# Generalized inverses of Markovian kernels in terms of properties of the Markov chain 

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## A R T I C L E I N F O

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#### Abstract

All one-condition generalized inverses of the Markovian kernel $I-P$, where $P$ is the transition matrix of a finite irreducible Markov chain, can be uniquely specified in terms of the stationary probabilities and the mean first passage times of the underlying Markov chain. Special sub-families include the group inverse of $I-P$, Kemeny and Snell's fundamental matrix of the Markov chain and the Moore-Penrose g-inverse. The elements of some sub-families of the generalized inverses can also be re-expressed involving the second moments of the recurrence time variables. Some applications to Kemeny's constant and perturbations of Markov chains are also considered.


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## 1. Introduction

Let $P=\left[p_{i j}\right]$ be the transition matrix of a finite irreducible, discrete time Markov chain $\left\{X_{n}\right\}$ $(n \geqslant 0)$, with state space $S=\{1,2, \ldots, m\}$. Such chains have a unique stationary distribution $\left\{\pi_{j}\right\}$ $(1 \leqslant j \leqslant m)$. Let $T_{i j}=\min \left[n \geqslant 1, X_{n}=j \mid X_{0}=i\right]$ be the first passage time from state $i$ to state $j$ (first return when $i=j$ ) and define $m_{i j}=E\left[T_{i j} \mid X_{0}=i\right]$ as the mean first passage time from state $i$

[^0]to state $j$ (or mean recurrence time of state $i$ when $i=j$ ). It is well known that for finite irreducible chains all the $m_{i j}$ are well defined and finite.

Generalized matrix inverses (g-inverses) of $I-P$ are typically used to solve systems of linear equations including a variety of the properties of the Markov chain. In particular the $\left\{\pi_{j}\right\}$ and the $\left\{m_{i j}\right\}$ can be found in terms of g -inverses, either in matrix form or in terms of the elements of the g-inverse. What is not known is that the elements of every g-inverse of $I-P$ can be expressed in terms of the stationary probabilities $\left\{\pi_{j}\right\}$ and the mean first passage times $\left\{m_{i j}\right\}$ of the associated Markov chain. The key thrust to this paper is to first identify the parameters that characterize different sub-families of $g$-inverses of $I-P$. Then to assign to each sub-family, thus characterized, explicit expressions for the elements of the $g$-inverses in terms of the $\left\{\pi_{j}\right\}$ and the $\left\{m_{i j}\right\}$.

## 2. Generalized inverses of the Markovian kernel I-P

A g-inverse of a matrix $A$ is any matrix $A^{-}$such that $A A^{-} A=A$. Matrices $A^{-}$are called "onecondition" g-inverses or "equation solving" g-inverses because of their use in solving systems of linear equations.

If $A$ is non-singular then $A^{-}$is $A^{-1}$, the inverse of $A$, and is unique. If $A$ is singular, $A^{-}$is not unique. Typically, in the equations that we wish to solve, we only need a one-condition g-inverse with the non-uniqueness being eliminated by the imposition of boundary conditions (such as $\sum_{i=1}^{m} \pi_{i}=1$ in the case of finding stationary distributions, and $m_{i i}=1 / \pi_{i}$ in the case of mean first passage times).

The following theorem in [5] gives a procedure for finding all one-condition g-inverses of $I-P$.
Theorem 1. Let $P$ be the transition matrix of a finite irreducible Markov chain with $m$ states and stationary probability vector $\pi^{T}=\left(\pi_{1}, \pi_{2}, \ldots, \pi_{m}\right)$.

Let $\boldsymbol{e}^{T}=(1,1, \ldots, 1)$ and $\boldsymbol{t}$ and $\boldsymbol{u}$ be any vectors.
(a) $I-P+\boldsymbol{t u}^{T}$ is non-singular if and only if $\boldsymbol{\pi}^{T} \boldsymbol{t} \neq 0$ and $\boldsymbol{u}^{T} \boldsymbol{e} \neq 0$.
(b) If $\boldsymbol{\pi}^{T} \boldsymbol{t} \neq 0$ and $\boldsymbol{u}^{T} \boldsymbol{e} \neq 0$ then $\left[I-P+\boldsymbol{t} \boldsymbol{u}^{T}\right]^{-1}$ is a one-condition $g$-inverse of $I-P$ and, further, all "one-condition" $g$-inverses of $I-P$ can be expressed as $A^{(1)}=\left[I-P+\boldsymbol{t} \boldsymbol{u}^{T}\right]^{-1}+\boldsymbol{e} \boldsymbol{f}^{T}+\boldsymbol{g} \boldsymbol{\pi}^{T}$ for arbitrary vectors $\boldsymbol{f}$ and $\mathbf{g}$.

Useful by-products of the proof of the above theorem were the following results:

$$
\begin{align*}
& {\left[I-P+\boldsymbol{t} \boldsymbol{u}^{T}\right]^{-1} \boldsymbol{t}=\frac{\boldsymbol{e}}{\boldsymbol{u}^{T} \boldsymbol{e}}}  \tag{2.1}\\
& \boldsymbol{u}^{T}\left[I-P+\boldsymbol{t} \boldsymbol{u}^{T}\right]^{-1}=\frac{\boldsymbol{\pi}^{T}}{\boldsymbol{\pi}^{T} \boldsymbol{t}} \tag{2.2}
\end{align*}
$$

Special multi-condition g-inverses of $A$ can also be considered by imposing additional conditions. Consider real conformable matrices $X$ (which in our context we assume to be square) such that:
(Condition 1) $A X A=A$.
(Condition 2) $X A X=X$.
(Condition 3) $(A X)^{T}=A X$.
(Condition 4) $(X A)^{T}=X A$.
(Condition 5) $A X=X A$.
Let $A^{(i, j, \ldots, l)}$ be any matrix that satisfies conditions $(i),(j), \ldots,(l)$ of the above itemised conditions. $A^{(i, j, \ldots, l)}$ is called an $(i, j, \ldots, l)$ g-inverse of $A$, under the assumption that condition 1 is always included. Let $A\{i, j, \ldots, l\}$ be the class of all $(i, j, \ldots, l)$ g-inverses of $A$.

The classification of $g$-inverses of the Markovian kernel $I-P$, can be done simply by means of the following results given in [8].

Theorem 2. If $G$ is any $g$-inverse of $I-P$, where $P$ is the transition matrix of a finite irreducible Markov chain with stationary probability vector $\boldsymbol{\pi}^{T}$, then $G$ can be uniquely expressed in parametric form as

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