BC Stats

Text Analytics:

Quantifying the Responses to Open-Ended Survey Questions

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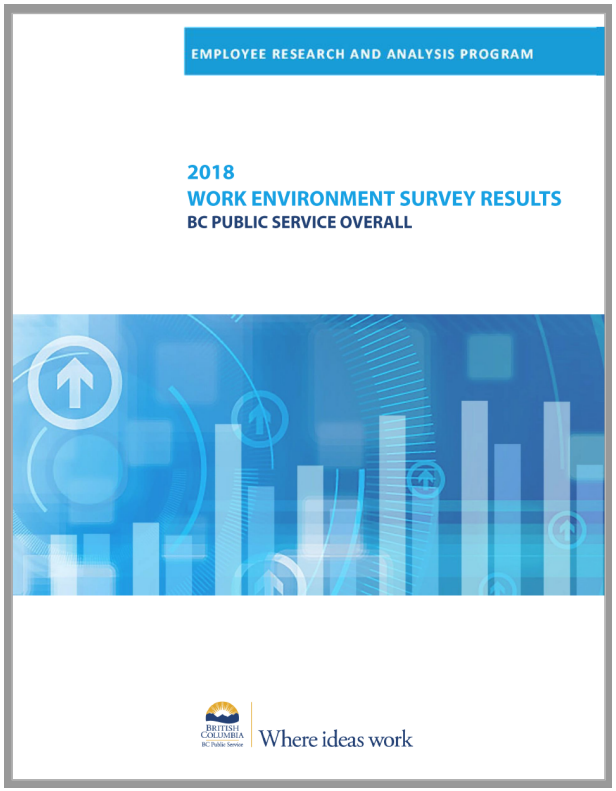
Introduction

The Survey



Work Environment Survey (WES)

- Conducted by BC Stats for employees within BC Public Service
- Measures the health of work environments and identifies areas for improvement
- ~80 quantitative questions (5 Likert scale) and 2 open-ended qualitative questions

Data

Open-ended Questions

Question 1

- **What one thing would you like your organization to focus on to improve your work environment?**

Example: *"Better health and social benefits should be provided."*

Question 2

- **Have you seen any improvements in your work environment and if so, what are the improvements?**

Example: *"Now we have more efficient vending machines."*

*Note: these examples are fake comments for privacy reasons.

Example of Data: Question 1

What one thing would you like your organization to focus on to improve your work environment?

Comments*	CPD	CB	EWC	...	CB_Improve_benefits	CB_Increase_salary
Better health and social benefits should be provided	0	1	0	...	1	0

Theme: CB = Compensation and Benefits

Subtheme: CB_Improve_benefits = Improve benefits

Question 1:

- Comments encoded into 12 themes and 63 subthemes
- +31,000 labelled comments for 2013, 2018, 2020, +12,000 additional comments from 2015

Question 2:

- Themes also encoded, but not as reliable as Question 1's
- +6,000 labelled comments for 2018, +9,000 additional comments from 2015, 2020

*Note: this is a fake comment as an example of the data.

Our Objectives

1) Build a model to automate multi-label text classification that:

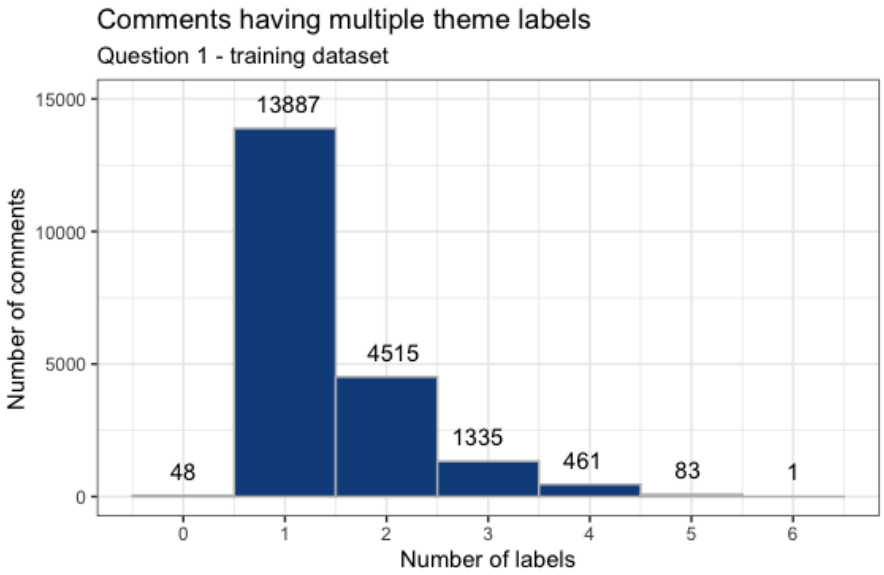
- Predicts label(s) for Question 1 and 2's main themes
- Predicts label(s) for Question 1's subthemes

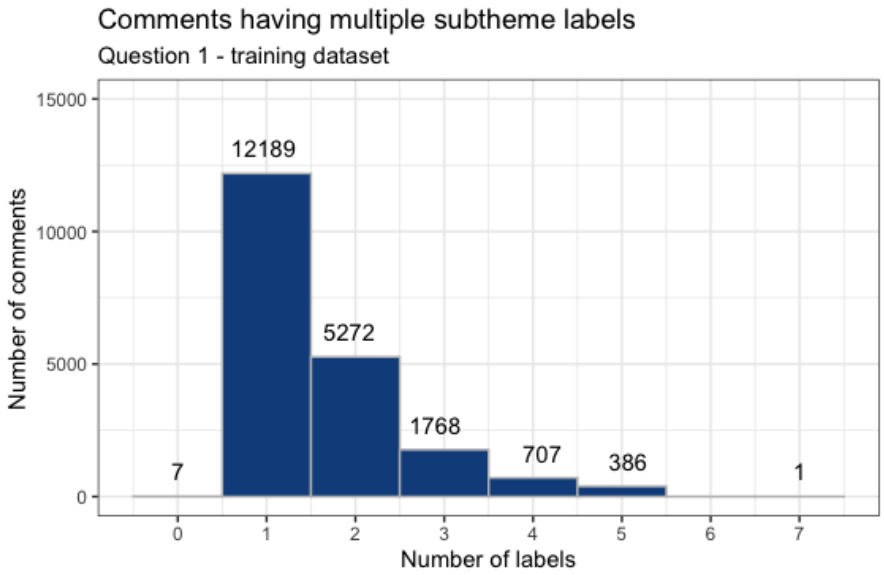
2) Build an app for visualizations of text data:

- Identify and compare common words used for each question
- Identify trends on concerns (Q1) and appreciations (Q2) for BC ministries over the given years

Challenges with data

1) Sparsity



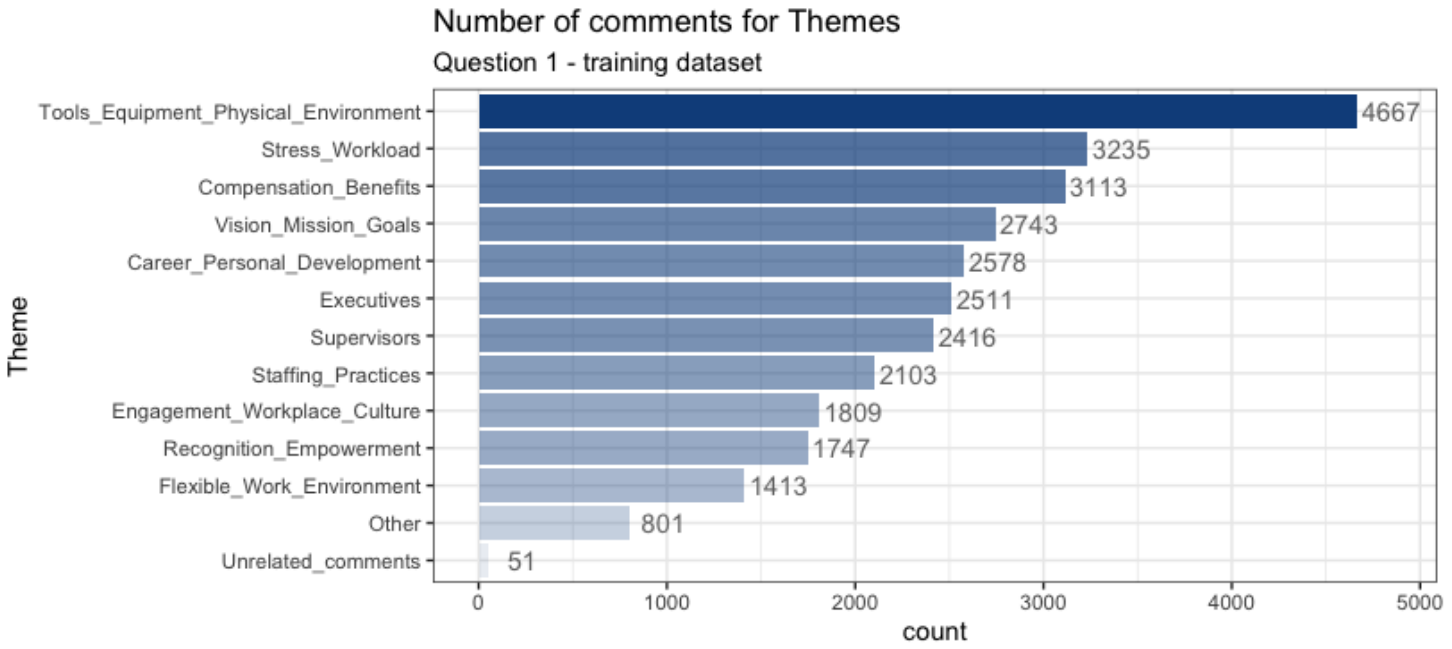


There are 12 themes and 62 subthemes that comments can be encoded into.

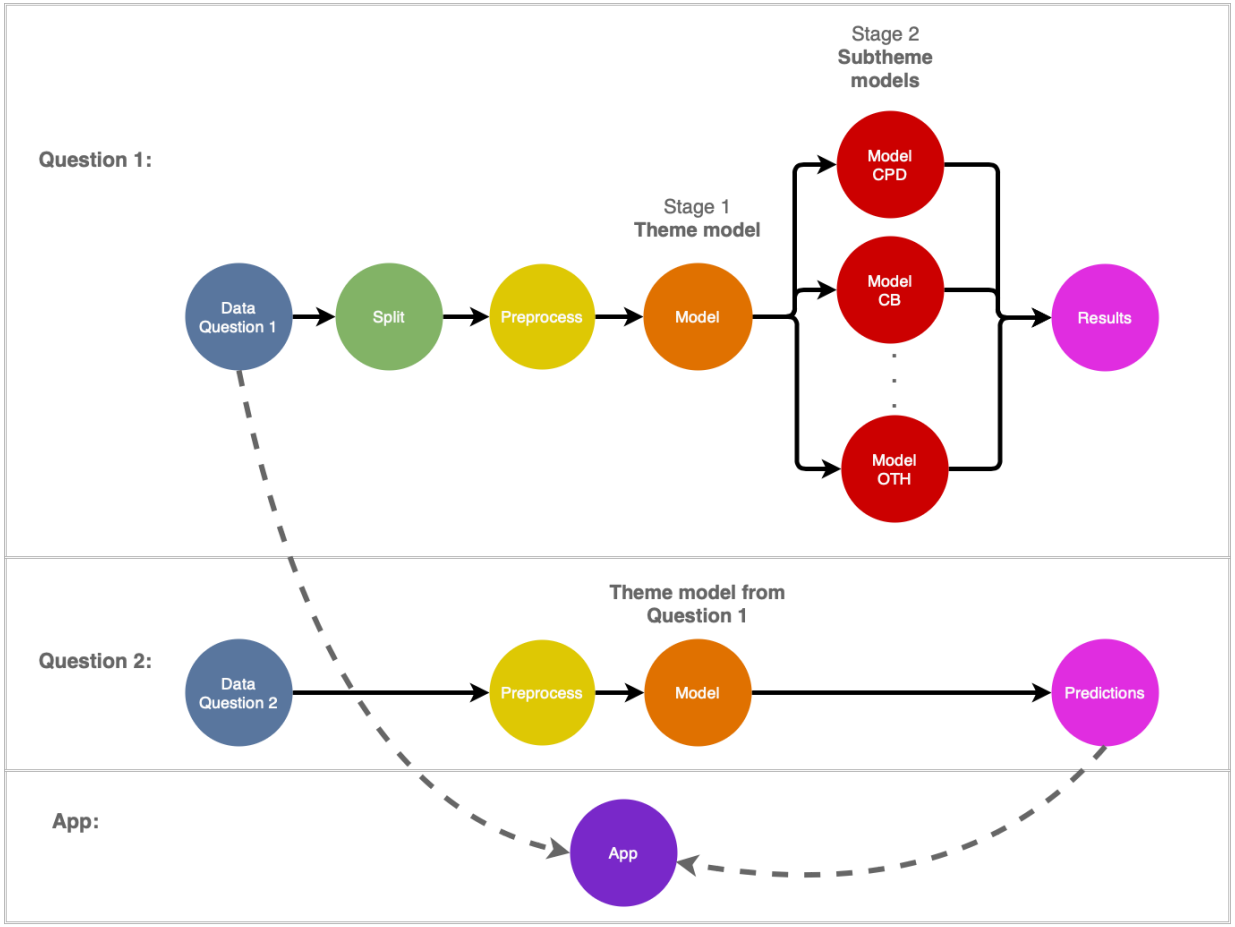
- Average number of labels per comment: **Themes = ~1.4 , Subthemes = ~1.6**

Challenges with data

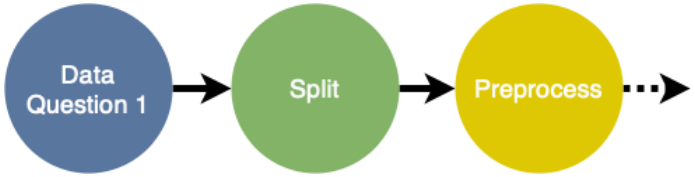
2) Class Imbalance



Text classification methodology



Data Split & Preprocess

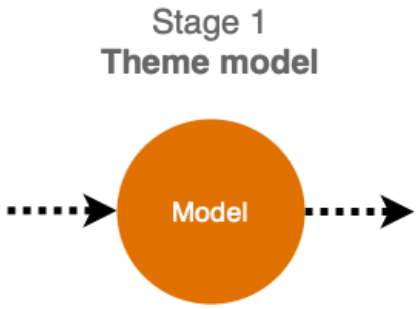


- Raw -> 80% train, 20% test.
- Training -> 80% train, 20% validation

- removed sensitive information using Named Entity Recognition (NER) to remove person, organization, location, and geopolitical entity

Example comment to get flagged: **"George and I love when the department gives us new coupons!"**

Modelling Techniques

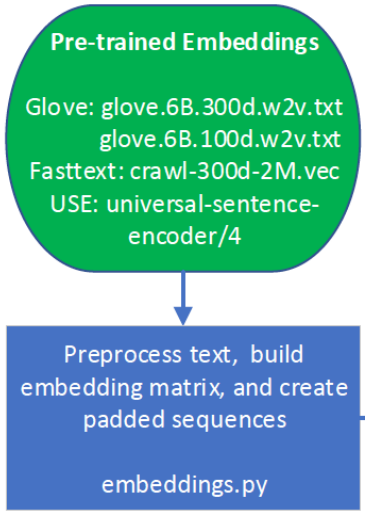


- **Baseline models:** used **TF-IDF Vectorizer** and traditional machine learning classifiers (RandomForest, GaussianNB, etc)
  - best results with **LinearSVC**

- **Deep Learning models:** ran multiple models including **CNNs** and **sequential models** with pre-trained embeddings

Pre-Trained Embeddings

Fasttext, Glove, Universal Sentence Encoder

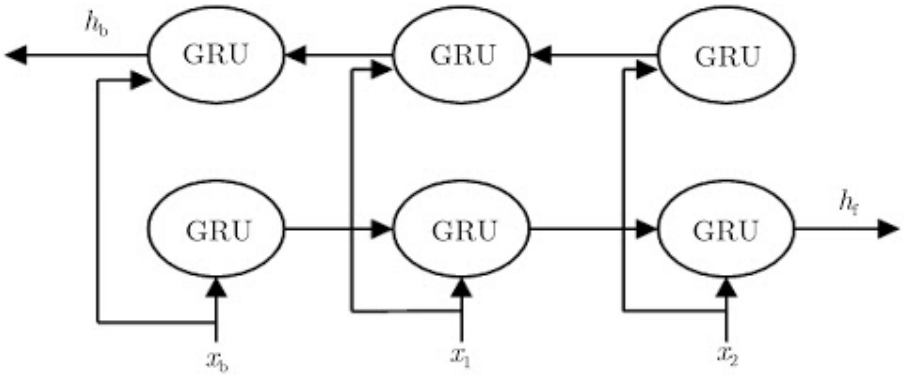


- **Fasttext**: trained on Common Crawl
- **Glove**: trained on Wikipedia and Gigaword (newswire text)
- **Universal Sentence Encoder**: trained on Wikipedia and Common Crawl
- Built embedding matrixes & transformed comments to padded sequential data to fit into embedding size.
- Embeddings allowed usage of public cloud services as data contains sensitive information.

Deep Learning Models

BiGRU

- **GRUs:** preserves order of words and has 2 gates (reset gate and update gate)
- **Bidirectional GRUs**: Uses sentence sequences from both left-to-right and right-to-left

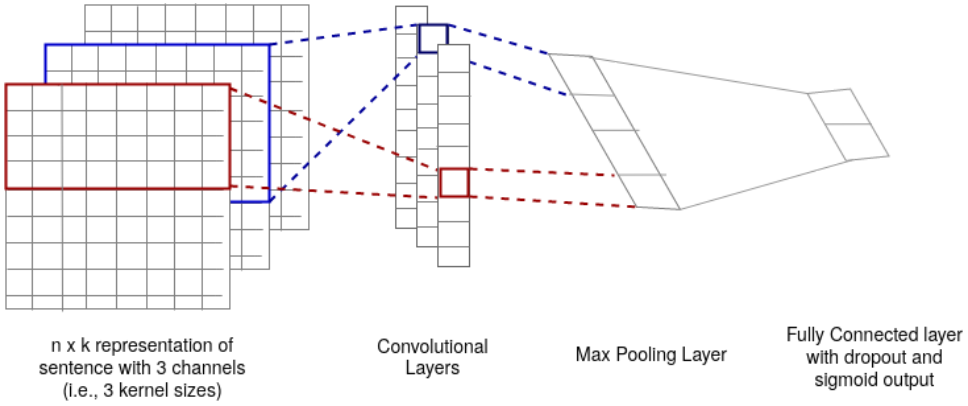


Source: Bi-directionalGated Recurrent Unit

Deep Learning Models

Multichannel CNNs

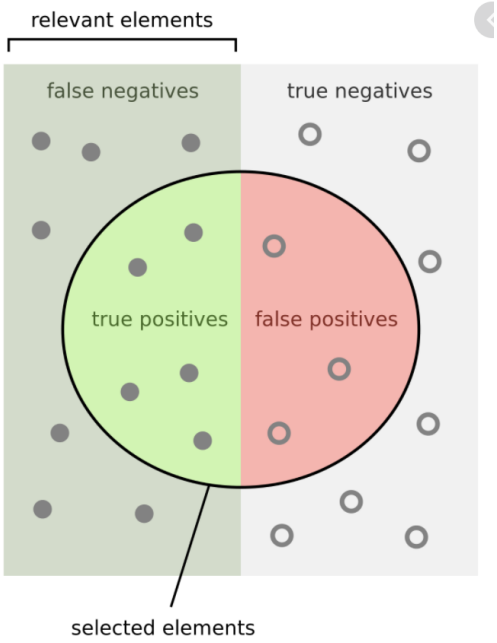
- Multiple versions of standard CNN models with different kernel sizes.
- Specifically, we have defined a model with 3 input channels for kernel sizes 4, 6 and 8

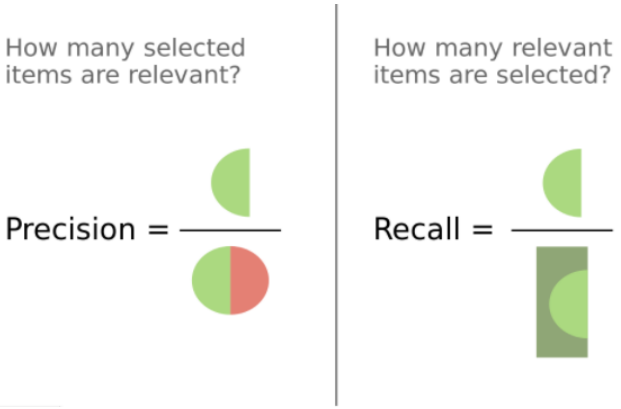


- n - number of words , k - dimension of the word embedding

How we measured success

Precision & Recall

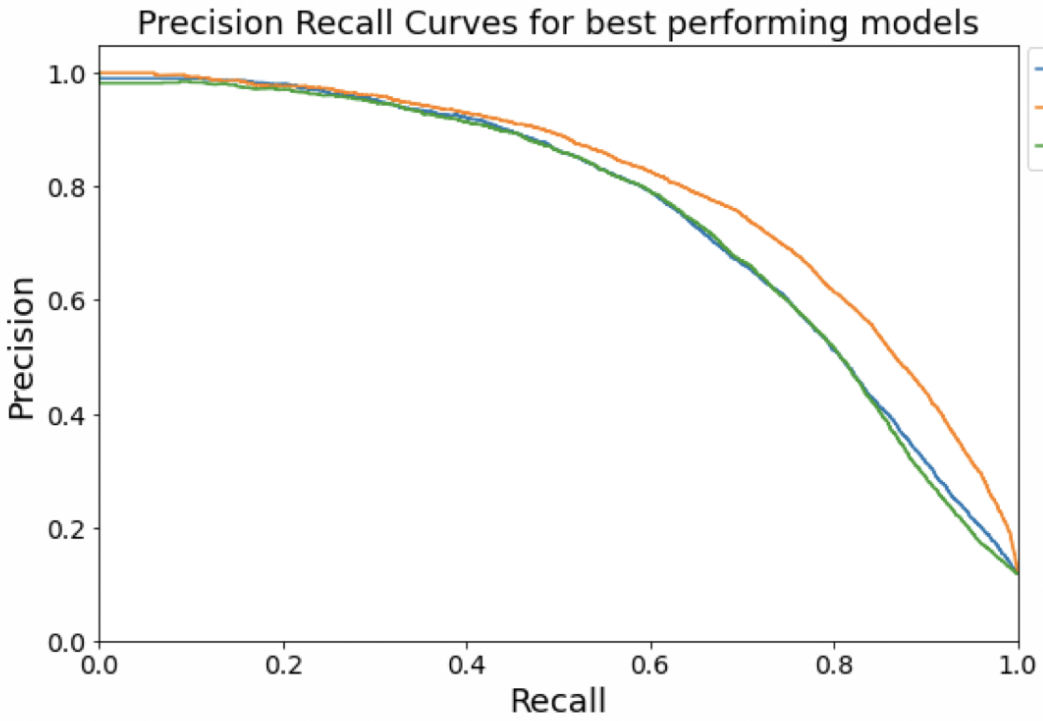




- Precision Recall curve: plotting precision vs recall at various threshold rates
- Micro-average: weighted average of the precision and recall

Source: Precision and Recall

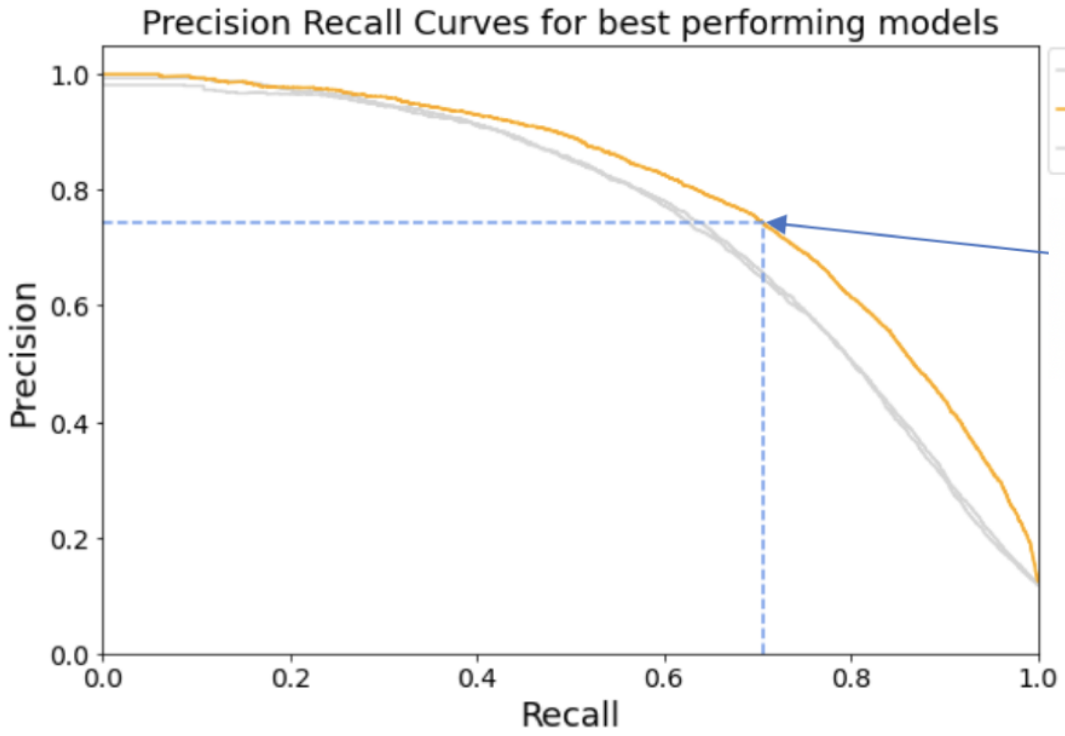
Precision Recall Curve for Q1 Theme Models



AUC Scores

Multichannel CNN + Fasttext	**0.756**
BiGRU + Fasttext	**0.799**
CNN + Fasttext	**0.751**

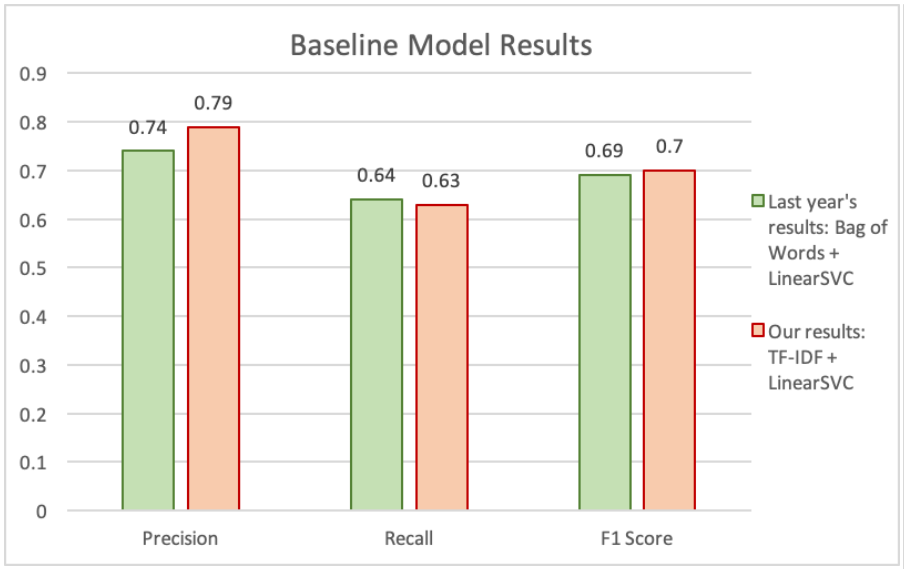
Advanced Model: Fasttext + BiGRU

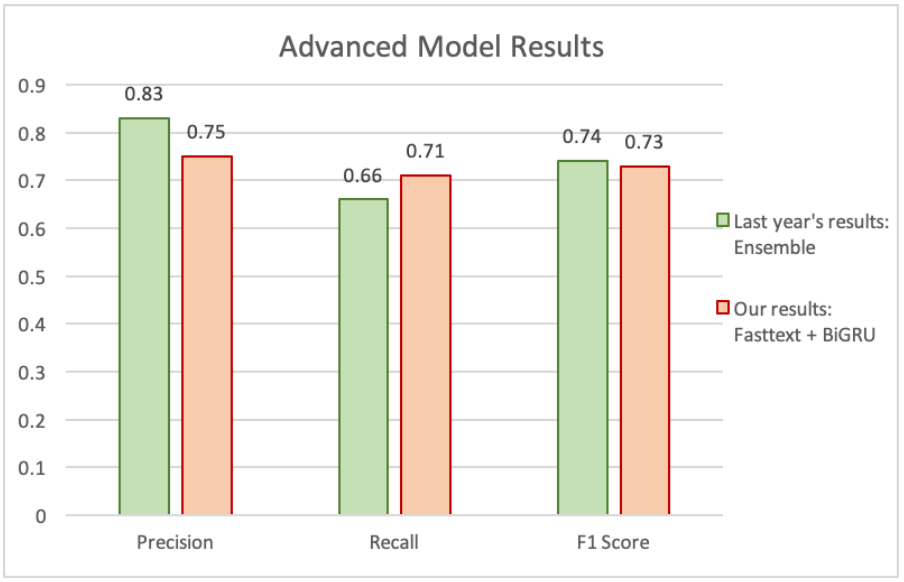


These are the test results at the 0.4 threshold:

Accuracy	0.531
Precision	0.751
Recall	0.709
F1	0.729

Results for Theme Labelling Models

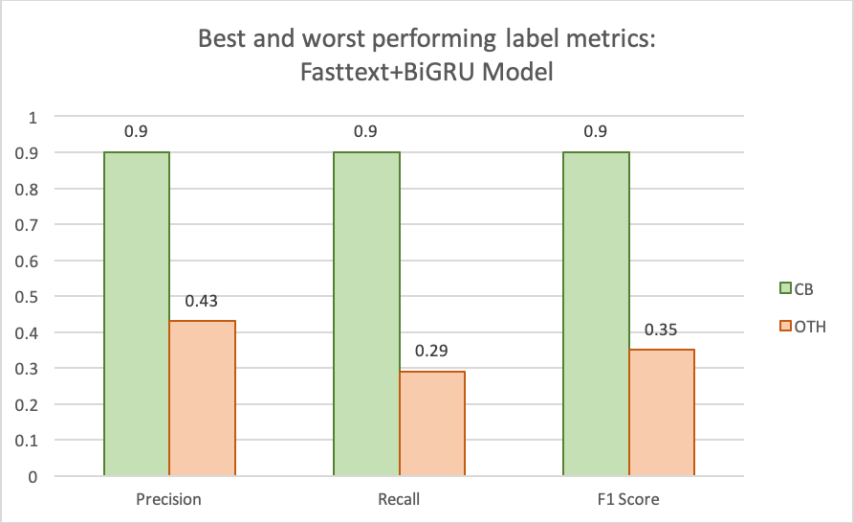




Source: [BC Stats Capstone 2019-Final Report, by A. Quinton, A. Pearson, F. Nie]

Label Wise Results for Fasttext + BiGRU

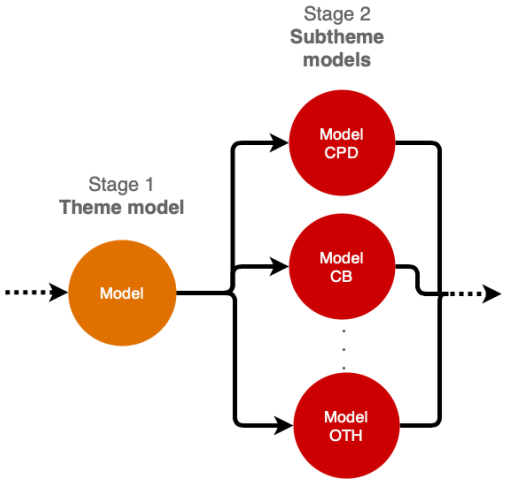
Predicting each theme



- Themes with high F1 scores (CB) can be encoded **automatically using the model**, while themes with lower scores (OTH) can be **manually verified** by BC Stats.
- Recommendation to use a **combination of machine learning and manual encoding.**
- Rest of the themes have the following ranges:
- **Precision: 0.69-0.92**
- **Recall: 0.51-0.85**

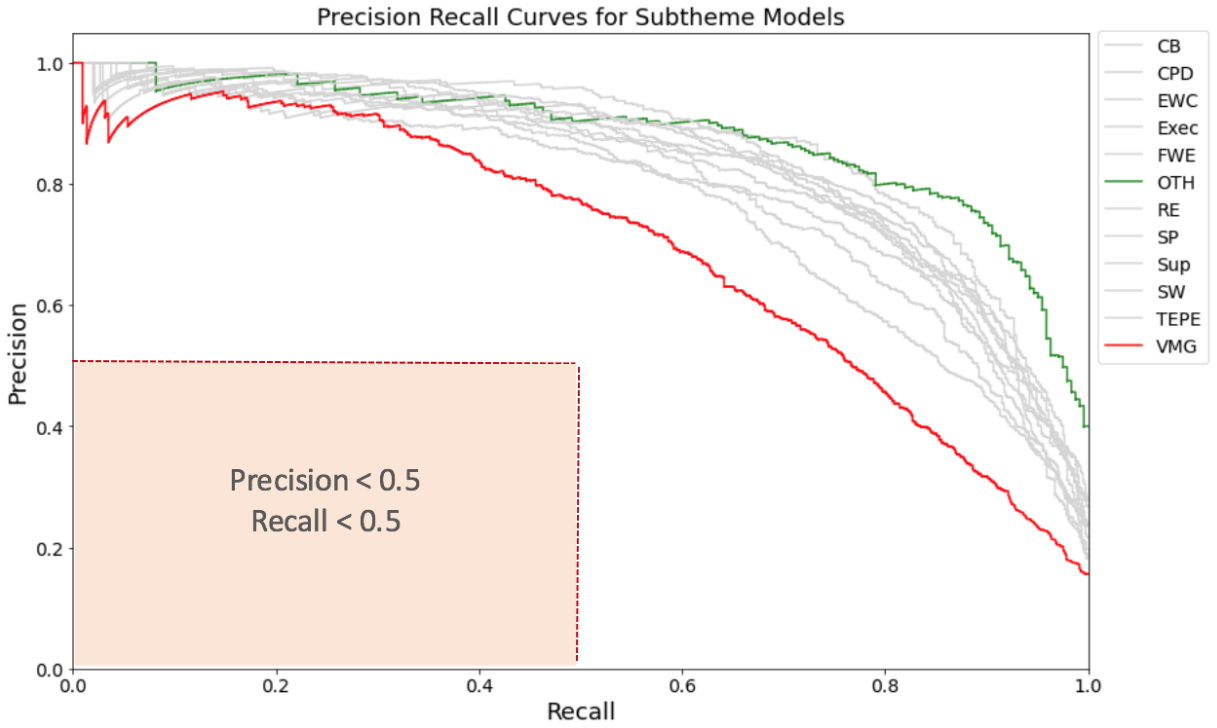
Building Subtheme Models

Hierarchical approach



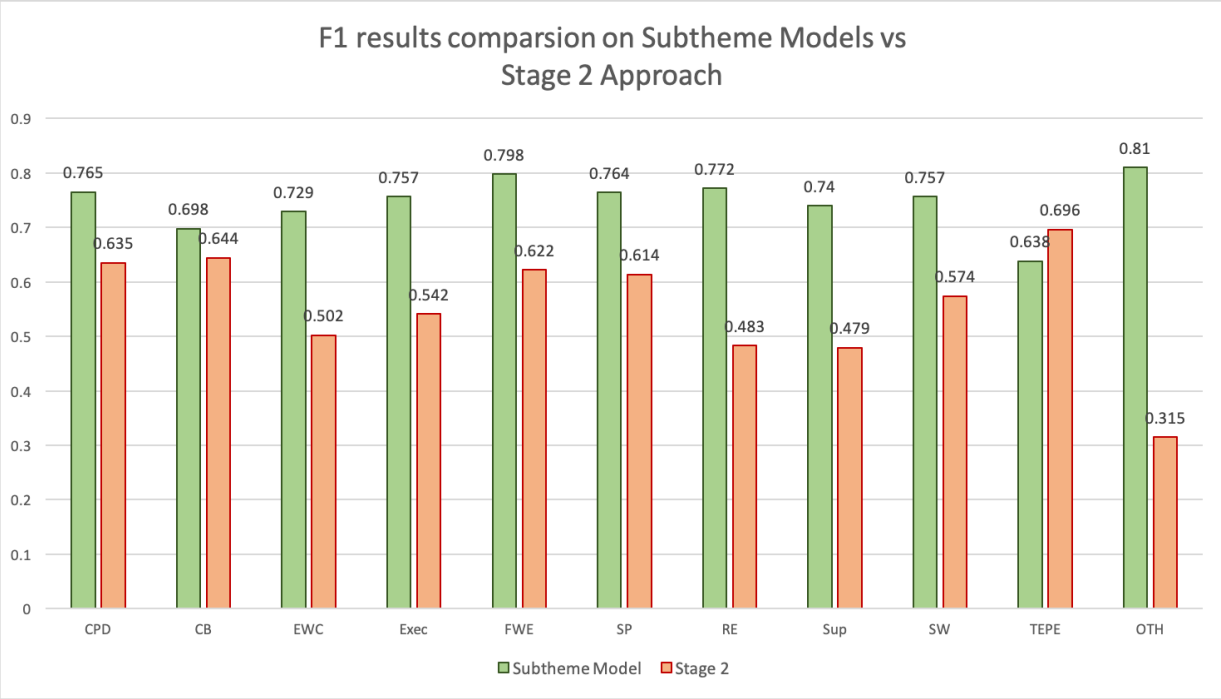
Subthemes are predicted based on the theme(s) our model has assigned to the comment.

Precision Recall Plot for Subtheme Models



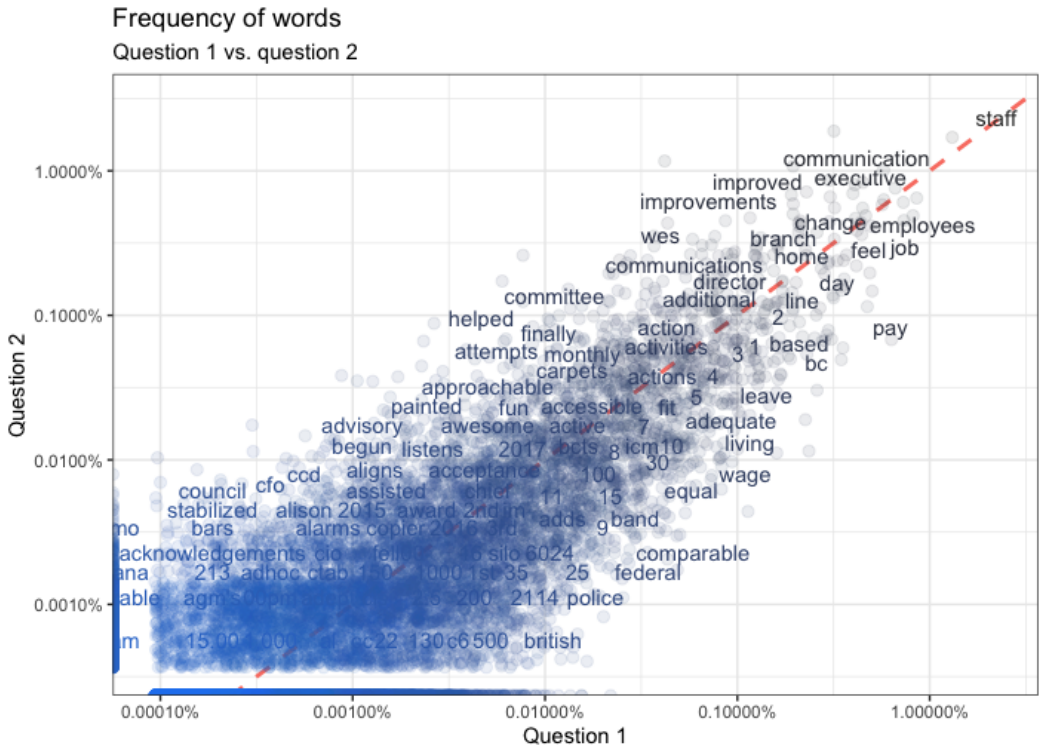
- The minimum desirable of both precision and recall values shared by BC Stats for labelling subthemes was 0.5.
- **All subtheme models surpassed this threshold.**

Subtheme models results



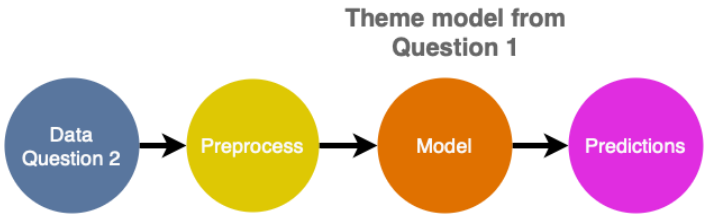
- $$F1 = 2 * \frac{precision * recall}{precision + recall}$$
- Increasing data for label OTH will improve results

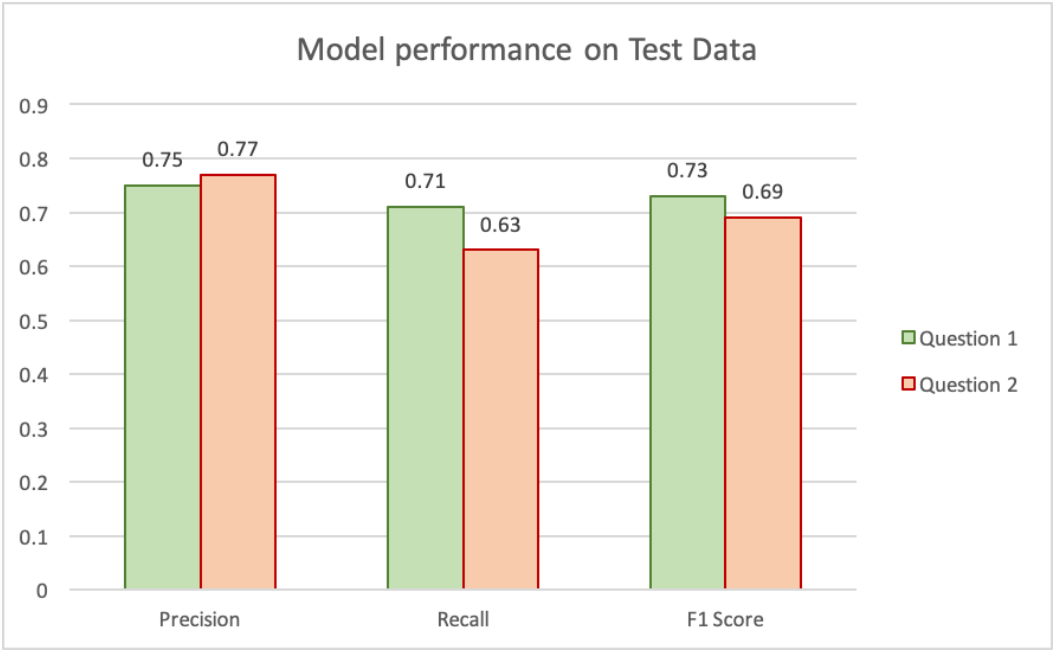
Comparing Question 2 to Question 1



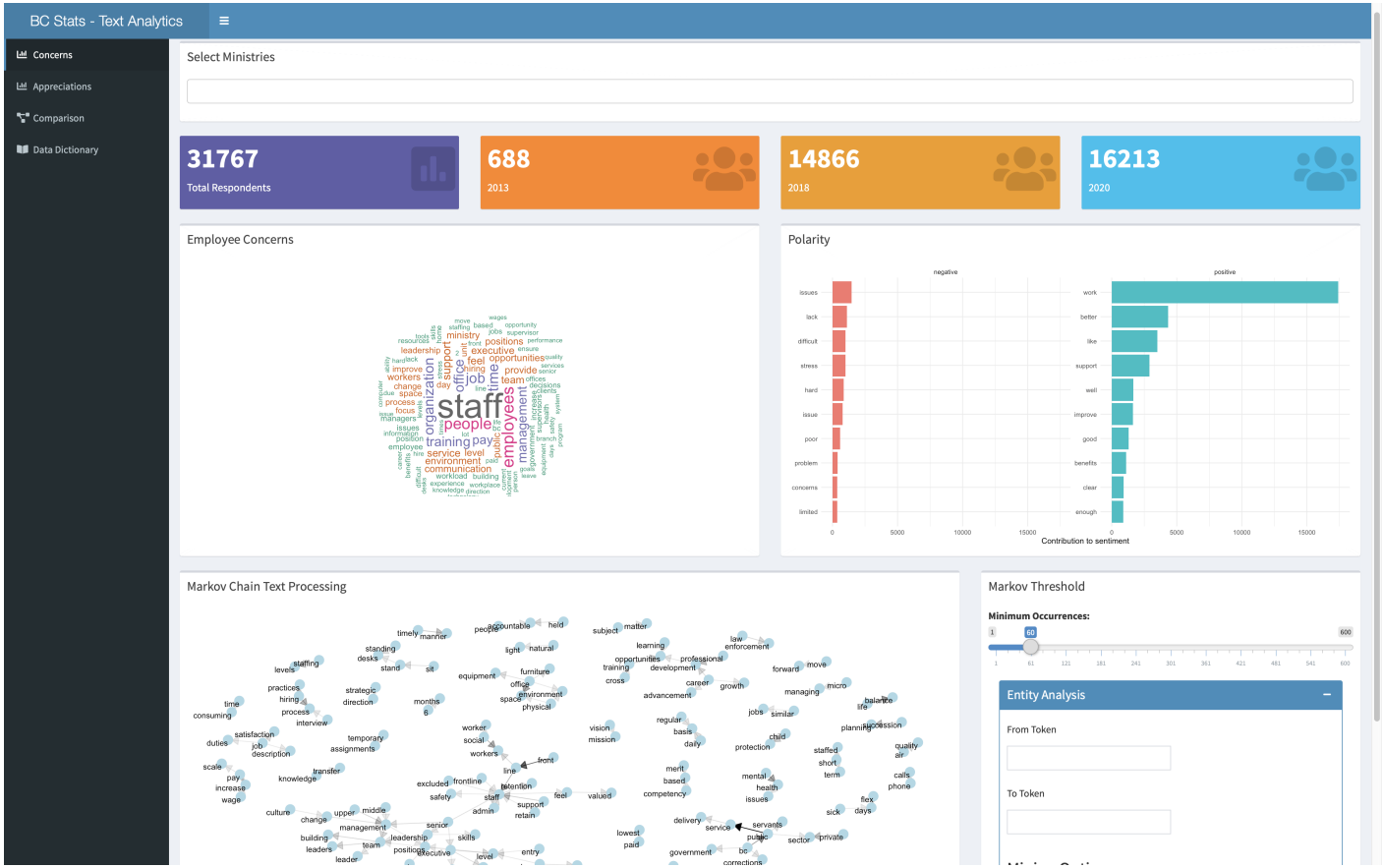
- Observed a **linear trend** in frequency of common words between Question 1 and Question 2.
- Validated **using the themes from Question 1** to label comments from Question 2.

Question 2: Predicting Themes



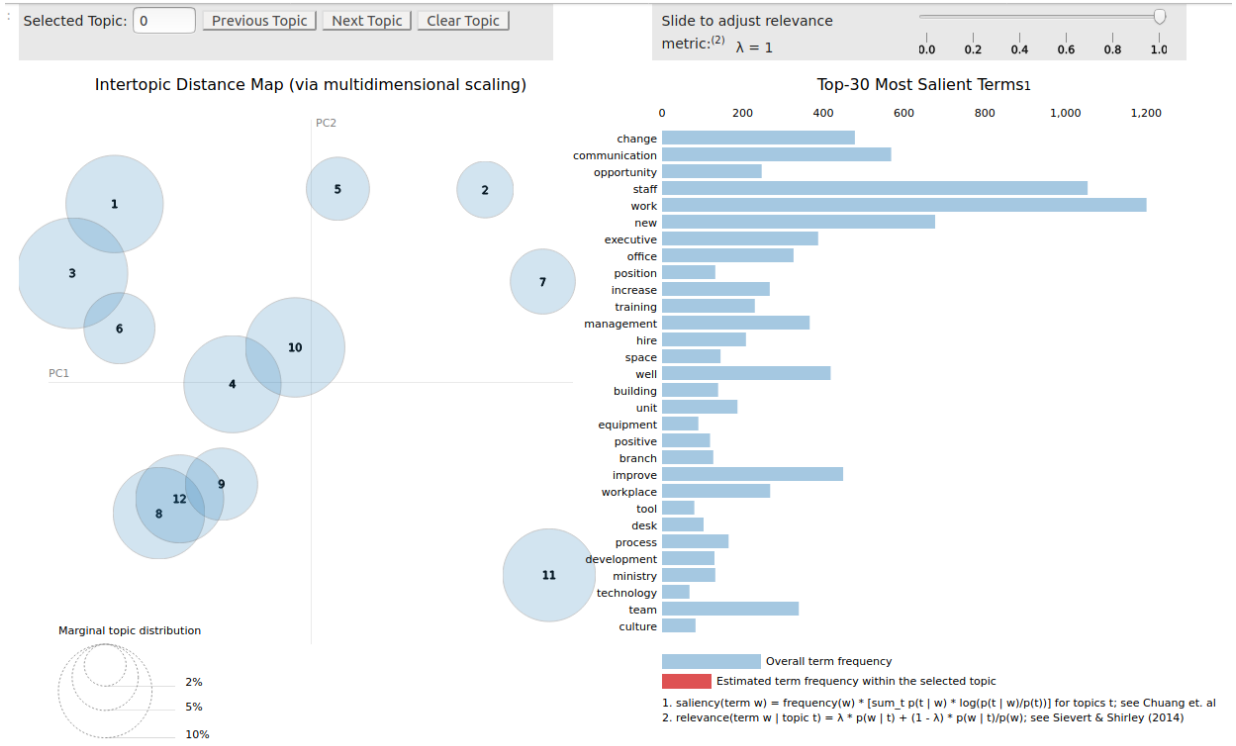


Dashboard


BC Stats - Text Analytics
Concerns
Appreciations
Comparison
Data Dictionary
Select Ministries
31767
Total Respondents
688
2013
14866
2018
16213
2020
Employee Concerns
Polarity
negative
positive
Contribution to sentiment
Markov Chain Text Processing
Markov Threshold
Minimum Occurrences:
Entity Analysis
From Token
To Token

Methodologies that did not work

- **Overfitting** in **CNNs** and **multi-channel CNNs**
- **Universal Sentence Encoder** embeddings
- **Topic modelling** for Question 2 (too much overlap in words, ambiguity)



Recommendations & Conclusions

- Expected to observe better results with **more data**
  - will improve results for subthemes using hierarchical approach

- Use model to automate labelling on themes and subthemes with high precision and recall
  - **CB, TEPE, CPD, SP,** and **FWE** (for theme model)
  - manually encode or verify model's results on other comments

Thank you. Questions?

Appendix A: Theme Model threshold levels

Results on various threshold values using validation data

Threshold	Accuracy	Precision	Recall	F1.measure
0.3	0.500491835530199	0.703502255240117	0.739403234802008	0.7210061182868
0.4	0.524099940979736	0.743642510657063	0.705382041271612	0.7240071556350
0.5	0.53393665158371	0.77415712211647	0.669129949804796	0.7178221524194
0.6	0.529018296281723	0.798985304408677	0.636781929726715	0.7087212911235
0.7	0.519771788313988	0.826897214217099	0.600111544896821	0.6954835582128
0.8	0.49990163289396	0.856865284974093	0.55340211935304	0.6724839037614
0.9	0.465276411567972	0.899328859060403	0.485778025655326	0.6308165851892