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


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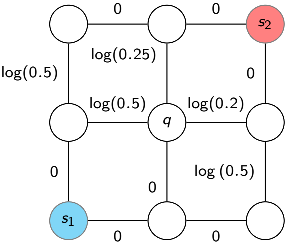
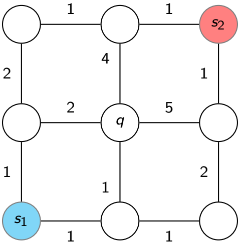
Notation: edge cost vs edge weight

$$w(e) = \exp(-\mu c(e)), \ \mu \geq 0$$



(a) Graph's edge-costs



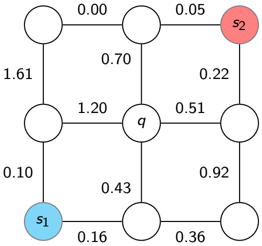
(b) Graph's edge-weights, $\mu = 1$

$$c(G) = \sum_{e \in E_G} c(e)$$

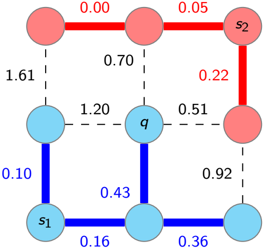
$$w(G) = \prod_{e \in E_G} w(e)$$

Watershed computes a minimum cost spanning forest (mSF)

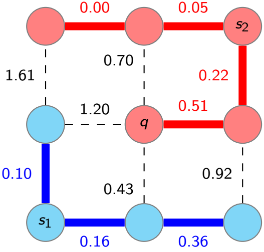
The assignment of q is doubtful



(a) Graph with two seeds



(b) mSF: Cost=1.32



(c) SF: Cost=1.4

Figure: (2a) Graph with edge-costs and two seeds. (2b)The mSF (Watershed segmentation) assigns q to seed s_1. (2c) Low cost, but not minimum, spanning forest connecting q to s_2. The Watershed has a winner-takes-all behaviour. It only considers the mSF while ignores the rest of seed separating spanning forests

Question to solve

What is the probability of sampling a forest such that a node of interest is assigned to a certain seed?

Gibbs Distribution of $\mathcal{F}_{s_1}^{s_2}$

$$\mathcal{F}_{s_1}^{s_2} := \{\text{2-forests separating } s_1 \text{ and } s_2\}$$

Definition: probability distribution over the forests

Given $J \in \mathbb{R}_{\geq 0}$

$$\Pr{}^* = \arg\min_{\Pr} \sum_{f \in \mathcal{F}_{s_1}^{s_2}} \Pr(f) c(f), \quad \text{s.t.} \quad \sum_{f \in \mathcal{F}_{s_1}^{s_2}} \Pr(f) = 1 \text{ and } \mathcal{H}(\Pr) = J, \tag{1}$$

where $\mathcal{H}(\Pr)$= entropy Pr

Solution: Gibbs Probability distribution

$$\Pr{}^*(f) = \frac{\exp(-\mu c(f))}{\sum_{f' \in \mathcal{F}_{s_1}^{s_2}} \exp(-\mu c(f'))} = \frac{w(f)}{\sum_{f' \in \mathcal{F}_{s_1}^{s_2}} w(f')}$$

Probabilistic Watershed

$$\mathcal{F}_{s_1}^{s_2} := \{\text{2-forests separating } s_1 \text{ and } s_2\}$$
$$\mathcal{F}_{s_1,q}^{s_2} := \{f \in \mathcal{F}_{s_1}^{s_2} \ : \ s_1 \text{ and } q \text{ are connected}\}$$

Probability q is connected with s_1

$$\Pr(q \sim s_1) := \frac{w\left(\mathcal{F}_{s_1,q}^{s_2}\right)}{w\left(\mathcal{F}_{s_1}^{s_2}\right)} = \frac{\sum\limits_{f \in \mathcal{F}_{s_1,q}^{s_2}} w(f)}{\sum\limits_{f \in \mathcal{F}_{s_1}^{s_2}} w(f)}.$$

Example

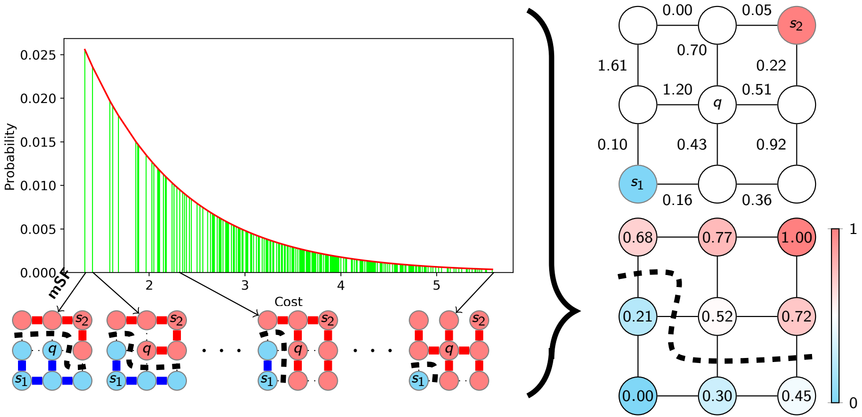


Figure: (**Top left**) Gibbs distribution over all spanning forests. (**Bottom right**) Probabilistic Watershed probabilities for assigning a node to s_2. The Probabilistic Watershed computes the expected seed assignment of every node for a Gibbs distribution over all exponentially many spanning forests in closed-form. It thus avoids the winner-takes-all behaviour of the Watershed.

Probabilistic Watershed

$$\mathcal{F}_{s_1}^{s_2} := \{\text{2-forests separating } s_1 \text{ and } s_2\}$$
$$\mathcal{F}_{s_1,q}^{s_2} := \{f \in \mathcal{F}_{s_1}^{s_2} \ : \ s_1 \text{ and } q \text{ are connected}\}$$

Probability q is connected to s_1

$$\Pr(q \sim s_1) := \frac{w\left(\mathcal{F}_{s_1,q}^{s_2}\right)}{w\left(\mathcal{F}_{s_1}^{s_2}\right)} = \frac{\sum\limits_{f \in \mathcal{F}_{s_1,q}^{s_2}} w(f)}{\sum\limits_{f \in \mathcal{F}_{s_1}^{s_2}} w(f)}.$$

Question: How do we compute $w(\mathcal{F}_{s_1}^{s_2})$, $w(\mathcal{F}_{s_2,q}^{s_1})$ and $w(\mathcal{F}_{s_1,q}^{s_2})$?
Answer: Matrix Tree Theorem (MTT).

Matrix Tree Theorem

Matrix Tree Theorem (MTT)

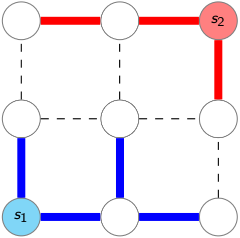
For any weighted multigraph G, the sum of the weights of the spanning trees of G, $w(\mathcal{T})$, is equal to

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

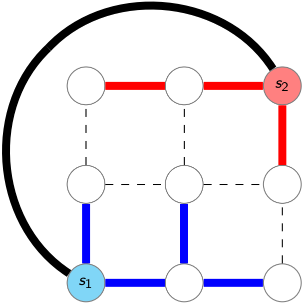
where $\mathbb{1}$ is the column of 1. $L^{[v]}$ is the matrix obtained from the Laplacian, L, after removing the row and column corresponding to an arbitrary node v.

Computation of $w(\mathcal{F}_{s_1}^{s_2})$

The relation between forests and trees allows the use of the MTT.



(a) Forest.



(b) Tree

Computation of $w(\mathcal{F}_{s_1}^{s_2})$

r_{uv}^{eff} = effective resistance metric between the nodes u and v.

Theorem (Consequence of the MTT)

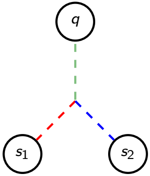
$$w(\mathcal{F}_{s_1}^{s_2}) = w(\mathcal{T}) r_{s_1 s_2}^{\text{eff}} \propto r_{s_1 s_2}^{\text{eff}}.$$

Computation of $w(\mathcal{F}^{q}_{s_1,s_2})$ and $w(\mathcal{F}^{q}_{s_2,s_1})$

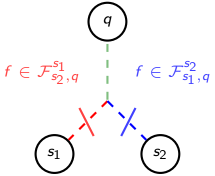
(a) spanning tree $t \in \mathcal{T}$

(b) forest $f \in \mathcal{F}^{s_2}_{s_1}$

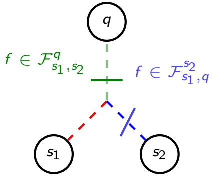
Figure: $\mathcal{F}^{s_2}_{s_1,q}$ and $\mathcal{F}^{s_1}_{s_2,q}$ form a partition of $\mathcal{F}^{s_2}_{s_1}$ since q must be connected either to s_1 or s_2, but not to both. Given an spanning tree (dashed lines represent all possible spanning trees), to form a forest in $\mathcal{F}^{s_2}_{s_1}$ we will have to remove an edge from the red part, forming a forest in $\mathcal{F}^{s_1}_{s_2,q}$, or from the blue part, forming a forest in $\mathcal{F}^{s_2}_{s_1,q}$.



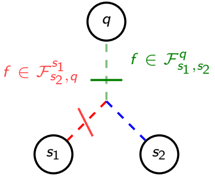
(a) spanning tree $t \in \mathcal{T}$



(b) forest $f \in \mathcal{F}^{s_2}_{s_1}$



(c) forest $f \in \mathcal{F}^{q}_{s_2}$



(d) forest $f \in \mathcal{F}^{q}_{s_1}$

Figure: Analogously (c) $\mathcal{F}^{q}_{s_2,s_1}$ and $\mathcal{F}^{s_2}_{q,s_1}$ form a partition of $\mathcal{F}^{q}_{s_2}$, and (d) $\mathcal{F}^{q}_{s_1,s_2}$ and $\mathcal{F}^{s_1}_{q,s_2}$ form a partition of $\mathcal{F}^{q}_{s_1}$.

Computation $w(\mathcal{F}^{q}_{s_1,s_2}), w(\mathcal{F}^{q}_{s_2,s_1})$

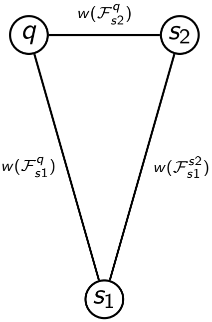
Linear system with 3 unknowns and 3 equations.

$$\begin{aligned}
w(\mathcal{F}^{s_2}_{s_1,q}) + w(\mathcal{F}^{q}_{s_1,s_2}) &= w(\mathcal{F}^{q}_{s_2}) \\
w(\mathcal{F}^{q}_{s_1,s_2}) + w(\mathcal{F}^{s_1}_{s_2,q}) &= w(\mathcal{F}^{q}_{s_1}) \\
w(\mathcal{F}^{s_2}_{s_1,q}) + w(\mathcal{F}^{s_1}_{s_2,q}) &= w(\mathcal{F}^{s_2}_{s_1}).
\end{aligned}$$

Probabilistic Watershed corresponds to the effective resistance metric

Probability measures the gap of the triangle inequality

$$\Pr(q \sim s_1) = \frac{w(\mathcal{F}^{q}_{s_2}) + w(\mathcal{F}^{s_2}_{s_1}) - w(\mathcal{F}^{q}_{s_1})}{2w(\mathcal{F}^{s_2}_{s_1})} = \frac{r^{\text{eff}}_{s_2 q} + r^{\text{eff}}_{s_2 s_1} - r^{\text{eff}}_{s_1 q}}{2 r^{\text{eff}}_{s_2 s_1}}. \tag{2}$$



$$\Pr(q \sim s_1) \geq \Pr(q \sim s_2) \iff r^{\text{eff}}_{s_1 q} \leq r^{\text{eff}}_{s_2 q}.$$

Random Walker[Grady, 2006] = Probabilistic Watershed

Theorem

The probability, $x_q^{s_2}$, that a Random Walker starting at node q reaches first s_2 before reaching s_1 ([Grady, 2006]) is equal to the probability defined by the Probabilistic Watershed.

$$x_q^{s_2} = P(q \sim s_2).$$

Power Watershed [Couprie et al., 2011]

Power Watershed minimization problem

$$x^* = \arg\min_x \sum_{e=(v,u)\in E} (w(e))^\alpha \left(|x_v - x_u|\right)^\beta, \text{ s.t. } x_{s_1} = 1,\ x_{s_2} = 0, \quad (3)$$

Random Walker: $\alpha = 1,\ \beta = 2$
Power Watershed: $\alpha \to \infty,\ \beta = 2$

α and μ are equivalent

$$w(e) = \exp(-\mu c(e)) \to (w(e))^\alpha = \exp(-\mu\alpha c(e)) = \exp(-\mu_\alpha c(e))$$

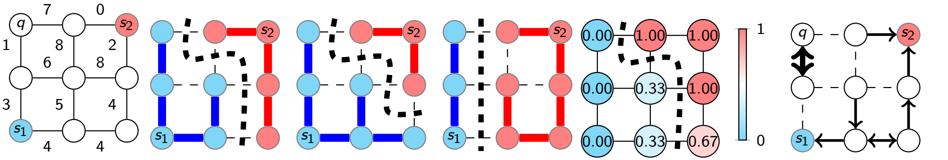
Power Watershed [Couprie et al., 2011]

Power Watershed counts minimum cost/maximum weight spanning forests

Given $S = \{s_1, s_2\}$ a set of seeds, let us denote the potential of node q being assigned to seed s_1 by the Power Watershed with $\beta = 2$ as $x_q^{\mathrm{PW}_1}$. Let further $w_{\max}$ be $\max_{f \in \mathcal{F}_{s_1}^{s_2}} w(f)$. Then

$$x_q^{\mathrm{PW}_1} = \Pr_\infty(q \sim s_1) := \frac{\left|\{f \in \mathcal{F}_{s_1,q}^{s_2} \ : \ w(f) = w_{\max}\}\right|}{\left|\{f \in \mathcal{F}_{s_1}^{s_2} \ : \ w(f) = w_{\max}\}\right|}.$$

Power Watershed counts mSF



(a) Graph (b) mSF1 (c) mSF2 (d) mSF3 (e) $P_\infty(\text{node} \sim s_2)$ (f) RW reachability

Figure: Forest-interpretation of Power Watershed. The Power Watershed computes the ratio between the mSFs connecting a node to s_2 and all possible mSFs. (7f) indicates the allowed Random Walker transitions when $\mu \to \infty$ with headed arrows. The Random Walker interpretation of the Power Watershed breaks down in the limit case since a Random Walker starting at node q does not reach any seed, but oscillates along the bold arrow.

Conclusion

- Probabilistic Watershed $=$ Random Walker.
- Random Walker/Probabilistic Watershed probabilities are proportional to the triangle inequality gap.

$$\Pr(q \sim s_1) \propto r^{\text{eff}}_{s_2 q} + r^{\text{eff}}_{s_2 s_1} - r^{\text{eff}}_{s_1 q}.$$

- Power Watershed counts minimum cost spanning forests.

References

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.

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Random walks for image segmentation.
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