Homework 2: ML Pipeline

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GitHub Repo: `https://github.com/jeansalac/ml-ppol`
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1. **Read Data:**

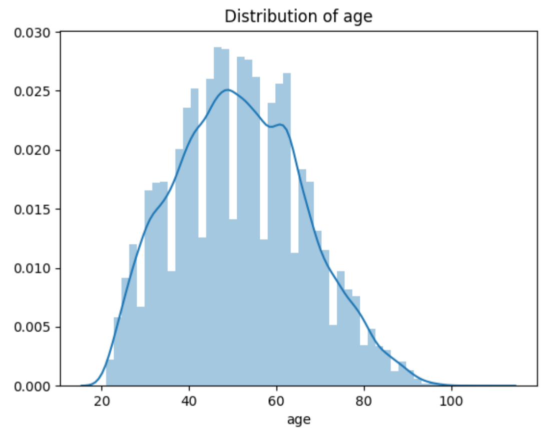
   - To read in the csv file, I wrote a function in my library *pipeLib.py* called that takes in the csv file through command line and converts it to a data frame using the PANDAS library function *read_csv()*.

2. **Explore Data:**

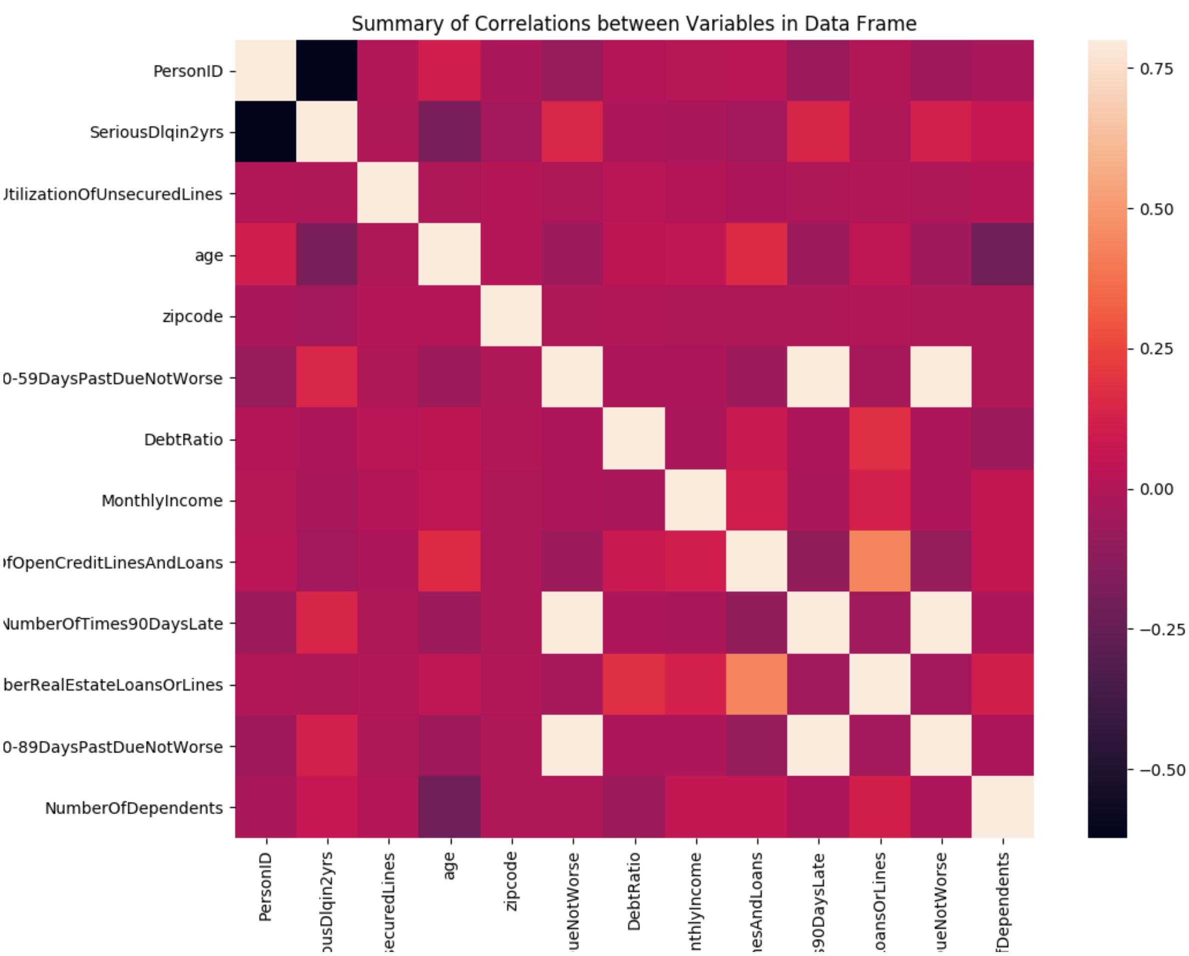
   - *dataSummary(dataFrame,var)*: This function takes in a *dataFrame* object and *var*, the variable you would like a data summary for and returns the summary statistics of *var*. Running this function on the variable *age* in *pipeTest.py* yields:

count	41016.000000
mean	51.683489
std	14.746880
min	21.000000
25%	41.000000
50%	51.000000
75%	62.000000
max	109.000000

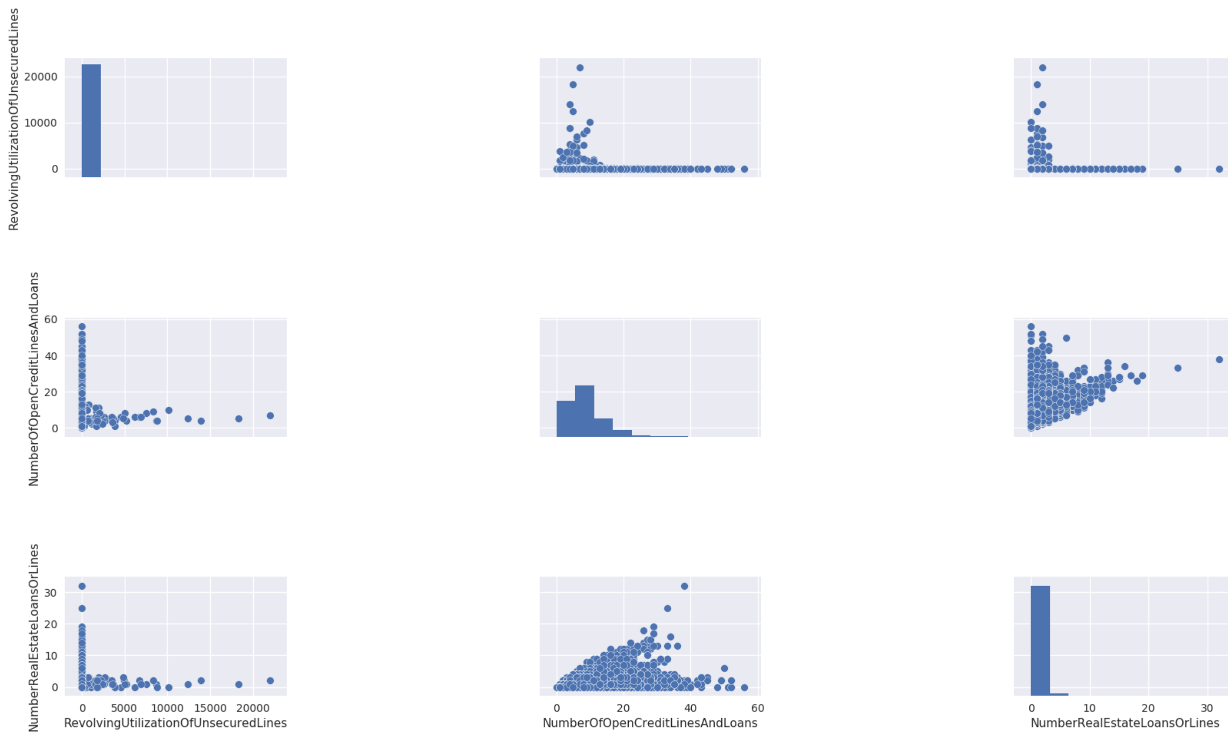
- *varDist(dataFrame,var)*: This function takes in a *dataFrame* object and *var*, the variable you would like to see a distribution plot for and returns a distribution plot of *var*. Running this function on variable *numberOfDependents* results in the plot below:



- *corrSummary(dataFrame)*: This function takes in a *dataFrame* and returns a heatmap of the correlations between all the variables. Running this on the credit data results in the heatmap below.



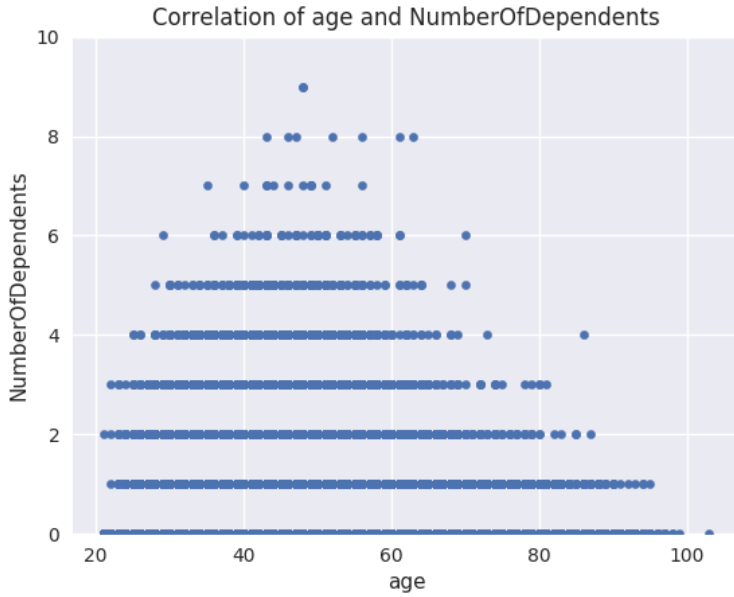
- *plotCorr(dataFrame,list)*: This function takes in a *dataFrame* object and a list of variables you would like to see a correlation for. It returns a plot of all the correlations for the variables provided. Running this on the variables *RevolvingUtilizationOfUnsecuredLines, NumberOfOpenCreditLinesAndLoans, NumberRealEstateLoansOrLines* results in the plot below:



- *findLowOutliers(dataFrame,var, num)*: This function takes in a *dataFrame* object, the variable *var* you want to find low outliers for, and the number of outliers you want *num*. Running this function on *debtRatio* to find the 3 lowest outliers yields the following array:
  $[-0.25573621, -0.25573621, -0.25573621]$

- *findHighOutliers(dataFrame,var,num)*: This function takes in a *dataFrame* object, the variable *var* you want to find high outliers for, and the number of outliers you want *num*. Running this function on *debtRatio* to find the 10 highest outliers yields the following array:
  $[18.64412907, 18.71742623, 20.32533443, 23.11834196, 25.08424891,$
  $29.6749657, 30.88552614, 37.63658024, 46.20077458, 82.21128292]]$

- *findBivariateOutliers(dataFrame,varX, varY,maxY)*: This function takes in a *dataFrame* object, the variable *varX* you want to be plotted on the x-axis,*varY* you want to be plotted on the y-axis, and *maxY*, the upper limit of *varY*. Running this function *age* and *numberOfDependents* results in the plot below:



3. **Pre-Process Data:**

   - *fillMissing(dataFrame,var,newVal)*: This function takes in the variable you want to fill in with missing data *var* and the value you want the missing data to have *newVal*. In *pipeTest.py*, I filled in the missing data for my continuous variables with that variable's median, and for the categorical variable *zipcode*, I filled missing values with 0.

4. **Generate Features and Predictors:**

   - *discretize(dataFrame,var,num)*: This function takes in the variable *var* you want to discretize and *num*, the number of bins you want to discretize *var* into. Running this function discretizes *age* into the following 5 bins:

     (a) (20.912, 38.6]

     (b) (38.6, 56.2]

     (c) (56.2, 73.8]

     (d) (73.8, 91.4]

     (e) (91.4, 109.0]

   - *createDummy(dataFrame,var)*: This function takes in the variable *var* you want to create dummy variables for. Running this function generates the following dummy variables for *zipcode* $[60601, 60618, 60625, 60629, 60637, 60644]$

5. **Build Classifier:**

   - *logReg(dataFrame,IV,listOfDVs)*: This function takes in the independent variable *IV* and the dependent variables *listOfDVs* you want to generate a logistic regression for. It returns the coefficients of the logistic regression, as well as its accuracy with the original data. Running this on the credit data resulted in 83.4% accuracy with the original data, as well as the following coefficients:

Intercept	[1.7464243465145182e-06]
RevolvingUtilizationOfUnsecuredLines	[-0.00016337547191778968]
age	[-0.03262736739776818]
zipcode	[5.897286708290562e-07]
NumberOfTime30-59DaysPastDueNotWorse	[0.04751821911375464]
DebtRatio	[-7.298373065337037e-05]
MonthlyIncome	[-3.17536592389569e-05]
NumberOfOpenCreditLinesAndLoans	[0.00987689310445205]
NumberOfTimes90DaysLate	[0.03450484254010904]
NumberRealEstateLoansOrLines	[0.006558732565761694]
NumberOfTime60-89DaysPastDueNotWorse")	[0.018844760061179952]
NumberOfDependents	[0.011227895523920409]

6. **Evaluate Classifier:**
   If we evaluate this classifier on accuracy with the original data, then an 89.4% accuracy is reasonably good, which is better than random. However, since we are only evaluating this model on the same data it trained on, this could be a case of overfitting. We do not know how this model will behave with new data points. Additionally, accuracy weighs all errors equally, which means that false positives and false negatives have the same importance. This may not be the case with our data. For example, it may be better to have a false positive that someone is at risk of a serious delinquency within 2 years and intervene, rather than a false negative that someone is not at risk and not intervene. Furthermore, accuracy is a poor metric when the dataset is skewed. In the credit data we have, most people do not have serious delinquencies within two years, so our 83.4% accuracy is misleading.