MATLAB Syntax
for
fminbnd, fminunc,
fminsearch, fmincon

ChE657 Supplementary Notes
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fminbnd

Find a minimum of a function of one variable on a fixed interval

$$\min_{x} f(x) \qquad \text{such that} \qquad x_1 < x < x_2$$

where x, x_1, and x_2 are scalars and *f(x)* is a function that returns a scalar.

Syntax

- `x = fminbnd(fun,x1,x2)`
- `x = fminbnd(fun,x1,x2,options)`
- `x = fminbnd(fun,x1,x2,options,P1,P2,...)`
- `[x,fval] = fminbnd(...)`
- `[x,fval,exitflag] = fminbnd(...)`
- `[x,fval,exitflag,output] = fminbnd(...)`
-

Description

`fminbnd` finds a minimum of a function of one variable within a fixed interval.

`x = fminbnd(fun,x1,x2)` returns a value `x` that is a local minimizer of the scalar valued function that is described in `fun` in the interval `x1 <= x <= x2`.

`x = fminbnd(fun,x1,x2,options)` minimizes with the optimization parameters specified in the structure `options`. Use `optimset` to set these parameters.

`x = fminbnd(fun,x1,x2,options,P1,P2,...)` provides for additional arguments, `P1`, `P2`, etc., which are passed to the objective function, `fun`. Use `options=[]` as a placeholder if no options are set.

`[x,fval] = fminbnd(...)` returns the value of the objective function computed in `fun` at the solution `x`.

`[x,fval,exitflag] = fminbnd(...)` returns a value `exitflag` that describes the exit condition of `fminbnd`.

`[x,fval,exitflag,output] = fminbnd(...)` returns a structure `output` that contains information about the optimization.

Input Arguments

Function Arguments contains general descriptions of arguments passed in to `fminbnd`. This section provides function-specific details for `fun` and `options`:

`fun` The function to be minimized. `fun` is a function that accepts a scalar `x` and returns a scalar `f`, the objective function evaluated at `x`. The function `fun` can be specified as a function handle.

- `x = fminbnd(@myfun,x1,x2)`
-

where `myfun` is a MATLAB function such as

- `function f = myfun(x)`
- `f = ...           % Compute function value at x.`
-

`fun` can also be an inline object.

- `x = fminbnd(inline('sin(x*x)'),x1,x2);`
-

`options` Options provides the function-specific details for the `options` parameters.

Output Arguments

Function Arguments contains general descriptions of arguments returned by `fminbnd`. This section provides function-specific details for `exitflag` and `output`:

`exitflag` Describes the exit condition:

`> 0`	The function converged to a solution `x`.
`0`	The maximum number of function evaluations or iterations was exceeded.
`< 0`	The function did not converge to a solution.

`output` Structure containing information about the optimization. The fields of the structure are:

`iterations`	Number of iterations taken.
`funcCount`	Number of function evaluations.
`algorithm`	Algorithm used.

Options

Optimization options parameters used by `fminbnd`. You can use `optimset` to set or change the values of these fields in the parameters structure, `options`. See Optimization Parameters, for detailed information:

`Display`	Level of display. `'off'` displays no output; `'iter'` displays output at each iteration; `'final'` displays just the final output; `'notify'` (default) dislays output only if the function does not converge.
`MaxFunEvals`	Maximum number of function evaluations allowed.
`MaxIter`	Maximum number of iterations allowed.
`TolX`	Termination tolerance on `x`.

Examples

A minimum of $\sin(x)$ occurs at

```
x = fminbnd(@sin,0,2*pi)
x =
     4.7124

```

The value of the function at the minimum is

```
y = sin(x)
y =
    -1.0000

```

To find the minimum of the function

- $f(x) = (x-3)^2 - 1$

on the interval (0,5), first write an M-file.

```
function f = myfun(x)
f = (x-3).^2 - 1;

```

Next, call an optimization routine.

```
x = fminbnd(@myfun,0,5)

```

This generates the solution

- `x =`
- `      3`
-

The value at the minimum is

- `y = f(x)`
-
- `y =`
- `    -1`
-

Algorithm

`fminbnd` is an M-file. The algorithm is based on Golden Section search and parabolic interpolation. A Fortran program implementing the same algorithm is given in [1].

Limitations

The function to be minimized must be continuous. `fminbnd` may only give local solutions.

`fminbnd` often exhibits slow convergence when the solution is on a boundary of the interval. In such a case, `fmincon` often gives faster and more accurate solutions.

`fminbnd` only handles real variables.

See Also

`@` (`function_handle`), `fminsearch`, `fmincon`, `fminunc`, `optimset`, `inline`

References

[1] Forsythe, G.E., M.A. Malcolm, and C.B. Moler, *Computer Methods for Mathematical Computations*, Prentice Hall, 1976.

fminunc

Find a minimum of an unconstrained multivariable function

- $$\min_x f(x)$$

where *x* is a vector and *f(x)* is a function that returns a scalar.

Syntax

- `x = fminunc(fun,x0)`
- `x = fminunc(fun,x0,options)`
- `x = fminunc(fun,x0,options,P1,P2,...)`
- `[x,fval] = fminunc(...)`
- `[x,fval,exitflag] = fminunc(...)`
- `[x,fval,exitflag,output] = fminunc(...)`
- `[x,fval,exitflag,output,grad] = fminunc(...)`
- `[x,fval,exitflag,output,grad,hessian] = fminunc(...)`
-

Description

`fminunc` finds a minimum of a scalar function of several variables, starting at an initial estimate. This is generally referred to as *unconstrained nonlinear optimization*.

`x = fminunc(fun,x0)` starts at the point `x0` and finds a local minimum `x` of the function described in `fun`. `x0` can be a scalar, vector, or matrix.

`x = fminunc(fun,x0,options)` minimizes with the optimization parameters specified in the structure `options`. Use `optimset` to set these parameters.

`x = fminunc(fun,x0,options,P1,P2,...)` passes the problem-dependent parameters `P1`, `P2`, etc., directly to the function `fun`. Pass an empty matrix for `options` to use the default values for `options`.

`[x,fval] = fminunc(...)` returns in `fval` the value of the objective function `fun` at the solution `x`.

`[x,fval,exitflag] = fminunc(...)` returns a value `exitflag` that describes the exit condition.

`[x,fval,exitflag,output] = fminunc(...)` returns a structure `output` that contains information about the optimization.

`[x,fval,exitflag,output,grad] = fminunc(...)` returns in `grad` the value of the gradient of `fun` at the solution `x`.

`[x,fval,exitflag,output,grad,hessian] = fminunc(...)` returns in `hessian` the value of the Hessian of the objective function `fun` at the solution `x`.

Input Arguments

Function Arguments contains general descriptions of arguments passed in to `fminunc`. This section provides function-specific details for `fun` and `options`:

`fun`

The function to be minimized. `fun` is a function that accepts a vector `x` and returns a scalar `f`, the objective function evaluated at `x`. The function `fun` can be specified as a function handle.

- `x = fminunc(@myfun,x0)`
-

where `myfun` is a MATLAB function such as

- `function f = myfun(x)`
- `f = ...            % Compute function value at x`
-

`fun` can also be an inline object.

- `x = fminunc(inline('norm(x)^2'),x0);`
-

If the gradient of `fun` can also be computed *and* the `GradObj` parameter is `'on'`, as set by

- `options = optimset('GradObj','on')`
-

then the function `fun` must return, in the second output argument, the gradient value `g`, a vector, at `x`. Note that by checking the value of `nargout` the function can avoid computing `g` when `fun` is called with only one output argument (in the case where the optimization algorithm only needs the value of `f` but not `g`).

- `function [f,g] = myfun(x)`
- `f = ...            % Compute the function value at x`
- `if nargout > 1     % fun called with 2 output arguments`
- `   g = ...         % Compute the gradient evaluated at`
  `x`
- `end`
-

The gradient is the partial derivatives $\partial f/\partial x$ of `f` at the point `x`. That is, the `i`th component of `g` is the partial derivative of `f` with respect to the `i`th component of `x`.
If the Hessian matrix can also be computed *and* the `Hessian` parameter is `'on'`, i.e., `options = optimset('Hessian','on')`, then the function `fun` must return the Hessian value `H`, a symmetric matrix, at `x` in a third output argument. Note that by checking the value of `nargout` we can avoid computing `H` when `fun` is called with only one or two output arguments (in the case where the optimization algorithm only needs the values of `f` and `g` but not `H`).

- `function [f,g,H] = myfun(x)`
- `f = ...     % Compute the objective function value at x`
- `if nargout > 1   % fun called with two output arguments`
- `   g = ...  % Gradient of the function evaluated at x`
- `   if nargout > 2`
- `   H = ...  % Hessian evaluated at x`

- end
-

The Hessian matrix is the second partial derivatives matrix of f at the point x. That is, the (i,j)th component of H is the second partial derivative of f with respect to x_i and x_j, $\partial^2 f/\partial x_i \partial x_j$. The Hessian is by definition a symmetric matrix.

options Options provides the function-specific details for the options parameters.

Output Arguments

Function Arguments contains general descriptions of arguments returned by fminunc. This section provides function-specific details for exitflag and output:

exitflag Describes the exit condition:

> 0	The function converged to a solution x.
0	The maximum number of function evaluations or iterations was exceeded.
< 0	The function did not converge to a solution.

output Structure containing information about the optimization. The fields of the structure are:

iterations	Number of iterations taken.
funcCount	Number of function evaluations.
algorithm	Algorithm used.
cgiterations	Number of PCG iterations (large-scale algorithm only).
stepsize	Final step size taken (medium-scale algorithm only).
firstorderopt	Measure of first-order optimality: the norm of the gradient at the solution x.

Options

fminunc uses these optimization parameters. Some parameters apply to all algorithms, some are only relevant when using the large-scale algorithm, and others are only relevant when using the medium-scale algorithm.You can use optimset to set or change the values of these fields in the parameters structure, options. See Optimization Parameters, for detailed information.

We start by describing the LargeScale option since it states a *preference* for which algorithm to use. It is only a preference since certain conditions must be met to use the large-scale algorithm.

For `fminunc`, the *gradient must be provided (*see the description of `fun` above to see how) or else the minimum-scale algorithm is used:

`LargeScale`	Use large-scale algorithm if possible when set to `'on'`. Use medium-scale algorithm when set to `'off'`.

Large-Scale and Medium-Scale Algorithms. These parameters are used by both the large-scale and medium-scale algorithms:

`Diagnostics`	Print diagnostic information about the function to be minimized.
`Display`	Level of display. `'off'` displays no output; `'iter'` displays output at each iteration; `'final'` (default) displays just the final output.
`GradObj`	Gradient for the objective function defined by user. See the description of `fun` above to see how to define the gradient in `fun`. The gradient *must* be provided to use the large-scale method. It is optional for the medium-scale method.
`MaxFunEvals`	Maximum number of function evaluations allowed.
`MaxIter`	Maximum number of iterations allowed.
`TolFun`	Termination tolerance on the function value.
`TolX`	Termination tolerance on `x`.

Large-Scale Algorithm Only. These parameters are used only by the large-scale algorithm:

`Hessian`

If `'on'`, `fminunc` uses a user-defined Hessian (defined in `fun`), or Hessian information (when using `HessMult`), for the objective function. If `'off'`, `fminunc` approximates the Hessian using finite differences.

`HessMult`

Function handle for Hessian multiply function. For large-scale structured problems, this function computes the Hessian matrix product *H*Y* without actually forming *H*. The function is of the form

- `W = hmfun(Hinfo,Y,p1,p2,...)`
-

where `Hinfo` and the additional parameters `p1,p2,...` contain the matrices used to compute `H*Y`.
The first argument must be the same as the third argument returned by the objective function `fun`.

- `[f,g,Hinfo] = fun(x,p1,p2,...)`
-

The parameters `p1,p2,...` are the same additional parameters that are passed to `fminunc` (and to `fun`).

- `fminunc(fun,...,options,p1,p2,...)`

-

Y is a matrix that has the same number of rows as there are dimensions in the problem. `W = H*Y` although `H` is not formed explicitly. `fminunc` uses `Hinfo` to compute the preconditioner.

> **Note** `'Hessian'` must be set to `'on'` for `Hinfo` to be passed from `fun` to `hmfun`.

See Nonlinear Minimization with a Dense but Structured Hessian and Equality Constraints for an example.

`HessPattern`	Sparsity pattern of the Hessian for finite-differencing. If it is not convenient to compute the sparse Hessian matrix `H` in `fun`, the large-scale method in `fminunc` can approximate `H` via sparse finite-differences (of the gradient) provided the *sparsity structure* of `H` -- i.e., locations of the nonzeros -- is supplied as the value for `HessPattern`. In the worst case, if the structure is unknown, you can set `HessPattern` to be a dense matrix and a full finite-difference approximation is computed at each iteration (this is the default). This can be very expensive for large problems so it is usually worth the effort to determine the sparsity structure.
`MaxPCGIter`	Maximum number of PCG (preconditioned conjugate gradient) iterations (see the *Algorithm* section below).
`PrecondBandWidth`	Upper bandwidth of preconditioner for PCG. By default, diagonal preconditioning is used (upper bandwidth of 0). For some problems, increasing the bandwidth reduces the number of PCG iterations.
`TolPCG`	Termination tolerance on the PCG iteration.
`TypicalX`	Typical `x` values.

Medium-Scale Algorithm Only. These parameters are used only by the medium-scale algorithm:

`DerivativeCheck`	Compare user-supplied derivatives (gradient) to finite-differencing derivatives.
`DiffMaxChange`	Maximum change in variables for finite-difference gradients.
`DiffMinChange`	Minimum change in variables for finite-difference gradients.
`LineSearchType`	Line search algorithm choice.

Examples

Minimize the function

$$f(x) = 3x_1^2 + 2x_1x_2 + x_2^2.$$

To use an M-file, create a file `myfun.m`.

```
function f = myfun(x)
f = 3*x(1)^2 + 2*x(1)*x(2) + x(2)^2;    % Cost function

```

Then call `fminunc` to find a minimum of `myfun` near `[1,1]`.

```
x0 = [1,1];
[x,fval] = fminunc(@myfun,x0)

```

After a couple of iterations, the solution, `x`, and the value of the function at `x`, `fval`, are returned.

```
x =
  1.0e-008 *
   -0.7512    0.2479
fval =
  1.3818e-016

```

To minimize this function with the gradient provided, modify the M-file `myfun.m` so the gradient is the second output argument

```
function [f,g] = myfun(x)
f = 3*x(1)^2 + 2*x(1)*x(2) + x(2)^2;    % Cost function
if nargout > 1
   g(1) = 6*x(1)+2*x(2);
   g(2) = 2*x(1)+2*x(2);
end

```

and indicate the gradient value is available by creating an optimization options structure with the `GradObj` parameter set to `'on'` using `optimset`.

```
options = optimset('GradObj','on');
x0 = [1,1];
[x,fval] = fminunc(@myfun,x0,options)

```

After several iterations the solution `x` and `fval`, the value of the function at `x,` are returned.

```
x =
  1.0e-015 *
   0.1110   -0.8882
fval2 =
  6.2862e-031

```

To minimize the function `f(x) = sin(x) + 3` using an inline object

```
f = inline('sin(x)+3');
```

- `x = fminunc(f,4)`
-

which returns a solution

```
x =
    4.7124
```

Notes

`fminunc` is not the preferred choice for solving problems that are sums-of-squares, that is, of the form

- $$\min f(x) = f_1(x)^2 + f_2(x)^2 + f_3(x)^2 + L$$

Instead use the `lsqnonlin` function, which has been optimized for problems of this form.

To use the large-scale method, the gradient must be provided in `fun` (and the `GradObj` parameter set to `'on'` using `optimset`). A warning is given if no gradient is provided and the `LargeScale` parameter is not `'off'`.

Algorithms

Large-Scale Optimization. By default `fminunc` chooses the large-scale algorithm if the user supplies the gradient in `fun` (and the `GradObj` parameter is set to `'on'` using `optimset`). This algorithm is a subspace trust region method and is based on the interior-reflective Newton method described in [2],[3]. Each iteration involves the approximate solution of a large linear system using the method of preconditioned conjugate gradients (PCG). See Trust-Region Methods for Nonlinear Minimization, and Preconditioned Conjugate Gradients.

Medium-Scale Optimization. `fminunc`, with the `LargeScale` parameter set to `'off'` with `optimset`, uses the BFGS Quasi-Newton method with a mixed quadratic and cubic line search procedure. This quasi-Newton method uses the BFGS ([1],[5],[8],[9]) formula for updating the approximation of the Hessian matrix. The DFP ([4],[6],[7]) formula, which approximates the inverse Hessian matrix, is selected by setting the `HessUpdate` parameter to `'dfp'` (and the `LargeScale` parameter to `'off'`). A steepest descent method is selected by setting `HessUpdate` to `'steepdesc'` (and `LargeScale` to `'off'`), although this is not recommended.

The default line search algorithm, i.e., when the `LineSearchType` parameter is set to `'quadcubic'`, is a safeguarded mixed quadratic and cubic polynomial interpolation and extrapolation method. A safeguarded cubic polynomial method can be selected by setting the `LineSearchType` parameter to `'cubicpoly'`. This second method generally requires fewer function evaluations but more gradient evaluations. Thus, if gradients are being supplied and can be calculated inexpensively, the cubic polynomial line search method is preferable. A full description of the algorithms is given in the Standard Algorithms chapter.

Limitations

The function to be minimized must be continuous.`fminunc` may only give local solutions.

`fminunc` only minimizes over the real numbers, that is, *x* must only consist of real numbers and *f(x)* must only return real numbers. When *x* has complex variables, they must be split into real and imaginary parts.

Large-Scale Optimization. To use the large-scale algorithm, the user must supply the gradient in `fun` (and `GradObj` must be set `'on'` in `options`). See Table 2-4, Large-Scale Problem Coverage and Requirements,, for more information on what problem formulations are covered and what information must be provided.

Currently, if the analytical gradient is provided in `fun`, the `options` parameter `DerivativeCheck` cannot be used with the large-scale method to compare the analytic gradient to the finite-difference gradient. Instead, use the medium-scale method to check the derivative with `options` parameter `MaxIter` set to 0 iterations. Then run the problem again with the large-scale method.

See Also

`@` (`function_handle`), `fminsearch`, `inline`, `optimset`

References

[1] Broyden, C.G., "The Convergence of a Class of Double-Rank Minimization Algorithms," *Journal Inst. Math. Applic.*, Vol. 6, pp. 76-90, 1970.

[2] Coleman, T.F. and Y. Li, "An Interior, Trust Region Approach for Nonlinear Minimization Subject to Bounds," *SIAM Journal on Optimization*, Vol. 6, pp. 418-445, 1996.

[3] Coleman, T.F. and Y. Li, "On the Convergence of Reflective Newton Methods for Large-Scale Nonlinear Minimization Subject to Bounds," *Mathematical Programming*, Vol. 67, Number 2, pp. 189-224, 1994.

[4] Davidon, W.C., "Variable Metric Method for Minimization," *A.E.C. Research and Development Report*, ANL-5990, 1959.

[5] Fletcher, R.,"A New Approach to Variable Metric Algorithms," *Computer Journal*, Vol. 13, pp. 317-322, 1970.

[6] Fletcher, R., "Practical Methods of Optimization," Vol. 1, *Unconstrained Optimization*, John Wiley and Sons, 1980.

[7] Fletcher, R. and M.J.D. Powell, "A Rapidly Convergent Descent Method for Minimization," *Computer Journal*, Vol. 6, pp. 163-168, 1963.

[8] Goldfarb, D., "A Family of Variable Metric Updates Derived by Variational Means," *Mathematics of Computing*, Vol. 24, pp. 23-26, 1970.

[9] Shanno, D.F., "Conditioning of Quasi-Newton Methods for Function Minimization," *Mathematics of Computing*, Vol. 24, pp. 647-656, 1970.

fminsearch

Find a minimum of an unconstrained multivariable function

- $\min_{x} f(x)$

where *x* is a vector and *f(x)* is a function that returns a scalar.

Syntax

- `x = fminsearch(fun,x0)`
- `x = fminsearch(fun,x0,options)`
- `x = fminsearch(fun,x0,options,P1,P2,...)`
- `[x,fval] = fminsearch(...)`
- `[x,fval,exitflag] = fminsearch(...)`
- `[x,fval,exitflag,output] = fminsearch(...)`
-

Description

fminsearch finds a minimum of a scalar function of several variables, starting at an initial estimate. This is generally referred to as *unconstrained nonlinear optimization*.

`x = fminsearch(fun,x0)` starts at the point `x0` and finds a local minimum `x` of the function described in `fun`. `x0` can be a scalar, vector, or matrix.

`x = fminsearch(fun,x0,options)` minimizes with the optimization parameters specified in the structure `options`. Use `optimset` to set these parameters.

`x = fminsearch(fun,x0,options,P1,P2,...)` passes the problem-dependent parameters `P1`, `P2`, etc., directly to the function `fun`. Use `options = []` as a placeholder if no options are set.

`[x,fval] = fminsearch(...)` returns in `fval` the value of the objective function `fun` at the solution `x`.

`[x,fval,exitflag] = fminsearch(...)` returns a value `exitflag` that describes the exit condition of fminsearch.

`[x,fval,exitflag,output] = fminsearch(...)` returns a structure `output` that contains information about the optimization.

Input Arguments

Function Arguments contains general descriptions of arguments passed in to `fminsearch`. This section provides function-specific details for `fun` and `options`:

`fun` The function to be minimized. `fun` is a function that accepts a vector `x` and returns a scalar `f`, the objective function evaluated at `x`. The function `fun` can be specified as a function handle.

- `x = fminsearch(@myfun,x0,A,b)`
-

where `myfun` is a MATLAB function such as

- `function f = myfun(x)`
- `f = ...            % Compute function value at x`
-

`fun` can also be an inline object.

- `x = fminsearch(inline('norm(x)^2'),x0,A,b);`
-

`options` Options provides the function-specific details for the `options` parameters.

Output Arguments

Function Arguments contains general descriptions of arguments returned by `fminsearch`. This section provides function-specific details for `exitflag` and `output`:

`exitflag` Describes the exit condition:

`> 0`	The function converged to a solution `x`.
`0`	The maximum number of function evaluations or iterations was exceeded.
`< 0`	The function did not converge to a solution.

`output` Structure containing information about the optimization. The fields of the structure are:

`iterations`	Number of iterations taken.
`funcCount`	Number of function evaluations.
`algorithm`	Algorithm used.

Options

Optimization options parameters used by `fminsearch`. You can use `optimset` to set or change the values of these fields in the parameters structure, `options`. See Optimization Parameters, for detailed information:

`Display` Level of display. `'off'` displays no output; `'iter'` displays output at each iteration; `'final'` displays just the final output; `'notify'` (default) dislays

	output only if the function does not converge.
`MaxFunEvals`	Maximum number of function evaluations allowed.
`MaxIter`	Maximum number of iterations allowed.
`TolFun`	Termination tolerance on the function value.
`TolX`	Termination tolerance on `x`.

Examples

Minimize the one-dimensional function `f(x) = sin(x) + 3`.

To use an M-file, i.e., `fun = 'myfun'`, create a file `myfun.m`.

```
function f = myfun(x)
f = sin(x) + 3;
```

Then call `fminsearch` to find a minimum of `fun` near `2`.

```
x = fminsearch(@myfun,2)
```

To minimize the function `f(x) = sin(x) + 3` using an inline object

```
f = inline('sin(x)+3');
x = fminsearch(f,2);
```

Algorithms

fminsearch uses the simplex search method of [1]. This is a direct search method that does not use numerical or analytic gradients as in `fminunc`.

If n is the length of `x`, a simplex in n-dimensional space is characterized by the `n+1` distinct vectors that are its vertices. In two-space, a simplex is a triangle; in three-space, it is a pyramid. At each step of the search, a new point in or near the current simplex is generated. The function value at the new point is compared with the function's values at the vertices of the simplex and, usually, one of the vertices is replaced by the new point, giving a new simplex. This step is repeated until the diameter of the simplex is less than the specified tolerance.

fminsearch is generally less efficient than `fminunc` for problems of order greater than two. However, when the problem is highly discontinuous, `fminsearch` may be more robust.

Limitations

fminsearch can often handle discontinuity, particularly if it does not occur near the solution. fminsearch may only give local solutions.

fminsearch only minimizes over the real numbers, that is, *x* must only consist of real numbers and *f(x)* must only return real numbers. When *x* has complex variables, they must be split into real and imaginary parts.

> **Note** fminsearch is not the preferred choice for solving problems that are sums-of-squares, that is, of the form
>
> $\min f(x) = f_1(x)^2 + f_2(x)^2 + f_3(x)^2 + L$. Instead use the `lsqnonlin` function, which has been optimized for problems of this form.

See Also

`@` (`function_handle`), `fminbnd`, `fminunc`, `inline`, `optimset`

References

[1] Lagarias, J.C., J. A. Reeds, M. H. Wright, and P. E. Wright, "Convergence Properties of the Nelder-Mead Simplex Method in Low Dimensions," *SIAM Journal of Optimization*, Vol. 9 Number 1, pp.112-147, 1998.

fmincon

Find a minimum of a constrained nonlinear multivariable function

- $\min_x f(x)$ subject to

- $$\begin{aligned} c(x) &\le 0 \\ ceq(x) &= 0 \\ A \cdot x &\le b \\ Aeq \cdot x &= beq \\ lb \le x &\le ub \end{aligned}$$

where *x, b, beq, lb,* and *ub* are vectors, *A* and *Aeq* are matrices, *c(x)* and *ceq(x)* are functions that return vectors, and *f(x)* is a function that returns a scalar. *f(x)*, *c(x)*, and *ceq(x)* can be nonlinear functions.

Syntax

- `x = fmincon(fun,x0,A,b)`
- `x = fmincon(fun,x0,A,b,Aeq,beq)`
- `x = fmincon(fun,x0,A,b,Aeq,beq,lb,ub)`
- `x = fmincon(fun,x0,A,b,Aeq,beq,lb,ub,nonlcon)`
- `x = fmincon(fun,x0,A,b,Aeq,beq,lb,ub,nonlcon,options)`
- `x = fmincon(fun,x0,A,b,Aeq,beq,lb,ub,nonlcon,options,P1,P2, ...)`
- `[x,fval] = fmincon(...)`
- `[x,fval,exitflag] = fmincon(...)`
- `[x,fval,exitflag,output] = fmincon(...)`
- `[x,fval,exitflag,output,lambda] = fmincon(...)`
- `[x,fval,exitflag,output,lambda,grad] = fmincon(...)`
- `[x,fval,exitflag,output,lambda,grad,hessian] = fmincon(...)`
-

Description

`fmincon` finds a constrained minimum of a scalar function of several variables starting at an initial estimate. This is generally referred to as *constrained nonlinear optimization* or *nonlinear programming*.

`x = fmincon(fun,x0,A,b)` starts at `x0` and finds a minimum `x` to the function described in `fun` subject to the linear inequalities `A*x <= b`. `x0` can be a scalar, vector, or matrix.

`x = fmincon(fun,x0,A,b,Aeq,beq)` minimizes `fun` subject to the linear equalities `Aeq*x = beq` as well as `A*x <= b`. Set `A=[]` and `b=[]` if no inequalities exist.

`x = fmincon(fun,x0,A,b,Aeq,beq,lb,ub)` defines a set of lower and upper bounds on the design variables, `x`, so that the solution is always in the range `lb <= x <= ub`. Set `Aeq=[]` and `beq=[]` if no equalities exist.

`x = fmincon(fun,x0,A,b,Aeq,beq,lb,ub,nonlcon)` subjects the minimization to the nonlinear inequalities `c(x)` or equalities `ceq(x)` defined in `nonlcon`. `fmincon` optimizes such that `c(x) <= 0` and `ceq(x) = 0`. Set `lb=[]` and/or `ub=[]` if no bounds exist.

`x = fmincon(fun,x0,A,b,Aeq,beq,lb,ub,nonlcon,options)` minimizes with the optimization parameters specified in the structure `options`. Use `optimset` to set these parameters.

`x = fmincon(fun,x0,A,b,Aeq,beq,lb,ub,nonlcon,options,P1,P2,...)` passes the problem-dependent parameters `P1`, `P2`, etc., directly to the functions `fun` and `nonlcon`. Pass empty matrices as placeholders for `A`, `b`, `Aeq`, `beq`, `lb`, `ub`, `nonlcon`, and `options` if these arguments are not needed.

`[x,fval] = fmincon(...)` returns the value of the objective function `fun` at the solution `x`.

`[x,fval,exitflag] = fmincon(...)` returns a value `exitflag` that describes the exit condition of `fmincon`.

`[x,fval,exitflag,output] = fmincon(...)` returns a structure `output` with information about the optimization.

`[x,fval,exitflag,output,lambda] = fmincon(...)` returns a structure `lambda` whose fields contain the Lagrange multipliers at the solution `x`.

`[x,fval,exitflag,output,lambda,grad] = fmincon(...)` returns the value of the gradient of `fun` at the solution `x`.

`[x,fval,exitflag,output,lambda,grad,hessian] = fmincon(...)` returns the value of the Hessian of `fun` at the solution `x`.

Input Arguments

Function Arguments contains general descriptions of arguments passed in to `fmincon`. This "Arguments" section provides function-specific details for `fun`, `nonlcon`, and `options`:

`fun` The function to be minimized. `fun` is a function that accepts a scalar `x` and returns a scalar `f`, the objective function evaluated at `x`. The function `fun` can be specified as a function handle.

```
x = fmincon(@myfun,x0,A,b)
```

where `myfun` is a MATLAB function such as

```
function f = myfun(x)
f = ...            % Compute function value at x
```

`fun` can also be an inline object.

```
x = fmincon(inline('norm(x)^2'),x0,A,b);
```

If the gradient of `fun` can also be computed *and* the `GradObj` parameter is `'on'`, as set by

- `options = optimset('GradObj','on')`
-

then the function `fun` must return, in the second output argument, the gradient value `g`, a vector, at `x`. Note that by checking the value of `nargout` the function can avoid computing `g` when `fun` is called with only one output argument (in the case where the optimization algorithm only needs the value of `f` but not `g`).

- `function [f,g] = myfun(x)`
- `f = ...          % Compute the function value at x`
- `if nargout > 1  % fun called with two output arguments`
- `   g = ...      % Compute the gradient evaluated at x`
- `end`
-

The gradient consists of the partial derivatives of `f` at the point `x`. That is, the `i`th component of `g` is the partial derivative of `f` with respect to the `i`th component of `x`.
If the Hessian matrix can also be computed *and* the `Hessian` parameter is `'on'`, i.e., `options = optimset('Hessian','on')`, then the function `fun` must return the Hessian value `H`, a symmetric matrix, at `x` in a third output argument. Note that by checking the value of `nargout` we can avoid computing `H` when `fun` is called with only one or two output arguments (in the case where the optimization algorithm only needs the values of `f` and `g` but not `H`).

- `function [f,g,H] = myfun(x)`
- `f = ...      % Compute the objective function value at x`
- `if nargout > 1   % fun called with two output arguments`
- `   g = ...  % Gradient of the function evaluated at x`
- `   if nargout > 2`
- `   H = ...  % Hessian evaluated at x`
- `end`
-

The Hessian matrix is the second partial derivatives matrix of `f` at the point `x`. That is, the (`i`,`j`)th component of `H` is the second partial derivative of `f` with respect to x_i and x_j, $\partial^2 f/\partial x_i \partial x_j$. The Hessian is by definition a symmetric matrix.

`nonlcon` The function that computes the nonlinear inequality constraints `c(x)<= 0` and the nonlinear equality constraints `ceq(x) = 0`. The function `nonlcon` accepts a vector `x` and returns two vectors `c` and `ceq`. The vector `c` contains the nonlinear inequalities evaluated at `x`, and `ceq` contains the nonlinear equalities evaluated at `x`. The function `nonlcon` can be specified as a function handle.

- `x = fmincon(@myfun,x0,A,b,Aeq,beq,lb,ub,@mycon)`
-

where `mycon` is a MATLAB function such as

- `function [c,ceq] = mycon(x)`
- `c = ...     % Compute nonlinear inequalities at x.`
- `ceq = ...   % Compute nonlinear equalities at x.`
-

If the gradients of the constraints can also be computed *and* the `GradConstr` parameter is 'on', as set by

- `options = optimset('GradConstr','on')`
-

then the function `nonlcon` must also return, in the third and fourth output arguments, `GC`, the gradient of `c(x)`, and `GCeq`, the gradient of `ceq(x)`. Note that by checking the value of `nargout` the function can avoid computing `GC` and `GCeq` when `nonlcon` is called with only two output arguments (in the case where the optimization algorithm only needs the values of `c` and `ceq` but not `GC` and `GCeq`).

```
function [c,ceq,GC,GCeq] = mycon(x)
c = ...            % Nonlinear inequalities at x
ceq = ...          % Nonlinear equalities at x
if nargout > 2     % nonlcon called with 4 outputs
   GC = ...        % Gradients of the inequalities
   GCeq = ...      % Gradients of the equalities
end
```

If `nonlcon` returns a vector `c` of `m` components and `x` has length `n`, where `n` is the length of `x0`, then the gradient `GC` of `c(x)` is an n-by-m matrix, where `GC(i,j)` is the partial derivative of `c(j)` with respect to `x(i)` (i.e., the `j`th column of `GC` is the gradient of the `j`th inequality constraint `c(j)`). Likewise, if `ceq` has `p` components, the gradient `GCeq` of `ceq(x)` is an n-by-p matrix, where `GCeq(i,j)` is the partial derivative of `ceq(j)` with respect to `x(i)` (i.e., the `j`th column of `GCeq` is the gradient of the `j`th equality constraint `ceq(j)`).

`options` Options provides the function-specific details for the `options` parameters.

Output Arguments

Function Arguments contains general descriptions of arguments returned by `fmincon`. This section provides function-specific details for `exitflag`, `lambda`, and `output`:

`exitflag` Describes the exit condition:

> 0	The function converged to a solution `x`.
0	The maximum number of function evaluations or iterations was exceeded.
< 0	The function did not converge to a solution.

`lambda` Structure containing the Lagrange multipliers at the solution `x` (separated by constraint type). The fields of the structure are:

`lower`	Lower bounds `lb`
`upper`	Upper bounds ub

`ineqlin`	Linear inequalities
`eqlin`	Linear equalities
`ineqnonlin`	Nonlinear inequalities
`eqnonlin`	Nonlinear equalities

`output` Structure containing information about the optimization. The fields of the structure are:

`iterations`	Number of iterations taken.
`funcCount`	Number of function evaluations.
`algorithm`	Algorithm used.
`cgiterations`	Number of PCG iterations (large-scale algorithm only).
`stepsize`	Final step size taken (medium-scale algorithm only).
`firstorderopt`	Measure of first-order optimality (large-scale algorithm only). For large-scale bound constrained problems, the first-order optimality is the infinity norm of `v.*g`, where `v` is defined as in Box Constraints, and `g` is the gradient. For large-scale problems with only linear equalities, the first-order optimality is the infinity norm of the *projected* gradient (i.e. the gradient projected onto the nullspace of `Aeq`).

Options

Optimization options parameters used by `fmincon`. Some parameters apply to all algorithms, some are only relevant when using the large-scale algorithm, and others are only relevant when using the medium-scale algorithm.You can use `optimset` to set or change the values of these fields in the parameters structure, `options`. See Optimization Parameters, for detailed information.

We start by describing the `LargeScale` option since it states a *preference* for which algorithm to use. It is only a preference since certain conditions must be met to use the large-scale algorithm. For `fmincon`, you must provide the gradient (see the description of `fun` above to see how) or else the medium-scale algorithm is used:

`LargeScale` Use large-scale algorithm if possible when set to `'on'`. Use medium-scale algorithm when set to `'off'`.

Medium-Scale and Large-Scale Algorithms. These parameters are used by both the medium-scale and large-scale algorithms:

`Diagnostics` Print diagnostic information about the function to be minimized.

`Display`	Level of display. `'off'` displays no output; `'iter'` displays output at each iteration; `'final'` (default) displays just the final output.
`GradObj`	Gradient for the objective function defined by user. See the description of `fun` above to see how to define the gradient in `fun`. You must provide the gradient to use the large-scale method. It is optional for the medium-scale method.
`MaxFunEvals`	Maximum number of function evaluations allowed.
`MaxIter`	Maximum number of iterations allowed.
`TolFun`	Termination tolerance on the function value.
`TolCon`	Termination tolerance on the constraint violation.
`TolX`	Termination tolerance on `x`.

Large-Scale Algorithm Only. These parameters are used only by the large-scale algorithm:

`Hessian`

If `'on'`, `fmincon` uses a user-defined Hessian (defined in `fun`), or Hessian information (when using `HessMult`), for the objective function. If `'off'`, `fmincon` approximates the Hessian using finite differences.

`HessMult`

Function handle for Hessian multiply function. For large-scale structured problems, this function computes the Hessian matrix product *H*Y* without actually forming *H*. The function is of the form

- `W = hmfun(Hinfo,Y,p1,p2,...)`
-

where `Hinfo` and the additional parameters `p1,p2,...` contain the matrices used to compute `H*Y`. The first argument must be the same as the third argument returned by the objective function `fun`.
[f,g,Hinfo] = fun(x,p1,p2,...)
The parameters `p1,p2,...` are the same additional parameters that are passed to `fmincon` (and to `fun`).

- `fmincon(fun,...,options,p1,p2,...)`
-

`Y` is a matrix that has the same number of rows as there are dimensions in the problem. `W = H*Y` although `H` is not formed explicitly. `fmincon` uses `Hinfo` to compute the preconditioner.

> **Note** `'Hessian'` must be set to `'on'` for `Hinfo` to be passed from `fun` to `hmfun`.

See Nonlinear Minimization with a Dense but Structured Hessian and Equality Constraints for an example.

`HessPattern`

Sparsity pattern of the Hessian for finite-differencing. If it is not convenient to compute the sparse Hessian matrix `H` in `fun`, the large-scale method in `fmincon` can approximate `H` via sparse finite-differences (of the gradient) provided the *sparsity structure* of `H` -- i.e., locations of the nonzeros -- is supplied as the value for `HessPattern`. In the worst case, if the

	structure is unknown, you can set `HessPattern` to be a dense matrix and a full finite-difference approximation is computed at each iteration (this is the default). This can be very expensive for large problems so it is usually worth the effort to determine the sparsity structure.
`MaxPCGIter`	Maximum number of PCG (preconditioned conjugate gradient) iterations (see the *Algorithm* section below).
`PrecondBandWidth`	Upper bandwidth of preconditioner for PCG. By default, diagonal preconditioning is used (upper bandwidth of 0). For some problems, increasing the bandwidth reduces the number of PCG iterations.
`TolPCG`	Termination tolerance on the PCG iteration.
`TypicalX`	Typical `x` values.

Medium-Scale Algorithm Only. These parameters are used only by the medium-scale algorithm:

`DerivativeCheck`	Compare user-supplied derivatives (gradients of the objective and constraints) to finite-differencing derivatives.
`DiffMaxChange`	Maximum change in variables for finite-difference gradients.
`DiffMinChange`	Minimum change in variables for finite-difference gradients.

Examples

Find values of *x* that minimize $f(x) = -x_1 x_2 x_3$, starting at the point `x = [10; 10; 10]` and subject to the constraints

- $0 \le x_1 + 2x_2 + 2x_3 \le 72$

First, write an M-file that returns a scalar value `f` of the function evaluated at `x`.

```
function f = myfun(x)
f = -x(1) * x(2) * x(3);
```

Then rewrite the constraints as both less than or equal to a constant,

- $-x_1 - 2x_2 - 2x_3 \le 0$
  $x_1 + 2x_2 + 2x_3 \le 72$

Since both constraints are linear, formulate them as the matrix inequality $A \cdot x \le b$ where

- $$A = \begin{bmatrix} -1 & -2 & -2 \\ 1 & 2 & 2 \end{bmatrix} \qquad b = \begin{bmatrix} 0 \\ 72 \end{bmatrix}$$

Next, supply a starting point and invoke an optimization routine.

```
x0 = [10; 10; 10];    % Starting guess at the solution
[x,fval] = fmincon(@myfun,x0,A,b)
```

After 66 function evaluations, the solution is

```
x =
    24.0000
    12.0000
    12.0000
```

where the function value is

```
fval =
    -3.4560e+03
```

and linear inequality constraints evaluate to be `<= 0`

```
A*x-b=
    -72
      0
```

Notes

Large-Scale Optimization. To use the large-scale method, the gradient must be provided in `fun` (and the `GradObj` parameter is set to `'on'`). A warning is given if no gradient is provided and the `LargeScale` parameter is not `'off'`. The function `fmincon` permits *g*(*x*) to be an approximate gradient but this option is not recommended; the numerical behavior of most optimization codes is considerably more robust when the true gradient is used.

The large-scale method in `fmincon` is most effective when the matrix of second derivatives, i.e., the Hessian matrix *H*(*x*), is also computed. However, evaluation of the true Hessian matrix is not required. For example, if you can supply the Hessian sparsity structure (using the `HessPattern` parameter in `options`), then `fmincon` computes a sparse finite-difference approximation to *H*(*x*).

If `x0` is not strictly feasible, `fmincon` chooses a new strictly feasible (centered) starting point.

If components of *x* have no upper (or lower) bounds, then `fmincon` prefers that the corresponding components of `ub` (or `lb`) be set to `Inf` (or `-Inf` for `lb`) as opposed to an arbitrary but very large positive (or negative in the case of lower bounds) number.

Several aspects of linearly constrained minimization should be noted:

- A dense (or fairly dense) column of matrix `Aeq` can result in considerable fill and computational cost.
- `fmincon` removes (numerically) linearly dependent rows in `Aeq`; however, this process involves repeated matrix factorizations and therefore can be costly if there are many dependencies.
- Each iteration involves a sparse least-squares solve with matrix
- $\overline{Aeq} = Aeq^T R^{-T}$

  where R^T is the Cholesky factor of the preconditioner. Therefore, there is a potential conflict between choosing an effective preconditioner and minimizing fill in $\overline{Aeq}$.

Medium-Scale Optimization. Better numerical results are likely if you specify equalities explicitly using `Aeq` and `beq,` instead of implicitly using `lb` and `ub`.

If equality constraints are present and dependent equalities are detected and removed in the quadratic subproblem, `'dependent'` is printed under the `Procedures` heading (when you ask for output by setting the `Display` parameter to `'iter'`). The dependent equalities are only removed when the equalities are consistent. If the system of equalities is not consistent, the subproblem is infeasible and `'infeasible'` is printed under the `Procedures` heading.

Algorithm

Large-Scale Optimization. By default `fmincon` will choose the large-scale algorithm *if* the user supplies the gradient in `fun` (and `GradObj` is `'on'` in `options`) *and* if *only* upper and lower bounds exist *or only* linear equality constraints exist. This algorithm is a subspace trust region method and is based on the interior-reflective Newton method described in [1], [2]. Each iteration involves the approximate solution of a large linear system using the method of preconditioned conjugate gradients (PCG). See the trust-region and preconditioned conjugate gradient method descriptions in the Large-Scale Algorithms chapter.

Medium-Scale Optimization. `fmincon` uses a Sequential Quadratic Programming (SQP) method. In this method, a Quadratic Programming (QP) subproblem is solved at each iteration. An estimate of the Hessian of the Lagrangian is updated at each iteration using the BFGS formula (see `fminunc`, references [7], [8]).

A line search is performed using a merit function similar to that proposed by [4], [5], and [6]. The QP subproblem is solved using an active set strategy similar to that described in [3]. A full description of this algorithm is found in Constrained Optimization in "Introduction to Algorithms."

See also SQP Implementation in "Introduction to Algorithms" for more details on the algorithm used.

Diagnostics

Large-Scale Optimization. The large-scale code does not allow equal upper and lower bounds. For example if `lb(2)==ub(2)`, then `fmincon` gives the error

- `Equal upper and lower bounds not permitted in this large-scale`
- `method.`
- `Use equality constraints and the medium-scale method instead.`
-

If you only have equality constraints you can still use the large-scale method. But if you have both equalities and bounds, you must use the medium-scale method.

Limitations

The function to be minimized and the constraints must both be continuous. `fmincon` may only give local solutions.

When the problem is infeasible, `fmincon` attempts to minimize the maximum constraint value.

The objective function and constraint function must be real-valued, that is they cannot return complex values.

Large-Scale Optimization. To use the large-scale algorithm, the user must supply the gradient in `fun` (and `GradObj` must be set `'on'` in `options`) , and only upper and lower bounds constraints may be specified, *or only* linear equality constraints must exist and `Aeq` cannot have more rows than columns. `Aeq` is typically sparse. See Table 2-4, Large-Scale Problem Coverage and Requirements,, for more information on what problem formulations are covered and what information must be provided.

Currently, if the analytical gradient is provided in `fun`, the `options` parameter `DerivativeCheck` cannot be used with the large-scale method to compare the analytic gradient to the finite-difference gradient. Instead, use the medium-scale method to check the derivative with `options` parameter `MaxIter` set to 0 iterations. Then run the problem with the large-scale method.

See Also

`@` (`function_handle`), `fminbnd`, `fminsearch`, `fminunc`, `optimset`

References

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[3] Gill, P.E., W. Murray, and M.H. Wright, *Practical Optimization,* Academic Press, London, 1981.

[4] Han, S.P., "A Globally Convergent Method for Nonlinear Programming," *Journal of Optimization Theory and Applications*, Vol. 22, p. 297, 1977.

[5] Powell, M.J.D., "A Fast Algorithm for Nonlineary Constrained Optimization Calculations," *Numerical Analysis*, ed. G.A. Watson, *Lecture Notes in Mathematics*, Springer Verlag, Vol. 630, 1978.

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