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Technical Appendix on Sparse Bayesian Regression

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Abstract. We report the technical details for a sparse bayesian approach to regression. It can be seen as an extension of the Relevance Vector Machine of Tipping *et al* [1] to a more general setting that can handle vector-valued regression and generic quadratic priors.

1 Quadratic Energies & Marginal Likelihood of the Data

We want to minimize in \mathbf{w} the following cost:

$$E(\mathbf{w}) = (\mathbf{t} - \Phi\mathbf{w})^\top \beta \mathbf{H} (\mathbf{t} - \Phi\mathbf{w}) + \mathbf{w}^\top (\mathbf{A} + \lambda \mathbf{R}) \mathbf{w} \quad (1)$$

and jointly optimize in $\mathbf{A} = \text{diag}(\mathbf{A}_i)$, β , λ . $\mathbf{w}|\mathbf{t}, \mathbf{A}, \lambda, \beta$ follows a Gaussian distribution $\mathcal{N}(\boldsymbol{\mu}, \Sigma)$, where

$$\boldsymbol{\mu} = \Sigma \Phi^\top \beta \mathbf{H} \mathbf{t}, \quad \Sigma = (\mathbf{A} + \lambda \mathbf{R} + \Phi^\top \beta \mathbf{H} \Phi)^{-1} \quad (2)$$

A key element is that the distribution of $\mathbf{t}|\mathbf{A}$ is also Gaussian, $\mathbf{t}|\mathbf{A} \sim \mathcal{N}(\mathbf{0}, \mathbf{C})$, with

$$\mathbf{C} = (\beta \mathbf{H})^{-1} + \Phi (\mathbf{A} + \lambda \mathbf{R})^{-1} \Phi^\top \quad (3)$$

Indeed, we see that:

$$\begin{aligned} p(\mathbf{t}|\mathbf{A}) &= \int p(\mathbf{t}|\mathbf{w})p(\mathbf{w}|\mathbf{A})d\mathbf{w} \\ &\propto \int \exp -\frac{1}{2}(\mathbf{t} - \Phi\mathbf{w})^\top \beta \mathbf{H} (\mathbf{t} - \Phi\mathbf{w}) \cdot \exp -\frac{1}{2}\mathbf{w}^\top (\mathbf{A} + \lambda \mathbf{R}) \mathbf{w} \cdot d\mathbf{w} \\ &\propto \exp -\frac{1}{2}\boldsymbol{\mu}^\top \Sigma^{-1} \boldsymbol{\mu} \cdot \exp -\frac{1}{2}\mathbf{t}^\top \beta \mathbf{H} \mathbf{t} \cdot \int \exp -\frac{1}{2}(\mathbf{w} - \boldsymbol{\mu})^\top \Sigma^{-1} (\mathbf{w} - \boldsymbol{\mu}) d\mathbf{w} \end{aligned}$$

where the integral sums to 1. Thus using (2),

$$p(\mathbf{t}|\mathbf{A}) \propto \exp -\frac{1}{2}\mathbf{t}^\top (\beta \mathbf{H}) \mathbf{t} - \frac{1}{2}\mathbf{t}^\top (\beta \mathbf{H}) \Phi \Sigma \Phi^\top (\beta \mathbf{H}) \mathbf{t}$$

$\mathbf{t}|\mathbf{A}$ is Gaussian since the distribution is proportional to a Gaussian, and by identification it ensues that $\mathbf{C}^{-1} = \beta \mathbf{H} - (\beta \mathbf{H}) \Phi \Sigma \Phi^\top (\beta \mathbf{H})$. We then get the desired result using a matrix inversion identity. The fast RVM algorithm proceeds by iteratively implementing a single change to one of the \mathbf{A}_i 's on the block-diagonal matrix \mathbf{A} ; specifically the one that maximizes the increase of a quantity known as the *evidence*, $\log p(\mathbf{t}|\mathbf{A})$, then re-estimating the parameters of the conditional posterior $\mathbf{w}|\mathbf{t}, \mathbf{A}, \lambda, \beta$ using (2). The algorithm starts with all \mathbf{A}_i set to ∞ . The computations involve rank-one "block" updates; it also turns out that the optimal \mathbf{A}_i 's are rank one matrices (so we actually have rank-one updates).

2 Computation of the gain in evidence for a given action

We want to evaluate the change in $\log p(\mathbf{t}|\mathbf{A}_{-i}, \mathbf{A}_i)$ when a single prior weight \mathbf{A}_i is changed. Recall that $\mathbf{t}|\mathbf{A}_{-i}, \mathbf{A}_i \sim \mathcal{N}(\mathbf{0}, \mathbf{C})$, thus

$$\log p(\mathbf{t}|\mathbf{A}_{-i}, \mathbf{A}_i) = -1/2 \{ \log |\mathbf{C}| + \mathbf{t}^\top \mathbf{C}^{-1} \mathbf{t} \} \quad (4)$$

Now let's single out the contribution of \mathbf{A}_i , for each of the two terms above. Noting the form of eq. (3), let $\mathbf{L} = (\mathbf{A} + \lambda \mathbf{R})^{-1}$. We can single out the contribution of the i th basis to \mathbf{L} first, as a rank one update:

$$\mathbf{L} = \begin{pmatrix} \mathbf{L}_{-i} & 0 \\ 0 & 0 \end{pmatrix} + \mathbf{U}_i l_i \mathbf{U}_i^\top \quad (5)$$

with $\mathbf{U}_i^\top = ((\lambda \mathbf{L}_{-i} \mathbf{R}_i)^\top \mathbf{I}^\top)$ and $l_i = \{\mathbf{A}_i + \lambda \mathbf{R}_{ii} - (\lambda \mathbf{R}_i)^\top \mathbf{L}_{-i} (\lambda \mathbf{R}_i)\}^{-1} \triangleq \{\mathbf{A}_i + \kappa_i\}^{-1}$. Note also that any basis for which $\mathbf{A}_j = \infty$ can be disregarded, since its corresponding line and column in \mathbf{L} and \mathbf{L}_{-i} will be null. We can interpret \mathbf{L} as a square matrix of dimension the number of active bases (including the basis under consideration), and the algorithmic complexity of matrix operations involving \mathbf{L} or \mathbf{L}_{-i} will indeed be related to the reduced sized of these matrices. This is also true for \mathbf{U}_i , as a direct consequence, and for all of the other quantities involved.

Injecting (5) into (3) gives a decomposition of \mathbf{C} into the sum of a term that does not depend on the i th basis and of a rank-one term:

$$\mathbf{C} = \mathbf{C}_{-i} + \Phi^i \mathbf{U}_i l_i \mathbf{U}_i^\top \Phi^{i\top} \quad (6)$$

Φ is superscripted with i to recall that along with all the other active bases, the i th basis ϕ_i is present in this matrix. Using rank-one updates for, respectively, the determinant and the inverse, and letting $\mathbf{C}_{-i}^{-1} \triangleq (\mathbf{C}_{-i})^{-1}$, we get the two following expressions:

$$|\mathbf{C}| = |\mathbf{C}_{-i}| |l_i| |l_i^{-1} + \mathbf{U}_i^\top \Phi^{i\top} \mathbf{C}_{-i}^{-1} \Phi^i \mathbf{U}_i| \quad (7)$$

$$\mathbf{t}^\top \mathbf{C}^{-1} \mathbf{t} = \mathbf{t}^\top \left(\mathbf{C}_{-i}^{-1} - \mathbf{C}_{-i}^{-1} \Phi^i \mathbf{U}_i \left\{ l_i^{-1} + \mathbf{U}_i^\top \Phi^{i\top} \mathbf{C}_{-i}^{-1} \Phi^i \mathbf{U}_i \right\}^{-1} \mathbf{U}_i^\top \Phi^{i\top} \mathbf{C}_{-i}^{-1} \right) \mathbf{t} \quad (8)$$

These quantities rewrite more compactly if we introduce appropriate notations. Namely, let $q_j(i) \triangleq \phi_j^\top \mathbf{C}_{-i}^{-1} \mathbf{t} \in \mathbb{R}^d$ and $s_{jk}(i) \triangleq \phi_j^\top \mathbf{C}_{-i}^{-1} \phi_k \in \mathcal{M}_{d,d}$. The concatenation of these q_j 's for all active bases plus the basis under scrutiny (total of m bases), a.k.a $\mathbf{q}_i \in \mathbb{R}^{d \times m}$, will come in helpful. Similarly $\mathbf{s}_i \in \mathcal{M}_{d \times m, d \times m}$ will denote the matrix with $s_{kl}(i)$ as (k, l) th coefficient, where indices span the set of active bases plus the i th basis. Now, let $q^i \triangleq \mathbf{U}_i^\top \Phi^{i\top} \mathbf{C}_{-i}^{-1} \mathbf{t} = \mathbf{U}_i^\top \mathbf{q}_i \in \mathbb{R}^d$, and $s^i \triangleq \mathbf{U}_i^\top \Phi^{i\top} \mathbf{C}_{-i}^{-1} \Phi^i \mathbf{U}_i = \mathbf{U}_i^\top \mathbf{s}_i \mathbf{U}_i \in \mathcal{M}_{d,d}$. With these notations in hand and recalling that $l_i^{-1} = \mathbf{A}_i + \kappa_i$, we can rewrite eq. (7) and eq. (8) as:

$$\log |\mathbf{C}| = \log |\mathbf{C}_{-i}| - \log |\mathbf{A}_i + \kappa_i| + \log |\mathbf{A}_i + \kappa_i + s^i| \quad (9)$$

$$\mathbf{t}^\top \mathbf{C}^{-1} \mathbf{t} = \mathbf{t}^\top \mathbf{C}_{-i}^{-1} \mathbf{t} - q^{i\top} \{ \mathbf{A}_i + \kappa_i + s^i \}^{-1} q^i \quad (10)$$

Ignoring the terms that do not depend on the i th basis, we see that the contribution to the evidence of the model for a given value of \mathbf{A}_i is directly related to:

$$l(\mathbf{A}_i) = \log |\mathbf{A}_i + \kappa_i| - \log |\mathbf{A}_i + \kappa_i + s^i| + q^{i\top} \{\mathbf{A}_i + \kappa_i + s^i\}^{-1} q^i \quad (11)$$

Naturally if $\lambda = 0$ (no additional regularization) this comes down to the regular RVM, with $q^i = q_i$, $s^i = s_{ii}$ and $\kappa_i = 0$.

3 Maximization of the gain in evidence

If $q^i q^{i\top} - s^i$ has no positive eigenvalue, the maximum \mathbf{A}_i lies at infinity and the basis should remain inactive, or be removed. Otherwise the gradient of Eq. (11) provides ground to look for rank-one maximizers $\mathbf{A}_i = \alpha_i \eta_i \eta_i^\top$. To that aim we compute $n_i = s^{i-1} q^i$ and

$$a_i = \frac{(n_i^\top s^i n_i)^2}{(n_i^\top q^i)^2 - n_i^\top s^i n_i} - n_i^\top \kappa_i n_i \quad (12)$$

If $a_i \geq 0$ the maximizer is given by $\alpha_i = a_i$ and $\eta_i = n_i$. Otherwise ($a_i < 0$) we set $\alpha_i = 0$ and numerically solve over the optimal orientation η_i . This latter case arises when the regularization level alone is sufficient to make additional "shrinkage" unnecessary.

4 Update of λ

We derive an update rule via an expectation-maximization procedure. Knowing \mathbf{w} , it would be straightforward to derive an estimate of λ by maximizing the log-likelihood of \mathbf{w} or the posterior of λ given \mathbf{w} . However \mathbf{w} is hidden in our model. Instead, we try to maximize the log-likelihood on average (i.e. to minimize the average loss): $\max_\lambda \mathbb{E}_{\mathbf{w} \sim \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma})} [\log p(\mathbf{t}, \mathbf{w} | \mathbf{A}, \lambda, \beta) | \mathbf{A}^*, \beta^*]$, where \mathbf{A}^* and β^* are our current estimates of the respective quantities. Discarding terms which are constants of λ , we obtain the following:

$$\lambda^* = \arg \max_\lambda -\frac{\lambda}{2} \text{tr}(\boldsymbol{\Sigma} \mathbf{R}) + \frac{1}{2} \log |\mathbf{A} + \lambda \mathbf{R}| - \frac{\lambda}{2} \boldsymbol{\mu}^\top \mathbf{R} \boldsymbol{\mu} \quad (13)$$

Deriving leads to:

$$\frac{\partial}{\partial \lambda} f(\lambda) \propto \text{tr}(\{\mathbf{A} + \lambda \mathbf{R}\}^{-1} \mathbf{R}) - \text{tr}(\boldsymbol{\Sigma} \mathbf{R}) - \boldsymbol{\mu}^\top \mathbf{R} \boldsymbol{\mu} \quad (14)$$

This is a decreasing function of λ and thus has at most one zero. If $\frac{\partial}{\partial \lambda} f(\lambda)$ is negative at the origin, $\lambda^* = 0$. Otherwise, we optimize by using the Newton method on a log scale. This is motivated by the fact that the function of interest is not only decreasing, but also smooth and convex. Lastly note that $\{\mathbf{A} + \lambda \mathbf{R}\}^{-1} \mathbf{R} = \{\mathbf{R}^{-1} \mathbf{A} + \lambda \mathbf{I}\}^{-1}$, so we can compute the eigenvalues δ_k of $\mathbf{A}^{1/2} \mathbf{R}^{-1} \mathbf{A}^{1/2}$ once and rely on the fact that $\text{tr}(\{\mathbf{A} + \lambda \mathbf{R}\}^{-1} \mathbf{R}) = \sum_k 1/(\delta_k + \lambda)$ to avoid repeated matrix inversions.

References

1. Tipping, M.E., Faul, A.C., et al.: Fast marginal likelihood maximisation for sparse bayesian models. In: Workshop on artificial intelligence and statistics. Volume 1., Jan (2003)