
Generating Coupled Exponential Random Variables

Coupled Box-Müller Method

Multivariate Coupled Box-Müller Method

The method is based on polar version of the Box-Muller method. The advantage is there is a clear procedure for extending the method to multiple dimensions. The disadvantage is that method uses sample rejection to form a unit n-sphere. Since the n-sphere is based on $R^2 = x_1^2 + \dots x_n^2$ as n increases the number of rejected samples increases. This will make the algorithm very slow for large dimensions.

In[241]:=

```
Clear[CoupledVariate];
CoupledVariate::lsigma =
  "Length of scale `1` does not equal length of mean `2`";
CoupledVariate[μ_ : 0, Σ_ : 1, κ_ : 1, n_ : 1] := Module[
  {UniformVariates, CoupledNormalVariates, radiusSquared,
   dimMean, dimScale, σAdj, j},
  dimMean = Length[μ];
  σAdj = If[(dimScale = Length[Σ]) ≠ dimMean,
    Message[CoupledVariate::lsigma, dimScale, dimMean];
    (*If[dimScale>dimMean,
      Σ[[;;dimMean]],
      PadRight[Σ,dimMean-dimScale,1],
      Σ
    ]*)
  ];
  UniformVariates = Table[0, n, Max[2, dimMean]];
  radiusSquared = Table[0, n];
  For[j = 1, j ≤ n, j++,
    While[Not[0 < radiusSquared[[j]] < 1],
      UniformVariates[[j]] = RandomReal[{-1, 1}, Max[2, dimMean]];
      (* Dividing by  $\sqrt{\text{Max}[2, \text{dimMean}]}$  seems to make solution closer to a
        multivariate t distribution, but needs to be proven; also this factor
        shouldn't change radiusSquared from being a uniform distribution,
        but it will reduce the number of rejections; furthermore this should
        be the same a drawing from a domain reduced from from {-1,1} *)
      radiusSquared[[j]] = (*  $\frac{1}{\sqrt{\text{Max}[2, \text{dimMean}]}}$  *)  $\sum_{i=1}^{\text{Max}[2, \text{dimMean}]}$  UniformVariates[[j, i]]2;
    ]
  ];
```

```

If[n == 1,
  CoupledNormalVariates =
    Table[ $\sqrt{\frac{\text{CoupledLogarithm}[\text{radiusSquared}[[1]]^{-2}, \kappa, 0]}{\text{radiusSquared}[[1] ]}}$  UniformVariates[[1, i]],
      {i, dimMean}
    ];
   $\mu$  + CoupledNormalVariates.CholeskyDecomposition[ $\Sigma$ ],
  Table[
    CoupledNormalVariates =
      Table[ $\sqrt{\frac{\text{CoupledLogarithm}[\text{radiusSquared}[[j]]^{-2}, \kappa, 0]}{\text{radiusSquared}[[j] ]}}$  UniformVariates[[j, i]],
        {i, dimMean}
      ];
     $\mu$  + CoupledNormalVariates.CholeskyDecomposition[ $\Sigma$ ],
    {j, n}
  ]
]
];

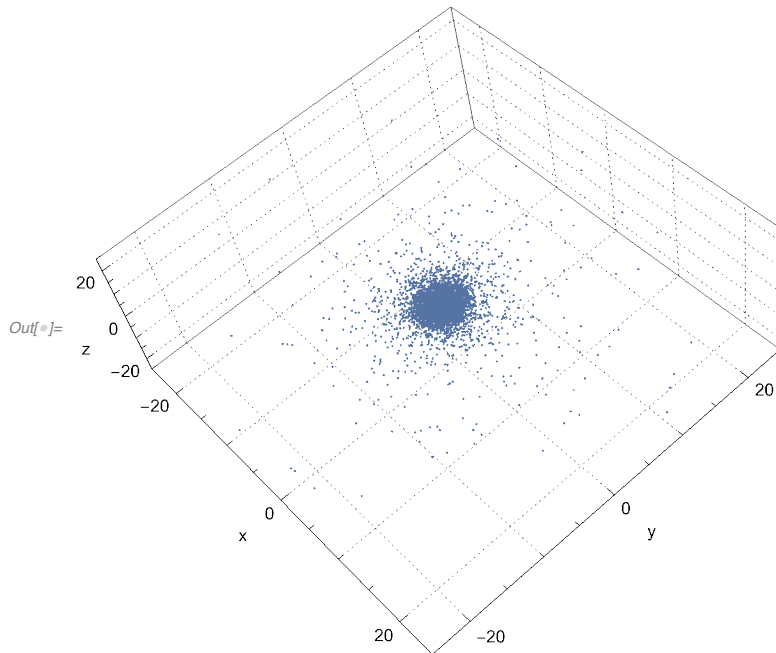
```

Examples compared with Mathematica MultivariateT generation

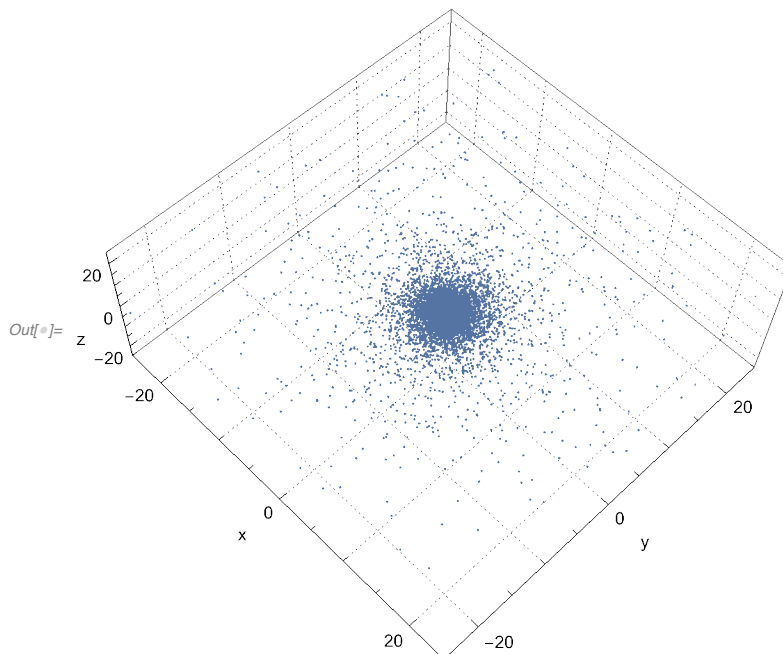
```

In[ ]:= ListPointPlot3D[
  CoupledVariate[{0, 0, 0}, {{1, 0, 0}, {0, 1, 0}, {0, 0, 1}}, 1, 10000],
  PlotTheme -> "Detailed",
  AxesLabel -> {"x", "y", "z"},
  PlotRange -> Table[{-25, 25}, 3]
]

```



```
In[ ]:= ListPointPlot3D[RandomVariate[
  MultivariateTDistribution[{0, 0, 0}, {{1, 0, 0}, {0, 1, 0}, {0, 0, 1}}, 1], 10 000],
  PlotTheme -> "Detailed",
  AxesLabel -> {"x", "y", "z"},
  PlotRange -> Table[{-25, 25}, 3]
]
```

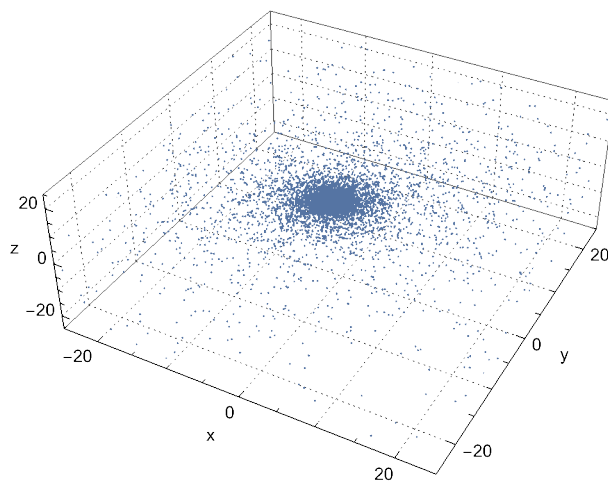
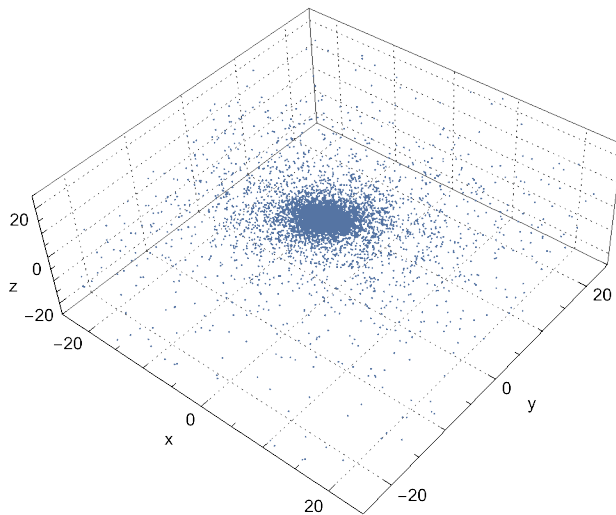


Examples side by side of CoupledVariate (left or top) and MultivariateT (right or bottom) variates show

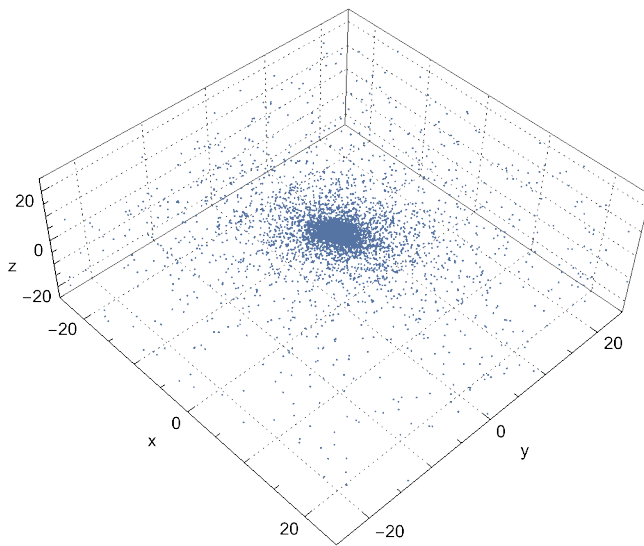
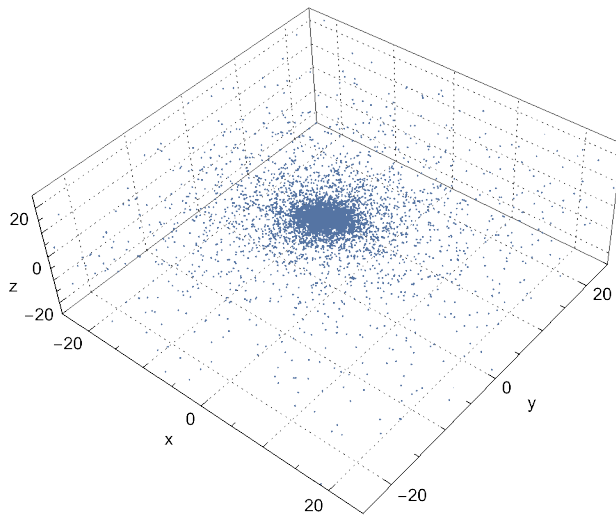
reasonable similarity

[{mean},{correlation matrix}, coupling, samples]

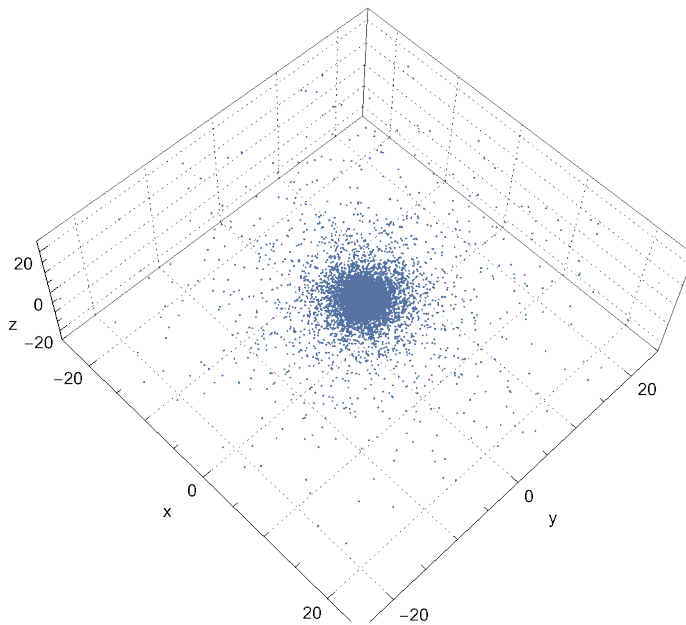
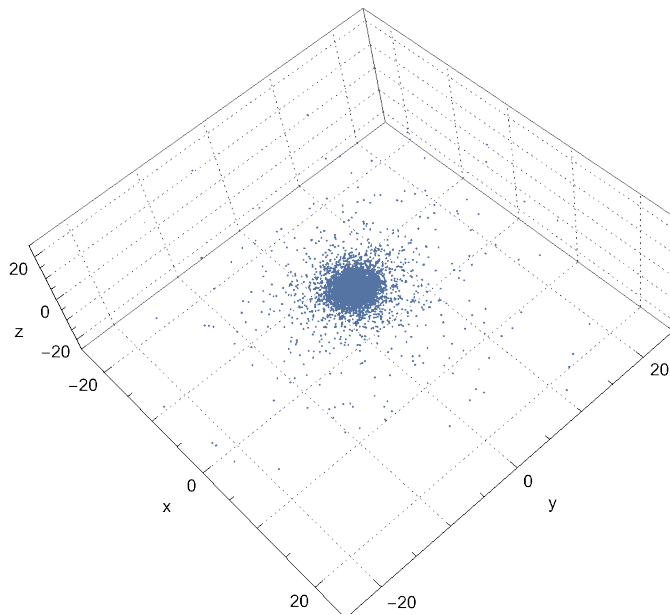
[{-2,1,1},{4,1,0},{1,2,1},{0,1,1}},3,10000]



[{-2,1,1},{4,1,0},{1,2,1},{0,1,1}},5,10000]



Cauchy Standard



Plots with \sqrt{k} multiplied by $1/\sigma$

Backup of Originals Generate and Plot Examples

Higher values of coupling

Visual Comparison Coupled Stretched Exp and Mittag-Leffler Distributions