# North Pole Problem in Random Orthogonal Matrices 

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- $M x_{0}$ is uniformly distributed on the unit sphere. (well known)
- Without loss of generality, we fix $x_{0}$ at the "North Pole",

$$
x_{0}=\left(\begin{array}{c}
1 \\
0 \\
\vdots \\
0
\end{array}\right)
$$

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- Numerical experiment shows in $\mathbb{R}^{3}, M^{2} x_{0}$ has a higher probability for sitting arround the $x_{0}, \mathbb{P}\left[x_{0}^{\prime} M^{2} x_{0}>0\right]>\frac{1}{2}$.


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- What is the probability density function for the random variable $x_{0}^{\prime} M^{k} x_{0}$ in any $n$-dimensional space?


## Numerical Results

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- The direction of each column vector of $M$ is again randomized by multiplying 1 or -1 to avoid bias in MATLAB.
- The $e_{1}$ component (or say $x$ component) of $M^{k} x_{0}$ is $x_{0}^{\prime} M^{k} x_{0}$.

$$
n=3, k=1
$$

$M x_{0}$ uniformly distributes on the unit sphere in $\mathbb{R}^{3}$.
$\Gamma x_{0}$


$$
n=3, k=2
$$

$M^{2} x_{0}$ tends to sit closer to the "North Pole", $x_{0}$.

$$
\Gamma^{2} x_{0}
$$



$$
n=3, k=3
$$

$M^{3} x_{0}$ has higher density in both polar regions.

$$
\Gamma^{3} x_{0}
$$



## $\mathbb{P}_{n}\left[x_{0}^{\prime} M^{2} x_{0}>0\right]$

| Dimension $n$ | 3 | 4 | 5 | 6 |
| :---: | :---: | :---: | :---: | :---: |
| $\mathbb{P}_{n}\left[x_{0}^{\prime} M^{2} x_{0}>0\right]$ | 0.707 | 0.682 | 0.664 | 0.651 |
| Dimension $n$ | 8 | 10 | 20 | 100 |
| $\mathbb{P}_{n}\left[x_{0}^{\prime} M^{2} x_{0}>0\right]$ | 0.632 | 0.619 | 0.586 | 0.540 |

Table: The probabilities $\mathbb{P}_{n}\left[x_{0}^{\prime} M^{2} x_{0}>0\right]$ in different dimension n .

## Theoretical Results

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- $M_{11}$ and $-M_{11}$ should have the same distribution due to the symmetry, the probability density function of $V_{1}$ is,

$$
\begin{equation*}
f_{n}(x)=\frac{\Gamma\left(\frac{n}{2}\right)}{\Gamma\left(\frac{1}{2}\right) \Gamma\left(\frac{n-1}{2}\right)}\left(1-x^{2}\right)^{(n-3) / 2} \tag{1}
\end{equation*}
$$

while $x$ ranges in $-1 \leq x \leq 1$ and $\Gamma$ is the gamma function.

## Distribution of $x_{0}^{\prime} M^{2} x_{0}$

- We will partition the matrix $M$ into the following parts,

$$
M=\left(\begin{array}{ll}
M_{11} & M_{12}  \tag{2}\\
M_{21} & M_{22}
\end{array}\right)
$$

where $M_{11} \in[-1,1], M_{12} \in[-1,1]^{1 \times(n-1)}$,
$M_{21} \in[-1,1]^{(n-1) \times 1}$ and $M_{22} \in[-1,1]^{(n-1) \times(n-1)}$.

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$M_{21} \in[-1,1]^{(n-1) \times 1}$ and $M_{22} \in[-1,1]^{(n-1) \times(n-1)}$.

- Then $V_{2}$ can be written as,

$$
\begin{equation*}
V_{2}=x_{0}^{\prime} M^{2} x_{0}=M_{11}^{2}+M_{12} M_{21} \tag{3}
\end{equation*}
$$

## Distribution of $x_{0}^{\prime} M^{2} x_{0}$

- We can further present $V_{2}$ as,

$$
\begin{equation*}
V_{2}=M_{11}^{2}+\left(1-M_{11}^{2}\right) \frac{M_{12}}{\left(1-M_{11}^{2}\right)^{1 / 2}} \frac{M_{21}}{\left(1-M_{11}^{2}\right)^{1 / 2}} \tag{4}
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\end{equation*}
$$

- The motivation for doing this is to normalize both $M_{12}$ and $M_{21}$ into norm one, so that the part $\frac{M_{12}}{\left(1-M_{11}^{2}\right)^{1 / 2}} \frac{M_{21}}{\left(1-M_{11}^{1}\right)^{1 / 2}}$ in the equation above can be seen as an inner product of two unit vectors in $\mathbb{R}^{(n-1)}$.


## Distribution of $x_{0}^{\prime} M^{2} x_{0}$

Let $\Pi$ and $\Delta$ be two fixed $n \times n$ orthogonal matrices, which has the form

$$
\Pi=\left(\begin{array}{cc}
1 & 0  \tag{5}\\
0 & \Pi_{1}
\end{array}\right), \Delta=\left(\begin{array}{cc}
1 & 0 \\
0 & \Delta_{1}
\end{array}\right),
$$

while $\Pi_{1}$ and $\Delta_{1}$ are $(n-1) \times(n-1)$ orthogonal matrices. Then,
$\Pi M \Delta=\left(\begin{array}{cc}1 & 0 \\ 0 & \Pi_{1}\end{array}\right)\left(\begin{array}{ll}M_{11} & M_{12} \\ M_{21} & M_{22}\end{array}\right)\left(\begin{array}{cc}1 & 0 \\ 0 & \Delta_{1}\end{array}\right)=\left(\begin{array}{cc}M_{11} & M_{12} \Delta_{1} \\ \Pi_{1} M_{21} & \Pi_{1} M_{22} \Delta_{1}\end{array}\right)$.

## Distribution of $x_{0}^{\prime} M x_{0}$

Due to the properties of orthogonal matrices, $M$ and $\Pi M \Delta$ should share the same distribution. This is because that the elements in $\mathcal{O}_{n}$ is one-to-one corresponding to the elements in $\Pi \mathcal{O}_{n} \Delta$, while $\mathcal{O}_{n}$ is the group of $n \times n$ orthogonal matrices. Then $V_{2}$ can also be expressed in the following way,

$$
\begin{gather*}
V_{2}=x_{0}^{\prime} \Pi M \Delta \Pi M \Delta x_{0}  \tag{7}\\
=M_{11}^{2}+\left(1-M_{11}^{2}\right) \frac{M_{12}}{\left(1-M_{11}^{2}\right)^{1 / 2}} \Delta_{1} \Pi_{1} \frac{M_{21}}{\left(1-M_{11}^{2}\right)^{1 / 2}} . \tag{8}
\end{gather*}
$$

## Distribution of $x_{0}^{\prime} M x_{0}$

$$
V_{2}=M_{11}^{2}+\left(1-M_{11}^{2}\right) \frac{M_{12}}{\left(1-M_{11}^{2}\right)^{1 / 2}} \Delta_{1} \Pi_{1} \frac{M_{21}}{\left(1-M_{11}^{2}\right)^{1 / 2}}
$$

Notice that this equation holds for all fixed $\Delta_{1}$ and $\Pi_{1}$. Thus, for any random orthogonal matrices $\Delta_{1}$ and $\Pi_{1}$, it should still hold, since $M$ and $\Pi M \Delta$ have the same distribution. Then we can choose $\Delta_{1}$ and $\Pi_{1}$ to be independent uniform on $\mathcal{O}_{(n-1)}$, so that $\Delta_{1} \Pi_{1}$ is again uniform on $\mathcal{O}_{(n-1)}$.

## Distribution of $x_{0}^{\prime} M x_{0}$

Let $u=\frac{M_{12}}{\left(1-M_{11}^{2}\right)^{1 / 2}}$ and $v=\frac{M_{21}}{\left(1-M_{11}^{2}\right)^{1 / 2}}$. As we already stated above, $u^{\prime}$ and $v$ are both unit vectors in $\mathbb{R}^{(n-1)}$. Then apply the following lemma, we can conclude that, the probability density function for

$$
\frac{M_{12}}{\left(1-M_{11}^{2}\right)^{1 / 2}} \Delta_{1} \Pi_{1} \frac{M_{21}}{\left(1-M_{11}^{2}\right)^{1 / 2}}
$$

must be $f_{n-1}(\cdot)$, as we defined in calculating $V_{1}$.
Lemma. If $u$ and $v$ are fixed unit vectors in $\mathbb{R}^{n}$, and $Q$ is uniform on $\mathcal{O}_{n}$, then the density function for $u^{\prime} Q v$ is $f_{n}(\cdot)$.

## Distribution of $x_{0}^{\prime} M x_{0}$

In the $n$ dimensional space, for $M$ be uniform distributed random orthogonal matrices, $V_{2}=x_{0}^{\prime} M^{2} x_{0}$ behaviors as,

$$
V_{2}=T+(1-T) Y
$$

where $T$ and $Y$ are two independent random variables.
Furthermore, $T$ obeys to the Beta distribution with parameters $\alpha=\frac{1}{2}$ and $\beta=\frac{n-1}{2}$, and the random variable $Y$ has density function $f_{n}{ }^{Y}$ satisfying

$$
f_{n}^{Y}(x)=f_{n-1}(x)=\frac{\Gamma\left(\frac{n-1}{2}\right)}{\Gamma\left(\frac{1}{2}\right) \Gamma\left(\frac{n}{2}-1\right)}\left(1-x^{2}\right)^{(n-4) / 2} .
$$

