

# Validating the Detection of Everyday Concepts in Visual Lifelogs

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# Overview

- **Introduction**

- **Introduction to lifelogging & the challenges involved**
- **Why Semantic Concept Detection in Lifelogs?**

- **Concept Detection Approach**

- Selecting concepts
- Processing concepts
- Image and event thresholds

- **Experimental Set-Up**

- **Results**

- **Conclusions**

- Future research

# Lifelogging

**Lifelogging is about digitally recording your daily life**

**Sometimes its for a reason**

Work                    e.g. security personnel, medical staff, etc.

Personal              e.g. diaries, etc.

**Sometimes its for posterity**

Recording vacations, family gatherings, social occasions

**Sometimes its because we can**

And we're not yet sure what we'll do with it e.g. MyLifeBits

# Lifelogging Devices

Tano *et. al.* University of Electro-Communications, Tokyo, Japan



# SenseCam

## SenseCam is a Microsoft Research Prototype

### Multi-sensor device

Colour camera

3 accelerometers

Light meter

Passive infrared sensor

### 1GB flash memory storage

### Smart image capture ~3 images/min

Since April 2006 we've had two SenseCams ... in 2007 we received 5 more



# How to Review Images?

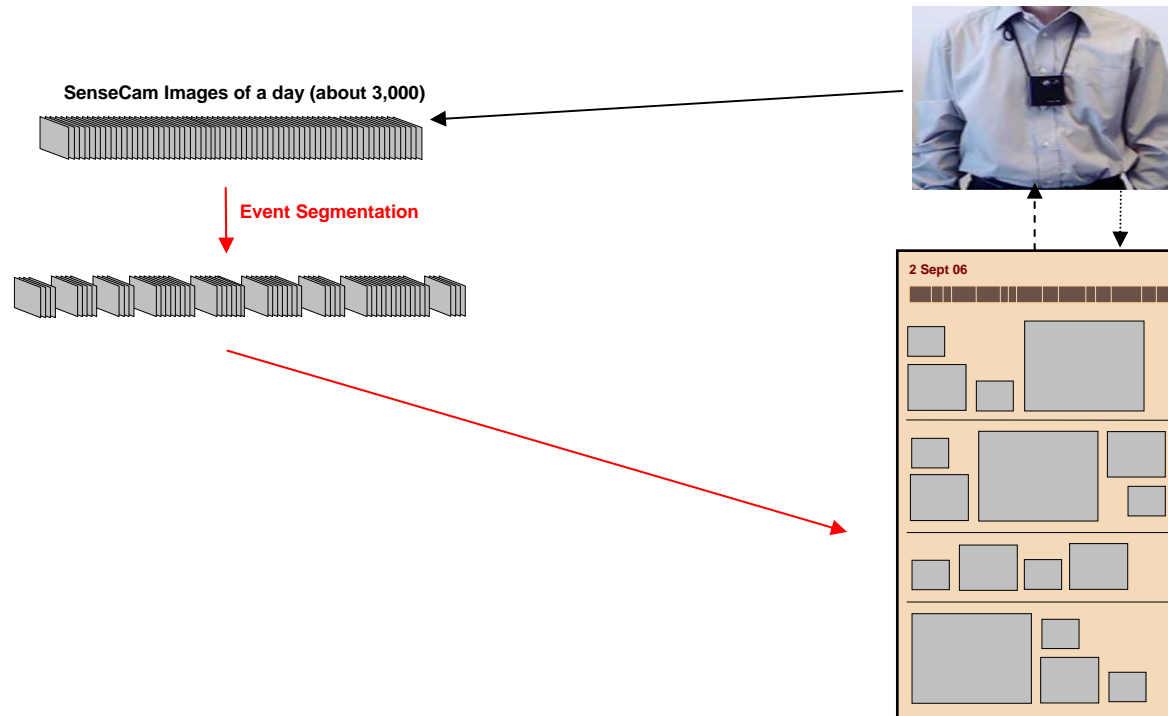
Make a 2 minute movie of your day!



# SenseCam & Memory

- SenseCam may be a very powerful memory aid
- In autobiographical (long-term) memory
  - **“Cued Recall” better than “Free Recall”**
  - **Visual Encoding has strong effect on retrieval**
- Memory studies on-going
  - **Cambridge, U.K.**
  - **Leeds, U.K.**
  - **Toronto, Canada**
  - **Illinois, USA**
  - **etc.**

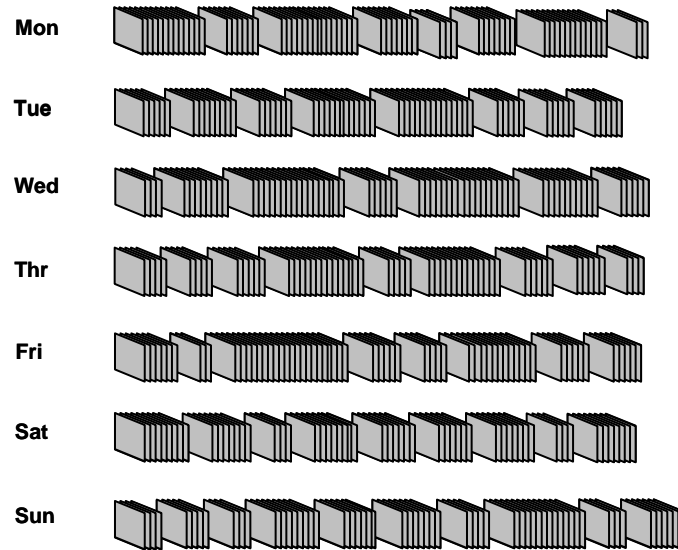
# Lifelog Processing



<http://www.cdvp.dcu.ie/SenseCam>



# Can't "recognise" events



We can detect this event

We know when this event is

**BUT**

We don't RECOGNISE the event i.e. we don't know "the what" of this event

# Contributions of this work...

- Exploration of applying semantic concept detection to the novel domain of lifelogging
- In-depth evaluation of concept detectors
- Allows possibilities to “gist” human lifestyle activities

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# Selecting Representative Concepts

- A subset of 5 user's collection was visually inspected by playing images in video-like fashion
- 150 concepts initially identified
- Through refinement we narrowed down to **27 concepts**
  - **Most representative concepts selected**
  - **Concepts should be generalisable across users & collections**



Vehicles External



Road



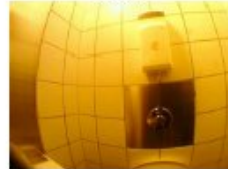
Steering wheel



Inside of vehicle



Indoors



Toilet/Bathroom



Door



Staircase



Outdoors



Buildings



Tree



View of Horizon



Grass



Sky



Vegetation



Screen



Reading



Meeting



Office



Giving Presentation



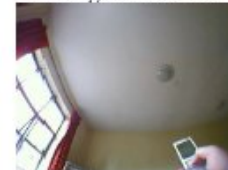
Food/eating



Hands



Holding a cup/glass



Holding a mobile



Faces

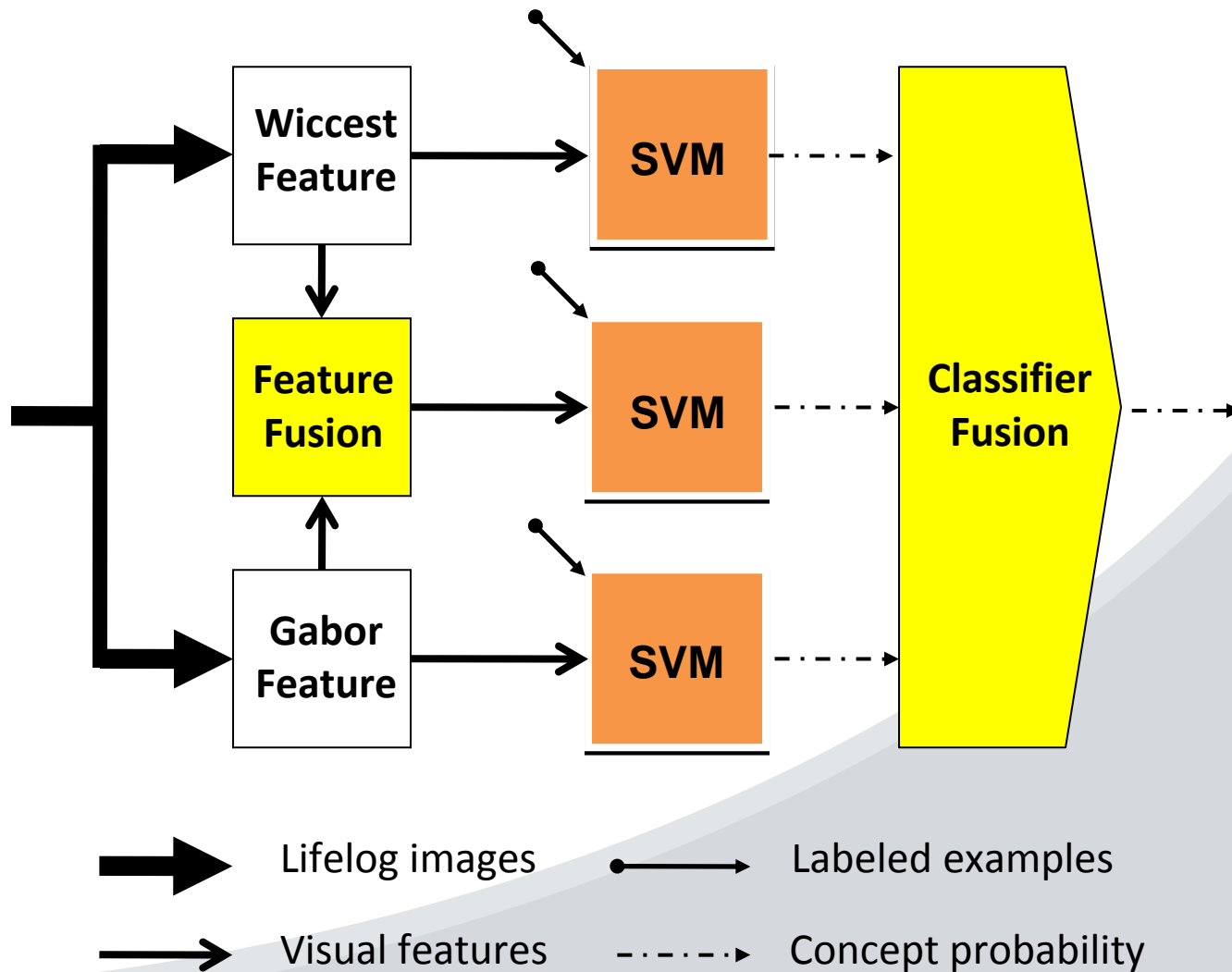


People

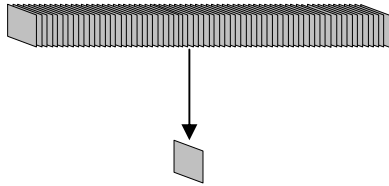


Shopping

# Concept detection process



# Image confidence values



Vehicles External = *0.002*

Road = *0.007*

Steering wheel = *0.003*

Sky = *0.002*

...

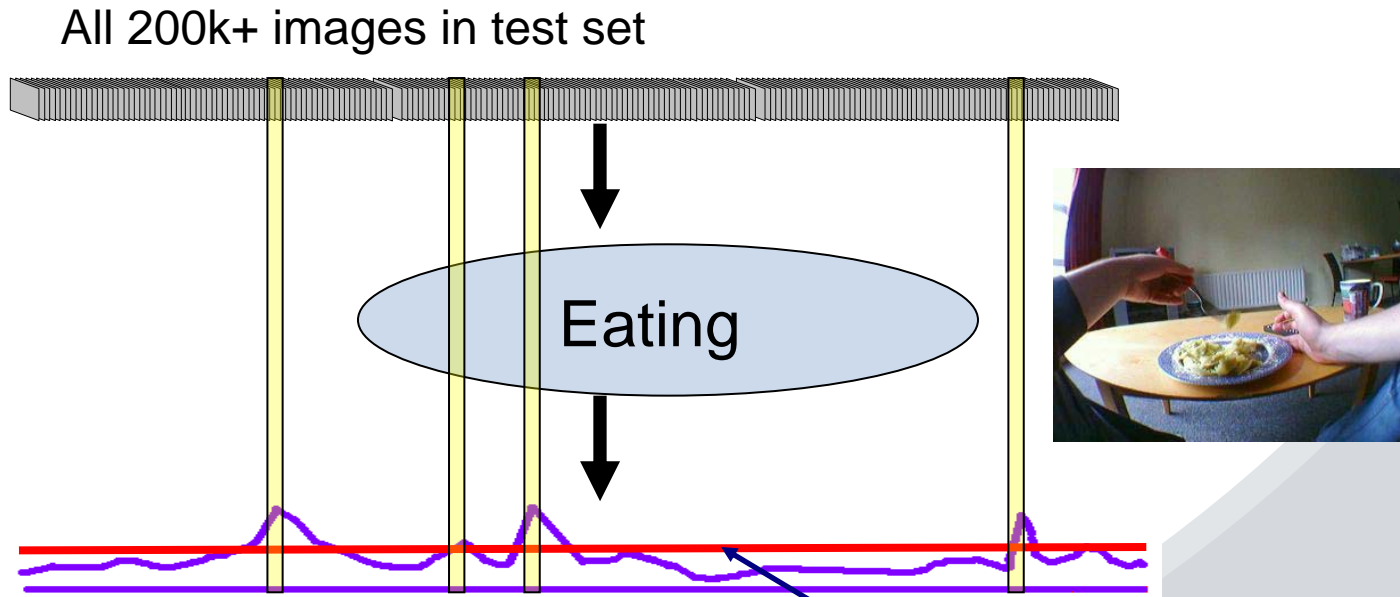
screen = *0.863*

People = *0.012*

Shopping = *0.003*

All values are independent

# Where are the <eating> images?

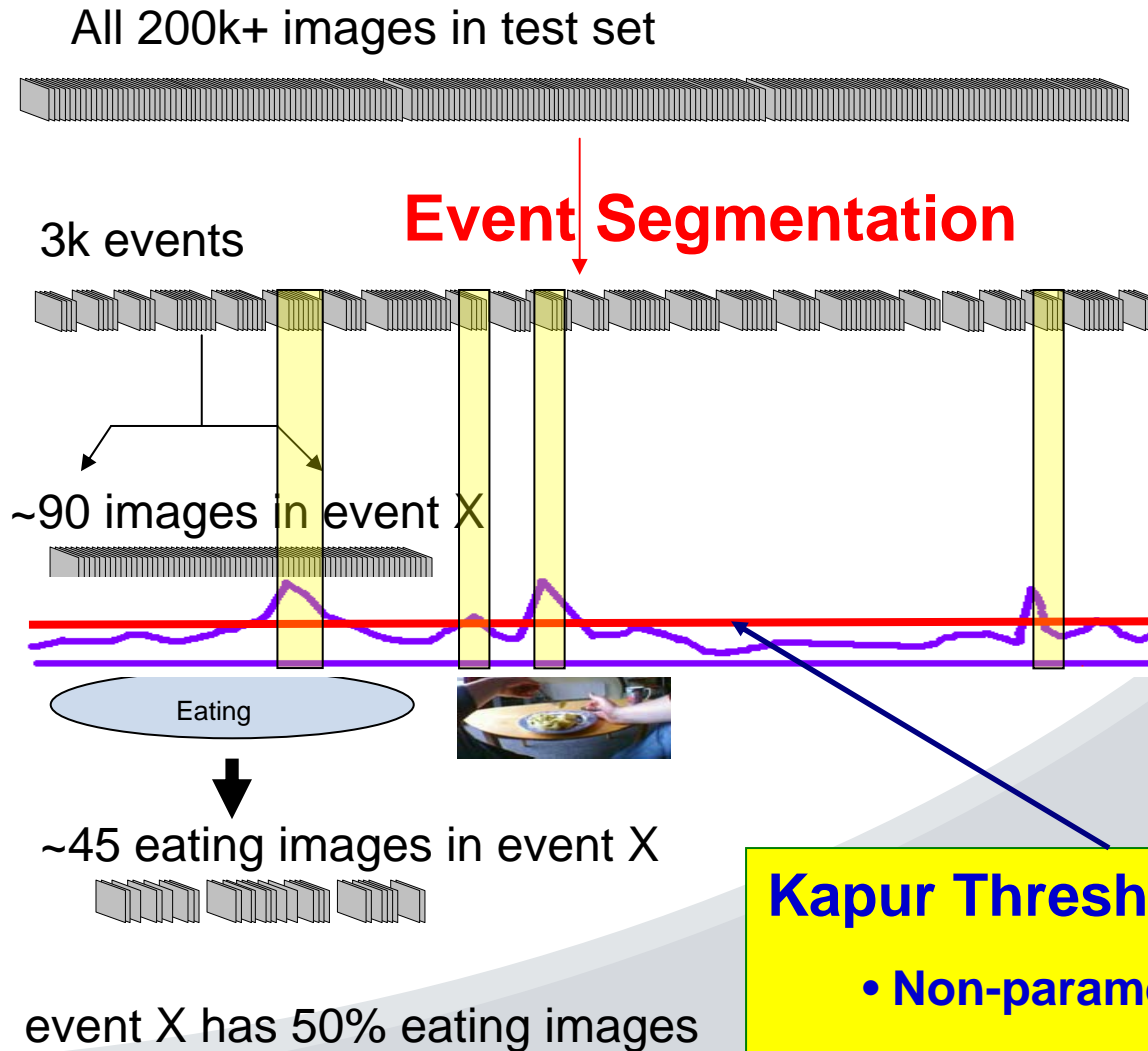


## Kapur Thresholding

- Non-parametric
- Entropy based



# Where are the <eating> events?



**Kapur Thresholding**

- Non-parametric
- Entropy based

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# Experimental Setup

- 5 users
- 1 month period each
- 257,518 images
- 3,030 events
  
- Firstly create annotated training set
  - **Every 5<sup>th</sup> image selected for training set**

Select image(s)

Select concept type

- Event 5921  
30/03/2007 09:22:04 - 09:22:04
- Event 5922  
30/03/2007 09:34:32 - 09:34:32
- Event 5923  
30/03/2007 09:40:08 - 09:40:08
- Event 5924  
30/03/2007 09:56:58 - 09:56:58
- Event 5925  
30/03/2007 10:27:48 - 10:27:48
- Event 5927  
30/03/2007 12:35:36 - 12:35:36
- Event 5928  
30/03/2007 12:46:42 - 12:46:42
- Event 5929  
30/03/2007 12:51:42 - 12:51:42
- Event 5930  
30/03/2007 13:43:54 - 13:43:54
- Event 5931  
30/03/2007 13:59:44 - 13:59:44
- Event 5932  
30/03/2007 14:17:52 - 14:17:52
- Event 5943  
30/03/2007 18:23:02 - 18:23:02
- Event 5944  
30/03/2007 18:33:26 - 18:33:26



- 1  vehicles (external view)
- 2  Road
- 3  Steering wheel (driving)
- 4  Inside of vehicle, not driving (airplane, taxi, car, bus)

SAVE PROGRESS!

DELETE!

Resize Images:

Select event

Select individual concept

# After annotation

- 38,206 images annotated (training set = 14.8%)
- 219,312 in test set (test set = 85.2%)
- **THEN we validated accuracy of detectors on test set**
  - 9 judges to validate system concepts
  - Each judge shown 200 positive & 200 negative images per concept
  - 50 “set” positive images & 50 “set” negative images per concept shown to all users (to investigate judge agreement)
  - **95,907 judgments made on test set!!!**



# Validation tool

**Interior of Vehicle** ← Find images which have been taken inside a vehicle. This may be a car, bus, tram, train or plane.

**Concept to identify**

**User selects positive examples**

**System Positive & Negative samples randomly displayed**

Zoom:  No. Judgements: 50

NEXT JUDGEMENTS

24%

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# Results

- Precision
  - Average = 0.57
  - Median = 0.60
- Judge Agreement
  - Fleiss's Kappa = 0.68
- Strong correlation of 0.75 between the number of concept training samples and test set performance



Vehicles External(46%)



Road (47%)



Steering wheel (72%)



Inside of vehicle (60%)



Indoors (82%)



Toilet/Bathroom (58%)



Door (69%)



Staircase (48%)



Outdoors (62%)



Buildings (59%)



Tree (63%)



View of Horizon (23%)



Grass (60%)



Sky (79%)



Vegetation (64%)



Screen (78%)



Reading (58%)



Meeting (34%)



Office (72%)



Presentation (29%)



Food/eating (41%)



Hands (68%)



Holding cup (35%)



Holding phone (39%)



Faces (61%)



People (45%)



Shopping (75%)



# Results

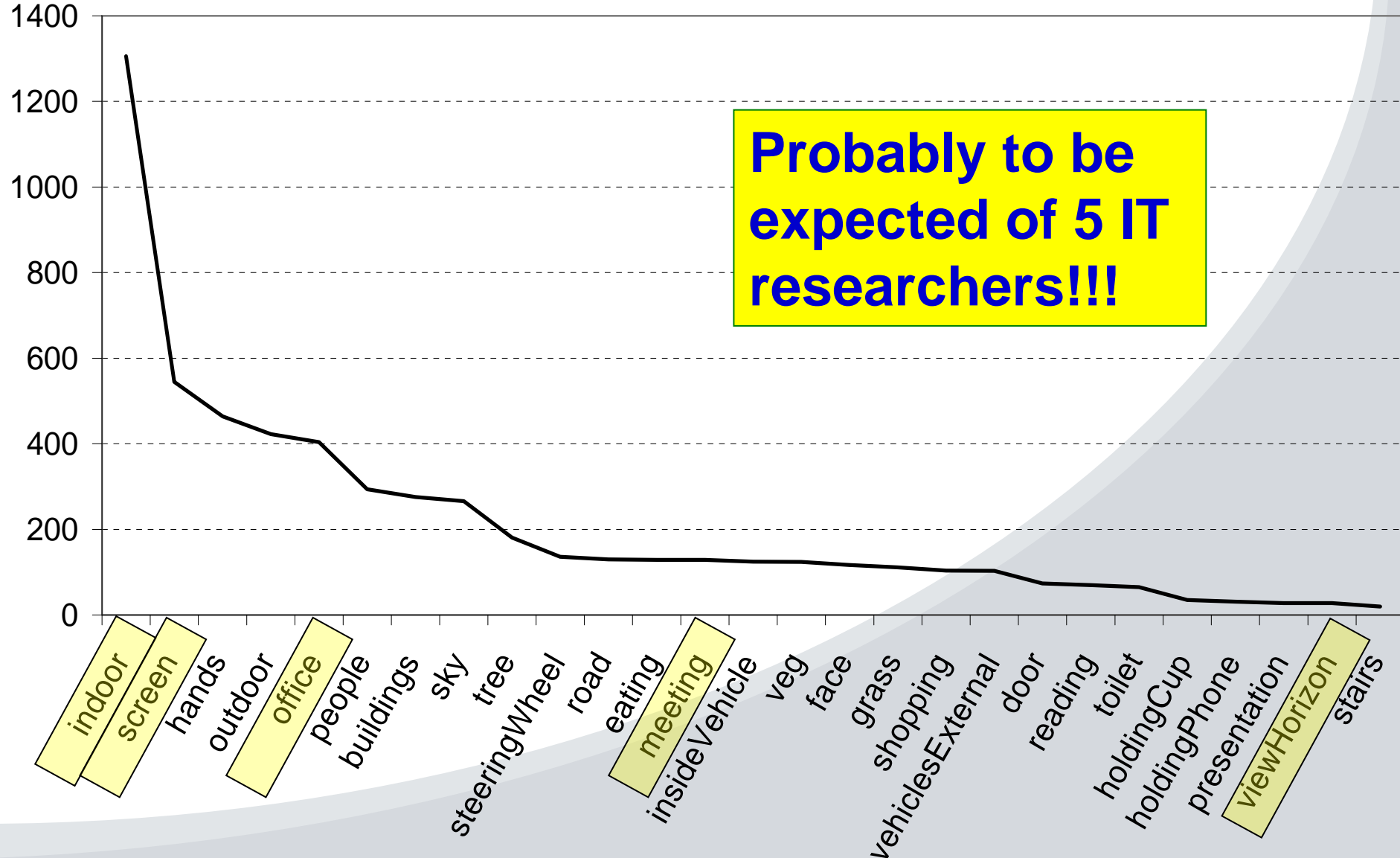
BUT applying on image level isn't so interesting

- **Many SenseCam images are blurred, grainy, obscured by hands, etc.**

## HOWEVER

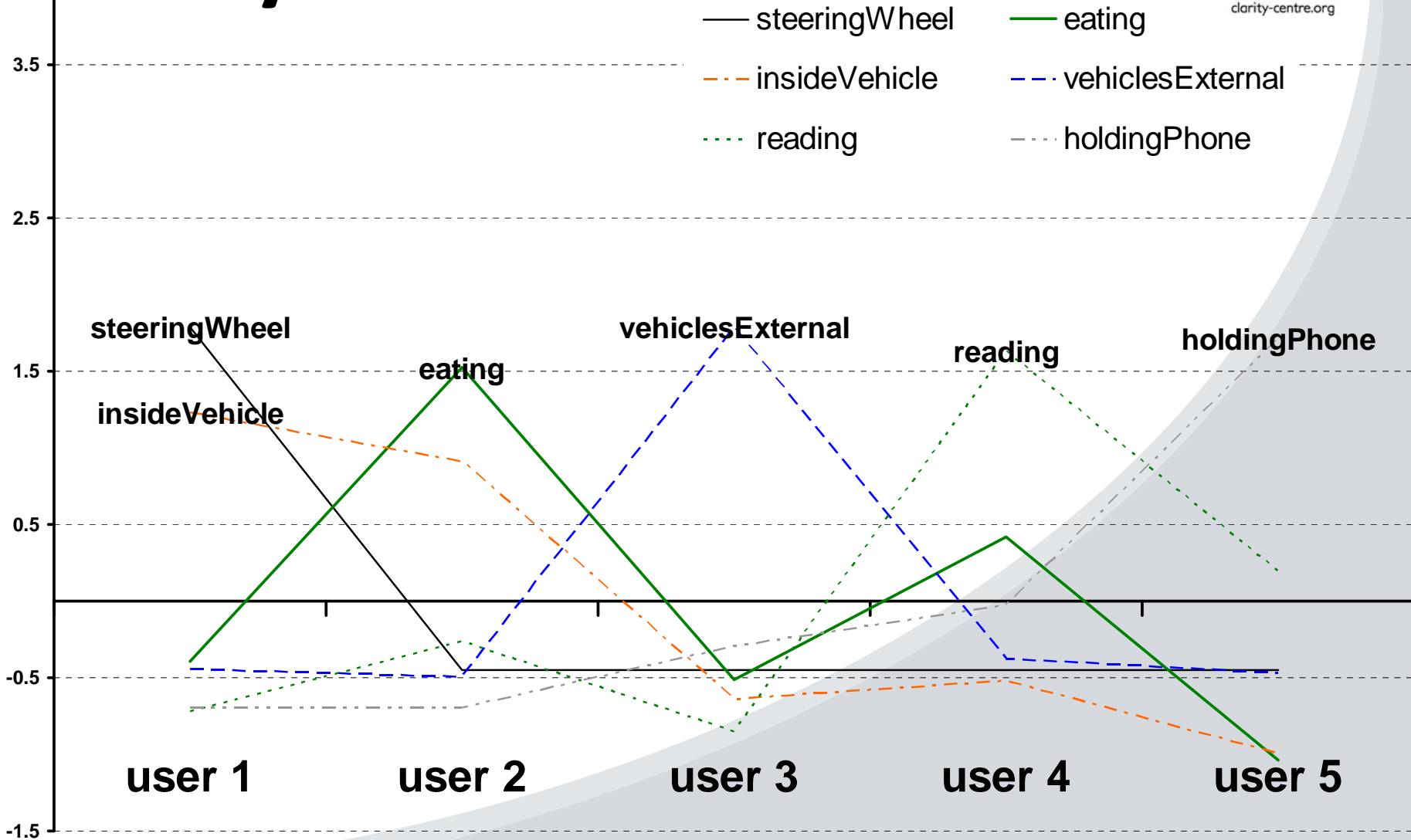
- **Considering groups of images (i.e. CONSIDERING EVENTS)**
  - Reduces inaccuracies
  - Allows us map “macro trends”

# Num Events Across 5 Users



# Lifestyle Variation

standard deviations away from sample mean



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# Conclusions

- For a long time focus of lifelogging community was on hardware minituration and storage
- Recently focus has shifted to data management
- Potential significance of SenseCam as memory aid
- However recent efforts only focused on “detection”, not **“recognition”**

# Conclusions

- Standard concept detection techniques applied to new exciting field of lifelogging
- Extensive evaluation carried out
  - 27 concepts selected from 257,518 images
  - 38,206 images annotated for training set
  - 95,907 test set images manually evaluated
  - 17 concepts with > 60% precision

# Conclusions

- Investigating concepts at the event level is exciting
  - Allows us to identify “macro” lifestyle trends/profiles/signatures
  - Enables us to compare lifestyles of individuals

# Future Work

- **Improve concept performance**

- Include sensor values
- Investigate “bag of words” approach
- Adaptively learn new concepts

- **Use concepts in search**

- Perhaps along with GPS & Bluetooth

- **Broadcast lifestyle signature/profile**

- e.g. in the last week I’ve been spending a lot of time in front of the PC but not so much time in the park



# Thank You

further information:

<http://www.cdvp.dcu.ie/SenseCam>

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