Documentation – heart-disease

Repo: https://github.com/HuberNicolas/heart-disease

About the project

Python Version: 3.8.5 (64-bit)

R Version: 4.0.4 (64-bit)

Name of the folder	Description
0 raw .data	Contains the raw data (incl. .md5 hashes) from the source.
1 raw .csv	Contains the renamed .csv files and the formatter script (incl. .md5 hashes).
2 formatted .csv	Contains the formatted .csv files without a header (incl. .md5 hashes).
data	Contains the datasets (incl. header) the analysis was run (incl. .md5 hashes).
logs	Contains the logfiles of the scripts.
plots	Contains the plots that were generated during the analysis.
rand_forest_feature_selection(25)	Contains the datasets (incl. header) after the random forest selection. These sets contain 25 features, that can "explain" 80% of the data.

About the datasets

The following explanations are based on the heart-disease.NAMES file.

# of Instances:

- Cleveland: 303
- Hungarian: 294
- Switzerland: 123
- Long Beach VA: 200

Number of Attributes: 76 (including the predicted attribute) See appendix for the complete list. (Missing Attribute Values: Several. Distinguished with value -9.0.)

"This database contains 76 attributes, but all published experiments refer to using a subset of 14 of them. In particular, the Cleveland database is the only one that has been used by ML researchers to this date."

Class distribution: (Classtype (domain [0,4]) is referring to feature 58 "num", diagnosis of heart disease (angiographic disease status). This indicates, how severe the disease is (0: no disease, 4: most severe disease)

Database	Class = 0	Class = 1	Class = 2	Class = 3	Class = 4	Total
Cleveland	164	55	36	35	13	303
Hungarian	188	37	26	28	15	294
Switzerland	8	48	32	30	5	123
Long Beach VA:	51	56	41	42	10	200

Description of the process-pipeline

General:

Note: For this data science project, **only the following. data files were used**:

Filename	Md5-Hash
cleveland.data	2388e97e27676171aa0a1c61bb4a3670
hungarian.data	ce4a62b8de90d93d616ede3253239851
long-beach-va.data	381cee4b51b786623402929e2cc1ccf9
switzerland.data	b2a3e9cc9c82dc0f8fa19bb851db495d

These .data files were **not** used:

Filename	Md5-Hash
new.data	046bd9f619c20148b261b3e392c02591
processed.cleveland.data	2d91a8ff69cfd9616aa47b59d6f843db
processed.hungarian.data	22e96bee155b5973568101c93b3705f6
processed.switzerland.data	9a87f7577310b3917730d06ba9349e20
processed.va.data	4249d03ca7711e84f4444768c9426170
reprocessed.hungarian	3698a53d41cccc2e4499e1273c055378

For the sake of completeness, nonetheless, we did include the whole folder.

Preparing the datasets:

First step: rename .data files (0 raw .data) to .csv (1 raw .csv).

Second step: format the .csv files via python script “formatter” (2 formatted .csv). This step was needed because the original data was badly formatted. The formatter.py formats the datasets, such that all features of one patient are one row and not scattered over multiple rows.

Third step: adding a header for the 76 features (data).

We finally get 4 files in our data folder:

Filename	Md5-Hash
cleveland_76_header.csv	a67792681f83998d97e332bfb41efee0
hungarian_76_header.csv	6c86829818559cfb434126c61d5cb25c
long-beach-va_76_header.csv	4dde4782acbbdac7b2198bb676fea13f
switzerland_76_header.csv	d4a1d37007107ee2fb73be8a4122bf32

Important note: At this moment, no entries were modified.

Process of Visualization and Analyse

The processing of the data was done in the following order. Pre-processing and (general) visualization, feature selection, reduction, and finally classification. We focus and start in this project on working with the whole dataset and not the already pre-processed files, which only include a tiny subset of the features, to finally compare the locations with each other.

It is in general a good idea to start with some visualizations get a rough overview and kind of an intuition of the (abstract) data. In a second step doing a feature, the selection is crucial, because 76 features go beyond the constraints of reasonable analysis. Using the RandomForestClassifier found 25 features that have the most impact on the data. The two other approaches were t-SNE and UMAP and in addition to this using autoencoders with R. Several different classification algorithms, namely

- Logistic Regression
- Naïve Bayes
- SVM (linear, poly (degree = 3) and kernel (rbf))
- KNN (nn = 5)
- Neural Networks
- Autoencoders (in R)

were processed before finally a conclusion was drawn from the results and plots.

Disclaimer:

- The Swiss dataset was highly unbalanced (very few 0's and 4's in the "num" section which is they-feature). That causes the ROC-score to struggle.
- In addition to this, the Swiss dataset has no information about the chol level (default 0). That means it was not possible to plot the second scatter plot.
- Overall, the Swiss data set was not very suitable for this kind of analysis. The above-mentioned difficulties were (amongst other things) for the low model accuracy.

In the following, there is a summary of all the different plots, how they were generated, and which technique/method/model was used.

I. PREPROCESSING & DATA VISUALIZATION

1. Visualize Max heart rate vs age with the target variable "num" (1-4) : Scatter Plot
2. Visualize cholesterol level vs age with the target variable "num" (1-4) : Scatter Plot
3. Visualize blood pressure vs chest pain : Box Plot
4. Visualize correlation between features and target variable "num" (1-4) : Bar Plot (.corrwith)
5. Visualize correlation between features and target variable "num" (1-4) : Heatmap (.corr)
6. Visualize blood pressure vs age with the target variable : LMplot (.lmplot : scatterplot with an optional overlaid regression line)
7. Visualize heart rate vs age with the target variable : LMplot (.lmplot : scatterplot with an optional overlaid regression line)

8. Visualize distribution of age according to the presence of heart disease : KDEplot (.kdeplot : represents the data using a continuous probability density curve)
9. Visualize comparison between the distribution of the disease according to age and sex : Bar Plot (.groupby)

II. FEATURE SELECTION

10. Visualize feature importance : Bar Plot (RandomForestClassifier) => saved under / rand_forest_feature_selection(25)

III. REDUCTION & VISUALISATION

11. Visualize feature reduction for different perplexities : Scatter Plot (TSNE)
12. Visualize feature reduction : Scatter Plot (UMAP)

IV. CLASSIFICATION

13. Visualize logistic regression : Heatmap (LogisticRegression)
14. Visualize performance of logistic regression : ROC plot + AUC result ; Print accuracy : (metrices.accuracy_score)
15. Visualize naïve Bayes : Heatmap (GaussianNB)
16. Visualize performance of naïve Bayes : ROC plot + AUC result ; Print accuracy : (metrices.roc_auc_score)
17. Visualize performance of SVM (linear kernel) : ROC plot + AUC result ; Print accuracy : (metrices.accuracy_score)
18. Visualize performance of SVM (poly (d=3) kernel) : ROC plot + AUC result ; Print accuracy : (metrices.accuracy_score)
19. Visualize performance of SVM (rbf kernel) : ROC plot + AUC result ; Print accuracy : (metrices.accuracy_score)
20. Visualize SVM (linear, poly (d=3) and rbf kernel) : Heatmap (svm.SVC(kernel = TYPE))
21. Visualize KNN : KNeighborsClassifier(n_neighbors = 5, algo = “ball_tree”) ; Print accuracy : (accuracy_score)
22. Visualize performance of KNN : ROC + plot ; Print cross validation : (cross_val_score)
23. Visualize performance of simple neural Network : model = Sequential(), model.fit()

V. ACCURACIES

		Accuracies			
Name	Method	Cleveland	Hungarian	Vancouver	Switzerland
Log regression Accuracy	metrics.accuracy_score(y_test, X_pred)	0.84	0.59	0.74	0.65
Log regression AUC-Score	metrics.roc_auc_score(y_test_bin, probs_X)	0.95	0.75	0.85	-
Naive Bayes Accuracy	metrics.accuracy_score(y_test, X_pred)	0.77	0.46	0.54	-
Naive Bayes AUC-Score	metrics.roc_auc_score(y_test_bin, probs_X)	0.93	0.55	0.88	-
SVC linearAccuracy	metrics.accuracy_score(y_test, svc_linear_pred)	0.86	0.58	0.84	-
SVC poly(deg 3) Accuracy	metrics.accuracy_score(y_test, svc_poly_pred)	0.68	0.62	0.38	-
SVC kernel (rbf) Accuracy	metrics.accuracy_score(y_test, svc_rbf_pred)	0.58	0.62	0.2	-
KNN Accuracy	accuracy_score(y_test, knn_pred)	0.73	0.57	0.46	0.42
Neural Accuracy	accuracy_score(y_test_bin, p)	0.48	0.42	0.08	0.23

Above is a summary of the scripts (and their log-files) of the accuracy in the form of a table. X is dependent on the associated method (first column) for instance using logistic regression, X_pred is named LR_pred).

VI. AUTOENCODERS

Cleveland analysis

- Feature selection (first five most important)

Laddist – "distal left anterior descending artery" seems to be one of the most important features. Indeed, it is part of the left main coronary artery (LAD), considered the most important because it supplies more than half of the blood to the heart.

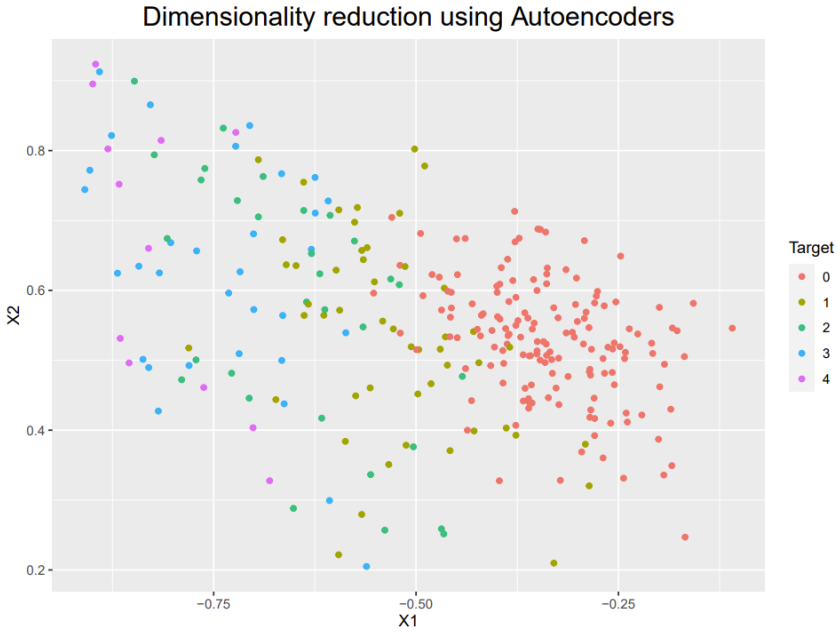
Thal – "exercise thallium scintigaphy" is a diagnostic method of nuclear medicine that enables visualization of well-perfused and vital tissue of myocardium by means of 201thallium absorbed by its cells. This method is used to evaluate the character of soft tissue lesions. The feature is divided into three categories from normal to defect.

Om1 – "first obtuse marginal branch" is also an important vessel that is part of the left main coronary artery (LAD).

Ca – "number of major vessels".

Rcaprox – "proximal right coronary artery" is part of the right coronary artery (RCA) in contrast to LAD.

- Autoencoders



Hungary analysis

- Feature selection (first five most important)

Cp – "chest pain" seems to be selected as the most important feature. It is divided into four categories: type: 1 = typical angina; 2 = atypical angina; 3 = non-angina pain; 4 = asymptomatic.

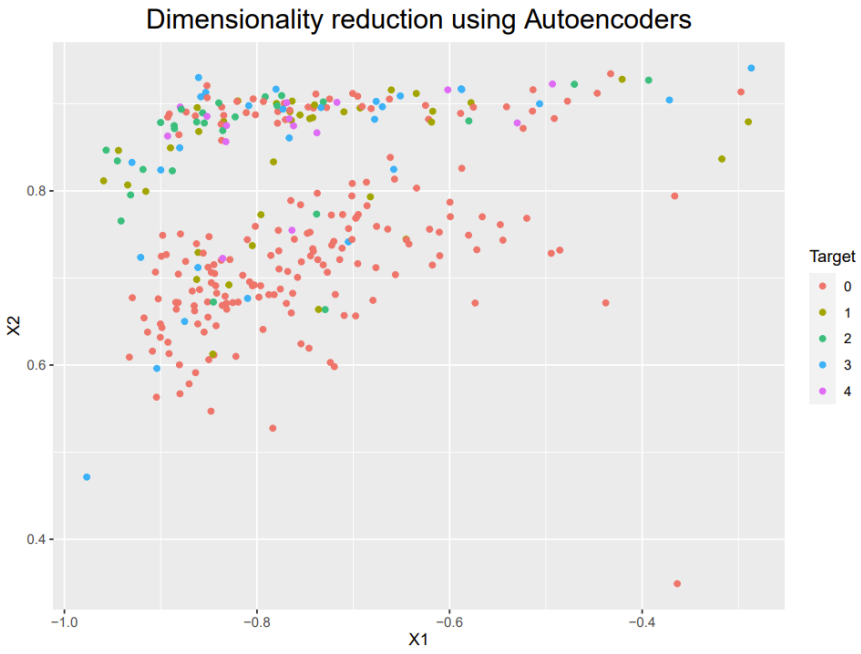
Painexer – "pain provoked by exertion". It is divided into two categories: 1 if the patient felt pain during effort, 0 otherwise.

Oldpeak – "exercise-induced ST depression relative to rest" is an exercise electrocardiography test to evaluate whether the trace in the ST segment is abnormally low below the baseline which is often a sign of myocardial ischemia.

Lvx4 – not used / not described / no information regarding this feature.

Exang – "Exercise-induced angina". It is divided into two categories: 1 if yes, 0 otherwise.

- Autoencoders



Switzerland analysis

- Feature selection (first five most important)

Cxmain – "circumflex". It is another vessel that is part of the left main coronary artery (LAD), considered the most important because it supplies more than half of the blood to the heart.

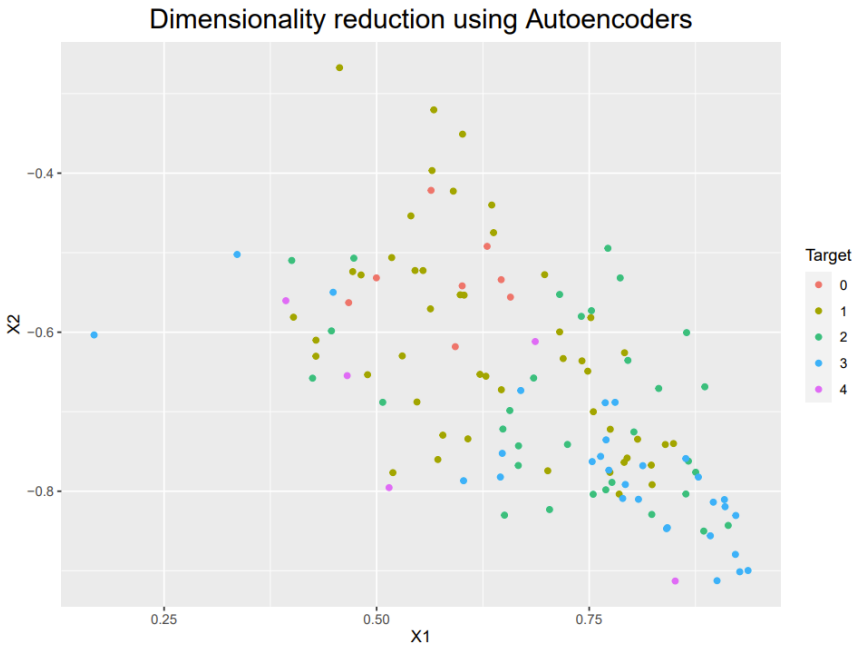
ID – not relevant.

Thalach – "maximum heart rate achieved" refers to the maximum heart rate achieved during thalium stress test. At first sight, we might suppose that the maximum heart rate is lower for those diagnosed with heart diseases. Indeed, it seems logical to assume that a higher rate indicates a satisfactory heart condition since it managed to increase its rate to such a level during the stress test.

Tpeakbps – "peak exercise systolic blood pressure".

Age – "age of the patients".

- Autoencoders



Long Beach analysis

- Feature selection (first five most important)

Rcaprox – "proximal right coronary artery" is part of the right coronary artery (RCA) in contrast to LAD.

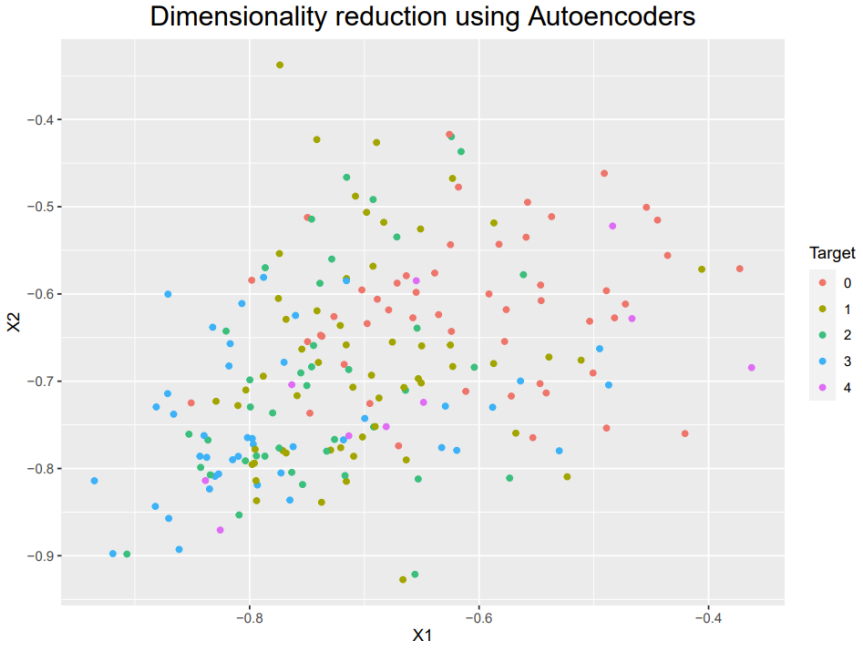
Ladprox – "proximal left anterior descending artery" which is part of LAD.

Cxmain – "circumflex". It is another vessel that is part of the left main coronary artery (LAD), considered the most important because it supplies more than half of the blood to the heart.

ID – not relevant.

Cday – "day of cardiac catheterization". Not relevant.

- Autoencoders



Conclusion:

The following 3 questions were formulated in our proposal:

"Are some parameters more likely to be associated with heart disease?"

"Can we predict heart disease while using statistical methods?"

"Can we find any differences between the different regions in terms of predicted risk factors?"

We will discuss our findings during the presentation and summarize the most important here:

With the random forest method, 25 features were selected that explain about 80% of the data. Since the list of features is relatively long, this trade-off has been made. It is notable that also obviously some features were selected, that have no impact on the risk of CVD (for instance ID in Switzerland and Vancouver). For the algorithm, the ID parameter seems to have an important impact on the outcome, whereas in the real world this is not the case and shows, how the "algorithm" thinks". Other parameters like the chest pain indicator for the Hungarian set were also selected (which makes also in medical perspective more sense). Naming a set of parameters for all locations seems not realistic, one reason that we came up with is, that the sheer list of features is just too much: Even the top (five) of the 25 selected features does only explain the outcome in a degree of the low percentage.

Regarding the prediction of heart disease, this project is sobering. For some datasets, the prediction was not good and there is a variation in the accuracy regarding the different methods of prediction. This is shown in the performance measurement table

There are only minor differences between the locations, this can be seen in various plots, for instance, distribution of age and the type of disease. One reason could be because the 4 locations have a similar socio-demographic structure.

Limitation and Outlook:

In retrospect, were now able to reflect on the project and to discuss improvements that could be made on further projects. We start with the limitation:

- The dataset was a bit outdated. The conditions have been changed and.
- The dataset of Switzerland is very unbalanced, which makes it hard to draw a reliable conclusion. This directly affects several models, such that it was not possible to generate them, even with shuffling the samples.
- The features were not described. We do not know, how these features were measured and if there are differences between the locations. Also, in some datasets are important features not existing, for instance, cholesterol in the Swiss dataset.
- Furthermore, it seems like some features are senseless, for instance, the day of cardiac catherization.
- It is not clear if the num=0 class is a control group or not.

Having said that, we also record some thoughts for further improvements:

- We can tune the model parameters for each dataset to achieve higher accuracy. That means the pipeline may look different and it may not be possible anymore to compare different regions, but (hopefully) the accuracy will increase.
- Expanding the choice of the features to maybe 50 would be interesting. Also, maybe a reduction could gain more insights.
- Working with a current dataset and then compare the results. What did change, what stayed the same.

Appendix:

Complete attribute documentation:

1. id: patient identification number
2. ccf: social security number (I replaced this with a dummy value of 0)
3. age: age in years
4. sex: sex (1 = male; 0 = female)
5. painloc: chest pain location (1 = substernal; 0 = otherwise)
6. painexer (1 = provoked by exertion; 0 = otherwise)
7. relrest (1 = relieved after rest; 0 = otherwise)
8. pncaden (sum of 5, 6, and 7)
9. cp: chest pain type
    - Value 1: typical angina
    - Value 2: atypical angina
    - Value 3: non-anginal pain
    - Value 4: asymptomatic
10. trestbps: resting blood pressure (in mm Hg on admission to the hospital)
11. htn
12. chol: serum cholestoral in mg/dl
13. smoke: I believe this is 1 = yes; 0 = no (is or is not a smoker)
14. cigs (cigarettes per day)
15. years (number of years as a smoker)
16. fbs: (fasting blood sugar > 120 mg/dl) (1 = true; 0 = false)
17. dm (1 = history of diabetes; 0 = no such history)
18. famhist: family history of coronary artery disease (1 = yes; 0 = no)
19. restecg: resting electrocardiographic results
    - Value 0: normal
    - Value 1: having ST-T wave abnormality (T wave inversions and/or ST elevation or depression of > 0.05 mV)
    - Value 2: showing probable or definite left ventricular hypertrophy by Estes' criteria
20. ekgmo (month of exercise ECG reading)
21. ekgday(day of exercise ECG reading)
22. ekgyr (year of exercise ECG reading)
23. dig (digitalis used furing exercise ECG: 1 = yes; 0 = no)
24. prop (Beta blocker used during exercise ECG: 1 = yes; 0 = no)
25. nitr (nitrates used during exercise ECG: 1 = yes; 0 = no)
26. pro (calcium channel blocker used during exercise ECG: 1 = yes; 0 = no)
27. diuretic (diuretic used used during exercise ECG: 1 = yes; 0 = no)
28. proto: exercise protocol
    - 1 = Bruce
    - 2 = Kottus
    - 3 = McHenry
    - 4 = fast Balke
    - 5 = Balke
    - 6 = Noughton
    - 7 = bike 150 kpa min/min (Not sure if "kpa min/min" is what was written!)
    - 8 = bike 125 kpa min/min

- 9 = bike 100 kpa min/min
- 10 = bike 75 kpa min/min
- 11 = bike 50 kpa min/min
- 12 = arm ergometer

29. thaldur: duration of exercise test in minutes
30. thaltime: time when ST measure depression was noted
31. met: mets achieved
32. thalach: maximum heart rate achieved
33. thalrest: resting heart rate
34. tpeakbps: peak exercise blood pressure (first of 2 parts)
35. tpeakbpd: peak exercise blood pressure (second of 2 parts)
36. dummy
37. trestbpd: resting blood pressure
38. exang: exercise induced angina (1 = yes; 0 = no)
39. xhypo: (1 = yes; 0 = no)
40. oldpeak = ST depression induced by exercise relative to rest
41. slope: the slope of the peak exercise ST segment
    - Value 1: upsloping
    - Value 2: flat
    - Value 3: downsloping
42. rldv5: height at rest
43. rldv5e: height at peak exercise
44. ca: number of major vessels (0-3) colored by flourosopy
45. restckm: irrelevant
46. exerckm: irrelevant
47. restef: rest raidonuclid (sp?) ejection fraction
48. restwm: rest wall (sp?) motion abnormality
    - 0 = none
    - 1 = mild or moderate
    - 2 = moderate or severe
    - 3 = akinesis or dyskmem (sp?)
49. exeref: exercise radinalid (sp?) ejection fraction
50. exerwm: exercise wall (sp?) motion
51. thal: 3 = normal; 6 = fixed defect; 7 = reversable defect
52. thalsev: not used
53. thalpul: not used
54. earlobe: not used
55. cmo: month of cardiac cath (sp?) (perhaps "call")
56. cday: day of cardiac cath (sp?)
57. cyr: year of cardiac cath (sp?)
58. num: diagnosis of heart disease (angiographic disease status)
    - Value 0: < 50% diameter narrowing
    - Value 1: > 50% diameter narrowing
      (in any major vessel: attributes 59 through 68 are vessels)
59. lmt
60. ladprox
61. laddist
62. diag
63. cxmain

64. ramus
65. om1
66. om2
67. rcaprox
68. rcadist
69. lvx1: not used
70. lvx2: not used
71. lvx3: not used
72. lvx4: not used
73. lvf: not used
74. cathef: not used
75. junk: not used
76. name: last name of patient (I replaced this with the dummy string "name")