CSE 548: Analysis of Algorithms

Lecture 4 (Divide-and-Conquer Algorithms: Polynomial Multiplication)

> Rezaul A. Chowdhury **Department of Computer Science SUNY Stony Brook** Fall 2019

Coefficient Representation of Polynomials

$$A(x) = \sum_{j=0}^{n-1} a_j x^j$$

= $a_0 + a_1 x + a_2 x^2 + \dots + a_{n-1} x^{n-1}$

A(x) is a polynomial of degree bound n represented as a vector $a = (a_0, a_1, \dots, a_{n-1})$ of coefficients.

The *degree* of A(x) is k provided it is the largest integer such that a_k is nonzero. Clearly, $0 \le k \le n-1$.

Evaluating A(x) at a given point:

Takes $\Theta(n)$ time using Horner's rule:

$$A(x_0) = a_0 + a_1 x_0 + a_2 (x_0)^2 + \dots + a_{n-1} (x_0)^{n-1}$$

= $a_0 + x_0 \left(a_1 + x_0 \left(a_2 + \dots + x_0 \left(a_{n-2} + x_0 (a_{n-1}) \right) \dots \right) \right)$

Coefficient Representation of Polynomials

Adding Two Polynomials:

Adding two polynomials of degree bound n takes $\Theta(n)$ time.

$$C(x) = A(x) + B(x)$$

where,
$$A(x) = \sum_{j=0}^{n-1} a_j x^j$$
 and $B(x) = \sum_{j=0}^{n-1} b_j x^j$.

Then
$$C(x) = \sum_{j=0}^{n-1} c_j x^j$$
, where, $c_j = a_j + b_j$ for $0 \le j \le n-1$.

Coefficient Representation of Polynomials

Multiplying Two Polynomials:

The product of two polynomials of degree bound n is another polynomial of degree bound 2n-1.

$$C(x) = A(x)B(x)$$

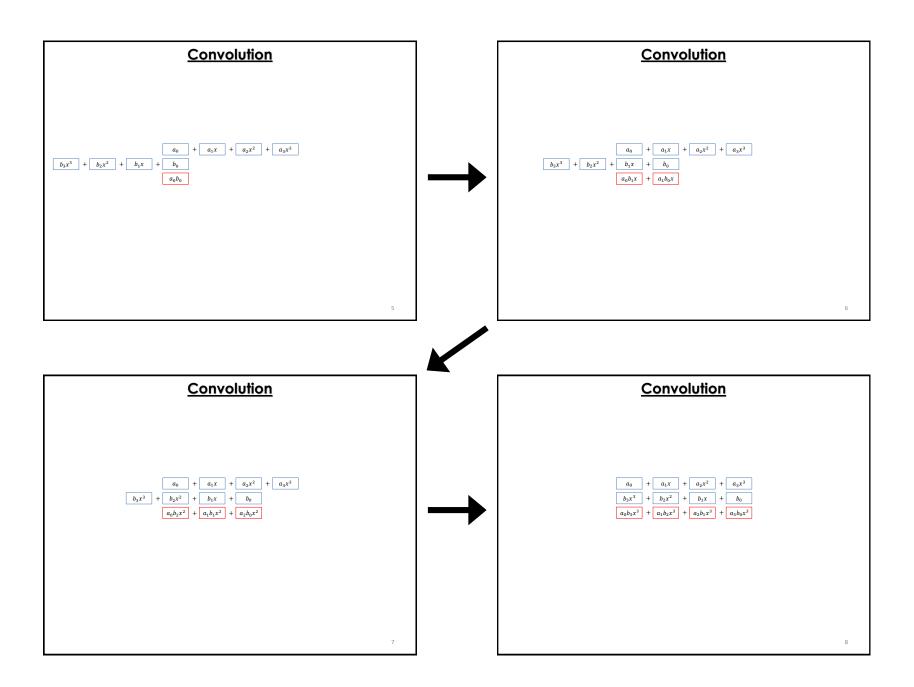
where,
$$A(x) = \sum_{j=0}^{n-1} a_j x^j$$
 and $B(x) = \sum_{j=0}^{n-1} b_j x^j$.

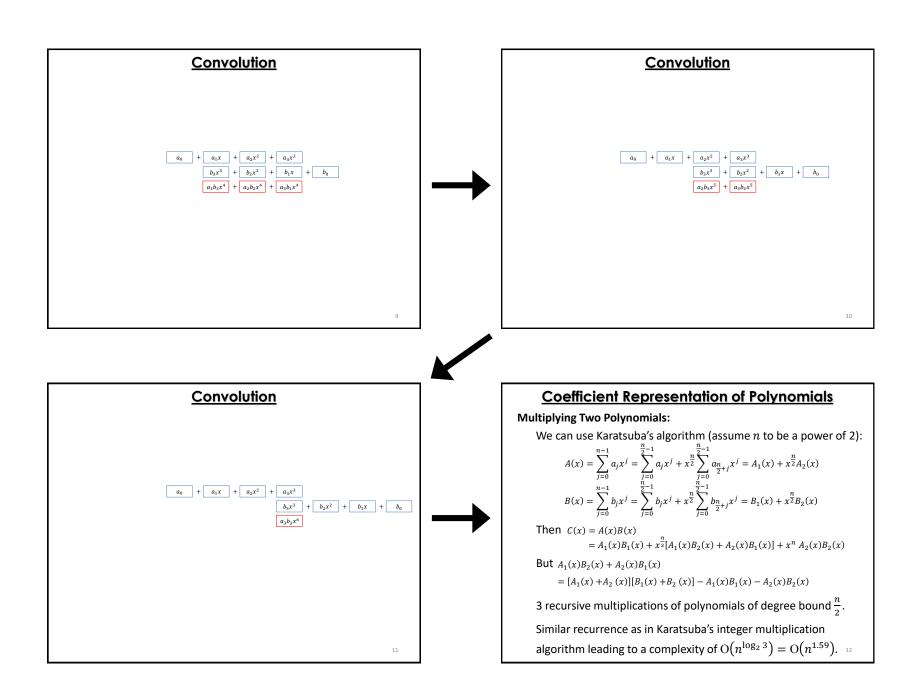
Then
$$C(x) = \sum_{j=0}^{2n-2} c_j x_j^j$$
 where, $c_j = \sum_{k=0}^{j} a_k b_{j-k}$ for $0 \le j \le 2n-2$.

The coefficient vector $c=(c_0,c_1,\cdots,c_{2n-2})$, denoted by $c=a\otimes b$, is also called the *convolution* of vectors $a = (a_0, a_1, \dots, a_{n-1})$ and $b = (b_0, b_1, \cdots, b_{n-1}).$

Clearly, straightforward evaluation of c takes $\Theta(n^2)$ time.







Point-Value Representation of Polynomials

A point-value representation of a polynomial A(x) is a set of n point-value pairs $\{(x_0,y_0),(x_1,y_1),\dots,(x_{n-1},y_{n-1})\}$ such that all x_k are distinct and $y_k=A(x_k)$ for $0\leq k\leq n-1$.

A polynomial has many point-value representations.

Adding Two Polynomials:

Suppose we have point-value representations of two polynomials of degree bound n using the same set of n points.

$$A \colon \{(x_0, y_0^a), (x_1, y_1^a), \dots, (x_{n-1}, y_{n-1}^a)\}$$

$$B: \{(x_0, y_0^b), (x_1, y_1^b), \dots, (x_{n-1}, y_{n-1}^b)\}$$

If C(x) = A(x) + B(x) then

$$C: \{(x_0, y_0^a + y_0^b), (x_1, y_1^a + y_1^b), ..., (x_{n-1}, y_{n-1}^a + y_{n-1}^b)\}$$

Thus polynomial addition takes $\Theta(n)$ time.

Point-Value Representation of Polynomials

Multiplying Two Polynomials:

Suppose we have *extended* (why?) point-value representations of two polynomials of degree bound n using the same set of 2n points.

$$A: \{(x_0, y_0^a), (x_1, y_1^a), ..., (x_{2n-1}, y_{2n-1}^a)\}$$

$$B: \{(x_0, y_0^b), (x_1, y_1^b), ..., (x_{2n-1}, y_{2n-1}^b)\}$$

If C(x) = A(x)B(x) then

$$C: \{(x_0, y_0^a y_0^b), (x_1, y_1^a y_1^b), \dots, (x_{2n-1}, y_{2n-1}^a y_{2n-1}^b)\}$$

Thus polynomial multiplication also takes only $\Theta(n)$ time! (compare this with the $\Theta(n^2)$ time needed in the coefficient form)

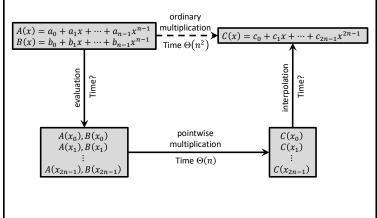
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<u>Faster Polynomial Multiplication?</u> (<u>in Coefficient Form</u>)



<u>Faster Polynomial Multiplication?</u> (in Coefficient Form)

$\textbf{Coefficient Representation} \Rightarrow \textbf{Point-Value Representation:}$

We select any set of n distinct points $\{x_0, x_1, \dots, x_{n-1}\}$, and evaluate $A(x_k)$ for $0 \le k \le n-1$.

Using Horner's rule this approach takes $\Theta(n^2)$ time.

Point-Value Representation ⇒ Coefficient Representation:

We can interpolate using Lagrange's formula:

$$A(x) = \sum_{k=0}^{n-1} \frac{\prod_{j \neq k} (x - x_j)}{\prod_{j \neq k} (x_k - x_j)} y_k$$

This again takes $\Theta(n^2)$ time.

In both cases we need to do much better!

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Coefficient Form ⇒ Point-Value Form

A polynomial of degree bound n: $A(x) = a_0 + a_1x + \cdots + a_{n-1}x^{n-1}$

A set of *n* distinct points: $\{x_0, x_1, ..., x_{n-1}\}$

Compute point-value form: $\{(x_0, A(x_0)), (x_1, A(x_1)), ..., (x_{n-1}, A(x_{n-1}))\}$

Using matrix notation: $[A(x_0)]$

We want to choose the set of points in a way that simplifies the multiplication.

In the rest of the lecture on this topic we will assume:

n is a power of 2.

Given a Polynomial of Degree Bound 8 Find 8 Distinct Points to Efficiently Evaluate it at

 $A(x) = a_0 + a_1x + a_2x^2 + a_3x^3 + a_4x^4 + a_5x^5 + a_6x^6 + a_7x^7$

 $+ a_1x_0 + a_2(x_0)^2 + a_3(x_0)^3 + a_4(x_0)^4 + a_5(x_0)^5 + a_6(x_0)^6 + a_7(x_0)^7$ $A(x_1) = a_0 + a_1x_1 + a_2(x_1)^2 + a_3(x_1)^3 + a_4(x_1)^4 + a_5(x_1)^5 + a_6(x_1)^6 + a_7(x_1)^7$ $A(x_2) \quad = \quad a_0 \quad + \quad a_1x_2 \quad + \ a_2(x_2)^2 \ + \ a_3(x_2)^3 \ + \ a_4(x_2)^4 \ + \ a_5(x_2)^5 \ + \ a_6(x_2)^6 \ + \ a_7(x_2)^7$ $A(x_3) = a_0 + a_1x_3 + a_2(x_3)^2 + a_3(x_3)^3 + a_4(x_3)^4 + a_5(x_3)^5 + a_6(x_3)^6 + a_7(x_3)^7$ $A(x_4) = a_0 + a_1x_4 + a_2(x_4)^2 + a_3(x_4)^3 + a_4(x_4)^4 + a_5(x_4)^5 + a_6(x_4)^6 + a_7(x_4)^7$ $A(x_5) = a_0 + a_1x_5 + a_2(x_5)^2 + a_3(x_5)^3 + a_4(x_5)^4 + a_5(x_5)^5 + a_6(x_5)^6 + a_7(x_5)^7$ $x_6 = -x_2$ $A(x_6) = a_0 + a_1x_6 + a_2(x_6)^2 + a_3(x_6)^3 + a_4(x_6)^4 + a_5(x_6)^5 + a_6(x_6)^6 + a_7(x_6)^7$

 $A(x_7) = a_0 + a_1x_7 + a_2(x_7)^2 + a_3(x_7)^3 + a_4(x_7)^4 + a_5(x_7)^5 + a_6(x_7)^6 + a_7(x_7)^7$

STRATEGY: Set $x_{4+i} = -x_i$ for $0 \le i < 4$



Given a Polynomial of Degree Bound 8 Find 8 Distinct Points to Efficiently Evaluate it at

 $A(x) = a_0 + a_1x + a_2x^2 + a_3x^3 + a_4x^4 + a_5x^5 + a_6x^6 + a_7x^7$

 $a_1x_0 + a_2(x_0)^2 + a_3(x_0)^3 + a_4(x_0)^4 + a_5(x_0)^5 + a_6(x_0)^6 + a_7(x_0)^7$ $A(x_1) \quad = \quad a_0 \quad + \quad a_1x_1 \quad + \ a_2(x_1)^2 \ + \ a_3(x_1)^3 \ + \ a_4(x_1)^4 \ + \ a_5(x_1)^5 \ + \ a_6(x_1)^6 \ + \ a_7(x_1)^7$ $A(x_2) = a_0 + a_1x_2 + a_2(x_2)^2 + a_3(x_2)^3 + a_4(x_2)^4 + a_5(x_2)^5 + a_6(x_2)^6 + a_7(x_2)^7$ $A(x_3) = a_0 + a_1x_3 + a_2(x_3)^2 + a_3(x_3)^3 + a_4(x_3)^4 + a_5(x_3)^5 + a_6(x_3)^6 + a_7(x_3)^7$ $x_4 = -x_0$ $A(-x_0) = a_0 - a_1x_0 + a_2(x_0)^2 - a_3(x_0)^3 + a_4(x_0)^4 - a_5(x_0)^5 + a_6(x_0)^6 - a_7(x_0)^7$ $A(-x_1) = a_0 - a_1x_1 + a_2(x_1)^2 - a_3(x_1)^3 + a_4(x_1)^4 - a_5(x_1)^5 + a_6(x_1)^6 - a_7(x_1)^7$ $A(-x_2) \quad = \quad a_0 \quad - \quad a_1x_2 \quad + \ a_2(x_2)^2 \ - \ a_3(x_2)^3 \ + \ a_4(x_2)^4 \ - \ a_5(x_2)^5 \ + \ a_6(x_2)^6 \ - \ a_7(x_2)^7$ $x_7 = -x_3$ $A(-x_2) = a_0 - a_1x_3 + a_2(x_3)^2 - a_3(x_3)^3 + a_4(x_3)^4 - a_5(x_3)^5 + a_6(x_3)^6 - a_7(x_3)^7$

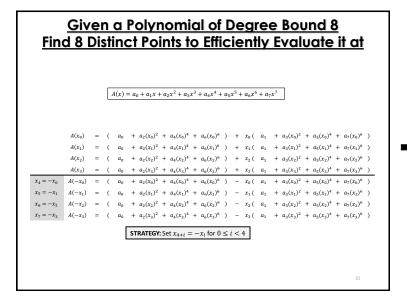
STRATEGY: Set $x_{4+i} = -x_i$ for $0 \le i < 4$

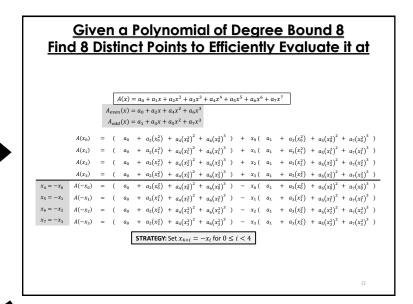
Given a Polynomial of Degree Bound 8 Find 8 Distinct Points to Efficiently Evaluate it at

 $A(x) = a_0 + a_1x + a_2x^2 + a_3x^3 + a_4x^4 + a_5x^5 + a_6x^6 + a_7x^7$

 $A(x_0) = a_0 + a_2(x_0)^2 + a_4(x_0)^4 + a_6(x_0)^6 + a_1x_0 + a_3(x_0)^3 + a_5(x_0)^5 + a_7(x_0)^7$ $A(x_1) \quad = \quad a_0 \quad + \ a_2(x_1)^2 \ + \ a_4(x_1)^4 \ + \ a_6(x_1)^6 \ + \quad a_1x_1 \quad + \ a_3(x_1)^3 \ + \ a_5(x_1)^5 \ + \ a_7(x_1)^7$ $A(x_2) = a_0 + a_2(x_2)^2 + a_4(x_2)^4 + a_6(x_2)^6 + a_1x_2 + a_3(x_2)^3 + a_5(x_2)^5 + a_7(x_2)^7$ $A(x_3) \quad = \quad a_0 \quad + \ a_2(x_3)^2 \ + \ a_4(x_3)^4 \ + \ a_6(x_3)^6 \ + \quad a_1x_3 \quad + \ a_3(x_3)^3 \ + \ a_5(x_3)^5 \ + \ a_7(x_3)^7$ $x_4 = -x_0$ $A(-x_0) = a_0 + a_2(x_0)^2 + a_4(x_0)^4 + a_5(x_0)^6 - a_1x_0 - a_3(x_0)^3 - a_5(x_0)^5 - a_7(x_0)^7$ $x_5 = -x_1 \qquad A(-x_1) = a_0 + a_2(x_1)^2 + a_4(x_1)^4 + a_6(x_1)^6 - a_1x_1 - a_3(x_1)^3 - a_5(x_1)^5 - a_7(x_1)^7$ $x_6 = -x_2 \qquad A(-x_2) \qquad = \quad a_0 \quad + \ a_2(x_2)^2 \ + \ a_4(x_2)^4 \ + \ a_6(x_2)^6 \ - \quad a_1x_2 \quad - \ a_3(x_2)^3 \ - \ a_5(x_2)^5 \ - \ a_7(x_2)^7$ $x_7 = -x_3$ $A(-x_2) = a_0 + a_2(x_3)^2 + a_4(x_3)^4 + a_6(x_3)^6 - a_1x_3 - a_2(x_2)^3 - a_5(x_3)^5 - a_7(x_3)^7$

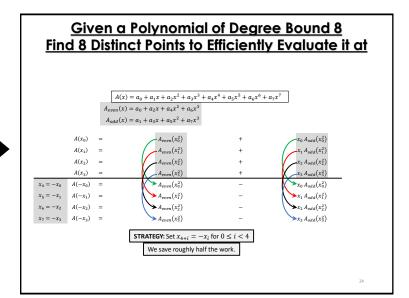
STRATEGY: Set $x_{4+i} = -x_i$ for $0 \le i < 4$

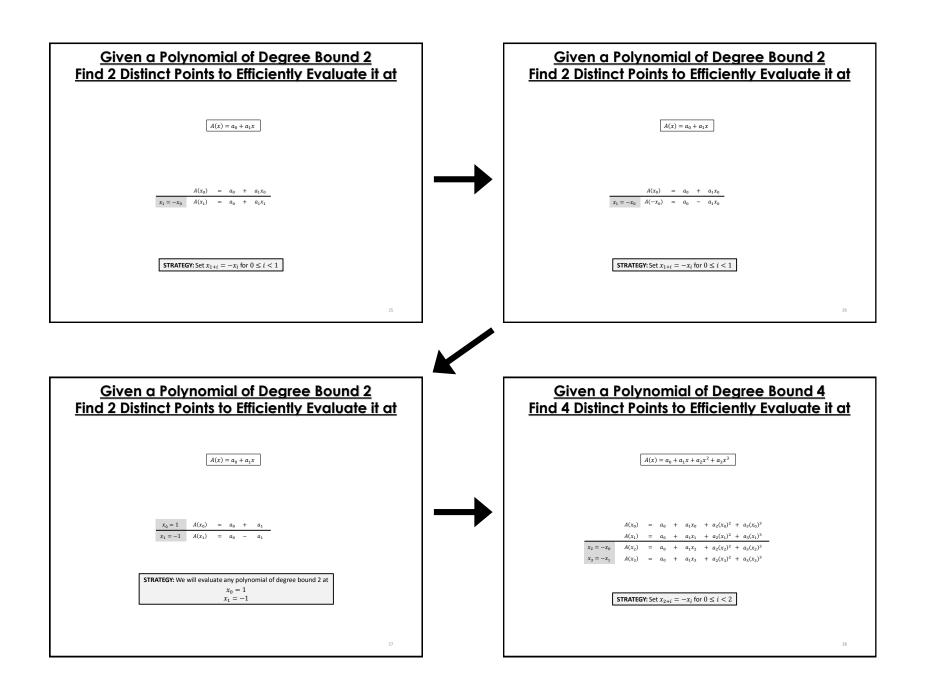


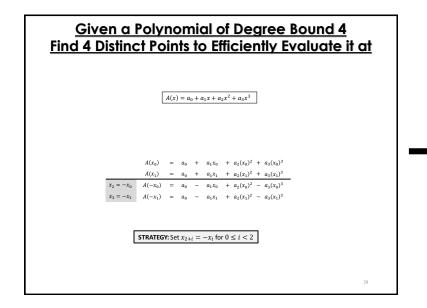


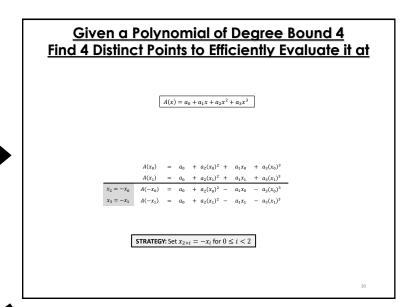


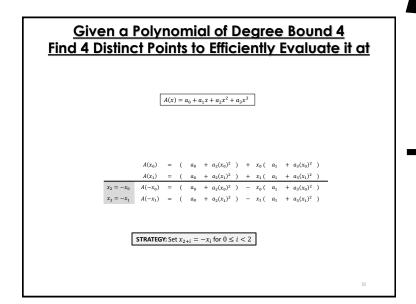
Given a Polynomial of Degree Bound 8 Find 8 Distinct Points to Efficiently Evaluate it at $A(x) = a_0 + a_1x + a_2x^2 + a_3x^3 + a_4x^4 + a_5x^5 + a_6x^6 + a_7x^7$ $A_{even}(x) = a_0 + a_2x + a_4x^2 + a_6x^3$ $A_{odd}(x) = a_1 + a_3x + a_5x^2 + a_7x^3$ $A(x_0)$ $A_{even}(x_0^2)$ $x_0 A_{odd}(x_0^2)$ $A(x_1)$ $A_{even}(x_1^2)$ $x_1 A_{odd}(x_1^2)$ $A(x_2) =$ $A_{even}(x_2^2)$ $x_2 A_{odd}(x_2^2)$ $A_{even}(x_3^2)$ $A(x_2) =$ $x_3 A_{odd}(x_3^2)$ $A(-x_0)$ $A_{even}(x_0^2)$ $x_0 A_{odd}(x_0^2)$ $A_{even}(x_1^2)$ $x_1\,A_{odd}\big(x_1^2\big)$ $A(-x_2) =$ $A_{even}(x_2^2)$ $x_2 A_{odd}(x_2^2)$ $x_7 = -x_3$ $A(-x_3) =$ $A_{even}(x_3^2)$ $x_3\,A_{odd}\big(x_3^2\big)$ **STRATEGY:** Set $x_{4+i} = -x_i$ for $0 \le i < 4$

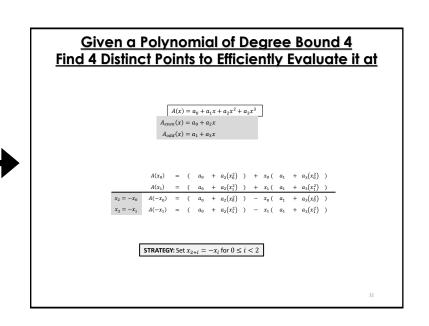


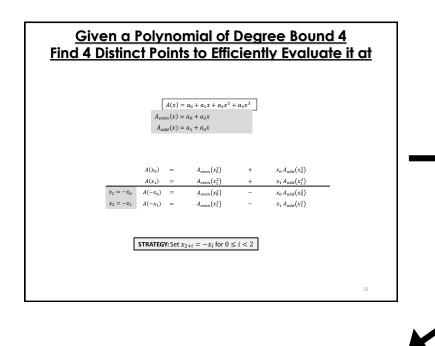


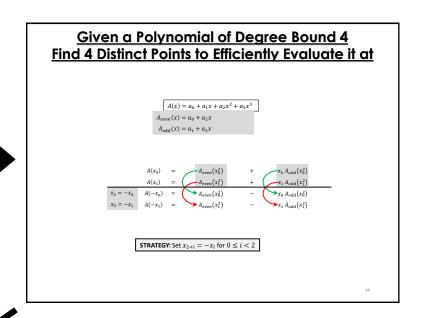


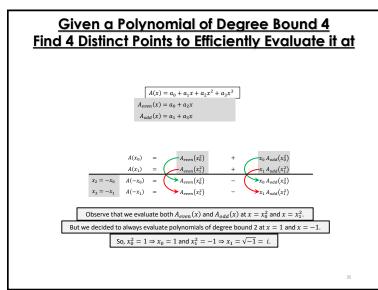


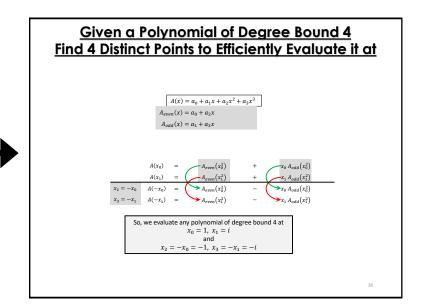


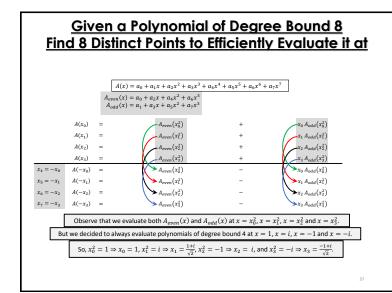


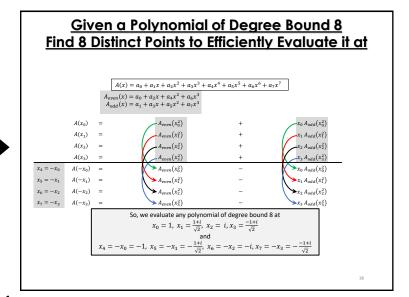












Given a Polynomial of Degree Bound $n = 2^k$ Find $n = 2^k$ Distinct Points to Efficiently Evaluate it at

degree bound	how did we find the points to evaluate the polynomial at?	the points	point property
21		1, -1	all 2 nd roots of unity
22	take positive and negative square roots of points used for degree bound 2 ¹ which are already the 2 nd roots of unity	1, i, -1, -i	all 4 th roots of unity
2^3	take positive and negative square roots of points used for degree bound 2 ² which are already the 4 th roots of unity	1, $\frac{1+i}{\sqrt{2}}$, i , $\frac{-1+i}{\sqrt{2}}$, -1 , $-\frac{1+i}{\sqrt{2}}$, $-i$, $-\frac{-1+i}{\sqrt{2}}$	all 8 th roots of unity
24	take positive and negative square roots of points used for degree bound 2 ³ which are already the 8 th roots of unity	1, $\frac{\sqrt{2+\sqrt{2}}}{2} + i \frac{\sqrt{2-\sqrt{2}}}{2}$,,,,,,,, .	all 16 th roots of unity
2 ^{k-1}	take positive and negative square roots of points used for degree bound 2^{k-2} which are already the 2^{k-2} th roots of unity		all 2^{k-1} th roots of unity
$n = 2^k$	take positive and negative square roots of points used for degree bound 2^{k-1} which are already the 2^{k-1} th roots of unity		all 2^k th roots of unity (i.e., n^{th} roots of unity)

How to Find all nth Roots of Unity

The n^{th} roots of unity are: 1, $\omega_n, (\omega_n)^2, (\omega_n)^3, \dots, (\omega_n)^{n-1}$, where $\omega_n = \cos \frac{2\Pi}{n} + i \sin \frac{2\Pi}{n} = e^{\frac{2\Pi 1}{n}}$ is known as the primitive n^{th} roots of unity.

The result above can be derived using Euler's Formula.

Euler's Formula: For any real number α , $\cos \alpha + i \sin \alpha = e^{i\alpha}$

Euler's formula follows very easily from the following three power series each of which holds for $-\infty < \alpha < +\infty$:

$$\cos \alpha = 1 - \frac{\alpha^2}{2!} + \frac{\alpha^4}{4!} - \frac{\alpha^6}{6!} + \frac{\alpha^8}{8!} - \cdots$$

$$\sin \alpha = \alpha - \frac{\alpha^3}{3!} + \frac{\alpha^5}{5!} - \frac{\alpha^7}{7!} + \frac{\alpha^9}{9!} - \cdots$$

$$e^{\alpha} = 1 + \alpha + \frac{\alpha^2}{2!} + \frac{\alpha^3}{3!} + \frac{\alpha^4}{4!} + \frac{\alpha^5}{5!} + \frac{\alpha^6}{6!} + \frac{\alpha^7}{7!} + \frac{\alpha^8}{8!} + \cdots$$

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How to Find all n^{th} Roots of Unity

Observe that for (any) real numbers α and p,

$$(\cos \alpha + i \sin \alpha)^p = (e^{i\alpha})^p = e^{i(p\alpha)} = \cos(p\alpha) + i \sin(p\alpha)$$

Also observe that for any integer k, $\cos(k \times 2\Pi) + i\sin(k \times 2\Pi) = 1 + i \times 0 = 1$

Then the n^{th} root of 1 (unity) is:

$$1^{\frac{1}{n}} = (\cos(k \times 2\Pi) + i\sin(k \times 2\Pi))^{\frac{1}{n}} = \cos\left(k \times \frac{2\Pi}{n}\right) + i\sin\left(k \times \frac{2\Pi}{n}\right)$$

Observe that $\cos\left(k \times \frac{2\Pi}{n}\right) + i\sin\left(k \times \frac{2\Pi}{n}\right)$ takes n distinct values for $0 \le k < n$, and then simply repeats those values for k < 0 and $k \ge n$.

When
$$k=1$$
, we have: $\cos\left(k\times\frac{2\Pi}{n}\right)+i\sin\left(k\times\frac{2\Pi}{n}\right)=\cos\left(\frac{2\Pi}{n}\right)+i\sin\left(\frac{2\Pi}{n}\right)$
$$=\omega_n=\text{primitive }n^{\text{th}}\text{ root of }1.$$

Clearly, for any
$$k$$
, $\cos\left(k \times \frac{2\Pi}{n}\right) + i\sin\left(k \times \frac{2\Pi}{n}\right) = \left(\cos\left(\frac{2\Pi}{n}\right) + i\sin\left(\frac{2\Pi}{n}\right)\right)^k = (\omega_n)^k$

Hence,
$$1^{\frac{1}{n}} = \cos\left(k \times \frac{2\Pi}{n}\right) + i\sin\left(k \times \frac{2\Pi}{n}\right) = (\omega_n)^k$$
, for $k = 0, 1, 2, \dots, n-1$.

In other words, the n^{th} roots of 1 (unity) are: 1, ω_n , $(\omega_n)^2$, $(\omega_n)^3$,, $(\omega_n)^{n-1}$

Coefficient Form ⇒ Point-Value Form

For a polynomial of degree bound $n=2^k$, we need to apply the trick recursively at most $\log n=k$ times.

We choose $x_0 = 1 = \omega_n^0$ and set $x_j = \omega_n^j$ for $1 \le j \le n - 1$.

Then we compute the following product:

$$\begin{bmatrix} y_0 \\ y_1 \\ y_2 \\ \vdots \\ y_{n-1} \end{bmatrix} = \begin{bmatrix} A(1) \\ A(\omega_n) \\ A(\omega_n^2) \\ \vdots \\ A(\omega_n^{n-1}) \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 & \cdots & 1 \\ 1 & \omega_n & (\omega_n)^2 & \cdots & (\omega_n)^{n-1} \\ 1 & \omega_n^2 & (\omega_n^2)^2 & \cdots & (\omega_n^2)^{n-1} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ 1 & \omega_n^{n-1} & (\omega_n^{n-1})^2 & \cdots & (\omega_n^{n-1})^{n-1} \end{bmatrix} \begin{bmatrix} a_0 \\ a_1 \\ a_2 \\ \vdots \\ a_{n-1} \end{bmatrix}$$

The vector $y = (y_0, y_1, \dots, y_{n-1})$ is called the *discrete Fourier transform* (DFT) of $(a_0, a_1, \dots, a_{n-1})$.

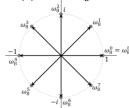
This method of computing DFT is called the *fast Fourier transform* (FFT) method. 42

Coefficient Form ⇒ Point-Value Form

Example: For $n = 2^3 = 8$:

$$A(x) = a_0 + a_1 x + a_2 x^2 + a_3 x^3 + a_4 x^4 + a_5 x^5 + a_6 x^6 + a_7 x^7$$

We need to evaluate A(x) at $x = \omega_8^i$ for $0 \le i < 8$.



complex 8^{th} roots of unity

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Now
$$A(x) = A_{even}(x^2) + x \cdot A_{odd}(x^2)$$

where
$$A_{even}(y) = a_0 + a_2 y + a_4 y^2 + a_6 y^3$$

and
$$A_{odd}(y) = a_1 + a_3 y + a_5 y^2 + a_7 y^3$$

Coefficient Form ⇒ Point-Value Form

Observe that:





 $\omega_8^4 = -\omega_8^0$ $\omega_8^5 = -\omega_8^1$ $\omega_8^6 = -\omega_8^2$

$$A(\omega_8^0) = A_{even}(\omega_8^0) + \omega_8^0 \cdot A_{odd}(\omega_8^0) = A_{even}(\omega_4^0) + \omega_8^0 \cdot A_{odd}(\omega_4^0),$$

$$A\left(\omega_8^1\right) \ = A_{even}\left(\omega_8^2\right) + \omega_8^1 \cdot A_{odd}\left(\omega_8^2\right) \quad = A_{even}\left(\omega_4^1\right) + \omega_8^1 \cdot A_{odd}\left(\omega_4^1\right),$$

$$A(\omega_8^2) = A_{even}(\omega_8^4) + \omega_8^2 \cdot A_{odd}(\omega_8^4) = A_{even}(\omega_4^2) + \omega_8^2 \cdot A_{odd}(\omega_4^2),$$

$$A(\omega_8^3) = A_{even}(\omega_8^6) + \omega_8^3 \cdot A_{odd}(\omega_8^6) = A_{even}(\omega_4^3) + \omega_8^3 \cdot A_{odd}(\omega_4^3),$$

$$A\left(\omega_8^4\right) \ = A_{even}\left(\omega_8^8\right) + \omega_8^4 \cdot A_{odd}\left(\omega_8^8\right) \quad = A_{even}\left(\omega_4^0\right) - \omega_8^0 \cdot A_{odd}\left(\omega_4^0\right),$$

$$A(\omega_8^5) = A_{even}(\omega_8^{10}) + \omega_8^5 \cdot A_{odd}(\omega_8^{10}) = A_{even}(\omega_4^1) - \omega_8^1 \cdot A_{odd}(\omega_4^1),$$

$$A(\omega_{8}^{6}) = A_{even}(\omega_{8}^{12}) + \omega_{8}^{6} \cdot A_{odd}(\omega_{8}^{12}) = A_{even}(\omega_{4}^{2}) - \omega_{8}^{2} \cdot A_{odd}(\omega_{4}^{2}),$$

$$A(\omega_8^7) = A_{even}(\omega_8^{14}) + \omega_8^7 \cdot A_{odd}(\omega_8^{14}) = A_{even}(\omega_4^3) - \omega_8^3 \cdot A_{odd}(\omega_4^3),$$

Coefficient Form ⇒ Point-Value Form

Rec-FFT ($(a_0, a_1, ..., a_{n-1})$) { $n = 2^k$ for integer $k \ge 0$ }

1. if n = 1 then

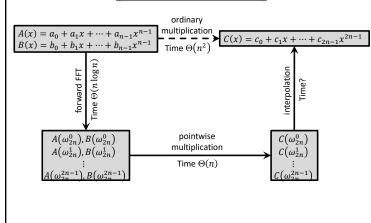
2. return (a_0) 3. $\omega_h \leftarrow e^{2\pi i/n}$ 4. $\omega \leftarrow 1$ 5. $y^{even} \leftarrow Rec-FFT ((a_0, a_2, ..., a_{n-2}))$ 6. $y^{odd} \leftarrow Rec-FFT ((a_1, a_2, ..., a_{n-1}))$ 7. $for \ j \leftarrow 0 \ to \ n/2 - 1 \ do$ 8. $y_j \leftarrow y_j^{even} + \omega y_j^{odd}$ 9. $y_{n/2-j} \leftarrow y_j^{even} - \omega y_j^{odd}$ 10. $\omega \leftarrow \omega \omega_h$

Running time:

$$T(n) = \begin{cases} \Theta(1), & \text{if } n = 1, \\ 2T\left(\frac{n}{2}\right) + \Theta(n), & \text{otherwise.} \end{cases}$$
$$= \Theta(n \log n)$$

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<u>Faster Polynomial Multiplication?</u> (in Coefficient Form)



Point-Value Form ⇒ Coefficient Form

Given: $\begin{bmatrix} 1 & 1 & 1 & \cdots & 1 \\ 1 & \omega_n & (\omega_n)^2 & \cdots & (\omega_n)^{n-1} \\ 1 & \omega_n^2 & (\omega_n^2)^2 & \cdots & (\omega_n^2)^{n-1} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ 1 & \omega_n^{n-1} & (\omega_n^{n-1})^2 & \cdots & (\omega_n^{n-1})^{n-1} \end{bmatrix} \begin{bmatrix} a_0 \\ a_1 \\ a_2 \\ \vdots \\ a_{n-1} \end{bmatrix} = \begin{bmatrix} y_0 \\ y_1 \\ y_2 \\ \vdots \\ y_{n-1} \end{bmatrix}$

$$\Rightarrow V(\omega_n) \cdot \bar{a} = \bar{y}$$

We want to solve: $\bar{a} = [V(\omega_n)]^{-1} \cdot \bar{y}$

It turns out that: $[V(\omega_n)]^{-1} = \frac{1}{n}V\left(\frac{1}{\omega_n}\right)$

That means $[V(\omega_n)]^{-1}$ looks almost similar to $V(\omega_n)!$

<u>Point-Value Form</u> ⇒ <u>Coefficient Form</u>

Show that: $[V(\omega_n)]^{-1} = \frac{1}{n}V\left(\frac{1}{\omega_n}\right)$ Let $U(\omega_n) = \frac{1}{n}V\left(\frac{1}{\omega_n}\right)$

We want to show that $U(\omega_n)V(\omega_n)=I_n$,

where I_n is the $n \times n$ identity matrix.

Observe that for $0 \le j, k \le n-1$, the $(j,k)^{th}$ entries are:

$$[V(\omega_n)]_{jk} = \omega_n^{jk}$$
 and $[U(\omega_n)]_{jk} = \frac{1}{n}\omega_n^{-jk}$

Then entry (p,q) of $U(\omega_n)V(\omega_n)$,

$$[U(\omega_n)V(\omega_n)]_{pq} = \sum_{k=0}^{n-1} [U(\omega_n)]_{pk} [V(\omega_n)]_{kq} = \frac{1}{n} \sum_{k=0}^{n-1} \omega_n^{k(q-p)}$$

Point-Value Form ⇒ Coefficient Form

$$[U(\omega_n)V(\omega_n)]_{pq} = \frac{1}{n} \sum_{k=0}^{n-1} \omega_n^{k(q-p)}$$

CASE p = q:

$$[U(\omega_n)V(\omega_n)]_{pq} = \frac{1}{n} \sum_{k=0}^{n-1} \omega_n^0 = \frac{1}{n} \sum_{k=0}^{n-1} 1 = \frac{1}{n} \times n = 1$$

CASE $p \neq q$:

$$[U(\omega_n)V(\omega_n)]_{pq} = \frac{1}{n} \sum_{k=0}^{n-1} (\omega_n^{q-p})^k = \frac{1}{n} \times \frac{(\omega_n^{q-p})^n - 1}{\omega_n^{q-p} - 1}$$
$$= \frac{1}{n} \times \frac{(\omega_n^n)^{q-p} - 1}{\omega_n^{q-p} - 1} = \frac{1}{n} \times \frac{(1)^{q-p} - 1}{\omega_n^{q-p} - 1} = 0$$

Hence $U(\omega_n)V(\omega_n)=I_n$

Point-Value Form ⇒ Coefficient Form

We need to compute the following matrix-vector product:

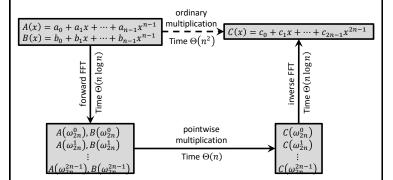
$$\begin{bmatrix} a_0 \\ a_1 \\ a_2 \\ \vdots \\ a_{n-1} \\ \bar{a} \end{bmatrix} = \frac{1}{n} \times \begin{bmatrix} 1 & 1 & 1 & \cdots & 1 \\ 1 & \frac{1}{\omega_n} & \left(\frac{1}{\omega_n}\right)^2 & \cdots & \left(\frac{1}{\omega_n}\right)^{n-1} \\ 1 & \frac{1}{\omega_n^2} & \left(\frac{1}{\omega_n^2}\right)^2 & \cdots & \left(\frac{1}{\omega_n^2}\right)^{n-1} \\ \vdots & \vdots & \ddots & \ddots & \ddots \\ 1 & \frac{1}{\omega_n^{n-1}} & \left(\frac{1}{\omega_n^{n-1}}\right)^2 & \cdots & \left(\frac{1}{\omega_n^{n-1}}\right)^{n-1} \end{bmatrix} \underbrace{ \begin{bmatrix} y_0 \\ y_1 \\ y_2 \\ \vdots \\ y_{n-1} \\ \bar{y} \end{bmatrix} }_{\bar{y}}$$

This inverse problem is almost similar to the forward problem, and can be solved in $\Theta(n \log n)$ time using the same algorithm as the forward FFT with only minor modifications!



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<u>Faster Polynomial Multiplication?</u> (<u>in Coefficient Form</u>)



Two polynomials of degree bound n given in the coefficient form can be multiplied in $\Theta(n \log n)$ time!

Some Applications of Fourier Transform and FFT

- Signal processing
- Image processing
- Noise reduction
- Data compression
- Solving partial differential equation
- Multiplication of large integers
- · Polynomial multiplication
- · Molecular docking

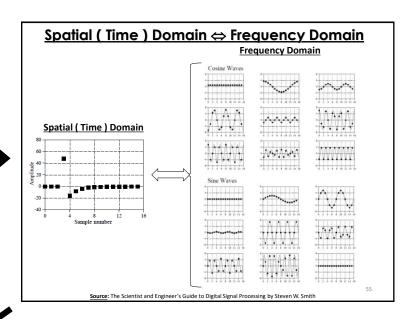
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Some Applications of Fourier Transform and FFT



Any periodic signal can be represented as a sum of a series of sinusoidal (sine & cosine) waves. [1807]

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Spatial (Time) Domain ⇔ Frequency Domain



Function s(x) (in red) is a sum of six sine functions of different amplitudes and harmonically related frequencies. The Fourier transform, S(f) (in blue), which depicts amplitude vs frequency, reveals the 6 frequencies and their amplitudes.

Source: http://en.wikipedia.org/wiki/Fourier_series#mediaviewer/File:Fourier_series and transform.gif (uploaded by Bob K.)

Spatial (Time) Domain ⇔ Frequency Domain

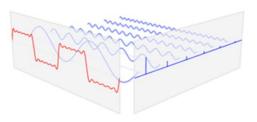


 $a_n \cos(nx) + b_n \sin(nx)$

Function s(x) (in red) is a sum of six sine functions of different amplitudes and harmonically related frequencies. The Fourier transform, S(f) (in blue), which depicts amplitude vs frequency, reveals the 6 frequencies and their amplitudes.

Source: http://en.wikipedia.org/wiki/Fourier_series#mediaviewer/File:Fourier_series_and_transform.gif (uploaded by Bob K.) 59





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Source: http://en.wikipedia.org/wiki/Fourier_series#mediaviewer/File:Fourier_series_and_transform.gif (uploaded by Bob K.)

Spatial (Time) Domain ⇔ Frequency Domain



S(f)

Function s(x) (in red) is a sum of six sine functions of different amplitudes and harmonically related frequencies. The Fourier transform, S(f) (in blue), which depicts amplitude vs frequency, reveals the 6 frequencies and their amplitudes.

Source: http://en.wikipedia.org/wiki/Fourier_series#mediaviewer/File:Fourier_series_and_transform.gif (uploaded by Bob K.) 61

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<u>Spatial (Time) Domain ⇔ Frequency Domain</u>



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<u>Spatial (Time) Domain ⇔ Frequency Domain</u> (<u>Fourier Transforms)</u>

Let $\boldsymbol{s}(t)$ be a signal specified in the time domain.

The strength of s(t) at frequency f is given by:

$$S(f) = \int_{-\infty}^{\infty} s(t) \cdot e^{-2\pi i f t} dt$$

Evaluating this integral for all values of f gives the frequency domain function.

Now s(t) can be retrieved by summing up the signal strengths at all possible frequencies:

$$s(t) = \int_{-\infty}^{\infty} S(f) \cdot e^{2\pi i f t} \, df$$

3

Why do the Transforms Work?

Let's try to get a little intuition behind why the transforms work. We will look at a very simple example.

Suppose: $s(t) = \cos(2\pi h \cdot t)$

$$\frac{1}{T} \int_{-T}^{T} s(t) \cdot e^{-2\pi i f t} dt = \begin{cases} 1 + \frac{\sin(4\pi f T)}{4\pi f T}, & \text{if } f = h, \\ \frac{\sin(2\pi (h - f)T)}{2\pi (h - f)T} + \frac{\sin(2\pi (h + f)T)}{2\pi (h + f)T}, & \text{otherwise.} \end{cases}$$

$$\Rightarrow \lim_{T \to \infty} \left(\frac{1}{T} \int_{-T}^{T} s(t) \cdot e^{-2\pi i f t} dt \right) = \begin{cases} 1, & \text{if } f = h, \\ 0, & \text{otherwise.} \end{cases}$$

So, the transform can detect if f = h!

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Noise Reduction















Source: http://www.mediacy.com/index.aspx?page=AH_FFTExample

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Data Compression

- Discrete Cosine Transforms (DCT) are used for lossy data compression (e.g., MP3, JPEG, MPEG)
- DCT is a Fourier-related transform similar to DFT (Discrete Fourier Transform) but uses only real data (uses cosine waves only instead of both cosine and sine waves)
- Forward DCT transforms data from spatial to frequency domain
- Each frequency component is represented using a fewer number of bits (i.e., truncated / quantized)
- Low amplitude high frequency components are also removed
- Inverse DCT then transforms the data back to spatial domain
- The resulting image compresses better



<u>Data Compression</u>

Transformation to frequency domain using cosine transforms work in the same way as the Fourier transform.

Suppose: $s(t) = \cos(2\pi h \cdot t)$

$$\frac{1}{T} \int_{-T}^{T} s(t) \cdot \cos(2\pi f t) dt = \begin{cases} 1 + \frac{\sin(4\pi f T)}{4\pi f T}, & \text{if } f = h, \\ \\ \frac{\sin(2\pi (h - f)T)}{2\pi (h - f)T} + \frac{\sin(2\pi (h + f)T)}{2\pi (h + f)T}, & \text{otherwise.} \end{cases}$$

$$\Rightarrow \lim_{T \to \infty} \left(\frac{1}{T} \int_{-T}^{T} s(t) \cdot \cos(2\pi f t) \, dt \right) = \begin{cases} 1, & \text{if } f = h, \\ 0, & \text{otherwise} \end{cases}$$

So, this transform can also detect if f = h.

can also detect if j = n.

Protein-Protein Docking

- ☐ Knowledge of complexes is used in
 - Drug design Structure function analysis
 - Studying molecular assemblies Protein interactions
- ☐ Protein-Protein Docking: Given two proteins, find the best relative transformation and conformations to obtain a stable complex.

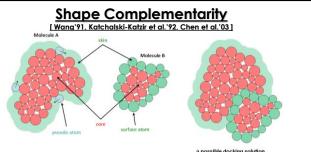








- ☐ Docking is a hard problem
 - Search space is huge (6D for rigid proteins)
 - Protein flexibility adds to the difficulty



To maximize skin-skin overlaps and minimize core-core overlaps

- assign positive real weights to skin atoms
- assign positive imaginary weights to core atoms

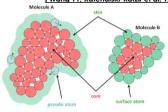
Let A' denote molecule A with the pseudo skin atoms.

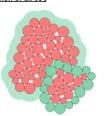
For $P \in \{A', B\}$ with M_P atoms, affinity function: $f_P(x) = \sum_{k=1}^{M_P} w_k \cdot g_k(x)$

Here $g_k(x)$ is a Gaussian representation of atom k, and w_k its weight.



Shape Complementarity [Wang'91, Katchalski-Katzir et al.'92, Chen et al.'03]





Let A' denote molecule A with the pseudo skin atoms.

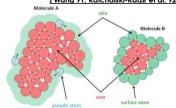
For $P \in \{A', B\}$ with M_P atoms, affinity function:

$$f_P(x) = \sum_{k=1}^{M_P} w_k \cdot g_k(x)$$

For rotation r and translation t of molecule B (i.e., $B_{t,r}$),

the interaction score, $F_{A,B}(t,r) = \int_{x}^{\infty} f_{A'}(x) f_{B_{t,r}}(x) dx$

Shape Complementarity [Wang'91, Katchalski-Katzir et al.'92, Chen et al.'03]





For rotation r and translation t of molecule B (i.e., $B_{t,r}$),

the interaction score, $F_{A,B}(t,r) = \int_{x} f_{A'}(x) f_{B_{t,r}}(x) dx$

 $Re(F_{A,B}(t,r))$ = skin-skin overlap score – core-core overlap score

 $Im(F_{A,B}(t,r)) =$ skin-core overlap score

