Integrated Likelihood Ratio Test

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Abstract

A general methodology called integrated likelihood ratio test is proposed which takes posterior Bayes factor and fractional Bayes factor as special cases. Our methodology also includes the statistics produced by approximation computation. Differentiating from Bayesian hypothesis testing, we treat the resulting test procedure as frequentist test which controls the significance level. Under certain regular conditions, the integrated likelihood ratio test shares similar frequency properties as the likelihood ratio test. We also apply the proposed method to testing the homogeneity in a two-component normal mixture model. This problem is fairly irregular and it is known that the likelihood ratio test statistic has undesirable local power behavior. In contrary, the integrated likelihood ratio test has good asymptotic power behavior. This demonstrate the superiority of the integrated likelihood ratio test.

KEYWORDS: *Bayes consistency; Bayes factor; Hypothesis testing.*

1 Introduction

The Bayes factor, proposed by Jeffreys (1931), is the conventional tool for Bayesian hypothesis testing and has been widely used by practitioners (See Kass and Raftery (1995) for a review). Compared with the methods in other Beyasian inference problem, such as point estimation and credible sets, Bayes factor is developed on its own ground and thus has its own nature. A notable feature of Bayes factor is that it can not be obtained solely from the posterior distribution of parameters. There are two consequence of this feature. First, the computation of Bayes factor is highly nontrivial. See Kass and Raftery (1995), Han and Carlin (2001), Raftery et al. (2006) and the references therein. Second, Bayes factor is sensitive to the choice of prior distribution. In fact, they asymptotic behavior of the Bayes factor relies on the prior density evaluated at the true parameter value. See, for example, Clarke and Barron (1990). In contrast, it is well known that the posterior distribution tends to become independent of the prior distribution as the sample size increases.

Several modifications of Bayes factor have been proposed. Aitkin (1991) proposed the posterior Bayes factor (PBF) which integrated the likelihood with respect to the posterior distribution. Another approach uses a portion of data as training sample. A posterior is computed using the training sample and then be used to calculate Bayes factor. Berger and Pericchi (1996) proposed the intrinsic Bayes factor by using all possible training samples of minimal size and averaging the resulting Bayes factor. O'Hagan (1995) found that the training sample approximates to the full likelihood raised to a fractional power. They called the resulting statistic an fractional Bayes factor (FBF). Compared with the Bayes factor, these testing methods are less sensitive to the prior distribution.

The computations of PBF and FBF are easier than that of Bayes factor since the PBF and FBF can be computed by sampling the likelihood according to posterior distribution or fractional posterior distribution. For moderately complex model, however, sampling from posterior may be difficult and hence some approximation methods may be used in practice. Variational inference is a popular method for approximating intractable posterior distribution. See Blei et al. (2017) and the references therein.

The frequentist properties of Bayesian methods have drawn much attention in recent years. See Ghosal et al. (2000), Shen and Wasserman (2001), van der Vaart and Ghosal (2007), Kleijn and Vaart (2012) and the references therein. These works show that many Bayesian methods still perform well when they are treated as frequentist methods. Existing research is largely concerned with the frequentist properties of Bayesian point estimation and credible sets. For these problems, Bayesian methods can be directly treated as frequentist methods. However, for testing problem, Bayesian methods are not required to control the type I error rate and hence can not be directly treated as frequentist methods. To formulate Bayes methods into frequentist tests, we would like to modify the critical value such that the resulting test procedures control the type I error rate asymptotically. Bayes factor is hard to be formulated into frequentist test since it is too sensitive to prior. In contrary, PBF and FBF can be successfully formulated into frequentist test. Compared with likelihood ratio test which utilize the maximum of the likelihood, Bayesian methods integrate the likelihood by a weight function. For PBF and FBF, the weight function relies on data. Motivated by this, we propose a flexible methodology called integrated likelihood ratio test (ILRT) which takes PBF and FBF as special examples. ILRT also includes methods that are produced by approximation computation.

Under certain regular conditions, we rigorously derive the asymptotic behavior of ILRT statistic. Our theoretical results show that ILRT shares similar frequency properties as the likelihood ratio test under regular conditions. For some irregular problems, the behavior of likelihood is complicated. Since the integral of the likelihood can smooth the irregular behavior of the likelihood, it can be expected that ILRT may have better behavior than likelihood ratio test. To illustrate this point, we apply the proposed method to testing the homogeneity in a two-component normal mixture model. This problem is fairly irregular and suffers from problems such as nonidentifiability and nonconvex likelihood. It is known that the likelihood ratio test has trivial power under $n^{-1/2}$ local alternative hypothesis. See, for example, Hall and Stewart (2005). In contrary, we show that the ILRT have nontrivial power under $n^{-1/2}$ local alternative hypothesis.

The paper is organized as follow. In Section 2, we introduce and investigate the asymptotic properties the ILRT under regular conditions. In Section 3, we apply ILRT to testing the homogeneity in a two-component normal mixture model. Section 4 concludes the paper. All technical proves are in Appendix.

2 Integrated likelihood ratio test

2.1 The test statistic

Let $\mathbf{X}^{(n)} = (X_1, \ldots, X_n)$ be independent identically distributed (iid) observations with values in some space $(\mathcal{X}; \mathscr{A})$. Suppose that there is a σ-finite measure μ on $\mathcal{X}$ and that the possible distribution P_θ of X_i has a density $p(X|\theta)$ with respect to μ. Denote by P_θ^n the joint distribution of $\mathbf{X}^{(n)}$. Let $p_n(\mathbf{X}^{(n)}|\theta) = \prod_{i=1}^n p(X_i|\theta)$ denote the density of P_θ^n with respect to the n-fold product measure μ^n. The parameter θ takes its values in Θ, a subset of $\mathbb{R}^p$. Suppose $\theta = (\nu^T, \xi^T)^T$, where ν is a p_0 dimensional subvector and ξ is a $p - p_0$ dimensional subvector. We would like to test the nested hypotheses

$$H_0 : \theta \in \Theta_0 \quad \text{v.s.} \quad \theta \in \Theta,$$

where the null space Θ_0 is a p_0-dimensional subspace of Θ defined as

$$\Theta_0 = \{(\nu^T, \xi^T)^T : (\nu^T, \xi^T)^T \in \Theta, \, \xi = \xi_0\}.$$

If the null hypothesis is true, we denote by $\theta_0 = (\nu_0^T, \xi_0^T)^T$ the true parameter which generates the data.

In Bayesian hypothesis testing framework, one puts prior $\pi(\nu)$ and $\pi(\theta)$ on parameters under the null and alternative hypotheses, respectively. The conventional Bayes factor is defined as

$$\frac{\int_\Theta p_n(\mathbf{X}^{(n)}|\theta)\pi(\theta)\, d\theta}{\int_{\tilde{\Theta}_0} p_n(\mathbf{X}^{(n)}|\nu, \xi_0)\pi(\nu)\, d\nu},$$

where $\tilde{\Theta}_0 = \{\nu : (\nu^T, \xi^T)^T \in \Theta_0\}$. However, Bayes factor is sensitive to the specification of prior, which may cause difficulties in the absense of a well-formulated subjective prior. See, for example, Shafer (1982). To deal with this problem, Aitkin (1991) proposed PBF which is defined to be

$$\frac{\int_\Theta p_n(\mathbf{X}^{(n)}|\theta)\pi(\theta|\mathbf{X}^{(n)})\, d\theta}{\int_{\tilde{\Theta}_0} p_n(\mathbf{X}^{(n)}|\nu, \xi_0)\pi(\nu|\mathbf{X}^{(n)})\, d\nu},$$

where $\pi(\nu|\mathbf{X}^{(n)})$ and $\pi(\theta|\mathbf{X}^{(n)})$ are the posterior densities under the null and alternative hypothesis, respectively. O'Hagan (1995) proposed FBF which is defiend to be

$$\frac{L_1}{L_b} \cdot \frac{L_b^*}{L_1^*} \quad \text{for} \quad 0 < b < 1,$$

where for $t > 0$,

$$L_t = \int_\Theta \left[p_n(\mathbf{X}^{(n)}|\theta)\right]^t \pi(\theta)\, d\theta, \quad L_t^* = \int_{\Theta_0} \left[p_n(\mathbf{X}^{(n)}|\nu, \xi_0)\right]^t \pi(\nu)\, d\nu.$$

We generalize the PBF and FBF and propose the ILRT statistic as

$$\frac{\int_\Theta \left[p_n(\mathbf{X}^{(n)}|\theta)\right]^a \pi(\theta;\mathbf{X}^{(n)})\, d\theta}{\int_{\tilde{\Theta}_0} \left[p_n(\mathbf{X}^{(n)}|\nu,\xi_0)\right]^a \pi(\nu;\mathbf{X}^{(n)})\, d\nu}, \tag{1}$$

where $a > 0$ is a hyperparameter, the weight functions $\pi(\theta;\mathbf{X}^{(n)})$ and $\pi(\nu;\mathbf{X}^{(n)})$ are probability density functions in Θ and $\tilde{\Theta}_0$ respectively. Note that $\pi(\theta;\mathbf{X}^{(n)})$ and $\pi(\nu;\mathbf{X}^{(n)})$ may be data dependent but does not need to be the posterior density. If we take the weight function as

$$\pi(\theta;\mathbf{X}^{(n)}) = \frac{\left[p_n(\mathbf{X}^{(n)}|\theta)\right]^b \pi(\theta)}{\int_\Theta \left[p_n(\mathbf{X}^{(n)}|\theta)\right]^b \pi(\theta)\, d\theta}, \quad \pi(\nu;\mathbf{X}^{(n)}) = \frac{\left[p_n(\mathbf{X}^{(n)}|\nu,\xi_0)\right]^b \pi(\nu)}{\int_{\tilde{\Theta}_0} \left[p_n(\mathbf{X}^{(n)}|\nu,\xi_0)\right]^b \pi(\nu)\, d\nu}, \tag{2}$$

then the ILRT statistic equals to

$$\Lambda_{a,b}(\mathbf{X}^{(n)}) = \frac{L_{a+b}}{L_b} \cdot \frac{L_b^*}{L_{a+b}^*}.$$

We shall call $\Lambda_{a,b}(\mathbf{X}^{(n)})$ the generalized FBF throughout the paper. The FBF and PBF are both the special cases of the generalized FBF. In fact, the FBF is equal to $\Lambda_{1,b}(\mathbf{X}^{(n)})$, the PBF is equal to $\Lambda_{2,1}(\mathbf{X}^{(n)})$.

The computation of the generalized FBF is simple. We can independently generate $\theta_1,\ldots,\theta_m$ and $\nu_1,\ldots,\nu_m$ according to (2) for a large m. Then $\Lambda_{a,b}(\mathbf{X}^{(n)})$ can be approximated by

$$\frac{\sum_{i=1}^m \left[p_n(\mathbf{X}^{(n)}|\theta)\right]^a}{\sum_{i=1}^m \left[p_n(\mathbf{X}^{(n)}|\nu,\xi_0)\right]^a}.$$

For some moderately complex models, (2) may be complicated. Consequently, sampling from (2) may be intractable. In this case, one may use some simple form weight function to approximate (2). A popular method for approximating (2) is variational inference. See. See, for example, Blei et al. (2017). In this case, the weight function in (1) is equals to the variational apprixomation of (2). The ILRT methodology also includes such approximate method.

2.2 Generalized FBF

In this section, we investigate the asymptotic behavior of the generalized FBF. The following assumption is adapted from Kleijn and Vaart (2012).

Assumption 1. *The parameter space Θ is an open subset of $\mathbb{R}^p$. The null space $\tilde{\Theta}_0$ is an open subset of $\mathbb{R}^{p_0}$. The parameter θ_0 is an inner point of Θ, ν_0 is an inner point of $\tilde{\Theta}_0$. The function $\theta \mapsto \log p(X|\theta)$ is differentiable at θ_0 P_{θ_0}-a.s. with derivative*

$$\dot{\ell}_{\theta_0}(X) = \frac{\partial}{\partial\theta} \log p(X|\theta)\Big|_{\theta=\theta_0}.$$

There's an open neighborhood V of θ_0 such that for every $\theta_1, \theta_2 \in V$,

$$|\log p(X|\theta_1) - \log p(X|\theta_2)| \leq m(X)\|\theta_1 - \theta_2\|,$$

where $m(X)$ is a measurable function satisfying $P_0 \exp[sm(X)] < \infty$ for some $s > 0$. The Fisher information matrix $I_{\theta_0} = P_{\theta_0}\dot{\ell}_{\theta_0}\dot{\ell}_{\theta_0}^T$ is positive-definite and as $\theta \to \theta_0$,

$$P_{\theta_0} \log \frac{p(X|\theta)}{p(X|\theta_0)} = -\frac{1}{2}(\theta - \theta_0)^T I_{\theta_0}(\theta - \theta_0) + o(\|\theta - \theta_0\|^2).$$

Assumption 1 is satisfied by many common models, it ensures a local asymptotic normality expansion of likelihood. See Lemma 1 in Appendix.

For $t > 0$, we say L_t is $\sqrt{n}$-consistent if for every $M_n \to \infty$,

$$\frac{L_t(\{\theta : \|\theta - \theta_0\| > M_n/\sqrt{n}\})}{L_t} \xrightarrow{P_{\theta_0}^n} 0,$$

where for a set $A \subset \Theta$, $L_t(A) = \int_A \left[p_n(\mathbf{X}^{(n)}|\theta)\right]^t \pi(\theta)\, d\theta$. The $\sqrt{n}$-consistency of L_t^* is similarly defined. Note that the consistency of L_1 is equivalent to the consistency of the posterior distribution. In Kleijn and Vaart (2012), the $\sqrt{n}$-consistency of posterior distribution is a key assumption to prove Bernstein-von Mises theorem. Likewise, the $\sqrt{n}$-consistency of L_t is a key assumption of the following theorem.

Theorem 1. *Suppose that Assumption 1 holds, L_{a+b}, L_b, L_{a+b}^* and L_b^* are $\sqrt{n}$-consistent, $\pi(\theta)$ is continuous at θ_0 with $\pi(\theta_0) > 0$, $\pi(\nu)$ is continuous at ν_0 with $\pi(\nu_0) > 0$. Then for $\{\theta_n\}$ such that $\sqrt{n}(\theta_n - \theta_0) \to \eta$,*

$$2 \log \Lambda_{a,b}(\mathbf{X}^{(n)}) \overset{P_{\theta_n}^n}{\rightsquigarrow} -(p - p_0) \log(1 + \frac{a}{b}) + a\chi_{p-p_0}^2(\delta),$$

where $\chi_{p-p_0}^2(\delta)$ is a noncentral chi-squared random variable with $p - p_0$ degrees of freedom and noncentrality parameter $\delta = \eta^T\big(I_{\theta_0} - I_{\theta_0}J(J^T I_{\theta_0}J)^{-1}J^T I_{\theta_0}\big)\eta$ and $J = (I_{p_0}, 0_{p_0\times(p-p_0)})^T$, "$\rightsquigarrow$" means weak convergence.

Theorem 1 gives the asymptotic distribution of $2 \log \Lambda_{a,b}(\mathbf{X}^{(n)})$ under the null hypothesis and the local alternative hypothesis. To obtain a test with asymptotic type I error rate α, the critical value of $2 \log \Lambda_{a,b}(\mathbf{X}^{(n)})$ can be defined to be $-(p-p_0)\log(1+a/b)+a\chi_{p-p_0,1-\alpha}^2$, where $\chi_{p-p_0,1-\alpha}^2$ is the $1-\alpha$ quantile of a chi-squared random variable with $p-p_0$ degrees of freedom. By Theorem 1, the resulting test has local asymptotic power

$$\Pr\big(\chi_{p-p_0}^2(\delta) > \chi_{p-p_0,1-\alpha}^2\big). \tag{3}$$

It is known that, under certain regular conditions, (3) is also the local asymptotic power of the likelihood ratio test. In this view, $\Lambda_{a,b}(\mathbf{X}^{(n)})$ enjoys good frequentist properties.

The $\sqrt{n}$-consistency of L_t is a key assumption of Theorem 1. Hence we would like to give sufficient conditions for the $\sqrt{n}$-consistency of L_t. First we consider the exponential family.

Proposition 1. *Suppose $p(X|\theta) = \exp\big[\theta^T T(X) - A(\theta)\big]$, Θ is an open subset of $\mathbb{R}^p$, θ_0 is an interior point of Θ,*

$$I_{\theta_0} = \frac{\partial^2}{\partial\theta\partial\theta^T} A(\theta_0) > 0.$$

Then L_t is consistent for $t > 0$.

Proposition 1 establishes the $\sqrt{n}$-consistent of L_t for all $t > 0$ under full-rank exponential family models. If the full model and the null model both belong to the full-rank exponential family, Assumption 1 is also satisfied. In this case, Theorem 1 implies that the generalized FBF can be used as frequentist test. However, for any test methodology, the success in the full-rank exponential family models is just a minimal requirement since for these models, LRT is also easy to implement and enjoys good asymptotic properties. We would like to consider more general models.

For general models, the likelihood function may not be convex. This often makes LRT hard to implement. A more serious problem is that the likelihood may be unbounded and thus LRT can not be defined. This problem may occur even if the likelihood function has good local analytical properties, such as location-scale mixture models. See Cam (1990) for more examples. A natural question is that if the fractional integrated likelihood L_t is always well defined. The following theorem shows that L_t is always well defined for $t \leq 1$ and is not well defined for some model for $t > 1$.

Proposition 2. *If $t \leq 1$, $L_t < +\infty$ $P_{\theta_0}^n$-a.s. for any models. If $t > 1$, $L_t = +\infty$ for some models.*

Because of the bad behavior of L_t for $t > 1$, next we only consider L_t for $t \leq 1$. For $t = 1$, the $\sqrt{n}$-consistency of L_t is equivalent to the $\sqrt{n}$-consistency of the posterior distribution. The consistency of posterior distribution has drawn much attention in the literature. See, for example, Ghosal et al. (2000), Shen and Wasserman (2001), van der Vaart and Ghosal (2007). A popular and convenient way of establishing the consistency of posterior is through the condition that suitable test sequences exist. This approach is adopted by Ghosal et al. (2000), van der Vaart and Ghosal (2007) and Kleijn and Vaart (2012).

Assumption 2. *For every $\epsilon > 0$, there exists a sequence of tests ϕ_n such that*

$$P_{\theta_0}^n \phi_n \to 0, \qquad \sup_{\|\theta-\theta_0\|\geq\epsilon} P_\theta^n(1-\phi_n) \to 0.$$

Assumption 2 is satisfied when the parameter space is compact and the model is suitably continuous. See Theorem 3.2 of Kleijn and Vaart (2012).

Proposition 3 (Kleijn and Vaart (2012), Theorem 3.1)**.** *Suppose θ_0 is an interior of Θ, $\pi(\theta)$ is continuous at θ_0 and $\pi(\theta_0) > 0$. Under Assumptions 1 and 2, L_1 is consistent.*

The consistency of L_t for $0 < t < 1$ is different from $t = 1$. Walker and Hjort (2001) considered the Hellinger consistency of $L_{1/2}$. However, they only consider $t = 1/2$ and didn't consider the $\sqrt{n}$-convergence result. We shall prove the consisency of L_t for $0 < t < 1$ under certain conditions on the Rényi divergence between distributions in the family $\{P_\theta : \theta \in \Theta\}$.

For two parameters θ_1 and θ_2, the α order Rényi divergence ($0 < \alpha < 1$) of P_{θ_1} from P_{θ_2} is defined to be

$$D_\alpha(\theta_1||\theta_2) = -\frac{1}{1-\alpha}\log\rho_\alpha(\theta_1,\theta_2),$$

where $\rho_\alpha(\theta_1, \theta_2) = \int_{\mathcal{X}} p(X|\theta_1)^\alpha p(X|\theta_2)^{1-\alpha}\, d\mu$ is the so-called Hellinger integral. The following assumption is needed for our $\sqrt{n}$-consistency result.

Assumption 3. *For some $\alpha \in (0, 1)$, there exist positive constancts δ, ϵ and C such that, $D_\alpha(\theta||\theta_0) \geq C\|\theta - \theta_0\|^2$ for $\|\theta - \theta_0\| \leq \delta$ and $D_\alpha(\theta||\theta_0) \geq \epsilon$ for $\|\theta - \theta_0\| > \delta$.*

Remark 1. A remarkable property of Rényi divergence is the equivalence of all D_α: If $0 < \alpha < \beta < 1$, then

$$\frac{\alpha}{1-\alpha}\frac{1-\beta}{\beta} D_\beta(\theta_1||\theta_2) \leq D_\alpha(\theta_1||\theta_2) \leq D_\beta(\theta_1||\theta_2).$$

See, for example, Bobkov et al. (2016). As a result, if Assumption 3 holds for some $\alpha \in (0, 1)$, then it will hold for every $\alpha \in (0, 1)$.

To appreciate Assumption 3, suppose, for example, that $D_\alpha(\theta||\theta_0)$ is twice continuously differentiable in θ. Since $\theta = \theta_0$ is a minumum point of $D_\alpha(\theta||\theta_0)$, the first order derivative of $D_\alpha(\theta||\theta)$ at $\theta = \theta_0$ is zero and the second order derivative at $\theta = \theta_0$ is positive semidefinite. By Taylor theorem, in a small neighbourhood of θ_0,

$$D_\alpha(\theta||\theta_0) = \frac{1}{2}(\theta - \theta_0)^T \frac{\partial^2}{\partial\theta\partial\theta^T} D_\alpha(\theta||\theta_0)\Big|_{\theta=\theta^*}(\theta - \theta_0),$$

where θ^* is between θ_0 and θ. If we further assume the second order derivative is positive definite at $\theta = \theta_0$, then in a small neighbourhood of θ_0, there is a positive constant C such that $D_\alpha(\theta||\theta_0) \geq C\|\theta - \theta_0\|^2$. Thus, Assumption 3 is a fairly weak condition.

Proposition 4. *Suppose θ_0 is an interior of Θ, $\pi(\theta)$ is continuous at θ_0 and $\pi(\theta_0) > 0$. Under Assumptions 1 and 3, for fixed $t \in (0, 1)$, L_t is consistent.*

Compared with Assumption 2, it appears that Assumption 3 is easier to verify. Note that the asymptotic power of $\Lambda_{a,b}(\mathbf{X}^{(n)})$ is independent of a, b. Hence it can be recommended to use the generalized FBF with $a + b < 1$.

2.3 General weight function

For some moderately complexi models, the densities (2) are not easy to calculate. In this case, we can use simpler weight functions to approximate (2).

Let $h = \sqrt{n}(\theta - \theta_0)$. For two densities $q_1(h)$ and $q_2(h)$, let $\|q_1(h) - q_2(h)\| = \int |p(h) - q(h)|\, dh$ be the total variation distance between $q_1(h)$ and $q_2(h)$. Theorem 2.1 of Kleijn and Vaart (2012) states that under Assumptions 1, 2,

$$\|\pi_n(h|\mathbf{X}^{(n)}) - \phi(h; \Delta_{n,\theta_0}, I_{\theta_0}^{-1})\| \overset{P_{\theta_0}^n}{\to} 0,$$

where $\Delta_{n,\theta_0} = n^{-1/2}\sum_{i=1}^n I_{\theta_0}^{-1}\dot{\ell}_{\theta_0}(X_i)$. We shall assume that the weight function inherits this property.

Assumption 4. *Let $\pi_n(h;\mathbf{X}^{(n)})$ be a weight function satisfying*

$$\|\pi_n(h;\mathbf{X}^{(n)}) - \phi(h;\Delta_{n,\theta_0}, b^{-1}I_{\theta_0}^{-1})\| \xrightarrow{P_{\theta_0}^n} 0 \tag{4}$$

Furthermore, assume that for every $\epsilon > 0$, there's a Lebesgue integrable function $T(h)$, a $K > 0$ and an $A > 0$ such that

$$\lim_{n\to\infty} P_{\theta_0}^n\left(\sup_{\|h\|\geq K\sqrt{n}} (\pi_n(h;\mathbf{X}^{(n)}) - T(h)) \leq 0\right) \geq 1-\epsilon \tag{5}$$

$$\lim_{n\to\infty} P_{\theta_0}^n\left(\sup_{\|h\|\leq K\sqrt{n}} \pi_n(h;\mathbf{X}^{(n)}) \leq A\right) \geq 1-\epsilon \tag{6}$$

The condition 5 assumes there is a function controlling the tail of weight function. For a statistical model, the likelihood value makes no sense when $\|\theta - \theta_0\| = n^{-1/2}h$ is large. The bad behavior of the tail of likelihood function may affect the behavior of posterior distribution. To avoid the bad behavior of the likelihood function for large $n^{-1/2}h$, we impose 5 on weight function instead. The condition 6 is satisfied in most usual case.

Theorem 2. *Suppose that Assumptions 1 and 4 hold, the true parameter θ_0 is an interior point of Θ, ν is a relative interior point of $\tilde{\Theta}_0$. If $a + b = 1$, we assume Assumption 2 holds. If $a + b < 1$, we assume Assumption 3 holds. Then, for bounded real numbers η_n, we have*

$$2\log\Lambda_{a,b}(\mathbf{X}^{(n)}) \overset{P_{\theta_n}^n}{\rightsquigarrow} -(p-p_0)\log(1+\frac{a}{b}) + a\chi^2_{p-p_0}(\delta).$$

A practical method to obtain simple form weight function $\pi_n(h;\mathbf{X}^{(n)})$ is the variational inference. See, for example, Blei et al. (2017). The following example shows that the weight function obtained from Rényi divergence variational inference satisfies Assumption 4.

Example 1. *Suppose $\pi_n(h;\mathbf{X}^{(n)})$ is obtain from Rényi divergence variational inference (Li and Turner, 2016):*

$$\pi_n(h;\mathbf{X}^{(n)}) = \min_{q\in\mathcal{Q}} -\frac{1}{1-\alpha}\log\int_{\mathcal{X}} q(h)^{\alpha}\pi(h|\mathbf{X}^{(n)})^{1-\alpha}\,d\mu,$$

where $\mathcal{Q}$ is the family of all p dimensional normal distribution. Since

$$-\frac{1}{1-\alpha}\log\int_{\mathcal{X}}\pi(h;\mathbf{X}^{(n)})^{\alpha}\pi(h|\mathbf{X}^{(n)})^{1-\alpha}\,d\mu \leq -\frac{1}{1-\alpha}\log\int_{\mathcal{X}}\phi(h;\Delta_{n,\theta_0}, I_{\theta_0}^{-1})^{\alpha}\pi(h|\mathbf{X}^{(n)})^{1-\alpha}\,d\mu. \tag{7}$$

By the equivalence of Rényi divergence and total variation distance and Bernstein-von Mise theorem, the right hand side of (7) tends to 0. Again by the equivalence of Rényi divegence and total variation distance, (4) holds. Since $\pi_n(h;\mathbf{X}^{(n)})$ is a normal density, (4) implies the mean and covariance parameter of $\pi_n(h;\mathbf{X}^{(n)})$ converges to Δ_{n,θ_0} and $I_{\theta_0}^{-1}$ respectively. Then (5) and (6) hold.

3 Normal mixture model

Normal mixture model is a highly irregular model. See Chen (2017) and the references therein. Due to partial loss of identifiability, the likelihood ratio test has undesirable behavior. For example, if the component variances are totally unknown, the likelihood is bounded and thus likelihood ratio test is not defined. (Cam, 1990). Since the integral of the likelihood can smooth the irregular behavior of the likelihood, it can be expected that ILRT may have better behavior than likelihood ratio test. For example, for unknown variances case, ILRT is at least well defined.

In this section, we investigate the asymptotic behavior of ILRT for a simple case, that is, variances are equal and known. Suppose $X_1, \ldots, X_n$ are i.i.d. distributed as a mixture of normal distributions

$$p(X|\omega, \xi) = \frac{1-\omega}{\sqrt{2\pi}} \exp\big(-\frac{1}{2}X^2\big) + \frac{\omega}{\sqrt{2\pi}} \exp\big(-\frac{1}{2}(X-\xi)^2\big),$$

where $0 \leq \omega \leq 1$ and $\mu \in \mathbb{R}$. We would like to test the hypotheses

$$\omega\xi = 0 \quad \text{vs.} \quad \omega\xi \neq 0. \tag{8}$$

Even for this simple case, the likelihood ratio test also has undesirable behavior. In particular, it has trivial power under $n^{-1/2}$ local alternative hypothesis. See ,for example, Hall and Stewart (2005).

We use FBF with $a + b < 1$. The prior of ω is Beta(α_1, α_2). We have the following theorem.

Theorem 3. *Suppose $\pi(\omega, \xi) = \pi_\omega(\omega)\pi_\xi(\xi)$, $\pi_\xi(\xi)$ is positive and continuous at $\xi = 0$, $\pi_\omega(\omega) \sim$ Beta(α_1, α_2) with $\alpha_1 > 1$. Suppose $a + b < 1$. Then,*

(i) under the null hypothesis,

$$2\log\Lambda_{a,b}(\mathbf{X}^{(n)}) \overset{P^n_{\theta_0}}{\rightsquigarrow} \log(1+\frac{a}{b}) + a\chi^2_1;$$

(ii) suppose for some $s < 1/4$, $\omega \geq n^{-s}$ for large n, $\sqrt{n}\omega\xi \to \eta$, then

$$2\log\Lambda_{a,b}(\mathbf{X}^{(n)}) \overset{P^n_{\theta_n}}{\rightsquigarrow} \log(1+\frac{a}{b}) + a\chi^2_1(\eta).$$

Theorem ii shows that under certain $\sqrt{n}$ local alternatives, ILRT has nontrival power. This illustrates the superiority of ILRT over likelihood ratio test.

4 Conclusion

In this paper, we proposed a flexible methodology ILRT which includes some existing method as special cases. We gave the asymptotic distribution of the generalized FPF, which is a special case of ILRT. We also investigates the asymptotic behavior of ILRT for general weight functions. This allows one to use a simple form approximation of the posterior distribution as weight function. In particular, we show that the weight function can be obtained from Rényi divergence variational inference.

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Appendices

Define

$$\dot{\ell}^*(X) = \frac{\partial}{\partial \nu} \log p(X|\nu, \xi_0)\Big|_{\nu=\nu_0}, \quad I^*_{\theta_0} = P_{\theta_0}\dot{\ell}^*_{\theta_0}\dot{\ell}^{*T}_{\theta_0}, \quad \Delta^*_{n,\theta_0} = \frac{1}{\sqrt{n}}\sum_{i=1}^{n} I^{*-1}_{\theta_0}\dot{\ell}^*_{\theta_0}(X_i).$$

Lemma 1 (Kleijn and Vaart (2012), Lemma 2.1.)**.** *Under Assumption 1, we have* $\|\dot{\ell}_{\theta_0}(X)\| \leq m(X)$ *P_0-a.s.,* $P_0\dot{\ell}_{\theta_0}(X) = 0$ *and for every* $M > 0$

$$\sup_{\|h\|\leq M} \Big| \log \frac{p_n(\mathbf{X}^{(n)}|\theta_0 + n^{-1/2}h)}{p_n(\mathbf{X}^{(n)}|\theta_0)} - h^T I_{\theta_0}\Delta_{n,\theta_0} + \frac{1}{2}h^T I_{\theta_0} h\Big| \xrightarrow{P_0^n} 0.$$

Lemma 2. *Under Assumptions 1 and 2, there exists for every* $M_n \to \infty$ *a sequence of tests* ϕ_n *and a constant* $\delta > 0$ *such that, for every sufficiently large* n *and every* $\|\theta - \theta_0\| \geq M_n/\sqrt{n}$,

$$P_0^n\phi_n \to 0, \quad P_\theta^n(1-\phi_n) \leq \exp[-\delta n(\|\theta - \theta\|^2 \wedge 1)].$$

(See der Vaart (2000) Lemma 10.3., Kleijn and Vaart (2012))

Appendix A Proofs in Section 2

Proof of Theorem 1. For fixed $t > 0$ and $M > 0$, we have

$$\begin{aligned}
&\log \int_{\{\theta:\|\theta-\theta_0\|\leq M/\sqrt{n}\}} \left[p_n(\mathbf{X}^{(n)}|\theta)\right]^t \pi(\theta)\, d\theta \\
=&\log \int_{\{\theta:\|\theta-\theta_0\|\leq M/\sqrt{n}\}} \left[p_n(\mathbf{X}^{(n)}|\theta)\right]^t d\theta + \log\pi(\theta_0) + o_{P^n_{\theta_0}}(1) \\
=&\log \int_{\{h:\|h\|\leq M\}} \exp\left[t\log p_n(\mathbf{X}^{(n)}|\theta_0 + n^{-1/2}h)\right] dh - \frac{p}{2}\log n + \log\pi(\theta_0) + o_{P^n_{\theta_0}}(1).
\end{aligned}$$

By Proposition 1,

$$
\begin{aligned}
&\log \int_{\{h:\|h\|\le M\}} \exp\big[t\log p_n(\mathbf{X}^{(n)}|\theta_0+n^{-1/2}h)\big]\,dh\\
=&\log \int_{\{h:\|h\|\le M\}} \exp\big[t\log p_n(\mathbf{X}^{(n)}|\theta_0)+th^T I_{\theta_0}\Delta_{n,\theta_0}-\frac{t}{2}h^T I_{\theta_0}h\big]\,dh+o_{P^n_{\theta_0}}(1)\\
=&\log \int_{\{h:\|h\|\le M\}} \exp\big[-\frac{t}{2}(h-\Delta_{n,\theta_0})^T I_{\theta_0}(h-\Delta_{n,\theta_0})\big]\,dh+\frac{t}{2}\Delta^T_{n,\theta_0}I_{\theta_0}\Delta_{n,\theta_0}+t\log p_n(\mathbf{X}^{(n)}|\theta_0)+o_{P^n_{\theta_0}}(1).
\end{aligned}
$$

Thus

$$
\begin{aligned}
&\log \int_{\{\theta:\|\theta-\theta_0\|\le M/\sqrt{n}\}} \big[p_n(\mathbf{X}^{(n)}|\theta)\big]^t\pi(\theta)\,d\theta\\
=&\log \int_{\{h:\|h\|\le M\}} \exp\big[-\frac{t}{2}(h-\Delta_{n,\theta_0})^T I_{\theta_0}(h-\Delta_{n,\theta_0})\big]\,dh\\
&+\frac{t}{2}\Delta^T_{n,\theta_0}I_{\theta_0}\Delta_{n,\theta_0}+t\log p_n(\mathbf{X}^{(n)}|\theta_0)-\frac{p}{2}\log n+\log\pi(\theta_0)+o_{P^n_{\theta_0}}(1).
\end{aligned}
$$

This equality holds for every $M>0$ and hence also for some $M_n\to\infty$. Note that Δ_{n,θ_0} is bounded in probability. Hence

$$
\begin{aligned}
&\log \int_{\{h:\|h\|\le M_n\}} \exp\big[-\frac{t}{2}(h-\Delta_{n,\theta_0})^T I_{\theta_0}(h-\Delta_{n,\theta_0})\big]\,dh\\
=&\log \int_{\mathbb{R}^p} \exp\big[-\frac{t}{2}(h-\Delta_{n,\theta_0})^T I_{\theta_0}(h-\Delta_{n,\theta_0})\big]\,dh+o_{P^n_{\theta_0}}(1)\\
=&\frac{p}{2}\log(2\pi)-\frac{p}{2}\log t-\frac{1}{2}\log|I_{\theta_0}|+o_{P^n_{\theta_0}}(1).
\end{aligned}
$$

Thus,

$$
\begin{aligned}
&\log \int_{\{\theta:\|\theta-\theta_0\|\le M_n/\sqrt{n}\}} \big[p_n(\mathbf{X}^{(n)}|\theta)\big]^t\pi(\theta)\,d\theta\\
=&\frac{p}{2}\log\big(\frac{2\pi}{n}\big)-\frac{p}{2}\log t-\frac{1}{2}\log|I_{\theta_0}|+\log\pi(\theta_0)+\frac{t}{2}\Delta^T_{n,\theta_0}I_{\theta_0}\Delta_{n,\theta_0}+t\log p_n(\mathbf{X}^{(n)}|\theta_0)+o_{P^n_{\theta_0}}(1).
\end{aligned}
$$

If $L_t(\mathbf{X}^{(n)})$ is consistent, then

$$
\begin{aligned}
&\log L_t(\mathbf{X}^{(n)})=\log\int_{\Theta}\big[p_n(\mathbf{X}^{(n)}|\theta)\big]^t\pi(\theta)\,d\theta\\
=&\frac{p}{2}\log\big(\frac{2\pi}{n}\big)-\frac{p}{2}\log t-\frac{1}{2}\log|I_{\theta_0}|+\log\pi(\theta_0)+\frac{t}{2}\Delta^T_{n,\theta_0}I_{\theta_0}\Delta_{n,\theta_0}+t\log p_n(\mathbf{X}^{(n)}|\theta_0)+o_{P^n_{\theta_0}}(1).
\end{aligned}
$$

Similarly, if $L^*_t(\mathbf{X}^{(n)})$ is consistent,

$$
\begin{aligned}
&\log L^*_t(\mathbf{X}^{(n)})=\log\int_{\tilde{\Theta}_0}\big[p_n(\mathbf{X}^{(n)}|\nu,\xi_0)\big]^t\pi(\nu)\,d\nu\\
=&\frac{p_1}{2}\log\big(\frac{2\pi}{n}\big)-\frac{p_1}{2}\log t-\frac{1}{2}\log|I^*_{\theta_0}|+\log\pi(\nu_0)+\frac{t}{2}\Delta^{*T}_{n,\theta_0}I^*_{\theta_0}\Delta^*_{n,\theta_0}+t\log p_n(\mathbf{X}^{(n)}|\theta_0)+o_{P^n_{\theta_0}}(1).
\end{aligned}
$$

These expansions, combined with the mutually contiguity of $P^n_{\theta_0}$ and $P^n_{\theta_n}$, yield

$$
\begin{aligned}
\log\Lambda_{a,b}(\mathbf{X}^{(n)})=&\log L_a(\mathbf{X}^{(n)})-\log L_b(\mathbf{X}^{(n)})-\log L^*_a(\mathbf{X}^{(n)})+\log L^*_b(\mathbf{X}^{(n)})\\
=&-\frac{p-p_1}{2}\log\frac{a}{b}+\frac{a-b}{2}\Big(\Delta^T_{n,\theta_0}I_{\theta_0}\Delta_{n,\theta_0}-\Delta^{*T}_{n,\theta_0}I^*_{\theta_0}\Delta^*_{n,\theta_0}\Big)+o_{P^n_{\theta_n}}(1).
\end{aligned}
$$

Note that

$$I^*_{\theta_0} = J^T I_{\theta_0} J, \quad \Delta^*_{n,\theta_0} = (J^T I_{\theta_0} J)^{-1} J^T I_{\theta_0} \Delta_{n,\theta_0}.$$

Then

$$\Delta^T_{n,\theta_0} I_{\theta_0} \Delta_{n,\theta_0} - \Delta^{*T}_{n,\theta_0} I^*_{\theta_0} \Delta^*_{n,\theta_0} = \Delta^T_{n,\theta_0} I^{1/2}_{\theta_0} \big(I_p - I^{1/2}_{\theta_0} J (J^T I_{\theta_0} J)^{-1} J^T I^{1/2}_{\theta_0} \big) I^{1/2}_{\theta_0} \Delta_{n,\theta_0},$$

where $I_p - I^{1/2}_{\theta_0} J (J^T I_{\theta_0} J)^{-1} J^T I^{1/2}_{\theta_0}$ is a projection matrix with rank $p - p_1$.

Now we need to derive the asymptotic distribution of Δ_{n,θ_0}. Let $h_n = \sqrt{n}(\theta_n - \theta_0)$. By Proposition 1 and CLT,

$$\begin{pmatrix} \frac{1}{\sqrt{n}} \sum_{i=1}^n \dot{\ell}_{\theta_0}(X_i) \\ \log \frac{p_n(\mathbf{X}^{(n)}|\theta_n)}{p_n(\mathbf{X}^{(n)}|\theta_0)} \end{pmatrix} = \begin{pmatrix} \frac{1}{\sqrt{n}} \sum_{i=1}^n \dot{\ell}_{\theta_0}(X_i) \\ \frac{1}{\sqrt{n}} \sum_{i=1}^n h_n^T \dot{\ell}_{\theta_0}(X_i) - \frac{1}{2} h_n^T I_{\theta_0} h_n \end{pmatrix} + o_{P_0^n}(1)$$

$$\overset{P_0^n}{\rightsquigarrow} N\left(\begin{pmatrix} 0 \\ -\frac{1}{2}\eta^T I_{\theta_0} \eta \end{pmatrix}, \begin{pmatrix} I_{\theta_0} & I_{\theta_0}\eta \\ \eta^T I_{\theta_0} & \eta^T I_{\theta_0} \eta \end{pmatrix} \right).$$

Hence by Le Cam's third lemma,

$$\frac{1}{\sqrt{n}} \sum_{i=1}^n \dot{\ell}_{\theta_0}(X_i) \overset{P^n_{\theta_n}}{\rightsquigarrow} N(I_{\theta_0}\eta, I_{\theta_0}).$$

Consequently, Δ_{n,θ_0} weakly converges to $N(\eta, I^{-1}_{\theta_0})$ in $P^n_{\theta_n}$. Hence

$$\Delta^T_{n,\theta_0} I_{\theta_0} \Delta_{n,\theta_0} - \Delta^{*T}_{n,\theta_0} I^*_{\theta_0} \Delta^*_{n,\theta_0} \overset{P^n_{\eta_n}}{\rightsquigarrow} \chi^2_{p-p_1}(\delta).$$

This completes the proof.

□

Proof of Proposition 1. By some algebra, we have

$$\Delta_{n,\theta_0} = n^{-1/2} \sum_{i=1}^n T(X_i) - \sqrt{n} \frac{\partial}{\partial \theta} A(\theta_0)$$

and

$$\log \frac{p_n(\mathbf{X}^{(n)}|\theta_0 + n^{-1/2}h)}{p_n(\mathbf{X}^{(n)}|\theta_0)} = h^T I_{\theta_0} \Delta_{n,\theta_0} - \frac{1}{2} h^T I_{\theta_0} h - g_n(h),$$

where

$$g_n(h) = n\Big(A(\theta_0 + n^{-1/2}h) - A(\theta_0) - n^{-1/2} h \frac{\partial}{\partial \theta} A(\theta_0) - \frac{1}{2n} h^T I_{\theta_0} h \Big).$$

Without loss of generality, we assume $M_n \to \infty$ and $M_n^3/\sqrt{n} \to 0$. Then by Taylor's theorem and the continuity of the third derivative of $A(\theta)$,

$$\max_{\{h: \|h\| \leq M_n\}} |g_n(h)| = O\Big(\frac{M_n^3}{\sqrt{n}} \Big) \to 0.$$

Then

$$
\begin{aligned}
&\int_\Theta \big[p_n(\mathbf{X}^{(n)}|\theta)\big]^t \pi(\theta)\,d\theta \ge \int_{\{\theta:\|\theta-\theta_0\|\le M_n/\sqrt{n}\}} \big[p_n(\mathbf{X}^{(n)}|\theta)\big]^t \pi(\theta)\,d\theta \\
&= (1+o_{P_0^n}(1)) n^{-p/2}\pi(\theta_0)\big[p_n(\mathbf{X}^{(n)}|\theta_0)\big]^t \int_{\{h:h\le M_n\}} \exp\big[t h^T I_{\theta_0}\Delta_{n,\theta_0} - \frac{t}{2} h^T I_{\theta_0} h\big]\,dh \\
&= (1+o_{P_0^n}(1)) n^{-p/2}\pi(\theta_0)\big[p_n(\mathbf{X}^{(n)}|\theta_0)\big]^t \int_{\mathbb{R}^p} \exp\big[t h^T I_{\theta_0}\Delta_{n,\theta_0} - \frac{t}{2} h^T I_{\theta_0} h\big]\,dh \\
&= (1+o_{P_0^n}(1)) n^{-p/2}\pi(\theta_0)\big[p_n(\mathbf{X}^{(n)}|\theta_0)\big]^t \exp\big[-\frac{t}{2}\Delta_{n,\theta_0}^T I_{\theta_0}\Delta_{n,\theta_0}\big](2\pi)^{p/2} t^{-p/2} |I_{\theta_0}|^{-1/2}.
\end{aligned}
$$

We have

$$
\begin{aligned}
&\max_{\{\theta:\|\theta-\theta_0\|=M_n/\sqrt{n}\}} \log \frac{p_n(\mathbf{X}^{(n)}|\theta)}{p_n(\mathbf{X}^{(n)}|\theta_0)} = \max_{\{h:\|h\|=M_n\}} \log \frac{p_n(\mathbf{X}^{(n)}|\theta_0+n^{-1/2}h)}{p_n(\mathbf{X}^{(n)}|\theta_0)} \\
&\le \|I_{\theta_0}\Delta_{n,\theta_0}\| M_n - \frac{\lambda_{\min}(I_{\theta_0})}{2} M_n^2 + \max_{\{h:\|h\|=M_n\}} |g_n(h)|,
\end{aligned}
$$

where $\lambda_{\min}(I_{\theta_0}) > 0$ is the minimum eigenvalue of I_{θ_0}. Also note that $I_{\theta_0}\Delta_{n,\theta_0}$ is bounded in probability. Hence with probability tending to 1,

$$
\max_{\{\theta:\|\theta-\theta_0\|=M_n/\sqrt{n}\}} \log \frac{p_n(\mathbf{X}^{(n)}|\theta)}{p_n(\mathbf{X}^{(n)}|\theta_0)} \le -\frac{\lambda_{\min}(I_{\theta_0})}{4} M_n^2.
$$

By the concavity of $\log p_n(\mathbf{X}^{(n)}|\theta)$, for $\|\theta-\theta_0\| \ge M_n/\sqrt{n}$,

$$
\frac{M_n/\sqrt{n}}{\|\theta-\theta_0\|}\Big(\log p_n(\mathbf{X}^{(n)}|\theta) - \log p_n(\mathbf{X}^{(n)}|\theta_0)\Big) \le \log p_n\Big(\mathbf{X}^{(n)}\Big|\theta_0 + \frac{M_n/\sqrt{n}}{\|\theta-\theta_0\|}(\theta-\theta_0)\Big) - \log p_n(\mathbf{X}^{(n)}|\theta_0).
$$

Thus,

$$
\begin{aligned}
\log \frac{p_n(\mathbf{X}^{(n)}|\theta)}{p_n(\mathbf{X}^{(n)}|\theta_0)} &\le \frac{\sqrt{n}\|\theta-\theta_0\|}{M_n} \log \frac{p_n\Big(\mathbf{X}^{(n)}\Big|\theta_0 + \frac{M_n/\sqrt{n}}{\|\theta-\theta_0\|}(\theta-\theta_0)\Big)}{p_n(\mathbf{X}^{(n)}|\theta_0)} \\
&\le \frac{\sqrt{n}\|\theta-\theta_0\|}{M_n}\Big(-\frac{\lambda_{\min}(I_{\theta_0})}{4} M_n^2\Big) \\
&= -\frac{\lambda_{\min}(I_{\theta_0})}{4}\sqrt{n}\|\theta-\theta_0\| M_n.
\end{aligned}
$$

For $\epsilon > 0$ such that $\sup_{\|\theta-\theta_0\|<\epsilon} \pi(\theta) \leq +\infty$, we have

$$
\begin{aligned}
&\int_{\{\theta:\|\theta-\theta_0\|>M_n/\sqrt{n}\}} \big[p_n(\mathbf{X}^{(n)}|\theta)\big]^t \pi(\theta)\, d\theta \\
\leq&\big[p_n(\mathbf{X}^{(n)}|\theta_0)\big]^t \int_{\{\theta:\|\theta-\theta_0\|>M_n/\sqrt{n}\}} \exp\Big[-\frac{t\lambda_{\min}(I_{\theta_0})}{4}\sqrt{n}\|\theta-\theta_0\|M_n\Big]\pi(\theta)\, d\theta \\
=&\big[p_n(\mathbf{X}^{(n)}|\theta_0)\big]^t \Big(\int_{\{\theta:M_n/\sqrt{n}\leq\|\theta-\theta_0\|\leq\epsilon\}} \exp\Big[-\frac{t\lambda_{\min}(I_{\theta_0})}{4}\sqrt{n}\|\theta-\theta_0\|M_n\Big]\pi(\theta)\, d\theta \\
&+\int_{\{\theta:\|\theta-\theta_0\|>\epsilon\}} \exp\Big[-\frac{t\lambda_{\min}(I_{\theta_0})}{4}\sqrt{n}\|\theta-\theta_0\|M_n\Big]\pi(\theta)\, d\theta\Big) \\
\leq&\big[p_n(\mathbf{X}^{(n)}|\theta_0)\big]^t \Big(\big(\sup_{\|\theta-\theta_0\|<\epsilon}\pi(\theta)\big)\int_{\{\theta:\|\theta-\theta_0\|\geq M_n/\sqrt{n}\}} \exp\Big[-\frac{t\lambda_{\min}(I_{\theta_0})}{4}\sqrt{n}\|\theta-\theta_0\|M_n\Big]\, d\theta \\
&+\exp\Big[-\frac{t\lambda_{\min}(I_{\theta_0})}{4}\epsilon\sqrt{n}M_n\Big]\Big) \\
=&\big[p_n(\mathbf{X}^{(n)}|\theta_0)\big]^t \Big(\big(\sup_{\|\theta-\theta_0\|<\epsilon}\pi(\theta)\big)n^{-p/2}\int_{\{h:\|h\|\geq M_n\}} \exp\Big[-\frac{t\lambda_{\min}(I_{\theta_0})}{4}\|h\|M_n\Big]\, dh \\
&+\exp\Big[-\frac{t\lambda_{\min}(I_{\theta_0})}{4}\epsilon\sqrt{n}M_n\Big]\Big).
\end{aligned}
$$

Thus,

$$
\begin{aligned}
&\frac{\int_{\{\theta:\|\theta-\theta_0\|>M_n/\sqrt{n}\}} \big[p_n(\mathbf{X}^{(n)}|\theta)\big]^t \pi(\theta)\, d\theta}{\int_{\Theta} \big[p_n(\mathbf{X}^{(n)}|\theta)\big]^t \pi(\theta)\, d\theta} \\
=&O_{P_{\theta_0}^n}(1)\Big(\int_{\{h:\|h\|\geq M_n\}} \exp\Big[-\frac{t\lambda_{\min}(I_{\theta_0})}{4}\|h\|M_n\Big]\, dh + n^{p/2}\exp\Big[-\frac{t\lambda_{\min}(I_{\theta_0})}{4}\epsilon\sqrt{n}M_n\Big]\Big) \\
=&o_{P_{\theta_0}^n}(1).
\end{aligned}
$$

□

Proof of Proposition 2. Note that L_1 is well defined $P_{\theta_0}^n$-a.s. since it has finite integral

$$\int_{\mathcal{X}^n} L_1\, d\mu^n = \int_{\Theta}\Big(\int_{\mathcal{X}^n} p_n(\mathbf{X}^{(n)}|\theta)\, d\mu^n\Big)\pi(\theta)\, d\theta = 1.$$

For $0 < t < 1$, by Hölder's inequality, we have $L_t \leq L_1^{1/t}$. This proves the first part of the proposition.

To prove the second part of the proposition, consider the following example. Suppose $X_1, \ldots, X_n$ are iid from the density

$$p(X|\theta) = C|X-\theta|^{-\gamma}\exp\big[-(X-\theta)^2\big],$$

where C is the normalizing constant and $\gamma \in (0,1)$ is a known hyperparameter. The parameter space Θ is equal to $\mathbb{R}$. Then

$$L_t = C^n \int_{-\infty}^{+\infty}\Big[\prod_{i=1}^n |X_i-\theta|\Big]^{-t\gamma}\exp\big[-t\sum_{i=1}^n (X_i-\theta)^2\big]\pi(\theta)\, d\theta.$$

Note that almost surely, there is no tie among $X_1, \ldots, X_n$. Consequently, $L_t(\mathbf{X}^{(n)}) = +\infty$ almost surely if and only if $t \geq \gamma^{-1}$. Since $\gamma^{-1} \in (1, +\infty)$, this example shows that L_t is not always well defined for $t > 1$.

$\square$

Proof of Proposition 4. Note that

$$\frac{L_t(\{\theta : \|\theta - \theta_0\| \geq \frac{M_n}{\sqrt{n}}\})}{L_t} = \frac{\int_{\left\{\theta:\|\theta-\theta_0\| \geq \frac{M_n}{\sqrt{n}}\right\}} \left[\frac{p_n(\mathbf{X}^{(n)}|\theta)}{p_n(\mathbf{X}^{(n)}|\theta_0)}\right]^t \pi(\theta)\, d\theta}{\int_\Theta \left[\frac{p_n(\mathbf{X}^{(n)}|\theta)}{p_n(\mathbf{X}^{(n)}|\theta_0)}\right]^t \pi(\theta)\, d\theta}. \tag{9}$$

Without loss of generality, we assume $M_n/\sqrt{n} \to 0$.

Consider the expactation of the numerator of 9. It follows from Fubini's theorem that

$$\begin{aligned}
&P_0^n \int_{\{\theta:\|\theta-\theta_0\| \geq \frac{M_n}{\sqrt{n}}\}} \left[\frac{p_n(\mathbf{X}^{(n)}|\theta)}{p_n(\mathbf{X}^{(n)}|\theta_0)}\right]^t \pi(\theta)\, d\theta \\
&= \int_{\{\theta:\|\theta-\theta_0\| \geq \frac{M_n}{\sqrt{n}}\}} \left\{ \int_{\mathcal{X}^n} \left[p_n(\mathbf{X}^{(n)}|\theta)\right]^t \left[p_n(\mathbf{X}^{(n)}|\theta_0)\right]^{1-t} d\mu^n \right\} \pi(\theta)\, d\theta \\
&= \int_{\{\theta:\|\theta-\theta_0\| \geq \frac{M_n}{\sqrt{n}}\}} \left[\rho_t(\theta, \theta_0)\right]^n \pi(\theta)\, d\theta \\
&= \int_{\{\theta:\|\theta-\theta_0\| \geq \frac{M_n}{\sqrt{n}}\}} \exp\left[-(1-t) n D_t(\theta||\theta_0)\right] \pi(\theta)\, d\theta.
\end{aligned}$$

Decompose the integral region into two parts $\{\theta : \frac{M_n}{\sqrt{n}} \leq \|\theta - \theta_0\| \leq \delta\}$ and $\{\theta : \|\theta - \theta_0\| > \delta\}$,

$$\begin{aligned}
&\int_{\{\theta:\|\theta-\theta_0\| \geq \frac{M_n}{\sqrt{n}}\}} \exp\left[-(1-t) n D_t(\theta||\theta_0)\right] \pi(\theta)\, d\theta \\
&= \int_{\{\theta:\frac{M_n}{\sqrt{n}} \leq \|\theta-\theta_0\| \leq \delta\}} \exp\left[-(1-t) n D_t(\theta||\theta_0)\right] \pi(\theta)\, d\theta + \int_{\{\theta:\|\theta-\theta_0\| > \delta\}} \exp\left[-(1-t) n D_t(\theta||\theta_0)\right] \pi(\theta)\, d\theta \\
&\leq \max_{\|\theta-\theta_0\| \leq \delta} \pi(\theta) \int_{\left\{\theta:\|\theta-\theta_0\| \geq \frac{M_n}{\sqrt{n}}\right\}} \exp\left[-(1-t) C n \|\theta - \theta_0\|^2\right] d\theta + \exp\left[-(1-t)\epsilon n\right] \\
&= \Big(\max_{\|\theta-\theta_0\| \leq \delta} \pi(\theta)\Big) n^{-p/2} \int_{\left\{h:\|h\| \geq M_n\right\}} \exp\left[-(1-t) C \|h\|^2\right] dh + \exp\left[-(1-t)\epsilon n\right].
\end{aligned}$$

Now we consider the denominator of (9).

$$\begin{aligned}
&\int_\Theta \left[\frac{p_n(\mathbf{X}^{(n)}|\theta)}{p_n(\mathbf{X}^{(n)}|\theta_0)}\right]^t \pi(\theta)\, d\theta \geq \int_{\{\theta:\|\theta-\theta_0\| \leq n^{-1/2}\}} \left[\frac{p_n(\mathbf{X}^{(n)}|\theta)}{p_n(\mathbf{X}^{(n)}|\theta_0)}\right]^t \pi(\theta)\, d\theta \\
&\geq \Big(\min_{\|\theta-\theta_0\| \leq n^{-1/2}} \left[\frac{p_n(\mathbf{X}^{(n)}|\theta)}{p_n(\mathbf{X}^{(n)}|\theta_0)}\right]^t \pi(\theta) \Big) \int_{\{\theta:\|\theta-\theta_0\| \leq n^{-1/2}\}} 1\, d\theta \\
&\geq \Big(\exp\Big[t \min_{\|\theta-\theta_0\| \leq n^{-1/2}} \log \frac{p_n(\mathbf{X}^{(n)}|\theta)}{p_n(\mathbf{X}^{(n)}|\theta_0)} \Big] \Big) \Big(\min_{\|\theta-\theta_0\| \leq n^{-1/2}} \pi(\theta) \Big) n^{-p/2} \frac{2\pi^{p/2}}{\Gamma(p/2)}.
\end{aligned}$$

By Proposition 1,

$$\min_{\|\theta-\theta_0\|\le n^{-1/2}} \log \frac{p_n(\mathbf{X}^{(n)}|\theta)}{p_n(\mathbf{X}^{(n)}|\theta_0)} \ge -\|I_{\theta_0}\Delta_{n,\theta_0}\| - \frac{1}{2}\|I_{\theta_0}\| + o_{P_0^n}(1).$$

Since $I_{\theta_0}\Delta_{n,\theta_0}$ is bounded in probability,

$$\min_{\|\theta-\theta_0\|\le n^{-1/2}} \log \frac{p_n(\mathbf{X}^{(n)}|\theta)}{p_n(\mathbf{X}^{(n)}|\theta_0)}$$

is lower bounded in probability. Note that

$$\min_{\|\theta-\theta_0\|\le n^{-1/2}} \pi(\theta) \to \pi(\theta_0) > 0.$$

Then for every $\epsilon' > 0$, there is a constant $c > 0$ such that with probability at least $1-\epsilon'$,

$$\int_\Theta \Big[\frac{p_n(\mathbf{X}^{(n)}|\theta)}{p_n(\mathbf{X}^{(n)}|\theta_0)}\Big]^t \pi(\theta)\, d\theta \ge c n^{-p/2}.$$

Combining the upper bound and the lower bound yields that with probability at least $1-\epsilon'$,

$$\begin{aligned}&\frac{L_t(\{\theta : \|\theta-\theta_0\| \ge \frac{M_n}{\sqrt{n}}\})}{L_t}\\ \le& c^{-1}\big(\max_{\|\theta-\theta_0\|\le\delta}\pi(\theta)\big)\int_{\{h:\|h\|\ge M_n\}} \exp\big[-(1-t)C\|h\|^2\big]\, d\theta + c^{-1}n^{p/2}\exp\big[-(1-t)\epsilon n\big] \to 0.\end{aligned}$$

Since ϵ is arbitrary, the theorem follows. □

Proof of Theorem 2. By contiguity, we only need to prove the convergence in P_0^n.

The proof consists of two steps. In the first part of the proof, let M be a fixed positive number. We prove

$$\Big|\int_{\|h\|\le M} \frac{p_n(\mathbf{X}^{(n)}|\theta_0+n^{-1/2}h)}{p_n(\mathbf{X}^{(n)}|\theta_0)}\pi_n(h;\mathbf{X}^{(n)})\, dh - \int_{\|h\|\le M} \exp\big[h^T I_{\theta_0}\Delta_{n,\theta_0} - \frac{1}{2}h^T I_{\theta_0}h\big]\phi(h;\Delta_{n,\theta_0}, I_{\theta_0}^{-1})\, dh\Big| \xrightarrow{P_0^n} 0 \tag{10}$$

Propostion 1 implies that

$$\int_{\|h\|\le M} \frac{p_n(\mathbf{X}^{(n)}|\theta_0+n^{-1/2}h)}{p_n(\mathbf{X}^{(n)}|\theta_0)}\pi_n(h;\mathbf{X}^{(n)})\, dh = \exp[o_{p_0^n}(1)]\int_{\|h\|\le M} \exp\big[h^T I_{\theta_0}\Delta_{n,\theta_0} - \frac{1}{2}h^T I_{\theta_0}h\big]\pi_n(h;\mathbf{X}^{(n)})\, dh \tag{11}$$

So we only need to consider $\int_{\|h\|\le M}\exp\big[h^T I_{\theta_0}\Delta_{n,\theta_0} - \frac{1}{2}h^T I_{\theta_0}h\big]\pi_n(h;\mathbf{X}^{(n)})\, dh$. By central limit theorem, Δ_{n,θ_0} weakly converges to a normal distribution. As a result, $\sup_{\|h\|\le M}\exp\big[h^T I_{\theta_0}\Delta_{n,\theta_0} - \frac{1}{2}h^T I_{\theta_0}h\big]$ is bounded in probability. It follows that

$$\begin{aligned}&\int_{\|h\|\le M} \exp\big[h^T I_{\theta_0}\Delta_{n,\theta_0} - \frac{1}{2}h^T I_{\theta_0}h\big]\big|\pi_n(h;\mathbf{X}^{(n)}) - \phi(h;\Delta_{n,\theta_0}, I_{\theta_0}^{-1})\big|\, dh\\ \le& \sup_{\|h\|\le M}\exp\big[h^T I_{\theta_0}\Delta_{n,\theta_0} - \frac{1}{2}h^T I_{\theta_0}h\big]\int_{\|h\|\le M}\big|\pi_n(h;\mathbf{X}^{(n)}) - \phi(h;\Delta_{n,\theta_0}, I_{\theta_0}^{-1})\big|\, dh \xrightarrow{P_0^n} 0.\end{aligned}$$

This, combined with (11), proves (10). This is true for every M and hence also for some $M_n \to \infty$.

In the second part, we prove

$$\psi(M) \stackrel{def}{=} \frac{\int_{\|h\|>M} p_n(\mathbf{X}^{(n)}|\theta_0 + n^{-1/2}h)\pi_n(h;\mathbf{X}^{(n)})\,dh}{\int p_n(\mathbf{X}^{(n)}|\theta_0 + n^{-1/2}h)\pi_n(h;\mathbf{X}^{(n)})\,dh} \xrightarrow{P_0^n} 0. \tag{12}$$

Let ϕ_n be a test function satisfying the conclusion of Lemma 2. We have

$$\psi(M) = \psi(M)\phi_n + \psi(M)(1-\phi_n).$$

Since $\psi(M) \le 1$, $\psi(M)\phi_n \le \phi_n \xrightarrow{P_0^n} 0$. So it's enough to prove

$$\psi(M)(1-\phi_n) \xrightarrow{P_0^n} 0$$

Fix a positive number U. Then

$$\psi(M)(1-\phi_n) \le \frac{\int_{\|h\|>M_n} p_n(\mathbf{X}^{(n)}|\theta_0 + n^{-1/2}h)\pi_n(h;\mathbf{X}^{(n)})\,dh}{\int_{\|h\|\le U} p_n(\mathbf{X}^{(n)}|\theta_0 + n^{-1/2}h)\pi_n(h;\mathbf{X}^{(n)})\,dh}(1-\phi_n). \tag{13}$$

First we give a lower bound of $\int_{\|h\|\le U} p_n(\mathbf{X}^{(n)}|\theta_0 + n^{-1/2}h)\pi_n(h;\mathbf{X}^{(n)})\,dh$. Note that

$$\begin{aligned}
&\int_{\|h\|\le U} p_n(\mathbf{X}^{(n)}|\theta_0 + n^{-1/2}h)\pi_n(h;\mathbf{X}^{(n)})\,dh\\
=&\exp[o_{P_0^n}(1)]p_n(\mathbf{X}^{(n)}|\theta_0)\int_{\|h\|\le U}\exp\left[h^T I_{\theta_0}\Delta_{n,\theta_0} - \frac{1}{2}h^T I_{\theta_0}h\right]\pi_n(h;\mathbf{X}^{(n)})\,dh\\
\ge&\exp[o_{P_0^n}(1)]p_n(\mathbf{X}^{(n)}|\theta_0)\Big\{\int_{\|h\|\le U}\exp\left[h^T I_{\theta_0}\Delta_{n,\theta_0} - \frac{1}{2}h^T I_{\theta_0}h\right]\phi(h;\Delta_{n,\theta_0}, I_{\theta_0}^{-1})\,dh\\
&-\sup_{\|h\|\le U}\exp\left[h^T I_{\theta_0}\Delta_{n,\theta_0} - \frac{1}{2}h^T I_{\theta_0}h\right]\int_{\|h\|\le U}\left|\pi_n(h;\mathbf{X}^{(n)}) - \phi(h;\Delta_{n,\theta_0}, I_{\theta_0}^{-1})\right|dh\Big\}\\
=&\exp[o_{P_0^n}(1)]p_n(\mathbf{X}^{(n)}|\theta_0)\Big\{\int_{\|h\|\le U}\exp\left[h^T I_{\theta_0}\Delta_{n,\theta_0} - \frac{1}{2}h^T I_{\theta_0}h\right]\phi(h;\Delta_{n,\theta_0}, I_{\theta_0}^{-1})\,dh - O_P(1)o_P(1)\Big\}.
\end{aligned}$$

Fix an $\epsilon > 0$. Since Δ_{n,θ_0} is uniformly tight, with probability at least $1-\epsilon/2$, $|\Delta_{n,\theta_0}| \le C$ for a constant C. If this event happens, we have

$$\int_{\|h\|\le U}\exp\left[h^T I_{\theta_0}\Delta_{n,\theta_0} - \frac{1}{2}h^T I_{\theta_0}h\right]\phi(h;\Delta_{n,\theta_0}, I_{\theta_0}^{-1})\,dh > 2c$$

for some $c > 0$. Thus, there is a $c > 0$ and an event $D_{1,n}$ with probability at least $1-\epsilon$ on which

$$\int_{\|h\|\le U} p_n(\mathbf{X}^{(n)}|\theta_0 + n^{-1/2}h)\pi_n(h;\mathbf{X}^{(n)})\,dh \ge c p_n(\mathbf{X}^{(n)}|\theta_0)$$

for sufficiently large n.

On the other hand, by Assumption 4, there is a $K > 0$, a $A > 0$ and an event $D_{2,n}$ with probability at least $1-\epsilon$ on which

$$\sup_{\|h\|>K\sqrt{n}}(\pi_n(h;\mathbf{X}^{(n)}) - T(h)) \le 0, \qquad \sup_{\|h\|\le K\sqrt{n}}\pi_n(h;\mathbf{X}^{(n)}) \le A$$

for sufficiently large n.

Combining these bounds yields

$$\psi(M)(1-\phi_n) \le \frac{\int_{\|h\|>M_n} p_n(\mathbf{X}^{(n)}|\theta_0+n^{-1/2}h)\big(A\mathbf{1}_{M_n\le\|h\|\le K\sqrt{n}}+T(h)\mathbf{1}_{\|h\|>K\sqrt{n}}\big)\,dh}{cp_n(\mathbf{X}^{(n)}|\theta_0)}(1-\phi_n)+\mathbf{1}\{D_{1,n}^C\cup D_{2,n}^C\}.$$

Hence for sufficiently large n,

$$\begin{aligned}
&P_0^n\psi(M)(1-\phi_n)\\
\le& c^{-1}\int_{\mathcal{X}^n}\int_{\|h\|>M_n}(1-\phi_n)p_n(\mathbf{X}^{(n)}|\theta_0+n^{-1/2}h)\big(A\mathbf{1}_{M_n\le\|h\|\le K\sqrt{n}}+T(h)\mathbf{1}_{\|h\|>K\sqrt{n}}\big)\,dh\,d\mu^n+2\epsilon\\
=& c^{-1}\int_{\|h\|>M_n}\Big(\int_{\mathcal{X}^n}(1-\phi_n)p_n(\mathbf{X}^{(n)}|\theta_0+n^{-1/2}h)\,d\mu^n\Big)\big(A\mathbf{1}_{M_n\le\|h\|\le K\sqrt{n}}+T(h)\mathbf{1}_{\|h\|>K\sqrt{n}}\big)\,dh+2\epsilon\\
\le& c^{-1}\int_{\|h\|>M_n}\exp\big[-\delta(\|h\|^2\wedge n)\big]\big(A\mathbf{1}_{M_n\le\|h\|\le K\sqrt{n}}+T(h)\mathbf{1}_{\|h\|>K\sqrt{n}}\big)\,dh+2\epsilon.
\end{aligned}$$

Note that $\delta(\|h\|^2\cap n)\ge\delta^*(\|h\|^2\wedge K^2n)$, where $\delta^*=\delta\min(1,K^{-2})$. Hence

$$\begin{aligned}
&\int_{\|h\|>M_n}\exp\big[-\delta(\|h\|^2\wedge n)\big]\big(A\mathbf{1}_{M_n\le\|h\|\le K\sqrt{n}}+T(h)\mathbf{1}_{\|h\|>K\sqrt{n}}\big)\,dh\\
\le&\int_{\|h\|>M_n}\exp\big[-\delta^*(\|h\|^2\wedge K^2n)\big]\big(A\mathbf{1}_{M_n\le\|h\|\le K\sqrt{n}}+T(h)\mathbf{1}_{\|h\|>K\sqrt{n}}\big)\,dh\\
\le& A\int_{\|h\|\ge M_n}e^{-\delta^*\|h\|^2}\,dh+e^{-\delta^*K^2n}\int_{\|h\|>K\sqrt{n}}T(h)\,dh\to 0.
\end{aligned}$$

Therefore $\psi(M)\xrightarrow{P_0^n}0$.

Finally we have

$$\begin{aligned}
&\left|\int\frac{p(\mathbf{X}^{(n)}|\theta_0+n^{-1/2}h)}{p(\mathbf{X}^{(n)}|\theta_0)}\pi_n(h;\mathbf{X}^{(n)})\,dh-2^{-\frac{p}{2}}\exp\big[\frac{1}{2}\Delta_{n,\theta_0}^TI_{\theta_0}\Delta_{n,\theta_0}\big]\right|\\
=&\left|\int\frac{p(\mathbf{X}^{(n)}|\theta_0+n^{-1/2}h)}{p(\mathbf{X}^{(n)}|\theta_0)}\pi_n(h;\mathbf{X}^{(n)})\,dh-\int_{\|h\|\le M_n}\frac{p(\mathbf{X}^{(n)}|\theta_0+n^{-1/2}h)}{p(\mathbf{X}^{(n)}|\theta_0)}\pi_n(h;\mathbf{X}^{(n)})\,dh\right|\\
&+\left|\int_{\|h\|\le M_n}\frac{p(\mathbf{X}^{(n)}|\theta_0+n^{-1/2}h)}{p(\mathbf{X}^{(n)}|\theta_0)}\pi_n(h;\mathbf{X}^{(n)})\,dh-\int_{\|h\|\le M_n}\exp\big[h^TI_{\theta_0}\Delta_{n,\theta_0}-\frac{1}{2}h^TI_{\theta_0}h\big]\phi(h;\Delta_{n,\theta_0},I_{\theta_0}^{-1})\,dh\right|\\
&+\left|\int_{\|h\|\le M_n}\exp\big[h^TI_{\theta_0}\Delta_{n,\theta_0}-\frac{1}{2}h^TI_{\theta_0}h\big]\phi(h;\Delta_{n,\theta_0},I_{\theta_0}^{-1})\,dh-2^{-\frac{p}{2}}\exp\big[\frac{1}{2}\Delta_{n,\theta_0}^TI_{\theta_0}\Delta_{n,\theta_0}\big]\right|\\
=&J_1+J_2+J_3
\end{aligned}$$

By the first step of the proof, we have $J_2\xrightarrow{P_0^n}0$. Hence

$$\int_{\|h\|\le M_n}\frac{p(\mathbf{X}^{(n)}|\theta_0+n^{-1/2}h)}{p(\mathbf{X}^{(n)}|\theta_0)}\pi_n(h;\mathbf{X}^{(n)})\,dh$$

is bounded in probability. Therefore

$$J_1 = \int_{\|h\| \le M_n} \frac{p(\mathbf{X}^{(n)}|\theta_0 + n^{-1/2}h)}{p(\mathbf{X}^{(n)}|\theta_0)} \pi_n(h; \mathbf{X}^{(n)})\, dh \left| \frac{\int p(\mathbf{X}^{(n)}|\theta_0 + n^{-1/2}h)\pi_n(h; \mathbf{X}^{(n)})\, dh}{\int_{\|h\| \le M_n} p(\mathbf{X}^{(n)}|\theta_0 + n^{-1/2}h)\pi_n(h; \mathbf{X}^{(n)})\, dh} - 1 \right|$$
$$= O_{P_0^n}(1) o_{P_0^n}(1)$$

And J_3 convenges to 0 for trivial reason.

Then we can apply the argument to both the numerator and denominator of integrated likelihood ratio statistics. By CLT,

$$I_{\theta_0}\Delta_{n,\theta_0} = \frac{1}{\sqrt{n}} \sum_{i=1}^{n} \dot{\ell}_{\theta_0}(X_i) \overset{P_0^n}{\rightsquigarrow} \xi, \tag{14}$$

where $\xi \sim N(0, I_{\theta_0})$.

$$I^*_{\theta_0}\Delta^*_{n,\theta_0} = \frac{1}{\sqrt{n}} \sum_{i=1}^{n} \dot{\ell}^*_{\theta_0}(X_i) \overset{P_0^n}{\rightsquigarrow} \xi^*, \tag{15}$$

where ξ^* is the first p_1 coordinates of ξ. Hence

$$\begin{aligned} \Lambda(X) &= \frac{2^{-\frac{p_2}{2}} \exp\{\frac{1}{2}\Delta^T_{n,\theta_0} I_{\theta_0}\Delta_{n,\theta_0}\} + o_{P_0^n}(1)}{2^{-\frac{p_1}{2}} \exp\{\frac{1}{2}\Delta^{*T}_{n,\theta_0} I^*_{\theta_0}\Delta^*_{n,\theta_0}\} + o_{P_0^n}(1)} \\ &\overset{P_0^n}{\rightsquigarrow} \frac{2^{-\frac{p_2}{2}} \exp\{\frac{1}{2}\xi^T I^{-1}_{\theta_0}\xi\}}{2^{-\frac{p_1}{2}} \exp\{\frac{1}{2}\xi^{*T} I^{*-1}_{\theta_0}\xi^*\}}. \end{aligned} \tag{16}$$

But

$$\xi^T I^{-1}_{\theta_0}\xi - \xi^{*T} I^{*-1}_{\theta_0}\xi^* = (I^{-\frac{1}{2}}_{\theta_0}\xi)^T \Big(I_{p_2\times p_2} - I^{\frac{1}{2}}_{\theta_0} \begin{pmatrix} I^{*-1}_{\theta_0} & 0 \\ 0 & 0 \end{pmatrix} I^{\frac{1}{2}}_{\theta_0}\Big)(I^{-\frac{1}{2}}_{\theta_0}\xi). \tag{17}$$

$I^{-\frac{1}{2}}_{\theta_0}\xi$ is a p_2-dimensional standard normal distribution, The middle term is a projection matrix with rank $p_2 - p_1$. Hence we have

$$2\log(\Lambda(X)) \overset{P_0^n}{\rightsquigarrow} \chi^2_{p_2-p_1} - (p_2 - p_1)\log(2). \tag{18}$$

□

Appendix B Proofs in Section 3

We would like to derive the asymptotics of

$$\int_\Theta \Big[\prod_{i=1}^{n} \frac{p(X_i|\omega, \xi)}{p_0(X_i)}\Big]^t \pi(\omega, \xi)\, d\omega d\mu. \tag{19}$$

Let $A(M_n) = \{(\omega, \xi) : \omega\big(2\Phi(|\xi|/2) - 1\big) \le M_n n^{-1/2}\}$, we have

Proposition 5. *If* $M_n \geq \frac{1}{4(t\wedge(1-t))}\log n$,

$$\mathrm{E}\int_{A(M_n)^c}\Big[\prod_{i=1}^n \frac{p(X_i|\omega,\xi)}{p_0(X_i)}\Big]^t \pi(\omega,\xi)\,d\omega d\mu = o(n^{-1/2}).$$

Proof.

$$\mathrm{E}\int_{A(M_n)^c}\Big[\prod_{i=1}^n \frac{p(X_i|\omega,\xi)}{p_0(X_i)}\Big]^t \pi(\omega,\xi)\,d\omega d\xi = \int_{A(M_n)^c}\big(\int p(X_1|\omega,\xi)^t p_0(X_1)^{1-t}\,d\mu\big)^n \pi(\omega,\xi)\,d\omega d\xi.$$

Note that

$$\begin{aligned}
&\int p(X_i|\omega,\xi)^t p_0(X_i)^{1-t}\,d\mu\\
\leq&\Big(\int \sqrt{p(X_i|\omega,\xi)p_0(X_i)}\,d\mu\Big)^{2(t\wedge(1-t))}\\
=&\Big(1-\frac{1}{2}\int\big(\sqrt{p(X_i|\omega,\xi)}-\sqrt{p_0(X_i)}\big)^2\,d\mu\Big)^{2(t\wedge(1-t))}\\
\leq&\exp\Big(-(t\wedge(1-t))\int\big(\sqrt{p(X_i|\omega,\xi)}-\sqrt{p_0(X_i)}\big)^2\,d\mu\Big)\\
\leq&\exp\Big(-\frac{1}{2}(t\wedge(1-t))\big(\int\big|p(X_i|\omega,\xi)-p_0(X_i)\big|\,d\mu\big)^2\Big)\\
=&\exp\Big(-\frac{1}{2}(t\wedge(1-t))\omega^2\big(\int\big|\phi(X_i-\xi)-\phi(X_i)\big|\,d\mu\big)^2\Big)\\
=&\exp\Big(-2(t\wedge(1-t))\omega^2\big(2\Phi(|\xi|/2)-1\big)^2\Big)
\end{aligned}$$

Thus,

$$\begin{aligned}
&\mathrm{E}\int_{A(M_n)^c}\Big[\prod_{i=1}^n \frac{p(X_i|\omega,\xi)}{p_0(X_i)}\Big]^t \pi_\omega(\omega)\pi_\xi(\xi)\,d\omega d\xi\\
\leq&\int_{A(M_n)^c}\exp\Big(-2(t\wedge(1-t))n\omega^2\big(2\Phi(|\xi|/2)-1\big)^2\Big)\pi_\omega(\omega)\pi_\xi(\xi)\,d\omega d\xi
\end{aligned}$$

If $M_n \geq \frac{1}{4(t\wedge(1-t))}\log n$,

$$\begin{aligned}
&\mathrm{E}\int_{A(M_n)^c}\Big[\prod_{i=1}^n \frac{p(X_i|\omega,\xi)}{p_0(X_i)}\Big]^t \pi_\omega(\omega)\pi_\xi(\xi)\,d\omega d\xi\\
\leq& n^{-1/2}\int_{A(M_n)^c}\pi_\omega(\omega)\pi_\xi(\xi)\,d\omega d\xi = o(n^{-1/2}).
\end{aligned}$$

□

Proof of Theorem ii. We have

$$\sum_{i=1}^n\big(\log p(X_i|\omega,\xi)-\log p_0(X_i)\big) = \sum_{i=1}^n \log\Big(1+\omega\big(\exp(\xi X_i-\xi^2/2)-1\big)\Big) = \sum_{i=1}^n \log(1+\omega\xi Y_i),$$

where $Y_i = \big(\exp(\xi X_i - \xi^2/2) - 1\big)/\xi$ if $\xi \neq 0$ and $Y_i = X_i$ if $\xi = 0$.

Let $r > 1$ and $s < 1/4$, on $A((\log n)^r) \cap \{\omega \geq n^{-s}\}$, we have $|\xi| = O\big((\log n)^r/n^{1/2-s}\big)$.

It is known that $\max_{1\leq i\leq n}|X_i| = O_P(\sqrt{\log n})$. On $A((\log n)^r)\cap\{\omega \geq n^{-s}\}$, we have $\max_{1\leq i\leq n}|\xi X_i - \xi^2/2| \leq |\xi|\max_{1\leq i\leq n}|X_i| + \xi^2/2 = O_P(|\xi|(\log n)^{1/2})$. Then on $A((\log n)^r) \cap \{\omega \geq n^{-s}\}$, uniformly for $i = 1, \ldots, n$, we have

$$\begin{aligned}
Y_i &= \xi^{-1}\Big(\xi X_i - \xi^2/2 + \frac{1}{2}(\xi X_i - \xi^2/2)^2 + O_P\big(|\xi|^3(\log n)^{3/2}\big)\Big)\\
&= X_i - \frac{1}{2}\xi + \frac{1}{2}\xi X_i^2 - \frac{1}{2}\xi^2 X_i + \frac{1}{8}\xi^3 + O_P\big(|\xi|^2(\log n)^{3/2}\big)\\
&= X_i + \frac{1}{2}\xi(X_i^2 - 1) + O_P\big(|\xi|^2(\log n)^{3/2}\big).
\end{aligned}$$

In particular, on $A((\log n)^r) \cap \{\omega \geq n^{-s}\}$, we have $\max_{1\leq i\leq n}|Y_i| = O_P(\sqrt{\log n})$. On $A((\log n)^r) \cap \{\omega \geq n^{-s}\}$, we have $\omega\xi = O((\log n)^r/\sqrt{n})$, then

$$\begin{aligned}
&\sum_{i=1}^n \log(1 + \omega\xi Y_i)\\
=&\omega\xi\sum_{i=1}^n Y_i - \frac{1}{2}\omega^2\xi^2\sum_{i=1}^n Y_i^2 + O_P(n\omega^3\xi^3(\log n)^{3/2})\\
=&\omega\xi\sum_{i=1}^n Y_i - \frac{1}{2}\omega^2\xi^2\sum_{i=1}^n Y_i^2 + o_P(1).
\end{aligned}$$

Note that

$$\begin{aligned}
&\omega\xi\sum_{i=1}^n Y_i = \omega\xi\sum_{i=1}^n X_i + \frac{1}{2}\omega\xi^2\sum_{i=1}^n (X_i^2 - 1) + O_P\big(n\omega|\xi|^3(\log n)^{3/2}\big)\\
=&\omega\xi\sum_{i=1}^n X_i + O_P\Big(\frac{(\log n)^{3r+3/2}}{n^{1/2-2s}}\Big) = \omega\xi\sum_{i=1}^n X_i + o_P(1),
\end{aligned}$$

and

$$\omega^2\xi^2\sum_{i=1}^n Y_i^2 = n\omega^2\xi^2 + o_P(1).$$

Then

$$\begin{aligned}
&\int_{A((\log n)^r)\cap\{\omega\geq n^{-s}\}}\Big[\prod_{i=1}^n \frac{p(X_i|\omega,\xi)}{p_0(X_i)}\Big]^t \pi(\omega,\xi)\,d\omega d\xi\\
=&(1 + o_P(1))\int_{A((\log n)^r)\cap\{\omega\geq n^{-s}\}} \exp\big\{t\omega\xi\sum_{i=1}^n X_i - \frac{1}{2}nt\omega^2\xi^2\big\}\pi(\omega,\xi)\,d\omega d\xi.
\end{aligned}$$

Note that on $A((\log n)^r)\cap\{\omega\ge n^{-s}\}$, $\pi_\xi(\xi)=(1+o(1))\pi_\xi(0)$. Then

$$\begin{aligned}
&\int_{A((\log n)^r)\cap\{\omega\ge n^{-s}\}}\exp\big\{t\omega\xi\sum_{i=1}^n X_i-\frac{1}{2}nt\omega^2\xi^2\big\}\pi(\omega,\xi)\,d\omega d\xi\\
=&(1+o_P(1))\pi_\xi(0)\int_{A((\log n)^r)\cap\{\omega\ge n^{-s}\}}\exp\big\{t\omega\xi\sum_{i=1}^n X_i-\frac{1}{2}nt\omega^2\xi^2\big\}\pi_\omega(\omega)\,d\omega d\xi\\
=&(1+o_P(1))\pi_\xi(0)\int_{n^{-s}}^1\pi_\omega(\omega)\,d\omega\int_{-2\Phi^{-1}\big((\log n)^r/(2\omega\sqrt{n})+1/2\big)}^{2\Phi^{-1}\big((\log n)^r/(2\omega\sqrt{n})+1/2\big)}\exp\big\{t\omega\xi\sum_{i=1}^n X_i-\frac{1}{2}nt\omega^2\xi^2\big\}d\xi.
\end{aligned}$$

Note that

$$\begin{aligned}
&\int_{-2\Phi^{-1}\big((\log n)^r/(2\omega\sqrt{n})+1/2\big)}^{2\Phi^{-1}\big((\log n)^r/(2\omega\sqrt{n})+1/2\big)}\exp\big\{t\omega\xi\sum_{i=1}^n X_i-\frac{1}{2}nt\omega^2\xi^2\big\}d\xi\\
=&\frac{1}{\omega}\sqrt{\frac{2\pi}{tn}}\exp\Big\{\frac{t}{2n}(\sum_{i=1}^n X_i)^2\Big\}\Big[\Phi\Big(2\sqrt{tn}\omega\Phi^{-1}\Big(\frac{(\log n)^r}{2\omega\sqrt{n}}+\frac{1}{2}\Big)-\sqrt{\frac{t}{n}}\sum_{i=1}^n X_i\Big)\\
&-\Phi\Big(-2\sqrt{tn}\omega\Phi^{-1}\Big(\frac{(\log n)^r}{2\omega\sqrt{n}}+\frac{1}{2}\Big)-\sqrt{\frac{t}{n}}\sum_{i=1}^n X_i\Big)\Big].
\end{aligned}$$

Note that

$$2\sqrt{tn}\omega\Phi^{-1}\Big(\frac{(\log n)^r}{2\omega\sqrt{n}}+\frac{1}{2}\Big)\ge\sqrt{2\pi t}(\log n)^r.$$

It follows that

$$\int_{-2\Phi^{-1}\big((\log n)^r/(2\omega\sqrt{n})+1/2\big)}^{2\Phi^{-1}\big((\log n)^r/(2\omega\sqrt{n})+1/2\big)}\exp\big\{t\omega\xi\sum_{i=1}^n X_i-\frac{1}{2}nt\omega^2\xi^2\big\}d\xi=\frac{1}{\omega}\sqrt{\frac{2\pi}{tn}}\exp\Big\{\frac{t}{2n}(\sum_{i=1}^n X_i)^2\Big\}(1+o_P(1)),$$

where the $o_P(1)$ term is uniform for ω. Thus,

$$\begin{aligned}
&\int_{A((\log n)^r)\cap\{\omega\ge n^{-s}\}}\exp\big\{t\omega\xi\sum_{i=1}^n X_i-\frac{1}{2}nt\omega^2\xi^2\big\}\pi(\omega,\xi)\,d\omega d\xi\\
=&(1+o_P(1))\pi_\xi(0)\sqrt{\frac{2\pi}{tn}}\exp\Big\{\frac{t}{2n}(\sum_{i=1}^n X_i)^2\Big\}\int_0^1\frac{1}{\omega}\pi_\omega(\omega)\,d\omega.
\end{aligned}$$

Now we consider $A((\log n)^r)\cap\{\omega\le n^{-s}\}$. By Theorem 2 of Liu and Shao (2004), we have

$$\sup_{\omega\in[0,1],t\in\mathbb{R}}\sum_{i=1}^n\big(\log p(X_i|\omega,\xi)-\log p_0(X_i)\big)=O_P(\log\log n).$$

Thus,

$$\begin{aligned}
&\int_{A((\log n)^r)\cap\{\omega\le n^{-s}\}}\Big[\prod_{i=1}^n\frac{p(X_i|\omega,\xi)}{p_0(X_i)}\Big]^t\pi(\omega,\xi)\,d\omega d\xi\\
=&\exp\big\{O_P(\log(\log n))\big\}\Pi\big(\omega(2\Phi(|\xi|/2)-1)\le(\log n)^r n^{-1/2},\omega\le n^{-s}\big).
\end{aligned}$$

We break the probability into two parts:

$$
\begin{aligned}
&\Pi\big(\omega(2\Phi(|\xi|/2)-1) \le (\log n)^r n^{-1/2}, \omega \le n^{-s}\big) \\
\le&\Pi\big(\omega(2\Phi(|\xi|/2)-1) \le (\log n)^r n^{-1/2}, \omega \le 2(\log n)^r n^{-1/2}\big) \\
&+\Pi\big(\omega(2\Phi(|\xi|/2)-1) \le (\log n)^r n^{-1/2}, 2(\log n)^r n^{-1/2} \le \omega \le n^{-s}\big).
\end{aligned}
$$

The first probability satisfies

$$
\begin{aligned}
&\Pi\big(\omega(2\Phi(|\xi|/2)-1) \le (\log n)^r n^{-1/2}, \omega \le 2(\log n)^r n^{-1/2}\big) \\
\le&\Pi\big(\omega \le 2(\log n)^r n^{-1/2}\big) \lesssim \int_0^{2(\log n)^r n^{-1/2}} w^{\alpha_1-1}\,d\omega \lesssim \Big(\frac{(\log n)^r}{\sqrt{n}}\Big)^{\alpha_1}.
\end{aligned}
$$

Next we deal with the second probability. On the event of the second probability, we have $(2\Phi(|\xi|/2)-1) \le \omega^{-1}(\log n)^r n^{-1/2} \le 1/2$, which implies the boundedness of ξ. It follows that $|\xi| \le C\omega^{-1}(\log n)^r n^{-1/2}$ for some constant $C>0$ on this event. Thus, on this event,

$$
\begin{aligned}
&\Pi\big(\omega(2\Phi(|\xi|/2)-1) \le (\log n)^r n^{-1/2}, 2(\log n)^r n^{-1/2} \le \omega \le n^{-s}\big) \\
\le&\Pi\big(|\xi| \le C\omega^{-1}(\log n)^r n^{-1/2}, 2(\log n)^r n^{-1/2} \le \omega \le n^{-s}\big) \\
\le&\Pi\big(|\xi| \le C\omega^{-1}(\log n)^r n^{-1/2}, \omega \le n^{-s}\big) \\
\lesssim&\int_0^{n^{-s}} \omega^{\alpha_1-1}\,d\omega \int_{-C\omega^{-1}(\log n)^r n^{-1/2}}^{C\omega^{-1}(\log n)^r n^{-1/2}} \pi_\xi(\xi)\,d\xi.
\end{aligned}
$$

There exits $\epsilon>0$ and $M>0$ such that $\pi_\xi(\xi) \le M$ for $\xi \in [-\epsilon, \epsilon]$. Then

$$
\begin{aligned}
&\int_0^{n^{-s}} \omega^{\alpha_1-1}\,d\omega \int_{-C\omega^{-1}(\log n)^r n^{-1/2}}^{C\omega^{-1}(\log n)^r n^{-1/2}} \pi_\xi(\xi)\,d\xi \\
\le&\int_0^{C(\log n)^r/(\epsilon\sqrt{n})} \omega^{\alpha_1-1}\,d\omega + \int_{C(\log n)^r/(\epsilon\sqrt{n})}^{n^{-s}} 2MC\omega^{\alpha_1-2}(\log n)^r n^{-1/2}\,d\omega \\
\lesssim&\Big(\frac{(\log n)^r}{\sqrt{n}}\Big)^{\alpha_1} + \frac{(\log n)^r}{\sqrt{n}}\left(\Big(\frac{(\log n)^r}{\sqrt{n}}\Big)^{\alpha_1-1} \vee \Big(\frac{1}{n^s}\Big)^{\alpha_1-1}\right) \\
=&\Big(\frac{(\log n)^r}{\sqrt{n}}\Big)^{\alpha_1} \vee \frac{(\log n)^r}{n^{1/2+s(\alpha_1-1)}}.
\end{aligned}
$$

Thus,

$$
\begin{aligned}
&\int_{A((\log n)^r)\cap\{\omega\le n^{-s}\}} \Big[\prod_{i=1}^n \frac{p(X_i|\omega,\xi)}{p_0(X_i)}\Big]^t \pi(\omega,\xi)\,d\omega d\xi \\
=&\exp\big\{O_P(\log(\log n))\big\}\left(\Big(\frac{(\log n)^r}{\sqrt{n}}\Big)^{\alpha_1} \vee \frac{(\log n)^r}{n^{1/2+s(\alpha_1-1)}}\right) = o_P(n^{-1/2}).
\end{aligned}
$$

Thus,

$$\begin{aligned}
&\int \Big[\prod_{i=1}^{n} \frac{p(X_i|\omega,\xi)}{p_0(X_i)}\Big]^t \pi(\omega,\xi)\, d\omega d\xi \\
=&\Big(\int_{A((\log n)^r)^c\}} + \int_{A((\log n)^r)\cap\{\omega<n^{-s}\}} + \int_{A((\log n)^r)\cap\{\omega\geq n^{-s}\}}\Big)\Big[\prod_{i=1}^{n} \frac{p(X_i|\omega,\xi)}{p_0(X_i)}\Big]^t \pi(\omega,\xi)\, d\omega d\xi \\
=&(1+o_P(1))\pi_\xi(0)\sqrt{\frac{2\pi}{tn}} \exp\Big\{\frac{t}{2n}(\sum_{i=1}^{n} X_i)^2\Big\} \int_0^1 \frac{1}{\omega}\pi_\omega(\omega)\, d\omega.
\end{aligned}$$

Thus,

$$2\log\Lambda_{a,b}(\mathbf{X}^{(n)}) = -\log(1+a/b) + \frac{a}{n}(\sum_{i=1}^{n} X_i)^2 + o_P(1).$$

$\square$

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