File "<ipython-input-22-4089ec26b745>", line 2 Read more on the example case here: https://github.com/seg/2016-ml-contest/blob/master/Facies_classifica tion.ipynb SyntaxError: invalid syntax You are given complete dataset of the field's Well Log Models generated from TNAV's software. There are 8 wells which dataset are not complete in some of the wells due to cost challenge imposed by the management as impact of Covid Crisis. Your senior engineer and Geologist have developed a Machine Learning model to predict Facies based Random Forest Algorithm. The accuracy of the model is 0.8678479783618837 (as shown at the end of the notebook). However you are challenged to beat the benchmark of the accuracy result using your own choice of Machine Learning algorithm. Instruction on How to Start

The instruction here is given to you to help you embark exploring your data and understanding how to build your first Machine

online resources on starting up your first Python program. This Youtube Video is one of the example on Anaconda tutorial:

https://www.youtube.com/watch?v=beh7GE4FdnM. You are free to use other programming Tools such as R or Matlab if you are

Reservoir Description Machine Learning Challenge

Your assignment is based on this SEG Machine Learning Contest https://github.com/seg/2016-ml-contest. Read more on the example case here: https://github.com/seg/2016-ml-contest/blob/master/Facies classification

1. Download Python Software to run this notebook. You can use Anaconda or your own favorite Python Toolkit. Anaconda installation link: https://repo.anaconda.com/archive/Anaconda3-2020.11-Windows-x86_64.exe 1. After you complete the installation, if you're not familiar with Python or Anaconda you can watch series of Youtube video or other

Learning algorithm.

more proficient in using those programming language.

1. If you have experienced using Python and has already build ML applications before then congratulations. The committee will evluate the level of difficulty for Machine Learning problems for the next round based on the best performing team. There are a lot of resources to learn about Machine Learning algorithms in Python, for further reading you can learn from Scikit-Learn, one of the

most popular ML library in python here: https://scikit-learn.org/stable/

Description bellow and lets begin to Code!

Python has a lot of Open Source libraries of functions that you could use for any type of Data Science or programming purposes. The

1. If you dont need introductary Python resources as mentioned on step 1 to 3 above, you can just go straight ahead to Case Invoke and install Python modules required for the work

beauty of these open source Libraries is you dont need to write your own function for generic Machine Learning application. However, every Machine Learning applications are built differently and need to be tuned in order to improve its accuracy. The following lines of

codes are necessary to call all the built in functions/Library for your ML project.s

In []: import pandas as pd import re import os

import matplotlib.pyplot as plt

import datetime as dt import xlrd import numpy as np %matplotlib inline import warnings warnings.filterwarnings('ignore') import pandas as pd import numpy as np import matplotlib as mpl

import matplotlib.colors as colors from mpl_toolkits.axes_grid1 import make_axes_locatable import seaborn as sns from pandas import set_option # set_option("display.max_rows", 10) pd.options.mode.chained_assignment = None ##### import stuff from scikit learn from sklearn.ensemble import RandomForestClassifier,RandomForestRegressor from sklearn.model_selection import KFold, cross_val_score,LeavePGroupsOut, LeaveOneGroupOut, cross_val_pred from sklearn.metrics import confusion_matrix, make_scorer, f1_score, accuracy_score, recall_score, precision from sklearn.multiclass import OneVsOneClassifier,OneVsRestClassifier

import matplotlib.pyplot as plt import seaborn as sns Set your working directory Before we go any further, set your own working folder. This is where you stored all the CSV files from TNAV well logs model. os.chdir('C:/Users/rim3dh/POD_Competition') Pro Tip: you will see a lot of hash (#) symbol. This indicate comment that I put to describe what I did to the code

Compile the wells dataset

In []: #Call all your Well Log CSV file as your dataframe

df1 = pd.read csv("I1.csv", delimiter=r"\s+")

df2 = pd.read_csv("I3.csv", delimiter=r"\s+") df2['WELLNAME'] = 'I3' df3 = pd.read_csv("W1.csv", delimiter=r"\s+") df3['WELLNAME'] = 'W1' df4 = pd.read_csv("W2.csv", delimiter=r"\s+") df4['WELLNAME'] = 'W2' df5 = pd.read_csv("W3.csv", delimiter=r"\s+") df5['WELLNAME'] = 'W3' df6 = pd.read csv("W4.csv", delimiter=r"\s+") df6['WELLNAME'] = 'W4'

df1['WELLNAME'] = "I1"

df7 = pd.read csv("W5.csv", delimiter=r"\s+") df7['WELLNAME'] = 'W5' df8 = pd.read csv("X1.csv", delimiter=r"\s+") df8['WELLNAME'] = 'x1'df = pd.concat([df1,df2, df3, df4, df5, df6, df7, df8])df =df.replace(-999.25, 0) **Exploring The Data**

Lets label your Facies according to geological description

facies dict = { 0: 'Shale', 1: 'Sandstone', 2: 'Silt', 3: 'Coal'}

#facies color map is a dictionary that maps facies labels to their respective colors

Count the number of unique entries for each facies, sort them by facies number (instead of by number of en

facies_counts.plot(kind='bar',color=facies_colors, title='Distribution of Training Data by Facies')

cmap facies = colors.ListedColormap(facies colors[0:len(facies colors)], 'indexed')

cluster=np.repeat(np.expand dims(logs['Facies'].values,1), 100, 1)

f, ax = plt.subplots(nrows=1, ncols=11, figsize=(15, 18))

ax[8].plot(logs.Core Porosity, logs.DEPTH, '-', color='red') ax[9].plot(logs.Core Permeability, logs.DEPTH, '-', color='gold')

im=ax[10].imshow(cluster, interpolation='none', aspect='auto', cmap=cmap facies, vmin=1, vmax=4)

cbar.set_label((17*' ').join(['Shale', 'SS', 'Silt', 'Coal']))

cax = divider.append axes("right", size="20%", pad=0.05)

cbar.set_ticks(range(0,1)); cbar.set_ticklabels('')

ax[i].locator_params(axis='x', nbins=3)

ax[1].set_xlim(logs.SP.min(),logs.SP.max())

ax[0].set_xlim(logs.GR.min(),logs.GR.max())

ax[2].set_xlim(logs.RES.min(),logs.RES.max())

ax[3].set_xlim(logs.RHOB.min(),logs.RHOB.max())

ax[4].set_xlim(logs.NPHI.min(),logs.NPHI.max())

ax[6].set_xlim(logs.PHIE.min(),logs.PHIE.max())

ax[8].set_xlim(logs.Core_Porosity.min(),logs.Core_Porosity.max())

f.suptitle('Well: %s'%logs.iloc[0]['WELLNAME'], fontsize=14,y=0.94)

hue_order=list(reversed(facies_labels)), size=1.25);

X_validation = validation_data[["SP","GR","RES","RHOB","NPHI","VSH","PHIE","SW"]]

make_facies_log_plot(df[df['WELLNAME'] == 'W4'], facies colors)

Preparing the data for machine learning

ax[9].set_xlim(logs.Core_Permeability.min(),logs.Core_Permeability.max())

ax[1].set_yticklabels([]); ax[2].set_yticklabels([]); ax[3].set_yticklabels([]) ax[4].set_yticklabels([]); ax[5].set_yticklabels([]); ax[6].set_yticklabels([]); ax[7].set_yticklabels([]); ax[8].set_yticklabels([]); ax[9].set_yticklabels([]);

training_data, validation_data = train_test_split(df, test_size=0.7, random_state=42, shuffle=True)

sns.pairplot(training_data.drop(['WELLNAME', "Facies"], axis=1), hue='FaciesLabels', palette=facies_color_magents.

scikit-learn includes a preprocessing module that can 'standardise' the data (giving each variable zero mean and unit variance, also

Many machine learning algorithms assume features will be standard normally distributed data (ie: Gaussian with zero mean and unit

The factors used to standardise the training set must be applied to any subsequent feature set that will be input to the classifier.

min samples split=50, class weight='balanced', random state=42, n jobs=-1)

min samples split=50, class weight='balanced', random state=42, n jobs=-1)

ax[5].set_xlim(logs.VSH.min(),logs.VSH.max())

ax[7].set_xlim(logs.SW.min(),logs.SW.max())

ax[8].set_xlabel("Core_Porosity")

ax[9].set xlabel("Core Permeability")

ax[2].plot(logs.RES, logs.DEPTH, '-', color='0.5') ax[3].plot(logs.RHOB, logs.DEPTH, '-', color='orange') ax[4].plot(logs.NPHI, logs.DEPTH, '-', color='black') ax[5].plot(logs.VSH, logs.DEPTH, '-', color='purple') ax[6].plot(logs.PHIE, logs.DEPTH, '-', color='cyan') ax[7].plot(logs.SW, logs.DEPTH, '-', color='blue')

0 =Sale, 1=sandstone, 2=c siltstone, 3=Coal

for ind, label in enumerate(facies labels):

Use facies labels to index each count facies counts.index = facies labels

Visualize The Well Data

import matplotlib.colors as colors

Replace numeric "Facies" with "FaciesLabels"

facies_colors = ['gray', '#F4D03F', 'green','black'] facies labels = ['Shale', 'Sandstone', 'Silt', 'Coal']

facies_color_map[label] = facies_colors[ind]

df["FaciesLabels"] = df["Facies"].replace(facies dict)

facies_counts = df['Facies'].value_counts().sort_index()

from mpl_toolkits.axes_grid1 import make_axes_locatable

ztop=logs.DEPTH.min(); zbot=logs.DEPTH.max()

def make facies log plot(logs, facies colors): #make sure logs are sorted by depth logs = logs.sort values(by='DEPTH')

ax[1].plot(logs.SP, logs.DEPTH, '-g') ax[0].plot(logs.GR, logs.DEPTH, '-')

divider = make axes locatable(ax[10])

cbar=plt.colorbar(im, cax=cax)

ax[i].set_ylim(ztop,zbot) ax[i].invert_yaxis()

for i in range(len(ax)-1):

ax[i].grid()

ax[1].set xlabel("SP")

ax[0].set xlabel("GR")

ax[2].set xlabel("RES")

ax[3].set xlabel("RHOB")

ax[4].set xlabel("NPHI")

ax[5].set xlabel("VSH")

ax[6].set xlabel("PHIE")

ax[10].set_xlabel('Facies')

ax[10].set_yticklabels([])

ax[10].set xticklabels([])

split the data into train and test set

Separate features from the labels for our training data

y_validation = validation_data["Facies"]

Standardising/whitening the data

scaler = preprocessing.StandardScaler().fit(X)

X validation = scaler.transform(X validation)

OVR = OneVsRestClassifier(Cl,n jobs=-1) groups = training data['WELLNAME']

lpgo = LeavePGroupsOut(n groups=2)

cv=lpgo.split(X, y, groups)

scores.append(validated)

scores = np.swapaxes(scores, 0, 1)

#Create a Gaussian Classifier

OVR = OneVsRestClassifier(Cl,n jobs=-1) groups = training data['WELLNAME']

lpgo = LeavePGroupsOut(n groups=2)

y pred=clf2.predict(X validation)

method list = ['RF submission 3','One vs Rest']

method list = ['RF submission 3','One vs Rest']

scores = pd.DataFrame(data=scores, columns=method list)

from sklearn.ensemble import RandomForestClassifier

Applying Random Forest Algorithm to validation data

#Train the model using the training sets y pred=clf.predict(X test)

In []: # Code for printing a pretty confusion matrix - hidden during presentation

"""Display confusion matrix with labels, along with metrics such as Recall, Precision and F1 score.

Based on Zach Guo's print cm gist at https://gist.github.com/zachguo/10296432

precision[np.isnan(precision)] = 0

recall[np.isnan(recall)] = 0

empty_cell = " " * columnwidth

print(" " + " Pred", end=' ')

" + " True")

if hide_zeros:

for i, label1 in enumerate(labels):

for j in range(len(labels)):

print(cell, end=' ')

print("Precision", end=' ') for j in range(len(labels)):

print(cell, end=' ')

print(" Recall", end=' ') for j in range(len(labels)):

print(cell, end=' ')

for j in range(len(labels)):

print(cell, end=' ')

predicted_labels = clf2.predict(X_validation)

F1", end=' ')

conf = confusion matrix(y validation, predicted labels)

Model Accuracy, how often is the classifier correct?

print("Accuracy:", metrics.accuracy_score(y_validation, y_pred))

In []: #Import scikit-learn metrics module for accuracy calculation

print("%{0}s".format(columnwidth) % 'Total')

F1[np.isnan(F1)] = 0

Print header

print(" # Print rows

for label in labels:

if display metrics: print()

print("

from sklearn import metrics

Your Task

def display_cm(cm, labels, hide_zeros=False, display_metrics=False):

precision = np.diagonal(cm)/cm.sum(axis=0).astype('float') recall = np.diagonal(cm)/cm.sum(axis=1).astype('float') F1 = 2 * (precision * recall) / (precision + recall)

total_precision = np.sum(precision * cm.sum(axis=1)) / cm.sum(axis=(0,1))

total recall = np.sum(recall * cm.sum(axis=1)) / cm.sum(axis=(0,1))

columnwidth = max([len(x) for x in labels]+[5]) # 5 is value length

total_F1 = np.sum(F1 * cm.sum(axis=1)) / cm.sum(axis=(0,1))

print("%{0}s".format(columnwidth) % label, end=' ')

print(" %{0}s".format(columnwidth) % label1, end=' ')

cell = "%{0}.3f".format(columnwidth) % precision[j]

print("%{0}.3f".format(columnwidth) % total_precision)

cell = "%{0}.3f".format(columnwidth) % recall[j]

print("%{0}.3f".format(columnwidth) % total_recall)

cell = "%{0}.3f".format(columnwidth) % F1[j]

display_cm(conf, facies_labels, display metrics=True, hide zeros=True)

print("%{0}.3f".format(columnwidth) % total_F1)

cell = cell if float(cm[i, j]) != 0 else empty_cell

cell = "%{0}d".format(columnwidth) % cm[i, j]

print("%{0}d".format(columnwidth) % sum(cm[i,:]))

clf2=RandomForestClassifier(n estimators=100, max features=0.1, min samples leaf=25,

Standardise the validation data using the same transform

Choosing an estimator: (Example Algorithm) Random Forest

Now it's time to build your firs Random Forest ML Model

C1 = RandomForestClassifier(n estimators=100, max features=0.1, min samples leaf=25,

validated = cross val score (method, X, y, scoring="f1 weighted", cv=cv, n jobs=-1)

from sklearn.model_selection import train_test_split

In []: X = training_data[["SP","GR","RES","RHOB","NPHI","VSH","PHIE","SW"]]

In []: #Example Display of Well Log

In []: #Split data train and validation

Visualize the dataset

y = training_data["Facies"]

In []: from sklearn import preprocessing

X = scaler.transform(X)

methods = [Cl, OVR]

for method in methods:

scores = np.array(scores)

In []: #Import Random Forest Model

methods = [Cl, OVR]

clf2.fit(X,y)

scores = []

In []: scores.head()

Standardise the training data

called whitening).

Do the same for our blind/validation data

In []: import matplotlib.pyplot as plt import seaborn as sns %matplotlib inline

ax[7].set xlabel("SW")

df.describe()

facies color map = {}

facies counts