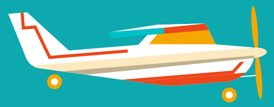
Bon Voyage! The Stress-Free, Automated Message Explainer (SAME)

Let the robots do the *same* ol’ work
so you don’t have to!

Contents



There are so many messages in my inbox!

The SIA[1] Customer Service Centre receives thousands of feedback, compliments and complaints every week

1: Singapore Airlines

Help me sort out the messages!

KrisFlyer & PPS Club (KF)

Lounge, Catering, Amenity (LCA) kits

Top 2 most-asked topics

Others

Objectives: SIA management hired us to

(1) Develop a predictive model to **automatically sort messages into the 3 topics**, and

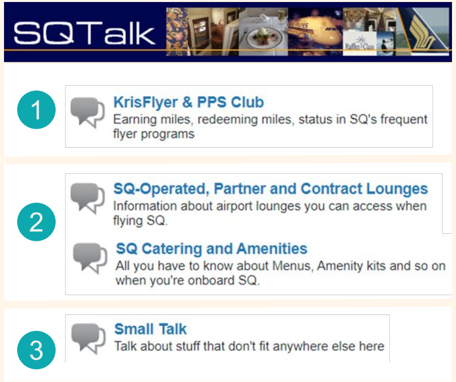
(2) Highlight the **frequently mentioned words and their sentiments** in KF and LCA

SAME:
Always on the move

SAME is a natural language processing model: it can do the same enquiry sorting as we can, but around the clock!

The Approach

Data extraction



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

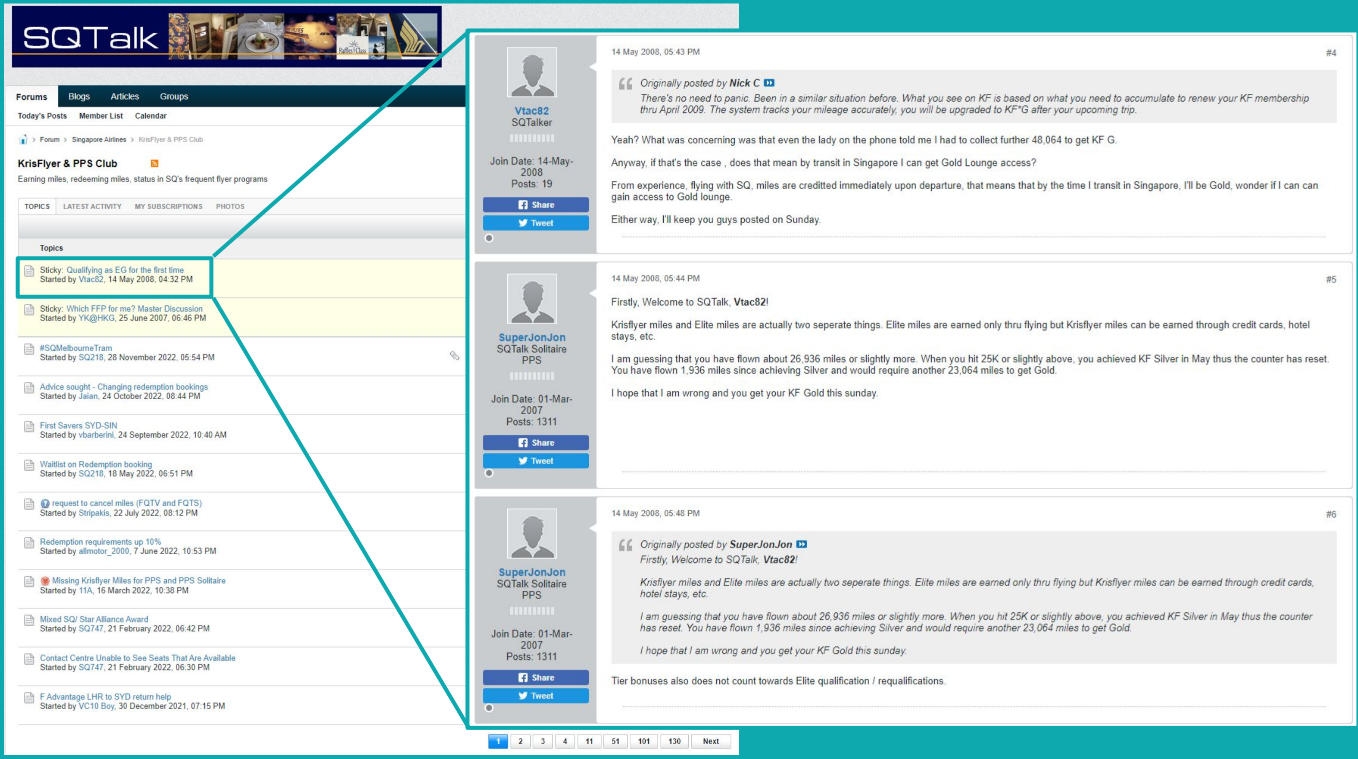
Modelling

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

Sentiment Analysis

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**
3. Replies to comments will **duplicate words**
4. **Thread titles are important** as they contain many key words

What's the Model Answer?

Bolded – different from baseline

Steps	Baseline	Alternate 1	Alternate 2	Alternate 3
Pre-processing	• Basic data cleaning	• Basic data Cleaning • **Remove duplicated sentences**	• Basic data Cleaning • **Remove duplicated sentences**	• Basic data Cleaning • **Remove duplicated sentences**
Vectorisation	CountVectoriser	CountVectoriser	**TFIDF**	**WordVectoriser**
Model	Multi-Naïve Bayes	Multi-Naïve Bayes	Multi-Naïve Bayes	Multi-Naïve Bayes

Best performing pre-processing & vectorisation combination

2 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.

Preprocess, Vectoriser Comparison

	Baseline Model	Alternate 1 *Best performance*	Alternate 2	Alternate 3
Pre-processing	- Basic cleaning	- Basic cleaning	- Basic cleaning - Remove duplicated sentences	- Basic cleaning - Remove duplicated sentences
Vectoriser	CountVectoriser	TFIDF	CountVectoriser	TFIDF
Model	Multinomial Naive Bayes	Multinomial Naive Bayes	Multinomial Naive Bayes	Multinomial Naive Bayes
Weighted-average ROC AUC	0.877	0.889	0.790	0.801
Weighted-average f1-score (kf, lca)	0.743	0.748	0.623	0.628

Best performance: Basic clean, TFIDF

Remarks:

- 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
Weighted-average ROC AUC	0.889	0.872	0.913	0.913
Weighted-average f1-score (kf, lca)	0.748	0.721	0.790	0.802

Best performance: SVM

Remarks:

- **Model 3 performed the best** with the following params:
  - TfidfVectorizer(max_features=500, stop_words='english')
  - 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

	count
miles	8899
SQ	8627
posted	7734
Originally	7367
PPS	5771
SIN	4730
flight	3692
KF	3616
just	3547
year	2822

Lounges, Catering, Amenity Kits (LCA)

	count
SIN	7319
lounge	4650
SQ	4337
posted	3819
Originally	3637
The	2213
served	2031
chicken	1928
flight	1872
vegetables	1805

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	Between -0.5 and -0.1	2
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

Remarks:

- 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	$(0.67 * 0.3) + (0.40 * 0.1) + (0.67 * 0.6)$ **= 0.64**
Boat	0.40	1	0.1	
Car	0.67	6	0.6	
Total	-	10	1.0	

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. (source)