### MIDDLEWARE TECHNOLOGIES FOR DISTRIBUTED SYSTEMS

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### POLITECNICO MILANO 1863

Matteo Moreschini Alessio Russo Introito Tommaso Scarlatti

### **Overview**

- 1. Projects definition and data preprocessing
- 2. A simplified version of Twitter using Kafka
- 3. Big-data platform with Akka
- 4. Parallel K-means with **OpenMP** and **MPI**
- 5. Results and conclusions

# PROJECTS DEFINITION

### Internal organization

- We split the work in **two phases**:
  - Each member worked on a different project to get acquainted with the technology
  - All members worked on the same project one by one
- We tested our deliverables first locally and then in a **wireless ad-hoc network** using static ip addresses



### Three technologies, three languages...

- 1. Apache Kafka (Python 3.7)
- 2. Akka (Java 8)
- 3. OpenMP / MPI (C++ 11)



### ...One dataset

- Retrieved recent **tweets** from (real) Twitter with *Twython* library
- Cleaned text, removed duplicates and retweets
- Tweets used as **input source** for the three projects in different ways



### **Tweets generation (Kafka)**

- Real tweets are used to publish "simplified" tweets
- Fields avaiable:
  - Author
  - Content
  - Tag (#)
  - Mention (@)

### Latent Semantic Analysis (Akka)

- Trained a LDA (Latent Dirichlet Allocation) model to automatically extract topics
- Label each tweet with the topic with the highest probability



### Latent Semantic Analysis (Akka)

- Each tweet has been assigned to a topic using LDA
- The following 12 topics have been extracted:

exercise	895
cooking	808
theatre	744
music	731
animal	643
painting	614
drawing	578
culture	547
health	453
sport	453
history	323
photography	260

### Key-value pairs (Akka)

- Each operator processes (key, value) pairs where both key and value are strings
- **Key** = topic
- Value = text

topic	text
cooking	Stuck between cooking and buy something
music	Why is there only 4 songs on

### **Doc2Vec (K-means clustering)**

- Map each tweet in a vector of n dimensions
- Performed with **Facebook InferSent**, a sentence embeddings method for English sentences

0.62 -4.54 2.37 8.21 -0.03 ...

• 7K tweets with 4096 dimensions





### Literature review

- LDA vs Doc2vec clustering
- Previous researches focused on:
  - Compare their performances in a topic recognition task
     [M. Campr, K. Ježek, Comparing Semantic Models for Evaluating Automatic Document Summarization. In: Král P., Matoušek V. (eds) Text, Speech, and Dialogue. TSD 2015]
  - Combine them in a two-steps approach
     [M. Alhawarat and M. Hegazi, Revisiting K-Means and Topic Modeling, a Comparison Study to Cluster Arabic Documents, in IEEE Access, 2018]

# 2. SIMPLIFIED TWITTER USING KAFKA

## github.com/tmscarla/**kafka-twitter**

### Scope

- Simplified version of Twitter: streaming message application using vanilla Kafka
- RESTful communication
- Basic operations:
  - Subscribing
  - Posting
  - Reading: batch/streaming
  - Filtering messages

### Kafka Twitter

- **Python** (3.7.4)
- confluent-kafka (0.11.6)
- **Tkinter** (8.5)
- Flask (1.1.1)





### Write

- AvroProducer: Avro serialization (avro 1.9.0)
- tweet\_schema.avsc: author, content...



### **Batch Reading**

- AvroConsumer, con diversi brokers
- Get latest N messages: adjust offset from the one of latest message to *(latest-N)*



### Streaming

- **5 min window** messages
- One request --> Stream of tweets



### Filtering





### **Graphical User Interface**



0 0	KafkaTwitter
What	do you want to do, Matteo?
	Read
	Streaming
	Write
	<b>Skafka</b> TWITTER

# **3**. BIG-DATA PLATFORM WITH AKKA



### Scope

- Implement a Big Data (batch and stream) processing engine using Akka actors
- Engine accepts a sequence of Operators (**Job**) with user-defined functions
  - $\circ \quad \text{Source} \to \text{Job} \to \text{Sink}$
- Each operator is performed in parallel through multiple Workers allocated on different nodes

### Workflow

- Starter node: main actors + a Worker for each operator
- Collaborator node: a Worker for each operator

- 1. Collaborator nodes are initialized
- 2. Starter node is launched
- 3. Actors instantiated across nodes
- 4. Computation begins



### Source

- Source node generate continuosly <Key, Value> messages with a specified frequency
- Can operate on two different modes:
  - Random: generate random messages within a keySize and valueSize range
  - Read: reads rows from a csv file with two columns
     ['Key', 'Value']



### Master node

- Is in charge of allocating all the Workers within its context. In this way is able to:
  - Choose local/remote deployment
  - Set dynamically the downstream of each Worker
  - Handle failures and perform recoveries



### **Batch vs Streaming**

- The engine can operate on two different modes
- Each operator hold a *batchSize* parameter

- **Streaming:** on receiving a message send it downstream as soon as it has been processed and it's ready
- **Batch:** put messages to be sent out in a queue with a FIFO policy. When *batchSize* is filled, send the batch out.

# Fault tolerance - What guaranteed delivery means?

- 1. The message is **sent out** on the network?
- 2. The message is **received** by the other host?
- 3. The message is put into the target actor's mailbox?
- 4. The message is starting to be **processed** by the target actor?
- 5. The message is **processed successfully** by the target actor?

### Fault tolerance mechanism

- Workers can crash during message processing
- Mailboxes configured as **priority queues**
- End-to-end exactly once delivery



### **REST API**

• Starter node hosts an HTTP server which exposes a REST API with the following endpoints:

#### • RANDOM SOURCE

curl -d '{"keySize":"10", "valueSize":"50"}' -H "Content-Type: application/json" -X POST http://localhost:808/source/random

#### O SUBMIT JOB

curl -d '{"id":"2"}' -H "Content-Type: application/json" -X
POST http://localhost:8080 /job

#### • STATISTICS

curl -X GET http://localhost:8080 /stats



## PARALLEL K-MEANS WITH OPENMP AND MPI

#### github.com/tmscarla/k-means-parallel

### Scope

- Implement the **K-means clustering** algorithm exploiting:
  - Resources within one computing node with multiple processing cores (**OpenMP**)
  - Resources across computing nodes (MPI)
- Maximize the performances

### **Initial Configuration:**

- *N* points represented in the space with a *M*-dim vector
- *P* processors defined as:
  - Node 0, Node 1, ..., Node *P*-1
- *K* clusters to be considered
- *L* number of maximum iterations to be performed

### **K-means algorithm**



Start!

### **Assumptions:**

- Points are independent
- A point belongs to one and only one cluster

### **Termination:**

- No changes in two adiacent iterations
  - Flag in each processor
- Number of iterations > *L*

### Workflow

- 1) Node 0 **loads data** and assigns *N/P* points to each node. Remaining points are assigned one by one.
- 2) Node 0 reads and sets initial **configuration parameters**: *K*, *M*, *L*
- 3) Node 0 chooses *K* points as initial centroids and **broadcasts** them to the other nodes

### Workflow:

- 4) Each node:
  - For each "local" point find the cluster membership among the *K* clusters
  - Distance calculation between points and centroids is performed in parallel using **OpenMP**
  - For each cluster, sum points dimensions values
- 5) After an **MPI\_Allreduce** operation, each node knows the number of points and the sum of their values within each cluster. Compute new centroids
- 6) Go to point 4) and repeat until termination



### **Centroids recomputation:**



### OpenMP

### **Distance metrics**

• Euclidean Distance:

$$d(\mathbf{p}, \mathbf{q}) = \sqrt{\sum_{i=1}^{n} (q_i - p_i)^2}$$

• Cosine Similarity:

$$Cosine(\mathbf{A}, \mathbf{B}) = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2} \sqrt{\sum_{i=1}^{n} B_i^2}}$$









# 5. RESULTS AND CONCLUSION

### LDA vs Doc2vec clustering

- Both **unsupervised** learning algorithms
- Both based on a **bag-of-words** (BoW) model
- Fuzzy vs disjoint clustering
  - LDA infers topics based on word counts
  - K-means leverages on the numeric representation of documents created by **doc2vec**

### Two methods, one goal

- Both methods are suited for **topic extraction** tasks
- Using **n\_topics = n\_clusters**, can we compare the two methods?
- In other words, can we quantify the similarity of the two approaches in labeling each tweet?

• We can **compare** the labels of the tweets within the same cluster and infer the topic!

### Doc2vec - 2D (t-SNE)



### K-means (cosine similarity)



### **Evaluation metric**

• **Purity:** a measure of the extent to which clusters contain a single class. How "pure" is respect to the dominant class:

$$purity = \frac{1}{N} \sum_{k} max_{j} |\omega_{k} \cap c_{j}|$$

- N number of tweets
- **k** number of clusters
- ω<sub>k</sub> dominant class
- cj real class

### Results

CLUSTER Ø		CLUSTER 8		CLUSTER 1		
	music	0.134670	cooking	0.720559	animal	0.98
	exercise	0.126074	painting	0.053892	cooking	0.01
	theatre	0.117479	drawing	0.039920		
	cooking	0.114613	exercise	0.039920		
	culture	0.108883	animal	0.021956		
	painting	0.094556	music	0.021956		
	drawing	0.077364	culture	0.019960		
	sport	0.068768	sport	0.019960		
	health	0.054441	history	0.017964		
	animal	0.045845	photography	0.015968		
	photography	0.042980	theatre	0.013972		
	history	0.014327	health	0.013972		

\_\_\_\_ 1 3607 6393

### Purity = 0.21137750

### Conclusions

- We explored three different technologies using three different programming languages
- We used **tweets** extracted from Twitter to create a **common thread** between the projects
- We tested our projects in a **really distributed scenario** using a wireless ad-hoc network between our three notebooks
- We compared **LDA** and **K-means** clustering of a **Doc2Vec** representation using purity as evaluation metric

# **THANK YOU!**

### **Questions?**



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