

Short HW1

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1 Variance of empirical mean

1.1

Given $\bar{X} = \frac{1}{m} \sum_i X_i$ and $E(X_i) = \mu$:

$$E(\bar{X}) \underbrace{=}_{\text{def of } \bar{X}} E\left(\frac{1}{m} \sum_i X_i\right) \underbrace{=}_{\text{linearity of E}} \frac{1}{m} \sum_i E(X_i) = \frac{1}{m} \sum_i \mu = \frac{1}{m} m \mu = \mu$$

1.2

Given $\text{var}(X_i) = \sigma^2$:

$$\begin{aligned} \text{var}(\bar{X}) &\underbrace{=}_{\text{def of } \bar{X}} \text{var}\left(\frac{1}{m} \sum_i X_i\right) = \left(\frac{1}{m}\right)^2 \text{var}\left(\sum_i X_i\right) \underbrace{=}_{\text{i.i.d}} \frac{1}{m^2} \sum_i \text{var}(X_i) = \frac{1}{m^2} \sum_i \sigma^2 \\ &= \frac{1}{m^2} m \sigma^2 = \frac{\sigma^2}{m} \end{aligned}$$

1.3

code

2 Identical coins and the Hoeffding bound

2.1

θ_i is a random variable describing the "success rate" (getting heads) of a series of binary trials (coin tossing) with fixed probability p .
Hence $\forall i : \theta_i \sim \text{Bin}(40, p)$.

2.2

The expected value of a random variable with Binomial distribution is np , hence
 $\forall i : E(\theta_i) = 40p$

2.3

According to Hoeffding's Inequality, $P[|\bar{\theta}(m) - \mu| > \epsilon] \leq 2\exp(-\frac{2m\epsilon^2}{(b-a)^2})$.

To achieve $P[|\bar{\theta}(m) - \mu| > \epsilon] \leq 0.05$ we need to find ϵ s.t. $2\exp(-\frac{2m\epsilon^2}{(b-a)^2}) = 0.05$
plugging in $m = 20, a = 0, b = 40$: we get:

$$2\exp(-\frac{2*20\epsilon^2}{40^2}) = 0.05$$

$$\exp(-\frac{\epsilon^2}{40}) = 0.025$$

$$-\frac{\epsilon^2}{40} = \ln(0.025)$$

$$\epsilon = 12.147$$

2.4

code

2.5

The estimators mean has a normal distribution. The central limit theorem explains this behavior. The theorem applies because the sample size is large enough ($tosses = 50 > 30$), the data points in the sample are independent of each other, and the variance is finite.

3 PSD matrices

3.1

$A\vec{v} = \lambda\vec{v}$ / multiply by \vec{v}^T from the left

$\vec{v}^T A\vec{v} = \vec{v}^T \lambda\vec{v}$ / A is PSD, hence $\forall \vec{v} : \vec{v}^T A\vec{v} \geq 0$

$\vec{v}^T \lambda\vec{v} \geq 0$ / λ is scalar

$\lambda \vec{v}^T \vec{v} \geq 0$ / $\vec{v}^T = (v_1, \dots, v_n)$

$\lambda \sum_i v_i^2 \geq 0$ / $\vec{v} \neq \vec{0}, \forall i : v_i^2 \geq 0 \Rightarrow \sum_i v_i^2 > 0$

$\lambda \geq 0$

3.2

$B^T A B$ is PSD. proof:

- $B^T A B$ is symmetric:

$$(B^T A B)^T = B^T A^T (B^T)^T \underbrace{=}_{A \text{ is symmetric}} B^T A B$$

- $\vec{v}^T (B^T A B) \vec{v} = (B\vec{v})^T A B\vec{v} \underbrace{=}_{\vec{x}=B\vec{v}} \vec{x}^T A \vec{x} \underbrace{\geq}_{A \text{ is PSD}} 0$

For $B^T A B$ to be PD we need $\vec{v}^T (B^T A B) \vec{v} > 0$

Looking at the last Inequality we got: $\vec{x}^T A \vec{x} \geq 0$ we infer two conditions:

1. A must be PD
2. B must be non-invertible

(\vec{x} must be a non zero vector. As $\vec{x} = B\vec{v}$ and \vec{v} could be any non-zero vector, we must demand that B will be non-invertible.)

4 Gradients

4.1

$$f(\vec{w}) = \vec{w}^T \vec{x} + b = \sum_i (w_i x_i) + b$$

$$\nabla_w f(\vec{w}) = \left(\frac{\partial f(\vec{w})}{\partial w_1}, \dots, \frac{\partial f(\vec{w})}{\partial w_d} \right) \underbrace{=}_{\frac{\partial f(\vec{w})}{\partial w_i} = x_i} (x_1, \dots, x_d) = \vec{x}$$

4.2

$$\nabla_w^2 f(\vec{w})_{m,n} = \frac{\partial^2 f(\vec{w})}{\partial w_m \partial w_n}$$

$$\forall m, n : x_m \text{ is independent of } w_n \Rightarrow \nabla_w^2 f(\vec{w})_{m,n} = 0 \Rightarrow \nabla_w^2 f(\vec{w}) = 0_{d \times d}$$

4.3

$0_{d \times d}$ is a PSD as:

$$\forall \vec{v} \neq \vec{0} : \vec{v}^T 0_{d \times d} \vec{v} = 0 \geq 0$$

4.4

$$g(\vec{w}) = \frac{1}{2} \lambda \|\vec{w}\|^2 = \frac{1}{2} \lambda \sum_i w_i^2$$

$$\nabla_w g(\vec{w}) = \left(\frac{1}{2} \lambda \cdot 2w_1, \dots, \frac{1}{2} \lambda \cdot 2w_d \right) = \lambda(w_1, \dots, w_d) = \lambda \vec{w}$$

4.5

$$\nabla_w^2 g(\vec{w})_{m,n} = \frac{\partial^2 g(\vec{w})}{\partial w_m \partial w_n} = \begin{cases} 0, & m \neq n \\ \lambda, & m = n \end{cases} \Rightarrow \nabla_w^2 g(\vec{w}) = \lambda I_{d \times d}$$

4.6

$\lambda I_{d \times d}$ is a PD as:

$$\forall \vec{v} \neq \vec{0} : \vec{v}^T \lambda I_{d \times d} \vec{v} = \lambda \vec{v}^T \vec{v} = \lambda \sum_i v_i^2 \underbrace{>}_{{\lambda > 0, \sum_i v_i^2 > 0}} 0$$

4.7

$$h(w_1, w_2) = 12w_1^3 - 36w_1w_2 - 2w_2^3 + 9w_2^2 - 72w_1 + 60w_2 + 5$$

$$\nabla_{\vec{w}} h(\vec{w}) = (36w_1^2 - 36w_2 - 72, -36w_1 - 6w_2^2 + 18w_2 + 60)$$

$$\nabla_{\vec{w}} h(\vec{w}) = 0 \Rightarrow \begin{cases} 36w_1^2 - 36w_2 - 72 = 0 \\ -36w_1 - 6w_2^2 + 18w_2 + 60 = 0 \end{cases} \Rightarrow \begin{cases} w_2 = w_1^2 - 2 \\ w_2^2 + 6w_1 - 3w_2 - 10 = 0 \end{cases} \xRightarrow{\text{plugging } w_2}$$

$$(w_1^2 - 2)^2 + 6w_1 - 3(w_1^2 - 2) - 10 = 0$$

$$w_1^4 - 4w_1^2 + 4 + 6w_1 - 3w_1^2 + 6 - 10 = 0$$

$$w_1(w_1^3 - 7w_1 + 6) = 0$$

$$w_1(w_1 + 3)(w_1 - 2)(w_1 - 1) = 0$$

$$\vec{w}^* = (0, -2), (-3, 7), (2, 2), (1, -1)$$

4.8

To determine max/min/saddle of the critical points, we will use the second partial derivative test. $h(w_1, w_2)$ is a polynomial real function, hence it is differentiable, and its second partial derivatives exist and are continuous.

$$\nabla_{\vec{w}}^2 h(\vec{w})_{1,1} = \frac{\partial^2 h(\vec{w})}{\partial^2 w_1} = 72w_1$$

$$\nabla_{\vec{w}}^2 h(\vec{w})_{1,2} = \frac{\partial^2 h(\vec{w})}{\partial w_1 \partial w_2} = -36$$

$$\nabla_{\vec{w}}^2 h(\vec{w})_{2,1} = \frac{\partial^2 h(\vec{w})}{\partial w_2 \partial w_1} = -36$$

$$\nabla_{\vec{w}}^2 h(\vec{w})_{2,2} = \frac{\partial^2 h(\vec{w})}{\partial^2 w_2} = -12w_2 + 18$$

$$|\nabla_{\vec{w}}^2 h(\vec{w})| = 72w_1 \cdot (-12w_2 + 18) - (-36) \cdot (-36) = -864w_1w_2 + 1296w_1 - 1296$$

calculating the det and second derivative at each critical point we get:

$$|\nabla_{\vec{w}}^2 h(0, -2)| = -1296 < 0 \Rightarrow \text{saddle point.}$$

$$|\nabla_{\vec{w}}^2 h(2, 2)| = -2160 < 0 \Rightarrow \text{saddle point.}$$

$$|\nabla_{\vec{w}}^2 h(-3, 7)| = 12,960 > 0 \text{ and } \frac{\partial^2 h(\vec{w})}{\partial^2 w_1} = -216 < 0 \Rightarrow \text{local Max.}$$

$$|\nabla_{\vec{w}}^2 h(1, -1)| = 864 > 0 \text{ and } \frac{\partial^2 h(\vec{w})}{\partial^2 w_2} = 30 > 0 \Rightarrow \text{local Min.}$$

4.9

$h(w_1, w_2)$ is not bounded from below or from above, hence it has no global min/max. proof:

$$h(w_1, 0) = 12w_1^3 - 72w_1 + 5$$

$$\lim_{w_1 \rightarrow \infty} h(w_1, 0) = \infty$$

$$h(0, w_2) = -2w_2^3 + 9w_2^2 + 5$$

$$\lim_{w_2 \rightarrow \infty} h(0, w_2) = -\infty$$