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A Probabilistic Model for the MRMC Method. Part 2. Validation and Applications

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Abstract

Rationale and Objectives—We have previously described a probabilistic model for the multiple-reader, multiple-case paradigm for ROC analysis. When the figure of merit is the Wilcoxon statistic, this model returns a seven-term expansion for the variance of this statistic as a function of the numbers of cases and readers. This probabilistic model also provides expressions for the coefficients in the seven-term expansion in terms of expectations over the internal noise, readers, and cases. Finally, this probabilistic model sets bounds on both the overall variance of the Wilcoxon statistic as well as the individual coefficients.

Materials and Methods—In this paper we will first validate the probabilistic model by comparing variances determined by direct computation of the expansion coefficients to empirical estimates of the variance using independent sampling. Validation of the probabilistic model will enable us to use the direct estimates of the expansion coefficients as a gold-standard to compare other coefficient-estimation techniques. Next, we develop a coefficient-estimation technique that employs bootstrapping to estimate the Wilcoxon statistic variance for different numbers of readers and cases. We then employ constrained, least-squares fitting techniques to estimate the expansion coefficients. The constraints used in this fitting are derived directly from the probabilistic model.

Results and Discussion—Using two different simulation studies, we show that the novel (and practical) bootstrapping/fitting technique returns estimates of the coefficients that are consistent with the gold standard. The results presented also serve to validate the seven-term expansion for the variance of the Wilcoxon statistic.

Keywords

ROC analysis; multiple reader multiple case; Wilcoxon statistic

1. INTRODUCTION

Receiver operating characteristic (ROC) analysis is the standard method used to assess imaging technologies for radiology, as well as other diagnostic procedures. ROC studies are typically time consuming and expensive. Therefore, considerable effort has been devoted to analyzing sources of variability and designing experiments to maximize statistical power. A large part of this effort involves identifying and estimating sources of variability in the area under the ROC curve (AUC) or other figures of merit associated with the ROC curve. The major sources

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of variability in ROC studies are caused by the finite number of readers, the finite number of cases, and the reader internal noise.

In the multiple-reader, multiple-case (MRMC) paradigm, each member of a sample of readers reads all of the cases in a sample of cases. Each reader produces a rating (or test statistic) for each case which represents her or his confidence that an abnormality, such as a tumor, is present. The end result is an array of test statistics which is then used to compute a figure of merit for the imaging system being tested. In MRMC analysis, we are not only interested in the value of the chosen figure of merit, we are also interested in the variance of this number as a function of the numbers of readers and cases. This information aids in the design of the ROC studies and can help ensure that the results are statistically meaningful.

Standard methods for MRMC analysis have used linear models and analysis of variance (ANOVA) techniques to determine the variance of the figure of merit as a function of numbers of readers and cases [1,2]. Bootstrapping techniques have also been employed using the same linear model [3]. With the linear model, one assumes that the figure of merit can be expanded as a sum of independent random variables; one that depends on the reader sample, one that depends on the case sample, one that depends on the reader-case interaction, and a final variable that describes internal reader noise. The variance of the figure of merit then becomes a sum of the variances of the individual terms. The validity of the results obtained using this model depends, of course, on the validity of the initial linear model. Even if the terms in the linear model are not independent, the expression for the variance can be considered a first-order expansion for the variance of the figure of merit.

The probabilistic approach, as described in Clarkson et al. [4], builds on the work of Hoeffding [5] and Lehmann [6] and is based on a probability model for the generation of reader test statistics. This probability model accounts for random cases, random readers, and internal noise. The readers are chosen independently from a population of readers, cases are chosen independently from a population of cases, and the reader sample is independent of the case sample. A reader's test statistic is a random variable whose distribution depends on the interaction of the reader with a case as well as the internal noise of the reader. When this probabilistic model is applied to the Wilcoxon statistic [7,8], the result is an exact, seven-term expansion for the variance of this statistic in terms of the numbers of readers and cases.

In this paper, we both validate the probabilistic model and present a method for computing the coefficients in the seven-term expansion. To validate the probabilistic model, we directly compute the expansion coefficients from expectations derived from the probabilistic model. The computation of these expectations combines analytical formulas with Monte-Carlo techniques to compute the relevant expectations. The variance derived from the direct computation of the expansion coefficients can then be compared to empirical estimates of variance computed using independent sampling. Once the probabilistic model has been validated, these direct estimates of the model coefficients can be used as a gold standard to compare our new estimation technique. Our estimation technique uses bootstrapping to estimate the variance of the Wilcoxon statistic at many choices of numbers of readers and cases. The resulting data are then fit to the seven-term expansion using constrained least-squares fitting techniques. The bounds on the coefficients derived from the probabilistic model are used as constraints for the fitting. This method, unlike the direct computation of the coefficients and the independent sampling technique, requires only a single reader and case sample.

Two separate simulations are used to validate the model and evaluate the bootstrap-estimation technique. For the first simulation (or data model), we employ a very simplistic representation for the cases and readers. A single case is represented by a Gaussian-distributed random variable, the mean of which depends on the truth state. A reader is represented by a pair of

numbers each sampled from a uniform distribution centered up 1.0. The reader-case interaction is described by a simple multiplication of one reader random variables with a case random variable. The truth state of the case determines which reader random variable is employed. After adding a Gaussian random variable to this product to simulate internal noise, we have the test statistic for the given reader and case. This model, while simplistic, does account for reader proficiency, reader-case interaction, and internal noise. One advantage of this model is that expectations over internal noise and cases can be computed analytically. All that is left is to perform the average over readers to compute the expectations needed for the direct computation of the expansion coefficients.

For the second, more realistic, simulation, we employ a lumpy background model for the signal-absent images and add in a known signal for the signal-present images. Detector noise is modeled as being Poisson distributed. A reader is described by an image called a template that has the same dimensions as the case images. The templates have a single, random width parameter that represents the reader variability. A reader reads an image by taking the inner product of the template with the image and adding Gaussian noise to account for internal noise. For this simulation, expectations over internal noise can still be performed analytically but Monte-Carlo methods must be used for averages over readers and cases.

By comparing the results from the direct computation to independent sampling results, we will validate the probabilistic model and the seven-term expansion. By comparing the results of the bootstrap method to the other two, we will demonstrate the usefulness of the bootstrap method for estimating the seven coefficients.

2. PROBABILISTIC MODEL

We will briefly review the probabilistic MRMC model. For a detailed derivation of this model, consult Clarkson et al. [4] and Barrett et al. [9]. The probabilistic models begins by considering random cases, readers, and test statistics. A case from the signal-absent ensemble is represented by a random vector \mathbf{g}_0 (bold-face type denotes vectors), while a case from a single-present ensemble is represented by the random vector \mathbf{g}_1 . These random vectors have corresponding distribution given by $pr(\mathbf{g}_0)$ and $pr(\mathbf{g}_1)$. A case sample is composed of N_0 independent samples from $pr(\mathbf{g}_0)$ and N_1 independent samples from $pr(\mathbf{g}_1)$.

A reader is represented by a random vector $\boldsymbol{\gamma}$ with distribution $pr(\boldsymbol{\gamma})$. This reader vector may represent a mathematical representation of a reader or simply an identifying string, *e.g.*, reader 58 out of 1000 or “Mary.” A reader sample consists of N_r independent samples from $pr_r(\boldsymbol{\gamma})$.

Given a reader $\boldsymbol{\gamma}$ and a case \mathbf{g}_a (a is 0 or 1), the test statistic t_a is a random variable with a conditional distribution give by $pr(t_a/\boldsymbol{\gamma}, \mathbf{g}_a)$. This conditional distribution encompasses the reader-case interaction and describes the internal noise for reader $\boldsymbol{\gamma}$. Given a case sample and reader sample, the entries in the test statistic matrix are independent samples from the corresponding conditional distributions, one for each reader-case pair. For example, the entry for the reader $\boldsymbol{\gamma}_r$ (*i.e.*, the r th reader in the reader sample), and signal-absent case \mathbf{g}_{0i} (*i.e.*, the i th signal-absent case in the case sample) is t_{0ri} and this is a sample from the distribution $pr(t/\boldsymbol{\gamma}_r, \mathbf{g}_{0i})$. Similarly, the entry for the reader $\boldsymbol{\gamma}_r$ and signal-present case \mathbf{g}_{1j} is t_{1rj} and this is a sample from the distribution $pr(t/\boldsymbol{\gamma}_r, \mathbf{g}_{1j})$.

Using this notation, the Wilcoxon figure of merit is given by

$$\hat{A} = \frac{1}{N_r N_0 N_1} \sum_{r=1}^{N_r} \sum_{i=1}^{N_0} \sum_{j=1}^{N_1} s(t_{1rj} - t_{0ri}), \quad (1)$$

where $s(\cdot)$ is the step function. The Wilcoxon statistic \hat{A} is an estimate of the area under the ROC curve (or AUC) averaged over all readers. We have previously shown [4] that the variance of \hat{A} can be written exactly as the seven-term expansion:

$$\text{Var}[\hat{A}] = \frac{a_1}{N_0} + \frac{a_2}{N_1} + \frac{a_3}{N_0 N_1} + \frac{a_4}{N_R} + \frac{a_5}{N_R N_0} + \frac{a_6}{N_R N_1} + \frac{a_7}{N_R N_0 N_1}. \quad (2)$$

Here the α_n are coefficients to be determined.

Not only does the probabilistic model return an exact, seven-term expansion, it also gives analytic expressions for each of the α_n terms. These expressions can be used in simulation studies to determine the correct values of the α_n for comparison with estimation methods. It is useful to first define,

$$s(\gamma_r, g_{0i}, g_{1j}) = \left\langle s(t_{1rj} - t_{0ri}) \right\rangle_{t_{1rj}, t_{0ri} | \gamma_r, g_{0i}, g_{1j}} \quad (3)$$

$$\bar{s}(g_{0i}, g_{1j}) = \left\langle s(\gamma_r, g_{0i}, g_{1j}) \right\rangle_{\gamma_r}. \quad (4)$$

For ease of notation, we drop the i, j , and r subscripts to arrive at $\bar{s}(\gamma, g_0, g_1)$ and $\bar{\bar{s}}(g_0, g_1)$. The term $\bar{s}(\gamma, g_0, g_1)$ represents the average step-function response of reader γ reading the pair of cases g_0 and g_1 . This is analogous to a two-alternative forced choice (2AFC) experiment where a particular reader is determining which of a pair images has the abnormality. It is well known that the fraction of correct decisions that the reader makes is the AUC for that reader on that set of images. Thus, $\bar{s}(\gamma, g_0, g_1)$ can be thought of as the AUC of a reader reading a pair of images when the reader has perfect memory loss after each reading; it is an average over reader-internal noise only. The term $\bar{\bar{s}}(g_0, g_1)$ is the average of $\bar{s}(\gamma, g_0, g_1)$ over all readers γ . Again, using the 2AFC analogy, $\bar{\bar{s}}(g_0, g_1)$ can be thought of as the average AUC of all readers reading the pair of images g_0 and g_1 .

With both $\bar{s}(\cdot)$ and $\bar{\bar{s}}(\cdot)$ defined, we can now write the first four α_n terms as

$$a_1 = \text{Var} \left[\left\langle \bar{s}(g_0, g_1) \right\rangle_{g_1 | g_0} \right] \quad (5)$$

$$a_2 = \text{Var} \left[\left\langle \bar{\bar{s}}(g_0, g_1) \right\rangle_{g_0 | g_1} \right] \quad (6)$$

$$a_3 = \text{Var} \left[\bar{\bar{s}}(g_0, g_1) \right] - a_1 - a_2 \quad (7)$$

$$a_4 = \text{Var} \left[\left\langle s(\gamma, g_0, g_1) \right\rangle_{g_0, g_1 | \gamma} \right] \quad (8)$$

The remaining terms, while not as simple as α_1 through α_4 , can also be written in terms of expectations of $s(\cdot)$,

$$a_5 = \left\langle \left\langle s(t_1 - t_0) \right\rangle_{t_1, g_1 | t_0, \gamma, g_0}^2 \right\rangle_{t_0, \gamma | g_0} - \left\langle \left\langle s(t_1 - t_0) \right\rangle_{t_1, g_1 | t_0, \gamma, g_0} \right\rangle_{t_0, \gamma | g_0}^2 - a_4 \quad (9)$$

$$a_6 = \left\langle \left\langle s(t_1 - t_0) \right\rangle_{t_0, g_0 | t_1, \gamma, g_1}^2 \right\rangle_{t_1, \gamma | g_1} - \left\langle \left\langle s(t_1 - t_0) \right\rangle_{t_0, g_0 | t_1, \gamma, g_1} \right\rangle_{t_1, \gamma | g_1}^2 - a_4 \quad (10)$$

$$a_7 = \left\langle \left\langle s^2(t_1 - t_0) \right\rangle_{t_0, t_1, \gamma | g_0, g_1} - \left\langle s(t_1 - t_0) \right\rangle_{t_0, t_1, \gamma | g_0, g_1}^2 \right\rangle_{g_0, g_1} - a_4 - a_5 - a_6. \tag{11}$$

Finally, utilizing the fact that variances must be positive and variances of quantities bounded between zero and one must not exceed $\frac{1}{4}$, we can derive bounds on each of the a_n . Namely,

$$0 \leq a_1 \leq \frac{1}{4} \tag{12}$$

$$0 \leq a_2 \leq \frac{1}{4} \tag{13}$$

$$0 \leq a_3 \leq \frac{1}{4} \tag{14}$$

$$0 \leq a_1 + a_2 + a_3 \leq \frac{1}{4}. \tag{15}$$

$$0 \leq a_4 \leq \frac{1}{4} \tag{16}$$

$$0 \leq a_4 + a_5 \leq \frac{1}{4} \tag{17}$$

$$0 \leq a_4 + a_6 \leq \frac{1}{4} \tag{18}$$

$$0 \leq a_4 + a_5 + a_6 + a_7 \leq \frac{1}{4}. \tag{19}$$

For a detailed derivation of these bounds, refer to Clarkson et al. [4].

3. METHODS

To both validate the probabilistic model and test methods for estimating the coefficients, we examined two data models. We first describe the two data models and then the coefficient-estimation techniques.

3.1 Data Model 1

The first data model was designed to include reader variability, case variability, reader-case interactions, and internal noise yet be simple enough to allow analytical computations of expectations (Eqns. 5–11). To achieve this simplicity, cases are represented by a single random variable g_0 or g_1 distributed as $N(0, 1)$ and $N(\mu, 1)$, respectively. Here, μ is an adjustable model parameter that represents the signal strength. A reader is represented by a pair of random variables c_0 and c_1 both independently distributed as $U(1 - \Delta, 1 + \Delta)$. The parameter Δ is an adjustable parameter relating to the reader variability. The test statistics are generated by

$$t_0 = g_0 c_0 + \eta_0 \tag{20}$$

$$t_1 = g_1 c_1 + \eta_1, \tag{21}$$

where η_0 and η_1 are both independently $N(0, \sigma_t^2)$ and represent the reader internal noise. The term σ_t controls the amount of internal noise. It should be noted that the terms c_0 and c_1 are random across readers but are fixed for a given reader.

The reason for using a pair of numbers for the readers is to account for varying reader skill. The reader-case interaction arises because the reader parameters are multiplied by the case variables. Note that for a fixed reader, t_0 and t_1 are Gaussian random variables. This fact means that averages over internal noise and cases conditioned on readers can be computed analytically. For our simulations, $\mu = 1$, $\Delta = 0.95$, and $\sigma_t = 0.3$.

3.2 Data Model 2

For the second, more realistic, data model we employed simulated images and linear readers. The cases are simulated images that are generated by a two-dimensional “lumpy” image model with Poisson noise added. The mean of the m th pixel in the lumpy image model is given by,

$$\bar{g}(r_m) = \sum_{l=1}^L l(r_m - c_l), \quad (22)$$

where r_m is the two-dimensional coordinate vector for the m th pixel, L is the number of lumps, $l(\cdot)$ is the lump function (typically Gaussian), and c_l is the center of the l th lump. Here, L is a Poisson-distributed random variable with mean L , and the c_l are random locations with a uniform distribution across the image. For signal-present cases, a small (relative to the lump size) Gaussian signal is added to the mean image at its center or the (0,0) location.

For this model, we chose an image size of 64 pixels by 64 pixels, *i.e.*, g is a 64^2 -dimensional vector. The mean number of lumps L was 25. This relatively small number ensures that the statistics governing g_0 and g_1 are not Gaussian. The lump function was a Gaussian with a standard deviation of 5 pixels and an amplitude of 20 units. The signal was a Gaussian function with a standard deviation of 3 pixels and an amplitude of 35 units.

A reader was simulated by also generating an image called a template. The m th pixel in this template is given by

$$\gamma(r_m) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{|r_m|^2}{2\sigma^2}\right). \quad (23)$$

Here σ is the width of the template. Note that this Gaussian template is always centered on the signal location. The width of the template σ is a random variable uniformly distributed between 1 and 10 pixels. Templates with different σ parameters will perform differently. Thus, the random σ parameter accounts for varying reader skill.

Finally, the test statistics are generated by taking the inner product of a reader template with an image and adding noise to simulate internal noise. That is,

$$t_0 = \gamma^t g_0 + \eta_0 \quad (24)$$

$$t_1 = \gamma^t g_1 + \eta_1. \quad (25)$$

Note that the random variables η_0 and η_1 are independent Gaussians with standard deviations of 5. Again, this model accounts for case variability, reader variability and internal noise. However, unlike the previous model, we will not be able to perform the case-averages analytically because of the non-Gaussian, high-dimensional distributions associated with g_0 and g_1 .

3.3 Variance Estimation Techniques

3.3.1 Direct Computation—An advantage of the probabilistic model is that it returns analytic expressions for the α_n coefficients. We have numerically evaluated Eqns. 5–11 to arrive at estimates for the α_n . For data model 1, any conditional expectation where the reader γ is fixed, such as $\bar{s}(\gamma, \mathbf{g}_0, \mathbf{g}_1)$, can be computed exactly in terms of error functions. Other expectations must be computed via Monte-Carlo integration. For data model 2, $\bar{s}(\gamma, \mathbf{g}_0, \mathbf{g}_1)$ can still be computed exactly but all other expectations must be computed by Monte-Carlo integration. When Monte-Carlo integration was required, we employed 10,000 samples to estimate the expectations. The α_n returned by this direct computation will serve as our gold standard which will be used to assess the other techniques.

It should be noted that direct computation of the α_n is not possible using a single dataset because replication over internal noise must be performed. Thus, this method is useful only for mathematical observers, validating the probabilistic model or validating new estimation techniques.

3.3.2 Independent sampling—To validate the seven-term expansion, we employed independent sampling to estimate the variance of the Wilcoxon statistic at varying numbers of readers and cases. For a given number of readers and cases, we generated 10,000 independent reader and case samples. We then generate the matrix of test statistics (with internal noise) by having each reader read each case in the corresponding sample (including internal noise). From these 10,000 test-statistic matrices, we compute 10,000 AUCs and estimate the AUC variance. Thus, we can estimate the AUC variance for any numbers of readers and cases (*i.e.*, any N_r , N_0 , and N_1) and compare these results to the results returned by direct computation.

3.3.3 Bootstrap sampling—With real data, one cannot use either of the first two techniques since independent samples are not readily available and the distributions of the random variables are not known. Typically, a single test-statistic matrix is all that we have to work with. With just a single sample, however, we can exploit bootstrapping techniques to estimate variances. In this procedure, reader and case samples are drawn by bootstrapping. We then extract all of the test statistics for the selected readers and cases. The AUC for this bootstrap sample can be readily computed using Eqn. 1. A total of 1000 test-statistic matrices are generated by bootstrapping for different choices of N_r , N_0 , and N_1 . By evaluating the AUC variance for different combinations of numbers of cases and readers, we can generate data which can be used to fit the α_n parameters in the seven-term expansion. This fitting process is not only linear (see Eqn. 2) but also constrained (Eqns. 12–19). Thus, constrained linear least-squares fitting is used to determine the α_n . These results can be compared with the direct computation technique to assess the usefulness of this procedure.

4. RESULTS

4.1 Data Model 1

Due to the simplicity of the first data model, many of the expectations in Eqns. 5–11 can be computed analytically. Only expectations over readers must be computed using Monte-Carlo methods. Thus, direct and accurate computation of the α_n can be performed. These α_n are used as the gold standard with which to compare the independent sampling and the bootstrap techniques for estimating the α_n . We employed 10,000 samples to compute expectations over readers.

Figure 1 compares the variance computed using the direct computation of the α_n (solid line) to the measured variance of AUC using 10,000 independent reader and case samples with varying N_r , N_0 and N_1 . In Fig. 1a, the N_r is varied from 1 to 50 and the N_0 and N_1 are both

fixed at 100. In Fig. 1b, N_r is fixed at 5 and both N_0 and N_1 are varied between 10 and 1000. These plots clearly indicate that the seven-term expansion is accurately predicting the variance of the Wilcoxon statistic for varying N_r , N_0 , and N_1 .

While the results presented in Fig. 1 are important, both the direct computation of the α_n and the independent sampling technique are impractical for real data. The direct computation technique requires expectations over internal noise and the independent sampling technique requires an impractical number of readers and cases to be useful. The bootstrapping technique, however, requires only a single sample of readers reading a single case sample to produce a test-statistic matrix. The bootstrap estimates of AUC variance can be used to estimate the individual α_n by using constrained, linear, least-squared curve fitting. Using a dataset of 25 readers and 1000 image pairs, we computed the bootstrap estimates of the α_n . To perform the fitting, a $3 \times 3 \times 3$ grid of N_r , N_0 , and N_1 was used. These 27 bootstrap estimates of variance were used in the constrained fitting algorithm to determine the α_n . This process was repeated 100 times to determine how this algorithm performs on average, *i.e.*, we determine the mean and the standard deviation of each estimated α_n parameter. The results of this study are summarized in Fig. 2. The solid line is the gold standard variance computed using the direction computation technique. The gray area represents the mean plus and minus one standard deviation of the bootstrap-estimated α_n . Clearly, the bootstrap technique is returning both accurate and precise estimates of α_n . We will see with the second data model that small sample sizes can introduce some bias into this estimation technique.

4.2 Data Model 2

We further validated the bootstrap technique using the second data model. This more realistic data model employs images with random backgrounds and Poisson detector noise. A reader was simulated by generating a random template which allows for varying reader skill. Finally, internal noise was simulated as Gaussian. Unlike data model 1, many of the expectations in Eqns. 5–11 cannot be computed analytically. Thus, we employed large samples of readers (10,000) and cases (10,000) to estimate these expectations directly. To ensure that our estimates of α_n were accurate, we repeated this experiment multiple times and found that our estimates of α_n did not vary through the first three significant digits. Thus, we employed these direct estimates of the α_n as the gold standard.

For this second data model, independent sampling is not feasible because of the time needed to generate sufficient numbers of images and readers. The direct computation technique also requires a large sample size. However, only one reader sample and case sample was necessary. Thus, we will present AUC variances determined using only bootstrap estimates of the α_n , further validating the bootstrap estimation technique. Figure 3 compares the variance determined using the direct computation of the α_n to the mean plus and minus one standard deviation of the variances determined using bootstrap estimates of the α_n . As with the first data model, 25 reader and 1000 image pairs were simulated. A $3 \times 3 \times 3$ grid of N_r , N_0 and N_1 was employed. Again, these 27 bootstrap estimates of variance were used in the constrained fitting algorithm to determine the α_n . Clearly, the fitting method is both accurate and precise.

Figure 4 shows similar results except that only 10 readers were simulated along with 100 pairs of images. Here, we begin to see that the bootstrap estimates of the variances might exhibit some bias when the initial sample is small. However, this bias appears to be small and in the positive direction. Note that Fig. 4 plots the predicted variances well beyond the 10 readers and 100 images pairs used to estimate the α_n .

5. CONCLUSIONS

Using the probabilistic model we previously showed that variance of the MRMC Wilcoxon statistic can be expressed as a seven-term expansion in terms of N_r , N_0 , and N_1 . The probabilistic formulation also results in exact expressions for the seven coefficients in this expansion. With the first data model in this paper, we showed that direct calculation of the coefficients using the probabilistic method gives variances that agree with those computed using independent sampling. This was an important validation to ensure that no mathematical mistakes were made in the rather complicated derivation of the seven-term expansion. Thus we feel confident in using the direct computation results as gold standards with which to compare other techniques for estimating the α_n .

Furthermore, with the first and second data models, we compared the results of our bootstrap/least-squared-fitting technique for estimating the α_n to our gold standard. In the first data model, the bootstrap estimation technique worked well in terms of bias and variance. For the second data model, a small bias was introduced when the number of readers is small (*i.e.*, around 5).

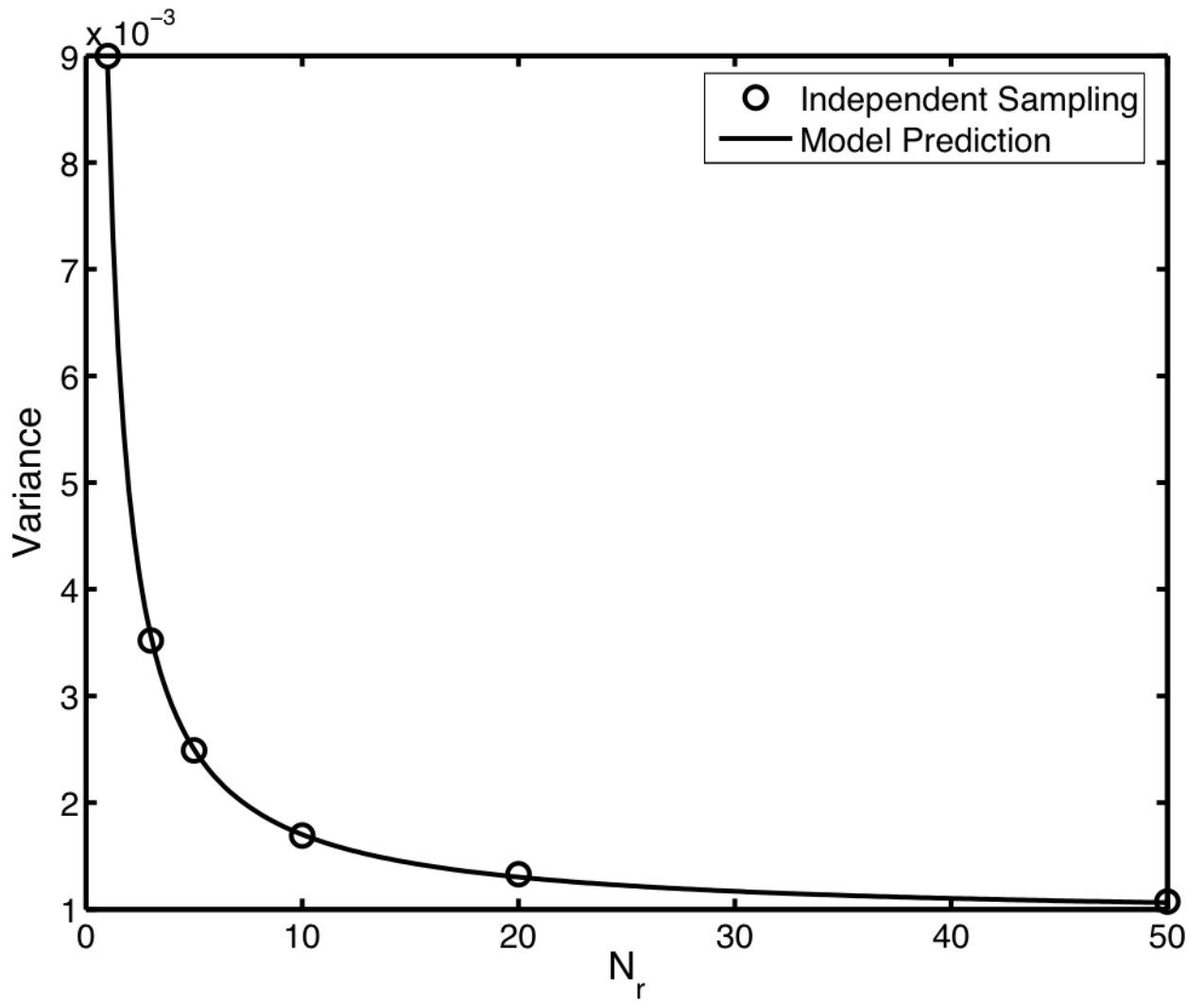
In the future, we plan to extend the probabilistic model and our estimation techniques to account for multiple modalities. Preliminary work indicates that an expansion similar to the seven-term expansion for one modality can be derived for two modalities.

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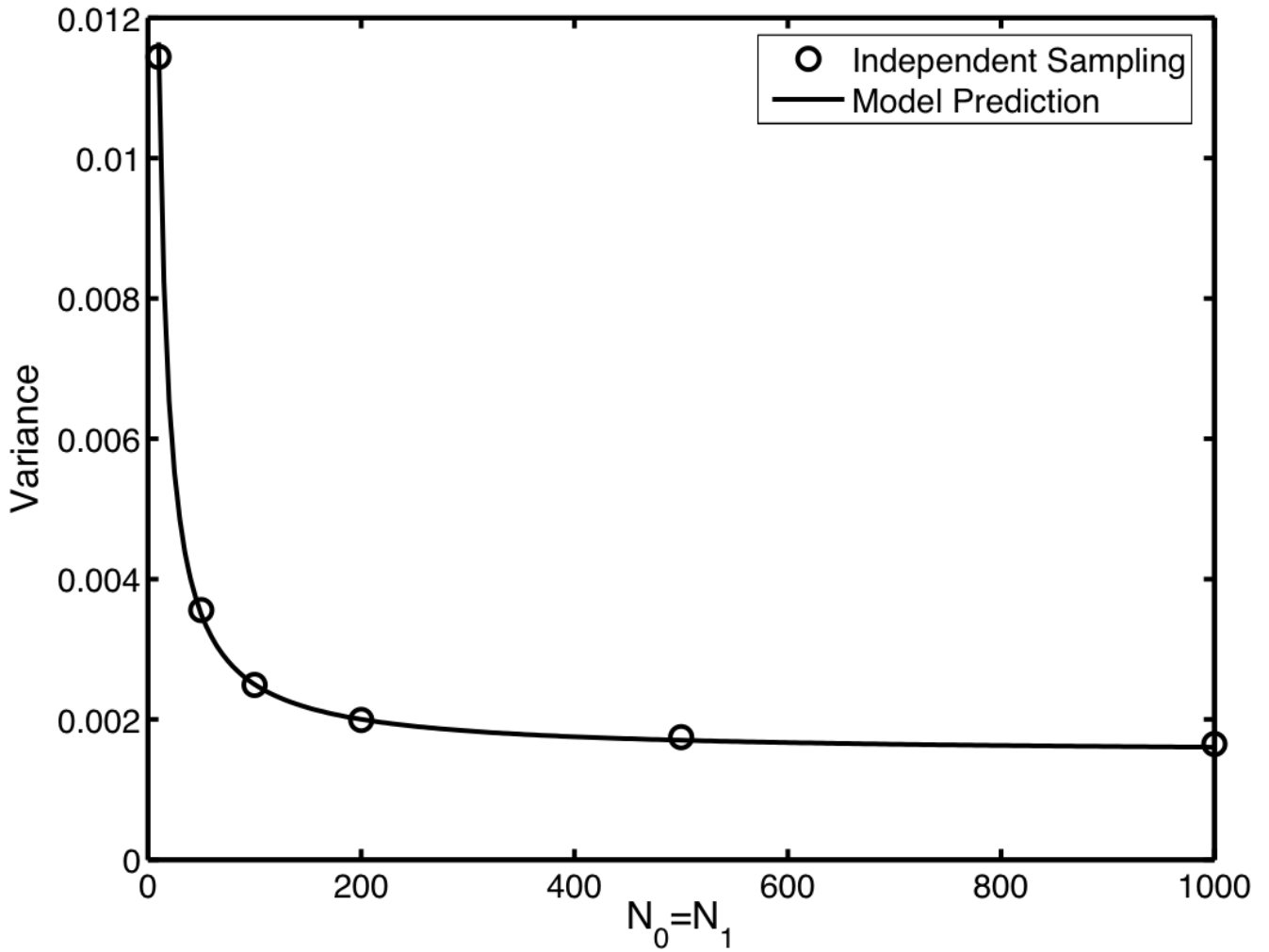
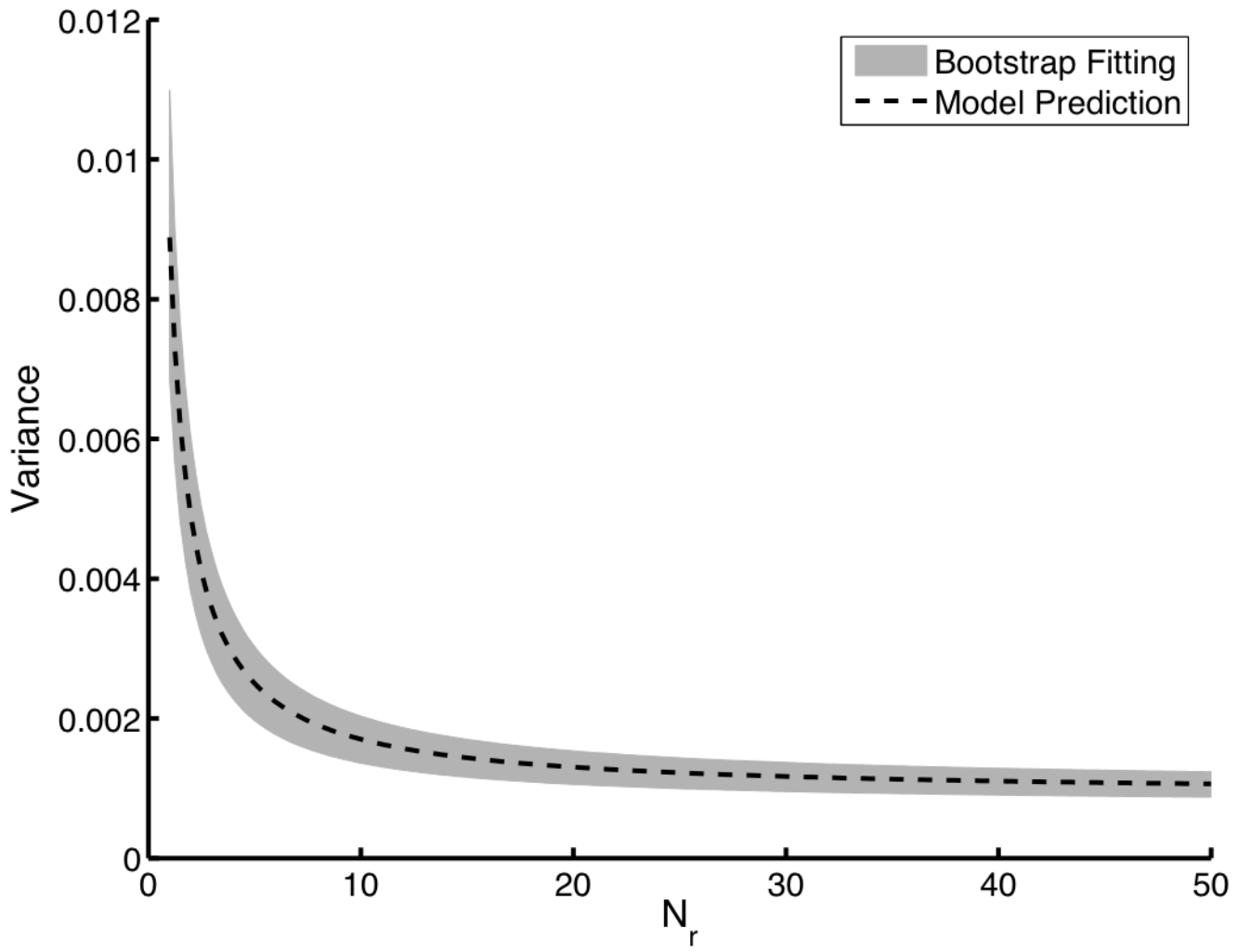
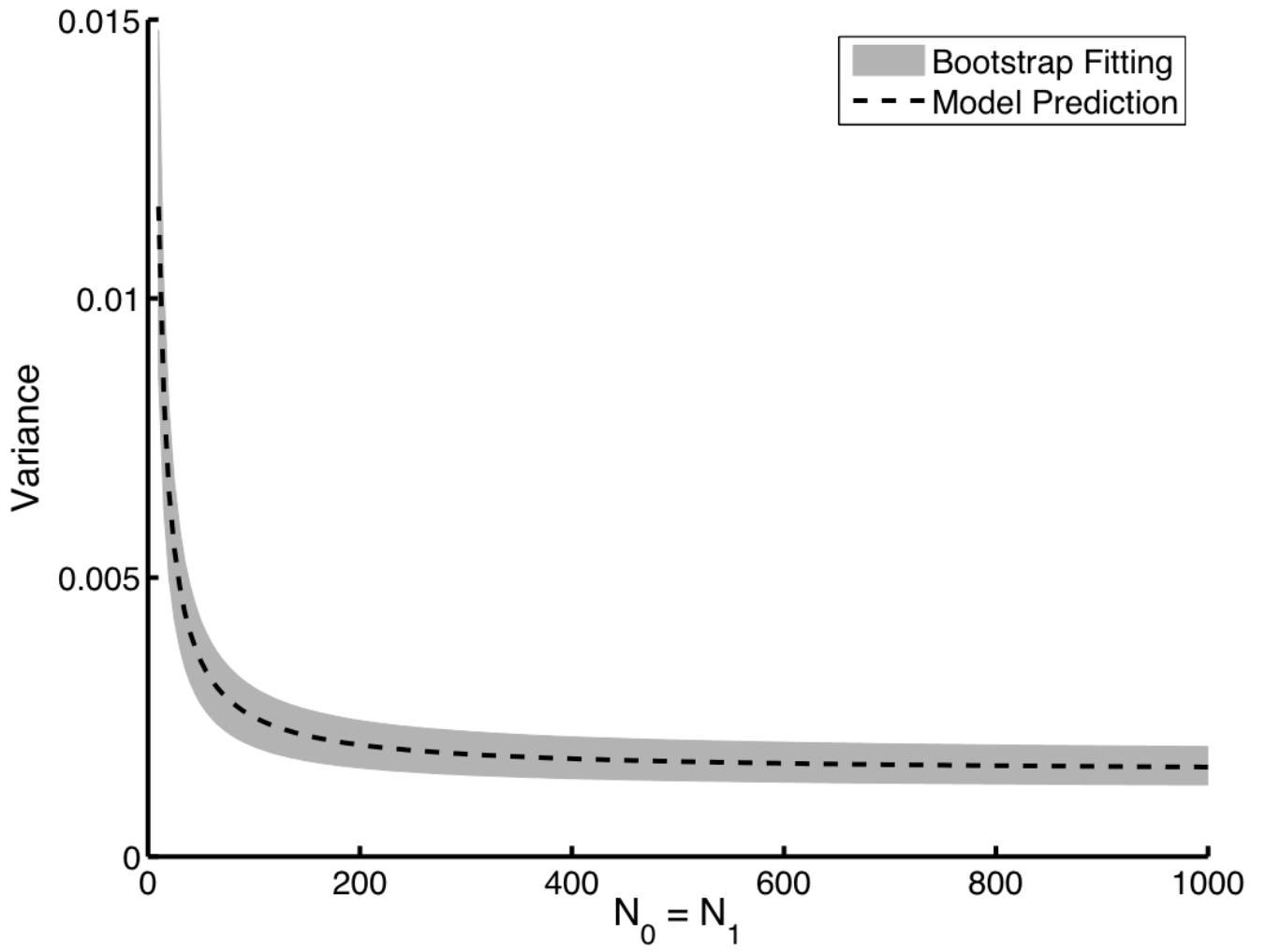


Fig 1.

Comparison of the variances predicted using direct computation of the expansion coefficients (solid line) to empirical estimates of the variance computed using independent sampling (circles). In (a), N_r is varied from 1 to 50 with both N_0 and N_1 fixed at 100. In (b), N_r was fixed at 5 while both N_0 and N_1 were varied from 10 to 1000. For the independent sampling, 10,000 repetitions were used.





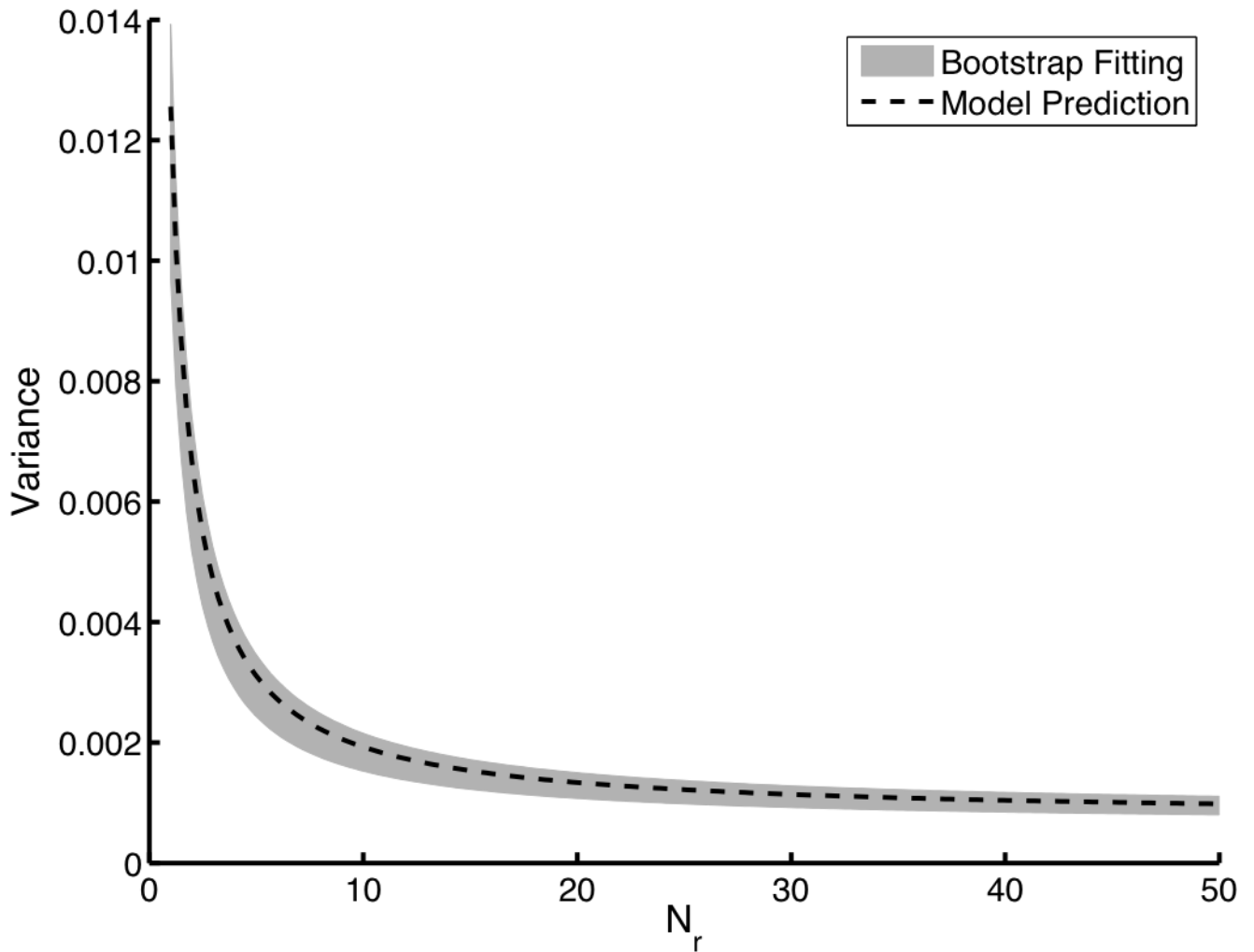
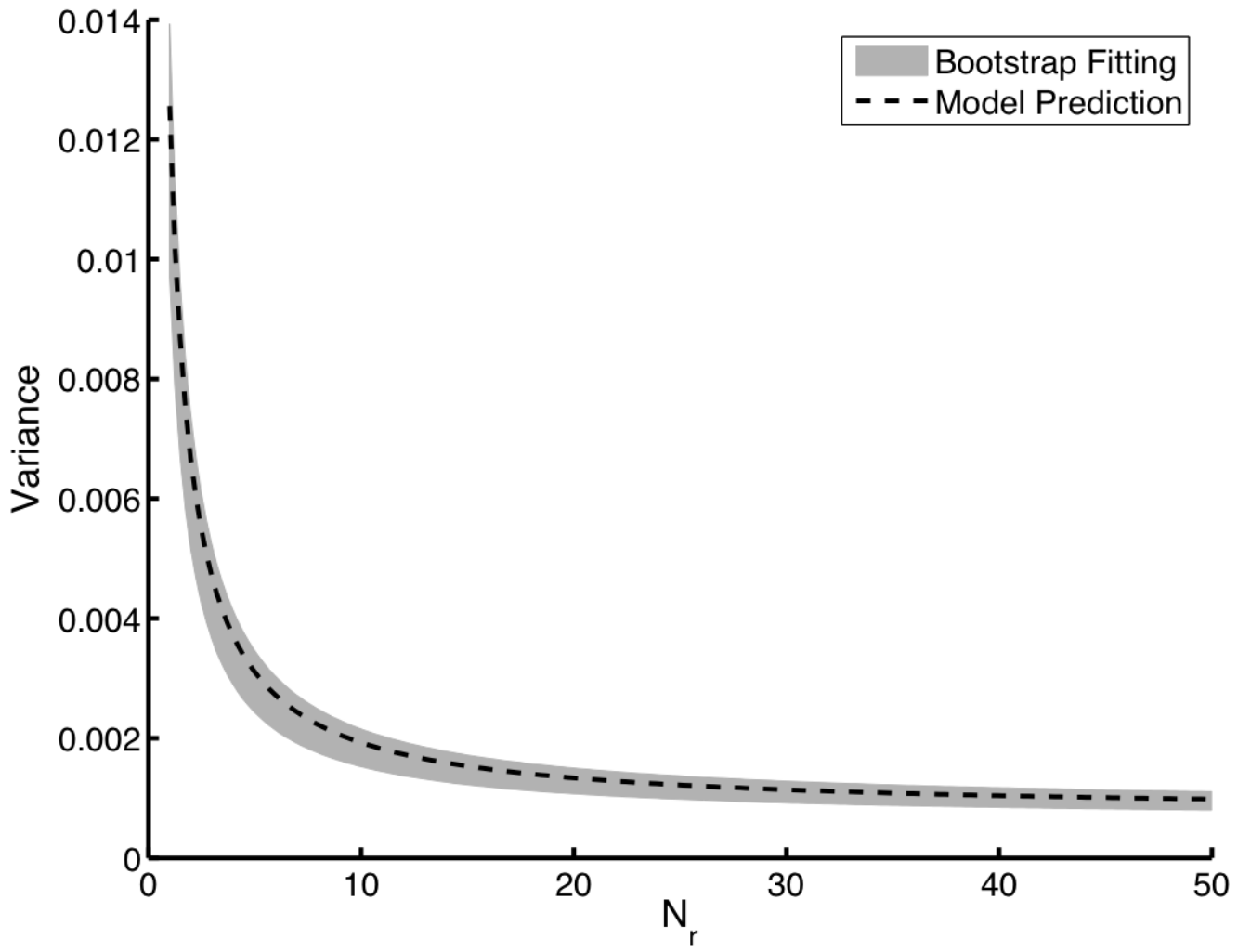


Fig 2.

An evaluation of the bootstrap coefficient estimation technique. The dashed line indicates the gold standard computed using the direct computation technique. The gray area represents the mean plus and minus one standard deviation of the variance predicted using the fitted α_n . For this study, a single dataset of 25 readers and 1000 image pairs was used to estimate the expansion coefficients. This process was repeated 100 times using 100 different datasets of the same size to determine the mean and the standard deviations of the estimates α_n . In (a), N_r is varied from 1 to 50 with both N_0 and N_1 fixed at 100. In (b), N_r was fixed at 5 while both N_0 and N_1 were varied from 10 to 1000.



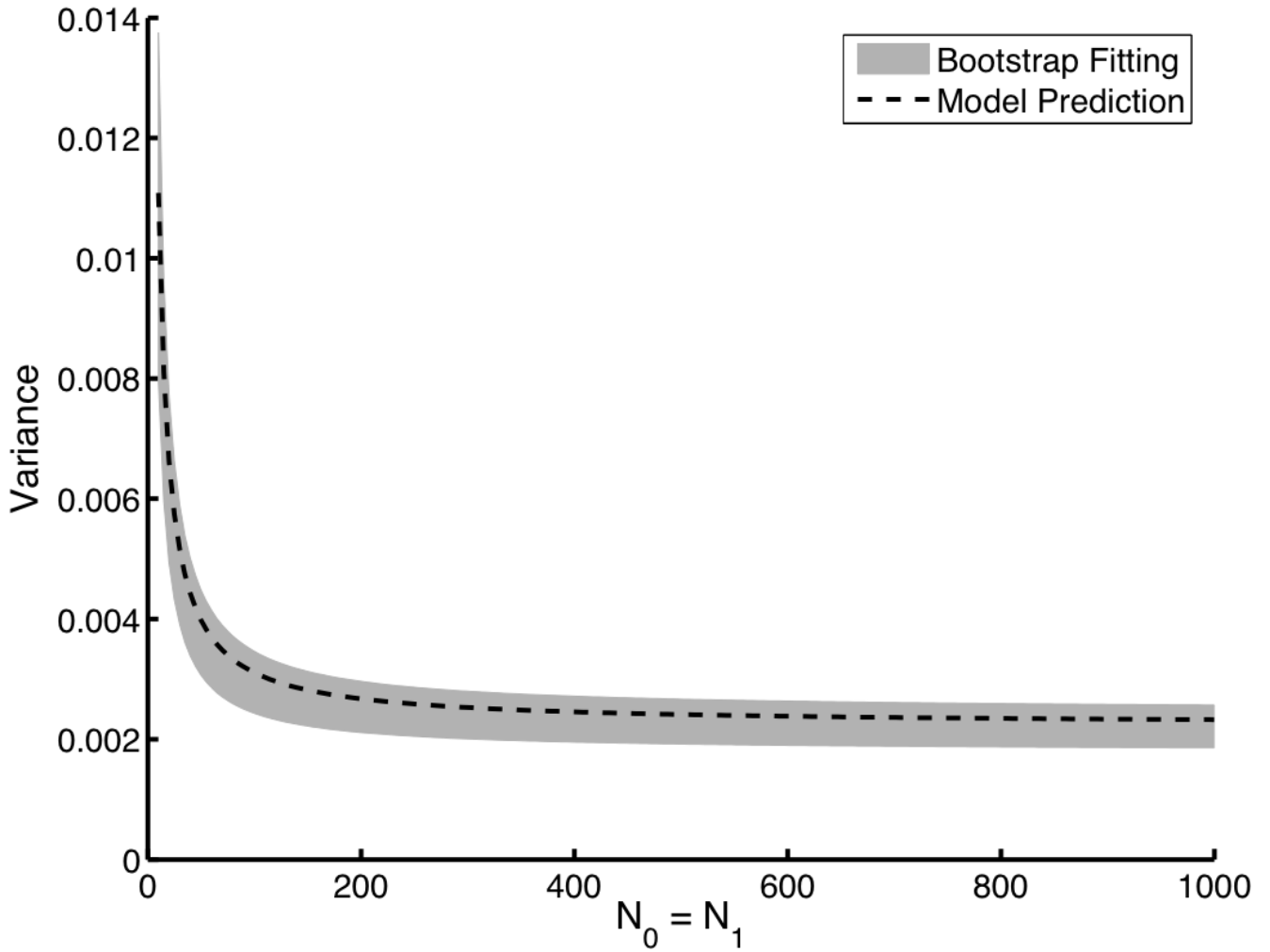
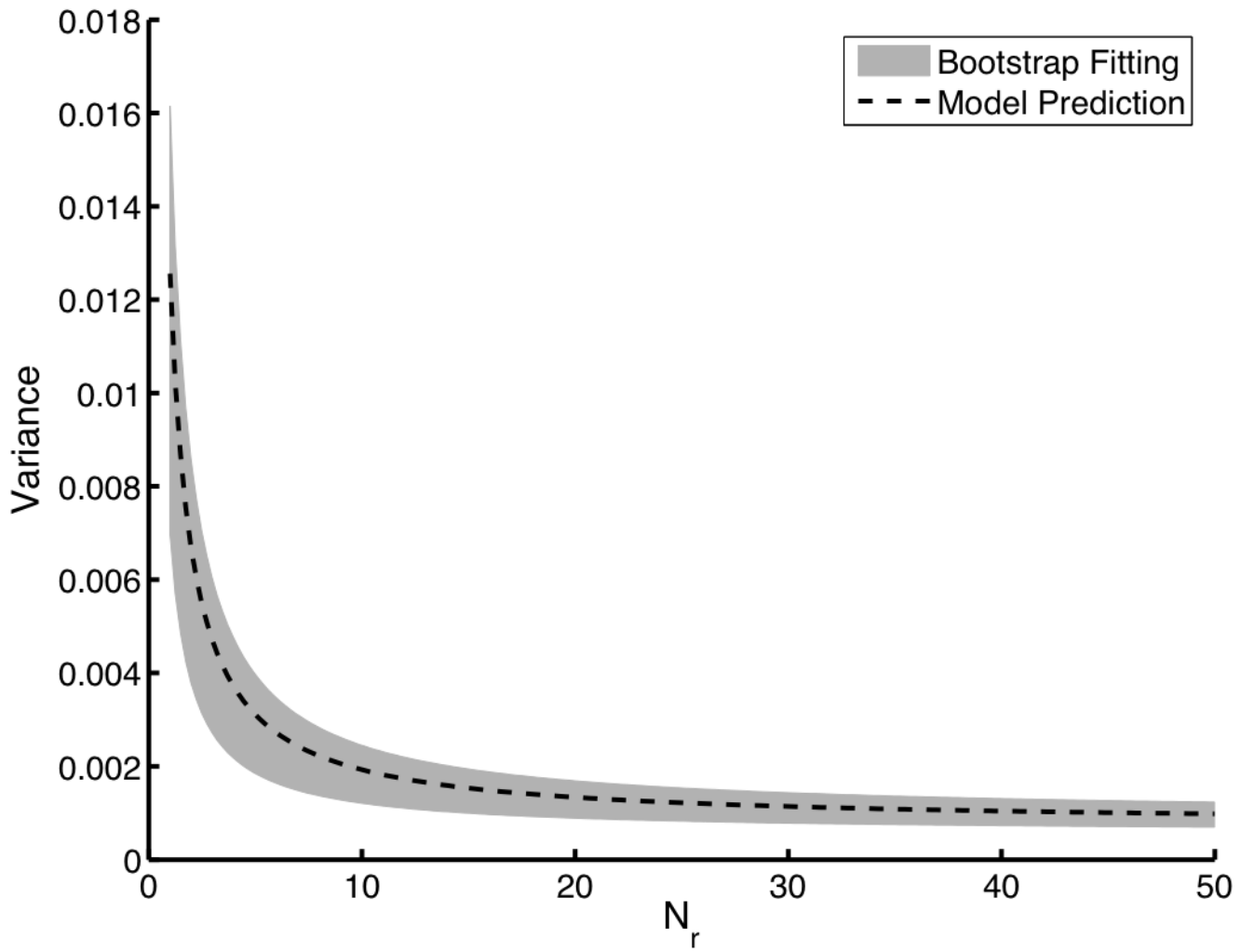


Fig 3.

An evaluation of the bootstrap coefficient estimation technique using the second data model. The dashed line indicates the gold standard computed using the direct computation technique. The gray area represents the mean plus and minus one standard deviation of the variance predicted using the fitted α_n . For this study, a single dataset of 25 readers and 1000 image pairs was used to estimate the expansion coefficients. This process was repeated 100 times using 100 different datasets of the same size to determine the mean and the standard deviations of the estimates α_n . In (a), N_r is varied from 1 to 50 with both N_0 and N_1 fixed at 100. In (b), N_r was fixed at 5 while both N_0 and N_1 were varied from 10 to 1000.



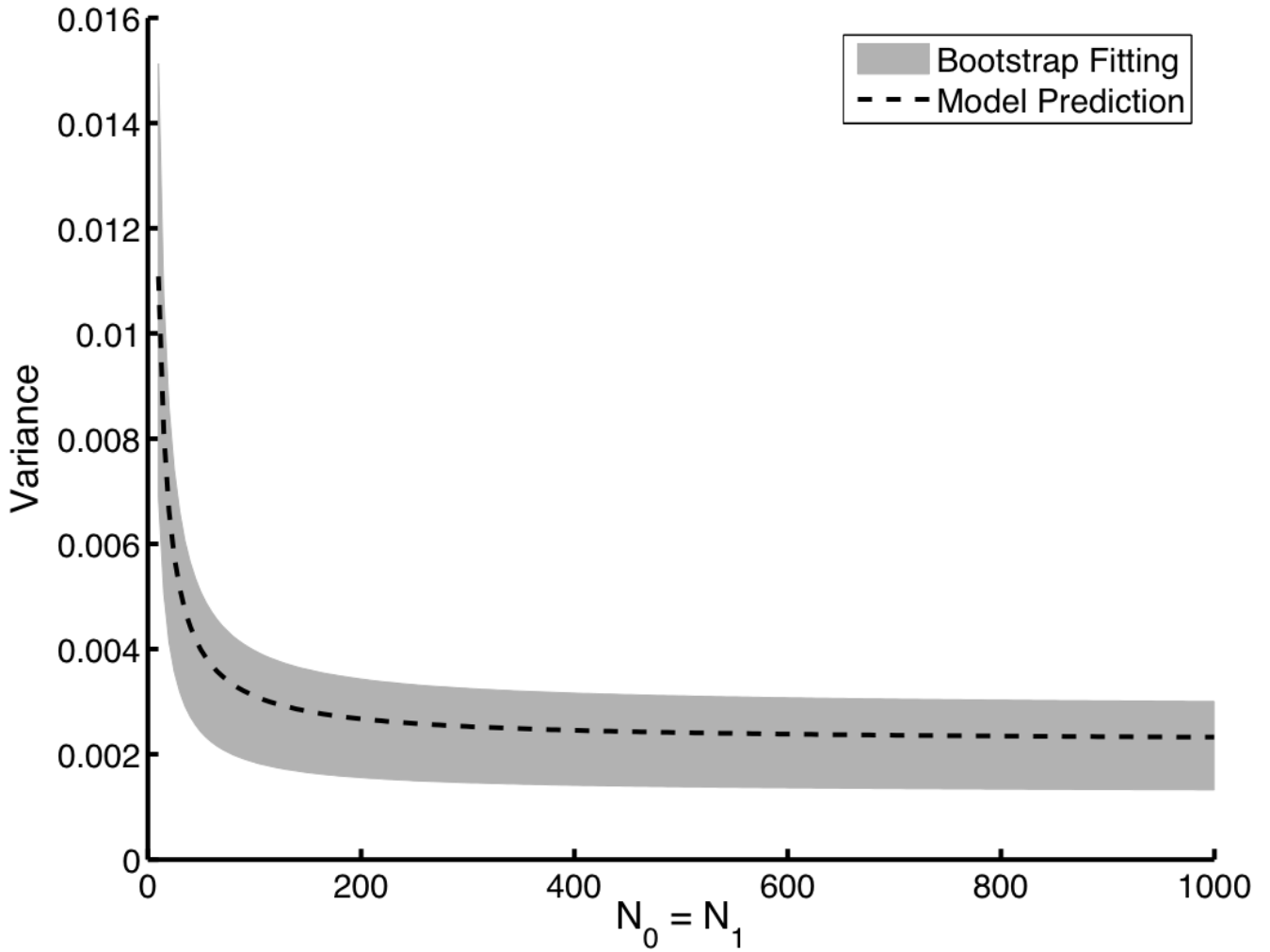


Fig 4.

An evaluation of the bootstrap coefficient estimation technique with small datasets. The dashed line indicates the gold standard computed using the direct computation technique. The gray area represents the mean plus and minus one standard deviation of the variance predicted using the fitted α_n . For this study, a single dataset of only 10 readers and 100 image pairs was used to estimate the expansion coefficients. This process was repeated 100 times using 100 different datasets of the same size to determine the mean and the standard deviations of the estimates α_n . In (a), N_r is varied from 1 to 50 with both N_0 and N_1 fixed at 100. In (b), N_r was fixed at 5 while both N_0 and N_1 were varied from 10 to 1000. Note that while the initial datasets were small, we are accurately predicting variances with much larger N_r , N_0 , and N_1 .