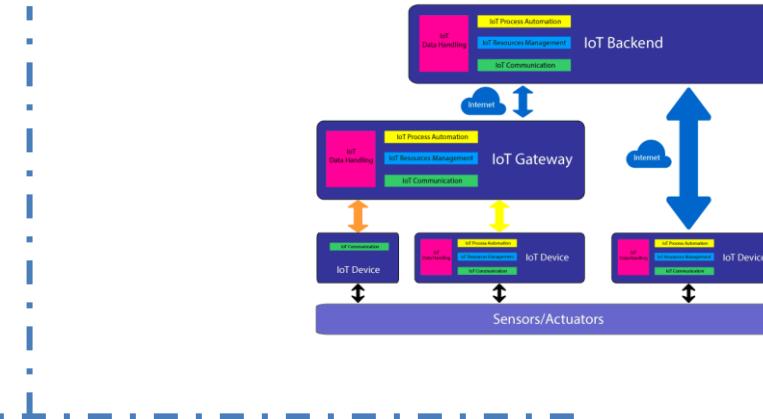


IoT Lecture 6



Sensor Signal Sampling

Session 1: Data Acquisition and Reduction

- Sampling and Filtering
- Data Reduction and Analytics
- SAX

Session 2: Data Handling

- Communication Costs
- Scenarios
- Stream Analytics

Session 3: Data Storage

- SQL
- NoSQL

- Sensors measure physical phenomena
- Sensors issue noisy signals featuring a max frequency
- Continuous data is sampled to generate a (digitized) time series
- Asynchronous sampling must be greater than twice the highest signal frequency
- **Exercise:** How much storage is required for one second of 12-bit values, sample time 1ms?

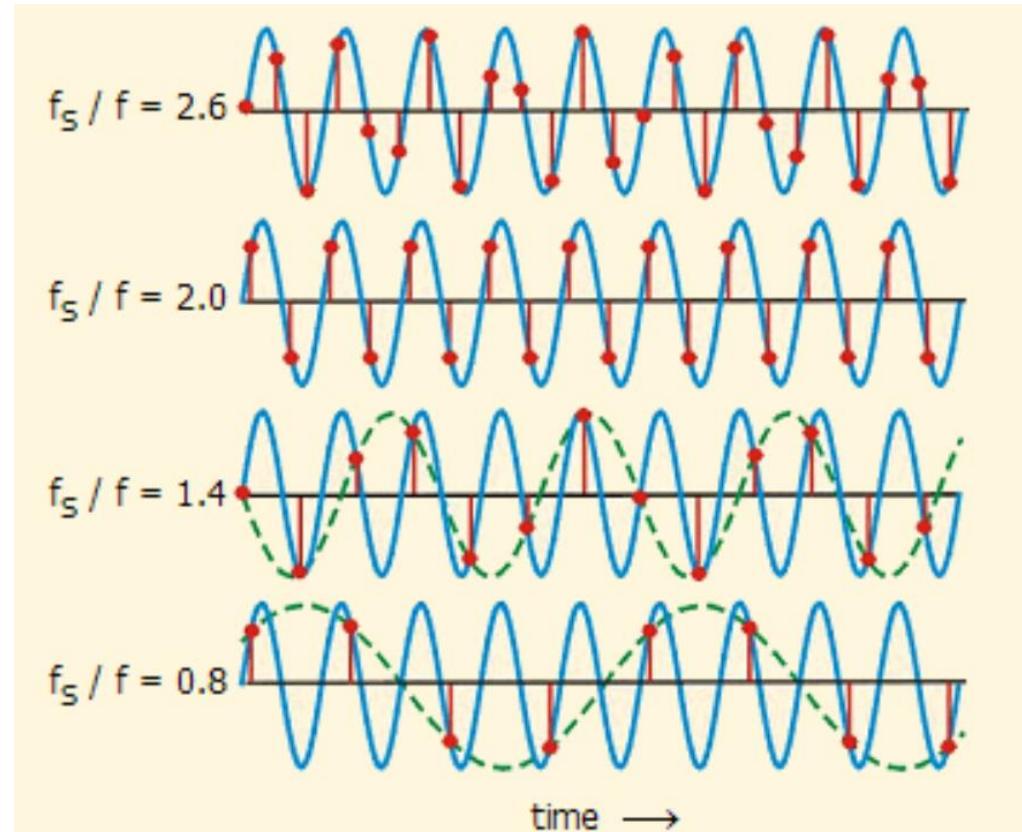


Figure 1. Sampling of a sinusoidal signal of frequency f at different sampling rates f_s . With dashed lines are shown the alias frequencies, occurring when $f_s/f < 2$.

http://195.134.76.37/applets/AppletNyquist/App1_Nyquist2.html

Learning Aim 1: The students will understand the principle of sampling and the Nyquist rule

Sensor Signal Filtering and Reconstruction (1)

Session 1: Data Acquisition and Reduction

- Sampling and Filtering
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- SAX

Session 2: Data Handling

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Session 3: Data Storage

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- NoSQL

- Process is:
- Condition the signal for sampling
 - HW filters for
 - High frequency noise reduction
 - Signal bandwidth limitations
- Signal capture per sample-and-hold
 - A/D conversion takes time and is noisy
- Make the time-series useful for analysis
 - **Smoothing** - filtering
 - **Data Reduction**

Learning Aim 2: The student will understand the necessity of filtering and/or smoothing

Sensor Signal Filtering and Reconstruction (2)

Session 1: Data Acquisition and Reduction

- Sampling and Filtering
- Data Reduction and Analytics
- SAX

Session 2: Data Handling

- Communication Costs
- Scenarios
- Stream Analytics

Session 3: Data Storage

- SQL
- NoSQL



Sensor Signal Filtering and Reconstruction (3)

Session 1: Data Acquisition and Reduction

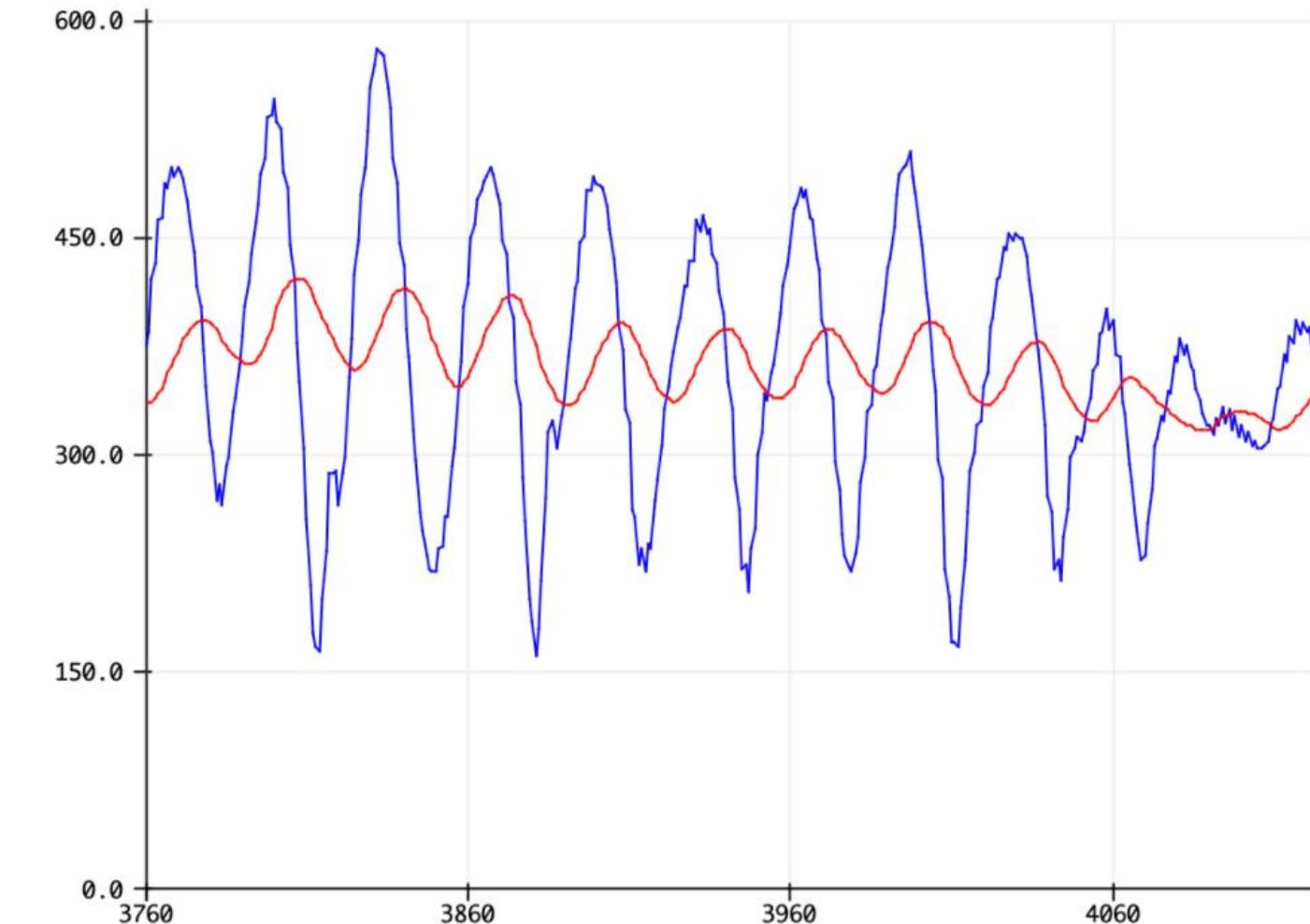
- Sampling and Filtering
- Data Reduction and Analytics
- SAX

Session 2: Data Handling

- Communication Costs
- Scenarios
- Stream Analytics

Session 3: Data Storage

- SQL
- NoSQL



Data Reduction

Session 1: Data Acquisition and Reduction

- Sampling and Filtering
- Data Reduction and Analytics
- SAX

Session 2: Data Handling

- Communication Costs
- Scenarios
- Stream Analytics

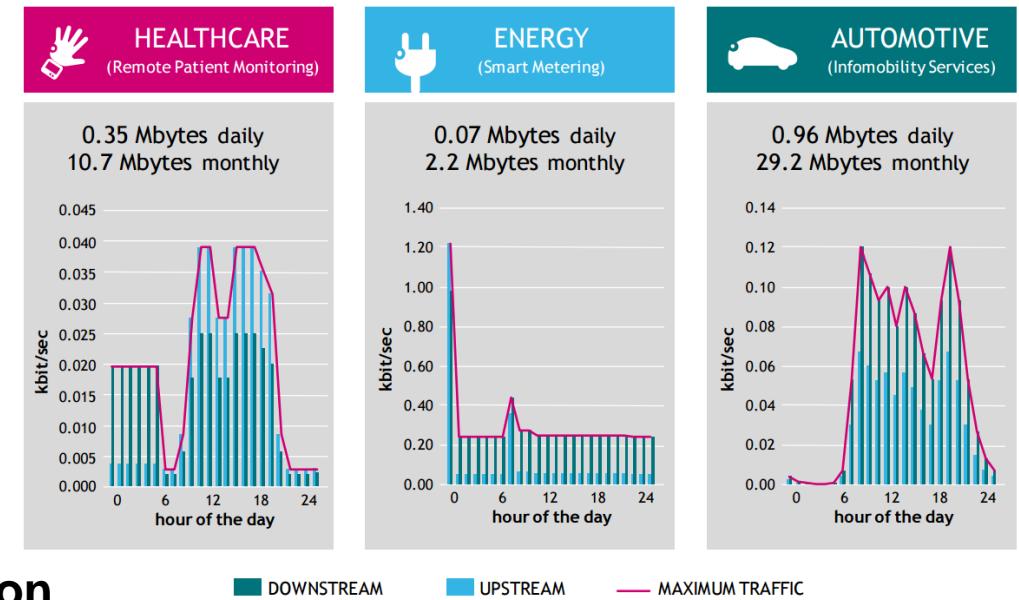
Session 3: Data Storage

- SQL
- NoSQL

- Different applications have different data generation patterns
- This data needs to be stored to be useful – storage is associated with costs
 - **Data Reduction**
- When enough data has accumulated then analytics can be applied
 - Fourier/wavelet transforms
 - **Symbolic aggregate approximation**

Learning Aim 3: The student will understand the necessity of data reduction

Figure 4: M2M Traffic Patterns for Different Applications



Data Reduction

Session 1: Data Acquisition and Reduction

- Sampling and Filtering
- Data Reduction and Analytics
- SAX

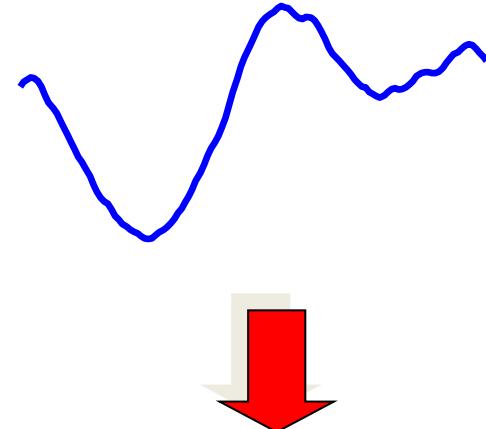
Session 2: Data Handling

- Communication Costs
- Scenarios
- Stream Analytics

Session 3: Data Storage

- SQL
- NoSQL

- Symbolic Aggregate Approximation (SAX) is interesting because out of a time series it creates a symbolic string
 - Reduces the sheer quantity of data (data reduction)
 - Can use cheap string algorithms to find interesting stuff (data analytics)
 - Reasonable sensitivity and selectivity



baabccbc

Learning Aim 1: The students will be able to convert a time series into a SAX representation

- Idea is to reduce a time series X of dimension n to a string of arbitrary length of dimension N where $n \gg N$

Session 1: Data Acquisition and Reduction

- Sampling and Filtering
- Data Reduction and Analytics
- SAX

Session 2: Data Handling

- Communication Costs
- Scenarios
- Stream Analytics

Session 3: Data Storage

- SQL
- NoSQL

- Steps are:
 - Normalise the time series (training set)
 - This allows us to compare apples with apples
 - Also the conversion into symbolic representation is dependent on the fact that a normalised time series tends towards a Gaussian distribution
 - Convert into a PAA (Piecewise Aggregate Approximation)
 - This performs the actual reduction in dimension
 - Convert the PAA representation into a string

SAX (1)

Session 1: Data Acquisition and Reduction

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- SAX

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Session 3: Data Storage

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- NoSQL

■ Example:

- Time series (x): **2, 3, 4.8, 6, 7.1, 3, 2, 2, 1, 1**
- Mean (μ): $\mu = (2 + 3 + 4.8 + 6 + 7.1 + 3 + 2 + 2 + 1 + 1)/10 = 3.19$
- Standard Deviation (σ): $= \text{Sqrt}(39.689/9) = 2.09997$

$$(2-3.19)^2 = 1.4161$$

$$(3-3.19)^2 = 0.0361$$

$$(4.8-3.19)^2 = 2.5921$$

$$(6-3.19)^2 = 7.8961$$

$$(7.1-3.19)^2 = 15.2881$$

$$(1-3.19)^2 = 4.7961$$

$$s = \sqrt{\frac{\sum_{i=1}^N (x_i - \bar{x})^2}{N - 1}}.$$

www.cs.ucr.edu/~eamonn/SAX.ppt

SAX (2)

- Time series (x): **2, 3, 4.8, 6, 7.1, 3, 2, 2, 1, 1**
- Normalisation: $z_i = (x_i - \mu) / \sigma$ $\sigma = 2.09997$, $\mu = 3.19$

Session 1: Data Acquisition and Reduction

- Sampling and Filtering
- Data Reduction and Analytics
- SAX

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- Stream Analytics

Session 3: Data Storage

- SQL
- NoSQL

$$(2-3.19) / 2.09997 = -0.57$$

$$(3-3.19) / 2.09997 = -0.09$$

$$(4.8-3.19) / 2.09997 = 0.77$$

$$(6-3.19) / 2.09997 = 1.33$$

$$(7.1-3.19) / 2.09997 = 1.86$$

$$(1-3.19) / 2.09997 = -1.04$$

- Normalised time series =

-0.57, -0.09, 0.77, 1.33, 1.86, -0.09, -0.57, -0.57, -1.04, -1.04

SAX (3)

- Time series (x): 2, 3, 4.8, 6, 7.1, 3, 2, 2, 1, 1
- Normalised time series -> -0.57, -0.09, 0.77, 1.33, 1.86, -0.09, -0.57, -0.57, -1.04, -1.04

- PAA calculation n = 10, N = 5

$$\bar{x}_i = \frac{N}{n} \sum_{j=\frac{n}{N}(i-1)+1}^{\frac{n}{N}i} x_j$$

- PAA representation: -0.328, 1.052, 0.885, -0.567, -1.04

SAX (4)

- PAA representation: **-0.328, 1.052, 0.885, -0.567, -1.04**
- Now need to convert this into symbols

Session 1: Data Acquisition and Reduction

- Sampling and Filtering
- Data Reduction and Analytics
- SAX

Session 2: Data Handling

- Communication Costs
- Scenarios
- Stream Analytics

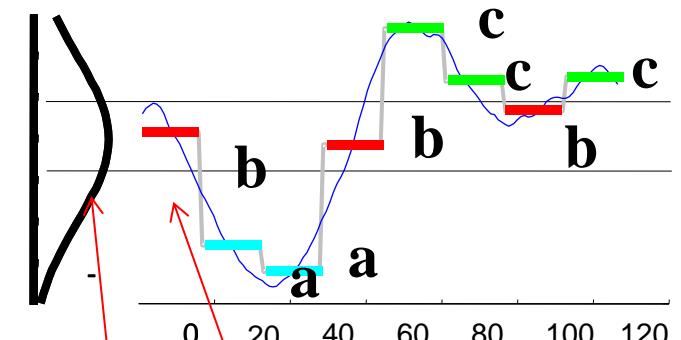
Session 3: Data Storage

- SQL
- NoSQL

β_i	3	4	5	6	7	8	9	10
β_1	-0.43	-0.67	-0.84	-0.97	-1.07	-1.15	-1.22	-1.28
β_2	0.43	0	-0.25	-0.43	-0.57	-0.67	-0.76	-0.84
β_3		0.67	0.25	0	-0.18	-0.32	-0.43	-0.52
β_4			0.84	0.43	0.18	0	-0.14	-0.25
β_5				0.97	0.57	0.32	0.14	0
β_6					1.07	0.67	0.43	0.25
β_7						1.15	0.76	0.52
β_8							1.22	0.84
β_9								1.28

Table 3: A lookup table that contains the breakpoints that divide a Gaussian distribution in an arbitrary number (from 3 to 10) of equiprobable regions

.. three letter alphabet



Normalised time series
assumed to have gaussian
distribution

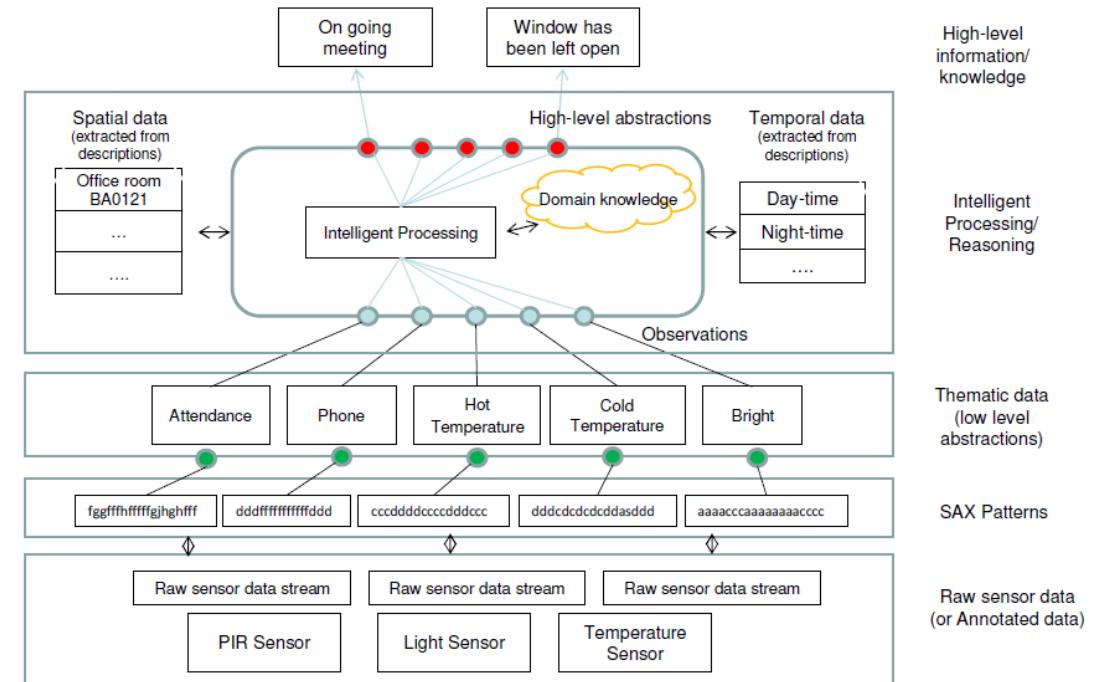
Where does one make the cut?

..

SAX (5)

- PAA representation: **-0.328, 1.052, 0.885, -0.567, -1.04**
- So for 4 letter alphabet cuts are **{-0.67, 0, 0.67}**
- SAX representation: **bddba**

■ Cute And now?



SAX (6)

- PAA representation: **-0.328, 1.052, 0.885, -0.567, -1.04**
- So for 4 letter alphabet cuts are **{-0.67, 0, 0.67}**
- SAX representation: **bddba**

- Cute or



Figure 5: The first three weeks of the power demand dataset. Note the repeating pattern of a strong peak for each of the five weekdays, followed by relatively quite weekends

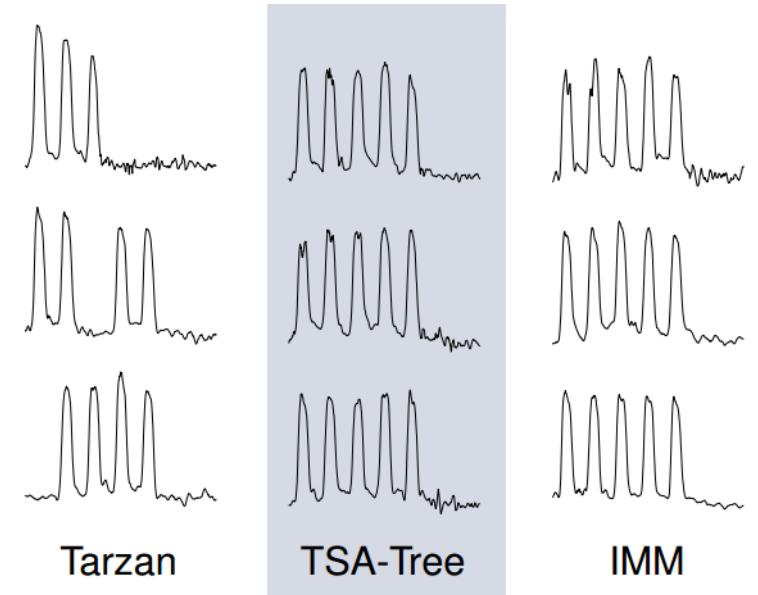


Figure 6: The three most surprising weeks in the power demand dataset, as determined by Tarzan, TSA-Tree and IMM

SAX Summary

Session 1: Data Acquisition and Reduction

- Sampling and Filtering
- Data Reduction and Analytics
- SAX

Session 2: Data Handling

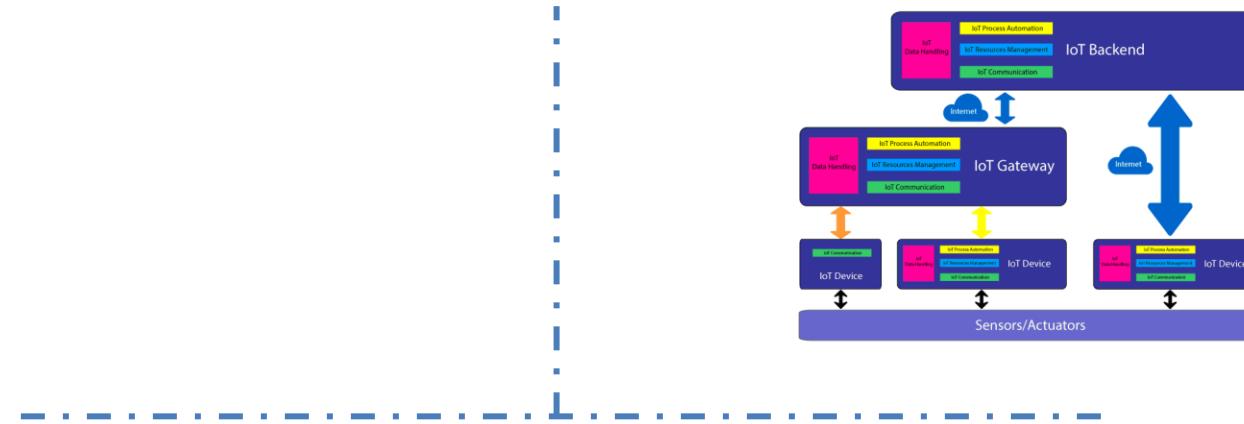
- Communication Costs
- Scenarios
- Stream Analytics

Session 3: Data Storage

- SQL
- NoSQL

- SAX is a fast way of reducing the size of data sets whilst keeping them useful and allowing analytics to discover patterns using standard algorithms
- **Exercise:** With the following data: 2,3,5,0,1,3,2,0
 - Calculate: normalised time series
 - Calculate: PAA with $N = 4$
 - Calculate SAX alphabet of 3

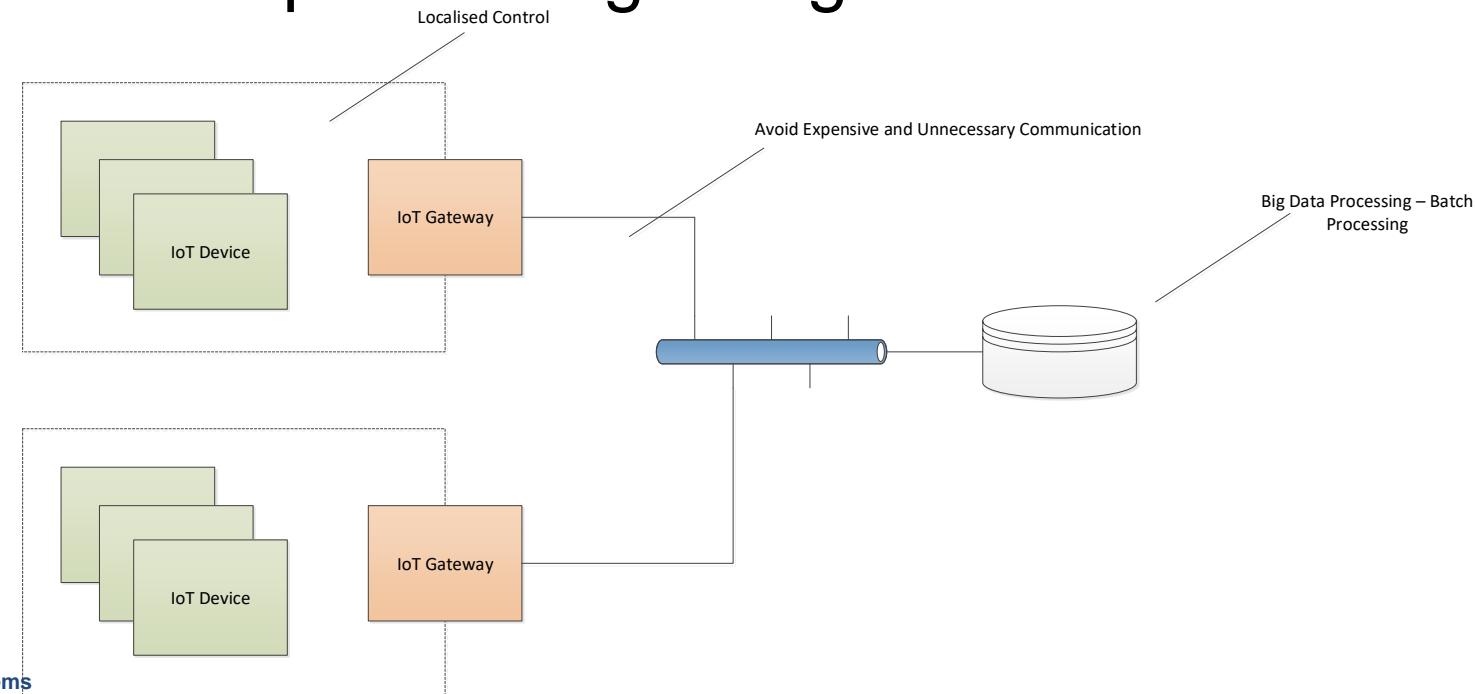
Session 2: IoT Data Handling



Learning Aim: The students will be able to explain the principle of application partitioning and its application to common IoT scenarios

IoT Scope

- IoT Systems have a large scope
 - Localised control
 - Communication to some mass storage media
 - Batch processing of big data



Data Formats: SenML (Sensor markup Language)

Session 1: Data Acquisition and Reduction

- Sampling and Filtering
- Data Reduction and Analytics
- SAX

Session 2: Data Handling

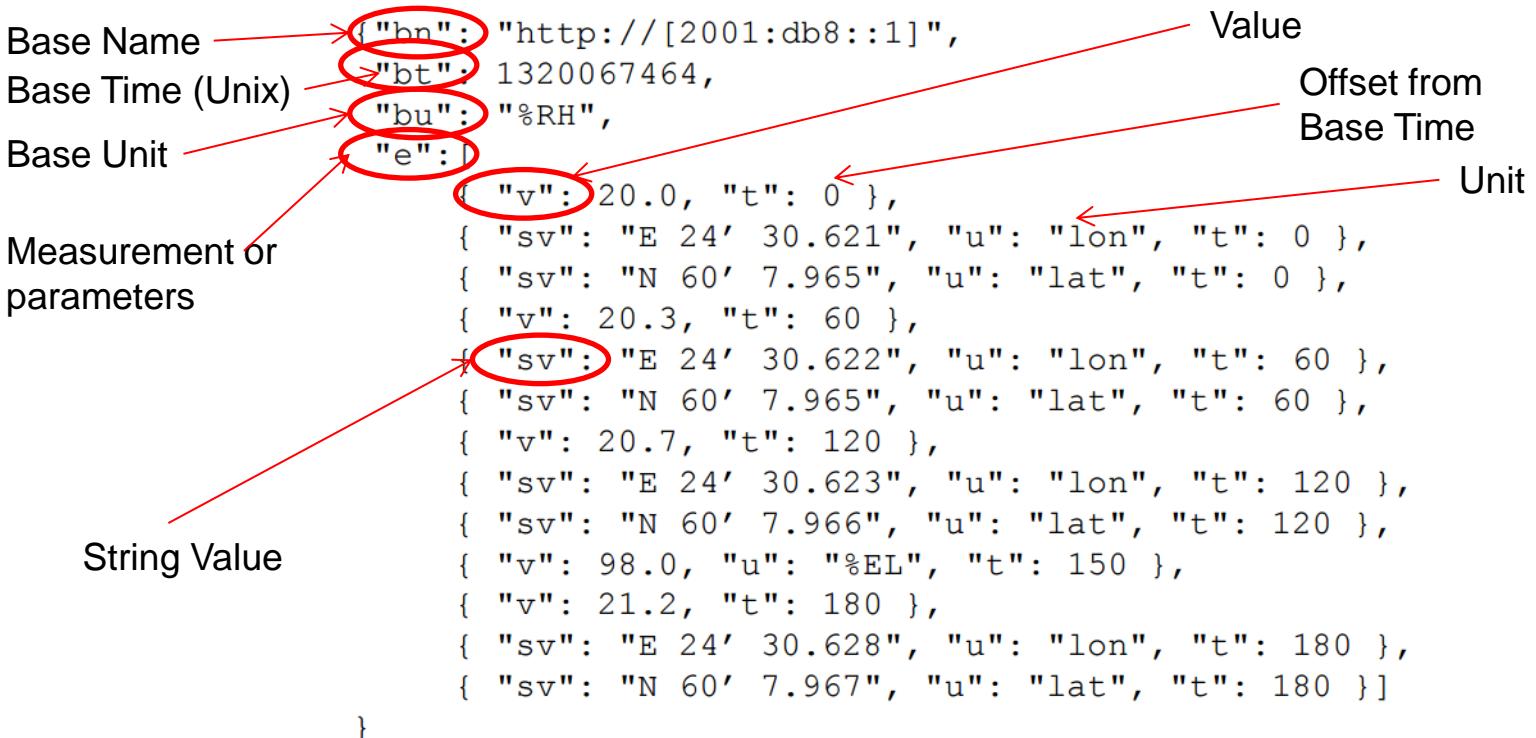
- Communication Costs
- Scenarios
- Stream Analytics

Session 3: Data Storage

- SQL
- NoSQL

■ Draft specification SenML

- <https://datatracker.ietf.org/doc/draft-jennings-core-senml/>
- Specifies XML, EXI and JSON formats



The diagram shows a SenML JSON document with annotations:

- Base Name**: Points to the key "bn": "http://[2001:db8::1]".
- Base Time (Unix)**: Points to the key "bt": 1320067464.
- Base Unit**: Points to the key "bu": "%RH".
- Measurement or parameters**: Points to the key "e": [
- String Value**: Points to the value "E 24' 30.621".
- Value**: Points to the value "20.0".
- Offset from Base Time**: Points to the key "t": 0.
- Unit**: Points to the key "u": "lon".

```
{ "bn": "http://[2001:db8::1]", "bt": 1320067464, "bu": "%RH", "e": [ { "v": 20.0, "t": 0 }, { "sv": "E 24' 30.621", "u": "lon", "t": 0 }, { "sv": "N 60' 7.965", "u": "lat", "t": 0 }, { "v": 20.3, "t": 60 }, { "sv": "E 24' 30.622", "u": "lon", "t": 60 }, { "sv": "N 60' 7.965", "u": "lat", "t": 60 }, { "v": 20.7, "t": 120 }, { "sv": "E 24' 30.623", "u": "lon", "t": 120 }, { "sv": "N 60' 7.966", "u": "lat", "t": 120 }, { "v": 98.0, "u": "%EL", "t": 150 }, { "v": 21.2, "t": 180 }, { "sv": "E 24' 30.628", "u": "lon", "t": 180 }, { "sv": "N 60' 7.967", "u": "lat", "t": 180 } ] }
```

Learning Aim: The students will be able to explain, code and decode the format of a SenML document

<https://tools.ietf.org/pdf/draft-jennings-core-senml-01.pdf>

Data Formats: SenML Exercise

- Decode this:

```
{"bn": "urn:dev:mac:0024beffffe804ff1/",
 "bt": 1276020076,
 "bu": "A",
 "ver": 1,
 "e": [
     { "n": "voltage", "u": "V", "v": 120.1 },
     { "n": "current", "t": -5, "v": 1.2 },
     { "n": "current", "t": -4, "v": 1.30 },
     { "n": "current", "t": -3, "v": 0.14e1 },
     { "n": "current", "t": -2, "v": 1.5 },
     { "n": "current", "t": -1, "v": 1.6 },
     { "n": "current", "t": 0, "v": 1.7 }
 ]}
```

- Using this:

SenML JSON Type			SenML JSON Notes		
Base Name	bn	String	Name	n	String
Base Time	bt	Number	Units	u	String
Base Units	bu	Number	Value	v	Floating point
Version	ver	Number	String Value	sv	String
Measurement or Parameters	e	Array	Boolean Value	bv	Boolean
			Value Sum	s	Floating point
			Time	t	Number
			Update Time	ut	Number

Data Formats: CBOR (Concise Binary Object Representation)

■ Draft specification CBOR

- <https://www.rfc-editor.org/rfc/rfc8949.html>
- JSON-like (conceptually) binary encoding of data (24 bytes)

Learning Aim: The students will be able to explain the principle of a CBOR document

```
name: "Strawberry Pie"  
data: <00 01 02 03 04 05 06 07 08 09>
```

Base64 Encoded JSON (51 bytes)

```
{"name": "Strawberry Pie", "data": "AAECAwQFBgcICQ=="}  
CBOR Encoded (35 bytes)
```

```
a2646e616d656e5374726177626572727920506965696a7065675f646174614a00010203040506070809
```

```
a2          -- Map, 2 pairs  
  64          -- String, length: 4  
    6e616d65  -- {Key:0}, "name"  
  6e          -- String, length: 14  
    5374726177626572727920506965 -- {Val:0}, "Strawberry Pie"  
  64          -- String, length: 4  
    64617461 -- {Key:1}, "data"  
  4a          -- Bytes, length: 10  
    00010203040506070809 -- {Val:1}, 00010203040506070809
```

Local Control

- Story: George gets an insurance reduction if he subscribes to a water leak detection service
- Exercise: Where is this service best located?

Session 1: Data Acquisition and Reduction

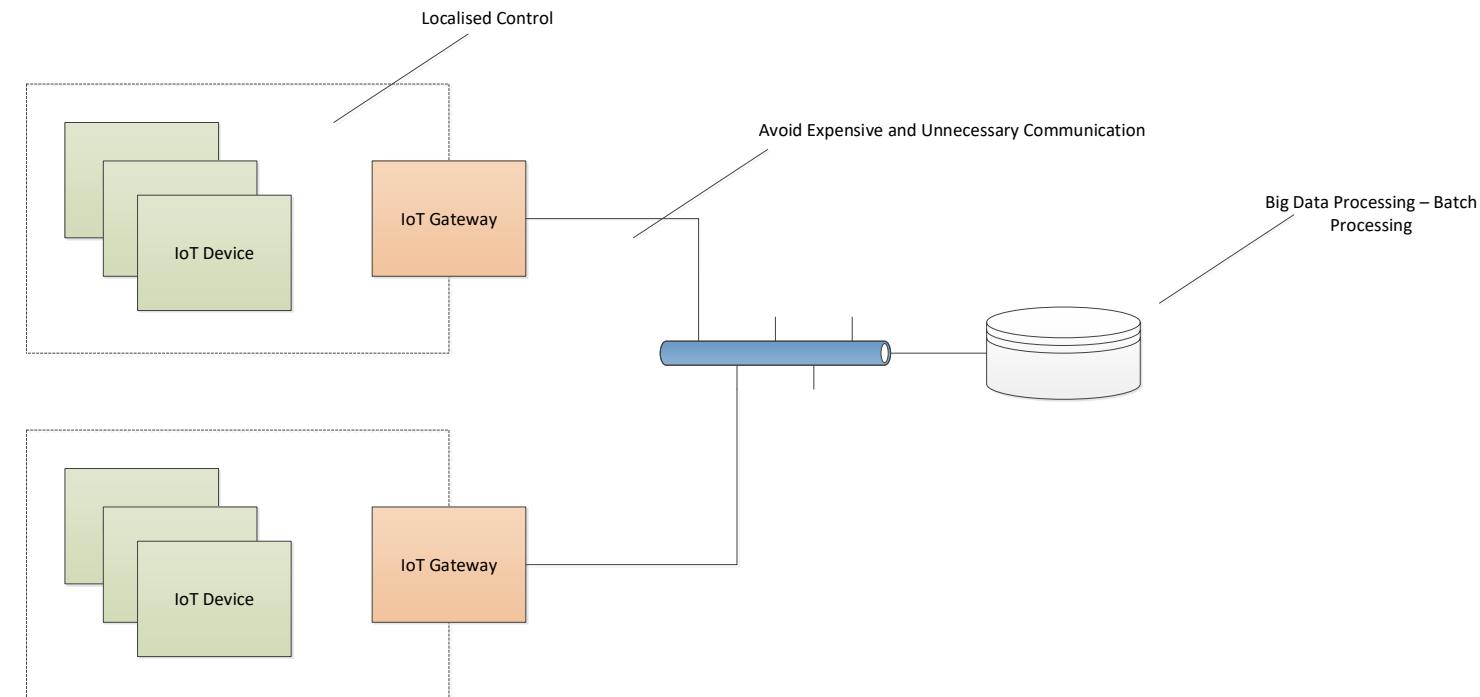
- Sampling and Filtering
- Data Reduction and Analytics
- SAX

Session 2: Data Handling

- Communication Costs
- Scenarios
- Stream Analytics

Session 3: Data Storage

- SQL
- NoSQL



Local Control - Platforms

Session 1: Data Acquisition and Reduction

- Sampling and Filtering
- Data Reduction and Analytics
- SAX

Session 2: Data Handling

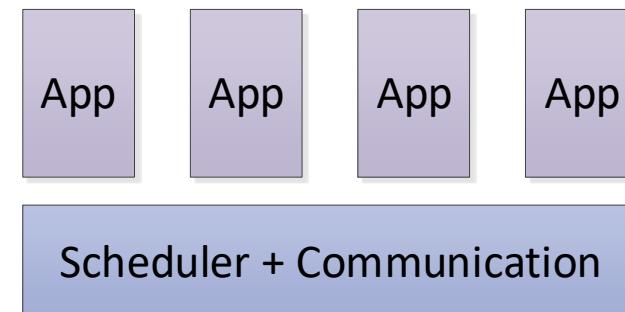
- Communication Costs
- Scenarios
- Stream Analytics

Session 3: Data Storage

- SQL
- NoSQL

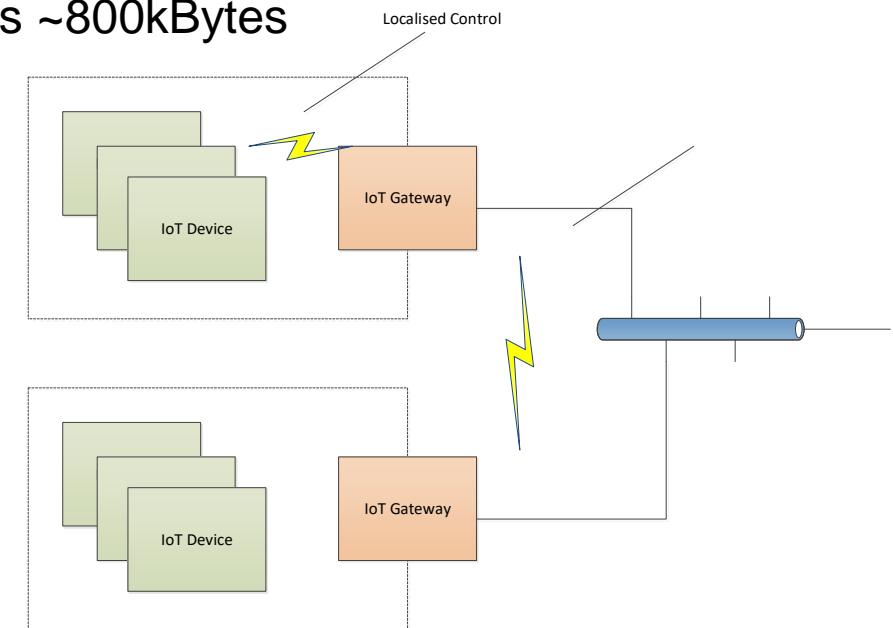
■ Apache Edgent

- Microkernel architecture
- Local data analysis can also be used to reduce communication costs and backend processing costs
- Edge devices can communicate with other edge devices
- Java based – core JARS and extensions ~800kBytes



Learning Aim: The students will be able to explain the principle of a microkernel architecture

Learning Aim: The students will be able to explain why a microkernel architecture is suited to IoT application distribution and orchestration



Backend Control

- Story: George wants monthly billing with 10% overpayment
- Exercise: Where is this service best located?

Session 1: Data Acquisition and Reduction

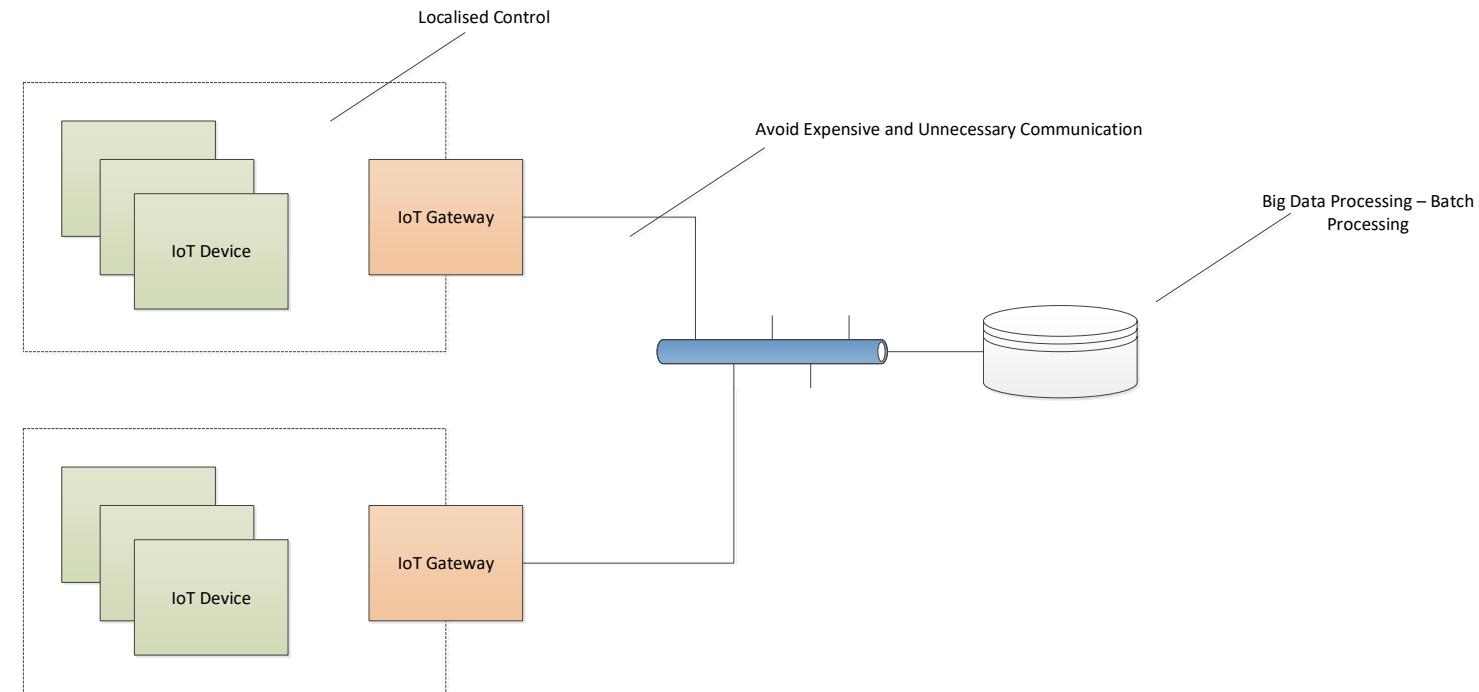
- Sampling and Filtering
- Data Reduction and Analytics
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Session 2: Data Handling

- Communication Costs
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Session 3: Data Storage

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- NoSQL

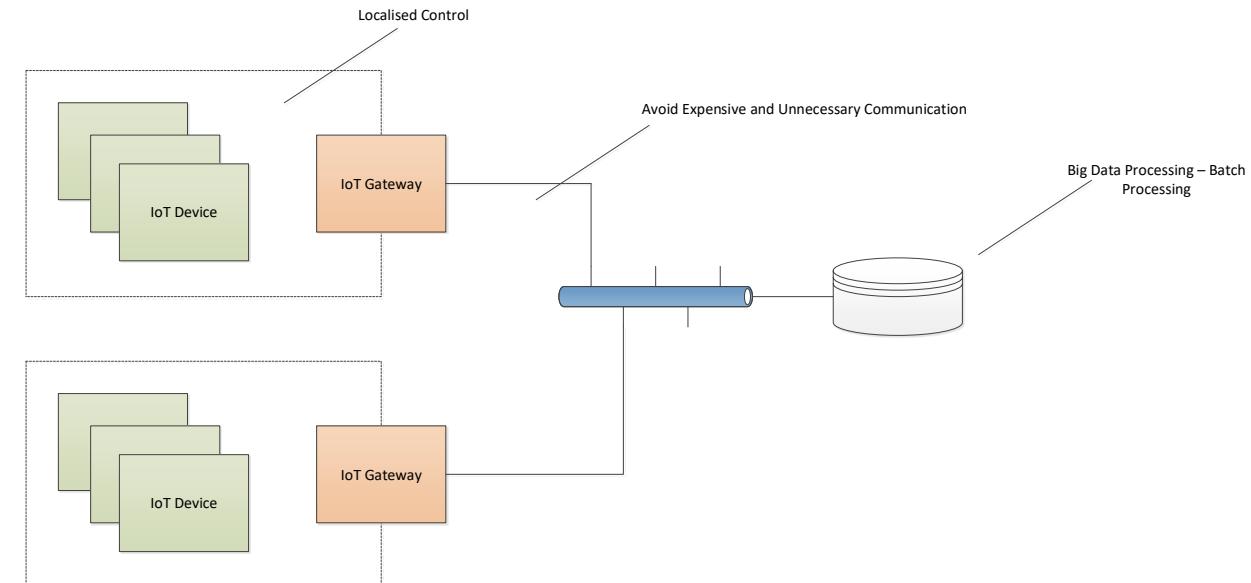


? Control

■ Story: Water corporation want to match supply with demand

- Near real-time processing using analytics and prediction algorithms

■ Exercise: Where is this service best located?



Answer - stream analytics

Session 1: Data Acquisition and Reduction

- Sampling and Filtering
- Data Reduction and Analytics
- SAX

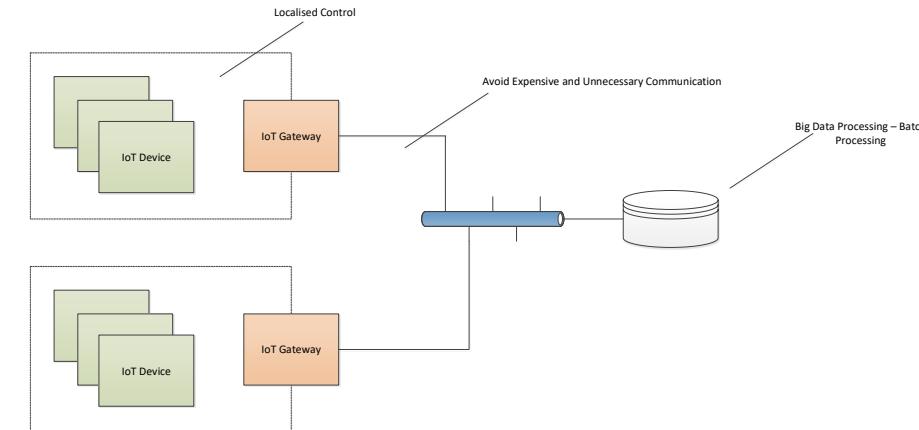
Session 2: Data Handling

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Session 3: Data Storage

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- Single pass over time series
 - Very low memory usage
- Processed continuously or in small batches
- Landmark Model
 - From current time to start of series
- Sliding Window Model
 - Window over the data
- Dampening Model
 - Assigns weights to values over time series
- Looking for: number and frequency of items, median, frequency, moments ...



Stream analytics - Locations

Session 1: Data Acquisition and Reduction

- Sampling and Filtering
- Data Reduction and Analytics
- SAX

Session 2: Data Handling

- Communication Costs
- Scenarios
- Stream Analytics

Session 3: Data Storage

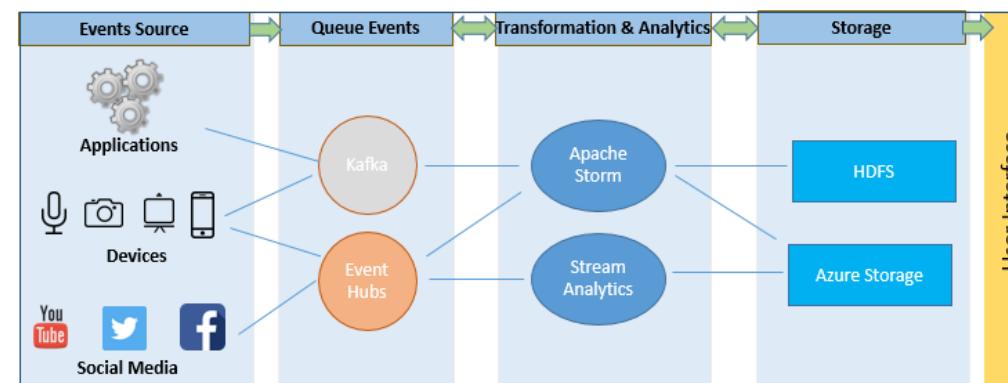
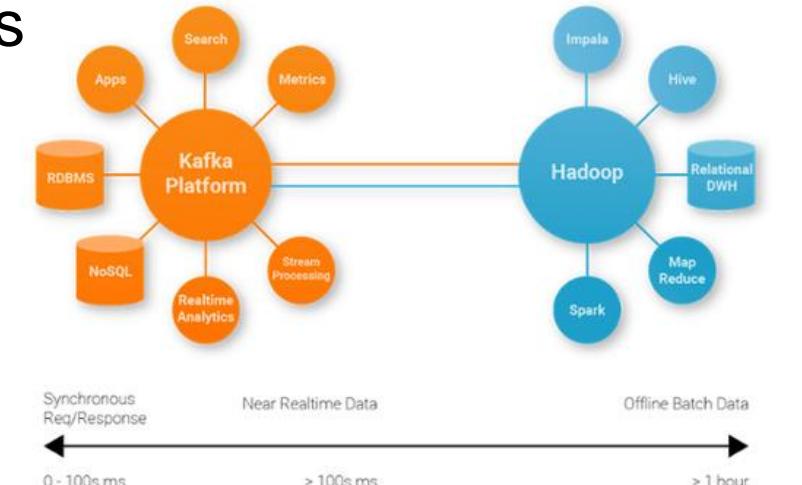
- SQL
- NoSQL

■ Stream analytics creates new streams

- reduce time series
- creates time series

■ New streams need a destination

■ Idea – combine stream analytics with messaging systems



<https://www.computerworld.com/article/2999864/big-data/how-apache-kafka-is-greasing-the-wheels-for-big-data.html>
<https://www.hcltech.com/blogs/apache-storm-hdinsight>

Stream analytics - Locations

Session 1: Data Acquisition and Reduction

- Sampling and Filtering
- Data Reduction and Analytics
- SAX

Session 2: Data Handling

- Communication Costs
- Scenarios
- Stream Analytics

Session 3: Data Storage

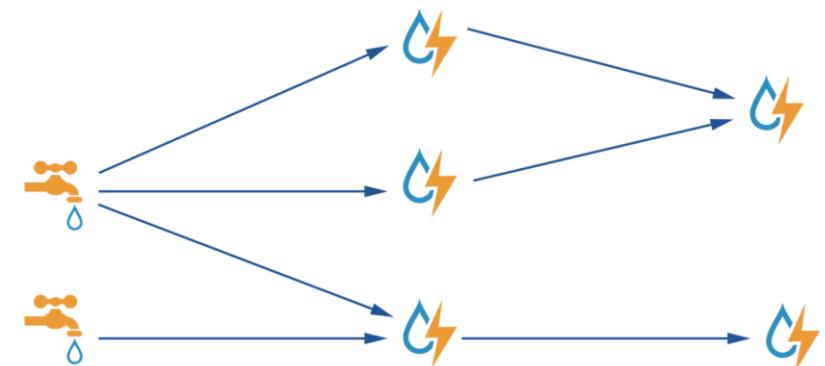
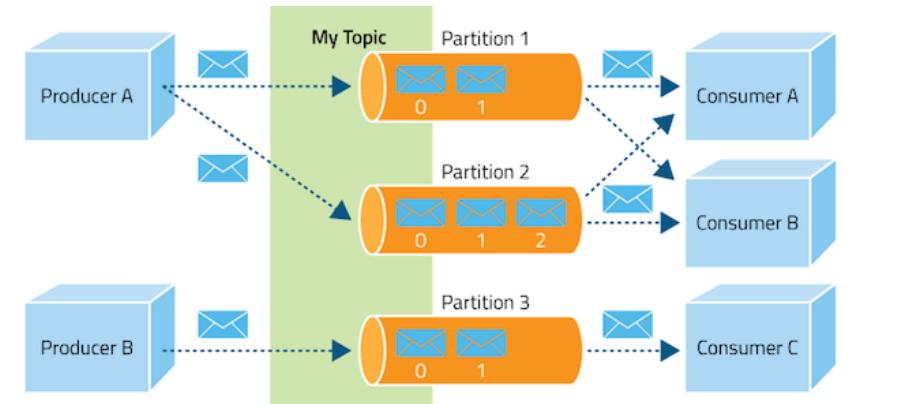
- SQL
- NoSQL

■ f.i Apache Kafka (LinkedIn)

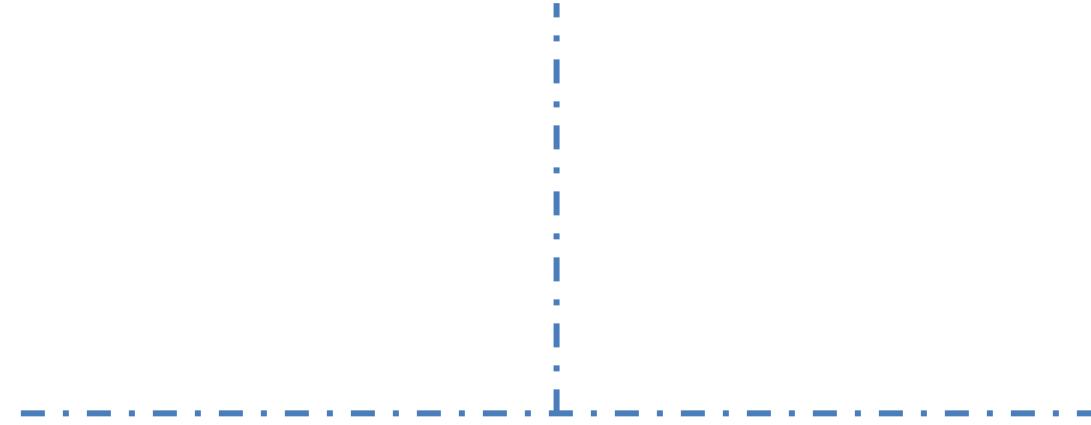
- Business-logic level messaging service
- Stores messages in queues
- Messages can be consumed
- Message lifetime a function of calendar time, not of consumption

■ f.i. Apache Storm

- Framework for streaming analytics
- Attachments for databases and Kafka



Session 3: Data Storage



Learning Aim 3: The students will be able to explain the difference between a relational and noSQL database

Session 1: Data Acquisition and Reduction

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■ Relational Databases

- Based around a table made up of columns of keys and rows of values
- Primary key is the searchable key
- Rows cannot be duplicated – primary key needs to be unique
- Simple key = one primary key. Composite key if made up of multiple columns
- Values can have various basic types

Teachers	
	teacherID
	name
	office
	phone
	email

- The table teachers has a primary and unique key teacherID

Data Bases

Session 1: Data Acquisition and Reduction

- Sampling and Filtering
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Session 2: Data Handling

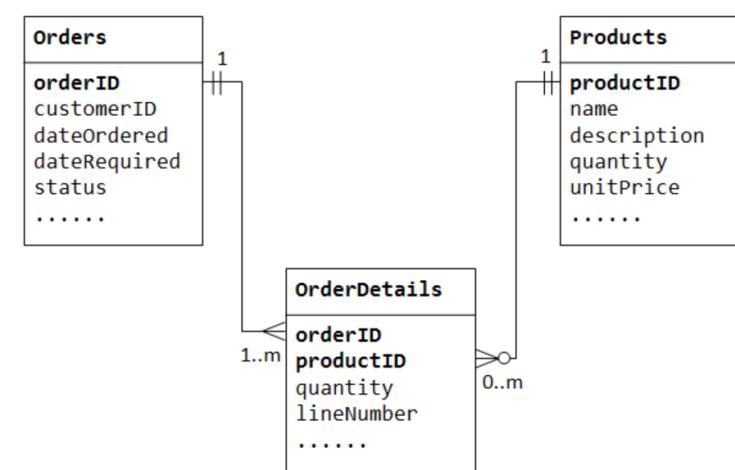
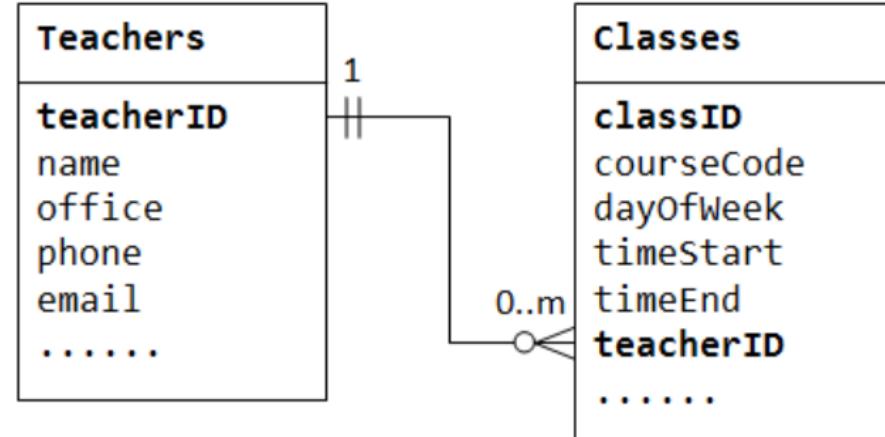
- Communication Costs
- Scenarios
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Session 3: Data Storage

- SQL
- NoSQL

■ Relational Database

- Relationships between tables
- one to many
- teacherID in table Classes is a *foreign key*
- Many to many managed over a junction table
 - To retrieve the details of an order need to search for orderID and find the particular products over the productID



Data Bases - SQL

Session 1: Data Acquisition and Reduction

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- Data Reduction and Analytics
- SAX

Session 2: Data Handling

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Session 3: Data Storage

- SQL
- NoSQL

■ Structured Query Language

- Interface between user and database
- Not as standard as it could be – details vary from DB to DB

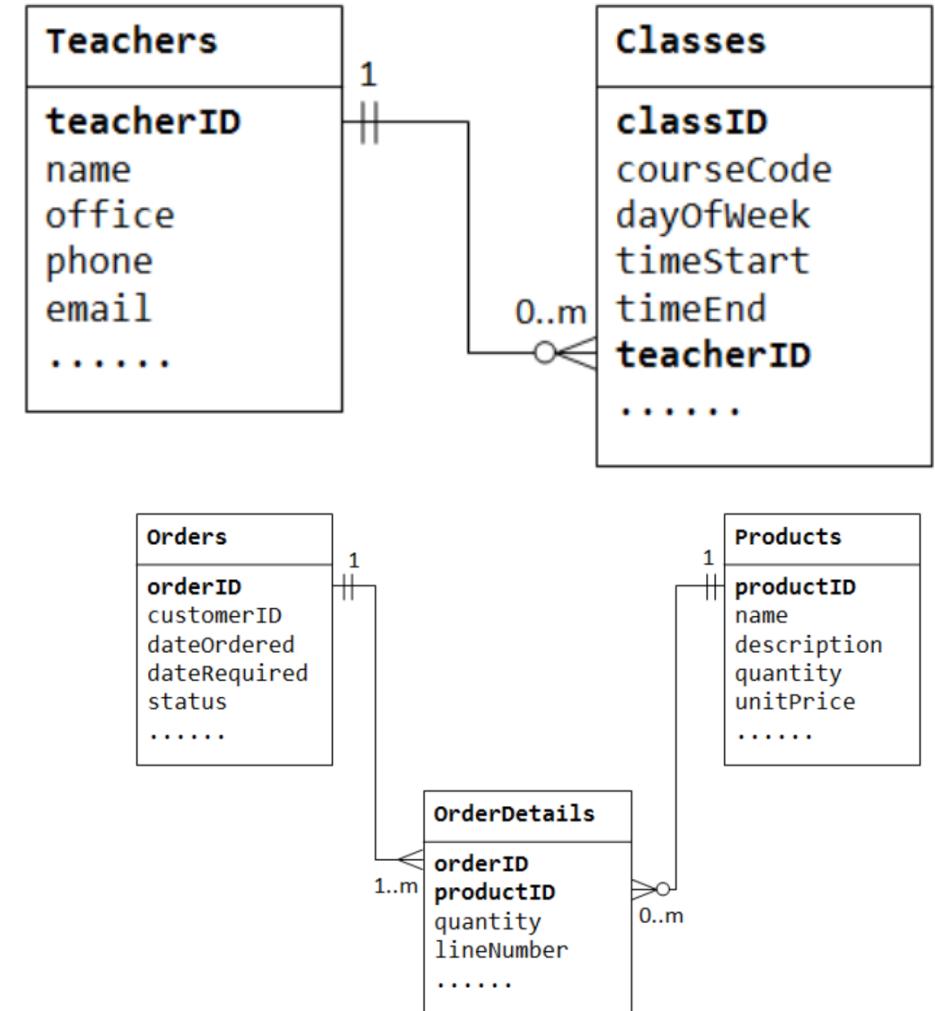
```
// Insert new data
INSERT Teachers (teacherID, name, office, email)
VALUES ('7676', 'Doran', 'TW114', 'donn@zhaw.ch')
```

```
// update data
UPDATE Teachers
SET office = 'TW108'
```

```
// read entry
SELECT name
FROM Teachers
WHERE office LIKE 'TW%'
```

```
// delete entry
DELETE Teachers
WHERE name = Doran
```

https://www.ntu.edu.sg/home/ehchua/programming/sql/Relational_Database_Design.html



Data Bases - SQL

Session 1: Data Acquisition and Reduction

- Sampling and Filtering
- Data Reduction and Analytics
- SAX

Session 2: Data Handling

- Communication Costs
- Scenarios
- Stream Analytics

Session 3: Data Storage

- SQL
- NoSQL

■ Join

- Selecting data sets

SQL JOIN Examples

Problem: List all orders with customer information

ORDER	
Id	-0
OrderDate	
OrderNumber	
CustomerId	
TotalAmount	

CUSTOMER	
Id	-0
FirstName	
LastName	
City	
Country	
Phone	

```
1. SELECT OrderNumber, TotalAmount, FirstName, LastName, City, Country
2.   FROM [Order] JOIN Customer
3.     ON [Order].CustomerId = Customer.Id
```

In this example using table aliases for [Order] and Customer might have been useful.

Results: 830 records.

OrderNumber	TotalAmount	FirstName	LastName	City	Country
542378	440.00	Paul	Henriot	Reims	France

Databases ACID

Session 1: Data Acquisition and Reduction

- Sampling and Filtering
- Data Reduction and Analytics
- SAX

Session 2: Data Handling

- Communication Costs
- Scenarios
- Stream Analytics

Session 3: Data Storage

- SQL
- NoSQL

■ Fundamental Property of Relational Databases

INSERT Teachers (teacherID, name, gender)

VALUES ('7676', 'Doran', 'neutral')

- Consistency -> if 'neutral' not allowed then **INSERT** will be rejected
- Atomicity -> the other values will not be stored either

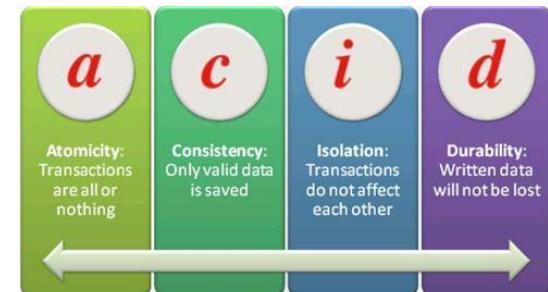
INSERT Teachers (teacherID, name, gender)

VALUES ('7676', 'Doran', 'female')

UPDATE Teachers (teacherID, name, gender)

VALUES ('7676', 'Doran', 'male')

- Isolation statement set -> first SQL block acquires lock and will finish before second
- Durability -> data will never be lost



Data Bases

Session 1: Data Acquisition and Reduction

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■ First and second generation databases:

- Generally use their own operating system /file systems
- Don't scale well - not good for huge data quantities
- not good for unstructured or semi-structured data
- Often represent single point of failure
- Tends towards slowness



NoSQL (1)

Session 1: Data Acquisition and Reduction

- Sampling and Filtering
- Data Reduction and Analytics

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- SQL
- NoSQL

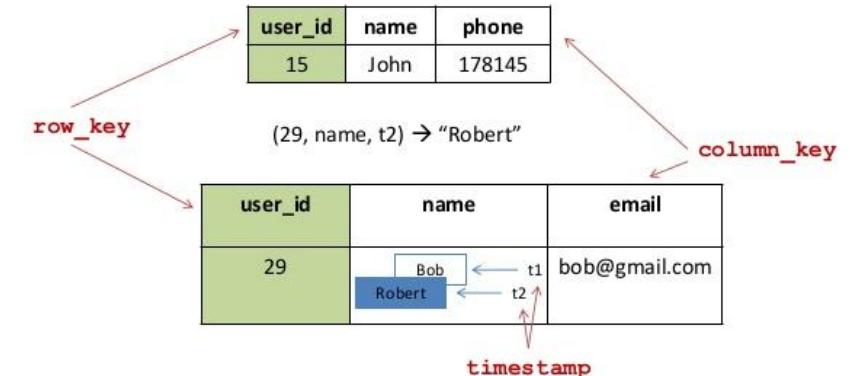
■ Consistency hard to achieve together with user response performance => NoSQL

- Name spawned by database w/o SQL and re-used to denote non relational DBs

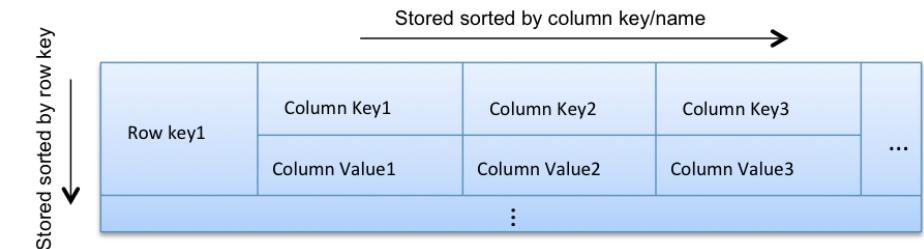
■ Tend towards key-value pairs

- BigTable from Google
 - Row + column+ timestamp
- Cassandra – facebook
 - Column orientated
 - No joins, must be handled by application

BigTable – Data Model



RDBMS Approach	user_id	name	phone	email
	15	John	178145	null
	29	Bob	null	bob@gmail.com



NoSQL (2)

- GraphDB
 - Store data as a graph

Session 1: Data Acquisition and Reduction

- Sampling and Filtering
- Data Reduction and Analytics
- SAX

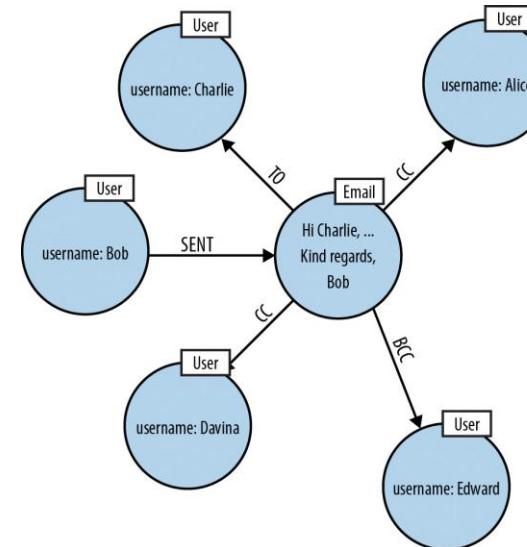
Session 2: Data Handling

- Communication Costs
- Scenarios
- Stream Analytics

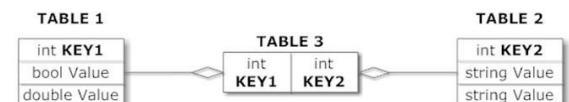
Session 3: Data Storage

- SQL
- NoSQL

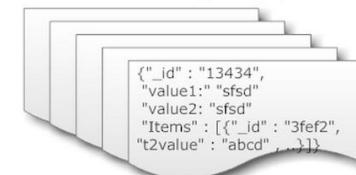
- Document Database
 - Key value pairs in f.i. JSON
 - Joins must be supported in application
 - Easy to map data from and to OO programs
 - MongoDB



Relational Model



Document Model
Collection ("Things")



<https://neo4j.com/blog/data-modeling-pitfalls/>

<https://www.morpheusdata.com/blog/2015-03-06-when-one-data-model-just-won-t-do-database-design-that-supports-polyglot-persistence>

Huge Data

Session 1: Data Acquisition and Reduction

- Sampling and Filtering
- Data Reduction and Analytics
- SAX

Session 2: Data Handling

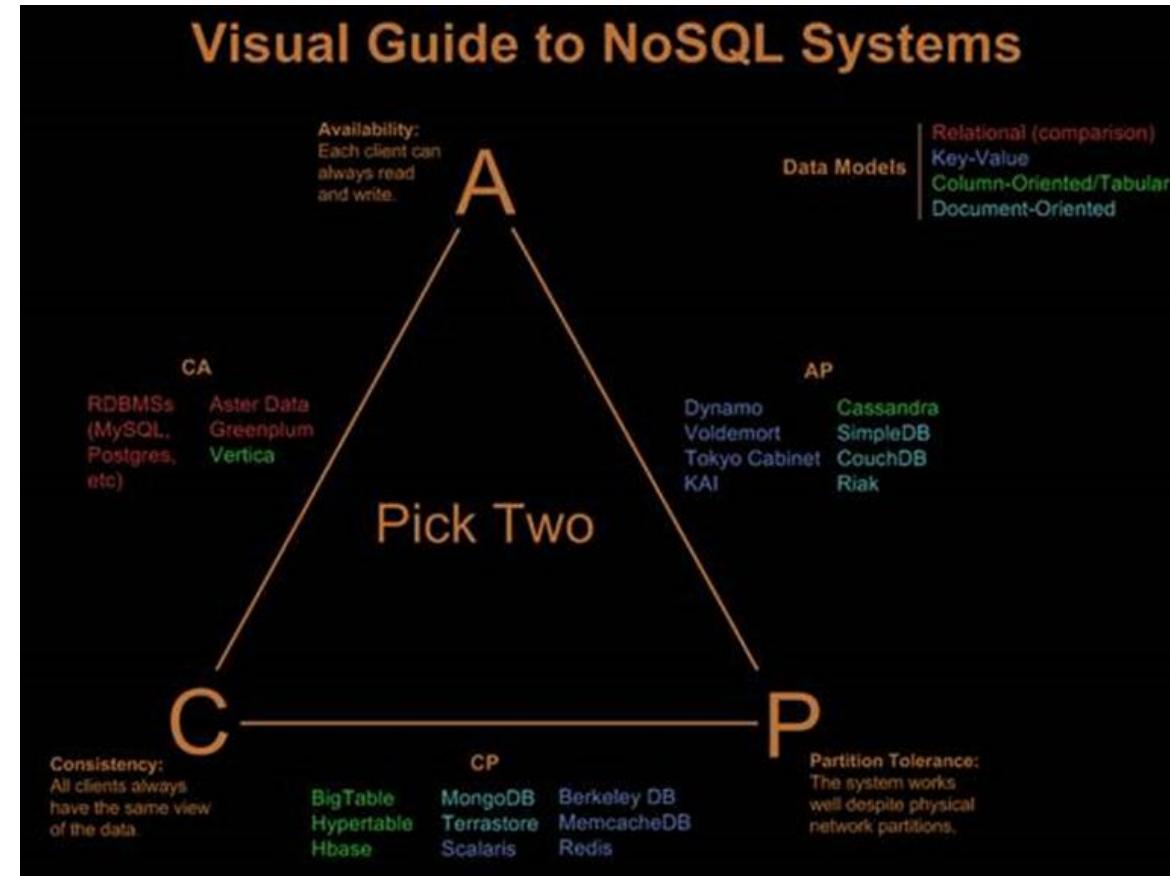
- Communication Costs
- Scenarios
- Stream Analytics

Session 3: Data Storage

- SQL
- NoSQL

■ NoSQL tend towards distributed databases

- Problem -> distributed, user experience and consistency are uneasy bedfellows
- CAP theory



Practical Issues (1)

Session 1: Data Acquisition and Reduction

- Sampling and Filtering
- Data Reduction and Analytics
- SAX

Session 2: Data Handling

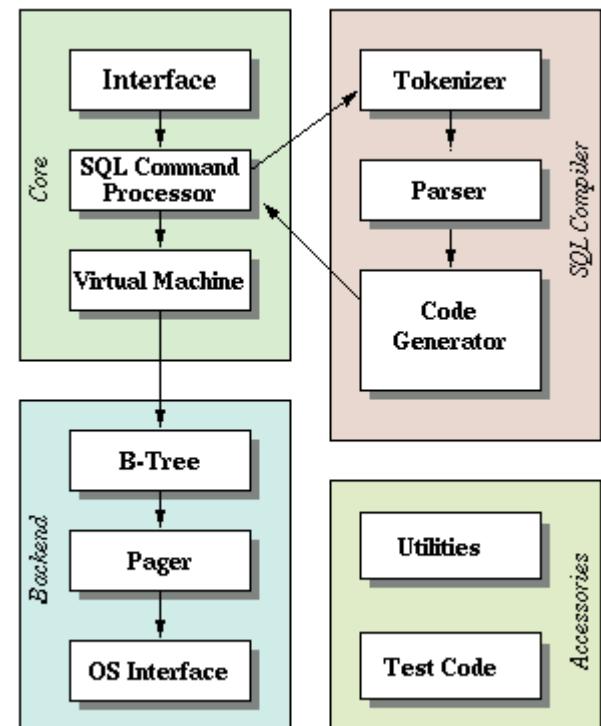
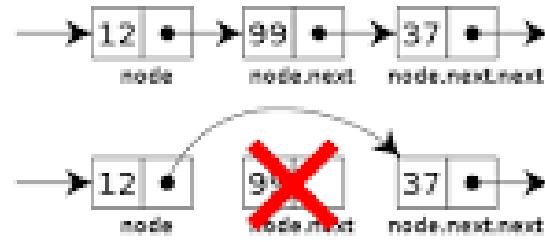
- Communication Costs
- Scenarios
- Stream Analytics

Session 3: Data Storage

- SQL
- NoSQL

Databases required on embedded devices

- Generally constrained implementations implemented using linked lists or some other such dynamic storage form
- SQLite uses files (therefore file system -> OS)
 - Min size ~300k, linux version ca 800k
- In large DB-s in-memory is often used to increase responsivity (file system/disk accesses expensive)



Practical Issues (2)

Session 1: Data Acquisition and Reduction

- Sampling and Filtering
- Data Reduction and Analytics
- SAX

Session 2: Data Handling

- Communication Costs
- Scenarios
- Stream Analytics

Session 3: Data Storage

- SQL
- NoSQL

- Databases required on embedded devices
 - Cassandra functions on raspberryPi
 - In our experience not well
- Seems to be a need for a solution that combines small resource use, inter device data persistence and cloud-sized DB connectivity for constrained applications.