

Graphs in Machine Learning

SSL with Graphs: Harmonic Functions

Gaussian Random Fields Solution

Michal Valko

Inria & ENS Paris-Saclay, MVA

Partially based on material by: Mikhail Belkin, Partha Niyogi, Olivier Chapelle, Bernhard Schölkopf

Zhu/Ghahramani/Lafferty: Semi-Supervised Learning Using Gaussian Fields and Harmonic Functions (ICML 2013)

http://mlg.eng.cam.ac.uk/zoubin/papers/zgl.pdf

Zhu/Ghahramani/Lafferty: Semi-Supervised Learning Using Gaussian Fields and Harmonic Functions (ICML 2013)

http://mlg.eng.cam.ac.uk/zoubin/papers/zgl.pdf

^{*}a seminal paper that convinced people to use graphs for SSL

Zhu/Ghahramani/Lafferty: Semi-Supervised Learning Using Gaussian Fields and Harmonic Functions (ICML 2013)

http://mlg.eng.cam.ac.uk/zoubin/papers/zgl.pdf

Idea 1: Look for a **unique** solution.

^{*}a seminal paper that convinced people to use graphs for SSL

Zhu/Ghahramani/Lafferty: Semi-Supervised Learning Using Gaussian

Fields and Harmonic Functions (ICML 2013) http://mlg.eng.cam.ac.uk/zoubin/papers/zgl.pdf

Idea 1: Look for a unique solution.

Idea 2: Find a smooth one.

Zhu/Ghahramani/Lafferty: Semi-Supervised Learning Using Gaussian Fields and Harmonic Functions (ICML 2013)

http://mlg.eng.cam.ac.uk/zoubin/papers/zgl.pdf

Idea 1: Look for a unique solution.

Idea 2: Find a smooth one. (harmonic solution)

^{*}a seminal paper that convinced people to use graphs for SSI

Zhu/Ghahramani/Lafferty: Semi-Supervised Learning Using Gaussian Fields and Harmonic Functions (ICML 2013)

http://mlg.eng.cam.ac.uk/zoubin/papers/zgl.pdf

Idea 1: Look for a unique solution.

Idea 2: Find a smooth one. (harmonic solution)

Harmonic SSL

1): As before, we constrain f to match the supervised data:

^{*}a seminal paper that convinced people to use graphs for SSI

Zhu/Ghahramani/Lafferty: Semi-Supervised Learning Using Gaussian Fields and Harmonic Functions (ICML 2013)

http://mlg.eng.cam.ac.uk/zoubin/papers/zgl.pdf

Idea 1: Look for a unique solution.

Idea 2: Find a smooth one. (harmonic solution)

Harmonic SSL

1): As before, we constrain f to match the supervised data:

$$f(\mathbf{x}_i) = y_i \quad \forall i \in \{1, \dots, n_l\}$$

^{*}a seminal paper that convinced people to use graphs for SSI

Zhu/Ghahramani/Lafferty: Semi-Supervised Learning Using Gaussian Fields and Harmonic Functions (ICML 2013)

http://mlg.eng.cam.ac.uk/zoubin/papers/zgl.pdf

Idea 1: Look for a unique solution.

Idea 2: Find a smooth one. (harmonic solution)
Harmonic SSL

1): As before, we constrain f to match the supervised data:

$$f(\mathbf{x}_i) = y_i \quad \forall i \in \{1, \ldots, n_l\}$$

2): We enforce the solution f to be harmonic:

^{*}a seminal paper that convinced people to use graphs for SSL

Zhu/Ghahramani/Lafferty: Semi-Supervised Learning Using Gaussian Fields and Harmonic Functions (ICML 2013)

http://mlg.eng.cam.ac.uk/zoubin/papers/zgl.pdf

*a seminal paper that convinced people to use graphs for SSI

Idea 1: Look for a unique solution.

Idea 2: Find a smooth one. (harmonic solution)

Harmonic SSL

1): As before, we constrain f to match the supervised data:

$$f(\mathbf{x}_i) = y_i \quad \forall i \in \{1, \dots, n_l\}$$

2): We enforce the solution f to be harmonic:

$$f(\mathbf{x}_i) = \frac{\sum_{i \sim j} f(\mathbf{x}_j) w_{ij}}{\sum_{i \sim i} w_{ij}} \quad \forall i \in \{n_l + 1, \dots, n_u + n_l\}$$

The harmonic solution is obtained from the mincut one ...

The harmonic solution is obtained from the mincut one ...

$$\min_{\mathbf{f} \in \{\pm 1\}^{n_l + n_u}} \infty \sum_{i=1}^{n_l} (f(\mathbf{x}_i) - y_i)^2 + \lambda \sum_{i,j=1}^{n_l + n_u} w_{ij} (f(\mathbf{x}_i) - f(\mathbf{x}_j))^2$$

The harmonic solution is obtained from the mincut one ...

$$\min_{\mathbf{f} \in \{\pm 1\}^{n_l + n_u}} \infty \sum_{i=1}^{n_l} (f(\mathbf{x}_i) - y_i)^2 + \lambda \sum_{i,j=1}^{n_l + n_u} w_{ij} (f(\mathbf{x}_i) - f(\mathbf{x}_j))^2$$

...if we just relax the integer constraints to be real ...

The harmonic solution is obtained from the mincut one ...

$$\min_{\mathbf{f} \in \{\pm 1\}^{n_l + n_u}} \infty \sum_{i=1}^{n_l} (f(\mathbf{x}_i) - y_i)^2 + \lambda \sum_{i,j=1}^{n_l + n_u} w_{ij} (f(\mathbf{x}_i) - f(\mathbf{x}_j))^2$$

...if we just relax the integer constraints to be real ...

$$\min_{\mathbf{f} \in \mathbb{R}^{n_l + n_u}} \infty \sum_{i=1}^{n_l} (f(\mathbf{x}_i) - y_i)^2 + \lambda \sum_{i,j=1}^{n_l + n_u} w_{ij} (f(\mathbf{x}_i) - f(\mathbf{x}_j))^2$$

The harmonic solution is obtained from the mincut one ...

$$\min_{\mathbf{f} \in \{\pm 1\}^{n_l + n_u}} \infty \sum_{i=1}^{n_l} (f(\mathbf{x}_i) - y_i)^2 + \lambda \sum_{i,j=1}^{n_l + n_u} w_{ij} (f(\mathbf{x}_i) - f(\mathbf{x}_j))^2$$

...if we just relax the integer constraints to be real ...

$$\min_{\mathbf{f} \in \mathbb{R}^{n_l + n_u}} \infty \sum_{i=1}^{n_l} (f(\mathbf{x}_i) - y_i)^2 + \lambda \sum_{i,j=1}^{n_l + n_u} w_{ij} (f(\mathbf{x}_i) - f(\mathbf{x}_j))^2$$

...or equivalently (note that $f(\mathbf{x}_i) = f_i$) ...

The harmonic solution is obtained from the mincut one ...

$$\min_{\mathbf{f} \in \{\pm 1\}^{n_l + n_u}} \infty \sum_{i=1}^{n_l} (f(\mathbf{x}_i) - y_i)^2 + \lambda \sum_{i,j=1}^{n_l + n_u} w_{ij} (f(\mathbf{x}_i) - f(\mathbf{x}_j))^2$$

...if we just relax the integer constraints to be real ...

$$\min_{\mathbf{f} \in \mathbb{R}^{n_l + n_u}} \infty \sum_{i=1}^{n_l} (f(\mathbf{x}_i) - y_i)^2 + \lambda \sum_{i,j=1}^{n_l + n_u} w_{ij} (f(\mathbf{x}_i) - f(\mathbf{x}_j))^2$$

...or equivalently (note that $f(\mathbf{x}_i) = f_i$) ...

$$\min_{\mathbf{f} \in \mathbb{R}^{n_l + n_u}} \sum_{i,j=1}^{n_l + n_u} w_{ij} \left(f(\mathbf{x}_i) - f(\mathbf{x}_j) \right)^2$$

s.t.
$$y_i = f(\mathbf{x}_i) \quad \forall i = 1, \dots, n_l$$

Properties of the relaxation from ± 1 to $\mathbb R$

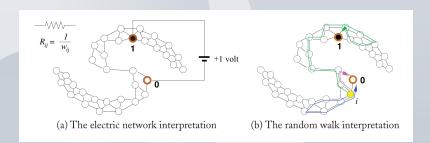
- there is a closed form solution for f
- this solution is unique
- globally optimal

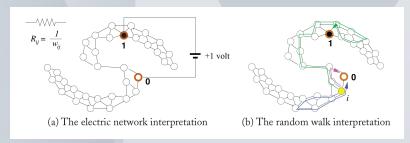
Properties of the relaxation from ± 1 to $\mathbb R$

- there is a closed form solution for f
- this solution is unique
- globally optimal
- $f(\mathbf{x}_i)$ may not be discrete
 - but we can threshold it

Properties of the relaxation from ± 1 to $\mathbb R$

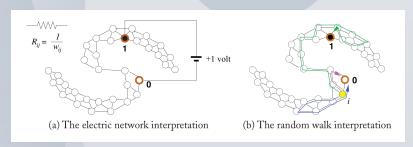
- there is a closed form solution for f
- this solution is unique
- globally optimal
- $f(\mathbf{x}_i)$ may not be discrete
 - but we can threshold it
- electric-network interpretation
- random-walk interpretation





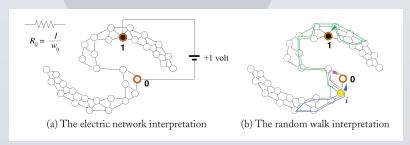
Random walk interpretation:

1) start from the vertex you want to label and randomly walk



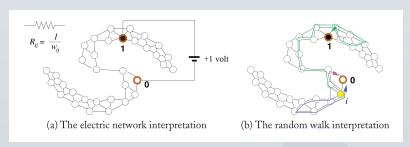
Random walk interpretation:

- 1) start from the vertex you want to label and randomly walk
- **2)** $P(j|i) = \frac{w_{ij}}{\sum_k w_{ik}}$



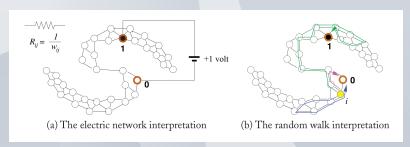
Random walk interpretation:

- 1) start from the vertex you want to label and randomly walk
- **2)** $P(j|i) = \frac{w_{ij}}{\sum_{k} w_{ik}} \equiv \mathbf{P} = \mathbf{D}^{-1}\mathbf{W}$



Random walk interpretation:

- 1) start from the vertex you want to label and randomly walk
- **2)** $P(j|i) = \frac{w_{ij}}{\sum_{k} w_{ik}} \equiv \mathbf{P} = \mathbf{D}^{-1}\mathbf{W}$
- 3) finish when a labeled vertex is hit

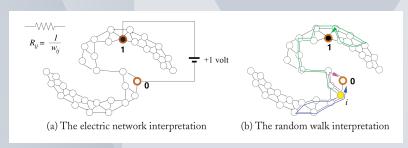


Random walk interpretation:

- 1) start from the vertex you want to label and randomly walk
- 2) $P(j|i) = \frac{w_{ij}}{\sum_{k} w_{ik}}$ \equiv $P = D^{-1}W$
- 3) finish when a labeled vertex is hit

absorbing random walk

$$f_i =$$



Random walk interpretation:

- 1) start from the vertex you want to label and randomly walk
- **2)** $P(j|i) = \frac{w_{ij}}{\sum_{l} w_{ik}}$ \equiv $\mathbf{P} = \mathbf{D}^{-1}\mathbf{W}$
- 3) finish when a labeled vertex is hit

absorbing random walk

 f_i = probability of reaching a positive labeled vertex

How to compute HS?

How to compute HS? Option A: iteration

How to compute HS? Option A: iteration/propagation

How to compute HS? Option A: iteration/propagation

Step 1: Set $f(\mathbf{x}_i) = y_i$ for $i = 1, ..., n_l$

How to compute HS? Option A: iteration/propagation

- **Step 1:** Set $f(\mathbf{x}_i) = y_i$ for $i = 1, ..., n_l$
- Step 2: Propagate iteratively (only for unlabeled)

$$f(\mathbf{x}_i) \leftarrow \frac{\sum_{i \sim j} f(\mathbf{x}_j) w_{ij}}{\sum_{i \sim j} w_{ij}} \quad \forall i \in \{n_l + 1, \dots, n_u + n_l\}$$

How to compute HS? Option A: iteration/propagation

- **Step 1:** Set $f(\mathbf{x}_i) = y_i$ for $i = 1, ..., n_l$
- Step 2: Propagate iteratively (only for unlabeled)

$$f(\mathbf{x}_i) \leftarrow \frac{\sum_{i \sim j} f(\mathbf{x}_j) w_{ij}}{\sum_{i \sim j} w_{ij}} \quad \forall i \in \{n_l + 1, \dots, n_u + n_l\}$$

Properties:

this will converge to the harmonic solution

How to compute HS? Option A: iteration/propagation

- **Step 1:** Set $f(\mathbf{x}_i) = y_i$ for $i = 1, ..., n_l$
- **Step 2:** Propagate iteratively (only for unlabeled)

$$f(\mathbf{x}_i) \leftarrow \frac{\sum_{i \sim j} f(\mathbf{x}_j) w_{ij}}{\sum_{i \sim j} w_{ij}} \quad \forall i \in \{n_l + 1, \dots, n_u + n_l\}$$

Properties:

- this will converge to the harmonic solution
- we can set the initial values for unlabeled nodes arbitrarily

How to compute HS? Option A: iteration/propagation

- **Step 1:** Set $f(\mathbf{x}_i) = y_i$ for $i = 1, ..., n_l$
- **Step 2:** Propagate iteratively (only for unlabeled)

$$f(\mathbf{x}_i) \leftarrow \frac{\sum_{i \sim j} f(\mathbf{x}_j) w_{ij}}{\sum_{i \sim j} w_{ij}} \quad \forall i \in \{n_l + 1, \dots, n_u + n_l\}$$

Properties:

- this will converge to the harmonic solution
- we can set the initial values for unlabeled nodes arbitrarily
- an interesting option for large-scale data

How to compute HS? Option B: Closed form solution

How to compute HS? Option B: Closed form solution

Define
$$\mathbf{f} = (f(\mathbf{x}_1), \dots, f(\mathbf{x}_{n_l+n_u}))$$

How to compute HS? Option B: Closed form solution

Define
$$\mathbf{f} = (f(\mathbf{x}_1), \dots, f(\mathbf{x}_{n_l + n_u})) = (f_1, \dots, f_{n_l + n_u})$$

How to compute HS? Option B: Closed form solution

Define
$$\mathbf{f} = (f(\mathbf{x}_1), \dots, f(\mathbf{x}_{n_l + n_u})) = (f_1, \dots, f_{n_l + n_u})$$

$$\Omega(\mathbf{f}) =$$

How to compute HS? Option B: Closed form solution

Define
$$f = (f(x_1), \dots, f(x_{n_l + n_u})) = (f_1, \dots, f_{n_l + n_u})$$

$$\Omega(\mathbf{f}) = \sum_{i,j=1}^{n_l + n_u} w_{ij} \left(f(\mathbf{x}_i) - f(\mathbf{x}_j) \right)^2$$

How to compute HS? Option B: Closed form solution

Define
$$\mathbf{f} = (f(\mathbf{x}_1), \dots, f(\mathbf{x}_{n_l+n_u})) = (f_1, \dots, f_{n_l+n_u})$$

$$\Omega(\mathbf{f}) = \sum_{i,j=1}^{n_l + n_u} w_{ij} (f(\mathbf{x}_i) - f(\mathbf{x}_j))^2 = \mathbf{f}^\mathsf{T} \mathbf{L} \mathbf{f}$$

L is a $(n_l + n_u) \times (n_l + n_u)$ matrix:

How to compute HS? Option B: Closed form solution

Define
$$\mathbf{f} = (f(\mathbf{x}_1), \dots, f(\mathbf{x}_{n_l + n_u})) = (f_1, \dots, f_{n_l + n_u})$$

$$\Omega(\mathbf{f}) = \sum_{i,j=1}^{n_l + n_u} w_{ij} (f(\mathbf{x}_i) - f(\mathbf{x}_j))^2 = \mathbf{f}^\mathsf{T} \mathbf{L} \mathbf{f}$$

L is a $(n_l + n_u) \times (n_l + n_u)$ matrix:

$$\mathbf{L} = \left[egin{array}{ccc} \mathbf{L}_{II} & \mathbf{L}_{Iu} \ \mathbf{L}_{uI} & \mathbf{L}_{uu} \end{array}
ight]$$

How to compute HS? Option B: Closed form solution

Define
$$\mathbf{f} = (f(\mathbf{x}_1), \dots, f(\mathbf{x}_{n_l+n_u})) = (f_1, \dots, f_{n_l+n_u})$$

$$\Omega(\mathbf{f}) = \sum_{i,j=1}^{n_l + n_u} w_{ij} (f(\mathbf{x}_i) - f(\mathbf{x}_j))^2 = \mathbf{f}^{\mathsf{T}} \mathbf{L} \mathbf{f}$$

L is a $(n_l + n_u) \times (n_l + n_u)$ matrix:

$$\mathbf{L} = \left[egin{array}{ccc} \mathbf{L}_{II} & \mathbf{L}_{Iu} \ \mathbf{L}_{uI} & \mathbf{L}_{uu} \end{array}
ight]$$

How to compute this **constrained** minimization problem?

How to compute HS? Option B: Closed form solution

Define
$$f = (f(x_1), ..., f(x_{n_l+n_u})) = (f_1, ..., f_{n_l+n_u})$$

$$\Omega(\mathbf{f}) = \sum_{i,j=1}^{n_l + n_u} w_{ij} (f(\mathbf{x}_i) - f(\mathbf{x}_j))^2 = \mathbf{f}^{\mathsf{T}} \mathbf{L} \mathbf{f}$$

L is a $(n_l + n_u) \times (n_l + n_u)$ matrix:

$$\mathbf{L} = \left[egin{array}{cc} \mathbf{L}_{II} & \mathbf{L}_{Iu} \ \mathbf{L}_{uI} & \mathbf{L}_{uu} \end{array}
ight]$$

How to compute this **constrained** minimization problem?

Yes, Lagrangian multipliers are an option, but . . .

Let us compute harmonic solution using harmonic property!

Let us compute harmonic solution using harmonic property!

$$(\mathbf{Lf})_{u} = \mathbf{0}_{u}$$

Let us compute harmonic solution using harmonic property!

$$(\mathbf{Lf})_u = \mathbf{0}_u$$

In matrix notation

$$\left[\begin{array}{cc} \mathbf{L}_{II} & \mathbf{L}_{Iu} \\ \mathbf{L}_{uI} & \mathbf{L}_{uu} \end{array}\right] \left[\begin{array}{c} \mathbf{f}_{I} \\ \mathbf{f}_{u} \end{array}\right] = \left[\begin{array}{c} \dots \\ \mathbf{0}_{u} \end{array}\right]$$

Let us compute harmonic solution using harmonic property!

$$(\mathbf{Lf})_u = \mathbf{0}_u$$

In matrix notation

$$\left[\begin{array}{cc} \mathbf{L}_{II} & \mathbf{L}_{Iu} \\ \mathbf{L}_{uI} & \mathbf{L}_{uu} \end{array}\right] \left[\begin{array}{c} \mathbf{f}_{I} \\ \mathbf{f}_{u} \end{array}\right] = \left[\begin{array}{c} \dots \\ \mathbf{0}_{u} \end{array}\right]$$

 \mathbf{f}_l is constrained to be \mathbf{y}_l and for \mathbf{f}_u

$$\mathbf{L}_{ul}\mathbf{f}_l+\mathbf{L}_{uu}\mathbf{f}_u=\mathbf{0}_u$$

Let us compute harmonic solution using harmonic property!

$$(\mathbf{Lf})_u = \mathbf{0}_u$$

In matrix notation

$$\left[\begin{array}{cc} \mathbf{L}_{II} & \mathbf{L}_{Iu} \\ \mathbf{L}_{uI} & \mathbf{L}_{uu} \end{array}\right] \left[\begin{array}{c} \mathbf{f}_{I} \\ \mathbf{f}_{u} \end{array}\right] = \left[\begin{array}{c} \dots \\ \mathbf{0}_{u} \end{array}\right]$$

 \mathbf{f}_l is constrained to be \mathbf{y}_l and for \mathbf{f}_u

$$\mathbf{L}_{ul}\mathbf{f}_l + \mathbf{L}_{uu}\mathbf{f}_u = \mathbf{0}_u$$

...from which we get

$$\mathbf{f}_{u} = \mathbf{L}_{uu}^{-1}(-\mathbf{L}_{ul}\mathbf{f}_{l})$$

Let us compute harmonic solution using harmonic property!

$$(\mathbf{Lf})_u = \mathbf{0}_u$$

In matrix notation

$$\left[\begin{array}{cc} \mathbf{L}_{II} & \mathbf{L}_{Iu} \\ \mathbf{L}_{uI} & \mathbf{L}_{uu} \end{array}\right] \left[\begin{array}{c} \mathbf{f}_{I} \\ \mathbf{f}_{u} \end{array}\right] = \left[\begin{array}{c} \dots \\ \mathbf{0}_{u} \end{array}\right]$$

 \mathbf{f}_l is constrained to be \mathbf{y}_l and for \mathbf{f}_u

$$\mathbf{L}_{ul}\mathbf{f}_l + \mathbf{L}_{uu}\mathbf{f}_u = \mathbf{0}_u$$

...from which we get

$$\mathbf{f}_{u} = \mathbf{L}_{uu}^{-1}(-\mathbf{L}_{ul}\mathbf{f}_{l}) = \mathbf{L}_{uu}^{-1}(\mathbf{W}_{ul}\mathbf{f}_{l}).$$

Let us compute harmonic solution using harmonic property!

$$(\mathbf{Lf})_u = \mathbf{0}_u$$

In matrix notation

$$\left[\begin{array}{cc} \mathbf{L}_{II} & \mathbf{L}_{Iu} \\ \mathbf{L}_{uI} & \mathbf{L}_{uu} \end{array}\right] \left[\begin{array}{c} \mathbf{f}_{I} \\ \mathbf{f}_{u} \end{array}\right] = \left[\begin{array}{c} \dots \\ \mathbf{0}_{u} \end{array}\right]$$

 \mathbf{f}_l is constrained to be \mathbf{y}_l and for \mathbf{f}_u

$$\mathbf{L}_{ul}\mathbf{f}_l + \mathbf{L}_{uu}\mathbf{f}_u = \mathbf{0}_u$$

...from which we get

$$\mathbf{f}_{u} = \mathbf{L}_{uu}^{-1}(-\mathbf{L}_{ul}\mathbf{f}_{l}) = \mathbf{L}_{uu}^{-1}(\mathbf{W}_{ul}\mathbf{f}_{l}).$$
 $\mathbf{L}_{ul} = \mathbf{0} - \mathbf{W}_{ul}$

Let us compute harmonic solution using harmonic property!

$$(\mathbf{Lf})_u = \mathbf{0}_u$$

In matrix notation

$$\left[\begin{array}{cc} \mathbf{L}_{II} & \mathbf{L}_{Iu} \\ \mathbf{L}_{uI} & \mathbf{L}_{uu} \end{array}\right] \left[\begin{array}{c} \mathbf{f}_{I} \\ \mathbf{f}_{u} \end{array}\right] = \left[\begin{array}{c} \dots \\ \mathbf{0}_{u} \end{array}\right]$$

 \mathbf{f}_l is constrained to be \mathbf{y}_l and for \mathbf{f}_u

$$\mathbf{L}_{ul}\mathbf{f}_l + \mathbf{L}_{uu}\mathbf{f}_u = \mathbf{0}_u$$

...from which we get

$$\mathbf{f}_{u} = \mathbf{L}_{uu}^{-1}(-\mathbf{L}_{ul}\mathbf{f}_{l}) = \mathbf{L}_{uu}^{-1}(\mathbf{W}_{ul}\mathbf{f}_{l}).$$
 $\mathbf{L}_{ul} = \mathbf{0} - \mathbf{W}_{ul}$

Note that \mathbf{f}_{μ} does not depend on \mathbf{L}_{μ} .

Can we see that this calculates the probability of a random walk?

$$\mathbf{f}_{u} = \mathbf{L}_{uu}^{-1}(-\mathbf{L}_{ul}\mathbf{f}_{l})$$

Can we see that this calculates the probability of a random walk?

$$\mathbf{f}_{u} = \mathbf{L}_{uu}^{-1}(-\mathbf{L}_{ul}\mathbf{f}_{l}) = \mathbf{L}_{uu}^{-1}(\mathbf{W}_{ul}\mathbf{f}_{l})$$

Can we see that this calculates the probability of a random walk?

$$\mathbf{f}_u = \mathbf{L}_{uu}^{-1}(-\mathbf{L}_{ul}\mathbf{f}_l) = \mathbf{L}_{uu}^{-1}(\mathbf{W}_{ul}\mathbf{f}_l)$$

Note $\mathbf{P} = \mathbf{D}^{-1}\mathbf{W}$ and

$$\mathbf{L}_{\textit{uu}}^{-1} = (\mathbf{D}_{\textit{uu}}(\mathbf{I} - \mathbf{P}_{\textit{uu}}))^{-1} = (\mathbf{I} - \mathbf{P}_{\textit{uu}})^{-1}\mathbf{D}_{\textit{uu}}^{-1}$$

Can we see that this calculates the probability of a random walk?

$$\mathbf{f}_u = \mathbf{L}_{uu}^{-1}(-\mathbf{L}_{ul}\mathbf{f}_l) = \mathbf{L}_{uu}^{-1}(\mathbf{W}_{ul}\mathbf{f}_l)$$

Note $\mathbf{P} = \mathbf{D}^{-1}\mathbf{W}$ and

$$\mathbf{L}_{\textit{uu}}^{-1} = (\mathbf{D}_{\textit{uu}}(\mathbf{I} - \mathbf{P}_{\textit{uu}}))^{-1} = (\mathbf{I} - \mathbf{P}_{\textit{uu}})^{-1}\mathbf{D}_{\textit{uu}}^{-1}$$

$$\mathbf{f}_u = (\mathbf{I} - \mathbf{P}_{uu})^{-1} \mathbf{P}_{ul} \mathbf{f}_l.$$

Can we see that this calculates the probability of a random walk?

$$\mathbf{f}_{\textit{u}} = \mathbf{L}_{\textit{uu}}^{-1}(-\mathbf{L}_{\textit{ul}}\mathbf{f}_{\textit{l}}) = \mathbf{L}_{\textit{uu}}^{-1}(\mathbf{W}_{\textit{ul}}\mathbf{f}_{\textit{l}})$$

Note $\mathbf{P} = \mathbf{D}^{-1}\mathbf{W}$ and

$$\mathbf{L}_{uu}^{-1} = (\mathbf{D}_{uu}(\mathbf{I} - \mathbf{P}_{uu}))^{-1} = (\mathbf{I} - \mathbf{P}_{uu})^{-1}\mathbf{D}_{uu}^{-1}$$

$$\mathbf{f}_{u} = (\mathbf{I} - \mathbf{P}_{uu})^{-1} \mathbf{P}_{ul} \mathbf{f}_{l}.$$

Split the equation into +ve & -ve part:

$$f_i = (\mathbf{I} - \mathbf{P}_{uu})_{iu}^{-1} \mathbf{P}_{ul} \mathbf{f}_l$$

Can we see that this calculates the probability of a random walk?

$$\mathbf{f}_{\textit{u}} = \mathbf{L}_{\textit{uu}}^{-1}(-\mathbf{L}_{\textit{ul}}\mathbf{f}_{\textit{l}}) = \mathbf{L}_{\textit{uu}}^{-1}(\mathbf{W}_{\textit{ul}}\mathbf{f}_{\textit{l}})$$

Note $\mathbf{P} = \mathbf{D}^{-1}\mathbf{W}$ and

$$\begin{split} \mathbf{L}_{uu}^{-1} &= (\mathbf{D}_{uu}(\mathbf{I} - \mathbf{P}_{uu}))^{-1} = (\mathbf{I} - \mathbf{P}_{uu})^{-1}\mathbf{D}_{uu}^{-1} \\ \mathbf{f}_{u} &= (\mathbf{I} - \mathbf{P}_{uu})^{-1}\mathbf{P}_{ul}\mathbf{f}_{l}. \end{split}$$

Split the equation into +ve & -ve part:

$$f_{i} = (\mathbf{I} - \mathbf{P}_{uu})_{iu}^{-1} \mathbf{P}_{ul} \mathbf{f}_{l}$$

$$= \underbrace{\sum_{j:y_{j}=1} (\mathbf{I} - \mathbf{P}_{uu})_{iu}^{-1} \mathbf{P}_{uj}}_{p_{i}^{(+1)}} - \underbrace{\sum_{j:y_{j}=-1} (\mathbf{I} - \mathbf{P}_{uu})_{iu}^{-1} \mathbf{P}_{uj}}_{p_{i}^{(-1)}}$$

Can we see that this calculates the probability of a random walk?

$$\mathbf{f}_{\textit{u}} = \mathbf{L}_{\textit{uu}}^{-1}(-\mathbf{L}_{\textit{ul}}\mathbf{f}_{\textit{l}}) = \mathbf{L}_{\textit{uu}}^{-1}(\mathbf{W}_{\textit{ul}}\mathbf{f}_{\textit{l}})$$

Note $\mathbf{P} = \mathbf{D}^{-1}\mathbf{W}$ and

$$\mathbf{L}_{uu}^{-1} = (\mathbf{D}_{uu}(\mathbf{I} - \mathbf{P}_{uu}))^{-1} = (\mathbf{I} - \mathbf{P}_{uu})^{-1}\mathbf{D}_{uu}^{-1}$$

$$\mathbf{f}_{u} = (\mathbf{I} - \mathbf{P}_{uu})^{-1}\mathbf{P}_{ul}\mathbf{f}_{l}.$$

Split the equation into +ve & -ve part:

$$f_{i} = (\mathbf{I} - \mathbf{P}_{uu})_{iu}^{-1} \mathbf{P}_{ul} \mathbf{f}_{l}$$

$$= \underbrace{\sum_{j:y_{j}=1} (\mathbf{I} - \mathbf{P}_{uu})_{iu}^{-1} \mathbf{P}_{uj}}_{p_{i}^{(+1)}} - \underbrace{\sum_{j:y_{j}=-1} (\mathbf{I} - \mathbf{P}_{uu})_{iu}^{-1} \mathbf{P}_{uj}}_{p_{i}^{(-1)}}$$

$$= p_{i}^{(+1)} - p_{i}^{(-1)}$$

Michal Valko

michal.valko@inria.fr Inria & ENS Paris-Saclay, MVA

https://misovalko.github.io/mva-ml-graphs