Intentional Control of Type I Error over Unconscious Data Distortion: a Neyman-Pearson Approach to Text Classification

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Abstract

Digital texts have become an increasingly important source of data for social studies. However, textual data from open platforms are vulnerable to manipulation (e.g., censorship and information inflation), often leading to bias in subsequent empirical analysis. This paper investigates the problem of data distortion in text classification when controlling type I error (a relevant textual message is classified as irrelevant) is the priority. The default classical classification paradigm that minimizes the overall classification error can yield an undesirably large type I error, and data distortion exacerbates this situation. As a solution, we propose the Neyman-Pearson (NP) classification paradigm which minimizes type II error under a user-specified type I error constraint. Theoretically, we show that while the classical oracle (i.e., optimal classifier) cannot be recovered under unknown data distortion even if one has the entire post-distortion population, the NP oracle is unaffected by data distortion and can be recovered under the same condition. Empirically, we illustrate the advantage of NP classification methods in a case study that classifies posts about strikes and corruption published on a leading Chinese blogging platform.

keywords: text classification, type I error, data distortion, censorship, information inflation, social media, Neyman-Pearson classification paradigm

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1 Introduction

The digitalization of public records and the rise of social media platforms have spurred the wide use of textual data in the social sciences. In political science, surveys on the techniques of utilizing textual data were updated frequently because of the rapid adoption of new methods (see Grimmer and Stewart (2013); Wilkerson and Casas (2017), among others). In sociology, Evans and Aceves (2016) and Lazer and Radford (2017) stress the enormous potential in using big textual data to study important social phenomena that are difficult to observe through traditional methods. In economics, Gentzkow et al. (2017) discuss the value and limitation of a wide range of textual analysis techniques in economic research.

Textual data on digital platforms are susceptible to manipulation. One prominent example of data manipulation is censorship. In non-democratic countries, some governments censor posts that could trigger regime-destabilizing political action (e.g., protests or strikes). For instance, numerous evidence shows that the Chinese government extensively censors social media (see King et al. (2013, 2014) among many others). Thus, in a dataset consisting of posts about political issues gathered from Chinese social media, the proportion of the post class that is informative of political action is likely to be much smaller than its true proportion in the uncensored population. Censorship represents a situation of downward distortion of information that is important for a specific purpose. An opposite situation is upward distortion of a class caused by information inflation. Well-known examples of this kind include social media posts injected by robots and “internet trolls.” More implicitly, information can be rapidly amplified when senders aim to conform to receivers’ opinions or cater to receivers’ preferences – the presence of “Yes Men” who blindly follow their supervisors and the occurrence of informational herding when Facebook or Twitter users tend to express similar opinions as their online peers.

This paper investigates these problems of data distortion in text classification, which is a key step to generate intermediate inputs for ultimate empirical analysis in many social studies. Generally speaking, classification is to predict discrete outcomes (e.g., class labels) for new observations, using algorithms trained on labeled data. In a binary classification problem where the class labels are usually coded as \(\{0, 1\}\), two types of errors occur: type I error (mislabel class 0 as class 1) and type II error (mislabel class 1 as class 0). The default classification objective in practice is the one that minimizes the overall classification error (i.e., risk), which is a weighted sum of type I and type II errors, with weights being the proportions of classes. We refer to such an objective as the classical paradigm. While being widely used, it may produce an undesirable level of type I error which may jeopardize a research project. For example, when using historical archives
and new reports to discover social events such as riots and protests in a particular locality, a large type I error (i.e., a large chance of classifying a relevant event as non-relevant) would cause missing observations of important events. In general, when controlling one type of error is much more important than the other type, the classification outcomes obtained from classical classifiers are not desirable.

Data distortion can exacerbate the conflict between asymmetric control of classification errors and the classical paradigm. Suppose that a fraction of class 0 information is eliminated. Then, in the objective function of the classical paradigm, the weight placed on type I error is reduced, and minimizing this objective naturally produces an increased type I error. Formally, we derive the classical oracle classifier (i.e., the optimal classifier under the classical paradigm if one knows the entire population) regarding the post-distortion population, and demonstrate that as long as the data distortion rates are unknown, the pre-distortion classical oracle classifier cannot be recovered even if one has the entire post-distortion population. Some data scientists propose the cost-sensitive learning paradigm to address the issue of asymmetric error importance, in which different costs are assigned to each error type (Elkan, 2001; Zadrozny et al., 2003). However, ad hoc assignment of costs can be misleading and the data distortion problem is not solved.

As a solution to data distortion and a strong preference towards controlling one type of error in text classification, we propose the Neyman-Pearson (NP) classification paradigm which minimizes type II error under a user-specified type I error constraint. The NP paradigm has the advantage that both type I and type I errors of the NP oracle classifier (i.e., the optimal classifier under the NP paradigm if one knows the entire population) are independent of class size proportion of the population. It has been used to address asymmetric importance in errors, such as severe disease diagnosis (Scott, 2005; Li and Tong, 2016). We show that the NP oracle is unaffected by any distortion scheme as long as the class conditional distributions of the features remain the same. To the best of our knowledge, the present paper is the first effort to apply the NP paradigm to address the issue of data distortion in classification.

To illustrate the working of the NP classification paradigm, we use an adaptable umbrella algorithm that utilizes state-of-the-art classification techniques (Tong et al., 2018a). We apply this algorithm to classify two datasets of posts about sensitive social events obtained from Sina Weibo, the largest microblog platform in China, which is known to be susceptible to unpredictable government manipulation (Chen and Ang, 2011; Qin et al., 2017). In the first example, we wish to classify posts about strikes into posts about real strike events and noisy information. The former class is extensively censored while the latter class is not. In the second example, we classify posts about corruption into reports of specific corrupt officials and general comments on corruption. The former class is likely to be censored, while the latter class is likely inflated because of
local government bloggers’ tendency to support central-government-backed anti-corruption campaigns. In both cases, although randomly sampled from all available data, the obtained datasets are still distorted. In the strike data, we show that type I errors generated from (classical) penalized logistic regression, Naive Bayes, support vector machine, random forests and sparse linear discriminant analysis range from .667 to 1. By contrast, these errors range from .153 to .196 when the NP counterparts are implemented with an upper bound of type I error of .2. Similarly well-controlled type I errors are achieved when NP classification methods are applied to the corruption data.

This paper poses questions along a new dimension in the statistical analysis of textual data in the social sciences. Social scientists have applied both unsupervised and supervised learning techniques to their problems. For example, Quinn et al. (2010) practice unsupervised learning via topic modeling. Collingwood and Wilkerson (2012) use supervised methods to apply Policy Agendas topic coding system to new domains. Grimmer and King (2011) apply a clustering approach that lead to discovery of an unnoticed genre of partisan taunting. Drutman and Hopkins (2013) use simple identification (i.e., screening) techniques to first exclude the 99% of observations that were not related to the issue under study. King et al. (2013) and Ceron et al. (2014) use supervised learning algorithms to study government censorship in China and citizens’ policy in Italy and France. In general, social scientists’ efforts were spent to improve the quality of training data labeling, the techniques of feature selection and feature engineering, the methods of sampling, and machine learning algorithms, among others. In this paper, we draw attention to an understudied aspect – the problem of data distortion, which is prominent when textual data are obtained from open platforms such as social media. The solution we propose, the Neyman-Pearson binary classification paradigm, works well when social scientists prefer one error type over the other. It bypasses the distortion issue and is easy to implement empirically.

The remainder of the paper is organized as follows. Section 2 illustrates the general pitfalls of using the classical classification paradigm to handle the text classification problem in the presence of unknown distortion. Section 3 introduces the NP paradigm and show how this approach bypasses distortion in classification. Section 4 presents a case study, classifying posts about “strikes” and “corruption” from Chinese microblog platform Sina Weibo. Section 5 concludes the paper. Technical details including alternative crowdsourcing labeling, subject keywords lists, label coding rules and general proposition are relegated to the Appendix.
2 Classification and Unknown Distortion Scheme

Binary classification is a supervised learning technique frequently used in textual analysis. It aims to classify a piece of textual message into a category that is relevant to a specific purpose and an irrelevant category. Formally, the aim of binary classification is to accurately predict class labels (i.e., $Y = 0$ or $1$) for new observations (i.e., features $X \in \mathbb{R}^d$) on the basis of labeled training data. Most binary classification methods minimize the overall classification error (i.e., risk), which is a weighted sum of type I and type II errors. The weights are the marginal probabilities of the classes. More concretely, let $h : \mathbb{R}^d \to \{0, 1\}$ be a binary classifier, $R_0(h) := \mathbb{P}(h(X) \neq Y|Y = 0)$ denote its type I error, and $R_1(h) := \mathbb{P}(h(X) \neq Y|Y = 1)$ denote its type II error, the (population) classification error $R(h)$ of $h$ can be decomposed as

$$R(h) = R_0(h) \cdot \mathbb{P}(Y = 0) + R_1(h) \cdot \mathbb{P}(Y = 1).$$

In this paper, we use the term classical paradigm to refer to the learning objective of minimizing $R(\cdot)$. It is well known that $h^*(x) = \mathbb{I}(\eta(x) > 1/2)$, where $\eta(x) = \mathbb{E}(Y|X = x) = \mathbb{P}(Y = 1|X = x)$, is the (classical) oracle classifier, i.e., the classifier that minimizes $R(\cdot)$ among all functions. The oracle (i.e., theoretically optimal) classifier is achievable if one knows the entire population, but not achievable given any finite sample.

2.1 Oracle under Data Distortion

In reality, textual data observed by researchers are often distorted. For instance, messages published on open platforms are vulnerable to manipulation, causing downward distortion (censorship) or upward distortion (information inflation). In this paper, we restrict our discussion of data distortion to the situation that distortion changes the class proportion in the population but the class conditional distributions of features do not change. To formulate a general situation of data distortion, denote the class $0$ distortion rate by $\beta_0 = (\beta_0^-, \beta_0^+)^T$, where $\beta_0^-$ is the class $0$ downward-distortion rate and $\beta_0^+$ is class $0$ upward-distortion rate. These rates are the proportions of class $0$ texts that are randomly deleted or injected. For example, when $\beta_0 = (.2, .1)^T$, it means $20\%$ of class $0$ texts are randomly deleted from the population, and $10\%$ of class $0$ texts are artificially injected, so the net effect is a $10\% = 20\% - 10\%$ decrease in class $0$ texts. Similarly, $\beta_1 = (\beta_1^-, \beta_1^+)^T$ is defined for class $1$ texts. Below, we derive the mathematical formula of the (classical) oracle classifier regarding the post-distortion population.

**Theorem 1.** Suppose that $(X|Y = 0)$ and $(X|Y = 1)$ have probability density functions $f_0$ and $f_1$, and
that class priors are \( \pi_0 = \mathbb{P}(Y = 0) \) and \( \pi_1 = \mathbb{P}(Y = 1) \). Let \( \beta_0 = (\beta_{0-}, \beta_{0+})^\top \) and \( \beta_1 = (\beta_{1-}, \beta_{1+})^\top \) be the distortion rates of class 0 and class 1 respectively. Then, the (classical) oracle classifier regarding the post-distortion population is

\[
    h^*_0(x) = \mathbb{I}\left( \frac{f_1(x)}{f_0(x)} > \frac{1 - \beta_{0-} + \beta_{0+}}{1 - \beta_{1-} + \beta_{1+}} \cdot \frac{\pi_0}{\pi_1} \right).
\]

Recall that the (classical) oracle classifier regarding the pre-distortion population is \( h^*(x) = \mathbb{I}(\eta(x) > 1/2) \), where the regression function \( \eta(x) = \mathbb{E}(Y|X = x) \) can be calculated as

\[
    \eta(x) = \frac{\pi_1 f_1(x)/f_0(x)}{\pi_1 f_1(x)/f_0(x) + \pi_0}.
\]

Therefore, \( h^*(x) = \mathbb{I}\left( \frac{f_1(x)}{f_0(x)} > \frac{\pi_0}{\pi_1} \right) \). When distortion with rates \( \beta_0 \) and \( \beta_1 \) is applied to class 0 and class 1 respectively, the class proportions become \( \pi_0(\beta_0, \beta_1) \) and \( \pi_1(\beta_0, \beta_1) \) which are defined as

\[
    \pi_0(\beta_0, \beta_1) = \frac{(1 - \beta_{0-} + \beta_{0+})\pi_0}{(1 - \beta_{0-} + \beta_{0+})\pi_0 + (1 - \beta_{1-} + \beta_{1+})\pi_1}
\]

and

\[
    \pi_1(\beta_0, \beta_1) = \frac{(1 - \beta_{1-} + \beta_{1+})\pi_1}{(1 - \beta_{0-} + \beta_{0+})\pi_0 + (1 - \beta_{1-} + \beta_{1+})\pi_1},
\]

while class conditional densities remain \( f_0 \) and \( f_1 \). Then, the oracle classifier regarding the post-distortion population is to replace \( \pi_0 \) and \( \pi_1 \) in \( h^* \) by \( \pi_0(\beta_0, \beta_1) \) and \( \pi_1(\beta_0, \beta_1) \) respectively:

\[
    h^*_0(x) = \mathbb{I}\left( \frac{f_1(x)}{f_0(x)} > \frac{\pi_0(\beta_0, \beta_1)}{\pi_1(\beta_0, \beta_1)} \right) = \mathbb{I}\left( \frac{f_1(x)}{f_0(x)} > \frac{1 - \beta_{0-} + \beta_{0+}}{1 - \beta_{1-} + \beta_{1+}} \cdot \frac{\pi_0}{\pi_1} \right).
\]

Theorem 1 suggests that the thresholds of \( f_1/f_0 \) in oracle classifiers \( h^* \) (pre-distortion) and \( h^*_0(\beta_0, \beta_1) \) (post-distortion) differ by a multiplicative constant \( (1 - \beta_{0-} + \beta_{0+})/(1 - \beta_{1-} + \beta_{1+}) \). The key message is that even if we have the entire post-distortion population, we can only recover \( \pi_0(\beta_0, \beta_1) \) and \( \pi_1(\beta_0, \beta_1) \), and hence mimic \( h^*_0(\beta_0, \beta_1) \). However, unless \( \beta_0 \) and \( \beta_1 \) are known or estimable, there is no hope to mimic \( h^* \). In view of Theorem 1, it is straightforward to characterize the relationship between distortion rates and type I/II errors of \( h^*_0(\beta_0, \beta_1) \).

**Corollary 1.** Under conditions in Theorem 1, it holds that, i). \( R_0(h^*_0(\beta_0, \beta_1)) \), type I error of \( h^*_0(\beta_0, \beta_1) \), increases in \( \beta_{0-} \) and decreases in \( \beta_{1-} \); ii). \( R_1(h^*_0(\beta_0, \beta_1)) \), type II error of \( h^*_0(\beta_0, \beta_1) \), decreases in \( \beta_{0-} \) and increases in \( \beta_{1-} \); and iii). when \( \beta_{0-} - \beta_{0+} = \beta_{1-} - \beta_{1+} \), \( h^*_0(\beta_0, \beta_1) = h^* \).

\footnote{Note that when writing \( R_0 \) and \( R_1 \), we don’t specify whether they are regarding pre-distortion population or post-distortion.}
Corollary 1 is intuitive. When a portion of class 0 data is deleted, the weight placed on the type I error in the objective function of the classical paradigm is reduced; accordingly, the relative weight placed on the type II error increases. Minimizing this modified objective function naturally yields a larger type I error and a smaller type II error. By the same token, deletion of class 1 data has the opposite effect. As for iii), it means that if the net effect of class 0 distortion is the same as that of the class 1 distortion, the post-distortion oracle is the same as the pre-distortion oracle. Theoretically, it implies that one can offset data distortion in one class by distortion in the other class. However, this is unlikely to be feasible in practice.

2.2 Impact of Censorship Rate under the Gaussian Model

The previous section discusses oracles pre-distortion and post-distortion in general. In this section, we provide visual contrast between these oracles and quantitative analysis under specific distributional assumptions. Concretely, we study the impact of downward-distortion (censorship) rate $\beta_{0}^-$ on type I error of the post-censorship oracle classifier under the linear discriminant analysis model, a canonical model in the classification literature. Other distortion parameters $\beta_{0}^+$, $\beta_{1}^-$ and $\beta_{1}^+$ can be analyzed similarly. Let $f_0 \sim \mathcal{N}(\mu_0, \Sigma)$ and $f_1 \sim \mathcal{N}(\mu_1, \Sigma)$, where $\mu_0$ and $\mu_1$ represent mean vectors for classes 0 and 1 respectively and $\Sigma$ is the common covariance matrix. In other words, the probability density functions $f_0$ and $f_1$ have the following format:

$$f_k(x) = \frac{1}{\sqrt{(2\pi)^d|\Sigma|^{1/2}}} \exp \left\{ -\frac{1}{2} (x - \mu_k) \Sigma^{-1} (x - \mu_k) \right\}, \text{ for } k = 0, 1,$$

where $d$ is the dimensionality of features $x$, $|\Sigma|$ denotes the determinant of matrix $\Sigma$, and $\Sigma^{-1}$ is the inverse of $\Sigma$.

In this paper, we call the linear discriminant analysis model as the Gaussian model while using the abbreviation LDA for Latent Dirichlet Allocation later. In the Gaussian model, the decision boundary \{ $x : \pi_0 f_0(x) = \pi_1 f_1(x)$ \} of the oracle $h^*$ is equivalent to:

$$x \Sigma^{-1}(\mu_0 - \mu_1) - \frac{1}{2} (\mu_0 - \mu_1) \Sigma^{-1}(\mu_0 + \mu_1) + \log \left( \frac{\pi_0}{\pi_1} \right) = 0.$$

(1)

When the censorship rate of class 0 is $\beta_{0}^-$, only $(1 - \beta_{0}^-)$ proportion of observations from class 0 remains population, because we assume that the data distortion under study does not change $f_0$ or $f_1$. 

and the rest get removed through censoring. Thus, the new proportions of class 0 and class 1 are respectively
\[
\pi_0(\beta^-_0) = \frac{(1 - \beta^-_0)\pi_0}{(1 - \beta^-_0)\pi_0 + \pi_1} \quad \text{and} \quad \pi_1(\beta^-_0) = \frac{\pi_1}{(1 - \beta^-_0)\pi_0 + \pi_1}.
\]  
(2)

Denote by \( h^*_\beta_{-}\pi_0 \) the post-distortion oracle classifier \(^2\). Its decision boundary is given by equation (3):
\[
x^\top\Sigma^{-1}(\mu_0 - \mu_1) - \frac{1}{2}(\mu_0 - \mu_1)^\top\Sigma^{-1}(\mu_0 + \mu_1) + \log\left(\frac{(1 - \beta^-_0)\pi_0}{\pi_1}\right) = 0.
\]  
(3)

Comparing oracle decision boundaries (1) and (3), we see that the shape of the decision frontier stays the same, but the left hands of the equations differ by a constant \( \log\left(\frac{(1 - \beta^-_0)\pi_0}{\pi_1}\right) - \log\left(\frac{\pi_0}{\pi_1}\right) = \log(1 - \beta^-_0) \). To visualize this difference, we plot an example in Figure 1; in this example, \( \mu_0 = (0, 0)^\top, \mu_1 = (2, 2)^\top, \Sigma = I, \) and \( \pi_0 = .5 \). In the left panel of Figure 1, the black line is the decision boundary of the pre-distortion oracle, and the red dashed line and the orange dashed line are the decision boundaries after censorship on class 0, with \( \beta^-_0 = .5 \) and \( \beta^-_0 = .95 \) respectively. The right panel of Figure 1 illustrates that \( R_0(h^*_{\beta^-_0,.5}) \), type I error of \( h^*_{\beta^-_0,.5} \), deteriorates as the censorship rate \( \beta^-_0 \) of class 0 increases.

Under general conditions, Proposition 1 below explores the relationship between type I error \( R_0(\cdot) \) and the censorship rate \( \beta^-_0 \) of class 0 for balanced classes (i.e., \( \pi_0 = .5 \)) under the Gaussian model. Since Proposition 1 follows from Proposition D.1 in the Appendix by fixing \( \pi_0 = .5 \), we omit its proof.

**Proposition 1.** Suppose probability densities of class 0 \( (X|Y = 0) \) and class 1 \( (X|Y = 1) \) follow distributions \( \mathcal{N}(\mu_0, \Sigma) \) and \( \mathcal{N}(\mu_1, \Sigma) \) respectively, and the two classes are balanced in the pre-distortion population (i.e., \( \pi_0 = \pi_1 = .5 \)). Let \( \beta^-_0 \in (0, 1) \) be the censorship rate of class 0, and \( h^*_{\beta^-_0} (= h^*_{\beta^-_0,.5}) \) be the (classical) oracle classifier in the post-distortion population. Then, type I error of \( h^*_{\beta^-_0} \) is calculated as:
\[
R_0(h^*_{\beta^-_0}) = \Phi\left(\frac{-\frac{1}{2}C - \log\left(1 - \beta^-_0\right)}{\sqrt{C}}\right),
\]  
(4)
where \( C = (\mu_0 - \mu_1)^\top\Sigma^{-1}(\mu_0 - \mu_1) \). Clearly, \( R_0(h^*_{\beta^-_0}) \) is a monotone increasing function of the censorship rate \( \beta^-_0 \in (0, 1) \). Moreover, we have i). if \( e^{3C/2} \leq 1, R_0(h^*_{\beta^-_0}) \) is a concave function of \( \beta^-_0 \in (0, 1), \) and ii). if \( e^{3C/2} \geq 1, R_0(h^*_{\beta^-_0}) \) is a convex function of \( \beta^-_0 \) for \( \beta^-_0 \in \left(0, 1 - \frac{1}{e^{3C/2}}\right) \), and it is a concave function for \( \beta^-_0 \in \left(1 - \frac{1}{e^{3C/2}}, 1\right) \).

\(^2\)Previously, when we write the general post-distortion oracle \( h^*_{(\beta_0, \beta_1)} \) in Theorem 1, the notation suppresses the dependency on the class priors for simplicity. But we introduce the explicit dependence on \( \pi_0 \) in \( h^*_{\beta^-_0,.\pi_0} \) because the explicit form of a classical oracle classifier and its errors do depend on the class priors. Also, in writing \( h^*_{\beta^-_0,.\pi_0} \), we assume \( \beta^+_0 = \beta^-_1 = \beta^+_1 = 0.\)
In Proposition 1, the quantity $C$ measures the difficulty of the classification problem: the larger $C$, the better class separation, and the easier the classification problem. When censorship on class 0 texts intensifies, class 0 in the post-distortion population represents a smaller proportion, and the post-distortion oracle will favor class 1 (i.e., favor type II error) more, leading to a rise in type I error.

## 3 Neyman-Pearson Classification Paradigm

Section 2 shows that under the classical paradigm, even having the entire post-distortion population does not permit reconstructing the pre-distortion oracle classifier, when the distortion scheme is unknown and un-estimable. Moreover, it also shows that in the presence of censorship on class 0 texts, it is easy to miss this class under the classical classification paradigm, an undesirable situation if class 0 is the more important class.

One existing solution to data distortion is to collect information that allows for a better understanding of the data generation process or to use other information to correct the distorted sample. For example, King et al. (2014) engineer a large-scale field experiment to understand how the Chinese government censors social media. To deal with the problem of information inflation, one may construct social networks and hypothesize the process of information diffusion over the networks. These approaches are highly valuable as
they help social scientists gain further knowledge about the subject matter. However, from the perspective of text classification, they are not only costly but also infeasible in general circumstances. For instance, given that the Chinese government’s censorship strategy is ad hoc and unpredictable (be to explained more in Section 4.1), knowledge obtained from one experiment may not generalize to other settings and periods; hence, models that are built to correct data distortion may be themselves misspecified.

We discuss two approaches that are widely used to address asymmetric importance in classification errors: the cost-sensitive learning paradigm and the Neyman-Pearson paradigm, and argue that the latter is a suitable paradigm to address the problem of data distortion.

### 3.1 Cost-sensitive (CS) Learning

An insight from studying the classical classification paradigm is that the relative size of classification errors comes largely from the relative weights placed on type I and type II errors in the objective function. So a natural candidate to adjust classification errors is to change the weights. This is the so-called cost-sensitive (CS) learning paradigm, in which users impose costs $C_0$ and $C_1$ to type I and type II errors, respectively. On the population level, instead of minimizing the overall classification error $R(\cdot)$, one minimizes the CS learning objective:

$$
\min_h R_c(h) := C_0 \pi_0 R_0(h) + C_1 \pi_1 R_1(h),
$$

or the following variant of (5):

$$
\min_h \bar{R}_c(h) := C_0 R_0(h) + C_1 R_1(h).
$$

Then, the CS oracle $h^{c*}$ under the cost-sensitive learning paradigm (5) can be shown to take the form

$$
h^{c*}(x) = \mathbb{I} \left( \frac{f_1(x)}{f_0(x)} > \frac{C_0}{C_1} \cdot \frac{\pi_0}{\pi_1} \right),
$$

and the CS oracle $\bar{h}^{c*}$ under (6) can be shown to take the form

$$
\bar{h}^{c*}(x) = \mathbb{I} \left( \frac{f_1(x)}{f_0(x)} > \frac{C_0}{C_1} \right).
$$

Similar to their counterparts in the classical paradigm, the post-distortion CS oracle classifier is different.
from the pre-distortion CS oracle, and the pre-distortion CS oracle cannot be recovered in view of an unknown distortion scheme. Lemma 1 follows from arguments similar to the proof of Theorem 1.

**Lemma 1.** Suppose that class 0 \((X|Y = 0)\) and class 1 \((X|Y = 1)\) have probability density functions \(f_0\) and \(f_1\), and that class priors are \(\pi_0\) and \(\pi_1\) respectively. Let \(\beta_0 = (\beta_0^-, \beta_0^+)\top\) and \(\beta_1 = (\beta_1^-, \beta_1^+)\top\) be the distortion rates of class 0 and class 1 respectively. Then, the oracle classifier under the cost-sensitive learning paradigm (5) regarding the post-distortion population is

\[
h_{(\beta_0, \beta_1)}^C(x) = \mathbb{I}\left(\frac{f_1(x)}{f_0(x)} > \frac{1 - \beta_0^- + \beta_0^+}{1 - \beta_1^- + \beta_1^+} \cdot \frac{C_0}{C_1} \cdot \frac{\pi_0}{\pi_1}\right).
\]

Similarly, the oracle classifier under the paradigm (6) regarding the post-distortion population is

\[
h_{(\beta_0, \beta_1)}^\bar{C}(x) = \mathbb{I}\left(\frac{f_1(x)}{f_0(x)} > \frac{1 - \beta_0^- + \beta_0^+}{1 - \beta_1^- + \beta_1^+} \cdot \frac{C_0}{C_1} \cdot \frac{\pi_0}{\pi_1}\right).
\]

Lemma 1 implies that even if we have the entire post-distortion population, we can only mimic \(h_{(\beta_0, \beta_1)}^C\) or \(h_{(\beta_0, \beta_1)}^\bar{C}\). However, unless \(\beta_0\) and \(\beta_1\) are known or estimable, there is no hope to mimic \(h_{(\beta_0, \beta_1)}^C\) or \(h_{(\beta_0, \beta_1)}^\bar{C}\).

### 3.2 NP Oracle Invariant to Distortion

In this subsection, we introduce the **Neyman-Pearson (NP) classification paradigm** that has three general advantages: i). bypass data distortion, ii). address the class imbalance issue, and iii). control type I error (the more severe error type) under a user-specified level. Recall that \(R(h) = R_0(h) \cdot \mathbb{P}(Y = 0) + R_1(h) \cdot \mathbb{P}(Y = 1)\).

Instead of minimizing \(R(\cdot)\) as in the classical paradigm, the NP paradigm mimics \(\phi^*_\alpha\), where

\[
\phi^*_\alpha = \arg\min_{\phi: R_0(\phi) \leq \alpha} R_1(\phi),
\]

in which \(\alpha\) is a user-specified upper bound on type I error. The NP oracle \(\phi^*_\alpha\) arises from the famous Neyman-Pearson Lemma (attached in Appendix E) in statistical hypothesis testing. While the third advantage is self-evident for the NP paradigm, the next theorem illustrates the first two advantages.

**Theorem 2.** Given any distributions for \((X|Y = 0)\) and \((X|Y = 1)\), the NP oracle classifier \(\phi^*_\alpha\) defined in (7) is invariant under distortion at various rates \(\beta_0\) (on class 0) and \(\beta_1\) (on class 1), regardless of whether pre-distortion classes are balanced.

The constrained optimization (7) that defines \(\phi^*_\alpha\) does not involve the class priors \(\pi_0 = \mathbb{P}(Y = 0)\) and
\[ \pi_1 = \mathbb{P}(Y = 1), \text{ so } \phi^*_\alpha \text{ does not depend on } \pi_0 \text{ or } \pi_1. \] Now suppose distortion with rates \( \beta_0 \) and \( \beta_1 \) is imposed on class 0 and class 1 respectively, then the post-distortion population have class 0 proportion 
\[ \frac{((1 - \beta^-_0 + \beta^+_0)\pi_0) + (1 - \beta^-_1 + \beta^+_1)\pi_1}{(1 - \beta^-_0 + \beta^+_0)\pi_0 + (1 - \beta^-_1 + \beta^+_1)\pi_1}, \]
and class 1 proportion 
\[ \frac{((1 - \beta^-_0 + \beta^+_0)\pi_0) + (1 - \beta^-_1 + \beta^+_1)\pi_1}{(1 - \beta^-_0 + \beta^+_0)\pi_0 + (1 - \beta^-_1 + \beta^+_1)\pi_1}, \]
while keeping the distributions of \((X|Y = 0)\) and \((X|Y = 1)\) unchanged. Since distortion at rates \( \beta_0 \) and \( \beta_1 \) only changes class proportion, which NP oracle does not depend upon, the NP oracle is invariant under distortion.

Figure 2 illustrates the difference between a classical oracle classifier and its NP counterpart in both balanced and imbalanced Gaussian settings. Clearly, the NP oracle is the same in both settings, while the classical oracles are different. As data distortion essentially amounts to a change in the class proportion, this figure also demonstrates a contrast between a shift in decision boundary of the classical oracle and the invariance of the NP oracle, under data distortion.

In addition to the data distortion issue, the datasets we will analyze are imbalanced, and our prediction problems are asymmetric in the sense that we would like to prioritize the chance to uncover the information related to the distorted class. Thus, the three advantages of the NP paradigm all come to effect.

### 3.3 NP Umbrella Algorithm

In this work, we adopt the NP umbrella algorithm proposed in Tong et al. (2018a). This wrapper method allows users to apply their favorite scoring-type classification methods (base algorithms), such as logistic regression, support vector machines (Vapnik, 1999), random forests (Breiman, 2001), under the NP paradigm. Specifically, when a user has a desired upper bound \( \alpha \) for the (population) type I error and a type I error violation rate upper bound \( \delta \), the NP umbrella algorithm outputs a classifier \( \hat{\phi} \) from the base algorithm specified by the user, such that its type I error violation rate is controlled, i.e.,

\[ \mathbb{P}(R_0(\hat{\phi}) \leq \alpha) \geq 1 - \delta, \]

and \( \hat{\phi} \) attains the smallest type II error among its base algorithm type. Figure 3 adapted from Tong et al. (2018a) illustrates the pseudocode of the NP umbrella algorithm. This umbrella algorithm uses part of class 0 data and all class 1 data to train the scoring-function in a base algorithm, and use the left-out class 0 data to determine the threshold of the scoring function based on order statistics. To achieve better stability, multiple \((M > 1)\) random splits of class 0 is usually used. In the case study (Section 4), we consider base
Figure 2: Classical vs. NP oracle classifiers in a Gaussian model example. The conditional distributions of $X$ under the two classes are $\mathcal{N}(0, 1)$ and $\mathcal{N}(2, 1)$ respectively. Suppose that a user prefers a type I error $\leq \alpha = 0.05$. When the two classes are balanced (i.e., $\mathbb{P}(Y = 0) = \mathbb{P}(Y = 1)$), the classical oracle $\mathbb{I}(X > 1)$ that minimizes the risk would result in a type I error $= 0.159$. On the other hand, the NP oracle $\mathbb{I}(X > 1.65)$ that minimizes the type II error under the type I error constraint ($\leq 0.05$) delivers the desirable type I error. In an imbalanced situation where $2\mathbb{P}(Y = 0) = \mathbb{P}(Y = 1)$, while the NP oracle does not change and retains the desirable type I error, the decision boundary of the classical oracle shifts left to $0.6534$ and results in a much larger type I error $= 0.257$. 
algorithms “penalized logistic regression (PLR)”, “naive bayes (NB)”, “svm”, “random forest (RF)” and “sparse linear discriminant analysis (sLDA)” (Mai et al., 2012; Tong et al., 2018b), and we set $M = 9$.

4 Case Study

In this section, we present a case study that serves two purposes. First, we empirically illustrate the problem of unknown data distortion in text classification. To this end, we collect public posts related to sensitive social issues from Sina Weibo (新浪微博), the Chinese equivalent of Twitter. Through a third-party content crawling agency, we obtained a dataset of approximately 10 million raw posts about public issues and social events in 2012. We are interested in two subjects: “strike” and “corruption”. Evidence shows that Chinese social media posts about collective action events including strikes are extensively censored, while posts about corruption are less so (King et al., 2014). On the other hand, because of the central government’s anti-corruption campaign, general comments about corruption and anti-corruption initiative can be considered as part of the propaganda engineered by local governments (Qin et al., 2017). Thus, the strike case represents an example of downward distortion of class 0 posts, and the corruption case is an example of downward distortion of class 0 but upward distortion of class 1 posts.

Second, we demonstrate how to implement the NP classification methods so that interested researchers can adopt them in their own research. Our goal is to classify posts into pre-defined categories (to be introduced later) in each subject. We use a hybrid of unsupervised and supervised approaches. Concretely, after pre-processing the posts, we first apply topic modeling to engineer new features that extract and reorganize information from text data. Then, we apply NP classification methods. For comparison purpose, classical classification methods are also implemented. The entire chain of data analysis is illustrated in Figure 4, where the data pre-processing steps are in solid squares.

4.1 Data Distortion in Chinese Social Media

Information regarding politicians’ wrongdoings and important social events is essential in citizens’ participation in political activities and holding politicians accountable (Strömberg, 2015). In authoritarian countries, however, this type of information is scarce due to strict government control of the media. The emergence of social media enables millions of citizens to generate and communicate information about social events and political issues. This has inspired both decision makers and social scientists to gather, decode and analyze the information produced on social media in authoritarian countries. However, severe manipulation of social
Algorithm An NP umbrella algorithm

1: input:
   training data: a mixed i.i.d. sample $S = S^0 \cup S^1$, where $S^0$ and $S^1$ are class 0 and class 1 samples respectively
   $\alpha$: type I error upper bound, $0 \leq \alpha \leq 1$; [default $\alpha = 0.05$]
   $\delta$: a small tolerance level, $0 < \delta < 1$; [default $\delta = 0.05$]
   $M$: number of random splits on $S^0$; [default $M = 1$]

2: function \textsc{RankThreshold}(n, $\alpha$, $\delta$)
   
3: for $k$ in \{1, ..., $n$\} do \hfill $\triangleright$ for each rank threshold candidate $k$
4:     $v(k) \leftarrow \sum_{j=k}^{n} \binom{n}{j} (1 - \alpha)^j \alpha^{n-j}$ \hfill $\triangleright$ calculate the violation rate upper bound
5:     $k^* \leftarrow \min \{k \in \{1, \ldots, n\} : v(k) \leq \delta\}$ \hfill $\triangleright$ pick the rank threshold
6: return $k^*$

7: procedure \textsc{NPClassifier}(S, $\alpha$, $\delta$, $M$)
8:     $n = \lceil |S^0|/2 \rceil$ \hfill $\triangleright$ denote half of the size of $|S^0|$ as $n$
9:     $k^* \leftarrow \textsc{RankThreshold}(n, \alpha, \delta)$ \hfill $\triangleright$ find the rank threshold
10:    for $i$ in \{1, ..., $M$\} do \hfill $\triangleright$ randomly split $S^0$ for $M$ times
11:       $S^0_{i,1}, S^0_{i,2} \leftarrow$ random split on $S^0$ \hfill $\triangleright$ each time randomly split $S^0$ into two halves with equal sizes
12:       $S^0_{i,1} \leftarrow S^0_{i,1} \cup S^1$ \hfill $\triangleright$ combine $S^0_{i,1}$ and $S^1$
13:       $S^0_{i,2} = \{x_1, \ldots, x_n\}$ \hfill $\triangleright$ write $S^0_{i,2}$ as a set of $n$ data points
14:       $f_i \leftarrow$ classification algorithm($S_i$) \hfill $\triangleright$ train a scoring function $f_i$ on $S_i$
15:       $T_i = \{t_{i,1}, \ldots, t_{i,n}\} \leftarrow \{f_i(x_1), \ldots, f_i(x_n)\}$ \hfill $\triangleright$ apply the scoring function $f_i$ to $S^0_{i,2}$ to obtain a set of score threshold candidates
16:       $\{t_{i,(1)}, \ldots, t_{i,(n)}\} \leftarrow \text{sort}(T_i)$ \hfill $\triangleright$ sort elements of $T_i$ in an increasing order
17:       $t_i^* \leftarrow t_{i,(k^*)}$ \hfill $\triangleright$ find the score threshold corresponding to the chosen rank threshold $k^*$
18:       $\phi_i(X) = \mathbb{I} (f_i(X) > t_i^*)$ \hfill $\triangleright$ construct an NP classifier based on the scoring function $f_i$ and the threshold $t_i^*$

19: output:
    an ensemble NP classifier $\hat{\phi}_\alpha(X) = \mathbb{I} \left( \frac{i}{M} \sum_{i=1}^{M} \phi_i(X) \geq 1/2 \right)$ \hfill $\triangleright$ by majority vote

Figure 3: Pseudocode for the NP umbrella algorithm adapted from Tong et al. (2018a) with permission.
media information is evident in China, Russia, and Turkey, among other countries. A notable example is the extensive censorship of collective action events (e.g., strikes and protests) that might affect regime stability in China. Given such manipulation, how to accurately classify the text data remaining on social media for the purpose of discovering and predicting hidden political events is a challenge faced by social scientists.

As hinted in Theorem 1, data distortion in text classification is solvable if the data distortion rates are known. However, such a solution is often not feasible because it is difficult or simply impossible to estimate. Consider the example of censorship on Chinese social media. It involves four parties that have different objectives and resources: 1) the central government, which is the ultimate controller of social media, 2) social media providers: private IT companies, 3) agents who mediate between government and providers, and 4) a large number of local governments who find ways to interfere with the operation of social media. These sources together create a huge hurdle for inferring the censorship scheme. First, the Chinese central government’s objective in censorship is volatile and subject to changes. Given its intention to collect bottom-up information for surveillance and monitoring local officials, the central government strategically censors information on social media. For instance, during a period of power transition, it is crucial to maintain social stability, and censorship will be much stricter than usual. Second, the implementation of censorship is carried out by service providers whose primary goals are financial gain. To maintain a high level of information traffic, they do not completely comply with the central government’s censorship demands. Third, the enforcement of censorship relies heavily on the government information officers, who issue daily directives on which specific topics and words should be censored. These directives are issued largely on an ad hoc basis, depending on the involving officers’ collection and interpretation of information. Finally, although local governments do not have the right to censor social media, they may bribe employees of social media providers to delete information that may reflect negatively on them. As a result of this complicated...
censorship process, the actual censorship scheme is highly volatile, unpredictable, and full of ambiguity.

Another format of data manipulation in Chinese social media is propaganda, which has been an important tool for the Chinese Communist Party to maintain regime stability (Qin et al., 2018+). In the typical manufacturing of propaganda, the central government initiates a subject-related campaign (e.g., anti-corruption), and then local governments follow by blogging propaganda content via their social media accounts. Local officials have strong career-related incentive to oversupply propaganda. Sina Weibo reported the existence of 50,000 government-affiliated accounts in 2012 while Qin et al. (2017) estimate 600,000 such accounts are actively operating on Sina Weibo. King et al. (2017) also show that Chinese local governments hire as many as 2 million internet trolls to fabricate deceptive information (including propaganda) on Chinese social media. Given such a decentralized mechanism of producing propaganda, it is unrealistic to try to estimate the rate of information inflation due to propaganda.

4.2 Data Pre-processing

Since the raw Weibo posts are unstructured data, we need to process them so that they can be fed to learning algorithms. The first step is to extract a subset of posts filtered according to a pre-selected set of keywords for each subject. For example, when the subject is political corruption, common keywords (for the list of keywords, please refer to Section B of the Appendix) related to corruption would be chosen and only posts containing these keywords are selected. The subject of strikes resulted in 221,229 posts and the subject of political corruptions resulted in 1,865,107 posts.

If a classification algorithm is able to learn from a small sample of correctly labeled posts, it could then automatically classify a large set of new posts without human intervention. To get labeled data, we hired a few Chinese-speaking subject experts to manually categorize the raw posts into “strike not related” (class 1) and “strike related” (class 0) for the subject of strikes, and into “general corruption related” (class 1) and “specific corrupted official related” (class 0) for the subject of corruption. For strikes, we took a sample of 4,579 posts from Guangdong Province in two randomly selected months in the year of 2012, among which 3,805 posts are labeled as “strike unrelated” and 774 are labeled as “strike related”. Guangdong Province was chosen because it has the most strikes of all the provinces in China. For corruption, we took a random sample of 3,000 posts for labeling, among which 2,142 posts are labeled as “general corruption related”, and

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3We also tried an alternative labeling strategy: recruiting workers on Amazon’s Mechanical Turk, to label the Sina Weibo posts. We did not use the labels got from this crowdsourcing method in our analysis due to their subpar label quality. A detailed Mechanical Turk implementation and discussions can be found in Section A of the Appendix.

4Please refer to Section C of the Appendix for an elaborated description of the post categories.
are labeled as “specific corrupted official related”.

The next step is to remove metadata from these posts. Since our data consist of raw posts copied directly from the original social media website, they contain meta-data such as timestamps and usernames. As we focus on prediction based on post content, these metadata must be removed. To extract meaningful content from the posts, extraneous symbols must also be filtered out. Social media posts tend to include spam words and symbols such as emoticons, links to external websites, and other nonsensical content. Including these does not increase relevant information. One note here is that in the raw dataset we received, multi-media content (e.g., pictures and videos) that may affect labeling, were excluded.

A Chinese sentence is comprised of many Chinese characters; multiple characters can form a word. Since the Chinese language does not deploy spaces between words, it is not a trivial task for a machine to decipher which Chinese characters form words that make sense in a sentence. To solve the problem, the messages are fed into a Chinese sentence segmentation tool called The Stanford Segmenter (Tseng et al., 2005). This segmenter uses a Chinese treebank (CTB) segmentation model and breaks down input messages into disjointed words separated by spaces.

The next step is to remove words that are not meaningful in the context. These include a list of pronouns, conjunctions, prepositions and articles. Then for each subject, we can create a dictionary of unique words. Based on the dictionary, we generate a frequency matrix that counts the number of times each word in the dictionary appears in each post. The “strike” matrix contains 4,579 rows (posts) and 16,895 columns (features) and the “political corruption” matrix contains 3,000 rows (posts) and 18,346 columns (features). These matrices are used in topic modeling for feature engineering, to be described in the next subsection.

4.3 Feature Engineering

In both of the pre-processed Sina Weibo datasets, the sizes of vocabulary dictionaries are much larger than the number of posts. In such high-dimensional settings, naively incorporating all words as features has the following potential problems: 1) a large number of predictors make a model not interpretable; 2) noise accumulation might lead to classification result no better than random guess; 3) statistical procedures can be computationally heavy. In the statistics literature, various methods have been proposed to reduce the feature dimensionality. For example, one can use marginal screening methods such as sure independence screening (Fan and Lv, 2008), nonparametric independence screening (Fan et al., 2011) and Kolmogorov-Smirnov (KS) test, interaction screening methods (Hao and Zhang, 2014; Fan et al., 2015), the forward stepwise selection, shrinkage methods such as LASSO (Tibshirani, 1996) and SCAD (Fan and Li, 2001), or dimension reduction
methods such as principal component analysis.

The above mentioned methods all overlook the semantic structures possessed by corpora datasets. Natural language is so complicated that pinning down a small subset of words (features) usually do not lend to good interpretation. In view of this, we adopt Latent Dirichlet Allocation (LDA) (Blei et al., 2003; Teh et al., 2007; Grimmer and Stewart, 2013), which is a popular generative probabilistic model especially designed for large corpora. LDA utilizes and extracts semantic information from the text. In this model, documents (posts) are represented as random mixtures over latent topics and each topic is represented as a distribution over words. Below we give a detailed review of LDA.

LDA unveils the underlying semantic structure of documents through hierarchical Bayesian modeling. Specifically, three objects are of interests: topics, words, and documents. We observe words of each document but the topics are the hidden variables representing the latent structure. Before laying out the generative model, we introduce a few notations. Let \( K \) be a pre-determined number of topics, \( V \) the size of the vocabulary dictionary, \( \gamma \) a \( K \)-dimensional positive vector and \( \eta \) a scalar. Denote by \( \text{Dir}(\gamma) \) a \( K \)-dimensional Dirichlet distribution with parameter vector \( \gamma \). It takes values in the standard \( (K-1) \) simplex and is the conjugate prior of the multinomial distribution. Symmetric Dirichlet is a special case where all coordinates in \( \gamma \) are equal. Let \( \text{Dir}_V(\eta) \) represent a \( V \)-dimensional symmetric Dirichlet with scalar parameter \( \eta \), then \( \text{Dir}_V(\eta) \) is the same as \( \text{Dir}(\gamma) \), where \( \gamma = (\eta, \cdots, \eta) \in \mathbb{R}^V \). Given these notations, the generative model is described as follows.

1. For the \( k \)-th topic, \( k \in \{1, \cdots, K\} \), draw a distribution over words: \( \beta_k \sim \text{Dir}_V(\eta) \).
2. For the \( d \)-th document,
   - Draw a vector of topic distribution \( \theta_d \sim \text{Dir}(\gamma) \).
   - For each of the \( q \) words contained in the \( d \)-th document
     - Draw a topic \( Z_{d,q} \sim \text{Multinomial}(\theta_d) \), taking value from \( \{1, \cdots, K\} \).
     - Draw a word \( W_{d,q} \sim \text{Multinomial}(\beta_{Z_{d,q}}) \) from the vocabulary dictionary.

We train the LDA model using the \texttt{R} package \texttt{topicmodels} and select “Gibbs sampling” as the fitting method. With a fixed \( K \), we extract \( K \) topics from the big corpora and they serve as our new features. The posterior distribution over these \( K \) topics in each document will be the feature values. Thus LDA engineers new features leveraging semantic structure and successfully reduces the dimensionality of feature space from \( V \) to \( K \).
Table 1: top 20 keywords for five topics from one repetition on the “strike” dataset.

4.4 Example: Strikes

4.4.1 Choosing the Number of Topics

When we apply LDA, the number of topics $K$ needs to be specified and the choice is essential. There is no single universal way to choose $K$. In this work, we use a “stability” criterion. Concretely, for a candidate $K$, we randomly select half of the documents (posts) and apply LDA. This process is repeated 50 times. Every time, LDA outputs $K$ topics. Each document is represented by posterior probabilities over these $K$ topics and each topic is represented by posterior probabilities over the vocabulary dictionary. We look at the top 20 keywords which have the largest posterior probabilities in each of the $K$ topics, and based on these words, we decide whether a topic is truly related to the subject (“strike” as in the current example).

Table 1 illustrates the top 20 keywords for each topic in one repetition when $K = 5$. Based on domain expertise, the first and the second selected topics are about general workers’ strikes and taxi-drivers’ strikes, while the rest 3 topics are irrelevant. So in this repetition, the proportion of relevant topics is 2/5. We consider the number of topics $K$ to be good if over 50 repetitions, the proportions of relevant topics have low variance. Figure 5 plots histograms of these proportions for $K = 5$ and 10 over 50 repetitions, and we prefer $K = 5$ due to its less spread out histogram.

5It is worth noting that, even though the word “strike” appears in all of the five topics, due to the complexity of Chinese language, combinations of “strike” with other words have different meanings. This is where human judgement is needed.
4.4.2 Classification under the Neyman-Pearson Paradigm

Fixing $K = 5$ in LDA, we apply both classical and NP classification methods to the “strike” dataset. The NP algorithms are implemented through the R package nproc. To better demonstrate the performance of NP classifiers, we implement two settings which have different class proportions in training and test data.

- **Setting 1:** We randomly split the whole dataset into training and test sets of equal sizes (half of class 0 and half of class 1 data in training) 100 times. In other words, in every experiment, the class 0 proportion in the training set is the same as that in the test set.

- **Setting 2:** We randomly split class 0 data into three folds of equal sizes, and split class 1 data into two halves. We take $1/3$ (one fold) class 0 data and $1/2$ class 1 data as the training set and use the other $2/3$ class 0 data and the other half class 1 data as the test set. Thus, the class 0 proportion in the training set is half as much as in the test set. We again repeat the experiment 100 times.

On each training set, we run LDA ($K = 5$) first and then apply classification methods on the transformed training set which has the learned topics as the new features. Then type I and type II errors are calculated using the corresponding transformed test set which has as features the topics learned from the training set. The classification methods implemented include the classical “penalized logistic regression (PLR)”, “naive bayes (NB)”, “Support Vector Machines (SVM)”, “random forest (RF)” and “sparse linear discriminant analyzer (LDA)”.

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6 We refer to the dataset at the end of pre-processing steps, i.e., the frequency matrix with words in dictionary as features.
Table 2: Average error rates with $\alpha = .2$, $\delta = .3$ for the strike dataset over 100 repetitions, under Setting 1.

| Error rates | PLR | NP-PLR | NB | NP-NB | SVM | NP-SVM | RF | NP-RF | sLDA | NP-sLDA |
|-------------|-----|--------|----|-------|-----|--------|----|-------|------|---------|
| type I      | .864| .191   | 1  | .196  | .773| .169   | .667| .174  | .762 | .186    |
| type II     | .007| .372   | 0  | .367  | .014| .769   | .052| .455  | .017 | .381    |

Table 3: Average error rates with $\alpha = .2$, $\delta = .3$ for the strike dataset over 100 repetitions, under Setting 2.

| Error rates | PLR | NP-PLR | NB | NP-NB | SVM | NP-SVM | RF | NP-RF | sLDA | NP-sLDA |
|-------------|-----|--------|----|-------|-----|--------|----|-------|------|---------|
| type I      | .946| .176   | 1  | .180  | .865| .153   | .781| .156  | .804 | .175    |
| type II     | .002| .406   | 0  | .414  | .007| .853   | .031| .526  | .013 | .410    |

Under Setting 1, Table 2 summarizes the average type I and type II errors of these methods over all 100 repetitions. As missing a strike related post (class 0) may lead to delayed government responses, and an event may accumulate to a large scale and spread to other regions, the government in general cares more about type I error compared to type II error. Table 2 illustrates how the NP approach serves this purpose better than the classical approach. For instance, type I error of the (classical) sLDA is .762. In contrast, NP-sLDA achieves type I error under control, even though its type II error is .381, which is larger than that achieved by the classical counterpart. A larger type II error means that more irrelevant information is collected and another round of screening may be needed. The cost of such further screening to precisely detect social events appears insignificant.

More interestingly, Table 3 summarizes the average type I and type II errors of these methods under Setting 2, over all 100 repetitions. In Setting 2, the class 0 proportion in the training set is half as much as its proportion in the test set. This mimics the real life scenario when censorship is imposed on posts of the more sensitive/important class and thus this class is more scarce in the observed data compared to the un-distorted population. As we explained theoretically and visually in Theorem 1 and Figure 1, the classical oracle classifier shifts its decision boundary in view of censorship on class 0, and its type I error gets worse as the censorship intensifies. This population level insight is confirmed by the numerical results. Taking penalized logistic regression (PLR) as an example, Setting 2 produces a type I error of .946, which is larger than the .864 in Setting 1. By contrast, the NP oracle is invariant to data distortion (Theorem 2),

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7For all NP methods, we set type I error upper bound $\alpha = .2$ and violation rate upper bound $\delta = .3$. These particular choices for $\alpha$ and $\delta$ are merely for illustration purpose. In practice, the choices of $\alpha$ and $\delta$ depend on users’ objectives. For example, suppose a local political leader wants to collect information about strikes within his or her administration from social media. If the purpose is to use this information as one of many indicators to gauge public sentiment, missing some strikes is not critical. Thus, it is harmless to set relatively large $\alpha$ and $\delta$. However, when the promotion of a local leader depends critically on how he or she responds to strikes (a more likely scenario), missing any strike might be damaging. Then this leader would choose small $\alpha$ and $\delta$. 

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and NP-PLR has a type I error controlled under the pre-specified $\alpha = 0.2$ in both Setting 1 and Setting 2. This phenomenon is consistent across all the five methods we implemented.

In summary, the selection of $\alpha$ and $\delta$ in NP classification methods governs the trade-off between type I and type II errors, and the balance of this trade-off depends on the decision maker’s objective and resources available. In the example of strikes and collective action in general, the consequence of making type I errors is severe – threatening regime stability and jeopardizing a politician’s career, while the cost of dealing with type II errors is typically small. Considering this together with the data distortion and imbalance issues, it is highly valuable to use classification methods under the NP paradigm rather than the classical paradigm.

4.5 Example: Corruption

In this section, we examine the “corruption” dataset. Recall that, class 0 posts in this dataset specifically talk about a corrupted official, and class 1 posts comment on the general issue of corruption. Under such labeling, class 0 posts contain important information on the public sentiment towards specific officials and is useful for detecting corruption. Thus, type I error should be the priority.

Following the same procedure for analyzing the “strike” dataset, we first apply LDA to create a few topics as new features and then classify posts using both classical and NP methods. For a candidate $K$, we apply LDA 50 times on randomly selected subsets. Table 4 illustrates the top 20 keywords for each topic in one repetition when $K = 5$. From this repetition, topics 1, 2 and 5 are general comments about corruption and government; while topics 3 and 4 are related to specific corrupted officials. For example, topic 3 mentions “王立军” (Lijun Wang), a former Chinese provincial police chief, and was convicted on charges of abuse of power, bribery, and defection, and sentenced to fifteen years in prison. It also mentions the title (department chief) and the department (bureau of public security) of the corrupted official. To decide between $K = 5$ and $K = 10$, we look at Figure 6, and conclude $K = 5$ gives the lower variance in the relevant topic proportions.

Fixing $K = 5$ in LDA, we apply both classical and NP classification methods to the “corruption” dataset. We randomly split the whole dataset into training and test sets of equal sizes for 100 times. Tables 5 and 6 present average type I and type II errors over these 100 repetitions, with two sets of parameters for NP methods: $(\alpha = .2, \delta = .3)$ and $(\alpha = .1, \delta = .3)$. The first set of parameters is the same as those used in the strike example. The second set of parameters is chosen to compare with a scenario when decision makers wish to impose more stringent control of type I error.

Tables 5 and 6 demonstrate that, across different NP classifiers, type I errors are uniformly controlled as we expected. The classifiers under the classical paradigm in general do not have good type I error performance,
### Table 4: Top 20 Keywords for Five Topics from One Repetition on the “Corruption” Dataset.

| Topic 1 | Corruption | Officials | Can | Be up | Benefit |
|---------|-------------|-----------|-----|-------|---------|
|         | Clean government | Clique | Society | Problem |
|         | Embezzlement | Person | Say | Let | Public money |
|         | Money | Leader | Three | Buy government posts | Scary |
|         | Now | Party secretary | Year | Pass | Village chief |
|         | Plant | Call | Beet | Out | Mayor |
| Topic 2 | Year | Take bribes | Former | RMB Yuan | Pervert the law |
|         | People | Court | Abuse | Favoritism | Case |
|         | Deputy department chief | Power | Department chief | Bureau of Public Security | Crime |
|         | Deputy department chief | In | Wang Lijun | Report on | Month-date | Imprisonment |
| Topic 3 | Deputy department chief | Suspected | Investigation | Call | Bribe | One hundred million |
|         | | Former | Serious | After | Position | |
|         | | Former | Serious | After | Position | |
|         | Vice | Commission for Discipline Inspection | Problem | Sell government posts | |
| Topic 4 | China | Corrupted officials | News | Country | May |
|         | Government | This | News | Go | Journalist |
|         | Police | Has | News | Go | Journalist |
|         | Race | Has | News | Go | Journalist |
|         | Event | USA | Has | News | Go | Journalist |
|         | Report | Please | Reply | Request | Law |

### Table 5: Average Error Rates with $\alpha = .2$, $\delta = .3$ for the Corruption Dataset over 100 Repetitions.

| Error rates | PLR | NP-PLR | NB | NP-NB | SVM | NP-SVM | RF | NP-RF | sLDA | NP-sLDA |
|-------------|-----|--------|----|-------|-----|--------|----|-------|------|--------|
| Type I      | .488 | .190   | 1  | .182  | .400 | .198   | .355| .189  | .441 | .178   |
| Type II     | .041 | .187   | 0  | .208  | .059 | .326   | .086| .193  | .053 | .210   |

with Naive Bayes being the most extreme one, where the type I error is 1. With ($\alpha = .2$, $\delta = .3$), type I errors of the NP classifiers are less than half of their classical counterparts. Under the more stringent objective ($\alpha = .1$, $\delta = .3$), type I errors of the NP classifiers are further controlled to be below the target level .1.

## Conclusion

Digital texts have become an important source of data for social scientists. With increasing sophistication in using textual data to discover social events and predict social behaviors, accurate classification of textual data for specific purposes is key to a successful empirical analysis. To improve classification accuracy, social
scientists, often partnering with data scientists, have endeavored to improve the quality of training data labeling, the techniques of feature engineering, the methods of sampling and machine learning algorithms. In this paper, we draw attention to an understudied aspect – the problem of data distortion, which is prominent when textual data are obtained from open platforms such as social media. Theoretically, we show that in the presence of unknown data distortion, the classical oracle classifier cannot be recovered even when the entire post-distortion population is available. By contrast, the Neyman-Pearson oracle classifier is unaffected by data distortion. With two examples of the classification of posts about sensitive social events (strikes and corruption) obtained from Sina Weibo which is known to be manipulated by the government, we demonstrate that when one type of classification error (e.g., type I error) is dominantly important, the NP classification algorithms allow users to intentionally control that type of error below a pre-specified level.

The NP approach we propose in this paper is not specific to text classification. It is useful in general when classification errors are asymmetric in importance. Plausible applications include crime detection, social surveillance, and monitoring risky financial decisions, among many others. Moreover, when observed classes are heavily imbalanced, down sampling techniques or oversampling methods, such as Random OverSampling Examples (ROSE) and Synthetic Minority Oversampling Technique (SMOTE), can be easily incorporated.
into the NP classification methods to potentially reduce type II error. The NP classification paradigm is still an active research field. Current efforts include exploring the time-dependent structure of the observations to modify the NP umbrella algorithm, developing feature selection criteria under the NP paradigm, and extending NP methods to multi-class settings.

A Amazon Mechanical Turk Instructions and Discussions

One important step in this text classification project is to label a sample of posts. To use labeled texts as training data, labels must have high quality. Moreover, when time and budget allow, we prefer to label more posts so as to create a larger training set. Towards this end, other than using subject experts, we explored a crowdsourcing option for the labeling task.

The Amazon Mechanical Turk (MTurk) is an open online platform that supports crowdsourcing of projects such as ours (Paolacci et al., 2010; Stewart et al., 2015; Difallah et al., 2015; Cheung et al., 2017). A requester of a project (in this case, us) can make a project publicly available on the MTurk online platform, and pay willing participants to take part in the project. In one study, we pulled out 3,000 Sina Weibo posts that are related to the subject of corruption, filtered by keywords (refer to Appendix B for a list of the keywords). In our project, each post was labeled independently by two participants and a label was only accepted if the two participants’ results were consistent.

Setting up a task on MTurk requires a requester account, which is open to all residents of the United States. Once a requester account has been created, credits can be added to the account through a linked bank account or credit card. These credits are used to pay workers, who are the participants on MTurk, for the completion of tasks. With a requester account, one can create a new project using one of the created templates, including a template for surveys, a template for data collection, a template for transcriptions of images, among others. There is also a generic “Other” template. Once a template is selected, one can further customize it by selecting the types of questions, such as multiple choices, short answers and check boxes. Since we wanted to get our data classified into a different categories, multiple choice questions are the most obvious option. For each multiple choice question, we can specify a set of questions to choose from and the possible answers. Our answers are the possible categories, and our questions are the set of posts that we want to label. MTurk allows a requester to customize many components their project: reward per post labelled, number of times a post needs to be labeled to be accepted, time allotted per task, the project expiration date, and whether the results are auto-approved after a certain number of date. Once these are
all set up, the project can be set to “publish”. Once published, workers on MTurk can see the project and attempt the tasks within the project.

The MTurk platform has powerful extensions. Other than the web interface, the MTurk platform allows an experienced web developer to directly connect to its servers via a command-based interface, which allows for greater customization of the project, such as the ability to create a qualification test that measures a potential worker’s competency in relevant skill. The inherent nature of our project dictates that participants would have to first pass a short online test in Chinese to prove their proficiency in the language. Once passed, they are paid 0.05 USD for each post that they classify.

However, ultimately we did not use the labels from MTurk in our analysis. This crowdsourcing attempt effectively failed as prediction results based on these labeled posts were far inferior to those based on expert labeled data. A manual check of some labels from this set by experts also showed errors. One possible explanation is that the Chinese language demands understanding beyond the surface, and can be very subtle when it comes to describing complex subjects such as corruption and strike. Indeed, the authors themselves sometimes find it difficult to label certain posts. The workers recruited on MTurk obviously did not seem to have adequate understanding of these subjects in Chinese.

B Filtering Keywords

We focus on two subjects for analysis: “strike” and “corruption”. For each subject, we use a keyword filter to select posts. The following is a list of keywords in Chinese commonly appearing with each subject and their English translations:

- For the subject of strike: 罢工 (strike), 工潮 (worker strike), 罢运 (transportation worker strike), 罢市 (merchant strike), 罢课 (student strike), 罢驶 (taxi driver strike).

- For the subject of corruption: 买官 (buy government position), 以权 (use position of authority), 侵占 (seize), 侵吞 (embezzle), 侵害 (infringe on), 公款 (public funds), 冤情 (injustice), 特权集团 (special interest group), 卖官 (sell government position), 占地 (seize of land), 受贿 (bribery), 名表 (expensive watch), 告官 (sue government official), 官商 (officials), 妥私 (favoritism), 情妇 (mistress), 挪用 (misappropriate), 收贿 (bribery), 权贵 (position of authority), 权钱 (power and wealth), 枉法 (abuse law), 污吏 (corrupt official), 涉黑 (involved with underground dealings), 渎职 (malfeasance), 滥用职权 (abuse position of authority), 灰色收入 (income from illegal activities), 灰色消费 (spend...
in illegal activities), 硕⿏ (big corrupt rat), 私分 (divide stolen goods), 私囊 (private pocket), 私生 (illegitimate), 索贿 (ask for bribery), 脏款 (stolen money), 腐败 (corruption), 舞弊 (cheating), 落马 (step down), 虚开 (fake report), 虚报 (fake report), 裙带关系 (nepotism), 裸官 ("naked official", referring to officials who stay in the country while their spouses and children reside abroad), 谋私 (smuggle), 贪官 (corrupt officials), 贪污 (corruption), 贿赂 (bribe), 贿选 (bribe an election), 跑官 (buy government position).

C Coding Rule

Coding of Strike Posts

Class 0. Posts talking about worker strikes, including student strikes, taxi driver strikes, and merchant strikes.

Class 1. Posts containing the word "strike" but using it to describe the malfunctioning of computers, elevators, or other machines.

Coding of Corruption Posts

Class 0. Posts coded as “Specific, Corruption” (category index= 0): this kind of post is about the allegations of specific officials and government departments without reference to governments’ anti-corruption activities. Posts of the following types belong to this category.

- Explicit allegations of specific officials or positions (such as a village head), or a department (such as a city government, the Public Security Bureau);

- Description of the wrongdoing and corruption of a specific official or department without referring to the action undertaken by the Government Discipline Inspection Departments and other monitoring bodies.

- Description of the fights between human rights lawyers, journalists, and democracy advocates fighters and specific officials and government departments.

Class 1. Posts coded as “General, corruption” (category index= 1): this kind of post is about general comment on corruption, without accusing specific government officials. Posts of the following types belong to this category.

- Discussion about the causes and impact of corruption, including corruption in foreign countries, public sector (schools, associations, etc.), state-owned enterprises, and celebrities.
• Posts containing the names of well-known corrupt officials, but just using them as examples to illustrate views and express sentiments.

• Comments on the government’s anti-corruption efforts and sanctions, including praise or questioning of government or state leaders, as well as comments on government action against corruption and callings for further action.

• Comment on the misconduct of corrupt officials investigated.

• Comments on individuals who consistently fight corruptions without allegations against specific government departments or bureaucrats.

• Comments on government reaction to corruption allegations without mentioning specific officials and retaliation of anti-corruption individuals.

• Discussion about corruption of foreign politicians or government officials and on international anti-corruption action.

• Comments on the deficiency of the political system and discussion about social problems with major reference to corruption.

• Comments on wrongdoings of officials, without direct accusation of corruption. These wrongdoings include government-related illegal business practices, crony capitalism, illegal incomes, nepotism, academic corruption, and mistresses phenomenon.

D Proposition D.1

Proposition 1 in the main text follows as a special case of the next Proposition. Denote by $h^{*}_{\beta \pi}$ the post downward-distortion classical oracle classifier whose decision boundary is characterized by equation (3). Proposition D.1 below explores the relationship between type I error $R_{0}(\cdot)$, the downward-distortion rate $\beta \pi$ of class 0 and the class size ratio $\pi_{0}/\pi_{1}$ for $h^{*}_{\beta \pi}$.

Proposition D.1. Suppose probability densities of class 0 $(X|Y = 0)$ and class 1 $(X|Y = 1)$ follow distributions $N(\mu_{0}, \Sigma)$ and $N(\mu_{1}, \Sigma)$ respectively; class 0 composes $\pi_{0} \in (0, 1)$ proportion of the population and $\beta \pi \in (0, 1)$ is the downward-distortion rate (i.e., the proportion of class 0 posts that were removed from some government censorship scheme). Let $h^{*}_{\beta \pi}$ denote the classical oracle classifier in the post-distortion
population. Then the type I error of \( h^*_{\beta_0^{-}, \pi_0} \) (regarding either the pre-distortion or post-distortion population) is calculated as:

\[
R_0(h^*_{\beta_0^{-}, \pi_0}) = \Phi \left( -\frac{1}{2} C - \log \left( \frac{1 - \beta^{-}_0}{\sqrt{C}} \right) \right),
\]

where \( C = (\mu_0 - \mu_1)^\top \Sigma^{-1}(\mu_0 - \mu_1) \) and \( p = \pi_0/(1 - \pi_0) \). Equation (8) implies that:

1. Keeping \( \pi_0 \) fixed (hence \( p \) is fixed), \( R_0(h^*_{\beta_0^{-}, \pi_0}) \) is a monotone increasing function of the down-distortion (censorship) rate \( \beta_0^{-} \in (0, 1) \). Moreover, we have i). if \( p e^{3C/2} \leq 1 \), \( R_0(h^*_{\beta_0^{-}, \pi_0}) \) is a concave function of \( \beta_0^{-} \in (0, 1) \); and ii). if \( p e^{3C/2} > 1 \), \( R_0(h^*_{\beta_0^{-}, \pi_0}) \) is a convex function of \( \beta_0^{-} \) for \( \beta_0^{-} \in \left(0, 1 - \frac{1}{pe^{3C/2}}\right) \), and a concave function for \( \beta_0^{-} \in \left(1 - \frac{1}{pe^{3C/2}}, 1\right) \).

2. Keeping \( \beta_0^{-} \) fixed, \( R_0(h^*_{\beta_0^{-}, \pi_0}) \) is a monotone decreasing function of the class ratio \( p = \pi_0/\pi_1 \). In other words, the larger the proportion of class 0 in the uncensored population, the smaller the type I error of \( h^*_{\beta_0^{-}, \pi_0} \). Moreover, \( R_0(h^*_{\beta_0^{-}, \pi_0}) \) is a convex function of \( p \) for \( p > \frac{1}{(1 - \beta_0^{-})e^{3C/2}} \), and it is a concave function of \( p \) for \( p \leq \frac{1}{(1 - \beta_0^{-})e^{3C/2}} \).

Since equation (3) is the decision boundary of \( h^*_{\beta_0^{-}, \pi_0} \), we have:

\[
R_0(h^*_{\beta_0^{-}, \pi_0}) = P_{X \sim \mathcal{N}(\mu_0, \Sigma)} \left\{ X^\top \Sigma^{-1}(\mu_0 - \mu_1) - \frac{1}{2} (\mu_0 - \mu_1)^\top \Sigma^{-1}(\mu_0 + \mu_1) + \log \left( \frac{1 - \beta_0^{-}}{\pi_1} \right) \right\} \leq 0 \right\}.
\]

For \( X \) in class 0, \( X^\top \Sigma^{-1}(\mu_0 - \mu_1) =: Z' \sim \mathcal{N}(\mu_0^1 \Sigma^{-1}(\mu_0 - \mu_1), (\mu_0 - \mu_1)^\top \Sigma^{-1}(\mu_0 - \mu_1)) \). Therefore,

\[
R_0(h^*_{\beta_0^{-}, \pi_0}) = P_{Z' \sim \mathcal{N}(\mu_0^1 \Sigma^{-1}(\mu_0 - \mu_1), (\mu_0 - \mu_1)^\top \Sigma^{-1}(\mu_0 - \mu_1))} \left\{ Z' \leq \frac{1}{2} (\mu_0 - \mu_1)^\top \Sigma^{-1}(\mu_0 + \mu_1) - \log \left( \frac{1 - \beta_0^{-}}{\pi_1} \right) \right\}
\]

\[
= \Phi \left( \frac{-\frac{1}{2} (\mu_0 - \mu_1)^\top \Sigma^{-1}(\mu_0 - \mu_1) - \log \left( \frac{1 - \beta_0^{-}}{\pi_1} \right)}{\sqrt{(\mu_0 - \mu_1)^\top \Sigma^{-1}(\mu_0 - \mu_1)}} \right).
\]

Regarding part 1, for fixed \( \pi_0 \), let \( f(\beta_0^{-}) = R_0(h^*_{\beta_0^{-}, \pi_0}) \).

\[
f'(\beta_0^{-}) = \phi \left( -\frac{1}{2} C - \log \left( \frac{1 - \beta_0^{-}}{\sqrt{C}} \right) \right), \frac{1}{\sqrt{C(1 - \beta_0^{-})}},
\]

where \( \phi(\cdot) \) is the probability density function of the standard normal random variable. This implies that for \( \beta_0^{-} \in (0, 1) \), \( f'(\cdot) \) is positive, so \( R_0(h^*_{\beta_0^{-}, \pi_0}) \) is a monotone increasing function of \( \beta_0^{-} \) for fixed \( \pi_0 \). Taking the
second derivative of \( f \), we have
\[
f''(\beta_0^-) = \phi'(\frac{-\frac{1}{2}C - \log((1 - \beta_0^-)p)}{\sqrt{C}}) \cdot \frac{1}{C(1 - \beta_0^-)^2} + \phi\left(\frac{-\frac{1}{2}C - \log((1 - \beta_0^-)p)}{\sqrt{C}}\right) \cdot \frac{1}{\sqrt{C}(1 - \beta_0^-)^2}.
\]

Let \( g(w) = \phi'(w) + \sqrt{C}\phi(w) \). Then
\[
g(w) = \frac{1}{\sqrt{2\pi}} e^{-\frac{w^2}{2}} \cdot (-w) + \frac{\sqrt{C}}{\sqrt{2\pi}} e^{-\frac{w^2}{2}}.
\]

Note that \( g(w) > 0 \) if \( w < \sqrt{C} \).

Therefore, \( f''(\beta_0^-) > 0 \) iff \( g\left(\frac{-\frac{1}{2}C - \log((1 - \beta_0^-)p)}{\sqrt{C}}\right) > 0 \) iff \( \frac{-\frac{1}{2}C - \log((1 - \beta_0^-)p)}{\sqrt{C}} < \sqrt{C} \) iff \( \beta_0^- < 1 - \frac{1}{pe^{3C/2}} \).

Similarly \( f''(\beta_0^-) < 0 \) iff \( \beta_0^- > 1 - \frac{1}{pe^{3C/2}} \).

Regarding part 2, for fixed \( \beta_0^- \), let \( k(p) = R_0(h_{\beta_0^-, \pi_0}^{*}) \)
\[
k'(p) = \phi\left(\frac{-\frac{1}{2}C - \log((1 - \beta_0^-)p)}{\sqrt{C}}\right) \cdot \frac{-1}{\sqrt{C}p}.
\]

Clearly, \( k'(p) < 0 \) for all \( p > 0 \).

\[
k''(p) = \phi'\left(\frac{-\frac{1}{2}C - \log((1 - \beta_0^-)p)}{\sqrt{C}}\right) \cdot \frac{1}{Cp^2} + \phi\left(\frac{-\frac{1}{2}C - \log((1 - \beta_0^-)p)}{\sqrt{C}}\right) \cdot \frac{1}{\sqrt{C}p^2}.
\]

Note that \( k''(p) > 0 \) iff \( \frac{-\frac{1}{2}C - \log((1 - \beta_0^-)p)}{\sqrt{C}} < \sqrt{C} \) iff \( p > \frac{1}{(1 - \beta_0^-)pe^{3C/2}} \).

The constant \( C \) can be considered as a measure of separability of the two classes. Note that when \( p = 1 \), that is when \( \pi_0 = 1 - \pi_0 = 1/2 \), if \( C \) is large (i.e., it is easy to separate the two classes), \( 1/(pe^{3C/2}) \approx 0 \), then \( R_0(h_{\beta_0^-, \pi_0}^{*}) \) is a convex function of \( \beta_0^- \in (0, 1) \). On the other hand, when \( C \) is so small (i.e., two classes are hard to separate) that \( pe^{3C/2} \leq 1 \), \( R_0(h_{\beta_0^-, \pi_0}^{*}) \) is a concave function of \( \beta_0^- \in (0, 1) \).

**E  Neyman-Pearson Lemma**

The oracle classifier under the NP paradigm (NP oracle) arises from its close connection to the Neyman-Pearson Lemma in statistical hypothesis testing. Hypothesis testing bears strong resemblance to binary classification if we assume the following model. Let \( P_1 \) and \( P_0 \) be two known probability distributions on \( \mathcal{X} \subset \mathbb{R}^d \). Assume that \( Y \sim \text{Bern}(\zeta) \) for some \( \zeta \in (0, 1) \), and the conditional distribution of \( X \) given \( Y \) is \( P_Y \). Given such a model, the goal of statistical hypothesis testing is to determine if we should reject the null
hypothesis that $X$ was generated from $P_0$. To this end, we construct a randomized test $\phi : X \rightarrow [0, 1]$ that
rejects the null with probability $\phi(X)$. Two types of errors arise: type I error occurs when $P_0$ is rejected yet
$X \sim P_0$, and type II error occurs when $P_0$ is not rejected yet $X \sim P_1$. The Neyman-Pearson paradigm in
hypothesis testing amounts to choosing $\phi$ that solves the following constrained optimization problem

$$\max \mathbb{E}[\phi(X)|Y = 1], \text{ subject to } \mathbb{E}[\phi(X)|Y = 0] \leq \alpha,$$

where $\alpha \in (0, 1)$ is the significance level of the test. A solution to this constrained optimization problem is
called a most powerful test of level $\alpha$. The Neyman-Pearson Lemma gives mild sufficient conditions for the
existence of such a test.

**Lemma 2** (Neyman-Pearson Lemma). Let $P_1$ and $P_0$ be two probability measures with densities $f_1$ and $f_0$
respectively, and denote the density ratio as $r(x) = f_1(x)/f_0(x)$. For a given significance level $\alpha$, let $C_\alpha$
be such that $P_0\{r(X) > C_\alpha\} \leq \alpha$ and $P_0\{r(X) \geq C_\alpha\} \geq \alpha$. Then, the most powerful test of level $\alpha$ is

$$\phi_\alpha^*(X) = \begin{cases} 1 & \text{if } r(X) > C_\alpha, \\ 0 & \text{if } r(X) < C_\alpha, \\ \frac{\alpha - P_0\{r(X) > C_\alpha\}}{P_0\{r(X) = C_\alpha\}} & \text{if } r(X) = C_\alpha. \end{cases}$$

Under mild continuity assumption, we take the NP oracle classifier

$$\phi_\alpha^*(x) = \mathbb{I}\{f_1(x)/f_0(x) > C_\alpha\} = \mathbb{I}\{r(x) > C_\alpha\}, \quad (9)$$

as our plug-in target for NP classification.

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