Big Data for Monitoring Mobile Applications

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- Guy Lahlou Djiken is a lecturer and researcher in the Applied Computing Laboratory of University of Douala and the Laboratory of Algorithm, Complexity and Logic (LACL);
- He is interested in mobility in communication systems more precisely in Communication Networks and Services, Big Data and Artificial Intelligence, Paravirtualization and IoT;
- The interoperability of the above fields of interest is at the core of this current research;
- One of the axes of exploration is the impact of paravirtualization in order to accelerate the inference of programs based on Artificial Intelligence given the lack of network infrastructures.

Outline

- Introduction
- Log analysis and Reporting of Artificial Intelligence
- Use case for the anomaly prediction
- Software architecture and Data streaming
- Artificial Intelligence Model and Results
- Conclusion and Future Work

Introduction

- ✓ Supervision of mobile application
- ✓ Log messages and log analysis
- ✓ Anomaly prediction and difficulties associated
- ✓ Standardization of formats during the data collection
- ✓ Mobile applications and using for the taking picture of experiments in biology

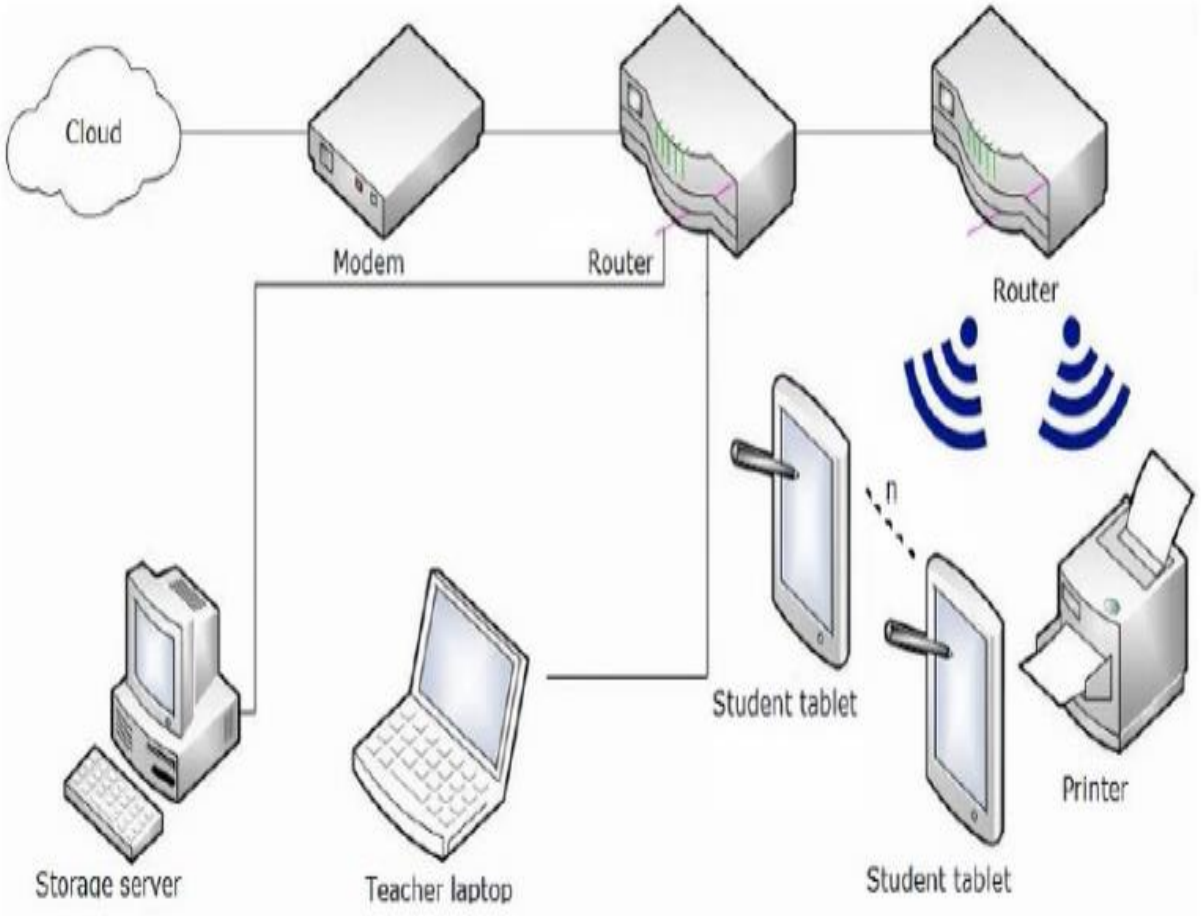
Log analysis and reporting of AI

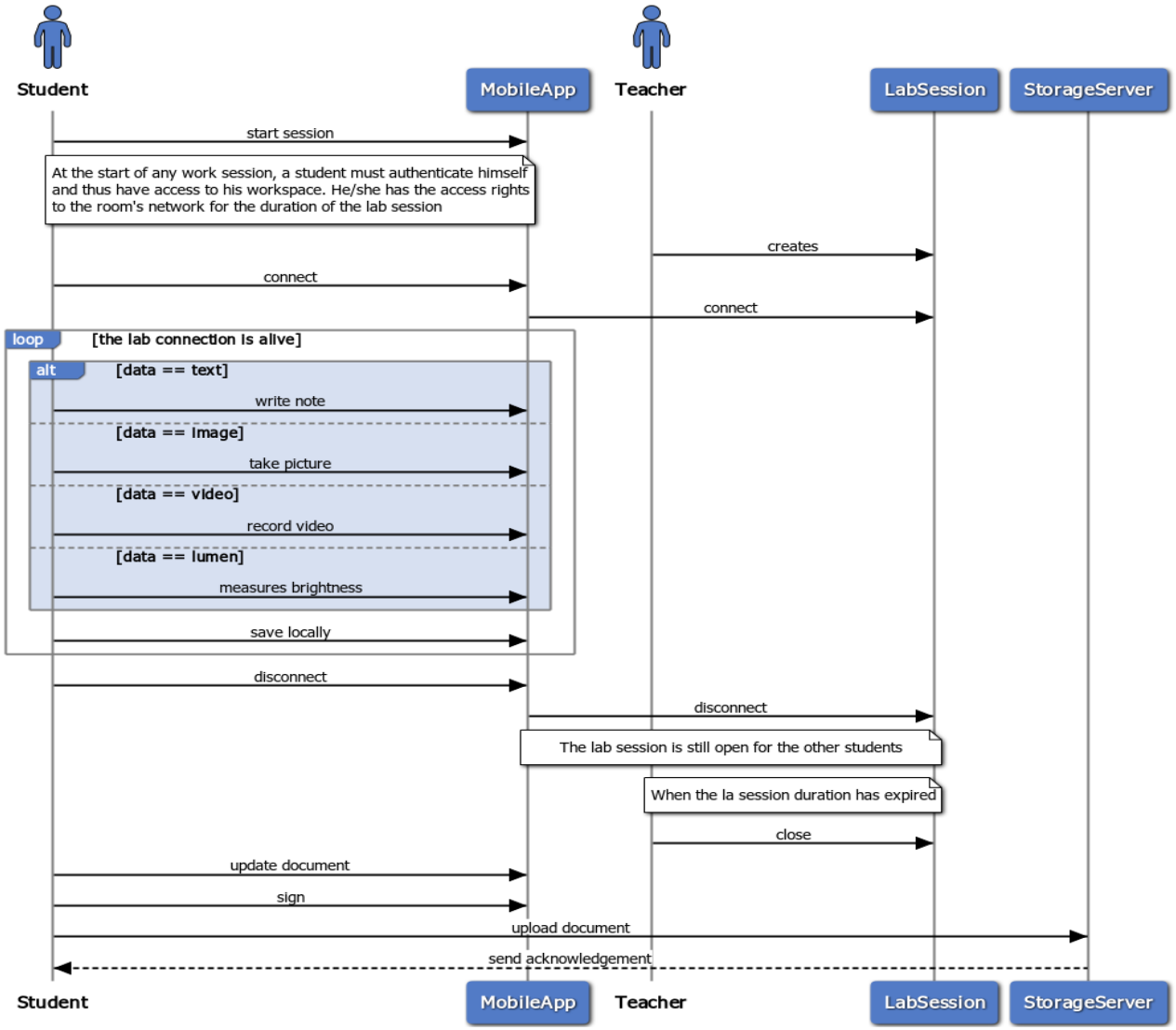
- ✓ Software monitoring and log analysis of distributed systems
- ✓ Development of Machine Learning and impacts on the use of logs
- ✓ Use of predictive machine learning models
  - Wei Luo and rulebook for AI model development
  - Henderson and Stevens for reporting
  - Dos Santos and reproductible analysis approach

Use case for the anomaly prediction

- ✓ Context description: analysis of an experiment in a laboratory
- ✓ Principes and nominal scenario during an experiment in a lab room
  - Student
  - MobileApp
  - Teacher
  - LabSession
  - StorageServer

Network and sequence diagram





Software architecture (1/3)

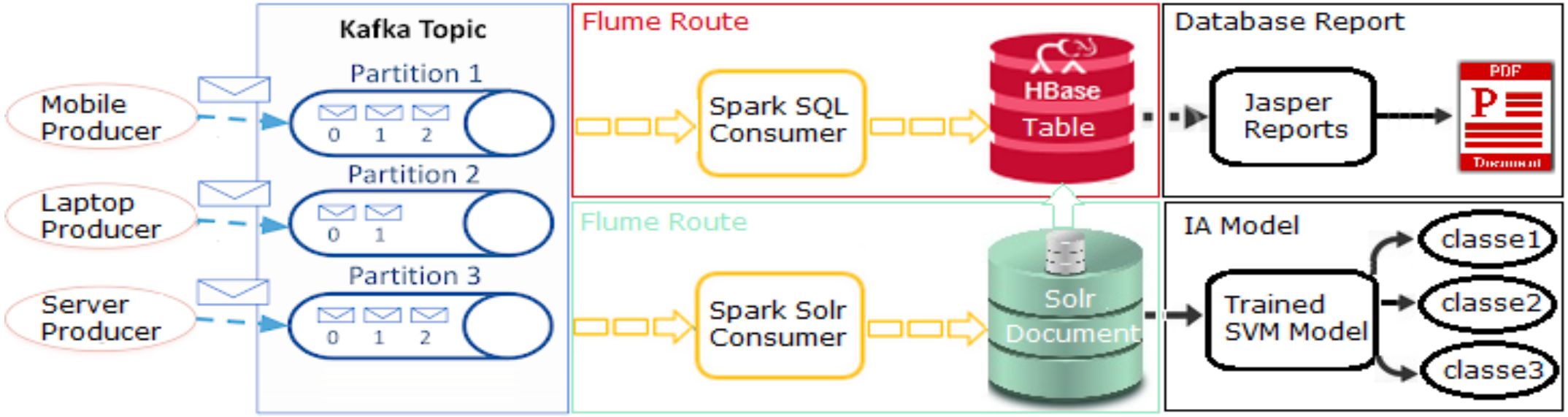
- ✓ The analysis of logs is more complex
  - the arrival of log data continuously
  - the need to impose a data schema to index the information
  - refine the search for information and the detection of anomalies
- ✓ Our goal is to collect and cross-reference information from the various sources
- ✓Thus, it is essential to monitor the events related to the management of the laboratory sessions.
- ✓In addition, any event related to an information capture or modification is useful.

Software architecture (2/3)

- ✓ The server application part is deployed on the storage server
- ✓ This part is developed with the Spring Boot library
- ✓ We use intensively the Spring configuration for the logs, but also for the persistence aspects
- ✓ The database is Postgresql version 10
- ✓ We focuse on describing our Big Data workflow from collection to building our AI model

Software architecture (3/3)

- ✓ Big Data architecture : Data collection and Big Data analysis
- ✓ Layer components of our project:
  - Kafka: kafka for topics partition
  - Flume: FlumeRoute (Spark SQL and Spark Solr) Consumer
  - Database: Jasper Reports
  - IA Model: SVM model by classifiers



Data streaming (1/3)

- ✓ Spark SQL Consumer : Kafka receiver class → DStream
- ✓ Spark SQL Consumer component aims to apply name conventions and a common structure
- ✓ We have defined a mapping between HBase and Spark tables, called Table Catalog
  - *The row key definition implies the creation of a specific key generator in our component.*
  - *The mapping between table column in Spark and the column family and column qualifier in HBase needs a declarative name convention*
- ✓ The HBase sink exploits the parallelism on the set of Region servers

Data streaming (2/3)

- ✓ The pipeline is built with Apache Spark and Apache Spark Solr connector
- ✓ Spark framework is used for distributed in memory compute, transform and ingest to build the pipeline
- ✓ The Apache Solr collection, which plays the role of a SQL table, is configured with shards
- ✓ The definition of shard is based on the number of partitions and the replicas rate for fault tolerance ability
- ✓ The Spark executors run a task, which transforms and enriches each log message

Data streaming (3/3)

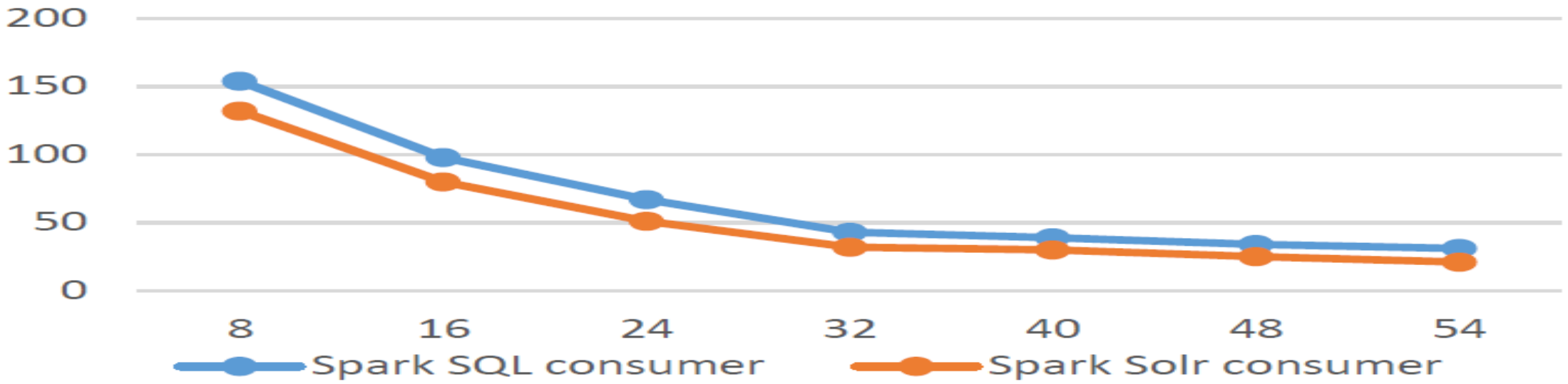
- ✓ Solr Cloud as a data source Spark is used when we create our ML model
- ✓ We send requests from Spark ML classes and read results from Solr with the use of Solr Resilient Distributed Dataset (SolrRDD class).
- ✓ With Spark SQL, we expose the results as SQL tables in the Spark session
- ✓ These data frames are the base of our ML model construction.
- ✓ The metrics called Term Factor (TF) and Inverse Document Frequency (IDF) are key features for the ML model.

AI Model and Results (1/3)

- ✓The concepts behind SVM algorithm are relatively simple
- ✓The classifier separates data points using a hyperplane with the largest amount of margin
- ✓In our working context, the margin between log patterns is a suitable discriminant
- ✓SVM offers very high accuracy compared to other classifiers such as logistic regression, and trees

AI Model and Results (2/3)

- ✓At runtime for our data set based on a unique log format, the cost of Spark SQL consumer decreases when the partitioning of dataset increases
- ✓We have to oversize the partitions and the gains are much less interesting



AI Model and Results (3/3)

- ✓ The analytical expression of the features precision, recall of retrieved log messages that are relevant to the find
- ✓ Our results for four classes are within acceptable ranges of values for the use of the model to be accepted

Class number	**Metrics**		
	Precision by label	***Recall by label***	***F1 score by label***
0.000000	0.815846	0.890100	0.896616
1.000000	0.911000	0.981000	0.991000
2.000000	0.854461	0.714857	0.851481
3.000000	0.852446	0.7589148	0.833129

Conclusion and Future Work (1/2)

- ✓ Our approach on log analysis and maintenance task prediction
  - We showed how an index engine is crucial for a suitable query engine
  - We have developed specific plugin for customizing the field types of our documents, but also for filtering the information from the log message
  - We have stressed the key role of our Spark components, one per data source
- ✓ We observed that our approach supported a large volume of logs
- ✓ From the filtered logs, we presented the construction of our SVM model based on work from the Center for Pattern Recognition and Data Analytics
- ✓ Our study also shows the limits that we want to push back, such as the management of log patterns

Conclusion and Future Work (2/2)

- ✓The indexing process based on a custom schema
- ✓We think that the use of DisMax query parser could be more suitable in log requests where messages are simple structured sentences
- ✓We want to extract dynamically the log format instead of the use of a static definition
- ✓We think also about malicious messages, which can perturb the indexing process and introduce bad request in our prediction step
- ✓The challenge needs to manage a set of malicious patterns and the quarantine of some message sequences

References

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Thank you for your attention

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