Executive Summary:

This project aims to address the challenges faced by restaurants in effectively handling customer feedback by implementing an automated system to save time, work on customer engagement proper online presence.

The primary objectives included sentiment analysis of customer feedback and generating appropriate responses using SEO keywords. The scope covered various types of feedback, sentiment analysis techniques, and a carefully curated list of SEO keywords relevant to the restaurant industry.

1- Introduction:

In the rapidly evolving restaurant industry, having a strong digital presence is now essential for attracting customers. A good restaurant is not only judged by its food service and delivery but also by its online interaction. Customer feedback is crucial for shaping the success and reputation of establishments. However, effectively interpreting, understanding, and responding to feedback is a constant challenge for restaurateurs. The project, "Developing a Sentiment Analysis and Keyword-based Response System for Customer Feedback in the Restaurant Industry," aims to revolutionize how restaurants engage with customers online by providing meaningful responses to feedback on various platforms.

2- Problem Statement:

The modern restaurant industry emphasizes more than just serving food; it focuses on delivering a complete experience, from online discovery to the actual visit, determining whether customers will return or recommend the place. Restaurateurs must manage customer feedback from various online platforms, but manual analysis is time-consuming and prone to oversights, potentially resulting in delayed or poorly written responses, leading to customer dissatisfaction. The goal is to avoid these issues in order to enhance the overall customer experience.

Additionally, the strategic integration of SEO keywords in response generation is often neglected, impacting the online visibility and reputation of restaurants. This critical gap necessitates the development of an automated system capable of seamlessly combining sentiment analysis with a rule-based model for response generation. Such a system should categorize feedback sentiments, identify relevant entities through Named Entity Recognition (NER), and strategically incorporate SEO keywords to enable restaurants to not only understand customer sentiments but also enhance their online presence.

3- Project Scope :

Our project takes a comprehensive approach, covering diverse aspects such as collecting customer feedback and strategically incorporating SEO keywords in response generation. The scope of the project includes:

<u>SEO Keyword Curation:</u> Curating a list of SEO keywords specific to the restaurant industry to enhance online visibility.

<u>Data Collection:</u> Gathering customer feedback to form the basis for sentiment analysis and Name Entity Recognition.

<u>Sentiment Analysis:</u> Applying NLP techniques to classify feedback into positive or negative sentiment.

<u>Named Entity Recognition (NER):</u> Utilizing advanced tools to identify relevant entities and sensitive topics within the feedback.

<u>Rule-Based Model:</u> Designing and implementing a rule-based system to generate contextually appropriate responses based on sentiment and strategically incorporating SEO keywords.

4- Methodology :

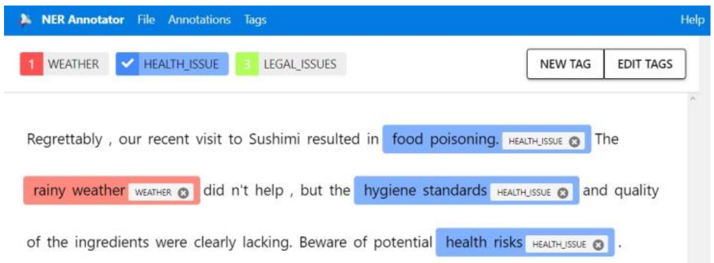
4.1 Data Collection :

We aimed to look for a prepared dataset. The internet is full of open and trusted sources of datasets we could potentially rely on. For our problem, we imported from kaggle a positive and negative restaurant feedback dataset.

Review	Liked
Wow... Loved this place.	1
Crust is not good.	0
Not tasty and the texture was just nasty.	0
Stopped by during the late May bank holiday off Rick Steve recomm	1
The selection on the menu was great and so were the prices.	1
Now I am getting angry and I want my damn pho.	0
Honeslty it didn't taste THAT fresh.)	0

For Name Entity Recognition, we made a little research and created our own dataset containing particular feedbacks using certain words in order to tackle our needed entities.

Using an open-source Name Entity Recognition Annotator we gave the Annotations to our feedbacks:



That's how we generated a json file containing our data annotated and ready to be processed.

For this case we chose to capture 3 relevant topics: Health, Legal and Weather Issues. This will help us generate a more customized answer.

4.2 Sentiment Analysis:

The sentiment analysis model is constructed using a deep learning approach, specifically BERT (Bidirectional Encoder Representations from Transformers), a pre-trained language representation model developed by researches in Google. The training process begins with data preprocessing, where reviews are cleaned and standardized. The dataset is then split into training and testing sets. Our BERT model is implemented through TensorFlow Hub, utilizing both the BERT preprocessor and encoder. The architecture of the model involves processing text inputs through the BERT preprocessor, followed by encoding with the BERT encoder. To capture contextual information effectively, the output is reshaped and passed through an LSTM (Long Short-Term Memory) layer with 64 units. A dropout layer is incorporated to prevent overfitting, and the final prediction is generated using a dense layer with a sigmoid activation function, enabling binary sentiment classification. The model is compiled with an Adam optimizer and binary cross entropy loss (since we have a binary classification).

This model represents a robust solution for sentiment analysis, combining the power of BERT embeddings and LSTM layers to capture nuanced contextual information in customer reviews.

4.3 Named Entity Recognition (NER):

The Named Entity Recognition (NER) model is implemented using spaCy to identify relevant entities and sensitive topics in customer feedback, enriching the depth of the analysis. and saving them later for the restaurant's use to work on their weak points of performance. The model is trained using a blank spaCy model, and annotations from the provided training data are added to create a training dataset. The training process is facilitated using a config file, enhancing the model's ability to recognize entities accurately.After the training we processes input text through the trained NER model, generating a dictionary of identified entities along with their corresponding labels.

This dictionary serves as a valuable resource for understanding the key entities and topics present in customer feedback, providing a nuanced perspective for answer generation and feedback analysis.

4.4 Rule-Based Model:

The rule-based model for generating responses is designed to craft personalized and contextually relevant replies based on the sentiment, SEO keywords, and identified Tag words. The function generating the answer takes input parameters, including the feedback sentiment, SEO keywords, and Tag words related to specific issues like weather, health, or legal concerns.

For positive sentiments, the model selects a response from a template, incorporating the relevant SEO keywords that help acknowledging the feedback and work on the restaurant’s visibility.

For negative sentiments, the model includes specific responses tailored to identified Tag words. If the negative feedback is associated with bad weather, a response acknowledging the weather-related inconvenience is provided. For health-related issues, a compassionate response encourages direct communication for prompt resolution. Similarly, if legal concerns are mentioned, an urgent invitation for contact is extended. While keeping in mind the use of adequate SEO keyword to each problem.

In cases of general negative feedback, the model offers a variety of empathetic responses, expressing regret and a commitment to improvement. The use of placeholders within the response templates allows for dynamic customization using proper SEO keywords and not falling under the repetition trap.

The rule-based approach enables the system to generate responses that are not only sentiment-aware but also contextually aligned with the identified issues and SEO keywords, ensuring a personalized and meaningful engagement with customers.

5- System Architectur :

The system architecture follows a streamlined flow to process customer feedback, extract key information, analyze sentiment, and generate a contextually relevant response. Here's a high-level over view of the system architecture :

Step 1 - Client Input and SEO Keywords: The process begins with the client inputting feedback, and relevant SEO keywords are extracted. This forms the initial data input for the system.

Step 2 – Keywords Mapping: Creating a dictionary from the SEO keywords input, which facilitates dynamic insertion of SEO keywords into response templates.

Step 3 – Extracting Sensitive Entities The system employs an entity extraction module to identify sensitive entities within the feedback. This step contributes to a more detailed analysis and customization of the response.

Step 4 – Analyzing feedback entities: The identified sensitive entities are then analyzed to determine specific issues or concerns. This step is crucial for tailoring responses to address the identified entities effectively.

Step 5 – Preparing Sentence for Sentiment Analysis: The feedback sentence undergoes preprocessing to ensure compatibility with the sentiment analysis model. This may include text normalization, cleaning, and any necessary adjustments to enhance the accuracy of sentiment prediction.

Step 6 – Predicting Sentiment: The preprocessed feedback is fed into a trained sentiment analysis model, which predicts the sentiment of the input. This step categorizes the feedback as positive, negative, or neutral.

Step 7 – Generate Response: Based on the predicted sentiment, identified sensitive entities, and SEO keywords, the system employs a rule-based model to generate a response. The response is crafted to be contextually relevant, addressing both sentiment and specific concerns highlighted in the feedback.

Step 8 - Output: The final response is outputted, providing a thoughtful and tailored reply to the customer feedback. This output can be displayed on the client interface or integrated into a broader customer relationship management (CRM) system.

The system works smoothly by taking in customer feedback, figuring out how the customer feels, and then crafting a personalized response. It uses different parts to dig deeper into the feedback, making sure it understands what the customer is saying, and then responds in a thoughtful way.

6- Results and Evaluation:

6.1 Sentiment Analysis :

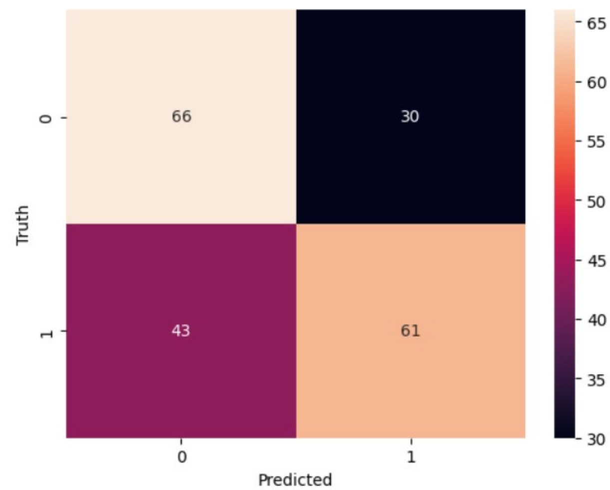
For the sentiment Analysis model, after some research and being based on previous experience, we chose to monitor the model’s performance through Accuracy Precision, Recall and F1 score.

the model demonstrates reasonably balanced performance for both classes, with a slight preference for class 0 (negative class) based on precision and recall metrics.

	precision	recall	f1-score	support
0	0.61	0.69	0.64	96
1	0.67	0.59	0.63	104
accuracy			0.64	200
macro avg	0.64	0.64	0.63	200
weighted avg	0.64	0.64	0.63	200

We Also chose to check our confusion matrix each time we were experimenting with training because theconfusion matrix is a powerful tool for evaluating sentiment analysis models, providing a detailed breakdown of performance metrics that enable a thorough analysis of the model's effectiveness and areas for improvement.

the confusion matrix reveals that the model is reasonably successful at identifying both positive and negative instances, but there are some misclassifications. The values in the matrix provide insights into the model's strengths and areas where it may need improvement.



Overall, the KPIs show some interesting results that are prone to improvement but also enough to experiment with.

6.3 Name entity Recognition :

This report shows the progression of the NER model's performance over different epochs and iterations. The model starts with higher losses but gradually converges to a state where both losses and evaluation metrics are optimized, indicating effective named entity recognition.

E	#	LOSS TOK2VEC	LOSS NER
0	0	0.00	45.21
33	200	191.76	1222.34
75	400	0.00	0.00
126	600	0.82	0.27

6.4 Rule Based Model :

Evaluating a rule-based model in our case is not a KPI monitoring matter, more of a shift of focus on simulations and manually improving the responses generated to make them more customizable. It was an individual effort to see how restaurants with good digital visibility respond and compare the already defined responses templates and modify them.

7- Discussion :

While the model seems to respond to basic feedback using basic SEO keywords, the solution has several limitations that we would surely want to work on.

7-1 Limitations :

Rule-based Model Rigidity: Due to the limited time and data resources, we opted for a rule-based approach in answer generation. While effective in capturing predefined scenarios, may be rigid in handling nuanced or evolving situations. The model's performance heavily relies on the predefined rules, and adapting to novel scenarios might require manual intervention.

Limited Context Understanding: The model's understanding of context is limited to the predefined rules and keywords. It may struggle to comprehend subtle nuances or sarcasm in user feedback that goes beyond the explicitly defined rules.

Handling Multilingual Inputs: The current approach may not be optimized for handling feedback in languages other than English. Adapting the model for multilingual support would be an area for improvement.

Handling Grammar errors: The current model does not handle grammar and syntax errors. which could heavily impact the Name Entity Recognition.

Limited Learning Capability: Unlike machine learning models that can learn from data, a rule-based model lacks the ability to learn from new examples. The model's improvement is contingent on manual updates to the rule set, which may not scale well in dynamic environments.

Inability to Handle Ambiguity: The model may struggle with ambiguous user feedback where the sentiment is unclear or there are multiple interpretations. Handling such ambiguity is a common challenge in rule-based systems.

Need for Regular Maintenance: The rule-based model requires regular maintenance to ensure that it remains aligned with evolving user behavior, language trends, and changes in the business domain. The need for manual updates introduces an ongoing maintenance overhead.

Standard SEO Keywords use: Although the answers are SEO research oriented. the model is still limited in its use to SEO's and still need human interference in order to create answers using adequate keywords.

7-2 Future Work:

Integration with OpenAI API: OpenAI provides APIs that allow developers to interact with their language models, including GPT-3. we can make API calls to generate responses based on user feedback using SEO keywords. As GPT-3 and 4 are quite performant in terms of text generation and conversational contexts.

Multilingual Support

Gather more feedback data

Enhanced Named Entity Recognition (NER): We can refine the NER component to handle a broader range of entities and improve accuracy. This can involve training the NER model on domain-specific data for better entity recognition.

Enhanced User Engagement Analytics: Integrate advanced analytics to monitor user engagement with the system. This can include tracking response effectiveness, user satisfaction, and user interactions to inform further improvements.

Dynamic Keyword Updating

Seasonal Keywords: Consider incorporating seasonal or temporal keywords that align with specific events, holidays, or seasonal trends. This can enhance the system's ability to generate responses that resonate with users during specific periods.

User Persona Consideration: Consider the personas of your target audience. Understand the language preferences and expressions of different user segments, and tailor the SEO keywords to resonate with diverse user groups.