Predictive Modeling Project Review I

Group 14

Heart Failure Prediction

19162121038 Dishwa Shah

19162121044 Tanishk Sethiya

19162121047 Yash Talati

20162122006 Jeel Patel

Index

Aim
Create a model for predicting mortality caused by heart failure.

About this dataset
Cardiovascular diseases (CVDs) are the number 1 cause of death globally, taking an estimated 17.9 million lives each year, which accounts for 31% of all deaths worldwide. Heart failure is a common event caused by CVDs and this dataset contains 12 features that can be used to predict mortality by heart failure.
Most cardiovascular diseases can be prevented by addressing behavioural risk factors such as tobacco use, unhealthy diet and obesity, physical inactivity and harmful use of alcohol using population-wide strategies.
People with cardiovascular disease or who are at high cardiovascular risk (due to the presence of one or more risk factors such as hypertension, diabetes, hyperlipidaemia or already established disease) need early detection and management wherein a machine learning model can be of great help.

Objective
- Clean the dataset to remove any existing outliers and extremes.
- Train the model to predict whether the patient is likely to face mortality due to heart failure considering his age, health and other lifestyle choices.
- Train the model to determine patterns amongst the various lifestyle and health aspects that are more likely to cause mortality due to heart failure.
- Perform exploratory analysis to find patterns and insights.

Tool used
To build our model, we will use IBM SPSS Modeler.

DATA DESCRIPTION

Attributes, their descriptions, ranges and number of entries:

- Age

Description: Age of patients (years)
Range: [40, 95]

- Anaemia

Description: Condition where red blood cells are decreased (Boolean: 0 for false, 1 for true)
0: 170, 1: 129

- Creatinine_phosphokinase

Description: Level of CPK enzyme in blood (mcg/L)
Range: [23, 7861]

- Diabetes

Description: Whether the patient has diabetes (Boolean: 0 for false, 1 for true)
0: 174, 1: 125

- Ejection_fraction

Description: Percentage of blood leaving from heart at each contraction (percentage)
Range: [14, 80]

- High_blood_pressure

Description: Whether the patient has high blood pressure (Boolean: 0 for false, 1 for true)
0: 194, 1: 105

- Platelets

Description: Platelets in blood (kiloplatelets/mL)
Range: [25100.0, 850000.0]

- Serum_creatinine

Description: Level of serum creatinine in blood (mg/dL)
Range: [0.5, 9.4]

- Serum_sodium

Description: Level of serum sodium in blood (mEq/L)
Range: [113, 148]

- Sex

Description: Man or Woman (Boolean: 0 for man, 1 for woman)
0: 105, 1: 194

- Smoking

Description: Whether the patient smokes or not (Boolean: 0 for false, 1 for true)
0: 203, 1: 96

- Time

Description: Follow-up period (days)
Range: [4, 285]

- Death_event

Description: If the patient dies during follow-up period (Boolean: 0 for false, 1 for true)
0: 203, 1: 96

Data Quantity

- **What is the format of the data?**

The data is of .csv format.

- **Which method is used to capture the data?**

Here, the method to capture the data is unknown since we are not a part of end-to-end process.

- **How large is the database?**

The database has 299 rows and 13 columns.

Data Quality

- **Does the data include characteristics relevant to the business perspective?**

Yes, the data does include characteristics relevant to the business perspective which can help us achieve our aim.

Fields: 13 in, 0 filtered, 6 renamed, 13 out

Field	Filter	Field
age	→	age
anaemia	→	anaemia
creatinine_phosphokinase	→	cpk
diabetes	→	diabetes
ejection_fraction	→	ejection
high_blood_pressure	→	bp
platelets	→	platelets
serum_creatinine	→	serum creatinine
serum_sodium	→	serum sodium
sex	→	sex
smoking	→	smoking
time	→	time
DEATH_EVENT	→	death

- **What data types are present?**

Field	Override	Storage	Input Format
age	☐	Integer	
anaemia	☐	Integer	
creatinine_phosphokinase	☐	Integer	
diabetes	☐	Integer	
ejection_fraction	☐	Integer	
high_blood_pressure	☐	Integer	
platelets	☐	Real	
serum_creatinine	☐	Real	
serum_sodium	☐	Integer	
sex	☐	Integer	
smoking	☐	Integer	
time	☐	Integer	
DEATH_EVENT	☐	Integer	

As we can see, We have integer and real data types and Flag and Continuous measurement levels.

- **Did you compute basic statistics for the key attributes? What insight did this provide into the business question?**

Yes, I did compute basic statistics for the key attributes.

Field	Measurement	Min	Max	Mean	Std. Dev	Skewness	Unique	Valid
age	Continuous	40	95	60.829	11.895	0.424	--	299
anaemia	Flag	0	1	--	--	--	2	299
cpk	Continuous	23	7861	581.839	970.288	4.463	--	299
diabetes	Flag	0	1	--	--	--	2	299
ejection	Continuous	14	80	38.084	11.835	0.555	--	299
bp	Continuous	0	1	0.351	0.478	0.627	--	299
platelets	Continuous	25100.000	850000.000	263358.029	97804.237	1.462	--	299
serum creatinine	Continuous	0.500	9.400	1.394	1.035	4.456	--	299
serum sodium	Continuous	113	148	136.625	4.412	-1.048	--	299
sex	Flag	0	1	--	--	--	2	299
smoking	Flag	0	1	--	--	--	2	299
time	Continuous	4	285	130.261	77.614	0.128	--	299
death	Flag	0	1	--	--	--	2	299

We can see that some of the data is skewed. We will see what this provides to our business questions further.

- **Are you able to prioritize relevant attributes? If not, are business analysts available to provide further insights?**

Yes, I did prioritize relevant attributes. All the fields can somehow be the cause of death. Hence, we are assigning the role of Input to all the attributes.

Field	Measurement	Values	Missing	Check	Role
age	Continuous	[40,95]		None	Input
anaemia	Flag	1/0		None	Input
cpk	Continuous	[23,7861]		None	Input
diabetes	Flag	1/0		None	Input
ejection	Continuous	[14,80]		None	Input
bp	Continuous	[0,1]		None	Input
platelets	Continuous	[25100.0,850000.0]		None	Input
serum creatinine	Continuous	[0.5,9.4]		None	Input
serum sodium	Continuous	[113,148]		None	Input
sex	Flag	1/0		None	Input
smoking	Flag	1/0		None	Input
time	Continuous	[4,285]		None	Input
death	Flag	1/0		None	Input

DATA EXPLORATION

Measurement levels

- Age, cpk, ejection level, blood pressure, platelets, serum creatinine, serum sodium, time and death are assigned Continuous measurement level since they all have values from a continuous range.
- Anaemia, diabetes, sex, smoking and death have been assigned Flag measurement level since they have 0/1 as their values.

Roles

- Currently, all fields have been assigned Input as their roles since we want to derive all the patterns among the attributes that will help build a connection between lifestyle and heart failure in order to prevent it rather than just predicting if the patient is likely to die or not.
- However, we will set death as a target in another Type node later to merely predict whether the patient is likely to die of heart failure of not.

Field	Measurement	Values	Missing	Check	Role
age_transfor...	Continuous	[-1.760536...		None	Input
creatinine_ph...	Continuous	[-0.757990...		None	Input
ejection_fracti...	Continuous	[-2.054378...		None	Input
platelets_tran...	Continuous	[-2.653651...		None	Input
serum_creati...	Continuous	[-1.171258...		None	Input
serum_sodiu...	Continuous	[-2.999999...		None	Input
time_transfor...	Continuous	[-1.647126...		None	Input
anaemia_tra...	Flag	1/0		None	Input
diabetes_tran...	Flag	1/0		None	Input
high_blood_p...	Flag	1/0		None	Input
sex_transfor...	Flag	1/0		None	Input
smoking_tran...	Flag	1/0		None	Input
DEATH_EVE...	Flag	1/0		None	Target

Format

indicates that there is maximum 4 digits in that field.

Field	Format	Justify	Column Width
age_transformed	#####.###	Auto	Auto
creatinine_phosphokinase_trans...	#####.###	Auto	Auto
ejection_fraction_transformed	#####.###	Auto	Auto
platelets_transformed	#####.###	Auto	Auto
serum_creatinine_transformed	#####.###	Auto	Auto
serum_sodium_transformed	#####.###	Auto	Auto
time_transformed	#####.###	Auto	Auto
anaemia_transformed	#####	Auto	Auto
diabetes_transformed	#####	Auto	Auto
high_blood_pressure_transformed	#####	Auto	Auto
sex_transformed	#####	Auto	Auto
smoking_transformed	#####	Auto	Auto
DEATH_EVENT_transformed	#####	Auto	Auto

Statistics

Data Audit of [13 fields] #76

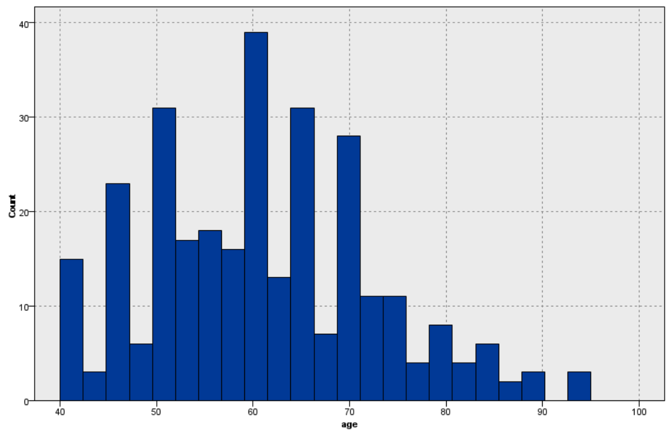
File Edit Generate

Audit Quality Annotations

Field	Graph	Measurement	Min	Max	Sum	Range	Mean	Mean Std. Err.	Std. Dev	Variance	Skewness	Skewness Std. Err.
age		Continuous	40	95	18188	55	60.829	0.688	11.895	141.491	0.424	0.141
anaemia		Flag	0	1	--	--	--	--	--	--	--	--
creatinine_phosphokinase		Continuous	23	7861	173970	7838	581.839	56.113	970.288	941458.571	4.463	0.141
diabetes		Flag	0	1	--	--	--	--	--	--	--	--
ejection_fraction		Continuous	14	80	11387	66	38.084	0.684	11.835	140.063	0.555	0.141
high_blood_pressure		Flag	0	1	--	--	--	--	--	--	--	--
platelets		Continuous	25100.000	850000.000	78744050.750	824900.000	263358.029	5656.165	97804.237	9565668749.449	1.462	0.141
serum_creatinine		Continuous	0.500	9.400	416.770	8.900	1.394	0.060	1.035	1.070	4.456	0.141
serum_sodium		Continuous	113	148	40851	35	136.625	0.255	4.412	19.470	-1.048	0.141

[1] Indicates a multimode result [2] Indicates a sampled result

- Age



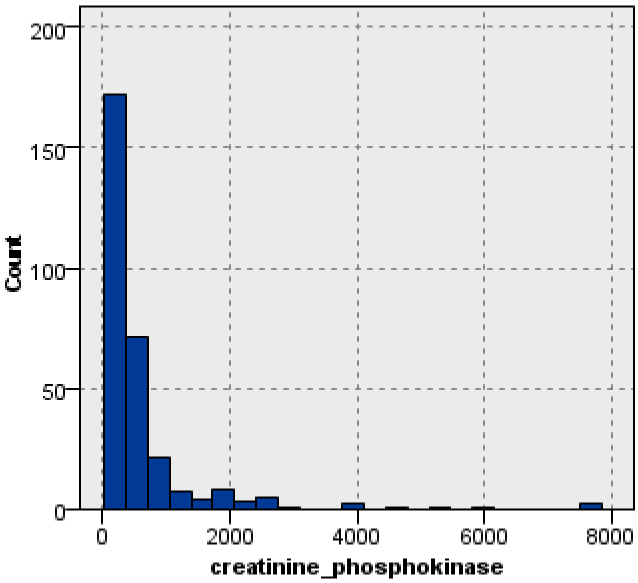
Min value: 40
Maximum value: 95
Sum of all values: 18188
Range: 55
Mean: 60.829
Mean std. error: 0.688
Std. deviation: 11.895
Variance: 141.491
Skewness: 0.424
Skewness std. error: 0.141
Kurtosis: -0.184
Kurtosis std. error: 0.281
Median: 60
Mode: 60
Valid values: 299

- Anaemia

Value	Proportion	%	Count
0		56.86	170
1		43.14	129

Min value: 0
Maximum value: 1
Mode: 0
Unique: 2
Valid values: 299

- Creatinine_phosphokinase



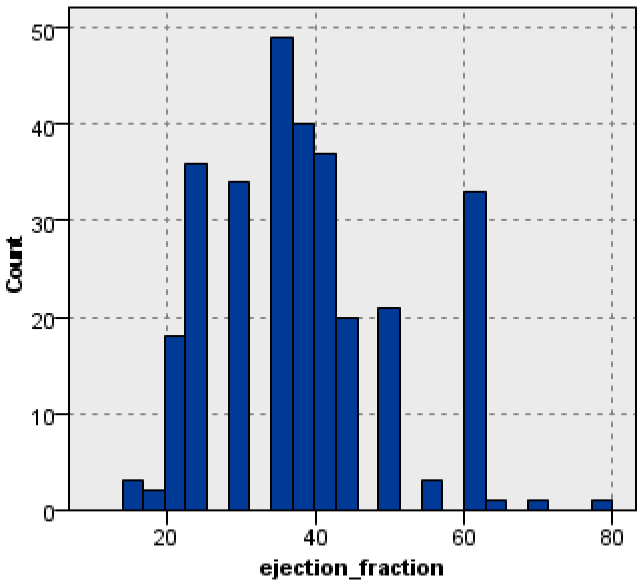
Min value: 23
Maximum value: 7861
Sum of all values: 173970
Range: 7838
Mean: 581.839
Mean std. error: 56.113
Std. deviation: 970.288
Variance: 941458.571
Skewness: 4.463
Skewness std. error: 0.141
Kurtosis: 25.149
Kurtosis std. error: 0.281
Median: 250
Mode: 582
Valid values: 299

- Diabetes

Value	Proportion	%	Count
0		58.19	174
1		41.81	125

Min value: 0
Maximum value: 1
Mode: 0
Unique: 2
Valid values: 299

- Ejection_fraction



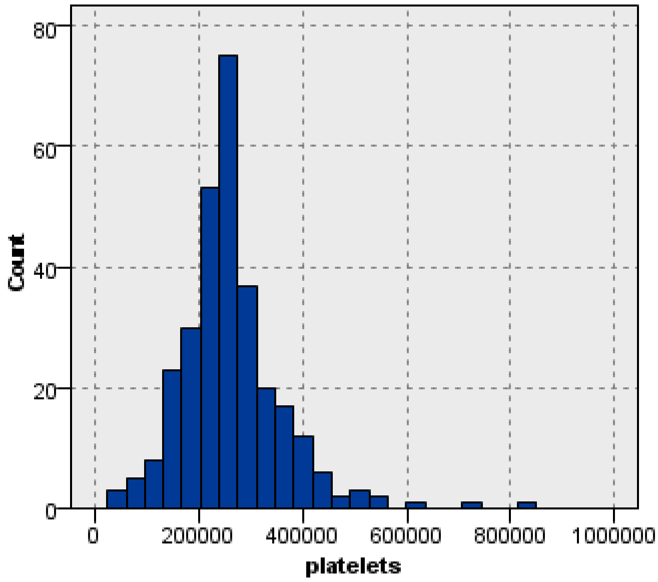
Min value: 14
Maximum value: 80
Sum of all values: 11387
Range: 66
Mean: 38.084
Mean std. error: 0.684
Std. deviation: 11.835
Variance: 140.063
Skewness: 0.555
Skewness std. error: 0.141
Kurtosis: 0.041
Kurtosis std. error: 0.281
Median: 38
Mode: 35
Valid values: 299

- High_blood_pressure

Value	Proportion	%	Count
0		64.88	194
1		35.12	105

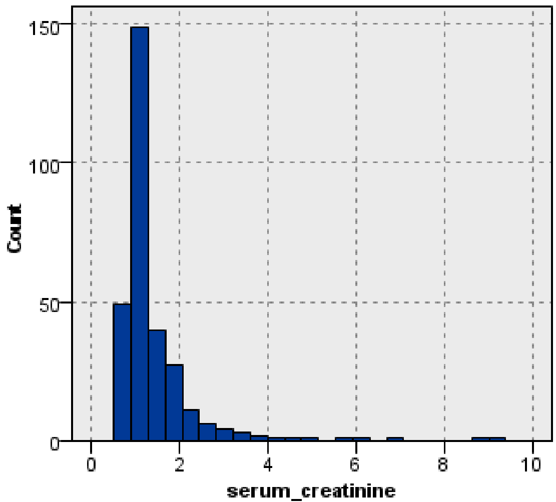
Min value: 0
Maximum value: 1
Mode: 0
Unique: 2
Valid values: 299

- Platelets



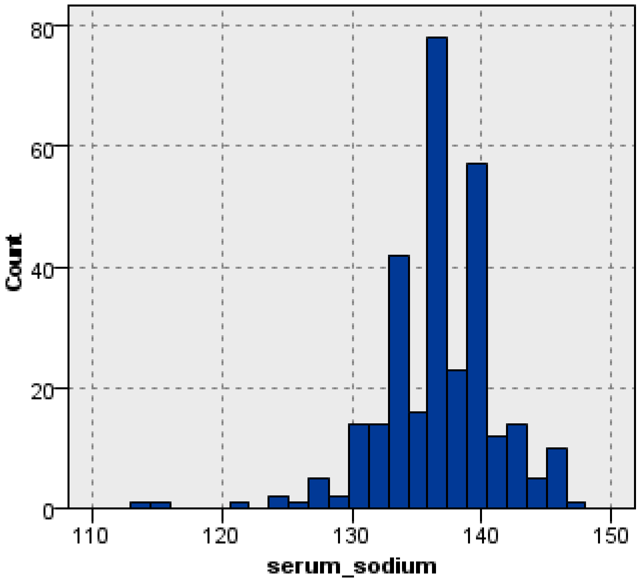
Min value: 25100.000
Maximum value: 850000.000
Sum of all values: 78744050.750
Range: 824900.000
Mean: 263358.029
Mean std. error: 5656.165
Std. deviation: 97804.237
Variance: 9565668749.449
Skewness: 1.462
Skewness std. error: 0.141
Kurtosis: 6.209
Kurtosis std. error: 0.281
Median: 262000.000
Mode: 263358.030
Valid values: 299

- Serum_creatinine



Min value: 0.500
Maximum value: 9.400
Sum of all values: 416.770
Range: 8.900
Mean: 1.394
Mean std. error: 0.060
Std. deviation: 1.035
Variance: 1.070
Skewness: 4.456
Skewness std. error: 0.141
Kurtosis: 25.828
Kurtosis std. error: 0.281
Median: 1.100
Mode: 1.000
Valid values: 299

- Serum_sodium



Min value: 113
Maximum value: 148
Sum of all values: 40851
Range: 35
Mean: 136.625
Mean std. error: 0.255
Std. deviation: 4.412
Variance: 19.470
Skewness: -1.048
Skewness std. error: 0.141
Kurtosis: 4.120
Kurtosis std. error: 0.281
Median: 137
Mode: 136
Valid values: 299

- Sex

Value	Proportion	%	Count
0		35.12	105
1		64.88	194

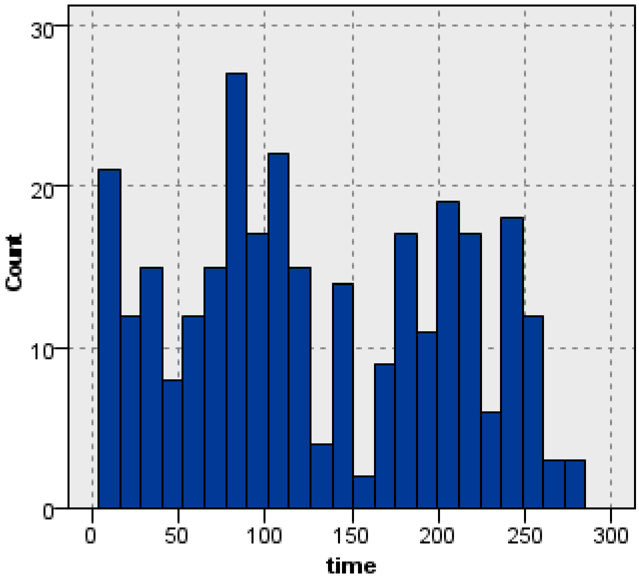
Min value: 0
Maximum value: 1
Mode: 1
Unique: 2
Valid values: 299

- Smoking

Value	Proportion	%	Count
0		67.89	203
1		32.11	96

Min value: 0
Maximum value: 1
Mode: 0
Unique: 2
Valid values: 299

- Time



Min value: 4
Maximum value: 285
Sum of all values: 38948
Range: 281
Mean: 130.261
Mean std. error: 4.489
Std. deviation: 77.614
Variance: 6023.965
Skewness: 0.128
Skewness std. error: 0.141
Kurtosis: -1.212

Kurtosis std. error: 0.281
Median: 115
Mode: 187
Valid values: 299

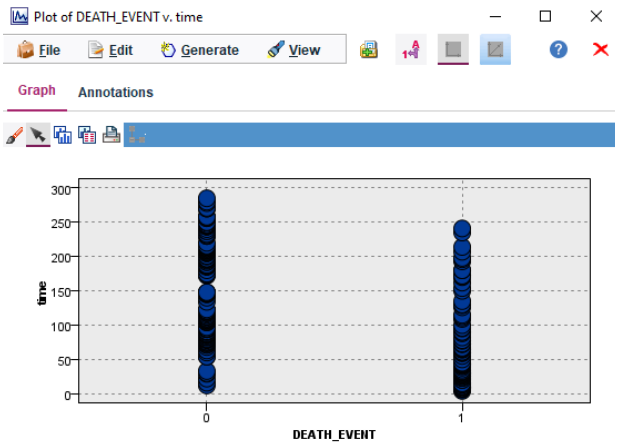
- Death_event

Value	Proportion	%	Count
0		67.89	203
1		32.11	96

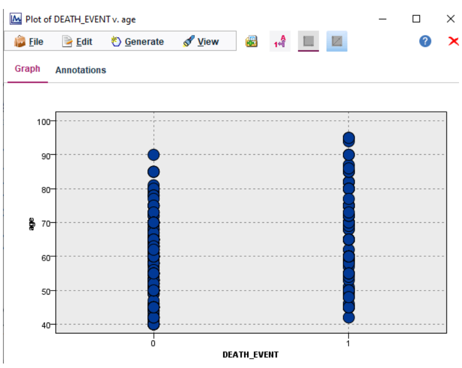
Min value: 0
Maximum value: 1
Mode: 0
Unique: 2
Valid values: 299

What sort of hypothesis have you formed about the data?

- Death rate caused by heart failure might decrease with the increase number of days the patient will be under observation since he would have discharged only after showing improvements.



- Deaths due to heart failure might be high in people aged 40-60 due to their unhealthy lifestyle.



- Deaths due to heart failure are related to all the health conditions in the database.
- Deaths due to heart failure might not be related to sex of the person.

Which attributes seem promising for further analysis?
Age, anaemia, creatinine_phosphokinase, diabetes, ejection_fraction, high_blood_pressure, serum_creatinine, serum_sodium and smoking are seeming to be the most promising for further analysis.

Have your explorations revealed new characteristics about your data?
Explorations helped us understand the data better but haven't revealed any new characteristics yet. It will probably happen during modeling.

How have your explorations changed your initial hypothesis?
Explorations have definitely helped us understand the data better and gave us the clarity of attributes which will be helpful during modeling. However, the initial hypothesis still stands the same.

Can you identify particular subsets of data for later use?
I am planning to segment each of my attributes with death to understand the individual patterns properly and to not miss out on anything.

Take another look at your data mining goals. Has this exploration altered the goals?
While the goals remain the same, I definitely believe that additional data might really help to predict deaths caused by heart failures.

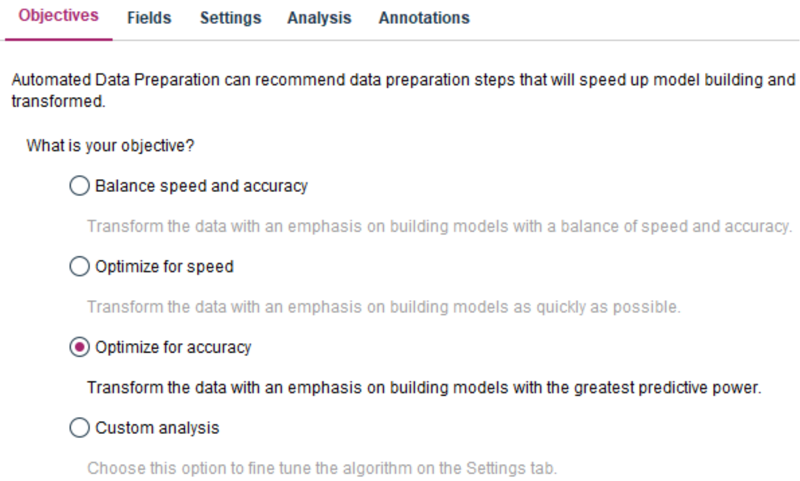
DATA QUALITY

Using data audit node, we can see there are some outliers and extremes that are skewing our data. Let us handle them.
Here, I have coerced the outliers and discarded the extremes and then connected the super node (newly generated) to auto data prep node.

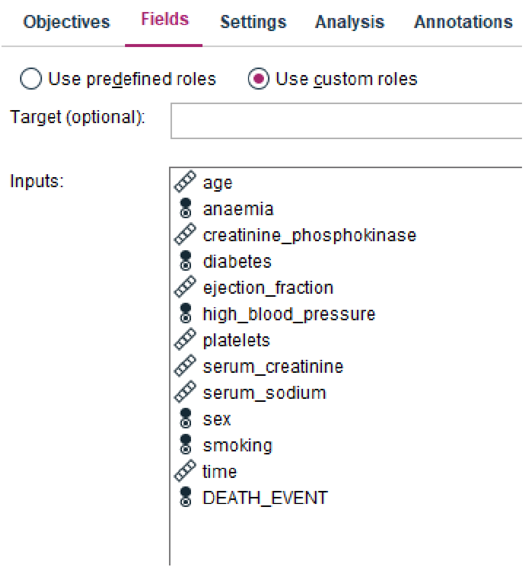
Complete fields (%): 100% Complete records (%): 100%

Field	Measurement	Outliers	Extremes	Action	Impute Missing	Method	% Complete	Valid Records	Null Value	Empty String	White Space
age	Continuous	0	0	None	Never	Fixed	100	299	0	0	
anaemia	Flag	--	--	--	Never	Fixed	100	299	0	0	
creatinine_p...	Continuous	4	3	Coerce outliers / discard extremes	Never	Fixed	100	299	0	0	
diabetes	Flag	--	--	--	Never	Fixed	100	299	0	0	
ejection_fract...	Continuous	1	0	Coerce	Never	Fixed	100	299	0	0	
high_blood_...	Flag	--	--	--	Never	Fixed	100	299	0	0	
platelets	Continuous	2	1	Coerce outliers / discard extremes	Never	Fixed	100	299	0	0	
serum_creati...	Continuous	3	3	Coerce outliers / discard extremes	Never	Fixed	100	299	0	0	
serum_sodi...	Continuous	2	1	Coerce outliers / discard extremes	Never	Fixed	100	299	0	0	
sex	Flag	--	--	--	Never	Fixed	100	299	0	0	
smoking	Flag	--	--	--	Never	Fixed	100	299	0	0	
time	Continuous	0	0	None	Never	Fixed	100	299	0	0	
DEATH_EVE...	Flag	--	--	--	Never	Fixed	100	299	0	0	

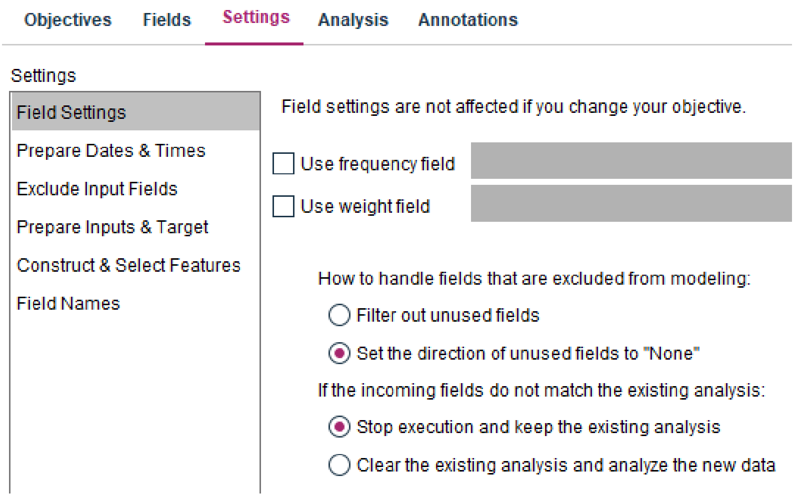
Let us optimize for accuracy rather then speed.



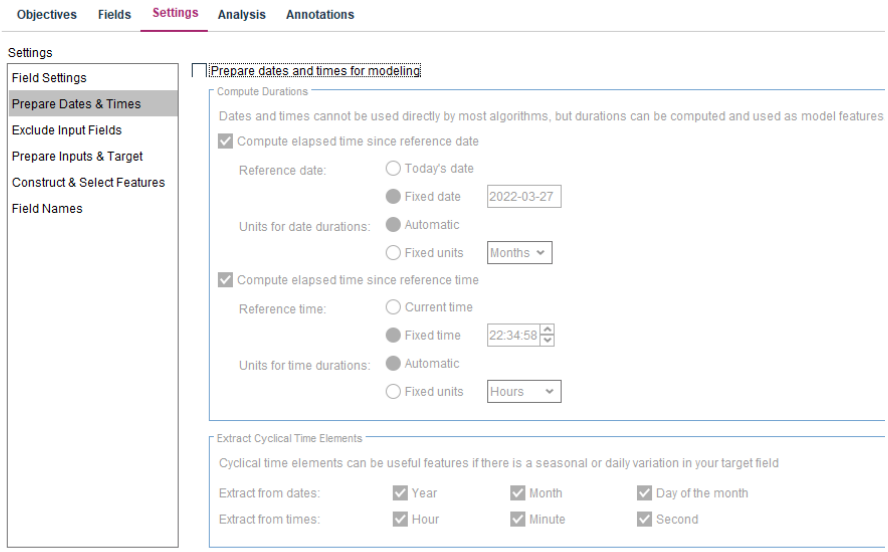
We have taken all fields as input and none as target.



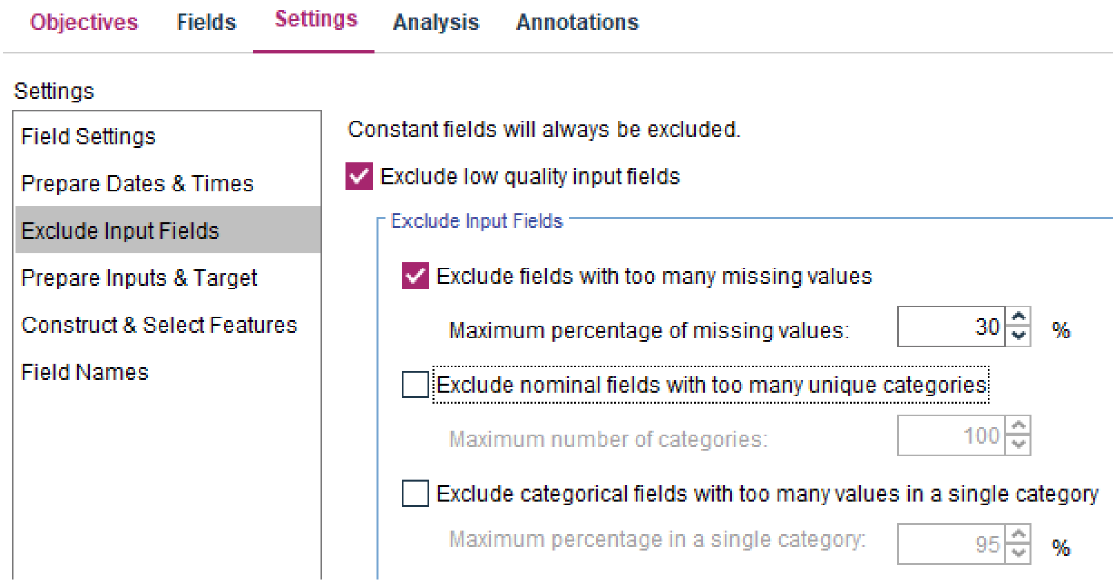
I have made a few changes in settings according to my dataset and requirements as shown.



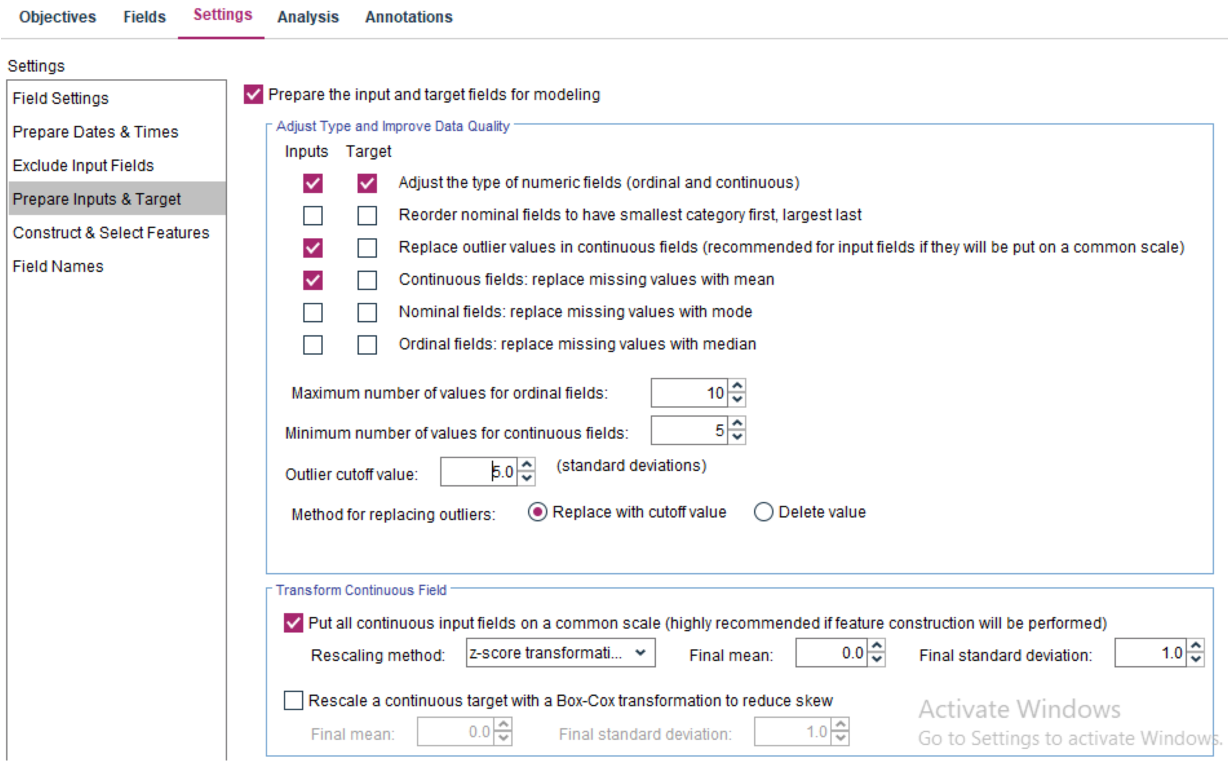
I do not need this because I have no dates and times in my data.



I unselected nominal and ordinal settings because I do not have data with those measurement levels.



Again, I only kept the ones having my measurement levels in it. I have kept the remaining settings unchanged since they did not require to be changed.



Now connect a data audit node to this auto data prep node.
We can see how the records having extremes have been removed from the data and how the outliers have been coerced.

Complete fields (%): 100% Complete records (%): 100%

Field	Measurement	Outliers	Extremes	Action	Impute Missing	Method	% Complete	Valid Records	Null Value	Empty String	White Space
age_transfor...	Continuous	0	0	None	Never	Fixed	100	291	0	0	
creatinine_p...	Continuous	0	0	None	Never	Fixed	100	291	0	0	
ejection_fract...	Continuous	0	0	None	Never	Fixed	100	291	0	0	
platelets_tra...	Continuous	0	0	None	Never	Fixed	100	291	0	0	
serum_creati...	Continuous	0	0	None	Never	Fixed	100	291	0	0	
serum_sodi...	Continuous	0	0	None	Never	Fixed	100	291	0	0	
time_transfor...	Continuous	0	0	None	Never	Fixed	100	291	0	0	
anaemia_tra...	Flag	--	--	--	Never	Fixed	100	291	0	0	
diabetes_tra...	Flag	--	--	--	Never	Fixed	100	291	0	0	
high_blood_...	Flag	--	--	--	Never	Fixed	100	291	0	0	
sex_transfor...	Flag	--	--	--	Never	Fixed	100	291	0	0	
smoking_tra...	Flag	--	--	--	Never	Fixed	100	291	0	0	
DEATH_EVE...	Flag	--	--	--	Never	Fixed	100	291	0	0	

This shows that the data has been cleaned according to the requirements.

Have you identified missing attributes and blank fields? If so, is there meaning behind such missing values?
No, there are no missing attributes and blank fields. However, the labels in sex attribute were not mentioned but I did my research and added them.

Are there spelling inconsistencies that may cause problems in later merges or transformations?
No, there are no spelling inconsistencies that may cause problems in later merges or transformations since the data has no alphabets or characters.

Have you explored deviations to determine whether they are "noise" or phenomena worth analysing further?
There is some skewness in a few attributes which can later be reduced to clean the noise.

Have you conducted a plausibility check for values? Take notes on any apparent conflicts (such as teenagers with high income levels).
Yes, I did conduct a plausibility check for values. There is no apparent conflict as such.

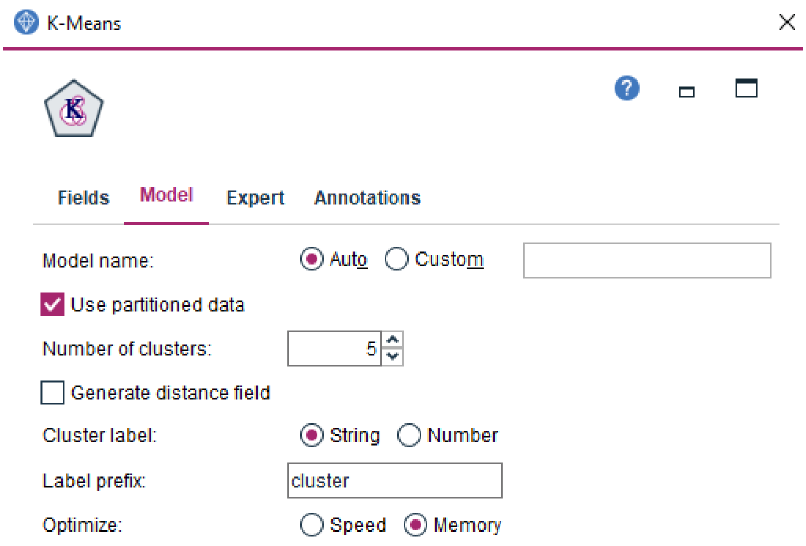
Have you considered excluding data that has no impact on your hypothesis?
Yes, I have. It concluded with the fact that all data is important for the analysis since each and every attribute might add up to the death caused by heart failure. So, I will not exclude any data.

Are the data stored in flat files? If so, are the delimiters consistent among files? Does each record contain the same number of fields?
Yes. The delimiters are consistent among files. Each record contains the same number of fields.

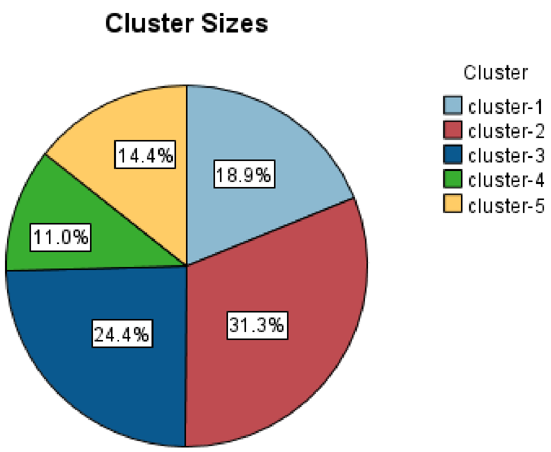
We have managed to successfully clean the data and will now move forward towards modeling.

MODELING

A. Segmentation (without target)



Here, we will use K-Means node and will create 5 clusters. We can see that the clusters have been created.



Size of Smallest Cluster	32 (11%)
Size of Largest Cluster	91 (31.3%)
Ratio of Sizes: Largest Cluster to Smallest Cluster	2.84

Table (27 fields, 291 records) #3

File Edit Generate

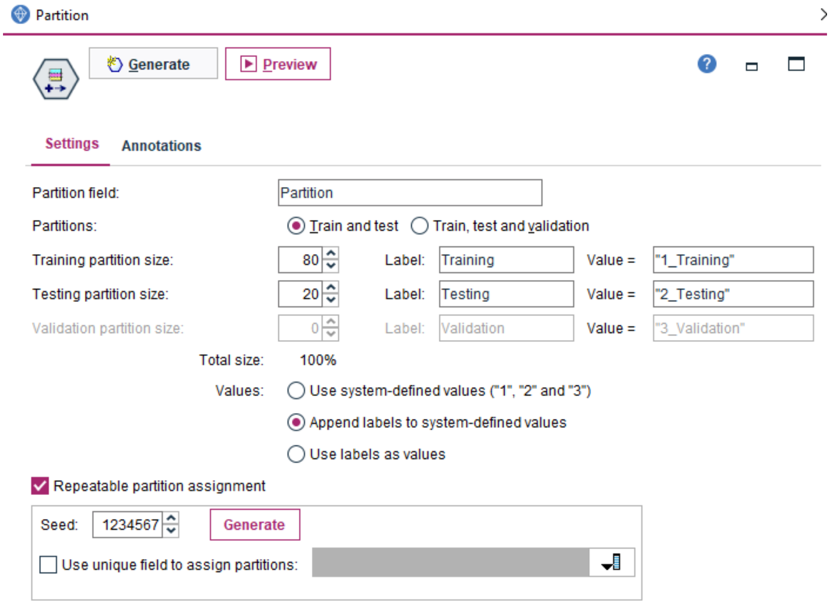
Table Annotations

	rmed	serum_sodium_transformed	time_transformed	anaemia_transformed	diabetes_transformed	high_blood_pressure_transformed	sex_transformed	smoking_transformed	DEATH_EVENT_transformed	$KM-K-Means
1	0.847	-1.655	-1.647	1	1	0	1	1	0	cluster-1
2	0.018	-1.902	-1.608	1	1	1	1	0	0	cluster-4
3	0.847	0.071	-1.608	0	1	1	1	1	0	cluster-1
4	2.000	-3.287	-1.595	0	0	1	0	1	0	cluster-2
5	1.135	-1.162	-1.595	0	1	0	1	0	0	cluster-5
6	0.162	0.071	-1.570	0	1	1	1	1	0	cluster-1
7	0.306	-1.409	-1.570	0	0	1	1	0	0	cluster-4
8	0.270	0.318	-1.570	1	1	1	0	1	0	cluster-1
9	3.874	-1.409	-1.570	0	1	0	1	0	0	cluster-5
10	0.595	0.811	-1.570	1	1	0	1	0	0	cluster-1
11	0.306	0.071	-1.557	0	1	1	1	1	0	cluster-1
12	0.306	0.071	-1.557	0	1	0	1	1	0	cluster-5
13	0.451	0.318	-1.544	0	1	0	0	1	1	cluster-5
14	0.018	-0.175	-1.531	0	1	1	1	1	0	cluster-1
15	0.595	0.811	-1.518	0	1	1	1	1	0	cluster-1
16	0.739	-2.396	-1.518	1	1	1	1	1	0	cluster-1
17	0.451	0.811	-1.505	0	1	0	0	1	0	cluster-5
18	0.847	-3.287	-1.505	0	0	1	0	1	0	cluster-2
19	0.018	0.071	-1.492	0	1	0	0	1	1	cluster-5
20	0.414	-0.175	-1.441	0	0	0	0	1	0	cluster-5
21	0.595	0.811	-1.441	0	1	0	1	0	0	cluster-5
22	0.739	-0.422	-1.415	1	0	1	1	1	1	cluster-2
23	0.746	-0.669	-1.402	1	0	0	0	1	0	cluster-1
24	0.847	1.798	-1.402	1	0	1	1	0	0	cluster-4
25	0.451	0.318	-1.389	0	1	0	0	1	0	cluster-5
26	0.018	-0.175	-1.363	1	0	0	1	0	0	cluster-4
27	4.591	-0.669	-1.363	0	1	1	1	1	0	cluster-1
28	0.162	-1.162	-1.363	1	0	1	1	0	0	cluster-4
29	0.746	-0.669	-1.350	1	0	0	1	1	0	cluster-1
30	2.432	-1.162	-1.337	1	1	1	1	1	0	cluster-1
31	0.451	-2.149	-1.337	0	0	0	0	1	0	cluster-5
32	0.162	0.318	-1.324	0	0	1	0	1	1	cluster-2
33	0.451	0.811	-1.324	1	0	0	1	1	0	cluster-1
34	3.153	-0.669	-1.311	1	0	1	1	1	0	cluster-4

These clusters will group the data for us, as to which group of lifestyle patterns is more likely to experience a heart failure.

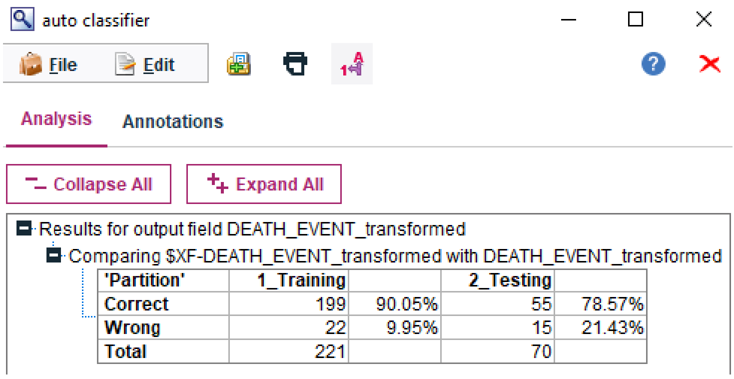
B. Supervised (with target)

Let us first partition our data in 80% training and 20% testing.



Now, let us check the accuracy of all supervised models and see some of the best:

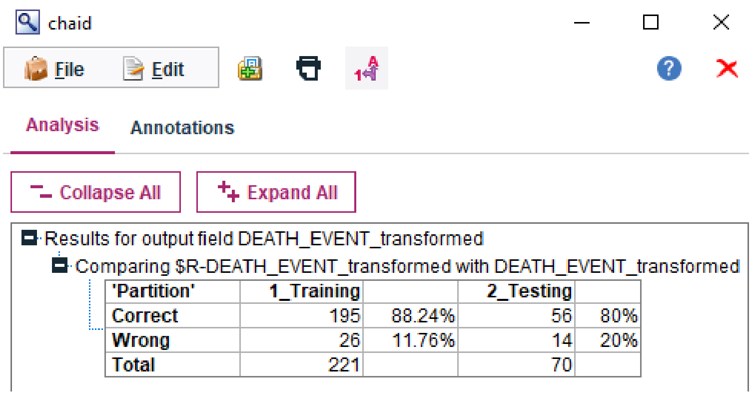
<u>Analysis of Auto Classifier:</u>



'Partition'	1_Training		2_Testing	
Correct	199	90.05%	55	78.57%
Wrong	22	9.95%	15	21.43%
Total	221		70	

We are getting 78.57% accuracy.

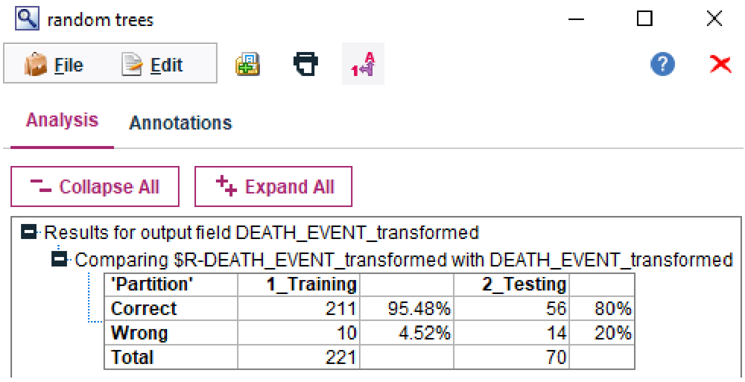
<u>Analysis of CHAID:</u>



'Partition'	1_Training		2_Testing	
Correct	195	88.24%	56	80%
Wrong	26	11.76%	14	20%
Total	221		70	

We are getting 80% accuracy.

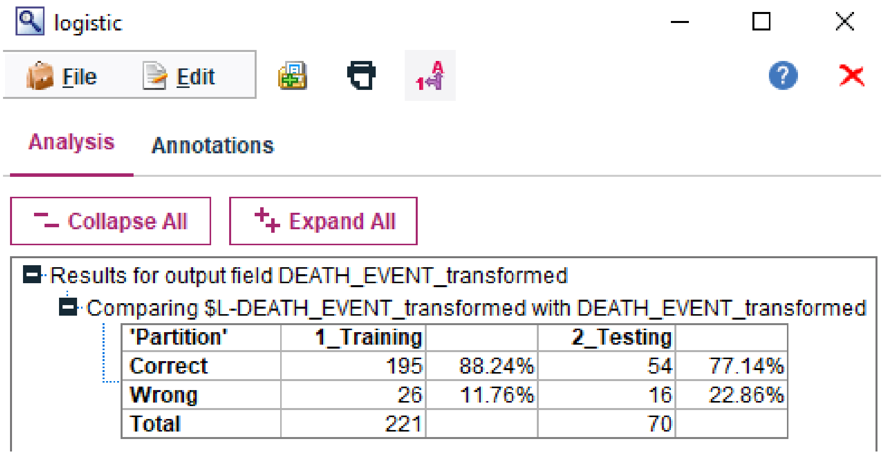
<u>Analysis of Random Trees:</u>



'Partition'	1_Training		2_Testing	
Correct	211	95.48%	56	80%
Wrong	10	4.52%	14	20%
Total	221		70	

We are getting 80% accuracy.

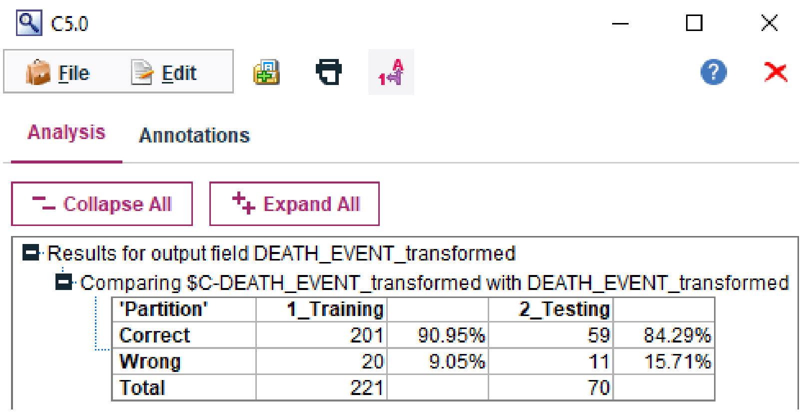
<u>Analysis of Logistic regression:</u>



'Partition'	1_Training		2_Testing	
Correct	195	88.24%	54	77.14%
Wrong	26	11.76%	16	22.86%
Total	221		70	

We are getting 77.14% accuracy.

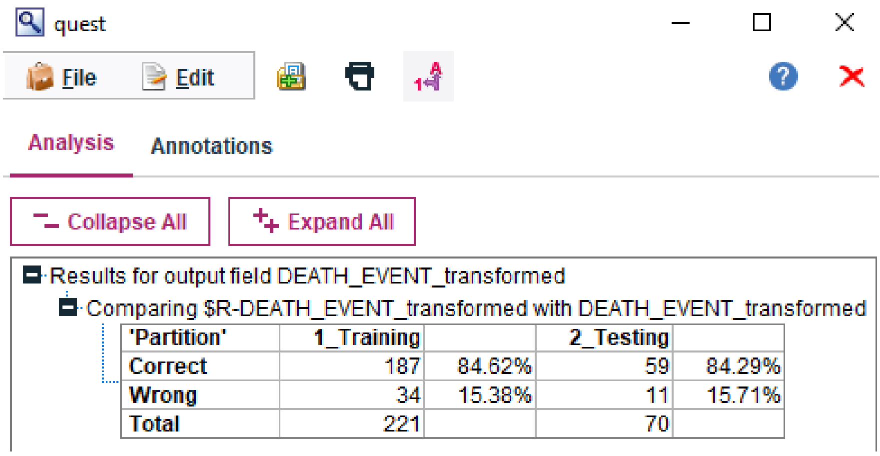
<u>Analysis of C5.0:</u>



'Partition'	1_Training		2_Testing	
Correct	201	90.95%	59	84.29%
Wrong	20	9.05%	11	15.71%
Total	221		70	

We are getting 84.29% accuracy.

Analysis of Quest:



'Partition'	1_Training		2_Testing	
Correct	187	84.62%	59	84.29%
Wrong	34	15.38%	11	15.71%
Total	221		70	

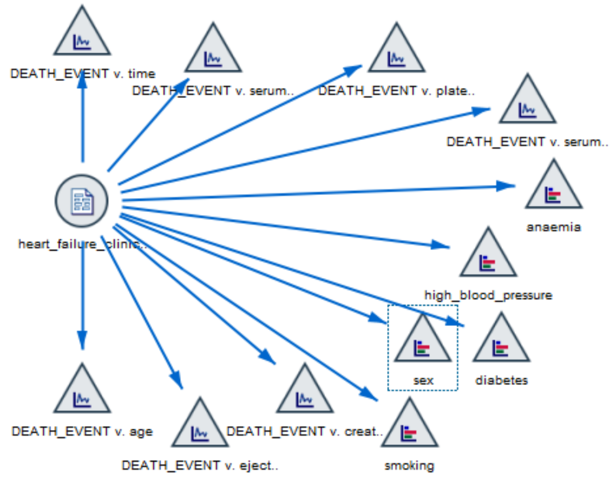
We are getting 84.29% accuracy.

Here, we are getting highest accuracy on testing data of 84.29% by C5.0 and Quest models.

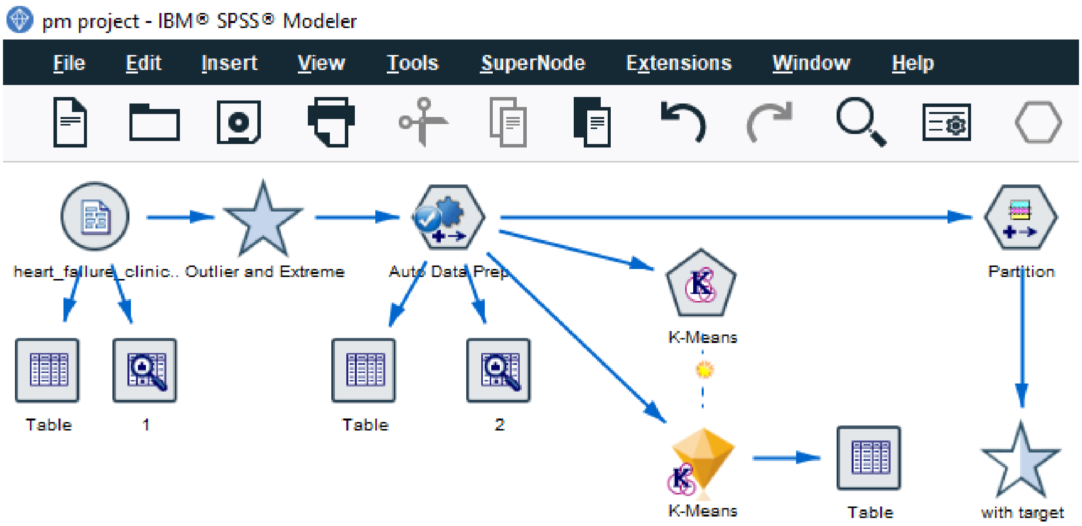
We can use this model to predict whether the person is likely to face mortality due to heart failure or not as per his lifestyle data/records.

FINAL STREAM

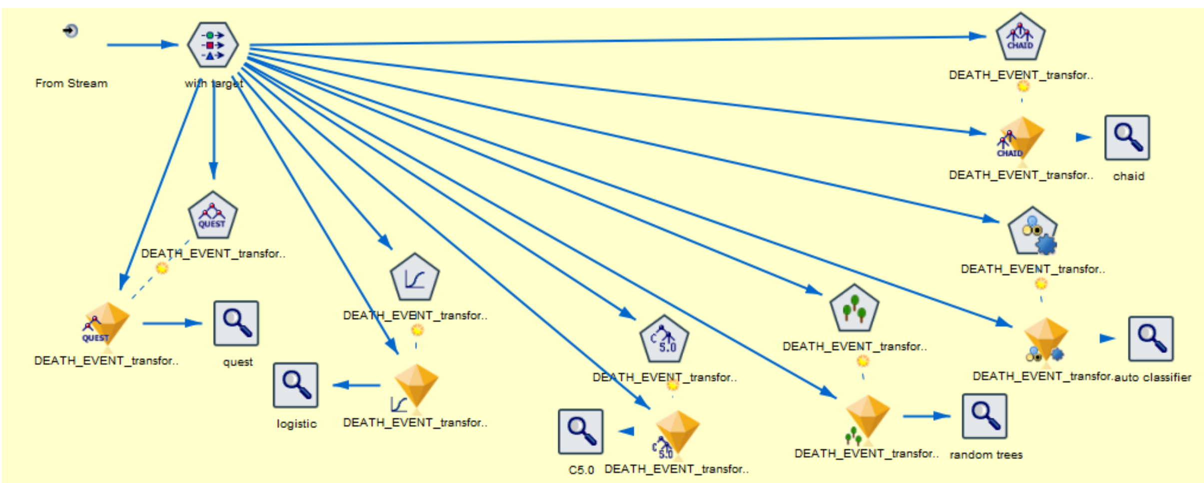
Visualization for hypothesis:



Data cleaning and segmentation using K-Means:



Supervised modeling of testing and training data using various models:



CONCLUSION

1. We have managed to successfully clean the data.

2. We segmented our data using K-Means model to divide it in 5 different clusters to predict and study the patterns of lifestyle that contributes to the heart failure.

3. We compared all the supervised modelling nodes where C5.0 and Quest models give the best accuracy of 84.29%.

4. We can further use these models for deployment and to predict the mortality caused by heart failure.