Identifying leading indicators of product recalls from online reviews using positive unlabeled learning and domain adaptation

Shreesh Bhat and Aron Culotta

Department of Computer Science Illinois Institute of Technology Chicago, IL 60616 skumarab@hawk.iit.edu, aculotta@iit.edu

Abstract

Consumer protection agencies are charged with safeguarding the public from hazardous products, but the thousands of products under their jurisdiction make it challenging to identify and respond to consumer complaints quickly. From the consumer's perspective, online reviews can provide evidence of product defects. but manually sifting through hundreds of reviews is not always feasible. In this paper, we propose a system to mine Amazon.com reviews to identify products that may pose safety or health hazards. Since labeled data for this task are scarce, our approach combines positive unlabeled learning with domain adaptation to train a classifier from consumer complaints submitted to the U.S. Consumer Product Safety Commission. On a validation set of manually annotated Amazon product reviews, we find that our approach results in an absolute F1 score improvement of 8% over the best competing baseline. Furthermore, we apply the classifier to Amazon reviews of known recalled products; the classifier identifies reviews reporting safety hazards prior to the recall date for 45% of the products. This suggests that the system may be able to provide an early warning system to alert consumers to hazardous products before an official recall is announced.

1 Introduction

The U.S. Consumer Product Safety Commission (CPSC), created by the 1972 Consumer Product Safety Act, is "charged with protecting the public from unreasonable risks of injury or death associated with the use of the thousands of types of consumer products under the agency's jurisdiction. Deaths, injuries, and property damage from consumer product incidents cost the nation more than \$1 trillion annually." Typically, the CPSC learns about hazardous products through consumer reports, either through a phone hot-line, or through their online portal SaferProducts.gov.

For a subset of these complaints, the CPSC may decide that action is warranted, which most commonly takes the form of a "cooperative recall," in which the manufacturer agrees to issue a voluntary recall based on the CPSC's findings. As the agency notes, "due to the large volume of reports received by the CPSC each year, agency staff, unfortunately, cannot investigate and respond to every report on an

individual basis."² For example, in FY2015, the CPSC completed 410 cooperative recalls; by comparison, the CPSC received 85,000 calls to their hot-line and 2,539 incidents submitted to their online portal.³

Given the large number of products under its jurisdiction, the CPSC faces a number of regulatory challenges:

- Triage: Given the many potential hazards to investigate, how should they be prioritized?
- Discovery: How can new product hazards be efficiently reported to the CPSC?
- Notification: The time lag from report to recall can span multiple months (involving investigation and negotiations with the firm). How can consumers be notified more quickly of a potential hazard?

In this paper, we propose a system to help with these tasks by identifying product reviews on Amazon.com that indicate a potential safety or health hazard. The resulting system helps with discovery by identifying hazards that may not be submitted to the CPSC directly; it helps with triage by enabling complaints to be aggregated to identify high priority products; and it helps with notification by enabling consumers to be alerted immediately when hazardous reviews are posted on Amazon.

To train the text classification system, we use consumer complaints data uploaded to the CPSC portal at ConsumerSafety.gov. These "positive" instances are combined with thousands of unlabeled instances from Amazon.com reviews using Positive Unlabeled Learning (Li and Liu 2005). However, standard training algorithms underperform on this task, because these two data sources differ in systematic ways. To deal with this issue, we build on work in learning under dataset shift (Heckman 1977; Zadrozny 2004) to train a more accurate classifier. The resulting classifier identifies reviews mentioning safety hazards with an F1 score of 84%, an absolute improvement of 8% over the best baseline. Furthermore, we applied the classifier to reviews of known recalled products, and found that for 45% of the products, the system detected a review reporting a health or safety hazard prior to the recall date. This suggests that the system may be able to provide an early

¹https://www.cpsc.gov/About-CPSC

²https://www.cpsc.gov/About-CPSC/Contact-Information

³https://www.cpsc.gov/s3fs-public/FY15AnnualReport.pdf

warning system to alert consumers to potentially hazardous products.

2 Data

Our goal is to build a text classifier to determine whether a product review on Amazon.com reports a potential safety or health hazard of a product. As we expect such reviews to be rare, it is difficult to construct a training set in the traditional way of annotating a random sample of reviews. Instead, we consider the consumer complaints database on the CPSC website SaferProducts.gov. We supplement this with a large set of unlabeled Amazon reviews to build the classifier using Positive Unlabeled learning. For validation, we consider two additional data sources: a small set of annotated Amazon reviews, and a set of products that were recalled by the CPSC over the past 10 years. Below, we describe these data in more detail.

2.1 CPSC Complaints Database

The Consumer Product Safety Improvement Act was passed in 2008 to strengthen the CPSC by increasing its budget and expanding its regulatory tools. In addition, the law mandated that the CPSC create a publicly searchable database of consumer submitted reports of hazardous products. The website was launched in 2011 as *SaferProducts.gov*. To reduce the number of false reports, the site requires information about the consumer, photographs to document the report, and information about the specific product and manufacturer. Once a report is submitted, it is vetted by the CPSC, and, if deemed valid, it is first sent to the manufacturer for comment. Thus, it can take approximately 15 business days for a report to appear on the website (though longer times are possible, depending on volume and capacity).

For this paper, we focus on children products, since these tend to be the most vulnerable to health and safety hazards. We collected 2,010 complaints from the "Babies & Kids" category from SaferProducts.gov, from March 2011 – May 2016. Table 1 shows the top five most frequent product types in this data.

Each report has an incident description, which ranges from 4 to 1,683 words (median=98). Two short example descriptions are below:

I went to change the sheets on my son's crib, and the mattress had broken in the middle. Plastic was all over the mattress. Springs are close to poking thru.

A piece of the toy fall out and my daughter almost swallow it. we have to put out hand in her mouth to take it back. My daughter cannot breathe for a second.

When training the classifier, we assume that these 2,010 incident descriptions are positive examples (i.e., indicative of health or safety hazard). We refer to this as the **complaints database**.

2.2 Amazon Product Reviews

We collect 915,446 Amazon reviews in the "Baby" category from the dataset introduced in McAuley et al. (2015), from

Product Type	Count
Cribs	407
Bassinets or Cradles	258
Diapers	209
Pacifiers or Teething Rings	186
Baby Exercises	132

Table 1: Top 5 product types from the "Babies & Kids" category in the consumer complaint database SaferProducts.gov (of 2,010 total complaints).

Label	Review snippet
1	"This item needs to be taken off the market.
	My son almost suffocated to death in this"
1	"I had this product 2 hours and the leg
	snapped. My baby rolled forward and hit his
	head. It is now in the trash!!"
1	"When I was cleaning the tray, my daugh-
	ter leaned forward and the whole chair with
	booster seat fell down. My daughter got a
	bump on her head"
0	"I'm sending this product back today!!! I
	thought the Recaro booster seat would be light
	weight and trendy. This seat was so heavy I
	could hardly get it out of the box."
0	"It's cheaply made. I washed it on the gentle
	cycle and it began to fall apart :("

Table 2: Example reviews labeled as consumer safety concern (1) or not (0).

August 2008 - July 2014.⁴ These reviews range from 1 to 4,546 words (median=55). We refer to this as the **reviews database**.

2.3 Labeled Review Data

For validation, we manually annotated 448 Amazon reviews as to whether they report a hazardous or unsafe product. To construct this data, we combined uniform sampling with keyword search to identify possible positive examples (e.g., terms like "hurt" and "dangerous"). The final dataset contains 97 positive (hazardous) reviews and 351 negative (non-hazardous) reviews.

Table 2 shows five examples (three positive, two negative). A key challenge is distinguishing between reviews indicating a safety hazard and reviews that indicate more benign faults of the product. We refer to this as the **validation data**.

2.4 Recall Database

Finally, to explore the practical impact of this classifier, we collected a set of products that were recalled by the CPSC and had reviews in the reviews database. To do so, we first collected 6,741 recalled products from cpsc.gov⁵. We

⁴http://jmcauley.ucsd.edu/data/amazon/

⁵API: https://www.cpsc.gov/Recalls/CPSC-Recalls-Application-Program-Interface-API-Information/

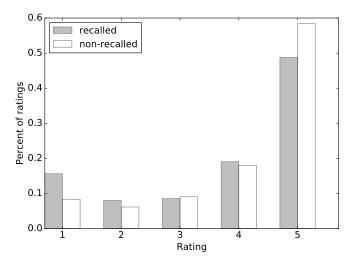


Figure 1: Amazon star rating distribution for reviews of recalled versus non-recalled products.

used a semi-automated process to match each recalled product with an Amazon product in the reviews database. To do so, we first filtered the recalled product list to those containing keywords relevant to the "Baby" category in Amazon: stroller, car seat, crib, child carrier, bath seat, infant carrier, bassinet, pacifier, rattle, swing, walker, dresser. This matched 482 of the original 6,741 recall records. We then extracted the product and/or company name from the Title field of the recall record, then returned Amazon products that matched at least two terms from the product and/or company name. This identified 3,523 products that partially matched one of 290 recall records. Finally, we manually verified the matches, resulting in a set of 137 Amazon products that matched one of 47 recall records (some recalls affect multiple products). Note that none of these recalled products were available on Amazon at the time of this writing; the historical reviews database allows us to identify reviews written before the product was taken off the market.

As this filtering makes clear, recalls are relatively rare events, so the data sparsity poses a challenge for typical machine learning training and validation workflows. This motivates our use of the complaints database to identify reviews indicating hazardous products.

Furthermore, it is worth noting that even recalled products can have many positive reviews. Figure 1 shows the distribution of star ratings for the recalled products compared with the non-recalled products. While recalled products have a slightly lower average rating than non-recalled products (3.8 vs. 4.1), nearly half of the reviews for recalled products have five stars. This suggests that using ratings alone is insufficient to identify hazardous products. We believe this is in part due to the fact that product defects may only affect a small subset of consumers, either due to the manufacturing process or the way in which the consumer uses the product. (It is also possible that fake reviews are having an impact here (Mukherjee, Liu, and Glance 2012)).

3 Methods

Our goal is to train a text classifier using the consumer complaints data to classify Amazon reviews as indicative of a hazardous product or not. We have as input a set of positive examples from the complaints database and a set of unlabeled examples from the reviews database. Let $\mathbf{x}_i \in \mathbb{R}^k$ be the k-dimensional feature vector representing document i and $y_i \in \{0,1\}$ be its class label, where 1 indicates a hazardous review. Then our input consists of a positively labeled dataset $L = \{(\mathbf{x}_1,1)\dots(\mathbf{x}_n,1)\}$ of consumer complaints and an unlabeled dataset $U = \{x_1\dots x_m\}$ of Amazon reviews.

This setting can be viewed as an instance of Positive Unlabeled learning (PU Learning (Li and Liu 2005)), since the training set consists of only positive and unlabeled instances. Below, we describe a simple baseline approach to this problem, identify a problem with this approach, then propose a new method that addresses this problem.

3.1 Baseline method

A simple approach to PU Learning is to assume that the unlabeled dataset U contains only negative examples; i.e., $U \triangleq \{(\mathbf{x}_1,0)\dots(\mathbf{x}_m,0)\}$. Of course, the unlabeled data may indeed contain positive examples; however, in our setting, hazardous reviews are rare in the reviews data, and so we expect the amount of label noise introduced to be low.

Furthermore, in this review domain, we also have the star rating of each review, which we can use to reduce the incidence of positive examples incorrectly annotated as negative examples in our training set. We expect reviews indicating safety hazards to have a low star rating. (While Figure 1 shows that recalled products can have high *average* ratings, we expect individual reviews mentioning health hazards to have low star ratings.) So, we introduce a threshold τ when sampling negative examples from the unlabeled data; only instances with star rating greater than or equal to τ are selected. We also use a second parameter s indicating the number of negative examples to sample during training.

We use logistic regression with L2 regularization as the baseline classifier. To handle class imbalance (there are many more negative examples than positive examples), we weight each instance inversely proportional to its class frequency. Thus, if there are p positive examples and n negative examples, each positive example receives weight $\frac{n+p}{2p}$, and each negative example receives weight $\frac{n+p}{2n}$. We use Scikitlearn's LogisticRegression implementation (Pedregosa et al. 2011).

3.2 Proposed method: Informed prior

In addition to the small amount of label noise introduced by the baseline method (positive examples labeled as negative), there is another, potentially more serious difficulty with the approach for this data. The problem stems from the selection bias in how the positive and negative examples are collected. Specifically, certain types of products like cribs, diapers, and night lights are over-represented in the complaints data relative to their prevalence in the reviews data. This leads to the inflation of coefficients related to these products — indeed, in the experiments below, we find that the terms "crib," "pampers," and "night light" are among the top ten highest weighted coefficients for the positive class for the baseline classifier. This can lead to a number of false positives, in which reviews of these types of products are erroneously labeled as hazardous.

If fine-grained product subtype information were available, we could apply standard adjustments to account for this sampling bias (e.g., survey weights (Gelman 2007) or propensity scores (Rosenbaum and Rubin 1983)). However, we do not have this product subcategory information for each complaint, nor would the schemas be equivalent between the complaints and review data.

Instead, we build on work in learning under dataset shift (Heckman 1977; Zadrozny 2004) and semi-supervised domain adaptation (Blitzer, McDonald, and Pereira 2006; Kumar, Saha, and Daume 2010; Chen, Weinberger, and Blitzer 2011). Our approach modifies the feature representation so that terms that are strongly predictive of the positive class in the unlabeled dataset have larger feature values than terms that are less predictive. Of course, we do not know the true labels in the unlabeled data; we instead use the baseline classifier to estimate them.

Our approach begins by fitting the baseline classifier, as defined in the previous section. Recall that the baseline classifier with parameters τ and s constructs a training set containing all complaint data as positive examples and a random sample of s Amazon reviews with a rating of at least τ as negative examples; we refer to this as the baseline training set. We then apply the classifier trained on the baseline training set to predict the labels for all unlabeled reviews in the Amazon review data; we refer to this as the **predicted** reviews data. Based on the examples above ("crib", "pampers," etc.), the key observation of our approach is that certain word features may be strongly associated with the positive class in the original training data, but may be weakly associated with the positive class in this predicted reviews data. For example, in one experiment below with $\tau = 5$ and s=20,000, we find that in the baseline training set, 91% of documents with the term "pampers" were annotated as positive examples (i.e., were from the complaints data). However, in the predicted reviews data, only 2% of documents containing the term "pampers" were predicted to be positive examples by the baseline classifier. So, our motivation is to use the feature statistics in the predicted reviews data to better inform the classifier trained on the baseline training set. Specifically, we want to increase the importance of features that are strongly associated with the positive class in the predicted reviews data. We do this by modifying the value for features proportional to their class conditional probability in the predicted reviews data, as described next.

In order to formalize this intuition, we must introduce some notation. Let $\hat{U} = \{(\mathbf{x}_1, \hat{y}_1) \dots (\mathbf{x}_m, \hat{y}_m)\}$ be the predicted reviews data; i.e., all Amazon reviews and the corresponding class labels predicted by the baseline classifier. Let $\theta_j \in \mathbb{R}$ be the coefficient in the baseline model associated with word feature j, and let $x_i^j \in \{0,1\}$ be the binary feature value for feature j in document i. For each term feature

ture, we compute the smoothed class conditional probability according to the predictions in \hat{U} . Let n_{jc} be the number of documents containing feature j that have been assigned label c by the baseline classifier:

$$n_{jc} = \sum_{(\mathbf{x}_i, \hat{y}_i) \in \hat{U}} \mathbb{1}[\hat{y}_i == c \land x_i^j == 1]$$

Then we can define the conditional probability with Laplacian smoothing as:

$$p(y=1|x^j=1) = \frac{1+n_{j1}}{2+n_{j1}+n_{j0}} \triangleq p_{j1}$$

and similarly for p_{i0} for class 0.

Let F^+ be the set of features with positive coefficients in the baseline classifier, and F^- be the set of features with negative coefficients in the baseline classifier. We will use p_{j1} to transform the feature values for F^+ , and p_{j0} to transform the feature values for F^- . In order to have the transformation be in the same scale for each class, we first normalize the conditional probabilities to sum to one for each class:

$$\hat{p}_{j1} = \frac{p_{j1}}{\sum_{j' \in F^+} p_{j'1}}$$

and similarly for \hat{p}_{j0} . To construct suitable feature values, we want to shift these values to have a mean of 1 and be non-negative, which we can do by multiplying each value by a constant factor ρ , the ratio of the number of features to the sum of the values \hat{p}_{jc} :

$$\rho = \frac{|F^+| + |F^-|}{\sum_{j \in F^+} \hat{p_{j1}} + \sum_{j \in F^-} \hat{p_{j0}}}$$

Finally, for all instances in the training and unlabeled data, we replace the value of feature j with the factor $(\rho * \hat{p}_{j1})$ if $j \in F^+$ or with $(\rho * \hat{p}_{j0})$ if $j \in F^-$.

As an example from one of the experiments below, the feature value for the bigram "very dangerous" is increased to 17.4, because 29% of documents in the unlabeled data containing "very dangerous" were classified as positive by the baseline classifier, the second highest rate of all features. Conversely, the term "crib" only has a feature value of 2.1, because only 3% of documents in the unlabeled data containing "crib" were classified as positive. This is particularly notable given that the baseline model assigns a higher coefficient to "crib" (1.34) than to "very dangerous" (0.55).

While it may seem that changing the feature value will not affect the final classifier, recall that we are using L2 regularization, and that we do not standardize the feature values prior to training. Thus, all else being equal, the regularization penalty will be effectively smaller for features with large values than for features with small values. Furthermore, because we optimize logistic regression with gradient descent, the gradients for features with large values will tend to be larger than for features with small values, causing features with high values to be updated faster than others.

4 Experimental Results

In the experiments below, we investigate four questions:

Model	Review Threshold (τ)	ROC AUC	F1	Precision	Recall
informed prior	5	97.0 ± 0.10	84.3 ± 0.42	85.8 ± 0.90	82.8 ± 0.28
informed prior	4	96.4 ± 0.19	82.7 ± 0.47	86.8 ± 0.35	79.0 ± 0.56
informed prior	3	96.3 ± 0.09	82.1 ± 0.41	87.6 ± 0.16	77.3 ± 0.84
baseline	5	96.1 ± 0.08	75.3 ± 0.43	72.8 ± 0.57	78.0 ± 0.28
baseline	4	95.9 ± 0.01	74.8 ± 0.36	73.7 ± 0.76	75.9 ± 0.28
baseline	3	95.7 ± 0.06	76.4 ± 0.54	78.4 ± 0.86	74.6 ± 0.28
baseline	none	94.0 ± 0.05	70.0 ± 0.24	79.0 ± 0.95	62.9 ± 0.97

Table 3: Comparison of the baseline classifier with our informed prior method on the validation data (with standard errors).

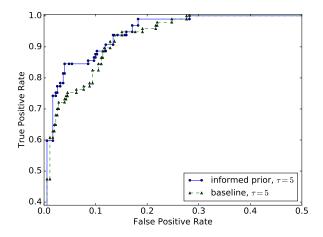


Figure 2: ROC curves for top informed prior and baseline classifiers from Table 3.

Model	Top terms
Informed	very dangerous, cpsc, mold, smacked, swal-
prior	low it, emergency room, recalled, recall, was
	playing, hazard, is unsafe, snapped, leaned
	forward, the consumer, got stuck, was hang-
	ing, burnt, injured, exploded, was chewing
Baseline	mold, pampers, fell, crib, rock, danger-
	ous, <i>night light</i> , hazard, broke, happened,
	gate, rash, light, recall, model, stuck, unsafe,
	caused, noticed, choking

Table 4: Top 20 terms for two models.

- 1. How does our informed prior approach compare to the baseline classifier?
- 2. How do the parameters τ (the star rating threshold) and s (the number of unlabeled examples used for training) affect accuracy?
- 3. How often does the classifier identify potential product hazards **before** a recall is issued for a product?
- 4. How well does the classifier prioritize products to be investigated for hazards?

We first tokenize all 915,446 Amazon reviews, retaining unigrams and bigrams that appear in at least 50 reviews and no more than 95% of all reviews, resulting in 136,160 total

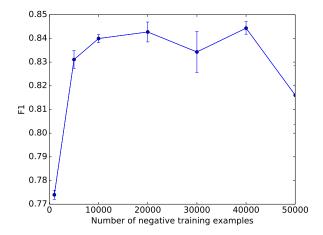


Figure 3: F1 of the informed prior classifier ($\tau = 5$) as the number of negative examples sampled for training (s) increases (standard error bars computed from three trials).

features. We represent each review as a binary feature vector. Using this pruned feature set, we then vectorize the 2,010 messages in the complaints dataset, as well as 448 labeled Amazon reviews in the validation data. For evaluation we use Precision/Recall/F1 as well as the area under the ROC curve.

Since the baseline training set is constructed by sampling s random reviews with rating $\geq \tau$ from the unlabeled Amazon review data, we average the results of three trials when reporting results below.

How does our informed prior approach compare to the baseline classifier? The primary classification results on the validation data are shown in Table 3. Here, we fix s=20,000 (we will explore it more below). We observe that across all performance measures the informed prior method produces more accurate results than the baseline. These results are also reinforced by the ROC curves in Figure 2, displaying the results for the top informed prior and top baseline classifiers.

To better understand these results, we report in Table 4 the 20 terms with the highest positive coefficients for the informed prior and baseline classifiers, using s=20,000 and $\tau=5$. We can see that the baseline model has many words that are likely due to sampling bias (italicized in the table), such as "pampers", "crib," "night light," "gate," and

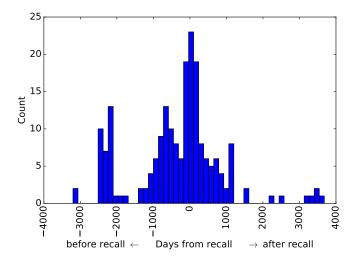


Figure 4: Histogram of when each of the identified hazardous reviews was submitted to Amazon relative to the date that the product was recalled.

"model." On the other hand, the informed prior model gives higher weight to features such as "very dangerous," "emergency room," and "is unsafe." Recall that both models are fit using the same training instances; the only difference is that feature values are increased for terms estimated to be predictive of the positive class in the unlabeled data. We also note that terms like "cpsc" and "recalled" arise from that fact that some reviews either discuss a pending or past recall of a product, or indicate that they have concurrently posted a complaint to the CPSC database.

When we manually examine the remaining errors of the classifier, we notice a few themes. For false positives, we observe that some reviews describe hazards of *other* products, as a way to emphasize the quality of the product being reviewed. A deeper syntactic analysis of the reviews may be able to identify such cases. For false negatives, we observe some reviews in which the consumer thinks there is a safety hazard, but did not experience a first-hand injury (e.g., "it seems flimsy" or "the setup is rickety"). Our classifier is perhaps too conservative in these instances, instead relying on more serious reports of injury.

How do the parameters τ and s affect accuracy? Table 3 also lists results as we change τ , the review threshold used when sampling examples from the unlabeled data to serve as negative training instances. We can see that increasing this threshold can greatly improve the recall of the classifier, while sometimes reducing precision. However, the overall AUC increases as τ increases. We conjecture that the boost in recall is in part because by removing reviews with low ratings, we remove from the training set reviews with negative sentiment that are labeled as non-hazardous reviews. Examples include the final two rows in Table 2, which are critical of the product, but do not report a specific safety concern. Reviews like these can potentially dilute the impact of such negative sentiment terms in reviews that do in fact report health hazards.

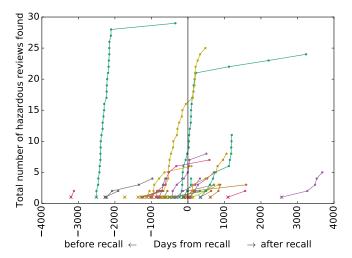


Figure 5: The number of hazardous reviews found for each recalled product over time (one line per product).

To investigate the impact of s, the number of negative reviews sampled, we report in Figure 3 the F1 score of the informed prior classifier ($\tau=5$) as s increases. We can see that generally accuracy is stable for s in the range 5,000-40,000. For values greater than 40,000, we suspect that the class imbalance becomes too extreme for the instance weighting method discussed in Section 3.1. For values less than 5,000, we may actually have more positive than negative examples in the training set, which is the reverse of what we expect in the unlabeled data.

How often does the classifier identify potential product hazards before a recall is issued for a product? Using the best classifier from Table 3 (informed prior; $\tau=5$; s=20,000), we next predict the label for the reviews of the Amazon products identified as being part of a CPSC recall (c.f., Section 2.4). After filtering products with fewer than 10 reviews, we are left with 7,318 reviews from 86 products, of which 204 reviews were predicted to report a safety hazard.

To investigate the ability to provide consumers with a quicker notification of potential hazards, Figure 4 shows a histogram of when each of the identified hazardous reviews were submitted to Amazon relative to the date that the product was recalled. We can see that many of these reviews are posted well before the recall date. There are some outliers appearing years before the recall date; we observe that this can happen when a recall is issued because of stores that continue to sell merchandise that had already been recalled (in this case, not Amazon, but another retailer). Additionally, there are reviews found well after the recall date, which can occur for products that have been discontinued on Amazon, but still have a page on which users can submit reviews. Often, users post messages to warn others that the product has been recalled.

As another view into this data, Figure 5 shows the cumulative number of hazardous reviews found for each recalled product over time (each line is a different product). This graph indicates that, while for many products the clas-

sifier only identifies one or two hazardous reviews, there are several products with five or more hazardous reviews posted well before the recall date.

Additionally, Table 5 lists five examples of hazardous reviews identified before the recall date, ranging from 592 to 117 days prior. In many cases, the specific complaint described in the Amazon review is also mentioned in the reason for the recall posted by the CPSC. For example, the first row indicates a problem with the front wheel assembly of a stroller, and the second row describes a faulty adaptor in a car seat. The fourth review indicates that the user has knowledge of a pending recall that had not yet been announced.

Taken together, these results suggest that there is an opportunity to mine Amazon reviews to provide earlier warnings to consumers about potentially hazardous products.

How well does the classifier prioritize products to be investigated for hazards? Finally, we apply the classifier to all 915K Amazon reviews and compute indirect estimates of accuracy. Overall, 10,857 were predicted to report a safety hazard. We observe that the percentage of reviews classified as hazardous among the non-recalled products is 1.2%; for recalled products, it is 2.8%. Thus, the classifier is more than twice as likely to classify a review as hazardous for a recalled product, lending further support to the accuracy of the model.

Next, we count the number of hazardous reviews identified for each product and plot the resulting histogram in Figure 6. We can see this follows the familiar long tail distribution; there are a few products with many hazardous reviews, and many products with a small number of hazardous reviews. This matches our expectation that recalls are rare events.

As a final estimate of precision, we identify the ten reviews with the highest posterior probability for the positive class. Of these, half are reviews of recalled products; for the other half, while no recall has been issued, the reviews contain strong language indicating that further investigation may be required. For example, one review reports of a child whose finger was stuck in a stroller, which is similar to an incident that led to a recall of a different stroller. Similar injuries are reported in the other reviews, and many contain phrases liked "This toy needs to be recalled ASAP!" and "Please do not buy this product. It is unsafe!"

To further determine how this approach may aid in the discovery of safety hazards, we also compared the number of hazardous reviews detected by year to the number of complaints submitted to the CPSC over the same time frame. The number of hazardous reviews detected indicates that many issues may be reported on Amazon, but not submitted through the online portal at the CPSC. For example, Figure 7 shows that the classifier detected 2,840 reviews of baby products reporting health or safety hazards in 2013; the CPSC complaint portal returns only 432 results for the same time period. This suggests that consumers detect many more product hazards than are submitted to CPSC (though it is possible some of these are reported to the phone hot-line, which are not made public to our knowledge). Furthermore, there is an inherent delay to the publication of consumer complaints submitted to CPSC, due to the time required to

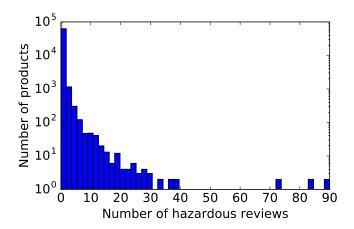


Figure 6: Number of reviews predicted to report a health hazard per product over all 915K Amazon reviews.

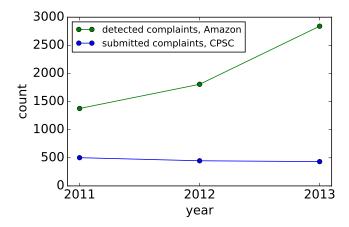


Figure 7: A comparison of the volume of consumer complaints in the "Babies & Kids" category submitted to Safer-Products.gov versus Amazon reviews classified as reporting a health hazard in the same category.

verify the complaint and contact the manufacturer. In our data, the median time from when the report is submitted by a consumer to when it is published on the CPSC website is 30 days. In contrast, Amazon reviews are published immediately upon submission.

These results suggests that this system may be used to both discover health hazards not submitted to the CPSC, as well as to prioritize complaints posted on Amazon for potential examination for safety hazards.

5 Related Work

To the best of our knowledge, this is the first published system to identify product health and safety hazards from online reviews with no manual human annotation required. Additionally, our time-series experiments indicate that these reviews can be identified prior to the product recall date.

Very recently, Winkler et al. (2016) used a keyword based

Product Name	Recall Date	Recall Reason	Review Date	Review Snippet
Contours Op-	2012-07-24	"the front wheel as-	2010-12-10	"after less than 4 months of use, it fell apart:
tions Tandem		sembly can break, pos-	(592 days	the front end collapsed because the two pins
Stroller		ing a fall hazard to the	prior)	holding it in place popped outI contacted
		child in the stroller" a		Kolcraft immediately and nearly a month later
				I still don't have a working stroller."
Phil & Teds	2014-06-04	"the plastic adaptors	2013-04-30	"I'm not sure if this attachment has a defect
Travel Sys-		used to connect an infant	(400 days	or if it is only supposed to have one button
tem Car Seat		car seat to a stroller can	prior)	on the adapter, but it makes the carseat very
Adaptor		crack, become unstable		wobbly and unstableIs mine defective? Ev-
		and break during use,		eryone else seems to have great reviews, but
		posing a fall hazard to		mine is so unstable it seems dangerous.
E' 1 D '	2007.05.20	infants." b	2007.01.14	(L) 1 1 1 TOTH C
Fisher-Price	2007-05-30	"infants can shift to one	2007-01-14	"It's a very poor design and needs a LOT of
Rainforest		side of the swing and be-	(136 days	work. And my daughter ends up in a crumbled
Infant Swing		come caught between the	prior)	up ball on one side of the swing more times than not."
		frame and seat, posing an entrapment hazard." c		than not.
Phil & Teds	2008-12-17	"the frame handle could	2008-08-18	"The US distributor, Regal Lager is recalling
Dash Buggy		fail to latch properly and	(121 days	all Dash strollersThe locking mechanism on
Strollers		break, posing a fall haz-	prior)	the right side is defective and does not lock."
		ard to small children." d		
Graco Activity	2002-06-12	"The toy track can	2002-02-15	"the wheel part broke off of the activity
Center		break, presenting a cut	(117 days	part and left very sharp edgeshe managed to
		or pinch hazard and	prior)	get his head stuck in between the spoiler and
		exposed small parts pose		the tray (T)he parrimedics had to comethe
		a choking hazard to		walker had to be cut to release him."
		young children." e		

a https://www.cpsc.gov/recalls/2012/kolcraft-recalls-contours-tandem-strollers-due-to-fall-and-choking-hazards

Table 5: Examples of hazardous reviews identified prior to recall date.

approach to identify online reviews that report injuries from toy products. In addition to the manual effort required to curate the keyword list, the approach appears to produce low precision rates (9-44%, depending on subcategory). Of the top 100 identified reviews, only sixteen mentioned an injury. The authors apply the same approach to detect defects in dishwashers, with similar precision values (Law, Gruss, and Abrahams 2017). In contrast, our proposed approach fits a statistical classifier with no human intervention required, resulting in >85% precision and >80% recall.

Other recent work has identified vehicle defects in consumer reviews using standard text classification, with accuracies ranging from 62%-77% (Abrahams et al. 2015). However, in many domains it is not feasible to annotate sufficient messages to use standard supervised learning. Additionally, Zhang et al. (2015) built an unsupervised approach to clustering vehicle defects by subcategory. Such a method may serve to complement our present work by providing more fine-grained clusters of reviews by hazard type.

6 Conclusion

We have presented a classification system to identify product reviews on Amazon.com that indicate a health or safety hazard. The classifier is trained without any additional human annotation or intervention by using the consumer complaint records submitted to SaferProducts.gov. To deal with data selection bias, we introduced a new domain adaptation approach that is easy to implement and results in an 8% absolute increase over the best competing baseline. An analysis of the historical reviews of recalled products indicates that the system can identify potential safety hazards well before the recall is issued.

In future work, we plan to build a web interface to make real-time predictions as reviews are submitted to Amazon and to produce a ranked list of potentially hazardous products. Additionally, we plan to investigate classification methods that assign a severity to the reported hazard, to further help consumer groups prioritize investigations.

b https://www.cpsc.gov/recalls/2014/philandteds-recalls-infant-car-seat-adaptors-for-strollers

c https://www.cpsc.gov/recalls/2007/fisher-price-rainforest-infant-swings-recalled-due-to-entrapment-hazard

 $^{^{\}rm d}\ https://www.cpsc.gov/recalls/2009/regal-lager-recall-to-replace-phil-teds-strollers-due-to-fall-hazard$

 $[^]e\ https://www.cpsc.gov/recalls/2002/cpsc-and-graco-announce-recall-of-toy-track-on-activity-centers$

References

- [Abrahams et al. 2015] Abrahams, A. S.; Fan, W.; Wang, G. A.; Zhang, Z. J.; and Jiao, J. 2015. An integrated text analytic framework for product defect discovery. *Production and Operations Management* 24(6):975–990.
- [Blitzer, McDonald, and Pereira 2006] Blitzer, J.; McDonald, R.; and Pereira, F. 2006. Domain adaptation with structural correspondence learning. In *Proceedings of the 2006 conference on empirical methods in natural language processing*, 120–128. Association for Computational Linguistics.
- [Chen, Weinberger, and Blitzer 2011] Chen, M.; Weinberger, K. Q.; and Blitzer, J. 2011. Co-training for domain adaptation. In *Advances in neural information processing systems*, 2456–2464.
- [Gelman 2007] Gelman, A. 2007. Struggles with survey weighting and regression modeling. *Statistical Science* 153–164.
- [Heckman 1977] Heckman, J. J. 1977. Sample selection bias as a specification error (with an application to the estimation of labor supply functions).
- [Kumar, Saha, and Daume 2010] Kumar, A.; Saha, A.; and Daume, H. 2010. Co-regularization based semi-supervised domain adaptation. In *Advances in neural information processing systems*, 478–486.
- [Law, Gruss, and Abrahams 2017] Law, D.; Gruss, R.; and Abrahams, A. S. 2017. Automated defect discovery for dishwasher appliances from online consumer reviews. *Expert Systems with Applications* 67:84–94.
- [Li and Liu 2005] Li, X.-L., and Liu, B. 2005. Learning from positive and unlabeled examples with different data distributions. In *European Conference on Machine Learning*, 218–229.
- [McAuley et al. 2015] McAuley, J.; Targett, C.; Shi, Q.; and van den Hengel, A. 2015. Image-based recommendations on styles and substitutes. In *Proceedings of the 38th International ACM SIGIR Conference on Research and Development in Information Retrieval*, 43–52. ACM.
- [Mukherjee, Liu, and Glance 2012] Mukherjee, A.; Liu, B.; and Glance, N. 2012. Spotting fake reviewer groups in consumer reviews. In *Proceedings of the 21st international conference on World Wide Web*, 191–200. ACM.
- [Pedregosa et al. 2011] Pedregosa, F.; Varoquaux, G.; Gramfort, A.; Michel, V.; Thirion, B.; Grisel, O.; Blondel, M.; Prettenhofer, P.; Weiss, R.; Dubourg, V.; et al. 2011. Scikitlearn: Machine learning in python. *Journal of Machine Learning Research* 12(Oct):2825–2830.
- [Rosenbaum and Rubin 1983] Rosenbaum, P. R., and Rubin, D. B. 1983. The central role of the propensity score in observational studies for causal effects. *Biometrika* 70(1):41–55.
- [Winkler et al. 2016] Winkler, M.; Abrahams, A. S.; Gruss, R.; and Ehsani, J. P. 2016. Toy safety surveillance from online reviews. *Decision support systems* 90:23–32.
- [Zadrozny 2004] Zadrozny, B. 2004. Learning and evaluating classifiers under sample selection bias. In *Proceedings of*

- the twenty-first international conference on Machine learning, 114.
- [Zhang et al. 2015] Zhang, X.; Niu, S.; Zhang, D.; Wang, G. A.; and Fan, W. 2015. Predicting vehicle recalls with user-generated contents: A text mining approach. In *Pacific-Asia Workshop on Intelligence and Security Informatics*, 41–50. Springer.