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What's the SAME & what's the difference?



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How can we use it?

There are so many messages in my inbox!

The SIA¹ Customer Service Centre receives thousands of feedback, compliments and complaints every week



Help me sort out the messages!





((2)

KrisFlyer & PPS Club (KF)

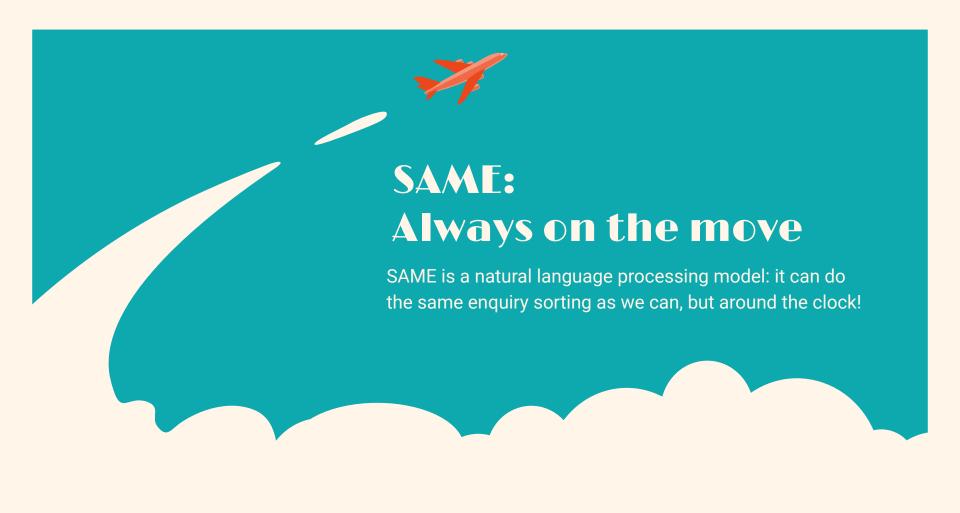
Lounge, Catering, **Amenity (LCA) kits**

Others

Top 2 most-asked topics

Objectives: SIA management hired us to

- (1) Develop a predictive model to automatically sort messages into the 3 topics, and
- Highlight the **frequently mentioned words and their sentiments** in KF and LCA



The Approach









All you have to know about Menus, Amenity kits and so on when you're onboard SQ.



16k (40%), 10k (24%), 14k (36%) data rows respectively



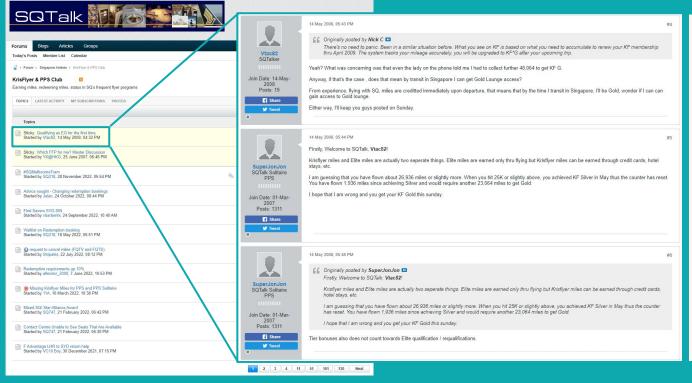
Modelling

Try different pre-processing, vectoriser, models & pick the best combination



Find the top comments of KF and LCA, and analyse the sentiments of these comments to derive insights

Strap in! Diving into the data



- 1. Properly spelled words
- 2. Absence of Singlish
- Replies to comments will duplicate words
- 4. Thread titles are important as they contain many key words

What's the Model Answer?

Lemmatisatio	n vs Stemming vs None:	Pre-processing & vectorisation trials:				
			Bol	ded – different from baselin		
Steps	Baseline	Alternate 1	Alternate 2	Alternate 3		
Pre- processing	Basic data cleaning	Basic data Cleaning	 Basic data Cleaning Remove duplicated sentences 	 Basic data Cleaning Remove duplicated sentences 		
Vectorisation	CountVectoriser	TFIDF	CountVectoriser	TFIDF		
Model	Multi-Naïve Bayes	Multi-Naïve Bayes	Multi-Naïve Bayes	Multi-Naïve Bayes		
	Best performing pre-processing & vectorisation combination					
3						
Modelling trials:						
Model	Multi-Naïve Bayes	Random Forest	XGBoost	SVM		

Weighted-average ROC AUC & weighted-average f1 (KF, LCA) scores used to evaluate model performance

^{*} The alternate 1, 2, 3 also had 4 additional stopwords (iirc, imo, imho, btw) extracted from a "SQTalk Abbreviations, Slangs, Definitions, Phrases" thread. This had little effect on the model performance.

1 Lemm vs Stem vs None

	Baseline 1	Baseline 2	Baseline 3
Pre-processing	Basic cleaning	- basic cleaning - lemm	- basic cleaning - stem
Vectoriser	CountVectoriser	CountVectoriser	CountVectoriser
Model	Multinomial Naive Bayes	Multinomial Naive Bayes	Multinomial Naive Bayes
macro-average ROC AUC	0.878	0.885	0.887
macro-average f1-score	0.737	0.747	0.752

- Baseline 3 (remove NA, with stem) performed the best
- Macro-average ROC AUC (One vs the Rest) and f1-score (labels = KF, LCA) used as key metrics
 - To compare the model's confidence to distinguish classifications, and focus
 on minimising false-positives and -negatives for KF and LCA

2 Preprocess, Vectoriser

	Baseline Model (from notebook 2)	Alternate 1 *Best performance*	Alternate 2	Alternate 3
Pre-processing	- Basic cleaning - Stem	- Basic cleaning - Stem	- Basic cleaning - Stem - Remove duplicated sentences	- Basic cleaning - Stem - Remove duplicated sentences
Vectoriser	CountVectoriser	TFIDF	CountVectoriser	TFIDF
Model	Multinomial Naive Bayes	Multinomial Naive Bayes	Multinomial Naive Bayes	Multinomial Naive Bayes
Macro-average ROC AUC	0.887	0.908	0.807	0.819
Macro-average f1-score (kf, lca)	0.752	0.759	0.625	0.630

Best performance: Basic clean, stem, TFIDF

- TFIDF had slightly better performance than CountVectoriser
- Removing duplicated comments seemed to have an adverse effect on model performance;
 this suggests that the comments that people reply to usually have crucial key words in them

Model Comparison

	Model 1 (from notebook 3)	Model 2	Model 3	Model 4 *Best performance*
Vectoriser	TFIDF	TFIDF	TFIDF	TFIDF
Model	Multinomial Naive Bayes	Random Forest	XGBoost	SVM
Macro-average ROC AUC	0.908	0.883	0.925	0.925
Macro-average f1-score (kf, lca)	0.759	0.719	0.807	0.815

Best performance: SVM

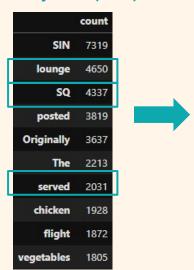
- Model 3 performed the best with the following params:
 - TfidfVectorizer(max_features=500, stop_words=stem_stopwords)
 - SVC(C=1, gamma=1, probability=True, random_state=42)
- SVM edged out due to its slightly better f1-score

Sentiment Analysis: Top Words

KrisFlyer & PPS Club



Lounges, Catering, Amenity Kits (LCA)



- 1. Find top words
- 2. Find sentences that contain these words
- 3. Sort the sentiment score by:

Sentiment	Score	Assigned value	
Very Negative	Under -0.5	1	
Negative	Negative Between -0.5 and -0.1		
Neutral	Between -0.1 and 0.1	3	
Positive	Between 0.1 and 0.5	4	
Very Positive	Over 0.5	5	

^{*} SpacyTextBlob

Sentiment Analysis: Results

Sentiment Score	KrisFlyer 'miles'	KrisFlyer 'PPS'	KrisFlyer 'KF'	LCA 'lounge'	LCA 'SQ'	LCA 'served'
Very negative (1)	<0.1	<0.1	<0.1	<0.1	<0.1	<0.1
Negative (2)	<0.1	<0.1	<0.1	<0.1	0.1	0.1
Neutral (3)	0.3	0.4	0.4	0.4	0.4	0.6
Positive (4)	0.6	0.6	0.6	0.5	0.4	0.3
Very positive (5)	<0.1	<0.1	<0.1	<0.1	<0.1	<0.1
Overall:	Positive	Positive	Positive	Positive	Positive	Positive

* Due to rounding, total may not add up to 1

- Sentiments for comments containing top words are positive → these are areas of strength for SIA
- Separate deep-dive into these comments can be conducted to find out the reasons why (e.g. good service, good exclusive deals for members, good food served etc.)

Conclusion



Model

Successfully developed SAME: a prediction model with weight-average ROC AUC (0.913) and f1-scores (0.802)



Sentiment Analysis

Comments with 'miles', 'PPS', 'KF', 'lounge', 'SQ', 'served' have **largely** positive sentiments → areas of strength for SIA



Next Steps (areas for future improvement)

- Sort by topic (e.g. KF, LCA, others): SAME can be used as a backend engine for a chatbot to sort incoming messages
- Sort by type (feedback, complaints, compliments): SAME + Sentiment Analysis
- **Incorporate Singlish** into sentiment analysis to improve performance
- Find top words with negative sentiments to identify and improve on areas of weaknesses

Thanks:

Your work will never be the *same* again



Annex A - Weighted Average f1-Score

Label	Per-Class F1 Score	Support	Support Proportion	Weighted Average F1 Score
Airplane	0.67	3	0.3	(0.6702)
≜ Boat	0.40	1	0.1	(0.67 * 0.3) + (0.40 * 0.1) +
€ Car	0.67	6	0.6	(0.67 * 0.6) = 0.64
Total	-	10	1.0	- 0.64

Support refers to the number of actual occurrences of the class in the dataset.

For example, the support value of 1 in Boat means that there is only one observation with an actual label of Boat. (<u>source</u>)