Surrounding Motion Predict Model for Autonomous Vehicle

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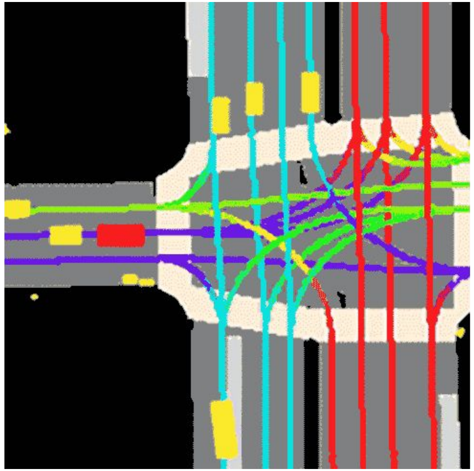
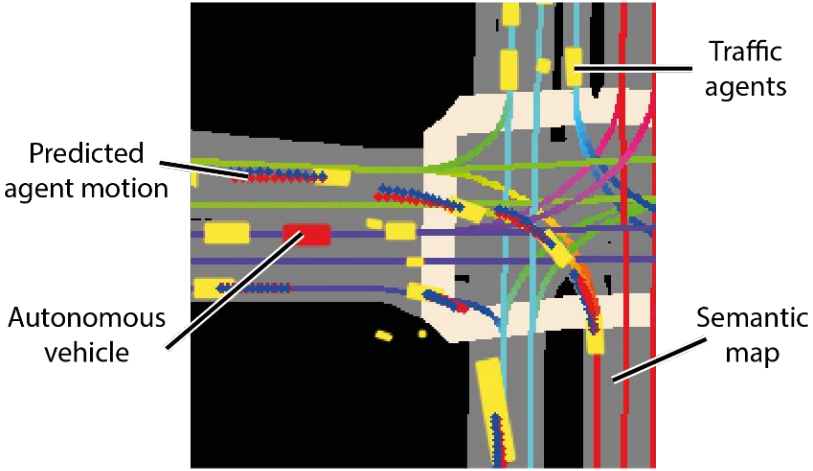
EE599 - Deep Learning - Fall 2020

USC Viterbi School of Engineering

Motivation





- Predict surrounding agents motions of the autonomous vehicle over 5s given their current and historical positions
  - Useful for planning self driving vehicle's movement
- Deep learning techniques (CNNs) + Ensemble Models

https://self-driving.lyft.com/level5/prediction/

Outline

- Overview
- Challenges
- Architecture
- Metrics
- Implementation
- Conclusions

Project Overview

- Use L5kit library to access and visualize the dataset
- Build motion prediction model using ResNet 34 (Baseline), MixNet-m, MixNet-l, MixNet-xl, Ensemble models
- Choose negative multi-log-likelihood as evaluate metric

https://arxiv.org/pdf/2006.14480v2.pd
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Challenges

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- Choose best architecture compromising model speed and prediction capability
- Understand MixNet architecture
- Decide which loss function to use on different training stages
- Ensemble models into multiple trajectories due to the high ambiguity of real world road environment
- Understand the influence of hyperparameters
  - Raster size
  - Pixel size
  - Batch size
  - Traffic lights

Dataset Introduction

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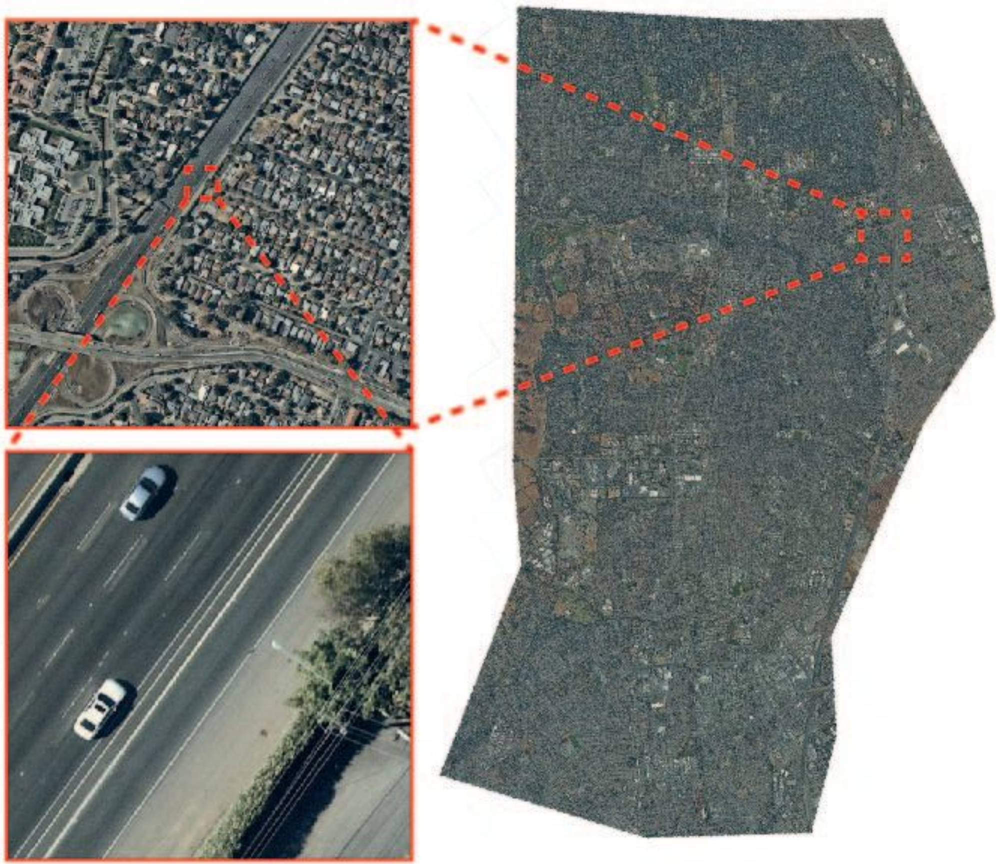
- No. of Scenes: **170,000** scenes
- Period: **25** seconds long
- Total time: **1,118** hours
- Semantic map: **8500** lane segments and **15000** annotated traffic agents.
- Agents: Cars (**92.47%**), pedestrians (**5.91%**) and cyclists (**1.62%**).
- Aerial image spanning **74 km²** at a resolution of **6 cm** per pixel



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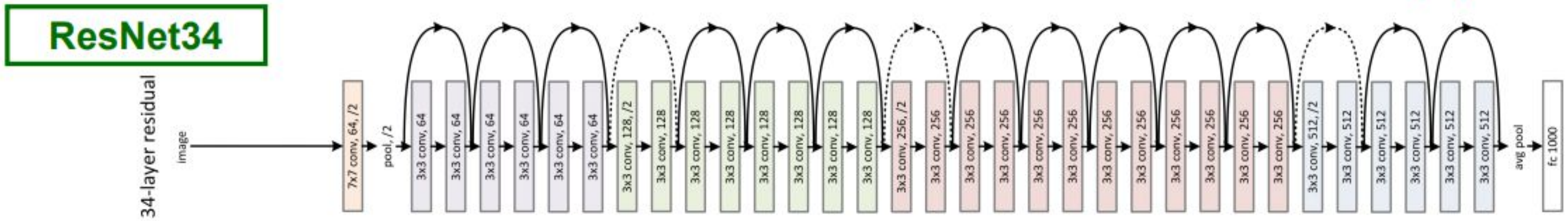
Architectures

Baseline Model: ResNet 34



- Input channels : 2 * (10 + 1) + 3 = 25
- Output size : 50 * 2 = 100

[He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 770-778).]

Architectures

MixNet

Intuition: The smaller kernels (3x3, 5x5) serve to capture lower resolution details, while the larger kernels (7x7, 9x9) capture higher resolution patterns and thus ultimately build a more efficient network.

MixConvs: Blend multiple kernels sizes into a single layer

MixNets: Ultimately using a range of 1-5 kernels was deemed to be the best standard. By leveraging Neural Architecture Search (NAS), the final MixNets models were built.

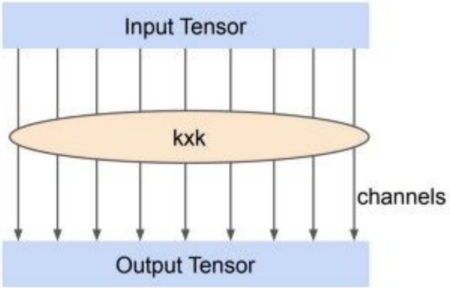


Figure: Vanilla Depthwise Convolution

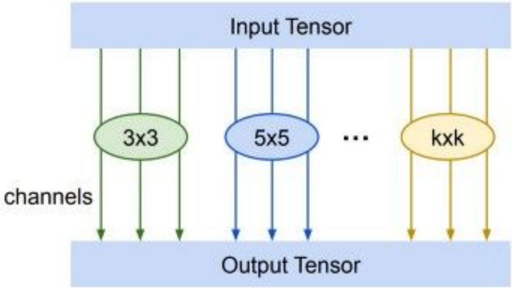


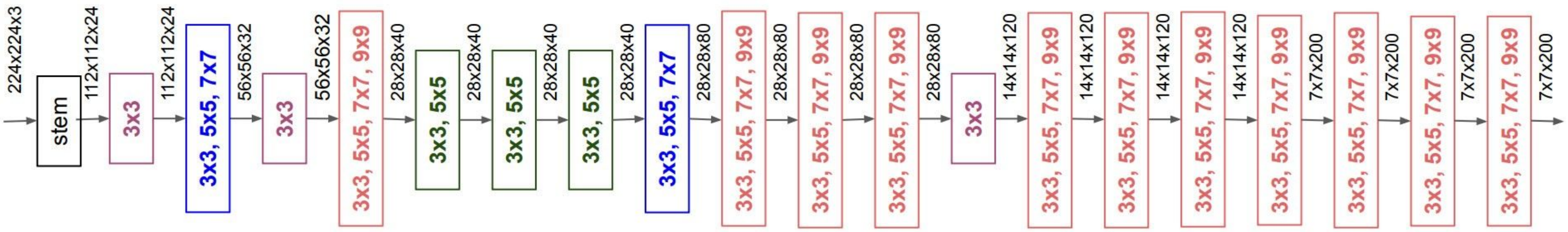
Figure: MixConv

TAN, LE: MIXCONV: MIXED DEPTHWISE CONVOLUTIONAL KERNELS

Architectures

3 hypotheses: MixNet-m, MixNet-l, MixNet-xl

- Input channels: 25
- Output size: 100



MixNet-M

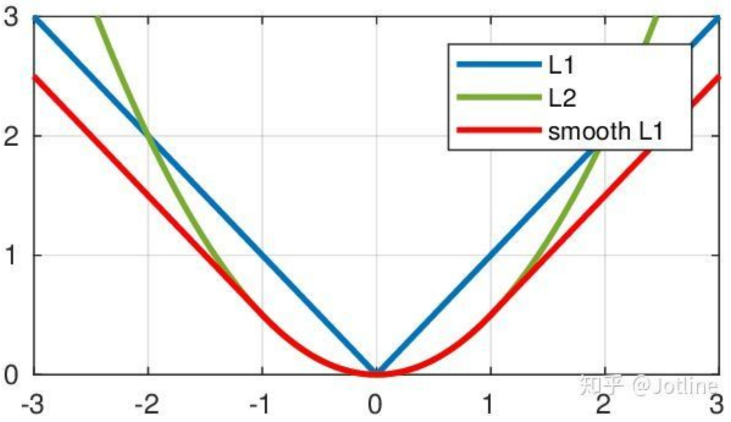
- m, l, xl are degrees of MixNet layers depth.
- E.g. MixNet-l is simply a 1.3 depth multiplier of -m

TAN, LE: MIXCONV: MIXED DEPTHWISE CONVOLUTIONAL KERNELS

Metrics

Training loss function 1: SmoothL1Loss

$$loss(x,y)=\frac{1}{n}\sum_{i=1}^{n}\begin{cases}0.5\times(y_i-f(x_i))^2, & if\ |y_i-f(x_i)|<1\\ |y_i-f(x_i)|-0.5, & otherwise\end{cases}$$



- Often used in regression problem or in the occasion that exist relatively big numbers in features
- Smooth gradient when prediction and ground truth are close

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Metrics

Training loss function 2: Negative Multi-Log-Likelihood

Ground truth positions of a sample trajectory: $x_1, x_2, \ldots, x_{50}, y_1, y_2, \ldots, y_{50}$

3 predicted positions, represented by means: $\bar{x}_1^3, \bar{x}_2^3, \ldots, \bar{x}_{50}^3, \bar{y}_1^3, \bar{y}_2^3, \ldots, \bar{y}_{50}^3$

Set 3 confidences c of the 3 hypotheses.

Assumptions: Independent Gaussian mixture model, yielding the likelihood:

$$P(x_{1,\ldots,50}, y_{1,\ldots,50} \mid c^{1,\ldots,3}, \bar{x}_{1,\ldots,50}^{1,2,3}, \bar{y}_{1,\ldots,50}^{1,2,3})$$
$$= \sum_{k=1}^{3} c^k N(x_{1,\ldots,50} \mid \bar{x}_{1,\ldots,50}^{k}, \Sigma = 1) N(y_{1,\ldots,50} \mid \bar{y}_{1,\ldots,50}^{k}, \Sigma = 1)$$
$$= \sum_{k=1}^{3} c^k \prod_{t=1}^{50} N(x_t \mid \bar{x}_t^k, \sigma = 1) N(y_t \mid \bar{y}_t^k, \sigma = 1)$$

$$NLL = -\log P(x_{1,\ldots,50}, y_{1,\ldots,50} \mid c^{1,2,3}, \bar{x}_{1,\ldots,50}^{1,2,3}, \bar{y}_{1,\ldots,50}^{1,2,3})$$
$$= -\log \sum_{k=1}^{3} e^{\log(c^k) - \frac{1}{2}\sum_{t=1}^{50}((\bar{x}_t^k - x_t)^2 + (\bar{y}_t^k - y_t)^2)}$$

https://github.com/lyft/l5kit/blob/master/competition.md

Implementation

1. Data generation and visualization using released Python toolkit l5kit by Lyft

Figure: Satellite View: Ground Truth Trajectory of Autonomous Vehicle

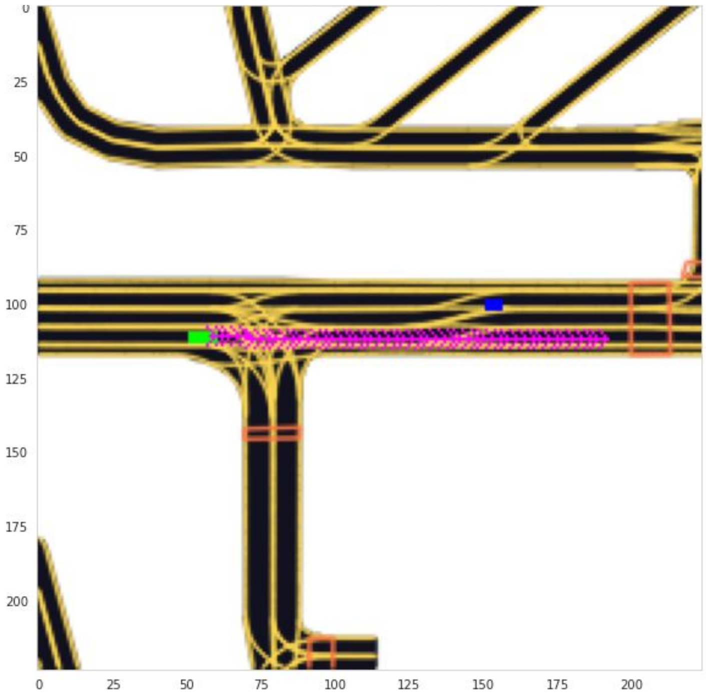

Figure: Semantic View: Ground Truth Trajectory of Autonomous Vehicle

Implementation

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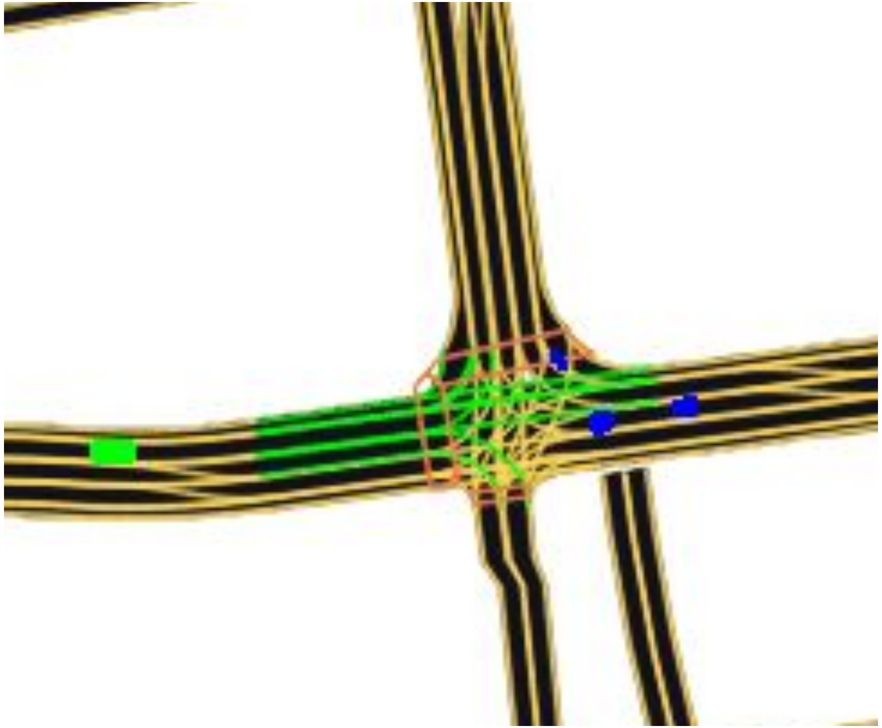

Figure. Self-driving Vehicle Movement during a scene

Implementation

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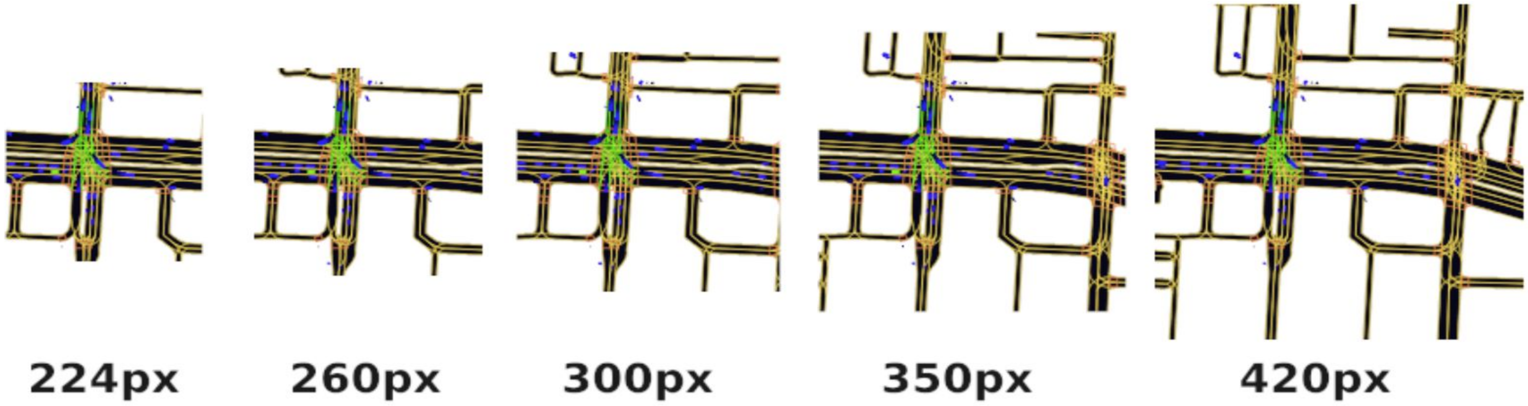
2. Set Configurations for training, validate dataset

- Raster Size: [300, 300]
- Pixel Size: [0.5, 0.5]
- Ego Center: [0.25, 0.5]
- Filter Agents Threshold: 0.5
- History Frames: 10
- Future Frames: 50
- Delta Time: 0.1
- Batch Size: 32
- Disable Traffic Light Faces: False

Implementation

2. Set Configurations for training, validate dataset

- Remove traffic light Mask Layer
    - Traffic light histories has counterproductive effects.
    - Agents velocity has already been considered.
- Image and raster size selection
    - raster_size decides the rasterized image final size in pixels (eg: [300, 300]).



Implementation

3. Training

- Model : **mixnet_xl**
  - batch size: **32**
  - Iterations: **43500**
- Learning Rate **1e-4** with L2 regularizer (weight decay rate) **1e-6**
- Adam optimizer
- Loss Function: use Smooth L1 to converge easier, then Negative Log Likelihood (NLL)

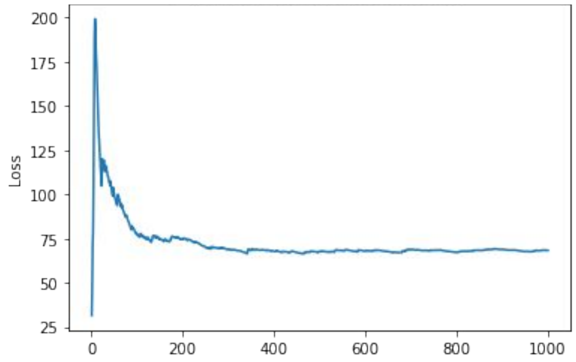


Figure. Average Loss during training, changing from L1 loss to NLL

Implementation

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4. Performance

Table. Negative Log Likelihood Loss vs. Several Configurations

Model	train	validation
mixnet_m, 1 traj, 35000 iterations	55.6	61.4
mixnet_l, 1 traj, 50000 iterations	52.9	53.0
mixnet_xl, 1 traj, 43500 iterations	48.3	**51.8**
Ensembled (with confidence), 3 traj	NULL	34.9
Ensembled (K-means), 3 traj	NULL	**31.4**

Implementation

4. Performance

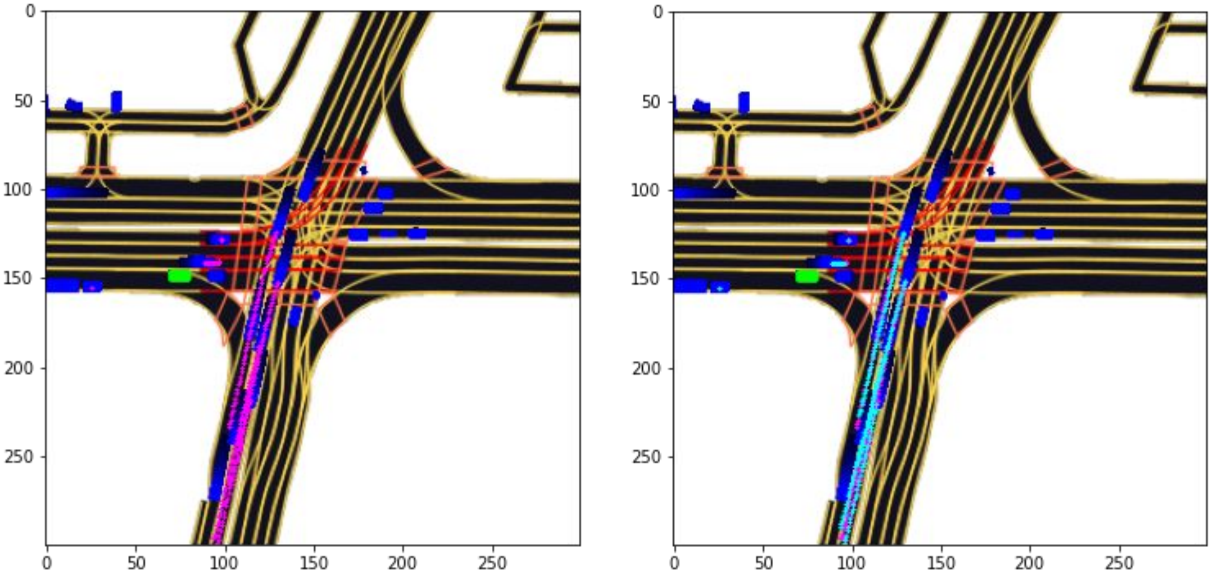
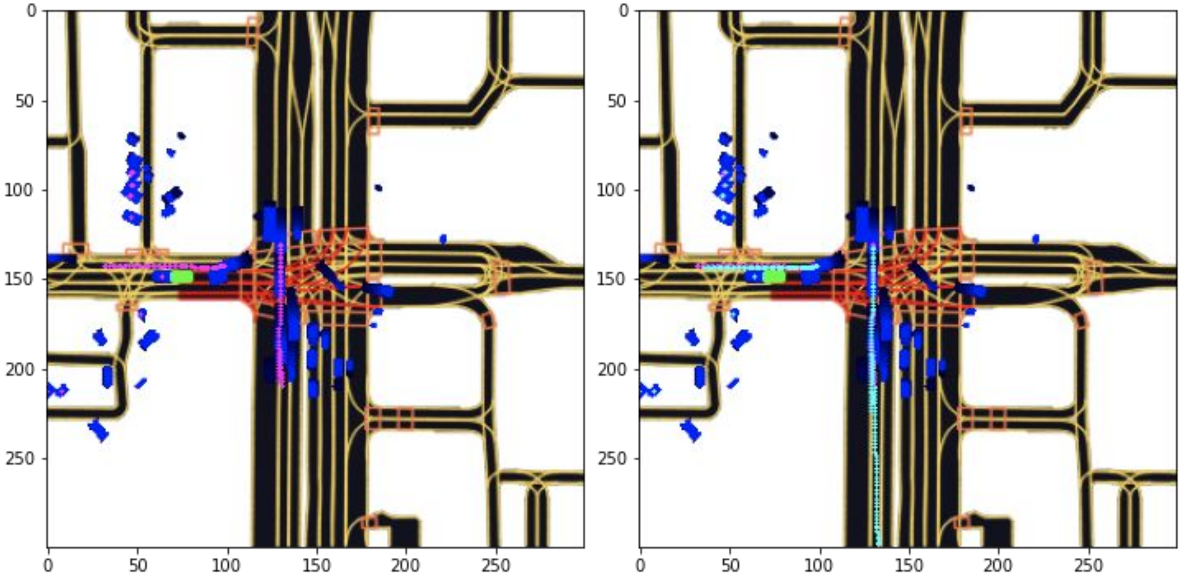


Figure. Example for ground truth (pink line, left) and model prediction (light blue line, right)

Implementation

4. Performance



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Implementation

4. Performance

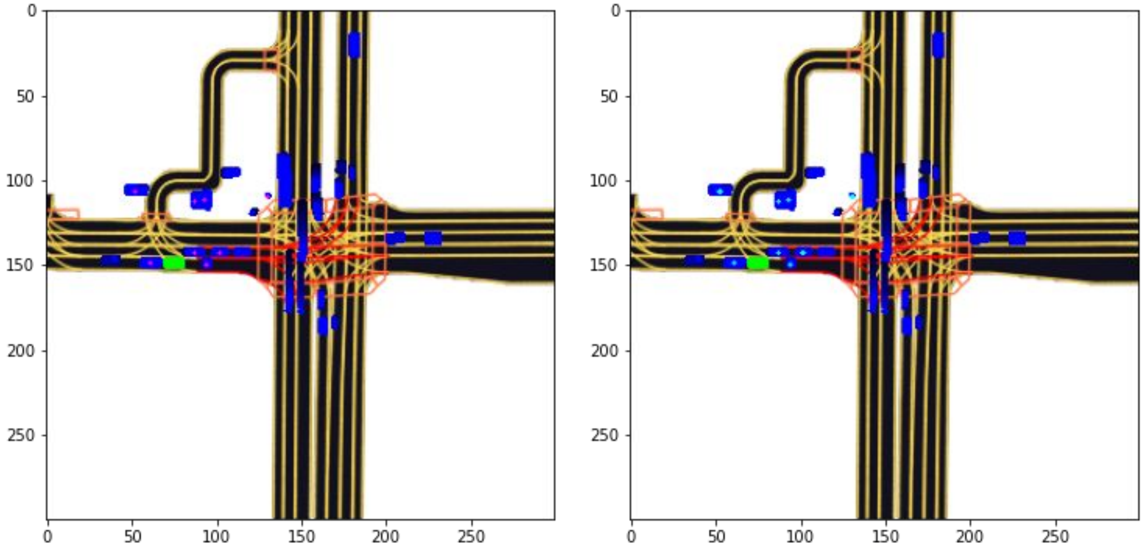

Figure. Example for ground truth (pink line, left) and model prediction (light blue line, right)

Tricks We Tried

- Penalize more on corner cases (pull over, turn, U-turn)
    - If yaw(deviation angle) approximately < 30 degree, set 0.5

$$Custom\ NLL = \begin{cases} NLL \times penalize \times arccos\left(\frac{|dx|}{\sqrt{dx^2+dy^2}}\right) & arccos\left(\frac{|dx|}{\sqrt{dx^2+dy^2}}\right) \geq 0.5 \\ NLL \times penalize \times 0.5 & arccos\left(\frac{|dx|}{\sqrt{dx^2+dy^2}}\right) < 0.5 \end{cases}$$

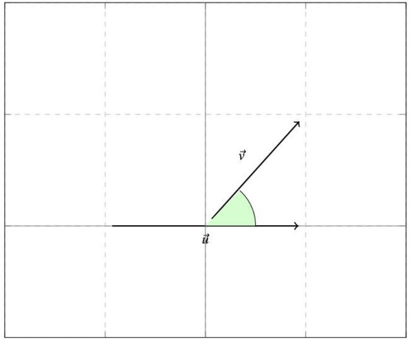

Figure. Penalize is proportion with arc-cosine function

- K-means algorithm: Ensemble 10 Models into 3
    - Clustering several models, vote 3 cluster centroids to represent them
    - Useful when checkpoints are set, not sure whether models are underfitting or overfitting
    - Outperform confidence ensemble by 3.5

Conclusions

- Do not quit too early
  - Train more than 200k samples to make sure performance
  - Be cautious about corner cases
- Be patient when fine-tuning hyperparameters
  - Underfitting model in most cases
  - Improve batch size
- Worth it to try different metrics as the loss function
  - Different metrics have different objectives
  - Smooth L1 VS. NLL VS. Customed NLL
- Future Work
  - GAN
  - LSTM Encoder & Decoder + Social Pooling Layer

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[KOSARAJU, SADEGHIAN: SOCIAL-BIGAT: MULTIMODAL TRAJECTORY FORECASTING USING BICYCLE-GAN AND GRAPH ATTENTION NETWORKS]