How do casual riders and annual members use Cyclistic bikes differently?

— more details about this case study

Chuang, Ya Chu (莊雅竹)

Scenario A case study form Coursera

This was a fiction company Cyclistic, a bike-share company in Chicago. It had two types of users,

1. **Casual riders:** single-ride passes and full-day passes
2. **Annual members:** annual memberships, according to finance analysts they are **more profitable**

The marketing team had an insight:

"Cyclistic's future success depends on maximizing the number of annual memberships. There is a very good chance to **convert casual riders into members** because they are already aware of the Cyclistic program "

Before designing marketing strategies aimed at converting casual riders into annual members, they needed to know…

"How do casual riders and annual members use Cyclistic bikes differently ?"

Materials From

https://divvy-tripdata.s3.amazonaws.com/index.html

Tools I Used

Prepare	Process	Analyze	Visualiztion
BigQuery (GCP)	Spreadsheet BigQuery	BigQuery	Looker studio Spreadsheet

Ask

1. How annual members and casual riders use our Cyclistic bikes differently?
2. Why would casual members upgrade to annual memberships?
3. How can Cyclistic use digital media to influence casual riders to become members?

Prepare

1. Download the previous 12 months (2023/07 - 2024/06) of trip data
2. Browse the file and check the structure of data
3. Upload to **Google Cloud Platform**
4. Upload to BigQuery with **bq command** (combine 12 csv files into one table)

Approximately **5,700,000 data in total**, and each had **13 columns**, including

STRING:

ride_id (=unique to every single trip), **rideable_type** (=bike type), **started_station_name, start_station_id, end_station_name, end_station_id, member_casual** (=membership type)

TIMESTAMP:

started_at, ended_at (=the time when they started or ended their ride)

FLOAT:

start_lat, start_lng, end_lat, end_lng (=where they started or ended their ride)

Process

1. Identify distinct value
2. Identify relation between columns
3. Check if there is a null value
4. Check if values are reasonable
5. Proxy null data

Process - Identify distinct value

1. **ride_id** should be unique, **but there were 221 duplicates**
2. Check the difference of data between them:

ride_id	rideable_type	started_at	ended_at	start_station_nai	start_station_id	end_station_nan	end_station_id	start_lat	start_lng	end_lat	enc
011C8EF97AB0I	classic_bike	2024-05-31 19:45:38.037000 UTC	2024-06-01 20:45:33.862000 UTC	Clifton Ave & Arr	TA1307000163			41.918216	-87.656936		
011C8EF97AB0I	classic_bike	2024-05-31 19:45:38.000000 UTC	2024-06-01 20:45:33.000000 UTC	Clifton Ave & Arr	TA1307000163			41.918216	-87.656936		
01406457A85B(	electric_bike	2024-05-31 23:54:59.000000 UTC	2024-06-01 00:01:47.000000 UTC			Damen Ave & Cl	13132	41.89	-87.67	41.895769	
01406457A85B(	electric_bike	2024-05-31 23:54:59.194000 UTC	2024-06-01 00:01:47.626000 UTC			Damen Ave & Cl	13132	41.89	-87.67	41.895769	
02606FBC7F85:	classic_bike	2024-05-31 17:55:01.000000 UTC	2024-06-01 18:54:53.000000 UTC	Pine Grove Ave	TA1307000150			41.94947274	-87.64645278		
02606FBC7F85:	classic_bike	2024-05-31 17:55:01.635000 UTC	2024-06-01 18:54:53.970000 UTC	Pine Grove Ave	TA1307000150			41.94947274	-87.64645278		
0354FD0756337	electric_bike	2024-05-31 23:34:36.273000 UTC	2024-06-01 00:14:29.238000 UTC					41.97	-87.66	41.96	
0354FD0756337	electric_bike	2024-05-31 23:34:36.000000 UTC	2024-06-01 00:14:29.000000 UTC					41.97	-87.66	41.96	
048C715F1DE0I	electric_bike	2024-05-31 23:53:44.401000 UTC	2024-06-01 00:12:26.776000 UTC					41.89	-87.66	41.89	
048C715F1DE0I	electric_bike	2024-05-31 23:53:44.000000 UTC	2024-06-01 00:12:26.000000 UTC					41.89	-87.66	41.89	
05D27072A33A:	classic_bike	2024-05-31 16:34:46.426000 UTC	2024-06-01 04:12:45.545000 UTC	Dearborn St & E	13045	DuSable Lake S	TA1309000039	41.893992	-87.629318	41.932588	

3. Data in most columns were the same, but slight different in **start_at** and **end_at**

⇒ **Exclude the duplicates**

Process - Identify relation between columns

1. Was **station_id** associated with **station_name**?
   There were **multiple station_names** with **the same station_id**!

end_station_id	end_station_name
TA1309000042	Lincoln Ave & Melrose St
TA1309000042	Lincoln Ave & Belmont Ave (Te…
TA1305000030	Wells St & Randolph St
TA1305000030	Clark St & Randolph St
KA1503000074	Museum of Science and Industry

2. Check the location (**lat & lng**) of these station, found their locations were close, I guessed <u>they might change their names</u> at different times

⇒ Remain these names

Process - Check if there is null value

1. The value in any one or more columns of **_station_name, _station_id, end_lat** and **end_lng** of **1,460,033 data (about 25%) were null !**

pe	started_at	ended_at	start_station_name	start_station_id	end_station_name	end_station_id	start_lat	start_lng	end_lat	end_lng	memb
ke	2024-05-...	2024-0...	null	null	null	null	42.0	-87.67	42.0	-87.66	casua
ke	2024-06-...	2024-0...	null	null	null	null	41.99	-87.65	42.0	-87.66	memb
ke	2024-04-...	2024-0...	null	null	null	null	42.01	-87.67	42.0	-87.66	casua
ke	2023-10-...	2023-1...	null	null	null	null	42.01	-87.68	42.0	-87.66	memb

tart_station_name	start_station_id	end_station_name	end_station_id	start_lat	start_lng	end_lat	end_lng	member_casual
lalsted St & Clybour...	331	null	null	41.909668	-87.648128	null	null	member
lalsted St & Clybour...	331	null	null	41.909668	-87.648128	null	null	casual
lalsted St & Clybour...	331	null	null	41.909668	-87.648128	null	null	casual
lenwood Ave & Tou...	525	null	null	42.012701	-87.666058	null	null	casual

Process - Check if there is null value

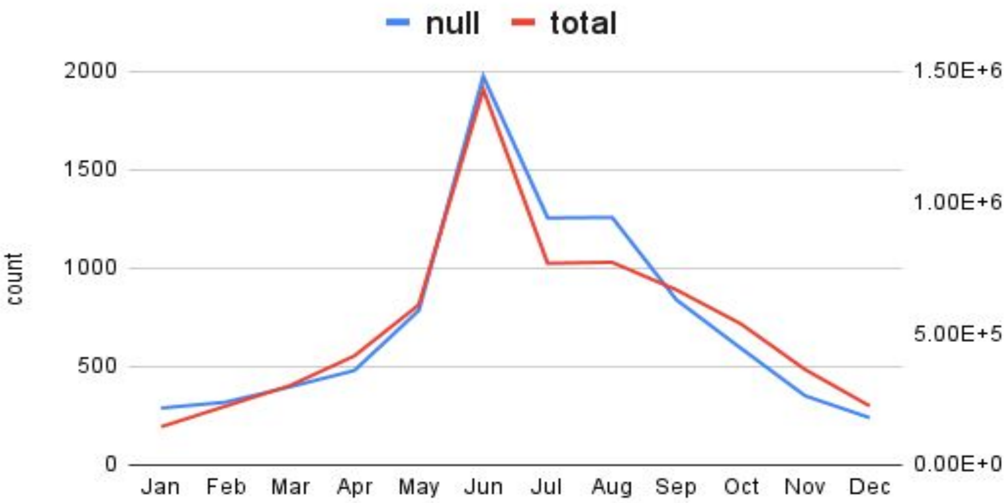
2. After drilling down, I found that
   a. The **start_lat** and **start_lng** of each trip **was always recorded.**
   b. If **sation_ids** were not recorded, the **latitude and longitude** of these locations **were less specific than recorded ones**. For me, these data were still reliable.

end_station_name	end_station_id	sta	sta	end_lat	end_lng	
University Library (NU)	605			42.052939	-87.673447	→specific
null	*null*			41.9	-87.76	→rough

3. In my opinion, **the data without any location info might be not reliable.**

Process - Check if there is null value

2. I checked whether there was any data that didn't record **station_id, lat or lng at the same time**, and there were **7,813 (about 0.1 %)**.
3. The distribution of these data throughout the year **was similar to** total data



⇒ It's fine to exclude them

Process - Check if values are reasonable

- **end_lat** and **end_lng** of some data **were zero**!

end_station_id	start_lat	start_lng	end_lat	end_lng
653B	41.893992	-87.629318	0.0	0.0
OH Charging Stx - Test	41.796642	-87.625923	0.0	0.0
OH Charging Stx - Test	41.86316583333...	-87.6798115	0.0	0.0

⇒ Replace them with the **average end_lat** and **end_lng (proxy the data)**

p.s. I also **filled the null data in end_lat and end_lng** in the same way.

Process - Check if values are reasonable

- **started_at** should be earlier then **ended_at**, **but 434 data showed earlier ended_at than started_at !**

ride_id	rideable_type	started_at	ended_at
2BFB23CDC9A75AB0	electric_bike	2023-08-26 10:19:36 UTC	2023-08-26 10:16:52 UTC
7934DBD46A7BB934	electric_bike	2023-12-06 16:07:40 UTC	2023-12-06 16:07:37 UTC
64BF86DB62A97011	electric_bike	2023-07-22 10:05:44 UTC	2023-07-22 10:05:41 UTC

⇒ Given that they were only a **small proportion** of the total, **exclude these data**

Analyze & Visualization

How do casual riders and annual members use Cyclistic bikes differently ?

1. In terms of rideable type
2. In terms of riding times
3. In terms of riding duration
4. In terms of which day of the week to ride
5. In terms of their destinations

Analyze - create new columns

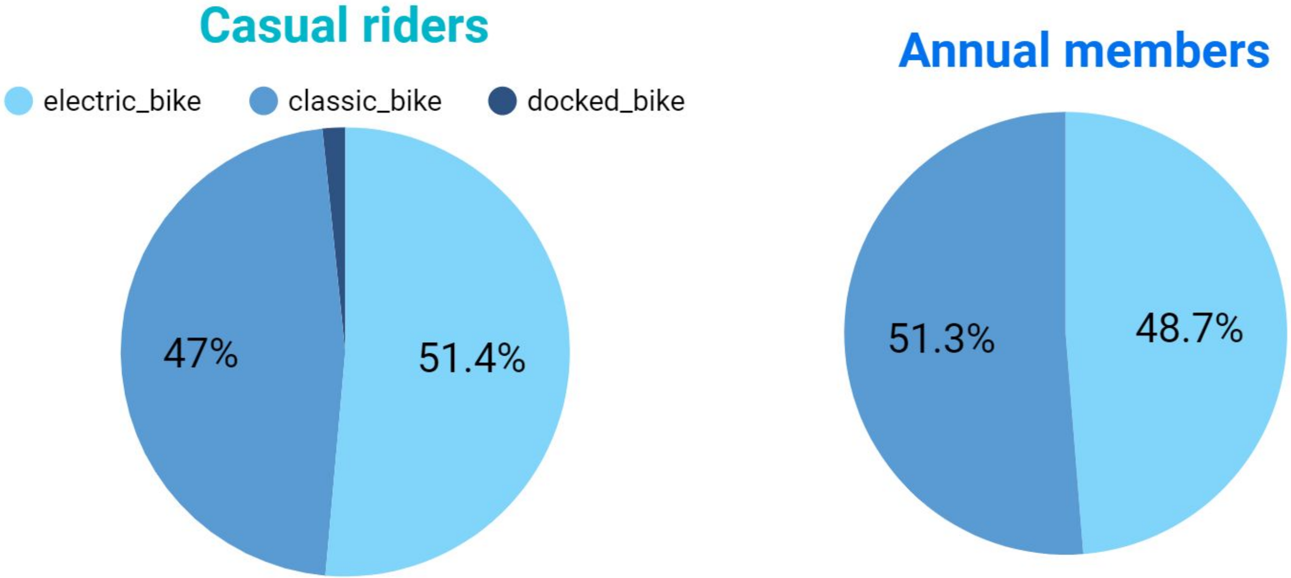
TIMESTAMP_DIFF(ended_at,started_at,MINUTE) AS **riding_duration** (minutes)

EXTRACT(DAYOFWEEK FROM started_at) AS **weekday** (1 for Sun, 2 for Mon, 3 for Tue….)

EXTRACT(MONTH FROM started_at) AS **month** (1 for Jun, 2 for Feb, 3 for Mar….)

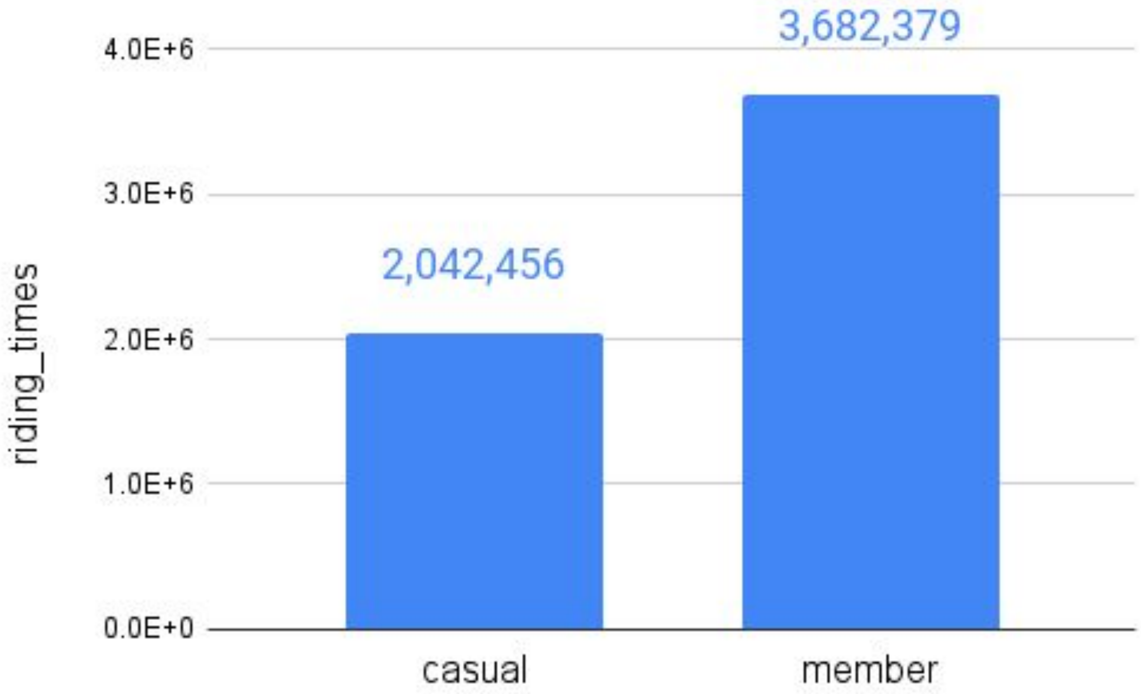
EXTRACT(HOUR FROM started_at) AS **time_hour** (1 for Jun, 2 for Feb, 3 for Mar….)

Analyze - In terms of rideable type



No significant difference between annual members and casual riders.
Note that **no annual member used docked_bike** in the past year.

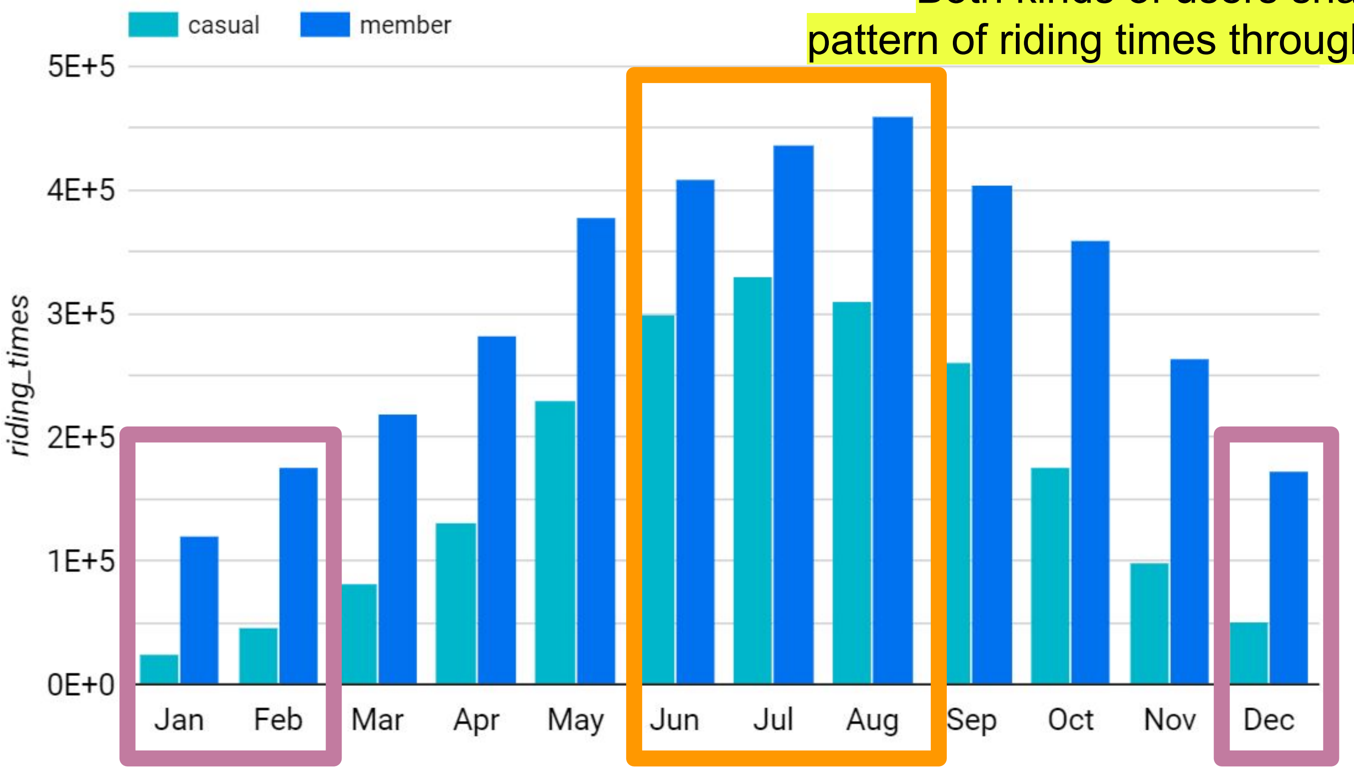
Analyze - In terms of riding times



Anual members rode 1.8 times more than casual riders !

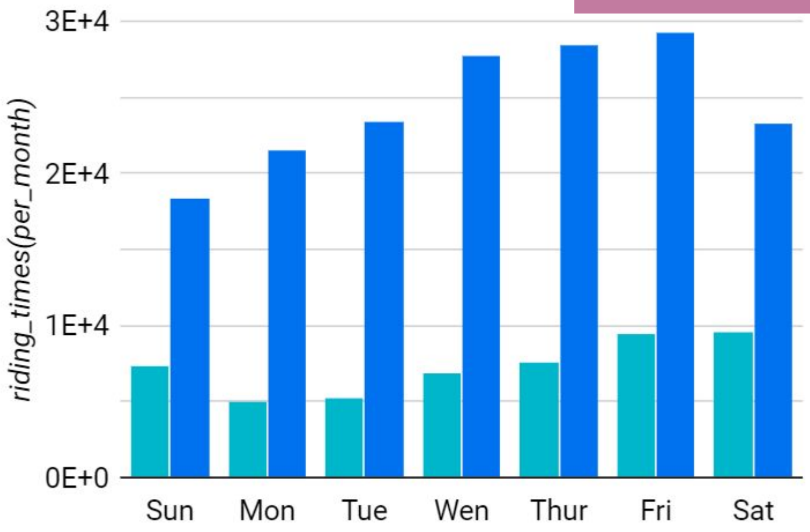
Analyze - In terms of riding times

Both kinds of users shared the same pattern of riding times throughout the year.

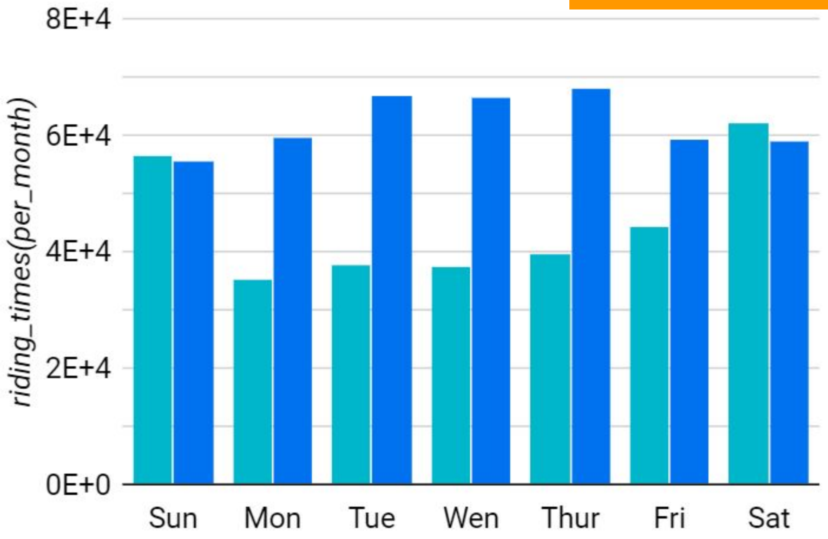


Analyze - In terms of riding times (off & peak)

off season

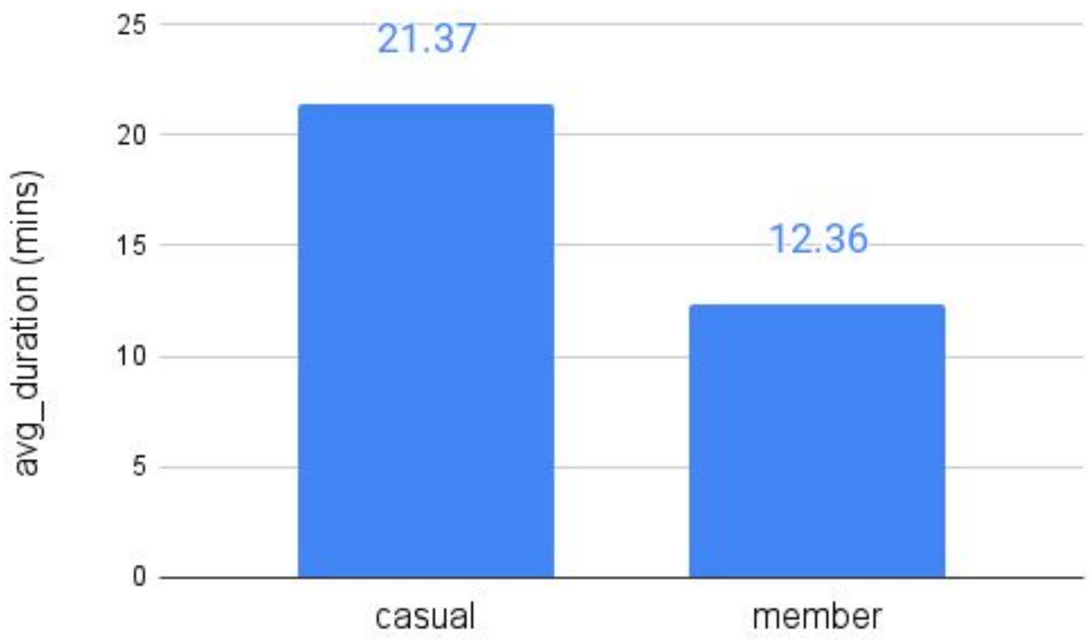


peak season



Casual riders used more often **on weekends in busy season**,
while aunal members prefered **weekdays** use **in both seansons**.

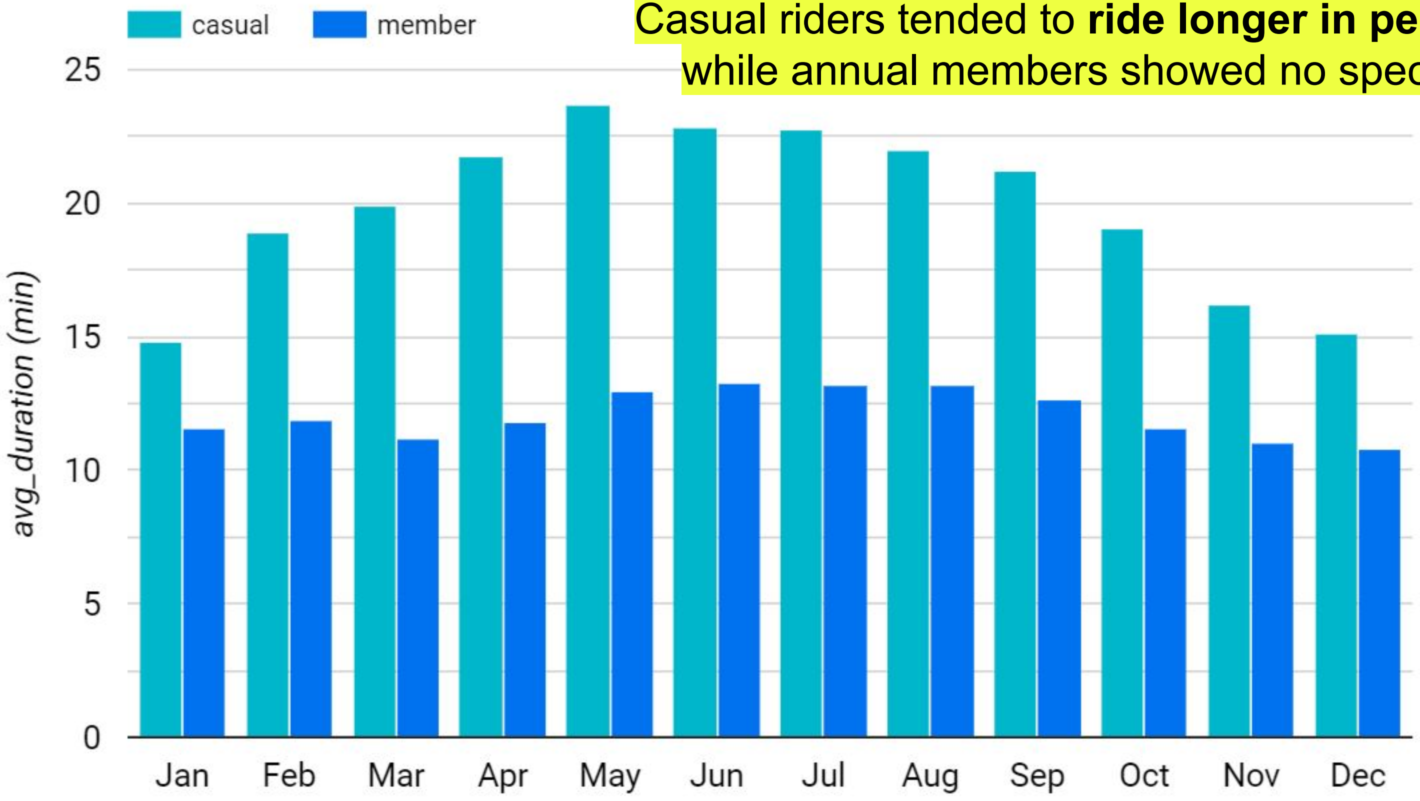
Analyze - In terms of riding duration



Casaul users rode 1.73 times longer than annual memebers!

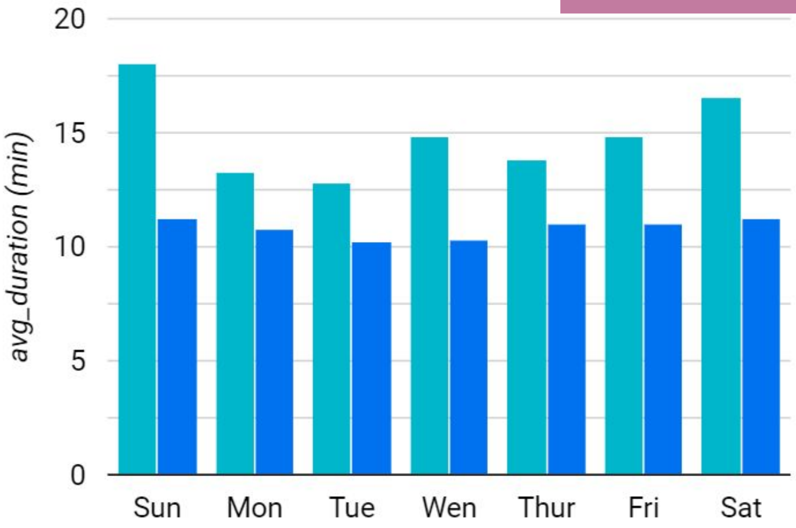
Analyze - In terms of riding duration

Casual riders tended to **ride longer in peak season**, while annual members showed no specific pattern.

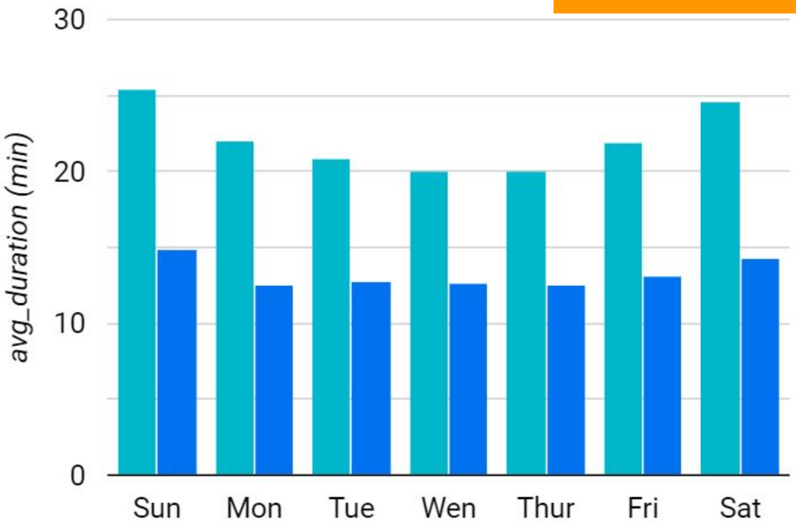


Analyze - In terms of riding duration (off & peak)

off season



peak season

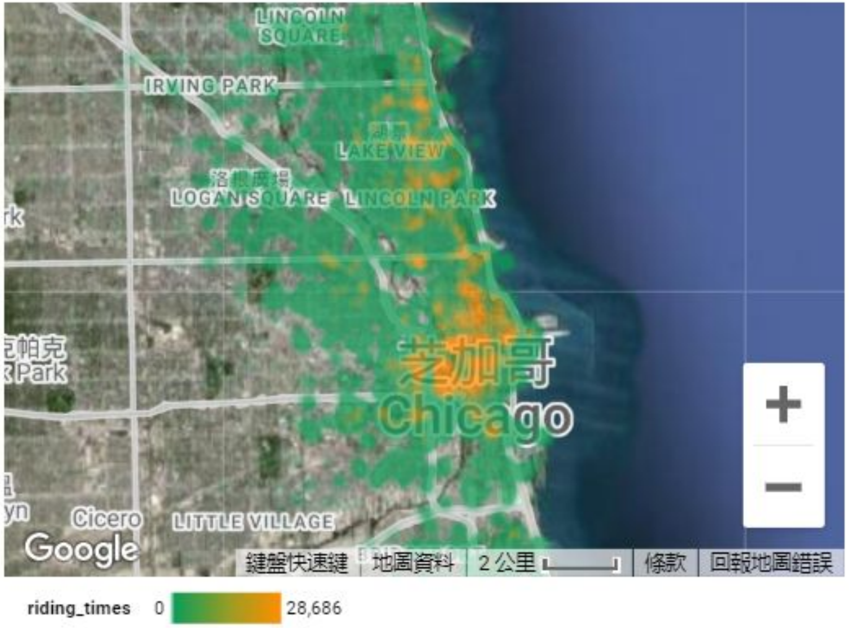


The patterns of riding duration **were similar** in off and busy season.
Casual riders tended to ride **longer on weekend**, while riding durations of annual members **were even throughout the week**

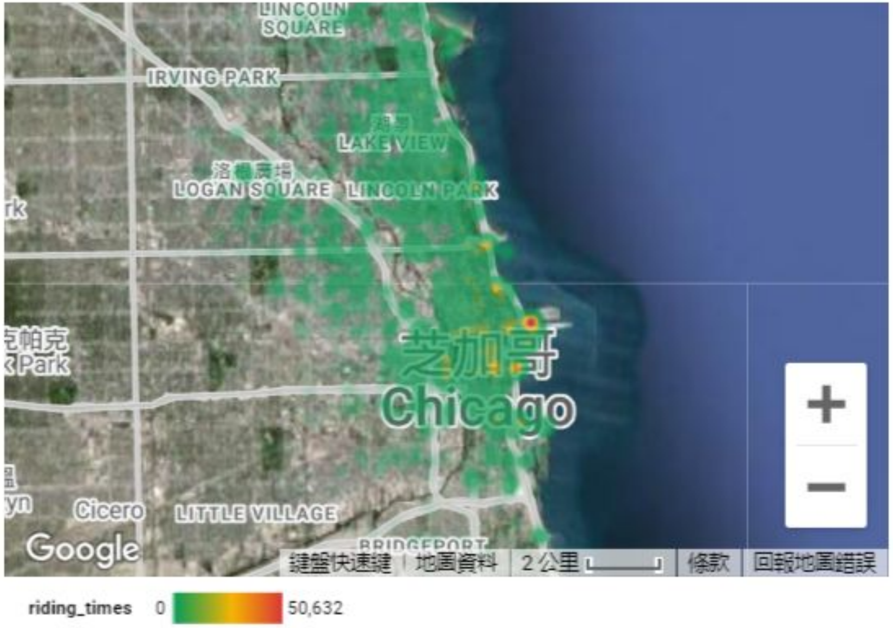
Analyze - In terms of their destinations

(visit times)

Annual members



Casual riders



Casual riders' destinations were **concentrated in specific areas**, while annual members' destinations were **scattered throughout Chicago**.

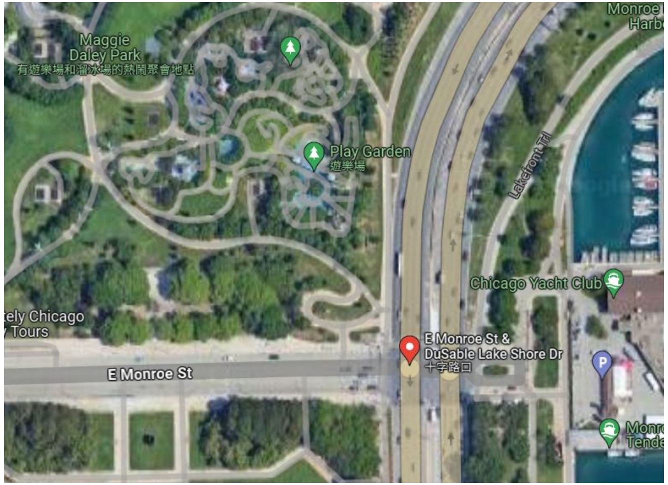
Analyze - In terms of their destinations

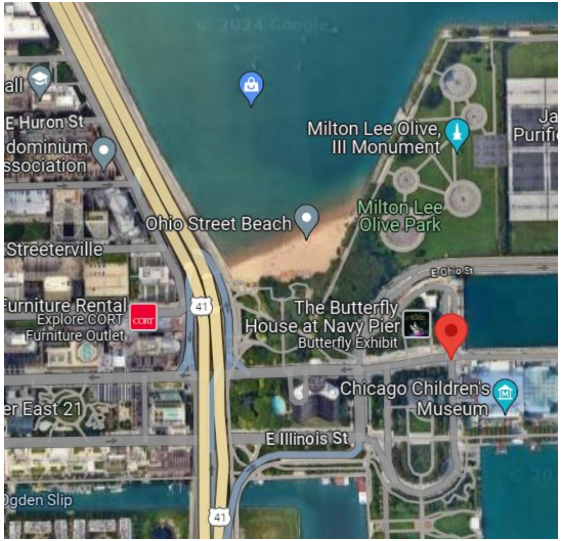
end_station_name	end_station_id	member	casual	(visit times)
Streeter Dr & Grand Ave	13022	14,080	50,635	**64,715**
DuSable Lake Shore Dr & M...	13300	11,282	29,726	**41,008**
DuSable Lake Shore Dr & N...	LF-005	15,688	23,870	**39,558**
Michigan Ave & Oak St	13042	14,133	24,303	**38,436**
Kingsbury St & Kinzie St	KA1503000043	26,846	8,080	**34,926**
Clark St & Elm St	TA1307000039	24,765	10,012	**34,777**
Clinton St & Washington Bl...	WL-012	28,686	6,077	**34,763**
Wells St & Concord Ln	TA1308000050	21,148	11,074	**32,222**

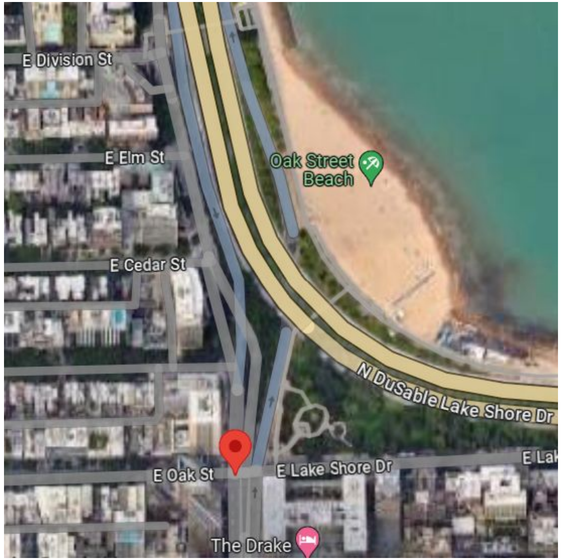
The most visited destinations of annual members and casual riders are different.

So, Where were they?

Analyze - In terms of casual riders' destinations

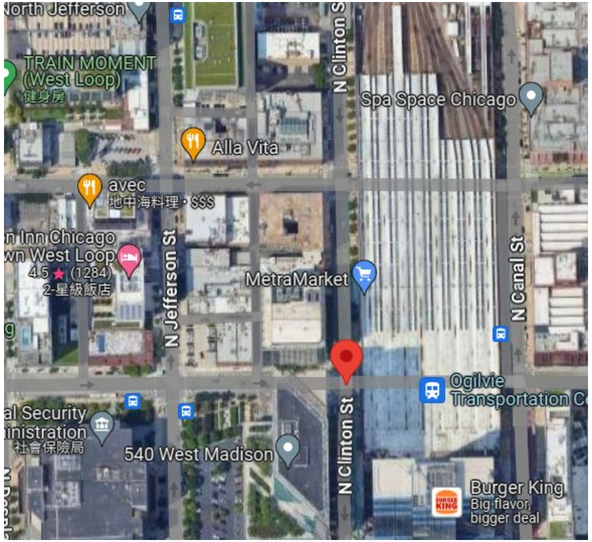


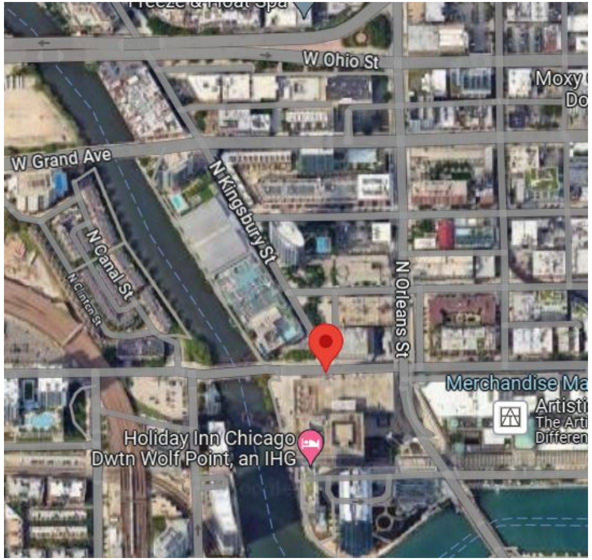


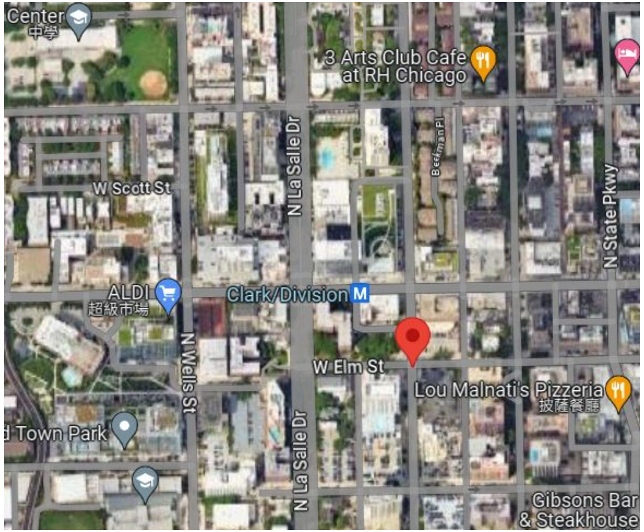


Casual riders tended to visit the **suburbans or beach**, while

Analyze - In terms of annual members' destinations







Casual riders tended to visit the **suburbans or beach**, while annual members tended to go to **downtown area**.

Conclusion

	Casual Rider	**Annual Member**
Number of times	**Fewer** overall	**Higher** overall
Duration	Longer overall, **especially in summer**	Shorter overall, **evenly** in every month
Prefer days of use (weekdays / weekends)	Used more often and longer **on weekends, especially in summer**	Used more often **on weekdays**
Destination	Mostly **tourist area**	Mostly **downtown**
Prefer rideable type	No preference	
Prerfer riding season (peak season)	**Summer** (From June to August)	

Conclusion

	Casual Rider	Annual Member
(peak season)		Summer (From June to August)

1. **Riding times were considerable** in both types of users, **annual members** especially. This showed high popularity of Cyclistic.
2. **Causal riders** tended to ride **longer**, while **annual members** contributed **more revenue** than casual rider, according to the finance analysts.
3. **Annual members** could **create more stable revenue** in terms of weekly usage, compared to casual riders.

⇒ **Turn casual riders to annual members** to gain more stable revenue!!

But how?

Conclusion

	Casual Rider	Annual Member
Number of times	**Fewer** overall	**Higher** overall
Destination	Mostly **tourist area**	Mostly **downtown**
Prefer rideable type	No preference	
Prerfer seasons (peak season)	**Summer** (From June to August)	

4. **Casual riders** tended to bike **on holidays or vacations.**
5. **Annual members** tended to bike **for regular use (commutation probably).**

⇒ Launch campaigns on holidays, encouraging the users commuting by bike.

Further things we can do...

1. **Comfirm the usage habit** of casual rider and annual member, for example by conducting a survey.
2. The survey should also include whether annual members have been casual riders and **why they chose to covert to annual**.
3. Develop marketing strategies after exploring **the type of digital media that Cyclistic users used**, including when to use and how often to use. (by a survey or data tracked by our app)
4. To set the "goal of successful marketing", it is important to figure out the **difference in fees between casual and annual membership** and how it influence the revenue.