AN EDGE-CENTRIC ENSEMBLE SCHEME FOR QUERIES ASSIGNMENT

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Introduction

- In the era of the Internet of Things (IoT), numerous devices form a vast infrastructure.
- Devices can process tasks and exchange data.
- Data can be processed at the devices, at the edge of the network (Edge/Fog) or at the Cloud.
**Edge Nodes**

- Current research efforts focus on the data streams management at the edge.

- Edge Nodes (ENs) act as distributed data repositories where queries can be executed.

- ENs are responsible to report the results to the requested entity.
**Edge Nodes**

- We deal with queries allocation to the appropriate ENs.
- Queries are reported into a set of **Query Controllers** (QCs).
- It is a multi-dimensional problem involving queries and ENs characteristics.
High Level Description

- **Step 1.** Classify queries into a set of complexity classes
- **Step 2.** Compare the requirements of queries with the ENs' load

We propose models for both steps

- An **ensemble similarity scheme** for the estimation of the complexity class
- Decision for the **selection of ENs** based on the current and future load
**High Level Description**

- A *Query Processor (QP)* is adopted in every EN to respond to any incoming query.

- QCss receive queries, `invoke' the appropriate QPs, get their responses and return the final result.
**High Level Description**

- In each EN, a dataset is formulated i.e., a geodistributed local data repository.

- Each dataset stores multivariate data.
MATCHING QUERIES WITH PROCESSORS

- Every EN/QP exhibits specific characteristics
- We adopt:
  - The load
  - The speed

- Queries also have a set of characteristics
- We adopt:
  - The complexity
  - The need for instant response

- We focus on the query class; it depicts the complexity
DELIVERING THE QUERY COMPLEXITY

- For delivering the complexity class, we propose a "fuzzy" approach and define a Fuzzy Classification Process (FCP)
- The FCP derives the membership of a query in each of the pre-defined classes

- We also adopt a dataset of historical queries together with their corresponding classes
- The same class may be involved in multiple tuples, thus, in multiple queries
Delivering the Query Complexity

- We build on top of a function $f$
- $f$ gets the query and delivers a similarity vector
- Example: $q^s = <0.2, 0.8, 0.3>$
- The ensemble scheme evaluates the final similarity between the query and every tuple in the training set
**The Ensemble Scheme**

- Similarity metrics are applied on each tuple classified into a class
- All the results are aggregated
- Every single result represents the membership of the query to a 'virtual' fuzzy set
- We adopt the **Hamacher product** for the final aggregation
Disagreements are managed through the use of top-k similarity values based on their significance level.

The **Significance Level (SL)** depicts if a value is ‘representative’ for many other results.

Density based: Only values with a ‘dense’ neighborhood are considered.
THE ENSEMBLE SCHEME

- Over a set of aggregated similarity values for a class, we apply an operator.
- We adopt the **Quasi-Arithmetic mean** for the second level of aggregation.
The Matching Process

- We consider an additional vector containing steps for each complexity class.
- The expected number of steps for a query is compared with the available load.
  - When the number of steps can be covered: reward
  - Otherwise: penalty
- We process both, the current and the future load.
EXPERIMENTAL EVALUATION

- Datasets
  - Queries found at http://www.tpc.org
  - For each, we define the complexity class (six classes)*

- Performance Metrics
  - \(\Psi\): seconds to allocate a query
  - \(\Xi\): difference of the selected load with the lowest

- Ties management
  - Scenario A: Random selection
  - Scenario B: The lowest load first

EXPERIMENTAL EVALUATION

- Complexity of the scheme*

* $|Q_D|$: size of the training dataset, $|E|$: number of similarity metrics, $|\Theta|$: number of classes
EXPERIMENTAL EVALUATION

- Conclusion time (in seconds)

| $|\mathcal{EN}|$ | Uniform | Gaussian |
|-----------------|---------|----------|
| 10              | 0.008   | 0.008    |
| 100             | 0.012   | 0.010    |
| 1,000           | 0.055   | 0.370    |
| 10,000          | 0.251   | 0.276    |

* $|\mathcal{EN}|$: number of nodes
EXPERIMENTAL EVALUATION

- The load of the selected EN
CONCLUSIONS AND FUTURE WORK

- The proposed model exhibits good performance
- We manage to perform efficient allocations

- Our future research plans involve the incorporation of more parameters
  - the deadline
  - the statistics of data
- The aim is to provide an adaptive mechanism
Thank You!!

Questions?