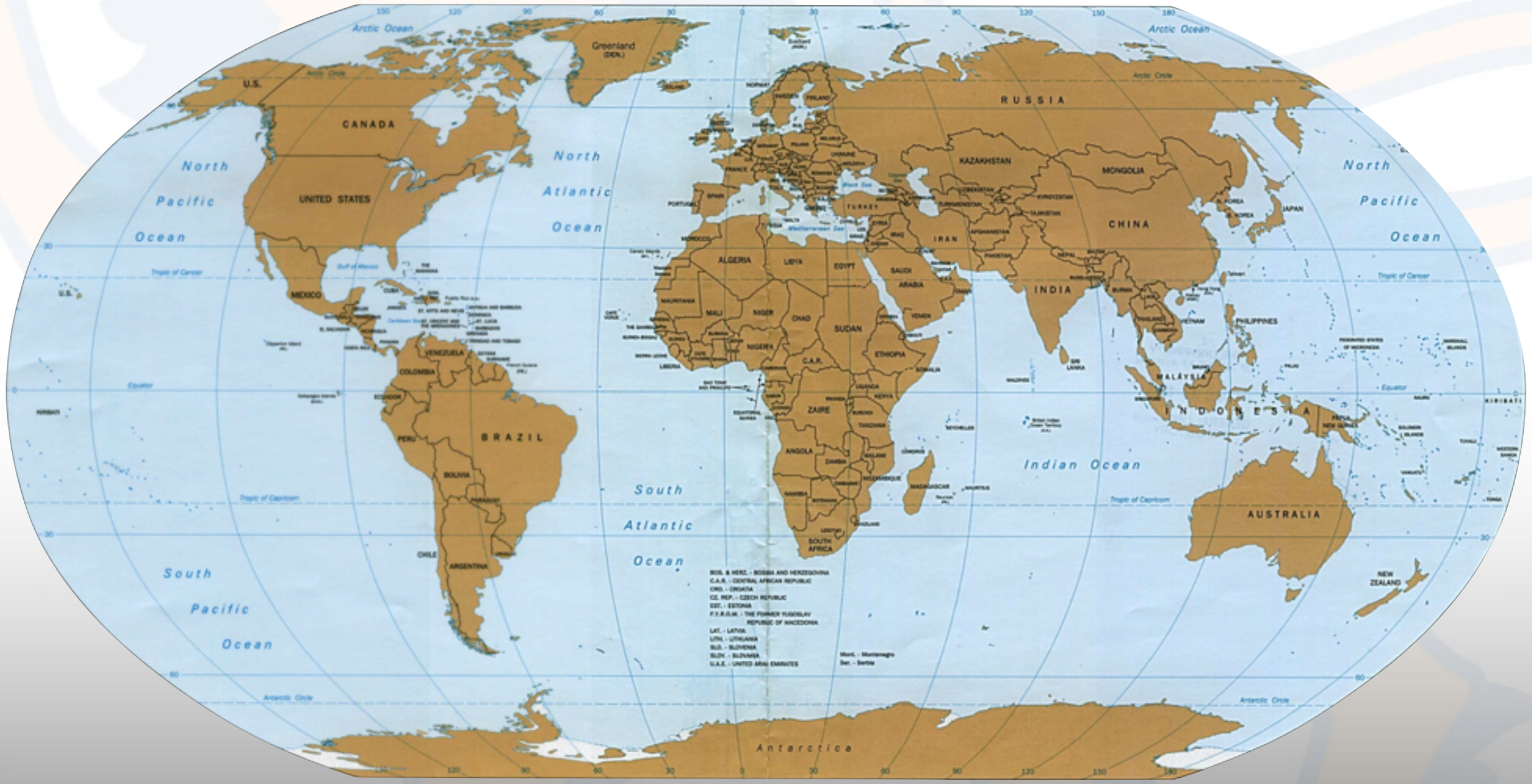
NUS
National University
of Singapore

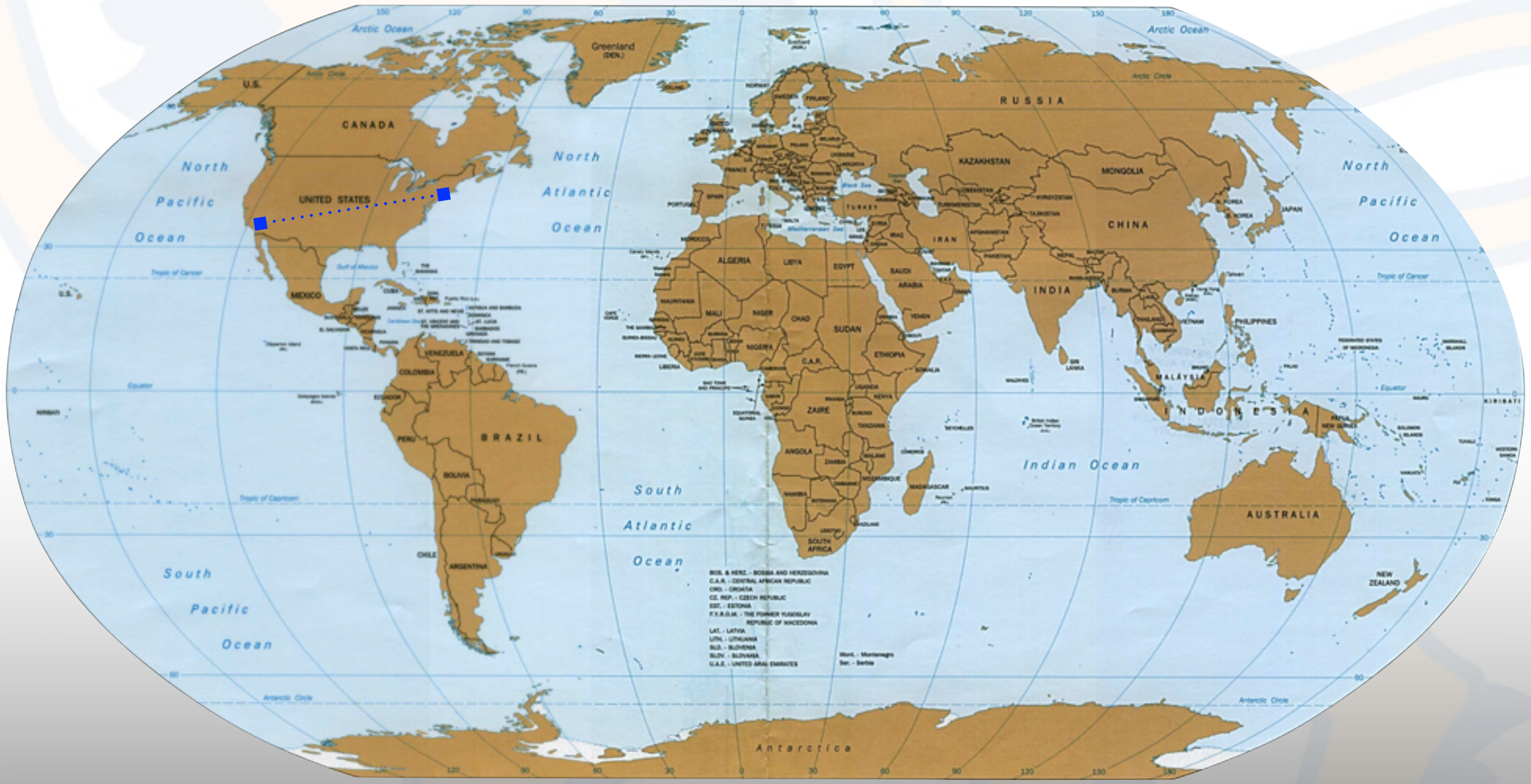
Felicitous Computing

David S. Rosenblum
School of Computing
National University of Singapore

From UCI to NUS



From UCI to NUS



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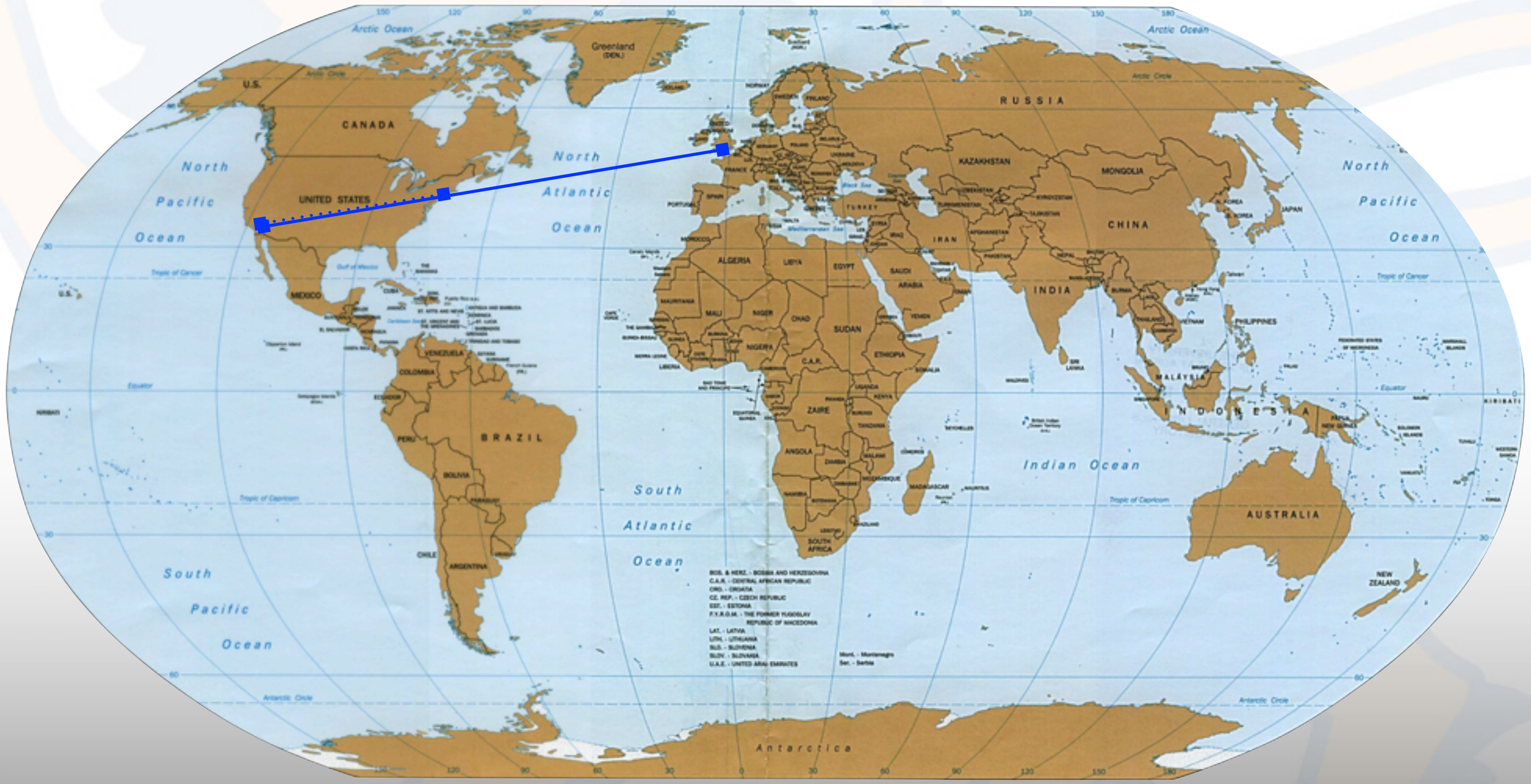
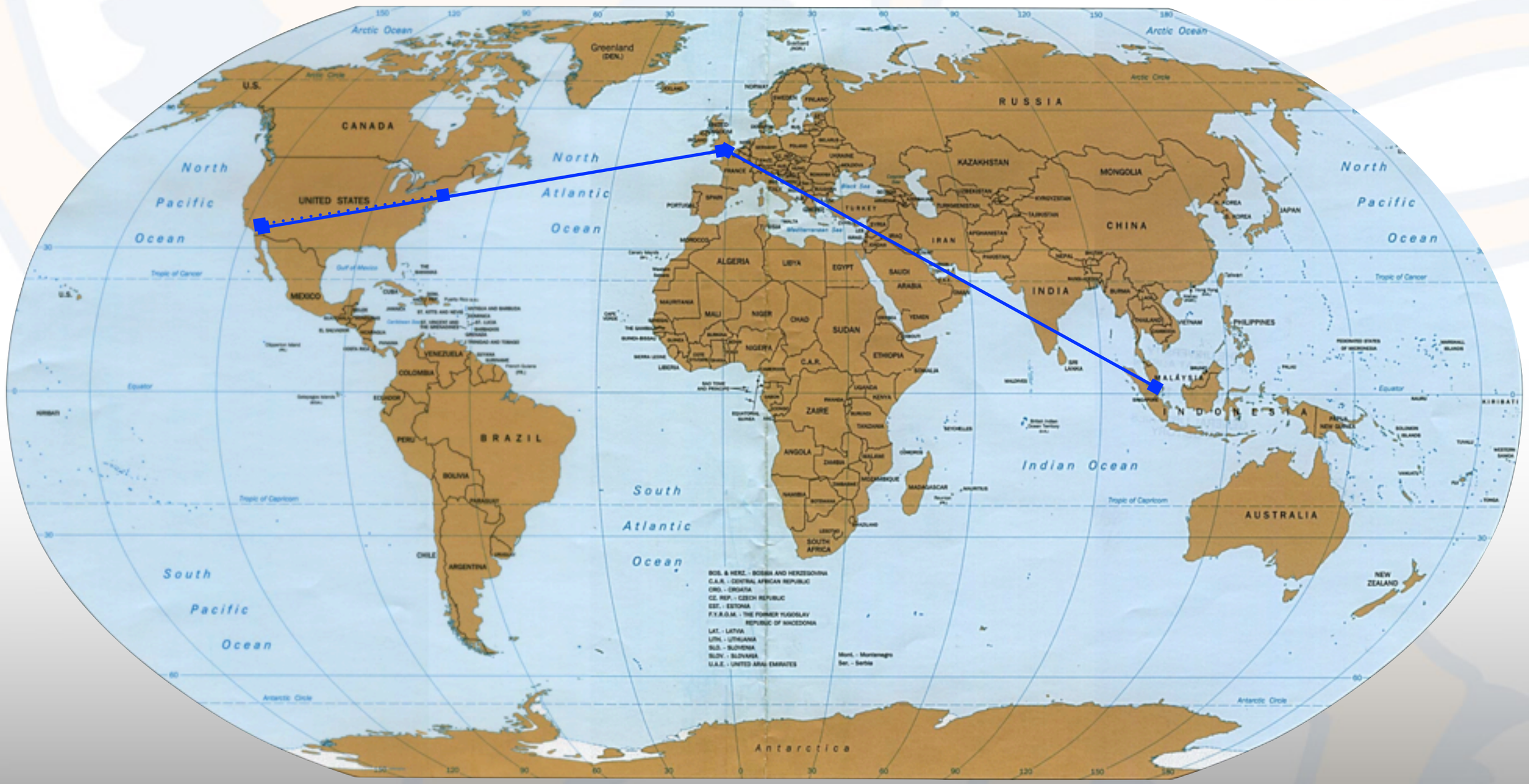


NUS National University of Singapore

From UCI to NUS



Singapore


Tampoi
Johor Bahru
Pasir
Gudang
Gelang
Patah
E3
Johor Strait
Tekong
Island
Singapore
Jurong
Island
Singapore
Singapore
Strait

Singapore


Granada Hills
North Hills
Tujunga
La Crescenta-Montrose
Van Nuys
Burbank
Altadena
Toluca Lake
Glendale
Pasadena
Arcadia
Glendora
Citrus
San Dimas
Claremont
Rancho Cucamonga
Covina
Alhambra
Beverly Hills
Monterey Park
West Covina
Los Angeles, CA
Los Angeles
Pomona
Ontario
Santa Monica
Culver City
Montebello
Walnut
Chino
Marina Del Rey
Huntington Park
Pico Rivera
Chino Hills
Mira Loma
Inglewood
Firestone Scout Reservation
Eastvale
Downey
Lynwood
La Habra
Hawthorne
Norwalk
Chino Hills State Park
Butterfield Stage Trail Park
Norco
Manhattan Beach
Gardena
Compton
Yorba Linda
Fullerton
Corona
Torrance
Lakewood
Bixby Knolls
Anaheim
El Cerrito
Palos Verdes Estates
Lomita
West Side
Cypress
Villa Park
Orange
Long Beach
Rancho Palos Verdes
Seal Beach
Westminster
Santa Ana
Silverado
Fountain Valley
Irvine
Foothill Ranch
Huntington Beach
Lake Forest
Newport Beach
San Joaquin Hills
Mission Viejo
Coto De Caza
Laguna Coast Wilderness Park
Ladera Ranch
Laguna Beach
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Google

Singapore


Angeles
San Antonio, Mount
Granada Hills
North Hills
Tujunga
La Crescenta-Montrose
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Burbank
Altadena
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Laguna Coast Wilderness Park
Ladera Ranch
Laguna Beach
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Data LDEO–Columbia, NSF, NOAA
Data SIO, NOAA, U.S. Navy, NGA, GEBCO
Google

Ubiquitous Computing

The Ideal

"The most profound technologies are those that disappear."

[Mark Weiser, *Scientific American*, 1991]

Weiser envisioned computing being

"an integral, invisible part of people's lives",

where

"the computers themselves ... vanish into the background"

Ubiquitous Computing

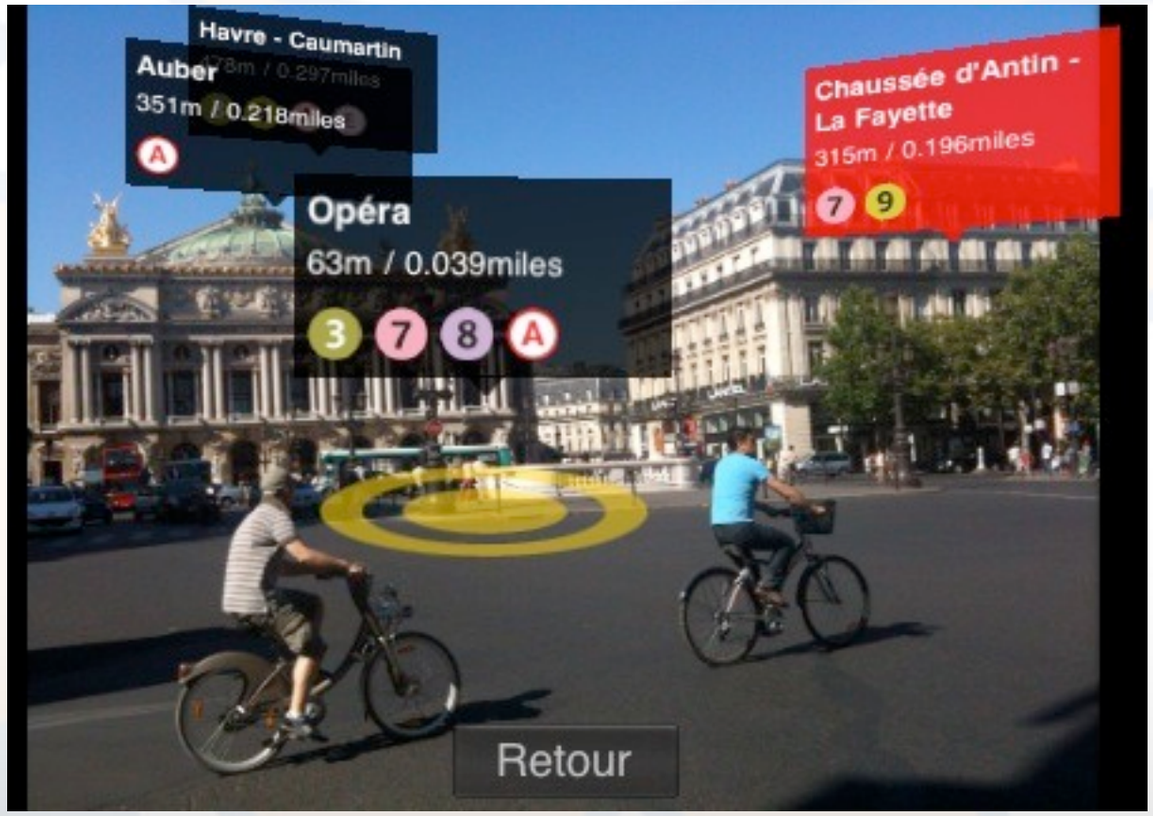
The Research Vision

Ubiquitous Computing

The Research Vision

Ubiquitous Computing

The Research Vision



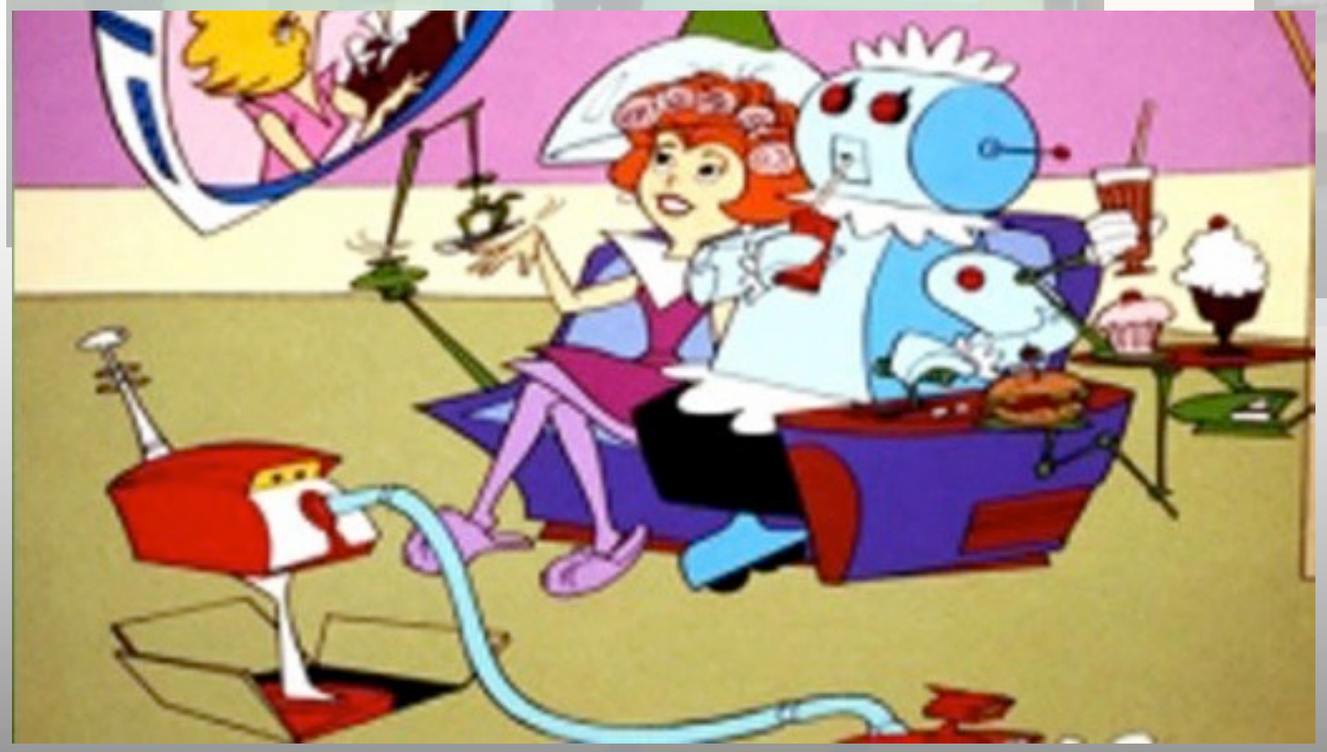
Ubiquitous Computing

The Research Vision

California PATH

Ubiquitous Computing

The Research Vision



California PATH

The Reality

Fading into the Background?

The Reality

Fading into the Background?

The Reality

Google Android Market (early 2012)

- The average price of the top 50 *paid* applications is *just US$3.79* [modymi.com]

The Reality

Google Android Market (early 2012)

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- 79.3% of paid applications have been downloaded *less than 100 times* [Distimo]

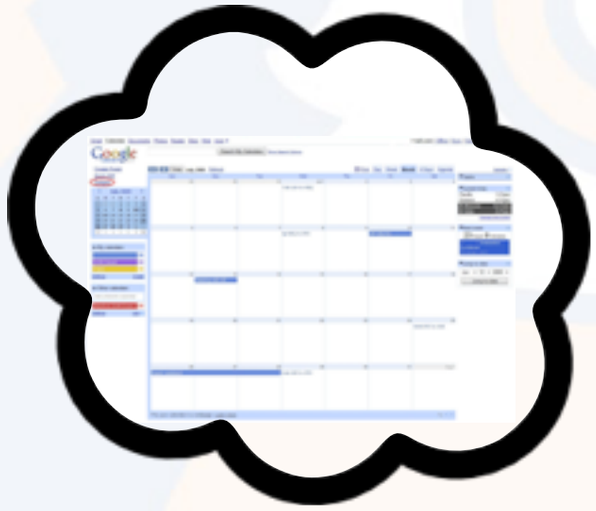
The Reality

Google Android Market (early 2012)

- The average price of the top 50 *paid* applications is *just US$3.79* [modymi.com]
- 79.3% of paid applications have been downloaded *less than 100 times* [Distimo]
- *Only 0.1%* of paid applications have been downloaded 50,000 times or more [Distimo]

The Reality

Stuff Just Doesn't Work Right



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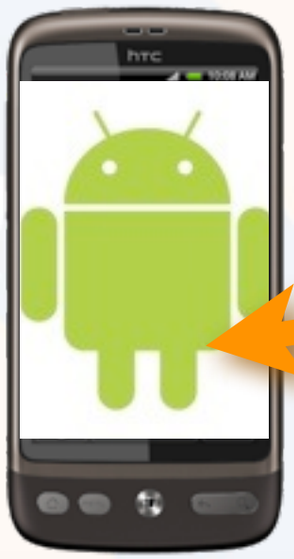

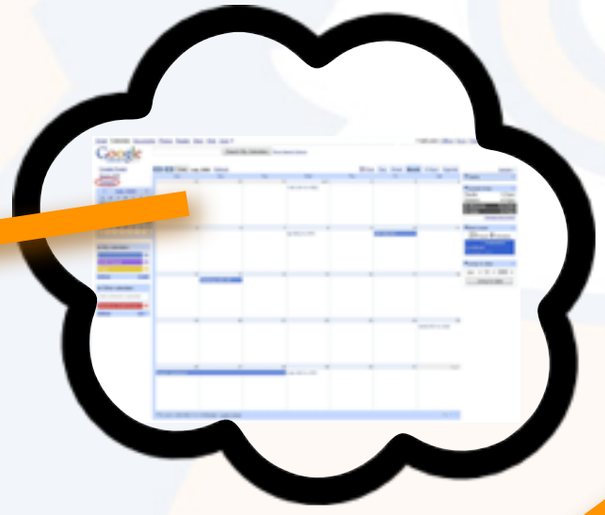

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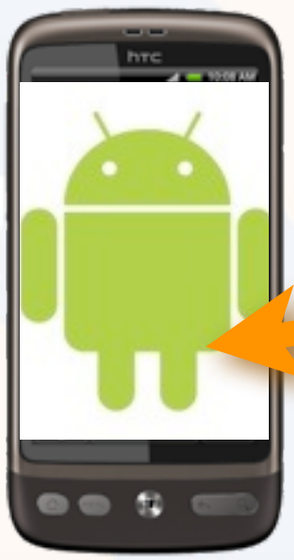
Stuff Just Doesn't Work Right



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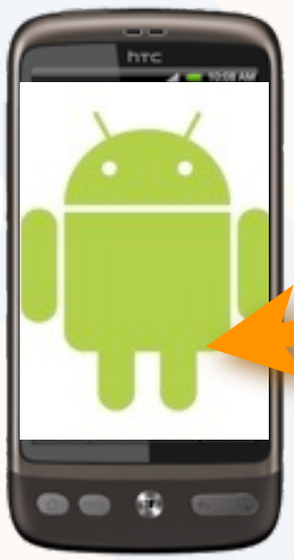

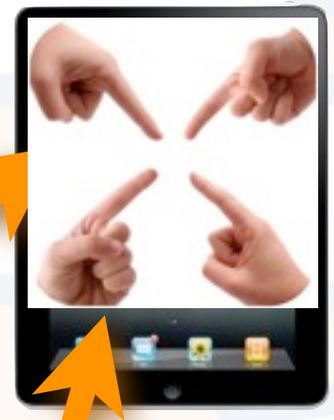

The Reality

Stuff Just Doesn't Work Right

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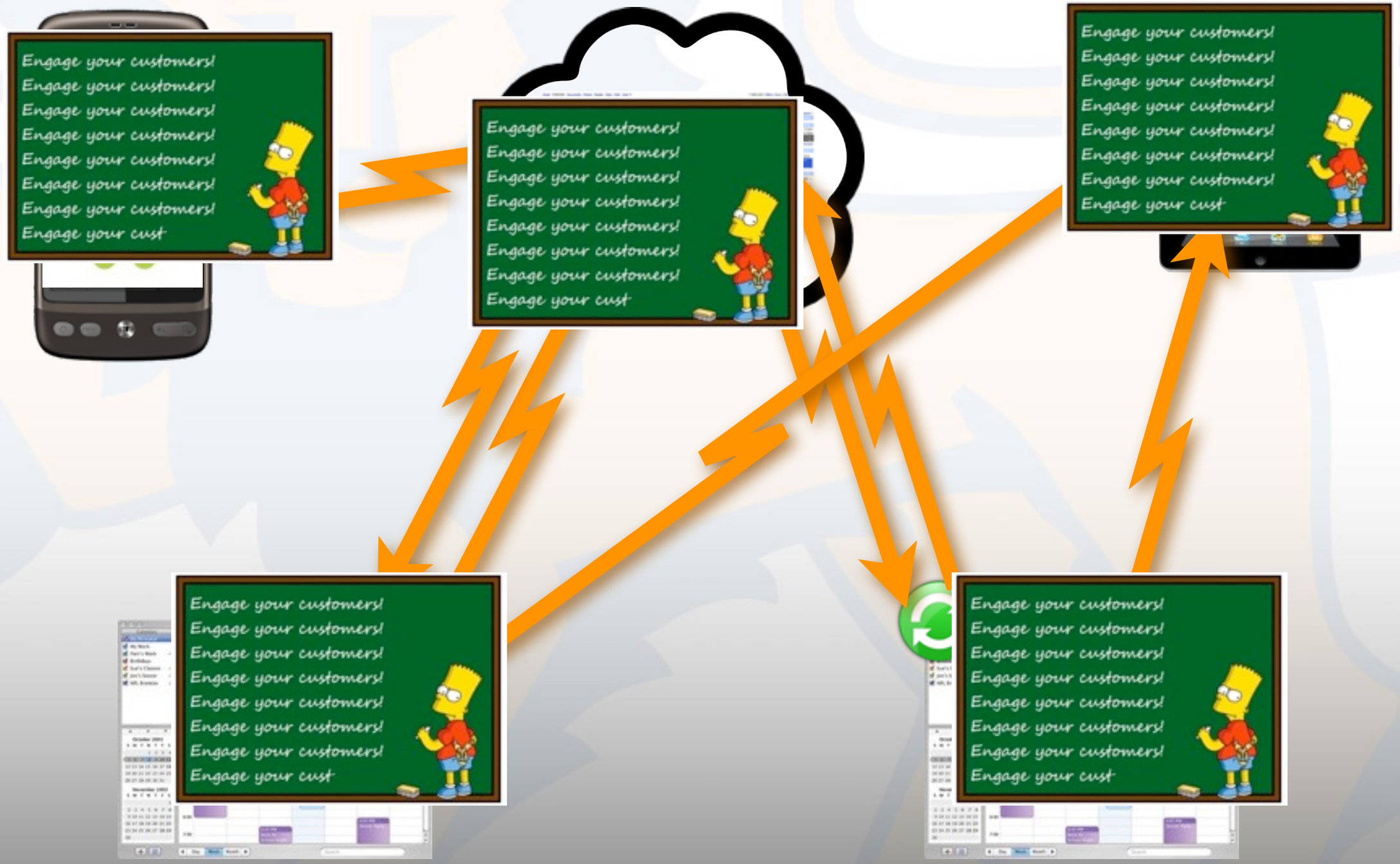
Stuff Just Doesn't Work Right



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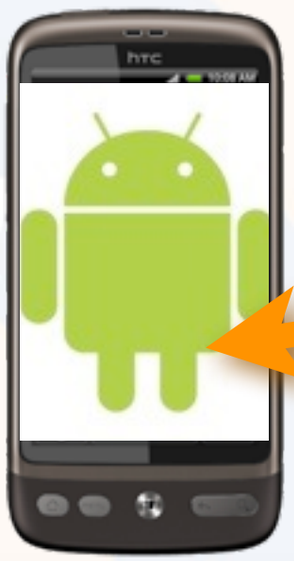

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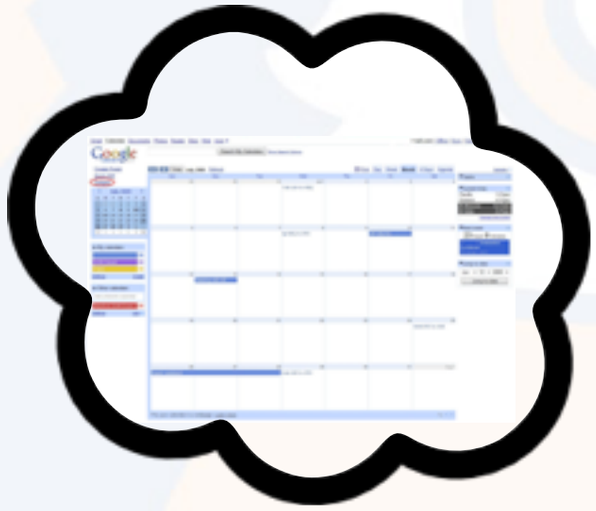

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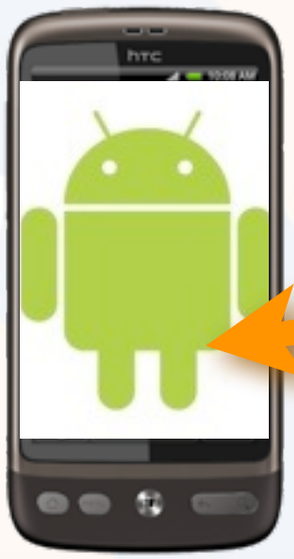

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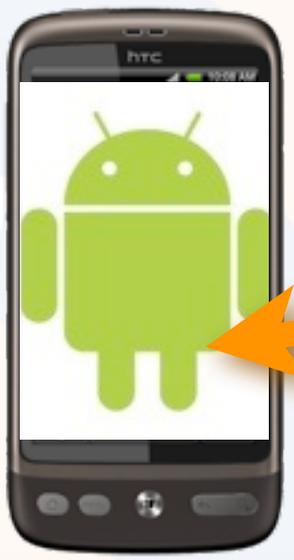

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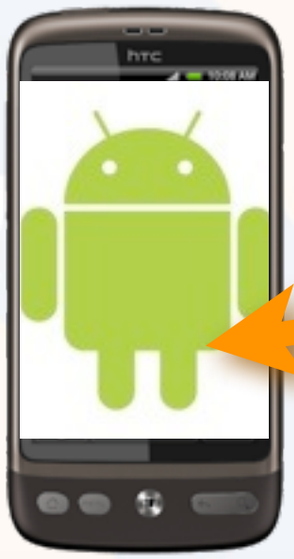


My Next Appointments Calendar?

Felicitous Computing Institute

Goal:
to realize the original ideals of ubiquitous computing

- A new multi-disciplinary research institute hosted in the NUS School of Computing
- Strongly driven by challenge problems in a variety of application domains

Felicitous Computing

Definition

fe•lic•i•tous, *adj.*, well chosen or suited to the circumstances; pleasing and fortunate

[Oxford American Dictionary]

- Computing that is not poorly chosen, ill-suited, displeasing or unfortunate!
- An overarching philosophy of technology development *and* evaluation

Felicitous Computing

Some Key Elements

Felicitous Computing

Some Key Elements

context-awareness

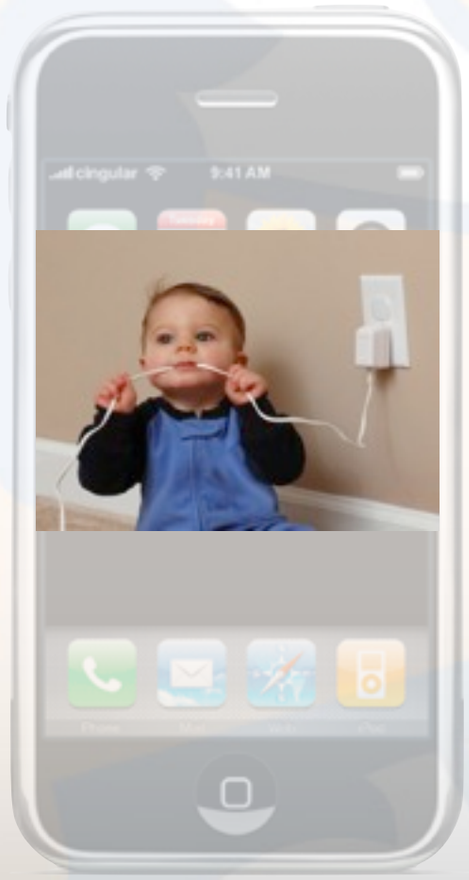
Felicitous Computing

Some Key Elements

intelligent, unobtrusive processing

Felicitous Computing

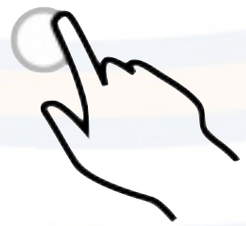
Some Key Elements



robustness

Felicitous Computing

Some Key Elements



multi-modal interaction

Felicitous Computing

Some Key Elements

- Beyond these technical characteristics ...

  Natural

  Useful

  Realistic

  Beneficial

  to Users

Felicitous Computing

Current Research Directions

- ✓ Context-Aware Adaptation
- ✓ Multi-Modal Interaction
- ✓ Emotion Sensing and Inference
- ✓ Software Engineering for Mobile Systems

Two Example Projects

1. Automated Fault Detection in Context-Aware Adaptive Applications (CAAAs)
2. Context-Aware Mobile Music Recommendation (CAMMR)

✓ Solved problems of both design and robustness

✓ Revealed new, interesting research challenges

CAAAs

Context-Aware Adaptive Applications

CAAAs

Context-Aware Adaptive Applications

CAAAs

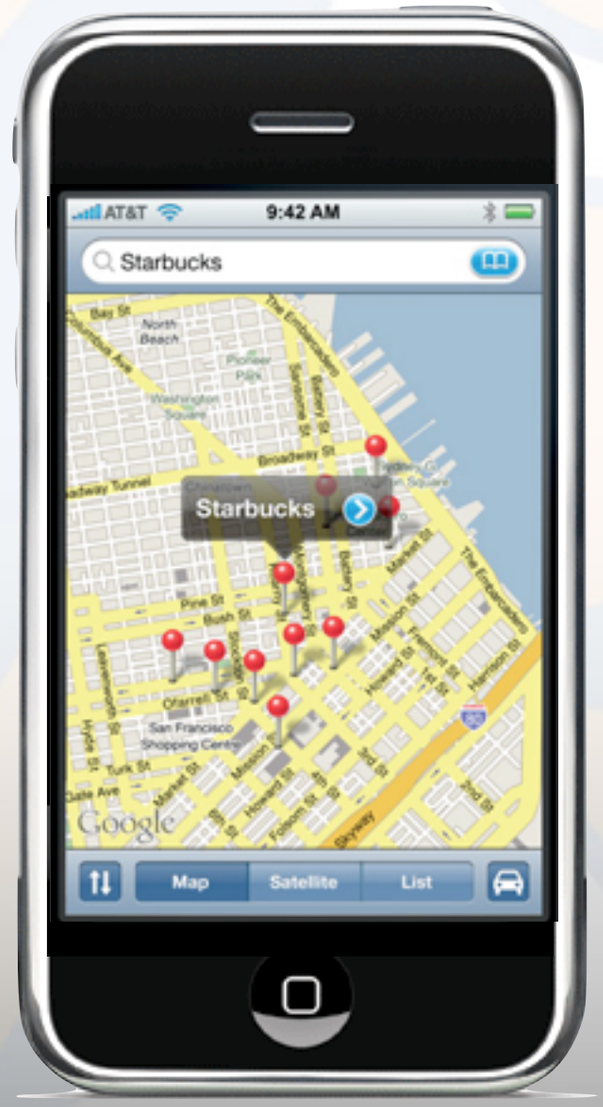
Context-Aware Adaptive Applications

CAAAs

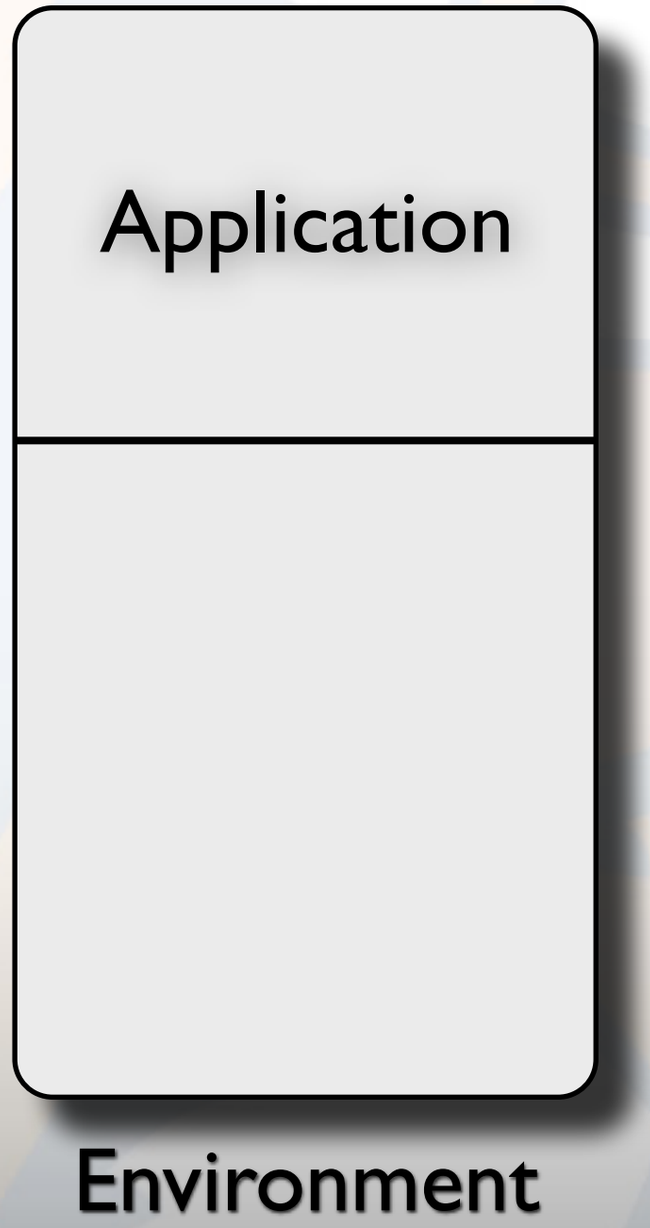
Context-Aware **Adaptive** Applications

CAAAs

Context-Aware **Adaptive** Applications



Adaptation in CAAAs



M. Sama, D.S. Rosenblum, Z. Wang and S. Elbaum, "Multi-Layer Faults in the Architectures of Mobile, Context-Aware Adaptive Applications", *Journal of Systems and Software*, Vol. 83, Issue 6, Jun. 2010, pp. 906–914.

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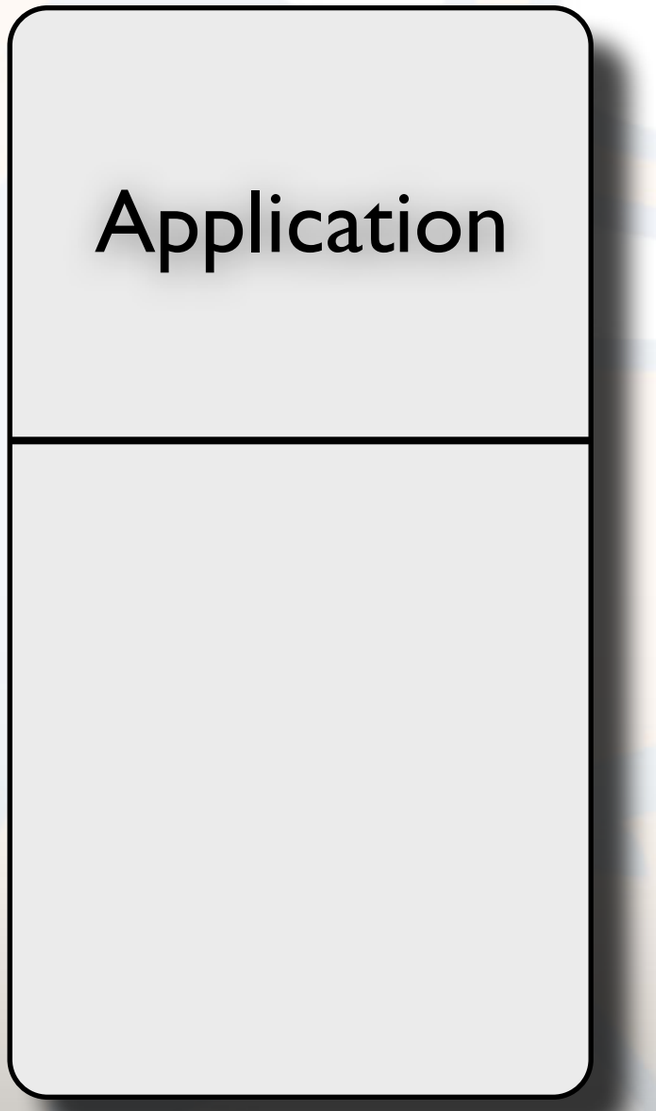

Physical Context

M. Sama, D.S. Rosenblum, Z. Wang and S. Elbaum, "Multi-Layer Faults in the Architectures of Mobile, Context-Aware Adaptive Applications", *Journal of Systems and Software*, Vol. 83, Issue 6, Jun. 2010, pp. 906–914.

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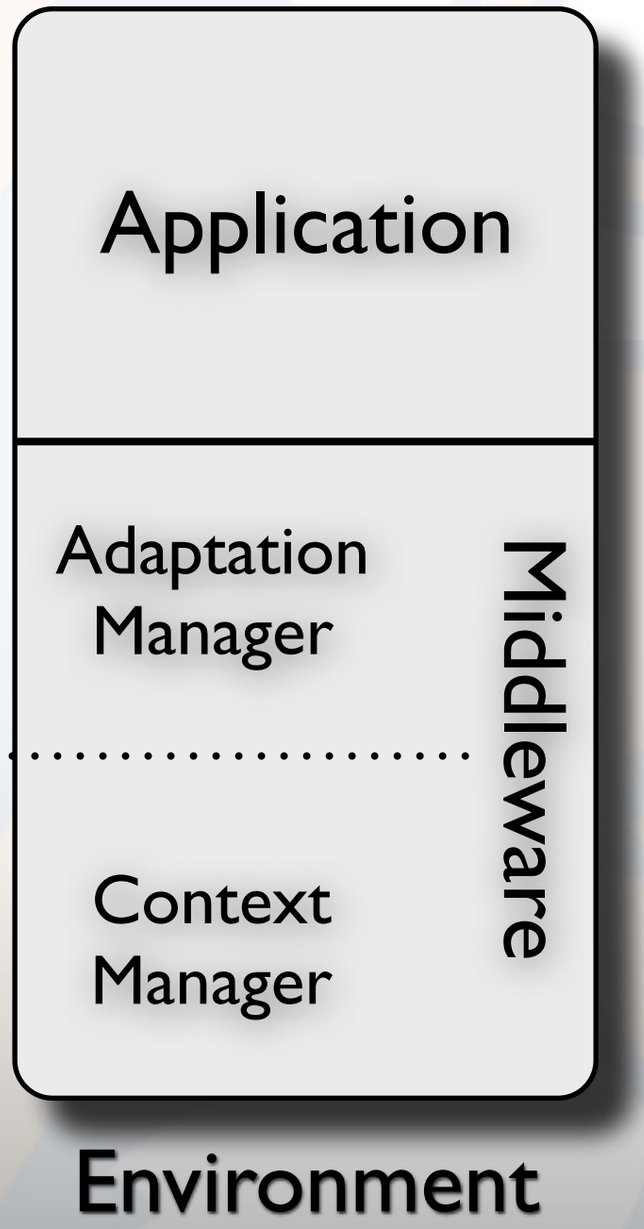

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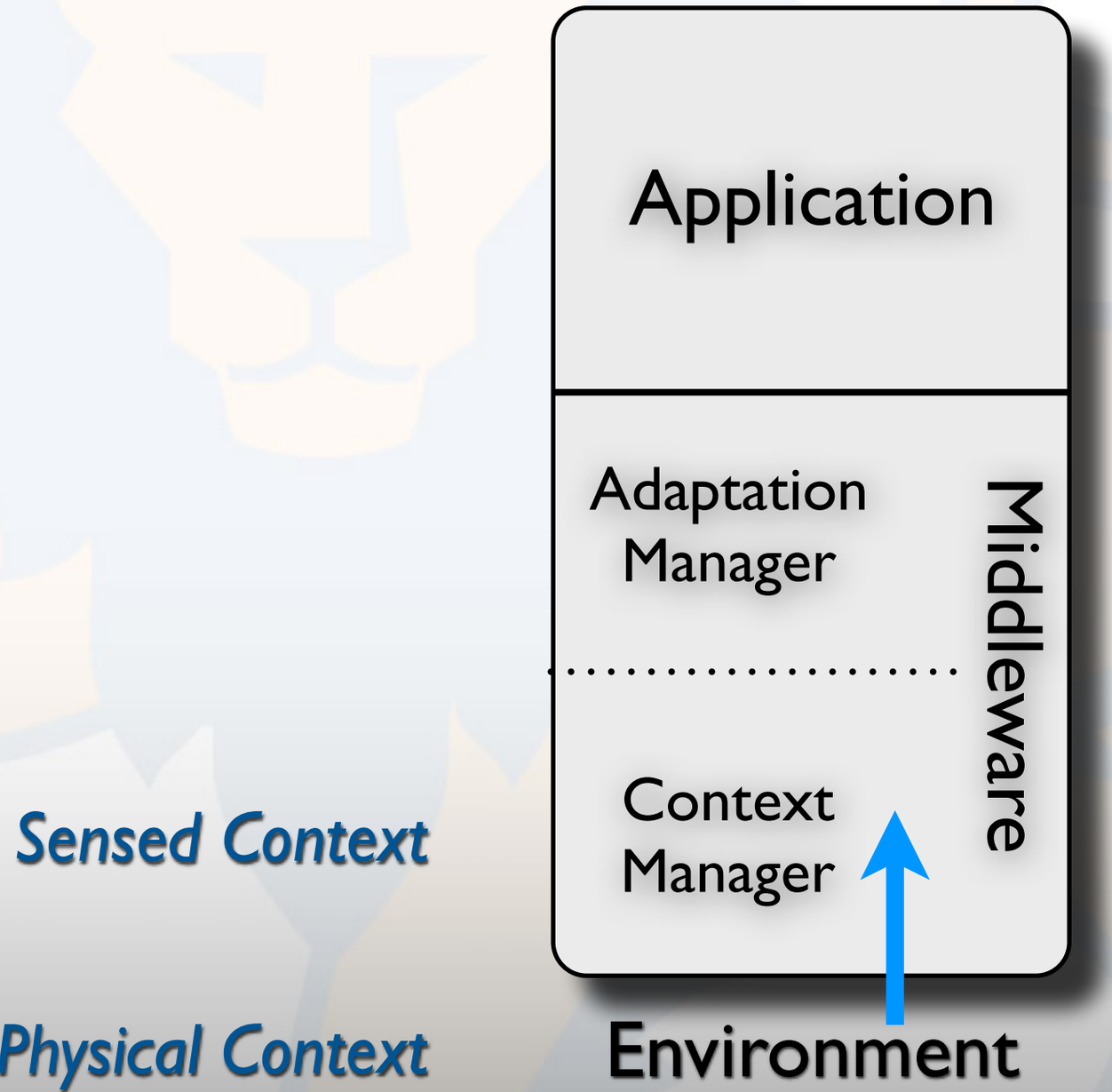

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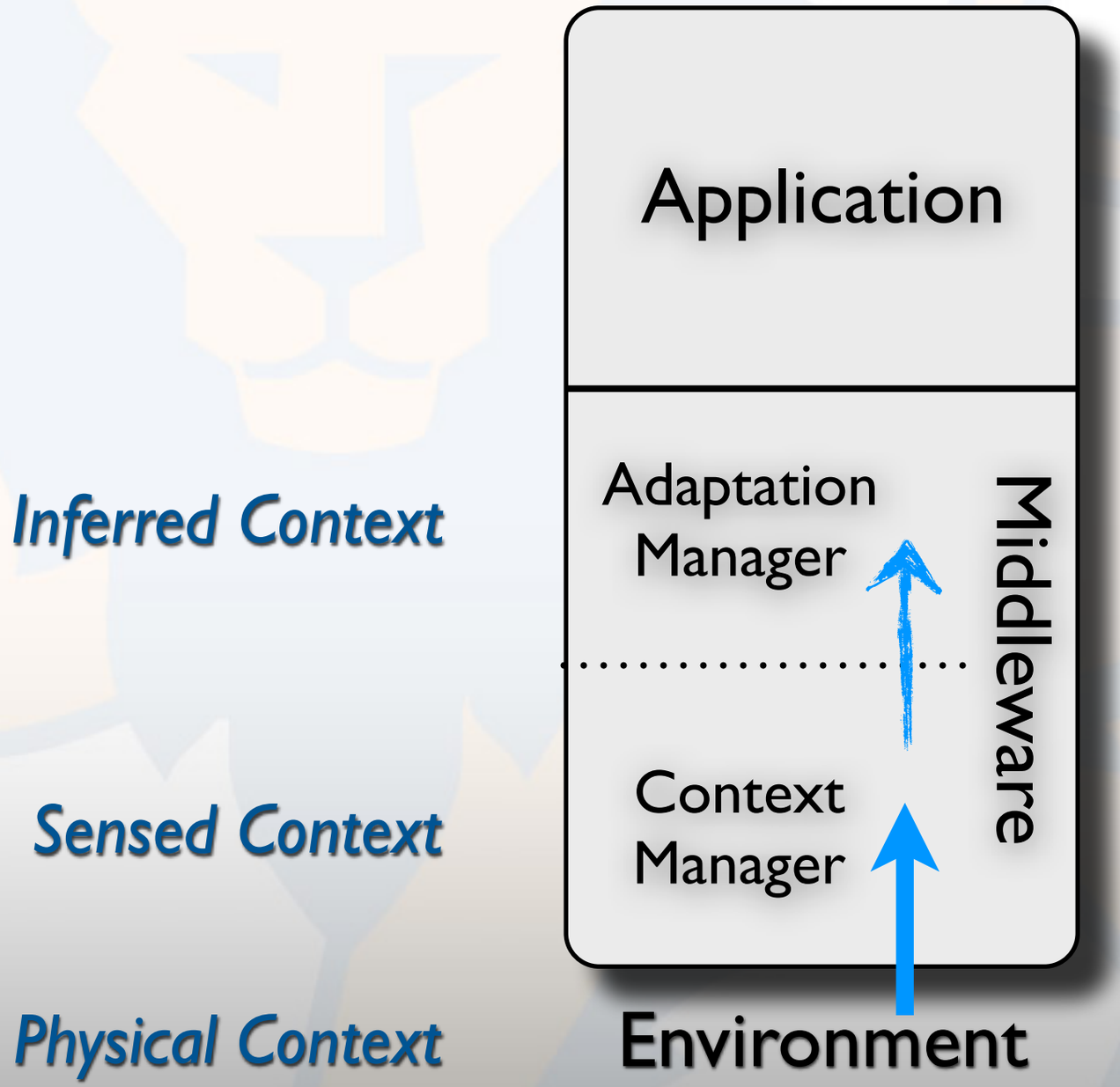

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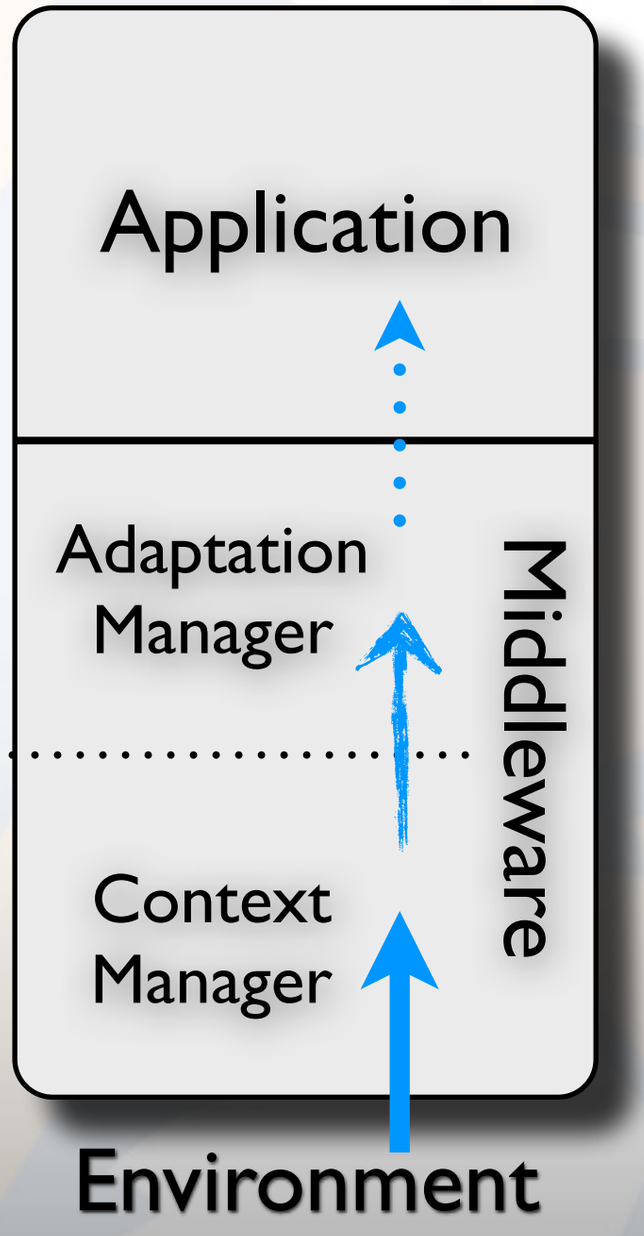
Adaptation in CAAAs

Presumed Context

Inferred Context

Sensed Context

Physical Context



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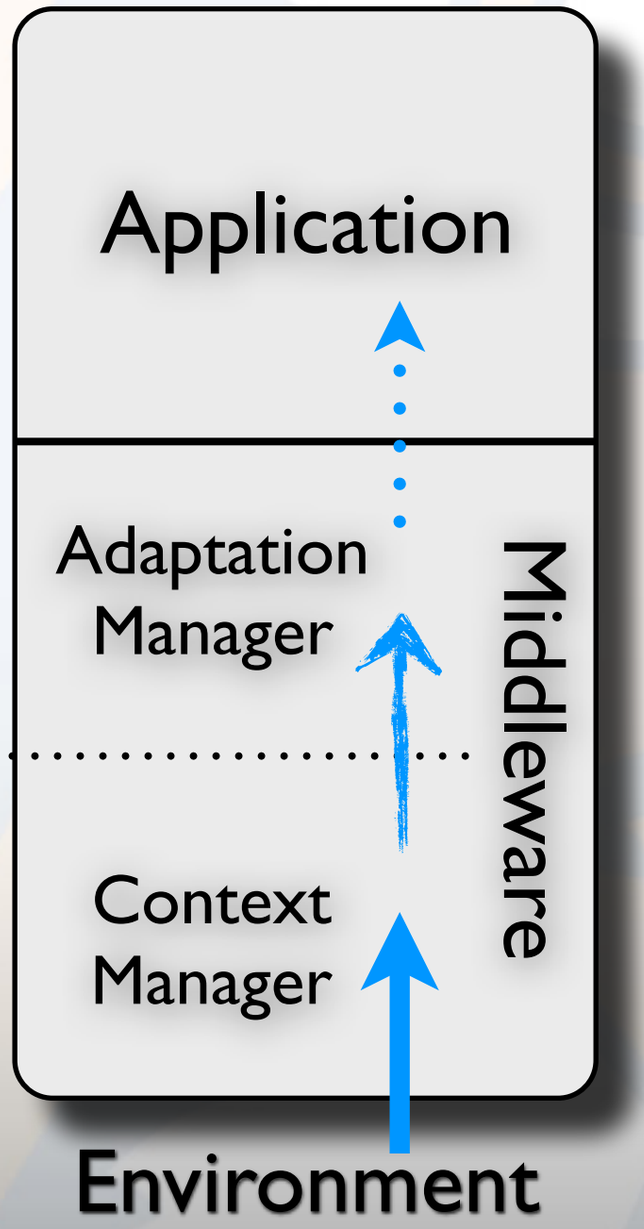

3rd-Party Libraries

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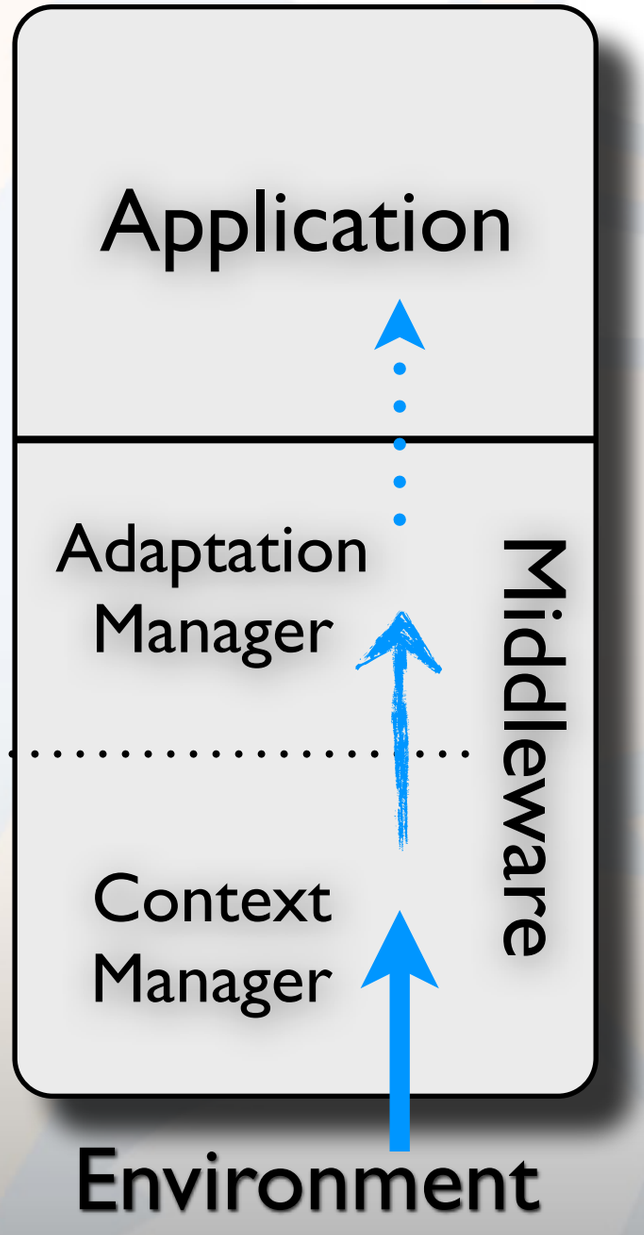

Rule Engine

3rd-Party Libraries

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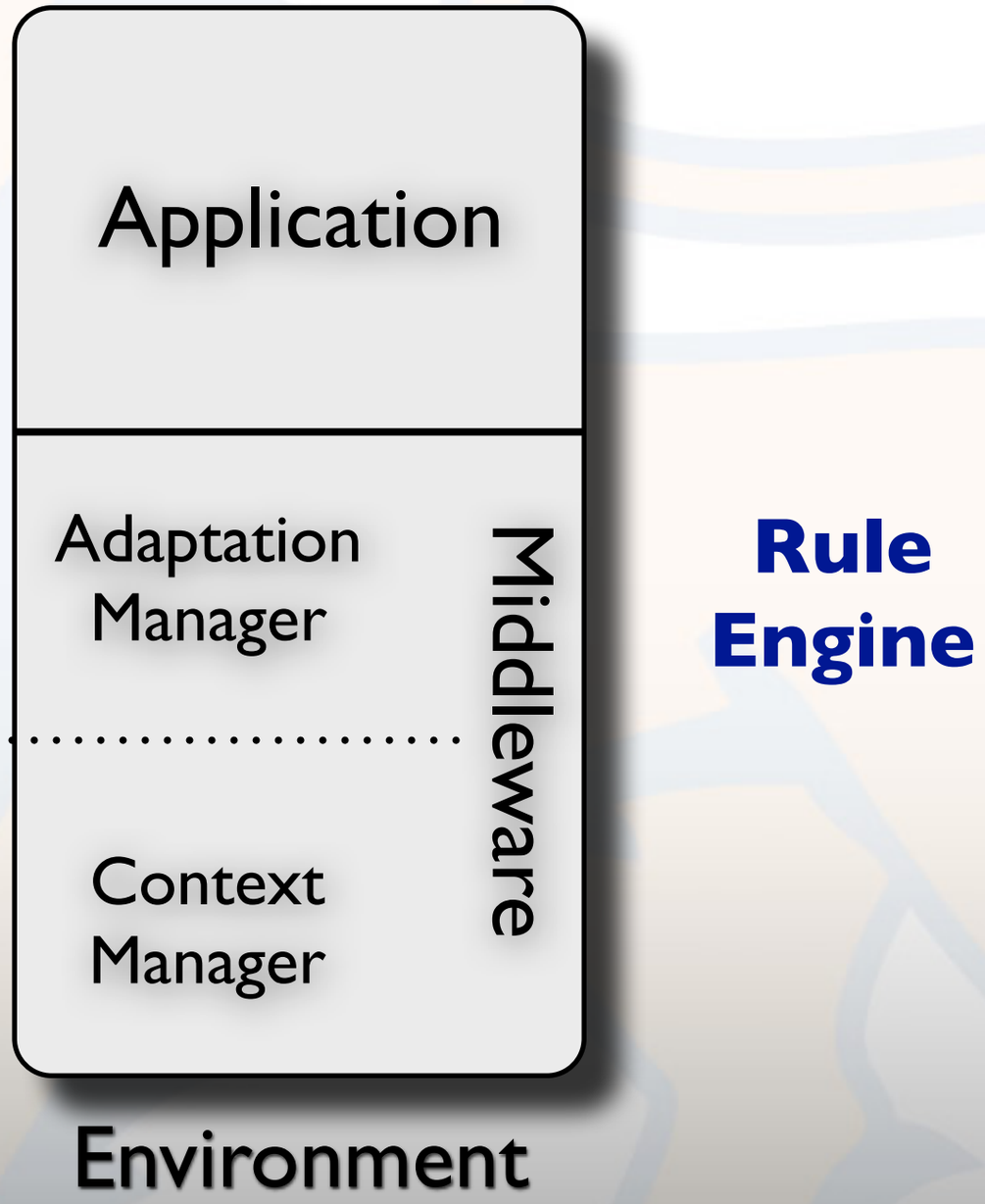
Validation of CAAAs

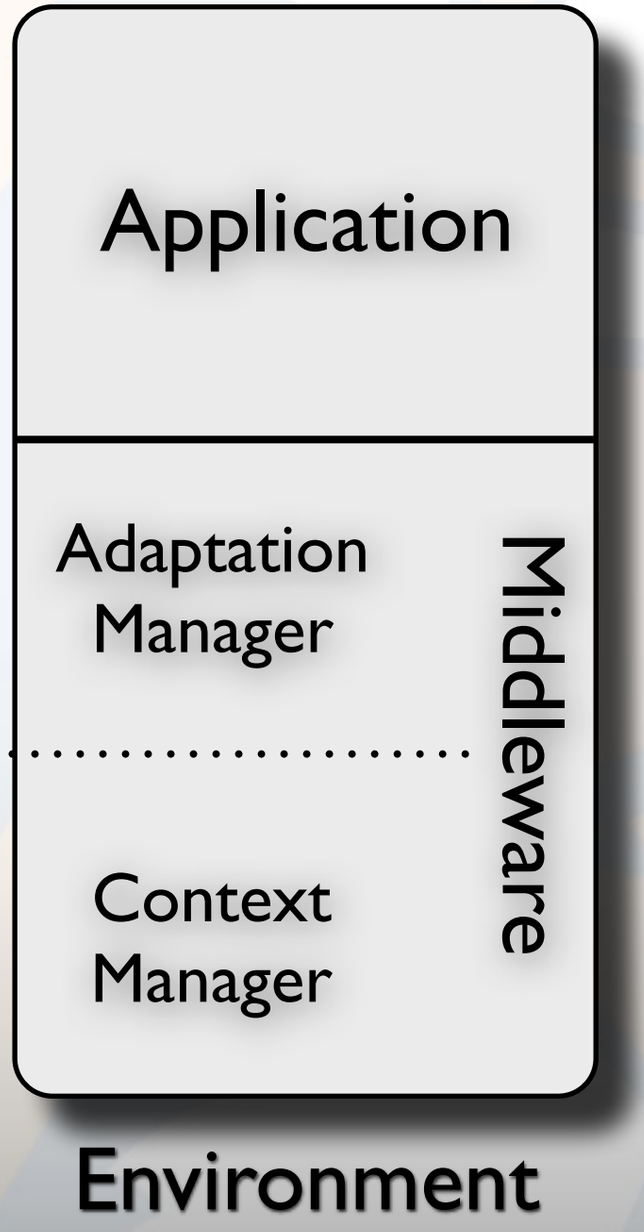


Validation of CAAAs

Rules are strongly interdependent

and have multiple priorities

which makes reasoning difficult even for a small number of rules



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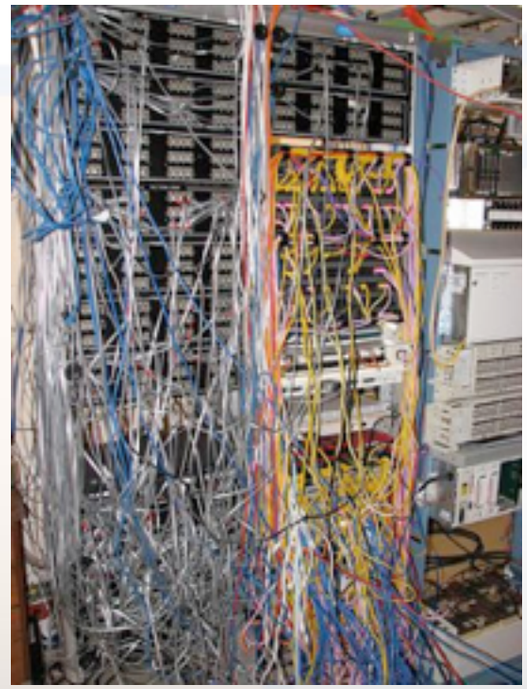


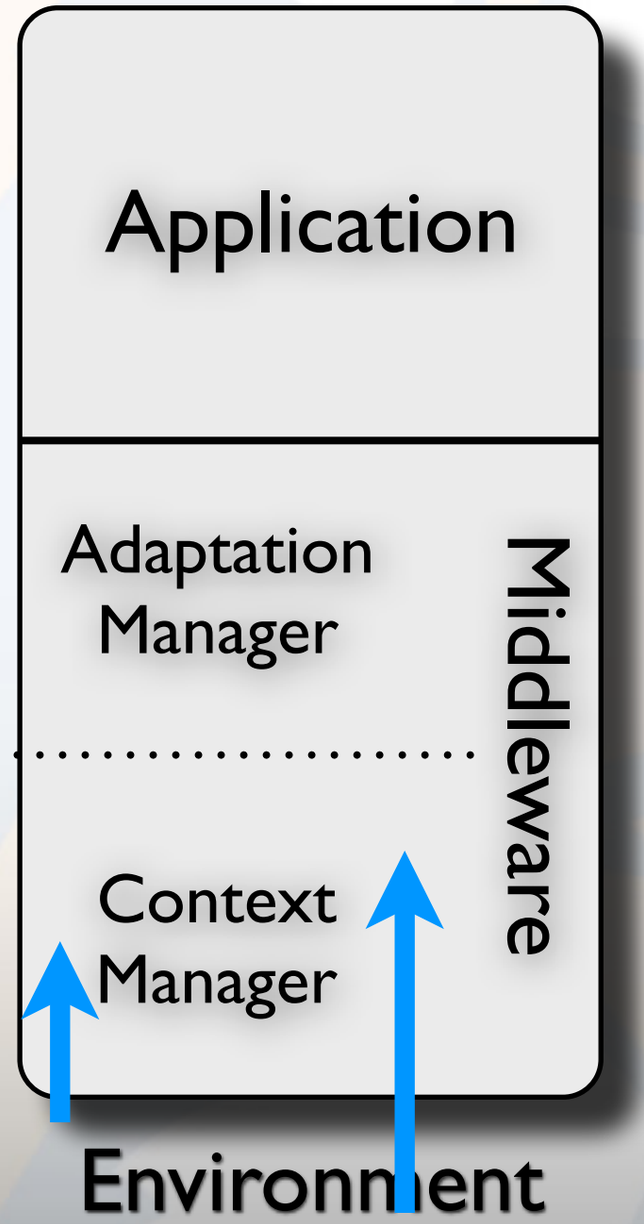
Validation of CAAAs

Validation of CAAAs

Context is sensed periodically

from multiple sources

at varying rates



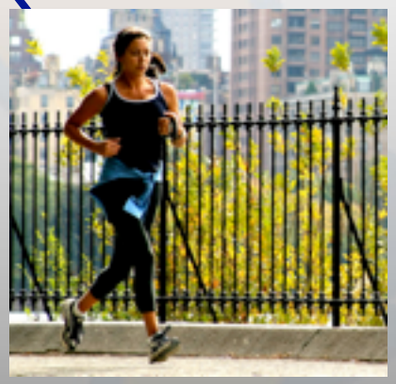
3rd-Party Libraries

Approach

1. Derive *Adaptation Finite-State Machine* (A-FSM) from rule logic
2. Explore state space of A-FSM to discover potential faults
   - ✓ *Enumerative algorithms*
   - ✓ *Symbolic algorithms*
3. (Confirm existence of discovered faults)

M. Sama, S. Elbaum, F. Raimondi and D.S. Rosenblum, "Context-Aware Adaptive Applications: Fault Patterns and Their Automated Identification", *IEEE Transactions on Software Engineering*, Vol. 36, No. 5, Sep./Oct. 2010, pp. 644-661.

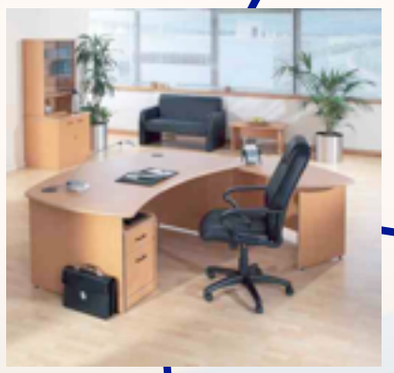
PhoneAdapter



PhoneAdapter

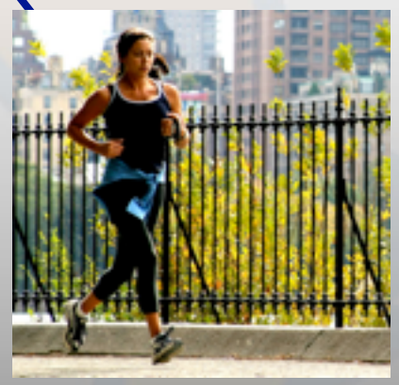
silent, vibrate

normal, vibrate



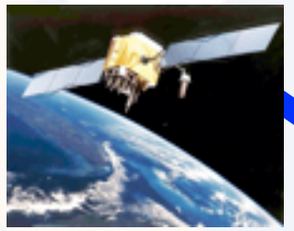
loud, divert to hands-free

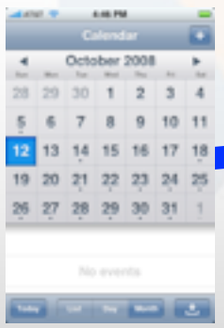
silent, divert to voicemail



loud, vibrate

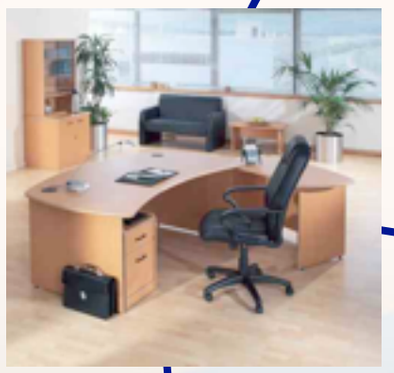
PhoneAdapter





silent, vibrate

normal, vibrate



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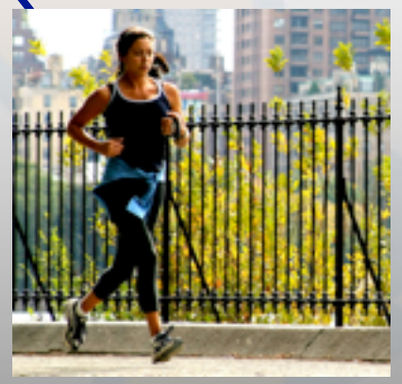
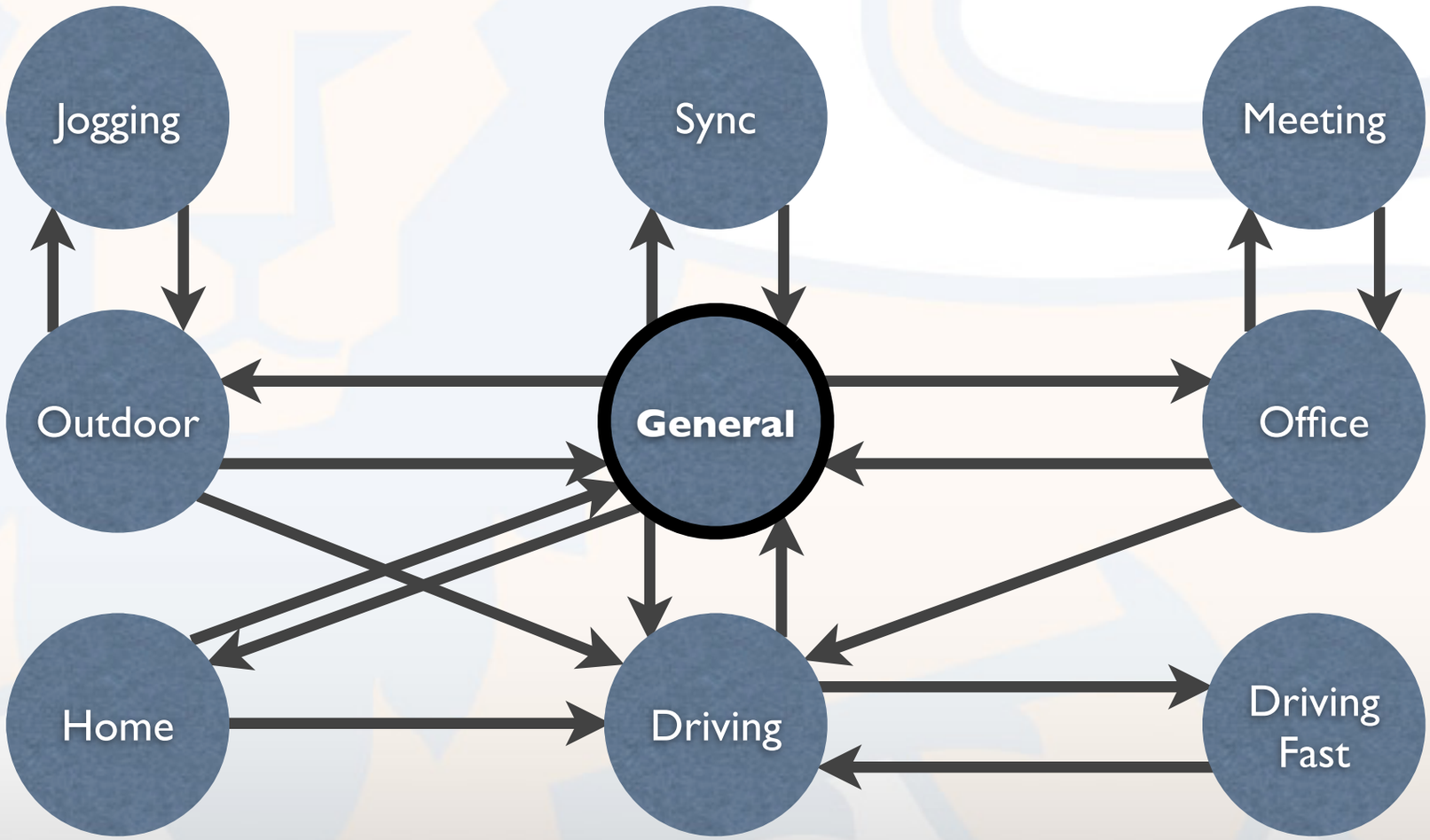
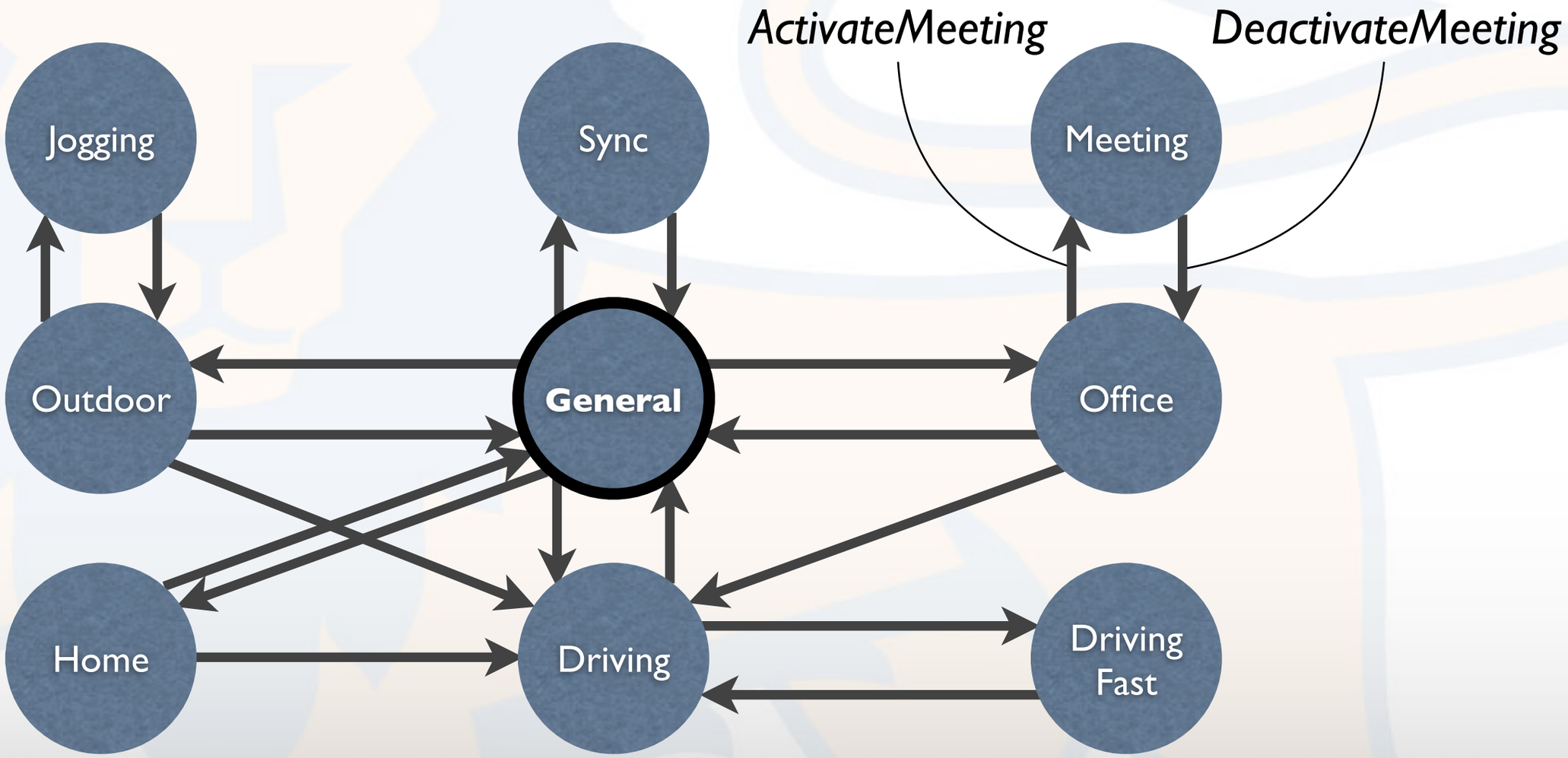


loud, vibrate

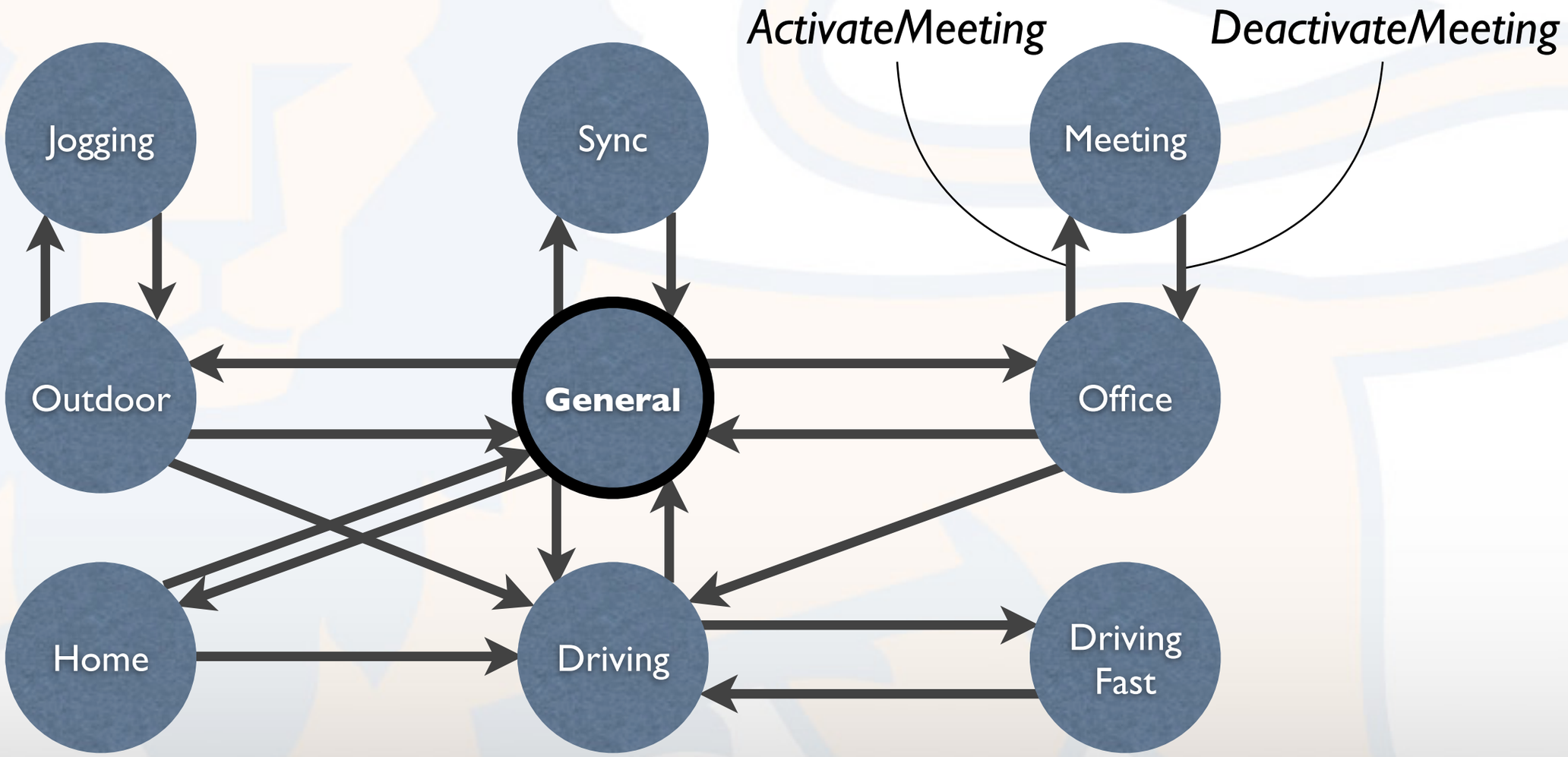
PhoneAdapter A-FSM



PhoneAdapter A-FSM



PhoneAdapter A-FSM



Global constraints:

checking location implies GPS is on

locations are mutually exclusive

speeds monotonically increase

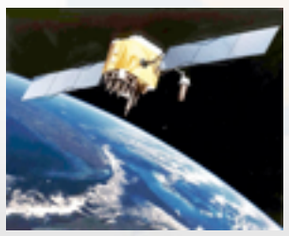
a meeting's end time is later than its start time

Example Faults in PhoneAdapter

Example Faults in PhoneAdapter

General

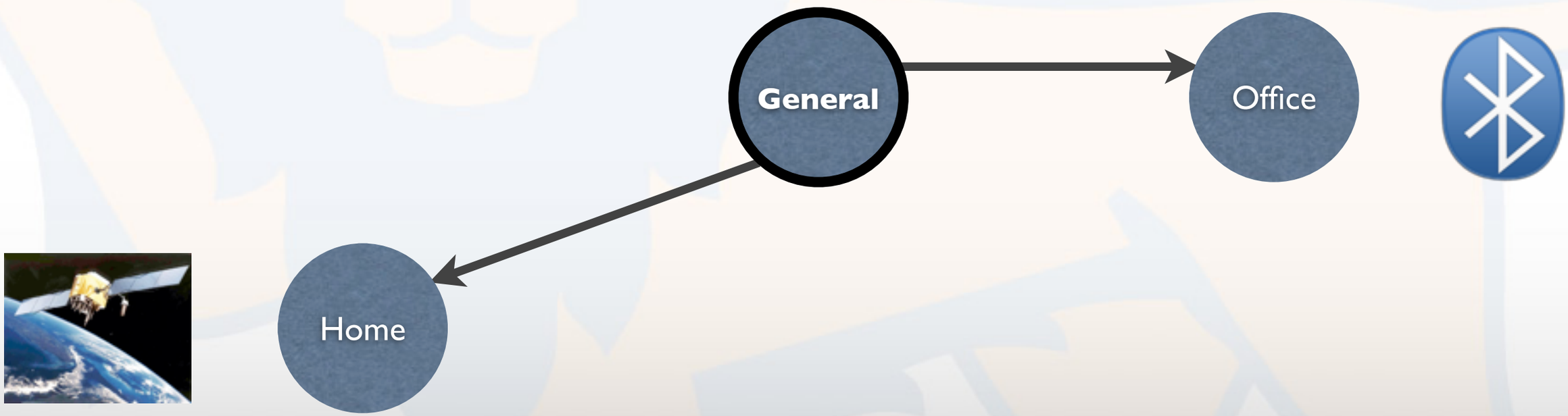
Office



Home

User's phone discovers office PC at home (or vice versa)

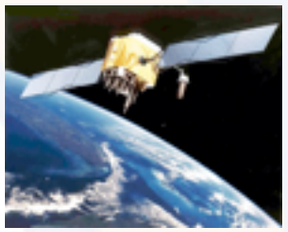
Example Faults in PhoneAdapter



Nondeterminism!

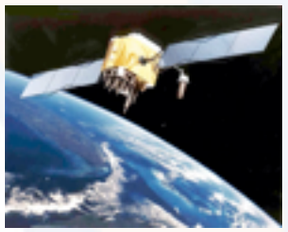
Example Faults in PhoneAdapter

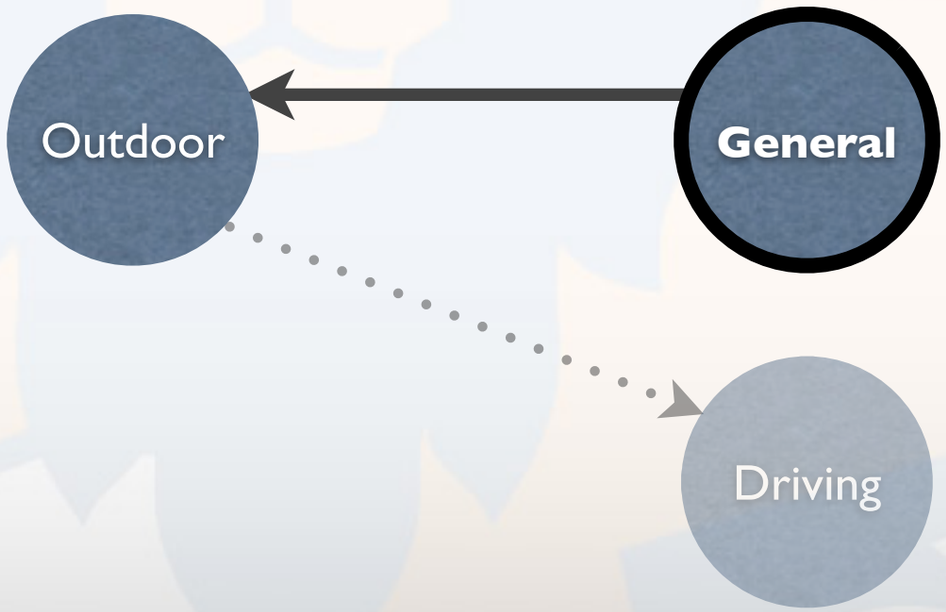
Example Faults in PhoneAdapter



User leaves home

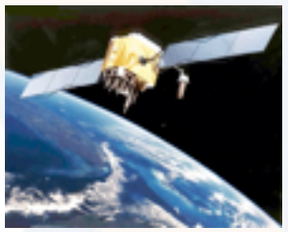
Example Faults in PhoneAdapter

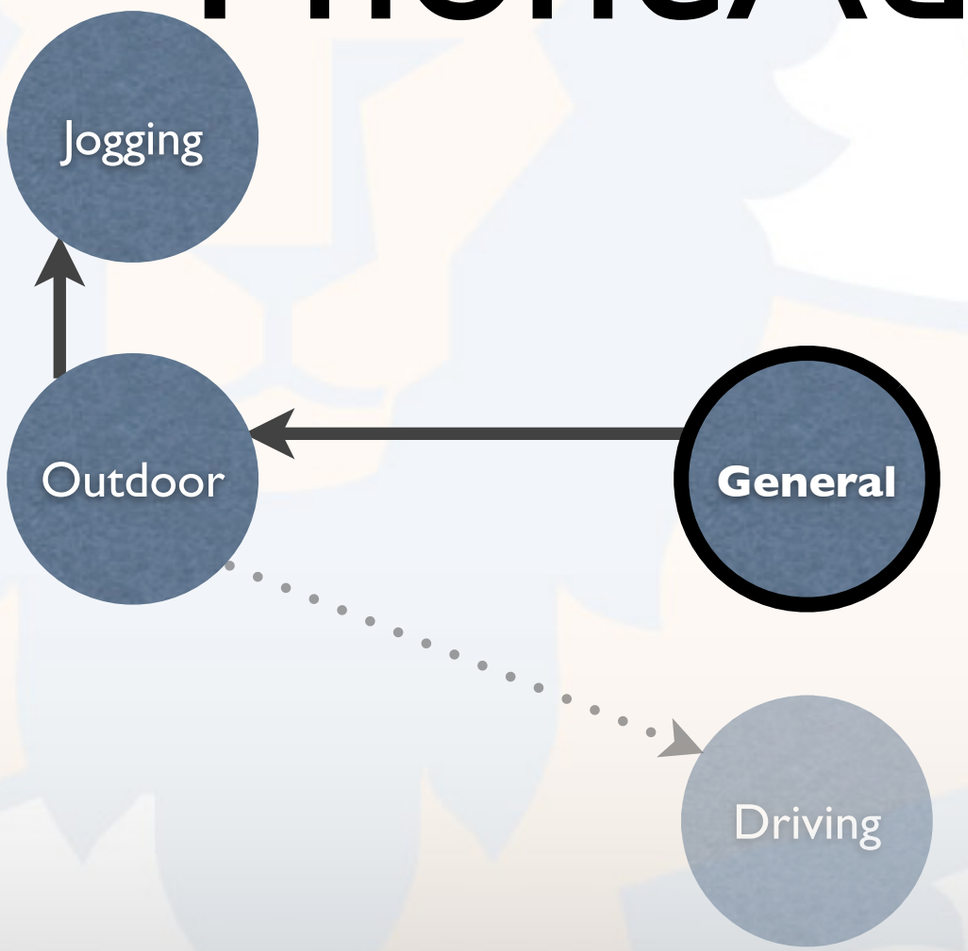




User starts driving before Bluetooth detects hands-free system

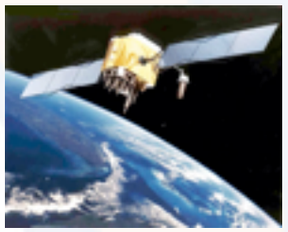
Example Faults in PhoneAdapter

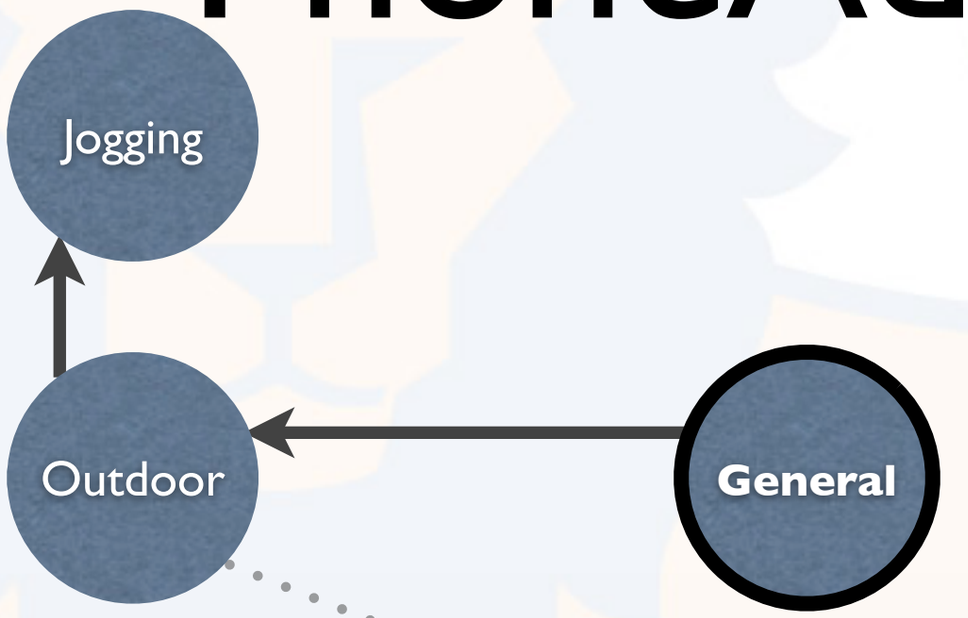


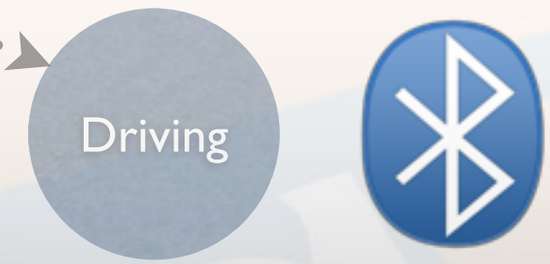


Activation hazard!

Example Faults in PhoneAdapter







Activation hazard!

Faults in CAAAs

- Behavioral Faults
  - *Nondeterminism*
  - *Dead rule*
  - *Dead state*
  - *Unreachable state*
  - *Activation race*
  - *Activation cycle*

Faults in CAAAs

- Behavioral Faults
  - *Nondeterminism*
  - *Dead rule*
  - *Dead state*
  - *Unreachable state*
  - *Activation race*
  - *Activation cycle*
- Hazards
  - *Hold hazard*
  - *Activation hazard*
  - *Priority inversion hazard*

PhoneAdapter Results

Behavioral Faults: Enumerative, Symbolic

State	Nondeterministic Adaptations	Dead Predicates	Adaptation		Unreachable States
			Races	Cycles	
General	37	1	45	13	0
Outdoor	3	0	135	23	0
Jogging	0	0	97	19	0
Driving	0	0	36	13	0
DrivingFast	0	0	58	19	0
Home	0	0	76	19	0
Office	0	0	29	1	0
Meeting	0	0	32	1	0
Sync	0	0	27	5	1

PhoneAdapter Results

Hazards: Enumerative

State	Context Hazards			
	Paths	Hold	Activ.	Prior.
General	14085	0	11	3182
Outdoor	161	0	0	52
Jogging	2	0	0	0
Driving	16	2	2	4
DrivingFast	2	0	0	0
Home	104	8	0	13
Office	82634	1828	368	2164
Meeting	0	0	0	0
Sync	2	2	0	0

CAAAs

Summary

- ✓ Rule-based CAAAs can be extremely fault-prone, even with a small set of rules and context variables
- ✓ The fault detection algorithms find many actual faults, with different tradeoffs
- ✓ Some alternative to rule-based adaptation is needed ...

CAMMR

Context-Aware Mobile Music Recommendation

✓ Users' short-term music needs are driven by their current activity

✓ Fully automated music recommendation requires solving the cold-start problem:

Which existing user will like a new song?

Which existing songs will a new user like?

X. Wang, D.S. Rosenblum and Y. Wang, "Context-Aware Mobile Music Recommendation for Daily Activities", Full Paper, *Proc. ACM Multimedia 2012* (ACMMM 2012), Nara, Japan, Oct.–Nov. 2012, pp. 91–108.

CAMMR

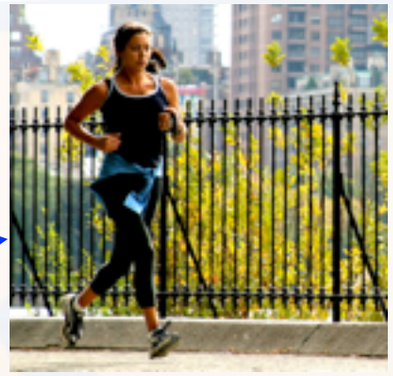
Functionality

CAMMR

Functionality

CAMMR

Functionality



CAMMR

Functionality

CAMMR

Key Characteristics

✓ Real-time sensor-driven activity inference

Running, Walking, Sleeping,
Working, Studying, Shopping

✓ Offline low-level audio content analysis

✓ Personalization of recommendations

CAMMR

Supervised Learning

✓ Machine learning, not handcrafted rules!

Ground truth:

Activity: Manually tagged sensor streams

Music: Activity-tagged Grooveshark playlists

Coupled with incremental learning of individual preferences

CAMMR

Architecture

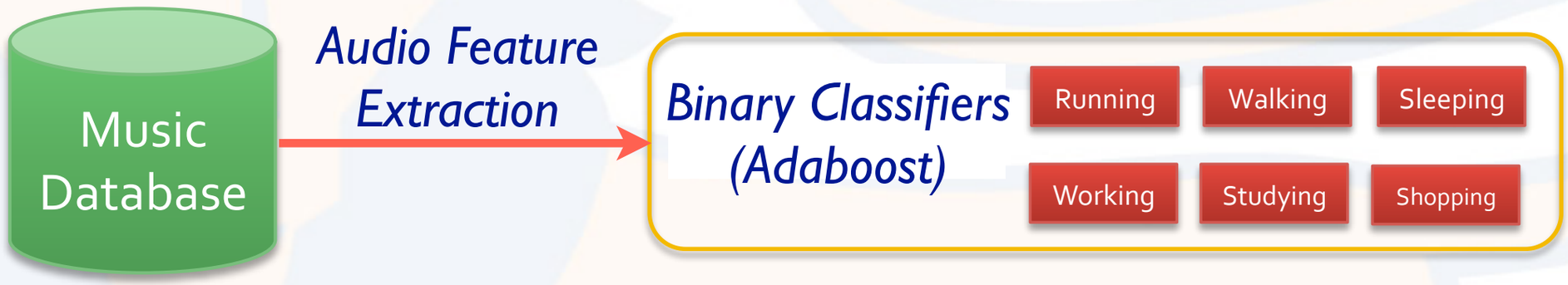
Back End

Front End

CAMMR

Architecture

Back End

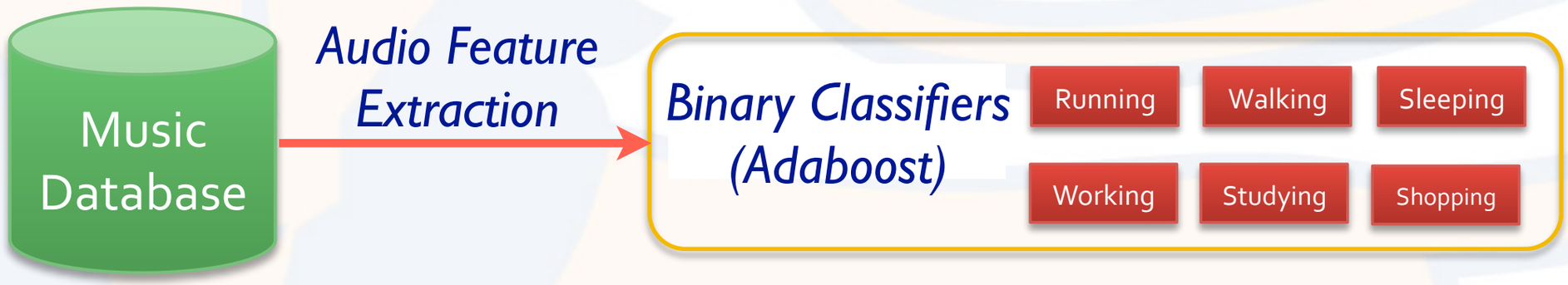


Front End

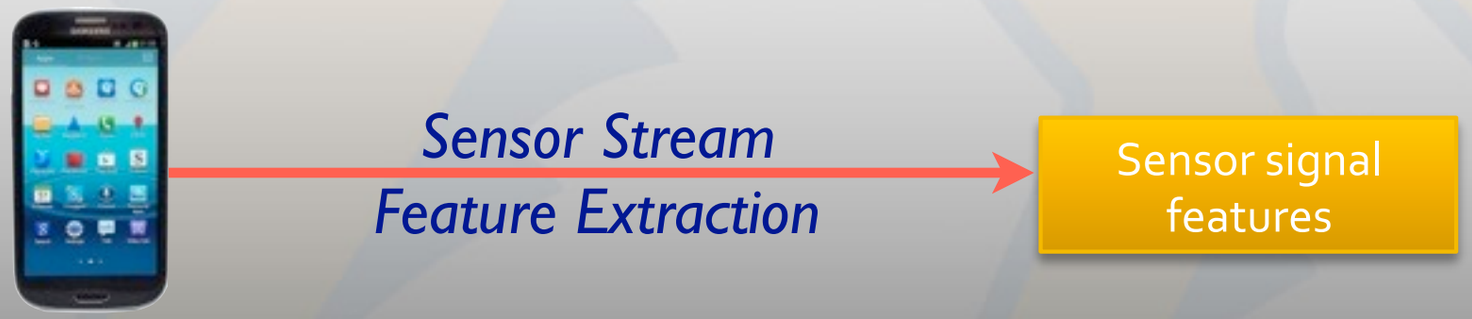
CAMMR

Architecture

Back End



Front End



CAMMR

Architecture

Back End

Music Database

Audio Feature Extraction

Binary Classifiers (Adaboost)

Running | Walking | Sleeping | Working | Studying | Shopping

Classification Results

ACACF
Probabilistic Graphical Model
(Naive Bayes)

Microphone, Accelerometer and Clock Features

Front End

Sensor Stream Feature Extraction

Sensor signal features

CAMMR

Architecture

Back End

Music Database

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Binary Classifiers (Adaboost)

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Classification Results

ACACF
Probabilistic Graphical Model
(Naive Bayes)

Recommendation

Music Play

Front End

Sensor Stream Feature Extraction

Sensor signal features

Microphone, Accelerometer and Clock Features

CAMMR

Architecture

Back End

Front End

Music Database

Audio Feature Extraction

Binary Classifiers (Adaboost)

Running

Walking

Sleeping

Working

Studying

Shopping

Classification Results

Recommendation

Music Play

User Feedback

ACACF
Probabilistic Graphical Model
(Naive Bayes)

Microphone, Accelerometer and Clock Features

Sensor Stream Feature Extraction

Sensor signal features

Results

Inter-Subject Agreement on Music Preferences

Activity	Kappa Agreement	Percent Agreement
Running	**0.27**	0.35
Working	0.03	0.02
Sleeping	**0.29**	0.28
Walking	0.03	0.03
Shopping	0.07	0.17
Studying	0.09	0.11

- 10 subjects
- Manual activity tagging of 1200 Grooveshark and YouTube songs
- $p < 0.0001$

Results

Precision of Activity Inference

Activity	AdaBoost	C4.5	LR	NB	SVM	KNN
Running	0.974	0.976	0.975	0.841	0.974	0.970
Working	0.933	0.932	0.921	0.876	0.929	0.922
Sleeping	0.999	0.999	0.999	0.994	0.999	0.993
Walking	0.961	0.960	0.955	0.909	0.960	0.953
Shopping	0.972	0.972	0.948	0.953	0.965	0.955
Studying	0.854	0.867	0.835	0.694	0.860	0.855
OVERALL	0.951	0.952	0.941	0.893	0.950	0.943

- 10 subjects, 6 activities, 30 minutes/session
- Naive Bayes provides very good precision *and* efficiency for smartphones

Results

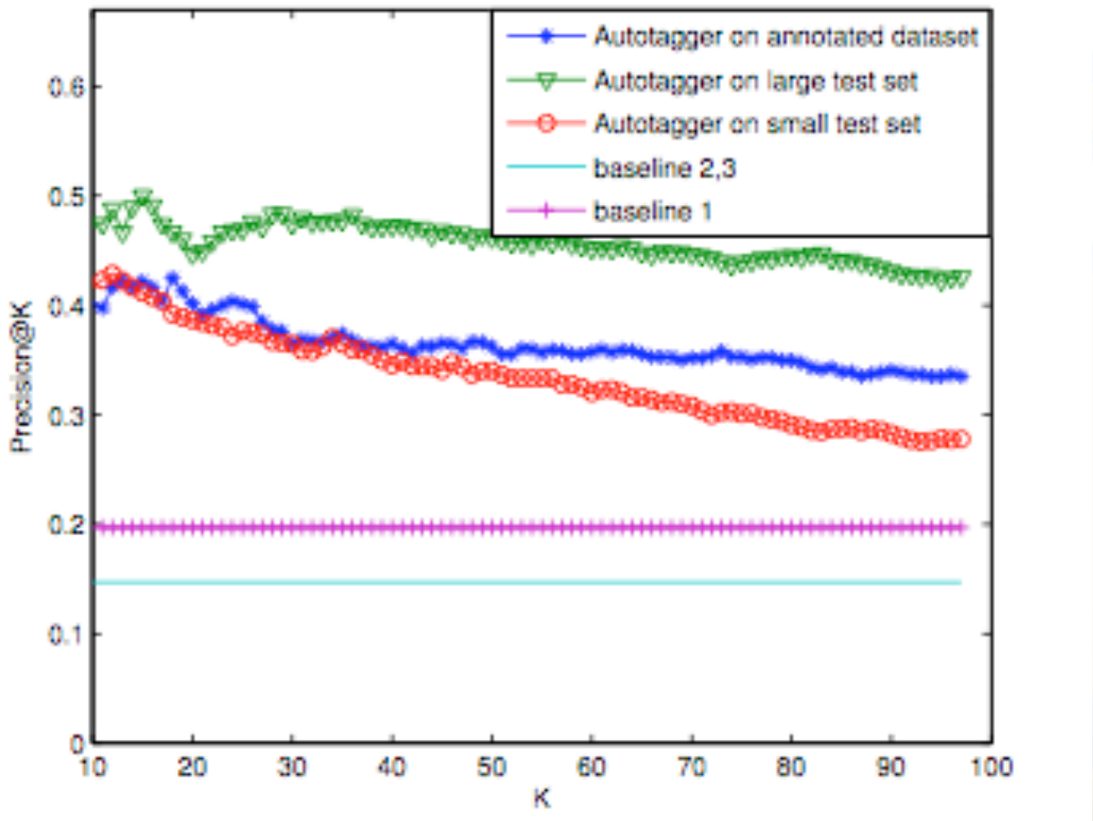
Precision of Activity Inference

Activity	AdaBoost	C4.5	LR	NB	SVM	KNN
Running	0.974	0.976	0.975	0.841	0.974	0.970
Working	0.933	0.932	0.921	0.876	0.929	0.922
Sleeping	0.999	0.999	0.999	0.994	0.999	0.993
Walking	0.961	0.960	0.955	0.909	0.960	0.953
Shopping	0.972	0.972	0.948	0.953	0.965	0.955
Studying	0.854	0.867	0.835	0.694	0.860	0.855
OVERALL	0.951	0.952	0.941	0.893	0.950	0.943

- 10 subjects, 6 activities, 30 minutes/session
- Naive Bayes provides very good precision *and* efficiency for smartphones

Results

Retrieval Performance

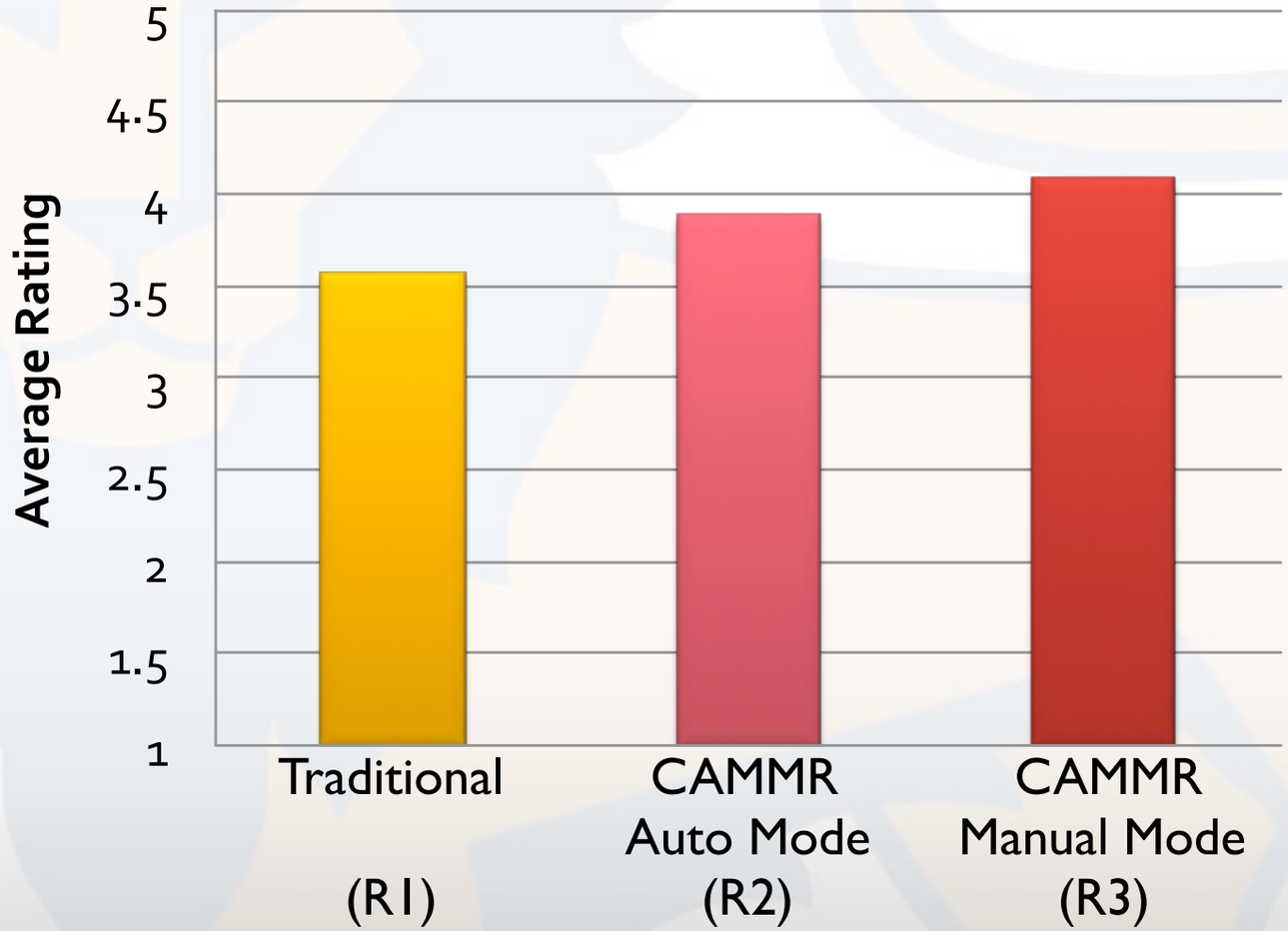


- Precision@K for top K songs
- Baselines are random rankings

Results

Accuracy of Music Recommendation

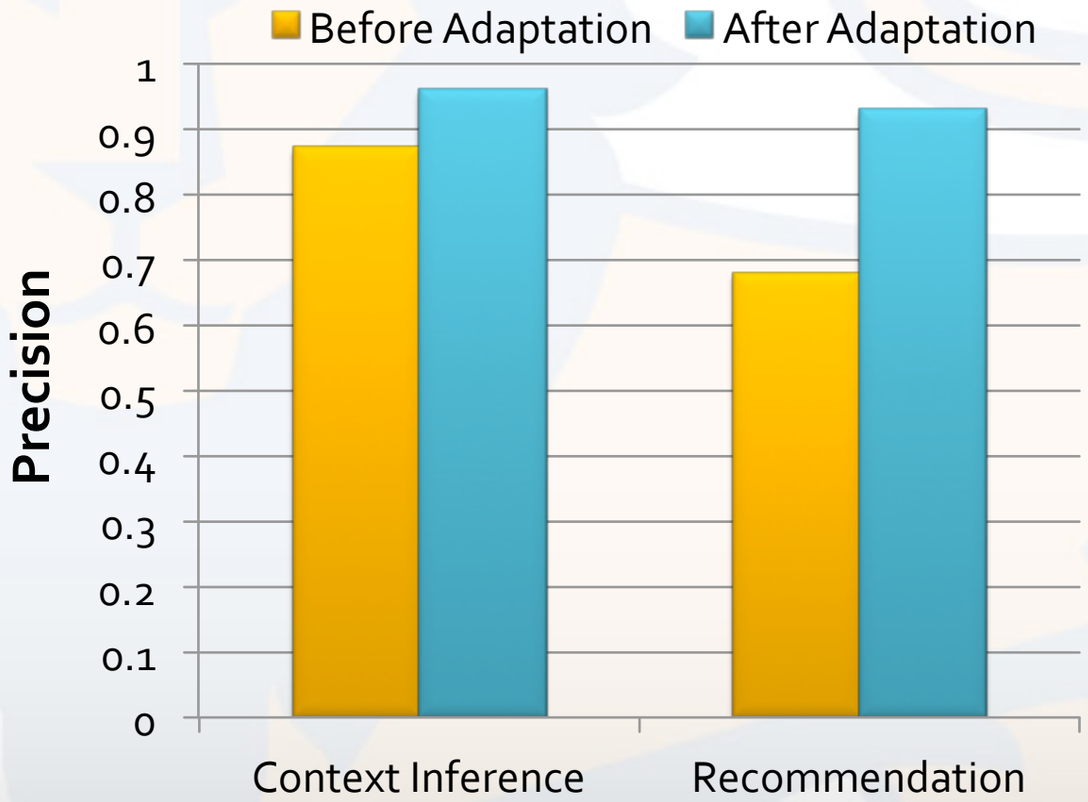
5-point Likert scale



- 10 subjects, divided into experimental and control group
- R2 vs R1: p = 0.0478
- R3 vs R2: p = 0.1374
- R3 vs R1: p = 0.0001

Results

Effectiveness of Incremental Adaptation



- 2 subjects, continuous usage for one week

CAMMR

Summary

✓ CAMMR is the first automated solution for short-term music listening needs

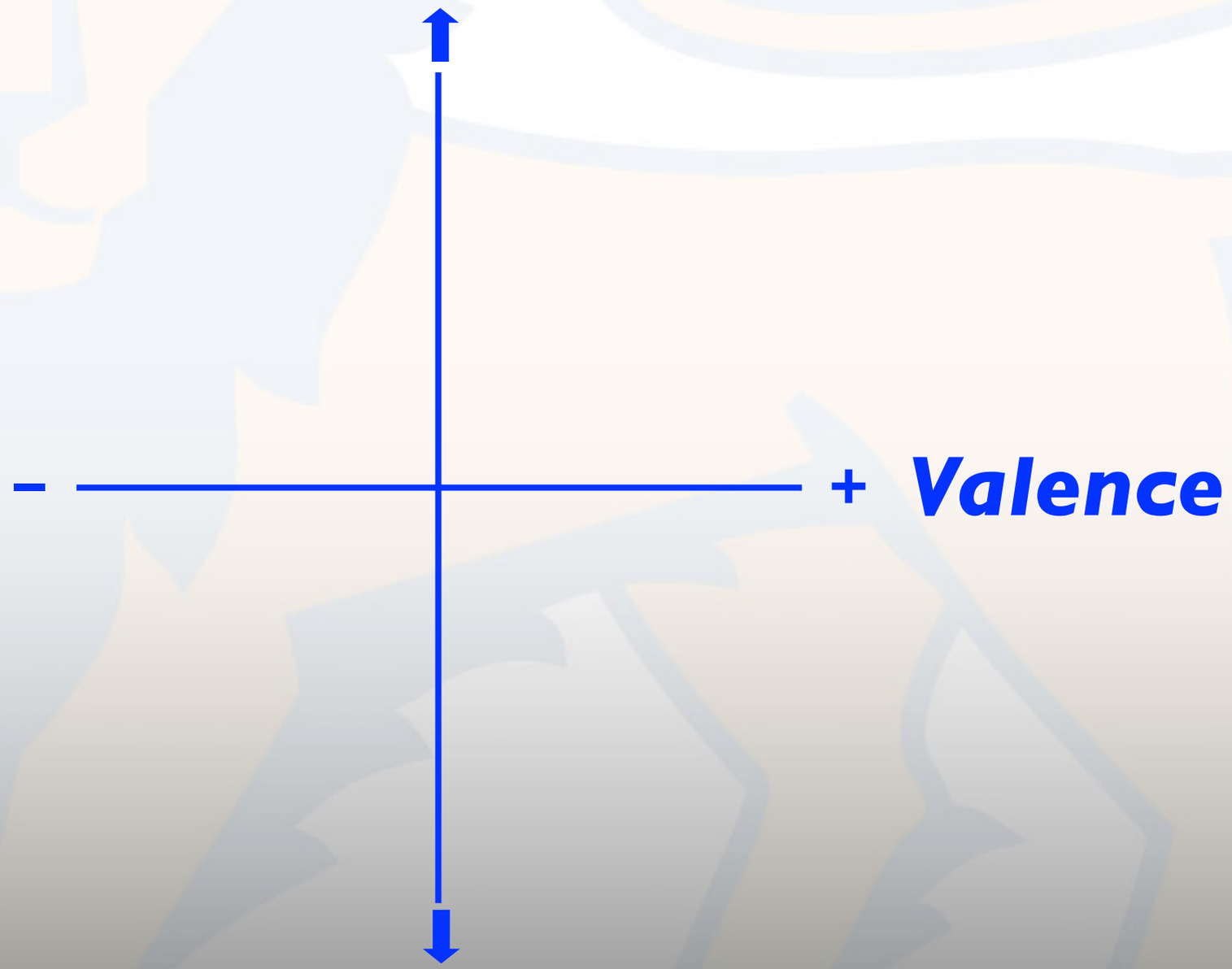
✓ Provides a complete solution to the cold-start problem

✓ Employs machine learning for more robust adaptation

Other Projects

Emotion Sensing

Arousal



Other Projects

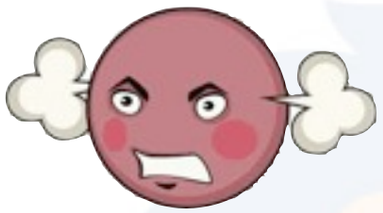
Emotion Sensing

Arousal

↑

–  + ***Valence***

↓



Other Projects

Emotion Sensing

- Sensing from Mobile & Wearable Sensors
  - Microphone: speech
  - Camera: facial expressions, eye tracking
  - Accelerometer: movement, orientation
  - MS Kinect: gesture
  - GPS: location
  - GSR: skin conductivity
  - HRM: pulse

Other Projects

Emotion Sensing

- Many Obstacles and Limitations
  - Lack of empirical evidence for biological signatures of emotions
  - Much variability in experiencing emotions
    - ➡ Short-term situations vs. long-term mood
    - ➡ Between and within cultures and languages
    - ➡ By the same individual
  - Difficulty of inducing spontaneous, genuine emotion in controlled experimental settings

Other Projects

Emotion Sensing

- Research Agenda

✓ Multimodal sensing of core affect

✓ Contextualization of emotion sensing

✓ Computational platform for sensing and processing

✓ Realistic empirical study designs

Felicitous Computing

Software Engineering Challenges

Felicitous Computing

Software Engineering Challenges

"There are known knowns; there are things we know we know. We also know there are known unknowns; that is to say, we know there are some things we do not know. But there are also unknown unknowns – the ones we don't know we don't know."

— Donald Rumsfeld

Felicitous Computing

Software Engineering Challenges

- Validation of ubiquitous computing systems is riddled with **uncertainty**
  - ➡ Unpredictable ambient environments
  - ➡ Imprecision of context inference
  - ➡ Disagreement among users and/or observers
  - ➡ Slippery slope between "known unknowns" and faults
- Similar in spirit (but not in character) to Weyuker's "non-testable programs"
- May need to employ relative quality comparison of systems rather than absolute quality assessment

Conclusion

- ✓ The technology for felicitous computing is here
- ✓ But building felicitous computing systems remains challenging
- ✓ We still lack a clear body of design and engineering principles
- ✓ At NUS we are pursuing research breakthroughs to make felicitous computing an integrated *and* invisible part of people's lives

Felicitous Computing

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School of Computing
National University of Singapore

Thank you!