Implosion_bias

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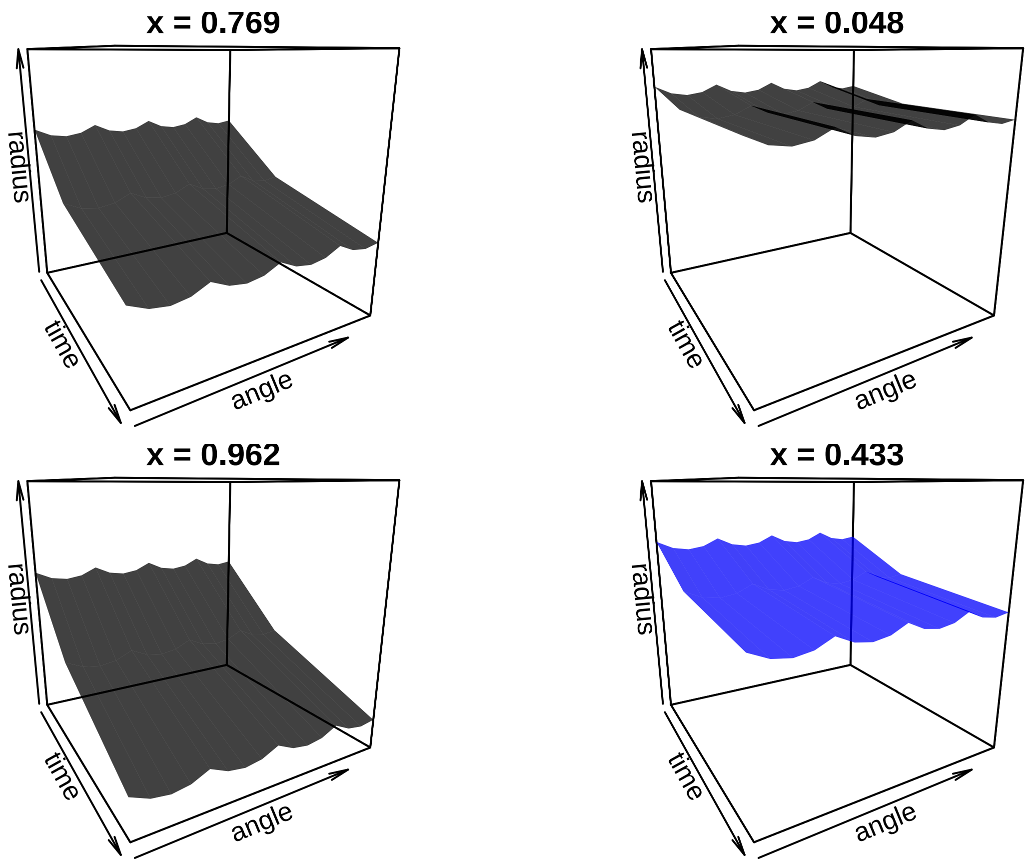
Here we consider the same Implosion experiment, however this time we add a periodic angle effect to the experimental data. Our simulator is no longer unbiased, so we must use the biased calibration techniques developed in Section 3.1 of laGP_calibration.pdf. In this example we will not add any noise to the data. We will see that the discrepancy model does a good job at learning the shape of this simple bias.

Below we show the observed data over time and angle for each of the four inputs. The first three will be used to calibrate and train the discrepancy model, the last will be kept as hold-out. Simulations are generated exactly as in Implosion_nobias.Rmd.



Data is pre-processed as usual. Details can be found in balldrop1_nobias.Rmd.

```
XTdata = transform_xt(Xsim,Tsim,Xobs,Tobs)
Ydata = transform_y(Ysim,YindSim,Yobs,YindObs,center = T,scale = T)

simBasis = get_basis(Ydata$sim$trans,nPC)
obsBasis = get_obs_basis(simBasis,Ydata$obs$trans,YindSim,YindObs,
```

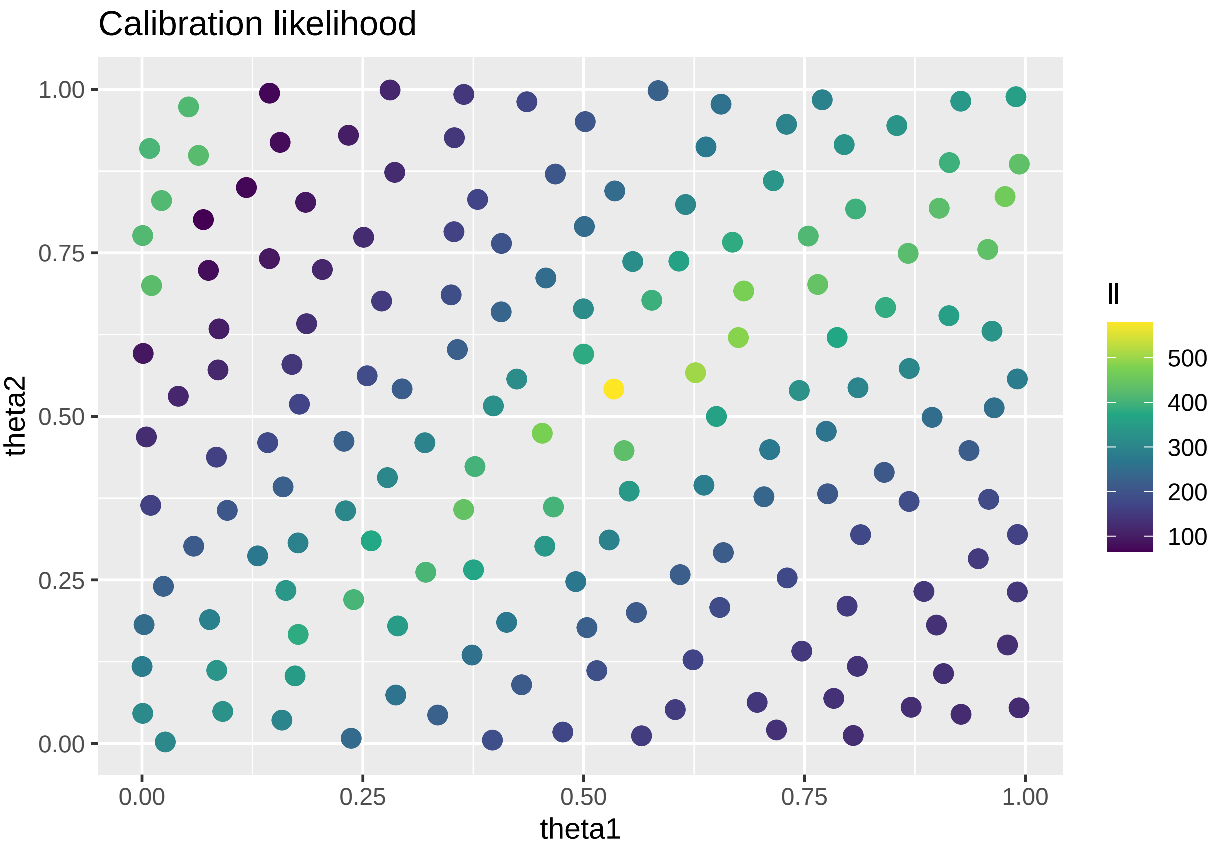
```
                           sigY=ifelse(sd_true>0,sd_true^2,1))

estLS = mv_lengthscales(XTdata,simBasis$Vt,g=1e-7)
SCinputs = get_SC_inputs(estLS,XTdata,nPC)

mvcData = list(XTdata=XTdata,
               Ydata=Ydata,
               simBasis=simBasis,
               obsBasis=obsBasis,
               estLS=estLS,
               SCinputs=SCinputs)
```

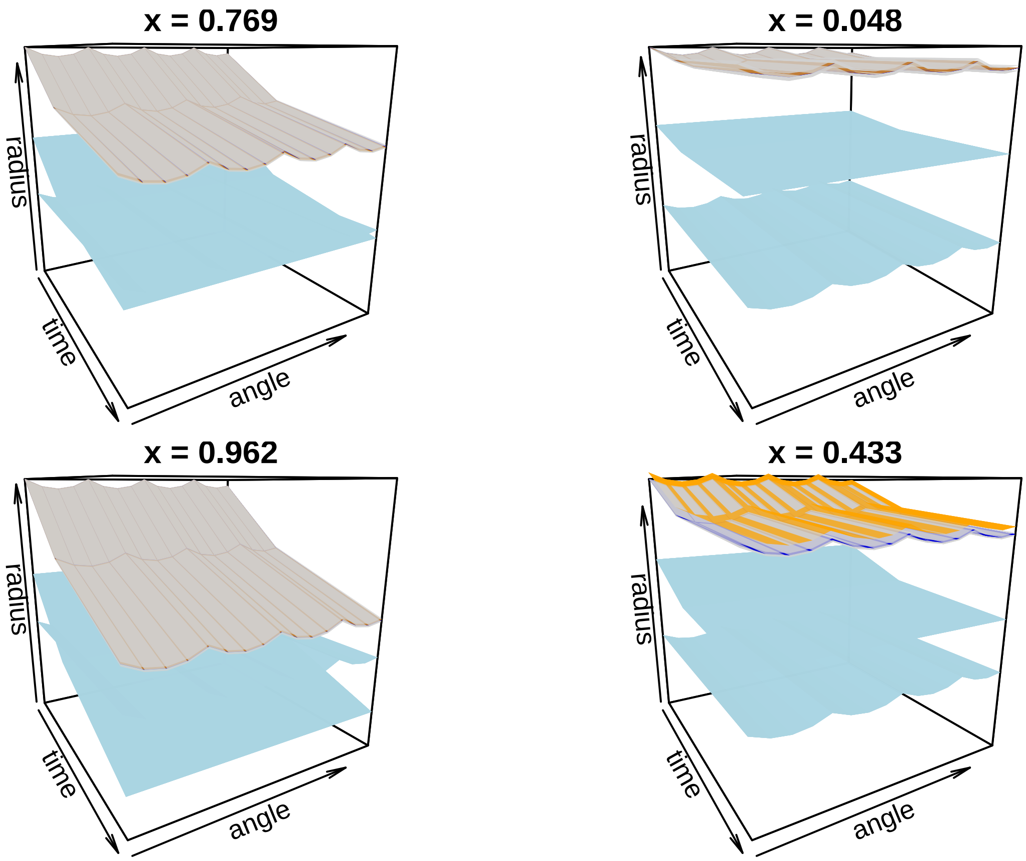
Here we nearly find the correct $t^* = c(.5, .5)$. This is somewhat unexpected actually. In biased calibration, we do not expect to recover the true calibration parameters because the calibration likelihood chooses the parameters such that the discrepancy model best fits the residuals between emulator and observed data. This is not necessarily when residuals are minimized, just when the likelihood of the model given the data is maximized.

```
##
## iterations: 24
## time:       5
```




```
## t*: 0.5538051 0.5380611
```

Unsurprisingly predictions 1-3 are very good. That is because we are predicting on data that trained the discrepancy model. Predictive intervals are also quite tight. When we move to out-of-sample prediction, we do correctly capture the shape of the discrepancy, but there is a clear under-prediction problem. This may simply be that three data points is not nearly enough to expect decent out-of-sample prediction.


x = 0.769
radius
time
angle
x = 0.048
radius
time
angle
x = 0.962
radius
time
angle
x = 0.433
radius
time
angle