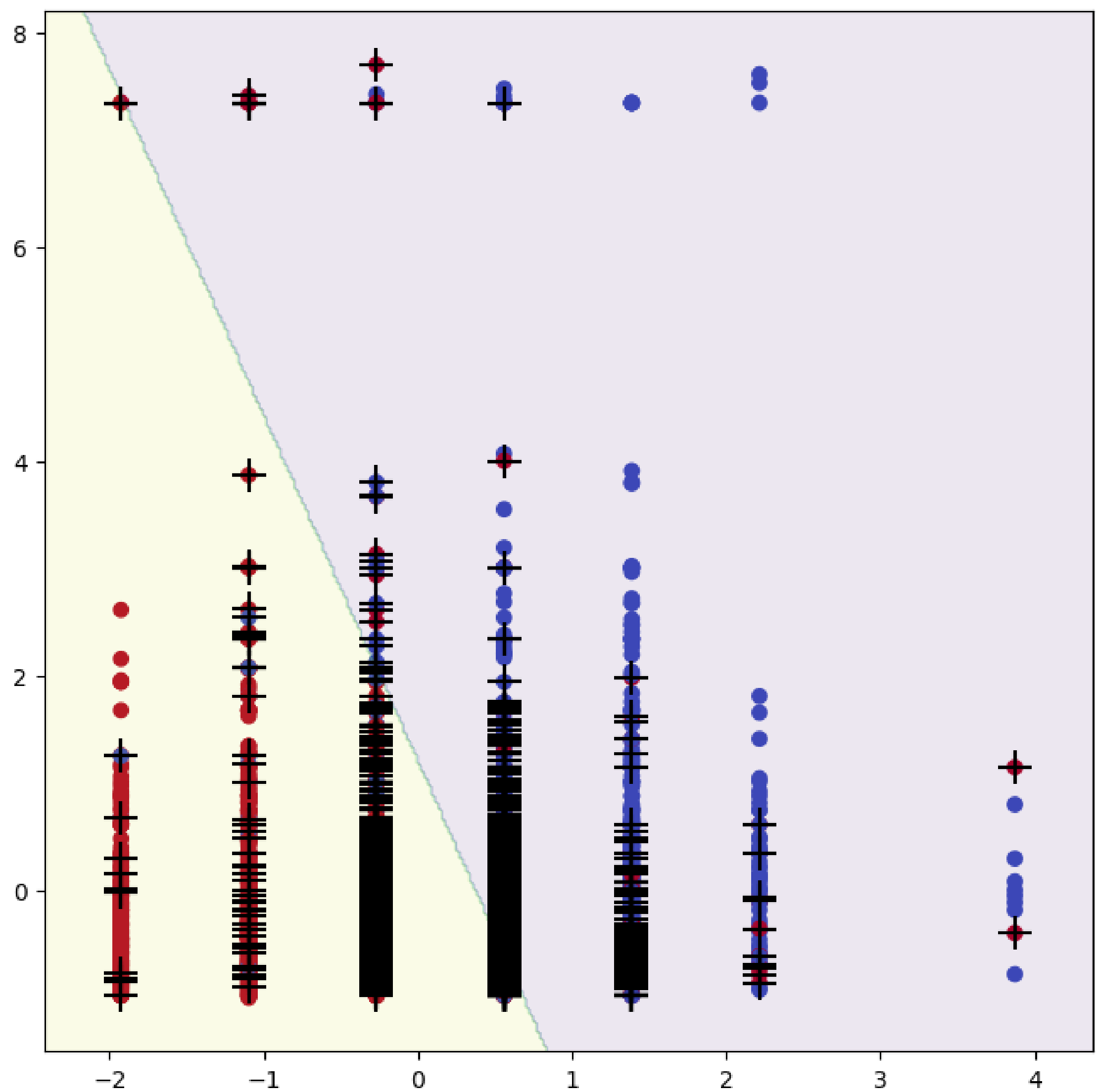
[ ]:
```
encoder = LabelEncoder()
encoder.fit_transform(y)

print(encoder.classes_)
```

```
['Owned' 'Rented']
```

0.3.2 'Cartoon' plot for a simplified model using 2 strong predictors

```
[ ]: X = df_young_adults[['Number of bedrooms', 'Total personal income']]
     y = df_young_adults['Ownership of dwelling']
     X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
      ↪random_state=1)
     X_train_scaled = scaler.fit_transform(X_train)
     X_test_scaled = scaler.transform(X_test)
```

```
[ ]: encoder = LabelEncoder()
     y_train_encoded = encoder.fit_transform(y_train)

     svm_linear = SVC(kernel="linear", C=0.01)
     svm_linear.fit(X_train_scaled, y_train_encoded)

     _, ax = plt.subplots(figsize=(8, 8))
     plot_svm(
         X_train_scaled,
         y_train_encoded,
         svm_linear,
         ax=ax,
         scatter_cmap=plt.cm.coolwarm,
         decision_cmap=plt.cm.viridis,
         alpha=0.1
     )
```


8
6
4
2
0
−2
−1
0
1
2
3
4