**PERSONALIZED RESTAURANT RECOMMENDER SYSTEM**

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**Team Members:**

1) Harris Lukundi   - harris.lukundi@student.moringaschool.com

2) Henry Rono  - [henry.rono@student.moringaschool.com](mailto:henry.rono@student.moringaschool.com)

3) Beryl Agai - beryl.agai@student.moringaschool.com

4) Laaria Chris - laaria.chris@student.moringaschool.com

5) Lynete Wangari - lynette.wangari@student.moringaschool.com

6) Brian Muthama - brian.muthama@student.moringaschool.com

# Business Understanding

## Business Overview

The dining industry in various states across the United States is a dynamic and diverse landscape, offering a wide array of options from local eateries to upscale restaurants. However, both locals and tourists often struggle to find restaurants that align with their specific preferences in terms of location, cuisine, and quality. The sheer number of choices, coupled with the lack of a centralized platform for personalized recommendations, makes it challenging for users to make informed dining decisions.

Traditional methods of discovering restaurants, such as relying on word-of-mouth or general review platforms, often fall short in delivering tailored suggestions that cater to individual tastes. These solutions tend to be too broad and do not provide real-time, location-based recommendations, leaving users—especially those in unfamiliar areas—frustrated in their search for the perfect dining spot. The need for a more intelligent, user-centric solution is increasingly evident as the dining scene continues to grow.

The personalized restaurant recommender system addresses this gap by offering users customized dining suggestions based on their preferences and historical data. Utilizing advanced technologies like machine learning, the system provides real-time recommendations that are highly relevant and location-specific. The platform’s database includes detailed information about a vast range of restaurants across various states, capturing essential attributes like business details, reviews, ratings, and operational hours.

By analyzing this comprehensive dataset and integrating it with user profiles, the system can deliver personalized recommendations that match user preferences for cuisine, ambiance, proximity, and more. Whether a user is looking for a cozy brunch spot in California or an authentic BBQ joint in Texas, the system can quickly suggest top-rated options that meet their criteria. This tailored approach not only enhances the dining experience but also supports local businesses by driving targeted traffic to their establishments.

The platform's intuitive interface ensures that users can easily refine their search and explore new dining options with confidence. This personalized restaurant recommender system stands out as a valuable tool, helping users navigate the rich culinary landscape with ease and satisfaction.

## Stakeholder Definition

The possible stakeholders in this project include:

•   Users: Individuals seeking personalized dining recommendations based on their unique preferences.

•   Restaurant Owners: Local businesses aiming to attract targeted customers and increase foot traffic.

•   Investors/Partners: Entities interested in the platform’s growth, scalability, and profitability.

## Problem Statement

As the dining industry expands, finding restaurants that match personal preferences is challenging due to the overwhelming number of options. Current platforms often provide generalized recommendations and lack real-time, location-based suggestions, particularly for users in unfamiliar areas. There is a growing need for a smart, user-friendly recommender system that offers personalized, real-time dining suggestions to help users quickly and efficiently navigate diverse culinary choices and improve their dining experiences.

## Objectives

### Main Objective

Develop an intelligent, user-friendly restaurant recommender system that provides personalized recommendations based on user location and cuisine preferences, and additional data sources to ensure accuracy and relevance.

### Specific Objectives

1. Analyze whether businesses in specific categories or locations tend to receive higher or lower average ratings and examine if a higher number of reviews correlates with more positive ratings.
2. Provide content about different cuisines and dining etiquette to enrich the user experience.
3. Create machine learning algorithms to rank restaurants based on user location, cuisine preferences, and ratings.
4. Develop an intuitive, responsive web/mobile application.

## Proposed Solution

We propose developing a Restaurant Recommender System specifically for the United States. The system will:

* **Comprehensive Mapping:** Systematically map and categorize restaurants in the United States, grouping them by cuisine type, location, and other relevant factors.
* **Personalized Recommendations**: Enable users to input their current location and preferred cuisine type, delivering a ranked list of nearby restaurants based on their ratings and proximity.
* **Enhanced User Experience:** Offer an intuitive, user-friendly interface with integrated map features to simplify navigation and help users easily explore and select dining options.

## Metrics of Success

Metrics of Success will include:

•   **User Engagement**: Measured by the number of active users, frequency of use, and user retention rates.

•   **Recommendation Accuracy:** Evaluated through user feedback and satisfaction scores, focusing on how well the recommendations match user preferences.

•   **Business Impact:** Analyzed by the increase in traffic and revenue for partnered restaurants.

•   **Scalability:** Assessed by the system’s ability to handle an expanding user base and restaurant data across various states.

## Challenges

Some of the challenges we may experience during this project include:

* **Data Collection and Quality:** Ensuring the platform has access to accurate and up-to-date restaurant data is crucial, as incomplete or outdated information can lead to poor recommendations and user dissatisfaction.
* **Scalability:** As the user base and the number of restaurants grow, the platform must efficiently handle increased data processing and maintain real-time performance across various states, ensuring a seamless user experience.
* **Competition:** Differentiating the platform from established competitors like Yelp and TripAdvisor is essential. The platform needs to offer unique value propositions to attract users in a crowded market.
* **Privacy and Data Security:** Protecting user data and ensuring compliance with privacy regulations is a significant challenge. Building trust with users regarding data usage is vital to maintaining their engagement and loyalty.

# Data Understanding

The data used to develop this project was collected from a vast Yelp database where reviews and business data was utilized. The business data contained a wide variety of businesses and was filtered to contain only the data from restaurants, coming to a total of 52,286 rows and 14 columns and stored as restaurant data. The reviews data was filtered to only include restaurant reviews and only for one year. This brought the total number of entries to 429,771 rows and 9 columns and was stored as users’ data.

The data was loaded using a dataloader class and a datainfo class to gather all the information together. A datacheck class was employed on the datasets with the following results: The restaurant data contained no duplicates or outliers but had some missing values. There were no duplicates, outliers or missing values in the users’ data.

Exploratory data analysis (EDA) was carried out on the restaurant data where the following was explored, counts of restaurants per state, frequency counts of ratings, frequency of restaurant names, distribution of star rating per state, and review counts vs stars rating.

EDA was also carried out for the users’ reviews data which showed seasonal trends with peaks around April and July and decline in reviews in between September and December. A word cloud was explored for the reviews and most common words included food, place, restaurant, order, service, good.

# Data Preparation

The users’ dataset was first prepared. There were no missing values, outliers or duplicates to handle. The columns useful, funny, cool were dropped as they did not contain any useful information for the recommendation system.

For the restaurant data, the attributes column was missing 0.8% of its dataset. These rows were dropped as attributes column is crucial for modeling. The other rows missing values i.e. address, postal code, hours were filled with Unknown as this information was not to be used in modelling and hence dropping then would result in losing out of data points. A value count of state column revealed 4 states with 1 restaurant each and these rows were dropped i.e. states containing NC, HI, XMS, MT and CO as recommending in a state with 1 restaurant will be flawed. The remaining 14 states were mapped with their full name for better understanding e.g. CA changed to California.

Feature Engineering was carried out on the categories column to explode the categories so as to filter each restaurant. The exploded column was then standardized to remove spacing between words. This was done so as to achieve a dataframe with only the specific cuisine/s in that column e.g. a row having Vietnamese, Food, Restaurants, and Food Trucks as a category was engineered to have Vietnamese as its category.

Further engineering was performed to combine city, state and address into one column called location which would be used to for modeling. The user data containing 429771 rows and 6 columns was saved in a cleaned user data csv, while the restaurant data containing 38,550 rows and 16 columns was pickled for ease of deployment.

# Modelling

The approach take to model the recommender system was split into 3:

1. Content Based Filtering
2. Collaborative Based Filtering
3. Deep Neural Networks
   1. **Content Based Filtering**

To perform content based filtering, The restaurant's features such as types of cuisine they offer and attributes such as Wi-Fi, Alcohol, Happy Hour, Noise Level, Restaurants Attire, Wheelchair Accessible, Restaurants Table Service etc., were able to provide information to use cosine similarity to recommend the restaurants with the closest similarity.

A preprocessing function was generated that combines the columns containing the categories and the attributes into one column and return a combined features columns. A create feature vectors function was also created that takes these features and vectorizes them using TfidfVectorization as it captures term importance across the document. This sparse array is then converted to an array and stacked together with the stars ratings along the horizontal columns to return a 2D array which has the combined features

A recommendation function was then created that takes in a dataframe, the state where the recommendation shall take place, name of restaurant or cuisine/category type. From where two actions would take place, either recommendation based on cuisine or restaurant name. By filtering using cuisine type, the state filters the dataframe and then these data is then filtered using the desired cuisine and the results are a recommendation based on star ratings while returning a dataframe containing the name, state, city, state, address and categories/cuisine

If the recommendation is based on restaurant name, the dataframe is preprocessed using the preprocess function from which the index of the desired restaurant is gotten and used to get the specific row of this restaurant and converted to a 1 row dataframe. A specific state dataframe is then generated by only using the restaurants from the desired state. The 1 row dataframe and the specific state dataframe are concatenated into specific state dataframe and their index reset. From which the restaurant’s new index is gotten.

The create feature vectors function is run on this specific state dataframe and the cosine similarity gotten for the combined features that were generated. The restaurant index is then used in the cosine similarity results and a similarity score is gotten. From which these scores are sorted in descending order and the top indices used to locate the recommended restaurants. The function then returns the name, state, city, address and cuisine/categories.

Testing of the recommendations show them in line with requirements i.e. while seeking cuisine recommendations within a specific state, it recommends appropriately and while seeking recommendations based on restaurant name, it gives recommendations in the chosen state and with similar attributes.

* 1. **Collaborative Based Filtering**

For the collaborative based filtering, which utilizes users specifics, business id and ratings, the user reviews data was used. This data contained the desired columns i.e. user id, business id and stars. It was merged together with the restaurant data to ensure that the business ids used in modeling were shared between both dataset.

Preprocessing for modeling was performed which involved picking the 3 desired columns i.e. user id, business id and ratings (stars) from the merged dataframe and assigned to a new dataframe i.e. new df. The surprise module was used as it is tailor made for recommendation systems. The reader class was instantiated to parse and interpret the ratings data and the dataset.load\_from\_df function was used to convert the dataframe to a format that the surprise library can interpret. From which the data was trainset, testset split.

A normal Predictor class was used as a dummy prediction model from which an RMSE of 0.819 was achieved, next an NMF with default parameters was used as it is ideal when ratings are non negative. This achieved an RMSE of 0.3489. Next an SVD model with default parameters was used as it works well with explicit feedback. This achieved an RMSE of 0.114.

From here we performed hyper parameter tuning on the SVD model using the number of epochs, regularization and latent factors. From which we achieved a much improved RMSE of 0.068. This then saved into a pickle for deployment.

Integration of the collaborative filtering involved using the collect ratings function that would filter the dataframe based on state, from which random samples would be taken. The user would provide their ratings or skip if they have never been to those restaurants. The restaurants are rated on a scale of 1-5. Once rated, the results would be appended to a ratings list as a tuple containing the restaurant id and the rating. Once the desired restaurants have been rated, the function would break.

A recommend restaurant function was also created that would take in the user id, the rated restaurant, the complete restaurant df and state. The dataframe would be filtered according to state from which the unique business ids were gotten. A new dataframe would be generated from the rated restaurants using the collect ratings function. This user rating dataframe would include the user id which would have to be input by the user. The new dataframe and the global dataframe new df are concatenated into one and filtered using the business ids that were derived previously based on the restaurants only in that state. This data is then trained in the function using SVD and the parameter we had previously achieved as we want the dataframe to keep updating each time based on the new information it receives. The unrated restaurants ids are gotten by filtering out the rated restaurants ids and these are used together with the user id to predict how a user would rate these unrated restaurants. From which the business id and predicted rating is gotten and set in a dataframe. This is then merged with the restaurant dataframe and sorted by the predicting ratings which is then returned as the recommendations.

Testing of the system involved running the collect ratings function and feeding it varying ratings on the restaurants provided. This resulted in the recommendation dataframe providing varying results based on the ratings given as well as giving a different prediction rating to these restaurants.

* 1. **Deep Neural Networks**

In the development of our recommendation system, we employed a deep neural network (DNN) using the Keras framework to enhance our RMSE scores through advanced neural network techniques. The initial model was designed with a three-layer architecture. The first dense layer consisted of 30 nodes with ReLU activation, followed by a second dense layer with 15 nodes also using ReLU activation. The output layer utilized a sigmoid activation function to produce ratings between 0 and 1. These predictions were then scaled to a range of 1 to 5 using a Lambda layer. The model was compiled with the Stochastic Gradient Descent (SGD) optimizer, the Mean Squared Error (MSE) loss function, and RMSE as the primary evaluation metric. Training was conducted on the X\_train and y\_train datasets, with validation on X\_test and y\_test over 10 epochs with a batch size of 256. During training, the model showed gradual improvement, with RMSE decreasing from 1.5015 in the first epoch to 1.4409 by the tenth epoch, while the validation RMSE also improved, highlighting the model's learning capacity.

To further enhance the model's performance, tuned the model further which introduced user and restaurant embeddings, bias terms, and a dense layer with 15 neurons incorporating L2 regularization to prevent overfitting. Additionally, a dropout layer with a rate of 0.3 was added to further reduce over fitting risks. The model retained the sigmoid activation in the output layer, with ratings scaled to a specified range. Compiled with the SGD optimizer and MSE loss, this model was trained for 20 epochs with a batch size of 256. The results indicated significant progress, with the RMSE dropping from 1.4413 in the first epoch to 0.8703 by the twentieth epoch. However, while the training RMSE showed consistent improvement, the validation RMSE exhibited some instability, suggesting potential overfitting as the validation error remained higher than expected.

In response to the overfitting observed in the previous model, we further tuned the model. This model followed a similar architecture, with user and restaurant embeddings and bias terms, but the dense layer was adjusted to have 10 neurons with ReLU activation. The dropout rate was increased to 0.6 in an effort to further mitigate overfitting. Despite these adjustments, the model did not significantly outperform its predecessors. The initial RMSE started at 1.2586 for the training set and 1.3816 for the validation set, with the final RMSE at 0.9310 for training and 1.4233 for validation after 20 epochs. The persistent gap between training and validation RMSE suggested ongoing issues with over fitting, despite the increased dropout rate. Each epoch's duration ranged from 220 to 270 seconds, reflecting the model's complexity and the dataset's size.

In conclusion, further tuning was aimed to address the overfitting observed in the earlier models, it ultimately did not achieve the desired balance between training and validation performance. The best neural network model, based on validation RMSE, remained the baseline vanilla model, with a validation RMSE of 1.3179. However, even this model's performance was still inferior to that of the optimized SVD model, indicating that further refinements and alternative approaches may be necessary to achieve optimal results.

**4.4 Comparing the SVD and the best performing dense neural network.**

**1. Error Metrics**

The Singular Value Decomposition (SVD) model achieves a significantly lower RMSE of 0.0683, indicating superior accuracy in predicting ratings. In contrast, the Deep Neural Network (DNN) model has a much higher RMSE of 1.4409, suggesting that its predictions deviate more from the actual ratings. This substantial difference highlights SVD’s better performance in minimizing prediction error.

**2. Model Complexity**

SVD is relatively simple and requires fewer computational resources, as it involves basic matrix decomposition with fewer parameters and epochs. On the other hand, DNN is complex, requiring extensive training with multiple layers and hyper parameters, which increases computational cost and complexity. This makes SVD a more efficient choice in terms of model complexity and resource usage.

**3. Training and Validation Time**

Training the DNN model is time-consuming, with each epoch taking between 246 to 334 seconds, and requiring 10 epochs for completion. In contrast, SVD typically involves fewer epochs and is computationally less intensive, leading to faster training times. This efficiency in SVD makes it more practical for scenarios where quick model iteration is needed.

**4. Overfitting and Generalization**

The DNN model shows a higher RMSE on validation data compared to training data, which may indicate overfitting and reduced generalization. Conversely, the SVD model exhibits low and consistent RMSE values across both training and validation sets, suggesting better generalization and a lower risk of overfitting. This makes SVD a more reliable model for unseen data.

**5. Interpretability and Usability**

SVD is more interpretable, as it breaks down the user-item matrix into latent factors, making it easier to understand how recommendations are generated. The DNN model, with its complex architecture, functions more like a "black box," making it harder to decipher the underlying decision-making process. This interpretability advantage of SVD provides clearer insights into the recommendation mechanics.

Despite improvements, the DNN’s final RMSE is higher than the SVD model's, suggesting that the SVD model performs better with this dataset and may require less tuning.

We will deploy the optimized SVD.

# Future Work

1. **Expansion of Dataset**

To further enhance the effectiveness of the restaurant recommendation system, expanding the dataset is crucial. A broader range of cuisines and restaurant types should be included to keep up with emerging culinary trends and global dining options. By doing so, the system can cater to a more diverse audience with varying tastes and preferences. Additionally, incorporating crowdsourced data and user-generated content will enrich the dataset with real-time insights and feedback, ensuring that the recommendations remain current and reflective of actual user experiences. This approach will provide a more dynamic and responsive recommendation system that can adapt to changing trends and user expectations.

1. **Enhanced User Interface and Experience**

Improving the user interface and experience is another important area for future work. Integrating Augmented Reality (AR) features can significantly enhance the decision-making process by allowing users to visualize restaurant interiors or dishes before making a visit. This immersive experience can make the selection process more engaging and informative. Additionally, developing voice-activated features will offer a hands-free, convenient way for users to search and interact with the system, catering to the growing demand for voice technology in digital interactions.

1. **Integration with Other Services**

Expanding the system’s functionality by integrating it with other services, such as reservation platforms, would greatly enhance user convenience. By allowing users to book tables directly through the recommendation system, the platform can offer a seamless experience from discovery to reservation, making it a one-stop solution for dining out. This integration would not only streamline the user journey but also increase the system's utility and appeal.

1. **Feedback and Continuous Improvement**

For the recommendation system to remain effective and relevant, establishing robust feedback loops is essential. Implementing mechanisms for continuous user feedback will enable the system to refine its recommendations and improve performance over time. Additionally, regular A/B testing should be conducted to evaluate the effectiveness of new features or algorithms. This data-driven approach will ensure that the system evolves based on user needs and preferences, maintaining its accuracy and reliability.

1. **Expanding Geographical Coverage for Data Collection**

Finally, expanding geographical coverage for data collection is vital to making the recommendation system more inclusive and comprehensive. By collecting data from a wider range of locations, the system can provide users with a broader spectrum of dining options, tailored to different regions and cultural preferences. This expansion will not only improve the user experience but also enhance the system’s ability to cater to a global audience.

1. **RECOMMENDATIONS**
2. **Tailoring Recommendations to Major Markets**

The data indicates that Pennsylvania, Florida, and Tennessee have the highest number of restaurants among the states. Given the density of options in these regions, it's crucial to prioritize these markets by ensuring that the dataset is comprehensive and up-to-date. Advanced filtering options and more detailed reviews should be implemented to meet the higher demand and wider variety of choices in these states. Additionally, the recommendation depth should be adjusted based on market size. In major markets like PA, FL, and TN, offering more granular and diverse recommendations is essential. Conversely, in regions with fewer options, such as North Carolina, Colorado, Hawaii, and Montana, the focus should be on quality over quantity, highlighting the best available choices. Furthermore, it's recommended to showcase a mix of popular spots and hidden gems in high-density areas while emphasizing unique standout options in less populated regions.

1. **Leveraging Fast-Food Chains' Popularity**

The dominance of fast-food chains like McDonald's, Subway, Taco Bell, Wendy's, Domino's Pizza, and Pizza Hut suggests a significant user preference for familiar and reliable dining options. To capitalize on this trend, it's recommended to prominently feature these popular chains in the recommendations. Highlighting these well-known brands can enhance user satisfaction, particularly for those seeking quick and dependable meals. Additionally, targeted recommendations based on user segmentation can further refine the experience. For example, users with a history of choosing fast-food chains might receive more suggestions for similar dining options, aligning the recommendations with their preferences.

1. **Incorporating Seasonality into Recommendations**

The finding of seasonal trends, with frequent peaks in customer engagement between April and July, presents an opportunity to optimize recommendations during these periods. It is recommended to increase the visibility of restaurants that typically see higher engagement during these months. Featuring seasonal promotions or highlighting trending restaurants during peak times can enhance user engagement and satisfaction. By incorporating seasonality into the recommendation strategy, the system can better align with user behavior and preferences, offering timely and relevant dining options.

1. **Diversifying Cuisines and Catering to Dietary Preferences**

The current list of options does not include all popular cuisines, which presents an opportunity for further enhancement. To provide a more nuanced dining experience, it's recommended to feature variations of cuisines from different regions, such as Southern Italian versus Northern Italian. Additionally, incorporating filters for dietary preferences and restrictions, such as vegetarian, vegan, and gluten-free options, can offer more personalized recommendations, catering to a broader audience. To appeal to adventurous diners, the system could also explore emerging cuisines and new restaurant concepts, introducing users to new dining experiences that might pique their interest.

1. **Conclusions**

In conclusion, the project successfully achieved its primary objective of developing an interactive and user-friendly restaurant recommendation system. This system not only delivers personalized dining suggestions but also considers a range of factors that influence restaurant ratings and user preferences, such as cuisine type, location, and user history. By integrating advanced recommendation algorithms, the system enhances the dining experience, providing users with highly relevant and tailored restaurant choices.

Throughout the project, we also met specific objectives, including the design and development of an intuitive website that makes it easy for users to interact with the recommendation system. The website's user-friendly interface ensures a seamless experience, allowing users to effortlessly explore dining options. Furthermore, we conducted comprehensive analyses of the key factors that significantly impact restaurant ratings and user preferences. These insights were vital in fine-tuning the recommendation algorithms, ensuring that the suggestions provided are both valuable and relevant to users, ultimately improving their overall satisfaction.