OSDA. Project report.

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Introduction

This project focuses on realization of so called lazy classification algorithms from the field of Formal Concept Analysis (FCA). Given a dataset I designed a basic lazy binary classification algorithm with three modifications and tested it on dataset by computing four different classification quality metrics. In order to have something to compare with I also ran three classic classification algorithms on the dataset such as Logistic Regression, SVM and Naive Bayes.

Dataset

In this project I used "Rain in Australia" dataset which contains daily weather observations from numerous Australian weather stations from Kaggle. The target attribute was "RainTomorrow".

Data contained 24 attributes and 56420 observations (objects). Before starting the exploration of the data I removed attributes "Date" and "RISK_MM" since the first one didn't help and the second one leaks the answers to the model and reduces its predictability.

After that, data contained 16 numerical features and 22 categorical ones. Here is the list of all attributes with explicit descriptions:

1. Date: the date of observation
2. Location: The common name of the location of the weather station
3. MinTemp: The minimum temperature in degrees celsius
4. MaxTemp: The maximum temperature in degrees celsius
5. Rainfall: The amount of rainfall recorded for the day in mm
6. Evaporation: The so-called Class A pan evaporation (mm) in the 24 hours to 9am

7. Sunshine: The number of hours of bright sunshine in the day.

8. WindGustDir: The direction of the strongest wind gust in the 24 hours to midnight

9. WindGustSpeed: The speed (km/h) of the strongest wind gust in the 24 hours to midnight

10. WindDir9am: Direction of the wind at 9am

11. WindDir3pm: Direction of the wind at 3pm

12. WindSpeed9am: Wind speed (km/hr) averaged over 10 minutes prior to 9am

13. WindSpeed3pm: Wind speed (km/hr) averaged over 10 minutes prior to 3pm

14. Humidity9am: Humidity (percent) at 9am

15. Humidity3pm: Humidity (percent) at 3pm

16. Pressure9am: Atmospheric pressure (hpa) reduced to mean sea level at 9am

17. Pressure3pm: Atmospheric pressure (hpa) reduced to mean sea level at 3pm

18. Cloud9am: Fraction of sky obscured by cloud at 9am. This is measured in ”oktas”, which are a unit of eigths. It records how many eigths of the sky are obscured by cloud. A 0 measure indicates completely clear sky whilst an 8 indicates that it is completely overcast.

19. Cloud3pm: Fraction of sky obscured by cloud (in ”oktas”: eighths) at 3pm. See Cload9am for a description of the values

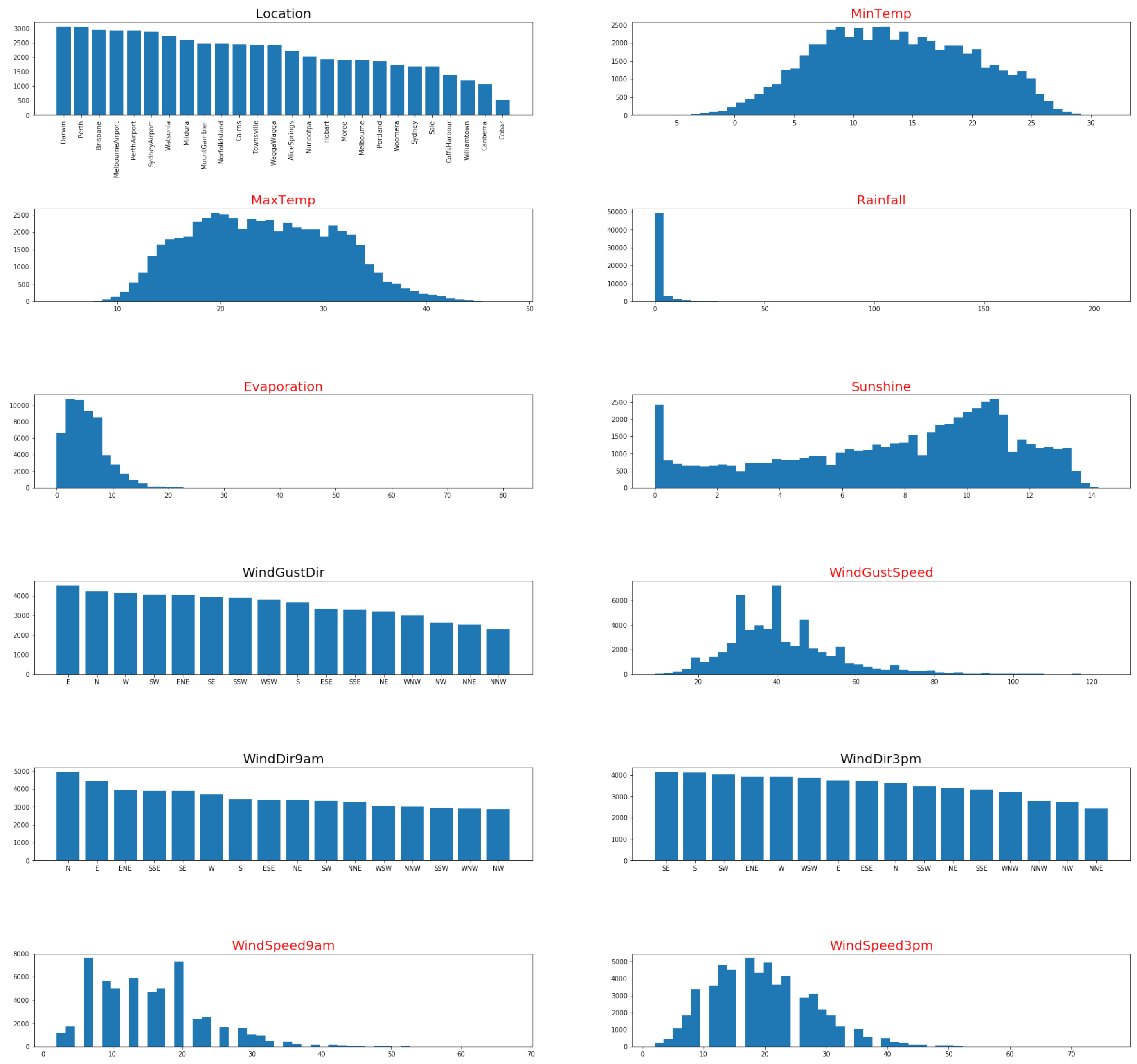
20. Temp9am: Temperature (degrees C) at 9am

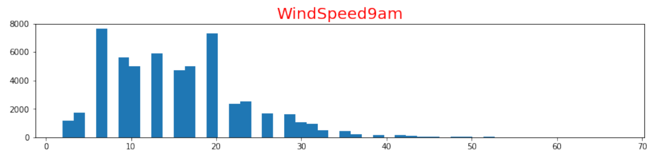
21. Temp3pm: Temperature (degrees C) at 3pm

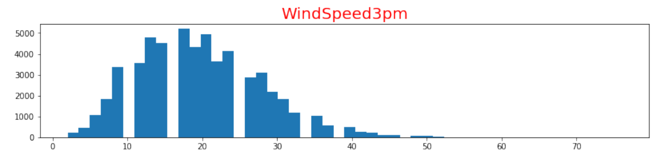
22. RainToday: Boolean 1 if precipitation (mm) in the 24 hours to 9am exceeds 1mm, otherwise 0

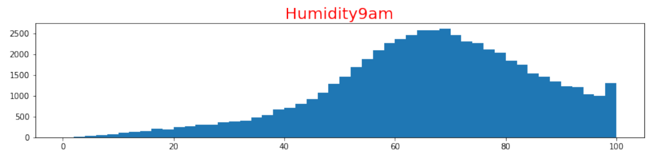
23. RainTomorrow: The target variable. Did it rain tomorrow?

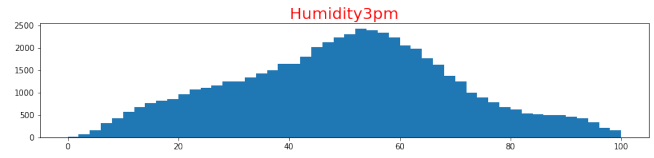
Next, I provide some graphic illustration on the distribution of attributes values in the dataset. The red attribute names means that the feature is numerical, otherwise it's categorical:

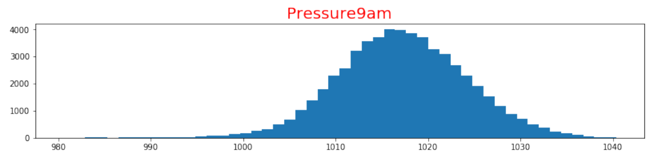

Location
Darwin
Perth
Brisbane
MelbourneAirport
PerthAirport
SydneyAirport
Watsonia
Mildura
MountGambier
NorfolkIsland
Cairns
Townsville
WaggaWagga
AliceSprings
Nuriootpa
Hobart
Moree
Melbourne
Portland
Woomera
Sydney
Sale
CoffsHarbour
Williamtown
Canberra
Cobar
MinTemp
MaxTemp
Rainfall
Evaporation
Sunshine
WindGustDir
E N W SW ENE SE SSW WSW S ESE SSE NE WNW NW NNE NNW
WindGustSpeed
WindDir9am
N E ENE SSE SE W S ESE NE SW NNE WSW NNW SSW WNW NW
WindDir3pm
SE S SW ENE W WSW E ESE N SSW NE SSE WNW NNW NW NNE
WindSpeed9am
WindSpeed3pm

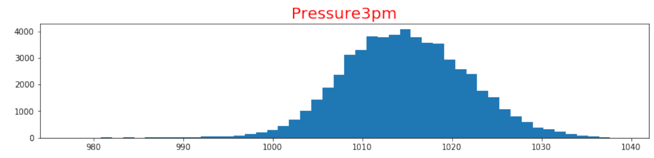

WindSpeed9am
0
2000
4000
6000
8000
0
10
20
30
40
50
60
70

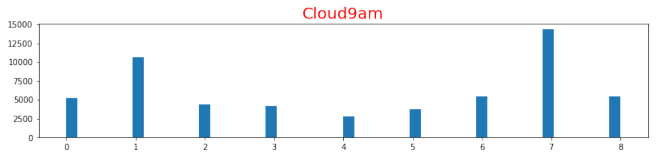

WindSpeed3pm
0
1000
2000
3000
4000
5000
0
10
20
30
40
50
60
70

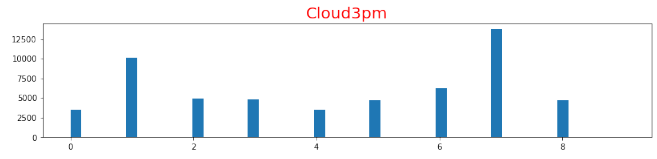

Humidity9am
0
500
1000
1500
2000
2500
0
20
40
60
80
100

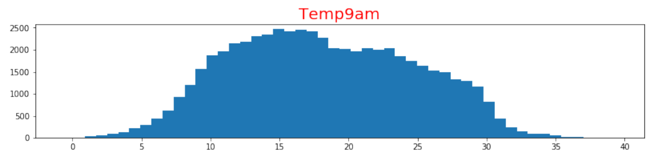

Humidity3pm
0
500
1000
1500
2000
2500
0
20
40
60
80
100

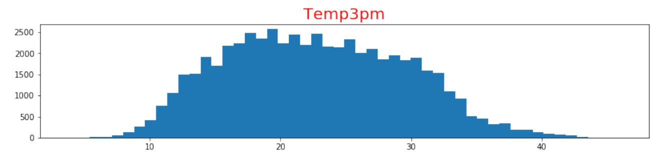

Pressure9am
0
1000
2000
3000
4000
980
990
1000
1010
1020
1030
1040

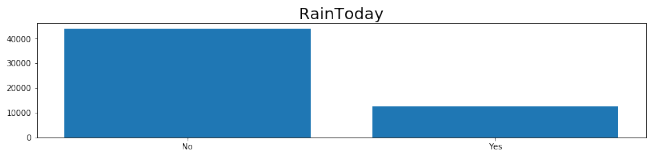

Pressure3pm
0
1000
2000
3000
4000
980
990
1000
1010
1020
1030
1040

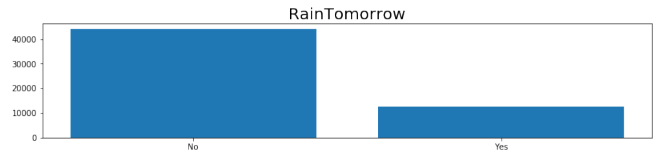

Cloud9am
0
2500
5000
7500
10000
12500
15000
0
1
2
3
4
5
6
7
8


Cloud3pm
0
2500
5000
7500
10000
12500
0
2
4
6
8


Temp9am
0
500
1000
1500
2000
2500
0
5
10
15
20
25
30
35
40


Temp3pm
0
500
1000
1500
2000
2500
10
20
30
40


RainToday
0
10000
20000
30000
40000
No
Yes


RainTomorrow
0
10000
20000
30000
40000
No
Yes

Binarization

As we know, In order for FCA lazy classification algorithm to work on some dataset it must contain only binary features. Thus, here I use some techiques to make this binarization:

- First of all, I did one-hot encoding on categorical features. This technique transformed all of my categorical features into binary ones, however it increased the number of attributes.
- For numerical I used two strategies. First one is to transform given numerical feature into two by applying so called Gini Split technique as it's done in decision trees.

  In order to split given attribute column in 2 columns I try to maximize this target function:

  $$Q(R, j) = H(R) - \frac{|R_0|}{|R|}H(R_0) - \frac{|R_1|}{|R|}H(R_1)$$

  Where, $H(R) = 1 - \sum_{k=0}^{1} p_k^2$ is Gini Index and R is is a given column, p_k - is a proportion of objects of class k, R_0 and R_1 two new columns after splitting R by threshold j (all objects $\leq j$ went to column R_0 with value 1 and 0 otherwise).

  To choose optimal threshold I maximize my target function Q.
- The second strategy for numerical attribute binarization is to split each numerical column in to three by using quantile intervals.

  First column value is 1 if it's less than 0.33 quantile and zero otherwise, second column value is 1 if it's between 0.33 and 0.66 quantiles and zero otherwise and the third column value is 1 if it's value is above 0.66 quantile and zero otherwise.

After the process of the binarization due to having two strategies for numerical attributes I ended up with two binary datasets "quantile_split_data" and "gini_split_data". Lazy classification algorithms were tested on them and baseline algorithms were tested on one-hot encoded data but with untouched numerical attributes.

Lazy classification

To begin with, I would like to note that due to computational and runtime difficulties I optet to significantly cut my datasets "quantile_split_data" and "gini_split_data" down to 1000 objects (random selection while maintaining the balance between the classes 500 "+" and 500 "-".

To evaluate all of the algorithms I used standart sklearn train and test split with proportion 0.8 to 0.2.

The first algorithm is as follows:

1. For unclassified object x I intersect it with all of the positive examples $g^+ \in G^+$ and all the negative examples $g^- \in G^-$. After each intersection $x \cap g^{+,-}$ I take it's cardinality $|x \cap g^{+,-}|$ and compare it with the threshold t I optimize later for this algorithm.

2. If $|x \cap g^+| \geq t$ I increment the positive votes *vote_pos* for object x and if $|x \cap g^-| \geq t$ I increment the negative votes *vote_neg* for object x.

3. To decide the class of x I compare *vote_pos* and *vote_neg*: if *vote_pos* $\geq$ *vote_neg* I label x as "+" and "-" otherwise.

The best results on "gini_split_data":

	Lazy Classifier 1
accuracy score	0.685
precision score	0.693
recall score	0.686
f1 score	0.689

The best results on "quantile_split_data":

	Lazy Classifier 1
accuracy score	0.745
precision score	0.754
recall score	0.788
f1 score	0.771

The second algorithm is as follows:

1. For unclassified object x I intersect it with all of the positive examples $g^+ \in G^+$ and all the negative examples $g^- \in G^-$. After each intersection $x \cap g^{+,-}$ I compute it's cardinality $|x \cap g^{+,-}|$ and add it to *intersection_neg* or *intersection_pos* variable depending on the class.

2. If $|x \cap g^+| \geq t$ I increment the positive votes *vote_pos* for object x and if $|x \cap g^-| \geq t$ I increment the negative votes *vote_neg* for object x.

3. To decide the class of x I compute the following formulas:

$$vote^- = \left(\frac{vote\_neg}{|G^-|} + 1\right) \cdot \frac{intersection\_neg}{N_{att}}$$

$$vote^+ = \left(\frac{vote\_pos}{|G^+|} + 1\right) \cdot \frac{intersection\_pos}{N_{att}}$$

4. Then, x is classified as "+" if $vote^+ \geq vote^-$ or as "-" otherwise. Parameter t again, is optimized in code.

The best results on "gini_split_data":

	Lazy Classifier 2
accuracy score	0.76
precision score	0.765
recall score	0.681
f1 score	0.72

The best results on "quantile_split_data":

	Lazy Classifier 2
accuracy score	0.765
precision score	0.773
recall score	0.78
f1 score	0.777

The third algorithm is as follows (simpler version of the second):

1. For unclassified object x I intersect it with all of the positive examples $g^+ \in G^+$ and all the negative examples $g^- \in G^-$. After each intersection $x \cap g^{+,-}$ I take it's cardinality $|x \cap g^{+,-}|$ and add it to *intersection_neg* or *intersection_pos* variable depending on the class.

2. To decide the class of x I compute the following formulas:

$$vote^- = \frac{intersection\_neg}{N_{att}}$$

$$vote^+ = \frac{intersection\_pos}{N_{att}}$$

3. To decide the class of x I compare $agg = \frac{vote\_pos}{vote\_neg}$ with optimized threshold t: if $agg \geq t$ I label x as "+" and otherwise as "-".

The best results on "gini_split_data":

	Lazy Classifier 3
accuracy score	0.745
precision score	0.72
recall score	0.696
f1 score	0.708

The best results on "quantile_split_data":

	Lazy Classifier 3
accuracy score	0.73
precision score	0.762
recall score	0.704
f1 score	0.732

Baseline algorithms

Below I provide the results on the baseline algorithms perfomance, again I tested them on randomly selected subset of 1000 objects (balanced by classes) of my data:

	Logistic Regression	SVM	Naive Bayes
accuracy score	0.725	0.72	0.67
precision score	0.742	0.693	0.672
recall score	0.721	0.826	0.711
f1 score	0.731	0.754	0.691

Conclusion

According to the results I think that lazy classification algorithms are good for scenarios with small dataset and binary nature of the data due to them being easy to apply and having good logical interpretation ability.

As we can see almost all lazy algorithms are comparable if not more precise than baseline ones. More to that, second algorithm beats baseline ones in almost every metric. This can be explained by the need of baseline algorithms to have a bigger data size for to produce competitive models.

However, unfortunately, I think lazy classification suffers with two big limitations: it's hard to apply on the data of non-binary nature and it's computational complexity grows exponentially with the size of the data.

Appendix

To do this project I used Python3 and it's libraries with Jupyter Notebook. I got the following files in github repository:

- "LazyClassifier.ipynb" - three lazy classification algorithms and their evaluation. Note, that I firstly executed all cells for "gini_split_data" and then for "quantile_split_data". Otherwise there might be a mistake since train/test split is named the same for both.
- "BaselineAlgorithms.ipynb" - SVM, Naive Bayes and Logistic regression evaluated.
- "Dataset_Preprocessing.ipynb" - splitting the dataset into "quantile_split_data" and "gini_split_data" depending on the strategy of numerical feature binarization.
- "weatherAUS.csv" - original dataset.
- "quantile_split_data", "gini_split_data" - preprocessed datasets.