ivarPro: individual variable priority vignette

Min Lu (luminwin@gmail.com)

Aster Shear (aster.shear@gmail.com)

Udaya B. Kogalur (ubk@kogalur.com)

Hemant Ishwaran (hemant.ishwaran@gmail.com)

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Understanding **individual-level variable importance** is essential for personalized modeling, yet it remains underexplored in traditional statistical and machine learning methods.

Most approaches assess variable importance at the **population level**, which can mask the **heterogeneity** of effects across individuals. In applications where **personalized decisions** are critical—such as precision medicine, targeted marketing, or individualized risk prediction—this can be a major limitation.

Enter iVarPro: Localized Gradient-Based Importance

iVarPro extends VarPro by defining individual-level feature importance through **local gradients**.

- The **gradient** reflects how small changes in a variable affect the **predicted outcome** for a specific individual.
- This provides a **natural and interpretable measure** of a variable's influence on an individual prediction—essentially a personalized sensitivity analysis.

How iVarPro Works

iVarPro builds on the structural consistency of VarPro's rules [1]:

1. Regions R defined by VarPro rules identify meaningful neighborhoods in the feature space.
2. Within each region, iVarPro fits a **local linear regression** to estimate the gradient of the outcome with respect to each variable.
3. However, data within a single region is often sparse—leading to unstable estimates.

To solve this, iVarPro uses release regions:

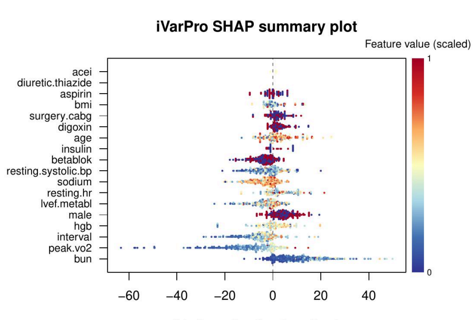
- A release region **loosens the constraint** on a specific variable S while keeping all others fixed.
- This targeted expansion injects **the variation needed along** S to accurately compute the **directional derivative**.
- The result: a more stable, interpretable, and localized measure of individual variable importance.

R example of case-specific importance matrix and visualization

```
data(peakVO2, package = "randomForestSRC")
o <- varpro(Surv(ttodead, died) ~ .,
            peakVO2, ntree = 50)
ivp <- ivarpro(o)
print(ivp[1:5, 1:8])

##      age    gender bmi   peak.vo2 chemo
## [1,]  0.041  NA  0.028   0.312   NA
## [2,]  NA     NA  0.011   0.284   0.022
## [3,]  0.014  0.031  NA   0.271   NA
## [4,]  0.033  NA  0.019   0.290   0.017
```

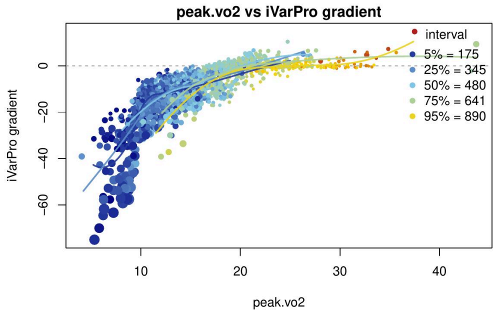
`ivarpro` returns an $N \times p$ matrix of case-specific importance values. `NA` = variable not important for that case.

```
imp <- ivarpro(o, cut.max = 2, adaptive = FALSE)
shap.ivarpro(imp)
```



The `shap.ivarpro` function provides SHAP-like beeswarm plot: each dot = one case, color = feature value, x-axis = individualized importance.

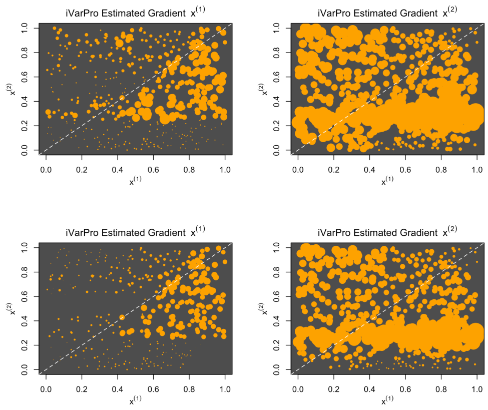
```
partial.ivarpro(imp, var = "peak.vo2",
                col.var = "interval",
                size.var = "y")
```



The `partial.ivarpro` function provides case-specific importance for `peak.vo2`, points colored by interval, sized by outcome `y`.

R example of a 2-signal simulation

```
## true regression function
true.function <- function(which.simulation) {
  if (which.simulation == 1) {
    function(x1,x2) {1*(x2<=.25) +
        15*x2*(x1<=.5 & x2>.25) + (7*x1+7*x2)*(x1>.5 & x2>.25)}
  }
  else if (which.simulation == 2) {
    function(x1,x2) {r=x1^2+x2^2;5*r*(r<=.5)}
  }
  else {
    function(x1,x2) {6*x1*x2}
  }
}

## simulation function
simfunction = function(n = 1000, true.function, d = 20, sd = 1) {
  d <- max(2, d)
  X <- matrix(runif(n * d, 0, 1), ncol = d)
  dta <- data.frame(list(x = X, y = true.function(X[, 1], X[, 2]) + rnorm(n, sd = s
d)))
  colnames(dta)[1:d] <- paste("x", 1:d, sep = "")
  dta
}

## iVarPro importance plot
ivarpro.plot <- function(dta, release=1, combined.range=TRUE,
                         cex=1.0, cex.title=1.0, sc=5.0, gscale=30, title=NULL) {
  x1 <- dta[,"x1"]
  x2 <- dta[,"x2"]
  x1n = expression(x^{(1)})
  x2n = expression(x^{(2)})
  if (release==1) {
    if (is.null(title)) title <- bquote("iVarPro Estimated Gradient " ~ x^{(1)})
    cex.pt <- dta[,"Importance.x1"]
  }
  else {
    if (is.null(title)) title <- bquote("iVarPro Estimated Gradient " ~ x^{(2)})
    cex.pt <- dta[,"Importance.x2"]
  }
  if (combined.range) {
    cex.pt <- cex.pt / max(dta[, c("Importance.x1", "Importance.x2")],na.rm=TRUE)
  }
  rng <- range(c(x1,x2))
  par(mar=c(4,5,5,1),mgp=c(2.25,1.0,0))
  par(bg="white")
  gscalev <- gscale
  gscale <- paste0("gray",gscale)
  plot(x1,x2,xlab=x1n,ylab=x2n,
       ylim=rng,xlim=rng,
       col = "#FFA500", pch = 19,
       cex=(sc*cex.pt),cex.axis=cex,cex.lab=cex,
       panel.first = rect(par("usr")[1], par("usr")[3], par("usr")[2], par("usr")[4],
                          col = gscale, border = NA))
  abline(a=0,b=1,lty=2,col= if (gscalev<50) "white" else "black")
  mtext(title,cex=cex.title,line=.5)
}

## simulate the data
which.simulation <- 1
df <- simfunction(n = 500, true.function(which.simulation))

## varpro analysis
o <- varpro(y~., df)

## canonical ivarpro analysis
imp1 <- ivarpro(o)

## ivarpro analysis with custom lambda
imp2 <- ivarpro(o, cut = seq(.05, .75, length=21))

## build data for plotting the results
df.imp1 <- data.frame(Importance = imp1, df[,c("x1","x2")])
df.imp2 <- data.frame(Importance = imp2, df[,c("x1","x2")])

## plot the results
par(mfrow=c(2,2))
ivarpro.plot(df.imp1,1)
ivarpro.plot(df.imp1,2)
ivarpro.plot(df.imp2,1)
ivarpro.plot(df.imp2,2)
```



Cite this vignette as

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```
@misc{LuVarProi,
    author = "Min Lu and Aster Shear and Udaya B. Kogalur and Hemant Ishwaran",
    title = {{ivarPro}: individual variable priority vignette},
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    howpublished = "\url{http://www.varprotools.org/articles/ivarpro.html}",
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}
```

1. Lu M, Ishwaran H. Individual variable priority: A model-independent local gradient method for variable importance. Artificial Intelligence Review. 2025;58:407.