Import Modules

```
!pip install bertopic -q
```

```
import pandas as pd
from tqdm import tqdm
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

1. Import Reviews Dataset

```
review_chunks = pd.read_csv('review_chunks_with_sentiment_clean.csv')
review_chunks.head()

# review_chunks = review_chunks[:20]
# review_chunks_sample.head()
```

	review_id	chunk_id	hotel_name	review_score	sentiment	chunk_text
0	1	1_Positive_0	A Hotel Joo Chiat	10.0	Positive	Comfortable and convenient This was a last min...
1	2	2_Positive_0	A Hotel Joo Chiat	7.0	Positive	Overall I'm quite happy with the stay

```
import pandas as pd
import numpy as np
from tqdm import tqdm
from bertopic import BERTopic
from sentence_transformers import SentenceTransformer
from sklearn.feature_extraction.text import CountVectorizer
from transformers import pipeline
import spacy

# Load spaCy
try:
    nlp = spacy.load("en_core_web_sm")
```

```
except:
    import os
    os.system("python -m spacy download en_core_web_sm")
    nlp = spacy.load("en_core_web_sm")

# Load sentiment classifier
sentiment_classifier = pipeline("sentiment-analysis", model="distilbert-base-ur

def topic_guided_sentiment(review_chunks, min_topic_size=10, verbose=True):
    """
    Topic-guided sentence-level sentiment classification (not true ABSA).

    Args:
        review_chunks (DataFrame): Must contain 'chunk_text', 'review_id', 'chu
        min_topic_size (int): Minimum size for topic extraction in BERTopic
        verbose (bool): Whether to print progress logs

    Returns:
        topic_sentiment_df (DataFrame): Sentence-level sentiment associated wit
    """
    if verbose:
        print("🔍 Loading sentence embedding model...")
    sentence_model = SentenceTransformer('all-MiniLM-L6-v2')

    texts = review_chunks['chunk_text'].tolist()

    if verbose:
        print("🧠 Creating document embeddings...")
    embeddings = sentence_model.encode(texts, show_progress_bar=verbose)

    if verbose:
        print("🧵 Running BERTopic for topic discovery...")
    vectorizer = CountVectorizer(stop_words="english")
    topic_model = BERTopic(
        vectorizer_model=vectorizer,
        min_topic_size=min_topic_size,
        verbose=verbose
    )
    topics, _ = topic_model.fit_transform(texts, embeddings)

    topic_labels = {}
    for topic_id in topic_model.get_topic_info()['Topic'].tolist():
        if topic_id != -1:
            words = topic_model.get_topic(topic_id)
            topic_labels[topic_id] = words[0][0] if words else f"Topic_{topic_i

    if verbose:
        print(f"📌 Extracted {len(topic_labels)} topic labels.")
        print("🔎 Classifying sentiment at sentence level...")

    results = []

    for i, row in enumerate(tqdm(review_chunks.itertuples(index=False), total=l
        review_id = row.review_id
        chunk_id = row.chunk_id
        hotel_name = row.hotel_name
        text = row.chunk_text
        topic_id = topics[i]

        if topic_id == -1:
            continue

        topic_words = topic_model.get_topic(topic_id)
        topic_label = topic_labels.get(topic_id, f"Topic_{topic_id}")
        topic_keywords = [w for w, _ in topic_words[:5]] if topic_words else []

        doc = nlp(text)

        for sentence in doc.sents:
            sent_text = sentence.text
            sent_text_lower = sent_text.lower()

            if any(word in sent_text_lower for word in topic_keywords):
                try:
                    sentiment_output = sentiment_classifier(sent_text)[0]
                    sentiment = sentiment_output["label"].capitalize()
                    confidence = round(sentiment_output["score"], 4)
                except Exception as e:
                    if verbose:
                        print(f"⚠️ Sentiment analysis failed: {e}")
                    continue

                results.append({
                    "review_id": review_id,
                    "chunk_id": chunk_id,
                    "hotel_name": hotel_name,
                    "topic_label": topic_label,
                    "sentence_sentiment": sentiment,
                    "sentiment_confidence": confidence,
                    "topic_id": topic_id
                })

    topic_sentiment_df = pd.DataFrame(results)

    # Step 1: Aggregate average confidence per sentiment
    avg_conf_df = (
        topic_sentiment_df
        .groupby(["review_id", "chunk_id", "topic_label", "sentence_sentiment"]
        .agg(avg_confidence=("sentiment_confidence", "mean"))
        .reset_index()
    )

    # Step 2: Select sentiment with highest average confidence
    resolved_df = (
        avg_conf_df.sort_values("avg_confidence", ascending=False)
                   .drop_duplicates(subset=["review_id", "chunk_id", "topic_lab
    )

    # Step 3: Merge metadata back in (hotel_name, topic_id)
    resolved_df = (
        resolved_df.merge(
            topic_sentiment_df[["review_id", "chunk_id", "topic_label", "hotel_
            on=["review_id", "chunk_id", "topic_label"],
            how="left"
        ).drop_duplicates(["review_id", "chunk_id", "topic_label"])
        .rename(columns={
            "sentence_sentiment": "final_sentiment",
            "avg_confidence": "final_confidence"
        })
        .reset_index(drop=True)
    )

    return resolved_df

# Run updated pipeline
topic_sentiment_df = topic_guided_sentiment(review_chunks, min_topic_size=20, v
topic_sentiment_df
```

```
Device set to use cpu
🔍 Loading sentence embedding model...
🧠 Creating document embeddings...
Batches:   0%|          | 0/9166 [00:00<?, ?it/s]
🧵 Running BERTopic for topic discovery...
2025-04-18 12:38:52,324 - BERTopic - Dimensionality - Fitting the dimension
2025-04-18 12:46:51,187 - BERTopic - Dimensionality - Completed ✓
2025-04-18 12:46:51,232 - BERTopic - Cluster - Start clustering the reduced
2025-04-18 12:47:51,631 - BERTopic - Cluster - Completed ✓
2025-04-18 12:47:51,803 - BERTopic - Representation - Fine-tuning topics us
2025-04-18 12:48:08,363 - BERTopic - Representation - Completed ✓
📌 Extracted 820 topic labels.
🔎 Classifying sentiment at sentence level...
100%|██████████| 293302/293302 [3:07:02<00:00, 26.13it/s]
```

	review_id	chunk_id	topic_label	final_sentiment	final_conf
0	38145	38145_Positive_0	clean	Positive	
1	133627	133627_Positive_0	breakfast	Positive	
2	133647	133647_Positive_0	singapore	Positive	
3	133649	133649_Positive_0	rooftop	Positive	

```
topic_sentiment_df.to_csv('topic_sentiment_df.csv', index=False)
print("Saved topic sentiment DataFrame to 'topic_sentiment_df.csv'")
```

```
Saved topic sentiment DataFrame to 'topic_sentiment_df.csv'
```

2. Preprocess Topic Labels

```
topic_sentiment_df = pd.read_csv('topic_sentiment_df.csv')
topic_sentiment_df
```

	review_id	chunk_id	topic_label	final_sentiment	final_conf
0	38145	38145_Positive_0	clean	Positive	
1	133627	133627_Positive_0	breakfast	Positive	
2	133647	133647_Positive_0	singapore	Positive	
3	133649	133649_Positive_0	rooftop	Positive	

```
# Total count of mentions per topic (across all sentiments)
topic_counts = (
    topic_sentiment_df
    .groupby("topic_label")
    .size()
    .sort_values(ascending=False)
)

print(f"Unique topics: {len(topic_counts)} \n")

# Top 10 most mentioned topics
print("🔥 Top topic labels by count:")
print(topic_counts.head(50))

# Bottom 10 least mentioned topics
print("\n❄️ Bottom topic labels by count:")
print(topic_counts.tail(50))
```

```
reception      782
desk           774
und            771
```

```
noisy          751
dtype: int64

❄️ Bottom topic labels by count:
topic_label
stayi              12
1159pm             12
january            11
frog               11
wheat              11
decentsize         10
chosen              9
stayfriends         9
1515                8
comeback            8
willinh             8
hosting             8
topnotch            8
tram                7
nontouristic        7
busnesses           7
butcher             6
ambiente            6
humle               6
serinity            6
cum                 6
195m                6
formed              6
smallalso           5
neatly              5
finished            5
hmlet               5
spacejust           5
capable             5
yeaahh              4
andcomfort          4
rmt                 4
facilitieswould     4
forcshort           4
nobu                4
findings            4
undrtstanding       4
interrsti           4
rubberised          4
critique            4
greatwe             4
focused             3
mainta              3
floorexcellent      3
horning             3
worldview           3
frm                 3
barspacious         2
```

```
billiard           2
withlocal          1
```

```
taxonomy = {
    "room": {
        "room_size": ["spacious", "compact", "smaller", "small", "tiny", "cramp
        "bed_comfort": ["bed", "beds", "mattress", "pillow", "pillows", "blanke
        "climate_control": ["aircon", "fan", "ventilation", "humid"],
        "room_cleanliness": ["clean", "cleaning", "dirty", "dusty", "tidy"],
        "furniture": ["desk", "chair", "sofa", "lighting", "mirror", "curtains'
        "noise_level": ["noise", "noisy", "quiet", "insulation", "soundproof",
        "room_design": ["modern", "dated", "ambience", "ambiente", "style"],
        "privacy": ["partition", "shared", "private"],
        "view": ["window", "windows", "balcony", "view"]
    },
    "bathroom": {
        "bathroom_cleanliness": ["mold", "mould", "smell", "odor", "wet", "soap
        "fixtures": ["shower", "bathtub", "bidet", "sink", "toilet", "toilets",
        "bathroom_design": ["bathroom", "bathrooms"],
        "ventilation": ["ventilation", "exhaust", "fan", "window"]
    },
    "location": {
        "proximity": ["orchard", "bugis", "chinatown", "sentosa", "marina", "ka
        "convenience": ["mrt", "metro", "accessible", "location", "nearby", "ce
        "neighborhood": ["geylang", "raffles", "mustafa", "shopping", "district
        "noise": ["traffic", "quiet", "noisy"]
    },
    "service": {
        "staff_attitude": ["friendly", "helpful", "rude", "polite", "welcoming'
        "checkin_checkout": ["check", "checkin", "checkout", "booking", "bookin
        "housekeeping": ["cleaning", "housekeeping", "laundry", "towels", "make
        "issue_resolution": ["complain", "complaints", "support", "maintenance'
    },
    "food": {
        "breakfast_quality": ["breakfast", "buffet", "variety", "spread"],
        "dietary_options": ["vegetarian", "halal", "gluten"],
        "food_availability": ["food", "restaurant", "dining", "meal", "snacks",
        "taste": ["delicious", "tasty", "cold", "bland"]
    },
    "amenities": {
        "tech": ["wifi", "tv", "usb", "power", "laptop"],
        "in_room": ["fridge", "kettle", "microwave", "minibar", "iron", "phone'
        "leisure": ["gym", "pool", "spa", "bar", "sauna", "billiard", "lounge"]
        "accessibility": ["accessible", "wheelchair", "elderly", "lift", "eleva
    },
    "value": {
        "price": ["price", "expensive", "cheap", "value", "budget", "affordable
        "worth_it": ["included", "free", "worth", "overpriced"]
    },
    "logistics": {
        "transport": ["bus", "taxi", "shuttle", "train", "tram", "monorail"],
        "parking": ["parking", "garage", "valet"],
        "storage": ["luggage", "locker", "suitcases", "bags", "storage"],
        "directions": ["map", "signage", "entrance"]
    }
}


# Clear topic category mapping (main_topic_category, sub_topic_category)
topic_category_mapping = {}
for main_category, subcategories in taxonomy.items():
    for subcategory, topic_keywords in subcategories.items():
        for keyword in topic_keywords:
            topic_category_mapping[keyword] = {
                "main_topic_category": main_category,
                "sub_topic_category": subcategory
            }

# Apply this mapping to the topic labels in df
mapped_topic_categories = topic_sentiment_df["topic_label"].apply(
    lambda label: topic_category_mapping.get(label, {"main_topic_category": "ot
)

# Expand into columns and merge
mapped_topic_df = pd.DataFrame(mapped_topic_categories.tolist())
topic_counts_categorized = pd.concat([topic_sentiment_df, mapped_topic_df], axi
topic_counts_categorized
```

	review_id	chunk_id	topic_label	final_sentiment	final_conf
0	38145	38145_Positive_0	clean	Positive	
1	133627	133627_Positive_0	breakfast	Positive	
2	133647	133647_Positive_0	singapore	Positive	
3	133649	133649_Positive_0	rooftop	Positive	

```
# count number of valid rows
topic_counts_categorized[topic_counts_categorized['main_topic_category'] != 'ot
```

```
83148
```

```
# Filter out rows labeled as "other"
filtered_topic_counts_categorized = topic_counts_categorized[topic_counts_cate
filtered_topic_counts_categorized
```

	review_id	chunk_id	topic_label	final_sentiment	final_conf
0	38145	38145_Positive_0	clean	Positive	
1	133627	133627_Positive_0	breakfast	Positive	
4	133653	133653_Positive_0	friendly	Positive	
6	35793	35793_Positive_0	airport	Positive	
7	133684	133684_Positive_0	spacious	Positive	

```
agg_df = filtered_topic_counts_categorized.groupby(["hotel_name", "main_topic_c
    count=("final_sentiment", "size"),
).reset_index()

agg_df
```

	hotel_name	main_topic_category	sub_topic_category	final_sentiment
0	30 Bencoolen	amenities	accessibility	Negative
1	30 Bencoolen	amenities	accessibility	Positive
2	30 Bencoolen	amenities	in_room	Negative
3	30 Bencoolen	amenities	leisure	Negative
4	30 Bencoolen	amenities	leisure	Positive
...	...	...	...	...
12237	voco Orchard Singapore by IHG	service	housekeeping	Negative

```
# Step 1: Pivot counts of Positive and Negative per hotel/topic
pivot_df = agg_df.pivot_table(
    index=["hotel_name", "main_topic_category", "sub_topic_category"],
    columns="final_sentiment",
    values="count",
    aggfunc="sum",
    fill_value=0
).reset_index()

# Step 2: Rename columns for clarity
pivot_df.columns.name = None
pivot_df = pivot_df.rename(columns={
    "Positive": "positive_count",
    "Negative": "negative_count"
})

# Step 3: Compute satisfaction_score
pivot_df["total_count"] = pivot_df["positive_count"] + pivot_df["negative_count
```

```
pivot_df["positive_sentiment_ratio"] = pivot_df["positive_count"] / pivot_df["t

# Step 4: Compute bayesian score for fairer comparison
aspect_avg_sentiment = (
    pivot_df.groupby("sub_topic_category")
    .apply(lambda df: df["positive_count"].sum() / df["total_count"].sum())
)

pivot_df["aspect_prior"] = pivot_df["sub_topic_category"].map(aspect_avg_sentim

m = 30 # Prior count for Bayesian smoothing
pivot_df["bayesian_score"] = (pivot_df["positive_count"] + m * pivot_df['aspect

pivot_df
```

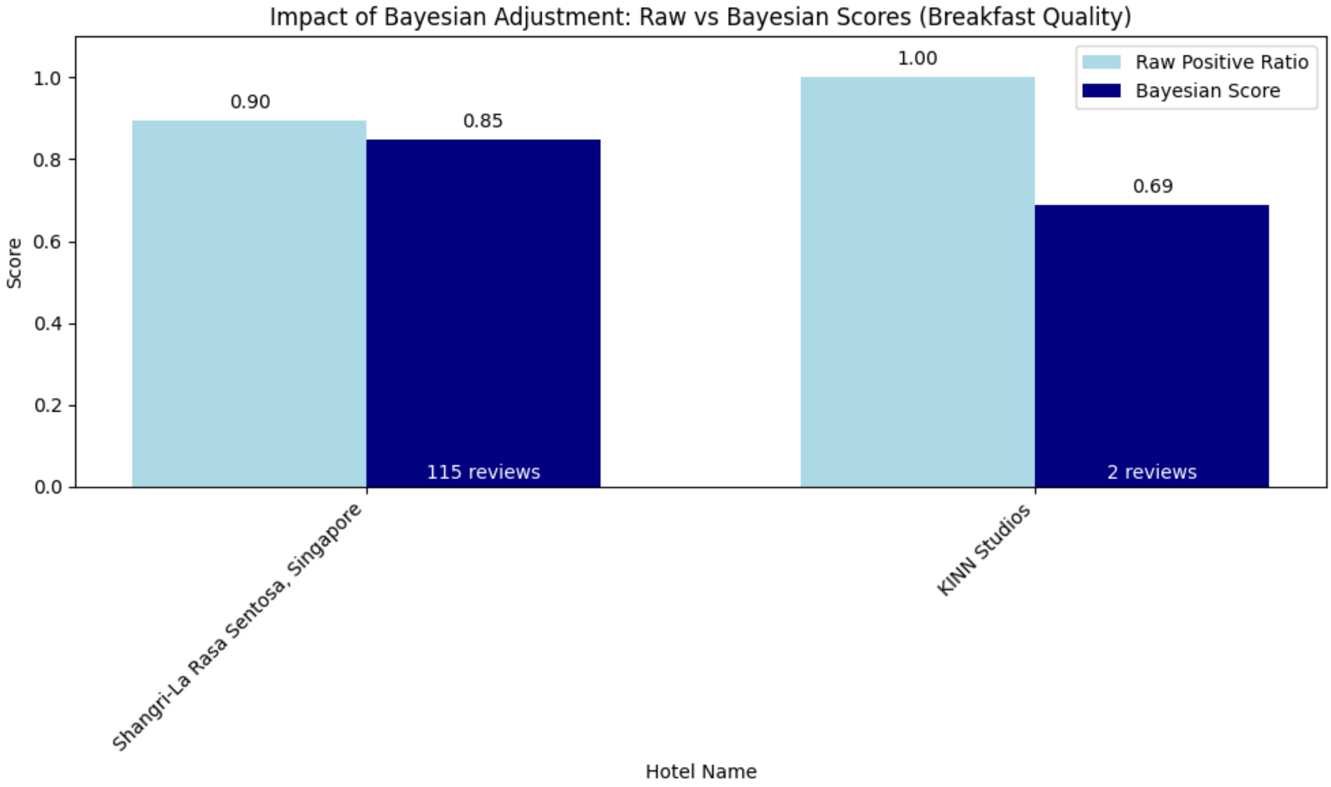
	hotel_name	main_topic_category	sub_topic_category	negative_count	p
0	30 Bencoolen	amenities	accessibility	1	
1	30 Bencoolen	amenities	in_room	7	
2	30 Bencoolen	amenities	leisure	35	
3	30 Bencoolen	amenities	tech	6	
4	30 Bencoolen	bathroom	bathroom_cleanliness	9	
...	...	...	...	...	
8357	voco Orchard Singapore by IHG	service	checkin_checkout	10	

```
pivot_df = pivot_df.drop(columns=["aspect_prior"])

pivot_df.to_csv('topic_sentiment_hotel_summary.csv', index=False)
print("Saved topic sentiment hotel summary to 'topic_sentiment_hotel_summary.cs
```

```
Saved topic sentiment hotel summary to 'topic_sentiment_hotel_summary.csv'
```

3. Visualisation

```
# Step 1: Filter for the aspect you want to focus on (e.g., 'breakfast_quality')
compare_df = pivot_df[pivot_df['sub_topic_category'] == 'breakfast_quality'].cop

# Step 2: Select interesting contrasts manually

# # (1) Small hotel: few reviews, large Bayesian adjustment
# small_hotel = compare_df[compare_df['total_count'] < 50].sort_values(
#     by='bayesian_score', ascending=False).head(1)

# (2) Large hotel: many reviews, minimal adjustment
large_hotel = compare_df[compare_df['total_count'] > 100].sort_values(
    by='bayesian_score', ascending=False).head(1)

# (3) High raw score but lower Bayesian score
high_raw_lower_bayesian = compare_df.sort_values(
    by='positive_sentiment_ratio', ascending=False).head(10)
high_raw_lower_bayesian = high_raw_lower_bayesian[
    high_raw_lower_bayesian['bayesian_score'] < high_raw_lower_bayesian['positiv
].head(1)

# # (4) Low raw score but better Bayesian score
# low_raw_higher_bayesian = compare_df.sort_values(
#     by='positive_sentiment_ratio', ascending=True).head(10)
# low_raw_higher_bayesian = low_raw_higher_bayesian[
#     low_raw_higher_bayesian['bayesian_score'] > low_raw_higher_bayesian['posit
# ].head(1)

# Step 3: Combine selections
selected_hotels = pd.concat([large_hotel, high_raw_lower_bayesian])

# Step 4: Plot
import numpy as np
x = np.arange(len(selected_hotels['hotel_name']))
width = 0.35

# Add bar labels and include review count as annotation
fig, ax = plt.subplots(figsize=(10, 6))

bars1 = ax.bar(x - width/2, selected_hotels['positive_sentiment_ratio'], width,
bars2 = ax.bar(x + width/2, selected_hotels['bayesian_score'], width, label='Bay

# Add text labels above each bar
for i, (bar1, bar2) in enumerate(zip(bars1, bars2)):
    count = selected_hotels.iloc[i]['total_count']
    ax.text(bar1.get_x() + bar1.get_width()/2, bar1.get_height() + 0.02
    ax.text(bar1.get_x() + bar1.get_width()/2, bar1.get_height() + 0.02,
            f"{bar1.get_height():.2f}", ha='center', va='bottom', fontsize=10)
    ax.text(bar2.get_x() + bar2.get_width()/2, bar2.get_height() + 0.02,
            f"{bar2.get_height():.2f}", ha='center', va='bottom', fontsize=10)
    ax.text(bar2.get_x() + bar2.get_width()/2, 0.01,
            f"{int(count)} reviews", ha='center', va='bottom', fontsize=10, colo

# Format axes
ax.set_xlabel('Hotel Name')
ax.set_ylabel('Score')
ax.set_title('Impact of Bayesian Adjustment: Raw vs Bayesian Scores (Breakfast Q
ax.set_xticks(x)
ax.set_xticklabels(selected_hotels['hotel_name'], rotation=45, ha="right")
ax.set_ylim(0, 1.1)
ax.legend()

plt.tight_layout()
plt.show()
```

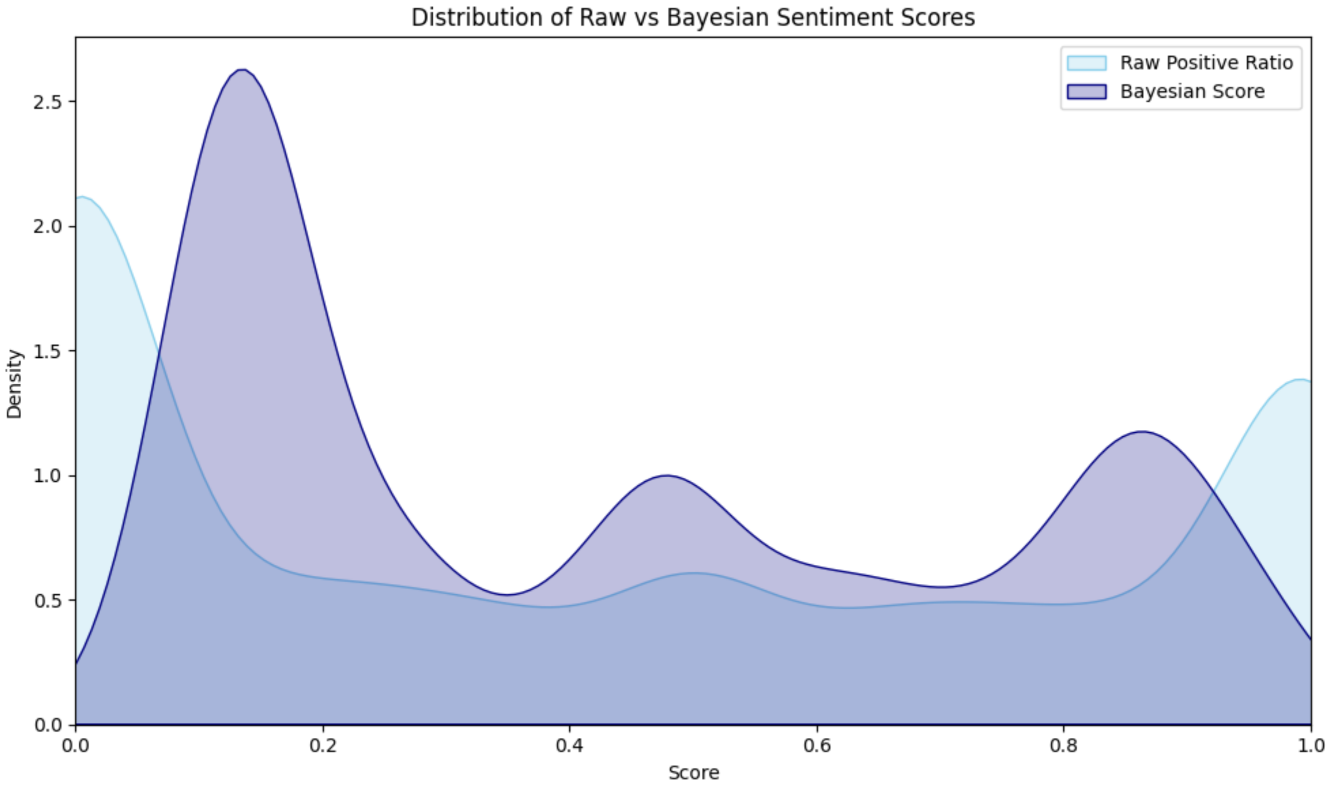

Impact of Bayesian Adjustment: Raw vs Bayesian Scores (Breakfast Quality)
Raw Positive Ratio
Bayesian Score
Score
1.0
0.8
0.6
0.4
0.2
0.0
0.90
0.85
1.00
0.69
115 reviews
2 reviews
Shangri-La Rasa Sentosa, Singapore
KINN Studios
Hotel Name

```
pivot_df
```

	hotel_name	main_topic_category	sub_topic_category	negative_count	p
0	30 Bencoolen	amenities	accessibility	1	
1	30 Bencoolen	amenities	in_room	7	
2	30 Bencoolen	amenities	leisure	35	
3	30 Bencoolen	amenities	tech	6	
4	30 Bencoolen	bathroom	bathroom_cleanliness	9	
...	...	...	...	...	
8357	voco Orchard Singapore by IHG	service	checkin_checkout	10	

```
# Filter to include only hotels with a reasonable number of total reviews to av
filtered_df = pivot_df[
    (pivot_df['total_count'] >= 5)
    # & (pivot_df['main_topic_category'] == 'amenities')
]

filtered_df = pivot_df.copy()
plt.figure(figsize=(10, 6))

# Plot overlapping KDE plots (distribution curves)
sns.kdeplot(filtered_df['positive_sentiment_ratio'], shade=True, label='Raw Pos
sns.kdeplot(filtered_df['bayesian_score'], shade=True, label='Bayesian Score',

plt.title('Distribution of Raw vs Bayesian Sentiment Scores')
plt.xlabel('Score')
plt.ylabel('Density')
plt.legend()
plt.xlim(0, 1)
plt.tight_layout()
plt.show()
```

```
C:\Users\ong_z\AppData\Local\Temp\ipykernel_15340\1615262375.py:11: FutureW

`shade` is now deprecated in favor of `fill`; setting `fill=True`.
This will become an error in seaborn v0.14.0; please update your code.

  sns.kdeplot(filtered_df['positive_sentiment_ratio'], shade=True, label='R
C:\Users\ong_z\AppData\Local\Temp\ipykernel_15340\1615262375.py:12: FutureW

`shade` is now deprecated in favor of `fill`; setting `fill=True`.
This will become an error in seaborn v0.14.0; please update your code.

  sns.kdeplot(filtered_df['bayesian_score'], shade=True, label='Bayesian Sc
```



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