**ghkfast() — GHK multivariate normal simulator using pregenerated points**

### Description

Please see [M-5] ghk(). The routines documented here do the same thing, but ghkfast() can be faster at the expense of using more memory. First, code $S = \text{ghkfast}_\text{init}(\ldots)$ and then use $\text{ghkfast}(S, \ldots)$ to obtain the simulated values. There is a time savings because the simulation points are generated once in $\text{ghkfast}_\text{init}()$, whereas for $\text{ghk()}$ the points are generated on each call to $\text{ghk}()$. Also, $\text{ghkfast()}$ can generate simulated probabilities from the generalized Halton sequence; see [M-5] halton().

$\text{ghkfast}_\text{init}(n, npts, dim, method)$ computes the simulation points to be used by $\text{ghkfast()}$. Inputs $n$, $npts$, and $dim$ are the number of observations, the number of repetitions for the simulation, and the maximum dimension of the multivariate normal (MVN) distribution, respectively. Input $method$ specifies the type of points to generate and can be one of "halton", "hammersley", "random", or "ghalton".

$\text{ghkfast}(S, X, V)$ returns an $n \times 1$ real vector containing the simulated values of the MVN distribution with $dim \times dim$ variance–covariance matrix $V$ at the points stored in the rows of the $n \times dim$ matrix $X$.

$\text{ghkfast}(S, X, V, dfdx, dfdv)$ does the same thing as $\text{ghkfast}(S, X, V)$ but also returns the first-order derivatives of the simulated probability with respect to the rows of $X$ in $dfdx$ and the simulated probability derivatives with respect to $\text{vech}(V)$ in $dfdv$. See $\text{vech}()$ in [M-5] vec() for details of the half-vectorized operator.

The $\text{ghk}_\text{query}_\text{n}(S)$, $\text{ghk}_\text{query}_\text{npts}(S)$, $\text{ghk}_\text{query}_\text{dim}(S)$, and $\text{ghk}_\text{query}_\text{method}(S)$ functions extract the number of observations, number of simulation points, maximum dimension, and method of point-set generation that is specified in the construction of the transmorphic object $S$. Use $\text{ghk}_\text{query}_\text{rseed}(S)$ to retrieve the uniform random-variate seed used to generate the "random" or "ghalton" point sets. The $\text{ghkfast}_\text{query}_\text{pointset}_i(S, i)$ function will retrieve the $i$th point set used to simulate the MVN probability for the $i$th observation.

The $\text{ghkfast}_i(S, X, V, i, \ldots)$ function computes the probability and derivatives for the $i$th observation, $i = 1, \ldots, n$. 
Syntax

\[ S = \text{ghkfast}_\text{init}(\text{real scalar } n, \text{ npts, dim, string scalar method}) \]

\[ (\text{varies}) \quad \text{ghkfast}_\text{init}_\text{pivot}(S \ [, \text{ real scalar pivot}]) \]
\[ (\text{varies}) \quad \text{ghkfast}_\text{init}_\text{antithetics}(S \ [, \text{ real scalar anti}]) \]
\[ \text{real scalar} \quad \text{ghkfast}_\text{query}_\text{n}(S) \]
\[ \text{real scalar} \quad \text{ghkfast}_\text{query}_\text{npts}(S) \]
\[ \text{real scalar} \quad \text{ghkfast}_\text{query}_\text{dim}(S) \]
\[ \text{string scalar} \quad \text{ghkfast}_\text{query}_\text{method}(S) \]
\[ \text{string scalar} \quad \text{ghkfast}_\text{query}_\text{rseed}(S) \]
\[ \text{real matrix} \quad \text{ghkfast}_\text{query}_\text{pointset}_\text{i}(S, i) \]
\[ \text{real colvector} \quad \text{ghkfast}(S, \text{ real matrix } X, V) \]
\[ \text{real colvector} \quad \text{ghkfast}(S, \text{ real matrix } X, V, \text{ dfdx, dfdv}) \]
\[ \text{real scalar} \quad \text{ghkfast}_i(S, \text{ real matrix } X, V, i) \]
\[ \text{real scalar} \quad \text{ghkfast}_i(S, \text{ real matrix } X, V, i, \text{ dfdx, dfdv}) \]

where \( S \), if it is declared, should be declared

\text{transmorphic } S

and where \text{method} specified in \text{ghkfast}_\text{init}() is

<table>
<thead>
<tr>
<th>\text{method}</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>&quot;halton&quot;</td>
<td>Halton sequences</td>
</tr>
<tr>
<td>&quot;hammersley&quot;</td>
<td>Hammersley’s variation of the Halton set</td>
</tr>
<tr>
<td>&quot;random&quot;</td>
<td>pseudorandom uniforms</td>
</tr>
<tr>
<td>&quot;ghalton&quot;</td>
<td>generalized Halton sequences</td>
</tr>
</tbody>
</table>

Remarks and examples

For problems where repetitive calls to the GHK algorithm are required, \text{ghkfast}() might be a preferred alternative to \text{ghk}(). Generating the points once at the outset of a program produces a speed increase. For problems with many observations or many simulation points per observation, \text{ghkfast}() will be faster than \text{ghk}() at the cost of requiring more memory.

If \text{ghkfast}() is used within a likelihood evaluator for \text{ml} or \text{optimize}(), you will need to store the transmorphic object \( S \) as an external global and reuse the object with each likelihood evaluation. Alternatively, the initialization function for \text{optimize}(), \text{optimize}_\text{init}_\text{argument}(), can be used.
Prior to calling ghkfast(), call ghkfast_init(npivot(S, 1)) to turn off the integration interval pivoting that takes place in ghkfast(). By default, ghkfast() pivots the wider intervals of integration (and associated rows/columns of the covariance matrix) to the interior of the multivariate integration to improve quadrature accuracy. This option may be useful when ghkfast() is used in a likelihood evaluator for [R] ml or [M-5] optimize() and few simulation points are used for each observation. Here the pivoting may cause discontinuities when computing numerical second-order derivatives using finite differencing (for the Newton-Raphson technique), resulting in a non-positive-definite Hessian.

Also the sequences "halton", "hammersley", and "random", ghkfast() will use the generalized Halton sequence, "ghalton". Generalized Halton sequences have the same uniform coverage (low discrepancy) as the Halton sequences with the addition of a pseudorandom uniform component. Therefore, "ghalton" sequences are like "random" sequences in that you should set the random-number seed before using them if you wish to replicate the same point set; see [M-5] runiform().

**Conformability**

All initialization functions have 1 × 1 inputs and have 1 × 1 or void outputs, and all query functions have the transmorphic input and 1 × 1 outputs except

ghkfast_init(n, npts, dim, method):

```
input:
   n: 1 × 1
   npts: 1 × 1
   dim: 1 × 1
   method: 1 × 1

output:
   result: transmorphic
```

ghkfast_query_pointset_i(S, i):

```
input:
   S: transmorphic
   i: 1 × 1

output:
   result: npts × dim
```

ghkfast(S, X, V):

```
input:
   S: transmorphic
   X: n × dim
   V: dim × dim (symmetric, positive definite)

output:
   result: n × 1
```

ghkfast(S, X, V, dfdx, dfdv):

```
input:
   S: transmorphic
   X: n × dim
   V: dim × dim (symmetric, positive definite)

output:
   result: n × 1
   dfdx: n × dim
   dfdv: n × dim(dim + 1)/2
```
ghkfast_i(S, X, V, i, dfdx, dfdv):

input:

- **S**: transmorphic
- **X**: \( n \times \text{dim} \) or \( 1 \times \text{dim} \)
- **V**: \( \text{dim} \times \text{dim} \) (symmetric, positive definite)
- **i**: \( 1 \times 1 \) (\( 1 \leq i \leq n \))

output:

- **result**: \( n \times 1 \)
- **dfdx**: \( 1 \times \text{dim} \)
- **dfdv**: \( 1 \times \text{dim}(\text{dim} + 1)/2 \)

Diagnostics

**ghkfast_init(n, npts, dim, method)** aborts with error if the dimension, **dim**, is greater than 20.

**ghkfast(S, X, V, ...)** and **ghkfast_i(S, X, V, i, ...)** require that **V** be symmetric and positive definite. If **V** is not positive definite, then the returned vector (scalar) is filled with missings.

Also see

[M-5] **ghk()** — Geweke–Hajivassiliou–Keane (GHK) multivariate normal simulator

[M-5] **halton()** — Generate a Halton or Hammersley set

[M-4] **Statistical** — Statistical functions