

# ON COMPUTING DOMINANT EIGENPAIR BY MARKOV CHAIN MONTE CARLO METHOD

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## Abstract

In this paper we introduce a Markov chain Monte Carlo(MCMC) approach for calculating dominant eigenpair of symmetric matrices. The algorithm is tested on large randomized symmetric matrices.

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**Additional Key Words and Phrases:** Markov chain, Monte Carlo, Matrix computations, eigenpair

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## 1. INTRODUCTION

Matrix eigenvalue problems arise in a large number of disciplines of sciences and engineering[5]. For example, Physics and chemistry provide numerous problems where obtaining largest eigenpair is important. It is known that Monte Carlo (MC) algorithms give statistical estimates for bilinear forms by performing random sampling of a certain random variable, whose mathematical expectation is the desired solution[1]. We are interested in the bilinear form of matrix powers since it is a basic task for many matrix computations

$$(v, A^k h). \quad (1)$$

Here, we consider the following problem of calculating eigenvalues performed by,

$$Ax = \lambda x \quad (2)$$

where the pair  $(\lambda, x)$  for  $x \neq 0$ , is called an eigenpair of  $A \in \mathfrak{R}^{n \times n}$  matrix.

## 2. POWER METHOD

The power method gives us an estimate for the dominant eigenvalue  $\lambda_1$ . Suppose  $A \in \mathfrak{R}^{n \times n}$  is a symmetric matrix and also

$$\lambda_{min} = \lambda_n < \lambda_{n-1} \leq \dots \leq \lambda_2 < \lambda_1 = \lambda_{max}$$

then the dominant eigenvalue can be obtained using the iteration process for large value of  $i$ ,

$$\lambda_1 \approx \frac{\langle h, A^i f \rangle}{\langle h, A^{i-1} f \rangle}. \quad (3)$$

### 3. MONTE CARLO IMPLEMENTATION

Consider matrix  $A \in \mathbb{R}^{n \times n}$  and two vectors  $f, h \in \mathbb{R}^n$ . Consider the following Markov chain  $T_i$  with length  $i$

$$T_i : k_0 \rightarrow k_1 \rightarrow \dots \rightarrow k_i$$

where for  $j = 1, \dots, i$ ;  $k_j \in \{1, 2, \dots, n\}$ . The statistical nature of constructing the chain (2) follow as

$$p(k_0 = \alpha) = p_\alpha, \quad p(k_j = \beta | k_{j-1} = \alpha) = p_{\alpha\beta}$$

where  $p_\alpha$  and  $p_{\alpha\beta}$  show the probability of starting chain at  $\alpha$  and transition probability from state  $\alpha$  to  $\beta$ , respectively.

Now, define the random variable  $W_j$  using the following recursion for

$$W_0 = 1 \quad , \quad W_j = W_{j-1} \frac{a_{k_{j-1}k_j}}{p_{k_{j-1}k_j}} \quad , j = 1, 2, \dots, i \quad (4)$$

From all possible permissible densities, we choose the following

$$p_\alpha = \frac{|h_\alpha|}{\sum_{\alpha=1}^n |h_\alpha|}$$

$$p_{\alpha\beta} = \frac{|a_{\alpha\beta}|}{\sum_{\beta=1}^n |a_{\alpha\beta}|} \quad \alpha = 1, 2, \dots, n$$

The choice of the initial density vector and the transition probability matrix leads to an Almost Optimal Monte Carlo algorithm.

**THEOREM 3.1.** *Using the above choice  $p = \{p_\alpha\}_{\alpha=1}^n$  and  $P = \{p_{\alpha\beta}\}_{\alpha,\beta=1}^n$  the variance of the unbiased estimator for obtaining the inverse matrix is minimized.*

*Proof.* See [2].

**THEOREM 3.2.** *Under above assumption we have*

$$E[W_i f_{k_i}] = \langle h, A^i f \rangle \quad i = 1, 2, \dots \quad (5)$$

*Proof.* See [3].

**Remark 3.3.** By simulating  $N$  random paths

$$T_i^s : k_0^{(s)} \rightarrow k_1^{(s)} \rightarrow \dots \rightarrow k_i^{(s)}$$

we can find

$$\Theta_k^{(s)}(h) = \frac{h_{k_0}}{p_{k_0}^{(s)}} W_k^{(s)} f_{k_i} \quad , \quad s = 1, \dots, N$$

The Monte Carlo estimation can be evaluated by

$$\Theta_k = \frac{1}{N} \sum_{s=1}^N \Theta_k^{(s)}(h)$$

which is an unbiased estimator of  $\langle h, A^i f \rangle$ . Therefore, from 3 and 5 we have

$$\lambda_1 \approx \frac{E[W_i f_{k_i}]}{E[W_{i-1} f_{k_{i-1}}]} \quad (6)$$

*Remark 3.4.* By setting  $h = e(r) = (0, \dots, 0, 1, 0, \dots, 0)^T$ , the  $r^{th}$  canonical unit vector, for  $r = 1, \dots, n$  the above random variable has expected value equal to the  $r^{th}$  component of the dominant eigenvector.

#### 4. NUMERICAL EXAMPLES

In this section, the experimental results for obtaining dominant eigenpair of a randomized symmetric matrix  $A_{100 \times 100}$  are given in the following table.

Table 1: Monte Carlo error to obtain eigenpair for randomized symmetric matrix

Number of trajectory	Eigenvector error	Eigenvalue error	Time(sec.)
100	0.7928	0.0061	0.98
200	0.6214	0.0036	2.05
400	0.5479	0.0020	4.07
800	0.4740	$3.3759 \times 10^{-4}$	8.05
1600	0.4201	0.0022	16.1
3200	0.4093	0.0020	32.18
6400	0.4031	0.0019	64.53

#### 5. CONCLUDING REMARKS

We have presented a iterative MCMC algorithm that enables the determination of the dominant eigenpair of a very large matrices. Experimental results show that the linear dependency between number of Markov chains and computational times in proposed MCMC method (Fig. 2). This method can be extended for finding more than one eigenpair. Also, The studied algorithm is easily programmable and parallelization.

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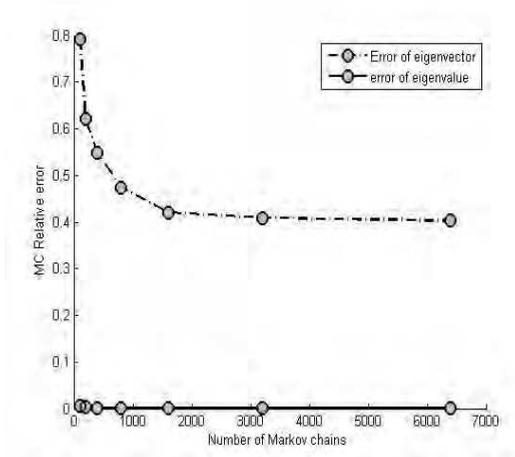


Fig. 1. Curve of relative error for various number of Markov chains

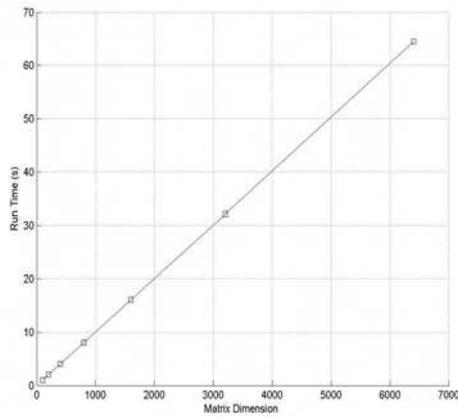


Fig. 2. Curve of CPU time for various number of matrices

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