```
In [18]: from scipy.stats import norm
  import numpy as np
  import matplotlib.pyplot as plt
  import scipy
```

Task 1: Probability

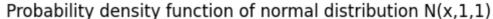
A: Plot the probability density function p(x) of a one dimensional Gaussian distribution N(x; 1, 1).

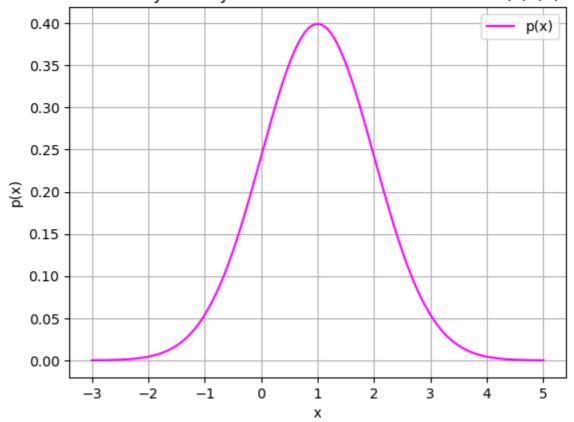
```
In [19]: # Distribution N(x,1,1)
y, z = 1, 1
x = np.linspace(-3,5,500)

def normal_distribution(z, x, t):
    norm_distribution = norm.pdf(z, x, t)

    return norm_distribution

plt.plot(x, normal_distribution(x,y,z), color = 'magenta', label = 'p(x)')
plt.xlabel('x')
plt.ylabel('p(x)')
plt.grid(True)
plt.title('Probability density function of normal distribution N(x,1,1)')
plt.legend(loc = 'upper right')
plt.show()
```





B: Calculate the probability mass that the random variable X is less than 0, that is, Pr $\{X <= 0\}$.

```
In [20]: def probability_mass(n, x, t):
    prob_mass = norm.cdf(n, x, t)

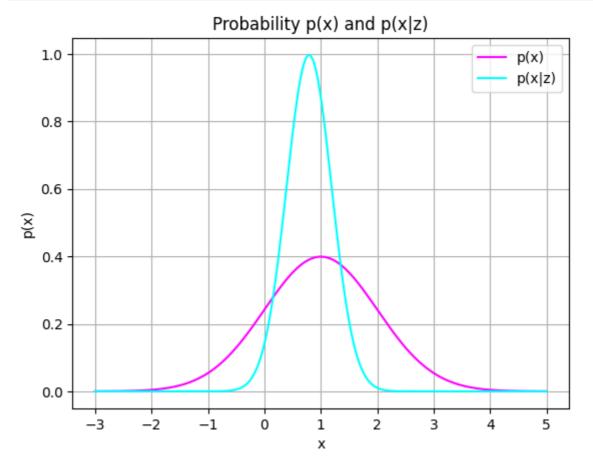
    return prob_mass

print('The probability =', probability_mass(0, y,z))
```

The probability = 0.15865525393145707

C: Consider the new observation variable z, it gives information about the variable x by the likelihood function $p(z|x) = N(z;x;\sigma^2)$, with variance $\sigma^2 = 0.2$. Apply the Bayes' theorem to derive the posterior distribution, p(x|z), given an observation z = 0.75 and plot it. For a better comparison, plot the prior distribution, p(x), too.

```
In [21]:
         #prob N(x,1,1)
         x = np.linspace(-3,5,200)
         z = 0.75
         sigma = 0.2
         prob_x= normal_distribution(x, 1, 1)
         prob_x_z = normal_distribution(x, (z + sigma)/(1 + sigma), sigma / 1 + sigma
         # prior_cdf = norm.cdf(numerical_pdf) - norm.cdf(-numerical_pdf)
         \# a = norm.pdf(0.75, x, 0.2)
         plt.plot(x, prob_x, color = 'magenta', label = 'p(x)')
         plt.plot(x, prob_x_z, color = 'cyan', label = 'p(x|z)')
         plt.grid(True)
         plt.legend()
         plt.xlabel('x')
         plt.ylabel('p(x)')
         plt.title('Probability p(x) and p(x|z)')
         plt.show()
```



Task 2: Multivariate Gaussian

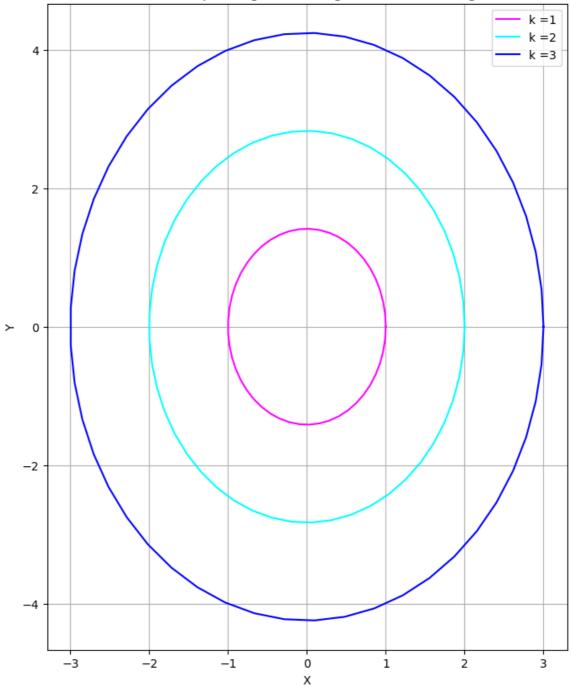
A: Write the function plot2dcov which plots the 2d contour given three core parameters: mean, covariance, and the iso-contour value k. You may add any other parameter such as color, number of points, etc. Then, use plot2dcov to draw the iso-contours corresponding to 1,2,3-sigma of the following Gaussian distributions:

$$N = (\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & 0 \\ 0 & 2 \end{bmatrix}), N = (\begin{bmatrix} 5 \\ 0 \end{bmatrix}, \begin{bmatrix} 3 & -0.4 \\ -0.3 & 2 \end{bmatrix}), N = (\begin{bmatrix} 2 \\ 2 \end{bmatrix}, \begin{bmatrix} 9.1 & 6 \\ 6 & 4 \end{bmatrix})$$

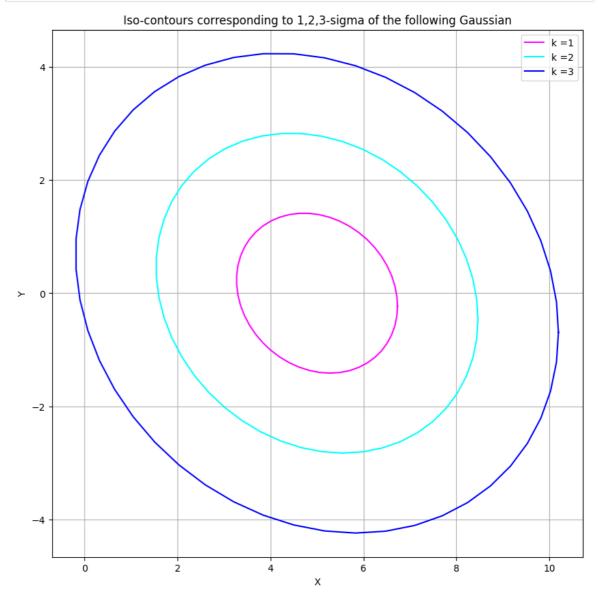
```
In [22]: def plot2dcov(mean, cov, k):
             color = ['magenta', 'cyan', 'blue']
             A = np.linalg.cholesky(cov)
             t = np.linspace(0, 2 * np.pi, 50)
             if k == 'full value':
                 for i in range(3):
                     x = (i + 1) * np.cos(t)
                     y = (i + 1) * np.sin(t)
                     coord = A @ np.array([x,y])
                     coord[0] += mean[0]
                     coord[1] += mean[1]
                     graf = plt.plot(coord[0], coord[1], color = color[i], label = 'k
                     plt.grid(True)
                     plt.legend(loc = 'upper right')
                     plt.xlabel('X')
                     plt.ylabel('Y')
             else:
                 x = k * np.cos(t)
                 y = k * np.sin(t)
                 coord = A @ np.array([x,y])
                 coord[0] += mean[0]
                 coord[1] += mean[1]
                 graf = [coord[0], coord[1]]
                 plt.grid(True)
                 plt.legend()
                 plt.xlabel('X')
                 plt.ylabel('Y')
             return graf
```

```
In [27]: mean = np.array([0, 0])
    cov = np.array(([1,0], [0,2]))
    plt.figure( figsize=(8,10) )
    plot2dcov(mean, cov, 'full value')
    plt.title('Iso-contours corresponding to 1,2,3-sigma of the following Gaussi
    plt.show()
```

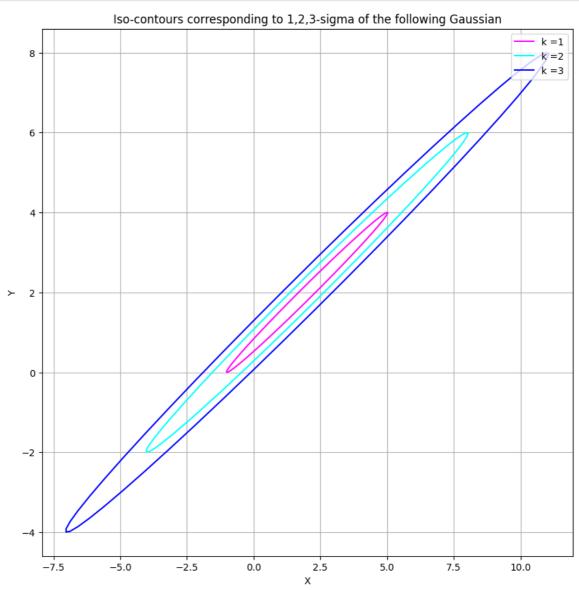




```
In [24]: mean = np.array([5, 0])
    cov = np.array(([3, -0.4], [-0.4, 2]))
    plt.figure(figsize=[10, 10])
    plt.title('Iso-contours corresponding to 1,2,3-sigma of the following Gaussi
    plot2dcov(mean, cov, 'full value')
    plt.show()
```



```
In [25]: mean = np.array((2, 2))
    cov = np.array(((9.1, 6), (6, 4)))
    plt.figure(figsize=[10, 10])
    plt.title('Iso-contours corresponding to 1,2,3-sigma of the following Gaussi
    plot2dcov(mean, cov, 'full value')
    plt.show()
```



B. Write the equation of sample mean and sample covariance of a set of points {xi}, in vector form as was shown during the lecture. You can provide your solution by using Markdown, latex, by hand, etc.

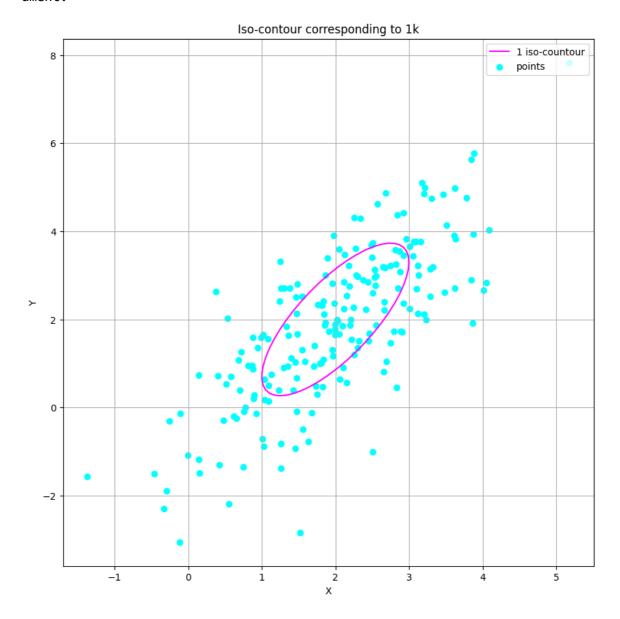
```
In [26]: def sample(mean, cov, t):
    x = np.random.randn(2, t)
    b = np.copy(mean)
    A = np.linalg.cholesky(cov)
    y = np.array([A @ x[:, i] + b for i in range(t)])
    return y
```

C. Draw random samples from a multivariate normal distribution. You can use the python function that draws samples from the univariate normal distribution N (0, 1). In particular, draw and plot 200 samples from $N=(\begin{bmatrix}2\\2\end{bmatrix},\begin{bmatrix}1&1.3\\1.3&1\end{bmatrix})$ given distribution; also plot their corresponding 1-sigma iso-contour. Then calculate the

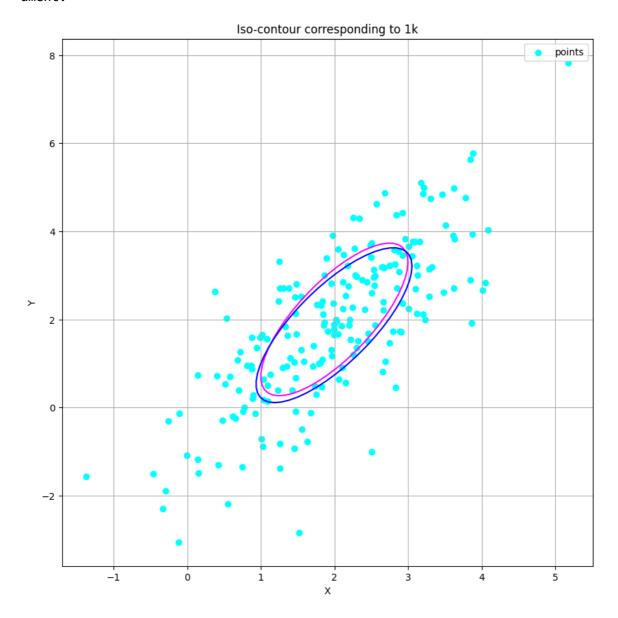
sample mean and covariance in vector form and plot again the 1-sigma iso-contour for the estimated Gaussian parameters. Run the experiment multiple times and try different number of samples. Comment on the results.

```
In [60]: mean = np.array([2, 2])
    cov = np.array(([1, 1.3], [1.3, 3]))

y = sample(mean,cov, 200)
    plt.figure(figsize=[10, 10])
    plt.title('Iso-contour corresponding to 1k')
    graf = plot2dcov(mean, cov, 1)
    plt.plot(graf[0], graf[1], color = 'magenta', label = '1 iso-countour')
    plt.scatter(y[:, 0], y[:, 1], color = 'cyan', label = 'points')
    plt.legend(loc='upper right')
    plt.show()
```



```
In [62]:
    plt.figure(figsize=[10, 10])
    graf = plot2dcov(mean, cov, 1)
    plt.plot(graf[0], graf[1], color = 'magenta' )
    plt.scatter(y[:, 0], y[:, 1], color = 'cyan', label = 'points')
    graf1 = plot2dcov(sample_mean, sample_cov, 1)
    plt.plot(graf1[0], graf1[1], color = 'blue' )
    plt.title('Iso-contour corresponding to 1k')
    plt.legend()
    plt.show()
```

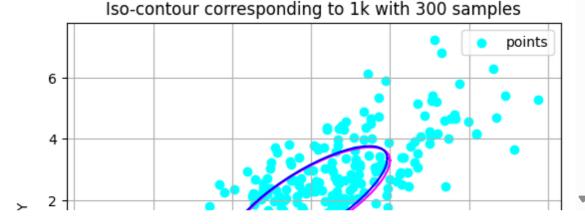


```
In [63]: sump = [300, 500, 800, 1000]
    for i in range (len(sump)):
        y1 = sample(mean, cov, sump[i])
        sample_mean, sample_cov = random_samples(y1)

        print(sample_mean, sample_cov, end = '\n')

        graf = plot2dcov(mean, cov, 1)
        plt.plot(graf[0], graf[1], color = 'magenta')
        plt.scatter(y1[:, 0], y1[:, 1], color = 'cyan', label = 'points')
        graf1 = plot2dcov(sample_mean, sample_cov, 1)
        plt.plot(graf1[0], graf1[1], color = 'blue')
        plt.title('Iso-contour corresponding to 1k with ' + str(sump[i])+ '
        plt.legend()
        plt.show()
```

```
[1.9482928 1.96199276] [[1.033944 1.42507291] [1.42507291 3.26724872]]
```



Conclusion: The more samples we have, the more accurate our results so the amount of samples the more accurate results we can obtain regarding the distribution parameters.

Task 3: Covariance Propagation

A: Write the equations corresponding to the mean and covariance after a single propagation of the holonomic platform.

$$A = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, B = \Delta_t \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, R = \Sigma_{\eta_t}$$

$$\mu_t = A\mu_{t-1} + Bu_t$$

$$\Sigma_t = A\Sigma_{t-1}A^T + R$$

B: How can we use this result iteratively?

We can use this result iteratively for finding the state PDF and it is moving at a given time

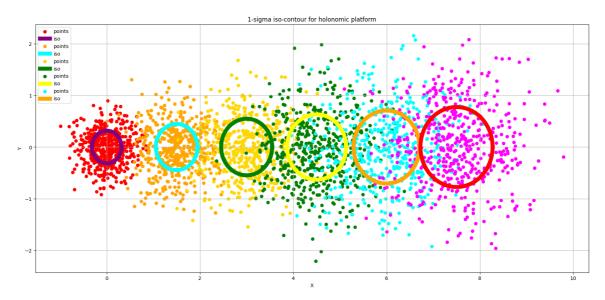
```
In [230]: dt = 0.5
          A = np. array([[1, 0],
                [0, 1]])
          B = np.array([[dt, 0],
                [0, dt]])
          mean = np.array([0,0])
          cov = np.array([[0.1, 0],
                            [0, 0.1]
          u = np.array([3, 0])
          def propagation_holon(A, B, mean, cov, u):
              mean_p = []
              cov_p = []
              mean_p.append(mean)
              cov_p.append(cov)
              for i in range(6):
                  mean_p_i = A @ mean_p[i] + B @ u
                  cov_p_i = A @ cov_p[i] @ A.T + cov
                  mean_p.append(mean_p_i)
                  cov_p.append(cov_p_i)
              cov_p = np.array(cov_p)
              mean_p = np.array(mean_p)
              return mean_p, cov_p
```

Type *Markdown* and LaTeX: α^2

C: Draw the propagation state PDF (1-sigma iso-contour) for times indexes t = 0, ..., 5 and the control sequence ut = [3, 0] T for all times t.

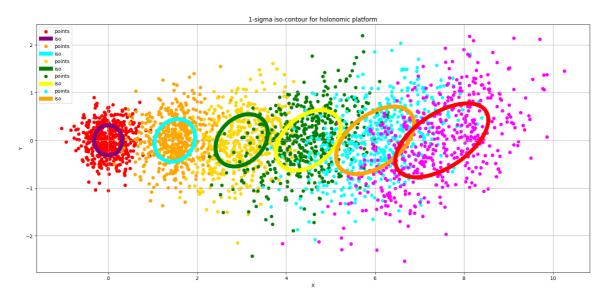
Type *Markdown* and LaTeX: α^2

```
In [237]: colors =['red','orange', 'gold', 'green', 'cyan', 'magenta']
    colors_iso = ['purple', 'cyan','green', 'yellow', 'orange', 'red']
    mean_p, cov_p = propagation_holon(A, B, mean, cov, u)
    plt.figure(figsize=[20, 9])
    for i in range(6):
        graf = plot2dcov(mean_p[i], cov_p[i], 1)
        y = sample(mean_p[i], cov_p[i], 500)
        plt.scatter(y[:, 0], y[:, 1], color = colors[i], label = 'points')
        plt.plot(graf[0], graf[1], color = colors_iso[i], linewidth= 8, label = plt.title('1-sigma iso-contour for holonomic platform')
        plt.show()
```



D. Somehow, the platform is malfunctioning; thus, it is moving strangely and its propagation model has changed... Draw the propagation state PDF (1-sigma isocontour and 500 particles) for times indexes $t = 0, \ldots, 5$

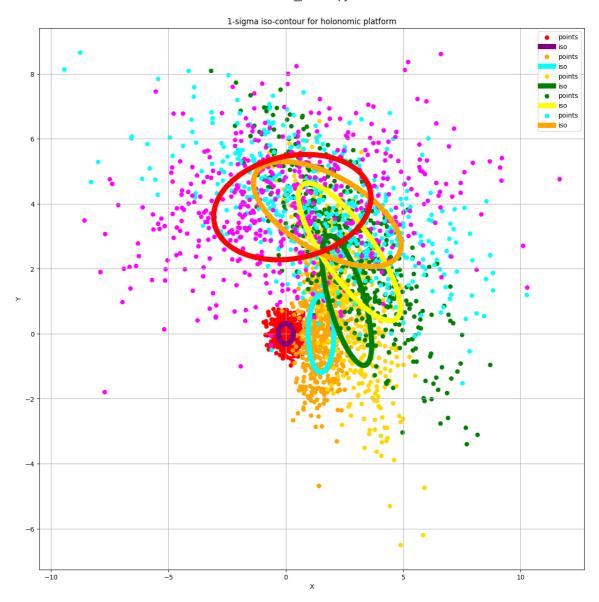
```
In [240]:
    mean_p, cov_p = propagation_holon(A_1, B, mean_1, cov_1, u)
    plt.figure(figsize=[20, 9])
    for i in range(6):
        graf = plot2dcov(mean_p[i], cov_p[i], 1)
        y = sample(mean_p[i], cov_p[i], 500)
        plt.scatter(y[:, 0], y[:, 1], color = colors[i], label = 'points')
        plt.plot(graf[0], graf[1], color = colors_iso[i], linewidth= 8, label = plt.title('1-sigma iso-contour for holonomic platform')
    plt.show()
```



E: Now, suppose that the robotic platform is non-holonomic, and the corresponding propagation model has changed. Propagate, as explained in class (linearize plus covariance propagation), for five time intervals, using the control $u_t = [3, 1.5]^{\mathsf{T}}$ showing the propagated Gaussian by plotting the 1-sigma iso-contour.

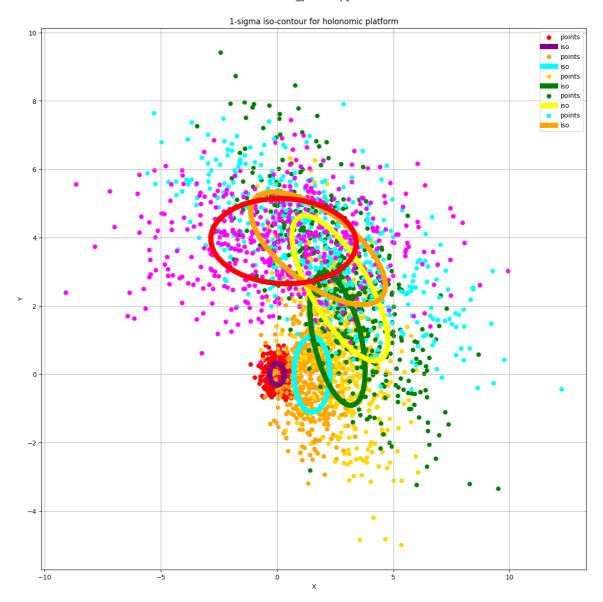
$$\begin{aligned} x_{t-1} &\sim N(\mu_{t-1}, \Sigma_{t-1}), \\ \varepsilon &\sim N(0, R) \\ x_t &\sim N(g(\mu_{t-1}, u_t), G_t \Sigma_{t-1} G_t^T + R) \end{aligned}$$

```
In [259]:
          A = np.eye(3)
          u = np.array([3, 1.5])
          R = np.array([[0.2, 0, 0],
                        [0, 0.2, 0],
                        [0, 0, 0.1]
          mean = np.zeros(3)
          cov = np.array([[0.1, 0, 0],
                          [0, 0.1, 0],
                          [0, 0, 0.5]]
          plt.figure(figsize=[15, 15])
          plt.title('1-sigma iso-contour for holonomic platform')
          for i in range(6):
              graf = plot2dcov(mean[:2], cov[:2, :2], 1)
              y = sample(mean[:2], cov[:2, :2], 500)
              t = mean[2]
              v = u[0]
              B = np.array([[0.5 * np.cos(t), 0],
                            [0.5 * np.sin(t), 0],
                            [0, 0.5]])
              G = np.array([[1, 0, -0.5 * v * np.sin(t)],
                            [0, 1, 0.5 * v * np.cos(t)],
                            [0, 0, 1]
              mean = A @ mean + B @ u
              cov = G @ cov @ G.T + R
              plt.scatter(y[:, 0], y[:, 1], color = colors[i], label = 'points')
              plt.plot(graf[0], graf[1], color = colors_iso[i], linewidth= 8, label =
```



F:Repeat the same experiment as above, using the same control input ut and initial state estimate, now considering that noise is expressed in the action space instead of state space.

```
In [262]:
          A = np.eye(3)
          u = np.array([3, 1.5])
          R = np.array([[2, 0], [0, 0.1]])
          mean = np.zeros(3)
          cov = np.array([[0.1, 0, 0],
                          [0, 0.1, 0],
                          [0, 0, 0.5]])
          plt.figure(figsize=[15, 15])
          plt.title('1-sigma iso-contour for holonomic platform')
          for i in range(6):
              graf = plot2dcov(mean[:2], cov[:2, :2], 1)
              y = sample(mean[:2], cov[:2, :2], 500)
              t = mean[2]
              v = u[0]
              B = np.array([[0.5 * np.cos(t), 0],
                            [0.5 * np.sin(t), 0],
                            [0, 0.5]])
              G = np.array([[1, 0, -0.5 * v * np.sin(t)],
                            [0, 1, 0.5 * v * np.cos(t)],
                            [0, 0, 1]
              mean = A @ mean + B @ u
              cov = G @ cov @ G.T + (B @ R) @ B.T
              plt.scatter(y[:, 0], y[:, 1], color = colors[i], label = 'points')
              plt.plot(graf[0], graf[1], color = colors_iso[i], linewidth= 8, label =
```



Conclusion: It can be observed that, from both equations for the resulting averages, the expected values of the centers are the same, and therefore, the noise effect can be disregarded when it comes to the average value in both cases. Therefore, we can see in the graph that there are larger and more deformed ellipses, which indicates that the noise is expressed in the action space rather than the state space.

In []: