Group Project 1

BUAN6320.504

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1: Choose a Dataset

Dataset: Lyft Dataset Boston

Business: Lyft

Source of the dataset: Kaggle.com

2: Business Understanding

Based on the investigation of the order delivery system of our company, Lyft, we found out that many drivers got a plethora of orders during peak hours whereas on the other hand, drivers were not getting enough orders during non-rush hours. To balance the order delivery amount, we investigate and analyze the customer's Lyft ordering patterns and improve the experience of both the customers as well as the drivers. We have chosen the orders records of the Boston area collected from November 2018 to December 2018.

Based on the available dataset, we have decided the following:

First of all, we will keep these columns from the original table based on our business goal: **Datetime**, **Source**, **Destination**, **Product_id**, **Price**, **Distance**, **Surge Multiplier**, **Weather**, **Day** and **Hour**.

Temperature. Then, for the column *Hours*, we will separate the hours into four categories: *Midnight* (0-5), *Morning* (6-11), *Afternoon* (12-17), *Night* (18-23) as a new column *Time*. In order to figure out which time period has more orders.

Third, based on the **Short_summary** which already classifies the data into nine types of weather. To find out which kind of weather customers tend to use Lyft more.

Next, through the data visualization, we will use the bar chart to figure out how different weather (*Weather*), location (*Source* and *Destination*) and day time (*Time*) will affect the Total Orders Amount. Also, we will do the basic statistical analysis of all continuous variables we have, for example, *Price*, *Distance*, *Temperature*. Besides that, we will use the box plot to figure out whether there are outliers for those variables.

3: Data understanding

Data description:

The columns delineate various aspects of the dataset such as the id, time of the day, the pick-up and drop location of the customers, the type of vehicle used such as Lyft Luxury, Luxury XL or was the ride a carpool or a shared ride, the pricing for each ride, distance, temperature, and the weather forecast for the day. All this information is lucrative in making strategies for pricing and rolling out offers for the users which can be helpful for both the customers as well as the company to grow.

- Off the 57 columns in the dataset, 29 columns have a float value, 17 columns have an integer value and 11 columns have an object value

Dataset analysis:

Statistical analysis

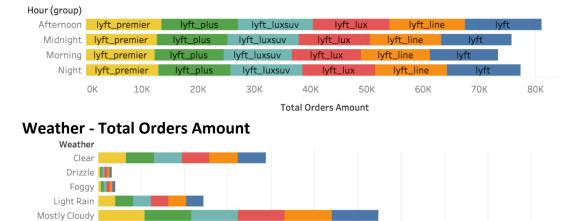
The range of order *Price* is from \$2.5 to \$97.5, and highest standard deviation (10.02), which means the records from *Price* are the most separate around it's mean (\$17.35), compared to other two, *Distance*

(1.09) and *Temperature* (6.73). And the range of *Distance* and *Temperature* are from 0.39 to 6.33 and 18.91 to 57.22, and the means are 2.18 and 39.60 separately.

Summary Statistics							
The MEANS Procedure							
Variable	N	Mean	Mode	Std Dev	Minimum	Median	Maximum
price distance temperature	307408 307408 307408	17.3513961 2.1869756 39.5963842	16.5000000 1.0600000 37.9200000	10.0191708 1.0866217 6.7304249	2.5000000 0.3900000 18.9100000	16.5000000 2.1400000 40.4900000	97.5000000 6.3300000 57.2200000

Daily - Total Orders Amount

From the bar chart which uses the *Time* (which is grouped from *Hours*) vs *Total Orders Amount* (which is from the count of *Product_id*). We can see that the afternoon has the highest amount of orders among the 4 time periods of the day. And the morning has the least.



For the bar chart of **Weather** vs **Total Orders Amount** (which is from the count of **Product_id**), when the weather is overcast, people are more likely to use Lyft, followed by mostly cloudy and partly cloudy. Also, the drizzle and foggy weather has the least number of orders.

60K

50K

Total Orders Amount

70K

80K

90K

100K

Product - price

Overcast
Partly Cloudy
Possible Drizzle

Rain OK

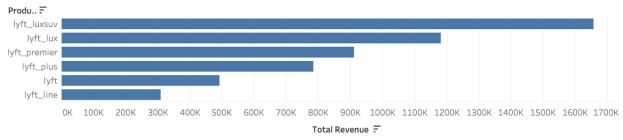
10K

20K

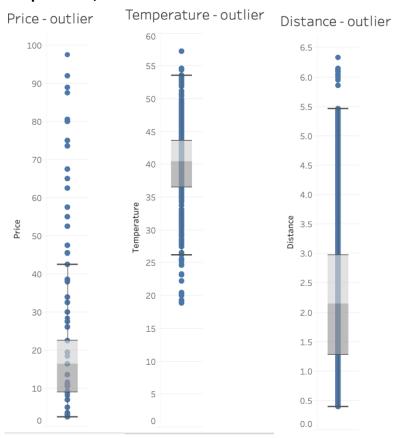
30K

40K

From the bar chart of total revenue and product_id, lytf_luxsuv has the highest revenue amount of all six types of Lyft product, followed by lyft_lux. And the lyft_line is the least welcomed product for this time period.



Outliers: price, temperature, and distance

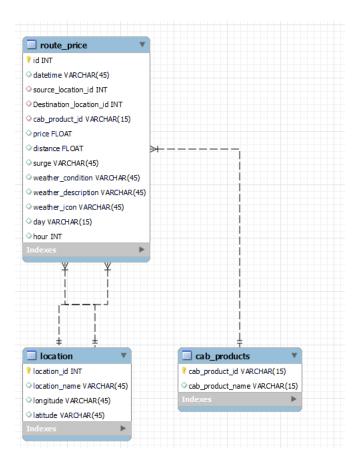


For the outlier, we are using the box plot to figure out the range of three continuous variables, *Price*, *Temperature* and *Distance*. From the box plot, we could see the variables of all three columns are all in a reasonable range, even though there are some variables are out of the maximum and minimum range of the box plot

4: Database design

Schema design and Schema normalization

ER diagram before normalization



BCNF -Normalization:

1. Functional dependency

```
Initial FDs:
F = {
    {Hour_id} → {Time_category},
    {Cab_products_id} → {Cab_products_name},
    {Weather_condition}, {Weather_icon}-> {weather_description},
    {Source_location_id, Destination_location_id} → { Location_name },
    {Location_id} → {Location_name},
    {datetime} → {day},
    }
    Infer FDs:
    {Source_location_id} → {Location_name}
```

```
\Rightarrow {Source location id, Location id} \rightarrow {Location name}
```

Check BCNF condition for all FDs:

```
F = \{ \{ \text{Hour\_id} \} \rightarrow \{ \text{Time\_catefory} \} \Rightarrow \underline{\text{in the same table } \times} \\ \{ \text{Cab\_products\_id} \} \rightarrow \{ \text{Cab\_products\_name} \} \Rightarrow \underline{\text{all in table Cab\_products\_and } \{ \text{Cab\_products\_id} \} \text{ is a key } \underbrace{\sqrt{}} \\ \{ \text{Weather\_condition, Weather\_icon } \} \rightarrow \{ \text{Weather\_description} \} \Rightarrow \underline{\text{in the same table } \times} \\ \{ \text{Source\_location\_id} \} \rightarrow \{ \text{Location\_name} \} \Rightarrow \underline{\text{not in the same table}} \underbrace{\sqrt{}} \\ \{ \text{Location\_id} \} \rightarrow \{ \text{day} \} \Rightarrow \underline{\text{in the same table}} \times} \\ \{ \text{Source\_location\_id}, \, \text{Location\_id} \} \rightarrow \{ \text{Location\_name} \} \Rightarrow \underline{\text{not in the same table}} \underbrace{\sqrt{}} \\ \{ \text{Source\_location\_id}, \, \text{Location\_id} \} \rightarrow \{ \text{Location\_name} \} \Rightarrow \underline{\text{not in the same table}} \underbrace{\sqrt{}} \\ \{ \text{Source\_location\_id}, \, \text{Location\_id} \} \rightarrow \{ \text{Location\_name} \} \Rightarrow \underline{\text{not in the same table}} \underbrace{\sqrt{}} \\ \{ \text{Source\_location\_id}, \, \text{Location\_id} \} \rightarrow \{ \text{Location\_name} \} \Rightarrow \underline{\text{not in the same table}} \underbrace{\sqrt{}} \\ \{ \text{Location\_id}, \, \text{Location\_id} \} \rightarrow \{ \text{Location\_name} \} \Rightarrow \underline{\text{not in the same table}} \underbrace{\sqrt{}} \\ \{ \text{Location\_id}, \, \text{Location\_id} \} \rightarrow \{ \text{Location\_name} \} \Rightarrow \underline{\text{not in the same table}} \underbrace{\sqrt{}} \\ \{ \text{Location\_id}, \, \text{Location\_id} \} \rightarrow \{ \text{Location\_name}} \} \Rightarrow \underline{\text{not in the same table}} \underbrace{\sqrt{}} \\ \{ \text{Location\_id}, \, \text{Location\_id} \} \rightarrow \{ \text{Location\_name}} \} \Rightarrow \underline{\text{Location\_name}} \} \Rightarrow \underline{\text{Location\_id}}
```

Decomposing BCNF:

A = {Id, datetime, Source_location_id, Destination_location_id, Cab_products_id, price, distance, surge, Weather_condition, Weather_description, Weather_icon, day, Hour_id, Time_category}

${Hour_id} \rightarrow {Time_category}$

- ⇒ violates BCNF ×
- ⇒ <u>decompose into</u> {Hour_id, Time_category}

<u>and</u> {Id, datetime, Source_location_id, Destination_location_id, Cab_products_id, distance,price, surge, Weather_condition, Weather_description, Weather_icon, day, Hour_id}

{Weather_condition, weather_description} → {Weather_icon}

- ⇒ violates BCNF ×
- ⇒ <u>decompose into</u> {Weather_condition, weather_id , weather_description ,Weather_icon} <u>and</u> {Id, datetime, Source_location_id, Destination_location_id, Cab_products_id, distance,price, surge, weather_id, day, Hour_id}

$\{datetime\} \rightarrow \{day\}$

- ⇒ violates BCNF ×
- ⇒ <u>decompose into</u> {datetime, day} <u>and</u> {Id, datetime, Source_location_id, Destination_location_id, Cab_products_id, distance,price, surge, weather_id,Hour_id}

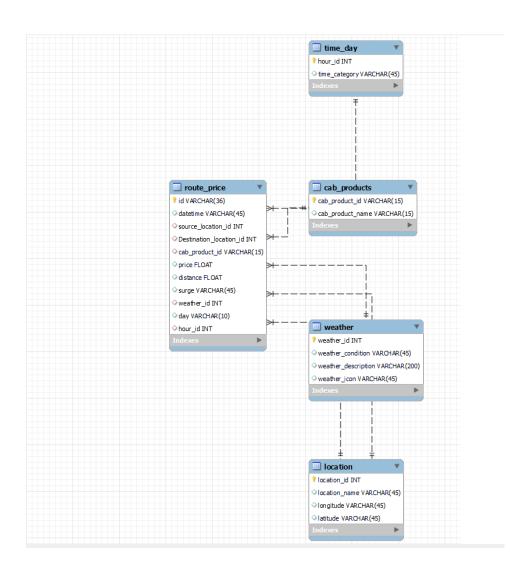
{Source location id, Destination location id} \rightarrow {location name}

 \Rightarrow no violation (Source location id, Destination location id location name) $\sqrt{}$

Final Database Schema:

```
{distance, price},
{Hour_id, Time_category},
{Weather_condition, Weather_icon, weather_description, weather_id},
{datetime, day},
{location_id,location_Name}
{Id, datetime, Source_location_id, Destination_location_id, Cab_products_id, surge, Weather_condition, distance, price, Weather_description, Hour_id}
```

ER- Diagram after schema normalization:



Errors and fixes:

<u>Error 1:</u> Alter table add AutoIncr option for Weather _id after all table creation with foreign key constraints added for Route_price_table column in referencing weather_ID

<u>Fix</u>: Foreign key constraint error when Modify column option is used in Weather table. Solved by ignoring forignkey constraint and set it back

SET FOREIGN_KEY_CHECKS=0;

Alter table weather modify column weather_id int AutoIncrement; SET FOREIGN_KEY_CHECKS=1;

Error 2: Inserting data to main table Route_price, got Lost connection error @ 30 sec. insert into route_price select id, STR_TO_DATE(src_lyft_landing.datetime, '%m/%d/%Y %T') as datetime, (select Location_id from Location where location_name = source) as source_location_id,(select

Location_id from Location where location_name = destination) as destination_location_id,product_id,price,distance,surge_multiplier, (select weather_id from weather where weather_condition = short_summary and weather_icon = icon) as weather_id,dayname(STR_TO_DATE(src_lyft_landing.datetime, '%m/%d/%Y %T')) as day, hour from src_lyft_landing;

 ✓
 1/4
 Z3:U5:40
 select *from route_price LIMIT 0, 1000
 U row(s) returned
 0.110 sec / 0.000 sec

 ▼
 175
 23:05:57
 insert into route_price select i"»¿id, STR_TO_DATE(src_lyft_landing.d...
 Error Code: 2013. Lost connection to MySQL server during query
 30.016 sec

Fix: Updated timeout interval to 6000 in system preference, solved the issue

Error 3: Inserting data to main table Route_price using above mentioned query at Error 3

"lock wait timeout exceeded try restarting transaction"

Fix: After so many attempts identified that query goes to deadlock because of missing column names in insert statement INSERT INTO table_name (column1, column2, column3, ...)

Updated Query:

insert into route_price (id,datetime,source_location_id,destination_location_id, cab_product_id,price,distance,surge,weather_id,day,hour_id) select id, STR_TO_DATE(src_lyft_landing.datetime, '%m/%d/%Y %T') as datetime, (select Location_id from Location where location_name = source) as source_location_id, (select Location_id from Location where location_name = destination) as destination_location_id,product_id,price,distance,surge_multiplier, (select weather_id from weather where weather_condition = short_summary and weather_icon = icon) as weather_id,dayname(STR_TO_DATE(src_lyft_landing.datetime, '%m/%d/%Y %T')) as day, hour from src_lyft_landing;

Error 4: Inserting main data took lot of time and execution went beyond 1 hour. **Fix**: Fixed this using main setting at my.ini file. "innodb_buffer_pool_size" to 2G. 3 lakh records got inserted in 95 sec.

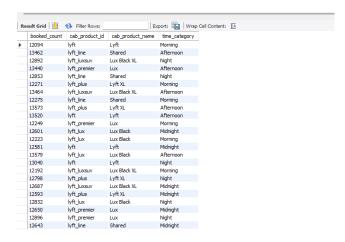
5: Data cleaning and database testing

Database testing and querying

Route booked and revenue by product and time of day

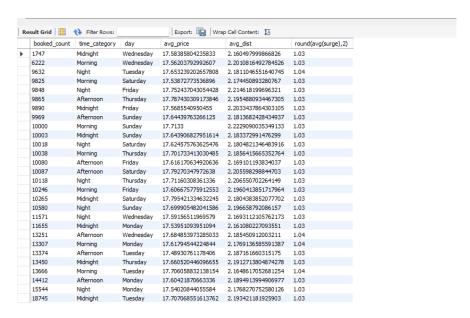
select count(rp.id) as booked_count, rp.cab_product_id, cp.cab_product_name,td.time_category from route_price rp

left join cab_products cp on rp.cab_product_id = cp.cab_product_id
left join time_day td on rp.hour_id = td.hour_id
group by cp.cab_product_id,td.time_category;



Route booked and revenue by day and time of day

select * from (select count(rp.id) as booked_count,td.time_category,rp.day, avg(rp.price) avg_price, avg(rp.distance) avg_dist,round(avg(surge),2) from route_price rp left join time_day td on rp.hour_id = td.hour_id group by td.time_category,rp.day) a order by a.booked_count,time_category,FIELD(a.day,'Sunday','Monday','Tuesday','Wednesday','Thursday','Friday ','Saturday');



Route booked and revenue by day

select count(rp.id) as booked_count,rp.day, sum(rp.price) tot_price, sum(rp.distance) tot_dist,avg(rp.price) avg_price, avg(rp.distance) avg_dist,round(avg(surge),2) from route_price rp left join time_day td on rp.hour_id = td.hour_id group by rp.day order by count(rp.id), td.time_category,FIELD(rp.day,'Sunday','Monday','Tuesday','Wednesday','Thursday','Friday','Saturday');

	booked_count	day	tot_price	tot_dist	avg_price	avg_dist	round(avg(surge),2)
•	32791	Wednesday	577884	71530.03008010983	17.623250282089597	2.1813921527281828	1.03
	40064	Friday	706548	87965.81014472246	17.63548322683706	2.195632242030812	1.03
	40195	Saturday	711026	87838.1201159954	17.689414106232118	2.1852996670231475	1.03
	40552	Sunday	716787	89056.08010226488	17.675749654764253	2.1960958794206173	1.03
	43471	Thursday	769903	95396.44015979767	17.710726691357458	2.194484602603981	1.03
	54918	Monday	965222	119547.13020849228	17.57569467205652	2.176829640709645	1.03
	55417	Tuesday	977828	120960.18020299077	17.644910406553947	2.182726964703805	1.03

• Route booked and revenue by weather

select count(rp.id) as booked_count,w.weather_condition,w.weather_icon, sum(rp.price) price ,avg(rp.price) avg_price , round(sum(rp.distance)) dist,avg(rp.distance) avg_dist, round(avg(surge),2) surge from route_price rp left join weather w on rp.weather_id = w.weather_id group by w.weather_id order by count(rp.id);

	booked_count	weather_condition	weather_icon	price	avg_price	dist	avg_dist	surge
•	3111	Drizzle	rain	54889	17.643522982963677	6775	2.177743493859234	1.03
	4002	Foggy	fog	71240	17.80109945027486	8810	2.2014592715140164	1.03
	8072	Possible Drizzle	rain	141546	17.535431119920712	17650	2.186551043536695	1.03
	10443	Rain	rain	183895	17.609403428133678	22865	2.1895518567379915	1.03
	11954	Clear	clear-day	210875	17.640538731805254	26059	2.1799088212829263	1.03
	24265	Partly Cloudy	partly-cloudy-day	428842	17.67327426334226	53128	2.1894795002530536	1.03
	24328	Light Rain	rain	428974	17.63293324564288	53148	2.1846308812403494	1.03
	26699	Clear	dear-night	469854	17.598187198022398	58162	2.1784280346879314	1.03
	26870	Mostly Cloudy	partly-cloudy-day	475320	17.68961667286937	58763	2.1869490171193102	1.03
	32398	Partly Cloudy	partly-cloudy-night	572995	17.686122600160505	71295	2.2006071393101942	1.03
	37850	Mostly Cloudy	partly-cloudy-night	670360	17.710964332893	83382	2.2029529753449415	1.03
	97416	Overcast	cloudy	1716408	17.619364375461938	212257	2.1788720572663296	1.03

• Route booked and revenue by weather and cab product

select count(rp.id) as booked_count, rp.cab_product_id, cp.cab_product_name,sum(rp.price) price ,w.weather_icon,w.weather_condition,avg(rp.price) avg_price , round(sum(rp.distance)) dist,avg(rp.distance) avg_dist,

round(avg(surge),2) surge from route_price rp
left join cab_products cp on rp.cab_product_id = cp.cab_product_id
left join weather w on rp.weather_id = w.weather_id
group by cp.cab_product_id,w.weather_id;

Т	booked count	cab product id	cab product name	price	weather icon	weather condition	avg price	dist	avg dist	surge
	4439	lyft	Lyft	43411	dear-night	Clear	9.779454832169408	9631	2.1696395626621867	1.04
	4076	lyft line	Shared	25002	rain	Light Rain	6.133954857703631	8945	2.1945215936117717	1
	5281	lyft luxsuv	Lux Black XL	205686	partly-doudy-night	Mostly Cloudy	32,747333227193124	13846	2.20447858983953	1.04
	5407	lyft	Lyft	52579	partly-doudy-night	Partly Cloudy	9.724246347327538	11774	2.177501390574268	1.04
	2005	lyft premier	Lux	36744	dear-day	Clear	18.326184538653365	4407	2.1980099786992677	1.04
	4513	lyft_line	Shared	27472	partly-cloudy-day	Mostly Cloudy	6.087303345889652	9762	2.163073346048508	1
	4102	lyft_plus	Lyft XL	64414	rain	Light Rain	15.703071672354948	8956	2.183300832142079	1.04
	16327	lyft_luxsuv	Lux Black XL	531085	cloudy	Overcast	32.528021069394256	35618	2.1815128349579576	1.04
-	4488	lyft_line	Shared	27346	clear-night	Clear	6.0931372549019605	9860	2.1968939436363875	1
	4447	lyft_plus	Lyft XL	70106	partly-cloudy-day	Mostly Cloudy	15.764785248482124	9741	2.1904407500992846	1.04
	4000	lyft_line	Shared	24450	partly-cloudy-day	Partly Cloudy	6.1125	8794	2.1984175034463407	1
	16268	lyft	Lyft	158873	cloudy	Overcast	9.765982296533071	35583	2.187295307086761	1.04
	4074	lyft	Lyft	39673	partly-cloudy-day	Partly Cloudy	9.738095238095237	8888	2.1816028509440817	1.04
	16148	lyft_line	Shared	98416	cloudy	Overcast	6.094624721327719	35140	2.1760899215209504	1
	4490	lyft_premier	Lux	81722	clear-night	Clear	18.200890868596883	9743	2.1699287339945412	1.04
	1714	lyft_lux	Lux Black	40101	rain	Rain	23.39614935822637	3771	2.199900821946744	1.03
	5455	lyft_lux	Lux Black	128085	partly-doudy-night	Partly Cloudy	23.480293308890925	12020	2.203532541929091	1.04
6	5274	lyft_lux	Lux Black	147995	partly-cloudy-night	Mostly Cloudy	23.588619700350655	13801	2.1997625149328086	1.04
4	4466	lyft_lux	Lux Black	105390	partly-cloudy-day	Mostly Cloudy	23.598298253470666	9782	2.1902463088922315	1.04
	3992	lyft	Lyft	39074	rain	Light Rain	9.78807615230461	8725	2.185501004656952	1.04
	16268	lyft_lux	Lux Black	380607	cloudy	Overcast	23.396053602163757	35422	2.1773930447845222	1.04
(652	lyft	Lyft	6401	fog	Foggy	9.817484662576687	1447	2.2194018402805358	1.04
	4056	lyft_plus	Lyft XL	64136	partly-cloudy-day	Partly Cloudy	15.812623274161735	8959	2.208870811780999	1.04
	4439	lyft_plus	Lyft XL	69724	clear-night	Clear	15.707141248028835	9641	2.1718990798938056	1.04
	4051	lyft_premier	Lux	73222	rain	Light Rain	18.07504319921007	8763	2.163241178349076	1.04
	1279	lyft_lux	Lux Black	30038	rain	Possible Drizzle	23.485535574667708	2800	2.189202508509765	1.04
	1991	lyft_lux	Lux Black	46463	clear-day	Clear	23.336514314414867	4287	2.1531541995191503	1.04
(562	lyft_line	Shared	4019	fog	Foggy	6.070996978851964	1452	2.1938217547454864	1
(6337	lyft_premier	Lux	116306	partly-doudy-night	Mostly Cloudy	18.35347956446268	14014	2.2115164936689315	1.04
	5418	lyft_luxsuv	Lux Black XL	176481	partly-cloudy-night	Partly Cloudy	32.573089700996675	11882	2.193111852867527	1.04

Route booked by source and destination:

select count(rp.id) as booked_count,l.location_name as source, l1.location_name as destination from route_price rp left join location I on rp.source_location_id =l.location_id left join location I1 on rp.Destination_location_id =l1.location_id group by rp.source_location_id,rp.Destination_location_id order by rp.source_location_id;

	booked_count	source	destination
Þ	4236	Haymarket Square	Back Bay
	4314	Haymarket Square	North Station
	4308	Haymarket Square	Theatre District
	4218	Haymarket Square	Beacon Hill
	4506	Haymarket Square	Financial District
	4032	Haymarket Square	West End
	4236	Back Bay	Haymarket Square
	4212	Back Bay	Fenway
	4548	Back Bay	North End
	4271	Back Bay	Northeastern University
	4164	Back Bay	Boston University
	4224	Back Bay	South Station
	4314	North Station	Haymarket Square
	4284	North Station	Fenway
	4194	North Station	North End
	4254	North Station	Northeastern University
	4230	North Station	Boston University
	4050	North Station	South Station
	4212	Fenway	Back Bay
	4284	Fenway	North Station
	4068	Fenway	Theatre District
	4200	Fenway	Beacon Hill
	4326	Fenway	Financial District
	4530	Fenway	West End
	4308	Theatre District	Haymarket Square
	4068	Theatre District	Fenway
	4164	Theatre District	North End
	4254	Theatre District	Northeastern University
	4416	Theatre District	Boston University
	4320	Theatre District	South Station

• Total Revenue by source and destination:

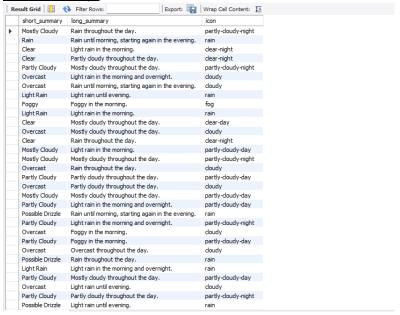
select sum(rp.price) as booked_count,l.location_name as source, l1.location_name as destination from route_price rp left join location I on rp.source_location_id =l.location_id left join location I1 on rp.Destination_location_id =l1.location_id group by rp.source_location_id,rp.Destination_location_id order by rp.source_location_id;

	booked_count	source	destination
Þ	75549	Haymarket Square	Back Bay
	54491	Haymarket Square	North Station
	60817	Haymarket Square	Theatre District
	57526	Haymarket Square	Beacon Hill
	58826	Haymarket Square	Financial District
	51376	Haymarket Square	West End
	81300	Back Bay	Haymarket Square
	62401	Back Bay	Fenway
	94574	Back Bay	North End
	59796	Back Bay	Northeastern University
	63420	Back Bay	Boston University
	71098	Back Bay	South Station
	56272	North Station	Haymarket Square
	83964	North Station	Fenway
	57419	North Station	North End
	88436	North Station	Northeastern University
	85220	North Station	Boston University
	65419	North Station	South Station
	62338	Fenway	Back Bay
	92880	Fenway	North Station
	81090	Fenway	Theatre District
	75285	Fenway	Beacon Hill
	111852	Fenway	Financial District
	89003	Fenway	West End
	70592	Theatre District	Haymarket Square
	89052	Theatre District	Fenway
	69413	Theatre District	North End
	81352	Theatre District	Northeastern University
	106579	Theatre District	Boston University
	58100	Theatre District	South Station

Clean up:

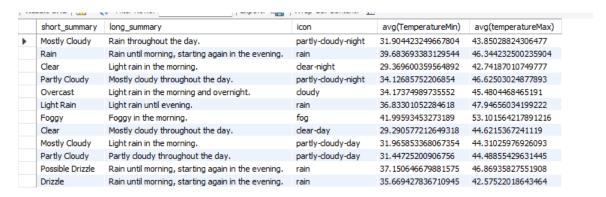
1. Dataset had typo/weak data on weather description. Eg: Clear condition had 3 different long summary. Used avg to find mostly used description and used the same

Before cleanup:



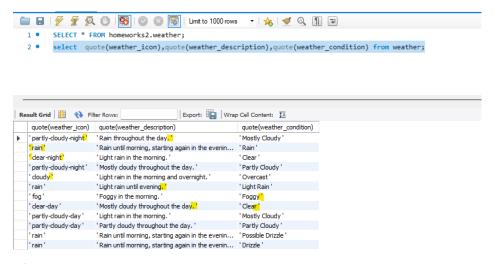
After Cleanup:

insert into weather (weather_condition,weather_description,weather_icon)
select short_summary,long_summary,icon from
(select distinct short_summary,long_summary,icon,avg(TemperatureMin),avg(temperatureMax) from
src_lyft_landing group by short_summary,icon) a;

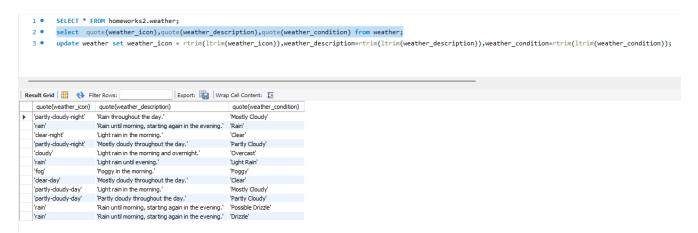


2. CSV to DB import: All text fields had space at the end in their data. Cleaned it across all tables. Note: This was identified after loading the data across all normalized tables. **Fix**: Remove trailing and preceding spaces for each varchar field.

Before cleanup:



After Cleanup:



The statistical analysis has been taken care of in step 3.

The error encountering and fixing part has been taken care of in step 4.

Strategies for business development:

- Based on the weather, cabs are booked more frequently on overcast days, but surge multiplier and the
 average price remains the same across all weather. So, we suggest a 1.25x surge multiplier will yield 80%
 profit for overcast day trips.
- Based on the day-to-day data, relatively higher number of cabs were booked during Mondays and Tuesdays from noon till midnight and thus, increasing the surge multiplier to 1.25x would yield more revenue.
- Based on the total pricing it can be concluded that although the booking counts are lower on the weekends, the revenue generated, and the average distance travelled is considerably higher.
- Based on the cab type and the weather data, it is conspicuous that during overcast and mostly cloudy days, regardless of the cab product type, the bookings are more than 50%. Usually, the cab products are normally distributed however, a slightly higher booking fraction is found for the Lyft Luxury vehicle during the aforementioned weathers.