Action and Attention in First-Person Vision

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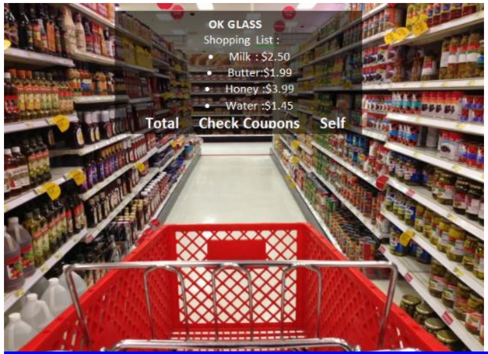
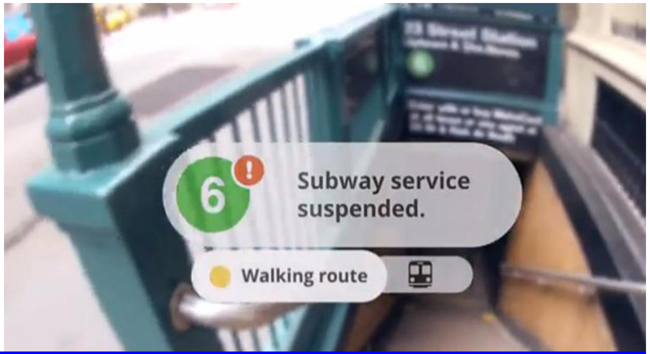
With Dinesh Jayaraman, Yong Jae Lee,
Yu-Chuan Su, Bo Xiong, Lu Zheng


~1990
Steve Mann

2015

New era for first-person vision





Augmented reality

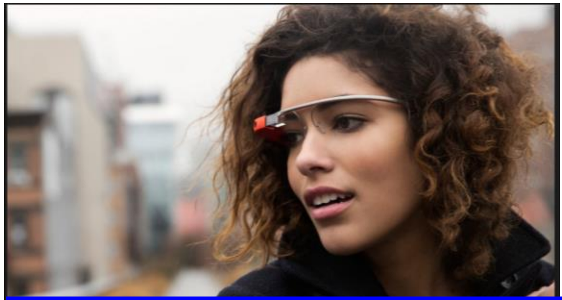
Health monitoring

Law enforcement

Infant figure from Linda Smith, et al.

Science

Robotics



Life logging

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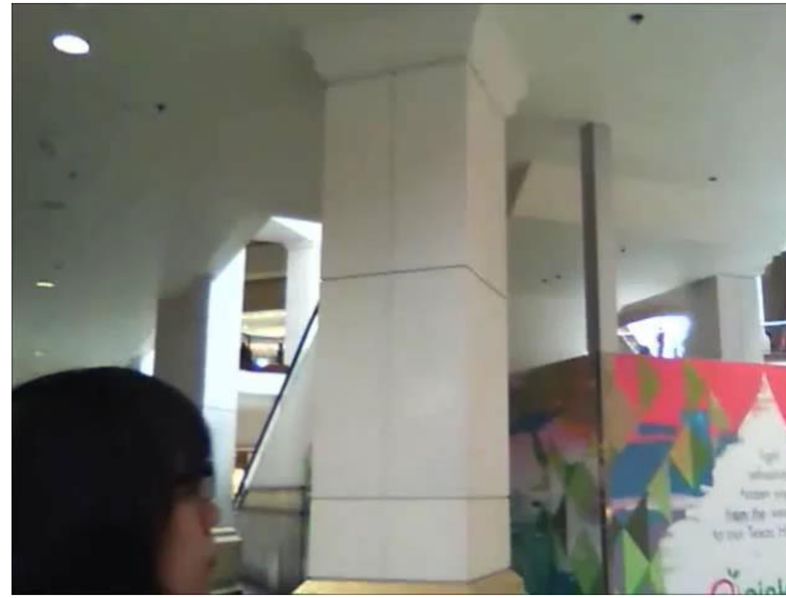
First person vs. Third person

Traditional third-person view



First-person view

UT TEA dataset

First person vs. Third person

First person “egocentric” vision:

- Linked to ongoing experience of the camera wearer
- World seen in context of the camera wearer’s activity and goals

Recent egocentric work

- Activity and object recognition

  [Spriggs et al. 2009, Ren & Gu 2010, Fathi et al. 2011, Kitani et al. 2011, Pirsiavash & Ramanan 2012, McCandless & Grauman 2013, Ryoo & Matthies 2013, Poleg et al. 2014, Damen et al. 2014, Behera et al. 2014, Li et al. 2015, Yonetani et al. 2015, …]

- Gaze and social cues

  [Yamada et al. 2011, Fathi et al. 2012, Park et al. 2012, Li et al. 2013, Arev et al. 2014, Leelasawassuk et al. 2015,…]

- Visualization, stabilization

  [Kopf et al. 2014, Poleg et al. 2015]

Talk overview

Motivation

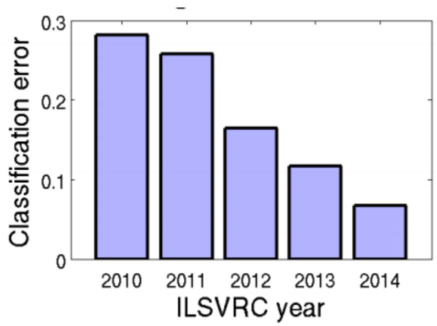
Account for the fact that camera wearer is active participant in the visual observations received

Ideas

1. Action: Unsupervised feature learning
   - How is visual learning shaped by ego-motion?
2. Attention: Inferring highlights in video
   - How to summarize long egocentric video?

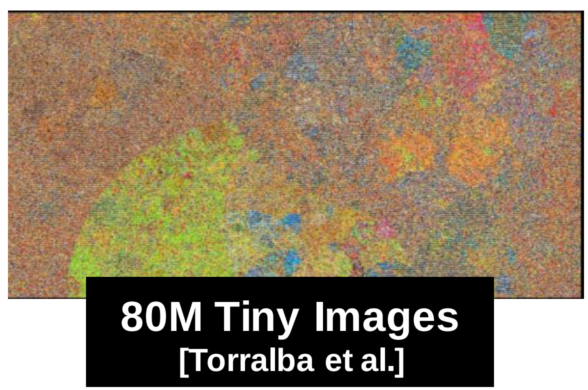
Visual recognition

- Recent major strides in category recognition



- Facilitated by large labeled datasets

ImageNet
[Deng et al.]



80M Tiny Images
[Torralba et al.]

SUN Database
[Xiao et al.]

[Papageorgiou & Poggio 1998, Viola & Jones 2001, Dalal & Triggs 2005, Grauman & Darrell 2005, Lazebnik et al. 2006, Felzenszwalb et al. 2008, Krizhevsky et al. 2012, Russakovsky IJCV 2015…]

Problem with today's visual learning

- **Status quo**: Learn from "disembodied" bag of labeled snapshots

- …yet visual perception develops in the context of acting and moving in the world

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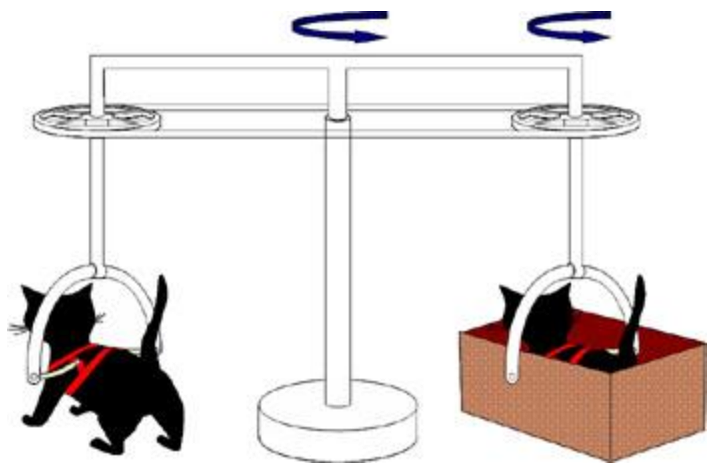
The kitten carousel experiment
[Held & Hein, 1963]

active kitten



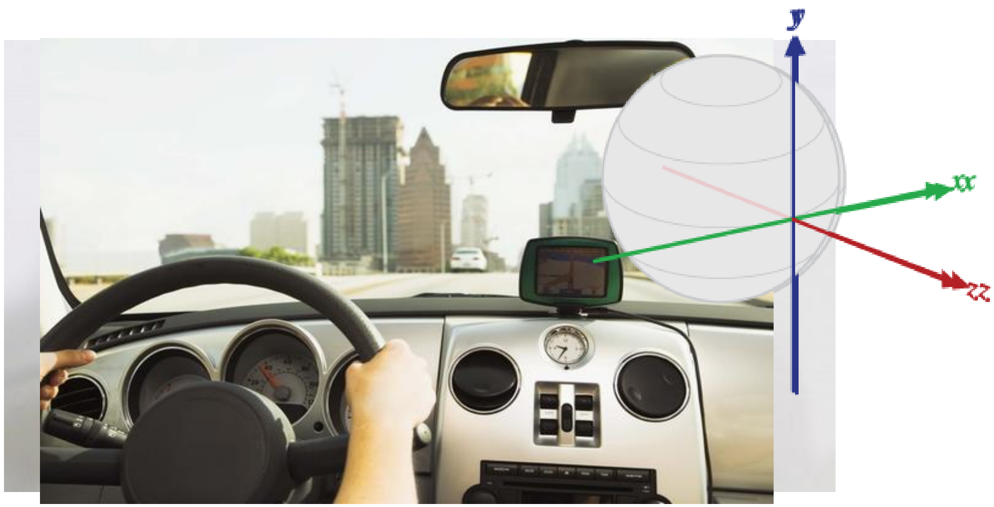
passive kitten

Key to perceptual development:
Self-generated motions + visual feedback

Our idea:
Feature learning with ego-motion

Goal: Learn the connection between
"how I move" ↔ "how visual surroundings change"

Approach: Unsupervised feature learning using motor signals accompanying egocentric video



[Jayaraman & Grauman, ICCV 2015]

Key idea: Egomotion equivariance

Invariant features: unresponsive to some classes of transformations

$$z(g\mathbf{x}) \approx z(\mathbf{x})$$

Equivariant features : *predictably* responsive to some classes of transformations, through simple mappings (e.g., linear)

"equivariance map"

$$z(g\mathbf{x}) \approx M_g z(\mathbf{x})$$

Invariance *discards* information, whereas equivariance *organizes* it.

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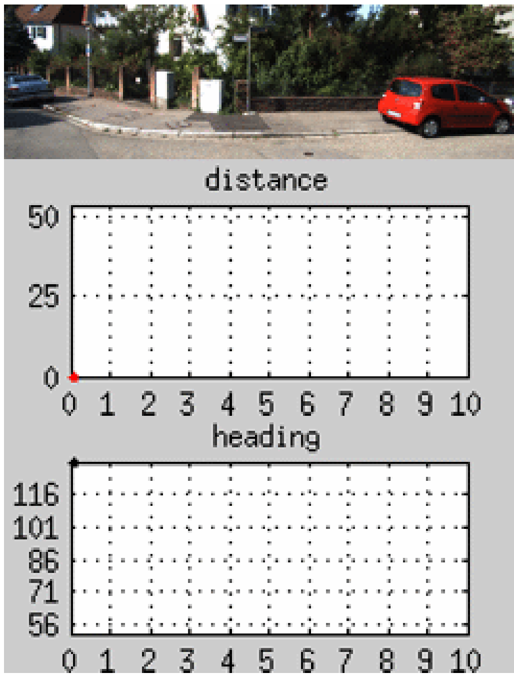
Key idea: Egomotion equivariance



Training data=

Unlabeled video
+
motor signals

Pairs of frames related by similar ego-motion should be related by same feature transformation

Equivariant embedding
organized by egomotions

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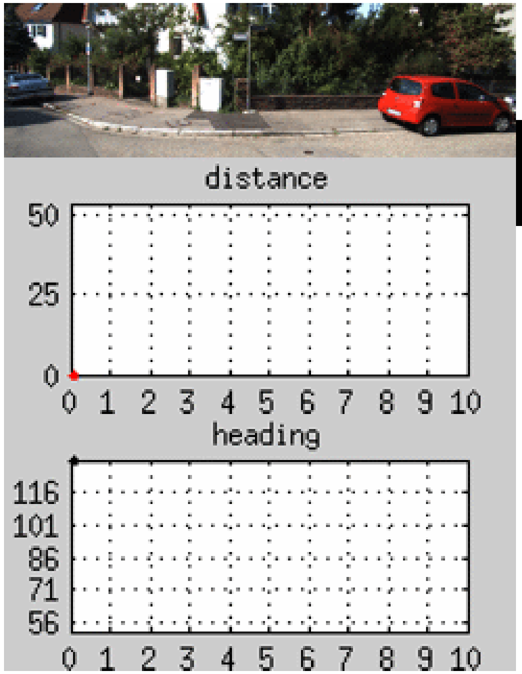
Key idea: Egomotion equivariance



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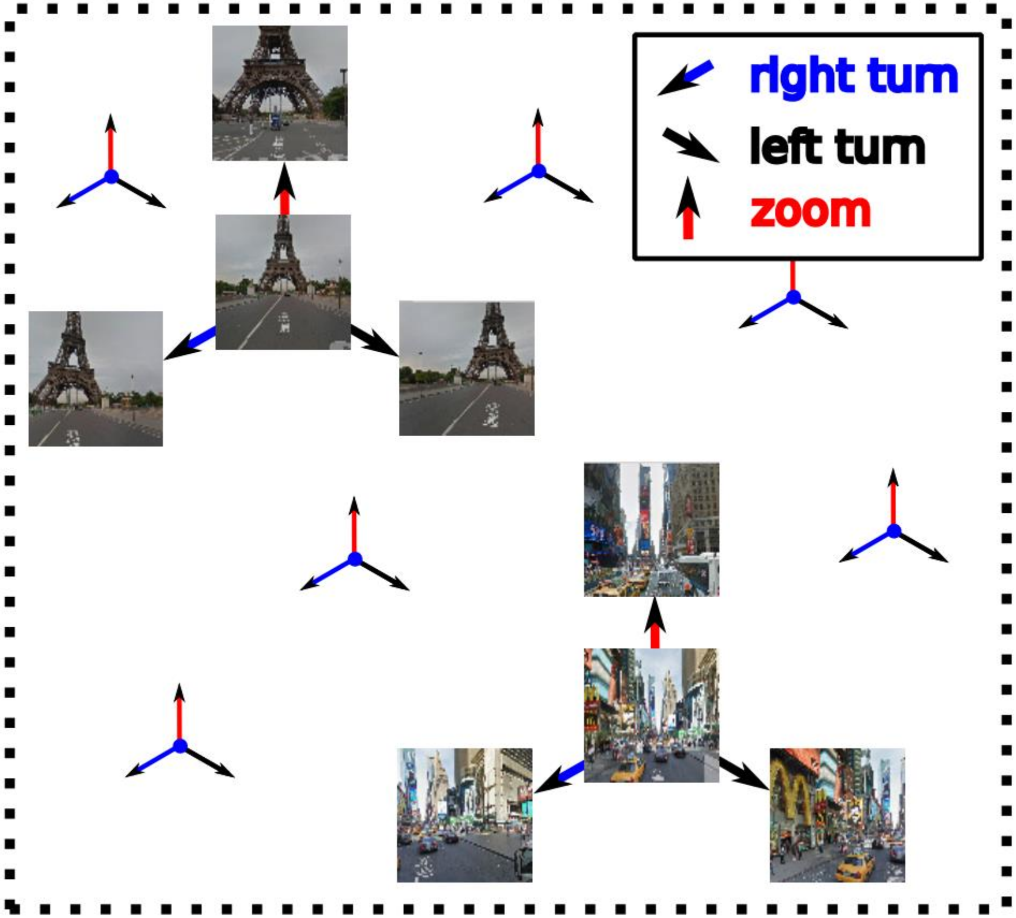

Equivariant embedding
organized by egomotions

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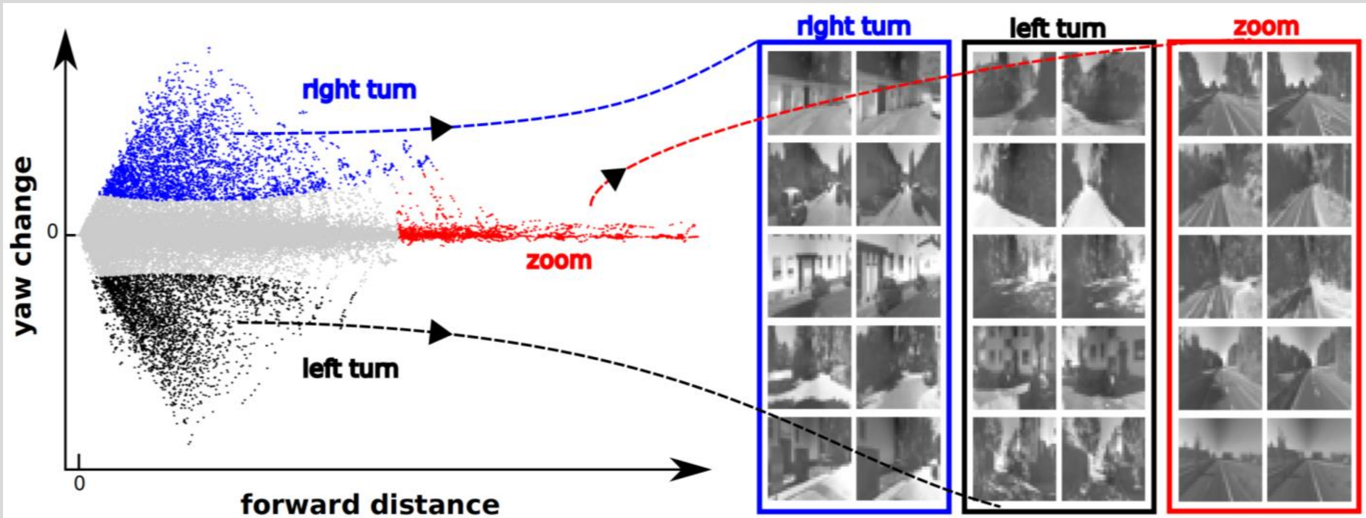
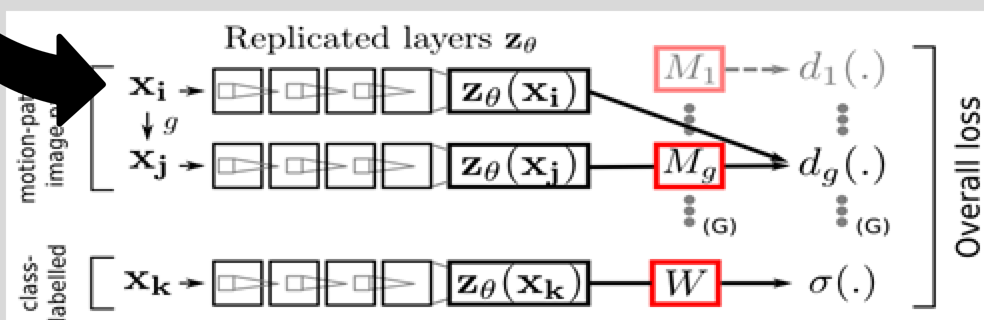
Approach

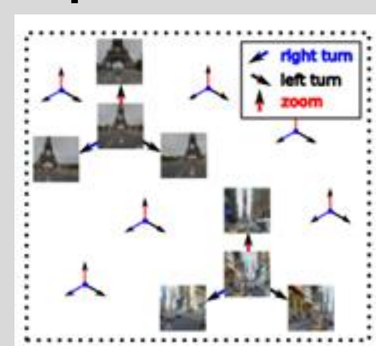
Ego motor signals + Observed image pairs



Deep learning architecture



Output embedding



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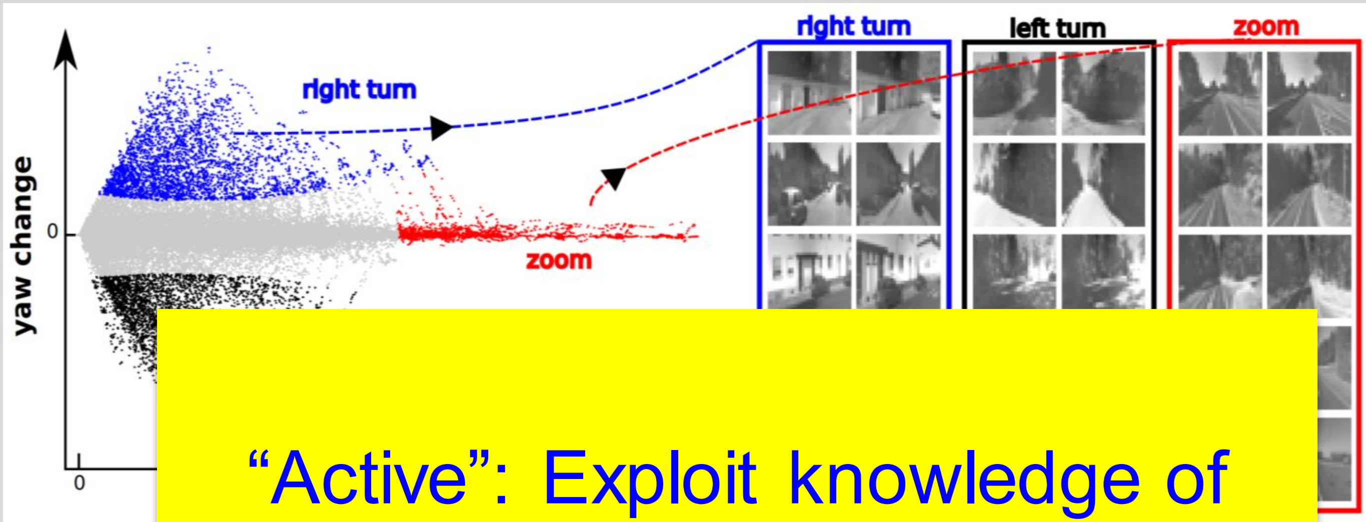
[Jayaraman & Grauman, ICCV 2015]

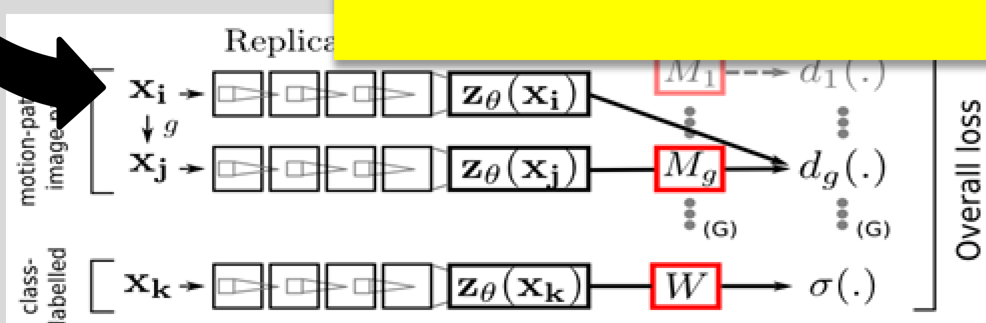
Approach

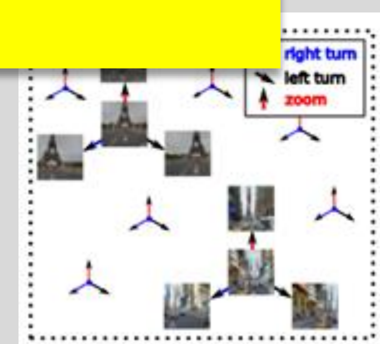
Ego motor signals + Observed image pairs



“Active”: Exploit knowledge of observer motion

Deep l … edding





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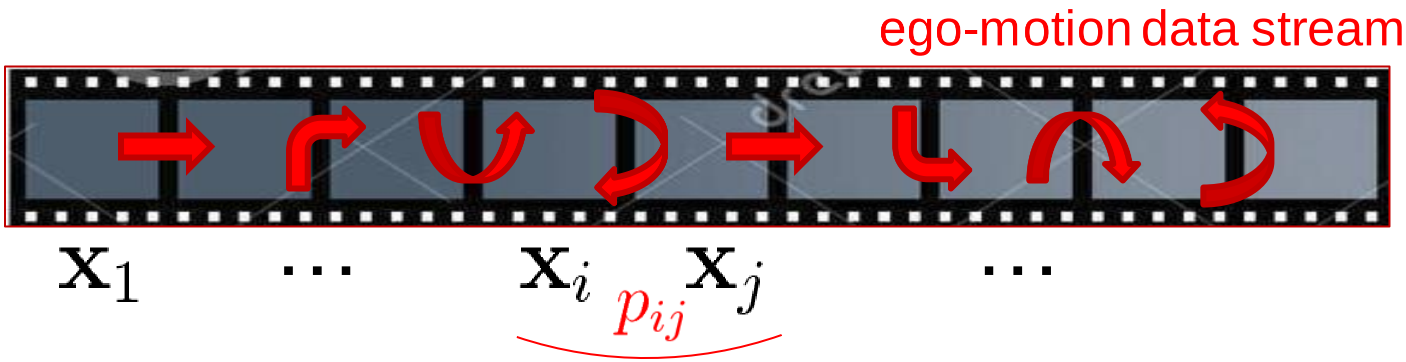
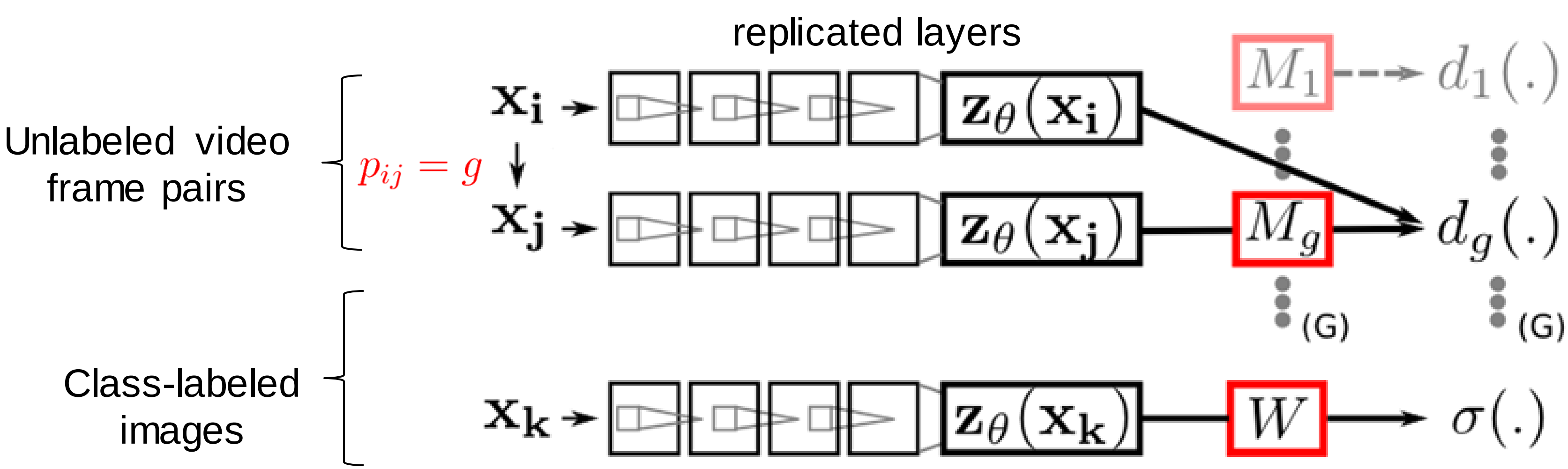
[Jayaraman & Grauman, ICCV 2015]

Learning equivariance

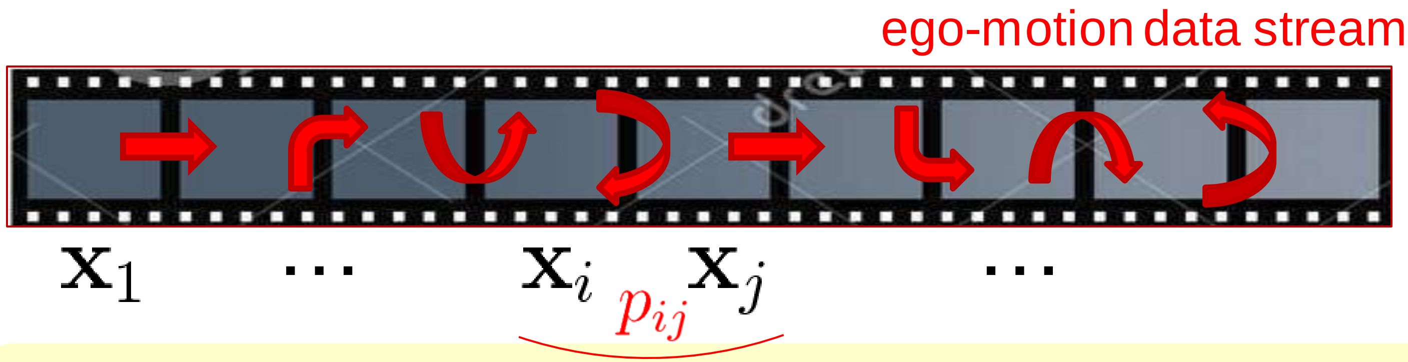


$$\forall \boldsymbol{x} \in \mathcal{X} : \mathbf{z}_{\boldsymbol{\theta}}(g\boldsymbol{x}) \approx M_g^* \mathbf{z}_{\boldsymbol{\theta}}(\boldsymbol{x})$$



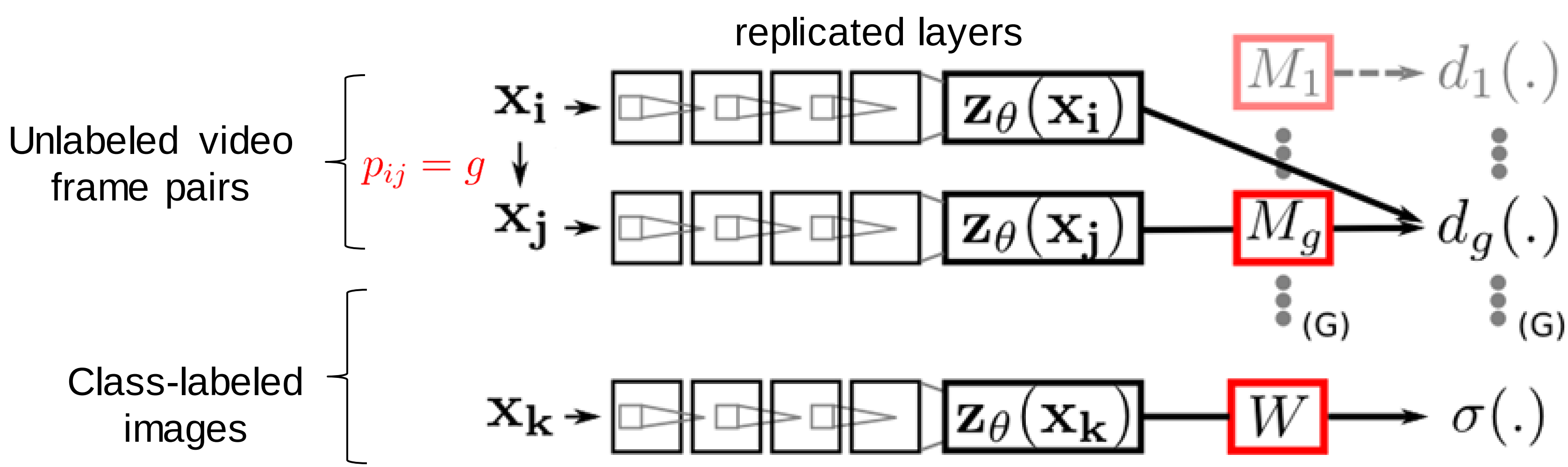
[Jayaraman & Grauman, ICCV 2015]

Learning equivariance



Embedding objective:

$$(\boldsymbol{\theta}^*, W^*, \mathcal{M}^*) = \arg\min_{\boldsymbol{\theta}, W, \mathcal{M}} \sum_{g,i,j} d_g\left(\mathbf{z}_{\boldsymbol{\theta}}(\boldsymbol{x}_i), M_g \mathbf{z}_{\boldsymbol{\theta}}(\boldsymbol{x}_j), p_{ij}\right) + \lambda L_c(W, \mathcal{L})$$



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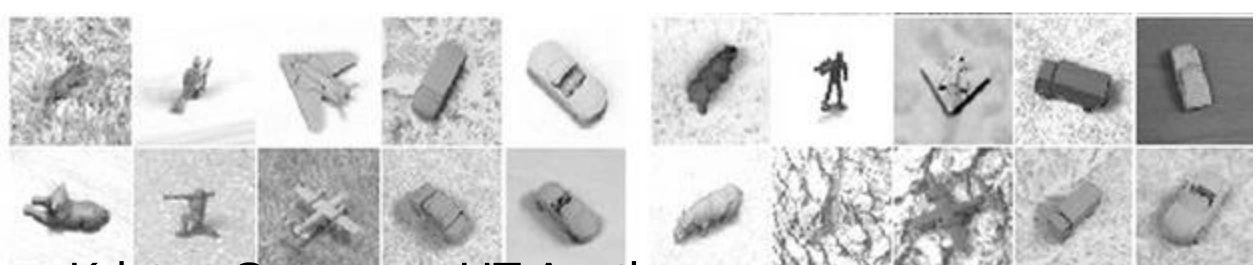
[Jayaraman & Grauman, ICCV 2015]

Datasets

KITTI video
[Geiger et al. 2012]
Autonomous car platform
Egomotions: yaw and forward distance

SUN images
[Xiao et al. 2010]
Large-scale scene classification task

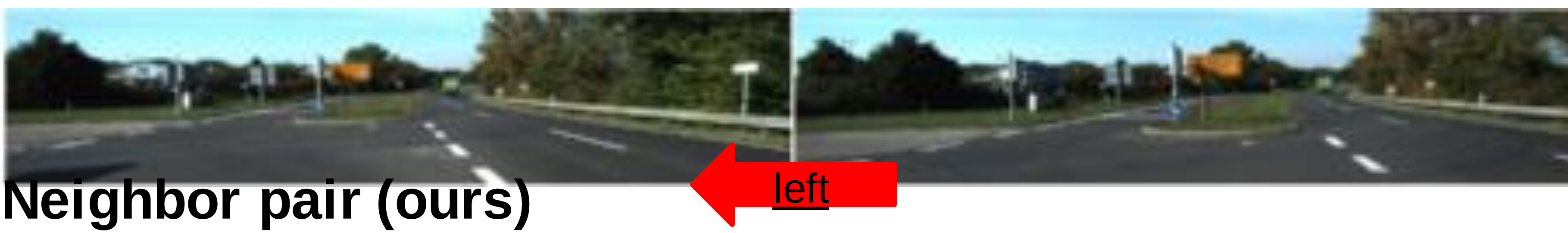
NORB images
[LeCun et al. 2004]
Toy recognition
Egomotions: elevation and azimuth



Results: Equivariance check

Visualizing how well equivariance is preserved

Query pair



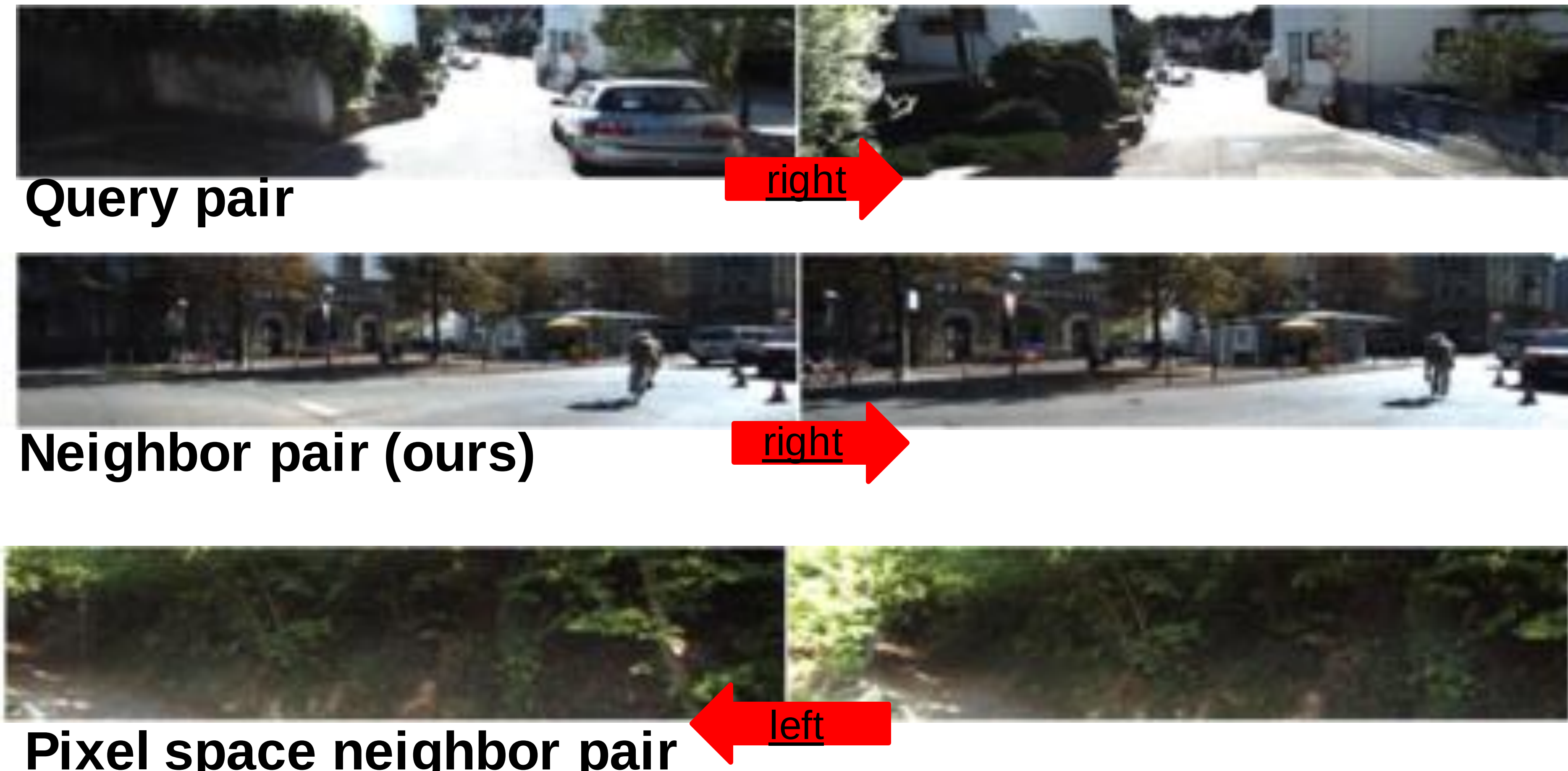
Neighbor pair (ours)

Pixel space neighbor pair

[Jayaraman & Grauman, ICCV 2015]

Results: Equivariance check

Visualizing how well equivariance is preserved



[Jayaraman & Grauman, ICCV 2015]

Results: Recognition

Learn from **autonomous car video** (KITTI)

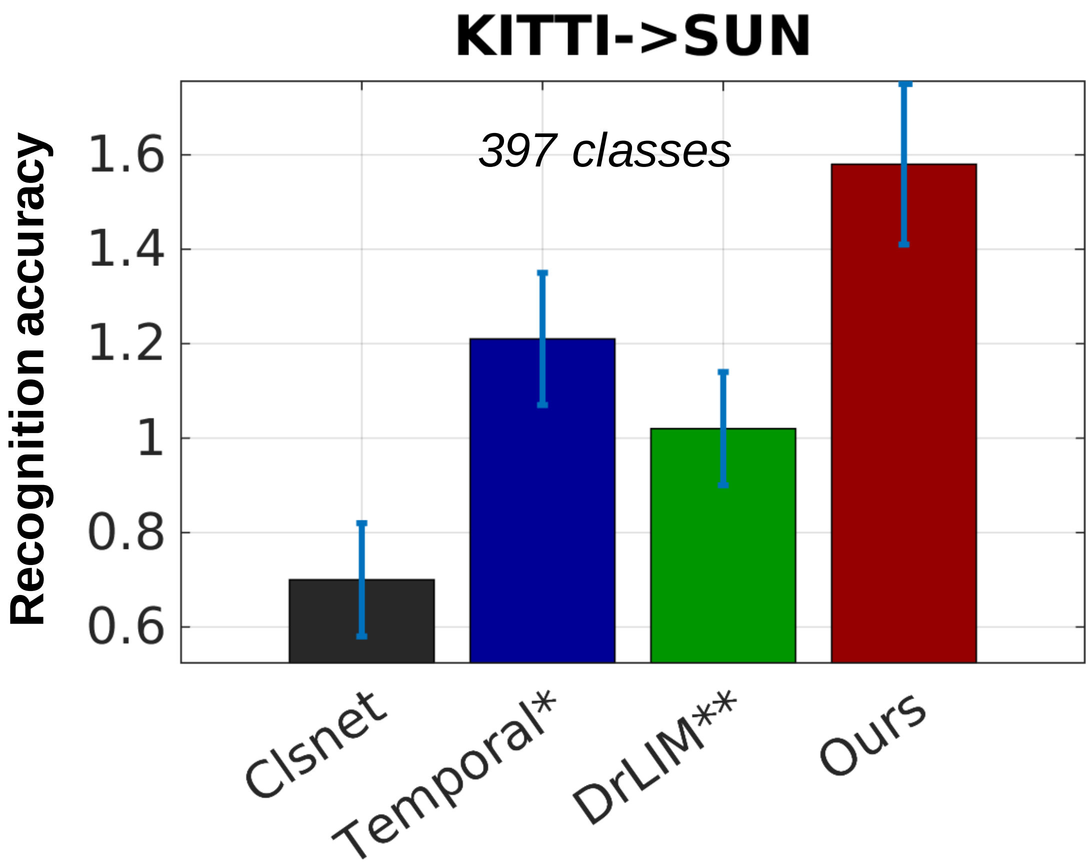
Exploit features for large multi-way
scene classification (SUN, 397 classes)

30% accuracy increase
for small labeled training sets

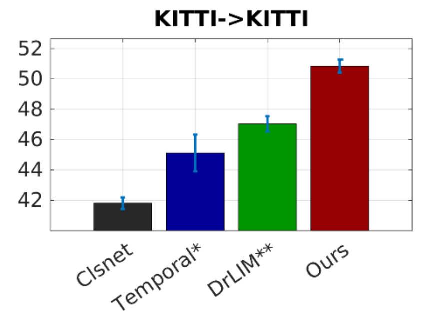
[Jayaraman & Grauman, ICCV 2015]

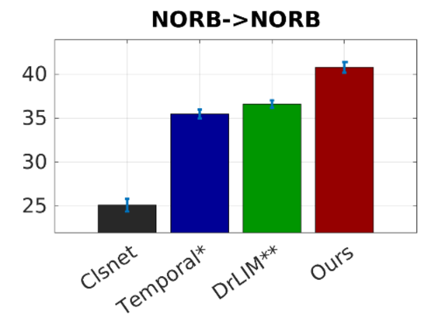
Results: Recognition

Do the learned features boost recognition accuracy?



6 labeled training examples per class





*Mobahi et al. ICML09; **Hadsell et al. CVPR06

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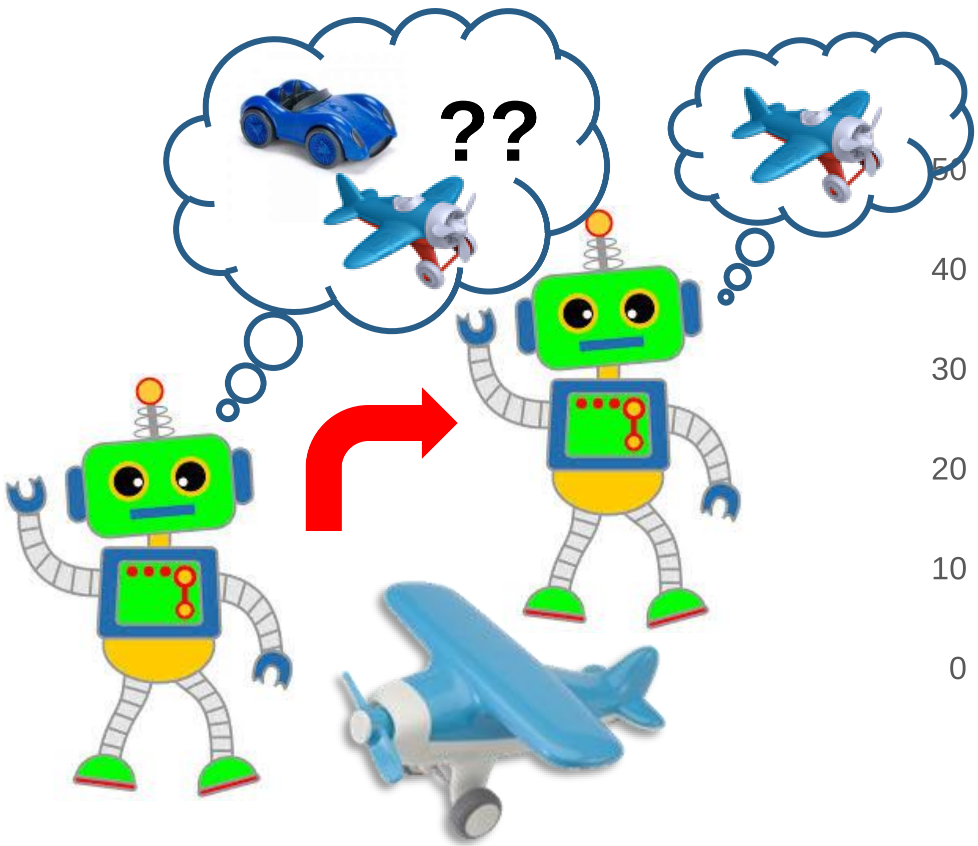
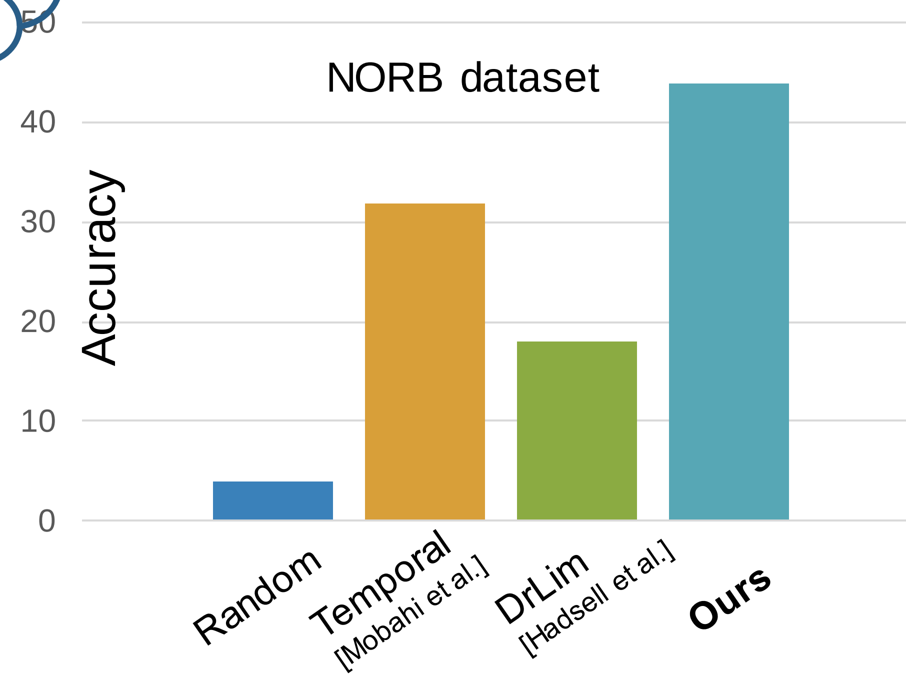
Results: Active recognition

Leverage proposed equivariant embedding to predict next best view for object recognition





[Schiele & Crowley 1998, Dickinson et al. 1997, Soatto 2009, Mishra et al. 2009,…]

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Next steps

- Dynamic objects
- Multiple modalities, e.g., depth
- Active ego-motion planning
- Tasks aside from recognition

Talk overview

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Ideas

1. Action: Unsupervised feature learning
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2. Attention: Inferring highlights in video
    - How to summarize long egocentric video?

Goal: Summarize egocentric video

Wearable camera

Input: Egocentric video of the camera wearer's day

9:00 am 10:00 am 11:00 am 12:00 pm 1:00 pm 2:00 pm

Output: Storyboard (or video skim) summary

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Potential applications of egocentric video summarization

Memory aid

Law enforcement

Mobile robot discovery

RHex Hexapedal Robot, Penn's GRASP Laboratory

Prior work: Video summarization

- Largely third-person
  - Static cameras, low-level cues informative
- Consider summarization as a *sampling* problem

[Wolf 1996, Zhang et al. 1997, Ngo et al. 2003, Goldman et al. 2006, Caspi et al. 2006, Pritch et al. 2007, Laganiere et al. 2008, Liu et al. 2010, Nam & Tewfik 2002, Ellouze et al. 2010,…]

What makes egocentric data hard to summarize?

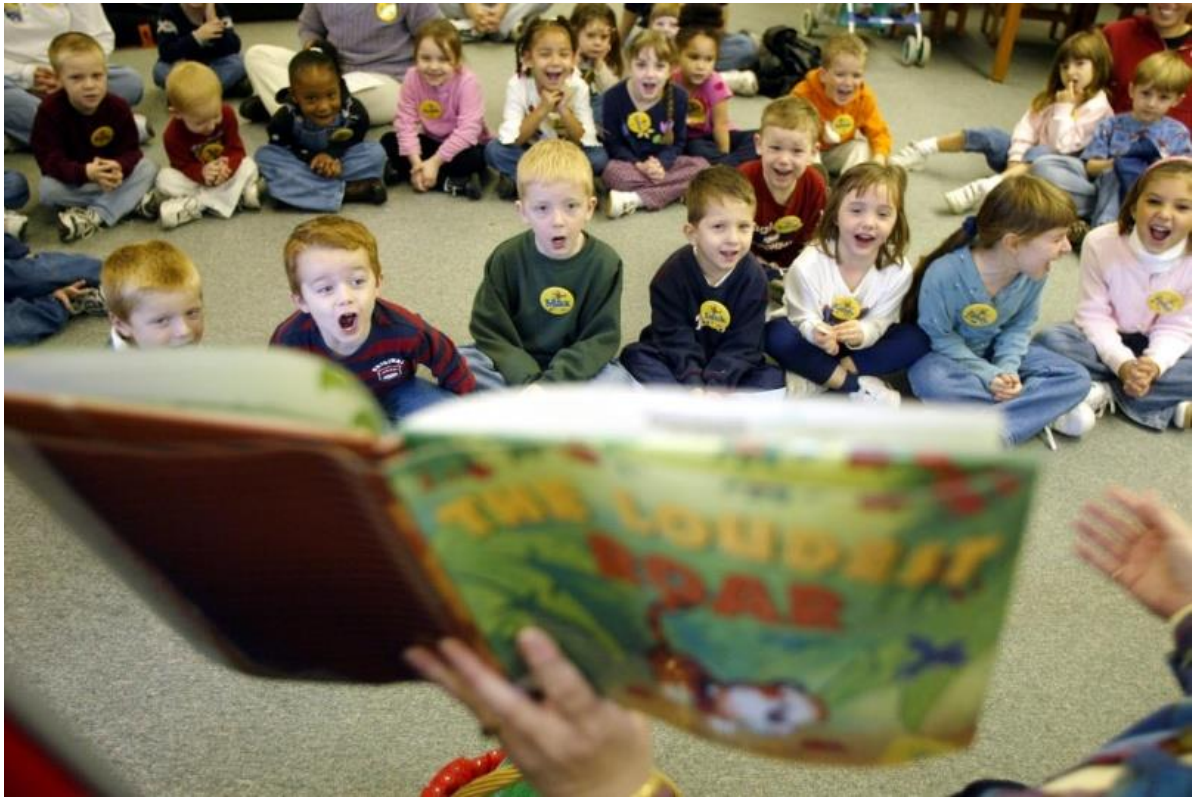
- Subtle event boundaries
- Subtle figure/ground
- Long streams of data

Summarizing egocentric video

Key questions

- What objects are important, and how are they linked?
- When is attention heightened?
- Which frames look "intentional"?

Goal: Story-driven summarization



Characters and plot ↔ Key objects and influence

Goal: Story-driven summarization

Characters and plot ↔ Key objects and influence

 [Lu & Grauman, CVPR 2013]

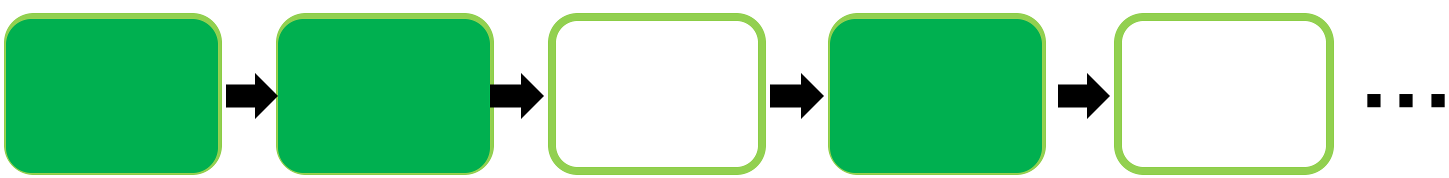
Summarization as subshot selection

Good summary = chain of *k* selected subshots in which each influences the next via some subset of key objects

$$S^* = \arg\max_{S \subset \mathcal{V}} \; \lambda_s \, \mathcal{S}(S) + \lambda_i \, \mathcal{I}(S) + \lambda_d \, \mathcal{D}(S)$$

influence **importance** **diversity**

Subshots



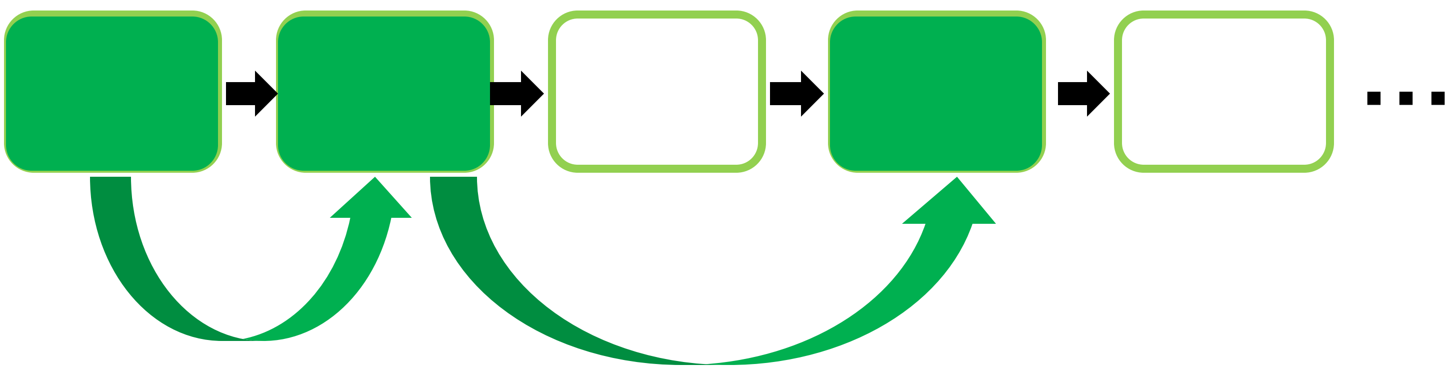
Kristen Grauman, UT Austin *[Lu & Grauman, CVPR 2013]*

Estimating visual influence

- Aim to select the *k* subshots that maximize the influence between objects (on the weakest link)

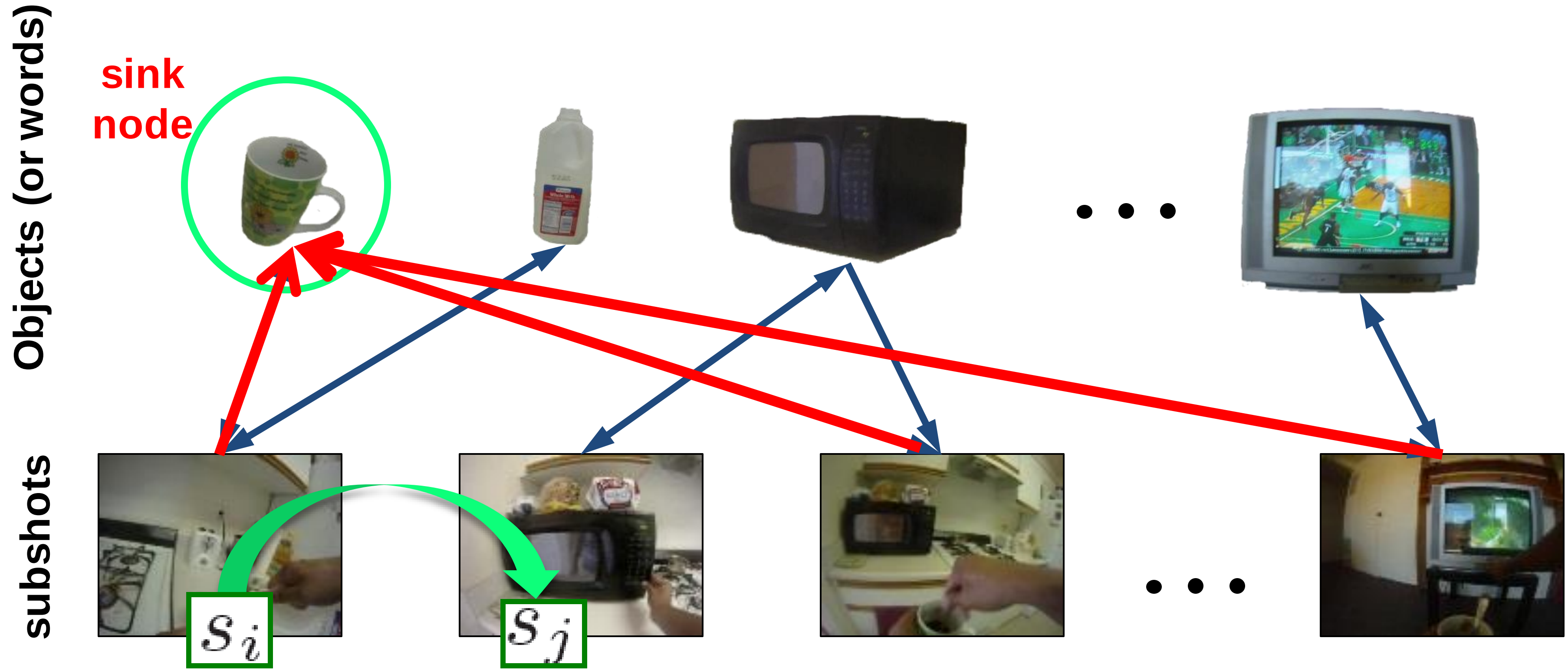
$$\mathcal{S}(S) = \max_{a} \min_{j=1,\ldots,K-1} \sum_{o_i \in O} a_{i,j} \textsc{Influence}(s_j, s_{j+1} | o_i)$$

Subshots



Kristen Grauman, UT Austin *[Lu & Grauman, CVPR 2013]*

Estimating visual influence



$$\textsc{Influence}(s_i, s_j | o) = \Pi_i(s_j) - \Pi_i^o(s_j)$$

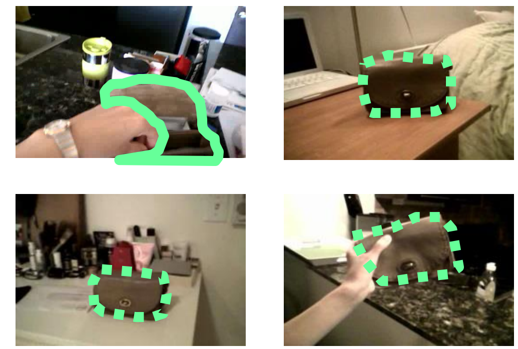
Captures how reachable subshot *j* is from subshot *i,* via any object *o*

Learning object importance

We learn to rate regions by their egocentric importance

distance to hand

distance to frame center



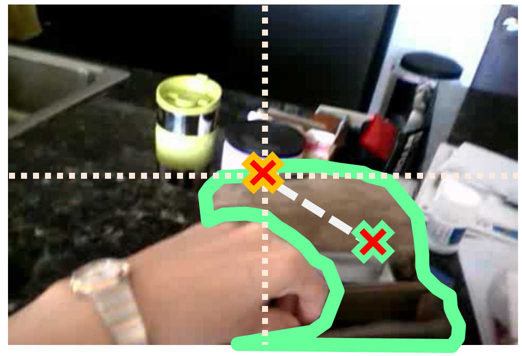
frequency

[Lee et al. CVPR 2012, IJCV 2015]

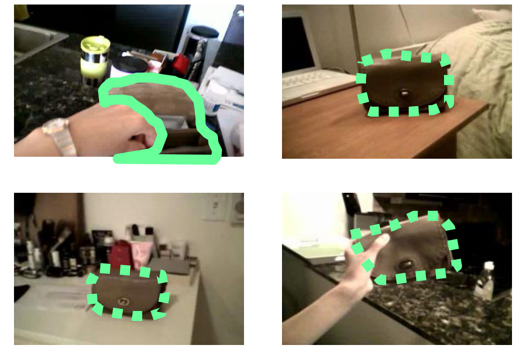
Learning object importance

We learn to rate regions by their egocentric importance

distance to hand



distance to frame center



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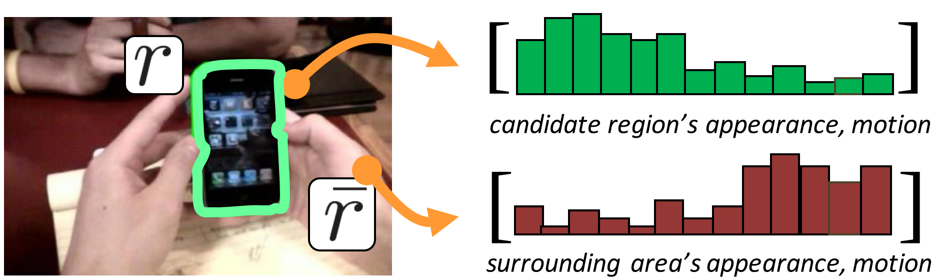
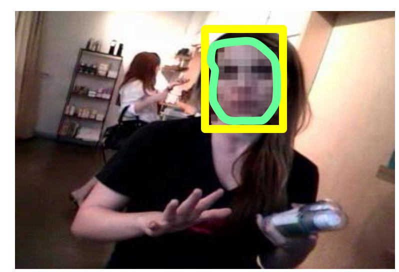


"Object-like" appearance, motion

[Endres et al. ECCV 2010, Lee et al. ICCV 2011]



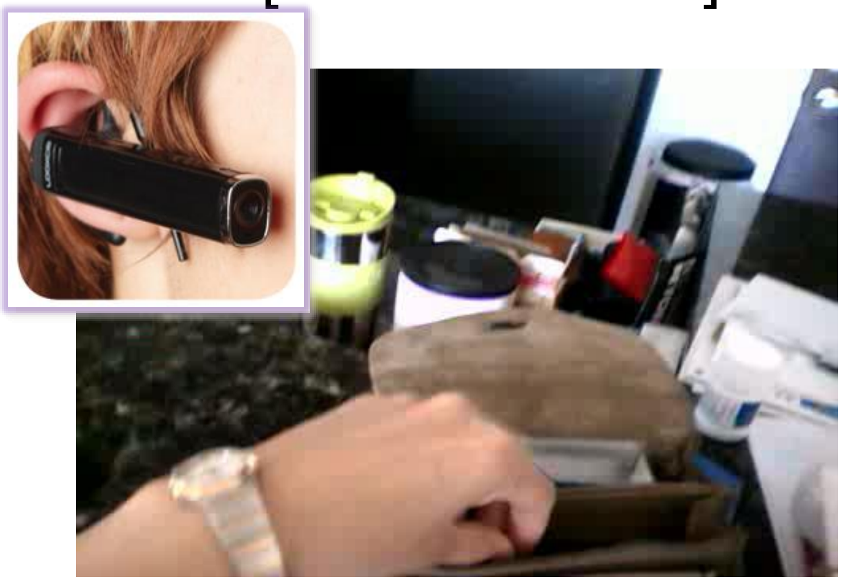
overlap w/ face detection

Region features: *size, width, height, centroid*

[Lee et al. CVPR 2012, IJCV 2015]

Datasets

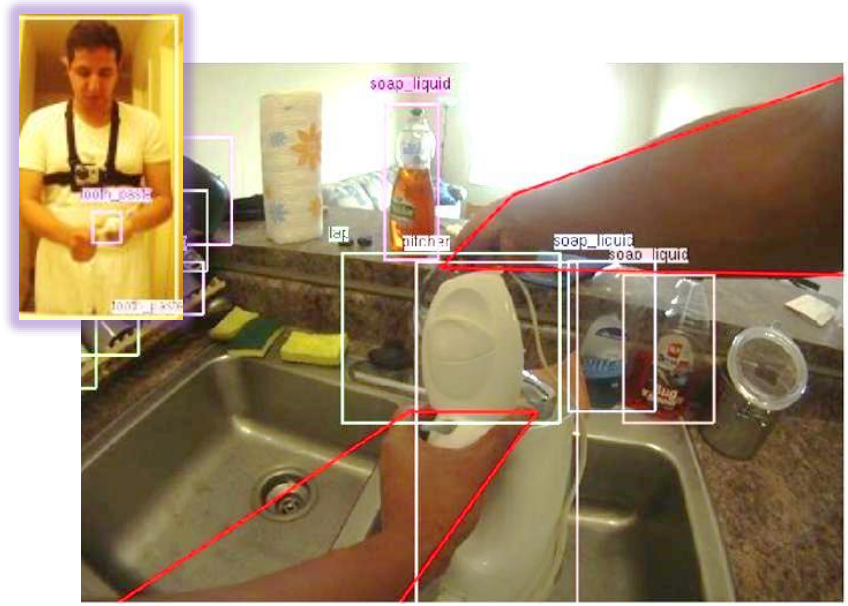
UT Egocentric (UT Ego)
[Lee et al. 2012]



4 videos, each 3-5 hours long, uncontrolled setting.

We use visual words and subshots.

Activities of Daily Living (ADL)
[Pirsiavash & Ramanan 2012]



20 videos, each 20-60 minutes, daily activities in house.

We use object bounding boxes and keyframes.

Example keyframe summary – UT Ego data

http://vision.cs.utexas.edu/projects/egocentric/

Original video (3 hours)

Our summary (12 frames)

[Lee et al. CVPR 2012, IJCV 2015]

Example keyframe summary – UT Ego data

Alternative methods for comparison

Uniform keyframe sampling (12 frames)

[Liu & Kender, 2002] (12 frames)

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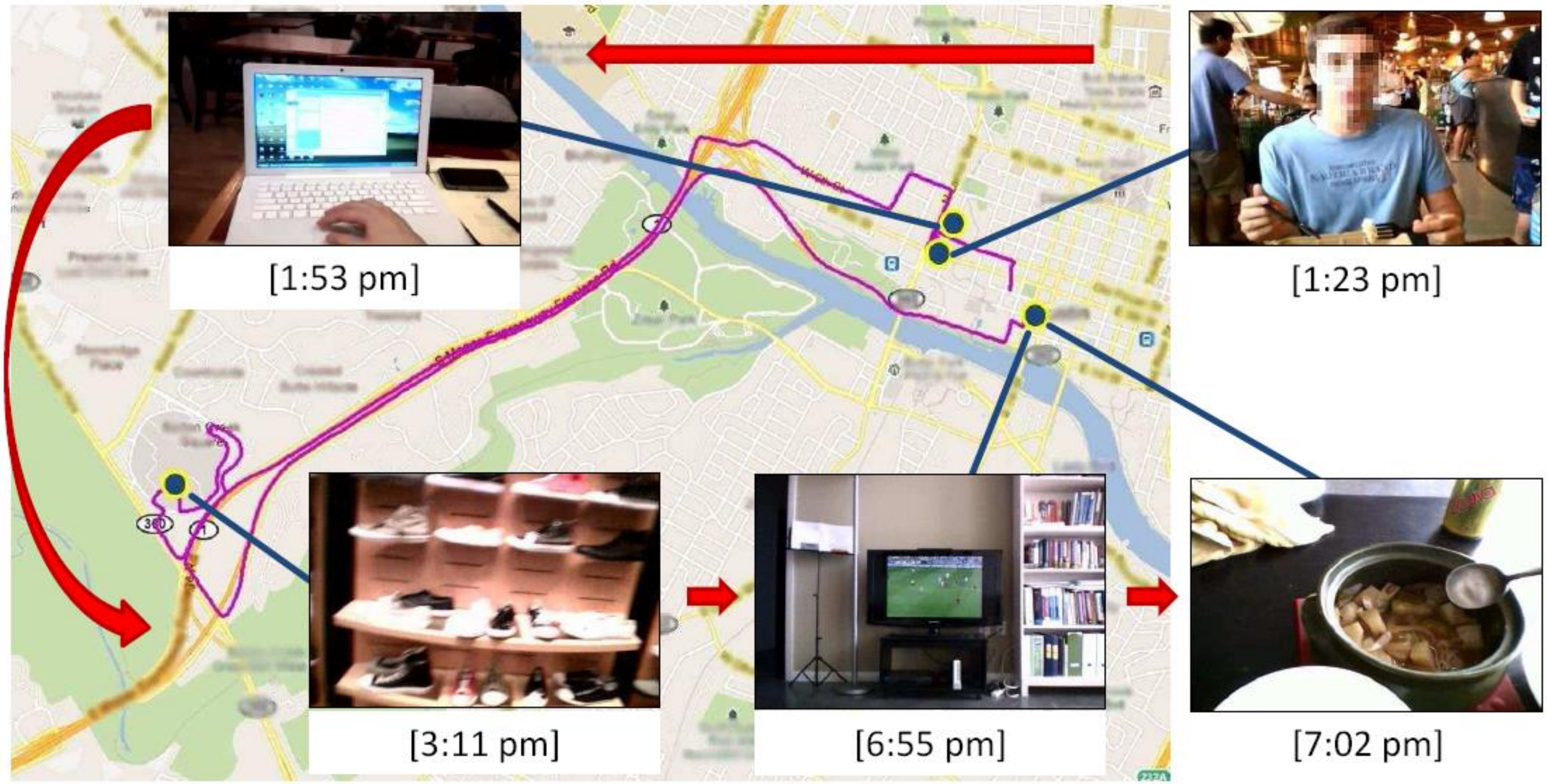
[Lee et al. CVPR 2012, IJCV 2015]

Generating storyboard maps



Augment keyframe summary with geolocations

[Lee et al., CVPR 2012, IJCV 2015]

Human subject results: Blind taste test

How often do subjects prefer our summary?

Data	Vs. Uniform sampling	Vs. Shortest-path	Vs. Object-driven Lee et al. 2012
UT Egocentric Dataset	**90.0%**	**90.9%**	**81.8%**
Activities Daily Living	**75.7%**	**94.6%**	**N/A**

34 human subjects, ages 18-60
12 hours of original video
Each comparison done by 5 subjects

Total 535 tasks, 45 hours of subject time

[Lu & Grauman, CVPR 2013]

Summarizing egocentric video

Key questions

- What objects are important, and how are they linked?
- When is attention heightened?
- Which frames look “intentional”?

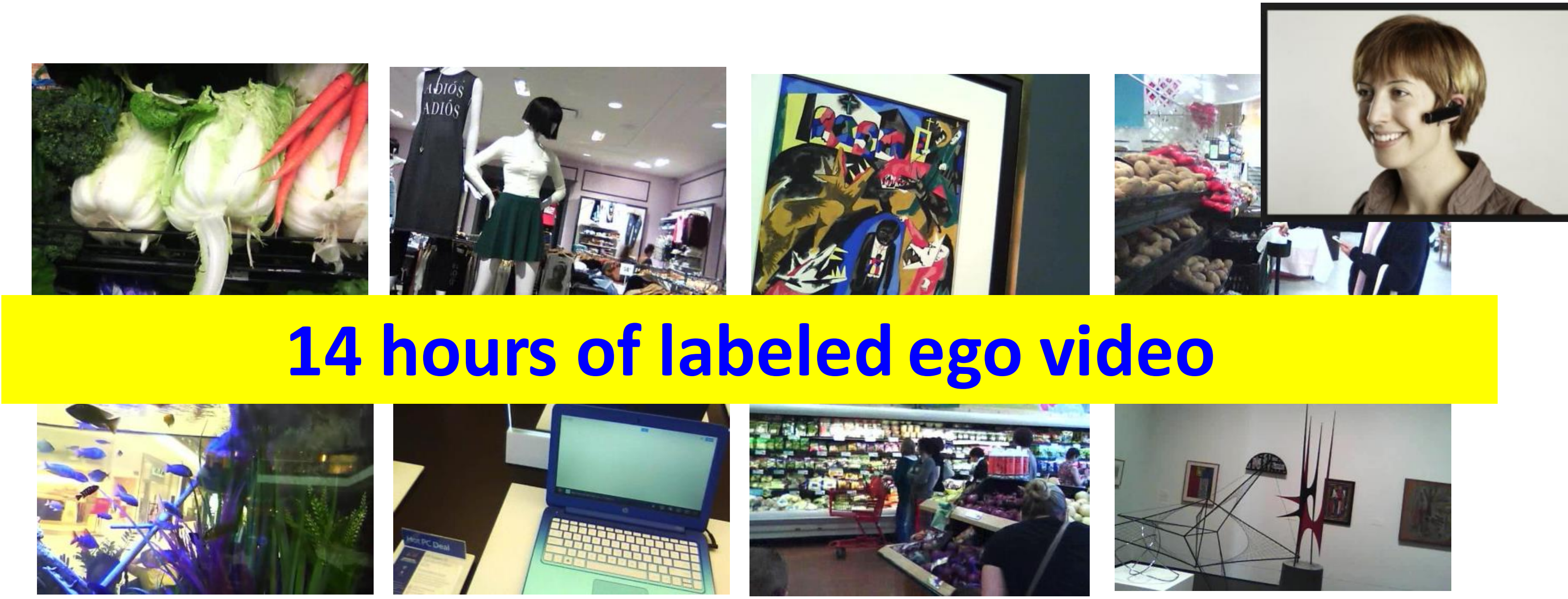
Goal: Detect heightened attention

Definition:

A time interval where the recorder is attracted by some object(s) and he interrupts his ongoing flow of activity to purposefully gather more information about the object(s)

[Su & Grauman, 2015]

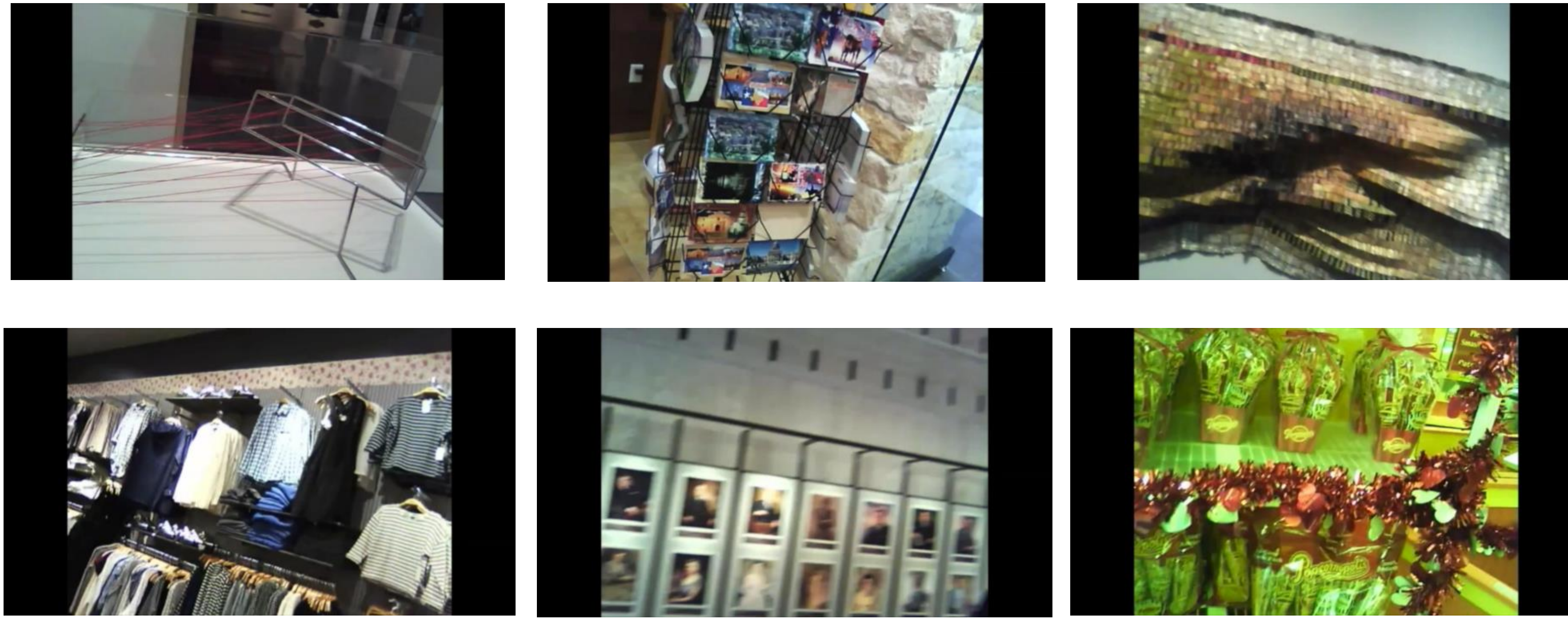
Temporal Ego-Attention Dataset



- “Browsing” scenarios, long & natural clips
- 14 hours of video, 9 recorders
- Frame-level labels x 10 annotators

[Su & Grauman, 2015]

Challenges in temporal attention

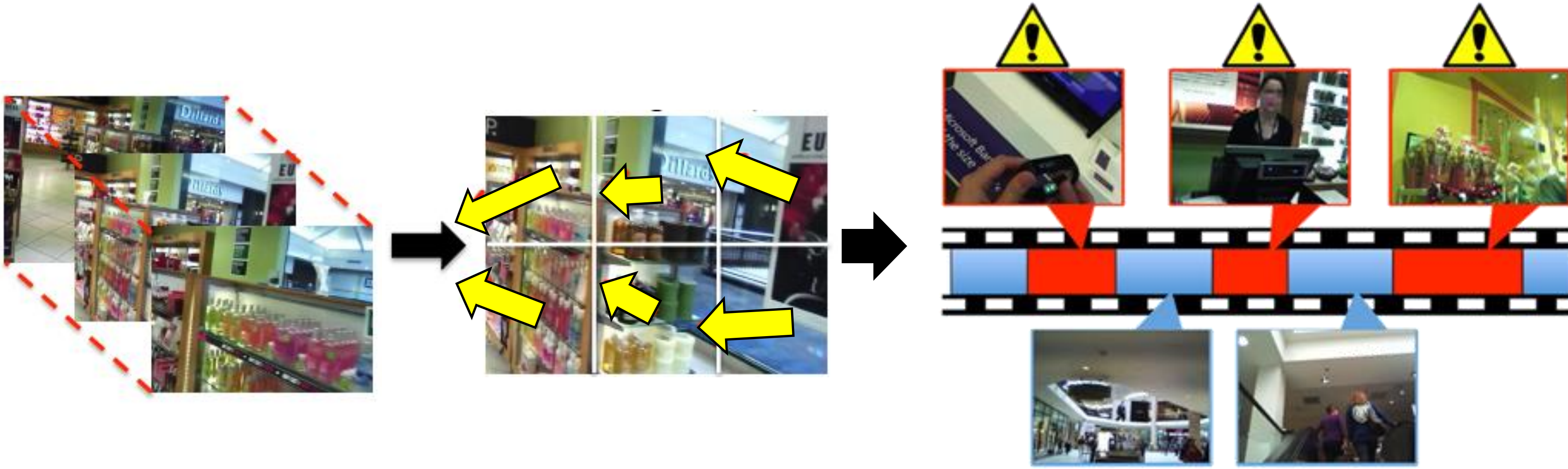


- Interesting things vary in appearance!
- Attention ≠ stationary
- High attention intervals vary in length
- Lack cues of active camera control

[Su & Grauman, 2015]

Our approach

Learn motion patterns indicative of attention



[Su & Grauman, 2015]

Results: detecting temporal attention

Blue=Ground truth
Red=Predicted

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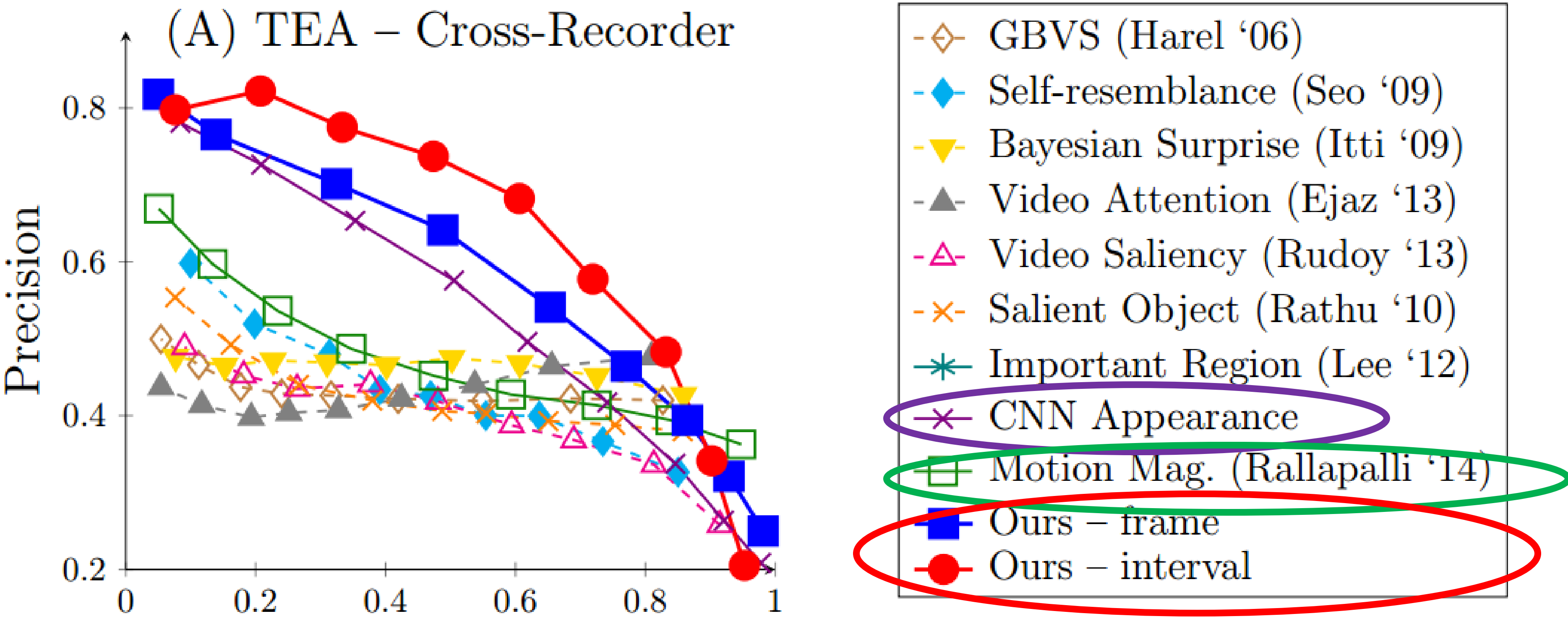
[Su & Grauman, 2015]

Results: detecting temporal attention



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[Su & Grauman, 2015]

Summarizing egocentric video

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Which photos were purposely taken by a human?

Incidental wearable camera photos

Intentional human taken photos

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[Xiong & Grauman, ECCV 2014]

Idea: Detect “snap points”

- Unsupervised data-driven approach to detect frames in first-person video that look intentional

[Xiong & Grauman, ECCV 2014]

Example snap point predictions

 [Xiong & Grauman, ECCV 2014]

Snap point predictions

 [Xiong & Grauman, ECCV 2014]

Next steps

- Video summary as an index for search
- Streaming computation
- Visualization, display
- Multiple modalities – e.g., audio

Summary

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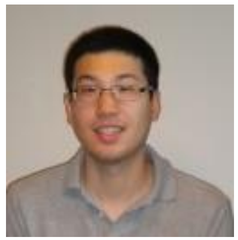
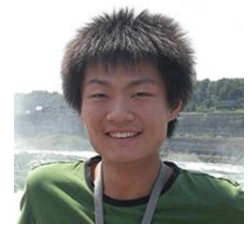
Dinesh Jayaraman


Yong Jae Lee


Yu-Chuan Su


Bo Xiong


Lu Zheng

- New opportunities with “always on” ego cameras
- Towards active first-person vision:
  - **Action**: “Embodied” feature learning from ego-video using both visual and motor signals
  - **Attention**: Egocentric summarization tools to cope with deluge of wearable camera data