# Rare event detection

Github repo : https://github.com/b04901056/Qualcomm-interview

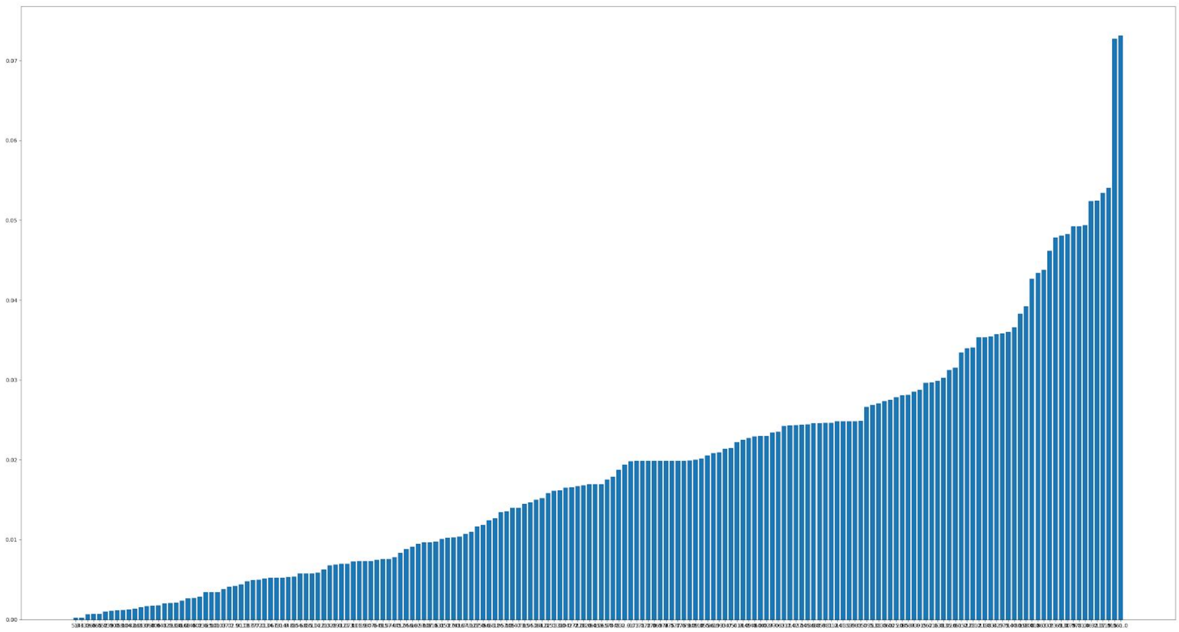
## *Data Analysis Summary & Cleanup procedure*

(1) Data in attribute #5 in training set and testing set are not consistent
=> Delete (It cannot help forecast label of attribute #4)
(2) Attribute #6 corresponds to the boolean value of attribute #4
=> Delete (otherwise, the problem will be meaningless, we can forecast the result by simply transform boolean expression to target category)
(3) Standard deviation of attribute #166,167,168,170,171,172,177 in training set are zero
=> Delete (It cannot help forecast label of attribute #4)
(4) Some testing samples have missing data or missing target (attribute #4) label
=> For missing data, fill in with the mean of this attribute from the training set;
For missing target, fill in according to the boolean value of attribute #6;
If both attribute #4 and #6 are missing, then give up this sample.

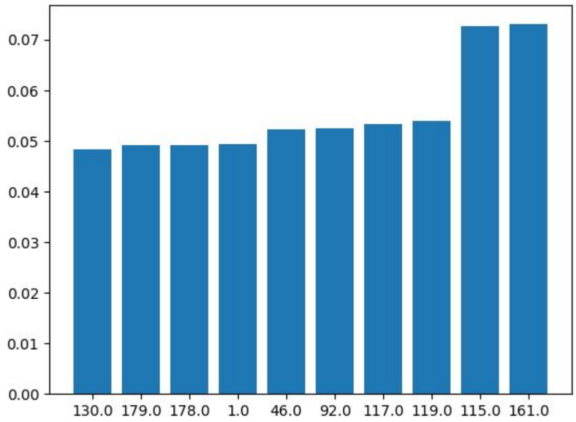
## *Inputation*

Sample #3 in training set have missing attribute #7, I used regression method to predict its value and fill it in.

The two figures below show every variable's correlation coefficient (absolute value) with attribute #4 and 10 features that are most correlated to attribute #4.



*-- python .\correlation.py .\DataMining_IV_x2\DataSet_IV_Training.csv .\DataMining_IV_x2\DataSet_IV_Test.csv*




Attribute #117,163 have higher correlation coefficient with attribute #4 compared with other variables.

I extracted 10 features that are most correlated to attribute #4 as the inputs of my Deep neural network (DNN) and attribute #4 as target, and use other samples in training set without missing data as training data to optimize my model for forecasting the value of missing data.

```
Train Epoch: 151 | [2048/2972 (67%)]     Total loss: 0.4431
predicted result:  [74763.10391301]
```

*-- python .\inputation_train.py -train .\DataMining_IV_x2\DataSet_IV_Training.csv -u 10  16 32 16 2 1*

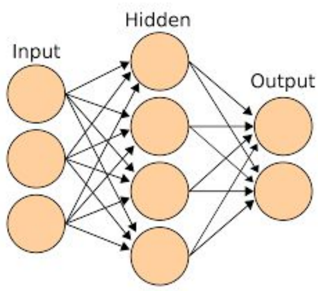
## *Transformation*

(1) Some attributes are in the form of TRUE/FALSE or category
=> Use one hot encoding to transform these attributes into binary representation
(2) Normalize each attribute, and record its mean and standard deviaton for forecasting
=> x' = (x - mean(x)) / std(x)

## *Model proposals & Results*

(1) Deep neural network (DNN)

```
DNN(
  (den): ModuleList(
    (0): Sequential(
      (0): Linear(in_features=170, out_features=32, bias=True)
      (1): ReLU()
      (2): Dropout(p=0.2)
    )
    (1): Sequential(
      (0): Linear(in_features=32, out_features=1, bias=True)
      (1): Dropout(p=0.2)
      (2): Sigmoid()
    )
  )
)
```



(http://inspirehep.net/record/1507419/plots)

*--python .\train.py -train .\DataMining_IV_x2\DataSet_IV_Training.csv -test .\DataMining_IV_x2\DataSet_IV_Test.csv -u 178 32 1*

Optimizer : Adam (momentum & adaptive learning rate)
Loss function : Binary cross entropy
Activation function : Relu (sparcity and avoiding gradient vanashing)

I used pytorch to implement a DNN with one hidden layer, and introduce dropout layer to avoid overfitting. The sigmoid function can bound the output of the model in [-1,1] for computation of binary cross entropy loss.

To make my model cost-sensitive, I adjust the weight of BCE loss function. Set higher weight for positive samples, lower one for negative samples.

Result on testing set (confusion matrix):

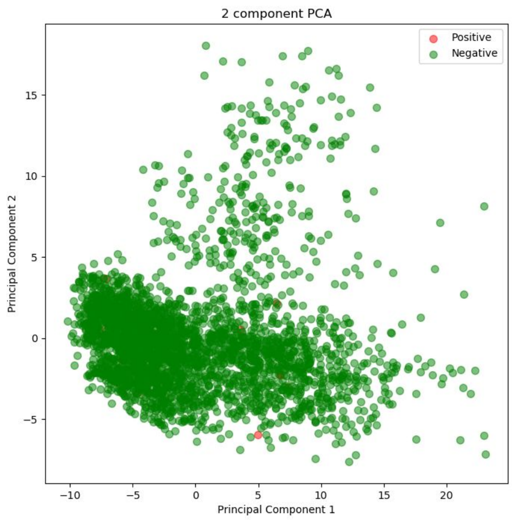
| | | Truth | |
|---|---|---|---|
| | | Positive | Negative |
| Prediction | Positive | 0 | 35 |
| | Negative | 7 | 1063 |

My model tends to recognize every sample as negative, because it put too much emphasis on negative samples buring training.

(2) DNN + over/down sampling

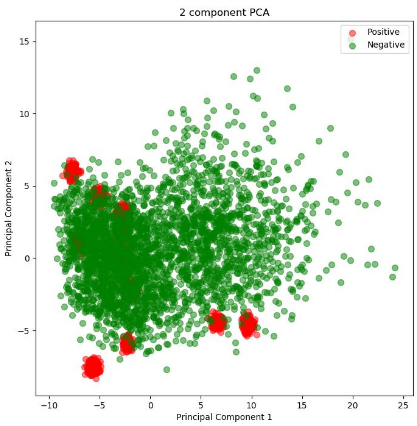
Due to imbalanced dataset, DNN model cannot learn how to detect rare event. So I tried oversampling the positive samples by simply copying them and adding small noise (avoid overfitting).

Similarly, I tried downsampling by deleting some negative samples to balance the training set. The figures below demonstrate the effect of over/down samping (use PCA to map the training data to a two-dimensional plane and plot it with matplotlib).

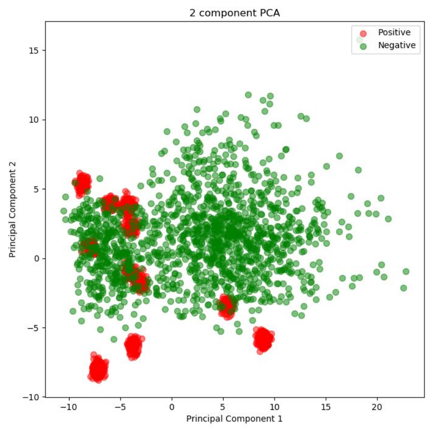




(original training data)




oversampling




over & down sampling

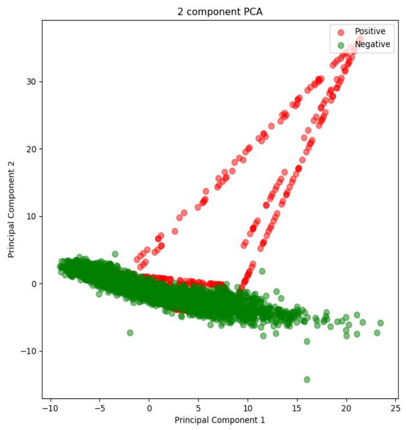
Result on testing set (confusion matrix):

| | | Truth | |
|---|---|---|---|
| | | Positive | Negative |
| Prediction | Positive | 0 | 94 |
| | Negative | 7 | 1004 |

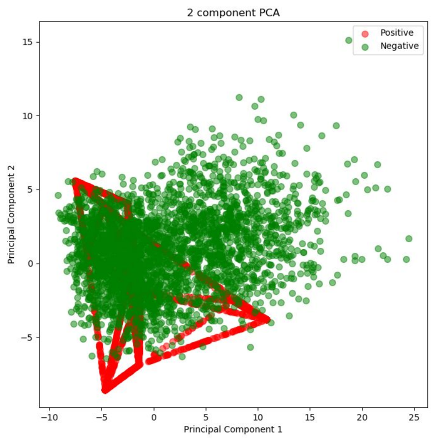
Although my model can detect rare events on validation set, it performs poorly on testing set. I conclude that over/down sampling are not enough to tackle the problem due to overfitting.

(3) DNN + Generated synthetic samples

I found an algorithm called SMOTE on the internet, which introduces randomness in generating the synthetic data instead of copies. I hope that it can help resolve the problem of overfitting.




SMOTE




SMOTE, remove outliers

Result on validation set (confusion matrix):

| | | Truth | |
|---|---|---|---|
| | | Positive | Negative |
| Prediction | Positive | 3 | 106 |
| | Negative | 0 | 189 |

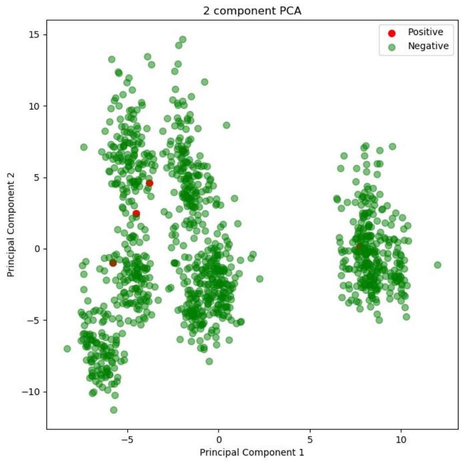
Result on testing set (confusion matrix):

| | | Truth | |
|---|---|---|---|
| | | Positive | Negative |
| Prediction | Positive | 0 | 10 |
| | Negative | 7 | 1088 |

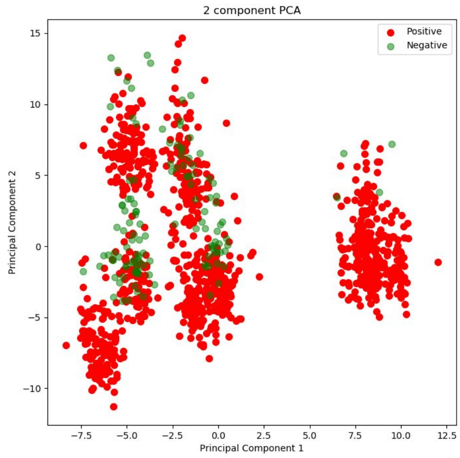
My model performs little bit better on validation set than testing set, so I guess that training set and testing set have different data distribution. I tried adding Dropout layers to prevent overfitting but didn't see much improvement.

SMOTE algorithm still cannot effectively resolve this problem, so I started to consider some classification approaches other than neural-based methods.

(4) Support vector machine (SVM) + Generated synthetic samples




Ground truth




Classification using SVM

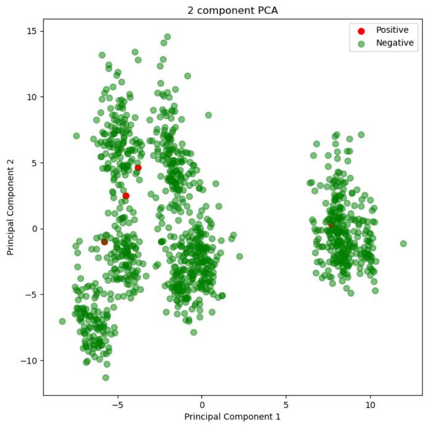
SVM combines hinge loss function and kernal trick, implicitly project data points into high-dimensional feature space to do non-linear binary classification. I use training set to optimize the SVM in sklearn package, and use it to forecast the result (with visualization).

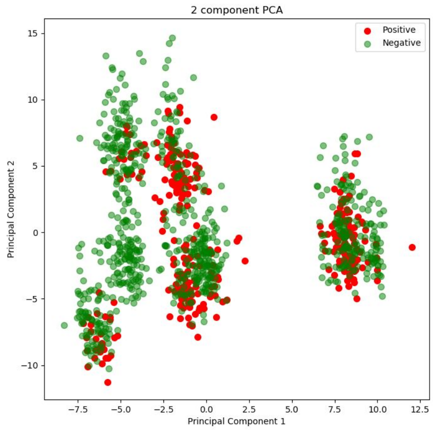
Result on testing set (confusion matrix):

<table>
<tr><td colspan="2" rowspan="2"></td><td colspan="2">Truth</td></tr>
<tr><td>Positive</td><td>Negative</td></tr>
<tr><td rowspan="2">Prediction</td><td>Positive</td><td>3</td><td>120</td></tr>
<tr><td>Negative</td><td>4</td><td>978</td></tr>
</table>

-- *python .\svm.py .\DataMining_IV_x2\DataSet_IV_Training.csv .\DataMining_IV_x2\DataSet_IV_Test.csv*

(5) Logistic regression + Generated synthetic samples




Ground truth

Classification using Logistic regression

Logistic regression uses cross entropy between two Bernoulli distribution as loss function and use gradient descent for model optimization. I use training data to optimize the logistic regression model in sklearn package, and use it to forecast the result (with visualization).

Result on testing set (confusion matrix):

| | | Truth | |
|---|---|---|---|
| | | Positive | Negative |
| Prediction | Positive | 1 | 338 |
| | Negative | 6 | 760 |

*-- python .\logistic_regression.py .\DataMining_IV_x2\DataSet_IV_Training.csv .\DataMining_IV_x2\DataSet_IV_Test.csv*

## *Conclusion*

Neural-based method can learn to detect rare event, but performs poorly on testing set due to overfitting, neither does non neural-based approaches. Although I tried over/down sampling and SMOTE algorithm to balance the dataset, the result is not significant. Therefore, I guess that more balanced dataset and customized methods is necessary to tackle this kind of rare event detection.