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Multi-Metric evaluation of Attention-Based Neural Network Architectures for Autonomous Driving

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Abstract: Autonomous driving is the capability of a vehicle to drive on its own. Self-driving cars can reduce human efforts, transportation cost, number of deaths in road accidents. Deep Learning (subset of Neural Network) has huge number of models with which the research on autonomous driving is made easy. Attention is a mechanism that gives different type of results when it is integrated with different Deep learning models. This paper evaluates some important Attention Mechanisms of Transformer model by calculating multiple metrics for each Mechanism.

Key words: Collision rate, Driving Score, F1 Score, IoU, mAP, Route Completion.

1. INTRODUCTION

A neural network is a computing system made up of a number of simple, highly interconnected nodes or processing elements, which process information by its dynamic state response to external inputs. In a neural network, the nodes are interconnected in a manner similar to how neurons are connected in the human brain. **Attention** [5] in neural networks is a mechanism that enables a model to focus on the most **relevant parts** of the input data while processing information, rather than treating all inputs equally. Just like humans focus on important details (while driving), an attention-based model selectively concentrates on important features and ignores less relevant ones. Transformer models [8] of Deep learning are mainly built on Attention mechanisms. Transformer model of Deep Neural networks uses Attention mechanisms [5] like self-Attention, Scaled Dot-Product Attention, Multi-Head Attention. This three Attention Mechanisms need to be Evaluated.

2. MULTI-METRICS OF AUTONOMOUS DRIVING

In order to evaluate the best attention mechanism Some important factors of Autonomous driving need to be calculated for each Attention Mechanism.

The Factors that are used in this research are as follows:

a) mAP

b) IoU

c) F1-Score

d) Collision rate

e) Driving Score

f) Route Completion %

a) mAP: mAP stands for mean Average precision. mAP is the metric to evaluate how well a model detect and classifies objects like cars.

$$mAP = \frac{1}{N}\sum_{c=1}^{N} AP_c$$

N = number of object classes, AP_c= Average Precision for Class ‘c’.

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A class refers to a predefined category of objects (e.g., car, pedestrian, cyclist) that a model is trained to detect and classify.

b) IoU(Intersection over Union): IoU [3] is a metric used in object detection to measure how well a predicted bounding box matches the actual (ground-level truth) box. It is the ratio between overlap area and union area. It ranges from 0 to 1.

Case 1: If IoU = 1 then it means perfect match

Case 2: if IoU = 0 then it means no overlap

Case 3: if 0 < IoU < 1 then it means partial match

c) F1-Score: F1-Score is a metric that uses both precision and recall. It talks about how well the model can balance between correctness and completeness.

$$F1\ Score = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

If F1-Score is 1 then the model is the best model. If the Score is 0 then the model said as the worst model.

d) Collision Rate: Collision rate [1] defines how often a vehicle (or model) results in a crash during testing or simulation.

$$Collision\ Rate = \frac{\text{Number of Collisions}}{\text{Total Exposure}}$$

Here Exposure can be Time or Distance or Episodes.

e) Driving Score: The Driving Score is the Score that is obtained by the model during Self driving. It is based on Success Rate(S), Collision Rate(C) and Lane Violation Rate(L).

$$S = \frac{N_{success}}{N_{total}}\ C = \frac{N_{collision}}{D_{total}}\ L = \frac{N_{lane\ violations}}{D_{total}}$$

N = Number, D = Distance

$$\text{Driving Score} = w_1 \times S - w_2 \times C - w_3 \times L$$

Here w_1, w_2, w_3 are the weights of Success Rate(S), Collision Rate(C) and Lane Violation Rate(L). A driving Score which is near to 1 is treated as best Driving and Driving Score =0 is worst Driving.

f) Route Completion %: In autonomous driving, Route Completion Percentage measures how much of a planned route the vehicle successfully completes.

$$Route\ Completion\ \% = \frac{Distance\ Travelled}{\text{Total Planned Route Distance}} \times 100$$

If it is Equal to 100 then it indicates that the total planned distance is travelled.

3. NEED FOR EVALUATION

Evaluation helps identify which attention mechanism performs best under the same conditions.
Different attention mechanisms may:

- detect objects differently
- focus on different regions
- require different computation time
- produce different driving performance

So, Evaluation allows fair comparison.

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Benefits of Evaluation

A. Performance Comparison

To determine which mechanism gives:

- higher accuracy
- better detection
- safer driving behaviour

B. To provide Safety

Autonomous driving is safety-critical [11].
evaluation helps identify:

- models with fewer collisions
- better road understanding
- more reliable decisions

C. Computational Efficiency

Some mechanisms:

- are more accurate but slower

Benchmarking [10] helps balance:

- accuracy
- speed
- memory usage

D. Robustness Analysis

Different attention methods behave differently under:

- rain
- fog
- night driving
- crowded traffic

Evaluation shows which model is more stable.

E. Research Validation

Without benchmarking, it is difficult to prove:

- why one model is better
- whether improvements are needed or not

4. EVALUATION

Since the evaluation requires various factors to calculate therefore this research uses mAP, IoU, F1-Score, Collision rate, Driving Score, Route Completion %. To train a model some simulator must be used. CARLA [6] is the best and open-source Simulator available for the Self-Driving Research. After enabling the CARLA environment [17], the model can capture the images to predict the future incidents. The above metrics are calculated for every individual Attention mechanism-based model. The following are the results that are exposed by the trained models.

Name of the Metric	Self-Attention	Scaled dot-product Attention	Multi-Head Attention
mAp	0.829	0.776	0.671
IoU	0.76	0.619	0.723
F1-Score	0.751	0.71	0.833
Collision Rate	0.142	0.007	0.027
Driving Score	81.44	70.53	81.6
Route Completion%	89.31	82.2	89.55

Table: Multi-Metric values of attention mechanisms

mAp values are calculated based on the Precision. The Self-Attention mechanism produced higher mAp values compared with other mechanisms which indicates that the trained model (following Self-Attention) detecting and locating objects

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accurately. Self-Attention scored higher IoU values showing that the predicted bounding box matches the actual (ground-level truth) box.

When it comes to F1-Score the Multi-Head Attention produced higher values. Generally, F1-Score is computed based on Precision and Recall. Multi-Head Attention is an extension of the attention mechanism in which multiple attention operations are performed in parallel, enabling the model to learn different feature representations and relationships simultaneously. It uses multiple Heads [5] where each Head focuses on different aspect of the upcoming event.

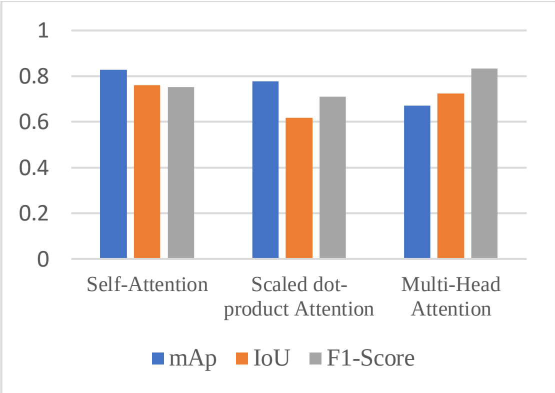

Chart 1: Comparison of mAp, IoU and F1-Score values

Collision Rate Explains about the number of Collisions occurred in a given amount of time. The Self-Attention mechanism produced a greater number of collisions because it can only focus on one aspect of the incoming event at a time. The remaining two mechanisms scored very less values when compared with the Self-Attention Mechanism.

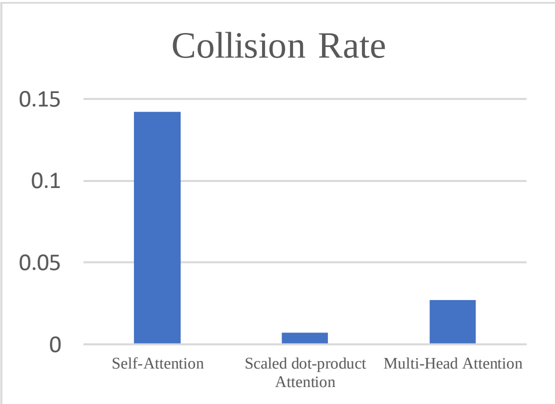

Chart 2: Collision Rate values Comparison

Good Driving Score is allotted to the drive which perform well. It considers all aspects of driving. It depends on number of successful episodes, number of collisions and number of lane violations. By observing the below chart, it is easy to tell that Scaled dot-product Attention scored lesser Driving Score compared with others. Route Completion percentage is the percentage of planned distance covered by a mechanism. It is necessary for an autonomous driving vehicle to complete the total given distance. Utilizing self-attention, scaled dot-product attention, and multi-head attention, the below given chart illustrates the percentages of distance (planned distance) covered in autonomous driving.

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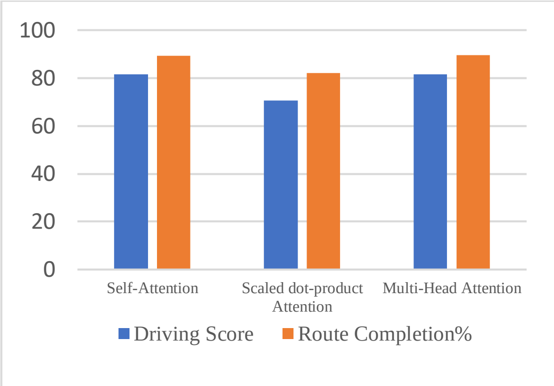

Chart 3: Driving Score and Route Completion percentage Comparison

Even in Route Completion aspect also Scaled dot-product Attention showed least value amongst all Attention Mechanisms (Self, Scaled dot-product and Multi-Head).

5.CONCLUSION

Because of the availability of various attention mechanisms in Neural Networks (e.g., Self-Attention, Scaled dot-product, Multi-Head), it is crucial to evaluate them, as it helps to increase the accuracy and efficiency of AI models. In this research metrics like mAp, IoU, F1-Score, Collision Rate, Driving Score, Route Completion percentage are used for this evaluation. In almost all metrics the Scaled dot-product attention scored lesser values. The collision rate is higher in self-Attention model (indicating more collisions). Apart from the collision rate and mAp, the two mechanisms named Self-Attention and Multi-Head attention performed well and almost equal in all aspects.

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