An Example of plspolychaos Use: ishigami20000

J.P. Gauchi and A. Bouvier

MaIAGE, INRA, Université Paris-Saclay, 78350 Jouy-en-Josas, France

April 27, 2016

Abstract

The **plspolychaos** R package computes sensitivity indexes from polynomial chaos expansions and regression PLS, for computer models with correlated continuous inputs. The functionalities and method are explained in the in-line manual of the package.

This paper illustrates the way of using the package on an example dataset, named <code>ishi20000</code>, which has 20000 rows and 3 correlated inputs. The dataset is stored in the file <code>ishigami20000.Rda</code> in the directory <code>ext-data</code> of the package. We analyze the full polynomial of degree 6, which corresponds to 83 monomials, then the polynomial reducted to 50 monomials by selection of the most significant ones.

Contents

1	Read Data	1
2	Building Legendre Polynomial	2
3	Computations	2
4	Plots	4
5	Monomials Selection	6

1 Read Data

> library("plspolychaos")
> load(system.file("extdata", "ishigami20000.Rda", package="plspolychaos"))
> X <- ishi20000[, -ncol(ishi20000)] #inputs
> Y <- ishi20000[, ncol(ishi20000)] #response</pre>

2 Building Legendre Polynomial

```
> degree <- 6 # polynomial degree
> pce <- polyLeg(X, Y, degree)
> print(pce)

Total number of monomials: 83
Number of inputs: 3
Polynomial degree: 6
Number of rows: 20000
```

3 Computations

```
> nc <- 30 # number of components
> ret <- calcPLSPCE(pce, nc=nc)
> print(ret)
```

Explanation level of the response (R2, its percentage and cumulated percentage)
R2 %R2cumulated

```
c1 0.3044 30.8609
                       30.8609
c2 0.4181 42.3873
                       73.2482
c3 0.0914 9.2668
                       82.5150
c4 0.1084 10.9885
                       93.5035
c5 0.0282 2.8629
                       96.3665
c6 0.0142 1.4361
                       97.8026
c7 0.0100 1.0103
                       98.8128
c8 0.0024 0.2414
                       99.0542
c9 0.0015 0.1487
                       99.2029
c10 0.0023 0.2370
                       99.4399
c11 0.0012 0.1236
                       99.5634
c12 0.0010 0.1021
                       99.6655
c13 0.0005 0.0549
                       99.7204
c14 0.0006 0.0583
                       99.7787
c15 0.0002 0.0192
                       99.7978
c16 0.0005 0.0534
                       99.8512
c17 0.0003 0.0286
                       99.8798
c18 0.0003 0.0269
                       99.9067
c19 0.0002 0.0200
                       99.9267
c20 0.0002 0.0175
                       99.9442
c21 0.0002 0.0178
                       99.9620
c22 0.0001 0.0151
                       99.9771
c23 0.0001
           0.0054
                       99.9825
c24 0.0000 0.0026
                       99.9852
c25 0.0000 0.0038
                       99.9889
c26 0.0000 0.0033
                       99.9923
c27 0.0000 0.0021
                       99.9944
c28 0.0000 0.0022
                       99.9966
c29 0.0000 0.0018
                       99.9984
c30 0.0000 0.0016
                      100.0000
```

```
c1 0.3042 0.3042
c2 0.6010 0.7224
c3 0.3292 0.8138
c4 0.5824 0.9222
c5 0.3631 0.9505
c6 0.2860 0.9646
c7 0.2819 0.9746
c8 0.0931 0.9770
c9 0.0629 0.9784
c10 0.1076 0.9807
c11 0.0621 0.9819
c12 0.0544 0.9829
c13 0.0300 0.9834
c14 0.0330 0.9840
c15 0.0096 0.9841
c16 0.0313 0.9846
c17 0.0162 0.9849
c18 0.0153 0.9851
c19 0.0108 0.9853
c20 0.0091 0.9854
c21 0.0093 0.9855
c22 0.0075 0.9856
c23 0.0005 0.9857
c24 0.0000 0.9857
c25 0.0000 0.9857
c26 0.0000 0.9857
c27 0.0000 0.9857
c28 0.0000 0.9857
c29 0.0000 0.9857
c30 0.0000 0.9857
Optimal number of components: 23
Explanation level of the optimal number of components
             %R2 %R2cumulated
       R2
c23 1e-04 0.0054
                      99.9825
Explanation-prediction level of the optimal number of components
       Q2 Q2cum
c23 5e-04 0.9857
Root Mean Square Prediction of the optimal number of components
c23 0.1176
PLS-PCE sensivity indexes
            PΕ
                    TPE
      LE
V1 0.1109 0.2643 0.5733
```

Explanation-prediction level of the response (Q2 and Q2cum)

Q2 Q2cum

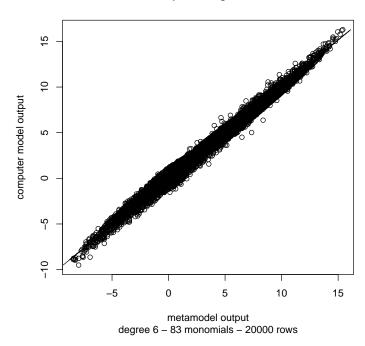
V2 0.0003 0.3954 0.4488 V3 0.0122 0.0162 0.3283

%PLS-PCE sensivity indexes LE PE TPE V1 89.8935 39.1033 42.4535 V2 0.2203 58.4972 33.2371 V3 9.8862 2.3995 24.3094

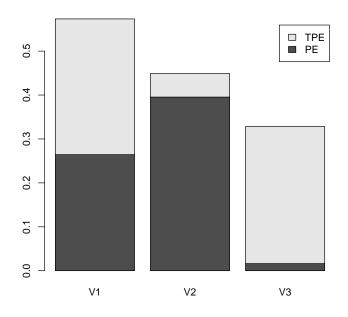
4 Plots

> plot(ret, pce) #apply method 'plot' on the returned object

Scatter plot and regression line

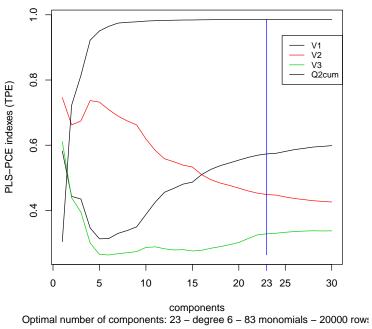


Polynomial (PE) and Total (TPE) PLS-PCE sensivity indexes



degree 6 - 83 monomials - 20000 rows

Total PLS-PCE sensivity indexes against components



5 Monomials Selection

When there are many monomials, some of them are often nonsignificants. We select the most significant ones by using the option forward of the function polyLeg: only the monomials for which the R^2 of the linear regression is the greatest are kept.

Here, only the 50 more significant monomials are kept. The calculations are then processed as usual by function calcPLSPCE.

```
> pcef <- polyLeg(X, Y, degree, forward=50)</pre>
> print(pcef)
Total number of monomials: 83
Number of selected monomials: 50
Number of inputs: 3
Polynomial degree: 6
Number of rows: 20000
> retf <- calcPLSPCE(pcef, nc=25)
> print(retf)
Explanation level of the response (R2, its percentage and cumulated percentage)
        R2
               %R2 %R2cumulated
c1 0.3537 36.0389
                        36.0389
c2 0.3629 36.9716
                        73.0105
c3 0.1404 14.3094
                        87.3199
c4 0.0755 7.6881
                        95.0080
   0.0184
           1.8743
                        96.8823
с5
с6
   0.0080 0.8141
                        97.6964
   0.0024
с7
           0.2469
                        97.9433
c8 0.0038
          0.3888
                        98.3321
c9 0.0018 0.1870
                        98.5191
c10 0.0030 0.3036
                        98.8227
c11 0.0014
                        98.9687
           0.1460
c12 0.0018 0.1806
                        99.1494
c13 0.0020 0.2015
                        99.3509
c14 0.0009 0.0909
                        99.4418
c15 0.0010 0.1021
                        99.5438
c16 0.0013 0.1351
                        99.6789
c17 0.0008 0.0819
                        99.7608
c18 0.0006 0.0570
                        99.8178
c19 0.0002
           0.0194
                        99.8372
c20 0.0005
           0.0526
                        99.8898
c21 0.0003 0.0303
                        99.9201
c22 0.0003 0.0304
                        99.9505
c23 0.0003
           0.0294
                        99.9799
c24 0.0001
           0.0127
                        99.9926
c25 0.0001
           0.0074
                       100.0000
```

```
c1 0.3535 0.3535
```

- c2 0.5613 0.7164
- c3 0.4954 0.8569
- c4 0.5275 0.9324
- c5 0.2720 0.9508
- c6 0.1621 0.9588
- c7 0.0582 0.9612
- c8 0.0978 0.9650
- c9 0.0516 0.9668
- c10 0.0888 0.9697
- C10 0.0000 0.3037
- c11 0.0460 0.9711
- c12 0.0599 0.9728
- c13 0.0715 0.9748
- c14 0.0336 0.9756
- c15 0.0392 0.9766
- c16 0.0550 0.9779
- c17 0.0342 0.9786
- c18 0.0238 0.9791
- c19 0.0062 0.9793
- c20 0.0223 0.9797
- c21 0.0115 0.9800
- c22 0.0116 0.9802
- c23 0.0110 0.9804
- c24 0.0023 0.9805
- 05 0 0000 0 0005
- c25 0.0000 0.9805

Optimal number of components: 24

 ${\tt Explanation \ level \ of \ the \ optimal \ number \ of \ components}$

R2 %R2 %R2cumulated

c24 1e-04 0.0127 99.9926

Explanation-prediction level of the optimal number of components

02 02cum

c24 0.0023 0.9805

Root Mean Square Prediction of the optimal number of components

c24 0.1366

PLS-PCE sensivity indexes

LE PE TPE

V1 0.1458 0.1594 0.7526

V2 0.0097 0.2000 0.5706

V3 0.0095 0.0101 0.6322

%PLS-PCE sensivity indexes

LE PE TPE

V1 88.3481 43.1479 38.4864

V2 5.9044 54.1247 29.1812