Big Homework OSDA

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Introduction

In this project will be introduced implementation of a Lazy FCA classification algorithm based on pattern structures. Proposed algorithm was compared with popular ML models: Logistic Regression, Random Forest, KNeighbors, Decision Tree. You can find all code in my GitHub repository: https://github.com/artemm26/Lazy-FCA

1) Selected Datasets

I used the following datasets in the project:

Income dataset: Income Dataset (kaggle.com)

Stroke prediction dataset: Stroke Prediction Dataset (kaggle.com)

Employee future prediction: Employee Future Prediction (kaggle.com)

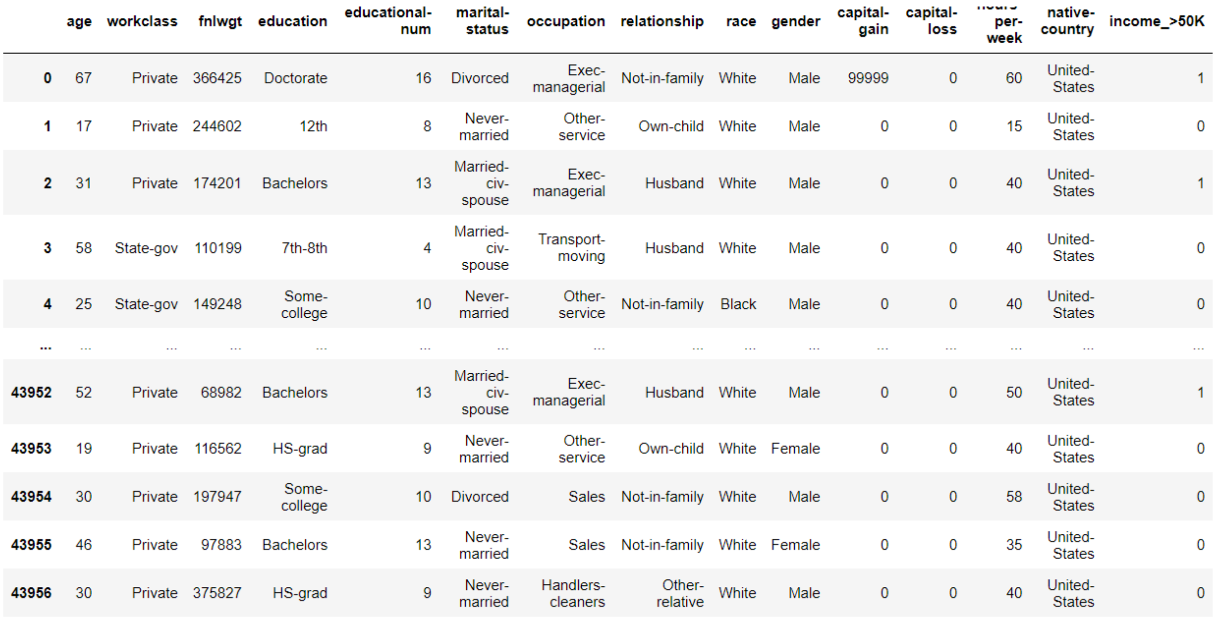
1.1) Income dataset

The dataset provided predictive feature like education, employment status, marital status to predict if the salary is greater than $50K.

Attribute Information:

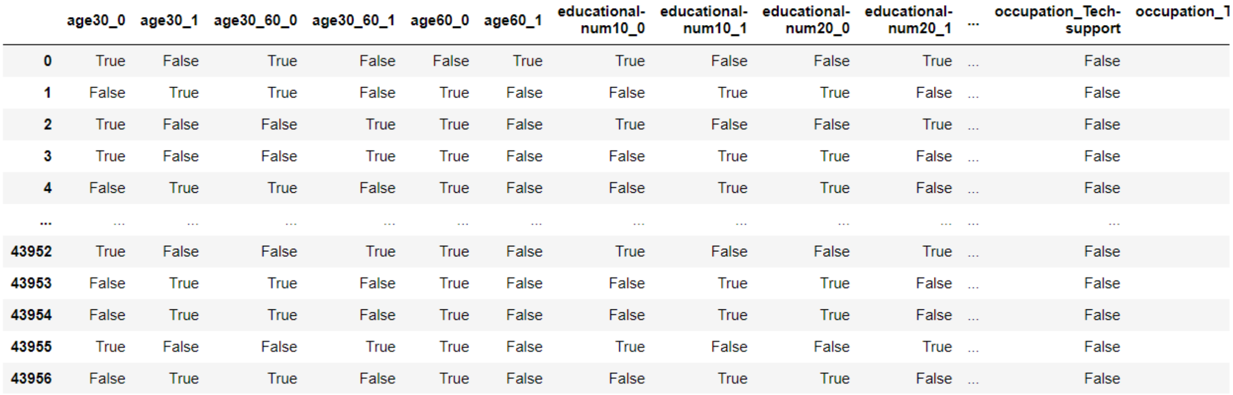
1) age: (17 - 90 y.o.)
2) workclass: type of job
3) fnlwgt: final weight
4) education: (HS-grad, some-college…)
5) educational-num: education as Integer
6) marital-status: marital status
7) occupation
8) relationship: relationship status (husband, not-in-family…)
9) race (white, black)
10) gender (male, female)
11) capital-gain
12) capital-loss
13) hours-per-week
14) native-country

Dataset is shown below:



	age	workclass	fnlwgt	education	educational-num	marital-status	occupation	relationship	race	gender	capital-gain	capital-loss	hours-per-week	native-country	income_>50K
0	67	Private	366425	Doctorate	16	Divorced	Exec-managerial	Not-in-family	White	Male	99999	0	60	United-States	1
1	17	Private	244602	12th	8	Never-married	Other-service	Own-child	White	Male	0	0	15	United-States	0
2	31	Private	174201	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	40	United-States	1
3	58	State-gov	110199	7th-8th	4	Married-civ-spouse	Transport-moving	Husband	White	Male	0	0	40	United-States	0
4	25	State-gov	149248	Some-college	10	Never-married	Other-service	Not-in-family	Black	Male	0	0	40	United-States	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
43952	52	Private	68982	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	50	United-States	1
43953	19	Private	116562	HS-grad	9	Never-married	Other-service	Own-child	White	Female	0	0	40	United-States	0
43954	30	Private	197947	Some-college	10	Divorced	Sales	Not-in-family	White	Male	0	0	58	United-States	0
43955	46	Private	97883	Bachelors	13	Never-married	Sales	Not-in-family	White	Female	0	0	35	United-States	0
43956	30	Private	375827	HS-grad	9	Never-married	Handlers-cleaners	Other-relative	White	Male	0	0	40	United-States	0

After binarization:



	age30_0	age30_1	age30_60_0	age30_60_1	age60_0	age60_1	educational-num10_0	educational-num10_1	educational-num20_0	educational-num20_1	...	occupation_Tech-support	occupation_T
0	True	False	True	False	False	True	True	False	False	True	...	False	
1	False	True	True	False	True	False	False	True	True	False	...	False	
2	True	False	False	True	True	False	True	False	False	True	...	False	
3	True	False	False	True	True	False	False	True	True	False	...	False	
4	False	True	True	False	True	False	False	True	True	False	...	False	
...	...	...	...	...	...	...	...	...	...	...	...	...	
43952	True	False	False	True	True	False	True	False	False	True	...	False	
43953	False	True	True	False	True	False	False	True	True	False	...	False	
43954	False	True	True	False	True	False	False	True	True	False	...	False	
43955	True	False	False	True	True	False	True	False	False	True	...	False	
43956	False	True	True	False	True	False	False	True	True	False	...	False	

1.2) Stroke prediction Dataset

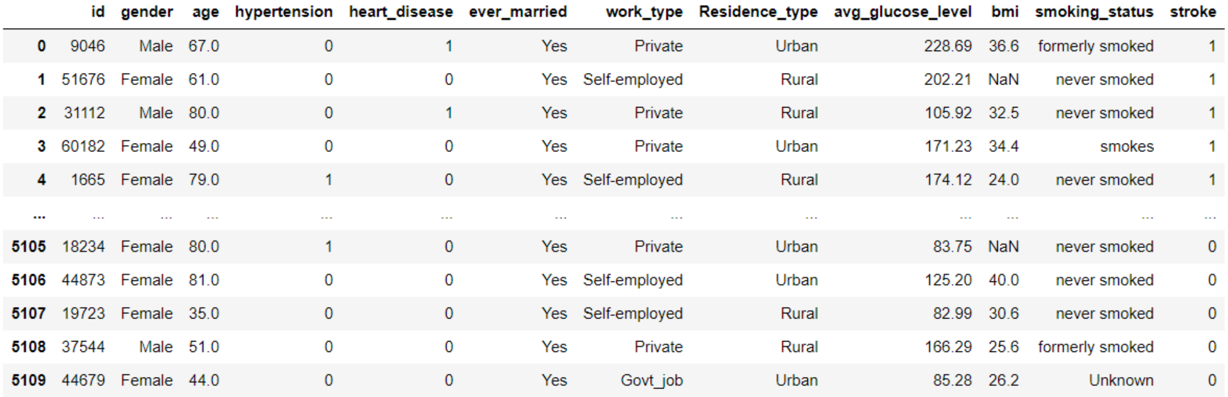
According to the World Health Organization (WHO) stroke is the 2nd leading cause of death globally, responsible for approximately 11% of total deaths. This dataset is used to predict whether a patient is likely to get stroke based on the input parameters like gender, age, various diseases, and smoking status. Each row in the data provides relavant information about the patient.

Attribute Information:

1) id: unique identifier
2) gender: "Male", "Female" or "Other"
3) age: age of the patient
4) hypertension: 0 if the patient doesn't have hypertension, 1 if the patient has hypertension
5) heart_disease: 0 if the patient doesn't have any heart diseases, 1 if the patient

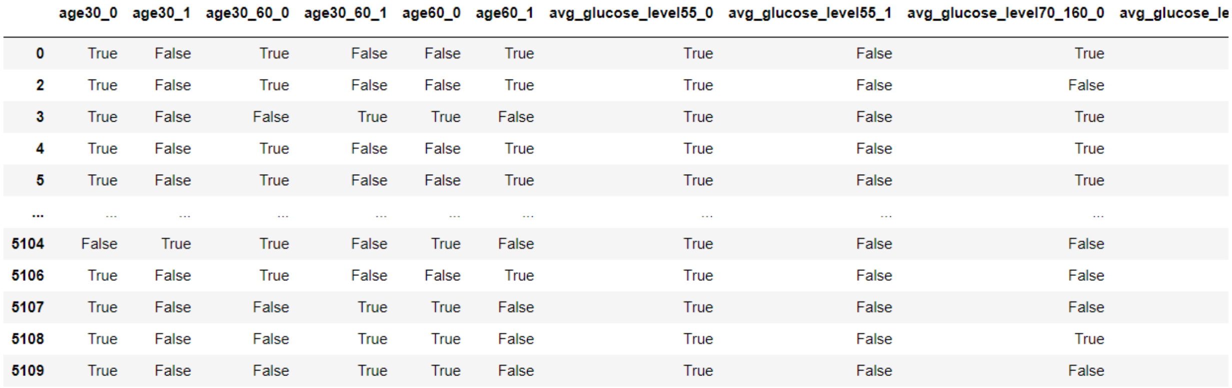
has a heart disease
6) ever_married: "No" or "Yes"
7) work_type: "children", "Govt_jov", "Never_worked", "Private" or "Self-employed"
8) Residence_type: "Rural" or "Urban"
9) avg_glucose_level: average glucose level in blood
10) bmi: body mass index
11) smoking_status: "formerly smoked", "never smoked", "smokes" or "Unknown"*
12) stroke: 1 if the patient had a stroke or 0 if not

Dataset is shown below:



	id	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_glucose_level	bmi	smoking_status	stroke
0	9046	Male	67.0	0	1	Yes	Private	Urban	228.69	36.6	formerly smoked	1
1	51676	Female	61.0	0	0	Yes	Self-employed	Rural	202.21	NaN	never smoked	1
2	31112	Male	80.0	0	1	Yes	Private	Rural	105.92	32.5	never smoked	1
3	60182	Female	49.0	0	0	Yes	Private	Urban	171.23	34.4	smokes	1
4	1665	Female	79.0	1	0	Yes	Self-employed	Rural	174.12	24.0	never smoked	1
...	...	...	...	...	...	...	...	...	...	...	...	...
5105	18234	Female	80.0	1	0	Yes	Private	Urban	83.75	NaN	never smoked	0
5106	44873	Female	81.0	0	0	Yes	Self-employed	Urban	125.20	40.0	never smoked	0
5107	19723	Female	35.0	0	0	Yes	Self-employed	Rural	82.99	30.6	never smoked	0
5108	37544	Male	51.0	0	0	Yes	Private	Rural	166.29	25.6	formerly smoked	0
5109	44679	Female	44.0	0	0	Yes	Govt_job	Urban	85.28	26.2	Unknown	0

After binarization:



	age30_0	age30_1	age30_60_0	age30_60_1	age60_0	age60_1	avg_glucose_level55_0	avg_glucose_level55_1	avg_glucose_level70_160_0	avg_glucose_le
0	True	False	True	False	False	True	True	False	True	
2	True	False	True	False	False	True	True	False	False	
3	True	False	False	True	True	False	True	False	True	
4	True	False	True	False	False	True	True	False	True	
5	True	False	True	False	False	True	True	False	True	
...	...	...	...	...	...	...	...	...	...	
5104	False	True	True	False	True	False	True	False	False	
5106	True	False	True	False	False	True	True	False	False	
5107	True	False	False	True	True	False	True	False	False	
5108	True	False	False	True	True	False	True	False	True	
5109	True	False	False	True	True	False	True	False	False	

1.3) Employee Future Prediction

A company's HR department wants to predict whether some customers would leave the company in next 2 years.

Attribute Information:

1) Education: education level

2) JoiningYear: year of joining company

3) City: city office, where posted

4) PaymentTier: (1- highest, 2-mid level, 3- lowest)

5) Age: current age

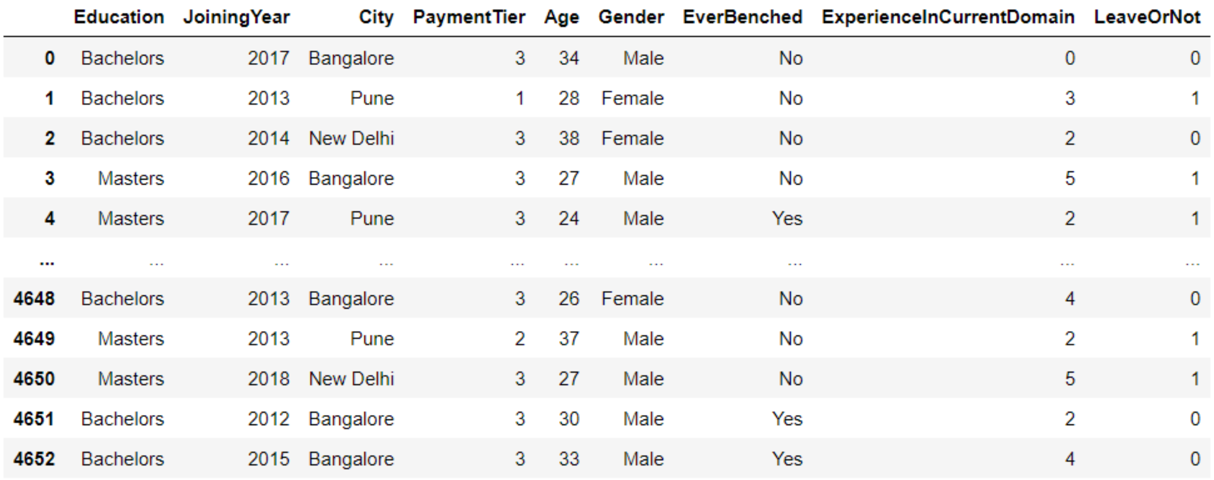
6) Genger (male, female)

7) EverBenched: ever kept out of projects for 1 month or more

8) ExperienceInCurrentDomain: experience in current field

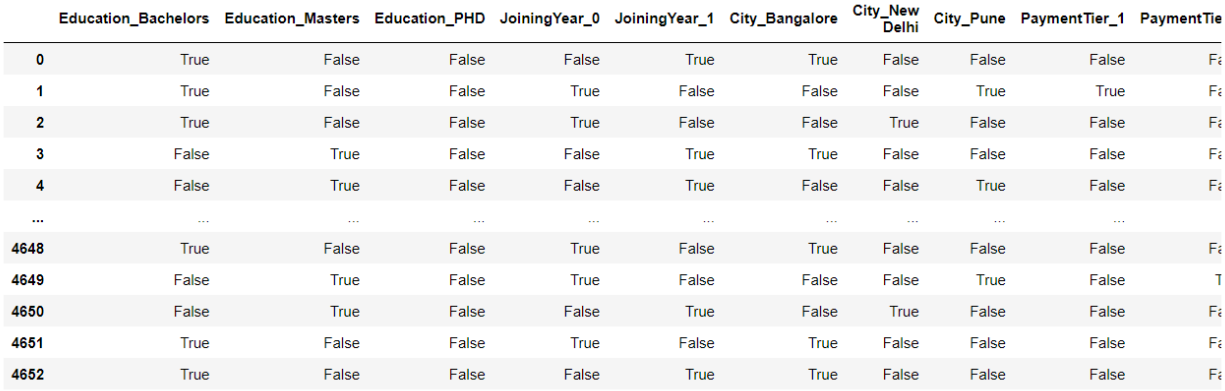
9) LeaveOrNot: whether employee leaves the company in next 2 years

Dataset is shown below:



	Education	JoiningYear	City	PaymentTier	Age	Gender	EverBenched	ExperienceInCurrentDomain	LeaveOrNot
0	Bachelors	2017	Bangalore	3	34	Male	No	0	0
1	Bachelors	2013	Pune	1	28	Female	No	3	1
2	Bachelors	2014	New Delhi	3	38	Female	No	2	0
3	Masters	2016	Bangalore	3	27	Male	No	5	1
4	Masters	2017	Pune	3	24	Male	Yes	2	1
...	...	...	...	...	...	...	...	...	...
4648	Bachelors	2013	Bangalore	3	26	Female	No	4	0
4649	Masters	2013	Pune	2	37	Male	No	2	1
4650	Masters	2018	New Delhi	3	27	Male	No	5	1
4651	Bachelors	2012	Bangalore	3	30	Male	Yes	2	0
4652	Bachelors	2015	Bangalore	3	33	Male	Yes	4	0

After binarization:



	Education_Bachelors	Education_Masters	Education_PHD	JoiningYear_0	JoiningYear_1	City_Bangalore	City_New Delhi	City_Pune	PaymentTier_1	PaymentTie
0	True	False	False	False	True	True	False	False	False	Fa
1	True	False	False	True	False	False	False	True	True	Fa
2	True	False	False	True	False	False	True	False	False	Fa
3	False	True	False	False	True	True	False	False	False	Fa
4	False	True	False	False	True	False	False	True	False	Fa
...	...	...	...	...	...	...	...	...	...	
4648	True	False	False	True	False	True	False	False	False	Fa
4649	False	True	False	True	False	False	False	True	False	T
4650	False	True	False	False	True	False	True	False	False	Fa
4651	True	False	False	True	False	True	False	False	False	Fa
4652	True	False	False	False	True	True	False	False	False	Fa

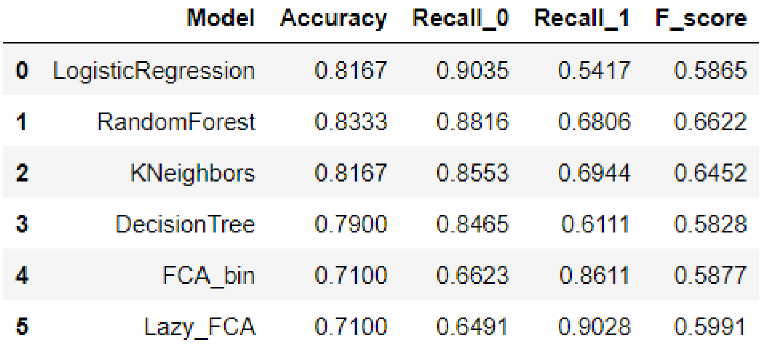
2) Classification with standard ML tools

After selecting 3 datasets I proceed Machine learning models. As the preprocessing I fixed obvious errors in data, like deliting nan values and fixed datatypes in the datasets: formatted numerical to int and float datatypes; converted categorical features. For encoding categorical data, I used One-hot encoding. For numerical – interval scaling. This preprocessing step aimed to enhance the overall quality of the datasets, ensuring they were well-structured and ready for consumption by a variety of classification algorithms.

The models were used: Logistic Regression, Random Forest, KNeighbors, Decision Tree. They have been selected for their widespread usage and proven performance in classification tasks. In this project, I employed accuracy score and F1-score as key metrics for evaluating the performance of classification models across three datasets. Accuracy score represents the ratio of correctly predicted instances to the total instances, providing a general overview of a model's correctness. On the other hand, F1-score balances precision and recall, making it particularly valuable when dealing with imbalanced datasets. It considers both false positives and false negatives, offering a more comprehensive assessment of a model's effectiveness in scenarios where different misclassification types bear varying consequences.

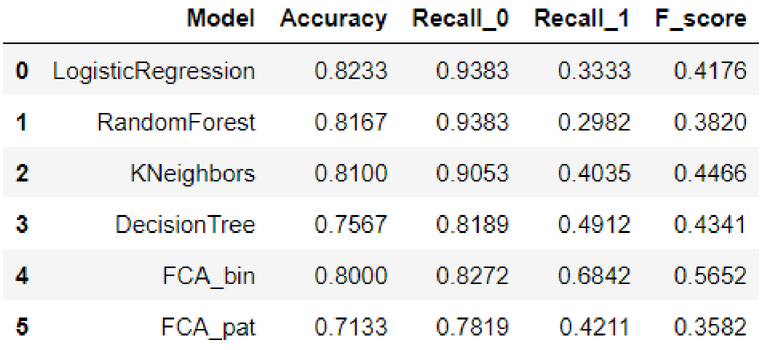
The following tables present how the machine learning models performed on the three different datasets. It includes accuracy results, recall 0, recall 1 and F1 scores for each model.

Income prediction:



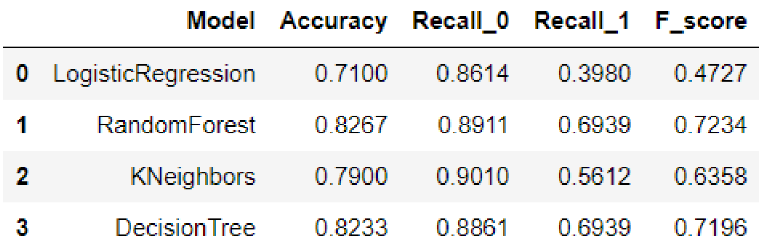
	Model	Accuracy	Recall_0	Recall_1	F_score
0	LogisticRegression	0.8167	0.9035	0.5417	0.5865
1	RandomForest	0.8333	0.8816	0.6806	0.6622
2	KNeighbors	0.8167	0.8553	0.6944	0.6452
3	DecisionTree	0.7900	0.8465	0.6111	0.5828
4	FCA_bin	0.7100	0.6623	0.8611	0.5877
5	Lazy_FCA	0.7100	0.6491	0.9028	0.5991

Stroke prediction:



	Model	Accuracy	Recall_0	Recall_1	F_score
0	LogisticRegression	0.8233	0.9383	0.3333	0.4176
1	RandomForest	0.8167	0.9383	0.2982	0.3820
2	KNeighbors	0.8100	0.9053	0.4035	0.4466
3	DecisionTree	0.7567	0.8189	0.4912	0.4341
4	FCA_bin	0.8000	0.8272	0.6842	0.5652
5	FCA_pat	0.7133	0.7819	0.4211	0.3582

Employee prediction:



	Model	Accuracy	Recall_0	Recall_1	F_score
0	LogisticRegression	0.7100	0.8614	0.3980	0.4727
1	RandomForest	0.8267	0.8911	0.6939	0.7234
2	KNeighbors	0.7900	0.9010	0.5612	0.6358
3	DecisionTree	0.8233	0.8861	0.6939	0.7196

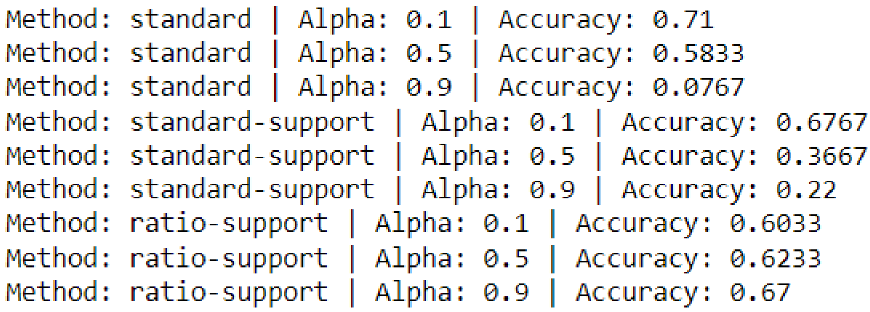
3) Lazy-FCA classification with binary attributes

For the use Lazy classification, I binarized every dataset and then perform Lazy Classification algorithm. I tuned hyperparameters: method (“standard”, “standard-support”, “ratio-support”) and alpha (0.1, 0.5, 0.9). As the result we can see values of accuracy score.

Income prediction:

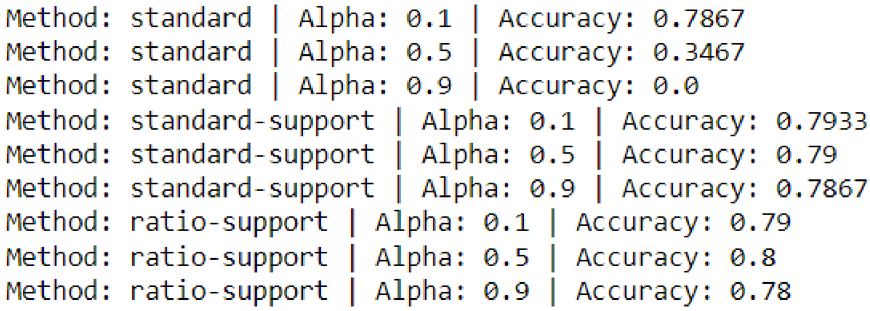
Best parameters:

Method = “standard”, alpha = 0.1



```
Method: standard | Alpha: 0.1 | Accuracy: 0.71
Method: standard | Alpha: 0.5 | Accuracy: 0.5833
Method: standard | Alpha: 0.9 | Accuracy: 0.0767
Method: standard-support | Alpha: 0.1 | Accuracy: 0.6767
Method: standard-support | Alpha: 0.5 | Accuracy: 0.3667
Method: standard-support | Alpha: 0.9 | Accuracy: 0.22
Method: ratio-support | Alpha: 0.1 | Accuracy: 0.6033
Method: ratio-support | Alpha: 0.5 | Accuracy: 0.6233
Method: ratio-support | Alpha: 0.9 | Accuracy: 0.67
```

Stroke prediction:

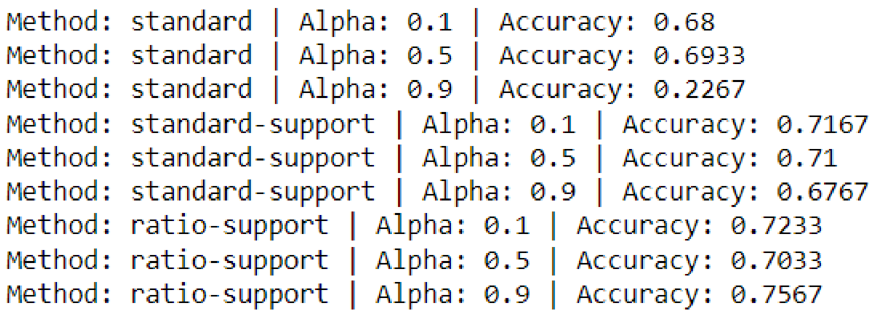


```
Method: standard | Alpha: 0.1 | Accuracy: 0.7867
Method: standard | Alpha: 0.5 | Accuracy: 0.3467
Method: standard | Alpha: 0.9 | Accuracy: 0.0
Method: standard-support | Alpha: 0.1 | Accuracy: 0.7933
Method: standard-support | Alpha: 0.5 | Accuracy: 0.79
Method: standard-support | Alpha: 0.9 | Accuracy: 0.7867
Method: ratio-support | Alpha: 0.1 | Accuracy: 0.79
Method: ratio-support | Alpha: 0.5 | Accuracy: 0.8
Method: ratio-support | Alpha: 0.9 | Accuracy: 0.78
```

Best parameters:

Method = “ratio-support”, alpha = 0.5

Employee prediction:



```
Method: standard | Alpha: 0.1 | Accuracy: 0.68
Method: standard | Alpha: 0.5 | Accuracy: 0.6933
Method: standard | Alpha: 0.9 | Accuracy: 0.2267
Method: standard-support | Alpha: 0.1 | Accuracy: 0.7167
Method: standard-support | Alpha: 0.5 | Accuracy: 0.71
Method: standard-support | Alpha: 0.9 | Accuracy: 0.6767
Method: ratio-support | Alpha: 0.1 | Accuracy: 0.7233
Method: ratio-support | Alpha: 0.5 | Accuracy: 0.7033
Method: ratio-support | Alpha: 0.9 | Accuracy: 0.7567
```

Best parameters:

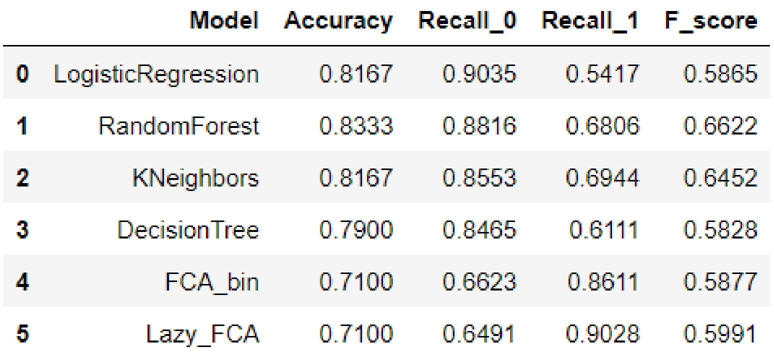
Method = “ratio-support”, alpha = 0.9

4) Lazy-FCA with pattern structures

I performed 9 times Lazy Classification algorithm with pattern structured in the same way.

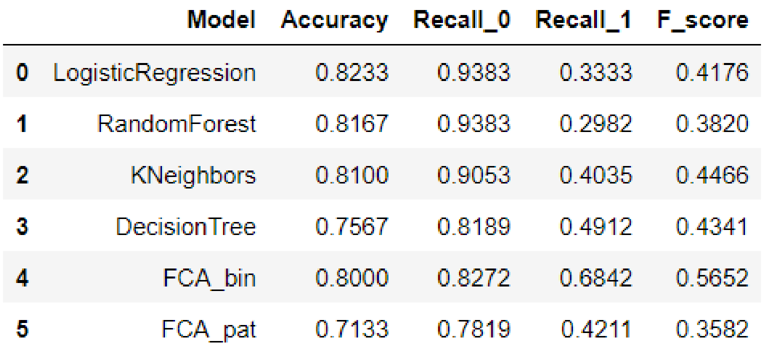
Final results are shown below:

Income prediction:



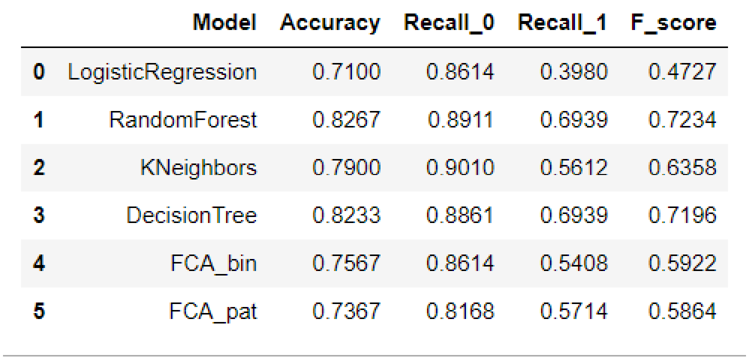
	Model	Accuracy	Recall_0	Recall_1	F_score
0	LogisticRegression	0.8167	0.9035	0.5417	0.5865
1	RandomForest	0.8333	0.8816	0.6806	0.6622
2	KNeighbors	0.8167	0.8553	0.6944	0.6452
3	DecisionTree	0.7900	0.8465	0.6111	0.5828
4	FCA_bin	0.7100	0.6623	0.8611	0.5877
5	Lazy_FCA	0.7100	0.6491	0.9028	0.5991

Stroke prediction:



	Model	Accuracy	Recall_0	Recall_1	F_score
0	LogisticRegression	0.8233	0.9383	0.3333	0.4176
1	RandomForest	0.8167	0.9383	0.2982	0.3820
2	KNeighbors	0.8100	0.9053	0.4035	0.4466
3	DecisionTree	0.7567	0.8189	0.4912	0.4341
4	FCA_bin	0.8000	0.8272	0.6842	0.5652
5	FCA_pat	0.7133	0.7819	0.4211	0.3582

Employee prediction:



	Model	Accuracy	Recall_0	Recall_1	F_score
0	LogisticRegression	0.7100	0.8614	0.3980	0.4727
1	RandomForest	0.8267	0.8911	0.6939	0.7234
2	KNeighbors	0.7900	0.9010	0.5612	0.6358
3	DecisionTree	0.8233	0.8861	0.6939	0.7196
4	FCA_bin	0.7567	0.8614	0.5408	0.5922
5	FCA_pat	0.7367	0.8168	0.5714	0.5864

Conclusion

I applied the Lazy (FCA) algorithm to three datasets. In the overall evaluation, it falls in the middle of the scoreboard. However, it's worth noting that the pattern classifier tends to perform poorly when all attributes in the datasets are numerical.