



Overview











The Business Problem

This analysis will...

Identify the strongest conditions that influence bike rental numbers.

Provide recommendations for optimal advertising periods.

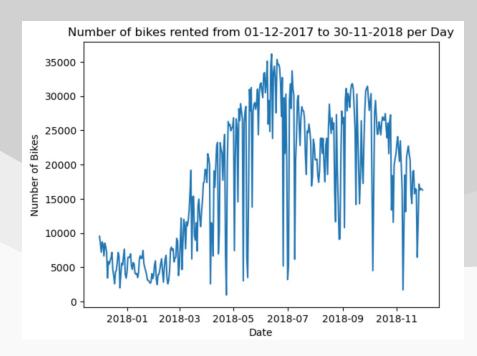


Seoul Metropolitan Government is looking to enhance their public e-bike rental marketing strategy by introducing real-time targeting and personalised advertising. They want to understand the factors that affect the rental demand.



The Data & Methods

The dataset used contained the number of bikes rented per hour in a 1-year period – from December 2017 to November 2018.



The purpose of our model is statistical inference.



The Data & Methods

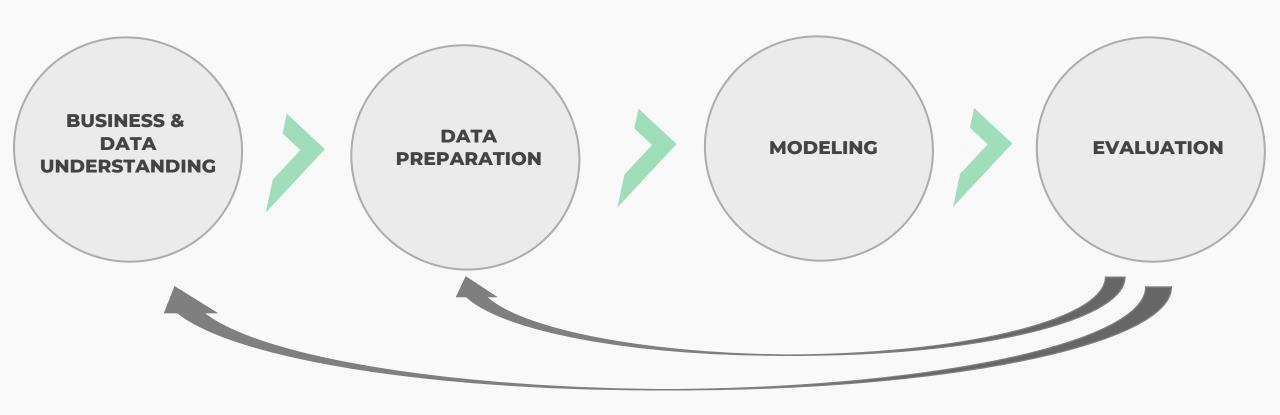
Data was still split into training and test data (80:20)

In addition to the weather and holiday information provided, the following metrics were added:

- The day of the week
- Whether the hour was in daylight or not



Methods





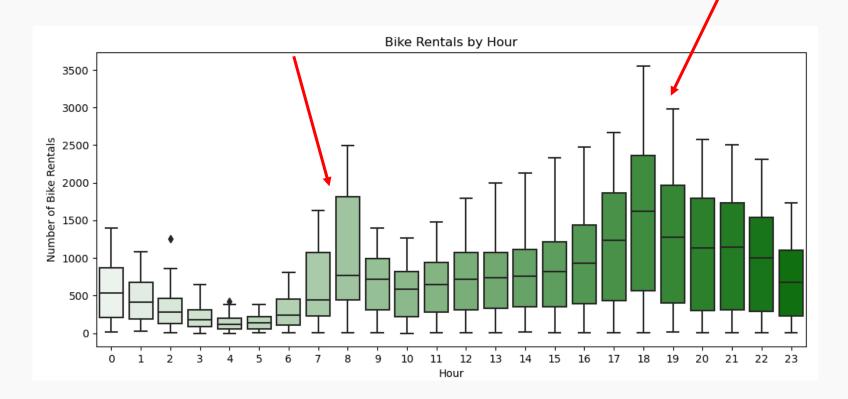
r2 = 0.736

```
264.49 * temp
          -106.85 * humidity
           1051.76 * hour_8
          1179.30 * hour_18
           910.45 * hour_19
           824.97 * hour_20
           817.14 * hour_21
           730.94 * hour_22
       -537.47 * rainfall_mm_1.0
         150.69 * holiday_0.0
           388.07 * month_5
           516.90 * month_6
           397.18 * month_9
          471.43 * month_10
    -49.39 * day_of_week_weekend
-841.63 * hour_8 * day_of_week_weekend
```



Baseline for Categorical Variables

- Hour = 5
- Month = 1
- Rainfall = no rainfall
- Holiday = was a holiday
- Day of week = weekday



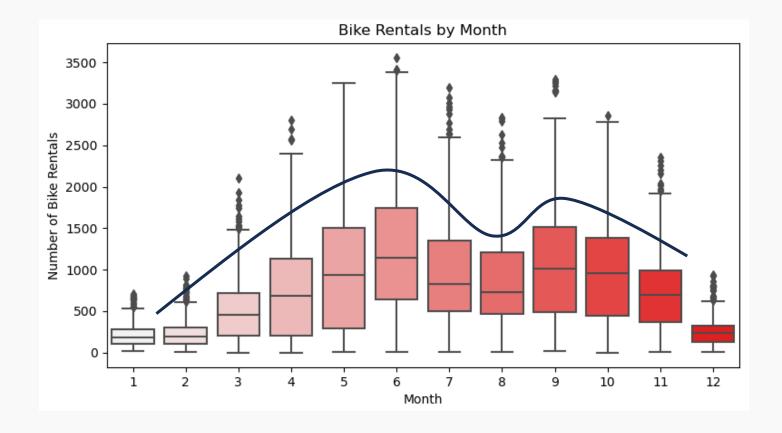
Rush hours (8am, and 6pm to 10pm) are associated with the greatest increase in rental bikes, suggesting majority of users are likely commuters.

The 8am peak is only seen on weekdays.

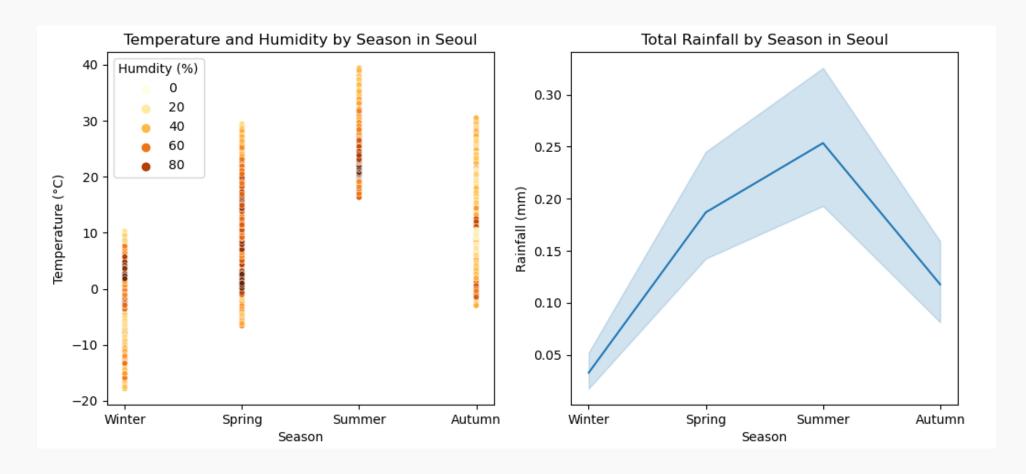


An increase in bike rentals is associated with an increase in temperature, but a decrease in humidity.

We can visualise this by looking at the monthly data – as we move out of Winter, bike rental numbers increase and peak at the start of Summer, dropping as we head into the hot, humid months of July and August. We then see a second, smaller peak in Autumn.









Recommendations & Next Steps



Personalised ads targeting commuters ahead of rush hours to encourage a prompt call to action.



Marketing campaigns to focus on the warmer months, avoiding monsoon and typhoon season in July and August.



Further studies should be conducted to examine changes to cycling trends since 2018 and to take into consideration different customer groups for a more personalised advertising approach.



Thank you



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Model

Dep. Variable:	bike	_count	R-squ	ared:	0.736				hour_15	299.5992	34.499	8.684	0.000	231.970	367.229
Model:		OLS	Adj. R-squared:		0.734				hour_16	407.6745	33.451	12.187	0.000	342.100	473.249
Method:	Least S	quares	F-statistic:		446.1				hour_17	692.2586	32.756	21.134	0.000	628.046	756.471
Date:	Tue, 10 Oc	t 2023 Pr	Prob (F-statistic):		0.00				hour_18	1179.3032	29.677	39.738	0.000	1121.127	1237.479
Time:	17	7:34:41	Log-Likelihood:		-48868.				hour_19	910.4515	28.719	31.703	0.000	854.154	966.749
No. Observations:		6772	AIC:		.782e+04				hour_20	824.9675	30.058	27.446	0.000	766.044	883.891
Df Residuals:		6729	BIC:		9.811e+04				hour_21	817.1397	29.298	27.891	0.000	759.706	874.573
Df Model:		42							hour_22	730.9405	29.270	24.972	0.000	673.562	788.319
Covariance Type:	non	robust						_	hour_23	494.1373	28.954	17.066	0.000	437.379	550.896
								ra	ainfall_mm_1.0	-537.4652	19.140	-28.080	0.000	-574.986	-499.944
		coef	std err	t	P> t	[0.025	0.975]		holiday_0	150.6873	19.112	7.884	0.000	113.221	188.154
	const	-44.4363	36.676	-1.212	0.226	-116.332	27.460		month_2	-43.2887	20.034	-2.161	0.031	-82.563	-4.015
	temp	264.4919	12.731	20.776	0.000	239.536	289.448		month_3	92.7417	22.878	4.054	0.000	47.893	137.590
	humidity	-106.8469	5.835	-18.311	0.000	-118.285	-95.408		month_4	241.2676	26.563	9.083	0.000	189.196	293.339
	solar_rad	37.4884	8.572	4.373	0.000	20.684	54.293		month_5	388.0728	30.245	12.831	0.000	328.784	447.362
	hour_0	390.0442	28.955	13.471	0.000	333.284	446.804		month_6	516.8982	34.001	15.203	0.000	450.246	583.550
	hour_1	265.9508	28.946	9.188	0.000	209.208	322.694		month_7	182.9718	38.162	4.795	0.000	108.162	257.782
	hour_2	168.5759	29.028	5.807	0.000	111.672	225.480		month_8	59.3197	38.814	1.528	0.126	-16.768	135.408
	hour_3	102.1746	28.984	3.525	0.000	45.357	158.992		month_9	397.1842	33.201	11.963	0.000	332.100	462.269
	hour_4	10.1475	28.978	0.350	0.726	-46.659	66.954		month_10	471.4292	26.317	17.914	0.000	419.840	523.018
	hour_6	156.1236	28.601	5.459	0.000	100.056	212.191		month_11	305.0255	23.020	13.250	0.000	259.899	350.152
	hour_7	419.3023	31.210	13.435	0.000	358.121	480.484		month_12	76.5441	19.614	3.903	0.000	38.094	114.994
	hour_8	1051.7571	33.806	31.112	0.000	985.488	1118.027	day_of_v	veek_weekend	-49.3902	9.130	-5.409	0.000	-67.289	-31.492
	hour_9	370.3955	32.145	11.523	0.000	307.381	433.411		daylight_1	76.8316	22.074	3.481	0.001	33.559	120.104
	hour_10	145.1350	33.116	4.383	0.000	80.218	210.052	hour_8*day_of_v	veek_weekend	-841.6325	45.583	-18.464	0.000	-930.990	-752.275
	hour_11	154.0098	34.328	4.486	0.000	86.717	221.303	Omnibus:	182.038 D u	ırbin-Watsoı	n: 2.	019			
	hour_12	209.5243	35.435	5.913	0.000	140.061	278.988	Prob(Omnibus):	0.000 Jar q	ue-Bera (JB): 370.	329			
	hour_13	207.6346	35.512	5.847	0.000	138.020	277.249	Skew:	0.170	Prob(JB): 3.84e	-81			
	hour_14	225.3194	35.219	6.398	0.000	156.280	294.359	Kurtosis:	4.094	Cond. No	o. 4	13.2			