Models

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1 The Prior

1.1 Theory

Question 1.1

A Gaussian likelihood encodes the inherent noise present in most real-world data. In other words, most probabilistic processes in nature tend to be noisy, and that noise tends to follow a Gaussian distribution. Hence this is generally a good place to start.

Noise in input data - assume noise is gaussian -> implies gaussian likelihood

Question 1.2

Choosing a spherical covariance matrix essentially means that we are assuming that the input noise is going to be equal in all directions, i.e. the distribution is equally likely to deviate from the mean in all directions. Again, this is a good place to start. Choosing a non-spherical covariance would imply that we know something in advance about the relationship between the input and output, which is not true in this case.

Question 2

TODO The covariance matrix would not be in terms of the identity matrix (for some reason). We would have non-zero values in the offset diagonals which correspond to the correlations between different things.

1.1.1 Linear Regression

Question 3

$$p(\mathbf{Y}|\mathbf{X}, \mathbf{W}, \beta) = \prod_{i=0}^{N} \mathcal{N}(y_i|\mathbf{W}^T \phi(x_i), \beta^-1) \tag{1}$$

Question 4

A distribution is conjugate to another if they both take the same algebraic form, i.e. are in the same probability distribution family. For example, Gaussians are conjugate to each other, and the conjugate to a Bernoulli distribution is a Beta distribution. Conjugates are used as a convenience used to avoid calculating the denominator in Baye's rule (the evidence) which can often be a tricky integral. If the prior and likelihood are conjugate, then their product will be proportional to the posterior.

Question 5

Euclidean distance from the mean

X appears only in the gaussian exponential part

Question 6

Derive posterior mean and covariance, start at conjugacy. Watch video https://www.youtube.com/watch?v=nrd4AnDLR3U

1.1.2 Non-parametric Regression

Question 7

Non-parametric: not defining parameters, just using what we know about the current data to classify new data points The simplest example of a. non-parementric model is a K-nearest neieghbour nmodel. The data are the parameters

Interpretability:

Question 8

This prior represents the space of all possible functions.

We think that smooth functions are more likely, but non-smooth functions e.q. sawtooth are non-zero but very unlikely

Question 9

All possible functions? Yes, but some are more likely than others

Question 10

$$p(\mathbf{Y}, \mathbf{X}, f, \theta) = p(Y|f)p(F|X, \theta)p(X)p(\theta) \tag{2}$$

Assumptions: - a - b

Question 11

The marginal in Eq. 2 connects the prior and the data ...

The uncertainty "filters" through this ...

The fact that θ is left on the LHS of the expression after marginalisation means that ...

Use the model diagram to help?

1.2 Practical

1.2.1 Linear Regression

Question 12.1

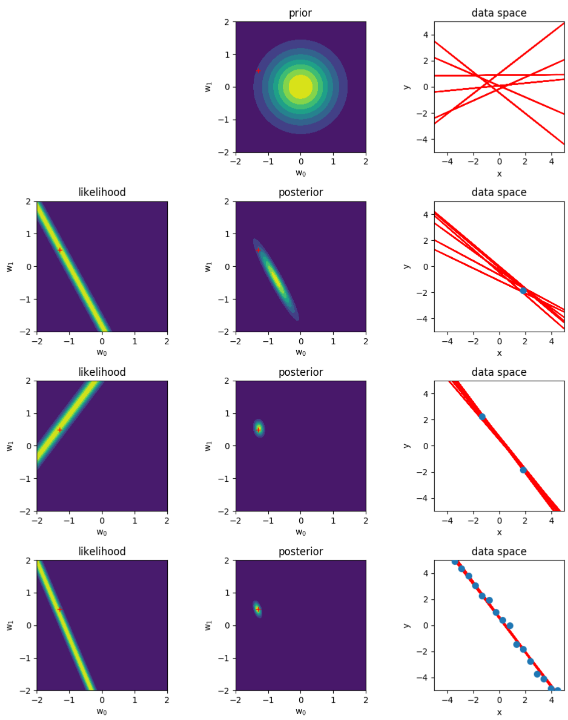

Figure 1: *TODO.*

2 Posterior

$$f \sim \mathcal{N}\left(\mathbf{0}, \beta^{-1}\mathbf{I}\right) \tag{3}$$
$$\beta \sim \Gamma(a) \tag{4}$$

3 Evidence