

# **Approximate Reasoning for Data-driven Tasks**

**Management at the Edge** 

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## Introduction

Emerging technologies such as the Internet of Things, social networking, and online games have caused a significant increase in the volume of data being generated at the network edge. Meanwhile, the concept of data-driven tasks has drawn increased attention in the last few years. Data-driven tasks rely heavily on data generated by smart devices (e.g., sensors and smartphones) to build knowledge and make decisions.

**Execution of data-driven tasks can happen on:** 

- Smart devices
- Cloud Computing or

## **Problem Statement**

EC system with  $N = \{n_1, n_2, n_3, \dots, n_n\}$  Nodes. Data points  $\mathbf{x} = [x_1, x_2, \dots, x_n]^T \in \mathbb{R}^d$ . Each node  $n_i$ has а neighbourhood  $N_i \subset N$  of directly communicating nodes. node  $n_i$  communicates Moreover, with endthe users/applications and a remote cloud server.  $n_i$  can execute locally certain data-driven tasks.



Edge computing

**Research question** : How can data-driven tasks obtain all the required data from various sources without sacrificing the device's computation resources?

## Methods & Results

### **Task Management Mechanism** Factors

introduce the basic factors for We inferring the right execution decision for each task  $T_k$  on each node  $n_k$ corresponding to :

### 1. Task popularity $p_k$



#### 2. Outliers $o_k$



**Figure 2.** The probability of offloading.

### Experiment

We used synthetic dataset to simulate while the tasks' popularities data

#### **Results**:

• Probability of offloading  $(r_k)$  for each task  $(T_{k}).$ 

**Table 1.** The probability of offloading  $r_k$  for each task  $T_k$ .

| $T_k$ | $p_k$ | $u_k$ | $u_k$ | $M_{1}(r_{k})$ | $M_2(r_k)$ | $M_{3}(r_{k})$ |
|-------|-------|-------|-------|----------------|------------|----------------|
| $T_1$ | Low   | Yes   | Low   | 83%            | 84%        | 57%            |
| $T_2$ | Med   | No    | High  | 30.4%          | 32%        | 42%            |
| $T_3$ | Low   | No    | Low   | 85%            | 86%        | 72.9%          |
| $T_4$ | Med   | No    | Med   | 65%            | 68%        | 53%            |
| $T_5$ | High  | No    | High  | 23%            | 17.6%      | 35%            |
| $T_6$ | Low   | Yes   | Low   | 85%            | 86.5%      | 72.7%          |
| $T_7$ | Med   | No    | Med   | 44.7%          | 37%        | 47%            |
|       | High  | Yes   | High  | 14.4%          | 14.5%      | 17.7%          |
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#### 3. Data overlapping $u_k$



#### **Fuzzy Reasoning Approach**

All factors are fed to a Fuzzy logic (FL) Inference System derive the to 'probability of offloading  $r_k$ '.



overlapping experiment has been carried out on real datasets that are collected by four Unmanned Surface Vehicles (USVs) working as nodes  $n_i$  to collect data from sensors in a coastal area, dataset link: Models: http://www.dcs.gla.ac.uk/essence/fundin EC, Ours, Cloud g.html#GNFUV. In order to obtain the task's data overlapping  $u_k$ , we have defined for each local dataset  $D_i$  the feature boundaries

 $D_i = [x_1^{min}, x_1^{max}, x_2^{min}, x_2^{mix}]$ 

The FL engine has been developed in MATLAB considering the popularity  $p_k$  of tasks  $T_k$  between [1, 40] and outlier  $o_k$ either 0 or 1, while the percentages of data overlapping  $u_k$  are between [1, 100].

High Yes High 15% 15.8% 27.1% l g Yes Low 67.2% 83% 85% T<sub>10</sub> Low 6/10 9/10 8/10

Data uploading speed and Execution time Simulator: CloudSim Plus [\*] **Performance Metrics:** 

- Data Uploading Speed
- Task Execution Time





## Conclusions

Our mechanism performance has been evaluated according to the probability of offloading data-driven analytics tasks to the correct nodes according to the optimal solution and against two other mechanisms. As evidenced by the results, our mechanism significantly outperforms the benchmark mechanisms in terms of decision-making accuracy. Furthermore, this mechanism can reduce the probability of a task being offloaded to an unsuitable node by up to 90 %. In addition, our method has been evaluated in terms of resource utilization, showing that it provides higher data uploading speeds compared to EC-based and cloudbased methods.

### References

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