Foundations of Machine Learning: Mathematics Assessment

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When you hear or see the following, what do you think? (Not whether you already know what's written but whether you're comfortable with the notation and/or language.)
Let S be the subspace spanned by the orthonormal vectors a and b. Let p be the projection of the vector v into S. Let $r = v - p$ be the residual vector. Then $r \perp S$ and $\{r, a, b\}$ form an orthonormal set.
$\hfill\square$ You're speaking my language - totally comfortable.
\square Familiar, but rusty. I'll be ready to go by the start of class.
\square Never properly learned this. I need to get up to speed.
\square Wait, this is what I'm signing up for?
When you hear or see the following, what do you think? (Not whether you already know what's written but whether you're comfortable with the notation and/or language.)
Given some data $(x_1, y_1), \ldots, (x_n, y_n) \in \mathbf{R}^d \times \mathbf{R}$, the ridge regression solution for regularization parameter $\lambda > 0$ is given by
$\hat{w} = \underset{w \in \mathbf{R}^d}{\arg\min} \frac{1}{n} \sum_{i=1}^n \left\{ w^T x_i - y_i \right\}^2 + \lambda w _2^2,$
where $ w _2^2 = w_1^2 + \cdots + w_d^2$ is the square of the ℓ_2 -norm of w .
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When you hear or see the following, what do you think? (Not whether you already know what's written but whether you're comfortable with the notation and/or language.):
For "loss" function $\ell: \mathcal{Y} \times \mathcal{Y} \to \mathbf{R}$, define the "risk" of a function $f: \mathcal{X} \to \mathcal{Y}$ by
$R(f) = \mathbb{E}\ell\left(f(x), y\right),$
where the expectation is over $(x, y) \sim P_{\mathcal{X} \times \mathcal{Y}}$, a distribution over $\mathcal{X} \times \mathcal{Y}$.
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4. When you hear or see the following, what do you think? (Not whether you already know what's written, but whether you're comfortable with the notation and/or language.):
If we fix a direction $u \in \mathbf{R}^d$, we can compute the directional derivative $f'(x;u)$ as
$f'(x;u) = \lim_{h \to 0} \frac{f(x+hu) - f(x)}{h}.$
 □ You're speaking my language - totally comfortable. □ Familiar, but rusty. I'll be ready to go by the start of class. □ Never properly learned this. I need to get up to speed. □ Wait, this is what I'm signing up for?
5. How comfortable are you answering the following question:
Verify, just by multiplying out the expressions on the RHS, that the following "completing the square" identity is true: For any vectors $x, b \in \mathbf{R}^d$ and symmetric invertible matrix $M \in \mathbf{R}^{d \times d}$, we have
$x^{T}Mx - 2b^{T}x = (x - M^{-1}b)^{T}M(x - M^{-1}b) - b^{T}M^{-1}b $ (1)
 □ So easy. If I had a whiteboard here, I'd do it for you right now. □ Yeah - easy. I'll have the answer to you in 5 minutes - I just have to check something on Google first. □ Hmmmm. This will be easy by the first day of class. □ :(
6. How comfortable are you answering the following question:
Take the gradient of the following w.r.t. w :
$L(w, b, \xi, \alpha, \lambda) = \frac{1}{2} w ^2 + \frac{c}{n} \sum_{i=1}^{n} \xi_i + \sum_{i=1}^{n} \alpha_i \left(1 - y_i \left[w^T x_i + b \right] - \xi_i \right) - \sum_{i=1}^{n} \lambda_i \xi_i$
\square So easy. If I had a whiteboard here, I'd do it for you right now.
\square Yeah - easy. I'll have the answer to you in 5 minutes – I just have to check something on Google first.
\Box Hmmmm. This will be easy by the first day of class. \Box :(
7. How comfortable are you answering the following question:
Consider x_1, \ldots, x_n sampled i.i.d. from a distribution P on \mathbf{R} . Write $\mu = \mathbb{E}x$, for $x \sim P$. Show that the mean $\bar{x} = \frac{1}{n} \sum_{i=1}^{n} x_i$ is an unbiased estimate of μ (i.e. show that $\mathbb{E}\bar{x} = x$). Similarly, show that the sample variance $\frac{1}{n-1} \sum_{i=1}^{n} (x_i - \bar{x})^2$ is an unbiased estimate for $\operatorname{Var}(x)$.
 □ So easy. If I had a whiteboard here, I'd do it for you right now. □ Yeah - easy. I'll have the answer to you in 5 minutes - I just have to check something on
Google first.
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\sqcup :(