Kalman fiilter in 1D

https://github.com/sharathsrini/Kalman-Filter-for-Sensor-Fusion/blob/master/Kalman_Filter.ipynb (https://github.com/sharathsrini/Kalman-Filter-for-Sensor-Fusion/blob/master/Kalman_Filter.ipynb)

In [1]:

```
import warnings
warnings.filterwarnings('ignore')
```

In [2]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib.mlab as mlab
import seaborn as sb
from scipy import stats
import time
```

In [3]:

```
np.random.seed(1214)
```

In [4]:

```
%matplotlib inline
fw = 10 # figure width
```

Predict

Both Distributions have to be merged together $\mu_{\text{new}} = \mu_0 + \mu_{\text{move}}$ is the new mean and $\sigma^2_{\text{new}} = \sigma^2_0 + \sigma^2_{\text{move}}$ is the new variance.

In [5]:

```
def predict(var, mean, varMove, meanMove):
    new_var = var + varMove
    new_mean= mean+ meanMove
    return new_var, new_mean
```

The more often you run the predict step, the flatter the distribution get

Correct

Now both Distributions have to be merged together $\sigma^2_{\text{new}} = \dfrac{1}{\dfrac{1}{\sigma^2_{\text{old}}} + \dfrac{1}{\sigma^2_{\text{Sensor}}}}$ is the new variance and the new mean value is $\mu_{\text{new}} = \dfrac{\sigma^2_{\text{Sensor}} \cdot \mu_{\text{old}} + \sigma^2_{\text{old}} \cdot \mu_{\text{Sensor}}}{\sigma^2_{\text{old}} + \sigma^2_{\text{Sensor}}}$

In [6]:

```
def correct(var, mean, varSensor, meanSensor):
    new_mean=(varSensor*mean + var*meanSensor) / (var+varSensor)
    new_var = 1/(1/var +1/varSensor)
    return new_var, new_mean
```

First cycle : prediction + correction

In [7]:

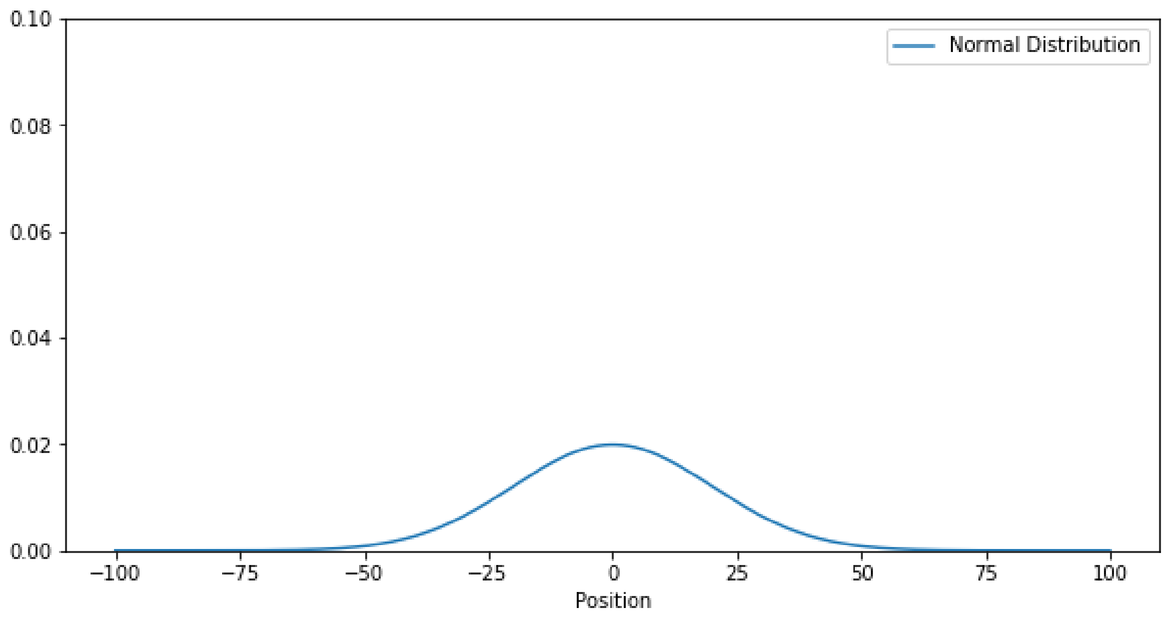
```
x = np.linspace(-100,100,1000)
```

In [26]:

```
mean0 = 0.0   # e.g. meters or miles
var0  = 20.0# 50.0#20.0
```

In [27]:

```
plt.figure(figsize=(fw,5))
plt.plot(x,mlab.normpdf(x, mean0, var0), label='Normal Distribution')
plt.ylim(0, 0.1);
plt.legend(loc='best');
plt.xlabel('Position');
```



Now we have something, which estimates the moved distance. VarMove is the estimated or determined with static measurements.

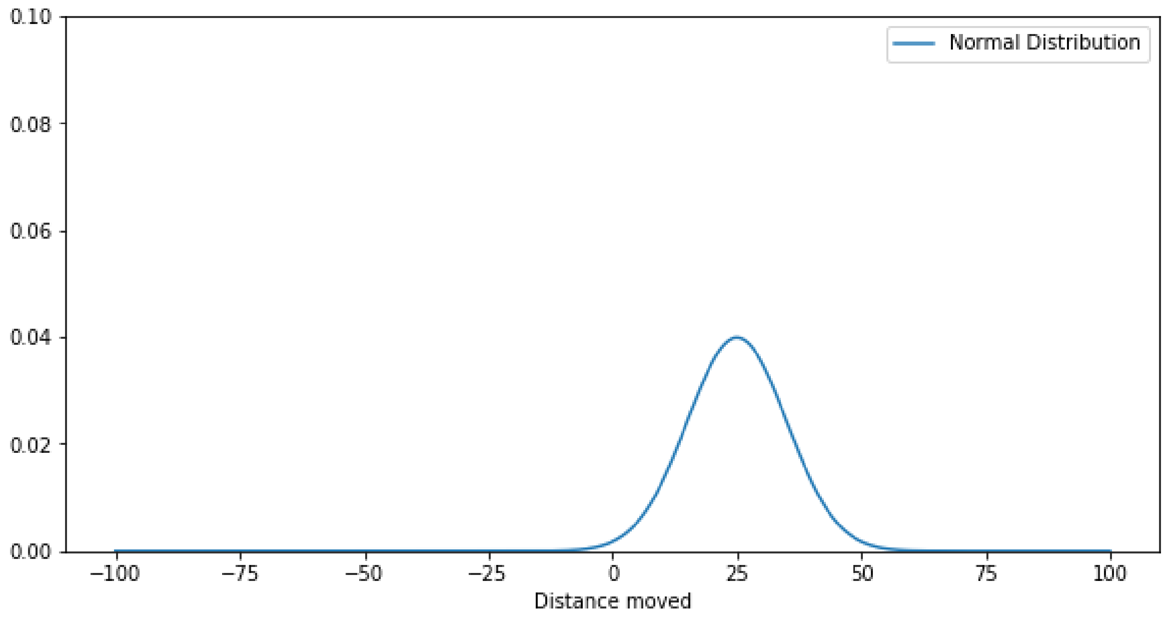
나는 한번에 이만큼 갈거 같음. (느낌으로)

In [10]:

```
meanMove = 25.0
varMove  = 10.0
```

In [11]:

```
plt.figure(figsize=(fw,5))
plt.plot(x,mlab.normpdf(x, meanMove, varMove), label='Normal Distribution')
plt.ylim(0, 0.1);
plt.legend(loc='best');
plt.xlabel('Distance moved');
```



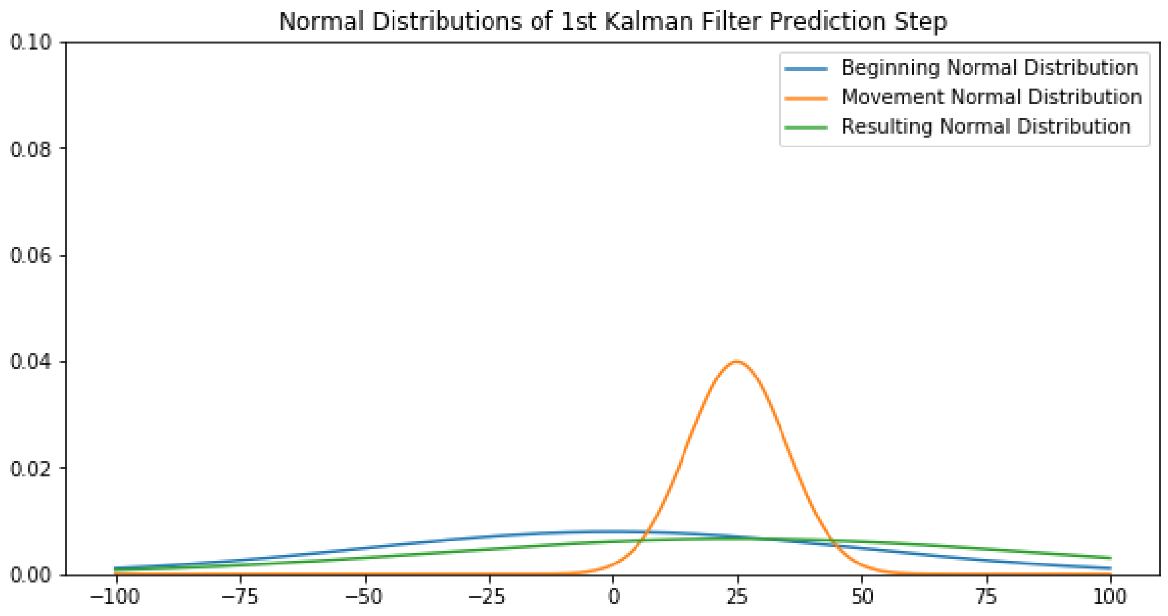
- First step : predict (느낌으로)

In [12]:

```
new_var, new_mean = predict(var0, mean0, varMove, meanMove)
```

In [13]:

```
plt.figure(figsize=(fw,5))
plt.plot(x,mlab.normpdf(x, mean0, var0), label='Beginning Normal Distribution')
plt.plot(x,mlab.normpdf(x, meanMove, varMove), label='Movement Normal Distribution')
plt.plot(x,mlab.normpdf(x, new_mean, new_var), label='Resulting Normal Distribution')
plt.ylim(0, 0.1);
plt.legend(loc='best');
plt.title('Normal Distributions of 1st Kalman Filter Prediction Step');
plt.savefig('Kalman-Filter-1D-Step.png', dpi=150)
```



Prediction : Sensor없이 그냥 이쯤이면 이만큼 갈것이다라고 예측한 값

Sensor Defaults for Position Measurements

(Estimated or determined with static measurements)

In [14]:

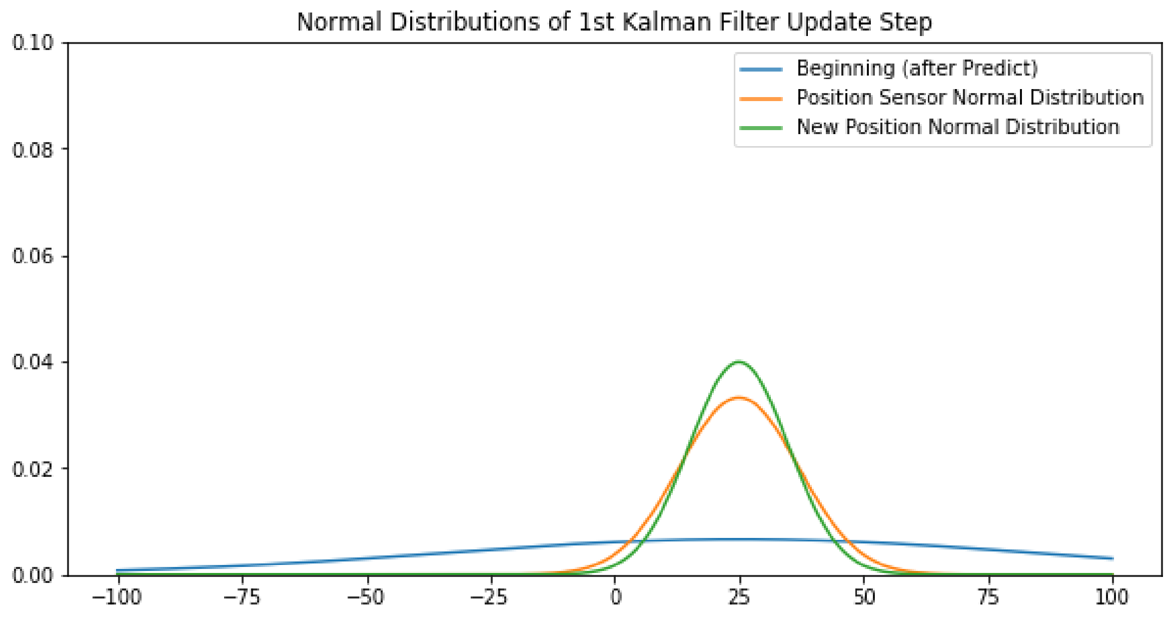
```
meanSensor  = 25.0
varSensor   = 12.0
```

In [15]:

```
var, mean = correct(new_var, new_mean, varSensor, meanSensor)
```

In [16]:

```
plt.figure(figsize=(fw,5))
plt.plot(x,mlab.normpdf(x, new_mean, new_var), label='Beginning (after Predict)')
plt.plot(x,mlab.normpdf(x, meanSensor, varSensor), label='Position Sensor Normal Distribution')
plt.plot(x,mlab.normpdf(x, mean, var), label='New Position Normal Distribution')
plt.ylim(0, 0.1);
plt.legend(loc='best');
plt.title('Normal Distributions of 1st Kalman Filter Update Step');
```



More cycles

Let's say, we have some measurements for position and for distance traveled. Both have to be fused with the 1D-Kalman Filter.

- Measurements

In [17]:

```
positions = (10, 20, 30, 40, 50)+np.random.randn(5)
```

In [18]:

```
distances = (10, 10, 10, 10, 10)+np.random.randn(5)
```

In [19]:

```
positions
```

Out[19]:

```
array([ 8.76480005, 18.95878458, 30.37963187, 40.69003491, 49.28458876])
```

In [20]:

```
distances
```

Out[20]:

```
array([10.05014253,  9.43583392, 10.6584072 ,  9.02168786,  9.78325434])
```

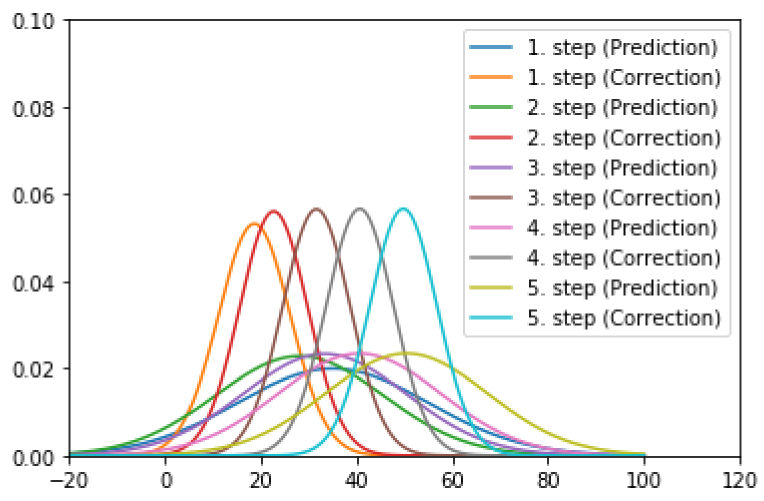
In [21]:

```
vvar_p =[]
vvar_c = []
```

In [22]:

```
for m in range(len(positions)):

    # Predict
    var, mean = predict(var, mean, varMove, distances[m])
    #print('mean: %.2f₩tvar:%.2f' % (mean, var))
    plt.plot(x, mlab.normpdf(x, mean, var), label='%i. step (Prediction)' % (m+1))

    vvar_p.append(var)

    # Correct
    var, mean = correct(var, mean, varSensor, positions[m])
    print('After correction:  mean= %.2f₩tvar= %.2f' % (mean, var))
    plt.plot(x,mlab.normpdf(x, mean, var), label='%i. step (Correction)' % (m+1))

    vvar_c.append(var)

plt.ylim(0, 0.1);
plt.xlim(-20, 120)
plt.legend();
```

```
After correction:  mean= 18.62  var= 7.50
After correction:  mean= 22.66  var= 7.12
After correction:  mean= 31.59  var= 7.05
After correction:  mean= 40.66  var= 7.04
After correction:  mean= 49.76  var= 7.04
```



The sensors are represented as normal distributions with their parameters (μ and σ^2) and are calculated together with addition or convolution. The prediction decreases the certainty about the state, the correction increases the certainty.

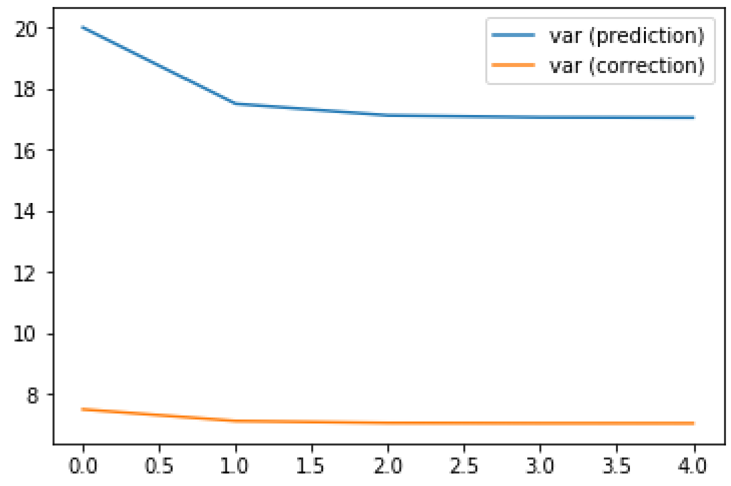
Prediction: Certainty ↓ Correction: Certainty ↑

In [23]:

```
plt.plot(vvar_p, label='var (prediction)')
plt.plot(vvar_c, label='var (correction)')
plt.legend()
```

Out[23]:

```
<matplotlib.legend.Legend at 0x7fb8a9dcd4e0>
```

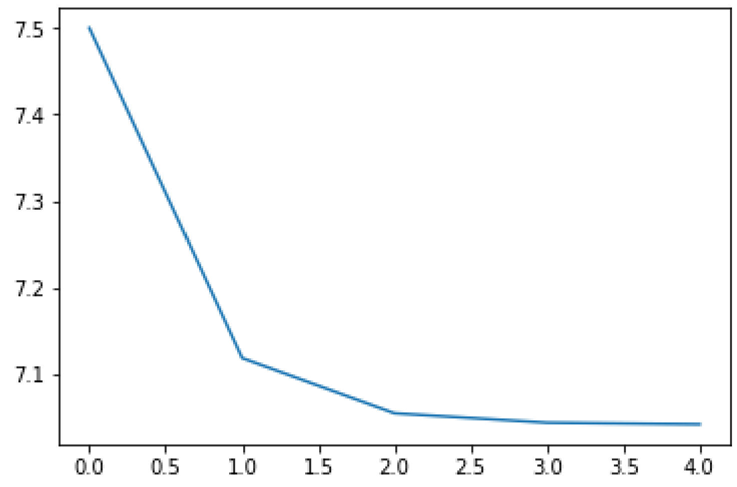


In [24]:

```
plt.plot(vvar_c)
```

Out[24]:

```
[<matplotlib.lines.Line2D at 0x7fb8a9d8ccc0>]
```



7.5
7.4
7.3
7.2
7.1
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0