Machine Learning Methods for Mortality Prediction in Patients with ST Elevation Myocardial Infarction

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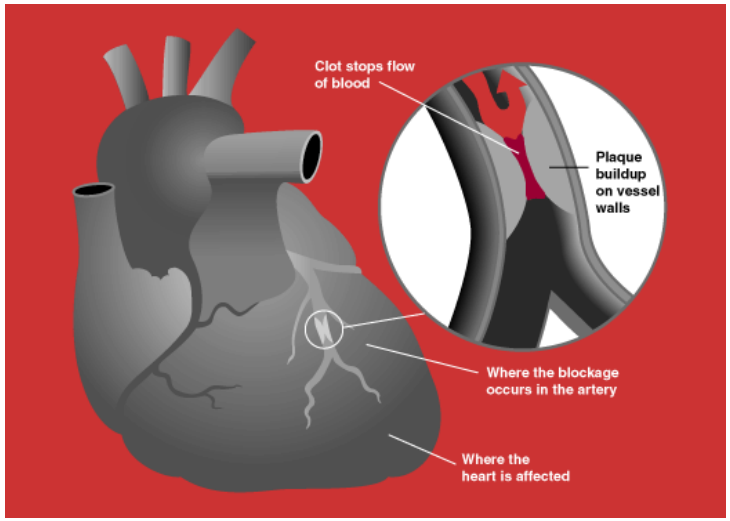
Acute Myocardial Infarction



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- An atherosclerotic plaque slowly builds up in the inner lining of a coronary artery.
- Suddenly, it ruptures, causing catastrophic thrombus formation.
- The thrombus totally occludes the artery and prevents blood flow downstream.

Acute Myocardial Infarction

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The heart cells in the territory of the occluded coronary artery die and do not grow back.

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- STEMI is the leading cause of death in developed countries
- Its treatment has a significant socio-economic impact

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- For each hospital compute the average of this probabilities and compare it with true mortality at that hospital.
- We need a prediction model that relates the mortality with attributes describing the health state at hospital admission.

Dataset of patients with STEMI

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- About each patient we knew whether he/she died within 30-days.
- Cardiologists selected 23 attributes that may influence STEMI mortality.

Attributes

Attribute	Code	type	value range in data
Gender	SEX	nominal	{male, female}
Age	AGE	real	[23, 94]
Height	HT	real	[145, 205]
Weight	WT	real	[35, 150]
Body Mass Index	BMI	real	[16.65, 48.98]
STEMI Location	STEMI	nominal	{inferior, anterior, lateral}
Killip classification at admission	KILLIP	integer	{1, 2, 3, 4}
Kalium	K	real	[2.25, 7.07]
Urea	UR	real	[1.6, 46.5]
Kreatinin	KREA	real	[17, 525]
Uric acid	KM	real	[109, 935]
Albumin	ALB	real	[23, 53.5]
HDL Cholesterol	HDLC	real	[0.38, 2.21]
Cholesterol	CH	real	[1.8, 9.59]
Triacylglycerol	TAG	real	[0.31, 8.13]
LDL Cholesterol	LDLC	real	[0.63, 7.79]
Glucose	GLU	real	[4.2, 25.7]
C-reactive protein	CRP	real	[0.3, 359]
Cystatin C	CYSC	real	[0.38, 5.22]
NT prohormone of brain natriuretic peptide	NTBNP	real	[22.2, 35000]
Troponin	TRPT	real	[0, 25]
Glomerular filtration rate (MDRD)	GFMD	real	[0.13, 7.31]
Glomerular filtration rate (Cystatin C)	GFCD	real	[0.09, 7.17]

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Tested methods

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We applied algorithms to both:

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- the data with the attribute set reduced by a method which selects a subsets of attributes highly correlated with the class while having low intercorrelation. We denote the method with extension .AS.

Evaluation Criteria

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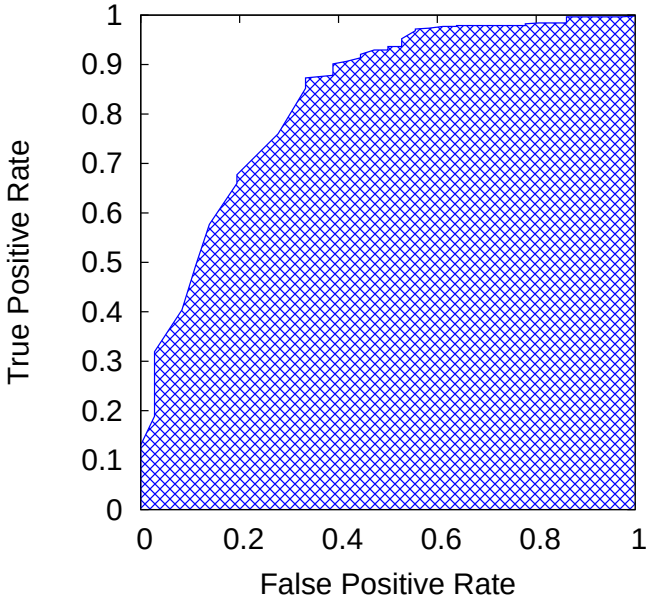
The ROC curve for LOG.BOOST on D.BIN.AS



Results

Classifier	Criteria	D.ORD	D.ORD.AS	D.DISCR	D.DISCR.AS	D.BIN	D.BIN.AS
LOG.BOOST	ACC	94.03	94.20	93.86	88.23	94.03	93.86
	AUC	0.618	0.646	0.722	0.640	0.802	**0.832**
LOG.REG	ACC	92.54	93.86	90.05	87.56	92.87	93.70
	AUC	0.792	0.821	0.646	0.607	0.743	0.798
C4.5	ACC	93.86	94.69	94.20	88.72	93.53	94.53
	AUC	0.618	0.569	0.600	0.544	0.547	0.610
NB	ACC	89.22	91.04	86.90	87.73	86.90	94.20
	AUC	0.820	0.813	0.806	0.649	0.811	0.809
NB.SIMPL	ACC	89.72	90.88	86.90	87.73	86.90	94.20
	AUC	0.828	0.769	0.806	0.649	0.811	0.809
NN	ACC	91.38	93.86	93.20	87.40	92.04	93.53
	AUC	0.763	0.746	0.737	0.550	0.767	0.759
BN.K2	ACC	NA	NA	92.04	94.53	94.03	94.36
	AUC	NA	NA	0.769	0.783	0.769	0.821
BN.TAN	ACC	NA	NA	92.04	88.89	94.20	**94.86**
	AUC	NA	NA	0.787	0.590	0.811	0.818

LOG.BOOST for D.ORD.AS and D.BIN.AS

```
0.87   + STEMI_lateral * -0.41
       + ALB * -0.08
       + HDLC * 0.21
       + CYSC * 0.24
       + KILLIP * 0.31
```

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0.87   + STEMI_lateral * -0.41
       + ALB * -0.08
       + HDLC * 0.21
       + CYSC * 0.24
       + KILLIP * 0.31

-1.64  + ALB_low * 0.76
       + CYSC_high * 0.62
       + KILLIP * 0.68
```

C4.5 for D.ORD.AS and D.BIN.AS

```
CYSC <= 1.64: 0 (553.0)
CYSC > 1.64
|   HDLC <= 0.56: 1 (5.0)
|   HDLC > 0.56
|   |   KILLIP <= 1
|   |   |   ALB <= 25.2: 1 (2.21)
|   |   |   ALB > 25.2: 0 (29.79)
|   |   KILLIP > 1
|   |   |   UR <= 15.8: 1 (6.0)
|   |   |   UR > 15.8: 0 (7.0)
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CYSC <= 1.64: 0 (553.0)
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|   |   |   UR <= 15.8: 1 (6.0)
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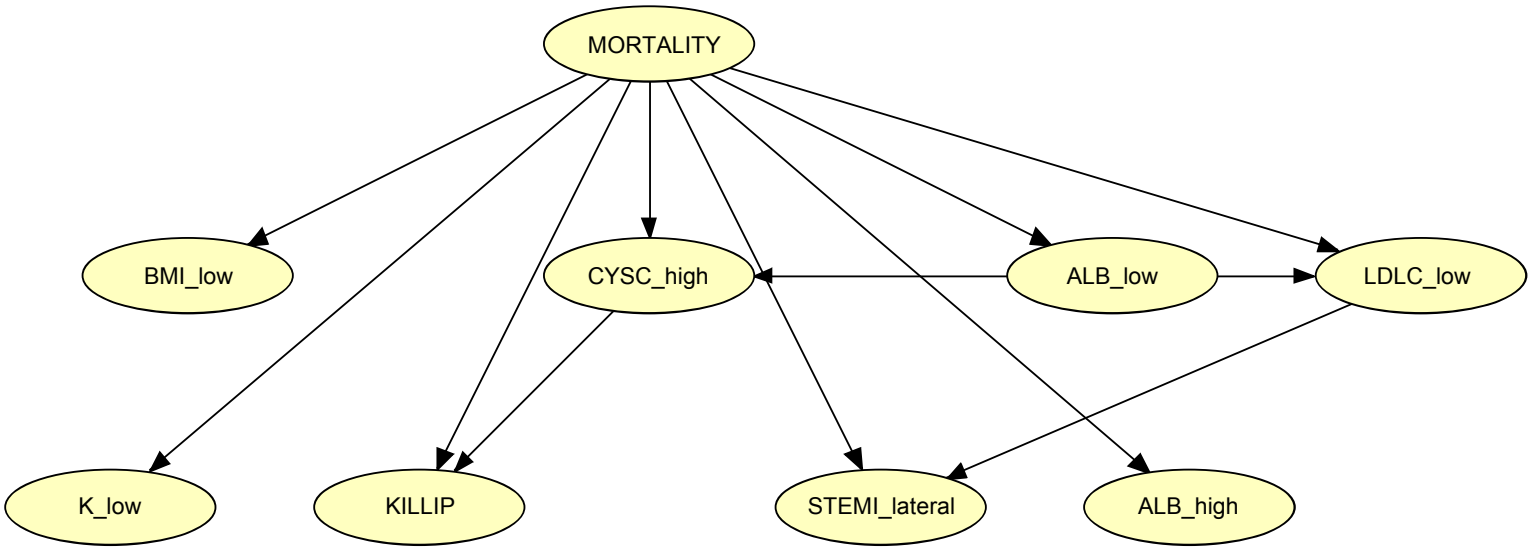
CYSC_high = 0: 0 (526.0)
CYSC_high = 1
|   ALB_low = 0: 0 (63.29)
|   ALB_low = 1: 1 (13.71)
```

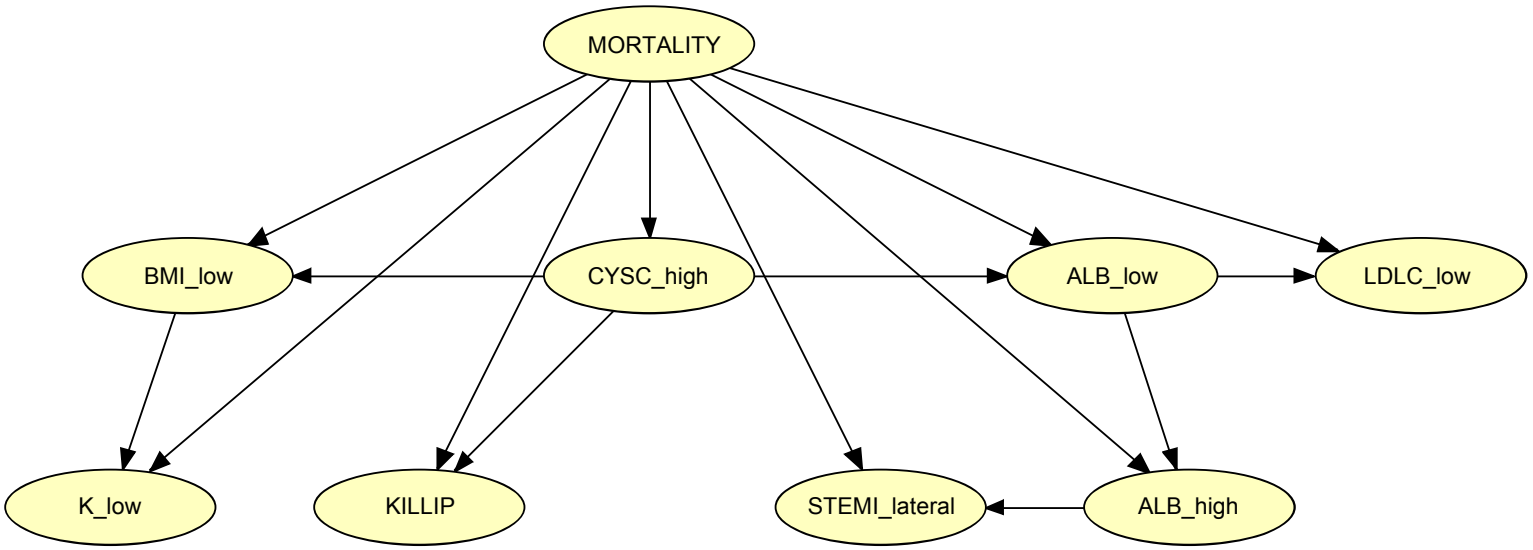
Bayesian networks

BN learned by K2 algorithm



Bayesian networks

BN learned by TAN



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- The best performance was achieved on discretized data where the discretization was based on the expert knowledge and the attributes had only two values.
- The best performing classifiers were based on logistic regression and on simple Bayesian networks.
- In future we would like to extend the set of attributes and get datasets with a larger number of patients.