MISSION

MAMMALS aims to provide low-latency inferences by running—close to the end user—simple machine learning models that can also take advantage of a (small) local datastore of examples. The focus is on algorithms to learn online what to store locally to improve inference quality and achieve domain adaptation.

PROJECT DESCRIPTION

A machine learning (ML) model is often trained for inference's purposes. Inference does not involve complex iterative algorithms and is therefore generally presumed to be easy. Nevertheless, it presents fundamental challenges that are likely to become dominant as ML adoption increases and ML systems are ubiquitously deployed and need to make timely and safe decisions in unpredictable environments [16]. Big cloud providers, such as Amazon, Microsoft, and Google, offer their “machine learning as a service” (MLaaS) solutions, but running the models in the cloud may fail to meet delay requirements, often below 10ms and below 1 ms for what is now called the tactile internet [15]. Such requirements can only be met by running ML prediction services at the edge of the network—directly on users’ devices or at nearby servers—without the computing and storage capabilities of the cloud. Privacy and data ownership also call for inference at the edge.

The current approach to run inference at the edge is to take state-of-the-art (SOTA) large ML models on users’ devices or at nearby servers—without the computing and storage capabilities of the cloud. Privacy and data ownership also call for inference at the edge.

The research is in the framework of the Inria's exploratory action MAMMALS (Memory-augmented Models for low-latency Machine-learning Servings). The postdoc will collaborate with a PhD student already hired.

MISSION CONFIEE

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REFERENCES

Principales activités

I. Design of online learning algorithms.

We plan to evaluate three different frameworks for learning online how to populate the local datastore.

1. Adapt existing caching policies like LRU, e.g., by inserting the content on the basis of its marginal utility (i.e., its contribution to inference quality). Ad-hoc policies in this spirit have been proposed to support image similarity search in [3] and in [8]. This framework leads usually to a combinatorial analysis with a focus on expected performance under a stochastic request process.

2. Study the problem as a discrete-space metrical task system (MTS) [2], where the state of the system is the set of instances in the datastore. Each state has a corresponding service cost (the loss of inference quality due to running a simpler model at the edge) and updating the datastore generates so-called movement costs. Competitive analysis is the common approach to study this setting.

3. When the set of possible instances is very large and roughly homogeneously distributed, at least over a low-dimension manifold, it is possible to consider the state space to be continuous. This setting is closer to online machine learning with regret as its main performance metric.

At the methodological level, we will explore gradient-based approaches. They are common in online machine learning, but, more recently, they have also been effectively employed to study combinatorial problems in the other two settings [1, 3, 14].

II. Characterization of datasets’ topological properties.

Which framework, among the three described above, is the most appropriate? The answer depends to a large extent on the topological properties of the space where instances lie. Whereas we are looking for collaborations with other research teams studying the topological and geometric structure of data, we will push a practical approach, starting from real traces. Many traces are available for recommender systems based on ML predictors. This application is particularly interesting for MAMMALS, as recommendations need to be customized to the user (a particular example of domain adaptation) and constantly updated to follow dynamic popularities of media contents or products.

III. Prototype implementation.

We plan to provide practical evidence of the potential improvements from MAMMALS new algorithms in a simpler context. In many ML and information retrieval applications it is required to retrieve fast the k nearest neighbours (k-NN) of a given point in a dataset. When the number of dimensions exceeds 10, exact k-NN computation essentially requires to scan the whole dataset [17], so approximate indexing structures have been proposed and are currently implemented in libraries like Facebook Faiss [7]. Now, these systems can also benefit from a fast memory that stores a small subset of the whole repository. Managing this memory dynamically presents many of the challenges described above with the advantage of 1) avoiding the additional complexity of the interaction with the model, and 2) having a clear evaluation framework with well established benchmarks and performance metrics.

Avantages

- Subsidized meals
- Partial reimbursement of public transport costs

Compétences

We are looking for one of the following profiles:

1) a candidate with solid analytical skills to design algorithms with strong performance guarantees,

2) a candidate expert on high-dimensional data analysis,

3) a candidate with hands-on experience on machine learning, able to reproduce state-of-the-art results like those in [12] and in [19].
- Leave: 7 weeks of annual leave + 10 extra days off due to RTT (statutory reduction in working hours) + possibility of exceptional leave (sick children, moving home, etc.)
- Possibility of teleworking (after 6 months of employment) and flexible organization of working hours
- Professional equipment available (videoconferencing, loan of computer equipment, etc.)
- Social, cultural and sports events and activities
- Access to vocational training
- Social security coverage

Rémunération

Gross Salary: 2653 € per month