

Graphs in Machine Learning Analysis of Online SSL

Quantization Error and Performance Analysis

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Partially based on material by: Branislav Kveton, Mikhail Belkin, Jerry Zhu

Want to bound $\frac{1}{N} \sum_{t=1}^{N} (\hat{\mathit{f}}_{soq,t}[t] - \mathit{y}_t)^2$

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What can we guarantee?

Three sources of error

- generalization error if all data: $(\hat{f}_{s,t} y_t)^2$
- online error data only incrementally: $(\hat{\mathit{f}}_{so,t}[t] \hat{\mathit{f}}_{s,t})^2$
- quantization error memory limitation:

$$(\hat{f}_{soq,t}[t] - \hat{f}_{so,t}[t])^2$$

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- generalization error if all data: $(\hat{f}_{s,t} y_t)^2$
- online error data only incrementally: $(\hat{\mathit{f}}_{\mathit{so},t}[t] \hat{\mathit{f}}_{\mathit{s},t})^2$
- quantization error memory limitation: $(\hat{f} + \hat{f} + \hat{f} + \hat{f})^2$

All together:

$$\frac{1}{N} \sum_{t=1}^{N} (\hat{f}_{soq,t}[t] - y_t)^2 \leq \frac{9}{2N} \sum_{t=1}^{N} (\hat{f}_{s,t} - y_t)^2 + \frac{9}{2N} \sum_{t=1}^{N} (\hat{f}_{so,t}[t] - \hat{f}_{s,t})^2 + \frac{9}{2N} \sum_{t=1}^{N} (\hat{f}_{soq,t}[t] - \hat{f}_{soq,t})^2 + \frac{9}{2N} \sum_{t=1}^{N} (\hat{f}_{soq,t}[t] - \hat{f}_{s$$

Bounding transduction error $(\hat{f}_{s,t} - y_t)^2$

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

$$R(\ell^{\star}) \leq \widehat{R}(\ell^{\star}) + \underbrace{\beta + \sqrt{\frac{2\ln(2/\delta)}{n_{l}}}(n_{l}\beta + 4)}_{\text{transductive error }\Delta_{T}(\beta, n_{l}, \delta)}$$

$$\beta \leq 2 \left[\frac{\sqrt{2}}{\gamma_{\mathsf{g}} + 1} + \sqrt{2n_{\mathsf{I}}} \frac{1 - c_{\mathsf{u}}}{c_{\mathsf{u}}} \frac{\lambda_{\mathsf{M}}(\mathbf{L}) + \gamma_{\mathsf{g}}}{\gamma_{\mathsf{g}}^2 + 1} \right]$$

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

$$R(\boldsymbol{\ell}^{\star}) = \frac{1}{N} \sum_{t} (\hat{f}_{s,t} - y_t)^2 \quad \text{and} \quad \widehat{R}(\boldsymbol{\ell}^{\star}) = \frac{1}{n_l} \sum_{t \in I} (\hat{f}_{s,t} - y_t)^2$$

Bounding transduction error $(\hat{f}_{s,t} - y_t)^2$

If all labeled examples I are i.i.d., $c_I = 1$ and $c_I \gg c_{II}$, then

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How should we set γ_g ?

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$$\beta \leq 2 \left[\frac{\sqrt{2}}{\gamma_{g} + 1} + \sqrt{2n_{l}} \frac{1 - c_{u}}{c_{u}} \frac{\lambda_{M}(\mathbf{L}) + \gamma_{g}}{\gamma_{g}^{2} + 1} \right]$$

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Idea: If L and \hat{L}_o are regularized, then HFSs get closer together.

since they get closer to zero

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ldea: If ${\bf L}$ and $\hat{{\cal L}}_o$ are regularized, then HFSs get closer together.

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Recall
$$\boldsymbol{\ell} = (\mathbf{C}^{-1}\mathbf{Q} + \mathbf{I})^{-1}\mathbf{y}$$
, where $\mathbf{Q} = \mathbf{L} + \gamma_g\mathbf{I}$

and also $\mathbf{v} \in \mathbb{R}^{n \times 1}$, $\lambda_m(A) \|\mathbf{v}\|_2 \leq \|A\mathbf{v}\|_2 \leq \lambda_M(A) \|\mathbf{v}\|_2$

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$$\|\boldsymbol{\ell}\|_2 \leq \frac{\|\mathbf{y}\|_2}{\lambda_{m}(\mathbf{C}^{-1}\mathbf{Q} + \mathbf{I})}$$

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Difference between offline and online solutions:

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Again, how should we set γ_g ? If we want $O\left(n_l^{-1/2}\right)$? Then $\gamma_g = \Omega\left(n_l^{3/4}\right)$

Bounding quantization error $\left(\hat{f}_{soq,t}[t] - \hat{f}_{so,t}[t]\right)^2$

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How are the quantized and full solution different?

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

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In $\mathbf{Q}!$ \hat{K}_o (online) vs. \tilde{K} (quantized)

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In \mathbf{Q} ! \hat{K}_o (online) vs. \tilde{K} (quantized)

We have: $\hat{\ell}_o = (\mathbf{C}^{-1}\hat{\mathcal{K}}_o + \mathbf{I})^{-1}\mathbf{y}$ vs. $\hat{\ell}_{oq} = (\mathbf{C}^{-1}\tilde{\mathcal{K}} + \mathbf{I})^{-1}\mathbf{y}$

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In $\mathbf{Q}!$ $\hat{\mathcal{K}}_o$ (online) vs. $\tilde{\mathcal{K}}$ (quantized)

We have:
$$\hat{\ell}_o=(\mathbf{C}^{-1}\hat{\mathcal{K}}_o+\mathbf{I})^{-1}\mathbf{y}$$
 vs. $\hat{\ell}_{oq}=(\mathbf{C}^{-1}\tilde{\mathcal{K}}+\mathbf{I})^{-1}\mathbf{y}$

With linear algebra we get

$$\|\hat{\ell}_{oq} - \hat{\ell}_o\|_2 \le \frac{\sqrt{n_I}}{c_u \gamma_g^2} \|\hat{K}_{oq} - \hat{K}_o\|_F$$

Bounding quantization error $\left(\hat{f}_{soq,t}[t] - \hat{f}_{so,t}[t]\right)^2$

The quantization error depends on $\|\hat{K}_{oq} - \hat{K}_{o}\|_{F} = \|\hat{L}_{oq} - \hat{L}_{o}\|_{F}$.

When can we keep $\|\hat{L}_{oq} - \hat{L}_{o}\|_{F}$ under control?

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Charikar guarantees distortion error of at most RR/(R-1)

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Assume manifold ${\cal M}$

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Charikar guarantees distortion error of at most RR/(R-1)

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

Assume manifold \mathcal{M}

- all $\{\mathbf{x}_i\}_{i\geq 1}$ lie on a smooth d-dimensional compact $\mathcal M$
- with boundary of bounded geometry Def. 11 of Hein [hein2007graph]
 - has finite volume V
 - has finite surface area A
 - should not intersect itself
 - should not fold back onto itself

Bounding quantization error $\left(\hat{f}_{soq,t}[t] - \hat{f}_{so,t}[t]\right)^2$

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

Consider k-sphere packing* of radius r with centers contained in \mathcal{M} . *only the centers are packed, not necessarily the entire ball

If k is large $\rightarrow r < \text{injectivity radius of } \mathcal{M} \text{ [hein2007graph]}$

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Consider k-sphere packing* of radius r with centers contained in \mathcal{M} . *only the centers are packed, not necessarily the entire ball

If k is large $\rightarrow r <$ injectivity radius of \mathcal{M} [hein2007graph] and r < 1:

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$$r < \left(\frac{V + Ac_{\mathcal{M}}}{kc_d}\right)^{1/d} = \mathcal{O}\left(\frac{1}{k^{1/d}}\right)$$

r-packing is a 2r-covering:

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r-packing is a 2r-covering:

$$\max_{i=1,\dots,N} \|\mathbf{x}_i - \mathbf{c}\|_2 \le R \frac{R}{R-1} \le 2\mathcal{O}\left(k^{-1/d}\right) = \mathcal{O}\left(k^{-1/d}\right)$$

But what about $\|\hat{L}_{oq} - \hat{L}_{o}\|_{F}$?

Bounding quantization error $\left(\hat{f}_{soq,t}[t] - \hat{f}_{so,t}[t]\right)^2$

If similarity is M-Lipschitz

Bounding quantization error $\left(\hat{f}_{soq,t}[t] - \hat{f}_{so,t}[t]\right)^2$

If similarity is M-Lipschitz, L is normalized

Bounding quantization error $\left(\hat{f}_{soq,t}[t] - \hat{f}_{so,t}[t]\right)^2$

If similarity is *M*-Lipschitz, **L** is normalized, $\forall i,j \; \frac{\sqrt{\hat{D}_{oji}}\hat{D}_{ojj}}{N} > c_{min}$

Bounding quantization error $\left(\hat{f}_{soq,t}[t] - \hat{f}_{so,t}[t]\right)^2$ If similarity is M-Lipschitz, \mathbf{L} is normalized, $\forall i,j \; \frac{\sqrt{\hat{D}_{oii}\hat{D}_{ojj}}}{N} > c_{min}$ $\|\hat{L}_{oq} - \hat{L}_o\|_F^2 \leq \mathcal{O}(MR^2/c_{min}) = \mathcal{O}(k^{-2/d}).$

Bounding quantization error $\left(\hat{f}_{soq,t}[t] - \hat{f}_{so,t}[t]\right)^2$

If similarity is *M*-Lipschitz, **L** is normalized, $\forall i, j \; \frac{\sqrt{\hat{D}_{oii}\hat{D}_{ojj}}}{N} > c_{min}$

$$\|\hat{L}_{oq} - \hat{L}_o\|_F^2 \leq \mathcal{O}(MR^2/c_{min}) = \mathcal{O}(k^{-2/d}).$$

Are the assumptions reasonable?

Bounding quantization error $\left(\hat{f}_{soq,t}[t] - \hat{f}_{so,t}[t]\right)^2$

We showed $\|\hat{L}_{oq} - \hat{L}_{o}\|_F^2 \leq \mathcal{O}(k^{-2/d})$

Bounding quantization error $\left(\hat{f}_{soq,t}[t] - \hat{f}_{so,t}[t]\right)^2$

We showed $\|\hat{L}_{oq} - \hat{L}_{o}\|_F^2 \leq \mathcal{O}(k^{-2/d}) = \mathcal{O}(1)$.

Bounding quantization error $\left(\hat{f}_{soq,t}[t] - \hat{f}_{so,t}[t]\right)^2$

We showed $\|\hat{\mathbf{L}}_{oq} - \hat{\mathbf{L}}_{o}\|_{F}^{2} \leq \mathcal{O}(k^{-2/d}) = \mathcal{O}(1)$.

$$\frac{1}{N} \sum_{t=1}^{N} (\hat{f}_{soq,t}[t] - \hat{f}_{so,t}[t])^2 \le \frac{n_l}{c_u^2 \gamma_g^4} \|\hat{L}_{oq} - \hat{L}_o\|_F^2$$

Bounding quantization error $\left(\hat{f}_{soq,t}[t] - \hat{f}_{so,t}[t]\right)^2$

We showed
$$\|\hat{\underline{L}}_{oq} - \hat{\underline{L}}_o\|_F^2 \le \mathcal{O}(k^{-2/d}) = \mathcal{O}(1)$$
.

$$\frac{1}{N} \sum_{t=1}^{N} (\hat{f}_{soq,t}[t] - \hat{f}_{so,t}[t])^2 \le \frac{n_I}{c_u^2 \gamma_g^4} \|\hat{L}_{oq} - \hat{L}_o\|_F^2 \le \frac{n_I}{c_u^2 \gamma_g^4}$$

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With properly setting γ_g , e.g., $\gamma_g = \Omega(n_l^{3/8})$, we can have

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With properly setting $\gamma_{\rm g}$, e.g., $\gamma_{\rm g}=\Omega(n_{\rm I}^{3/8})$, we can have

$$\frac{1}{N} \sum_{t=1}^{N} \left(\hat{f}_{soq,t}[t] - y_t \right)^2 = \mathcal{O}\left(n_l^{-1/2} \right).$$

Bounding quantization error $\left(\hat{f}_{soq,t}[t] - \hat{f}_{so,t}[t]\right)^2$

We showed $\|\hat{\mathbf{L}}_{oq} - \hat{\mathbf{L}}_{o}\|_F^2 \leq \mathcal{O}(k^{-2/d}) = \mathcal{O}(1)$.

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What does that mean?

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