

# Prediction of short-term success of electrical cardioversion

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<https://github.com/matfija/Elektrokonverzija>

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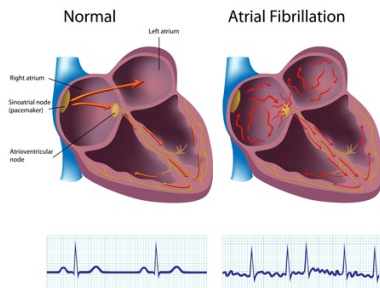


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# The problem

- Electrical cardioversion is a medical technique that uses synchronized electrical shocks to restore normal heart rhythm in people with persistent arrhythmia.
- This kind of heart rate problem is usually associated with a disease called atrial fibrillation.



# Goals and methods

- This paper aimed to create a classification model that accurately predicts whether the procedure will be successful in the short term, based on data on the clinical picture, other indications, and drug therapy prescribed to patients undergoing it.
- The focus was initially on Bayesian networks, a well-known probabilistic graphical model. They, however, proved inferior to other methods of classification and machine learning, such as the random forest classifier and artificial neural networks.

## Methods (cont.)

- Fitted models were compared by their accuracy, sensitivity (recall), specificity, and other relevant metrics.
- Extra attention was given to data preprocessing and exploratory analysis, as well as predictor (feature) importance.



# Dataset

- Dataset consists of 147 unique instances and was obtained from the Pacemaker Center of the Clinical Center of Serbia.
- It pertains to electrical cardioversions performed from 2014 to 2019.
- Several groups of attributes – basics (age, sex...), baseline (clinical picture and other indications), drug therapy (and other), cardioversion data, other irrelevant data (patient status after the procedure).

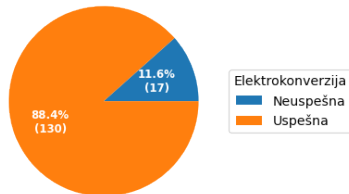
# Preprocessing

- Dataset contained many irrelevant, mixed-type and missing values.
- Removed – cardioversion date, medical record number, number in the database...
- Missing values – special value (-1) and neighborhood mean imputation
- Mixed data types – numerical transformation (e.g. if column represents number of months, then 2 is OK, but 5mes  $\rightarrow$  5 and 1god  $\rightarrow$  12)



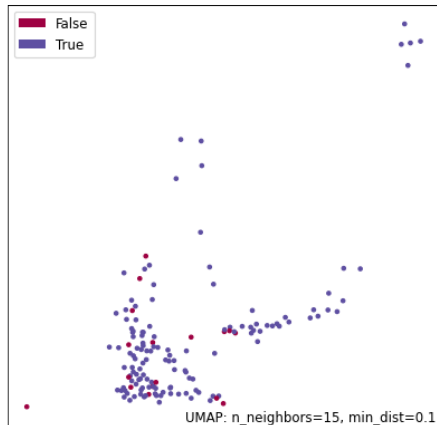
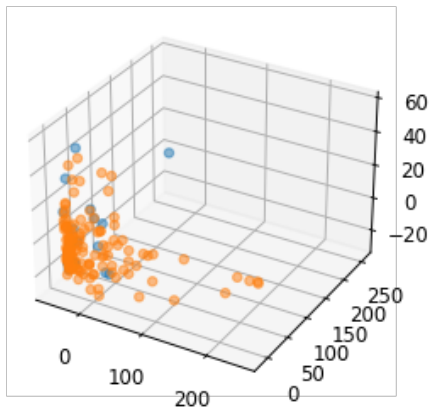
# Target class

- Even though the recurrence rate of atrial fibrillation is very high, most cardioversions are initially successful.
- Successful procedures (88.4 %) were marked as class True and unsuccessful (11.6 %) as class False.





# Separability

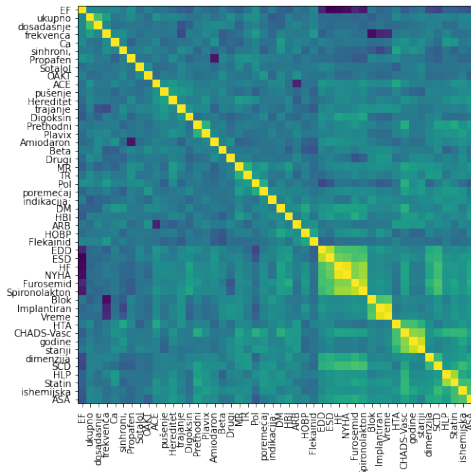
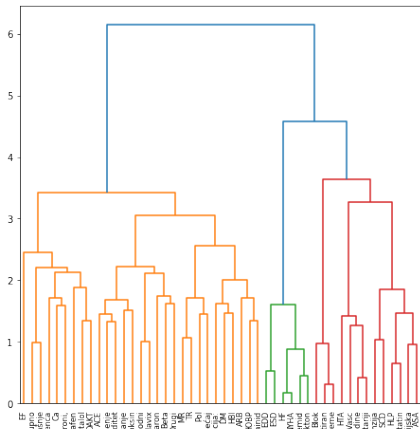


# Feature importance

- Something old:
  - domain knowledge – date irrelevant
- Something new:
  - low correlation with target attribute
  - high rate of missing values
  - low variance – no information
  - high correlation – doubled info
- Something borrowed:
  - model predictor importance – later
- Something **blue**:
  - dendrogram and heatmap – stay tuned



# Correlation dendrogram



# To sum up

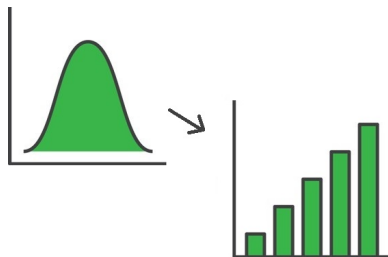
- At the end, dataset dimensions are  $147 \times 49$ .
- All input variables are of integer type, with no missing values, while target class is boolean, with somewhat inverted modalities.
- Dataset is imbalanced with concern to the target class.
- This is, of course, a binary classification problem.
- According to PCA and UMAP, this seems like a hard problem.
- It is possible to reduce dimensionality, if needed.

# Bayesian networks

- Bayesian networks are a well-known probabilistic graphical model.
- Simply put, BN is a directed acyclic graph of attributes (vertices), and belief is propagated through its edges.
- Discrete form – each vertex stores conditional probability distribution table of its attribute, given attributes of its parents
- Inference – starts from known attributes, then propagates to target

# Binning

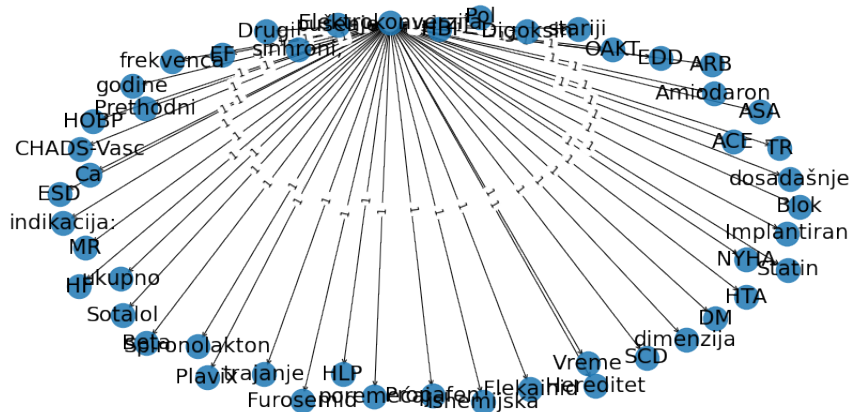
- All data is already discrete; however, it had to be discretized even more to get a good Bayesian network.
- For example, there is only one patient under 30, and his procedure failed. This doesn't mean that youth is a risk factor. Solution – bin ages  $< 30$ , then  $30 - 39$ ,  $40 - 49$ ...



# Naïve Bayes

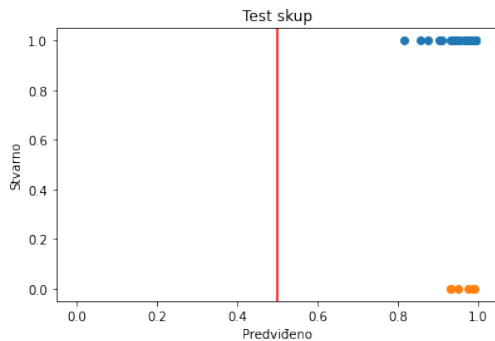
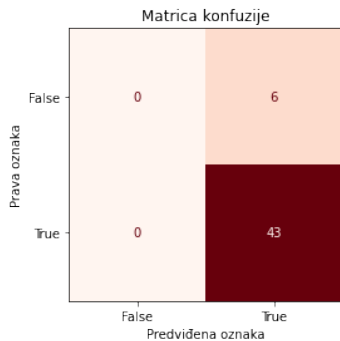
- Specific graph structure of the network, such that its branches are directed exclusively from the target to the input attributes.
- All such branches exist, and no other.
- Implication – all input variables are independent, given target.
- Very simple, but totally under-fitted – every procedure is predicted as successful, which is equal to absolutely naïve (dummy) classifier.

# Model graph





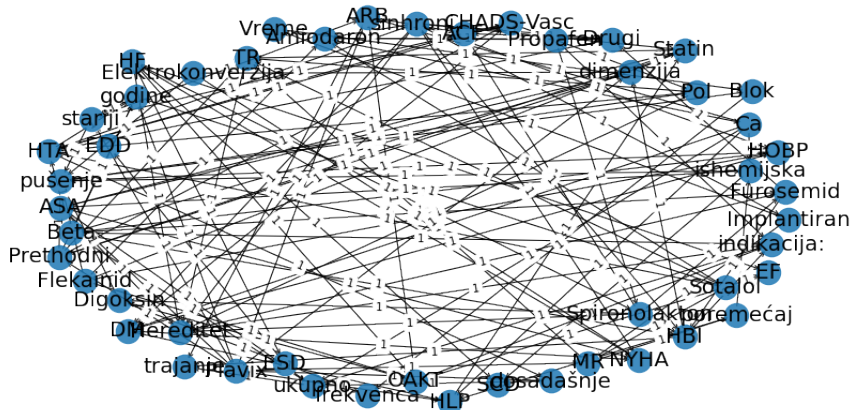
# Test performance



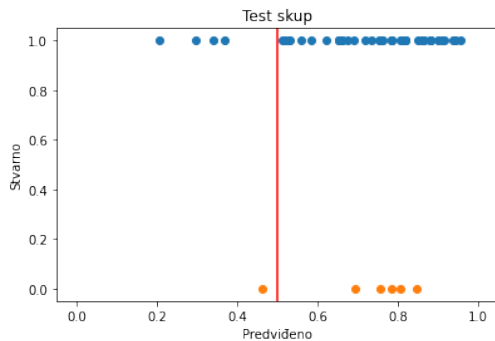
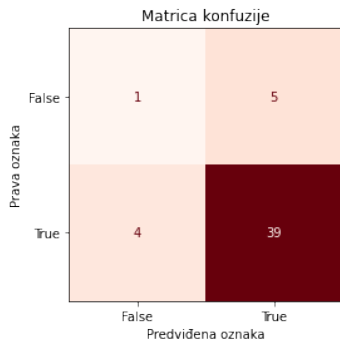
# Strucutre learning

- Hill climbing is used as the optimization technique for computing the best model graph.
- Several scoring measures, including Bayesian information criterion
- This model is much better on training partition, but it is still bad at test partition, which means it is overfitted.

# Model graph



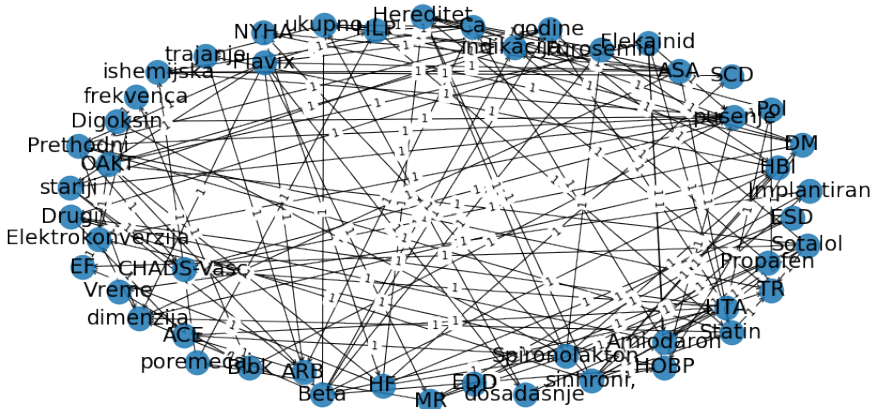
# Test performance



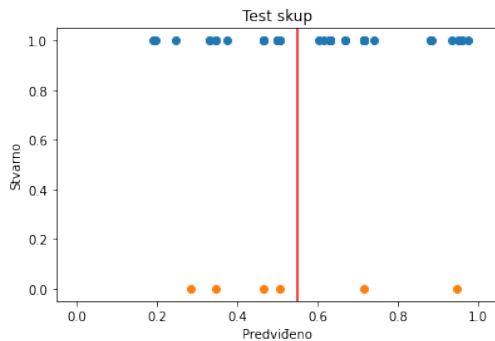
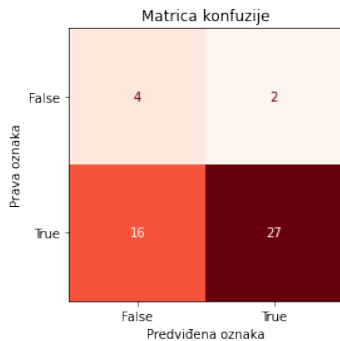
# Fixed edges

- Some edges can be fixed before the start of hill climbing optimization.
- It is most sensible to fix edges of type input  $\rightarrow$  target.
- Model predictor importance (decision tree, random forest...) and dendrogram helped in finding the best combination.
- First try – patient age, heart rate, total duration of the indicated heart disease, ejection fraction
- Second try – heart rate on admission, oral anticoagulant therapy, left atrial diameter, ejection fraction

## Model graph



# Test performance

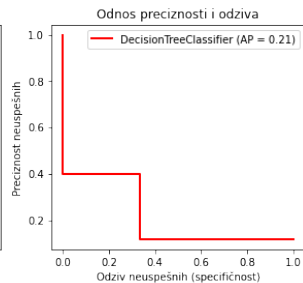
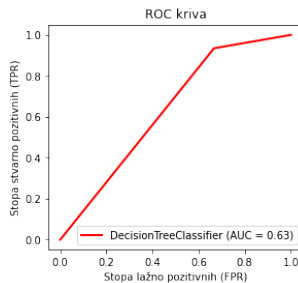
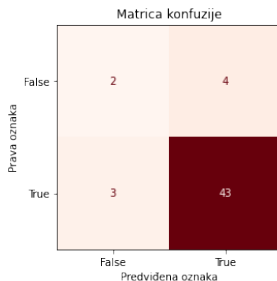


# Other models

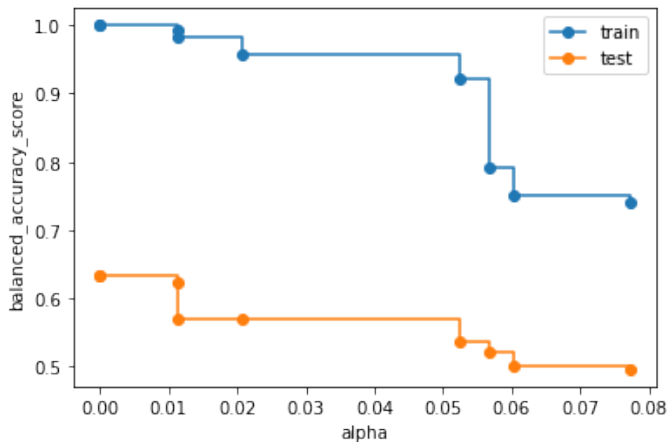
- Bayesian networks didn't turn out that good.
- Luckily, other models saved the day.
- Follows: decision trees, support vector machine...



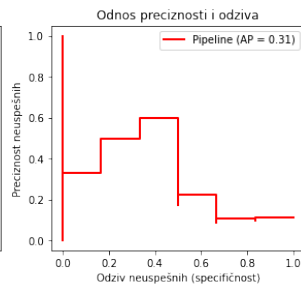
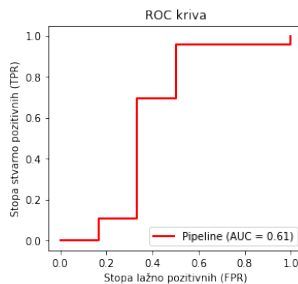
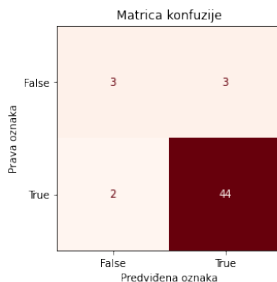
# Decision tree



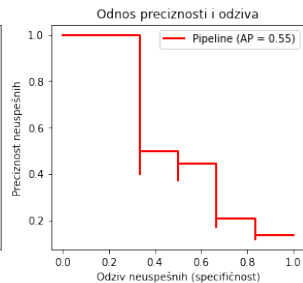
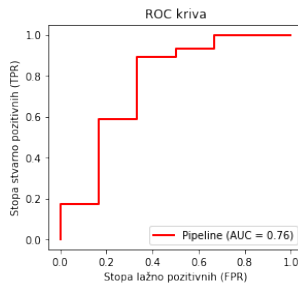
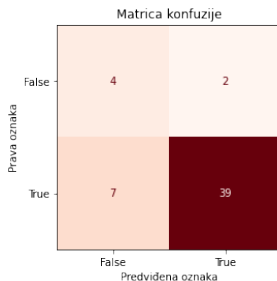
# Tree pruning



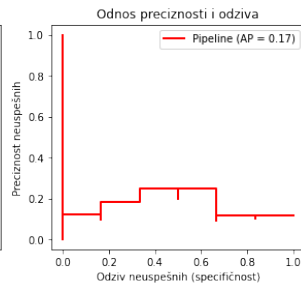
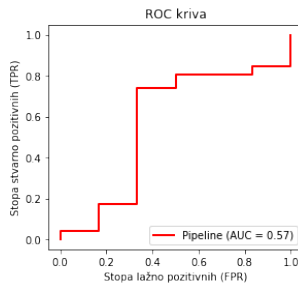
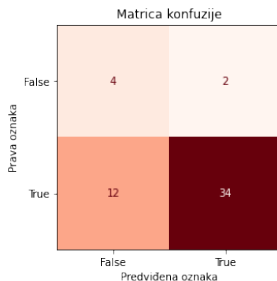
# Complement naïve Bayes



# Multilayer perceptron



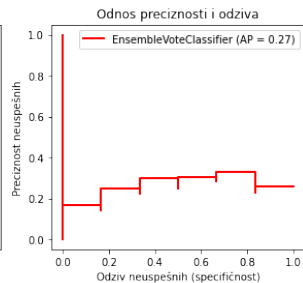
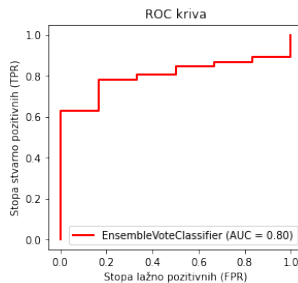
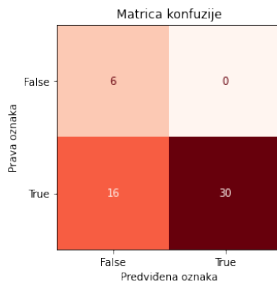
# Support vector machine



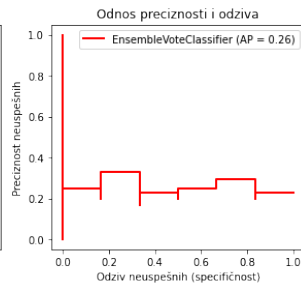
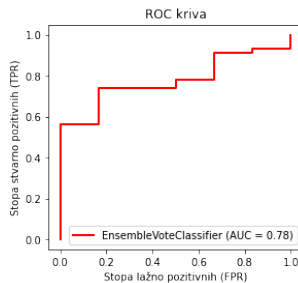
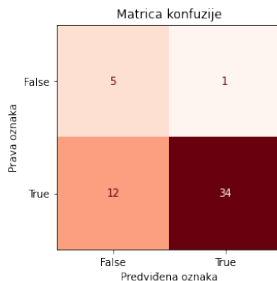
# Ensembles

- Finally, it is possible to combine several models into one.
- One way to do so is by using simple voting ensembles.
- It is best to favorize important unsuccessful procedures.
- Decision function – conjunction (product) of all input estimators:
  - of course,  $\text{False} \wedge \text{False} = \text{False}$ ,
  - of course,  $\text{True} \wedge \text{True} = \text{True}$ ,
  - also,  $\text{False} \wedge \text{True} = \text{False}$ ,
  - also,  $\text{True} \wedge \text{False} = \text{False}$ .

# MLP-SVC ensemble

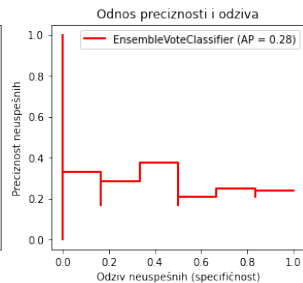
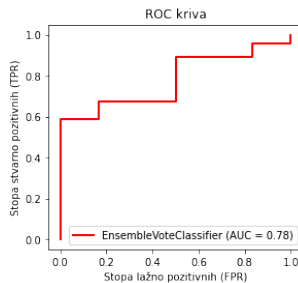
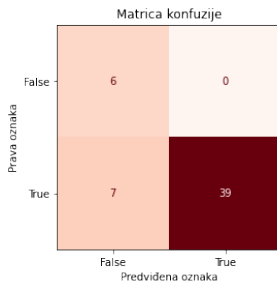


# RFC-CNB ensemble





# MLP-CNB ensemble



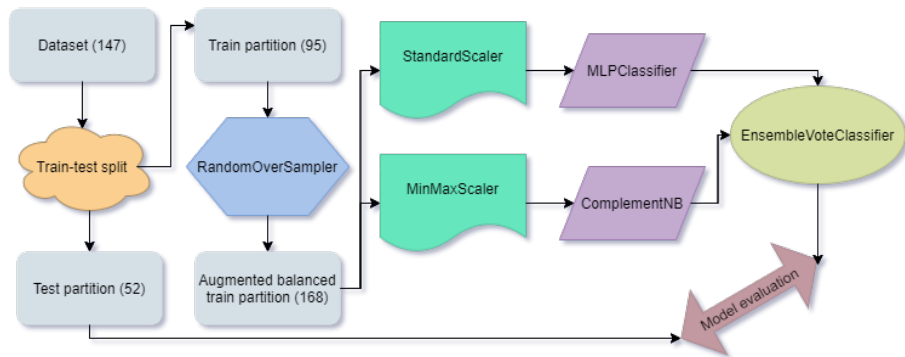
# MLP-CNB clasification report

	precision	recall	f1-score	support
False	0.46	1.00	0.63	6
True	1.00	0.85	0.92	46
accuracy			0.87	52
macro avg	0.73	0.92	0.77	52
weighted avg	0.94	0.87	0.88	52

# MLP-CNB pipeline

- Train-test split with augmented train partition
  - RandomOverSampler (imblearn)
- EnsembleVoteClassifier (mlxtend)
  - MLPClassifier (sklearn)
    - StandardScaler (sklearn)
    - solver='sgd'
    - activation='tanh'
    - hidden\_layer\_sizes=(15, 10)
    - learning\_rate='invscaling'
    - learning\_rate\_init=0.001
    - power\_t=0.6
    - batch\_size=5
    - max\_iter=400
  - ComplementNB (sklearn)
    - MinMaxScaler (sklearn)
    - no special parameters

# MLP-CNB flowchart



# Conclusion

- All in all, predicting short-term success (immediate outcome) of electrical cardioversion isn't an easy task.
- Bayesian networks failed to detect innate dependencies.
- Other models were more efficient, with ensembles being the best.
- MLP-CNB ensemble managed to score full 100 % specificity.
- Still, precision on important class False is only 46 %.