In [ ]:
```
import importlib
import seaborn as sns
import ps1_functions as ps
import matplotlib.pyplot as plt
import pandas as pd
```

In [ ]:
```
importlib.reload(ps)
```

Out[ ]:
```
<module 'ps1_functions' from '/Users/venugopalbhatia/Documents/Deep Learning The
ory and Applications/Assignment 1/ps1_functions.py'>
```

Problem 1

Machine Learning Algorithms are those that can learn from past data and experience to make predictions. The machine is capable of learning by itself without human intervention or programming fixed rules. Most Machine Learning algorithms usually has three important components:

1. A decision function which makes predictions based on patterns in the data that may be labelled or unlabelled.
2. An error function to evaluate how off the algorithm's predictions are from true labels.
3. An optimization procedure which usually may involve something like the minimization of a cost function and adjusting feature weights accordingly.

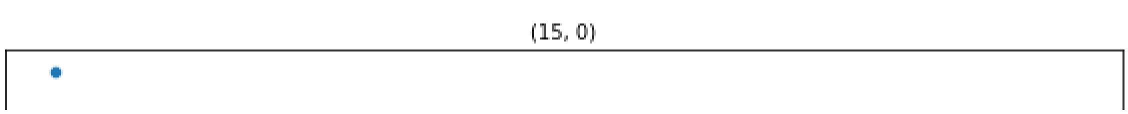
Problem 2

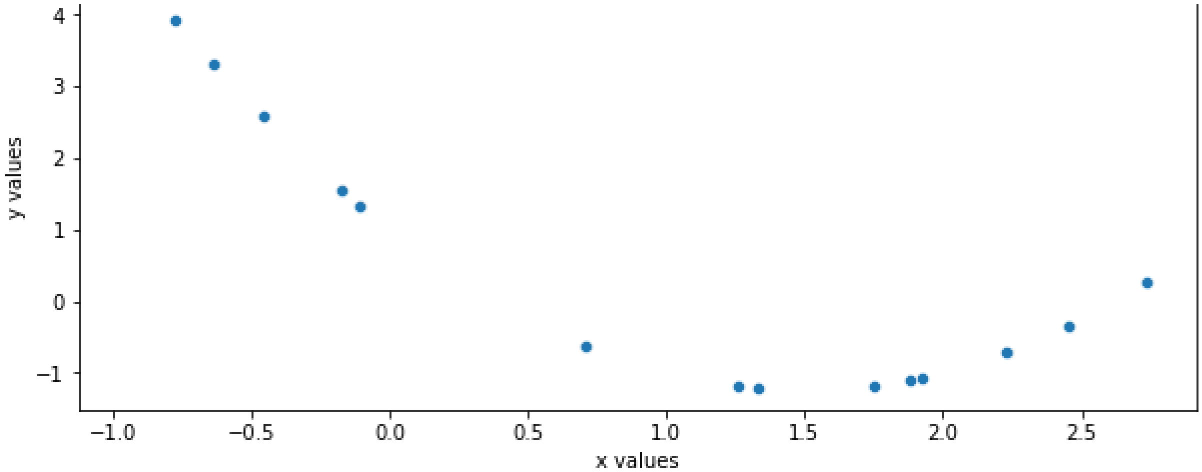
2.1

In [ ]:
```
N = [15,100]
sigma = [0,0.05,0.2]
points_set = {}
for n in N:
    for s in sigma:
        points_set[(n,s)] = ps.problem2_evaluate_function_on_random_noise(n,s) #
```

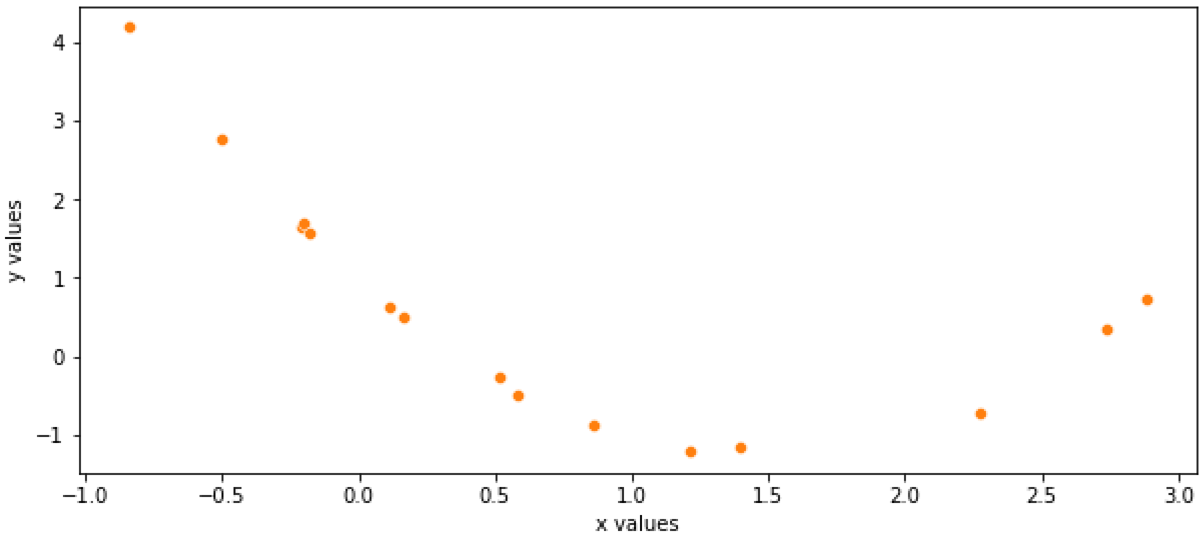
Plots

In [ ]:
```
fig, ax = plt.subplots(6,1,figsize=(10,30))
j = 0
color_lst = sns.color_palette()
for i in points_set.keys():
  sns.scatterplot(x = points_set[i][0],y = points_set[i][1],color = color_lst[j]
  ax[j].set_title(i,fontsize = 10)
  ax[j].set_xlabel("x values")
  ax[j].set_ylabel("y values")
  j+=1
```

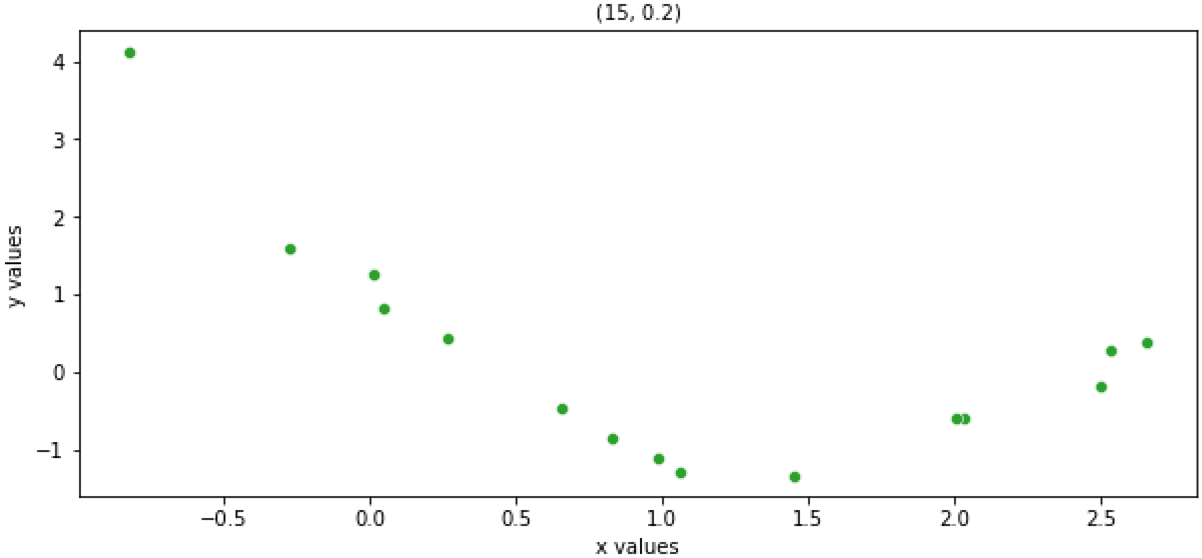




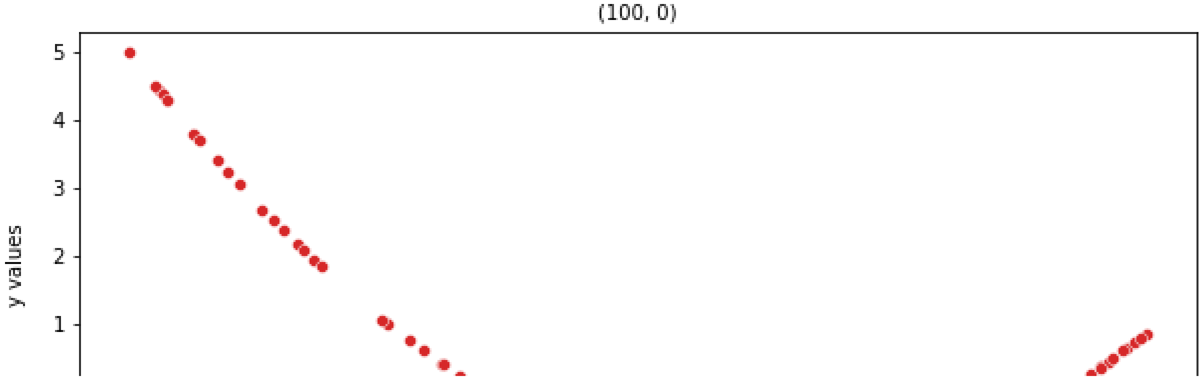
(15, 0.05)

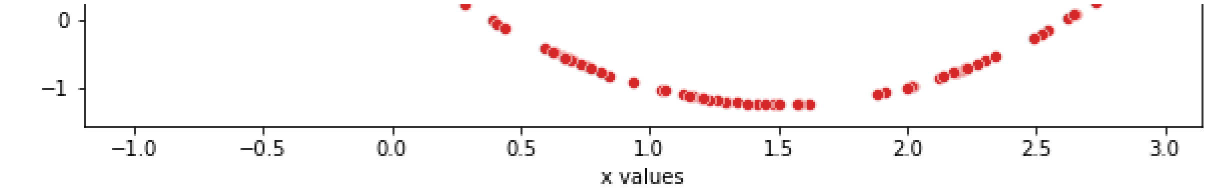


(15, 0.2)

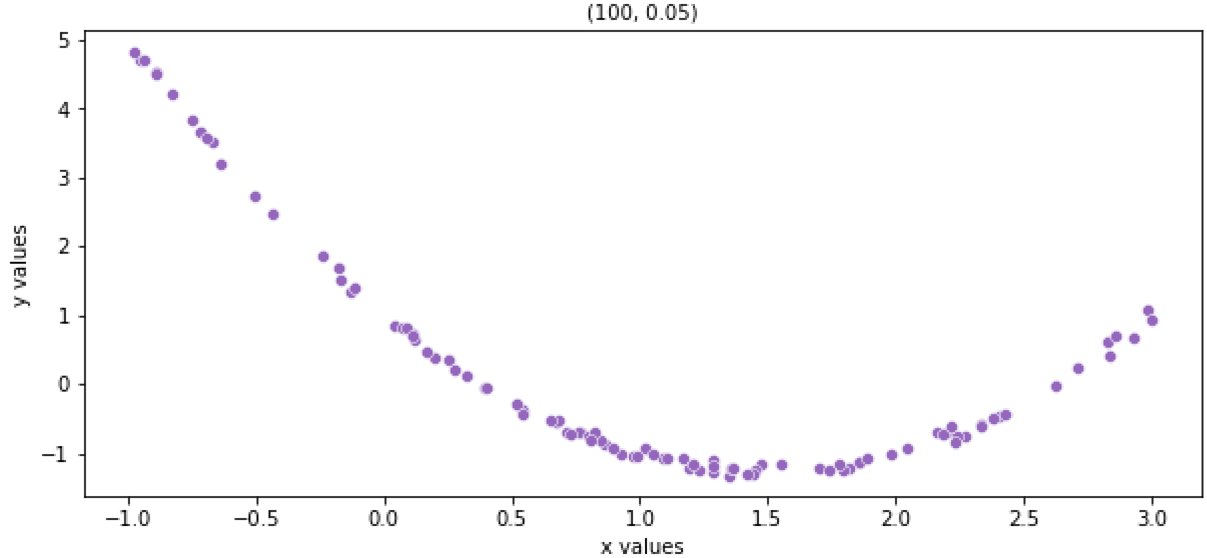


(100, 0)

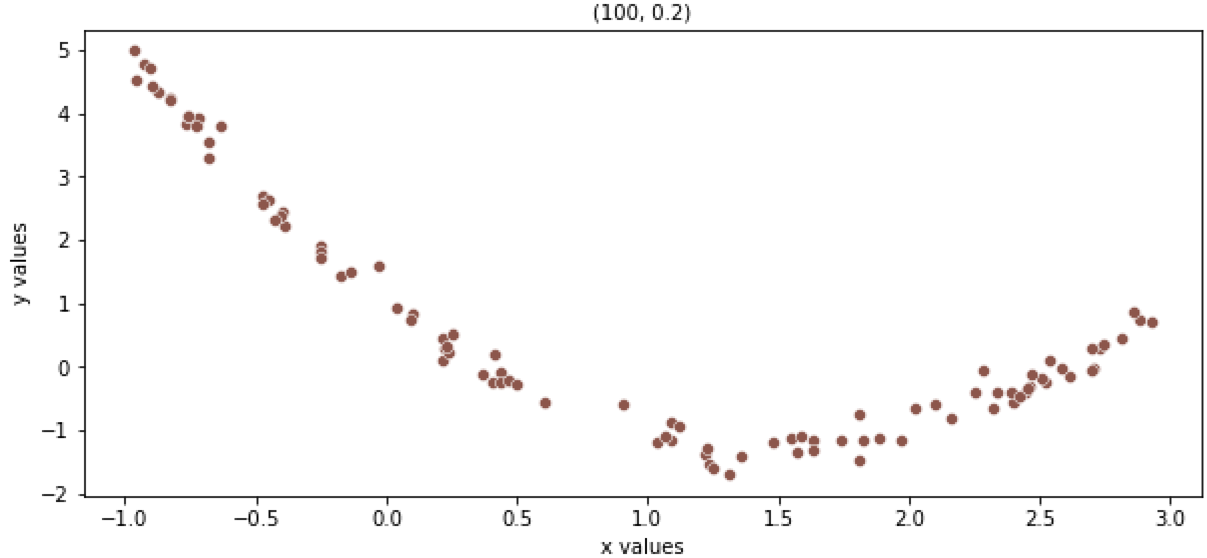




(100, 0.05)



(100, 0.2)



2.2

In [ ]:

```
import numpy as np
```

In [ ]:

```
importlib.reload(ps)
```

Out[ ]:

```
<module 'ps1_functions' from '/Users/venugopalbhatia/Documents/Deep Learning The
ory and Applications/Assignment 1/ps1_functions.py'>
```

In [ ]:

```
points_set.keys()
```

Out[ ]:

```
dict_keys([(15, 0), (15, 0.05), (15, 0.2), (100, 0), (100, 0.05), (100, 0.2)])
```

In [ ]:

```
def getX(deg,points):
```

```
    deg+=1
    points = np.array(points)
    arr = [points**i for i in range(deg)]
    arr = np.transpose(arr)
    X = np.array(arr)
    return X
```

In [ ]:

```
def genPlot(deg,x,y,ax = None,reg = None):
    X = getX(deg,x)
    weights = ps.problem2_fit_polynomial(x,y,degree = deg,regularization=reg)
    np.array(weights)
    y_cap = np.dot(X,weights)
    mse = ((y-y_cap)**2).mean()
    if(ax):
        sns.scatterplot(x=x,y=y,ax=ax)
        sns.lineplot(x=x,y=y_cap,ax=ax)
    else:
        sns.scatterplot(x=x,y=y)
        sns.lineplot(x=x,y=y_cap)
    return weights,mse
```

Degree 1 plots and table

In [ ]:

```
fig, ax = plt.subplots(2,3,figsize=(30,10))
fig.suptitle("Degree 1 {subplots (n,sigma)}")
degree_1_weights_mse = {}
res = None
for i,n in enumerate(N):
    for j,s in enumerate(sigma):
        points = points_set[(n,s)]
        res = genPlot(1,x=list(points[0]),y=list(points[1]),ax=ax[i,j])
        degree_1_weights_mse[(n,s)] = res
        ax[i,j].set_title((n,s))
```

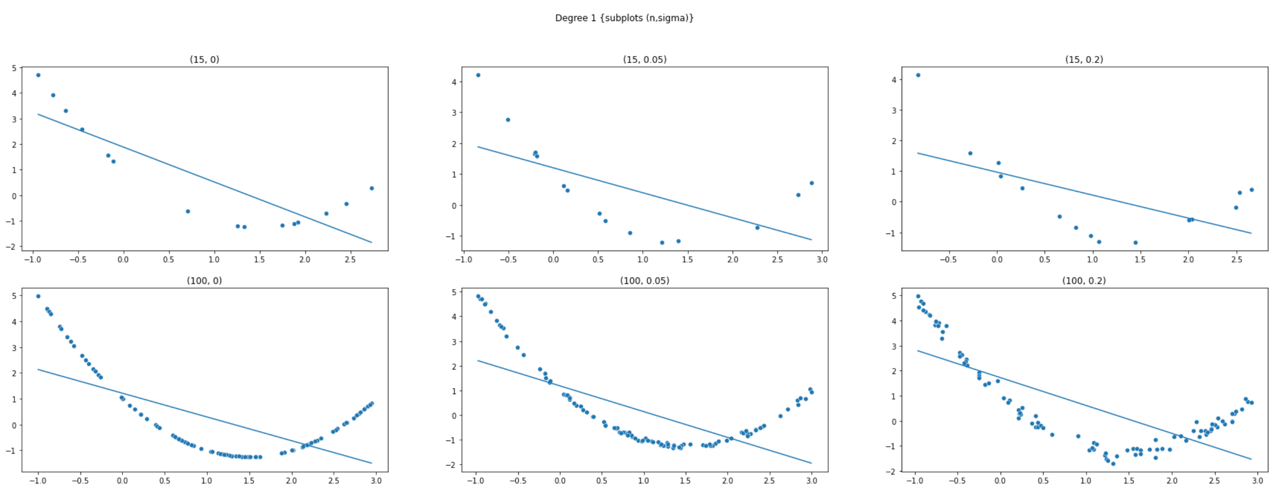


Table for degree 1 weights and MSE

In [ ]:

```
weights_sep = pd.DataFrame(table1['Weights'].tolist(),index = table1.index)
pd.concat([weights_sep,table1],axis = 1)
```

Out[ ]:

	0	1	Weights	MSE
(15, 0)	1.879221	-1.364174	[1.8792208059141515, -1.3641741706339205]	1.132380
(15, 0.05)	1.203535	-0.807622	[1.2035345398075352, -0.8076221135074123]	1.399525
(15, 0.2)	0.964022	-0.750415	[0.9640222319220002, -0.7504149662524976]	1.242017
(100, 0)	1.211371	-0.919357	[1.211370761450031, -0.9193571587996119]	1.588721
(100, 0.05)	1.186106	-1.043580	[1.1861057549091194, -1.0435800515009457]	1.509685
(100, 0.2)	1.720281	-1.113110	[1.720280906426236, -1.1131103217927516]	1.561374

In [ ]:

```
table1 = pd.DataFrame.from_dict(degree_1_weights_mse,orient = "index")
table1.rename({0:'Weights',1:"MSE"},axis = "columns",inplace=True)
weights_sep = pd.DataFrame(table1['Weights'].tolist(),index = table1.index)
table1 = pd.concat([weights_sep,table1],axis = 1)
table1
```

Out[ ]:

	0	1	Weights	MSE
(15, 0)	1.879221	-1.364174	[1.8792208059141515, -1.3641741706339205]	1.132380
(15, 0.05)	1.203535	-0.807622	[1.2035345398075352, -0.8076221135074123]	1.399525
(15, 0.2)	0.964022	-0.750415	[0.9640222319220002, -0.7504149662524976]	1.242017
(100, 0)	1.211371	-0.919357	[1.211370761450031, -0.9193571587996119]	1.588721
(100, 0.05)	1.186106	-1.043580	[1.1861057549091194, -1.0435800515009457]	1.509685
(100, 0.2)	1.720281	-1.113110	[1.720280906426236, -1.1131103217927516]	1.561374

Degree 2 plots and table

In [ ]:

```
fig, ax = plt.subplots(2,3,figsize=(30,10))
fig.suptitle("Degree 2 {subplots (n,sigma)}")
degree_2_weights_mse = {}
res = None
for i,n in enumerate(N):
    for j,s in enumerate(sigma):
        points =  points_set[(n,s)]
        res = genPlot(2,x=list(points[0]),y=list(points[1]),ax=ax[i,j])
        degree_2_weights_mse[(n,s)] = res
        ax[i,j].set_title((n,s))
```

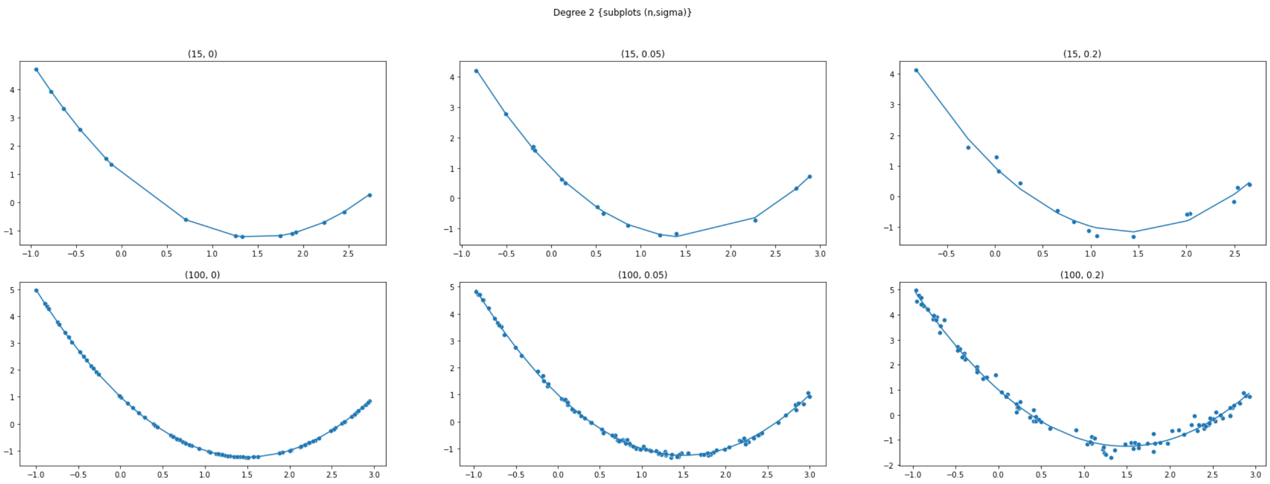


Table for degree 2 weights and MSE

In [ ]:

```
table2 = pd.DataFrame.from_dict(degree_2_weights_mse,orient = "index")
table2.rename({0:'Weights',1:"MSE"},axis = "columns",inplace=True)
weights_sep = pd.DataFrame(table2['Weights'].tolist(),index = table2.index)
table2 = pd.concat([weights_sep,table2],axis = 1)
table2
```

Out[ ]:

	0	1	2	Weights	MSE
(15, 0)	1.000000	-3.000000	1.000000	[1.0, -3.000000000000005, 1.0000000000000022]	9.420314e-30
(15, 0.05)	0.981414	-3.028709	1.018438	[0.9814139109461174, -3.0287091434941935, 1.01...	2.332230e-03
(15, 0.2)	0.957007	-3.002843	1.058303	[0.9570066003325552, -3.002843390245458, 1.058...	3.597332e-02
(100, 0)	1.000000	-3.000000	1.000000	[0.9999999999999998, -2.9999999999999982, 0.99...	1.244428e-30
(100, 0.05)	0.999535	-3.002946	0.999400	[0.9995354732353314, -3.0029463712111113, 0.99...	3.533661e-03
(100, 0.2)	0.998409	-3.039987	1.022641	[0.9984087351078339, -3.039986854497805, 1.022...	3.269226e-02

Degree 9 plots and table

In [ ]:

```
fig, ax = plt.subplots(2,3,figsize=(30,10))
fig.suptitle("Degree 9 {subplots (n,sigma)}")
degree_9_weights_mse = {}
res = None
for i,n in enumerate(N):
    for j,s in enumerate(sigma):
        points =  points_set[(n,s)]
        res = genPlot(9,x=list(points[0]),y=list(points[1]),ax=ax[i,j])
        degree_9_weights_mse[(n,s)] = res
        ax[i,j].set_title((n,s))
```

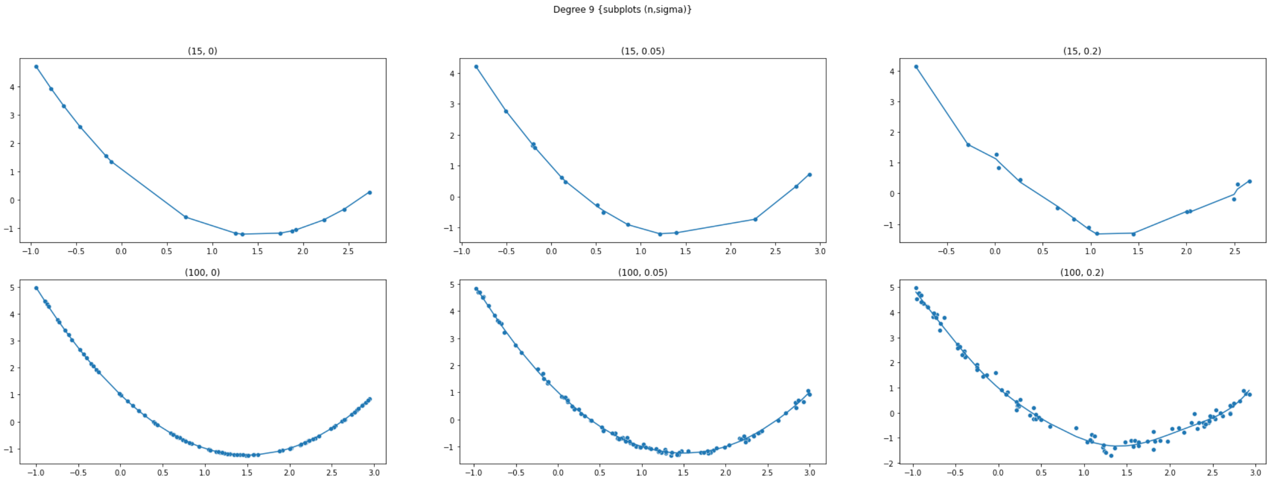


Table for degree 9 weights and MSE

In [ ]:

```
table3 = pd.DataFrame.from_dict(degree_9_weights_mse,orient = "index")
table3.rename({0:'Weights',1:"MSE"},axis = "columns",inplace=True)
weights_sep = pd.DataFrame(table3['Weights'].tolist(),index = table3.index)
table3 = pd.concat([weights_sep,table3],axis = 1)
table3
```

Out[ ]:

	0	1	2	3	4	5	(
(15, 0)	1.000000	-3.000000	1.000000	-6.930350e-10	9.604264e-10	-5.129550e-10	1.600711e-1(
(15, 0.05)	0.969609	-3.187779	1.496195	4.549030e-01	-2.224640e+00	9.506752e-01	1.711533e+0(
(15, 0.2)	1.163141	-3.219564	-1.485216	1.294180e+01	-1.561997e+01	-6.516661e+00	2.434842e+0
(100, 0)	1.000000	-3.000000	1.000000	-8.217285e-10	-4.365575e-11	1.382432e-10	1.891749e-1(
(100, 0.05)	1.004592	-2.989460	0.917301	-2.883290e-02	1.925708e-01	-6.711887e-02	-1.022529e-0
(100, 0.2)	0.984619	-2.976995	1.340729	-4.222023e-01	-5.700316e-01	6.577567e-01	1.017509e-0

It seems like degree 9 plots seem to overfit, this is evident in the 15,0.2 plot, probably would be even more evident in all the plots if the image size and scale are adjusted. Degree 1 plots are obviously underfit and overall degree 2 curves seem to fit best, however with degree 9 curves for 100 values the curves seem to have fit quite well, comparable to degree 2 which is also suggested by the weights.

2.3

L2 Norm to N -> {15,100}, sigma = 0.05, 3 custom lambda values

In [ ]:

```
fig, ax = plt.subplots(2,3,figsize=(30,25))
fig.suptitle("L2 Regularization {subplots (n,sigma,lambda)}",fontsize = 25)
L2_weights_MSE = {}
res = None
N_L2 = [15,100]
sigma_L2 = [0.05]
lambda_L2 = [0.0005,0.3,0.9]
for i,n in enumerate(N_L2):
    for j,s in enumerate(sigma_L2):
        for k,l in enumerate(lambda_L2):
            points =  points_set[(n,s)]
            res = genPlot(9,x=list(points[0]),y=list(points[1]),ax=ax[i,k],reg=l
            L2_weights_MSE[(n,s,l)] = res
            ax[i,k].set_title((n,s,l),fontsize = 20)
```

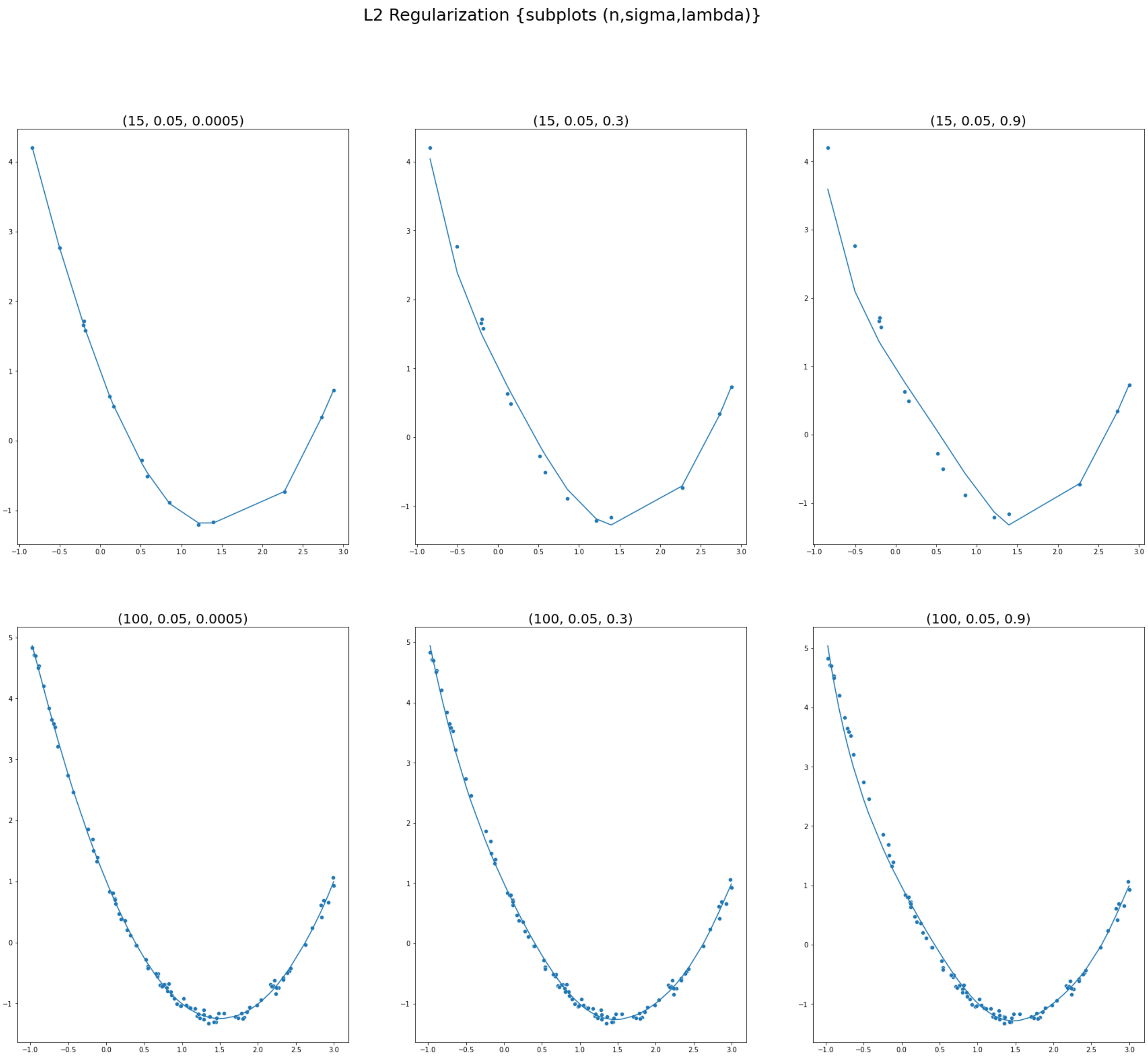


Table for L2 Norm - Degree 9 weights and MSE

In [ ]:

```
table4 = pd.DataFrame.from_dict(L2_weights_MSE,orient = "index")
table4.rename({0:'Weights',1:"MSE"},axis = "columns",inplace=True)
weights_sep = pd.DataFrame(table4['Weights'].tolist(),index = table4.index)
table4 = pd.concat([weights_sep,table4],axis = 1)
table4
```

Out[ ]:

	0	1	2	3	4	5	6	7
(15, 0.05, 0.0005)	0.984615	-3.109325	1.148757	0.124943	-0.808411	0.514174	0.587338	-0.738103
(15, 0.05, 0.3)	1.006529	-2.326888	0.417059	-0.522469	0.491643	-0.100202	0.258069	-0.279775
(15, 0.05, 0.9)	0.966087	-1.834666	0.346373	-0.644099	0.385002	-0.215637	0.339332	-0.202677
(100, 0.05, 0.0005)	1.004580	-2.987723	0.915264	-0.032596	0.198509	-0.067253	-0.105855	0.092494
(100, 0.05, 0.3)	0.994516	-2.704775	0.740087	-0.399535	0.432881	0.026062	-0.127767	0.029067
(100, 0.05, 0.9)	0.974775	-2.438656	0.584635	-0.542630	0.473109	-0.020840	0.057768	-0.112978

Problem 3

In [ ]:

```
importlib.reload(ps)
```

Out[ ]:

```
<module 'ps1_functions' from '/Users/venugopalbhatia/Documents/Deep Learning The
ory and Applications/Assignment 1/ps1_functions.py'>
```

In [ ]:

```
import pandas as pd
data = pd.read_csv('data/problem3_data_seed.dat',sep = r'\s+',header = None)
```

In [ ]:

```
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()

data_t = scaler.fit_transform(data.iloc[:,0:7])
```

In [ ]:

```
y = data[7]
y = y.values
```

In [ ]:

```
data_t
```

Out[ ]:

```
array([[0.44098206, 0.50206612, 0.5707804 , ..., 0.48610121, 0.18930164,
        0.34515017],
       [0.40509915, 0.44628099, 0.66243194, ..., 0.50106914, 0.03288302,
        0.21516494],
       [0.34938621, 0.34710744, 0.87931034, ..., 0.50392017, 0.25145302,
        0.1506647 ],
       ...,
       [0.24645892, 0.25826446, 0.7277677 , ..., 0.42908054, 0.98166664,
        0.26440177],
```

```
       [0.11803588, 0.16528926, 0.39927405, ..., 0.14682823, 0.36834441,
        0.25849335],
       [0.16147309, 0.19214876, 0.54718693, ..., 0.24518888, 0.63346292,
        0.26784835]])
```

In [ ]:
```
# from sklearn.model_selection import train_test_split

# x_train,x_test,y_train,y_test = train_test_split(data_t,y,stratify = y)
```

In [ ]:
```
#predicted_labels = ps.problem3_knn_classifier(x_train,y_train,x_test,5)
```

In [ ]:
```
def getAccuracy(predicted_labels,true_labels):
    return sum(predicted_labels == true_labels)/len(true_labels)
```

In [ ]:
```
def split(a, n):
    k, m = divmod(len(a), n)
    return (a[i*k+min(i, m):(i+1)*k+min(i+1, m)] for i in range(n))
```

In [ ]:
```
def kFoldSplit(k,x,y):
    shuffler = np.random.permutation(len(data_t))
    x = x[shuffler]
    y = y[shuffler]
    x_split = list(split(x,k))
    y_split = list(split(y,k))

    return x_split,y_split
```

In [ ]:
```
def kFoldCV(k_folds,x,y,fcn,**kwargs):
    x_split,y_split = kFoldSplit(k_folds,x,y)
    accuracy_folds = {}
    accuracy_folds_train = {}
    #print(len(x_split))
    for i in range(k_folds):

        t_x = x_split.copy()
        t_y = y_split.copy()

        x_fold_cv = t_x.pop(i)
        y_fold_cv = t_y.pop(i)

        t_y = np.concatenate(t_y).ravel()
        t_x = np.vstack(t_x)
        #print(y_fold_cv[0:5])
        #predicted_labels_test = ps.problem3_knn_classifier(t_x,t_y,x_fold_cv,kn
        predicted_labels_test = fcn(t_x,t_y,x_fold_cv,**kwargs)
        predicted_labels_train = fcn(t_x,t_y,t_x,**kwargs)
        test_accuracy = getAccuracy(predicted_labels_test,y_fold_cv)
        train_accuracy = getAccuracy(predicted_labels_train,t_y)
        fold = "fold_"+str(i)
```

```
        accuracy_folds[fold] = test_accuracy
        accuracy_folds_train[fold] = train_accuracy
    return accuracy_folds,accuracy_folds_train
```

In [ ]:

```
def getAverageKFoldAccuracy(folds):
    return sum(list(folds.values()))/len(list(folds.values()))
```

Plotting test error versus k

In [ ]:

```
test_error_kFoldCV= {}
train_error_kFoldCV= {}
k = [1,5,10,15]
k_folds = [5,len(data_t)]
for i in k_folds:
    test_error_kFoldCV[i] = {}
    train_error_kFoldCV[i] = {}
    for num_neighbors in k:
        accuracy_ = None
        train_accuracy = None
        error_ = None
        train_error = None
        accuracy_,train_accuracy = kFoldCV(i,data_t,y,fcn = ps.problem3_knn_clas
        error_ = 1 - getAverageKFoldAccuracy(accuracy_)
        train_error = 1 - getAverageKFoldAccuracy(train_accuracy)
        test_error_kFoldCV[i][num_neighbors] = error_
        train_error_kFoldCV[i][num_neighbors] = train_error
```

Given Below are the train and test errors, k = 1 seems like an overfit while k = 15 seems like an underfit

In [ ]:

```
test_error_kFoldCV
```

Out[ ]:

```
{5: {1: 0.07619047619047614,
  5: 0.080952380952381,
  10: 0.07619047619047614,
  15: 0.07142857142857151},
 210: {1: 0.05714285714285716,
  5: 0.0714285714285714,
  10: 0.080952380952381,
  15: 0.080952380952381}}
```

In [ ]:

```
train_error_kFoldCV
```

Out[ ]:

```
{5: {1: 0.0,
  5: 0.03809523809523818,
  10: 0.05595238095238976,
  15: 0.06666666666666665},
 210: {1: 0.0,
  5: 0.042788790157212264,
  10: 0.057142857142858605,
  15: 0.07174755069492056}}
```

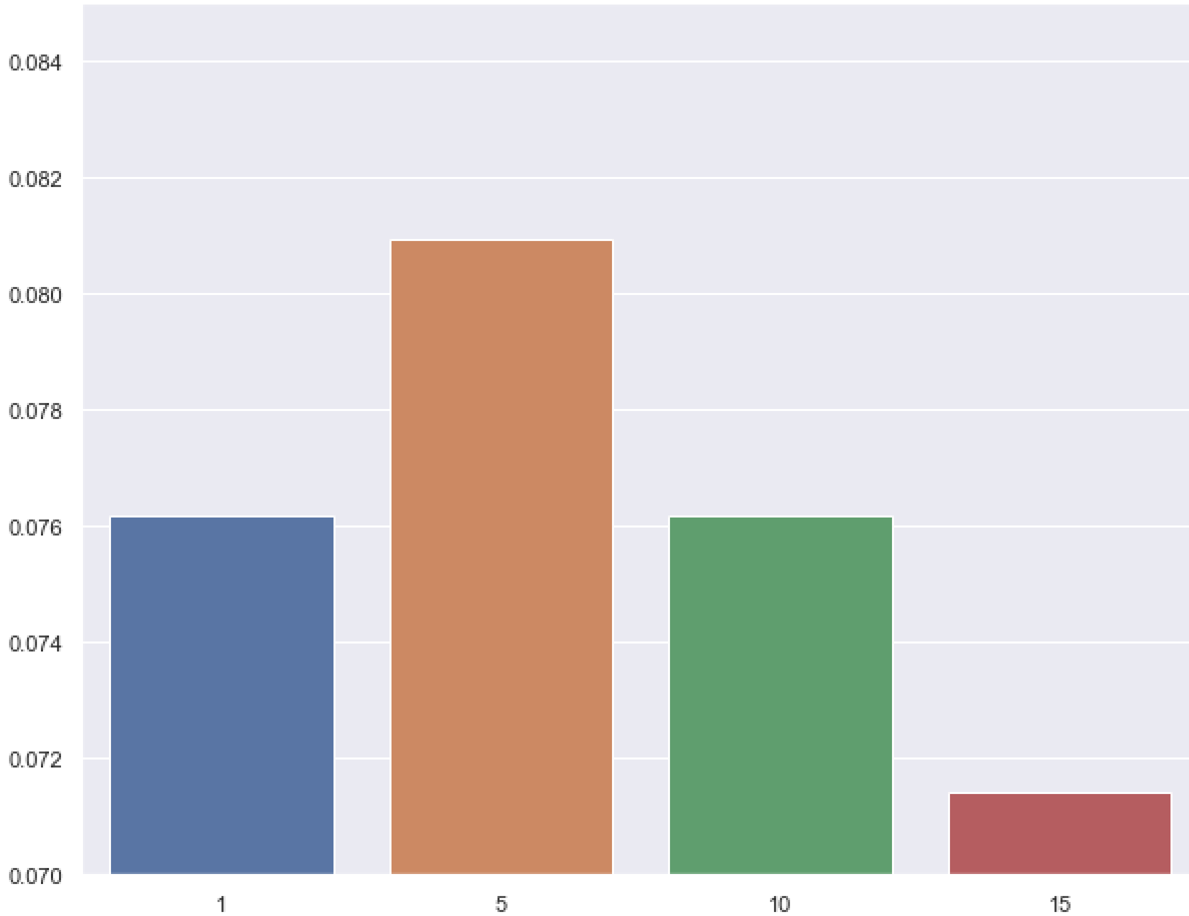
5 fold CV errors

In [ ]:

```
nbr_kf = list(test_error_kFoldCV[5].keys())
error_kf = list(test_error_kFoldCV[5].values())
```

```
sns.set(rc = {'figure.figsize':(10,8)})
kf = sns.barplot(x = nbr_kf,y = error_kf)
kf.set_ylim(0.07,0.085)
```

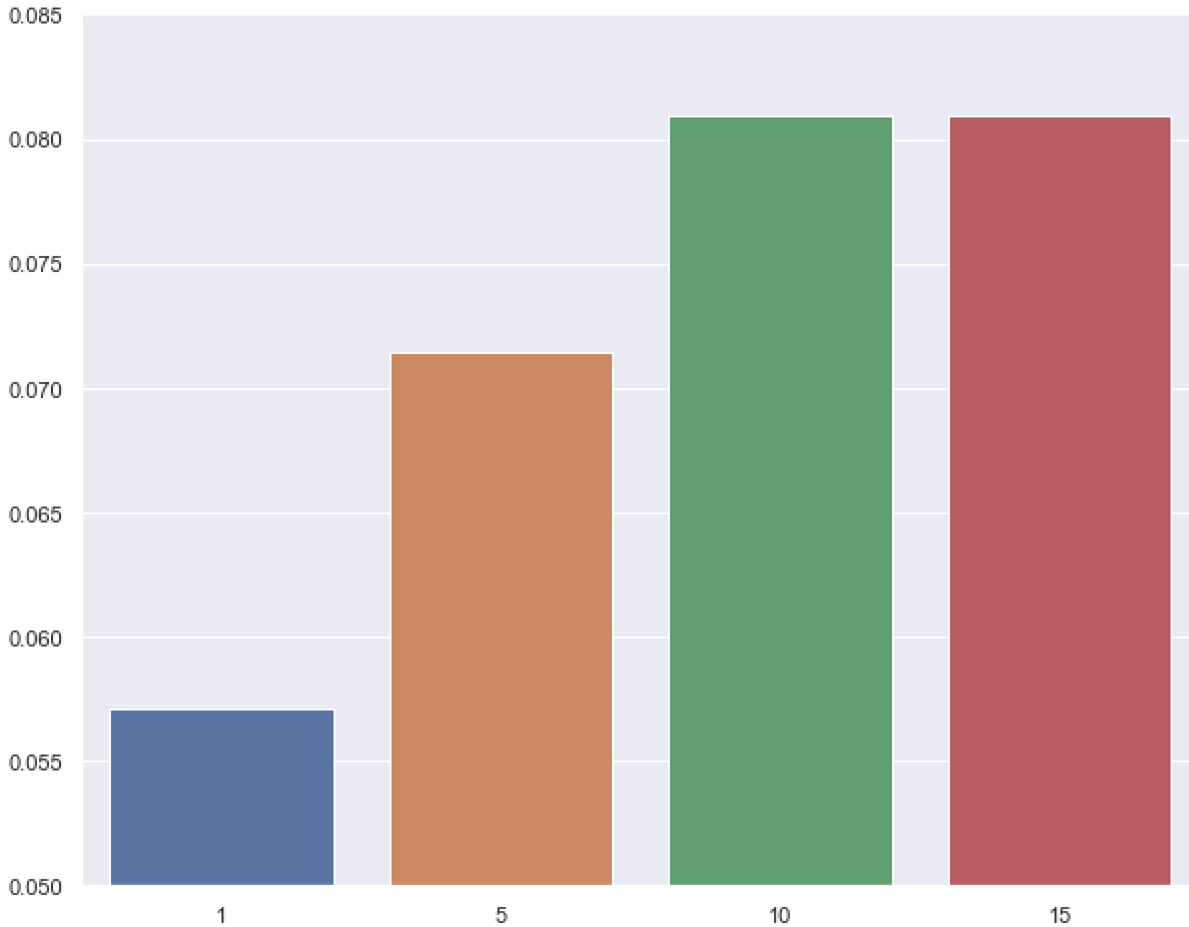
Out[ ]: (0.07, 0.085)



LOOCV errors

In [ ]:
```
nbr_kf = list(test_error_kFoldCV[210].keys())
error_kf = list(test_error_kFoldCV[210].values())
sns.set(rc = {'figure.figsize':(10,8)})
kf = sns.barplot(x = nbr_kf,y = error_kf)
kf.set_ylim(0.05,0.085)
```

Out[ ]: (0.05, 0.085)



3.3

In [ ]:
```
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier as RFC
```

In [ ]:
```
## Writing wrapper fcns here to work with kFoldCV(), though could have written j
def SVM_classifier(x,y,x_test,**kwargs):
    clf = SVC(gamma = "auto",**kwargs)
    clf.fit(x,y)
    y_pred  = clf.predict(x_test)
    return y_pred
def RF_classifier(x,y,x_test,**kwargs):
    clf = RFC(oob_score = True,**kwargs)
    clf.fit(x,y)
    y_pred  = clf.predict(x_test)
    return y_pred
```

In [ ]:
```
x_split,y_split = kFoldSplit(5,data_t,y)
t_x = x_split.copy()
t_y = y_split.copy()
x_fold_cv = t_x.pop(1)
y_fold_cv = t_y.pop(1)

t_y = np.concatenate(t_y).ravel()
t_x = np.vstack(t_x)
```

```
y_predictions = SVM_classifier(t_x,t_y,t_x,C = 2,kernel = 'linear')
getAccuracy(y_predictions,t_y)
```

```
SVC(C=2, gamma='auto', kernel='linear')
```

Out[ ]:
```
0.9523809523809523
```

Testing the SVM function

In [ ]:
```
# Could have used GridSearchCV or Hyperopt but manually going through values her
test_error_kFoldCV = {}
train_error_kFoldCV = {}
C = [0.1,1.0,5.0,10.0,100.0]
k_folds = [5,len(data_t)]
kernels = ['rbf','linear','poly']
for i in k_folds:
    test_error_kFoldCV[i] = {}
    train_error_kFoldCV[i] = {}
    for C_vals in C:
        for kernel in kernels:
            accuracy_ = None
            train_accuracy = None
            error_ = None
            train_error = None
            accuracy_,train_accuracy = kFoldCV(i,data_t,y,fcn = SVM_classifier,C

            error_ = 1 - getAverageKFoldAccuracy(accuracy_)
            train_error = 1 - getAverageKFoldAccuracy(train_accuracy)
            test_error_kFoldCV[i][(C_vals,kernel)] = error_
            train_error_kFoldCV[i][(C_vals,kernel)] = train_error
```

In [ ]:
```
df_svm_test = pd.DataFrame.from_dict(test_error_kFoldCV,orient = "index")
```

In [ ]:
```
df_svm_train = pd.DataFrame.from_dict(train_error_kFoldCV,orient = "index")
```

Reporting train and test errors for SVC for choices of the hyperparameters C and kernel, C values are in the first row, SVM kernel values in the second row

In [ ]:
```
df_svm_test
```

Out[ ]:

		0.1			1.0			5.(	
	rbf	linear	poly	rbf	linear	poly	rbf	linear	pol;
5	0.066667	0.076190	0.466667	0.076190	0.071429	0.419048	0.066667	0.066667	0.438095
210	0.066667	0.066667	0.733333	0.066667	0.066667	0.733333	0.066667	0.066667	0.73333

In [ ]:
```
df_svm_train
```

Out[ ]:

		0.1			1.0			5.0	
	rbf	linear	poly	rbf	linear	poly	rbf	linear	pol;
5	0.064286	0.065476	0.390476	0.071429	0.063095	0.390476	0.069048	0.063095	0.40119(

			0.1			1.0			5.0
	rbf	linear	poly	rbf	linear	poly	rbf	linear	poly
210	0.065755	0.057781	0.385509	0.065755	0.057781	0.385509	0.065755	0.057781	0.385509

Here the poly kernel seems to underfit the data while for C = 10 we can see a slight overfitting for the rbf kernel. Overall performance is slightly better, about 1% when compared to 10 fold CV

Testing Random Forest Classifier

In [ ]:

```
from tqdm.notebook import tqdm
test_error_kFoldCV = {}
train_error_kFoldCV = {}
n_estimators = [1,5,15,35,75,150]
k_folds = [5,len(data_t)]
max_depth = [1,5,10,25]
for i in tqdm(k_folds):
    test_error_kFoldCV[i] = {}
    train_error_kFoldCV[i] = {}
    for estimator in n_estimators:
        for depth in max_depth:
            accuracy_ = None
            train_accuracy = None
            error_ = None
            train_error = None
            accuracy_,train_accuracy = kFoldCV(i,data_t,y,fcn = RF_classifier,n_

            error_ = 1 - getAverageKFoldAccuracy(accuracy_)
            train_error = 1 - getAverageKFoldAccuracy(train_accuracy)
            test_error_kFoldCV[i][(estimator,depth)] = error_
            train_error_kFoldCV[i][(estimator,depth)] = train_error
```

Here in the tables below column 0 has the various values for number of estimators, column 1 has the various values of max depth, while column 2 has 5foldCV values and column 2 has LOOCV values

In [ ]:

```
df_rfc_test = pd.DataFrame.from_dict(test_error_kFoldCV)
df_rfc_test
```

Out[ ]:

		5	210
1	**1**	0.442857	0.385714
	5	0.123810	0.090476
	10	0.114286	0.119048
	25	0.157143	0.119048
5	**1**	0.147619	0.247619
	5	0.119048	0.090476
	10	0.090476	0.090476
	25	0.076190	0.080952
15	**1**	0.223810	0.147619

		5	210
	5	0.071429	0.066667
	10	0.061905	0.076190
	25	0.090476	0.085714
35	1	0.176190	0.119048
	5	0.061905	0.071429
	10	0.085714	0.066667
	25	0.066667	0.071429
75	1	0.180952	0.133333
	5	0.071429	0.052381
	10	0.071429	0.066667
	25	0.071429	0.066667
150	1	0.200000	0.119048
	5	0.066667	0.066667
	10	0.066667	0.071429
	25	0.071429	0.066667

In [ ]:

```
df_rfc_train = pd.DataFrame.from_dict(train_error_kFoldCV)
df_rfc_train
```

Out[ ]:

		5	210
1	1	0.361905	0.366097
	5	0.055952	0.061062
	10	0.035714	0.045728
	25	0.042857	0.044498
5	1	0.205952	0.190021
	5	0.022619	0.022420
	10	0.007143	0.011073
	25	0.010714	0.010276
15	1	0.103571	0.129506
	5	0.010714	0.011369
	10	0.002381	0.002165
	25	0.001190	0.002051
35	1	0.094048	0.111939
	5	0.002381	0.008157
	10	0.000000	0.000684
	25	0.000000	0.000365

		5	210
75	**1**	0.109524	0.105081
	5	0.003571	0.006516
	10	0.000000	0.000023
	25	0.000000	0.000023
150	**1**	0.104762	0.103828
	5	0.005952	0.005354
	10	0.000000	0.000000
	25	0.000000	0.000000

Here max depth 1 and 5 seems to show significant over fitting across the table, along with over fitting in case of fewer number of estimators, performance is comparable to the above two methods and the best fit seems to be 15 estimators with a maximum depth of 5

Problem 4

Pls refer to Problem 4.pdf in the folder

Problem 5

In [ ]:
```
import fcnn as ps5
```

In [ ]:
```
importlib.reload(ps5)
```

```
train data shape: torch.Size([60000, 784])
train label shape: torch.Size([60000])
test data shape: torch.Size([2000, 784])
test label shape: torch.Size([2000])
```

Out[ ]:
```
<module 'fcnn' from '/Users/venugopalbhatia/Documents/Deep Learning Theory and A
pplications/Assignment 1/fcnn.py'>
```

In [ ]:
```
ps5.train()
```

```
  1%|          | 1/100 [00:01<02:08,  1.30s/it]
train acc: 92.90166666666667     test acc: 90.75         at epoch: 0
 11%|█         | 11/100 [00:13<01:51,  1.25s/it]
train acc: 97.58166666666666     test acc: 96.25         at epoch: 10
 21%|██        | 21/100 [00:26<01:38,  1.25s/it]
train acc: 98.54         test acc: 96.55         at epoch: 20
 31%|███       | 31/100 [00:39<01:29,  1.30s/it]
train acc: 98.68333333333334     test acc: 96.65         at epoch: 30
 41%|████      | 41/100 [00:51<01:13,  1.24s/it]
train acc: 99.06333333333333     test acc: 96.3  at epoch: 40
 51%|█████     | 51/100 [01:04<01:01,  1.25s/it]
train acc: 98.64166666666667     test acc: 95.75         at epoch: 50
 61%|██████    | 61/100 [01:16<00:49,  1.26s/it]
train acc: 99.23833333333333     test acc: 96.65         at epoch: 60
```

```
 71%|███████   | 71/100 [01:29<00:35,  1.23s/it]
train acc: 99.36833333333334     test acc: 97.15         at epoch: 70
 81%|████████  | 81/100 [01:41<00:23,  1.22s/it]
train acc: 99.42833333333333     test acc: 96.95         at epoch: 80
 91%|█████████ | 91/100 [01:53<00:10,  1.22s/it]
train acc: 99.42833333333333     test acc: 96.85000000000001     at epoch: 90
100%|██████████| 100/100 [02:04<00:00,  1.25s/it]
[[173   0   0   0   0   0   0   1   0   1]
 [  0 231   0   2   0   0   0   0   1   0]
 [  1   0 212   0   0   0   2   3   1   0]
 [  0   0   0 204   0   0   0   2   0   1]
 [  1   0   2   0 211   0   1   0   0   2]
 [  0   0   0   4   1 167   4   1   1   1]
 [  2   0   0   0   0   2 172   0   2   0]
 [  0   3   2   1   0   1   0 194   2   2]
 [  1   0   1   1   0   0   0   1 187   1]
 [  0   0   0   3   2   0   0   2   1 186]]
```

Out[ ]:

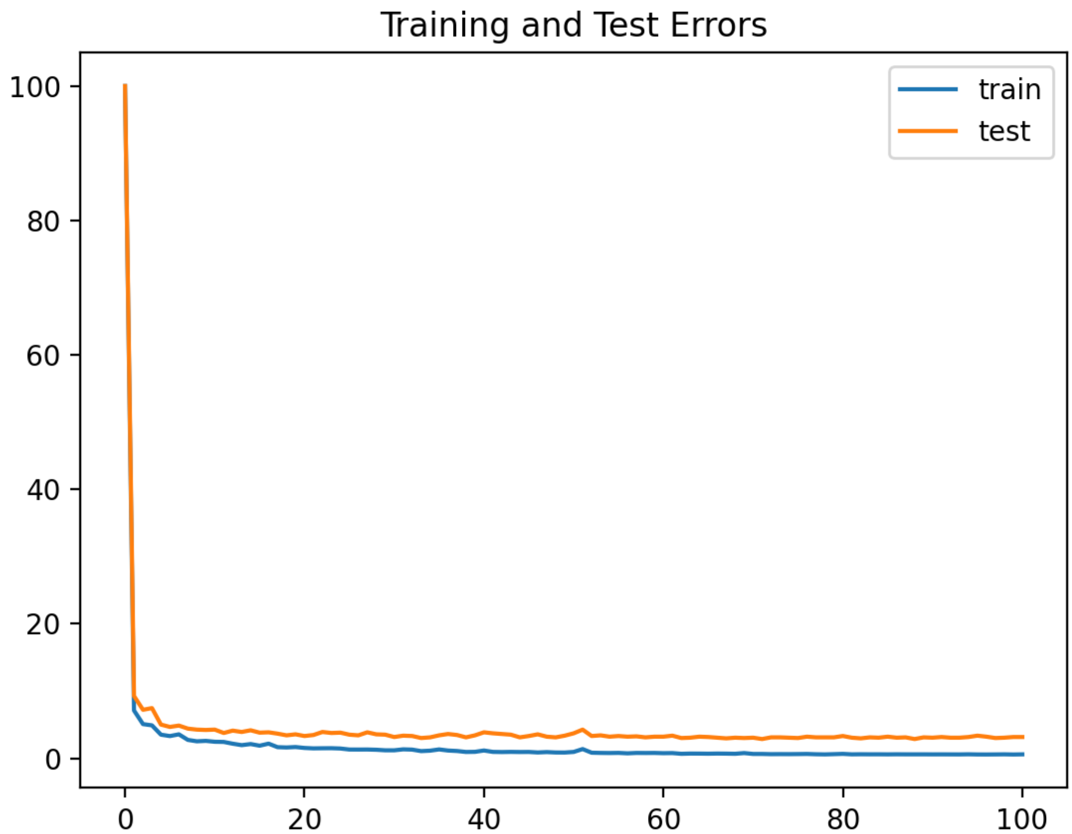
```
(array([[ 0.        ,  0.        ],
        [92.90166667, 90.75      ],
        [94.93166667, 92.8       ],
        [95.115     , 92.55      ],
        [96.5       , 95.       ],
        [96.70833333, 95.35      ],
        [96.45      , 95.15      ],
        [97.27833333, 95.6       ],
        [97.48833333, 95.75      ],
        [97.425     , 95.8       ],
        [97.555     , 95.75      ],
        [97.58166667, 96.25      ],
        [97.845     , 95.9       ],
        [98.06      , 96.1       ],
        [97.89666667, 95.85      ],
        [98.14      , 96.2       ],
        [97.83666667, 96.15      ],
        [98.36      , 96.35      ],
        [98.405     , 96.6       ],
        [98.34      , 96.45      ],
        [98.47666667, 96.7       ],
        [98.54      , 96.55      ],
        [98.52166667, 96.1       ],
        [98.51333333, 96.25      ],
        [98.56      , 96.2       ],
        [98.71      , 96.5       ],
        [98.715     , 96.6       ],
        [98.70833333, 96.15      ],
        [98.745     , 96.45      ],
        [98.82666667, 96.5       ],
        [98.82833333, 96.85      ],
        [98.68333333, 96.65      ],
        [98.72333333, 96.7       ],
        [98.94666667, 97.        ],
        [98.88166667, 96.9       ],
        [98.695     , 96.6       ],
        [98.86166667, 96.4       ],
        [98.93      , 96.55      ],
        [99.07333333, 96.9       ],
        [99.055     , 96.6       ],
        [98.855     , 96.15      ],
        [99.06333333, 96.3       ],
        [99.085     , 96.4       ],
        [99.06333333, 96.5       ],
        [99.08166667, 96.9       ],
        [99.07166667, 96.7       ],
```

```
        [99.14833333, 96.45      ],
        [99.09      , 96.8       ],
        [99.15166667, 96.9       ],
        [99.15833333, 96.65      ],
        [99.06833333, 96.3       ],
        [98.64166667, 95.75      ],
        [99.18333333, 96.7       ],
        [99.215     , 96.6       ],
        [99.23      , 96.8       ],
        [99.21      , 96.7       ],
        [99.27833333, 96.8       ],
        [99.21666667, 96.75      ],
        [99.22666667, 96.9       ],
        [99.21666667, 96.8       ],
        [99.255     , 96.8       ],
        [99.23833333, 96.65      ],
        [99.34666667, 97.        ],
        [99.31166667, 96.95      ],
        [99.31666667, 96.8       ],
        [99.33166667, 96.85      ],
        [99.31      , 96.95      ],
        [99.32166667, 97.05      ],
        [99.345     , 96.95      ],
        [99.23666667, 97.        ],
        [99.36833333, 96.95      ],
        [99.36833333, 97.15      ],
        [99.4       , 96.9       ],
        [99.39166667, 96.9       ],
        [99.39666667, 96.95      ],
        [99.385     , 97.        ],
        [99.36833333, 96.8       ],
        [99.41333333, 96.9       ],
        [99.43666667, 96.9       ],
        [99.39833333, 96.9       ],
        [99.35666667, 96.7       ],
        [99.42833333, 96.95      ],
        [99.41333333, 97.05      ],
        [99.42166667, 96.9       ],
        [99.42      , 96.95      ],
        [99.43      , 96.8       ],
        [99.41833333, 96.95      ],
        [99.425     , 96.9       ],
        [99.42666667, 97.15      ],
        [99.425     , 96.9       ],
        [99.43166667, 96.95      ],
        [99.42833333, 96.85      ],
        [99.43333333, 96.95      ],
        [99.43833333, 96.95      ],
        [99.41833333, 96.85      ],
        [99.44333333, 96.65      ],
        [99.44833333, 96.8       ],
        [99.43833333, 97.        ],
        [99.425     , 96.95      ],
        [99.45      , 96.85      ],
        [99.42833333, 96.85      ]]),
Fully_Connected_Neural_Net(
  (layer1): Linear(in_features=784, out_features=75, bias=True)
  (layer2): Linear(in_features=75, out_features=64, bias=True)
  (layer3): Linear(in_features=64, out_features=10, bias=True)
  (nonlin1): ReLU()
  (nonlin2): ReLU()
  (nonlin3): Sigmoid()
))
```

5.2

In [ ]:
```
from IPython.display import Image
Image(filename='TrainingTestingError.png')
```

Out[ ]:



The error went down signifcantly by epoch 10 and we saw marginal improvements thereafter.

5.3

Confusion Matrix

[[173 0 0 0 0 0 0 1 0 1] [0 231 0 2 0 0 0 0 1 0] [1 0 212 0 0 0 2 3 1 0] [0 0 0 204 0 0 0 2 0 1] [1 0 2 0 211 0 1 0 0 2] [0 0 0 4 1 167 4 1 1 1] [2 0 0 0 0 2 172 0 2 0] [0 3 2 1 0 1 0 194 2 2] [1 0 1 1 0 0 0 1 187 1] [0 0 0 3 2 0 0 2 1 186]]

In [ ]:
```
[[173   0   0   0   0   0   0   1   0   1]
 [  0 231   0   2   0   0   0   0   1   0]
 [  1   0 212   0   0   0   2   3   1   0]
 [  0   0   0 204   0   0   0   2   0   1]
 [  1   0   2   0 211   0   1   0   0   2]
 [  0   0   0   4   1 167   4   1   1   1]
 [  2   0   0   0   0   2 172   0   2   0]
 [  0   3   2   1   0   1   0 194   2   2]
 [  1   0   1   1   0   0   0   1 187   1]
 [  0   0   0   3   2   0   0   2   1 186]]
```

The confusion matrix is also printed above with the output. It seems that the neural net tends to predict 9 more, so for instance in the last column we can see two instances of 4 and 7 being predicted as 9. Similarly we have 2 and 7, as well as 5 and 6.

5.4

The Neural Net gave a best test accuracy of 96.85%. I used a three layer Network, layer 1 had 75 nodes, layer 2 had 64 nodes, the first and second layer activations were relu while the third layer activation was sigmoid. I did experiment with more layers, different activations and regularization, but rather than overengineering the network, this configuration trained pretty quickly on my machine and gave decent results.