Summary

We started with cleaning the data sets and here are the steps:

1. For the dataset cab_rides, we selected the variables (distance, cab_type, time_stamp, destination, source, price, surge_multiplier, id, product_id and name), converted time_stamp to standard time format, got the hour of the day and deleted all the rows with NAs.
2. For the dataset weather, we selected the variables (temp, location, clouds, pressure, time_stamp, humidity and wind), got the hour of the day ,converted time_stamp to standard time format, and deleted all the rows with NAs.
3. We combine the two data sets by time and location.

Then we explored the internal and external influence, and made a linear model to predict the price. For the internal influence, we draw the scatter plots and histograms of distance, location,time and carb type; For the external influence, we draw the plots of weather and big events. Finally, we used the model to see how well it fitted our dataset by comparing the predicted values with the actual values. The prediction model shows that distance, ride hour, rains, and surge multiplier have positive influence to the cab price.

Data Cleaning

- data cleaning cab_rides.csv

```
%%bq query

create or replace table `ba770b-team4.Team_Dataset.cab_rides` as
SELECT distance, cab_type, time_stamp, destination, source, price, surge_multiplier, id, product_id, name,
format_timestamp("%Y-%m-%d %H:%M:%S", timestamp_millis(time_stamp) ) as ride_time,
extract(hour from timestamp_millis(time_stamp)) as ride_hour
FROM `ba770b-team4.Team_Dataset.cab_rides`
where distance is not null
and cab_type is not null
and time_stamp is not null
and destination is not null
and source is not null
and price is not null
and surge_multiplier is not null
and id is not null
and product_id is not null;
```

distance	cab_type	time_stamp	destination	source	price	surge_multiplier	id	product_id	name	ride_time	ride_hour
1.43	Lyft	1543612078291	Back Bay	Fenway	7.0	1.0	316f4f8c-f827-4105-863b-93d3f2bacb01	lyft	Lyft	2018-11-30 21:07:58	21
1.57	Lyft	1543882984574	Back Bay	Fenway	7.0	1.0	1dcfa602-ab44-48c6-87e2-efdccb2525d6	lyft	Lyft	2018-12-04 00:23:04	0
1.46	Lyft	1543790282040	Back Bay	Fenway	7.0	1.0	9629b197-ae8b-46ee-b2ca-4d2ddbeb67cf	lyft	Lyft	2018-12-02 22:38:02	22
1.49	Lyft	1543532284999	Back Bay	Fenway	7.0	1.0	f9d6b430-b420-4a78-b368-b1cc707e1b7e	lyft	Lyft	2018-11-29 22:58:04	22
1.48	Lyft	1543263071586	Back Bay	Fenway	13.5	2.0	0dfe4ff4-24c3-4527-ba80-88c947ba6d66	lyft	Lyft	2018-11-26 20:11:11	20
1.48	Lyft	1543756386851	Back Bay	Fenway	7.0	1.0	cc8f13b4-d6a6-4da3-ac24-6cd4cbab73ac	lyft	Lyft	2018-12-02 13:13:06	13
1.44	Lyft	1545005405224	Back Bay	Fenway	7.0	1.0	023c25c3-c0cc-4559-9370-2554c7e3cb49	lyft	Lyft	2018-12-17 00:10:05	0

1.43	Lyft	1543585379420	Back Bay	Fenway	7.0	1.0	9f47e57d-d8d6-4051-a5ce-88656dfe35ea	lyft	Lyft	2018-11-30 13:42:59	13
1.45	Lyft	1544847903386	Back Bay	Fenway	9.0	1.25	7e74da48-30a3-4d61-a390-7c4614c6409a	lyft	Lyft	2018-12-15 04:25:03	4
1.47	Lyft	1544962811294	Back Bay	Fenway	9.0	1.25	d6230586-d1e5-4fd3-b757-ba58e04539c8	lyft	Lyft	2018-12-16 12:20:11	12
1.45	Lyft	1544983212511	Back Bay	Fenway	7.0	1.0	4bce613c-994a-419a-bf02-cef818d72705	lyft	Lyft	2018-12-16 18:00:12	18
1.44	Lyft	1543812180504	Back Bay	Fenway	7.0	1.0	e9870614-4e2e-4e01-965d-e6832580de09	lyft	Lyft	2018-12-03 04:43:00	4
1.57	Lyft	1543619887675	Back Bay	Fenway	9.0	1.0	24db3b35-20eb-464c-8ecc-3e34b361deab	lyft	Lyft	2018-11-30 23:18:07	23
1.42	Lyft	1545085203956	Back Bay	Fenway	9.0	1.0	eab81ee8-923e-455c-8074-a6985bb16dd5	lyft	Lyft	2018-12-17 22:20:03	22
1.57	Lyft	1543769282458	Back Bay	Fenway	7.0	1.0	06910d82-9dde-4e6a-9de4-c4536ea894e7	lyft	Lyft	2018-12-02 16:48:02	16
1.46	Lyft	1543443521181	Back Bay	Fenway	9.0	1.0	7bc58877-8477-47e8-9632-5b4f7d0b8ff1	lyft	Lyft	2018-11-28 22:18:41	22
1.43	Lyft	1543357642806	Back Bay	Fenway	10.5	1.5	5e65faca-df1c-471f-a421-e7137fea75f9	lyft	Lyft	2018-11-27 22:27:22	22
3.05	Lyft	1545016808728	West End	Fenway	10.5	1.0	e26bf717-bbaf-47ab-89e0-2826f5a09135	lyft	Lyft	2018-12-17 03:20:08	3
2.84	Lyft	1543471676057	West End	Fenway	11.0	1.0	181bb8d7-99d6-46d3-b6c1-f516af2fcfef	lyft	Lyft	2018-11-29 06:07:56	6
2.79	Lyft	1545012911143	West End	Fenway	11.0	1.0	d54eb940-e57d-44e2-97cc-54c1e312301c	lyft	Lyft	2018-12-17 02:15:11	2
2.83	Lyft	1543647177926	West End	Fenway	10.5	1.0	e6ffdf28-58bf-4941-822c-086193fd1947	lyft	Lyft	2018-12-01 06:52:57	6
3.05	Lyft	1544734508247	West End	Fenway	10.5	1.0	1757d97e-60fe-4736-a79b-f1e40f692f26	lyft	Lyft	2018-12-13 20:55:08	20
2.83	Lyft	1543316243697	West End	Fenway	11.0	1.0	3fa32a97-593b-48c7-83f1-25a06a97f9c9	lyft	Lyft	2018-11-27 10:57:23	10
2.78	Lyft	1543362682446	West End	Fenway	9.0	1.0	ab0ca221-550a-4496-8da3-77880f9ed63d	lyft	Lyft	2018-11-27 23:51:22	23
2.79	Lyft	1545042603371	West End	Fenway	11.0	1.25	f73c1563-8ac6-48f4-8bd3-e2d9c721433f	lyft	Lyft	2018-12-17 10:30:03	10

(rows: 637976, time: 11.1s, 89MB processed, job: job_8XrfeUV59TEDWGYeUs6Lh4UNJyl4)

- data cleaning weather.csv

```
%%bq query

create or replace table `ba770b-team4.Team_Dataset.weather` as
select temp, location, clouds, pressure, time_stamp, humidity, wind,
format_timestamp("%Y-%m-%d %H:%M:%S", timestamp_seconds(time_stamp))as weather_time,
extract(hour from timestamp_seconds(time_stamp)) as weather_hour,
case when rain is null then 0
else rain end as rain
from `ba770b-team4.Team_Dataset.weather`
where weather_time is not null;
```

temp	location	clouds	pressure	time_stamp	humidity	wind	weather_time	weather_hour	rain
41.65	Haymarket Square	0.81	990.63	1543344320	0.76	10.15	2018-11-27 18:45:20	18	0.0
41.42	North Station	0.81	990.53	1543344320	0.75	12.13	2018-11-27 18:45:20	18	0.0
41.31	Boston University	0.81	990.57	1543344320	0.76	12.0	2018-11-27 18:45:20	18	0.0
41.83	Fenway	0.79	990.84	1543346120	0.75	10.42	2018-11-27 19:15:20	19	0.0
41.81	Northeastern University	0.79	990.84	1543346120	0.75	10.41	2018-11-27 19:15:20	19	0.0
41.95	North Station	0.81	991.63	1543347920	0.73	10.87	2018-11-27 19:45:20	19	0.0
43.05	Northeastern University	0.81	990.82	1543347920	0.72	8.31	2018-11-27 19:45:20	19	0.0
43.28	Back Bay	0.81	990.81	1543347920	0.71	8.3	2018-11-27 19:45:20	19	0.0
41.89	West End	0.81	991.64	1543347920	0.74	10.88	2018-11-27 19:45:20	19	0.0
43.43	Financial District	0.71	991.08	1543349720	0.7	8.79	2018-11-27 20:15:20	20	0.0
43.11	Haymarket Square	0.71	991.08	1543349720	0.71	8.75	2018-11-27 20:15:20	20	0.0
43.01	North Station	0.71	991.07	1543349720	0.71	8.73	2018-11-27 20:15:20	20	0.0
43.15	North End	0.71	991.07	1543349720	0.71	8.77	2018-11-27 20:15:20	20	0.0
43.2	Back Bay	0.72	991.1	1543349720	0.71	8.72	2018-11-27 20:15:20	20	0.0
43.21	Beacon Hill	0.72	991.09	1543349720	0.71	8.73	2018-11-27 20:15:20	20	0.0
42.96	West End	0.72	991.08	1543349720	0.72	8.73	2018-11-27 20:15:20	20	0.0
42.9	Theatre District	0.72	991.09	1543349720	0.72	8.77	2018-11-27 20:15:20	20	0.0
43.36	South Station	0.71	991.09	1543349722	0.71	8.8	2018-11-27 20:15:22	20	0.0
41.73	Boston University	0.66	991.47	1543355120	0.7	9.34	2018-11-27 21:45:20	21	0.0
39.97	Fenway	0.28	991.6	1543358720	0.71	8.15	2018-11-27 22:45:20	22	0.0
39.58	North End	0.23	991.69	1543360520	0.72	9.18	2018-11-27 23:15:20	23	0.0
40.31	South Station	0.22	991.71	1543360520	0.7	9.15	2018-11-27 23:15:20	23	0.0
39.58	Back Bay	0.23	991.72	1543360520	0.72	8.97	2018-11-27 23:15:20	23	0.0
39.46	West End	0.23	991.69	1543360520	0.72	9.09	2018-11-27 23:15:20	23	0.0
39.45	Northeastern University	0.23	991.75	1543360520	0.72	8.9	2018-11-27 23:15:20	23	0.0

(rows: 6276, time: 2.4s, 578KB processed, job: job_AGxhhwjj2_Cx-QAYWBSN8vYje_Ax)

Distance vs Price

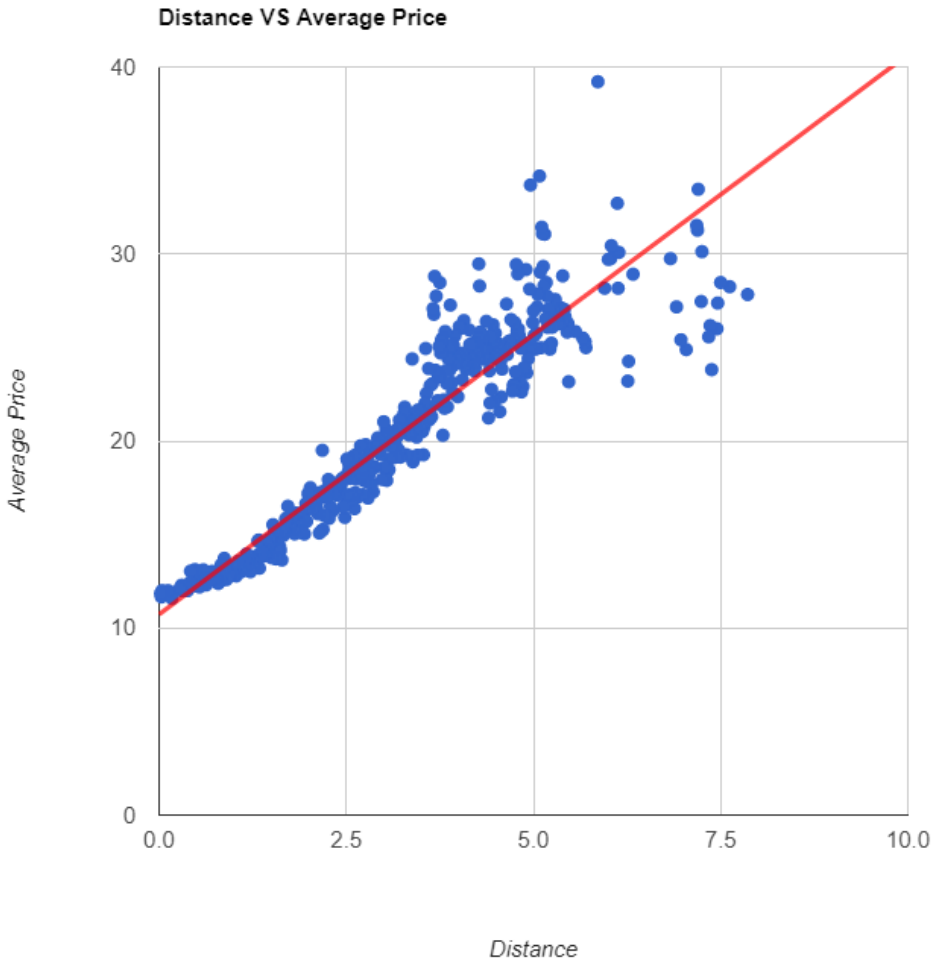
We use scatter polt to show the relationship between `price` and `distance`. As we see, distance and price have positive relationship, as the distance increases, in most of cases, the price increases.

- Scatter plot of distance & average price

```
%%bq query -n distance
select distance, avg(price) as avg_price

FROM `ba770b-team4.Team_Dataset.cab_rides`

group by distance
order by distance DESC;
```

```
%%chart scatter -d distance
```

```
title: Distance VS Average Price
height: 800
width: 800
vAxis:
  title: Average Price

hAxis:
  title: Distance
legend: none
trendlines: { 0: {
      type: 'linear',
      color: 'red',
      lineWidth: 3,
      opacity: 0.7,
      showR2: true,
      visibleInLegend: true
            }
          }
```



Time VS Price

- Top 10 rush hour of cab price

```
%%bq query
select ride_hour, avg(price) as avg_price
FROM `ba770b-team4.Team_Dataset.cab_rides`
```

```
FROM `ba770b-team4.Team_Dataset.cab_rides`

group by ride_hour
order by avg_price DESC
limit 10;
```

ride_hour	avg_price
17	16.6079964381
21	16.6043230655
8	16.6033263196
20	16.599207961
22	16.5953567342
4	16.5793110048
0	16.5747690145
2	16.5618033659
11	16.5585056895
19	16.5524372294

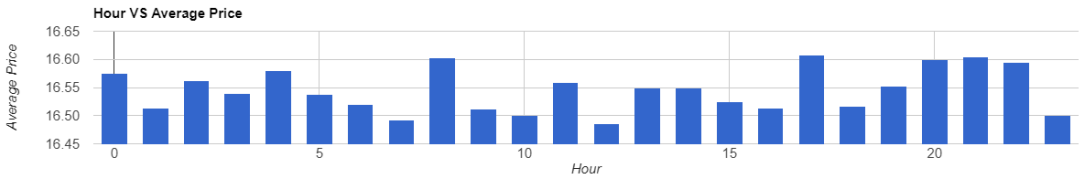
(rows: 10, time: 1.0s, 10MB processed, job: job_Aq2GCwTtEAXF-HC_vqTd4Ltzkyy5)

- Bar chart of rides hours & price

We use bar chart to analysis the relationship between `ride hour` and `average price`. Regardless of what time it is, the average price vibrates around $16.55. The highest average price is $16.608 around 17:00 which is around the rush hour, and the lowest average price is $16.486 around noon.

```
%%bq query -n hour
select  ride_hour,avg(price) as avg_price

FROM `ba770b-team4.Team_Dataset.cab_rides`

group by ride_hour
order by ride_hour DESC;
```

```
%%chart columns -d hour
title: Hour VS Average Price
hAxis:
  title: Hour
vAxis:
  title: Average Price
legend: none
```



Geographic Location VS Average Price

- Source/Destination Navigation

In the beginning, we got the distinct values of `source` (the district that the ride starts) and `destination` (the district that the ride ends) in our cleaned dataset `cab_rides`.

```
%%bq query
select distinct(destination)
from `ba770b-team4.Team_Dataset.cab_rides`;
```

destination
Back Bay

Back Bay
West End
Beacon Hill
North Station
Theatre District
Financial District
Fenway
North End
South Station
Haymarket Square
Boston University
Northeastern University

(rows: 12, time: 0.4s, cached, job: job_SFkg6h4LEe0wDwFvWZLGUptk05Ax)

```
%%bq query
select distinct(source)
from `ba770b-team4.Team_Dataset.cab_rides`;
```

source
Fenway
Back Bay
West End
North End
Beacon Hill
North Station
South Station
Haymarket Square
Theatre District
Boston University
Financial District
Northeastern University

(rows: 12, time: 0.2s, cached, job: job_GUONLkwF9oMe-YOCbw9hCscDOCAa)

From results, we can see that for both `source` and `destination`, each of them has 12 unique districts, and these 12 districts values are identical for `source` and `destination`.

Also, we navigate the number of trips for `source` and `destination` respectively.

- Source vs Avg Price & Destination vs Avg Price

In order to investigate relationships between the start district and the end district, we computed the average prices for each distinct district in `source` and `destination`.

```
%%bq query
select destination, avg(price) as avg_price,count(id) as numberoftrips
from `ba770b-team4.Team_Dataset.cab_rides`
group by destination
order by avg_price DESC
limit 5;
```

destination	avg_price	numberoftrips
Boston University	18.9421366911	53171
Fenway	18.1464187639	53166
Financial District	18.0462798937	54192
Northeastern University	17.8275167874	53165

North Station	16.8052380318	52577

(rows: 5, time: 1.0s, 39MB processed, job: job_pIG1qvpLpUnccrTeCK75xWp9dGNQ)

```
%%bq query
select source, avg(price) as avg_price, count(id) as numberoftrips
from `ba770b-team4.Team_Dataset.cab_rides`
group by source
order by avg_price DESC
limit 5;
```

source	avg_price	numberoftrips
Boston University	18.8530335515	53172
Fenway	18.3794906519	53166
Financial District	18.1813716626	54197
Northeastern University	17.9011238808	53164
Theatre District	16.5969944174	53201

(rows: 5, time: 0.1s, cached, job: job_TyYcuuiVxCXOpFcPS2Ow4GyD1KP1)

- Bar chart of Source vs Avg Price & Destination vs Avg Price

From the bar chart, we can see that for both `source` and `destination`, the district `Boston University` has the highest average price.

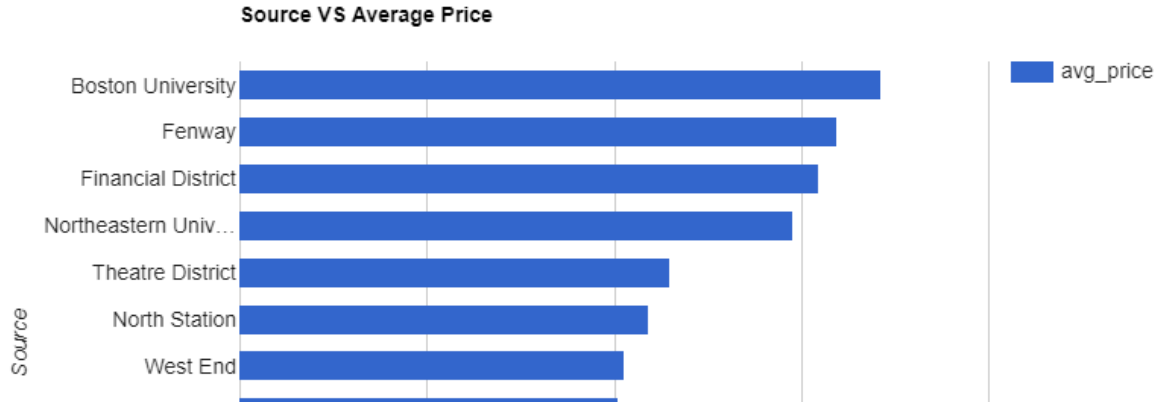
In other words, compared with other starting districts, the rides started from Boston University have the highest average price.

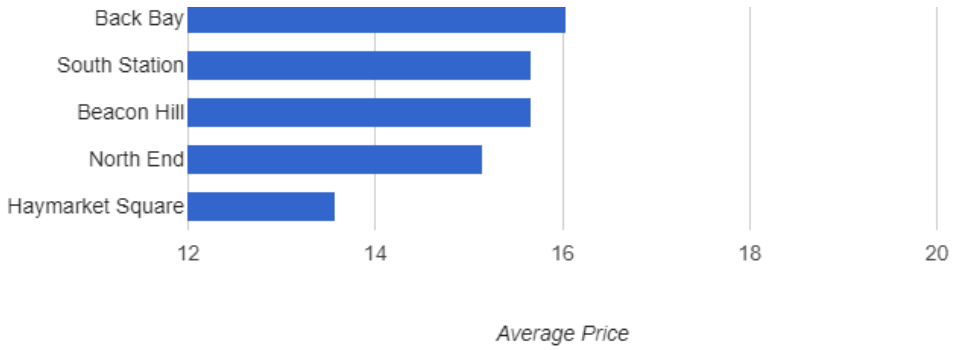
Also, the rides ends from Boston University have the highest average price compared with other destinations.

Specifically, though by average price, orders in graphs of source vs avg_price and destination vs avg_price are similar to each other, they are not completely identical. For example, as starting district, rides from Beacon Hill has 10th average price. However, as ending district, rides from Beacon Hill has 6th average price, with difference of 4 instead.

```
%%bq query -n limits
select source, avg(price) as avg_price from `ba770b-team4.Team_Dataset.cab_rides`
group by source
order by avg_price DESC;
```

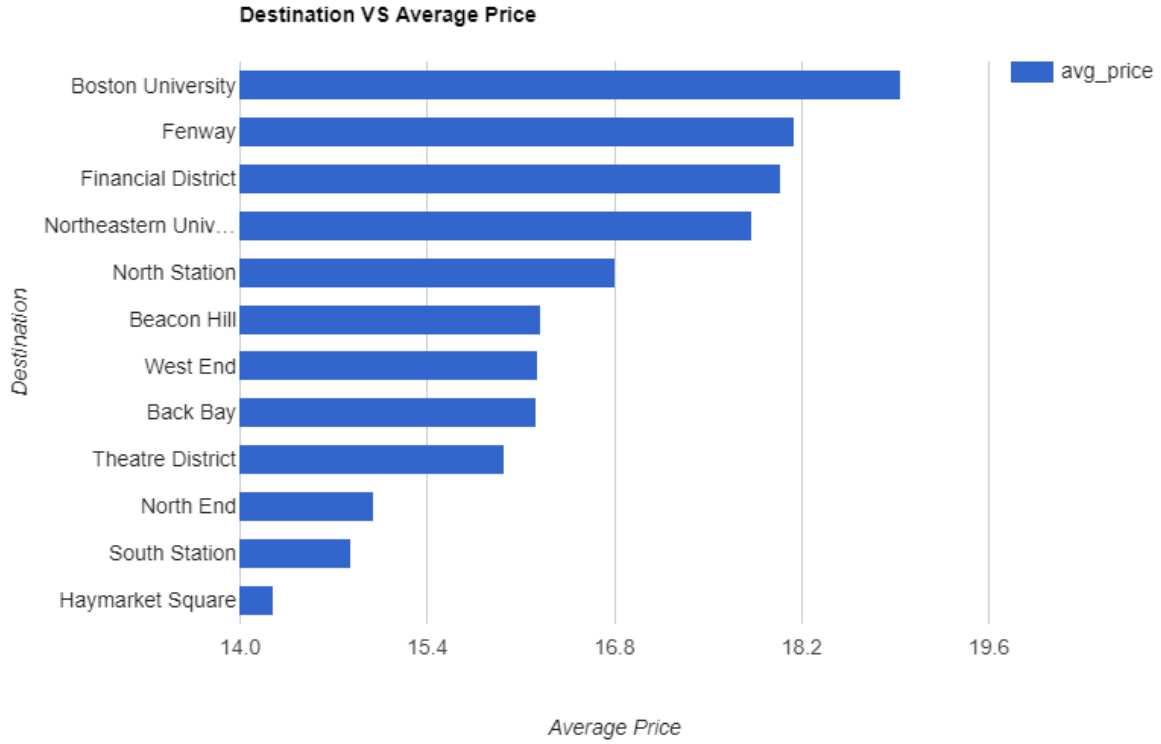
```
%%chart bars --data limits
title: Source VS Average Price
height: 600
width: 800
hAxis:
  title: Average Price
vAxis:
  title: Source
legend: average price
```






```
%%bq query -n limitd
select destination, avg(price) as avg_price from `ba770b-team4.Team_Dataset.cab_rides`
group by destination
order by avg_price DESC;
```

```
%%chart bars --data limitd
title: Destination VS Average Price
height: 600
width: 800
hAxis:
  title: Average Price
vAxis:
  title: Destination
legend: average price
```



- Connecting distinct routes by source and destination

To get better understanding, we computed 72 distinct routes by concating distinct values of source and destination.

```
%%bq query
SELECT
CONCAT(source, '-', destination) AS trip,
count(id) as number_of_trips
```

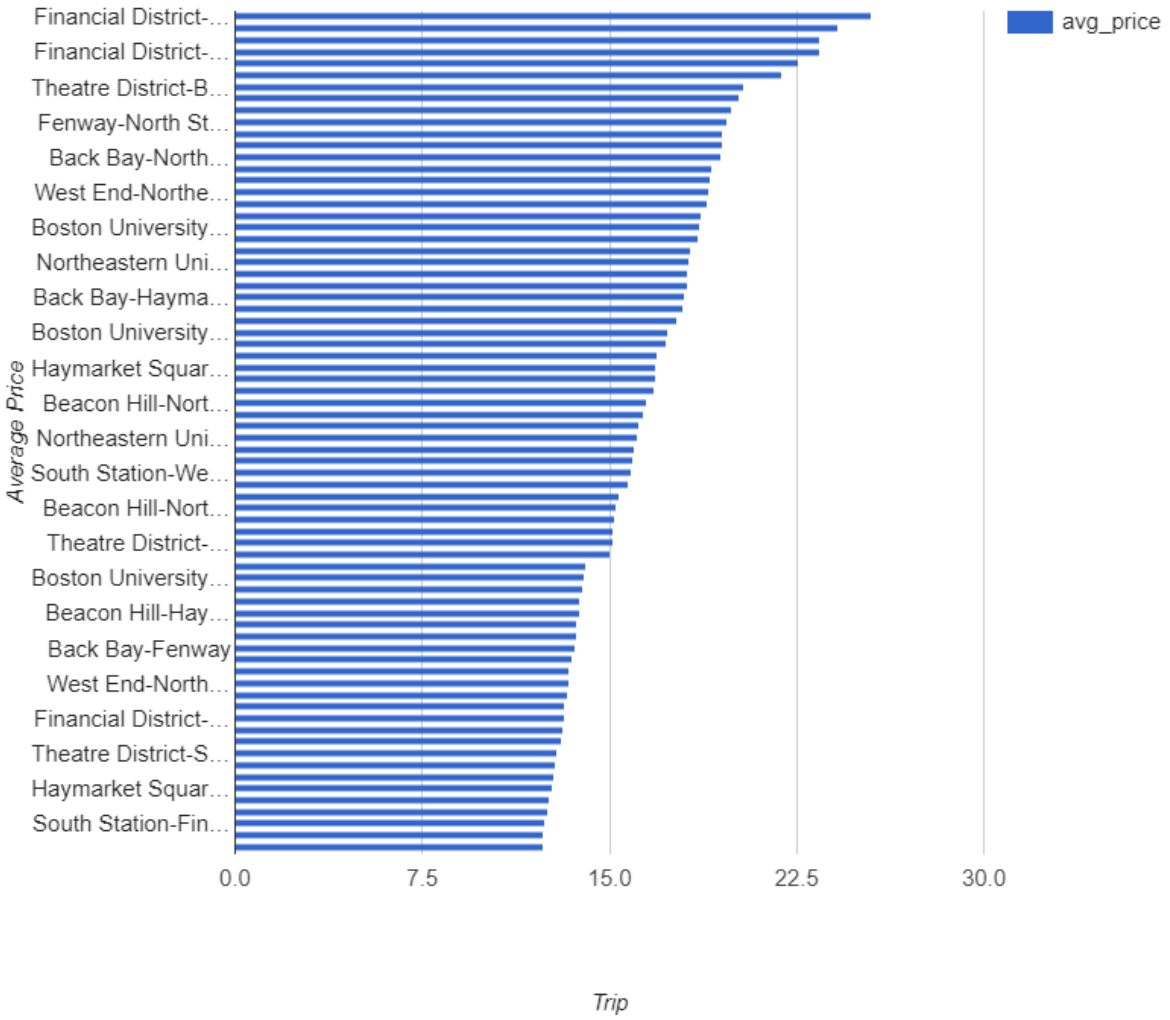
```
count(id) as number_of_trips,
avg(price) as avg_price
FROM   `ba770b-team4.Team_Dataset.cab_rides`
group by trip
order by avg_price DESC;
```

trip	number_of_trips	avg_price
Financial District-Boston University	8940	25.4984340045
Boston University-Financial District	8940	24.1460850112
Fenway-Financial District	8916	23.4388178555
Financial District-Fenway	8928	23.4048499104
Northeastern University-Financial District	8874	22.582093757
Financial District-Northeastern University	8868	21.9185836716
Theatre District-Boston University	9173	20.3606617246
Boston University-North Station	8730	20.1853379152
Northeastern University-North Station	8904	19.9109389039
Fenway-North Station	8970	19.7018394649
North End-Back Bay	9414	19.550934778
North Station-Northeastern University	8904	19.5378481581
Back Bay-North End	9414	19.473018908
South Station-Back Bay	8712	19.103822314
Theatre District-Fenway	8502	19.069277817
West End-Northeastern University	8778	18.9649692413
North Station-Boston University	8730	18.9315578465
Boston University-Theatre District	9174	18.689557445
Boston University-West End	9162	18.61176599
North Station-Fenway	8970	18.5476031215
Fenway-Theatre District	8508	18.2327221439
Northeastern University-West End	8772	18.2041552668
Fenway-West End	9360	18.1618055556
West End-Boston University	9156	18.1571647007
Back Bay-Haymarket Square	8838	17.9873840235

(rows: 72, time: 1.2s, 48MB processed, job: job_ySGuWLWB1IMic-r3AKeIoaLsrux2)

```
%%bq query -n trip
SELECT CONCAT(source, '-', destination) AS trip,
      avg(price) avg_price
      FROM   `ba770b-team4.Team_Dataset.cab_rides`
      group by trip
order by avg_price DESC;
```

```
%%chart bars --data trip
title: Trip VS Average Price
height: 900
width: 800
hAxis:
  title: Trip
vAxis:
  title: Average Price
legend: average price
```



According to the aboved table and chart, there are 72 distinct routes in total on the graph. By moving mouse pointer to each individual column, the full name of each route and its average price could be seen.

It is clearly that the route from `Haymarket Square` to `North Station` has the lowest price, while both two places are closed to each other geographically. Meanwhile, the route of `Financial District` to `Boston University` is the most expensive route with average price of $25.498, while two places are relatively far compared with most of other routes.

- Improvement and Other considerations

1. Due to limited tools that could be used, we could not create a map with each route labled geographically.
2. We tried to combine two trips whose starting station is identical to another trip's end district and vice versa. For example:
   route1: source- Back Bay, Destination - Financial Center
   route2: Source - Financial Center, destination - Back Bay.

   However, if we did that, the graph and data that we got would miss many informations. Even though their source and destination are interchangeable, due to different trip id and other different factors, such as time, weather, etc, we cannot just analyze these two trips as one identical trip.

Cab Type VS Price

- Top 10 Cab Type of Price

```
%%bq query
select name,cab_type,avg(price) as avg_price from `ba770b-team4.Team_Dataset.cab_rides`
group by name, cab_type
order by avg_price DESC
limit 10;
```

```
limit 10;
```

name	cab_type	avg_price
Lux Black XL	Lyft	32.324086074
Black SUV	Uber	30.2867631044
Lux Black	Lyft	23.0624680394
Black	Uber	20.5237861875
Lux	Lyft	17.771240363
UberXL	Uber	15.6781436039
Lyft XL	Lyft	15.3093627403
UberX	Uber	9.76507423676
WAV	Uber	9.76501923915
Lyft	Lyft	9.61088474676

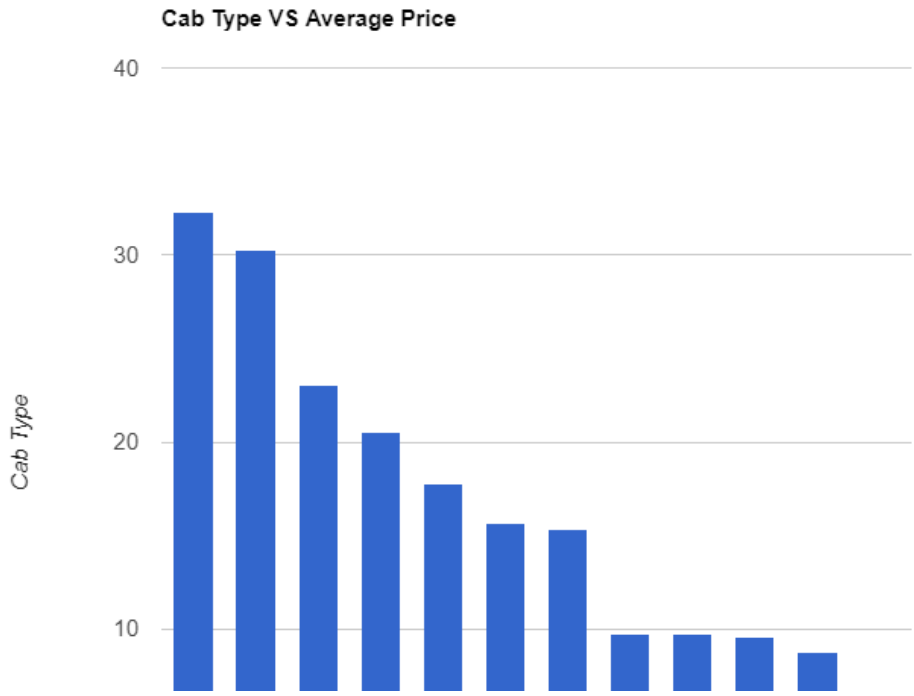
(rows: 10, time: 1.8s, 14MB processed, job: job_NupBCbOjtHAkba-2sA6Xbotzhph-)

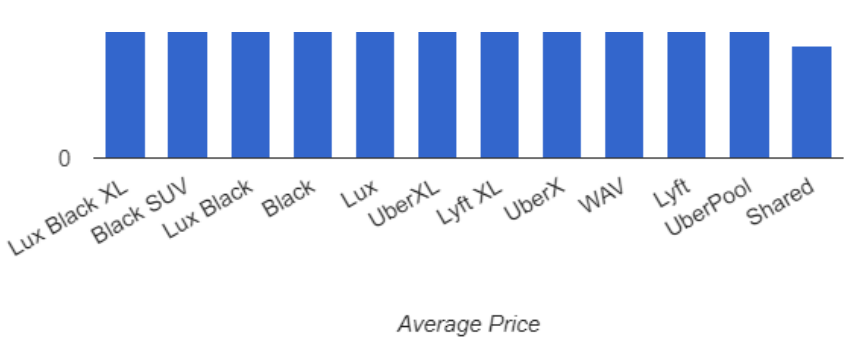
- Bar chart of Cab Type & Price

It's clear that different cab type would have different price. We use bar chart to analyze the relationship between `cab type` and `price`. According to the plot, Lux Black XL has the highest average price, while shared cab has the lowest.

```
%%bq query -n cab_type
select name,avg(price) as avg_price from `ba770b-team4.Team_Dataset.cab_rides`
group by name
order by avg_price DESC;
```

```
%%chart columns --data cab_type
title: Cab Type VS Average Price
height: 800
width: 800
hAxis:
  title: Average Price
vAxis:
  title: Cab Type
legend: none
```





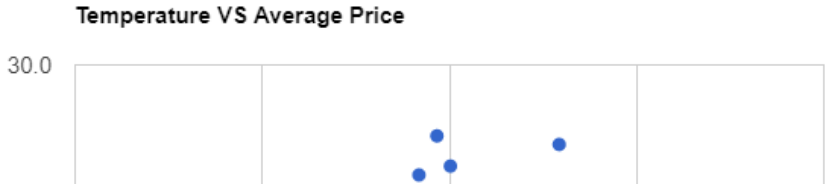
Weather VS Price

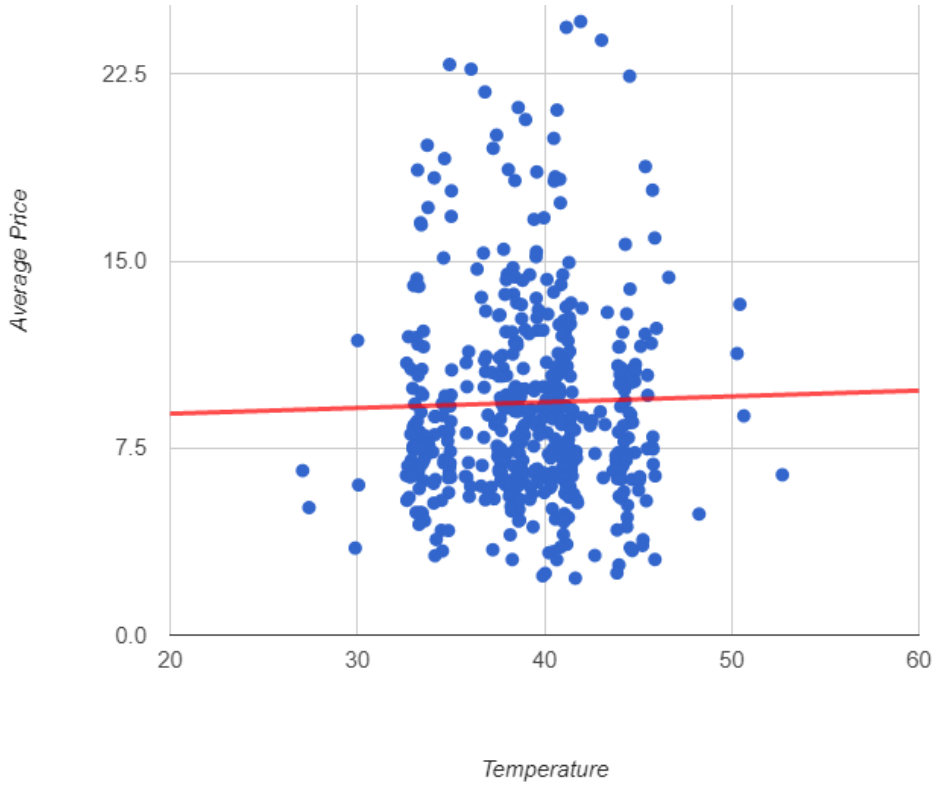
- Temperature

We computed the average price of (price/distance) by temperature , deleted one extreme value and then drew a scatter plot.

```
%%bq query -n temperature
select temp, avg_price
from
(
select temp, avg(price/distance) as avg_price
FROM
(SELECT distance, cab_type, c.time_stamp, destination,source, price, surge_multiplier, product_id, name, ride_time, ride_hou
r, id, temp, location, clouds, pressure, humidity, wind, rain
FROM `ba770b-team4.Team_Dataset.cab_rides` AS c
FULL outer JOIN  `ba770b-team4.Team_Dataset.weather` AS w
ON ride_time = weather_time AND source = location)
where price is not null and temp is not null
group by temp
order by avg_price DESC
)
where avg_price < 100;
```

```
%%chart scatter -d temperature
title: Temperature VS Average Price
height: 800
width: 800
hAxis:
  title: Temperature
vAxis:
  title: Average Price
legend: none
trendlines: { 0: {
      type: 'linear',
      color: 'red',
      lineWidth: 3,
      opacity: 0.7,
      showR2: true,
      visibleInLegend: true
            }
          }
```





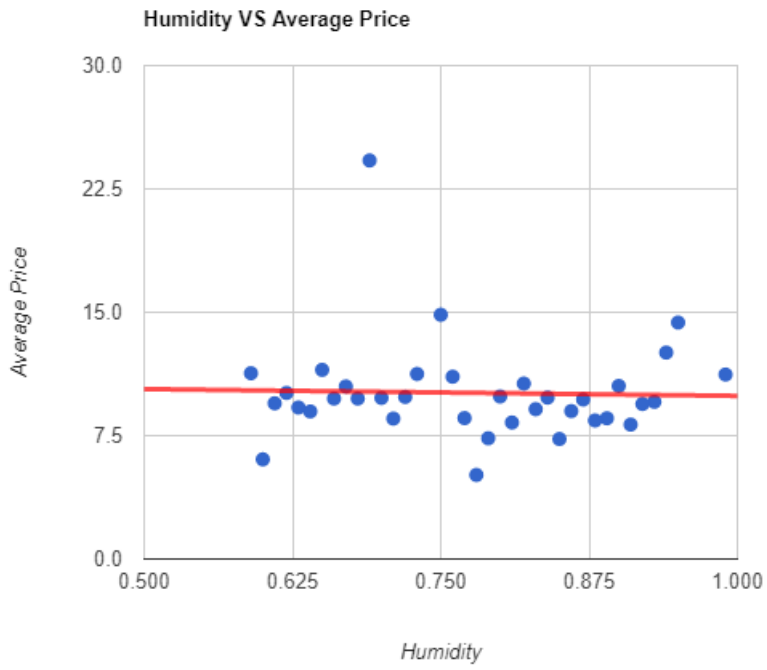
Based on this scatter plot, most data points are distributed mostly at (8,40) and it seems that there is no relationship between the average price and temperature. We also added a trend line to see the relationship but the line seems like very horizontal.

- Humidity

We computed the average price of `(price/distance)` by `humidity`, then draw a scatter plot.

```
%%bq query -n Humidity
select humidity, avg(price/distance) as avg_price
FROM
(SELECT distance, cab_type, c.time_stamp, destination, source, price, surge_multiplier, product_id, name, ride_time, ride_ho
ur, id, temp, location, clouds, pressure, humidity, wind, rain
FROM `ba770b-team4.Team_Dataset.cab_rides` AS c
FULL outer JOIN  `ba770b-team4.Team_Dataset.weather` AS w
ON ride_time = weather_time AND source = location)
    where price is not null
  and humidity is not null
group by Humidity
order by avg_price DESC;
```

```
%%chart scatter -d Humidity
title: Humidity VS Average Price
height: 500
width: 600
hAxis:
  title: Humidity
vAxis:
  title: Average Price
legend: none
trendlines: { 0: {
      type: 'linear',
      color: 'red',
      lineWidth: 3,
      opacity: 0.7,
      showR2: true,
      visibleInLegend: true
            }
          }
```



This scatter plot shows most data points are distributed on a horizontal line, thus we conclude there is nonlinear relationship between humidity and average price.

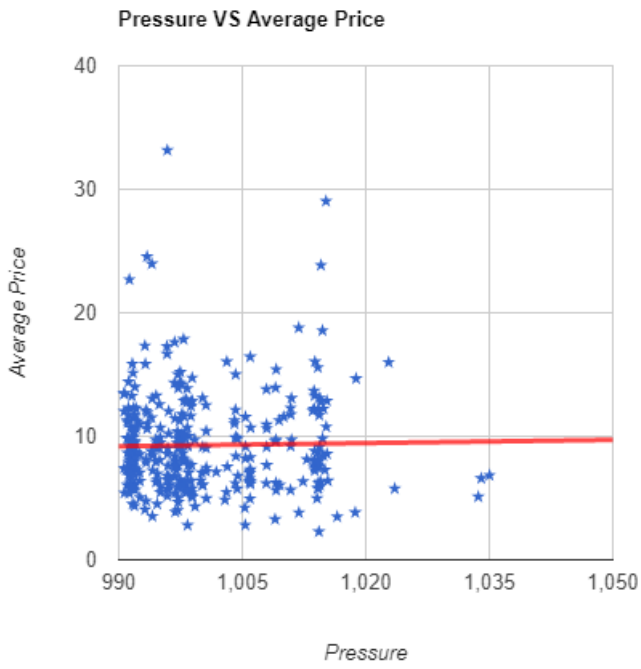
- `Pressure`

We computed the average price of `(price/distance)` by `pressure`, deleted one extreme value and then draw a scatter plot.

```
%%bq query -n pressure
select pressure, avg_price
from
(
select avg(price/distance) as avg_price,pressure
  FROM
(SELECT distance, cab_type, c.time_stamp, destination,source, price, surge_multiplier, product_id, name, ride_time, ride_hou
r, id, temp, location, clouds, pressure, humidity, wind, rain
FROM `ba770b-team4.Team_Dataset.cab_rides` AS c
FULL outer JOIN  `ba770b-team4.Team_Dataset.weather` AS w
ON ride_time = weather_time AND source = location)
    where price is not null
  and pressure is not null
group by pressure
order by avg_price DESC
)
where avg_price < 100;
```

```
%%chart scatter -d pressure
title: Pressure VS Average Price
height: 500
width: 500
hAxis:
  title: Pressure
vAxis:
  title: Average Price
legend: none

pointShape: 'star'
trendlines: { 0: {
      type: 'linear',
```

```
    color: 'red',
    lineWidth: 3,
    opacity: 0.7,
    showR2: true,
    visibleInLegend: true
          }
        }
```



We added a trendline on this scatter plot but it seems like there is no relationship between avergae price and pressure since most data points are distributed in a square so we conclude there is nonlinear relationship between pressure and average price.

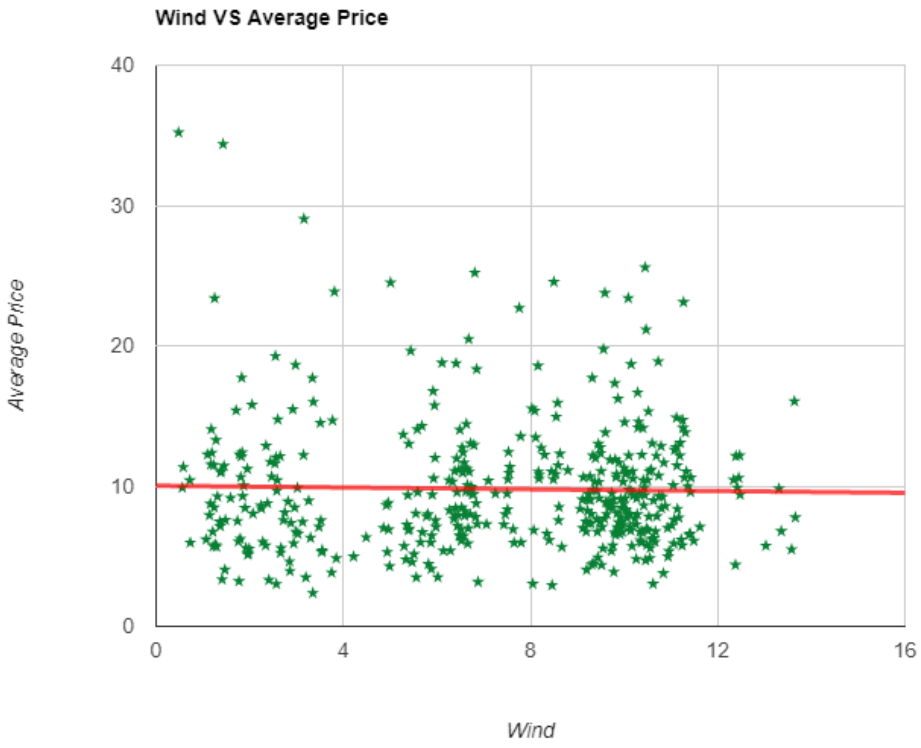
- `Wind`

We computed the average price of (`price/distance`) by `wind` , deleted one extreme value and then draw a scatter plot.

```
%%bq query -n wind
select wind, avg_price
from
(
select avg(price/distance) as avg_price,wind
  FROM
(SELECT distance, cab_type, c.time_stamp, destination,source, price, surge_multiplier, product_id, name, ride_time, ride_hou
r, id, temp, location, clouds, pressure, humidity, wind, rain
FROM `ba770b-team4.Team_Dataset.cab_rides` AS c
FULL outer JOIN  `ba770b-team4.Team_Dataset.weather` AS w
ON ride_time = weather_time AND source = location)
    where price is not null
  and wind is not null
group by wind
order by avg_price DESC
)
where avg_price < 100;
```

```
%%chart scatter -d wind
title: Wind VS Average Price
height: 600
width: 800
hAxis:
  title: Wind
vAxis:
```

```
 title: Average Price
legend: none
colors: ['#088035']
pointShape: 'star'
trendlines: { 0: {
    type: 'linear',
    color: 'red',
    lineWidth: 3,
    opacity: 0.7,
    showR2: true,
    visibleInLegend: true
        }
      }
```



Based on this scatter plot, it seems there is nonlinear relationship between wind and average price.

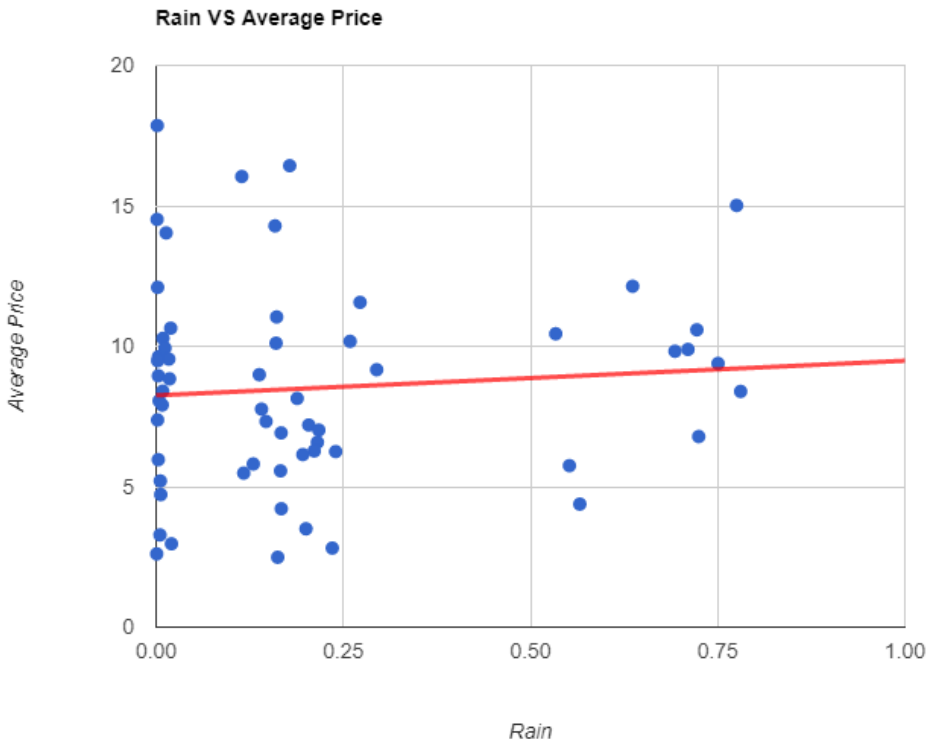
- `Rain`

We used the average price of (`price/distance`) and `wind` to draw a scatter plot

```
%%bq query -n rain
select rain, avg(price/distance) as avg_price
  FROM
(SELECT distance, cab_type, c.time_stamp, destination,source, price, surge_multiplier, product_id, name, ride_time, ride_hou
r, id, temp, location, clouds, pressure, humidity, wind, rain
FROM `ba770b-team4.Team_Dataset.cab_rides` AS c
FULL outer JOIN  `ba770b-team4.Team_Dataset.weather` AS w
ON ride_time = weather_time AND source = location)
where price is not null
and wind is not null
and rain <> 0
group by rain
order by avg_price DESC;
```

```
%%chart scatter -d rain
title: Rain VS Average Price
```

```
height: 600
width: 800
hAxis:
  title: Rain
vAxis:
  title: Average Price
legend: none
trendlines: { 0: {
      type: 'linear',
      color: 'red',
      lineWidth: 3,
      opacity: 0.7,
      showR2: true,
      visibleInLegend: true
            }
          }
```



Based on this scatter plot, it seems a week positive realtionship between rain and average price. In addition, we added a linear trend line which is y=5.187*(10^-3)x + 0.163.

Influence of Big Event

When it comes to the big events like sport matches, the cab price would increase sharply. As our rides time data between November and December, we pick Boston Celtics matches as the example to analyse the influence of big events to the cab price.

- Average Cab Price of Important Game Day

```
%%bq query
with calendar_game as
(
select
extract(date from timestamp_millis(time_stamp)) as ride_date,
avg(price) as avg_price
```

```
from `ba770b-team4.Team_Dataset.cab_rides`
inner JOIN `ba770b-team4.Team_Dataset.celtics`
ON date = extract(date from timestamp_millis(time_stamp))
where source = 'South Station'
group by ride_date
order by avg_price DESC
)
select avg(avg_price) as game_price
from calendar_game;
```

game_price
15.6575024589

(rows: 1, time: 0.9s, 19MB processed, job: job_rejQEBXCurNieLqzx4c5y480APvT)

- Average Cab Price of Normal Day

```
%%bq query
with calendar_normal as
(
select
extract(date from timestamp_millis(time_stamp)) as date,
avg(price) as avg_price
from `ba770b-team4.Team_Dataset.cab_rides`
where source = 'South Station'
and extract(date from timestamp_millis(time_stamp)) <> '2018-12-10'
and extract(date from timestamp_millis(time_stamp)) <> '2018-12-14'
and extract(date from timestamp_millis(time_stamp)) <> '2018-11-30'
group by date
)
select avg(avg_price) as normal_price
from calendar_normal;
```

normal_price
15.6301247459

(rows: 1, time: 1.0s, 19MB processed, job: job_KHsll38iUGRUfDG6hslGgJaeYGbQ)

According to the aboved tables, the average price of game days is slightly higher than the average price of normal days.

Price Prediction

We want to study how other factors may influence the price of cab riding. As mentioned aboved, only `rain` shows the influence to the price in all weather factors, we set up a linear regression model to predict the rides price by using the factors of distance, ride hour, rains, and surge multiplier. We use half of the data to train the model, while the others to evaluate the model.

- Set regression database

Firstly, we join the two table together in order to select data more convenient.

```
%%bq query
create or replace table `ba770b-team4.Team_Dataset.Join_Data` AS
(
select distinct id, distance, cab_type, time_stamp, destination,source, price, surge_multiplier, product_id, name, ride_time, ride
_hour, temp, location, clouds, pressure, humidity, wind, rain
from
(
SELECT distance, cab_type, c.time_stamp, destination,source, price, surge_multiplier, product_id, name, ride_time, ride_hour
, id, temp, location, clouds, pressure, humidity, wind, rain
FROM `ba770b-team4.Team_Dataset.cab_rides` AS c
FULL outer JOIN  `ba770b-team4.Team_Dataset.weather` AS w
ON ride_time = weather_time AND source = location
)
```

```
)
where id is not null
and pressure is not null
);
```

id	distance	cab_type	time_stamp	destination	source	price	surge_multiplier	product_id	name	ride_time
b81d2253-177f-47e9-b0e8-7ad2b01d3b29	5.22	Lyft	1543464558894	Boston University	Financial District	26.0	1.0	lyft_premier	Lux	2018-11-29 04:09:18
6f1f1cb5-61a8-40fd-aa7e-14e7a5921cf4	5.22	Lyft	1543464558894	Boston University	Financial District	47.5	1.0	lyft_luxsuv	Lux Black XL	2018-11-29 04:09:18
b44a6b9b-7a90-4765-84a6-9bf8a7d2496a	5.22	Lyft	1543464558894	Boston University	Financial District	22.5	1.0	lyft_plus	Lyft XL	2018-11-29 04:09:18
053d69b4-fd8e-4dbb-ade0-dc3c40531268	5.22	Lyft	1543464558894	Boston University	Financial District	38.0	1.0	lyft_lux	Lux Black	2018-11-29 04:09:18
176ce282-1e5b-47f7-b092-5f4b673bf2b7	2.44	Uber	1543451968560	Northeastern University	Financial District	10.5	1.0	9a0e7b09-b92b-4c41-9779-2ad22b4d779d	WAV	2018-11-29 00:39:28
25ec9fd7-c8c0-4ed7-9b77-2b13dae26437	2.44	Uber	1543451968560	Northeastern University	Financial District	19.5	1.0	6f72dfc5-27f1-42e8-84db-ccc7a75f6969	UberXL	2018-11-29 00:39:28
9eec6998-7d32-43e2-a032-6d9f12a2a57a	2.2	Uber	1543468659630	Haymarket Square	Back Bay	9.5	1.0	9a0e7b09-b92b-4c41-9779-2ad22b4d779d	WAV	2018-11-29 05:17:39
e78d77fe-9560-4c25-9f20-b4b7a8fbfc0f	1.03	Lyft	1543220463837	North End	Financial District	16.5	1.0	lyft_lux	Lux Black	2018-11-26 08:21:03
d498ac35-98a2-415d-8790-c143ed17fe93	1.03	Lyft	1543220463837	North End	Financial District	10.5	1.0	lyft_premier	Lux	2018-11-26 08:21:03
17ced235-fefa-4076-bbb4-070ef1920f4e	4.55	Uber	1543457206095	Financial District	Northeastern University	12.5	1.0	9a0e7b09-b92b-4c41-9779-2ad22b4d779d	WAV	2018-11-29 02:06:46
0ec14a81-92f9-4582-9aca-b6e665beef29	2.61	Uber	1543457206095	Beacon Hill	Northeastern University	9.0	1.0	997acbb5-e102-41e1-b155-9df7de0a73f2	UberPool	2018-11-29 02:06:46
256ab02d-ea00-45e5-b5c1-e1820dd7fc2e	4.55	Uber	1543457206095	Financial District	Northeastern University	20.5	1.0	6f72dfc5-27f1-42e8-84db-ccc7a75f6969	UberXL	2018-11-29 02:06:46
ec27910f-859e-455c-bea9-63fa4fe36286	1.73	Lyft	1543457238361	Haymarket Square	Theatre District	7.0	1.0	lyft_line	Shared	2018-11-29 02:07:18
ecd5a978-2dd8-483c-b781-b9f3635db470	1.73	Lyft	1543457238361	Haymarket Square	Theatre District	19.5	1.0	lyft_lux	Lux Black	2018-11-29 02:07:18
15842b24-76c9-4594-ab2b-81dac816d7be	1.61	Uber	1543457238911	Haymarket Square	Theatre District	8.0	1.0	997acbb5-e102-41e1-b155-9df7de0a73f2	UberPool	2018-11-29 02:07:18
ed72d9f8-e9bf-4174-b296-8a5bbb5219de	4.96	Lyft	1543457238919	Boston University	Theatre District	57.5	1.75	lyft_lux	Lux Black	2018-11-29 02:07:18
a0d22de9-048f-4361-91c1-3871f08011b4	2.17	Uber	1543284922192	South Station	North Station	29.5	1.0	6d318bcc-22a3-4af6-bddd-b409bfce1546	Black SUV	2018-11-27 02:15:22
b3ebd6e4-1a8c-4ec1-8643-	1.34	Uber	1543284922278	South Station	North Station	10.0	1.0	997acbb5-e102-41e1-b155-	UberPool	2018-11-27 02:15:22

e68ed300114f								9df7de0a73f2		
ad2b40fb-3d83-47ba-a480-85cde80165a7	1.34	Uber	1543284922278	South Station	North Station	9.5	1.0	9a0e7b09-b92b-4c41-9779-2ad22b4d779d	WAV	2018-11-27 02:15:22
c877c625-e37a-444d-97e7-e252d2cce8bc	1.34	Uber	1543284922278	South Station	North Station	9.5	1.0	55c66225-fbe7-4fd5-9072-eab1ece5e23e	UberX	2018-11-27 02:15:22
aae67706-97b5-4aea-afb5-1c6e86e0d68f	2.78	Uber	1543284922605	Northeastern University	North Station	22.0	1.0	6c84fd89-3f11-4782-9b50-97c468b19529	Black	2018-11-27 02:15:22
daa7426f-07af-4017-9ff6-f37069f0ab3b	2.78	Uber	1543284922605	Northeastern University	North Station	9.5	1.0	9a0e7b09-b92b-4c41-9779-2ad22b4d779d	WAV	2018-11-27 02:15:22
a55775c8-bdb9-443e-a248-d2678c184260	3.39	Uber	1543406527379	North Station	Boston University	10.5	1.0	55c66225-fbe7-4fd5-9072-eab1ece5e23e	UberX	2018-11-28 12:02:07
a6620524-361c-4822-b935-a8ebe34b624e	3.5	Lyft	1543406527975	North Station	Boston University	19.5	1.0	lyft_plus	Lyft XL	2018-11-28 12:02:07
9ebc1d84-6d9d-40b8-99db-6a874dcf7c45	3.5	Lyft	1543406527975	North Station	Boston University	27.5	1.0	lyft_lux	Lux Black	2018-11-28 12:02:07

(rows: 3548, time: 4.5s, 108MB processed, job: job_9QYRyp73P15CNA7vsC5SBnmiIA8z)

- Create Regression Model of `price`.

```
%%bq query
create or replace model `ba770b-team4.Team_Dataset.regression_with_distance`
options(
model_type = 'linear_reg',
input_label_cols = ['price']
) as
select price, distance, ride_hour, rain, surge_multiplier
from `ba770b-team4.Team_Dataset.Join_Data`
where MOD(ABS(FARM_FINGERPRINT(id)),2) = 1;
```

Done

- Get training statistics

We can get the training statistics by using ml.training_info function. In this case, we can get that the loss of this model is 78.889, represents 'the loss metric calculated after the given iteration on the training dataset'.

```
%%bq query
select *
from ml.training_info(model `ba770b-team4.Team_Dataset.regression_with_distance`);
```

training_run	iteration	loss	eval_loss	learning_rate	duration_ms
0	0	71.9394330005	78.3321895292		13135

(rows: 1, time: 0.6s, 0B processed, job: job_-LxO15lvFQUHmFIa8jh7n1GsT9sd)

- Evaluate the model

By using the ml.evaluation fuction, we can evaluate the result of our model. In this case, rmse shows the average difference between the predicted price and the actual price, which is 8.61.

```
%%bq query
with eval_table as
```

```
(
select *, price as lable
from `ba770b-team4.Team_Dataset.Join_Data`
where MOD(ABS(FARM_FINGERPRINT(id)),2) = 0
)

SELECT SQRT(mean_squared_error) AS rmse
FROM
ML.evaluate(MODEL `ba770b-team4.Team_Dataset.regression_with_distance`, TABLE eval_table);
```

rmse
8.60997507398

(rows: 1, time: 0.6s, 276KB processed, job: job_T4MPvCku4fsHkWQ4vIgB4MEU7iCG)

- Weights of variables

The following table shows the coefficients of the variables. We could easily find that the distance influence the rides price the most, since it has the highest weight. Distance, ride hour, rian, and temperature have positive effect on the price, while clouds, wind, and humidity have negative effective on the price.

```
%%bq query
SELECT *
FROM
ml.weights(MODEL `ba770b-team4.Team_Dataset.regression_with_distance`)
```

processed_input	weight
distance	2.4247700788
ride_hour	0.0331250342623
rain	-0.269895836983
surge_multiplier	19.0841520189
__INTERCEPT__	-8.54337950954

(rows: 5, time: 0.5s, 40B processed, job: job_JeZzpClvydsRfwHPmnY_4tVLb5_l)

- Prediction by using the model

With the regression model, we can predict the ride price by using the variables in the model. We try to predict the price by using the other half of the data.

```
%%bq query
select *
from ml.predict
(
  model `ba770b-team4.Team_Dataset.regression_with_distance`,
  (
    select price as actual_price, distance, ride_hour, rain, surge_multiplier
    from `ba770b-team4.Team_Dataset.Join_Data`
    where MOD(ABS(FARM_FINGERPRINT(id)),2) = 0
  )
)
```

predicted_price	actual_price	distance	ride_hour	rain	surge_multiplier
23.3305724578	47.5	5.22	4	0.0	1.0
23.3305724578	22.5	5.22	4	0.0	1.0
16.4572115017	10.5	2.44	0	0.0	1.0
16.4572115017	19.5	2.44	0	0.0	1.0
13.3032859646	16.5	1.03	8	0.0	1.0
13.3032859646	10.5	1.03	8	0.0	1.0
21.6397264364	12.5	4.55	2	0.0	1.0
14.8018748142	19.5	1.73	2	0.0	1.0

36.9469961829	57.5	4.96	2	0.0	1.75
15.8307723151	29.5	2.17	2	0.1408	1.0
13.8182131496	9.5	1.34	2	0.1408	1.0
17.3098820631	22.0	2.78	2	0.1408	1.0
17.3098820631	9.5	2.78	2	0.1408	1.0
19.4249681963	19.5	3.5	12	0.0	1.0
19.4249681963	27.5	3.5	12	0.0	1.0
19.4249681963	10.5	3.5	12	0.0	1.0
20.2244824573	21.5	3.98	1	0.0	1.0
20.2244824573	32.0	3.98	1	0.0	1.0
26.216526367	45.5	0.48	6	0.0	1.75
12.1216416599	16.5	0.57	6	0.0	1.0
12.1216416599	9.0	0.57	6	0.0	1.0
12.1216416599	3.0	0.57	6	0.0	1.0
13.8674761166	7.0	1.29	6	0.0	1.0
22.1998078542	27.5	4.74	5	0.0	1.0
14.9739930194	16.5	1.76	5	0.0	1.0

(rows: 1778, time: 1.4s, 276KB processed, job: job_fLzzbSP4A78V3Uw5-1u-hWchBVgF)