

Graphs in Machine Learning

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Partially based on material by: Branislav Kveton, Partha Niyogi

March 3, 2015

MVA 2014/2015

Last Lecture

- Inductive and transductive semi-supervised learning
- Manifold regularization
- Theory of Laplacian-based manifold methods
- Transductive learning stability based bounds
- SSL Learnability
- Online Semi-Supervised Learning
- Online incremental k-centers



This Lecture

- Analysis of online SSL
- When does graph-based SSL provably help?
- Scaling harmonic functions to millions of samples
- Online decision-making on graphs
- Graph Bandits



Previous Lab Session

- 24. 2. 2015 by Daniele.Calandriello@inria.fr
- Content
 - Semi-supervised learning
 - Graph quantization
 - Online face recognizer
 - Install OpenCV (if you still have problems contact Daniele)
- Short written report (graded, each lab around 5% of grade)
- Daniele: Use CHFS instead of SHFS (material updated)
- Questions to Daniele.Calandriello@inria.fr
- Deadline: 10. 3. 2015
- http://researchers.lille.inria.fr/~calandri/ta/graphs/td2_handout.pdf



Next Lab Session

- ▶ 10. 3. 2015 by Daniele.Calandriello@inria.fr
- Content
 - GraphLab
 - Large-Scale Graph Learning
- AR1: Get the GraphLab license
- AR2: Install VirtualBox
- AR3: Download virtual machine (online very soon)
- Short written report (graded, each lab around 5% of grade)
- Questions to Daniele.Calandriello@inria.fr
- Deadline: 24. 3. 2015
- http://researchers.lille.inria.fr/~calandri/ta/graphs/td3_handout.pdf

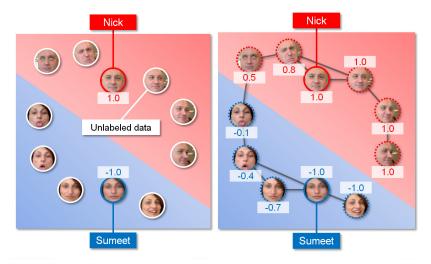


Final Class projects

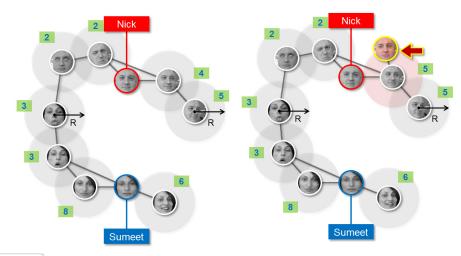
- preferred option: you come up with the topic
- details and list of suggested topics on the class website
- theory/implementation/review or a combination
- one or two people per project (exceptionally three)
- grade: report + short presentation of the team
- Deadlines
 - taking projects 17. 3. 2015 (recommended 10. 3. 2015)
 - ▶ 11. 4. 2015 final report
 - ▶ 13. 4. 2015 afternoon (tentative), presentation in class

http://researchers.lille.inria.fr/~valko/hp/serve?from=slides&what=mvaprojects



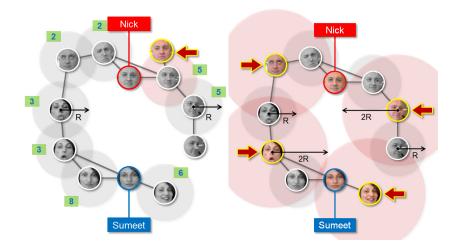


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Video examples

http://www.bkveton.com/videos/Coffee.mp4

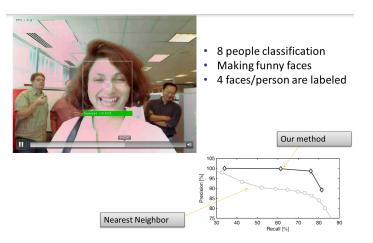
http://www.bkveton.com/videos/Ad.mp4

http://researchers.lille.inria.fr/~valko/hp/serve.php?
what=publications/kveton2009nipsdemo.adaptation.mov

http://researchers.lille.inria.fr/~valko/hp/serve.php?
what=publications/kveton2009nipsdemo.officespace.mov

http://bcove.me/a2derjeh



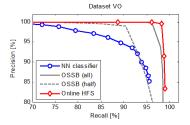




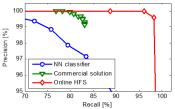
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- One person moves among various indoor locations
- 4 labeled examples of a person in the cubicle









Online HFS outperforms OSSB (even when the weak learners are chosen using future data)

Online HFS yields better results than a commercial solution at 20% of the computational cost



- Logging in with faces instead of password
- Able to learn and improve







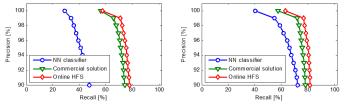


16 people log twice into a tablet PC at 10 locations









Online HFS yields better results than a commercial solution at 20% of the computational cost



What can we guarantee?

Three sources of error

- generalization error if all data: $(\ell_t^{\star} y_t)^2$
- online error data only incrementally: $(\ell_t^{o}[t] \ell_t^{\star})^2$
- quantization error memory limitation: $(\ell_t^{q}[t] \ell_t^{o}[t])^2$

All together:

$$\frac{1}{n}\sum_{t=1}^{n} (\ell_t^{q}[t] - y_t)^2 \le \frac{9}{2n}\sum_{t=1}^{n} (\ell_t^{\star} - y_t)^2 + \frac{9}{2n}\sum_{t=1}^{n} (\ell_t^{o}[t] - \ell_t^{\star})^2 + \frac{9}{2n}\sum_{t=1}^{n} (\ell_t^{q}[t] - \ell_t^{o}[t])^2$$

Since for any a, b, c, $d \in [-1, 1]$:

$$(a-b)^2 \leq \frac{9}{2} \left[(a-c)^2 + (c-d)^2 + (d-b)^2 \right]$$



Online SSL with Graphs: Analysis Bounding transduction error $(\ell_t^* - y_t)^2$

If all labeled examples / are i.i.d., $c_l = 1$ and $c_l \gg c_u$, then

$$R(\ell^{\star}) \leq \widehat{R}(\ell^{\star}) + \underbrace{\beta + \sqrt{\frac{2\ln(2/\delta)}{n_{l}}}(n_{l}\beta + 4)}_{\text{transductive error } \Delta_{T}(\beta, n_{l}, \delta)}$$
$$\beta \leq 2\left[\frac{\sqrt{2}}{\gamma_{g} + 1} + \sqrt{2n_{l}}\frac{1 - \sqrt{c_{u}}}{\sqrt{c_{u}}}\frac{\lambda_{M}(\mathbf{L}) + \gamma_{g}}{\gamma_{g}^{2} + 1}\right]$$

holds with the probability of $1-\delta$, where

$$R(\ell^{\star}) = \frac{1}{n} \sum_{t} (\ell_t^{\star} - y_t)^2 \quad \text{and} \quad \widehat{R}(\ell^{\star}) = \frac{1}{n_l} \sum_{t \in I} (\ell_t^{\star} - y_t)^2$$

How should we set γ_g ? Want $\Delta_T(\beta, n_l, \delta) = o(1) \rightarrow \beta = o(n_l^{-1/2})$

 $\begin{array}{l} \text{Vant } \Delta_T(\beta, n_l, \delta) = o(1) \to \beta = o\left(n_l^{-1/2}\right) \\ \\ \to \gamma_g = \Omega\left(n_l^{1+\alpha}\right) \text{ for any } \alpha > 0. \end{array}$

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Lecture 6 - 14/29

Bounding online error $(\ell_t^{\circ}[t] - \ell_t^{\star})^2$

Idea: If L and L^o are regularized, then HFSs get closer together.

since they get closer to zero

Recall $\boldsymbol{\ell} = (\mathbf{C}^{-1}\mathbf{Q} + \mathbf{I})^{-1}\mathbf{y}$, where $\mathbf{Q} = \mathbf{L} + \gamma_{g}\mathbf{I}$ and also $\mathbf{v} \in \mathbb{R}^{n \times 1}$, $\lambda_{m}(A) \|\mathbf{v}\|_{2} \le \|A\mathbf{v}\|_{2} \le \lambda_{M}(A) \|\mathbf{v}\|_{2}$

$$\|\boldsymbol{\ell}\|_2 \leq \frac{\|\boldsymbol{y}\|_2}{\lambda_m(\boldsymbol{\mathsf{C}}^{-1}\boldsymbol{\mathsf{Q}}+\boldsymbol{\mathit{I}})} = \frac{\|\boldsymbol{y}\|_2}{\frac{\lambda_m(\boldsymbol{\mathsf{Q}})}{\lambda_M(\boldsymbol{\mathsf{C}})}+1} \leq \frac{\sqrt{n_l}}{\gamma_g+1}$$

Difference between offline and online solutions:

$$(\boldsymbol{\ell}_t^{\mathrm{o}}[t] - \boldsymbol{\ell}_t^{\star})^2 \leq \|\boldsymbol{\ell}^{\mathrm{o}}[t] - \boldsymbol{\ell}^{\star}\|_{\infty}^2 \leq \|\boldsymbol{\ell}^{\mathrm{o}}[t] - \boldsymbol{\ell}^{\star}\|_2^2 \leq \left(\frac{2\sqrt{n_l}}{\gamma_g + 1}\right)^2$$

Bounding quantization error $(\ell_t^{q}[t] - \ell_t^{o}[t])^2$

How are the quantized and full solution different?

$$\ell^{\star} = \min_{\ell \in \mathbb{R}^n} \ (\ell - \mathbf{y})^{\mathsf{T}} \mathbf{C} (\ell - \mathbf{y}) + \ell^{\mathsf{T}} \mathbf{Q} \ell$$

In
$$\mathbf{Q}$$
! \mathbf{Q}^{o} (online) vs. \mathbf{Q}^{q} (quantized)

We have:
$$\ell^{\mathrm{o}} = (\mathbf{C}^{-1}\mathbf{Q}^{\mathrm{o}} + \mathbf{I})^{-1}\mathbf{y}$$
 vs. $\ell^{\mathrm{q}} = (\mathbf{C}^{-1}\mathbf{Q}^{\mathrm{q}} + \mathbf{I})^{-1}\mathbf{y}$

Let $\mathbf{Z}^{q} = \mathbf{C}^{-1}\mathbf{Q}^{q} + \mathbf{I}$ and $\mathbf{Z}^{o} = \mathbf{C}^{-1}\mathbf{Q}^{o} + \mathbf{I}$.

$$\ell^{q} - \ell^{o} = (\mathsf{Z}^{q})^{-1}\mathsf{y} - (\mathsf{Z}^{o})^{-1}\mathsf{y} = (\mathsf{Z}^{q}\mathsf{Z}^{o})^{-1}(\mathsf{Z}^{o} - \mathsf{Z}^{q})\mathsf{y}$$

= $(\mathsf{Z}^{q}\mathsf{Z}^{o})^{-1}\mathsf{C}^{-1}(\mathsf{Q}^{o} - \mathsf{Q}^{q})\mathsf{y}$



Bounding quantization error $(\ell_t^{q}[t] - \ell_t^{o}[t])^2$

$$\ell^{q} - \ell^{o} = (\mathsf{Z}^{q})^{-1}\mathsf{y} - (\mathsf{Z}^{o})^{-1}\mathsf{y} = (\mathsf{Z}^{q}\mathsf{Z}^{o})^{-1}(\mathsf{Z}^{o} - \mathsf{Z}^{q})\mathsf{y}$$
$$= (\mathsf{Z}^{q}\mathsf{Z}^{o})^{-1}\mathsf{C}^{-1}(\mathsf{Q}^{o} - \mathsf{Q}^{q})\mathsf{y}$$

$$\|\boldsymbol{\ell}^{\mathrm{q}} - \boldsymbol{\ell}^{\mathrm{o}}\|_{2} \leq \frac{\lambda_{M}(\mathbf{C}^{-1})\|(\mathbf{Q}^{\mathrm{q}} - \mathbf{Q}^{\mathrm{o}})\mathbf{y}\|_{2}}{\lambda_{m}(\mathbf{Z}^{\mathrm{q}})\lambda_{m}(\mathbf{Z}^{\mathrm{o}})}$$

 $||\cdot||_F$ and $||\cdot||_2$ are compatible and \mathbf{y}_i is zero when unlabeled:

$$\|(\mathbf{Q}^{\mathrm{q}}-\mathbf{Q}^{\mathrm{o}})\mathbf{y}\|_{2}\leq \|\mathbf{Q}^{\mathrm{q}}-\mathbf{Q}^{\mathrm{o}}\|_{\textit{F}}\cdot\|\mathbf{y}\|_{2}\leq \sqrt{n_{\textit{I}}}\|\mathbf{Q}^{\mathrm{q}}-\mathbf{Q}^{\mathrm{o}}\|_{\textit{F}}$$

Furthermore,
$$\lambda_m(\mathbf{Z}^{\circ}) \geq \frac{\lambda_m(\mathbf{Q}^{\circ})}{\lambda_M(\mathbf{C})} + 1 \geq \gamma_g$$
 and $\lambda_M(\mathbf{C}^{-1}) \leq c_u^{-1}$

We get
$$\|\boldsymbol{\ell}^{\mathrm{q}}-\boldsymbol{\ell}^{\mathrm{o}}\|_{2}\leq rac{\sqrt{n_{l}}}{c_{u}\gamma_{g}^{2}}\|\mathbf{Q}^{\mathrm{q}}-\mathbf{Q}^{\mathrm{o}}\|_{F}$$

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Bounding quantization error $(\ell_t^{q}[t] - \ell_t^{o}[t])^2$

The quantization error depends on $\|\mathbf{Q}^{q} - \mathbf{Q}^{o}\|_{F} = \|\mathbf{L}^{q} - \mathbf{L}^{o}\|_{F}$.

When can we keep $\|\mathbf{L}^{q} - \mathbf{L}^{o}\|_{F}$ under control?

Charikar guaranteed **distortion** error of Rm/(m-1)

For what kind of data $\{\mathbf{x}_i\}_{i=1,...,n}$ is the distortion small?

Assume manifold \mathcal{M}

- ▶ all $\{\mathbf{x}_i\}_{i \ge 1}$ lie on a smooth *s*-dimensional compact \mathcal{M}
- ▶ with boundary of bounded geometry Def. 11 of Hein [HAL07]
 - should not intersect itself
 - should not fold back onto itself
 - has finite volume V
 - has finite surface area A



Online SSL with Graphs: Analysis Bounding quantization error $(\ell_t^q[t] - \ell_t^o[t])^2$

Bounding $\|\mathbf{L}^{q} - \mathbf{L}^{o}\|_{F}$ when $\mathbf{x}_{i} \in \mathcal{M}$

Consider k-sphere packing of radius r with centers contained in \mathcal{M} .

What is the maximum volume of this packing?

 $kc_sr^s \leq V + Ac_{\mathcal{M}}r$ with $c_s, c_{\mathcal{M}}$ depending on dimension and \mathcal{M} .

If k is large $\rightarrow r <$ injectivity radius of \mathcal{M} [HAL07] and r < 1:

$$r < \left(\left(V + A c_{\mathcal{M}}\right) / (k c_s)\right)^{1/s} = \mathcal{O}\left(k^{-1/s}\right)$$

r-packing is a 2*r*-covering:

$$Rm/(m-1) = \max_{i=1,\dots,n} \|\mathbf{x}_i - \mathbf{c}\|_2 = 2(1+\varepsilon)\mathcal{O}\left(k^{-1/s}\right) = \mathcal{O}\left(k^{-1/s}\right)$$

But what about $\|\mathbf{L}^{q} - \mathbf{L}^{o}\|_{F}$?

Bounding quantization error $(\ell_t^{q}[t] - \ell_t^{o}[t])^2$

If similarity is *M*-Lipschitz, **L** is normalized, $c_{ij}^{o} = \sqrt{D_{ii}^{o}D_{jj}^{o}} > c_{min}n$.

$$\begin{split} \mathbf{L}_{ij}^{\mathrm{q}} - \mathbf{L}_{ij}^{\mathrm{o}} &= \frac{\mathbf{W}_{ij}^{\mathrm{q}}}{c_{ij}^{\mathrm{q}}} - \frac{\mathbf{W}_{ij}^{\mathrm{o}}}{c_{ij}^{\mathrm{o}}} \\ &\leq \frac{\mathbf{W}_{ij}^{\mathrm{q}} - \mathbf{W}_{ij}^{\mathrm{o}}}{c_{ij}^{\mathrm{q}}} + \frac{\mathbf{W}_{ij}^{\mathrm{q}}(c_{ij}^{\mathrm{q}} - c_{ij}^{\mathrm{o}})}{c_{ij}^{\mathrm{o}}c_{ij}^{\mathrm{q}}} \\ &\leq \frac{4MRm}{(m-1)c_{min}n} + \frac{4M(nMRm)}{((m-1)c_{min}n)^2} \\ &= O\left(\frac{R}{n}\right) \end{split}$$

Finally, $\|\mathbf{L}^{q} - \mathbf{L}^{o}\|_{F}^{2} \leq n^{2}\mathcal{O}(R^{2}/n^{2}) = \mathcal{O}(k^{-2/s}).$

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Are the assumptions reasonable?

Online SSL with Graphs: Analysis Bounding quantization error $(\ell_t^q[t] - \ell_t^o[t])^2$

We showed $\|\mathbf{L}^{\mathbf{q}} - \mathbf{L}^{\mathbf{o}}\|_{F}^{2} \leq n^{2}\mathcal{O}(R^{2}/n^{2}) = \mathcal{O}(k^{-2/s}) = \mathcal{O}(1).$

$$\frac{1}{n}\sum_{t=1}^{''}(\boldsymbol{\ell}_t^{\mathrm{q}}[t] - \boldsymbol{\ell}_t^{\mathrm{o}}[t])^2 \leq \frac{n_l}{c_u^2\gamma_g^4}\|\mathbf{L}^{\mathrm{q}} - \mathbf{L}^{\mathrm{o}}\|_F^2 \leq \frac{n_l}{c_u^2\gamma_g^4}$$

This converges to zero at the rate of $\mathcal{O}(n^{-1/2})$ with $\gamma_g = \Omega(n^{1/8})$.

With properly setting γ_g , e.g., $\gamma_g = \Omega(n^{1/8})$, we can have:

$$\frac{1}{n}\sum_{t=1}^{n}\left(\boldsymbol{\ell}_{t}^{\mathrm{q}}[t]-\boldsymbol{y}_{t}\right)^{2}=\mathcal{O}\left(\boldsymbol{n}^{-1/2}\right)$$

What does that mean?



Why and when it helps?

Can we guarantee benefit of SSL over SSL?

Are there cases when **manifold** SSL is provably helpful?

Say $\mathcal X$ is supported on manifold $\mathcal M$. Compare two cases:

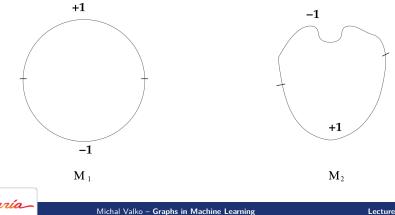
- SL: does not know about \mathcal{M} and only knows (\mathbf{x}_i, y_i)
- ▶ SSL: perfect knowledge of $\mathcal{M} \equiv$ humongous amounts of \mathbf{x}_i

http://people.cs.uchicago.edu/~niyogi/papersps/ssminimax2.pdf



Set of learning problems:

 $\mathcal{P} = \cup_{\mathcal{M}} \mathcal{P}_{\mathcal{M}} = \{ p \in \mathcal{P} | p_{\mathcal{X}} \text{ is uniform on } \mathcal{M} \}$



Lecture 6 - 23/29

Set of problems $\mathcal{P} = \bigcup_{\mathcal{M}} \mathcal{P}_{\mathcal{M}} = \{p \in \mathcal{P} | p_{\mathcal{X}} \text{ is uniform on } \mathcal{M}\}$ Regression function $m_p = \mathbb{E}[y | x]$ when $x \in \mathcal{M}$ Algorithm A and labeled examples $\bar{z} = \{z_i\}_{i=1}^n = \{(\mathbf{x}_i, y_i)\}_{i=1}^n$ Minimax rate

$$R(n,\mathcal{P}) = \inf_{A} \sup_{p \in \mathcal{P}} \mathbb{E}_{\bar{z}} \left[\|A(\bar{z}) - m_{p}\|_{L^{2}(p_{\mathbf{X}})} \right]$$

Since $\mathcal{P} = \cup_{\mathcal{M}} \mathcal{P}_{\mathcal{M}}$

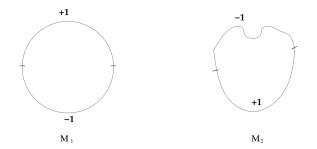
$$R(n,\mathcal{P}) = \inf_{A} \sup_{\mathcal{M}} \sup_{p \in \mathcal{P}_{\mathcal{M}}} \mathbb{E}_{\bar{z}} \left[\|A(\bar{z}) - m_{p}\|_{L^{2}(p_{\mathbf{X}})} \right]$$

(SSL) When A is allowed to know \mathcal{M}

$$Q(n,\mathcal{P}) = \sup_{\mathcal{M}} \inf_{A} \sup_{p \in \mathcal{P}_{\mathcal{M}}} \mathbb{E}_{\bar{z}} \left[\|A(\bar{z}) - m_{p}\|_{L^{2}(P_{\mathbf{X}})} \right]$$

In which cases there is a gap between $Q(n, \mathcal{P})$ and $R(n, \mathcal{P})$?

Hypothesis space \mathcal{H} : half of the circle as +1 and the rest as -1



Case 1: \mathcal{M} is known to the learner $(\mathcal{H}_{\mathcal{M}})$

What is a VC dimension of $\mathcal{H}_{\mathcal{M}}$? 2

Optimal rate
$$Q(n, \mathcal{P}) \leq 2\sqrt{\frac{3\log n}{n}}$$

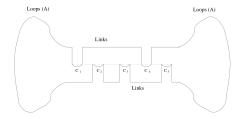
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Case 2: \mathcal{M} is unknown to the learner

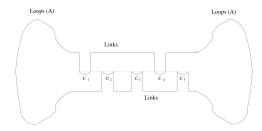
$$R(n,\mathcal{P}) = \inf_{A} \sup_{p \in \mathcal{P}} \mathbb{E}_{\bar{z}} \left[\|A(\bar{z}) - m_{p}\|_{L^{2}(p_{\mathbf{X}})} \right] = \Omega(1)$$

We consider 2^d manifolds of the form

$$\mathcal{M} = \mathsf{Loops} \cup \mathsf{Links} \cup C$$
 where $C = \cup_{i=1}^{d} C_i$



Main idea: *d* segments in *C*, d - I with no data, 2^{I} possible <u>choices</u> for labels, which helps us to lower bound $||A(\bar{z}) - m_p||_{L^2(p_X)}$



Knowing the manifold helps

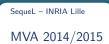
- C₁ and C₄ are close
- ▶ C₁ and C₃ are far
- we also need: target function varies smoothly
- \blacktriangleright altogether: closeness on manifold \rightarrow similarity in labels

What does it mean to know \mathcal{M} ?

Different degrees of knowing $\ensuremath{\mathcal{M}}$

- set membership oracle: $\mathbf{x} \stackrel{!}{\in} \mathcal{M}$
- approximate oracle
- \blacktriangleright knowing the harmonic functions on ${\cal M}$
- \blacktriangleright knowing the Laplacian $\mathcal{L}_{\mathcal{M}}$
- knowing eigenvalues and eigenfunctions
- topological invariants, e.g., dimension
- metric information: geodesic distance





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