House Tenure Prediction Analysis

Abstract

This study analyses and predicts whether a residence is owned or rented by the people who live there. In this report, we will focus on the factors that influence people's decisions about owning or renting properties. Some of these factors include the age of the household members, their income, their education, the year the property was constructed, and others. Our analysis will be based on census data for Washington state from IPUMS USA. We will use Support Vector Machines with linear, radial, and polynomial kernels to predict homeownership status. From our analysis, we find that age, cost of water and total household members are important factors that determines homeownership and renting among the people and our support vector model with radial basis function kernel gives us the better accuracy about 80% compared to other kernels. These insights will be useful to policymakers looking to improve housing stability and reduce economic differences.

Introduction

Homeownership is one of the most crucial components that defines one's economic stability and social welfare in the society. We used the housing dataset obtained via the US Census and accessed through IPUMS USA. The data includes various factors such as age, income, education attainment, electricity, water, gas and fuel costs, and other attributes related to the property, such as the year it was built, number of rooms, value of the house and many more. There are around 75,388 rows and 24 columns in the dataset. This report will use Support Vector Machines (SVMs) to classify and predict whether individuals are homeowners or renters based on the mentioned factors. We will apply three different kernels such as linear, radial, and polynomial kernels to uncover patterns that could inform better insights for policy-making which is aimed at increasing homeownership rates. Our goal from this study and report is to provide policymakers with data-driven recommendations that ensures relevance and effectiveness in enhancing homeownership.

Background

Support Vector Machine (SVM) is a supervised machine learning algorithm used for classification and regression problems. But they are generally effective in solving classification problems. In this algorithm, data is classified into two or more classes by determining the correct line or hyperplane that maximizes the marginal distance between the datapoints closest to the line or hyperplane on opposite sides of the classes.

A hyperplane is defined as a decision boundary that separates the data points of different classes in N-dimensional space. The data points that fall on either sides of the hyperplane can be classified into different classes. The dimension of the hyperplane depends on the number of input points used to classify the data. If the number of features is two, the hyperplane will be a line. If number of features exceeds 3 and beyond (let's say N), the hyperplane becomes a 2-D or N-1 plane.

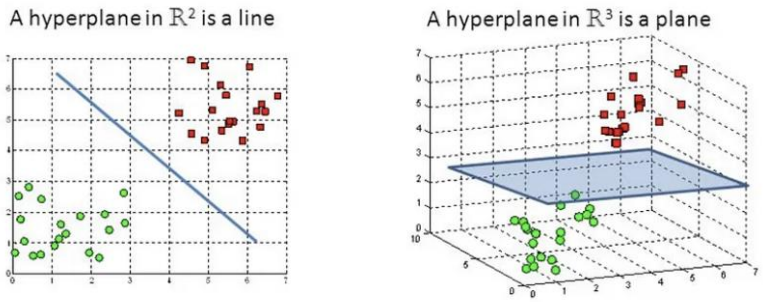

Figure-1: - Hyperplanes in 2-D and 3-D space. (Source: - Rohith Gandhi, (2018))

Let's take an example. There is data which is represented by red squares and blue circles (shown in Figure 2). It is evident that there are multiple hyperplanes that classify this data into two classes. But we want the best hyperplane that classifies the data appropriately (in this case red squares and blue circles). So, in order to achieve this, first we create a hyperplane that separates the data into two classes. After that, we calculate the maximum distance between the points and the hyperplane. This will classify the data appropriately. The distance between the closest points and the hyperplane determines the margin (see figure-2) and the closest points that determine these margins are known as support vectors. This support vector maximizes marginal distances. These support vectors play a crucial part in determining the ideal hyperplane as it can change the marginal distance and the position of the hyperplane. *(Rohith Gandhi, 2018)*

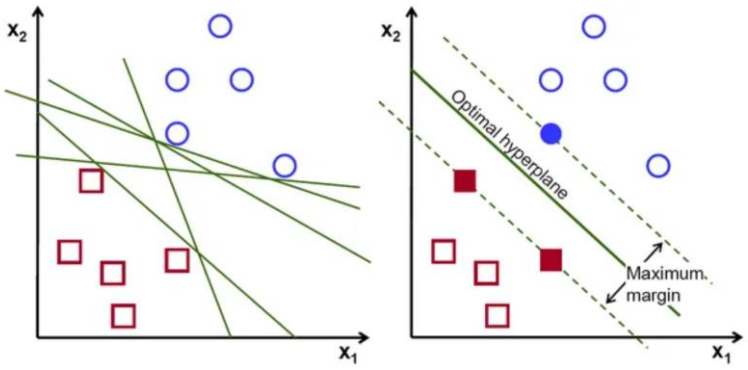

Figure-2: - Possible number of hyperplanes. (Source: - Rohith Gandhi, (2018))

The datapoints can be within or outside the margin, and in fact on the other side of the hyperplane. So, to handle this, the support vector machine ensures that the points within the margin do not have any influence on the computation. It also sets a cost (C) value as a limit on the number of points allowed for misclassification. When the value of C is small, SVM focuses more on a larger margin. This allows for more misclassifications in the training data, which can result in a wider margin between the classes. When the value of C is large, SVM focuses on a smaller margin, and this can lead to less misclassification in the training data. However, the margin will be narrower between the classes. *(baeldung, 2024)*

Kernels are one of the key parameters in Support Vector Machines. They are the math functions to help the model understand the data more accurately in higher dimensions. Kernels are used to convert input data into a high-dimensional feature space, which makes it easier to classify between classes. Kernels also implicitly map the data into the feature space, rather than manually inputting the co-ordinates of the data points. Kernels determine the decision boundary. A kernel function computes the dot product between two points in the feature space to calculate the degree of similarity between them.

The most common kernels used in SVM are linear, polynomial, and radial basis function (rbf) kernels.

A linear kernel is most commonly used in SVMs and is the dot product between the input data-points in the feature space. It can be represented by

$$K(x , y) = x . y$$

Where x and y are the input data points and the dot product is the measure of distance in the feature space these points are in.

The decision boundary in linear kernel is also linear and is very useful when the data is already separable by this linear decision boundary or while dealing with the data in high dimension.

The polynomial kernel is a non-linear kernel which converts input data into high dimension space to get the non-linear relationship between the input data. It can be represented by

$$K(x,y) = d(x \cdot y + c)$$

where x and y are input points , c is some constant value and d is the degree of polynomial. The degree of polynomial kernel determines model complexity. A high degree can result in overfitting the data, capturing the noisy data instead of just the pattern, while a low degree can result in underfitting, capturing the simple pattern instead of the complex one. In addition, polynomial kernels can be used to obtain a deeper analysis of input data due to their nonlinear hyperplanes.

The radial basis function (rbf) kernel is also a nonlinear kernel that is used to map the input data into a higher-dimensional space using a Gaussian function. It can be defined as

$$K(x, y) = \exp(-\text{gamma} * ||x - y||^2)$$

Where x and y are the input data points, gamma is a parameter that controls the width of the Gaussian function, and $||x - y||^2$ is the squared Euclidean distance, a measure of the straight-line distance between two data points. The width of the Gaussian function determines the degree of nonlinearity in the decision boundary and can be calculated as a function of gamma. Selecting a gamma parameter can be challenging, as a smaller value may result in underfitting, while a larger value may result in overfitting. *(Major Kernel Functions, article by javatpoint)*

Methodology

Data Cleaning and Preprocessing

The original housing data contains 75388 rows and 24 columns. For our house ownership analysis, we will focus on the five factors that classify people into owners and renters of properties. Among these factors are the age of household members, their marital status, their educational attainments, the electricity cost and water cost.

After selecting the features, we filtered the data. First, we focus on the age column where we set a range of the age of member from 18 years to 80 years. After filtering the age column, we focused on the education attainment column. We selected a range from people in 12th grade to those with 5+ years of education. There were some missing values in this column, and they are coded as 99 which means missing data. So, by focusing on the specified range, these values are removed from our dataset.

After filtering the education column, we focused on the properties built between 2000 and 2021. So, we filter the year of establishment based on the range specified.

After filtering the columns, we dropped all the unnecessary columns. These were columns related to ownership in detail, education attainment in detail, birth year income total of household members after paying income tax, number of couples, families, and persons as well. These were redundant and were conveying somewhat the same information and taking up space. Furthermore, we dropped columns related to density and columns related to how many persons in the U.S. population are represented by a given person in an IPUMS sample (PERWT column). We scale our data to improve the models performances using standard scaler function.

There were multiple entries for same serial numbers of household members in our data. So, to handle them, we group the data with serial number and aggregated it.
After filtering and preprocessing the data, we encoded the categorical variables using the label encoder function (here, the marital status and education attainment) by converting them to factors. After that, we split the data into training and testing sets with 70 to 30 ratio.

Now that our data is ready, we started our analysis using the SVM models with different kernels.

SVM Models

- Linear Kernel

  The linear kernel SVM model used the age of the household member (AGE) and total household income (HHINCOME) to predict whether people who live in the dwelling are identified as an owner or a renter of that dwelling. Following the selection of these features, we set the cost value parameter to 1. Next, we fitted the model to our training and testing sets using the mentioned features, and we calculated the accuracy.

  To improve the accuracy of the model, we also performed a 5-fold cross validation and used GridSearchCV() to get the optimal cost value. Also, we set the parameters for cost value between 0.01 and 100. After performing cross validation, we found that 0.01 was the ideal cost value for our model. We then calculated the accuracy of the model with ideal cost value.

  During the process of cross-validation, we also constructed confusion matrices. We then constructed a graph for the decision boundary with age and household income as variables and ownership as encoding.

- Polynomial Kernel

  In the polynomial kernel model, we looked at three features: age of household members (AGE), household income (HHINCOME), and marital status (MARST). We basically followed the same steps as in linear kernel, except that we added a second parameter degree and set its value to 2. Again, we did a cross-validation and got a cost value of 0.1 and a best degree value of 5.

  Based on the ideal cost and degree values, we refitted the model and calculated the accuracy. Lastly, we constructed a 2D graph for the decision boundary as it's difficult to interpret a 3D graph for both kernels.

- Radial Basis Function (RBF) Kernel

  The RBF kernel model includes features such as age and total income of household members, education attainment of household members, and the cost of water and electricity to analyse its impact on ownership of a dwelling. We carried out the same steps as in polynomial kernel, but added one more parameter, gamma, and set it to 1. We then performed cross validation to obtain the best gamma and cost values, and then fitted the SVM model with ideal values. For each model, we calculated accuracy and confusion matrices before and after cross-validation. A 2D decision boundary graph was constructed using the selected features for RBF kernel to determine who is an owner and who is a renter.

After performing the SVM models on all the kernels, we extracted the strong predictors that can be influential for homeownership using the permutation importance function.

Results

The following table below, represents the computational results for all SVM models with different kernels. The table shows accuracy before and after cross validation based on testing data.

Kernel	**Accuracy before CV**	**Accuracy after CV**
Linear	77. 27%	77.61%
Polynomial	75.28%	77.1%
Radial Basis Function	80.8%	80.59%

Table 1: - Performance statistics of SVM models with different kernels

From our analysis, Radial Basis Function performed better compared to other kernels giving us the best accuracy around 80.59% after cross validation classifying the people into owners or renters of a particular property or dwelling.

After cross-validation, our linear and polynomial models did improve slightly but couldn't match the accuracy achieved in radial basis function models. So, we suggest going with radial basis function model as it uncovers more patterns and did classify based on the factors filtered in it and more accurately.

The following figures show the confusion matrices obtained after cross validation and Decision boundary graphs for all the SVM models with different kernels.

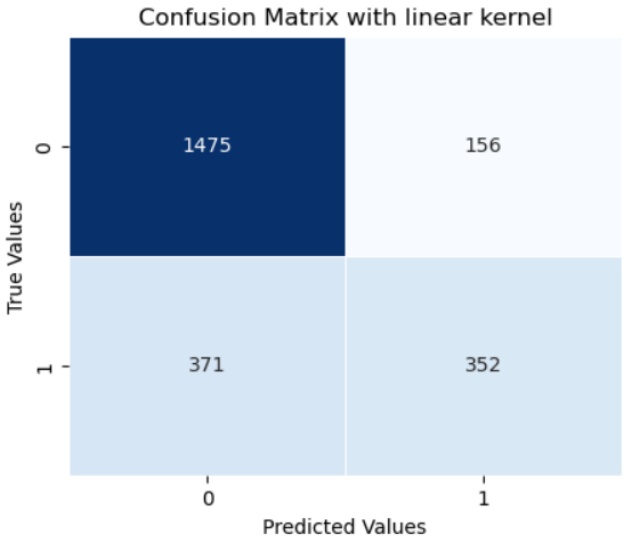

Fig 3a: - Confusion Matrix for Linear SVM Model

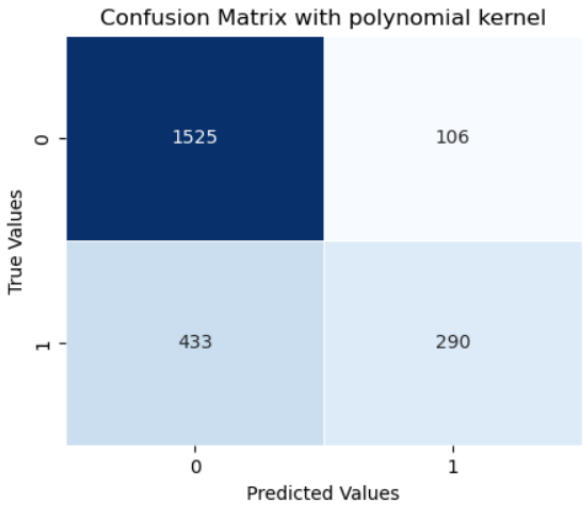

Fig 3b: - Confusion Matrix for Polynomial SVM Model

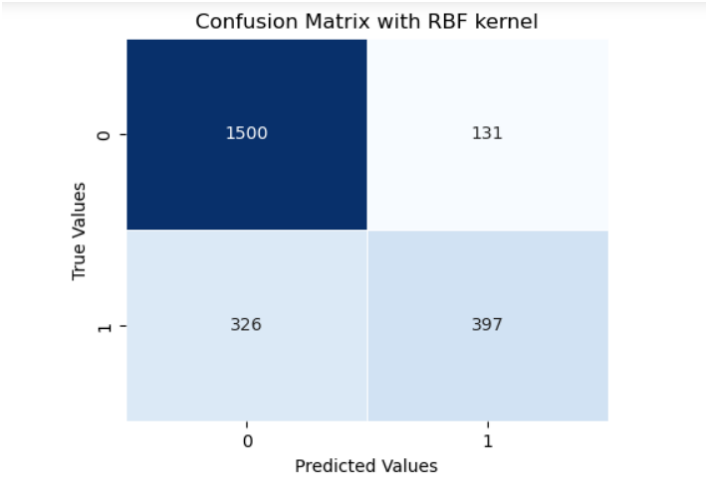

Fig 3c: - Confusion Matrix for RBF SVM Model

From the confusion matrices, we can see that the models didn't overfit the data and it didn't result in bias results. There were few misclassifications while predicting the owners and predictors but most of the time models did a pretty good job in classifying the owners and renters of the dwelling. Comparing the RBF model with the linear and polynomial models, it made the most accurate predictions. As a result, the RBF kernel model is more effective as it has captured more complex data patterns compared to other kernels.

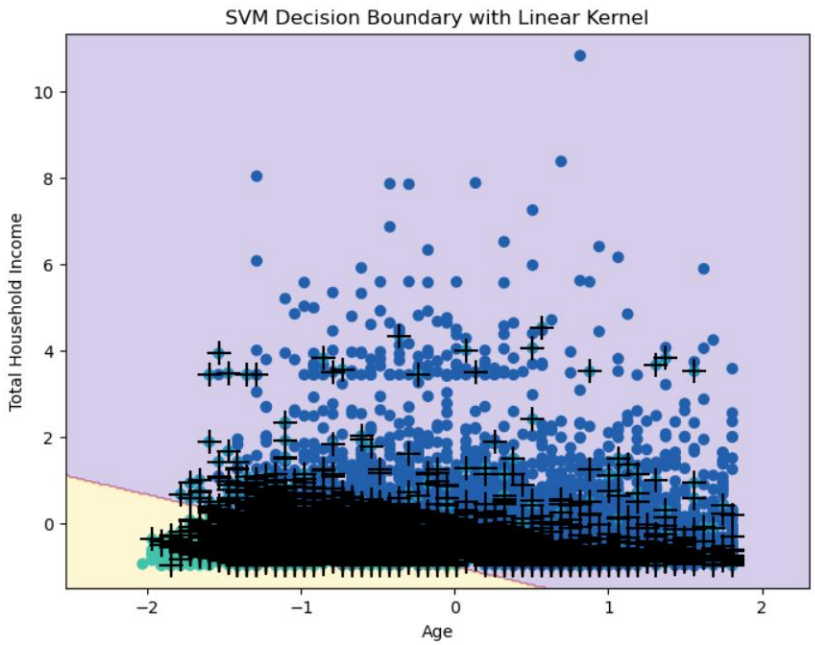

Fig 4a:- Decision Boundary Graph for Linear Kernel Model

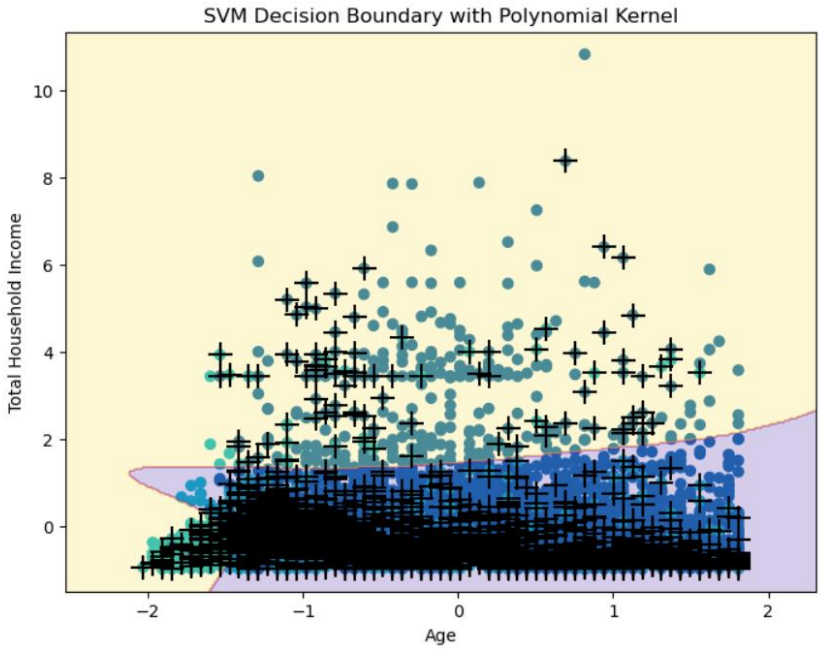

Fig 4b: - Decision Boundary Graph for Polynomial Kernel model

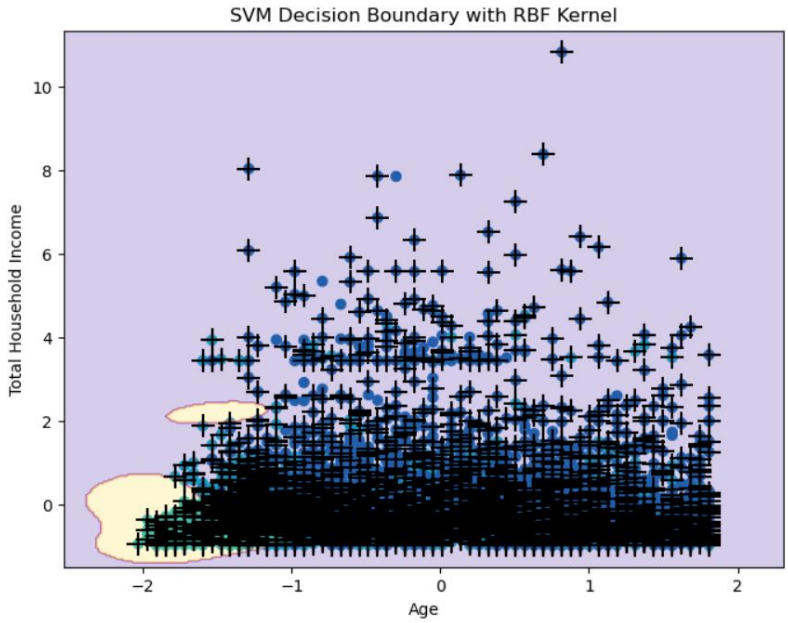

Fig 4c: - Decision Boundary Graph for RBF Kernel model

The Decision Boundary Graphs were built on selected variables Age of the household Members (AGE) and Total household income (HHINCOME). The blue points represent the people who are owners and light green points represent the people who are renters. The plane divides these points into classes and imparted a color in the regions according ownership variable. It was difficult to imagine the hyperplane for more than 2 features as it will result into a more dimensional hyperplane, and it would be difficult to interpret the outcome from them. So, for simplicity, we constructed 2-D graphs for all the kernels. As

polynomial and rbf kernels have more than two factors to look for, the decision boundaries appear to a pattern to capture those support vectors and the points that were misclassified.

The accuracies of our model could have been better if we used different techniques and also could have added more features instead of the limited features we added to perform the predictions.

Discussion

There are many factors that can tell us about the people owning and renting the property. The most important factor that we got from analysis is the age and it does make a point that the age of member matters as it tells us about how many years they have worked on into order to make the money to own or rent a house and to become stable in life. We filtered our data ranging from the age 18 years and upto 80 years and the reason for this is that people who are under age of 18 are probably living with their parents and people who are age of 80 might still be alive and can still own a place or on a rent and we don't the status of people beyond this age. They might already be passed away. There are also the cost of water and total household income that were important in order to predict the status of homeownership. The following figure shows the graph with important predictors of homeownership decision.

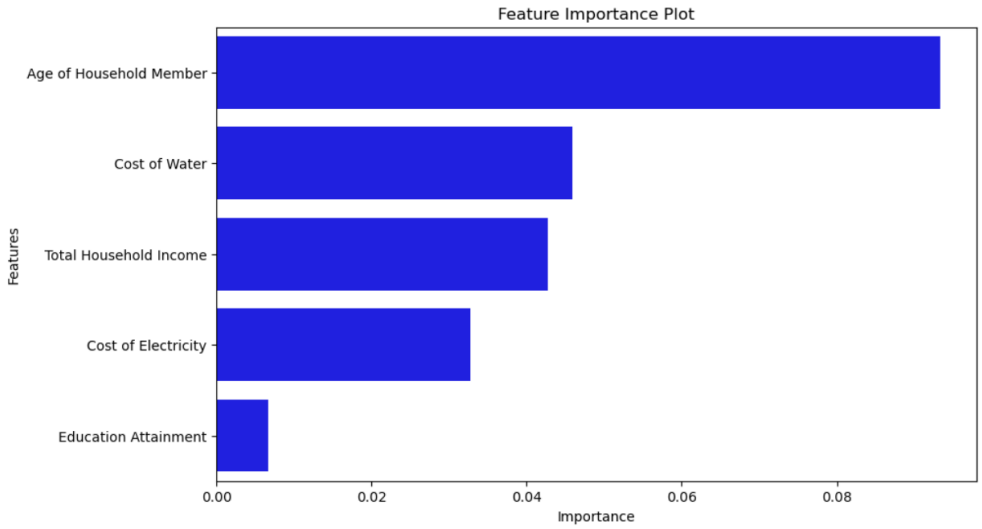

Fig 5: - Importance Feature Graph For Homeownership Analysis

We selected a few factors out of the many that were present in the data. So, the results we got can be improved. We could have considered more features and did our analysis on that. But by doing so, we would have to tune the parameters in such a way that it precisely determines owners and renters. That could certainly improve the performance of the models and reveal the unseen patterns that are missed.

From the all the decision boundary graphs that the people how are old like in their mid 20s and earning more are likely to be homeowners and if they are young (early twenties) are more likely be renters.

There are many challenges that affect the ownership of a house. Our analysis did uncover some of them. So, let say for instance, if you have acquired a good education and started earning decent money, you could at least become a renter of a particular dwelling and if you keep hustling and earn more money in the future, you will be closer to owning a house and maybe could buy a house. Also, there is a market to consider as well in deciding if it's the right time to purchase a house. The reason behind this is that if people decide to sell the property or decide to rent it, then there should be a fair number of deals that can be given to prospective buyers or renters to think about. Also, you must look for mortgages, property taxes and many more if you are owners of a house. Our models did a good job in uncovering them, but further improvements and consideration of other features will give us new perspective about homeownership status.

Conclusion

Our analysis showed us that age and income of the people have a significant impact on the status of homeownership. However, there are different factors can influence the decision of owning a house and our models would have a different insight if we started looking into them and it can cover different set of analysis which could solidify the people's decision of owning or renting a property.

There are various insights that policymakers can take note of. They can start by looking at ways to support young people who are in the process of completing a degree and started earning can help them to consider for ownership or to become a renter of the place they are gone live. There are many initiatives that can be planned for them. Some of them can be first-time homebuyer programs, schemes that involves first month of signing a lease will be covered in your security deposit for properties that are on rent or there can be affordable housing developments that can reduce the equity gap in owning a property. By recognizing and

responding appropriately, policymakers can make homeownership an achievable goal for most people, while also fostering economic growth and stability in their communities.

References

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Appendix

Housing Tenure Prediction Analysis

April 29, 2024

0.1 Housing Tenure Prediction Analysis

0.1.1 Libraries requires for this project

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from matplotlib.pyplot import subplots, cm
import matplotlib.pyplot as plt
from mlxtend.plotting import plot_decision_regions
from sklearn import svm
from sklearn.svm import SVC
import sklearn.model_selection as skm
from sklearn.model_selection import train_test_split, GridSearchCV, KFold
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.metrics import classification_report, confusion_matrix,␣
 ↪accuracy_score
from sklearn.metrics import RocCurveDisplay
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import GridSearchCV
from ISLP import load_data, confusion_table
from ISLP.svm import plot as plot_svm
from sklearn.inspection import permutation_importance
```

0.1.2 Loading the 'Housing Data'

[2]:
```
Housing_Data = pd.read_csv("Housing.csv")
Housing_Data
```

[2]:

	SERIAL	DENSITY	OWNERSHP	OWNERSHPD	COSTELEC	COSTGAS	COSTWATR	\
0	1371772	920.0	1	13	9990	9993	360	
1	1371773	3640.9	2	22	1080	9993	1800	
2	1371773	3640.9	2	22	1080	9993	1800	
3	1371774	22.5	1	13	600	9993	9993	
4	1371775	3710.4	2	22	3600	9993	9997	
…	…	…	…	…	…	…	…	
75383	1402573	2754.9	2	22	9990	7200	960	

```
75384  1402573   2754.9         2         22      9990     7200        960
75385  1402573   2754.9         2         22      9990     7200        960
75386  1402573   2754.9         2         22      9990     7200        960
75387  1402573   2754.9         2         22      9990     7200        960

       COSTFUEL  HHINCOME   VALUEH  …  NFAMS  NCOUPLES  PERNUM  PERWT  AGE  \
0          9993     75000   700000  …      1         0       1     14   52
1          9993     13600  9999999  …      2         0       1     83   22
2          9993     13600  9999999  …      2         0       2    106   22
3          9993      7000   800000  …      1         0       1     33   62
4          9993     50500  9999999  …      1         0       1    297   50
…           …        …       …    …    …       …      …     …  …
75383      9993     86700  9999999  …      1         2       1    229   30
75384      9993     86700  9999999  …      1         2       2    331   30
75385      9993     86700  9999999  …      1         2       3    331    5
75386      9993     86700  9999999  …      1         2       4    157   64
75387      9993     86700  9999999  …      1         2       5    225   60

       MARST  BIRTHYR  EDUC  EDUCD   INCTOT
0          6     1969     7     71    75000
1          6     1999    10    101     5600
2          6     1999     7     71     8000
3          4     1959     6     63     7000
4          3     1971     7     71    16000
…       …       …   …    …       …
75383      1     1991     6     63    35000
75384      1     1991     6     64    50000
75385      6     2016     0      2  9999999
75386      1     1957     6     63     1700
75387      1     1961     7     71        0

[75388 rows x 24 columns]
```

[3]:
```
# Now let's see the columns in our data set
Housing_Data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 75388 entries, 0 to 75387
Data columns (total 24 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   SERIAL     75388 non-null  int64
 1   DENSITY    75388 non-null  float64
 2   OWNERSHP   75388 non-null  int64
 3   OWNERSHPD  75388 non-null  int64
 4   COSTELEC   75388 non-null  int64
 5   COSTGAS    75388 non-null  int64
 6   COSTWATR   75388 non-null  int64
```

```
 7   COSTFUEL   75388 non-null  int64
 8   HHINCOME   75388 non-null  int64
 9   VALUEH     75388 non-null  int64
 10  ROOMS      75388 non-null  int64
 11  BUILTYR2   75388 non-null  int64
 12  BEDROOMS   75388 non-null  int64
 13  VEHICLES   75388 non-null  int64
 14  NFAMS      75388 non-null  int64
 15  NCOUPLES   75388 non-null  int64
 16  PERNUM     75388 non-null  int64
 17  PERWT      75388 non-null  int64
 18  AGE        75388 non-null  int64
 19  MARST      75388 non-null  int64
 20  BIRTHYR    75388 non-null  int64
 21  EDUC       75388 non-null  int64
 22  EDUCD      75388 non-null  int64
 23  INCTOT     75388 non-null  int64
dtypes: float64(1), int64(23)
memory usage: 13.8 MB
```

[4]:
```
# Let's check the shape of our dataset
Housing_Data.shape
```

[4]:
```
(75388, 24)
```

[5]:
```
# Lets calculate the summary statistics for our dataset for imputation
Housing_Data.describe()
```

[5]:

	SERIAL	DENSITY	OWNERSHP	OWNERSHPD	COSTELEC	\
count	7.538800e+04	75388.000000	75388.000000	75388.000000	75388.000000	
mean	1.387234e+06	2423.430017	1.266050	15.152146	2155.588184	
std	8.903828e+03	2526.581859	0.441894	4.114694	1918.598151	
min	1.371772e+06	22.500000	1.000000	12.000000	48.000000	
25%	1.379509e+06	448.200000	1.000000	13.000000	1080.000000	
50%	1.387292e+06	1667.900000	1.000000	13.000000	1680.000000	
75%	1.394971e+06	3843.300000	2.000000	22.000000	2400.000000	
max	1.402573e+06	13284.600000	2.000000	22.000000	9997.000000	

	COSTGAS	COSTWATR	COSTFUEL	HHINCOME	VALUEH	\
count	75388.000000	75388.000000	75388.000000	7.538800e+04	7.538800e+04	
mean	6532.804850	3282.154680	9132.200363	1.325857e+05	3.115290e+06	
std	4379.021441	3968.876334	2704.300467	1.300609e+05	4.178808e+06	
min	48.000000	4.000000	4.000000	-7.100000e+03	1.000000e+03	
25%	1200.000000	500.000000	9993.000000	5.500000e+04	4.000000e+05	
50%	9992.000000	1200.000000	9993.000000	1.000000e+05	6.500000e+05	
75%	9993.000000	9993.000000	9993.000000	1.640000e+05	9.999999e+06	
max	9997.000000	9997.000000	9997.000000	1.674500e+06	9.999999e+06	

```
       …          NFAMS      NCOUPLES        PERNUM         PERWT  \
count  …  75388.000000  75388.000000  75388.000000  75388.000000
mean   …      1.120138      0.772722      2.133072    100.746644
std    …      0.520437      0.466072      1.347956     79.428151
min    …      1.000000      0.000000      1.000000      2.000000
25%    …      1.000000      1.000000      1.000000     54.000000
50%    …      1.000000      1.000000      2.000000     80.000000
75%    …      1.000000      1.000000      3.000000    117.000000
max    …     13.000000      3.000000     16.000000   1113.000000

                AGE         MARST       BIRTHYR          EDUC         EDUCD  \
count  75388.000000  75388.000000  75388.000000  75388.000000  75388.000000
mean      41.737040      3.466599   1979.262960      6.553802     67.954754
std       23.497059      2.323782     23.497059      3.368158     33.507170
min        0.000000      1.000000   1928.000000      0.000000      1.000000
25%       22.000000      1.000000   1960.000000      6.000000     61.000000
50%       42.000000      4.000000   1979.000000      7.000000     71.000000
75%       61.000000      6.000000   1999.000000     10.000000    101.000000
max       93.000000      6.000000   2021.000000     11.000000    116.000000

             INCTOT
count  7.538800e+04
mean   1.741325e+06
std    3.730804e+06
min   -8.700000e+03
25%    1.560000e+04
50%    4.800000e+04
75%    1.250000e+05
max    9.999999e+06

[8 rows x 24 columns]
```

0.1.3 Data Cleaning and Preprocessing

For our analysis, we will be looking for owners/renters whose age falls between the range 18 years to 80 years

[6]:
```
# So, lets filter our data accordingly to condition
Housing_Data = Housing_Data[(Housing_Data['AGE'] >= 18) & (Housing_Data['AGE']␣
 ↪<= 80)]
```

After that, We will be considering the education of owners/renters to who have education attainment from 12th grade to 5+ years of college. There are some missing values in our data (code 99 means missing). So handling that and also getting rid of the column 'EDUCD' which means education attainment [detailed version] to handle redundancy.

[7]:
```
# Filtering the data accordingly
```

```
Housing_Data = Housing_Data[(Housing_Data['EDUC'] >= 6) & (Housing_Data['EDUC']␣
 ↪<= 11) & Housing_Data['EDUC'] != 99]

# Removing the 'EDUCD' column
Housing_Data.drop('EDUCD', axis=1, inplace=True)
```

[8]:
```
# Removing the 'DENSITY' column
Housing_Data.drop('DENSITY', axis=1, inplace=True)
```

[9]:
```
# Looking for properties built from the year 2000 to 2021
# So, Filtering our datase accordingly
Housing_Data = Housing_Data[(Housing_Data['BUILTYR2'] >= 9) &␣
 ↪(Housing_Data['BUILTYR2'] <= 26)]
```

[10]:
```
# Removing the 'PERWT' column
Housing_Data.drop('PERWT', axis=1, inplace=True)
```

[11]:
```
# Removing the 'BIRTHYR' column
Housing_Data.drop('BIRTHYR', axis=1, inplace=True)
```

[12]:
```
# Removing the 'OWNERSHPD' column
Housing_Data.drop('OWNERSHPD', axis=1, inplace=True)
```

[13]:
```
# Removing the 'INCTOT' column
Housing_Data.drop('INCTOT', axis=1, inplace=True)
```

[14]:
```
# Removing the 'NFAMS' column
Housing_Data.drop('NFAMS', axis=1, inplace=True)
```

[15]:
```
# Removing the 'NCOUPLES' column
Housing_Data.drop('NCOUPLES', axis=1, inplace=True)
```

[16]:
```
# REmoving the 'PERNUM' column
Housing_Data.drop('PERNUM', axis=1, inplace=True)
```

[17]:
```
Housing_Data.head(10)
```

[17]:

	SERIAL	OWNERSHP	COSTELEC	COSTGAS	COSTWATR	COSTFUEL	HHINCOME	\
20	1371783	1	1920	1440	50	9993	30000	
21	1371783	1	1920	1440	50	9993	30000	
32	1371786	2	1800	9993	1400	9993	62000	
33	1371786	2	1800	9993	1400	9993	62000	
34	1371787	1	960	360	5000	9993	507500	
35	1371787	1	960	360	5000	9993	507500	
38	1371788	1	1200	9997	110	9993	115600	
39	1371788	1	1200	9997	110	9993	115600	
79	1371802	1	1560	9993	9993	9993	12000	

```
81  1371803         2      3600      9993      9993      9993     45800

     VALUEH  ROOMS  BUILTYR2  BEDROOMS  VEHICLES  AGE  MARST  EDUC
20    15000      3        15         3         4   40      6     6
21    15000      3        15         3         4   32      6     6
32  9999999      4         9         3         2   28      6    11
33  9999999      4         9         3         2   26      6    10
34  5279000     10        15         6         2   37      1    10
35  5279000     10        15         6         2   36      1    10
38   375000      5         9         4         2   71      1    10
39   375000      5         9         4         2   71      1     7
79   550000      7        15         4         2   67      5    10
81  9999999      9         9         5         2   44      4     6
```

[18]:
```
# Group by 'SERIAL' and aggregating the data
# Serial number of household members are associated with different variables so␣
 ↪grouping them with it
Housing_Data = Housing_Data.groupby('SERIAL').agg({
    'OWNERSHP': 'first',
    'COSTELEC': 'first',
    'COSTGAS': 'first',
    'COSTWATR': 'first',
    'COSTFUEL': 'first',
    'HHINCOME': 'first',
    'VALUEH': 'first',
    'ROOMS': 'first',
    'BUILTYR2': 'first',
    'BEDROOMS': 'first',
    'VEHICLES': 'first',
    'MARST': 'first',
    'AGE' : 'max',    # Taking the highest age of household member assuming that␣
 ↪he is earning the highest among the others
    'EDUC': 'max'     # Highest education attainment of that household member
}).reset_index()
```

[19]:
```
# Final housing data set after cleaning and prefrocessing
Housing_Data.head(10)
```

[19]:
```
     SERIAL  OWNERSHP  COSTELEC  COSTGAS  COSTWATR  COSTFUEL  HHINCOME  \
0   1371783         1      1920     1440        50      9993     30000
1   1371786         2      1800     9993      1400      9993     62000
2   1371787         1       960      360      5000      9993    507500
3   1371788         1      1200     9997       110      9993    115600
4   1371802         1      1560     9993      9993      9993     12000
5   1371803         2      3600     9993      9993      9993     45800
6   1371804         1      2400     1800        40      9993    775000
7   1371807         1      1320      360      2200        50     95500
```

```
8  1371810         1      1800      1200      1800      9993    172500
9  1371811         1       480       600       110      9993     84000
```

	VALUEH	ROOMS	BUILTYR2	BEDROOMS	VEHICLES	MARST	AGE	EDUC
0	15000	3	15	3	4	6	40	6
1	9999999	4	9	3	2	6	28	11
2	5279000	10	15	6	2	1	37	10
3	375000	5	9	4	2	1	71	10
4	550000	7	15	4	2	5	67	10
5	9999999	9	9	5	2	4	60	7
6	950000	8	9	5	3	1	51	11
7	285000	6	9	4	2	1	80	10
8	950000	9	9	6	2	1	41	10
9	750000	6	25	4	2	1	35	7

0.1.4 Encoding the categorical variables

[20]:
```
# Converting 'MARST' and 'EDUC' to categorical using the label-Encoder
le = LabelEncoder()
Housing_Data['MARST'] = le.fit_transform(Housing_Data['MARST'])
Housing_Data['EDUC'] = le.fit_transform(Housing_Data['EDUC'])
```

[21]:
```
# Scaling our data to improve the perfomance of models
# We will be using standard scaler function
scaler = StandardScaler()

# This will not consider ownership as one of the feature
# Also, it is our target variable
features = Housing_Data.columns.difference(['OWNERSHP'])

# Fit the scaler to your data
Housing_Data[features] = scaler.fit_transform(Housing_Data[features])
```

0.1.5 Splitting the dataset into Training and Testing set

[22]:
```
# Splitting the dataset (70 - 30 ratio)
Housing_train_set, Housing_test_set = train_test_split(Housing_Data, test_size␣
 ↪= 0.3, random_state = 1)
```

0.1.6 Models

- SVM Model with linear kernel

[23]:
```
# Support Vector Machine model with linear kernel and using cost value = 1
# I used max_iterations as the model was taking time to execute
svm_linear_model = svm.SVC(kernel = 'linear', C = 1, max_iter = 10000)
```

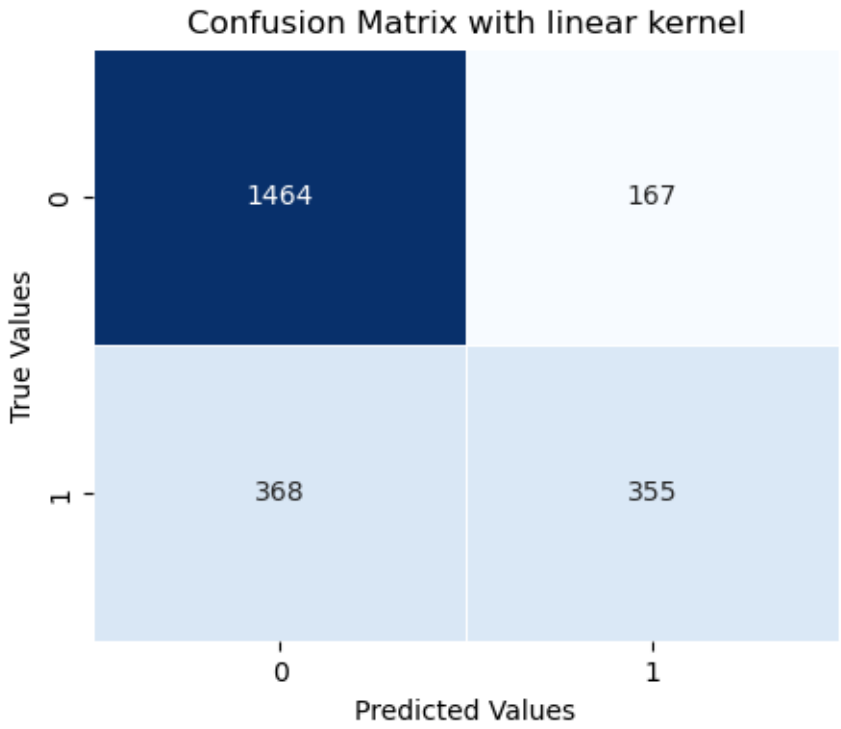
```
svm_linear_model.fit(Housing_train_set[['AGE', 'HHINCOME']],␣
 ↪Housing_train_set['OWNERSHP'])
```

[23]:
```
SVC(C=1, kernel='linear', max_iter=10000)
```

[24]:
```
# Predicting the ownership status on the test set
lin_model_predicts = svm_linear_model.predict(Housing_test_set[['AGE',␣
 ↪'HHINCOME']])

# Evaluating the model
print(classification_report(Housing_test_set['OWNERSHP'], lin_model_predicts))
print("Accuracy:", round(accuracy_score(Housing_test_set['OWNERSHP'],␣
 ↪lin_model_predicts), 4))
```

```
              precision    recall  f1-score   support

           1       0.80      0.90      0.85      1631
           2       0.68      0.49      0.57       723

    accuracy                           0.77      2354
   macro avg       0.74      0.69      0.71      2354
weighted avg       0.76      0.77      0.76      2354

Accuracy: 0.7727
```

[25]:
```
# Lets construct a confusion matrix for our predictions
linear_matrix = confusion_matrix(Housing_test_set['OWNERSHP'],␣
 ↪lin_model_predicts)

# Plotting the confusion matrix
plt.figure(figsize=(5, 4))
sns.heatmap(linear_matrix, annot=True, fmt="d", linewidths=.5, cmap="Blues",␣
 ↪cbar=False)
plt.xlabel('Predicted Values')
plt.ylabel('True Values')
plt.title('Confusion Matrix with linear kernel')
plt.show()
```



So, with the linear kernel and default cost value, our model was poorly performing with the accuracy around 72.38%.

Now, we apply cross validation using skm.GridSearchCV() to select the best C value for our SVM model with a linear kernel.

[26]:
```
# Defining the KFold cross-validation for 5 folds
kfold = skm.KFold(5, random_state = 1, shuffle=True)

# Let's set up a grid for our cost value
c_values = {'C':[0.01, 0.1, 1, 10, 100]}

# Lets apply 5 fold cross validation using GridSearchCV() to get the best␣
 ↪c-value for our model
# we will be using the above model for cross-validation
grid = skm.GridSearchCV(svm_linear_model, c_values, cv = kfold, scoring =␣
 ↪'accuracy');

# refitting the model after cross-validation
grid.fit(Housing_train_set[['AGE', 'HHINCOME']], Housing_train_set['OWNERSHP'])
grid.best_params_
```

```
C:\Users\hirshikesh\anaconda3\lib\site-packages\sklearn\svm\_base.py:297:
ConvergenceWarning: Solver terminated early (max_iter=10000).  Consider pre-
```

```
processing your data with StandardScaler or MinMaxScaler.
  warnings.warn(
C:\Users\hirshikesh\anaconda3\lib\site-packages\sklearn\svm\_base.py:297:
ConvergenceWarning: Solver terminated early (max_iter=10000).  Consider pre-
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  warnings.warn(
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C:\Users\hirshikesh\anaconda3\lib\site-packages\sklearn\svm\_base.py:297:
ConvergenceWarning: Solver terminated early (max_iter=10000).  Consider pre-
processing your data with StandardScaler or MinMaxScaler.
  warnings.warn(
```

[26]:
```
{'C': 0.01}
```

Now, lets refit the model with this c-value and check if ourt accuracy has been improved or not.

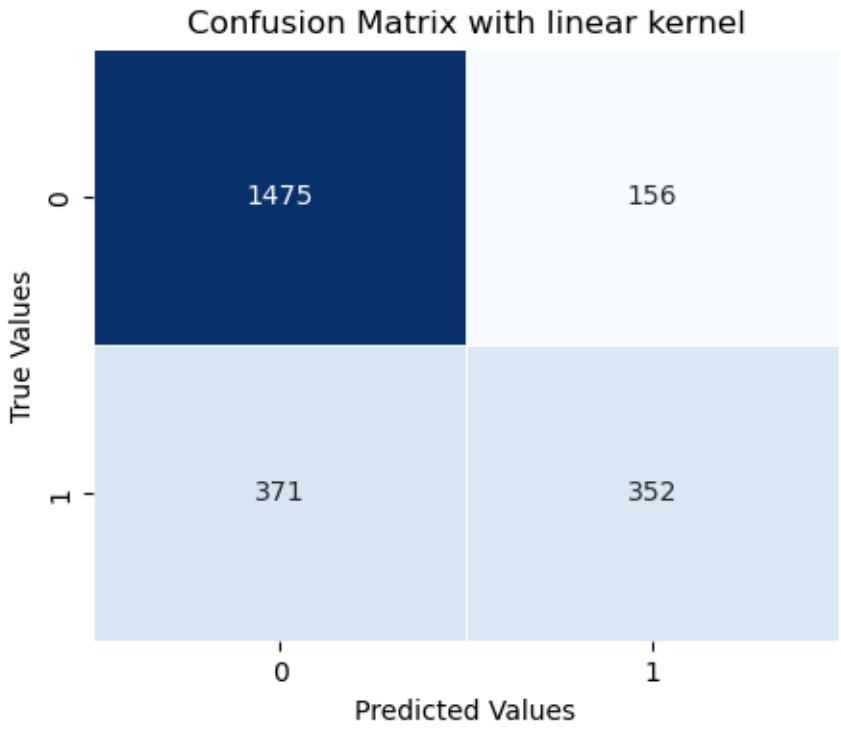
[27]:
```python
best_linear_model = grid.best_estimator_

# Predicting the ownership status on the test set
lin_model_predictsCV = best_linear_model.predict(Housing_test_set[['AGE',␣
↪'HHINCOME']])
```

```
# Evaluating the model
print(classification_report(Housing_test_set['OWNERSHP'], lin_model_predictsCV))
print("Accuracy:", round(accuracy_score(Housing_test_set['OWNERSHP'],␣
 ↪lin_model_predictsCV), 4))
```

```
              precision    recall  f1-score   support

           1       0.80      0.90      0.85      1631
           2       0.69      0.49      0.57       723

    accuracy                           0.78      2354
   macro avg       0.75      0.70      0.71      2354
weighted avg       0.77      0.78      0.76      2354

Accuracy: 0.7761
```

So after cross-validation, the SVM linear kernel model with best cost value of 100 slighty decreased the accuracy around 72.25%.

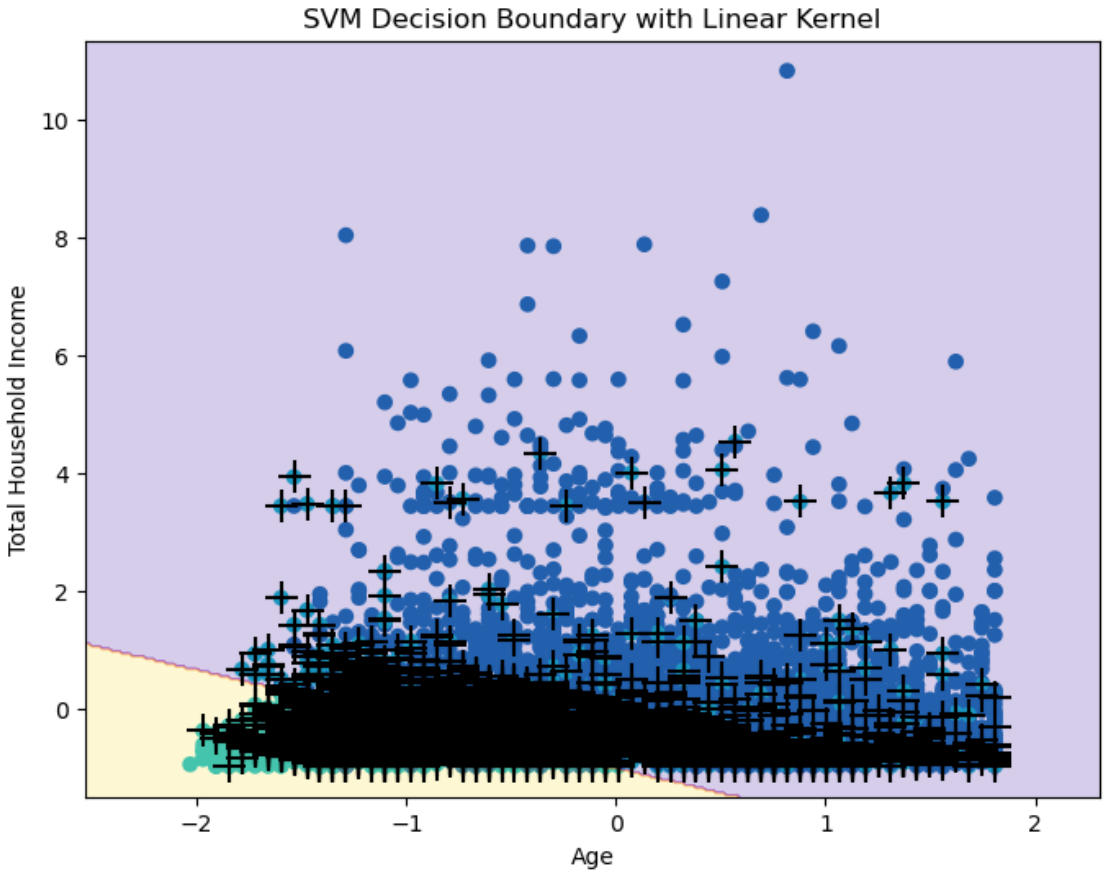
[28]:
```
# Lets construct a confusion matrix for our predictions
linear_matrixCV = confusion_matrix(Housing_test_set['OWNERSHP'],␣
 ↪lin_model_predictsCV)

# Plotting the confusion matrix
plt.figure(figsize=(5, 4))
sns.heatmap(linear_matrixCV, annot=True, fmt="d", linewidths=.5, cmap="Blues",␣
 ↪cbar=False)
plt.xlabel('Predicted Values')
plt.ylabel('True Values')
plt.title('Confusion Matrix with linear kernel')
plt.show()
```



Let's construct a plot to get the decision boundry about the ownership based on age and total household income

[29]:
```
# Extracting the features values (Age and total house income values) and target␣
↪variable (ownership values) used in the SVM
X_train = Housing_train_set[['AGE', 'HHINCOME']].values
y_train = Housing_train_set['OWNERSHP'].values

fig, ax = subplots(figsize=(8,6))
plot_svm(X_train,
         y_train,
         best_linear_model,
         ax=ax)
ax.set_xlabel('Age')
ax.set_ylabel('Total Household Income')
ax.set_title('SVM Decision Boundary with Linear Kernel')
plt.show()
```

```
C:\Users\hirshikesh\anaconda3\lib\site-packages\sklearn\base.py:493:
UserWarning: X does not have valid feature names, but SVC was fitted with
feature names
  warnings.warn(
```



- SVM Model with polynomial kernel

[30]:
```
# Support Vector Machine model with polynomial kernel and using cost value = 1␣
↪and degree = 2
svm_poly_model = svm.SVC(kernel = 'poly', C = 1, degree = 2, max_iter = 10000)
svm_poly_model.fit(Housing_train_set[['AGE', 'MARST','HHINCOME']],␣
↪Housing_train_set['OWNERSHP'])
```

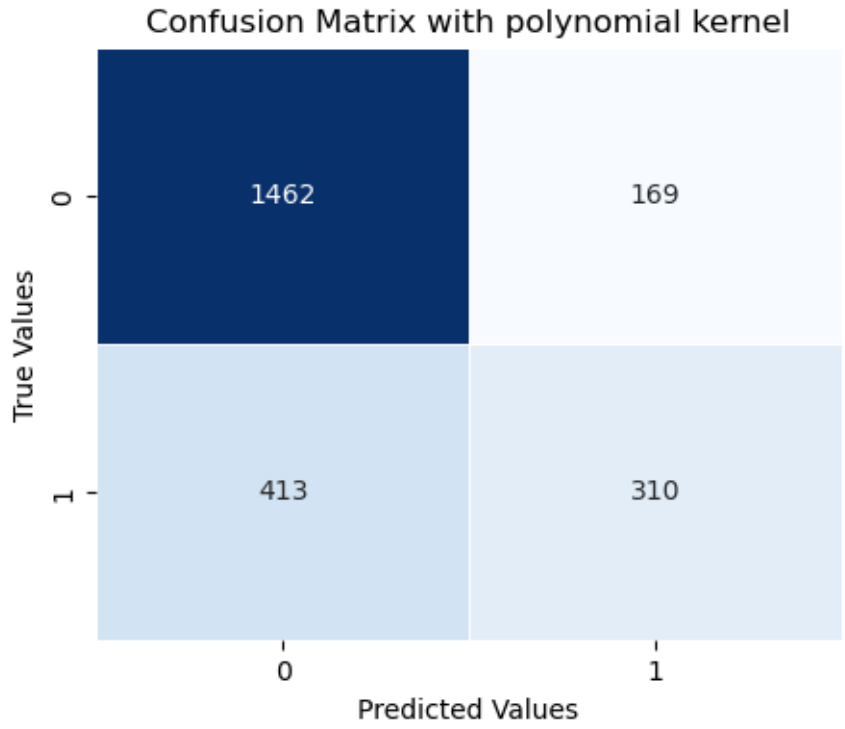
[30]:
```
SVC(C=1, degree=2, kernel='poly', max_iter=10000)
```

[31]:
```
# Predicting the ownership status on the test set
poly_model_predicts = svm_poly_model.predict(Housing_test_set[['AGE', 'MARST',␣
↪'HHINCOME']])

# Evaluating the model
print(classification_report(Housing_test_set['OWNERSHP'], poly_model_predicts))
print("Accuracy:", round(accuracy_score(Housing_test_set['OWNERSHP'],␣
↪poly_model_predicts), 4))
```

```
              precision    recall  f1-score   support
```

```
              1       0.78      0.90      0.83      1631
              2       0.65      0.43      0.52       723

    accuracy                           0.75      2354
   macro avg       0.71      0.66      0.67      2354
weighted avg       0.74      0.75      0.74      2354

Accuracy: 0.7528
```

[32]:
```
# Lets construct a confusion matrix for our predictions
poly_matrix = confusion_matrix(Housing_test_set['OWNERSHP'],␣
 ↪poly_model_predicts)

# Plotting the confusion matrix
plt.figure(figsize=(5, 4))
sns.heatmap(poly_matrix, annot=True, fmt="d", linewidths=.5, cmap="Blues",␣
 ↪cbar=False)
plt.xlabel('Predicted Values')
plt.ylabel('True Values')
plt.title('Confusion Matrix with polynomial kernel')
plt.show()
```



[33]:
```
# Defining the KFold cross-validation for 5 folds
kfold = skm.KFold(5, random_state = 1, shuffle=True)

# Let's set up a grid for our cost value and degree values
para_values = {'C':[0.01, 0.1, 1, 10, 100], 'degree':[2,3,4,5]}

# Lets apply 5 fold cross validation using GridSearchCV() to get the best␣
↪c-value for our model
# we will be using the above model for cross-validation
grid = skm.GridSearchCV(svm_poly_model, para_values, cv = kfold, scoring =␣
↪'accuracy');

# refitting the model after cross-validation
grid.fit(Housing_train_set[['AGE', 'MARST', 'HHINCOME']],␣
↪Housing_train_set['OWNERSHP'])
grid.best_params_
```

```
C:\Users\hirshikesh\anaconda3\lib\site-packages\sklearn\svm\_base.py:297:
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```

```
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  warnings.warn(
```

[33]:
```
{'C': 0.1, 'degree': 5}
```

[34]:
```
# Support Vector Machine model with polynomial kernel and using cost value = 0.
 ↪1 and degree = 5 after cross validation
svm_poly_modelCV = svm.SVC(kernel = 'poly', C = 0.1, degree = 5, max_iter =␣
 ↪10000)
svm_poly_modelCV.fit(Housing_train_set[['AGE', 'MARST','HHINCOME']],␣
 ↪Housing_train_set['OWNERSHP'])
```

```
C:\Users\hirshikesh\anaconda3\lib\site-packages\sklearn\svm\_base.py:297:
ConvergenceWarning: Solver terminated early (max_iter=10000).  Consider pre-
processing your data with StandardScaler or MinMaxScaler.
  warnings.warn(
```

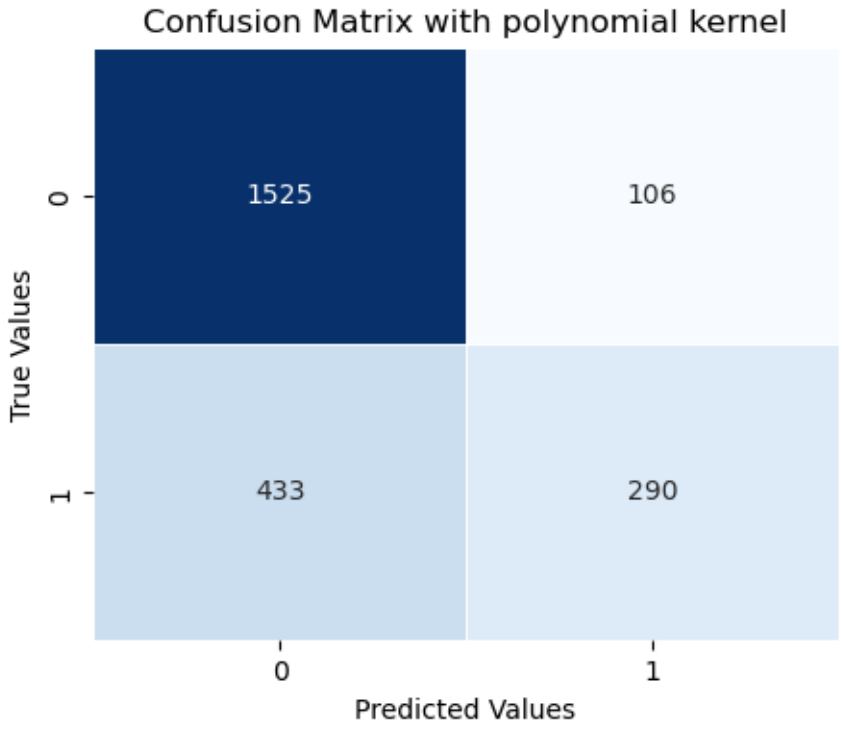
[34]:
```
SVC(C=0.1, degree=5, kernel='poly', max_iter=10000)
```

[35]:
```
# Predicting the ownership status on the test set
poly_model_predictsCV = svm_poly_modelCV.predict(Housing_test_set[['AGE',␣
 ↪'MARST', 'HHINCOME']])

# Evaluating the model
print(classification_report(Housing_test_set['OWNERSHP'],␣
 ↪poly_model_predictsCV))
print("Accuracy:", round(accuracy_score(Housing_test_set['OWNERSHP'],␣
 ↪poly_model_predictsCV), 4))
```

```
              precision    recall  f1-score   support

           1       0.78      0.94      0.85      1631
           2       0.73      0.40      0.52       723

    accuracy                           0.77      2354
   macro avg       0.76      0.67      0.68      2354
weighted avg       0.76      0.77      0.75      2354

Accuracy: 0.771
```

[36]:
```
# Lets construct a confusion matrix for our predictions
poly_matrixCV = confusion_matrix(Housing_test_set['OWNERSHP'],␣
 ↪poly_model_predictsCV)
```

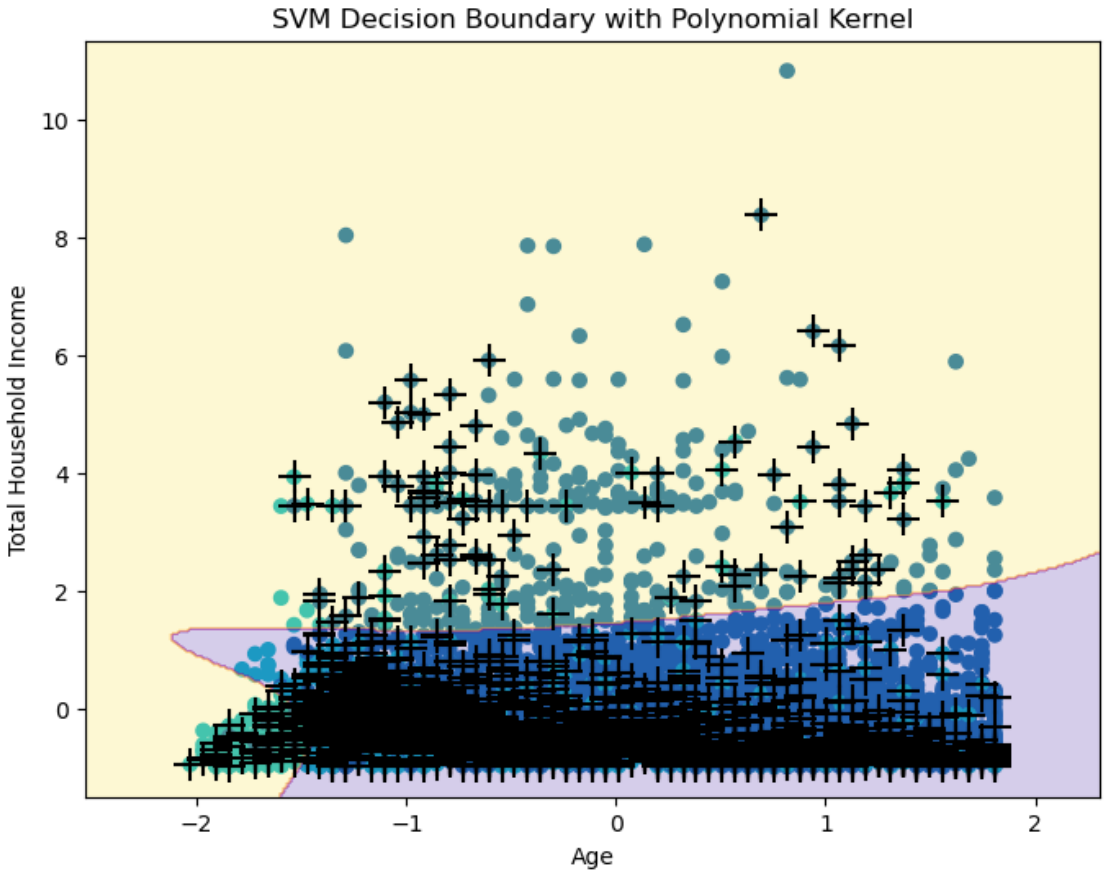
```
# Plotting the confusion matrix
plt.figure(figsize=(5, 4))
sns.heatmap(poly_matrixCV, annot=True, fmt="d", linewidths=.5, cmap="Blues",␣
 ↪cbar=False)
plt.xlabel('Predicted Values')
plt.ylabel('True Values')
plt.title('Confusion Matrix with polynomial kernel')
plt.show()
```



[37]:
```
# Decision Boundary Plot for polynomial kernel

# Assuming a mode value for the MARST (marital status)
mode_MARST = Housing_train_set['MARST'].mode()

# Creating a meshgrid for plotting based on the mode values from MARST variable
X = np.c_[X_train[:, :2], np.full(len(X_train), fill_value=mode_MARST)]

# Plotting the decision boundary graph
fig, ax = plt.subplots(figsize=(8, 6))
plot_svm(X, y_train, svm_poly_modelCV, ax=ax)
ax.set_xlabel('Age')
ax.set_ylabel('Total Household Income')
ax.set_title('SVM Decision Boundary with Polynomial Kernel')
```

```
plt.show()
```

```
C:\Users\hirshikesh\anaconda3\lib\site-packages\sklearn\base.py:493:
UserWarning: X does not have valid feature names, but SVC was fitted with
feature names
  warnings.warn(
```



- SVM Model with radial basis function (rbf) kernel

[38]:
```
# Support Vector Machine model with rbf kernel and using cost value = 1 and␣
 ↪degree = 2 and gamma = 1
svm_rbf_model = svm.SVC(kernel = 'rbf', C = 1, degree = 2, gamma = 1, max_iter␣
 ↪= 10000)
svm_rbf_model.fit(Housing_train_set[['AGE','HHINCOME',␣
 ↪'COSTWATR','COSTELEC','EDUC']], Housing_train_set['OWNERSHP'])
```

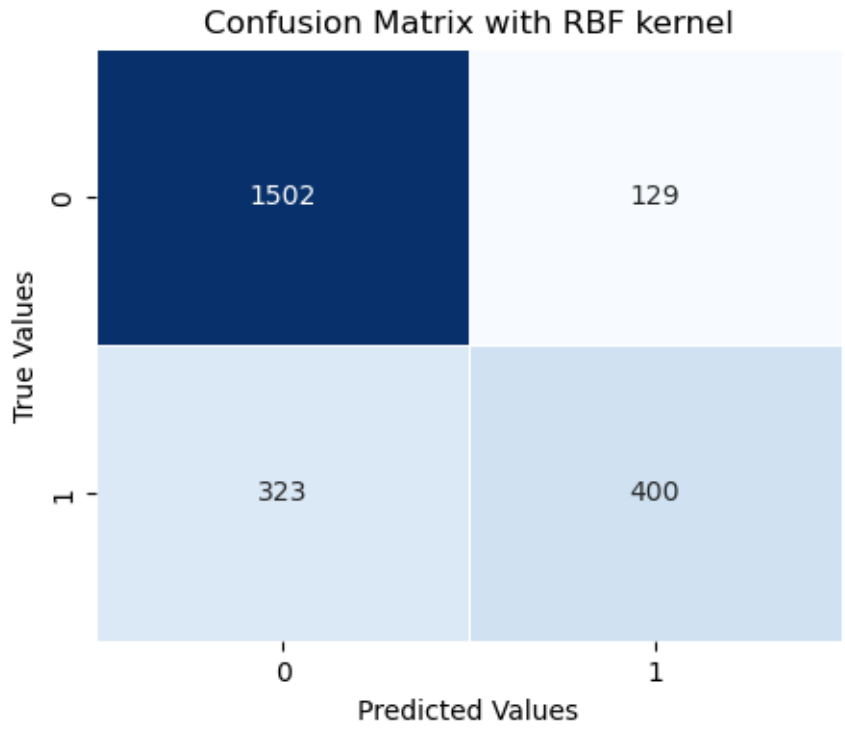
```
C:\Users\hirshikesh\anaconda3\lib\site-packages\sklearn\svm\_base.py:297:
ConvergenceWarning: Solver terminated early (max_iter=10000).  Consider pre-
processing your data with StandardScaler or MinMaxScaler.
  warnings.warn(
```

[38]:
```
SVC(C=1, degree=2, gamma=1, max_iter=10000)
```

[39]:
```
# Predicting the ownership status on the test set
rbf_model_predicts = svm_rbf_model.predict(Housing_test_set[['AGE', 'HHINCOME',␣
 ↪'COSTWATR','COSTELEC','EDUC']])

# Evaluating the model
print(classification_report(Housing_test_set['OWNERSHP'], rbf_model_predicts))
print("Accuracy:", round(accuracy_score(Housing_test_set['OWNERSHP'],␣
 ↪rbf_model_predicts), 4))
```

```
              precision    recall  f1-score   support

           1       0.82      0.92      0.87      1631
           2       0.76      0.55      0.64       723

    accuracy                           0.81      2354
   macro avg       0.79      0.74      0.75      2354
weighted avg       0.80      0.81      0.80      2354

Accuracy: 0.808
```

[40]:
```
# Lets construct a confusion matrix for our predictions
rbf_matrix = confusion_matrix(Housing_test_set['OWNERSHP'], rbf_model_predicts)

# Plotting the confusion matrix
plt.figure(figsize=(5, 4))
sns.heatmap(rbf_matrix, annot=True, fmt="d", linewidths=.5, cmap="Blues",␣
 ↪cbar=False)
plt.xlabel('Predicted Values')
plt.ylabel('True Values')
plt.title('Confusion Matrix with RBF kernel')
plt.show()
```



[41]:
```
# Defining the KFold cross-validation for 5 folds
kfold = skm.KFold(5, random_state = 1, shuffle=True)

# Let's set up a grid for our cost value and degree values
para_values = {'C':[0.01, 0.1, 1, 10, 100], 'degree':[3,4,5], 'gamma':[3,4]}

# Lets apply 5 fold cross validation using GridSearchCV() to get the best␣
 ↪c-value for our model
# we will be using the above model for cross-validation
grid = skm.GridSearchCV(svm_rbf_model, para_values, cv = kfold, scoring =␣
 ↪'accuracy');

# refitting the model after cross-validation
grid.fit(Housing_train_set[['AGE', 'HHINCOME', 'COSTELEC', 'COSTWATR',␣
 ↪'EDUC']], Housing_train_set['OWNERSHP'])
grid.best_params_
```

```
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```

[41]:

```
{'C': 1, 'degree': 3, 'gamma': 3}
```

[42]:

```
# Support Vector Machine model with rbf kernel and using cost value = 1 and␣
↪degree = 3 and gamma = 3 after cross validation
```

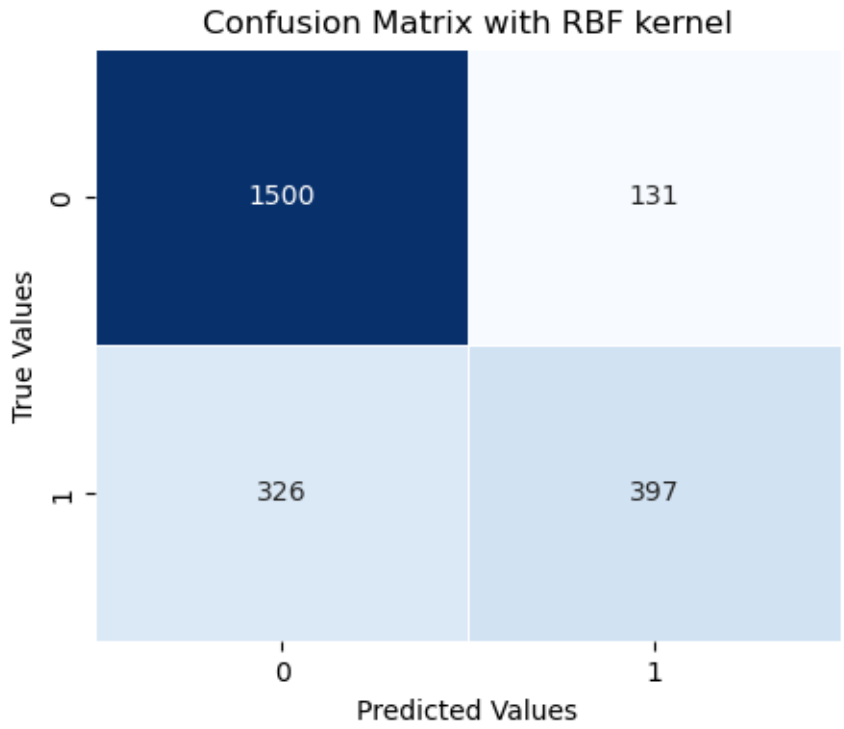
```
svm_rbf_modelCV = svm.SVC(kernel = 'rbf', C = 1, degree = 3, gamma = 3,␣
 ↪max_iter = 10000)
svm_rbf_modelCV.fit(Housing_train_set[['AGE','HHINCOME', 'COSTELEC',␣
 ↪'COSTWATR', 'EDUC']], Housing_train_set['OWNERSHP'])
```

[42]:
```
SVC(C=1, gamma=3, max_iter=10000)
```

[43]:
```
# Predicting the ownership status on the test set
rbf_model_predictsCV = svm_rbf_modelCV.predict(Housing_test_set[['AGE',␣
 ↪'HHINCOME', 'COSTELEC', 'COSTWATR','EDUC']])

# Evaluating the model
print(classification_report(Housing_test_set['OWNERSHP'], rbf_model_predictsCV))
print("Accuracy:", round(accuracy_score(Housing_test_set['OWNERSHP'],␣
 ↪rbf_model_predictsCV), 4))
```

```
              precision    recall  f1-score   support

           1       0.82      0.92      0.87      1631
           2       0.75      0.55      0.63       723

    accuracy                           0.81      2354
   macro avg       0.79      0.73      0.75      2354
weighted avg       0.80      0.81      0.80      2354

Accuracy: 0.8059
```

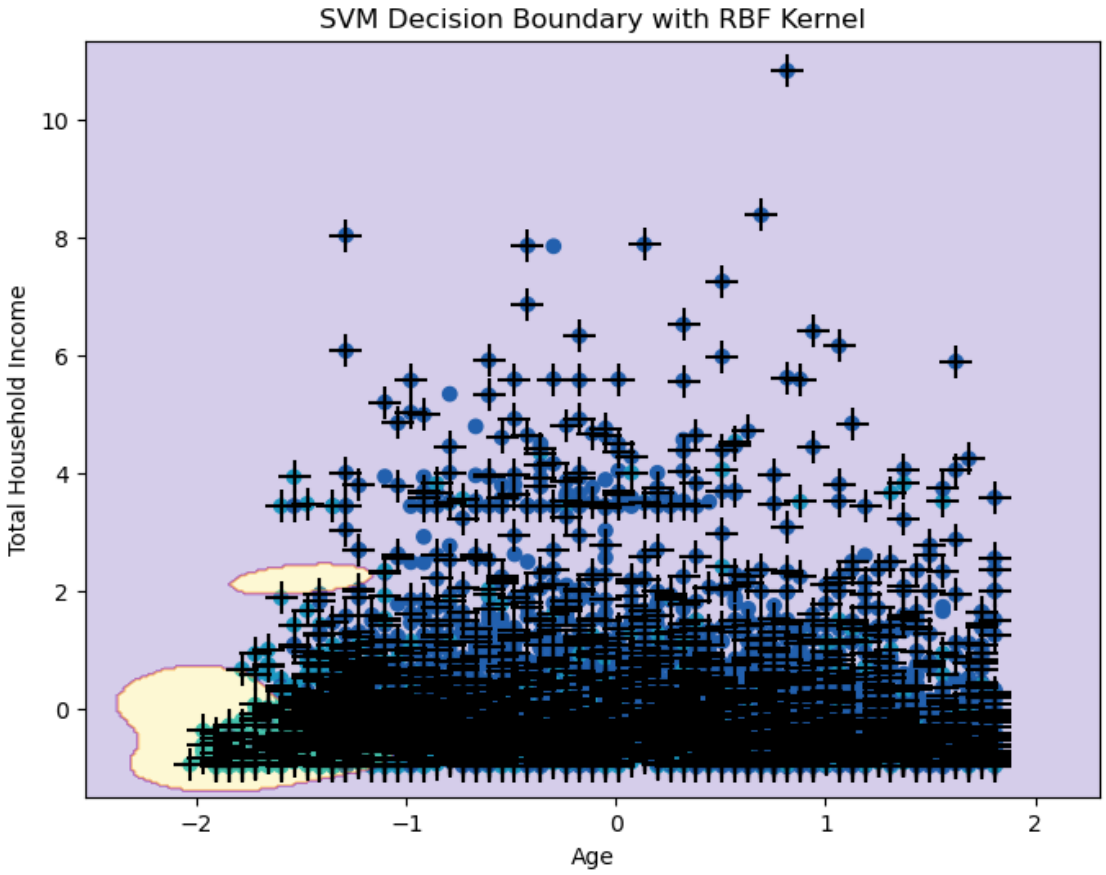
[44]:
```
# Lets construct a confusion matrix for our predictions
rbf_matrixCV = confusion_matrix(Housing_test_set['OWNERSHP'],␣
 ↪rbf_model_predictsCV)

# Plotting the confusion matrix
plt.figure(figsize=(5, 4))
sns.heatmap(rbf_matrixCV, annot=True, fmt="d", linewidths=.5, cmap="Blues",␣
 ↪cbar=False)
plt.xlabel('Predicted Values')
plt.ylabel('True Values')
plt.title('Confusion Matrix with RBF kernel')
plt.show()
```



[45]:
```
# Decision Boundary Plot for rbf kernel

# Selecting median values for COSTWATR and COSTELEC to make them constant␣
 ↪values for the sake of the graph
median_COSTELEC = Housing_train_set['COSTELEC'].median()
median_COSTWATR = Housing_train_set['COSTWATR'].median()

# gettting the mode for EDUC as it is a categorical variable to make it␣
 ↪constant as well
mode_EDUC = Housing_train_set['EDUC'].mode()[0]

# Creating the feature grid for the fixed values
X = np.c_[X_train[:, 0:2],
               np.full(len(X_train), fill_value = median_COSTELEC),
               np.full(len(X_train), fill_value = median_COSTWATR),
               np.full(len(X_train), fill_value = mode_EDUC)]

# plotting the decision boundary graph for rbf kernel
fig, ax = plt.subplots(figsize=(8, 6))
plot_svm(X, y_train, svm_rbf_modelCV, ax=ax)
ax.set_xlabel('Age')
ax.set_ylabel('Total Household Income')
ax.set_title('SVM Decision Boundary with RBF Kernel')
```

```
plt.show()
```

```
C:\Users\hirshikesh\anaconda3\lib\site-packages\sklearn\base.py:493:
UserWarning: X does not have valid feature names, but SVC was fitted with
feature names
  warnings.warn(
```

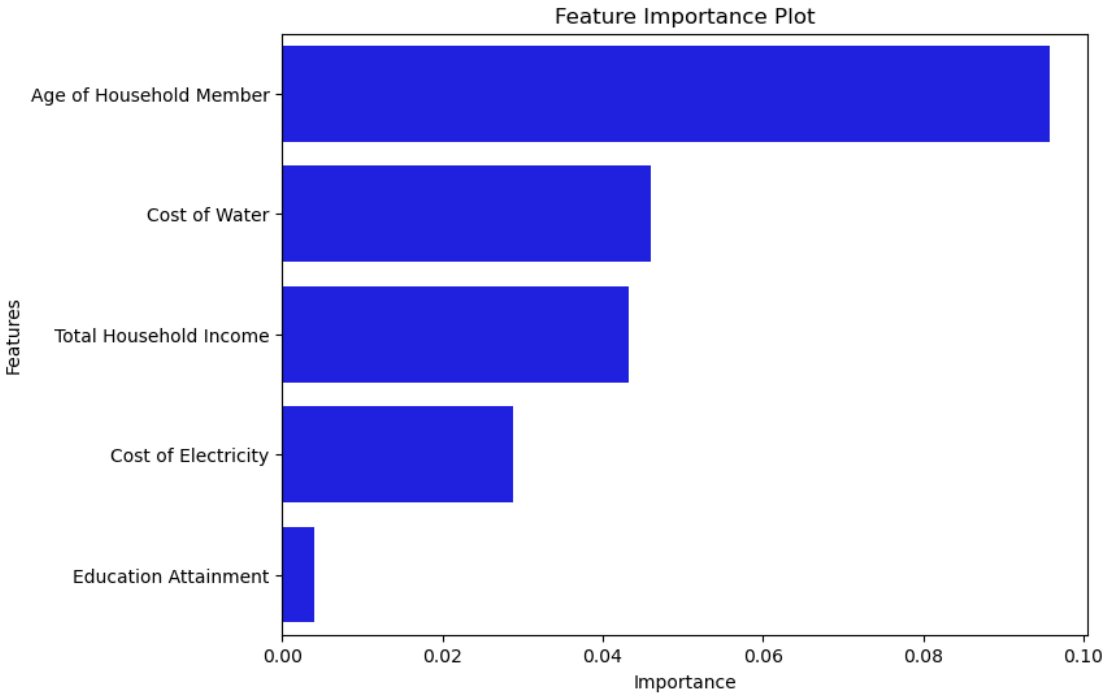


0.2 Getting the Strong Predictors

[46]:
```
# Computing the permutation importance for SVM models on the selected features
# permutation importance is used in observing the impact on model performance␣
 ↪for any SVM models with different kernels
# As our rbf model got the best accuracy, we will get the importance on this␣
 ↪model
# We will be using permutation_importance() function from the sklearn␣
 ↪inspections library
results = permutation_importance(svm_rbf_modelCV, Housing_test_set[['AGE',␣
 ↪'HHINCOME', 'COSTELEC', 'COSTWATR', 'EDUC']], Housing_test_set['OWNERSHP'],␣
 ↪n_repeats=10)
```

```
# Getting the feature names
names = ['Age of Household Member', 'Total Household Income', 'Cost of␣
 ↪Electricity', 'Cost of Water', 'Education Attainment']

# Now putting the results into a DataFrame and sorting them in descending order
imp_df = pd.DataFrame({'Feature': names, 'Importance': results.
 ↪importances_mean})
imp_df = imp_df.sort_values(by='Importance', ascending=False)
```

[47]:
```
# Feature Importance Plot
plt.figure(figsize=(8, 6))
sns.barplot(x='Importance', y='Feature', data=imp_df, color='blue')
plt.title('Feature Importance Plot')
plt.xlabel('Importance')
plt.ylabel('Features')
plt.show()
```



0.3 References

1) Ch9-1 and Ch9-2 python files
2) lecture notes
3) Python Documentation on scikit learn and other functions
   - https://scikit-learn.org/stable/modules/svm.html

- https://scikit-learn.org/stable/user_guide.html