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# Introduction

In an economy increasingly driven by e-commerce, optionality for consumers has never been greater [SOURCE]. Furthermore, the structure of online reviews allows consumers unprecedented access to information about prospective products and services. In order to compete in the digital age, companies must be able to analyse these customer reviews to evaluate and improve their digital image and reputation. In the context of “stars” or a rating system, this is a fairly trivial matter. However, when no such linear system exists, it becomes a much more challenging and ambiguous task. To properly categorize reviews at scale, a potential solution is to employ sentiment analysis to ascertain the relative quantity of positive to negative reviews. Due to the subjective and specific nature of sentiment analysis, this is a potential application for a machine learning model. Therefore, this project will aim to create a model to classify online customer reviews. To restrict the investigation scope, this project with only explore the potential for decision-tree models.

This model will be constructed from one such dataset of unlabelled customer reviews sourced from TrustPilot, an online review platform. These reviews pertain to a company called ASOS. Given that the model will be used to drive aggregate information about a large corpus of data, success criteria for this project will be creating a model that can classify consumer reviews as ‘positive’, ‘negative’, or ‘neutral’ with an accuracy of at least 80%.

# Background

## Sentiment Analysis

Sentiment Analysis is a form of Natural Language Processing (NLP) that works to identify and classify opinions expressed in text.

Challenges related to the subjective nature

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## Decision Trees

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## Lexicon-Based Labelling

This project will employ a lexicon to label the training data. A lexicon is a corpus of words and phrases associated with a sentiment value on a certain scale. One such lexicon is the AFINN lexicon. Developed at the Technical University of Denmark in 2011, the AFINN lexicon was specifically developed for sentiment analysis of “microblogs”, or short chunks of text casually posted online [3]. AFINN was developed using twitter posts from 2009, then refined against leading lexicons at the time such as ANEW.

## Term Frequency & Inverse Document Frequency

Term Frequency - Inverse Document Frequency (TF-IDF) is a method used to determine the relative importance of a given token within an instance. This value is derived from the number of times a token appears in a given instance in relation to the relative frequency of that token across the dataset [1]. When applied, it

# Method & Approach

## Project Plan

This project can be broken down into three distinct problems. First, the training data must be properly labelled to facilitate supervised learning. Then, the data must be cleaned and transformed into a format that can be modeled. Finally, the appropriate model must be built and refined using these preprocessed data.

To label the training data, a combination of a manual and lexical labelling will be employed. Approximately 10% of the given data will be initially labelled manually. Then the AFINN lexicon will be applied across all instances to the review title and review contents separately. The relative distribution of the scores for labelled instances will be analysed, moderating for the given label, to determine logical boundaries for the classification. These boundaries will then be applied across all instances to label the training data.

To transform the data into a workable format, TF-IDF vectorization will be applied to the preprocessed tokenized data. This will yield a set of features that represent important tokens across the dataset.

Finally, to build and refine the model, attribute selection will first be applied to the TF-IDF results to significantly reduce dimensionality. Once this has been performed, the selected decision tree model will be applied and then fine-tuned to produce the most promising result.

## Preprocessing

The initial state of the data was 2000 unlabeled reviews in plain text. To clean the data, a tokenizer was first applied to break the text into discrete words. Frequently occurring words with little to no significance in the context of sentiment analysis are known as stopwords. Removing these stopwords from the token list can help reduce noise and improve the accuracy of the model [2] In this instance stopwords are removed using a set of common stopwords provided by the nltk library in python.

The next step in preprocessing is to apply TF-IDF vectorization to the remaining to derive numeric attributes that will then be used in classification. In this instance the vectorizer generates 1000 attributes per instance of the most important tokens in the dataset.

## Modeling

Given the restriction of the project scope to decision tree models, the optionality for potential models is naturally limited. Three common approaches to decision trees include the C4.5, random tree, and random forest algorithms.

The C4.5 Algorithm represents a more classic approach to the creation of decision trees, using relative information entropy and gain for attribute selection to produce a reliably accurate decision tree [3]. Th C4.5 algorithm benefits from variability and relative transparency in the classification process.

Random trees...

## Evaluation

The model will be evaluated using a holdout test set of 100 examples labelled in the same way as the

# Results

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1. Hyperparameter Tuning Results

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##### Discussion

The preferred spelling of the word “acknowledgment” in America is without an “e” after the “g”. Avoid the stilted expression “one of us (R. B. G.) thanks ...”. Instead, try “R. B. G. thanks...”. Put sponsor acknowledgments in the unnumbered footnote on the first page.

##### Conclusion

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