# PM PROJECT REVIEW I

## G14: HEART FAILURE PREDICTION

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# AIM

CREATE A MODEL FOR PREDICTING MORTALITY CAUSED BY HEART FAILURE.

# ABOUT 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.

# DATA DESCRIPTION REPORT

## KNOW YOUR DATA

# DATA DESCRIPTION ANALYSIS

- Age: Age of patients (years)
- Anaemia: Condition where red blood cells are decreased (Boolean: 0 for false, 1 for true)
- Creatinine_phosphokinase: Level of CPK enzyme in blood (mcg/L)
- Diabetes: Whether the patient has diabetes (Boolean: 0 for false, 1 for true)
- Ejection_fraction: Percentage of blood leaving from heart at each contraction (percentage)
- High_blood_pressure: Whether the patient has high blood pressure (Boolean: 0 for false, 1 for true)
- Platelets: Platelets in blood (kiloplatelets/mL)
- Serum_creatinine: Level of serum creatinine in blood (mg/dL)
- Serum_sodium: Level of serum sodium in blood (mEq/L)
- Sex: Man or Woman (Boolean: 0 for man, 1 for woman)
- Smoking: Whether the patient smokes or not (Boolean: 0 for false, 1 for true)
- Time: Follow-up period (days)
- Death_event: If the patient dies during follow-up period (Boolean: 0 for false, 1 for true)

# DATA DESCRIPTION ANALYSIS

- **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.

- **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.

- **What data types are present?**

We have integer and real data types and Flag and Continuous measurement levels.

# DATA DESCRIPTION ANALYSIS

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

| 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 |

# DATA DESCRIPTION ANALYSIS

- **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 REPORT

EXPLORE YOUR DATA

# 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.

# DATA EXPLORATION

**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 |

# DATA EXPLORATION

## 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 |

# DATA EXPLORATION

## 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

Activate Windows
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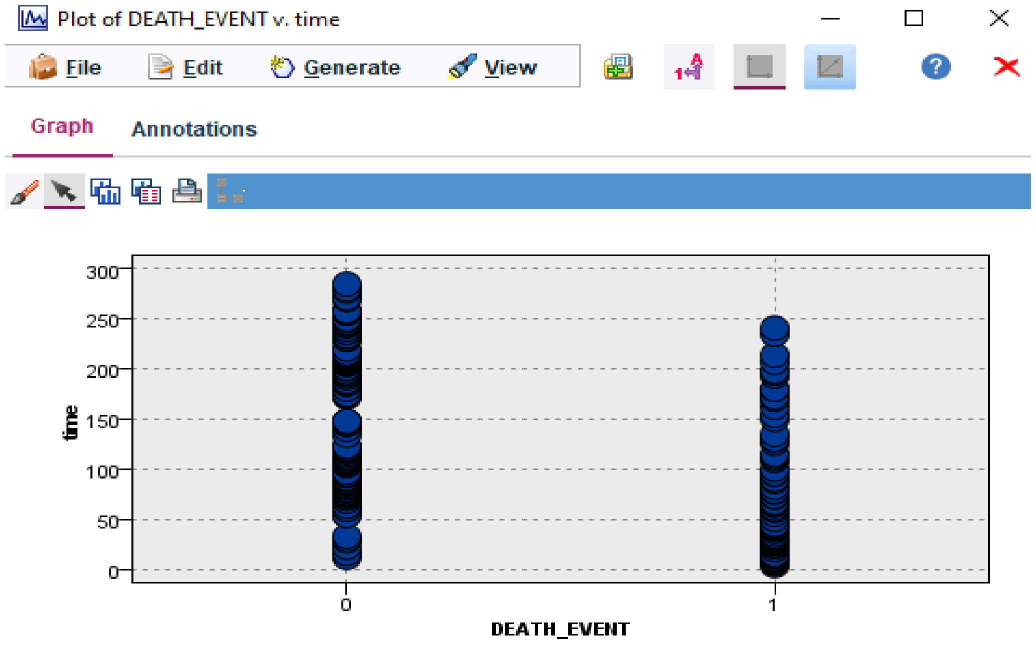
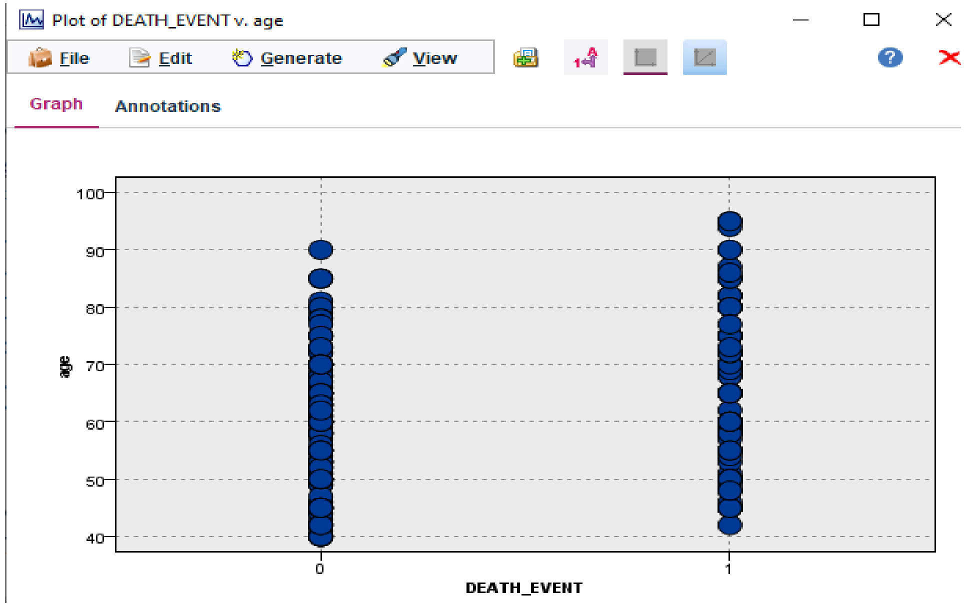
# DATA EXPLORATION

**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.



# DATA EXPLORATION

**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 REPORT

EVALUATE THE QUALITY OF YOUR DATA

# DATA QUALITY

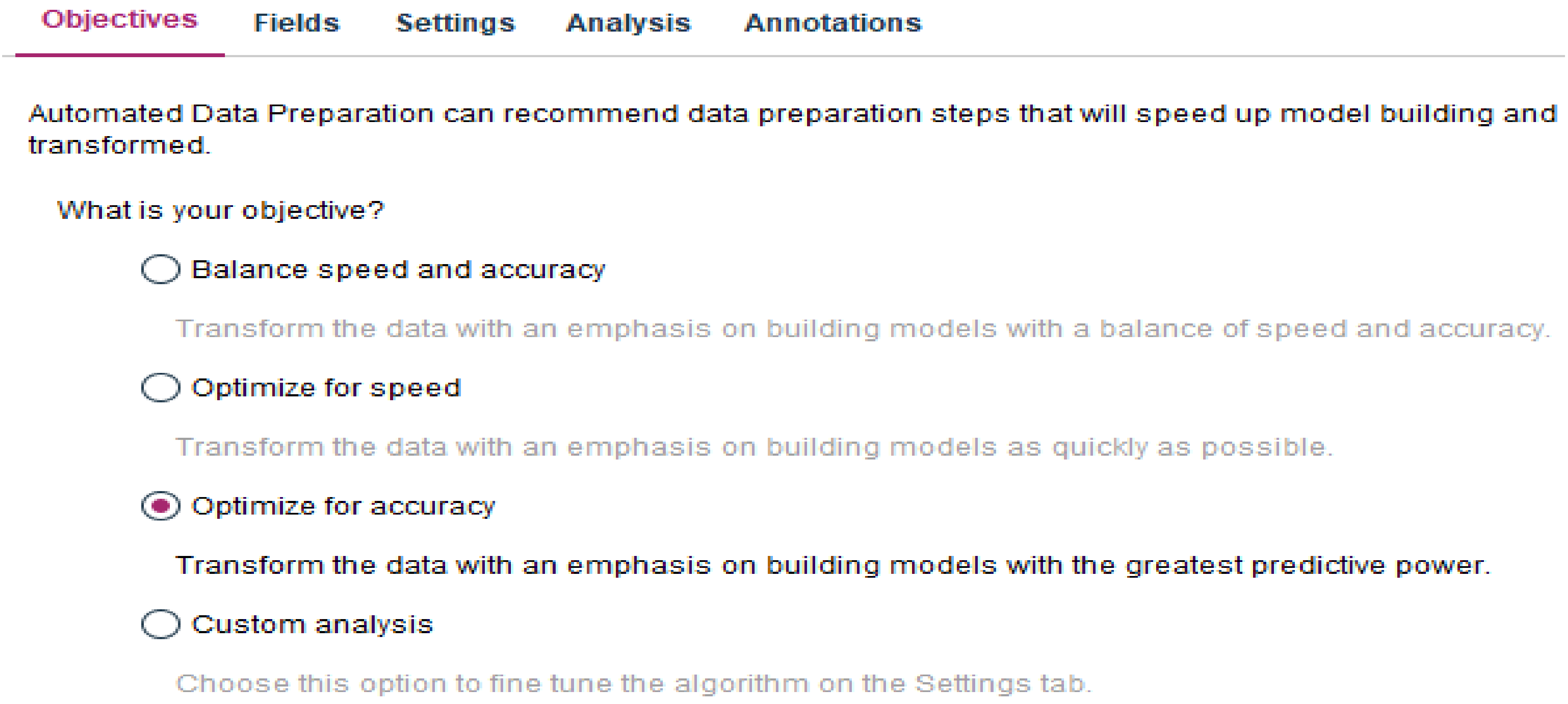
Using data audit node, we can see there are some outliers and extremes that are skewing our data. Let us handle them. Here, I have coerced the outliers and discarded the extremes and then connected the super node (newly generated) to auto data prep node.

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 | |

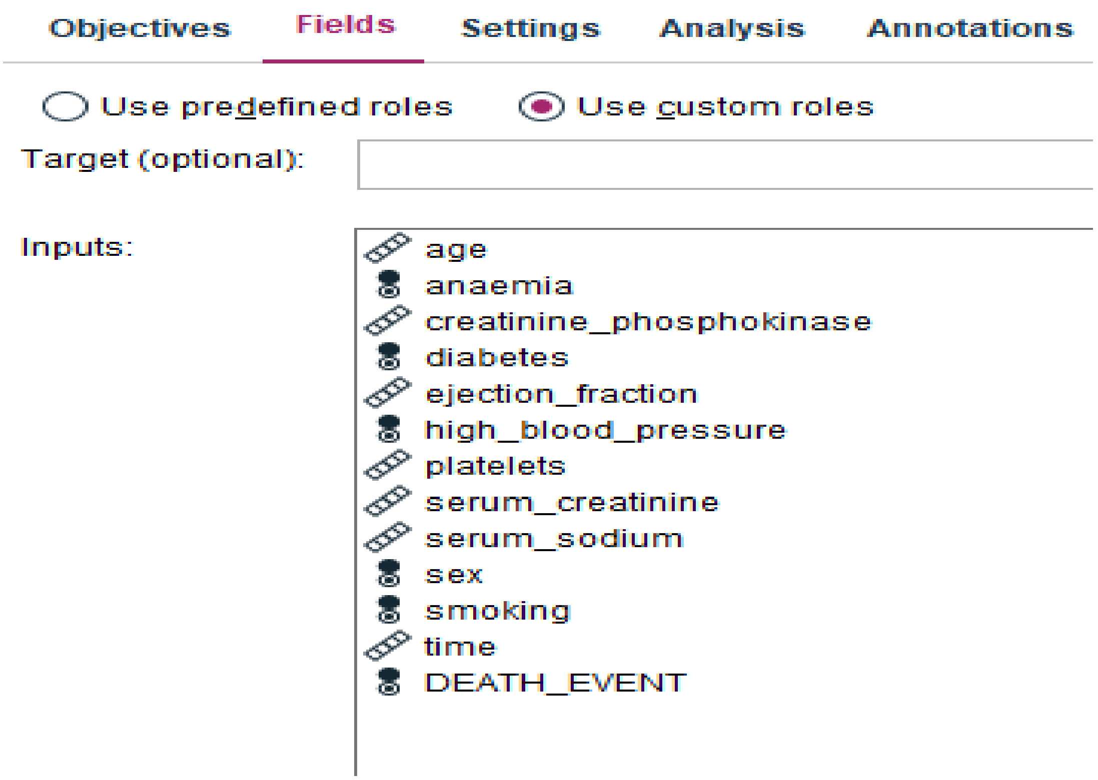
# DATA QUALITY

- Let us optimize for accuracy rather then speed.



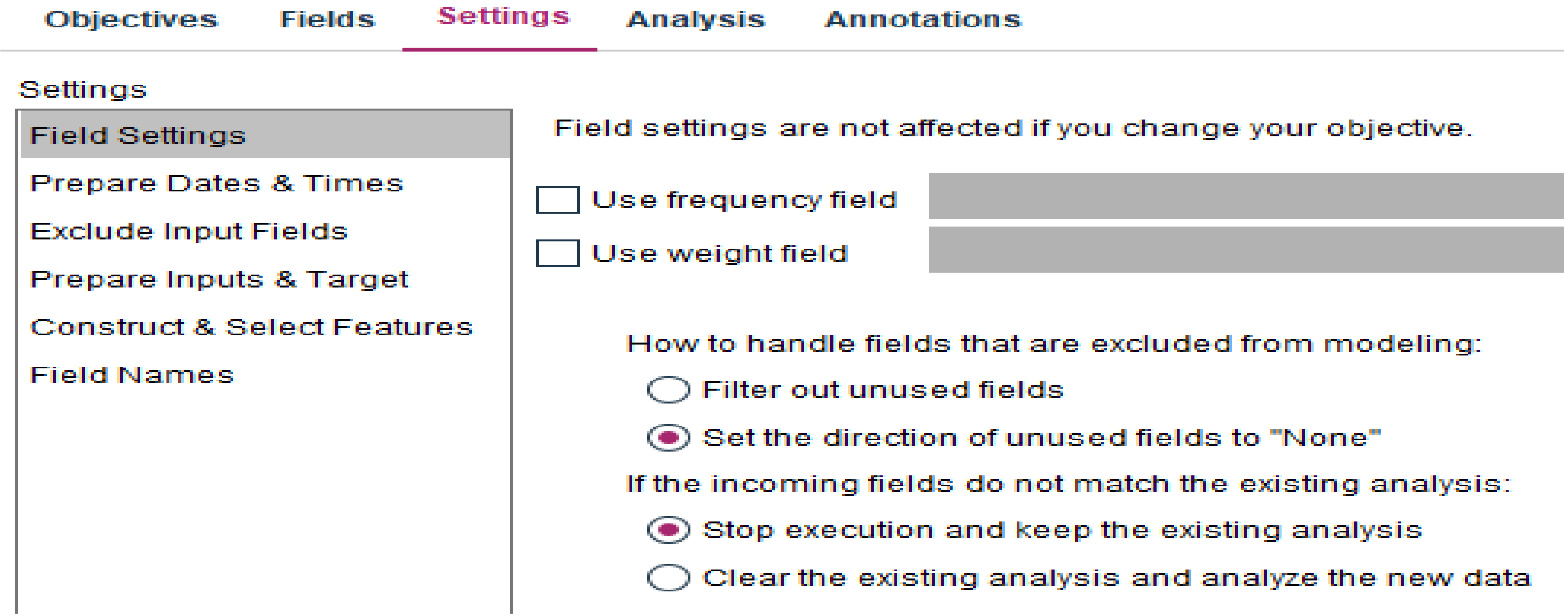
# DATA QUALITY

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



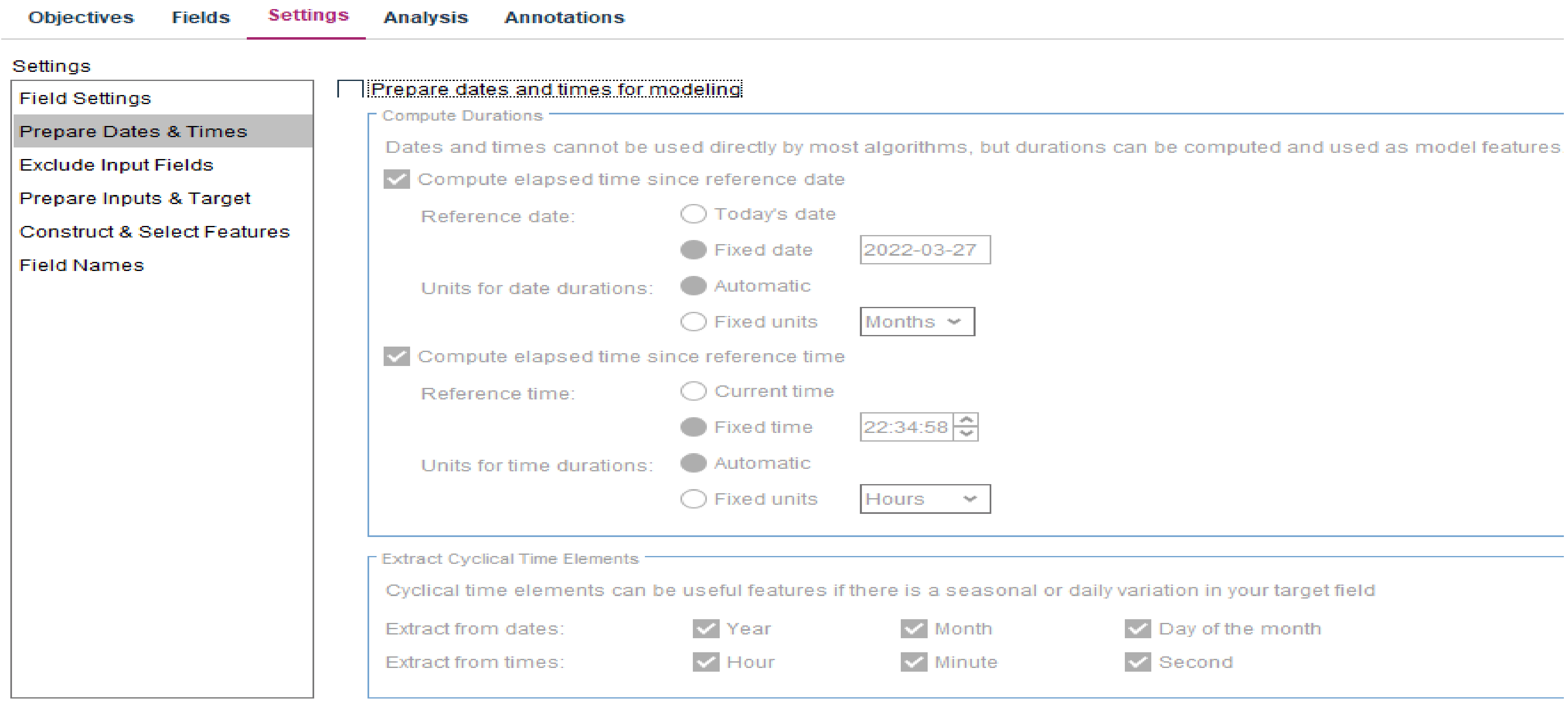
# DATA QUALITY

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



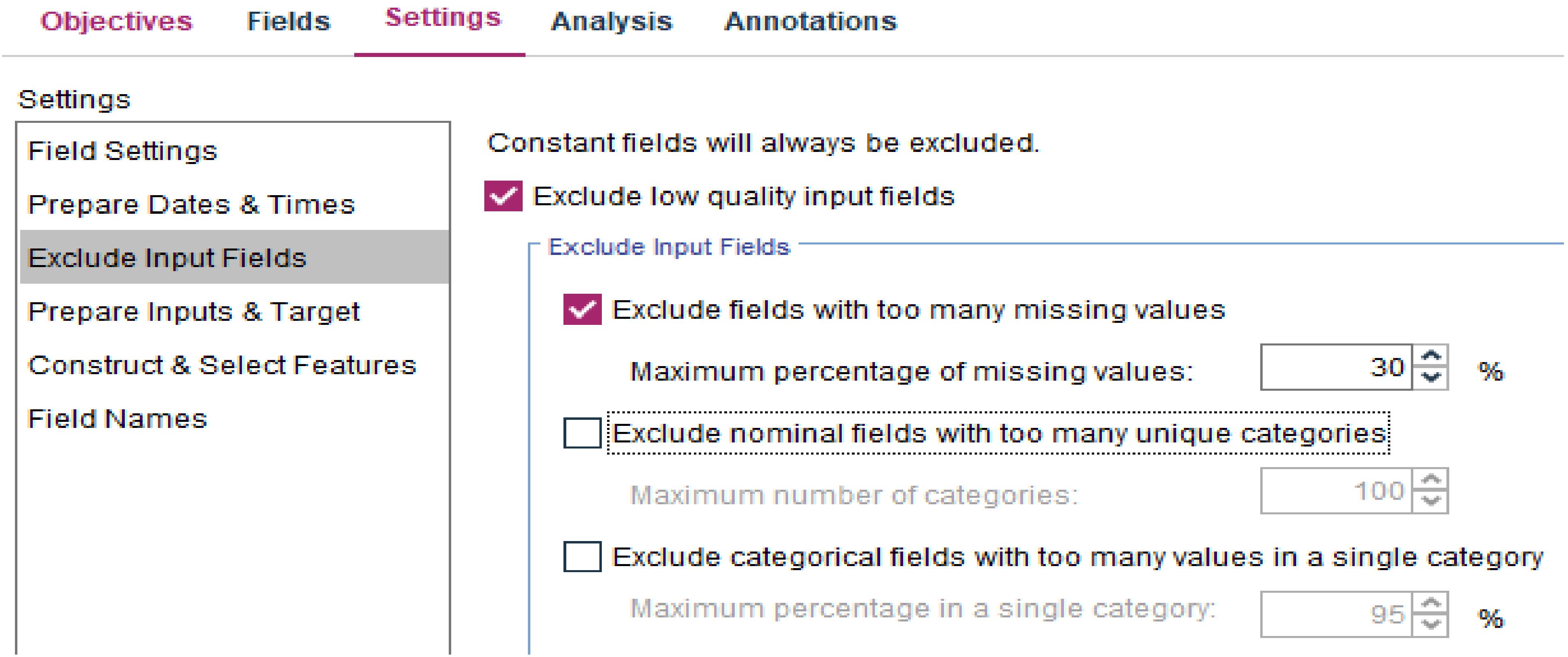
# DATA QUALITY

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



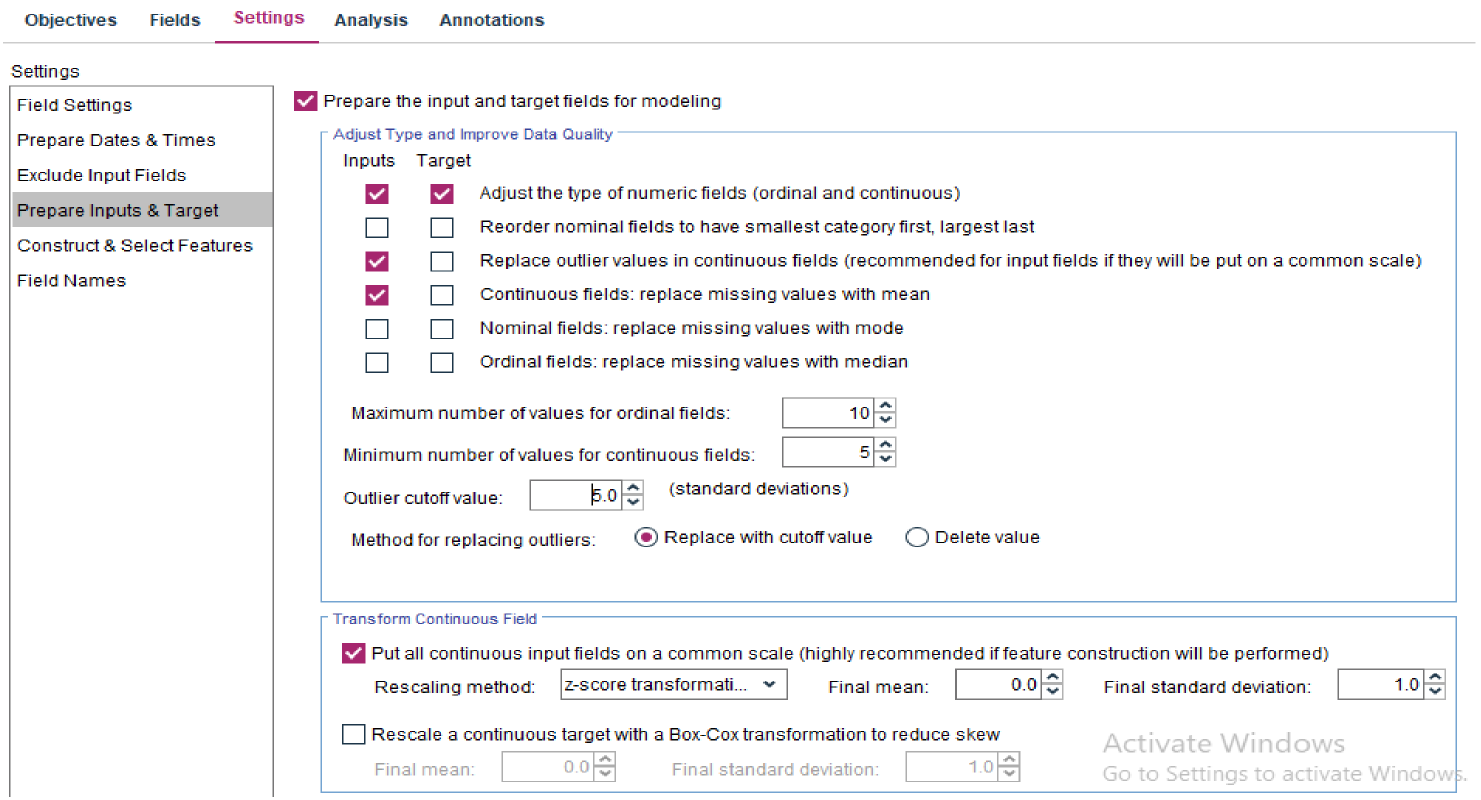
# DATA QUALITY

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



# DATA QUALITY

- 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.



# DATA QUALITY

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

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 | |

# DATA QUALITY

- **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.

# DATA QUALITY

- **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?**

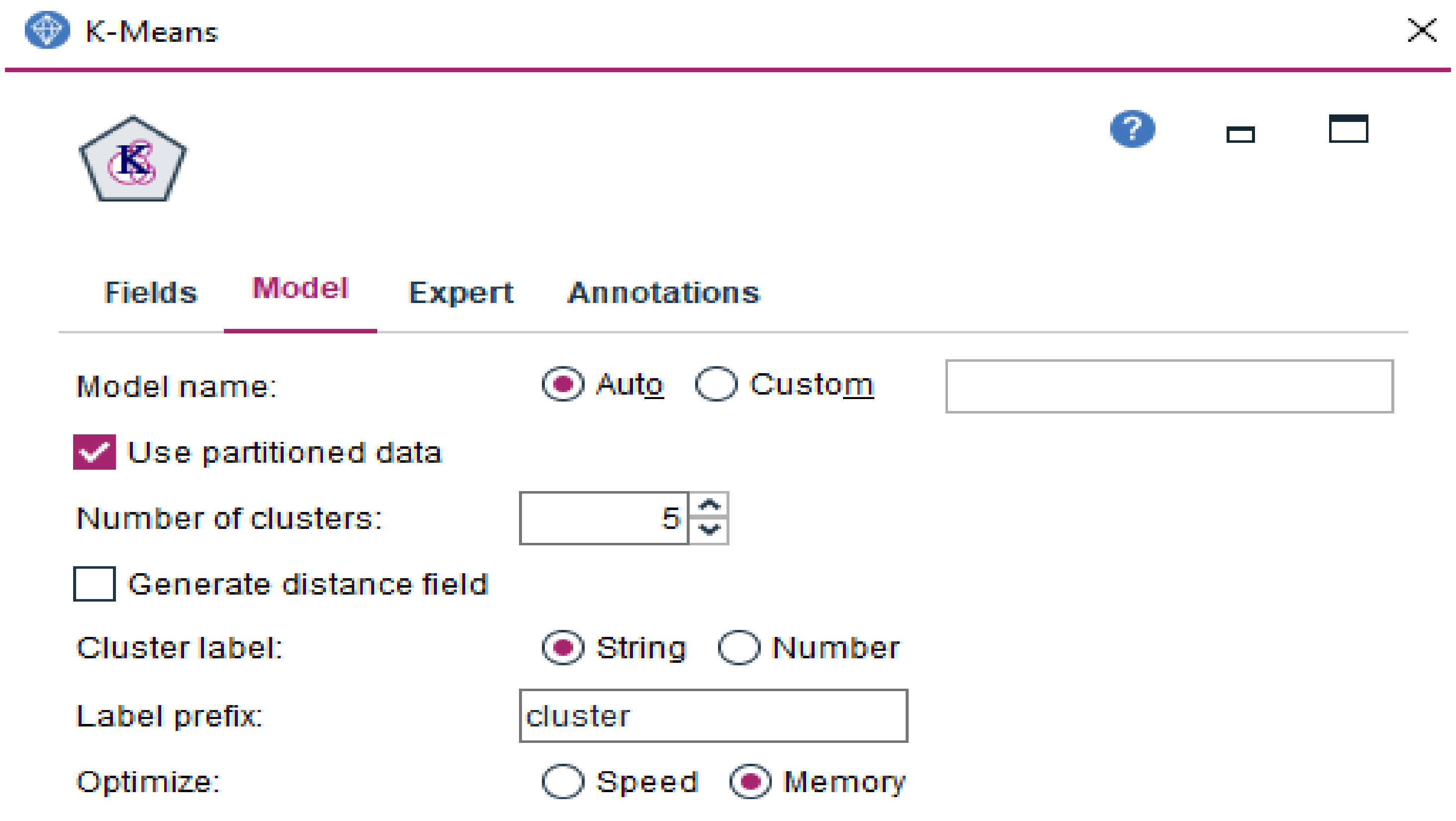
Yes, I have. It concluded with the fact that all data is important for the analysis since each and every attribute might add up to the death caused by heart failure. So, I will not exclude any data.

- **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.

# SEGMENTATION MODELING

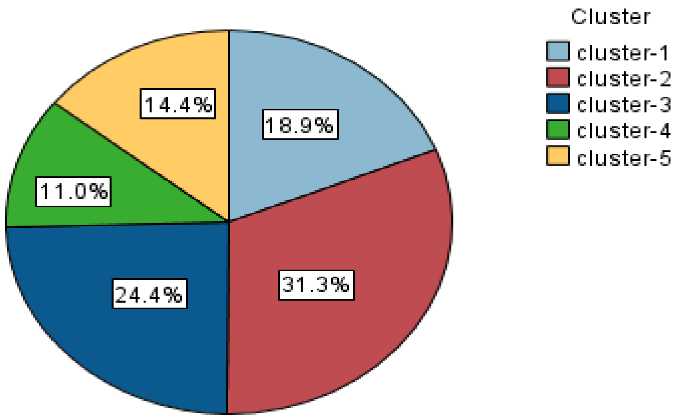
- We will use K-Means model to create 5 clusters of our data.



# SEGMENTATION MODELING

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

**Cluster Sizes**




| | |
|---|---|
| **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 |

Activate Windows
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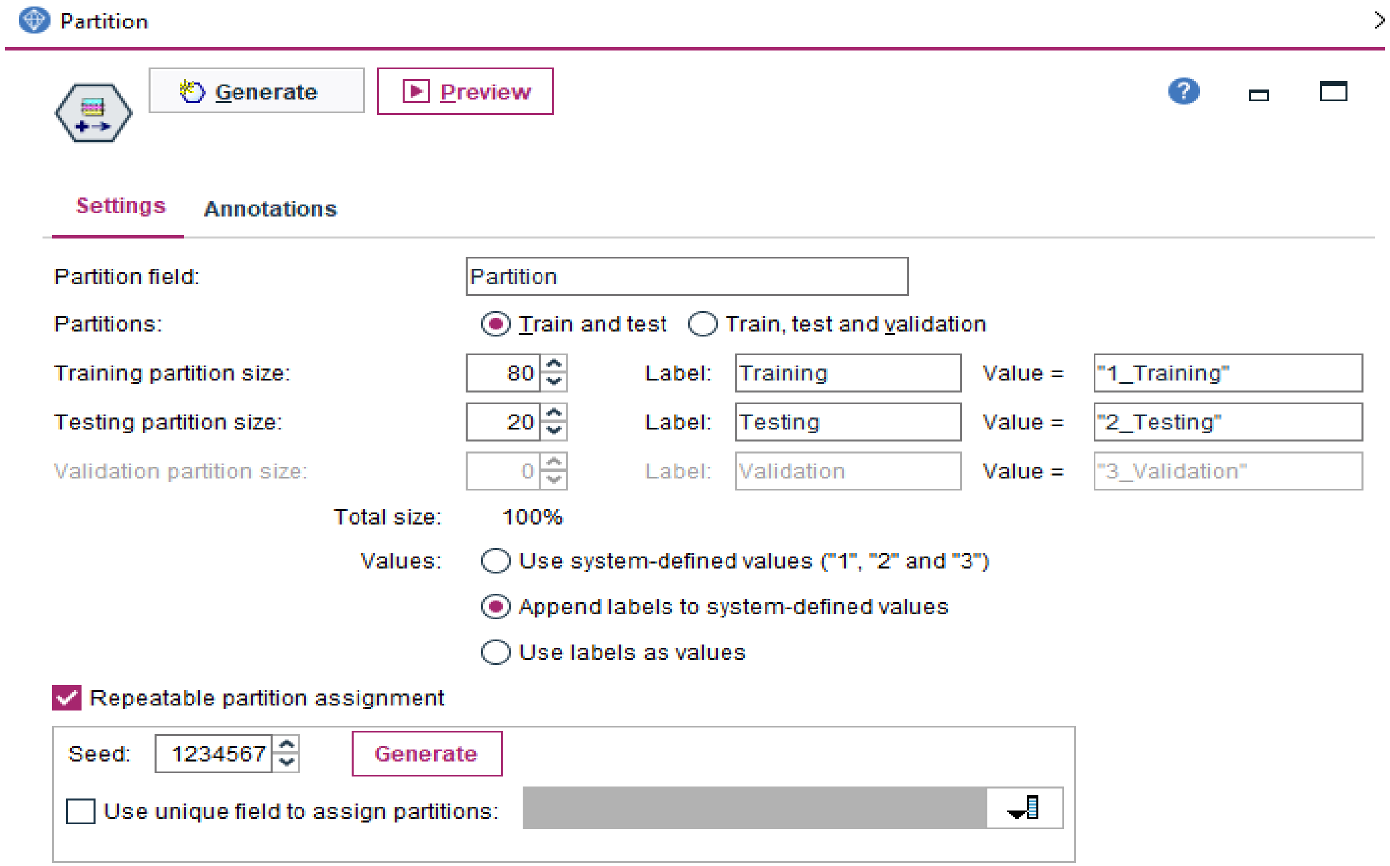
# SUPERVISED MODELING

- We will partition the data into 80% training and 20% testing.



# SUPERVISED MODELING

- Now, after checking accuracies of all the models, C5.0 and Quest give us the best accuracy of 84.29%
- 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.

quest

File Edit

Analysis Annotations

Collapse All Expand All

Results for output field DEATH_EVENT_transformed

Comparing $R-DEATH_EVENT_transformed with DEATH_EVENT_transformed

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

# CONCLUSION

- We have managed to successfully clean the data.
- 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.
- We compared all the supervised modelling nodes where C5.0 and Quest models give the best accuracy of 84.29%.
- We can further use these models for deployment and to predict the mortality caused by heart failure.