Should penalized least squares regression be interpreted as Maximum A Posteriori estimation?

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Abstract

Penalized least squares regression is often used for signal denoising and inverse problems, and is commonly interpreted in a Bayesian framework as a Maximum A Posteriori (MAP) estimator, the penalty function being the negative logarithm of the prior. For example, the widely used quadratic program (with an ℓ^1 penalty) associated to the LASSO / Basis Pursuit Denoising is very often considered as the MAP under a Laplacian prior. The objective of this paper is to highlight the fact that, while this is *one* possible Bayesian interpretation, there can be other equally acceptable Bayesian interpretations. Therefore, solving a penalized least squares regression problem with penalty $\varphi(x)$ should not necessarily be interpreted as assuming a prior $C \cdot \exp(-\varphi(x))$ and using the MAP estimator. In particular, we show that for *any* prior $p_X(x)$, the conditional mean can be interpreted as a MAP with some prior $C \cdot \exp(-\varphi(x))$. Vice-versa, for *certain* penalties $\varphi(x)$, the solution of the penalized least squares problem is indeed the *conditional mean*, with a certain prior $p_X(x)$. In general we have $p_X(x) \neq C \cdot \exp(-\varphi(x))$.

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I. INTRODUCTION

Consider the problem of estimating an unknown signal $x \in \mathbb{R}^n$ from a noisy observation $y = x + b$, also known as *denoising*. Given an arbitrary noisy observation y the goal is to estimate the noiseless

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signal x: in practice, designing a denoising scheme amounts to choosing a function $\psi : \mathbb{R}^n \to \mathbb{R}^n$ which provides estimates of the form $\hat{x} = \psi(y)$. However, unless we specify further what we mean by ”noise” and ”signal”, denoising is a completely ill-posed problem since any pair x, b such that $y = x + b$ can be replaced by $x' = x + z$, $b' = b - z$. Practical denoising schemes hence have to rely on various types of prior information on x and b to design an appropriate denoising function ψ.

A. *Bayesian estimation*

A standard statistical approach to the denoising problem consists in assuming that x and b are drawn independently at random from known *prior* probability distributions P_X and P_B. Under this *model*, given a cost function $\mathcal{C}(\hat{x}, x)$ that measures the quality of an estimator $\hat{x}$ in comparison to the true quantity to estimate x, the Bayes estimator is defined as an estimator ψ with minimum expected cost:

$$\arg\min_{\psi} \mathbb{E}\left\{\mathcal{C}(\psi(X+B), X)\right\}.$$

For a quadratic cost function $\mathcal{C}(\hat{x}, x) := \|\hat{x} - x\|_2^2$ the Bayes estimator is the conditional mean [5]

$$\psi_\star(y) := \mathbb{E}(X|Y = y). \tag{I.1}$$

Even though this estimator is ”optimal” in the above defined sense, its computation involves a high-dimensional integral and cannot generally be done explicitly. In practice, Monte-Carlo simulations can be used to approximate the integral.

Often more amenable to efficient numerical optimization is the popular Maximum A Posteriori (MAP) criterion, which exploits Bayes rule

$$\begin{aligned} \psi_{MAP}(y) &:= \arg\max_x p(x|y) = \arg\max_x p(y|x)p(x) \\ &= \arg\min_x \left\{-\log p_B(y-x) - \log p_X(x)\right\}. \end{aligned}$$

For white Gaussian noise b, since $p_B(b) \propto \exp(-\|b\|_2^2/2)$, the MAP under the prior p_X can be expressed as

$$\arg\min_x \frac{1}{2}\|y - x\|_2^2 + [-\log p_X(x)]. \tag{I.2}$$

B. *Regularization*

Optimization problems of the type (I.2) have also been often considered in signal processing without explicit reference to probabilities or priors, under the generic form

$$\arg\min_x \frac{1}{2}\|y - x\|_2^2 + \varphi(x). \tag{I.3}$$

The deterministic objective is to achieve a tradeoff between the data-fidelity term $\|y-x\|_2^2$ and the penalty term $\varphi(x)$, which promotes solutions with certain properties. In particular, when the function φ is non-smooth at the origin, such as $\varphi(x)=|x|^p, 0<p\leq 1$, the optimum of the criterion (I.3) is known to have few nonzero entries. Regularization with such penalty functions is at the basis of *shrinkage* techniques [3] for signal denoising. More recently, these approaches have become a very popular mean of promoting *sparse* solutions to under-determined or ill-conditioned linear inverse problems $y=\mathbf{A}x+b$, and are now a key tool for compressed sensing [4].

C. Plurality of Bayesian interpretations of regularization

Given the identity of the optimization problems (I.2) and (I.3) when[1] $p_X(x) \propto \exp(-\varphi(x))$, the regularization problem (I.3) is often interpreted as ”solving the MAP under the prior $C\cdot\exp(-\varphi(x))$ (and white Gaussian noise)”. In particular, when $\varphi(x)=\|x\|_1$, a possible interpretation of (I.3) is MAP denoising under a Laplacian prior on x and white Gaussian noise.

The main objective of this paper is to highlight the fact that while the MAP with prior $C\cdot\exp(-\varphi(x))$ is *one* Bayesian interpretation of the estimator (I.3), *there can be other Bayesian interpretations*. We focus on white Gaussian denoising, and we show that for *any* prior $p_X(x)$, the conditional mean can be interpreted as a MAP with some prior $C\cdot\exp(-\varphi(x))$. Vice-versa, for certain functions φ, the estimator (I.3) can equally be interpreted as the *conditional mean*, with a prior $p_X(x)$. In general we do not have $p_X(x)\propto\exp(-\varphi(x))$.

II. MAIN RESULTS

From now on we focus on Gaussian denoising: $B\in\mathbb{R}^n$ is a centered normal Gaussian variable with law $\mathcal{N}(0,\mathbf{I}_n)$ and probability density function (pdf) $p_B(b)\propto\exp(-\|b\|_2^2/2)$. We let $X\in\mathbb{R}^n$ be a random variable independent of B, with law P_X and pdf[2] $p_X(x)$ and $Y=X+B$ be the noisy observation.

In this setting the conditional mean is (see Appendix A)

$$\psi_\star(y)=y+\frac{1}{p_Y(y)}\left[\frac{\partial}{\partial y_i}p_Y(y)\right]_{i=1}^n=y+\nabla\log p_Y(y) \tag{II.1}$$

where $p_Y:=p_X\star p_B$ is the pdf[3] of the noisy observation y.

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[1] The notation $f(x)\propto g(x)$ means $f(x)=C\cdot g(x)$ for all x, where $C\neq 0$ is some constant independent of x.

[2] For simplicity we consider random variables which admit a pdf.

[3] The pdf p_Y is sometimes refered to as the *evidence* of the observation.

Next we study whether $\psi_\star$ can also be written as the optimum of an optimization problem of the MAP type (I.3), with an appropriate choice of φ. Namely, we investigate when $\psi_\star$ can be identified with the *proximity operator* [2] of a function φ, where we recall the definition

$$\mathrm{prox}_\varphi(y) := \arg\min_{z\in\mathbb{R}^n} \left\{ \frac{1}{2}\|y-z\|_2^2 + \varphi(z) \right\}. \tag{II.2}$$

For smooth φ we have the implicit characterization [2]

$$\mathrm{prox}_\varphi(y) := y - \nabla\varphi[\mathrm{prox}_\varphi(y)], \quad \forall y \in \mathbb{R}^n. \tag{II.3}$$

Comparing with (II.3), we see that if $\psi_\star = \mathrm{prox}_\varphi$ then

$$\nabla\varphi[\psi_\star(y)] = -\nabla \log p_Y(y), \quad \forall y \in \mathbb{R}^n. \tag{II.4}$$

Since $\psi_\star$ is *one-to-one* from $\mathbb{R}^n$ to $\mathrm{Im}\psi_\star$ (see Corollary A.2 in Appendix B), the relation (II.4) characterizes the functions φ such that $\psi_\star = \mathrm{prox}_\varphi$, leading to our theorem.

Theorem II.1. *Consider $Y = X + B$ where $B \sim \mathcal{N}(0, \mathbf{I}_n)$ and $X \sim P_X$ are independent.*

1) *The conditional mean $\psi_\star(\cdot)$ is one-to-one and C^∞ from $\mathbb{R}^n$ onto Im$\psi_\star$. Its reciprocal $\psi_\star^{-1}(\cdot)$: Im$\psi_\star \to \mathbb{R}^n$ is also C^∞.*
2) *We have $\psi_\star = prox_{\varphi_\star}$ where $\varphi_\star : \mathbb{R}^n \to \mathbb{R}\cup\{+\infty\}$ is defined by:*

$$\begin{aligned} \varphi_\star(x) :=\ & -\tfrac{1}{2}\|\nabla \log p_Y(\psi_\star^{-1}(x))\|_2^2 - \log p_Y[\psi_\star^{-1}(x)], \\ & \textit{for } x \in \textit{Im}\psi_{CM}; \\ \varphi_\star(x) :=\ & +\infty, \\ & \textit{for } x \notin \textit{Im}\psi_\star. \end{aligned} \tag{II.5}$$

3) *If $\tilde{\varphi}$ satisfies $\psi_\star = prox_{\tilde{\varphi}}$ then there is a constant $c \in \mathbb{R}$ such that $\tilde{\varphi}(x) = \varphi_\star(x) + c$ for all $x \in$ Im$\psi_\star$.*
4) *For every $y \in \mathbb{R}^n$, the value $\psi_\star(y) = prox_{\varphi_\star}(y)$ is the* unique local minimum *of the function $\frac{1}{2}\|y-x\|^2 + \varphi_\star(x)$.*

The conditional mean with prior p_X and white Gaussian noise is therefore also the MAP with prior $C \cdot \exp(-\varphi_\star(x))$ and white Gaussian noise.

Remark II.2. Even though the function $x \mapsto \frac{1}{2}\|y-x\|^2 + \varphi_\star(x)$ admits a unique local minimum for any y, the function $\varphi_\star$ defined in (II.5) can be nonconvex, as shown with the following single variable example ($n = 1$). A function $\psi : \mathbb{R} \to \mathbb{R}$ can be written $\psi = \mathrm{prox}_\varphi$ with φ a proper lower semi-continuous function from $\mathbb{R}$ to $\mathbb{R}$ if, and only if, the function ψ is non-expansive and increasing [2]. Here, in the case $n = 1$, $\psi_\star$ is increasing (cf Lemma A.1 in Appendix B), but for certain priors p_X it is expansive (see Remark A.3 in Appendix B): its derivative exceeds one at some point. Since the associated $\varphi_\star$ is C^∞, it is proper and continuous, hence it cannot be convex.

Remark II.3. Caution is in order when interpreting $\psi_\star$ as ”the MAP estimator with prior $\exp(-\varphi_\star(x))$”. This only makes sense if the function $x \mapsto \exp(-\varphi_\star(x))$ is integrable, although in the opposite case some authors refer to the MAP with a ”non-informative prior”.

III. DISCUSSION

For Gaussian priors $X \sim \mathcal{N}(0, \Sigma)$, the conditional mean is the Wiener filter, which is also the MAP and the minimum mean square linear estimator [5], so $\varphi_\star(x) = -\log p_X(x)$.

However, the MAP and the conditional mean are not generically equivalent, so there are choices of p_X (non Gaussian) for which we *do not* have the identity $\varphi_\star(x) = -\log p_X(x)$. Indeed, observe that for any prior $p_X(x)$, the penalty function $\varphi_\star(x)$ defined in Theorem II.1 has the following properties:

- the function $\varphi_\star : \mathrm{Im}\psi_\star \to \mathbb{R}$ is C^∞;
- for any y, the function $x \mapsto \frac{1}{2}\|y - x\|_2^2 + \varphi_\star(x)$ admits a unique local minimum.

Therefore, the identity $\varphi_\star(x) = -\log p_X(x)$ cannot be satisfied if $-\log p_X(x)$ fails to satisfy one of these properties.

For example, generalized Gaussian priors $p_X(x) \propto \exp(-\alpha\|x\|_p^p)$ with $0 < p \leq 1$ are *not smooth* at $x = 0$, hence not in C^∞: for such priors we cannot even have the identity $\varphi_\star(x) = a - b\log p_X(x)$ for any $a, b \in \mathbb{R}$.

One may also wonder whether a reciprocal to Theorem II.1 is possible. Given a penalty function $\varphi(x)$, one can always define $\psi(y) = \mathrm{prox}_\varphi(y)$, and define $q(y) = \psi(y) - y$. However, the main difficulty is to understand when one can write $q(y) = \nabla(p_X \star p_B)(y)$ for some pdf p_X. This is not always possible, for example if $\varphi(x)$ is not sufficiently smooth.

IV. CONCLUSION AND PERSPECTIVES

We proved that the conditional mean estimator for Gaussian denoising can always be written as a MAP (and that the MAP estimator with certain penalty functions can be interpreted as a conditional mean). These results, in conjunction with Nikolova’s highlighting of model distortions brought by MAP estimation [6], indicate that one should be cautious when interpreting penalized least squares regression scheme in terms of priors:

- *If* the data follows a prior $C \cdot \exp(-\varphi(x))$ and *if* we choose the MAP as a criterion for estimating it, *then* the resulting denoising scheme takes the form of penalized least squares regression with penalty $\varphi(x)$. However, this MAP estimator may have poor denoising performance for this type of data [6].
- In practice, the choice of penalized least squares regression with penalty $\varphi(x)$ is seldomly associated to the *belief* that the data follows the prior $C \cdot \exp(-\varphi(x))$. Instead, it rather stems from the *need* for numerical efficiency and the *empirical observation* that it achieves good denoising performance for the considered class of data.

Given an arbitrary penalty $\varphi(x)$, it remains an open problem to understand for which priors $p_X(x)$ we obtain ”good” denoising performance of penalized least squares regression (for example: performance comparable to the conditional mean).

One can imagine concrete applications of the results presented here for certain priors: in general the conditional mean $\psi_\star(y)$ is *a priori* expressed as an intractable high-dimensional integral; however, if the penalty function $\varphi_\star(x)$ admits a simple expression amenable to efficient numerical optimization (e.g., convex optimization), then the conditional mean can be computed efficiently. Developping such approaches requires a more in depth understanding of the properties of penalty functions $\varphi_\star(x)$ obtained through Theorem II.1. Of particular interest would be the construction of explicit examples where $\varphi_\star(x)$ is ”simple” while p_Y involves an intractable integral.

Another interesting perspective is to obtain alternate statistical interpretations of a larger class of penalized least squares regression estimators (e.g., with non-smooth $\varphi(x)$ such as those leading to sparse estimates). As remarked above, the lack of smoothness makes it impossible to interpret such estimators in terms of a conditional mean, however one may seek interpretations that leave the strict Bayesian framework: for example, one may wish to obtain an interpretation as the optimum of a hybrid Bayesian cost function

$$\min_{\psi} \{\mathbb{E}\mathcal{C}(\psi(X+B), X) + \mathbf{K}(\psi)\}$$

where the term $\mathbf{K}(\cdot)$ forces the function ψ to be in some function class. Eventually, one may also wish to extend theses results to ill-posed linear inverse problems of the type $y = \mathbf{A}x + b$, and to deal with non-Gaussian noise.

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APPENDIX

A. *Proof of the identity* (II.1)

If ψ minimizes the expected square loss, then by the orthogonality relation [5], for any function $\delta : y \mapsto \delta(y)$ we must have $\mathbb{E}\langle \psi(Y) - X, \delta(Y)\rangle = 0$. Hence we obtain the condition

$$\forall \delta, \quad \mathbb{E}\langle \psi(Y) - Y, \delta(Y)\rangle = -\mathbb{E}\langle B, \delta(Y)\rangle.$$

Since $Y = X + B$ has the pdf $p_Y = p_X \star p_B$, we thus require that for any δ

$$\int p_Y(y)\langle \psi(y) - y, \delta(y)\rangle dy = -\mathbb{E}\langle B, \delta(Y)\rangle.$$

Using argument similare to those involved in Stein's risk estimator [7], [1], the right hand side above can be rewritten as follows:

$$\begin{aligned}
-\mathbb{E}\langle B, \delta(X+B)\rangle &= -\mathbb{E}_X \int p_B(b)\langle b, \delta(X+b)\rangle db \\
&= +\mathbb{E}_X \int \langle \nabla p_B(b), \delta(X+b)\rangle db \\
&= \iint p_X(x) \sum_{i=1}^{n} \tfrac{\partial}{\partial b_i} p_B(b) \cdot \delta_i(x+b) dx db \\
&\overset{(a)}{=} \sum_{i=1}^{n} \iint p_X(x) \frac{\partial}{\partial b_i} p_B(y-x) \cdot \delta_i(y) dx dy \\
&= \sum_{i=1}^{n} \int (p_X \star \frac{\partial}{\partial b_i} p_B)(y) \cdot \delta_i(y) dy \\
&= \int \sum_{i=1}^{n} \frac{\partial}{\partial b_i} (p_X \star p_B)(y) \cdot \delta_i(y) dy \\
&= \int \langle \nabla p_Y(y), \delta(y)\rangle dy.
\end{aligned}$$

In (a) we used the change of variable $y = x + b$. We finally obtain the condition: for all y, $p_Y(y)[\psi(y) - y] = \nabla p_Y(y)$. It is easy to check that $p_Y(y)$ cannot vanish, hence this eventually reads $\psi(y) - y = \frac{1}{p_Y(y)} \nabla p_Y(y) = \nabla \log p_Y(y)$.

B. Other technical lemmata

We begin by proving that $\psi_\star$ is always one-to-one.

Lemma A.1. *Denote* $\psi_\star(y) = \left(\psi_\star^i(y)\right)_{i=1}^n$ *where* $\psi_\star^i(\cdot) : \mathbb{R}^n \to \mathbb{R}$ *is scalar valued. The* $n \times n$ *Jacobian matrix* $J[\psi_\star](y) := \left[\frac{\partial}{\partial y_j}\psi_\star^i(y)\right]_{ij}$ *is symmetric positive definite:*

$$\langle v, J[\psi_\star](y) \cdot v\rangle > 0, \quad \forall y \in \mathbb{R}^n, v \neq 0.$$

and satisfies the identity

$$J[\psi_\star](y) = \left[\delta_{ij} + \frac{\partial^2}{\partial y_i \partial y_j} \log p_Y(y)\right]_{ij} = \mathbf{I} + \nabla^2 \log p_Y(y).$$

Proof: For simplicity, we do the proof in the single variable case ($n = 1$). The extension to higher dimension follows the same steps and poses no special difficulty. We indicate the main differences when needed. Since $\psi_\star(y) := y + p'_Y(y)/p_Y(y)$ we have $\psi'(y) = \left(p_Y^2(y) + p''_Y(y)p_Y(y) - [p'_Y(y)]^2\right)/p_Y^2(y)$. Since $n = 1$, what we need to prove is $\psi'(y) > 0$ for all y, or equivalently

$$p_Y^2(y) + p''_Y(y)p_Y(y) - [p'_Y(y)]^2 > 0, \qquad \forall y.$$

Since $p_Y = p_X \star p_B$, $p'_Y = p_X \star p'_B$, $p''_Y = p_X \star p''_B$ and $p_B(b) \propto \cdot e^{-b^2/2}$, we have

$$\begin{aligned} p'_B(b) &\propto e^{-b^2/2} \cdot (-b), \\ p''_B(b) &\propto e^{-b^2/2} \cdot (b^2 - 1) \end{aligned}$$

therefore $p_Y^2(y) + p''_Y(y)p_Y(y) - [p'_Y(y)]^2$ is proportional to

$$\begin{aligned} & \iint p_X(y-b)p_X(y-b') \cdot e^{-(b^2+b'^2)/2} \\ & \cdot \left(1 + \tfrac{b^2-1}{2} + \tfrac{b'^2-1}{2} - bb'\right) dbdb' \\ = & \iint p_X(y-b)p_X(y-b') \\ & \cdot e^{-(b^2+b'^2)/2} \cdot \tfrac{(b-b')^2}{2} dbdb' \geq 0 \end{aligned} \tag{A.1}$$

where we used the non-negativity of the integrand[4]. With the change of variable $x = y - b$, $x' = y - b'$, we conclude that $\psi'(y) \geq 0$ with equality only if the function $(x, x') \mapsto p_X(x)p_X(x')$ is identically zero on $\mathbb{R}^2 \backslash \{(x, x), x \in \mathbb{R}\}$. This implies $p_X(x) = 0$ for all x, which is impossible since p_X is a proper pdf.

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[4] For $n > 1$ the scalar factor $(b - b')^2$ in (A.1) becomes $\langle b - b', v\rangle^2$.

Corollary A.2. *The function $y \mapsto \psi_\star(y)$ is one-to-one from $\mathbb{R}^n$ to Im$\psi_\star$: for any pair $y, y' \in \mathbb{R}^n$, if $\psi_\star(y) = \psi_\star(y')$ then $y = y'$. Moreover, it is C^∞ and its reciprocal is C^∞.*

Proof: We let the reader check that p_Y cannot vanish and is C^∞, hence $\psi_\star$ is C^∞. To prove that $\psi_\star$ is one-to-one, we proceed by contradiction, assuming that $\psi_\star(y) = \psi_\star(y')$ while $y' \neq y$. We define $v := (y'-y)/\|y'-y\|_2$ and the function $f : t \mapsto f(t) := \langle v, \psi_\star(y+tv)\rangle \in \mathbb{R}$. We have $f(0) = f(\|y'-y\|_2)$, and f is smooth, hence its derivative must vanish for some $0 < t < \|y'-y\|_2$. However by Lemma A.1 the derivative is $f'(t) = \langle v, J[\psi_\star](y+tv)\cdot v\rangle > 0$ which yields a contradiction.

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Remark A.3. The computations done in the proof of Lemma A.1 indicate that for certain choices of the prior p_X we can ensure that $\psi_\star$ is *not* a non-expansive function. We will show it in the single variable case, and similar examples can be built in higher dimensions. By definition, a function $f : \mathbb{R} \to \mathbb{R}$ is non-expansive if $|f(y') - f(y)| \leq |y'-y|$ for all y, y'. If f is differentiable and non-expansive we must have $|f'(y)| \leq 1$ for all y. We prove below that if p_X is symmetric ($\forall x, p_X(-x) = p_X(x)$) and if from some $\varepsilon > 0$ we have $p_X(x) = 0$ for $|x| \leq 1+\varepsilon$, then $\psi'_\star(0) > (1+\varepsilon)^2$.

Proof: It can be checked using the computations done in the proof of Lemma A.1 that

$$\psi'_\star(0) = \frac{\iint p_X(-b)p_X(-b')\cdot e^{-(b^2+b'^2)/2}\cdot \frac{(b-b')^2}{2}dbdb'}{\iint p_X(-b)p_X(-b')\cdot e^{-(b^2+b'^2)/2}dbdb'} > 0.$$

Since p_X is symmetric, easy manipulations show

$$\begin{aligned}\psi'_\star(0) &= \frac{\iint p_X(b)p_X(b')\cdot e^{-(b^2+b'^2)/2}\cdot \frac{b^2+b'^2}{2}dbdb'}{\iint p_X(b)p_X(b')\cdot e^{-(b^2+b'^2)/2}dbdb'}\\ &= \frac{\iint p_X(b)p_X(b')\cdot e^{-(b^2+b'^2)/2}\cdot b^2 dbdb'}{\iint p_X(b)p_X(b')\cdot e^{-(b^2+b'^2)/2}dbdb'}\end{aligned}$$

Since $p_X(x) = 0$ for $|x| \leq 1+\varepsilon$ we obtain $\psi'_\star(0) \geq (1+\varepsilon)^2$. ■

C. Proof of Theorem II.1

The fact that $\psi_\star$ is one-to-one and C^∞ with C^∞ reciprocal function was proved in Corollary A.2. We now wish to check that the proximity operator of $\varphi_\star$ defined by (II.5) is indeed $\psi_\star$. The definition of $\varphi_\star(x)$ for $x \notin$ Im$\psi_\star$ ensures that prox$_{\varphi_\star}$ takes its values in Im$\psi_\star$. We let the reader check that a consequence of Lemma A.1 is that the set Im$\psi_\star$ is open. The key point will be to check that there is a *unique* local minimum of $x \mapsto \frac{1}{2}\|y-x\|_2^2 + \varphi_\star(x)$, which is exactly at $\psi_\star(y)$. This will imply in particular that the global minimum $\mathrm{prox}_{\varphi_\star}(y)$ is equal to $\psi_\star(y)$. Denoting x any local mimimum, and u such that $\psi_\star(u) = x$, u must be a local minimum of

$$\begin{aligned}\frac{1}{2}\|y - \psi_\star(u)\|_2^2 + \varphi_\star[\psi_\star(u)] \quad &= \quad \frac{1}{2}\|\psi_\star(u) - y\|_2^2 \\ &\quad -\frac{1}{2}\|\nabla q(u)\|_2^2 - q(u)\end{aligned}$$

(where for the sake of brevity we denoted $q(y) = \nabla \log p_Y(y)$) hence it must satisfy the stationary point equation

$$J[\psi_\star](u) \cdot \big[\psi_\star(u) - y\big] - \nabla^2 q(u) \cdot \nabla q(u) - \nabla q(u) = 0.$$

Using the relation $J[\psi_\star](u) = 1 + \nabla^2 q(u) > 0$ (Lemma A.1) this becomes

$$J[\psi_\star](u) \cdot \big[\psi_\star(u) - y - \nabla q(u)\big] = 0$$

hence $\psi_\star(u) = y + \nabla q(u)$. Since $\psi_\star(u) = u + \nabla q(u)$ we conclude that $u = y$, and therefore $x = \psi_\star(u) = \psi_\star(y)$.

To conclude, assume the function $\tilde{\varphi} : \mathbb{R}^n \to \mathbb{R} \cup \{+\infty\}$ satisfies $\psi_\star = \mathrm{prox}_{\tilde{\varphi}}$. By (II.4) we must have for all y: $\nabla\tilde{\varphi}[\psi_\star(y)] = -\nabla \log p_Y(y) = \nabla\varphi_\star[\psi_\star(y)]$. In other words, for any $x \in \mathrm{Im}\psi_\star$, $\nabla(\tilde{\varphi} - \varphi_\star)(x) = 0$. Since $\psi_\star$ is a one-to-one mapping of $\mathbb{R}^n$ onto $\mathrm{Im}\psi_\star$, the set $\mathrm{Im}\psi_\star$ is connected hence there must be a constant $C \in \mathbb{R}$ such that for all $x \in \mathrm{Im}\psi_\star$, $\tilde{\varphi}(x) = \varphi_\star(x) + C$.

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