12th Workshop on Planning, Perception, Navigation for Intelligent Vehicle @ IROS2020

Impact of Traffic Lights on Trajectory Forecasting of Human-driven Vehicles Near Signalized Intersections

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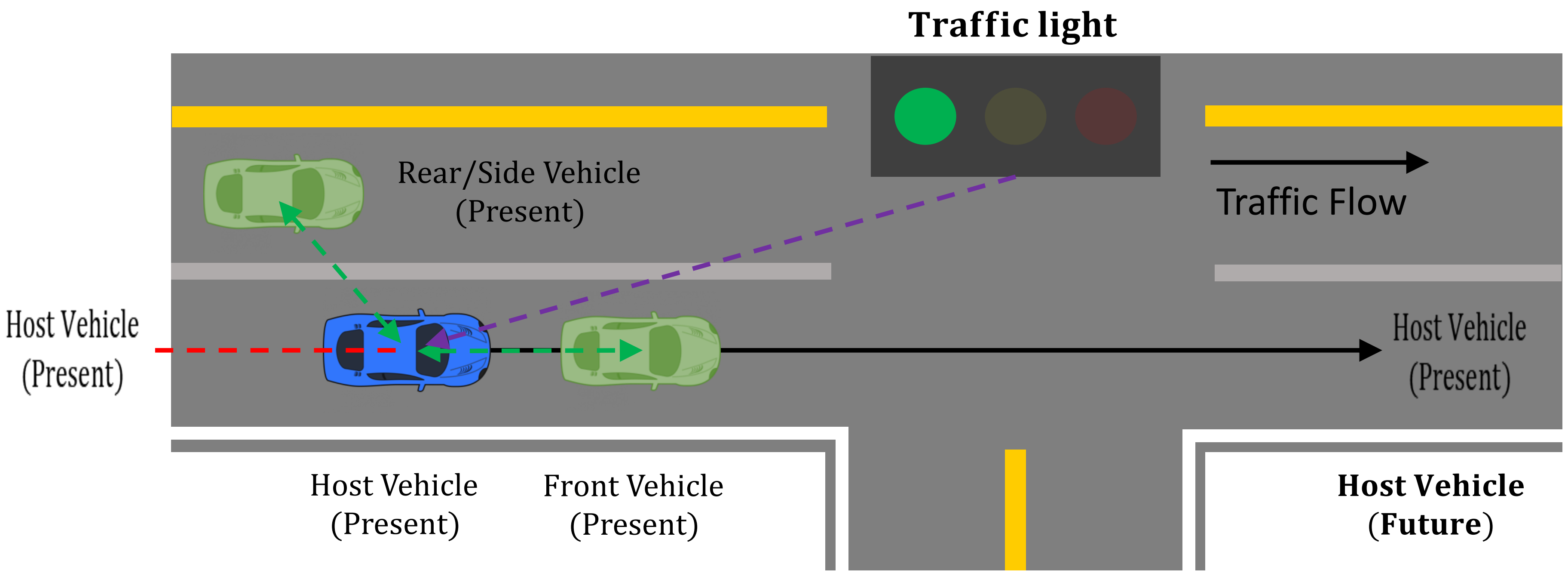
Video Reference: Waymo

We tackle this challenging vehicle forecasting problem near traffic lights (TLs)

Goal: Trajectory forecasts for the host vehicle, $X_{0:T}^{HV}$.



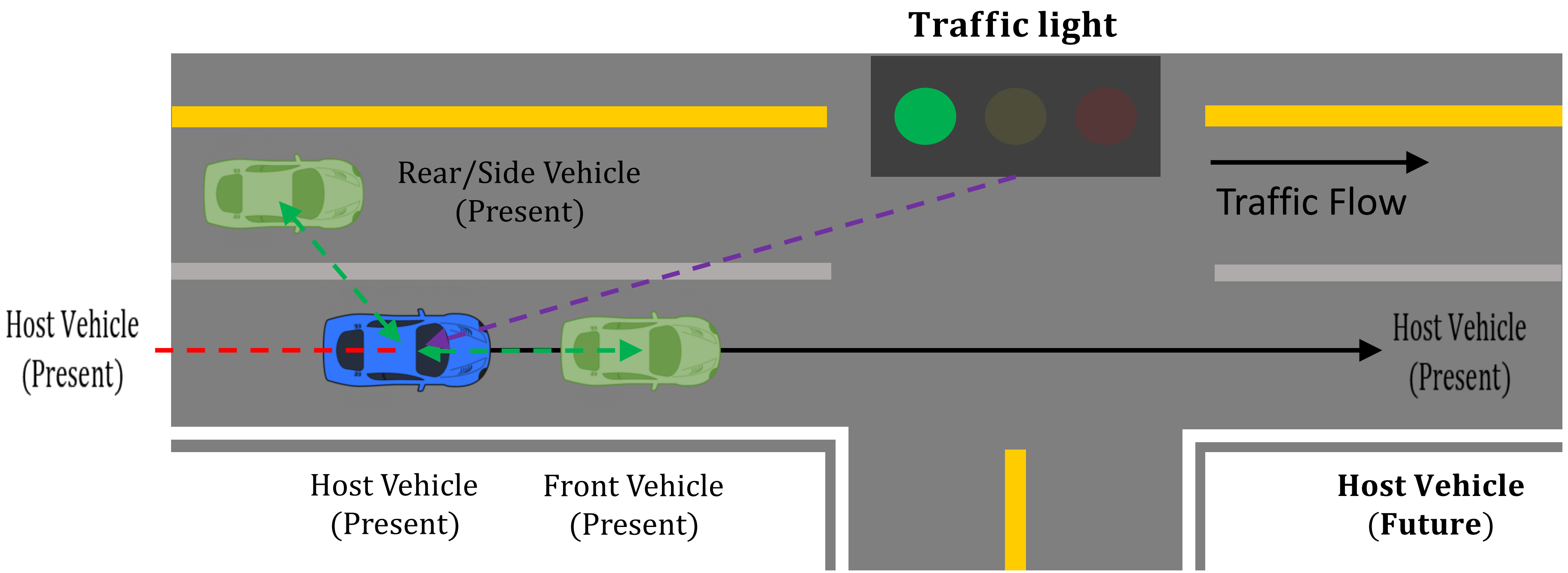
Core elements of prediction near TL include:

Well addressed in literatures

1. History of the host vehicle (HV), $X_{-\tau:0}^{HV}$
2. Interactions with other vehicles, $X_{-\tau:0}^{FV}$, $X_{-\tau:0}^{RV}$, $X_{-\tau:0}^{SV}$
3. Rule imposed by traffic light (TL), X_{t}^{TL} → **Has received much less attention, despite the importance.**

We tackle this challenging vehicle forecasting problem near traffic lights (TLs)

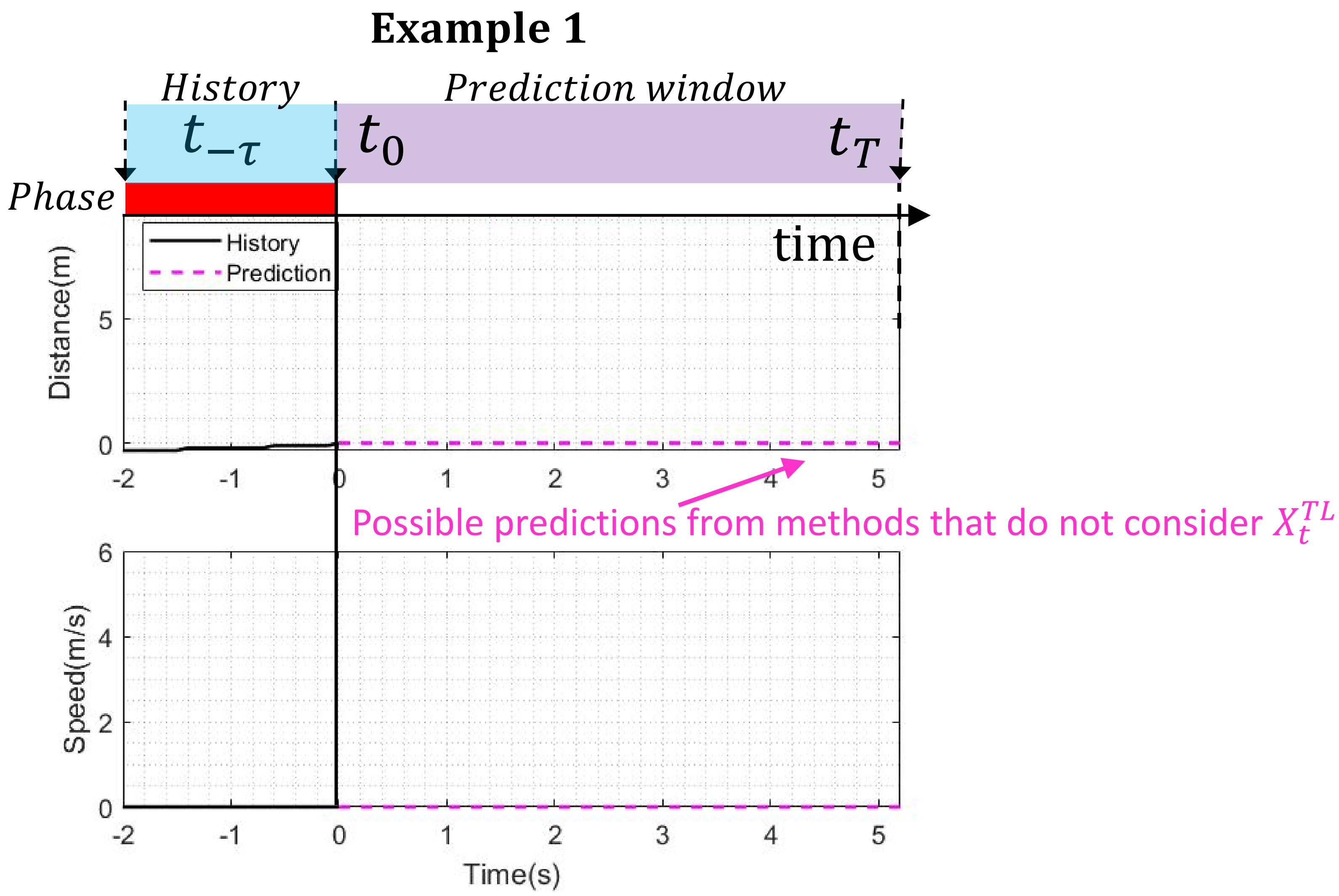
Goal: Trajectory forecasts for the host vehicle



Our contribution:

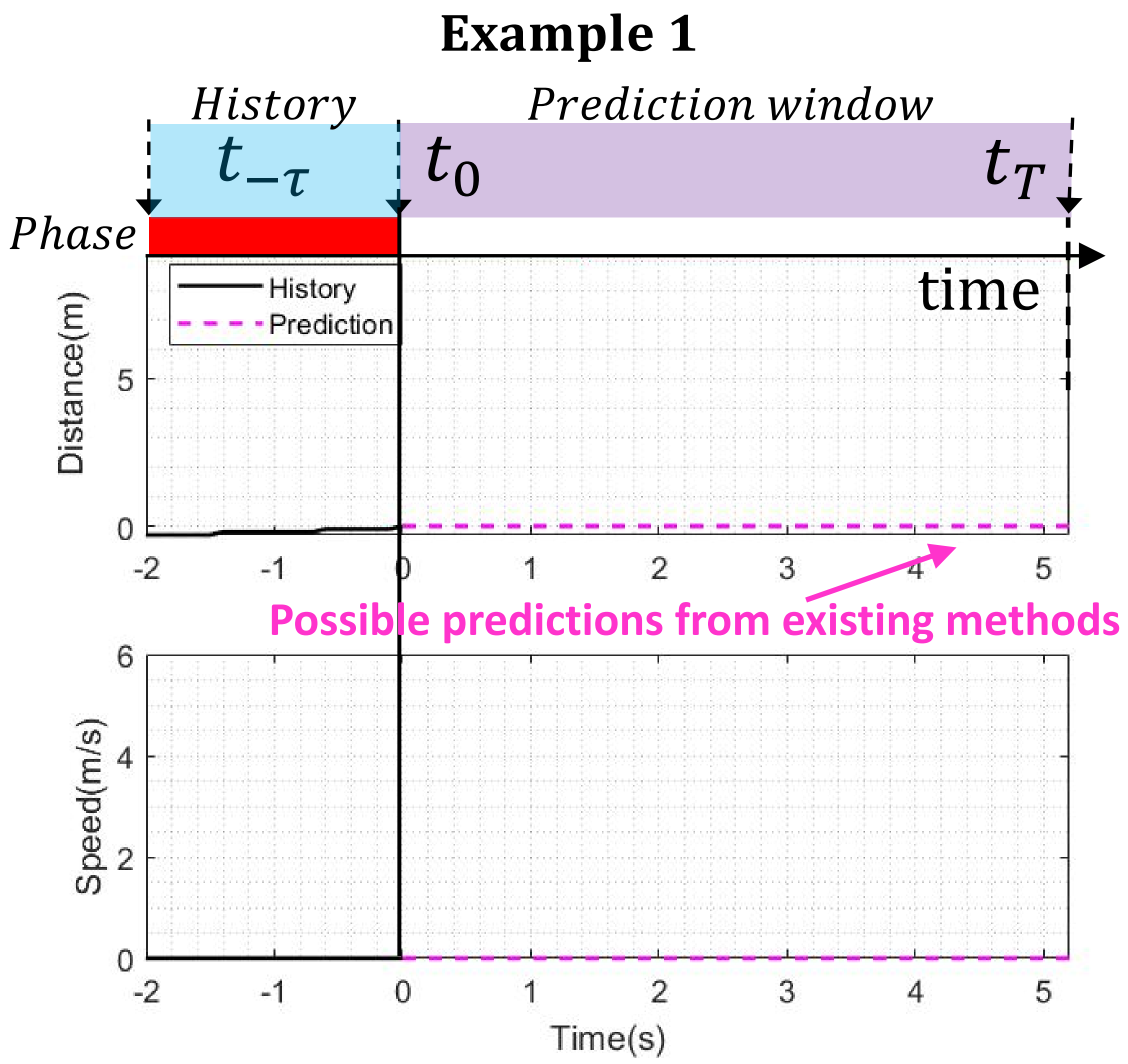
1. **Identification of the impacts of traffic lights** on prediction; qualitative and quantitative
2. **A novel prediction approach** that is mindful of the impacts which utilizes vehicle-to-infrastructure (V2I) communications.

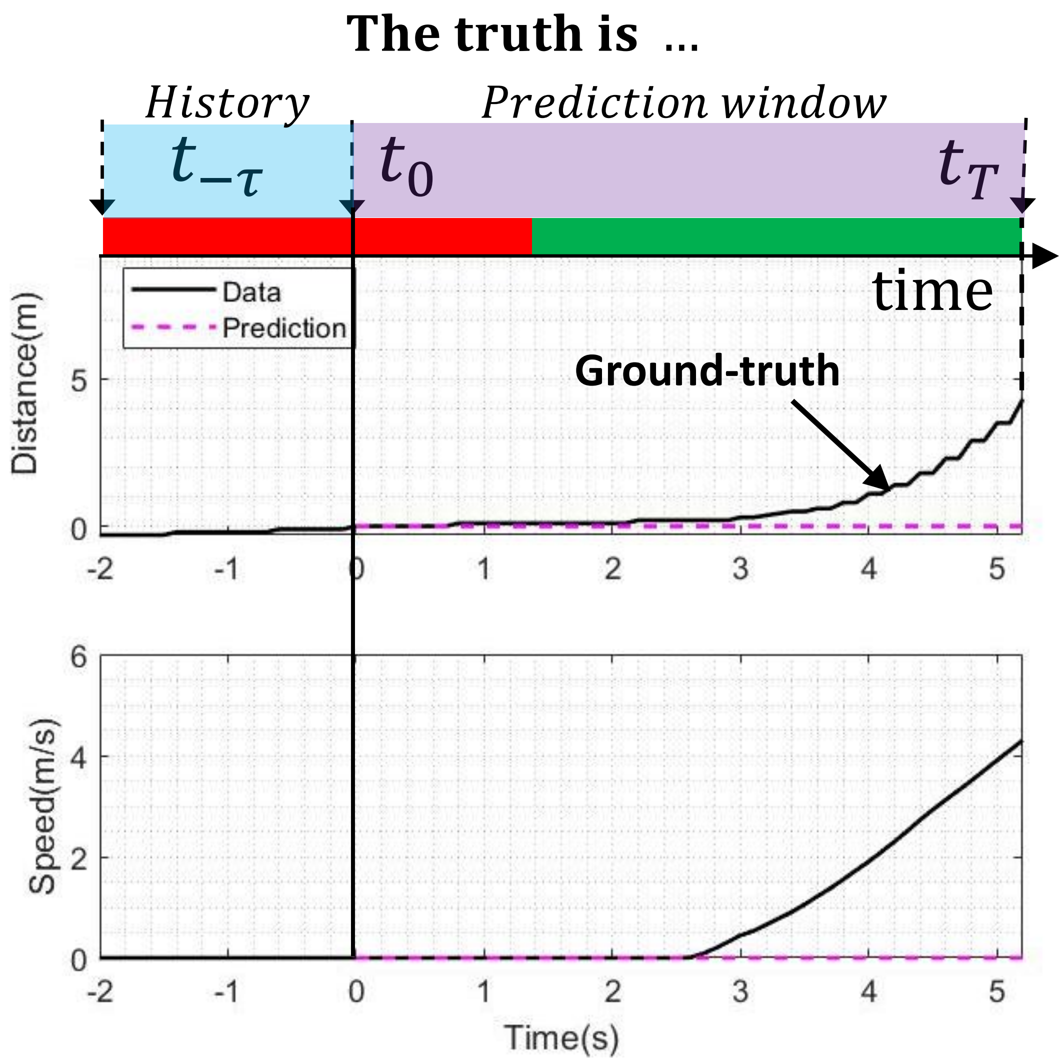
How does traffic light impact the prediction?



Given the phase (Red) at t=0, $X_{-\tau:0}^{HV}$, $X_{-\tau:0}^{FV}$
Existing methods would predict HV to stay put

How does traffic light impact the prediction?

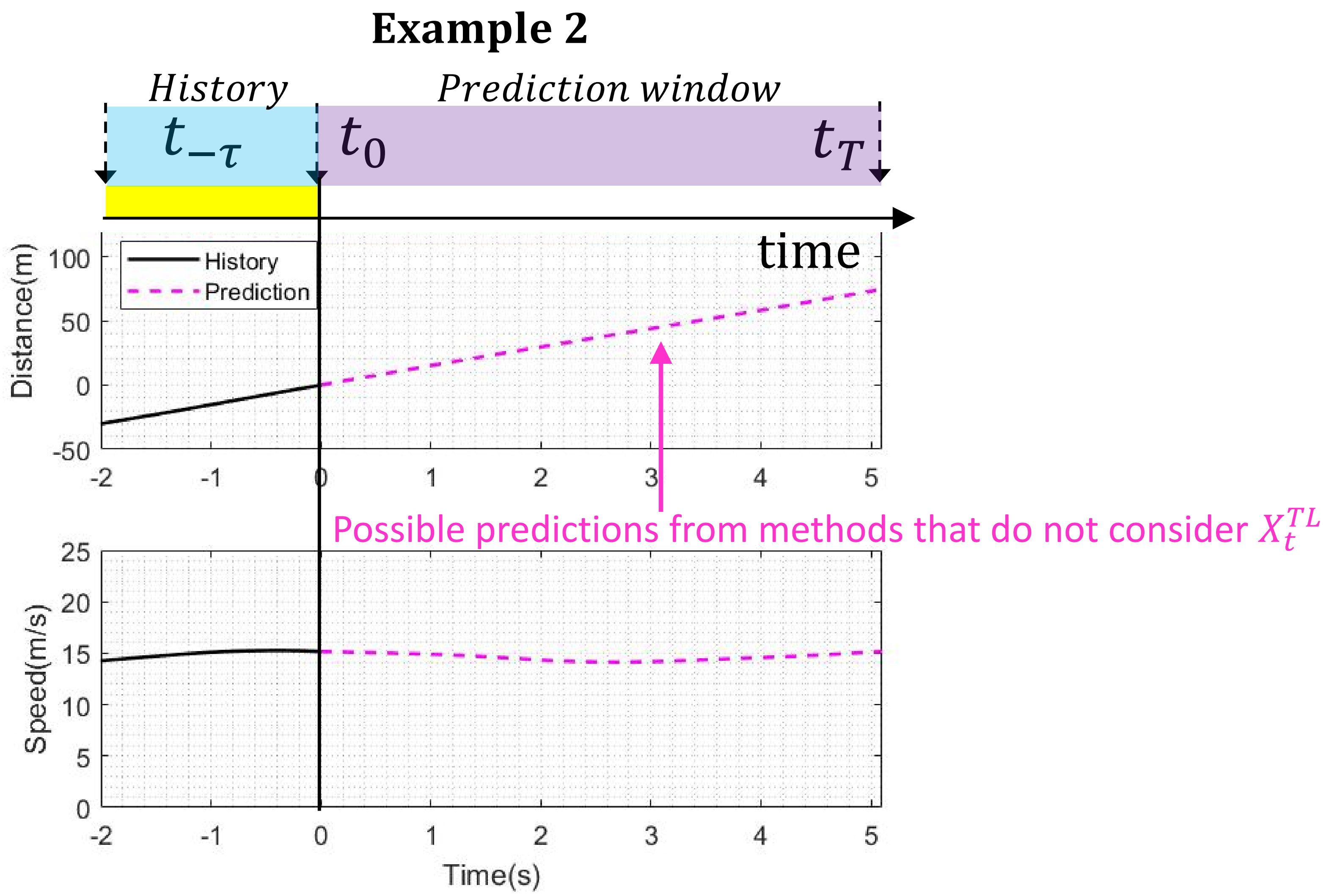




Given the phase (Red) at t=0, $X^{HV}_{-\tau:0}$, $X^{FV}_{-\tau:0}$
Existing methods would predict HV to stay put

Actually, the phase changed to Green shortly after.
The ground-truth trajectory started accelerating.

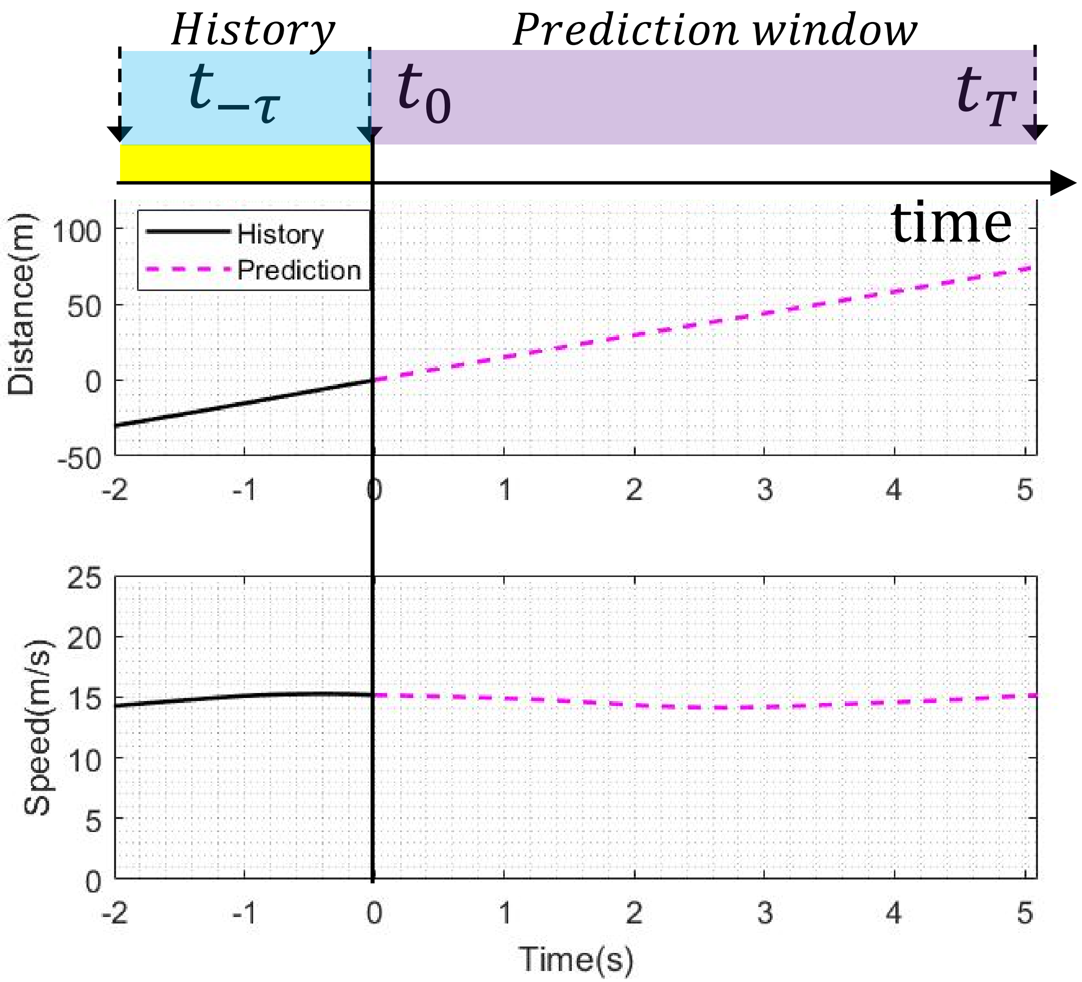
How does traffic light impact the prediction?



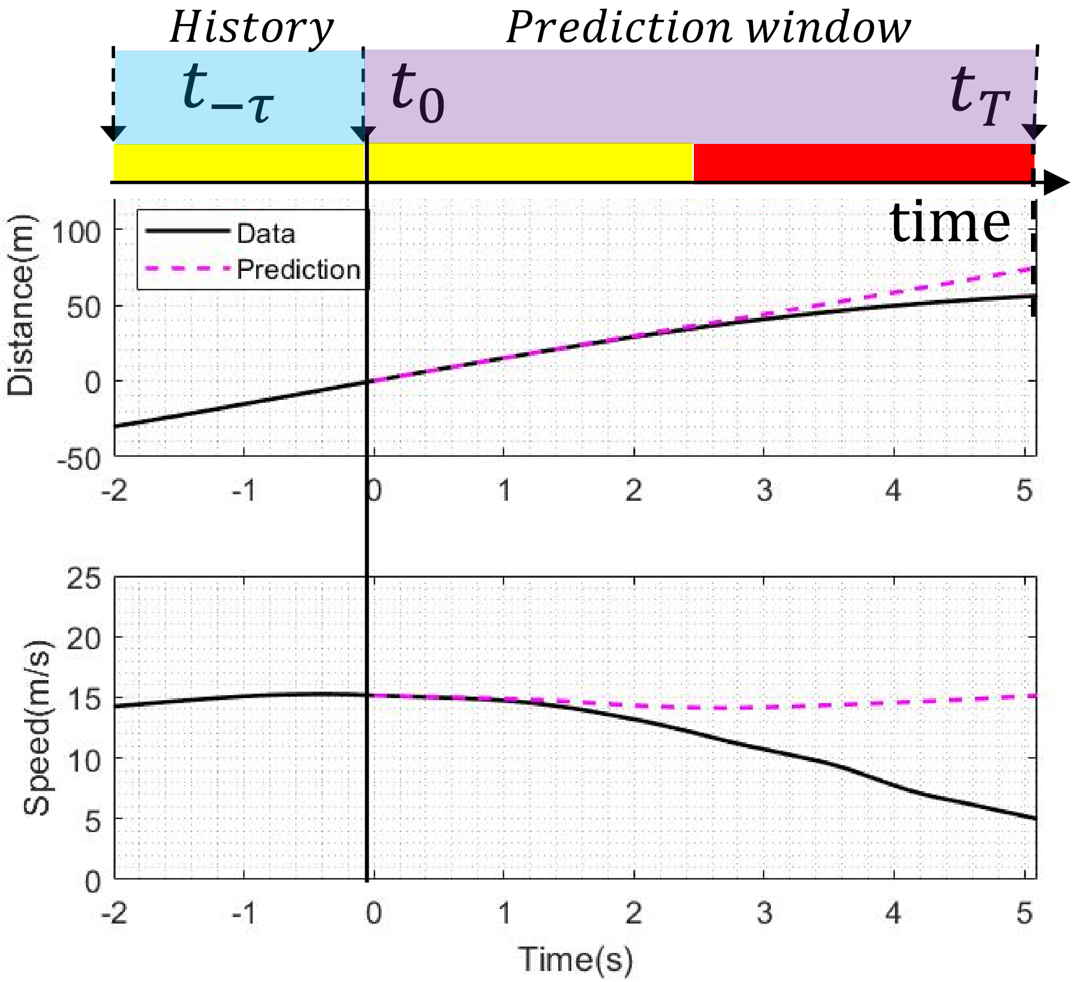
Given the phase (Yellow) at t=0, $X_{-\tau:0}^{HV}$, $X_{-\tau:0}^{FV}$
Existing methods would predict HV to keep the speed

How does traffic light impact the prediction?

Example 2



The truth is …



Given the phase (Yellow) at t=0, $X^{HV}_{-\tau:0}$, $X^{FV}_{-\tau:0}$
Existing methods would predict HV to keep the speed

Actually, the phase changed to Red shortly,
The ground-truth trajectory started decelerating.

We propose a solution to the problem we identified

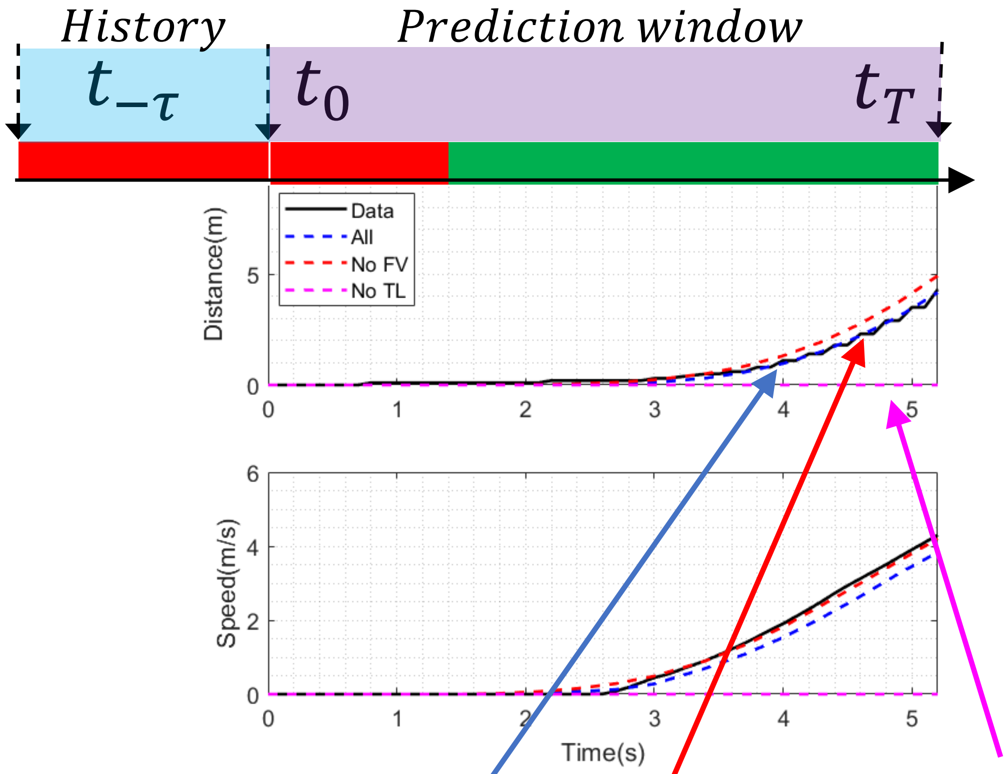
Idea: Utilizing vehicle communications to infrastructures (V2I),
obtain the future profiles of TL states ahead of time

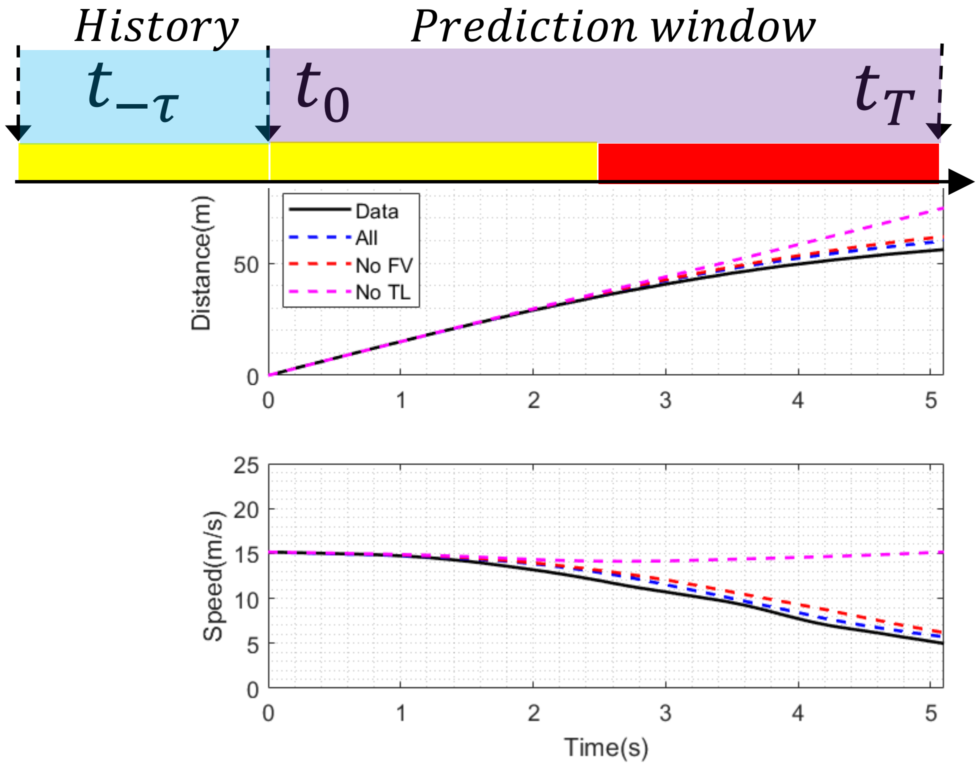
Image Reference: USDOT

Future phase and timing can be shared through V2I

A sneak peek of the results

When we leverages the future profiles of TL ($X_{0:5s}^{TL}$),
the predictions are so much better!

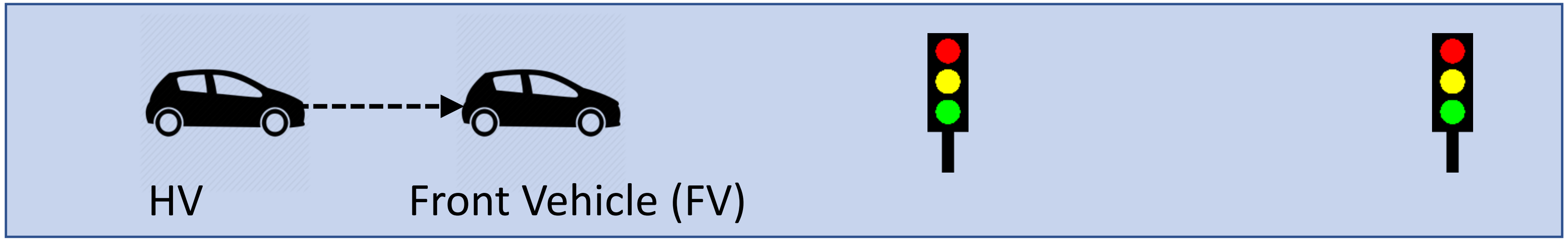




Pink: methods that do not leverage $X_{0:5s}^{TL}$

Blues and Reds (Fig. 4) are trajectories forecasted from our methods

Prediction model - setup



A data-driven approach

A mapping function f from states to actions

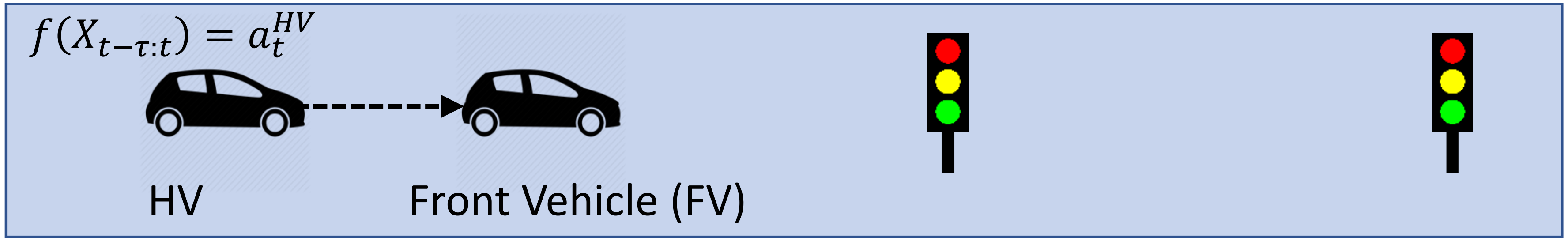
$$f(X_{t-\tau:t}) = a_t^{HV}$$

X_t: state of the host vehicle + environment at time t
a_t^{HV}: action of the host vehicle (acceleration)

We simplify the problem:

longitudinal prediction with the presence of a preceding vehicle
Dataset limitation: rear/side vehicles were not modeled.

Prediction model - setup



In detail, a state is defined as: $X_t \coloneqq [X_t^{HV}, X_t^{FV}, X_t^{TL}, TOD_t]$

Host vehicle state (X^{HV}): Longitudinal position (i.e., distance to the intersection) & speed

Context ($C \coloneqq [X^{FV}, X^{TL}, TOD]$):

- $X^{FV} \coloneqq [FV_t, r_t, \dot{r}_t]$ FV state: captures interactions with the front vehicle (binary flag for presence of FV, relative pos, speed)
- $X^{TL} \coloneqq [P_t, T_t]$ TL state: captures interactions with traffic light (**phase** (G,Y,R) and **timing** (time elapsed since the phase change))
- TOD Time of the day (0-24): macro-scopic traffic characteristics

Output: Action taken by HV (longitudinal acceleration)

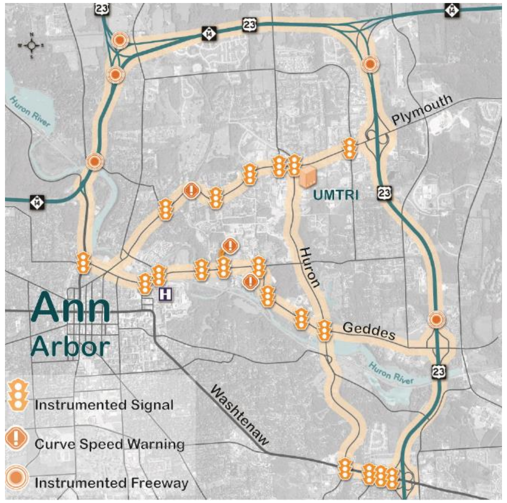
Image Reference: Google Map, UMTRI

Dataset

We used real-world driving records & traffic light states from SPMD:

Naturalistic Driving Records of 3,000 vehicles over 2 years

- Host vehicle (GPS, kinematics, time information)
- Traffic light (TL state profile)
- Front Camera (post-processed information on FV)

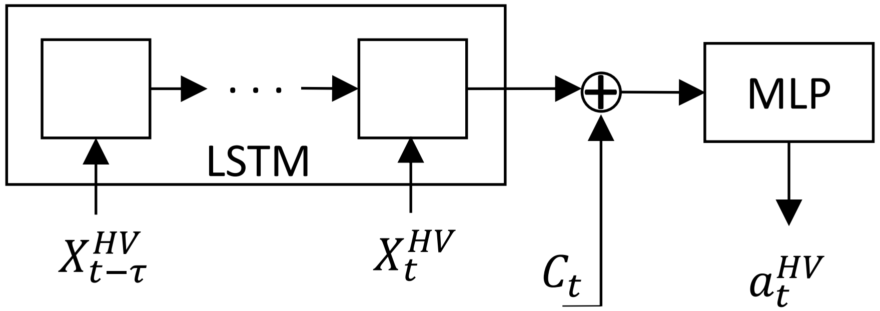


SPMD is a dataset established by USDOT & UMTRI

A signalized intersection (Plymouth-Huron Pkwy, Ann Arbor) was used for a study
The study includes 50 cars passed through the intersection
Total 502,253 sample trips made during 03/2015 – 05/2017 (27 months)

Prediction model

Deterministic Policy (f_d) Learning: RNN



(a) $f_d(X_{t-\tau:t}^{HV}, C_t) = a_t^{HV}$

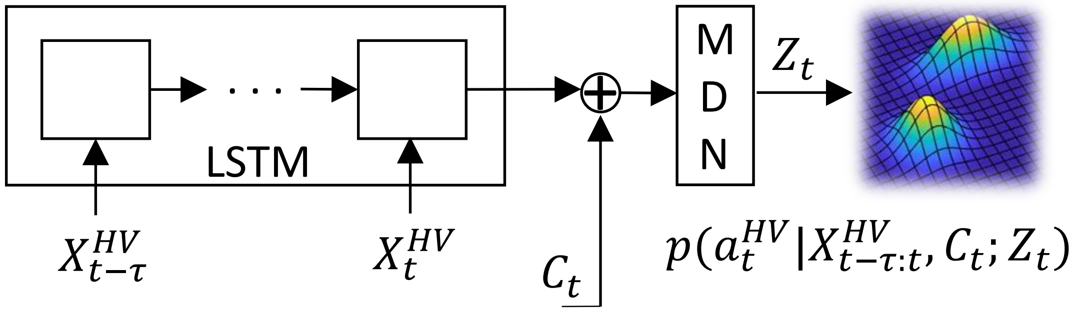
Modeling Intuition

RNN(LSTM) models

temporal dependencies

$$L_d := \sum_{t=1}^{T} (a_t^{HV} - f_d(X_{t-\tau:t}^{HV}, C_t))^2$$

Probabilistic Policy (f_p) Learning: RNN-MDN



(b) $f_p(X_{t-\tau:t}^{HV}, C_t) = Z_t$

MDN captures

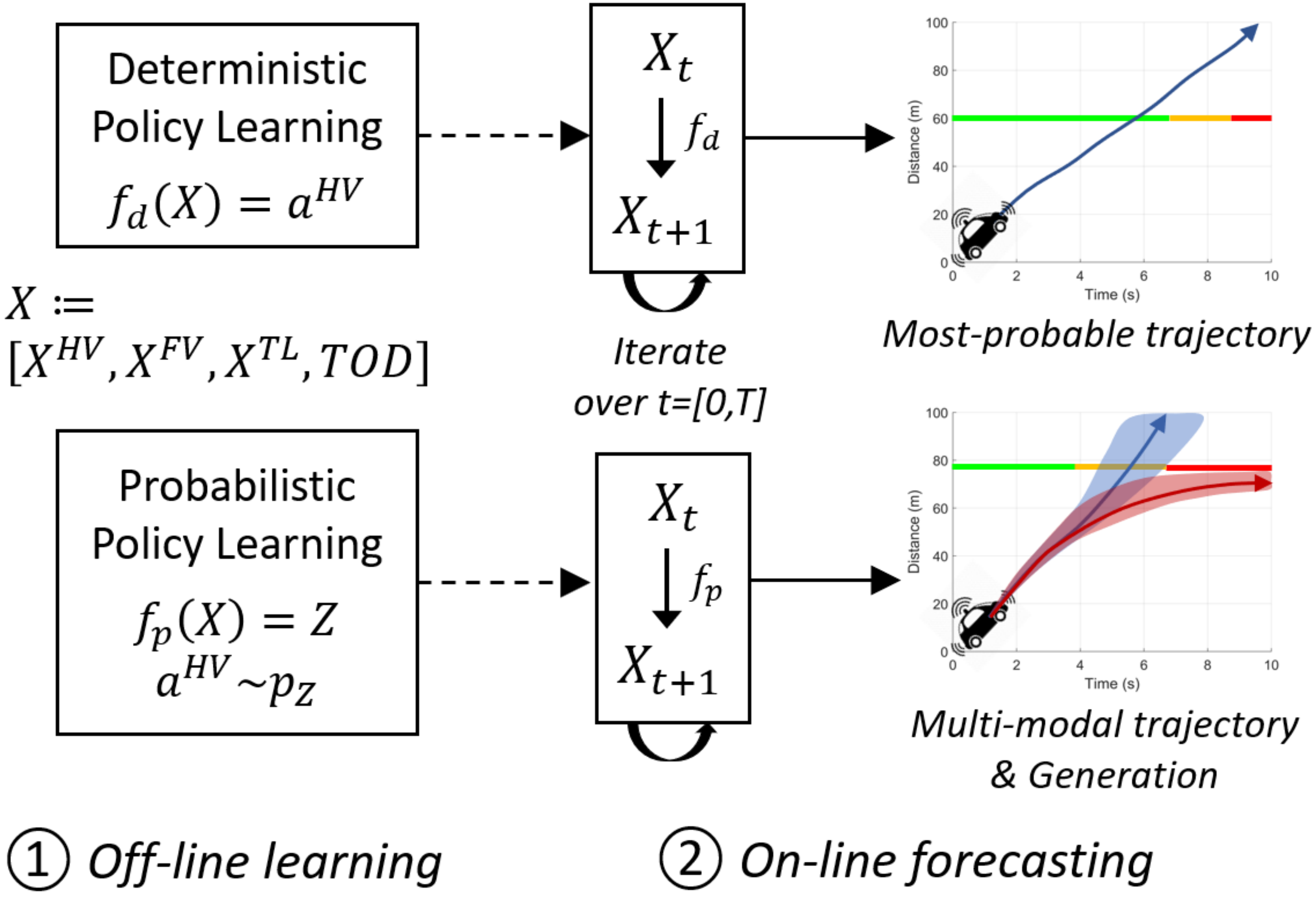
competing policies

And allows

probabilistic interpretation

$$L_p := \sum_{t=1}^{T} -log(p(a_t^{HV} | X_{t-\tau:t}^{HV}, C_t; Z_t))$$

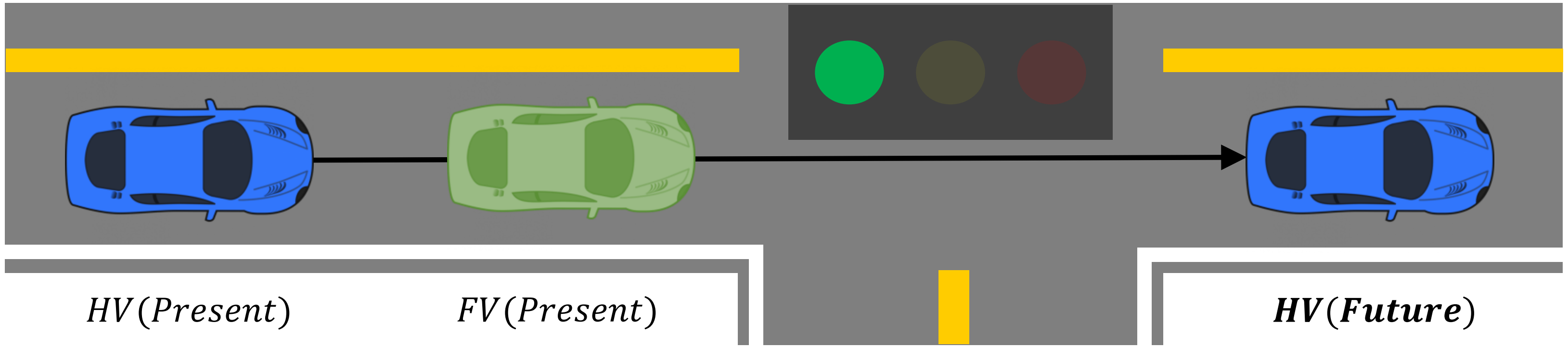
Prediction framework



Autoregressive prediction using the learned policies to obtain the roll-outs

Qualitative evaluation

Problem



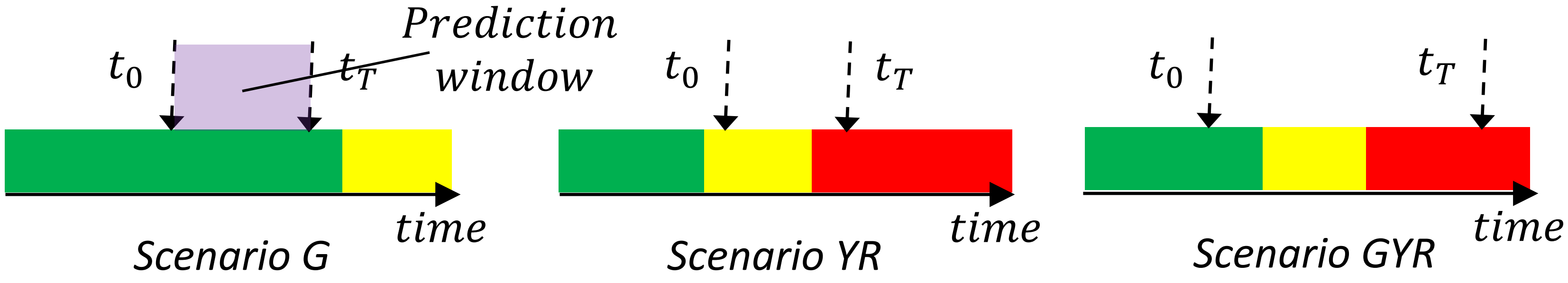
The deterministic policies

f_d	$[X^{HV}, X^{FV}, X^{TL}, TOD] \rightarrow a^{TL}$
f_d^{NoFV}	$[X^{HV}, \quad , X^{TL}, TOD] \rightarrow a^{TL}$
f_d^{NoTL}	$[X^{HV}, X^{FV}, \quad , TOD] \rightarrow a^{TL}$

The impact of TL:

f_d vs f_d^{NoTL}

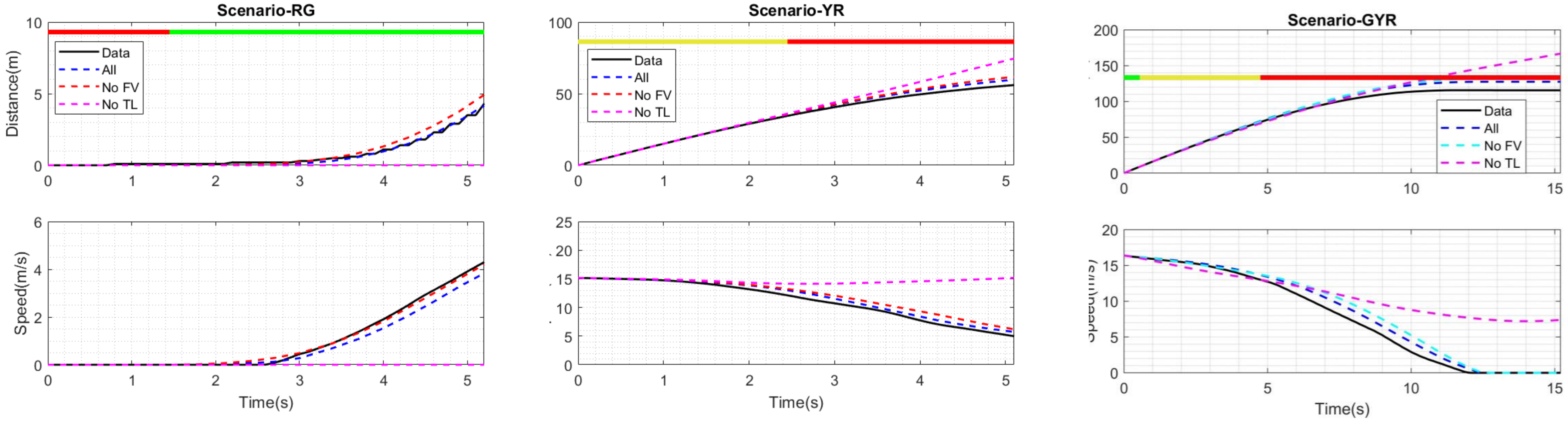
Scenarios



Qualitative evaluation with 3 sample episodes: TL vs NoTL

Given **ground-truth (Black)** trajectories, the trajectory forecasts from the following 3 models are compared:

All (f_d , Blue) : a model which uses both $\boldsymbol{X}^{FA}$ and future $\boldsymbol{X}^{TL}$
No FV (f_d^{NoFV}, Red) : a model which doesn't use $\boldsymbol{X}^{FA}$ → **Our approach**
No TL (f_d^{NoFV}, Pink) : a model which doesn't use future $\boldsymbol{X}^{TL}$ → Benchmarking purpose



Our models (blue and red) produce more accurate predictions than the model (pink) that doesn't utilize future $\boldsymbol{X}^{TL}$

The results demonstrate how the utilization of the future $\boldsymbol{X}^{TL}$ can improve the predictions

Quantitative evaluation with 3111 test samples & ablation study

Models for the ablation study:

f_d	$[X^{HV}, X^{FV}, X^{TL}, TOD] \rightarrow a^{TL}$
f_d^{NoFV}	$[X^{HV}, \quad , X^{TL}, TOD] \rightarrow a^{TL}$
f_d^{NoTL}	$[X^{HV}, X^{FV}, \quad , TOD] \rightarrow a^{TL}$
f_d^{NoFVTL}	$[X^{HV}, \quad\quad , TOD] \rightarrow a^{TL}$

The impact of TL:

f_d vs f_d^{NoTL}

Evaluation metrics:

$$MAE := \frac{\sum_{k=1}^{N} |\hat{X}_k^{HV} - X_k^{HV}|}{N}$$

$$TWAE := \frac{\sum_{k=1}^{N} (t_k |\hat{X}_k^{HV} - X_k^{HV}|)}{\sum_{k=1}^{N} t_k}$$

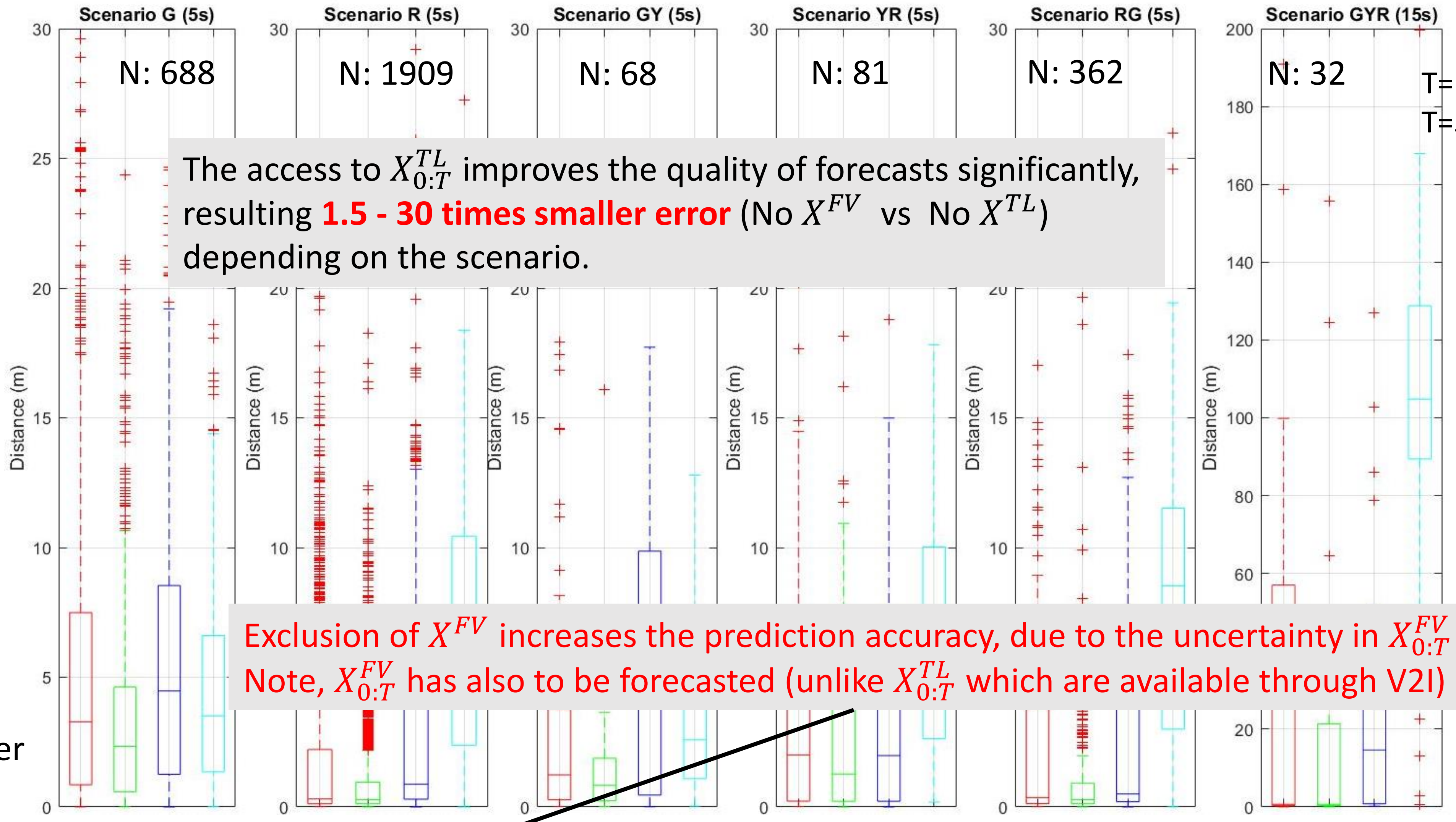
$$ADN := |\hat{X}_N^{HV} - X_N^{HV}|$$

Scenarios:

G, R,
GY, YR, RG,
GYR

Quantitative evaluation with 3111 test samples & ablation study

Sample Size N



T=15s for GYR
T=5s for others

The access to $X^{TL}_{0:T}$ improves the quality of forecasts significantly, resulting **1.5 - 30 times smaller error** (No X^{FV} vs No X^{TL}) depending on the scenario.

Exclusion of X^{FV} increases the prediction accuracy, due to the uncertainty in $X^{FV}_{0:T}$
Note, $X^{FV}_{0:T}$ has also to be forecasted (unlike $X^{TL}_{0:T}$ which are available through V2I)

ADN: Lower the better

Red: All X:=[$X^{HV}, X^{FV}, X^{TL}, TOD$] Green: No X^{FV} Blue: No X^{TL} Cyan: No X^{FV}, X^{TL}

Accuracy: **No X^{FV}** > All X >>> No X^{TL} > No X^{FV}, X^{TL}

Contribution

(1) Identification of a new problem where the existing forecasting methods might suffer

(2) Demonstration of how the access to future TL states improve the predictions

(3) Longitudinal trajectory forecasting algorithms which solve the problem

Conclusion

We identified the scenarios where the existing forecasting methods could perform poor and proposed a novel solution to this problem that leverages the future TL states.

Due to the dataset availability, interactions with rear & side cars were not considered and no perception data (e.g., lidar, radar) was used.

Nevertheless, we believe that the proposed solution makes a step forward towards more accurate modeling and trajectory forecasting of human-driven vehicles.

Thank You