Passion_v5.1

July 20, 2020

1 Welcome to Passion!

Passion is a model that can detection anomaly using different methods (Both supervised and unsupervised)

- 1. The goal for this project is to study the difference between different anomaly detection model, and to find the state of art method for detecting anomaly in real world data
- 2. Evaluate the results based on this :real server data+ https://www.kaggle.com/sohier/30-years-of-european-wind-generation + https://github.com/numenta/NAB
- 3. Also use real data generated from server.
- 4. The model has the following fuctions:
 - a. Visualize the input data. Help the user to find critical features within the inputs.
 - b. Give user options to choose different models that are suitable for different circumstances.
 - c. Evaluate the performance based on the rules in this link https://github.com/numenta/NAB
 - d. Save model. Easy to be appplied to other dataset.
- 5. Add un-labeled and labeled data

2 What's new in version 5.1

- 1. Add labeled data
- 2. Apply MLSTM_FCN to labeled data
- 3. Apply ATTLSTM_FCN to labeled data
- 4. More plots

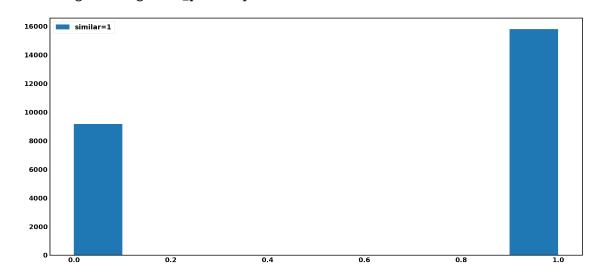
In [1]: # import packages

```
from matplotlib.pylab import rc
import torch
from scipy.stats import chisquare
from scipy.stats import pearsonr
import pickle
import pandas as pd
import datetime
```

```
import matplotlib
        import tensorflow as tf
        import sklearn
        import math
        import matplotlib.pyplot as plt
        import xgboost
        from xgboost import XGBClassifier
        from xgboost import plot_importance
        import numpy as np
        from sklearn.model_selection import train_test_split
        import sklearn
        from sklearn import preprocessing
        from sklearn.preprocessing import LabelEncoder
        import copy
        import scipy
        import datetime
        import time
        import os
        from sklearn.model_selection import KFold
        from sklearn.metrics import roc curve
        from sklearn.metrics import roc_auc_score
        from sklearn.decomposition import PCA
        from sklearn.cluster import KMeans
        from sklearn.covariance import EllipticEnvelope
        from sklearn.ensemble import IsolationForest
        from sklearn.svm import OneClassSVM
        import gc
        import json
        plot_path = "plots/"
In [2]: # Real server data
        root_path = "Data/Ant_202007/"
        cif = pd.read_json(root_path+'cif.json', orient='index')
        paycore = pd.read_json(root_path+'paycore.json', orient='index')
        paydecision = pd.read_json(root_path+'paydecision.json', orient='index')
        paydecision2 = pd.read_json(root_path+'paydecision2.json', orient='index')
        paydecision3 = pd.read_json(root_path+'paydecision3.json', orient='index')
        df = pd.DataFrame()
        df["time stamp"] = cif.index
        df["cif"] = cif[0].values
        df["paycore"] = paycore[0].values
        df["paydecision"] = paydecision[0].values
        df["paydecision2"] = paydecision2[0].values
        df["paydecision3"] = paydecision3[0].values
```

```
# Optional
        if False:
            df.to_csv(root_path+"fusion.csv")
        # convert time stamp
        df['time_stamp'] = pd.to_datetime(df['time_stamp'])
        names_array = np.array(df.keys()[1:],dtype="str")
        os.listdir(root_path)
Out[2]: ['.ipynb_checkpoints',
         'cif.json',
         'fusion.csv',
         'paycore.json',
         'paydecision.json',
         'paydecision2.json',
         'paydecision3.json']
In [3]: if False:
            # calculate previous hour high low:
            # convert to seconds
            temp = df['time_stamp'] - min(df['time_stamp'])
            temp = temp.dt.total_seconds().astype(int)
            df["hours"] = temp//3600
            h_max = max(df["hours"])+1
            for n in range(len(names_array)):
                df[names_array[n]+"_open"] = df[names_array[n]]
                df[names_array[n]+"_close"] = df[names_array[n]]
                df [names_array[n]+"_max"] = df [names_array[n]]
                df [names_array[n]+"_min"] = df [names_array[n]]
            for j in range(1,h_max):
                mask_j = df["hours"] == j-1
                max_val = df[mask_j][names_array].max(axis=0).values
                min_val = df[mask_j][names_array].max(axis=0).values
                open_val = df[mask_j][names_array].values[0,:]
                close_val = df[mask_j][names_array].values[-1,:]
                mask_i = df["hours"]==j
                r = df[mask_i][names_array].shape[0]
                df.loc[mask_i,[r+"_open" for r in names_array]] = np.tile(open_val,(r,1))
                df.loc[mask_i,[r+"_close" for r in names_array]] = np.tile(close_val,(r,1))
                df.loc[mask_i,[r+"_max" for r in names_array]] = np.tile(max_val,(r,1))
                df.loc[mask_i,[r+"_min" for r in names_array]] = np.tile(min_val,(r,1))
```

```
In [4]: # labeled data:
        root_path2 = "Data/Ant_labeled/"
        today = []
        history = []
        label = []
        count=0
        with open(root_path2+"train_data.txt") as f:
            for line in f:
                temp = json.loads(line)
                today.append(temp["today"])
                history.append(temp["history"])
                label.append(temp["label"])
                count+=1
        today = np.array(today)
        history = np.array(history)
        label = np.array(label).ravel()
In [20]: # For labeled data, we use today+history+diff to check them:
         X = np.c_[today,history]
         \#X = np.atleast_3d(X)
         # X = np.dstack((today,history))
         y = label
         # Hyper parameters
         # Attention LSTM simple model
         n_epoch=40
         n_cell = 50
         # predict 1 minute for now
         N output=1
         N_{input} = 5
         index_name= 0
         rate_dropout=0.2
         checkpoint_path = "CNN_1D/cp.ckpt"
         checkpoint_dir = os.path.dirname(checkpoint_path)
         ## Try log10?
         np_scaled = np.log10(X)
         # split train test:
         X_train, X_test, y_train, y_test = train_test_split(np_scaled, y, test_size=0.3, shuf;
<ipython-input-20-fab922c116ee>:23: RuntimeWarning: divide by zero encountered in log10
```

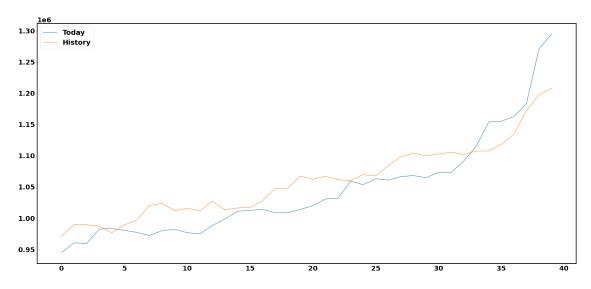


```
fig = matplotlib.pyplot.gcf()

fig.set_size_inches(35,16)
save_path = plot_path + "labeled_example" + ".png"

fig.savefig(save_path, dpi=150)
```

One day data y=1



```
In [21]: # Try xgboost
    params={}
    params['booster'] = "gbtree"
    params['gpu_id'] = 0
    params['max_bin'] = 512
    params['tree_method'] = 'gpu_hist'

model = XGBClassifier(n_estimators=1000,n_jobs=-1,**params)
    model.fit(X_train,y_train)
```

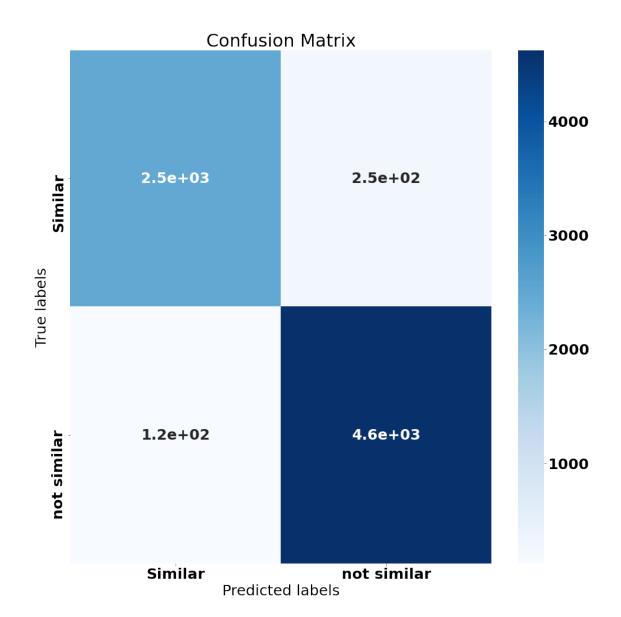
[20:55:41] WARNING: /workspace/src/learner.cc:480: Parameters: { verbose } might not be used.

This may not be accurate due to some parameters are only used in language bindings but passed down to XGBoost core. Or some parameters are not used but slip through this verification. Please open an issue if you find above cases.

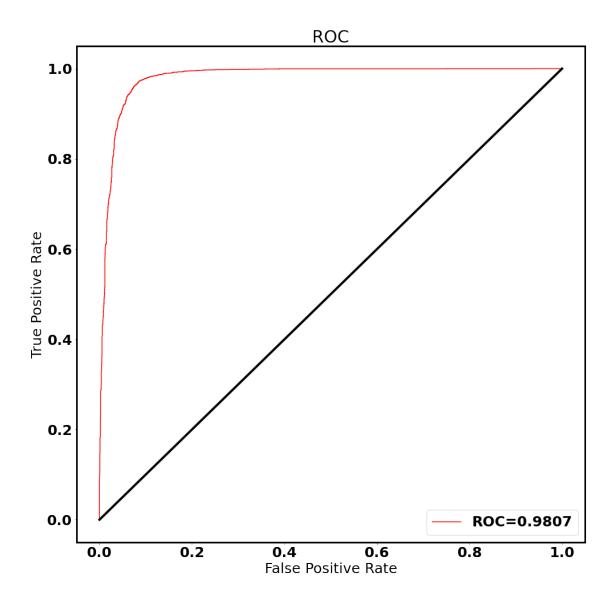
```
Out[21]: XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
                      colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=0,
                      importance_type='gain', interaction_constraints='',
                      learning_rate=0.300000012, max_bin=512, max_delta_step=0,
                      max_depth=6, min_child_weight=1, missing=nan,
                      n_estimators=3000, n_jobs=-1, num_parallel_tree=1, random_state=0,
                      reg_alpha=0, reg_lambda=1, scale_pos_weight=1, subsample=1,
                      tree_method='gpu_hist', validate_parameters=1, verbose=2,
                      verbosity=None)
In [26]: Y_predict_test = model.predict(X_test)
        mask_good = abs(Y_predict_test-y_test)<0.01</pre>
        print("Good=%d Bad=%d"%(len(Y_predict_test[mask_good]),len(Y_predict_test)-len(Y_pred
        print("Accuracy=%.4f for testing set"%(len(Y_predict_test[mask_good])/len(Y_predict_test[mask_good])/
Good=7115 Bad=370
Accuracy=0.9506 for testing set
In [48]: def confusion_matrix(y_pred,y_true):
            TP = len(y_pred[(y_pred==1)&(y_true==1)])
            TN = len(y_pred[(y_pred==1)&(y_true==0)])
            # type1 error : false alarm
            FP = len(y_pred[(y_pred==1)&(y_true==0)])
            # type 2 error. Fail to make alarm
            FN = len(y_pred[(y_pred==0)&(y_true==1)])
            recall = TP/(TP+FN)
            precision = TP/(TP+FP)
            accuracy = (TP+TN)/len(y_pred)
            f1_score = 2/(1/precision+1/recall)
            return TP,TN,FP,FN,recall,precision,accuracy,f1_score
        temp = confusion_matrix(y_pred=y_pred,y_true=y_test)
        f1 = temp[-1]
        print("F1 score=%.4f"%f1)
F1 score=0.9615
In [43]: from sklearn.metrics import confusion_matrix
```

import seaborn as sns

```
font = {'family': 'normal', 'weight': 'bold',
       'size': 25}
matplotlib.rc('font', **font)
rc('axes', linewidth=3)
labels = ["Similar","not similar"]
cm = confusion_matrix(y_test, Y_predict_test)
ax= plt.subplot()
sns.heatmap(cm, annot=True, ax = ax,cmap=plt.cm.Blues)
# labels, title and ticks
ax.set_xlabel('Predicted labels')
ax.set_ylabel('True labels')
ax.set_title('Confusion Matrix')
ax.xaxis.set_ticklabels(labels)
ax.yaxis.set_ticklabels(labels)
fig = matplotlib.pyplot.gcf()
fig.set_size_inches(16,16)
save_path = plot_path + "labeled_confusion" + ".png"
fig.savefig(save_path, dpi=150)
```



```
## draw ROC:
         fpr, tpr, thresholds = roc_curve(testy, probs)
         font = {'family': 'normal', 'weight': 'bold',
                 'size': 25}
        matplotlib.rc('font', **font)
        rc('axes', linewidth=3)
        plt.plot(fpr, tpr, color='r', label='ROC=%.4f'%auc)
        plt.plot([0, 1], [0, 1], color='k', linewidth=4)
        plt.xlabel('False Positive Rate')
        plt.ylabel('True Positive Rate')
        plt.title('ROC')
        plt.legend()
        fig = matplotlib.pyplot.gcf()
        fig.set_size_inches(16,16)
         save_path = plot_path + "labeled_AUROC" + ".png"
         fig.savefig(save_path, dpi=150)
AUROC: 0.9807
```



2.1 Now we reach 95% accuracy and 0.98 AUROC, which means the model has high robustness

3 Try NN model since it's faster in testing:

```
In []: if False:
          #### Model: need to re-think first
          from keras.models import Model
          from keras.layers import Input, Dense, LSTM, multiply, concatenate, Activation, Management from keras.layers import Conv1D, BatchNormalization, GlobalAveragePooling1D, Permurence
```

data:

```
\#X = np.c_[today, history]
\#X = np.atleast_3d(X)
X = np.dstack((today,history))
y = label
# Hyper parameters
# Attention LSTM simple model
n_{epoch=40}
n_cell = 50
index_name= 0
rate_dropout=0.2
checkpoint_path = "NN_classifier/cp.ckpt"
checkpoint_dir = os.path.dirname(checkpoint_path)
## Try log10?
np_scaled = np.log10(X)
# split train test:
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, shuffle=T
# model:
def generate_model(MAX_TIMESTEPS,MAX_NB_VARIABLES):
    ip = Input(shape=(MAX_TIMESTEPS,MAX_NB_VARIABLES))
    \# split into x and y two channels
    x = Masking()(ip)
    x = Flatten()(x)
    x = Dense(100)(x)
    x = Dropout(rate_dropout)(x)
    x = Dense(50, activation='relu')(x)
    out = Dense(1, activation='softmax')(x)
    print(out.shape)
    model = Model(ip, out)
    model.summary()
    # add load model code here to fine-tune
```

```
model = generate_model(X.shape[1],X.shape[2])
            model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
            #model.summary()
            callback = tf.keras.callbacks.ModelCheckpoint(filepath=checkpoint_path,
                                                              save_weights_only=True,
                                                             verbose=1)
            # Let's do it!
           h = model.fit(X_train, y_train, epochs=n_epoch, batch_size=64, validation_data=(X_
In [ ]: # NN model doesn't perform well due to low dimension. Maybe try logistic regression?
  Logistic regression
not as good as xgboost
In [69]: from sklearn.datasets import load_iris
         from sklearn.linear_model import LogisticRegression
         X = np.c_[today,history]
         \#X = np.atleast_3d(X)
         \# X = np.dstack((today, history))
         y = label
         X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, shuffle=True
         clf = LogisticRegression(random_state=0).fit(X_train, y_train)
         y_pred = clf.predict(X_test)
/home/jc6933/anaconda3/envs/tf22/lib/python3.8/site-packages/sklearn/linear_model/_logistic.py
```

return model

STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:

https://scikit-learn.org/stable/modules/preprocessing.html Please also refer to the documentation for alternative solver options:

```
https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
 n_iter_i = _check_optimize_result(
In [70]: mask_good = abs(y_pred-y_test)<0.01</pre>
         print("Good=%d Bad=%d"%(len(y_pred[mask_good]),len(y_pred)-len(y_pred[mask_good])))
         print("Accuracy=%.4f for testing set"%(len(y_pred[mask_good])/len(y_pred)))
Good=6586 Bad=899
Accuracy=0.8799 for testing set
In [71]: def confusion_matrix(y_pred,y_true):
             TP = len(y_pred[(y_pred==1)&(y_true==1)])
             TN = len(y_pred[(y_pred==1)&(y_true==0)])
             # type1 error : false alarm
             FP = len(y_pred[(y_pred==1)&(y_true==0)])
             # type 2 error. Fail to make alarm
             FN = len(y_pred[(y_pred==0)&(y_true==1)])
             recall = TP/(TP+FN)
             precision = TP/(TP+FP)
             accuracy = (TP+TN)/len(y_pred)
             f1_score = 2/(1/precision+1/recall)
             return TP,TN,FP,FN,recall,precision,accuracy,f1_score
         temp = confusion_matrix(y_pred=y_pred,y_true=y_test)
         f1 = temp[-1]
         print("F1 score=%.4f"%f1)
F1 score=0.9052
In [73]: # not very good :(
         clf.score(X, y)
Out[73]: 0.8785072951739619
In [ ]:
In []:
In []:
In [108]:
In [109]:
```

- In []:
- In []: