3. Obtain the 10 target (output(y)) datapoints for the following equation for uniformly spaced input variable(x) in the range [0,10].

$$y = (x+3) + noise$$

where, *noise* can be Gaussian noise added to the actual signal.

Now, obtain the model parameters (theta) using gradient descent that will best fit to the corrupted data points. Plot the cost function *vs.* number of iterations. Also plot the data points, actual line and predicted line on the same figure.

Vary the number of datapoints and observe the number of iterations required for converge. Also vary the values of learning parameter (alpha) and observe its effect on convergence. You can also vary the slope and intercept values of the given line and validate the performance of gradient descent.

4. Find out the model parameters (theta) for above datapoints using psudo-inverse method.

In [36]:

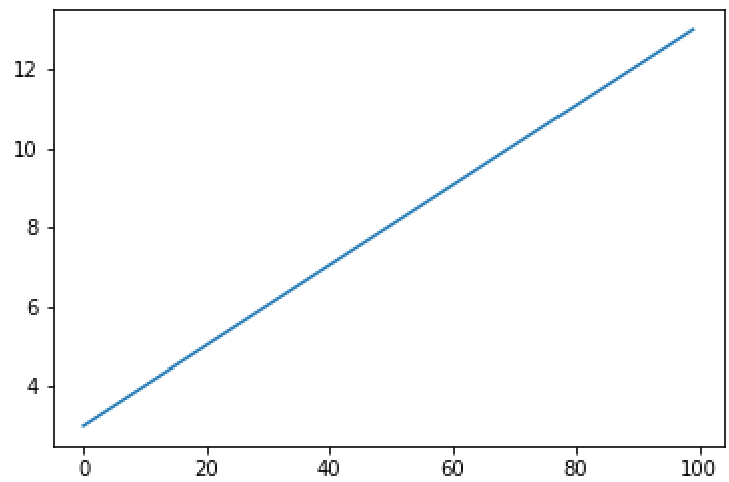
```
import numpy as np
import matplotlib.pyplot as plt
```

In [37]:

```
#plotting line y=x+3
x=np.linspace(0,10,num=100)
y=x+3
plt.plot(y)
```

Out[37]:

```
[<matplotlib.lines.Line2D at 0x240431494e0>]
```

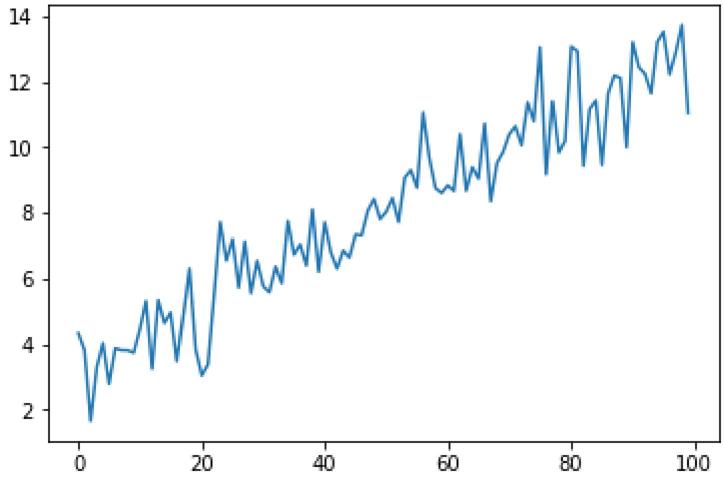


In [38]:

```
#plotting line y=(x+3)+noise
noise = np.random.normal(0, 1,x.shape)
ynew=y+noise
plt.plot(ynew)
```

Out[38]:

```
[<matplotlib.lines.Line2D at 0x240431af5c0>]
```

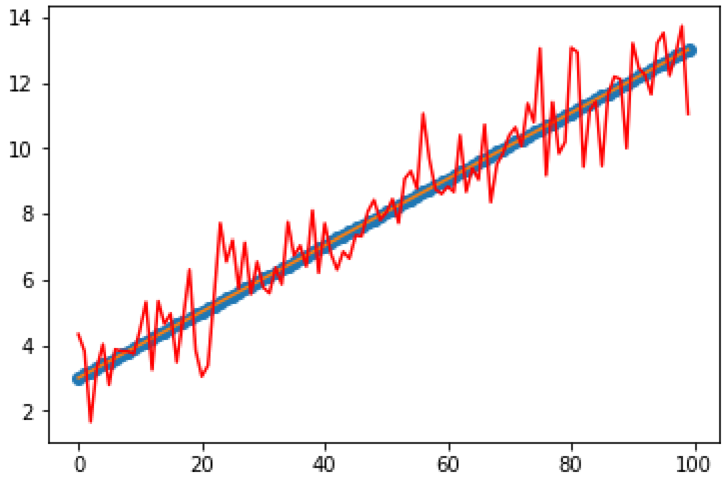


In [39]:

```
#plotting original line and line with noise
plt.plot(x+3,'o',y,'-',ynew,'r')
```

Out[39]:

```
[<matplotlib.lines.Line2D at 0x24040703e80>,
 <matplotlib.lines.Line2D at 0x2404320d710>,
 <matplotlib.lines.Line2D at 0x2404320da90>]
```



In [40]:

```
#adding column of 1 to feature set
x_norm=np.c_[np.ones(x.shape[0]),x]
x_norm.shape
```

Out[40]:

```
(100, 2)
```

In [41]:

```
#initializing theta with zeros
theta = np.zeros(2)
# Parameters required for Gradient Descent
alpha = 0.001   #learning rate
m = y.size  #no. of samples
np.random.seed(10)
def gradient_descent(x_norm,ynew,m,theta,alpha):
    cost_list=[]
    theta_list=[]
    prediction_list=[]
    cost_list.append(1e3)#large inital cost=10^3
    run=True
    i=0
    #iterating gradient descent
    while run:
        y_pred=np.dot(x_norm,theta) #predicted y value i.e x0*theta0+x1*theta1...
        prediction_list.append(y_pred)
        error=y_pred-ynew
        #cost=sum[error^2]
        cost=1/(2*m)*np.dot(error.T,error)
        cost_list.append(cost)
        #theta=theta- alpha * (1/m) * sum[error*x]
        theta=theta-(alpha*(1/m)*np.dot(x_norm.T,error))
        theta_list.append(theta)
        if cost_list[i]-cost_list[i+1]< 1e-9:#checking if the change in cost function
            run=False
        i=i+1
    cost_list.pop(0)#remove intital cost
    return prediction_list, cost_list, theta_list
```

In [42]:

```
prediction_list, cost_list, theta_list = gradient_descent(x_norm,y,m,theta,alpha)
```

In [43]:

```
#final theta values
theta=theta_list[-1]
theta
```

Out[43]:

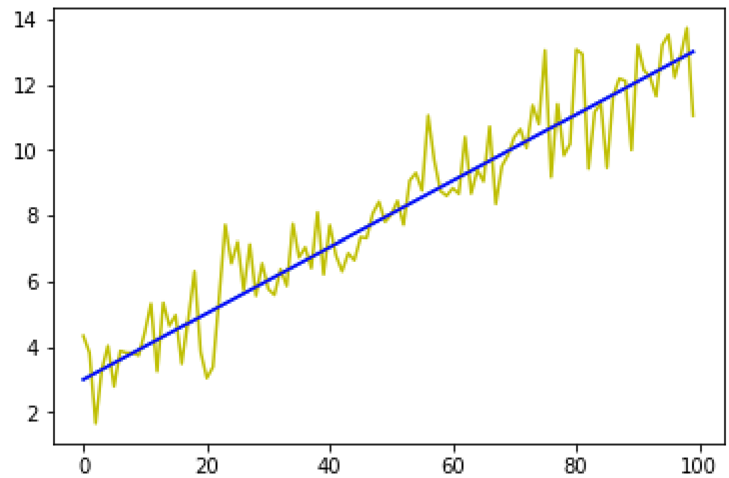
```
array([2.99601792, 1.00059875])
```

In [44]:

```
#original and predicted line along with data points
plt.plot(y,'-',ynew,'y',prediction_list[-1],'b')
```

Out[44]:

```
[<matplotlib.lines.Line2D at 0x24042b85358>,
 <matplotlib.lines.Line2D at 0x24042b854a8>,
 <matplotlib.lines.Line2D at 0x24042b857f0>]
```



Using Psuedo Inverse

In [45]:

```
#formula for psuedo inverse
psuedo=np.dot(np.linalg.inv(np.dot(x_norm.T,x_norm)),x_norm.T)
```

In [46]:

```
#final theta values
theta_=np.dot(psuedo,ynew)
theta_
```

Out[46]:

```
array([3.20817371, 0.97424859])
```

In [47]:

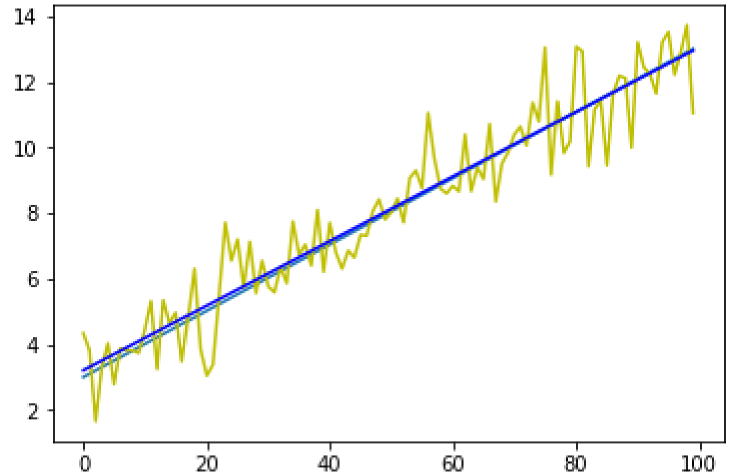
```
prediction=np.dot(x_norm,theta_)
```

In [48]:

```
#original and predicted line along with data points
plt.plot(y,'-',ynew,'y',prediction,'b')
```

Out[48]:

```
[<matplotlib.lines.Line2D at 0x2404081fc50>,
 <matplotlib.lines.Line2D at 0x2404081fda0>,
 <matplotlib.lines.Line2D at 0x24040751128>]
```



Conclusion

Gradient Descent Approach is better than Psuedo inverse Approach for Large data points