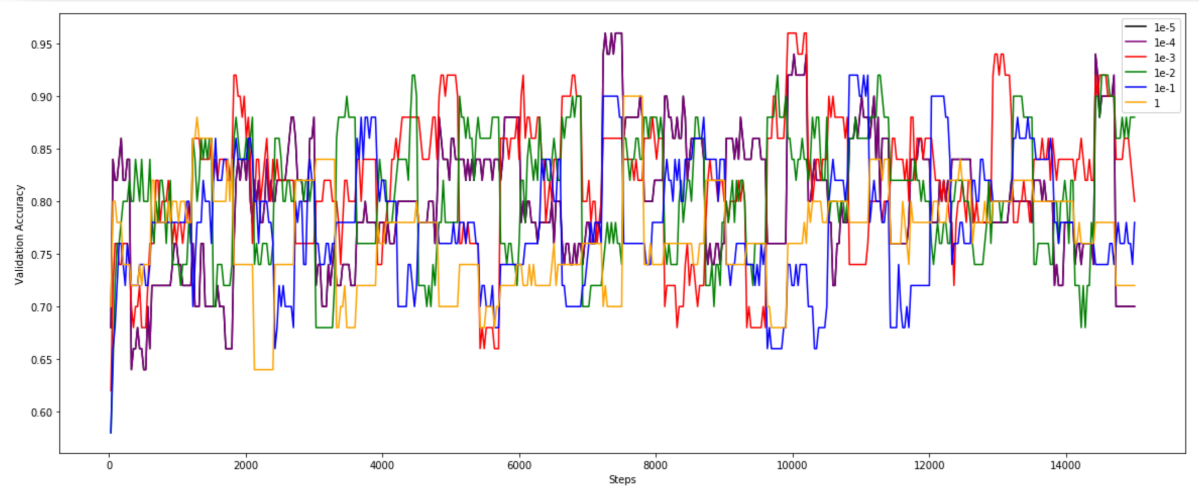
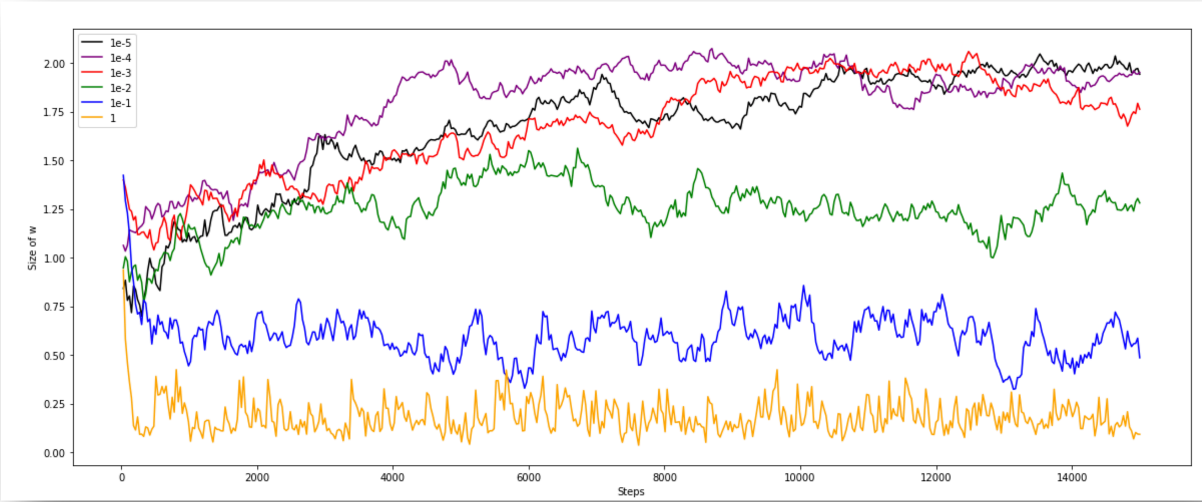
1 Best Accuracy on the Test Set

The Best Score = 80.9 (Lambda = 0.0001, learning rate = 0.01)

2 Validation Accuracy every 30 steps each Regularization Constant



3 Magnitude of the coefficient vector for every 30 steps for each Regularization Constant



4 Best Value of Regularization Constant

The best value of Regularization constant is **0.0001**. This regularization constant is being chosen, because the cost seems to be **lowest cost** among other regularization constant (0.001, 0.00001 etc). The cost has been average over the 50 validation examples taken from the shuffle training set runs which extract per each session(50 session total), each have 300 steps , cost being taken after each 30 steps for each session per regularization constant)

```
In [156]: mean_step_accuracy
Out[156]:
```

lam	step_count	accuracy	weight	cost
$\boxed{0.00010}$	7515	0.81316	1.713457	$\boxed{0.411725}$
0.00001	7515	0.79976	1.579662	0.438796
0.01000	7515	0.80100	1.260753	0.441195
0.00100	7515	0.79796	1.621979	0.444650
0.10000	7515	0.78016	0.567340	0.473968
1.00000	7515	0.76104	0.149041	0.497892

The best Learning rate seems to be **0.01** (&gradually decrease in every steps). The reason is because of low average cost (below screen shot). The learning rate 0.001 seems to be slow and takes lots of steps to reach global minimum, however we are not going that many steps for each session (also can be seen from the Held Out error rate – 0.48). The 0.02 and 0.03 seems to be close in terms of average error rate, however 0.01 seems to be good enough

<table>
<tr><th>Learning Rate</th><th>Error Rate</th><th>Learning Rate</th><th>Error Rate</th></tr>
<tr>
<td>learning_rate = 0.01
Min Cost = 0.41</td>
<td>In [156]: mean_step_accuracy
Out[156]:
<table>
<tr><th>lam</th><th>step_count</th><th>accuracy</th><th>weight</th><th>cost</th></tr>
<tr><td>0.00010</td><td>7515</td><td>0.81316</td><td>1.713457</td><td>0.411725</td></tr>
<tr><td>0.00001</td><td>7515</td><td>0.79976</td><td>1.579662</td><td>0.438796</td></tr>
<tr><td>0.01000</td><td>7515</td><td>0.80100</td><td>1.260753</td><td>0.441195</td></tr>
<tr><td>0.00100</td><td>7515</td><td>0.79796</td><td>1.621979</td><td>0.444650</td></tr>
<tr><td>0.10000</td><td>7515</td><td>0.78016</td><td>0.567340</td><td>0.473968</td></tr>
<tr><td>1.00000</td><td>7515</td><td>0.76104</td><td>0.149041</td><td>0.497892</td></tr>
</table></td>
<td>learning_rate = 0.001
Min Cost = 0.48</td>
<td>In [163]: mean_step_accuracy
Out[163]:
<table>
<tr><th>lam</th><th>step_count</th><th>accuracy</th><th>weight</th><th>cost</th></tr>
<tr><td>0.01000</td><td>7515</td><td>0.78720</td><td>0.950306</td><td>0.480694</td></tr>
<tr><td>0.00001</td><td>7515</td><td>0.78596</td><td>1.176147</td><td>0.489647</td></tr>
<tr><td>0.00010</td><td>7515</td><td>0.77796</td><td>0.966849</td><td>0.503070</td></tr>
<tr><td>0.00100</td><td>7515</td><td>0.77672</td><td>1.084492</td><td>0.511731</td></tr>
<tr><td>1.00000</td><td>7515</td><td>0.75924</td><td>0.182009</td><td>0.523346</td></tr>
<tr><td>0.10000</td><td>7515</td><td>0.77880</td><td>0.855116</td><td>0.527411</td></tr>
</table></td>
</tr>
<tr>
<td>learning_rate = 0.02
Min Cost = 0.42</td>
<td>In [172]: mean_step_accuracy
Out[172]:
<table>
<tr><th>lam</th><th>step_count</th><th>accuracy</th><th>weight</th><th>cost</th></tr>
<tr><td>0.00001</td><td>7515</td><td>0.81184</td><td>1.760650</td><td>0.418581</td></tr>
<tr><td>0.01000</td><td>7515</td><td>0.81116</td><td>1.275712</td><td>0.433244</td></tr>
<tr><td>0.00010</td><td>7515</td><td>0.79952</td><td>1.781195</td><td>0.444456</td></tr>
<tr><td>0.10000</td><td>7515</td><td>0.79712</td><td>0.629876</td><td>0.461543</td></tr>
<tr><td>0.00100</td><td>7515</td><td>0.78928</td><td>1.753470</td><td>0.467791</td></tr>
<tr><td>1.00000</td><td>7515</td><td>0.77916</td><td>0.191137</td><td>0.472393</td></tr>
</table></td>
<td>learning_rate = 0.03
Min Cost = 0.42</td>
<td>In [184]: mean_step_accuracy
Out[184]:
<table>
<tr><th>lam</th><th>step_count</th><th>accuracy</th><th>weight</th><th>cost</th></tr>
<tr><td>0.01000</td><td>7515</td><td>0.81856</td><td>1.398639</td><td>0.419919</td></tr>
<tr><td>0.00001</td><td>7515</td><td>0.80948</td><td>1.874968</td><td>0.433681</td></tr>
<tr><td>0.00100</td><td>7515</td><td>0.80580</td><td>1.799913</td><td>0.440902</td></tr>
<tr><td>0.00010</td><td>7515</td><td>0.79364</td><td>1.818535</td><td>0.458516</td></tr>
<tr><td>0.10000</td><td>7515</td><td>0.79044</td><td>0.679954</td><td>0.478117</td></tr>
<tr><td>1.00000</td><td>7515</td><td>0.75892</td><td>0.206018</td><td>0.521731</td></tr>
</table></td>
</tr>
</table>

5 Entire Code

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline


def load_dataset(filepath='data/',print_ind=False):
    columns = ['age','workclass','fnlwgt','education','education-num',
'marital-status','occupation','relationship','race','sex','capital-gai
n','capital-loss','hours-per-week','native-country','target']
    train = pd.read_csv("data/train.txt",names=columns)
    test = pd.read_csv("data/test.txt",names=columns[:-1])

    train['target'].replace(' <=50K',-1,inplace=True)
    train['target'].replace(' >50K',1,inplace=True)
    label=np.array(train['target']).reshape(len(train['target']),1)
    train.drop('target',axis=1,inplace=True)
    train = np.array(train)
    test = np.array(test)
    label = label.astype(int)
    if (print_ind):
        print ("Train Shape: {} Test Shape{}".format(train.shape,test.
shape))
    return train,test,label


def preprocessing(data):
    #train,test,label=load_dataset()
    train=extract_contineous(data)
    #test=extract_contineous(test)
    train_scale=feature_scaling(train)
    test_scale=feature_scaling(test)
    train_with_label = np.append(train_scale,label,axis=1)
    return train_with_label,test_scale

def extract_contineous(data):
    cont_columns = [0,2,4,10,11,12]
    return (data[:,cont_columns]).astype(float)


def feature_scaling(data,print_ind=False):
    feature_mean=data.mean(axis=0).astype(float)
    feature_var =data.var(axis=0).astype(float)
    data = (data - feature_mean) / np.sqrt(feature_var)
    if (print_ind):
        print ("Scale Shape:{}".format(input_df_scale.shape))
    return data

def penalty_term(a):
    return 1/2 * np.asscalar(np.transpose(a).dot(a))

def obj_func(a,b,data):
    obj = np.dot(a.T,data)+b
    return obj
```

```python
def gradient_calc(w,lam,data):
    X = data[:-1]
    y = data[-1]
    a = w[:-1]
    b = w[-1]
    diff = y * obj_func(a,b,X)
    a_delta = np.array([])
    b_delta = 0
    if (diff >= 1):
        a_delta = lam*a
        b_delta = 0
    else:
        a_delta = np.subtract(lam * a, (y * X).reshape(6, 1))
        b_delta = -y
    gradient = (np.append(np.array(a_delta), np.array([b_delta]))).res
hape(7, 1)
    return gradient


def cost_function(w,lam,data):
    a = w[:-1]
    b = w[-1:]
    m=len(data)
    temp_max_val=0

    for e in data:
        X = e[:-1]
        y = e[-1:]
        obj = obj_func(a,b,X)
        error = 1 - y * obj
        temp_max_val+=max(0, np.asscalar(error))

    max_val = ((1/m)*temp_max_val) + lam * penalty_term(a)
    return max_val


def pred_calc(w,X):
    a = w[:-1]
    b = w[-1][0]
    obj = obj_func(a,b,X)
    pred = np.sign(obj)[0]
    return pred


def evaluate_model(w,lam,data):
    num_correct = 0
    for d in data:
        X = d[:-1]
        y = d[-1]
        pred = pred_calc(w,X)
        if (pred == y):
            num_correct += 1
    return (num_correct/len(data))


def train_test_split(data,eval_percent):
    np.random.shuffle(data)
    end_loc = len(data)//eval_percent
    eval_data=data[:end_loc]
```

```
    train_data=data[end_loc:]
    return train_data,eval_data


def train_model(train):
    w = np.random.rand(7,1) #initialize weight
    weight_cost = {}
    step_count=0
    num_epochs = 50 #initialize number of epochs
    num_steps = 300 #initialize number of steps
    #l_rate = 0.001 #initialize learning rate
    #l_rate = (1/(0.01*i+50))
    costs = []
    accuracy_step_wise = []
    accuracy_lam_wise = []
    #train,test=preprocessing()
    np.random.shuffle(train) # Shuffle train Dataset
    train_set,eval_set=train_test_split(train,10) #|--10%(valid_set)--
-|------------------90%(train_set)------------------|
    epoch_data = train_set[:50]  #|-(50 epoch_data)--|---------------90
%-50 Example(train_data)------------------|
    train_data = train_set[50:]  #|-(50 epoch_data)--|---------------90
%-50 Example(train_data)------------------|
    for l in [1e-5,1e-4,1e-3,1e-2,1e-1,1]:
        for i in range(num_epochs):
            for j in range(num_steps):
                step_count += 1
                gradient = gradient_calc(w,l,train_data[j])
                l_rate = (1/(0.01*i+100))
                step = l_rate * gradient
                w = np.subtract(w, step)
                if (step_count % 30 == 0): #Each Step = 30
                    acuuracy_step=evaluate_model(w,l,epoch_data) #Each
Step Level (epoch_data)
                    cost_step = cost_function(w, l, epoch_data) #Each
Step Level (epoch_data)
                    accuracy_step_wise.append([l,step_count,acuuracy_s
tep,np.sqrt(np.sum(w[:-1]**2)),cost_step]) #Each Step Level
            np.random.shuffle(train_set) #|------------------90%(train_
set)(Shuffle)------------------|
            epoch_data = train_set[:50]  #|-(50 epoch_data)--|--------
------90%-50 Example(train_data)------------------|
            train_data = train_set[50:]  #|-(50 epoch_data)--|--------
------90%-50 Example(train_data)------------------|
        acuuracy_lam=evaluate_model(w,l,eval_set) #Each lamda level (e
poch_data)
        cost_lam = cost_function(w, l, eval_set) #Each lambda level (e
poch_data)
        weight_cost[l] = {'W':w,'Accuracy':acuuracy_lam, 'Cost':cost_l
am}
        accuracy_lam_wise.append([l,step_count,acuuracy_lam,np.sqrt(np
.sum(w[:-1]**2)),cost_lam]) #Each Step Level
        step_count=0
        np.random.shuffle(train) # Shuffle train Dataset
        train_set,eval_set=train_test_split(train,10) #|--10%(valid_se
t)---|------------------90%(train_set)------------------|
        epoch_data = train_set[:50]  #|-(50 epoch_data)--|------------
--90%-50 Example(train_data)------------------|
        train_data = train_set[50:]  #|-(50 epoch_data)--|------------
--90%-50 Example(train_data)------------------|
        w = np.random.rand(7,1) #initialize weight
```

```python
    #step_accuracy=np.array(accuracy_step_wise)
    #lam_accuracy=np.array(accuracy_lam_wise)
    #return step_accuracy,lam_accuracy
    return accuracy_step_wise,accuracy_lam_wise,weight_cost



def plot_val_accuracy(step_accuracy):
    plt.subplots(figsize=(20,8))
    plt.plot(step_accuracy[step_accuracy[:,0] == 0.00001][:,1],step_accuracy[step_accuracy[:,0] == 0.0001][:,2],color='black')
    plt.plot(step_accuracy[step_accuracy[:,0] == 0.0001][:,1],step_accuracy[step_accuracy[:,0] == 0.0001][:,2],color='purple')
    plt.plot(step_accuracy[step_accuracy[:,0] == 0.001][:,1],step_accuracy[step_accuracy[:,0] == 0.001][:,2],color='red')
    plt.plot(step_accuracy[step_accuracy[:,0] == 0.01][:,1],step_accuracy[step_accuracy[:,0] == 0.01][:,2],color='green')
    plt.plot(step_accuracy[step_accuracy[:,0] == 0.1][:,1],step_accuracy[step_accuracy[:,0] == 0.1][:,2],color='blue')
    plt.plot(step_accuracy[step_accuracy[:,0] == 1][:,1],step_accuracy[step_accuracy[:,0] == 1][:,2],color='orange')
    plt.legend(['1e-5','1e-4','1e-3','1e-2','1e-1','1'])
    plt.xlabel('Steps')
    plt.ylabel('Validation Accuracy')


def plot_magnitude_w(step_accuracy):
    plt.subplots(figsize=(20,8))
    plt.plot(step_accuracy[step_accuracy[:,0] == 0.00001][:,1],step_accuracy[step_accuracy[:,0] == 0.00001][:,3],color='black')
    plt.plot(step_accuracy[step_accuracy[:,0] == 0.0001][:,1],step_accuracy[step_accuracy[:,0] == 0.0001][:,3],color='purple')
    plt.plot(step_accuracy[step_accuracy[:,0] == 0.001][:,1],step_accuracy[step_accuracy[:,0] == 0.001][:,3],color='red')
    plt.plot(step_accuracy[step_accuracy[:,0] == 0.01][:,1],step_accuracy[step_accuracy[:,0] == 0.01][:,3],color='green')
    plt.plot(step_accuracy[step_accuracy[:,0] == 0.1][:,1],step_accuracy[step_accuracy[:,0] == 0.1][:,3],color='blue')
    plt.plot(step_accuracy[step_accuracy[:,0] == 1][:,1],step_accuracy[step_accuracy[:,0] == 1][:,3],color='orange')
    plt.legend(['1e-5','1e-4','1e-3','1e-2','1e-1','1'])
    plt.xlabel('Steps')
    plt.ylabel('Size of w')

def pred_test(w,test):
    sr_pred_test=[]
    for data in test:
        pred_test_val=pred_calc(w,data)
        if (pred_test_val == -1):
            pred = '<=50K'
        elif(pred_test_val == 1):
            pred = '>50K'
        sr_pred_test.append(pred)
        #sr_pred_test.append(pred_test_val)
    pd.DataFrame(sr_pred_test).to_csv("submission.txt",index=False,header=False)


def main(show):
    train,test,label=load_dataset()
    train_contineous=extract_contineous(train)
```

```
    train_scale=feature_scaling(train_contineous)
    train_with_label = np.append(train_scale,label,axis=1)

    test_contineous=extract_contineous(test)
    test_scale=feature_scaling(test_contineous)
    #train_with_label = np.append(train_scale,label,axis=1)

    #train,test=preprocessing()
    step_accuracy,lam_accuracy,weight_cost=train_model(train_with_labe
l)
    if (show):
        plot_val_accuracy(np.array(step_accuracy))
        plot_magnitude_w(np.array(step_accuracy))
    pred_test(pd.DataFrame(weight_cost).T.loc[0.0001].loc['W'],test_sc
ale)
    return step_accuracy,pd.DataFrame(lam_accuracy,columns=['lam','ste
p_count','accuracy','weight','cost']).sort_values(by='cost'),pd.DataFr
ame(weight_cost).T,pd.DataFrame(step_accuracy,columns=['lam','step_cou
nt','accuracy','weight','cost']).groupby('lam').mean().sort_values(by=
'cost')


step_accuracy,lam_accuracy,weight_cost,mean_step_accuracy=main(False)
```