PAC-Bayes, Sample Compress & Kernel Methods

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Outline

In this lecture, we will :

- Review some elements of the **Sample-Compress theory**
- See how we can describe a SVM as a **Majority Vote of Sample-Compressed classifiers** (the Sc-SVM)
- Use the **PAC-Bayes** theory to **upper-bound** the risk of our Sc-SVM
- **Minimize** this PAC-Bayes bound and present **experimental results**
- and Conclude...

The Classification problem

We consider a training set S of m examples

$$S \stackrel{\text{def}}{=} (\mathbf{z}_1, \mathbf{z}_2, \ldots, \mathbf{z}_m)$$

where each $\mathbf{z}_i$ is a input-output pair:

$$\begin{array}{lcll} \mathbf{z}_i & \stackrel{\text{def}}{=} & (\mathbf{x}_i, y_i) & \\ \mathbf{x}_i & \in & \mathcal{X} \subseteq \mathbb{R}^n & \textit{(Real atttibutes)} \\ y_i & \in & \mathcal{Y} = \{-1, +1\} & \textit{(Binary classif.)} \end{array}$$

Each example $\mathbf{z}_i$ is drawn *IID* according to an unknown probability distribution D on $\mathcal{X} \times \mathcal{Y}$. Hence :

$$S \sim D^m$$

.

Elements of the Sample Compression theory

A **sc-classifier** $h_{\mathbf{i}}^{\mu}$ is a data-dependent classifier described by two variables:

- A **compression-set** $S_{\mathbf{i}}$ containing a subset of the training sequence S describing the classifier
  - $\mathbf{i} \stackrel{\text{def}}{=} \langle i_1, i_2, \ldots, i_{|\mathbf{i}|} \rangle$ with $1 \leq i_1 < i_2 < \ldots < i_{|\mathbf{i}|} \leq m$
- A **message string** μ containing the additional information needed to construct the classifier.
  - μ is choosen among $\mathcal{M}_{\mathbf{i}}$, a predefined set of all messages that can be supplied with $S_{\mathbf{i}}$.

Given $S_{\mathbf{i}}$ and μ, a **reconstruction function** $\mathcal{R}$ outputs a classifier :

$$h_{\mathbf{i}}^{\mu} \stackrel{\text{def}}{=} \mathcal{R}(S_{\mathbf{i}}, \mu)\,.$$

Risk of a sc-classifier

The **risk** (or generalization error) of a classifier h is defined as

$$R_D(h) \stackrel{\text{def}}{=} \mathop{\mathbf{E}}_{(\mathbf{x},y)\sim D} I(h(\mathbf{x}) \neq y) = \Pr_{(\mathbf{x},y)\sim D} (h(\mathbf{x}) \neq y)$$

where $I(a) = 1$ if predicate a is true and 0 otherwise.

The **empirical risk** of a sc-classifier $h_{\mathbf{i}}^{\mu}$ on the training set S is defined by

$$R_S(h_{\mathbf{i}}^{\mu}) \stackrel{\text{def}}{=} \frac{1}{m} \sum_{j=1}^{m} R_{\langle(\mathbf{x}_j,y_j)\rangle}(h_{\mathbf{i}}^{\mu}),$$

where

$$R_{\langle(\mathbf{x}_j,y_j)\rangle}(h_{\mathbf{i}}^{\mu}) \stackrel{\text{def}}{=} \begin{cases} I(h_{\mathbf{i}}^{\mu}(\mathbf{x}_j) \neq y_j) & \text{if } j \notin \mathbf{i} \\ 0 & \text{otherwise.} \end{cases}$$

Thus, $\quad mR_s(h_{\mathbf{i}}^{\mu}) \sim \mathrm{Bin}\Big(m - \|\mathbf{i}\|, R_D(h_{\mathbf{i}}^{\mu})\Big)\,.$

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Redefining the SVM as a Majority Vote of sc-classifiers

We denote $\mathcal{H}^S$ the set of all sc-classifiers. Each $h_{\mathbf{i}}^{\mu} \in \mathcal{H}^S$ is such as :

- The **compression-set** contains one training example :

$$S_{\mathbf{i}} \in \{S_{\langle 1 \rangle}, S_{\langle 2 \rangle}, \ldots, S_{\langle m \rangle}\}$$

- The **message string** is formed by a real number and a sign :

$$\mu \in \mathcal{M}_{\mathbf{i}} = [-1, 1] \times \{+, -\}$$

We consider **pairs of boolean complement classifiers** such as :

$$h_{\mathbf{i}}^{(\sigma,-)}(\mathbf{x}) = -h_{\mathbf{i}}^{(\sigma,+)}(\mathbf{x}) \quad \forall\, \mathbf{x} \in \mathcal{X},\, \sigma \in [-1, 1]\,.$$

sc-classifier $h_{\mathbf{i}}^{\mu} \in \mathcal{H}^S$

Comp-set: $S_{\mathbf{i}} \in \{S_{\langle 1 \rangle}, \ldots, S_{\langle m \rangle}\}$
Message: $\mu \in \mathcal{M}_{\mathbf{i}} = [-1, 1] \times \{+, -\}$

Distribution Q

$Q(h_{\mathbf{i}}^{\mu}) = Q_{\mathcal{I}}(\mathbf{i}) Q_{S_{\mathbf{i}}}(\mu)$
$Q(h_{\mathbf{i}}^{(\sigma,+)}) - Q(h_{\mathbf{i}}^{(\sigma,-)}) = w_{\mathbf{i}}$

Let Q be a **probability distribution** over $\mathcal{H}^S$. We denote

- $Q_{\mathcal{I}}$, the probability that a compression-set $S_{\mathbf{i}}$ is chosen by Q:

$$Q_{\mathcal{I}}(\mathbf{i}) \stackrel{\text{def}}{=} \int_{\mu \in \mathcal{M}_{\mathbf{i}}} Q(h_{\mathbf{i}}^{\mu}) d\mu$$

- $Q_{S_{\mathbf{i}}}$, the probability of choosing message μ given $S_{\mathbf{i}}$:

$$Q_{S_{\mathbf{i}}}(\mu) \stackrel{\text{def}}{=} Q(h_{\mathbf{i}}^{\mu} | S_{\mathbf{i}})$$

- Therefore, $Q(h_{\mathbf{i}}^{\mu}) = Q_{\mathcal{I}}(\mathbf{i}) Q_{S_{\mathbf{i}}}(\mu)$.

The **output** of the majority vote classifier (*bayes classifier*) is given by :

$$B_Q(\mathbf{x}) \stackrel{\text{def}}{=} \operatorname{sgn}\left[\mathop{\mathbf{E}}_{h \sim Q} h(\mathbf{x}) \right]$$

sc-classifier $h_{\mathbf{i}}^{\mu} \in \mathcal{H}^S$

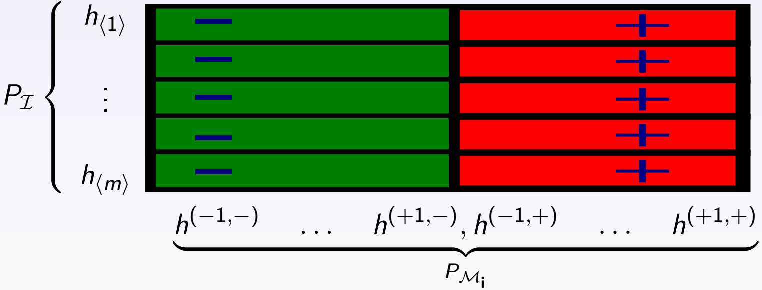
Comp-set: $S_{\mathbf{i}} \in \{S_{\langle 1 \rangle}, \ldots, S_{\langle m \rangle}\}$
Message: $\mu \in \mathcal{M}_{\mathbf{i}} = [-1, 1] \times \{+, -\}$

Distribution Q

$Q(h_{\mathbf{i}}^{\mu}) = Q_{\mathcal{I}}(\mathbf{i}) Q_{S_{\mathbf{i}}}(\mu)$
$Q(h_{\mathbf{i}}^{(\sigma,+)}) - Q(h_{\mathbf{i}}^{(\sigma,-)}) = w_{\mathbf{i}}$

Before seing the data, we define a **prior distribution** over the compression-sets and the message strings. This gives us indirectly a prior P over $\mathcal{H}^S$ such as :

- $P_{\mathcal{I}}$ is an uniform distribution over all possible compression-sets ;
- For each compression-set $S_{\mathbf{i}}$, $P_{S_{\mathbf{i}}}$ is uniform over all messages.



sc-classifier $h_{\mathbf{i}}^{\mu} \in \mathcal{H}^S$

Comp-set: $S_{\mathbf{i}} \in \{S_{\langle 1 \rangle}, \ldots, S_{\langle m \rangle}\}$
Message: $\mu \in \mathcal{M}_{\mathbf{i}} = [-1, 1] \times \{+, -\}$

Distribution Q

$Q(h_{\mathbf{i}}^{\mu}) = Q_{\mathcal{I}}(\mathbf{i}) Q_{S_{\mathbf{i}}}(\mu)$
$Q(h_{\mathbf{i}}^{(\sigma,+)}) - Q(h_{\mathbf{i}}^{(\sigma,-)}) = w_{\mathbf{i}}$

We say that a posterior Q is **aligned on** a prior P when for all $\mathbf{i}$ and σ:

$$Q(h_{\mathbf{i}}^{(\sigma,+)}) + Q(h_{\mathbf{i}}^{(\sigma,-)}) = P(h_{\mathbf{i}}^{(\sigma,+)}) + P(h_{\mathbf{i}}^{(\sigma,-)})$$

Moreover, we say that a posterior Q is **strongly aligned** when for all $\mathbf{i}$, there is a $w_{\mathbf{i}}$ such that for all σ:

$$Q(h_{\mathbf{i}}^{(\sigma,+)}) - Q(h_{\mathbf{i}}^{(\sigma,-)}) = w_{\mathbf{i}}$$

By restricting ourself to strongly aligned posterior, we obtain a posterior distribution totally defined by the $w_{\mathbf{i}}$'s :

$$\begin{aligned} Q(h_{\mathbf{i}}^{(\sigma,+)}) &= \frac{1}{2}\left(P(h_{\mathbf{i}}^{(\sigma,+)}) + P(h_{\mathbf{i}}^{(\sigma,-)}) + w_{\mathbf{i}}\right) \\ Q(h_{\mathbf{i}}^{(\sigma,-)}) &= \frac{1}{2}\left(P(h_{\mathbf{i}}^{(\sigma,+)}) + P(h_{\mathbf{i}}^{(\sigma,-)}) - w_{\mathbf{i}}\right) \end{aligned}$$

sc-classifier $h_{\mathbf{i}}^{\mu} \in \mathcal{H}^{S}$

Comp-set: $S_{\mathbf{i}} \in \{S_{\langle 1 \rangle}, \ldots, S_{\langle m \rangle}\}$

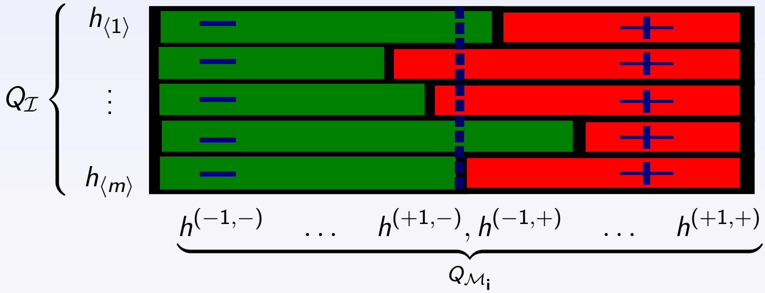
Message: $\mu \in \mathcal{M}_{\mathbf{i}} = [-1, 1] \times \{+, -\}$

Distribution Q

$Q(h_{\mathbf{i}}^{\mu}) = Q_{\mathcal{I}}(\mathbf{i}) Q_{S_{\mathbf{i}}}(\mu)$

$Q(h_{\mathbf{i}}^{(\sigma,+)}) - Q(h_{\mathbf{i}}^{(\sigma,-)}) = w_{\mathbf{i}}$

$$
\begin{aligned}
Q(h_{\mathbf{i}}^{(\sigma,+)}) &= \frac{1}{2}\left(P(h_{\mathbf{i}}^{(\sigma,+)}) + P(h_{\mathbf{i}}^{(\sigma,-)}) + w_{\mathbf{i}}\right) \\
Q(h_{\mathbf{i}}^{(\sigma,-)}) &= \frac{1}{2}\left(P(h_{\mathbf{i}}^{(\sigma,+)}) + P(h_{\mathbf{i}}^{(\sigma,-)}) - w_{\mathbf{i}}\right)
\end{aligned}
$$



sc-classifier $h_{\mathbf{i}}^{\mu} \in \mathcal{H}^S$

Comp-set: $S_{\mathbf{i}} \in \{S_{\langle 1\rangle}, \ldots, S_{\langle m\rangle}\}$
Message: $\mu \in \mathcal{M}_{\mathbf{i}} = [-1,1] \times \{+,-\}$

Distribution Q

$Q(h_{\mathbf{i}}^{\mu}) = Q_{\mathcal{I}}(\mathbf{i}) Q_{S_{\mathbf{i}}}(\mu)$
$Q(h_{\mathbf{i}}^{(\sigma,+)}) - Q(h_{\mathbf{i}}^{(\sigma,-)}) = w_{\mathbf{i}}$

Consider any similarity function $k(\cdot,\cdot) : \mathcal{X} \times \mathcal{X} \to [-1,1]$.
We say that **reconstruction function** $\mathcal{R}$ is associated to k when :

$$h_{\langle i\rangle}^{(\sigma,+)}(\mathbf{x}) \stackrel{\text{def}}{=} \begin{cases} +1 & \text{if } \sigma < k(\mathbf{x}_i, \mathbf{x}) \\ -1 & \text{otherwise} \end{cases}$$

$$h_{\mathbf{i}}^{(\sigma,-)}(\mathbf{x}) \stackrel{\text{def}}{=} -h_{\mathbf{i}}^{(\sigma,+)}(\mathbf{x}) \, .$$

We finally obtain that our strongly aligned posterior will be such that:

$$Q_{\mathcal{I}}(\langle i\rangle) = \frac{1}{m} \, , \quad w_{\langle i\rangle} \cdot k(\mathbf{x}_i, \mathbf{x}) = \int_{\mu \in \mathcal{M}_{\langle i\rangle}} h_{\langle i\rangle}^{\mu}(\mathbf{x}) \cdot Q_{\langle i\rangle}(\mu) \; d\mu \, .$$

Thus, the majority vote output $B_Q(\mathbf{x}) = \operatorname{sgn}\left[\mathop{\mathbf{E}}_{h\sim Q} h(\mathbf{x})\right]$ will be the same as $f_{\text{SVM}}(\mathbf{x}) = \operatorname{sgn}\left(\sum_{i=1}^{m} y_i \alpha_i k(\mathbf{x}_i, \mathbf{x})\right)$ when $w_{\langle i\rangle} = \dfrac{y_i \alpha_i}{Z \cdot m}$. $\left(Z \stackrel{\text{def}}{=} \sum_{i=1}^{m} \alpha_i\right)$

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PAC-Bayes bounds for Sc-SVM

PAC-Bayes theorems allow us to bound the risk of a majority vote classifier B_Q by bounding the **risk of the Gibbs classifier** G_Q, related to B_Q

- Given $\mathbf{x}$, G_Q draws h according to Q and classifies $\mathbf{x}$ according to h.
- It follows that $R_D(B_Q) \leq 2R_D(G_Q)$.

In our setting, the Gibbs risk $R_D(G_Q)$ will be likely near $1/2$, even if the Bayes risk is close to 0.

- Each sc-classifier $h_{\mathbf{i}}^{\mu} \in \mathcal{H}^S$ might be really weak.

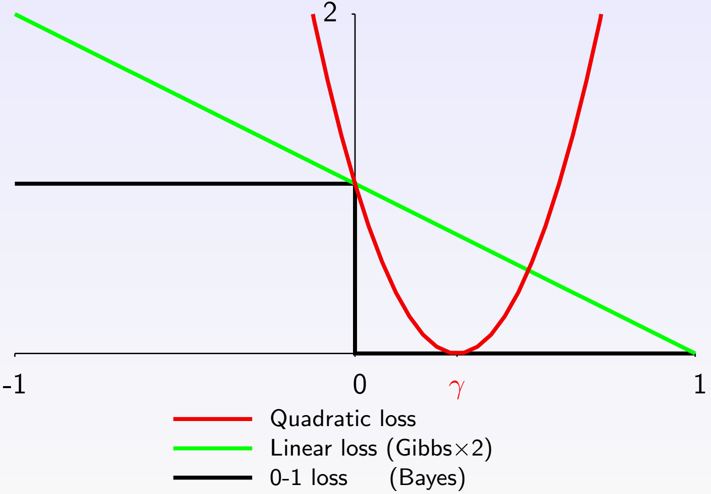
We want to bound a **more relevant risk**!

Similary at [Germain et al. *PAC-Bayes bounds for general loss functions* (2006)], we can consider any non-negative loss ζ that can be expended by a Taylor series around the margin $M_Q(\mathbf{x}, y) = 0$.

Margin of the majority vote classifier

$$M_Q(\mathbf{x}, y) \stackrel{\text{def}}{=} \mathbf{E}_{h^\mu_\mathbf{i} \sim Q}\, y\, h^\mu_\mathbf{i}(\mathbf{x}) = 1 - 2R_{\langle(\mathbf{x}_j, y_j)\rangle}(G_Q)$$

We choose to use the **quadratic loss** function $\zeta_\gamma(\alpha) = \left(1 - \frac{1}{\gamma}\alpha\right)^2$.



First PAC-Bayes theorem

We adapted the **Catoni's theorem** to consider:

- A general loss function ζ
- A set of (data-dependent) sc-classifiers of size $\leq l$

Theorem

For any D, any family $(\mathcal{H}^S)_{S\in\mathcal{D}^m}$ of sets of sc-classifiers of size at most l, any prior P, any $\delta \in (0,1]$, any $C_1 \in \mathbb{R}^+$ and any margin loss function ζ of degree $\frac{m}{l}$:

$$\Pr_{S\sim D^m}\left(\begin{array}{l}\forall\, Q \;\; on \;\; \mathcal{H}^S: \\ \zeta_D^Q \;\; \leq \;\; C' \cdot \left(\zeta_S^Q + \frac{\zeta'(1)\cdot \mathrm{KL}(Q\|P) + \zeta(1)\cdot \ln\frac{1}{\delta}}{C_1\cdot m}\right)\end{array}\right) \geq 1-\delta\,,$$

where $\mathrm{KL}(\cdot\|\cdot)$ is the Kullback-Leibler divergence and $C' = \dfrac{C_1 \cdot \frac{m}{m-l\cdot\deg\zeta}}{1-e^{-C_1\cdot\frac{m-l\cdot\deg\zeta}{m}}}$.

Finding Q that minimizes this bound is equivalent to finding Q minimizing:

$$f(Q) \stackrel{\mathrm{def}}{=} C\cdot \zeta_S^Q + KL(Q\|P) \qquad \text{(where } C \text{ is an hyperparameter)}$$

Second PAC-Bayes theorem

We adapted the **Langford and Seeger's theorem** which use the KL divergence between two Bernoulli distributions of prob of success p and q:

$$\mathrm{kl}(q\|p) \quad \stackrel{\text{def}}{=} \quad q \ln \frac{q}{p} + (1-q) \ln \frac{1-q}{1-p} \quad = \quad \mathrm{kl}(1-q\|1-p)$$

The usual term $\mathrm{KL}(Q\|P)$ disappear as we consider aligned posteriors:

$$Q(h) + Q(-h) = P(h) + P(-h) \; \forall h \in \mathcal{H}$$

Theorem

For any D, any family $(\mathcal{H}^S)_{S\in\mathcal{D}^m}$ of sets of sc-classifiers of size at most l, any prior P, any $\delta \in (0,1]$, any margin loss function ζ of degree $< m/l$, we have

$$\Pr_{S\sim D^m}\left(\begin{array}{l} \forall Q\in\mathcal{H}^S \;\; \textbf{aligned on } P: \\ \mathrm{kl}\left(\frac{1}{\zeta(1)}\cdot\zeta_S^Q \middle\| \frac{1}{\zeta(1)}\cdot\zeta_D^Q\right) \leq \frac{\ln\frac{m+1}{\delta}}{m-l\cdot\deg\zeta} \end{array}\right) \geq 1-\delta$$

This bound suggests to minimize the empirical risk: $f(Q) \stackrel{\text{def}}{=} \zeta_S^Q$

We want to bound random variable $\mathbf{E}_{h\sim P} e^{m\cdot \mathrm{kl}(R_S(h)\|R(h))}$ in term of $R(G_Q)$.

General theorem

Term $\mathrm{KL}(Q\|P)$ arises when transforming expectation over P into expectation over Q:

$$\begin{aligned}
& \ln\left[\mathbf{E}_{h\sim P} e^{m\cdot \mathrm{kl}(R_S(h)\|R(h))}\right] \\
= & \ln\left[\mathbf{E}_{h\sim Q} \frac{P(h)}{Q(h)} e^{m\cdot \mathrm{kl}(R_S(h),R(h))}\right] \\
\geq & \mathbf{E}_{h\sim Q} \ln\left[\frac{P(h)}{Q(h)} e^{m\cdot \mathrm{kl}(R_S(h),R(h))}\right] \\
= & m \mathbf{E}_{h\sim Q} \mathrm{kl}(R_S(h), R(h)) - \mathrm{KL}(Q\|P) \\
\geq & m \cdot \mathrm{kl}(\mathbf{E}_{h\sim Q} R_S(h), \mathbf{E}_{h\sim Q} R(h)) - \mathrm{KL}(Q\|P) \\
= & m \cdot \mathrm{kl}(R_S(G_Q), R(G_Q)) - \mathrm{KL}(Q\|P)\,.
\end{aligned}$$

Aligned posterior theorem

Here, we do the same operation for "free" (proof on next slide):

$$\begin{aligned}
& \ln\left[\mathbf{E}_{h\sim P} e^{m\cdot \mathrm{kl}(R_S(h)\|R(h))}\right] \\
= & \ln\left[\mathbf{E}_{h\sim Q} e^{m\cdot \mathrm{kl}(R_S(h)\|R(h))}\right] \\
\geq & \mathbf{E}_{h\sim Q} \ln\left[e^{m\cdot \mathrm{kl}(R_S(h),R(h))}\right] \\
= & m \mathbf{E}_{h\sim Q} \mathrm{kl}(R_S(h), R(h)) \\
\geq & m \cdot \mathrm{kl}(\mathbf{E}_{h\sim Q} R_S(h), \mathbf{E}_{h\sim Q} R(h)) \\
= & m \cdot \mathrm{kl}(R_S(G_Q), R(G_Q))\,.
\end{aligned}$$

The two "$\geq$" come from Jensen's inequality: $\mathbf{E}\, f(X) \geq f(\mathbf{E}\, X)$ for convex f.

First, note that as we have $h \in \mathcal{H}^S \Rightarrow -h \in \mathcal{H}^S$:

$$\mathop{\mathbf{E}}_{h\sim P} e^{m\cdot \mathrm{kl}(R_S(h)\|R(h))} = \int_{h\in\mathcal{H}} P(h) e^{m\cdot \mathrm{kl}(R_S(h)\|R(h))} = \int_{h\in\mathcal{H}} P(-h) e^{m\cdot \mathrm{kl}(R_S(-h)\|R(-h))} .$$

Then, following that $Q(h) + Q(-h) = P(h) + P(-h)$:

$$\begin{aligned}
2 \mathop{\mathbf{E}}_{h\sim P} & e^{m\cdot \mathrm{kl}(R_S(h)\|R(h))} \\
&= \int_{h\in\mathcal{H}} P(h) e^{m\cdot \mathrm{kl}(R_S(h)\|R(h))} + \int_{h\in\mathcal{H}} P(-h) e^{m\cdot \mathrm{kl}(R_S(-h)\|R(-h))} \\
&= \int_{h\in\mathcal{H}} P(h) e^{m\cdot \mathrm{kl}(R_S(h)\|R(h))} + \int_{h\in\mathcal{H}} P(-h) e^{m\cdot \mathrm{kl}(1-R_S(h)\|1-R(h))} \\
&= \int_{h\in\mathcal{H}} \left(P(h) + P(-h)\right) e^{m\cdot \mathrm{kl}(R_S(h)\|R(h))} \\
&= \int_{h\in\mathcal{H}} \left(Q(h) + Q(-h)\right) e^{m\cdot \mathrm{kl}(R_S(h)\|R(h))} \\
&= \int_{h\in\mathcal{H}} Q(h) e^{m\cdot \mathrm{kl}(R_S(h)\|R(h))} + \int_{h\in\mathcal{H}} Q(-h) e^{m\cdot \mathrm{kl}(R_S(-h)\|R(-h))} \\
&= 2 \mathop{\mathbf{E}}_{h\sim Q} e^{m\cdot \mathrm{kl}(R_S(h)\|R(h))} .
\end{aligned}$$

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We have designed two learning algorithms

Remember that Q is **strongly aligned**: $Q(h_{\mathbf{i}}^{(\sigma,+)}) - Q(h_{\mathbf{i}}^{(\sigma,-)}) = w_{\mathbf{i}}$.

The task of the algorithms is to find a vector $\mathbf{w} = (w_1, \ldots, w_m)$,

$$\begin{aligned} w_i &\stackrel{\text{def}}{=} w_{\langle i \rangle} = Q(h_{\langle i \rangle}^{(\sigma,+)}) - Q(h_{\langle i \rangle}^{(\sigma,-)}) \\ |w_j| &\leq \frac{1}{m} \quad \forall j \in \{1, \ldots, m\} \end{aligned}$$

The empirical margin $\widehat{M}_Q$ is now defined by

$$\widehat{M}_Q(\mathbf{x}_j, y_j) = \sum_{k=0}^{m} y_j \, w_k \, \widehat{G}(\mathbf{x}_k, \mathbf{x}_j)$$

where

$$\widehat{G}(\mathbf{x}_j, \mathbf{x}_l) \stackrel{\text{def}}{=} \begin{cases} k(\mathbf{x}_j, \mathbf{x}_l) & \forall j \in \{1, .., m\} \text{ and } j \neq l \\ 1 & \forall j \in \{1, .., m\} \text{ and } j = l \end{cases}$$

Algorithm with KL (Based on our first PAC-Bayes theorem)

Find $\mathbf{w}$ that minimizes $f(\mathbf{w}) \stackrel{\text{def}}{=} C \cdot \sum_{j=0}^{m} \zeta_\gamma \left(y_j \, \mathbf{w} \, \widehat{\mathbf{G}}(\mathbf{x}_j) \right) + \mathrm{KL}(Q_{\mathbf{w}} || P)$

Parameters to tune :

- C, the trade-off between the two terms to minimize
- γ, the minimum of the quadratic risk

Algorithm without KL (Based on our second PAC-Bayes theorem)

Find $\mathbf{w}$ that minimizes $f(\mathbf{w}) \stackrel{\text{def}}{=} \sum_{j=0}^{m} \zeta_\gamma \left(y_j \, \mathbf{w} \, \widehat{\mathbf{G}}(\mathbf{x}_j) \right)$

Parameter to tune :

- γ, the minimum of the quadratic risk

Both objective functions are **convex**. $\Rightarrow$ Only one global minimum.

Experimental results (RBF kernel, 10-folds CV)

Dataset	$\lvert T \rvert$	$\lvert S \rvert$	n	**Classic SVM**	**SC-SVM** (with KL)	**SC-SVM** (w/o KL)
Usvotes	200	235	16	0.065	**0.060**	**0.060**
Liver	175	170	6	**0.303**	0.371	**0.303**
Credit-A	300	353	15	0.187	0.170	**0.150**
Glass	107	107	9	0.159	**0.131**	0.178
Haberman	150	144	3	**0.273**	0.287	0.287
Heart	147	150	13	0.184	**0.163**	0.190
sonar	104	104	60	0.183	0.144	**0.135**
BreastCancer	340	343	9	0.038	**0.035**	**0.035**
Tic-tac-toe	479	479	9	0.023	**0.015**	**0.015**
Ionosphere	175	176	34	0.051	**0.029**	**0.029**
Wdbc	284	285	30	0.070	0.092	**0.067**
MNIST:0vs8	1916	500	784	0.005	**0.004**	**0.004**
MNIST:1vs7	1922	500	784	0.012	**0.008**	0.010
MNIST:1vs8	1936	500	784	0.013	**0.011**	**0.011**
MNIST:2vs3	1905	500	784	0.023	**0.016**	0.018
Letter:AB	1055	500	16	**0.001**	**0.001**	**0.001**
Letter:DO	1058	500	16	0.013	**0.009**	**0.009**
Letter:OQ	1036	500	16	**0.014**	0.017	0.017
Adult	10000	1809	14	0.160	**0.157**	**0.157**
Mushroom	4062	4062	22	**0.000**	**0.000**	**0.000**
Waveform	4000	4000	21	**0.068**	0.069	**0.068**
Ringnorm	3700	3700	20	0.015	0.016	**0.012**

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Future works

We presented a general framework to apply the PAC-Bayes theory to kernels methods.

For now, we compare ourself to the Support Vector Machine, but there is many other possibilities.

Three future research ideas (among others) :

- Experimentations with **non-PSD kernels**
- Consider a majority vote of sc-classifiers of **maximum size** > 1
- Consider **non-strongly aligned** posteriors.