Task 2

February 7, 2018

```
In [1]: import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
        import seaborn as sns
        sns.set()

        %matplotlib inline

In [2]: from sklearn.linear_model import LogisticRegression
        from sklearn.svm import LinearSVC
        from sklearn.neighbors import NearestCentroid
        from sklearn.model_selection import train_test_split, cross_val_score, GridSearchCV, KFo
        from sklearn.preprocessing import StandardScaler

In [3]: from sklearn.datasets import fetch_covtype

In [4]: data = fetch_covtype(data_home='task2_data')

In [5]: data

Out[5]: {'DESCR': 'Forest covertype dataset.\n\nA classic dataset for classification benchmarks,
         'data': array([[  2.59600000e+03,   5.10000000e+01,   3.00000000e+00, ...,
                  0.00000000e+00,   0.00000000e+00,   0.00000000e+00],
                [  2.59000000e+03,   5.60000000e+01,   2.00000000e+00, ...,
                  0.00000000e+00,   0.00000000e+00,   0.00000000e+00],
                [  2.80400000e+03,   1.39000000e+02,   9.00000000e+00, ...,
                  0.00000000e+00,   0.00000000e+00,   0.00000000e+00],
                ...,
                [  2.38600000e+03,   1.59000000e+02,   1.70000000e+01, ...,
                  0.00000000e+00,   0.00000000e+00,   0.00000000e+00],
                [  2.38400000e+03,   1.70000000e+02,   1.50000000e+01, ...,
                  0.00000000e+00,   0.00000000e+00,   0.00000000e+00],
                [  2.38300000e+03,   1.65000000e+02,   1.30000000e+01, ...,
                  0.00000000e+00,   0.00000000e+00,   0.00000000e+00]]),
         'target': array([5, 5, 2, ..., 3, 3, 3], dtype=int32)}

In [6]: cov = pd.DataFrame(data['data'])
        cov['Cover_Type'] = data['target']
```

In [7]:
```
# Get column names
feature_file = open('feature_names','r')
features = []
for line in feature_file:
    features.append(line.split()[0])
```

In [8]:
```
wildareas = [features[10] + str(i) for i in range(1,5)]
soiltypes = [features[11] + str(i) for i in range(1,41)]
features = features[:10] + wildareas + soiltypes + [features[12]]
```

In [9]:
```
cov.columns = features
```

In [10]:
```
cov.head()
```

Out[10]:

	Elevation	Aspect	Slope	Horizontal_Distance_To_Hydrology	\
0	2596.0	51.0	3.0	258.0	
1	2590.0	56.0	2.0	212.0	
2	2804.0	139.0	9.0	268.0	
3	2785.0	155.0	18.0	242.0	
4	2595.0	45.0	2.0	153.0	

	Vertical_Distance_To_Hydrology	Horizontal_Distance_To_Roadways	\
0	0.0	510.0	
1	-6.0	390.0	
2	65.0	3180.0	
3	118.0	3090.0	
4	-1.0	391.0	

	Hillshade_9am	Hillshade_Noon	Hillshade_3pm	\
0	221.0	232.0	148.0	
1	220.0	235.0	151.0	
2	234.0	238.0	135.0	
3	238.0	238.0	122.0	
4	220.0	234.0	150.0	

	Horizontal_Distance_To_Fire_Points	...	Soil_Type32	Soil_Type33	\
0	6279.0	...	0.0	0.0	
1	6225.0	...	0.0	0.0	
2	6121.0	...	0.0	0.0	
3	6211.0	...	0.0	0.0	
4	6172.0	...	0.0	0.0	

	Soil_Type34	Soil_Type35	Soil_Type36	Soil_Type37	Soil_Type38	\
0	0.0	0.0	0.0	0.0	0.0	
1	0.0	0.0	0.0	0.0	0.0	
2	0.0	0.0	0.0	0.0	0.0	
3	0.0	0.0	0.0	0.0	0.0	
4	0.0	0.0	0.0	0.0	0.0	

```
   Soil_Type39  Soil_Type40  Cover_Type
0          0.0          0.0           5
1          0.0          0.0           5
2          0.0          0.0           2
3          0.0          0.0           2
4          0.0          0.0           5

[5 rows x 55 columns]
```

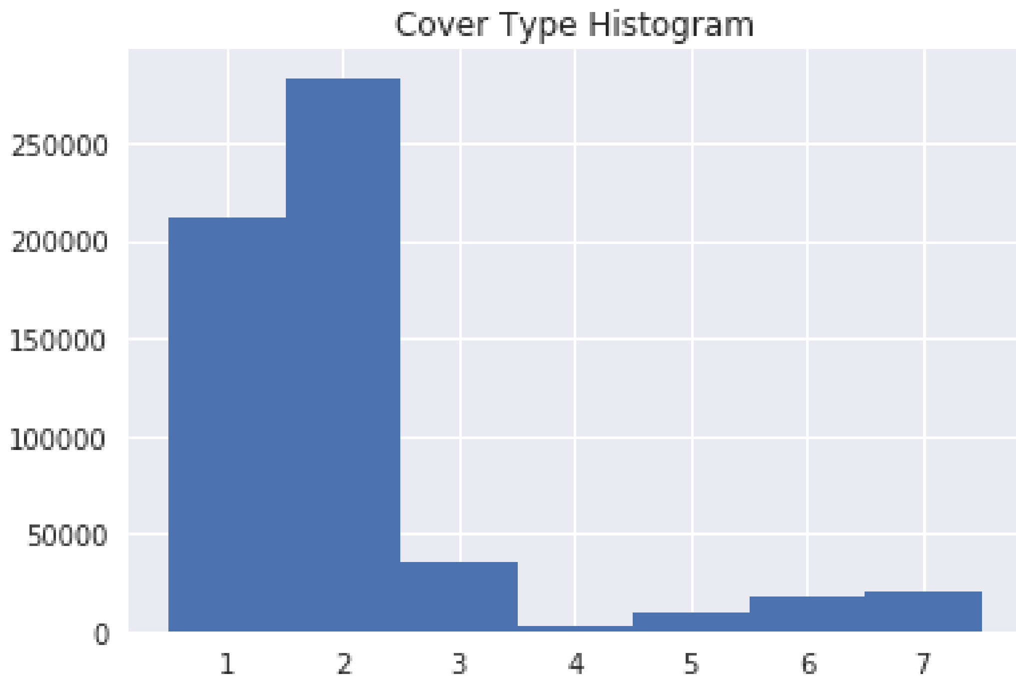
In [11]:
```
cov.shape
```

Out[11]:
```
(581012, 55)
```

0.0.1 Task 2.1: Visualize the univariate distribution of each feature, and the distribution of the target

In [12]:
```
fig = plt.figure(figsize=(20,25))
fig.subplots_adjust(hspace=0.5, wspace=0.5)
for i in range(1, 55):
    ax = fig.add_subplot(11, 5, i)
    cov[cov.columns[i-1]].hist(ax=ax)
    ax.set(title=cov.columns[i-1])
```

In [13]:
```
#Distribution of target
plt.hist(cov['Cover_Type'],range=(0.5,7.5),bins=7)
_ = plt.title('Cover Type Histogram')
```



0.0.2 Task 2.2: Split data into training and test set. Evaluate Logistic Regression, linear support vector machines and nearest centroids using cross-validation

```
In [14]: X_train, X_test, y_train, y_test = train_test_split(data['data'],data['target'],random_
```

X_train = X_train[:50000] y_train = y_train[:50000]

```
In [15]: #Evaluate Logistic Regression
         logit_score = np.mean(cross_val_score(LogisticRegression(tol=0.0001), X_train, y_train)

In [16]: #Linear SVM
         linearSVM_score = np.mean(cross_val_score(LinearSVC(tol=0.0001, dual=False), X_train, y

In [17]: #Nearest Centroid
         NC_score = np.mean(cross_val_score(NearestCentroid(), X_train, y_train))

In [18]: print(logit_score)
         print(linearSVM_score)
         print(NC_score)
```

```
0.708256150789
0.705947542451
0.194639694306
```

```
In [19]: #Use standardScaler
         scaler = StandardScaler()
         X_train_scaled = scaler.fit_transform(X_train)
```

```
In [20]: slogit_score = np.mean(cross_val_score(LogisticRegression(tol=0.0001), X_train_scaled,
         slinearSVM_score = np.mean(cross_val_score(LinearSVC(tol=0.0001, dual=False), X_train_s
         sNC_score = np.mean(cross_val_score(NearestCentroid(), X_train_scaled, y_train))
```

```
In [21]: print(slogit_score)
         print(slinearSVM_score)
         print(sNC_score)
```

```
0.715418375449
0.712604890841
0.548706947943
```

Logistic regression and Linear SVM have close scores - Logistic regression is slightly better, while Nearest Centroid has very bad score compared to other 2 algorithms. When applying StandardScaler, all 3 algorithms improve in score: logistic regression from 70.8% to 71.5%, linear SVM from 70.6% to 71.3%. Nearest Centroid improves the greatest from 19.5% to 54.9%, althought final score is still far behind other 2 algorithms.

0.0.3 Task 2.3: Tune the parameters using GridSearchCV

```
In [22]: #Tune logistic regression
         param_grid_logit = {'C':np.logspace(-2,2,6)}
         grid_logit = GridSearchCV(LogisticRegression(tol=0.0001,random_state=20), param_grid_lo
         grid_logit.fit(X_train_scaled, y_train)
         print(grid_logit.best_params_)
         print(grid_logit.best_score_)
```

```
{'C': 100.0}
0.715496409713
```

```
In [23]: #Tune Linear SVM
         param_grid_svm = {'C':np.logspace(-2,2,6)}
         grid_svm = GridSearchCV(LinearSVC(tol=0.0001, dual=False, random_state=20), param_grid_
         grid_svm.fit(X_train_scaled, y_train)
         print(grid_svm.best_params_)
         print(grid_svm.best_score_)
```

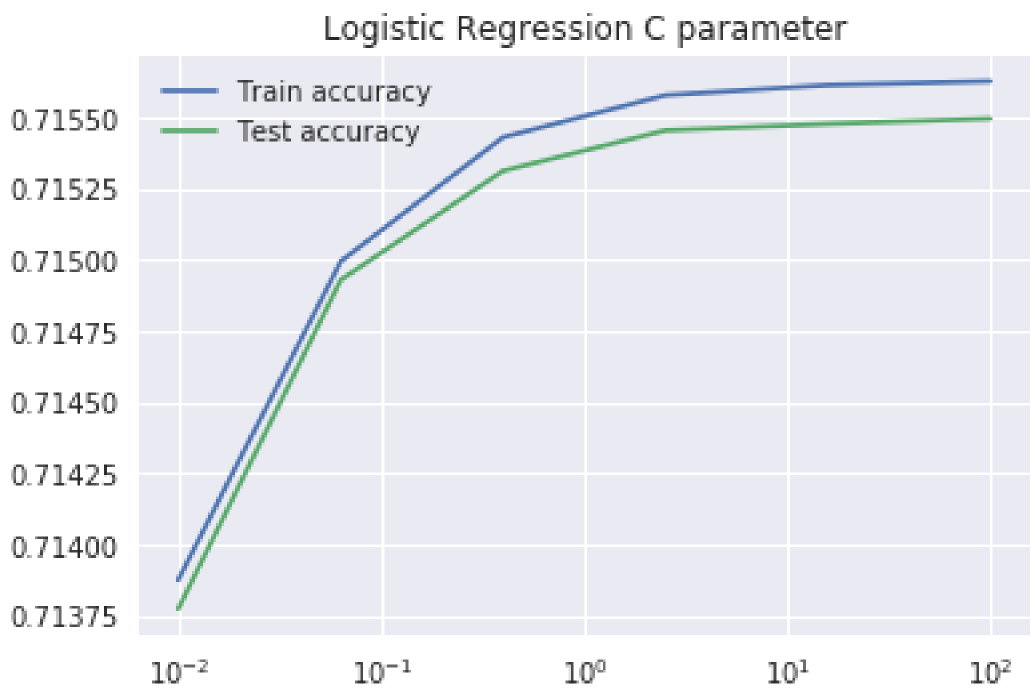
```
{'C': 2.5118864315095824}
0.712616377401
```

```
In [24]: #Tune Nearest Centroid
         param_grid_NC = {'shrink_threshold':np.linspace(0,20,11)}
```

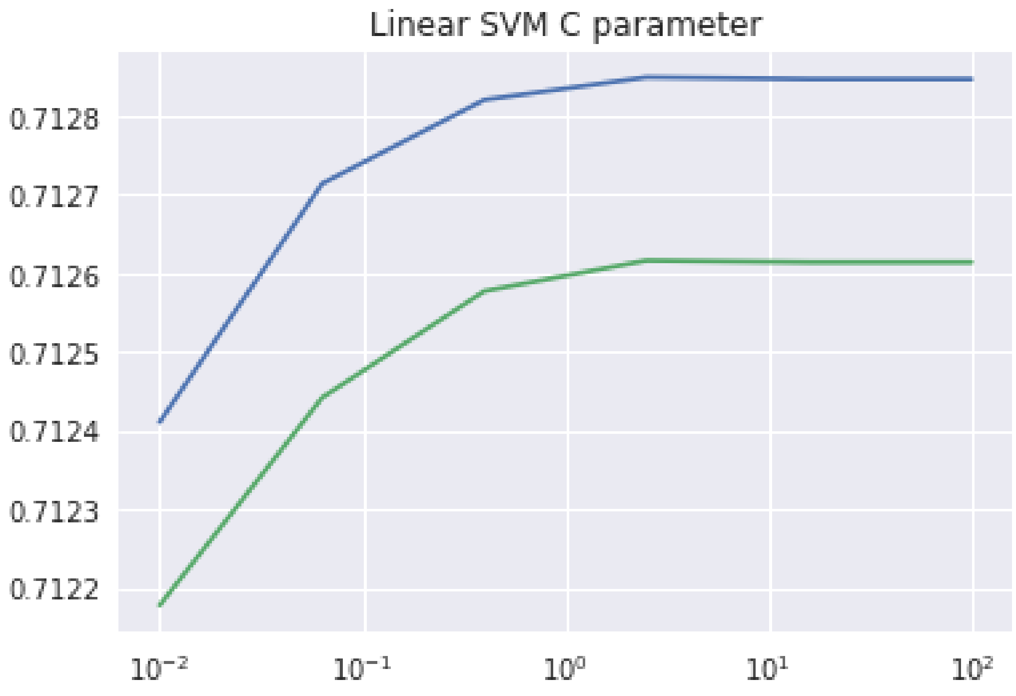
```
grid_NC = GridSearchCV(NearestCentroid(), param_grid_NC)
grid_NC.fit(X_train_scaled, y_train)
print(grid_NC.best_params_)
print(grid_NC.best_score_)
```

```
{'shrink_threshold': 0.0}
0.54870696876
```

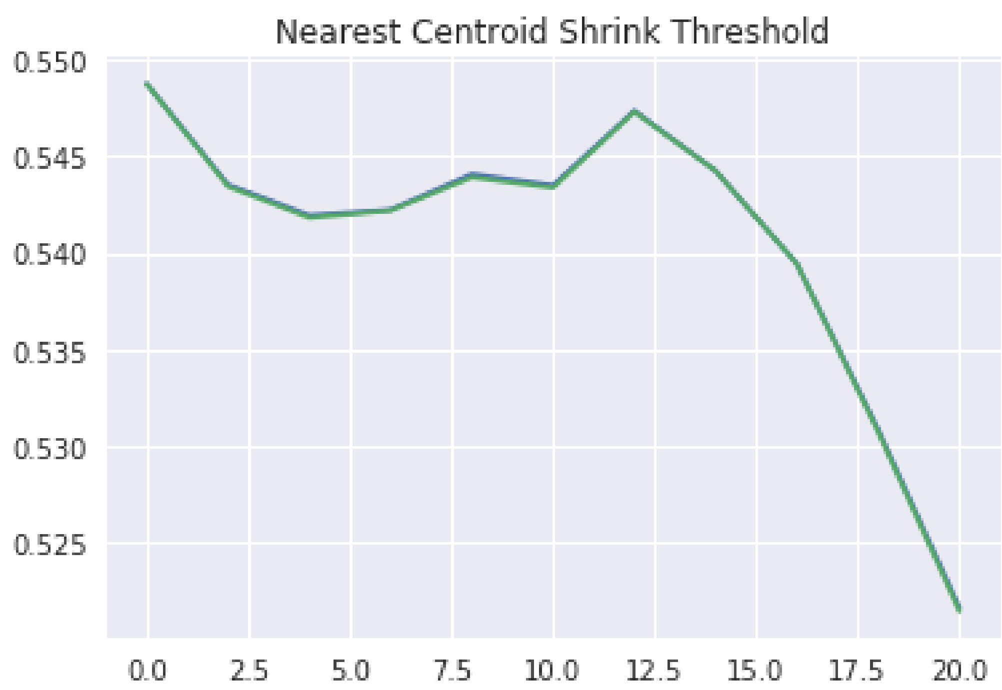
In [25]:
```
#Visualize GridSearch results
plt.semilogx(param_grid_logit['C'],grid_logit.cv_results_['mean_train_score'],label='Tr
plt.semilogx(param_grid_logit['C'],grid_logit.cv_results_['mean_test_score'],label='Tes
_ = plt.title('Logistic Regression C parameter')
_ = plt.legend()
```



In [26]:
```
plt.semilogx(param_grid_svm['C'],grid_svm.cv_results_['mean_train_score'],label='Train
plt.semilogx(param_grid_svm['C'],grid_svm.cv_results_['mean_test_score'],label='Test ac
_ = plt.title('Linear SVM C parameter')
_ = plt.legend()
```




```
In [27]: plt.plot(param_grid_NC['shrink_threshold'],grid_NC.cv_results_['mean_train_score'],labe
         plt.plot(param_grid_NC['shrink_threshold'],grid_NC.cv_results_['mean_test_score'],label
         _ = plt.title('Nearest Centroid Shrink Threshold')
         _ = plt.legend()
```



After GridSearch, the scores for all 3 algorithms do not improve by too much.

0.0.4 Task 2.4: Change the cross-validation strategy from 'stratified k-fold' to 'kfold' with shuffling

```
In [28]: #Change cross-validation strategy to KFold with shuffling and run GridSearch
         kfoldshuffle = KFold(shuffle=True, random_state=1)
```

```
In [29]: #Tune logistic regression with KFold with shuffling
         grid_logit_kfold = GridSearchCV(LogisticRegression(tol=0.0001,random_state=20), param_g
         grid_logit_kfold.fit(X_train_scaled, y_train)
         print(grid_logit_kfold.best_params_)
         print(grid_logit_kfold.best_score_)
```

```
{'C': 100.0}
0.715503294252
```

```
In [30]: #Tune Linear SVM with KFold with shuffling
         grid_svm_kfold = GridSearchCV(LinearSVC(tol=0.0001, dual= False, random_state=20), para
         grid_svm_kfold.fit(X_train_scaled, y_train)
         print(grid_svm_kfold.best_params_)
         print(grid_svm_kfold.best_score_)
```

```
{'C': 2.5118864315095824}
0.712731119724
```

```
In [31]: #Tune Nearest Centroid with KFold with shuffling
         grid_NC_kfold = GridSearchCV(NearestCentroid(), param_grid_NC,cv=kfoldshuffle)
         grid_NC_kfold.fit(X_train_scaled, y_train)
         print(grid_NC_kfold.best_params_)
         print(grid_NC_kfold.best_score_)
```

```
{'shrink_threshold': 0.0}
0.548782698694
```

```
In [32]: #Change random seed of the shuffling
         kfoldshuffle2 = KFold(shuffle=True, random_state=2)
```

```
In [33]: #Tune logistic regression with KFold with shuffling
         grid_logit_kfold2 = GridSearchCV(LogisticRegression(tol=0.0001,random_state=20), param_
         grid_logit_kfold2.fit(X_train_scaled, y_train)
         print(grid_logit_kfold2.best_params_)
         print(grid_logit_kfold2.best_score_)
```

```
{'C': 15.848931924611142}
0.715455102476
```

```
In [34]: #Tune Linear SVM with KFold with shuffling
         grid_svm_kfold2 = GridSearchCV(LinearSVC(tol=0.0001,dual=False, random_state=20), param
         grid_svm_kfold2.fit(X_train_scaled, y_train)
         print(grid_svm_kfold2.best_params_)
         print(grid_svm_kfold2.best_score_)
```

```
{'C': 15.848931924611142}
0.71274718365
```

```
In [35]: #Tune Nearest Centroid with KFold with shuffling
         grid_NC_kfold2 = GridSearchCV(NearestCentroid(), param_grid_NC,cv=kfoldshuffle2)
         grid_NC_kfold2.fit(X_train_scaled, y_train)
         print(grid_NC_kfold2.best_params_)
         print(grid_NC_kfold2.best_score_)
```

```
{'shrink_threshold': 0.0}
0.548617469748
```

```
In [52]: #Change random state of split and run GridSearch
         X_train3, X_test3, y_train3, y_test3 = train_test_split(data['data'],data['target'],ran
         X_train3_scaled = scaler.fit_transform(X_train3)
```

```
In [56]: #Tune logistic regression with different random split
         grid_logit_split2 = GridSearchCV(LogisticRegression(tol=0.0001,random_state=3), param_g
         grid_logit_split2.fit(X_train3_scaled, y_train3)
         print(grid_logit_split2.best_params_)
         print(grid_logit_split2.best_score_)
```

```
{'C': 100.0}
0.714791891848
```

```
In [62]: #Tune Linear SVM with with different random split
         grid_svm_split2 = GridSearchCV(LinearSVC(tol=0.0001,dual=False,random_state=3), param_g
         grid_svm_split2.fit(X_train3_scaled, y_train3)
         print(grid_svm_split2.best_params_)
         print(grid_svm_split2.best_score_)
```

```
{'C': 2.5118864315095824}
0.712142942554
```

In [58]:
```
#Tune Nearest Centroid with different random split
grid_NC_split2 = GridSearchCV(NearestCentroid(), param_grid_NC)
grid_NC_split2.fit(X_train3_scaled, y_train3)
print(grid_NC_split2.best_params_)
print(grid_NC_split2.best_score_)
```

```
{'shrink_threshold': 0.0}
0.548819416237
```

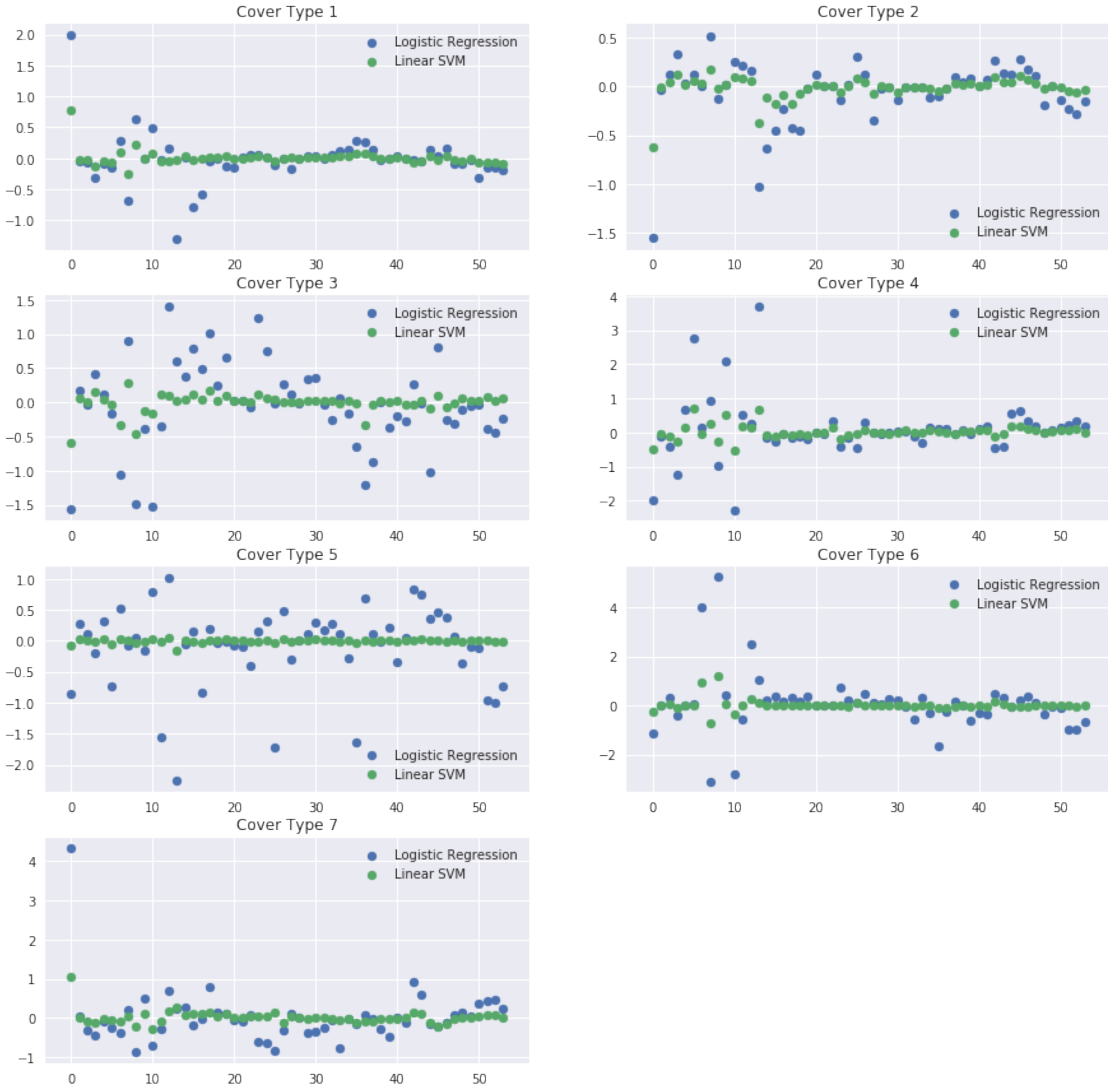
The parameters after GridSearch do not change after changing from StratifiedKFold to KFold with shuffling. However the parameters do change when we change the random state of the shuffling, from (100,2.5) for Logistic Regression and Linear SVM to (15.8,15.8). When changing the random state of the split into training and test data, the parameters also do not change compared to original set of parameters. In the 3 cases, parameters of Nearest Centroid do not change.

0.0.5 Task 2.5: Visualize the coefficients for LogisticRegression and Linear Support Vector Machines

In [42]:
```
#Logistic regression model
logitmodel = LogisticRegression(tol=0.0001,C=grid_logit.best_params_['C'],random_state=
logitmodel.fit(X_train_scaled,y_train)
#Linear SVM model
linearSVMmodel = LinearSVC(tol=0.0001, dual=False, C=grid_svm.best_params_['C'], random
linearSVMmodel.fit(X_train_scaled, y_train)
```

Out[42]:
```
LinearSVC(C=2.5118864315095824, class_weight=None, dual=False,
     fit_intercept=True, intercept_scaling=1, loss='squared_hinge',
     max_iter=1000, multi_class='ovr', penalty='l2', random_state=20,
     tol=0.0001, verbose=0)
```

In [43]:
```
fig = plt.figure(figsize=(15,15))
for i in range(1,8):
    ax = fig.add_subplot(4,2,i)
    ax.scatter(range(X_train.shape[1]), logitmodel.coef_[i-1],label='Logistic Regressio
    ax.scatter(range(X_train.shape[1]), linearSVMmodel.coef_[i-1],label='Linear SVM')
    ax.set(title='Cover Type '+str(i))
    plt.legend()
```


Cover Type 1
Logistic Regression
Linear SVM
Cover Type 2
Logistic Regression
Linear SVM
Cover Type 3
Logistic Regression
Linear SVM
Cover Type 4
Logistic Regression
Linear SVM
Cover Type 5
Logistic Regression
Linear SVM
Cover Type 6
Logistic Regression
Linear SVM
Cover Type 7
Logistic Regression
Linear SVM