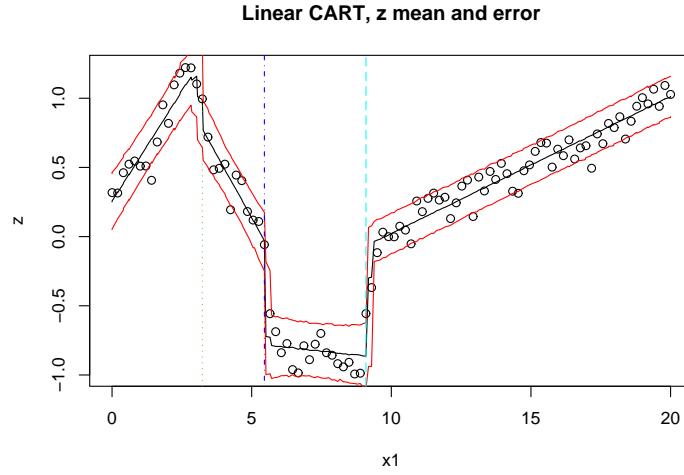


```
> plot(sin.btlm, main = "Linear CART,", layout = "surf")
```



```
> tgp.trees(sin.btlm)
```

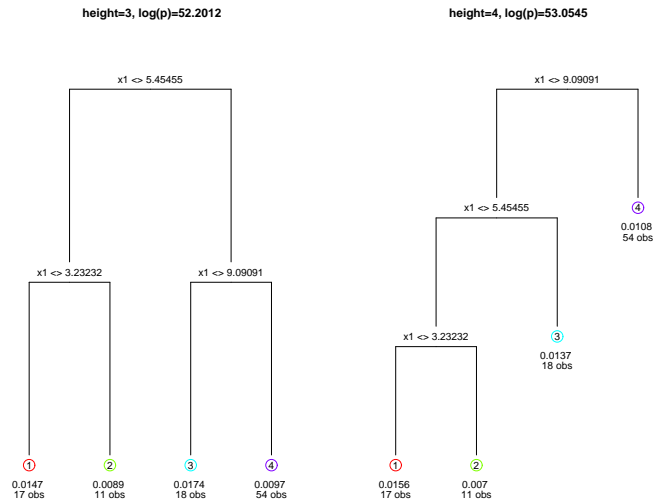
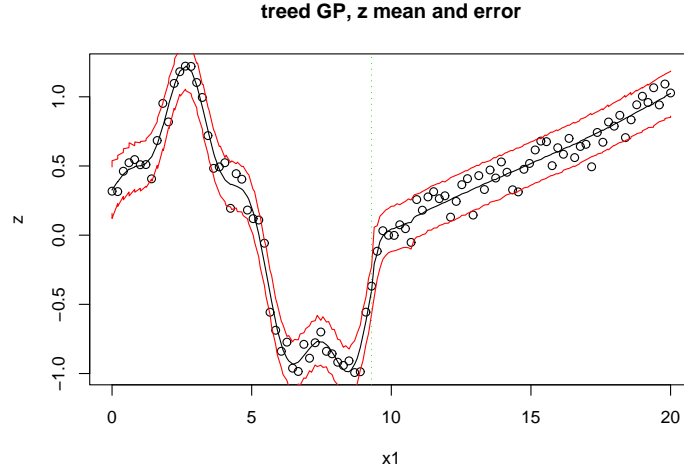


Figure 6: *Top*: Posterior predictive distribution using `btlm` on synthetic sinusoidal data: mean and 90% credible interval, and MAP partition (\hat{T}); *Bottom* MAP trees for each height encountered in the Markov chain showing $\hat{\sigma}^2$ and the number of observation n , at each leaf.

3.3 Synthetic 2-d Exponential Data

The next example involves a two-dimensional input space in $[-2, 6] \times [-2, 6]$. The true response is given by

$$z(\mathbf{x}) = x_1 \exp(-x_1^2 - x_2^2). \quad (15)$$



```
> tgp.trees(sin.btgp)
```

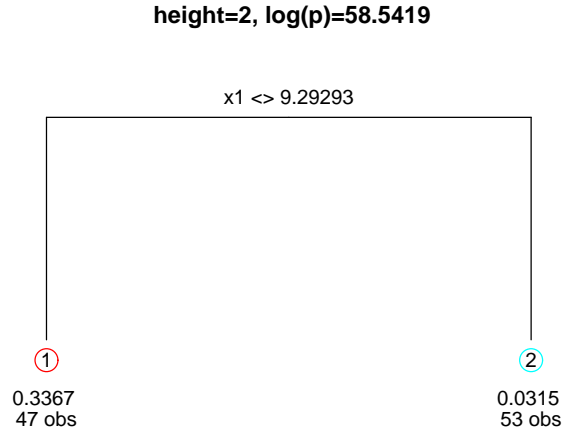


Figure 7: *Top*: Posterior predictive distribution using **btgp** on synthetic sinusoidal data: mean and 90% credible interval, and MAP partition (\hat{T}); *Bottom* MAP trees for each height encountered in the Markov chain.

A small amount of Gaussian noise (with $sd = 0.001$) is added. Besides its dimensionality, a key difference between this data set and the last one is that it is not defined using step functions; this smooth function does not have any artificial breaks between regions. The **tgp** package provides a function for data subsampled from a grid of inputs and outputs described by (15) which concen-

trates inputs (\mathbf{X}) more heavily in the first quadrant where the response is more interesting. Predictive locations (\mathbf{XX}) are the remaining grid locations.

```
> exp2d.data <- exp2d.rand()
> X <- exp2d.data$X
> Z <- exp2d.data$Z
> XX <- exp2d.data$XX
```

Linear CART is clearly just as inappropriate for this data as it was for the sinusoidal data in the previous section. However, a stationary GP fits this data just fine. After all, the process is quite well behaved. In two dimensions one has a choice between the isotropic and separable correlation functions. Separable is the default in the `tgp` package. For illustrative purposes here, I shall use the isotropic power family.

```
> exp.bgp <- bgp(X = X, Z = Z, XX = XX, corr = "exp")

> plot(exp.bgp, main = "GP,")
```

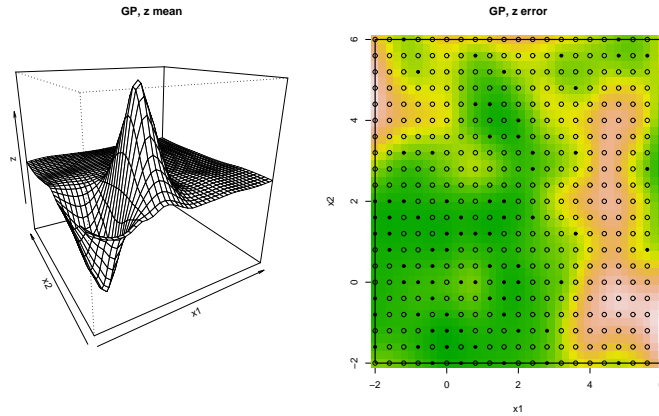


Figure 8: *Left*: posterior predictive mean using `bgp` on synthetic exponential data; *right* image plot of posterior predictive variance with data locations \mathbf{X} (dots) and predictive locations \mathbf{XX} (circles).

Progress indicators are suppressed. Figure 8 shows the resulting posterior predictive surface under the GP in terms of means (*left*) and variances (*right*) in the default layout. The sampled locations (\mathbf{X}) are shown as dots on the *right* image plot. Predictive locations (\mathbf{XX}) are circles. Predictive uncertainty for the stationary GP model is highest where sampling is lowest, despite that the process is very uninteresting there.

A treed GP seems more appropriate for this data. It can separate out the large uninteresting oart of the input space from the interesting part. The result is speedier inference and region-specific estimates of predictive uncertainty.

```
> exp.btgp <- btgp(X = X, Z = Z, XX = XX, corr = "exp")
```