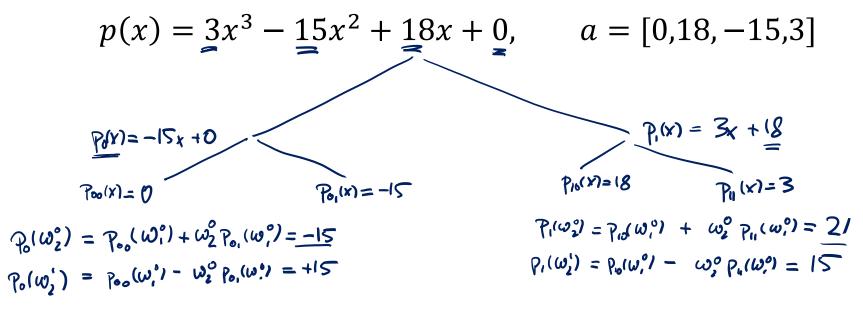
Example





$$\begin{aligned} P(W_{y}^{\circ}) &= P_{0}(W_{2}^{\circ}) + W_{y}^{\circ} P_{1}(W_{2}^{\circ}) = -15 + 21 = 6 \\ P(W_{y}^{\circ}) &= P_{0}(W_{2}^{\circ}) + W_{y}^{\prime} P_{1}(W_{2}^{\circ}) = \pm 15 + 105 \\ P(W_{y}^{\circ}) &= P_{0}(W_{2}^{\circ}) - W_{y}^{\circ} P_{1}(W_{2}^{\circ}) = -15 - 21 = \pm 36 \\ P(W_{y}^{\circ}) &= P_{0}(W_{2}^{\circ}) - W_{y}^{\circ} P_{1}(W_{2}^{\circ}) = -15 - 21 = \pm 36 \\ P(W_{y}^{\circ}) &= P_{0}(W_{2}^{\circ}) - W_{y}^{\circ} P_{1}(W_{2}^{\circ}) = -15 - 21 = \pm 36 \\ P(W_{y}^{\circ}) &= P_{0}(W_{2}^{\circ}) - W_{y}^{\circ} P_{1}(W_{2}^{\circ}) = -15 - 21 = \pm 36 \\ P(W_{y}^{\circ}) &= P_{0}(W_{2}^{\circ}) - W_{y}^{\circ} P_{1}(W_{2}^{\circ}) = -15 - 21 = \pm 36 \\ P(W_{y}^{\circ}) &= P_{0}(W_{2}^{\circ}) - W_{y}^{\circ} P_{1}(W_{2}^{\circ}) = -15 - 21 = \pm 36 \\ P(W_{y}^{\circ}) &= P_{0}(W_{2}^{\circ}) - W_{y}^{\circ} P_{1}(W_{2}^{\circ}) = -15 - 21 = \pm 36 \\ P(W_{y}^{\circ}) &= P_{0}(W_{2}^{\circ}) - W_{y}^{\circ} P_{1}(W_{2}^{\circ}) = -15 - 21 = \pm 36 \\ P(W_{y}^{\circ}) &= P_{0}(W_{2}^{\circ}) - W_{y}^{\circ} P_{1}(W_{2}^{\circ}) = -15 - 21 = \pm 36 \\ P(W_{y}^{\circ}) &= P_{0}(W_{2}^{\circ}) - W_{y}^{\circ} P_{1}(W_{2}^{\circ}) = -15 - 21 = \pm 36 \\ P(W_{y}^{\circ}) &= P_{0}(W_{2}^{\circ}) - W_{y}^{\circ} P_{1}(W_{2}^{\circ}) = -15 - 21 = \pm 36 \\ P(W_{y}^{\circ}) &= P_{0}(W_{2}^{\circ}) - W_{y}^{\circ} P_{1}(W_{2}^{\circ}) = -15 - 21 = \pm 36 \\ P(W_{y}^{\circ}) &= P_{0}(W_{2}^{\circ}) - W_{y}^{\circ} P_{1}(W_{2}^{\circ}) = -15 - 21 = \pm 36 \\ P(W_{y}^{\circ}) &= P_{0}(W_{2}^{\circ}) - W_{y}^{\circ} P_{1}(W_{2}^{\circ}) = -15 - 21 = \pm 36 \\ P(W_{y}^{\circ}) = P_{0}(W_{2}^{\circ}) - W_{y}^{\circ} P_{1}(W_{2}^{\circ}) = -15 - 21 = \pm 36 \\ P(W_{y}^{\circ}) = P_{0}(W_{2}^{\circ}) - W_{y}^{\circ} P_{1}(W_{2}^{\circ}) = -15 - 21 = \pm 36 \\ P(W_{y}^{\circ}) = P_{0}(W_{2}^{\circ}) = -15 - 21 = \pm 36 \\ P(W_{y}^{\circ}) = P_{0}(W_{2}^{\circ}) = -15 - 21 = \pm 36 \\ P(W_{y}^{\circ}) = P_{0}(W_{2}^{\circ}) = -15 - 21 = \pm 36 \\ P(W_{y}^{\circ}) = P_{0}(W_{2}^{\circ}) = -15 - 21 = \pm 36 \\ P(W_{y}^{\circ}) = -15 - 21 = \pm 36 \\ P(W_{y}^{\circ}) = -15 - 21 = \pm 36 \\ P(W_{y}^{\circ}) = -15 - 21 = \pm 36 \\ P(W_{y}^{\circ}) = -15 - 21 = \pm 36 \\ P(W_{y}^{\circ}) = -15 - 21 = \pm 36 \\ P(W_{y}^{\circ}) = -15 - 21 = \pm 36 \\ P(W_{y}^{\circ}) = -15 - 21 = \pm 36 \\ P(W_{y}^{\circ}) = -15 - 21 = \pm 36 \\ P(W_{y}^{\circ}) = -15 - 21 = \pm 36 \\ P(W_{y}^{\circ}) = -15 - 21 = \pm 36 \\ P(W_{y}^{\circ}) = -15 - 21 = \pm 36 \\ P(W_{$$

Faster Polynomial Multiplication?



Idea to compute $p(x) \cdot q(x)$ (for polynomials of degree < n):



Evaluation at $\omega_{2n}^0, \omega_{2n}^1, \dots, \omega_{2n}^{2n-1}$ using **FFT** O(ngr)

2 × 2*n* point-value pairs $(\omega_{2n}^k, p(\omega_{2n}^k))$ and $(\omega_{2n}^k, q(\omega_{2n}^k))$

Point-wise multiplication

0(n)

2n point-value pairs $\left(\omega_{2n}^k, p(\omega_{2n}^k)q(\omega_{2n}^k)\right)$

Interpolation

p(x)q(x) of degree 2n - 2, 2n - 1 coefficients

Interpolation



Convert point-value representation into coefficient representation $\begin{cases} x_1, \dots, x_n, y_n \\ y_n, \dots, (x_{n-1}, y_{n-1}) \end{cases}$ with $x_i \neq x_j$ for $i \neq j$

Output:

Degree-(n-1) polynomial with coefficients a_0, \dots, a_{n-1} such that

$$\begin{array}{l} p(x_0) &= a_0 + a_1 x_0 &+ a_2 x_0^2 &+ \dots + a_{n-1} x_0^{n-1} = y_0 \\ p(x_1) &= a_0 + a_1 x_1 &+ a_2 x_1^2 &+ \dots + a_{n-1} x_1^{n-1} = y_1 \\ \vdots && \vdots \\ p(x_{n-1}) = a_0 + a_1 x_{n-1} + a_2 x_{n-1}^2 + \dots + a_{n-1} x_{n-1}^{n-1} = y_{n-1} \end{array}$$

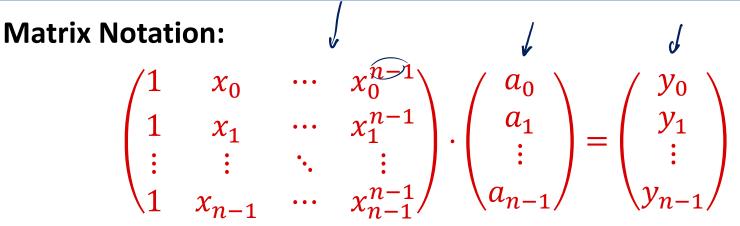
 \rightarrow linear system of equations for a_0, \dots, a_{n-1}

Algorithm Theory, WS 2016/17

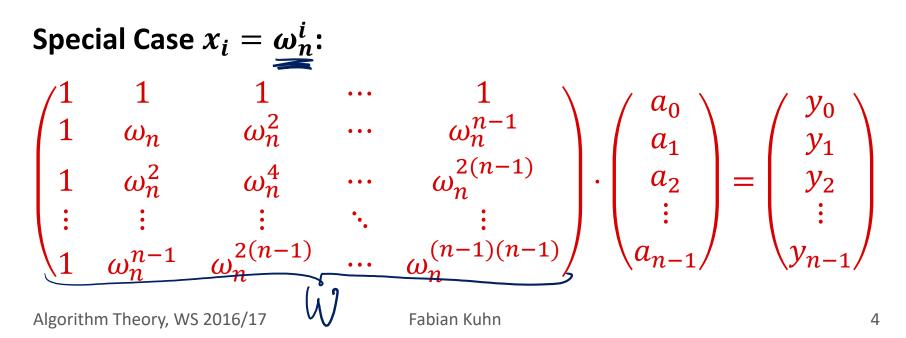
Fabian Kuhn

Interpolation





• System of equations solvable iff $x_i \neq x_j$ for all $i \neq j$



Interpolation



• Linear system:

$$\underbrace{W \cdot a = y}_{W_{i,j} = \omega_n^{ij}} \Rightarrow \underbrace{a = W^{-1} \cdot y}_{a_{n-1}}$$

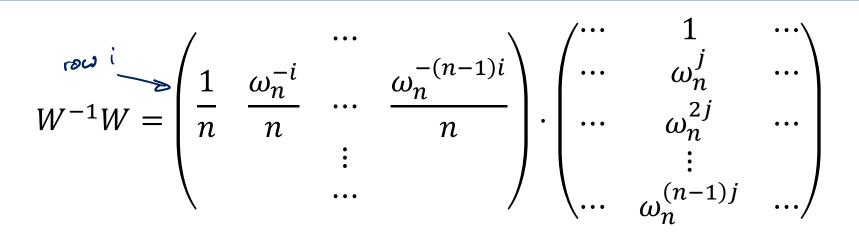
$$\underbrace{W_{i,j} = \omega_n^{ij}}_{a_{n-1}} = a = \begin{pmatrix} a_0 \\ \vdots \\ a_{n-1} \end{pmatrix}, \quad y = \begin{pmatrix} y_0 \\ \vdots \\ y_{n-1} \end{pmatrix}$$

Claim:

$$W_{ij}^{-1} = \frac{\omega_n^{-ij}}{\underline{n}}$$

Proof: Need to show that $W^{-1}W = I_n$

DFT Matrix Inverse



 $\omega_{i} = \frac{\omega_{i}}{n}$

 $(\mathcal{Y}_{i}) = \omega'_{u}$

$$\left(\boldsymbol{\boldsymbol{\mathcal{W}}}^{-1}\boldsymbol{\boldsymbol{\mathcal{W}}}\right)_{i,j} = \frac{1}{n} \cdot \sum_{\boldsymbol{\boldsymbol{\mathcal{R}}}=0}^{n-1} \boldsymbol{\boldsymbol{\omega}}_{n}^{-i,\boldsymbol{\boldsymbol{\mathcal{C}}}} \cdot \boldsymbol{\boldsymbol{\omega}}_{n}^{j\boldsymbol{\boldsymbol{\mathcal{R}}}} = \frac{1}{n} \sum_{\boldsymbol{\boldsymbol{\mathcal{R}}}=0}^{n-1} \boldsymbol{\boldsymbol{\omega}}_{n}^{\boldsymbol{\boldsymbol{\mathcal{C}}}(j-i)}$$

DFT Matrix Inverse

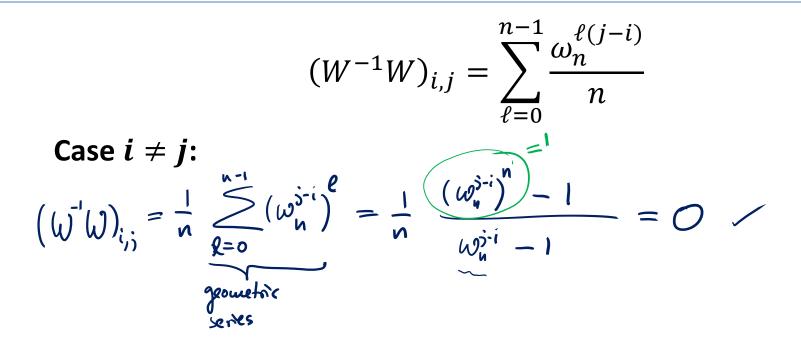


$$(W^{-1}W)_{i,j} = \sum_{\ell=0}^{n-1} \frac{\omega_n^{\ell(j-i)}}{n}$$

Need to show $(W^{-1}W)_{i,j} = \begin{cases} 1 & \text{if } i = j \\ 0 & \text{if } i \neq j \end{cases}$
Case $i = j$:
 $(\omega^{-1}\omega)_{i,i} = \frac{1}{N} \sum_{\ell=0}^{n-1} \frac{\omega_n^{\ell-0}}{1} = l$

DFT Matrix Inverse





 $\sum_{q=0}^{n-1} q^{q} = \frac{q^{n-1}}{q-1}$

Inverse DFT



•
$$W^{-1} = \begin{pmatrix} \frac{1}{n} & \frac{\omega_n^{-k}}{n} & \dots & \frac{\omega_n^{-(n-1)k}}{n} \\ & \vdots & & \ddots \end{pmatrix} \qquad \begin{pmatrix} (\omega_j^{-1}) = \frac{\omega_n^{-ij}}{n} \\ & \vdots & & \ddots \end{pmatrix}$$

• We get $\underline{\underline{a}} = \underline{W^{-1}} \cdot \underline{\underline{y}}$ and therefore

$$a_{k} = \begin{pmatrix} \frac{1}{n} & \frac{\omega_{n}^{-k}}{n} & \dots & \frac{\omega_{n}^{-(n-1)k}}{n} \end{pmatrix} \cdot \begin{pmatrix} y_{0} \\ y_{1} \\ \vdots \\ y_{n-1} \end{pmatrix}$$

$$=\frac{1}{n}\cdot\sum_{j=0}^{n-1}\omega_n^{-kj}\cdot y_j$$

DFT and Inverse DFT



 $a_{k} = \frac{1}{n} \cdot \sum_{j=0}^{n-1} (\omega_{n}^{-kj} \cdot y_{j})$ (x) = -Z= Wik

Define polynomial $q(x) = y_0 + y_1x + \dots + y_{n-1}x^{n-1}$: •

DFT:

Inverse DFT:

Polynomial $p(x) = a_0 + a_1x + \dots + a_{n-1}x^{n-1}$:

$$y_k = p(\omega_n^k)$$

DFT and Inverse DFT



$$q(x) = y_0 + y_1 x + \dots + y_{n-1} x^{n-1}, \qquad a_k = \frac{1}{n} \cdot q(\omega_n^{-k}):$$

• Therefore:

$$(\underbrace{a_0, a_1, \dots, a_{n-1}}) = \frac{1}{\underline{n}} \cdot \left(q(\omega_n^{-0}), q(\omega_n^{-1}), q(\omega_n^{-2}), \dots, q(\omega_n^{-(n-1)}) \right)$$
$$= \frac{1}{\underline{n}} \cdot \left(q(\omega_n^{0}), q(\omega_n^{n-1}), q(\omega_n^{n-2}), \dots, q(\omega_n^{1}) \right)$$

• Recall:

$$\underline{\text{DFT}_n(\boldsymbol{y})} = \left(\underline{q(\omega_n^0), q(\omega_n^1), q(\omega_n^2), \dots, q(\omega_n^{n-1})}\right)$$
$$= \underbrace{n \cdot (a_0, a_{n-1}, a_{n-2}, \dots, a_2, a_1)}_{\boldsymbol{z}}$$

DFT and Inverse DFT



• We have $DFT_n(y) = n \cdot (a_0, a_{n-1}, a_{n-2}, ..., a_2, a_1)$:

$$a_{i} = \begin{cases} \frac{1}{n} \cdot (\mathrm{DFT}_{n}(\boldsymbol{y}))_{0} & \text{if } i = 0\\ \frac{1}{n} \cdot (\mathrm{DFT}_{n}(\boldsymbol{y}))_{n-i} & \text{if } i \neq 0 \end{cases}$$

- DFT and inverse DFT can both be computed using FFT algorithm in O(n log n) time.
- 2 polynomials of degr. < n can be multiplied in time $O(n \log n)$.

Faster Polynomial Multiplication?



Idea to compute $p(x) \cdot q(x)$ (for polynomials of degree < n):

p, q of degree n - 1, n coefficients

Evaluation at $\omega_{2n}^0, \omega_{2n}^1, \dots, \omega_{2n}^{2n-1}$ using **FFT**

2 × 2*n* point-value pairs $(\omega_{2n}^k, p(\omega_{2n}^k))$ and $(\omega_{2n}^k, q(\omega_{2n}^k))$

Point-wise multiplication

2n point-value pairs $\left(\omega_{2n}^k, p(\omega_{2n}^k)q(\omega_{2n}^k)
ight)$

Interpolation using FFT

p(x)q(x) of degree 2n - 2, 2n - 1 coefficients

O(ulogn loglyn)

Algorithm Theory, WS 2016/17

Convolution



• More generally, the polynomial multiplication algorithm computes the convolution of two vectors:

$$a = (a_0, a_1, \dots, a_{m-1})$$

 $b = (b_0, b_1, \dots, b_{n-1})$

$$\boldsymbol{a} * \boldsymbol{b} = (\underbrace{c_0, c_1, \dots, c_{m+n-2}}_{\text{where } c_k} = \sum_{\substack{(i,j): i+j=k \\ i < m, j < n}} a_i b_j$$

 c_k is exactly the coefficient of x^k in the product polynomial of the polynomials defined by the coefficient vectors a and b

More Applications of Convolutions



Signal Processing Example:

- Assume *a* = (*a*₀, ..., *a*_{n-1}) represents a sequence of measurements over time
- Measurements might be noisy and have to be smoothed out
- Replace a_i by weighted average of nearby last m and next m measurements (e.g., Gaussian smoothing):

- New vector \boldsymbol{a}' is the convolution of \boldsymbol{a} and the weight vector $\frac{1}{Z} \cdot \left(e^{-m^2}, e^{-(m-1)^2}, \dots, e^{-1}, 1, e^{-1}, \dots, e^{-(m-1)^2}, e^{-m^2}\right)$
- Might need to take care of boundary points...

More Applications of Convolutions



a, a,

Combining Histograms:

- Vectors *a* and *b* represent two histograms
- E.g., annual income of all men & annual income of all women
- Goal: Get new histogram *c* representing combined income of all possible pairs of men and women:

$$c = a * b$$

Also, the DFT (and thus the FFT alg.) has many other applications!

DFT in Signal Processing $e^{i\varphi} = \cos(\varphi) + i\sin(\varphi)$



Assume that y(0), y(1), y(2), ..., y(T-1) are measurements of a time-dependent signal.

- <u>Converts signal</u> from time domain to frequency domain
- Signal can then be edited in the frequency domain
 - e.g., setting some $c_k = 0$ filters out some frequencies