HW3

September 23, 2021

[3]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

[4]:
```
hitters = pd.read_csv("Assignment_3_Hitters.csv")
```

0.1 Data Preprocessing & Cleaning

We want to fill in missing salary data instead of just dropping the missing data rows. One way to do this is by filling in the mean salary (imputation). However we can be smarter about this and check the average sal by NewLeague. For example:

Avg salaries in the NewLeague A is slightly higher than Avg salaries in the NewLeague N

[3]:
```
print(round(hitters[["Salary","NewLeague"]][hitters["NewLeague"] =="A"].mean()))
```

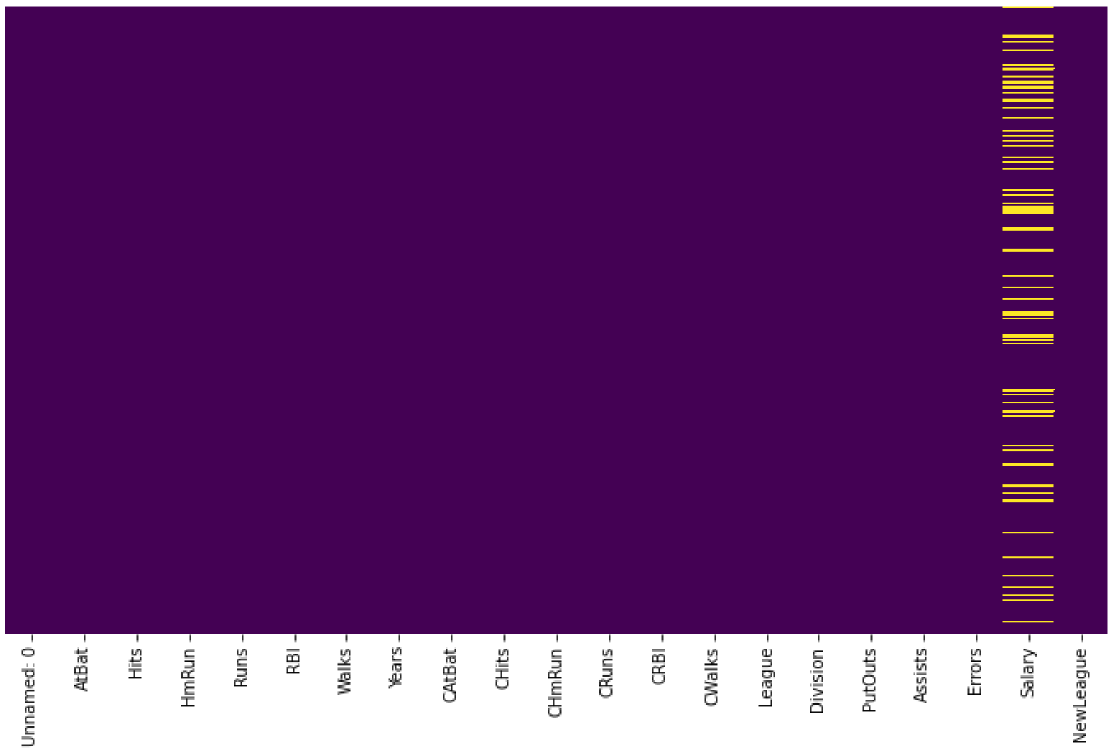
```
Salary    537.0
dtype: float64
```

[4]:
```
print(round(hitters[["Salary","NewLeague"]][hitters["NewLeague"] =="N"].mean()))
```

```
Salary    535.0
dtype: float64
```

[5]:
```
# Heatmap to check for the missing values
plt.figure(figsize=(12, 7))
sns.heatmap(hitters.isnull(),yticklabels=False,cbar=False,cmap='viridis')
```

[5]:
```
<AxesSubplot:>
```



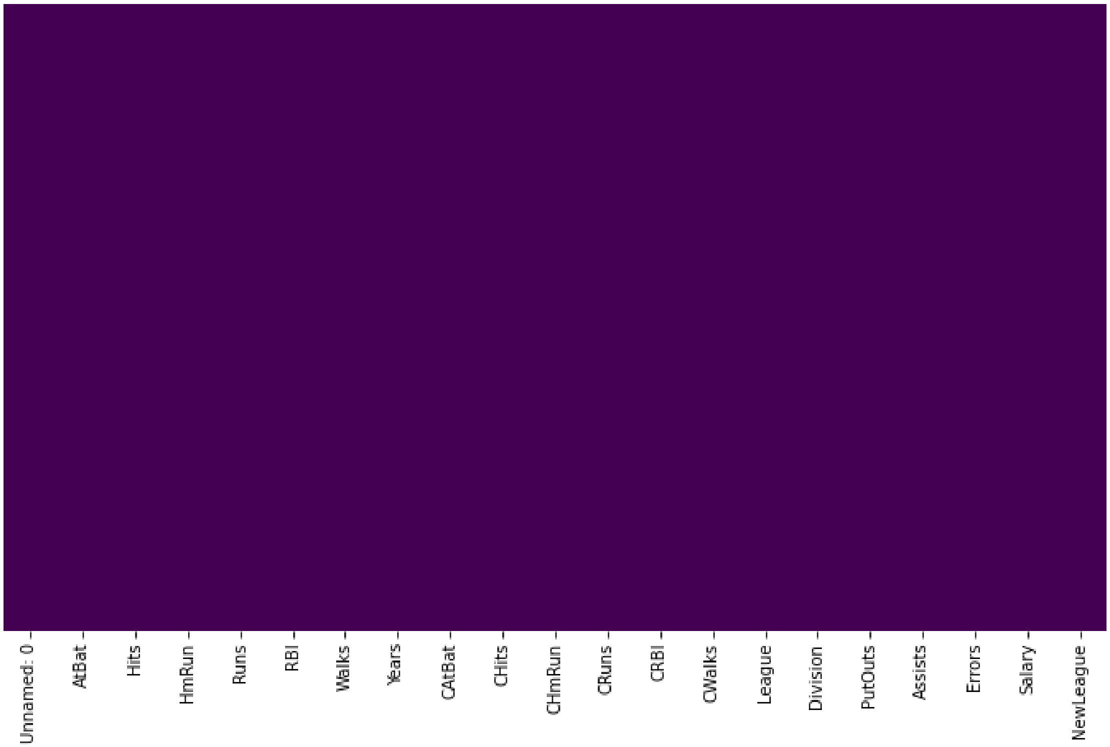
[6]:
```
def impute_sal(cols):

    sal = cols[0]
    league = cols[1]

    if pd.isnull(sal):

        if league == "A":
            return 537

        else:
            return 535

    else:
        return sal
```

[7]:
```
hitters['Salary'] = hitters[['Salary','NewLeague']].apply(impute_sal,axis=1)
```

Now let's check that heat map again!

[8]:
```
plt.figure(figsize=(12, 7))
sns.heatmap(hitters.isnull(),yticklabels=False,cbar=False,cmap='viridis')
```

[8]: <AxesSubplot:>



0.2 Converting Categorical Features

We'll need to convert categorical features to dummy variables using pandas! Otherwise our machine learning algorithm won't be able to directly take in those features as inputs.

[9]:
```
hitters.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 322 entries, 0 to 321
Data columns (total 21 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   Unnamed: 0  322 non-null    object
 1   AtBat       322 non-null    int64
 2   Hits        322 non-null    int64
 3   HmRun       322 non-null    int64
 4   Runs        322 non-null    int64
 5   RBI         322 non-null    int64
 6   Walks       322 non-null    int64
 7   Years       322 non-null    int64
 8   CAtBat      322 non-null    int64
 9   CHits       322 non-null    int64
```

```
 10   CHmRun      322 non-null    int64
 11   CRuns       322 non-null    int64
 12   CRBI        322 non-null    int64
 13   CWalks      322 non-null    int64
 14   League      322 non-null    object
 15   Division    322 non-null    object
 16   PutOuts     322 non-null    int64
 17   Assists     322 non-null    int64
 18   Errors      322 non-null    int64
 19   Salary      322 non-null    float64
 20   NewLeague   322 non-null    object
dtypes: float64(1), int64(16), object(4)
memory usage: 53.0+ KB
```

[10]:
```
league = pd.get_dummies(hitters['League'],drop_first=True)
division = pd.get_dummies(hitters['Division'],drop_first=True)
```

[11]:
```
hitters.drop(['League','Division','Unnamed: 0'],axis=1,inplace=True)
```

[12]:
```
hitters = pd.concat([hitters,league,division],axis=1)
```

[13]:
```
X = hitters.drop(["Salary","NewLeague"],axis=1)
y = hitters['Salary']
```

[14]:
```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
scaler.fit(X)
X = scaler.transform(X)
```

[15]:
```
X = np.array(X)
y = np.array(y)
```

0.3 Train Test Split

[16]:
```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=10)
```

[18]:
```
# Initialize the weights and bias randomly
def initialize_parameters(X):
    b = np.random.rand()
    w = np.random.rand(X.shape[1],1)
    return w, b
```

[19]:
```
def model(X, y, lr, iterations, lamb, regular):

    costs = []

    counter = 0
    n = len(X)
    w, b = initialize_parameters(X)


    while iterations > counter:


        z = np.dot(w.T, X.T) + b

        if z.all() >= 0:
            pred = z

        else:
            pred = z * 0.05

        #Calculate Loss Function
        MSE = np.square(np.subtract(y, pred)).mean()

        if regular == 'L1':

            cost = MSE + (lamb * abs(np.sum((w))))
            dw = 1/n * (np.dot(X.T, (pred - y).T) + lamb)
            db = 1/n* np.sum(pred - y)

            w = w - lr * dw
            b = b - lr * db

        elif regular == 'L2':
            cost = MSE + ((lamb / 2) * (np.sum((w)**2)))

            dw = 1/n * (np.dot(X.T, (pred - y).T) + lamb)
            db = 1/n* np.sum(pred - y)

            w = w - lr * dw
            b = b - lr * db

        else:
            cost = MSE
            dw = 1/n * np.dot(X.T, (pred - y).T)
            db = 1/n* np.sum(pred - y)

            w = w - lr * dw
```

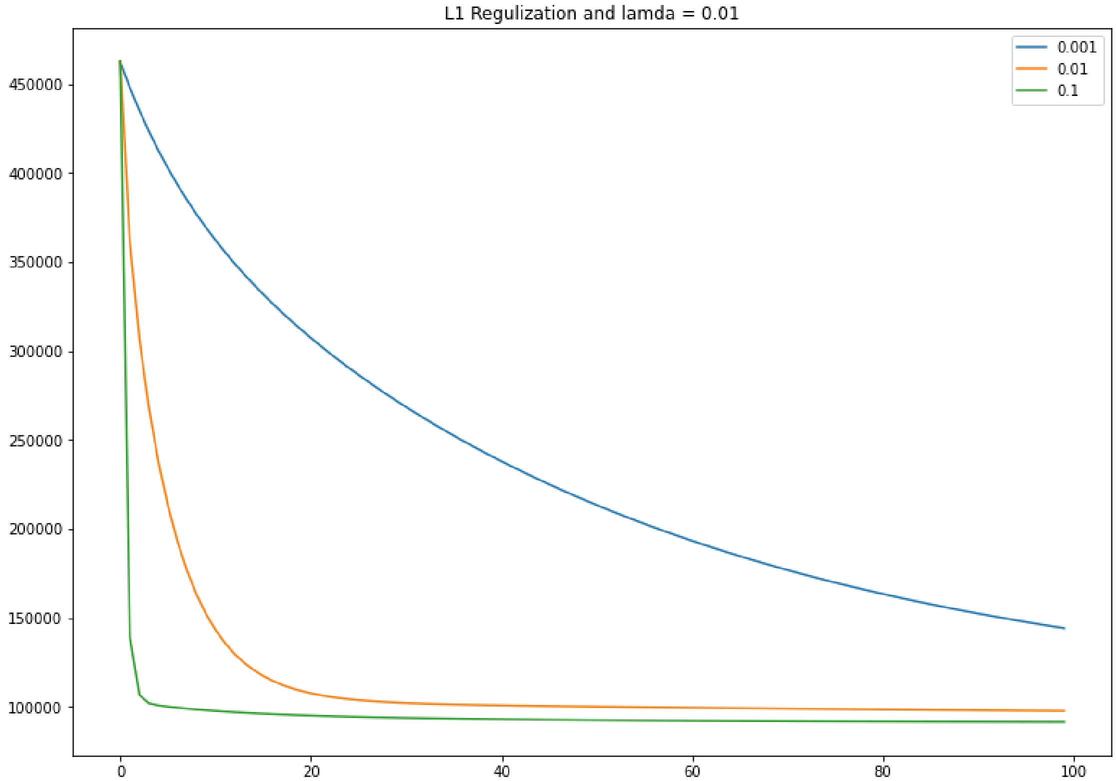
```
            b = b - lr * db

        if counter % 10 == 0:
            costs.append(cost)


        counter+= 1

    return w, b, costs
```

[20]:
```
def plot(cost, dataset):
    plt.figure(figsize = (15,7))
    sns.lineplot(x = list(range(0,len(cost))), y = cost)
    plt.title("MSE - "+ dataset)
    plt.xlabel("# of iterations")
    plt.ylabel("MSE")
    plt.show()
```

[ ]:
```

```

[21]:
```
cost_lr1 = []
w, b, cost_lr1 = model(X_train, y_train, lr = 0.001, iterations = 1000, lamb =␣
↪0.01, regular = "L1")

cost_lr2 = []
w, b, cost_lr2 = model(X_train, y_train, lr = 0.01, iterations = 1000, lamb = 0.
↪01, regular = "L1")

cost_lr3 = []
w, b, cost_lr3 = model(X_train, y_train, lr = 0.1, iterations = 1000, lamb = 0.
↪01, regular = "L1")

fig = plt.figure(figsize = (10,7))

ax = fig.add_axes([0,0,1,1])

ax.plot(list(range(0,len(cost_lr1))), cost_lr1, label="0.001")
ax.plot(list(range(0,len(cost_lr2))), cost_lr2, label="0.01")
ax.plot(list(range(0,len(cost_lr3))), cost_lr3, label="0.1")
ax.legend()
ax.set_title("L1 Regulization and lamda = 0.01")
```

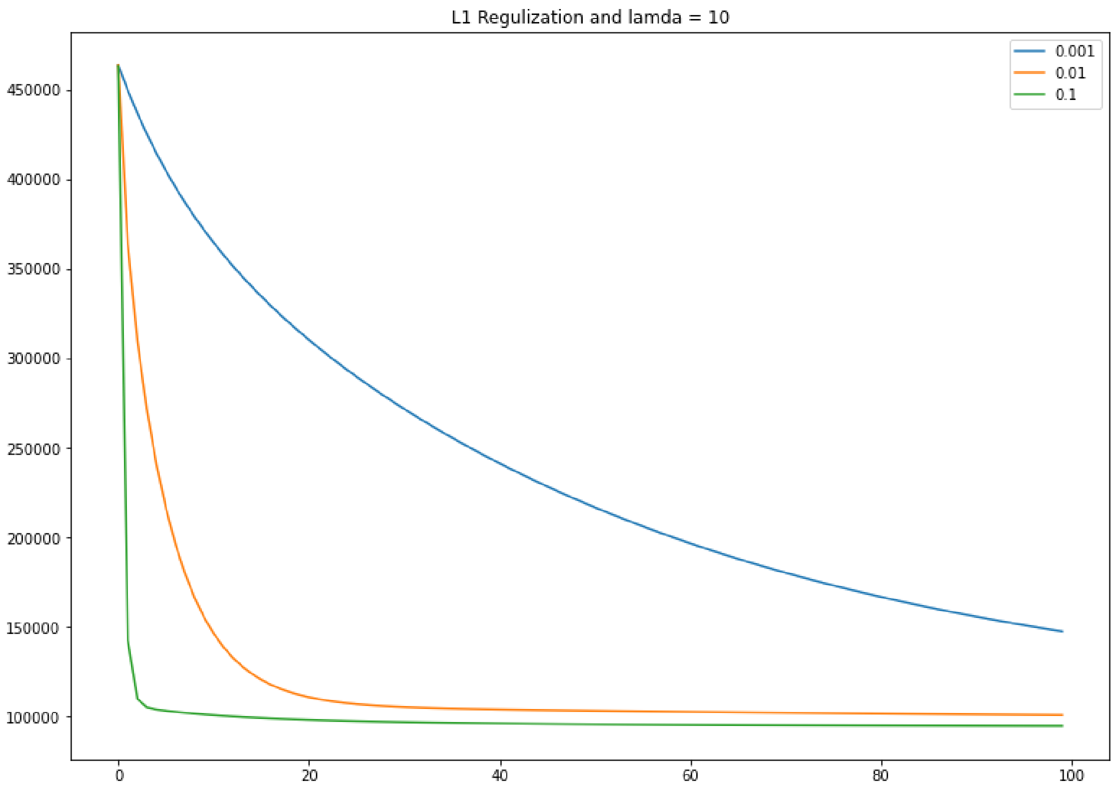
[21]:
```
Text(0.5, 1.0, 'L1 Regulization and lamda = 0.01')
```



[22]:
```
cost1 = []
w, b, cost1 = model(X_train, y_train, lr = 0.001, iterations = 1000, lamb = 10,␣
 ↪regular = "L1")

cost2 = []
w, b, cost2 = model(X_train, y_train, lr = 0.01, iterations = 1000, lamb = 10,␣
 ↪regular = "L1")

cost3 = []
w, b, cost3 = model(X_train, y_train, lr = 0.1, iterations = 1000, lamb = 10,␣
 ↪regular = "L1")


fig = plt.figure(figsize = (10,7))

ax = fig.add_axes([0,0,1,1])

ax.plot(list(range(0,len(cost1))), cost1, label="0.001")
ax.plot(list(range(0,len(cost2))), cost2, label="0.01")
ax.plot(list(range(0,len(cost3))), cost3, label="0.1")
ax.legend()
```

```
ax.set_title("L1 Regulization and lamda = 10")
```

[22]: Text(0.5, 1.0, 'L1 Regulization and lamda = 10')



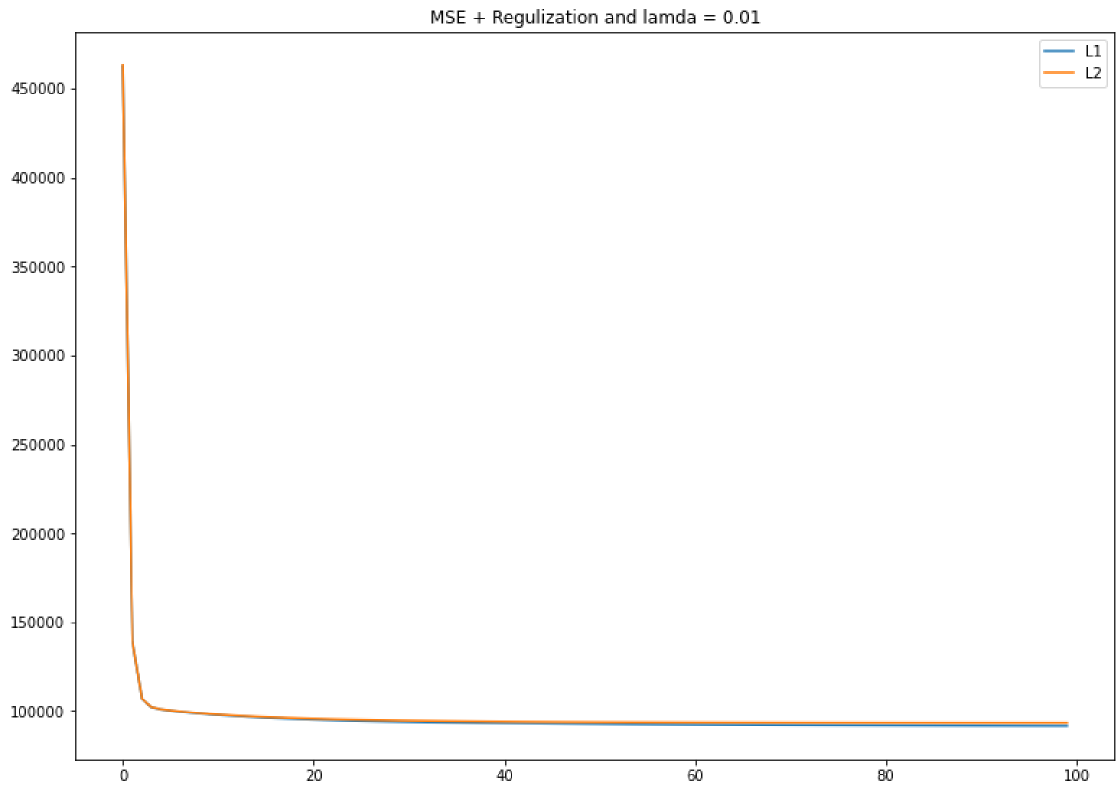
[ ]:

1 Question b

[23]:
```
w, b, cost_l1 = model(X_train, y_train, lr = 0.1, iterations = 1000, lamb = 0.
↪01, regular = "L1")
w, b, cost_l2 = model(X_train, y_train, lr = 0.1, iterations = 1000, lamb = 0.
↪01, regular = "L2")

fig = plt.figure(figsize = (10,7))

ax = fig.add_axes([0,0,1,1])

ax.plot(list(range(0,len(cost_l1))), cost_l1, label="L1")
ax.plot(list(range(0,len(cost_l2))), cost_l2, label="L2")

ax.legend()
```

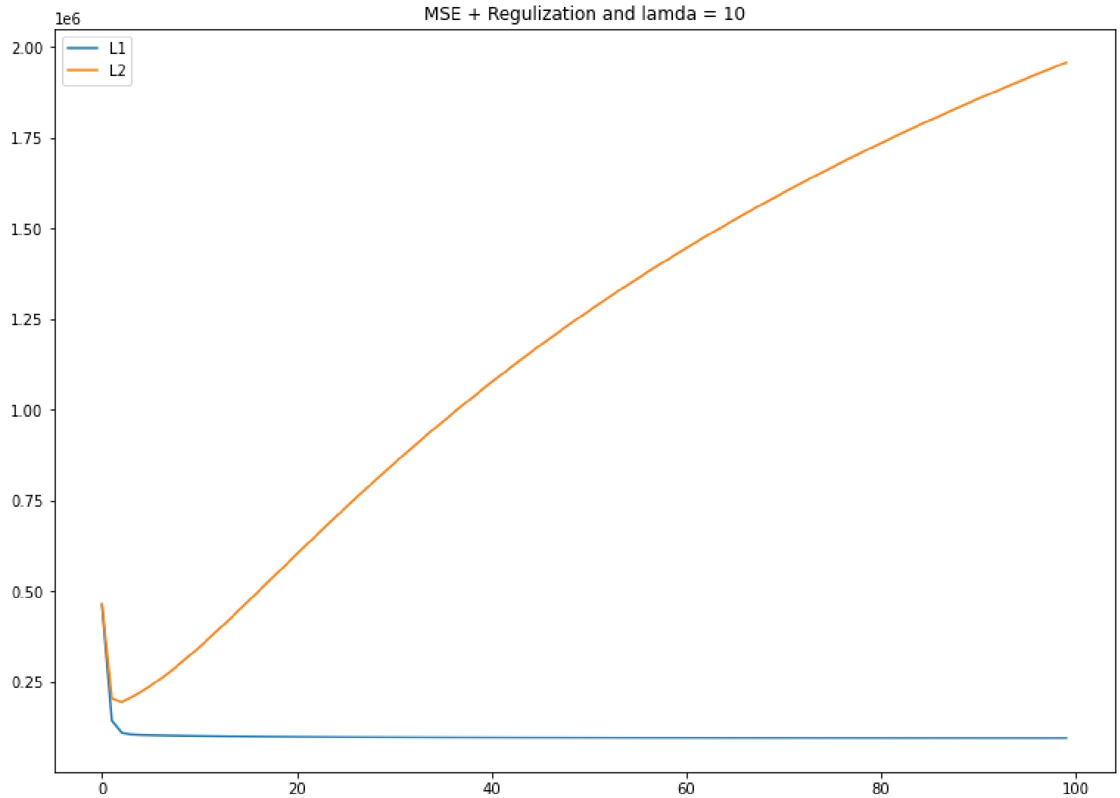
```
ax.set_title("MSE + Regulization and lamda = 0.01")
```

[23]: Text(0.5, 1.0, 'MSE + Regulization and lamda = 0.01')



[24]:
```
w, b, cost_l10 = model(X_train, y_train, lr = 0.1, iterations = 1000, lamb =␣
↪10, regular = "L1")
w, b, cost_l20 = model(X_train, y_train, lr = 0.1, iterations = 1000, lamb =␣
↪10, regular = "L2")

fig = plt.figure(figsize = (10,7))

ax = fig.add_axes([0,0,1,1])

ax.plot(list(range(0,len(cost_l10))), cost_l10, label="L1")
ax.plot(list(range(0,len(cost_l20))), cost_l20, label="L2")

ax.legend()
ax.set_title("MSE + Regulization and lamda = 10")
```

[24]: Text(0.5, 1.0, 'MSE + Regulization and lamda = 10')



2 Question c

[30]:
```
w, b, cost = model(X_train, y_train, lr = 0.1, iterations = 1000, lamb = 0.01,␣
↪regular = " ")
print(w)
print(b)
```

```
[[-343.15973279]
 [ 277.5775284 ]
 [  40.83031855]
 [  21.84520716]
 [  12.93811884]
 [ 108.80121632]
 [ -69.87977358]
 [-143.9329687 ]
 [ 110.66963903]
 [ -15.17880344]
 [ 278.28105077]
 [ 132.61631644]
 [-148.84750659]
 [  72.21145126]
```

```
 [  50.0079578 ]
 [ -23.23434862]
 [  19.16740063]
 [ -51.44894543]]
536.8780465801783
```

[31]:
```python
w1, b, cost = model(X_train, y_train, lr = 0.1, iterations = 1000, lamb = 0.01,␣
 ↪regular = "L2")
print(w1)
print(b)
```

```
[[-343.13394452]
 [ 277.54560912]
 [  40.83554999]
 [  21.86594244]
 [  12.92606202]
 [ 108.79484642]
 [ -69.90078774]
 [-143.80468858]
 [ 110.55023864]
 [ -15.23844484]
 [ 278.22860184]
 [ 132.72449526]
 [-148.83693451]
 [  72.21133605]
 [  50.00371497]
 [ -23.23524857]
 [  19.1654448 ]
 [ -51.45127244]]
536.8782078227231
```

[32]:
```python
w1, b, cost = model(X_train, y_train, lr = 0.1, iterations = 1000, lamb = 10,␣
 ↪regular = "L2")
print(w1)
print(b)
```

```
[[-343.06163154]
 [ 277.51895133]
 [  40.80932971]
 [  21.79801621]
 [  12.93033854]
 [ 108.80174349]
 [ -70.00978535]
 [-143.64675895]
 [ 110.22271425]
 [ -15.41281822]
 [ 278.38393118]
 [ 132.99586313]
```

```
 [-148.87432205]
 [  72.17677675]
 [  49.95923573]
 [ -23.25411641]
 [  19.11255317]
 [ -51.49663071]]
536.8777037507759
```

[33]:
```
w1, b, cost = model(X_train, y_train, lr = 0.1, iterations = 1000, lamb = 0.01,␣
 ↪regular = "L1")
print(w1)
print(b)
```

```
[[-343.18957855]
 [ 277.61266476]
 [  40.83301917]
 [  21.8420923 ]
 [  12.93282661]
 [ 108.80414032]
 [ -69.89763312]
 [-143.78063732]
 [ 110.5688946 ]
 [ -15.18004255]
 [ 278.24648291]
 [ 132.61699227]
 [-148.84835891]
 [  72.21183694]
 [  50.00439025]
 [ -23.23304799]
 [  19.16611698]
 [ -51.44943597]]
536.8781793876768
```

[34]:
```
w2, b, cost = model(X_train, y_train, lr = 0.1, iterations = 1000, lamb = 10,␣
 ↪regular = "L1")
print(w1)
print(b)
```

```
[[-343.18957855]
 [ 277.61266476]
 [  40.83301917]
 [  21.8420923 ]
 [  12.93282661]
 [ 108.80414032]
 [ -69.89763312]
 [-143.78063732]
 [ 110.5688946 ]
 [ -15.18004255]
```

```
 [ 278.24648291]
 [ 132.61699227]
 [-148.84835891]
 [  72.21183694]
 [  50.00439025]
 [ -23.23304799]
 [  19.16611698]
 [ -51.44943597]]
536.8775848161747
```

[ ]:
```

```

[ ]:
```

```