Lane Changing Prediction Modeling on Highway Ramps: Approaches and Analysis

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FA17 CS229 Final Project

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PREDICTING

Learning the decision-making of a lane-change maneuver is essential to model autonomous vehicles, in terms of avoiding unnecessary or unsafe merging, and encouraging lane-changes that could increase travel efficiency. Briefly, we

- proposed 3 machine learning approaches to predict an intended lane changing,
- identified indicating features of probable lane-changes in the near future.

Results show that a lane change maneuver is predictable in all 3 algorithms, and the accuracy reaches over 80%, with a maximum of 97%.

DATASET & FEATURES

The vehicle trajectory data on US-101 and I-80 highway are provided by the Next Generation Simulation. We identified 645 lane-change events and 663 lane keeping events as dataset.

We defined the ego vehicle (in red) to be the vehicle of interest. At each time step, the ego car observes 14 variables.

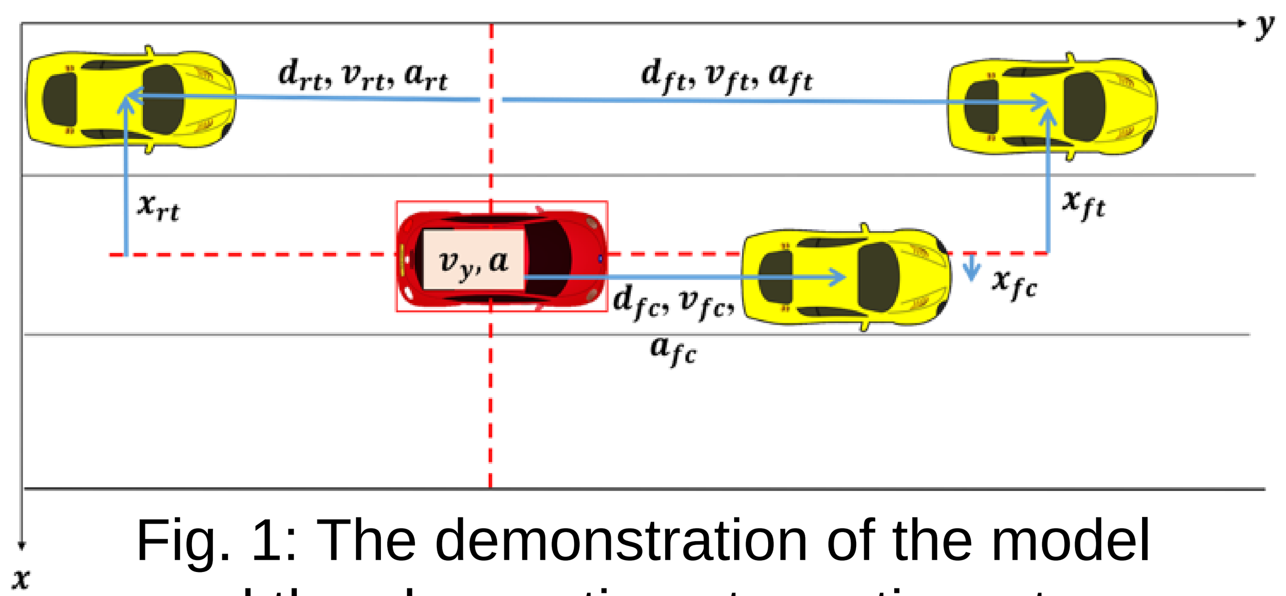

Fig. 1: The demonstration of the model and the observation at one time step.

Assuming a Markov process, we modeled the feature set of a lane-change event as the concatenation of the features of 6 time steps (dt = 0.5 s) before a lane-change event happens. The lane-keep events were found around 15 seconds prior to a lane-change. Dimension of the entire feature vector is 84.

MODELS & APPROACHES

Logistic Regression (LR)

Binary logistic regression with regularized average empirical loss was used,

$$J(\theta) = \frac{1}{m}\sum_{i=1}^{m} \log\left(1 + e^{-y^{(i)}\theta^T x^{(i)}}\right) + \frac{\lambda}{2}\|\theta\|^2$$

where $y^{(i)} \in \{-1, 1\}$ indicates whether it is a lane-keep or lane change example, and λ is a hyperparameter that controls the amount of regularization.
Newton's method was used as the solver.

Support Vector Machine (SVM)

SVM is an efficient way to classify high dimensional features. An SVM classifies data by finding the best hyperplane that separates all data points of one class from those of the other class. We used regularized hinge loss,

$$J(w,b) = \sum_{i=1}^{m} \left[1 - y^{(i)}\left(w^T x^{(i)} - b\right)\right]_+ + \frac{\lambda}{2}\|w\|^2,$$

and Gaussian kernel,

$$K(x,z) = \exp\left(-\frac{\|x-z\|^2}{2\sigma^2}\right).$$

Artificial Neural Network (ANN)

Feed forward neural network: the weight and bias values were initialized by Nguyen-Widrow method.
Hyperbolic tangent sigmoid function was used as the activation function of the first layer, and log-sigmoid activation function was used in the output layer. Gradient descent with momentum weight and bias defines the learning function.

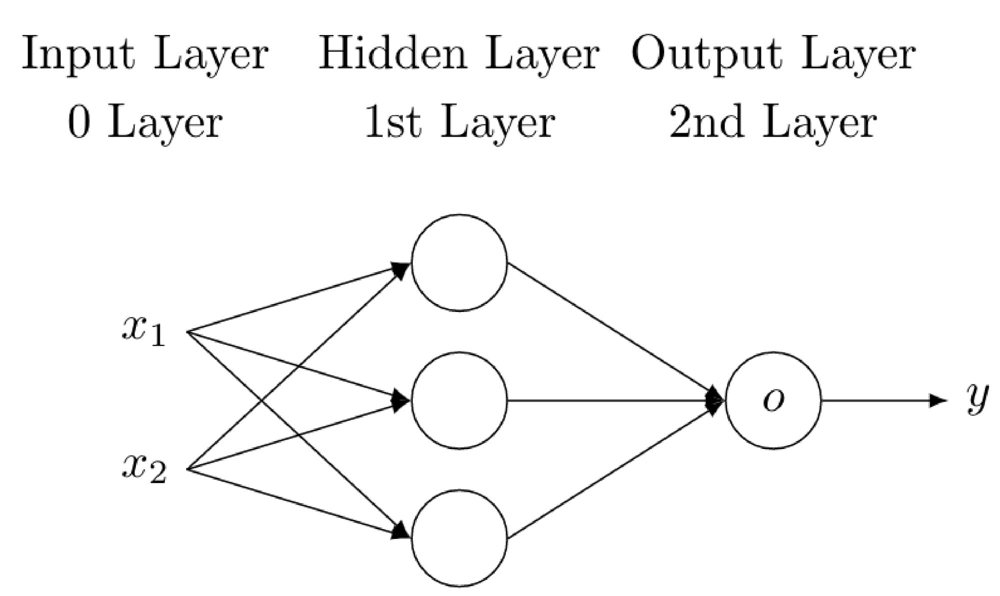

Fig. 2: Schematic of a fully connected two layers feed forward neural network.

Hyperparameters Optimization

The values of hyperparameter have significant impact on the performance of the learning algorithm. We randomly split samples into three subsets:

- training set (70% of the data),
- hold-out cross validation/dev set (15%),
- test set (15%)

For a given set of hyperparameters, we train the model in the training set and evaluate its performance upon the metric—the area under the receiver operating characteristic (ROC) curve (AUROC), in the dev set.
The set of hyperparameters that results the best performance in the dev set will be the set of optimal hyperparameters.

Table 1: Hyperparameters.

LR	SVM	ANN
n_f, λ	n_f, λ, σ	n_f, n_{neuron}

RESULTS

Table 2: Performance comparison of LR, SVM, and ANN on test set with threshold=0.5.

	Accuracy	Precision	Sensitivity	F1-Score
LR	82.1%	80.4%	83.0%	0.817
SVM	85.1%	88.4%	80.9%	0.845
ANN	96.9%	94.9%	98.9%	0.969

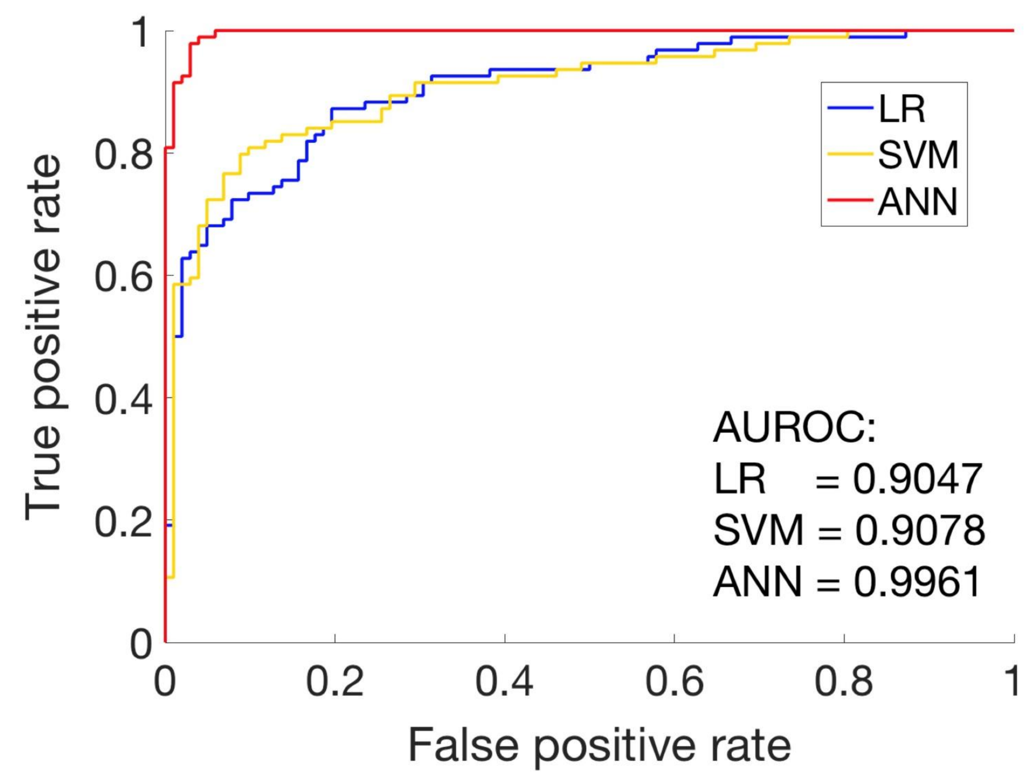

Fig. 3: ROC Curves with threshold from 0 to 1.

DISCUSSION & FUTURE WORK

1) Top four deterministic features that affect an lane change maneuver decision:
$$d_{ft}, x_{fc}, v_{fc}, v_y$$
2) The classification results of ANN outperforms LR and SVM in all means. The test set performance of SVM is better than LR, but overall performance of SVM and LR is similar.
3) Future work: extend the lane change predication to multiple outputs, e.g. lane change direction, steering angle, etc.

References:

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[2] Hou, Y., Edara, P., & Sun, C. (2015). Situation assessment and decision making for lane change assistance using ensemble learning methods. Expert Systems with Applications, 42(8), 3875-3882.
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