Predicting Success of Bank Telemarketing Machine Learning Approach

Atul Joshi, Anurag Sharma 2018msbda005@curaj.ac.in, 2018msbda004@curaj.ac.in



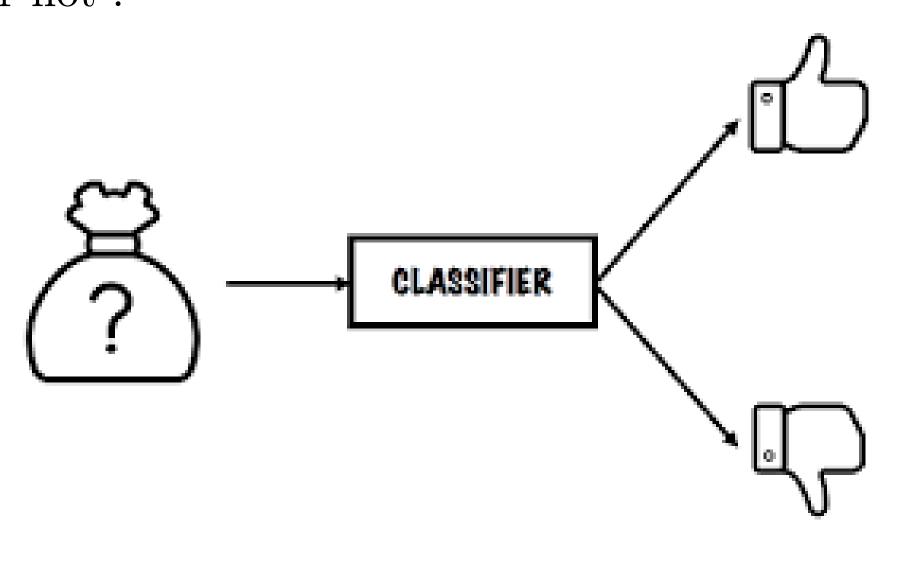
Problem

To design a Decision Support System to predict the success of bank telemarketing calls for selling Long Term Deposits .

Objective: Selecting the best set of clients or targeting the right segments of customers, i.e., those who are more likely to subscribe a product.

The given problem can be posed as a Classification problem (Supervised Learning)

Classification Goal: Assigning predicted/dependent variable Y, values Yes/No, based on whether a client has subscribed a term deposit or not.



Dataset Description

Data is related to direct marketing campaigns of a Portuguese banking institution. The marketing campaigns were based on phone calls.

Variables: 20

Observations: 41188

Numeric: 8(2 were removed)

Categorical: 10

Independent Variables are based on Client, Current campaign, Previous Campaign and Socio-

economic context . High Correlation:

nr.employed, euribor3m

euribor3m, emp.var.rate

hence, euribor3m and nr.employed removed

Models

Logistic Regression (Self developed and sklearn) Decision Trees(IDB Tree)

Naive Bayes (GaussianNB)

Neural Networks (MLP Classifier)

References

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- [2] David Arnott, Graham Pervan, Eight key issues for the decision support systems discipline, Decision Support Systems 44 (3) (2008).
- [3] David L. Olson, Dursun Delen, Yanyan Meng, Comparative analysis of data mining methods for bankruptcy prediction, Decision Support Systems 52 (2) (2012).

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Comparing Results from the Trained Models

Classification Metrics for Naive Bayes				Classification Metrics for sklearn LR						
cation_repo	rt(ytest_	num,y_pred	NB,target_	names= target_names))	target names	= ['No'. 'Ye	es ' 1			
precision	recall	f1-score	support				-	num, ypredl	LR, target_	names=target_names))
0.93	0.90	0.92	7345			precision	recall	f1-score	support	
0.37	0.48	0.42	893		No	0.93	0.98	0.95	7345	
0.85	0.85	0.85	8238		Yes	0.68	0.38	0.49	893	
							0.91	0.91	8238	
0.07	0.03	0.00	0200		_		0.68 0.91	0.72 0.90	8238 8238	
n Metric	s for M	LP Class	sifier		Classifica	tion Metric	s for se	elf develo	ped LR	
ation_repo	rt(ytest_	num,ypredM	LP,target_	names=target_names))	print(classi	fication_repo	ort(ytest_	num, final	out, target	_names=target_names))
recision	recall	f1-score	support			precision	recall	f1-score	support	
0.91	0.99	0.95	7345		No	0.92	0.98	0.95	7345	
0.72	0.19	0.30	893		Yes	0.64	0.34	0.45	893	
0.90	0.90	0.90	8238		-		0.91	0.91	8238	
0.82	0.59	0.62	8238		_					
0.89	0.90	0.88	8238		weighted dvg	0.03	0.51	0.50	0230	
	orecision 0.93 0.37 0.85 0.65 0.87 On Metric ation_repo recision 0.91 0.72 0.90 0.82	cation_report(ytest_orecision recall	cation_report(ytest_num,y_prediction) precision recall f1-score 0.93 0.90 0.92 0.37 0.48 0.42 0.85 0.85 0.85 0.65 0.69 0.67 0.87 0.85 0.86 precision recall f1-score ation_report(ytest_num,ypredMorecision recall f1-score 0.91 0.99 0.95 0.72 0.19 0.30 0.90 0.90 0.90 0.82 0.59 0.62	cation_report(ytest_num,y_predNB,target_recision recall f1-score support 0.93	cation_report(ytest_num,y_predNB,target_names= target_names)) precision recall f1-score support 0.93	Classification_report(ytest_num,y_predNB,target_names= target_names))	target_names = ['No', 'Ye	Cation_report(ytest_num,y_predNB, target_names= target_names)	Cation_report(ytest_num,y_predNB, target_names= target_names) target_names = ['No', 'Yes'] print(classification_report(ytest_num, ypredNB, target_names) target_names = ['No', 'Yes'] print(classification_report(ytest_num, ypredNB, target_names) precision recall f1-score print(classification_report(ytest_num, ypredNB, target_names) precision recall f1-score print(classification_report(ytest_num, ypredNB, target_names) precision precision	Cation_report(ytest_num,y_predNB, target_names

Classification Metrics for Decision Tree Classifier

print(classification_	_report(ytest_	_num,ypredDT,targe	t_names=target_names))

	precision	recall	f1-score	support
Υe	0.94 es 0.50	0.94 0.54	0.94	7345 893
micro av macro av weighted av	/g 0.72	0.89 0.74 0.89	0.89 0.73 0.89	8238 8238 8238

Accuracy scores

Self developed Logistic Regression

ROC - AUC SCORE

roc auc score(ytest num,probSLR)

0.8706899876470297

roc auc score(ytest num,probNB)

0.847934273678733

roc auc score(ytest num,probLR)

0.9234242479712003

roc auc score(ytest num,probDT)

0.7259488359081159

roc_auc_score(ytest_num,probMLP)

0.8783862738122785

accuracy_score(ytest_num,finalout)

0.9015537751881525

sklearn Logistic Regression

accuracy_score(ytest_num,ypredLR)

0.9073804321437242

Naive Bayes' Classifier

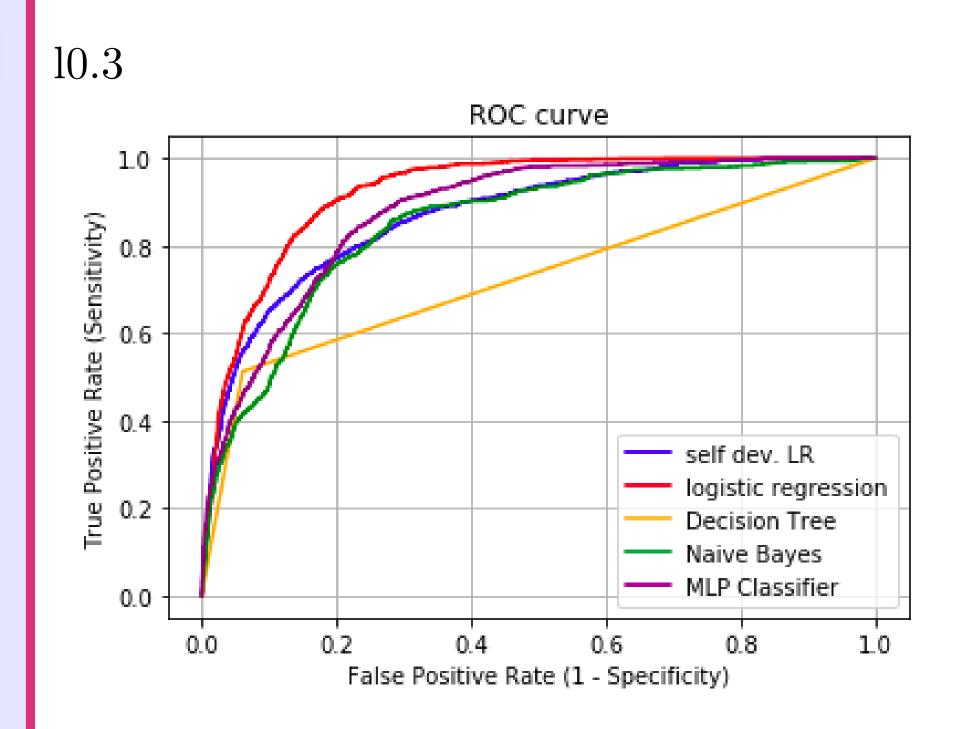
accuracy_score(ytest_num,y_predNB)

0.8555474629764506

Decision Tree Classifier

accuracy_score(ytest_num,ypredDT)

0.8914785142024764



MLP Classifier

accuracy_score(ytest_num,ypredMLP)

0.8810390871570769