# Course "Trees - The Ubiquitous Structure in Computer Science and Mathematics", JASS'08 

# The Number of Spanning Trees in a Graph 

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## Definition 1

Let $G=(V, E)$ with $V=\{1, \ldots, n\}$ and $E=\left\{e_{1}, \ldots, e_{m}\right\}$ be a directed graph. Then the incidence matrix $S_{G} \in M(n, m)$ of $G$ is defined as:

$$
\left(S_{G}\right)_{i, j}:=\left\{\begin{array}{cl}
1 & \text { if } e_{j} \text { ends in } i \\
-1 & \text { if } e_{j} \text { starts in } i \\
0 & \text { else }
\end{array}\right.
$$

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\end{array}\right.
$$

## Remark 1

For an undirected graph $G$ every $S_{\bar{G}}$ of some arbitrarily oriented directed variant $\bar{G}$ of $G$ can be taken as the incidence matrix.

## Example 2



$$
S_{G}=\left(\begin{array}{ccccc}
1 & 0 & 0 & 1 & 0 \\
-1 & -1 & 0 & 0 & 1 \\
0 & 1 & -1 & 0 & 0 \\
0 & 0 & 1 & -1 & -1
\end{array}\right)
$$

Theorem 3
The rank of the incidence matrix of a graph on $n$ vertices is:

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$$

Proof.
Reorder the edges and vertices so that:

$$
S_{G}=\left(\begin{array}{cccc}
S_{G_{1}} & & \ldots & 0 \\
& S_{G_{2}} & & \vdots \\
\vdots & & \ddots & \\
0 & \ldots & & S_{G_{r}}
\end{array}\right)
$$

Remark 2
Since $(1, \ldots, 1) \cdot S_{G}=0$, we can remove an arbitrary row from $S_{G}$ without losing information.

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Definition 4
For every $A \in M(n, m)$ define $\tilde{A} \in M(n-1, m)$ as $A$ without the $n$-th row.

## Example 5


$\tilde{S}_{G} \cdot \tilde{S}_{G}^{T}=$

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$$
\left(\begin{array}{ccccc}
-1 & 0 & 0 & 1 & 0 \\
1 & -1 & 0 & 0 & 1 \\
0 & 1 & -1 & 0 & 0
\end{array}\right) \cdot\left(\begin{array}{ccc}
-1 & 1 & 0 \\
0 & -1 & 1 \\
0 & 0 & -1 \\
1 & 0 & 0 \\
0 & 1 & 0
\end{array}\right)=\left(\begin{array}{ccc}
2 & -1 & 0 \\
-1 & 3 & -1 \\
0 & -1 & 2
\end{array}\right)
$$

Theorem 6 (Kirchhoff)
The number of spanning trees of a graph $G$ can be calculated as:

$$
\operatorname{det}\left(D_{G}\right) \text { where } D_{G}=\tilde{S}_{G} \cdot \tilde{s}_{G}^{T}
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$$

Remark 3

$$
\left(D_{G}\right)_{i, j}=\left\{\begin{array}{cl}
\operatorname{deg}(i) & \text { if } i=j \\
-1 & \text { if }\{i, j\} \in E \\
0 & \text { else }
\end{array}\right.
$$

## Lemma 7

Let $T=(V, E)$ be a directed tree that is rooted at $n$. We can order $E$ so that $e_{i}$ ends in $i$.

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Take $e_{i}:=(p(i), i)$, where $p(i)$ is the parent of $i$.

## Lemma 7

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Proof.
Take $e_{i}:=(p(i), i)$, where $p(i)$ is the parent of $i$.

## Remark 4

Every undirected tree on $V$ has exactly one undirected variant that is rooted at n . So for constructing/counting spanning trees we only have to consider graphs with $i \in e_{i}$.

## Lemma 8

Let $G=(V, E)$ with $|E|=n-1$ be a directed graph which is not a tree.
Then $\operatorname{det}\left(\tilde{S}_{G}\right)=0$.

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Proof.
Since $|E|=n-1, G$ is not "weakly" connected.
So $\operatorname{rank}\left(\tilde{S}_{G}\right)=\operatorname{rank}\left(S_{G}\right) \leq n-2$.

## Lemma 9

Let $T=(V, E)$ be a tree with $e_{i} \in E$ ending in $i \in V$.

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## Proof.

Order the vertices (and edges simultaneously - $e_{i}$ has to end in $i$ ) so that $p(i)>i$. Then,

$$
\tilde{S}_{T}=\left(\begin{array}{cccc}
1 & * & \ldots & * \\
0 & 1 & \ddots & \vdots \\
\vdots & \ddots & \ddots & * \\
0 & \ldots & 0 & 1
\end{array}\right)
$$

Proof of Kirchhoff's theorem.
We observe that the $i$-th column of $D_{G}$ is the sum of "incidence vectors" that correspond to edges in $G$ that have endpoints in the $i$-th vertex.

Figure: First column of $D_{G}$

$$
D_{., 1}=\left(\begin{array}{c}
3 \\
-1 \\
-1
\end{array}\right)=\left(\begin{array}{c}
1 \\
-1 \\
0
\end{array}\right)+\left(\begin{array}{c}
1 \\
0 \\
-1
\end{array}\right)+\left(\begin{array}{l}
1 \\
0 \\
0
\end{array}\right)
$$

## Proof of Kirchhoff's theorem.

We observe that the $i$-th column of $D_{G}$ is the sum of "incidence vectors" that correspond to edges in $G$ that have endpoints in the $i$-th vertex. If we now use the linearity of the determinant in every column we obtain:

Figure: Expansion of the determinant

$$
\begin{gathered}
\operatorname{det}(D)=\left|\begin{array}{ccc}
3 & -1 & -1 \\
-1 & 4 & -1 \\
-1 & -1 & 4
\end{array}\right| \\
=\left|\begin{array}{ccc}
1 & -1 & -1 \\
-1 & 4 & -1 \\
0 & -1 & 4
\end{array}\right|+\left|\begin{array}{ccc}
1 & -1 & -1 \\
0 & 4 & -1 \\
-1 & -1 & 4
\end{array}\right|+\left|\begin{array}{ccc}
1 & -1 & -1 \\
0 & 4 & -1 \\
0 & -1 & 4
\end{array}\right|=\ldots
\end{gathered}
$$

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$$
\operatorname{det}\left(D_{G}\right)=\sum_{H \in \mathcal{H}} \operatorname{det}\left(\tilde{S}_{H}\right)
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where $\mathcal{H}$ is the set of all subgraphs of $G$ which correspond to a selection of $n-1$ edges, with $e_{i}$ ending in $i$.

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where $\mathcal{H}$ is the set of all subgraphs of $G$ which correspond to a selection of $n-1$ edges, with $e_{i}$ ending in $i$.
To prove the theorem it is now sufficient to use the preceding lemmata.

Definition 10
For a weighted graph $G$ with edge weights $w_{i, k}$ let $S_{G}(x)$ be the incidence matrix $S_{G}$ with every column corresponding to $(i, k) \in E$ rescaled by $x^{w_{i, k}}$.

## Definition 10

For a weighted graph $G$ with edge weights $w_{i, k}$ let $S_{G}(x)$ be the incidence matrix $S_{G}$ with every column corresponding to $(i, k) \in E$ rescaled by $x^{w_{i, k}}$.

$$
\left(S_{G}(x)\right)_{i, j}=\left\{\begin{array}{cl}
x^{w_{k, i}} & \text { if } e_{j}=(k, i) \\
-x^{w_{i, k}} & \text { if } e_{j}=(i, k) \\
0 & \text { else }
\end{array}\right.
$$

## Example 11 (Toy graph H)

$$
S_{G}(x)=\left(\begin{array}{ccccccc}
-x^{2} & -x^{2} & -x^{4} & 0 & 0 & 0 & 0 \\
x^{2} & 0 & 0 & -x & -x & 0 & 0 \\
0 & 0 & 0 & x & 0 & -x & 0 \\
0 & x^{2} & 0 & 0 & x & x & -x^{3} \\
0 & 0 & x^{4} & 0 & 0 & 0 & x^{3}
\end{array}\right)
$$

Theorem 12 (Matrix-Tree Theorem for weighted graphs)
The generating function of the number of spanning trees by weight $w$ is the determinant of

$$
D_{G}(x)=\tilde{S}_{G}(x) \cdot \tilde{S}_{G}^{T}
$$

where $\tilde{S}_{G}(x)$ and $\tilde{S}_{G}$ are defined as above.

Theorem 12 (Matrix-Tree Theorem for weighted graphs)
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D_{G}(x)=\tilde{S}_{G}(x) \cdot \tilde{S}_{G}^{T}
$$

where $\tilde{S}_{G}(x)$ and $\tilde{S}_{G}$ are defined as above.
In other words:

$$
\operatorname{det}\left(D_{G}(x)\right)=\sum_{w=0}^{\infty} \mid S T \text { by weight } w \mid \cdot x^{w}
$$

## Example 13



$$
\begin{aligned}
D_{G}(x)= & \left(\begin{array}{cccc}
x^{4}+2 x^{2} & -x^{2} & 0 & -x^{2} \\
-x^{2} & x^{2}+2 x & -x & -x \\
0 & -x & 2 x & -x \\
-x^{2} & -x & -x & x^{3}+x^{2}+2 x
\end{array}\right) \\
& \operatorname{det}\left(D_{G}(x)\right)=2 x^{10}+5 x^{9}+8 x^{8}+6 x^{7}
\end{aligned}
$$

## Remark 5

It is easy to check that we can also write down $D_{G}(x)$ for any given graph $G$ directly:

$$
\left(D_{G}(x)\right)_{i, j}=\left\{\begin{array}{cl}
\sum_{\{i, k\} \in E} x^{w_{i, k}} & \text { if } i=j \\
-x^{w_{i, j}} & \text { if }\{i, j\} \in E \\
0 & \text { else }
\end{array}\right.
$$

## Proof.

As above.
Here each spanning tree by weight $w$ contributes $x^{w}$ to the determinant of $D_{G}(x)$.

- Should we try to calculate $\operatorname{det}\left(D_{G}(x)\right)$ ?
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- $\operatorname{det}\left(D_{G}(x)\right)$ can have $\Omega\left(2^{n}\right)$ coefficients
- Compute only the number of minimal spanning trees (the coefficient of the minimum degree monomial).
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- If $w_{\text {min }}$ is the minimal weight for a spanning tree, clearly $x^{w_{\text {min }}}$ must divide $\operatorname{det}\left(D_{G}(x)\right)$
- Compute only the number of minimal spanning trees (the coefficient of the minimum degree monomial).
- If $w_{\text {min }}$ is the minimal weight for a spanning tree, clearly $x^{w_{\text {min }}}$ must divide $\operatorname{det}\left(D_{G}(x)\right)$
- Try to factor out the minimum degree monomial of each column and use the linearity of the determinant.

$$
\begin{aligned}
& \operatorname{det}\left(D_{G}(x)\right)= \\
& \left|\begin{array}{cccc}
x^{4}+2 x^{2} & -x^{2} & 0 & -x^{2} \\
-x^{2} & x^{2}+2 x & -x & -x \\
0 & -x & 2 x & -x \\
-x^{2} & -x & -x & x^{3}+x^{2}+2 x
\end{array}\right|=x^{5} \cdot\left|\begin{array}{cccc}
x^{2}+2 & -x & 0 & -x \\
-1 & x+2 & -1 & -1 \\
0 & -1 & 2 & -1 \\
-1 & -1 & -1 & x^{2}+x+2
\end{array}\right|
\end{aligned}
$$

## Example 14 (Factor $\operatorname{det}\left(D_{G}(x)\right)$ )


$\operatorname{det}\left(D_{G}(x)\right)=$

$$
\left|\begin{array}{cccc}
x^{4}+2 x^{2} & -x^{2} & 0 & -x^{2} \\
-x^{2} & x^{2}+2 x & -x & -x \\
0 & -x & 2 x & -x \\
-x^{2} & -x & -x & x^{3}+x^{2}+2 x
\end{array}\right|=x^{5} \cdot\left|\begin{array}{cccc}
x^{2}+2 & -x & 0 & -x \\
-1 & x+2 & -1 & -1 \\
0 & -1 & 2 & -1 \\
-1 & -1 & -1 & x^{2}+x+2
\end{array}\right|
$$

The entries of the $i$ 'th column of $D_{G}(x)$ correspond to edges in the cut ( $i, \mathcal{N}(i))$ :


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Change the cuts?

Theorem 15
If we have a minimal spanning tree $T$ of $G$, we can modify $D_{G}(x)$ (without changing the determinant) so that the product of the minimum degree monomials of each column is $w_{\text {min }}$.

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## Algorithm A: Modify $D_{G}(x)$

$T:=\operatorname{mst}(G)$
$D^{\prime}(x):=D_{G}(x)$
while $T \neq\{ \}$ do
$i$ := arbitrary leaf of $T$ with $i \neq n$
$p$ := parent of $i$
add the $i$-th column in $D^{\prime}$ to the $p$-th column $T:=T \backslash\{i\}$
od

## Example 16 (MST of $H$ and corresponding $\sigma(i)$ )


$\operatorname{det}\left(D^{\prime}(x)\right)=$

$$
\left|\begin{array}{cccc}
x^{4}+2 x^{2} & x^{4}+x^{2} & 0 & x^{4} \\
-x^{2} & x & -x & 0 \\
0 & x & 2 x & 0 \\
-x^{2} & -x^{2}-2 x & -x & x^{3}
\end{array}\right|=x^{7} \cdot\left|\begin{array}{cccc}
x^{2}+2 & x^{3}+x & 0 & x \\
-1 & 1 & -1 & 0 \\
0 & 1 & 2 & 0 \\
-1 & -x-2 & -1 & 1
\end{array}\right|
$$

## Lemma 17

The $i$-th column of $D^{\prime}(x)$ contains the sum of the columns in $D_{G}(x)$ corresponding to $\sigma(i)$.

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Writing out the entries of $D^{\prime}(x)$ we get:
For $i \notin \sigma(j)$

$$
D_{i, j}^{\prime}(x)=-\sum_{\{i, k\} \in E: k \in \sigma(j)} x^{w_{k, i}}
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$$
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$$

For $i \in \sigma(j)$ the above cancels with $D_{i, i}$

$$
D_{i, j}^{\prime}(x)=\sum_{\{i, k\} \in E: k \notin \sigma(j)} x^{w_{k, i}}
$$

## Proof.

So the $j^{\prime}$ th column of $D^{\prime}$ contains only terms corresponding to edges in the cut $(\sigma(j), V \backslash \sigma(j))$.

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The only edge of $T$ in the $j$ 'th cut is $(p(j), j)$.

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The only edge of $T$ in the $j$ 'th cut is $(p(j), j)$.
All the other edges from the cut must have higher weight because $T$ is minimal.

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The only edge of $T$ in the $j$ 'th cut is $(p(j), j)$.
All the other edges from the cut must have higher weight because $T$ is minimal.

$$
\prod_{i=1}^{n-1} w_{p(i), i}=w_{\min }
$$

The runtime of our implementation so far is $O(m n+M(n))$ where $M(n)$ is the time required to multiply two $n \times n$ matrices. $O(M(n))$ can be thought of as " $O\left(n^{2+\epsilon}\right)$ ".

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- calculating the negative and positive entries separately.

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In the following $E$ is sorted so that $p(j)>j$.

For $i \notin \sigma(j)$ no entries cancel - the naive approach works.

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Algorithm B1: Negative Entries of $D^{\prime}$
for $j=1$ to $n-1$ do
for $i \notin \sigma(j)$ do
$D_{i, j}^{\prime}:=\min \_d\left(D_{G}(x)_{i, j}+\sum_{k \text { child of } j \text { in } T} D_{i, k}^{\prime}\right)$
/* min_d computes the minimum degree monomial */
od
od

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od
This is $O\left(n^{2}\right)$.

For $i \in \sigma(j)$ we use the explicit formula

$$
D_{i, j}^{\prime}=\sum_{\{i, k\} \in E: k \notin \sigma(j)} x^{w_{k, i}}
$$

and run over the rows first.

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Algorithm B2: Positive Entries of $D^{\prime}$
for $i=1$ to $n-1$ do
$L:=\operatorname{sort}(\mathcal{N}(i))$
for $j=1$ to $n-1, i \in \sigma(j)$ do
$L:=L \backslash \sigma(j)$
if $L \neq\{ \}$
$k$ := first_element( $L$ )
$D_{i, j}^{\prime}:=x^{w_{i, k}} \cdot\left|s \in L: w_{i, k}=w_{i, s}\right|$
fi
od
od

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$D_{i, j}^{\prime}:=x^{w_{i, k}} \cdot\left|s \in L: w_{i, k}=w_{i, s}\right|$
fi
od
od
This is $O\left(n^{2} \log n\right)$.

Conclusion:

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- We can find the number of minimal spanning trees in $O\left(n^{2}+m \log n+M(n)\right)=O(M(n))$

