Final exam, 機器學習, Fall 2020. Closed book, no calculators/cell phones allowed. Answers may include e^2 , $\sqrt{2}$, etc. but simplify when possible.

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The above contour plots represent bivariate normal distributions $\mathcal{N}(\mu_X, \mu_Y, \sigma_X, \sigma_Y, \rho)$, over (X,Y); with X plotted on the horizontal axis, and Y on the vertical axis. Six different plots are presented. For all six $(\mu_X, \mu_Y) = (0, 0)$ and $\sigma_x = 1$. For each distribution: $\sigma_Y \in \{0.7, 1, 1.5\}, \rho \in \{0.0, 0.2, 0.5, 0.9\}$.

ID	σ_Y	ρ	Comment
А			
В			
С			
D			
Е			
F			

Your Name: _____

Problem 2.

Question 2a Give (and justify) the simplest example you can find of a joint probability distribution over variables $\{A, B, C\}$. Such that A and B are pairwise independent but $A \not\bowtie B | C$.

Question 2b Give (and justify) the simplest example you can find of a joint probability distribution over variables $\{A, B, C\}$. Such that $A \perp B \mid C$, but A and B are **not** pairwise independent.

Your Name: _

Problem 3.

Assume we know of two linear functions of x:

$$F_1(x) = mx + b_1; \quad F_2(x) = mx + b_2$$

with known values of m, b_1 , and b_2 , with $b_1 < b_2$.

Further suppose we have n points of data in the form of x, y points (e.g. the point (x=0,y=0) or (x=2,y=3), etc.) where some of the points were generated by: $y_i = F_1(x_i) + \mathcal{N}(0, \sigma_1^2)$ and some of the points were generated by $y_i = F_2(x_i) + \mathcal{N}(0, \sigma_2^2)$. We are not told which points are from which function, but we are told that the ratio of points from F_1 to those from F_2 is $\sigma_1 : \sigma_2$, i.e. the number of points from F_1 is $\frac{n\sigma_1}{\sigma_1+\sigma_2}$.

Question: in terms of parameters given above $(m, b_1, b_2, \sigma_1, \sigma_2)$ give an optimal decision rule for classifying a point (x, y) as belonging to F_1 or F_2 . Where optimal means fewest expected mistakes.

Your Name: _

Problem 4. Background:

Recall two methods we discussed for deciding priors; Laplace and Jeffreys. The Laplace method places a uniform distribution over the parameter to be estimated, while the more complicated Jeffreys method guarantees equivalent priors regardless of the problem parameterization.

The most common way to parameterize a 'coin-flipping' problem uses p: the probability of 'success' (e.g. the probability of heads for a coin). For this purposes of this question, I call this the "*p*-parameterization". The likelihood function is:

$$\mathcal{L}(p; n_0, n_1) = \binom{n}{n_0} (1-p)^{n_0} p^{n_1}$$
(2)

Where $n = n_0 + n_1$ is the total number of data samples, and n_0 and n_1 denote the number of failures and successes respectively.

We can use a beta distribution to represent the prior probability distribution of p; convenient because it is conjugate to the likelihood function. Recall the standard beta distribution is defined as:

$$\operatorname{Beta}(p;\alpha,\beta) \stackrel{\text{\tiny def}}{=} \frac{p^{\alpha-1}(1-p)^{\beta-1}}{\mathcal{B}(\alpha,\beta)}, \qquad \text{ where } \mathcal{B}(\alpha,\beta) \stackrel{\text{\tiny def}}{=} \frac{\Gamma(\alpha)\Gamma(\beta)}{\Gamma(\alpha+\beta)}$$

Question 4a Under the Jeffreys prior, what is the prior probability of p = 0.5 divided by that of p = 0.75? In other words, using the notation pd(p = x) to represent the probability density of p = x for some $x, 0 \le x \le 1$, what is pd(p = 0.5)/pd(p = 0.75)?

Question continued on next page.

Problem 4. (continued)

An alternative parameterization of uses the ratio of the probability of success to failure: $r = \frac{p}{1-p}$. Here I will denote this as the "r-parameterization".

Question 4b Write the likelihood function in terms of r.

Question 4c Assuming we use Jeffreys method to compute the prior for the *r*-parameterization. What should pd(r = 1)/pd(r = 3) be?

Your Name: _

Problem 5.



The graph above is a Bayesian network with nodes {A,B,C,D,E,F,G}, but, except A, the node labels are hidden. The graph structure implies the following relationships:

Pairwise dependencies: A,B; A,D; A,G; B,E; D,E

Conditional independencies: A,B|F; A,D|F; A,D|G; D,F|G; D,E|F

Conditional dependencies: A,B|C; A,B|D; A,E|F; C,D|B

(at least, the above list not complete).

Question: What labeling of the nodes is consistent with those independence relationships? In the graph at top, fill in node names.