Semi-Supervised Learning in Topic Modelling

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Problem Statement

Suppose you are a new hire at XYZ company and it's your first day at work, after a routine orientation with HR, your boss summons you to his office.



Problem Statement

Thinking that this is a basic <u>unsupervised learning task</u> with the well-established LDA and NMF, you get down to work, only to realise that these don't work very well for <u>multi-label</u> <u>classification</u>. Further, there seems to be nothing much you can do further to improve the model's accuracy.

Luckily, you remember your lessons from DSI and decide to combine supervised and unsupervised methods to build a model that can perform decently well.

Problem Statement

Intended outcome:

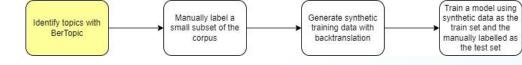
Text	Price	Flavor	Packaging
I think it's delicious and affordable!	1	1	0
The design could be more well thought out	0	0	1

Data:

- ~10,000 documents in corpus
- No labels; no information on latent topics at all

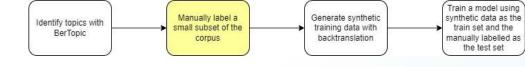
Pipeline Overview





BerTopic

- Uses BERT sentence embeddings to vectorize text, unlike LDA and NMF which uses statistical methods
- Stochastic process, therefore results are not reproducible
- Does not do well in multi-label problems; insufficient as standalone topic modelling tool
- Produced > 100 topics, condensed to 7 topics



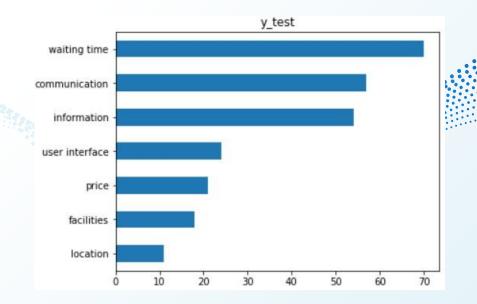
Manual Labelling

Important to guide downstream modelling

Labelled ~200 records, with each topic having at least 10

rows

Act as test dataset



Data Augmentation





BackTranslation

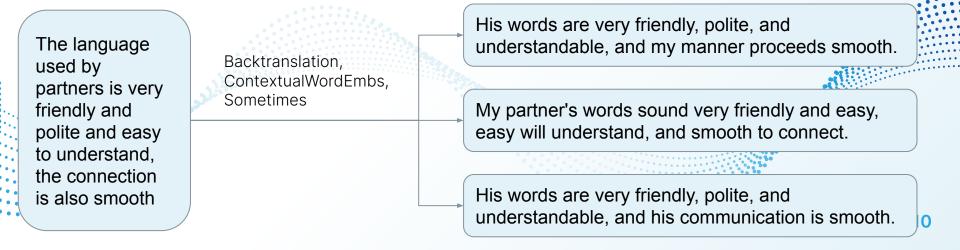
Translates text into another language and back

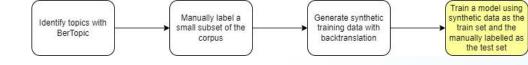




BackTranslation

- "Softer" way of altering text
- Better to use languages that are more different from English
- However, this leaks information into training data





Model Training

Baseline model → Zero Shot Classification

```
{'sequence': '\nThe language used by partners is very friendly and polite and easy to understand, the connection is
also smooth\n',
 'labels': ['communication',
  'information',
  'facilities',
  'user interface',
  'location',
  'price',
                                                         Weighted F1 score = 54%
  'waiting time'],
 'scores': [0.9803360104560852,
 0.7030088901519775,
 0.6719058156013489,
 0.6212607622146606,
 0.3871709108352661,
 0.33242109417915344,
 0.13848033547401428]}
                                                                                                                  11
```

Model Training

- Multi-label classification → OneVsRestClassifier
- SVC as default classifier due to superior performance

Expt	Vectorizer	Weighted F1-score (test set)	
1	Word2Vec	88%	
2	BERT	80%	
3	BERT with PCA	92%	
4	BERT (fine-tuned)	72%	
5	BERT (fine-tuned) with PCA	90%	

Much more whitespace to finetune compared to LDA/NMF/BerTopic alone!

Further Evaluation (Holdout set)

Expt	Vectorizer	Weighted F1-score (holdout set)	
1	Word2Vec	63%	
3	BERT with PCA	54%	
5	BERT (fine-tuned) with PCA	35%	

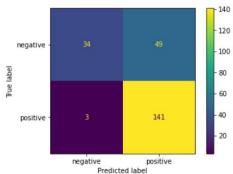
Limitations

- Volatile changes in %
- Language is subjective; could have multiple interpretations how a text should be labelled

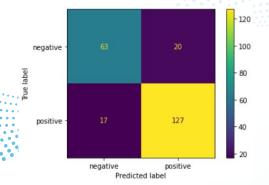
Further Evaluation (Inspecting "Others")

sequence	w2v	bert_untuned	bert_tuned
my problem is now 6 weeks old and	others	information	waiting time
as to the staff it really varies per br	others	others	others
there was clearly a language barrie	others	information, waiting time	waiting time
the space was small and in the mid	others	waiting time, information	waiting time
i think that the call agents can be m	others	others	waiting time
I had an excellent experience with	information, user interface	information	others
The person at the counter mention	information, price	others	others
Very good way of explaining what	information	others	others
Repair notification process: because	waiting time	others	others
I have a [REDACTED] Smart TV Wh	information	others	others
I took my phone in after a update a	information	others	waiting time
For me I am satisfy with the service	price	others	others
I walked into Harvey Norman with	information	others	waiting time
When I first called the retail shop t	communication, price	others	waiting time
Because from the original, the sma	information, user interface,	others	information

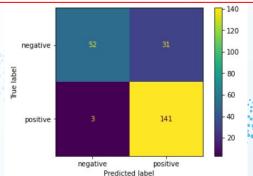
Sentiment Analysis



cardiffnlp/twitter-roberta-base-sentiment (F1-weighted = 74%)

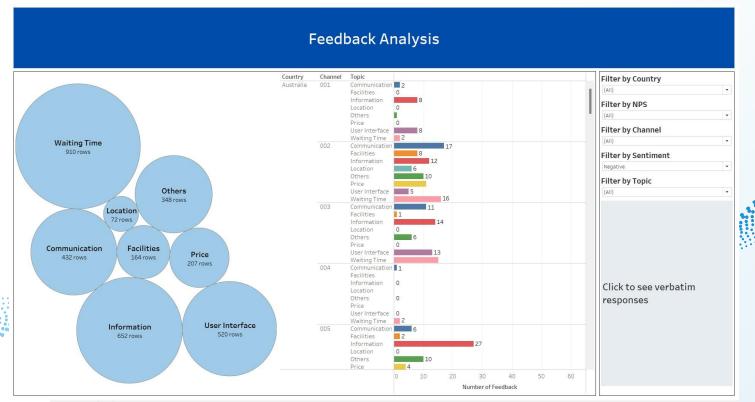


negative 54 29 -120 -100 -80 -60 -60 -40 -20 facebook/bart-large-mnli (F1-weighted = 84%)



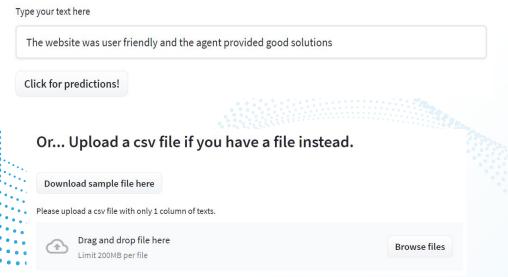
Majority Vote (F1-weighted = 84%)

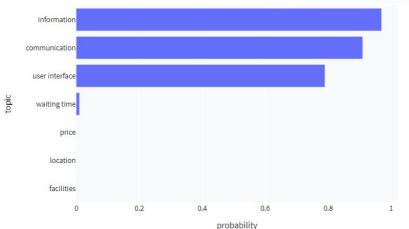
Presentation

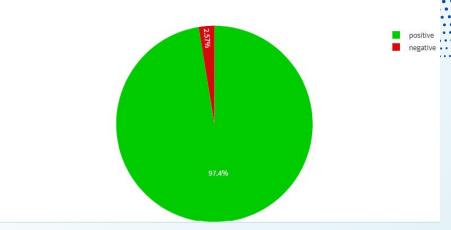


Deployment

Text Classification for Service Feedback







Conclusion

- Even with advancement of technology, topic modelling is notoriously hard to gauge model effectiveness without sufficient labelled data.
- With this pipeline, despite its theoretical flaws, the model performed decently.
- Also provided much whitespace to fine-tune to the context of the task, which is typically limited in topic modelling.

Future Work

Test out the pipeline on labelled dataset with multi-labels



Credits

- Instructors Shilpa and Leo
- TAs Mark, Samuel and Jun Kai
- My project groupmates and classmates who have made the course more enjoyable with all the nonsense and jokes:)

Thanks!

LinkedIn | Email | GitHub | App Deployment

