Group 10: Motion Prediction in Autonomous Cars

Summary:

- Autonomous driving is one of the big things in machine learning right now and so improving the motion prediction for these vehicles is important for safety. The data for training, validation, and testing is from 20 second tracked motion data for car surroundings. The model for this project is a encoder/decoder transformer that is meant to challenge and surpass a baseline MCG model. The MCG model outperformed this current version of the transformer model, but incorporating more training data and more diverse data may improve upon this. Also, including a temporal aspect of this project is the next step which could also improve its performance. With safety being the prime concern for autonomous vehicles, there are many more aspects to consider going forward to improve the accuracy of this model.

High Level Problem Description: P-1.5

- The group did provide a description of the problem, but no real reason as to why the problem is a problem in the first place. The problem description says that predicting the trajectory of surrounding objects for autonomous vehicles is important, but not why it's important. Are there non-obvious reasons as to why this is a huge problem? Obviously there are some quite obvious reasons, but that's obvious to us who have background in this and might not to someone who does not.

Technical ML Problem Description: ML-2

- The description of why ML is particularly applicable to this problem is clear and concise. The only thing that we think is missing is perhaps a mention of what models are typically used for problems like this, outside of what the group is using in the project. It would be nice to get an overview of what some other people in the field are using or have been tried in the past that are more deep learning focused: i.e. have people tried RNNs or their variants? Vision based models? The like.

Data Used: DT-2

- The data section is very detailed. We did have a few questions though that we think answering in the section would have made the project clearer. The data includes other agents but the section does not describe what sort of agents those can be, which leaves us wondering if it was just cars, pedestrians, a combination, even more things beyond that like trucks or perhaps things in the road. Another question is if there was a reason for those specific 8 categories of trajectories chosen (Stationary, Straight, Straight Left, Straight Right, Left Turn, Right Turn, Left-U-Turn, Right U-Turn). Was there a reason to not go more fine grained? Less fine grained?

Algorithms Implemented/Why: A-2

- Good reason for why the architecture they used is given as well as detailed diagrams for what it looks like. An improvement that we think could be made is laying out more exactly what the MCG blocks do. They're an approximation of cross attention, but what is cross attention? We also think that this section would have been bolstered by laying out the Multipath++ diagram alongside the modified version to see what was changed between the two.

Final Results: R-2

- Thorough reporting of results. One thing that we wish there would have been is roadgraph networks from the MCG network in addition to the transformer network. We think that this would have shown how much better MCG was in realistic scenarios rather than just the scores. Additionally, we were unsure what the "miss rate" score was referring to and would have appreciated at least a little explanation as to what it was.

Discussion of Results: D-2

- Discussion of results was also thorough. The mention of hyperparameter tuning as one of the reasons that the transformer might have performed worse got us curious: what sort of hyperparameter tuning was done on that architecture? Another thing that we feel would have made the discussion of results better is any sort of benefits of the transformer architecture over the MCG. Was it faster at inference time, smaller, etc…?

Next Steps: NS-2

- There were three next steps clearly described with the inclusion of an end goal as well. We think those are some great ideas to try moving forward, particularly expanding the temporal aspect of the project because that might add a new important element.

Feedback: F-2

- The main suggestion the group received was implemented in the form of a comparative study which is a good way to compare models in this field. There are also some future steps to expand on this described afterwards. This is the only feedback mentioned so we assume this was the general consensus for the peer and instructor feedback and any other minor feedback was also included.

Novelty: N-1.5

- Perhaps the group's *specific* architecture is novel, but there are a few other articles found that apply transformer architectures to this relatively same application. Additionally, as far as we could find, there were no other articles that compared MCG to transformer architecture.

Learnings: L-1

- As far as we can tell, there was not much discussion of what was learned. Perhaps some discussion was indirectly had when the group mentioned why the transformer architecture might not have been performing well, but we would have liked to see more specific learnings from the project described somewhere. Was anything learned about autonomous vehicle movement prediction, or the specific architectures that were used? It would have been interesting to hear about that.

Future Work Suggestions:

- This is a really interesting project and, in the future after more tuning of the transformer model is done, we think it would be really interesting to see these models applied to physical agents. A real life test would show just how well each model does in the situations and better differentiate than just a graph visualization. Additionally, we think it would just be really cool!
- The group mentioned some limitations of the current model including challenges with increased complexity and how it deals with noise and uncertainty. Because of this, we would like to see the group expand the data set and implement some strategies for denoising which might improve the results without necessarily changing the model. Part of this could include getting data from other locations, since many parts of the world have very unique driving patterns and surroundings.
- We think you should consider expanding the number of different motions in the project. While 8 options is already a lot for training, with safety being such a large concern for these autonomous driving cars, it might still be important since real life objects can move in any way and direction. This would be challenging for training obviously as well but we think it is at least something to consider for the Waymo challenge.
- Good luck in the Waymo open challenge!