

# CMAT Newsletter: January 2004

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## 1 General Remarks

## 2 Modifications of Features

### 2.1 Fixed Bugs

1. A very serious bug with the transpose of a matrix was fixed. The transpose function reshuffles the matrix inside the same memory and does not need a copy in work space. However, it needs the prime number factorization of the matrix dimension. For very large matrices we had an integer overflow which turned an integer product into a negative number.
2. A large number of bugs were fixed for the `svm()` function. Most of them had to do with the tuning algorithm which was never tested in practical applications.

There are still two known bugs in `svm`:

1. The DQP method does not work properly.
2. Parsing function arguments for nested functions.

### 2.2 Changes in `svm()` Function

A few new options are now available for `svm()`:

Option Name	Second Column	Meaning
"ppar"		print vector of parameter estimates $\alpha$
"block"	int	fold number for block cross validation
"split"	int	fold number for split cross validation
"random"	int	fold number for random cross validation
"tunitr"	int	max iterations for tuning
"tuntim"	int	max time in seconds for tuning
"tunftol"	real	$f$ termination for tuning
"tunxtol"	real	$x$ termination for tuning
"tunsel"	"test"	test error is tuning selection criterion
	"train"	training error is tuning selection criterion

Note, that the `seed` parameter is now valid also for random cross validation. (It was already needed for the SMO method.)

1. Example for Grid Search Parameter Tuning:

```

data = rspfile("../tdata\\heart_scale.dat");
modl = "1 = 2 : 14";
class = 1;

/* [1] tuning by grid search: specify values */
c = [ .001 .1 1. 10. 100. ];
kp1 = [ .2 : .05 : .8 ];
tun_g = c |> kp1 ;

```

For simplicity we use the fast PSVM method. For nonlinear kernel we could also use the fast methods LSVM or SSVM. For linear kernel we could also use the fast ASVM method.

```

optn = [ "print"          3 ,
         "tun"           "gsrch" ,
         "split"         10 ,
         "kern"          "rbf2" ,
         "meth"          "psv" ];
< alfa,sres,vres,yptr > = svm(data,modl,optn,class,tun_g);

```

Note, that each line of the following history output requires  $fold + 1 = 11$  optimizations. The first one is training with the complete data set, the remaining  $fold = 10$  are for the cross validation with about  $Nobs/fold$  observations left out from model fitting.

```

*****
Results of Grid Search for 2 Parameters
*****

```

N	C	KF1	NMisc	Perct	TrainErr
1	0.0010000	0.2000000	120	44.44	120.000000
2		0.2500000	120	44.44	120.000000
3		0.3000000	120	44.44	120.000000
4		0.3500000	120	44.44	120.000000
5		0.4000000	120	44.44	120.000000
6		0.4500000	120	44.44	120.000000
7		0.5000000	120	44.44	120.000000
8		0.5500000	120	44.44	120.000000

9		0.600000	120	44.44	120.000000
10		0.650000	120	44.44	120.000000
11		0.700000	120	44.44	120.000000
12		0.750000	120	44.44	120.000000
13		0.800000	120	44.44	120.000000
14	0.1000000	0.200000	45	16.67	38.000000
15		0.250000	47	17.41	36.000000
16		0.300000	49	18.15	35.000000
17		0.350000	46	17.04	35.000000
18		0.400000	49	18.15	32.000000
19		0.450000	48	17.78	30.000000
20		0.500000	52	19.26	30.000000
21		0.550000	55	20.37	29.000000
22		0.600000	57	21.11	27.000000
23		0.650000	63	23.33	25.000000
24		0.700000	65	24.07	22.000000
25		0.750000	66	24.44	23.000000
26		0.800000	69	25.56	23.000000

27	1.0000000	0.200000	51	18.89	21.000000
28		0.250000	53	19.63	17.000000
29		0.300000	52	19.26	17.000000
30		0.350000	52	19.26	15.000000
31		0.400000	53	19.63	11.000000
32		0.450000	53	19.63	11.000000
33		0.500000	54	20.00	9.000000
34		0.550000	54	20.00	9.000000
35		0.600000	56	20.74	8.000000
36		0.650000	57	21.11	8.000000
37		0.700000	60	22.22	5.000000
38		0.750000	61	22.59	5.000000
39		0.800000	62	22.96	5.000000
40	10.000000	0.200000	57	21.11	4.000000
41		0.250000	59	21.85	3.000000
42		0.300000	61	22.59	2.000000
43		0.350000	62	22.96	1.000000
44		0.400000	62	22.96	1.000000
45		0.450000	62	22.96	1.000000
46		0.500000	62	22.96	1.000000
47		0.550000	63	23.33	1.000000

N	C	KF1	NMisc	Perct	TrainErr
48	10.000000	0.600000	63	23.33	1.000000
49		0.650000	61	22.59	1.000000

50		0.700000	64	23.70	1.00000000
51		0.750000	65	24.07	1.00000000
52		0.800000	65	24.07	0.00000000
53	100.00000	0.200000	67	24.81	1.00000000
54		0.250000	64	23.70	0.00000000
55		0.300000	63	23.33	0.00000000
56		0.350000	63	23.33	0.00000000
57		0.400000	63	23.33	0.00000000
58		0.450000	64	23.70	0.00000000
59		0.500000	64	23.70	0.00000000
60		0.550000	63	23.33	0.00000000
61		0.600000	63	23.33	0.00000000
62		0.650000	64	23.70	0.00000000
63		0.700000	65	24.07	0.00000000
64		0.750000	66	24.44	0.00000000
65		0.800000	67	24.81	0.00000000

Best 10 Results of Grid Search

```

-----
      N          C          KF1 NMisc  Perct   TrainErr
14  0.1000000  0.2000000   45  16.67  38.0000000
17  0.1000000  0.3500000   46  17.04  35.0000000
15  0.1000000  0.2500000   47  17.41  36.0000000
19  0.1000000  0.4500000   48  17.78  30.0000000
18  0.1000000  0.4000000   49  18.15  32.0000000
16  0.1000000  0.3000000   49  18.15  35.0000000
27  1.0000000  0.2000000   51  18.89  21.0000000
30  1.0000000  0.3500000   52  19.26  15.0000000
29  1.0000000  0.3000000   52  19.26  17.0000000
20  0.1000000  0.5000000   52  19.26  30.0000000

```

Best solution with C=0.1 and kernel parameter=0.2 selected.

---Start Training Cycle: Technique= PSVM---

```

*****
Evaluation of Training Data Fit
*****

```

Index	Value	StdErr
Absolute Classification Error	38	.
Classification Accuracy	85.92592593	.

Concordant Pairs	72.53333333	.
Discordant Pairs	1.866666667	.
Tied Pairs	25.60000000	.
Goodman-Kruskal Gamma	0.949820789	0.017697016
Kendall Tau_b	0.714651854	0.042657886
Stuart Tau_c	0.697942387	0.044058227
Somers D C R	0.706666667	0.043560090

Classification Table

```

-----
      |      Predicted
      |      -1      1
-----|-----
-1 |      136     14
 1 |       24     96

```

---Start CrossValidation: Technique= PSVM---

\*\*\*\*\*  
K=10 Fold Cross Validation  
\*\*\*\*\*

Fold	Nmiss	+Ch	-Ch
1	7	5	2
2	5	3	2
3	4	4	0
4	3	2	1
5	6	2	4
6	2	1	1
7	3	2	1
8	8	4	4
9	4	3	1
10	3	2	1

Runtime for K=10 fold cross validation in seconds: 2

\*\*\*\*\*  
Evaluation of Cross Validation Data Fit  
\*\*\*\*\*

Index	Value	StdErr
-------	-------	--------

Absolute Classification Error	45	.
Classification Accuracy	83.33333333	.
Concordant Pairs	67.97777778	.
Discordant Pairs	2.644444444	.
Tied Pairs	29.37777778	.
Goodman-Kruskal Gamma	0.925110132	0.024224006
Kendall Tau_b	0.661675238	0.045783874
Stuart Tau_c	0.645267490	0.046741328
Somers D C R	0.653333333	0.046482972

Classification Table

Observed	Predicted	
	-1	1
-1	133	17
1	28	92

Regularization Parameter C . . . . .	0.1
Norm of Longest Vector . . . . .	1.41421
Number Misclassifications (Training Data) . . . . .	38
Number Misclassifications (Split Cross Validation) . . . . .	45
Total Number of Kernel Calls . . . . .	6.80922e+007
Time for Optimization . . . . .	0
Total Processing Time . . . . .	95
Optimization Criterion . . . . .	.
Geometric Margin . . . . .	1.08558 ( $ w ^2= 3.39419$ )
Number Support Vectors . . . . .	270 (100.00 %)
Number Support Vectors on Margin . . . . .	38
Bias . . . . .	-0.00072126
Radius of Sphere Around SV . . . . .	1.33031
Estimated VCdim of Classifier . . . . .	7.00675
KT Threshold . . . . .	6.99029e-018
Number CV Computations . . . . .	10
CV Estimate of Error (Nmis=45) . . . . .	16.6667 %
CV Estimate of Recall . . . . .	76.6667 %
CV Estimate of Precision . . . . .	84.4037 %

Even though one training takes less than one second, the complete tuning process requires 93 seconds:

```

Total Number of Kernel Calls: 6.80922e+007
Time for Optimization: 0
Total Processing Time: 95
Time for Parameter Tuning: 93

```

## 2. Example for Bounded Optimal Parameter Tuning:

```

/*--- FQP: QPNUSP: with Split Cross Validation ---*/
data = rspfile("../tdata/heart_scale.dat");
modl = "1 = 2 : 14";
class = 1;

/* [2] tuning by automatic NMS: specify bounds */
tun_s = [ 1.e-6  100. ,
          1.e-6   .5 ];

/*--- PSVM: bounded automatic tuning ---*/
optn = [ "print"      3 ,
         "tun"        "bound" ,
         "split"      10 ,
         "kern"       "rbf2" ,
         "meth"       "psv" ];
< alfa,sres,vres,yptr > = svm(data,modl,optn,class,tun_s);

```

---Start Tuning Cycle: Technique= PSVM---

```

*****
Results of Grid Search for 2 Parameters
*****

```

N	C	KF1	NMisc	Perct	TrainErr
1	1.00e-006	1.00e-006	120	44.44	120.000000
2		0.0050010	120	44.44	120.000000
3		0.0500009	120	44.44	120.000000
4		0.5000000	120	44.44	120.000000
5	1.0000010	1.00e-006	120	44.44	120.000000
6		0.0050010	44	16.30	38.0000000
7		0.0500009	44	16.30	39.0000000
8		0.5000000	54	20.00	9.00000000
9	10.000001	1.00e-006	120	44.44	120.000000
10		0.0050010	41	15.19	38.0000000

11		0.0500009	52	19.26	21.0000000
12		0.5000000	62	22.96	1.0000000
13	100.00000	1.00e-006	117	43.33	119.000000
14		0.0050010	45	16.67	35.0000000
15		0.0500009	58	21.48	8.0000000
16		0.5000000	64	23.70	0.0000000

Best solution with C=10 and kernel parameter=0.00500099 selected.

Iteration Start:

N. Variables	2	N. Mask Constr.	0
N. Bound. Constr.	4	N. Active Constraints	0
Criterion	132.9899993		

Iter	rest	nfun	act	optcrit	nmis	difcrit	std	size
1	0	5	0	132.856	41	0.49270	0.2080	1.50000
						15.0000009	0.00250100	
2	0	6	0	132.856	41	0.13412	6e-002	1.50000
						15.0000009	0.00250100	
3	0	8	0	132.856	41	0.03590	1e-002	1.12500
						15.0000009	0.00250100	
4	0	10	0	132.848	120	0.02318	1e-002	0.75000
						11.8750009	0.00312599	
5	0	12	0	132.825	120	0.03099	1e-002	0.46875
						11.7187509	0.00265724	
6	0	13	0	132.825	120	0.02270	1e-002	0.54688
						11.7187509	0.00265724	
7	0	15	0	132.825	120	3e-003	1e-003	0.58594
						11.7187509	0.00265724	
8	0	17	0	132.821	120	6e-003	2e-003	0.36328
						9.98046965	0.00306740	
9	0	19	0	132.821	120	4e-003	1e-003	0.37354
						9.98046965	0.00306740	
10	0	21	0	132.819	42	5e-003	2e-003	0.78809
						7.93212983	0.00371925	
11	0	23	0	132.819	42	3e-003	1e-003	0.64545
						7.93212983	0.00371925	
12	0	25	0	132.816	41	4e-003	2e-003	0.36017
						7.89611909	0.00382607	
13	0	27	0	132.816	41	2e-003	1e-003	0.19881
						7.89611909	0.00382607	
14	0	28	0	132.816	41	2e-003	8e-004	0.32272
						7.89611909	0.00382607	

Convergence: Simplex with small differences 0.00179004 in function values.



Tuning Result by Optimization F=132.816 (Nmis=41)

\*\*\*\*\*

Regularization C	7.8961191
First Kernel Par	0.0038261

---Start Training Cycle: Technique= PSVM---

\*\*\*\*\*

Evaluation of Training Data Fit

\*\*\*\*\*

Index	Value	StdErr
Absolute Classification Error	38	.
Classification Accuracy	85.92592593	.
Concordant Pairs	72.95555556	.
Discordant Pairs	1.95555556	.
Tied Pairs	25.08888889	.
Goodman-Kruskal Gamma	0.947789973	0.018021781
Kendall Tau_b	0.714298727	0.042853057
Stuart Tau_c	0.701234568	0.043906720
Somers D C R	0.710000000	0.043392908

Classification Table

```
-----  
      | Predicted  
Observed | -1  1  
-----|-----  
      -1 | 134 16  
      1 |  22 98
```

---Start CrossValidation: Technique= PSVM---

\*\*\*\*\*

K=10 Fold Cross Validation

\*\*\*\*\*

Fold	Nmiss	+Ch	-Ch
1	5	3	2

2	6	3	3
3	5	5	0
4	3	1	2
5	5	1	4
6	0	0	0
7	2	1	1
8	8	4	4
9	4	3	1
10	3	2	1

Runtime for K=10 fold cross validation in seconds: 2

\*\*\*\*\*  
 Evaluation of Cross Validation Data Fit  
 \*\*\*\*\*

Index	Value	StdErr
Absolute Classification Error	41	.
Classification Accuracy	84.81481481	.
Concordant Pairs	71.13333333	.
Discordant Pairs	2.30000000	.
Tied Pairs	26.56666667	.
Goodman-Kruskal Gamma	0.937358148	0.020748504
Kendall Tau_b	0.691703996	0.044255926
Stuart Tau_c	0.679835391	0.045074591
Somers D C R	0.688333333	0.044666408

Classification Table

```

-----
      | Predicted
Observed | -1  1
-----|-----
    -1 | 132 18
     1 |  23 97
  
```

Regularization Parameter C . . . . .	7.89612
Norm of Longest Vector . . . . .	1.41421
Number Misclassifactions (Training Data) . . . . .	38
Number Misclassifactions (Split Cross Validation). . . . .	41
Total Number of Kernel Calls . . . . .	4.91617e+007
Time for Optimization. . . . .	0
Total Processing Time. . . . .	76

```

Optimization Criterion . . . . .
Geometric Margin . . . . . 0.245851 (|w|^2= 66.1786)
Number Support Vectors . . . . . 270 (100.00 %)
Number Support Vectors on Margin . . . . . 38
Bias . . . . . -5.67557e-005
Radius of Sphere Around SV . . . . . 0.284634
Estimated VCdim of Classifier. . . . . 6.36157
KT Threshold . . . . . 1.2747e-017

Number CV Computations . . . . . 10
CV Estimate of Error (Nmis=41) . . . . . 15.1852 %
CV Estimate of Recall. . . . . 80.8333 %
CV Estimate of Precision . . . . . 84.3478 %

```

The full QP method takes much more time than the PSVM method:

```

/*--- FQP: bounded automatic tuning ---*/
optn = [ "print"      3 ,
         "tun"       "bound" ,
         "split"     10 ,
         "kern"      "rbf2" ,
         "meth"      "fqp" ];
< alfa,sres,vres,yptr > = svm(data,modl,optn,class,tun_s);

```

---Start Tuning Cycle: Technique= FQP---

```

*****
Results of Grid Search for 2 Parameters
*****

```

N	C	KF1	NMisc	Perct	TrainErr
1	1.00e-006	1.00e-006	105	38.89	42.0000000
2		0.0050010	118	43.70	42.0000000
3		0.0500009	112	41.48	120.0000000
4		0.5000000	120	44.44	120.0000000
5	1.0000010	1.00e-006	118	43.70	120.0000000
6		0.0050010	45	16.67	42.0000000
7		0.0500009	45	16.67	41.0000000
8		0.5000000	55	20.37	19.0000000
9	10.000001	1.00e-006	93	34.44	72.0000000
10		0.0050010	46	17.04	41.0000000
11		0.0500009	51	18.89	25.0000000
12		0.5000000	64	23.70	1.0000000

13	100.00000	1.00e-006	44	16.30	44.0000000
14	100.00000	0.0050010	48	17.78	38.0000000
15		0.0500009	57	21.11	8.0000000
16		0.5000000	59	21.85	0.0000000

Best solution with C=100 and kernel parameter=1e-006 selected.

Iteration Start:

N. Variables	2	N. Mask Constr.	0
N. Bound. Constr.	4	N. Active Constraints	0
Criterion	752.9234286		

Iter	rest	nfun	act	optcrit	nmis	difcrit	std	size
1	0	5	1	255.076	44	516.397	239.18	3.00000
						97.5000000	1.000e-006	
2	0	6	1	255.076	44	497.848	234.51	2.25000
						97.5000000	1.000e-006	
3	0	8	2	254.708	44	1.10504	0.4595	1.00000
						100.0000000	1.000e-006	
4	1	12	2	254.708	44	0.00000	0.0000	0.00000
						100.0000000	1.000e-006	

Convergence: Simplex with small differences 0 in function values.

Tuning Result by Optimization F=254.708 (Nmis=44)

\*\*\*\*\*

Regularization C	100.00000
First Kernel Par	1.00e-006

---Start Training Cycle: Technique= FQP---

\*\*\*\*\*

Evaluation of Training Data Fit

\*\*\*\*\*

Index	Value	StdErr
Absolute Classification Error	44	.
Classification Accuracy	83.70370370	.
Concordant Pairs	68.48888889	.
Discordant Pairs	2.48888889	.
Tied Pairs	29.02222222	.
Goodman-Kruskal Gamma	0.929868503	0.023102582
Kendall Tau_b	0.669438681	0.045290515

Stuart Tau\_c                    0.651851852   0.046395230  
 Somers D C|R                   0.660000000   0.046108568

Classification Table

```

-----
                |      Predicted
Observed |      -1      1
-----|-----
      -1 |      134     16
         |      28     92
         1 |
  
```

---Start CrossValidation: Technique= FQP---

\*\*\*\*\*  
 K=10 Fold Cross Validation  
 \*\*\*\*\*

Fold	Nmiss	+Ch	-Ch
1	4	4	0
2	5	3	2
3	6	6	0
4	3	2	1
5	5	1	4
6	1	1	0
7	4	3	1
8	8	4	4
9	4	3	1
10	4	2	2

Runtime for K=10 fold cross validation in seconds: 8

\*\*\*\*\*  
 Evaluation of Cross Validation Data Fit  
 \*\*\*\*\*

Index	Value	StdErr
Absolute Classification Error	44	.
Classification Accuracy	83.70370370	.
Concordant Pairs	68.25000000	.
Discordant Pairs	2.416666667	.
Tied Pairs	29.33333333	.
Goodman-Kruskal Gamma	0.931603774	0.022839544

Kendall Tau_b	0.669895779	0.045131914
Stuart Tau_c	0.650205761	0.046403557
Somers D C R	0.658333333	0.046121568

Classification Table

Observed	Predicted	
	-1	1
-1	135	15
1	29	91

```

Regularization Parameter C . . . . . 100
Norm of Longest Vector . . . . . 1
Number Misclassifactions (Training Data) . . . . . 44
Number Misclassifactions (Split Cross Validation). . . . . 44
Total Number of Kernel Calls . . . . . 3.37982e+007
Time for Optimization. . . . . 1
Total Processing Time. . . . . 413
Optimization Criterion . . . . . -23658.2
Infinity Norm of Gradient. . . . . 2.09388e-013
Geometric Margin . . . . . 0.0764978 (|w|^2= 683.536)
Number Support Vectors . . . . . 241 ( 89.26 %)
Number Support Vectors on Margin . . . . . 238
Bias . . . . . -0.00178453
Radius of Sphere Around SV . . . . . 0.00461052
Estimated VCdim of Classifier. . . . . 1.01453
KT Threshold . . . . . 0

Number CV Computations . . . . . 10
CV Estimate of Error (Nmis=44) . . . . . 16.2963 %
CV Estimate of Recall. . . . . 75.8333 %
CV Estimate of Precision . . . . . 85.8491 %

```

## 2.3 New Functions

New functions are implemented:

**sir** Sliced Inverse Regression (S. Weisberg, 2002)

**generead** not finished yet.

## 3 New Developments

### 3.1 Function sir

---

`< gof,parm,atst,ptst,res > = sir(a,model<,"sopt"<,optn<,slic<,class>>>>)`

---

**Purpose:** The `sir` function implements a number of methods for finding a valid subspace of predictors for given uni- or multivariate response  $\mathbf{Y}$ . It implements asymptotic tests as well as a permutation test for determining the correct dimension.

**Input:**  $\mathbf{a}$  the  $N \times M$  input data set containing the  $N \times p$  predictor matrix  $\mathbf{X}$  and the  $N \times k$  response vector or matrix  $\mathbf{Y}$  in its columns. Which columns are selected must be specified with the model string.

**model :** The analysis model is specified in form of a string, e.g. `model="3=1 2"`, containing column numbers for variables. The model string specifies which variables (columns) are independent (predictors, covariates) and which are dependent (response variables) and is of the form

$$Y_1 \dots Y_r = X_{effect_1} \dots X_{effect_n}$$

where  $X_{effect_i}$  may be one of the following:

- a single variable  $x_i$  is an effect
- effects that are interactions among multiple  $x$  variables, separated by the `*` operator,  $x_i * \dots * x_l$
- nested effects: that are single variables or interactions followed by a list of variables inside parentheses,  $(x_i \dots x_l)$ . Note that only categorical variables without interactions can be listed inside parentheses.

The parameters of the effects are estimated for each response variable  $Y_i$  separately. Additionally for the `glim` function you may specify so-called "effects/trials" response variables in the form

$$Y_{effects}/Y_{trials} = X_{effect_1} \dots X_{effect_n}$$

i.e. by listing two data column numbers separated by a forward slash. There are a number of additional features which can make it easier to use such a kind of model specification:

- You may use the `|` (bar) operator, for the shorter notation of `model = "3 = 1 2 1*2"` by `model="3 = 1 | 2"`.
- You may use the colon operator to express a successive number single variable effects, e.g. `"4= 1 : 3 * 5"` is the same as `"4= 1 2 3*5"`.

- Instead of specifying the entire model in one long string variable you may use a vector of strings. However, each effect must be entirely contained in one vector entry and cannot be continued with the next entry. E.g. the above example could be split into the vector `v` as `v[1]="4="; v[2]="1 2"; v[3]="3*5"; .` Note, that the order of the effect listing is important for stepwise regression and Type I estimates.

The syntax of the `model` string argument is the same as for the `glmod()` function except for the additional *events / trial* response specification.

**sopt** This must be a string specifying the method:

”sir” sliced inverse regression (Li, 1991; Cook, 1998)

”save” sliced average variance estimation (Cook & Weisberg, 1991)

”rphd” principal Hessian direction (residuals) (Li, 1992; Cook, 1998)

”yphd” principal Hessian direction (response  $y$ )

”qphd” quadratic principal Hessian direction (Li, 1992)

**optn** : The option argument is specified in form of a two column matrix where the first column defines the option as string value (in quotes) and the second column can be used for a numeric or string specification of the option. Some of the options are similar to those of the `glmod()` and `glmixd()` functions. See table below for content.

**slic** This can be a scalar (for one response) or a vector of  $k$  values, where  $k$  is the number of response variables. It specifies the number of slices for each response  $y_j, j = 1, \dots, k$ .

**class** : This optional argument should be an integer scalar or vector of integer scalars naming the number of columns which are considered categorical (nominal scaled) variables.

**Options Matrix Argument:** The option argument is specified in form of a two column matrix:

Option Name	Second Column	Meaning
"alpha"	real	the significance level for $p$ values; default is $\alpha = 0.05$
"freq"	int	column number of FREQ variable
"nperm"	int	replications for permutation test
"numdir"	int	number directions to be tested, default is $rank(X)$
"offset"	int	column number of offset variable
"print"	int	amount of printed output
"seed"	real	seed value for random generator
"slic"	int	number of slices (only for univariate response)
"vardef"	string	variance divisor
"weight"	int	column number of weight variable

**Output:** `gof` goodness-of-fit coefficients



**parm** eigenvalues and eigenvectors  
**atst** asymptotic test table  
**ptst** permutation test table  
**res** residuals

**Restrictions:** 1. The input data set should not contain missing values, string or complex data.

**Relationships:** factor(), sem(), pls()

**Examples:** 1. Australian Institute of Sport (ais) data set (Weisberg, 2002):

```
options NOECHO;
ais = [
%inc "..\tdata\ais.dat";
];
options ECHO;
cname = [ "Sex" "Ht" "Wt" "LBM" "RCC" "WCC" "Hc" "Hg" ];
ais = shape(ais,.,8);
nobs = nrow(ais); nvar = ncol(ais);
ais = ais -> log(ais[,5]);
```

Using the "sir" method:

```
modl = "4 = 2 3 9 6";
optn = [ "slic"      8 ,
        "dec"       "svd" ,
        "numdir"    4 ,
        "print"     3 ,
        "nperm"    499 ,
        "seed"     123 ];
< gof,parm,atst,ptst > = sir(ais,modl,"sir",optn);
```

```
*****
Model Information
*****
```

```
Number Valid Observations  202
Response Variable          Y[4]
N Independent Variables    4
Reduction Method          SIR
Number of Sclices         8
N Test Directions         4
Significance Level:       0.0500000
Random Seed                123
```

\*\*\*\*\*  
 Model Effects  
 \*\*\*\*\*

X2 + X3 + X9 + X6

\*\*\*\*\*  
 Simple Statistics  
 \*\*\*\*\*

Column	Nobs	Mean	Std Dev	Skewness	Kurtosis
Y[4]	202	64.873713	13.070197	0.3611965	-0.2158696
X[2]	202	180.10396	9.7344945	-0.2007970	0.5717271
X[3]	202	75.008168	13.925574	0.2424318	0.4254397
X[9]	202	1.5468840	0.0963023	0.1185203	-0.1197264
X[6]	202	7.1086634	1.8005490	0.8413109	1.5149690

\*\*\*\*\*  
 Parameter Information  
 \*\*\*\*\*

Parameter | Meaning

-----  
 1 | X2  
 2 | X3  
 3 | X9  
 4 | X6

Slice Sizes

-----

1 :	26	26	25	25	25
6 :	27	30	18		

Eigenvectors

	Dir1	Dir2	Dir3	Dir4
X1	0.01054752	1.569e-004	0.10750718	0.00919795
X2	0.02374812	-0.00409125	-0.06248766	-0.01928675
X3	0.99960915	0.99996148	-0.99211547	0.75708759
X4	-0.01031144	-0.00776400	0.01563290	0.65296386

	Dir1	Dir2	Dir3	Dir4
Eigenvalues	0.87789585	0.15017504	0.03972711	0.01737281
R <sup>2</sup> (OLS dr)	0.70079174	0.95966284	0.99681662	1.00000000

Asymptotic Chi-Square Tests for Dimension  
\*\*\*\*\*

	ChiSqu	df	p-value
0D vs >= 1D	219.204503	28	0.0000
1D vs >= 2D	41.8695414	18	0.0012
2D vs >= 3D	11.5341836	10	0.3174
3D vs >= 4D	3.50930731	4	0.4765

Permutation Test Results (Nperm=499)  
\*\*\*\*\*

	ChiSqu	p-value
0D vs >= 1D	219.204503	0.0000
1D vs >= 2D	41.8695414	0.0020
2D vs >= 3D	11.5341836	0.3080
3D vs >= 4D	3.50930731	0.4020

```
print "GOF=",gof;
print "Parm=",parm;
print "Atst=",atst;
print "Ptst=",ptst;
```

	X1	X2	X3	X4
Eigenvalues	0.87790	0.15018	0.03973	0.01737
R <sup>2</sup> (OLS dr)	0.70079	0.95966	0.99682	1.00000
X1	0.01055	0.00016	0.10751	0.00920
X2	0.02375	-0.00409	-0.06249	-0.01929
X3	0.99961	0.99996	-0.99212	0.75709
X4	-0.01031	-0.00776	0.01563	0.65296

Atst=

	ChiSquare	DF	p-value
0D vs >= 1D	219.205	28.000	2e-031
1D vs >= 2D	41.870	18.000	0.001

2D vs >= 3D	11.534	10.000	0.317
3D vs >= 4D	3.509	4.000	0.476

Ptst=

LOW	ChiSquare	p-value
0D vs >= 1D	219.205	0
1D vs >= 2D	41.870	0.002
2D vs >= 3D	11.534	0.308
3D vs >= 4D	3.509	0.402

Using the "save" method:

```

modl = "4 = 2 3 9 6";
optn = [ "slic"      8 ,
        "dec"      "svd" ,
        "numdir"   4 ,
        "print"    3 ,
        "nperm"    499 ,
        "seed"     123 ];
< gof,parm,atst,ptst > = sir(ais,modl,"save",optn);

```

Slice Sizes

-----					
1 :	26	26	25	25	25
6 :	27	30	18		

Eigenvectors

	Dir1	Dir2	Dir3	Dir4
X1	2.550e-004	0.25690992	-0.00542506	0.00365180
X2	0.02785912	-0.14344669	-0.00152016	-0.00561149
X3	0.99935272	-0.88860377	0.99899078	0.99882543
X4	-0.02275826	0.35185747	0.04456093	-0.04798888

	Dir1	Dir2	Dir3	Dir4
Eigenvalues	0.80277774	0.38219979	0.15647959	0.09020895
R^2(OLS dr)	0.70079174	0.95966284	0.99681662	1.00000000

Permutation Test Results (Nperm=499)

\*\*\*\*\*

	ChiSqu	p-value
0D vs >= 1D	289.196546	0.0020
1D vs >= 2D	127.035442	0.1700
2D vs >= 3D	49.8310850	0.8240
3D vs >= 4D	18.2222083	0.7800

Using the "rphd" method:

```

modl = "4 = 2 3 9 6";
optn = [ "slic"      8 ,
        "dec"      "svd" ,
        "numdir"   4 ,
        "print"    3 ,
        "nperm"    499 ,
        "seed"     123 ];
< gof,param,atst,ptst > = sir(ais,modl,"rphd",optn);

print "GOF=",gof;
print "Parm=",param;
print "Atst=",atst;
print "Ptst=",ptst;

```

### Eigenvectors

	Dir1	Dir2	Dir3	Dir4
X1	0.12764099	-3.378e-004	0.00555008	-0.02548627
X2	-0.02163115	0.03261381	-0.00734152	0.01343129
X3	-0.74347735	0.98164633	0.99993021	0.99908616
X4	0.65611074	-0.18790078	-0.00740800	0.03157356

	Dir1	Dir2	Dir3	Dir4
Eigenvalues	1.43025337	1.17504352	1.12441046	0.39992542
R <sup>2</sup> (OLS dr)	0.70079174	0.95966284	0.99681662	1.00000000

### Asymptotic Chi-Square Tests for Dimension

\*\*\*\*\*

	ChiSqu	df	p-value	IndepT	General
0D vs >= 1D	35.0150809	10	0.0001	0.0054	0.0181
1D vs >= 2D	20.2482800	6	0.0025	.	0.0320
2D vs >= 3D	10.2811903	3	0.0163	.	0.0553
3D vs >= 4D	1.15456526	1	0.2826	.	0.2663

Permutation Test Results (Nperm=499)  
 \*\*\*\*\*

	ChiSqu	p-value
0D vs >= 1D	35.0150809	0.0080
1D vs >= 2D	20.2482800	0.0140
2D vs >= 3D	10.2811903	0.0520
3D vs >= 4D	1.15456526	0.3240

Using the "yphd" method:

```

modl = "4 = 2 3 9 6";
optn = [ "slic"      8 ,
        "dec"       "svd" ,
        "numdir"    4 ,
        "print"     3 ,
        "nperm"     499 ,
        "seed"      123 ];
< gof,parm,atst,ptst > = sir(ais,modl,"yphd",optn);

```

Eigenvectors

	Dir1	Dir2	Dir3	Dir4
X1	0.07148043	-0.01776378	-0.00294621	0.03686273
X2	-0.06585991	0.01185685	-0.00301142	-0.00523703
X3	-0.98952448	-0.96941019	0.99998202	0.99890219
X4	0.10674416	0.24451532	0.00426841	0.02842752

	Dir1	Dir2	Dir3	Dir4
Eigenvalues	10.4455178	1.75295405	1.73428918	1.56858401
R <sup>2</sup> (OLS dr)	0.70079174	0.95966284	0.99681662	1.00000000

Asymptotic Chi-Square Tests for Dimension  
 \*\*\*\*\*

	ChiSqu	df	p-value
0D vs >= 1D	69.5582534	10	0.0000
1D vs >= 2D	5.04973979	6	0.5374
2D vs >= 3D	3.23297730	3	0.3571
3D vs >= 4D	1.45469739	1	0.2278

Permutation Test Results (Nperm=499)  
\*\*\*\*\*

	ChiSqu	p-value
0D vs >= 1D	69.5582534	0.0000
1D vs >= 2D	5.04973979	0.5440
2D vs >= 3D	3.23297730	0.2440
3D vs >= 4D	1.45469739	0.0980

### 3.2 Function generead