In [1]:

```
import numpy as np
import pandas as pd
pd.options.display.max_columns=100
from sklearn.model_selection import train_test_split, cross_val_score, cross
from sklearn.preprocessing import StandardScaler as SSc
from sklearn.preprocessing import MinMaxScaler as MMS
from sklearn.tree import DecisionTreeClassifier as DTC
from sklearn.ensemble import RandomForestClassifier as RFC
from sklearn.neighbors import KNeighborsClassifier as KNC
from sklearn.feature_selection import SelectKBest, f_classif, mutual_info_cl
import matplotlib.pyplot as plt
%matplotlib inline

#set width of window to preference
from IPython.core.display import display, HTML
display(HTML("<style>.container { width:90% !important; }</style>"))
```

In [2]:

```
data = pd.read_csv("Data-Prepped.csv",index_col=0)
data = data.astype(np.float32)
data.head()
```

Out[2]:

	Bronze	Silver	Gold	Platinum	Diamond	Master	GrandMaster	LeagueIndex	Age	HoursPerWe
0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	5.0	27.0	1
1	0.0	0.0	0.0	0.0	1.0	0.0	0.0	5.0	23.0	1
2	0.0	0.0	0.0	1.0	0.0	0.0	0.0	4.0	30.0	1
3	0.0	0.0	1.0	0.0	0.0	0.0	0.0	3.0	19.0	2
4	0.0	0.0	1.0	0.0	0.0	0.0	0.0	3.0	32.0	1

1 - Trying to predict the league (approximate skill level) in which the game was played

Split data into X,Y where Y is which league the game was played in, then normalize the inputs.

In [3]:

```
# Bronze-GrandMaster as Y and all others (not including LeagueIndex) as X
X = data.iloc[:,8:]
Y = data.iloc[:,:7]

def SSc_normalize(X):
    #transform input data (normalize)
    ssc = SSc()
    Xft = ssc.fit_transform(X)
    X = pd.DataFrame(Xft)
    return X
def MMC_normalize(X):
    #transform input data (normalize)
    mms = MMS()
    Xft = mms.fit_transform(X)
    X = pd.DataFrame(Xft)
    return X

X_SSc = SSc_normalize(X)
X_MMC = MMC_normalize(X)

print("Xtr(Xtrain),Xtst(Xtest),Ytr(Ytrain),Ytst(Ytest) shapes: ")
Xtr,Xtst,Ytr,Ytst = train_test_split(X_SSc,Y,test_size=0.2)#,random_state=20
print(Xtr.shape,Xtst.shape,Ytr.shape,Ytst.shape)

Xtr_MMC,Xtst_MMC,Ytr_MMC,Ytst_MMC = train_test_split(X_MMC,Y,test_size=0.2)#
```

```
Xtr(Xtrain),Xtst(Xtest),Ytr(Ytrain),Ytst(Ytest) shapes:
(2670, 18) (668, 18) (2670, 7) (668, 7)
```

Create and train models on training data then check their accuracy on test data to check accuracy of region prediction

In [4]:

```
print("Classifier scores:\n"+"-"*18+"\n")

tree = DTC(max_depth=5)
tree.fit(Xtr,Ytr)
scr = cross_val_score(tree,Xtst,Ytst, cv=5)
print("Tree \nscore avg:"+str(sum(scr)/5)+"\nscore = "+str(scr)+"\n\n"+"-"*6

for i in range(1,20,2):
    forest = RFC(n_estimators=i,max_depth=5)
    forest.fit(Xtr,Ytr)
    scr = cross_val_score(forest,Xtst,Ytst, cv=5)
    print("\nRandom Forest trees = "+str(i)+" depth = 5 \nscore avg: "+str(s

print("\n"+"-"*64)

for i in range(1,16,3):
    knn = KNC(n_neighbors=i)
    knn.fit(Xtr,Ytr)
    scr = cross_val_score(knn,Xtst,Ytst, cv=5)
    print("\nK-Nearest Neighbors "+str(i)+"-neighbors\nscore avg:"+str(sum(s
          str(scr))
```

```
Classifier scores:
------------------

Tree
score avg:0.2034564021995287
score = [0.26119403 0.15671642 0.28358209 0.15037594 0.16541353]

----------------------------------------------------------------

Random Forest trees = 1 depth = 5
score avg: 0.22174840085287845
scores: [0.19402985 0.2761194  0.06716418 0.30075188 0.27067669]

Random Forest trees = 3 depth = 5
score avg: 0.10473571989675681
scores: [0.13432836 0.11940299 0.09701493 0.09774436 0.07518797]

Random Forest trees = 5 depth = 5
score avg: 0.09730669958478286
scores: [0.08955224 0.1119403  0.08955224 0.09774436 0.09774436]

Random Forest trees = 7 depth = 5
score avg: 0.08228032768488384
scores: [0.10447761 0.08208955 0.09701493 0.03759398 0.09022556]

Random Forest trees = 9 depth = 5
score avg: 0.07782515991471214
scores: [0.09701493 0.09701493 0.05223881 0.08270677 0.06015038]

Random Forest trees = 11 depth = 5
score avg: 0.06733251038042869
scores: [0.1119403  0.06716418 0.04477612 0.06766917 0.04511278]

Random Forest trees = 13 depth = 5
score avg: 0.04635843339692514
```

```
scores: [0.07462687 0.05223881 0.04477612 0.04511278 0.01503759]

Random Forest trees = 15 depth = 5
score avg: 0.06880260352373471
scores: [0.08208955 0.1119403  0.05223881 0.04511278 0.05263158]

Random Forest trees = 17 depth = 5
score avg: 0.05686230501627203
scores: [0.07462687 0.08208955 0.02985075 0.03759398 0.06015038]

Random Forest trees = 19 depth = 5
score avg: 0.05685108293120862
scores: [0.05970149 0.10447761 0.02985075 0.05263158 0.03759398]

----------------------------------------------------------------

K-Nearest Neighbors 1-neighbors
score avg:0.26348333520368084
score = [0.2761194  0.24626866 0.26119403 0.20300752 0.33082707]

K-Nearest Neighbors 4-neighbors
score avg:0.09879923689821568
score = [0.10447761 0.08955224 0.10447761 0.09774436 0.09774436]

K-Nearest Neighbors 7-neighbors
score avg:0.1406351700145887
score = [0.17164179 0.14925373 0.15671642 0.11278195 0.11278195]

K-Nearest Neighbors 10-neighbors
score avg:0.06287734261025699
score = [0.09701493 0.03731343 0.05223881 0.08270677 0.04511278]

K-Nearest Neighbors 13-neighbors
score avg:0.08527662439681293
score = [0.12686567 0.05223881 0.1119403  0.07518797 0.06015038]
```

In [5]:

```
DT = []
KN = []
RF = []
def cscore(model,X,Y):
    cr_v = cross_validate(model, X, Y, scoring=scoring,cv=5, return_train_sc
    return cr_v
breakline = "-"*64
scoring = {'FVE': 'explained_variance',
           'MSE': 'neg_mean_squared_error',
           'R2': 'r2'}
def test(X,Y):
    #DTree
    for i in range(1,3):
        dpth = i
        tree = DTC(max_depth=dpth)
        tree.fit(Xtr,Ytr)
        scr = cscore(tree,Xtst,Ytst)
        print("\n"+"-"*10+"Decision Tree, depth of {}:".format(dpth))
        for j,k in enumerate(scr.keys()):
            if j > 1:
                if(k=='test_MSE'):
                    print("-----{} (0.0 is best)\navg score: {}\nscores:   {
                else:
                    print("-----{} (1.0 is best)\navg score: {}\nscores:   {


    print("\n\n"+"-"*36)
    #KNN
    for l in range(1,101,20):
        knn = KNC(n_neighbors=l)
        knn.fit(Xtr,Ytr)
        scr = cscore(knn,Xtst,Ytst)
        print("\n"+"-"*10+"K-Nearest Neighbors, {}-neighbors scores:".format
        for j,k in enumerate(scr.keys()):
            if j > 1:
                if(k=='test_MSE'):
                    print("-----{} (0.0 is best)\navg score: {}\nscores:   {
                else:
                    print("-----{} (1.0 is best)\navg score: {}\nscores:   {


    print("\n\n"+"-"*36)

    #Random Forest
    dpth=4
    for l in range(1,31,10): #change number of trees
        forest = RFC(n_estimators=l,max_depth=dpth)
        forest.fit(Xtr,Ytr)
        scr = cscore(forest,Xtst,Ytst)
        print("\n"+"-"*10+"Random Forest, {} trees of depth {} scores:".form
        for j,k in enumerate(scr.keys()):
            if j > 1:
                if(k=='test_MSE'):
                    print("-----{} (0.0 is best)\navg score: {}\nscores:   {
                else:
                    print("-----{} (1.0 is best)\navg score: {}\nscores:   {
```

```
57
58
59
60
61      print()
62  test(X,Y)
```

```
----------Decision Tree, depth of 1:
-----test_FVE (1.0 is best)
avg score: 0.028571631227220805
scores:   [0.00000000e+00 2.55448478e-07 1.42857075e-01 4.25747463e-07
 4.00202615e-07]
-----test_MSE (0.0 is best)
avg score: -0.1428571492433548
scores:   [-0.14285715 -0.14285715 -0.14285715 -0.14285715 -0.14285715]
-----test_R2 (1.0 is best)
avg score: -0.15064314078090923
scores:   [-0.17750418 -0.17703627 -0.04039133 -0.1776191  -0.18066481]

----------Decision Tree, depth of 2:
-----test_FVE (1.0 is best)
avg score: -0.015064314433506556
scores:   [-0.04410059 -0.04925038  0.14285707 -0.02795205 -0.09687562]
-----test_MSE (0.0 is best)
avg score: -0.1456434339284897
scores:   [-0.14498936 -0.14498936 -0.14285715 -0.14285715 -0.15252416]
-----test_R2 (1.0 is best)
avg score: -0.1698131624876523
scores:   [-0.19007749 -0.19028851 -0.04039133 -0.1776191  -0.25068938]


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----------K-Nearest Neighbors, 1-neighbors scores:
-----test_FVE (1.0 is best)
avg score: -0.7244635718209402
scores:   [-0.72403313 -0.75020748 -0.59455887 -0.75385154 -0.79966683]
-----test_MSE (0.0 is best)
avg score: -0.21043333113193513
scores:   [-0.20682304 -0.21535181 -0.21108742 -0.22771214 -0.19119225]
-----test_R2 (1.0 is best)
avg score: -0.7356963837443675
scores:   [-0.73138677 -0.76282553 -0.59916472 -0.76628844 -0.81881647]

----------K-Nearest Neighbors, 21-neighbors scores:
-----test_FVE (1.0 is best)
avg score: -0.04676267760140555
scores:   [-0.07450446 -0.06978713  0.06334788 -0.11578116 -0.03708851]
-----test_MSE (0.0 is best)
avg score: -0.14734918773174285
scores:   [-0.14498936 -0.14605545 -0.15031983 -0.15145005 -0.14393125]
-----test_R2 (1.0 is best)
avg score: -0.17910316237957966
scores:   [-0.19051349 -0.19675118 -0.08247015 -0.23962922 -0.18615176]

----------K-Nearest Neighbors, 41-neighbors scores:
-----test_FVE (1.0 is best)
```

```
avg score: 0.029139646462031765
scores:   [ 0.00605224  0.01350709  0.1330627   0.00901855 -0.01594235]
-----test_MSE (0.0 is best)
avg score: -0.1407201409339905
scores:   [-0.13965885 -0.13752666 -0.14392324 -0.1396348  -0.14285715]
-----test_R2 (1.0 is best)
avg score: -0.1371777423990998
scores:   [-0.15864423 -0.1451674  -0.04764241 -0.15579279 -0.17864188]

----------K-Nearest Neighbors, 61-neighbors scores:
-----test_FVE (1.0 is best)
avg score: 0.029239148753029957
scores:   [ 7.31883730e-03  4.00582382e-03  1.42857075e-01  4.25747463e-07
 -7.98641784e-03]
-----test_MSE (0.0 is best)
avg score: -0.1422174870967865
scores:   [-0.14072494 -0.14179105 -0.14285715 -0.14285715 -0.14285715]
-----test_R2 (1.0 is best)
avg score: -0.14639866972722668
scores:   [-0.16493088 -0.17041015 -0.04039133 -0.1776191  -0.17864188]

----------K-Nearest Neighbors, 81-neighbors scores:
-----test_FVE (1.0 is best)
avg score: 0.030347124167851035
scores:   [3.61250128e-03 2.55448478e-07 1.42857075e-01 4.25747463e-07
 5.26536363e-03]
-----test_MSE (0.0 is best)
avg score: -0.1424291044473648
scores:   [-0.14179105 -0.14285715 -0.14285715 -0.14285715 -0.14178303]
-----test_R2 (1.0 is best)
avg score: -0.1478297088445107
scores:   [-0.17121753 -0.17703627 -0.04039133 -0.1776191  -0.17288431]


-------------------------------------

----------Random Forest, 1 trees of depth 4 scores:
-----test_FVE (1.0 is best)
avg score: -0.19231484276907782
scores:   [-0.25462059 -0.36159252  0.03076109 -0.07108964 -0.30503254]
-----test_MSE (0.0 is best)
avg score: -0.16209179759025574
scores:   [-0.16631131 -0.17803839 -0.15031983 -0.14607947 -0.16971   ]
-----test_R2 (1.0 is best)
avg score: -0.2742129756693533
scores:   [-0.30658095 -0.42108149 -0.07053884 -0.1943651  -0.3784985 ]

----------Random Forest, 11 trees of depth 4 scores:
-----test_FVE (1.0 is best)
avg score: 0.009910350186484198
scores:   [ 0.00572377 -0.02202272  0.13834614 -0.03072694 -0.04176851]
-----test_MSE (0.0 is best)
avg score: -0.14222229421138763
scores:   [-0.13859275 -0.14285715 -0.14072494 -0.14393125 -0.14500538]
-----test_R2 (1.0 is best)
avg score: -0.14761613508820826
scores:   [-0.15235757 -0.176275   -0.02959432 -0.18362796 -0.19622583]
```

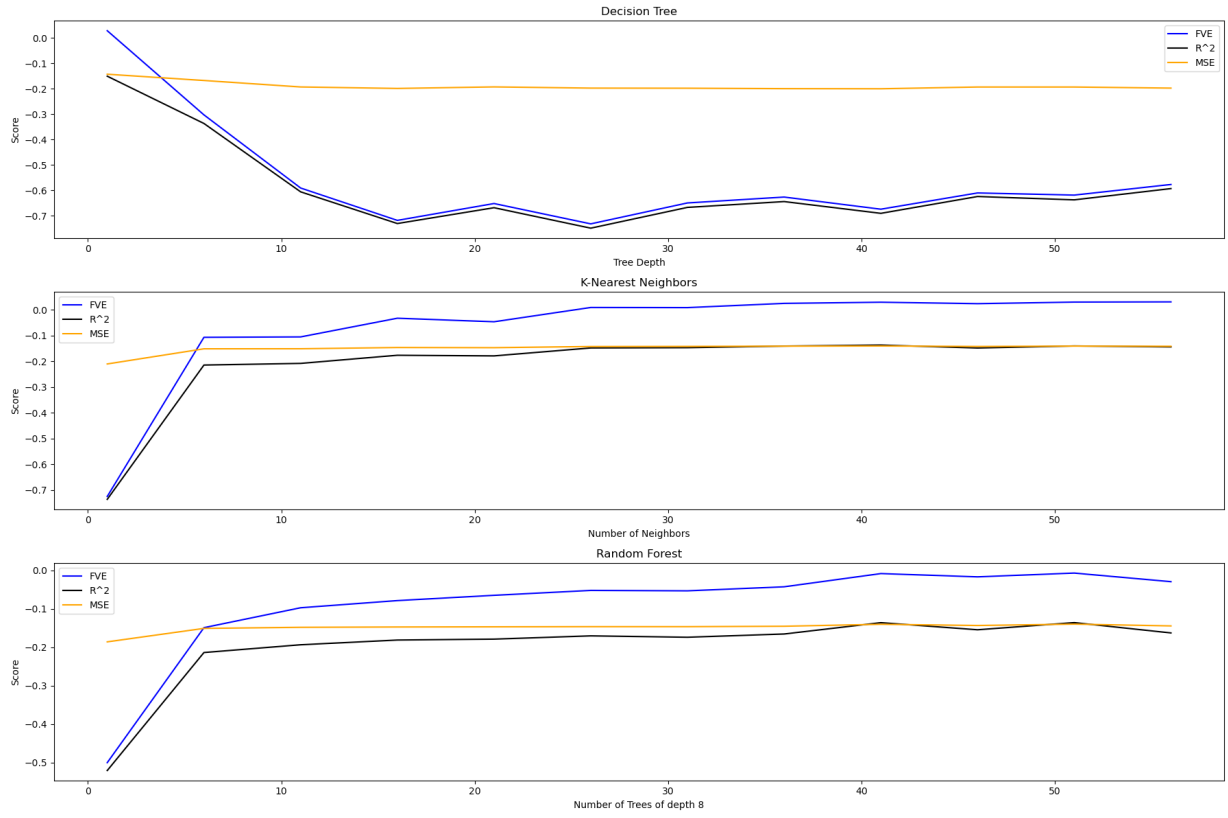
```
----------Random Forest, 21 trees of depth 4 scores:
-----test_FVE (1.0 is best)
avg score: 0.007334217003413612
scores:   [-0.02303534 -0.01026447  0.09712818 -0.00067816 -0.02647913]
-----test_MSE (0.0 is best)
avg score: -0.1432819813489914
scores:   [-0.14392325 -0.14072494 -0.14712153 -0.14178303 -0.14285715]
-----test_R2 (1.0 is best)
avg score: -0.15358865378658887
scores:   [-0.18379084 -0.16302276 -0.06777483 -0.17035053 -0.18300431]
```

In [6]:

```
def testGraph(X,Y):
    scores = [
        [[],[],[]],  #decision tree       -- [test_FVE],[test_MSE],[test_R^2
        [[],[],[]],  #K-Nearest Neighbors -- [test_FVE],[test_MSE],[test_R^2
        [[],[],[]]   #Random Forest       -- [test_FVE],[test_MSE],[test_R^2
    ]
    x = []

    RFDpth=8
    for l in range(1,60,5):
        x.append(l)
        dpth = l
        tree = DTC(max_depth=dpth)
        tree.fit(Xtr,Ytr)
        scr = cscore(tree,Xtst,Ytst)
        for k in scr.keys():
            if(k=='test_FVE'):
                scores[0][0].append(scr[k].mean())
            elif(k=='test_MSE'):
                scores[0][1].append(scr[k].mean())
            elif(k=='test_R2'):
                scores[0][2].append(scr[k].mean())

        #KNN
        knn = KNC(n_neighbors=l)
        knn.fit(Xtr,Ytr)
        scr = cscore(knn,Xtst,Ytst)
        for k in scr.keys():
            if(k=='test_FVE'):
                scores[1][0].append(scr[k].mean())
            elif(k=='test_MSE'):
                scores[1][1].append(scr[k].mean())
            elif(k=='test_R2'):
                scores[1][2].append(scr[k].mean())

        #Random Forest
        forest = RFC(n_estimators=l,max_depth=RFDpth)
        forest.fit(Xtr,Ytr)
        scr = cscore(forest,Xtst,Ytst)
        for k in scr.keys():
            if(k=='test_FVE'):
                scores[2][0].append(scr[k].mean())
            elif(k=='test_MSE'):
                scores[2][1].append(scr[k].mean())
            elif(k=='test_R2'):
                scores[2][2].append(scr[k].mean())

        print('.', end="")
        if ((l+1)%10==0):
            print(l+1)

    print("\nPredicting a player's league")
    fig,ax = plt.subplots(3, figsize=(18,12), dpi=100)
    ax[0].plot(x, scores[0][0], color='blue', label='FVE')
    ax[0].plot(x, scores[0][2], color='black', label='R^2' )
    ax[0].plot(x, scores[0][1], color='orange', label='MSE')
```

```
    ax[0].set_title("Decision Tree")
    ax[0].set_xlabel("Tree Depth")

    ax[1].plot(x, scores[1][0], color='blue', label='FVE')
    ax[1].plot(x, scores[1][2], color='black', label='R^2' )
    ax[1].plot(x, scores[1][1], color='orange', label='MSE')
    ax[1].set_title("K-Nearest Neighbors")
    ax[1].set_xlabel("Number of Neighbors")

    ax[2].plot(x, scores[2][0], color='blue', label='FVE')
    ax[2].plot(x, scores[2][2], color='black', label='R^2' )
    ax[2].plot(x, scores[2][1], color='orange', label='MSE')
    ax[2].set_title("Random Forest")
    ax[2].set_xlabel(f"Number of Trees of depth {RFDpth}")

    for i in range(3):
        ax[i].legend()
        ax[i].set_ylabel("Score")
    plt.tight_layout()
    plt.show()
testGraph(X,Y)
```

.....
Predicting a player's league

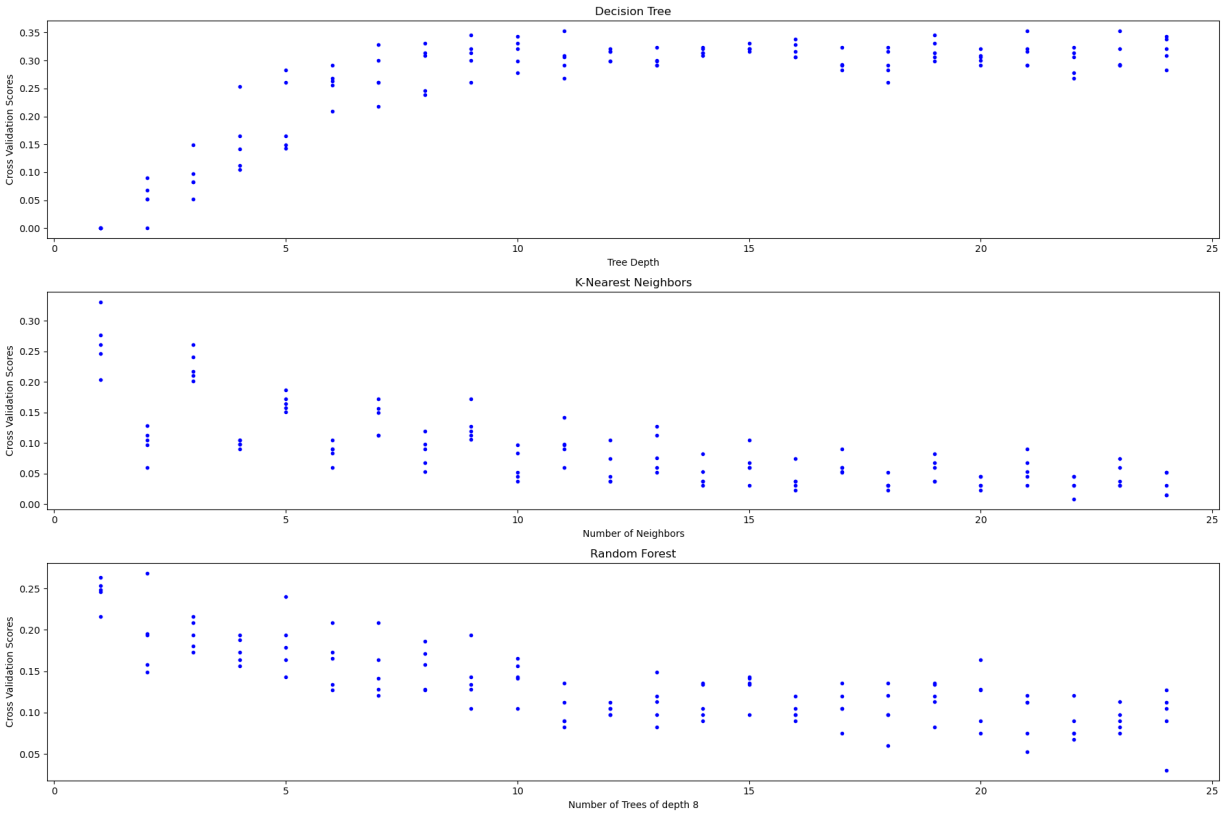


In [7]:

```
def crossScore(model, X, Y):
    cvs = cross_val_score(model,X,Y,cv=5,scoring='accuracy')
    return cvs

def testGraph(X,Y):
    scores = [[],[],[]]
    x = []

    RFDpth=8
    lsum=0
    for l in range(1,25):
        lsum+=1
        x.append(l)
        dpth = l
        tree = DTC(max_depth=dpth)
        tree.fit(Xtr,Ytr)
        scr = crossScore(tree,Xtst,Ytst)
        scores[0].append(scr)

        #KNN
        knn = KNC(n_neighbors=l)
        knn.fit(Xtr,Ytr)
        scr = crossScore(knn,Xtst,Ytst)
        scores[1].append(scr)

        #Random Forest
        forest = RFC(n_estimators=l,max_depth=RFDpth)
        forest.fit(Xtr,Ytr)
        scr = crossScore(forest,Xtst,Ytst)
        scores[2].append(scr)

        print('.', end="")
        if ((l+1)%10==0):
            print(l+1)

    print("\nPredicting a player's league\nCloser to Zero is Better")
    for i in (scores[:][1]):
        i = -i

    fig,ax = plt.subplots(3, figsize=(18,12), dpi=100)
    iList = []
    for h in range(3):
        for i in range(5):
            iList = []
            for j in range(lsum):
                iList.append(scores[h][j][i])
            ax[h].scatter(x, iList, color='blue',marker='.', label='Cross Va

    ax[0].set_title("Decision Tree")
    ax[0].set_xlabel("Tree Depth")


    ax[1].set_title("K-Nearest Neighbors")
    ax[1].set_xlabel("Number of Neighbors")


```

```
    ax[2].set_title("Random Forest")
    ax[2].set_xlabel(f"Number of Trees of depth {RFDpth}")

    for i in range(3):
        #ax[i].legend()
        ax[i].set_ylabel("Cross Validation Scores")
    plt.tight_layout()
    plt.show()
testGraph(X,Y)
```

```
.........10
..........20
.....
Predicting a player's league
Closer to Zero is Better
```



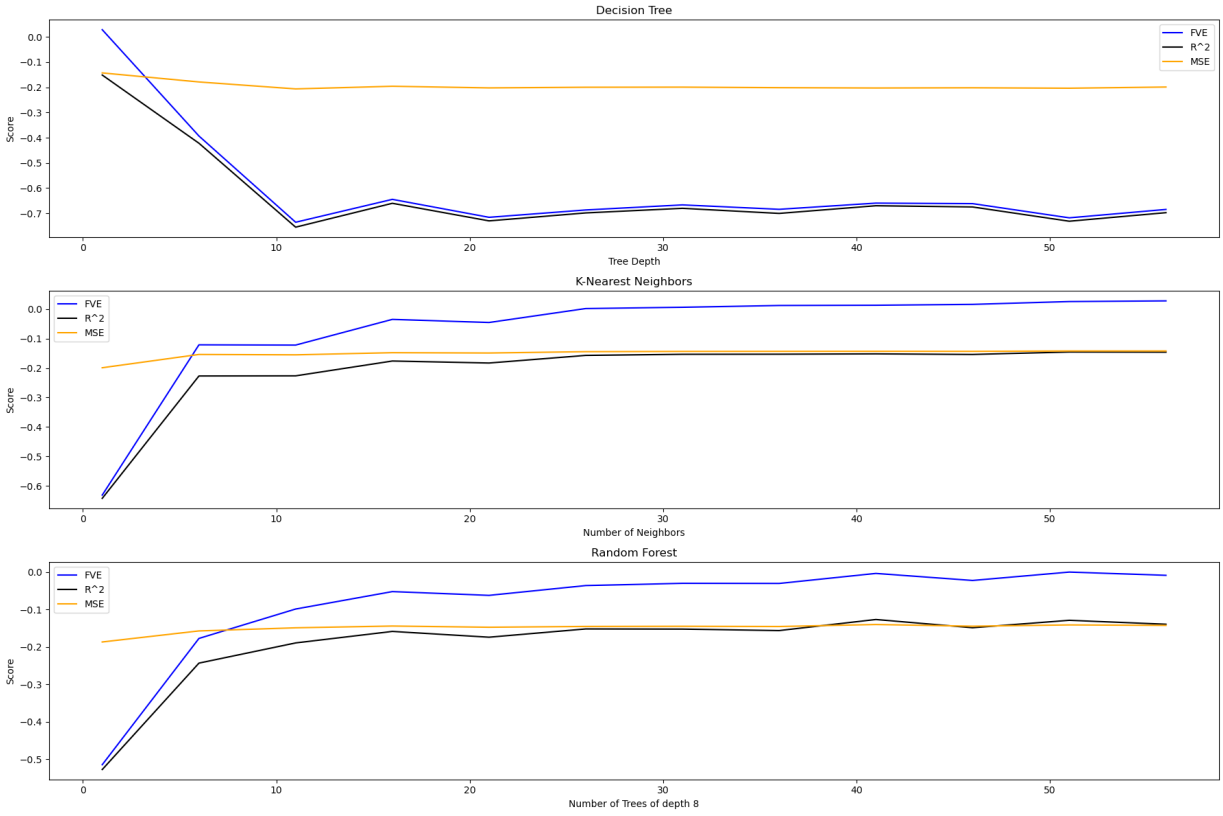
Now try with MinMaxScaler instead of StandardScaler

In [8]:

```
def testGraph(X,Y):
    scores = [
        [[],[],[]],  #decision tree       -- [test_FVE],[test_MSE],[test_R^2
        [[],[],[]],  #K-Nearest Neighbors -- [test_FVE],[test_MSE],[test_R^2
        [[],[],[]]   #Random Forest       -- [test_FVE],[test_MSE],[test_R^2
    ]
    x = []

    RFDpth=8
    for l in range(1,60,5):
        x.append(l)
        dpth = l
        tree = DTC(max_depth=dpth)
        tree.fit(Xtr_MMC,Ytr_MMC)
        scr = cscore(tree,Xtst_MMC,Ytst_MMC)
        for k in scr.keys():
            if(k=='test_FVE'):
                scores[0][0].append(scr[k].mean())
            elif(k=='test_MSE'):
                scores[0][1].append(scr[k].mean())
            elif(k=='test_R2'):
                scores[0][2].append(scr[k].mean())

        #KNN
        knn = KNC(n_neighbors=l)
        knn.fit(Xtr_MMC,Ytr_MMC)
        scr = cscore(knn,Xtst_MMC,Ytst_MMC)
        for k in scr.keys():
            if(k=='test_FVE'):
                scores[1][0].append(scr[k].mean())
            elif(k=='test_MSE'):
                scores[1][1].append(scr[k].mean())
            elif(k=='test_R2'):
                scores[1][2].append(scr[k].mean())

        #Random Forest
        forest = RFC(n_estimators=l,max_depth=RFDpth)
        forest.fit(Xtr_MMC,Ytr_MMC)
        scr = cscore(forest,Xtst_MMC,Ytst_MMC)
        for k in scr.keys():
            if(k=='test_FVE'):
                scores[2][0].append(scr[k].mean())
            elif(k=='test_MSE'):
                scores[2][1].append(scr[k].mean())
            elif(k=='test_R2'):
                scores[2][2].append(scr[k].mean())

        print('.', end="")
        if ((l+1)%10==0):
            print(l+1)

    print("\nPredicting a player's league")
    fig,ax = plt.subplots(3, figsize=(18,12), dpi=100)
    ax[0].plot(x, scores[0][0], color='blue', label='FVE')
    ax[0].plot(x, scores[0][2], color='black', label='R^2' )
    ax[0].plot(x, scores[0][1], color='orange', label='MSE')
```

```
    ax[0].set_title("Decision Tree")
    ax[0].set_xlabel("Tree Depth")

    ax[1].plot(x, scores[1][0], color='blue', label='FVE')
    ax[1].plot(x, scores[1][2], color='black', label='R^2' )
    ax[1].plot(x, scores[1][1], color='orange', label='MSE')
    ax[1].set_title("K-Nearest Neighbors")
    ax[1].set_xlabel("Number of Neighbors")

    ax[2].plot(x, scores[2][0], color='blue', label='FVE')
    ax[2].plot(x, scores[2][2], color='black', label='R^2' )
    ax[2].plot(x, scores[2][1], color='orange', label='MSE')
    ax[2].set_title("Random Forest")
    ax[2].set_xlabel(f"Number of Trees of depth {RFDpth}")

    for i in range(3):
        ax[i].legend()
        ax[i].set_ylabel("Score")
    plt.tight_layout()
    plt.show()
testGraph(X,Y)
```

.....
Predicting a player's league



From the testing of various parameters with the above code, it seems optimal to use a

between 7 and 11 neighbors for KNN and to use about 5 trees of depth 2-3 for random forests, but it seems impossible to get good results based on the current setup

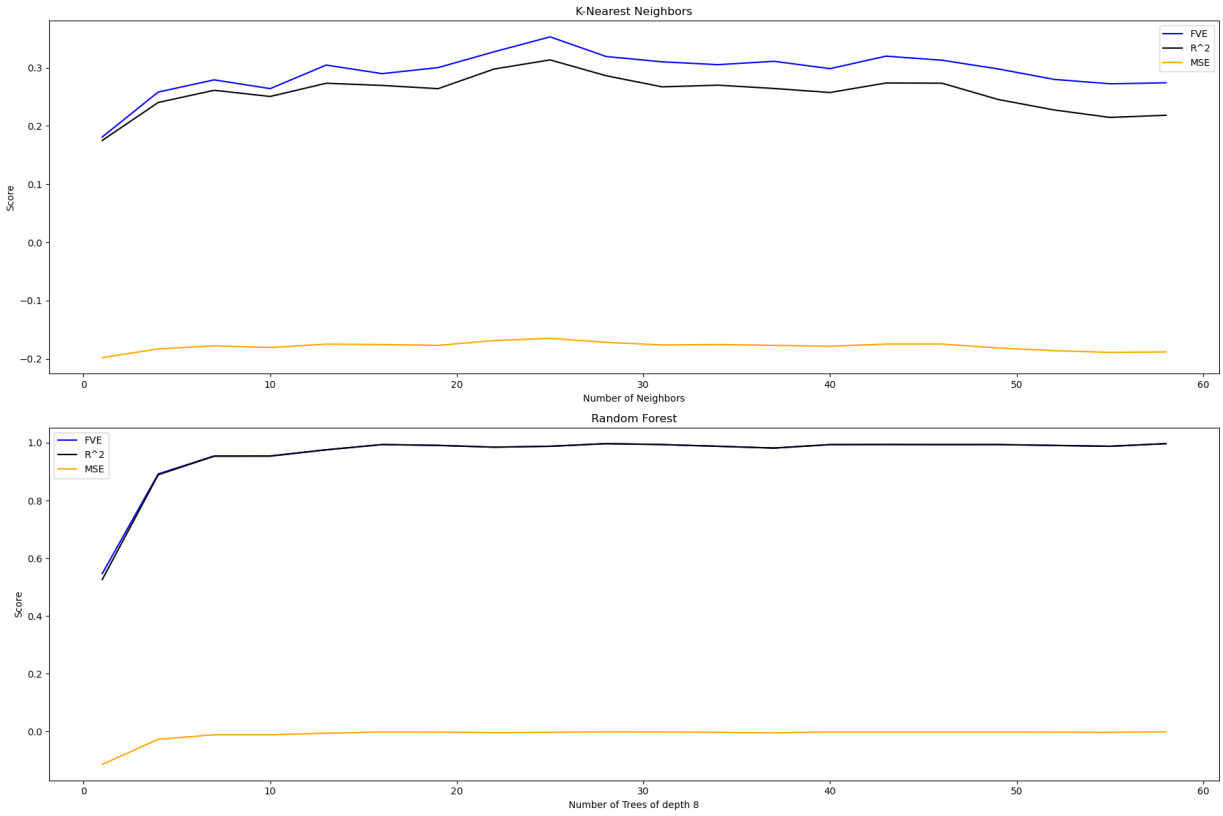
Grouped Leagues: 3 Groups

In [9]:

```
data = pd.read_csv("Data-Prepped-ELO-3-Groups.csv",index_col=0)
data = data.astype(np.float32)
#print(data.head(1))

#  as Y and all others (not including LeagueIndex) as X
X = data.iloc[:,4:]
Y = data.iloc[:,:2]
#transform input data (normalize)
ssc = SSc()
Xft = ssc.fit_transform(X)
X = pd.DataFrame(Xft)
print("Xtr(Xtrain),Xtst(Xtest),Ytr(Ytrain),Ytst(Ytest) shapes: ")
Xtr,Xtst,Ytr,Ytst = train_test_split(X,Y,test_size=0.2,random_state=2020)
print(Xtr.shape,Xtst.shape,Ytr.shape,Ytst.shape)

def testGraph(X,Y):
    scores = [
        [[],[],[]],  #K-Nearest Neighbors -- [test_FVE],[test_MSE],[test_R^2
        [[],[],[]]   #Random Forest       -- [test_FVE],[test_MSE],[test_R^2
    ]
    x = []

    RFDpth=8
    for l in range(1,60,3):
        x.append(l)
        dpth = l

        #KNN
        knn = KNC(n_neighbors=l)
        knn.fit(Xtr,Ytr)
        scr = cscore(knn,Xtst,Ytst)
        for k in scr.keys():
            if(k=='test_FVE'):
                scores[0][0].append(scr[k].mean())
            elif(k=='test_MSE'):
                scores[0][1].append(scr[k].mean())
            elif(k=='test_R2'):
                scores[0][2].append(scr[k].mean())

        #Random Forest
        forest = RFC(n_estimators=l,max_depth=RFDpth)
        forest.fit(Xtr,Ytr)
        scr = cscore(forest,Xtst,Ytst)
        for k in scr.keys():
            if(k=='test_FVE'):
                scores[1][0].append(scr[k].mean())
            elif(k=='test_MSE'):
                scores[1][1].append(scr[k].mean())
            elif(k=='test_R2'):
                scores[1][2].append(scr[k].mean())

        print('.', end="")
        if ((l+1)%10==0):
            print(l+1)

    print("\nPredicting a player's league")
```

```
    fig,ax = plt.subplots(2, figsize=(18,12), dpi=100)
    ax[0].plot(x, scores[0][0], color='blue', label='FVE')
    ax[0].plot(x, scores[0][2], color='black', label='R^2' )
    ax[0].plot(x, scores[0][1], color='orange', label='MSE')
    ax[0].set_title("K-Nearest Neighbors")
    ax[0].set_xlabel("Number of Neighbors")

    ax[1].plot(x, scores[1][0], color='blue', label='FVE')
    ax[1].plot(x, scores[1][2], color='black', label='R^2' )
    ax[1].plot(x, scores[1][1], color='orange', label='MSE')
    ax[1].set_title("Random Forest")
    ax[1].set_xlabel(f"Number of Trees of depth {RFDpth}")

    for i in range(2):
        ax[i].legend()
        ax[i].set_ylabel("Score")
    plt.tight_layout()
    plt.show()
testGraph(X,Y)
```

```
Xtr(Xtrain),Xtst(Xtest),Ytr(Ytrain),Ytst(Ytest) shapes:
(2670, 19) (668, 19) (2670, 2) (668, 2)
.......20
..........50
...
Predicting a player's league
```



While K-Nearest Neighbors still performs quite poorly, Random Forests can perform incredibly well once the 7 groups have been grouped together into low/medium/high ELO groups. I think that this is mostly due to the extreme similarity of adjacent leagues (except maybe grandmaster which has some notable variations from the norm as seen in "1 - Data Comprehension"), making it difficult to differentiate between them but when grouped the differences grow due to the distance between the leagues.