## GENERALIZED RYBICKI PRESS ALGORITHM

## SIVARAM AMBIKASARAN

 $\mathcal{O}(N)$  direct solver and determinant computation of exponential covariance and general semi-separable matrices

Abstract. This article discusses a more general and numerically stable Rybicki Press algorithm, which enables inverting and computing determinants of covariance matrices, whose elements are sums of exponentials. The algorithm is true in exact arithmetic and relies on introducing new variables and corresponding equations, thereby converting the matrix into a banded matrix of larger size. Linear complexity banded algorithms

determinants of covariance matrices, whose elements are sums of exponentials. The algorithm is true in exact arithmetic and relies on introducing new variables and corresponding equations, thereby converting the matrix into a banded matrix of larger size. Linear complexity banded algorithms for solving linear systems and computing determinants on the larger matrix enable linear complexity algorithms for the initial semi-separable matrix as well. Benchmarks provided illustrate the linear scaling of the algorithm.

Key words. Semi-separable matrices, Rybicki Press algorithm, fast direct solver, fast determinant computation, exponential covariance, CARMA processes

AMS subject classifications. 15A23, 15A15, 15A09

1. Introduction. Large dense covariance matrices arise in a wide range of applications in computational statistics and data analysis. Storing and performing numerical computations on such large dense matrices is computationally intractable. However, most of these large dense matrices are structured (either in exact arithmetic or finite arithmetic), which can be exploited to construct fast algorithms. One such class of data sparse matrices are semi-separable matrices, which have raised a lot of interest and have been studied in detail across a wide range of applications including integral equations [1–3] and computational statistics [4–8]. For a detailed bibliography on semi-separable matrices, the reader is referred to Vandebril et be working with the following definition:

DEFN 1.1.  $A \in \mathbb{R}^{N \times N}$  is termed a semi-separable matrix with semi-separable matrices. In this article, we will be working with the following definition:

DEFN 1.1.  $A \in \mathbb{R}^{N \times N}$  is termed a semi-separable matrix with semi-separable matrices to some of these references [10–15] and the references therein. In this article, we propose a new  $\mathcal{O}(N)$  direct solver and determinant computation for semi-separable matrices.

The main contributions of this article include:

• A new  $\mathcal{O}(N)$  direct solver for semi-separable matrice

$$(1.1) A = D + triu(B_p) + tril(C_p)$$

- A numerically stable generalized Rybicki Press algorithm is derived using these ideas. To be specific, fast, stable, direct algorithms are derived for solving and computing determinants (both scaling as  $\mathcal{O}(N)$ ) for covariance matrices of the form:

(1.2) 
$$A_{ij} = \sum_{l=1}^{p} \alpha_l \exp(-\beta_l |t_i - t_j|)$$

where  $i, j \in \{1, 2, \dots, n\}$ , the points  $t_i$  are distinct and are distributed on an interval. The covariance matrix in Equation (1.2) is frequently encountered in computational statistics in the context of Continuous time AutoRegressive-Moving-Average (abbreviated as CARMA) models [16–18].

• Another advantage of this algorithm from a practical view-point is that the algorithm relies only on sparse linear algebra and thereby can easily use the existing mature sparse linear algebra libraries.

The algorithm discussed in this article has been implemented in C++ and the implementation is made available at https://github.com/sivaramambikasaran/ESS [19] under the license provided by New York University.

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2. Sparse embedding of semi-separable matrix with semi-separable rank 1. To motivate the general idea, we will first look at the sparse embedding for a  $4 \times 4$  semi-separable matrix, whose semi-separable rank is 1. The matrix A is as shown in Equation (2.1).

(2.1) 
$$A = \begin{bmatrix} a_{11} & u_1v_2 & u_1v_3 & u_1v_4 \\ u_1v_2 & a_{22} & u_2v_3 & u_2v_4 \\ u_1v_3 & u_2v_3 & a_{33} & u_3v_4 \\ u_1v_4 & u_2v_4 & u_3v_4 & a_{44} \end{bmatrix}$$

And the corresponding linear system is Ax = b, where  $b = \begin{bmatrix} b_1 & b_2 & b_3 & b_4 \end{bmatrix}^T$ Introduce the following variables:

$$(2.2) r_4 = v_4 x_4$$

$$(2.3) r_3 = v_3 x_3 + r_4$$

$$(2.4) r_2 = v_2 x_2 + r_3$$

$$(2.5) l_1 = u_1 x_1$$

$$(2.6) l_2 = u_2 x_2 + l_1$$

$$(2.7) l_3 = u_3 x_3 + l_2$$

Introducing the variables the linear system Ax = b is now of the form

$$(2.8) a_{11}x_1 + u_1r_2 = b_1$$

$$(2.9) v_2l_1 + a_{22}x_2 + u_2r_3 = b_2$$

$$(2.10) v_3l_2 + a_{33}x_3 + u_3r_4 = b_3$$

$$(2.11) v_4 l_3 + a_{44} x_4 = b_4$$

The extended linear system (after appropriate ordering of equations and unknowns) is then of the form

Note that Equation (2.12) is a banded matrix of bandwidth 2 and has a sparsity structure even within the band. In general, let A be an  $N \times N$  semi-separable matrix, with the semi-separability rank 1 as written in Equation (2.13).

(2.13) 
$$A(i,j) = \begin{cases} a_{ii} & \text{if } i = j \\ u_j v_i & \text{if } i > j \\ u_i v_j & \text{if } i < j \end{cases}$$

where  $i, j \in \{1, 2, ..., N\}$ . One would then need to add the variables  $r_2, r_3, ..., r_N$  and  $l_1, l_2, ..., l_{N-1}$ , where  $r_N = v_N x_N$ ,  $l_1 = u_1 x_1$  and

$$(2.14) r_k = v_k x_k + r_{k+1}$$

$$(2.15) l_k = u_k x_k + l_{k-1}$$

where  $k \in \{2, ..., N-1\}$ . Hence, we have a total of 3N-2 variables and 3N-2 equations. Therefore, the extended matrix will be a  $(3N-2) \times (3N-2)$  banded matrix, whose bandwidth is 2. This is illustrated pictorially for a  $8 \times 8$  matrix in Figure 2.1.

3. Sparse embedding of a general semi-separable matrix. Let A be a  $N \times N$  matrix, whose semi-separable rank is p, i.e., we have

(3.1) 
$$A(i,j) = \begin{cases} a_{ii} & \text{if } i = j \\ \sum_{l=1}^{p} u_j^{(l)} v_i^{(l)} & \text{if } i > j \\ \sum_{l=1}^{p} u_i^{(l)} v_j^{(l)} & \text{if } i < j \end{cases}$$

where  $i,j \in \{1,2,\ldots,N\}$ . We then add the following variables  $r_2^{(p)}, r_3^{(p)},\ldots, r_N^{(p)}$  and  $l_1^{(p)}, l_2^{(p)},\ldots, l_{N-1}^{(p)}$  as before. However, not surprisingly, these new variables  $r_i^{(p)}$ 's and  $l_j^{(p)}$ 's will be vectors of length p. Let  $U_k^{(p)} = \begin{bmatrix} u_k^{(1)} & u_k^{(2)} & u_k^{(3)} & \cdots & u_k^{(p)} \end{bmatrix}$  and  $V_k^{(p)} = \begin{bmatrix} v_k^{(1)} & v_k^{(2)} & v_k^{(3)} & \cdots & v_k^{(p)} \end{bmatrix}$ . We then have the following relations for the additional vector variables.

$$(3.2) r_N^{(p)} = V_N^T x_N$$

$$(3.3) l_1^{(p)} = U_1^T x_1$$

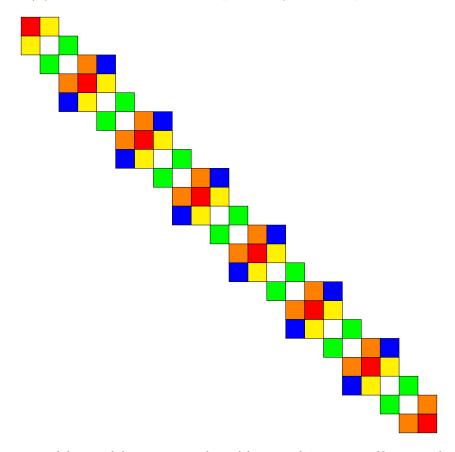


Fig. 2.1. Pictorial description of the extended sparse matrix obtained from a rank 1 semi-separable matrix where N=8. The color code is as shown below.

$$= a_{kk};$$
  $= u_i^{(p)};$   $= v_j^{(p)};$   $= -1;$   $= 1;$ 

and

$$(3.4) r_k^{(p)} = V_k^T x_k + r_{k+1}^{(p)}$$

$$(3.5) l_k^{(p)} = U_k^T x_k + l_{k-1}^{(p)}$$

where  $k \in \{2, \dots, N-1\}$ . Hence, we now have (2p+1)N-2p variables (this includes the N  $x_k$ 's, N-1 vector variables  $r_k^{(p)}$  and  $l_k^{(p)}$  of length p) and (2p+1)N-2p equations relating them. Therefore, we end up with a  $((2p+1)N-2p)\times((2p+1)N-2p)$  extended sparse matrix, whose bandwidth is (2p+1). This is illustrated in Figure 3.1 for  $10\times 10$  semi-separable matrix, whose semi-separable rank is 4.

The computational complexity of the algorithm clearly scales as  $\mathcal{O}(N)$ , since the extended sparse matrix has a bandwidth of  $\mathcal{O}(p)$  and the matrix of size  $\mathcal{O}(pN) \times \mathcal{O}(pN)$ . It is also possible to analyze the scaling with respect to the semi-separable rank p, though this is of little practical relevance since  $p = \mathcal{O}(1)$  for most interesting semi-separable matrices. A detailed analysis shows that the computational complexity of the algorithm is  $\mathcal{O}(p^2N)$ . Numerical benchmarks presented in Section 7 validate the scaling of the algorithm.

4. Determinant of extended sparse matrix. Claim 4.1. The determinant of the extended sparse matrix is the

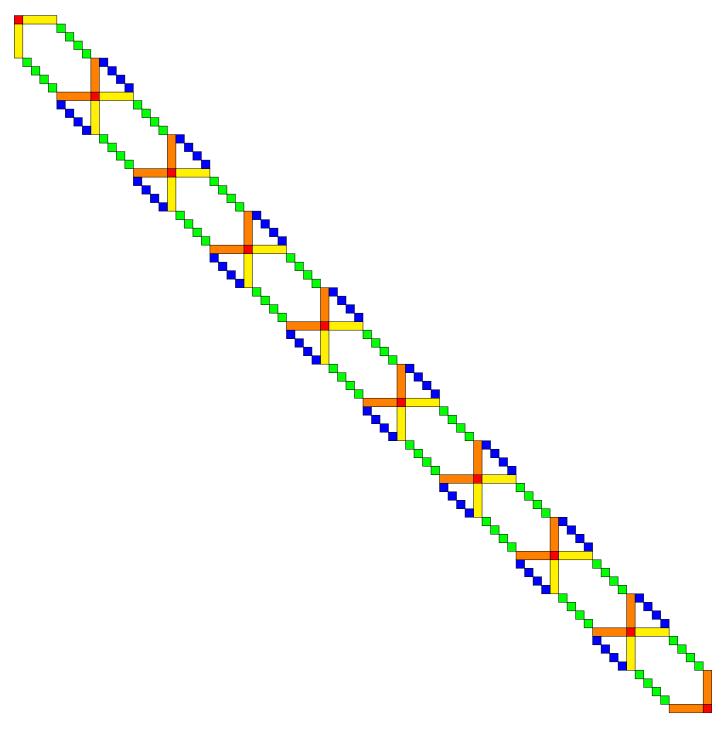


Fig. 3.1. Pictorial description of the extended sparse matrix where N = 10 and p = 4. The color code is as shown below.



same as the determinant of the original dense matrix up to a sign.

The extended system, denoted by  $A_{ex}$  on appropriate reordering of rows and columns can be written as

$$(4.1) P_{1}A_{ex}P_{2} \begin{vmatrix} l_{1}^{(p)} \\ l_{2}^{(p)} \\ \vdots \\ l_{N-1}^{(p)} \\ r_{2}^{(p)} \\ r_{3}^{(p)} \\ \vdots \\ r_{N}^{(p)} \\ x_{1} \\ x_{2} \\ \vdots \\ x_{N} \end{vmatrix} = \begin{bmatrix} L_{\Delta} & 0 & U_{a} \\ 0 & U_{\Delta} & V_{a} \\ 0 & U_{\Delta} & V_{a} \\ V_{b} & U_{b} & D \end{bmatrix} \begin{vmatrix} l_{1}^{(p)} \\ l_{2}^{(p)} \\ \vdots \\ l_{N-1}^{(p)} \\ r_{2}^{(p)} \\ r_{3}^{(p)} \\ \vdots \\ r_{N}^{(p)} \\ x_{1} \\ x_{2} \\ \vdots \\ x_{N} \end{vmatrix}$$

where  $P_1$ ,  $P_2$  are permutation matrices, the matrix  $L_{\Delta}$  is a highly sparse lower-triangular matrix with 1's on the diagonal and -1's at a few places in the lower-triangular part (the precise location is unimportant for determinant computations as we will see later), the matrix  $U_{\Delta}$  is a highly sparse upper-triangular matrix with 1's on the diagonal and -1's at a few places in the upper-triangular part and D is a diagonal matrix with  $D_{ii} = a_{ii}$ . The first set of rows, i.e.,  $\begin{bmatrix} L_{\Delta} & 0 & U_a \end{bmatrix}$ , correspond to adding the variables  $l_k^{(p)}$ , i.e.,  $l_k^{(p)} = U_k^T x_k + l_{k-1}^{(p)}$ . The next set of rows, i.e.,  $\begin{bmatrix} 0 & U_{\Delta} & V_a \end{bmatrix}$ , correspond to adding the variables  $r_k^{(p)}$ , i.e.,  $r_k^{(p)} = V_k^T x_k + r_{k+1}^{(p)}$ . The last set of rows, i.e.,  $\begin{bmatrix} V_b & U_b & D \end{bmatrix}$ , correspond to the initial set of equations with the  $l_k^{(p)}$ 's and  $r_k^{(p)}$ 's introduced. We then have

$$(4.2) \qquad \det(P_1 A_{ex} P_2) = \underbrace{\det\left(\begin{bmatrix} L_{\Delta} & 0 & U_a \\ 0 & U_{\Delta} & V_a \\ V_b & U_b & D \end{bmatrix}\right)}_{} = \det\left(\begin{bmatrix} L_{\Delta} & 0 \\ 0 & U_{\Delta} \end{bmatrix}\right) \det\left(D - \begin{bmatrix} V_b & U_b \end{bmatrix} \begin{bmatrix} L_{\Delta} & 0 \\ 0 & U_{\Delta} \end{bmatrix}^{-1} \begin{bmatrix} U_a \\ V_a \end{bmatrix}\right)$$

Block determinant formula

Now note that  $\det(L_{\Delta}) = 1 = \det(U_{\Delta})$ , due to the fact that  $L_{\Delta}$  and  $U_{\Delta}$  are triangular matrices with 1's on the diagonal. Hence,

(4.3) 
$$\det \left( \begin{bmatrix} L_{\Delta} & 0 \\ 0 & U_{\Delta} \end{bmatrix} \right) = \det(L_{\Delta}) \det(U_{\Delta}) = 1 \times 1 = 1$$

Further, note that the matrix  $D - \begin{bmatrix} V_b & U_b \end{bmatrix} \begin{bmatrix} L_{\Delta} & 0 \\ 0 & U_{\Delta} \end{bmatrix}^{-1} \begin{bmatrix} U_a \\ V_a \end{bmatrix}$  is the Schur complement obtained by eliminating the variables  $l_i^{(p)}$ ,  $r_i^{(p)}$  and hence is the initial dense matrix A we began with, i.e.,

$$(4.4) D - \begin{bmatrix} V_b & U_b \end{bmatrix} \begin{bmatrix} L_{\Delta} & 0 \\ 0 & U_{\Delta} \end{bmatrix}^{-1} \begin{bmatrix} U_a \\ V_a \end{bmatrix} = A$$

Hence, we have

(4.5) 
$$\det(P_1 A_{ex} P_2) = \det \left( D - \begin{bmatrix} V_b & U_b \end{bmatrix} \begin{bmatrix} L_{\Delta} & 0 \\ 0 & U_{\Delta} \end{bmatrix}^{-1} \begin{bmatrix} U_a \\ V_a \end{bmatrix} \right) = \det(A)$$

which gives us that

$$\det(A_{ex}) = \pm \det(A)$$

where the ambiguity in the sign arises due to the determinant of the permutation matrices.

5. Reinterpretation of Rybicki Press algorithm in terms of sparse embedding. We will first naively reinterpret the Rybicki Press algorithm in terms of the extended sparse matrix algebra. Recall that the Rybicki Press algorithm [20] inverts a correlation matrix A given by Equation (5.1).

$$(5.1) A(i,j) = \exp\left(-\beta |t_i - t_j|\right)$$

where  $t_i$ 's lies on an interval and are monotone. The original Rybicki Press algorithm relies on the fact that the inverse of A happens to be a tridiagonal matrix. The key ingredient of their algorithm is the following property of exponentials:

$$(5.2) \qquad \exp(\beta(t_i - t_i)) \exp(\beta(t_i - t_k)) = \exp(\beta(t_i - t_k))$$

In our sparse interpretation as well, we will use this property to recognize that the matrix A is a semi-separable matrix, whose semi-separable rank is 1. This can be seen by setting  $u_k = \exp(\beta t_k)$  and  $v_k = \exp(-\beta t_k)$ . This then gives us (i < j) that  $A(i,j) = u_i v_j = \exp(\beta t_i) \exp(-\beta t_j) = \exp(\beta (t_i - t_j))$  and similarly for i > j. This shows that the matrix A is semi-separable with semi-separable rank 1. Hence, we can mimic the same approach as in the earlier sections to obtain an  $\mathcal{O}(N)$  algorithm. However, there is an issue that needs to be addressed from a numerical perspective. If the  $t_i$ 's are spread over a large interval, then  $u_i$  is exponentially large, while  $v_i$  is exponentially small, and hence embedding into a sparse matrix as such could prove to be a catastrophic leading to underflow and overflow of the relevant entries. This issue though can be circumvented by a suitable analytic preconditioning, by an appropriate change of variables. This is illustrated for a  $4 \times 4$  linear system. We will use the notation  $t_{ij}$  to denote  $|t_i - t_j|$ . The linear equation is

$$\begin{bmatrix} 1 & \exp(-\beta t_{12}) & \exp(-\beta t_{13}) & \exp(-\beta t_{14}) \\ \exp(-\beta t_{12}) & 1 & \exp(-\beta t_{23}) & \exp(-\beta t_{24}) \\ \exp(-\beta t_{13}) & \exp(-\beta t_{23}) & 1 & \exp(-\beta t_{34}) \\ \exp(-\beta t_{14}) & \exp(-\beta t_{24}) & \exp(-\beta t_{34}) & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \\ b_4 \end{bmatrix}$$

Now lets introduce the additional variables as follows:

$$(5.4) r_4 = x_4$$

$$(5.5) r_3 = x_3 + \exp(-\beta t_{34})r_4$$

$$(5.6) r_2 = x_2 + \exp(-\beta t_{23})r_3$$

$$(5.7) l_2 = x_1 \exp(-\beta t_{12})$$

$$(5.8) l_3 = (x_2 + l_2) \exp(-\beta t_{23})$$

$$(5.9) l_4 = (x_3 + l_3) \exp(-\beta t_{34})$$

The equations then become

$$(5.10) x_1 + \exp(-\beta t_{12})r_2 = b_1$$

$$(5.11) l_2 + x_2 + \exp(-\beta t_{23})r_3 = b_2$$

$$(5.12) l_3 + x_3 + \exp(-\beta t_{24})r_4 = b_3$$

$$(5.13) l_4 + x_4 = b_4$$

Embedding this in an extended sparse matrix, we obtain

Note that the sparsity pattern of the matrix is the same as before, which is to be expected, since all we have done essentially is to scale elements appropriately and hence the zero fill-ins remain the same.

6. Numerically stable generalized Rybicki Press. The same idea carries over the generalized Rybicki Press algorithm, i.e., if we consider a CARMA(p,q) process which has the covariance matrix given by

(6.1) 
$$K(r) = \begin{cases} d & \text{if } r = 0\\ \sum_{l=1}^{p} \alpha_l(p, q) \exp(-\beta_l r) & \text{if } r > 0 \end{cases}$$

then it immediately follows that that the matrix is semi-separable with semi-separable rank being p. To avoid numerical overflow and underflow, as shown in the previous section, appropriate sets of variables need to be introduced. Let

$$\alpha = \begin{bmatrix} \alpha_1 & \alpha_2 & \cdots & \alpha_p \end{bmatrix}^T$$

and

(6.3) 
$$\gamma_k = \left[ \exp(-\beta_1 t_{k,k+1}) \quad \exp(-\beta_2 t_{k,k+1}) \quad \cdots \quad \exp(-\beta_p t_{k,k+1}) \right]^T$$

Now introduce the variables

(6.4) 
$$r_k = \alpha x_k + D^{(k,k+1)} r_{k+1}$$

$$(6.5) l_k = \gamma_{k-1} x_{k-1} + D^{(k-1,k)} l_{k-1}$$

where  $k \in \{2, 3, ..., N\}$ , with  $r_{N+1} = l_1 = 0$  and  $D^{(k,k+1)}$  is a  $p \times p$  diagonal matrix, with its diagonal being  $\gamma_k$ . The initial equations become

(6.6) 
$$\alpha^T l_k + dx_k + \gamma_k^T r_{k+1} = b_k$$

where  $k \in \{1, 2, ..., N\}$ . Now form the extended sparse matrix using the variables  $x_k, l_k$  and  $r_k$ , with the equations being Equations (6.4), (6.5), (6.6). The sparsity pattern of the extended sparse matrix is the same and hence the computational complexity scales as  $\mathcal{O}(N)$ .

7. Numerical benchmarks. We present a few numerical benchmarks illustrating the scaling of the algorithm and the error. In all these benchmarks, the semi-separable matrix is of the form

(7.1) 
$$A(i,j) = \begin{cases} d & \text{if } i = j \\ \sum_{l=1}^{p} \alpha_l \exp\left(-\beta_l |t_i - t_j|\right) & \text{if } i \neq j \end{cases}$$

where the  $t_i$ 's lie on a on-dimensional manifold and are sorted in increasing fashion. Apart from the time taken for the assembly, factorization and solve, the infinity norm of the residual, i.e.,  $||Ax-b||_{\infty}$  and the relative error in the log determinant are also presented. For the purposes of benchmark,  $t_i$ 's are chosen at random from the interval [0, 20] and then sorted;  $\alpha_l$ 's,

 $\beta_l$ 's are chosen at random from the interval [0,2]; and d is set equal to  $1+\sum_{l=1}^p \alpha_l$ . Throughout the benchmarks the original

dense matrix will be referred to as A, while the corresponding extended sparse matrix will be referred to as  $A_{ex}$ .

The extended sparse linear system, i.e.,  $A_{ex}x_{ex} = b_{ex}$ , is solved using the sparse LU factorization (SparseLU) in Eigen [21]. This relies on the sequential SuperLU package [22–24], which performs sparse LU decomposition with partial pivoting. The preordering of the unknowns is performed using the COLAMD method [25]. It is to be noted that despite the preordering and partial pivoting, which inturn affects the banded structure, the computational cost as shown in Figures 7.1, 7.2 for the extended sparse system scales linearly in the number of unknowns. The extended sparse matrix is stored using a triplet list in Eigen [21], which internally converts it into compressed column/row storage format. The exact implementation can be found at https://github.com/sivaramambikasaran/ESS [19].

**7.1. Benchmark** 1. In this benchmark, we illustrate the linear scaling of the algorithm with the number of unknowns N for different choices of p. The solution obtained using the sparse LU factorization is compared with the partial pivoted LU algorithm (PartialPivLU) in Eigen [21], which is used to solve the initial dense linear system Ax = b. Table 7.1 shows the scaling of the algorithm and the maximum error in the residual for a fixed semi-separable rank of p = 5.

Table 7.1 Scaling of the algorithm with system size N for a fixed semi-separable rank p = 5. The time taken is reported in milliseconds.

System size	Time taken in milliseconds						Error in residual		Error in log-det
N	Assembly		Factorize		Solve		measured in $\ \cdot\ _{\infty}$		$\frac{\log( A_{ex} / A )}{\log( A )}$
	Usual	Fast	Usual	Fast	Usual	Fast	Usual	Fast	- 1, 1,
500	15.5	1.15	12	8	0.233	1.36	$2 \times 10^{-14}$	$2.2 \times 10^{-15}$	$1.08 \times 10^{-15}$
1000	49.2	1.73	91.6	15.5	0.862	2.02	$4 \times 10^{-14}$	$3.8 \times 10^{-15}$	$1.46 \times 10^{-15}$
2000	188	3.28	643	30.8	2.80	4.41	$9 \times 10^{-14}$	$5.6 \times 10^{-15}$	$1.67 \times 10^{-15}$
5000	1150	9.11	9360	83.1	14.4	10.4	$2 \times 10^{-13}$	$6.4 \times 10^{-15}$	$5.44 \times 10^{-16}$
10000	4760	20.5	71900	167	58.1	20.5	$3 \times 10^{-13}$	$8.0 \times 10^{-15}$	$3.74 \times 10^{-15}$
20000	_	49.1	_	333	_	42.9	_	$1.0 \times 10^{-14}$	_
50000	_	116	_	838	_	108	_	$1.5 \times 10^{-14}$	_
100000	_	216	_	1680	_	213	_	$1.8 \times 10^{-14}$	_
200000	_	441	_	3380	_	425	_	$2.6 \times 10^{-14}$	_
500000	_	1330	_	8500	_	1070	_	$3.4 \times 10^{-14}$	_
1000000	_	2700	_	17600	_	2330	_	$3.9 \times 10^{-14}$	_

- Assembly time Time taken to assemble the dense matrix versus extended sparse matrix.
- Factorization time Time taken to factorize the dense matrix versus extended sparse matrix.
- Solve time Time taken to solve the dense linear system versus the extended sparse linear system (once the factorization has been obtained).

- Error in residual Comparision of  $||Ax b||_{\infty}$  and  $||A_{ex}x_{ex} b_{ex}||_{\infty}$ .
- Error in log-det Relative error of the log of the absolute value of the determinant of the dense matrix and the extended sparse matrix.

Figure 7.1 illustrates the scaling of the assembly, factorization and solve time with system size. The different components of the algorithm, i.e., assembly, factorization and solve, scale linearly in the number of unknowns. Also, as expected the pre-factor infront of the linear scaling increases with the semi-separable rank p, i.e., in our case the number of exponentials.

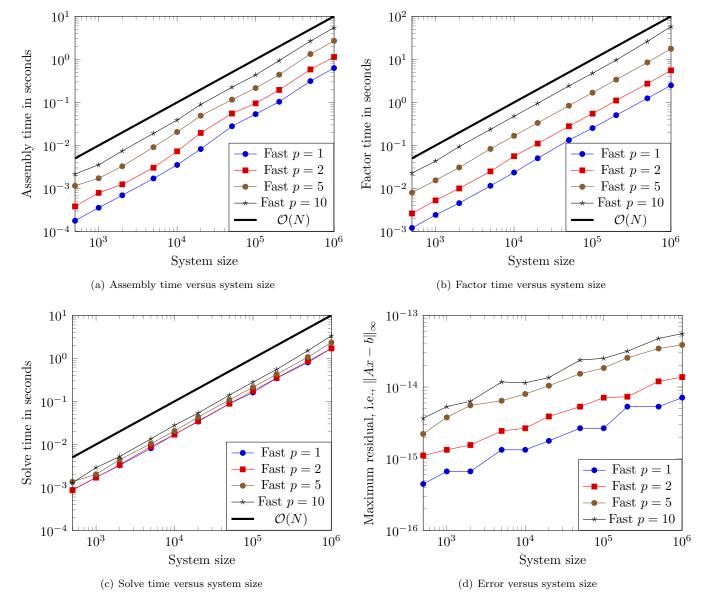


Fig. 7.1. Scaling of the algorithm with system size. From the benchmarks, it is clear that the computational cost for the fast algorithm scales as  $\mathcal{O}(N)$  for assembly, factorization and solve stages, where N is the number of unknowns. The maximum residual is less than  $10^{-13}$  even for a system with million unknowns.

**7.2.** Benchmark 2. In this benchmark, we illustrate the scaling of the time taken (assembly, factorization and solve) for algorithm with p, the number of exponentials added (equivalently the semi-separable rank).

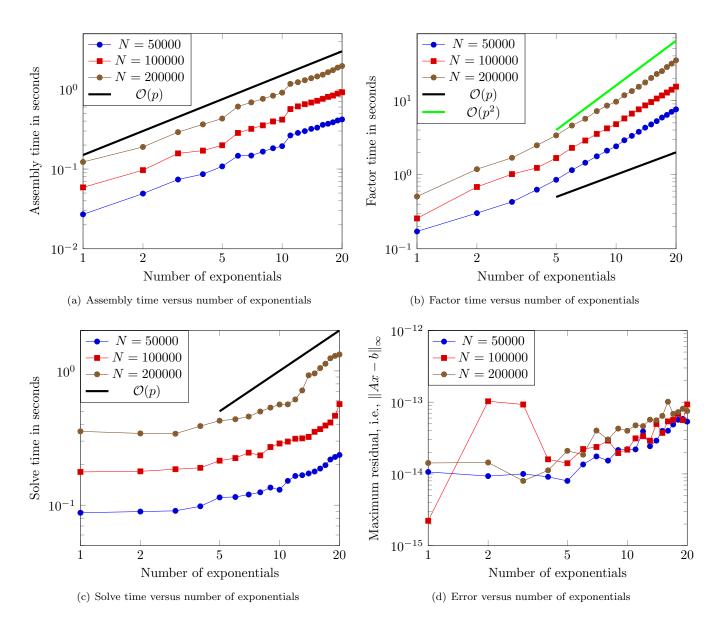


Fig. 7.2. Scaling of the fast algorithm with the number of exponentials added. From the benchmarks, it is clear that the computational cost for the fast algorithm scales as  $\mathcal{O}(p)$  for assembly and solve stages, while it scales as  $\mathcal{O}(p^2)$  for the factorization stage, where p is the number of exponentials (equivalently the semi-separable rank). The maximum residual is less than  $10^{-13}$  almost always.

Figure 7.2 illustrates the scaling of different parts of the algorithm with the semi-separable rank p. Note that the assembly time scales linearly with the semi-separable rank, while the factorization time scales quadratically with the semi-separable rank as expected. The error in the solution seems to be more or less independent of the semi-separable rank.

8. Conclusion. The article discusses a numerically stable, generalized Rybicki Press algorithm, which relies on the fact that a semi-separable matrix can be embedded into a larger banded matrix. This enables  $\mathcal{O}(N)$  inversion and determinant computation of covariance matrices, whose entries are sums of exponentials. This also immediately provides a fast matrix vector product for semi-separable matrices. This publication also serves to formally announce the release of the implementation of the extended sparse semi-separable factorization and the generalized Rybicki Press algorithm. The implementation is in C++ and is made available at https://github.com/sivaramambikasaran/ESS [19] under the license provided by New York University.

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