

vivid-R-journal

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Packages

```
# devtools::install_github("AlanInglis/vivid")
# devtools::install_github("cbhurley/condivis2")
if(!require(network)){
  install.packages("network")
}
if(!require(sp)){
  install.packages("sp")
}

library("vivid") # for visualisations
library("randomForest") # to create model
library('xgboost') # to create model
library("ggplot2") # for visualisations
library('MASS') # for data
```

Get data and fit models

```
set.seed(1701) # for reproducibility

# get data
data("Boston")

# Model fits -----

# random forest:
rf <- randomForest(medv ~ ., data = Boston, importance = TRUE)

# gbm:
gbst <- xgboost(
  data = as.matrix(Boston[,c(1:13)]),
  label = as.matrix(Boston[,14]),
  nrounds = 100
)
```

Create vivid matrix

```
# vivi function -----

# vivi for rf
set.seed(1701)

viviRf <- vivi(fit = rf,
              data = Boston,
              response = "medv",
              reorder = FALSE,
              normalized = FALSE,
              importanceType = 'agnostic',
              gridSize = 50,
              nmax = 500,
              class = 1,
              predictFun = NULL)

# predict function for gbm
pFun <- function(fit, data, prob = FALSE) predict(fit, as.matrix(data[,1:13]))

# vivi for GBM
set.seed(1701)
viviGBst <- vivi(fit = gbst,
                data = Boston,
                response = "medv",
                reorder = FALSE,
                normalized = FALSE,
                predictFun = pFun)
```

vip2vivid function

```
# vip2vivid -----

library("vip")
# get model specific VImps using vip package
vipVImp <- vi(rf, method = 'model')
# get VInts using vip package
vipVInt <- vint(rf, feature_names = names(Boston[-14]))

# turn into vivi-matrix
vipViviMat <- vip2vivid(importance = vipVImp, interaction = vipVInt)
```

vivid matrix set up

```
# vivi matrix -----

# average over matrices and seriate to get common ordering
```

```

viviAvg <- (viviRf + viviGBst) / 2
viviAvgReorder <- vividReorder(viviAvg)

# reorder vivi-matrices
ord <- colnames(viviAvgReorder)
viviRf <- viviRf[ord,ord]
viviGBst <- viviGBst[ord,ord]

```

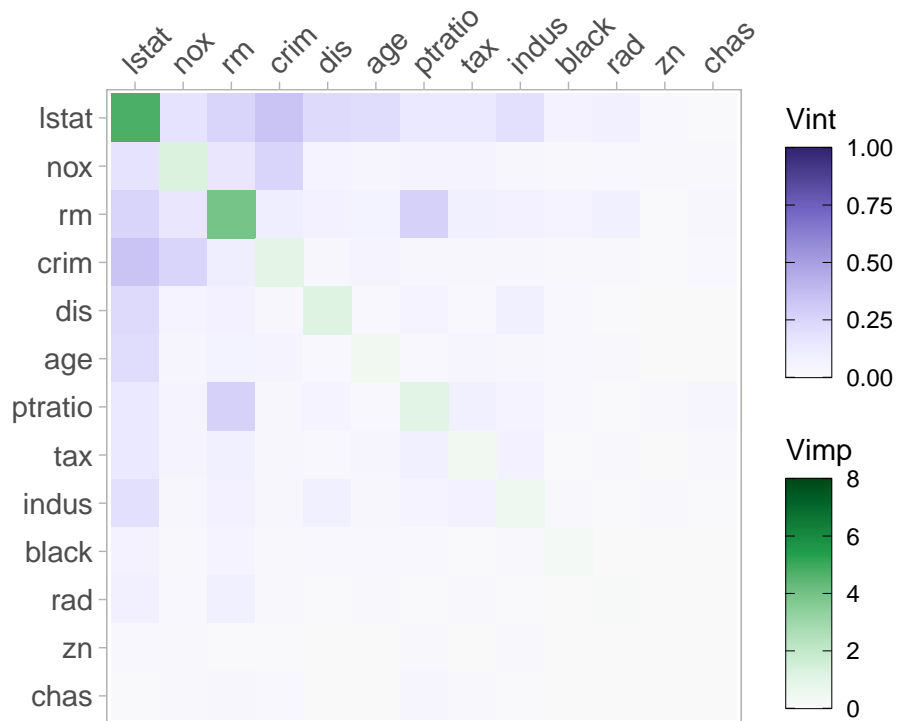
Heatmap plot

Figure 2

```

# heatmap for random forest
viviHeatmap(viviRf, angle = 45, intLims = c(0,1), implims = c(0,8))

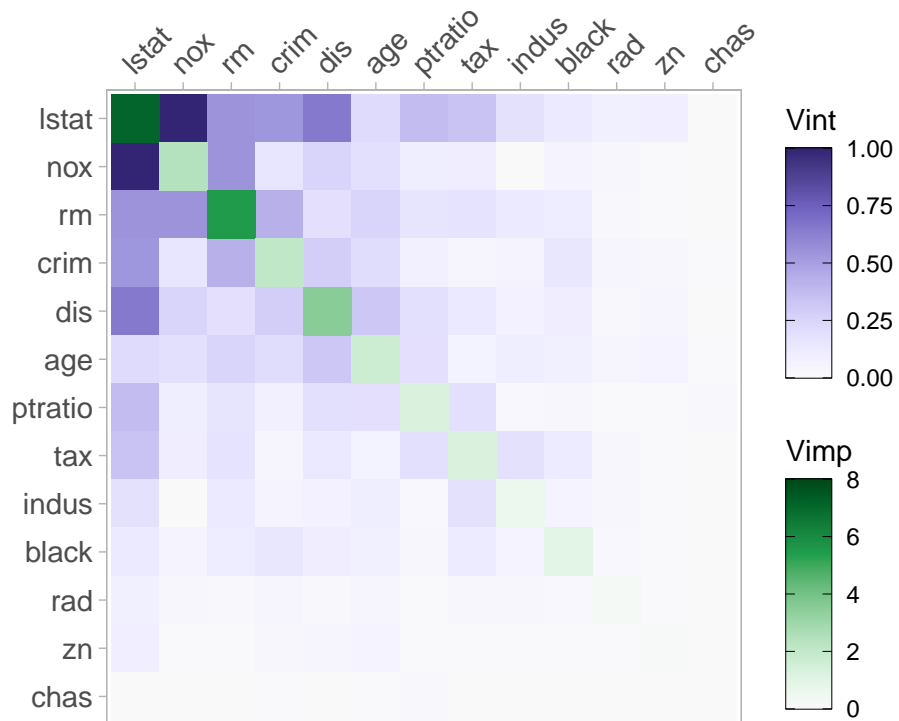
```



```

# heatmap for GBM
viviHeatmap(viviGBst, angle = 45, intLims = c(0,1), implims = c(0,8))

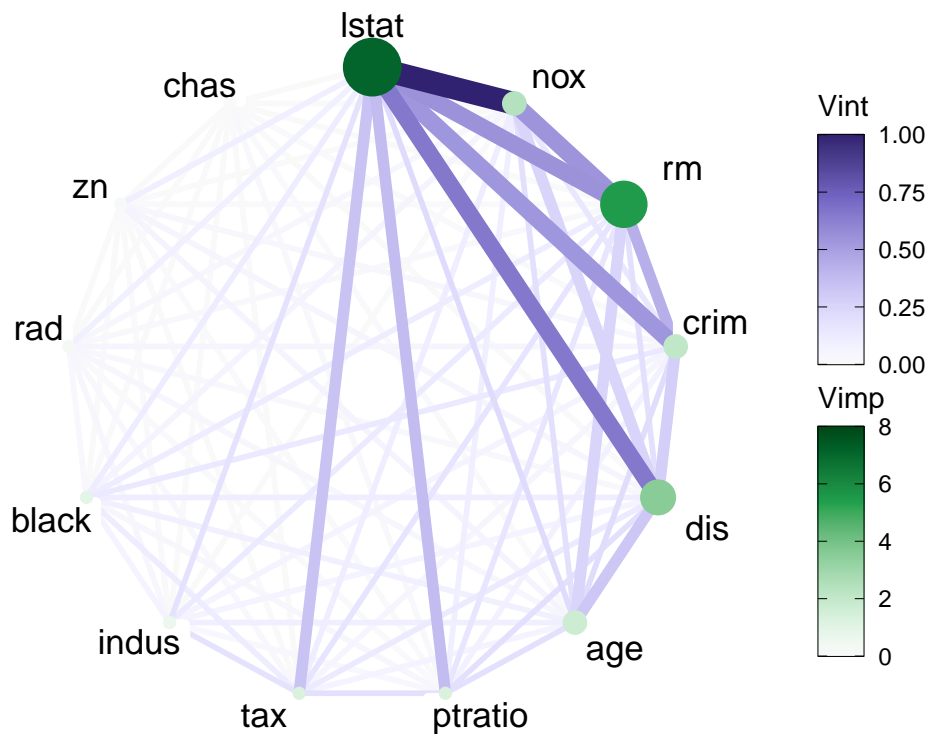
```



Network plot

Figure 3

default network plot for GBM shown in Figure 2 (a)
 viviNetwork(viviGBst)



```

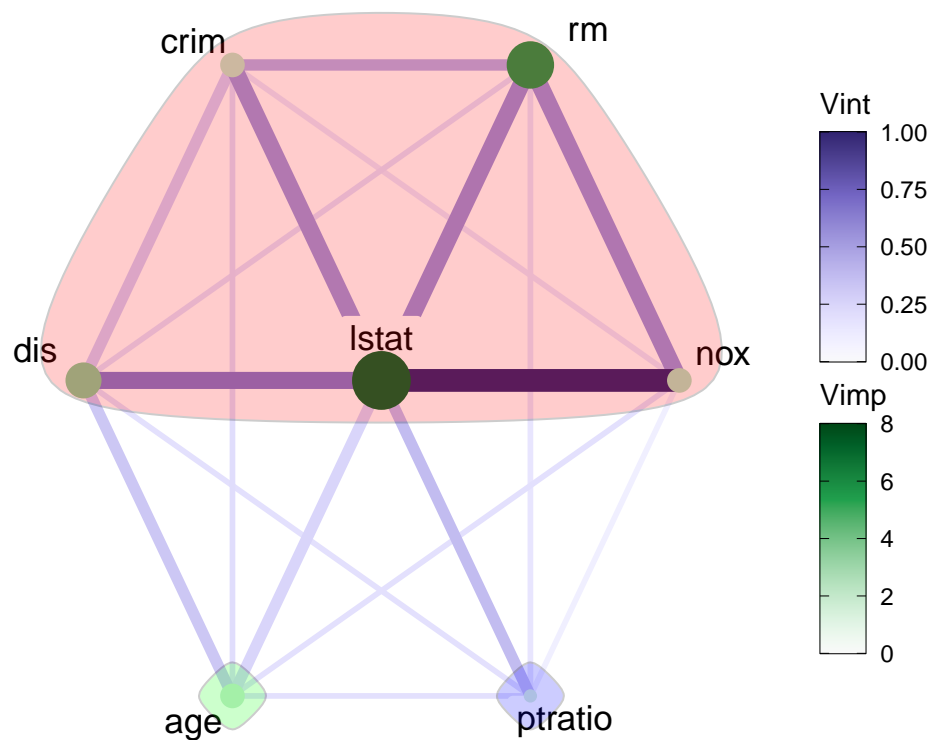
# clustered and filtered network for GBM shown in Figure 2 (b)
intVals <- viviGBst
diag(intVals) <- NA

# select VIVI values above median value
sv <- which(diag(viviGBst) > median(diag(viviGBst))) |
  apply(intVals, 1, max, na.rm=TRUE) > median(apply(intVals, 1, max, na.rm=TRUE)))

# perform hierarchical clustering
h <- hclust(-as.dist(viviGBst[sv,sv]), method="single")

# plot graph clustering by high VIVI
viviNetwork(viviGBst[sv,sv],
  intLims = c(0,1),
  impLims = c(0,8),
  cluster = cutree(h, k = 3), # specify number of groups
  layout = igraph::layout_as_star)

```



vivid dataframe

```
head(as.data.frame(viviRf), 4)
```

```

##          lstat      nox      rm      crim      dis      age      ptratio
## lstat  4.7720394 0.1789794 0.2562817 0.3371364 0.22668020 0.21651732 0.13766704
## nox    0.1789794 1.3070659 0.1558134 0.2500224 0.07291952 0.04626609 0.06121573
## rm     0.2562817 0.1558134 3.9296588 0.1070185 0.08261184 0.07595697 0.27238691
## crim   0.3371364 0.2500224 0.1070185 0.9506134 0.03999383 0.06023689 0.04538070
##          tax      indus      black      rad      zn      chas
## lstat  0.13711979 0.18967729 0.07459025 0.08754038 0.026026784 0.007842981

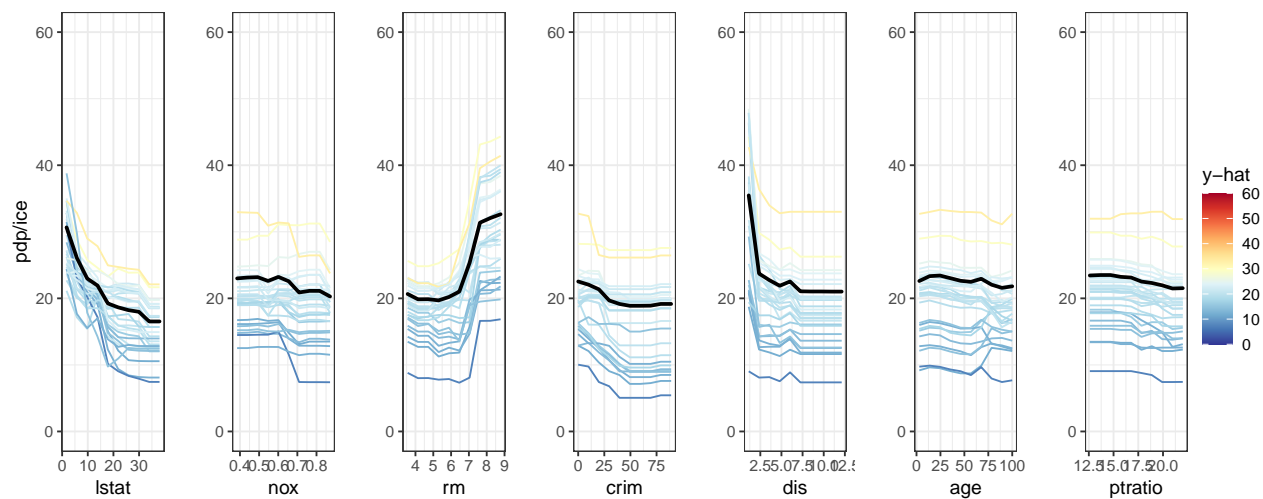
```

```
## nox    0.05786027 0.04290793 0.01929860 0.03231187 0.023965214 0.019481521
## rm     0.08928171 0.08253460 0.06791441 0.09102666 0.012697135 0.035426704
## crim   0.04378221 0.04490474 0.01675859 0.01530794 0.009210787 0.028336857
```

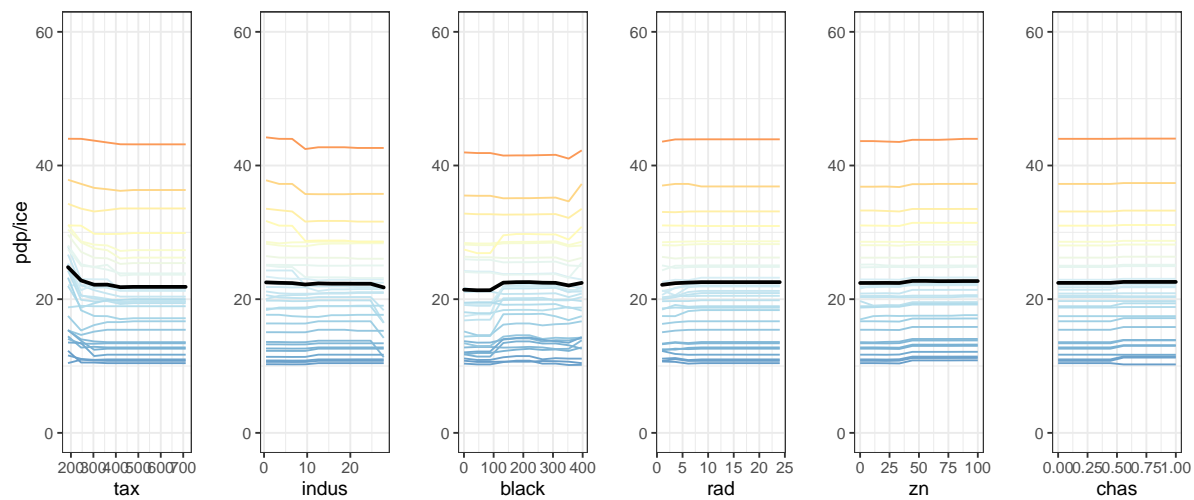
PDP

Figure 4

```
# create PDPs for GBM
pdpVars(data = Boston,
         fit = gbst,
         response = 'medv',
         vars = colnames(viviGBst)[1:7],
         predictFun = pFun)
```



```
pdpVars(data = Boston,
         fit = gbst,
         response = 'medv',
         vars = colnames(viviGBst)[8:13],
         predictFun = pFun)
```



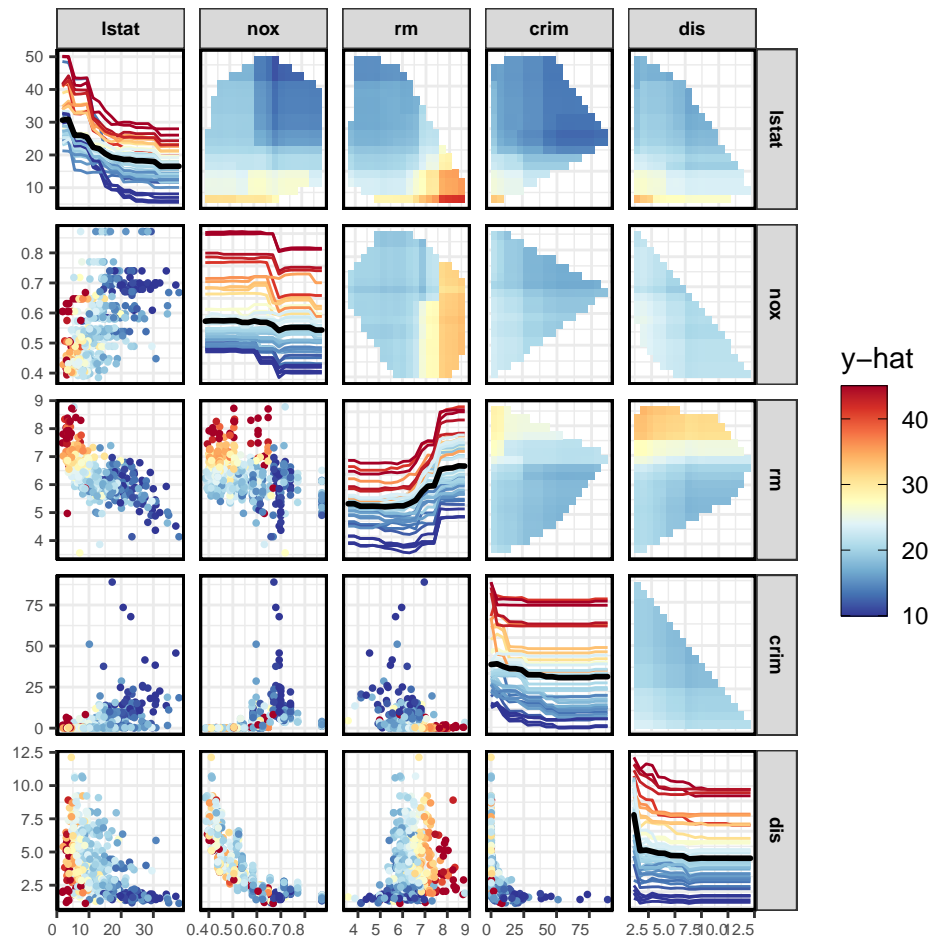
GPDP

Figure 5

```
# filter matrix:
filteredVars <- colnames(viviGBst)[1:5]

# select rows to plot associated ICE curves:
rmHigh <- sample(which(Boston$rm > mean(Boston$rm)), 25)
lstatLow <- sample(which(Boston$lstat < mean(Boston$lstat)), 25)

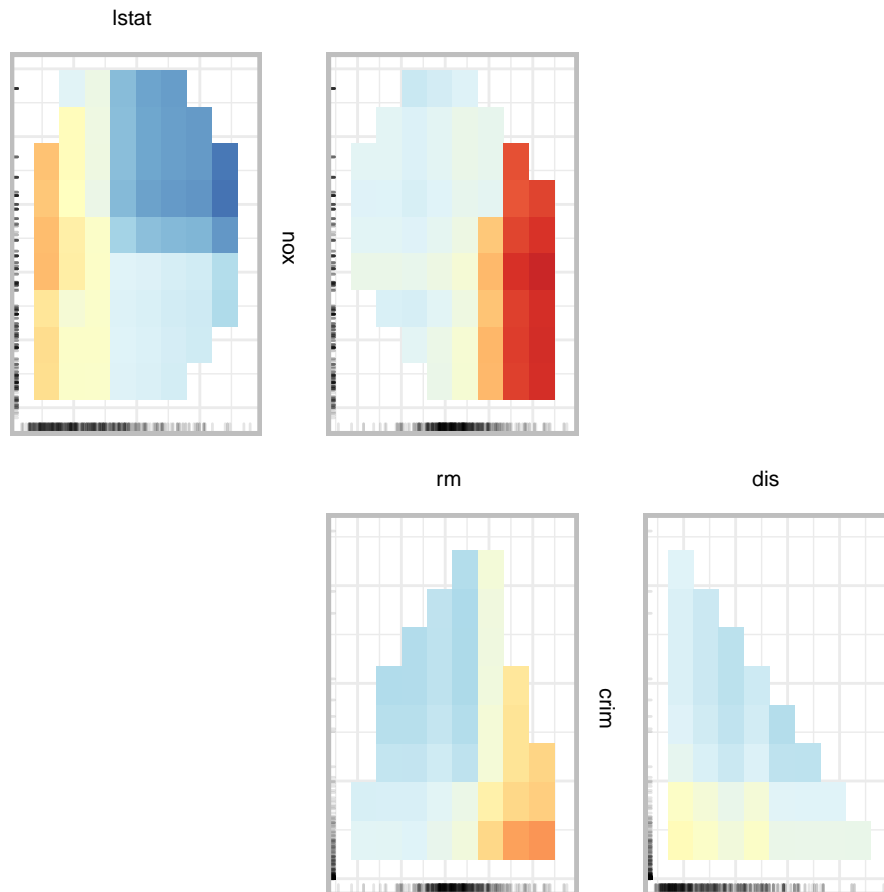
# create GPDP for gbm:
set.seed(1701)
pdpPairs(data = Boston,
  fit = gbst,
  response = "medv",
  gridSize = 20,
  nIce = c(rmHigh, lstatLow),
  var = filteredVars,
  convexHull = TRUE,
  fitlims = "pdp",
  predictFun = pFun)
```



ZPDP

Figure 6

```
# create ZPDP for gbm:
pdpZen(data = Boston,
        fit = gbm,
        response = "medv",
        convexHull = TRUE,
        zpath = colnames(viviGBst)[1:5],
        predictFun = pFun)
```



ZPDP

Figure 7

```
# find the 90% quantile of the interactions
qVIntBst <- quantile(intVals, 0.9, na.rm=TRUE)

# set zpaths with different parameters
zpGw <- zPath(viv = viviGBst, cutoff = qVIntBst, method = 'greedy.weighted')
zpSw <- zPath(viv = viviGBst, cutoff = qVIntBst, connect = FALSE, method = 'strictly.weighted')

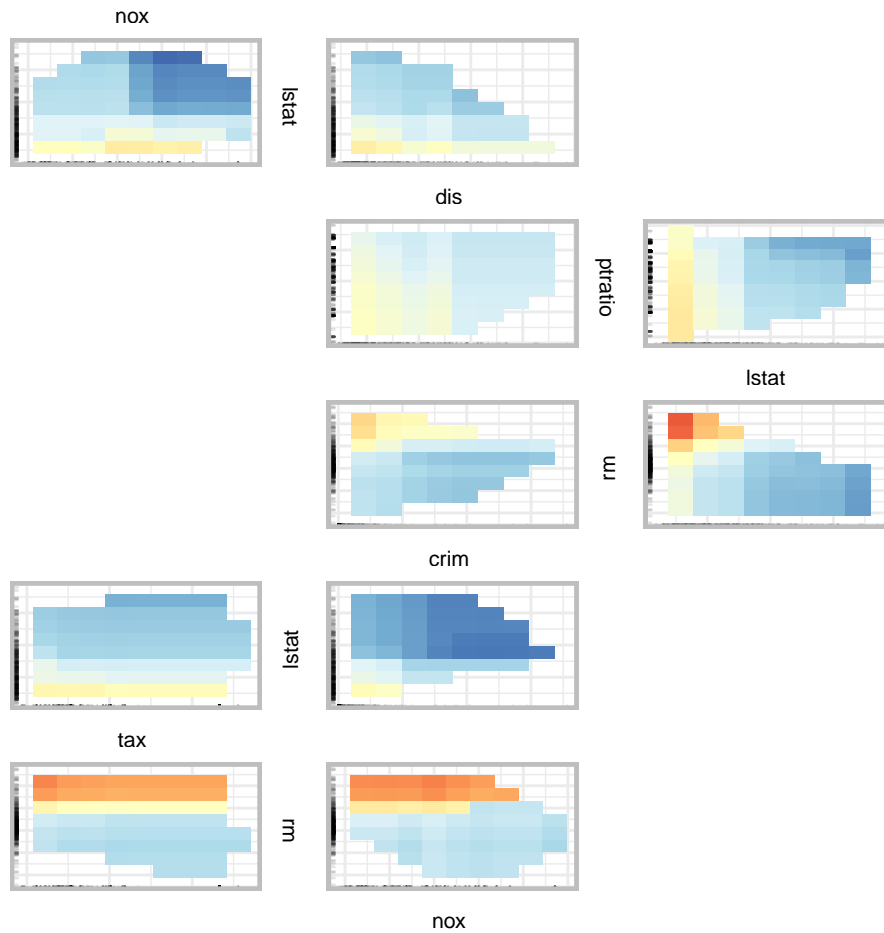
# plots
pdpZen(data = Boston,
```



```

fit = gbst,
response = "medv",
zpath = zpGw,
convexHull = TRUE,
predictFun = pFun)

```



```

pdpZen(data = Boston,
fit = gbst,
response = "medv",
zpath = zpSw,
convexHull = TRUE,
predictFun = pFun)

```

