## QNT 402 Quantum Information Homework 7

- 1. [35] *A simple model test*. In this problem we'll generate some fake data and then try to fit it to determine if modeling it as linear or quadratic function is more reasonable.
  - a.) [5] First generate some fake data using the Python code:

slope = 1 offset = 0.25 time = np.linspace(0,10,10) data = np.random.normal(slope\*time + offset,1) sigma = 1\*np.random.normal(np.ones(len(data)),0.01)

and plot it with the pyplot errorbar() function. This is obviously linear data but it's pretty noisy as you'll see.

- b.) [15] Now use curve\_fit to fit a linear function (bx + a) and a quadratic function  $(cx^2 + bx + a)$  and add the plot of the best fits to the plot with the data on it.
- c.) [15] Now calculate the  $\chi^2/\nu$  of each of these and try to determine which is a more likely model.
- 2. [25] *Variance vs. Slope detection: a more accurate comparison.* In class, we found that the minimum sensitivity for slope detection was:

$$\Phi_{min}^{slope} = \frac{\sigma_p}{\gamma t}$$

where, assuming the qubit state detection is given by a binomial distribution,  $\sigma_p = \frac{\sigma_{N1}}{N} = \sqrt{\frac{p_1(1-p_1)}{N}}$ . We said for  $p_1 \approx \frac{1}{2}$  this leads to the standard quantum limit of:

$$\Phi_{min}^{slope} = \frac{1}{2 v t \sqrt{N}}$$

Meanwhile for variance detection we found

$$\Phi_{min}^{variance} = \frac{\sqrt{\sigma_p}}{\gamma t}$$

We then said for detection at  $p \approx 0$  we expect  $\sigma_p = 0$  and therefore variance detection is not limited by quantum projection noise.

However, the approximation that  $p_1 \approx \frac{1}{2}$  for slope detection and  $p_1 \approx 0$  for variance detection are not quite true. Obviously if we are detecting a signal there is some change in  $p_1$ , so we have for slope detection  $p_1 \approx \frac{1}{2} + \delta p_1$  and  $p_1 \approx \delta p_1$ . Therefore, the uncertainty on  $\sigma_p$  is a bit different than we estimated above.

- a.) [20] Work out the expressions for  $\Phi_{min}$  both slope and variance including the corrections to  $p_1$  above. Make sure and write  $\delta p_1$  in terms of the sensitivity  $\gamma$ , the field strength  $\Phi$ , and the phase accumulation time t.
- b.) [5] What is the ratio of  $\Phi_{min}^{slope}/\Phi_{min}^{variance}$ ? Ignoring technical noise (which you can't do in the real world!), when is variance detection better than slope detection?

3. [50] Alright, alright, alright, let's work with some quantum data. In this problem we will generate data from a quantum sensing experiment. We know that for a Ramsey sequence (we worked it out last quarter) that for a qubit starting in |0⟩ the probability of finding the qubit in state 1 is given as:

$$P_1 = 1 - \frac{\Omega^2}{\Omega'^4} \left( \Omega' \cos \left( \frac{\delta t_w}{2} \right) \sin \left( \Omega' t_p \right) - 2\delta \sin \left( \frac{\delta t_w}{2} \right) \sin^2 \left( \frac{\Omega' t_p}{2} \right) \right)^2$$

This expression is for two  $\pi/2$  pulses of length  $t_p$  separated by a free evolution time of  $t_w$ .

- a.) [20] Write a Python function that generates realistic data for N repetitions of such a sequence. This function will output a value for  $P_1$  that comes from a binomial distribution described by the true value of  $P_1$  and the number of trials N. Use this function to make a plot of the "measured" values of  $P_1$  versus  $t_w$  for the a binomial the parameters  $\Omega = 2\pi$  and  $\delta = \frac{\pi}{4}$  for N = 1,10,100,1000.
- b.) [20] Now simulate the signal for slope detection. Find the wait time for the first  $P_1 = \frac{1}{2}$  point (i.e. the one near  $t_w = 2$ ) and plot  $P_1$  vs  $\Phi$  for  $-1 \le \Phi \le 1$ . Assume  $\gamma = 1$ . Make the plots for N = 1,10,100,1000. Also plot the expected signal we derived in class.
- c.) [10] Take the plot you made for N = 100 and add the expected signal plot to it as well as the expected signal plus  $\sigma_p$  and the expected signal minus  $\sigma_p$ . Is it what you expect?
- 4. [60] One last dance with the QHO. Here, we're going to examine the effect of squeezing on a QHO.
  - a.) [10]Define a Python function that that takes time, t, as its input and returns the time evolution operator a time t for the Hamiltonian  $H_o = \hbar\omega\left(\hat{a}^{\dagger}\hat{a} + \frac{1}{2}\right)$ . Use that function to calculate  $|\alpha(t)\rangle = \hat{U}(t)|\alpha\rangle$  for various times during the oscillation period of the oscillator. Plot the expectation value of position and momentum in the (x,p) plane for  $\alpha = 1$  make sure to make your basis is big enough for this size coherent state. Choose  $\omega = 2\pi$  and m = 1. Here, you'll likely find QuTip's displace() function handy.
  - b.) [10] Calculate  $\sigma_x$  and  $\sigma_p$  at each of the times you chose in part (a) and plot  $\sigma_x$ ,  $\sigma_p$ , and  $\sigma_x \sigma_p$  versus time.
  - c.) [15] QuTip has a function called squeeze() that implements the squeeze operator we discussed in class. Create a squeezed coherent state by first applying the squeeze operator (with squeeze parameter r = 1; fyi, QuTip uses z for the parameter r from class) and then applying the displacement operator used in part (a). Now, remake the plots of part (a) and part(b). What do you notice?
  - d.) [20] The squeeze operator is a bit of shortcut, so let's make sure we know how to implement it on real hardware. Add a drive to QHO of the form  $V = \beta_1 x \sin(2\omega t) + \beta_2 x^2 \sin(2\omega t)$  use e.g. sesolve to find the evolution. Choose  $\beta_1 = \beta_2 = 1$ . Make the same plots you made in part (a) and part (b). Is this squeezing?
  - e.) [5] What are the two terms in the potential V? Try setting e.g.  $\beta_1 = 0$  and describe what you see.