# Matrix Polynomial Factorization via Higman Linearization 

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#### Abstract

In continuation to our recent work [AJ22] on noncommutative polynomial factorization, we consider the factorization problem for matrices of polynomials and show the following results. - Given as input a full rank $d \times d$ matrix $M$ whose entries $M_{i j}$ are polynomials in the free noncommutative ring $\mathbb{F}_{q}\left\langle x_{1}, x_{2}, \ldots, x_{n}\right\rangle$, where each $M_{i j}$ is given by a noncommutative arithmetic formula of size at most $s$, we give a randomized algorithm that runs in time polynomial in $d, s, n$ and $\log _{2} q$ that computes a factorization of $M$ as a matrix product $M=M_{1} M_{2} \cdots M_{r}$, where each $d \times d$ matrix factor $M_{i}$ is irreducible (in a well-defined sense) and the entries of each $M_{i}$ are polynomials in $\mathbb{F}_{q}\left\langle x_{1}, x_{2}, \ldots, x_{n}\right\rangle$ that are output as algebraic branching programs. We also obtain a deterministic algorithm for the problem that runs in $\operatorname{poly}(d, n, s, q)$. - A special case is the efficient factorization of matrices whose entries are univariate polynomials in $\mathbb{F}[x]$. When $\mathbb{F}$ is a finite field the above result applies. When $\mathbb{F}$ is the field of rationals we obtain a deterministic polynomial-time algorithm for the problem.


Keywords: Noncommutative Polynomials, Arithmetic Circuits, Factorization, Identity testing.

## 1 Introduction

Let $\mathbb{F}\langle X\rangle$ denote the free noncommutative polynomial ring in variables $X=\left\{x_{1}, x_{2}, \ldots, x_{n}\right\}$ over a field $\mathbb{F}$. The elements of $\mathbb{F}\langle X\rangle$ are noncommutative polynomials: finite $\mathbb{F}$-linear combinations of monomials (words) over the variables $X$.

Definition 1.1 (Matrix Polynomials). For a positive integer $d$, a $d \times d$ matrix $M \in \mathbb{F}\langle X\rangle^{d \times d}$ over the noncommutative polynomial ring $\mathbb{F}\langle X\rangle$ is a matrix polynomial. Equivalently, we can consider $M$ as an element of the ring $\mathbb{F}^{d \times d}\langle X\rangle$ of noncommutative polynomials whose coefficients are from the scalar matrix ring $\mathbb{F}^{d \times d}$.

In this paper we study the problem of factorization of matrix polynomials in $\mathbb{F}\langle X\rangle^{d \times d}$ with the aim of designing efficient algorithms. To the best of our knowledge, this is the first algorithmic study of the problem from the viewpoint of obtaining polynomial-time algorithms for it.

The mathematics that underlies such factorizations in noncommutative rings is a general theory of the so-called free ideal rings due to Cohn [Coh06]. The matrix ring $\mathbb{F}\langle X\rangle^{d \times d}$ for $d>1$, unlike the

[^0]polynomial ring $\mathbb{F}\langle X\rangle$ itself, is not a domain because it contains zero divisors (and even nilpotent elements). However, Cohn's factorization theory applies to full matrices: a matrix $M \in \mathbb{F}\langle X\rangle^{d \times d}$ is full if it cannot be expressed as a product
$$
M=A B
$$
of matrices $A \in \mathbb{F}\langle X\rangle^{d \times r}$ and $B \in \mathbb{F}\langle X\rangle^{r \times d}$, where $r<d$. In other words, a full matrix in $\mathbb{F}\langle X\rangle^{d \times d}$ has noncommutative rank $d$. We note here that the problem of computing noncommutative rank has received a lot of attention in recent years [GGdOW20, IQS18].

A matrix $U \in \mathbb{F}\langle X\rangle^{d \times d}$ is a unit if it is invertible in $\mathbb{F}\langle X\rangle^{d \times d}$. That is, there is a matrix $U^{\prime} \in \mathbb{F}\langle X\rangle^{d \times d}$ such that $U U^{\prime}=U^{\prime} U=I_{d}$. Analogous to the usual setting of commutative unique factorization domains, we are interested in the factorization of non-units that are full matrices in $\mathbb{F}\langle X\rangle^{d \times d}$. A full non-unit matrix $M \in \mathbb{F}\langle X\rangle^{d \times d}$ is an atom if $M=A B$ implies either $A$ or $B$ is a unit $\int^{1}$

Elements $A \in \mathbb{F}\langle X\rangle^{d \times d}$ and $B \in \mathbb{F}\langle X\rangle^{d^{\prime} \times d^{\prime}}$ are called stable associates or simply associates if there are positive integers $t$ and $t^{\prime}$ such that $d+t=d^{\prime}+t^{\prime}$ and units $P, Q \in \mathbb{F}\langle X\rangle^{(d+t) \times(d+t)}$ such that $A \oplus I_{t}=P\left(B \oplus I_{t^{\prime}}\right) Q$. Notice that if $A$ and $B$ are full non-unit matrices that are stable associates then $A$ is atom if and only if $B$ is atom [Coh06].

Let $M \in \mathbb{F}\langle X\rangle^{d \times d}$ be a full non-unit matrix polynomial. By a complete factorization ${ }^{2}$ of $M$ we mean expressing $M$ as a product of matrix polynomials

$$
M=M_{1} M_{2} \cdots M_{r},
$$

where each $M_{i} \in \mathbb{F}\langle X\rangle^{d \times d}$ is an atom.
As the first result in this paper, we consider the factorization of matrix polynomials $M \in \mathbb{F}\langle X\rangle^{d \times d}$ over a finite field $\mathbb{F}=\mathbb{F}_{q}$ where the entries of $M$ are given as input by noncommutative arithmetic formulas of size $s$ and we obtain a poly $\left(d, s, \log _{2} q\right.$ ) time randomized algorithm (we also obtain a deterministic poly $(d, s, q)$ time). Indeed, the only place where we require randomness is for univariate polynomial factorization over large characteristic fields $\mathbb{F}_{q}$.

Unfortunately, we do not have a similar result for matrix polynomials when the underlying field $\mathbb{F}=\mathbb{Q}$ because the above method is based on Ronyai's algorithm for computing a nontrivial common invariant subspace for a collection of matrices which is not known to have an efficient algorithm over rationals [Rón87, FR85]. However, the approach works for factorization of matrix polynomials over the univariate ring $\mathbb{Q}[x]$.

Before we proceed we recall some basic definitions. Let $\mathbb{F}$ be any field and $X=\left\{x_{1}, x_{2}, \ldots, x_{n}\right\}$ be a set of $n$ free noncommuting variables. Let $X^{*}$ denote the set of all free words (which are monomials) over the alphabet $X$ with concatenation of words as the monoid operation and the empty word $\epsilon$ as identity element. The free noncommutative ring $\mathbb{F}\langle X\rangle$ consists of all finite $\mathbb{F}$-linear combinations of monomials in $X^{*}$, where the ring addition + is coefficient-wise addition and the ring multiplication $*$ is the usual convolution product.

For $f \in \mathbb{F}\langle X\rangle$ let $f(m) \in \mathbb{F}$ denote the coefficient of monomial $m$ in $f$. We can write $f=$ $\sum_{m} f(m) m$. The degree of a monomial $m \in X^{*}$ is its length, and the degree $\operatorname{deg} f$ of a polynomial $f \in \mathbb{F}\langle X\rangle$ is the degree of a largest degree monomial in $f$ with nonzero coefficient.

[^1]For further required background on Cohn's factorization theory we refer the reader to our recent arxiv paper [AJ22] on which the present work is based. Cohn's texts [Coh06, Coh11] contain a comprehensive treatment.

### 1.1 Overview of the results

We show the following results.

1. Given a full non-unit matrix polynomial $M \in \mathbb{F}_{q}\langle X\rangle^{d \times d}$, where each of its entries $M_{i j}$ is given as input by a noncommutative arithmetic formula of size $s$, a factorization $M=M_{1} M_{2} \cdots M_{r}$ can be computed in randomized time poly $\left(s, \log _{2} q,|X|\right)$, where each $M_{i} \in \mathbb{F}_{q}\langle X\rangle^{d \times d}$ is an atom whose entries are output as algebraic branching programs (of size poly $\left(s, \log _{2} q,|X|\right)$ ). We also obtain a deterministic poly $(s, q,|X|)$ time algorithm for the problem.
2. For a univariate matrix polynomial $M \in \mathbb{Q}[x]^{d \times d}$ that is a full non-unit matrix we give a deterministic time poly $(d, s)$ time algorithm to compute factorization $M=M_{1} M_{2} \cdots M_{r}$ where each $M_{i} \in \mathbb{Q}[x]^{d \times d}$ is an atom and $s$ bounds the bit complexity of the rational coefficients of the matrix entries $M_{i j} \in \mathbb{Q}[x], 1 \leq i, j \leq d$.

To the best of our knowledge, these are the first algorithms with polynomially bounded running time for the above problems.

Remark 1.2. We note that for univariate matrix polynomials over finite fields the first result yields a randomized $\operatorname{poly}\left(s, \log _{2} q,|X|\right)$ time algorithm and a deterministic poly $(s, q,|X|)$ time algorithm. However, over rationals we do not have an analogous efficient algorithm for factorizing matrix polynomials in $\mathbb{Q}\langle X\rangle^{d \times d}$ ever for $d=1$. As explained in [AJ22] the approach to factorization we use breaks down over $\mathbb{Q}$ because the problem of computing nontrivial common invariant subspaces of a collection of rational matrices is at least as hard as factoring square-free integers [FR85].

The algorithm for matrix polynomial factorization uses the same strategy as we did for noncommutative polynomial factorization [AJ22]. We briefly outline it.

- Higman linearization Given a non-unit matrix polynomial $M \in \mathbb{F}\langle X\rangle^{d \times d}$, where each entry is input by a noncommutative formula, we transform it into a linear matrix $L$ such that $M \oplus I=P L Q$, where $P, Q, L \in \mathbb{F}\langle X\rangle^{r \times r}$ for $r=O\left(d^{2} s\right), P$ is upper triangular with all 1 's diagonal, $Q$ is lower triangular with all 1's diagonal, and $L$ is a full non-unit linear matrix.
- Linear Matrix Factorization Next, we factorize the linear matrix $L$ as a product of atomic linear factors using our algorithm described in [AJ22]. This algorithm is based on ideas from Cohn's factorization theory [Coh06] and uses Ronyai's algorithm for computing common invariant subspaces of a collection of matrices over finite fields [Rón90].
- Recovering the factors of $M$ This part requires a new algorithm but similar to the case of a single polynomial [AJ22]. The factor recovery algorithm is based on an algorithm for trivializing a matrix product relation of the form $A B=0$, where $A \in \mathbb{F}_{q}\langle X\rangle^{s \times r}$ is a linear matrix and $B \in \mathbb{F}_{q}\langle X\rangle^{r \times t}$ is a matrix of polynomials. We efficiently compute an invertible
matrix $N \in \mathbb{F}_{q}\langle X\rangle^{r \times r}$ such that $N^{-1}$ is also in $\mathbb{F}_{q}\langle X\rangle^{r \times r}$ (which means $N$ is a unit in the ring $\left.\mathbb{F}_{q}\langle X\rangle^{r \times r}\right)$. Then $A B=0$ can be recast as $(A N)\left(N^{-1} B\right)=0$ which is trivialized by $N$ in the following sense: for every index $i \in[r]$ either the $i^{t h}$ column of $A N$ is zero or the $i^{\text {th }}$ row of $N^{-1} B$ is zero. Using this algorithm repeatedly we are able to recover the factorization of $M$ from the factorization of $L$.

Plan of the paper. In Section 2 we present the algorithm for factorization of matrix polynomials over the noncommutative ring $\mathbb{F}_{q}\langle X\rangle$. In Section 3 we present a deterministic polynomial time algorithm for factorization of matrix polynomials over the commutative polynomial ring $\mathbb{Q}[x]$.

## 2 Factorization of matrix polynomials over $\mathbb{F}_{q}\langle X\rangle$

In this section we prove the main theorem showing a randomized polynomial-time algorithm for factorization of full non-unit matrices over $\mathbb{F}_{q}\langle X\rangle$. As explained in the introduction, the algorithm strategy has three broad steps:
(a) Higman linearization of the input matrix polynomial $M$ which produces a linear matrix $L$ which is an associate of $M$. The input matrix $M$ is assumed of full noncommutative rank (hence $L$ will also be of full rank).
(b) Factorization of the linear matrix $L$ by using Cohn's factorization theory to reduce the problem to computation of a common invariant subspace for a collection of scalar matrices over $\mathbb{F}_{q}$ which can be solved in randomized polynomial-time using Ronyai's algorithm [Rón90].
(c) The efficient recovery of the factors of $M$ from the factors of $L$.

The same strategy was used in [AJ22] for the factorization of noncommutative polynomials. The algorithms for the first two steps (a) and (b) for matrix polynomials follow from the results in AJ22]. Efficient computation of Higman linearization works for matrix polynomials as well [GGdOW20].

Theorem 2.1. GGdOW20, Proposition A.2] Let $M \in \mathbb{F}\langle X\rangle^{n \times n}$ such that $M_{i, j}$ is computed by a noncommutative arithmetic formula of size at most $s$ and bit complexity at most $b$. Then, for $\ell=O(s)$, in time poly $(s, b)$ we can compute the matrices $P, Q$ and $L$ in $\mathbb{F}\langle X\rangle^{(n+\ell) \times(n+\ell)}$ of Higman's linearization such that

$$
\left(\begin{array}{c|c}
M & 0 \\
\hline 0 & I_{\ell}
\end{array}\right)=P L Q .
$$

Moreover, the entries of the matrices $P$ and $Q$ as well as $P^{-1}$ and $Q^{-1}$ are given by polynomial-size algebraic branching programs which can also be obtained in polynomial time.

Noncommutative linear matrix factorization is already dealt with in [AJ22] as mentioned above.
Theorem 2.2. AJ22] On input a full and right (or left) monic linear matrix $L=A_{0}+\sum_{i=1}^{n} A_{i} x_{i}$ where $A_{i} \in \mathbb{F}^{d \times d}$ for $i \in[n]$, there is a randomized polynomial time $\operatorname{poly}\left(n, d, \log _{2} q\right)$ algorithm to compute a factorization $L=F_{1} F_{2} \cdots F_{r}$, where each $F_{i}$ is a linear matrix atom. Furthermore, there is a deterministic time $\operatorname{poly}(n, d, q)$ algorithm for the problem.

Remark 2.3. We explain the above theorem statement in detail. The linear matrix $L$ is called right monic if the matrix $\left[A_{1} A_{2} \cdots A_{n}\right]$ has full row rank [Coh06]. As explained in [AJ22], the factorization problem for full linear matrices can be reduced to the factorization of full and right monic linear matrices. Furthermore, the factorization algorithm for linear matrices in [AJ22] is based on Ronyai's common invariant subspace algorithm, and that reduction requires $A_{0}$ to be invertible. Transforming $L$ to fulfill this property will, in general, requires a blow-up in the matrix dimension. This is achieved by first finding a matrix substitution $x_{i} \leftarrow M_{i}$ such that $L\left(M_{1}, M_{2}, \ldots, M_{n}\right)$ is invertible. This can be computed in deterministic polynomial time using the noncommutative rank algorithm of [QS18] (specifically, see Section 1.2 in [QS18]/3, where $M_{i}$ are matrices of dimension $r=\operatorname{poly}(s, d)$. Then, the substitution $x_{i} \leftarrow Y_{i}+M_{i}$, where each $Y_{i}$ is $r \times r$ matrix of fresh noncommuting variables, results in a blown-up $r d \times r d$ linear matrix $L^{\prime}$ whose constant term $A_{0}^{\prime}$ is now invertible. The linear matrix factorization algorithm in AJ22 (Theorem 2.2 finds a complete factorization of $L^{\prime}$ and, in polynomial time, recovers from it a complete factorization of $L$.

In summary, we observe that in fact the linear matrix factorization algorithm of AJ22] is really a deterministic polynomial-time reduction to the problem of univariate polynomial factorization over $\mathbb{F}_{q}$. Hence, we have a randomized $\operatorname{poly}\left(n, d, \log _{2} q\right)$ time algorithm for it and, alternatively, a deterministic time $\operatorname{poly}(n, d, q)$ time-bounded algorithm.

The new contribution is in step (c) for recovering the factorization of $M$ from the factorization of the linear matrix $L$. We now proceed to describe this algorithm.

### 2.1 Trivialization of matrix relations

For matrices $C \in \mathbb{F}\langle X\rangle^{d \times r}$ and $D \in \mathbb{F}\langle X\rangle^{r \times s}$ the condition

$$
C D=0
$$

is called a matrix relation [Coh06]. A unit $M \in \mathbb{F}\langle X\rangle^{r \times r}$ is said to trivialize the matrix relation $C D=0$ if for every index $i, 1 \leq i \leq r$ either the $i^{t h}$ column of the matrix $C M$ is all zeros or the $i^{t h}$ row of the matrix $M^{-1} D$ is all zeros.

The existence of $M$ is proved using an argument about bases for finite-dimensional modules in Cohn's book [Coh06]. However, a natural algorithmic problem is the complexity of computing the matrix unit $M$. For matrices over fields (finite fields or $\mathbb{Q}$ ) $M$ can be found in polynomial time using standard linear algebraic computation. In [AJ22] we give a deterministic polynomial-time algorithm when $C \in \mathbb{F}\langle X\rangle^{d \times r}$ is a linear matrix and $D \in \mathbb{F}\langle X\rangle^{r \times 1}$ is a column vector of polynomials, where the underlying field is a finite field. The algorithm computes $M$ and its inverse $M^{-1}$ in $\mathbb{F}\langle X\rangle^{r \times r}$ such that their entries are given by polynomial-size algebraic branching programs.

For the problem of matrix factorization considered in this paper, we require a generalization of this to the case when $C$ is a linear matrix and $D$ is a matrix of polynomials. A simple trick allows us to adapt the algorithm of [AJ22].

Lemma 2.4. Let $C \in \mathbb{F}\langle X\rangle^{k \times \ell}$ be a linear matrix and $\tilde{D} \in \mathbb{F}\langle X\rangle^{\ell \times m}$ be a matrix polynomial with entries of $\tilde{D}$ are given by algebraic branching programs such that $C \tilde{D}=0$. Then, in deterministic polynomial time we can compute a invertible matrix $N \in \mathbb{F}\langle X\rangle^{\ell \times \ell}$ such that

[^2]- For $1 \leq i \leq \ell$ either the $i^{\text {th }}$ column of $C N$ is all zeros or the $i^{\text {th }}$ row of $N^{-1} \tilde{D}$ is zero.
- Each entry of $N$ is a polynomial of degree at most $\ell^{2}$ and is computed by a polynomial size ABP, and also each entry of $N^{-1}$ is computed by a polynomial size $A B P$.
Proof. Let $\tilde{D}_{i}$ denotes the $i^{\text {th }}$ column of $\tilde{D}$ for $i \in[m]$. Let $v \in \mathbb{F}\langle X\rangle^{\ell \times 1}$ be a column of polynomials defined as, $v=\sum_{i=1}^{m} \tilde{D}_{i} y^{i}$ where $y \notin X$ is a fresh noncommuting variable. We clearly have, $C \tilde{D}=0$ if and only if $C \tilde{D}_{i}=0$ for all $i \in[m]$ if and only if $C v=0$.

To keep the paper self-contained we reproduce the algorithm from [AJ22]. We describe it as a recursive procedure Trivialize that takes matrix $C$ and column vector $v$ as parameters and returns a matrix $N$ as claimed in the statement. The key additional point to note is that the variable $y$ occurs only in $v$ and not in $C$, and the construction of $N$ is such that its entries are only polynomials in variables used in $C$.

Procedure Trivialize $\left(C \in \mathbb{F}\langle X\rangle^{k \times \ell}, v \in \mathbb{F}\langle X\rangle^{\ell \times 1}\right)$

1. If $d=1$ then (since $C v=0$ iff either $C=0$ or $v=0$ because the $\operatorname{ring} \mathbb{F}\langle X\rangle$ has no zero divisors) return the identity matrix.
2. If $d>1$ then
3. write $C=C_{0}+C_{1}$, where $C_{0}$ is a scalar matrix and $C_{1}$ is the degree 1 homogeneous part of $C$. Let $e$ be the degree of the highest degree nonzero monomials in the polynomial vector $v$, and let $m$ be a nonzero degree $e$ monomial. Let $v(m) \in \mathbb{F}_{q}^{\ell \times 1}$ denote its (nonzero) coefficient in $v$. Then $C v=0$ implies $C_{1} v(m)=0$. Let $T_{0} \in \mathbb{F}_{q}^{\times \times \ell}$ be a scalar invertible matrix with first column $v(m)$ obtained by completing the basis.
(a) If $C_{0} v(m)=0$ then the first column of $C T_{0}$ is zero.
(b) Otherwise, $C T_{0}$ has first column as the nonzero scalar vector $C v(m)=C_{0} v(m)$. Suppose $i^{\text {th }}$ entry of $C v(m)$ is a nonzero scalar $\alpha$. With column operations we can drive the $i^{\text {th }}$ entry in all other columns of $C T_{0}$ to zero. Let the resulting matrix be $C T_{0} T_{1}$ (where the matrix $T_{1}$ is invertible as it is a product of elementary matrices corresponding to these column operations, each of which is of the form $\left.\mathrm{Col}_{i} \leftarrow\left(\operatorname{Col}_{i}+\operatorname{Col}_{1} \cdot \alpha_{0}+\sum_{i} \alpha_{i} x_{i}\right)\right)$. Notice that $C T_{0} T_{1}$ is still linear.
(c) As $C v=\left(C T_{0} T_{1}\right)\left(T_{1}^{-1} T_{0}^{-1} v\right)$, and in the $i^{t h}$ row of $C T_{0} T_{1}$ the only nonzero entry is $\alpha$ which is in its first column, we have that the first entry of $T_{1}^{-1} T_{0}^{-1} v$ is zero.
4. Let $C^{\prime} \in \mathbb{F}\langle X\rangle^{k \times(\ell-1)}$ obtained by dropping the first column of $C T_{0} T_{1}$. Let $v^{\prime} \in \mathbb{F}\langle X\rangle^{(\ell-1) \times 1}$ be obtained by dropping the first entry of $T_{1}^{-1} T_{0}^{-1} v$. Note that $C^{\prime}$ is still linear.
5. Recursively call Trivialize $\left(C^{\prime} \in \mathbb{F}\langle X\rangle^{k \times(\ell-1)}, v^{\prime} \in \mathbb{F}\langle X\rangle^{(\ell-1) \times 1}\right)$. and let the matrix returned by the call be $T_{2} \in \mathbb{F}\langle X\rangle^{(\ell-1) \times(\ell-1)}$.
6. Putting it together, return the matrix $T_{0} T_{1}\left(I_{1} \oplus T_{2}\right)$.

Now, since $v=\sum_{i=1}^{m} \tilde{D}_{i} y^{i}$, for all $j \in[\ell]$, we have $j^{t h}$ entry of $v$ is equal to 0 if and only if $j^{t h}$ entry of all the columns $\tilde{D}_{i}$ is equal to zero for $i \in[m]$. Consequently we get, $j^{t h}$ entry of $v$ is equal
to 0 iff $j^{t h}$ row of $\tilde{D}$ is all zero for all $j \in[\ell]$. So the matrix $N$ satisfies the required property, namely for $1 \leq i \leq \ell$ either the $i^{\text {th }}$ column of $C N$ is all zeros or the $i^{\text {th }}$ row of $N^{-1} \tilde{D}$ is all zero.

To complete the proof, we note that a highest degree monomial $m$ of the vector $v$ such that its (scalar) coefficient vector $v(m) \neq 0$ is easy to compute in deterministic polynomial time when each polynomial $v_{i}$ is given by a noncommutative algebraic branching program: we can use the PIT algorithm of Raz and Shpilka [RS05] to find the coefficient of $m$ in each $v_{i}$ to obtain the vector $v(m)$. Now, for the recursive call we require $C^{\prime}$ to be also a linear matrix and each entry of the new polynomial vector $v^{\prime}$ to have a small ABP. The matrix $C^{\prime}$ is linear because $C T_{0} T_{1}$ is a linear matrix: because $C T_{0}$ is linear and its first column is scalar, and each column operation performed by $T_{1}$ is scaling the first column of $C T_{0}$ by a linear form and subtracting from another column of $C T_{0}$. Regarding the polynomial vector $v^{\prime}$, each entry of it has a small ABP because $T_{0}^{-1}$ is scalar and the entries of the matrix $T_{1}^{-1}$ have ABPs of polynomial size because $T_{1}$ (and hence also $T_{1}^{-1}$ ) is a product of units which correspond to elementary column operations. Finally, we note that $T_{1}$ is a product of at most $\ell-1$ linear matrices each corresponding to a column operation, and $N$ is an iterated product of $\ell$ such matrices. Hence, each entry of $N$ as well as $N^{-1}$ is a polynomial of degree at most $\ell^{2}$ and is computable by a small ABP.

### 2.2 Factor extraction algorithm

We first recap the overall algorithm to see where the factor extraction algorithm will fit in. For an input $M \in \mathbb{F}\langle X\rangle^{d \times d}$, which is a full matrix whose entries are computed by noncommutative arithmetic formulas, we apply Higman linearization [GGdOW20] to compute in polynomial time the following

$$
\left(\begin{array}{cc}
M & 0  \tag{1}\\
0 & I
\end{array}\right)=P L Q,
$$

where $L$ is a full linear matrix, $P$ is an upper triangular matrix will all ones diagonal, $Q$ is a lower triangular matrix with all ones diagonal and the entries of $P$ and $Q$ are computed by noncommutative ABPs.

Next, we apply the linear matrix factorization algorithm of AJ22] to $L$ and compute a complete factorization as

$$
L=L_{1} L_{2} \cdots L_{t},
$$

where each $L_{i}$ is a linear matrix atom. The factor extraction algorithm will find a complete factorization of the matrix $M=M_{1} M_{2} \cdots M_{t}$ as a product of $t$ matrix atoms. It is based on the following lemma which will allow us to recover the factors one by one.

Lemma 2.5 (Factor Extraction Lemma). Let $M \in \mathbb{F}\langle X\rangle^{m \times m}$ be a matrix polynomial and $V \in \mathbb{F}\langle X\rangle^{k \times k}$ be a unit with

$$
\left(\begin{array}{cc}
M & U  \tag{2}\\
0 & V
\end{array}\right)=P C D,
$$

such that

- $U \in \mathbb{F}\langle X\rangle^{m \times k}$ is a matrix polynomial, $C \in \mathbb{F}\langle X\rangle^{\ell \times \ell}$ is a full linear matrix that is a non-unit, $P \in \mathbb{F}\langle X\rangle^{\ell \times \ell}$ is upper triangular with all 1 's diagonal, and $D \in \mathbb{F}\langle X\rangle^{\ell \times \ell}$ is a full non-unit matrix which is also an atom, where $\ell=m+k$.
- The entries of $M, U, V, P, D$ are all given as input by algebraic branching programs and the linear matrix C is given explicitly.

Then we can compute in deterministic polynomial time a nontrivial factorization $M=G \cdot H$ of the matrix $M$ where both $G$ and $H$ are full non-unit matrices and, moreover, the matrix $H$ is an atom.

Proof. Let

$$
C=\left(\begin{array}{ll}
c_{1} & c_{3} \\
c_{2} & c_{4}
\end{array}\right) \text { and } D=\left(\begin{array}{ll}
d_{1} & d_{3} \\
d_{2} & d_{4}
\end{array}\right),
$$

written as $2 \times 2$ block matrices where $c_{1}, d_{1}$ are $m \times m$ blocks and $c_{4}$ and $d_{4}$ are $k \times k$ blocks. By dropping the first $m$ rows of the matrix in the left hand side of Equation 2 and the first $m$ row of $P$ we get

$$
(0 V)=\left(0 P^{\prime}\right) C D,
$$

where $P^{\prime}$ is also an upper triangular matrix with all 1's diagonal. Equating the block consisting of the first $m$ columns on both sides we have

$$
\begin{aligned}
& 0=\left(\begin{array}{ll}
0 & P^{\prime}
\end{array}\right)\left(\begin{array}{ll}
c_{1} & c_{3} \\
c_{2} & c_{4}
\end{array}\right)\binom{d_{1}}{d_{2}}, \text { which implies that } \\
& 0=P^{\prime}\left(c_{2} c_{4}\right)\binom{d_{1}}{d_{2}}, \text { and hence } \\
& 0=\left(c_{2} c_{4}\right)\binom{d_{1}}{d_{2}}, \text { since } P^{\prime} \text { is invertible. }
\end{aligned}
$$

Since $\left(\begin{array}{ll}c_{2} & c_{4}\end{array}\right) \in \mathbb{F}\langle X\rangle^{k \times \ell}$ is a matrix with linear entries and $\binom{d_{1}}{d_{2}} \in \mathbb{F}\langle X\rangle^{\ell \times m}$ is a matrix of polynomials which are given by ABPs as input, this is a matrix relation to which we can apply the trivializing algorithm of Lemma 2.4. The trivializing algorithm computes a unit $N$ whose entries are all given by ABPs such that for $1 \leq i \leq \ell$, either the $i^{\text {th }}$ column of $\left(c_{2}^{\prime} c_{4}^{\prime}\right)=\left(c_{2} c_{4}\right) N$ is all zero or the $i^{\text {th }}$ row of $\binom{d_{1}^{\prime}}{d_{2}^{\prime}}=N^{-1}\binom{d_{1}}{d_{2}}$ is all zero.

Since $D$ is a full matrix, the matrix $N^{-1} D$ is also full which implies $\binom{d_{1}^{\prime}}{d_{2}^{\prime}}$ has at least $m$ non-zero rows as stated in the Claim below.
Claim 2.6. The $\ell \times m$ matrix $\binom{d_{1}^{\prime}}{d_{2}^{\prime}}$ has at least $m$ non-zero rows.
As at least $m$ rows of the matrix $\binom{d_{1}^{\prime}}{d_{2}^{\prime}}$ are nonzero, it follows that at least $m$ columns of $\left(c_{2}^{\prime} c_{4}^{\prime}\right)$ are all zeros because the matrix $N$ trivializes the relation (that is, for every $i \in[\ell]$ we have either $i^{\text {th }}$ column of $\left(c_{2}^{\prime} c_{4}^{\prime}\right)$ is all zero or the $i^{\text {th }}$ row of $\binom{d_{1}^{\prime}}{d_{2}^{\prime}}$ is all zeros). Hence, there exists a permutation matrix $\Pi$ such that the first $m$ columns of $\left(c_{2}^{\prime} c_{4}^{\prime}\right) \Pi$ are all zeros and the first $m$ rows of $\Pi^{-1}\binom{d_{1}^{\prime}}{d_{2}^{\prime}}$ are all nonzero.

$$
\begin{gathered}
\text { Consider the matrices } C^{\prime \prime}=C N \Pi=\left(\begin{array}{cc}
c_{1}^{\prime \prime} & c_{3}^{\prime \prime} \\
c_{2}^{\prime \prime} & c_{4}^{\prime \prime}
\end{array}\right) \text { and } D^{\prime \prime}=\Pi^{-1} N^{-1} D=\left(\begin{array}{ll}
d_{1}^{\prime \prime} & d_{3}^{\prime \prime} \\
d_{2}^{\prime \prime} & d_{4}^{\prime \prime}
\end{array}\right) \text {. Let } \\
P=\left(\begin{array}{cc}
P_{1} & * \\
0 & P_{2}
\end{array}\right),
\end{gathered}
$$

where both $P_{1}$ and $P_{2}$ are upper triangular matrices with all ones diagonal. Then, we have

$$
P^{-1}\left(\begin{array}{cc}
M & U \\
0 & V
\end{array}\right)=\left(\begin{array}{cc}
P_{1}^{-1} M & * \\
0 & P_{2}^{-1} V
\end{array}\right)=\left(\begin{array}{cc}
c_{1}^{\prime \prime} & c_{3}^{\prime \prime} \\
c_{2}^{\prime \prime} & c_{4}^{\prime \prime}
\end{array}\right)\left(\begin{array}{ll}
d_{1}^{\prime \prime} & d_{3}^{\prime \prime} \\
d_{2}^{\prime \prime} & d_{4}^{\prime \prime}
\end{array}\right),
$$

where $c_{2}^{\prime \prime}$ is all zero block of size $k \times m$ and $d_{1}^{\prime \prime}$ is matrix of size $m \times m$ such that all rows of $d_{1}^{\prime \prime}$ are non-zero. By looking at $(2,2)^{t h}$ block in the above equation, we can see that $c_{4}^{\prime \prime}$ and $d_{4}^{\prime \prime}$ are units as $P_{2}^{-1} V$ is a unit. Now observing $(2,1)^{t h}$ matrix block in the above equation, we get $d_{2}^{\prime \prime}$ is all zero as $c_{4}^{\prime \prime}$ is a unit. Clearly, we have $P_{1}^{-1} M=c_{1}^{\prime \prime} \cdot d_{1}^{\prime \prime}$. Now, since $C$ and $D$ are non-units (by assumption), the matrices $C^{\prime \prime}$ and $D^{\prime \prime}$ are also non-units. Therefore, $c_{1}^{\prime \prime}$ is not a unit for otherwise $C^{\prime \prime}$ would be a unit. Similarly, $d_{1}^{\prime \prime}$ is not a unit. It follows that $M=P_{1} c_{1}^{\prime \prime} d_{1}^{\prime \prime}$ is a nontrivial factorization of $M$, noting that $P_{1}$ is a unit (being upper triangular with all ones diagonal).

Furthermore, since $D$ is an atom and $D^{\prime \prime}=\Pi N^{-1} D$ where both $\Pi$ and $N$ are units in $\mathbb{F}\langle X\rangle^{d \times d}$ it follows that $D^{\prime \prime}$ is also an atom. As $D^{\prime \prime}=\left(\begin{array}{cc}d_{1}^{\prime \prime} & d_{3}^{\prime \prime} \\ 0 & d_{4}^{\prime \prime}\end{array}\right)$ and $d_{4}^{\prime \prime}$ is invertible, we get

$$
\left(\begin{array}{cc}
I_{m} & 0 \\
0 & \left(d_{4}^{\prime \prime}\right)^{-1}
\end{array}\right) \cdot D^{\prime \prime}=\left(\begin{array}{cc}
d_{1}^{\prime \prime} & d_{3}^{\prime \prime} \\
0 & I_{k}
\end{array}\right)
$$

Now applying suitable row operations to the matrix $\left(I_{m} \oplus\left(d_{4}^{\prime \prime}\right)^{-1}\right) D^{\prime \prime}$ we can drive $d_{3}^{\prime \prime}$ to zero. So we have $W\left(I_{m} \oplus\left(d_{4}^{\prime \prime}\right)^{-1}\right) D^{\prime \prime}=\left(d_{1}^{\prime \prime} \oplus I_{k}\right)$ for a unit $W$. Hence $d_{1}^{\prime \prime}$ is an associate of $D^{\prime \prime}$ and therefore $d_{1}^{\prime \prime}$ is an atom because $D^{\prime \prime}$ is an atom.

Thus, we conclude that the above algorithm computes a nontrivial factorization of $M$ as

$$
M=G \cdot H
$$

where $G=P_{1}^{-1} c_{1}^{\prime \prime}$ is a full non-unit matrix, and $H=d_{1}^{\prime \prime}$ is an atom, and $P_{1}$ is a unit.

### 2.3 The Factorization Algorithm

We now put everything together and describe the factorization algorithm.
Theorem 2.7. Let $\mathbb{F}\langle X\rangle=\mathbb{F}_{q}\langle X\rangle$ and let $M \in \mathbb{F}\langle X\rangle^{d \times d}$ be a matrix of noncommutative polynomials where each of its entries $M_{i j}$ is given by an arithmetic formula of size at most s as input instance. Then there is a poly $(s, \log q)$ time randomized algorithm that outputs a complete factorization of $M$ as a product $M=M_{1} M_{2} \cdots M_{r}$ such that each matrix factor $M_{i}$ is an atom, and the entries of the matrix factors are output as algebraic branching programs. Moreover, there is also a deterministic $p o l y(s, q)$ time deterministic algorithm for the problem.
Proof. Given $M \in \mathbb{F}\langle X\rangle^{d \times d}$ as input, we apply Higman linearization followed by the linear matrix factorization algorithm stated in Theorem 2.2 (see [AJ22] for details) to obtain the factorization

$$
M \oplus I_{s}=P F_{1} F_{2} \ldots F_{r} U
$$

where each linear matrix $F_{i}$ is an atom, the matrix $P$ is upper triangular with all 1's diagonal, and the matrix $U$ is a unit. Moreover, the entries of $P$ and $U$ are given by algebraic branching programs.

We will now apply Lemma 2.5 to extract the factors of $M$ (one by one from the right).
For the first step, let $C=F_{1} F_{2} \cdots F_{r-1}$ and $D=F_{r} U$ in Lemma 2.5. The proof of Lemma 2.5 yields the matrix $N_{r}=N \Pi$ such that both matrices $C^{\prime \prime}=P F_{1} F_{2} \cdots F_{r-1} N_{r}$ and $D^{\prime \prime}=N_{r}^{-1} F_{r} U$ has the first $d$ column all zeros except the top left $d \times d$ block of entries $c_{1}^{\prime \prime}$ and $d_{1}^{\prime \prime}$ which yields the nontrivial factorization $M=c_{1}^{\prime \prime} d_{1}^{\prime \prime}$, where $d_{1}^{\prime \prime}=M_{r}$ is an atom. Renaming $c_{1}^{\prime \prime}$ as $G_{r}$ we have from the structure of $C^{\prime \prime}$ :

$$
\left(\begin{array}{cc}
G_{r} & * \\
0 & V_{r}
\end{array}\right)=P\left(F_{1} F_{2} \cdots F_{r-2}\right)\left(F_{r-1} N_{r}\right) .
$$

Setting $C=F_{1} F_{2} \cdots F_{r-2}$ and $D=F_{r-1} N_{r}$ in Lemma 2.5 we can compute the matrix $N_{r-1}$ using which we will obtain the next factorization $G_{r}=G_{r-1} M_{r-1}$, where $M_{r-1}$ is an atom by Lemma 2.5 Note that Lemma 2.5 is applicable as all conditions are met by the matrices in the above equation (note that the matrix $V_{r}$ will be a unit).

Continuing thus, at the $i^{\text {th }}$ stage we will have $M=G_{r-i+1} M_{r-i+1} M_{r-i+2} \cdots M_{r}$ after obtaining the rightmost $i$ irreducible factors by the above process. At this stage we will have

$$
\left(\begin{array}{cc}
G_{r-i+1} & * \\
0 & V_{r-i+1}
\end{array}\right)=P\left(F_{1} F_{2} \cdots F_{r-i-1}\right)\left(F_{r-i} N_{r-i+1}\right),
$$

where $V_{r-i+1}$ is a unit and all other conditions are satisfied for application of Lemma 2.5 .
Thus, after $r$ stages we will obtain the complete factorization of the input matrix $M$ as

$$
M=M_{1} M_{2} \cdots M_{r},
$$

where each factor $M_{i}$ is an atom.

## Running Time Analysis

The Higman Linearization of $M$ is computed in deterministic polynomial time. For the resulting linear matrix $L=A_{0}+\sum_{i=1}^{n} A_{i} x_{i}$, as explained in Remark 2.3, its factorization as a product of linear matrix atoms can be computed in randomized poly $\left(s, n, d, \log _{2} q\right)$ time as well as in deterministic $\operatorname{poly}(s, n, d, q)$ time.

For the rest of the running time, it suffices to note that the matrix $N$ computed in Lemma 2.5 is a product of degree at most $d^{2}$ many linear matrices (corresponding to the column operations). Thus, at the $i^{\text {th }}$ of the above iteration, the sizes of the ABPs for the entries of $N_{r-i+1}$ are independent of the stages. Hence, the overall randomized algorithm has running time poly $\left(s, n, d, \log _{2} q\right)$. The deterministic factorization algorithm has running time poly $(s, n, d, q)$.

## 3 Factorization of matrices over $\mathbb{Q}[x]$

In this section we describe a deterministic polynomial-time algorithm for the factorization of full non-unit matrices with univariate polynomial entries over rationals (i.e., the matrix entries are
from $\mathbb{Q}[x])$. As there is only one variable $x$, the noncommutative ring $\mathbb{F}\langle x\rangle$ coincides with the commutative ring $\mathbb{F}[x]$. Thus, over a finite field $\mathbb{F}=\mathbb{F}_{q}$ we note that the algorithm of the previous section also solves matrix factorization over $\mathbb{F}_{q}[x]$ as a special case.

Our technique is essentially the same: we first transform the input matrix $M$ into a linear matrix $L$ by Higman linearization (see Theorem 2.1). We obtain

$$
\left(\begin{array}{c|c}
M & 0 \\
\hline 0 & I_{\ell}
\end{array}\right)=P L Q .
$$

where $P, Q$ and $L$ are matrices with entries from $\mathbb{Q}[x]$.
As mentioned in the introduction, the problem of factorization of multivariate noncommutative polynomials over $\mathbb{Q}$ (i.e., over the free noncommutative ring $\mathbb{Q}\langle X\rangle$ ) is not amenable to our approach [AJ22] because the problem of computing a nontrivial common invariant subspace for a set of matrices over $\mathbb{Q}$ seems intractable in general [Rón87]. However, in the univariate case we need to compute a nontrivial invariant subspace for a single rational matrix which can be done efficiently using basic linear algebra. This gives us a deterministic polynomial-time algorithm for factorizing matrix polynomials over $\mathbb{Q}[x]$.

In the first subsection below we will present an efficient trivializing algorithm for the matrix relation $C D=0$ where $C \in \mathbb{Q}[x]^{d \times r}$ is a univariate linear matrix and $D \in \mathbb{Q}[x]^{d \times s}$ is a matrix of univariate polynomials over rationals. In the next subsection we will present the algorithm for factorization of linear matrices $L$ in one variable $x$ over $\mathbb{Q}$.

### 3.1 Trivializing matrix relations algorithm over $\mathbb{Q}$

Let $C \in \mathbb{Q}[x]^{d \times r}$ and $U \in \mathbb{Q}[x]^{r \times s}$ be given as input such that $C U=0$, where $C$ is a linear matrix. We describe a polynomial-time algorithm for computing an invertible matrix $N$ such that:

1. The matrix $N \in \mathbb{Q}[x]^{r \times r}$ is a unit: $\operatorname{det} N$ is a nonzero scalar (equivalently $N^{-1}$ is a matrix with polynomial entries).
2. The matrix relation $(C N)\left(N^{-1} U\right)=0$ is trivialized: for each $i \in[r]$ either the $i^{\text {th }}$ column of $C N$ is all zeros or the $i^{t h}$ row of $N^{-1} U$ is all zeros.

We note that the algorithm we have already described in Section 2.1 solves the problem over $\mathbb{F}_{q}$ in the multivariate case. That algorithm performs a polynomial number of arithmetic operations over $\mathbb{F}_{q}$. However, working over $\mathbb{Q}$ we need to additionally control the binary encoding lengths of the matrix coefficients that will result from the repeated column operations. As such it is not clear to us that the above-mentioned algorithm over $\mathbb{F}_{q}$ has this additional property when we use it for $\mathbb{Q}$. However, we present direct a polynomial-time algorithm for this problem over $\mathbb{Q}$ in the univariate case.

Let $C=C^{\prime}+C^{\prime \prime} x \in \mathbb{Q}[x]^{d \times r}$. The heart of the trivialization algorithm is to first efficiently transform $C$ into a suitable normal form (which we refer to as $T$-normal form). It turns out that once we have the matrix $C$ in T-normal form it is easy to compute a trivializing matrix $N$ as required. We will first define the T-normal form and show that if the linear matrix $C$ is in T-normal form, the trivializing matrix $N$ can be computed in polynomial time (taking into account the binary encoding
lengths of all integers involved). Then we will give a polynomial-time algorithm to transform $C$ into T-normal form.

Let $D \in \mathbb{Q}[x]^{d \times k}$ be a linear matrix and let $D_{i}$ denote the $i^{\text {th }}$ column of $D, 1 \leq i \leq k$. Writing $D=D^{\prime}+D^{\prime \prime} x$, where $D^{\prime}, D^{\prime \prime} \in \mathbb{Q} d \times k$, for $1 \leq i \leq k$ we have

$$
D_{i}=D_{i}^{\prime}+D_{i}^{\prime \prime} x,
$$

where $D_{i}^{\prime}$ and $D_{i}^{\prime \prime}$ are the $i^{t h}$ columns of $D^{\prime}$ and $D^{\prime \prime}$, respectively. The $i^{\text {th }}$ column $D_{i}$ of $D$ is a scalar column if all the entries of $D_{i}$ are scalars (i.e. $D_{i}^{\prime \prime}=0$ ) otherwise it is a non-scalar column.
Encoding sizes. For an integer $a$, the encoding size of $a$ (denoted as $\mathfrak{b}(a)$ ) is the number of bits required to express $a$ in binary. For a rational number $r=\frac{a}{b}, b \neq 0$, the encoding size of $r$ is $\mathfrak{b}(r)=$ $\max (\mathfrak{b}(a), \mathfrak{b}(b))$. Extending this further, for a univariate polynomial $f=a_{0}+a_{1} x+\ldots+a_{t} x^{t} \in \mathbb{Q}[x]$, we define the binary encoding size of $f$ as $\mathfrak{b}(f)=t \cdot \max _{i=0}^{t} \mathfrak{b}\left(a_{i}\right)$. For an univariate polynomial matrix $C \in \mathbb{Q}[x]^{d \times k}$, the encoding size of $C$ is, $\mathfrak{b}(C)=k d \cdot \max _{1 \leq i \leq d, 1 \leq j \leq k} \mathfrak{b}\left(C_{i, j}\right)$ where $C_{i, j}$ is the $(i, j)^{\text {th }}$ entry of $C$.

Let $C$ be a $d \times k$ matrix. For index sets $I \subseteq[d], J \subseteq[k]$, let $C(I, J)$ denote the submatrix of $C$ with rows from $I$ and columns from $J$.

Definition 3.1. [T-normal form] A linear matrix $D=[0 A B] \in \mathbb{Q}[x]^{d \times r}$ is said to be in T-normal form if its columns are partitioned into the three parts, as indicated, such that:

- The first set of columns of $D$ is all zeros, followed by the second set $A$ of scalar columns, and then the third set $B=B^{\prime}+B^{\prime \prime} x$ consists of non-scalar columns.
- The matrix $\left[\begin{array}{ll}A B^{\prime \prime}\end{array}\right]$ is of full column rank.

Before we proceed we note that, analogous to Section 2.1, it is convenient to transform the given matrix relation $C U=0$ into another relation $C u=0$ where $u$ is a column vector whose entries are bivariate polynomials in $\mathbb{Q}[x, y]$, where $y$ is a fresh commuting variable.

For a matrix $U \in \mathbb{Q}[x]^{r \times s}$, we define the column vector $u \in \mathbb{Q}[x, y]^{r \times 1}$ as

$$
u=\sum_{j=1}^{s} U_{j} y^{j}
$$

where $U_{j}, 1 \leq j \leq s$ are the $s$ columns of the matrix $U$. We note that $C U=0$ if and only if $C u=0$. We also have the following.

Lemma 3.2. A matrix $N \in \mathbb{Q}[x]^{r \times r}$ trivializes the relation $(C N)\left(N^{-1} U\right)=0$ if and only if it trivializes the relation $(C N)\left(N^{-1} u\right)=0$.

We first show that the relation $D u=0$ is easy to trivialize for a linear matrix $D \in \mathbb{Q}[x]^{d \times r}$ which is in T-Normal form.

Lemma 3.3. Let $D \in \mathbb{Q}[x]^{d \times r}$ be a linear matrix in $T$-normal form and $u \in \mathbb{Q}[x, y]^{r}$ be a column vector of polynomials given as input such that the matrix relation $D u=0$ holds. Then there is a polynomial (poly $(d, r, \mathfrak{b}(D), \mathfrak{b}(u)))$ time deterministic algorithm to compute a full rank matrix $N \in \mathbb{Q}[x]^{r \times r}$ such that $\mathfrak{b}(N) \leq \operatorname{poly}(d, r) \cdot \mathfrak{b}(D)$, the matrix $N^{-1} \in \mathbb{Q}[x]^{r \times r}$ (i.e., $N$ is a unit in the ring $\mathbb{Q}[x]^{r \times r}$ ), and the relation $(D N)\left(N^{-1} u\right)=0$ is trivialized.

Proof. Let $D=\left[\begin{array}{lll}0 & A & B\end{array}\right]$ and $J_{1}, J_{2}$ and $J_{3}$ be the column indices of the three parts: $0, A$ and $B$ witnessing that $D$ is in T-normal form. The columns of $A$ are linearly independent. So there is a subset of row indices $I \subseteq[k]$ such that $D\left[I, J_{2}\right]$ is a full rank square submatrix of $A$. Hence, each column $D(I, j), j \in J_{3}$ of the corresponding submatrix of $B$ can be expressed as

$$
D(I, j)=\sum_{i \in J_{2}}\left(a_{j i}+b_{j i} x\right) D(I, i), \quad j \in J_{3}
$$

where $a_{j i}$ and $b_{j i}$ are rational numbers. We can compute these numbers $a_{j i}$ and $b_{j i}$ by Cramer's rule. Hence, $\mathfrak{b}\left(a_{j i}\right), \mathfrak{b}\left(b_{j i}\right) \leq \operatorname{poly}(k, n) \mathfrak{b}(D)$ for all column indices $j \in J_{3}$.

Now let $N$ be $d \times d$ column transformation matrix which implements the column operations $D_{j}=\sum_{i \in J_{2}}\left(a_{j i}+b_{j i} x\right) D_{i}$ for all column indices $j \in J_{3}$. We note the following.

Claim 3.4. $N$ is an $r \times r$ upper triangular matrix with all diagonal entries 1 and

$$
N_{i, j}=-\left(a_{j, i}+b_{j, i} x\right) \quad \text { for } i \in J_{2} \text { and } j \in J_{3}
$$

Furthermore, $N^{-1} \in \mathbb{Q}[x]^{r \times r}$ and can be efficiently computed.
After performing these column operations we have the matrix $E=D N=[0 A C]$, where $C$ is zero on all the rows indexed by $I$. Let $N^{-1} u=w=\left[\begin{array}{lll}w_{1} & w_{2} & \ldots \\ w_{r}\end{array}\right]^{T}$. The row indices of $w$ can be correspondingly partitioned into $[r]=J_{1} \sqcup J_{2} \sqcup J_{3}$. We denote the corresponding subvectors of $w$ by $w_{J_{1}}, w_{J_{2}}$ and $w_{J_{3}}$. Since $E\left(I, J_{3}\right)=0$ and $E\left(I, J_{1}\right)=0$ it follows that

$$
E\left(I, J_{2}\right) w_{J_{2}}=0
$$

As $E\left(I, J_{2}\right)=D\left(I, J_{2}\right)$ is an invertible scalar matrix it follows that the subvector $w_{J_{2}}=0$. Therefore, we have

$$
E w=C w_{J_{3}}=0
$$

Now, consider the submatrix $C=C^{\prime}+C^{\prime \prime} x$ of $E$. Since the matrix $D=[0 A B]$ is in T-normal form, the matrix $\left[A B^{\prime \prime}\right]$ has full column rank where $B=B^{\prime}+B^{\prime \prime} x$ and both $B^{\prime}$ and $B^{\prime \prime}$ are scalar matrices. Now, since $C$ is obtained from $A$ and $B$ by the column operations defined by $N$ notice that the matrix $\left[A C^{\prime \prime}\right]$ is also of full column rank because the columns of $C^{\prime \prime}$ are

$$
E_{j}^{\prime \prime}=D_{j}^{\prime \prime}+\sum_{i \in J_{2}} b_{j i} D_{i}, \quad \text { for all } j \in J_{3}
$$

Hence $C^{\prime \prime}$ is full column rank. Let $K \subset[d]$ be row indices such that $D^{\prime \prime}\left[K, J_{3}\right]$ is an invertible submatrix of $C^{\prime \prime}$. Then the submatrix $D\left[K, J_{3}\right]$ of the linear matrix $C$ is also invertible in the field of fractions $\mathbb{Q}(x)$. Therefore, $C w_{J_{3}}=0$ forces $w_{J_{3}}=0$.

Putting it together, we have shown that the matrix $N$ trivializes the relation $D v=(D N)\left(N^{-1} u\right)=$ 0 . This completes the proof.

Now we describe a polynomial-time algorithm that transforms the input linear matrix $C=$ $C^{\prime}+C^{\prime \prime} x$ into a linear matrix $D$ in T-normal form.

Lemma 3.5. Given as input a linear matrix $C=C^{\prime}+C^{\prime \prime} x \in \mathbb{Q}[x]^{k \times d}$ in deterministic time poly $(k, d, \mathfrak{b}(C))$ we can compute a matrix $M \in \mathbb{Q}[x]^{d \times d}$ such that

- $D=C M$ is in T-normal form.
- The $d \times d$ matrix $M$, which is a product of elementary column operation matrices, is a unit in $\mathbb{Q}[x]^{d \times d}$ (i.e., it has nonzero scalar determinant).

Proof. We describe the algorithm along with the correctness of each step, side by side.
Input $C=C^{\prime}+C^{\prime \prime} x \in \mathbb{Q}[x]^{k \times d}$.

1. By permuting the columns of $C$ write it as $[0 A B]$, consisting of a block of 0 columns followed by a block of scalar columns $A$ and then the columns containing the linear submatrix $B$.
2. By performing column operations on $A$ we can drive all linearly dependent columns to zero and move such columns to the left. Thus the block of columns $A$ can be assumed to be linearly independent.
3. Let $B=B^{\prime}+B^{\prime \prime} x$, with $B^{\prime}$ and $B^{\prime \prime}$ scalar.
(a) while the matrix $\left[A B^{\prime \prime}\right]$ is not full column rank do
(b) Let $\left\{A_{i} \mid i \in I\right\} \cup\left\{B_{j}^{\prime \prime} \mid j \in J\right\}$ be a dependent set of columns. Then for some $j_{0} \in J$ there are scalars $\alpha_{i}, \beta_{j} \in Q$ such that $B_{j_{0}}^{\prime \prime} x=\sum_{j \in J \backslash\left\{j_{0}\right\}} \beta_{j} B_{j}^{\prime \prime} x+\sum_{i \in I} \alpha_{i} A_{i} x$.
(c) Applying the corresponding column operations we can drive $B_{j_{0}}^{\prime \prime}$ to zero. Note that during this process, the scalar part of $B_{j_{0}}$ will also get updated as $B_{j_{0}}^{\prime} \leftarrow B_{j_{0}}^{\prime}+\sum_{j \in J \backslash\left\{j_{0}\right\}} \beta_{j} B_{j}^{\prime}$.
(d) $A:=A \cup\left\{B_{j_{0}}^{\prime}\right\}$ and $B^{\prime \prime}:=B^{\prime \prime} \backslash\left\{B_{j_{0}}^{\prime \prime}\right\}$.
(e) If $B_{j_{0}}^{\prime}$ is linearly dependent on $A$ we can drive it to zero.
(f) end-while

In order to see the correctness, notice that each time the while loop executes the number of columns in $B^{\prime \prime}$ decreases and the number of columns in the submatrix $[0 A]$ increases: if $B_{j_{0}}^{\prime}$ is linearly independent of $A$ then it is included in $A$ and the number of columns of $A$ (all linearly independent) increases or we can drive $B_{j_{0}}^{\prime}$ to zero using columns operations with the columns of $A$. Therefore, the number of times the while loop executes is bounded by $d$. Hence the overall number of arithmetic operations performed is also bounded by poly $(k, d)$. Now we analyze the growth of the coefficients of the matrices $A$ and $B$ as the algorithm iterates. Note that whenever we express certain column as linear combination of some other columns, using Cramer's rule we can polynomially bound all the coefficients involved in the linear combination. Now, the only step in which a column changes and is used again is when the column $B_{j_{0}}^{\prime}$ gets modified in the process of driving the column $B_{j_{0}}^{\prime \prime}$ to zero, and then the modified column $B_{j_{0}}^{\prime}$ is used again as part of the set $A$. Crucially, we note that the columns of $A$ do not cause the change in coefficients of $B_{j_{0}}^{\prime}$. It is only modified by the coefficients $\beta_{j}, j \in J \backslash\left\{j_{0}\right\}$ because in the linear combination the columns $A_{i}, i \in I$ are multiplied by $\alpha_{i} x$. Thus, it follows the encoding sizes of all rational numbers involved in the matrix $[0 A B]$ at any stage of the computation remains polynomially bounded in $\mathfrak{b}(C)$. Finally, we note that the matrix $M$ is a product of $\operatorname{poly}(d)$ many elementary matrices, corresponding to the elementary column operations. Since the entries of $[0 A B]$ has polynomially bounded encoding size in all stages of the computation, the rational entries in each such elementary matrix also has encoding size polynomially bounded in $\mathfrak{b}(C)$. This completes the proof of the lemma.

Putting it together we have show the following.
Theorem 3.6. Given the matrix product relation $C U=0$, where $C \in \mathbb{Q}[x]^{d \times r}$ is a linear matrix and $U \in \mathbb{Q}[x]^{r \times s}$ is a matrix of polynomials, in deterministic polynomial time (in bit complexity) we can compute an invertible matrix $N \in \mathbb{Q}[x]^{d \times d}$ such that its inverse $N^{-1} \in \mathbb{Q}[x]^{d \times d}$ such that the matrix product $(C N)\left(N^{-1} U\right)=0$ trivializes the relation $C U=0$.

### 3.2 Univariate linear matrix factorization over $\mathbb{Q}$

The goal of this subsection is a deterministic polynomial-time algorithm that takes as input a full rank linear matrix $L=A_{0}+A_{1} x \in \mathbb{Q}[x]^{d \times d}$ and computes a complete factorization of $L$. We will require two conditions on $L$ before we proceed with the algorithm.

Definition 3.7. A linear matrix $L=A_{0}+A_{1} x$ is called monic if the matrix $A_{1}$ is invertible. ${ }^{4}$
Lemma 3.8. Given a full linear matrix $L=A_{0}+A_{1} x \in \mathbb{Q}[x]^{d \times d}$ that is not monic we can compute, in deterministic polynomial (in $d$ and $\mathfrak{b}(C)$ ) time, units $U, U^{\prime} \in \mathbb{Q}[x]^{d \times d}$ and scalar invertible matrices $S, S^{\prime} \in \mathbb{Q}^{d \times d}$ such that
1.

$$
U L S=\left(\begin{array}{c|c}
W & 0 \\
\hline 0 & I_{\ell}
\end{array}\right)
$$

where $W$ is a full monic linear matrix and $\ell>0$.
2.

$$
S^{\prime} L U^{\prime}=\left(\begin{array}{c|c}
W^{\prime} & 0 \\
\hline 0 & I_{\ell^{\prime}}
\end{array}\right),
$$

where $W^{\prime}$ is a full monic linear matrix and $\ell^{\prime}>0$.
Proof. We will prove only the first part, the second part follows symmetrically. We first compute the T-normal form of the transpose matrix $L^{T}=A_{0}^{T}+A_{1}^{T} x$ by applying the algorithm of Lemma 3.5 This yields the T-normal form

$$
L^{T} M=\left[\begin{array}{ll}
A & B
\end{array}\right]
$$

where the matrix $M \in \mathbb{Q}[x]^{d \times d}$ is a unit: in the $T$-normal form notice that there are no zero columns as $L$ is full rank, and the scalar matrix $\left[A B^{\prime \prime}\right]$ is full rank where $B=B^{\prime}+B^{\prime \prime} x$. Let $A \in \mathbb{Q}^{d \times e}$. We note that $d>e>0$ as $L$ is a non-unit but not monic. We apply the following sets of row/column operations on the matrix $[A B]$ :

- Swap the columns of $[A B]$ to get $[B A]$.
- Since $A$ is a $d \times e$ matrix of rank $e$, we can permute the rows and transform $[B A]$ to $\left(\begin{array}{l|l}\hat{B}_{1} & \hat{A}_{1} \\ \hline \hat{B}_{2} & \hat{A}_{2}\end{array}\right)$ such that the $e \times e$ scalar matrix $\hat{A}_{2}$ is full rank.

[^3]- Using the invertible $e \times e$ scalar submatrix $\hat{A}_{2}$ we can perform column operations that drives the submatrix $\hat{B}_{2}$ to zero to obtain $\left(\begin{array}{c|c}\hat{B}_{3} & \hat{A}_{1} \\ \hline 0 & \hat{A}_{2}\end{array}\right)$. Notice that these column operations will be realized by post-multiplication with a matrix unit $N \in \mathbb{Q}[x]^{d \times d}$ whose entries are linear in $x$. Moreover, writing $\hat{B}_{3}=\hat{B}_{3}^{\prime}+\hat{B}_{3}^{\prime \prime} x$, we note that the matrix $\left(\begin{array}{c|c}\hat{B}_{3}^{\prime \prime} & \hat{A}_{1} \\ \hline 0 & \hat{A}_{2}\end{array}\right)$ has full column rank as $\left[B^{\prime \prime} A\right.$ ] has full column rank.
- Next, with scalar row operations we can use $\hat{A}_{2}$ to drive $\hat{A}_{1}$ to zero to obtain $\left(\begin{array}{c|c}\hat{B}_{3} & 0 \\ \hline 0 & \hat{A}_{2}\end{array}\right)$.
- Finally, with scalar row and column operations we can drive $\hat{A}_{2}$ to the identity matrix $I_{e}$ to obtain $\left(\begin{array}{c|c}\hat{B}_{3} & 0 \\ \hline 0 & I_{e}\end{array}\right)$.

Putting it together, we have

$$
S_{1} L^{T} M S_{2} N S_{3}=\left(\begin{array}{c|c}
\hat{B}_{3} & 0 \\
\hline 0 & I_{e}
\end{array}\right)
$$

where $S_{1}, S_{2}, S_{3}$ are invertible scalar matrices, and $M$ and $N$ are matrix units. Since $U^{T}=M S_{2} N S_{3}$ is also a matrix unit, by again taking transpose we obtain the required

$$
U L S=\left(\begin{array}{c|c}
W & 0 \\
\hline 0 & I_{e}
\end{array}\right)
$$

where $W=\hat{B}_{3}^{T}$ and $S=S_{1}^{T}$. To see that $W$ is monic it suffices to note that the transformation $N$ is essentially equivalent to performing column operations on the full rank scalar matrix [ $A B^{\prime \prime}$ ] which cannot lower the column rank of the resulting matrix. This completes the proof of the part one, for second part, we start with the linear matrix $L$ itself, instead of $L^{T}$ and carry out all the steps symmetrically.

Thus, it suffices to solve the factorization problem for full and monic linear matrices.
Let $L=A_{0}+A_{1} x \in \mathbb{Q}[x]^{d \times d}$ be a full and monic linear matrix. Notice that $\operatorname{det} L \in \mathbb{Q}[x]$ is a univariate degree- $d$ polynomial which is not identically zero as $L$ is a full linear matrix. Therefore, for some $i \in[d+1]$ the matrix $A_{0}+A_{1} i$ is invertible. Thus, replacing $x$ by $x+i$ we can assume that $A_{0}$ is also invertible. We can rewrite the linear matrix as $L=\left(-A_{0} A_{1}^{-1}-x I_{d}\right)\left(-A_{1}^{-1}\right)$. Therefore, setting $A=-A_{0} A_{1}^{-1}$, the problem is equivalent to computing the factorization of $A-x I_{d}$, where $A \in \mathbb{Q}^{d \times d}$ is an invertible matrix.

## Factorization of linear matrix $A-x I$

It turns out that using standard linear algebra [HK71] we can efficiently compute a complete factorization of $A-x I_{d}$.

Theorem 3.9. Given as input an invertible matrix $A \in \mathbb{Q}^{d \times d}$ there is an algorithm that computes a complete factorization of $A-x I_{d}$ into a product of linear matrix atoms in deterministic time $\operatorname{poly}(d, \mathfrak{b}(A))$.

Proof. The determinant $\operatorname{det}\left(A-x I_{d}\right)$ is the characteristic polynomial $\chi_{A}(x)$ of $A$. Using the LLL algorithm we first compute the complete factorization of $\chi_{A}(x)$ over $\mathbb{Q}$

$$
\chi_{A}=f_{1}^{d_{1}} f_{2}^{d_{r}} \cdots f_{t}^{d_{t}}
$$

where each $f_{i}$ is a distinct irreducible factor. The algorithm works in two phases.
In this first phase, we compute the minimal polynomial $m_{A}(x) \in \mathbb{Q}[x]$ of $A$ and also factorize it using the LLL algorithm to get

$$
m_{A}(x)=f_{1}^{e_{1}} f_{2}^{e_{2}} \cdots f_{t}^{e_{t}} .
$$

By standard linear algebra HK71] each $e_{i}>0$.
The algorithm computes a basis for each of the following $t$ subspaces of $\mathbb{Q}^{d}$ :

$$
V_{i}=\left\{v \in \mathbb{Q}^{d} \mid f_{i}(A)^{e_{i}}(v)=0\right\}, 1 \leq i \leq t .
$$

The subspace $V_{i}$ consists of precisely those vectors that are annihilated by $f_{i}^{e_{i}}$. Since the different $f_{i}$ are relatively prime we have the following direct sum decomposition

$$
\mathbb{Q}^{d}=V_{1} \oplus V_{2} \oplus \cdots \oplus V_{t} .
$$

Furthermore, since each $V_{i}$ is an $A$-invariant subspace, by choosing a basis for $\mathbb{Q}^{d}$ a union of bases for $V_{1}, V_{2}, \ldots V_{t}$, in that order, and writing the linear matrix $A-x I_{d}$ in that basis we obtain the following block diagonal form (essentially, the primary decomposition theorem [HK71]):

$$
T\left(A-x I_{d}\right) T^{-1}=\left(\begin{array}{ccccc}
L_{1} & 0 & 0 & \ldots & 0  \tag{3}\\
0 & L_{2} & 0 & \ldots & 0 \\
0 & 0 & L_{3} & \ldots & 0 \\
& & & \ddots & \\
0 & 0 & 0 & \ldots & L_{t}
\end{array}\right) .
$$

The above matrix clearly factorizes as a product of $t$ linear matrices of the form

$$
\left(\begin{array}{ccccc}
I & 0 & 0 & \ldots & 0 \\
0 & I & 0 & \ldots & 0 \\
& \ddots & L_{i} & \ldots & 0 \\
0 & 0 & 0 & \ddots & 0 \\
0 & 0 & 0 & \ldots & I
\end{array}\right) .
$$

Thus, it suffices to now consider the factorization of each linear matrix $L_{i}$ which is also of the form $L_{i}=A_{i}-x I_{n_{i}}$, where $n_{i}=d_{i} \cdot \operatorname{deg} f_{i}$ is the dimension of the subspace $V_{i}$.

We now describe Phase 2 of the algorithm. Notice that the characteristic polynomial and minimal polynomial of $A_{i}$ are $f_{i}^{d_{i}}$ and $f_{i}^{e_{i}}$ respectively, where $f_{i}$ is an irreducible polynomial. At this point we will need some linear algebra about the matrices whose characteristic polynomial is the power of an irreducible polynomial.

Let $B \in \mathbb{Q}^{n \times n}$ be a matrix with $\chi_{B}=f^{\ell}$ and minimal polynomial $f^{e}$, where $f \in \mathbb{Q}[x]$ is irreducible of degree $k$. Then $\ell k=n$. We define subspaces

$$
U_{j}=\left\{u \in \mathbb{Q}^{n} \mid f^{j}(B) u=0\right\} \text { for } 1 \leq j \leq e .
$$

By definition $U_{j}$ is the subspace of vectors annihilated by $f^{j}(B)$. We note that

$$
U_{1} \subset U_{2} \subset \cdots U_{e}=\mathbb{Q}^{n}
$$

where each $U_{j}$ is a proper subspace of $U_{j+1}$ for $1 \leq j<e$ [HK71]. Furthermore, each $U_{j}$ is a $B$-invariant subspace because $B \cdot g(B)=g(B) B$ for any polynomial $g$. For each $j<e$ we can alternatively describe $U_{j+1}$ as

$$
\begin{equation*}
U_{j+1}=\left\{u \in \mathbb{Q}^{n} \mid f(B) u \in U_{j}\right\} . \tag{4}
\end{equation*}
$$

Also,

$$
U_{1}=\left\{u \in \mathbb{Q}^{n} \mid f(B) u=0\right\} .
$$

Thus $B$ restricted to $U_{1}$ has both minimal polynomial and characteristic polynomial $f(x)$. Similarly, for each $j<e$ the polynomial $f(x)$ is both the minimal and characteristic polynomial of $B$ restricted to the quotient space $U_{j+1} / U_{j}, 1 \leq j<e$, where the quotient vector space $U_{j+1} / U_{j}$ consists of vectors of the form $u+U_{j}, u \in U_{j+1}$ and $U_{j}$ is the zero element of the vector space. Let $v_{1}=\operatorname{dim} U_{1}$ and $v_{j+1}=\operatorname{dim}\left(U_{j+1} / U_{j}\right)$. Then $\operatorname{dim} U_{j}=v_{1}+v_{2}+\cdots+v_{j}, j \leq e$.
Claim 3.10. The B-invariant subspace $U_{1}$ is a direct sum of $v_{1} / k$ many $B$-invariant $k$-dimensional subspaces.
Proof of Claim 3.10 To see this claim we note that for any nonzero vector $u \in U_{1}$ the so-called cyclic subspace spanned by the cyclic basis $\left\{u, B u, B^{2} u \ldots, B^{k-1} u\right\}$ is a $B$-invariant subspace of $U_{1}$ and we can repeatedly pick such subspaces until the whole of $U_{1}$ is covered. Thus, $U_{1}$ has a good basis which is the union of $v_{1} / k$ many such cyclic bases, each of size $k$. With respect to this good basis the matrix $B$ restricted to $U_{1}$ is block diagonal with $v_{1} / k$ many blocks, each of size $k \times k$.

We generalize this claim to define a good basis for the quotient space $U_{j+1} / U_{j}$. The matrix $B-x I$ will be easy to factorize when expressed in terms of the basis consisting of the union of the good bases obtained for the quotient spaces $U_{j+1} / U_{j}$.
Claim 3.11. For the quotient space $U_{j} / U_{j-1}, j \geq 2$ there is a collection of $v_{j} / k$ pairwise disjoint sets of $k$ vectors

$$
\mathcal{B}_{j i}=\left\{u_{j i}, B\left(u_{j i}\right), \ldots, B^{k-1}\left(u_{j i}\right)\right\}, \quad 1 \leq i \leq v_{j} / k
$$

such that

1. $\mathcal{B}_{j i} \cup U_{j-1}$ spans a subspace $U_{j i}$ of $U_{j}$ of dimension $k+\operatorname{dim} U_{j-1}$ for each $i$.
2. $U_{j i} \cap U_{j i^{\prime}} \subseteq U_{j-1}$ for all $i \neq i^{\prime}$.
3. The quotient space $U_{j} / U_{j-1}$ is a direct sum of the quotient spaces $U_{j i} / U_{j-1}$, each of which is a $k$-dimensional subspace
4. The bases $\mathcal{B}_{| \rangle}$can all be computed in deterministic polynomial time.

Proof of Claim 3.11 The proof is quite similar to the proof of the previous claim. For any vector $u \in U_{j} \backslash U_{j-1}$ the subset of $k$ vectors $\left\{u, B u, \ldots, B^{k-1} u\right\}$ are linearly independent of $U_{j-1}$. Together with $U_{j-1}$ they will give a subspace of $U_{j}$ of dimension $k+v_{j-1}$. We can keep finding such a cyclic subsets of $k$ vectors as long as we have a proper subspace of $U_{j}$. Thus, we will obtain $v_{j} / k$ many such cyclic subsets $\mathcal{B}_{j i}$ as claimed. The construction of these bases is in deterministic polynomial time. As defined in the claim we have the subspaces $U_{j i}$ defined by these bases. Since $f$ is irreducible, any two distinct subspaces can intersect only in $U_{j-1}$. Thus, the quotient spaces $U_{j i} / U_{j-1}$ give a direct sum decomposition of the quotient space $U_{j} / U_{j-1}$.

We define a new basis $\mathfrak{B}$ obtained by putting together the good bases for each $U_{j}, 1 \leq j \leq e$ in that order. With respect to this basis the matrix $B-x I_{\ell}$ will assume the following form

$$
T_{1}\left(B-x I_{\ell}\right) T_{1}^{-1}=\left(\begin{array}{ccccc}
L_{1}^{\prime} & 0 & 0 & \ldots & 0  \tag{5}\\
* & L_{2}^{\prime} & 0 & \ldots & 0 \\
* & * & L_{3}^{\prime} & \ldots & 0 \\
& & & \ddots & \\
* & * & * & \ldots & L_{e}^{\prime}
\end{array}\right)
$$

where the blocks below the diagonal blocks marked by * could contain nonzero linear forms, but the blocks above the diagonal blocks are all zeros. Each block $L_{j}^{\prime}, j \geq 2$ corresponds to the quotient space $U_{j} / U_{j-1}$ and, by choice of a good basis, the block $L_{j}^{\prime}$ itself will be block diagonal with blocks of size $k$ each ( $v_{j} / k$ many blocks). This yields a factorization of $B-x I_{n}$ as a product of $\ell=n / k$ many linear matrix factors which are atoms by using the following factorization repeatedly

$$
\left(\begin{array}{c|c}
A & 0  \tag{6}\\
\hline D & B
\end{array}\right)=\left(\begin{array}{c|c}
A & 0 \\
\hline 0 & I
\end{array}\right) \cdot\left(\begin{array}{c|c}
I & 0 \\
\hline D & I
\end{array}\right) \cdot\left(\begin{array}{c|c}
I & 0 \\
\hline 0 & B
\end{array}\right) .
$$

In the above equation, if the matrix on the left is a full non-unit linear matrix then the first and third factors are full non-unit linear matrices. The middle factor is actually a unit and can be absorbed with either the first or the third factor.

To summarize we present below the steps of the linear matrix factorization algorithm. Input: matrix $A-x I$, where $A \in \mathbb{Q}^{d \times d}$ is full rank.

1. Compute the characteristic and minimal polynomials $\chi_{A}(x)=\prod_{i=1}^{t} f_{i}^{d_{i}}$ and $m_{A}(x)=\prod_{i=1}^{t} f_{i}^{e_{i}}$ of $A$ with the factorization structure as stated above.

Phase 1 Compute bases for the subspaces

$$
V_{i}=\left\{v \in \mathbb{Q}^{d} \mid f_{i}^{e_{i}}(A)=0\right\} .
$$

and take their union in that order as the new basis. Then $\mathbb{Q}^{d}=\oplus_{i=1}^{t} V_{i}$ and w.r.t. the new basis the matrix $A-x I$ is in block diagonal form where the $i^{t h}$ block on the diagonal is of the form $A_{i}-x I$ which has characteristic polynomial $f_{i}^{d_{i}}$ and minimal polynomial $f_{i}^{e_{i}}$.

Phase 2 for each $1 \leq i \leq t$ do
2. Call procedure $\operatorname{GoodBasis}\left(A_{i}\right)$ which returns a good basis $\mathfrak{B}_{i}$ corresponding to $A_{i}$.
3. Find the matrix representation of $A-x I$ w.r.t. the basis $\cup_{i=1}^{t} \mathfrak{B}_{i}$.
4. Compute factorization of this matrix by repeated application of Equation 6.

Procedure GoodBasis(B);
(a) Let $\chi_{B}=f^{\ell}$ and $m_{B}=f^{\ell}, f$ is degree $k$ irreducible. Suppose $B$ is $n \times n$. Then $n=k \ell$.
(b) Find tower of subspaces $U_{1} \subset U_{2} \subset \cdots \subset U_{e}=\mathbb{Q}^{n}$ such that $U_{j}$ is annihilated by $f^{j}, 1 \leq j \leq e$.
(c) Let $\mathfrak{C}_{j}$ be some basis for each subspace $U_{j}$ computed in the above process such that $\mathfrak{C}_{j} \subset \mathfrak{C}_{j+1}$ for all $j$.
(d) $\mathfrak{C}_{0}=\emptyset$.
(e) for each $1 \leq j \leq e$ do
(f) $\mathfrak{B}_{j}=\mathfrak{C}_{j-1}$.
(g) while $\mathfrak{B}_{j}$ does not span $U_{j}$ do
(h) pick a vector $u \in \mathfrak{C}_{j}$ that is not in span of $\mathfrak{B}_{j}$ and include $\left\{u, B u, \ldots, B^{k-1} u\right\}$ in $\mathfrak{B}_{j}$.
(i) end-while.
(j) return $\mathfrak{B}=\bigcup_{j=1}^{e} \mathfrak{B}_{j}$.

Running time analysis. It is evident from the algorithm description that the total number of field operations is polynomially bounded in the dimension $d$ of the matrix $A$. We now argue that the encoding sizes of the rational numbers involved in the computation are all also polynomially bounded. The basis change matrix $T$ used in Phase 1 (see Equation 3 ) has entries of polynomial encoding size as it is standard Gaussian elimination. In Phase 2, the calls to Procedure GoodBasis $\left(A_{i}\right)$ for each $i$ are essentially independent of each other. Thus, it suffices to analyze one call to Procedure GoodBasis(B). Again, the computation of some basis $\mathfrak{C}_{J}$ for $U_{j}, 1 \leq j \leq e$ is by standard Gaussian elimination. Hence the encoding size $\mathfrak{b}\left(\mathfrak{C}_{j}\right)$ is polynomially bounded for each $j$. The computation of the good basis $\mathfrak{B}_{j}$ for the quotient space $U_{j} / U_{j-1}$ is done using only $\mathfrak{C}_{j}$ and $\mathfrak{C}_{j-1}$. It follows that for each $j$ we have $\mathfrak{b}\left(\mathfrak{B}_{j}\right)$ is polynomially bounded, and hence $\mathfrak{b}(\mathfrak{B})$ is polynomially bounded.

### 3.3 The Factorization Algorithm for Matrices over $\mathbb{Q}[x]$

Theorem 3.12. Let $M \in \mathbb{Q}[x]^{d \times d}$ be a matrix of univariate polynomials over rationals where each entry of matrix $M$ is a polynomial of degree at most $D$. Then there is a $\operatorname{poly}(d, D, \mathfrak{b}(M))$ time deterministic algorithm that outputs a complete factorization of $M$ as a product $M=M_{1} M_{2} \cdots M_{r}$ such that each matrix factor $M_{i}$ is an atom whose entries are polynomials in $\mathbb{Q}[x]$ of degree at most $D$.

Proof. Given $M$ as input, we apply Higman linearization followed by the monicity algorithm of Lemma 3.8 (second part) and the linear matrix factorization algorithm of Theorem 3.9 to obtain the factorization

$$
M \oplus I_{s}=P S^{\prime} F_{1} F_{2} \ldots F_{r} U^{\prime} Q
$$

where each linear matrix $F_{i}$ is an atom, the matrix $P$ is upper triangular with all 1's diagonal, the matrix $Q$ is lower triangular with all 1's diagonal, the matrix $S^{\prime}$ is a scalar invertible matrix and $U^{\prime}$ is a unit. By absorbing $S^{\prime}$ in $F_{1}$ and setting $U=U^{\prime} Q$ we can without loss of generality assume that the factorization has the following form

$$
M \oplus I_{s}=P F_{1} F_{2} \ldots F_{r} U
$$

where $U$ is a unit. Moreover, the entries of $P$ and $U$ are all polynomials in $\mathbb{Q}[x]$ of degree at most $D$.

We will now apply Lemma 2.5 to extract the factors of $M$ (one by one from the right).
For the first step, let $C=F_{1} F_{2} \cdots F_{r-1}$ and $D=F_{r} U$ in Lemma 2.5 The proof of Lemma 2.5 yields the matrix $N_{r}=N \Pi$ such that both matrices $C^{\prime \prime}=P F_{1} F_{2} \cdots F_{r-1} N_{r}$ and $D^{\prime \prime}=N_{r}^{-1} F_{r} U$ has the first $d$ column all zeros except the top left $d \times d$ block of entries $c_{1}^{\prime \prime}$ and $d_{1}^{\prime \prime}$ which yields the nontrivial factorization $M=c_{1}^{\prime \prime} d_{1}^{\prime \prime}$, where $d_{1}^{\prime \prime}=M_{r}$ is an atom. Renaming $c_{1}^{\prime \prime}$ as $G_{r}$ we have from the structure of $C^{\prime \prime}$ :

$$
\left(\begin{array}{cc}
G_{r} & * \\
0 & V_{r}
\end{array}\right)=P\left(F_{1} F_{2} \cdots F_{r-2}\right)\left(F_{r-1} N_{r}\right) .
$$

Setting $C=F_{1} F_{2} \cdots F_{r-2}$ and $D=F_{r-1} N_{r}$ in Lemma 2.5 we can compute the matrix $N_{r-1}$ using which we will obtain the next factorization $G_{r}=G_{r-1} M_{r-1}$, where $M_{r-1}$ is an atom by Lemma 2.5 Note that Lemma 2.5 is applicable as all conditions are met by the matrices in the above equation (note that the matrix $V_{r}$ will be a unit).

Continuing thus, at the $i^{t h}$ stage we will have $M=G_{r-i+1} M_{r-i+1} M_{r-i+2} \cdots M_{r}$ after obtaining the rightmost $i$ irreducible factors by the above process. At this stage we will have

$$
\left(\begin{array}{cc}
G_{r-i+1} & * \\
0 & V_{r-i+1}
\end{array}\right)=P\left(F_{1} F_{2} \cdots F_{r-i-1}\right)\left(F_{r-i} N_{r-i+1}\right),
$$

where $V_{r-i+1}$ is a unit and all other conditions are satisfied for application of Lemma 2.5 ,
Thus, after $r$ stages we will obtain the complete factorization of the input matrix $M$ as

$$
M=M_{1} M_{2} \cdots M_{r}
$$

where each factor $M_{i}$ is an atom.

## Running Time Analysis

The Higman Linearization of $M$ is computed in deterministic polynomial time. For the resulting linear matrix $L=A_{0}+A_{1} x$, by Theorem 3.9 its factorization as a product of linear matrix atoms can be computed in deterministic time poly $(d, D, \mathrm{~b}(L))$.

Given factorization of $L$ into atoms, we extract atomic factorization of the input polynomial matrix $M$ as discussed above. At each stage we invoke Lemma 2.5 to extract an atomic factor of $M$ from right. There are total $r$ stages, $r \leq D$, where $D$ is an upper bound on the degree of polynomial entries of $M$. To see the bound $r \leq D$, note that the degree of det $M$ is bounded by $D$ and as for each atomic factor $M_{i}$ of $M$, we have degree of det $M_{i}$ at least 1 . Consequently, $r$ is upper bounded
by $D$. So clearly, we can find complete factorization of $M$ into atoms in polynomially many field operations.

Now we show that the overall bit complexity of the algorithm is polynomially bounded. A crucial point to note is, the trivialization matrix $N_{j}$ at any stage (computed by the trivialization algorithm of Theorem 3.6), only depends upon $C=F_{1} F_{2} \cdots F_{j-1}$, so the bit complexity of $N_{j}$ and $N_{j}^{-1}$ is polynomially bounded. Clearly, the extracted atomic factor $N_{j}^{-1} F_{j} N_{j+1}$ has polynomially bounded bit complexity. Moreover, the extracted factors play no role at all in the subsequent computation. This proves that the overall bit complexity of the algorithm is upper bounded by $\operatorname{poly}(d, D, \mathfrak{b}(M))$. This completes the proof of the theorem.

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[^1]:    ${ }^{1}$ Following Cohn [Coh06] we refer to such matrices as atoms rather than irreducibles.
    ${ }^{2} \mathbb{F}\langle X\rangle^{d \times d}$ is not a UFD in the usual sense, nevertheless factorization in $\mathbb{F}\langle X\rangle^{d \times d}$ is unique under stable associativity as shown in [Coh06. However, in the current work we are not interested in this aspect, our goal is simply to find any factorization of given matrix polynomial into atoms

[^2]:    ${ }^{3}$ In AJ22] we used a different result DM17] for this purpose which, in randomized polynomial time, gives such a matrix substitution with entries of matrices from possibly some extension field of $\mathbb{F}_{q}$. However, in [IQS18] such a matrix substitution is obtained in deterministic polynomial time. Moreover, it can be ensured that the entries of the obtained matrices reside in $\mathbb{F}_{q}$ itself even for small $q$, at the cost of slightly larger dimensional matrix substitution.

[^3]:    ${ }^{4}$ The notions of right and left monic, defined in the multivariate setting [Coh06 AJ22], coincide in the univariate case which we refer to as simply monic here.

