

1.) Poisson dist<sup>n</sup>:  $P(X=x) = \frac{\lambda^x e^{-\lambda}}{x!}$   $x = 0, 1, 2, \dots$

In the limit of large  $\lambda$ , show that Poisson dist<sup>n</sup>  $\rightarrow$  Normal dist<sup>n</sup>

Sterling's Approximation:  $x! \approx \sqrt{2\pi x} \left(\frac{x}{e}\right)^x$  good approx. if  $x$  is large.  
 Since  $\lambda$  large,  $P$  is only appreciable if  $x$  also is large.  
 So this approximation is quite good.

$$P(X=x) \approx \frac{\lambda^x e^{-\lambda} e^x}{\sqrt{2\pi x} x^x}$$

in order to expand this, we will approximate.  $x = \lambda + y$ , where  $|y| \ll \lambda$ .  
 Once again, this is since  $P$  is only appreciable when  $x$  is near  $\lambda$ .

$$P(X=x) \approx \frac{\lambda^{\lambda+y} e^{-\lambda} e^{\lambda+y}}{\sqrt{2\pi(\lambda+y)} (\lambda(1+\frac{y}{\lambda}))^{\lambda+y}}$$

approximate  $\sqrt{\lambda+y} \approx \sqrt{\lambda}$   
 introducing negligible error as  $(1+\frac{y}{\lambda}) \approx 1$

$$\ln P = y - \frac{1}{2} \ln(2\pi\lambda) - (\lambda+y) \ln(1+\frac{y}{\lambda})$$

Since  $|\frac{y}{\lambda}| \ll 1$ , expand  $\ln(1+\frac{y}{\lambda}) \approx \ln(1) + \frac{y}{\lambda} - \frac{y^2}{2\lambda^2} + \dots$

$$\ln P \approx y - \frac{1}{2} \ln(2\pi\lambda) - (\lambda+y) \left[ \frac{y}{\lambda} - \frac{y^2}{2\lambda^2} \right]$$

$$\ln P \approx y - \frac{1}{2} \ln(2\pi\lambda) - y + \frac{y^2}{2\lambda} - \frac{y^2}{\lambda} + \frac{y^3}{2\lambda^2}$$

get rid of terms  $O\left(\frac{y^2}{\lambda^2}\right)$  as  $\frac{y}{\lambda} \ll 1$

$$\ln P \approx -\frac{1}{2} \ln(2\pi\lambda) - \frac{y^2}{2\lambda}$$

$$P \approx \frac{1}{\sqrt{2\pi\lambda}} \exp\left(-\frac{y^2}{2\lambda}\right) \quad \text{recall: } x = \lambda + y \Rightarrow y = x - \lambda$$

$$\Rightarrow \underline{\underline{P \approx \frac{1}{\sqrt{2\pi\lambda}} \exp\left(-\frac{(x-\lambda)^2}{2\lambda}\right)}}$$

Given  $\sigma^2 = \lambda$  for Poisson distributions, this form matches the Gaussian distribution.

2.) See Email w/ attached Github Repo!

3.)  $n$  Gaussian distributed data pts., all with true stdev  $= \sigma$ .  
All have true (unknown) mean  $\lambda$ . What is ML error on  $\hat{\lambda}$ ?

$$\text{model: } \langle d \rangle = \begin{pmatrix} \frac{1}{\sigma^2} \\ \frac{1}{\sigma^2} \\ \vdots \\ \frac{1}{\sigma^2} \end{pmatrix} \lambda \quad \hat{\lambda} = \frac{\sum w_i d_i}{\sum w_i} \quad w_i = \frac{1}{\sigma_i^2}$$

$$\text{all errors are the same: } \sigma_i = \sigma: \quad \hat{\lambda} = \frac{\sum \frac{d_i}{\sigma^2}}{\sum \frac{1}{\sigma^2}} = \frac{\frac{d_1}{\sigma^2}}{\sum \frac{1}{\sigma^2}} + \frac{\frac{d_2}{\sigma^2}}{\sum \frac{1}{\sigma^2}} + \dots$$

$$\Rightarrow \text{Var}(\hat{\lambda}) = \frac{\sum \frac{\text{Var}(d_i)}{\sigma^4}}{\left(\sum \frac{1}{\sigma^2}\right)^2} = \frac{n \frac{\sigma^2}{\sigma^4}}{(n \frac{1}{\sigma^2})^2} = \frac{\sigma^2}{n}$$

$$\text{error on } \hat{\lambda} = \Delta\lambda = \sqrt{\text{Var}(\hat{\lambda})} = \sqrt{\frac{\sigma^2}{n}} = \frac{\sigma}{\sqrt{n}}$$

Now, if we get half of the errs on our data wrong by a factor  $\sqrt{2}$ , what is the true error on the new non-optimal mean?

$$\hat{\lambda} = \frac{\sum_{i=1}^{n/2} \frac{d_i}{\sigma^2} + \sum_{i=1}^{n/2} \frac{d_i}{(\sqrt{2}\sigma)^2}}{\sum_{i=1}^{n/2} \frac{1}{\sigma^2} + \sum_{i=1}^{n/2} \frac{1}{(\sqrt{2}\sigma)^2}}$$

$$\Rightarrow \text{Var}(\hat{\lambda}) = \frac{\sum_{i=1}^{n/2} \frac{\text{Var}(d_i)}{\sigma^4} + \sum_{i=1}^{n/2} \frac{\text{Var}(d_i)}{4\sigma^4}}{\left(\sum_{i=1}^{n/2} \frac{1}{\sigma^2} + \sum_{i=1}^{n/2} \frac{1}{2\sigma^2}\right)^2}$$

$$= \frac{\frac{n\sigma^2}{2\sigma^4} + \frac{n\sigma^2}{8\sigma^4}}{\left(\frac{n}{2\sigma^2} + \frac{n}{4\sigma^2}\right)^2} = \frac{\frac{5n}{8\sigma^2}}{\left(\frac{3n}{4\sigma^2}\right)^2} = \frac{10}{9} \frac{\sigma^2}{n}$$

$$\Rightarrow \Delta\lambda = \frac{\sqrt{10}}{3} \frac{\sigma}{\sqrt{n}}$$

factor of  $\frac{\sqrt{10}}{3} \approx 1.054$  different than mean when we get errs correct

Now we underweight 1% of data by factor of 100: fl 1%,  $w_i = \frac{1}{100\sigma^2}$

$$\hat{\lambda} = \frac{\sum_{i=1}^{99n/100} \frac{d_i}{\sigma^2} + \sum_{i=1}^{n/100} \frac{d_i}{100\sigma^2}}{\sum_{i=1}^{99n/100} \frac{1}{\sigma^2} + \sum_{i=1}^{n/100} \frac{1}{100\sigma^2}}$$

$$\Rightarrow \text{Var}(\hat{\lambda}) = \frac{\frac{99n}{100} \left[ \frac{\sigma^2}{\sigma^4} \right] + \frac{n}{100} \left[ \frac{\sigma^2}{100^2\sigma^4} \right]}{\left( \frac{99n}{100} \frac{1}{\sigma^2} + \frac{n}{100} \frac{1}{100\sigma^2} \right)^2} = \frac{0.990001 \frac{n}{\sigma^2}}{(0.9803 \frac{n}{\sigma^2})^2} = 1.009898 \frac{\sigma^2}{n}$$

$$\Rightarrow \Delta\lambda = 1.0049 \frac{\sigma}{\sqrt{n}} \quad \text{Close to true error: underweighting not a big deal}$$

overweight 1%: fl 1%,  $w_i = \frac{100}{\sigma^2}$

$$\hat{\lambda} = \frac{\sum_{i=1}^{99n/100} \frac{d_i}{\sigma^2} + \sum_{i=1}^{n/100} \frac{d_i (100)}{\sigma^2}}{\sum_{i=1}^{99n/100} \frac{1}{\sigma^2} + \sum_{i=1}^{n/100} \frac{100}{\sigma^2}}$$

$$\Rightarrow \text{Var}(\hat{\lambda}) = \frac{\frac{99n}{100} \left[ \frac{\sigma^2}{\sigma^4} \right] + \frac{n}{100} \left[ \frac{100^2 \sigma^2}{\sigma^4} \right]}{\left[ \frac{99n}{100} \frac{1}{\sigma^2} + \frac{n}{100} \frac{100}{\sigma^2} \right]^2}$$

$$= \frac{100.99 \frac{n}{\sigma^2}}{\left( 1.99 \frac{n}{\sigma^2} \right)^2} = 25.50 \frac{\sigma^2}{n}$$

$$\Rightarrow \underline{\underline{\Delta \lambda = 5.05 \frac{\sigma}{\sqrt{n}}}}$$

errors are a factor of 5 wrong!  
Overweighting errors very impactful.

4.) Assume model is correct:  $\langle d \rangle = A m_{\text{true}}$

least squares solution:  $\hat{m} = (A^T N^{-1} A)^{-1} A^T N^{-1} d$

$$\begin{aligned} \langle \hat{m} \rangle &= \langle (A^T N^{-1} A)^{-1} A^T N^{-1} d \rangle \\ &= (A^T N^{-1} A)^{-1} A^T N^{-1} \langle d \rangle \quad \text{but } \langle d \rangle = A m_{\text{true}} \\ &= (A^T N^{-1} A)^{-1} A^T N^{-1} A m_{\text{true}} \\ &= I m_{\text{true}} \end{aligned}$$

$$\Rightarrow \underline{\underline{\langle \hat{m} \rangle = m_{\text{true}}}}$$

5.) Github!