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Cross-City Analysis of Pedestrian Demand Estimation Models: Insights from Sydney, and Melbourne

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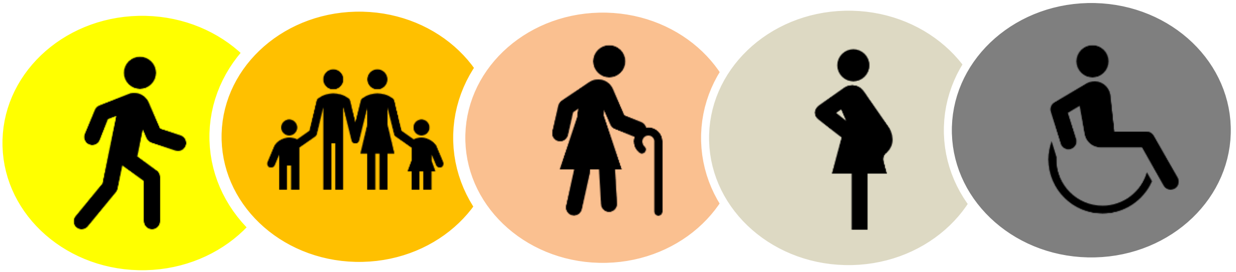
Introduction

Background

- Pedestrian travel modeling and trip generation analysis are fundamental components of urban transportation planning.
- Sustainable transportation mode.
- Pedestrian travel modeling addresses unique characteristics and behaviors.
- They have not been well-researched.

Our Research

- Focuses on studying and predicting the movement of individuals on foot within urban areas.
- Pedestrian travel trip generation at the LGA level in Sydney, Melbourne.
- Built a transformable model.
- Making a suitable and transferable pedestrian model.



Previous Studies

- Transferability of the models.
- key differences in pedestrian demand dynamics across cities

Title	Author /Year	Finding	Limitations
Adding temporal information to direct-demand models: Hourly estimation of bicycle and pedestrian traffic in Blacksburg, VA	Lu et al, 2018	• Spatial and temporal walking and cycling traffic volume. • Stepwise linear regression	1. Small town data 2. generalized
A walk trip generation model for Portland, OR	Tian et al, 2017	• home-based walk trips in Portland, investigating the influence of built environment variables and sociodemographic factors. • Used two stage models: 1. Probability of home-based trips. 2. Predict the number of home-based trips • negative binomial regression model.	1. Specified in one city (Portland) 2. Data limitation 3. Does not consider pedestrian behavior. 4. How many of the variables are important
Representing pedestrian activity in travel demand models: Framework and application	Kelly Cliffton, et al, 2016	1. The cross-classification models predict the number of trips.	1. The model can not be transferred (generalized) 2. Data limitation 3. How many of the variables are important
Facility-Demand Models of Peak Period Pedestrian and Bicycle Traffic	Hankey et al, 2016	Step-wise linear regression model to predict the pedestrian and bicycle traffic volume.	1. Generalized. 2. Lack of checking other methods.

1. Lu, T., Mondschein, A., Buehler, R. and Hankey, S., 2018. Adding temporal information to direct-demand models: Hourly estimation of bicycle and pedestrian traffic in Blacksburg, VA. Transportation Research Part D: Transport and Environment, 63, pp.244-260.
2. Tian, G. and Ewing, R., 2017. A walk trip generation model for Portland, OR. *Transportation Research Part D: Transport and Environment*, *52*, pp.340-353.
3. Clifton, K.J., Singleton, P.A., Muhs, C.D. and Schneider, R.J., 2016. Representing pedestrian activity in travel demand models: Framework and application. Journal of transport geography, 52, pp.111-122.
4. Hankey, S. and Lindsey, G., 2016. Facility-demand models of peak period pedestrian and bicycle traffic: comparison of fully specified and reduced-form models. Transportation research record, 2586(1), pp.48-58.

Data

Census Household Travel Survey Data

Sydney (45 LGAs) (2016~2019)

Melbourne (32 LGAs)(2012~2020)

Brisbane (8 LGAs) (2019~2022)

Trips, weighted population, Vehicles, Household Income

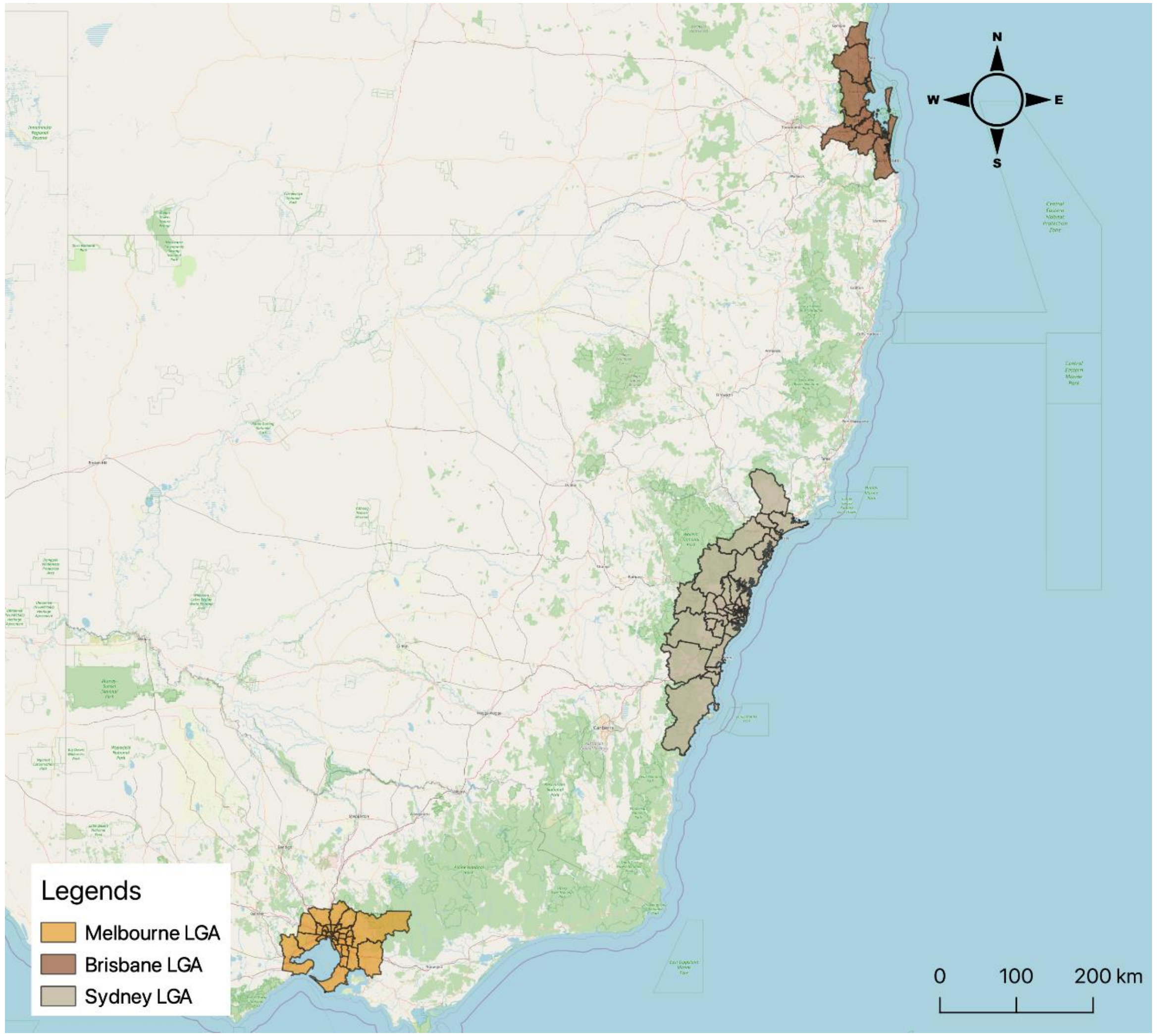
Land use

Industrial, Commercial, Hospital, Education, Residential, Production, Parkland, Transportation, Water, Other

Point Of Interest(POI)

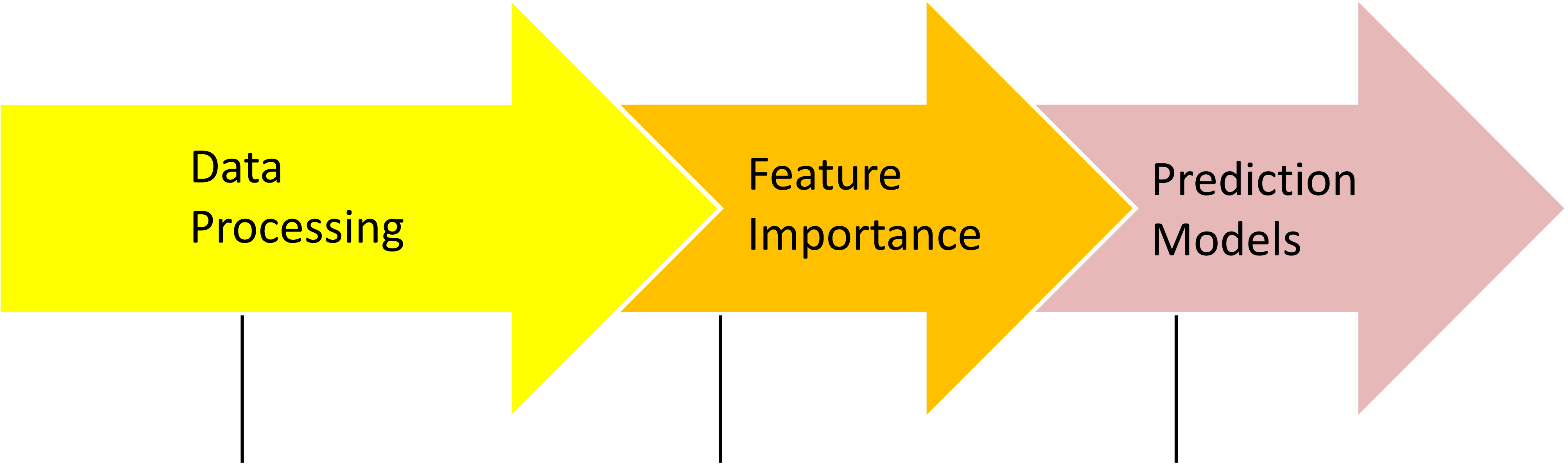
Point of Interest:

OSMNX



Methodology

Diagram



Data Processing

1. Census data processing
2. Percentage of Land use
3. Weighted trip Calculation

Feature Importance

1. Variance Inflation Factor (VIF)
2. Lasso feature selection
3. Pearson Correlation
4. Random Forest Feature selection

Prediction Models

1. Linear Regression
2. Poisson Regression
3. Random Forest

Results-Feature Importance

VIF

Sydney

Variable	VIF
%of industrail landuse	3.55
%of commercial landuse	4.26
POIs	5.71
Weighted Population	5.89
Weekly household income	39.90
%of hospital landuse	2.46
%of education landuse	9.18
%of other landuse	6.09
%of parkland landuse	23.99
%of primary production landuse	11.41
%of residential landuse	44.13
%of transport landuse	2.32
%of water landuse	1.59
Vehicle/Population	94.82

Melbourne

Variable	VIF
%of industrial landuse	5.35
%of commercial landuse	14.09
POIs	33.34
Weighted Population	21.76
Weekly household income	155.82
%of hospital landuse	14.85
%of education landuse	9.89
%of other landuse	10.88
%of parkland landuse	32.40
%of primary production landuse	43.28
%of residential landuse	262.53
%of transport landuse	1.97
%of water landuse	7.88
Vehicle/Population	278.30

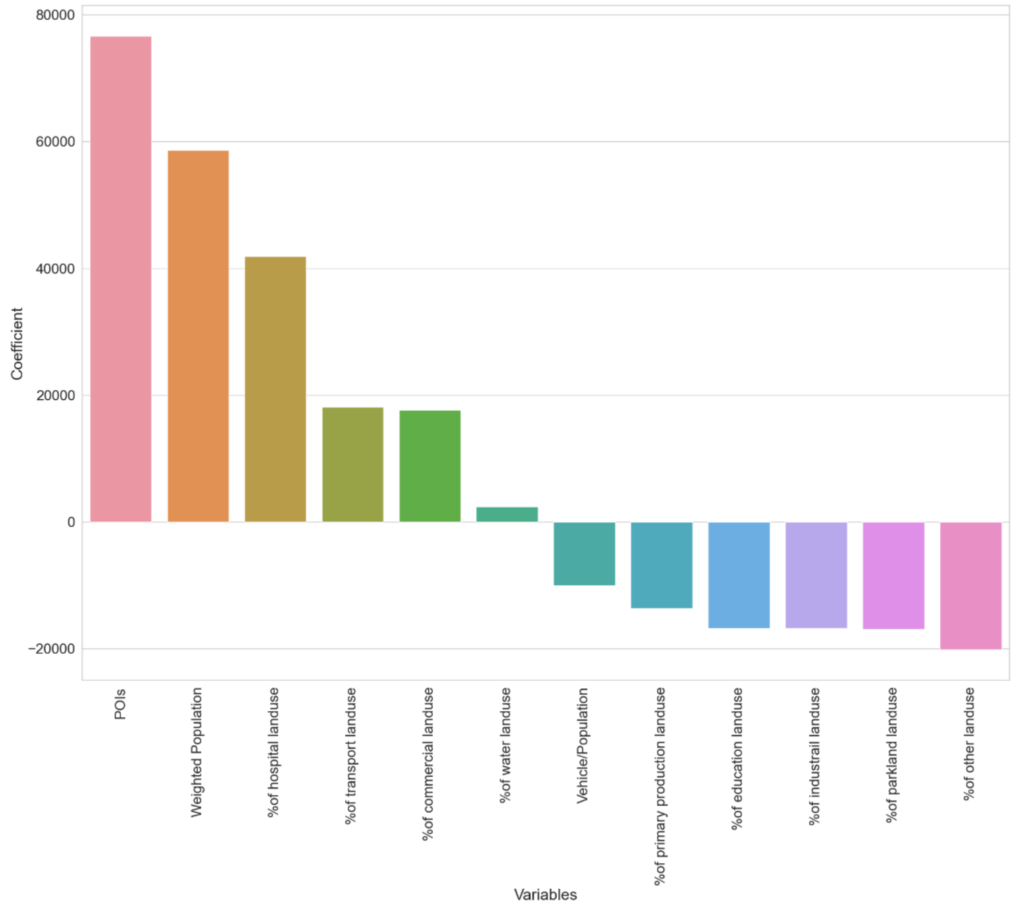
Brisbane

Variable	VIF
Weekly household income	inf
%of commercial landuse	inf
%of education landuse	inf
%of hospital landuse	inf
%of industrial landuse	inf
%of other landuse	inf
%of parkland landuse	inf
%of primary production landuse	inf
%of residential landuse	inf
%of transport landuse	inf
%of water landuse	inf
POIs	inf
Weighted Population	inf
Vehicle/Population	inf

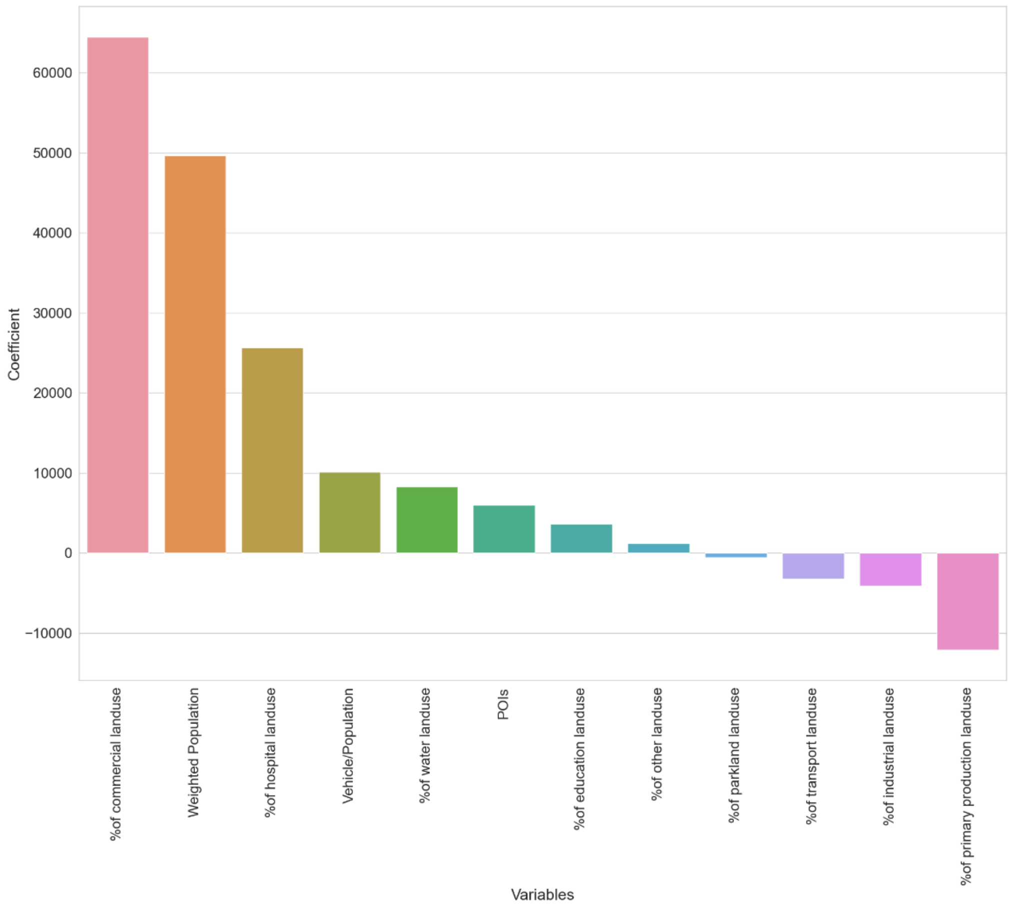
Results-Feature Importance

Lasso Regression

Sydney



Melbourne



Results-Feature Importance

Lasso Regression

Sydney

Variable	Coefficient
POIs	76598.580269
Weighted Population	58638.824649
%of hospital landuse	41872.705570
%of transport landuse	18177.943914
%of commercial landuse	17676.321337
%of water landuse	2428.266375
Vehicle/Population	-10000.129913
%of primary production landuse	-13658.135366
%of education landuse	-16771.507135
%of industrail landuse	-16788.531646
%of parkland landuse	-16878.342339
%of other landuse	-20111.482582

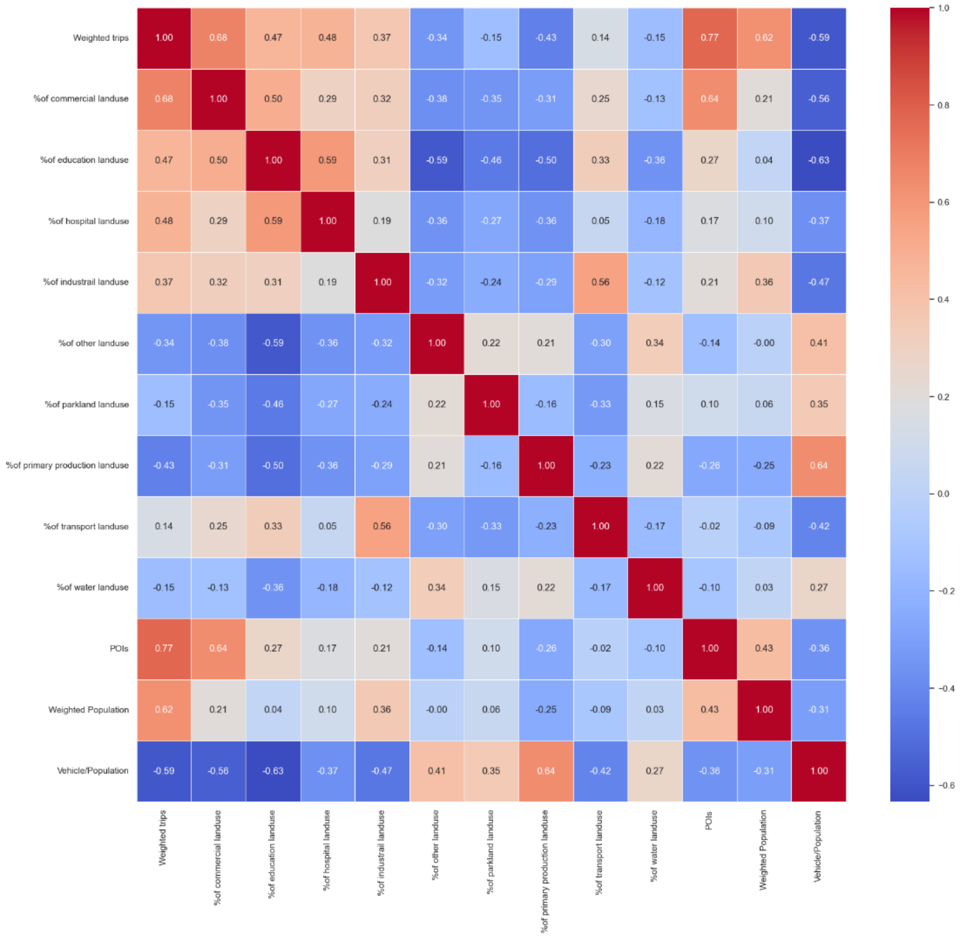
Melbourne

Variable	Coefficient
%of commercial landuse	64454.999642
Weighted Population	49655.573918
%of hospital landuse	25676.121602
Vehicle/Population	10098.003292
%of water landuse	8290.833335
POIs	5997.492306
%of education landuse	3631.418152
%of other landuse	1262.873552
%of parkland landuse	-531.079730
%of transport landuse	-3193.478010
%of industrial landuse	-4105.760064
%of primary production landuse	-12086.982912

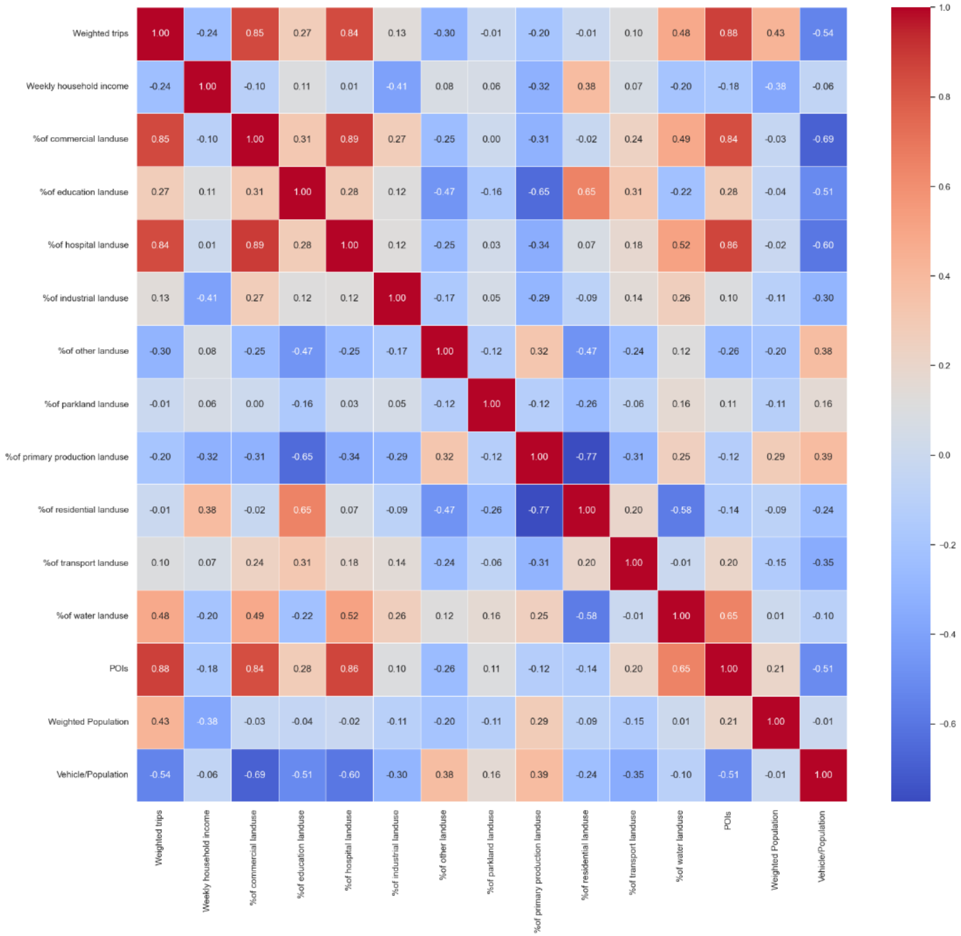
Results-Feature Importance

Pearson Correlation

Sydney



Melbourne



Results-Feature Importance

Pearson Correlation: >0.55

Sydney

Variable	Corr
POIs	0.77
% of Commercial Land use	0.68
Weighted Population	0.63
Vehicle/Population	-0.60

Melbourne

Variable	Corr
POIs	0.88
% of Commercial Land use	0.85
% of Hospital Land use	0.84
Vehicle/ population	-0.55

Results-Feature Importance

Random Forest

Sydney

Variable	Feature Importance
POIs	0.306
Weighted Population	0.213
Vehicle/Population	0.189
%of commercial landuse	0.093
%of hospital landuse	0.054
%of education landuse	0.052
%of industrail landuse	0.028
%of primary production landuse	0.019
%of parkland landuse	0.017
%of transport landuse	0.013
%of water landuse	0.007
%of other landuse	0.007

Melbourne

Variable	Feature Importance
Weighted Population	0.283
Vehicle/Population	0.159
%of hospital landuse	0.158
POIs	0.141
%of commercial landuse	0.118
%of water landuse	0.089
%of industrial landuse	0.011
%of other landuse	0.008
%of transport landuse	0.007
%of parkland landuse	0.007
%of residential landuse	0.006
Weekly household income	0.006
%of education landuse	0.005
%of primary production landuse	0.002

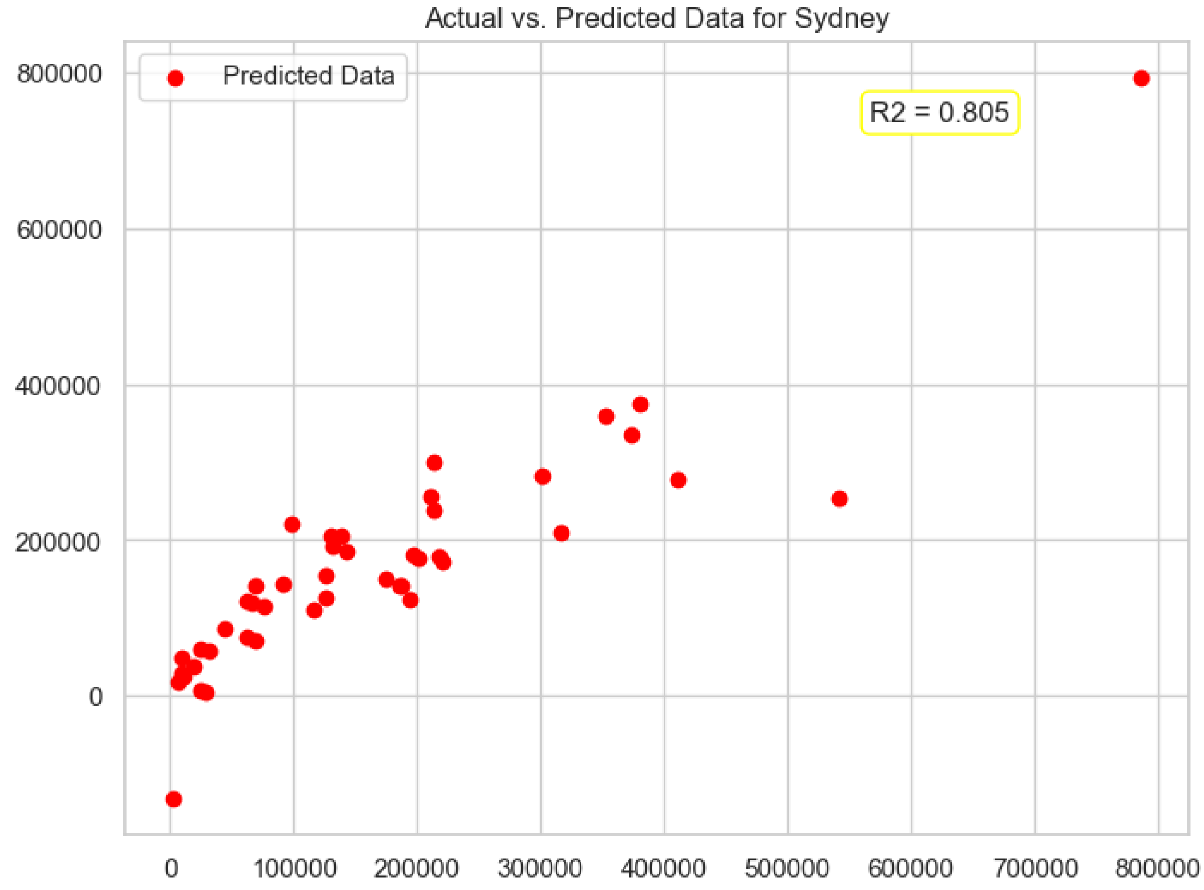
Results-Selected Variables

Target Variable
Weighted trips in each LGA
Dependent Variables
POIs
Weighted Population
Vehicle/Population
% of Commercial Land use
% of Hospital/Medical Land use
% of Industrial Land use
% of Primary Production Land use
% of Park Land use

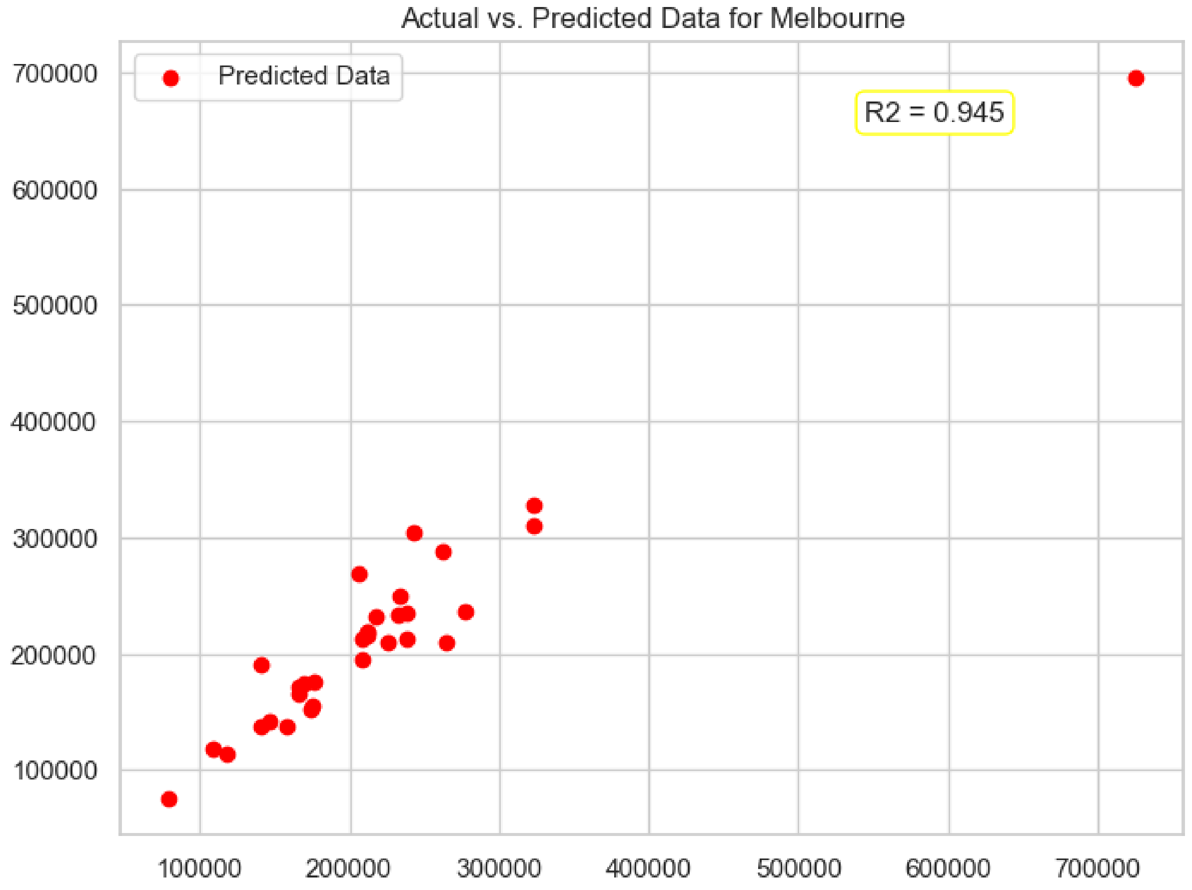
Results-Regression Models

Linear Regression

Sydney



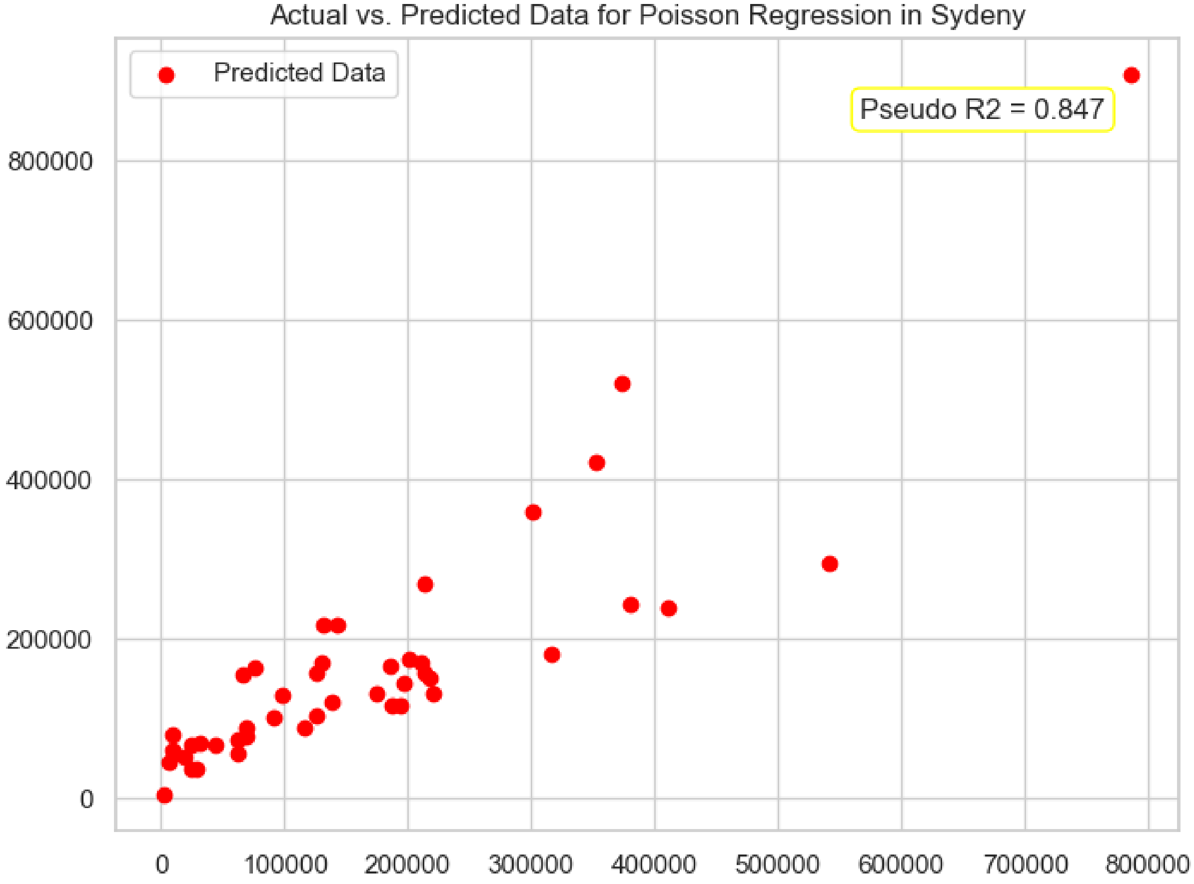
Melbourne



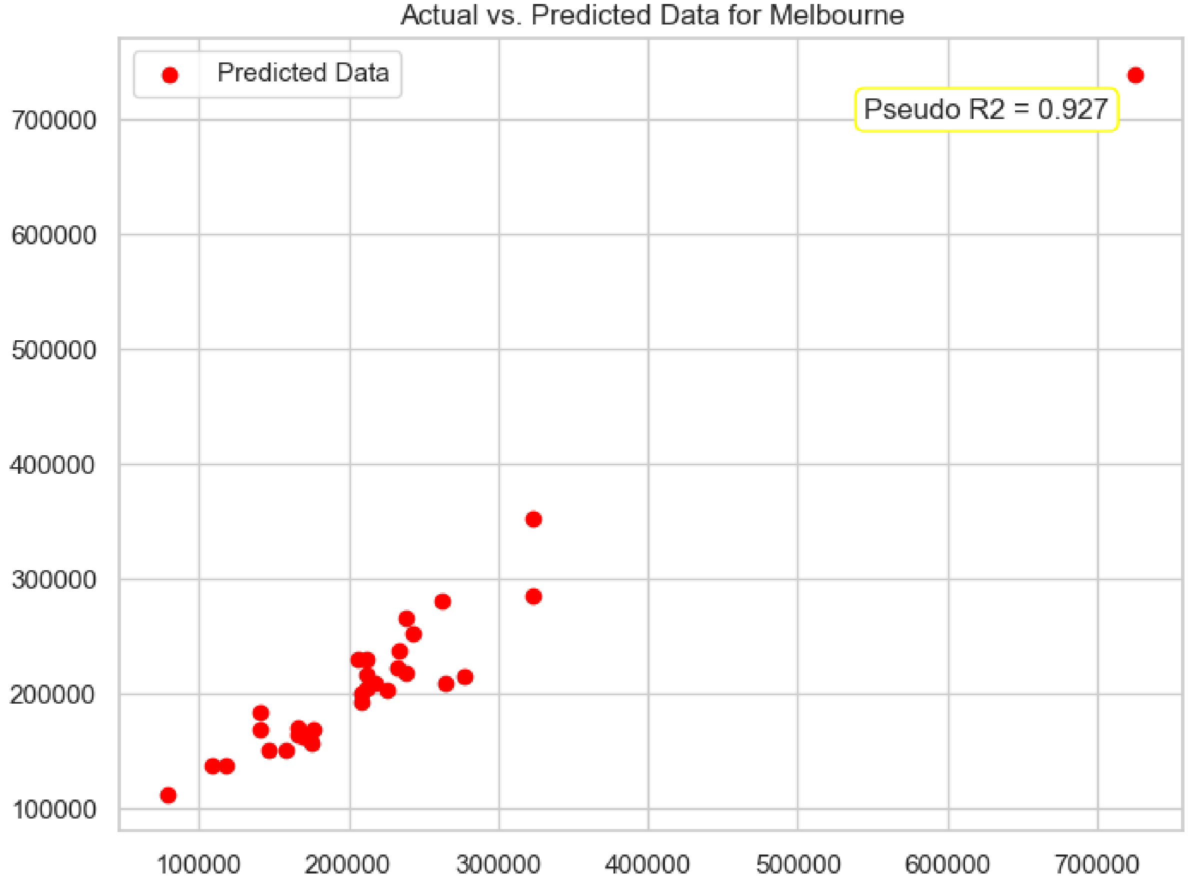
Results-Regression Models

Poisson Regression

Sydney



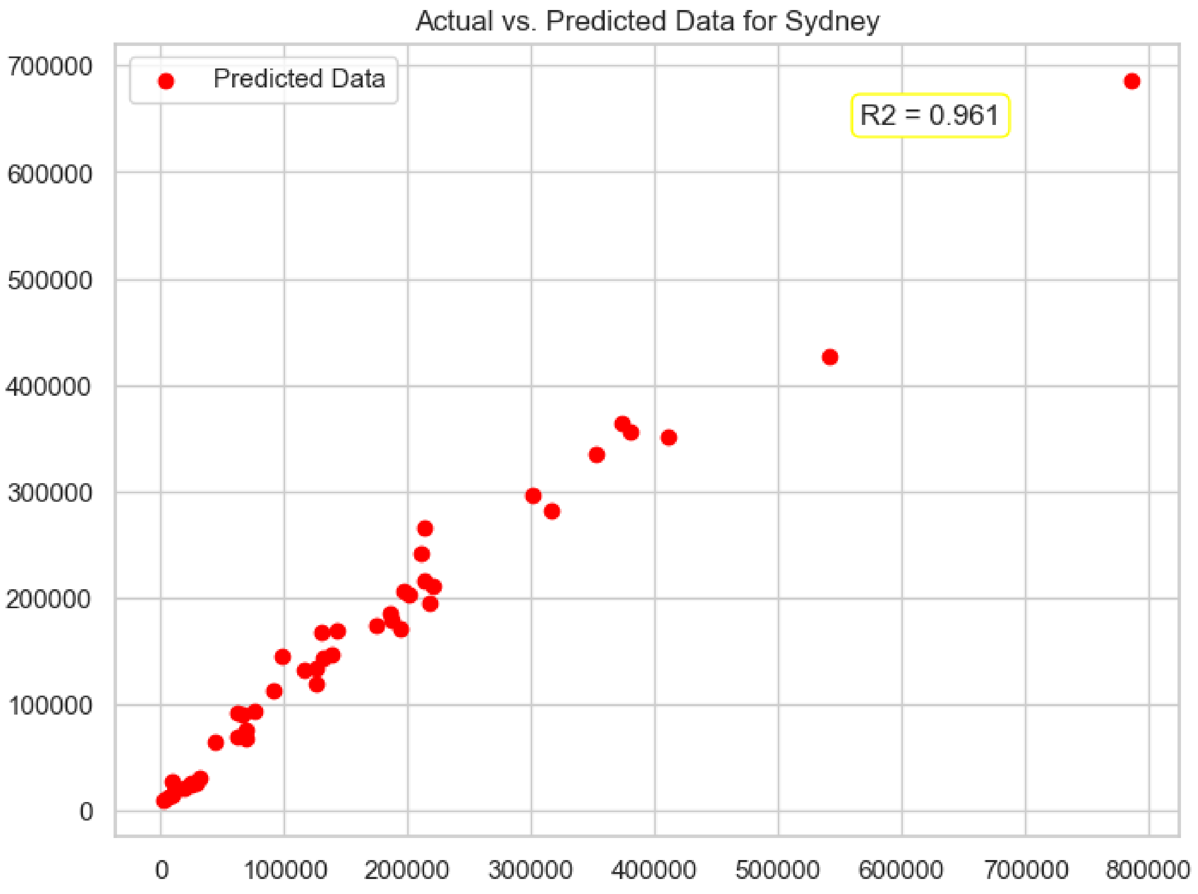
Melbourne



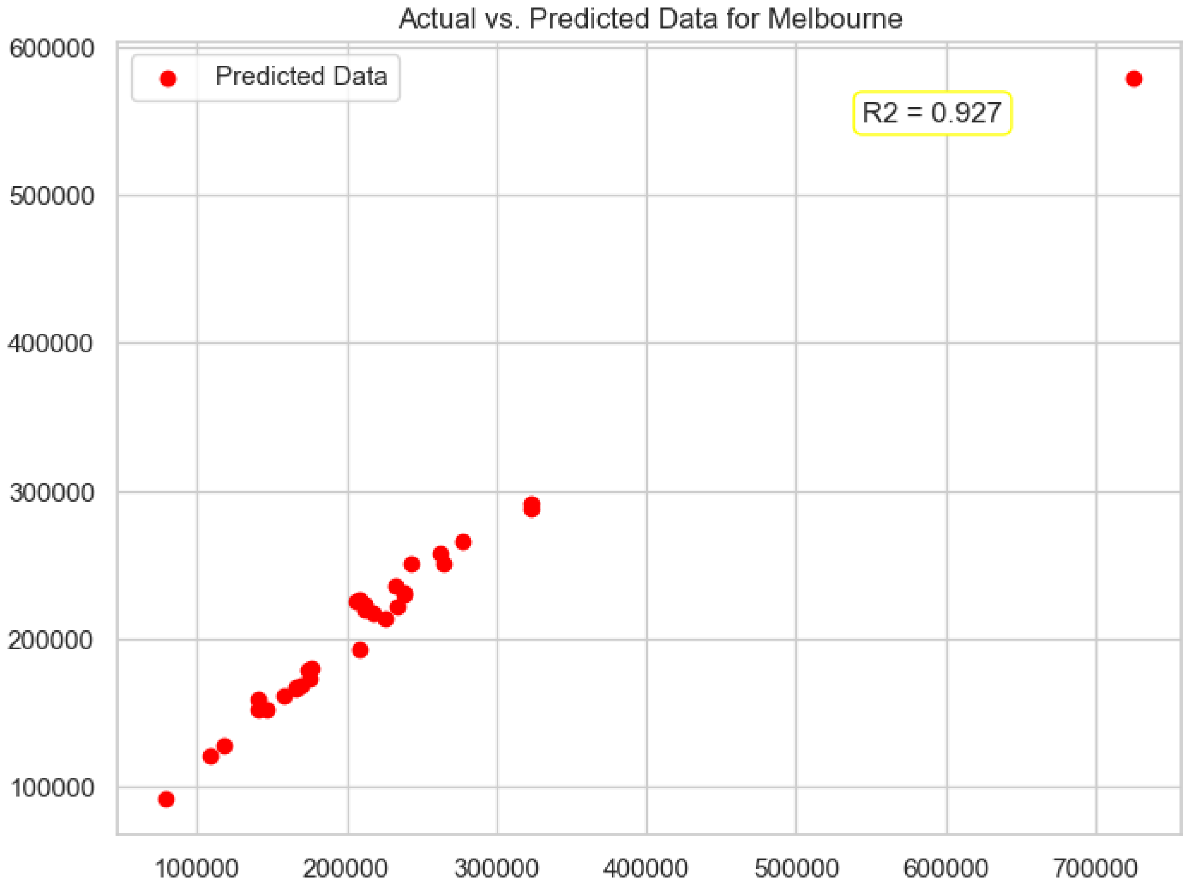
Results-Machine Learning Models

Random Forest Regression

Sydney



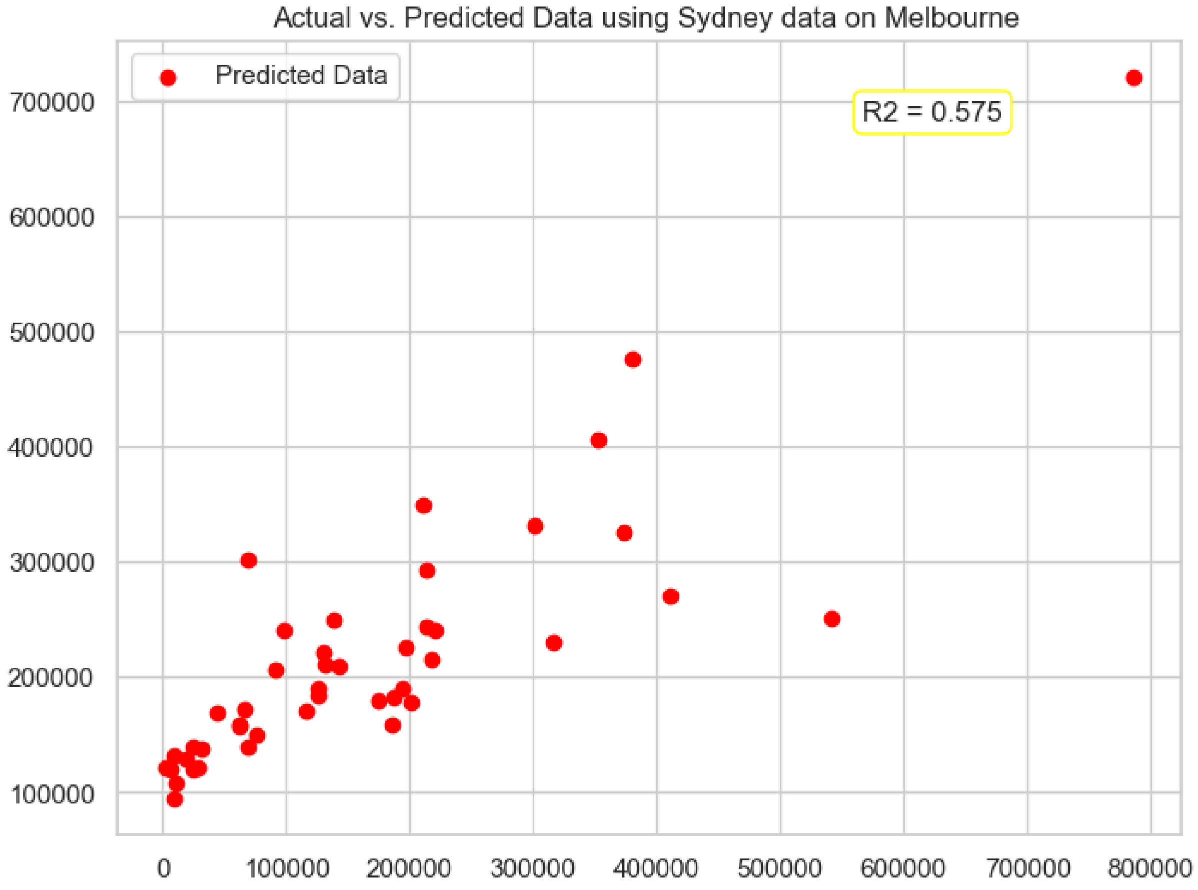
Melbourne



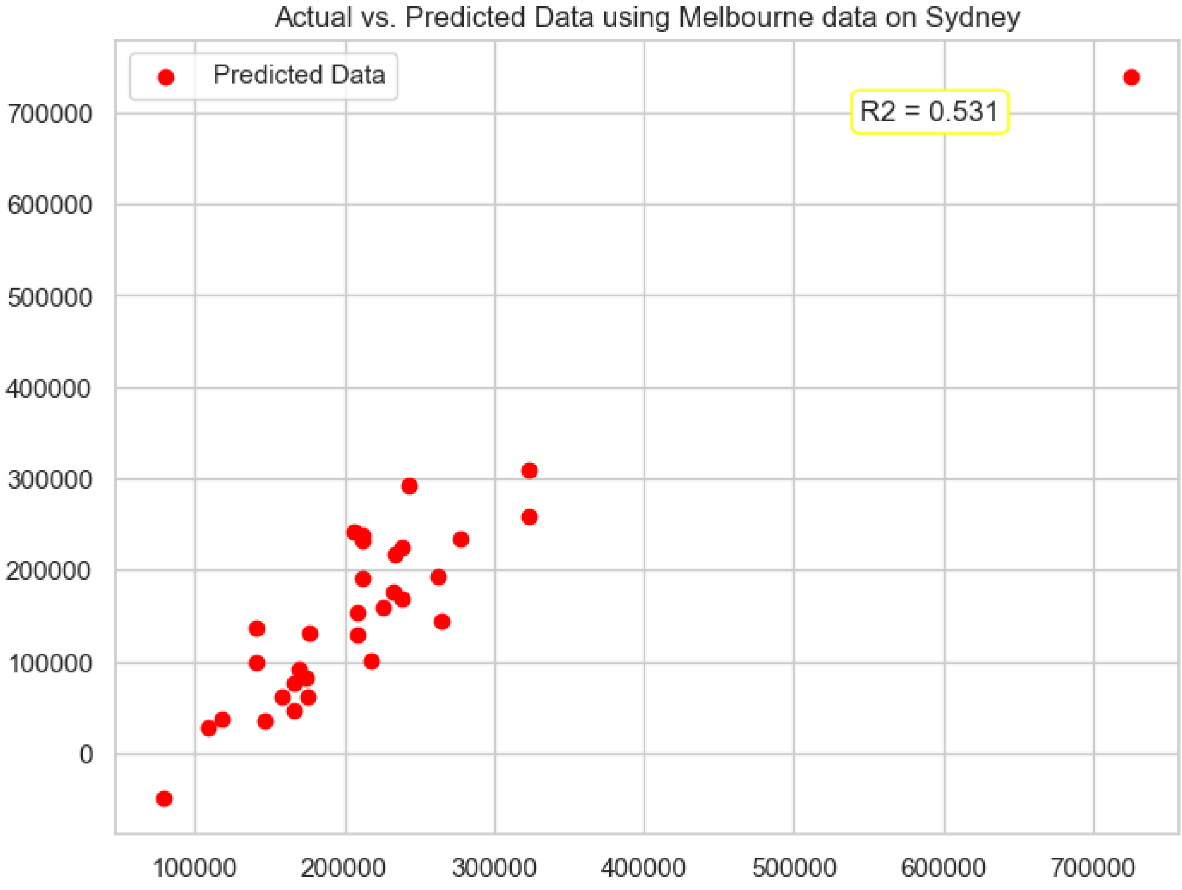
Results-Transferability-Regression Models

Linear Regression

Sydney in Melbourne model



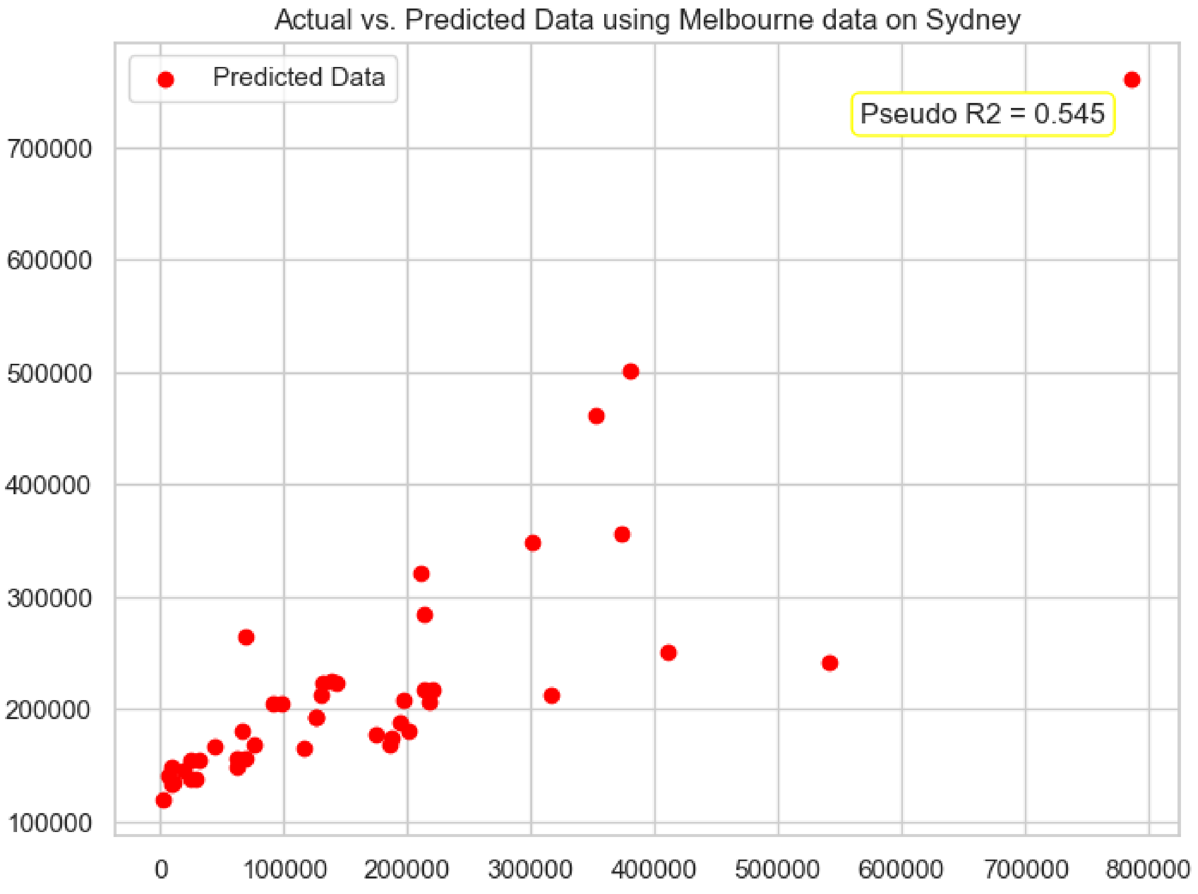
Melbourne in Sydney model



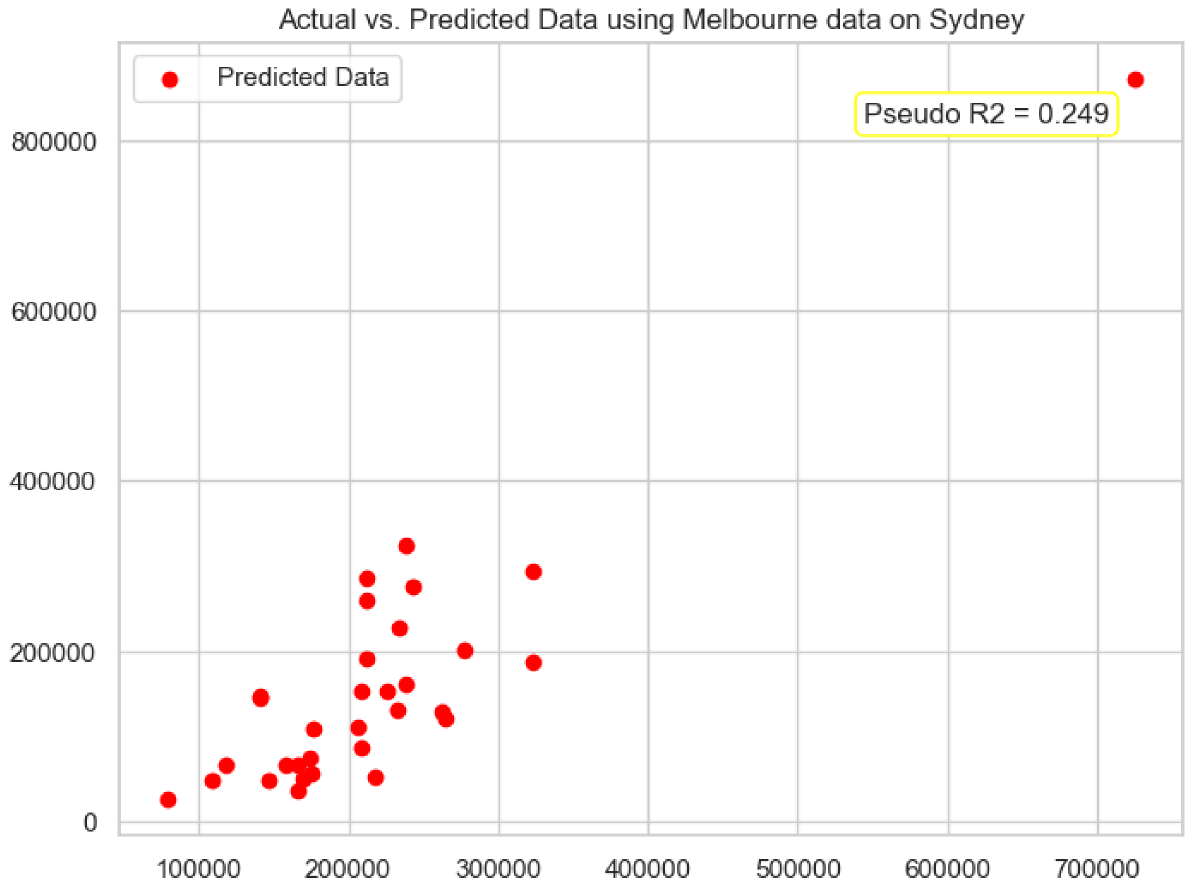
Results-Transferability-Regression Models

Poisson Regression

Sydney in Melbourne model



Melbourne in Sydney model



Conclusion

- POI, Commercial, and Population variables showed the most effect in the walking data.
- The models show high performance for both statistics and ML models.
- The model transferability can be seen for the Linear Regression and Poisson Regression model in the top 4 most important variables.

Future Work

- Add different variables to train the model.
- Check the transferability for Brisbane data.
- Check the transferability for other models.

Thank You!

Any Question?