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Handbook of Measurement Error Models

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Measurement Error Models - A Brief Account of Past Developments and Modern Advancements

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by **Grace Y. Yi and Jeffrey S. Buzas**

1.1 Introduction

Measurement error arises in applications across many different fields and has been a longstanding concern in various disciplines including epidemiological studies, environmental studies, economics, survey sampling, etc.

While we may attempt to collect good quality data by careful design, measurement error is inevitable. Measurement error arises with different reasons and from different sources. Measurement error may refer to random noise, sampling error, or uncertainty and variation involved with the measuring process. An absence of clear and understandable rules, guidelines, and standards for data collection and reporting processes can result in imprecise measurements. Due to the sensitivity of certain questions, reporting errors commonly arise so that the corresponding variables cannot be accurately measured. Sometimes, variables are impossible to measure precisely due to the nature of the variables themselves. For example, some variables represent averages of certain quantities over time, and any measurements at a particular time point would fluctuate around the long term averages. In practice, we may artificially manipulate the measurements for security and confidentiality reasons. In other situations, it may be too expensive or time consuming to obtain a precise measurement of a variable, resulting in use of less expensive and/or convenient procedures to obtain surrogate measurements.

In this chapter, we take a brief tour of the development of measurement error strategies so as to appreciate the challenges facing analysts hoping to address measurement error in applications. To conduct sensible analyses for real world data which are commonly error-corrupted, it is critical to understand the impact of measurement error effects and develop correction adjustments for measurement error effects accordingly. Additionally, readers with an interest in the field of measurement error as a scientific discipline may gain an appreciation of the significant depth and breadth of results in the field of measurement error research.

In the literature, research on measurement error models may be categorized into three areas: (1) measurement error in covariates, (2) measurement error in the response variable, and (3) measurement error in both covariate and response variables. Our discussion here is directed to the first category with the highlight on how research in measurement error evolves over time.

1.2 Linear Measurement Error Model

In this section, we define a simple linear regression measurement error model and describe the effect of ignoring measurement error on estimation of the slope parameter.

Let $\{(Y_i, X_i) : i = 1, \ldots, n\}$ be a sequence of independent and identically distributed random variables, where n is the sample size, Y_i is a response variable, and X_i is a covariate for $i = 1, \ldots, n$. In the presence of covariate measurement error, X_i is often not observed, but a surrogate measurement X_i^* is available for $i = 1, \ldots, n$. In the following discussion, we may drop the index i and use the symbols $\{Y, X, X^*\}$ from time to time for ease of exposition.

Research on measurement error problems began with the simple linear regression measurement error model:

$$Y_i = \beta_0 + \beta_x X_i + \epsilon_i \tag{1.1}$$

with

$$X_i^* = X_i + e_i \tag{1.2}$$

for $i = 1, \ldots, n$, where β_0 and β_x are regression parameters, ϵ_i is independent of X_i with mean zero and a constant variance σ^2, and e_i has zero mean and a constant variance σ_e^2. Usually, e_i is assumed to be independent of $\{X_i, \epsilon_i\}$, which implies that *non-differential* measurement error is considered, i.e., that $f(y|x, x^*) = f(y|x)$ so that X_i^* provides no additional information about the outcome Y_i when X_i is observed. Here and in the sequel, $f(\cdot|\cdot)$ represents the conditional probability density or mass function of the variables corresponding to the arguments.

Without a full distributional assumption for ϵ_i, the least squares regression method is a natural option for estimation of the regression parameter $\beta = (\beta_0, \beta_x)^{\mathrm{T}}$. In the absence of measurements of the X_i, it is tempting to directly replace the X_i with the available surrogate measurements X_i^* in estimation procedures.

Let $\widehat{\beta}_x^*$ denote the resulting estimator of the slope β_x, given by

$$\widehat{\beta}_x^* = \frac{\sum_{i=1}^n (X_i^* - \overline{X}^*)(Y_i - \overline{Y})}{\sum_{i=1}^n (X_i^* - \overline{X}^*)^2},$$

where $\overline{X}^* = n^{-1} \sum_{i=1}^n X_i^*$ and $\overline{Y} = n^{-1} \sum_{i=1}^n Y_i$; this estimator is called a *naive* estimator of β_x.

The naive estimator $\widehat{\beta}_x^*$ is generally not a consistent estimator for the slope β_x (Fuller 1987). In fact,

$$\widehat{\beta}_x^* \xrightarrow{p} \beta_x^* \quad \text{as } n \to \infty \tag{1.3}$$

where $\beta_x^* = \lambda \beta_x$ with $\lambda = \sigma_x^2/(\sigma_x^2 + \sigma_e^2)$, and σ_x^2 is the variance of X_i. The factor λ, called the *reliability ratio*, is the ratio of the variability of X_i to that of X_i^*:

$$\lambda = \frac{\mathrm{var}(X_i)}{\mathrm{var}(X_i^*)}.$$

Since λ is no greater than 1, covariate measurement error in this case has an *attenuating* effect on estimation of the covariate effect β_x. The effects of measurement error on parameter estimation are much more complicated when multiple covariates are measured with error or there are additional covariates measured without error that are correlated with the mis-measured variable(s). For further details see Carroll et al. (2006) and Gustafson (2021a).

1.3 Induced Regression and Regression Calibration

In contrast to the response model (1.1), we now examine the relationship between Y and X^* via the conditional expectation $E(Y|X^*)$. Assuming the nondifferential measurement error mechanism (the error model does not have to be (1.2)), iterating expectations gives that

$$\begin{aligned} E(Y|X^*) &= E\{E(Y|X^*)|X^*, X\} \\ &= E\{E(Y|X^*, X)|X^*\} \\ &= E\{E(Y|X)|X^*\}. \end{aligned}$$

The above identities hold for general linear or nonlinear regression models. Recognizing expectation as a smoothing operation, we conclude that the measurement error induced regression results in smoothing (or obscuring) the regression relationship between the outcome Y and the predictor X.

For model (1.1),

$$\begin{aligned} E(Y|X^*) &= E\{E(Y|X)|X^*\} \\ &= \beta_0 + \beta_x E(X|X^*) \\ &= E\{Y|X = E(X|X^*)\}. \end{aligned}$$

This motivates the *regression calibration* method (Prentice 1982) which estimates β_x by regressing Y on the conditional expectation $E(X|X^*)$. The implementation of the regression calibration method relies on the determination of $E(X|X^*)$, which requires the ability to estimate the density function of the latent variable X. This represents a difficult deconvolution problem, and typically approximations are used to avoid it. Assuming model (1.2), the best linear approximation to the regression of X on X^* is

$$E(X|X^*) \approx \mu_x + \sigma_{x|x^*}\sigma_{x^*}^{-2}(X^* - \mu_x)$$

where μ_x is the mean of X, $\sigma_{x|x^*} = \text{Cov}(X, X^*) = \sigma_x^2$ and $\sigma_{x^*}^2 = \sigma_x^2 + \sigma_e^2$. The approximation suggests that additional data are needed for estimation and inference in the expanded model that includes $E(X|X^*)$. The need for additional informatoin is common to many estimation and inference approaches when there is covariate measurement error.

1.4 Identifiability

When the true covariate is not observed, it is natural to ask whether the model parameters can be consistently estimated, or even identifiable. In (1.1) and (1.2), if we impose a normal distribution on ϵ_i and e_i as well as X_i, i.e.,

$$\epsilon_i \sim N(0, \sigma^2),\ e_i \sim N(0, \sigma_e^2),\ \text{and } X_i \sim N(\mu_x, \sigma_x^2), \tag{1.4}$$

where $\sigma^2, \sigma_e^2, \mu_x$, and σ_x^2 are unknown parameters, then the joint distribution of Y_i and X_i^* is

$$N\left(\begin{pmatrix} \mu_y \\ \mu_x \end{pmatrix}, \begin{pmatrix} \sigma_y^2 & \sigma_{yx^*} \\ \sigma_{yx^*} & \sigma_{x^*}^2 \end{pmatrix}\right), \tag{1.5}$$

where $\sigma_y^2 = \beta_x^2\sigma_x^2 + \sigma^2$, $\sigma_{x^*}^2 = \sigma_x^2 + \sigma_e^2$, $\sigma_{yx^*} = \beta_x\sigma_x^2$, and $\mu_y = \beta_0 + \beta_x\mu_x$.

The initial models (1.1) and (1.2), together with (1.4), have six parameters, but the distribution (1.5) of Y_i and X_i^* involves only five parameters, expressed as functions of the original model parameters. This suggests that the original model parameters cannot be consistently estimated using the observed data $\{(Y_i, X_i^*) : i = 1, \ldots, n\}$, because they are not even identifiable from the model for the observed data.

To consistently estimate all the parameters, side conditions (or auxiliary data) are needed for estimation. Adcock (1877, 1878) considered estimation when the ratio σ_x^2/σ_e^2 is assumed to be known, resulting in orthogonal least squares estimation for β_x. Alternatively, other common identifiability choices are used in applications by adding a constraint on the parameters, including fixing the reliability ratio $\lambda = \sigma_x^2/(\sigma_x^2 + \sigma_e^2)$, σ^2, or σ_e^2 to be a given value or estimated with auxiliary data.

The linear model received much attention in the 1940s and 1950s, with many results focused on identifiability published in the econometrics literature. Neyman and Scott (1948) provided an interesting example of the failure of maximum likelihood when the number of parameters grows with the sample size, even when the model is identified.

Interestingly, if X_i is not normal, the model is identified (Geary 1942,1943), and instrumental variable approaches (to be discussed below) can be used to construct consistent estimators. Geary developed instrumental variable estimators assuming higher central moments of X_i are not zero. Wald (1940) developed an estimator based on grouping observations that seemed not to require additional identification information. However, his estimator requires an instrumental variable to define the groupings, and the existence of the instrumental variable requires certain knowledge of the measurement error distribution. Durbin (1954) provided another early example of an instrumental variable estimator in the context of Berkson measurement error. Some early references on identifiability issues include Reiersøl(1950), Robinson (1974), and Geraci (1976).

In a Bayesian context, Gustafson (2005) showed that there can be *indirect* learning about unidentified parameters that results from learning about identified parameters. Recently, Schennach and Hu (2013) showed that a very large class of regression models with covariate measurement error are identified without the need for auxiliary data. They proposed sieve regression for estimation. Bertrand, Van Keilegom and Legrand (2019) provided a novel method for estimating the measurement error variance that does not rely on auxiliary data, but assumes compact support for the distribution of the unobserved covariate X. Delaigle and Van Keilegom (2021) discussed estimation of the error distribution with or without extra data.

The recent identifiability results are impressive and in principle allow estimation without the need for auxiliary data (e.g., Gustafson 2021b). However, while measurement error models may be identified without auxiliary data, Carroll et al. (2006) strongly recommended designing studies to obtain internal validation data whenever possible, because "... *it can be used with all known techniques, permits direct examination of the error structure, and typically leads to much greater precision of estimation and inference.*" Most methods used in practice utilize auxiliary data; Wang (2021a) provided an overview of this topic.

1.5 Nonlinear Models

A substantial literature comprising impressive results was developed for linear measurement error models prior to 1980. Research for nonlinear models was sparse prior to 1980, but then exploded, beginning with the seminal papers by Prentice (1982) and Carroll et al. (1984). Prentice (1982) studied measurement error in survival models and suggested regression calibration as an approach to ameliorating the effects of measurement error. Carroll et al. (1984) proposed maximum likelihood estimators for probit and other models for a binary outcome, with application to the Framingham data, and also suggested the use of regression calibration. Regression calibration was developed for logistic regression by Rosner, Willet and Spiegelman (1989) and Rosner, Spiegelman and Willet (1990). All those approaches require additional information for parameter estimation.

Using the same argument as in Section1.3 and again assuming nondifferential measurement error, with a nonlinear regression model with parameter β_x, we have that

$$\begin{aligned} E(Y|X^*) &= E\{E(Y|X)|X^*\} \\ &\neq E\{Y|X = E(X|X^*)\}. \end{aligned}$$

The non-equality results from the non-linearity of $E[Y|X]$ as a function of X. Therefore, regressing Y on $E(X|X^*)$ may not produce consistent estimation of β_x due to the nonlinear structure in the regression model. Using the regression calibration method may only lead to an *approximately* consistent estimator in nonlinear regression models.

For example, consider the logistic regression model for the binary response Y and the covariate vector X,

$$P(Y = 1|X) = F(\beta_0 + \beta_x^{\mathrm{T}} X),$$

where $F(v) = (1+e^{-v})^{-1}$, and β_0 and β_x are regression parameters. Under the nondifferential error assumption, Carroll et al. (1984) examined the induced regression model linking Y and the surrogate X^*:

$$\begin{aligned} P(Y=1|X^*) &= \int P(Y=1|X=x, X^*=x^*) f(x|x^*)dx \\ &= \int P(Y=1|X=x) f(x|x^*)dx \\ &= \int F(\beta_0 + \beta_x^{\mathrm{T}} x) f(x|x^*)dx, \end{aligned}$$

where the integral is replaced by the summation if X is discrete.

The final integral in the series of identities is typically analytically intractable, necessitating the approximation in the last line. When $\beta_x^2\sigma^2$ is not too large, $P(Y = 1|X^*)$ can be reasonably approximated by $F\{\beta_0 + \beta_x E(X|X^*)\}$ (Carroll et al. 1984). Therefore, in contrast to the linear model, replacing X with $E(X|X^*)$ and running standard logistic analyses will only yield an approximately consistent estimator for the regression parameter β_x. An analogous statement holds for nonlinear models generally.

1.6 Development Timeline

While many important results on linear regression models with covariate measurement error were established in the mid-20th century, research on estimation and testing in nonlinear regression models with covariate measurement error increased rapidly beginning in the 1980s and continues to the present.

In this section we briefly discuss the development of several approaches to ameliorating the effects of covariate measurement error in a variety of inferential settings. We attempt a coarse-grained grouping of the methods according to the time (decade) when they emerged or were first most intensely studied, and mention a small sample of research articles that were important in the development of the methods. Not all papers cited fall within the designated decade.

1.6.1 1980-1989

In the period of 1980-1989, the following are major approaches and areas explored.

Likelihood Methods

Not surprisingly, likelihood methods were considered in some of the earliest papers to explore measurement error in nonlinear models, including the aforementioned Prentice (1982) and Carroll et al. (1984). Major challenges with likelihood approaches are modeling the unobserved distribution for X

and the potential sensitivity to mis-specification of this distribution, integrating over that distribution to obtain the likelihood of the observable data, and maximizing the resultant likelihood. These challenges, at least in part, spurred the development and use of regression calibration and other methods that do not require a model for the distribution of X.

Schafer (1987) is an early paper on the use of likelihood methods in covariate measurement error problems. He cast the measurement error problem as a missing data problem and proposed use of the EM algorithm to obtain approximate likelihood estimators. Fuller (1987) and Carroll et al. (1984) obtained the likelihood analytically for the linear regression and Probit models, respectively. Likelihood methods continued to be explored in the 1990s and beyond, with significant effort directed toward flexible parametric and semi-parametric approaches to modeling the latent distribution for X, see, for example, Roeder, Carroll and Lindsay (1996). Additional advancements were made in computation and maximization of likelihoods, see, for example, Schafer (2001, 2002). The Bayesian approach to measurement error adds priors to the likelihood and circumvents integration challenges with, typically, Markov chain Monte Carlo sampling (MCMC), discussed below. Research on likelihood methods continues to the present day, and discussions on this topic can be found in Yi (2021). Ma (2021) presented an account of semiparameteric methods rooted in the likelihood formation.

Regression Calibration

As noted in Section 1.3, regression calibration was proposed in proportional hazards models by Prentice (1982), and mention of the approach was made for linear models by Fuller (1987). Carroll and Stefanski (1990) developed regression calibration for a large class of models and expanded the model to provide better approximations in highly nonlinear models.

In its simplest guise, regression calibration imputes the unobserved X with the best linear approximation to $E(X|X^*)$. The analyst then proceeds with the usual analysis (noting that standard errors will likely need revision). As noted above, regression calibration serves as an approximation to the induced regression of Y on X^*, and can also be considered as an approximation to the likelihood for the observed data.

Although the regression calibration method only partially removes the bias induced from covariate measurement error in nonlinear models, its generality and straightforward implementation make this strategy popular in applications. A refined variant of regression calibration was developed by Freedman et al. (2004) using the moment reconstruction idea. Regression calibration has been implemented in Stata (Hardin, Schmiediche and Carroll 2003). An account of this topic was provided by Shaw (2021).

Conditional Scores

Stefanski and Carroll (1987) developed the conditional score approach to generalized linear models with covariate measurement error. Conditional scores are attractive because they essentially retain optimality properties enjoyed by likelihood estimators. The idea is to find a sufficient statistic for the unobserved covariate X assuming other model parameters are known. Analysis is then conditional on this sufficient statistic, thereby removing dependence of the conditional likelihood score on the unobserved X, see also Lindsay (1982).

The conditional score for logistic regression with normally distributed additive measurement error is straightforward to construct, and in our experience is difficult to improve upon when the measurement error distribution is misspecified. The method was extended to the instrumental variable setting by Buzas and Stefanski (1996a), and to proportional hazards models with longitudinal covariates by Tsiatis and Davidian (2001). Conditional scores were developed for a large class of models by Tsiatis and Ma (2004). Research on conditional score methods is ongoing, with Stoklosa, Lee and Hwang (2019) as a recent example. See Zucker (2021) for the discussion on the methods.

Hypothesis Testing

Tosteson and Tsiatis (1988) provided an early and important paper in the area of hypothesis testing for the association between Y and X. They showed that, for generalized linear models, the optimal score test for no effects is obtained by replacing X^* with $E(X|X^*)$, i.e., regression calibration results in the optimal score test when X^* is observed. It follows that when $E(X|X^*)$ is linear in X^*, ignoring measurement error and proceeding with the usual score test results in the optimal test of no effects. Nevertheless, covariate measurement error can result in a significant loss of power, and tests of no effects due to the accurately observed X may not be valid. Stefanski and Carroll (1990a) developed an estimator of $E(X|X^*)$ that results in approximately efficient score tests, and they also explored the Wald test.

A useful approximation for the sample size required to maintain power in the presence of covariate measurement error is $n_{X^*} = n_X/\rho^2_{XX^*}$, where n_X is the sample size needed in the absence of measurement error and ρ_{XX^*} is the correlation coefficient between X and X^*. See McKeown-Eyssen and Tibshirani (1994) for the detail.

Deconvolution/Nonparametric Inference

Under the classical error model (1.2), the observed covariate X^* is a convolution of X and the measurement error e. The distribution of X is often of interest, either for scientific reasons or, for example, to estimate $E(X|X^*)$ (recall that $E(X|X^*)$ is used in both regression calibration estimation and construction of the optimal score test discussed by Tosteson and Tsiatis (1988)). Estimation of the distribution of X is termed *deconvolution*. Deconvolution estimators were studied intensely in the late 1980s and early 1990s, and research on the deconvolution problem continues to the present day. The first deconvolution kernel density estimators were proposed and studied by Carroll and Hall (1988) and Stefanski and Carroll (1990b). These authors showed that deconvolution kernel density estimators have very slow rates of convergence; see also Fan (1991). For example, if the measurement error e is normally distributed, the deconvolution density estimator converges at a rate no faster than $(\log n)^{-2}$. This slow convergence rate would seem to rule out the use of deconvolution estimators. However, Stefanski and Carroll (1991) showed that estimation of the calibration function $E(X|X^*)$ using deconvolved density estimates enjoys rates of convergence reaching $n^{-4/5}$. Later studies of deconvolution estimators employed 'small sigma' asymptotics, i.e., deconvolution estimators were studied as $n \to \infty$ and $\sigma_e^2 \to 0$. This asymptotic scenario is relevant to the situation where $\text{Var}(X)$ is large relative to $\text{Var}(e)$. Estimators of the density of X were obtained with standard nonparametric convergence rates without having to fully specify the distribution of the measurement error. Detailed discussion on this is given by Delaigle and Van Keilegom (2021).

Interest in this topic continues to grow, as is evident from, for example, Carroll and Hall (2004), Delaigle (2007, 2014), Delaigle, Hall and Qiu (2006), Carroll, Delaigle and Hall (2007), Delaigle and Meister (2011), and Delaigle and Hall (2014). See Delaigle (2016) and Carroll et al. (2006) for excellent summaries of results for deconvolution estimators. Detailed overviews of this topic can also be found in Apanasovich and Liang (2021), Delaigle (2021), Kang and Qiu (2021), and Song (2021).

Misclassification

Research into the effects of misclassified categorical or discrete covariates/exposures has been spread over several decades, making it difficult to identify a decade where the area was studied most intensely.

An early example demonstrating the attenuating effects of misclassified binary exposures on the odds ratio was studied by Bross (1954). He concluded that, similar to the effects of measurement error on hypothesis testing mentioned above, misclassification may not affect the validity of a hypothesis test of no effects, but can affect power. See also Greenland (1980), Greenland and Robins (1985), and Greenland (1988).

Misclassified discrete covariates/responses are governed by the missclassification matrix consisting of entries, say π_{jk}, representing the probability that the covariate/response is classified as category j when the true category is k. Successful analysis of misclassified data often requires validation data for estimation of the missclassification matrix (Spiegelman, Rosner and Logan 2000). Missclassified binary and ordinal responses have also been studied by Copas (1988) and Neuhaus (1999). Helmut et al. (2006) developed the simulation-extrapolation (SIMEX) method for misclassified covariates and/or missclassified responses. An R package implementing their methods is available through the **simex** function. A discussion on misclassification was given by Gustafson and Greenland (2014).

Breslow and Cain (1988) and Carroll, Gail and Lubin (1993) studied misclassification in logistic regression models for case-control data. Matched case-control studies with misclassification were studied by Gustafson, Le and Saskin (2001), Prescott and Garthwaite (2005), and Hogg et al. (2019). Mak, Best and Rushton (2015) studied the sensitivity of case-control studies to misclassification.

1.6.2 1990-1999

In the period of 1990-1999, the following are major approaches and areas explored.

Instrumental Variable Methods

Instrumental variables are additional measurements of X, denoted V, such that (i) V is non-differential, i.e., $f(y|x,v) = f(y|x)$; (ii) V is correlated with X; and (iii) V is independent of $X^* - X$. Replicate observations of X are instrumental variables, but instrumental variables need not be replicates.

As mentioned above, instrumental variable estimators were proposed early in the study of covriate measurement error in linear models.

In the statistical literature, instrumental variable estimation in non-linear models began in earnest in the early 1990s. Stefanski and Buzas (1995) developed a measurement error correction method using instrumental variables for binary regression models. Buzas and Stefanski (1996a) discussed parameter estimation under probit measurement error models using instrumental variables. Buzas and Stefanski (1996b) extended the conditional score method to instrumental variables in a class of generalized linear models, and Buzas (1997) developed an instrumental variable estimation approach for nonlinear models that provide consistent estimators without having to specify the measurement error distribution.

Carroll and Stefanski (1994) discussed using instrumental variables to handle problems that arise in regression meta-analysis when the predictor of interest is measured with error. They demonstrated that a single correction for attenuation is not possible when the measurement error variances differ across studies, and they suggested that study specific corrections are generally necessary.

Gustafson (2007) considered a strategy of measurement error modeling using an approximate instrumental variable. Hu and and Schennach (2008) discussed the use of instrumental variables for nonclassical measurement error models and established very general identifiability results. Under generalized linear mixed models, Wang (2021b) described semiparametric estimation using instrumental variables. For additional discussion of instrumental variable methods, see Lewbel (2021).

Simulation Extrapolation

The simulation extrapolation (SIMEX) method, proposed by Cook and Stefanski (1994) and Stefanski and Cook (1995), is an attractive simple approach for reducing bias due to measurement error in a wide variety of models, and it has been widely used in practice. This approach is well suited to the settings with classical additive measurement error models with the error following a normal distribution, though the method is not limited to this model. Theoretical justification to this approach and the asymptotic distribution of the simulation extrapolation estimators were investigated by Carroll et al. (1996).

The idea is intuitive. To understand how the magnitude of covariate measurement error affects bias in parameter estimation, the analyst sequentially simulates increasing amounts of measurement error in the covariate, computes the naive estimate using a standard method developed for error-free settings, and then examines the naive estimates (averaged over simulated samples) against the amount of measurement errorby fitting a regression model. The final step is to extrapolate the relationship between bias and magnitude of measurement error back to the case of no measurement error. Carroll et al. (2006) provided a detailed discussion of both the theoretical and practical aspects of the SIMEX method.

A commercial implementation of SIMEX is available in STATA, and SIMEX has also been implemented in R.

Bayesian Approaches

Bayesian approaches to covariate measurement error problems are straightforward conceptually. As with general Bayesian approaches, Bayesian covariate measurement error models start with the likelihood and add priors to all unknown quantities. In the covariate measurement error setting, this requires specification of a distribution for the latent X, priors for parameters of this distribution and priors for regression parameters in the model relating outcome to predictors. Finally, priors for parameters in the measurement error model also require specification. The resulting posterior is typically intractable analytically, and consequently there was limited research in Bayesian measurement error methods prior to around 1990.

The rapid development in the late 1980s and 1990s of computational approaches to approximating posterior distributions spurred research into Bayesian approaches for covariate measurement error problems. The result is that in the measurement error setting, MCMC sampling is typically used to obtain a sample from the (approximate) posterior distribution for all unknown quantities. A strength of this approach is that numerical evaluation of intractable integrals is avoided. Another advantage, at least in principle, is that no special techniques need to be developed for different types of regression models and measurement error models – simply apply the Bayesian machinery to the proposed models. However, the additional modeling required by covariate measurement error necessitates care in choosing priors and checking for sensitivity to mis-specification. More complex models may require specialized adaptations of MCMC algorithms, and/or careful selection of tuning parameters, starting values and scaling of covariates for use in existing algorithms.

Early research into application of Bayesian methods in the presence of covariate measurement error includes Richardson and Gilks (1993), Stephens and Dellaportas (1992), and Mallick and Gelfand (1996). Some recent work of Bayesian methods concerning error-prone data can be found in Gustafson, Le and Vallee (2002), Gustafson and Greenland (2006), Hossain and Gustafson (2009), and Xia and Gustafson (2018), among many others.

The book by Gustafson (2004) provides an excellent introduction to Bayesian models for covariate measurement error, and Carroll et al. (2006) contains a chapter devoted to Bayesian measurement error models. A recent account of this topic can be found in Sinha (2021) and Stamey and Seaman Jr. (2021).

Survival Analysis

Survival data pose new challenges for error-prone data, including censoring, skewed data and semi-parametric hazard functions. Research on error-prone survival data dated back to the 1980s, marked by the seminal work of Prentice (1982) who considered the proportional hazards model with covariate measurement error. Since then, examining the measurement error effects on survival analysis has attracted attention. Available work in the period from 1990 - 1999 includes Pepe, Self and Prentice (1989), Hughes (1993), Gong, Whittemore and Grosser (1990), Nakamura (1992), Wang et al. (1997), Hu, Tsiatis and Davidian (1998), and Buzas (1998).

Since 2000, there has been extensive interest in accommodating measurement error effects into inferential procedures about survival data. A variety of inference methods have been developed from different perspectives. To name a few, Xie, Wang and Prentice (2001), Liao et al. (2011), and Shaw and Prentice (2012), developed variants of the usual regression calibration method by incorporating the risk set information, a feature which is typical for survival data. Hu, Tsiatis and Davidian (1998) developed a likelihood based method that requires the specification of the distribution of the true covariates. Huang and Wang (2000) proposed a nonparametric approach which requires repeated measurements for mismeasured covariates to be available for each subject. Gorfine, Hsu and Prentice (2003) examined estimation approaches for correlated failure times in the presence of covariate measurement error. Under stratified Cox models, Gorfine, Hsu, and Prentice (2004) explored nonparametric correction for covariate measurement error. With semiparametric survival regression, Zucker (2005) presented a pseudo-partial likelihood method to address the effects due to covariate measurement error. Yan and Yi (2016) developed several functional correction methods for measurement error effects under the additive hazards model.

Buzas (2021) offered an overview of covariate measurement error in survival data models.

Analysis of Longitudinal/Correlated Data

Since the 1990s, attention on measurement error effects emerged from studies on correlated data, such as clustered data, multivariate data, longitudinal data, and times series. For example, with multivariate responses and error-contaminated covariates, Chesher (1991) derived approximations to distributions and then examined the resultant measurement error effects. With clustered data Concerning covariate measurement error, Wang and Davidian (1996) examined measurement error effects under nonlinear mixed effects models. For longitudinal studies, Wang et al. (1998) and Tosteson, Buonaccorsi and Demidenko (1998) explored covariate measurement error effects, respectively under generalized linear mixed models and linear mixed models. With error in responses, Neuhaus (2002) investigated effects of misclassified binary response variables on analysis of longitudinal or clustered data. Regarding error-prone times series data, Koons and Foutz (1990) discussed estimation of moving average parameters. An overview measurement error models in settings of time series was given by Buonaccorsi (2021), and discussion of time-varying covariates subject to measurement error was provided by Wu, Liu and Zhang (2021).

Methods of accommodating measurement error effects have spawned in late 1990s and continue to grow since 2000. To name a few, Higgins, Davidian and Giltinan (1997) proposed a two-stage estimation method for nonlinear mixed measurement error models. Zidek et al. (1998) discussed a nonlinear regression analysis method for clustered data. Wang, Wang and Wang (2000) proposed the expected estimating equations method, and Buonaccorsi, Demidenko and Tosteson (2000) developed likelihood-based methods for linear mixed models with measurement error. Chen, Yi and Wu (2011) proposed estimating equation methods to handle clustered binary responses subject to misclassification.

Attention on error-prone longitudinal data has been further paid to investigations of joint effects with other features. Some early work on joint modeling of survival data and error-contaminated longitudinal covariates was given by Tsiatis, Degruttola and Wulfsohn (1995), and later studied by Tsiatis and Davidian (2001), where the survival process was described by the Cox porportional hazards model. In contrast, with the accelerated failure time model employed to characterize the survival process, Tseng, Hsieh and Wang (2005) explored a joint modelling approach to handle error-contaminated covariates which are described by the linear mixed effects model.

When both measurement error and missing observations are present, Liang, Wang and Carroll (2007) derived estimation procedures under partially linear models. Wang et al. (2008), Yi (2005, 2008), and Yi, Ma and Carroll (2012) developed marginal methods to incorporate measurement error and missingness effects. Liu and Wu (2007) and Yi, Liu and Wu (2011) took a mixed model framework for the response process and described likelihood-based methods. Detailed discussions on this topic were given by Carroll et al. (2006, Ch. 11), Buonaccorsi (2010, Ch.11, Ch.12), Wu (2009, Ch.3, Ch.8), and Yi (2017, Ch.5). A discussion of measurement error and missing data can be found in Keogh and Bartlett (2021).

1.6.3 After 2000

After 2000, the following are major approaches and areas explored.

Variable Selection

Variable selection methods for low dimensional data in the absence of covariate measurement error have been studied for decades. High dimensional variable selection methods in the absence of covariate measurement error began in earnest in the early 2000s. Variable selection methods in the presence of measurement error began around 2010, with Liang and Li (2009) and Ma and Li (2010) as early examples. These authors developed variable selection approaches using penalized regression methods. Yi, Tan and Li (2015) proposed variable selection methods in the longitudinal data setting when there is covariate measurement error and possibly missing observations. They developed a variation of SIMEX in their approach.

Several approaches for variable selection in the presence of covariate measurement error have been proposed that are applicable to the situation where the number of predictors is large relative to the sample size. Sørensen, Frigessi and Thoresen (2013) defined a corrected Lasso that results in consistent covariate selection in the presence of measurement error. Datta and Zou (2017) also developed a Lasso based method, dubbed CoCoLasso for convex conditioned Lasso, for variable selection in high dimensional settings with covariate measurement error.

Some of the aforementioned methods apply primarily to linear models. Recently, Brown, Weaver and Wolfson (2019) developed a variable selection procedure for high dimensional data where covariate measurement error is present. Their method, dubbed MEBoost, is extendable to a very large class of regression models where estimating equations that correct for the measurement error effects have already been proposed. In a somewhat reverse scenario, Stefanski, Wu and White (2014) developed an approach to variable selection in the absence of measurement error utilizing ideas from measurement error modeling.

Causal Inference

Interest in causal inference about error-prone data began with studying measurement error effects. Zidek et al. (1996) illustrated that measurement error may conspire with multicollinearity among confounders to mask the effects of causal variables. Hernán and Cole (2009) employed causal diagrams to represent various types of measurement error. Babanezhad, Vansteelandt and Goetghebeur (2010) studied the asymptotic bias of misclassified exposure on various causal effect estimators, and VanderWeele, Valeri and Ogburn (2012) examined measurement error effects on mediation analysis. Regier, Moodie and Platt (2014) conducted simulation studies to assess the effects of mismeasured confounders on the estimation of the causal effects.

Identifying conditions for conducting causal inference with measurement error is another topic of interest. For example, Lewbel (2007) discussed identification and estimation of the average treatment effect in nonparametric and semiparametric regression with misclassified treatment or exposure. Imai and Yamamoto (2010) investigated identification issues in the presence of a misclassified binary treatment variable. Díaz and van der Laan (2013) explored a sensitivity analysis to circumvent the cases with unidentifiable or not estimable model parameters.

Regarding estimation of the causal effects with error-corrupted confounders, McCaffrey, Lockwood and Setodji (2013) and Shu and Yi (2019ab) explored inverse-probability-weighted estimation approaches, and Shu and Yi (2019c) developed an R package for implementing of the method of Shu and Yi (2019a). Further, Shu and Yi (2019d, 2020) studied the biases due to a misclassified binary outcome together with missingness or covariate measurement error, and developed estimation methods to accommodate those effects. A more detailed discussion on this topic is available in Valeri (2021).

1.7 Some Applications in Epidemiology

There are many applications of measurement error methodology in epidemiology. In one of the early papers on the topic of exposure error in studies of air pollution, Shy, Kleinbaum and Morgenstern (1978) described the measurement error problem and addressed its consequences in an epidemiologic framework. Willett (1989) provided an overview of issues related to the correction of non-differential exposure measurement error in epidemiological studies. Rosner, Willett and Spiegelman (1989) considered the correction of logistic regression relative risk estimates and confidence intervals for systematic within person measurement error. They gave methodology (including regression calibration) and applied it to dietary fat intake and risk of breast cancer. MacMahon et al. (1990) was one of the first important practical applications, correcting for the regression dilution bias resulting from measurement error in diastolic blood pressure.

Gail (1991) included a bibliography and comments on the use of statistical models in epidemiology in the 1980s. Chen (1989) reviewed the methods for misclassified categorical data in epidemiological studies. Thomas, Stram and Dwyer (1993) presented an overview of the exposure error or misdassification problem from the general epidemiologic perspective. Spiegelman, McDermott and Rossner (1997) investigated the regression calibration scheme for correcting the bias due to measurement error in nutritional epidemiology. The central issues of measurement error modeling to progress in nutritional epidemiology were recognized and emphasized by many authors such as Prentice et al. (2002), Prentice and Huang (2011), and Buzas, Stefanski and Tosteson (2014), among others.

Recently there have been several systematic reviews of the use of corrections for measurement error in applied settings. The results are somewhat discouraging. Brakenhoff et al. (2018) found that almost half (247/565) of research studies published in 2016 in top 12 general medicine and epidemiological journals mention measurement error, but only 7% of the 247 (18) did something about it (investigated the effect or did a measurement error analysis). Brakenhoff et al. (2018) give some recommendations for increasing the use of measurement error methods.

In a review article, Bennett et al. (2017) examined measurement error in a continuous exposure in nutritional epidemiology. They identified 126 studies that addressed measurement error. Among them, 43 were methodological and 83 applied existing methods. They found that regression calibration is by far the most widely used method in nutritional epidemiology. However, the underlying assumptions are not always met, and hence, they recommended that sensitivity analyses should be used to assess departures from model assumptions.

The review by Shaw et al. (2018) had findings consistent with those of the two aforementioned studies. Recently, Keogh et al. (2020) and Shaw et al. (2020) provided excellent and comprehensive overviews of measurement error and misclassification in epidemiological studies.

1.8 Monographs on Measurement Error Models

The effect of mismeasured variables in statistical and econometric analysis is one of the oldest known problems, dating from the 1870s in Adcock (1878). Long (1976) reviewed some methods of estimation and hypothesis testing in linear measurement error models. Research results based on a workshop on errors-in-variables were summarized in a volume of *Statistics in Medicine* (Byar and Gail 1989). The volume, edited by Davidian et al. (2014), contains Raymond J. Carroll's research on measurement error models and commentary on its impact, together with history and anecdotes. The book provides a review and discussion on a range of topics including semiparametric and nonparametric regression, measurement error modeling, and quantitative methods for nutritional epidemiology. Chang and Keller (2021) provided an overview of methods to account for measurement error effects in the context of environmental epidemiology.

The problem of measurement errors in predictor variables in regression analysis has been carefully studied in the statistics and epidemiologic literature for several decades. Fuller (1987) summarized early research on linear regression with so-called "errors-in-x" variables. Carroll, Ruppert and Stefanski (1995) extended this literature to generalized linear models including Poisson, logistic, and survival regression analyses. Carroll et al. (2006) further documented up-to-date methods with a comprehensive discussion on various topics on nonlinear measurement error models, including Bayesian analysis methods. With an emphasis on the use of relatively simple methods, Buonaccorsi (2010) described methods to correct for measurement error and misclassification effects for regression models. Under the Bayesian paradigm, Gustafson (2004) provided a dual treatment of mismeasurement in both continuous and categorical variables. Other relevant books on this topic include Biemer et al. (1991), Cheng and Van Ness (1999), Wansbeek and Meijer (2000), and Dunn (2004).

A recent monograph by Yi (2017) emphasized unique features in modeling and analyzing measurement error and misclassification problems arising from medical research and epidemiological studies. The emphasis is on gaining insights into problems coming from a wide range of fields, including event history data (such as survival data and recurrent event data), correlated data (such as longitudinal data and clustered data), multi-state event data, and data arising from case-control studies.

1.9 Concluding Remarks

As the ease in collecting data increases, there is the growing use of data (e.g., EHR/EMR data, large scale administrative data) from sources not originally intended for answering scientific questions. Therefore, developing methods for handling faulty data becomes increasingly important. As pointed out by Brakenhoff et al. (2018), more guidance and tutorials are necessary to assist applied researchers with the assessment of the type and amount of measurement error as well as the steps that can subsequently be taken to minimize its impact on the studied relationships.

Even though there is intensive research into the development of methodology to handle covariate measurement error, measurement error methods are not used frequently in the situations that merit their use. There are a couple of reasons which hinder the use of measurement error methodology. Lack of adequate understanding of measurement error impacts is perhaps the primary reason. Developing proper methods to address measurement error effects requires analytical skills and knowledge of the measurement error models. This presents a significant hurdle for introducing suitable corrections in the analysis. Furthermore, general-purposed software packages are lacking for analysts to implement the available correction methods developed in the literature, though some software packages have been available (e.g., Yi 2017, Ch. 9; Guolo 2021). Most importantly, the difficulty of obtaining auxiliary data often discourages the researchers to accommodate the feature of measurement error in their data analyses.

It seems difficult to offer universal guidelines. Study design, measurement error models and analytic approaches can depend on many factors, including the form of the response and measurement error/misclassification models, the association structures among the covariates, the magnitude of mismeasurement in variables, and the availability of computing facilities, as noted by Carroll et al. (2006) and Yi (2017), among others.

The STRATOS initiative is a collaborative effort to "*to provide accessible and accurate guidance in the design and analysis of observational studies*" (STRATOS initiative website: https://www.stratos-initiative.org/). The group recently published a two part guidance document describing types of measurement error, the effect of measurement error on parameter estimation, and methods for amelioration (see Keogh et al. (2020) and Shaw et al. (2020)). We are optimistic that continued efforts to interface with scientists through these types of publications, including this handbook, will result in an increased use of methods to correct for the effects of measurement error.

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