## SPGL1

Oct 05, 2021
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SPGL1 is a solver for large-scale one-norm regularized least squares.
It is designed to solve any of the following three problems:

1. Basis pursuit denoise (BPDN):

$$
\min \quad\|\mathbf{x}\|_{1} \quad \text { subj.to } \quad\|\mathbf{A} \mathbf{x}-\mathbf{b}\|_{2}<=\sigma
$$

2. Basis pursuit (BP):

$$
\min \|\mathbf{x}\|_{1} \quad \text { subj.to } \quad \mathbf{A} \mathbf{x}=\mathbf{b}
$$

3. Lasso:

$$
\min \quad\|\mathbf{A x}-\mathbf{b}\|_{2} \quad \text { subj.to } \quad\|\mathbf{x}\|_{1}<=\tau
$$

The matrix A can be defined explicitly, or as a scipy.sparse.linalg.LinearOperator that returns both both $\mathbf{A x}$ and $\mathbf{A}^{H} \mathbf{b}$.

SPGL1 can solve these three problems in both the real and complex domains.

## CHAPTER 1

## References

The algorithm implemented by SPGL1 is described in these two papers:

- E. van den Berg and M. P. Friedlander, Probing the Pareto frontier for basis pursuit solutions, SIAM J. on Scientific Computing, 31(2):890-912, November 2008
- E. van den Berg and M. P. Friedlander, Sparse optimization with least-squares constraints, Tech. Rep. TR-2010-02, Dept of Computer Science, Univ of British Columbia, January 2010


## CHAPTER 2

History

SPGL1 has been initially implemented in MATLAB by E. van den Berg and M. P. Friedlander. This project is aimed at porting of their algorithm in Python. Small modifications are implemented in some areas of the code where more appropriate implementation choices were identified for the Python programming language.

### 2.1 Installation

Python 3.5 or greater is required. This package may also work for Python 2.7 or greater, however we do not provide any guarantee neither we will make any effort to maintain back compatibility with Python 2.

### 2.1.1 From PyPI

To install spgl1 within your current environment, simply type:

```
>> pip install spgl1
```


### 2.1.2 From source

First of all clone the repository. To install spgl1 within your current environment, simply type:

```
>> make install
```

or as a developer:

```
>> make dev-install
```

To install spgl1 in a new conda environment, type:

```
>> make install_conda
```

or as a developer:

```
>> make dev-install_conda
```


### 2.2 SPGL1 API

### 2.2.1 Main Solver

$\operatorname{spg} 11(\mathrm{~A}, \mathrm{~b}[$, tau, sigma, x 0, fid, $\ldots]) \quad$ SPGL1 solver.
spgl1.spgl1
spgl1.spgl1 $\left(A, b\right.$, tau $=0$, sigma $=0, x 0=$ None, fid $=$ None, verbosity $=0$, iter_lim=None, $n \_p r e v \_v a l s=3$, $b p \_t o l=1 e-06, \quad l s \_t o l=1 e-06, \quad$ opt_tol $=0.0001, \quad d e c \_t o l=0.0001, \quad$ step_min=1e-16, step_max=100000.0, active_set_niters=inf, subspace_min=False, iscomplex=False, max_matvec $=i n f, \quad$ weights $=$ None, project $=<f u n c t i o n ~ \_n o r m \_l l \_p r o j e c t>, ~ p r i-~$ mal_norm=<function_norm_ll_primal>,dual_norm=<function_norm_ll_dual> )
SPGL1 solver.
Solve basis pursuit (BP), basis pursuit denoise (BPDN), or LASSO problems [1] [2] depending on the choice of tau and sigma:

| (BP) | minimize $\|\|x\|\| \_1$ subj. to $A x=b$ |
| :--- | :--- | :--- |
| (BPDN) | minimize $\|\|x\|\| \_1$ subj. to $\|\|A x-b\|\| \_2<=$ sigma |
| (LASSO) | minimize $\|\|A x-b\|\| \_2$ subj, to $\|\|x\|\| \_1<=$ tau |

The matrix A may be square or rectangular (over-determined or under-determined), and may have any rank.

## Parameters

A [\{sparse matrix, ndarray, LinearOperator\}] Representation of an m-by-n matrix. It is required that the linear operator can produce $A x$ and $A^{\wedge} T x$.
b [array_like, shape (m,)] Right-hand side vector b.
tau [float, optional] LASSO threshold. If different from None, spgl1 solves LASSO problem
sigma [float, optional] BPDN threshold. If different from None, spgl1 solves BPDN problem
$\mathbf{x 0}$ [array_like, shape ( $n$,), optional] Initial guess of $x$, if None zeros are used.
fid [file, optional] File ID to direct $\log$ output, if None print on screen.
verbosity [int, optional] $0=$ quiet, $1=$ some output, $2=$ more output.
iter_lim [int, optional] Max. number of iterations (default if $10 * m$ ).
n_prev_vals [int, optional] Line-search history lenght.
bp_tol [float, optional] Tolerance for identifying a basis pursuit solution.
ls_tol [float, optional] Tolerance for least-squares solution. Iterations are stopped when the ratio between the dual norm of the gradient and the L2 norm of the residual becomes smaller or equal to ls_tol.
opt_tol [float, optional] Optimality tolerance. More specifically, when using basis pursuit denoise, the optimility condition is met when the absolute difference between the L2 norm of the residual and the sigma is smaller than opt_tol.
dec_tol [float, optional] Required relative change in primal objective for Newton. Larger decTol means more frequent Newton updates.
step_min [float, optional] Minimum spectral step.
step_max [float, optional] Maximum spectral step.
active_set_niters [float, optional] Maximum number of iterations where no change in support is tolerated. Exit with EXIT_ACTIVE_SET if no change is observed for activeSetIt iterations
subspace_min [bool, optional] Subspace minimization (True) or not (False)
iscomplex [bool, optional] Problem with complex variables (True) or not (False)
max_matvec [int, optional] Maximum matrix-vector multiplies allowed
weights [\{float, ndarray \}, optional] Weights $W$ in $||W x|| \_1$
project [func, optional] Projection function
primal_norm [func, optional] Primal norm evaluation fun
dual_norm [func, optional] Dual norm eval function

## Returns

$\mathbf{x}$ [array_like, shape ( n, )] Inverted model
r [array_like, shape (m,)] Final residual
g [array_like, shape (h,)] Final gradient
info [dict] Dictionary with the following information:
tau, final value of tau (see sigma above)
rnorm, two-norm of the optimal residual
rgap, relative duality gap (an optimality measure)
gnorm, Lagrange multiplier of (LASSO)
stat, 1: found a BPDN solution, 2: found a BP solution; exit based on small gradient, 3: found a BP solution; exit based on small residual, 4: found a LASSO solution, 5: error: too many iterations, 6: error: linesearch failed, 7: error: found suboptimal BP solution, 8: error: too many matrix-vector products
niters, number of iterations
nProdA, number of multiplications with A
nProdAt, number of multiplications with $A^{\prime}$
n_newton, number of Newton steps
time_project, projection time (seconds)
time_matprod, matrix-vector multiplications time (seconds)
time_total, total solution time (seconds)
niters_lsqr, number of lsqr iterations (if subspace_min=True)
xnorm1, L1-norm model solution history through iterations
rnorm2, L2-norm residual history through iterations
lambdaa, Lagrange multiplier history through iterations

## References

[1], [2]

## Examples using spgl1.spgl1

- sphx_glr_tutorials_spgl1.py


### 2.2.2 Other Solvers

| oneprojector(b, d, tau) | One projector. |
| :--- | :--- |
| spg_bp(A, b, **kwargs) | Basis pursuit (BP) problem. |
| spg_bpdn(A, b, sigma, ${ }^{* *}$ kwargs) | Basis pursuit denoise (BPDN) problem. |
| spg_lasso(A, b, tau, $* *$ kwargs $)$ | LASSO problem. |
| spg_mmv(A, B[, sigma $)$ | MMV problem. |

## spgl1.oneprojector

```
spgl1.oneprojector ( }b,d,\mathrm{ tau)
```

One projector.
Projects b onto the (weighted) one-norm ball of radius tau. If $\mathrm{d}=1$ solves the problem:
minimize_x $||b-x|| \_^{2}$ subject to $||x|| \_1<=$ tau.
else:
minimize_x $||b-x|| \_2$ subject to $||D x|| \_1<=$ tau.

## Parameters

b [ndarray] Input vector to be projected.
d [\{ndarray, float \}] Weight vector (or scalar)
tau [float] Radius of one-norm ball.

## Returns

$\mathbf{x}$ [array_like] Projected vector

## spgl1.spg_bp

spgl1.spg_bp ( $A, b$, **kwargs)
Basis pursuit (BP) problem.
spg_bp is designed to solve the basis pursuit problem:
(BP) minimize $||x|| \_1$ subject to $A x=b$,
where A is an M-by-N matrix, b is an M-vector. A can be an explicit M-by-N matrix or a scipy. sparse. linalg.LinearOperator.
This is equivalent to calling " $\operatorname{spg} 11(\mathrm{~A}, \mathrm{~b}$, tau$=0, \operatorname{sigma}=0)$

## Parameters

A [\{sparse matrix, ndarray, LinearOperator\}] Representation of an m-by-n matrix. It is required that the linear operator can produce $A x$ and $A^{\wedge} T x$.
b [array_like, shape (m,)] Right-hand side vector b.
kwargs [dict, optional] Additional input parameters (refer to spgII.spgII for a list of possible parameters)

## Returns

$\mathbf{x}$ [array_like, shape ( n, )] Inverted model
r [array_like, shape (m,)] Final residual
g [array_like, shape (h,)] Final gradient
info [dict] See splg1.

## Examples using spgl1.spg_bp

- sphx_glr_tutorials_spgl1.py


## spgl1.spg_bpdn

spgl1.spg_bpdn ( $A, b$, sigma, **kwargs $)$
Basis pursuit denoise (BPDN) problem.
spg_bpdn is designed to solve the basis pursuit denoise problem:
(BPDN) minimize $||x|| \_1$ subject to $||A x-b||<=$ sigma
where $A$ is an M-by-N matrix, $b$ is an M-vector. A can be an explicit M-by-N matrix or a scipy. sparse. linalg.LinearOperator.
This is equivalent to calling " $\operatorname{spgl1}(\mathrm{A}, \mathrm{b}$, tau$=0$, sigma=sigma)

## Parameters

A [\{sparse matrix, ndarray, LinearOperator\}] Representation of an m-by-n matrix. It is required that the linear operator can produce $A x$ and $A^{\wedge} T x$.
b [array_like, shape (m,)] Right-hand side vector b.
kwargs [dict, optional] Additional input parameters (refer to spglI.spgII for a list of possible parameters)

## Returns

$\mathbf{x}$ [array_like, shape ( n, )] Inverted model
$\mathbf{r}$ [array_like, shape (m,)] Final residual
g [array_like, shape (h,)] Final gradient
info [dict] See spgl1.

## Examples using spgl1.spg_bpdn

- sphx_glr_tutorials_spgl1.py


## spgl1.spg_lasso

spgl1.spg_lasso ( $A, b$, tau, **kwargs)
LASSO problem.
spg_lasso is designed to solve the Lasso problem:
(LASSO) minimize $||A x-b|| \_2$ subject to $||x|| \_1<=$ tau
where $A$ is an M-by-N matrix, $b$ is an M-vector. A can be an explicit M-by-N matrix or a scipy. sparse. linalg.LinearOperator.

This is equivalent to calling " $\operatorname{spgl1}(\mathrm{A}, \mathrm{b}$, tau$=\mathrm{tau}, \operatorname{sigma}=0)$

## Parameters

A [\{sparse matrix, ndarray, LinearOperator $\}]$ Representation of an m-by-n matrix. It is required that the linear operator can produce $A x$ and $A^{\wedge} T x$.
b [array_like, shape ( m, )] Right-hand side vector b.
kwargs [dict, optional] Additional input parameters (refer to spgli.spgII for a list of possible parameters)

## Returns

$\mathbf{x}$ [array_like, shape (n,)] Inverted model
$\mathbf{r}$ [array_like, shape (m,)] Final residual
g [array_like, shape (h,)] Final gradient
info [dict] See spgl1.

Examples using spgl1.spg_lasso

- sphx_glr_tutorials_spgl1.py


## spgl1.spg_mmv

spgl1.spg_mmv $(A, B$, sigma $=0, * * k w a r g s)$
MMV problem.
spg_mmv is designed to solve the multi-measurement vector basis pursuit denoise:

$$
\text { (MMV) minimize }||X|| \ldots 1,2 \text { subject to }||A X-B|| \ldots 2,2<=\text { sigma }
$$

where $A$ is an M-by-N matrix, $b$ is an M-by-G matrix, and `sigma is a nonnegative scalar. A can be an explicit M-by-N matrix or a scipy.sparse.linalg.LinearOperator.

## Parameters

A [\{sparse matrix, ndarray, LinearOperator $\}]$ Representation of an M-by-N matrix. It is required that the linear operator can produce $A x$ and $A^{\wedge} T x$.
b [array_like, shape (m,)] Right-hand side matrix b of size M-by-G.
sigma [float, optional] BPDN threshold. If different from None, spgl1 solves BPDN problem
kwargs [dict, optional] Additional input parameters (refer to spglI.spgII for a list of possible parameters)

## Returns

$\mathbf{x}$ [array_like, shape ( n, )] Inverted model
r [array_like, shape (m,)] Final residual
g [array_like, shape (h,)] Final gradient
info [dict] See spgl1.

Examples using spgl1.spg_mmv

- sphx_glr_tutorials_mmvnn.py
- sphx_glr_tutorials_spgl1.py


### 2.3 Contributors

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## Bibliography

[1] E. van den Berg and M. P. Friedlander, "Probing the Pareto frontier for basis pursuit solutions", SIAM J. on Scientific Computing, 31(2):890-912. (2008).
[2] E. van den Berg and M. P. Friedlander, "Sparse optimization with least-squares constraints", Tech. Rep. TR-201002, Dept of Computer Science, Univ of British Columbia (2010).

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