ALEPlot

Accumulated Local Effects (Ale) Plots and Partial Dependence (Pd) Plots

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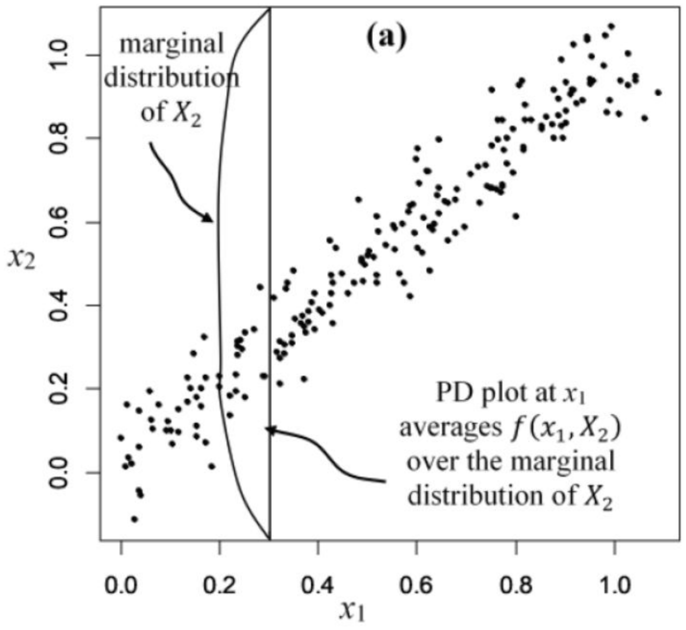
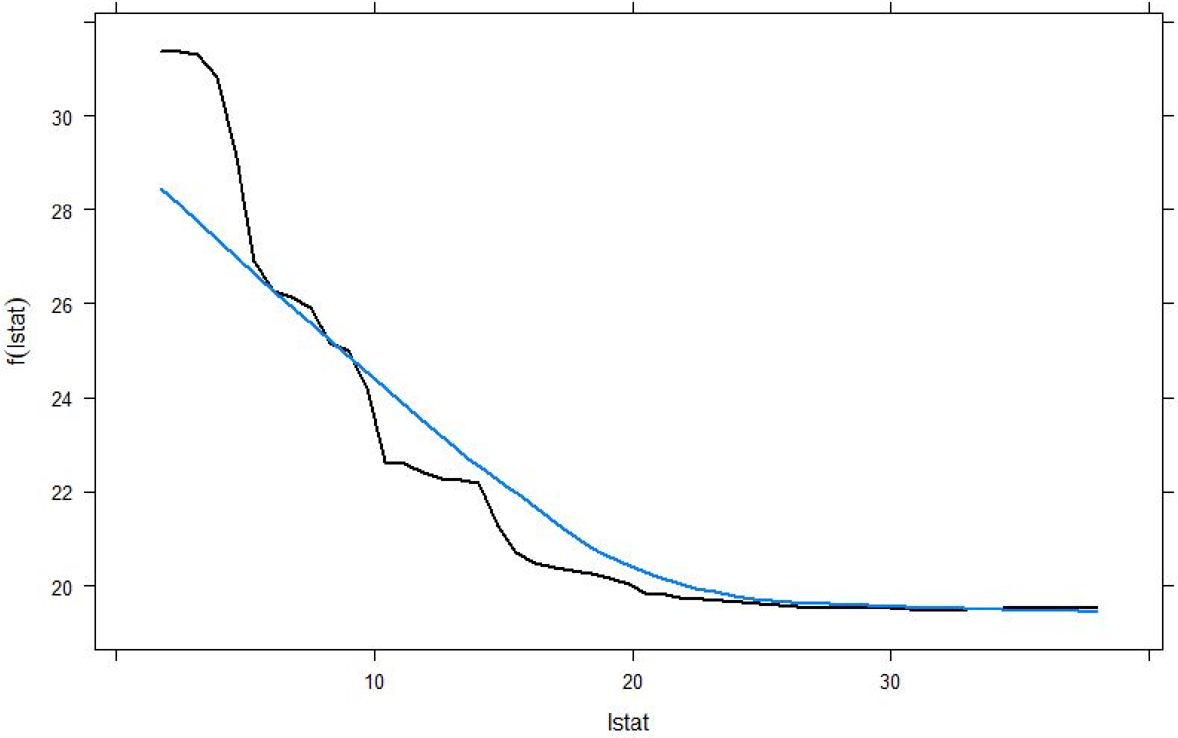
Partial dependence plots

$$f_{1,PD}(x_1) = E[f(x_1, X_2)]$$

$$\hat{f}_{1,PD}(x_1) = \frac{1}{n}\sum_{i=1}^{n} f(x_1, x_{i,2})$$



```r
library(randomForest)
library(pdp)
set.seed(101)
data(boston, package = "pdp")
boston.rf <- randomForest(cmedv ~ ., data = boston, importance = TRUE)
boston.rf %>% partial(pred.var = "lstat") %>% plotPartial(smooth = TRUE, lwd = 2, ylab = expression(f(lstat)))
```

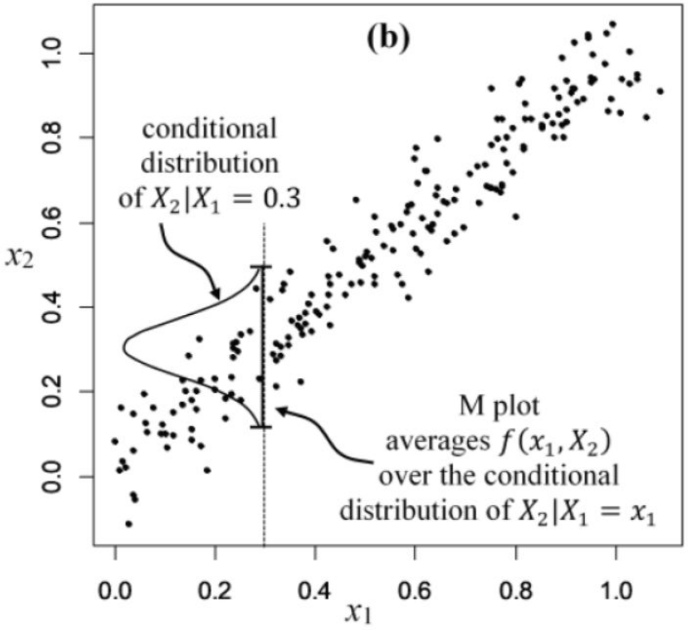


https://journal.r-project.org/archive/2017/RJ-2017-016/RJ-2017-016.pdf

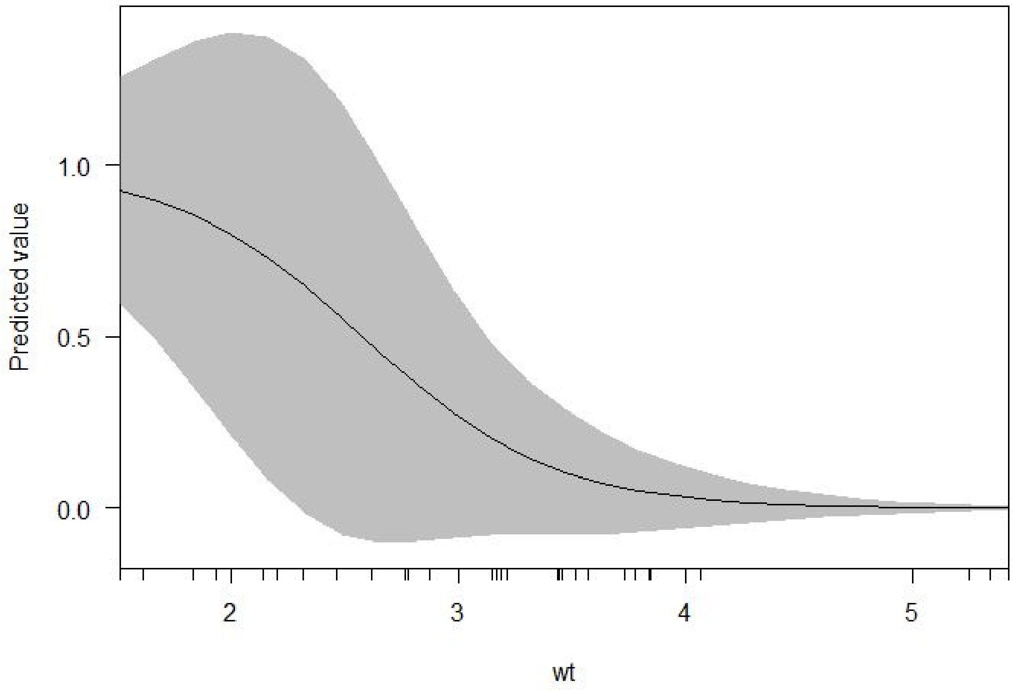
Marginal plots

$$f_{1,M}(x_1) = E[f(X_1, X_2)|X_1 = x_1]$$

$$\hat{f}_{1,M}(x_1) = \frac{1}{n(x_1)} \sum_{i \in N(x_1)} f(x_1, x_{i,2})$$



```r
library(margins)
m <- glm(am ~ wt*drat, data = mtcars, family = binomial)
cplot(m, x = "wt", se.type = "shade")
```



https://cran.r-project.org/web/packages/margins/README.html

ALE Plots

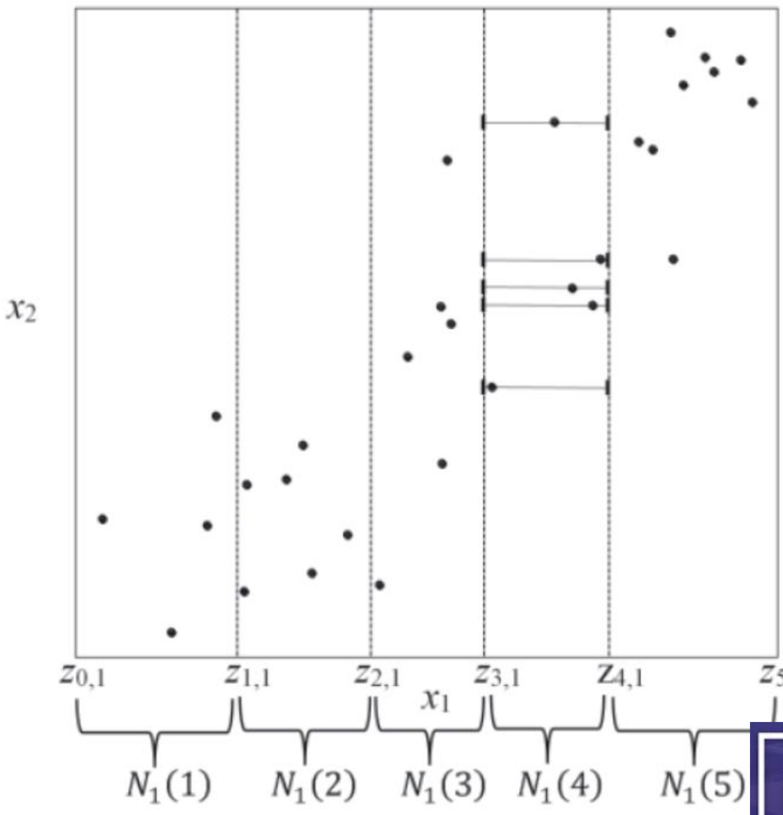
Problemy z poprzednimi rozwiązaniami:

- ekstraplocja
- OVB - ommited variable bias

ALE main effects

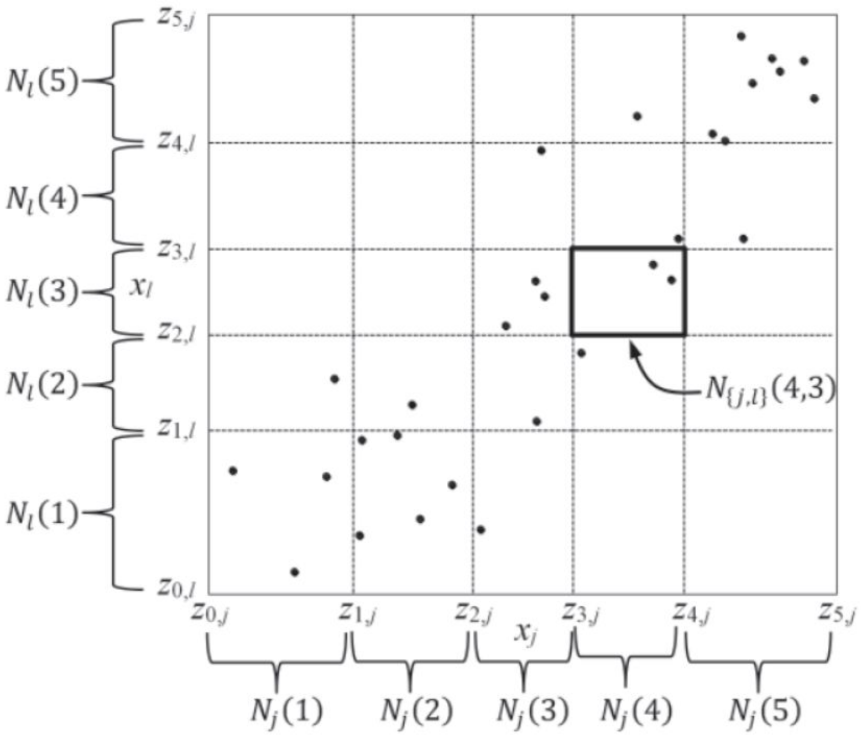
$$f_{j,ALE}(x_j) = \int_{z_{0,j}}^{x_j} E[\frac{\partial f(X_1, ..., X_d)}{\partial X_j})|X_j = z_j]dz_j - c_1$$

$$\hat{f}_{j,ALE}(x) = \sum_{k=1}^{k_j(x)} \frac{1}{n_j(k)} \sum_{i:x_{i,j} \in N_j(k)} [f(z_{k,j}, x_{i,\setminus j}) - f(z_{k-1,j}, x_{i,\setminus j})] - \hat{c_1}$$



ALE second-order effects

$$f_{\{j,l\},ALE}(x_j, x_l) = \int_{z_{0,l}}^{x_l}\int_{z_{0,j}}^{x_j} E[\frac{\partial^2 f(X_1,...,X_d)}{\partial X_j \partial X_l}|X_j = z_j, X_l = z_l]dz_j dz_l - g_j(x_j) - g_l(x_l) - c_2$$



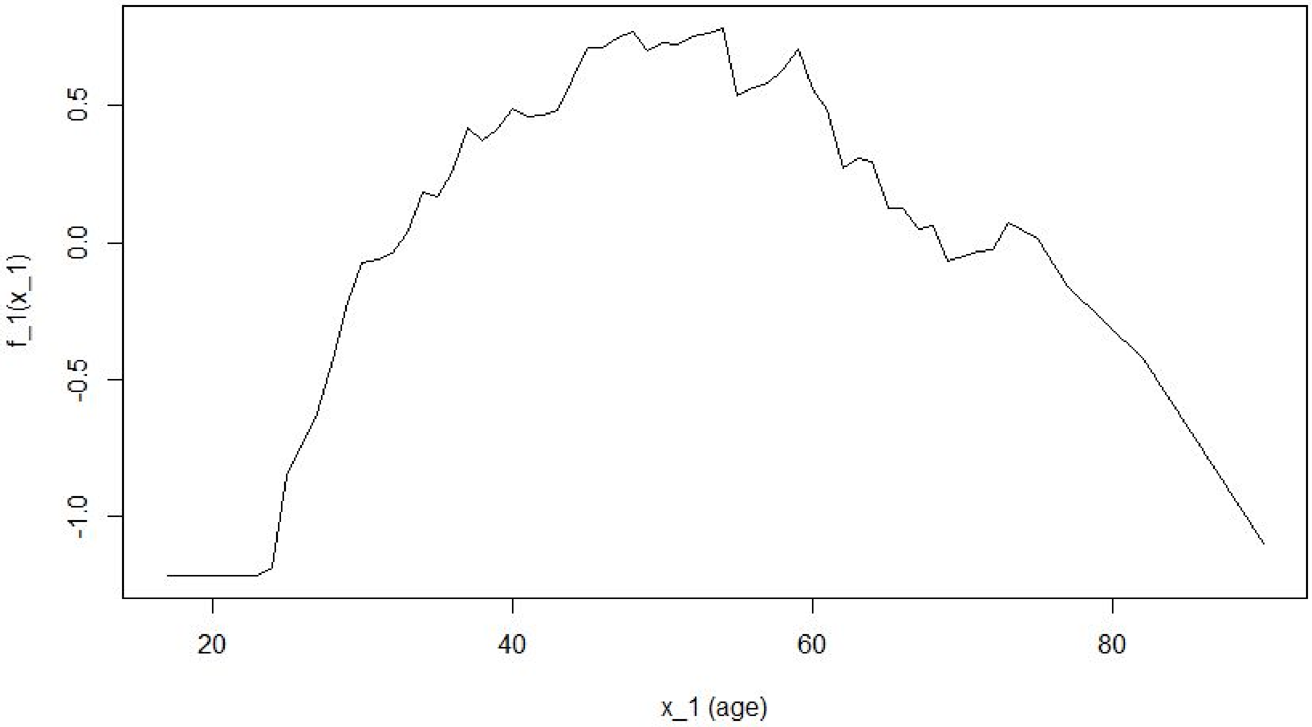
Pakiet ALEPlot

Przykład: Przychody

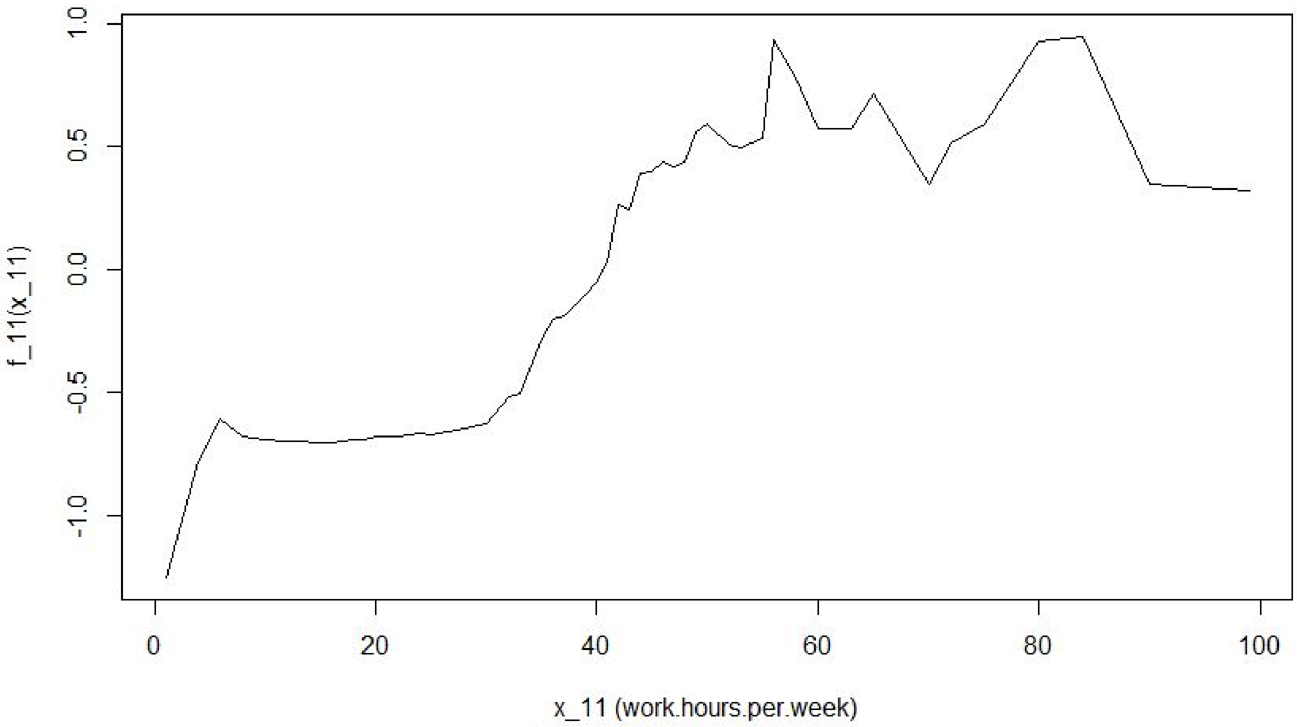
```
library(ALEPlot)
library(gbm)

data = read.csv("adult.data.csv", header = TRUE, strip.white = TRUE,
                na.strings = "?")
data = na.omit(data)

gbm.data <- gbm(income==">50K" ~ ., data= data[,-c(3,4)],
                distribution = "bernoulli", n.trees=6000, shrinkage=0.02,
                interaction.depth=3)

yhat <- function(X.model, newdata) as.numeric(predict(X.model, newdata,
                                                       n.trees = 6000, type="link"))
```

archive.ics.uci.edu/ml/datasets/Census+Income

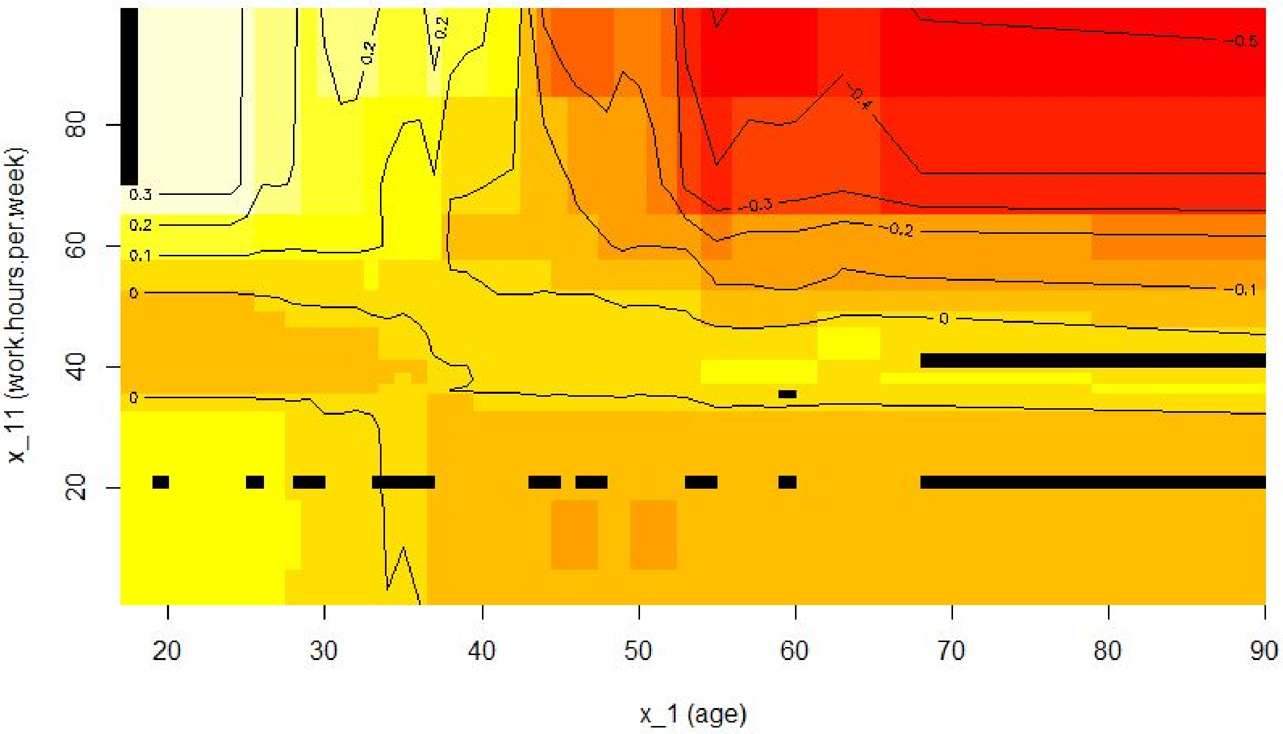
```
ALE.1=ALEPlot(data[,-c(3,4,15)], gbm.data, pred.fun=yhat, J=1, K=500, NA.plot = TRUE)
```



```
ALE.11=ALEPlot(data[,-c(3,4,15)], gbm.data, pred.fun=yhat, J=11, K=500, NA.plot = TRUE)
```



```
ALE.1and11=ALEPlot(data[,-c(3,4,15)], gbm.data, pred.fun=yhat, J=c(1,11), K=50, NA.plot = FALSE)
```



Bibliografia

- **Accumulated Local Effect (ALE) and Package ALEPlot** https://cran.r-project.org/web/packages/ALEPlot/vignettes/AccumulatedLocalEffectPlot.pdf
- **Visualizing the Effects of Predictor Variables in Black Box Supervised Learning Models,** Daniel W. Apley, https://arxiv.org/abs/1612.08468
- **pdp: An R Package for Constructing Partial Dependence Plots,** Brandon M. Greenwell, https://journal.r-project.org/archive/2017/RJ-2017-016/RJ-2017-016.pdf