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1 SKOLTECH, Experimental Data Processing

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In [39]:
```
import numpy as np
import scipy as sp
from matplotlib import pyplot as plt
from numpy.linalg import inv
import matplotlib as mplb
from matplotlib.font_manager import FontProperties
%matplotlib inline
from numpy.random import normal
mplb.rc('xtick', labelsize=5)
mplb.rc('ytick', labelsize=5)
```

2 PART 1

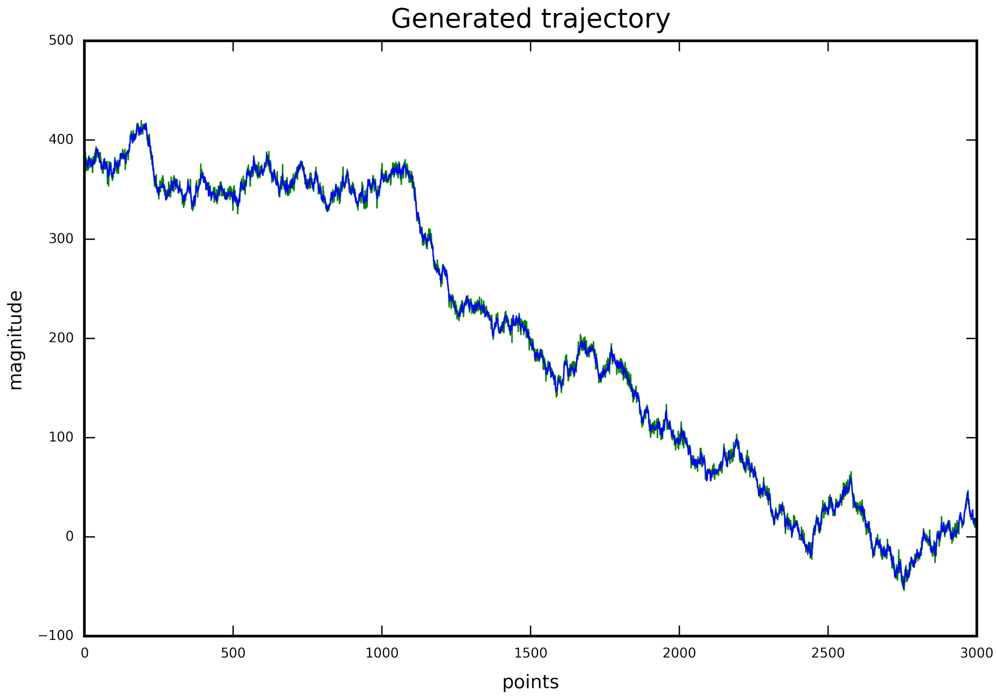
2.1 Generating

In [40]:
```
N = 3000
sigma_w = np.array([0,8**0.5])  #[0] refers to experimentally determined value,
                                #[1] to assigned by us
sigma_n = np.array([0,16**0.5])
w = normal(0, sigma_w[1], N)
n = normal(0, sigma_n[1], N)
window = np.tril(np.ones((N,N)))    #here we build a matrix to easily calc
                                    #sum from 0 to n w_i
X_0 = 10
```

In [41]:
```
X = np.ones_like(w)*10 + w.dot(window) #use of matrix
z = X + n
```

In [42]:
```
fig, ax = plt.subplots(1,1, figsize=(6,4), dpi = 600)
ax.set_title('Generated trajectory', fontsize = 10)
ax.plot(range(N),z,'g', label = 'measurements z', linewidth = 0.5 )
ax.plot(range(N),X,'b', label = 'true X', linewidth = 0.5 )
ax.set_xlabel('points', fontsize = 7)
ax.set_ylabel('magnitude', fontsize = 7)
```

Out[42]: <matplotlib.text.Text at 0x7fd4b6a1da20>



2.2 Counting σ_w^2 and σ_n^2

In [43]:
```
n1 = np.roll(n, 1) #shifts the array
n1[0] = 0
n2 = np.roll(n1,1)
n2[0] = 0
w1 = np.roll(w,1)
w1[0] = 0
```

In [44]:
```
v = w + n - n1
p = w + w1 - n -n2
```

In [45]:
```
Ev = np.average((v*v)[1:])
Ep = np.average((p*p)[2:])
```

In [46]:
```
sigma_w[0] = (Ep - Ev)**0.5
sigma_n[0] = ((2*Ev - Ep)/2)**0.5
```

In [47]:
```
print(r'experimental sigma_w_exp^2 = %.2f, in program sigma_w^2 = %.2f'
       % tuple(sigma_w**2))
```

```
experimental sigma_w_exp^2 = 6.00, in program sigma_w^2 = 8.00
```

```
In [48]: print(r'experimental sigma_n_exp^2 = %.2f, in program sigma_n^2 = %.2f'
                 % tuple(sigma_n**2))
```

```
experimental sigma_n_exp^2 = 16.73, in program sigma_n^2 = 16.00
```

2.3 Determine optimal χ and α

```
In [11]: chi = (sigma_w/sigma_n)**2

In [12]: alpha = 0.5*(-chi + (chi**2 + 4*chi)**0.5)

In [13]: print(r'chi experimental = %.2f, chi in program = %.2f' % tuple(chi) )
```

```
chi experimental = 0.65, chi in program = 0.50
```

```
In [14]: print(r'alpha experimental = %.2f, alpha in program = %.2f' % tuple(alpha) )
```

```
alpha experimental = 0.54, alpha in program = 0.50
```

3 PART 2

```
In [21]: N = 300
         sigma_w = np.array([0,28])  #[0] refers to experimentally determined value,
                                     #[1] to assigned by us
         sigma_n = np.array([0,97])
         w = normal(0, sigma_w[1], N)
         n = normal(0, sigma_n[1], N)
         window = np.tril(np.ones((N,N)))
         X_0 = 10

In [22]: X = np.ones_like(w)*10 + w.dot(window)
         z = X + n

In [23]: n1 = np.roll(n, 1)
         n1[0] = 0
         n2 = np.roll(n1,1)
         n2[0] = 0
         w1 = np.roll(w,1)
         w1[0] = 0

In [24]: v = w + n - n1
         p = w + w1 - n -n2

In [25]: Ev = np.average((v*v)[1:])
         Ep = np.average((p*p)[2:])

In [26]: sigma_w[0] = (Ep - Ev)**0.5 # here it might break due to Ev > Ep! but it's natural
         sigma_n[0] = ((2*Ev - Ep)/2)**0.5

In [27]: chi = (sigma_w/sigma_n)**2

In [28]: alpha = 0.5*(-chi + (chi**2 + 4*chi)**0.5)
```

3.1 Running mean

```
In [29]: M = int(np.round((2-alpha)/alpha)[1])
```

```
In [30]: running_window = np.ones(M)/M
```

```
In [31]: X_meaned = np.convolve(X, running_window, mode='same')
```

3.2 Exponential mean

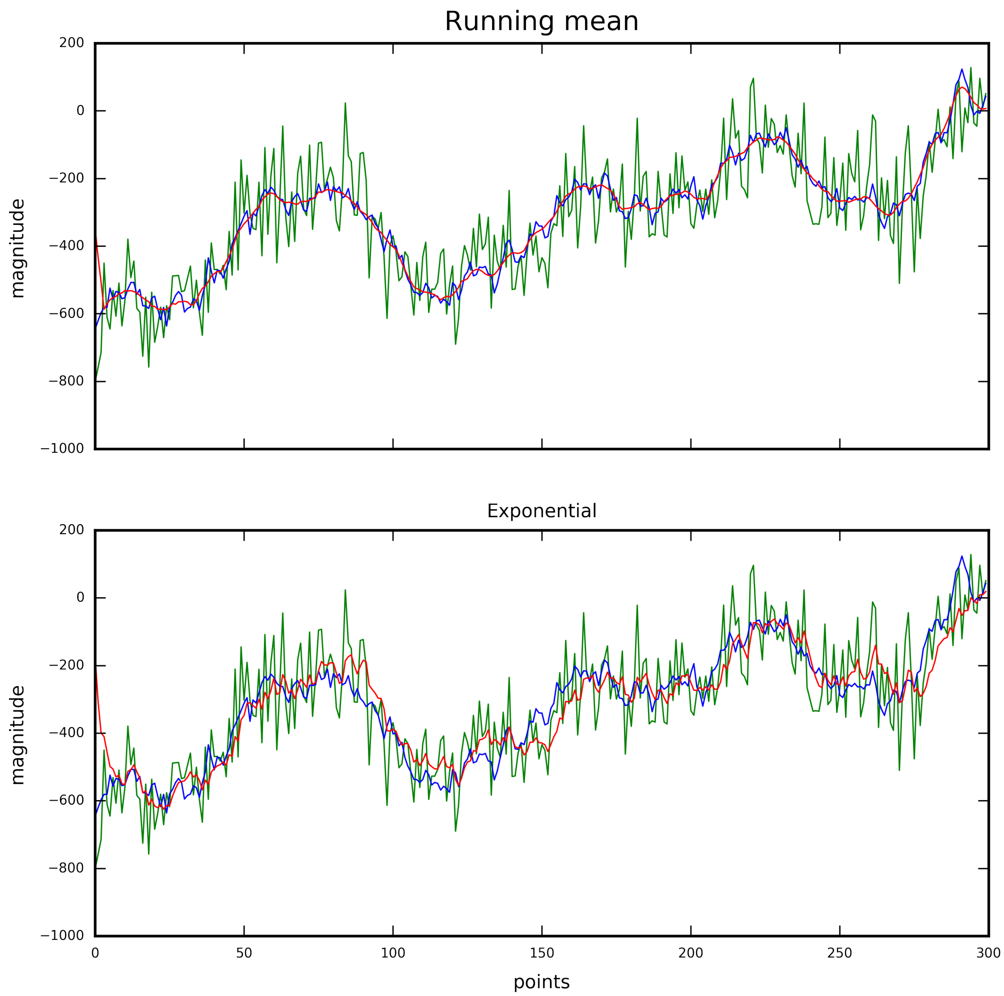
```
In [32]: X_quasi = np.zeros_like(X)
         X_quasi[0] = X_0 + alpha[0]*(z[0] - X_0)
```

```
In [33]: for i in range(1,N):
             X_quasi[i] = X_quasi[i-1] + alpha[0]*(z[i]-X_quasi[i-1])
```

3.2.1 Plotting

```
In [36]: fig, ax = plt.subplots(2,1, figsize=(6,6), dpi = 600, sharex =True)
         ax[0].set_title('Running mean', fontsize = 10)
         ax[0].plot(range(N),z,'g', label = 'measurements z', linewidth = 0.5 )
         ax[0].plot(range(N),X,'b', label = 'true X', linewidth = 0.5 )
         ax[0].plot(range(N),X_meaned,'r', label = 'running mean method', linewidth = 0.5 )
         #ax[0].set_xlabel('points', fontsize = 5)
         ax[0].set_ylabel('magnitude', fontsize = 7)
         ax[1].set_title('Exponential', fontsize = 7)
         ax[1].plot(range(N),z,'g', label = 'measurements z', linewidth = 0.5 )
         ax[1].plot(range(N),X,'b', label = 'true X', linewidth = 0.5 )
         ax[1].plot(range(N),X_quasi,'r', label = 'exponential mean', linewidth = 0.5)
         ax[1].set_xlabel('points', fontsize = 7)
         ax[1].set_ylabel('magnitude', fontsize = 7)
```

```
Out[36]: <matplotlib.text.Text at 0x7fd4b6aa7f60>
```



3.2.2 **For this particular trajectory Running Mean method works better and Exponential method generates result closer to z than to X**

3.2.3 **Exponential method in fact doesn't take into account this projectory details properly**

3.2.4 **This should happen due to huge** $\frac{\sigma_n}{\sigma_w} > 1$

3.2.5 **Today we learned how to use Exponential method and compared it to Running Mean method.**