## Efficient multiplication



## Matrix multiplication

## If you have square matrices A and B ,

 then $\mathrm{C}=\mathrm{A} * \mathrm{~B}$ is defined as:$$
c_{i, j}=\sum_{k=0}^{n} a_{i, k} \cdot b_{k, j}
$$

$$
\text { For } \mathbf{A}=\left[\begin{array}{ll}
1 & 0 \\
2 & 1
\end{array}\right] \text { and } \mathbf{B}=\left[\begin{array}{cc}
5 & 4 \\
-5 & 1
\end{array}\right]
$$

$$
\mathbf{A B}=\left[\begin{array}{ll}
1 & 0 \\
2 & 1
\end{array}\right]\left[\begin{array}{cc}
5 & 4 \\
-5 & 1
\end{array}\right]=\left[\begin{array}{ll}
5 & 4 \\
5 & 9
\end{array}\right]
$$

$$
\mathbf{B A}=\left[\begin{array}{cc}
5 & 4 \\
-5 & 1
\end{array}\right]\left[\begin{array}{ll}
1 & 0 \\
2 & 1
\end{array}\right]=\left[\begin{array}{cc}
13 & 4 \\
-3 & 1
\end{array}\right]
$$

## Takes $\mathrm{O}\left(\mathrm{n}^{3}\right)$ time

## Matrix multiplication

## Can we do better?

What is the theoretical lowest running time possible?

## Matrix multiplication

## Can we do better?

 Yes!What is the theoretical lowest running time possible?
$\mathrm{O}\left(\mathrm{n}^{2}\right)$, must read every value at least once

## Matrix multiplication

## Block matrix multiplication says:

$$
\left[\begin{array}{l|l}
\mathbf{A}_{1} & \mathbf{A}_{2} \\
\hline \mathbf{A}_{3} & \mathbf{A}_{4}
\end{array}\right]\left[\begin{array}{l|l}
\mathbf{B}_{1} & \mathbf{B}_{2} \\
\hline \mathbf{B}_{3} & \mathbf{B}_{4}
\end{array}\right]=\left[\begin{array}{l|l}
\mathbf{C}_{1} & \mathbf{C}_{2} \\
\hline \mathbf{C}_{3} & \mathbf{C}_{4}
\end{array}\right]
$$

Thus $\mathrm{C}_{1}=\mathrm{A}_{1} * \mathrm{~B}_{1}+\mathrm{A}_{2} * \mathrm{~B}_{3}$,
We can use this fact to make a recursive definition

## Matrix multiplication

Divide\&conquer algorithm: Mult(A,B)
If $|\mathrm{A}|==1$, return A * B (scalar)
else... divide A\&B into 4 equal parts

$$
\begin{aligned}
& \mathrm{C} 1=\operatorname{Mult}(\mathrm{A} 1, \mathrm{~B} 1)+\operatorname{Mult}(\mathrm{A} 2, \mathrm{~B} 3) \\
& \mathrm{C} 2=\operatorname{Mult}(\mathrm{A} 1, \mathrm{~B} 2)+\operatorname{Mult}(\mathrm{A} 2, \mathrm{~B} 4) \\
& \mathrm{C} 3=\operatorname{Mult}(\mathrm{A} 3, \mathrm{~B} 1)+\operatorname{Mult}(\mathrm{A} 4, \mathrm{~B} 3) \\
& \mathrm{C} 4=\operatorname{Mult}(\mathrm{A} 3, \mathrm{~B} 2)+\operatorname{Mult}(\mathrm{A} 4, \mathrm{~B} 4)
\end{aligned}
$$

## Matrix multiplication

## Running time:

Base case is $\mathrm{O}(1)$
Recursive part needs to add two $\mathrm{n} / 4 \mathrm{x} \mathrm{n} / 4$ matrices, so $\mathrm{O}\left(\mathrm{n}^{2}\right)$ 8 recursive calls, each size $n / 2$

$$
\begin{aligned}
& \mathrm{T}(\mathrm{n})=8 \mathrm{~T}(\mathrm{n} / 2)+\mathrm{O}\left(\mathrm{n}^{2}\right) \\
& \mathrm{T}(\mathrm{n})=\mathrm{O}\left(\mathrm{n}^{\log 28}\right)=\mathrm{O}\left(\mathrm{n}^{3}\right)
\end{aligned}
$$



## Strassen's method

Although the simple divide\&conquer did not improve running time...

Can eliminate one recursive call to get $\mathrm{O}\left(\mathrm{n}^{\log 27}\right)$ with fancy math

Has a much larger constant factor, so not useful unless matrix big

## Strassen's method

## Step 1: compute some S's (just 'cause!)

S1=B2-B4
S6=B1+B4
S2=A1+A2
S7=A2-A4
S3=A3+A4
S8=B3+B4
S4=B3-B1
S9=A1-A3
$\mathrm{S} 5=\mathrm{A} 1+\mathrm{A} 4$
$\mathrm{S} 10=\mathrm{B} 1+\mathrm{B} 2$

## Strassen's method

## Step 2: compute some P's $(7<8)$ <br> P1=A1*S1 <br> $\mathrm{P} 2=\mathrm{S} 2 * \mathrm{~B} 4$ <br> P3=S3*B1

P4=A4*S4
P5=S5*S6
P6=S7*S8
P7=S9*S10

## Strassen's method

Step 3: + Magic!
$\mathrm{C} 1=\mathrm{P} 5+\mathrm{P} 4-\mathrm{P} 2+\mathrm{P} 6$
$\mathrm{C} 2=\mathrm{P} 1+\mathrm{P} 2$
$\mathrm{C} 3=\mathrm{P} 3+\mathrm{P} 4$

C 4 = P5 + P1 - P3 - P7
(Book works out algebra for you)

## Strassen's method

In practice, you should never use this on a matrix smaller than $16 x 16$

The break-point is debatable, but Strassen's is better if over $100 \times 100$

Theoretical methods exist to reduce to $\mathrm{O}\left(\mathrm{n}^{2.3728639}\right)$, but not practical at all

## Fast Fourier Transform

The FFT is a very nice algorithm (ranks up there with bucket sort)

It has many uses, but we will use it to solve polynomial multiplication

Naive approach takes $\mathrm{O}\left(\mathrm{n}^{2}\right)$ time (i.e. FOIL)

## Fast Fourier Transform

## Assume we have polynomials:

 $A(x)=\sum_{j=0}^{n} a_{j} \cdot x^{j}, B(x)=\sum_{j=0}^{n} b_{j} \cdot x^{j}$$\mathrm{C}(\mathrm{x})=\mathrm{A}(\mathrm{x}) * \mathrm{~B}(\mathrm{x})$
$C(x)=\sum_{j=0}^{2 \cdot n} c_{j} x^{j}$

$$
c_{j}=\sum_{k} a_{k} \cdot b_{j-k}
$$

$\mathrm{O}(\mathrm{n})$ per $\mathrm{c}_{\mathrm{j}}$, up to $2 \mathrm{nc} \mathrm{c}_{\mathrm{j}} \mathrm{s}=\mathrm{O}\left(\mathrm{n}^{2}\right)$

## Fast Fourier Transform

Rather than directly computing $\mathrm{C}(\mathrm{x})$, map to a different representation
$A(x)=\left(x_{0}, y_{0}\right),\left(x_{1}, y_{1}\right), \ldots\left(x_{n}, y_{n}\right)$
Theorem 30.1: If $\mathrm{x}_{\mathrm{i}} \neq \mathrm{x}_{\mathrm{j}}$ for all $\mathrm{i} \neq \mathrm{j}$,
then above gives a unique polynomial

## Fast Fourier Transform

## Proof: (direct)

Represent in matrix form:
$\left[1 \mathrm{x}_{0} \mathrm{x}_{0}{ }^{2} \ldots \mathrm{x}_{0}{ }^{\mathrm{n}}\right]\left[\mathrm{a}_{0}\right] \quad\left[\mathrm{y}_{0}\right]$
$\left[1 \mathrm{x}_{1} \mathrm{x}_{1}{ }^{2} \ldots \mathrm{x}_{1}^{\mathrm{n}}\right]\left[\mathrm{a}_{1}\right]=\left[\mathrm{y}_{1}\right]$
$\left[1 x_{n} x_{n}{ }^{2} \ldots x_{n}^{n}\right]\left[a_{n}\right] \quad\left[y_{n}\right]$
The left matrix is invertible, done

## Fast Fourier Transform

Q: Why bother with point-values? A : We can do $\mathrm{A}(\mathrm{x}) * \mathrm{~B}(\mathrm{x})$ in $\mathrm{O}(\mathrm{n})$ in this space

Namely, $\left(\mathrm{x}_{\mathrm{i}}, \mathrm{cy}_{\mathrm{i}}\right)=\left(\mathrm{x}_{\mathrm{i}}, \mathrm{ay}_{\mathrm{i}}{ }^{*} \mathrm{by}_{\mathrm{i}}\right)$
Need to get to point-value and back to coefficients in less than $\mathrm{O}\left(\mathrm{n}^{2}\right)$

## Fast Fourier Transform



## Coming soon! (next time)

