

A General Method for Robust Bayesian Modeling

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Editor:

Abstract

Robust Bayesian models are appealing alternatives to standard models, providing protection from data that contains outliers or other departures from the model assumptions. Historically, robust models were mostly developed on a case-by-case basis; examples include robust linear regression, robust mixture models, and bursty topic models. In this paper we develop a general approach to robust Bayesian modeling. We show how to turn an existing Bayesian model into a robust model, and then develop a generic strategy for computing with it. We use our method to study robust variants of several models, including linear regression, Poisson regression, logistic regression, and probabilistic topic models. We discuss the connections between our methods and existing approaches, especially empirical Bayes and James-Stein estimation.

Keywords: robust statistics, empirical Bayes, probabilistic models, variational inference, expectation-maximization, generalized linear models, topic models

1. Introduction

Modern Bayesian modeling enables us to develop custom methods to analyze complex data (Gelman et al., 2003; Bishop, 2006; Murphy, 2013). We use a model to encode the types of patterns we want to discover in the data—either to predict about future data or explore existing data—and then use a posterior inference algorithm to uncover the realization of those patterns that underlie the observations. Innovations in scalable inference allow us to use Bayesian models to analyze massive data (Hoffman et al., 2013; Welling and Teh, 2011; Ahn et al., 2012; Xing et al., 2013); innovations in generic inference allow us to easily explore a wide variety of models (Ranganath et al., 2014; Wood et al., 2014; Hoffman and Gelman, 2014). Consequently, modern Bayesian modeling has had an impact on many fields, including natural language processing (Teh, 2006), computer vision (Fei-Fei and Perona, 2005), the natural sciences (Pritchard et al., 2000), and the social sciences (Grimmer, 2009).

But, as George Box famously quipped, all models are wrong (Box, 1976). Every Bayesian model will fall short of capturing at least some of the nuances of the true distribution of the data. This is the important problem of model mismatch, and it is prevalent in nearly every application of modern Bayesian modeling. (Even if a model is not wrong in theory, which is rare, it is often wrong in practice, where some data are inevitably corrupted such as by measurement error or other problems.) One way to cope with model mismatch is to refine our model, diagnosing how it falls short and trying to fix its issues. To this end, diagnostic tools such as posterior predictive checks are crucial (Gelman et al., 1996). They help us weed out systematic directions of model mismatch and guide us to iteratively develop better models.

But refining the model *ad infinitum* is not a solution to model mismatch—taking the process of model refinement to its logical conclusion leaves us with a model as complex as the data we are trying to simplify. Rather, we seek models simple enough to understand the data and to generalize from it, but flexible enough to accommodate its natural complexity. These are models that both discover important predictive patterns in the data and flexibly ignore unimportant issues, such as outliers due to measurement error. This is a trade off: A model that is too flexible will fail to generalize; a model that is too rigid will be lead astray by unsystematic deviations in the data.

To develop appropriately flexible procedures, statisticians have traditionally appealed to *robustness*, the idea that inferences about the data should be “insensitive to small deviations from the assumptions.” (Huber and Ronchetti, 2009). The goal of robust statistics is to safeguard against the kinds of deviations that are too difficult or not important enough to diagnose. One popular approach to robust modeling is to use M-estimators (Huber, 1964), where the basic idea is to reweigh samples to account for data irregularity. Another approach, which we build on, is to replace common distributions with heavy-tailed distributions, distributions that allow for extra dispersion in the data. For example, this is the motivation for replacing a Gaussian with a student’s *t* in robust linear regression (Lange et al., 1989; Fernández and Steel, 1999; Gelman et al., 2003) and robust mixture modeling (Peel and McLachlan, 2000; Svensén and Bishop, 2005). In discrete data, robustness arises via contagious distributions, such as the Dirichlet-multinomial, where seeing one type of observation increases the likelihood of seeing it again. For example, this is the type of robustness that is captured by the bursty topic model of Doyle and Elkan (2009).

Robust models are powerful, but each must be developed on a case-by-case basis. Each is born from an existing model and each requires a researcher to derive a specific algorithm for that model. This is in contrast to the way Bayesian modeling has evolved. As we mentioned above, modern Bayesian modeling is becoming a general methodology for analyzing data. An investigator creates a model for the problem at hand and then uses generic approximate inference methods to analyze data. Robust modeling is not yet generally applicable in the same way.

In this paper we bridge this gap, bringing the idea of robust modeling into the general Bayesian modeling picture. We outline a method for building a robust version of any Bayesian model and derive a generic algorithm for computing with them. We demonstrate that our methods allow us easily to build and use robust Bayesian models, models that are less sensitive to inevitable deviations from their underlying assumptions.

Technical summary. We use two ideas to build robust Bayesian models: localization and empirical Bayes. At its core, a Bayesian model involves a parameter β , a likelihood $p(x_i | \beta)$, a prior over the

parameter $p(\beta | \alpha)$, and a hyperparameter α . In a classical Bayesian model all data are assumed drawn from the parameter (which is assumed drawn from the prior),

$$p(\beta, \mathbf{x}) = p(\beta | \alpha) \prod_{i=1}^n p(x_i | \beta). \quad (1)$$

To make it robust, we turn this classical model into a localized model. In a localized model, each data point is assumed drawn from an individual realization of the parameter $p(x_i | \beta_i)$ and that realization is drawn from the prior $p(\beta_i | \alpha)$,

$$p(\beta, \mathbf{x}) = \prod_{i=1}^n p(\beta_i | \alpha) p(x_i | \beta_i). \quad (2)$$

This is a naturally more heterogeneous and robust model because it can explain unlikely data points by deviations in their individualized parameters. This perspective is not new—it describes and generalizes many existing distributions that are used for robust modeling. For example, the student’s t distribution, Dirichlet-multinomial distributions, and negative Binomial distribution all arise from marginalizing out the local parameter β_i under various prior distributions.

But there is an issue. The model of Equation 1 uses the parameter β to share information across data points; the hyperparameter can be safely fixed, and often is in many applications of Bayesian models. In the localized model of Equation 2, however, each data point is completely independent of the others. Thus, to effectively share information across data we must fit (or infer) the hyperparameter α . This is where the second idea comes in, empirical Bayes (Robbins, 1964; Copas, 1969; Maritz and Lwin, 1989). We develop a general algorithm to optimize the hyperparameter α to maximize the likelihood of the data in the robust model. This algorithm is a central contribution of this paper; it generalizes the case-by-case algorithms of many existing robust models.

We show that our recipe can be used to robustify a wide class of models, including intractable models that rely on approximate posterior inference. As a demonstration, we use our strategy to study robust generalized linear models (McCullagh and Nelder, 1989)—linear regression, Poisson regression, and logistic regression—as well as robust topic models (Blei et al., 2003; Doyle and Elkan, 2009). We find that robust Bayesian models enjoy improved predictive performance and better estimates of unknown quantities.

Organization of this paper. Section 2 briefly reviews classic Bayesian modeling and introduces the idea of localization to robustify a Bayesian model. Section 3 presents several examples of how to apply this idea, developing robust variants of exponential family models, generalized linear models, and topic models. Section 4 describes how to compute with a robust Bayesian model using expectation maximization and nonconjugate variational inference. Finally, Section 5 reports results with several models on both synthetic and real data.

2. A General Method for Robust Bayesian Modeling

We first describe standard Bayesian modeling, and the key ingredients on which we will develop. We then expand on it to develop robust Bayesian modeling.

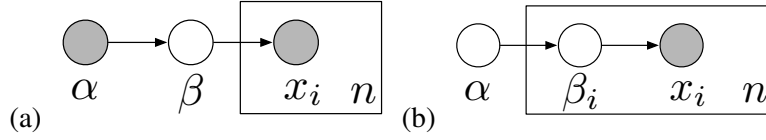


Figure 1: (a) A graphical model for a standard Bayesian model (b) A graphical model for a localized model. By drawing a new parameter β_i for each data point, the localized model allows individual data points to vary more than the standard Bayesian model as in (a). Note the robust model *requires* that we fit the hyperparameter α . Otherwise the data are rendered completely independent.

2.1 Bayesian models

Bayesian modeling uses probability to capture uncertainty around unknown parameters in a statistical model (Gelman et al., 2003). A Bayesian model is a joint distribution of parameters β (also called global latent variables) and a data set \mathbf{x} . In an exchangeable model, this joint factorizes into a product of likelihood terms for each data point $p(x_i | \beta)$ and a prior of the parameters $p(\beta | \alpha)$ (Equation 1). The prior is governed by the hyperparameter α .

Figure 1 (a) shows the graphical model. This model easily generalizes to include conditional models, such as in Bayesian linear regression and logistic regression (Bishop, 2006), local latent variables, such as in Bayesian mixtures (Corduneanu and Bishop, 2001) and topic models (Blei et al., 2003; Blei, 2012), and non-exchangeable data, such as in a hidden Markov model (Rabiner, 1989) or Kalman filter (Kalman, 1960). For now we focus on the simplest setting.

When we use a model we condition on data and compute the corresponding posterior, the conditional distribution of the parameter given the data. We then employ the posterior in an application, such as to form predictions or to investigate properties of the data.

The posterior is proportional to the product of the prior and the data likelihood,

$$p(\beta | \mathbf{x}, \alpha) \propto p(\beta | \alpha) \prod_{i=1}^n p(x_i | \beta). \quad (3)$$

When the number of data is small then the prior plays an important role in the posterior; with more data the likelihood dominates the prior. As the number of data gets large, the posterior becomes peaked and converges to a point mass (Gelman et al., 2003). (Technically, this is only true in finite-dimensional models.) Note this property is agnostic to the “truth”—the posterior will become peaked even if the data did not truly come from the model.

We can use the posterior to form the posterior predictive distribution, the distribution of a new data point conditional on the observed data. The posterior predictive distribution is

$$p(x_{\text{new}} | \mathbf{x}, \alpha) = \int p(x_{\text{new}} | \beta) p(\beta | \mathbf{x}, \alpha) d\beta. \quad (4)$$

It integrates the data likelihood $p(x_{\text{new}} | \beta)$ under the posterior distribution $p(\beta | \mathbf{x}, \alpha)$. The posterior predictive distribution is an important idea in Bayesian modeling. It is used both to form predictions about the future and to check, diagnose, and select models (Geisser and Eddy, 1979; Rubin, 1984; Gelman et al., 1996).

2.2 Robust Bayesian models

One of the virtues of Bayesian modeling is that the model’s prediction about the future does not rely on a single point estimate of the parameter, and averaging over the posterior can mitigate overfitting. However, the Bayesian pipeline does not explicitly aim for a good predictive distribution on future data—the posterior predictive of Equation 4 is the true distribution of unseen data only when the chosen model represents the true distribution of the data (Bernardo and Smith, 1994).

In practice, we use models to simplify a complex data generating process (Box, 1980). Thus there is always a mismatch between the posterior predictive distribution and the true distribution of future data. This motivates the philosophy behind robust statistics (Huber and Ronchetti, 2009), which aims to develop methods that are not sensitive to small changes in the modeling assumptions.

We develop robust Bayesian models, models that can usefully accommodate deviation from the underlying assumptions. We will use two ideas: localization and empirical Bayes.

The localized model. The first idea behind our method is *localization*. As we discussed above, a traditional Bayesian model independently draws the data \mathbf{x} conditional on the parameter β , which is drawn from the prior. The localized model relaxes this to a hierarchical model, which governs each data point with an individual parameter β_i that is drawn from the prior. The joint distribution of the individualized parameters $\beta = \beta_{1:n}$ and data is in Equation 2. The localized model can capture heterogeneity in the data; it explains atypical data that deviates from the norm (i.e., outliers) by deviations in their parameters.

One way to view the localized model is as one where each data point is drawn independently and identically distributed (IID) from an integrated likelihood,

$$p(x_i | \alpha) = \int p(x_i | \beta_i) p(\beta_i | \alpha) d\beta_i. \quad (5)$$

When the parameter β_i controls the dispersion of the data, this results in a heavier-tailed distribution than the original (unintegrated) observation model. For example, suppose the original model assumes data are from a Gaussian distribution. Localizing the variance under an inverse gamma prior reveals the student’s t-distribution, a commonly-used distribution for adding robustness to models of continuous data (Gelman et al., 2003). In Section 3 we show that many methods in robust statistics can be interpreted in this way.

Empirical Bayes estimation. Crucially, localization requires that we infer the hyperparameter—it is now α that carries common information about the data. We can see this graphically. Localization takes us from the traditional Bayesian model in Figure 1 (a) to the model in Figure 1 (b). In Figure 1 (b), fixing α renders the data completely independent.

We fit the hyperparameter with maximum likelihood. This amounts to finding a prior on β_i that maximizes the integrated likelihood of the data in the robust model,

$$\hat{\alpha} = \arg \max_{\alpha} \sum_{i=1}^n \log \int p(x_i | \beta_i) p(\beta_i | \alpha) d\beta_i. \quad (6)$$

Here we marginalize out the individualized parameters β_i from Equation 2. Thus fitting a robust model implicitly optimizes the predictive distribution. One recently related work, population empirical Bayes (Kucukelbir and Blei, 2015), also optimizes the predictive distribution to mitigate model misspecification.)

Directly optimizing the likelihood can be difficult because of the integral inside the log function. We defer this issue to Section 4, where we show how to optimize with a combination of variational inference (Jordan et al., 1999) and the expectation maximization algorithm (Dempster et al., 1977). Our approach—localizing a global variable and then fitting its prior—allows us to develop robust variants of many Bayesian models.

Fitting the hyperparameter is a type of empirical Bayes estimation (Robbins, 1964; Efron and Morris, 1973, 1975; Robbins, 1980; Carlin and Louis, 2000a,b) on the localized model. Generally, empirical Bayes uses data to estimate a hyperparameter. Specifically, setting α to maximize Equation 6 gives a parametric empirical Bayes estimate of the prior on β_i (Morris, 1983; Kass and Steffey, 1989).¹ While localization is not typically part of the empirical Bayes recipe—one can just as easily fit the hyperparameters to maximize the marginal probability of the data under the original Bayesian model—hierarchical models of the form of Figure 1 (b) appear extensively in the empirical Bayes literature (Efron and Morris, 1973, 1975; Morris, 1983; Kass and Steffey, 1989; Efron, 1996; Carlin and Louis, 2000b; Efron, 2010). Other names for the localized model include a compound sampling model, a two-stage sampling model, and an empirical Bayes model. For perspective on empirical Bayes, see the excellent review by Carlin and Louis (2000a).

The predictive distribution. With a localized model and estimated hyperparameter, we form predictions about future data with the corresponding predictive distribution

$$p(x^* | \hat{\alpha}) = \int p(x^* | \beta^*) p(\beta^* | \hat{\alpha}) d\beta^*.$$

Notice this has the same form as the likelihood term in the objective of Equation 6.

This predictive procedure motivates our approach to localize parameters and then fit hyperparameters with empirical Bayes. One goal of Bayesian modeling is to make better predictions about unseen data by using the integrated likelihood, and the traditional Bayesian approach of Equation 4 is to integrate relative to the posterior distribution. For making predictions, however, the traditional Bayesian approach is mismatched because the posterior is not formally optimized to give good predictive distributions of each data point. (As we mentioned, it is only the right procedure when the data comes from the model.)

In contrast, the robust modeling objective of Equation 6—the objective that arises from localization and empirical Bayes—explicitly values a distribution of β that gives good predictive distributions for each data point, even in the face of model mismatch.

In this section we presented a general approach to building robust Bayesian models. We next outline several examples (Section 3), a generic algorithm for computing with them (Section 4), and a case study that demonstrates the improved performance of robust models (Section 5).

1. Alternatively, we can put priors on α to seek maximum a prior (MAP) estimate or full Bayesian treatment. In this paper however, for simplicity, we focus on the maximum likelihood estimate. We emphasize that all these choices retain a model of uncertainty around the parameter β .

3. Practicing Robust Bayesian Modeling

Machine learning and Bayesian statistics have produced a rich constellation of Bayesian models and general algorithms for computing about them (Gelman et al., 2003; Bishop, 2006; Murphy, 2013). We have described an approach to robustifying Bayesian models in general, without specifying a model in particular. The recipe is to form a model, localize its parameters, and then fit the hyperparameters with empirical Bayes. In Section 4, we will develop general algorithms for implementing this procedure. First we describe some of the types of models that an investigator may want to make robust, and give some concrete examples.

Many models contain hidden variables within $p(x_i | \beta)$, termed *local variables* in Hoffman et al. (2013). Examples of local variables include document-level variables in topic models (Blei et al., 2003), component assignments in mixture models (McLachlan and Peel, 2000), and per-data point component weights in latent feature models (Salakhutdinov and Mnih, 2008). We will show how to derive and compute with robust versions of Bayesian models with local hidden variables. For example, the bursty topic models of Doyle and Elkan (2009) and the robust mixture models of Peel and McLachlan (2000) can be seen as variants of robust Bayesian models.

Some models contain two kinds of parameters, and the investigator may only want to localize one of them. For example the Gaussian is parameterized by a mean and variance. As we have discussed, when developing a robust Gaussian model we need only localize the variance; this results in the student’s t-distribution. These settings are straightforward. Divide the parameter into two parts $\beta = [\beta_1, \beta_2]$ and form a prior that divides similarly $\alpha = [\alpha_1, \alpha_2]$. Localize one of the parameters and estimate its corresponding hyperparameter.

Last, many models are not fully generative, but draw each data point conditional on covariates. Examples include linear regression, logistic regression, and all other generalized linear models (McCullagh and Nelder, 1989). This setting is also straightforward in our framework. We will show how to build robust generalized linear models, such as Poisson regression and logistic regression, and how to fit them with our algorithm.

We now show how to build robust versions of several types of Bayesian models. These models connect to existing robust methods in the research literature, each one originally developed on a case-by-case basis. In contrast, our approach and algorithms generalize to many models.

3.1 Conjugate exponential families

The simplest Bayesian model draws data from an exponential family and draws its parameter from the corresponding conjugate prior. The density of the exponential family is

$$p(x | \eta) = h(x) \exp \left\{ \eta^\top t(x) - a_x(\eta) \right\},$$

where $t(x)$ is the vector of sufficient statistics, η is the natural parameter, and $h(x)$ is the base measure. The log normalizer $a_x(\eta)$ ensures that the density integrates to one,

$$a_x(\eta) = \int \exp \left\{ \eta^\top t(x) \right\} dx. \quad (7)$$

The density is defined by the sufficient statistics and natural parameter. When x_i comes from an exponential family we use the notation $x_i \sim \text{EXPfam}(\eta, t(x))$.

Every exponential family has a conjugate prior (Diaconis and Ylvisaker, 1979). Suppose the data come from $x_i \sim \text{EXPfam}(\eta, x)$, i.e., the exponential family where x is its own sufficient statistic. The conjugate prior on η is

$$p(\eta | \alpha) = h(\eta) \exp \left\{ \alpha^\top [\eta, -a_x(\eta)] - a_\eta(\alpha) \right\}.$$

This is an exponential family whose sufficient statistics concatenate the parameter η and the negative log normalizer $-a_x(\eta)$ in the likelihood of the data. The parameter divides into two components $\alpha = [\alpha_1, \alpha_2]$ where α_1 has the same dimension as η and α_2 is a scalar. Note the difference between the two log normalizers: $a_x(\eta)$ normalizes the data likelihood; $a_\eta(\alpha)$ normalizes the prior. In our notation, $\eta \sim \text{EXPfam}([\alpha_1, \alpha_2], [\eta, -a_x(\eta)])$.

Given data \mathbf{x} , the posterior distribution of η is in the same exponential family as the prior,

$$\eta | \mathbf{x}, \alpha \sim \text{EXPfam}([\alpha_1 + \sum_i x_i, \alpha_2 + n], [\eta, -a_x(\eta)]). \quad (8)$$

This describes the general set-up behind all commonly used conjugate prior-likelihood pairs, such as the Beta-Bernoulli, Dirichlet-Multinomial, Gamma-Poisson, and others. Each of these models first draws a parameter η from a conjugate prior, and then draws n data points x_i from the corresponding exponential family.

Following Section 2.2, we define a generic localized conjugate exponential family,

$$\begin{aligned} \eta_i &\sim \text{EXPfam}([\alpha_1, \alpha_2], [\eta, -a_x(\eta)]) \\ x_i &\sim \text{EXPfam}(\eta_i, x). \end{aligned}$$

We fit the hyperparameters α to maximize the likelihood of the data in Equation 6. In a conjugate exponential-family pair, the integrated likelihood has a closed form expression. It is a ratio of normalizers,

$$\begin{aligned} p(x_i | \alpha) &= \int p(x_i | \eta) p(\eta | \alpha) d\eta \\ &= \exp \{ a_\eta([\alpha_1 + x_i, \alpha_2 + 1]) - a_\eta([\alpha_1, \alpha_2]) \}. \end{aligned} \quad (9)$$

In this setting the log likelihood of Equation 6 is

$$\mathcal{L}(\alpha_1, \alpha_2; \mathbf{x}) = (\sum_{i=1}^n a_\eta(\alpha_1 + x_i, \alpha_2 + 1)) - n a_\eta(\alpha_1, \alpha_2).$$

This general story connects to specific models in the research literature. As we described above, it leads to the student's t-distribution when the data come from a Gaussian with a fixed mean and localized variance $x_i \sim \mathcal{N}(\mu, \sigma_i^2)$, and when the variance σ_i^2 has an inverse Gamma prior. It is “robust” when the dispersion parameter is individualized; the model can explain outlier data by a large dispersion. Fitting the hyperparameters amounts to maximum likelihood estimation of the student's t-distribution.

This simple exchangeable model also connects to James-Stein estimation, a powerful method from frequentist statistics that can be understood as an empirical Bayes procedure (Efron and Morris, 1973; Efron, 2010). Here the data are from a Gaussian with fixed variance and localized mean $x_i \sim \mathcal{N}(\mu_i, \sigma^2)$, and the mean μ_i has a Gaussian prior $\mu_i \sim \mathcal{N}(0, \lambda^2)$. (This is the conjugate prior.) We recover a shrinkage estimate similar to James-Stein estimation by fitting the prior variance with maximum likelihood.

3.2 Generalized linear models

Generalized linear models (GLM) are conditional models of a response variable y given a set of covariates x (McCullagh and Nelder, 1989). Specifically, canonical GLMs assume the response is drawn from an exponential family with natural parameters equal to a linear combination of coefficients w and covariates.

$$\begin{aligned}\eta_i &= w^\top x_i \\ y_i &\sim \text{EXPfam}(\eta_i, y).\end{aligned}$$

Many conditional models are generalized linear models; some of the more common examples are linear regression, logistic regression, and Poisson regression. For example, Poisson regression sets $\eta_i = w^\top x_i$ to be the log of the rate of the Poisson distribution of the response. (This fits our notation—the log of the rate is the natural parameter of the Poisson.)

We use the method from Section 2.2 to construct a robust GLM. We replace the deterministic natural parameter with a Gaussian random variable,

$$\eta_i \sim \mathcal{N}(w^\top x_i, \lambda^2).$$

Its mean is the linear combination of coefficients and covariates, and we fit the coefficients w and variance λ^2 with maximum likelihood. This model captures heterogeneity among the response variables. It accommodates outliers and enables more robust estimation of the coefficients.

Unlike Section 3.1, however, this likelihood-prior pair is typically not conjugate—the conditional distribution of η_i will not be a Gaussian and the integrated likelihood is not available in closed form. We will handle this nonconjugacy with the algorithms in Section 4.

In our examples we will always use Gaussian priors. However, we can replace them with other distributions of the reals. We can interpret the choice of prior as a regularizer on a per-data point “shift parameter.” This is the idea behind She and Owen (2011) (for linear regression) and Tibshirani and Manning (2013) (for logistic regression). These papers set up a shift parameter with L_1 regularization, which corresponds to a Laplace prior in the models described here.

We give two examples of robust generalized linear models: robust logistic regression and robust Poisson regression. (We discuss robust linear regression below, when we develop robust overdispersed GLMs.)

Example: Robust logistic regression. In logistic regression y_i is a binary response,

$$y_i \sim \text{Bernoulli}(\sigma(w^\top x_i))$$

where $\sigma(t) = (1 + \exp(-t))^{-1}$ is the logistic function; it maps the reals to the unit interval.

We apply our method to form robust logistic regression. The model is

$$\begin{aligned}\eta_i &\sim \mathcal{N}(w^\top x_i, \lambda^2) \\ y_i &\sim \text{Bernoulli}(\sigma(\eta_i)),\end{aligned}$$

where we estimate w and λ^2 by maximum likelihood. This model is robust to outliers in the sense that the per-data distribution on η_i allows individual data to be “misclassified” by the model. As we mentioned for the general case, the Gaussian prior is not conjugate to the logistic likelihood; we can use the approximations we develop in Section 4 to compute with this model.

There are several existing variants of robust logistic regression. [Pregibon \(1982\)](#) and [Stefanski et al. \(1986\)](#) use M-estimators ([Huber, 1964](#)) to form more robust loss functions, which are designed to reduce the contribution from possible outliers. Our approach can be viewed as a likelihood-based robust loss function, where we integrate the likelihood over the individual parameter β_i . This induces uncertainty around individual observations, but without explicitly defining the form of a robust loss.

Closer to our method is the shift model of [Tibshirani and Manning \(2013\)](#), who use L_1 regularization, as well as the more recent theoretical work of [Feng et al. \(2014\)](#). We note that none of this work estimates hyperparameters λ . Using empirical Bayes to estimating such hyperparameters is at the core of our procedure, and we found in practice that it is an important component.

Example: Robust Poisson regression. The Poisson distribution is an exponential family on positive integers. Its parameter is a single a positive value, called the rate. Poisson regression is a conditional model of a count-valued response,

$$y_i \sim \text{Poisson} \left(\exp \left\{ w^\top x_i \right\} \right).$$

Following our technique, a robust Poisson regression model is

$$\begin{aligned}\eta_i &\sim \mathcal{N}(w^\top x_i, \lambda^2) \\ y_i &\sim \text{Poisson}(\exp \{\eta_i\}).\end{aligned}$$

As for all the models above, this allows individual data points to deviate from their expected value. Notice this is particularly important when the data are Poisson, where the variance equals the mean. In classical Poisson regression, the mean is $\mathbb{E}[Y_i | x_i] = w^\top x_i$ and the variance is $\text{Var}[Y_i | x_i] = w^\top x_i$. Here we can marginalize out the per-data point parameter in the robust model to reveal a larger variance,

$$\begin{aligned}\mathbb{E}[Y_i | x_i] &= \exp \left\{ w^\top x_i + \lambda^2/2 \right\} \\ \text{Var}[Y_i | x_i] &= \exp \left\{ w^\top x_i + \lambda^2/2 \right\} + (\exp \{\lambda^2\} - 1) \exp \left\{ 2w^\top x_i + \lambda^2 \right\}.\end{aligned}$$

These marginal moments comes from the fact that $\exp \{w^\top x_i\}$ follows a log normal. Intuitively, as the prior variance λ^2 goes to zero they approach the moments for classical Poisson regression.

Robust Poisson regression relates to negative binomial regression (Cameron and Trivedi, 2013), which also introduces per-data flexibility. Negative binomial regression is

$$\begin{aligned}\epsilon_i &\sim \text{Gamma}(a, b) \\ \eta_i &= w^\top x_i + \log \epsilon_i \\ y_i &\sim \text{Poisson}(\exp \{\eta_i\}).\end{aligned}$$

In this notation, this model assumes that ϵ_i drawn from a Gamma distribution and further estimates its parameters with empirical Bayes. In our study, we found that our robust Poisson model outperformed negative binomial regression; we suspect this is because of the empirical Bayes step. (See Section 5 for details.)

3.3 Overdispersed generalized linear models

An overdispersed exponential family extends the exponential family with a dispersion parameter, a positive scalar that controls the variance. An overdispersed exponential family is

$$p(y | \eta, \tau) = h(y, \tau) \exp \left\{ \frac{\eta^\top t(y) - a_y(\eta)}{\tau} \right\}, \quad (10)$$

where τ is the dispersion. We denote this $y \sim \text{OVEXPfam}(\eta, t(y), \tau)$. One example of an overdispersed exponential family is the Gaussian—the parameter η is the mean and τ is the variance. (We can also form a Gaussian in a standard exponential family form, where the natural parameter combines the mean and the variance.)

An overdispersed GLM draws the response from an overdispersed exponential family (Jorgensen, 1987). Following our method, we can localize the dispersion parameter τ to create a robust overdispersed GLM. In this case we draw τ from a Gamma,

$$\begin{aligned}\tau_i &\sim \text{Gamma}(a, b) \\ y_i &\sim \text{OVEXPfam}(w^\top x_i, y_i, \tau_i)\end{aligned}$$

Localizing the dispersion connects closely with our intuitions around robustness. An outlier is one that is overdispersed relative to what the model expects; thus a per-data point dispersion parameter can easily accommodate outliers.

For example consider the GLM that uses a unit-variance Gaussian with unknown mean (an exponential family). This is classical linear regression. Now form the overdispersed GLM—this is linear regression with unknown variance—and localize the dispersion parameter under the Gamma prior. Marginalizing out the per-data dispersion, this model draws the response from a student's t,

$$y_i \sim t_{2a}(\cdot | w^\top x_i, 1/(ab))$$

where the student's t notation $t_\nu(y | \mu, \phi)$ is

$$t_\nu(y | \mu, \phi) = \frac{\Gamma(\frac{\nu+1}{2})}{\Gamma(\frac{\nu}{2})\sqrt{\pi\nu\phi}} \left(1 + \frac{1}{\nu} \frac{(y - \mu)^2}{\phi} \right)^{-\frac{\nu+1}{2}}.$$

This is a robust linear model, an alternative parameterization of the model of [Lange et al. \(1989\)](#) and [Fernández and Steel \(1999\)](#).

Intuitively, localized overdispersed models lead to heavy-tailed distributions because it is the dispersion that varies from data point to data point. When working with the usual exponential family (as in Section 3.1 and Section 3.2), the heavy-tailed distribution arises only when the dispersion is contained in the natural parameter; note this is the case for our previous examples, logistic regression and Poisson regression. Here, the dispersion is localized by design.

3.4 Generative models with local and global variables

We have described how to build robust versions of simple models—conjugate prior-exponential families, generalized linear models, and overdispersed generalized linear models. Modern machine learning and Bayesian statistics, however, has developed much more complex models, using exponential families and GLMs as components in structured joint distributions ([Bishop, 2006](#); [Murphy, 2013](#)). Examples include models of time series, hierarchies, and mixed-membership. Further, thanks to efficient and general approximate inference methods, such as Markov chain Monte Carlo ([Robert and Casella, 2004](#)) or variational inference ([Jordan et al., 1999](#)), investigators need not be hampered by the difficulty of computing the exact posterior. They can freely express their assumptions in the model and then approximate the posterior. We now describe how to build robust versions of such models.

Each complex Bayesian model is a joint distribution of hidden and observed variables. [Hoffman et al. \(2013\)](#) divide the variables into two types: local variables \mathbf{z} govern the distribution of each data point; global variables β govern the distribution of all the data. A model with local and global variables is

$$p(\beta, \mathbf{z}, \mathbf{x}) = p(\beta) \prod_{i=1}^n p(z_i, x_i | \beta).$$

This describes a wide class of models, including Bayesian mixture models ([Ghahramani and Beal, 2000](#); [Attias, 2000](#)), hierarchical mixed membership models ([Blei et al., 2003](#); [Erosheva et al., 2007](#)), and Bayesian nonparametric models ([Antoniak, 1974](#); [Teh et al., 2006](#)).²

To make a robust Bayesian model, we localize some of its global variables—we bring them inside the likelihood of each data point, endowing each with a prior, and then fit that prior with empirical Bayes. Localizing global variables accommodates outliers by allowing how each data point expresses the global patterns to deviate from the norm. Figure 2 shows the graphical model where β_i is the localized global variable and z_i is the original local variable.

As an example, consider latent Dirichlet allocation (LDA) ([Blei et al., 2003](#)). LDA is a mixed-membership model of a collection of documents; each document is a collection of words. LDA draws each document from a mixture model, where the mixture proportions are document-specific and the mixture components (or “topics”) are shared across the collection.

2. Again we restrict ourselves again to exchangeable models. Non-exchangeable models only contain global variables, such as time series models ([Rabiner, 1989](#); [Fine et al., 1998](#); [Fox et al., 2011](#); [Paisley and Carin, 2009](#)) and models for network analysis [Airoldi \(2007\)](#); [Airoldi et al. \(2009\)](#).

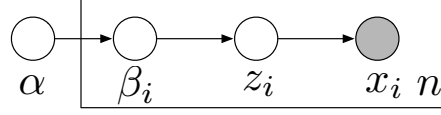


Figure 2: Robust modeling with with local latent variable β_i, z_i and observation $x_i, i = 1, \dots, n$.

Formally, define each topic β_k to be a distribution over a fixed vocabulary and fix the number of topics K . LDA assumes that a collection of documents comes from the following process:

1. Draw topic $\beta_k \sim \text{Dir}(\eta)$ for $k = 1, 2, \dots, K$.
2. For each document d ,
 - (a) Draw topic proportions $\theta_d \sim \text{Dir}(\alpha)$.
 - (b) For each word n ,
 - i. Draw topic assignment $z_{dn} \sim \text{Mult}(\theta_d)$.
 - ii. Draw word $w_{dn} \sim \text{Mult}(\beta_{z_{dn}})$.

The local variables are the topic assignments and topic proportions; they are local to each document. The global variables are the topics; they are involved in the distribution of every document.

For simplicity, denote steps (a) and (b) above as $\mathbf{w}_d \sim \text{LDA}(\beta, \alpha)$, where $\beta = \{\beta_1, \dots, \beta_K\}$. To make LDA robust, we localize the topics. Robust LDA still draws each document from a mixture of K topics, but the topics are themselves drawn anew for each document. Each per-document topic β_{dk} is drawn from its own distribution with a “master” topic parameter η_k . Localized LDA draws each document from the following process:

1. Draw per-document topic $\beta_{dk} \sim \text{Dir}(\eta_k)$, for $k = 1, 2, \dots, K$.
2. Draw $\mathbf{w}_d \sim \text{LDA}(\beta_d, \alpha)$.

We then fit the hyperparameters η_k , which are Dirichlet parameters for each topic. These hyperparameters are the corpus-wide topics; in the generative process they are perturbed to form the per-document topics.

This robust LDA model is roughly equivalent to the topic model proposed in [Doyle and Elkan \(2009\)](#), which accounts for “burstiness” in the distribution of documents. Burstiness, also called contagion, is the idea that when we see one word in a document we are more likely to see that word again. This is a property of the marginal distribution of words obtained by integrating out a Dirichlet variable, which is called a Dirichlet-multinomial compound distribution.

Burstiness is a good property in topic models. In a traditional topic model, repeated terms provide increased evidence for the importance of that term in its topic. In contrast, the bursty topic model can partly explain repeated terms by per-document burstiness. Consequently, the model does not overestimate that term’s importance in its topic.

LDA is just one example. With this method we can build robust versions for mixtures, time-series models, Bayesian nonparametric models, and many others. As for GLMs, we have a choice of what to localize. In topic models we localized the topics, resulting in a bursty topic model ([Doyle](#)

and Elkan, 2009). In other cases we can localize dispersion parameters, such as in robust Gaussian mixtures (Svensén and Bishop, 2005).

4. Fitting robust Bayesian models

We have shown how to robustify a wide class of Bayesian models. The remaining question is how to analyze data with them. We now show how to adapt existing approximate inference algorithms to compute with robust Bayesian models. We provide a general strategy that can be used with simple models (e.g., conjugate exponential families), nonconjugate models (e.g., generalized linear models), and complex models with local and global variables (e.g., LDA).

The key algorithmic problem is to fit the hyperparameter in Equation 6. We use an expectation-maximization (EM) algorithm to fit the model (Dempster et al., 1977). In many cases, some of the necessary quantities are intractable to compute. We approximate them with variational methods (Jordan et al., 1999; Wainwright and Jordan, 2008).

Consider a generic robust Bayesian model. The data come from an exponential family and the parameter from a general prior,

$$\begin{aligned}\beta_i &\sim p(\cdot | \alpha) \\ x_i &\sim \text{EXPfam}(x_i, \beta_i).\end{aligned}$$

Note this is not necessarily the conjugate prior. Following Section 2.2, we fit the hyperparameters α according to Equation 6 to maximize the marginal likelihood of the data.

We use a generalization of the EM algorithm, derived via variational methods. Consider an arbitrary distribution of the localized variables $q(\beta_{1:n})$. With Jensen’s inequality, we use this distribution to bound the marginal likelihood. Accounting for the generic exponential family, the bound is

$$\mathcal{L}(\alpha) \geq \sum_{i=1}^n \mathbb{E}_q[\beta_i]^\top x_i - \mathbb{E}_q[a(\beta_i)] + \mathbb{E}_q[\log p(\beta_i | \alpha)] - \mathbb{E}_q[\log q(\beta_i)]. \quad (11)$$

This is a variational bound on the marginal likelihood (Jordan et al., 1999), also called the ELBO (“the Evidence Lower BOund”). Variational EM optimizes the ELBO by coordinate ascent—it iterates between optimizing with respect to $q(\beta_{1:n})$ and with respect to the hyperparameters α .

Optimizing Equation 11 with respect to $q(\beta_{1:n})$ minimizes the Kullback-Leibler divergence between $q(\beta_{1:n})$ and the exact posterior $p(\beta_{1:n} | \mathbf{x})$.

In a localized model, the posterior factorizes,

$$p(\beta_{1:n} | \mathbf{x}, \alpha) = \prod_{i=1}^n p(\beta_i | x_i, \alpha).$$

Each factor is a posterior distribution of the per-data point parameter, conditional on the data point and the hyperparameters. If each posterior factor is computable then we can perform an exact E-step, where we set $q(\beta_i)$ equal to the exact posterior. In the context of empirical Bayes models, this is the algorithm suggested by Carlin and Louis (2000b).

In many cases the exact posterior will not be available. In these cases we use variational inference (Jordan et al., 1999). We set $q(\beta_i)$ to be a parameterized family of distributions over the i th variable β_i and then optimize Equation 11 with respect to $q(\cdot)$. This is equivalent to finding the distributions $q(\beta_i)$ that are closest in KL divergence to the exact posteriors $p(\beta_i | x_i, \alpha)$. It is called a variational E-step.

The M-step maximizes Equation 11 with respect to the hyperparameter α . It solves the following optimization problem,

$$\hat{\alpha} = \arg \max_{\alpha} \sum_{i=1}^n \mathbb{E}_q [\log p(\beta_i | \alpha)]. \quad (12)$$

At first this objective might look strange—the data do not appear. But notice the expectation is taken with respect to the (approximate) posterior $p(\beta_i | x_i, \alpha)$ for each localized parameter β_i ; this posterior summarizes the i th data point. We solve this optimization with gradient methods.

Nonconjugate models. As we described above, the E-step amounts to computing $p(\beta_i | x_i, \alpha)$ for each data point. When the prior and likelihood form a conjugate-pair (Section 3.1) then we can compute an exact E-step.³ For many models, however, the E-step is not computable and we need to approximate $p(\beta_i | x_i, \alpha)$.

One type of complexity comes from nonconjugacy, where the prior is not conjugate to the likelihood. As a running example, robust GLM models (Section 3.2) are generally nonconjugate. (Robust linear regression is an exception.) In a robust GLM, the goal is to find optimal coefficients w and variance λ^2 that maximizes the robust GLM ELBO,

$$\mathcal{L}(w, \alpha) = \sum_{i=1}^n \mathbb{E}_q [\eta_i]^\top y_i - \mathbb{E}_q [a(\eta_i)] + \mathbb{E}_q [\log p(\eta_i | w^\top x_i, \lambda^2)] - \mathbb{E}_q [\log q(\eta_i)]. \quad (13)$$

The latent variables are η_i , the per-data point natural parameters. Their priors are Gaussians, each with mean $w^\top x_i$ and variance λ^2 .

In an approximate E-step, we hold the parameters w and λ^2 fixed and approximate the per-data point posterior $p(\eta_i | y_i, x_i, w, \lambda^2)$. In theory, the optimal variational distribution is

$$q(\eta_i) \propto \exp \left(\eta_i y_i - a(\eta_i) + \log p(\eta_i | w^\top x_i, \alpha) \right).$$

But this does not easily normalize.

We address the problem with Laplace variational inference (Wang and Blei, 2013). Laplace variational inference approximates the optimal variational distribution with

$$q(\eta_i) \approx \mathcal{N}(\hat{\eta}_i, -h^{-1}(\hat{\eta}_i)). \quad (14)$$

The value $\hat{\eta}_i$ maximizes the following function,

$$f(\eta_i) = \eta_i y_i - a(\eta_i) + \log p(\eta_i | w^\top x_i, \lambda^2), \quad (15)$$

3. In this setting we can also forgo the EM algorithm and directly optimize the marginal likelihood with gradient methods—the integrated likelihood is computable in conjugate-exponential family pairs (Equation 9).

Algorithm 1: Variational EM for a robust GLM.

```

Initialize  $w$  and  $\alpha$ .
repeat
  for  $i \in \{1, 2, \dots, n\}$  do
    | Update variational distribution  $q(\eta_i)$  (Equation 14).
  end
  Update  $w$  and  $\alpha$  using gradient ascent (Equation 16).
until the ELBO converges.

```

where $h(\cdot)$ is the Hessian of that function. Finding the $\hat{\eta}_i$ can be done using many off-the-shelf optimization routines, such as conjugate gradient.

Given these approximations to the variational distribution, the M-step estimates w and α ,

$$[\hat{w}, \hat{\alpha}] = \arg \max_{w, \alpha} \sum_{i=1}^n \mathbb{E}_{q(\eta_i)} \left[\log p(\eta_i | w^\top x_i, \alpha) \right]. \quad (16)$$

In robust GLMs, the prior is Gaussian and we can compute the expectation in closed form. Algorithm 1 shows the algorithm. In general nonconjugate models, however, we may need to approximate the expectation. Here we use the multivariate delta method to approximate the objective (Bickel and Doksum, 2007; Wang and Blei, 2013).

Complex models with local and global variables. We can also use variational inference when we localize more complex models, such as mixture models or topic models. Here we outline a strategy that roughly follows Hoffman et al. (2013).

We discussed complex Bayesian models in Section 3.4; see Figure 2. Observations are $x_{1:n}$ and local latent variables are $z_{1:n}$ and $\beta_{1:n}$. (We have localized the global variable β .) The joint distribution is

$$p(\beta_{1:n}, x_{1:n}, z_{1:n} | \alpha) = \prod_{i=1}^n p(\beta_i | \alpha) p(z_i, x_i | \beta_i). \quad (17)$$

Assume these distributions are in the exponential family,

$$p(z_i, x_i | \beta_i) = h_\ell(z_i, x_i) \exp \{ \beta_i^\top t_\ell(z_i, x_i) - a_\ell(\beta_i) \} \quad (18)$$

$$p(\beta_i | \alpha) = h(\beta_i) \exp \{ \alpha^\top t(\beta_i) - a(\alpha) \}, \quad (19)$$

The term $t(\beta_i)$ has the form $t(\beta_i) = [\beta_i, -a_\ell(\beta_i)]$. It is conjugate to $p(z_i, x_i | \beta_i)$.

This model satisfies *conditional conjugacy*. The conditional posterior $p(\beta_i | z_i, x_i)$ in the same family as the prior $p(\beta_i | \alpha)$. We emphasize that this differs from classical Bayesian conjugacy—when we marginalize out z_i the posterior of β_i is no longer in the same family.

The goal is to find the optimal α that maximizes the ELBO,

$$\mathcal{L}(\alpha) = \sum_{i=1}^n \mathbb{E}_q [\log p(x_i, z_i | \beta_i)] + \mathbb{E}_q [p(\beta_i | \alpha)] - \mathbb{E}_q [\log p(z_{1:n}, \beta_{1:n})], \quad (20)$$

Algorithm 2: Variational EM for robust models with local and global variables.

```

Initialize  $\alpha$ .
repeat
  for  $i \in \{1, 2, \dots, n\}$  do
    Update  $q(\beta_i)$  (Equation 22).
    Update  $q(z_i)$  (Equation 23).
  end
  Plug  $q(\beta_i)$  and  $q(z_i)$  into Equation 20 and update parameter  $\alpha$  with gradient ascent.
until the ELBO converges.

```

where the distribution $q(z_{1:n}, \beta_{1:n})$ contains both types of latent variables.

To specify $q(\cdot)$, we use the mean-field family. It assumes a fully factorized distribution,

$$q(z_{1:n}, \beta_{1:n}) = \prod_{i=1}^n q(\beta_i)q(z_i). \quad (21)$$

In the E-step we optimize the variational distribution. We iterate between optimizing $q(z_i)$ and $q(\beta_i)$ for each data point. Because of conditional conjugacy, these updates are in closed form,

$$q(\beta_i) \propto h(\beta_i) \exp \left((\alpha + [\mathbb{E}_{q(z_i)} [t(z_i, x_i)], 1])^\top t(\beta_i) \right), \quad (22)$$

$$q(z_i) \propto h(z_i, x_i) \exp \left(([t(z_i, x_i), 1])^\top \mathbb{E}_{q(\beta_i)} [t(\beta_i)] \right). \quad (23)$$

Each $q(\cdot)$ will be in the same exponential family as its complete conditional. For fixed α , the variational distribution converges as we iterate between these updates.

In the M-step, we plug the fitted variational distributions into Equation 20 and optimize α . Algorithm 2 shows the algorithm. Using this general method, for example, is a way to fit bursty topic models or robust mixture models.

5. Empirical Study

We study two types of robust Bayesian models—robust generalized linear models and robust topic models. We present results on both simulated and real-world data. For each model, we use the general algorithmic strategy of Section 4. We find robust models outperform their non-robust counterparts.

5.1 Robust generalized linear models

We first study the robust generalized linear models (GLMs) of Section 3.2 and Section 3.3—linear regression, logistic regression, and Poisson regression. Each involves modeling a response variable y_i conditional on a set of covariates x_i . The response is governed (possibly through a localized variable) by a linear combination with coefficients $w^\top x_i$.

We study robust GLMs with simulated data. Our goal is to determine whether our method for robust modeling gives better models when the training data is corrupted by noise. The idea is to fit various models to corrupted training data and then evaluate those models on uncorrupted test data.

Each simulation involves a problem with five covariates. We first generated true coefficients w (a vector with five components) from a standard normal; we then generated 500 test data points (y_i, x_i) from the true model. For each data point, the five covariates are each drawn from $\text{Unif}[-5, 5]$ and the form of the response depends on which model we are studying. Next, we generate corrupted training sets, varying the amount of corruption. (How we corrupt the training set changes from problem to problem; see below.) Finally, we fit robust and non-robust models to each training set and evaluate their corresponding predictions on the test set. We repeat the experiments with different random seeds 50 times.

Robust GLMs form better predictions than traditional GLMs in the face of corrupted training data.⁴ Further, as expected, the performance gap increases as the training data is more corrupted.

Linear regression. We first use simulated data to study linear regression. In the true model $y_i | x_i \sim \mathcal{N}(w^\top x_i + b, 0.02)$. In the corrupted training data, we set a noise level k and generate data from $y_i \sim \mathcal{N}(w^\top x_i + b, \sigma_i + 0.02)$, where $\sigma_i \sim \text{Gamma}(k, 1)$. As k gets larger, there are more outliers. We simulated training sets with different levels of outliers; we emphasize the test data does not include outliers.

We compare robust linear regression (with our general algorithm) to standard regression. After fitting coefficients \hat{w} under the robust model, we form predictions on test data as for linear regression $\hat{y}_{\text{new}} = \hat{w}^\top x_{\text{new}}$. We evaluate performance using three metrics: predictive L1, $\text{pL1} \triangleq 1 - (\sum |y - \hat{y}|) / (\sum |y|)$; predictive R2, $\text{pR2} \triangleq 1 - (\sum (y - \hat{y})^2) / (\sum y^2)$; and the mean squared error to the true parameter (MSE). Figure 3 shows the results. The robust model is better than standard linear regression when the training data is corrupted. This is consistent with the findings of [Lange et al. \(1989\)](#) and [Gelman et al. \(2003\)](#).

Logistic regression. We next study logistic regression. In the true model, $y_i | x_i \sim \text{Bernoulli}(\sigma(w^\top x_i))$, and $\sigma(\cdot)$ is the logistic function. To contaminate the training data, we randomly flip a percentage of the true labels, starting with those points close to the true decision boundary.

We compare our robust logistic regression to traditional logistic regression. Figure 4 shows the results. Robust models are better than standard models in terms of three metrics: classification error, negative predictive log likelihood, and mean square error (MSE) to the true data generating parameter w .

Poisson regression. Finally we study Poisson regression. In the true model $y_i | x_i \sim \text{Poisson}(\exp\{w^\top x_i\})$. We corrupt the training data by sampling a per-data point noise component $\epsilon_i \sim \mathcal{N}(0, \sigma^2)$ and then generating data from $y_i | x_i \sim \text{Poisson}(\exp\{w^\top x_i + \epsilon_i\})$. The variance σ^2 controls the amount of noise in the training data.

We compare our robust Poisson regression to traditional Poisson regression and to negative binomial regression. Figure 5 shows the results. We used three metrics: predictive L1 (as for linear regres-

4. We compared our methods to the R implementations of traditional generalized linear models. Linear, logistic, and Poisson regression are implemented in the GLM package; negative binomial regression is in the MASS package ([Venables and Ripley, 2002](#)).

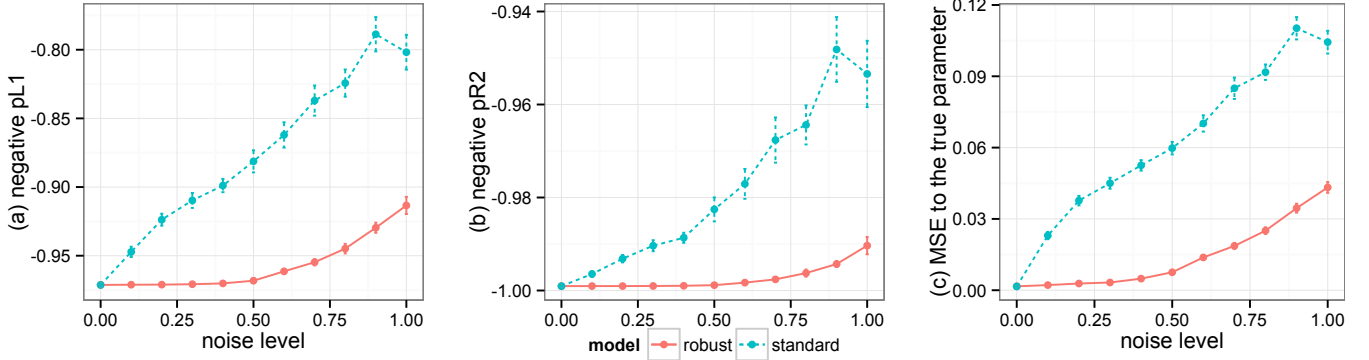


Figure 3: Robust linear regression compared to classical regression on simulated data. The x-axis is additional noise in the training data, not captured by the model or present in test data. Robust models perform better in the face of outliers. (a) Negative predictive L1; (b) Negative predictive R2. (c) MSE to the true parameter. For all metrics, lower is better.

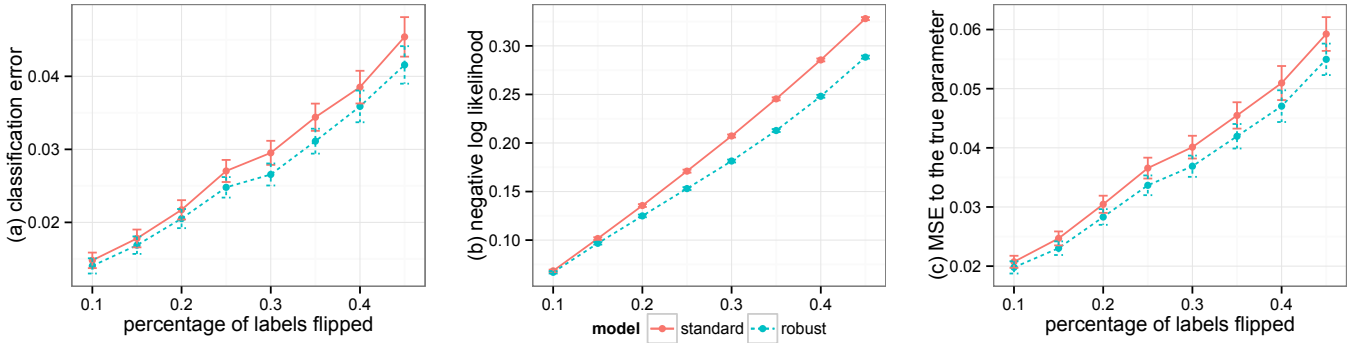


Figure 4: Experimental results for (robust) logistic regression on simulated data. Noise level (X-axis) indicates the proportion of the labels in the training data are flipped. (a) Classification error; (b) Negative predictive log likelihood. (c) MSE to the true parameter. All metrics: the *lower* the better. Robust model perform better when noise is presented.

sion), negative predictive log likelihood, and negative MSE to the true coefficients. Robust models are better than both standard Poisson regression and the negative binomial regression, especially when there is large noise.

Note that negative binomial regression is also a robust model. In a separate study, we confirmed that it is the empirical Bayes step, where we fit the variance around the per-data point parameter, that explains our better performance. Using our robust Poisson model without fitting that variance (but still fitting the coefficients) gave similar performance to negative binomial regression.

Summary. We summarize these experiments with Figure 6 showing the improvement of robust models over standard models in terms of log likelihood. (For linear regression, we use pR2.) Robust models give greater improvement when the data is noisier.

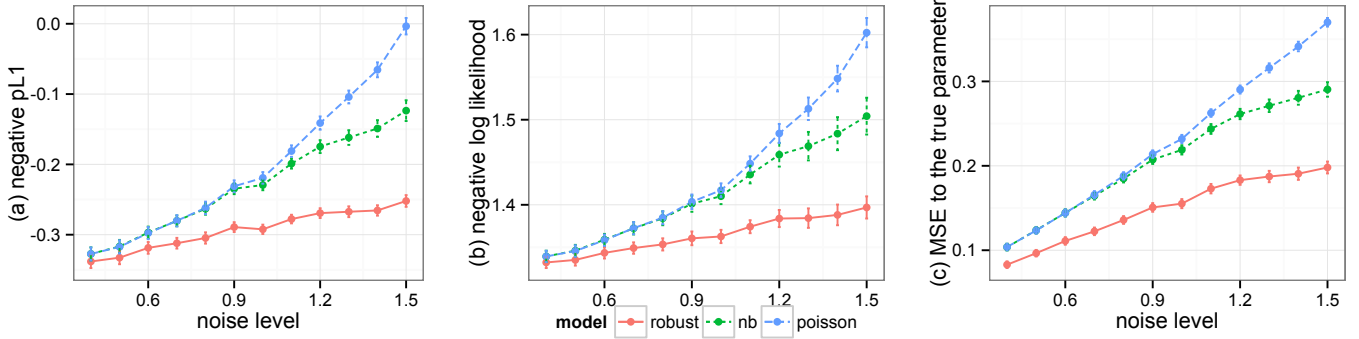


Figure 5: Experimental results for (robust) Poisson regression on simulated data. (a) Negative predictive L1; (b) Negative predictive log likelihood. (c) MSE to the true parameter. All metrics: the *lower* the better. Robust models tend to perform better than both Poisson regression and negative binomial regression (nb) when noise is presented.

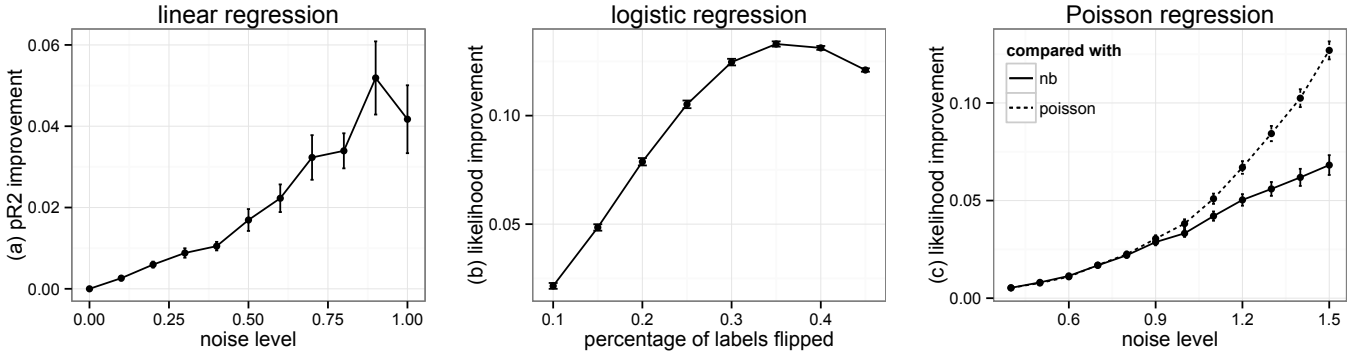


Figure 6: Improvement of robust models over standard models. (a) Predictive R2 improvement for linear regression; (b) log likelihood improvement for logistic regression (c) log likelihood improvement for Poisson regression.

5.2 Robust topic modeling

We also study robust latent Dirichlet allocation, an example of a complex Bayesian model (Section 3.4). We have discussed that robust LDA is a bursty topic model (Doyle and Elkan, 2009).

We analyze three document corpora: *Proceedings of the National Academy of Sciences* (PNAS), *Science*, and a subset of *Wikipedia*. The PNAS corpus contains 13,000 documents and has a vocabulary of 7,200 terms; the *Science* corpus contains 16,000 documents and has a vocabulary of 4,400 terms; the *Wikipedia* corpus contains about 10,000 documents and has a vocabulary of 15,300 terms. We run a similar study to the one in Doyle and Elkan (2009), comparing robust topic models to traditional topic models.

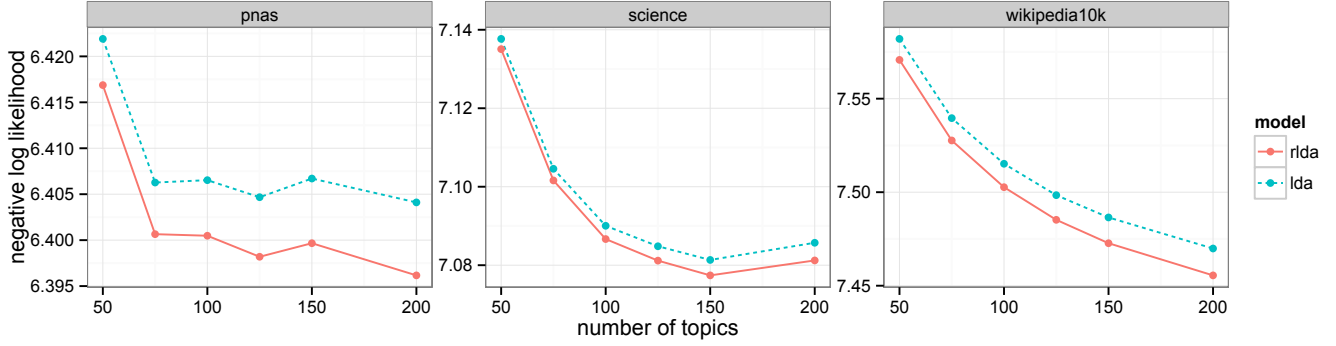


Figure 7: Predictive negative log likelihood on test data. The lower the better. The robust model (rlda) also performs better over a range of topics.

Evaluation metric. To evaluate the methods, we hold out 20% documents from each corpus and calculate their predictive likelihood. We follow the metric used in recent topic modeling literature (Blei and Lafferty, 2007; Asuncion et al., 2009; Wang et al., 2011; Hoffman et al., 2013), where we hold out part of the document and try to predict its remainder.

Specifically, for each document in the test set \mathbf{w}_d , we split it in into two parts, $\mathbf{w}_d = [\mathbf{w}_{d1}, \mathbf{w}_{d2}]$. We compute the predictive likelihood of \mathbf{w}_{d2} given \mathbf{w}_{d1} and $\mathcal{D}_{\text{train}}$. The per-word predictive log likelihood is

$$\text{likelihood}_{\text{pw}} \triangleq \frac{\sum_{d \in \mathcal{D}_{\text{test}}} \log p(\mathbf{w}_{d2} | \mathbf{w}_{d1}, \mathcal{D}_{\text{train}})}{\sum_{d \in \mathcal{D}_{\text{test}}} |\mathbf{w}_{d2}|},$$

where $|\mathbf{w}_{d2}|$ is the number of tokens in \mathbf{w}_{d2} . This evaluation measures the quality of the estimated predictive distribution. This is similar to the strategy used in Hoffman et al. (2013).

For a standard LDA model, conditioning on \mathbf{w}_{d1} estimates the topic proportions θ_d from corpus-wide topics. These topic proportions are then used to compute the predictive likelihood of \mathbf{w}_{d2} . Robust LDA is different because conditioning on \mathbf{w}_{d1} estimates both the topic proportions and the per-document topics; the predictive likelihood of \mathbf{w}_{d2} uses both quantities.

Results. Figure 7 shows the results. (Note, in the figure we use negative log likelihood so that it is consistent with other plots in this paper.) Robust topic models perform better than traditional topic models. This result is consistent with that reported in Doyle and Elkan (2009).

6. Summary

We developed a general method for robust Bayesian modeling. Investigators can create a robust model from a standard Bayesian model by localizing the global variables and then fitting the resulting hyperparameters with empirical Bayes; we described a variational EM algorithm for fitting the model. We demonstrated our approach on generalized linear models and topic models.

Acknowledgments

DMB is supported by NSF BIGDATA NSF IIS-1247664, NSF NEURO NSF IIS-1009542, ONR N00014-11-1-0651, DARPA FA8750-14-2-0009, Facebook, Adobe, Amazon, the Sloan Foundation, and the John Templeton Foundation. The authors thank Rajesh Ranganath and Yixin Wang for helpful discussions about this work.

References

- Sungjin Ahn, Anoop Korattikara, and Max Welling. Bayesian posterior sampling via stochastic gradient fisher scoring. *arXiv preprint arXiv:1206.6380*, 2012.
- E. Airoldi. *Bayesian Mixed-Membership Models of Complex and Evolving Networks*. PhD thesis, Carnegie Mellon University, 2007.
- E. Airoldi, D. Blei, S. Fienberg, and E. Xing. Mixed membership stochastic blockmodels. In *Neural Information Processing Systems*, 2009.
- C. Antoniak. Mixtures of Dirichlet processes with applications to Bayesian nonparametric problems. *The Annals of Statistics*, 2(6):1152–1174, 1974.
- A. Asuncion, M. Welling, P. Smyth, and Y. Teh. On smoothing and inference for topic models. In *Uncertainty in Artificial Intelligence*, 2009.
- H. Attias. A variational Bayesian framework for graphical models. In *Advances in Neural Information Processing Systems*, 2000.
- J. Bernardo and A. Smith. *Bayesian theory*. John Wiley & Sons Ltd., Chichester, 1994.
- P. Bickel and K. Doksum. *Mathematical Statistics: Basic Ideas and Selected Topics*, volume 1. Pearson Prentice Hall, Upper Saddle River, NJ, 2nd edition, 2007.
- C. Bishop. *Pattern Recognition and Machine Learning*. Springer New York., 2006.
- D. Blei. Probabilistic topic models. *Communications of the ACM*, 55(4):77–84, 2012.
- D. Blei and J. Lafferty. A correlated topic model of Science. *Annals of Applied Statistics*, 1(1):17–35, 2007.
- D. Blei, A. Ng, and M. Jordan. Latent Dirichlet allocation. *Journal of Machine Learning Research*, 3:993–1022, January 2003.
- G. Box. Science and statistics. *Journal of the American Statistical Association*, 71(356):791–799, 1976.
- G. Box. Sampling and Bayes’ inference in scientific modeling and robustness. *Journal of the Royal Statistical Society, Series A*, 143(4):383–430, 1980.
- A Colin Cameron and Pravin K Trivedi. *Regression analysis of count data*, volume 53. Cambridge university press, 2013.

- B. Carlin and T. Louis. Empirical Bayes: Past, present and future. *Journal of the American Statistical Association*, 95(452):1286–1289, 2000a.
- B. Carlin and T. Louis. *Bayes and Empirical Bayes Methods for Data Analysis, 2nd Edition*. Chapman & Hall/CRC, 2000b.
- J. B. Copas. Compound decisions and empirical bayes. *Journal of the Royal Statistical Society. Series B (Methodological)*, 31(3):pp. 397–425, 1969. ISSN 00359246. URL <http://www.jstor.org/stable/2984345>.
- A. Corduneanu and C. Bishop. Variational Bayesian model selection for mixture distributions. In *International Conference on Artificial Intelligence and Statistics*, 2001.
- A. Dempster, N. Laird, and D. Rubin. Maximum likelihood from incomplete data via the EM algorithm. *Journal of the Royal Statistical Society, Series B*, 39:1–38, 1977.
- P. Diaconis and D. Ylvisaker. Conjugate priors for expontial families. *The Annals of Statistics*, 7(2):269–281, 1979.
- Gabriel Doyle and Charles Elkan. Accounting for burstiness in topic models. In *Proceedings of the 26th Annual International Conference on Machine Learning, ICML '09*, pages 281–288, New York, NY, USA, 2009. ACM.
- B. Efron. Empirical Bayes methods for combining likelihoods. *Journal of the American Statistical Association*, 91(434):538–550, 1996.
- B. Efron. *Large-scale inference: empirical Bayes methods for estimation, testing, and prediction*, volume 1. Cambridge University Press, 2010.
- B. Efron and C. Morris. Combining possibly related estimation problems. *Journal of the Royal Statistical Society, Series B*, 35(3):379–421, 1973.
- B. Efron and C. Morris. Data analysis using Stein’s estimator and its generalizations. *Journal of the American Statistical Association*, 70(350):311–319, 1975.
- E. Erosheva, S. Fienberg, and C. Joutard. Describing disability through individual-level mixture models for multivariate binary data. *Annals of Applied Statistics*, 2007.
- L. Fei-Fei and P. Perona. A Bayesian hierarchical model for learning natural scene categories. *IEEE Computer Vision and Pattern Recognition*, pages 524–531, 2005.
- Jiashi Feng, Huan Xu, Shie Mannor, and Shuicheng Yan. Robust logistic regression and classification. In *Advances in Neural Information Processing Systems*, pages 253–261, 2014.
- Carmen Fernández and Mark FJ Steel. Multivariate student-t regression models: Pitfalls and inference. *Biometrika*, 86(1):153–167, 1999.
- S. Fine, Y. Singer, and N. Tishby. The hierarchical hidden Markov model: Analysis and applications. *Machine Learning*, 32:41–62, 1998.

- E. Fox, E. Sudderth, M. Jordan, and A. Willsky. A sticky HDP-HMM with application to speaker diarization. *Annals of Applied Statistics*, 5(2A):1020–1056, 2011.
- Seymour Geisser and William F Eddy. A predictive approach to model selection. *Journal of the American Statistical Association*, 74(365):153–160, 1979.
- A. Gelman, X. Meng, and H. Stern. Posterior predictive assessment of model fitness via realized discrepancies. *Statistica Sinica*, 6:733–807, 1996.
- A. Gelman, J. Carlin, H. Stern, and D. Rubin. *Bayesian Data Analysis, Second Edition*. Chapman & Hall, London, 2nd edition, 2003.
- Zoubin Ghahramani and Matthew J. Beal. Variational inference for Bayesian mixtures of factor analysers. In *NIPS*, 2000.
- Grimmer. A Bayesian hierarchical topic model for political texts: Measuring expressed agendas in senate press releases. 2009.
- M. Hoffman, D. Blei, C. Wang, and J. Paisley. Stochastic variational inference. *Journal of Machine Learning Research*, 14(1303–1347), 2013.
- Matthew D. Hoffman and Andrew Gelman. The no-U-turn sampler: Adaptively setting path lengths in Hamiltonian Monte Carlo. *Journal of Machine Learning Research*, 15(Apr):1593–1623, 2014.
- P. Huber and E. Ronchetti. *Robust Statistics*. Wiley, 2nd edition, 2009.
- Peter J Huber. Robust estimation of a location parameter. *The Annals of Mathematical Statistics*, 35(1):73–101, 1964.
- M. Jordan, Z. Ghahramani, T. Jaakkola, and L. Saul. Introduction to variational methods for graphical models. *Machine Learning*, 37:183–233, 1999.
- B. Jorgensen. Exponential dispersion models. *Journal of the Royal Statistical Society. Series B (Methodological)*, pages 127–162, 1987.
- R. Kalman. A new approach to linear filtering and prediction problems a new approach to linear filtering and prediction problems,”. *Transaction of the AMSE: Journal of Basic Engineering*, 82: 35–45, 1960.
- R. Kass and D. Steffey. Approximate Bayesian inference in conditionally independent hierarchical models (parametric empirical Bayes models). *Journal of the American Statistical Association*, 84 (407):717–726, 1989.
- Alp Kucukelbir and David Blei. Population Empirical Bayes. In *Proceedings of the 31th conference on Uncertainty in artificial intelligence*. AUAI Press, 2015.
- K. Lange, R. Little, and J. Taylor. Robust statistical modeling using the t distribution. *Journal of the American Statistical Association*, 84(408):881, 1989.
- J. Maritz and T. Lwin. *Empirical Bayes methods*. Monographs on Statistics and Applied Probability. Chapman & Hall, London, 1989.

- P. McCullagh and J. Nelder. *Generalized Linear Models*. London: Chapman and Hall, 1989.
- G. McLachlan and D. Peel. *Finite mixture models*. Wiley-Interscience, 2000.
- C. Morris. Parametric empirical Bayes inference: Theory and applications. *Journal of the American Statistical Association*, 78(381):47–65, 1983.
- K. Murphy. *Machine Learning: A Probabilistic Approach*. MIT Press, 2013.
- B. Paisley and L. Carin. Nonparametric factor analysis with beta process priors. In *International Conference on Machine Learning*, 2009.
- D. Peel and G. J. McLachlan. Robust mixture modelling using the t distribution. *Statistics and Computing*, 10(4):339–348, 2000.
- Daryl Pregibon. Resistant fits for some commonly used logistic models with medical applications. *Biometrics*, pages 485–498, 1982.
- Jonathan K Pritchard, Matthew Stephens, and Peter Donnelly. Inference of population structure using multilocus genotype data. *Genetics*, 155(2):945–959, 2000.
- L. R. Rabiner. A tutorial on hidden Markov models and selected applications in speech recognition. *Proceedings of the IEEE*, 77:257–286, 1989.
- R. Ranganath, S. Gerrish, and D. Blei. Black box variational inference. In *Artificial Intelligence and Statistics*, 2014.
- H. Robbins. The empirical bayes approach to statistical decision problems. *The Annals of Mathematical Statistics*, pages 1–20, 1964.
- H. Robbins. An empirical bayes estimation problem. *Proceedings of the National Academy of Sciences*, 77(12):6988, 1980.
- C. Robert and G. Casella. *Monte Carlo Statistical Methods*. Springer Texts in Statistics. Springer-Verlag, New York, NY, 2004.
- D. Rubin. Bayesianly justifiable and relevant frequency calculations for the applied statistician. *The Annals of Statistics*, 12(4):1151–1172, 1984.
- R. Salakhutdinov and A. Mnih. Probabilistic matrix factorization. In *Neural Information Processing Systems*, 2008.
- Y. She and A. Owen. Outlier detection using nonconvex penalized regression. *Journal of the American Statistical Association*, 106(494), 2011.
- Leonard A Stefanski, Raymond J Carroll, and David Ruppert. Optimally bounded score functions for generalized linear models with applications to logistic regression. *Biometrika*, 73(2):413–424, 1986.
- Markus Svensén and Christopher M. Bishop. Robust Bayesian mixture modelling. *Neurocomput.*, 64:235–252, March 2005. ISSN 0925-2312.

- Y. Teh, M. Jordan, M. Beal, and D. Blei. Hierarchical Dirichlet processes. *Journal of the American Statistical Association*, 101(476):1566–1581, 2006.
- Y. W. Teh. A hierarchical Bayesian language model based on Pitman-Yor processes. In *Proceedings of the 21st International Conference on Computational Linguistics and 44th Annual Meeting of the Association for Computational Linguistics*, pages 985–992, 2006. URL <http://www.aclweb.org/anthology/P/P06/P06-1124>.
- Julie Tibshirani and Christopher D. Manning. Robust logistic regression using shift parameters. *CoRR*, abs/1305.4987, 2013.
- W. N. Venables and B. D. Ripley. *Modern Applied Statistics with S*. Springer, New York, fourth edition, 2002. URL <http://www.stats.ox.ac.uk/pub/MASS4>. ISBN 0-387-95457-0.
- M. Wainwright and M. Jordan. Graphical models, exponential families, and variational inference. *Foundations and Trends in Machine Learning*, 1(1–2):1–305, 2008.
- C. Wang, J. Paisley, and D. Blei. Online variational inference for the hierarchical Dirichlet process. In *International Conference on Artificial Intelligence and Statistics*, 2011.
- Chong Wang and David M Blei. Variational inference in nonconjugate models. *The Journal of Machine Learning Research*, 14(1):1005–1031, 2013.
- Max Welling and Yee W Teh. Bayesian learning via stochastic gradient langevin dynamics. In *Proceedings of the 28th International Conference on Machine Learning (ICML-11)*, pages 681–688, 2011.
- F. Wood, J. W. van de Meent, and V. Mansinghka. A new approach to probabilistic programming inference. In *Artificial Intelligence and Statistics*, pages 1024–1032, 2014.
- Eric P Xing, Qirong Ho, Wei Dai, Jin Kyu Kim, Jinliang Wei, Seunghak Lee, Xun Zheng, Pengtao Xie, Abhimanu Kumar, and Yaoliang Yu. Petuum: A new platform for distributed machine learning on big data. *arXiv preprint arXiv:1312.7651*, 2013.