ITEC874 — Big Data Technologies

Week 11 Lecture 1: Analysing Streaming Data

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Programme

Reading

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Programme

1. Data Streams
2. The Stream Model
3. Technologies for Stream Analytics

Data Streams

What is a data stream?

- A data stream is a sequence of data that are processed before the sequence ends.
- Data streams may be never-ending.

Examples

Image Data: Surveillance cameras, satellite imaginery, ...

Sensor data: Temperature, GPS coordinates, heart rate, ...

Internet and Web Traffic :

- Search queries;
- Posts from Twitter, Facebook, ...
- IP packets;
- Clicks.

Applications I

Mining query streams

Google wants to know what queries are more frequent today than yesterday.

Mining click streams

Sydney Morning Herald wants to know which of its pages are getting an unusual number of hits in the past hour.

Mining social network news feeds

E.g. A news agency looking for newsworthy topics on Twitter, Facebook.

Applications II

Sensor networks

Many sensors feeding into a central controller.

Telephone call records

Data feeds into customer bills as well as settlements between telephone companies.

IP packets monitored at a switch

- Gather information for optimal routing.
- Detect denial-of-service attacks.

Data Streams as "Big Data"

The four "V's" of Big Data applied to streams.

Velocity: Data may arrive faster than we can process it.

Volume: Accumulated data might not fit in the available storage space. We can think of data as infinite.

Variety: Data may change in time. Data that happened some time ago might not be relevant any more. We can think of data as non-stationary.

$\Rightarrow$ (This is not the standard meaning of variety . . .)

We still need to handle the "classic" issue of variety: we may need to handle multiple streams at once.

Veracity: Sensors may be faulty or temporarily down.

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Issues in Stream Processing

Issues

Velocity: We may need to give up on processing all data.

Volume: We may need to build summaries.

- Not all ad-hoc questions can be answerable.

Possible Solution

- Obtain an approximate answer to the question rather than an exact answer.
- For example, stream processing often focuses on the most recent data.

⇒ Focussing on recent data also addresses the issue of variety.

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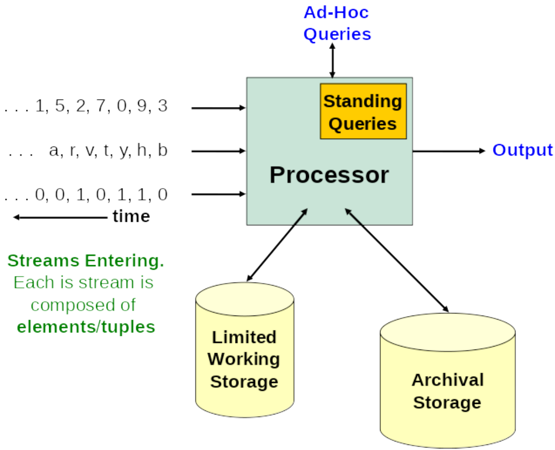
The Stream Model



http://www.mmds.org/

Storage in the Stream Model

Archival Storage

- Large storage for archival purposes.
- We assume it is not possible to answer queries from the archival store.
- Can be used only under special circumstances using time-consuming retrieval processes.

Working Store

- Holds summaries or parts of streams.
- Can be used for answering queries.
- Might be in disk or in main memory.
- Cannot store all the data from all the streams.

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Types of Queries

Standing Queries

- Queries that are always performed on the data.
- In a sense, these are queries that are permanently executing.
- Since these queries are known in advance, it is fairly easy to design efficient storage and query processes to handle them.

Ad-Hoc Queries

- Queries that are not known in advance.
- These queries are created, for example, by a user or operator.
- We need to find a way to query the current state of the stream.

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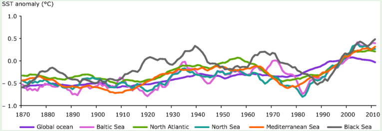
Examples of Standing Queries

Example: Ocean Surface Temperature Sensor



1. Alert when the temperature exceeds 25 degrees centigrade.
2. Average the 24 most recent readings.
3. Maximum temperature ever recorded.
4. Average temperature.

Question

What information do we need to keep in the working storage to answer each of these standing queries?

Examples of Working Storage Needs

Q1: Alert when the temperature exceeds 25°C

- No information required (we do not need to keep any samples in the working storage).

Q2: Average the 24 most recent readings

- 24 variables, one per reading.

Q3: Maximum temperature ever recorded

- 1 variable with the value of the maximum so far.

Q4: Average temperature of all readings so far

- 1 variable with the value of the sum of readings so far.
- 1 variable that counts the number of readings so far.

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Question: An effective way to compute the average temperature

Q4: Average temperature

If we keep the sum of readings so far we may have problems with data overflow (the sum may exceed the capacity of storage)

1. How serious is this problem?
2. How could we fix this problem?

Examples of Ad-hoc Queries

Example: Web Site

1. What were the unique users in the past month?
2. What were the users from Australia?
3. What were the users which generated most traffic?

Note

- If the above were questions were known beforehand they would be standing queries.
- Given an application we can optimise it to enable the processing of some kinds of ad-hoc queries.
- In general, it is impossible to be able to accurately answer all possible ad-hoc queries.

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3. Technologies for Stream Analytics
   - StreamSQL
   - Machine Learning on Streams

Some Platforms for Stream Analytics

- Azure Stream Analytics https://azure.microsoft.com/en-au/services/stream-analytics/
- Amazon Kinesis https://aws.amazon.com/kinesis/
- Apache Flink https://flink.apache.org/
- Apache Kafka https://kafka.apache.org/
- SAS Event Stream Processing https://www.sas.com/en_au/software/event-stream-processing.html
- SQLStream https://sqlstream.com/
- IBM Streaming Analytics https://www.ibm.com/cloud/streaming-analytics

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StreamSQL

- StreamSQL is a query language that extends SQL with the ability to process real-time data streams.
- Various platforms for stream analytics incorporate their own versions of StreamSQL.
  - Apache Flink uses Apache Calcite's proposal https://calcite.apache.org/docs/stream.html.
  - Imply's Druid is also based on Apache Calcite.
  - Apache Kafka uses Confluent KSQL https://www.confluent.io/product/ksql/.
  - Azure Stream Analytics uses a subset of Transact-SQL https://docs.microsoft.com/en-au/stream-analytics-query/stream-analytics-query-language-reference.
- Can be linked to event stream processing.
  - The StreamSQL query defines a pattern to be captured in an event.

StreamSQL Example 1

Example

This example defines a standing SQL query that is continuously triggered and processes the last second of a stream.
https://en.wikipedia.org/wiki/Event_stream_processing

```
SELECT DataStream
    Orders.TimeStamp, Orders.orderId, Orders.ticker,
    Orders.amount, Trade.amount
FROM Orders
JOIN Trades OVER (RANGE INTERVAL '1' SECOND FOLLOWING)
ON Orders.orderId = Trades.orderId;
```

StreamSQL Example 2

Example

This example defines a standing SQL query that is triggered when a man wearing tuxedo appears, followed by a person wearing a gown and either church bells or flying rice.
https://en.wikipedia.org/wiki/Event_stream_processing

```
WHEN Person.Gender  EQUALS "man" AND
     Person.Clothes EQUALS "tuxedo"
FOLLOWED-BY
  Person.Clothes EQUALS "gown" AND
  (Church_Bell OR Rice_Flying)
WITHIN 2 hours
ACTION Wedding
```

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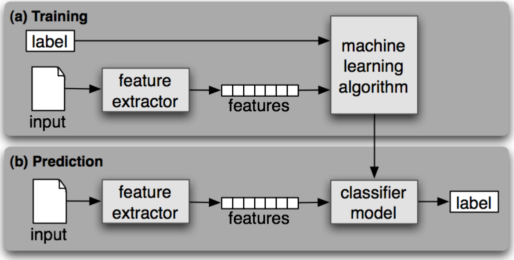
Machine Learning on Streams

- Supervised approaches for machine learning require training data.
- It is important that the training data must be a representative sample of the real data.
- But data in streams never ends.
- Even worse, data in streams may change ("drift") over time.



Solution 1: Training with Batches

- Re-train the system regularly.
    - The frequency of re-train depends on how fast the data changes.
- If a lot of data has been generated since last training, keep a sample of the training data.
    - E.g. keep the most recent data from the stream for training.

BUT

- The system may not handle unexpected drifts in the data.
- Re-training can take much computation time and resources.

Solution 2: Online Machine Learning

- Keep an infinite training loop.
- Update the trained model from data sampled from the stream.

```
Initialise model parameters;
while True do
    Sample from the stream;
    Update model parameters;
    Save model for production;
end
```

Take-home Messages

- Applications of Stream Processing.
- The Four V's of Big Data for Stream Processing.
- The Stream Model.
- StreamSQL.
- Machine Learning on Streams.

What's Next

Week 12

- Ethics.
- Thursday 28 October: Assignment 3 due.
- Take-home final exam: Questions released end week 12. There will be a sample for practice in iLearn.