Capstone Project 2: Milestone Report
Spring Board Data Science Career Track
~ By Zach Nguyen

Data Story

Business Problem: Nowadays, companies juggle with quite a few product brands. Despite their maintenance cost, product brands are strong value generation engines for many established companies. For this reason, companies are constantly looking out across Blogs, Forums, and other Social media platforms, etc. to check the sentiment for their various products and competitor products to learn how their brand resonates in the market. This type of Sentiment analysis helps them as part of their post-launch market research to determine the effectiveness of the brand of the product they have released into the market.

Client: For the sake of the scenario, the client is a Canadian pharmaceutical company who is interested in understanding how their drug brand products are doing. This intelligence is especially useful in the Canadian pharmaceutical industry as the country's rigorous regulatory and bureacratic processes mean that companies can only exploit a developed patented drug for a short window of time before the curse of patent cliff kicks in, and the drug patent is released to the public, causing a steep decline in sales[1].

Even though this problem is significant in the medical industry, it can be very similar in many other consumer-driven industries like food, clothing retail, e-commerce etc .. With the Canadian pharmaceutical market declining in growth[2], a reasonable business strategy on domestic products is not to expand market share and invest aggresively in R&D, but to improve the margin on existing brands. A good start to that is to track the impact of current drugs. With a good algorithm, companies can flag good and bad products for review and generate real-time metrics on how their products are useful or non-useful to consumers.

In the scenario played by this report, I will assume the role of a data scientist of a pharmaceutical company to conduct and assess the use of various sentiment analysis techniques on the collected dataset. I will then attempt to bridge the results of the Data Science/ Machine Learning pipeline with the realistic requirements of the company in order to make business recommendations on how to proceed. The guiding questions of the project are as followed:

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[1] Retrieved from: https://www.fraserinstitute.org/sites/default/files/intellectual-property-rights-protection-and-the%20biopharmaceutical-industry.pdf
[2] Retrieved from: https://www.ic.gc.ca/eic/site/lsg-pdsv.nsf/eng/hn01768.html

- Is the collected data useful now for the task of sentiment discrimination? Should the company invest in collecting more data?
- Is the recent advance in Natural Languages Processing (NLP) good enough to make machine classification viable? Will it be in the future?
- Can the data be valuable elsewhere?
- How should we improve on the data analysis? Should it invest in better infratructures and personel for Machine Learning?

Data source: The data found is from a sentiment analysis[3] hackathon hosted by Analytics Vidhya. It was collected from a real pharmarceutical and is an excellent example of how messy and challenging text data can be, even for a very traditional task of sentiment analysis. The data contains reviews of over 100 different drugs with 3 sentiment labels (positive, negative and neutral). Due to the of the confidentiality of the data and the fact that the competition is over, the data cannot be shared for reproduceability.

Methodology:

- The use of text analysis techniques will be employed to explore the data and address any data preprocessing and data imbalance (with python packages such as Pandas, Seaborn, nltk, gensim).
- Modern Natural Language Processing (NLP) techniques will be use to conduct text classification (using scikitlearn for shallow algorithms and gensim, keras-tensorflow for neural-based techniques).
- Analysis and selection of the algorithm used
- Business plan and recommendation for the use case of the algorithm.

Deliverables: Slide Deck, Report, Code

[3] Retrieved From: https://datahack.analyticsvidhya.com/contest/innoplexus-online-hiring-hackathon/

Data Wrangling and Preprocessing

After defining and using a simple function to check random reviews of different sentiments. One of such reviews can be seen here:

```
This is an update of the Cochrane review "Teriflunomide for multiple sclerosis" (first published in The Cochrane Library 2012,
Issue 12).Multiple sclerosis (MS) is a chronic immune-mediated disease of the central nervous system. It is clinically characte
rized by recurrent relapses or progression, or both, often leading to severe neurological disability and a serious decline in q
uality of life. Disease-modifying therapies (DMTs) for MS aim to prevent occurrence of relapses and disability progression. Ter
iflunomide is a pyrimidine synthesis inhibitor approved by both the US Food and Drug Administration (FDA) and the European Medi
cines Agency (EMA) as a DMT for adults with relapsing-remitting MS (RRMS).  OBJECTIVES: To assess the absolute and comparative
effectiveness and safety of teriflunomide as monotherapy or combination therapy versus placebo or other disease-modifying drugs
(DMDs) (interferon beta (IFNβ), glatiramer acetate, natalizumab, mitoxantrone, fingolimod, dimethyl fumarate, alemtuzumab) for
modifying the disease course in people with MS.  SEARCH METHODS: We searched the Cochrane Multiple Sclerosis and Rare Diseases
of the CNS Group Specialised Trials Register (30 September 2015). We checked reference lists of published reviews and retrieved
articles and searched reports (2004 to September 2015) from the MS societies in Europe and America. We also communicated with i
nvestigators participating in trials of teriflunomide and the pharmaceutical company, Sanofi-Aventis.  SELECTION CRITERIA: We i
ncluded randomized, controlled, parallel-group clinical trials with a length of follow-up of one year or greater evaluating ter
iflunomide, as monotherapy or combination therapy, versus placebo or other approved DMDs for people with MS without restriction
s regarding dose, administration frequency and duration of treatment.  DATA COLLECTION AND ANALYSIS: We used the standard metho
dological procedures of Cochrane. Two review authors independently assessed trial quality and extracted data. Disagreements wer
e discussed and resolved by consensus among the review authors. We contacted the principal investigators of included studies fo
r additional data or confirmation of data.  MAIN RESULTS: Five studies involving 3231 people evaluated the efficacy and safety
of teriflunomide 7 mg and 14 mg, alone or with add-on IFNβ, versus placebo or IFNβ-1a for adults with relapsing forms of MS and
an entry Expanded Disability Status Scale score of less than 5.5.Overall, there were obvious clinical heterogeneities due to di
versities in study designs or interventions and methodological heterogeneities across studies. All studies had a high risk of d
etection bias for relapse assessment and a high risk of bias due to conflicts of interest. Among them, three studies additional
ly had a high risk of attrition bias due to a high dropout rate and two studies had an unclear risk of attrition bias. The stud
```

As can be seen, a few aspects were discovered that could hinder the quality of the data:

- None of the reviews are missing, so removal or imputation is unnecessary.
- The sentiments have three classes (0: positive, 1:negative, 2:neutral), thus multi-class algorithms are a must.
- The reviews include a high data imbalance, which could be rectified with resampling techniques to including appropriate weights in our algorithm.
- Many reviews and are confusing to classify, even for humans! This is due to the fact that a review could talk about other drugs (and therefore, could express different sentiment than the drug in question).
- Some of the samples seem to be misclassified by humans. This is a technical issue that should be resolved in the data-collection step.
- The reviews include a lot of punctuations and numerics and occasional links/urls that could hinder Bag of Word analysis.
- The drug-name sometimes include hyphens and numerics, so caution must be taken to ensure the drug name remains in-tact.
- The reviews include a lot of contractions, which could create inaccurate lemma (example: "don't" is not the same as "do" when lemmatizing).

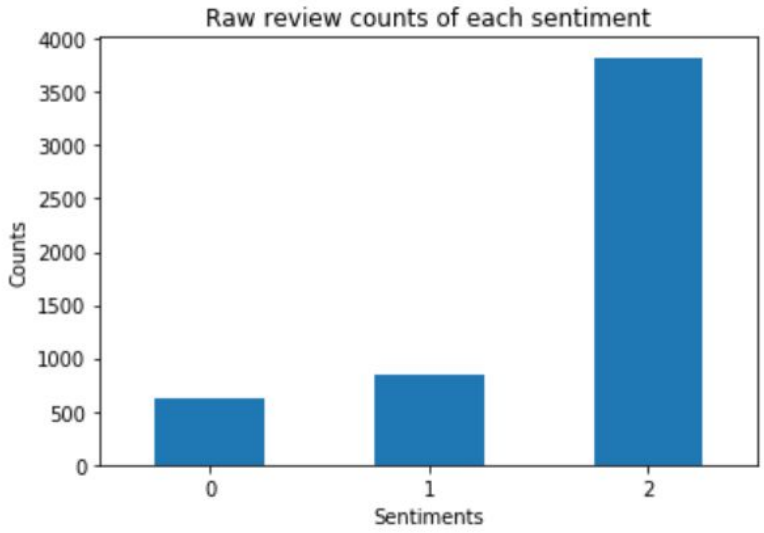
To resolve the above issues, the steps performed for data cleaning include:

- Convert the text to lower-cased.
- Expand all contractions using a custom contraction mapping dictionary.
- Remove all links.
- Remove all punctuation except hyphens.
- Remove all numerics and hyphens which stand by themselves (between two spaces).

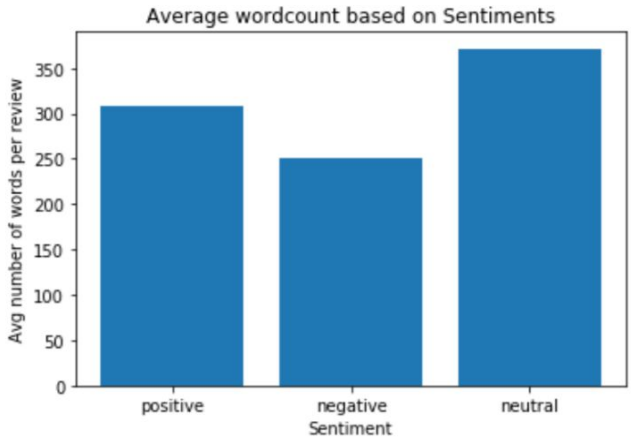
- Lemmatize each document with respect to its Part-of-speech using a lemmatizing function.

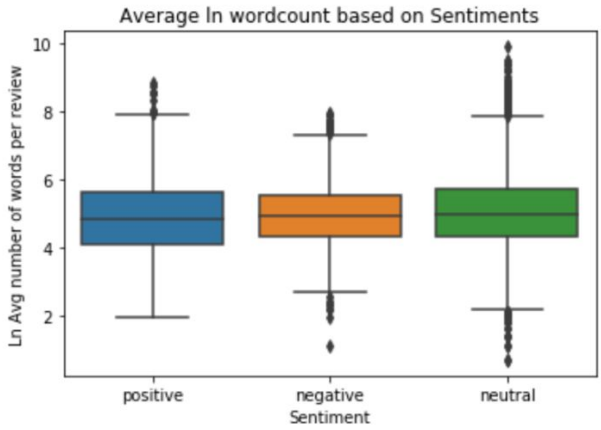
Exploratory Data Analysis

1. **Sentiment break-down:** Our sample displays high imbalance with a strong bias towards the neutral class. This tendency is surprising, since people don't usually write reviews for products they feel neutral about. Note, however, that the reviews here contain comments to other reviews as well. The reasonable next step is to look at the word count of sentiments.



2. **Average Word Count:** There looks to be a difference in the average word count of the different sentiments. Specifically, negative reviews tend to be more curt and neutral reviews more verbose. However, upon closer inspection using boxplot, we can see that the median wordcount and the interquartile ranges is quite close among all three sentiments. This suggests that neutral reviews tend to be more on the extreme.





A question arises as to whether the average word count is really statistically significant. Using the Kruskal-Wallis H test (The ANOVA one way cannot be used due to its assumptions of normality, which is clearly violated with our samples), we can be confident that they are with F-stat of 11.9 and a p-value of less than 0.05.

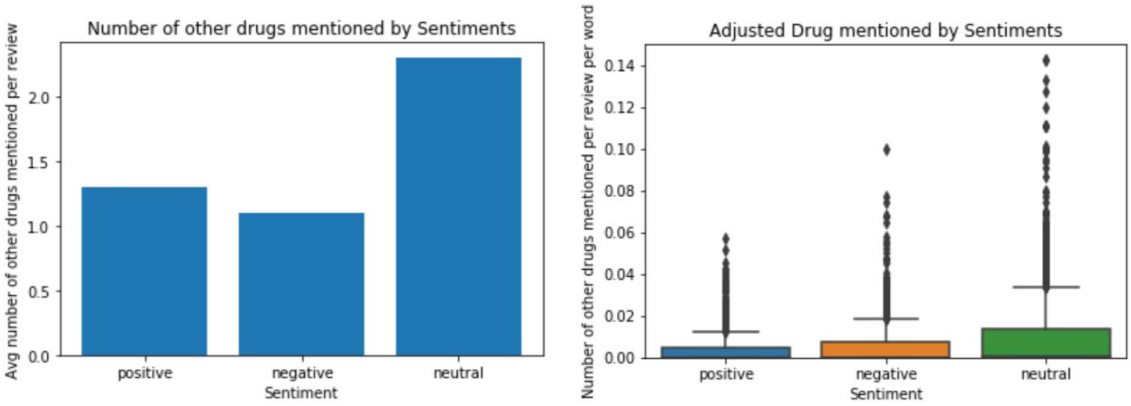
3. **Innate drug quality:** A question arises to whether each drug has innate quality that allows sentiment on them to be judged as negative/positive/neutral. Investigation shows that there are drugs with correspondingly 100% positive/negative/neutral reviews. Thus, it can be concluded that what type of drugs being reviewed can affect the sentiments. Here is an example of 10 drugs which only has neutral reviews:

```
# Sort the dictionary and display the items with highest neutral rates

sorted(neutral_rate.items(), key = lambda x: x[1], reverse = True)[0:10]
```

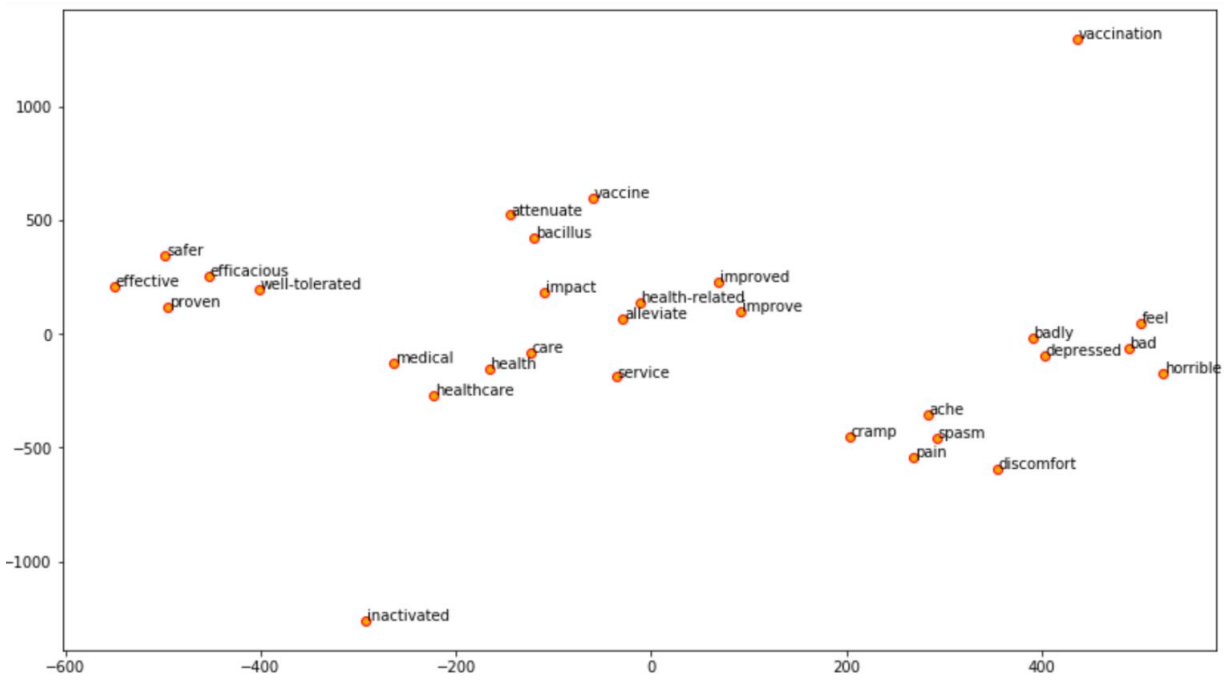
```
[('pan-retinal photocoagulation', 1.0),
 ('ipilimumab', 1.0),
 ('ixifi', 1.0),
 ('teriflunomide', 1.0),
 ('zykadia', 1.0),
 ('yervoy', 1.0),
 ('amjevita', 1.0),
 ('pemrolizumab', 1.0),
 ('tafinlar', 1.0),
 ('gilotrif', 1.0)]
```

4. **Number of drugs mentioned adjusted for length of review:** Another question arises to whether or not other drugs mentioned in the review contribute to its sentiments. An example is a review comment which lists out many different types of drugs as an objective (neutral) suggestion. Neutral reviews seem to have high drug mentions, even when adjusted for number of words in such review.



Once again, Kruskal-Wallis H test reinforces our belief with a p-value close to 0.

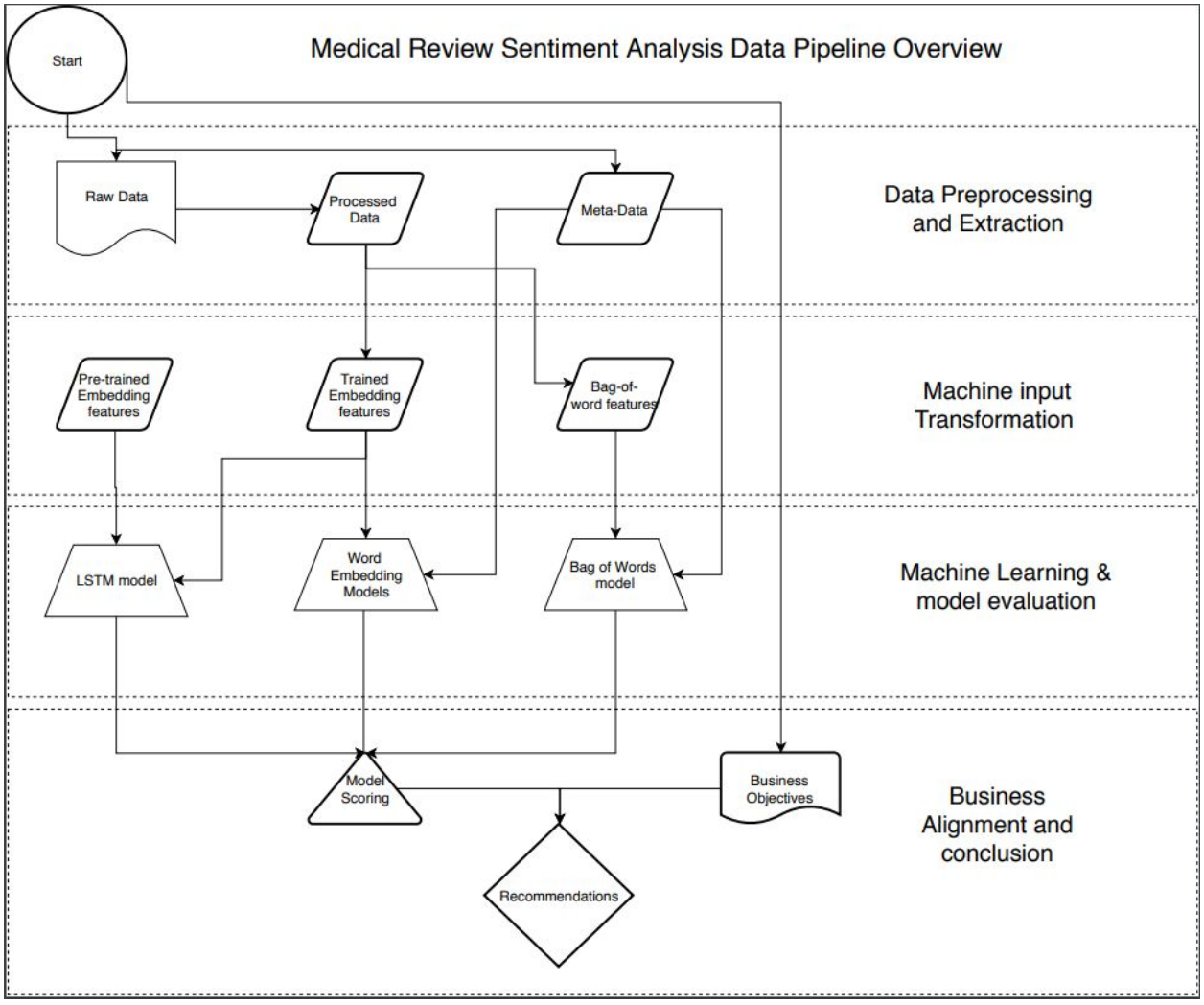
5. Word2Vec visualization: Due to the difficulty of this sentiment analysis task (it is difficult even for me, a human, to classify many of the sample reviews), we will want to know if our data is discriminative enough to provide value for the business. If not, the business is better off pursuing other opportunities. A few ways to visualize the discriminativeness of text data is to use WordCloud, LDA topic modelling and Word embeddings. This time, we will use TSNE dimensionality reduction technique to visualize word embeddings. To prevent clutter, I will use 2 words of each sentiment ('health', 'vaccine', 'effective', 'improve', 'bad', 'pain') and their 4 similar words to visualize the spread in two dimensions:



The result shows some distinctions. Positive words are on the middle and top left, whereas negative sentiments are in the bottom right. However, some neutral words are blurred with positive words, which could increase the possibility of misclassifications.

6. **Dataset conclusion and plan:** With the above analysis, it we were able to discover some discriminative features despite the foreseen difficulty in the classification task. The following plan is put forward as an attempt to build a valuable sentiment classification algorithm.

In general, we will conduct simultaneously data processing and business alignment. On one hand, we will conduct sentiment analysis through our machine learning pipeline with the goal of finding the strongest all-around classification architecture measured by F1 Macro Score. On the other hand, we will consult with business personnel to analyze the cost-benefit of ML integration and build a Pay-Off matrix to translate the result of the algorithm into business values. In the end, we will tweek the best algorithm using custom architecture and make recommendations which can align with business objectives. The Overview of the project is outlined in the diagram below:


Medical Review Sentiment Analysis Data Pipeline Overview
Start
Raw Data
Processed Data
Meta-Data
Data Preprocessing and Extraction
Pre-trained Embedding features
Trained Embedding features
Bag-of-word features
Machine input Transformation
LSTM model
Word Embedding Models
Bag of Words model
Machine Learning & model evaluation
Model Scoring
Business Objectives
Recommendations
Business Alignment and conclusion

Machine Learning

This section explore how we will run the data through our pipeline. Please refer to the pipeline diagram again for a clear process flow. The steps in the diagram are detailed as followed:

- With data pre-processing, we will preprocess the raw data and extract meta-data (which contains some discriminative information and can be useful as input for some of our machine learning algorithms). The diagram below shows the meta-data we scraped from the text. For specific information, please refer to the Jupyter Notebook:

sentiment	n_upper	word_count	char_count	avg_wlen	adj_drug_count	n_stop	n_num	drug_category
0	13.423015	308.270665	1847.124797	5.849231	0.012825	110.696921	3.735818	55.956240
1	10.480287	251.029869	1425.449223	5.647172	0.010839	96.967742	2.487455	51.097969
2	15.746144	371.469020	2254.862484	5.855146	0.012616	127.210196	4.871373	53.692026

- To extract readable features for our machine, we will use bag of words features, pretrained word embeddings and custom trained word-embeddings as our features. The data processed is transformed through the Bag of Word, Tfidf, Word2Vec, Matrix Factorization algorithms. Additionally, pre-trained word vectors from Google[4] (3 million vocabulary from webscrape) and Stanford[5] (400,000 vocabulary from wikipedia corpus) will be tried as our feature input.
- Next, we will run machine learning through cross validated grid-search on a variety of algorithms on our three types of feature input. For bag of word input features, the choice of algorithm is Logistic Regression (basic and simple parametric model), Naive Bayes (traditionally great on text andsparse data), Support Vector Machine and Linear Support Vector Machine with SGD training (great for high dimensional data), and Random Forest. We will choose the best model out of these to run the word embedding family feature input. Finally, we will build a recurrent neural network with LSTM layer to run on the text sequences with and without previous word embeddings.
- For evaluation, we will use F1 macro score (precision and recall in every class has equal weights) to address class imbalance in the dataset.

A. Bag of word models

We begin with running the aforementioned algorithms on the bag of word input, specifically the vanilla bag of word and the TFIDF version. TFIDF stands for Term Frequency Inverse Document Frequency and helps to the algorithms to filter out common words that exists

[4] Retrieved from: https://drive.google.com/file/d/0B7XkCwpI5KDYNlNUTTlSS21pQmM/edit
[5] Retrieved from: https://nlp.stanford.edu/projects/glove/

throughout many documents and focus on the rare ones that can actually discriminate one sentiment from another. The results of the algorithms are summarized below:

	model	f1_macro
7	lr_tfidf.sav	0.505540
6	lr_bow.sav	0.489985
4	svc_bow.sav	0.483195
0	nb_bow.sav	0.472725
1	nb_tfidf.sav	0.454624
8	sgd_bow.sav	0.442978
9	sgd_tfidf.sav	0.398064
2	rf_bow.sav	0.392240
3	rf_tfidf.sav	0.372747
5	svc_tfidf.sav	0.349863

Out of all the algorithms, Logistic Regression, especially the tfidf version, seems to pull ahead in terms of cross validation score. This is an expected result as logistic regression is a simple parametric approach that adds weights and is not prone to overfitting on small dataset. On the other hand, tree-based algorithms performed the worst due to the small number of samples and its tendency to overfit in sparse data (it's advantages are finding non-linear patterns). Support Vector Machine works very well with simple Bag of Word input but very poorly on TFIDF input. It seems that the normal bag of word approach allows the SVC to show its strengths in the high dimensionality of the data. Naive Bayes performs very fast and relatively well but it's not our favorite. A possible explanation for logistic regression's success is possibly the small sample size that the algorithms have to work with. It is possible that as we obtain more and more data, logistic regression will cease to improve. However, it is the best model we have to work with currently.

Stacking the bag of word feature spaces with meta-data obtained from pre-processing also improved logistic regression marginally. However, stacking meta-data into the input space hampered all the other algorithms as can be seen below.

	model	f1_macro
1	lr_stacked.sav	0.524992
3	sgd_stacked.sav	0.459783
0	nb_stacked.sav	0.444112
2	svc_stacked.sav	0.359722

B. Word2Vec Embedding models

There are two weaknesses of the Bag-Of-Word approaches to sentiment analysis.

- First of all, BOW methods cannot handle comparison. If a document compares two products and say, for example, that Product 1 is better than Product 2, BOW will register a positive sentiment due to the word "better" regardless of whether the sentiment is about product 1 or 2. We can see that problem as there is a high confusion between Class 0 and Class 1 (positive and negative sentiment) than between Class 0 or 1 and Class 2 (neutral sentiment).
- Secondly, BOW methods don't fare so well for negations since they don't register semantics from words. Thus, "not terrible" will be seen as a negative sentiment solely because it has the word "terrible".

The Word2Vec family of input transformation addresses these two issues by adding a semantic layer which model the relationship between different words. Each word is represented with a number of dimensions that describe its distance with respect to other words. The distance can loosely be interpreted as some form of semantics. The result of running logistic regression on the word embedding input space (average embeddings of all words for a document) is outlined below:

	Model	F1-Macro-Score
0	Word2Vec	0.489108
1	Word2Vec Stacked	0.484752
3	Pretrained Glove	0.462909
2	Pretrained Word2Vec	0.457218
4	Fasttext	0.366151

The vanilla custom-built word2vec embeddings input space works the best with a slightly lower score than the TFIDF input space in the previous section. This is arguably an improvement, as the model was able to get a good score with a dense matrix of only 200 dimensions, as oppose to the sparse matrix of before. Interestingly, stacking meta data into the input space cause the model to do worse. The pre-trained model from Google and Stanford wasn't too effective, most likely due to the fact that vocabularies the medical area is unlikely to be represented in a semantically similar way with other web corpus such as wikipedia.

C. LSTM with RNN

The final family of model we will experiment with is Neural Networks, more specifically, recurrent neural network (RNN). With this method, we can express the information in terms of sequence to extract another aspect of semantics (the ordering of words). Additionally, we'll be using Long Short Term Memory architecture for our RNN in order to help the model retain long-term information within a sequence and pre-trained word embeddings so that it can integrate other semantic aspects. The result of the models can be shown below.

	model	F1-macro-score
0	Vanilla LSTM	0.424657
2	LSTM with Custom-trained Word2Vec Embeddings	0.400438
1	LSTM With Pre-trained Glove Embeddings	0.314330

The Vanilla LSTM performs the best. A reason why it would perform better than with the Word2Vec embeddings is that its default embedding layers can learn more accurately. However, the RNN's performance pales in comparison to the algorithms we have explored so far. An explanation for this could be the small amount of sample size we have (most neural network requires 60,000 sample or more incomparison to approximately 4000 training example we have).

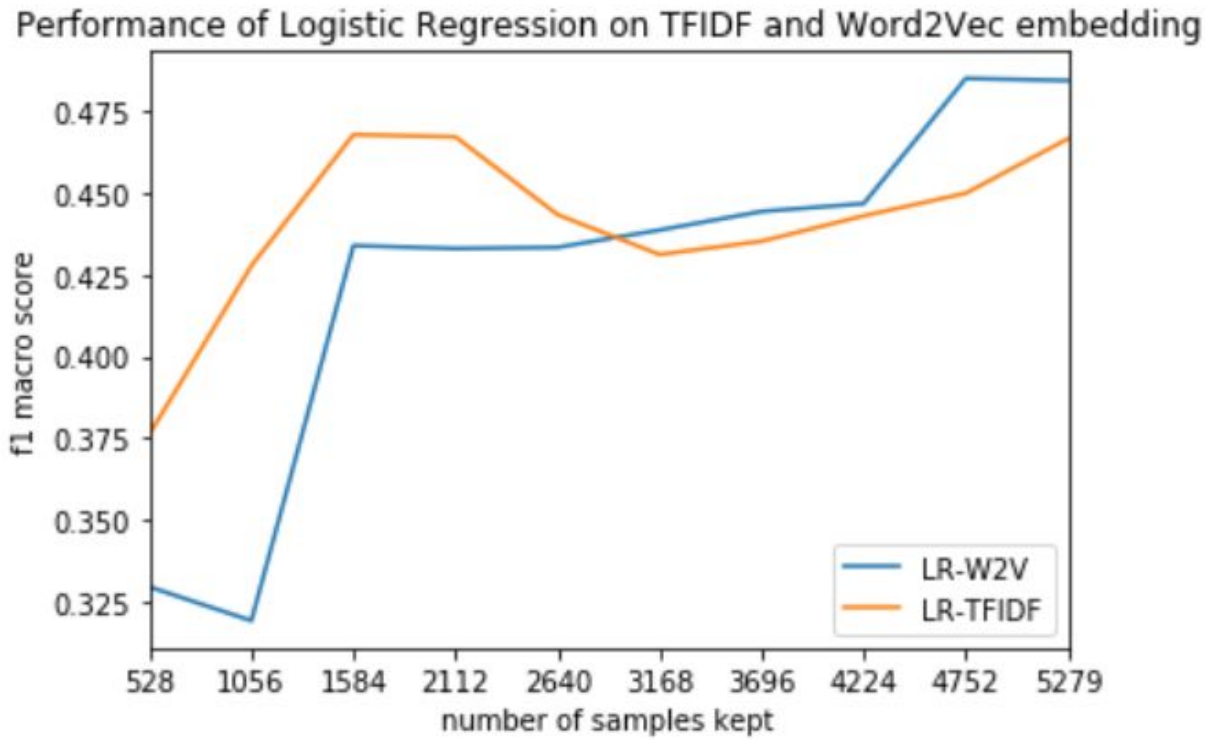
D.Model selection

Performance-wise, our Logistic Regression model on TfIdf features stacked with meta features did the best, with 0.52 F1-Macro-Score. Our Logistic Regression model on Word2Vec embeddings came close with 0.49 F1-Macro-Score. Unfortunately, the state-of-the-art LSTM model didn't come close with 0.42 F1-Macro-Score. Possibly, the model needs more tuning (which would require more computing power) or is weak on small datasets as a deep-learning approach.

Some possible reasons why logistic regression on TfIdf features may perform better than on Word2Vec features are:

- The model is extremely noisy so a simple approach is more robust.
- The model has low sample count so Word2Vec has not been able to learn the best embeddings.

To test the effectiveness of sample size on these two models, reduced sample size were trained on both models. The graph below shows the difference between the two model's performance as we cut down on sample size:



As the sample size is reduced, the word embedding approach seems to undergo a steeper decline in performance than the normalized bag-of-word approach. We can extrapolate with some confidence that as the sample size increases, the word embedding approach will gain a steeper increase in performance.

To conclude, we will choose the Logistic Regression over TF-IDF feature space stacked with our meta data since it has the best performance over the given data. However, more consideration for deep learning approaches such as Word2Vec should be taken into account were more data to be collected.

E. Business Alignment

The following were communicated to the brand manager of the pharmaceutical division:

```
Precision for positive sentiment is 0.29, Recall for positive sentiment is 0.45
Precision for negative sentiment is 0.39, Recall for negative sentiment is 0.54
Precision for neutral sentiment is 0.84, Recall for neutral sentiment is 0.70
```

- Out of all the times the model predicted a positive sentiment class, the model was right 29% of the time. And the model was only able to find 45% of all positive sentiment reviews which exists in the test set.

- Out of all the times the model predicted a negative sentiment class, the model was right 39% of the time. But the model was only able to find 54% of all negative sentiment reviews which exists in the test set.
- Out of all the times the model predicted a neutral sentiment class, the model was right 84% of the time. And the model was only able to find 70% of all neutral sentiment reviews which exists in the test set.

Clearly, the model is much better at predicting neutral sentiment since it has more data on neutral sentiment and there were naturally more neutral sentiment in the distribution. After discusion about the results, the brand manager explained that the idea of collecting data for the review was to figure out which drugs was underperforming. This information will affect customer service as well as future R&D decisions. Thus, we can tweak the model to improve its detection of the second class. For that, we group the positive and neutral sentiment into class 0 to improve the model's ability to discriminate, then run gridsearch on the model once again.

```
Precision for negative sentiment is 0.37, Recall for negative sentiment is 0.55
```

Out of 175 negative-labeled review in the test set, the model was only able to find 97 negative reviews (55%). It made 166 mislabel as the result. Next, let's try tuning it to maximize recall and calling gridsearch on the logistic regression.

```
Precision for negative sentiment is 0.27, Recall for negative sentiment is 0.62
```

Out of 175 negative-labeled review in the test set, the model was able to find 109 negative reviews (62%). However, as the result of the tuning, it mislabeled 302 other reviews as negative.

Let's explore the effectiveness of this automation model to see whether it's worth pursuing. Before we begin, we need to make some assumptions.

Assumptions:

1. Average word count of 350 (based on exploratory analysis)
2. Average human reading speed of 200 words/min[6] (lower end to account for breaks and decision-making)

Thus, Average reviews read an hour $\frac{200}{350} \times 60 = 34\ (reviews)$

3. Average hourly wage of reviewer job[7] = CDN 30 / hour

Thus, Average cost per review is $\frac{30}{34} = 88\ cents$

4. Effectiveness of human labeling = 90% (since we did even find mislabeled data!)
5. Negative review chance = $\frac{177}{1054}$ = 16.8% (as per the test set)

Results:

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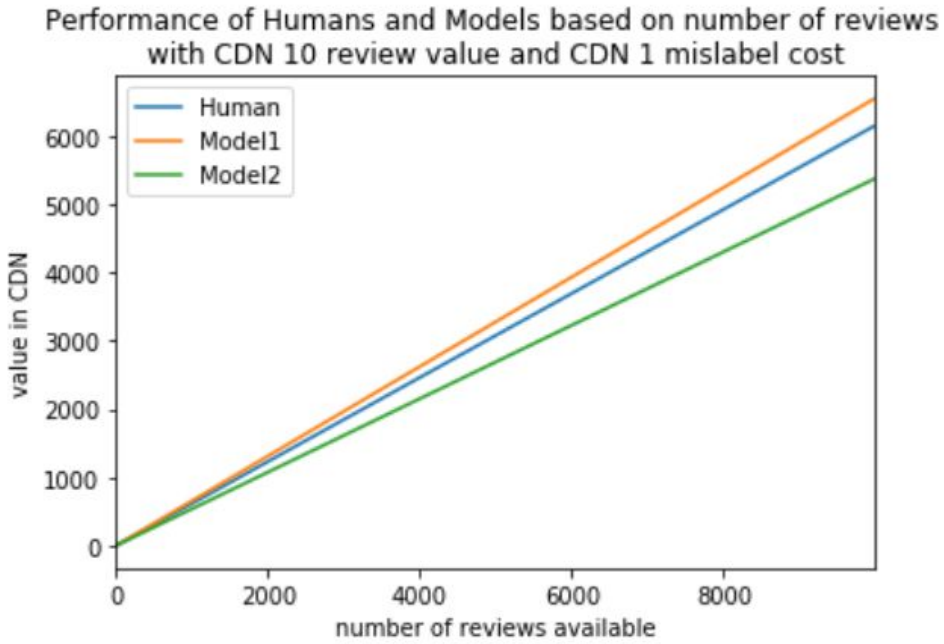
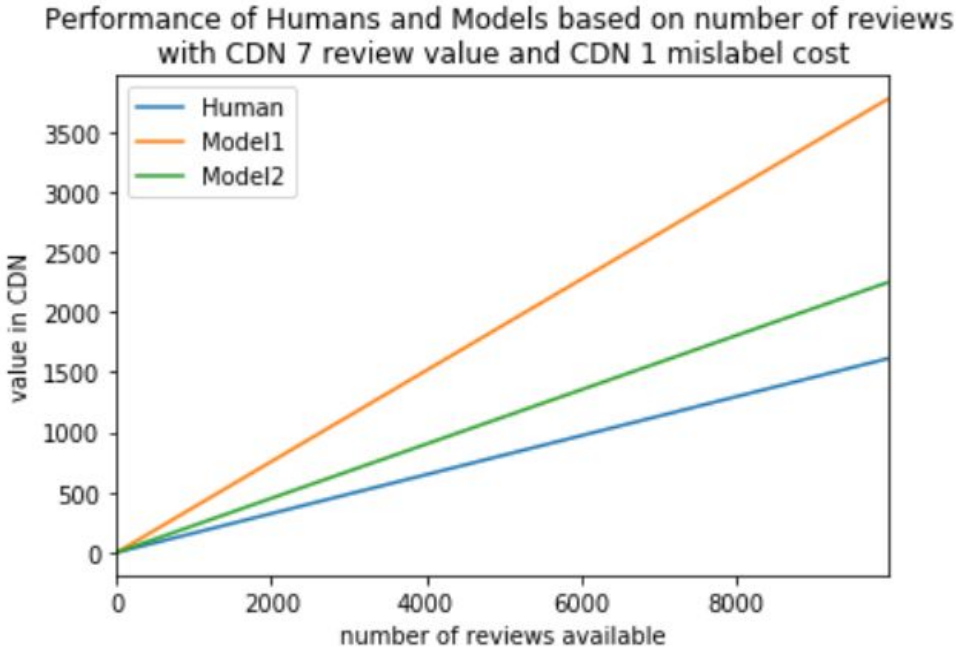
[6] Retrieved From: https://www.irisreading.com/what-is-the-average-reading-speed/

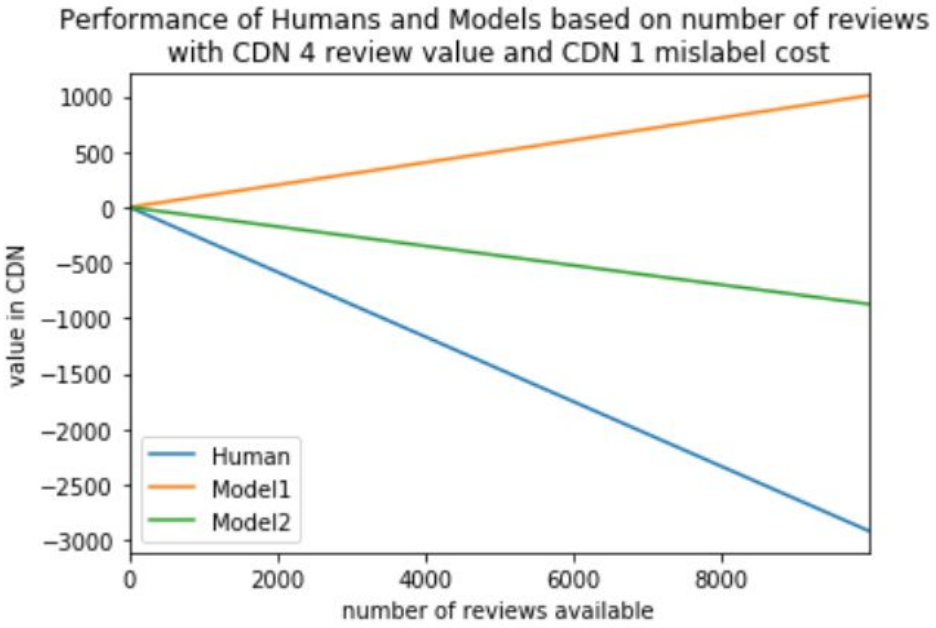
[7] Retrieved From: https://ca.indeed.com/jobs?q=office%20clerk&l=Toronto%2C%20ON&radius=50&vjk=354b63dc5c2edecb

Using the above assumptions, we can vary number of reviews received, the value of a negative review identified and the cost of mislabelling a review as negative.

Change in negative review value:

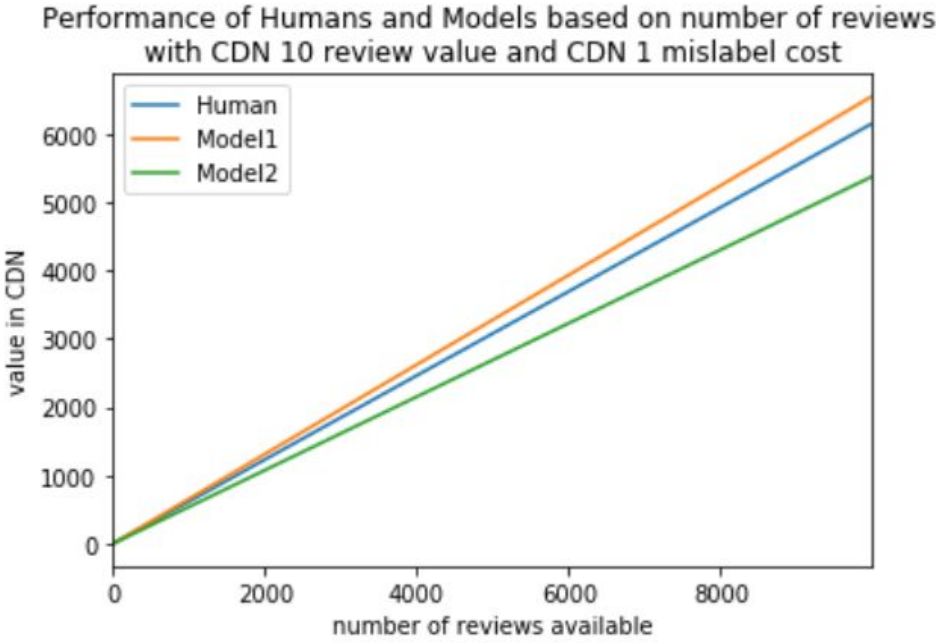


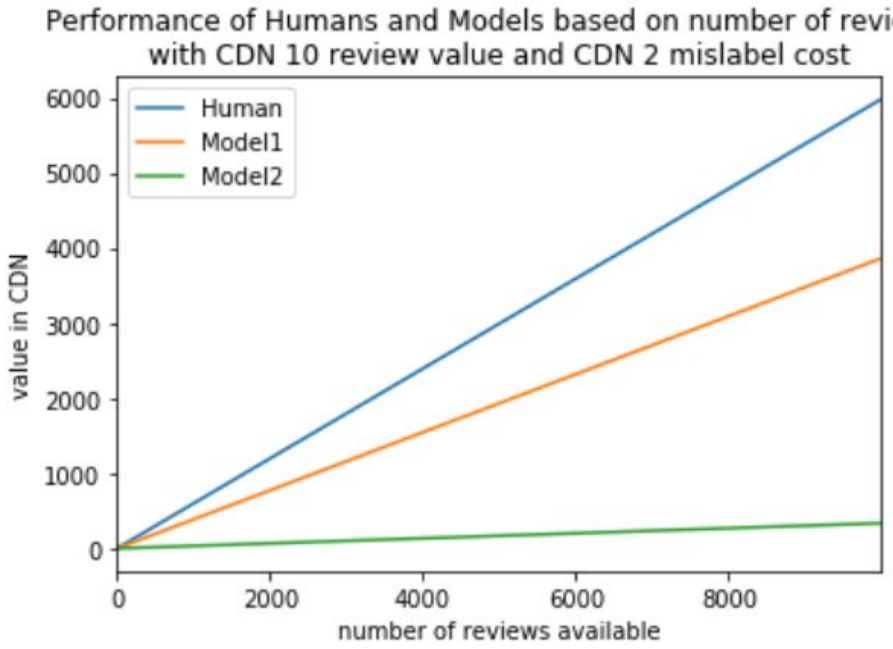


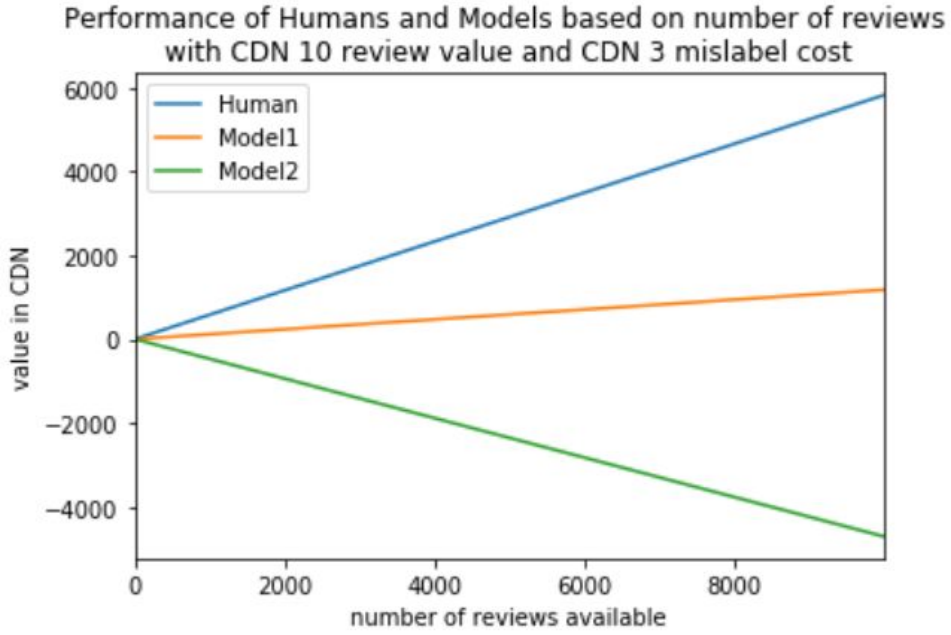


Model 1 (The balanced model) outperforms both Model 2 and the humans. Human's effectiveness decrease greatly as review value goes down.

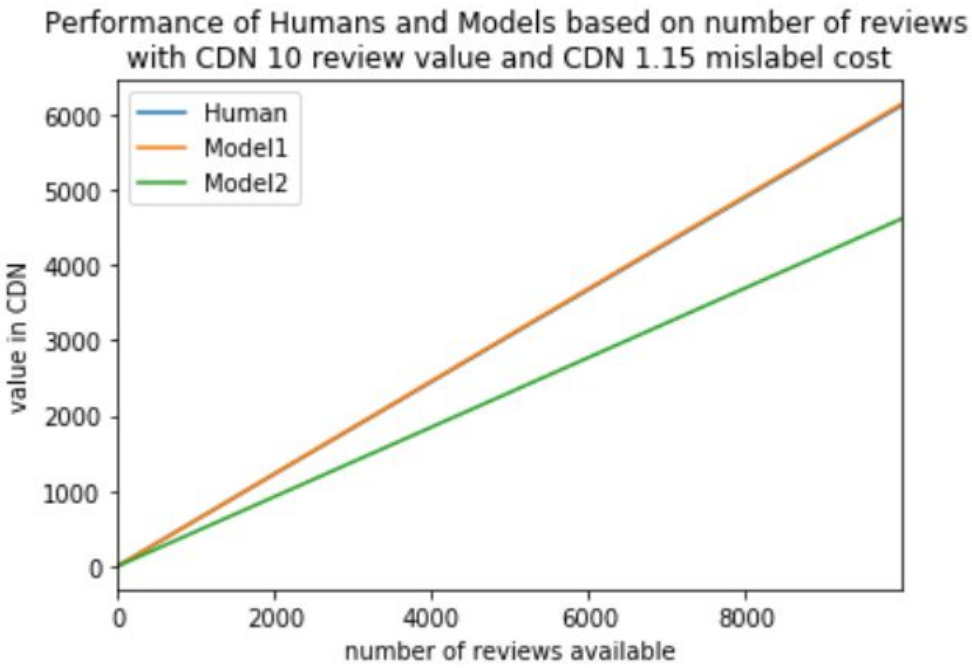
Change in mislabeled review value:







Humans outperform both models as the cost of mislabelling increases.



Investment in model one starts to pay off when mislabel cost is smaller than CDN 1.15.