PlaceAvoider

Steering First-Person Cameras away from Sensitive Spaces

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Cameras are commonplace in our computing landscape

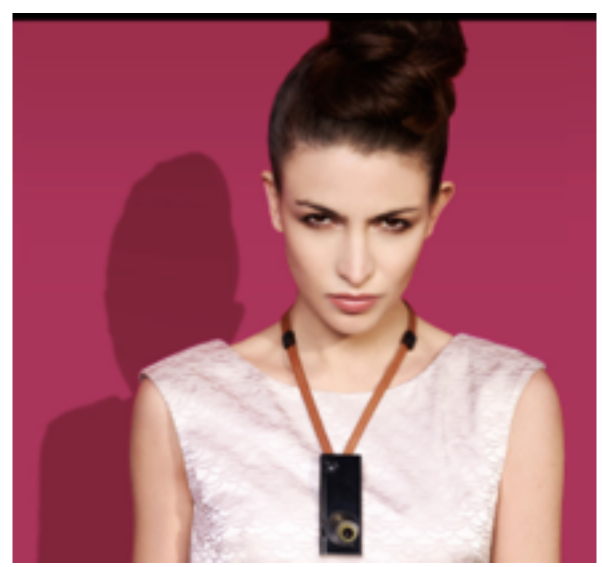
http://www.steves-digicams.com/New-pope.jpg

Mobile cameras are not limited to smartphones

http://www.getnarrative.com

http://www.google.com/glass

http://www.vuzix.com



http://www.autographer.com

http://bits.blogs.nytimes.com/2014/02/23/samsung-introduces-two-new-smart-watches/

Wearable cameras have many interesting uses

http://blog.autographer.com/2013/05/the-future-of-lifelogging-interview-with-gordon-bell/

Gordon Bell
logging his life since 2001

Wearable cameras have many interesting uses

http://www.nydailynews.com
Saving precious moments

http://www.digitalavmagazine.com
Assisting with surgery

http://blog.autographer.com/2013/05/the-future-of-lifelogging-interview-with-gordon-bell/
Gordon Bell
logging his life since 2001

http://www.siliconbeat.com
Law enforcement

http://blog.memoto.com
Therapeutic use

What about privacy?

http://www.bangkokpost.com

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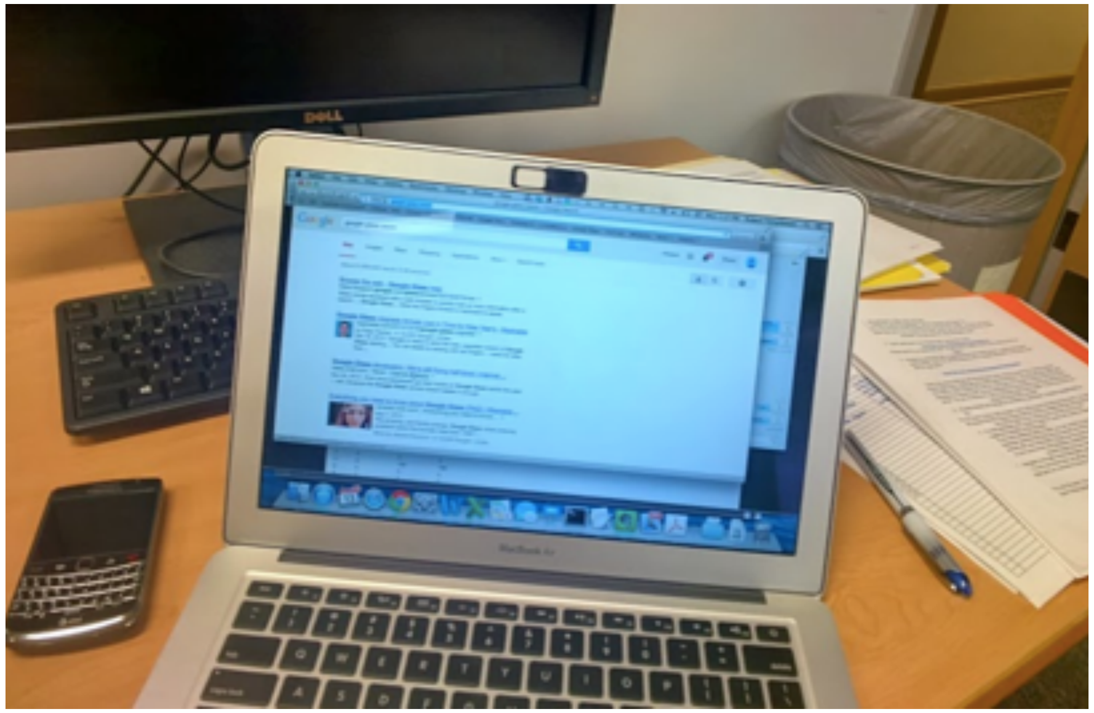
What about *the device owner's* privacy?



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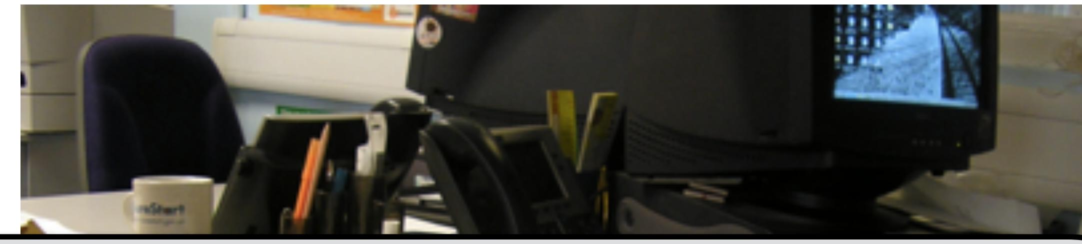
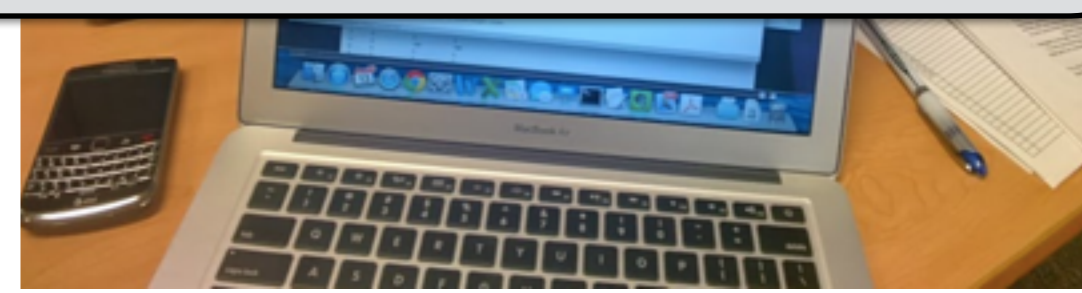
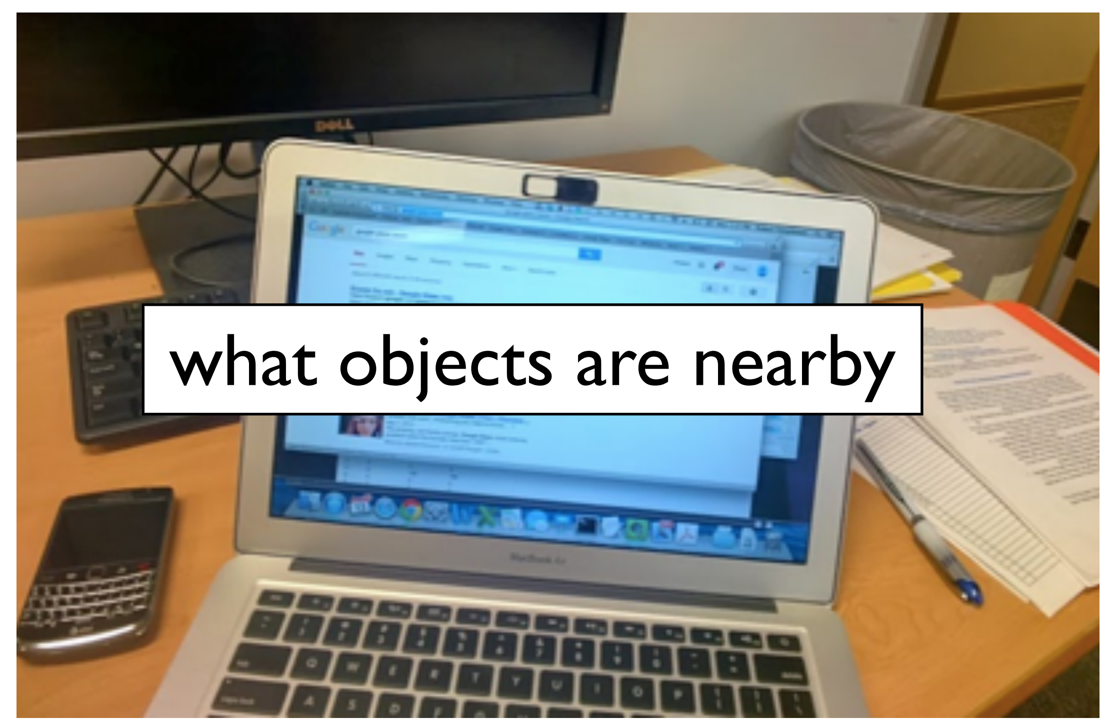


Controlling the collection of images
CRePE - Conti et al.

Controlling access to images after collection
DARKLY - Jana et al.

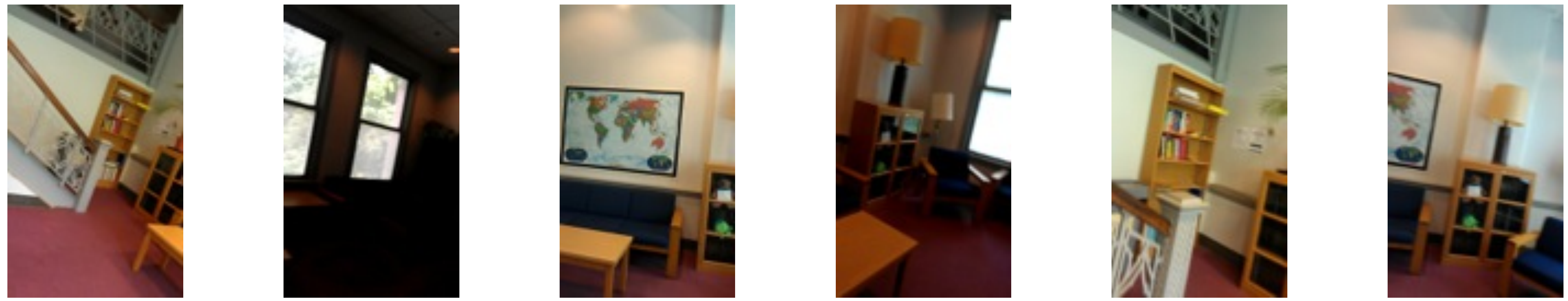
What makes images sensitive?



We seek to control images based on scene location

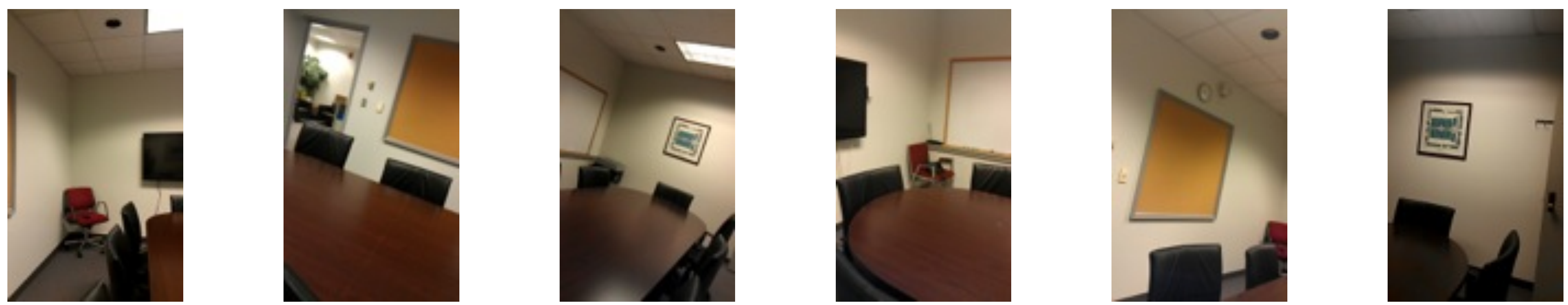
Share

student lounge



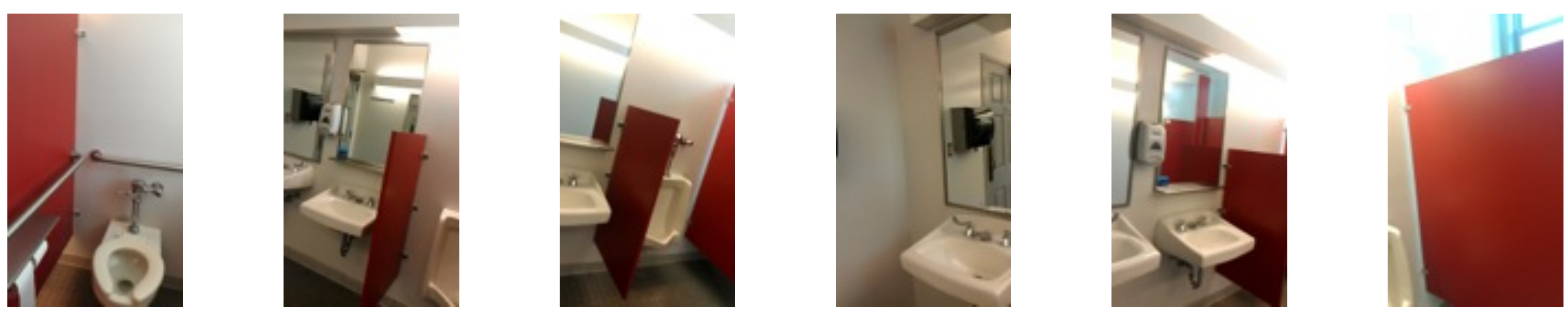
Don't Share

conference room

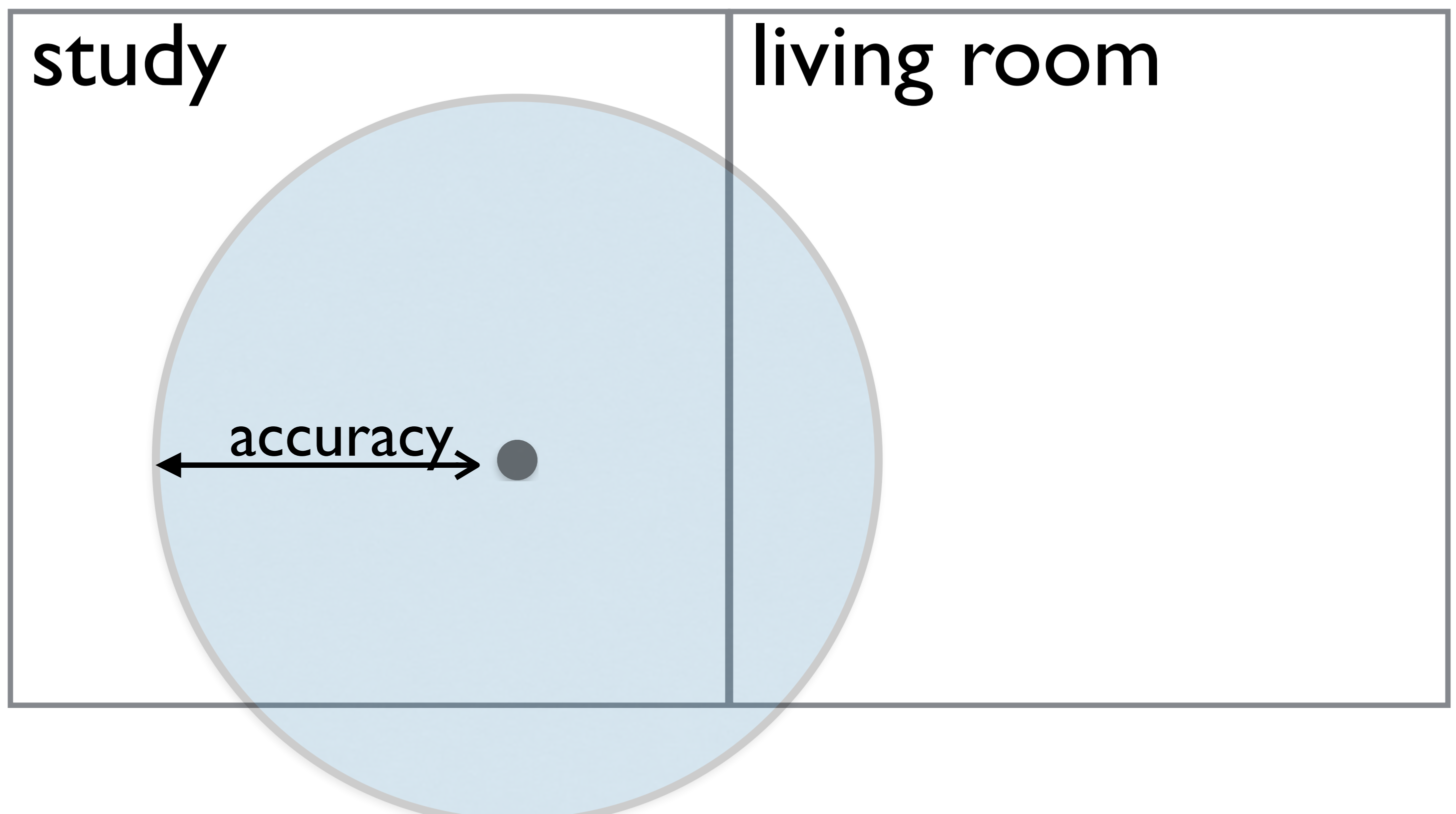


Don't Share

bathroom



Existing localization has too much error



GPS accuracy ~ 5m
Network-based accuracy > 30m

Camera location may significantly differ from image scene location

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PlaceAvoider concept

+ ‘student lounge’
public access

+ ‘bathroom’
forbidden

Policy

PlaceAvoider element

PlaceAvoider concept

+ ‘student lounge’
public access

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forbidden

Policy
Locale - Lindley Hall
‘student lounge’ - PUBLIC
‘bathroom’ - DELETE

PlaceAvoider element

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Policy
Locale - Lindley Hall
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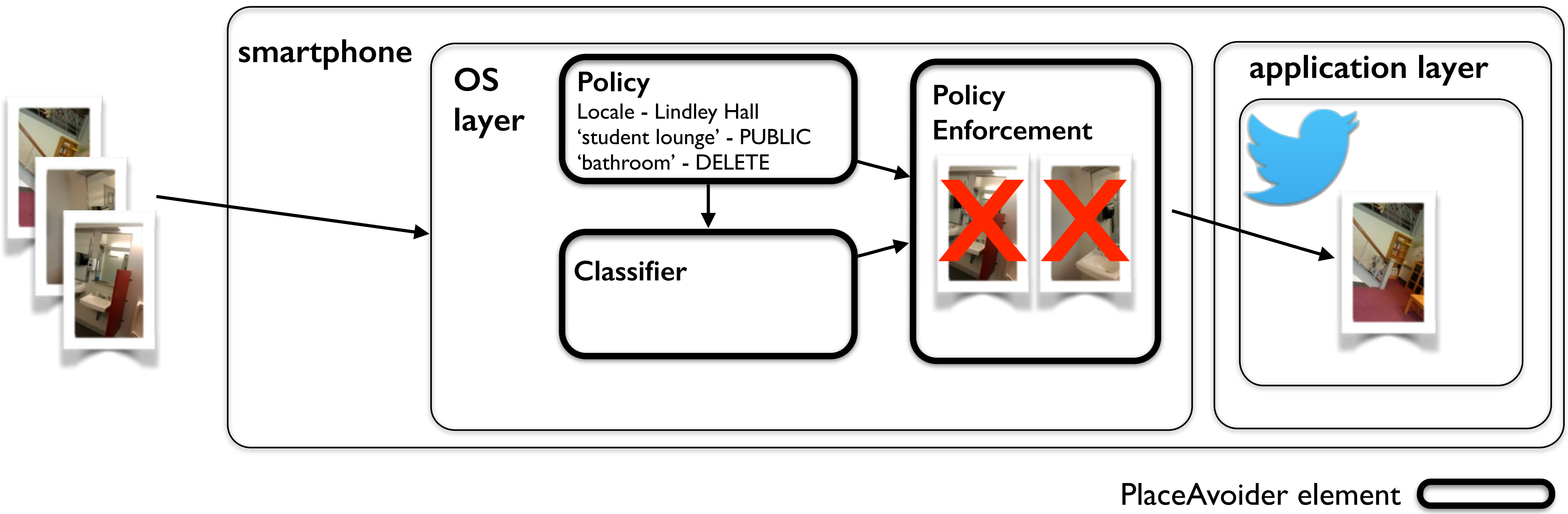
Classifier

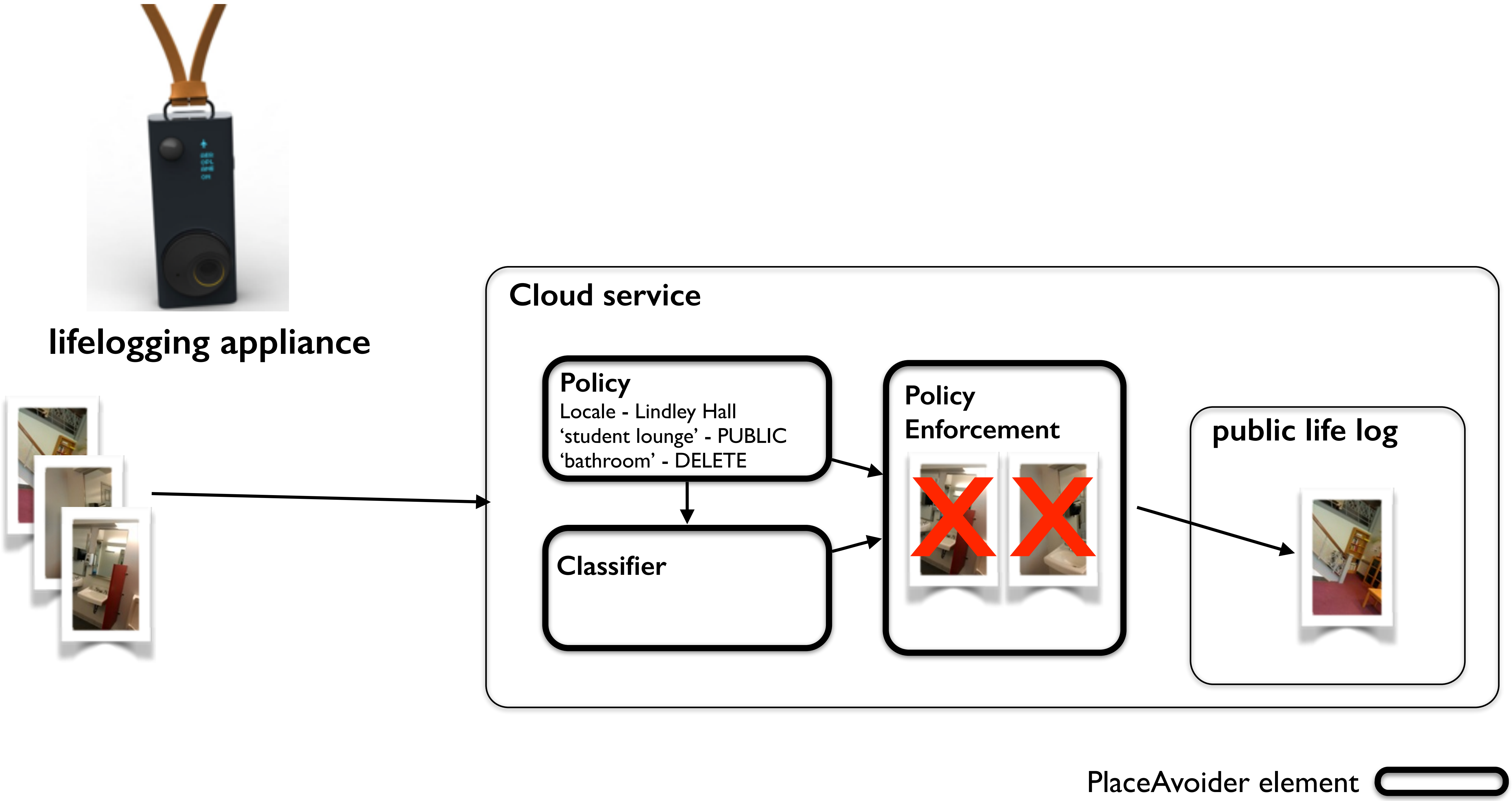
Policy Enforcement

PlaceAvoider element

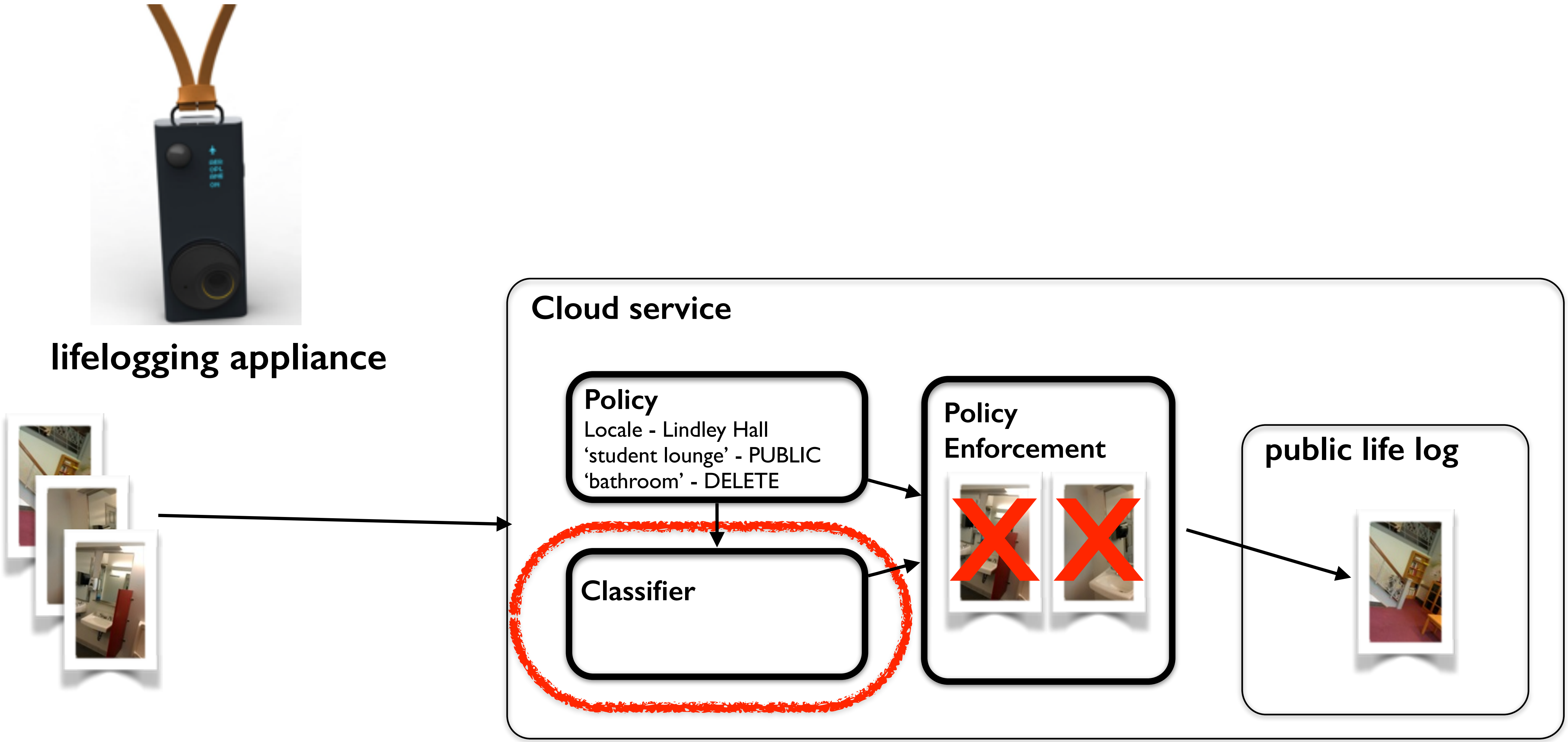
PlaceAvoider within the OS



PlaceAvoider in the cloud

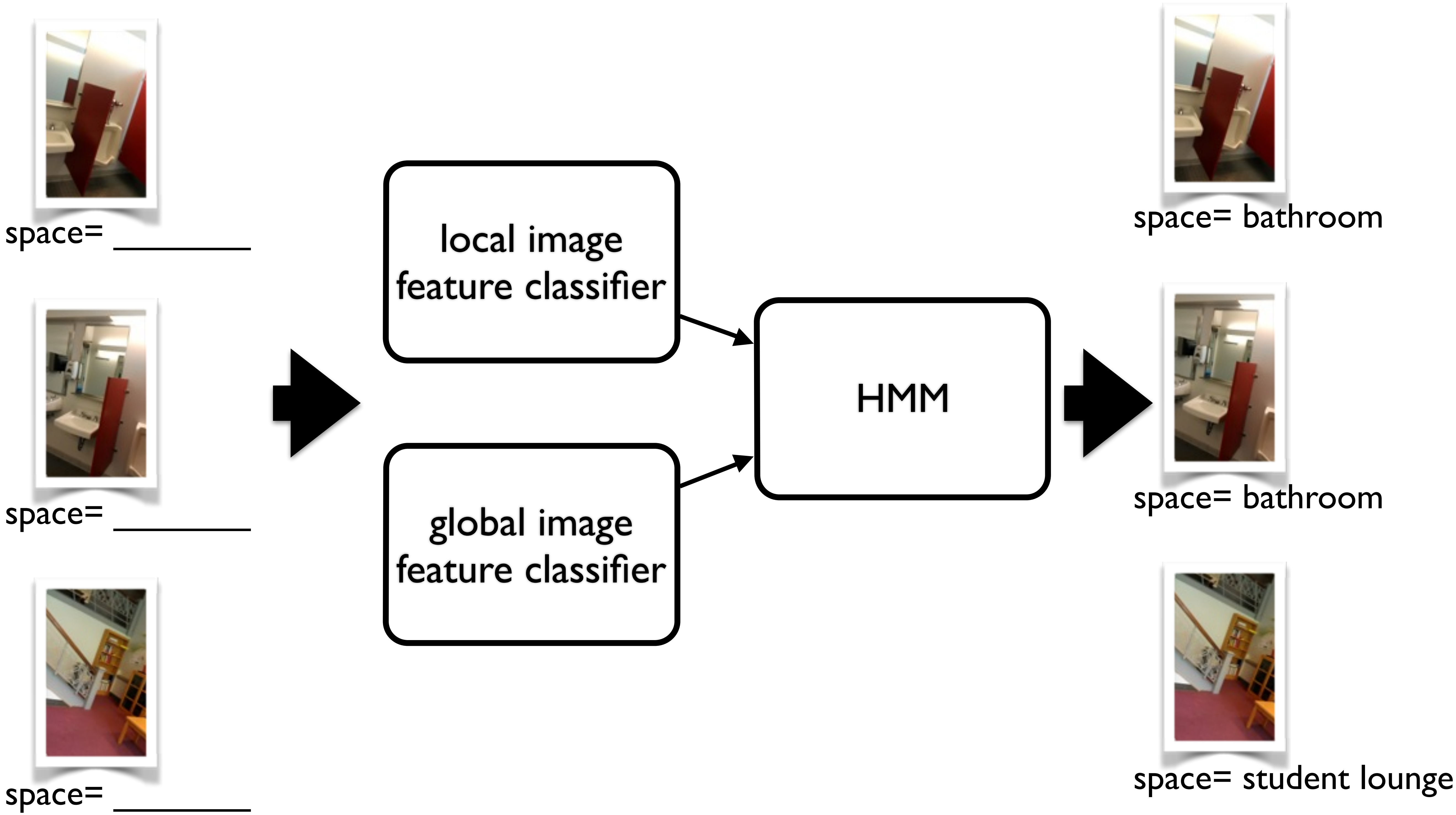


PlaceAvoider in the cloud



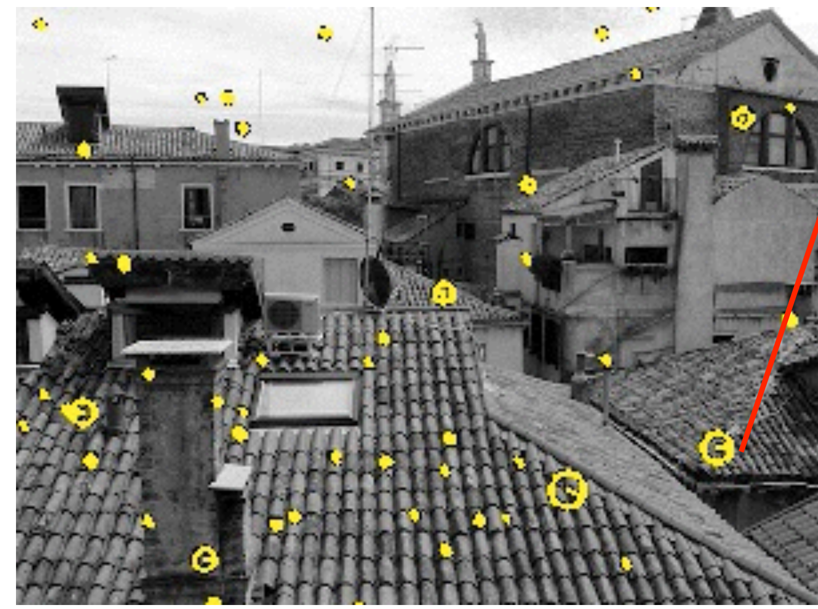
PlaceAvoider element

PlaceAvoider classifier



Two types of image features

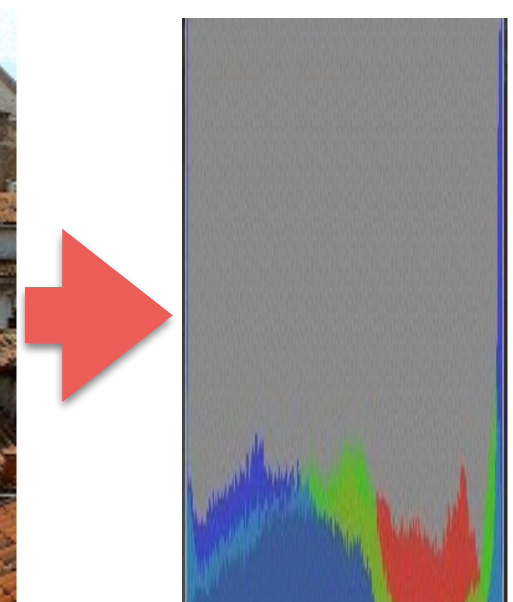
***Local* image features**
describe a sub-region of a spatial image
- key point detector SIFT



51 0 0 0 2 5 5 19
111 0 0 0 16 32 16 66
2 0 0 0 149 107 8 7 0
0 0 0 22 19 11 1 88 9
3 8 3 0 0 0 153 9 0 0
36 17 0 21 16 0 0 0
153 81 0 6 0 0 0 2 58
18 2 0 99 16 4 3 0 0
0 1 153 23 0 0 28 4 0
2 31 3 0 0 153 62 0 1
0 0 0 1 78 36 1 0 78
7 0 0 0 0 0 2 153 21
0 0 12 6 0 5 37 2 0 0
153 53 0 4 0 0 0 3 90
11 0 0

http://www.vlfeat.org/overview/sift.html

***Global* image features**
describe an entire image
- sparse SIFT
- dense grid SIFT
- grid HOG



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Matching with *distinctive* features

bathroom

lab

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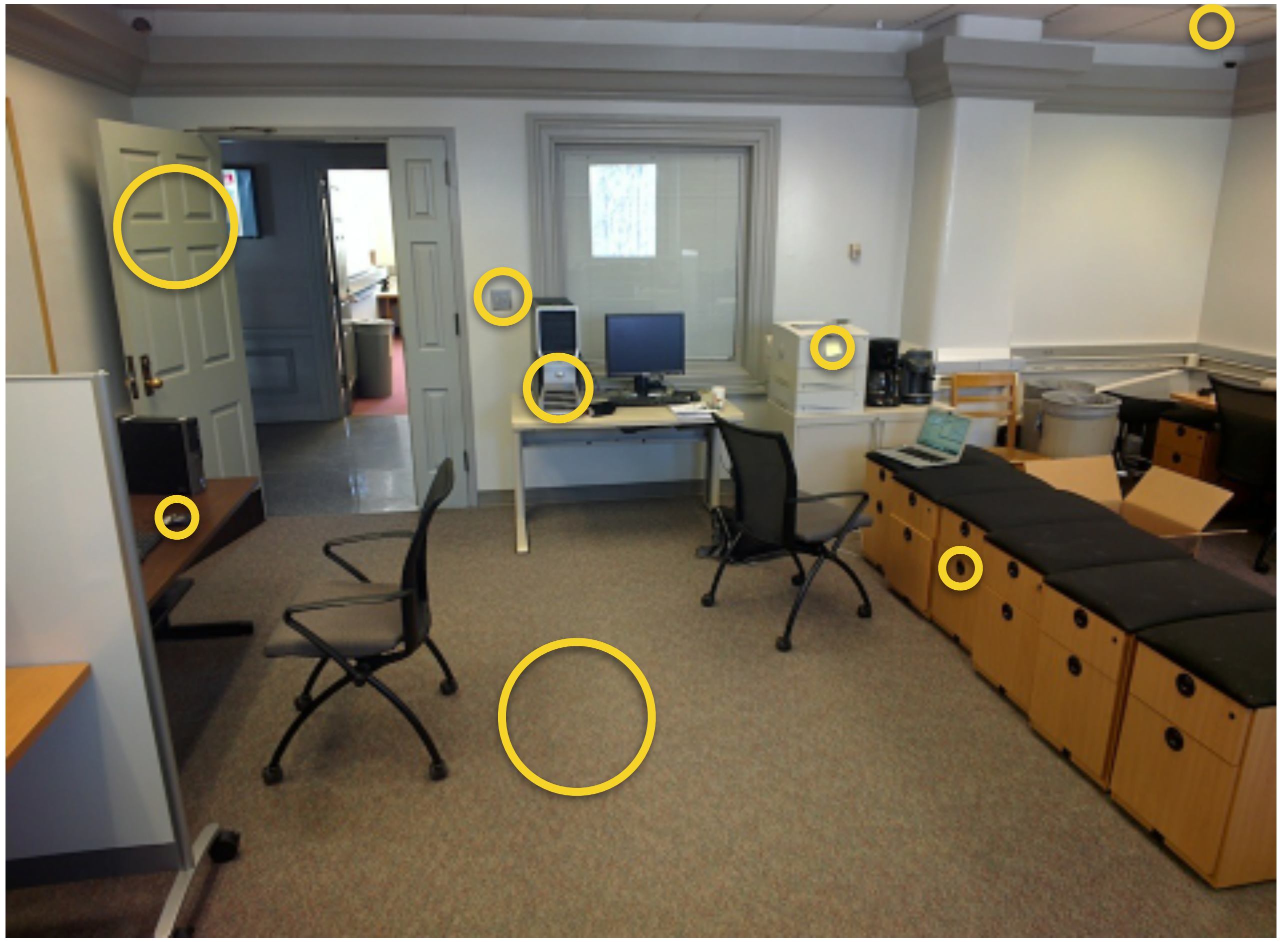
bathroom



lab

SIFT feature detector identifies *interesting* features

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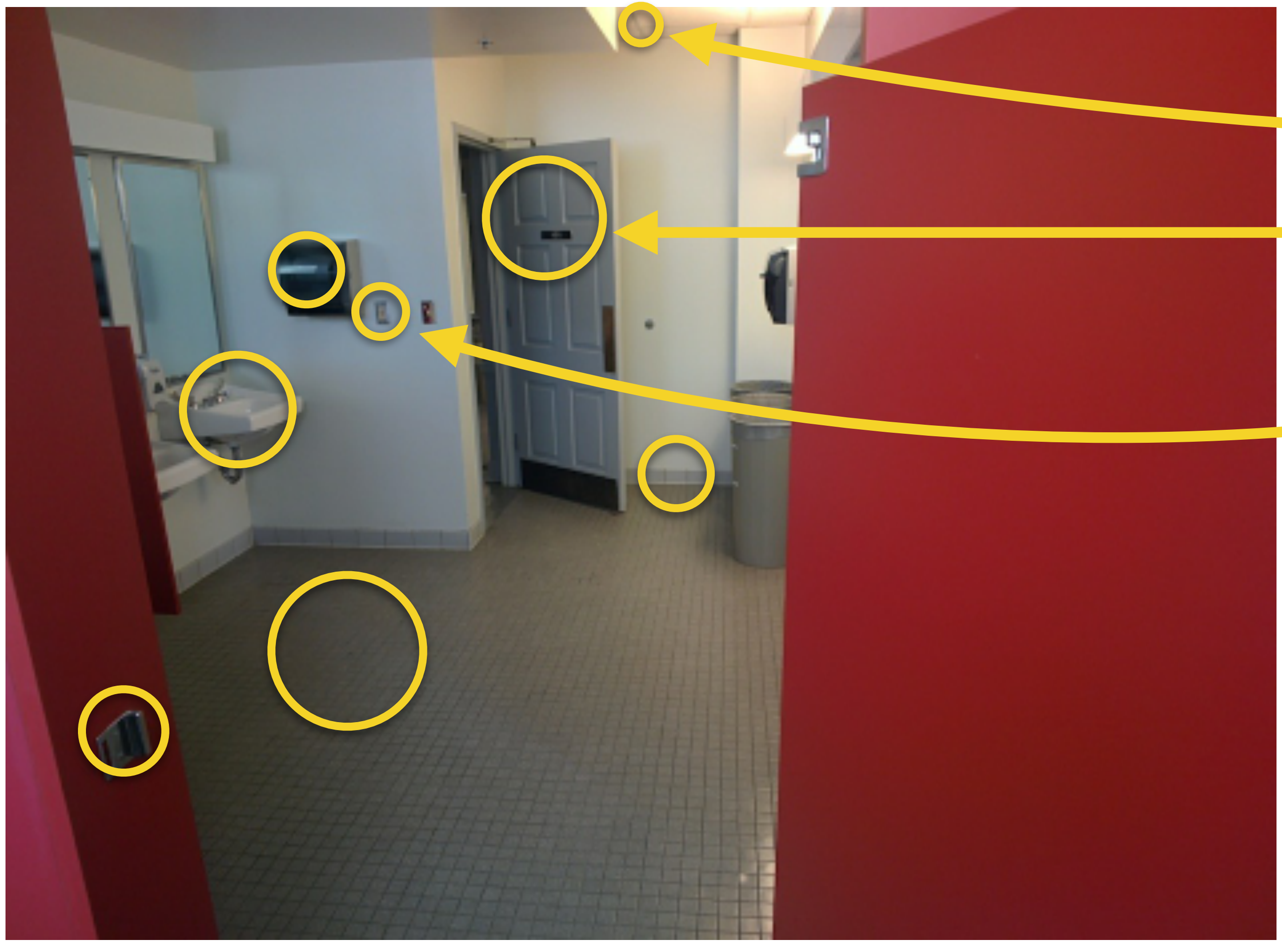
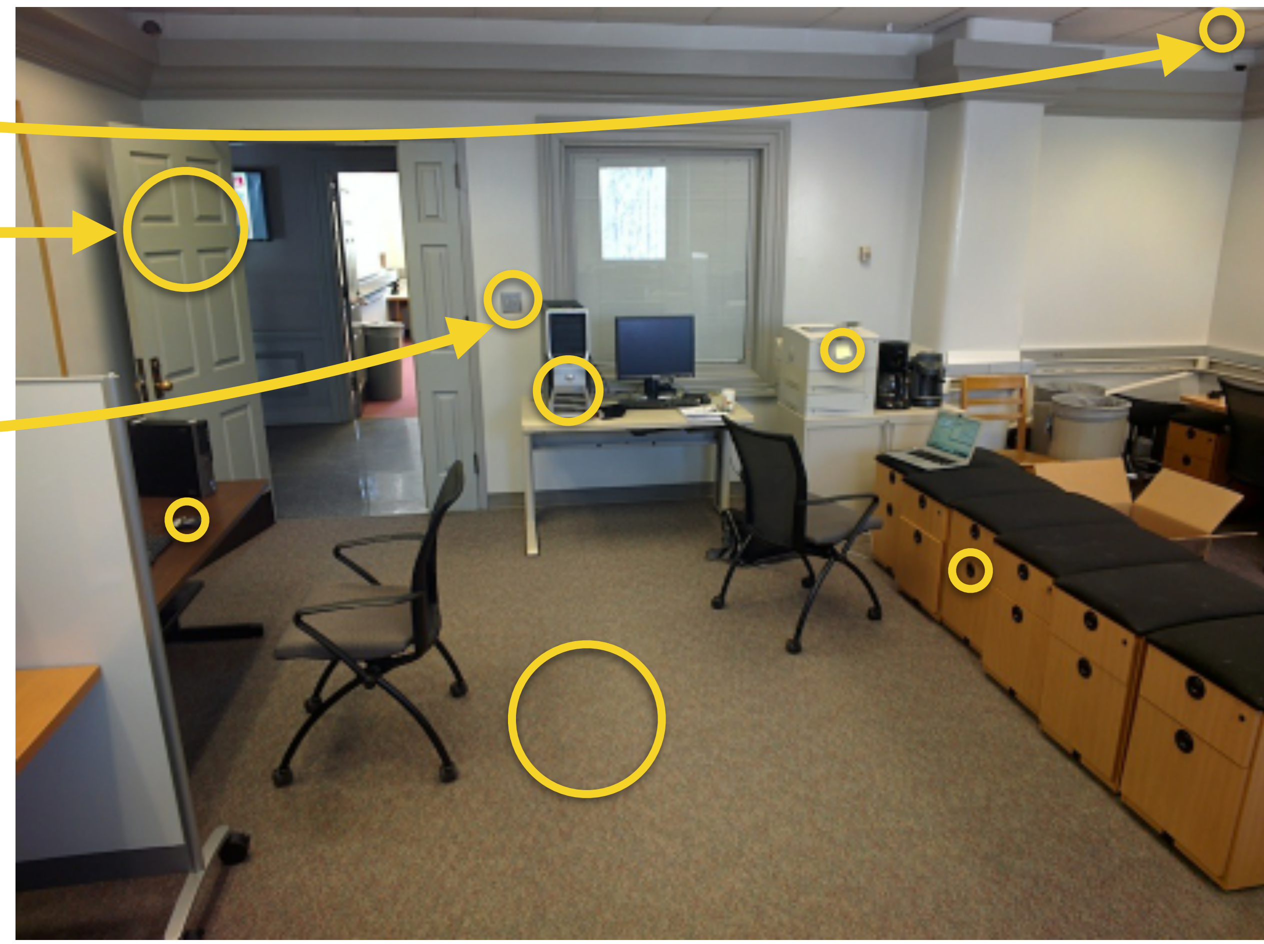
Matching with *distinctive* features



bathroom

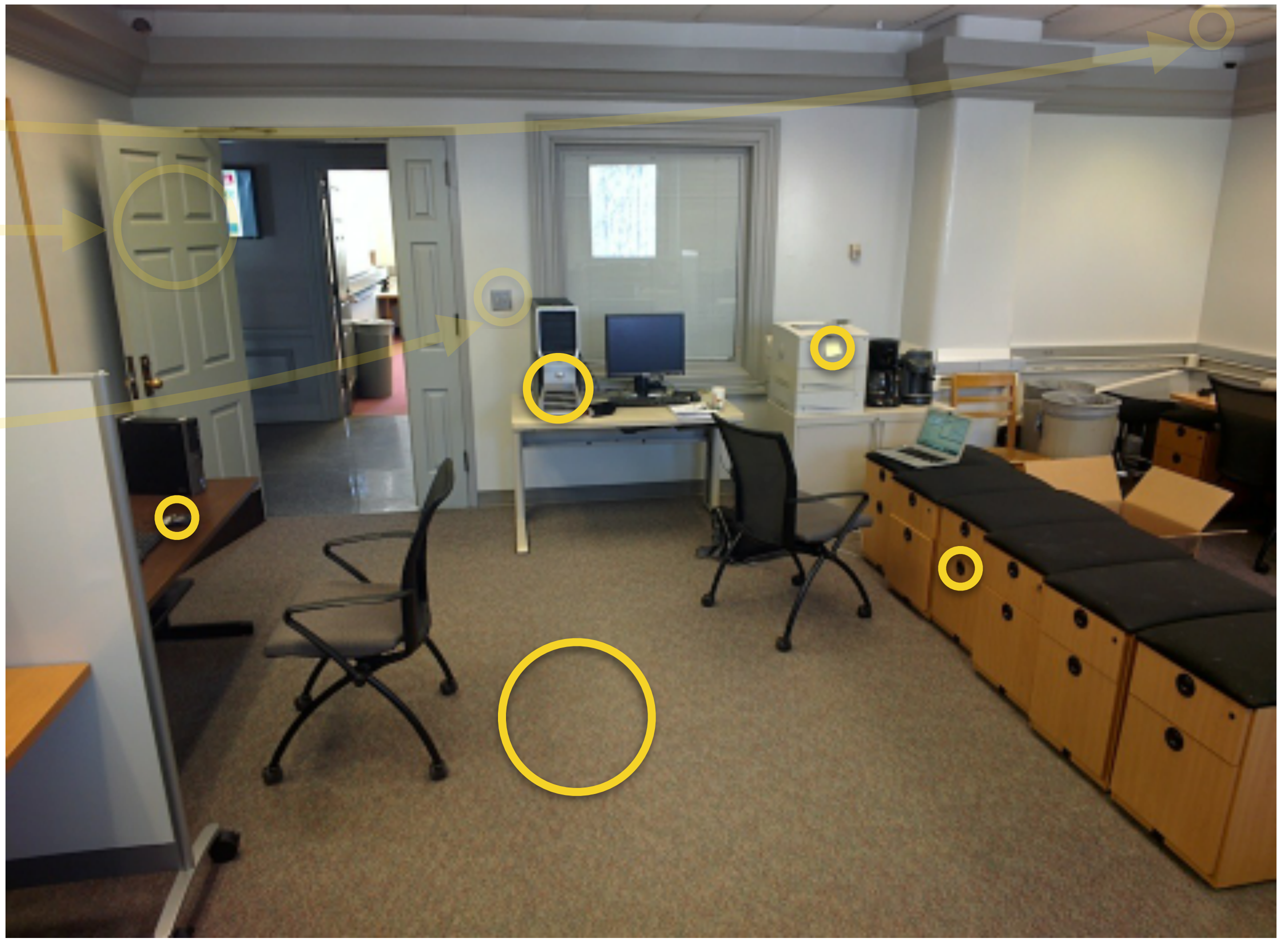


lab

similar features across spaces offer no discriminative value

Matching with *distinctive* features

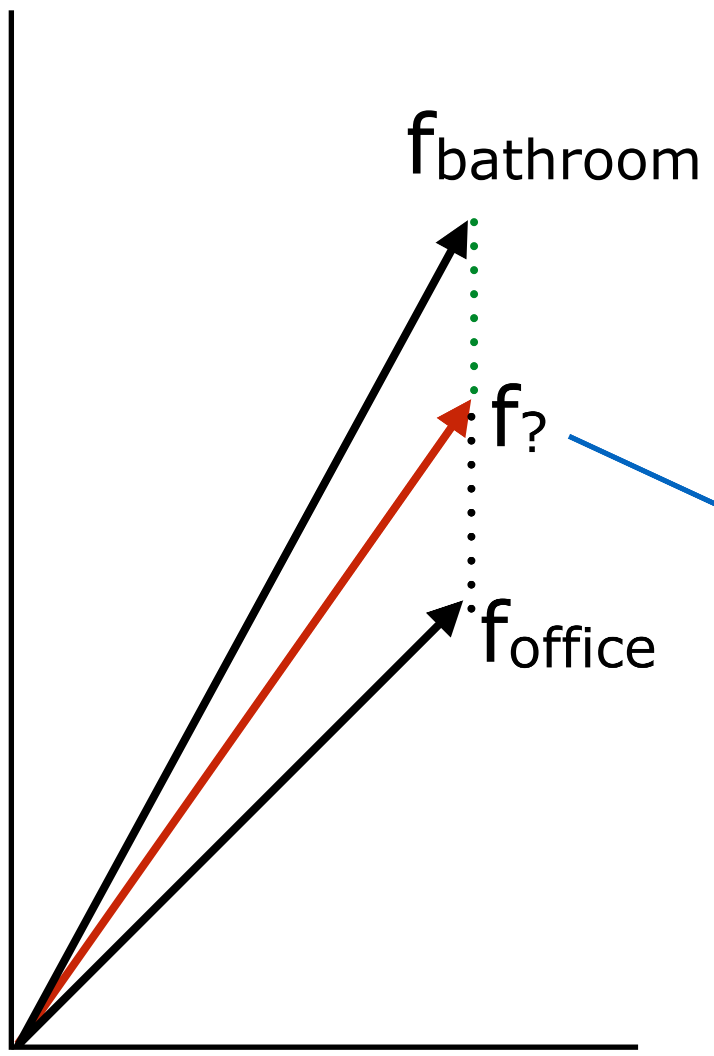
bathroom



lab

represent scenes via discriminating features

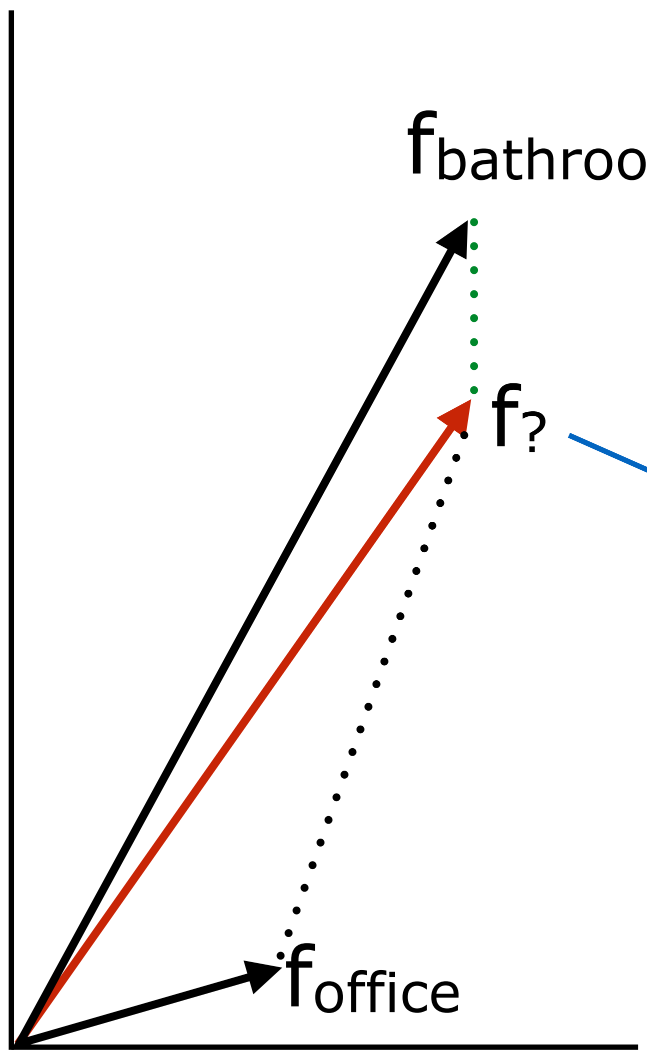
Matching with *distinctive* features



$$\frac{|f_? - f_{bathroom}|}{|f_? - f_{office}|} > \tau$$

this feature is not distinctive

Matching with *distinctive* features

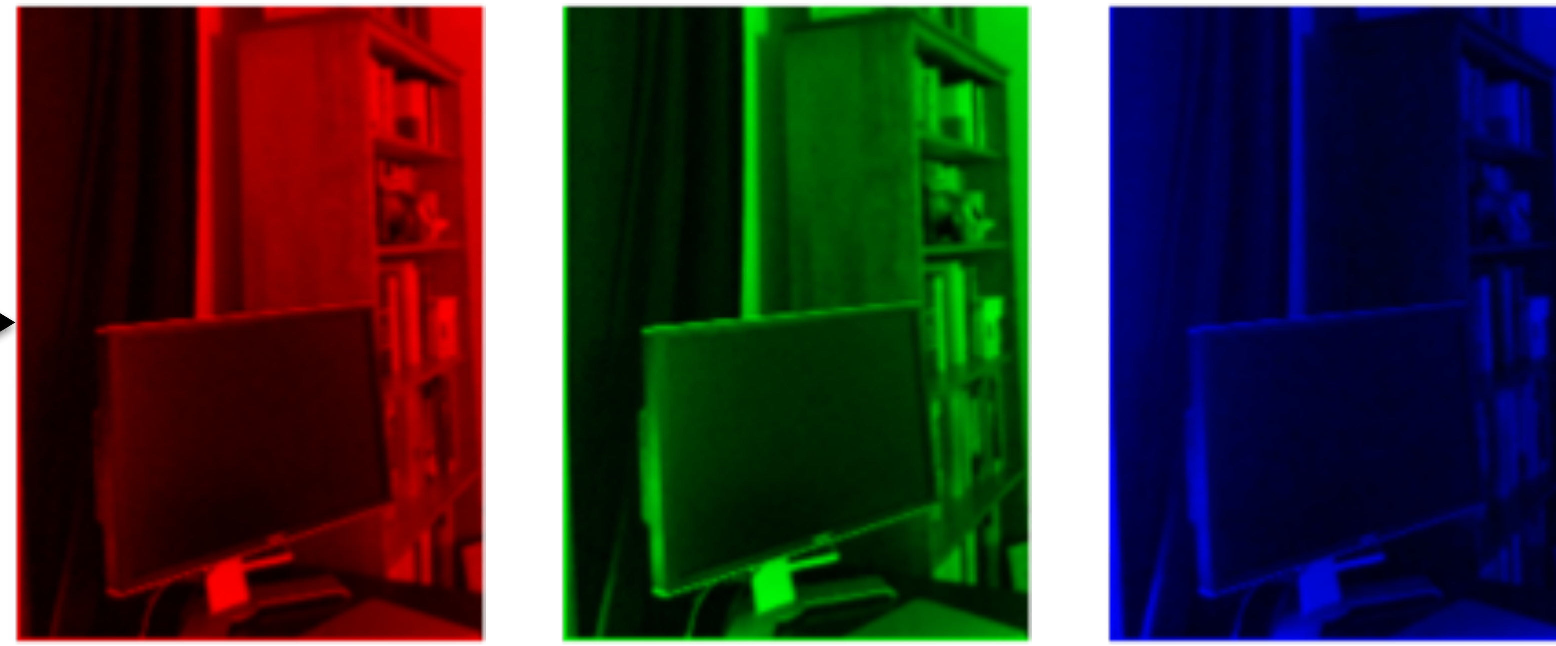


$$\frac{|f_? - f_{bathroom}|}{|f_? - f_{office}|} \leq \tau$$

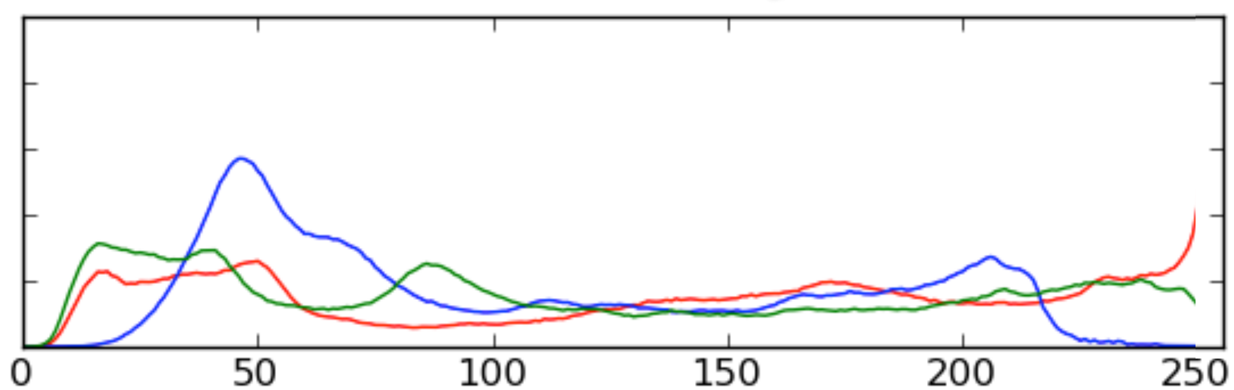
this feature **IS** distinctive

Color histograms

Original image



Red, green, and blue color channels



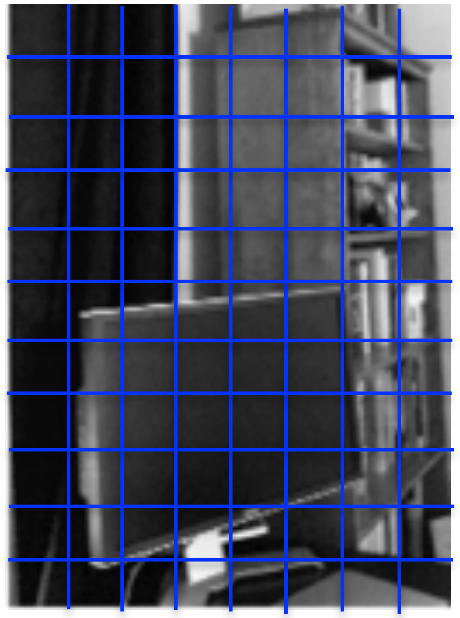
Histograms over pixel intensities

Modeling scene textures (HOG)

original
image

Modeling scene textures (HOG)

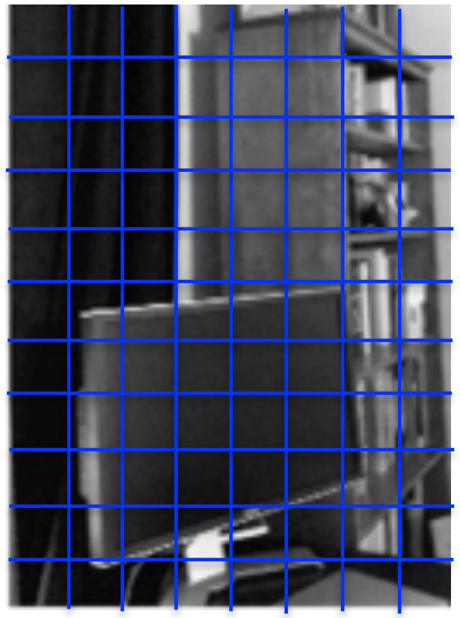
original
image



partitioned in
8x8 windows

Modeling scene textures (HOG)

original
image



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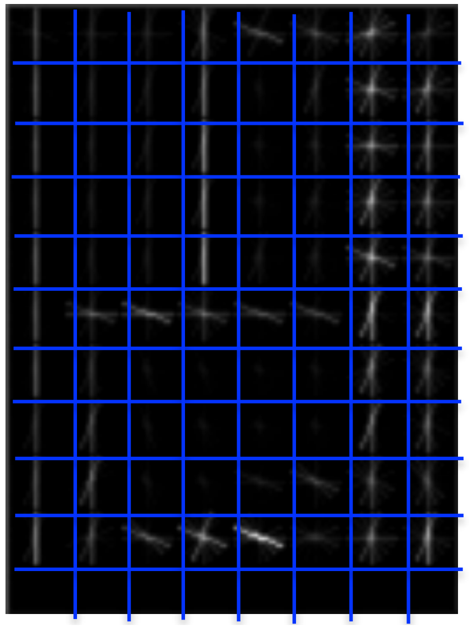
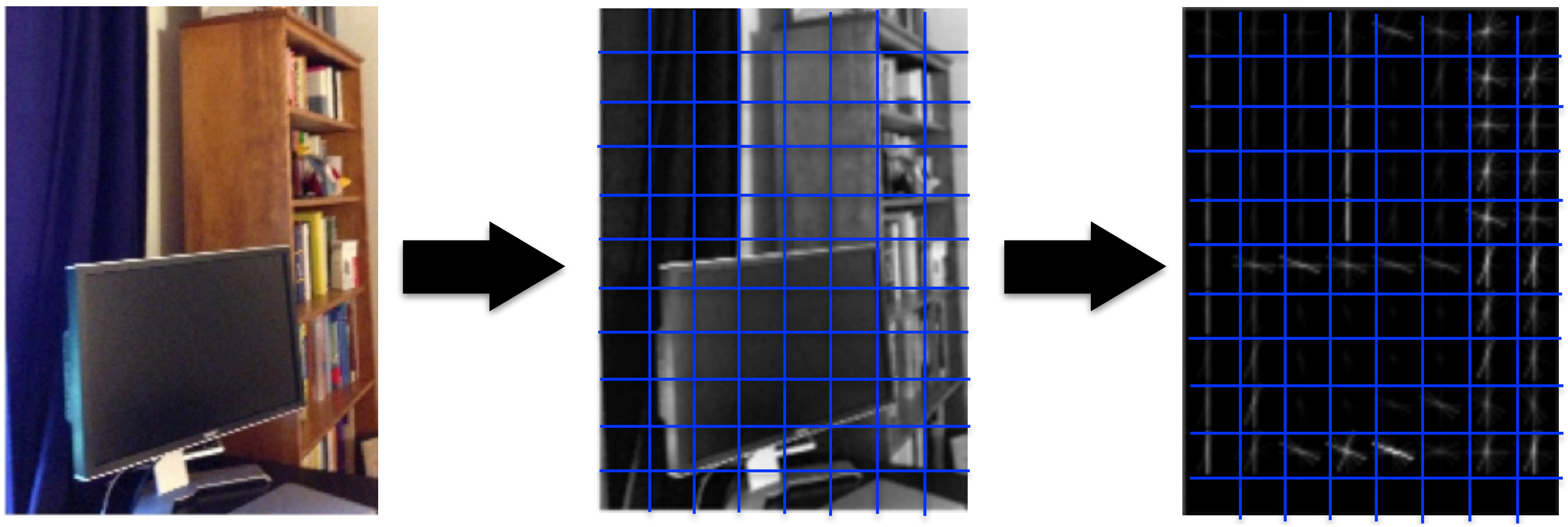


compute distribution of
edge orientations
in each window

Modeling scene textures (HOG)



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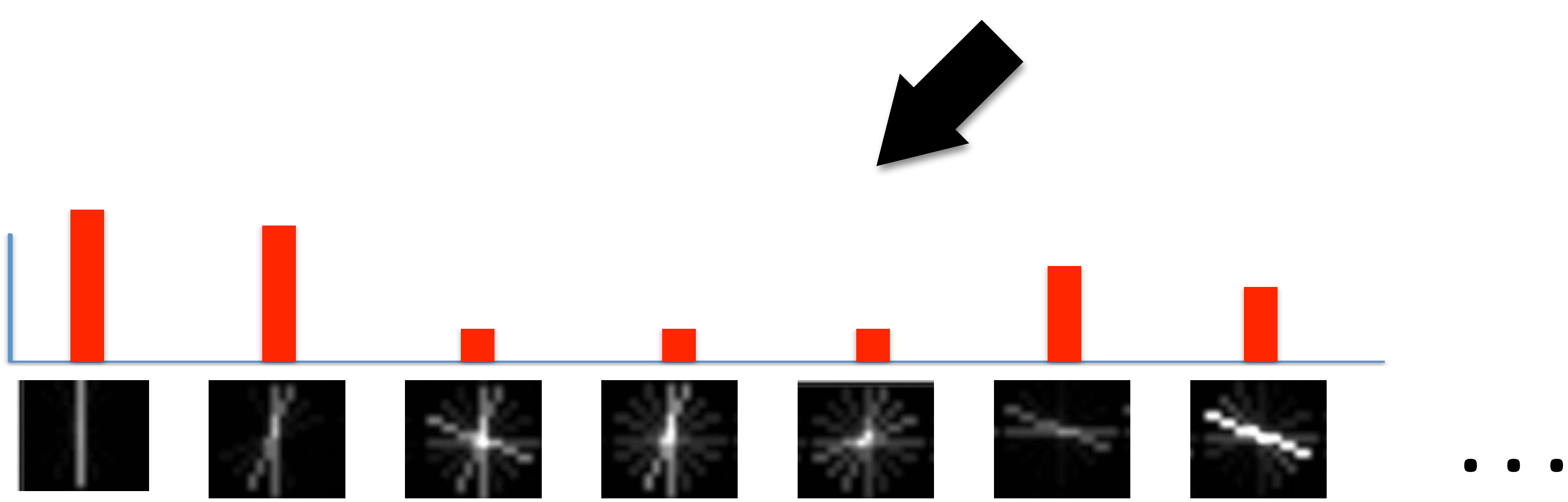

histogram over edge orientation patterns

Classifying photo streams with HMMs

Bathroom Living Living Living Living Living Office Office

Probabilities with individual photo classifiers:

Bathroom:	0.931	0.023	0.002	0.007	0.009	0.018	0.016	0.073
Bedroom:	0.006	0.734	0.461	0.120	0.082	0.002	0.885	0.018
Garage:	0.006	0.192	0.117	0.744	0.746	0.168	0.059	0.003
Living:	0.014	0.020	0.420	0.127	0.162	0.811	0.023	0.005
Office:	0.042	0.031	0.001	0.001	0.001	0.001	0.018	0.901

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	✓	✗	✗	✗	✗	✓	✗	✓

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	✓	✗	✗	✗	✗	✓	✗	✓

Probabilities after applying HMM:

Bathroom:	**0.896**	0.436	0.060	0.015	0.010	0.006	0.002	0.000
Bedroom:	0.010	0.052	0.026	0.004	0.002	0.002	0.002	0.000
Garage:	0.009	0.045	0.024	0.004	0.002	0.002	0.006	0.001
Living:	0.079	**0.441**	**0.881**	**0.968**	**0.975**	**0.873**	0.125	0.005
Office:	0.006	0.027	0.009	0.009	0.012	0.116	**0.865**	**0.994**

Classifying photo streams with HMMs

Bathroom Living Living Living Living Living Office Office

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Evaluation

We evaluated PlaceAvoider in 5 settings

2 office buildings and 3 homes (authors')
5 rooms evaluated at each location

Enrollment imagesets
deliberately captured
not structured (cover a space)
average of 70 images per space

Test imagesets
opportunistically captured, ~3s frequency
temporally ordered (stream)
323 to 629 images per location

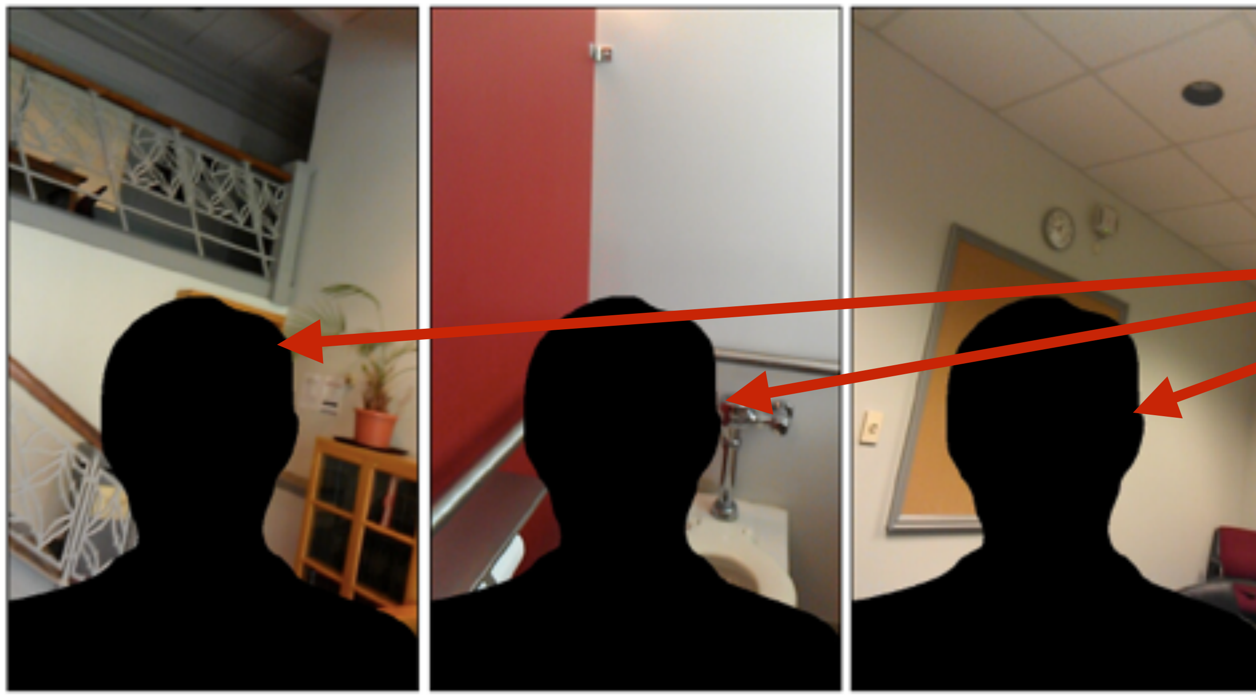
Local features perform better at classifying single images

Dataset	Baseline	Local features	Global features
House 1	29.8%	**52.9%**	48.3%
House 2	31.0%	41.8%	**49.1%**
House 3	20.9%	**81.5%**	80.0%
Workplace 1	32.1%	**75.9%**	74.6%
Workplace 2	28.9%	**71.6%**	69.4%
Average	28.5%	**64.7%**	64.3%

Joint classifier with HMM provides much higher accuracy

Dataset	Baseline	Local features + HMM	Global features + HMM	Local+global features + HMM
House 1	29.8%	89.2%	64.0%	**89.2%**
House 2	31.0%	55.0%	56.4%	**74.6%**
House 3	20.9%	97.4%	86.9%	**98.7%**
Workplace 1	32.1%	75.5%	89.2%	**87.7%**
Workplace 2	28.9%	92.3%	81.2%	**98.7%**
Average	28.5%	81.9%	74.8%	**89.8%**

PlaceAvoider is robust in the presence of scene occlusion



apply 30% mask to a random fraction of images in the *workplace 2* stream

% of occluded images in stream	Local classifier accuracy	Global classifier accuracy
0	71.6%	69.4%
100	68.0%	69.8%

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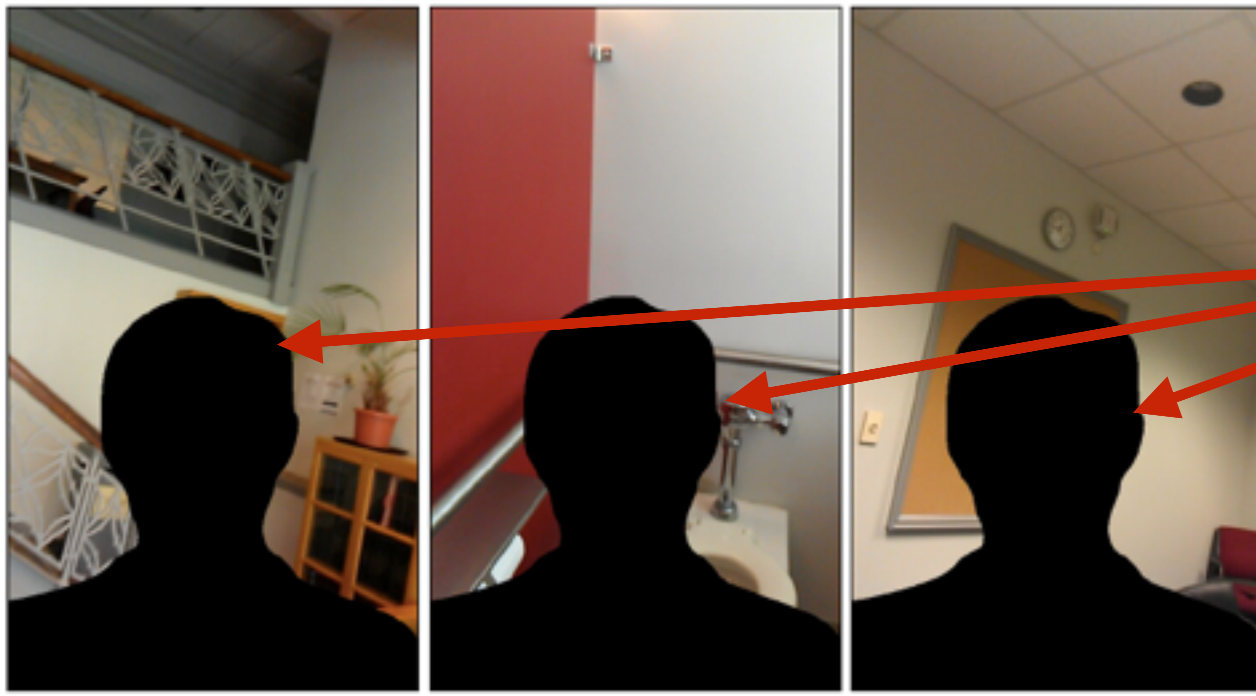


apply 30% mask to a random fraction of images in the *workplace 2* stream

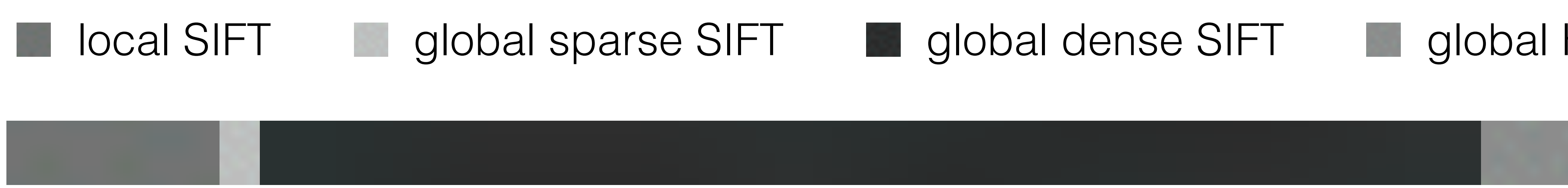
% of occluded images in stream	Local classifier accuracy	Global classifier accuracy	HMM accuracy
0	71.6%	69.4%	**100%**
100	68.0%	69.8%	**100%**

Running time for prototype system

Feature extraction and classification: 18.421 seconds.

Classifier framework: R
SIFT feature extraction: Lowe's binary
Classifier components: C++, Python, R

Hardware: 2.6 GHz Xeon workstation (one thread)



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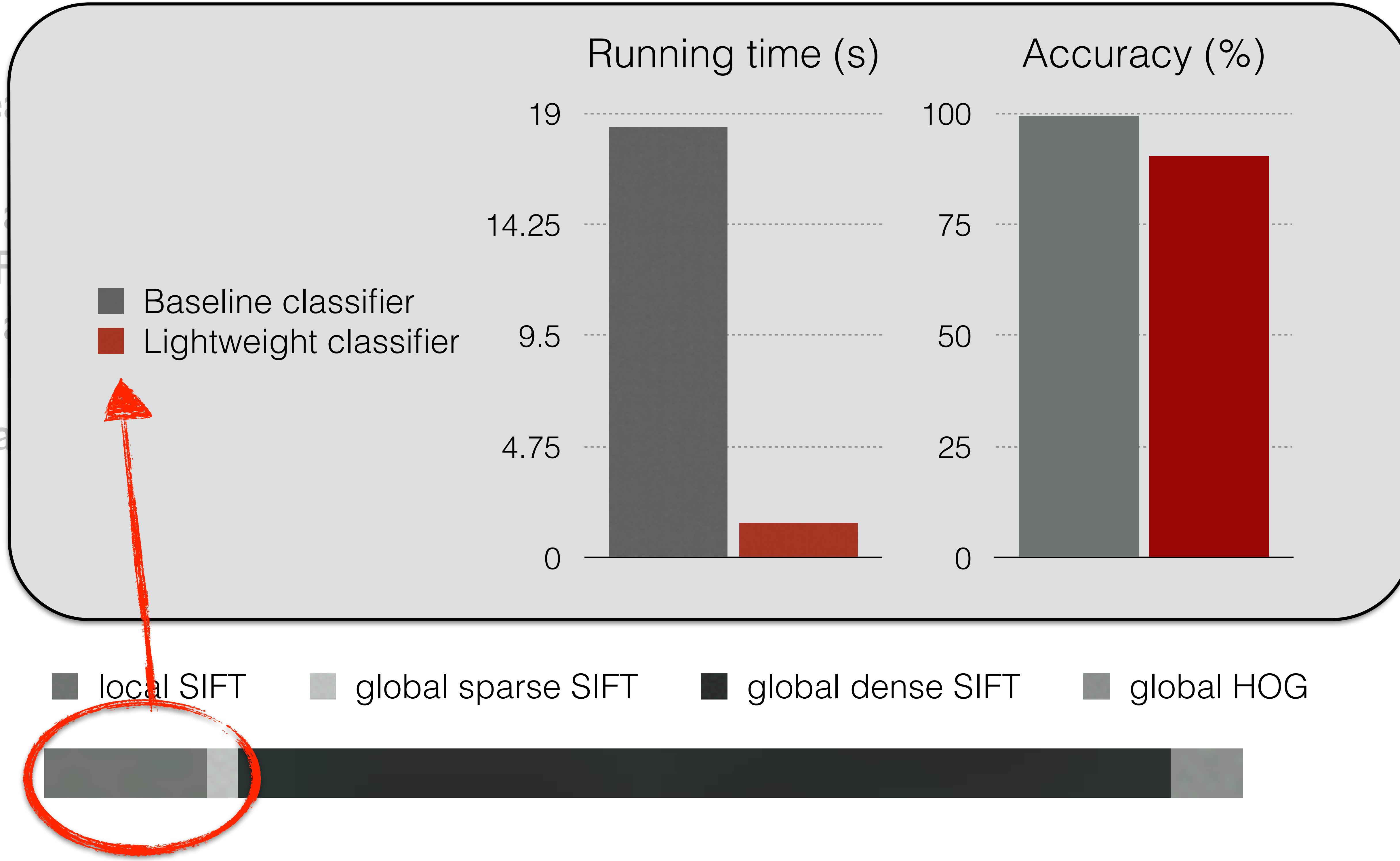

Discussion

System improvements

more usable enrollment

topological mapping

Other sensitive content types

policies that control imaging of sensitive objects

Protecting the privacy of bystanders

making *others* enforce *your* policies

In conclusion…

Modern camera devices make it *too* easy to collect and share images

PlaceAvoider explores imposing boundaries on *where* cameras can be used

Much work remains to be done to explore other attempts to classify sensitive images

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Questions?

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