Lecture 15: Spatial Prediction and Model Selection

Conditional Multivariate Normal Theory

The conditional distribution, $p(Y_1|Y_2, \beta, \sigma^2, \phi, \tau^2)$ is normal with:

- $E[Y_1|Y_2] = \mu_1 + \Omega_{12}\Omega_{22}^{-1}(Y_2 \mu_2)$
- $Var[Y_1|Y_2] = \Omega_{11} \Omega_{12}\Omega_{22}^{-1}\Omega_{21}$

Posterior Predictive Distribution

The (posterior) predictive distribution $p(Y(s_0)|y)$ can be written as

$$p(Y(s_0)|y) = \int p(Y(s_0)|y, \boldsymbol{\theta}) p(\boldsymbol{\theta}|y) d\boldsymbol{\theta}$$

where $\boldsymbol{\theta} = \{\boldsymbol{\beta}, \sigma^2, \phi, \tau^2\}.$

The posterior predictive distribution gives a probabilistic forecast for the outcome of interest that does not depend on any unknown parameters.

These are the individual samples for a specific point that we have seen in STAN.

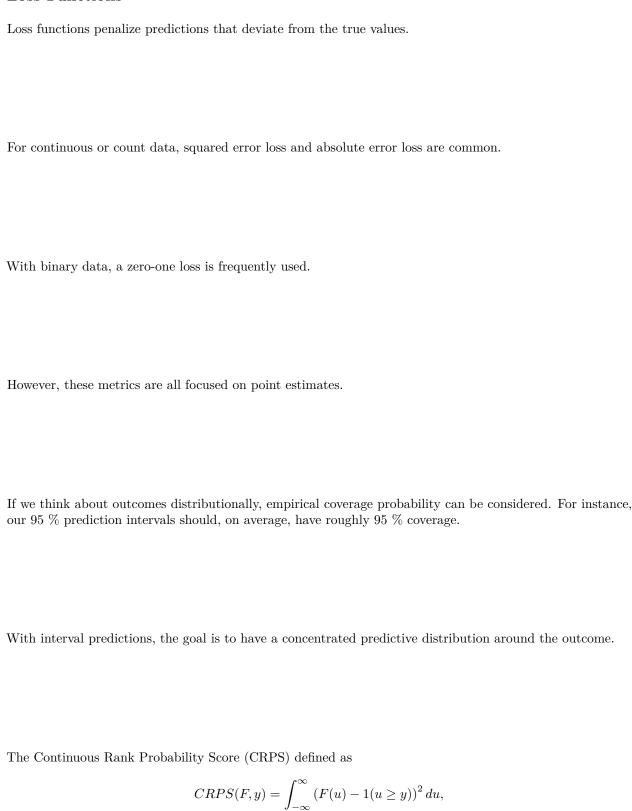
Prediction

We will use cross-validation or a test/training approach to compare predictive models.

Consider three data structures: continuous, count, and binary; how should we evaluate predictions in these situations?

Loss Functions

value and a distribution.



where F is the CDF of the predictive distribution, is a metric that measures distance between an observed

CRPS

Consider fou	r situations a	nd sketch	the predictive	${\it distribution}$	and the	he resultant	CRPS for	${\rm each}$	scenario
How does the	MSE function	on in each	setting?						

low	does the MSE function in each setting?
1.	Narrow predictive interval centered around outcome.
2.	Wide predictive interval centered around outcome.
3.	Narrow predictictive interval with outcome in tail.
4.	Wide predictive interval with outcome in tail.