BEACONHOUSE NATIONAL UNIVERSITY

Wasail

PRJ-F23/333

DESIGN DOCUMENT

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SCHOOL OF COMPUTER & IT

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Introduction

The design document presented here outlines a comprehensive approach to developing a demand forecasting system for grocery stores and creating an environment to aid the communication between them and the vendors. Leveraging a diverse set of technologies, the system integrates machine learning models with a robust backend infrastructure and a user-friendly front end. The document delves into various components such as development tools, programming languages, data storage, machine learning frameworks, and cloud services. It also provides detailed insights into the system architecture, data design, and the integration of machine learning for demand forecasting. With a focus on feature engineering and model selection, the document showcases the meticulous process involved in preparing datasets, cleaning, and transforming them for accurate predictions.

Development Tools

Programming Languages

- Python
- JavaScript
- Dart

Machine Learning

- TensorFlow
- PyTorch
- Scikit-Learn
- Prophet (Facebook)
- LightGBM
- N-BEATS
- DeepAR (Amazon)
- Temporal Fusion Transformer (Google)

Cloud Services

- Digital Ocean

Web Development

- Front-End
    - HTML
    - CSS
    - Bootstrap
    - React
- Back-End
    - Node.js
    - Express.js
    - Flask

Data Storage

- MySQL

Object Relational Mapper

- Sequelize

Mobile Development

- Flutter

Version Control

- GitHub

Project Management

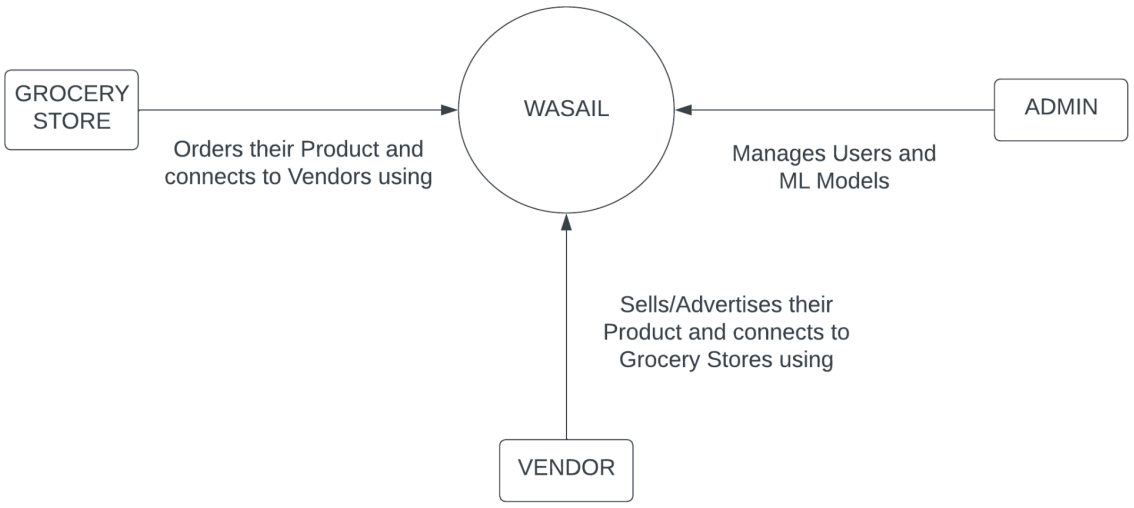
- Jira

Collaboration

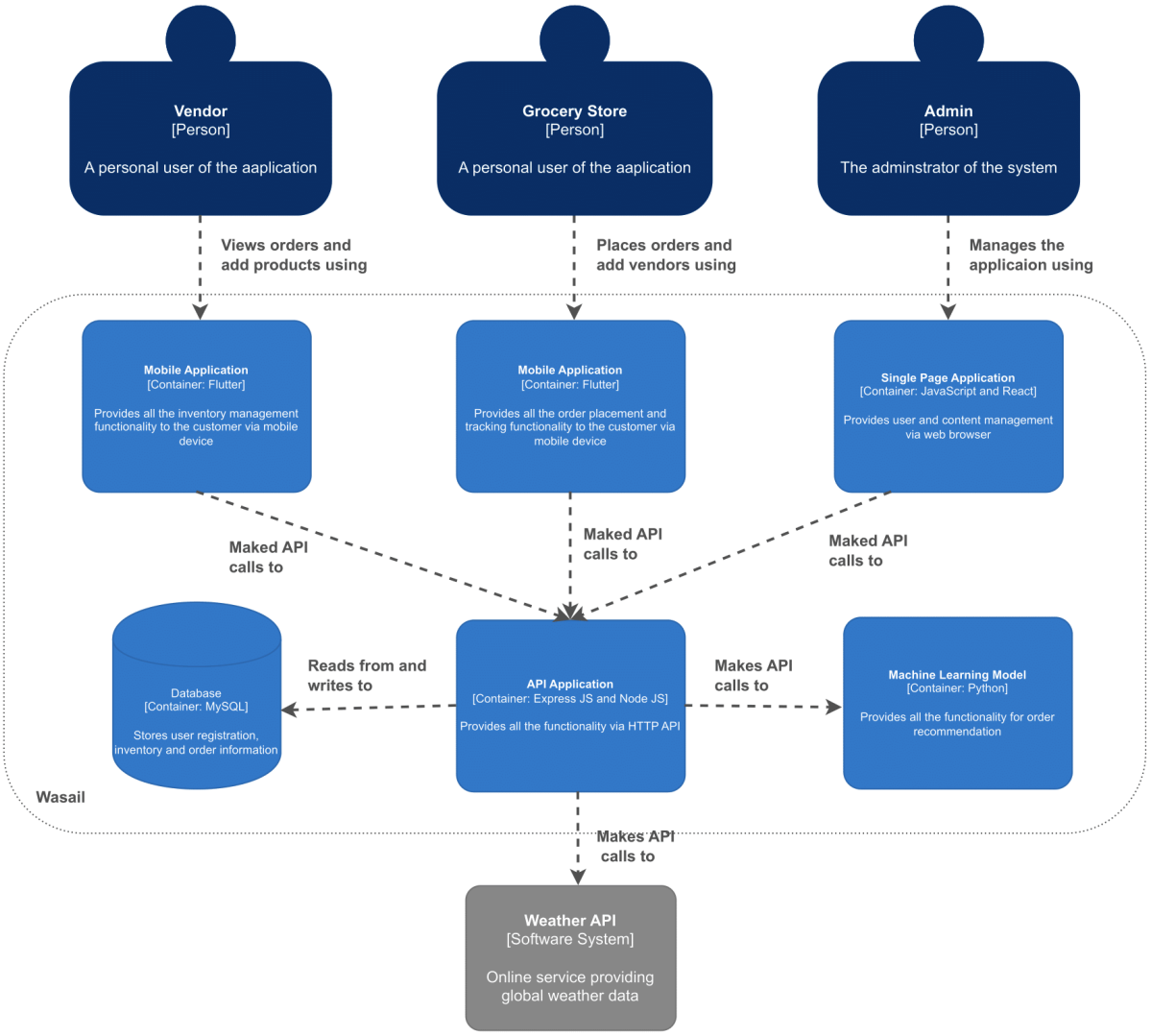
- Discord

System Architecture

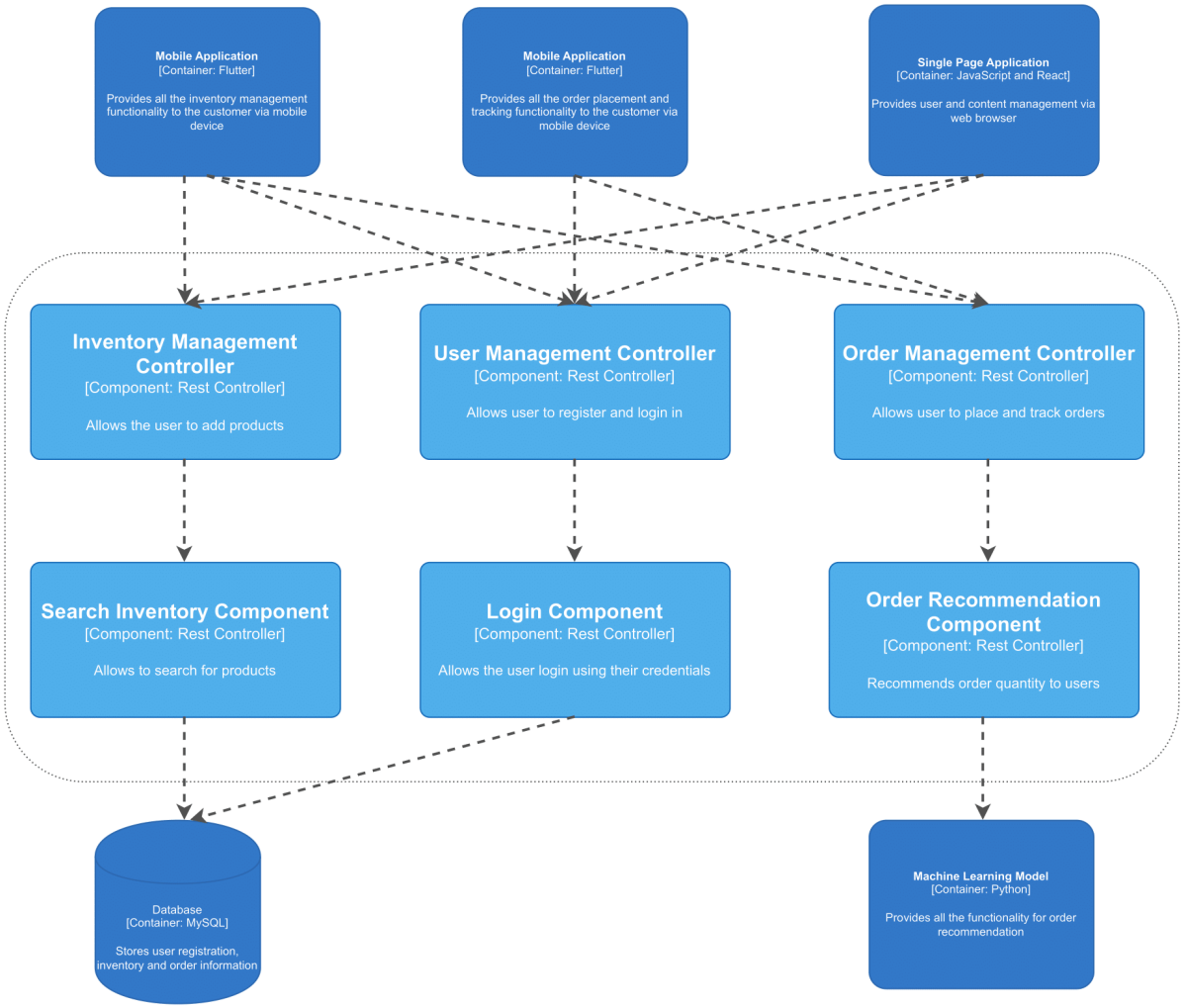
System Context Diagram



Container Diagram

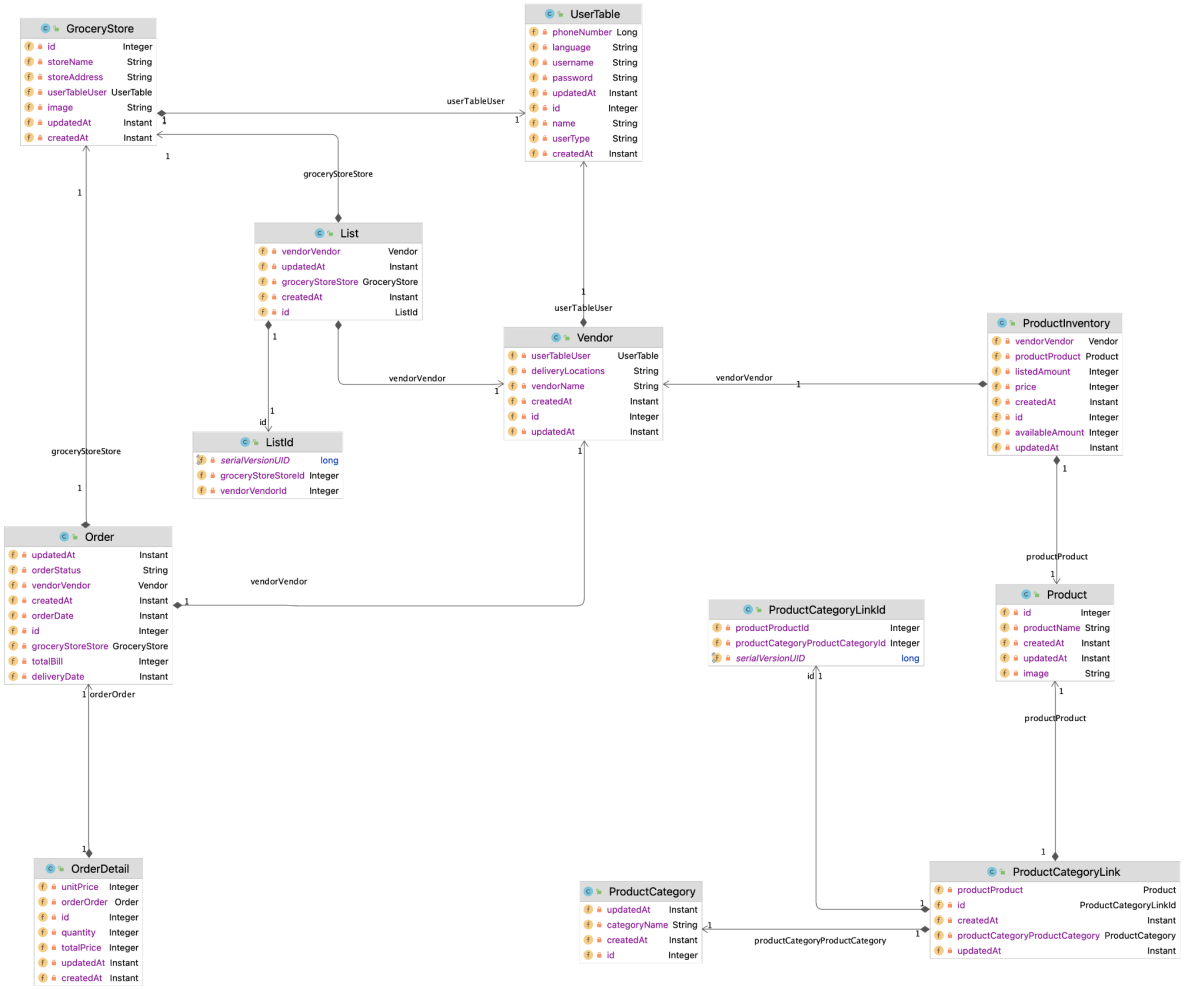


Component Diagram

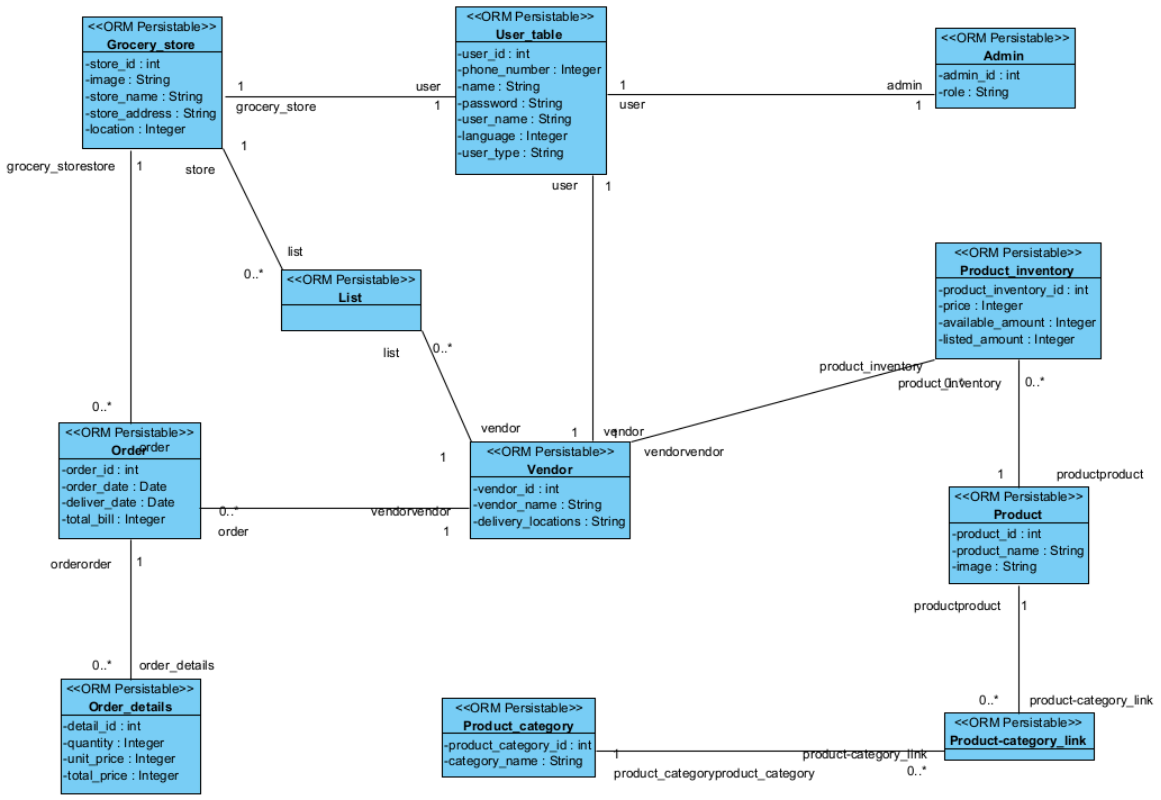


Class Diagram

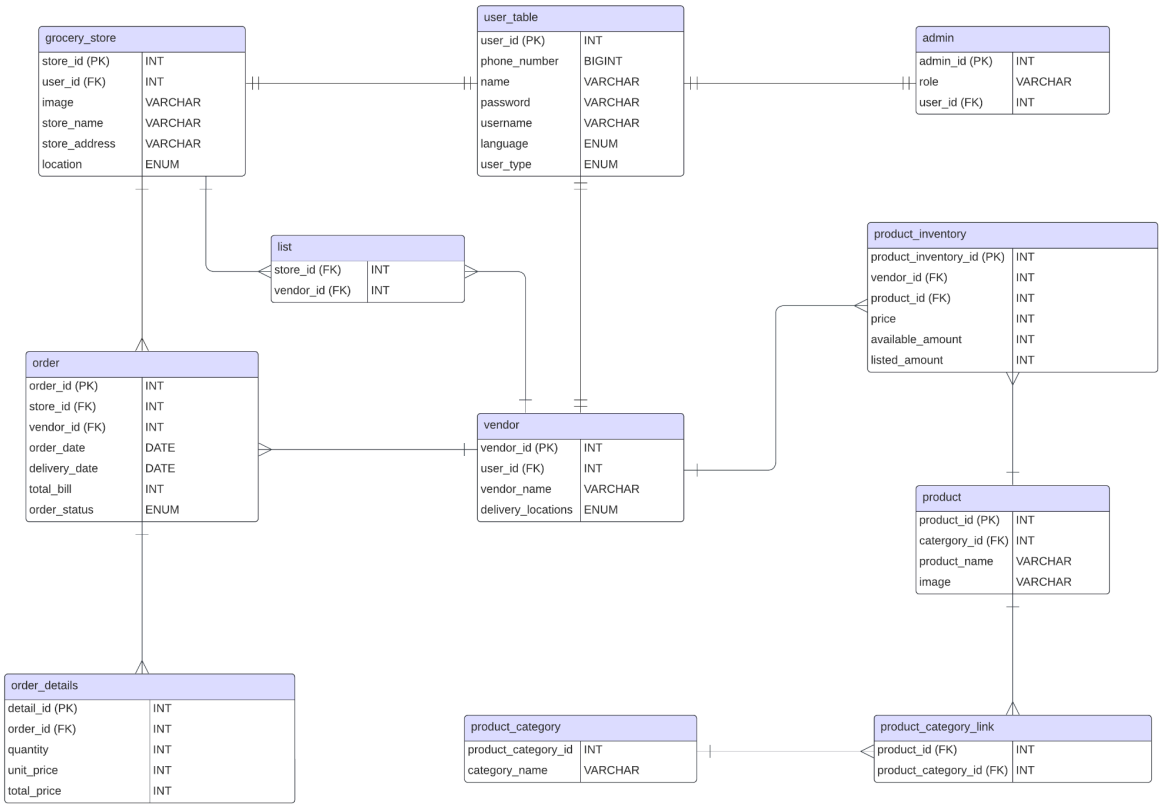
(Automatically generated using JetBrains)



(Automatically generated using VisualParadigm)



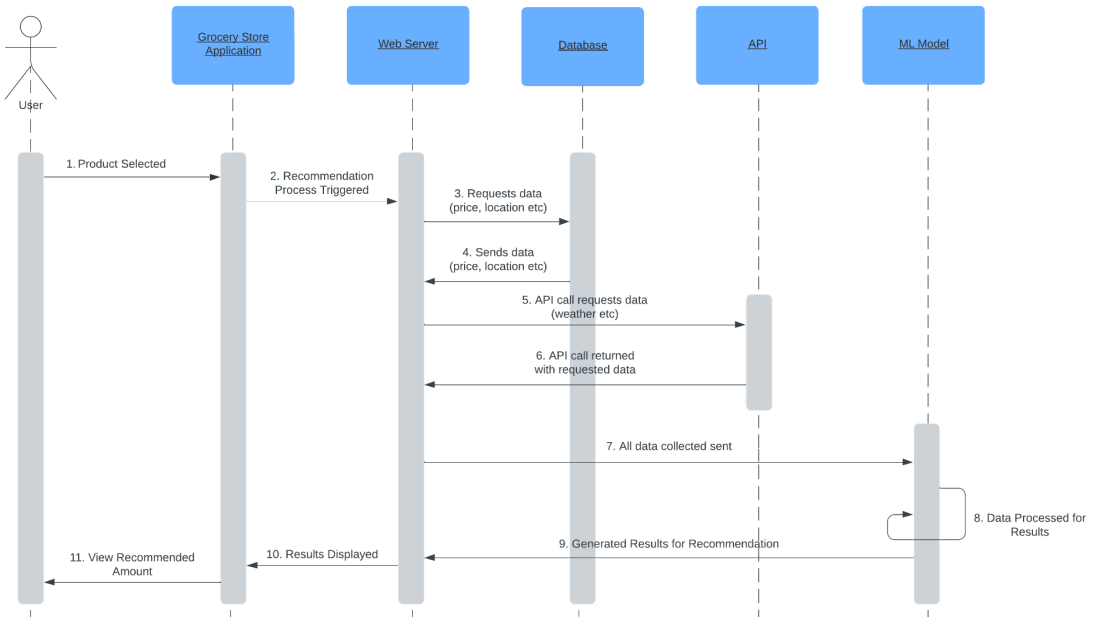
Data Design



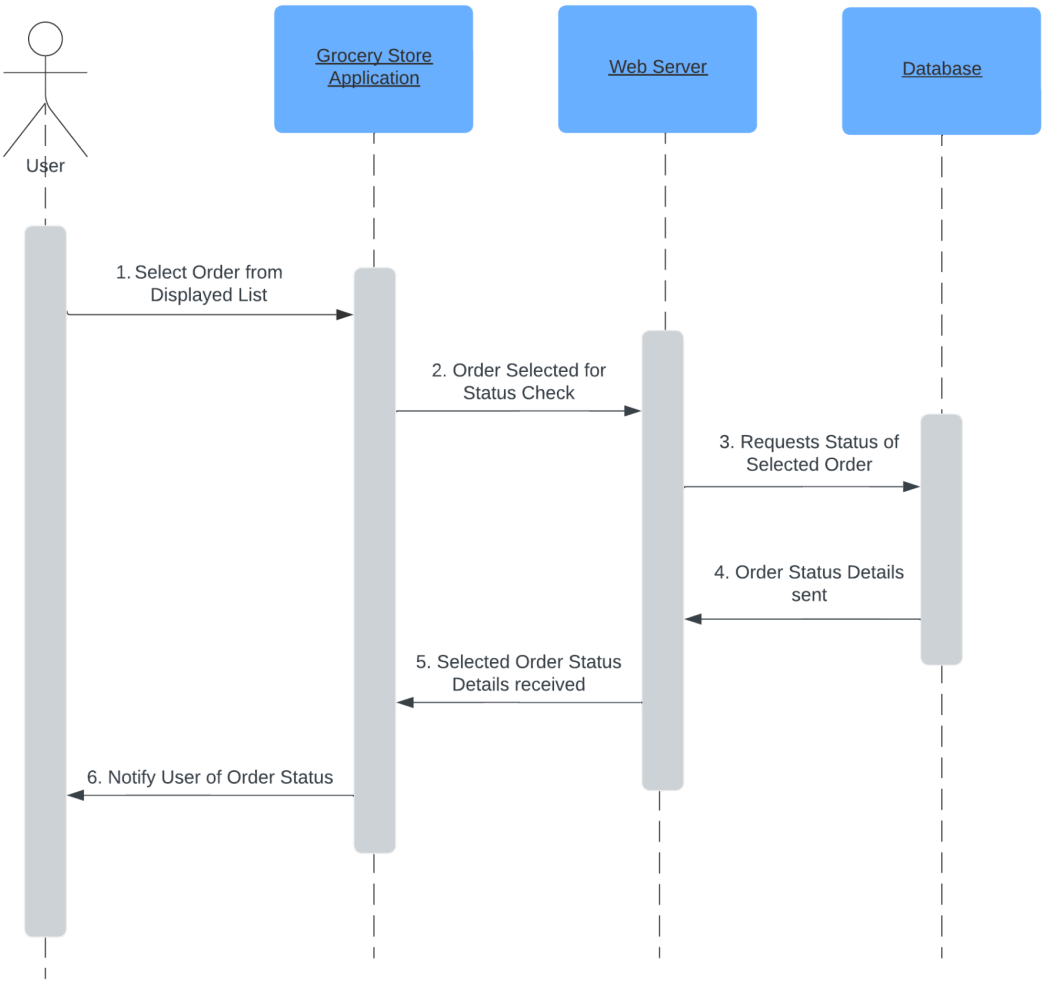
When designing the database diagram, it was mainly divided into three sections; user management, inventory management, and order management. Under user management the tables that were created were user table, vendor, grocery store and admin. All the common attributes including phone number, name, password, user name, language and user type were in the user table which had a one to one relation with grocery store, vendor and admin. Since a grocery store and vendor had a many to many relationship (one grocery store can have many vendors and vice versa), it required a pivot table (called lists), since a many to many relation can not be made in the diagram. Next, under the inventory management section, the tables that were created were product (a table from which the vendor will add products to their own inventory), product inventory (the vendors' own inventory), product category (the table that will contain the categories of the product) and product category link. Similar to the vendor and grocery store table, the product and product category tables also have a many to many relation and hence requires a pivot table. Lastly, under order management, order and order details were the two tables that were created.

Sequence Diagrams

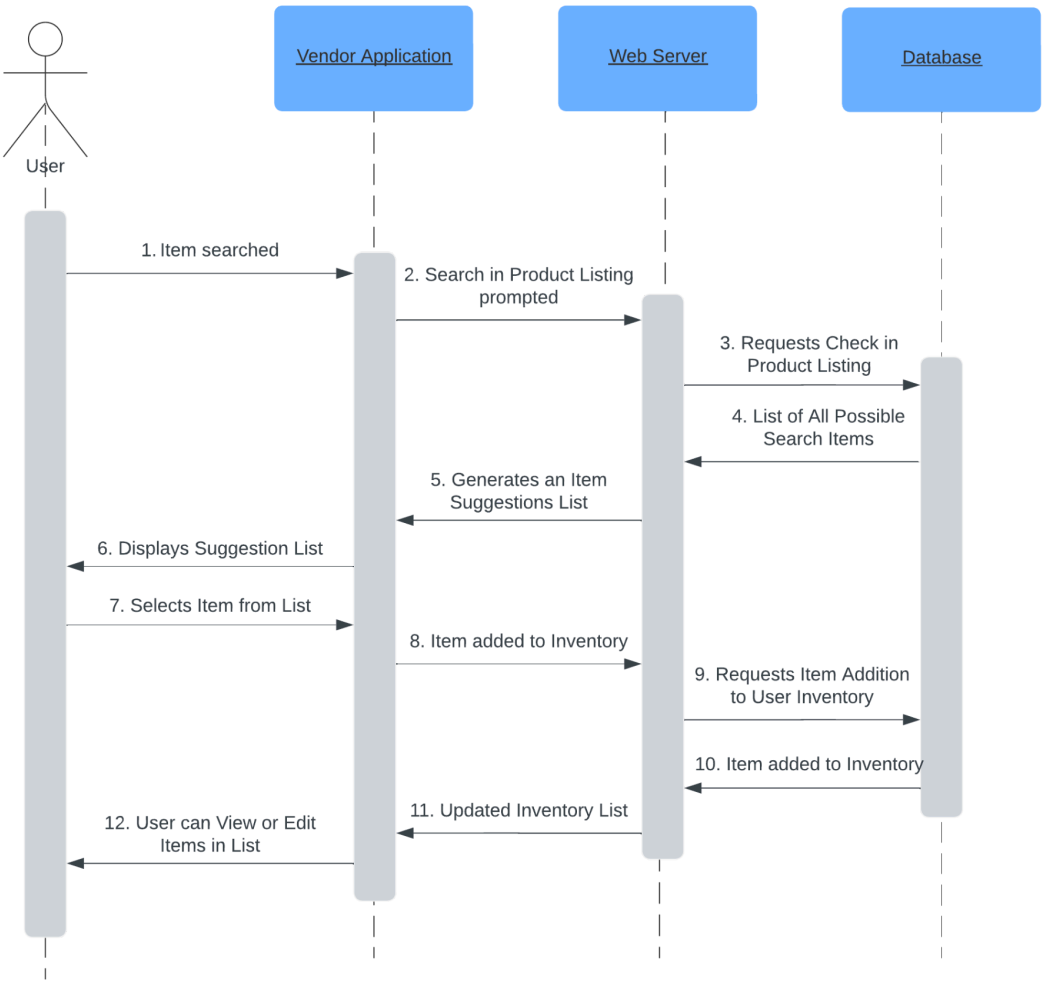
Order Recommendation



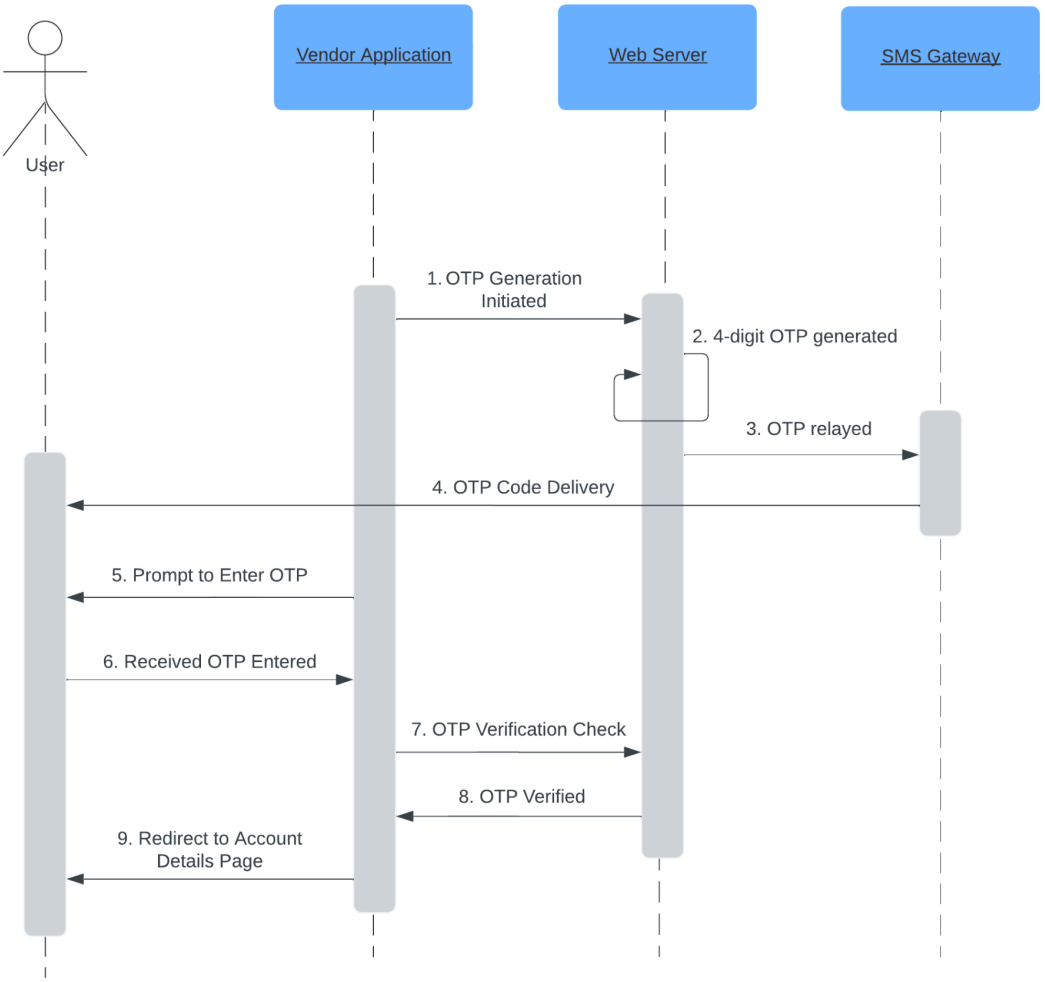
Order Tracking



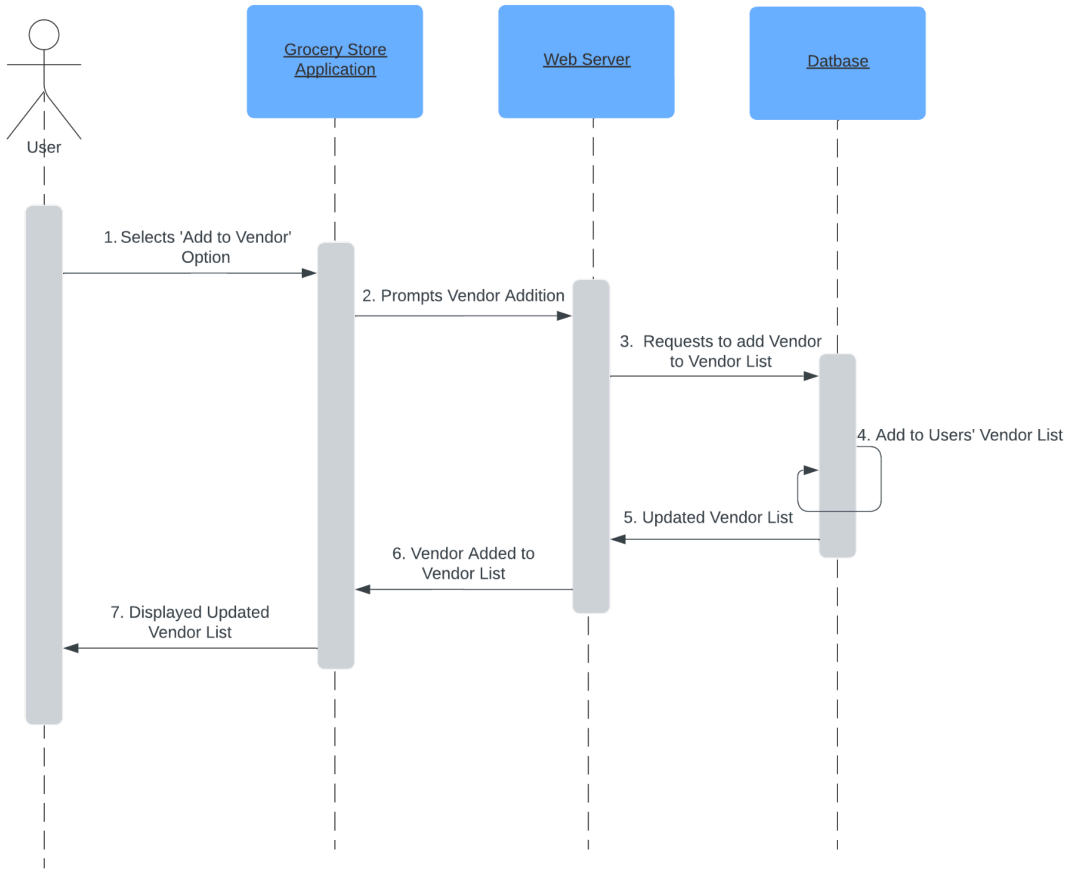
All Products Search



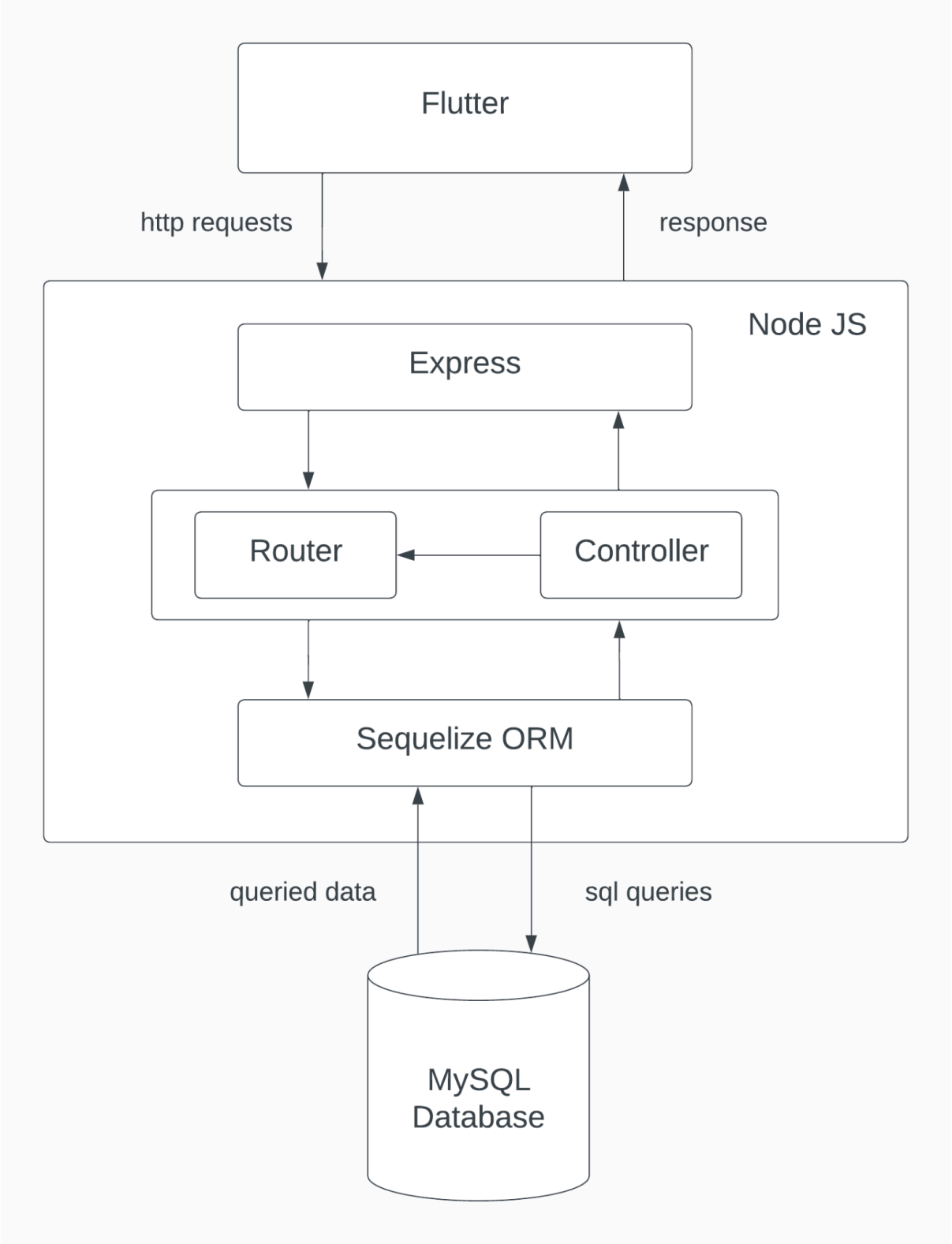
OTP Code Generation and Delivery



Add Vendor to Vendor List



API Design


Flutter
http requests
response
Node JS
Express
Router
Controller
Sequelize ORM
queried data
sql queries
MySQL
Database

ML Design

Data Collection

Local Pharmacy Dataset

Attributes:

1. saleinvcode
2. customerref
3. date
4. invdiscperc
5. flatdisc
6. misccharges
7. invsalestax
8. remarks
9. looseqty
10. packqty
11. price
12. itemdiscperc
13. packunits
14. batch
15. expiry
16. salestax
17. itemname
18. datestring
19. customer
20. rowid

Instances: 300,000

Format: XLS

Time Frame: July 2022 to June 2023

Description: The data needs to be cleaned. saleinvcode, customerref, invdiscperc, flatdisc, misccharges, invsalestax, packqty, itemdiscperc, batch, salestax, datestring customer, and rowid need to be removed as they are either empty, zero, same for every entry, or irrelevant to demand forecasting. The remarks attribute is used to enter the names of customers, therefore, it should be removed to ensure privacy. The date attribute contains the date and the time, it should be split into two parts, date and time. The sales are only recorded in terms of looseqty. The dataset also contains expiry dates which will enable us to analyse the perishable aspect of products. This dataset is uploaded on our GitHub repository.

Corporación Favorita Grocery Sales Forecasting

Datasets:

Training Data

1. Date
2. On Promotion
3. Unit Sales
4. Store Number
5. Item Number

Stores

1. City
2. State
3. Type
4. Cluster

Items

1. Class
2. Perishable
3. Family

Transactions

1. Date
2. Transactions

Oil

1. Date
2. Oil Price

Holidays

1. Type
2. Locale
3. Locale Name
4. Description
5. Transferred

Instances: 126 Million

Size: 4.7 GB (Training Data)

Format: CSV

Time Frame: January 2013 to August 2017

Description: This is a dataset from Corporación Favorita Grocery Sales Forecasting competition hosted on Kaggle 6 years ago. The dataset contains millions of instances, spanning over 5 years, including key variables such as holidays, oil prices, and location. The dataset is considered credible based on the fact it's shared by a large grocery store chain, hosted as a competition on Kaggle with prizes of $30,000 and 1500+ participants, and most importantly is used for demand forecasting in several research papers including [1] and [2].

Instacart Market Basket Analysis

Datasets:

Aisles

1. aisle_id
2. aisle

Departments

1. department_id
2. department

Prior Product Orders

1. order_id
2. product_id
3. add_to_cart_order
4. reordered

Orders

1. order_id
2. user_id
3. eval_set
4. order_number
5. order_dow
6. order_hour_of_day
7. days_since_prior_order

Products

1. product_id
2. product_name
3. aisle_id
4. department_id

Instances: 3.4 Million

Format: CSV

Description: This is a dataset from the Instacart Market Basket Analysis competition hosted on Kaggle 6 years ago. The dataset contains millions of instances, including key variables such as aisle, department, day of week, and hour of day. The dataset is considered credible based on the fact it's shared by a large grocery delivery company, hosted as a competition on Kaggle with prizes of $25,000 and 2500+ participants.

Other Datasets for Further Exploration

- Grupo Bimbo Inventory Demand
- Store Item Demand Forecasting Challenge

Feature Engineering

Local Pharmacy Dataset

We got one year's data from the pharmacy. There was a separate csv for each month. So, the first step was to combine the csv files into one dataset (Figure 1).

```
import pandas as pd
import glob
```

```
csv_files_path = '../../Data/Pharmacy/'
```

```
csv_files = sorted(glob.glob(csv_files_path + '*.csv'))
```

```
combined_data = pd.DataFrame()
```

```
for csv_file in csv_files:
    month_data = pd.read_csv(csv_file)
    combined_data = pd.concat([combined_data, month_data], ignore_index=True)
```

Figure 1 Combining monthly csv files into one dataset

Then, the dataset is inspected (Figure 2). It is noticed that the data needs to be cleaned. saleinvcode, customerref, invdiscperc, flatdisc, misccharges, invsalestax, packqty, itemdiscperc, batch, salestax, datestring customer, and rowid need to be removed as they are either empty, zero, same for every entry, or irrelevant to demand forecasting. The remarks attribute is used to enter the names of customers, therefore, it should be removed to ensure privacy (Figure 3).

```
In [3]: df.head()
```

saleinvcode	CustomerRef	date	invdiscperc	flatdisc	misccharges	invsalestax	remarks	looseqty	packqty	price	itemdiscperc	packunits	batch	expiry	salestax	itemname	datestring	customer	rowid
115439	NaN	7/1/22 0:02	0.0	0.0	0	0	NaN	1	0	18.00	0.0	1	.	7/5/24 0:00	0	PEDITRAL (LEMON) ORS SACHET	1/7/2022	****CASH SALES CUSTOMER	226819
115440	NaN	7/1/22 0:03	0.0	3.0	0	0	NaN	3	0	6.31	0.0	20	.	2/8/24 0:00	0	SPIROMIDE 20MG TAB	1/7/2022	****CASH SALES CUSTOMER	226820
115440	NaN	7/1/22 0:03	0.0	3.0	0	0	NaN	2	0	7.83	0.0	30	.	8/1/25 0:00	0	CARLOV 6.25MG TAB(30'S)	1/7/2022	****CASH SALES CUSTOMER	226821
115440	NaN	7/1/22 0:03	0.0	3.0	0	0	NaN	2	0	34.29	0.0	14	.	10/1/24 0:00	0	NEXUM 40MG CAP	1/7/2022	****CASH SALES CUSTOMER	226822
115441	NaN	7/1/22 0:04	0.0	0.0	0	0	NaN	8	0	6.31	0.0	20	.	2/8/24 0:00	0	SPIROMIDE 20MG TAB	1/7/2022	****CASH SALES CUSTOMER	226823

Figure 2 Inspecting the dataset

```
df.head()
```

	date	looseqty	price	packunits	expiry	itemname	datestring
0	7/1/22 0:02	1	18.00	1	7/5/24 0:00	PEDITRAL (LEMON) ORS SACHET	1/7/2022
1	7/1/22 0:03	3	6.31	20	2/8/24 0:00	SPIROMIDE 20MG TAB	1/7/2022
2	7/1/22 0:03	2	7.83	30	8/1/25 0:00	CARLOV 6.25MG TAB(30'S)	1/7/2022
3	7/1/22 0:03	2	34.29	14	10/1/24 0:00	NEXUM 40MG CAP	1/7/2022
4	7/1/22 0:04	8	6.31	20	2/8/24 0:00	SPIROMIDE 20MG TAB	1/7/2022

Figure 3 Dataset after removing the aforementioned columns

The date attribute contains the date and the time, it should be split into two parts, date and time (Figure 4).

```
df[['date', 'time']] = df['date'].str.split(' ', 1, expand=True)
```

```
df.head()
```

	date	time	itemname	packunits	expiry	price	looseqty
0	1/7/2022	0:02	PEDITRAL (LEMON) ORS SACHET	1	7/5/24	18.00	1
1	1/7/2022	0:03	SPIROMIDE 20MG TAB	20	2/8/24	6.31	3
2	1/7/2022	0:03	CARLOV 6.25MG TAB(30'S)	30	8/1/25	7.83	2
3	1/7/2022	0:03	NEXUM 40MG CAP	14	10/1/24	34.29	2
4	1/7/2022	0:04	SPIROMIDE 20MG TAB	20	2/8/24	6.31	8

Figure 4 Date is split in date and time

There were multiple instances of sales for each item for each day. So, daily sales data was aggregated based on date and itemname (Figure 5).

```
agg_functions = {
    'packunits': 'first',
    'expiry': 'first',
    'price': 'first',
    'looseqty': 'sum'
}
```

```
combined_df = df.groupby(['date', 'itemname'], as_index=False).agg(agg_functions)
```

```
combined_df.head()
```

	date	itemname	packunits	expiry	price	looseqty
0	2022-07-01	10CC SHIFA D/SYRINGE(UNJT)(BM)	100	12/12/24	30.00	6
1	2022-07-01	1CC BD SYRINGE	100	12/12/24	30.00	1
2	2022-07-01	3CC SYRINGE INJEKT	100	3/1/24	15.00	3
3	2022-07-01	ACCU CHECK LANCET (CHINA)	200	12/12/24	3.00	50
4	2022-07-01	ACDERMIN GEL	1	5/1/23	278.44	1

Figure 5 Aggregating daily sales data for each item

Lastly, we filtered the data for 'PANADOL TAB' and saved the filtered dataset (Figure 6) .

```
filtered_df = df[df['itemname'] == 'PANADOL TAB']
```

```
filtered_df.head(10)
```

	date	itemname	packunits	expiry	price	looseqty
376	01/07/2022	PANADOL TAB	200	4/25/24	1.70	60
952	02/07/2022	PANADOL TAB	200	4/25/24	1.70	70
1490	03/07/2022	PANADOL TAB	200	4/25/24	1.70	55
2671	05/07/2022	PANADOL TAB	200	4/25/24	1.45	20
4407	08/07/2022	PANADOL TAB	200	4/25/24	1.70	70

Figure 6 Filtering Panadol Tab rows

Corporación Favorita Grocery Sales Forecasting

The initial step involved loading the various datasets required for the analysis including the training set, test set, holiday events (Figure 1.1), oil prices (Figure 1.2), store information (Figure 1.3), and transaction data. After loading the datasets, we examined their content and shape to gain insights into the structure and size of each dataset as part of data exploration.

```
In [3]: holiday_events.head()
```

Out[3]:

	date	type	locale	locale_name	description	transferred
0	2012-03-02	Holiday	Local	Manta	Fundacion de Manta	False
1	2012-04-01	Holiday	Regional	Cotopaxi	Provincializacion de Cotopaxi	False
2	2012-04-12	Holiday	Local	Cuenca	Fundacion de Cuenca	False
3	2012-04-14	Holiday	Local	Libertad	Cantonizacion de Libertad	False
4	2012-04-21	Holiday	Local	Riobamba	Cantonizacion de Riobamba	False

Figure 1.1 Holiday Events

```
In [4]: oil.head()
```

Out[4]:

	date	dcoilwtico
0	2013-01-01	NaN
1	2013-01-02	93.14
2	2013-01-03	92.97
3	2013-01-04	93.12
4	2013-01-07	93.20

Figure 1.2 Oil Prices

```
In [6]: stores.head()
```

Out[6]:

	store_nbr	city	state	type	cluster
0	1	Quito	Pichincha	D	13
1	2	Quito	Pichincha	D	13
2	3	Quito	Pichincha	D	8
3	4	Quito	Pichincha	D	9
4	5	Santo Domingo	Santo Domingo de los Tsachilas	D	4

Figure 1.3 Store Information

Then, the date feature in each dataset was, initially a string, converted to the datetime data type (Figure. 1.4). This step is crucial for time series analysis.

```
In [10]: holiday_events["date"] = pd.to_datetime(holiday_events.date)
         oil["date"] = pd.to_datetime(oil.date)
         test["date"] = pd.to_datetime(test.date)
         train["date"] = pd.to_datetime(train.date)
         transactions["date"] = pd.to_datetime(transactions.date)
```

Figure 1.4 Converting date feature to datetime data type

To understand the sales patterns over time, a visualisation (Figure 1.5) of the time series was plotted.

```
In [11]: def plot_series(time, series, format="-", start=0, end=None):
             fig, ax = plt.subplots(figsize=(14,5))
             plt.plot(time[start:end], series[start:end], format)
             plt.xlabel("Time")
             plt.ylabel("Sales")
             plt.grid(True)
             plt.show()
             plt.close()

In [12]: plot_series(train["date"], train["sales"], format="-", start=0, end=None)
```

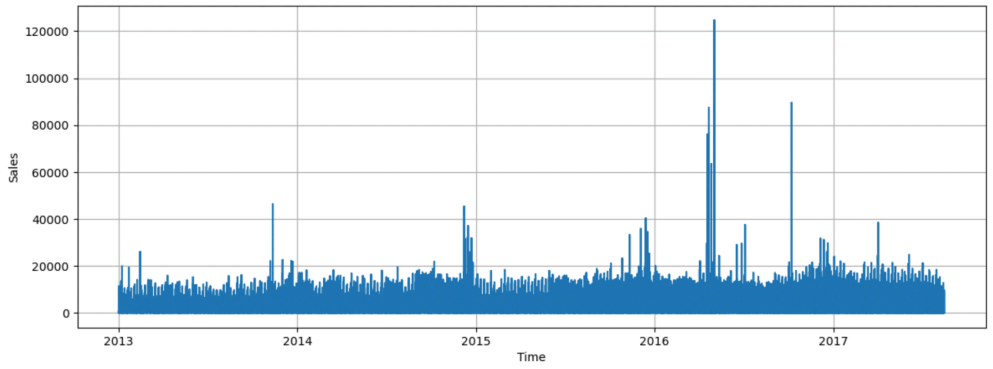


Figure 1.5 Visualising time series data

Next, data merging was performed (Figure 1.6), holiday events, oil prices, and store information were merged with the training and test sets. Transactions data was not utilised because it isn't available for the test set. The merging operations were conducted sequentially: first with holiday events based on the 'date' column, then second with the oil prices using the 'date' column; and finally with store-specific details using the 'store_nbr' column. The final expanded dataset was as seen in Figure 1.7.

```
In [13]: holiday_events = holiday_events.drop_duplicates(subset=['date'], keep='last')

In [14]: train.shape
Out[14]: (3000888, 6)

In [15]: train = pd.merge(train,holiday_events,how="left",on='date', validate="many_to_one")

In [16]: train.shape
Out[16]: (3000888, 11)

In [17]: train = pd.merge(train,oil,how="left",on='date')

In [18]: train.shape
Out[18]: (3000888, 12)

In [19]: train = pd.merge(train,stores,how="left",on="store_nbr",suffixes=("holiday","stores"))

In [20]: train.shape
Out[20]: (3000888, 16)
```

Figure 1.6 Joining holiday_events, oil, and stores

```
In [21]: train.head()
```

Out[21]:

	id	date	store_nbr	family	sales	onpromotion	typeholiday	locale	locale_name	description	transferred	dcoilwtico	city	state	typestores	cluster
0	0	2013-01-01	1	AUTOMOTIVE	0.0	0	Holiday	National	Ecuador	Primer dia del ano	False	NaN	Quito	Pichincha	D	13
1	1	2013-01-01	1	BABY CARE	0.0	0	Holiday	National	Ecuador	Primer dia del ano	False	NaN	Quito	Pichincha	D	13
2	2	2013-01-01	1	BEAUTY	0.0	0	Holiday	National	Ecuador	Primer dia del ano	False	NaN	Quito	Pichincha	D	13
3	3	2013-01-01	1	BEVERAGES	0.0	0	Holiday	National	Ecuador	Primer dia del ano	False	NaN	Quito	Pichincha	D	13
4	4	2013-01-01	1	BOOKS	0.0	0	Holiday	National	Ecuador	Primer dia del ano	False	NaN	Quito	Pichincha	D	13

Figure 1.7 Training with holiday_events, oil, and stores features

Extracting time features like the day of the week, month, and year from the date in both training and test sets was crucial (Figure 1.8). The 'day_of_week', ‘month’, and ‘year’ features, breaking down the week into days, played a key role in capturing and adapting to sales patterns on a weekly, monthly, and yearly basis. This enhanced the model's ability to recognize variations within a week, improving time series forecasting.

```
In [29]: train['day_of_week'] = train['date'].dt.day_of_week
         train['day_of_week'] = train['day_of_week']+1
         train['month'] = train['date'].dt.month
         train['year'] = train['date'].dt.year

In [30]: train.head()
```

Out[30]:

	id	date	store_nbr	family	sales	onpromotion	typeholiday	locale	locale_name	description	transferred	dcoilwtico	city	state	typestores	cluster	day_of_week	month	year
0	0	2013-01-01	1	AUTOMOTIVE	0.0	0	Holiday	National	Ecuador	Primer dia del ano	False	NaN	Quito	Pichincha	D	13	2	1	2013
1	1	2013-01-01	1	BABY CARE	0.0	0	Holiday	National	Ecuador	Primer dia del ano	False	NaN	Quito	Pichincha	D	13	2	1	2013
2	2	2013-01-01	1	BEAUTY	0.0	0	Holiday	National	Ecuador	Primer dia del ano	False	NaN	Quito	Pichincha	D	13	2	1	2013
3	3	2013-01-01	1	BEVERAGES	0.0	0	Holiday	National	Ecuador	Primer dia del ano	False	NaN	Quito	Pichincha	D	13	2	1	2013
4	4	2013-01-01	1	BOOKS	0.0	0	Holiday	National	Ecuador	Primer dia del ano	False	NaN	Quito	Pichincha	D	13	2	1	2013

Figure 1.8 Extracting weekday, month, and year

The 'transferred' column in the holiday events dataset was used to identify and convert transferred holidays to normal days (Figure 1.9). This step ensures consistency in the holiday feature across the dataset.

```
In [37]: test["typeholiday"]=np.where(test["transferred"]==True,'NDay',test["typeholiday"])
         test["typeholiday"]=np.where(test["typeholiday"]=='Work Day','NDay',test["typeholiday"])
         test["typeholiday"]=test["typeholiday"].fillna("NDay")

In [38]: display(test["typeholiday"].value_counts(dropna=False))

typeholiday
NDay       26730
Holiday     1782
Name: count, dtype: int64
```

Figure 1.9 Changing transferred holidays to normal days

Then, zeros in the oil prices column were addressed by interpolating the data. Visualisations before (Figure 1.10) and after interpolation (Figure 1.11) are presented.

```
In [41]: plot_series(train["date"], train["dcoilwtico"], format="-", start=0, end=None)
```

Figure 1.10 Missing values in oil prices

```
In [43]: train["dcoilwtico"]=np.where(train["dcoilwtico"] ==0, np.nan, train["dcoilwtico"])
         train.dcoilwtico.interpolate(limit_direction='both',inplace=True)

In [44]: train.shape

Out[44]: (3000888, 19)

In [45]: plot_series(train["date"], train["dcoilwtico"], format="-", start=0, end=None)
```

Figure 1.11 Fixing missing values in oil prices

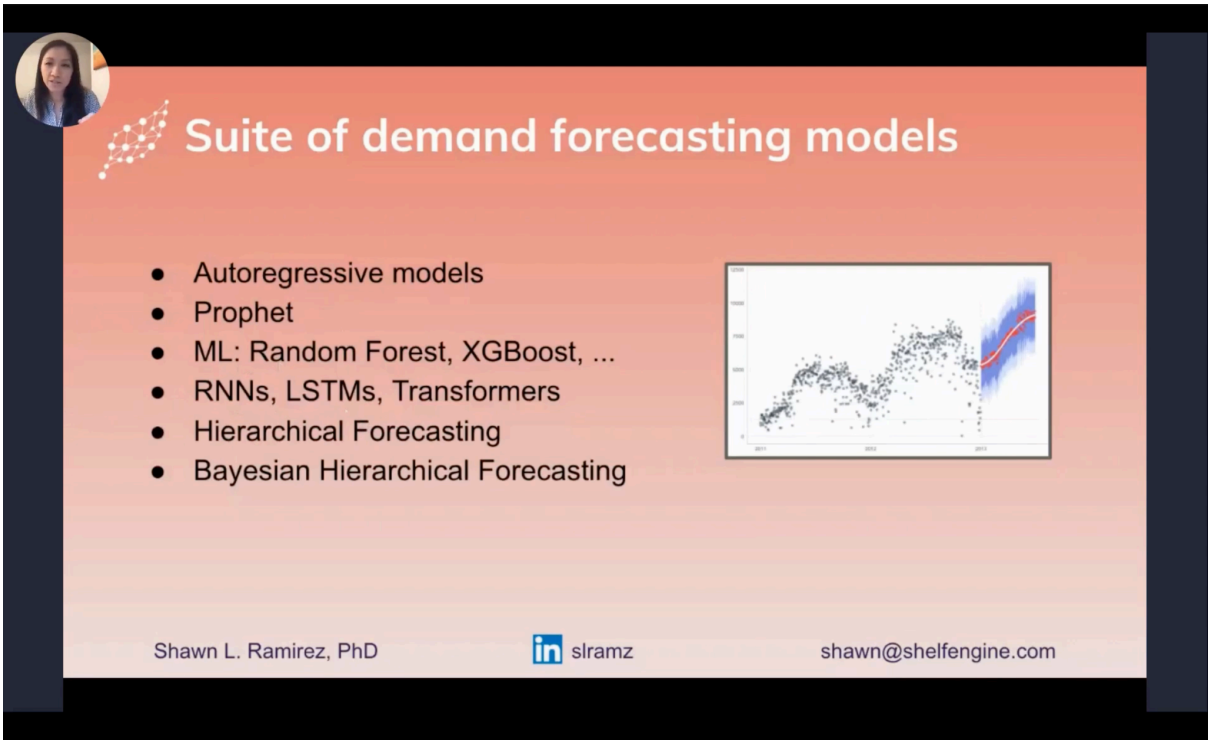
Based on info seen (Figure 1.12), 'locale', 'locale_name', 'description', 'transferred' were dropped and new csv files were generated comprising the final test and training dataset that the model was trained on.

```
In [50]: test.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 28512 entries, 0 to 28511
Data columns (total 18 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   id           28512 non-null  int64
 1   date         28512 non-null  datetime64[ns]
 2   store_nbr    28512 non-null  int64
 3   family       28512 non-null  object
 4   onpromotion  28512 non-null  int64
 5   typeholiday  28512 non-null  object
 6   locale       1782 non-null   object
 7   locale_name  1782 non-null   object
 8   description  1782 non-null   object
 9   transferred  1782 non-null   object
 10  dcoilwtico   28512 non-null  float64
 11  city         28512 non-null  object
 12  state        28512 non-null  object
 13  typestores   28512 non-null  object
 14  cluster      28512 non-null  int64
 15  day_of_week  28512 non-null  int32
 16  month        28512 non-null  int32
 17  year         28512 non-null  int32
dtypes: datetime64[ns](1), float64(1), int32(3), int64(4), object(9)
memory usage: 3.6+ MB
```

Figure 1.12 Removing ID and columns with mostly null values

Model Shortlisting



Shelf Engine: Demand Forecasting Models

Project Part I

As the inspiration behind our idea of demand forecasting was Shelf Engine, we initially decided to use the same models that they did, since their results using these models were extremely accurate.

Random Forest

We started the exploration with Random Forest because of its simplicity, flexibility, and our past experience with it making it a good choice. What makes Random Forest special, is its ability to capture complex non-linear patterns without extensive tuning.

XGBoost

Since we have structured data, XGBoost was considered a suitable choice. It is known to perform well in time series forecasting problems as evident by its popularity in competitions related to demand forecasting on kaggle. Due to the size of our dataset, XGBoost's speed and efficiency really helped in going over several iterations of training and testing.

Prophet (Facebook)

Prophet is designed specifically for time series forecasting with daily observations that display patterns like seasonality and holidays. As we had historical data for several seasons, Prophet seemed like a solid choice.

RNN (LSTM/GRU)

RNNs are powerful in modelling sequential patterns, making them suitable for time series forecasting. They can capture temporal dependencies in sales data over different time intervals.

Project Part II

The models that were used for FYP I provided a solid foundation, whereas the models that will be implemented in FYP II leverage recent advancements to further enhance prediction accuracy and address specific challenges in the time series domain.

LightGBM

LightGBM has shown excellent performance in time series forecasting, as evidenced by its success in the M5 competition. Its efficiency makes it suitable for handling large grocery store datasets.

N-BEATS

N-BEATS has proven effective in recent competitions, outperforming well-established methods, such as demonstrating superior performance compared to traditional statistical approaches.

DeepAR (Amazon)

DeepAR model is based on a set of RNN models, where each model is trained on a specific subset of the data. Finally, the predictions from all of the models are combined allowing deepAR to handle multiple time series effectively.

Temporal Fusion Transformer (Google)

According to [3], Temporal Fusion Transformer outperforms all prominent Deep Learning models for time series forecasting.

Training and Testing

Deployment

We created a sub directory, ModelDeployment, in our GitHub repository for version control. Installed Anaconda for package management and created a Conda environment (deployment) for the project. Developed a Flask web application in Python. Incorporated a simple form in the html template to take input (family and date) from the user. Added our demand forecasting model, trained on the kaggle dataset, and saved as joblib files. Updated the Flask application to handle model predictions based on the family and date user enters, along with related features (whether it was a holiday on that date or what was the price of the oil on that date). Modified the html to display the model's prediction and the actual sales from the selected date for the selected family. Uploaded pre-trained models to a 'models' folder in the project directory. Adjusted the app.py file to load models and handle form submissions. Checked the functioning of the model locally by selecting the date and family

and obtaining predictions. Prepared for deployment by creating a requirements.txt file listing necessary libraries. Used Digital Ocean to deploy the Flask application, connecting it to the GitHub repository. Resolved errors during deployment and awaited the completion of the deployment process. Checked the live url to access the deployed demand forecasting web application.

Conclusion

In conclusion, this design document provides a comprehensive blueprint for developing a sophisticated demand forecasting system tailored for the grocery retail industry. The integration of diverse technologies, ranging from backend development tools to machine learning frameworks, highlights the depth and complexity of the solution. The document not only emphasises the importance of data design and feature engineering but also sheds light on the selection and deployment of machine learning models for accurate demand predictions. The deployment on Digital Ocean, underscores the practicality and real-world applicability of the proposed solution. Overall, this document serves as a guide for building a robust and scalable system that can significantly enhance the efficiency of inventory management in the grocery retail sector.

References

[1] G. Kechyn, L. Yu, Y. Zang, S. Kechyn, "Sales Forecasting using WaveNet within the Framework of the Kaggle Competition," arXiv:1803.04037v1 [cs.LG], Mar. 11, 2018.

[2] V. Prabhakar, D. Sayiner, U. Chakraborty, T. Nguyen, M. A. Lanham, "Demand forecasting for a large grocery chain in Ecuador."

[3] Shereen Elsayed et al. Do We Really Need Deep Learning Models for Time Series Forecasting?