Taylor King, Michael Moore, Ashlyn Woodward, Caleb Yost

Dr. Sayed Khushal Shah

CSCE 5290.001 NLP

Project Proposal

Generating and Evaluating Synthetic Reviews

1 Project Summary

Over the last 30 years the world has seen a major shift from in person shopping in local market places to online shopping. While this change is convenient for most individuals it has come with some unforeseen risks to consumers. One such risk that is given to the consumers is finding reputable producers from which they can purchase their goods. The most common metric that consumers use is the reviews of a seller from previous customers that the seller has interacted with and also the quality of the product that is being sold. With such large trust in this metric there has been an epidemic in the online shopping community in the form of fake reviews using trained neural networks to gain consumer trust.

To summarize this project our group will be making two models. The first model will be trained on genuine product reviews found from amazon. This model will out pout fake reviews that should be indistinguishable form the real reviews that were used for training. Then we will take these fake reviews generated by our first model and train a second model to identify fake reviews. This will be done to help combat the problem that diminishes consumer trust in online shopping.

The motivation for this project stems is driven from our observation of demand for the product within the global market. “152 billion dollar problem” Fake reviews take up an estimated 4% of all online reviews. Although many consider populating items with fake reviews unethical, the market for these reviews is undeniably large. Often these reviews are copy and pasted over many profiles and easily detectable. Our motivation is to make a model to generate unique reviews based on the product's information. However, with this large market the use of these reviews can be unethically. Fake reviews on a product can be the deciding factor if a consumer will purchase the item. For this reason our group will also design a model to help identify the fake reviews. This project will aim to help combat the epidemic of fake reviews that we have been facing since the boom of the online market.

2 Goals and Objectives

The significance of this project comes from the amount of money that can be made from the application of both models. The market for fake reviews is estimated to influence $3.8 trillion of global e-commerce spend in 2021, according to Jonathan Marciano from theprint.com [3]. A model that creates non generic and unique reviews is extremely valuable for the arguably unethical market. In order to combat this, models which can tell the difference between real and synthetic reviews are also exceptionally beneficial. Especially since most companies which buy fake reviews use them for low quality, previously one-star products in order to boost those sales [2]. This project will help solidify the lessons taught in class by practically working with a text-based dataset and a neural network.

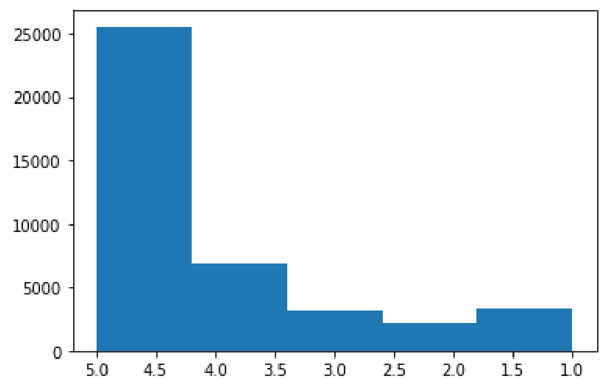
The objective of our project is to generate fake reviews for a product and to build a model to identify whether a given review is fake or not. We will start this by making a machine learning model that generates fake reviews. to accomplish this, we will be using the Amazon review dataset used in these publications [1] [4]. All features and an example for each can be found in Table 1. Once we create fake reviews, we will be able to move to the next part of our project of identifying them with a machine learning model. This part of the project will be done via supervised learning, labeling the reviews from the amazon dataset as true and our synthetic dataset as false. By the end of our project, we ultimately hope to have a model that can recognize the synthetic reviews with an accuracy of at least eighty percent and a model that can generate realistic-looking reviews. These goals conflict with each other, so for the purposes of this class we will keep our focus mainly on the identification of the reviews.

Feature Name	Origin	Description	Example
asin	Reviews & Metadata	ID of the product	0000031852
title	Metadata	Name of the product	TUTU Botiquecutie TM Girls Ballet Zebra Hot Pink
price	Metadata	Price of the product	$17.99
imurl	Metadata	Product image url	https://m.media-amazon.com/images/I/718HTZfwz6L._AC_SX679_.jpg
related	Metadata	Products related to the product	Also bought: {"B00JHONN1S"} Also viewed: {"B002BZX8Z6"}
salesRank	Metadata	Sales rank information for product	{"Toys & Games": 211836}
brand	Metadata	Product Brand	Coxlures
categories	Metadata	Product sales categories	[["Sports & Outdoors", "Other Sports", "Dance"]]
reviewerID	Reviews	ID of the reviewer	A2SUAM1J3GNN3B
reviewerName	Reviews	Name of reviewer	J. McDonald
helpful	Reviews	Helpfulness of review	2, 3
reviewText	Reviews	Review Text	"I bought this for my husband who plays the piano. He is having a wonderful time playing these old hymns. The music is at times hard to read because we think the book was published for singing from more than playing from. Great purchase though!"
overall	Reviews	Rating of review	5.0
summary	Reviews	Summary of review	Heavenly Highway Hymns
unixReviewTime	Reviews	Time of review (unix time)	1252800000
reviewTime	Reviews	Time of review (raw)	09 13, 2009

Table 1: Amazon Dataset Features to be used in our Analysis

3 Increment One

For this increment our group was mostly focused on getting on cleaning and doing some pre-processing on the data. We used the dataset as described about. We have started out work on a subset of the data to make testing more straight forward. For our design we have gathered all of our data into a data frame. Items are combined into a look up table where we can look up all the review text, cost, description, review rating, and review summary for a single item. We will do this for ever item in every category to create the smallest overhead possible. This data will then be used to train a model to replicate similar reviews. To Analyze the data we wanted to see what are some key features of what we are working we decided to make some graphs. One such graph is a histogram of all of the review scores so that we could get a sense of what sentiment we have behind our data, but first we will limit this . We hope to get a even skew of review types to generate a good model for each review score. The following was the result of our analysis:



We noticed that a significant number of our results were in the 5 star category. In future we will expand it to be every category in our data set. currently this plot is limited to just the Home and Appliances section of the reviews. As we expand the categories that we include we expect that this skew will even out a bit more. Once we have this we expect to be able to feed all of this data into an model. This model will take in a variety of features. We will for sure be including the review title and the review text. As a stretch goal the group will aim to include other variables in our generation such as price and review score(1-5 stars) in our feature list. It is our belief that these features could influence how people write their reviews. Once we have generated these reviews we will feed those results along with some genuine human made reviews into a model to classify them as either ”fake” or ”genuine”. We hope to be better than randomly guessing which would be an accuracy rate of above 50 percent. Ideally we want to identify as many genuine or fake reviews as possible.

For iteration one we started by implementing the ground work for our project. This was broken into the following task: Ashlyn downloaded a sample of the dataset; Michael and Caleb wrote code to ingest the data and format it in a machine readable way; Taylor did some preliminary data analysis. Each member of the team contributed equally 25 percent to the project efforts. All the work can be found in our Github repository.

Looking forward to iteration two, we hope to implement a model that can generate fake reviews. This will be carried out by Clay and Taylor. Caleb and Ashlyn will be responsible for implement a model that tries to correctly classify our synthetic reviews from the real ones. As of now, we foresee possible issues working with the full dataset, as it is quite large. To mitigate this issue, we plan on using subsets of the full dataset. We hope this will give us enough data to generate realistic reviews without having to incur the training times of the full dataset.

References

[1] Ruining He and Julian McAuley. Ups and downs: Modeling the visual evolution of fashion trends with one-class collaborative filtering. In *proceedings of the 25th international conference on world wide web*, pages 507–517, 2016.

[2] Sherry He, Brett Hollenbeck, and Davide Proserpio. The market for fake reviews. *Available at SSRN 3664992*, 2021.

[3] Jonathan Marciano, Apoorva Mandhani, Shubhangi Misra, and Shobhaa De. Almost 4% of all online reviews are fake. their impact is costing us $152 billion, Aug 2021.

[4] Julian McAuley, Christopher Targett, Qinfeng Shi, and Anton Van Den Hengel. Image-based recommendations on styles and substitutes. In *Proceedings of the 38th international ACM SIGIR conference on research and development in information retrieval*, pages 43–52, 2015.