----------------- Collinear features and their effect on linear models----------------

In [68]:

```
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")
import pandas as pd
import numpy as np
from sklearn.datasets import load_iris
from sklearn.linear_model import SGDClassifier
from sklearn.model_selection import GridSearchCV
import seaborn as sns
import matplotlib.pyplot as plt
```

In [69]:

```
data = pd.read_csv('task_d.csv') #loading data
```

In [70]:

```
data.head()
```

Out[70]:

	x	y	z	x*x	2*y	2*z+3*x*x	w	target
0	-0.581066	0.841837	-1.012978	-0.604025	0.841837	-0.665927	-0.536277	0
1	-0.894309	-0.207835	-1.012978	-0.883052	-0.207835	-0.917054	-0.522364	0
2	-1.207552	0.212034	-1.082312	-1.150918	0.212034	-1.166507	0.205738	0
3	-1.364174	0.002099	-0.943643	-1.280666	0.002099	-1.266540	-0.665720	0
4	-0.737687	1.051772	-1.012978	-0.744934	1.051772	-0.792746	-0.735054	0

In [71]:

```
X = data.drop(['target'], axis=1).values
Y = data['target'].values
#X.shape
feature_names=data.columns[:-1]
```

In [72]:

```
# unquotes to see how our model performs while data with non collinear features

'''X = data.drop(["x*x","2*y","2*z+3*x*x",'target'], axis=1).values         #dropping collinear features
Y = data['target'].values

feature_names=["x","y","z","w"]
X.shape'''
```

Out[72]:

```
'X = data.drop(["x*x","2*y","2*z+3*x*x",\'target\'], axis=1).values         #dropping collinear features\nY = data
[\'target\'].values\n\nfeature_names=["x","y","z","w"]\nX.shape'
```

Task: 1 Logistic Regression

1)Finding the Correlation between the features

In [73]:

```
data.corr()     #getting correlation of features
```

Out[73]:

	x	y	z	x*x	2*y	2*z+3*x*x	w	target
x	1.000000	-0.205926	0.812458	0.997947	-0.205926	0.996252	0.583277	0.728290
y	-0.205926	1.000000	-0.602663	-0.209289	1.000000	-0.261123	-0.401790	-0.690684
z	0.812458	-0.602663	1.000000	0.807137	-0.602663	0.847163	0.674486	0.969990
x*x	0.997947	-0.209289	0.807137	1.000000	-0.209289	0.997457	0.583803	0.719570
2*y	-0.205926	1.000000	-0.602663	-0.209289	1.000000	-0.261123	-0.401790	-0.690684
2*z+3*x*x	0.996252	-0.261123	0.847163	0.997457	-0.261123	1.000000	0.606860	0.764729
w	0.583277	-0.401790	0.674486	0.583803	-0.401790	0.606860	1.000000	0.641750
target	0.728290	-0.690684	0.969990	0.719570	-0.690684	0.764729	0.641750	1.000000

Heatmap

In [74]:

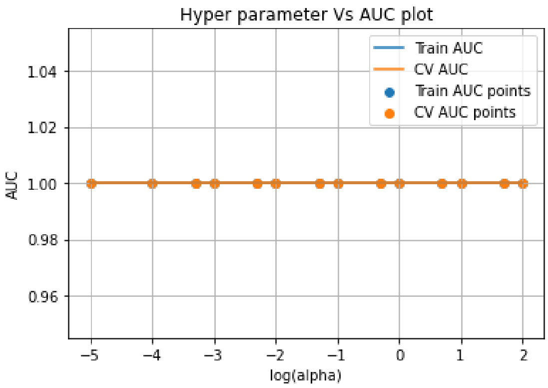
```
plt.figure(figsize = (10,10))  #how to draw correlation heatmap: https://www.geeksforgeeks.org/how-to-create-a-seaborn-correlatio
dataplot = sns.heatmap(data.corr(), cmap="Blues", annot=True)
```

2) Finding the best model for the given data

In [75]:

```
parameters = {'alpha':[0.00001,0.0005, 0.0001,0.005,0.001,0.05,0.01,0.1,0.5,1,5,10,50,100]}
lr=SGDClassifier(loss="log_loss")                                                      #Logistic regression
clf=GridSearchCV(lr,parameters,cv=3, scoring='roc_auc',return_train_score=True)    #hyper parameter tuning

clf.fit(X, Y)                                               #fitting the LR model with train data

results = pd.DataFrame.from_dict(clf.cv_results_)   #storing Gridsearch results

results = results.sort_values(['param_alpha'])

train_auc= results['mean_train_score']       #storing required Gridsearch results in required variable
train_auc_std= results['std_train_score']
cv_auc = results['mean_test_score']
#cv_auc_std= results['std_test_score']
alpha =  results['param_alpha'].tolist()
print(" alpha ----> ",alpha)
print(" log(alpha)---->  ",np.log10(alpha))

plt.plot(np.log10(alpha), train_auc, label='Train AUC')   #plotting auc vs log(alpha) values
plt.plot(np.log10(alpha), cv_auc, label='CV AUC')

plt.scatter(np.log10(alpha), train_auc, label='Train AUC points')
plt.scatter(np.log10(alpha), cv_auc, label='CV AUC points')
plt.legend()
plt.xlabel("log(alpha)")
plt.ylabel("AUC")
plt.title("Hyper parameter Vs AUC plot")
plt.grid()
plt.show()
```

```
alpha ---->  [1e-05, 0.0001, 0.0005, 0.001, 0.005, 0.01, 0.05, 0.1, 0.5, 1, 5, 10, 50, 100]
log(alpha)---->   [-5.      -4.      -3.30103 -3.      -2.30103 -2.      -1.30103 -1.
-0.30103  0.       0.69897  1.       1.69897  2.     ]
```



Fitting the best model with the original data and getting weight vector

In [76]:

```
best_model=SGDClassifier(loss="log_loss",alpha=1)      #finding best model with best alpha

best_model.fit(X,Y)                                     #fitting the best model
best_model_accuracy=best_model.score(X, Y)
weights=best_model.coef_
```

3) modifying the original data(pertubation) and with that fitting the best model again

In [77]:

```
X_pretubated=X+0.01            #adding small noise to data X
```

In [78]:

```
best_model=SGDClassifier(loss="log_loss",alpha=1)

best_model.fit(X_pretubated,Y)          #fitting the pertubated data with the best alpha model
best_model_accuracy_edited = best_model.score(X_pretubated, Y)
weights_edited=best_model.coef_         #getting the weight vector
```

4) Checking deviations in metric and weights

In [79]:

```
precentage_change_in_weights=(abs(weights-weights_edited)/weights)*100
absolute_precentage_change_in_weights=abs(precentage_change_in_weights)       #absolute value of percentage change in weigh
sorted_percentage_weight_index=(-absolute_precentage_change_in_weights).argsort()   #soring index according to the decenting orde
```

In [80]:

```
#printing the top 4 feature names which has most precentage change in weight after pertubation
for n, i in enumerate( sorted_percentage_weight_index[0]):
    if n <4:
        print(feature_names[i])
```

```
x*x
2*z+3*x*x
x
w
```

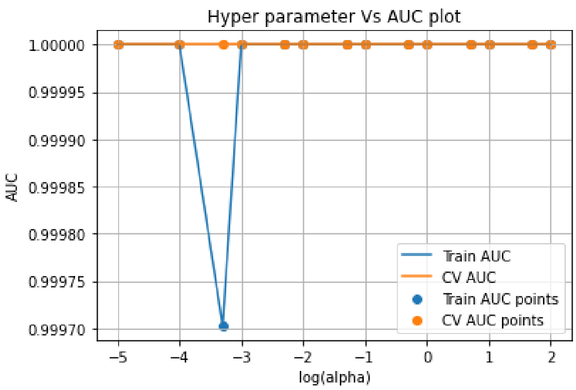
SVM

2) Finding the best model for the given data

In [81]:

```
parameters = {'alpha':[0.00001,0.0005, 0.0001,0.005,0.001,0.05,0.01,0.1,0.5,1,5,10,50,100]}
svm=SGDClassifier(loss="hinge")
clf=GridSearchCV(svm,parameters,cv=3, scoring='roc_auc',return_train_score=True)       #hyper parameter tuning

clf.fit(X, Y)    #fitting the SVM model with train data

results = pd.DataFrame.from_dict(clf.cv_results_)   #storing Gridsearch results

results = results.sort_values(['param_alpha'])

train_auc= results['mean_train_score']       #storing required Gridsearch results in required variable
train_auc_std= results['std_train_score']
cv_auc = results['mean_test_score']
alpha =  results['param_alpha'].tolist()
print(" alpha--------->  ",alpha)
print(" log(alpha)------->  ",np.log10(alpha))

plt.plot(np.log10(alpha), train_auc, label='Train AUC')
plt.plot(np.log10(alpha), cv_auc, label='CV AUC')

plt.scatter(np.log10(alpha), train_auc, label='Train AUC points')
plt.scatter(np.log10(alpha), cv_auc, label='CV AUC points')
plt.legend()
plt.xlabel("log(alpha)")
plt.ylabel("AUC")
plt.title("Hyper parameter Vs AUC plot")
plt.grid()
plt.show()
#results.head
```

```
 alpha--------->   [1e-05, 0.0001, 0.0005, 0.001, 0.005, 0.01, 0.05, 0.1, 0.5, 1, 5, 10, 50, 100]
 log(alpha)------->   [-5.      -4.      -3.30103 -3.      -2.30103 -2.      -1.30103 -1.
 -0.30103  0.       0.69897  1.       1.69897  2.     ]
```



In [82]:

```
best_model=SGDClassifier(loss="hinge",alpha=1)   #creating model with best alpha
best_model.fit(X,Y)
best_model_accuracy=best_model.score(X, Y)
weights=best_model.coef_                        #obtaining weight vectors

#print(best_model_accuracy)
```

3) modifying the original data(pertubation) and with that fitting the best model again

In [83]:

```
X_pretubated=X+0.01    #adding small noise to the data
```

In [84]:

```
best_model=SGDClassifier(loss="hinge",alpha=1)      #fitting the pertubated data with the best alpha model
best_model.fit(X_pretubated,Y)
best_model_accuracy_edited=best_model.score(X_pretubated, Y)
weights_edited=best_model.coef_
```

4) Checking deviations in metric and weights

In [85]:

```
precentage_change_in_weights=(abs(weights-weights_edited)/weights)*100
absolute_precentage_change_in_weights=abs(precentage_change_in_weights)   #absolute value of percentage change in weight
sorted_percentage_weight_index=(-absolute_precentage_change_in_weights).argsort()    #soring index according to the decenting ord
```

In [86]:

```
#printing the top 4 feature names which has most precentage change in weight after pertubation
for n, i in enumerate( sorted_percentage_weight_index[0]):
    if n <4:
        print(feature_names[i])
```

```
x*x
2*z+3*x*x
w
x
```

Observation

- we can see that when adding small noise(pertubating) to the dataset, the **top features which has higher percentage change in their respective weights** are all the features((ie, **highly collinear features**) which are combination of other basic non collinear features.
- this is because these featuers are **combination of other non collinear features**.so adding pretubation to the non collinear features have effect on the collinear features with greater value.
- these collinear features ruins the **interpretability of the model**.
- so this pertubation method helps to find the highly collinear features and we can remove them to build robust model.