ReviewToRevenue: 레스토랑 경영 인사이트 서비스

Team | ZeroSugar (NLP 2팀)
21기 강서연, 윤채영 22기 김종현, 백서현

CONTENTS

1. 프로젝트 소개

01. 주제 선정

- 미국 온라인 평점 플랫폼 Yelp의 공개 데이터셋을 활용
- 목표 : 로컬 식당의 리뷰 데이터에서 핵심 이슈와 감정을 추출하여 고객 피드백 분석 자동화
- 주제 선정 배경

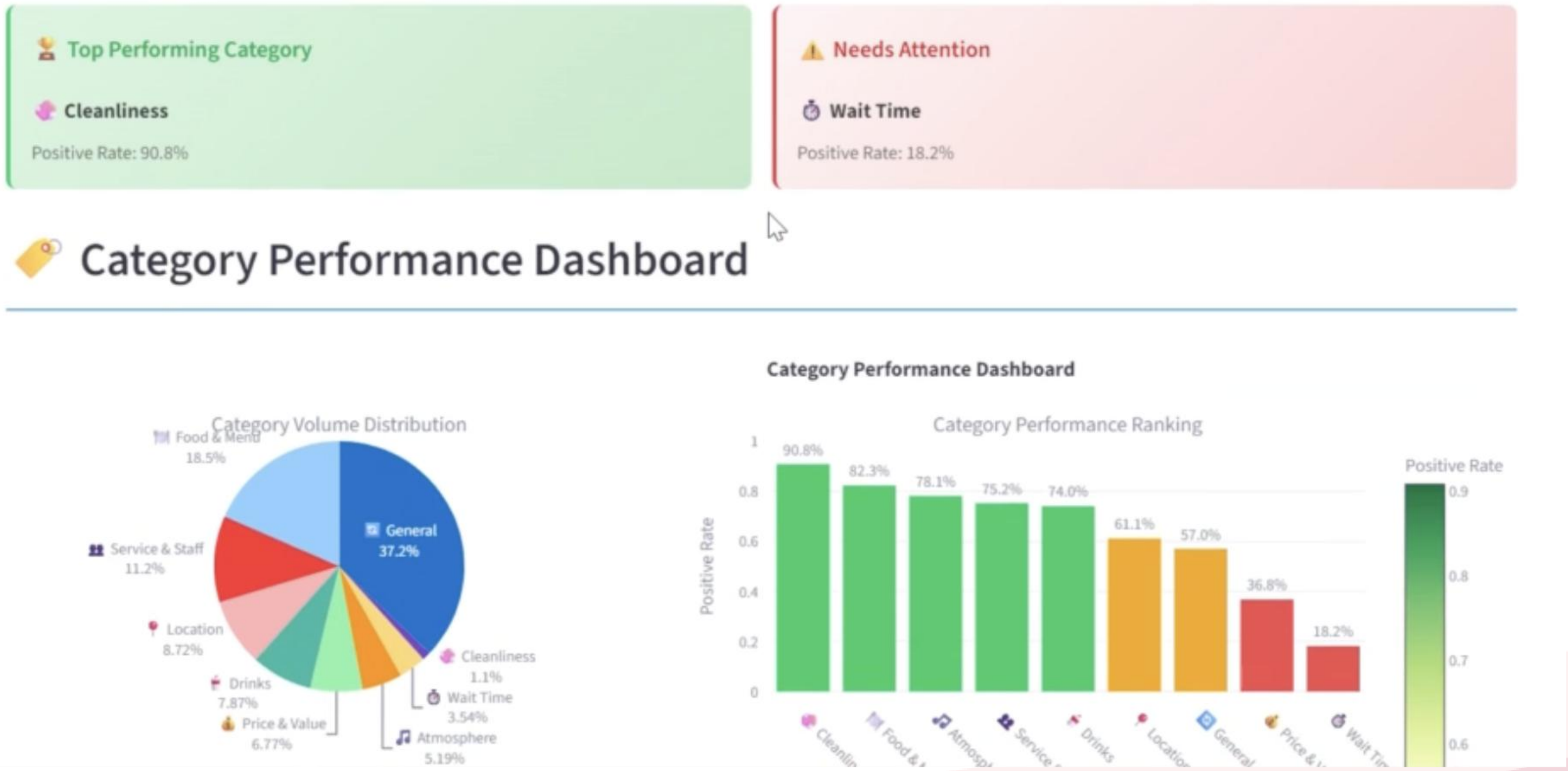
1. 수많은 리뷰를 수작업으로 분석하는 것의 한계
2. 고객 만족 / 불만 요인을 체계적으로 파악하기 어려움

➔ 업체의 강점과 보완점을 명확하게 보여주는 데이터 기반 비즈니스 의사결정 지원 필요

01. 특징

- 문장 단위로 피드백을 정확도 있게 분석

- 토픽별 분류 및 감정 분석을 통한 구체적인 인사이트 제공



01. 프로젝트 파이프라인

분석대상 식당 리뷰 필터링

감성분석 리뷰 텍스트를 문장 단위로 쪼개어 이진분류 감성분석

NLI 기반 multi-label 분석
문장별로 약 36개의 세부적인 aspect에 매칭 (맛, 서비스, 청결도..)
Multi-label을 허용한 zero shot classification 진행

Streamlit 기반 분석 결과 시각화
가장 많이 언급된 토픽, 긍정/부정 리뷰 요약
시계열 감정 분석 등 대시보드 시각화

02. 감성분석

02. 감성분석

🛠️ 사용 모델: distilbert-base-uncased-finetuned-sst-2-English

→ 사전학습된 DistilBERT 모델을 SST-2 데이터셋으로 파인튜닝한 감성 분석 모델

* DistilBERT: BERT의 경량화 버전 모델(60% 빠른 속도, 95% 정도의 성능 유지)

02. 감성분석

📈 감성분석 process

리뷰 텍스트 문장 단위 분할	- 한 리뷰 안의 <u>복합적인 국소 감정</u>을 세밀하게 캡처하기 위함 - NLTK의 sent_tokenize 활용
⬇	
토큰화	- max_chars = 256으로 설정 → 문장 <u>잘라내기/패딩/마스킹</u> 수행
⬇	
이진 감성 분류 수행	- input: 각 리뷰 문장 - output: 감성 <u>label</u>(POSITIVE/NEGATIVE), <u>score</u>(선택된 라벨의 softmax 확률값)

02. 감성분석

🗂️ 감성분석 결과물

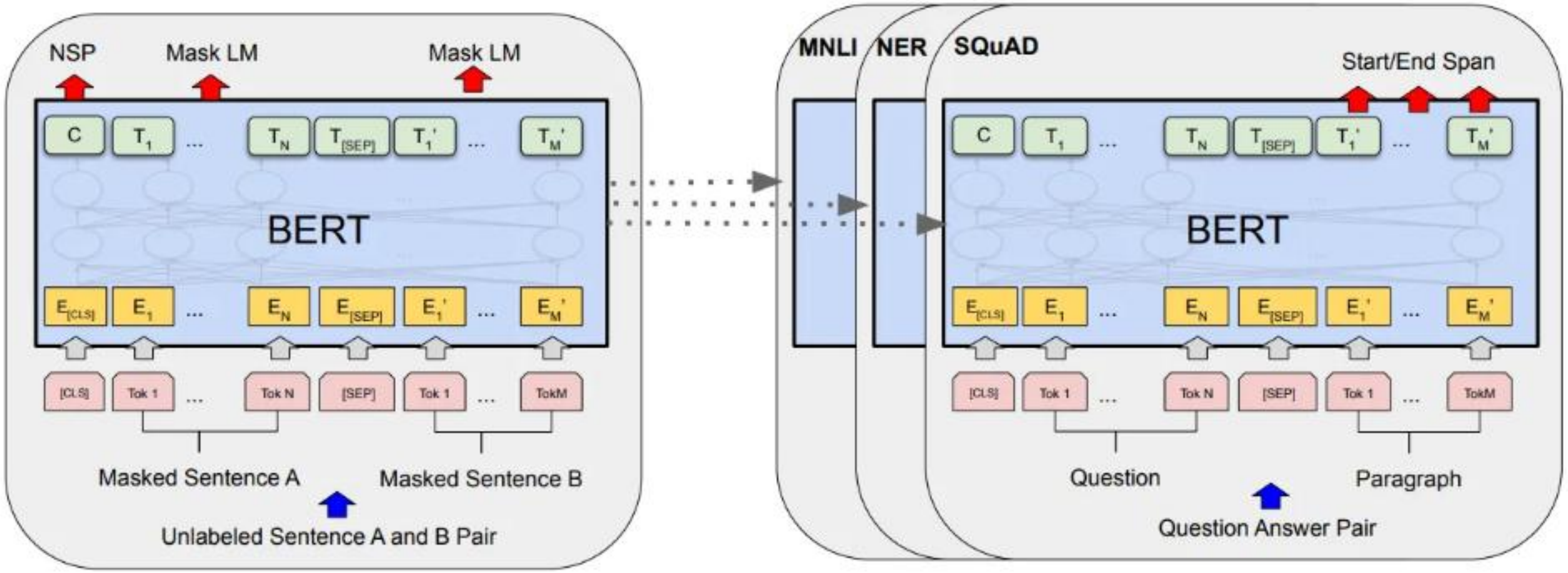
...	sentence	label	score
1285	Davis was our server and he was great and very accommodating.	POSITIVE	0.9998724460601808
3652	The fries and that jalapeño ketchup are pretty badass, too.	NEGATIVE	0.999627947807312
3094	Would recommend getting there early.	POSITIVE	0.9850822687149048
1419	Get the white trash hash and enjoy delicious brunch!	POSITIVE	0.9998194575309752
1426	I ordered a burger while my dining companion decided to go with the traditional brun	POSITIVE	0.5552936792373657
1245	Very fresh and tasty.	POSITIVE	0.9998835325241088
7878	Definitely a fun place to go with your gals or your guy.	POSITIVE	0.9998537302017212
4077	My Jack and coke was $9.50.	NEGATIVE	0.9775879383087158
3835	If I ever find myself in Nashville I will revisit and try to patron the other associated estal	NEGATIVE	0.9860202670097352
1376	Sweet potato chips were amazing.	POSITIVE	0.9998539686203004

03. 토픽 분류

03. Bertopic 기반 분류

BERTopic 기본 구조

- 문서 → BERT 임베딩(all-MiniLM-L6-v2) → 차원 축소(UMAP)
  → 클러스터링(HDBSCAN) → 주제 추출(c-TF-IDF)



Pre-training

Fine-Tuning

03. Bertopic 기반 분류

비지도 학습의 문제점

- 새로운 클러스터를 식별하기 위한 용도로서만 적합함.

[UMAP 구조]

$$p_{j|i} = \exp\left(-\frac{\|x_i - x_j\|^2}{\sigma_i}\right)$$ x: 고차원 벡터 p: 고차원에서의 근접성 σ : 정규화 파라미터

$$q_{ij} = \frac{1}{1 + a\,\|y_i - y_j\|^{2b}}$$ y: 저차원 벡터 q: 저차원에서의 근접성

$$\mathcal{L} = \sum_{i \neq j} \left[p_{ij} \log \frac{p_{ij}}{q_{ij}} + (1 - p_{ij}) \log \frac{1 - p_{ij}}{1 - q_{ij}} \right]$$

- 클러스터는 데이터셋 구조에 따라서 변화

03. 제로샷 라벨링 -> BERTopic

초기 구상 - 제로샷 대분류 (bart) 이후 BERTopic 시행

: 각 대분류 별로 세부 Topic이 도출되긴 하지만 대분류-중분류의 개념보다는 동일한 분류를 두 번 진행한 것 같은 결과.

(각 대분류별로 다른 data set으로 인식하기에 data set마다 유사도가 다르게 정의된 결과)

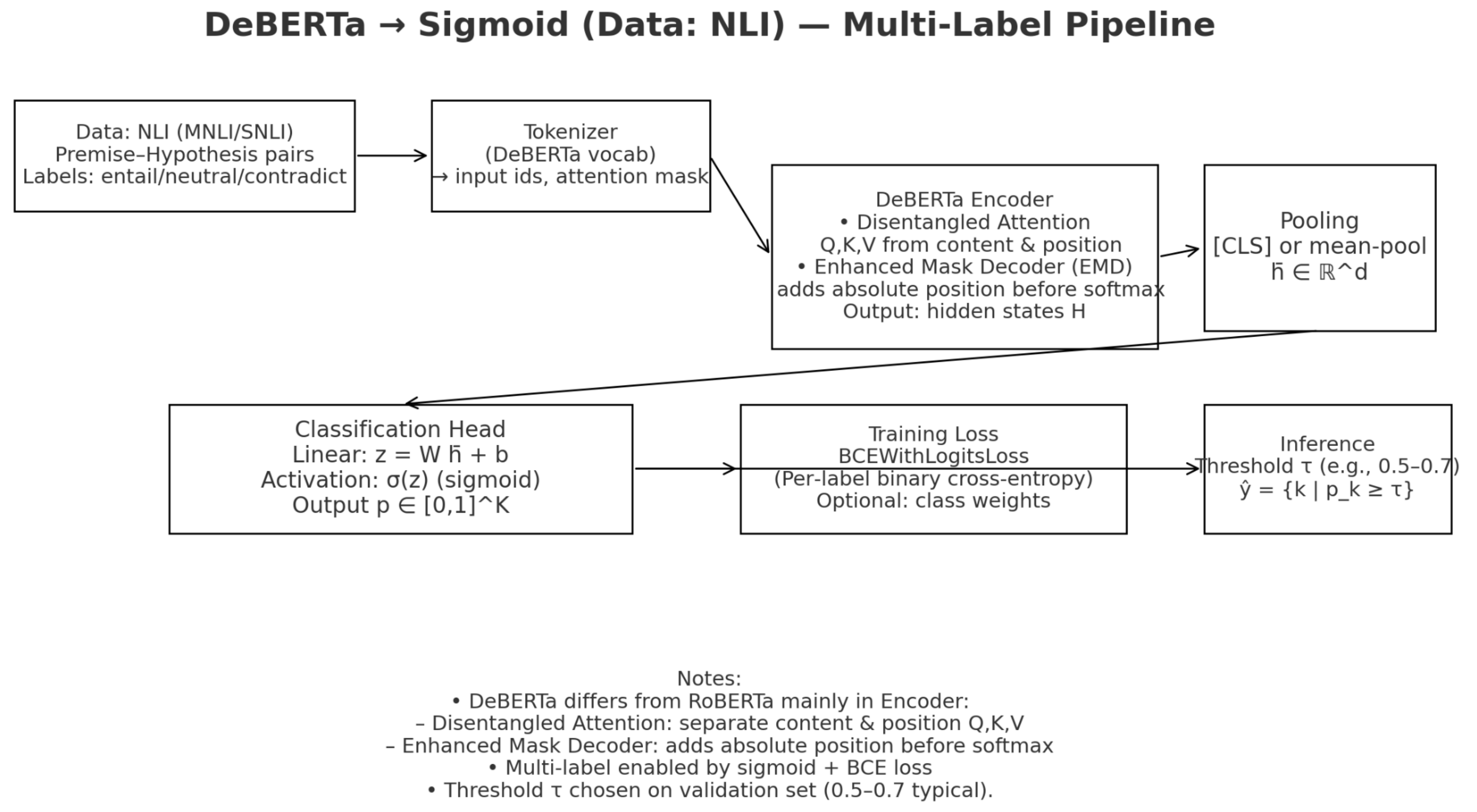
→ 비지도학습은 데이터셋 의존도가 높기에, 지도학습의 도입을 고려.

coarse_label	topic_id	size	label
atmosphere and interior design	0	104	restaurant • brunch • brunch spot
atmosphere and interior design	1	72	restaurant • restaurants • dining
location and accessibility	0	6	indy milk • loved restaurant • indy
location and accessibility	1	5	seating brunch • saturday brunch • brunch
location and accessibility	2	5	restaurant • lunch limited • waiter
location and accessibility	3	4	favorite restaurant • popular spot • food service
location and accessibility	4	4	creamery milk • concept milktooth • point creamery
location and accessibility	5	3	lucky restaurant • restaurant • foodthis spot
price and value for money	0	9	restaurant • meal • ordered grilled
price and value for money	1	7	restaurant • indy • pay food
price and value for money	2	5	price quality • prices amazingly • overrated expensive
price and value for money	3	5	customers waitresses • waitress • customers
price and value for money	4	5	restaurant • kind food • didnt food
price and value for money	5	4	great staff • experience staff • worth steak
price and value for money	6	3	brunch food • brunch options • eating brunch
price and value for money	7	3	milktooth yelp • milktooth great • new restaurant
price and value for money	8	3	serve lamb • food serve • ham
speed of service and staff friendliness	0	57	glazed bacon • sorghum bacon • flavors
speed of service and staff friendliness	1	50	restaurants • dining • indy
speed of service and staff friendliness	2	11	asked waitress • latte • hostess

03. DeBERTa (RoBERTa 기반)

리뷰 토픽 라벨링 목표 : 주어진 리뷰들을 제로샷 클러스터(실험자가 미리 정해준)를 기반으로 분류 →

→지도학습이 적절, DeBERTa(NLI) 모델 사용결정 (Sigmoid-tunned)



03. DeBERTa (RoBERT 기반)

EMD(Enhanced Mask Decoder): Softmax Layer에 절대위치 임베딩 추가

$$P(w_i \mid \mathbf{x}_{\backslash i}) = \mathrm{softmax}(h_i W + p_i)$$

h_i: Transformer layer 출력(hidden state)

W: 단어 예측용 가중치 행렬

p_i: **absolute position embedding** (Enhanced Mask Decoder에서 추가)

Disentangled Attention : 내용, 상대위치 임베딩을 나누어 attention

$$A_{i,j} = [H_i,\ P_{i|j}]\,[H_j,\ P_{j|i}]^\top = H_i H_j^\top + H_i P_{j|i}^\top + P_{i|j} H_j^\top + P_{i|j} P_{j|i}^\top$$

$$\delta(i,j) = \begin{cases} 0 & \text{if } i-j \le -k \\ 2k-1 & \text{if } i-j \ge k \\ i-j+k & \text{otherwise.} \end{cases}$$

$$p_{i|j} = W_p \delta_{i|j}$$

A : $attention\ score$

03. NLI 기반 토픽 분류

NLI 데이터셋
(SNLI, Bowman et al. 2015)

- 연구 목적

자연어 의미 이해의 핵심 관계인 entailment (함의), contradiction (모순), neutral (독립)을 대규모 학습이 가능한 데이터셋으로 제공.

- 라벨링

Premise 문장 하나를 (Flickr30k 캡션에서 추출) 고른 후 작업자가 3개의 Hypothesis 문장을 직접 작성 (Entailment / Neutral / Contradiction)

03. NLI 기반 토픽 분류

LABEL_CORE

Service/Operations

Cleanliness/Safety

Environment/Ambience

Accessibility/Family

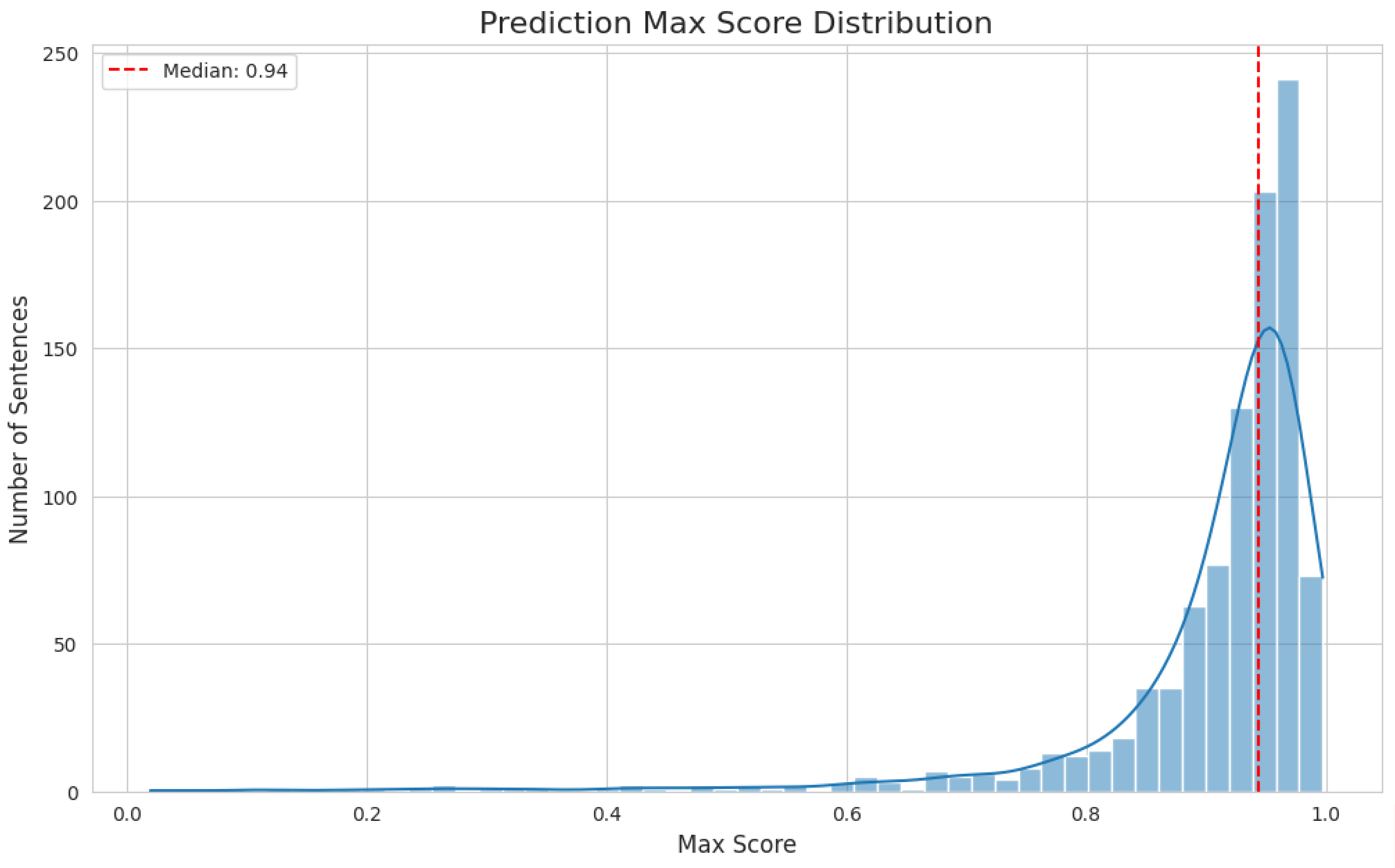
Menu/Value/Food

Delivery/Takeout

등 총 36개의 세부Label

03. NLI 기반 토픽 분류

문장별 max score distribution 추출을 통해서 Threshold (유사도 임계치) 설정 : 0.8



03. NLI 기반 토픽 분류

길이가 짧은 문장의 모든 라벨에 대한 유사도가 높게 나오는 경향.

1. MLM 모델의 한계점 (포함관계면 유사하다고 식별) ex) The food is tasty and Great! / Its Great
2. NLI 모델의 Word-Overlap Bias

이후 문장 길이(토큰)의 하한선을 정해 텍스트 전처리 (4개이상)

```
=== Threshold: 0.8 ===
포함 문장 예시 (5개):
- The food is consistently good if overpriced Mexican entrees
- IT WORKS
- I was expecting a larger group and some people were running late canceled last minute and we were sitting outside
- The doctor saw me and prescribed me an inhaler
- I had been with ATT for years
제외 문장 예시 (5개):
- This was my first time at Cheddar s and it was not a very good impression
- Labeling of food for pickup sometimes off slightly but that s a slight problem that can usually get solved easily at time of pickup
- If you are looking at Yelp to pick a great place to eat please focus on the more recent reviews and you might just want to give them a try it is really VERY VERY good
- I take stars off because of their process service each time I go there s something funky with the service
- If you like your seaweed I assure you that you won t like this version

=== Threshold: 0.85 ===
포함 문장 예시 (5개):
- IT WORKS
- I was expecting a larger group and some people were running late canceled last minute and we were sitting outside
- The doctor saw me and prescribed me an inhaler
- I had been with ATT for years
- I will be back
제외 문장 예시 (5개):
- The food is consistently good if overpriced Mexican entrees
- This was my first time at Cheddar s and it was not a very good impression
- high priced and lousey food
```

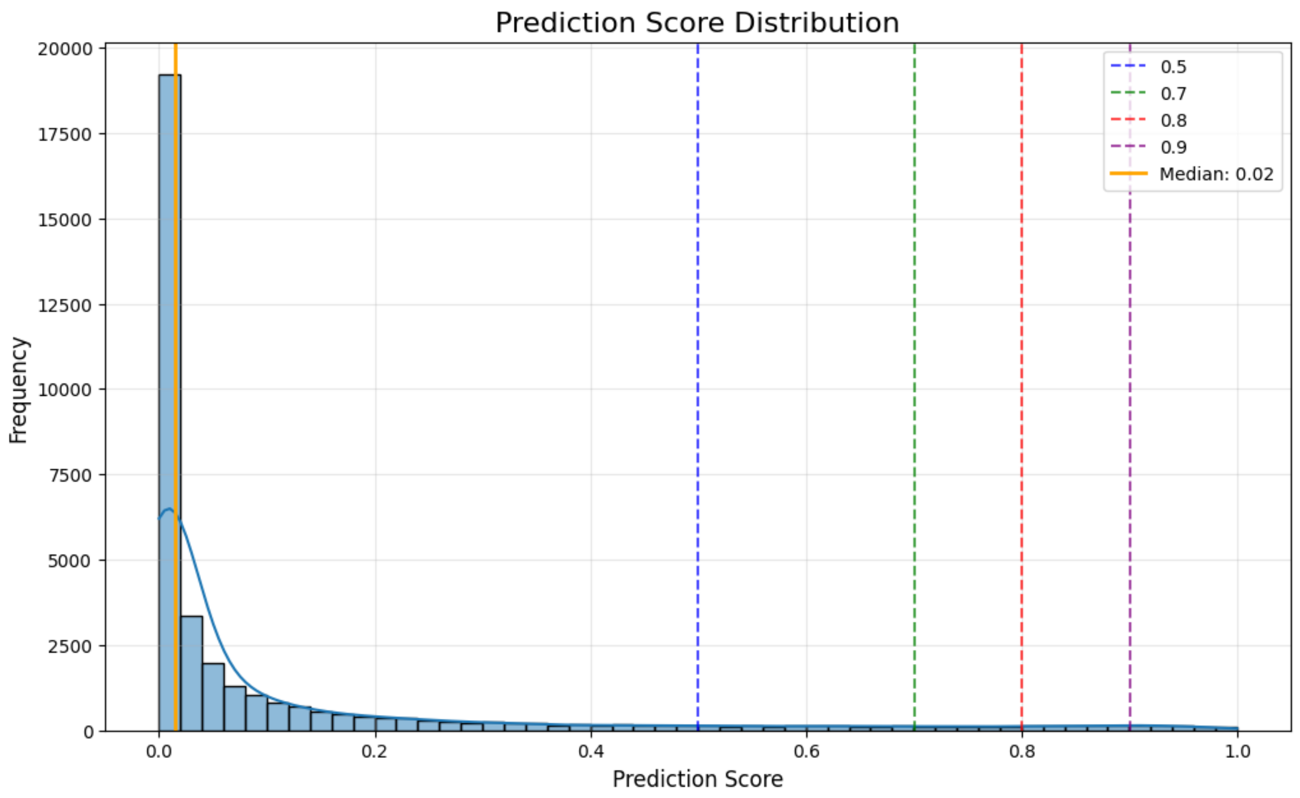
03. NLI 기반 토픽 분류

36개 label에 대한 유사도 분포 추정.

- Threshold 0.8일 때 각 문장과 label 관계의 3.5%정도가 유의하게 검출되었음.

→한 문장 안에 평균적으로 1.6개 정도의 세부토픽이 존재. (짧은 문장으로 인해 과다평가)

→ex) 샐러드가 신선해요! (신선도, 비건메뉴)



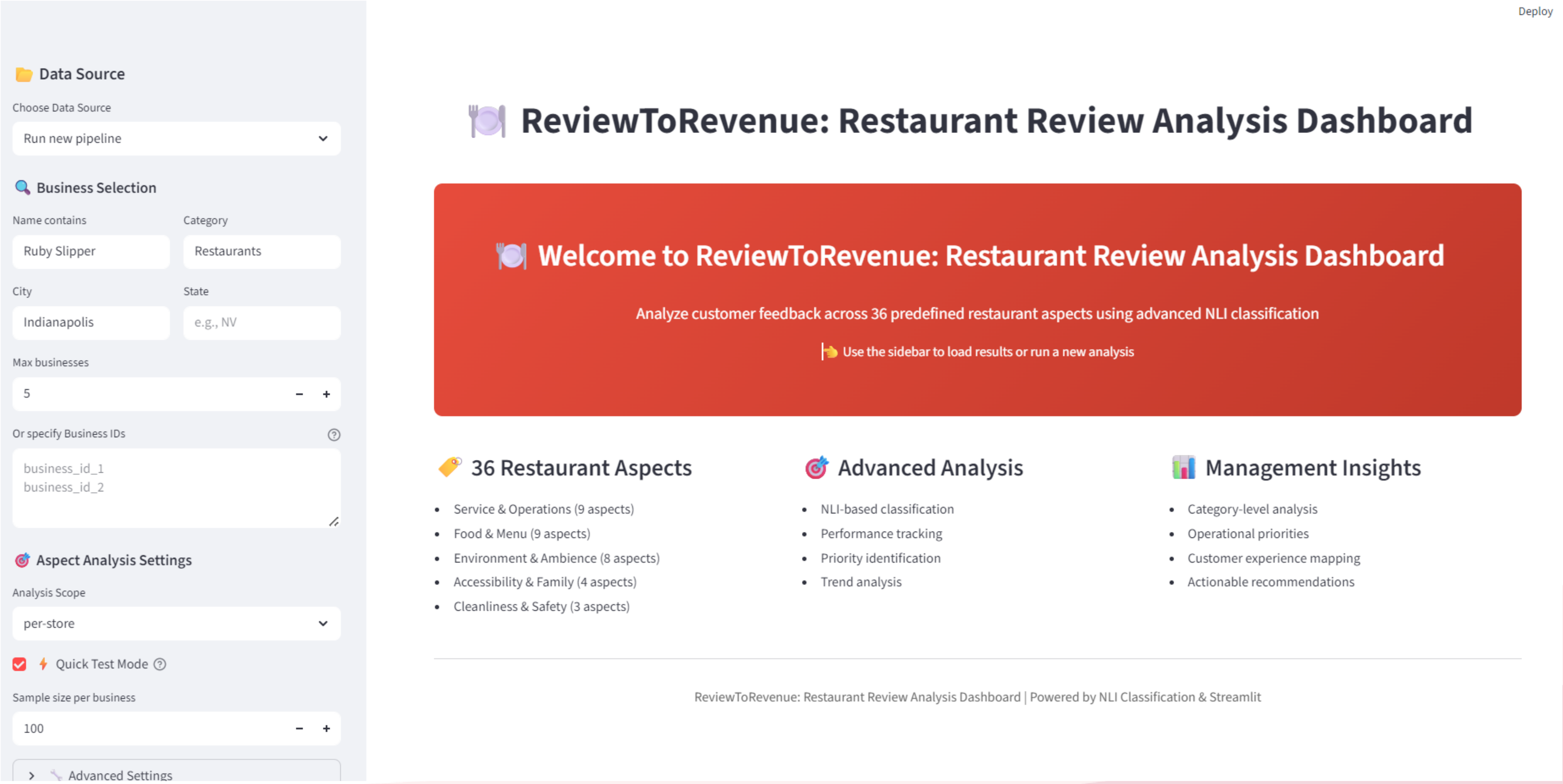

```
=== 점수 통계 ===
평균: 0.117
중앙값: 0.015
표준편차: 0.219
최소값: 0.000
최대값: 0.999

=== Threshold별 결과 ===
≥0.50:   3062/36000 (  8.5%)
≥0.60:   2448/36000 (  6.8%)
≥0.70:   1833/36000 (  5.1%)
≥0.80:   1271/36000 (  3.5%)
≥0.85:    953/36000 (  2.6%)
≥0.90:    613/36000 (  1.7%)
≥0.95:    260/36000 (  0.7%)
```

04. Streamlit

04. Streamlit

- Streamlit으로 서비스 제공

- 식당 이름 및 조건 검색 → 감성분석 → NLI 토픽 분류 → 분석 결과 제공 end-to-end 가능



04. Streamlit

- 총 리뷰 문장 개수 및 전체적인 별점, 감성 비율 제시
- 토픽 중 가장 긍정/부정적인 토픽 제시

📊 Restaurant Aspect Analysis Results

📊 Total Review Sentences Analyzed	🏷️ Aspects Identified	⭐ Average Satisfaction	😊 Positive Sentiment Rate
1,369	36	4.1/5.0	84.8%
		↑ 1.1 vs neutral	↑ 34.8% vs 50%

🚨 Most Critical Aspect

order accuracy and missing items

Positive Rate: 53.8% | Mentions: 39

✨ Strongest Performance

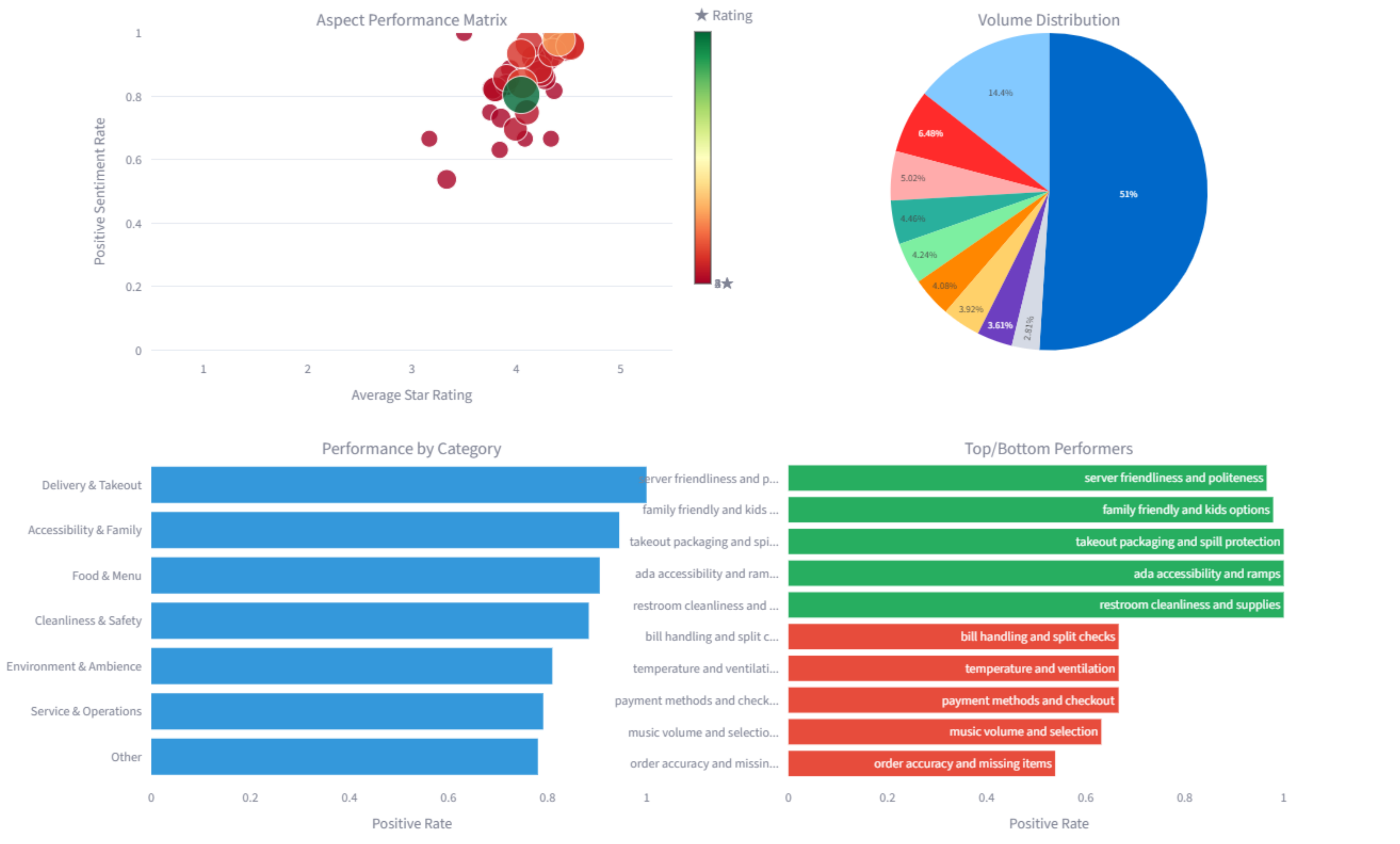
takeout packaging and spill protection

Positive Rate: 100.0% | Mentions: 4

04. Streamlit

Overview

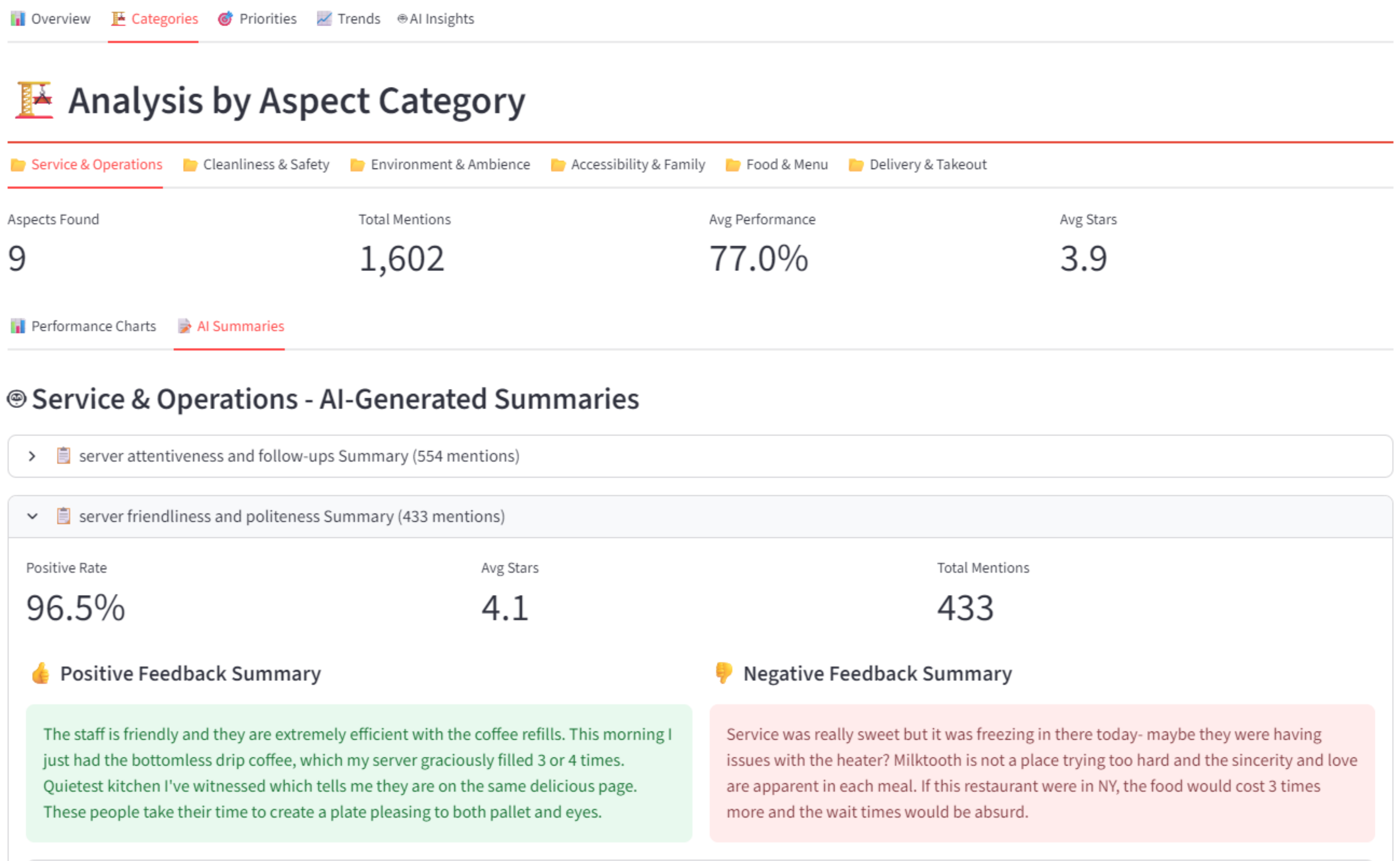
- 전체적인 performance matrix / 토픽 분포 비율
- 카테고리별 비율 / 상위 긍정/부정 토픽



04. Streamlit

Categories

- 카테고리 및 토픽 별 요약 제시
- Facebook/bart-large-cnn 모델 (BART 모델 활용 요약 결과 제시



04. Streamlit

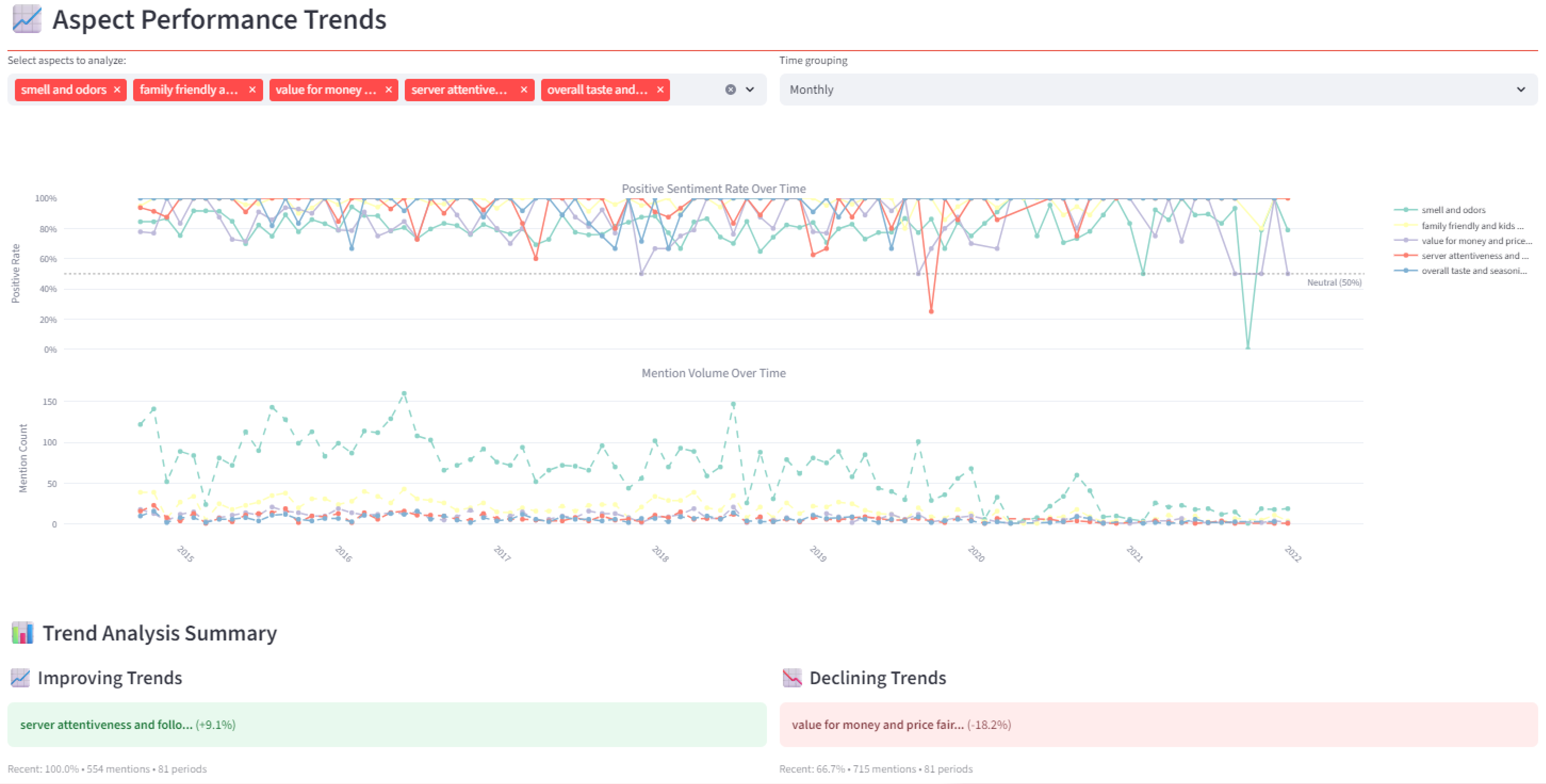
Priorities

- 레스토랑 입장에서 가장 빠르게 해결해야 할 토픽 사안들 제시
- 토픽에 속해 있는 리뷰 개수 및 부정 비율 반영하여 plot 제시

04. Streamlit

Trends

- 토픽별 시간에 따른 긍정/부정 비율 트렌드 제시(월별)
- 특정 시기에 해당 토픽의 평가 확인 가능 + 평가가 좋아지고 있는/나빠지고 있는 토픽 제시



04. Streamlit

AI Insights

- GPT API 기반 분석 결과 제시 – 토픽 분석 결과 및 예시 문장 프롬프트로 입력
- 전체적인 요약 및 가장 집중해서 발전해야 할 사안, 액션 플랜 제시

📋 Restaurant Management Analysis

Download Report

Executive Summary

1. **High Customer Satisfaction**: The restaurant enjoys a strong overall positive rate of 84.8%, with several aspects, such as takeout packaging (100% positive) and ADA accessibility (100% positive), receiving exceptional praise. This i customer experience.
2. **Service & Operations Challenges**: The aspect of order accuracy is notably weak, with only 53.8% positive feedback. This is a critical area for improvement as it directly impacts customer satisfaction and repeat business.
3. **Ambience and Experience**: Customers frequently praise the restaurant's atmosphere, decor, and server friendliness. However, complaints about temperature control and music volume suggest that while the environment is gene detract from the overall experience.
4. **Family-Friendly Focus**: The restaurant is recognized for being family-friendly, with a high positive rating (97.9%). However, there are mentions of limited traditional breakfast options, which could alienate some family demograpl

Category-Level Insights

- **Strongest Categories**:
  - **Accessibility & Family**: High praise for family-friendly options and ADA compliance.
  - **Environment & Ambience**: Positive feedback on decor and seating comfort, indicating a well-designed space.
- **Weakest Categories**:
  - **Service & Operations**: Order accuracy and payment handling are significant pain points.
  - **Delivery & Takeout**: While not heavily discussed, the aspects related to delivery could be improved based on customer expectations.
- **Praise and Complaints**:
  - **Praise**: Customers appreciate the friendly service, unique decor, and creative menu items.
  - **Complaints**: Issues with order accuracy, temperature control, and limited traditional breakfast options are recurring themes.
- **Recommendations**:
  - Enhance training for staff on order accuracy and payment processes.
  - Consider expanding the breakfast menu to include more traditional options.

Customer Voice Analysis

- **Recurring Themes in Positive Feedback**:
  - Friendly and attentive service.
  - Unique and enjoyable atmosphere.
  - Creative and flavorful menu items.
- **Specific Pain Points**:

Customer Experience Journey

- **Connection of Aspects**: Positive experiences are often linked to the quality of service and the ambiance, which enhances the overall dining experience. However, negative experier
- **Critical Moments**: Customers frequently mention the initial interaction with servers and the quality of food as pivotal moments in their dining experience.
- **Service Recovery Opportunities**: Addressing complaints about temperature and order issues promptly can turn a negative experience into a positive one, fostering customer loyal

Evidence-Based Action Plan

1. **Implementable Recommendations**:
   - **Order Accuracy**: Introduce a checklist system for servers to confirm orders before they are sent to the kitchen.
   - **Temperature Control**: Regularly monitor and adjust HVAC settings based on customer feedback.
   - **Menu Expansion**: Add traditional breakfast options to cater to families looking for familiar fare.
2. **Success Metrics**:
   - Increase order accuracy ratings to above 80% within three months.
   - Achieve a customer satisfaction score of 90% for temperature comfort within six months.
   - Track the introduction of new menu items and their acceptance through customer feedback.
3. **Timeline Suggestions**:
   - **Immediate (1-3 months)**: Focus on staff training for order accuracy and implement HVAC monitoring.
   - **Short-term (3-6 months)**: Evaluate the impact of changes on customer satisfaction and adjust strategies accordingly.
   - **Long-term (6-12 months)**: Review menu performance and customer feedback to assess the success of new offerings.

By focusing on these actionable insights and aligning operational strategies with customer expectations, the restaurant can enhance its overall performance and customer satisfactior

+α) 추후 개선 방안

추후 개선 방안

- 단순한 문장에 대한 DeBERTa 모델 추가 파인튜닝으로 토픽 분류 성능 개선
- 크롤링 도입을 통한 실시간 리뷰 분석 서비스 제공
- 감성분석 및 NLI 분석 시간 개선

Thank You