Esha Adhawade

Homework 2

CSCE 421 500

October 11, 2022

Question 1: Machine Learning with Pokemon GO

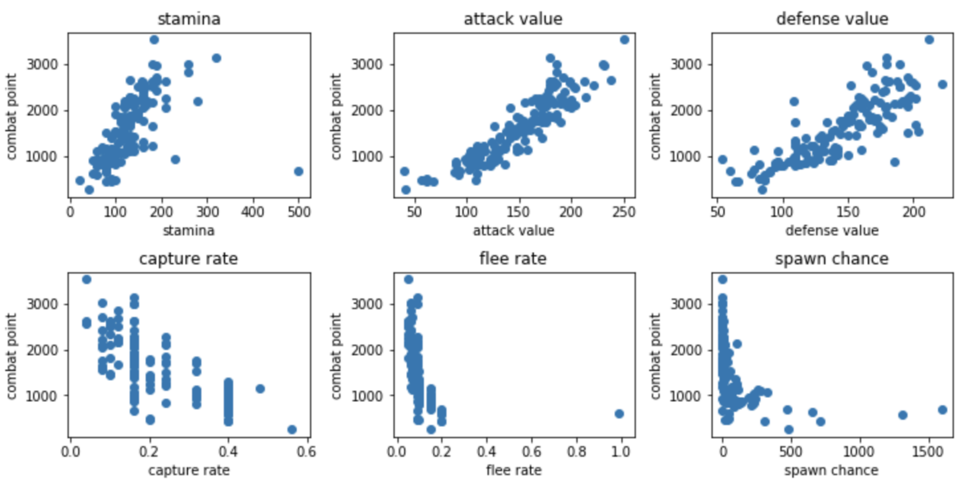
(i) (1 point) Data exploration: Plot 2-D scatter plots and compute the Pearson's correlation coefficient between the features and the outcome of interest. Which features are the most predictive of the number of combat points? Note: Pearson's correlation coefficient is a measure of linear association between two variables. It ranges between -1 and 1, with values closer to 1 indicating high degree of association between a feature and the outcome.

Code

```
#Scatterplots
fig, rltsp = plt.subplots(2, 3, figsize=(10,5), constrained_layout = True)

#stamina vs combat point
rltsp[0,0].scatter(df["stamina"], df["combat_point"])
rltsp[0,0].set_title('stamina')
rltsp[0,0].set_xlabel('stamina')
rltsp[0,0].set_ylabel('combat point')

#attack value vs combat point
rltsp[0,1].scatter(df["attack_value"], df["combat_point"])
rltsp[0,1].set_title('attack value')
rltsp[0,1].set_xlabel('attack value')
rltsp[0,1].set_ylabel('combat point')


#defense value vs combat point
rltsp[0,2].scatter(df["defense_value"], df["combat_point"])
rltsp[0,2].set_title('defense value')
rltsp[0,2].set_xlabel('defense value')
rltsp[0,2].set_ylabel('combat point')

#capture rate vs combat point
rltsp[1,0].scatter(df["capture_rate"], df["combat_point"])
rltsp[1,0].set_title('capture rate')
rltsp[1,0].set_xlabel('capture rate')
rltsp[1,0].set_ylabel('combat point')

#flee rate vs combat point
rltsp[1,1].scatter(df["flee_rate"], df["combat_point"])
rltsp[1,1].set_title('flee rate')
rltsp[1,1].set_xlabel('flee rate')
rltsp[1,1].set_ylabel('combat point')

#spawn chance vs combat point
rltsp[1,2].scatter(df["spawn_chance"], df["combat_point"])
rltsp[1,2].set_title('spawn chance')
rltsp[1,2].set_xlabel('spawn chance')
rltsp[1,2].set_ylabel('combat point')

plt.show()
```

```python
#Pearson Correlation Calculations

#stamina vs combat point
stamina_corr,_ = pearsonr(df["stamina"], df["combat_point"])
print("Stamina:        ", stamina_corr)

#Attack Value vs combat point
attack_corr,_ = pearsonr(df["attack_value"], df["combat_point"])
print("Attack Value:  ", attack_corr)

#Defense Value vs combat point
defense_corr,_ = pearsonr(df["defense_value"], df["combat_point"])
print("Defense Value: ", defense_corr)

#Capture Rate vs combat point
capture_corr,_ = pearsonr(df["capture_rate"], df["combat_point"])
print("Capture Rate: ", capture_corr)

#Flee Rate vs combat point
flee_corr,_ = pearsonr(df["flee_rate"], df["combat_point"])
print("Flee Rate:     ", flee_corr)

#Spawn Chance vs combat point
spawn_corr,_ = pearsonr(df["spawn_chance"], df["combat_point"])
print("Spawn Chance: ", spawn_corr)
```

Output




```
Stamina:         0.582831703222926
Attack Value:    0.9075315401042733
Defense Value:   0.8262293053572931
Capture Rate:   -0.7430078083529397
Flee Rate:      -0.40703421142159646
Spawn Chance:   -0.42132699465983586
```

Reflections

The features that seem to be the most predictive of combat points are stamina, attack value, and defense value.

(ii) (1 point) Data exploration: Plot 2-D scatter plots and compute the Pearson's correlation coefficient between the features themselves. Which features are the most correlated to each other?

Code

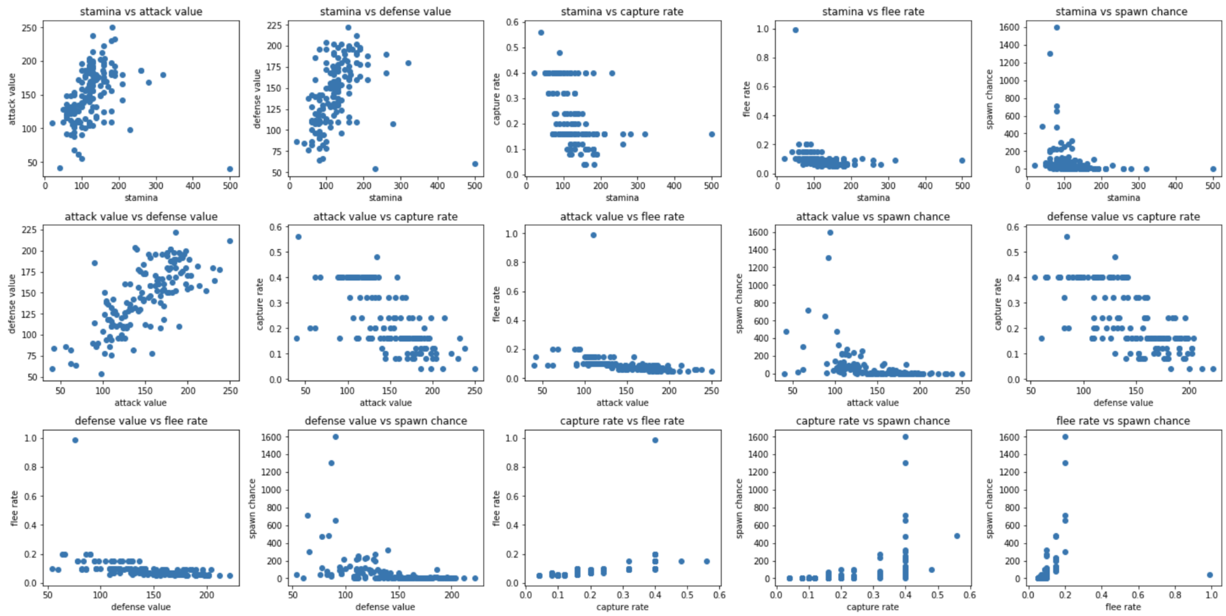
```
#Scatterplots
fig, rltsp = plt.subplots(3, 5, figsize=(20,10), constrained_layout = True)

#stamina vs attack value
rltsp[0,0].scatter(df["stamina"], df["attack_value"])
rltsp[0,0].set_title('stamina vs attack value')
rltsp[0,0].set_xlabel('stamina')
rltsp[0,0].set_ylabel('attack value')

#stamina vs defense value
rltsp[0,1].scatter(df["stamina"], df["defense_value"])
rltsp[0,1].set_title('stamina vs defense value')
rltsp[0,1].set_xlabel('stamina')
rltsp[0,1].set_ylabel('defense value')

#stamina vs capture rate
rltsp[0,2].scatter(df["stamina"], df["capture_rate"])
rltsp[0,2].set_title('stamina vs capture rate')
rltsp[0,2].set_xlabel('stamina')
rltsp[0,2].set_ylabel('capture rate')

#stamina vs flee rate
rltsp[0,3].scatter(df["stamina"], df["flee_rate"])
rltsp[0,3].set_title('stamina vs flee rate')
rltsp[0,3].set_xlabel('stamina')
rltsp[0,3].set_ylabel('flee rate')

#stamina vs spawn chance
rltsp[0,4].scatter(df["stamina"], df["spawn_chance"])
rltsp[0,4].set_title('stamina vs spawn chance ')
rltsp[0,4].set_xlabel('stamina')
rltsp[0,4].set_ylabel('spawn chance')

#attack value vs defense value
rltsp[1,0].scatter(df["attack_value"], df["defense_value"])
rltsp[1,0].set_title('attack value vs defense value')
rltsp[1,0].set_xlabel('attack value')
rltsp[1,0].set_ylabel('defense value')

#attack value vs capture rate
rltsp[1,1].scatter(df["attack_value"], df["capture_rate"])
rltsp[1,1].set_title('attack value vs capture rate')
rltsp[1,1].set_xlabel('attack value')
rltsp[1,1].set_ylabel('capture rate')
```

```
#attack value vs flee rate
rltsp[1,2].scatter(df["attack_value"], df["flee_rate"])
rltsp[1,2].set_title('attack value vs flee rate')
rltsp[1,2].set_xlabel('attack value')
rltsp[1,2].set_ylabel('flee rate')

#attack value vs spawn chance
rltsp[1,3].scatter(df["attack_value"], df["spawn_chance"])
rltsp[1,3].set_title('attack value vs spawn chance')
rltsp[1,3].set_xlabel('attack value')
rltsp[1,3].set_ylabel('spawn chance')

#defense value vs capture rate
rltsp[1,4].scatter(df["defense_value"], df["capture_rate"])
rltsp[1,4].set_title('defense value vs capture rate')
rltsp[1,4].set_xlabel('defense value')
rltsp[1,4].set_ylabel('capture rate')

#defense value vs flee rate
rltsp[2,0].scatter(df["defense_value"], df["flee_rate"])
rltsp[2,0].set_title('defense value vs flee rate')
rltsp[2,0].set_xlabel('defense value')
rltsp[2,0].set_ylabel('flee rate')

#defense value vs spawn chance
rltsp[2,1].scatter(df["defense_value"], df["spawn_chance"])
rltsp[2,1].set_title('defense value vs spawn chance')
rltsp[2,1].set_xlabel('defense value')
rltsp[2,1].set_ylabel('spawn chance')

#capture rate vs flee rate
rltsp[2,2].scatter(df["capture_rate"], df["flee_rate"])
rltsp[2,2].set_title('capture rate vs flee rate')
rltsp[2,2].set_xlabel('capture rate')
rltsp[2,2].set_ylabel('flee rate')

#capture rate vs spawn chance
rltsp[2,3].scatter(df["capture_rate"], df["spawn_chance"])
rltsp[2,3].set_title('capture rate vs spawn chance')
rltsp[2,3].set_xlabel('capture rate')
rltsp[2,3].set_ylabel('spawn chance')

#flee rate vs spawn chance
rltsp[2,4].scatter(df["flee_rate"], df["spawn_chance"])
rltsp[2,4].set_title('flee rate vs spawn chance')
rltsp[2,4].set_xlabel('flee rate')
rltsp[2,4].set_ylabel('spawn chance')
```

```python
#Pearson Correlation Calculations

#stamina vs attack value
corr1,_ = pearsonr(df["stamina"], df["attack_value"])
print("Stamina vs Attack Value:        ", corr1)

#stamina vs defense value
corr2,_ = pearsonr(df["stamina"], df["defense_value"])
print("Stamina vs Defense Value:       ", corr2)

#stamina vs capture rate
corr3,_ = pearsonr(df["stamina"], df["capture_rate"])
print("Stamina vs Capture Rate:       ", corr3)

#stamina vs flee rate
corr4,_ = pearsonr(df["stamina"], df["flee_rate"])
print("Stamina vs Flee Rate:          ", corr4)

#stamina vs spawn chance
corr5,_ = pearsonr(df["stamina"], df["spawn_chance"])
print("Stamina vs Spawn Chance:       ", corr5)

#attack value vs defense value
corr6,_ = pearsonr(df["attack_value"], df["defense_value"])
print("Attack Value vs Defense Value:  ", corr6)

#attack value vs capture rate
corr7,_ = pearsonr(df["attack_value"], df["capture_rate"])
print("Attack Value vs Capture Rate:  ", corr7)

#attack value vs flee rate
corr8,_ = pearsonr(df["attack_value"], df["flee_rate"])
print("Attack Value vs Flee Rate:     ", corr8)

#attack value vs spawn chance
corr9,_ = pearsonr(df["attack_value"], df["spawn_chance"])
print("Attack Value vs Spawn Chance:  ", corr9)

#defense value vs capture rate
corr10,_ = pearsonr(df["defense_value"], df["capture_rate"])
print("Defense Value vs Capture Rate: ", corr10)

#defense value vs flee rate
corr11,_ = pearsonr(df["defense_value"], df["flee_rate"])
print("Defense Value vs Flee Rate:    ", corr11)
```

```python
#defense value vs spawn chance
corr12,_ = pearsonr(df["defense_value"], df["spawn_chance"])
print("Defense Value vs Spawn Chance: ", corr12)

#capture rate vs flee rate
corr13,_ = pearsonr(df["capture_rate"], df["flee_rate"])
print("Capture Rate vs Flee Rate:      ", corr13)

#capture rate vs spawn chance
corr14,_ = pearsonr(df["capture_rate"], df["spawn_chance"])
print("Capture Rate vs Spawn Chance:   ", corr14)

#flee rate vs spawn chance
corr15,_ = pearsonr(df["flee_rate"], df["spawn_chance"])
print("Flee Rate vs Spawn Chance:      ", corr15)
```

Output




```
Stamina vs Attack Value:          0.3029949826738916
Stamina vs Defense Value:         0.30266333625368935
Stamina vs Capture Rate:         -0.4468503047144601
Stamina vs Flee Rate:            -0.2710475393248393
Stamina vs Spawn Chance:         -0.2764202078836037
Attack Value vs Defense Value:    0.7367766467515237
Attack Value vs Capture Rate:    -0.6905726716022137
Attack Value vs Flee Rate:       -0.36906414197600723
Attack Value vs Spawn Chance:    -0.4326484402010869
Defense Value vs Capture Rate:   -0.6972657162131648
Defense Value vs Flee Rate:      -0.42385975623729333
Defense Value vs Spawn Chance:   -0.43249856208332005
Capture Rate vs Flee Rate:        0.44051150728059624
Capture Rate vs Spawn Chance:     0.4727927266445679
Flee Rate vs Spawn Chance:        0.29322169222082034
```

Reflections

Features such as attack value vs defense value are highly correlated to each other. There are also others such as capture vs flee rate, capture rate vs spawn chance, stamina vs attack and defense value, etc.

(iii) (2 points) Predicting combat points: The goal of this question is to predict the combat points using the considered features. Implement a linear regression model using the ordinary least squares (OLS) solution. How many parameters does the model have? To test your model, randomly split the data into 5 folds and use a 5-fold cross-validation. For each fold compute the square root of the residual sum of squares error (RSS) between the actual and predicted outcome variable. Also compute the average square root of the RSS over all folds.

Code

Split Data into 5 folds/train & test sets

```
#5 fold cross validation |
def fiveFolds(df):
    folds = 5
    divide = len(df)//5
    count = 0
    splits = [None]*folds

    for i in range(folds):
        splits[i] = df.loc[count:min(len(df),count+divide)]
        count += divide

  #make train sets and test sets
    train_data = [None]*folds
    test_data = [None]*folds

    for i in range(folds):
        train_data[i] = pd.concat([splits[j] for j in range(len(splits)) if j != i])
        test_data[i] = splits[i]
    return (train_data,test_data)
```

Ordinary Least Squares solution/ RSS / average of RSS

```
#OLS
def findRSS(x_train,y_train,x_test,y_test):
    #this function gets weights and returns RSS
    x_t = np.array(x_train).transpose()
    xt_inv = np.linalg.inv(np.matmul(x_t,np.array(x_train)))
    xt_y = np.matmul(x_t,np.array(y_train))
    weight= np.matmul(xt_inv,xt_y)

    #find rss
    rss = 0
    for i in range(len(x_test)):
        getTest = x_test.iloc[i]
        error = (y_test.iloc[i]-getTest.dot(weight))**2
        rss += error
    return rss

def featureSet(train,test,output):
    #takes the train and test data and splits according to features
    feat_train = train
    x_train = feat_train.drop([output],axis=1)
    y_train = feat_train[[output]]

    feat_test = test
    x_test = feat_test.drop([output],axis=1)
    y_test = feat_test[[output]]
    return (x_train,y_train,x_test,y_test)


#linear regression for all folds
flag=None
def RSSError(flag):
    errorArr = []

    for i in range(0, 5):
        x_train,y_train,x_test,y_test = featureSet(train_data[i],test_data[i],'combat_point')

        if flag != None:
            x_train = x_train[flag]
            x_test = x_test[flag]
        error = findRSS(x_train,y_train,x_test,y_test)
        errorArr.append(error.iloc[len(error)-1]**(1/2))
    print("RSS: ", errorArr)
    return sum(errorArr)/len(errorArr)
```

Output

```
#call function to split into folds
train_data,test_data= fiveFolds(df)

print("Average: ",RSSError(None))
```

```
RSS:  [1167.5167379753095, 368.4866962081964, 1114.5757273554198, 1523.6527834997257, 883.3171301999934]
Average:  1011.509815047729
```

Reflections

The code above splits the data into 5 folds and takes four parameters to compute RSS and find the weight using this equation: w*= (XT X)^−1 XTY. It then takes all the RSS values, adds them to a list called errorArr and takes the average of all five-fold RSS values.

(iv) (1 point) Based on your findings from questions (i) and (ii), use linear regression and experiment with different feature combinations. Please report your results. Note: We would like to have an informative but non-redundant feature space, i.e., the features should be predictive of the outcome of interest but not too correlated to each other.

Code

The algorithm is the same as in part three.

```
print("Stamina Average: ",RSSError(["stamina"]), "\n")
print("Attack Value Average: ",RSSError(["attack_value"]), "\n")
print("Defense Value Average:" ,RSSError(["defense_value"]), "\n")

print("Stamina vs Attack Value Average: ",RSSError(["stamina","attack_value"]), "\n")
print("Stamina vs Defense Value Average:",RSSError(["stamina","defense_value"]), "\n")
print("Attack Value vs Defense Value Average:",RSSError(["attack_value","defense_value"]), "\n")

print("Capture Rate vs Flee Rate Average:" ,RSSError(["capture_rate","flee_rate"]), "\n")
print("Capture Rate vs Spawn Chance Average:" ,RSSError(["capture_rate","spawn_chance"]), "\n")
print("Flee Rate vs Spawn Chance Average:" ,RSSError(["flee_rate","spawn_chance"]), "\n")
```

Output

```
RSS:  [2132.141961383829, 2821.1133626466267, 2481.8223018563713, 6057.690479053119, 3239.1284955501314]
Stamina Average:  3346.3793200980153

RSS:  [1523.7671541619195, 1775.6430069862768, 1968.7128934540337, 1790.0316668174917, 2351.0168037367484]
Attack Value Average:  1881.8343050312942

RSS:  [1752.6942276902187, 2130.4500117532352, 2090.700672073352, 2650.2802900504194, 2886.426631006638]
Defense Value Average: 2302.1103665147725

RSS:  [1526.83464521661, 1657.114153178969, 1727.5090871701339, 2264.9714686982256, 1977.3850720635608]
Stamina vs Attack Value Average:  1830.7628852654998

RSS:  [1753.8748667916511, 1733.9202776763088, 1853.4620013101505, 3163.7113376080733, 2429.726647977822]
Stamina vs Defense Value Average: 2186.939026272801

RSS:  [1515.212463337345, 1774.824436344691, 1864.091913892799, 1753.8598773724723, 2385.938544466725]
Attack Value vs Defense Value Average: 1858.7854470828067

RSS:  [6676.323317137456, 6865.333102391353, 21016.401542481282, 5879.628160011018, 8252.53165550059]
Capture Rate vs Flee Rate Average: 9738.04355550434

RSS:  [11430.80250320777, 6704.7141804976445, 6950.394988163606, 5791.226177766999, 7896.58529720442]
Capture Rate vs Spawn Chance Average: 7754.744629368089

RSS:  [5704.550290206069, 6764.415610305948, 17686.66571409399, 6206.317049723616, 8501.519291278757]
Flee Rate vs Spawn Chance Average: 8972.693591121675
```

Reflections

For this part I used all feature combinations that were correlated with each other. For example, the Attack vs Defense value is a good example.

(v) (2 points) Use the sample mean of the combat point outcome to binarize the data (i.e., assign samples with number of combat points larger than the mean to class 1 and samples with number of combat points less than the mean to class -1). Implement a linear perceptron algorithm to classify between class 1 and -1. To evaluate the model, randomly split the data into 5 folds and use a 5-fold cross-validation. Report the accuracy of the classifier on the test data for each fold, as well as the average across all folds.

Code

```
#linear perceptron
def classify(df):
    dfCopy = df.copy() #make a copy of df
    average = dfCopy['combat_point'].mean() #take the mean
    dfCopy['class'] = 1 #add a class column
    #adds features into class 1 or -1
    dfCopy.loc[dfCopy['combat_point'] < average, 'class'] = -1
    dfCopy=dfCopy.drop(['combat_point'], axis = 1)

    colNum = len(dfCopy.columns)
    weight = pd.DataFrame(columns = dfCopy.columns)
    weight = weight.drop(['class'], axis = 1)
    weight.loc[len(weight.index)] = len(weight.columns)*[1]
    return (dfCopy, weight)

def featureClassification(weight, x, y):
    #determine what is correctly classified or misclassified
    correctlyClassified = []
    incorrectlyClassified = []

    for i in range(len(x)):
        row = x.iloc[i]
        classRow = y.iloc[i].iloc[0]
        temp = weight.dot(row).iloc[0]

        if(temp >= 0):
            if(classRow == 1):
```

```
            if(classRow == 1):
                correctlyClassified.append((row, classRow))
            else:
                incorrectlyClassified.append((row, classRow))
        else:
            if(classRow == 1):
                incorrectlyClassified.append((row, classRow))
            else:
                correctlyClassified.append((row, classRow))
    return(correctlyClassified, incorrectlyClassified )

def linearPercep(weight, x_train, y_train, x_test, y_test, folds):
    correctlyClassified = []
    incorrectlyClassified = []

    for i in range(folds):
        if i != 0:
            if(len(correctlyClassified)/len(incorrectlyClassified) >= 3):
                break    #breaks the algorith. after certain amt of iterations
            misclassified = random.choice(incorrectlyClassified)
            misclassifiedClass = random.choice(incorrectlyClassified)
```

```
            misclassifiedClass = random.choice(incorrectlyClassified)
            weight = weight + (misclassifiedClass*misclassified)
        correctlyClassified = featureClassification(weight, x_train, y_train)
        incorrectlyClassified = featureClassification(weight, x_train, y_train)
    testCorrectlyClassified = featureClassification(weight, x_test, y_test)
    testIncorrectlyClassified = featureClassification(weight, x_test, y_test)
    print("Test Size: ",len(x_test), "Perceptron: ",len(testCorrectlyClassified), "Error: ",len(testIncorrectlyClassifi
    return len(testIncorrectlyClassified)/len(x_test)

flag = None
#perform linear perceptron for all five folds
def final(flag):
    dfCopy = classify(df)
    weight = classify(df)
    train = fiveFolds(dfCopy)
    test = fiveFolds(dfCopy)
    errorArr = []

    for i in range(0, 5):
        x_train,y_train,x_test,y_test = featureSet(train_data[i],test_data[i],'class')
        error = linearPercep(weight, x_train, y_train, x_test, y_test, 25)
        errorArr.append(error)
    print(error)
    print("Average: ", sum(errorArr)/len(errorArr))
    return sum(errorArr)/len(errorArr)
```

Output

```
Test Size: 30 Perceptron: 25 Error: 5
Test Size: 30 Perceptron: 24 Error: 6
Test Size: 30 Perceptron: 23 Error: 7
Test Size: 30 Perceptron: 24 Error: 6
Test Size: 30 Perceptron: 24 Error: 6
[0.166666666666, 0.2, 0.23333333333334, 0.2, 0.2]
Average: 0.2
```

Reflections

The output shows the test data size that was split into 5 even folds, along with the perceptron and error rate. It also shows the average of all the folds.