Comparing Classifiers

Overview: In this practical application, the goal is to compare the performance of the classifiers encountered in this section, namely k-Nearest Neighbor, Logistic Regression, Decision Trees, and Support Vector Machines.

Getting Started

The dataset comes from the UCI Machine Learning repository link. The data is from a Portuguese banking institution and is a collection of the results of multiple marketing campaigns.

Data Set Information

The data is related with direct marketing campaigns of a Portuguese banking institution. The marketing campaigns were based on phone calls. Often, more than one contact to the same client was required, in order to access if the product (bank term deposit) would be ('yes') or not ('no') subscribed.

Understanding the Features

Examine the data description below, and determine if any of the features are missing values or need to be coerced to a different data type.

Input variables:

bank client data:

1 - age (numeric)

2 - job : type of job (categorical: 'admin.','blue-collar','entrepreneur','housemaid','management','retired','self-employed','services','student','technician','unemployed','unknown')

3 - marital : marital status (categorical: 'divorced','married','single','unknown'; note: 'divorced' means divorced or widowed)

4 - education (categorical: 'basic.4y','basic.6y','basic.9y','high.school','illiterate','professional.course','university.degree','unknown')

5 - default: has credit in default? (categorical: 'no','yes','unknown')

6 - housing: has housing loan? (categorical: 'no','yes','unknown')

7 - loan: has personal loan? (categorical: 'no','yes','unknown')

related with the last contact of the current campaign:

8 - contact: contact communication type (categorical: 'cellular','telephone')

9 - month: last contact month of year (categorical: 'jan', 'feb', 'mar', ..., 'nov', 'dec')

10 - day_of_week: last contact day of the week (categorical: 'mon','tue','wed','thu','fri')

11 - duration: last contact duration, in seconds (numeric).

other attributes:

12 - campaign: number of contacts performed during this campaign and for this client (numeric, includes last contact)

13 - pdays: number of days that passed by after the client was last contacted from a previous campaign (numeric; 999 means client was not previously contacted)

14 - previous: number of contacts performed before this campaign and for this client (numeric)

15 - poutcome: outcome of the previous marketing campaign (categorical: 'failure','nonexistent','success')

social and economic context attributes

16 - emp.var.rate: employment variation rate - quarterly indicator (numeric)

17 - cons.price.idx: consumer price index - monthly indicator (numeric)

18 - cons.conf.idx: consumer confidence index - monthly indicator (numeric)

19 - euribor3m: euribor 3 month rate - daily indicator (numeric)

20 - nr.employed: number of employees - quarterly indicator (numeric)

Output variable (desired target):

21 - y - has the client subscribed a term deposit? (binary: 'yes','no')

Analyze Features

Some features have *unknown* values, this may impact the models, by checking the feature importance chart, one approach is to assign null to less important features, remove those null tuples from the dataset later on.

Feature	**Importance**
emp.var.rate	0.093042
poutcome	0.047772
cons.conf.idx	0.026913
contact	0.005341
default	0.001988

Feature	Importance
job	0.001256
age	0.000928
month	0.000579
campaign	0.000469
marital	0.000361
housing	0.000024
loan	0.000004
day_of_week	-0.000019
education	-0.000128

Columns Transformations

Although, this can be done with encoders, a direct transformation was used because each feature required analysis individually, they are used in correlation matrix after the transformation:

- job is categorical, factorize to transform it to numeric
- marital is categorical, factorize to transform it to numeric
- education is categorical, used mapping to transform it to numeric: {'basic.4y':2,'basic.6y':3,'basic.9y':4,'high.school':5,'illiterate':1,'professional.course':6,'university.degree':7,'unknown':0}
- features default, housing and loan have yes/no/unknown values, mapped as: {'no':1,'yes':2,'unknown':0}
- education is categorical, mapped to transform it to numeric: {'mon':1,'tue':2,'wed':3,'thu':4,'fri':5}
- poutcome is categorical, mapped to transform it to numeric: {'failure':1,'nonexistent':0,'success':2}

Finally, transformed the target variable y, yes/no values to 1/0

Feature Overlapping

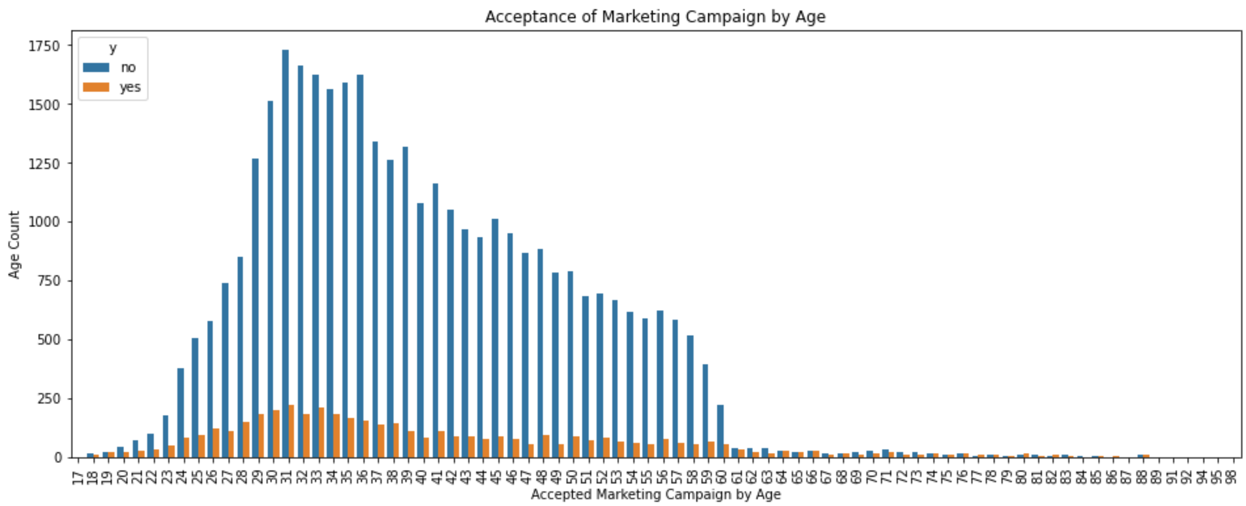
The subset of data is considered for a baseline model which has 7 bank-client features: 'age', 'job', 'marital', 'education', 'default', 'housing' and 'loan'. This yields 2085 unique groups of feature overlapping failing to identify yes/no classes in y distinctly. This is effecting 19528 rows in the entire population which is **47%** of dataset.

The full dataset has 237 unique groups of feature overlapping failing to identify yes/no classes in y distinctly. This is effecting 3665 rows in the entire population which is **9%** of dataset, this is impacting the ability of models to predict outcome for such corner cases.

These observations should be kept in the baseline calculation.

Features

Seniors over age 60 accept campaigns more, as do illiterate people, in contrast to all professions this seem to preserve the same ratio.



Business Objective

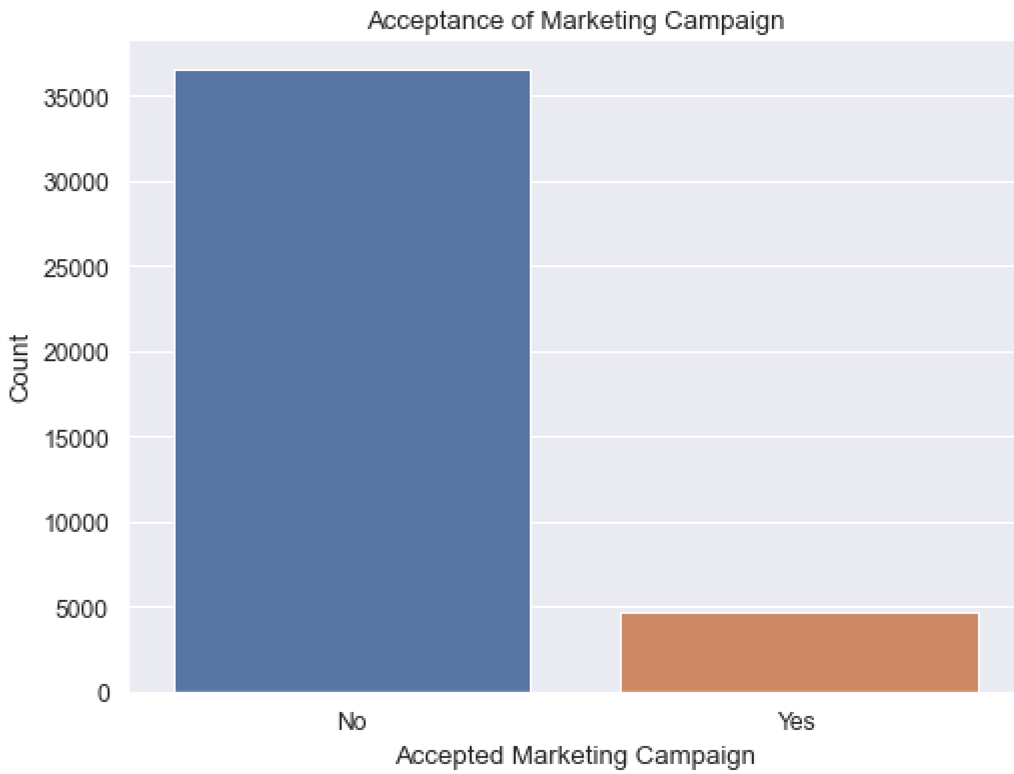
Due to domestic competition and current financial crisis, there is pressure on Portuguese banks to increase financial asset. To overcome this issue, one strategy would be to offer attractive long-term deposit applications with good interest rates, particularly by using directed marketing campaigns.

Thus, there is a need for **improvement in efficiency**: reduced customer contacts while maintaining the same success rate, namely **rate** of *clients subscribing to the deposit* must be retained.

A Baseline Model

First a baseline model is to be established. This will outline the baseline performance that our classifier should aim to beat.

The distribution of target variable shows 89% of observations is No, only 11% is Yes shown in below plot:



The baseline is **89%** by the target variables outlined in the count plot, the model should be better than this baseline! However, the feature overlap rate above indicates only 53% can be properly classified, 47% being arbitrarily due to feature overlapping. If we assume 50-50, best we can get is **77%** for this dataset as baseline versus simply rely on 89% by the target observations.

After running all 4 models with default hyperparameters, the outcome on recall metric is not very promising, the outcome of Logistic Regression, k-Nearest Neighbors, Decision Tree and Support Vector Machines all performed poorly, there is no outstanding result:

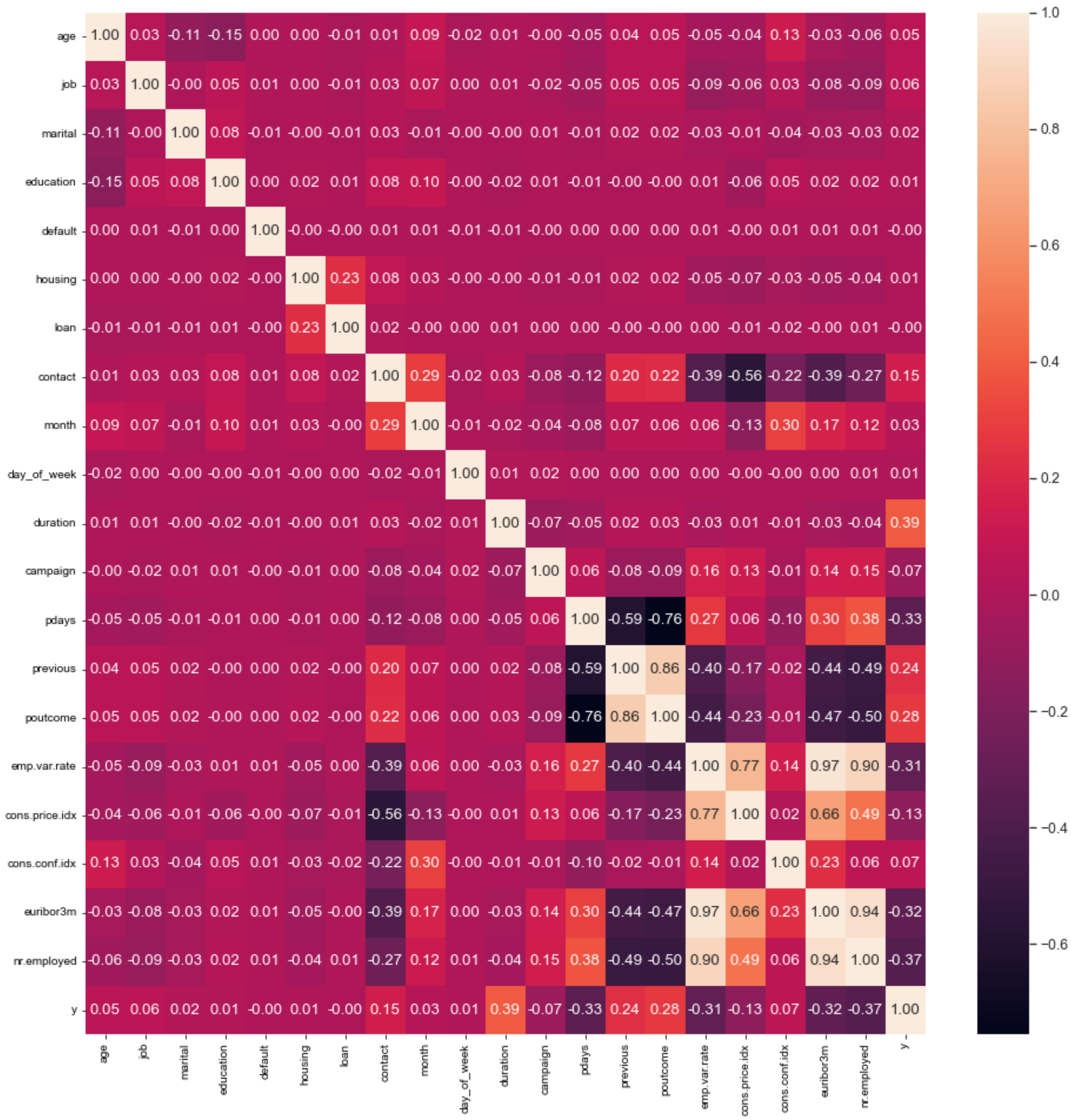
Model	**Train Time**	**Train Accuracy**	**Test Accuracy**
Logistic Regression	0.013428	0.000000	0.000000
KNN	0.012411	0.126886	0.063937
Decision Tree	0.031382	0.308901	0.099856
SVM	19.583614	0.016939	0.009339

The score of Logistic Regression came out as 0.0 and fastest, SVM being the slowest of all.

Improving the Model

Dataset Allocation

Since all features transformed to numeric representation, a correlation matrix can be checked since there are not many features in the dataset:



Per correlation matrix above, there are some strong correlation among these independent variables which is indicating multicollinearity in the dataset:

- poutcome strongly correlated with pdays (negative) and previous (positive)
- emp.var.rate strongly positive correlated with cons.price.idx, euribor3m and nr.employed I can safely remove those features which are highly correlated above 75%. Later, I would run a multicollinearity analysis on the dataset to verify those findings.

Also, 9% of full dataset cannot be correctly classified as the remaining features on it cannot distinctly define boundaries in the final outcome. Again, if we assume 50-50 distribution, the best outcome will be 95% but realiably accurate outcome is 91% on the full dataset.

Model Building

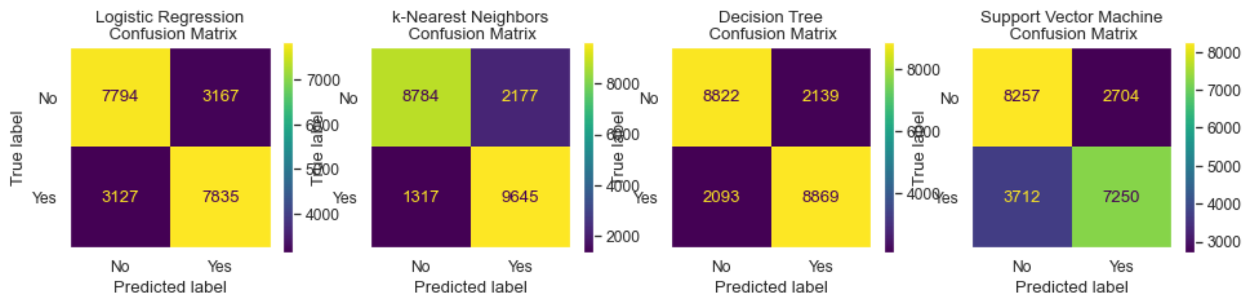
All 4 models Logistic Regression, k-Nearest Neighbors, Decision Tree and Support Vector Machines were built and fed into GridSearchCV by using roc_auc in scoring hyperparameter. It is created by plotting the fraction of true positives out of the positives (TPR = true positive rate) vs. the fraction of false positives out of the negatives (FPR = false positive rate), at various threshold settings. TPR is also known as sensitivity, and FPR is one minus the specificity or true negative rate."

Each model fed with hyperparameter list to evaluate best outcome, they are captured in a table.

Model Results

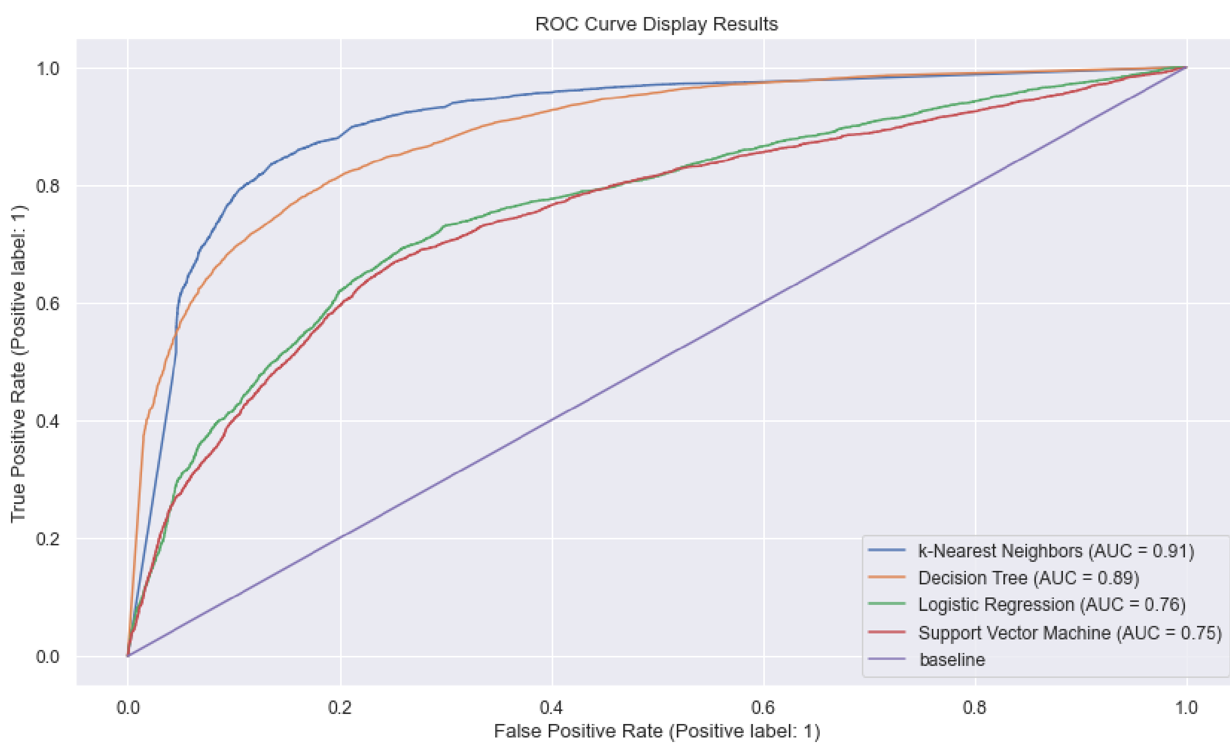
k-Nearest Neighbors with *91%* is pretty close to our performance metric projection due to feature overlapping. **Decision Tree** is pretty good too, their train time is pretty close 31 seconds each and reasonable with the magnitude of data. However, Logistic Regression is one click better than Support Vector Machine and fastest train time. SVM took over an hour to train with no parallelism and performed worst in both test accuracy and train time.

Model	Train Time	Train Accuracy	Test Accuracy	Hyperparameters
Logistic Regression	0.033166	0.759782	0.763205	{'C': 100, 'max_iter': 1000, 'solver': 'lbfgs'}
k-Nearest Neighbors	0.030518	0.995653	0.908220	{'n_neighbors': 13, 'p': 1, 'weights': 'distance'}
Decision Tree	0.071775	0.929373	0.891593	{'criterion': 'entropy', 'max_depth': 33, 'min_samples_leaf': 2, 'min_samples_split': 0.001}
Support Vector Machine	55.611333	0.746876	0.750658	{'C': 0.001, 'cache_size': 1000, 'gamma': 0.01, 'kernel': 'rbf'}



The logistic regression came out with a weaker C hyperparameter for regularization and chose lbfgs as solver and being fastest. KNN chose 13 neighbors and best estimator, followed by Decision Tree went with entropy more computationally heavy than gini but train time still less than KNN due to less hyperparameter combinations. Finally, Support Vector Machine came out as the worst performer in both time and score although it picked slightly smaller gamma which is higher dimension also higher bias and smaller variance by C.

As shown in the confusion matrix, KNN has fewer misclassifications, and better area under the curve (AUC) below:



As shown in Receiver Operating Characteristics curve, the performance of KNN and Decision Tree similar and similarly Logistic Regression and Support Vector Machines.

Conclusion

k-Nearest Neighbors came at *91%* outperformed all other models which is inline with my performance metric projection due to the overlapping features. Second best is **Decision Tree**, its train time is also the second best was 31 seconds. Logistic Regression and Support Vector Machine models are the worst performers. Especially, SVM with no parallelism took over an hour to train the model, it is very costly but yielding not far better results.

KNN is best performing, easy to train and second less costly after Logistic Regression.