

Lower Bounds for some Algebraic Models of Computation

Prerona Chatterjee

August 27, 2024

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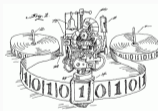
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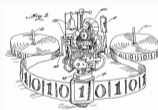


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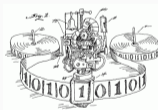
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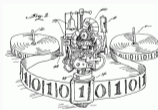
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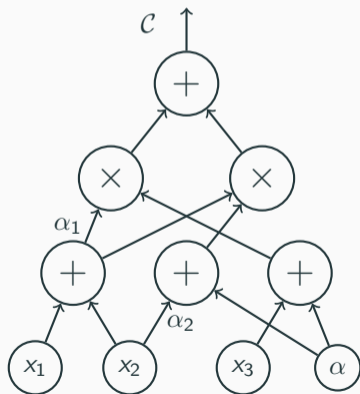
Matrix Multiplication Exponent (ω): Smallest number k such that the product of two $n \times n$ matrices can be found using n^k multiplications.

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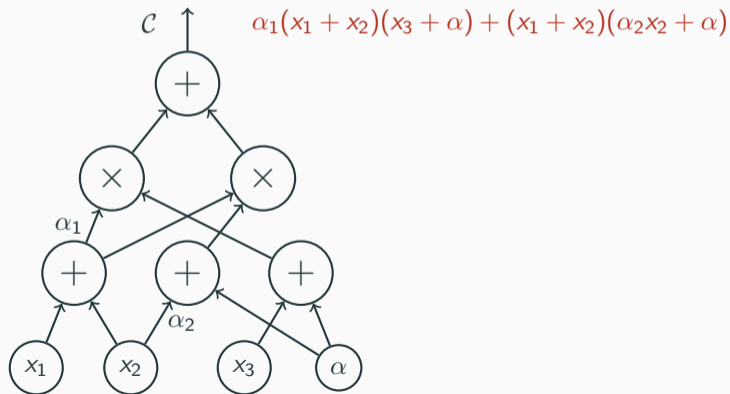
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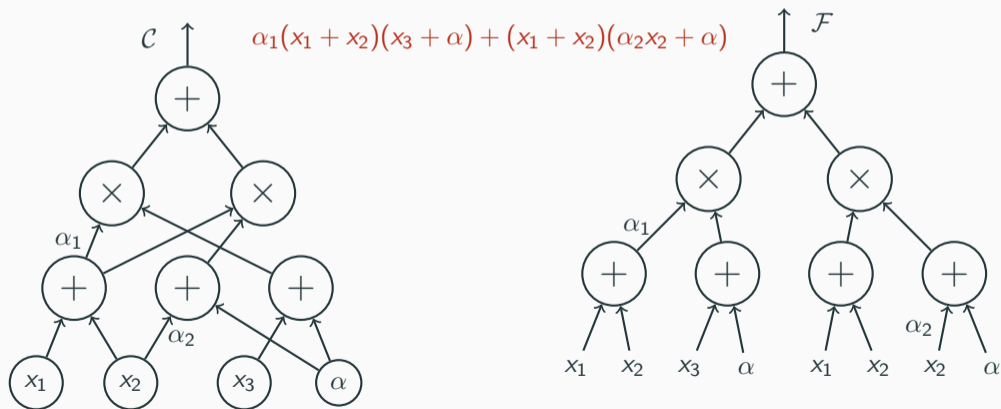
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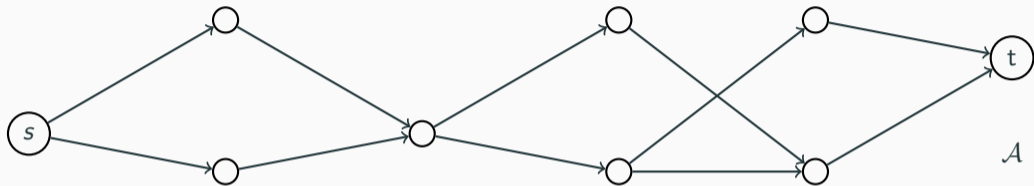


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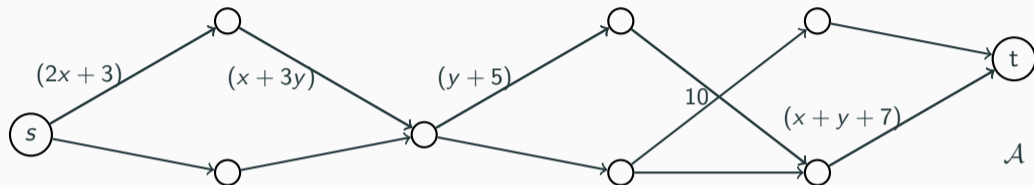
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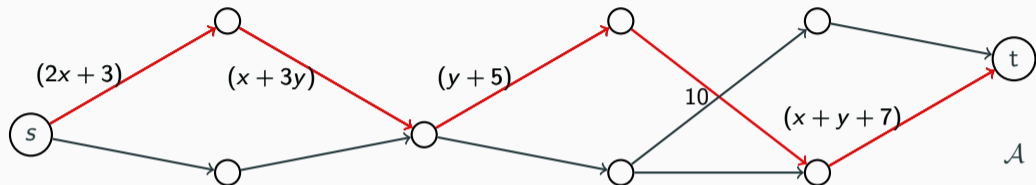


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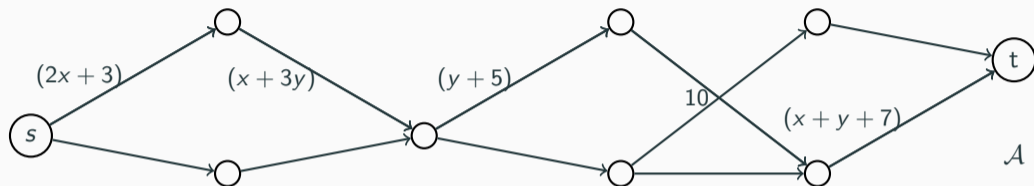
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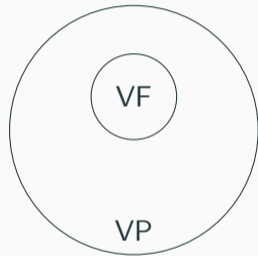


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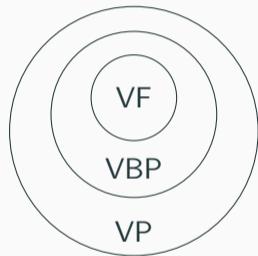
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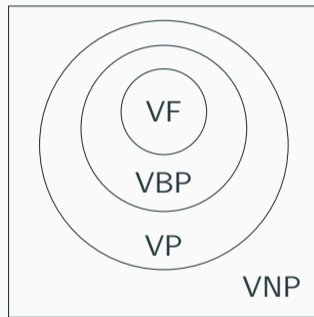
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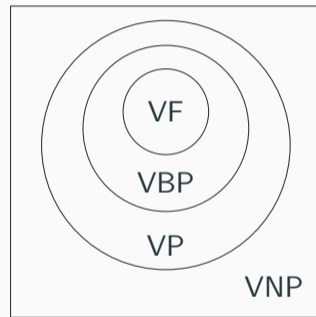
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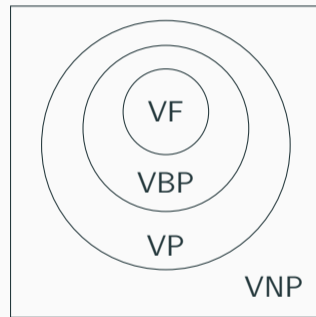
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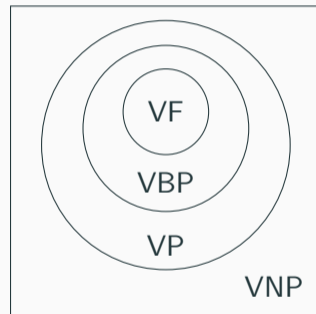
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Other Motivating Questions: Are the other inclusions tight?

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$$\text{ESYM}_{n,d}(\mathbf{x}) = \sum_{i_1 < \dots < i_d \in [n]} x_{i_1} \cdots x_{i_d}.$$

How does one make progress?

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Show that if a structured n -variate, degree- d polynomial is computable by a general model of size s , then they can also be computed by a structured model of size $\text{func}(s, n, d)$ for some function func .

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[C-Kush-Saraf-Shpilka 24]: For $\omega(\log n) = d \leq n$, there is a polynomial $G_{n,d}(\mathbf{x})$ which is set-multilinear w.r.t $\mathbf{x} = \{\mathbf{x}_1, \dots, \mathbf{x}_d\}$, where $|\mathbf{x}_i| \leq n$ for every $i \in [d]$, such that:

- $G_{n,d}$ is computable by a set-multilinear ABP of size $\text{poly}(n)$,
- any \sum osmABP computing $G_{n,d}$ must have super-polynomial total-width.

Set-Multilinearity

The variable set is divided into buckets.

$$\mathbf{x} = \mathbf{x}_1 \cup \dots \cup \mathbf{x}_d \quad \text{where} \quad \mathbf{x}_i = \{x_{i,1}, \dots, x_{i,n_i}\}.$$

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computes a set-multilinear monomial with respect to $\{\mathbf{x}_1, \dots, \mathbf{x}_d\}$.

Near Tightness of ABP Set-Multilinearisation

For $\sigma \in S_d$, an ABP is σ -ordered set-multilinear with respect to $\{\mathbf{x}_1, \dots, \mathbf{x}_d\}$ if

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[C-K-S-S 24]: Super polynomial lower bound against total-width of \sum osmABP for a polynomial of degree $d = \omega(\log n)$ that is computable by polynomial-sized ABPs.

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$$\text{OSym}_{n,d}(\mathbf{x}) = \sum_{1 \leq i_1 < \dots < i_d \leq n} x_{i_1} \cdots x_{i_d}$$

has size $\Omega(nd)$ for $d \leq \frac{n}{2}$.

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has size $\Omega(nd)$ for $d \leq \frac{n}{2}$. The lower bound is tight for homogeneous non-commutative circuits.

Non-Commutativity

$$f(x, y) = (x + y) \times (x + y) = x^2 + xy + yx + y^2 \neq x^2 + 2xy + y^2$$

Non-Commutative Models: The multiplication gates, additionally, respect the order.

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Further, there is a non-commutative circuit of size $O(n \log^2 n)$ that computes $\text{OSym}_{n,n/2}(\mathbf{x})$.

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position indices \equiv bucket indices

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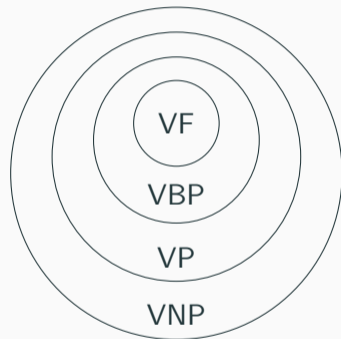
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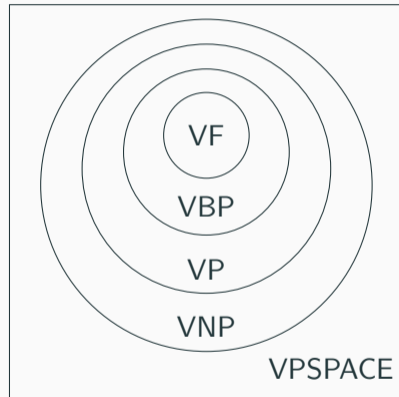
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If an n -variate polynomial is abecedarian with respect to $\{X_1, \dots, X_m\}$ for $m = \log n$, then any formula computing f can be made abecedarian with only $\text{poly}(n)$ blow-up in size.



Classes Beyond VNP

$VPSPACE_b$: Polynomials whose coefficients can be computed in $PSPACE/poly$ and have degree bounded by $poly(n)$.

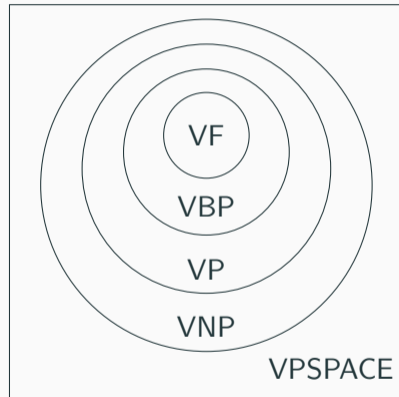


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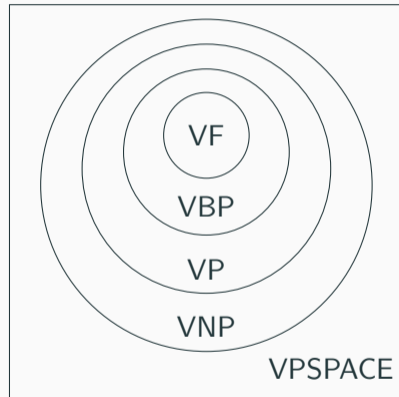
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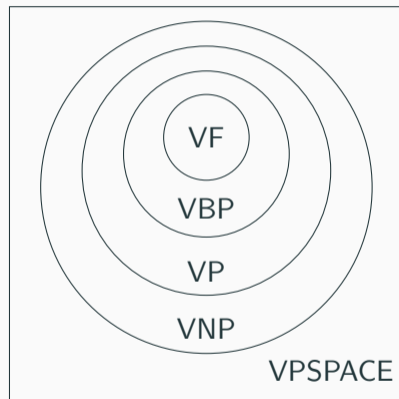
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[C-Gajjar-Tengse 24]: $\text{VNP} \neq \text{VPSPACE}_b$ in the monotone setting.



Lower Bound Against Sum of Ordered Set-Multilinear ABPs

Super-Polynomial Lower Bound against \sum osmABPs

An ABP is σ -ordered set-multilinear with respect to $\{\mathbf{x}_1, \dots, \mathbf{x}_d\}$ if

- there are d layers in the ABP
- every edge in layer i is labelled by a homogeneous linear form in $\mathbf{x}_{\sigma(i)}$

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[C-Kush-Saraf-Shpilka 24]: For $\omega(\log n) = d \leq n$, there is a polynomial $G_{n,d}(\mathbf{x})$ which is set-multilinear w.r.t $\mathbf{x} = \{\mathbf{x}_1, \dots, \mathbf{x}_d\}$, where $|\mathbf{x}_i| \leq n$ for every $i \in [d]$, such that:

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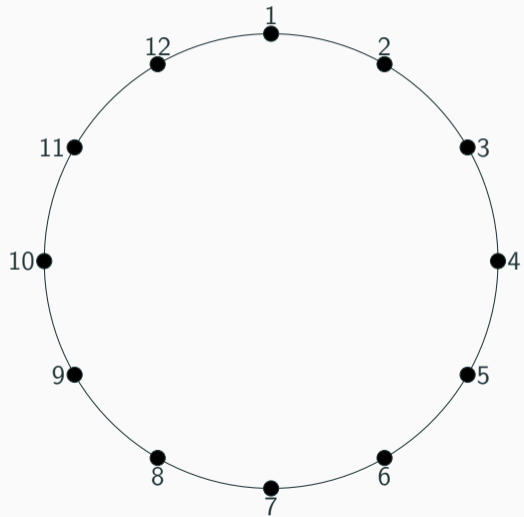
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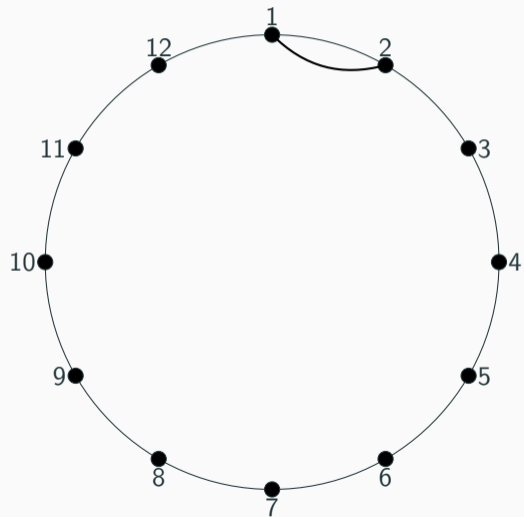
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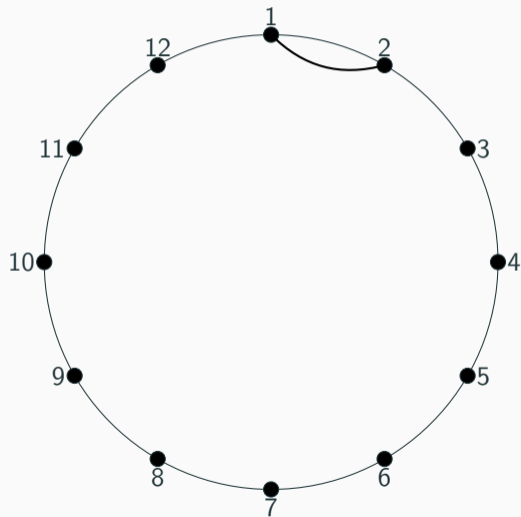
Arc Partition



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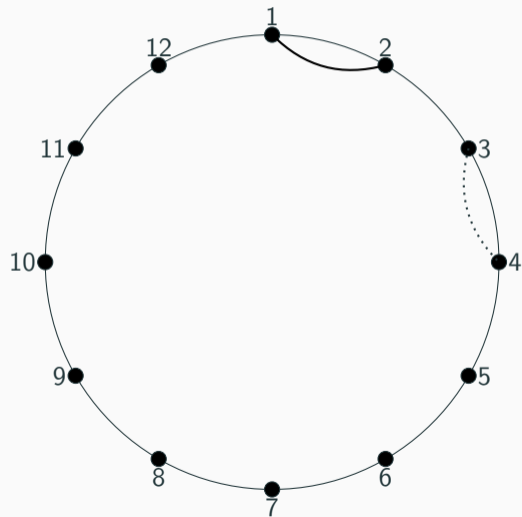


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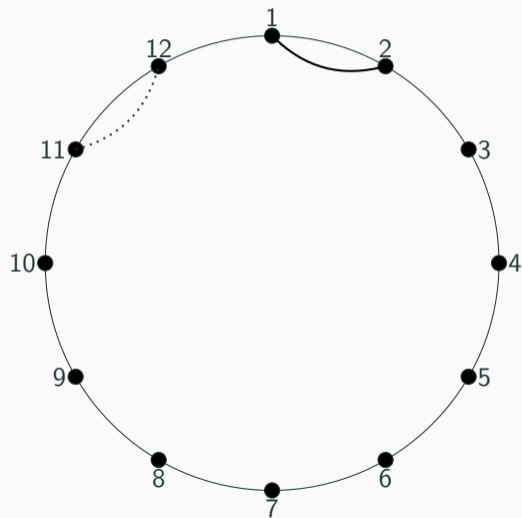
$$\mathcal{P}_1 = \{(1, 2)\}$$

Arc Partition



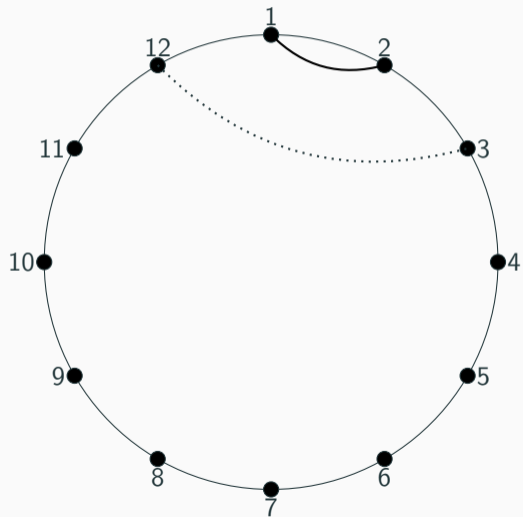
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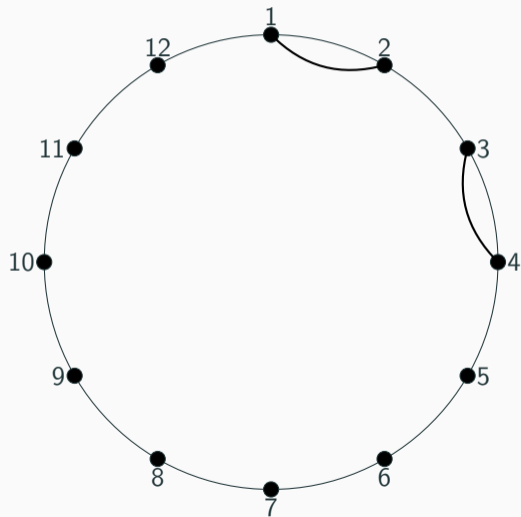
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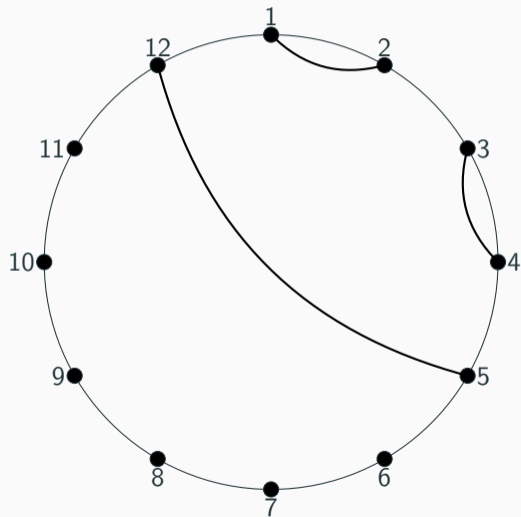
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Arc Partition

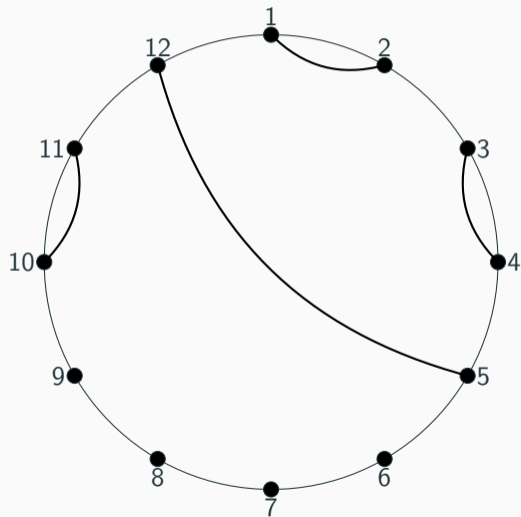


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Arc Partition



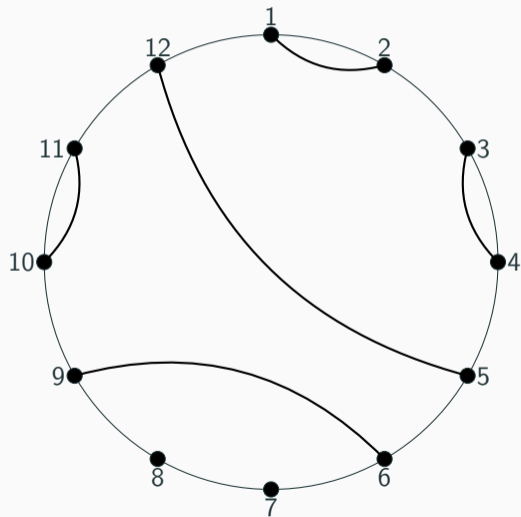
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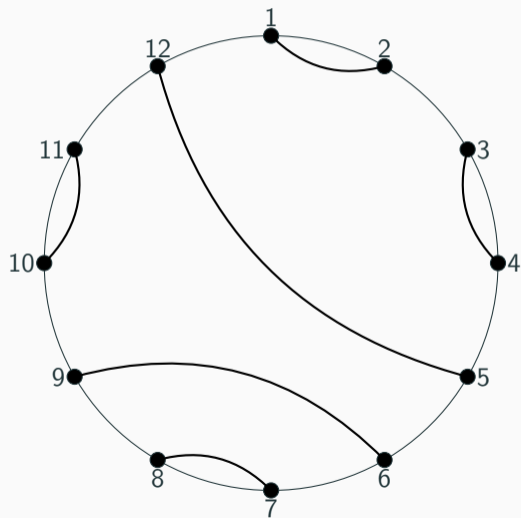
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Arc Partition



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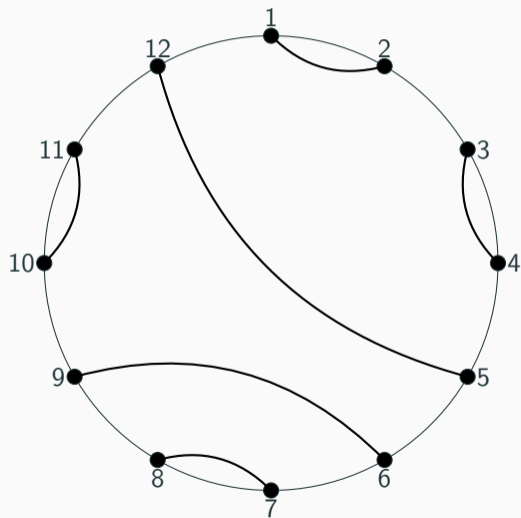
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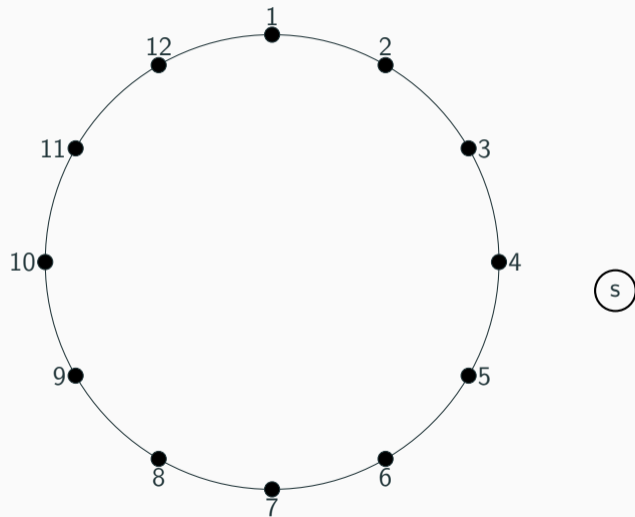
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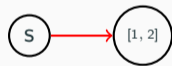
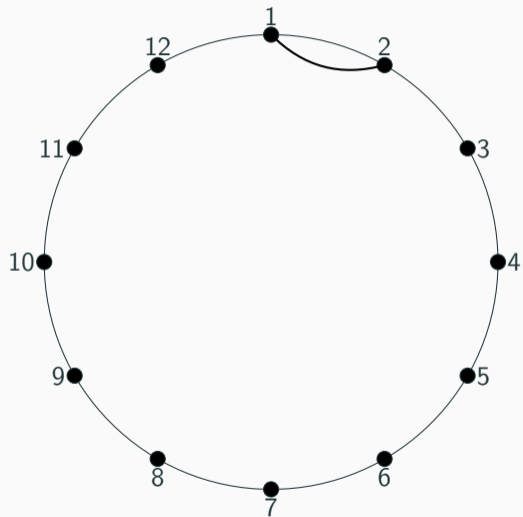
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$\mathbf{P}_6 =$ All possible sequences of such pairs.

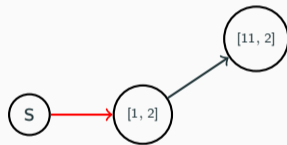
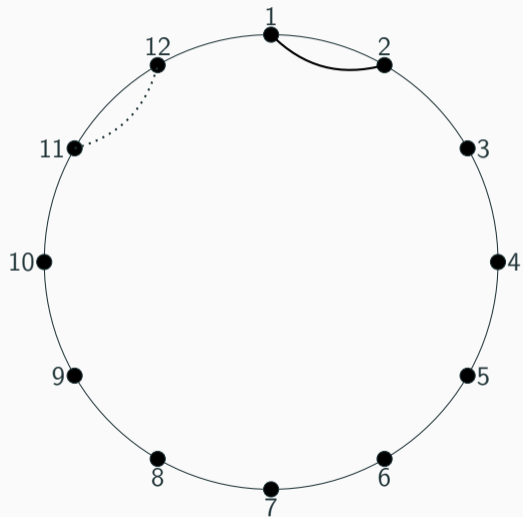
The ABP Upper Bound



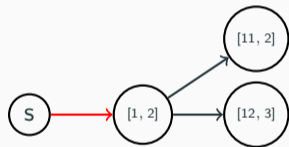
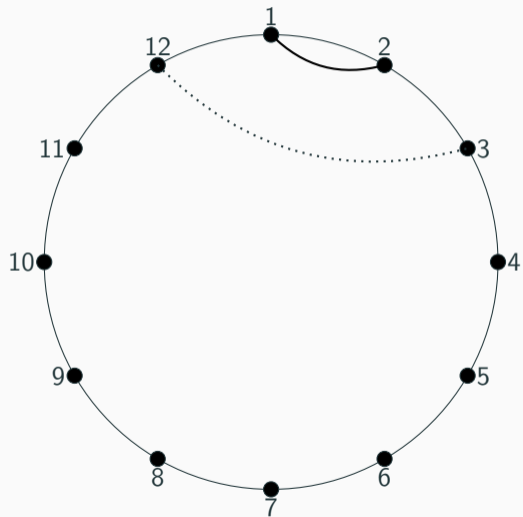
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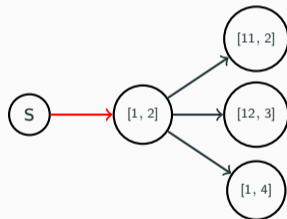
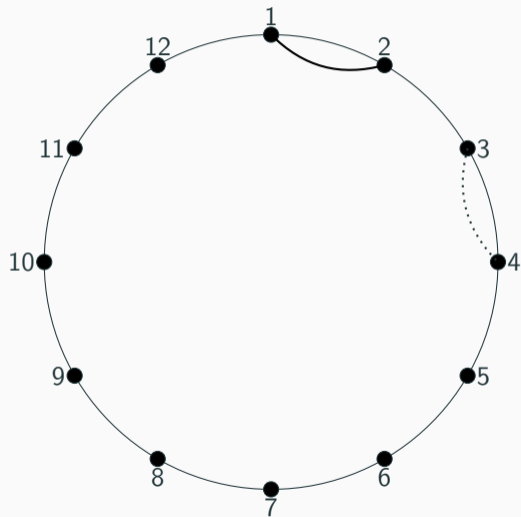
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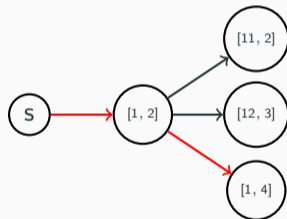
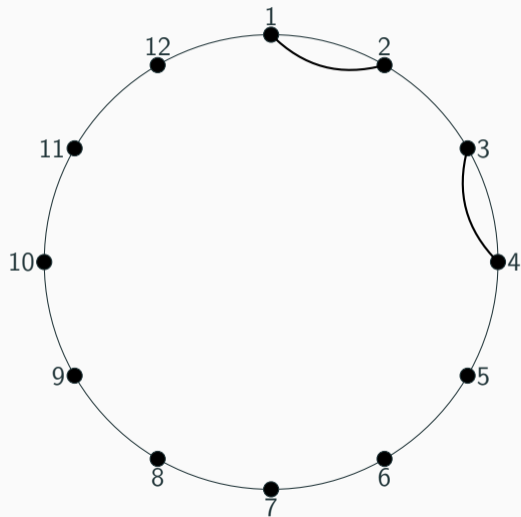
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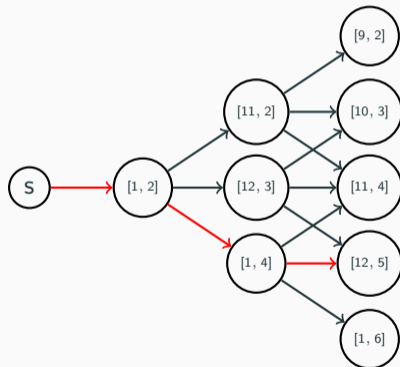
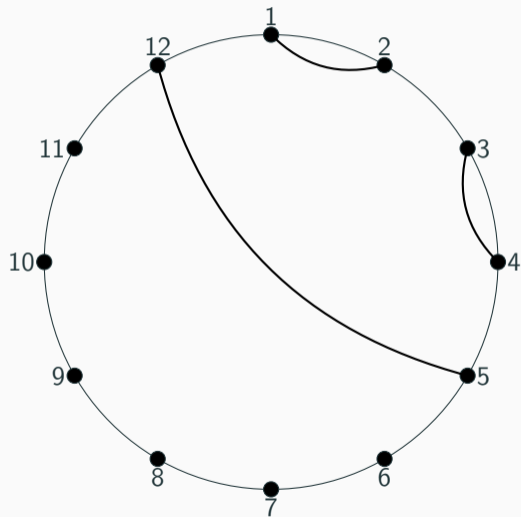
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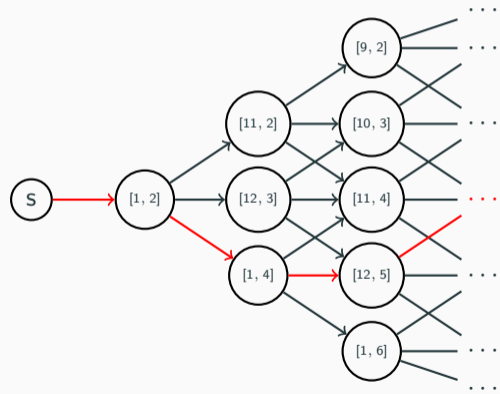
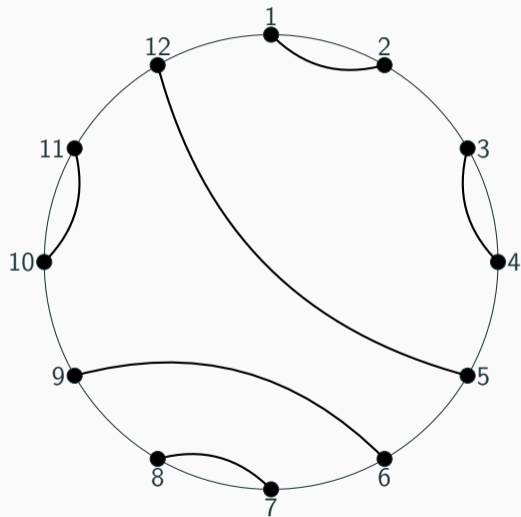
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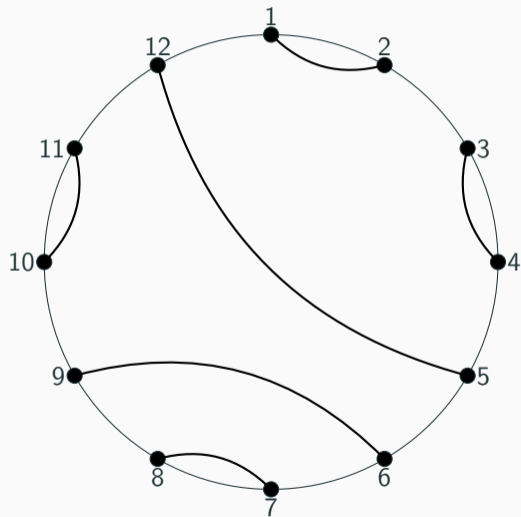
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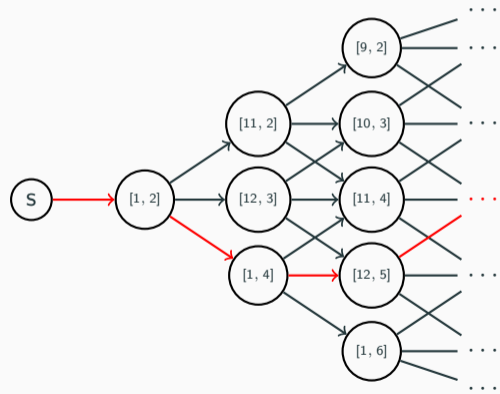
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Every path corresponds to an element in $\mathbf{P}_{d/2}$.



The Hard Polynomial

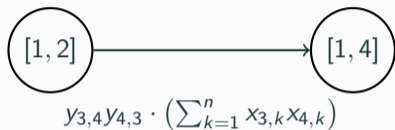


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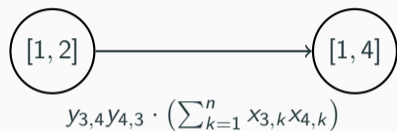
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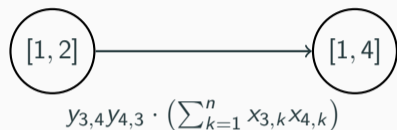
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$(y_{3,4}y_{4,3})$: To select.

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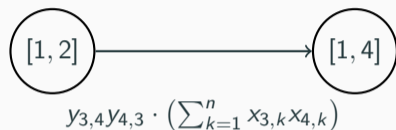


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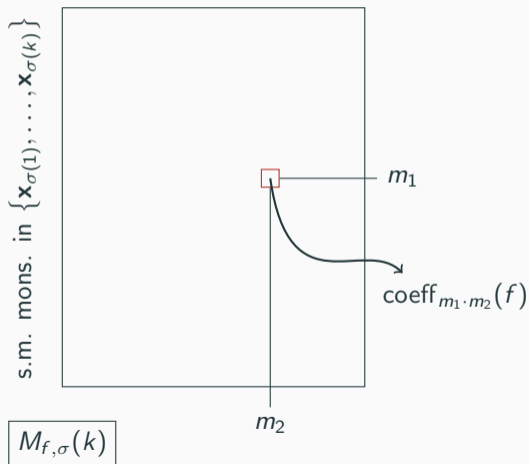
$(\sum_{k=1}^n x_{3,k}x_{4,k})$: To achieve full-rank.

	$x_{4,1}$	$x_{4,2}$	\dots	\dots	$x_{4,n}$
$x_{3,1}$	1	0	\dots	\dots	0
$x_{3,2}$	0	1	\dots	\dots	0
\vdots	\vdots	\vdots			\vdots
\vdots	\vdots	\vdots			\vdots
$x_{3,n}$	0	0	\dots	\dots	1

Lower Bound for a single osmABP

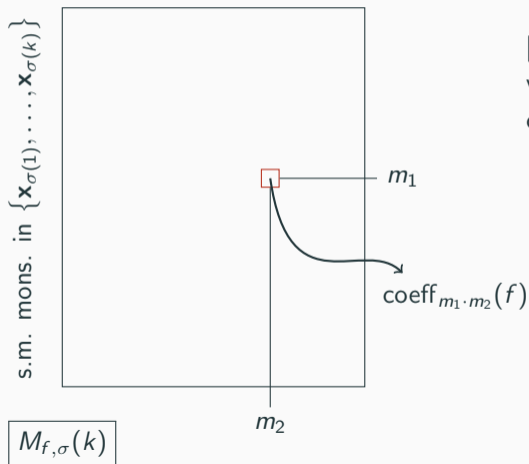
s.m. mons. in $\{\mathbf{x}_{\sigma(k+1)}, \dots, \mathbf{x}_{\sigma(d)}\}$

f is a set-multilinear poly. w.r.t $\{\mathbf{x}_1, \dots, \mathbf{x}_d\}$.



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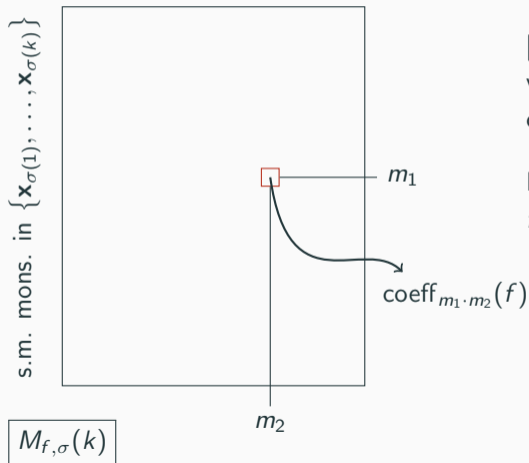


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[Nisan 91]: For every $1 \leq k \leq d$, the number of vertices in the k -th layer of the smallest osmABP(σ) computing f is equal to the rank of $M_{f, \sigma}(k)$.

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If \mathcal{A} is the smallest osmABP (in order σ) computing f , then

$$\text{size}(\mathcal{A}) = \sum_{i=1}^d \text{rank}(M_{f, \sigma}(k)).$$

Lower Bound for a single osmABP (contd.)

$$G_{n,d} = \sum_{\mathcal{P} \in \mathbf{P}_{d/2}} \prod_{(i,j) \in \mathcal{P}} y_{i,j} y_{j,i} \cdot \left(\sum_{k=1}^n x_{i,k} x_{j,k} \right).$$

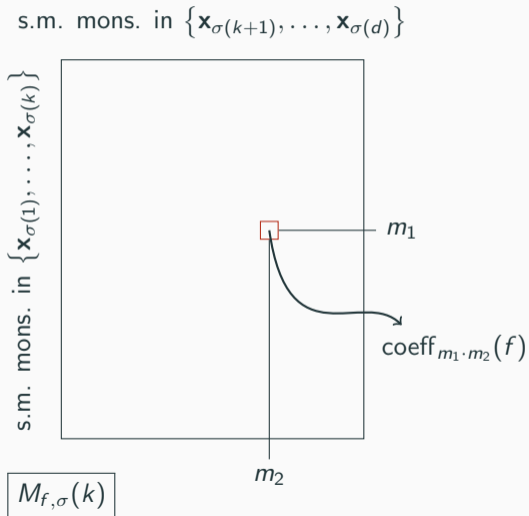
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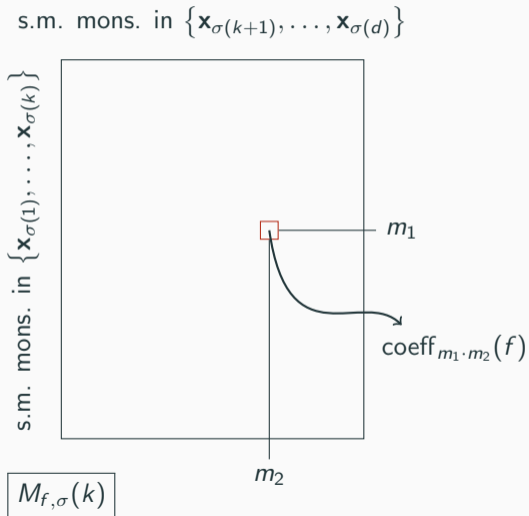


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Therefore,

$$\text{rank}(M_{G_{n,d}, \sigma}(d/2)) = \Omega(n^{d/8}).$$

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Future Research Plans

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- Separating formulas and ABPs in the non-commutative setting?
- Defining a hierarchy, similar to PH, in the algebraic setting?

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Teaching

Courses I would be happy to teach

Basic Courses

- Problem Solving Using Computers and Computer Programming (CS1100, CS1111, CS2110, CS2700, CS2810)
- Discrete Mathematics for CS (CS1200, CS2100)
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I would be happy to teach/design other courses depending on interest and/or requirement.

Thank you!!!