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A Matlab toolbox to make optimization on manifolds

feel as simple as unconstrained optimization

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$\begin{array}{ll} \min & f(x) \\ \text{subject to} & x \in \mathcal{M} \end{array}$

Why care for such optimization problems?

Even if you do, why a new toolbox?



What is the minimal framework you need for steepest descent optimization?

$$\min_{x \in \mathbb{R}^n} \quad f(x)$$



Now what is the framework for this?

$\begin{array}{ll} \min & f(x) \\ \text{subject to} & x \in \mathcal{M} \end{array}$











We only need the search space to be a Riemannian manifold

We need...

A notion of directions along which we can move tangent space, tangent vector

A notion of steepest descent direction inner product, gradient

A means of moving along a direction Geodesics, retractions



Symmetry leads to manifold structures

\mathcal{M} Applications

Grassmann manifold dimensionality reduction Unit norm vector independent comp.analysis Orthonormal matrix sparse and robust PCA Rotation matrix synchronization of rotations Positive definite matrix diffusion tensor imaging Fixed-rank matrix low-rank matrix completion Semidefinite fixed-rank matrix covariance estim. Euclidean distance matrix data visualization

The theory is mature at this point.

What's been missing is matching software.



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With generic solvers, a library of manifolds and diagnostics tools

Example code for dominant eigenvectors

$$\max_{\|x\|=1} \quad x^T A x$$

$$\mathcal{M} := \{x \in \mathbb{R}^n : ||x|| = 1$$
$$f(x) = x^T A x$$
$$\nabla f(x) = 2A x$$



```
% Generate the problem data.
n = 1000;
A = randn(n);
A = .5*(A+A');
```

```
% Create the problem structure and specify the manifold.
problem.M = spherefactory(n);
```

```
% Define the problem cost function and its gradient.
problem.cost = @(x) -x'*(A*x);
problem.egrad = @(x) -2*A*x;
```

% Numerically check gradient consistency. checkgradient(problem);

Gradient check



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```
% Solve.
[x, xcost, info] = trustregions(problem);
```

>> [x, xcost, info] = trustregions(problem);

					f: 1.571531e+000	grad : 4.456216e+001	
REJ TR-	k:	1	num_inner:	1	f: 1.571531e+000	grad : 4.456216e+001	negative curvature
acc	k:	2	num_inner:	1	f: -2.147351e+001	grad : 3.053440e+001	negative curvature
acc	k:	3	num_inner:	2	f: -3.066561e+001	grad : 3.142679e+001	negative curvature
acc	k:	4	num_inner:	2	f: -3.683374e+001	grad : 2.125506e+001	exceeded trust region
acc	k:	5	num_inner:	3	f: -4.007868e+001	grad : 1.389614e+001	exceeded trust region
acc	k:	6	num_inner:	4	f: -4.237276e+001	grad : 9.687523e+000	exceeded trust region
acc	k:	7	num_inner:	6	f: -4.356244e+001	grad : 5.142297e+000	exceeded trust region
acc	k:	8	num_inner:	8	f: -4.412433e+001	grad : 2.860465e+000	exceeded trust region
acc	k:	9	num_inner:	20	f: -4.438540e+001	grad : 3.893763e-001	reached target residual-kappa
acc	k:	10	num_inner:	20	f: -4.442759e+001	grad : 4.116374e-002	reached target residual-kappa
acc	k:	11	num_inner:	24	f: -4.442790e+001	grad : 1.443240e-003	reached target residual-theta
acc	k:	12	num_inner:	39	f: -4.442790e+001	grad : 1.790137e-006	reached target residual-theta
acc	k:	13	num_inner:	50	f: -4.442790e+001	grad : 3.992606e-010	dimension exceeded

Gradient norm tolerance reached.

Total time is 2.966843 [s] (excludes statsfun)

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```
% Display some statistics.
semilogy([info.iter], [info.gradnorm], '.-');
```



Riemannian optimization is...

Well-understood

Theory is available for robust algorithms

Useful

Leverage the symmetry of your constraints

Easy

With Manopt, you simply provide the cost

Manopt is open source and documented www.manopt.org



Maniwhat now?

Manifolds are mathematical sets with a smooth geometry, such as spheres. If you are facing a nonlinear (and possibly nonconvex) optimization problem with nice-looking constraints or invariance properties, Manopt may just be the tool for you. Check out the manifolds library to find out!

Key features

Manopt comes with a large library of manifolds and readyto-use Riemannian optimization algorithms. It is well documented and includes diagnostics tools to help you get started quickly. It provides flexibility in describing your cost function and incorporates an optional caching system for more efficiency.

It's open source

Check out the license and let us know how you use Manopt. Please cite this paper if you publish work using Manopt (bibtex).