Proposal for a Forecasting Methodology to Predict Commercial Real Estate Values in Istanbul Using Social Big Data

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Contents

Problem Statement & Motivation

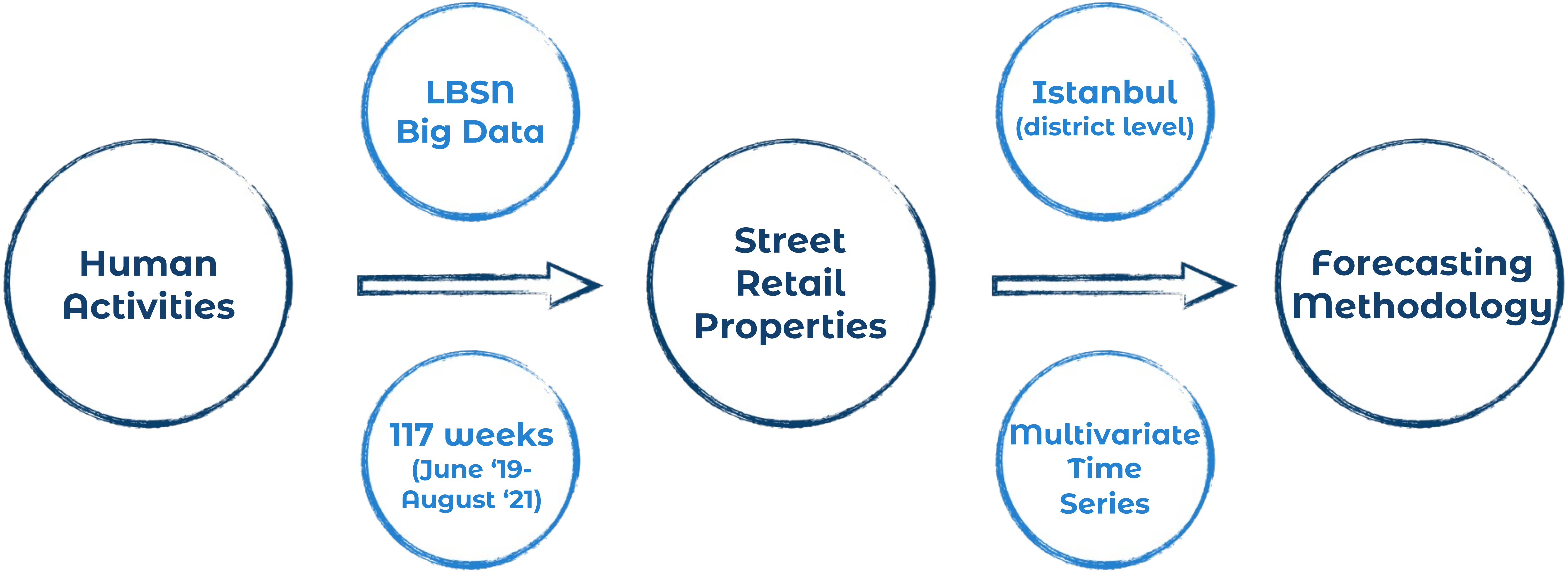
Problem:

The **fluctuations in the retail property prices** in a city with 16 million inhabitants combined with the **insufficient public indicators** about commercial real estates in Turkey result in significant **risks for the decision-makers**.

Motivations:

- The unveiled dependence of real estate sector to **human activity**
- The potential of adapting **new technologies** real estate studies
- Covering the need for a **reliable forecasting methodology** to minimize the investor risks

Introduction



Literature Review

Author(s)	Year	LBSN Platform	Outcomes
Cheng et al.	2011	Twitter	A correlation between **user mobility** with the **city population density** and **city average household income** is found.
Salas-Olmedo et al.	2018	Twitter, Foursquare & Panoramio	**Tourist activities** are mapped as an opportunity to **enhance retail investments.**
Zhou & Zhang	2016	Twitter & Foursquare	The **venues are classified** for Boston and Chicago are used for, such as shop & service, nightlife, food & restaurant areas.
Gupta et al.	2018	Twitter	The **higher activity zones** are visualized and **different economic activities** within the city of London are described.
Cranshaw et al.	2012	Foursquare	**Distinctly characterized clusters** called "Livehoods" within the city of Pittsburgh are created using 18 million **check-ins.**
Marti et al.	2017	Foursquare	The **public space usage of people** is illustrated in Alicante.
Agryzkov et al.	2016	Foursquare	A correlation between traditional methods and check-in frequencies is found in **analyzing public spaces.**
Song et al.	2020	Instagram & Flickr	LBSN data are found to reflect the **urban park popularity** in Singapore better than traditional surveys.
Zamani & Schwartz	2017	Twitter	**Twitter language** is found useful while **forecasting residential indicators.**
Hannum et al.	2019	Twitter	**Twitter sentiment** is found to be correlated with **housing prices** and **price appreciation** in Istanbul.
Tan & Guan	2021	Twitter	**Twitter sentiment** is applied to **housing prices** in the U.S. and a positive correlation is found between them.
Lifang et al.	2020	Sina Weibo (Chinese Twitter)	Check-ins are used to **map people's activity** within Wuhan and the **changes in rental housing prices** are investigated.

Framework of the Study

Data Collection & Preparation

Data Sources
- LBSN Data
  - Instagram
  - Twitter
- Real Estate Data

Language & Platform
- Python 3.8
- Jupyter Notebook

Model Specification

- Preliminary Analyses
- Constructing the Methodology

Language & Platform
- R
- R-Studio

Forecasting

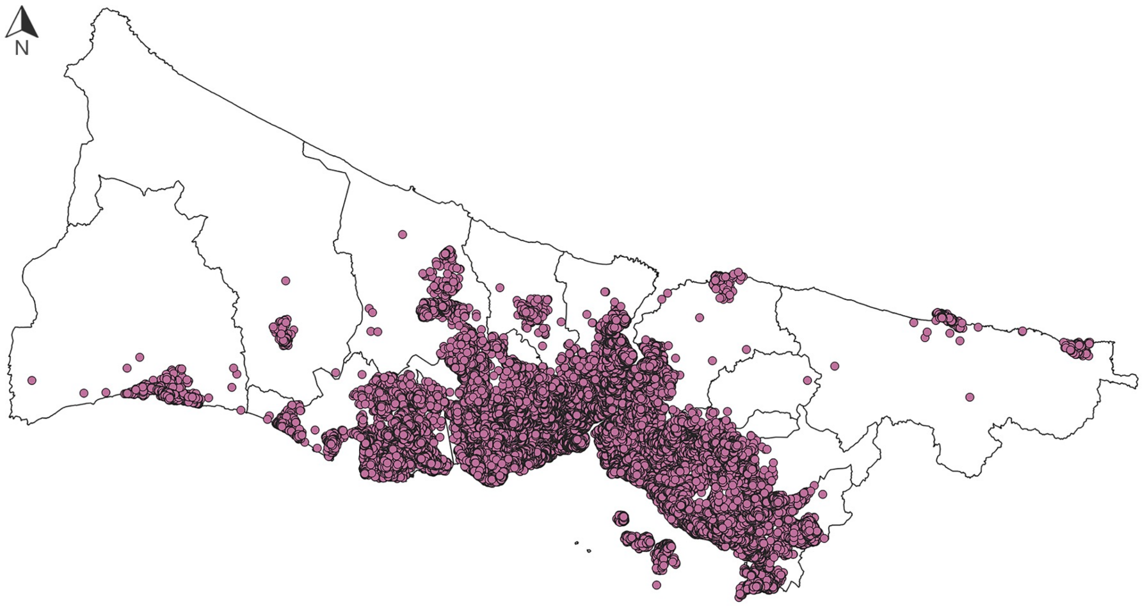
Scope
27 Districts of Istanbul

Language & Platform
- R
- R-Studio

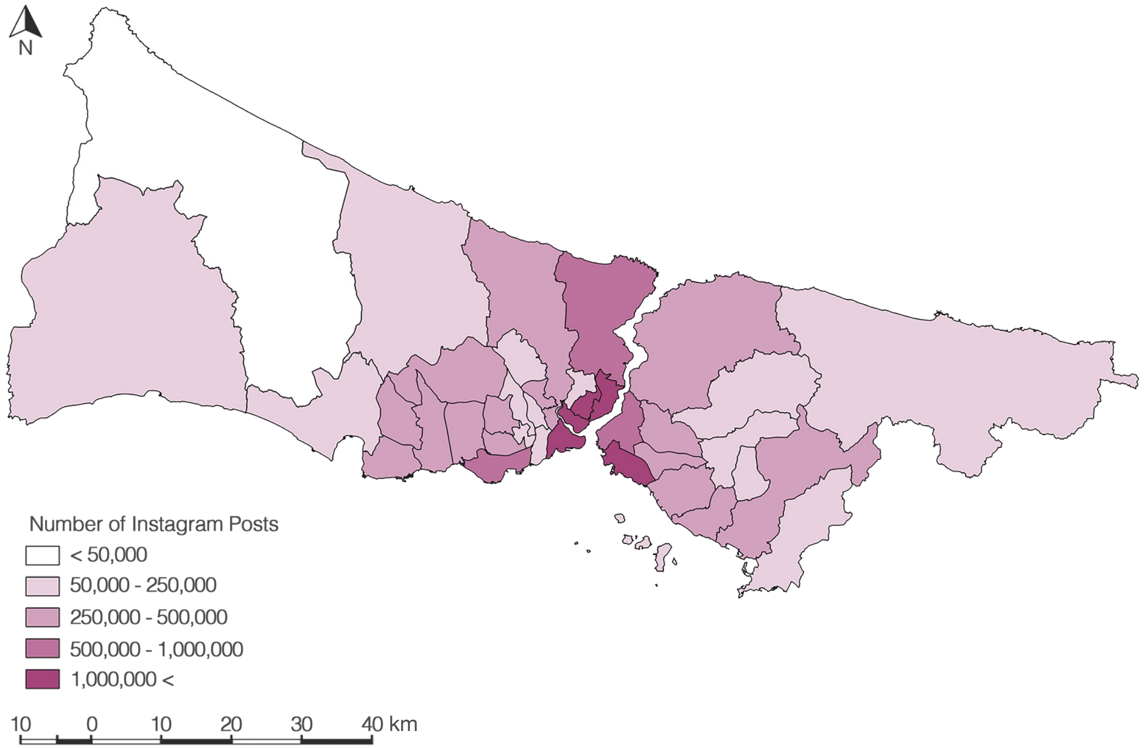
Data Collection & Preparation

INSTAGRAM DATA

- Venue Scraper – **152,145** venues



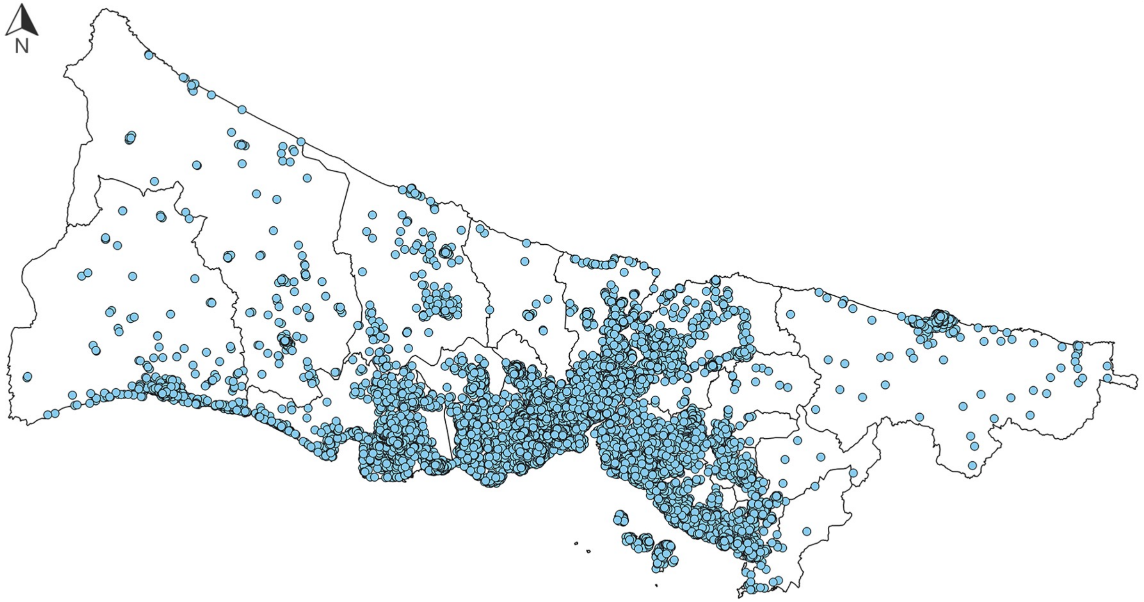
- Post Scraper - **17,161,015** posts



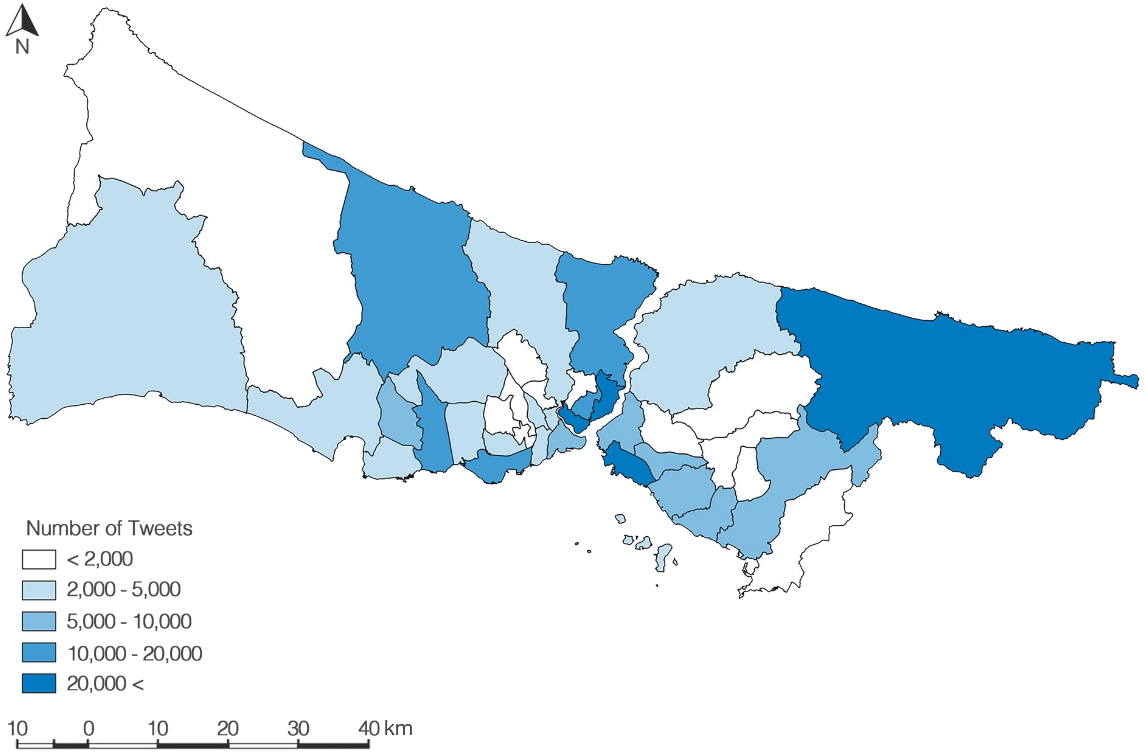
Data Collection & Preparation

TWITTER DATA

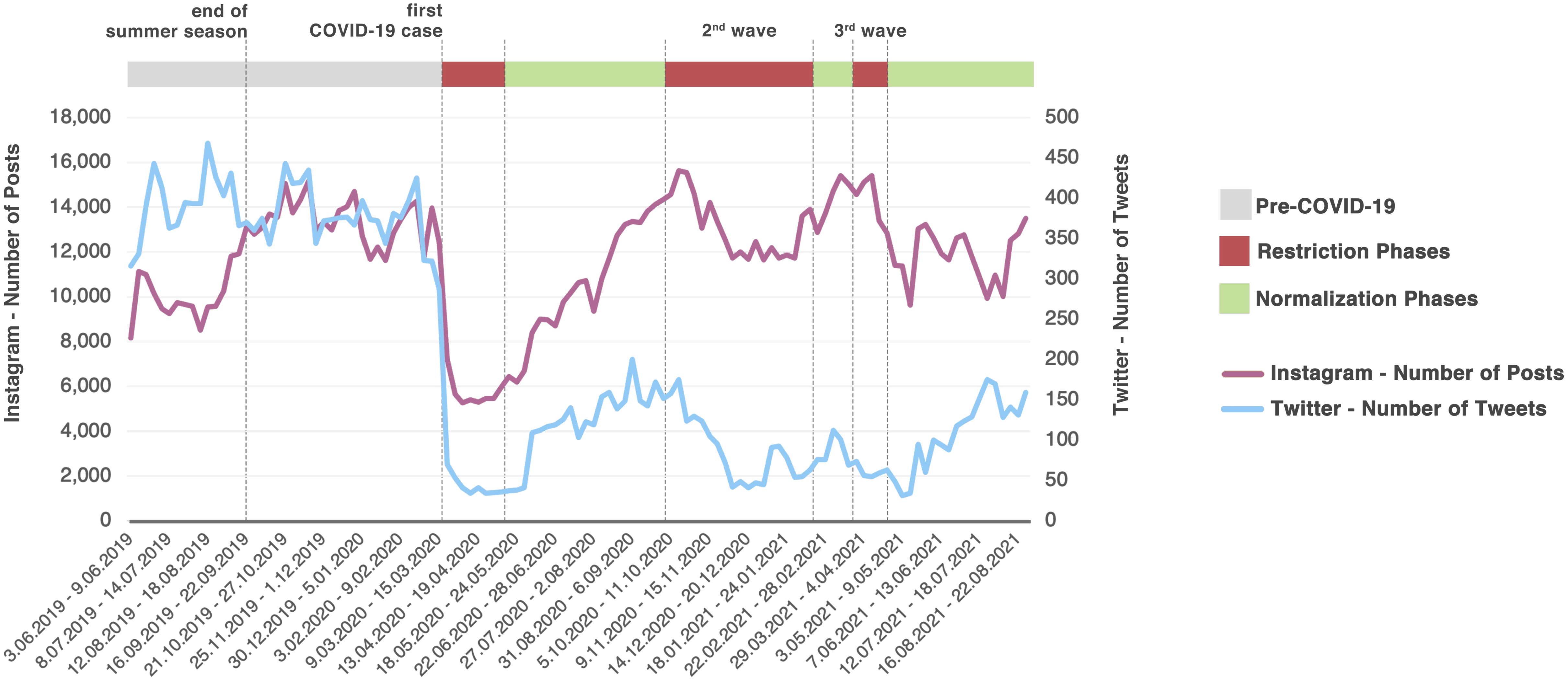
- Venue Scraper – **21,875** venues



- Tweet Scraper – **250,458** tweet



Data Collection & Preparation



Data Collection & Preparation

REAL ESTATE DATA

emlakjet

shop & store listings in Istanbul
(June 2019-August 2021)

38,185 listings for sale

52,235 listings for rent

FINAL DATA SET

week : week range of the time series

c_rental : count of listings for rent per week
av_rent : average rental level per week
c_sales : count of listings for sale per week
av_price : average price level per week
av_days : average days on market

c_post : count of Instagram posts per week
c_tweet : count of Tweets per week

Model Specification

- Time Series Forecasting → ARIMA(p,d,q)
- **Multivariate** Time Series Forecasting → R package ***marima***

*(based on an estimation method for **VARMA models** with **exogenous variables)***

$$\boldsymbol{y_t} = \begin{pmatrix} y_{t,1} \\ y_{t,2} \\ \dots \\ y_{k,t} \end{pmatrix}, \quad \textbf{\textit{and}} \quad \boldsymbol{u_t} = \begin{pmatrix} u_{t,1} \\ u_{t,2} \\ \dots \\ u_{k,t} \end{pmatrix}, \quad \boldsymbol{t = \{1, 2, \dots, N\}} \quad (1)$$

$$\boldsymbol{y_t + \varphi_1 y_{t-1} + \cdots + \varphi_p y_{t-p} = u_t + \theta_1 u_{t-1} + \cdots + \theta_q u_{t-q}} \quad (2)$$

$$\boldsymbol{y_t + \varphi_1 y_{t-1} + \cdots + \varphi_p y_{t-p} + x_t + \beta_1 x_{t-1} + \cdots + \beta_p x_{t-l} = u_t + \theta_1 u_{t-1} + \cdots + \theta_q u_{t-q}} \quad (3)$$

Model Specification

Collect and prepare the data

Apply auto.arima() to determine *d* order differencing for the minimum AIC

Ensure stationary with unit root tests

Determine the potential variables with pairwise Granger causality test

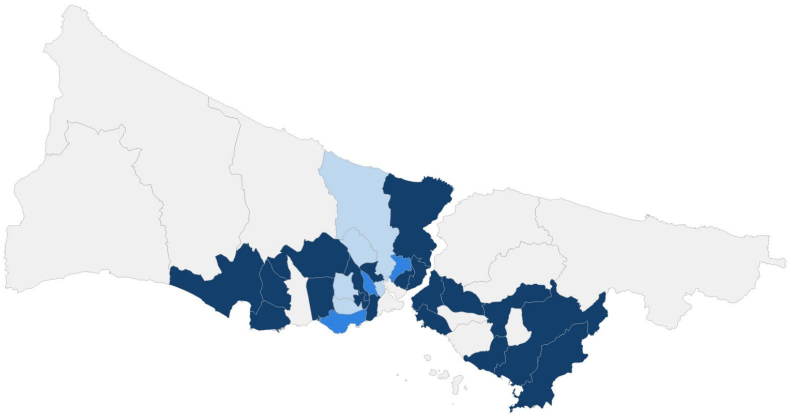
	Model	Model Dimension	Exogenous Variables	
			n_rental, n_sales, av_days	n_insta AND/OR n_tweet
Baseline	A	univariate	-	-
	B	multivariate	-	-
	C1	multivariate	X	-
LBSN-Supported	C2	multivariate	-	X
	C3	multivariate	X	X

- ***p* and *q* pairs from {0, 1, 2, 1-2} → 15 combinations (except for p=0 ∧ q=0)**
- **135 models in total with different *p* & *q* orders and variables**

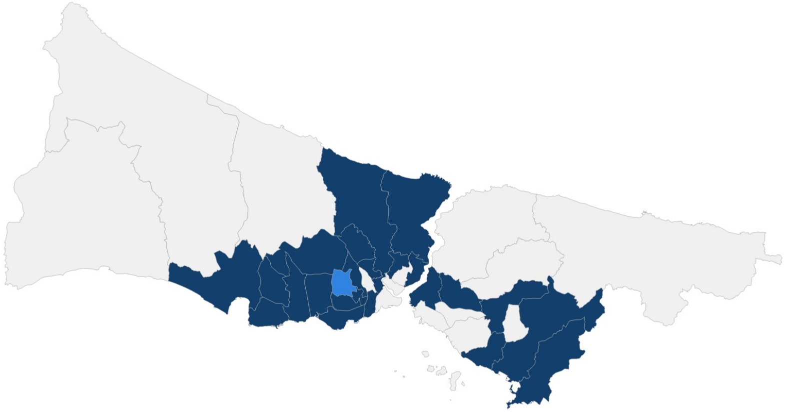
Forecasting Results

District	Sales Price Forecasts: Continuity – Occasional	Sales Price Forecasts: Continuity – Consistent	Sales Price Forecasts: Degree of Improvement – Sligh	Sales Price Forecasts: Degree of Improvement – Moderate	Sales Price Forecasts: Degree of Improvement – Strong	Rental Price Forecasts: Continuity – Occasional	Rental Price Forecasts: Continuity – Consistent	Rental Price Forecasts: Degree of Improvement – Slight	Rental Price Forecasts: Degree of Improvement – Moderate	Rental Price Forecasts: Degree of Improvement – Strong
Avcılar		X			X		X			X
Bağcılar		X	X				X		X	
Bahçelievler	X		X				X			X
Bakırköy		X		X			X			X
Başakşehir		X			X		X			X
Beşiktaş		X			X		X			X
Beylikdüzü		X			X		X			X
Büyükçekmece		X			X		X			X
Esenler		X			X		X			X
Esenyurt		X			X		X			X
Eyüpsultan		X	X				X			X
Gaziosmanpaşa	X				X	X				X
Güngören		X			X		X			X
Kağıthane	X			X			X			X
Kartal		X			X		X			X
Küçükçekmece		X			X		X			X
Pendik		X			X		X			X
Sancaktepe		X			X		X			X
Sarıyer		X			X		X			X
Sultangazi		X	X				X			X
Tuzla	X				X		X			X
Ümraniye		X			X		X			X
Üsküdar		X			X		X			X
Zeytinburnu		X			X		X			X
Bayrampaşa		X		X						
Kadıköy		X			X					
Şişli		X			X					

Sales Price Forecasts



Rental Price Forecasts



Forecasting Results

Beşiktaş District (N=62)

Week(s)	Sales Value Forecasts					
	MAPE			RMSE		
	Baseline	LBSN-Supported	Improvement	Baseline	LBSN-Supported	Improvement
1	0.0091	0.0024	**73.4%**	284.25	75.52	**73.4%**
2	0.0415	0.0183	**56.0%**	1,421.02	661.09	**53.5%**
3	0.1409	0.0691	**50.9%**	4,523.15	2,670.06	**41.0%**
4	0.1171	0.0569	**51.4%**	4,363.77	2,151.81	**50.7%**

Week(s)	Rental Value Forecasts					
	MAPE			RMSE		
	Baseline	LBSN-Supported	Improvement	Baseline	LBSN-Supported	Improvement
1	0.0411	0.0257	**37.4%**	3.91	2.44	**37.4%**
2	0.0412	0.0238	**42.2%**	4.43	3.04	**31.5%**
3	0.0715	0.0707	**1.1%**	10.64	10.01	**5.9%**
4	0.0877	0.0798	**9.0%**	11.51	9.67	**16.0%**

Forecasting Results

Kadıköy District (N=75)

Week(s)	Sales Value Forecasts					
	MAPE			RMSE		
	Baseline	LBSN-Supported	**Improvement**	Baseline	LBSN-Supported	**Improvement**
1	0.0678	0.0354	**47.7%**	991.25	518.06	**47.7%**
2	0.1869	0.0667	**64.3%**	2,689.32	934.22	**65.3%**
3	0.1490	0.1018	**31.7%**	2,296.58	1,702.31	**25.9%**
4	0.1178	0.0875	**25.7%**	1,867.27	1,400.95	**25.0%**

Şişli District (N=65)

Week(s)	Sales Value Forecasts					
	MAPE			RMSE		
	Baseline	LBSN-Supported	**Improvement**	Baseline	LBSN-Supported	**Improvement**
1	0.1520	0.0522	**65.7%**	3,946.48	1,353.91	**65.7%**
2	0.1208	0.0467	**61.4%**	3,613.78	1,674.73	**53.7%**
3	0.1205	0.1053	**12.6%**	3,275.44	3,050.69	**6.9%**
4	0.1344	0.1173	**12.7%**	4,174.00	4,053.79	**2.9%**

Conclusion

- This study discovers the **power of social media data** (Instagram & Twitter) to forecast the future **rent/price levels** of retail properties in Istanbul.

- The methodology is constructed by creating baseline models with the variations of real estate related variables, and **introducing the social media** related variables upon them.

- The multivariate time series analyses are conducted in R package ***marima***, and the **improvements in MAPE and RMSE metrics** are observed.

Conclusion

- The proposed methodology is tested for **27 districts of Istanbul**, and the results demonstrate that the big data arising from LBSN platforms **strongly improve** the retail property forecasts.

- The methodology allows the forecasters to **better predict the trends** in the sector and **adapt to potential changes** in the market in the volatile nature of an emerging market.

- Further research could extend the application of this methodology to **micro levels**, including street level forecasts.

Many thanks for your attention!

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