In [1]:
```
import warnings
warnings.filterwarnings("ignore")
```

In [2]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

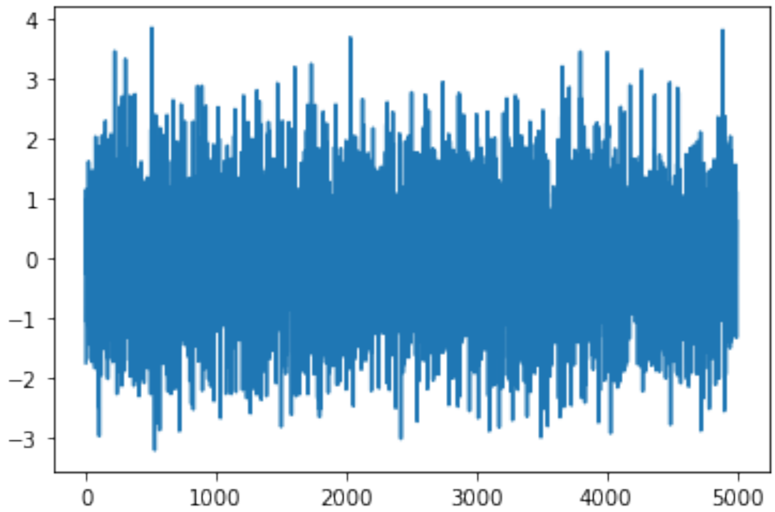
In [3]:
```
from statsmodels.tsa.stattools import acf, pacf
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from pandas.plotting import lag_plot
```

White noise

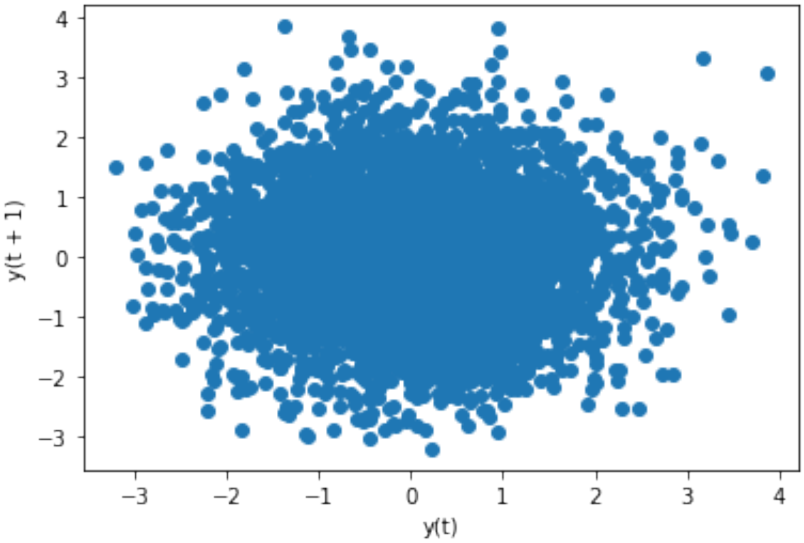
In [4]:
```
np.random.seed(100)
```

In [5]:
```
noise=np.random.normal(0,1,5000)
```

In [6]:
```
plt.plot(noise);
```

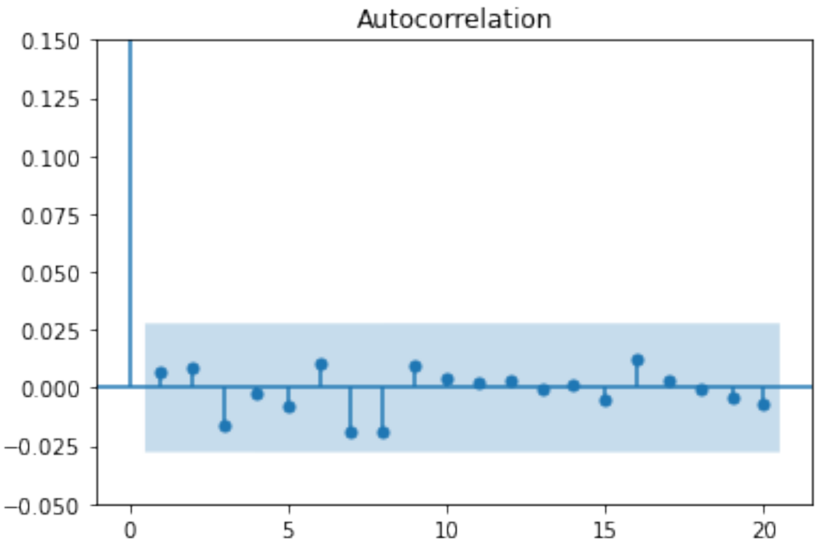


In [7]:
```
lag_plot(pd.DataFrame(noise));
```

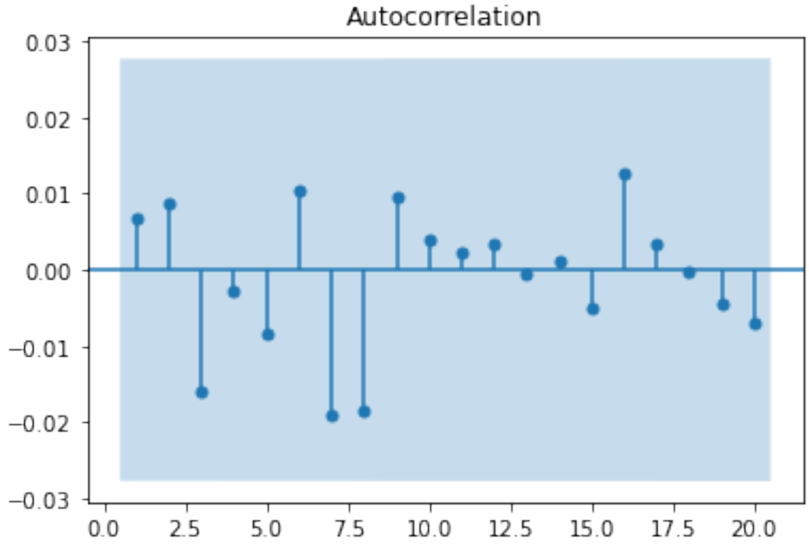


In [8]:
```
fig=plot_acf(noise,lags=20,zero=True)
plt.ylim([-0.05,0.15])
```

Out[8]:
```
(-0.05, 0.15)
```



In [9]:
```
fig=plot_acf(noise,lags=20,zero=False)
```



All displayed coefficients (apart from the one for zero lag) are within the confidence interval. We expect that there are no correlations.

In [10]:
```
from statsmodels.stats.diagnostic import acorr_ljungbox
from statsmodels.tsa.stattools import adfuller, kpss
```

The null hypothesis for the Ljung-Box test is that the first k autocorrelation coefficients are not statistically different from zero (no correlations)

In [11]:
```
acorr_ljungbox(noise,lags=[20],return_df=True) # k=20 in this examp
```

Out[11]:

	lb_stat	lb_pvalue
20	8.336363	0.989398

In [12]:
```
acorr_ljungbox(noise,lags=20,return_df=True) # show the result of t
```

Out[12]:

	lb_stat	lb_pvalue
1	0.229938	0.631569
2	0.623022	0.732340
3	1.907348	0.591858
4	1.946470	0.745604
5	2.290745	0.807625
6	2.845835	0.827933
7	4.660490	0.701315
8	6.384800	0.604212
9	6.846002	0.653149
10	6.925453	0.732463
11	6.948587	0.803232
12	7.005011	0.857282
13	7.006085	0.901838
14	7.012527	0.934228
15	7.140195	0.953642
16	7.940500	0.950618
17	7.997305	0.966604
18	7.997421	0.978675
19	8.100006	0.985636
20	8.336363	0.989398

How do we test for stationarity?

Augmented Dickey-Fuller test|

In [13]:
```
adfuller(noise) # null hypothesis time series is non-stationary
```

Out[13]:
```
(-70.23025939421295,
 0.0,
 0,
 4999,
 {'1%': -3.431658793968827,
  '5%': -2.862118345383404,
  '10%': -2.567077853953267},
 14281.458777106282)
```

p value is very low we have to reject the null hypothesis

Kwiatkowski-Phillips-Schmidt-Shin test

In [14]:
```
kpss(noise) # null hypothesis time series is stationary
```

```
/Users/mirek/opt/anaconda3/lib/python3.8/site-packages/statsmodels
/tsa/stattools.py:1910: InterpolationWarning: The test statistic i
s outside of the range of p-values available in the
look-up table. The actual p-value is greater than the p-value retu
rned.

  warnings.warn(
```

Out[14]:
```
(0.07767083532759042,
 0.1,
 32,
 {'10%': 0.347, '5%': 0.463, '2.5%': 0.574, '1%': 0.739})
```

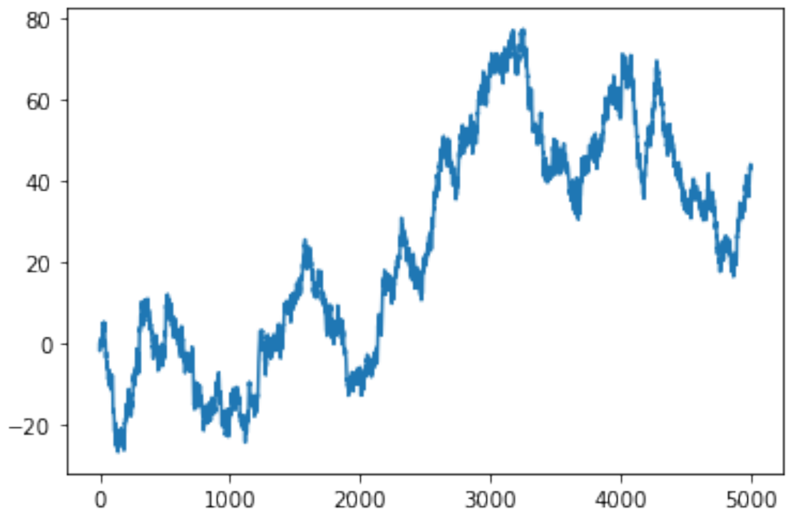
p value is greater than 0.05 - the hypothesis stands

Random walk

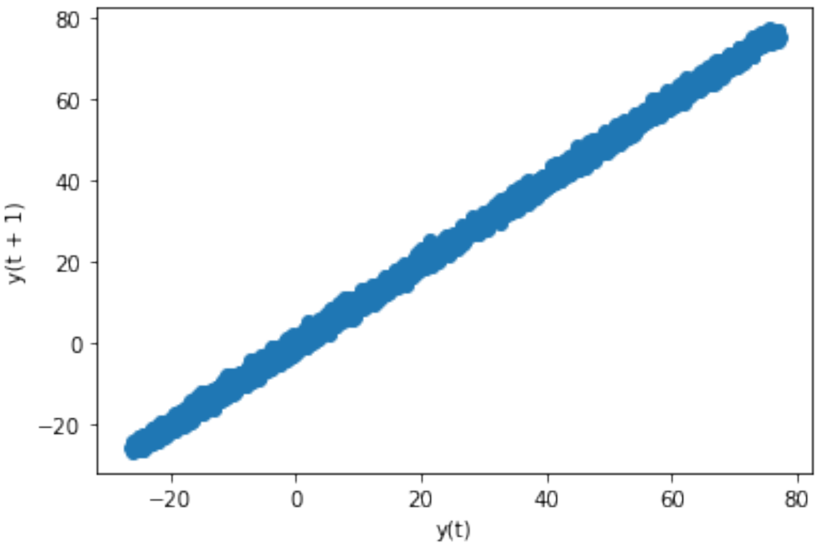
In [15]:
```
walk=[0]
```

In [16]:
```
for i in range(len(noise)):
    walk.append(walk[-1] + noise[i])
```

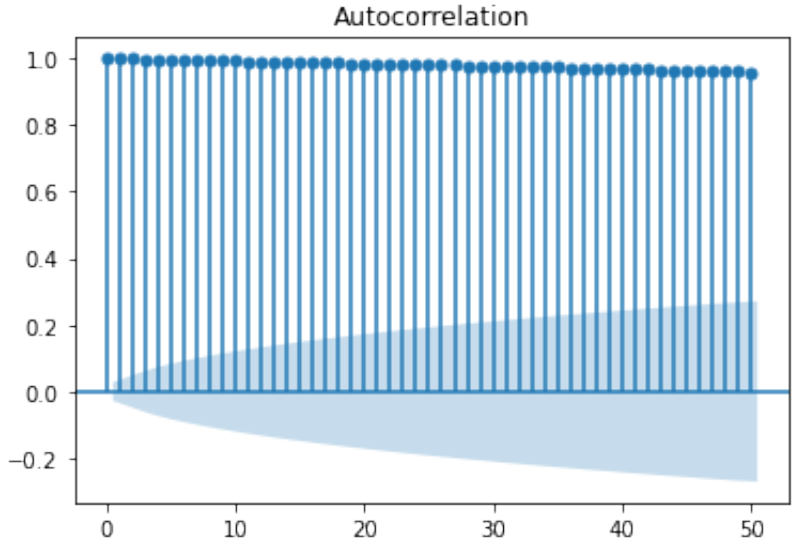
In [17]:
```
plt.plot(walk);
```



In [18]:
```
lag_plot(pd.DataFrame(walk));
```



In [19]:
```
fig=plot_acf(walk,lags=50)
```



Please note that all corelation coefficients are outside the confidence interval.

In [20]:
```
acorr_ljungbox(walk,lags=[20],return_df=True)
```

Out[20]:

	lb_stat	lb_pvalue
20	98631.463889	0.0

Ljung-Box test corroborates the existence of correlations.

In [21]:
```
adfuller(walk)
```

Out[21]:
```
(-1.3446405969248876,
 0.6085099698691658,
 0,
 5000,
 {'1%': -3.431658532075464, '5%': -2.8621182296803203, '10%': -2.5
6707779236},
 14282.414424011165)
```

In [22]:
```
kpss(walk,nlags=20)
```

```
/Users/mirek/opt/anaconda3/lib/python3.8/site-packages/statsmodels
/tsa/stattools.py:1906: InterpolationWarning: The test statistic i
s outside of the range of p-values available in the
look-up table. The actual p-value is smaller than the p-value retu
rned.

  warnings.warn(
```

Out[22]:
```
(16.67854878432449,
 0.01,
 20,
 {'10%': 0.347, '5%': 0.463, '2.5%': 0.574, '1%': 0.739})
```

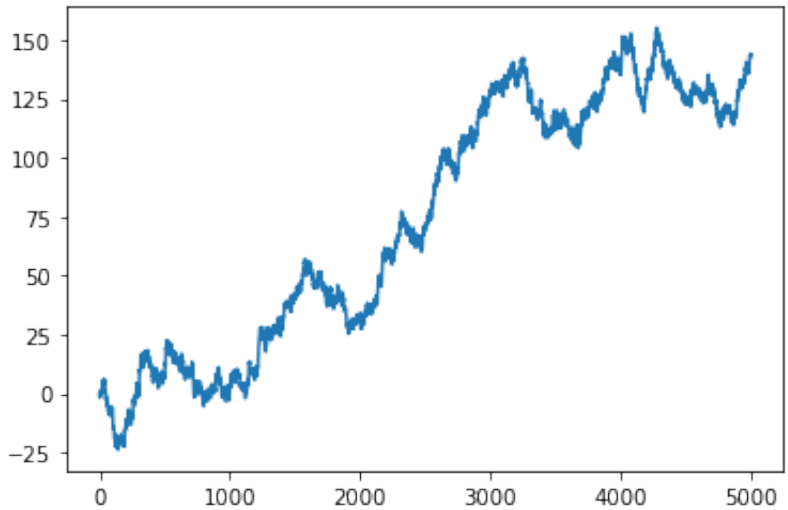
Both adf and kpss indicate that random walk is non-stationary.

Random walk with drift

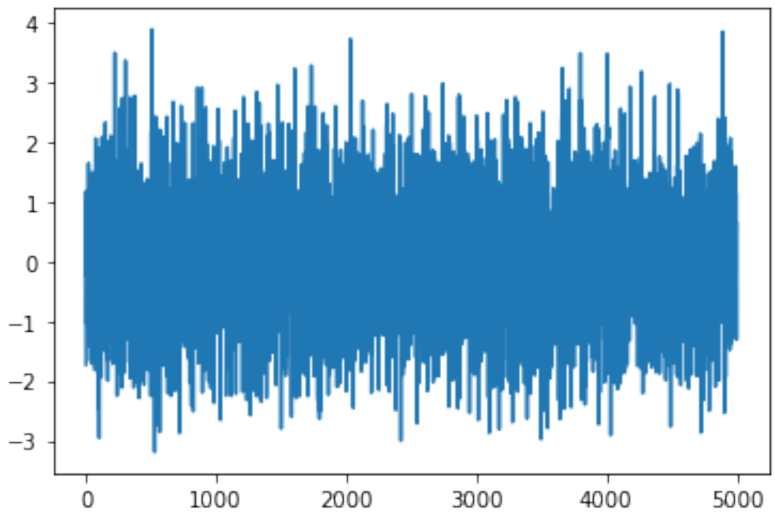
In [23]:
```
drift_walk=[0]
drift=0.02
```

In [24]:
```
for i in range(len(noise)):
    drift_walk.append(drift_walk[-1] +drift+ noise[i])
```

In [25]:
```
plt.plot(drift_walk);
```



In [26]:
```
plt.plot(pd.DataFrame(drift_walk).diff());
```



After differencing we recover noise used to generate both walks. Differencing is the simplest invertible method for reducing or eliminating time series non-stationarity.