

# Midterm

Jeffrey Zhuohui Liang

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## Introduction

Cardiovascular disease is the leading disease burden in U.S, according to *www.cdc.com* [1], on average one person die from heart disease every 36 seconds. And 1 in 4 death is caused by cardiovascular disease. Heavy disease burden of cardiovascular disease should be manage to improve population health.

One of many important manners is screening, *American Heart Association*[2] lists that

- Blood Pressure
- Fasting Lipoprotein Profile
- Body Weight
- Blood Glucose
- Smoking, physical activity, diet

are important screening that help monitor heart condition.

In light of aiding the screening process, we will use **Heart Disease Data Set** from UCI [3] to build our models and select one for applications.

The **Heart Disease Data** is a dataset with 76 attributes, all data were collected from 4 sites, namely Cleveland, Hungary, Switzerland, and the VA Long Beach. Of all 76 attributes, we selected 14 variables as our training data in this case as there're previously researchs have done similar job and used these 14 pre-selected variables. The predictors used are:

- age: The person's age in years
- sex: The person's sex (1 = male, 0 = female)
- cp: chest pain type — Value 0: asymptomatic — Value 1: atypical angina — Value 2: non-anginal pain — Value 3: typical angina
- trestbps: The person's resting blood pressure (mm Hg on admission to the hospital)
- chol: The person's cholesterol measurement in mg/dl
- fbs: The person's fasting blood sugar ( $> 120$  mg/dl, 1 = true; 0 = false)
- restecg: resting electrocardiographic results — Value 0: showing probable or definite left ventricular hypertrophy by Estes' criteria — Value 1: normal — Value 2: having ST-T wave abnormality (T wave inversions and/or ST elevation or depression of  $> 0.05$  mV)
- thalach: The person's maximum heart rate achieved
- exang: Exercise induced angina (1 = yes; 0 = no)
- oldpeak: ST depression induced by exercise relative to rest ('ST' relates to positions on the ECG plot. See more here)
- slope: the slope of the peak exercise ST segment — 0: downsloping;

- 1: flat;
- 2: upsloping
- ca: The number of major vessels (0–3)
- thal: A blood disorder called thalassemia Value 0: NULL (dropped from the dataset previously)
  - Value 1: fixed defect (no blood flow in some part of the heart)
  - Value 2: normal blood flow
  - Value 3: reversible defect (a blood flow is observed but it is not normal)
- target: Heart disease (1 = no, 0= yes)

Table 1: Data summary

Name	hrt_data
Number of rows	920
Number of columns	15
Column type frequency:	
factor	9
numeric	6
Group variables	None

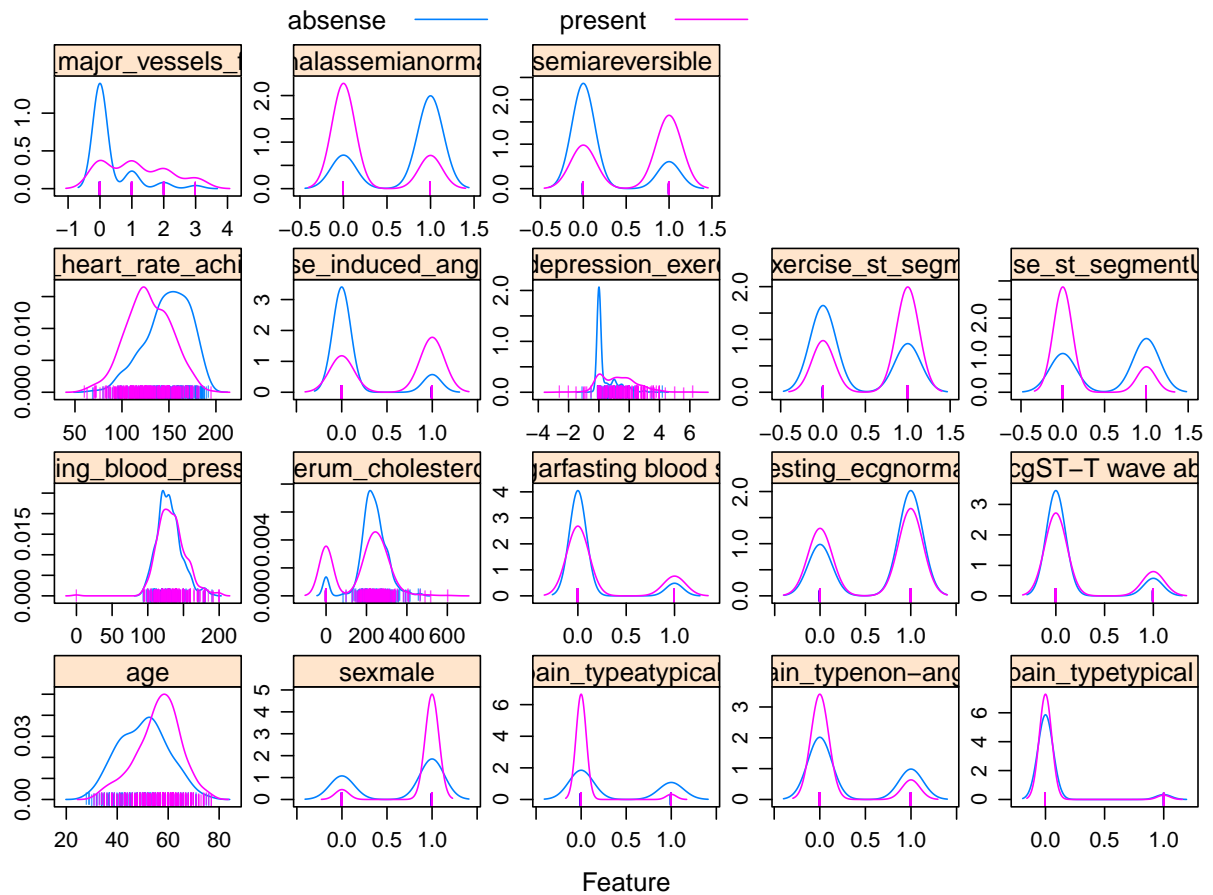
#### Variable type: factor

skim_variable	n_missing	complete_rate	ordered	n_unique	top_counts
diagnosis_heart_disease	0	1.00	FALSE	2	pre: 509, abs: 411
location	0	1.00	FALSE	4	cle: 303, hun: 294, va: 200, swi: 123
sex	0	1.00	FALSE	2	mal: 726, fem: 194
chest_pain_type	0	1.00	FALSE	4	asy: 496, non: 204, aty: 174, typ: 46
fasting_blood_sugar	90	0.90	FALSE	2	fas: 692, fas: 138
resting_ecg	2	1.00	FALSE	3	nor: 551, lef: 188, ST-: 179
exercise_induced_angina	55	0.94	FALSE	2	no: 528, yes: 337
peak_exercise_st_segment	309	0.66	FALSE	3	Fla: 345, Up-: 203, Dow: 63
thalassemia	486	0.47	FALSE	3	nor: 196, rev: 192, fix: 46

#### Variable type: numeric

skim_variable	n_missing	complete_rate	mean	sd	p0	p25	p50	p75	p100
age	0	1.00	53.51	9.42	28.0	47	54.0	60.0	77.0
resting_blood_pressure	59	0.94	132.13	19.07	0.0	120	130.0	140.0	200.0
serum_cholesterol	30	0.97	199.13	110.78	0.0	175	223.0	268.0	603.0
max_heart_rate_achieved	55	0.94	137.55	25.93	60.0	120	140.0	157.0	202.0
st_depression_exercise	62	0.93	0.88	1.09	-2.6	0	0.5	1.5	6.2
num_major_vessels_flouro	611	0.34	0.68	0.94	0.0	0	0.0	1.0	3.0

## Exploratory analysis



From above plot, some features are well distinguish for disease status, eg. `num_major_vessels`, `chest_pain_typeatypical`, `angina_st_depression_exercise`, these variables may be statistical significant for the model.

## Modeling

As shown, there are missing values in our data. Assuming that these values are missing at random, we impute these values with `knnImpute` method. All data were center and scale before training.

To train classifiers, we choose Lasso logistics, MARS, KNN, LDA, QDA and TREE models to train our data with 5-fold cross validation.

When training, ROC is used as loss function for our model, as we intent to build a model with highest classification ability to predict whether a client has heart disease.

## Model tuning

lasso logistics regression is logistics regression which loss function is modified with L1 penalty, we tune this L1 penalty term  $\lambda$  for lasso regression model training with cross-validation.

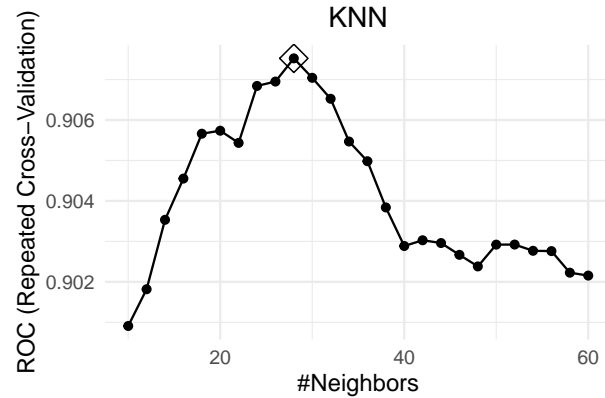
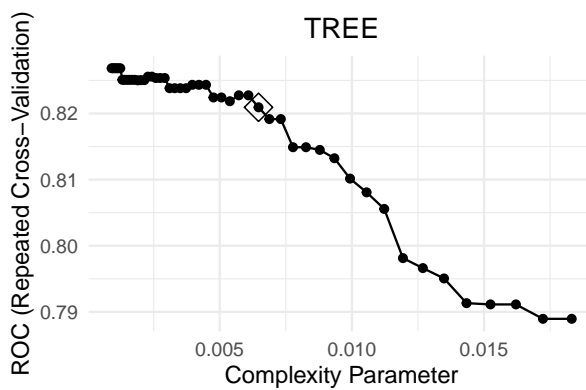
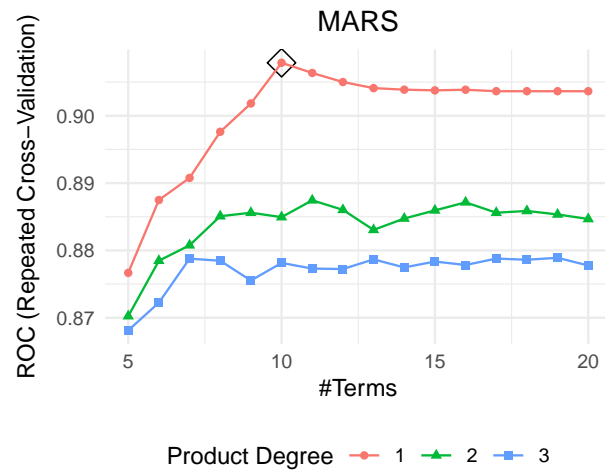
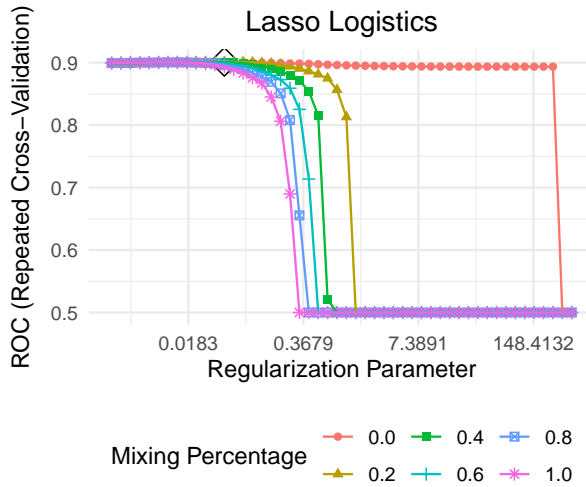
MARS has model predictors' order and prune remaining term as parameters for tuning. Assuming that data can be well-explain with at most cubic model, we tune the order from 1-3 and leaving cross validation to choose for prune term.

TREE model has tree complexity for tuning.

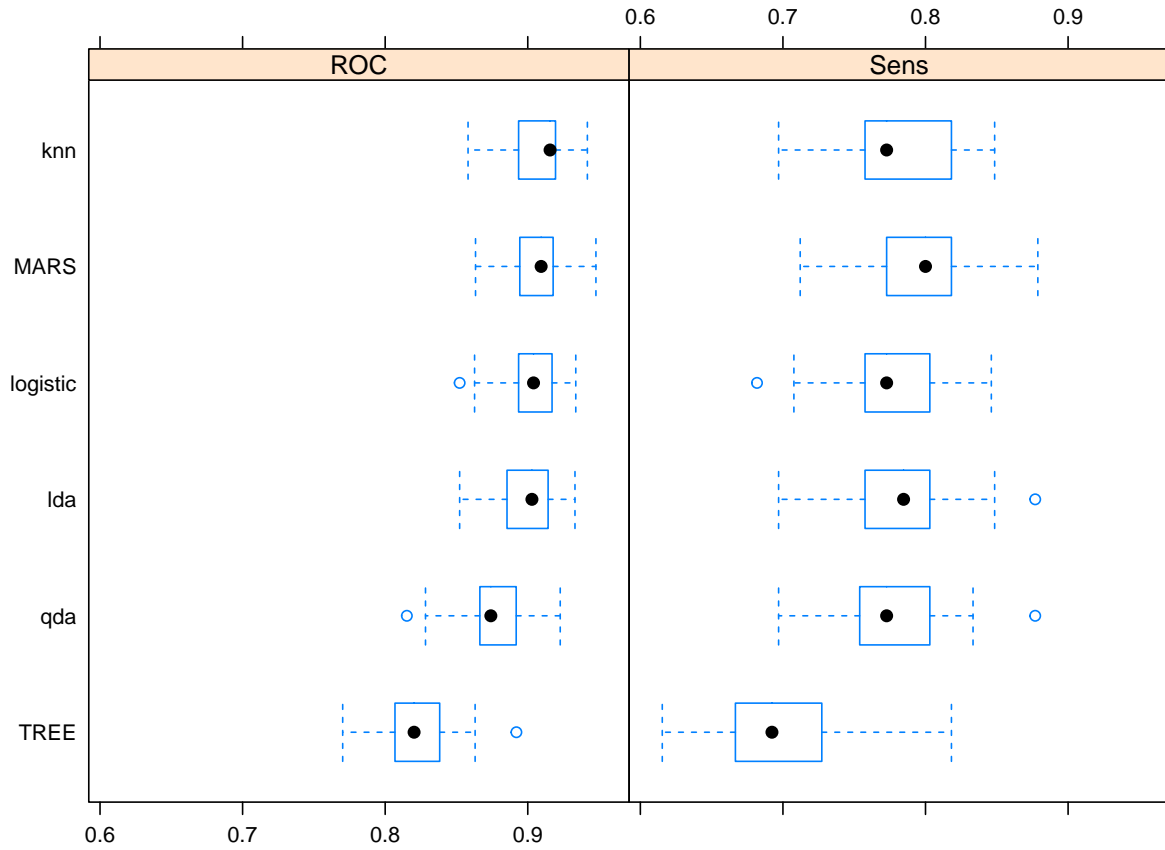
KNN has the number of closest neighbor as tuning parameter.

LDA and QDA do not have tuning parameters.

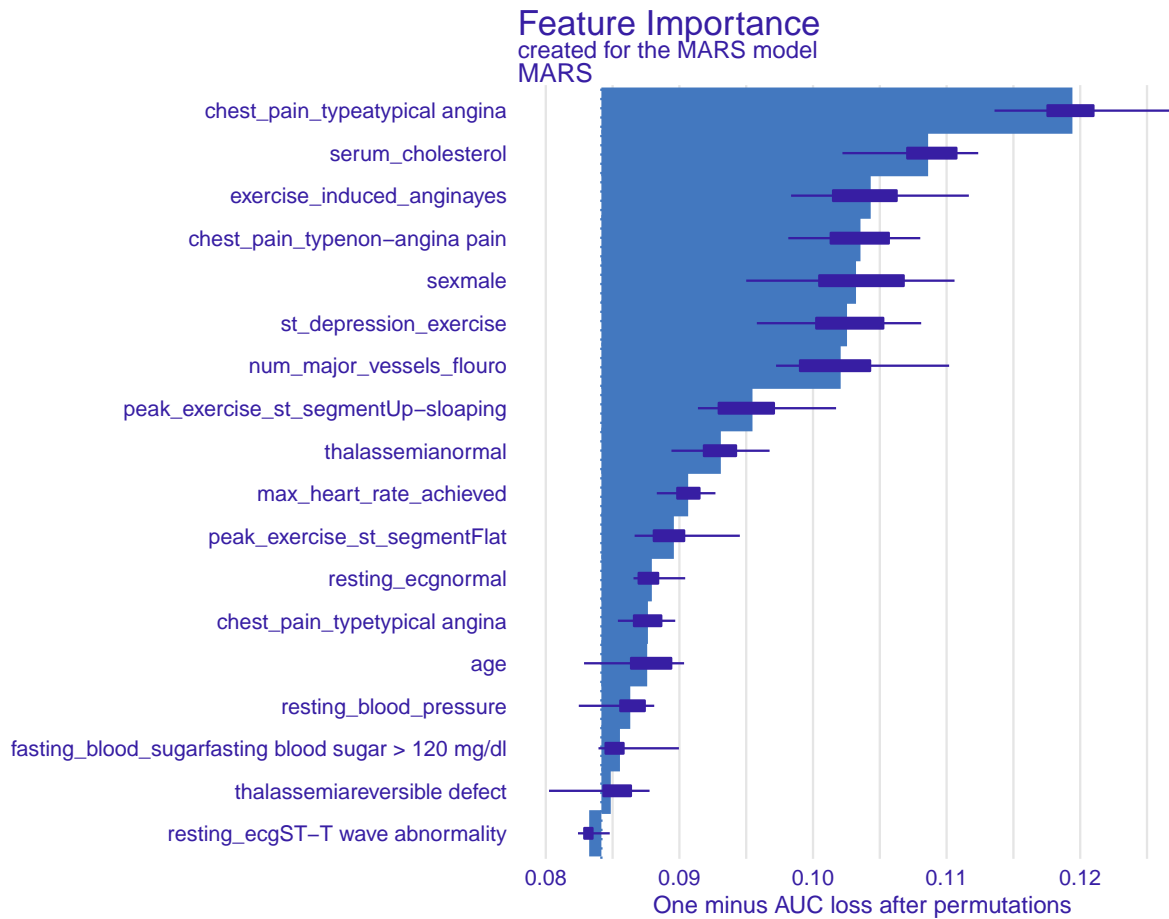
All parameter is tune by 5-fold cross validation and choose the one with highest ROC.



## Performance comparison

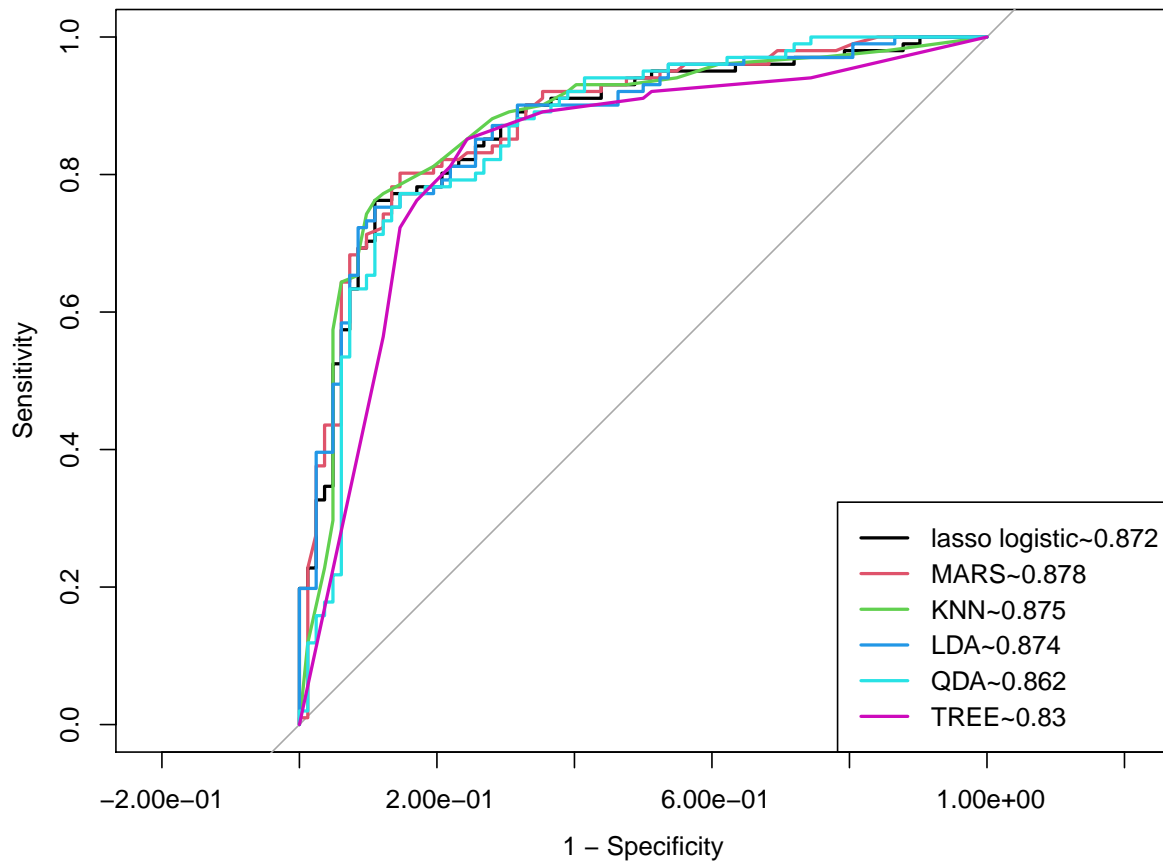


In our trained model have similar ROC performance excepted for **TREE** and **qda**. Considering our model is used for improving screening process, we would prefer model with higher sensitivity. Considering both metrics, MARS method which has high ROC and highest mean sensitivity is chosen as our model.



In the MARS model, **chest pain type: atypical angina** has the highest importance, followed by **serum cholesterol** and **st depression exercercise**. Against our assumption in exploration, **fasting blood sugar** has second lowest importance to AUC loss in the MARS model.

The models, included others not selected model is test against the test data. The test performance is similar to the train performance.



## Conclusion

MARS model has high predictability and high sensitivity, which is suitable for screening. The MARS model, with its nature of spline, also provides good reference for critical values for labs/ testing result for diagnosis.

## References

- [1] Centers for Disease Control and Prevention: <https://www.cdc.gov/heartdisease/facts.htm#:~:text=Heart%20Disease%20in%20the%20United%20States&text=One%20person%20dies%20every%2036,1%20in%20every%204%20deaths.&text=Heart%20disease%20costs%20the%20United,year%20from%202014%20to%202015.>
- [2] American Heart Association: Heart-Health Screenings:
- [3] USI: <http://archive.ics.uci.edu/ml/datasets/heart+Disease>