Using Origin-Destination Flow Graph and Public Transit Information to Enhance Short-Term Ridership Prediction in Bike-Sharing Systems

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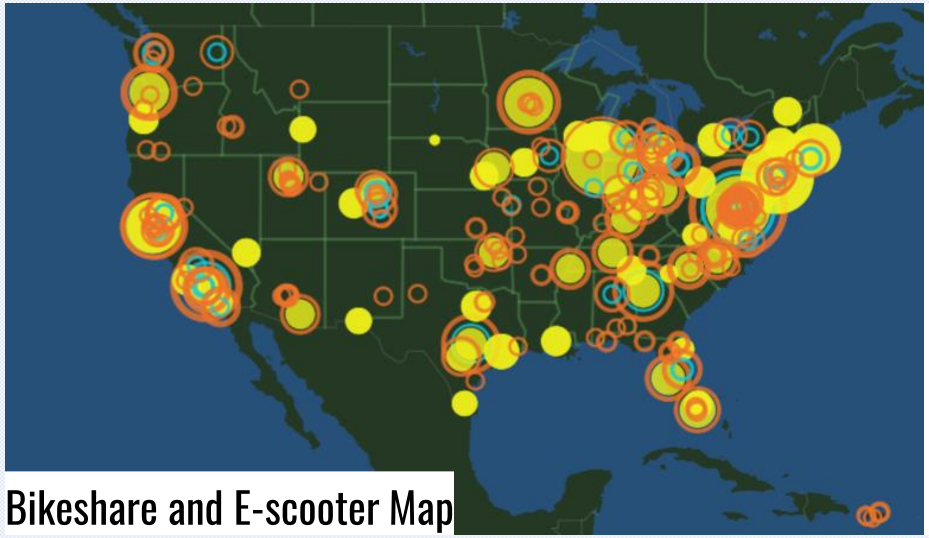
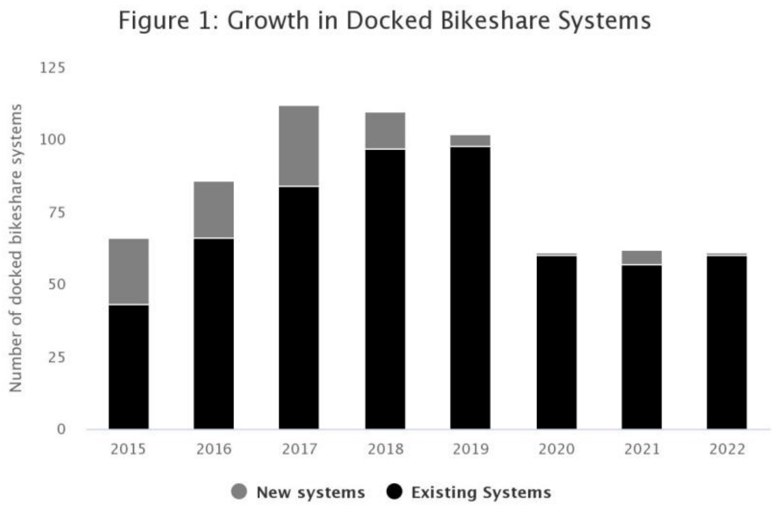
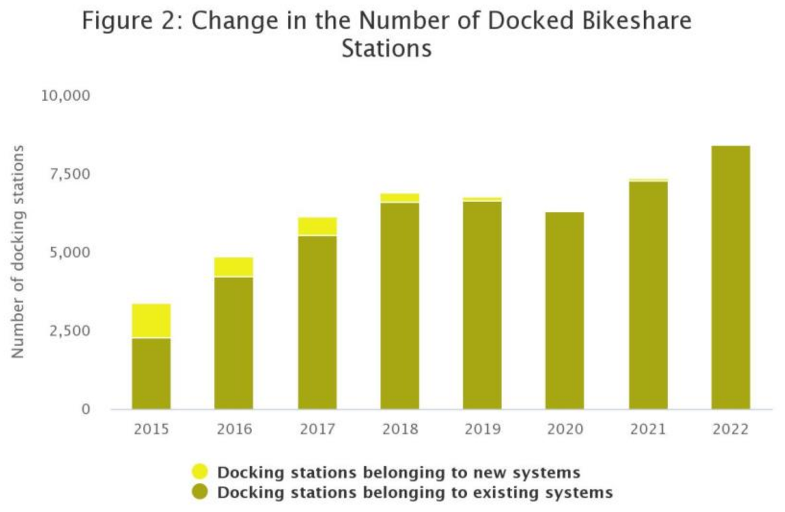
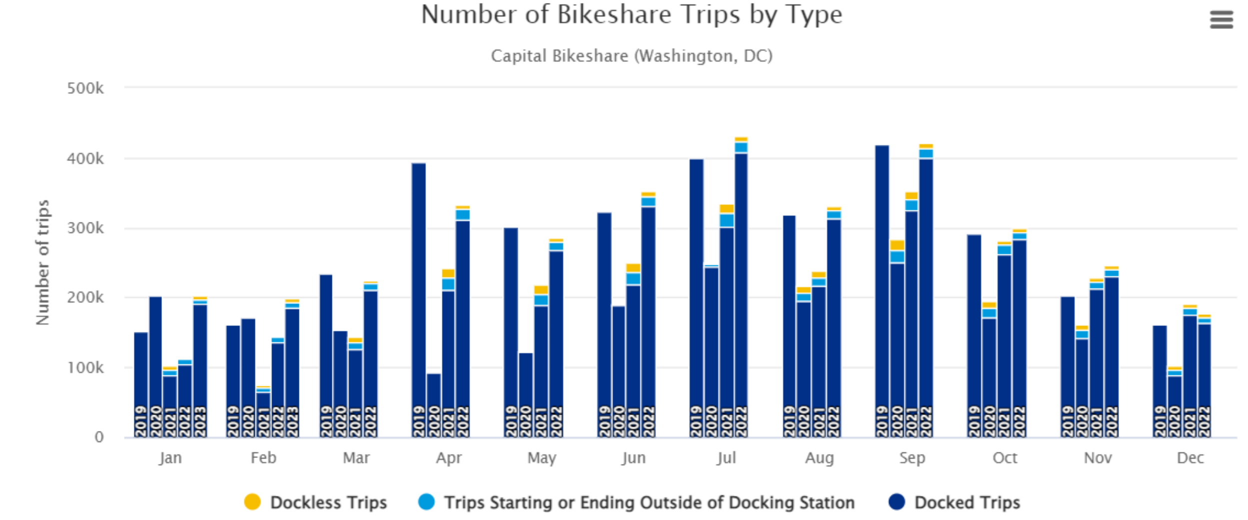
Bike-Sharing Market Is Blooming in Transportation Landscape



Bikeshare and E-scooter Map







- As of July 2022, 61 docked bikeshare systems open to the general public operated 8,473 docking stations in the U.S.
- In Washington D.C., there are about more than 200,000 bikeshare trips each month, most of which are docked trips.
- Bike-sharing system is blooming in transportation landscape.

Source: https://data.bts.gov/stories/s/Bikeshare-and-e-scooters-in-the-U-S-/fwcs-jprj/

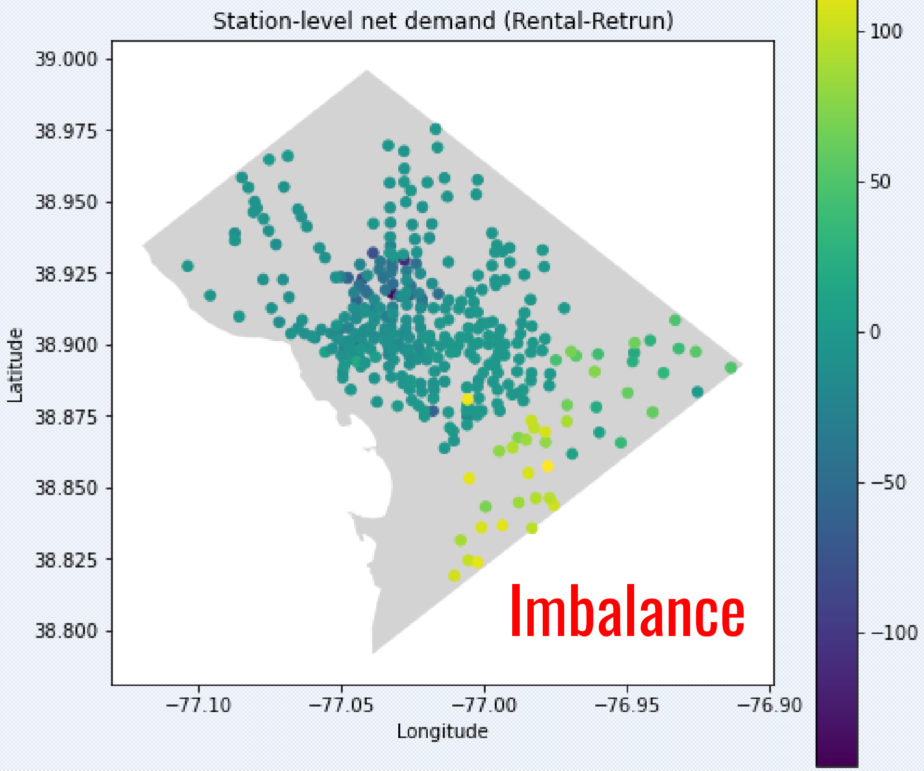
Bike-Sharing System Is Shaping New Transportation Landscape

Potentials

- Reducing people's dependencies on private vehicles
- Encouraging the use of public transit
- Improving accessibility, mobility, affordability

However,

Issue still exists



- Potential solution: Accurate spatiotemporal prediction of bike-sharing ridership is crucial to assist decision-makers in formulating effective bike dispatching and rebalancing plans and mitigating spatiotemporal imbalance.

Background

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Research Question

How to improve the accuracy of short-term ridership prediction in bike-sharing system?

Literature Review

Types of dealing with docked bike ridership forecasting problems :

- *Forecast unit*: (1) at an individual station level (Lin et al. 2018); (2) at an aggregated group level (Li et al. 2015). The latter is preferred due to high flexibility of sharing bikes, and ridership biases and uncertainties among adjacent stations, which makes station-level prediction highly challenging.
- *Forecast model*:
  - Parametric statistical models (Kaltenbrunner et al. 2010): time-series prediction model, i.e., ARIMA (Jaber et al. 2022)
  - Machine learning approaches (Cho et al., 2021): random forest and support vector machine (Gao and Chen, 2022), convolutional neural networks (Li et al. 2023), and graph neural networks (Lin et al. 2018)

However, there is a lack of a feature engineering approach to predicting bike-sharing ridership that can compromise among data need, computing power, model interpretation, and prediction accuracy.

Background

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Research Question

How to improve the accuracy of short-term ridership prediction in bike-sharing system?

Literature Review

The key to feature engineering is how to extract features significantly contributing to the accuracy of bike ridership prediction:

- *Temporal feature*: hour of a day, day of a week, holidays (Jaber et al. 2022)
- *Meteorology*: temp, humidity, wind, precipitation (Cantelmo et al. 2020)
- *Built environment*: design, density, diversity, accessibility (Liu & Lin, 2019)
- *Public transit*: metro & bus schedules and ridership (Fan et al. 2019)
- *Origin-destination flow graph*: there are unexplored features present in time-series data of bike trips than may improve the prediction precision.

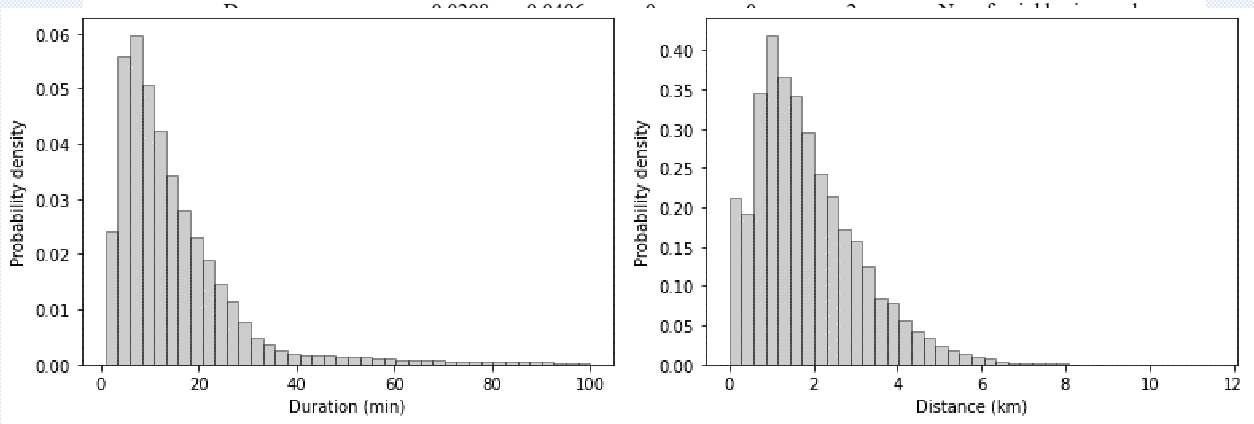
Most of feature engineering approaches was based on the association between bike-sharing ridership and the first three feature groups.

A big research gap: whether bike trip flow and public transit information can further improve the accuracy of bike-sharing ridership prediction?

Approach: Data and Methods

Table 2 Descriptive statistics affiliated to the 100 clustered centroids in Washington D.C.

Metric	Statistical indicator					Variable description
	Mean	Std	Min	Median	Max	
Hourly ridership	1.7971	3.9791	0	0	72	Hourly volume of bike trips
Graph attributes						
Relative humidity	62.30	20.80	15	62	100	Continuous (%)
Wind speed	9.2003	4.7373	0	9	29	Continuous (mph)
Wind direction	174.97	109.70	0	180	360	Continuous
Precipitation	0.0021	0.0090	0	0	0.1025	Continuous (inch)



- **Data:**
  - Bikeshare trip data in Washington D.C. during March 2020.
  - GTFS data in Washington D.C. during March 2020.
  - OpenStreetMap and socio-demographics & built environment
  - Hourly meteorological data during March 2020

- **Methods:**
  - Modelling paradigm: Network Science & Machine Learning.
  - Research method: A data-driven variable selection and feature engineering approach for short-term bike-sharing ridership prediction.
  - Research design:
    - Data preprocessing and preparation
      - Bike station clustering: K-means clustering to group 352 bike stations into 100 clusters based on spatial proximity
      - OD flow graph construction and feature extraction: Nodes, Edges, and Weights & Degree, Betweenness, and PageRank
      - Public transit information: static and dynamic number of transit (bus or metro) stops around clustered centroids
      - Data aggregation: bike trip data, meteorology, built environment, OD graph and public transit information at the same scale

Approach: Data and Methods

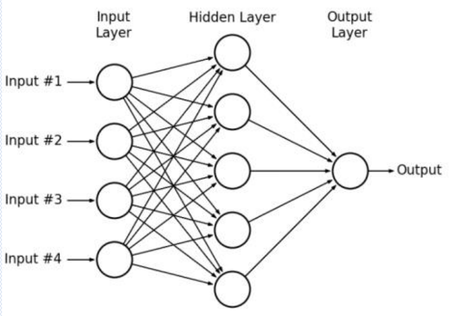
- **Methods (continued):**
  - Research design (continued):
    - Variable selection: A Spatial Vector Autoregressive LASSO (SpVAR-LASSO) Model
      - Dependent variables: $y_{i,t}$ - Bike-sharing ridership data at 100 clustered centroids
      - Independent variables: $\boldsymbol{x}_i$ - Population density, housing unit density, land use diversity, bike lane density, static and dynamic number of metro and bus stops around bike centroids, $\boldsymbol{y}_{i,t-1\sim t-n}$ - bike-sharing ridership data in the last 168 hours (1 week)
      - Model form:

$$y_{i,t} = \beta_0 + \boldsymbol{\beta_1 x}_i + \beta_2 \sum_j w_{ij} y_{j,t} + \boldsymbol{\beta_3 y}_{i,t-1\sim t-n} + \gamma \sum_j |\boldsymbol{\beta}_j| + \varepsilon_{i,t};\ \boldsymbol{\beta} = \underset{\boldsymbol{\beta}}{\text{argmin}}\left[(\boldsymbol{Y}_t - (\boldsymbol{X}, \boldsymbol{Y}_{t-1\sim t-n})\boldsymbol{\beta})'(\boldsymbol{Y_t} - (\boldsymbol{X}, \boldsymbol{Y}_{t-1\sim t-n})\boldsymbol{\beta}) + \gamma \sum_j |\boldsymbol{\beta}_j|\right]$$

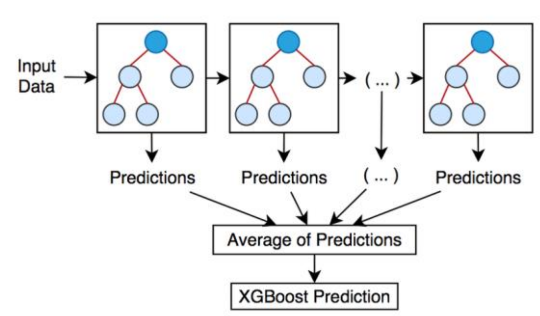
    - Short-term bike-sharing ridership prediction: Baseline model (HA, ARIMA), OLS, MLP, and **XGBoost** (a feature engineering approach)
      - Dependent variables: Y – Bike-sharing ridership data at 100 clustered centroids
      - Independent variables: X – Temporal variables, spatial variables, graph attributes, public transit information, and meteorology selected from the SpVAR-LASSO Model
      - Model form:

OLS: $Y = AX + b + \varepsilon$

MLP:

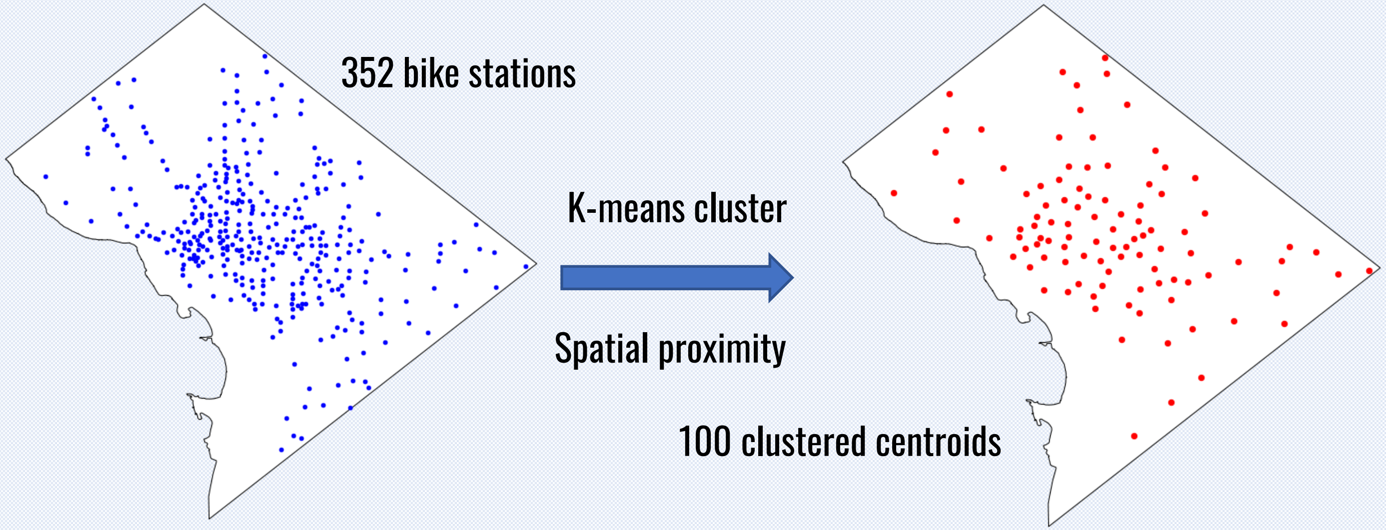


XGBoost:

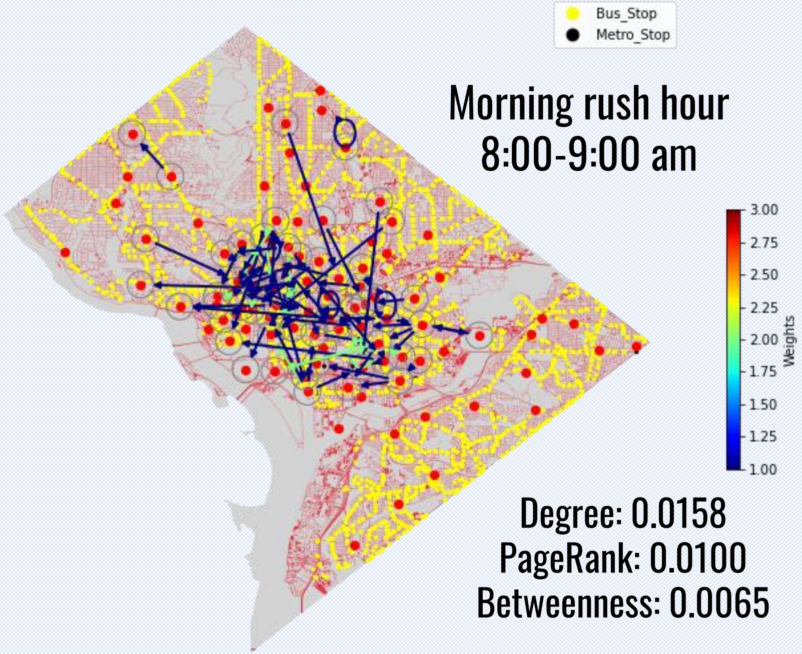


Results – Data Preprocessing and Aggregation

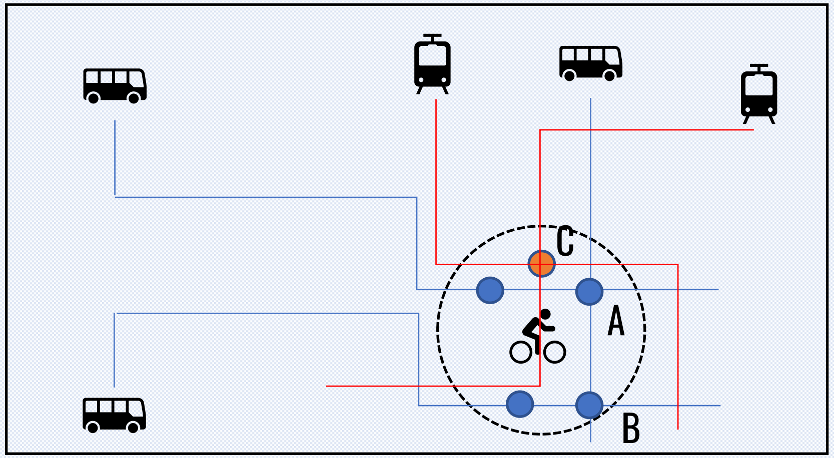
- **Bike station clustering:** 352 bike stations into 100 bike centroids



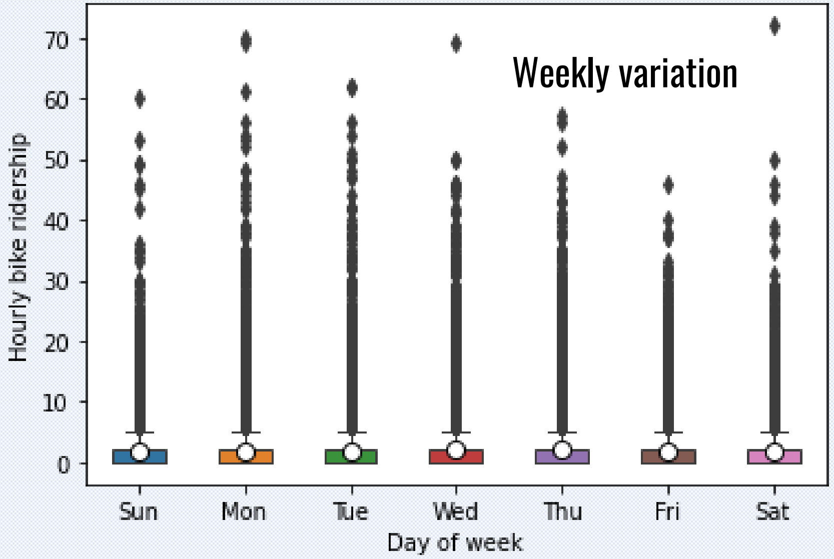
- **Graph construction and attributes:**
  - Nodes: 100 centroids of 352 bike stations.
  - Edges: A travel flow from A to B.
  - Weights: The hourly number of trips from A to B.

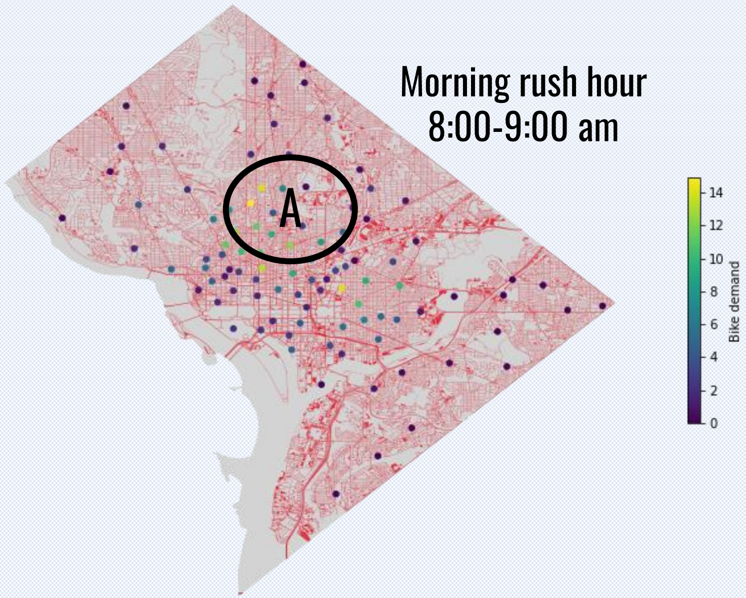


- **Public transit information:**
  - Dynamic number of metro stops nearby: 2
  - Dynamic number of bus stops nearby: 6
  - Static number of metro stops nearby: 1
  - Static number of bus stops nearby: 4

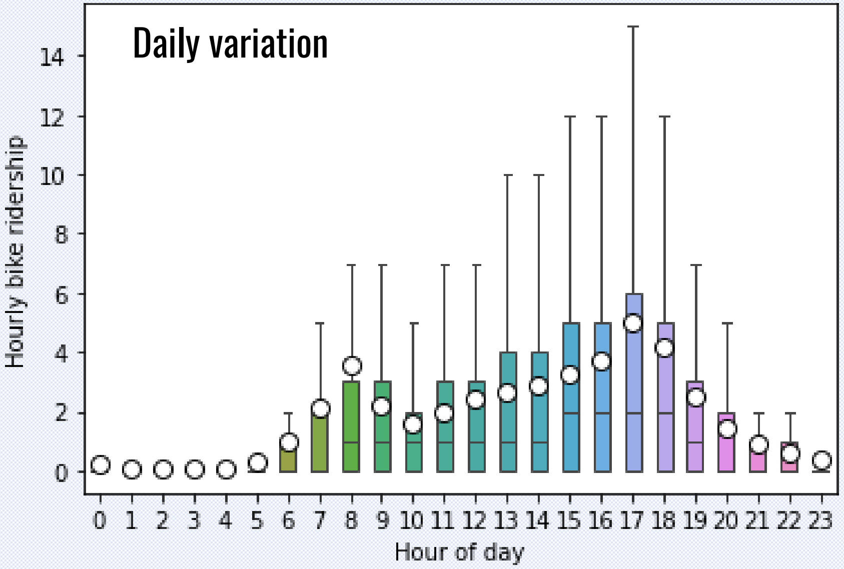


Results – Spatiotemporal Distribution of Bike Ridership

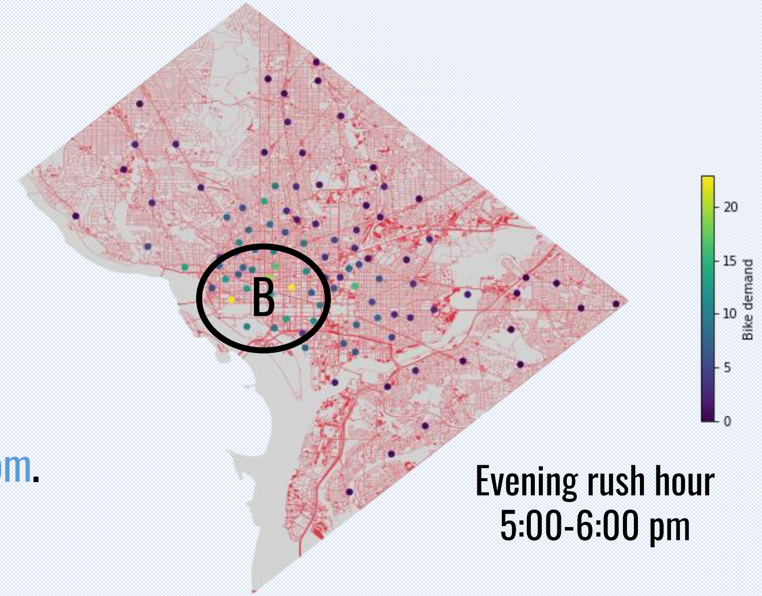




- **Spatial distribution:**
  - Downtown > Surroundings.
  - Implying land use patterns:
  - A: more likely to be residential areas.
  - B: more likely to be commercial areas or workplace

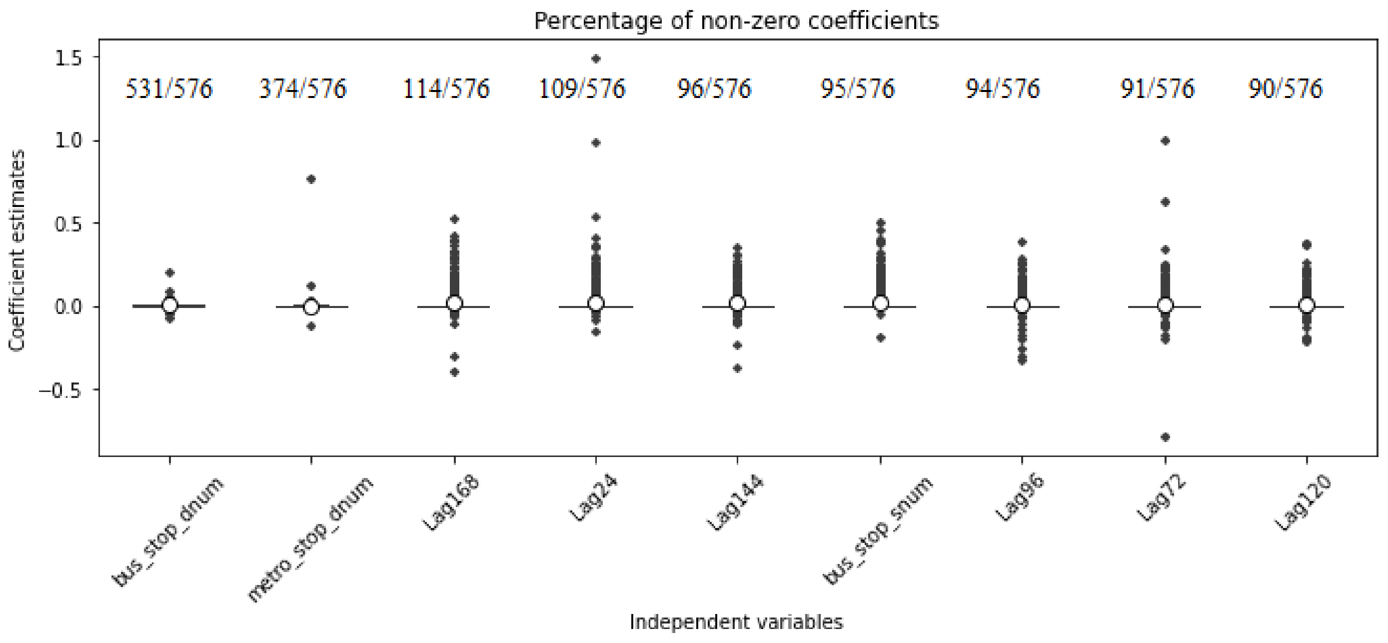


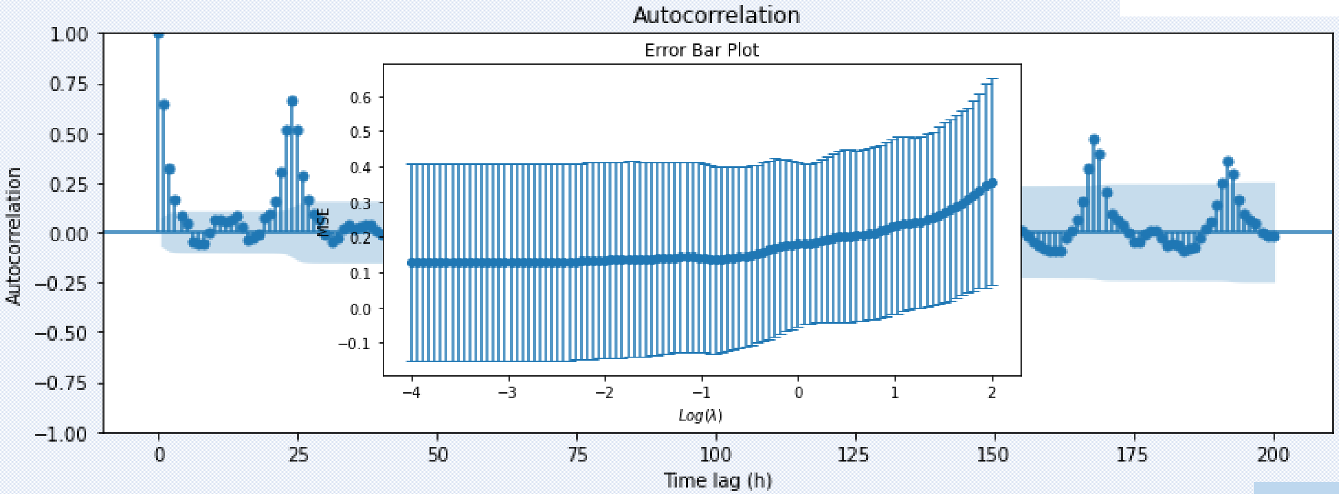
- **Temporal distribution:**
  - No significant weekly variation.
  - Significant daily variation.
  - Two peaks occurred at 8-9 am and 5-6 pm.



Results – Variable Selection for Ridership Prediction

- **SpVAR-LASSO**: both temporal and spatial information.
  - Hyperparameter:
    - Time lag: 168 (based on ACF)
    - Penalty: γ=0.0001 (based on CV)
  - Experiment design:
    - Perform 576 regressions (CV) for each hour
    - Count the number of each variable with non-zero coefficient estimates





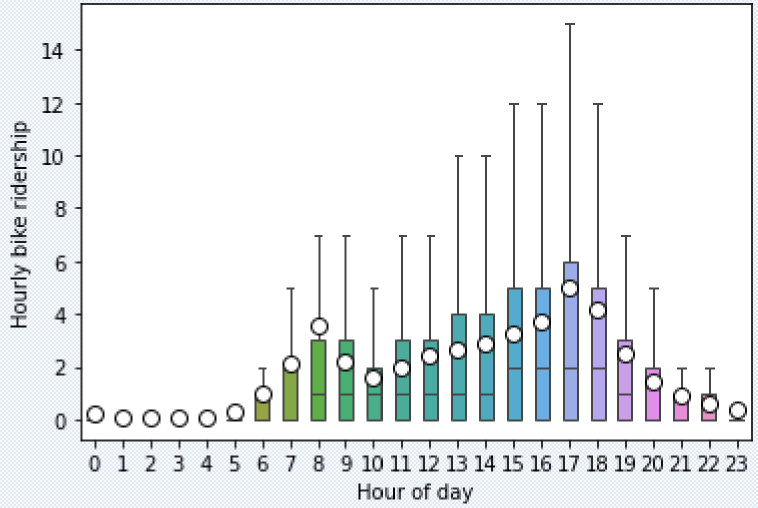
- **Variable Selection and Importance:**
  - Spatial variables: dynamic number of bus and metro stops, as well as static number of bus stops.
  - Temporal variables: bike demand data in the last 168th, 24th, 144th, 96th, 72nd, and 120th hours.

Results – Short-Term Bike Ridership Prediction

- **Experimental Design:**
  - Model inputs (Table 1).
  - Experimental design:
    - Basic scenario (S0): T+M as model inputs
    - Effect of spatial dependency (S1): T+M+S as model inputs
    - Effect of graph attributes (S2): T+M+S+G as model inputs
    - Effect of public transit information (S3): T+M+S+PT as model inputs
    - Effect of all features (S4): T+M+S+G+PT as model inputs
- Model: HA, ARIMA, OLS, MLP, XGBoost.
- Data: training (80%) and testing (20%) data
  - All data set (D0): All data sets as model inputs
  - Partial data set 1 (D1): Non-zero data sets
  - Partial data set 2 (D2): Rush-hour data sets
- Evaluation indices:
  - MSE and r^2

Table 3 Variables in the XGBoost model

Y: Dependent variable	Hourly ridership of sharing bikes in the next hour (+ 1 h)
X: Independent variable	
Temporal features (T)	Time-lagged bike-sharing ridership (-24, -72, -96, -120, -144, -168 h)
Meteorological factors (M)	Visibility, temperature, dew point temperature, relative humidity, wind speed & direction, precipitation
Spatial features (S)	Geographically weighted bike-sharing ridership
Time-lagged graphs (G)	Time-lagged degree, PageRank, and betweenness (-24, -72, -96, -120, -144, -168 h)
Public transit (PT)	Dynamic number of metro & bus stops, static number of bus stops around centroids



Results – Short-Term Bike Ridership Prediction

- **Prediction Accuracy:**
  - XGBoost > MLP > OLS > HA & ARIMA
  - Effect of feature inputs:
    - Key: temporal & spatial features
    - Graph + Public Transit can further improve accuracy
  - Effect of dataset:
    - All > rush-hour > nonzero dataset
    - In any dataset, public transit information is important
    - In all or nonzero datasets, graph is less important; while in rush-hour dataset, graph is more important.

Table 4 Comparison of prediction accuracy

Model	Dataset / Scenario	All dataset (N=57,600) MSE	All dataset (N=57,600) r^2	Non-zero dataset (N=23,162) MSE	Non-zero dataset (N=23,162) r^2	Rush-hour dataset (N=19,200) MSE	Rush-hour dataset (N=19,200) r^2
HA	T	15.57	-2.93	24.79	-5.22	29.27	-1.64
ARIMA		19.97	-0.58	N/A			
OLS	T+M	4.54/4.33	0.65/0.64	9.45/9.36	0.58/0.59	7.43/7.61	0.68/0.66
	T+M+S	4.14/3.90	0.68/0.68	8.71/8.41	0.61/0.63	6.80/6.25	0.70/0.73
	T+M+S+G	4.10/3.89	0.68/0.68	8.62/8.31	0.62/0.64	6.57/6.79	0.72/0.69
	T+M+S+PT	4.12/3.88	0.68/0.68	8.65/8.40	0.61/0.63	6.63/6.84	0.71/0.69
	T+M+S+G+PT	4.08/3.87	0.68/0.68	8.57/8.30	0.62/0.64	6.55/6.77	0.72/0.69
MLP	T+M	3.31/3.88	0.74/0.68	7.53/7.38	0.66/0.68	5.48/6.14	0.76/0.72
	T+M+S	3.10/3.57	0.76/0.71	6.74/6.62	0.70/0.71	4.97/4.86	0.78/0.79
	T+M+S+G	2.90/3.47	0.77/0.71	6.34/6.81	0.72/0.70	4.34/5.49	0.81/0.75
	T+M+S+PT	2.97/3.46	0.77/0.71	6.53/6.68	0.71/0.71	4.55/5.57	0.80/0.75
	T+M+S+G+PT	2.88/3.49	0.78/0.71	6.22/6.86	0.72/0.70	4.68/5.84	0.80/0.74
XGBoost	T+M	3.07/3.70	0.76/0.70	6.46/7.14	0.71/0.69	4.26/5.45	0.82/0.75
	T+M+S	2.83/3.41	0.78/0.72	5.98/6.56	0.73/0.71	4.16/4.96	0.82/0.79
	T+M+S+G	2.82/3.42	0.78/0.72	5.95/6.63	0.73/0.71	4.02/5.46	0.83/0.75
	T+M+S+PT	2.68/3.27	0.79/0.73	5.80/6.37	0.74/0.72	3.96/5.19	0.83/0.77
	T+M+S+G+PT	**2.67/3.25**	**0.79/0.73**	**5.71/6.44**	**0.75/0.72**	**3.93/5.30**	**0.83/0.76**

Note: a/b in MSE and R^2 columns represent training and testing MSE and R^2, respectively.

Results – Short-Term Bike Ridership Prediction

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All dataset

OLS Regression Results

Dep. Variable:	lag_0	R-squared:	0.681
Model:	OLS	Adj. R-squared:	0.681
Method:	Least Squares	F-statistic:	3962.
Date:	Mon, 24 Apr 2023	Prob (F-statistic):	0.00
Time:	14:10:01	Log-Likelihood:	-1.2196e+05
No. Observations:	57600	AIC:	2.440e+05
Df Residuals:	57568	BIC:	2.443e+05
Df Model:	31		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-0.9855	0.232	-4.247	0.000	-1.440	-0.531
lag_24	0.3410	0.003	100.195	0.000	0.334	0.348
lag_96	0.0434	0.003	12.732	0.000	0.037	0.050
lag_120	0.0370	0.004	9.884	0.000	0.030	0.044
lag_144	0.0804	0.004	21.966	0.000	0.073	0.088
lag_168	0.1610	0.003	48.888	0.000	0.155	0.167
gw_lag_0	0.4896	0.006	77.199	0.000	0.477	0.502
degree_24	-2.0401	0.285	-7.165	0.000	-2.598	-1.482
pagerank_24	0.4538	0.368	1.232	0.218	-0.268	1.176
betweenness_24	-1.5621	0.470	-3.322	0.001	-2.484	-0.640
degree_96	-2.0880	0.282	-7.397	0.000	-2.641	-1.535
pagerank_96	1.8029	0.381	4.732	0.000	1.056	2.550
betweenness_96	0.4549	0.474	0.960	0.337	-0.474	1.384
degree_120	-1.2003	0.279	-4.306	0.000	-1.747	-0.654
pagerank_120	1.2817	0.384	3.339	0.001	0.529	2.034
betweenness_120	-0.0568	0.475	-0.120	0.905	-0.988	0.874
degree_144	-1.7707	0.276	-6.426	0.000	-2.311	-1.231
pagerank_144	1.3110	0.387	3.388	0.001	0.553	2.069
betweenness_144	-0.5192	0.479	-1.084	0.279	-1.458	0.420
degree_168	-1.5701	0.278	-5.651	0.000	-2.115	-1.025
pagerank_168	1.2008	0.394	3.045	0.002	0.428	1.974
betweenness_168	-1.1023	0.476	-2.315	0.021	-2.035	-0.169
metro_dnum_0	-0.0004	0.000	-1.472	0.141	-0.001	0.000
bus_dnum_0	-0.0023	0.000	-14.119	0.000	-0.003	-0.002
bus_snum_0	0.0986	0.006	16.894	0.000	0.087	0.110
visibility	0.0087	0.007	1.259	0.208	-0.005	0.022
temperature	0.0353	0.008	4.417	0.000	0.020	0.051
dew_point_temp	-0.0329	0.008	-3.969	0.000	-0.049	-0.017
relative_humidity	0.0069	0.002	3.120	0.002	0.003	0.011
wind_speed	-0.0135	0.002	-6.352	0.000	-0.018	-0.009
wind_direction	-0.0001	8.46e-05	-1.346	0.178	-0.000	5.19e-05
precipitation	1.6520	0.944	1.750	0.080	-0.199	3.503

Omnibus:	44407.355	Durbin-Watson:	1.800
Prob(Omnibus):	0.000	Jarque-Bera (JB):	4815275.152
Skew:	3.006	Prob(JB):	0.00
Kurtosis:	47.387	Cond. No.	2.32e+04

Non-zero dataset

OLS Regression Results

Dep. Variable:	lag_0	R-squared:	0.621
Model:	OLS	Adj. R-squared:	0.620
Method:	Least Squares	F-statistic:	1223.
Date:	Mon, 24 Apr 2023	Prob (F-statistic):	0.00
Time:	14:24:25	Log-Likelihood:	-57684.
No. Observations:	23162	AIC:	1.154e+05
Df Residuals:	23130	BIC:	1.157e+05
Df Model:	31		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-0.7840	0.557	-1.409	0.159	-1.875	0.307
lag_24	0.3285	0.005	61.707	0.000	0.318	0.339
lag_96	0.0435	0.005	8.045	0.000	0.033	0.054
lag_120	0.0396	0.006	6.665	0.000	0.028	0.051
lag_144	0.0856	0.006	14.741	0.000	0.074	0.097
lag_168	0.1547	0.005	29.652	0.000	0.144	0.165
gw_lag_0	0.5192	0.011	48.971	0.000	0.498	0.540
degree_24	-3.6869	0.638	-5.776	0.000	-4.938	-2.436
pagerank_24	2.3008	1.050	2.192	0.028	0.243	4.358
betweenness_24	-0.7553	0.870	-0.868	0.385	-2.460	0.950
degree_96	-3.1206	0.602	-5.184	0.000	-4.301	-1.941
pagerank_96	3.3281	[illegible]	[illegible]	[illegible]	1.303	5.353
betweenness_96	1.7308	[illegible]	[illegible]	[illegible]	-0.013	3.474
degree_120	-1.5707	[illegible]	[illegible]	[illegible]	-2.728	-0.413
pagerank_120	2.0223	[illegible]	[illegible]	[illegible]	-0.075	4.119
betweenness_120	1.4860	[illegible]	[illegible]	[illegible]	-0.282	3.254
degree_144	-2.5494	[illegible]	[illegible]	[illegible]	-3.673	-1.426
pagerank_144	2.5721	[illegible]	[illegible]	[illegible]	0.495	4.649
betweenness_144	1.0238	0.903	[illegible]	[illegible]	-0.747	2.794
degree_168	-2.1754	0.575	[illegible]	[illegible]	-3.303	-1.048
pagerank_168	3.7155	1.130	3.289	0.001	1.502	5.929
betweenness_168	0.0161	0.917	0.018	0.986	-1.781	1.813
metro_dnum_0	-0.0002	0.000	-0.388	0.698	-0.001	0.001
bus_dnum_0	-0.0023	0.000	-8.571	0.000	-0.003	-0.002
bus_snum_0	0.0372	0.011	3.350	0.001	0.015	0.059
visibility	0.0196	0.023	0.840	0.401	-0.026	0.065
temperature	0.0599	0.017	3.592	0.000	0.027	0.093
dew_point_temp	-0.0442	0.017	-2.567	0.010	-0.078	-0.010
relative_humidity	0.0072	0.005	1.453	0.146	-0.003	0.017
wind_speed	-0.0188	0.005	-3.810	0.000	-0.028	-0.009
wind_direction	-0.0003	0.000	-1.562	0.118	-0.001	8.3e-05
precipitation	-0.4739	4.026	-0.118	0.906	-8.364	7.416

Omnibus:	13473.526	Durbin-Watson:	1.806
Prob(Omnibus):	0.000	Jarque-Bera (JB):	459443.214
Skew:	2.224	Prob(JB):	0.00
Kurtosis:	24.361	Cond. No.	4.92e+04

Temporal + Spatial + Degree + PageRank + Public Transit + Wind + Temperature

Rush-hour dataset

OLS Regression Results

Dep. Variable:	lag_0	R-squared:	0.713
Model:	OLS	Adj. R-squared:	0.713
Method:	Least Squares	F-statistic:	1538.
Date:	Mon, 24 Apr 2023	Prob (F-statistic):	0.00
Time:	14:14:25	Log-Likelihood:	-45352.
No. Observations:	19200	AIC:	9.077e+04
Df Residuals:	19168	BIC:	9.102e+04
Df Model:	31		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-0.2863	0.519	-0.551	0.581	-1.304	0.732
lag_24	0.3951	0.006	69.658	0.000	0.384	0.406
lag_96	0.0344	0.006	5.927	0.000	0.023	0.046
lag_120	0.0297	0.007	4.516	0.000	0.017	0.043
lag_144	0.0762	0.006	11.960	0.000	0.064	0.089
lag_168	0.1537	0.005	28.033	0.000	0.143	0.164
gw_lag_0	0.5155	0.011	48.634	0.000	0.495	0.536
degree_24	-5.2390	0.651	-8.047	0.000	-6.515	-3.963
pagerank_24	1.0737	1.235	0.870	0.385	-1.346	3.494
betweenness_24	0.2846	0.998	0.285	0.776	-1.671	2.240
degree_96	-1.7893	0.592	-3.025	0.002	-2.949	-0.630
pagerank_96	4.1715	1.384	3.015	0.003	1.459	6.884
betweenness_96	1.2429	1.040	1.195	0.232	-0.796	3.281
degree_120	-0.3456	0.575	-0.601	0.548	-1.473	0.782
pagerank_120	1.4789	1.405	1.052	0.293	-1.275	4.233
betweenness_120	-0.6703	1.030	-0.651	0.515	-2.689	1.349
degree_144	-2.5175	0.557	-4.518	0.000	-3.610	-1.425
pagerank_144	1.9807	1.417	1.398	0.162	-0.797	4.759
betweenness_144	2.0144	1.038	1.940	0.052	-0.020	4.049
degree_168	-2.2351	0.552	-4.050	0.000	-3.317	-1.153
pagerank_168	0.2867	1.428	0.201	0.841	-2.512	3.086
betweenness_168	-0.0180	1.028	-0.017	0.986	-2.033	1.997
metro_dnum_0	-0.0010	0.000	-2.098	0.036	-0.002	-6.64e-05
bus_dnum_0	-0.0016	0.000	-5.774	0.000	-0.002	-0.001
bus_snum_0	0.0772	0.013	6.112	0.000	0.052	0.102
visibility	-0.0242	0.016	-1.558	0.119	-0.055	0.006
temperature	0.0286	0.018	1.626	0.104	-0.006	0.063
dew_point_temp	-0.0034	0.019	-0.183	0.855	-0.040	0.033
relative_humidity	-0.0017	0.005	-0.347	0.729	-0.012	0.008
wind_speed	-0.0198	0.005	-4.152	0.000	-0.029	-0.010
wind_direction	-0.0009	0.000	-4.635	0.000	-0.001	-0.001
precipitation	1.4465	2.185	0.662	0.508	-2.836	5.729

Omnibus:	11288.765	Durbin-Watson:	1.799
Prob(Omnibus):	0.000	Jarque-Bera (JB):	465101.489
Skew:	2.197	Prob(JB):	0.00
Kurtosis:	26.708	Cond. No.	2.55e+04

Summary

Conclusions

Bike Ridership Distribution

- Significant daily variations and spatial distribution patterns

SpVAR-LASSO: Variable Selection

- Bike ridership prediction: public transit, bike ridership in the last 168^{th},24^{th},144^{th},96^{th},72^{nd},120^{th} hours.

XGBoost: Bike Ridership Prediction

- Graph (rush-hour) and public transit can improve accuracy.

Discussion

Innovation:

(1) To propose a feature engineering approach for bike ridership prediction

(2) To reveal the impact of OD flow graph and transit information on the prediction accuracy

Implication:

(1) Bike fleet rebalancing to reduce the spatiotemporal imbalance

(2) Insights into the interaction between bike-sharing system and public transit

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