BUSINESS SCHOOL | RWTH AACHEN UNIVERSITY

INTRODUCTION

EDA & MODELLING

RESULTS & FUTURE SCOPE

DEVELOP A DISCRETE CHOICE MODEL OF PEDESTRIAN WALKING BEHAVIOR

Analytics Project SoSe 2023
Prof. Dr. Sven Müller

LITERATURE REVIEW

Presented by:
Ambika Goyal
Divya Khanolkar
Siddhi Chavan
Urmi Ganguly

Introduction: Start With 'WHY' ?

- It is pivotal to model a successful ADAS (autonomous driving assistant system).
- If integrated into an ADAS with sufficient accuracy, it enables quick decision making within a specified factor of safety.
- Discrete Choice Models are cheaper and easier to implement with decent accuracy than Neural Network's when relevant data is available.
- Another application would be to aid decision making for handicapped pedestrians, via a chip like neuralink.

Problem Statement

- The objective is to develop a discrete choice model of pedestrian walking behavior to gain insights into how pedestrians make decisions when crossing roads under stressful conditions.
- To achieve this objective, the project will involve obtaining data from IKA, which captures the walking behavior of pedestrians when crossing a street with an approaching car under different scenarios.
- The project will focus on performing data engineering to make the data usable for discrete choice modeling and specifying a series of choice models using the data.

IKA Simulation

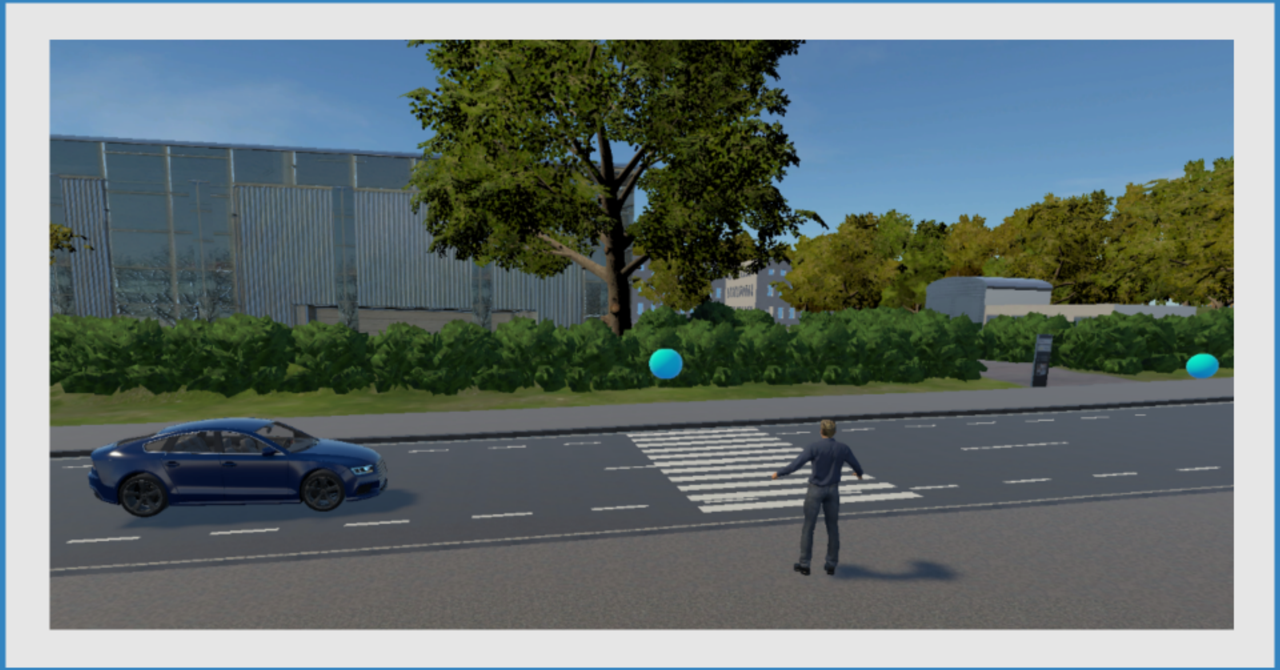

Fig. 1 Persons POV

Fig. 2 Aerial View

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Literature Review

1. Discrete Choice Models of pedestrian walking behavior

Gianluca Antonini, Michel Bierlaire , Mats Weber (2015)

- The authors propose a multi-agent discrete choice framework for modeling pedestrian dynamics and their short-term behavior as a response to the presence of other pedestrians.
- Pedestrian behavior is considered as a series of multinomial choice decisions.
- Pedestrians are simulated to navigate a maze-like environment.

2. Specification, Estimation and Validation of a pedestrian walking behavior model

Th. Robin, G. Antonini, M. Bierlaire, J.Cruz

- The paper proposes discrete choice model and identifies unconstrained and constrained pedestrian behaviors.
- Focuses on short range behavior in normal conditions.
- An individual-specific & adaptive discretization of the space is obtained to generate 33 alternatives.
- The spatial correlation between the alternatives is captured by a cross nested logit model.
- It is validated using a bi-directional flow data set.

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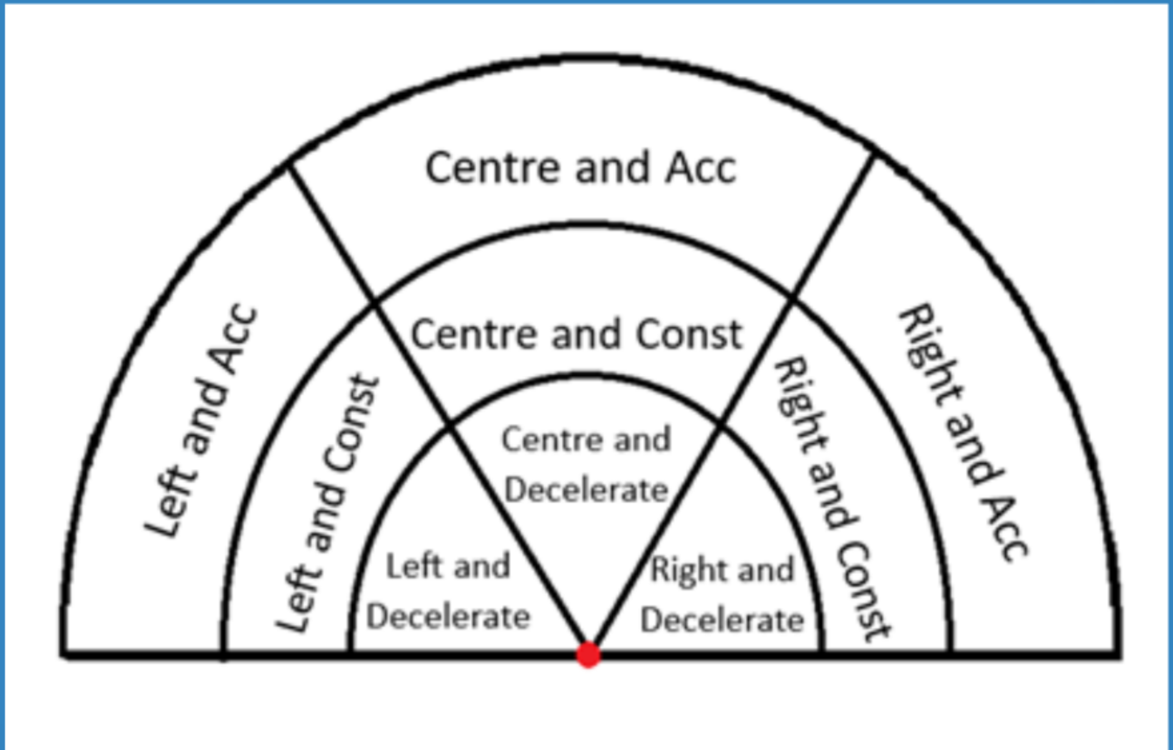
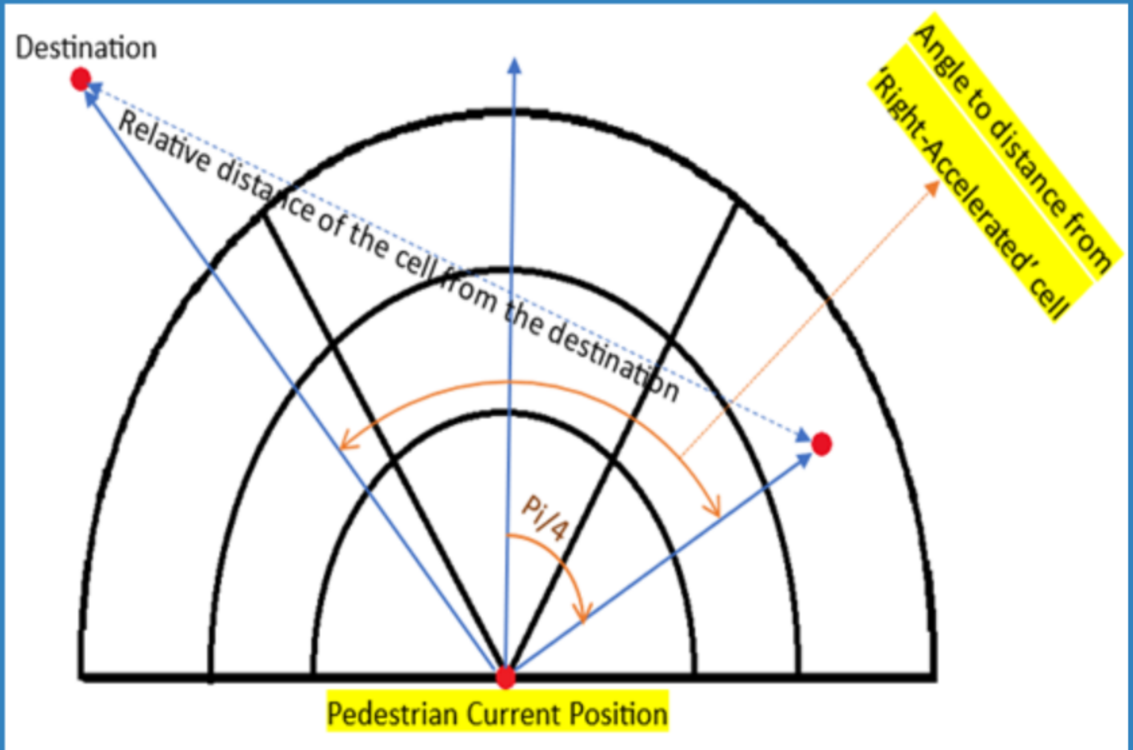
Modelling

9 Alternatives Model





Discrete Choice Model

- Statistical approach aiming to predict how individuals make choices among a set of alternatives to choose one that maximizes their utility.

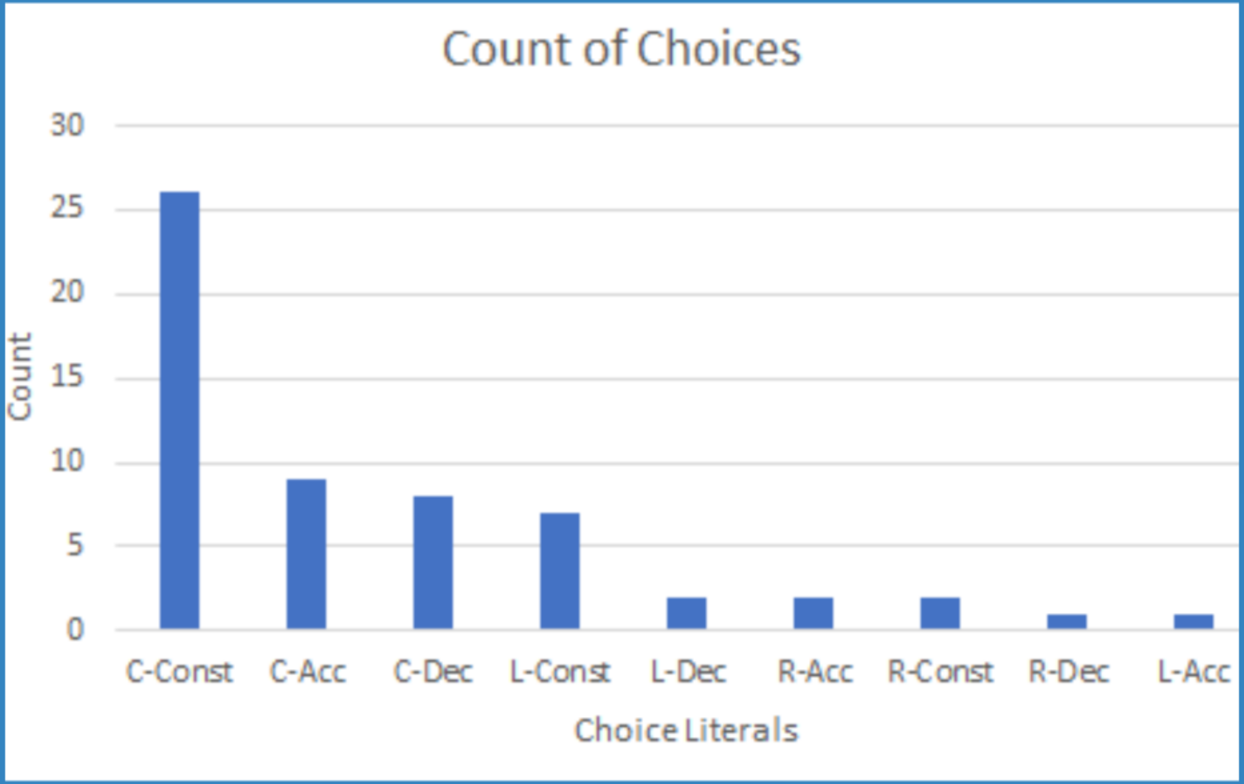
- Revealed preference(observing individuals' actual choices) data is used.

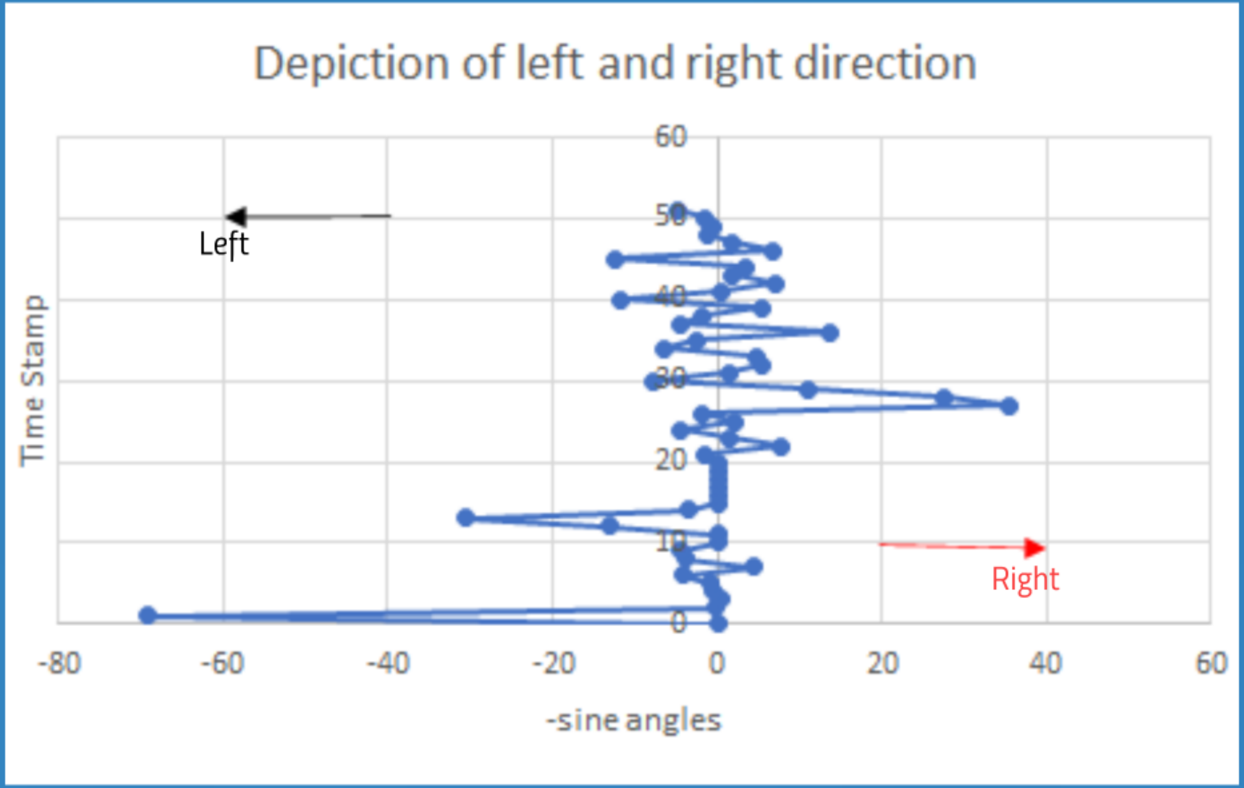
- The main algorithm : **Maximum Likelihood Estimation** method.

- The choice probabilities in discrete choice models are modeled as a **function of the alternative-specific variables**. These variables can include characteristics of the alternatives (e.g., vehicle velocity, relative distance from destination).

- The initial model implemented in the project: **Multinomial Logit (MNL)** model: choice probabilities are proportional to the exponential of the utility of each alternative.

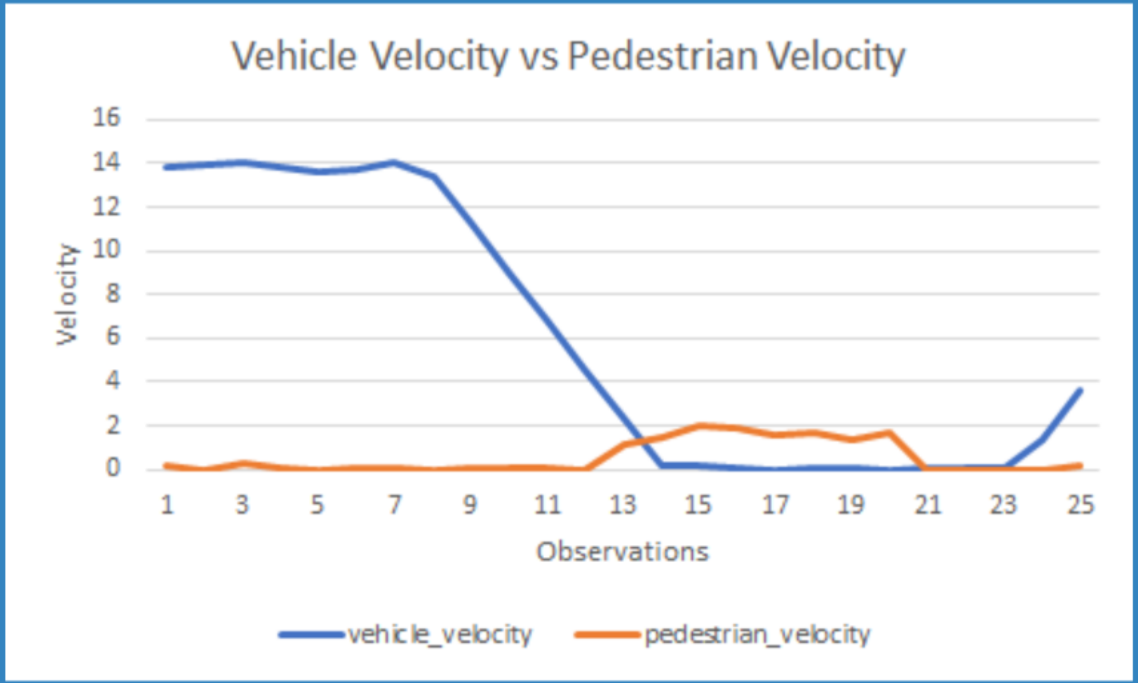
Data Exploration



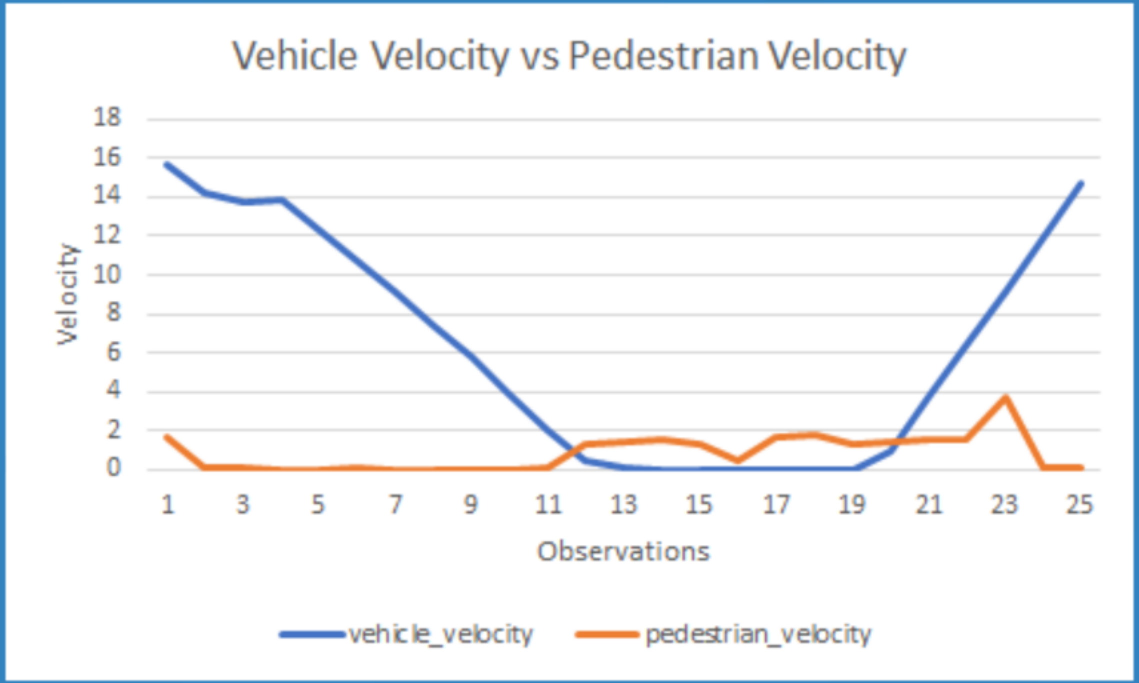


Data Exploration ctd.

Cross Walk



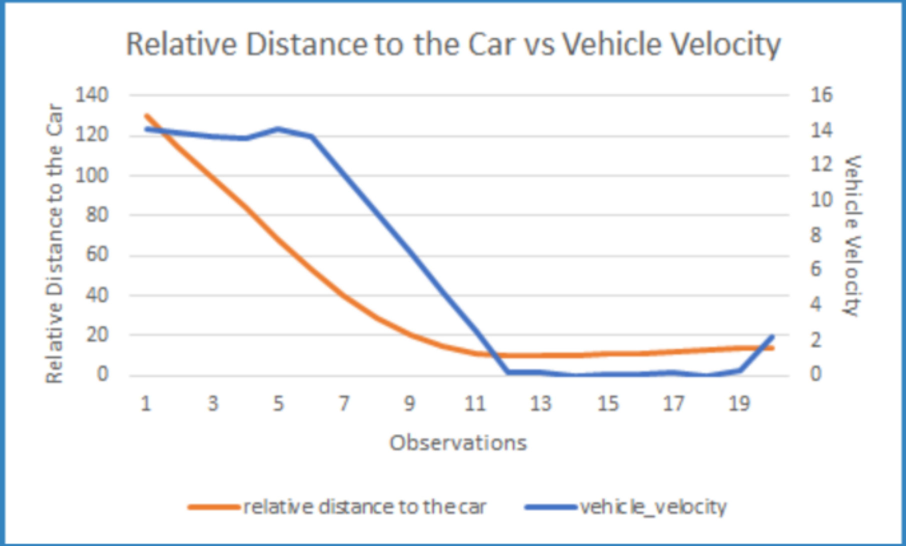
Non-Cross Walk

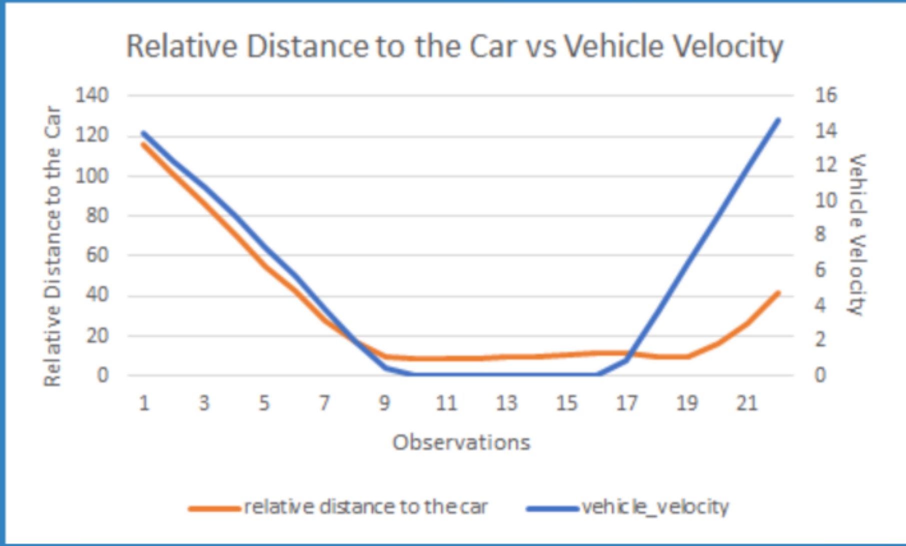


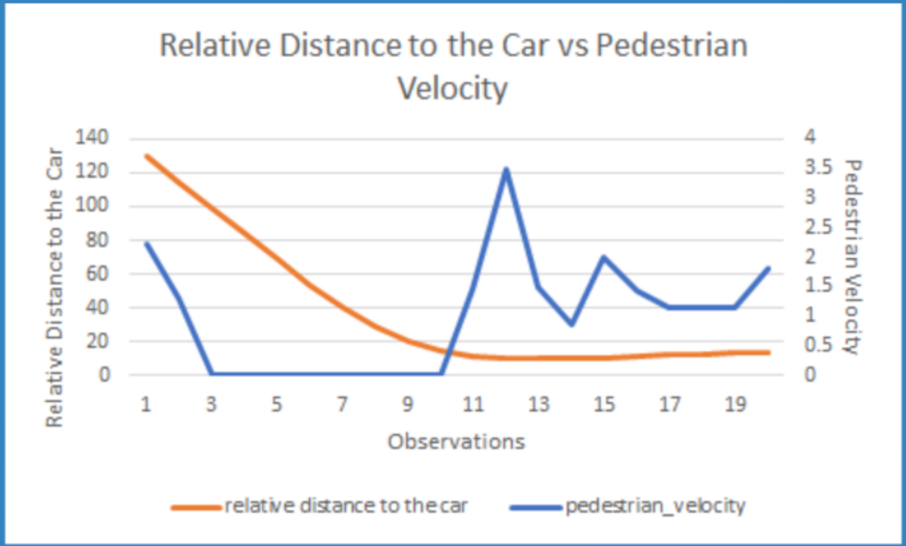
Data Exploration ctd.

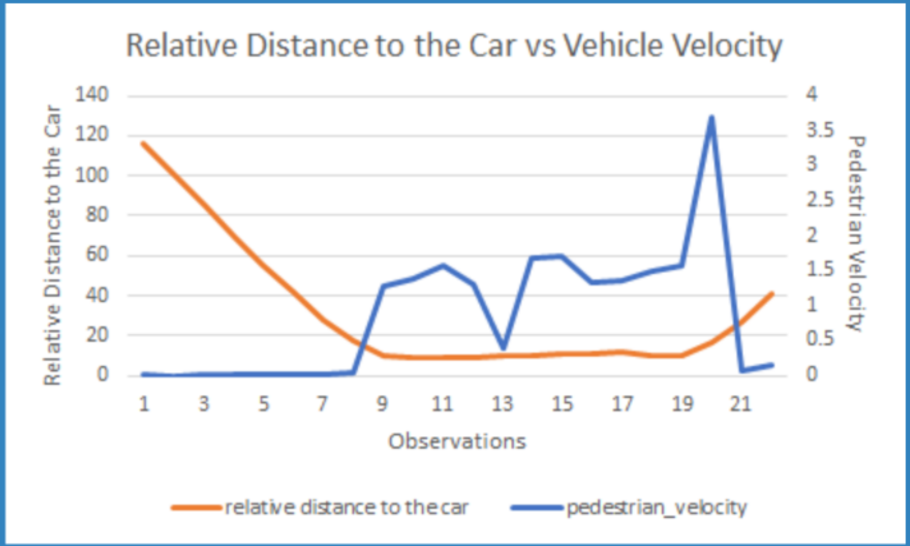
Cross Walk

Non-Cross Walk

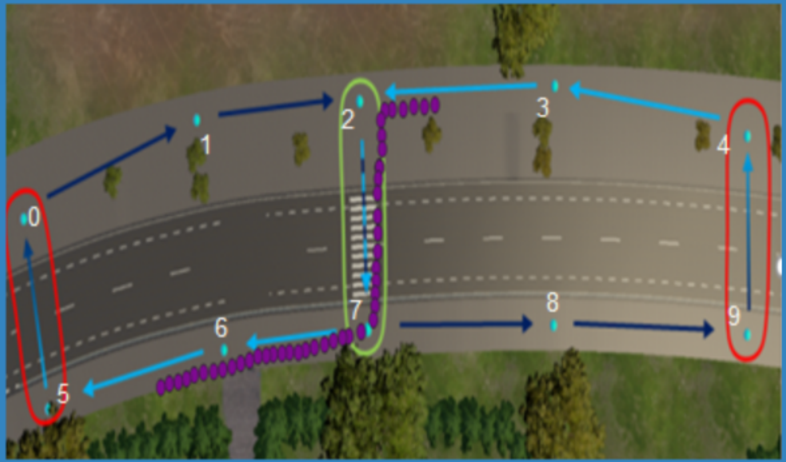




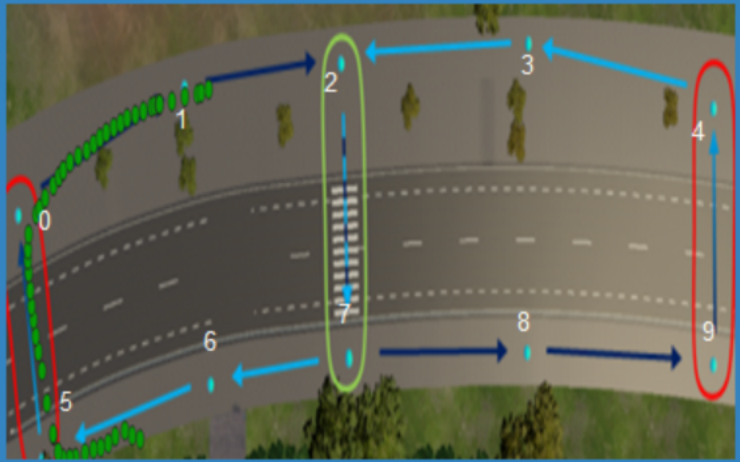




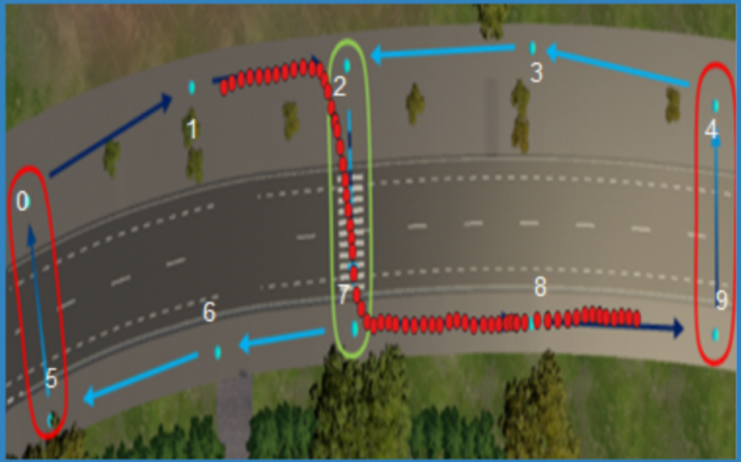
Georeferencing Output



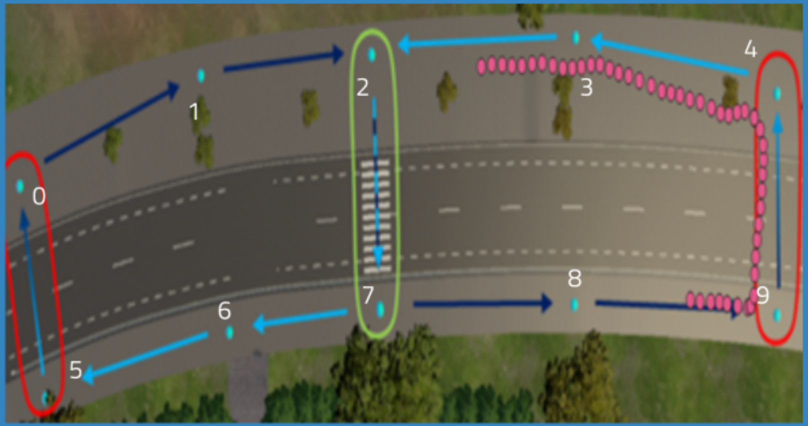
Scenario 1



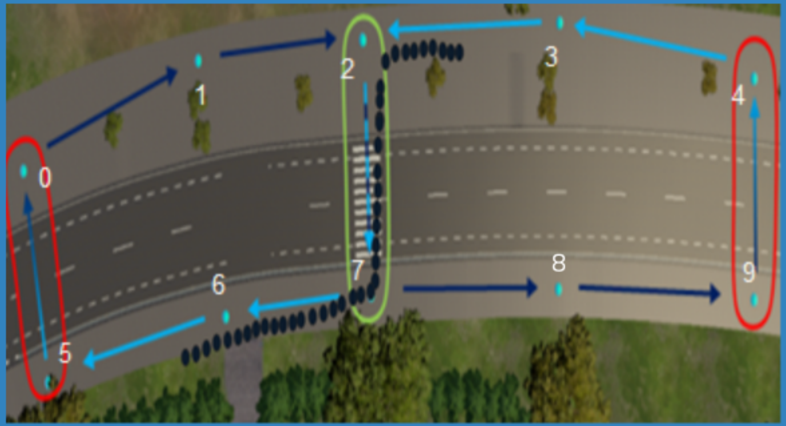
Scenario 2



Scenario 3



Scenario 4



Scenario 5

- Geo-referencing techniques is used to map the way the subject moves using the left foot position coordinates.
- Overlapped the given simulation image with a layer of point clusters of the pedestrians head position coordinates.

Data Engineering

$$Speed = (current\ velocity\ of\ pedestrian) \Big/ (previous\ velocity\ of\ pedestrian)$$

$$Acc = \begin{cases} 1, if\ Speed \geq 1.5 \\ 0, if\ Speed < 1.5 \end{cases}$$

$$Dec = \begin{cases} 1, if\ Speed \leq 0.5 \\ 0, if\ Speed > 0.5 \end{cases}$$

$$Const = \begin{cases} 1, if\ 0.5 < Speed < 1.5 \\ \quad 0, if\ otherwise \end{cases}$$

$$Velocity\_gradient = Gradient\ of\ velocity\ per\ timestamp$$

$$Sin\_Angle\ (degrees) = (Vector\ cross\ multiplication\ between\ 2\ vectors((curr\ x, y), (\ prev\ x, y)))$$

$$Left = \begin{cases} 1, if\ sin\_Angle \geq 10 \\ 0, if\ sin\_Angle < 10 \end{cases}$$

$$Right = \begin{cases} 1, if\ sin\_Angle \leq (-10) \\ 0, if\ sin\_Angle > (-10 \end{cases}$$

$$Central = \begin{cases} 1, if\ \ -10 < sin\_Angle \leq 10 \\ \quad 0, if\ otherwise \end{cases}$$

$$Direction\ = L, R\ or\ \ C$$

$$dest = Nearest\ destination\ from\ current\ point\ of\ pedestrian$$

$$Curr\_dist\_left\_dec\_x\ = Matrix\ point\ x\ of\ left\ dec$$

$$Curr\_dist\_left\_dec\_z\ = Matrix\ point\ z\ of\ left\ dec$$

Data Engineering

$$\begin{aligned}&Curr\_dist\_left\_dec\\&= \ Distance\ of\ nearest\ destination\ from\ Matrix\ point\ (x, z\ )\ of\ left\ dec\end{aligned}$$

$$\begin{aligned}&Car\_dist\_left\_dec\\&= \begin{cases}Distance\ of\ car\ from\ Matrix\ point\ (x, z)\ of\ left\ dec\ while\ crossing\\ 600, otherwise\end{cases}\end{aligned}$$

$$v\_Vehicle\_Effect\ = \begin{cases}Velocity\ of\ car\ when\ the\ pedestrian\ is\ crossing\\ 0, otherwise\end{cases}$$

$$\begin{aligned}&Angle\_Left\_Acc\\&= \ Angle\ between\ the\ nearest\ destination\ and\ Matrix\ (x, z)\ of\ left\ dec\end{aligned}$$

$$Choice\_Literal\ = \ Choice\ of\ the\ Pedestrian$$

$$Choice\ = \ Numeric\ Choice$$

$$\begin{aligned}&PrevChoice\ (\gamma)_{\mathrm{LA}}\\&\qquad = \begin{cases}1, if\ the\ pedestrian\ took\ Choice(\mathrm{LA})\ in\ the\ previous\ step\\ 0, if\ otherwise\end{cases}\end{aligned}$$

$$InvID\ = \ Individual\ ID$$

Utility Functions

1. Constants Only Model

$$V_{n,CC,t} = 0$$

$$V_{n,LC,t} = ß_{LC,t}$$

$$V_{n,RC,t} = ß_{RC,t}$$

$$V_{n,CA,t} = ß_{CA,t}$$

$$V_{n,LA,t} = ß_{LA,t}$$

$$V_{n,RA,t} = ß_{RA,t}$$

$$V_{n,CD,t} = ß_{CD,t}$$

$$V_{n,LD,t} = ß_{LD,t}$$

$$V_{n,RD,t} = ß_{RD,t}$$

```
LL(start)                               : -1065.65
LL at equal shares, LL(0)               : -1065.65
LL at observed shares, LL(C)            : -582.86
LL(final)                               : -582.86
Rho-squared vs equal shares              :  0.4531
Adj.Rho-squared vs equal shares          :  0.4455
Rho-squared vs observed shares           :  0
Adj.Rho-squared vs observed shares       :  -0.0137
```

```
These outputs have had the scaling used in estimation applied to them.
Estimates:
                  Estimate        s.e.   t.rat.(0)    Rob.s.e. Rob.t.rat.(0)
asc_left_acc        -4.184      0.4506      -9.284      0.4510        -9.275
asc_right_acc       -4.001      0.4120      -9.712      0.4125        -9.701
asc_centre_acc      -2.104      0.1675     -12.564      0.1676       -12.551
asc_left_dec        -3.847      0.3820     -10.071      0.3824       -10.061
asc_right_dec       -4.406      0.5029      -8.761      0.5034        -8.754
asc_centre_dec      -2.079      0.1656     -12.553      0.1658       -12.541
asc_left_const      -2.658      0.2157     -12.320      0.2159       -12.308
asc_right_const     -2.359      0.1879     -12.555      0.1881       -12.541
```

Utility Functions

2. Multinomial Logit Model

$$V_{n,LA,t} = ß_{LA,t} + ß_{dir} * DD_{LA,t} + ß_{acc} * VG_{n,t} + ß_{car-dist} * CD_{LA,t} + ß_{angle} * Angle_{LA,t} + ß_{prevCh} * \gamma_{n,LA,(t-1)} + ß_{car} * VE_t$$

$$V_{n,RA,t} = ß_{RA,t} + ß_{dir} * DD_{RA,t} + ß_{acc} * VG_{n,t} + ß_{car-dist} * CD_{RA,t} + ß_{angle} * Angle_{RA,t} + ß_{prevCh} * \gamma_{n,RA,(t-1)} + ß_{car} * VE_t$$

$$V_{n,CA,t} = ß_{CA,t} + ß_{dir} * DD_{CA,t} + ß_{acc} * VG_{n,t} + ß_{car-dist} * CD_{CA,t} + ß_{angle} * Angle_{CA,t} + ß_{prevCh} * \gamma_{n,CA,(t-1)} + ß_{car} * VE_t$$

$$V_{n,LD,t} = ß_{LD,t} + ß_{dir} * DD_{LD,t} + ß_{dec} * VG_{n,t} + ß_{car-dist} * CD_{LD,t} + ß_{angle} * Angle_{LD,t} + ß_{prevCh} * \gamma_{n,LD,(t-1)} + ß_{car} * VE_t$$

$$V_{n,RD,t} = ß_{RD,t} + ß_{dir} * DD_{RD,t} + ß_{dec} * VG_{n,t} + ß_{car-dist} * CD_{RD,t} + ß_{angle} * Angle_{RD,t} + ß_{prevCh} * \gamma_{n,RD,(t-1)} + ß_{car} * VE_t$$

Abbreviations Used:

LA = Left Acceleration
RA = Right Acceleration
CA = Central Acceleration
LD = Left Decceleration
RD = Right Decceleration
DD = Distance to Destination
VG = Velocity Gradient
CD = Distance to car
VE = Effect of Car's Velocity

Utility Functions

$$V_{n,CD,t} = ß_{CD,t} + ß_{dir} * DD_{CD,t} + ß_{dec} * VG_{n,t} + ß_{car-dist} * CD_{CD,t} + ß_{angle} * Angle_{CD,t} + ß_{prevCh} * \gamma_{n,CD,(t-1)} + ß_{car} * VE_t$$

$$V_{n,LC,t} = ß_{LC,t} + ß_{dir} * DD_{LC,t} + ß_{const} * VG_{n,t} + ß_{car-dist} * CD_{LC,t} + ß_{angle} * Angle_{LC,t} + ß_{prevCh} * \gamma_{n,LC,(t-1)} + ß_{car} * VE_t$$

$$V_{n,RC,t} = ß_{RC,t} + ß_{dir} * DD_{RC,t} + ß_{const} * VG_{n,t} + ß_{car-dist} * CD_{RC,t} + ß_{angle} * Angle_{RC,t} + ß_{prevCh} * \gamma_{n,RC,(t-1)} + ß_{car} * VE_t$$

$$V_{n,CC,t} = ß_{dir} * DD_{CC,t} + ß_{const} * VG_{n,t} + ß_{car-dist} * CD_{CC,t} + ß_{angle} * Angle_{CC,t} + ß_{prevCh} * \gamma_{n,CC,(t-1)} + ß_{car} * VE_t$$

Abbreviations Used:

CD = Central Decceleration
LC = Left Constant
RC = Right Constant
CC = Central Constant
DD = Distance to Destination
VG = Velocity Gradient
CD = Distance to car
VE = Effect of Car's Velocity

Utility Functions

MNL Output

```
LL(start)                                  : -1065.65
LL at equal shares, LL(0)                  : -1065.65
LL at observed shares, LL(C)               : -582.86
LL(final)                                  : -506.67
Rho-squared vs equal shares                 :  0.5245
Adj.Rho-squared vs equal shares             :  0.5105
Rho-squared vs observed shares              :  0.1307
Adj.Rho-squared vs observed shares          :  0.105
```

These outputs have had the scaling used in estimation applied to them.
Estimates:

	Estimate	s.e.	t.rat.(0)	Rob.s.e.	Rob.t.rat.(0)
b_car_dist	-0.42894	0.31758	-1.35066	0.32905	-1.30359
b_dir	0.02084	0.25655	0.08125	0.31079	0.06707
b_angle	1.72377	0.55802	3.08910	0.74888	2.30180
b_acc	2.88850	0.48607	5.94253	0.68352	4.22591
b_dec	-1.66403	0.39565	-4.20580	0.53228	-3.12620
b_const	0.00000	NA	NA	NA	NA
b_car_vel	0.08739	0.03322	2.63085	0.03519	2.48314
b_prevChoice	0.95534	0.14054	6.79771	0.14061	6.79409
asc_right_acc	-4.80204	0.56799	-8.45441	0.63367	-7.57820
asc_centre_acc	-2.11398	0.25837	-8.18207	0.25824	-8.18605
asc_left_dec	-4.72016	0.56127	-8.40974	0.72393	-6.52021
asc_right_dec	-5.05863	0.62038	-8.15410	0.65437	-7.73056
asc_centre_dec	-1.87013	0.23630	-7.91430	0.28697	-6.51673
asc_left_const	-3.45393	0.45695	-7.55870	0.60484	-5.71046
asc_right_const	-2.90015	0.39916	-7.26567	0.48418	-5.98981
asc_left_acc	-5.39111	0.63462	-8.49501	0.72364	-7.45002

Model Comparison:

	M1 vs. M2	M2 vs. M3	M2 vs. M4	M2 vs. M5	M2 vs. M6	M2 vs. M7
Subject ID: 1						
LR value	178.58	176.72	173.34	171.74	168.82	141.14
Degrees Of Freedom	7	6	5	4	3	2
P-value	3.886e-35	1.687e-35	1.414e-35	4.426e-36	2.288e-36	2.248e-31
Subject ID: 3						
LR value	152.38	149.8	136.38	126.44	87.14	75.56
Degrees Of Freedom	7	6	5	4	3	2
P-value	1.284e-29	8.528e-30	1.052e-27	2.247e-26	9.01e-19	3.912e-17

M1: Null model
M2: M1+ dist from grip position
M3: M2+ Vehicle Velocity effect
M4: M3+ distance of destination from grid position

M5: M4+ Previous Choice
M6: M5+ Angle between car, destination and person
M7: M6+ Velocity Gradient

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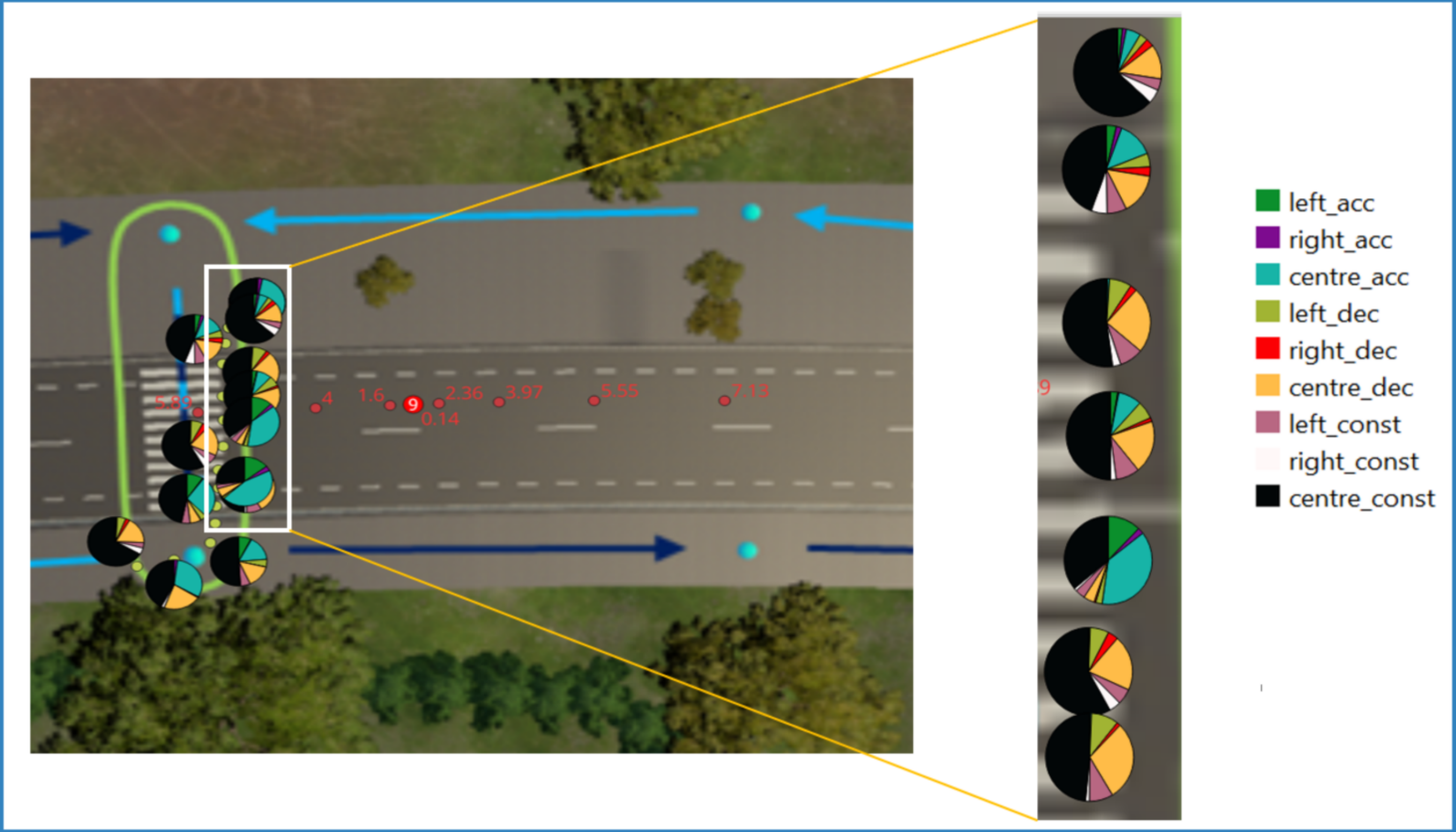
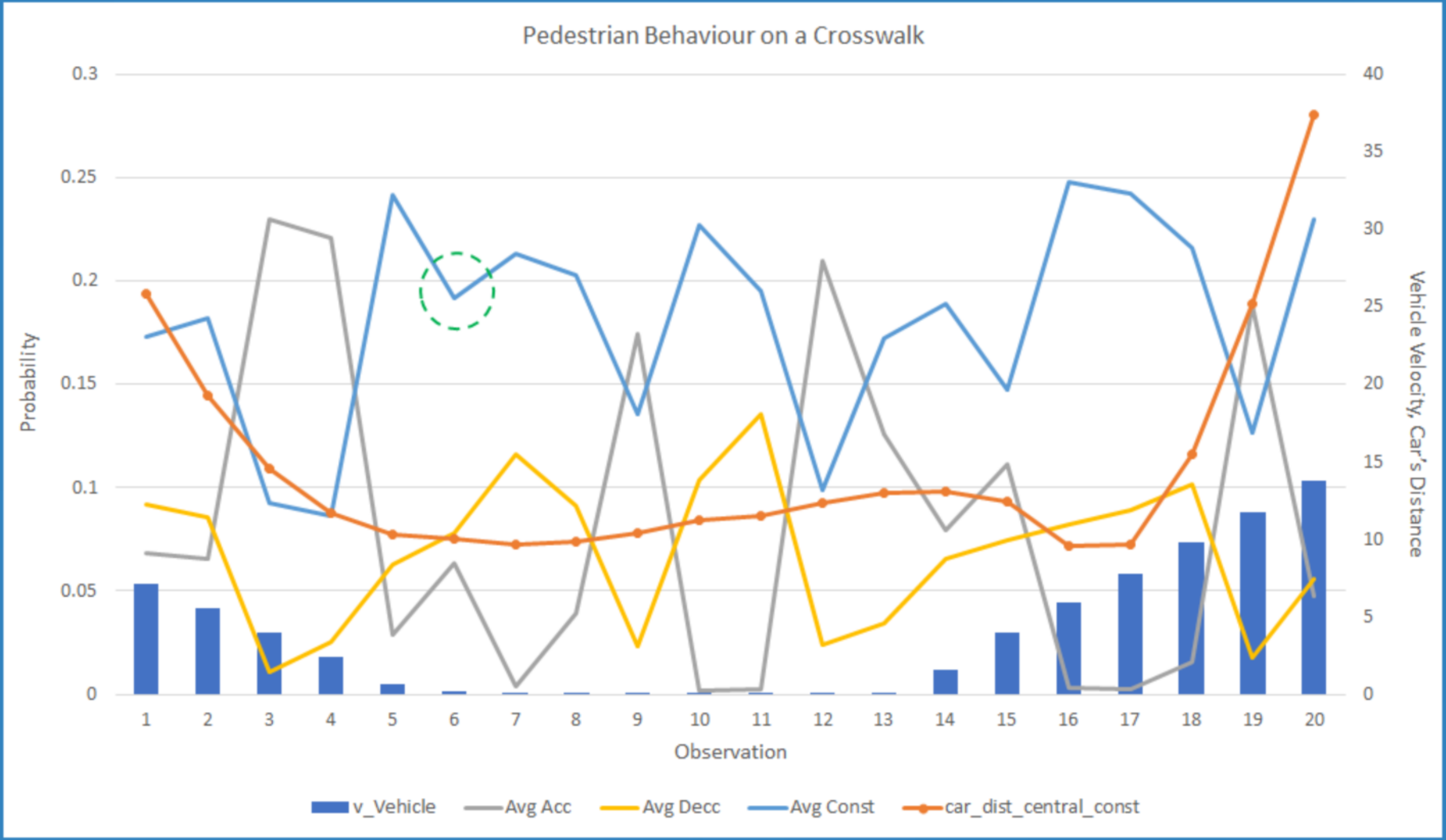
Crossing Behaviour

1. Crosswalk



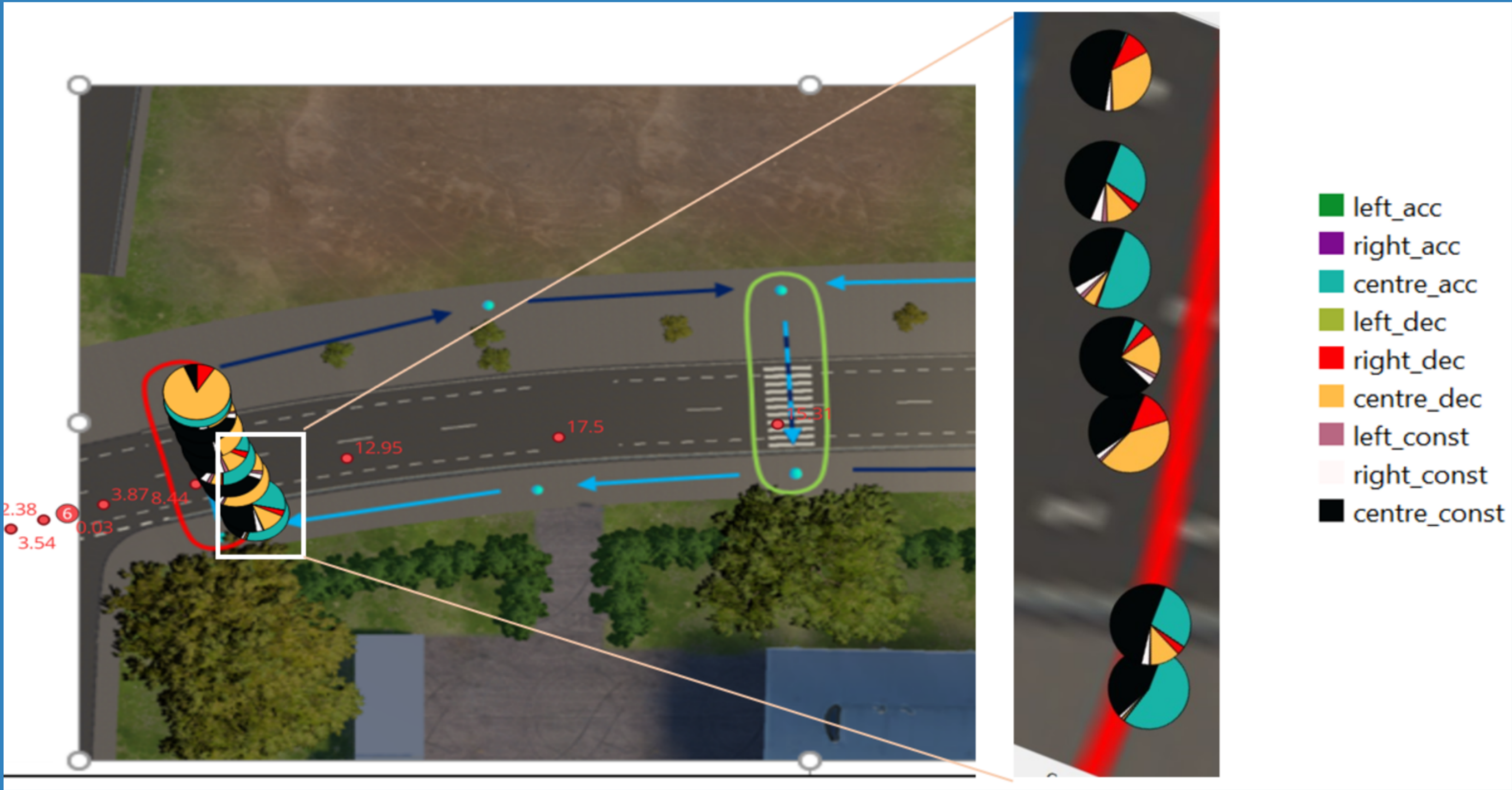
Crossing Behaviour

1. Crosswalk



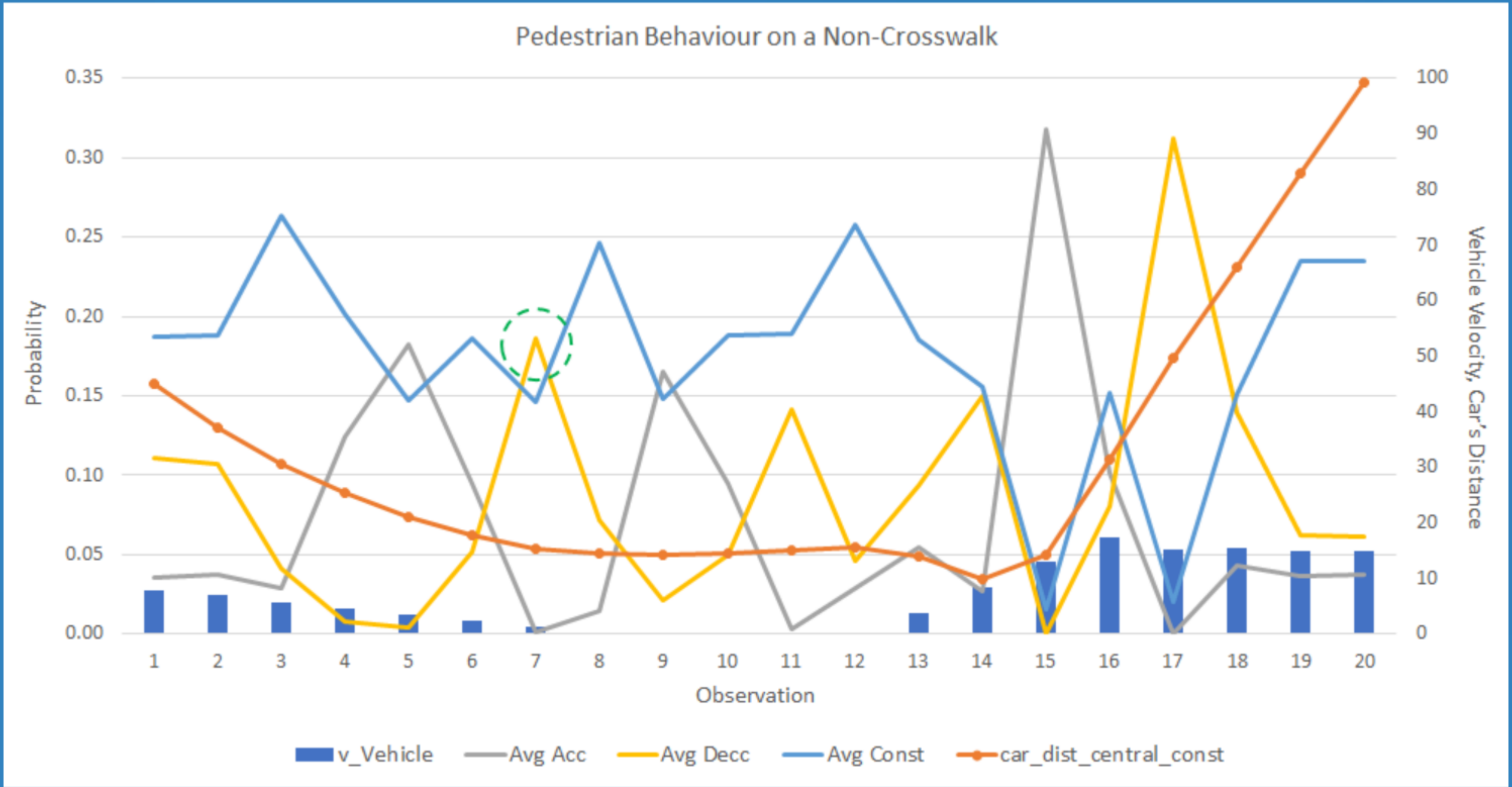
Crossing Behaviour

1. Non - Crosswalk

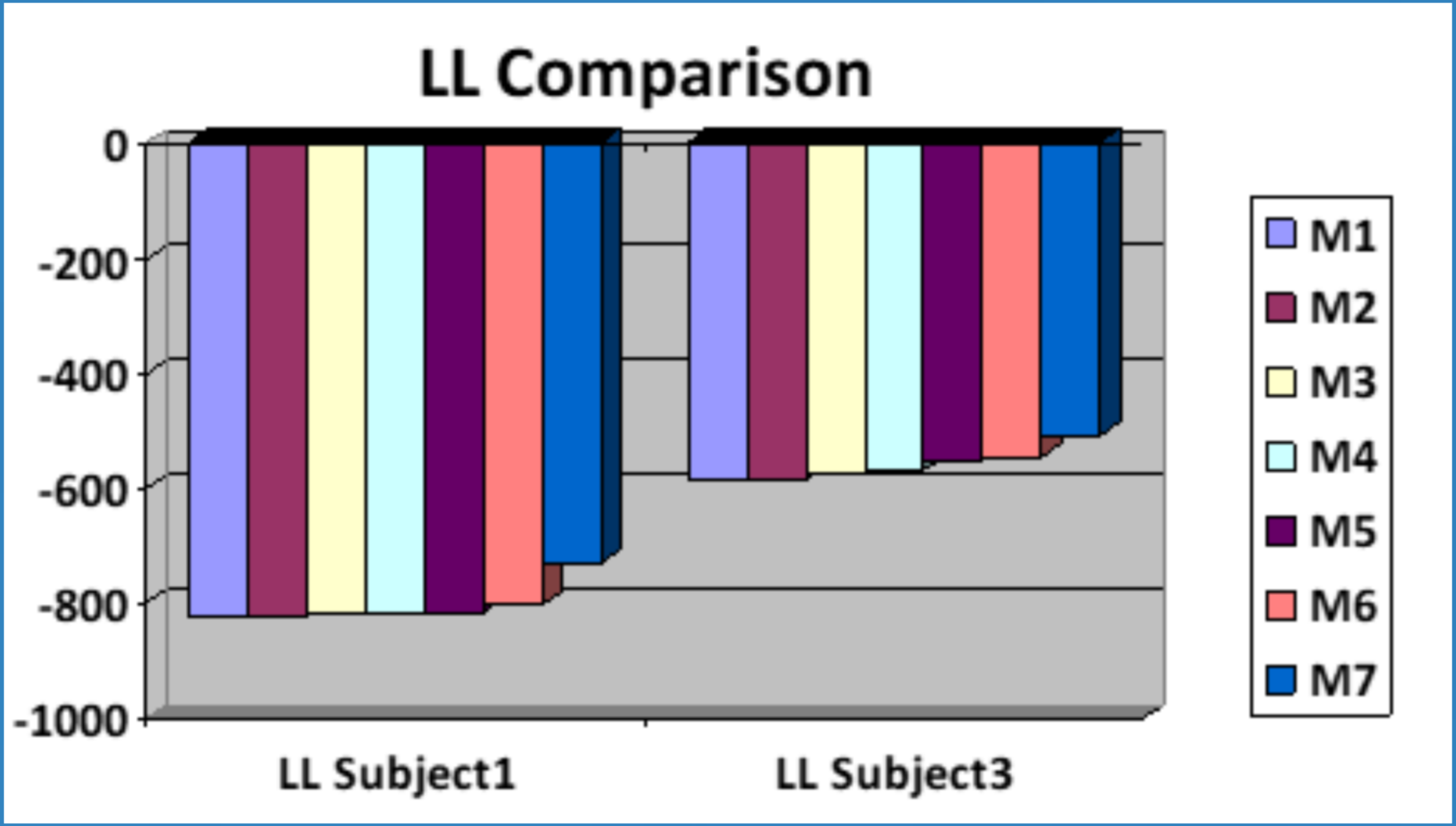


Crossing Behaviour

1. Non - Crosswalk

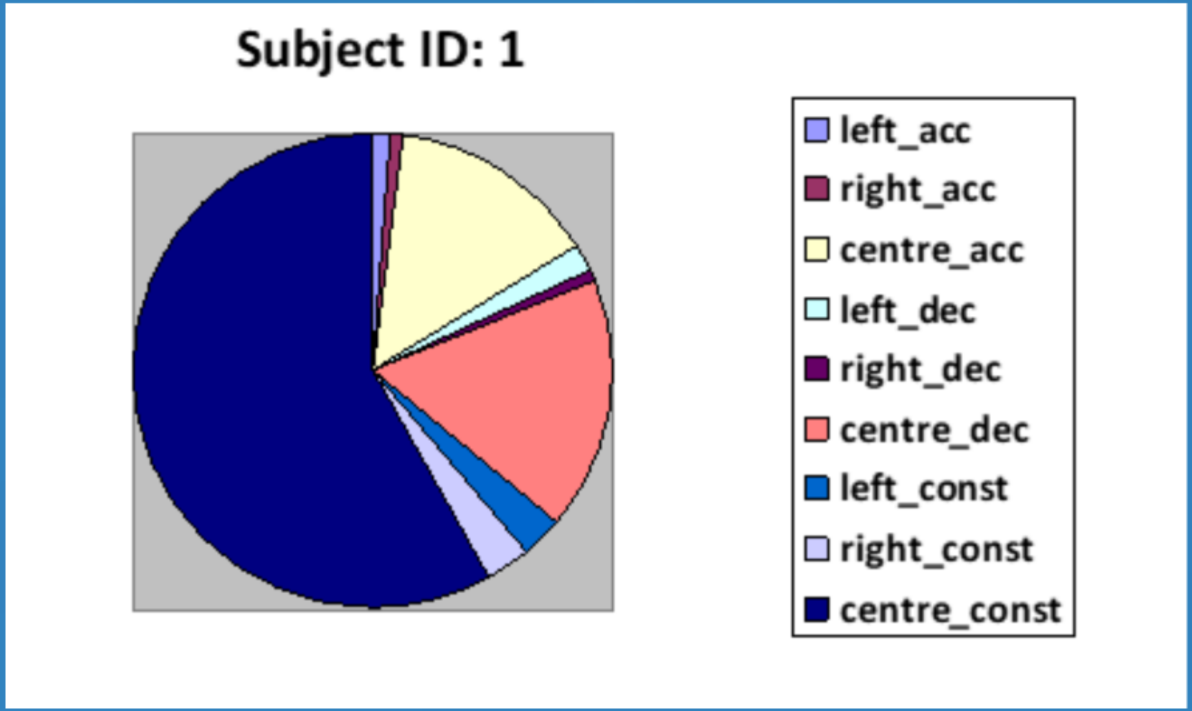


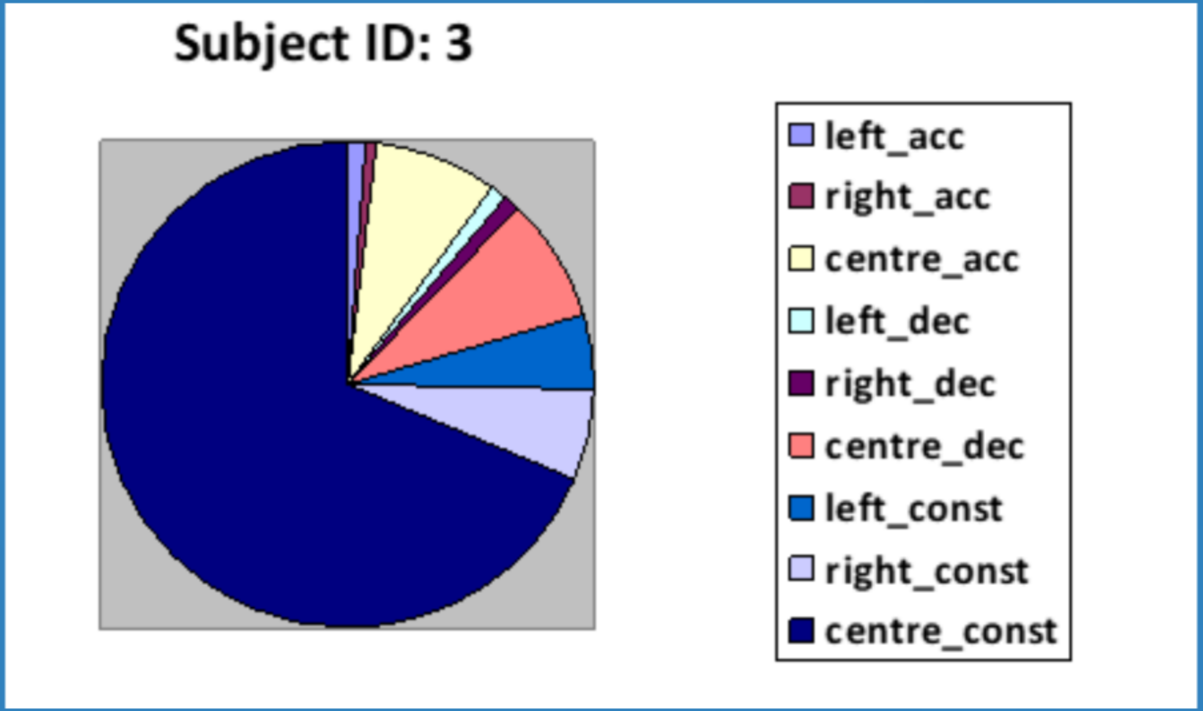
Results & Analysis



Results & Analysis

Prediction results:





Future Scope

1. Data-driven models and Sensor Technologies for ADAS systems

2. Urban planning and design

3. Intelligent transportation systems

4. Pedestrian safety applications: Pedestrian collision warning systems and pedestrian tracking for surveillance purposes.

Overall, this model can be integrated with many advanced systems to improve overall pedestrian safety and make navigation easier for everyone.

References

- Gianluca Antonini, Michel Bierlaire , Mats Weber, Discrete choice models of pedestrian walking behavior(2015), Transportation Research Part B 40 (2006) 667–687.

- Specification, estimation and validation of a pedestrian walking behavior model by Th. Robin, G. Antonini, M. Bierlaire, J.Cruz

ANY QUESTIONS?

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