CS 189 Spring 2013 | Introduction to Machine Learning | **Midterm**

- You have 1 hour 20 minutes for the exam.
- The exam is closed book, closed notes except your one-page crib sheet.
- Please use non-programmable calculators only.
- Mark your answers ON THE EXAM ITSELF. If you are not sure of your answer you may wish to provide a *brief* explanation. All short answer sections can be successfully answered in a few sentences AT MOST.
- For true/false questions, fill in the *True/False* bubble.
- For multiple-choice questions, fill in the bubbles for **ALL** CORRECT CHOICES (in some cases, there may be more than one). For a question with p points and k choices, every false positive wil incur a penalty of $p/(k-1)$ points.

First name	
Last name	
SID	

For staff use only:

Q1.	True/False	/14
Q2.	Multiple Choice Questions	/21
Q3.	Short Answers	/15
	Total	/50

Q1. [14 pts] True/False

(a) [1 pt] In Support Vector Machines, we maximize $\frac{\|w\|^2}{2}$ subject to the margin constraints.

◯ True ◯ False

(b) [1 pt] In kernelized SVMs, the kernel matrix $\mathbf{K}$ has to be positive definite.

◯ True ◯ False

(c) [1 pt] If two random variables are independent, then they have to be uncorrelated.

◯ True ◯ False

(d) [1 pt] Isocontours of Gaussian distributions have axes whose lengths are proportional to the eigenvalues of the covariance matrix.

◯ True ◯ False

(e) [1 pt] The RBF kernel ($K(x_i, x_j) = exp(-\gamma\|x_i - x_j\|^2)$) corresponds to an infinite dimensional mapping of the feature vectors.

◯ True ◯ False

(f) [1 pt] If (X, Y) are jointly Gaussian, then X and Y are also Gaussian distributed.

◯ True ◯ False

(g) [1 pt] A function $f(x, y, z)$ is convex if the Hessian of f is positive semi-definite.

◯ True ◯ False

(h) [1 pt] In a least-squares linear regression problem, adding an L_2 regularization penalty cannot decrease the L_2 error of the solution w on the training data.

◯ True ◯ False

(i) [1 pt] In linear SVMs, the optimal weight vector w is a linear combination of training data points.

◯ True ◯ False

(j) [1 pt] In stochastic gradient descent, we take steps in the exact direction of the gradient vector.

◯ True ◯ False

(k) [1 pt] In a two class problem when the class conditionals $P(x|y = 0)$ and $P(x|y = 1)$ are modelled as Gaussians with different covariance matrices, the posterior probabilities turn out to be logistic functions.

◯ True ◯ False

(l) [1 pt] The perceptron training procedure is guaranteed to converge if the two classes are linearly separable.

◯ True ◯ False

(m) [1 pt] The maximum likelihood estimate for the variance of a univariate Gaussian is unbiased.

◯ True ◯ False

(n) [1 pt] In linear regression, using an L_1 regularization penalty term results in sparser solutions than using an L_2 regularization penalty term.

◯ True ◯ False

Q2. [21 pts] Multiple Choice Questions

(a) [2 pts] If $X \sim \mathcal{N}(\mu, \sigma^2)$ and $Y = aX + b$, then the variance of Y is:

○ $a\sigma^2 + b$ ○ $a^2\sigma^2 + b$ ○ $a\sigma^2$ ○ $a^2\sigma^2$

(b) [2 pts] In soft margin SVMs, the slack variables ξ_i defined in the constraints $y_i(w^T x_i + b) \geq 1 - \xi_i$ have to be

○ < 0 ○ ≤ 0 ○ > 0 ○ ≥ 0

(c) [4 pts] Which of the following transformations when applied on $X \sim \mathcal{N}(\mu, \Sigma)$ transforms it into an axis aligned Gaussian? ($\Sigma = UDU^T$ is the spectral decomposition of Σ)

○ $U^{-1}(X - \mu)$ ○ $(UD)^{-1}(X - \mu)$ ○ $UD(X - \mu)$

○ $(UD^{1/2})^{-1}(X - \mu)$ ○ $U(X - \mu)$ ○ $\Sigma^{-1}(X - \mu)$

(d) [2 pts] Consider the sigmoid function $f(x) = 1/(1 + e^{-x})$. The derivative $f'(x)$ is

○ $f(x) \ln f(x) + (1 - f(x)) \ln(1 - f(x))$ ○ $f(x)(1 - f(x))$

○ $f(x) \ln(1 - f(x))$ ○ $f(x)(1 + f(x))$

(e) [2 pts] In regression, using an L_2 regularizer is equivalent to using a ____________ prior.

○ Laplace, $2\beta \exp(-|x|/\beta)$ ○ Exponential, $\beta \exp(-x/\beta)$, for $x > 0$

○ Gaussian with $\Sigma = cI, c \in R$ ○ Gaussian with diagonal covariance ($\Sigma \neq cI, c \in R$)

(f) [2 pts] Consider a two class classification problem with the loss matrix given as $\begin{pmatrix} \lambda_{11} & \lambda_{12} \\ \lambda_{21} & \lambda_{22} \end{pmatrix}$. Note that λ_{ij} is the loss for classifying an instance from class j as class i. At the decision boundary, the ratio $\frac{P(\omega_2|x)}{P(\omega_1|x)}$ is equal to:

○ $\frac{\lambda_{11}-\lambda_{22}}{\lambda_{21}-\lambda_{12}}$ ○ $\frac{\lambda_{11}-\lambda_{21}}{\lambda_{22}-\lambda_{12}}$ ○ $\frac{\lambda_{11}+\lambda_{22}}{\lambda_{21}+\lambda_{12}}$ ○ $\frac{\lambda_{11}-\lambda_{12}}{\lambda_{22}-\lambda_{21}}$

(g) [2 pts] Consider the L_2 regularized loss function for linear regression $L(w) = \frac{1}{2}\|Y - Xw\|^2 + \lambda\|w\|^2$, where λ is the regularization parameter. The Hessian matrix $\nabla_w^2 L(w)$ is

○ $X^T X$ ○ $2\lambda X^T X$ ○ $X^T X + 2\lambda I$ ○ $(X^T X)^{-1}$

(h) [2 pts] The geometric margin in a hard margin Support Vector Machine is

○ $\frac{\|w\|^2}{2}$ ○ $\frac{1}{\|w\|^2}$ ○ $\frac{2}{\|w\|}$ ○ $\frac{2}{\|w\|^2}$

(i) [3 pts] Which of the following functions are convex?

○ $\sin(x)$ ○ $|x|$ ○ $\min(f_1(x), f_2(x))$, where f_1 and f_2 are convex ○ $\max(f_1(x), f_2(x))$, where f_1 and f_2 are convex

Q3. [15 pts] Short Answers

(a) [4 pts] For a hard margin SVM, give an expression to calculate b given the solutions for w and the Lagrange multipliers $\{\alpha_i\}_{i=1}^N$.

(b) Consider a Bernoulli random variable X with parameter p ($P(X=1)=p$). We observe the following samples of X: $(1,1,0,1)$.

(i) [2 pts] Give an expression for the likelihood as a function of p.

(ii) [2 pts] Give an expression for the derivative of the negative log likelihood.

(iii) [1 pt] What is the maximum likelihood estimate of p?

(c) [6 pts] Consider the weighted least squares problem in which you are given a dataset $\{\tilde{x}_i, y_i, w_i\}_{i=1}^N$, where w_i is an importance weight attached to the i^{th} data point. The loss is defined as $L(\beta) = \sum_{i=1}^N w_i(y_i - \beta^T x_i)^2$. Give an expression to calculate the coefficients $\tilde{\beta}$ in closed form.
Hint: You might need to use a matrix W such that $diag(W) = [w_1 w_2 \ldots w_N]^T$
.

Scratch paper

Scratch paper