

Probabilistic Watershed

Sampling all spanning forests for seeded segmentation
and semi-supervised learning



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What do we do?

We count forests!



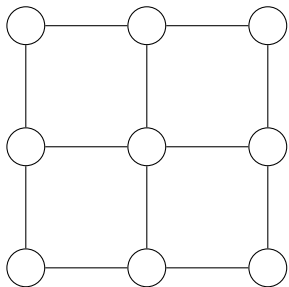
1



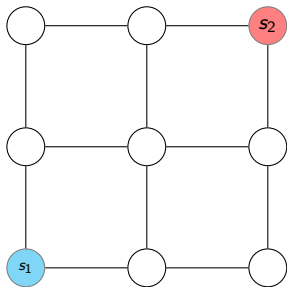
2



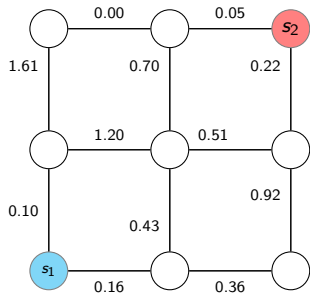
3



- **Graph**

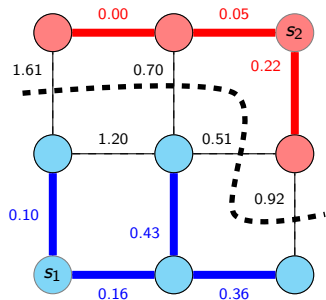


- Graph
- **Seeds (labeled nodes)**

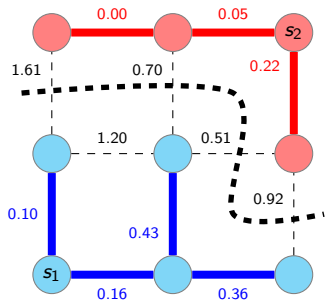


- Graph
- Seeds (labeled nodes)
- **Edge-Costs** \sim affinity between nodes

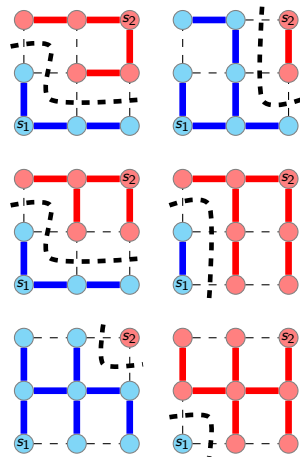
Framework



- Graph
- Seeds (labeled nodes)
- Edge-Costs \sim affinity between nodes
- **Forest**



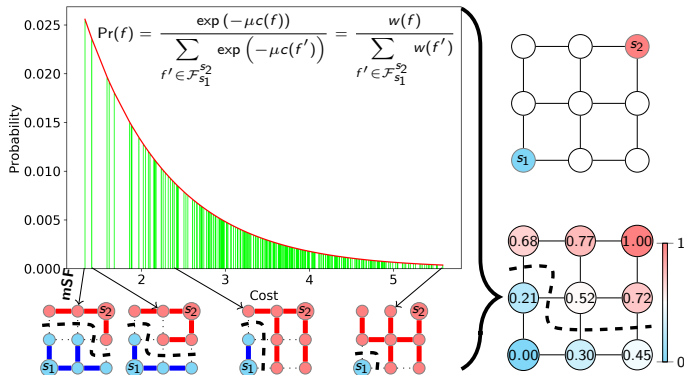
Watershed forest/
 minimum cost Spanning Forest (**mSF**)



$$\Pr(\textcircled{q} \sim \textcircled{s_2}) = \frac{\mathcal{F}_{s_2, q}^{s_1}}{\mathcal{F}_{s_1}^{s_2}}$$

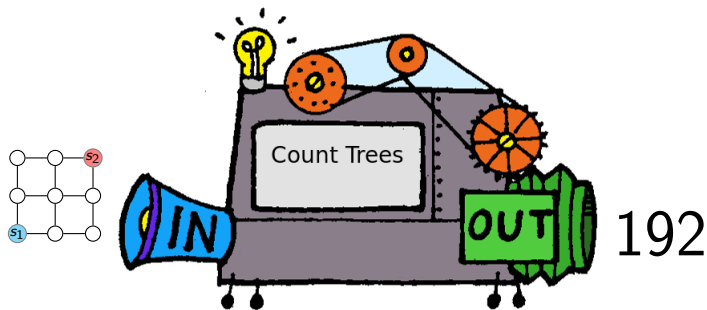
The diagram illustrates the probability of a forest q being associated with site s_2 . The numerator shows a forest with a red tree labeled q and a blue tree behind it, labeled $\mathcal{F}_{s_2, q}^{s_1}$. The denominator shows two forests: one with a red tree labeled q and a blue tree behind it, labeled $\mathcal{F}_{s_2, q}^{s_1}$, and one with a blue tree labeled q and a red tree behind it, labeled $\mathcal{F}_{s_1, q}^{s_2}$. A bracket under the denominator is labeled $\mathcal{F}_{s_1}^{s_2}$.

Probabilistic Watershed



Probabilistic Watershed $\rightarrow \Pr(q \sim s_2) := \sum_{f \in \mathcal{F}_{s_2, q}^{s_1}} \Pr(f) = \frac{w(\mathcal{F}_{s_2, q}^{s_1})}{w(\mathcal{F}_{s_2}^{s_1})} = \frac{\sum_{f \in \mathcal{F}_{s_2, q}^{s_1}} w(f)}{\sum_{f \in \mathcal{F}_{s_2}^{s_1}} w(f)}$.

How do we count the forests?

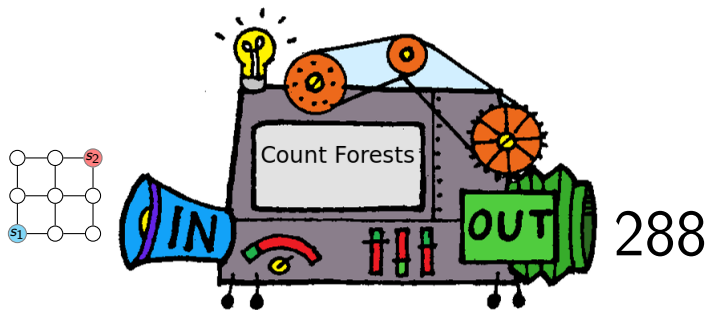


Matrix Tree Theorem [Kirchhoff, 1847]

Let $G = (V, E, w)$ an edge-weighted multigraph, $w(\mathcal{T})$, the sum of the weights of the spanning trees of G , $\mathbb{1}$ is a column vector of 1's, L is the Laplacian matrix and $L^{[v]}$ is the Laplacian matrix after removing an arbitrary row and column v , then

$$w(\mathcal{T}) := \sum_{t \in \mathcal{T}} w(t) = \sum_{t \in \mathcal{T}} \prod_{e \in E_t} w(e) = \frac{1}{|V|} \det \left(L + \frac{1}{|V|} \mathbb{1} \mathbb{1}^\top \right) = \det(L^{[v]}).$$

How do we count the forests?

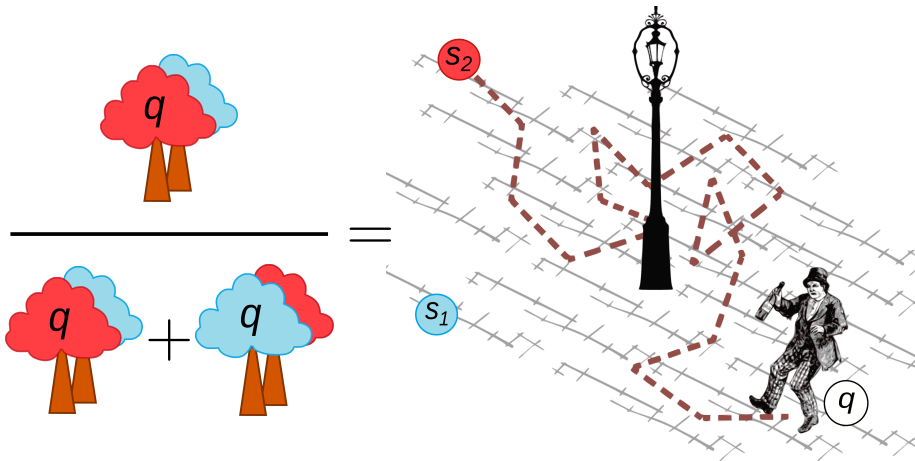


Modification Matrix Tree Theorem

Let $G = (V, E, w)$ be an undirected edge-weighted connected graph, r_{uv}^{eff} the effective resistance distance between $u, v \in V$ arbitrary vertices and $w(\mathcal{F}_u^v)$ the sum of the weights of the 2-trees spanning forests separating u and v , then

$$w(\mathcal{F}_u^v) = w(\mathcal{T})r_{uv}^{\text{eff}}.$$

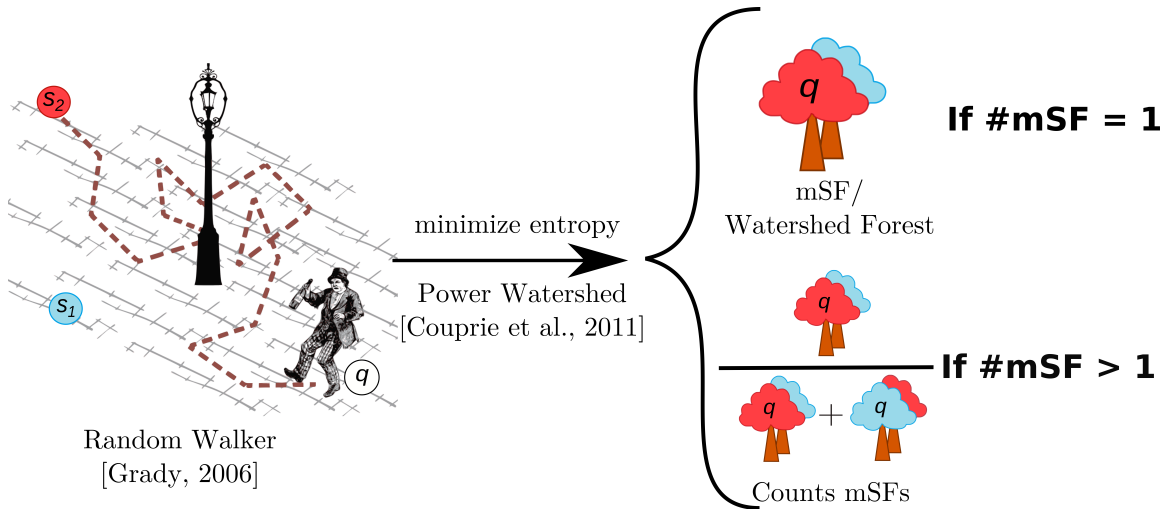
Probabilistic Watershed=Random Walker[Grady, 2006]



Probabilistic Watershed

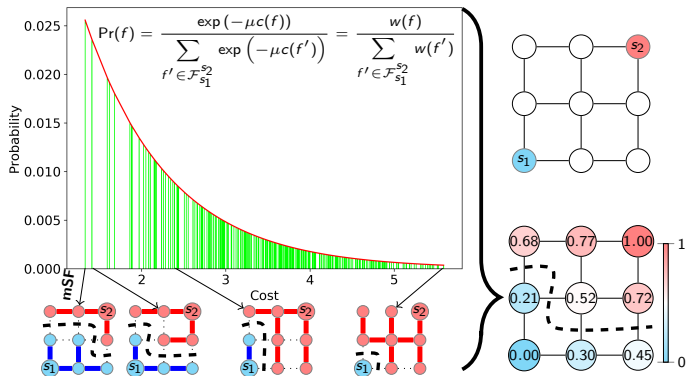
Random Walker [Grady, 2006]

Power Watershed new interpretation






Summary

- Probabilistic Watershed=Random Walker [Grady, 2006].
- New interpretations of the Power Watershed [Couprie et al., 2011].
- Technique to count forests.



Poster

Room East Exhibition Hall B + C #81
10:45 AM – 12:45 PM

-  Couprie, C., Grady, L., Najman, L., and Talbot, H. (2011).
Power watershed: A unifying graph-based optimization framework.
IEEE Transactions on Pattern Analysis and Machine Intelligence.
-  Grady, L. (2006).
Random walks for image segmentation.
IEEE Transactions on Pattern Analysis and Machine Intelligence.
-  Kirchhoff, G. (1847).
Über die Auflösung der Gleichungen, auf welche man bei der Untersuchung der linearen
Vertheilung galvanischer Ströme geführt wird.
Annalen der Physik, 148:497–508.