| ~ | 1/1 points |
|--|--|
| 1. | |
| Prior | is said to be conjugate to a likelihood function if: |
| 0 | the prior, the likelihood function and the posterior would be in a same family of distributions |
| 0 | the posterior would stay in the same family of distributions as prior |
| _ | |
| | rrect sterior and prior are both distributions over $	heta$, so they can lie in the same family |
| 0 | the prior is from the same family of distributions as the likelihood |
| 0 | the prior lies in the same family of distributions as the likelihood |
| ~ | 1/1 points |
| 2. | |
| Finding a conjugate prior is useful because: | |
| | It leads to a better MAP estimate |
| _ | |
| Ur | -selected is correct |
| | We can perform analytical inference and find posterior distribution instead of taking point MAP estimate |
| | rrect |
| Sir | ce posterior lies in a known family of distributions, we will be able to perform analytical inference |
| | It is the only prior for which it is possible to perform analytical inference |
| Ur | -selected is correct |
| | As long as posterior will stay in the same family with prior, the integral $p(x_{new} \mid x) = \int p(x_{new} \mid \theta) p(\theta \mid x) d\theta$ which is used for prediction is also tractable |
| | rrect is integral is called the evidence and it can be computed analytically if prior, likelihood and posterior are known |
| ✓ 3. | 1/1 points |
| | |

| Out of the following pairs of priors and likelihood functions, choose those that are conjugate: |
|---|
| $\Gamma(\lambda \mid \alpha, \beta) \text{ prior over parameter } \lambda \text{ of } Exp(x \mid \lambda) \text{ likelihood } (\Gamma(x, \mid \alpha, \beta) = \frac{\beta^{\alpha}}{\Gamma(\alpha)} x^{\alpha - 1} e^{-\beta x} \text{ and } Exp(x \mid \lambda) = \lambda e^{-\lambda x})$ |
| Correct Multiplying these distribution and grouping the terms will lead to gamma distribution again |
| $igsqcup \mathcal{N}(\mu_1 m,s^2)$ prior over parameter μ_1 for $\mathcal{N}(X \mu_1,\sigma_1^2)$ likelihood |
| Correct This example was discussed in a lecture |
| $\ \ \ \ \ \Gamma(\sigma_1^2 lpha,eta)$ prior over parameter σ_1^2 of $\mathcal{N}(X \mu_1,\sigma_1^2)$ likelihood |
| Un-selected is correct |
| $igcap \mathcal{N}(\sigma_1^2 m,s^2)$ prior over parameter σ_1^2 of $\mathcal{N}(X \mu_1,\sigma_1^2)$ likelihood |
| Un-selected is correct |
| ✓ 1/1 points |
| |
| 4. |
| 4. Which of the following prior distributions over parameter σ^2 are conjugate to likelihood $\mathcal{N}(x \mid \mu, \sigma^2)$? |
| |
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| Which of the following prior distributions over parameter σ^2 are conjugate to likelihood $\mathcal{N}(x \mid \mu, \sigma^2)$? Inverse gamma with pdf $p(\sigma^2 \mid \alpha, \beta) = \frac{\beta^{\alpha}}{\Gamma(\alpha)(\sigma^2)^{-\alpha-1} \exp\left(-\frac{\beta}{\sigma^2}\right)}$ Correct |
| Which of the following prior distributions over parameter σ^2 are conjugate to likelihood $\mathcal{N}(x \mid \mu, \sigma^2)$? Inverse gamma with pdf $p(\sigma^2 \mid \alpha, \beta) = \frac{\beta^{\alpha}}{\Gamma(\alpha)(\sigma^2)^{-\alpha-1} \exp\left(-\frac{\beta}{\beta^2}\right)}$ Correct Multiplying these distribution and grouping the terms will lead to normal distribution |
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| Which of the following prior distributions over parameter σ^2 are conjugate to likelihood $\mathcal{N}(x \mid \mu, \sigma^2)$? Inverse gamma with pdf $p(\sigma^2 \mid \alpha, \beta) = \frac{\beta^{\alpha}}{\Gamma(\alpha)(\sigma^2)^{\alpha-1}\exp(-\frac{\beta}{2})}$ Correct Multiplying these distribution and grouping the terms will lead to normal distribution $Exp(\sigma^2 \mid \lambda) = \lambda e^{-\lambda \sigma^2}$ Un-selected is correct Scaled inverse chi-squared with pdf $f(\sigma^2 \mid \nu, \tau) = \frac{(\tau^2 \nu/2)^{\alpha/2} \exp(-\frac{\nu^2}{2})}{\Gamma(\nu/2)}$ Correct Multiplying these distribution and grouping the terms will lead to normal distribution |

| 5. |
|--|
| Choose the correct statements: |
| For arbitrary likelihood and prior pair, we can always perform inference and compute posterior analytically |
| Un-selected is correct |
| Although not for every pair of prior and likelihood there is an analytical expression for posterior, we can always find a conjugate prior in some simple family and compute posterior analytically |
| Un-selected is correct |
| Putting initial knowledge into prior distribution is an advantage of Bayesian approach |
| Correct That's the one |
| For some problems conjugate prior may be inadequate Correct That's true |
| ✓ 1/1 points |
| 6. |
| Imagine that you want to pat your friend's cat Becky. Cats are really random creatures. |
| Becky might get grumpy and scratch you with probability p or curl up and start purring (with prob. $1-p$). You don't know Becky well yet, so you estimate prior on p to be distributed as $Beta(2,2)$. Within one evening, Becky has scratched you 6 times and only 2 times she purred. What will be the parameters for posterior distribution over p ? What is the MAP-estimate for p ? |
| Enter your answers separated by comma: e.g. if you think that correct answer is $Beta(1,0.2)$ and MAP is 3, you should enter 1,0.2,3. Express real numbers as decimals with dot as delimiter. |
| Enter answer here |
| Correct Response |
| |