AN EMPIRICAL ANALYSIS OF TRAJECTORY PREDICTION TECHNIQUES FOR MOTION PREDICTION IN WAYMO DATASET

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Reception: 15/02/2023 **Acceptance**: 21/04/2023 **Publication**: 10/07/2023

Suggested citation:

Devansh, A., Parul, A. And Ritika, W. (2023). **An Empirical Analysis of Trajectory Prediction Techniques for Motion Prediction in Waymo Dataset.** *3C Tecnología. Glosas de innovación aplicada a la pyme, 12(2)*, 49-63. https://doi.org/10.17993/3ctecno.2023.v12n2e44.49-63

ABSTRACT

The Waymo is the prime and most varied autonomous driving dataset that improves and enhances itself every year. Motion Prediction is a considerable challenge in 2023. This manuscript analyses five considerable methods namely MTR-A, Wayformer, DenseTNT, Golfer and MultiPath++ for their technology applied. The analysis revealed that the Transformer network could achieve a state of the art trajectory prediction as well as scale to many workloads.

KEYWORDS

Trajectory Prediction, Waymo Dataset, Motion Prediction, Transformer Network, Autonomous Driving.

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https://doi.org/10.17993/3ctecno.2023.v12n2e44

1. INTRODUCTION

Google, Uber, Tesla, Mobileye, and numerous automakers have lately made substantial investments in autonomous driving systems, a futuristic use [7]. The autonomous driving technology permits the car to drive itself without human assistance [15]. The car with autonomous driving capacity detects its surroundings, determines its position, and drives itself safely to the given target without human intervention [27]. Demand for this solution continues to rise, resulting in increased industry investment [17]. Mobileye is a pioneer in computer vision-based autonomous driving technology, and Intel just purchased the company for $15.3 billion. Forecasts indicate that by 2035, the market for driverless vehicles will be worth $77 billion [4]. The number of autonomous vehicles is expected to reach 18 million by 2035, which represents 25% of the market [3].

From robot axes to self-driving trucks, it is anticipated that autonomous driving technology will enable a vast array of applications with the potential to save numerous lives [1],[18]. The public availability of large-scale datasets and yardsticks has led to substantial growth in the fields of image categorization, object recognition, object trailing, semantic segmentation, and instance segmentation. Images obtained from numerous high-resolution cameras and sensor readings from numerous high-quality LiDAR scanners installed on a convoy of autonomous vehicles make up the Waymo open data set, the largest and most diversified multimodal autonomous driving dataset to date [6]. When compared to other autonomous driving datasets, ours captures a far wider geographical range, both in terms of overall area covered and allotment of that coverage across geographies [13]. Several cities, including San Francisco, Phoenix, and Mountain View, were sampled across a variety of environmental circumstances, and a vast geographical area was sampled within each city [5],[13],[20]. The dataset demonstrates that the disparities in these regions result in a significant domain gap, hence opening up intriguing potential for research in the field of domain adaptation [6]. Both 3D ground truth bounding boxes for the LiDAR data and 2D bounding boxes that closely fit the camera images are included in the Waymo dataset, which has a large number of them [12]. Track IDs are present in all ground truth containers to assist object tracking [26]. Finally, with our provided rolling shutter aware projection software, scientists can derive 2D a modal camera boxes from 3D LiDAR boxes [2]. Studies involving LiDAR and camera annotations are bolstered by the multimodal ground truth. There are about 12 million camera box annotations, 12 million LiDAR object tracks, and about 250 thousand camera image tracks [10]. Professional labelers used labelling tools suitable for production to make and verify all annotations. It captured all of the sensor data in our dataset using an industrial-strength sensor suite consisting of numerous high-resolution cameras and multiple high-quality LiDAR sensors. Moreover, we provide camera and LiDAR synchronization, which enables exciting cross-domain learning and transfer [2]. Every pixel in the range images we supply also includes accurate information about the vehicle's attitude, in addition to sensor attributes like as elongation. Since this is the original synchronized dataset with such low-level information, it will facilitate studies of alternative LiDAR input formats to the

https://doi.org/10.17993/3ctecno.2023.v12n2e44.49-63
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standard 3D point set format [6],[8]. Now, there are 1000 scenarios used for training and validation, along with 150 scenes used for testing; every scene lasts for 20 seconds [6]. To see how effectively the models, we've trained on our dataset generalize to new environments, we might choose test set scenarios from a geographical holdout area [24],[26].

2. ADDING LABELS AND CHALLENGES TO WAYMO OPEN DATASET.

To broaden the scope of academic inquiry, new labels have been added to the Waymo Open Dataset [6]. The following are included in the extension: The evaluation of central features and spatial context can be a useful extension of models for predicting perception and behavior. Subtle cues, such as a bicycle signaling a turn, are not lost on them. The key point label release is the largest dataset of its kind that is freely accessible for research into autonomous vehicles. We're energized to see how the research neighborhood at large puts it to use to progress the field of human posture evaluation.

Although segmentation has long been recognized as a valuable tool in the academic world, the vast majority of publicly available datasets for autonomous driving only provide bounding boxes to characterize and categorize objects, which might lead to the absence of critical information. In order to identify and categorize each pixel in an image or LiDAR point cloud as part of a certain object, segmentation labelling is employed [11]. This remarkable level of granularity is made possible by the insertion of 3D segmentation labels for 23 classes and 1,150 segments of the Waymo Open Dataset [6],[17].

It could be confusing or time-consuming to match up the bounding boxes from a 2D camera with their 3D equivalents in LiDAR labels. In order to promote further research on sensor fusion for object recognition and detection, we have added labels based on the standard 2D-to-3D bounding box correspondence.

Along from all these new tools, Waymo has also launched the 2023 Waymo Open Dataset Challenges, which will have participants forecast the whereabouts of up to eight agents eight seconds into the future using only the agents' historical one-second tracks on an associated map [14],[23],[25].

3. WAYMO OPEN DATASET: MOTION PREDICTION CHALLENGE

The capacity to predict the behavior of other drivers is essential for safe and successful driving [25]. Important questions can be: Is that the sound of a pedestrian trying to cross? How close is that car to entering my lane, and is it parallel parked? Is the speeding car going to roll through the stop sign? One of the most demanding

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aspects of autonomous driving is accurately predicting the behavior of other road users. There are also serious safety concerns; being able to precisely predict the actions of other drivers is crucial for avoiding collisions. While researchers in the ground of autonomous vehicles have made significant strides in recent years in solving the problem of motion prediction, the industry would benefit from having access to even more high-quality open-source motion data.

To the best of our knowledge, the Waymo Open Dataset motion challenge is the largest interactive dataset released to date for study of behavior prediction and motion forecasting for autonomous driving, and we've expanded it in this work. In order to help any research group looking into how to construct its own high-quality motion data, we are reviewing all the articles describing the state-of-the-art research perception method used to annotate the motion dataset. This is especially true of high-quality motion data, which can be difficult to come by and sometimes costs a lot of money to obtain.

An advanced perception system is needed to build a motion dataset with high-quality labels, as this requires the ability to reliably identify agents and objects from camera and LidaR data, as well as track their movement within the image. The collection of compelling motion data is similarly difficult. Most commutes are uneventful, therefore there is little to no useful information to use in developing a system to anticipate what can happen on the road under extreme circumstances. As a result, there are usually just a few of interesting interactions included in the datasets that are publicly available.

The Waymo Open Dataset is designed to address these issues. Predict the positions of up to eight agents eight seconds into the future, given their 1 second-ago tracks on a comparable map. The ground truth future data for the test set is concealed from challenge participants in order to facilitate the motion prediction task. As a result, the test sets only include one second of historical data. The validation sets contain the actual future ground truth data for use in model building. In addition, the test and validation sets include a list of up to eight predicted object tracks in the scene. They are chosen for their engaging behavior and variety of object types.

4. LEADERBOARD BEST SOLUTIONS

Each Scenario Predictions proto within a motion prediction submission corresponds to a single scenario in the test set and contains up to eight predictions for the objects indicated in the tracks to predict field of the scenario [19],[9]. While these are distinct forecasts, each Joint Predictions proto comprises a prediction for a single item. Each Multi Modal Prediction prototype will include a maximum of six trajectory predictions, each accompanied by a confidence rating. Trajectory forecasts must include precisely 16 position samples, each corresponding to the next 8 seconds and sampled at a rate of 2 Hz. Wayformer's attention-based scene encoder/decoder is modest [16]. Nigamaa Nayakanti and all study scene encoder early, late, and hierarchical input

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fusion [16]. Factorized or latent query attention balances efficiency and quality for each fusion type. Nigamaa Nayakanti and all design philosophy proves that early fusion, despite its simplicity, is modality neutral and performs at the top of the Waymo Open Motion Dataset (WOMD) and Argoverse leaderboards. Shaoshuai Shi and all offer a distinctive Motion Transformer framework for multimodal motion prediction, which initiates a restricted set of novel motion query pairs for producing superior multimodal future trajectories by conducting intention localization and iterative motion refining simultaneously [19]. Balakrishnan Varadarajan and all in their manuscript directly uses agent state information and compact polylines to describe road features (e.g., position, velocity, acceleration) [22]. Balakrishnan Varadarajan et. al. examines pre-defined, static anchors and develop a model to discover latent anchor embeddings end-to-end. Balakrishnan Varadarajan et. al. use ensembling and output aggregation approaches from other ML areas to find appropriate probabilistic multimodal output representations. Yueming Zhang introduces a real-time 2D object detection algorithm from photos [25]. Yueming Zhang aggregate multiple common one-stage object detectors and train various input strategy models independently to improve multi-scale identification of each category, notably small objects. TensorRT optimizes detection pipeline inference time for model acceleration. Junru Gu offer an anchor-free model, dubbed DenseTNT, which performs opaque goal probability estimate for trajectory prediction [9]. Without relying on the value of heuristically set goal anchors, its performance vastly improves. In the next section we will compare and analyze the leaderboard solutions and understand the research areas where work can be done.

5. RESULTS

Table 1 below highlights the research gaps we discovered of our analysis of the five above methodologies. These gaps lay the ground for considerable future research.

TABLE 1. Comparison of Considerable Leaderboard Solutions for Motion Prediction in Waymo Dataset

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S. No.	Title	Ref.	Methodology	Findings	Research Gaps
1	MTR-A: 1st Place Solution for 2022 Waymo Open Dataset Challenge - Motion Prediction	[19]	We introduce the Motion Transformer, a novel architecture for multimodal motion prediction that uses simultaneous intention localization and iterative motion refinement to generate better multimodal future trajectories. To further improve the performance of the final model, a basic model ensemble technique with non-maximal suppression is employed.	Approach came in first on the leaderboard and did better than all the other submissions in terms of Soft mAP, mAP, and the miss rate. This means that their method is better at predicting multimodal future trajectories.	Agent-centric modelling forecasts the multimodal future trajectories of a single interested agent while redundantly encoding the situation for additional interested actors. So, it is an upcoming problem to build a multimodal motion prediction system for several actors. Even when using a rule-based post-processing method, accuracy in predicting the minADE/minFDE can be low. If you want a more solid structure, it's worth your time to learn how to generate 6 possible future trajectories using multimodal predictions (e.g., 64 predictions).

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2	DenseTNT: Waymo Open Dataset Motion Prediction	[9]	DenseTNT is a model without anchors that conducts dense goal probability estimate for trajectory prediction. The author extracts sparse scene context characteristics before employing a dense probability estimation to construct the probability distribution of the goal candidates. A trajectory completion module then generates trajectories depending on a set of selected objectives.	The objective candidates are densely dispersed over the map in DenseTNT. We display the probability of the dense goals and the anticipated trajectories based on the specified goals. DenseTNT provides different predictions, including travelling straight, making left/right turns, and U-turns.	Complex trajectory generation in dense TNT is computationally intensive and time consuming, especially in dynamic environments with moving obstacles. As a result, its usefulness in real-time contexts may be hampered. In addition, Dense TNT is highly sensitive to the initial conditions, with even a small shift in the robot's or the obstacles' starting position leading to a dramatically different path. In applications where the initial conditions are uncertain or may change during the plan's execution, this can be problematic.

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3	Wayformer: Motion Forecasting via Simple & Efficient Attention Networks	[16]	Wayformer is a simple and unified family of attention-based architectures for motion prediction introduced in this paper. A scene encoder and decoder that is based on attention are the meat and potatoes of Wayformer's model description. We explore the use of early, late, and hierarchical input fusion in the scene encoder. We look into methods of achieving a happy medium between speed and accuracy, using either factorized or latent query attention, for every possible combination of	The results obtained by Wayformer on the Waymo Open Motion Dataset (WOMD) and the Argoverse leaderboards validate the effectiveness of our design philosophy and show that early fusion is not only modality agnostic but also delivers state-of-the-art outcomes.	The following are the limits placed on the scope of this investigation: Processing the same data over and again is a burden for egocentric modelling in complex settings. This can be avoided by encoding the scene only once, in a world-at-once reference frame. The input to the system is a vague and generalized description of the world, which leaves out important details in complex situations, such as indications from human eyes or fine-grained contour or wheel angle information for vehicles. Gaining an all-encompassing understanding of perception and prediction could pave the way for progress. Each agent's distribution over possible futures is modelled separately in time and space, and each agent's distribution over possible futures is modelled conditionally independently in time and space given their goal.

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4	Golfer: Trajectory Prediction with Masked Goal Conditioning MnM Network	[21]	For the purpose of AV trajectory prediction, authors provide a universal Transformer-like architectural module MnM network with innovative masked goal conditioning training methods.	It has been demonstrated that the resulting MnM network, which consists of solely MnM blocks stacked on top of one another, is superior since it can predict trajectories given point-like agent and road inputs. On May 23, 2022, authors golfer-named trajectory prediction model, which was enhanced with the new masked goal conditioning and MnM network, was rated second on the Waymo Open Motion Dataset leaderboard.	In order to learn cross-correlations between items in a set, the proposed Mix and Match (MnM) block, a broad kind of set transformation, has been shown to be particularly useful. This building block may not be suitable for use in all circumstances, though.

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5	Multipath++: efficient information fusion and trajectory aggregation for behavior prediction	[20]	The MultiPath framework can cope with the problem of a multimodal output space by using a Gaussian Mixture Model to characterize the extremely multimodal output distributions. With the help of static trajectory anchors, an external input to the model, this method can overcome the common problem of mode collapse in the learning process. This useful technique provides experts with a fundamental strategy for guaranteeing consistency and an extra measure of control for modelers through the creation of such anchors.	The provided model performs at the state-of-the-art level in both the Argoverse Motion Forecasting Competition and the Waymo Open Dataset Motion Prediction Challenge. Sparse encoding, efficient fusion methods, control-based approaches, and learned anchors were all shown to be crucial by the authors. Furthermore, we provided a practical guidance for implementing different training and inference procedures to enhance robustness, diversity, missing data handling, and training convergence speed.	Multipath++ is only capable of predicting a path a few seconds into the future. While this may be sufficient for some applications, others may necessitate more advanced prediction techniques.

6. CONCLUSION

MTRA, Golfer and Wayformer underlined that Transformer can be trained substantially faster than recurrent or convolutional layer-based designs. The Transformer utilizes multi-headed focus in three distinct ways. In an encoder-decoder architecture, the memory's keys and values are produced by the encoder, while queries are passed down from the previous decoder layer. This allows the decoder's input positions to process the entire sequence. This is similar to the focus mechanisms of encoder-decoder models used in sequence-to-sequence models. The encoder has layers for introspective processing. In a self-attention layer, the output of

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the previous layer's encoder is used as the source for all keys, values, and queries. The encoder's architecture allows for all of the previous layer's positions to be serviced from any given place. Like the encoder, the decoder has self-attention layers that allow any location in the decoder to pay attention to all other positions. The auto-regressive property can only be preserved by blocking leftward information flow in the decoder.

7. FUTURE SCOPE

Based on what we learned from our analysis, we conclude that Transformers networks, modified to improve their baseline architecture of input encodings and overall models, produce the best results. With transformers, one can interpret which parts of the input sequence are most crucial to generating the output thanks to their attention mechanisms. This allows transformers to achieve state-of-the-art results in the case of trajectory prediction and scale to a wide range of tasks.

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https://doi.org/10.17993/3ctecno.2023.v12n2e44