# Understanding V2V Driving Scenarios Through Traffic Primitives (Wang, et al)

reading group 8/11

# Background

- **Goal**: to identify a minimal set of features which describe vehicle-to-vehicle (V2V) interactions

- Prior approaches:
  - GMM + HMM
    - GMM does not consider the dependency between discrete states
  - DBN; stiff requirements on regularity of features
  - Prerequisite determination of potential discrete states

- **Contributions**:
  - Traffic primitive-based framework to investigate driving encounters based on Bayesian nonparametric learning;
  - Clustering approach for primitives of driving encounters over spatiotemporal space;
  - Demonstrating and analyzing the essential components of driving encounters based on naturalistic driving data.

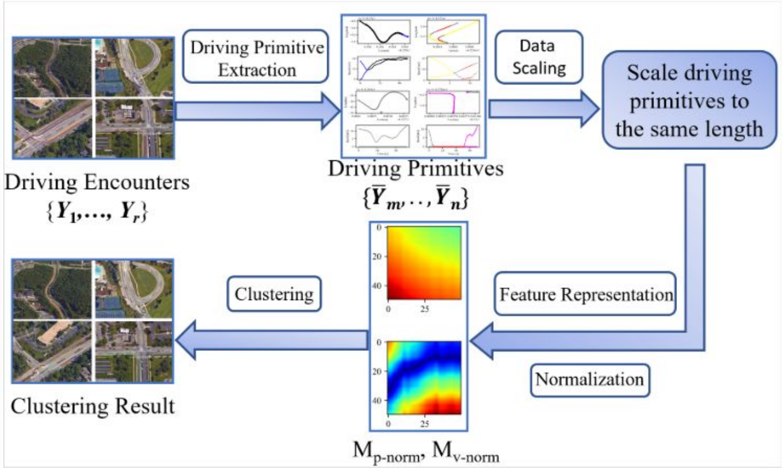
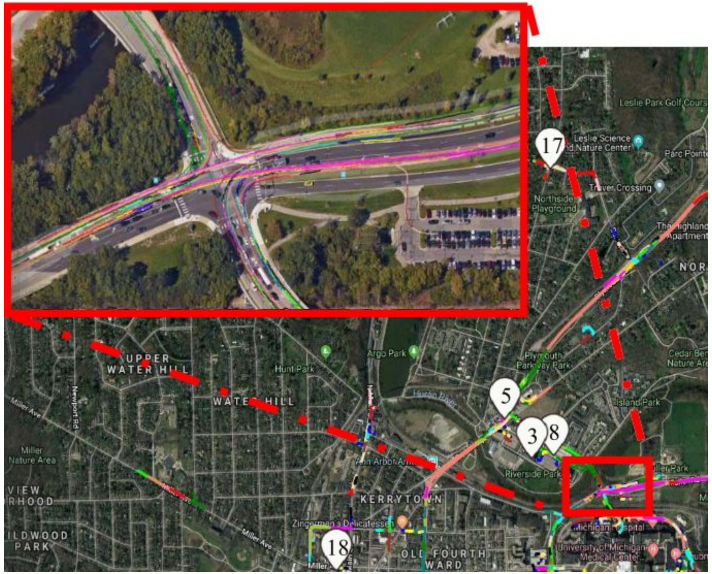



Fig. 1. Diagram of our proposed traffic primitive-based framework.

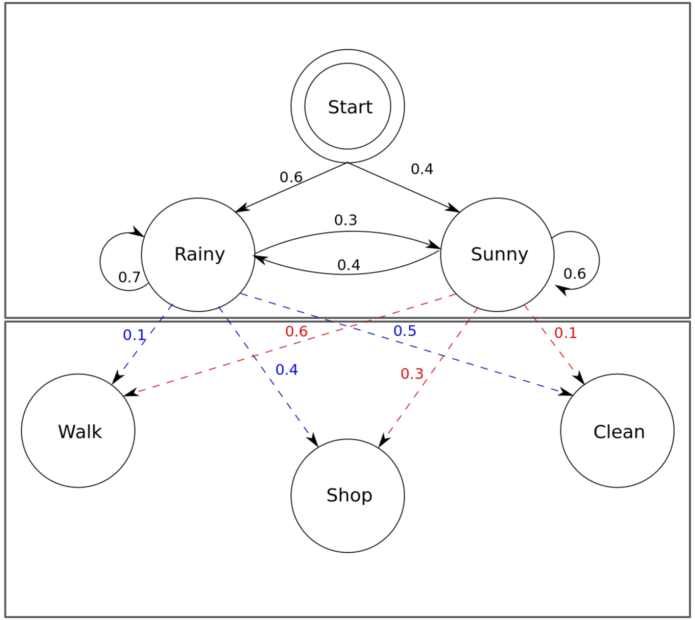
# Common concepts




- **Driving Encounters**
  - Two-vehicle encounters considered; apparent scalability
  - Daily driving encounters typically consist of:
    - Perception
    - Decision-making
    - Control
  - Time-series data from encounters:
    - $y(t) = [\ (\text{longitude}, \text{latitude}), (\text{speed})\ ]$ (for each vehicle)
    - Single encounter defined by: $Y = \{ y(1), \ldots, y(t), \ldots, y(T) \}$
- **Traffic Primitives**
  - "...the fundamental building blocks of driving encounters over the spatiotemporal space…"
  - Traffic primitives do not have *temporal* overlap with one another
  - $\bar{Y} = \{ y(m), \ldots, y(n) \}$
    - $\bar{Y} \subseteq Y$
    - $m \leq n \leq T$

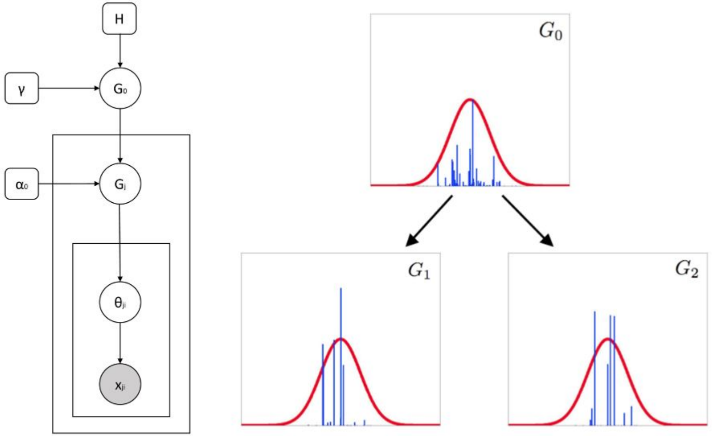
Traffic Primitive Extraction (1/2: HMM + HDP)

- **Hidden Markov model (HMM)**
  - Hidden layer + observed layer




$$x_t | x_{t-1} \sim \pi_{x_{t-1}}$$
$$y_t | x_t \sim F(\theta_{x_t}) \quad (3)$$

- **Hierarchical Dirichlet process (HDP)**
  - A model for grouped data




$$G_0 = \sum_{i=1}^{\infty} \beta_i \delta_{\theta_i}, \qquad \theta \sim H \quad (4a)$$

$$\beta_i = v_i \prod_{\ell=1}^{i-1} (1 - v_\ell), \qquad v_i \sim Beta(1, \gamma) \quad (4b)$$

# Traffic Primitive Extraction (2/2: Sticky HDP-HMM)

Sampled weights; sum to one

Griffiths-Engen-McCloskey sampling (“stick breaking construction”)

$$\beta|\gamma \sim GEM(\gamma)$$

Dirichlet process

Transition probabilities given hyperparameters and self-transition probability term

$$\pi_i|\alpha, \beta, k \sim DP(\alpha + k, \frac{\alpha\beta + k\delta_i}{\alpha + k})$$

Hidden state at time t given hidden state at time t - 1

$$x_t|x_{t-1} \sim \pi_{x_{t-1}}$$

Transition probability at time t - 1

Observation at time t given hidden state at time t

$$y_t|x_t \sim F(\theta_{x_t})$$

Emission function w/ parameter $\theta$xt

$$\theta_i|H \sim H$$

Latent parameters drawn from base measure

Base measure

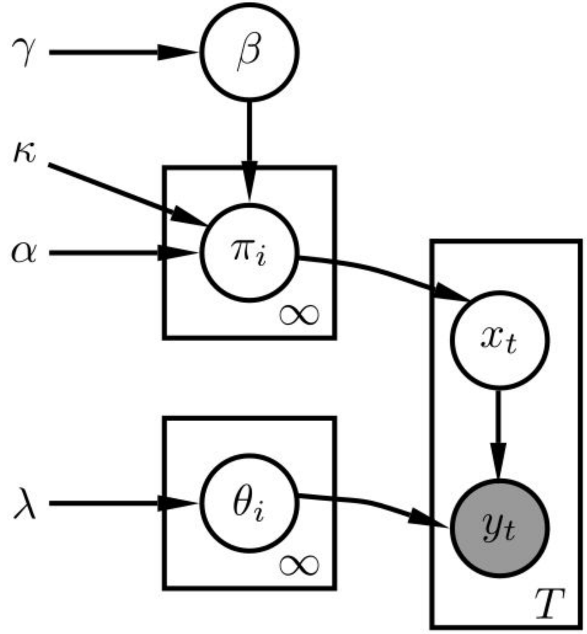



Fig. 2. Illustration of the sticky HDP-HMM approach.

Feature Representation

- Distance measure:
    - **DTW**
- Position feature matrix **Mp**
- Speed feature matrix **Mv**

$$M_p = \begin{bmatrix} P_{1,1} & \cdots & P_{1,n-m+1} \\ P_{2,1} & \cdots & P_{2,n-m+1} \\ \vdots & \ddots & \vdots \\ P_{n-m+1,1} & \cdots & P_{n-m+1,n-m+1} \end{bmatrix} \quad (7)$$

$$M_v = \begin{bmatrix} V_{1,1} & \cdots & V_{1,n-m+1} \\ V_{2,1} & \cdots & V_{2,n-m+1} \\ \vdots & \ddots & \vdots \\ V_{n-m+1,1} & \cdots & V_{n-m+1,n-m+1} \end{bmatrix}. \quad (8)$$

$$P_{i,j} = D_p(p_i^{(1)}, p_j^{(2)})$$

$$V_{i,j} = D_v(v_i^{(1)}, v_j^{(2)})$$

$$D_p(p_i^{(1)}, p_j^{(2)}) = \| p_i^{(1)} - p_j^{(2)} \|_2$$

$$D_v(v_i^{(1)}, v_j^{(2)}) = \| v_i^{(1)} - v_j^{(2)} \|_1$$

## Scaling & Normalization

$$y_t = \left[ p_0 + (t - t_0)\frac{p_1 - p_0}{t_1 - t_0},\ v_0 + (t - t_0)\frac{v_1 - v_0}{t_1 - t_0} \right] \quad (11)$$

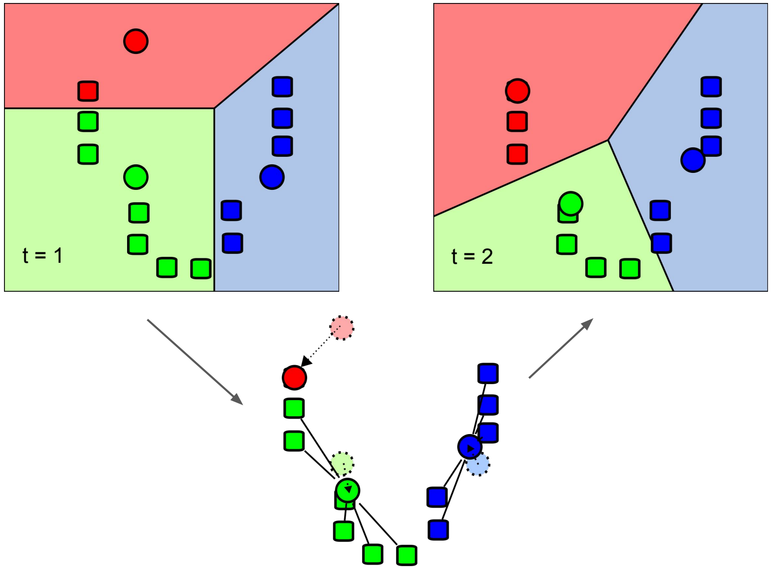
- Need to handle variable length extracted traffic primitives
  - Scale traffic primitives into equal lengths via linear interpolation
- Normalize distance measurements into same operating space via feature matrices

$$\bar{M}_p = \frac{M_p}{\max(M_p)} \quad (12a)$$

$$\bar{M}_v = \frac{M_v}{\max(M_v)} \quad (12b)$$

- Authors use k-means clustering
- Reformat feature matrices into position and speed feature vectors $\phi$
- HDP and related approaches unsupervised
  - Evaluation scheme using within- and between- cluster measures

$$\min \sum_{i=1}^{k} \sum_{\phi_i \in C_i} \|\phi_i - \mu_i\|^2 \tag{13}$$




$$\lambda_w = \frac{\sum_{i=1}^{k} \sum_{\phi_i \in C_i} \|\phi_i - \mu_i\|^2}{N - k} \tag{14a}$$

$$\lambda_b = \frac{\sum_{i=1}^{k} n_i \|\mu_i - \bar{\mu}\|^2}{k - 1} \tag{14b}$$

## Data collection and extraction

- Michigan Safety Pilot Model Development (SPMD) database at UMTRI
  - ~6 million trips from 3500 vehicles
  - Data collected from ‘encounters’ (when two vehicles are within 100 meters)
  - Position is obtained in form of latitude and longitude
  - Speed is collected from wire-speed sensors
  - Data collected at 10 Hz
- Post-cleaning, final dataset of 976 encounters w/ duration >10 seconds
  - Apply sticky HDP-HMM to encounters to obtain 4126 primitives
  - Expected primitive duration set at 5.00 seconds (k = 50)
- For scaling and eventual clustering:
  - Only consider traffic primitives with a duration longer than 0.2 seconds for sampling
    - “...recalling that traffic primitives with short duration provide limited useful information”

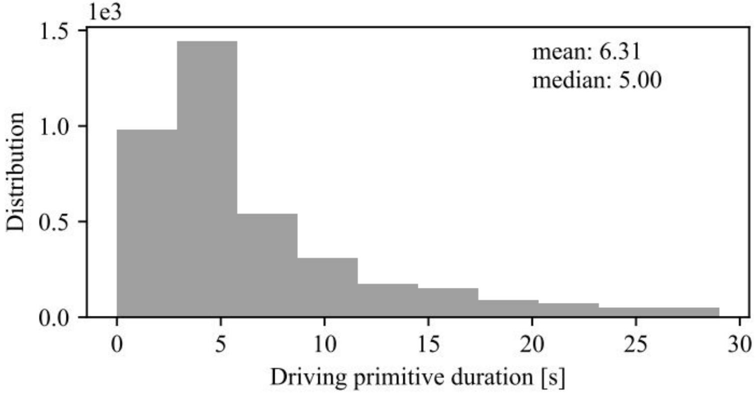
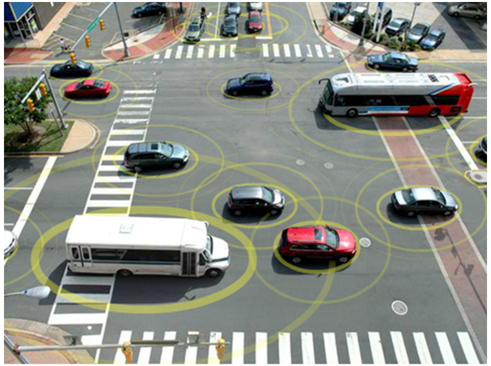



Fig. 3. The distribution of duration of the extracted traffic primitives.



## Results and Analysis (1/2: traffic primitives)

- Traffic primitive extraction
  - Extracted traffic primitives align with subjective, human expectation
  - Driving encounters may consist of **different types** as well as **different numbers** of traffic primitives
  - Speed as complement to trajectory to preserve feature information
    - Fig. 4(a)

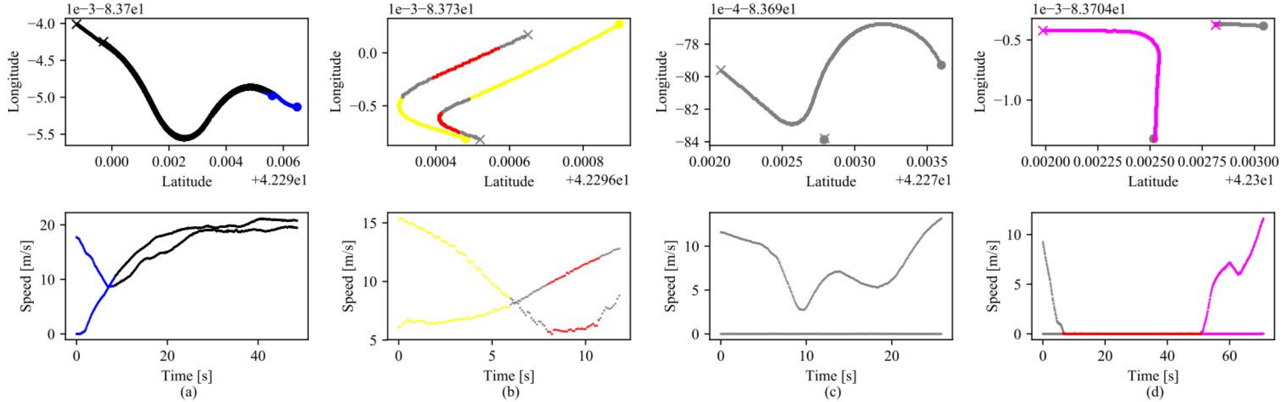



Fig. 4. Examples of four traffic primitives extraction results, consisting of vehicles' position trajectories (top) and speed (bottom).

- Traffic primitive feature analysis
  - Visualized DTW results using heat-maps
  - Red (long local distance)
  - Blue (short local distance)

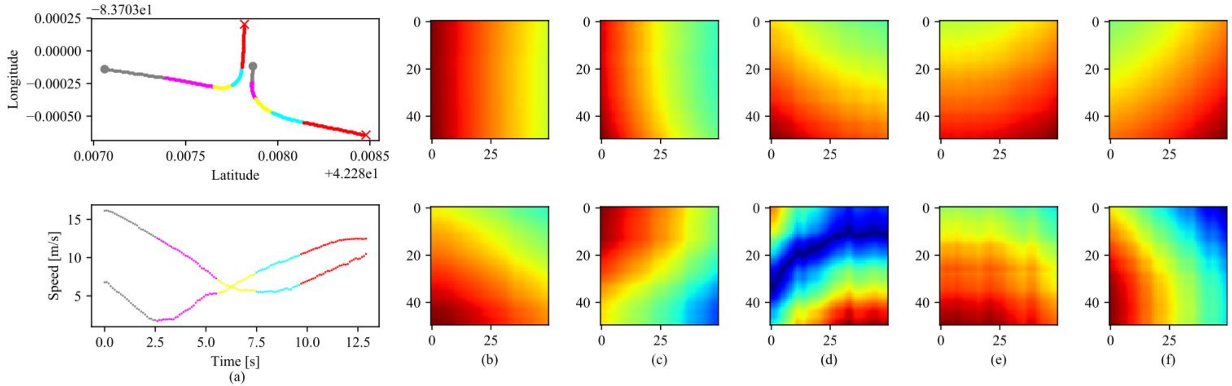
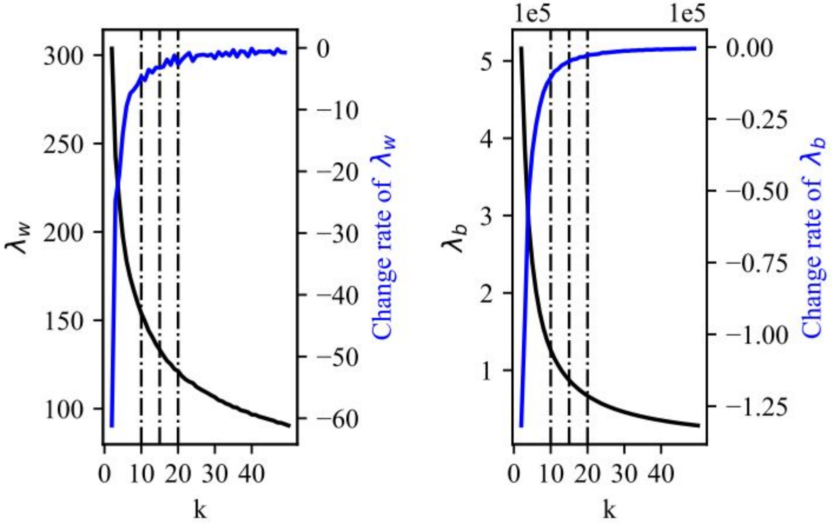



Fig. 5. Example of driving encounters with position trajectories and speed feature matrices for traffic primitives. (a) The trajectory and speed of the whole driving encounter, (b) – (f) The feature matrices calculated by DTW of each traffic primitive, corresponding to each primitive in (a).

Results and Analysis (2/2: clustering)

- Chosen parameters:
  - k = 20
  - Traffic primitives in clusters #1 and #3 most common
  - Most common to have ~3 traffic primitives in a given encounter (mean of 4.1)



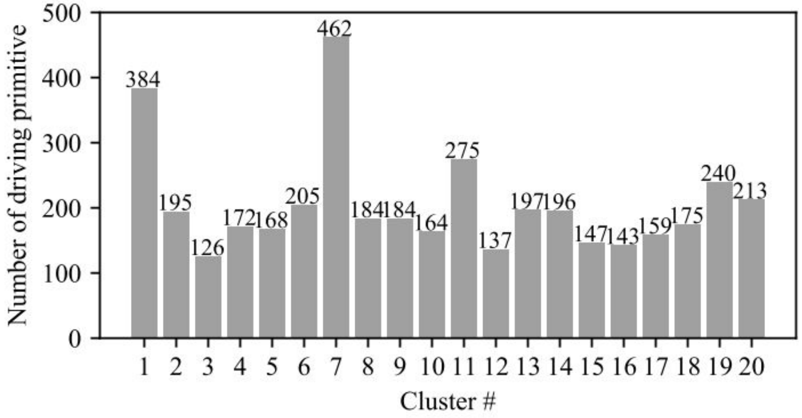




Fig. 7. Distribution of 20 clusters calculated using *k*-means clustering.

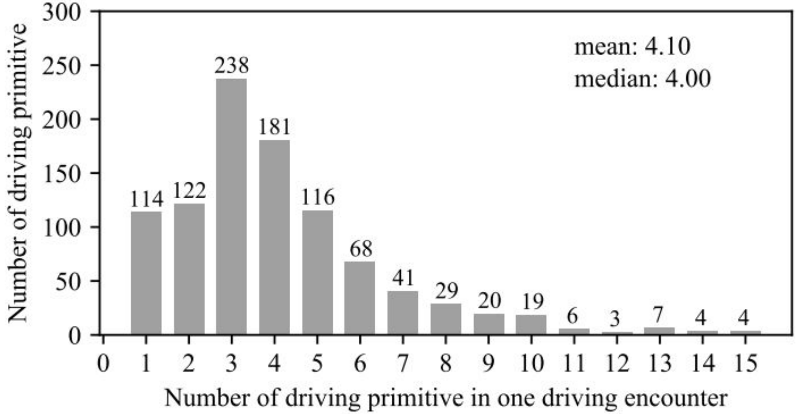
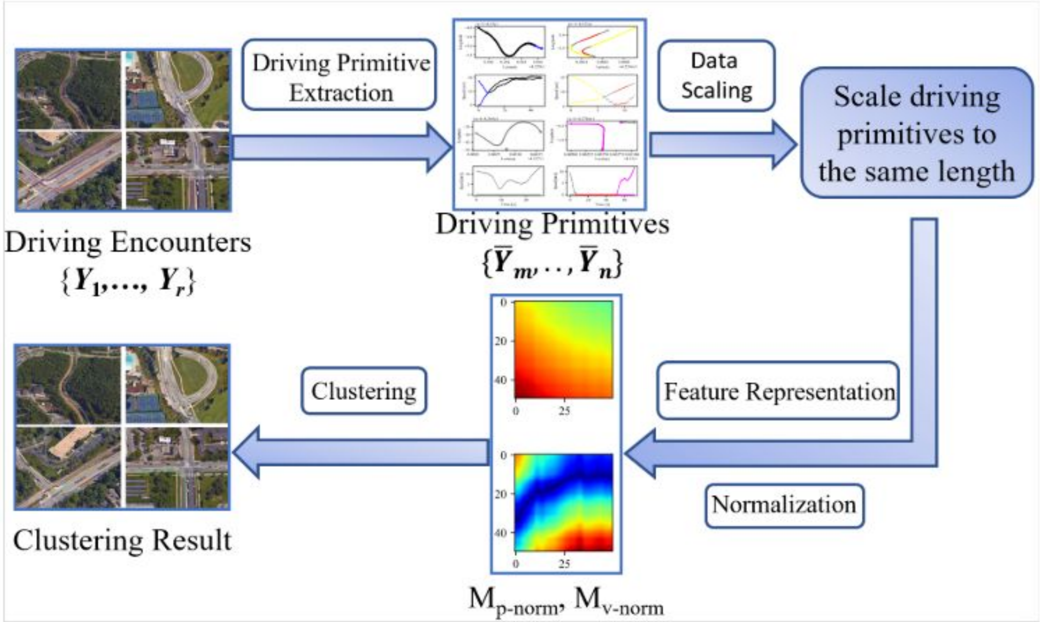



Fig. 8. Distribution of the number of traffic primitives in individual driving encounters.

# Discussion

- Quality of raw data
- Clustering criteria
- Potential applications
    - “We suggest that the proposed framework should be applied for autonomous vehicle safety evaluation.”

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