# Machine Learning/Deep Learning Pre-quiz AMSI Summer School 2023 

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Problem 1 Suppose we have a column vector $x$ and a square matrix $A$. Let $f(x)=x^{T} A x$. Show that

$$
\nabla f(x)=\left(A+A^{T}\right) x
$$

Problem 2 Suppose that $X$ is an $n \times m$ matrix, $U$ is an $n \times r$ matrix, and $V$ is an $r \times m$ matrix. Let $f(X, U, V)=\|X-U V\|_{2}^{2}$. Show that

$$
\nabla_{X} f(X, U, V)=-2 U^{T}(X-U V)
$$

Problem 3 Take the function $f(x, y)=\log \left(e^{x}+e^{y}\right)$. Show that the gradient of $f$ at $(0, \log (2))$ is given by $[1 / 3,2 / 3]$. Approximate $f$ at $\left(\epsilon_{1}, \log (2)+\epsilon_{2}\right)$ using the gradient.

Problem 4 Suppose you have two random variables $X, Y$ with joint density $p_{X, Y}(x, y)=4 x y$ for $x, y \in[0,1]$ and zero otherwise. What is the covariance of $X$ and $Y$ ?

Problem 5 You obtain a single observation which is the number 3 from the random variable which has density $\alpha \exp (-\alpha x)$ for some value $\alpha>0$. What is the maximum likelihood estimate for $\alpha$ ?

Problem 6 Show that the KL divergence $D(q \| p):=E_{q}[\log q-\log p]$ is nonnegative for all distribution $p$ and $q$.
Problem 7 For any random variable $X$ that follows a probability distribution $P$ with pdf $p$, the Shannon entropy is defined as $H(X)=-E_{x \sim P}[\log p(x)]$. We can similarly define the joint entropy $H(X, Y)$ of a pair of random variables $(X, Y)$ as $H(X, Y)=-E_{(x, y) \sim P}\left[\log p_{X, Y}(x, y)\right]$. The conditional entropy $H(Y \mid X)$ is defined as $H(Y \mid X)=-E_{(x, y) \sim P}[\log p(y \mid x)]$.
The mutual information of $(X, Y)$, written $I(X, Y)$, measure how much information is shared between $X$ and $Y$, loosely speaking. It is defined as

$$
I(X, Y)=H(X, Y)-H(Y \mid X)-H(X \mid Y)
$$

Test your intuition by confirming the following quantities are all equivalent to $I(X, Y)$ :

- $H(X)-H(X \mid Y)$
- $H(Y)-H(Y \mid X)$
- $H(X)+H(Y)-H(X, Y)$

