Challenge mdi 343

Machine Learning - MS BigData

Christophe Thibault

Telecom ParisTech

February 11, 2018

Table of contents

- 1. Objective
- 2. First approach
- 3. Second approach
- 4. Conclusion

Challenge nmdi 343

Find a weight matrix \mathcal{M} 15x15 that represents all combinations between 14 algorithms with time constraint (600ms) with p=14 and n=2048840:

$$\begin{pmatrix} 0 & \cdots & w_{1p} \\ \vdots & \ddots & \vdots \\ 0 & \cdots & w_{np} \end{pmatrix}$$

```
# Running time of each algorithm (in milliseconds)
alg times = np.zeros((14,1))
alg times[0] = 163
alg times[1] = 163
alg times[2] = 190
alg times[3] = 190
alg times [41 = 206]
alg times[5] = 206
alg times[6] = 120
alg times [7] = 120
alg times[8] = 83
alg times[9] = 83
alg times[10] = 83
alg times[11] = 83
alg times[12] = 170
alg times[13] = 170
```

Figure 1: Algorithms running times

Data exploration

```
In [4]: import random
         import matplotlib.pyplot as plt
         import seaborn as sns
         f, ax = plt.subplots(figsize=(10, 8))
        corr = train.corr()
         sns.heatmap(corr, mask=np.zeros like(corr, dtype=np.bool), cmap=sns.diverging palette(220, 10, as cmap=True),
                    square=True, ax=ax)
Out[4]: <matplotlib.axes. subplots.AxesSubplot at 0x1154747b8>
         0
                                                                         - 0.96
         н
         2
         m
                                                                         0.88
         4
                                                                         - 0.80
         9
         4
                                                                         - 0.72
         9
                                                                         - 0.64
         Ξ
         12
         13
                                                                         0.56
         4
```

Figure 2: Matrix correlation

Data exploration

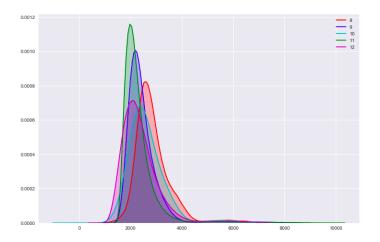


Figure 3: Probability density of scores (algorithms 8, 9, 10, 11 and 12)

5 / 10

Recurcive Feature Elimination

Recurcive Feature Elimination (REF)

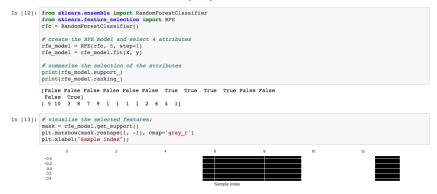


Figure 4: Recurcive Feature Elimination with random forest - Five most important are 7, 8, 9, 10 and 14

Density probability - Random Forest on the whole data set

Best Features importance

with 8 - 9 - 10 - 11 - 13 - 14 algorithms

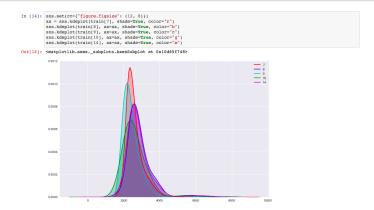


Figure 5: Density probability of scores (algorithms 7, 8, 9, 10 and 14

Find the combination: Use of Feature Importances

Best score

with 8 - 9 - 10 - 11 - 14 algorithms

3) PolynomialFeatures sur 8-9-10-11-14 avec AdaBoost

Le score sur le test est de 0.065, ce qui est mieux. Essayons maintenant avec une simple combinaison linéaire.

3b) Adaboost sur la combinaison 8, 9, 10, 11, et 14

```
X_red = np.array([X[:,7],X[:,8],X[:,9], X[:,10], X[:,13]]).reshape(2048840,5)
from sklearn.ensemble import AdaBoostClassifier
ada = AdaBoostClassifier(n_estimators=50)
ada.fit(X_red, y)
print(ada.feature_importances_)
[ 0.18 0.2 0.18 0.24 0.2 ]
```

Figure 6: Adaboost (with estimators=50) on linear and quadradic (degree=2) combination

FRR minimize

- Find the best combination that minimizes the FRR (with time constraint)
- Use of itertools to compute all combinations and calcule the FRR for each one

Results

Best combination: 8, 9, 10, 11, and 14

- ullet Use of AdaBoost classifier \Longrightarrow find the coefficients of each algorithm
- M[0,8]=0.18; M[0,9]=0.2; M[0,10]=0.18; M[0,11]=0.14; M[0,14]=0.2

Conclusion

- Best score **0.0638** with 8-9-10-11-14 algorithms
- linear combination M[0, 8] = 0.201 ; M[0,9] = 0.263; M[0, 10] = 0.181 ; M[0,11] = 0.131 ; M[0;14] = 0.147
- In any cases, best score with linear combination rather than quadratric combination.