BC Stats

Text Analytics:

Quantifying the Responses to Open-Ended Survey Questions

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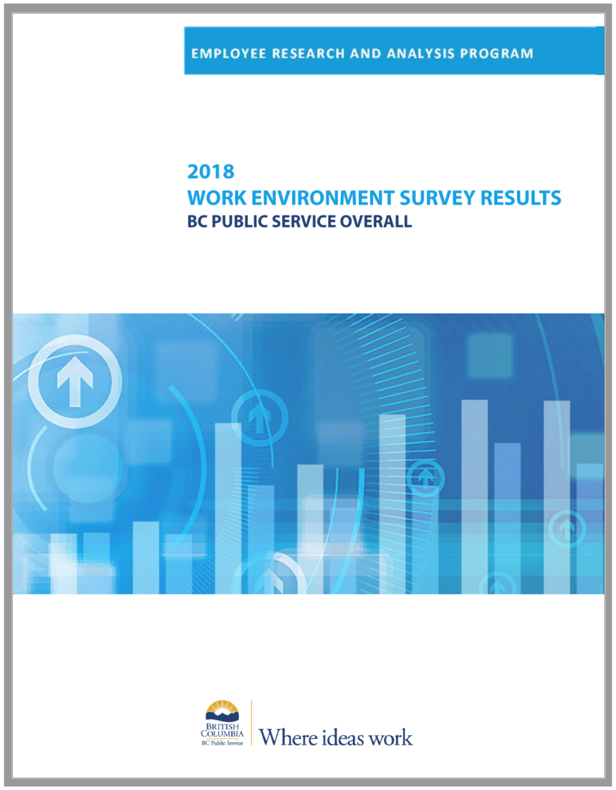
Introduction

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 multiple choice questions (5 point scale) and 2 open-ended 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:

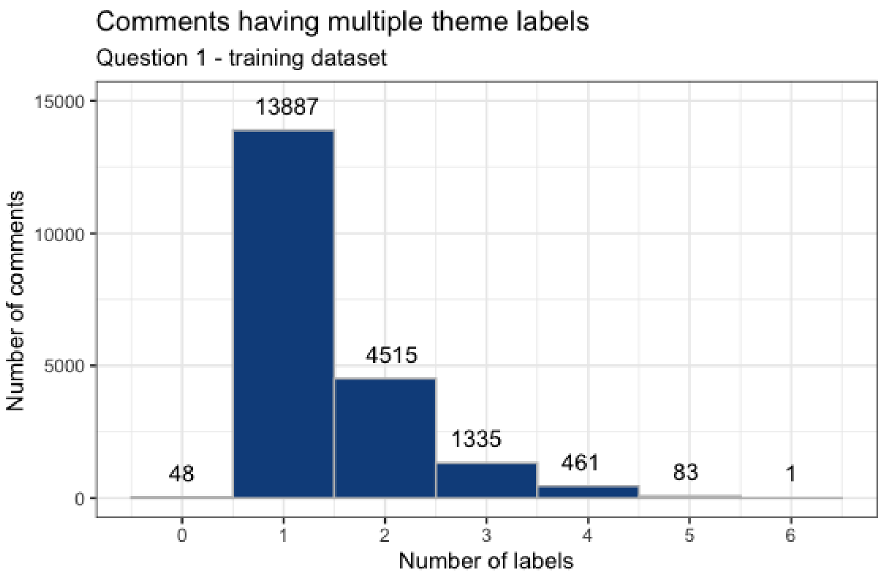
- predicts label(s) for Question 1 and 2's main themes
- predicts label(s) for Question 1's sub-themes

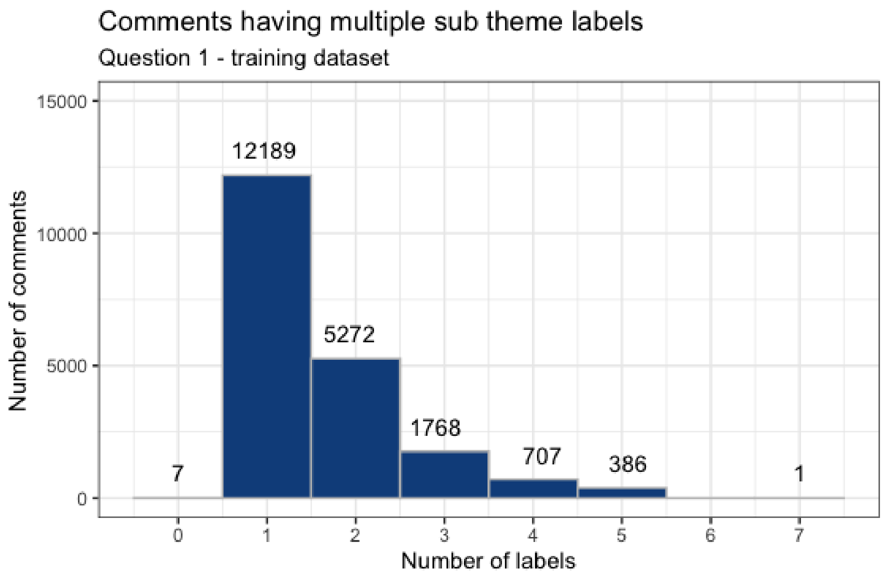
2) Build an app for visualizations on text data:

- 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 63 subthemes that comments can be encoded into.

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

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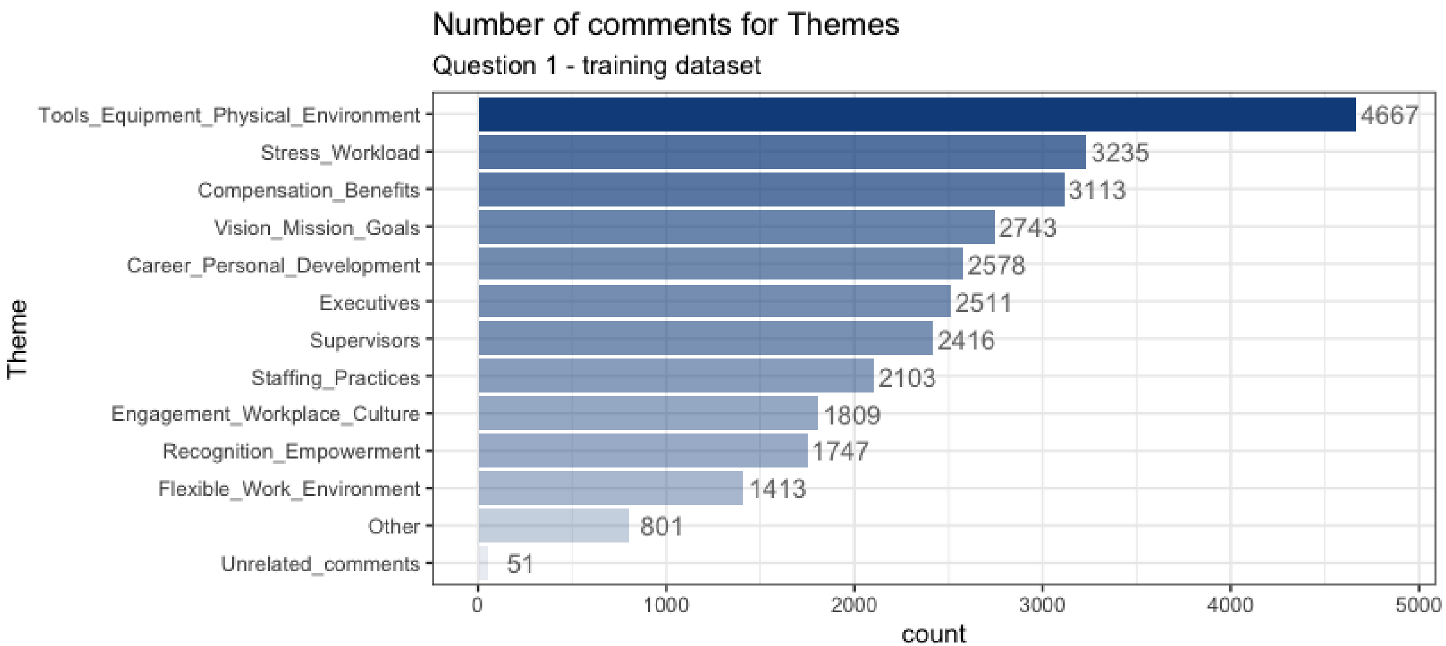
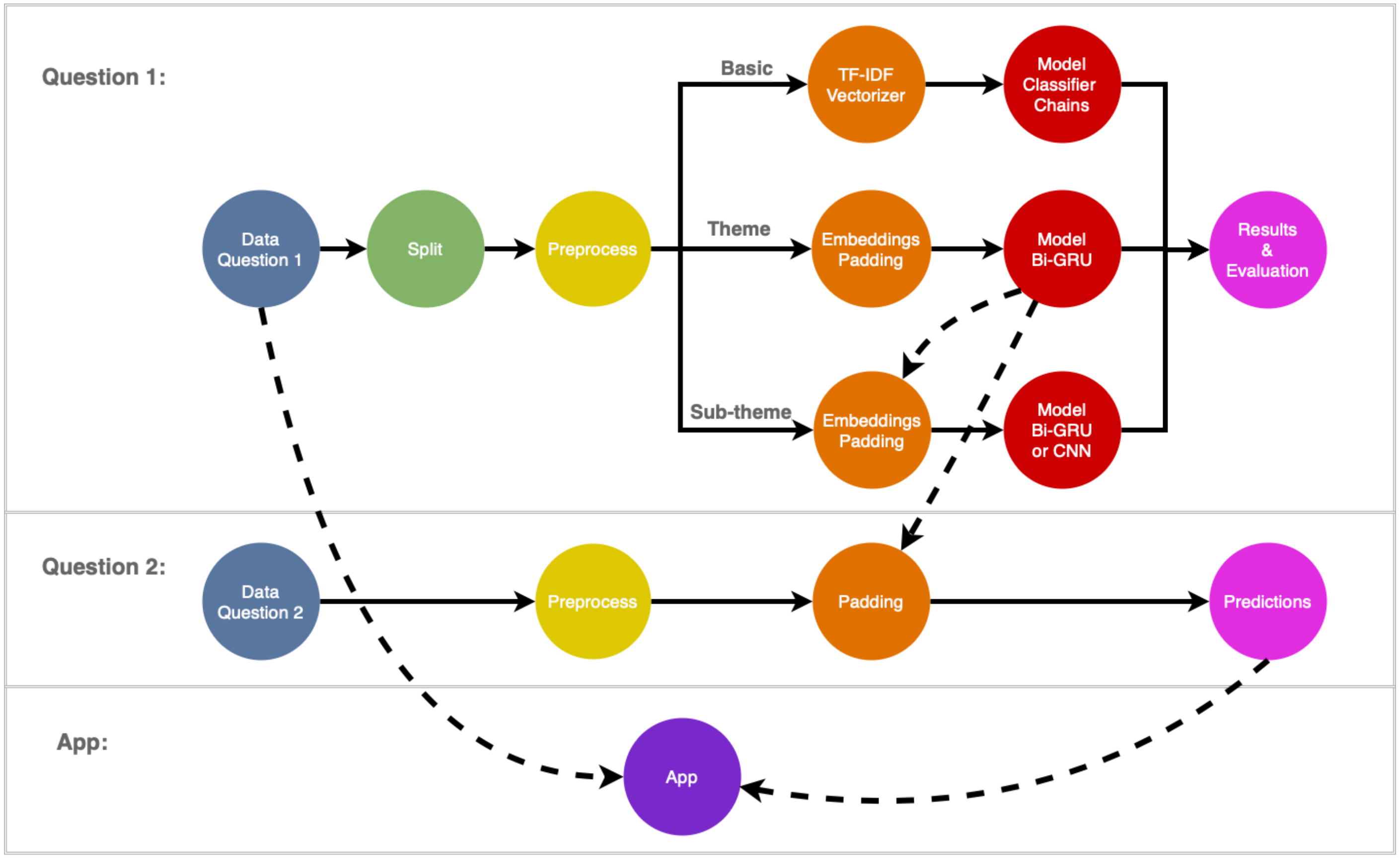
Challenges with data

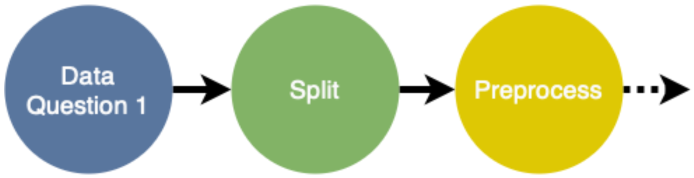
2) Class Imbalance



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
- changed social media handles from "Facebook", "Instagram", "Twitter" to "social media"
- removed punctuation and lowercase for tokenization

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

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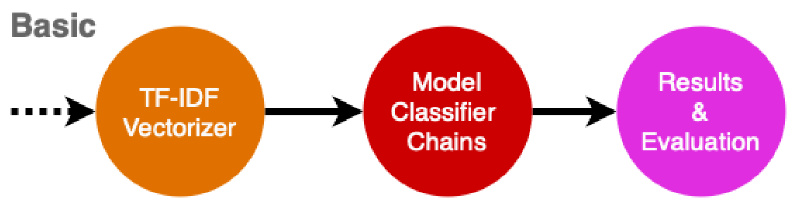
Baseline Model: Classifier Chains

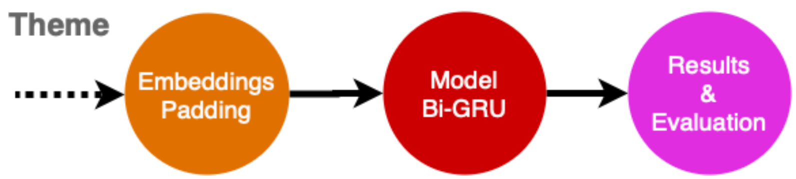


TF-IDF Vectorizer uses weights instead of token counts (CountVectorizer).

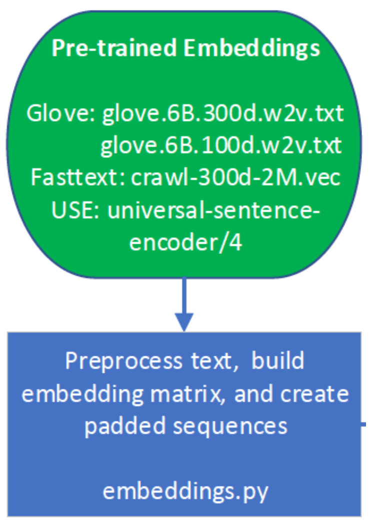
Classifier Chains is a multi-label classification method which preserves order and occurence of labels.

- ran multiple scikit-learn base classifiers (RandomForest, GaussianNB, etc)
- best result with **LinearSVC**

Advanced Model: Pre-Trained Embeddings



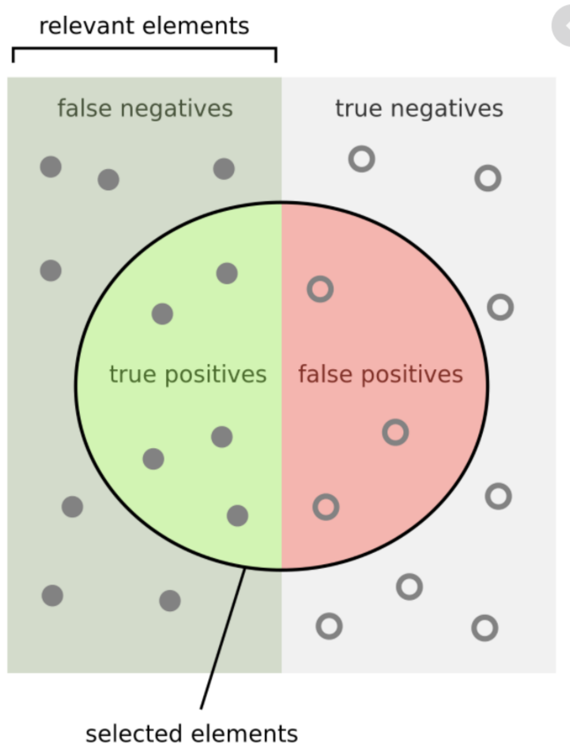
Fasttext, Glove, Universal Sentence Encoder



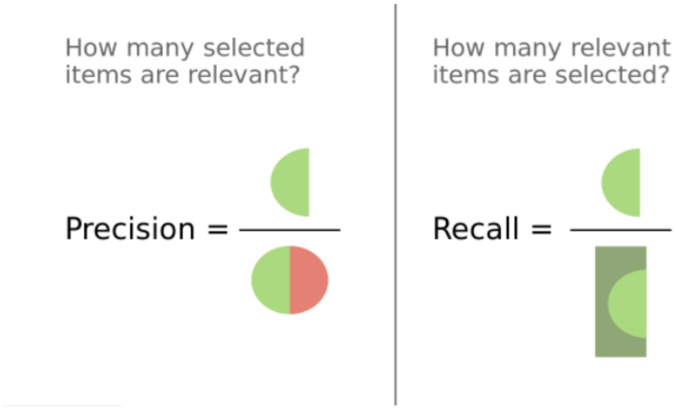
- explored several embeddings on various models
- built embedding matrix & transformed comments to padded sequenced data to fit into embedding size
- used these saved embeddings on public cloud services as data contains sensitive information

How we measured success

Precision & Recall



Source: Precision and Recall



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

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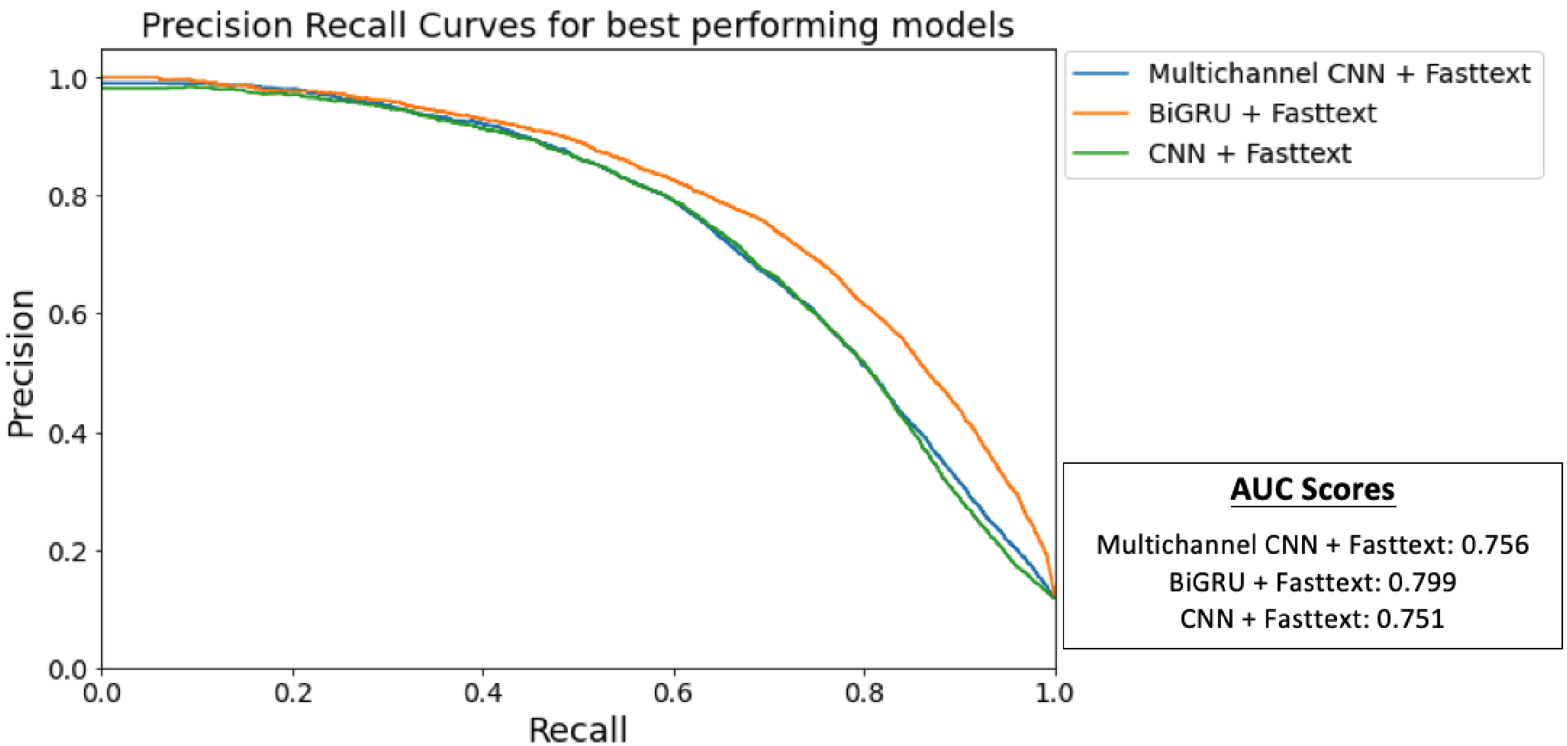
Precision Recall Curve for Q1 Theme Models



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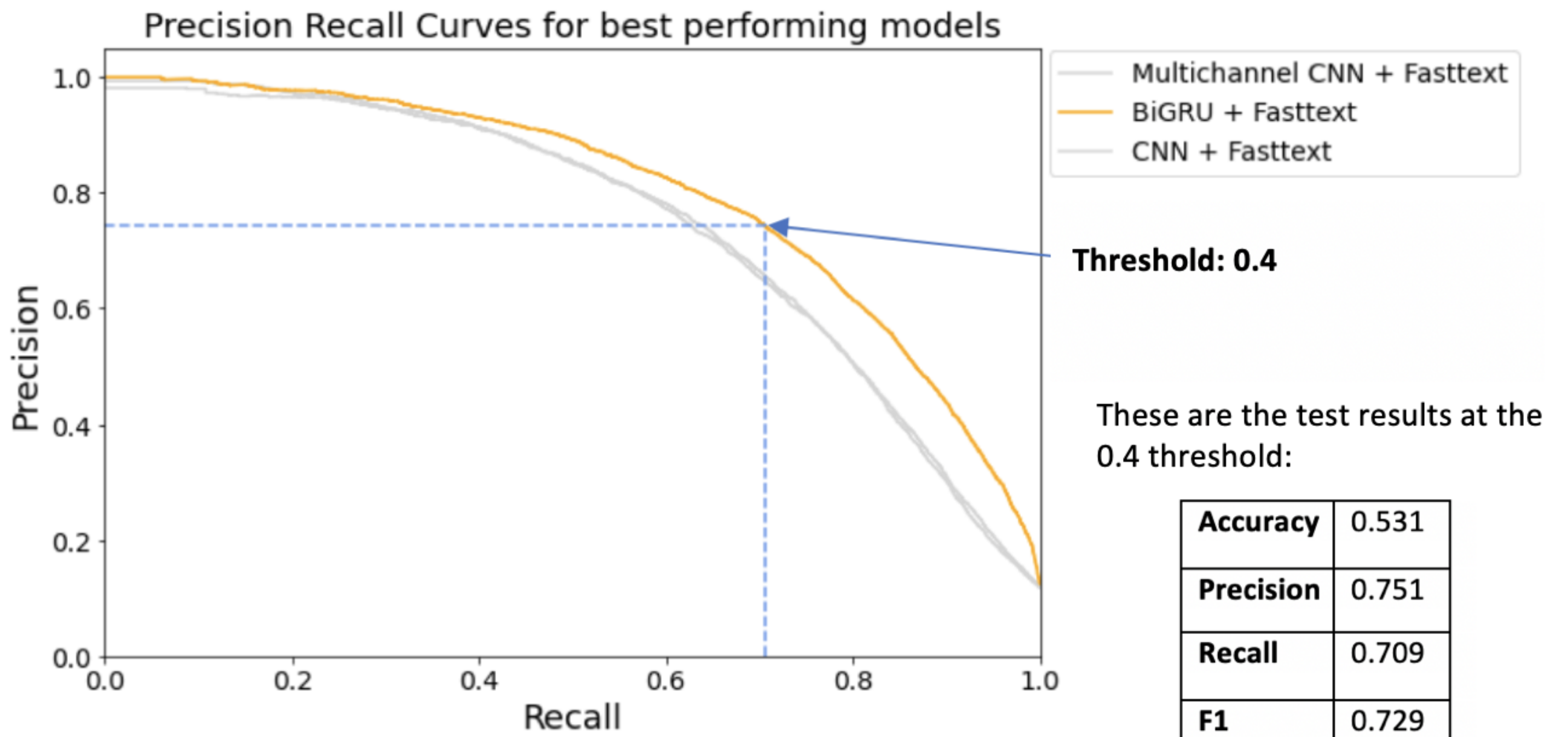
Advanced Model: Fasttext + BiGRU



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

Model	Accuracy	Precision	Recall	F1
TF-IDF + LinearSVC	0.50	0.79	0.63	0.70
Fasttext + BiGRU	0.53	0.75	0.71	0.73

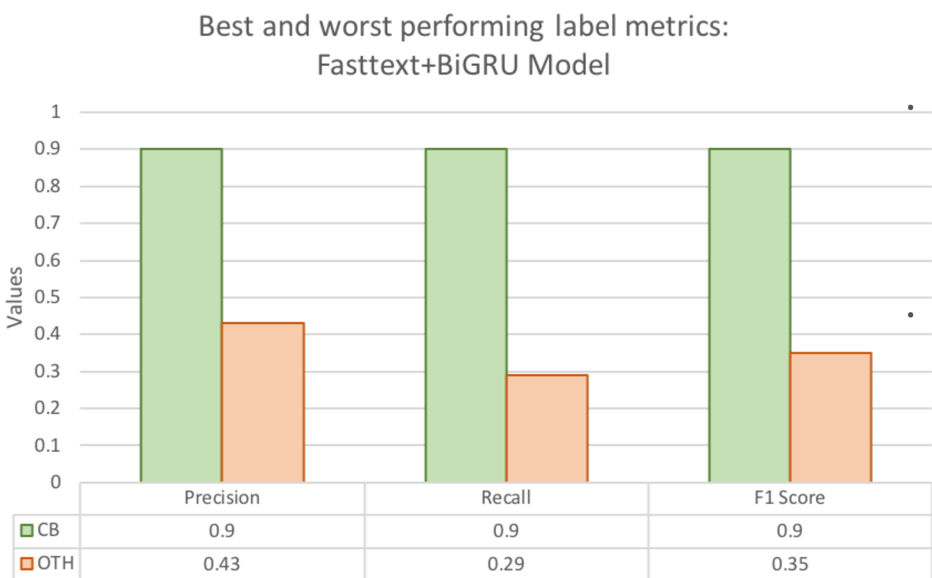
Last year's capstone team's results of models:

Model	Accuracy	Precision	Recall	F1
Bag of Words + LinearSVC	0.45	0.74	0.64	0.69
Ensemble Model	0.53	0.83	0.66	0.74

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 low score (OTH) should be **manually verified** by BC Stats
- Recommendation to use a **combination of machine learning and manual encoding.**

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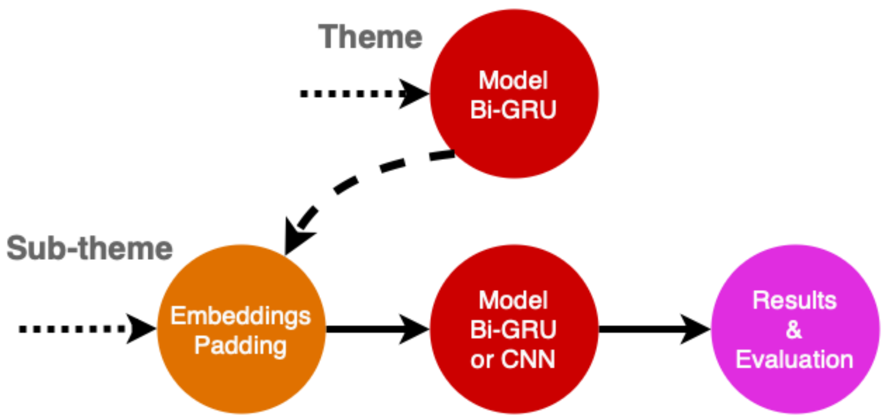
Building Subtheme Models

Hierarchical approach



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

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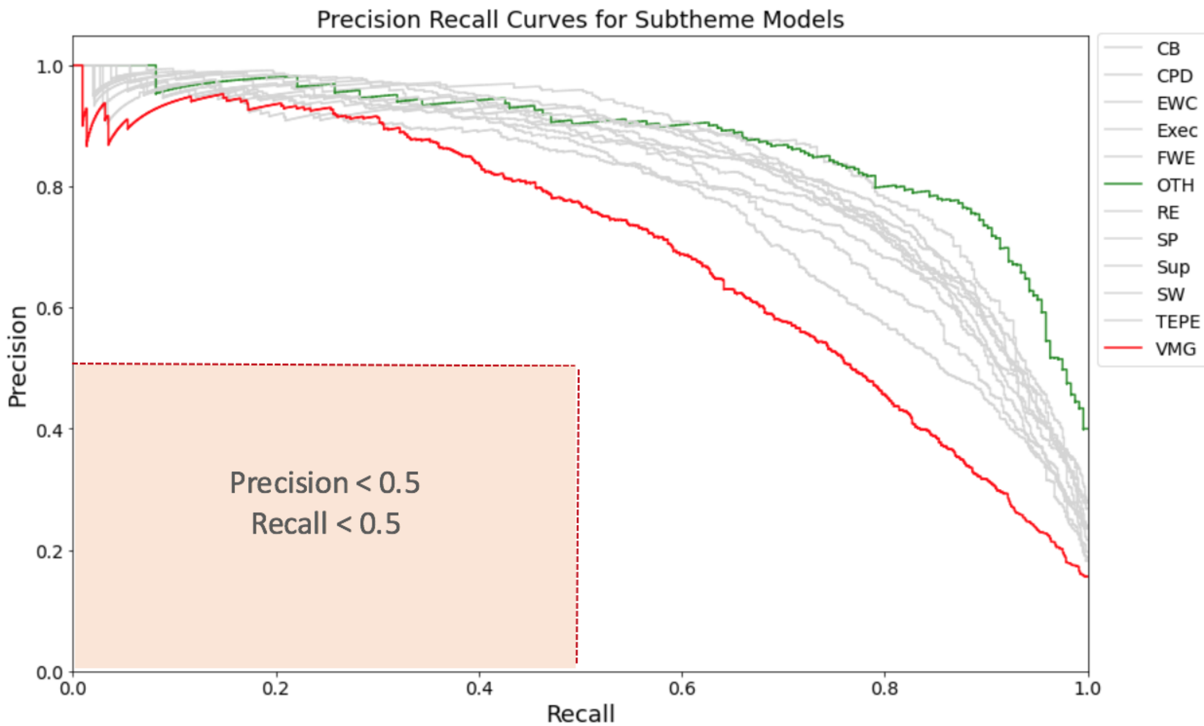
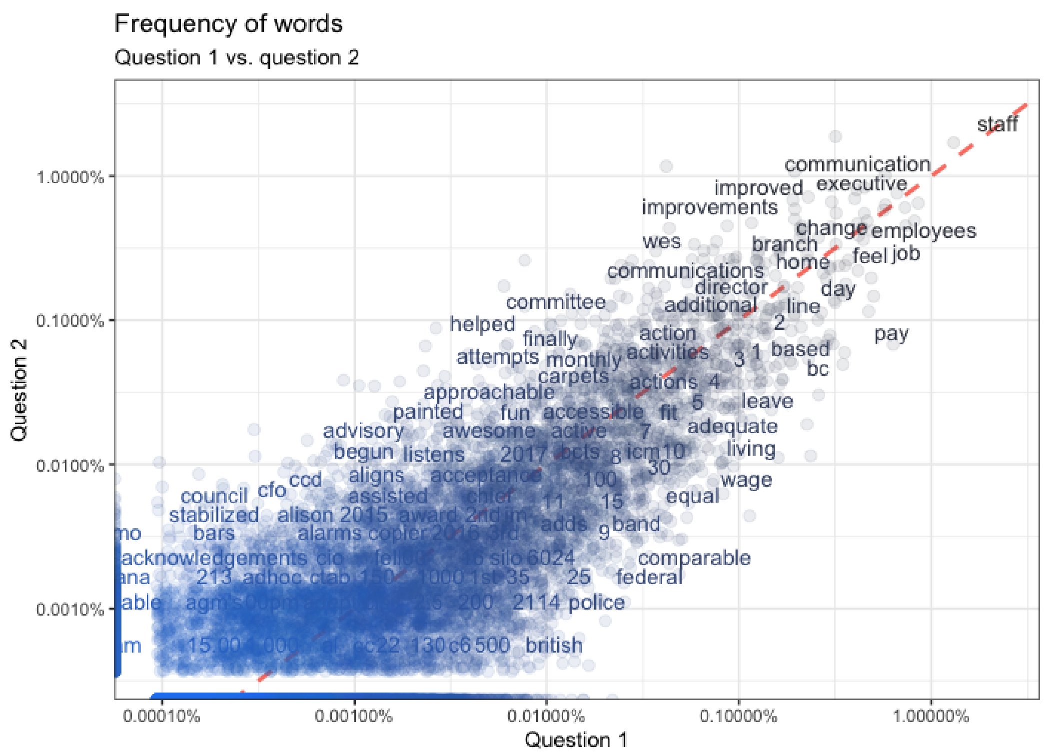
Precision Recall Plot for Subtheme Models



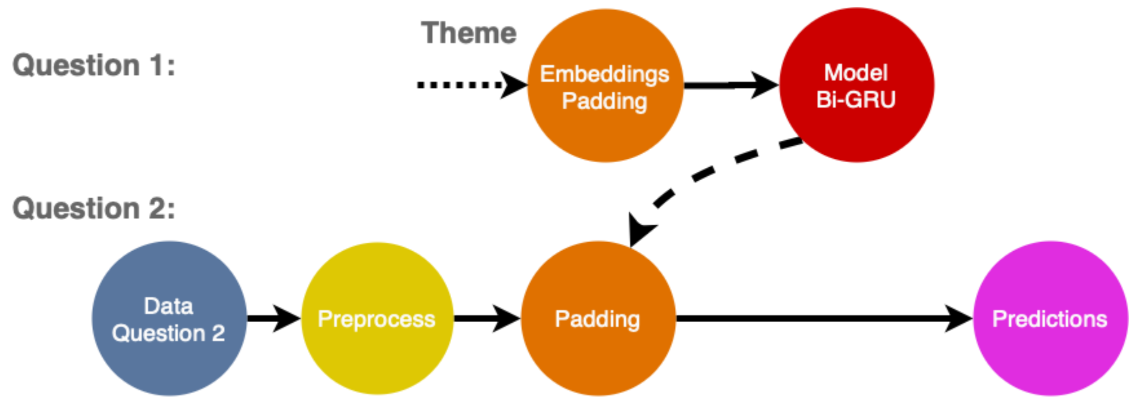
- The minimum desirable of both precision and recall values shared by BC Stats for labelling subthemes was 0.5.
- **All subtheme models surpassed this threshold.**

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



Results of our model predicting on sample data of Question 2 manually encoded by BC Stats (at 0.4 threshold):

Accuracy	Precision	Recall	F1
0.46	0.77	0.63	0.69

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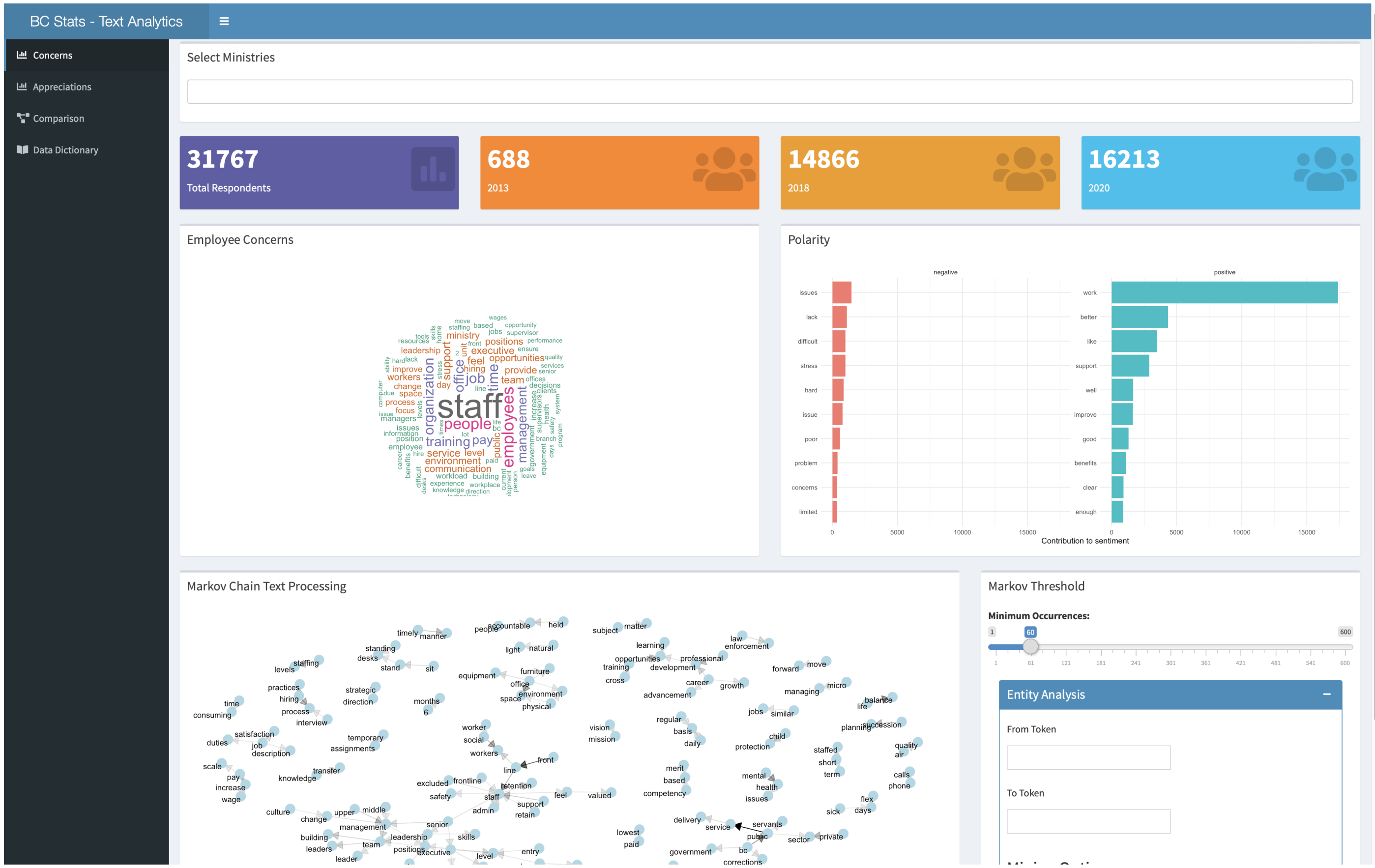
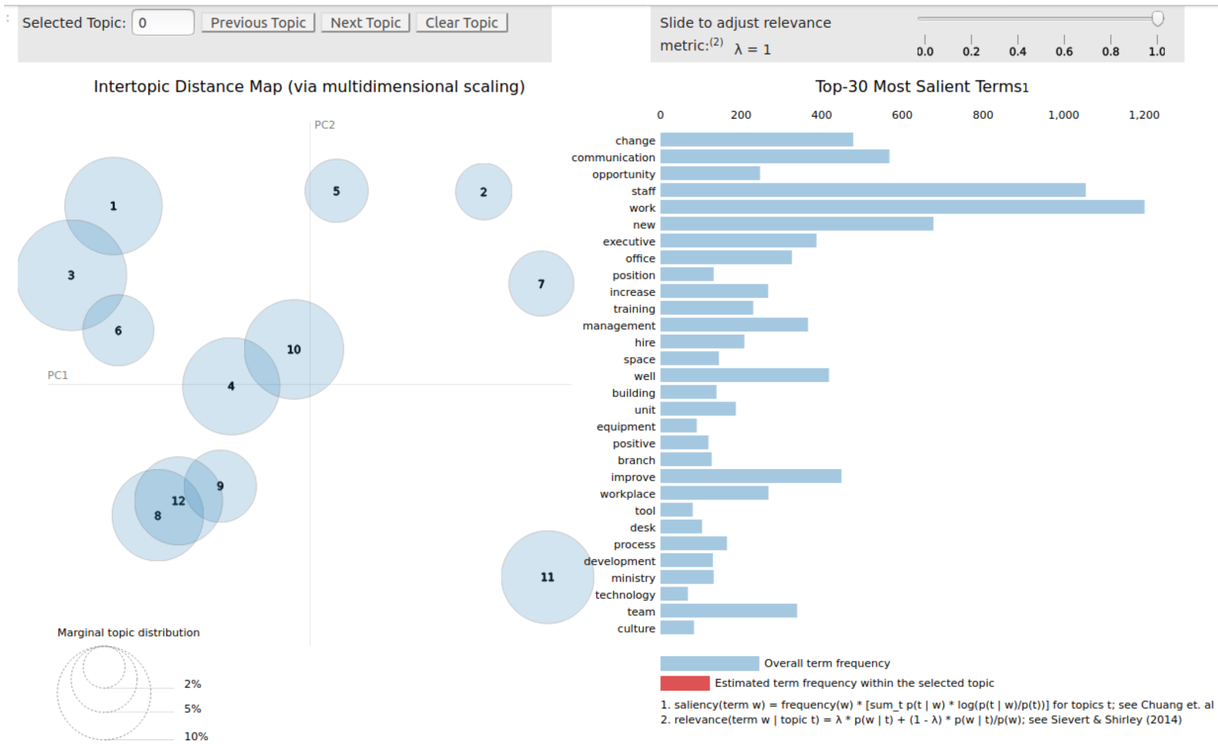
Dashboard


BC Stats - Text Analytics
Concerns
Appreciations
Comparison
Data Dictionary
Select Ministries
31767
Total Respondents
688
2013
14866
2018
16213
2020
Employee Concerns
Polarity
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** and **BERT** embeddings
- **Topic modelling** for Question 2 (too much overlap in words, ambiguity)



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Recommendations

- observe better results with more **more data**
- use embeddings and padded data on **public cloud services** (Google Gollab, AWS) to apply complex machine learning algorithms on sensitive data
- **BERT**
- **Topic modelling** for Question 2 after removing commonly repeated words

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Thank you! Questions?