## CS 594: Representations in Algorithm Design

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Lecture 21: 03/29/2022
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## 1 Last time and today

- Tensor Rank and Matrix multiplication
- Quadratic problem
- Bilinear problem
- Matrix multiplication as a Bilinear problem


## 2 Tensor rank - bilinear problem

Proof: Consider a Bilinear problem:

$$
\begin{gathered}
X=\left(x_{1}, x_{2}, \ldots \ldots x_{n-1}, x_{n}\right) \text { and } Y=\left(y_{1}, y_{2}, \ldots \ldots y_{m-1}, y_{m}\right) \\
F=\left(f_{1}, f_{2}, \ldots \ldots, f_{k}\right),
\end{gathered}
$$

where $f_{k}$ is a bilinear function.

$$
\begin{equation*}
f_{k}=\sum_{i=1}^{N} \sum_{j=1}^{M} t_{i j k} * x_{i} * y_{j} \tag{1}
\end{equation*}
$$

Goal: Compute $f_{1}, f_{2}, \ldots ., f_{k}$ for given:

$$
X=\left(x_{1}, x_{2}, \ldots \ldots . x_{n-1}, x_{n}\right) \text { and } Y=\left(y_{1}, y_{2}, \ldots \ldots . y_{m-1}, y_{m}\right)
$$

$$
x_{i, j} * y_{j, k} \text { where } \mathrm{i}, \mathrm{j}, \mathrm{k}=(1 \text { to } \mathrm{n}) \text { and, }
$$

$$
\begin{equation*}
z_{i, k}=\sum_{j=1}^{n} x_{i j} * y_{j k} \tag{2}
\end{equation*}
$$

where $\mathrm{i}=$ row, $\mathrm{y}=$ column in $\mathrm{X} * \mathrm{Y}$

$$
z_{i, k}=\sum_{i, j^{\prime}, j, k^{\prime}, k, i^{\prime}} t_{\left(i, j^{\prime}\right)\left(j, k^{\prime}\right)\left(i^{\prime}, k\right)} * x_{i j^{\prime}} * y_{j k^{\prime}}= \begin{cases}1, & \text { if } i=i^{\prime}, j=j^{\prime}, k=k^{\prime}  \tag{3}\\ 0, & \text { otherwise }\end{cases}
$$

### 2.1 Trilinear Problem

$$
\begin{equation*}
\sum_{i, j, k} t_{i j k} * x_{i} * y_{j} * z_{k} \tag{4}
\end{equation*}
$$

where $z_{k}$ represents function $f_{k}$, and $t_{i j k}$ represents order 3 tensor,

$$
\begin{aligned}
\vec{z} & =(1,0,0,0,0 \ldots \ldots ., 0) \\
& =(0,1,0,0,0 \ldots \ldots ., 0) \\
& =(0,0,1,0,0 \ldots \ldots ., 0)
\end{aligned}
$$

### 2.2 Rank of Tensor

Rank of :

$$
\sum_{i, j, k}^{N, M, K} t_{i j k} * x_{i} * y_{j} * z_{k},
$$

is the minimum of $l$, such that:

$$
\begin{aligned}
& \exists \vec{\mu}=\left(\mu_{\lambda_{1}}, \mu_{\lambda_{2}}, \ldots \ldots \ldots, \mu_{\lambda_{n}}\right), \\
& \vec{\nu}=\left(\nu_{\lambda_{1}}, \nu_{\lambda_{2}}, \ldots \ldots ., \nu_{\lambda_{n}}\right), \\
& \vec{\omega}=\left(\omega_{\lambda_{1}}, \omega_{\lambda_{2}}, \ldots \ldots ., \omega_{\lambda_{n}}\right), \\
& \text { for all } 1 \leq \lambda \leq 1
\end{aligned}
$$

$$
\begin{equation*}
\sum_{i, j, k}^{N, M, K} t_{i j k} * x_{i} * y_{j} * z_{k}=\sum_{\lambda=1}^{l}\left(\left(\sum_{i=1}^{N} \mu_{\lambda_{i}} * x_{i}\right) *\left(\sum_{j=1}^{M} \nu_{\lambda_{j}} * y_{j}\right) *\left(\sum_{k=1}^{K} \omega_{\lambda_{k}} * z_{k}\right)\right) \tag{5}
\end{equation*}
$$

for given $\overrightarrow{\mu_{\lambda}}, \overrightarrow{\nu_{\lambda}}, \overrightarrow{\omega_{\lambda}}$, where

3 CONNECTING THE TENSOR RANK WITH RUNNING TIME OF MATRIX MULTIPLICATION3

$$
\begin{equation*}
\mu_{\lambda} \bigotimes \nu_{\lambda} \bigotimes \omega_{\lambda}=\left(\sum_{i=1}^{N} \mu_{\lambda_{i}} * x_{i}\right) *\left(\sum_{j=1}^{M} \nu_{\lambda_{j}} * y_{j}\right) *\left(\sum_{k=1}^{K} \omega_{\lambda_{k}} * z_{k}\right) \tag{6}
\end{equation*}
$$

the atomic tensors are defined in the above mentioned way, and atomic tensors are basically the tensors with rank 1.

### 2.2.1 Complexity to evaluate tensors

In order to evaluate single atomic tensor, the running time is $\mathrm{O}(\mathrm{N}+\mathrm{M}+\mathrm{K})$ If the rank of tensor is $(\mathrm{l})$, then running time $=\mathrm{O}\left(\left(\mathrm{N}^{*} \mathrm{M} * \mathrm{~K}\right) * \mathrm{l}\right)$

## 3 Connecting the tensor rank with running time of matrix multiplication

### 3.1 Defining computing model :

Straight-line program model (SLP)

$$
\begin{array}{r}
\text { Input }=X_{1} \ldots \ldots X_{n} \\
\text { Goal }=F\left(X_{1} \ldots \ldots X_{N}\right),
\end{array}
$$

a sequence of operations $\left(g_{1} \ldots . . g_{s}\right)=\mathrm{F}\left(X_{1} \ldots . . X_{n}\right)$, where operations allowed are :

$$
\begin{gather*}
g_{i}=X_{j} \bigodot X_{j}  \tag{7}\\
g_{i}=X_{j} \bigodot C, \text { whereC is a constant }  \tag{8}\\
g_{i}=X_{j} \bigodot g_{k}, \text { wherek }<i  \tag{9}\\
g_{i}=g_{j} \bigodot C, \text { whereC is a constant }  \tag{10}\\
g_{i}=g_{j} \bigodot g_{k}, \text { where }(j, k<i) \tag{11}
\end{gather*}
$$

where $\odot=\left(+,-,{ }^{*}, /\right)$
Complexity $\mathrm{C}(\mathrm{F})=$ minimum number of operations used in an SLP to compute F Complexity of using only multiply $\left(^{*}\right)$ and divide (/) operations :
$C^{* /}=$ minimum number of multiply $\left({ }^{*}\right)$ and divide (/) operations used in SLP for (F)

## 4 Strassen Algorithm (1973)

Theorem: For a bilinear function (F) : $\left(X_{1}, \ldots \ldots, X_{n}\right)$ and $\left(Y_{1}, \ldots \ldots, Y_{m}\right)$, if complexity $C^{* /}=1$, then ( F ) is a linear combination of :

$$
\begin{equation*}
P_{\lambda}=\left(\sum_{i=1}^{n} \mu_{\lambda_{i}} * x_{i}\right) *\left(\sum_{j=1}^{m} \nu_{\lambda_{j}} * y_{j}\right) \tag{12}
\end{equation*}
$$

for all $1 \leq \lambda \leq l$ and for a tensor $(\mathrm{t})$, if $C^{* /}(\mathrm{t})=l$, then

$$
\begin{equation*}
C^{* /}(t) \leq R(t) \leq Z * C^{* /}(t) \tag{13}
\end{equation*}
$$

where $R(t)$ is the rank of tensor $(t)$,
Above equation implies that :

$$
\begin{equation*}
\omega \leq \log _{n} R(<n, n, n>) \tag{14}
\end{equation*}
$$

where $\omega$ is used to denote the exponent of number of operations used.

### 4.1 Kronecker Product

Let ( t ) be a tensor : $N \times M \times K$ and $t^{\prime}$ be a tensor : $N^{\prime} \times M^{\prime} \times K^{\prime}$, then

$$
\begin{gather*}
\left(t \bigotimes t^{\prime}\right)_{i i^{\prime}, j j^{\prime}, k k /} i \text { a a tensor }=N N^{\prime} \times M M^{\prime} \times K K^{\prime}  \tag{15}\\
\left(t \bigotimes t^{\prime}\right)_{i i^{\prime}, j j^{\prime}, k k^{\prime}}=t_{i j k} t_{i^{\prime} j^{\prime} k^{\prime}} \tag{16}
\end{gather*}
$$

