Generalization bounds for variational inference

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Elements de maths. pour l'IA

May 15, 2019

Notations

Assume that we observe $X_1, \dots, X_n$ i.i.d from P_{θ_0} in a model $\{P_\theta, \theta \in \Theta\}$ dominated by Q : $\frac{\mathrm{d}P_\theta}{\mathrm{d}Q} = p_\theta$. Prior π on Θ.

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The tempered posterior - $0 < \alpha < 1$

$$\pi_{n,\alpha}(\mathrm{d}\theta) \propto [L_n(\theta)]^\alpha \pi(\mathrm{d}\theta).$$

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For these reasons, in the past 20 years, many methods targeting an approximation of $\pi_{n,\alpha}$ became popular : **ABC**, **EP algorithm**, variational inference, **approximate MCMC** ...

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Examples :

- parametric approximation

$$\mathcal{F} = \left\{ \mathcal{N}(\mu, \Sigma) : \mu \in \mathbb{R}^d, \Sigma \in \mathcal{S}_d^+ \right\}.$$

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- mean-field approximation, $\Theta = \Theta_1 \times \Theta_2$ and

$$\mathcal{F} : \{\rho : \rho(\mathrm{d}\theta) = \rho_1(\mathrm{d}\theta_1) \times \rho_2(\mathrm{d}\theta_2)\}.$$

Empirical lower bound (ELBO)

Note that :

$$\tilde{\pi}_{n,\alpha} = \arg\min_{\rho\in\mathcal{F}} \mathcal{K}(\rho, \pi_{n,\alpha})$$
$$= \arg\min_{\rho\in\mathcal{F}} \underbrace{\left\{ -\alpha \int \frac{1}{n} \sum_{i=1}^{n} \log p_\theta(X_i) \rho(\mathrm{d}\theta) + \mathcal{K}(\rho, \pi) \right\}}_{-\mathrm{ELBO}(\rho)}.$$

Empirical lower bound (ELBO)

Note that :

$$\begin{aligned}\tilde{\pi}_{n,\alpha} &= \arg\min_{\rho\in\mathcal{F}} \mathcal{K}(\rho, \pi_{n,\alpha}) \\ &= \arg\min_{\rho\in\mathcal{F}} \underbrace{\left\{ -\alpha \int \frac{1}{n}\sum_{i=1}^{n} \log p_\theta(X_i)\rho(\mathrm{d}\theta) + \mathcal{K}(\rho,\pi) \right\}}_{-\mathrm{ELBO}(\rho)}.\end{aligned}$$

So we have the equivalent definition :

$$\tilde{\pi}_{n,\alpha} := \arg\max_{\rho\in\mathcal{F}} \ \mathrm{ELBO}(\rho).$$

Outline of the talk

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We will see that fast algorithms from sequential optimization can be used in some cases. This also allows to do variational inference on a data stream that cannot be stored.

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   - Bayesian inference
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   - Outline of the talk
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   - Theoretical results
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   - Sequential estimation problem
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Tools for the consistency of VB

The α-Rényi divergence for $\alpha \in (0,1)$

$$D_{\alpha}(P,R) = \frac{1}{\alpha - 1} \log \int (\mathrm{d}P)^{\alpha} (\mathrm{d}R)^{1-\alpha}.$$

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All the properties derived in :

T. Van Erven & P. Harremos. Rényi divergence and Kullback-Leibler divergence. *IEEE Transactions on Information Theory*, 2014.

Among others, for $1/2 \leq \alpha$, link with Hellinger and Kullback :

$$\mathcal{H}^2(P,R) \leq D_\alpha(P,R) \xrightarrow[\alpha \nearrow 1]{} \mathcal{K}(P,R).$$

What do we know about $\pi_{n,\alpha}$?

$$\mathcal{B}(r) = \{\theta \in \Theta : \mathcal{K}(P_{\theta_0}, P_\theta) \leq r\} .$$

Theorem, variant of (Bhattacharya, Pati & Yang)

For any sequence (r_n) such that

$$-\log \pi[B(r_n)] \leq n r_n$$

we have

$$\mathbb{E}\left[\int D_\alpha(P_\theta, P_{\theta_0}) \pi_{n,\alpha}(\mathrm{d}\theta)\right] \leq \frac{1+\alpha}{1-\alpha} r_n .$$

A. Bhattacharya, D. Pati & Y. Yang. Bayesian fractional posteriors. *The Annals of Statistics*, 2019.

Extension of previous result to VB

Theorem (A. & Ridgway)

If there is $\rho_n \in \mathcal{F}$ and (r_n) such that

$$\begin{cases} \int \mathcal{K}(P_{\theta_0}, P_\theta)\rho_n(\mathrm{d}\theta) \leq r_n, \\ \text{and} \\ \mathcal{K}(\rho_n, \pi) \leq n r_n, \end{cases}$$

then, for any $\alpha \in (0,1)$,

$$\mathbb{E}\left[\int D_\alpha(P_\theta, P_{\theta_0})\tilde{\pi}_{n,\alpha}(\mathrm{d}\theta)\right] \leq \frac{1+\alpha}{1-\alpha} r_n.$$

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P. Alquier & J. Ridgway. Concentration of tempered posteriors and of their variational approximations. *The Annals of Statistics*, to appear.

Misspecified case

Assume now that $X_1, \ldots, X_n$ i.i.d $\sim Q \notin \{P_\theta, \theta \in \Theta\}$. Put :

$$\theta^* := \arg\min_{\theta \in \Theta} \mathcal{K}(Q, P_\theta).$$

Theorem (A. and Ridgway)

Assume that there is $\rho_n \in \mathcal{F}$ such that

$$\int \mathbb{E}\left[\log \frac{\mathrm{d}P_{\theta^*}}{\mathrm{d}P_\theta}\right] \rho_n(\mathrm{d}\theta) \leq r_n \text{ and } \mathcal{K}(\rho_n, \pi) \leq n r_n,$$

then, for any $\alpha \in (0, 1)$,

$$\mathbb{E}\left[\int D_\alpha(P_\theta, Q) \tilde{\pi}_{n,\alpha}(\mathrm{d}\theta)\right] \leq \frac{\alpha}{1-\alpha} \mathcal{K}(Q, P_{\theta^*}) + \frac{1+\alpha}{1-\alpha} r_n.$$

First example : nonparametric regression

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- prior : $f(\cdot) = \sum_{j=1}^{K} \beta_j \phi_j(\cdot)$, random K and β_j's, (φ_j) basis...
- variational approx : β_j mutually independent...

Under suitable assumptions, $r_n \sim \left(\frac{\log(n)}{n}\right)^{\frac{2s}{2s+1}}$.

More examples covered in the paper

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2. matrix completion : we prove that the approx. in

Y. J. Lim & Y. W. Teh. Variational Bayesian approach to movie rating prediction. *Proceedings of KDD cup and workshop*, 2007.

leads to minimax-optimal estimation.

				
Claire	4	?	3	...
Nial	?	4	?	...
Brendon	?	5	4	...
Andrew	?	4	?	...
Adrian	1	?	?	...
Damien	?	1	?	...
⋮	⋮	⋮	⋮	⋱

Extensions

1. case $\alpha = 1$, *i.e* approximation of the "usual" posterior :

F. Zhang & C. Gao. Convergence Rates of Variational Posterior Distributions. *Preprint arXiv*, 2017.

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2. approximation based on another distance, for example :

$$\tilde{\pi}_{n,\alpha} := \arg\min_{\rho \in \mathcal{F}} \mathcal{W}(\rho, \pi_{n,\alpha}) \text{ (Wasserstein distance),}$$

J. Huggins, T. Campbell, M. Kasprzak & T. Broderick. Practical bounds on the error of Bayesian posterior approximations : a nonasymptotic approach. *Preprint arXiv*, 2018.

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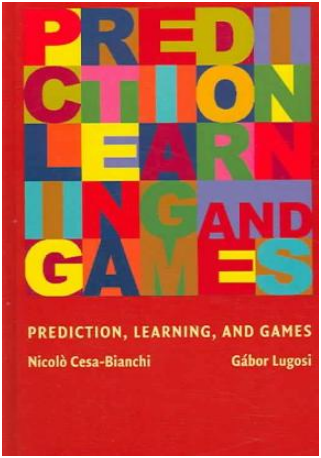
4. . . .

Objective : make sure that we learn to predict well **as fast as possible**. Keep

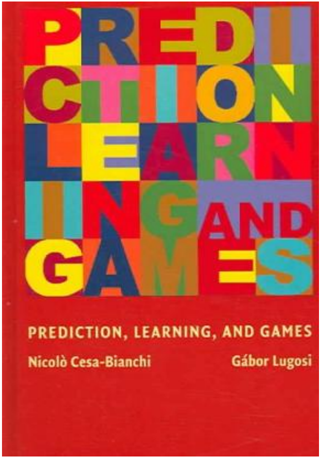
$$\sum_{t=1}^{T} [-\log p_{\theta_t}(x_t)]$$

as small as possible for any T, **without stochastic assumptions on the data.**

Reference


PREDICTION LEARNING AND GAMES
PREDICTION, LEARNING, AND GAMES
Nicolò Cesa-Bianchi
Gábor Lugosi

Reference



The regret :

$$\mathrm{R}(T) = \sum_{t=1}^{T} [-\log p_{\theta_t}(x_t)] - \inf_{\theta\in\Theta} \sum_{t=1}^{T} [-\log p_{\theta}(x_t)].$$

EWA strategy / multipicative update...

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Algorithm 2 Exponentially Weighted Aggregation

for $t = 1, 2, \ldots$ **do**
    $\theta_t = \mathbb{E}_{\theta \sim p_t}[\theta]$,
    x_t revealed, update $p_{t+1}(\mathrm{d}\theta) = \frac{[p_\theta(x_t)]^\alpha p_t(\mathrm{d}\theta)}{\int [p_\vartheta(x_t)]^\alpha p_t(\mathrm{d}\vartheta)}$.
end for

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4: **end for**

Note that $p_t = \pi_{n,\alpha}$ the tempered posterior, so problem : how can we compute θ_t ?

A regret bound for EWA

From now, $\theta \mapsto [-\log p_\theta(x_t)]$ is convex + bounded : $|\cdot| \leq C$.

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$$\sum_{t=1}^{T}[-\log p_{\theta_t}(x_t)] \leq \inf_p \left[\sum_{t=1}^{T} \mathbb{E}_{\theta\sim p}[-\log p_\theta(x_t)] + \frac{\alpha C^2 T}{2} + \frac{\mathcal{K}(p,\pi)}{\alpha}\right].$$

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Under similar assumptions than in the batch case, that is, the prior gives enough mass to relevant θ, and $\alpha \sim 1/\sqrt{T}$,

$$\sum_{t=1}^{T} [-\log p_{\theta_t}(x_t)] \leq \inf_{\theta\in\Theta} \sum_{t=1}^{T} [-\log p_\theta(x_t)] + \mathrm{cst.}\sqrt{T}$$

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Assuming that $x_1,\dots,x_T$ are actually i.i.d from Q, with density q, define

$$\hat{\theta}_T = \frac{1}{T}\sum_{t=1}^{T}\theta_T,$$

we have (“online-to-batch” conversion) :

$$\mathbb{E}\left[\mathcal{K}\left(Q, P_{\hat{\theta}_T}\right)\right] \leq \inf_{\theta\in\Theta}\mathcal{K}\left(Q, P_{\theta}\right) + \frac{\mathrm{cst}}{\sqrt{T}}.$$

Variational approximations of EWA

B.-E. Chérief-Abdellatif, P. Alquier & M. E. Khan. A Generalization Bound for Online Variational Inference. *Preprint arXiv*, 2019.

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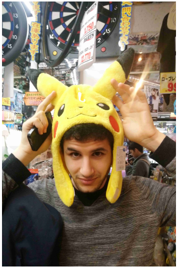

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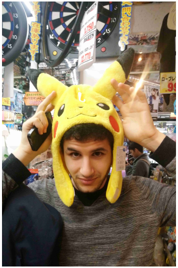

Parametric variational approximation : $\mathcal{F} = \{q_\mu, \mu \in M\}$.
Objective : propose a way to update $\mu_t \to \mu_{t+1}$ so that q_{μ_t} leads to similar performances as p_t in EWA...

SVA and SVB strategies

Algorithm 3 SVA (Sequential Variational Approximation)

1: **for** $t = 1, 2, \ldots$ **do**

2: $\theta_t = \mathbb{E}_{\theta \sim q_{\mu_t}}[\theta]$,

3: x_t revealed, update

$$\mu_{t+1} = \arg\min_{\mu \in M} \left[\mu^T \nabla_\mu \sum_{i=1}^{t} \mathbb{E}_{\theta \sim q_\mu}[-\log p_\theta(x_i)] + \frac{\mathcal{K}(q_\mu, \pi)}{\alpha} \right].$$

4: **end for**

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SVB (Streaming Variational Bayes) has update

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NGVI strategy

NGVI (Natural Gradient Variational Inference) : fix some $\beta > 0$,

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NGVI strategy

NGVI (Natural Gradient Variational Inference) : fix some $\beta > 0$,

$$\mu_{t+1} = \arg\min_{\mu \in M} \left[\mu^T \nabla_\mu \mathbb{E}_{\theta \sim q_\mu} [- \log p_\theta(x_t)] + \frac{\mathcal{K}(q_\mu, \pi)}{\alpha} + \frac{\mathcal{K}(q_\mu, q_{\mu_t})}{\beta} \right].$$

M. E. Khan & W. Lin. Conjugate-computation variational inference : Converting variational inference in non-conjugate models to inferences in conjugate models. *AISTAT*, 2017.

An example : SVB with Gaussian approximations

As an example, assume that $\theta \in \mathbb{R}^d$, the prior is $\pi = \mathcal{N}(0, s^2 I)$ and that we use the variational approximation family :
$$q_\mu = q_{m,\sigma} = \mathcal{N}\left(m, \begin{pmatrix} \sigma_1^2 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & \sigma_d^2 \end{pmatrix} \right).$$

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In this case, the update in SVB is :

$$m_{t+1} = m_t - \alpha \sigma_t^2 \odot \nabla_{m=m_t} \mathbb{E}_{\theta \sim q_{m,\sigma_t}} [-\log p_\theta(x_t)]$$

$$\sigma_{t+1} = \sigma_t \odot h\left(\frac{\alpha \sigma_t \nabla_{\sigma=\sigma_t} \mathbb{E}_{\theta \sim q_{m_t,\sigma}} [-\log p_\theta(x_t)]}{2} \right)$$

where $\odot$ means "componentwise multiplication" and $h(x) = \sqrt{1+x^2} - x$ is also applied componentwise.

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where $\odot$ means "componentwise multiplication" and $h(x) = \sqrt{1+x^2} - x$ is also applied componentwise. We also have explicit formulas for SVA and NGVI (see the paper).

A regret bound for SVA

Theorem (Chérief-Abdellatif, A. & Khan)

Assume that $\mu \mapsto \mathbb{E}_{\theta\sim q_\mu}[-\log p_\theta(x_t)]$ is L-Lipschitz and convex.

A regret bound for SVA

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Assume that $\mu \mapsto \mathbb{E}_{\theta\sim q_\mu}[-\log p_\theta(x_t)]$ is L-Lipschitz and convex. (this is for example the case as soon as the log-likelihood is concave in θ and L-Lipschitz, and μ is a location-scale parameter).

A regret bound for SVA

Theorem (Chérief-Abdellatif, A. & Khan)

Assume that $\mu \mapsto \mathbb{E}_{\theta\sim q_\mu}[-\log p_\theta(x_t)]$ is L-Lipschitz and convex. Assume that $\mu \mapsto \mathcal{K}(p_\mu, \pi)$ is γ-strongly convex. Then SVA satisfies :

$$
\begin{aligned}
&\sum_{t=1}^{T}[-\log p_{\theta_t}(x_t)] \\
&\leq \inf_{\mu\in M}\left\{\mathbb{E}_{\theta\sim q_\mu}\left[\sum_{t=1}^{T}[-\log p_\theta(x_t)]\right] + \frac{\alpha L^2 T}{\gamma} + \frac{\mathcal{K}(q_\mu,\pi)}{\alpha}\right\}.
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For SVB : some results in the Gaussian case.

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For SVB : some results in the Gaussian case. For NGVI : we were not able to derive regret bounds until now.

Test on a simulated dataset

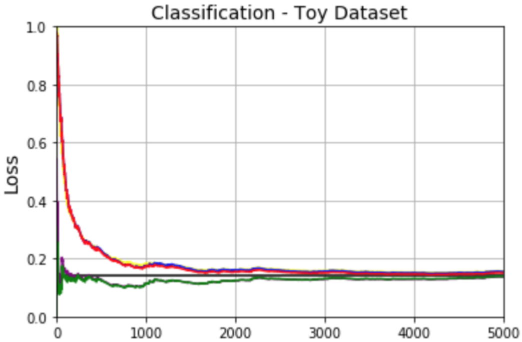
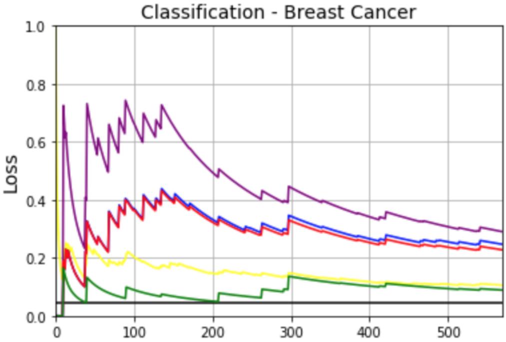


Figure – Average cumulative losses on different datasets for classification and regression tasks with OGA (yellow), OGA-EL (red), SVA (blue), SVB (purple) and NGVI (green).

Test on the Breast dataset



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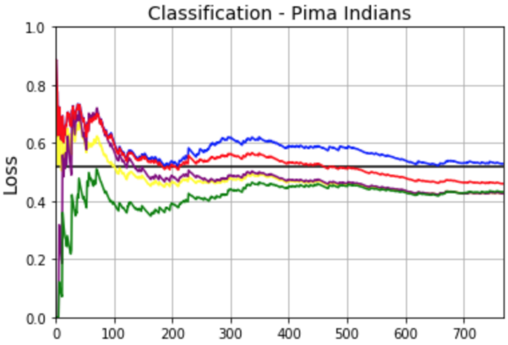
Test on the Pima Indians dataset



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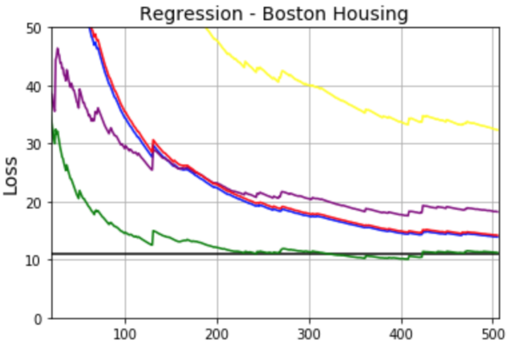
Test on the Boston Housing dataset



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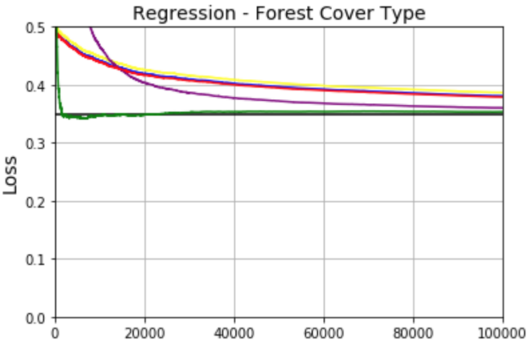
Test on the Forest Cover Type dataset



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Conclusions

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1. Using online-to-batch conversion, we now have algorithms for variational inference with provable statistical properties after a finite number of steps.
2. SVA, SVB competitive with OGA (online gradient algorithm, "non-Bayesian").
3. NGVI is the best method on all datasets. Its theoretical analysis is thus an important open problem. Cannot be done with our current techniques (using natural parameters in exponential models lead to non-convex objectives).

Thank you !