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# Chapter 1

## Introduction

### 1.1 Curve Fitting

#### Problem 1

This can be solved by substituting the definition of:

$$y(x, \mathbf{w}) = \sum_{j=0}^M w_j x^j$$

into the error function and then taking the derivative.

$$\begin{aligned} E(\mathbf{w}) &= \frac{1}{2} \sum_{n=1}^N (y(x, \mathbf{w}) - t_n)^2 \\ &= \frac{1}{2} \sum_{n=1}^N \left( \sum_{j=0}^M w_j x^j - t_n \right)^2 && \text{Substitute} \\ \frac{dE(\mathbf{w})}{dw_i} &= \sum_{n=1}^N \left( \left( \sum_{j=0}^M w_j x^j - t_n \right) x^i \right) && \text{Take the derivative} \\ 0 &= \sum_{n=1}^N \left( \left( \sum_{j=0}^M w_j x^j - t_n \right) x^i \right) && \text{Set derivative to 0} \\ 0 &= \sum_{n=1}^N \left( \sum_{j=0}^M w_j x^j x^i - t_n x^i \right) && \text{Set derivative to 0} \\ \sum_{n=1}^N t_n x^i &= \sum_{n=1}^N \sum_{j=0}^M w_j x^j x^i \\ \sum_{n=1}^N t_n x^i &= \sum_{n=1}^N \sum_{j=0}^M w_j x^{i+j} \end{aligned}$$

## Problem 2

This is solved in almost the same way we just have one additional term for the regularization so:

$$\begin{aligned} E(\mathbf{w}) &= \frac{1}{2} \sum_{n=1}^N (y(x, \mathbf{w}) - t_n)^2 + \frac{\lambda}{2} \|\mathbf{w}\|^2 \\ &= \frac{1}{2} \sum_{n=1}^N \left( \sum_{j=0}^M w_j x^j - t_n \right)^2 + \frac{\lambda}{2} \|\mathbf{w}\|^2 \end{aligned}$$

$$\frac{dE(\mathbf{w})}{dw_i} = \sum_{n=1}^N \left( \left( \sum_{j=0}^M w_j x^j - t_n \right) x^i \right) + \lambda w_i$$

$$-\lambda w_i = \sum_{n=1}^N \left( \left( \sum_{j=0}^M w_j x^j - t_n \right) x^i \right) + \lambda w_i$$

$$-\lambda w_i = \sum_{n=1}^N \left( \sum_{j=0}^M w_j x^j x^i - t_n x^i \right)$$

$$\sum_{n=1}^N t_n x^i - \lambda w_i = \sum_{n=1}^N \sum_{j=0}^M w_j x^j x^i$$

$$\sum_{n=1}^N t_n x^i - \lambda w_i = \sum_{n=1}^N \sum_{j=0}^M w_j x^{i+j}$$

## 1.2 Probability Theory

**Problem 3** The Probability of Selecting an Apple can be decomposed as:

$$\begin{aligned} \mathcal{P}(apple) &= \mathcal{P}(apple, red) + \mathcal{P}(apple, blue) + prob(apple, green) \\ &= \mathcal{P}(apple|red)\mathcal{P}(red) + \mathcal{P}(apple|blue)\mathcal{P}(blue) + \mathcal{P}(apple|green)\mathcal{P}(green) \\ &= (.3)(.2) + (.5)(.2) + (.3)(.6) \\ &= .34 \end{aligned}$$

The probability that observing an orange came from the green box

can be solved using Bayes rule:

$$\begin{aligned}\mathcal{P}(\text{green}|\text{orange}) &= \frac{\mathcal{P}(\text{orange}|\text{green})\mathcal{P}(\text{green})}{\mathcal{P}(\text{orange})} \\ &= \frac{(.3)(.6)}{.66} \\ &= .27\end{aligned}$$

## Problem 5

$$\begin{aligned}\text{Var}[X] &= \mathbb{E}[(X - \mathbb{E}[X])^2] \\ &= \mathbb{E}[X^2 - 2X\mathbb{E}[X] + \mathbb{E}[X]^2] && \text{Distributive Law} \\ &= \mathbb{E}[X^2] + \mathbb{E}[-2X\mathbb{E}[X]] + \mathbb{E}[\mathbb{E}[X]^2] && \text{Linearity of } \mathbb{E}[X] \\ &= \mathbb{E}[X^2] + -2\mathbb{E}[X\mathbb{E}[X]] + \mathbb{E}[X]^2 && \mathbb{E}[\alpha X] = \alpha\mathbb{E}[X] \\ &= \mathbb{E}[X^2] + -2\mathbb{E}[X]^2 + \mathbb{E}[X]^2 && \mathbb{E}[X] \text{ is just another constant} \\ &= \mathbb{E}[X^2] - \mathbb{E}[X]^2\end{aligned}$$

## Problem 6

$$\begin{aligned}\text{Cov}[X, Y] &= \mathbb{E}[X, Y] - \mathbb{E}[X]\mathbb{E}[Y] \text{ But because} \\ X \perp Y \Rightarrow \mathbb{E}[X, Y] &= \mathbb{E}[X]\mathbb{E}[Y] \Rightarrow \text{Cov}[X, Y] = 0\end{aligned}$$

## Problem 7

$$\begin{aligned}
I^2 &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \exp \left( -\frac{1}{2\sigma^2}x^2 - \frac{1}{2\sigma^2}y^2 \right) dx dy \\
&= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \exp \left( -\frac{1}{2\sigma^2}(x^2 + y^2) \right) dx dy \\
&= \int_0^{\infty} \int_0^{2\pi} \exp \left( -\frac{1}{2\sigma^2} [r^2 \cos^2(\theta) + r^2 \sin^2(\theta)] \right) r d\theta dr \\
&= \int_0^{\infty} \int_0^{2\pi} \exp \left( -\frac{r^2}{2\sigma^2} \right) r d\theta dr \\
&= 2\pi \int_0^{\infty} \exp \left( -\frac{r^2}{2\sigma^2} \right) r dr \\
&= 2\pi \int_0^{\infty} \exp \left( -\frac{u}{2\sigma^2} \right) \frac{1}{2} du \\
&= -2\pi\sigma^2 \exp \left( -\frac{u}{2\sigma^2} \right) \Big|_0^{\infty} \\
&= 2\pi\sigma^2
\end{aligned}$$

Now we just need to show that this normalizes the Gaussian. Take  $y = x - \mu$  then

$$\begin{aligned}
\mathcal{N}(x|\mu, \sigma^2) &= \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi\sigma^2}} \exp \left( -\frac{1}{2\sigma^2}(x - \mu)^2 \right) dx \\
&= \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi\sigma^2}} \exp \left( -\frac{1}{2\sigma^2}y^2 \right) dy
\end{aligned}$$

### Problem 8

$$\begin{aligned}
 \mathbb{E}[x] &= \int_{-\infty}^{\infty} \mathcal{N}(x|\mu, \sigma^2) x dx \\
 &= \int_{-\infty}^{\infty} \frac{x}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{1}{2\sigma^2}(x-\mu)^2\right) dx \\
 &= \frac{1}{\sqrt{2\pi\sigma^2}} \int_{-\infty}^{\infty} (y+\mu) \exp\left(-\frac{1}{2\sigma^2}y^2\right) dy \quad y = x - \mu
 \end{aligned}$$

Now split this into the sum of two integrals. The second integral has the form:

$$\frac{1}{\sqrt{2\pi\sigma^2}} \int_{-\infty}^{\infty} \mu \exp\left(-\frac{1}{2\sigma^2}y^2\right) dy$$

Which is just a normalized Gaussian times  $\mu$  so this is just  $\mu$ . Now since we are trying to prove that this equals  $\mu$  I'm fairly confident that the left integral will go to zero. Let's try and prove this.

$$\frac{1}{\sqrt{2\pi\sigma^2}} \int_{-\infty}^{\infty} y \exp\left(-\frac{1}{2\sigma^2}y^2\right) dy$$

Well if we visualize this function it looks odd which would imply that the integral from  $[-\infty, \infty]$  is 0. Let's prove that it is odd quickly. We want to show that  $f(x) = -f(-x)$  where  $f(x) = y \exp\left(-\frac{1}{2\sigma^2}y^2\right)$

$$-(-y) \exp\left(-\frac{1}{2\sigma^2}(-y)^2\right) = y \exp\left(-\frac{1}{2\sigma^2}y^2\right)$$

Thus our integral in question is odd and evaluates to 0 yielding  $\mu$  as the desired result.

Next we need to show that:

$$\mathbb{E} [x^2] = \int_{-\infty}^{\infty} \mathcal{N}(x|\mu, \sigma) x^2 dx = \mu^2 + \sigma^2$$

To do this differentiate both sides by  $\sigma^2$  as follows:

$$\begin{aligned} \frac{1}{\sqrt{2\pi\sigma^2}} \int_{-\infty}^{\infty} \exp\left(-\frac{1}{2\sigma^2}(x - \mu)^2\right) dx &= 1 \\ \int_{-\infty}^{\infty} \exp\left(-\frac{1}{2\sigma^2}(x - \mu)^2\right) dx &= \sqrt{2\pi\sigma^2} \\ \int_{-\infty}^{\infty} \frac{d}{d\sigma^2} \exp\left(-\frac{1}{2\sigma^2}(x - \mu)^2\right) dx &= \frac{d}{d\sigma^2} \sqrt{2\pi\sigma^2} \\ \frac{1}{2\sigma^4} \int_{-\infty}^{\infty} \exp\left(-\frac{1}{2\sigma^2}(x - \mu)^2\right) (x - \mu)^2 dx &= \frac{\pi}{\sqrt{(2\pi\sigma^2)}} \\ \int_{-\infty}^{\infty} \exp\left(-\frac{1}{2\sigma^2}(x - \mu)^2\right) (x - \mu)^2 dx &= \frac{2\pi\sigma^4}{\sqrt{(2\pi\sigma^2)}} \\ \frac{1}{\sqrt{2\pi\sigma^2}} \int_{-\infty}^{\infty} \exp\left(-\frac{1}{2\sigma^2}(x - \mu)^2\right) (x - \mu)^2 dx &= \sigma^2 \\ \text{Var}[x] &= \sigma^2 \end{aligned}$$

The left hand side of this equation is just the definition of variance. Now to complete the proof of (1.50) just use the alternate formulation of variance:

$$\begin{aligned}
\mathbb{E}[(x - \mu)^2] &= \mathbb{E}[x^2] - \mathbb{E}[x]^2 \\
&= \mathbb{E}[x^2] - \mu^2 && \text{By part 1} \\
\sigma^2 &= \mathbb{E}[x^2] - \mu^2 && \text{By above} \\
\mathbb{E}[x^2] &= \sigma^2 + \mu^2
\end{aligned}$$

**Problem 9**

$$\begin{aligned}
\mathcal{N}(x|\mu, \sigma^2) &= \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{1}{2\sigma^2}(x - \mu)^2\right) \\
\frac{d\mathcal{N}(x|\mu, \sigma^2)}{dx} &= -\frac{1}{\sigma^2} \mathcal{N}(x|\mu, \sigma^2)(x - \mu) \\
0 &= \mathcal{N}(x|\mu, \sigma^2)(x - \mu)
\end{aligned}$$

But since  $\mathcal{N}(x|\mu, \sigma^2)(x - \mu) > 0$  the only term that matters is  $(x - \mu)$ , which goes to 0 at  $x = \mu$

The proof for the multivariate case is almost identical and is omitted

**Problem 10**

$$\begin{aligned}
\log p(\mathbf{x}|\mu, \sigma^2) &= -\frac{1}{\sqrt{2\pi\sigma^2}} \sum_{n=1}^N (x_n - \mu)^2 - \frac{N}{2} \log \sigma^2 - \frac{N}{2} \log(2\pi) \\
\frac{d \log p(\mathbf{x}|\mu, \sigma^2)}{d\mu} &= -\frac{1}{\sqrt{\pi\sigma^2}} \sum_{n=1}^N (x_n - \mu) \\
0 &= \sum_{n=1}^N (x_n - \mu) \\
&= \sum_{n=1}^N x_n - \sum_{n=1}^N \mu \\
\mu &= \sum_{n=1}^N x_n
\end{aligned}$$

## Problem 11

Just take the derivative with respect to  $\mu$  of our function:

$$\ln(x|\mu, \sigma^2) = -\frac{1}{2\sigma^2} \sum_{n=1}^N (x_n - \mu)^2 - \frac{N}{2} \ln \sigma^2 - \frac{N}{2} \ln(2\pi)$$

$$\begin{aligned} \frac{d}{d\mu} \ln(x|\mu, \sigma^2) &= \frac{1}{\sigma^2} \sum_{n=1}^N x_n - \mu \\ 0 &= \sum_{n=1}^N x_n - \mu \\ \sum_{n=1}^N \mu &= \sum_{n=1}^N x_n \\ N\mu &= \sum_{n=1}^N x_n \\ \mu &= \frac{1}{N} \sum_{n=1}^N x_n \end{aligned}$$

Now repeat the same for  $\sigma^2$

$$\begin{aligned}
\frac{d}{d\mu} \ln(x|\mu, \sigma^2) &= \frac{1}{2\sigma^4} \sum_{n=1}^N (x_n - \mu)^2 - \frac{N}{2\sigma^2} \\
0 &= \frac{1}{2\sigma^4} \sum_{n=1}^N (x_n - \mu)^2 - \frac{N}{2\sigma^2} \\
\frac{N}{2\sigma^2} &= \frac{1}{2\sigma^4} \sum_{n=1}^N (x_n - \mu)^2 \\
\sigma^2 &= \frac{1}{N} \sum_{n=1}^N (x_n - \mu)^2
\end{aligned}$$

**Problem 17**

The gamma function is defined as:

$$\Gamma(x) = \int_0^\infty u^{x-1} e^{-u} du$$

We use integration by parts with the following substitutions

$$\begin{aligned}
u &= u^{x-1} & v &= -e^{-u} \\
du &= (x-1)u^{x-2}du & dv &= e^{-u}du
\end{aligned}$$

By integration by parts we have:

$$\begin{aligned}
\Gamma(x) &= -u^{x-1}e^{-u}|_0^\infty + (x-1) \int_0^\infty u^{x-2}e^{-u}du \\
&= (x-1) \int_0^\infty u^{x-2}e^{-u}du \\
&= (x-1)\Gamma(x-1) \\
&= z\Gamma(z) \quad z = x+1
\end{aligned}$$

Now see that  $\Gamma(1) = 1$

$$\begin{aligned}
\Gamma(1) &= \int_0^\infty u^0 e^{-u} du \\
&= \int_0^\infty e^{-u} du \\
&= -e^{-u}|_0^\infty \\
&= 1
\end{aligned}$$

To show that for all  $x \in \mathbb{Z}^+$   $\Gamma(x+1) = x!$  we use an inductive argument. Our base case is  $\Gamma(1) = 1$  which we have already done. Now let's assume that our inductive hypothesis is true and  $\Gamma(x+1) = x!$ . Then  $\Gamma(x+2) = (x+1)\Gamma(x+1) = (x+1)x!$  and we are done.

### Problem 18

We want to solve for  $S_D$  the surface area of a  $D$  dimensional sphere.

$$\prod_{i=1}^D \int_{-\infty}^\infty e^{-x_i^2} = S_D \int_0^\infty e^{-r^2} r^{D-1} dr$$

Let's solve the left hand side first. From problem 7 above we know that

$$\int_{-\infty}^{\infty} e^{-\frac{1}{2\sigma^2}x^2} = \sqrt{2\pi\sigma^2}$$

By setting  $\sigma^2 = \frac{1}{2}$  we get that

$$\begin{aligned} \prod_{i=1}^D \int_{-\infty}^{\infty} e^{-x_i^2} &= \prod_{i=1}^D \sqrt{\pi} \\ &= \pi^{\frac{D}{2}} \end{aligned}$$

Now let's look at the right hand side of the equation. We can tease this function into the Gamma function by making the substitution  $u = r^2$  which implies that  $dr = \frac{1}{2}u^{-1/2}du$ . With this insight we see that:

$$\begin{aligned} \int_0^{\infty} e^{-r^2} r^{D-1} dr &= \frac{1}{2} \int_0^{\infty} e^{-u} u^{\frac{D}{2}-1} du \\ &= \frac{1}{2} \Gamma(D/2) \end{aligned}$$

Now just use simple algebra:

$$\begin{aligned} \pi^{\frac{D}{2}} &= S_D \frac{1}{2} \Gamma(D/2) \\ S_D &= \frac{2\pi^{D/2}}{\Gamma(D/2)} \end{aligned}$$

Next integrate the surface area with respect to the radius in order to get the equation for volume:

$$\begin{aligned}
 V_D &= S_D \int_0^1 r^{D-1} dr \\
 &= S_D \left. \frac{r}{D} \right|_0^1 \\
 &= \frac{S_D}{D}
 \end{aligned}$$

Now to derive some common known volumes. For D = 2:

$$\begin{aligned}
 \frac{2\pi^{D/2}}{D\Gamma(D/2)} &= \frac{2\pi}{2\Gamma(1)} \\
 &= \pi
 \end{aligned}$$

For D=3:

$$\begin{aligned}
 \frac{2\pi^{D/2}}{D\Gamma(D/2)} &= \frac{2\pi^{3/2}}{3\Gamma(3/2)} \\
 &= \frac{2\pi^{3/2}}{\frac{3\sqrt{\pi}}{2}} \\
 &= \frac{4\pi}{3}
 \end{aligned}$$

### Problem 19