Topic: Designing and training foundation models for positioning applications

Foundation models (like OpenAI's GPT-4/ChatGPT [\[1\]](#page-1-0) or Meta's Llama 2 [\[2\]\)](#page-1-1) have been a disruptive technology that within just few months has started to transform the modus operandi of several industries. There have been already notable applications on tax/legal [\[3\],](#page-1-2) public health [\[4\]](#page-1-3) and computer code generatio[n \[5\]](#page-1-4) domains, among others.

Despite their undeniable success, these models – even after being fine-tuned – are not a "one size fits them all" solution, as there are use cases (such as the positioning applications addressed in this Thesis [\[6\]\)](#page-1-5) that require a different line of thought. Here, an ideal solution/algorithm would inherently support multiple tasks during deployment, without the necessity of specialized fine-tuning:

- 1. predict the current position of a user equipment (UE, e.g., a cell phone)
- 2. given the current UE track, generate potential future positions (i.e., generate plausible future UE tracks)
- 3. given a sequence of positions, generate the expected measurements (pure generative model)
- 4. Given a UE track with measurements but with missing ground truth labels (true positions), infer the most probable sequence of positions for the missing parts
- 5. given measurements and position predictions from positioning system X, provide an estimate on the achieved positioning accuracy of the system.

Even though notable efforts in the direction of semi-supervised learning/generative modeling for positioning systems exist [\[7\],](#page-1-6) [\[8\],](#page-1-7) a unified approach that can address all the above points is yet to be reported.

In the present Thesis, we take a radical approach and formulate the given positioning problem as an offline reinforcement learning (RL) setting that falls under the partially observable Markov decision process (POMDP) class [\[9\].](#page-1-8) Interestingly, in this setting, we can utilize novel approaches that suggest utilization of foundation models for the robust training of multi-task, offline RL agents [\[10\],](#page-1-9) as a starting point. Here, the state space of the POMDP contains relevant information and measurements (e.g., LOS/NLOS conditions, coarse initial position, (compressed) channel input response (CIR) information, movement type, etc.) while actions and rewards are the predicted positions and the positioning error of the system respectively.

Our main hypothesis, that needs to be verified by the Thesis, is that by moving further from the "passive" positioning approach that relies on estimation theory towards a more "active" approach that treats the problem as a sequential decision making one, we can devise an algorithm (or a family of algorithms) that enables multi-task-aware training and addresses all five points/tasks of the ideal solution defined above.

For the training and evaluation of the algorithm, data from a specific area under different static (geometry) and dynamic (e.g., reflection properties, movement of UEs and obstacles, etc.) will be generated using QuaDRiGa [\[11\].](#page-1-10) The successful completion of the Thesis would demonstrate the efficiency of the developed algorithm in all different tasks defined above, under various UE/obstacle movement patterns and environment geometries.

The proposed work consists of the following parts:

- Literature review on sequence-based offline RL algorithms (1 month)
- Selection of proper/meaningful inputs for the model/algorithm and definition of training/test scenarios for all tasks to be addressed (1 month)
- Data generation for the training/evaluations and implementation of the equivalent OpenAI Gym/Gymnasium environments (0.5 months)
- Design of an experimental protocol for evaluating the effect of the different model parameters/properties (0.5 months)
- Experimental evaluation (2 months)
- Writing of thesis (1 month)

The thesis must contain a detailed description of all developed and used algorithms as well as a profound result evaluation and discussion. The implemented code must be documented and provided.

References

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