Predicting Root Causes of Safety Observations

Predicting Root Causes of Safety Observations using Deep Learning Models

An assignment submitted in fulfillment of the requirements of IBM Introduction to Machine Learning Specialization

By

Minhaj Ahmed Ansari

1. Introduction

1.1. The target of this machine learning exercise is to identify the best model to predict the root causes of the recorded Safety Observations.

1.2. A root cause analysis refers to the process of identifying the underlying cause of an issue or incident. Whether you're investigating an employee who crushed their foot when they dropped a heavy box or one who tripped over a cord in a poorly lit office, an RCA goes beyond simply removing the immediate cause of the accident

1.3. The brief objective of this Deep learning exercise is to preempt the root causes of the safety observations by learning from the historical labelled data.

2. Brief description of the data set and a summary of its attributes

2.1. The data which I am using here is a dump from the Safety Observation System of a Major Company. Each row of data consists of the observation description along with pre-selected category and root cause (Classes).

2.2. The objective of this program would be to develop a Deep Learning Model which would be able to predict the EHS Observations based on the historical data. We will try to fit different Deep Learning Models, tuning them for optimal number of input parameters, to arrive at the best model.

2.3. By implication this exercise is an Natural Language Processing Exercise, as we will be extracting features from text (Observation Description) and using those for training our clustering model.

2.4. The number of columns in the dataset is 3 and the no of rows is 1028493. The target variable here will be 'Sub-Category' and the input variable will be 'Observation'. Another column is 'UA/UC' which broadly categorizes observations into different types of unsafe acts and conditions.

2.5. The overall plan includes

- Cleaning the data by removing stops and performing EDA.
- Feature extraction to arrive on most important features.
- Feature selection and dimension reduction using Non-Negative Matrix Factorization.
- Training our different models and measure the performance using pre-identified class labels
- Evaluation of Models and selection of best model.
- Summary and Future action.

3. Data Cleaning and Wrangling

3.1. Plan

- Bring all words on same case (lower case).
- Detect the missing values and treat them accordingly.
- Drop various Stop words which don't add any information to the model.

3.2. Actions

- Importing the necessary module for text preprocessing and feature extraction.

```
[4]: #Let us first bring in all the required modules

     from sklearn.feature_extraction.text import TfidfVectorizer
     from sklearn.preprocessing import LabelEncoder
     from nltk.corpus import stopwords
     from nltk.stem import WordNetLemmatizer
     from collections import Counter
```

- During this process it was identified that there are lot of null value columns in the entire datasets.

```
[5]: #Lets first drop the 'UA/UC' Column which is not required for this exercise.

     df_obs.drop('UA/UC', axis = 1, inplace = True)

[6]: df_obs.head()
```

[6]:

	Observation	Sub-Category
0	worker used drilling machine without green tag.	NaN
1	Worker used a plug top for multiple electrica...	No Plug top
2	worker use drilling machine at site without gr...	NaN
3	Site supervisor is not available at site whi...	NaN
4	worker use electric grinder without green tag.	No Inspection Done

```
[7]: # Lets check the missing values

     df_obs.isnull().sum()

[7]: Observation     961881
     Sub-Category    996100
     dtype: int64
```

- Also, there were lot of missing labels for almost half of the data. Now this leaves a lot of room for improvement in data collection and labelling process. Unfortunately, we must leave out all these rows from our modelling.

```
[9]: # Lets check how many values are missing in target variable after dropping missing feature rows
     df_obs.shape[0], df_obs.isnull().sum()

[9]: (66612,
      Observation         0
      Sub-Category    34219
      dtype: int64)
```

We can see that we missing lables for almost half of the data. Now this leaves a lot of room for improvement in data collection and labelling process. Unfortunately, we have to leave out all these rows from our modelling.

```
[10]: #droping values
      df_obs.dropna(subset = ['Sub-Category'], axis = 0, inplace = True)
      df_obs.shape[0], df_obs.isnull().sum()

[10]: (32393,
       Observation     0
       Sub-Category    0
       dtype: int64)
```

So, in the end we are now left with 32,393 Nos of individual observations

```
[11]: # Lets check for the duplicates in the observation column

      df_obs.duplicated(subset = ['Observation'], keep = 'first').sum()

[11]: 6806
```

- There were also lot of duplicate observations which may skew the results of the modelling.

```
[12]: df_obs.drop_duplicates(subset = 'Observation', keep = 'first', ignore_index = True, inplace = True)
```

- After all, above exercise, the number of columns in the dataset is 2 and the no of rows is 25587

3.3. Summary

- We dropped the null values and duplicated observations to reduce the dimensions of the data
- This also ensures that we avoid assigning higher weightage to certain duplicated observations at the time of feature extraction.
- We also dropped UA/UC columns as we want to explore this dataset purely from NLP perspective.

4. Exploratory Data Analysis

4.1. Plan

- Remove punctuation marks and any other extra space.
- Lemmatize all the words so that different words stemming from same root word are not counted as separate features.
- Label Encode the target variables

- Check the weight of each class and discuss on the possibility of the oversampling, under sampling or resampling.
- Extract features from our observation text using tf-idf method
- Perform Dimensionality Reduction using NMF

4.2. Actions

- Lemmatization is the process of grouping together the different inflected forms of a word so they can be analyzed as a single item. Lemmatization is similar to stemming but it brings context to the words. So, it links words with similar meaning to one word.
- For effective lemmatization, punctuations and other similar spaces are also removed.
- For lemmatization, the module which has been used is Word Net Lemmatizer under NLTK library.

```
[17]: def lemmatize_text(word_list):
          lem_word_list = [wordlemmatize.lemmatize(word, pos = 'v') for word in word_list.split()]
          new_lem_word_list = [wordlemmatize.lemmatize(word) for word in lem_word_list]
          return " ".join(new_lem_word_list)

[18]: df_obs.Observation = df_obs.Observation.apply(lemmatize_text)

[19]: #Lets check our cleaned dataframe

      df_obs.sample(10)
```

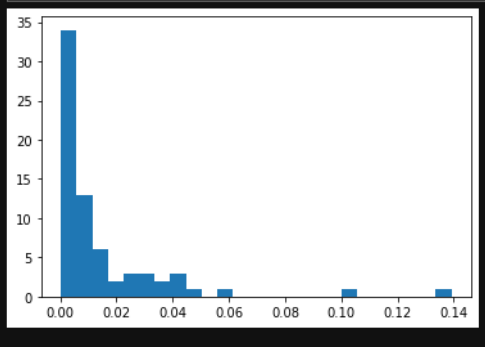
[19]:

	Observation	Sub-Category
3847	Poor electrical joint in cable lay on grind	Improper Cable joints
3741	plug top not implement naked wire use to opera...	No Plug top
22650	improper housekeep be find in work area	Poor Housekeeping
22764	Wooden ladder be find to be use for access egr...	Improper ladder arrangement
20453	material keep on road without barricade	Hard Barricades not provided
19321	Electrical cable tray be use for access egress...	Unsafe/ Blocked Access & Egress
16366	contractor supervisor engage to it work withou...	Workmen engaged without screening/ Induction
15664	Enercom Workmen bhupendra kumar deploy directl...	Workmen engaged without screening/ Induction
23298	Trench pit we re find open condition and witho...	Openings not covered/ barricaded
6842	weld work be carry out without remove water fr...	Unsafe Electrical connections/Practices ...

- If you watch closely lemmatization has taken effect on many words for ex- against index 7778 the word 'been' has been stemmed to 'be', the word 'kept' has been changed back to 'keep' at 7656. These words would have been extracted as separate features thereby increasing the overall feature dimension
- The target variable is label encoded.

```
[20]: labelencoder = LabelEncoder()
      df_obs['Sub-Category'] = labelencoder.fit_transform(df_obs['Sub-Category'])

[21]: plt.hist(df_obs['Sub-Category'].value_counts(normalize = True), bins = 25,);
```



- This shows that our classes have quite severe imbalance. And this can impact our final model's performance. Instead of opting for any sampling approach let's try to model our data using imbalanced classes by maintaining class imbalance in the train and test split. We will use class_weight feature wherever available to penalize the imbalance.
- Next and probably most important step for modelling is to extract features from text data. Now there are many methods to achieve this objective but the most important from all is Term Frequency and Inverse Document Frequency Method.
- In information retrieval, tf–idf, TF*IDF, or TFIDF, short for term frequency–inverse document frequency, is a numerical statistic that is intended to reflect how important a word is to a document in a collection or corpus. It is often used as a weighting factor in searches of information retrieval, text mining, and user modeling. The tf–idf value increases proportionally to the number of times a word appears in the document and is offset by the number of documents in the corpus that contain the word, which helps to adjust for the fact that some words appear more frequently in general. tf–idf is one of the most popular term-weighting schemes today.
- Another important term that you will come across would be N-grams. In the fields of computational linguistics and probability, an n-gram is a contiguous sequence of n items from a given sample of text or speech. The items can be phonemes, syllables, letters, words, or base pairs according to the application. The n-grams typically are collected from a text or speech corpus. When the items are words, n-grams may also be called shingles.

- Using Latin numerical prefixes, an n-gram of size 1 is referred to as a "unigram"; size 2 is a "bigram" (or, less commonly, a "digram"); size 3 is a "trigram". For example, a feature - 'Safety' is unigram whereas a feature 'Safety Helmet' would be bigram
- The words which are generally filtered out before processing a natural language are called stop words. These are the most common words in any language (like articles, prepositions, pronouns, conjunctions, etc.) and does not add much information to the text. Also, I have set min_df = 10, which means words that occurred in too few documents, in this case less than 10, should be filtered out.

```
[23]: # So Lets instantiate our tfidfvectorizer by setting feature output for both unigrams and bigrams and Stop words from English
tfidf = TfidfVectorizer(ngram_range = (1,2),
                        stop_words = 'english',
                        min_df = 10,
                       )
```

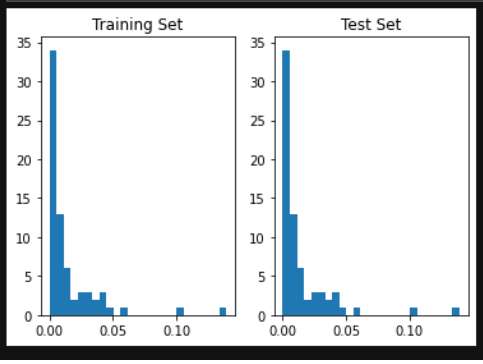
- I would highly recommend the reader to go through sklearn's working with text data resources. https://scikit-learn.org/stable/tutorial/text_analytics/working_with_text_data.html
- Before vectorizing, the data is split into training and test sets.

```
[25]: X_train, X_test, y_train, y_test = train_test_split(df_obs.Observation, df_obs['Sub-Category'],
                                                         test_size = 0.3, random_state = 1000,
                                                         stratify = df_obs['Sub-Category']
                                                        )
```

```
[26]: #Lets check the class imbalance in both of train and test splits

fig, (ax1, ax2) = plt.subplots(1, 2)

ax1.hist(y_train.value_counts(normalize = True), bins = 25,);
ax1.set(title = 'Training Set');
ax2.hist(y_test.value_counts(normalize = True), bins = 25,);
ax2.set(title = 'Test Set');
```



- I have used stratify attribute in train_test_split. So, the class distribution is maintained in train and test splits.

- Next, I have extracted features for further modelling using tfidfvectorizer. A Sample feature matrix is hown below.

```
[27]: features = tfidf.fit_transform(X_train, y_train).toarray()

      print(f'The feature matrix contains {features.shape[0]} observations with {features.shape[1]} features')

      The feature matrix contains 17910 observations with 2582 features

[28]: # Let us create the feature matrix for our future reference

      feature_matrix = pd.DataFrame(data = features, columns = tfidf.get_feature_names())
      feature_matrix.head()
```

[28]:

	aaa	absence	access	access approach	access area	access arrangement	access available	access block	access egress	access filter	...	workplace screen	wtp	xi	xi im	yadav	yadav engage	yard	zone
0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

5 rows × 2582 columns

- The feature selection is done using the chi-square test. The Null hypothesis that there is no significance association between the input variable and target variable. While our alternate hypothesis is that there is significance association between the input variable and target variable. Consequently, we will select only those features which have p_value less that 0.05 (Significance level), so that we can reject our null hypothesis.
- Finally, there are 1303 statistically significant features.
- Now, its time to reduce the dimensionality of the feature matrix so that the process of further modelling can be eased and improved. We will use Non-Negative Matrix Factorization (NMF).
- The objective of NMF is to find two non-negative matrices (W, H) whose product approximates the non- negative matrix X. This factorization can be used for example for dimensionality reduction, source separation or topic extraction.
- We will reduce dimensions to 5 and 10 components.

```
[40]: # importing NMF library

      from sklearn.decomposition import NMF

[42]: #Creating the nmf model 1

      nmf_model_1 = NMF(n_components = 5,
                        init = 'random',
                        random_state = 100)

[46]: nmf_features_1 = nmf_model_1.fit_transform(final_feature_matrix)

[47]: #Creating the nmf model 2

      nmf_model_2 = NMF(n_components = 10,
                        init = 'random',
                        random_state = 100)

[48]: nmf_features_2 = nmf_model_2.fit_transform(final_feature_matrix)

[49]: nmf_test_features_1 = nmf_model_1.transform(test_set_final_features_matrix)
      nmf_test_features_2 = nmf_model_2.transform(test_set_final_features_matrix)
```

4.3. Summary

- We realized that our data consists of highly imbalanced classes. We tried to take that into consideration by splitting our data using stratified option under train_test_split function.
- This ensured that we maintained the equal amount of imbalance in our test as well as train split.
- Next step was to prepare the text data for further feature extraction. We applied various transformations such as lemmatization and achieving homogenization by converting all words into lower case.
- We encoded our target variables.
- Finally, we used tfidfvectorizer to extract features from our text data. The tf–idf value increases proportionally to the number of times a word appears in the document and is offset by the number of documents in the corpus that contain the word, which helps to adjust for the fact that some words appear more frequently in general.
- As usual we fitted and transformed tfidfvectorizer over train data and used that fitted model to transform our test data.
- We performed chi2 test to extract the best associated features with p-value less than 0.05.
- Finally, we used NMF method to decompose our features into 5 and 10 Components

5. Model Selection and Evaluation

5.1. Plan

- In this step, we will,
  - Select the best model and subsequently the best values for model parameters.
  - Also, we will try to reach best compromise over the precision and recall values.

5.2. Action

- We created three models with following parameters,
  - Learning rate = 0.003
  - Hidden layers = 2 Nos with 1000 units each.
  - Dropouts = 2 Dropouts with rate of 0.25
  - Input Shape
    - Model 1 = 5
    - Model 2 = 10
    - Model 3 = 1303
  - Activation = RELU in hidden layers and SoftMax in output layer

```
[101]: model_1.summary()

Model: "sequential_11"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_33 (Dense)             (None, 1000)              6000
_________________________________________________________________
dropout_20 (Dropout)         (None, 1000)              0
_________________________________________________________________
dense_34 (Dense)             (None, 1000)              1001000
_________________________________________________________________
dropout_21 (Dropout)         (None, 1000)              0
_________________________________________________________________
dense_35 (Dense)             (None, 70)                70070
=================================================================
Total params: 1,077,070
Trainable params: 1,077,070
Non-trainable params: 0
_________________________________________________________________
```

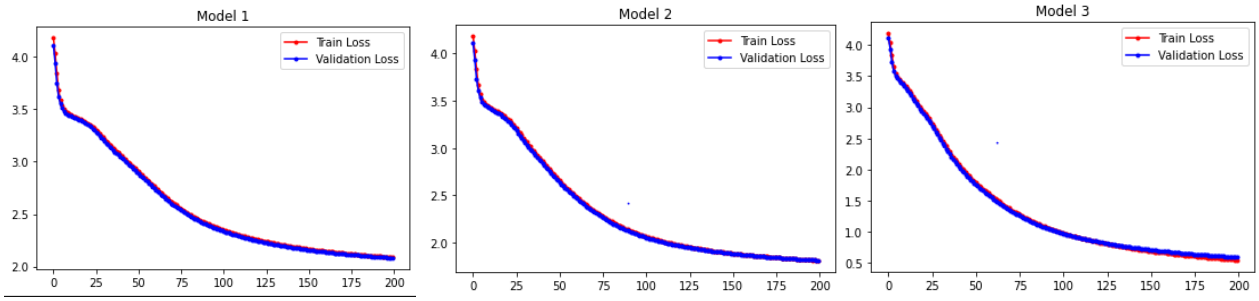
```
[107]: model_2.summary()

Model: "sequential_13"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_39 (Dense)             (None, 1000)              11000
_________________________________________________________________
dropout_24 (Dropout)         (None, 1000)              0
_________________________________________________________________
dense_40 (Dense)             (None, 1000)              1001000
_________________________________________________________________
dropout_25 (Dropout)         (None, 1000)              0
_________________________________________________________________
dense_41 (Dense)             (None, 70)                70070
=================================================================
Total params: 1,082,070
Trainable params: 1,082,070
Non-trainable params: 0
_________________________________________________________________
```

```
[118]: model_3.summary()

Model: "sequential_14"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_42 (Dense)             (None, 1000)              1304000
_________________________________________________________________
dropout_26 (Dropout)         (None, 1000)              0
_________________________________________________________________
dense_43 (Dense)             (None, 1000)              1001000
_________________________________________________________________
dropout_27 (Dropout)         (None, 1000)              0
_________________________________________________________________
dense_44 (Dense)             (None, 70)                70070
=================================================================
Total params: 2,375,070
Trainable params: 2,375,070
Non-trainable params: 0
_________________________________________________________________
```

- For each model, the loss plot is shown below,



- Also, the Performance metrics achieved for each model is shown below,

[217]:

	NN Model 1 (n_components = 5)				NN Model 2 (n_components = 10)				NN Model 3 (n_components = 1303)			
	precision	recall	f1-score	support	precision	recall	f1-score	support	precision	recall	f1-score	support
micro avg	0.704947	0.259867	0.379747	7677.0	0.691323	0.351830	0.466333	7677.0	0.889822	0.773219	0.827432	7677.0
macro avg	0.050067	0.044537	0.044189	7677.0	0.098482	0.079131	0.082222	7677.0	0.555545	0.426130	0.463574	7677.0
weighted avg	0.262660	0.259867	0.251446	7677.0	0.380102	0.351830	0.351640	7677.0	0.850100	0.773219	0.794048	7677.0
samples avg	0.259867	0.259867	0.259867	7677.0	0.351830	0.351830	0.351830	7677.0	0.773219	0.773219	0.773219	7677.0

5.3. Summary

- We tried to train 3 models,
  1. Model 1 (n_components = 5)
  2. Model 2 (n_compenents = 10)
  3. Model 3 (n_compoenents = 1303)
- We set forth our expectations clearly,
  1. High Precision and Recall
  2. Higher micro average f1-score.

- Both of which were met by Model 3 with 1303 components (input features). The model had micro precision, recall and f1 score of 0.889, 0.773 and 0.827 respectively
- In general, Micro-, and macro-averages (for whatever metric) will compute slightly different things, and thus their interpretation differs. A macro-average will compute the metric independently for each class and then take the average (hence treating all classes equally), whereas a micro-average will aggregate the contributions of all classes to compute the average metric. In a multi-class classification setup, micro-average is preferable if you suspect there might be class imbalance (i.e., you may have many more examples of one class than of other classes).
- In our case, class imbalance is definitely present, and a high micro average definitely preferred, which our model achieves.
- As explained earlier, there is huge imbalance in dataset and trying to classify each minority class correctly may lead to overfitting. Thus, it would be better to avoid false alarms by opting for better precision. Additionally, correct prediction of majority class was must; let me explain in detail.
    - Almost all safety systems are based on basic philosophy of identifying the root causes and correcting them. This means that if you have truly identified a root cause and treated it appropriately, there would be no repetition of similar observation. This is of course an ideal situation. However, in real life these incidents may still recur, and it may not be possible to completely eliminate them due to various factors. Thus, the next best measure which is adopted by most organizations is counting repetition of root causes. Higher the count more serious the issue and thus more immediate action required. This frequency is then multiplied with probable consequence to get the actual risk of incident. However, this model is concerned with only getting the frequency right.
- Thus, it makes sense to identify majority classes with higher precision and recall, hence the choice of measure - Micro F1 Score for selecting best estimator.

6. Conclusion and Future Directions

6.1. In conclusion, we chose Model 3 for purpose of deployment for future predictions. The model not only shows great prediction power, it gives lower false positives at the same time has higher micro average f1-score, precision and recall.

6.2. Going further, in future we may improve our modelling performance by,

- Oversampling or Under sampling or combining both to check whether we can achieve better classification.
- At the time of feature extraction, we only used unigrams and bigrams, we can also use further higher degree of feature such as trigram (combination of three words)
- While training models with lesser components, the accuracy achieved was very poor. Additionally, the change or decrease in losses was very slow. Thus, we may try increasing the learning rate to check where actually we achieve optimal results for Model 1 (5 components) and Model 2 (10 components).
- We may also try to increase the number of epochs parallelly to check the convergence.
- The Error metrics used for fitting were AUC and Accuracy. We may try other metrics; refer - https://www.tensorflow.org/api_docs/python/tf/keras/metrics
- Finally, we can actually re-work on our input data to maybe eliminate some of the labels by combining with other similar labels, thus reducing some granularity in data when not required.