Objective of analysis

- To Understand given terminologies
- To Analyze trends in the given data
- To Develop a classification model for the column "worked"
- To Develop a regression model for the column "percentage_returns given"

Modules

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score
#Regression models
from sklearn.svm import SVR
from sklearn.ensemble import RandomForestRegressor
#Classification
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
#Scoring
from sklearn.metrics import r2_score,confusion_matrix,precision_recall_fscore_support,ac
```

```
C:\Users\jgan2\AppData\Roaming\Python\Python39\site-packages\numpy\_distributor_init.py:
30: UserWarning: loaded more than 1 DLL from .libs:
C:\Users\jgan2\AppData\Roaming\Python\Python39\site-packages\numpy\.libs\libopenblas.EL2
C6PLE4ZYW3ECEVIV3OXXGRN2NRFM2.gfortran-win_amd64.dll
C:\Users\jgan2\AppData\Roaming\Python\Python39\site-packages\numpy\.libs\libopenblas64__
v0.3.21-gcc_10_3_0.dll
  warnings.warn("loaded more than 1 DLL from .libs:"
```

In [2]:
```
df=pd.read_csv("XPREP8.csv")
```

In [3]:
```
df.head(0)
```

Out[3]:

Close	Volume	EMA5	EMA13	EMA26	MACD	SIGNAL	RSI	ROC	worked?	percentage_returns given

Definitions and meanings:

- Closing Price CP :Last price of a stock being sold
- A moving average sums up the data points(CP) of a financial security over a specific time period and divides the total by the number of data points to arrive at an average. It is called a “moving” average because it is continually recalculated based on the latest price data.
- SMA and EMA:
  - SMA(n): sum of previous n data/n
  - EMA(n): [CP(n)-EMA(n-1)] x (2/n+1) + EMA(n-1)
    - EMA N , really depends on starting point, eg EMA 5 can be calculated after 5 trading days while EMA 20 takes 20 days.
- MACD

- Moving Average Convergence
- When MACD turns up from below zero it is considered bullish. When it turns down from above zero it is considered bearish.
- When the MACD line crosses from below to above the signal line, the indicator is considered bullish. The further below the zero line the stronger the signal.
- When the MACD line crosses from above to below the signal line, the indicator is considered bearish. The further above the zero line the stronger the signal.

- ROC
  - Rate of Change , basically change in stock price/ earlier price , so rate is obtained.
- RSI
  - Relative strength index
    - greater than 70 => uptrend
    - less than 50 => downtrend
    - in between =>normal

1) Data Engineering

- Engineering MACD to produce new columns.
- Engineered macd

At each point n,

```
- val= 0
- if crosses 0 from below, +1 to val
- no cross , +sigmoid(signal strength) to val
- if crosses 0 from above, -1 to val
- if crosses signal from below , +1 to val
- no cross, +sigmoid(signal strength) to val
- if crosses signal from above , -1 to val
- Final: val/2
- strength of signal
    - MACD[n] - MACD[n-1]
    - Why signed sigmoid? to compress between -1 and 1
```

Seperating columns and assigning them to variables and also scaling columns

In [4]:
```
sc=StandardScaler()
feauts=df.iloc[:,:9].values
worked=df.iloc[:,-2].values
returns=df.iloc[:,-1].values
scaledfeauts=sc.fit_transform(feauts)
returnssc=sc.fit_transform(returns.reshape(928,1))
#------------------------------------Seperating into different variables for easier acce
CP=feauts[:,0]
Volume=feauts[:,1]
EMA5=feauts[:,2]
EMA13=feauts[:,3]
EMA26=feauts[:,4]
MACD=feauts[:,5]
```

```
SIGNAL=feauts[:,6]
RSI=feauts[:,7]
ROC=feauts[:,8]
#---------------------------------------Scaled Versions-------------------------------
CPsc=scaledfeauts[:,0]
Volumesc=scaledfeauts[:,1]
EMA5sc=scaledfeauts[:,2]
EMA13sc=scaledfeauts[:,3]
EMA26sc=scaledfeauts[:,4]
MACDsc=scaledfeauts[:,5]
SIGNALsc=scaledfeauts[:,6]
RSIsc=scaledfeauts[:,7]
ROCsc=scaledfeauts[:,8]
```

sigmoid function

In [5]:
```
def sigmoid(x):
    from math import exp
    return (x/ ((1 + exp(-x))* abs(x)))
```

Produce Engineered MACD

In [6]:
```
engmacd=[1]
for i in range(1,MACD.shape[0]):
    sigstr=MACD[i]-MACD[i-1]
    val=0
    if(MACD[i-1]<0 and MACD[i]>0 ):
        val+=1
    elif(MACD[i-1]>0 and MACD[i]<0):
        val-=1
    else:
        val+=sigmoid(sigstr)
    if(MACD[i-1]<SIGNAL[i-1] and MACD[i]>SIGNAL[i] ):
        val+=1
    elif(MACD[i-1]>SIGNAL[i-1] and MACD[i]<SIGNAL[i]):
        val-=1
    else:
        val+=sigmoid(sigstr)
    engmacd.append(val/2)
df["Engineered_MACD"]=engmacd
df
```

Out[6]:

	Close	Volume	EMA5	EMA13	EMA26	MACD	SIGNAL	RSI	ROC	worked
0	1136.95	3594297	1126.883592	1124.903001	1113.181837	12.016158	17.498908	58.490715	2.635974	
1	1147.40	6885679	1133.722395	1128.116858	1115.716515	12.897172	16.578561	61.178123	3.457914	
2	1160.75	8929987	1142.731597	1132.778736	1119.052329	14.505406	16.163930	64.353228	2.336346	
3	1155.65	4729914	1147.037731	1136.046059	1121.763268	15.193278	15.969800	62.258378	4.192400	
4	1138.60	2541804	1144.225154	1136.410908	1123.010433	14.198952	15.615630	55.727237	3.246282	
...	...	...	...	...	...	...	...	...	...	.
923	1787.15	4354074	1760.529346	1739.380217	1728.172574	12.646800	5.999303	62.175044	5.123379	
924	1792.30	6034233	1771.119564	1746.940186	1732.922754	15.816717	7.962785	62.953964	5.559809	
925	1787.45	4732492	1776.563043	1752.727302	1736.961809	17.733127	9.916854	61.666071	4.989721	
926	1779.40	4326924	1777.508695	1756.537688	1740.105379	18.390337	11.611550	59.490646	4.137649	

927	1759.40	6621839	1771.472463	1756.946589	1741.534610	17.100226	12.709286	54.359741	1.260432

928 rows × 12 columns

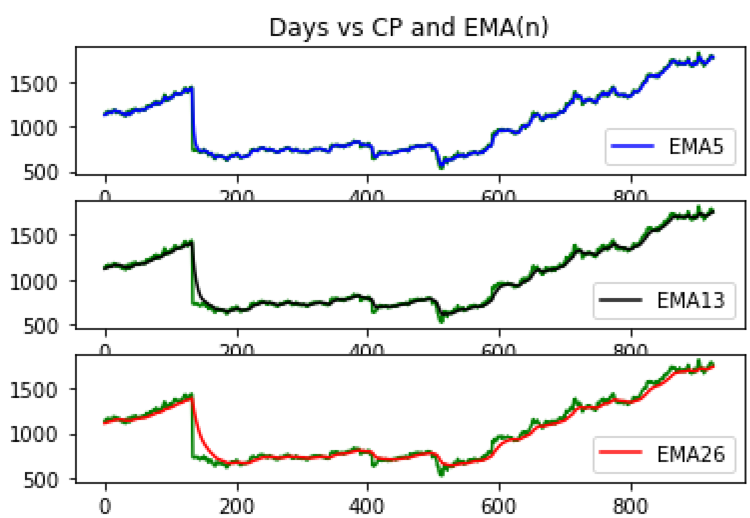
2)Visualizations

x-axis

In [7]:
```
days=[x for x in range(EMA5.shape[0])]
```

Exploring EMA vs CP trends

In [8]:
```
_,ax=plt.subplots(3,1)
ax[0].set_title("Days vs CP and EMA(n)")
ax[0].plot(days,CP,color="green")
ax[0].plot(days,EMA5,color="blue",label="EMA5")
ax[0].legend()
ax[1].plot(days,CP,color="green")
ax[1].plot(days,EMA13,color="black",label="EMA13")
ax[1].legend()
ax[2].plot(days,CP,color="green")
ax[2].plot(days,EMA26,color="red",label="EMA26")
ax[2].legend()
plt.show()
```



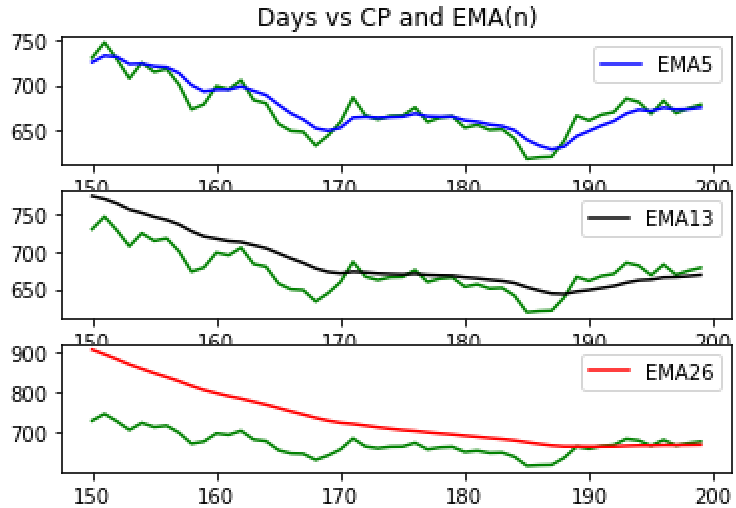
We can observe that if n is larger, it captures long-term dependency(is more resilient to sudden and sharp changes, hence can be useful for long term investments)

and if n is smaller it captures short term dependency(gives very high importance to recent data, hence useful for short term invesments)

Let us observe closely for a few amount of days, where change was sudden.

In [9]:
```
_,ax=plt.subplots(3,1)
ax[0].set_title("Days vs CP and EMA(n)")
ax[0].plot(days[150:200],CP[150:200],color="green")
ax[0].plot(days[150:200],EMA5[150:200],color="blue",label="EMA5")
ax[0].legend()
ax[1].plot(days[150:200],CP[150:200],color="green")
ax[1].plot(days[150:200],EMA13[150:200],color="black",label="EMA13")
```

```
ax[1].legend()
ax[2].plot(days[150:200],CP[150:200],color="green")
ax[2].plot(days[150:200],EMA26[150:200],color="red",label="EMA26")
ax[2].legend()
plt.show()
```



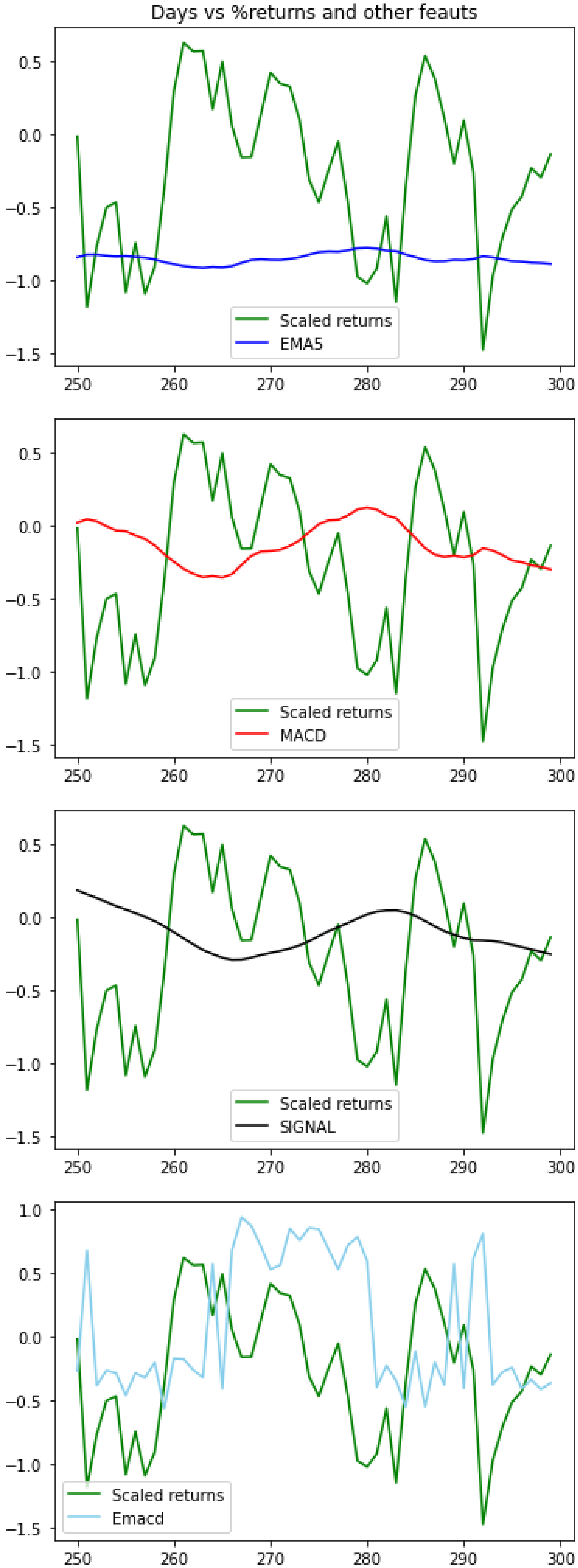
Inference:

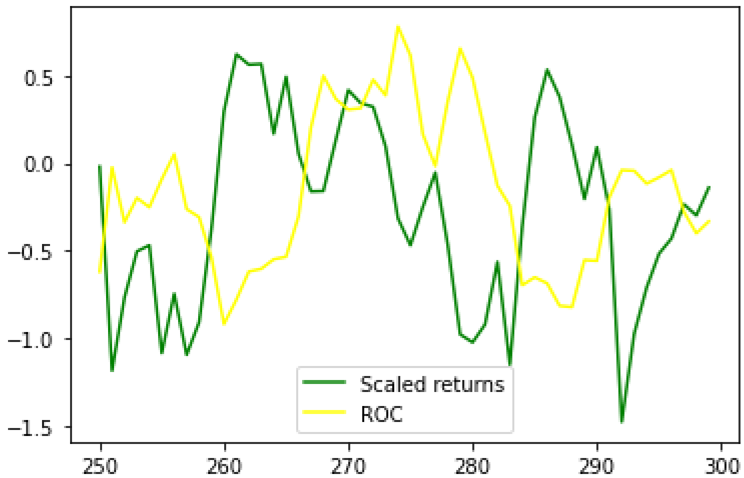
EMA5 reacts to quick changes in CP faster than EMA13 and EMA26. So to predict %trends and worked/not within a 7 day period, EMA5 and EMA13 would be more useful than EMA26

Exploring trends between different feautures and % returns

In [10]:

```
plt.title("Days vs %returns and other feauts")
plt.plot(days[250:300],returnssc[250:300],color="green",label="Scaled returns")
plt.plot(days[250:300],EMA5sc[250:300],color="blue",label="EMA5")
plt.legend()
plt.show()
plt.plot(days[250:300],returnssc[250:300],color="green",label="Scaled returns")
plt.plot(days[250:300],MACDsc[250:300],color="red",label="MACD")
plt.legend()
plt.show()
plt.plot(days[250:300],returnssc[250:300],color="green",label="Scaled returns")
plt.plot(days[250:300],SIGNALsc[250:300],color="black",label="SIGNAL")
plt.legend()
plt.show()
plt.plot(days[250:300],returnssc[250:300],color="green",label="Scaled returns")
plt.plot(days[250:300],engmacd[250:300],color="skyblue",label="Emacd")
plt.legend()
plt.show()
plt.plot(days[250:300],returnssc[250:300],color="green",label="Scaled returns")
plt.plot(days[250:300],RSIsc[250:300],color="pink",label="RSI")
plt.legend()
plt.show()
plt.plot(days[250:300],returnssc[250:300],color="green",label="Scaled returns")
plt.plot(days[250:300],ROCsc[250:300],color="yellow",label="ROC")
plt.legend()
plt.show()
plt.show()
```


Days vs %returns and other feauts
Scaled returns
EMA5
Scaled returns
MACD
Scaled returns
SIGNAL
Scaled returns
Emacd

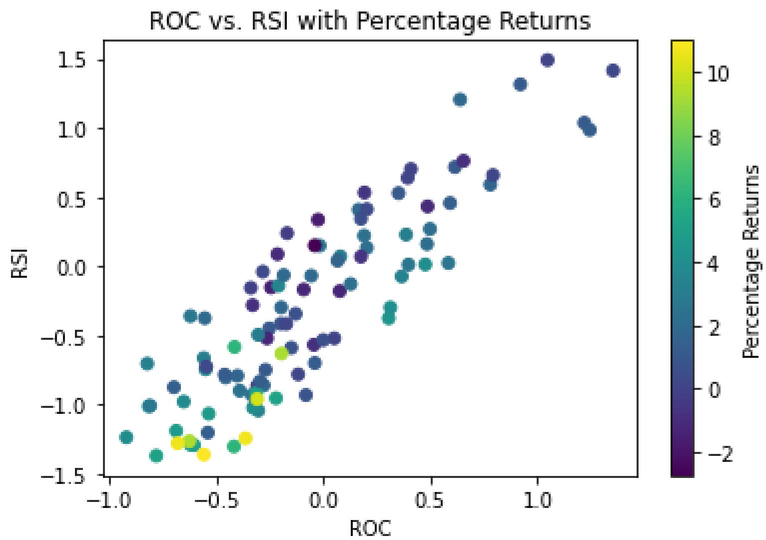


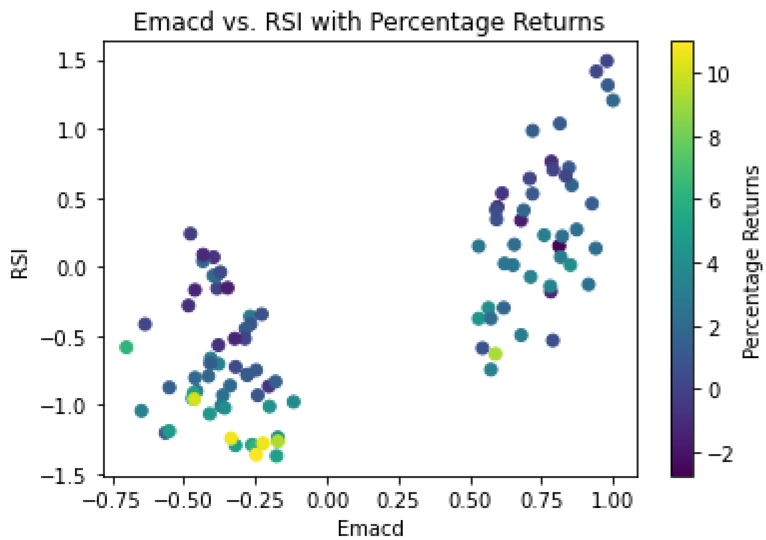
Inference

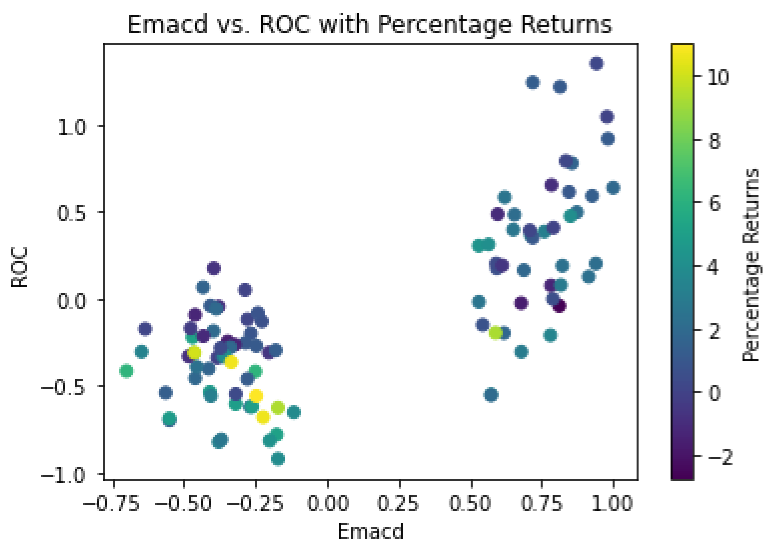
A strong feeling is present which says ROC , RSI and Engineered MACD can be used together to capture trends in % returns very well

Testing the inference,

In [11]:
```
plt.scatter(ROCsc[250:350],RSIsc[250:350], c=returns[250:350])
plt.colorbar(label='Percentage Returns')
plt.xlabel('ROC')
plt.ylabel('RSI')
plt.title('ROC vs. RSI with Percentage Returns')
plt.show()
plt.scatter(engmacd[250:350],RSIsc[250:350], c=returns[250:350])
plt.colorbar(label='Percentage Returns')
plt.xlabel('Emacd')
plt.ylabel('RSI')
plt.title('Emacd vs. RSI with Percentage Returns')
plt.show()
plt.scatter(engmacd[250:350],ROCsc[250:350], c=returns[250:350])
plt.colorbar(label='Percentage Returns')
plt.xlabel('Emacd')
plt.ylabel('ROC')
plt.title('Emacd vs. ROC with Percentage Returns')
plt.show()
```







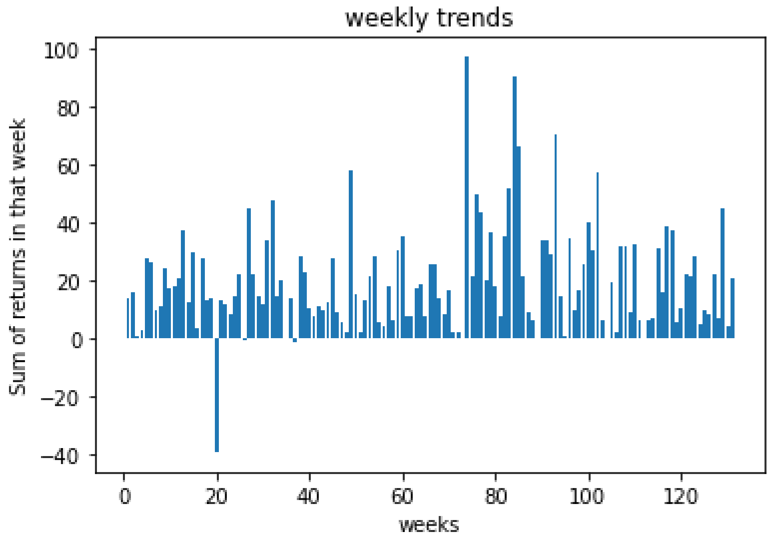
There is existence of some relation between Emacd,RSI,ROC with % returns.

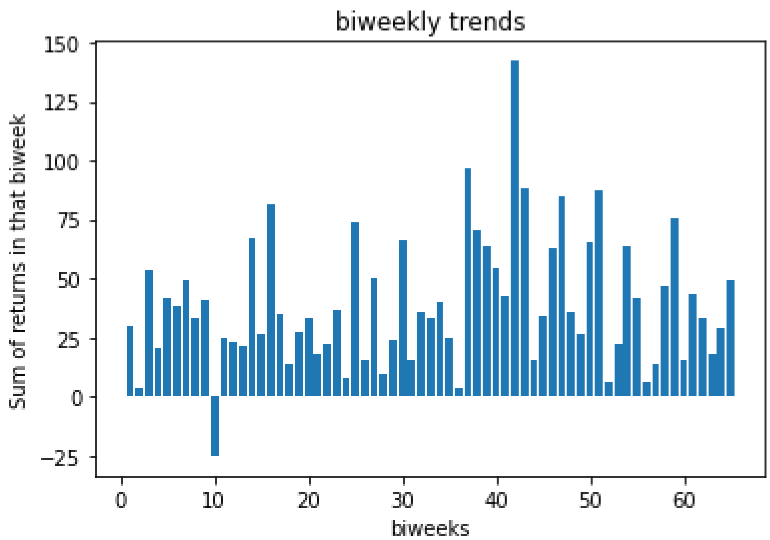
Bar plots to observe seasonal trends

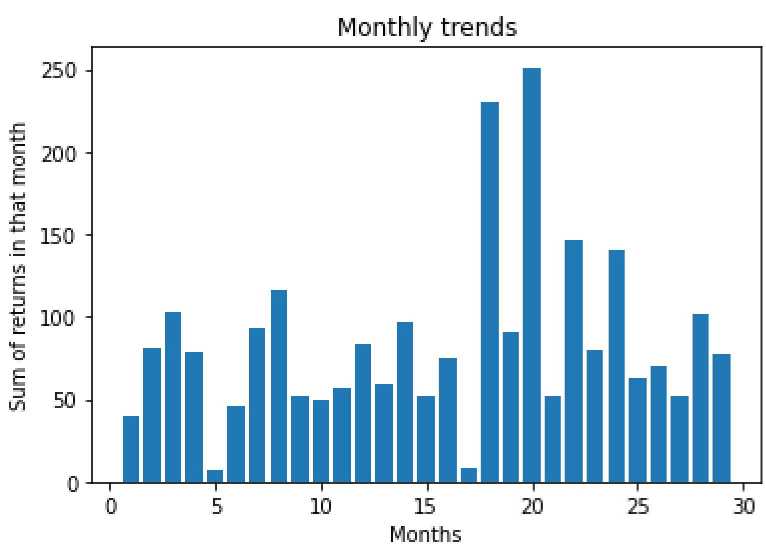
In [12]:

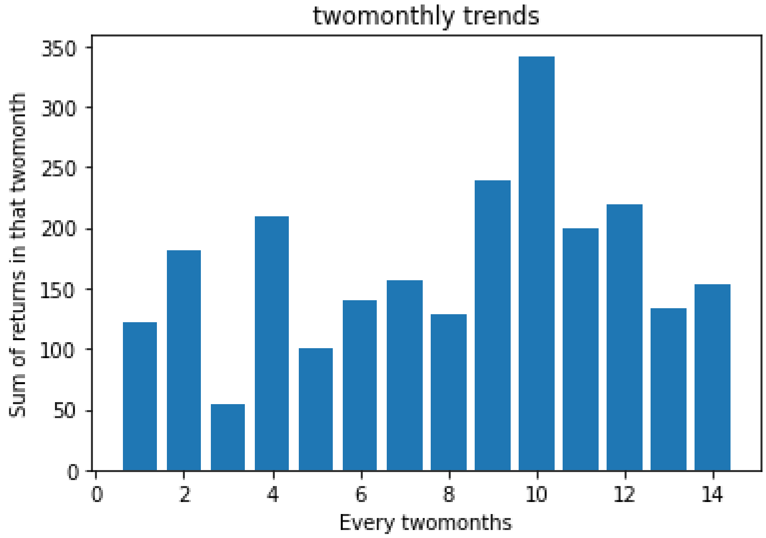
```
weekly_max_returns=[]
for i in range(1,returns.shape[0]//7):
    start=(i-1)*7
    end=i*7
    weekly_max_returns.append(sum(returns[start:end]))
weeks=[i for i in range(1,len(weekly_max_returns)+1)]
```

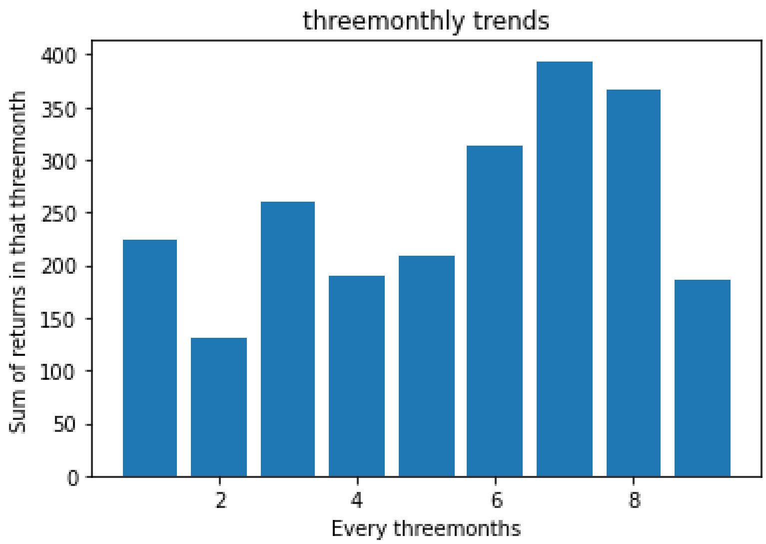
```
plt.bar(weeks,weekly_max_returns)
plt.title("weekly trends")
plt.xlabel("weeks")
plt.ylabel("Sum of returns in that week")
plt.show()
biweekly_max_returns=[]
for i in range(1,returns.shape[0]//14):
    start=(i-1)*14
    end=i*14
    biweekly_max_returns.append(sum(returns[start:end]))
biweeks=[i for i in range(1,len(biweekly_max_returns)+1)]
plt.bar(biweeks,biweekly_max_returns)
plt.title("biweekly trends")
plt.xlabel("biweeks")
plt.ylabel("Sum of returns in that biweek")
plt.show()
monthly_max_returns=[]
for i in range(1,returns.shape[0]//30):
    start=(i-1)*30
    end=i*30
    monthly_max_returns.append(sum(returns[start:end]))
months=[i for i in range(1,len(monthly_max_returns)+1)]
plt.bar(months,monthly_max_returns)
plt.title("Monthly trends")
plt.xlabel("Months")
plt.ylabel("Sum of returns in that month")
plt.show()
twomonthly_max_returns=[]
for i in range(1,returns.shape[0]//60):
    start=(i-1)*60
    end=i*60
    twomonthly_max_returns.append(sum(returns[start:end]))
twomonths=[i for i in range(1,len(twomonthly_max_returns)+1)]
plt.bar(twomonths,twomonthly_max_returns)
plt.title("twomonthly trends")
plt.xlabel("Every twomonths")
plt.ylabel("Sum of returns in that twomonth")
plt.show()
threemonthly_max_returns=[]
for i in range(1,returns.shape[0]//90):
    start=(i-1)*90
    end=i*90
    threemonthly_max_returns.append(sum(returns[start:end]))
threemonths=[i for i in range(1,len(threemonthly_max_returns)+1)]
plt.bar(threemonths,threemonthly_max_returns)
plt.title("threemonthly trends")
plt.xlabel("Every threemonths")
plt.ylabel("Sum of returns in that threemonth")
plt.show()
```


weekly trends
Sum of returns in that week
weeks
100
80
60
40
20
0
−20
−40
0
20
40
60
80
100
120


biweekly trends
Sum of returns in that biweek
biweeks
150
125
100
75
50
25
0
−25
0
10
20
30
40
50
60


Monthly trends
Sum of returns in that month
Months
250
200
150
100
50
0
0
5
10
15
20
25
30





Inference

Every peak is followed immediately by a dip, and every dip is followed by a peak. Why such a trend?

3)Models and Plan

- We will build a set of classifiers and regressors and pick the best performing one.
- Train them on vanilla data and inferred data and choose the better data
- Models being built for classification
  - Kernel SVM
  - Random Forest
- Models being built for regression
  - Kernel SVR
  - Random Forest

In [13]:
```
df
```

Out[13]:

	Close	Volume	EMA5	EMA13	EMA26	MACD	SIGNAL	RSI	ROC	worked
0	1136.95	3594297	1126.883592	1124.903001	1113.181837	12.016158	17.498908	58.490715	2.635974	
1	1147.40	6885679	1133.722395	1128.116858	1115.716515	12.897172	16.578561	61.178123	3.457914	

2	1160.75	8929987	1142.731597	1132.778736	1119.052329	14.505406	16.163930	64.353228	2.336346	
3	1155.65	4729914	1147.037731	1136.046059	1121.763268	15.193278	15.969800	62.258378	4.192400	
4	1138.60	2541804	1144.225154	1136.410908	1123.010433	14.198952	15.615630	55.727237	3.246282	
...	...	...	...	...	...	...	...	...	...	.
923	1787.15	4354074	1760.529346	1739.380217	1728.172574	12.646800	5.999303	62.175044	5.123379	
924	1792.30	6034233	1771.119564	1746.940186	1732.922754	15.816717	7.962785	62.953964	5.559809	
925	1787.45	4732492	1776.563043	1752.727302	1736.961809	17.733127	9.916854	61.666071	4.989721	
926	1779.40	4326924	1777.508695	1756.537688	1740.105379	18.390337	11.611550	59.490646	4.137649	
927	1759.40	6621839	1771.472463	1756.946589	1741.534610	17.100226	12.709286	54.359741	1.260432	

928 rows × 12 columns

3.1 Data Preprocessing

Loading

In [14]:
```
df1=df.iloc[:,[2,3,7,8,9,10,11]] # Without MACD , SIGNAL , EMA26 but EMACD
df2=df.iloc[:,[2,3,5,6,7,8,9,10]] # With MACD,SIGNAL but no EMACD
```

In [15]:
```
x1=df1.iloc[:,[0,1,2,3,6]].values # Feautures of first dataset
x2=df2.iloc[:,[0,1,2,3,4,7]].values # Feautures of second dataset
y=df1.iloc[:,[-3,-2]].values # Labels , common to both dataset and same.
```

In [16]:
```
yc,yr=y[:,0],y[:,1] # yc: y classification, yr: y regression
```

Split- Regression

Variable naming convention

- x (or) y: feauture/label
- i: dataset number
- c (or) empty: classification/regression
- tr: train, t: test

eg so x1ctr => feautures from dataset 1 for classification's training task

In [17]:
```
x1tr,x1t,y1tr,y1t=train_test_split(x1,yr,test_size=0.2)
x2tr,x2t,y2tr,y2t=train_test_split(x2,yr,test_size=0.2)
```

Split-Classification

In [18]:
```
x1ctr,x1ct,y1ctr,y1ct=train_test_split(x1,yc,test_size=0.2)
x2ctr,x2ct,y2ctr,y2ct=train_test_split(x2,yc,test_size=0.2)
```

Scaling

In [19]:
```
x1tr,x2tr=sc.fit_transform(x1tr),sc.fit_transform(x2tr)
```

```
x1ctr,x2ctr=sc.fit_transform(x1ctr),sc.fit_transform(x2ctr)
x1t,x2t =sc.fit_transform(x1t ),sc.fit_transform(x2t )
x1ct,x2ct=sc.fit_transform(x1ct),sc.fit_transform(x2ct)
```

3.2 Classification

Choosing the better dataset

In [20]:
```
model1=RandomForestClassifier(n_estimators=250)
model2=SVC(kernel="rbf")
```

In [21]:
```
model1.fit(x1ctr,y1ctr)
print("Model1, dataset 1: ",model1.score(x1ct,y1ct))
model1.fit(x2ctr,y2ctr)
print("Model1, dataset 2: ",model1.score(x2ct,y2ct))
```

```
Model1, dataset 1:  0.6129032258064516
Model1, dataset 2:  0.978494623655914
```

In [22]:
```
model2.fit(x1ctr,y1ctr)
print("Model2, dataset 1: ",model2.score(x1ct,y1ct))
model2.fit(x2ctr,y2ctr)
print("Model2, dataset 2: ",model2.score(x2ct,y2ct))
```

```
Model2, dataset 1:  0.6451612903225806
Model2, dataset 2:  0.9623655913978495
```

Running on RandomForest and finding best of the 2 dataset by averaging 100 random samples

In [23]:
```
d1=d2=0
for i in range(100):
    #Split
    x1ctr,x1ct,y1ctr,y1ct=train_test_split(x1,yc,test_size=0.2)
    x2ctr,x2ct,y2ctr,y2ct=train_test_split(x2,yc,test_size=0.2)
    #Scale
    x1ctr,x2ctr=sc.fit_transform(x1ctr),sc.fit_transform(x2ctr)
    x1ct,x2ct=sc.fit_transform(x1ct),sc.fit_transform(x2ct)
    #Score
    model1.fit(x1ctr,y1ctr)
    d1+=model1.score(x1ct,y1ct)
    model1.fit(x2ctr,y2ctr)
    d2+=model1.score(x2ct,y2ct)
#Average
print(d1/100," ",d2/100)
```

```
0.6650537634408603   0.969623655913979
```

Inference

Thus second dataset, which has macd , signal is better than the dataset which combines both into engineered macd

Choosing the better model - Cross validation

In [24]:
```
model1=RandomForestClassifier(n_estimators=250)
model2=SVC(kernel="rbf")
acc=cross_val_score(estimator=model1,X=x2ctr,y=y2ctr,cv=10)
print("RandomForest standard deviation of accuracies: ",acc.std())
print("RandomForest mean of accuracies: ",acc.mean())
acc=cross_val_score(estimator=model2,X=x2ctr,y=y2ctr,cv=10)
```

```
print("SVM standard deviation of accuracies: ",acc.std())
print("SVM mean of accuracies: ",acc.mean())
```

```
RandomForest standard deviation of accuracies:  0.004054054054054065
RandomForest mean of accuracies:  0.9986486486486486
SVM standard deviation of accuracies:  0.012300699130170753
SVM mean of accuracies:  0.964972972972973
```

Random forest is far better than svm.

Training the final model

In [25]:

```
clasr=RandomForestClassifier(n_estimators=250) #Random forest
x2ctr,x2ct,y2ctr,y2ct=train_test_split(x2,yc,test_size=0.2) #second dataset
x2ctr=sc.fit_transform(x2ctr) #scaling
x2ct=sc.fit_transform(x2ct)
clasr.fit(x2ctr,y2ctr) #fitting
ypred=clasr.predict(x2ct) #predictions
#Evaluation
cm=confusion_matrix(y2ct,ypred)
acc=accuracy_score(y2ct,ypred)
precision,recall,fscore,support=precision_recall_fscore_support(y2ct,ypred,average="bina
print("Confusion matrix: \n",cm)
print("Accuracy: ", acc)
print("avg.Precision: ", precision,"\navg.Recall: ",recall,"\navg.Fscore: ",fscore)
```

```
Confusion matrix:
 [[109   0]
 [  4  73]]
Accuracy:  0.978494623655914
avg.Precision:  1.0
avg.Recall:  0.948051948051948
avg.Fscore:  0.9733333333333333
```

3.3 Regression

Choosing the better dataset

In [26]:

```
model1=RandomForestRegressor(n_estimators=250)
model2=SVR(kernel="rbf")
```

In [27]:

```
x1tr,x1t,y1tr,y1t=train_test_split(x1,yr,test_size=0.2)
x2tr,x2t,y2tr,y2t=train_test_split(x2,yr,test_size=0.2)
x1tr,x2tr=sc.fit_transform(x1tr),sc.fit_transform(x2tr)
x1t,x2t =sc.fit_transform(x1t ),sc.fit_transform(x2t )
```

In [28]:

```
model1.fit(x1tr,y1tr)
print("Model1, dataset 1: ",model1.score(x1t,y1t))
model1.fit(x2tr,y2tr)
print("Model1, dataset 2: ",model1.score(x2t,y2t))
```

```
Model1, dataset 1:  0.018842310772447468
Model1, dataset 2:  0.9446964489298323
```

In [29]:

```
model2.fit(x1tr,y1tr)
print("Model1, dataset 1: ",model2.score(x1t,y1t))
model2.fit(x2tr,y2tr)
print("Model1, dataset 2: ",model2.score(x2t,y2t))
```

```
Model1, dataset 1:  0.1100360085209795
Model1, dataset 2:  0.822107600925591
```

Running on RandomForest and finding best of the 2 dataset by averaging 100 random samples

In [30]:
```
d1=d2=0
for i in range(100):
    #Split
    x1tr,x1t,y1tr,y1t=train_test_split(x1,yr,test_size=0.2)
    x2tr,x2t,y2tr,y2t=train_test_split(x2,yr,test_size=0.2)
    #Scale
    x1tr,x2tr=sc.fit_transform(x1tr),sc.fit_transform(x2tr)
    x1t,x2t =sc.fit_transform(x1t ),sc.fit_transform(x2t )
    #Score
    model1.fit(x1tr,y1tr)
    d1+=model1.score(x1t,y1t)
    model1.fit(x2tr,y2tr)
    d2+=model1.score(x2t,y2t)
print(d1/100," ",d2/100)
```

```
0.08128598520777475   0.8580582588091386
```

Inference

Thus second dataset, which has macd , signal is better than the dataset which combines both .

Choosing the better model

In [31]:
```
model1=RandomForestRegressor(n_estimators=100)
model2=SVR(kernel="rbf")
acc=cross_val_score(estimator=model1,X=x2tr,y=y2tr,cv=10)
print("RandomForest standard deviation of accuracies: ",acc.std())
print("RandomForest mean of accuracies: ",acc.mean())
acc=cross_val_score(estimator=model2,X=x2tr,y=y2tr,cv=10)
print("SVM standard deviation of accuracies: ",acc.std())
print("SVM mean of accuracies: ",acc.mean())
```

```
RandomForest standard deviation of accuracies:  0.1319685513343272
RandomForest mean of accuracies:  0.943419919208431
SVM standard deviation of accuracies:  0.24196065982630027
SVM mean of accuracies:  0.7898262433388763
```

Random Forest is chosen.

Training final model

In [32]:
```
regr=RandomForestRegressor(n_estimators=200) #Random forest
x2tr,x2t,y2tr,y2t=train_test_split(x2,yr,test_size=0.2) #split
x2tr=sc.fit_transform(x2tr) #scale
x2t =sc.fit_transform(x2t )
regr.fit(x2tr,y2tr) # train
#score
ypred=regr.predict(x2t)
r2score=r2_score(ypred,y2t)
print("R Squared score is :",r2score)
```

```
R Squared score is : 0.9869184634143403
```

4)Evaluation

4.1) Classifier

- Model: RandomForest Classifier, trees=250

```
Confusion matrix:
 [[109   0]
 [  4  73]]
Accuracy:  0.978494623655914
avg.Precision:  1.0
avg.Recall:  0.948051948051948
avg.Fscore:  0.9733333333333333
```

Scores

4.2)Regressor

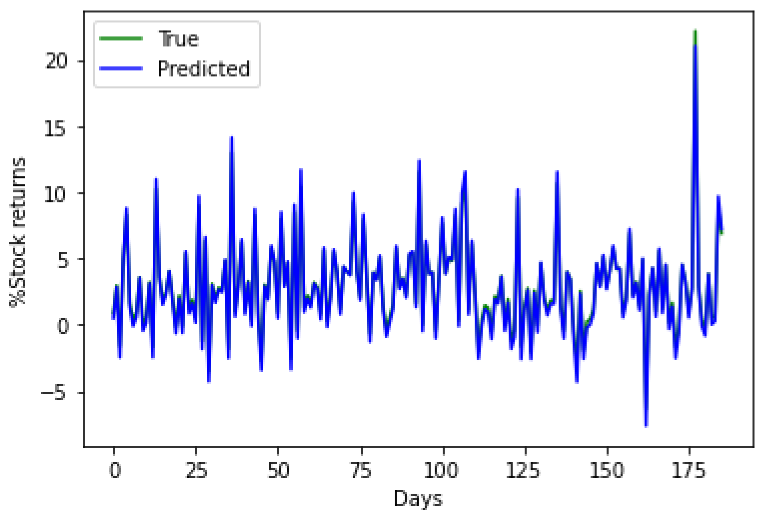
- Model: RandomForest Regressor, trees=200

```
R Squared score is : 0.9869184634143403
```

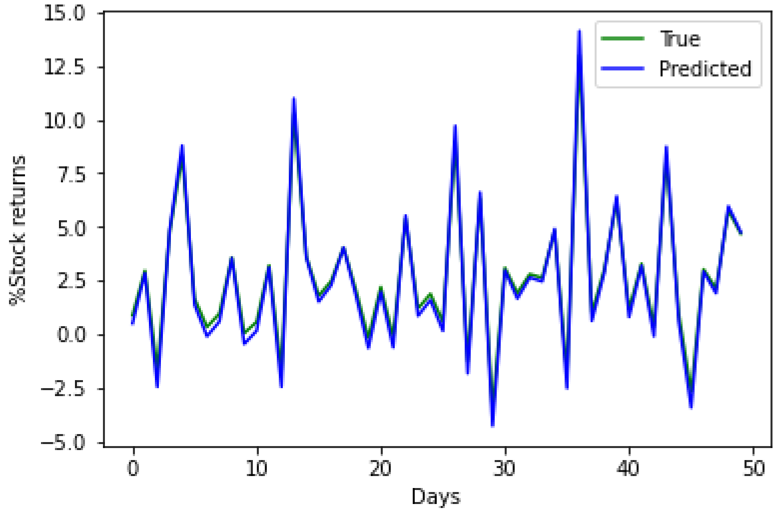
Scores

Visualizing Regression Output

In [33]:
```
days=[i for i in range(ypred.shape[0])]
plt.plot(days,y2t,color="green",label="True")
plt.plot(days,ypred,color="blue",label="Predicted")
plt.xlabel("Days")
plt.ylabel("%Stock returns")
plt.legend()
plt.show()
```



In [34]:
```
days=[i for i in range(ypred.shape[0])]
plt.plot(days[:50],y2t[:50],color="green",label="True")
plt.plot(days[:50],ypred[:50],color="blue",label="Predicted")
plt.xlabel("Days")
plt.ylabel("%Stock returns")
plt.legend()
plt.show()
```



In [35]:

```
days=[i for i in range(ypred.shape[0])]
plt.plot(days[:50],y2t[:50],color="green",label="True")
plt.plot(days[:50],ypred[:50],color="orange",label="Predicted")
plt.xlabel("Days")
plt.ylabel("%Stock returns")
plt.legend()
plt.show()
```