Sensor and sense-ability: Building systems in the face of uncertainty

“Where theory meets practice...”

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Overview

- An emerging class of systems are driven by data sensed directly from the real world
  - Adapt and/or exhibit behaviour without detailed human control
  - Uncertain and imprecise inputs, consistent output
- How should we program these systems?
- Our aim
  - Explore past work and future challenges in building sensorised, context-aware adaptive systems
The place of computer science

- The new microscope
  - The “third pillar” alongside theory and experiment
  - Simulation, sensors, visualisation, …
- Foundational understanding
  - Formal description of how a process operates
  - Languages, systems, network science, …
- Societal impact
  - Engineering complex systems reliably
  - Systems engineering, mobility, security, …
• “Garbage in, garbage out”
  • The wrong data will generate the wrong output

• If the parameters don't meet the rely conditions, the results won't (always) meet the guarantee conditions
On two occasions I have been asked, "Pray, Mr. Babbage, if you put into the machine wrong figures, will the right answers come out?" ... I am not able rightly to apprehend the kind of confusion of ideas that could provoke such a question.


Quoted from http://en.wikipedia.org/wiki/Garbage_In,_Garbage_Out
Really a confusion of ideas?

- Babbage's assertion perhaps reflects a scientific determinism we no longer share
  - Heisenberg uncertainty, chaotic dynamics, ...
- We are used to the idea that systems come with *inherent* uncertainty
  - Can't be engineered away
  - Systems must still behave “correctly” – even if their inputs are “garbage” (or at least imperfect)
Sensor networks – 1

- Sensor networks
  - Lots of small “motes”
  - Simple processing, communications, memory
  - Low-power
- Collect data from their environment and return to a base station
Sensor networks – 2

- Are – and will remain – challenging
  - Don't get a Moore's Law effect to improve performance over time
  - Sensors have limited precision, accuracy and temporal resolution
  - Node failure is unexceptional
  - Network must survive interruptions (although individual nodes won't)
Control

- Often need to do adaptive control in these environments
  - Change mode, duty cycle, processing, …
  - Ensure scientific (mission) goals are maintained across adaptations
- Basis for control is (imprecise) measurement

Sensor-driven activity

- Increasing “sensorisation” of the environment
- Drive action directly from sensed values
  - Data is *evidence* of fact, not fact
  - Noise makes exact determination problematic
- Match observations against a *model* of what we *expect* to observe
  - Leverage the structure of behaviour

Sensors may see some, all or no people; agree or disagree on their identities; repeat observations; report with different footprints and frequencies

Noise is (often) random; phenomena of interest (often) aren’t
The rest of this talk

To what extent can we continue to generate the right answers from the wrong figures?

- Programming in the presence of uncertainty
  - Represent data in a form suitable for open-ended reasoning tasks
  - Resolve inconsistencies, tolerate small (and essentially unavoidable) errors in sensing etc
  - What are the appropriate programming structures for this environment?
Systems thinking

**STATE OF THE SEAL**

The seal is hunting for food, and diving really quickly.

**SENSE**

What can we sense? Can we get evidence from different sources?

- What do we know about the animal’s behaviour? How does the sensor data back-up hypotheses about what’s happening?
- What else might cause this observation?

**ACT**

Increase sampling rate; communicate with nearby animals to see if they’re doing the same thing.

**DECIDE**

**ANALYSE**
In pervasive computing there are a wide variety of definitions for the core concepts:

- **Context**: the environment in which a system operates, understood symbolically
- **Situation**: an interpretation of the current context in terms of an expectation model of the world
- **Behaviour**: the observables arising from the system's responses

Typically represented using RDF

Semantics of what's happening

Affect the environment, possibly generating feedback
Context and situations – 2

- Context is often redundant and conflicting
  - Many different contexts determine the *same* information (situation)

- Situation identification
  - Semantic: given a context, what situation are we in?
  - Programming: how do we make this decision?

Situation transitions provide a workflow for how the user’s situation is expected to evolve.
Why not work with context?

- Situations are closer to how designers think about systems
Example: location

- Surprisingly (or perhaps not) subtle domain

  Co-ordinates and named spaces
  - “At 55deg3minN, 3deg45minW”
  - “In A1.15”

  By negation
  - “Not …”

  Unknown
  - “No idea”

  Functional spaces
  - “In a conference room”
  - “In his office”
  - “In Willard’s office”
  - “In his car”

  Temporal
  - “At 1000 he will be…”
  - “At 0800 he was…”

  Spatial
  - “Within 250m of…”
  - “Between … and …”
  - Either at … or … or …”

  Proxy
  - “His badge was last seen at …”

  Located task
  - “Meeting Willard”

  Default
  - “At this time he is often/usually at …”

  Non-located task
  - “Out/on holiday”

Sources of uncertainty

- Dynamism
  - People move
- Engineering
  - Precision, accuracy, timeliness, calibration
- Inference
  - Track the imprecision
  - Recognise uncertainty in conclusions explicitly

Not all movements invalidate all sensor readings or inferences

Approaches

- Predicates
  - What ranges of data map to what

- Bayesian inference
  - $P(S | C)$ – being in situation given a particular set of observations

- Dempster-Schafer evidence theory
  - Distribute mass of belief

- Case-based reasoning
  - Use similarity to past, human-classified cases
Sources of knowledge

- Human understanding
  - Possible, impossible, likelihood
- Data sets
  - Future will be like the past (?)
  - Learn patterns from past observation
  - Precision, recall, F-measure

Only classify rates broadly

There is a critical shortage of good, clean, marked-up data sets
Situvis

- Exploratory specification of predicates
- Visualise how system would respond


http://www.situvis.com
Structuring situations

- Situations have structure
  - “Meeting” vs “meeting with Erica” vs “Group meeting” vs …
  - Capture this using a lattice relating observations to the situations they are consistent with

Profile of results

- All these methods tend to identify particular classes of situations well – but not all

- Is there a “best” method?
Impact

• How *unlike* normal programming!
  • Not sure what condition we're in
  • ...therefore can't decide certainly on what behaviour we should exhibit
  • Data comes with provenance
  • ...and with unusual types, with non-subsumptive relationships

• How should we best present this new domain to software developers?
Programming challenges

- Stability
  - Errors must damp-down inherently
- Multiple possibilities
  - Accept multiple behaviours, and their overlaps
- Reversing
  - All decisions are tentative and must be undone or mitigated
Mission languages

- Goal: capture the mission of an adaptive system
  - The *raison d’être* for which it is deployed
  - The parameters it's allowed to adapt, and limits
  - The tactics it can deploy

  "Swim outward against the curl of the flow field to find the edges"

  "Maximise the lifetime value of each node"

  "(Re-)deploy appropriate resources to each event"

Dobson *et alia*. From physical models to well-founded control. Proc. IEEE EASe. 2009.
Behaviour

• Can't usually narrow-down to exactly what's being observed
  • Impossible, possible, most likely

May be able to divide-up behaviour more finely, e.g. active intersection of behaviour
No ifs

- Decisions are less crisp
  - How certain is “certain enough”?
- Thresholding throws away the weight of the evidence
- Weight may change rapidly
  - Make a decision, plan how to reverse it later
  - Truth- or confidence-maintenance
5 things to take away

- Can't avoid encountering uncertain data with complex provenance
- Embrace it: it's better than assuming things are different than they are
- Can capture a lot of uncertainty generically
- Programming involves identifying possible and consistent situations
- Needs new constructs and languages that match the domains of modern interest
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