Identifying Multimodal Conflicts with Machine Learning

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Agenda

1. Why conflict analysis?
2. Data collection and processing
3. Conflict analysis on Bloor Street
4. Training machine learning classifiers
5. Improving classifier performance
6. Conclusion

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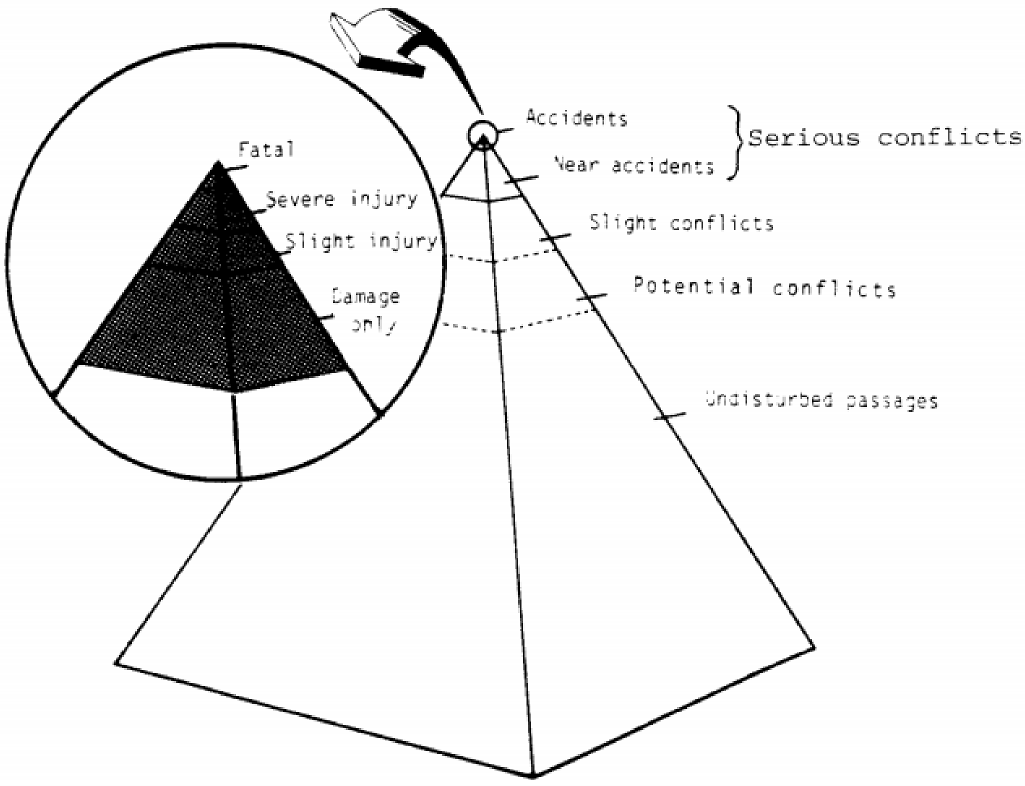
Multimodal safety

- Typically analyzed with collision frequency
- However…
  - Highway Safety Manual's method of collision frequency estimation not designed for complex urban streets
  - Collisions are not always reported
  - Takes a long time to collect data
  - Need to wait for collisions to happen

A potential solution?

- Surrogate safety measures: Relate to events that occur more frequently than collisions
  - Separation distance between modes
  - Time to departure on a roadway
  - Headway
  - Conflicts!

Conflicts



The “figure one” of traffic conflict techniques (Hyden, 1987)

- *“An observable situation in which two or more road users approach each other in time and space for such an extent that there is risk of collision if their movements remain unchanged”*

Potential difficulties with multimodal conflict analysis

- Conflict identification criteria may not be appropriate for unmotorized modes
- Not all criteria are appropriate for complex, non lane-based movements
- Correlation to collisions for non-vehicle users is not established

Why machine learning?

- Conflict analysis is time consuming if done manually.
- Machine learning: training a computer to automatically recognize a pattern

Thesis objectives

- To apply conflict analysis to analyze the safety impacts of the Bloor Street bike lane project
- To investigate the use of machine learning algorithms in conflict identification

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Summary of data collection and processing

Collect video footage

↓

Manually identify conflicts

↓

Measure trajectories

↓

Calculate parameters from trajectories

Video footage collection

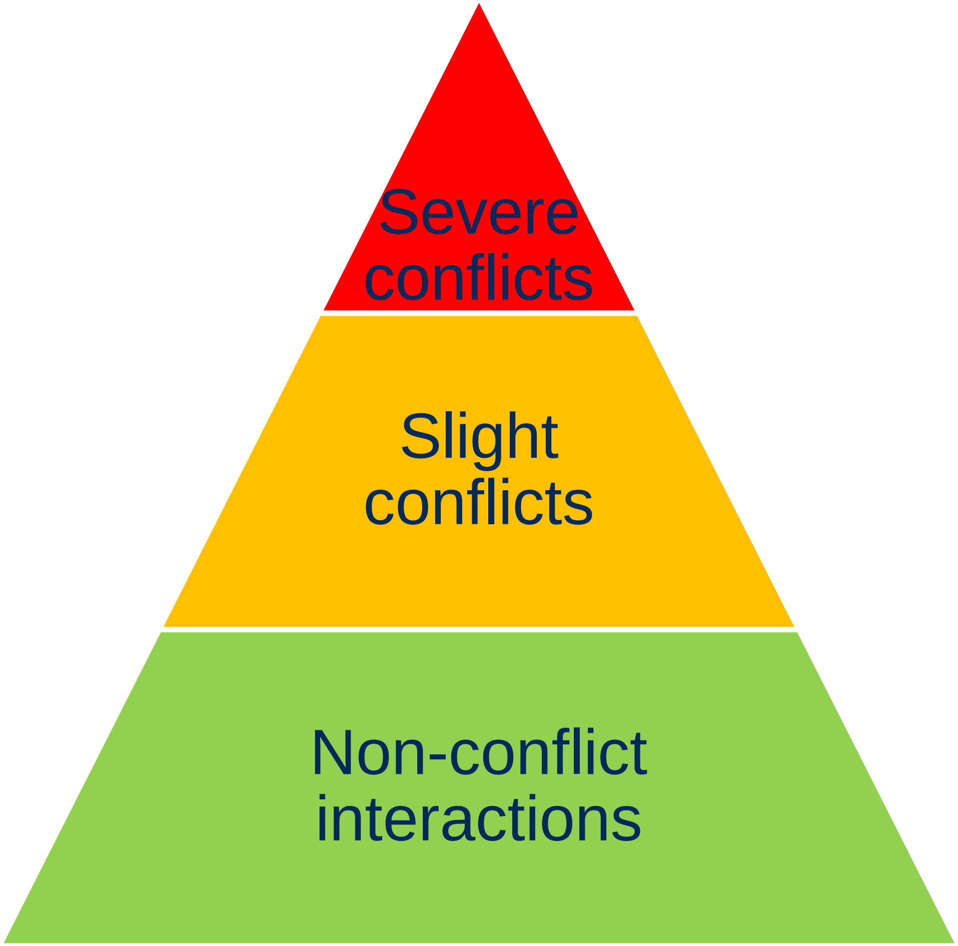
- June 14^{th}-June 16^{th}, 2016
- October 11^{th}-October 13^{th}, 2016
- 7AM-7PM periods only
- Interactions between curbs only
- Focussed on midblocks

- Overall, 284 hours of videos were studied

Monitoring locations

Manual identification of events

- Need to make a dataset of conflicts and non-conflicts
- Manually classified events based on probability of collision and the potential consequences had a collision occurred



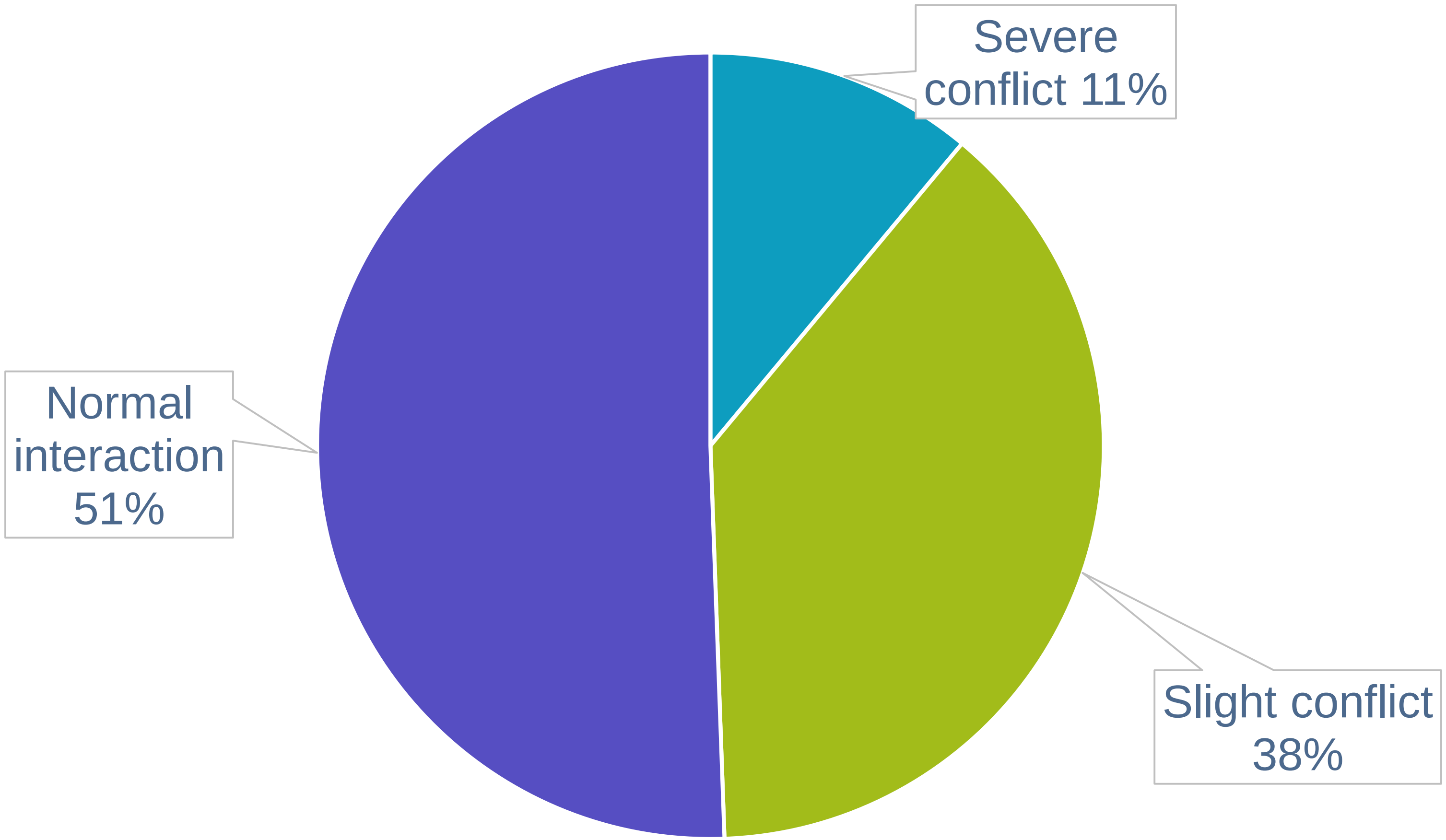
Identifying conflicts

- Severity of braking or swerving manoeuvers (Baguley, 1984).
- Control and rapidity in the braking or lane change behaviour (Older & Spicer, 1976)
- Distance between two users, speeds of the two users, the strength of acceleration and deceleration, the time span available with which to perform an evasive manoeuver (Erke, 1984)
- Available time and distance with which to perform an evasive manoeuver (Muhlrad & Dupre, 1984)
- Awareness of the two road-users to their potential collision (Hyden, 1987)
- Consequences of a potential collision (Kraay, van der Horst, and Oppe, 2013)

Manual identification of events

Event type	Normal interaction	Slight conflict	Severe conflict
Description	A user observes typical user behaviour well in advance and is able to react smoothly and comfortably. **Low collision probability.**	An unexpected action occurs, but users still have adequate time and space to react and manoeuvre, such that the manoeuvre is unlikely to fail and result in a collision. **Higher collision probability.**	There is also an increased chance for evasive manoeuvre to fail, and an elevated potential for road user to be seriously injured if evasive manoeuvre fails. **High collision probability and high chance of injury.**
Example	A jaywalker times their crossing to right after a car passes	A car slows down to avoid hitting a jaywalker in the roadway	A pedestrian runs across the path of a moving car, which does not slow down, and with little temporal clearance between users.

878 events identified



Measuring user trajectories

- Measure user trajectories on the screen during the most critical point of the conflict and two additional timesteps

  $\Delta t = 0.33s$

Matrix transformation

$$X = \frac{ax + by + c}{gx + hy + 1}$$

$$Y = \frac{dx + ey + f}{gx + hy + 1}$$

Where:

$$\begin{bmatrix} x_1 & y_1 & 1 & 0 & 0 & 0 & -x_1X_1 & -y_1X_1 \\ x_2 & y_2 & 1 & 0 & 0 & 0 & -x_2X_2 & -y_2X_2 \\ x_3 & y_3 & 1 & 0 & 0 & 0 & -x_3X_3 & -y_3X_3 \\ x_4 & y_4 & 1 & 0 & 0 & 0 & -x_4X_4 & -y_4X_4 \\ 0 & 0 & 0 & x_1 & y_1 & 1 & -x_1Y_1 & -y_1Y_1 \\ 0 & 0 & 0 & x_2 & y_2 & 1 & -x_2Y_2 & -y_2Y_2 \\ 0 & 0 & 0 & x_3 & y_3 & 1 & -x_3Y_3 & -y_3Y_3 \\ 0 & 0 & 0 & x_4 & y_4 & 1 & -x_4Y_4 & -y_4Y_4 \end{bmatrix} \cdot \begin{bmatrix} a \\ b \\ c \\ d \\ e \\ f \\ g \\ h \end{bmatrix} = \begin{bmatrix} X_1 \\ X_2 \\ X_3 \\ X_4 \\ Y_1 \\ Y_2 \\ Y_3 \\ Y_4 \end{bmatrix}$$

- Transformed from screen pixel coordinates to real-life frame of reference
- Resultant coordinates can be used to calculate relevant indicators

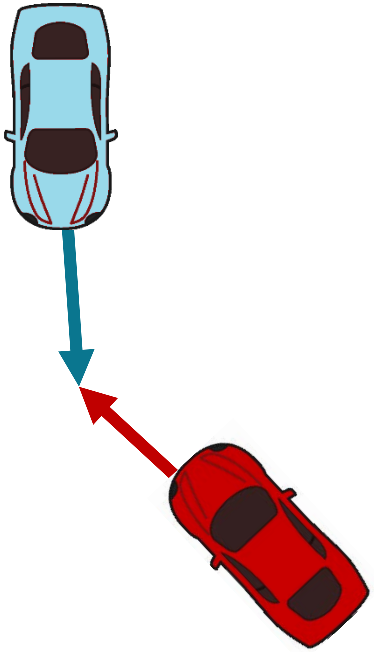
Parameters of interest

- Status quo: thresholds for time-to-collision and post-encroachment time
  - Do not take into account user mode, which can affect a user's maneuverability and their vulnerability in event of a collision

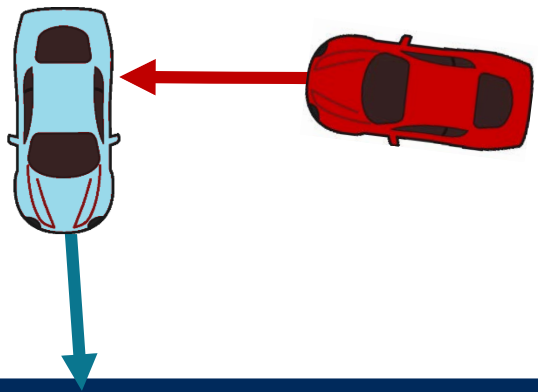
- Machine learning can take into account many potentially influential variables

Conflict characterization

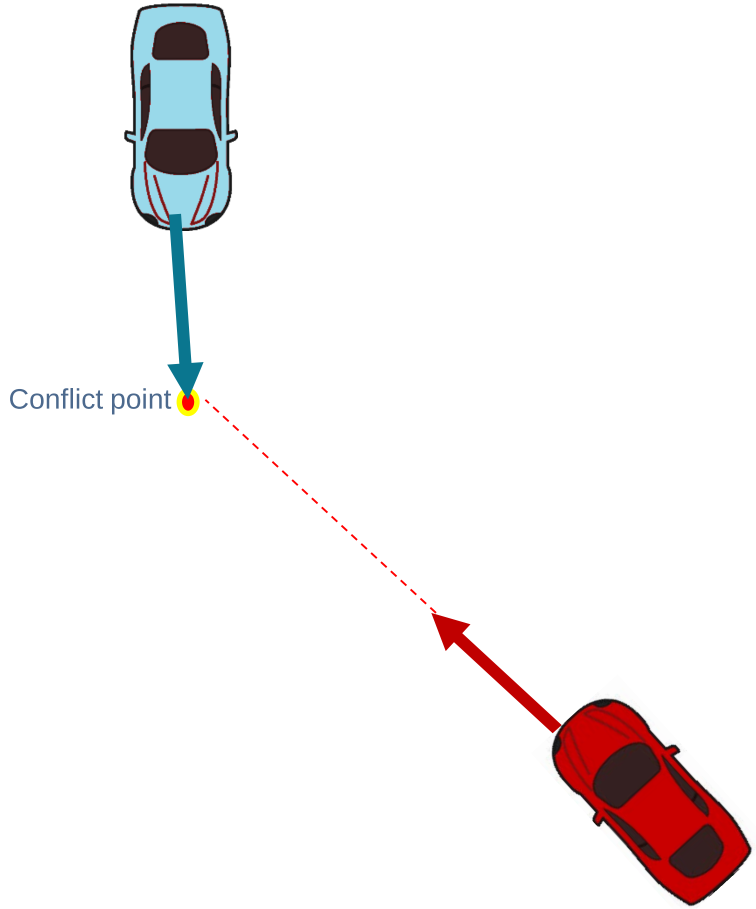
- TTC



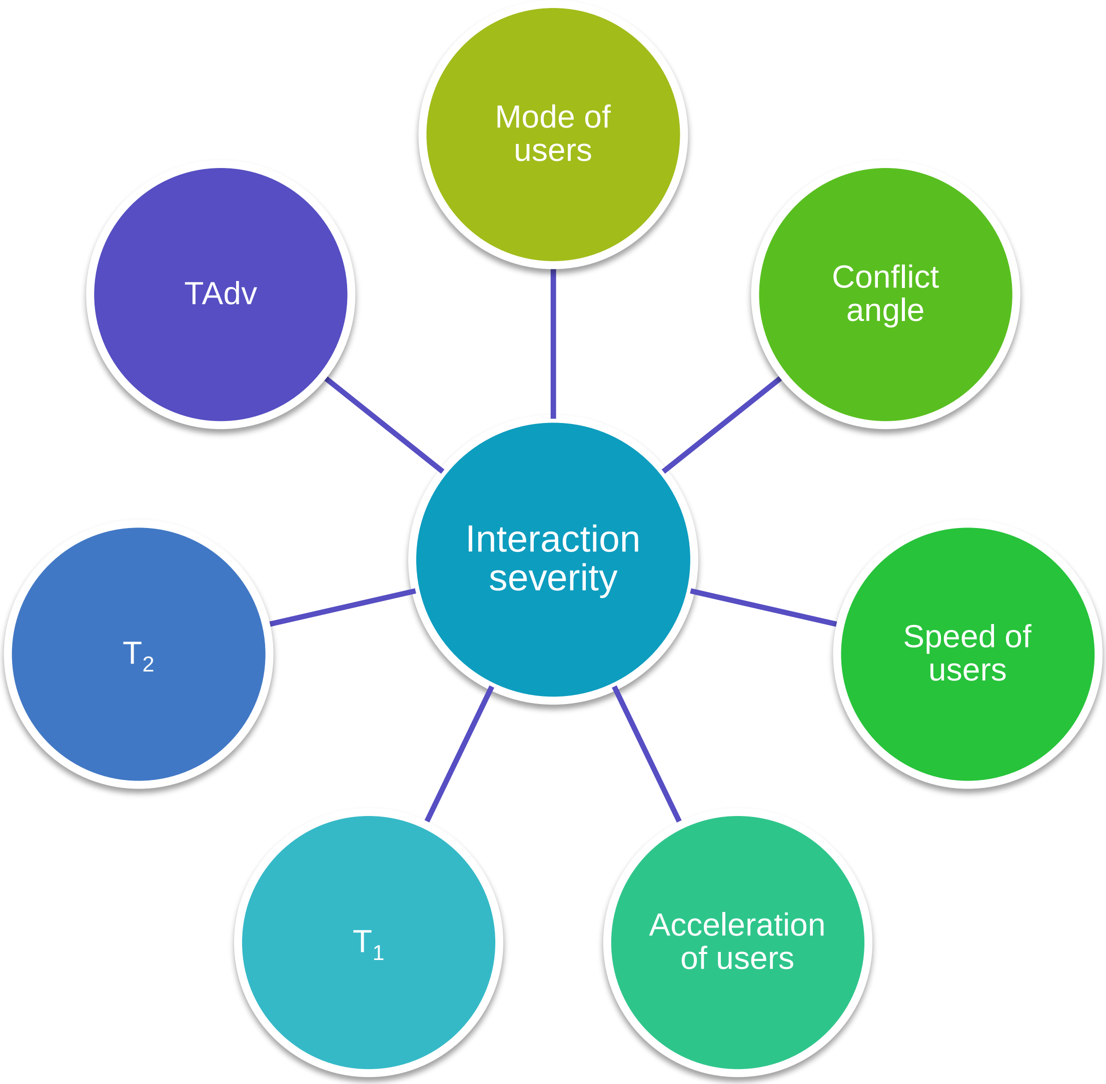
- PET



- T_1, T_2, and TAdv



Composition of event dataset



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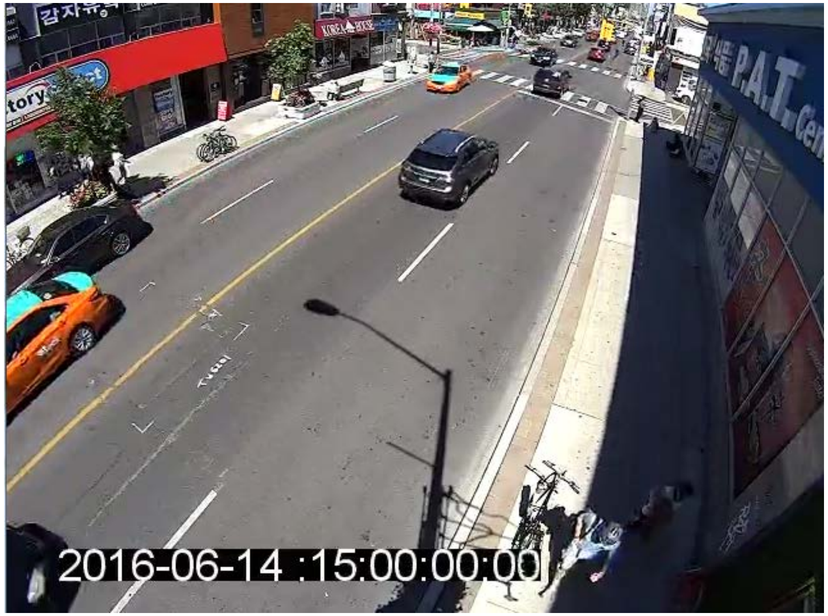
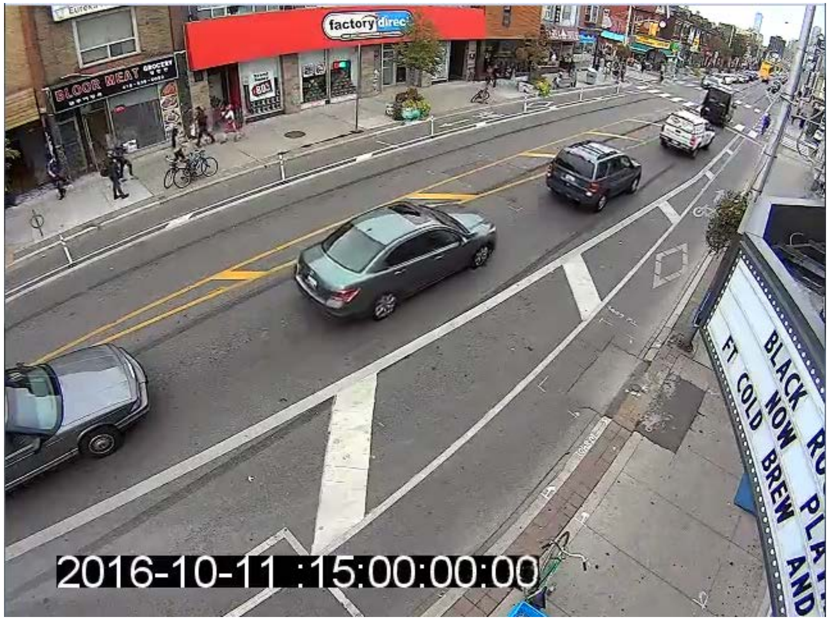
Bloor Street between Clinton Street and Manning Avenue

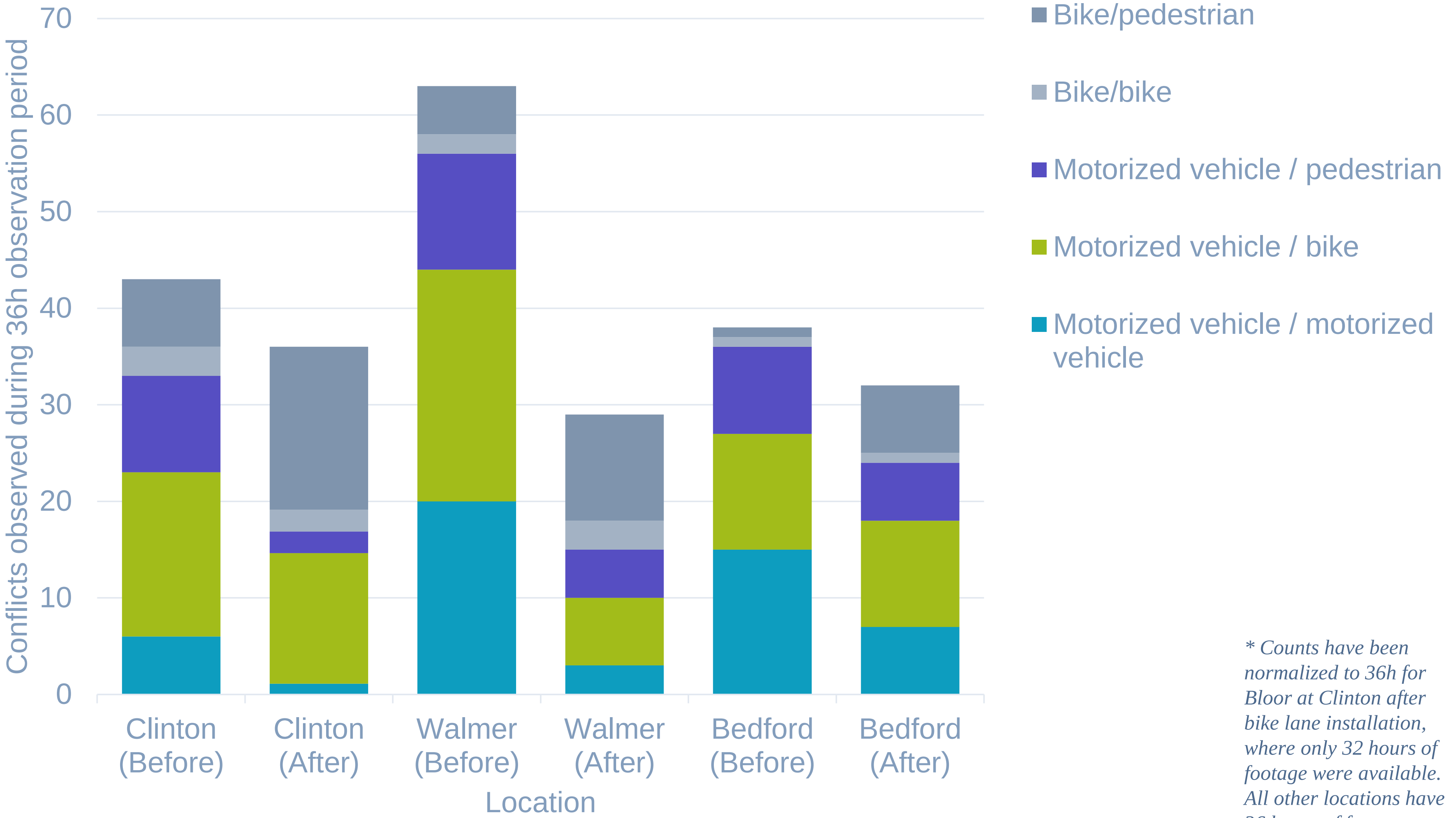




Bloor Street between Walmer and Sussex Mews

Bloor Street between Bedford Road and Devonshire Place

Conflicts before and after

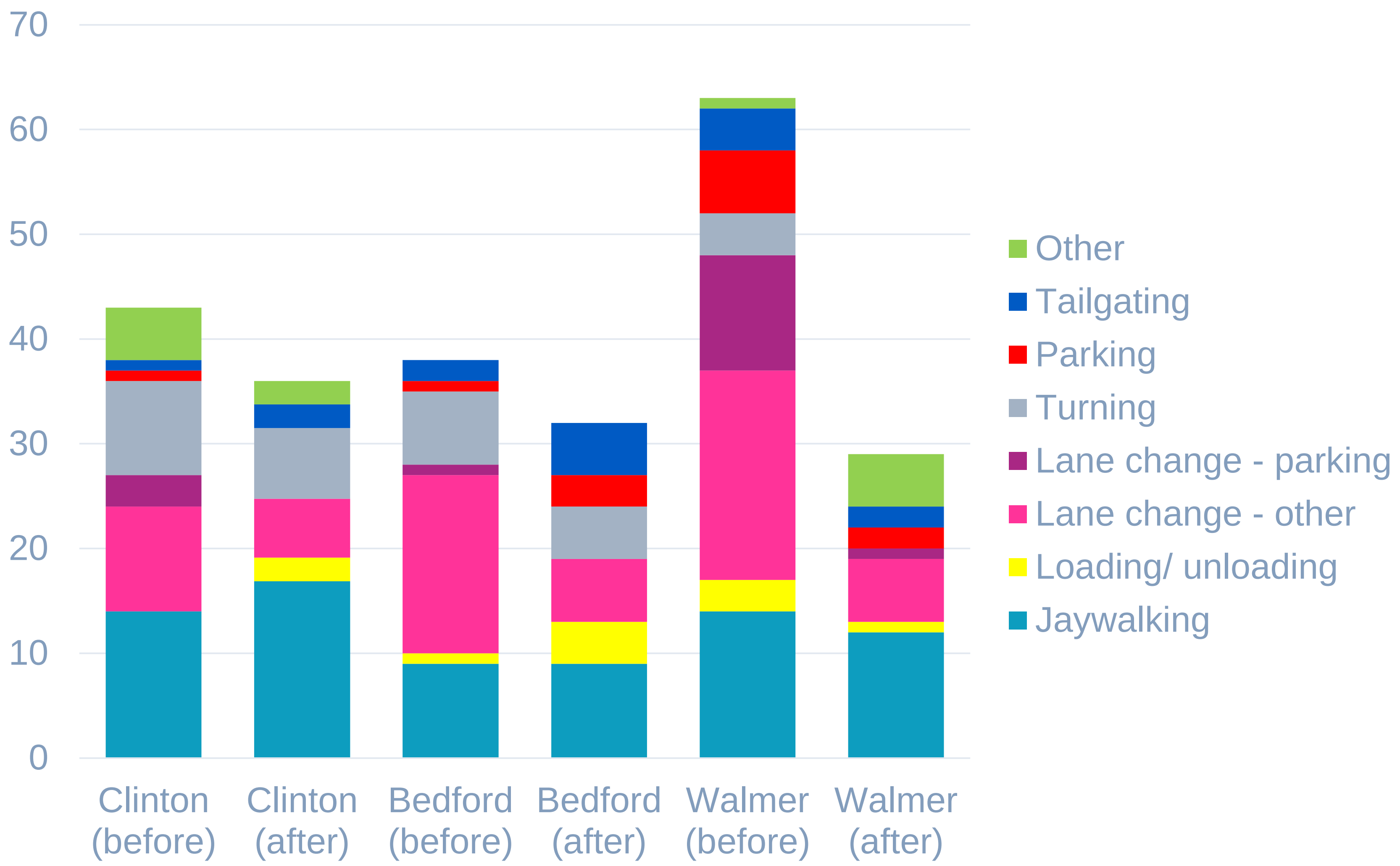


** Counts have been normalized to 36h for Bloor at Clinton after bike lane installation, where only 32 hours of footage were available. All other locations have 36 hours of footage.*

User behaviours during conflicts

- Conflicts involving pedestrians:
  - Jaywalking
  - Loading/unloading behaviour
  - Other: walking in bike lane, mounting bicycle in bike lane…
- Conflicts not involving pedestrians:
  - Lane changes as a result of parked vehicle
  - Lane changes – other
  - Parking and loading
  - Tailgating
  - Turning across the path of another user (e.g. out of driveway, U-turn)
  - Other: Wrong-way movement, unexplained swerving

Behaviours during conflicts



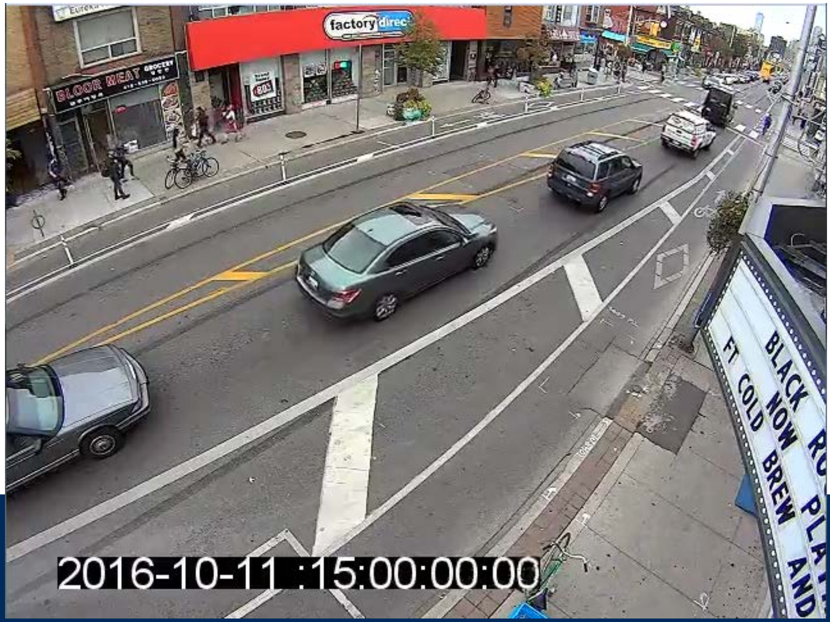
Significance

- Use Hauer’s 1996 techniques to determine significance
- Conflicts as a poisson process

- Used 90% significance level

Bloor Street between Clinton Street and Manning Avenue

- **84%** decrease in vehicle-vehicle conflicts
  - Conflicts between motorized vehicles during lane changes: **-49%**
- **80%** decrease in pedestrian/vehicle conflicts
  - Jaywalking-related conflicts between pedestrians and motorized vehicles: **-78%**
- **111%** increase in pedestrian/bike conflicts
  - Jaywalking-related conflicts with bikes **+144%**
- The number of motorized vehicle/bike conflicts during lane changes decreased significantly **(-49%).**



Bloor Street between Walmer and Sussex Mews

- **86%** decrease in vehicle/vehicle conflicts
  - Conflicts between motorized vehicles during lane changes **(-100%),** parking **(-67%),** and tailgating **(-60%).**
- **72%** decrease in vehicle/bike conflicts
  - Conflicts between motorized vehicles and bikes during lane changes **(-72%),** turning **(-100%),** and parking **(-80%).**
- **62%** decrease in vehicle/pedestrian conflicts
  - Jaywalking-related conflicts between motorized vehicles and pedestrians **(-67%)**
- No significant change in frequency in bike/bike conflicts or bike/pedestrian conflicts

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Bloor Street between Bedford Road and Devonshire Place

- **-56%** Motorized vehicle/motorized vehicle conflicts
  - Conflicts between motorized vehicles during lane changes**: -80%**
- **+250%** Bicycle/pedestrian conflicts
- Significant decrease **(-70%)** in vehicle/bike conflicts caused by lane changes.
- The total number of and behaviour during vehicle/pedestrian conflicts and bike/bike conflicts did not change significantly.

The takeaway

- Total number of conflicts decreased slightly
  - Driven by decreases in vehicle-related conflicts and lane-changing behaviours
  - Motorized/motorized conflicts decreased at all locations
  - Saw significant increases in bike/pedestrian conflicts in two locations (Clinton, Bedford) even though motorized/ped conflicts decreased in all locations

However…

- Conflicts only reflect 125m of the 2.3km bike lane installation
  - Study area included only three legal parking spaces (all at Bloor and Walmer) but parking on bike lanes and bike lane buffer is very common

- Also recommend additional study of jaywalking behaviour and volumes.

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Classifiers trained

Ordinal logit model
- Good explanatory power
- Monotonic variable relationships only
- Parametric

Decision tree
- Nonparametric
- Good explanatory power
- Good for non-linear relationships between variables

K-nearest neighbours
- “Black box”
- Nonparametric
- Good for non-linear relationships between variables

Classifiers

- 3 classifiers trained on full set of explanatory variables
- 3 classifiers trained on T_1, T_2, and TAdv only
- 1 ruleset representing conventional conflict classification methods

- Trained classifiers on 80% of dataset
- Tested classifiers on 20% of dataset

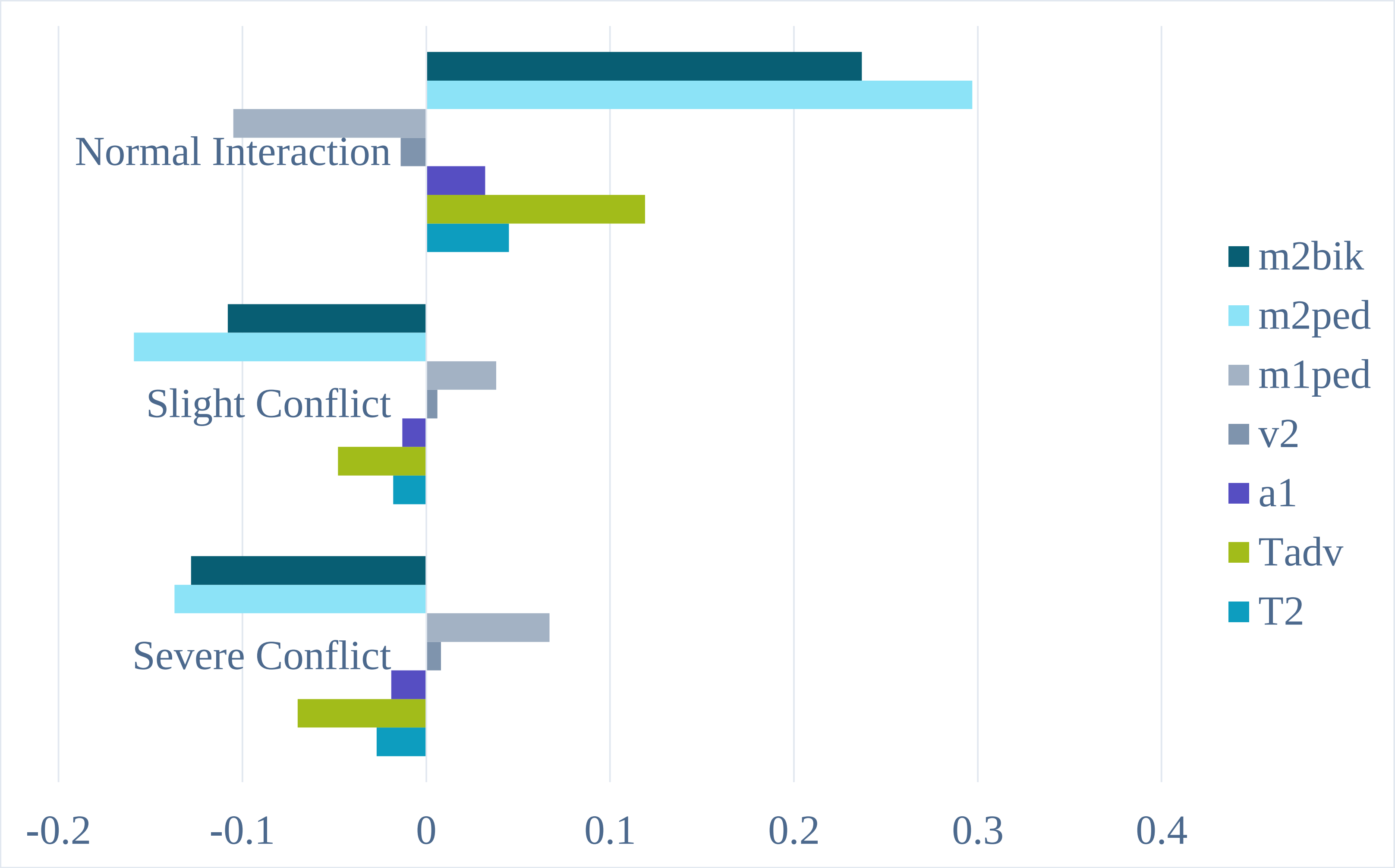
Ordered logit model POLR-0

Logit Model Fit		
Log likelihood of full model	-1072.3	
Log likelihood of constant-only model	-1173.3	
Number of observations	1068	
Rho-squared value	0.086	
Variables	Coefficient	T-stat
Time-to-conflict point of trailing user (T_2)	0.187	4.567
Time advantage (TAdv)	0.444	7.193
Intercepts	Coefficient	T-stat
Severe Conflict / Slight Conflict	0.309	2.752
Slight Conflict / Normal Interaction	1.915	14.792

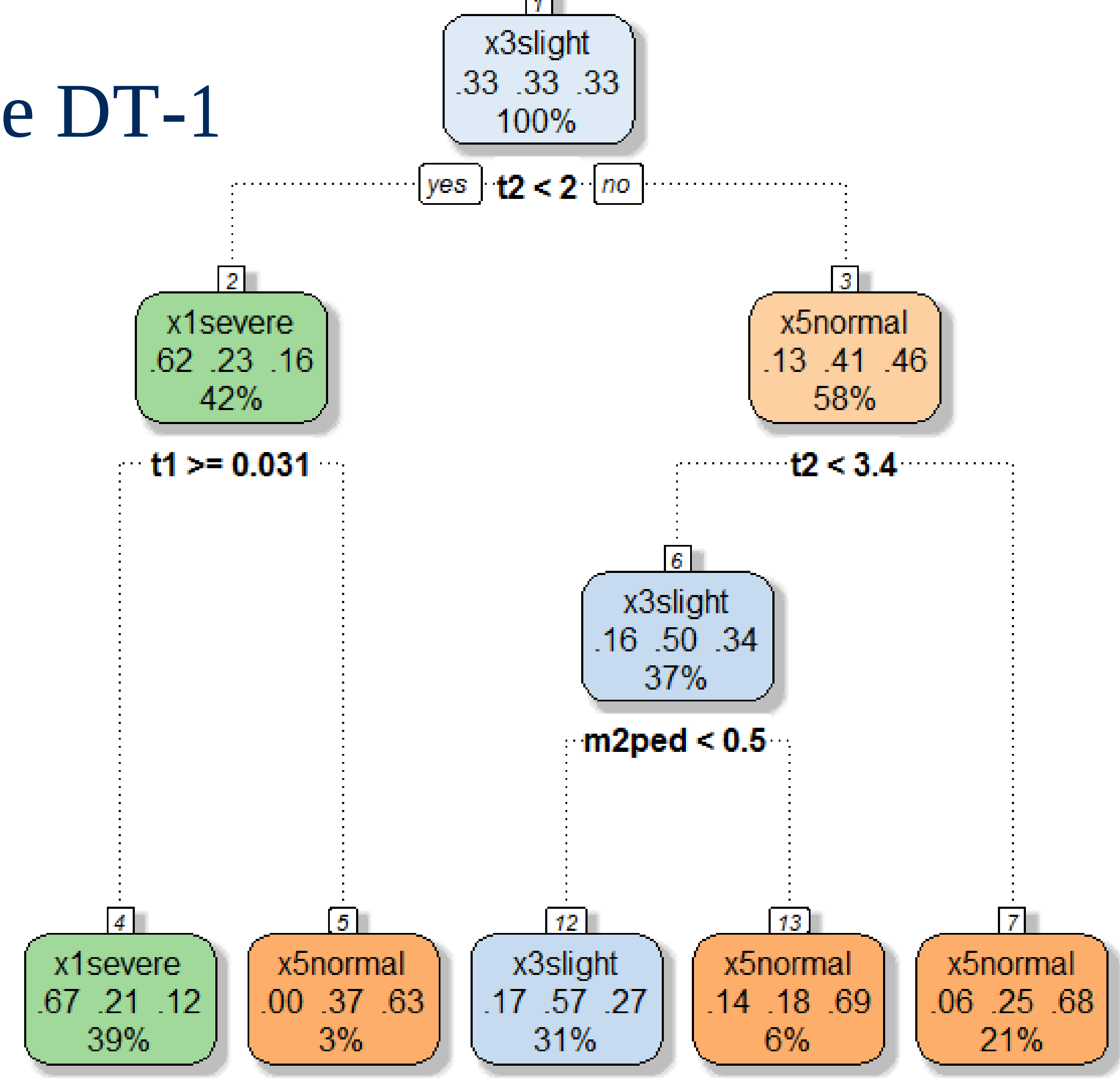
Ordered logit model POLR-1

Logit Model Fit		
Log likelihood of full model	-1013.7	
Log likelihood of constant-only model	-1173.3	
Number of observations	1068	
Rho-squared value	0.136	
Variables	Coefficient	T-stat
Time-to-conflict point of trailing user (T_2)	0.182	4.230
Time advantage (TAdv)	0.480	7.336
Acceleration of leading user (a1)	0.130	3.635
Speed of trailing user (v2)	-0.055	-2.380
Mode of leading user – pedestrian (m1ped)	-0.433	-3.167
Mode of trailing user – pedestrian (m2ped)	1.234	5.824
Mode of trailing user – bicycle (m2bik)	0.966	7.046
Intercepts	Coefficient	T-stat
Severe Conflict / Slight Conflict	0.262	1.297
Slight Conflict / Normal Interaction	2.022	9.395

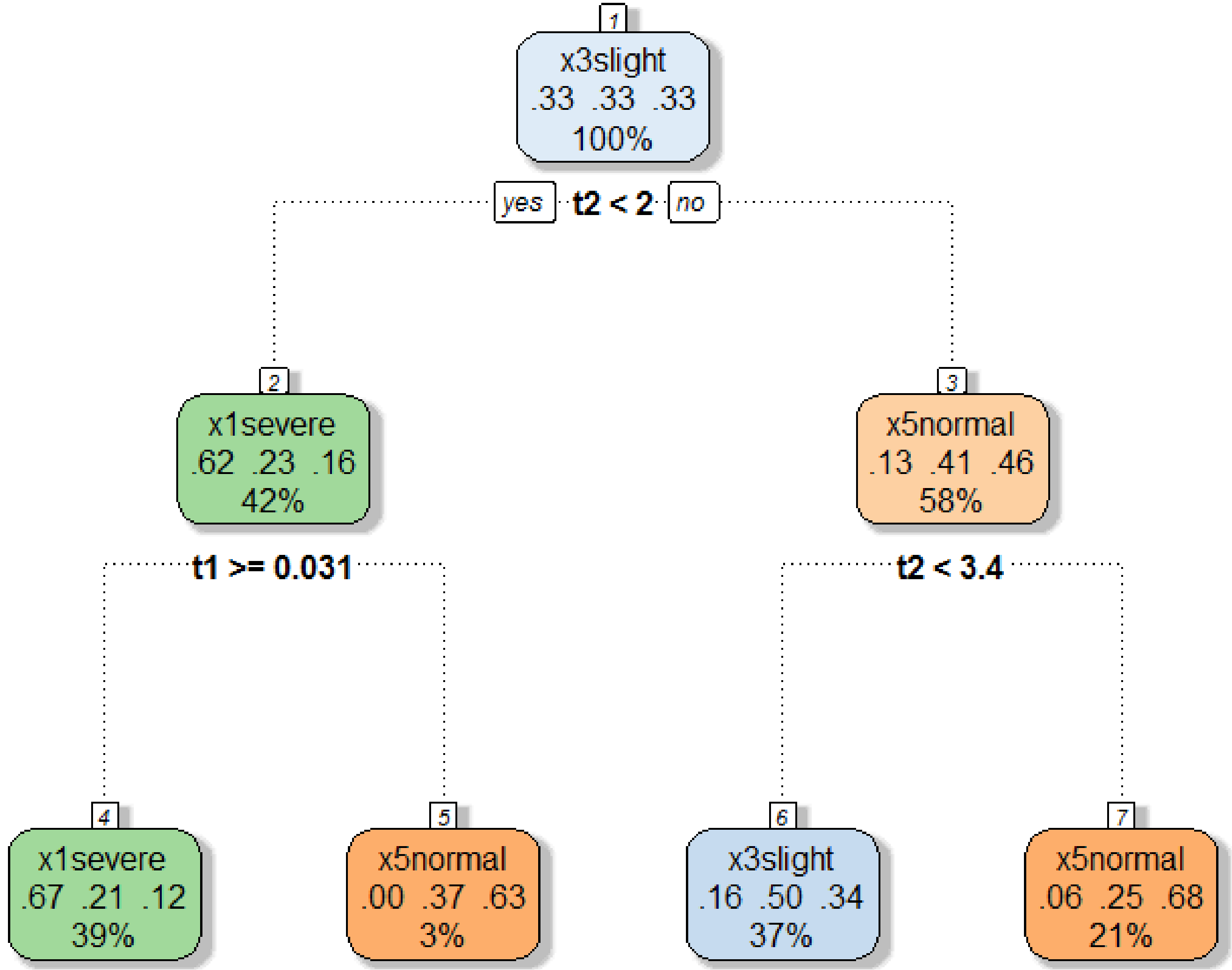
Marginal effect of variables in POLR-1



Decision tree DT-1



Decision tree DT-0



K-nearest neighbours KNN-0

- K=13
  - T1
  - Time advantage

K-nearest neighbours

- K=14
  - Time-to-conflict point of leading vehicle
  - Time advantage
  - Leading user is a vehicle
  - Leading user is a pedestrian
  - Trailing user is a vehicle

Conventional conflict classification

Interaction type	Original criteria	Modified criteria
Severe conflict	TTC < 1.5s OR PET <1s	0s< T_2 <1.5s and TAdv < 0.5s OR PET <1s
Slight conflict	1.5s < TTC <3s OR 1s < PET < 3s	1.5s < T_2 <3s and TAdv < 0.5s OR 1s < PET < 3s
Normal interaction	All other interactions.	All other interactions.

Classifier predictions

Ordinal Logit Model (POLR-1)

		Reference		
		Severe	Slight	Non-conflict
Predicted	Severe	12	18	14
	Slight	6	28	28
	Non-conflict	1	21	46

Decision Tree (DT-1)

		Reference		
		Severe	Slight	Non-conflict
Predicted	Severe	15	18	13
	Slight	4	31	28
	Non-conflict	0	18	47

K-Nearest Neighbours (KNN-1)

		Reference		
		Severe	Slight	Non-conflict
Predicted	Severe	13	18	11
	Slight	4	32	31
	Non-conflict	2	17	46

Ordinal Logit Model (POLR-0)

		Reference		
		Severe	Slight	Non-conflict
Predicted	Severe	15	27	17
	Slight	4	24	30
	Non-conflict	0	16	41

Decision Tree (DT-0)

		Reference		
		Severe	Slight	Non-conflict
Predicted	Severe	15	18	13
	Slight	4	33	36
	Non-conflict	0	16	39

K-Nearest Neighbours (KNN-0)

		Reference		
		Severe	Slight	Non-conflict
Predicted	Severe	12	18	11
	Slight	7	29	32
	Non-conflict	0	20	45

Conventional conflict classification thresholds (CR-1)

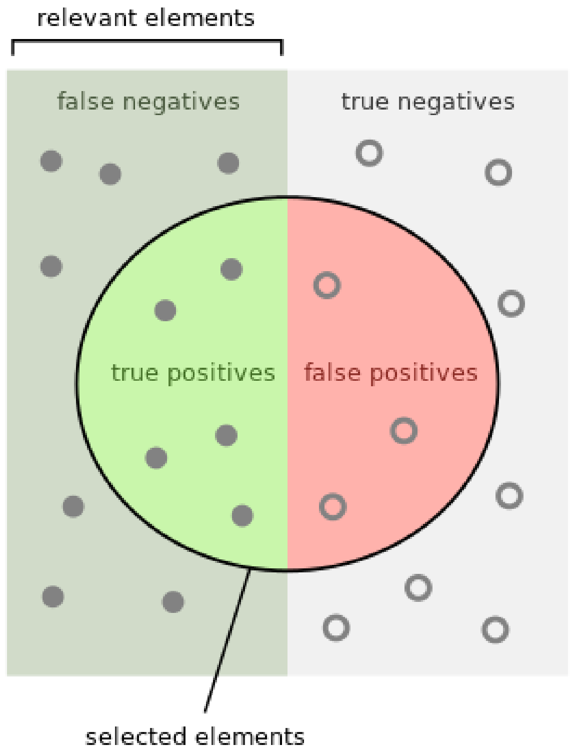
		Reference		
		Severe	Slight	Non-conflict
Predicted	Severe	15	26	27
	Slight	4	31	33
	Non-conflict	0	10	28

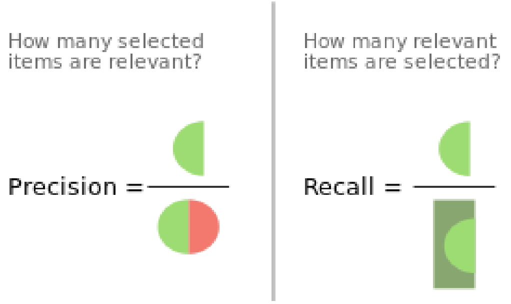
Precision, recall, and F1 scores

$$Precision = \frac{True\ Positives}{True\ positives + False\ positivies}$$

$$Recall = \frac{True\ Positives}{True\ positives + False\ negatives}$$

$$F1 = \frac{2}{\frac{1}{True\ positives} + \frac{1}{False\ negatives}}$$





Precision, recall, and F1

Ordinal Logit Model (POLR-1)			
	Severe	Slight	Non-Conflict
Precision	0.273	0.452	0.676
Recall	0.632	0.418	0.523
F1 Score	0.381	0.434	0.590

Ordinal Logit Model (POLR-0)			
	Severe	Slight	Non-Conflict
Precision	0.254	0.414	0.719
Recall	0.789	0.358	0.466
F1 Score	0.385	0.384	0.566

Conventional conflict classification thresholds (CR-1)			
	Severe	Slight	Non-Conflict
Precision	0.221	0.456	0.737
Recall	0.789	0.463	0.318
F1 Score	0.345	0.459	0.444

Decision Tree (DT-1)			
	Severe	Slight	Non-Conflict
Precision	0.326	0.492	0.723
Recall	0.789	0.463	0.534
F1 Score	0.462	0.477	0.614

Decision Tree (DT-0)			
	Severe	Slight	Non-Conflict
Precision	0.326	0.452	0.709
Recall	0.789	0.493	0.443
F1 Score	0.462	0.471	0.545

K-Nearest Neighbours (KNN-1)			
	Severe	Slight	Non-Conflict
Precision	0.310	0.478	0.708
Recall	0.684	0.478	0.523
F1 Score	0.426	0.478	0.601

K-Nearest Neighbours (KNN-0)			
	Severe	Slight	Non-Conflict
Precision	0.293	0.426	0.692
Recall	0.632	0.433	0.511
F1 Score	0.400	0.430	0.588

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Changing classifier structure

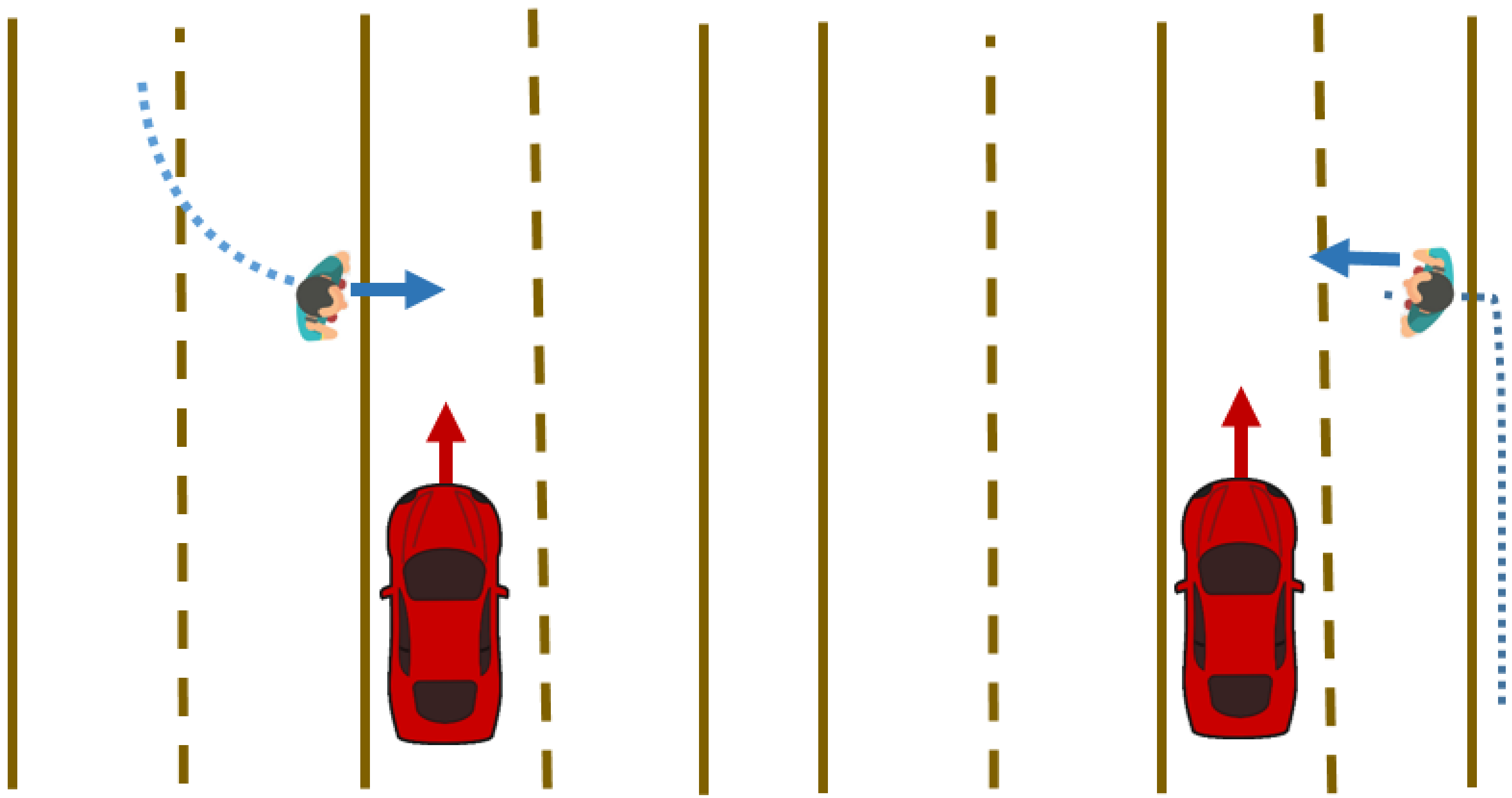
- Boosted trees

- Two-stage classifiers

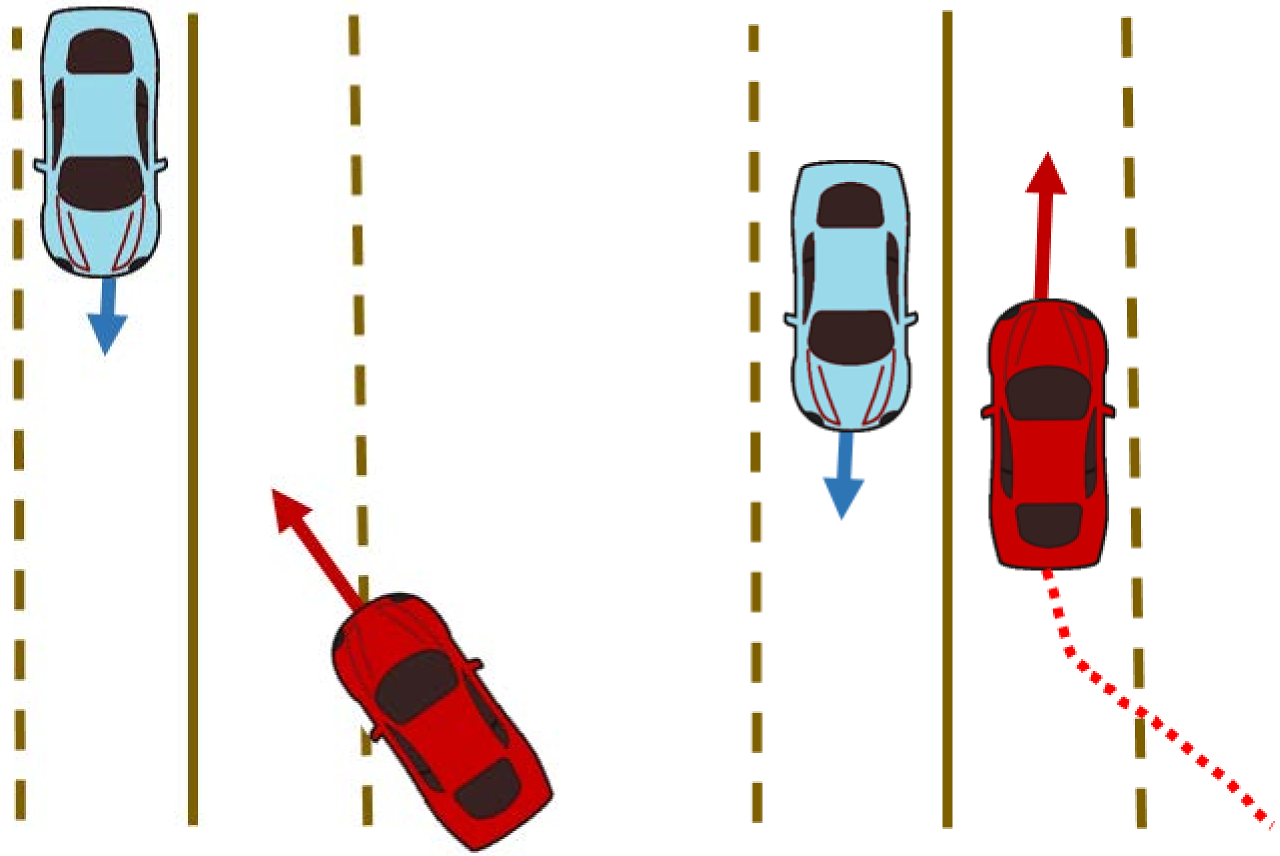
Dataset improvements

- Bigger dataset
- More observers -> better consistency in training set
- More explanatory variables…

Awareness and predictability



Intent



Solution: Automated video analysis

- Automated video analysis is a natural complement to machine learning
- Can use it to easily increase size of training dataset
- Can use it to develop more explanatory variables

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Contributions

- Affirmed usefulness of conflict analysis through Bloor Street bike lane case study
- Machine learning classifiers: useful for identifying conflicts in multimodal streets
- Considering user mode, speed, and acceleration can improve performance of machine learning methods over that of conventional conflict identification methods

Future Research

- Improve classifier performance through increasing size of training dataset and improved trajectory analysis

- Combine with automated trajectory analysis from video to identify conflicts on a large scale

- Explore correlation between non-motorized conflicts and collisions

The End

Thank you for listening!

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