



Lazy FCA Report

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Dataset

Body signal of smoking:

<https://www.kaggle.com/datasets/kukuroo3/body-signal-of-smoking>

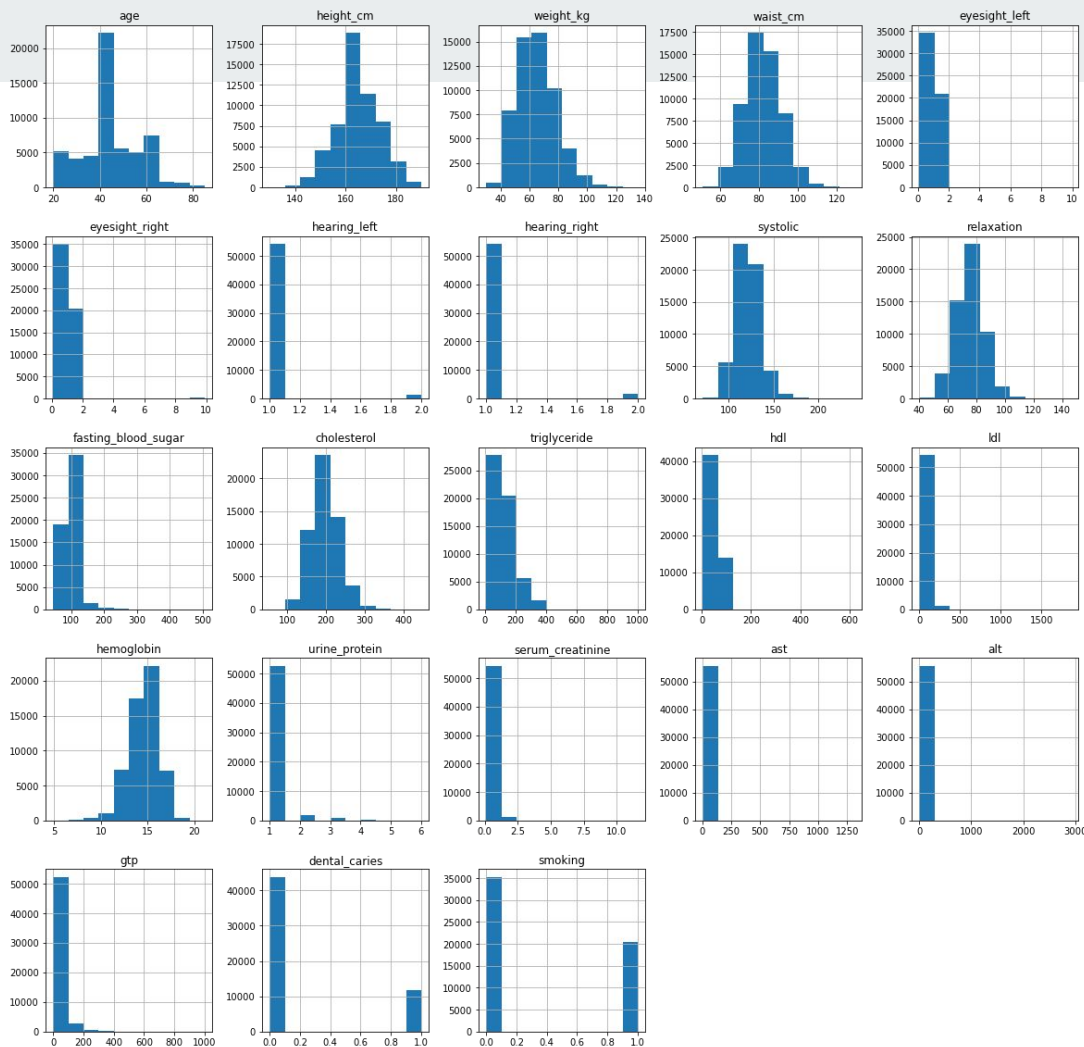
Target: find smokers based on their vital signs and medical data

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 55692 entries, 0 to 55691
Data columns (total 26 columns):
 #   Column              Non-Null Count  Dtype  
---  -
 0   gender              55692 non-null object  
 1   age                 55692 non-null int64  
 2   height_cm           55692 non-null int64  
 3   weight_kg           55692 non-null int64  
 4   waist_cm            55692 non-null float64 
 5   eyesight_left       55692 non-null float64 
 6   eyesight_right      55692 non-null float64 
 7   hearing_left        55692 non-null float64 
 8   hearing_right       55692 non-null float64 
 9   systolic            55692 non-null float64 
10  relaxation           55692 non-null float64 
11  fasting_blood_sugar  55692 non-null float64 
12  cholesterol          55692 non-null float64 
13  triglyceride         55692 non-null float64 
14  hdl                  55692 non-null float64 
15  ldl                  55692 non-null float64 
16  hemoglobin           55692 non-null float64 
17  urine_protein        55692 non-null float64 
18  serum_creatinine     55692 non-null float64 
19  ast                  55692 non-null float64 
20  alt                  55692 non-null float64 
21  gtp                  55692 non-null float64 
22  oral                 55692 non-null object  
23  dental_caries        55692 non-null int64  
24  tartar               55692 non-null object  
25  smoking              55692 non-null int64  
dtypes: float64(18), int64(5), object(3)
memory usage: 11.0+ MB
```

Dataset

- categoric values are converted to indicator values via `pd.get_dummies()`
- continuous values are first converted to categorical via `pd.qcut()` method that assigns labels to values according to bins, and then to indicator values via `pd.get_dummies()`



Quality measure



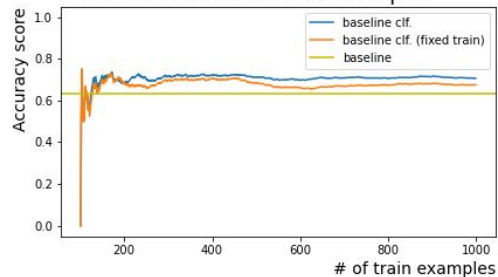
Let's use two metrics: accuracy score and F1 score.

- accuracy score is a valid metric, because the dataset is balanced (there is no clear imbalance between "non-smokers" and "smokers")
- F1 score minimizes the False Negative prediction which is the most harmful in the case of our dataset (when someone is a smoker but was not detected as such)

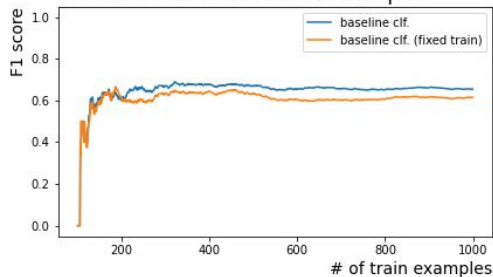
Original prediction function



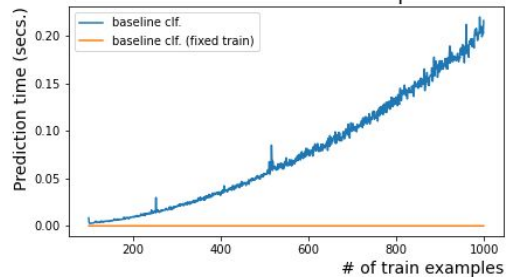
Accuracy score progression
w.r.t. the number of train examples



F1 score progression
w.r.t. the number of train examples



Prediction time progression
w.r.t. the number of train examples



Time: 1min 9s with train updates and 2.28 s without train updates

Numpy-modified prediction function



Principle:

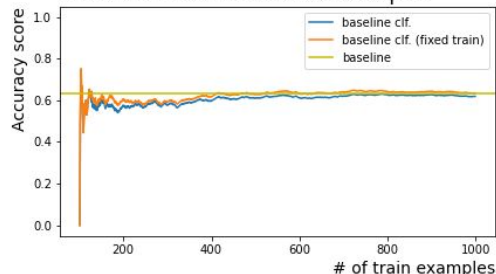
1. List[set] -> 2D np.array
2. Loop through rows in X_pos and calculate intersections_pos = x & row of X_pos -> x.reshape(1, -1) & X_pos
3. Length of intersection >= min_cardinality -> intersection.sum() >= min_cardinality
4. Count X_neg that contain intersection -> calculate zeros in the product of the intersection and negated transposed X_neg

example for principle 4:

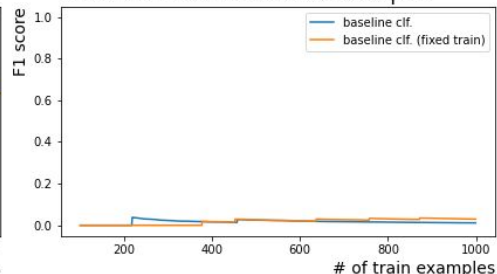
```
intersec (0, 0, 1, 0); x_neg (0, 1, 0, 1); ~x_neg (1, 0, 1, 0) -> intersec @ (~x_neg.T) = 1 -> not contained
intersec (0, 0, 1, 0); x_neg (0, 1, 1, 1); ~x_neg (1, 0, 0, 0) -> intersec @ (~x_neg.T) = 0 -> contained
intersec (1, 0, 1, 0); x_neg (0, 1, 1, 1); ~x_neg (1, 0, 0, 0) -> intersec @ (~x_neg.T) = 1 -> not contained
```

Numpy-modified prediction function

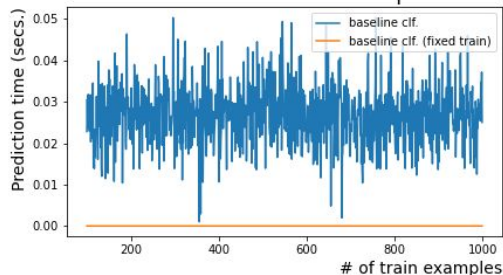
Accuracy score progression
w.r.t. the number of train examples



F1 score progression
w.r.t. the number of train examples



Prediction time progression
w.r.t. the number of train examples



- Accuracy and F1 scores are lower than in the original algorithm
- But runtime improved significantly

Time: 24.2 s with train updates and 529 ms without train updates

Model comparison



Accuracy scores of:

DecisionTreeClassifier: 0.68 RandomForestClassifier: 0.71 CatBoostClassifier: 0.73

Versus accuracy score of Lazy algorithms:

Original: 0.7063403781979978 Modified: 0.6184649610678532

Conclusion



- the chosen dataset of binary classification was prepared and binarized for the task
- the original lazy classifier was used for prediction with resulting scores: **accuracy score: 0.7063403781979978, F1 score: 0.6544502617801047**; time spent for prediction was **1min 9s** with train updates and **2.28 s** without train updates
- lazy classifier was enhanced and translated to numpy; resulting scores in prediction: **accuracy score: 0.6184649610678532, F1 score: 0.011527377521613834**; time spent for predictions: **24.2 s** with train updates and **529 ms** without train updates
- popular rule-based models were used for prediction with resulting accuracy scores: **DecisionTreeClassifier: 0.68, RandomForestClassifier: 0.71, CatBoostClassifier: 0.73**