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E-commerce price formation

the role of user-generated comment in three dimensions

(David) Wenzhu Tang

Dr. Di Zeng

Assoc. Prof. Alec Zuo

University of Adelaide

adelaide.edu.au

Background

- **E-commerce popularity → 19% retail sales**
(Shields, 2021)
- **Pandemic → behavioural change → online↑**
(Abdelrhim & Elsayed, 2020; Gao et al., 2020)
- **User-generated comments: valuable source to understand consumers**

Research gap

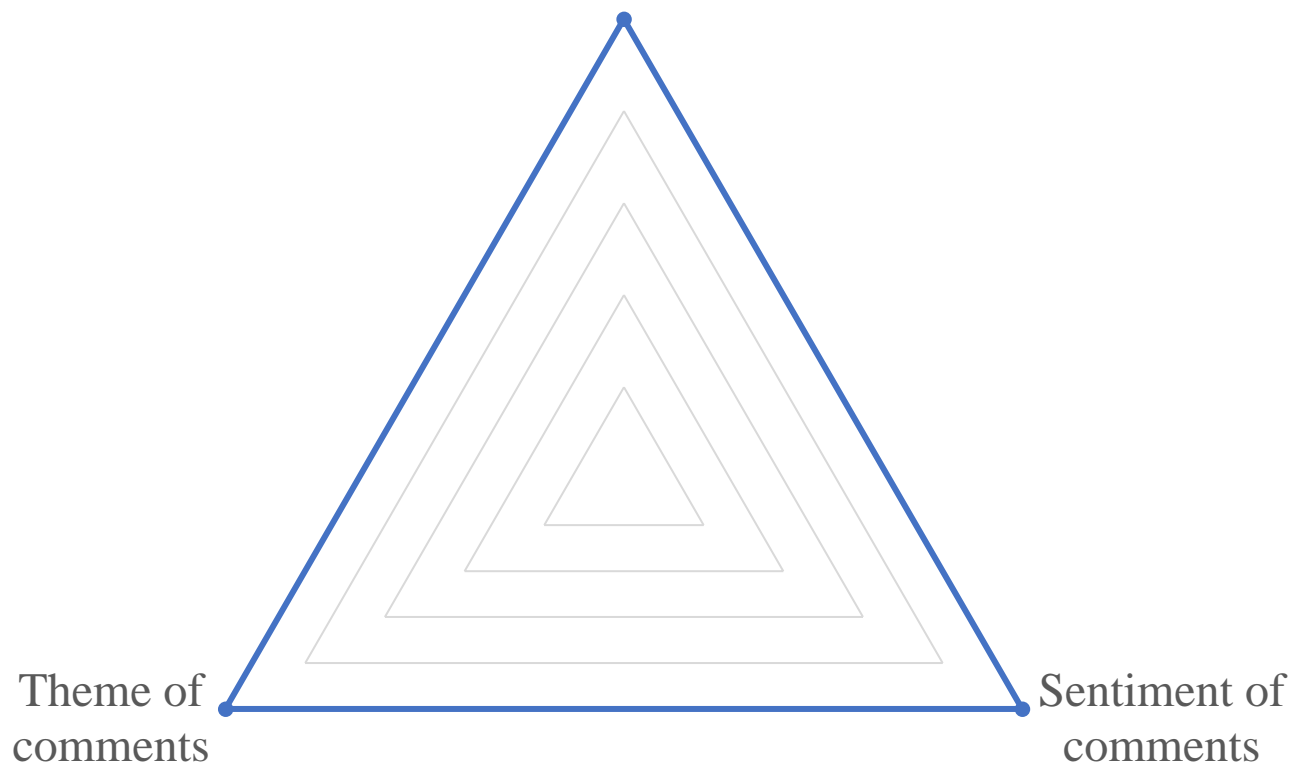
- **Current literature for user-generated comments**
 - **Dimensions:** number of comments / comment sentiment / comment themes
 - **Research subject:** price premium, business performance, sales volume
 - **Industry:** hospitality industry (hotel, restaurant, travel destination)

∴ Underresearched and gap identified
- **Aim: to understand the role of user-generated comments in 3 dimensions on price formation in the e-commerce context**

Three dimensions of comments

Method: counting

Number of
comments



Method: keyword matching

Methods: complicated

Methods (texts → numbers)

- **Manual inspection**

- **Lexical methods**

- **Frequency-based methods**

- **Syntax-based methods**

- **Other rule-based methods**

Rule-based

- **Traditional machine learning methods**

- **Transformer-based methods**

Machine learning algos

Language model comparison

Method	Type	Examples	Pros	Cons	Word embedding	Feature extraction
Keyword matching	Rule-based	n/a	<ul style="list-style-type: none"> Intuitive algorithm and easy to implement 	<ul style="list-style-type: none"> Require rich prior knowledge Cannot distinguish ambiguous words or irony Domain knowledge dependent 	×	Static
Sentiment lexicon mapping	Rule-based	<ul style="list-style-type: none"> Sentiwordnet BosonNLP ... 	<ul style="list-style-type: none"> Intuitive algorithm and easy to implement Sufficient lexicon resources 	<ul style="list-style-type: none"> Performance highly dependent on lexicon quality Cannot distinguish ambiguous words or irony Domain knowledge dependent 	×	Static
Traditional machine learning models	Machine learning	<ul style="list-style-type: none"> SVM Naïve Bayes Random Forest Neural network ... 	<ul style="list-style-type: none"> General machine learning algorithm Reasonable performance 	<ul style="list-style-type: none"> Tedious feature engineering requirement Domain knowledge dependent 	√	Static
Pre-trained deep-learning models	Machine learning	<ul style="list-style-type: none"> BERT* ELMo** GPT*** ... 	<ul style="list-style-type: none"> Outstanding performance Context understanding Domain-transferable Open-source pre-trained checkpoints 	<ul style="list-style-type: none"> Algorithm hard to understand Almost black-box application Expensive pre-training (including corpus resource, hardware requirement and time cost) 	√	Contextual

*BERT: Bidirectional Encoder Representation from Transformers

**ELMo: Embedding from language models

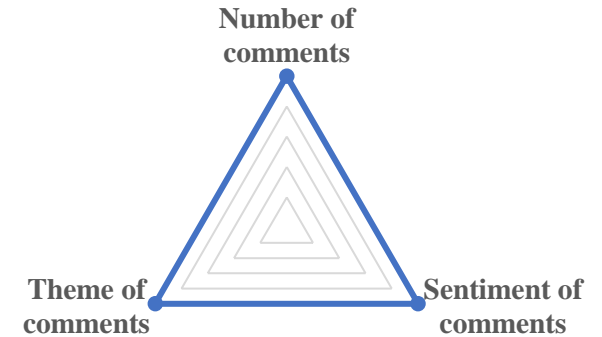
***GPT: Generative Pre-trained Transformer

Source: Author

Adopted language model

- **BERT** (Bidirectional Encoder Representation from Transformers, see Devlin et al. 2018)
 - **Scripts borrowed and modified from *Wang (2019)***
 - **Model pre-trained by *Google (2018)***
 - *Pre-trained checkpoint: bert_Chinese_L-12_H-768_A-12 (Google 2018)*
 - *Fine-tuning text corpus: dianping_train_test (Wang 2019)*
 - **Quick fine-tuning**
 - **Reasonable accuracy**
-

Hypothesis



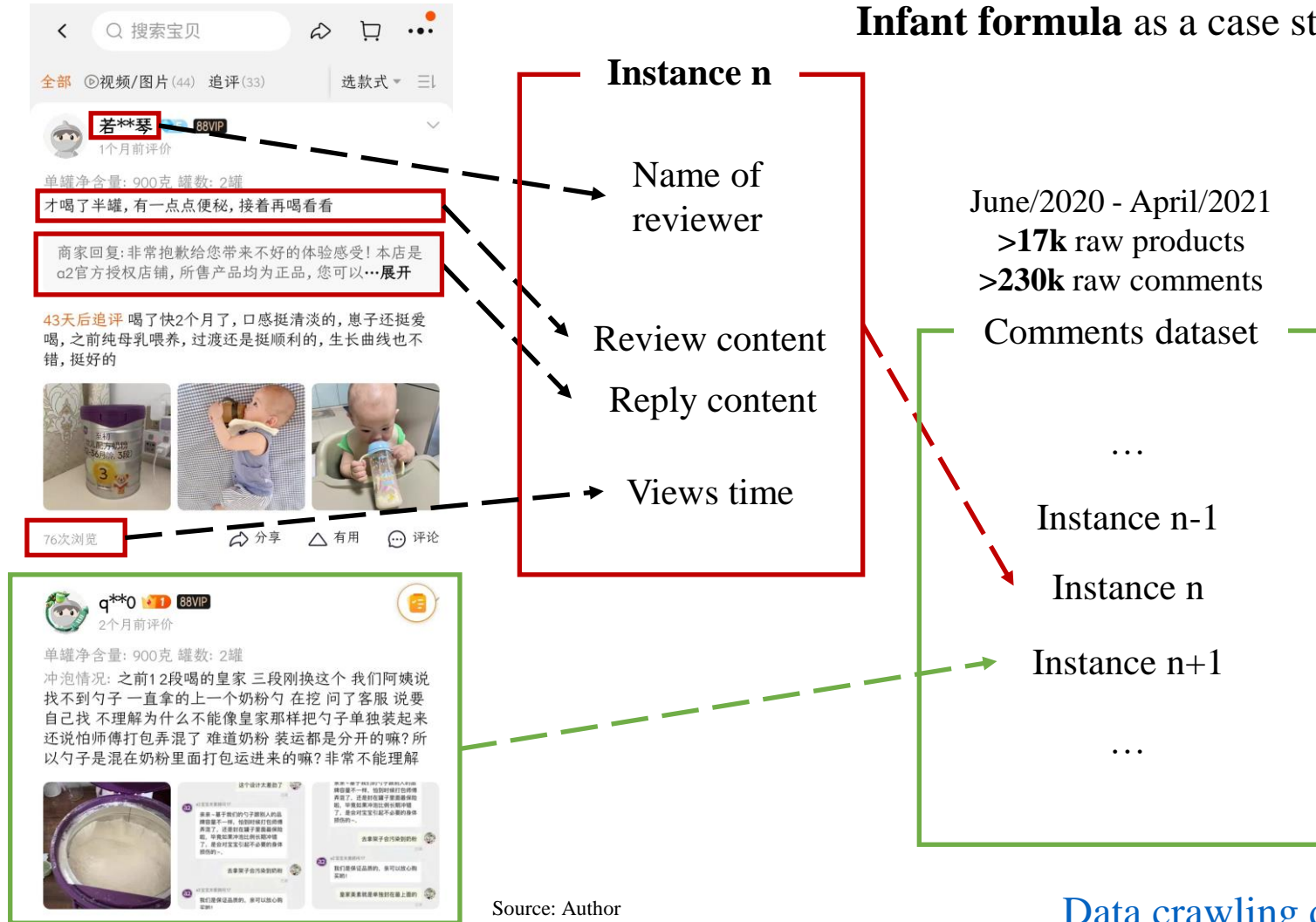
H1: Number of comments $\overset{(+)}{\longleftrightarrow}$ *Unit price*

H2: Positive sentiment (SI, SI_n20, SI_p20) $\overset{(+)}{\longleftrightarrow}$ *Unit price*

H3: Comment themes $\overset{(+/-)}{\longleftrightarrow}$ *Unit price*

Data & method

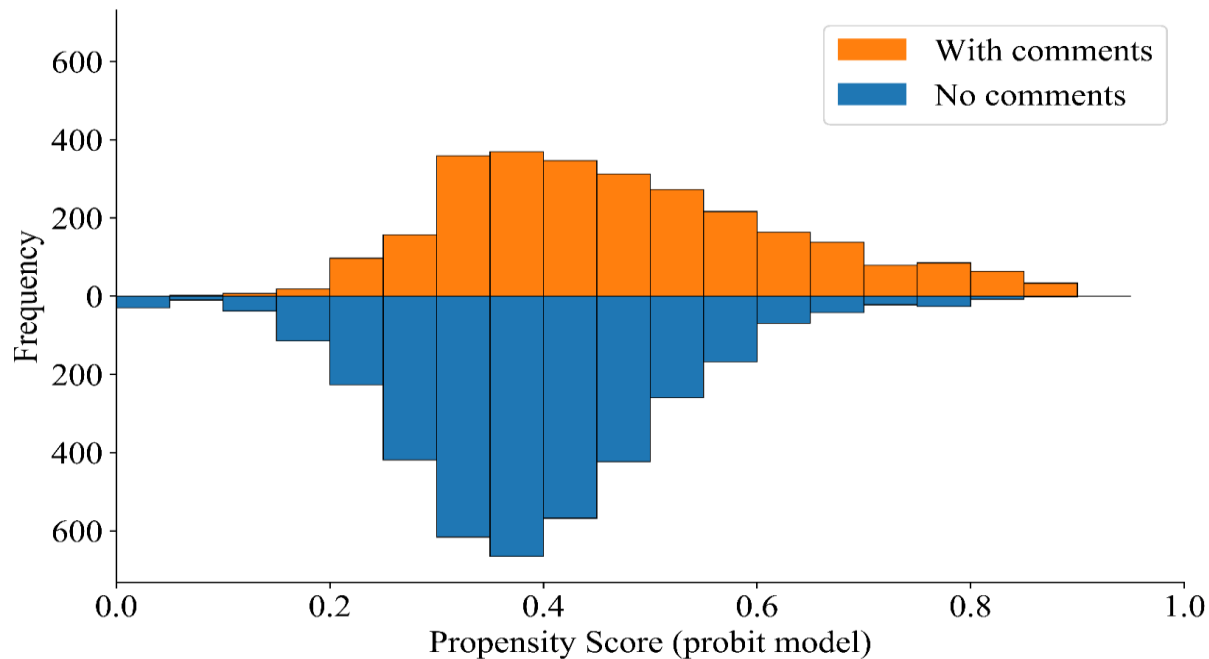
Infant formula as a case study



Data description

Variable	Obs	Mean	Std.dev.	Min	Max
Unit price	6,424	242.75	214.26	5.10	2000.00
CCFI 4w lag	6,424	1238.06	363.16	839.19	2071.71
SDR 4w lag	6,424	93.42	1.87	89.56	96.11
Monthly sales (in log)	6,424	4.90	1.49	0.00	9.21
Weight (in log)	6,424	6.75	0.65	4.61	9.47
HHI	6,424	23.08	31.57	5.72	232.41
Market share	6,424	0.29	0.66	0.00	11.78
Total cover picture number	6,424	4.84	0.95	1	7
dummy. Flagship store	6,424	0.56	0.50	0	1
Comment count	6,424	8.43	21.24	0	178
SI	2,716	0.73	0.30	0.0001	0.9993
SI_n20	2,716	0.42	0.41	0.0001	0.9993
SI_p20	2,716	0.88	0.31	0.0001	0.9995

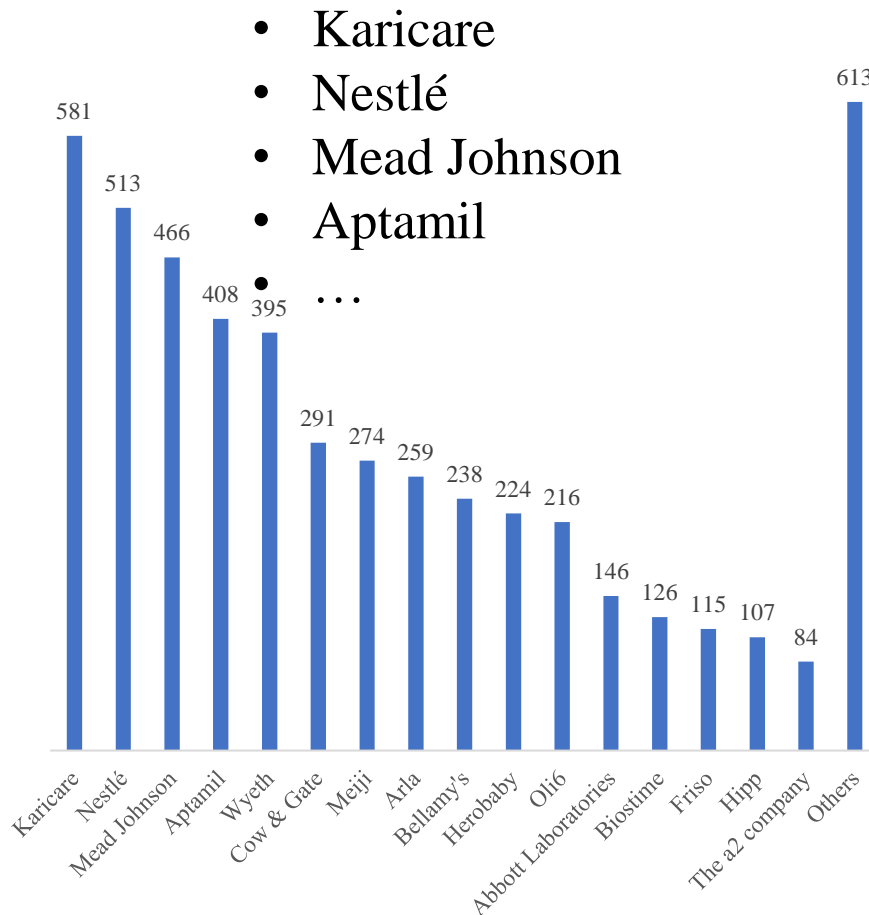
Selection bias examination



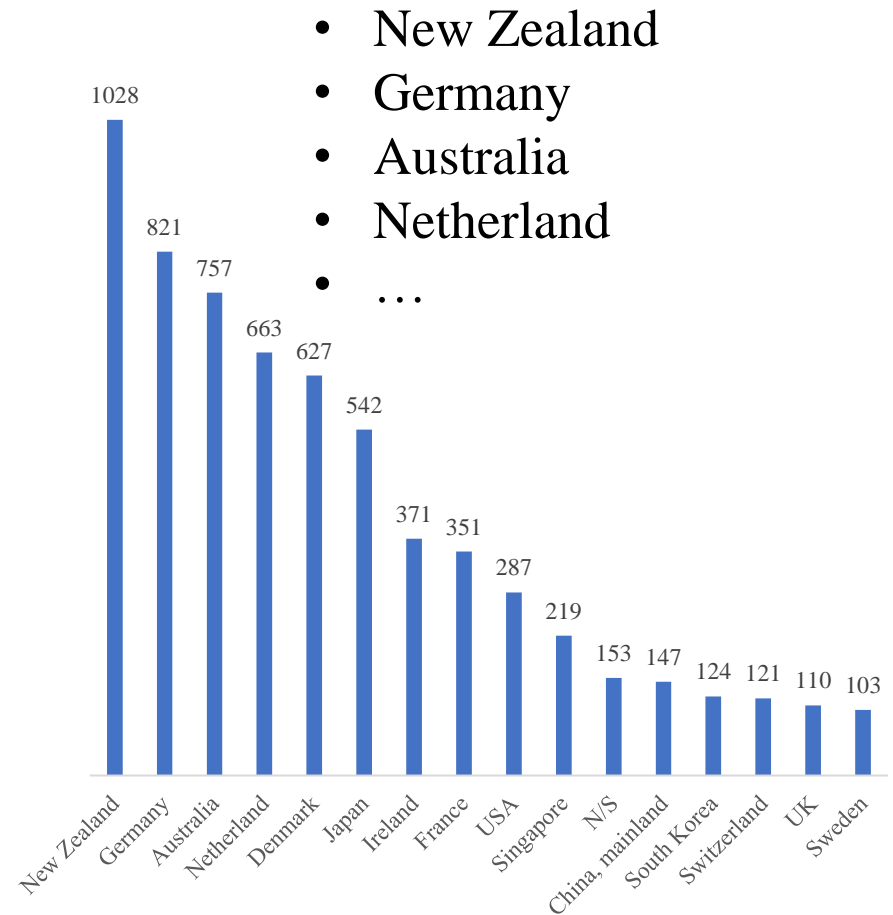
- **Similar propensity score distribution**
- **Paired t-test**
 - **N/S difference**
 - **Significant but minor**
- **∴ selection bias is minor**

Popular brands and origins

Infant formula brand



Country of origin



Aspects in most negative comments

Aspects in the 5% most negative comments

Aspect	Complaint rate
customer service quality	37%
product quality	31%
low value-of-money or price dispute	18%
free-gift dispute	17%
authenticity	10%
logistics quality	9%
package design	5%
wrong sendout	5%
refund dispute	4%
inventory shortage	1%

OLS (sentiment, n=2,716)

Y: unit price (¥ /kg)

Xs:

- Lag vars
- Control vars
- Market structure
- Place of origin (set of dummies): 16 countries/regions
- **Comment vars:**
 - Comment count (CC)
 - Sentiment index (SI)
 - *SI_neg20 (SI for the most negative 20% comments)*
 - *SI_pos20 (SI for the most positive 20% comments)*
 - *CC # SI (or SI_neg20 or SI_pos20)*

OLS (theme, n=2,716)

Y: unit price (¥ /kg)

Xs:

- Lag vars
- Control vars
- Market structure
- Place of origin (set of dummies): 16 countries/regions
- Comment vars
- **Comment themes (set of dummies)**

Result (sentiment, n=2,716)

Variable	Correlation	Conclusion
Comment count	+ (***)	H1: number of comments ↔ price ✓
SI	n/s	n/s when interaction effect with CC not considered H2: SI and negative comment SI ↔ price ✗
SI_n20	n/s	
SI_p20	+ (***/**)	H2: positive comment SI ↔ price ✓
CC # SI	n/s	More important for better selling products Not casual but correlational H2 extended: CC ↑ ↔ SI_n20 more important & SI_p20 less important ✓
CC # SI_n20	+ (**)	
CC # SI_p20	- (***)	

Result (sentiment, n=2,716)

- **Number of comments is important**
 - Encourage customers to leave comments
- **In a later phase of the business/product cycle:**
 - Negative comment importance \uparrow , \therefore **avoiding negative comments is essential for business operation**
 - Positive comment importance \downarrow , \therefore **do not invest in faking extreme good comments**

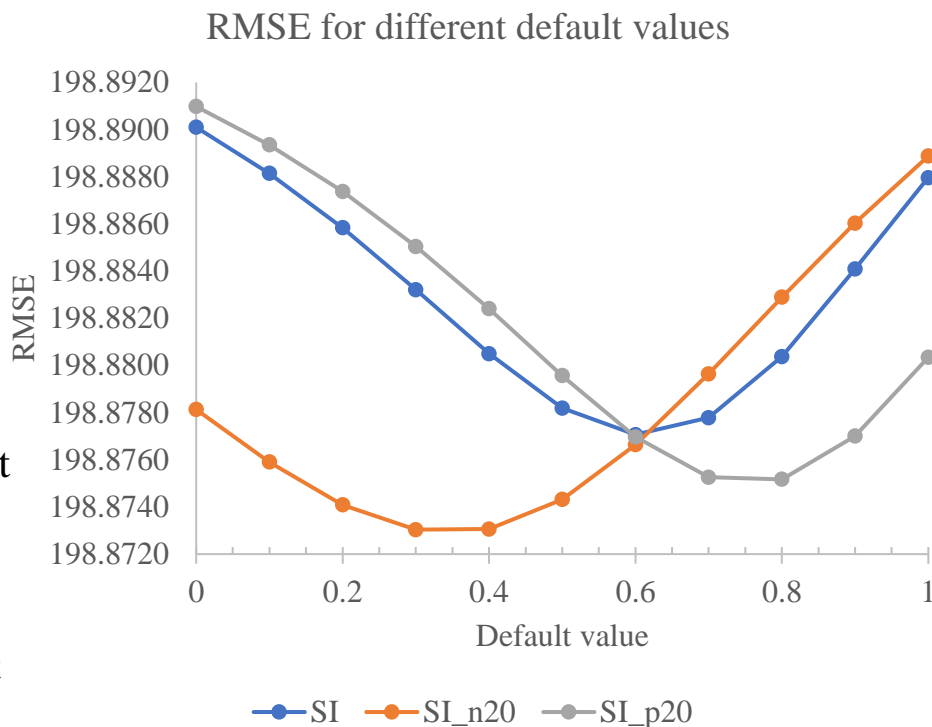
Result (theme, n=2,716)

Item	Price	Attention	Bad comment	Good comment	Consumer pattern
Authenticity	-	n/s	n/s	n/s	-
Customer service	↑	↑(***)	↑(***)	n/s	high expectation
Logistics quality	↑	↓(***)	n/s	↓(***)	take for granted
Package design	↑	↑(**)	n/s	↑(***)	compliments
Value-of-money	↑	↑(**)	↑(*)	↑(**)	controversy between cheap buyers and quality seekers
Product quality	↑	n/s	↓(*)	n/s	good quality

H3: theme ↔ price ✓

Latent sentiment for product with no comments

- **Default SI: 0.6** (<0.73)
SI: sentiment index
- **Default SI_n20: 0.3** (<0.42)
SI_n20: SI for most negative 20% comment
- **Default SI_p20: 0.8** (<0.88)
SI_p20: SI for most positive 20% comment



- **Less trust for products without comments?**

Key take-aways

Number

- **Encourage customers to leave comments (trust building)**

Sentiment

- **Avoid negative comments is essential for business operation**
- **Do not invest in faking extreme good comments**

Theme

- **Customer service (37%) & product quality (31%) are most mentioned in the negative comments**
- **Customer service is critical for highly-priced products**
- **Invest in package design is best to harvest satisfaction**

Reference

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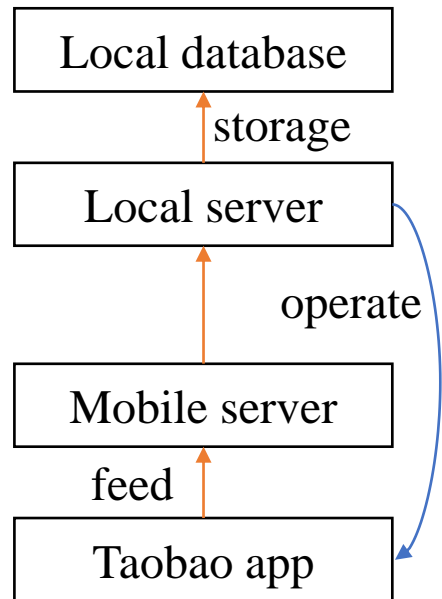


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Q&A

Materials for Qs

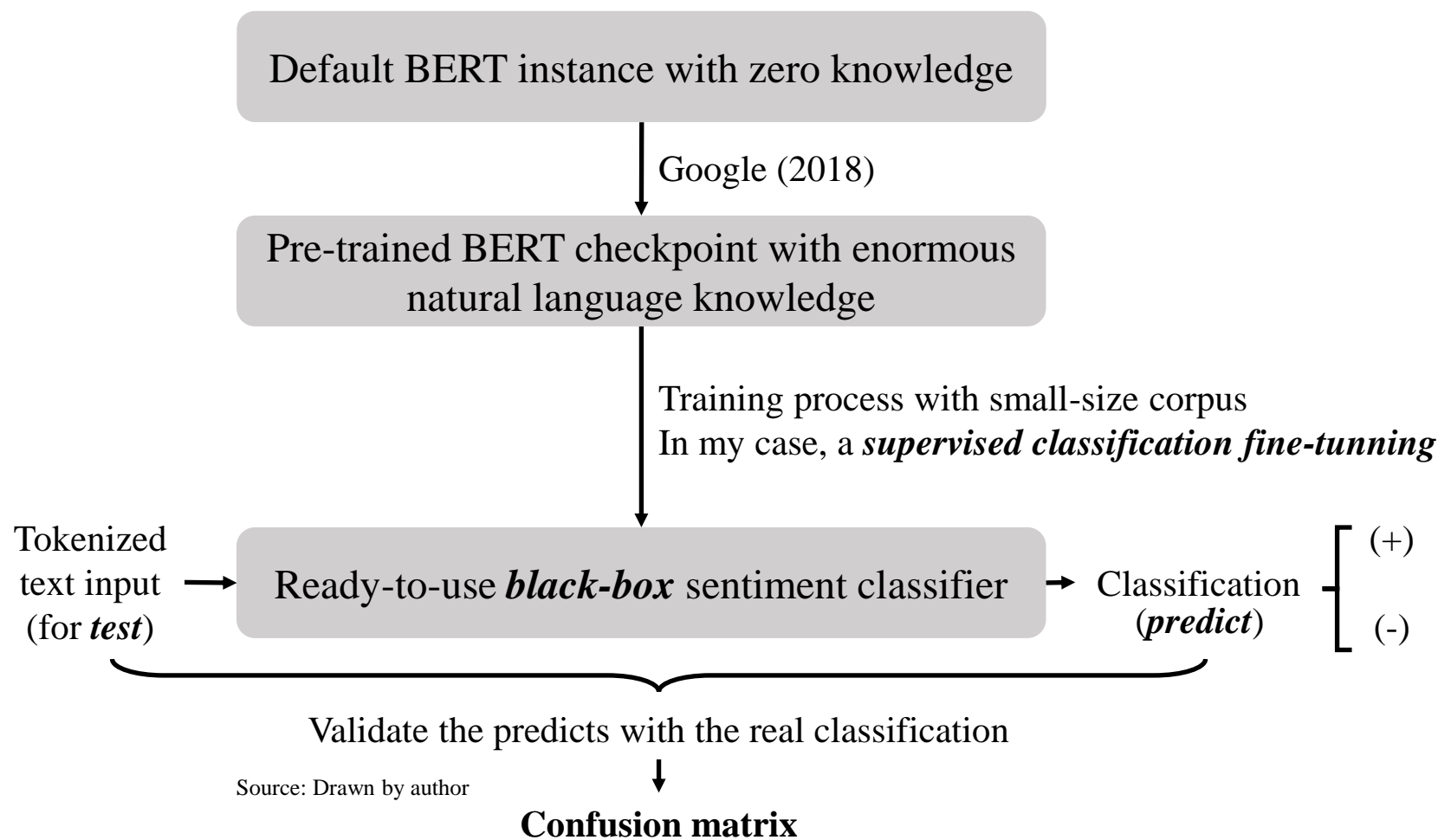
Data crawling



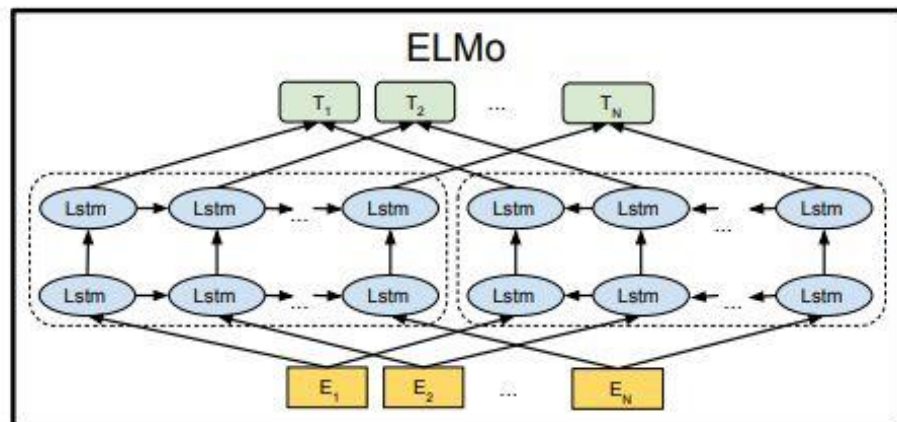
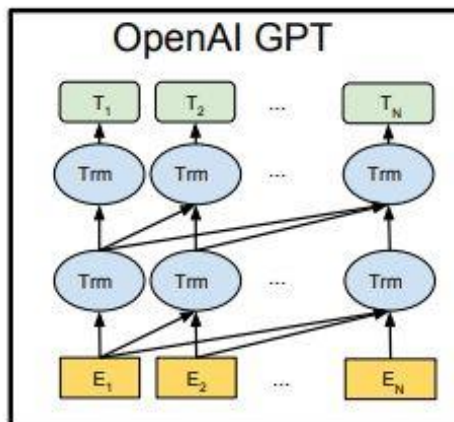
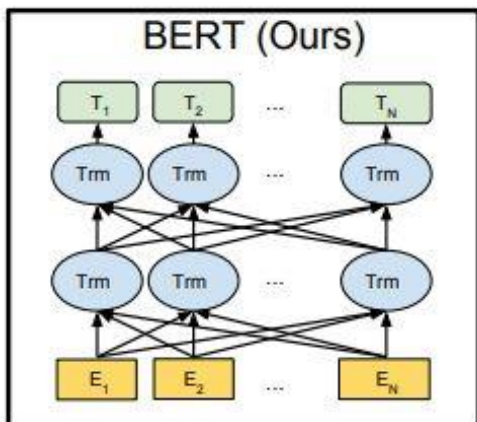
- Simulate human operation to bypass anti-crawler strategies
- Key python libraries involved: appium, selenium, pymongo

- “import milk powder” (进口奶粉)
- “import infant formula” (进口婴幼儿奶粉)
- “foreign import milk powder” (国外进口奶粉)
- “foreign infant formula” (国外婴幼儿奶粉)

BERT



BERT



Confusion matrix

Real \ Predict	Positive	Negative
Positive	True positive (TP)	False negative (FN)
Negative	False Positive (FP)	True negative (TN)

Source: Drawn by author

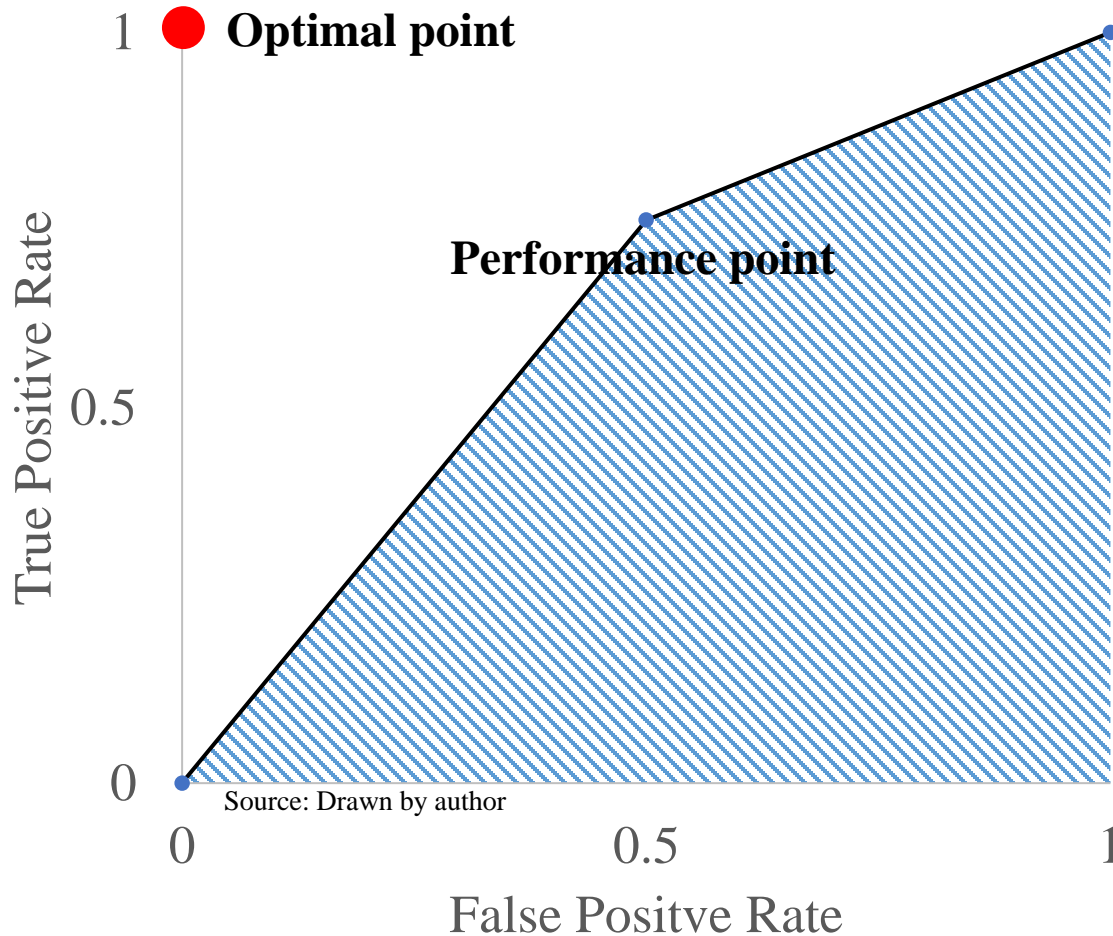
$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1_{score} = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

ROC curve & AUC



- ROC: Receiver Operating Characteristic
- *AUC: area under curve of ROC*

$$TPR = \frac{TP}{TP + FN}$$

$$FPR = \frac{FP}{FP + TN}$$

Sentence-level sentiment index (SSI)

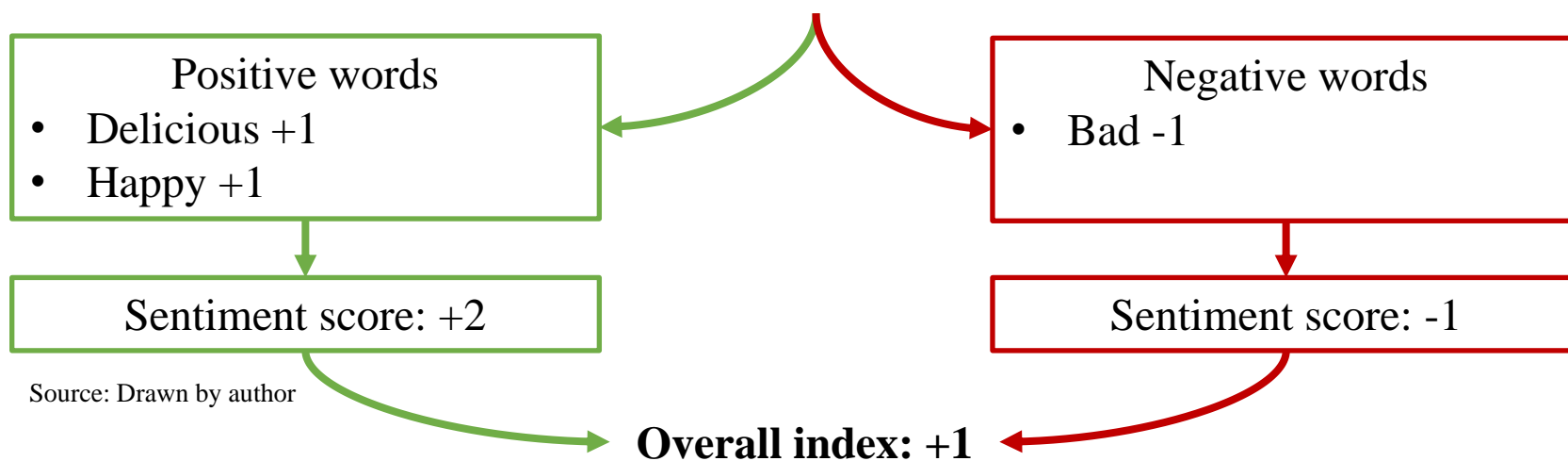
$$SSI = \frac{\log(P(neg))}{\log(P(neg)) + \log(P(pos))}$$

$$SI_i = \frac{1}{n} \sum_{1}^n SSI_{i,n}$$

Keyword matching (basic)

真的很好吃，小朋友一口一个吃得好开心，谢谢店主，买了这么多次没有不好的。

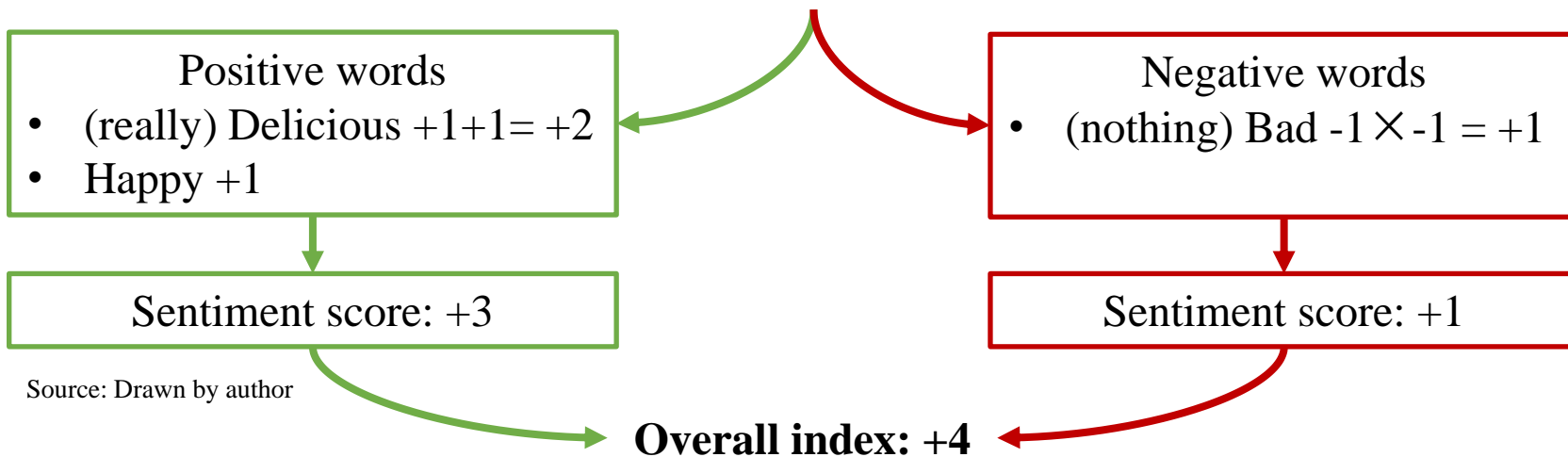
Really delicious! The kids are very happy to eat. Thank you! There is nothing bad after buying so many times.



Keyword matching (+ syntax)

真的很好吃，小朋友一口一个吃得好开心，谢谢店主，买了这么多次没有不好的。

Really delicious! The kids are very happy to eat one by one. Thank you! There is nothing bad after buying so many times.

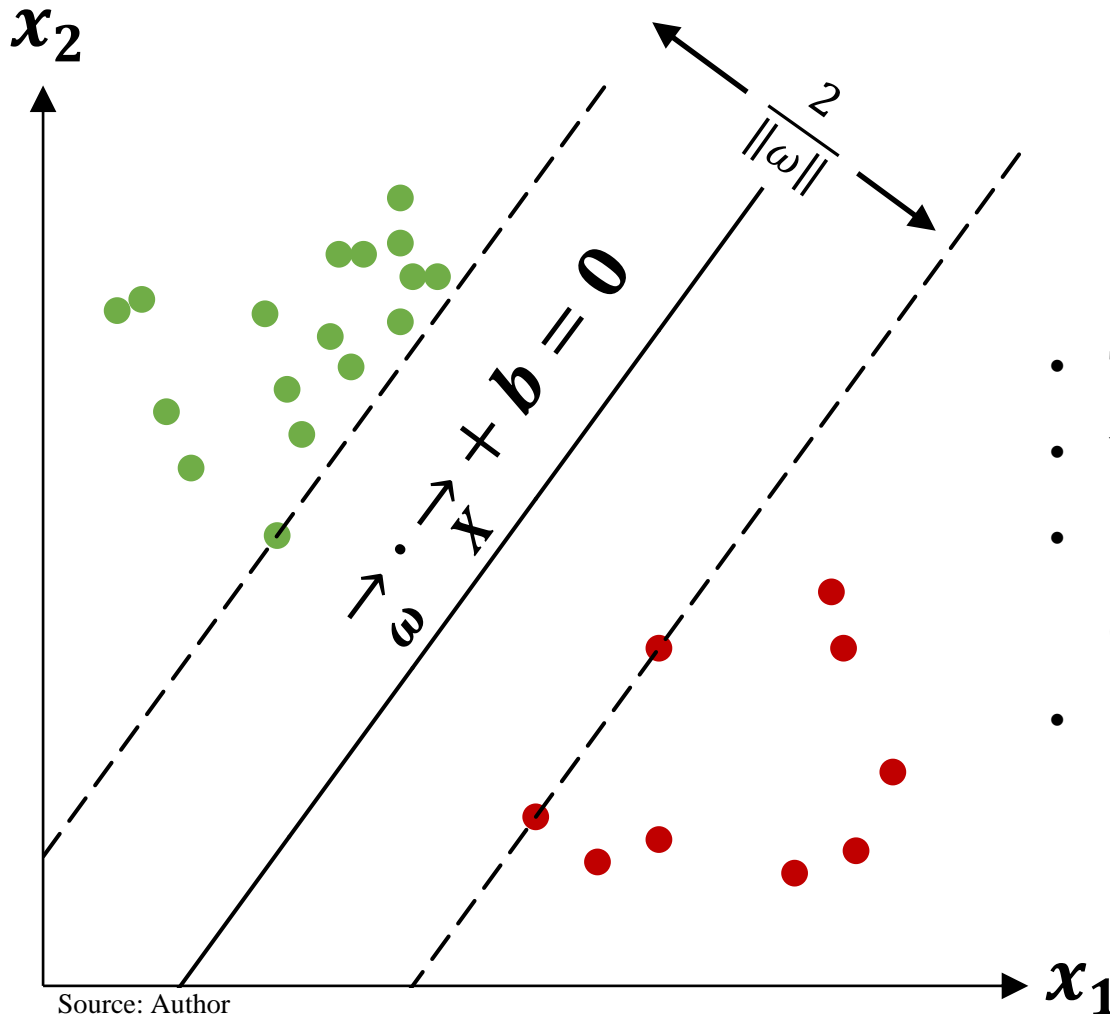


Sentiment lexicon mapping

Word	Sentiment polarity
good	1.31
great	1.59
impressive	1.66
remarkable	1.68
excellent	1.70
fantastic	1.71

- Captures the polarity of words
- Lexicon quality
- Static lexicon (ambiguous words)
 - e.g. 轻薄:
 - Frivolous (general context) -
 - Light and thin (laptop review) +

Traditional machine learning methods



e.g. SVM →

- Text → word vectors \vec{X}
- Word embedding: e.g. word2vec
- Sentiment score: distance to the decision boundary
- $\vec{x} = (x_1, x_2, \dots, x_n)$

BERT performance

<u>Item</u>	<u>Value</u>
AUC	89.16%
Evaluation accuracy	89.18%
F1_score	88.53%
false_negatives	504
false_positives	175
loss	0.397199
precision	93.74%
recall	83.87%
true_negatives	2979
true_positives	2620
global_step	150

- **Quick fine-tuning**
- **Reasonable accuracy**

Herfindahl-Hirschman index (HHI)

Market-level competition indicator

$$HHI_m = \sum_{i=1}^n CR_{i,m}^2$$

OLS (baseline, n=6,424)

Y: unit price (¥ /kg)

Xs:

- **Lag vars:**
 - CCFI (freight price indicator)
 - SDR (exchange rate indicator)
 - **Control vars:**
 - Monthly sales (count, in log)
 - Net weight (gram, in log)
 - Total number of cover pictures (count)
 - Flagship store status (dummy)
 - **Market structure:**
 - Herfindahl-Hirschman index ([HHI](#))
 - Market share (%)
 - **Place of origin (set of dummies): 16 countries/regions**
-

Result (baseline, n=6,424)

- CCFI: n/s **freight price** ✕
- NCP: positive (***) **cost** ↑ **price** ↑
- SDR: negative (***) **LCPP** ↑ **price** ↓
- Monthly sales: negative (***, n/s)
- Market share: negative (***) **economies of scale**
- Weight: negative (***)
- Flagship store: negative (***) **trust premium**
- HHI: positive (***) **market competition** ↑ **price** ↓

Result (sentiment, n=2,716)

	(4)	(5A)	(5B)	(5C)	(6A)	(6B)	(6C)	(7A-TNC)	(7B-TNC)	(7C-TNC)
Lag variables
Control variables
Market Structure
Comment										
Sentiment index		11.63 (10.38)			6.149 (10.68)			11.13 (10.68)		
Sentiment index mean of 20% negative			4.317 (9.971)			-14.04 (10.61)			-3.976 (10.53)	
Sentiment index mean of 20% positive				18.88** (8.017)			37.78*** (13.25)			35.37*** (13.45)
Comment count		1.316*** (0.186)	1.338*** (0.186)	1.305*** (0.186)	0.119 (1.289)	0.769*** (0.266)	17.23** (8.066)	-0.191 (1.277)	0.766*** (0.263)	14.94* (8.318)
SI#CC					1.381 (1.489)			1.686 (1.475)		
SI_n20#CC						1.249** (0.510)			1.198** (0.501)	
SI_p20#CC							-15.94** (8.065)			-13.68 (8.316)
Place of origin

Sentence-level sentiment index

Review content in Chinese	classification	log(P(neg))	log(P(pos))	SSI*	Review content in English
甜甜脆脆的营养价值非常高。真的很棒，就像这个提子口味是我想要的，果味清香的，颜色看起来特别的喜人，散发自然果香，一口咬下去，汁很多。甜可口，水果店的超市的和这个完全没得比。	+	-4.13	-0.02	0.995	Very sweet and crunchy. It's really good! The taste of this raisin is what I want. It is fruity and fragrant. The colour looks particularly gratifying. It has a natural fruity fragrance. It is very juicy after one bite. It's sweet and delicious. Those in the supermarket or in the fruit shop cannot compete with this.
买给家里小朋友吃的，结果大家都喜欢吃呢，三斤到手给小朋友留了一小串，其余的居然一次性就吃完了。葡萄味道很赞，不剥皮的口感也是好的，家里小朋友吃都没有剥皮。物流包装还是很棒，完全不用担心到手上有坏果哦！	+	-4.41	-0.01	0.998	I bought it for the kids at home, and everyone likes to eat it. I left a small bunch for the kids out of the three kilos, and the rest was eaten all at once. The grapes taste great, and the texture without peeling is also good. The kids ate them without peeling. The logistics packaging is still great, so there is no need to worry about bad fruits on hand!
很甜，果肉特别的多，吃起来非常的好吃葡萄颗颗饱满，这香甜的味道真的太爱了，有一种清香，总觉得在葡萄上吃出了荔枝的甜味。又大又黑，水分足，洗一串追剧的时候吃刚刚好，分量很足，也很新鲜	+	-4.39	-0.01	0.998	It's very sweet, with a lot of flesh. It tastes very delicious. The grapes are good-looking. This sweet taste is really loved. It has a delicate fragrance. I always feel the sweetness of lychee on the grapes. It's big and dark, and it's full of moisture. It's just right for snacks when you watch TV shows. The give enough weight and really fresh.
拆开快递看起来份量挺多的啦，再把里面的透明包装打开份量真的太多啦，金手指有点脆脆，口感味道好甜，皮好薄，太喜欢了，惹人爱，葡萄确实新鲜，口感也挺好，家里两个孩子都喜欢吃这样葡萄，既好看又好吃	+	-4.41	-0.01	0.998	Before unpacking the express, it already looked like a lot. And after opening the transparent package inside, the weight is really too much. The golden fingers are a bit crunchy, the taste is so sweet, the skin is so thin. I like it too much. The lovely grapes are indeed fresh and tasty. Both my children like to eat grapes like this. They are both beautiful and delicious.
烂了好多。还发霉了。物流还特别慢。	-	-0.03	-3.38	0.009	It sucks a lot. Also mouldy. Logistics is particularly slow.
这是收到的第二天 可能没放冰箱吧 第一天反正还行吧 感觉不算那种特别新鲜的	+	-1.44	-0.27	0.842	This is the second day I received it. Maybe because I didn't put the refrigerator in the first day, the grapes were so so at the first day. The grapes are not very fresh.
垃圾，都是坏的，还发霉，不要买呀用户0天后追评垃圾呀，千万不要买	-	0.00	-5.32	0.000	Garbage, it's all bad and mouldy. Don't buy it. User reviews again 0 days later: All garbage. Do not buy!

*SSI = $\log(P(\text{neg})) / (\log(P(\text{neg})) + \log(P(\text{pos})))$