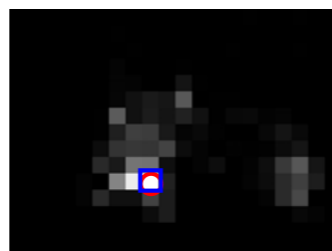
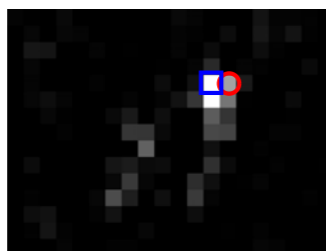
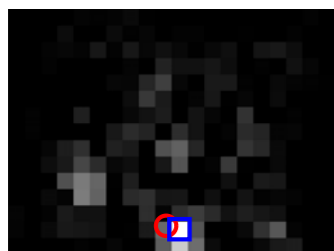
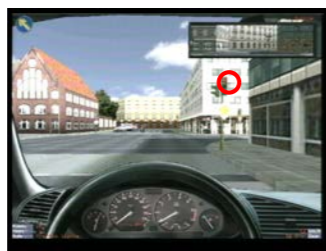


5TH INTERNATIONAL WORKSHOP
ON PERVASIVE EYE TRACKING
AND MOBILE EYE-BASED INTERACTION

Computational Modeling of Bottom-up and Top-down Visual Attention

Ali Borji

Sept. 7, 2015



Outline

- Introduction to visual attention
- Bottom-up attention
- Top-down attention
- Applications
- Related topics
- Summary





Visual saliency: Fundamentals, Applications, and Recent Progress

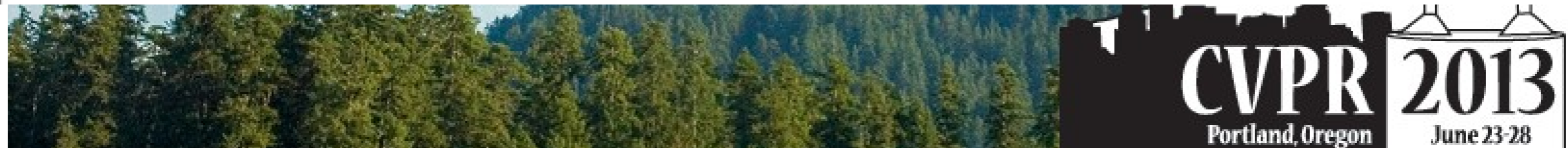
[ICIP 2015 Tutorial](#) at September 27th, Morning Sessions (09:00 – 12:30)

Instructors

- Ali BORJI, University of Wisconsin-Milwaukee, USA
- Neil D. B. BRUCE, University of Manitoba, Canada
- Ming-Ming CHENG, Nankai University, China
- Jian LI, National University of Defense Technology, China

Course Motivation and Description

Recently, visual saliency has received extensively growing attention across many disciplines including cognitive psychology, neurobiology, image processing, and computer vision. Based on our observed reaction times and estimated signal transmission times along biological pathways, human attention theories hypothesize that the human visual system processes only parts of an image in detail, with only limited processing of areas outside of the focus of attention. From an engineering perspective, such visual attention mechanisms have inspired a series of key research topics in the last few decades. One of the key forces behind these rapid



Visual Attention

- Behavioral Findings
- Computational Models





Everyone knows what attention is.

WILLIAM JAMES
father of modern psychology



What is attention?

- **Attention** is the cognitive process of selectively concentrating on one aspect of the environment while ignoring other things. Attention has also been referred to as the allocation of processing resources.

Finding “interesting” information?

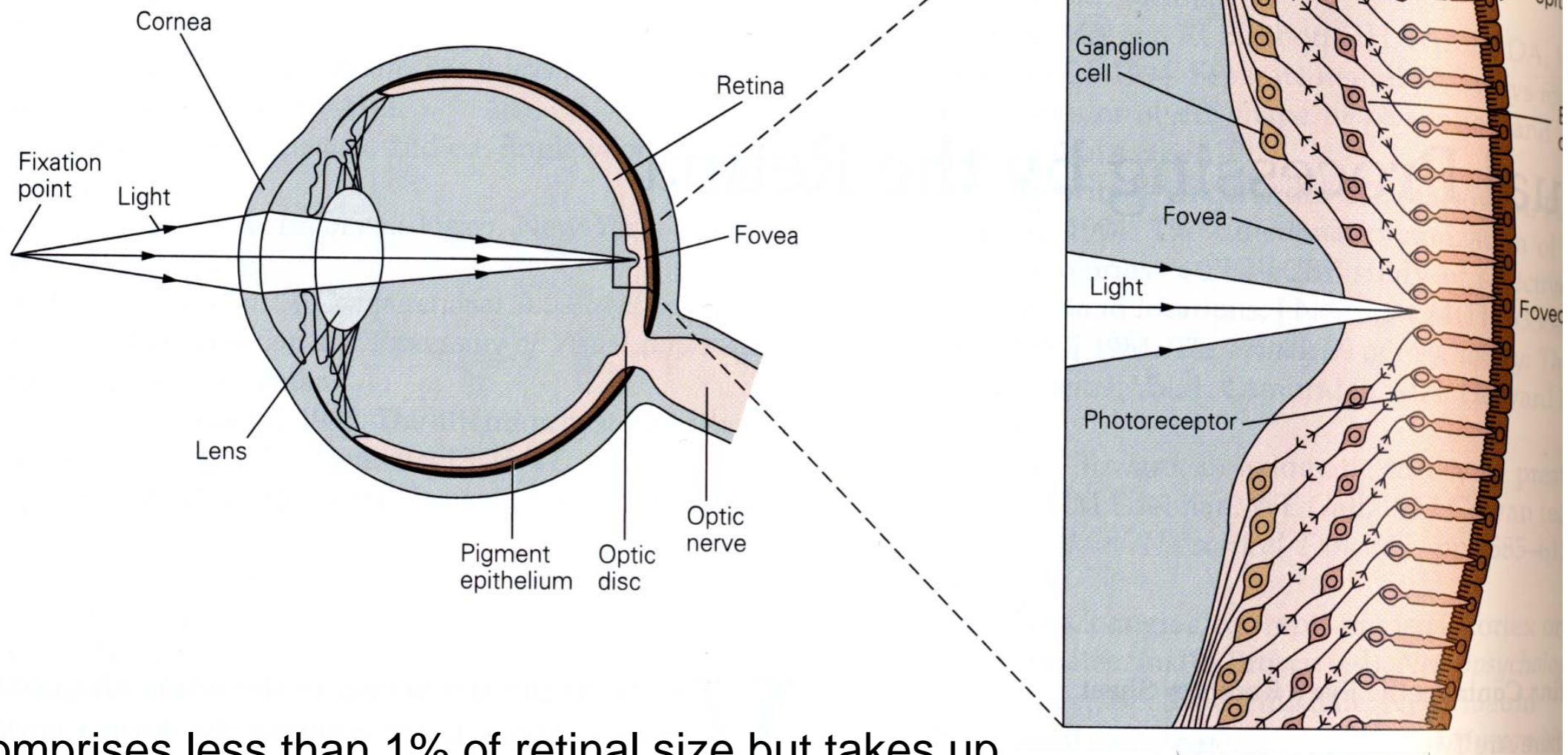
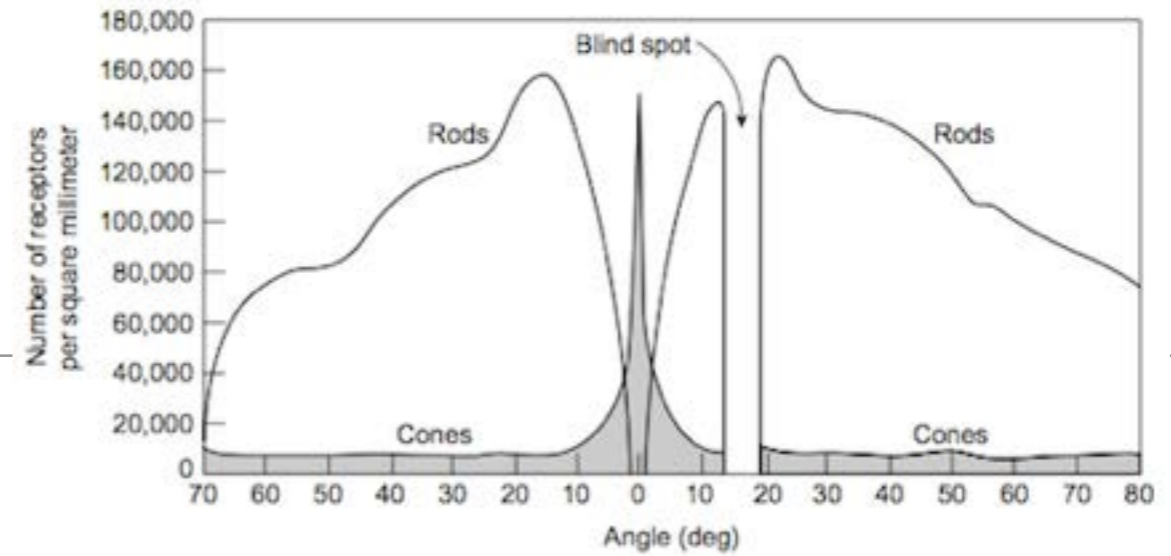
- In **principle**, very complex task:
 - Need to attend to all objects in scene?
 - Then recognize each attended object?
 - Finally evaluate set of recognized objects against behavioral goals?
- In **practice**, survival depends on ability to quickly locate and identify important information.
- Need to develop simple **heuristics** or approximations:
 - **Bottom-up** guidance towards salient locations *[Perceptual]*
 - **Top-down** guidance towards task-relevant locations *[Cognitive]*

Retinal structure

120 million rods (intensity)

7 million cones (color)

Fovea: 2 degrees of the visual field



Fovea comprises less than 1% of retinal size but takes up over 50% of the [visual cortex](#) in the brain.



Change blindness


Precursors: visual memory - Observers were found to be poor at detecting change if old and new displays were separated by an ISI of more than 60-70 ms.
saccades - observers were found to be poor at detecting change, with detection good only for a change in the saccade target

Two conclusions:

- observers never form a complete, detailed representation of their surroundings.
- attention is required to perceive change, and that in the absence of localized motion signals it is guided on the basis of high-level "interest".



<http://www.psych.ubc.ca/~rensink/flicker/download/>

A scene from a classic British murder mystery film. In a grand, ornate room, a man in a dark suit lies motionless on a patterned rug, his head resting on a small wooden box. Several people are gathered around: a man in a grey overcoat stands on the left; a police officer in a dark uniform and hat stands in the center; a woman in a green dress and hat stands to the right; a man in a dark suit and white shirt stands further right; a woman in a dark dress and white apron stands next to him; and a person in a black bear costume stands on the far right. The room features a chandelier, a large painting, a mounted deer head, and a table with a large bouquet of pink flowers in the foreground. The text "WHODUNNIT?" is overlaid in large, bold, yellow letters across the center of the image.

WHODUNNIT?

Bottom-up (BU) Attention



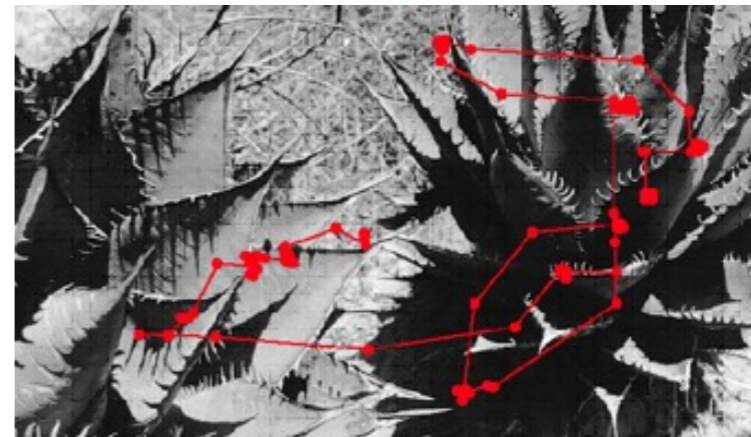
Visual salience (or **visual saliency**) is the distinct subjective perceptual quality which makes some items in the world stand out from their neighbors and immediately grab our attention.

Laurent Itti, Scholarpedia

What attracts attention (BU)?

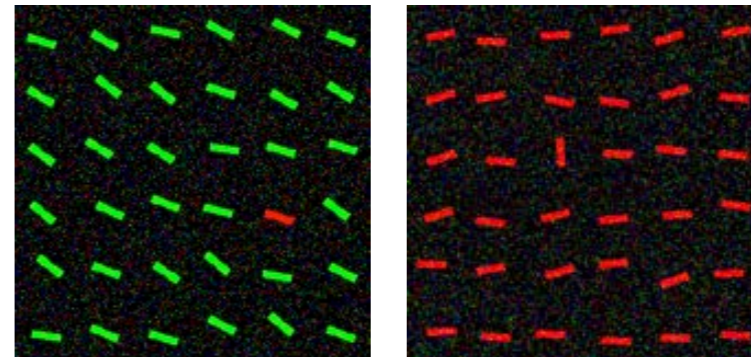
Local image statistics

E.g., Barth et al. '98; Reinagel & Zador '99;
Privitera & Stark '00; Parkhurst & Niebur '03;
Einhauser et al. '06; Tatler et al. '07



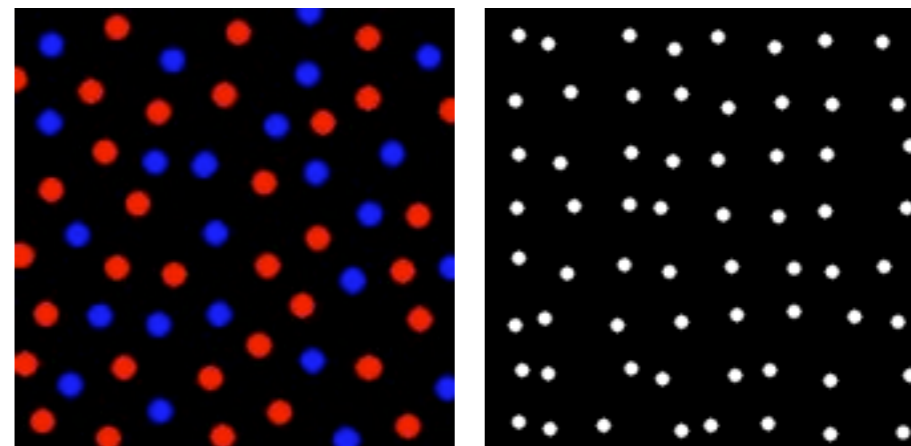
Spatial outliers – Saliency

E.g., Treisman & Gelade '80; Koch & Ullman '85;
Tsotsos et al. '95; Li, '98; Itti, Koch & Niebur '98;
Burce & Tsotsos '06; Gao & Vasconcelos '07;
Zhang et al. '07

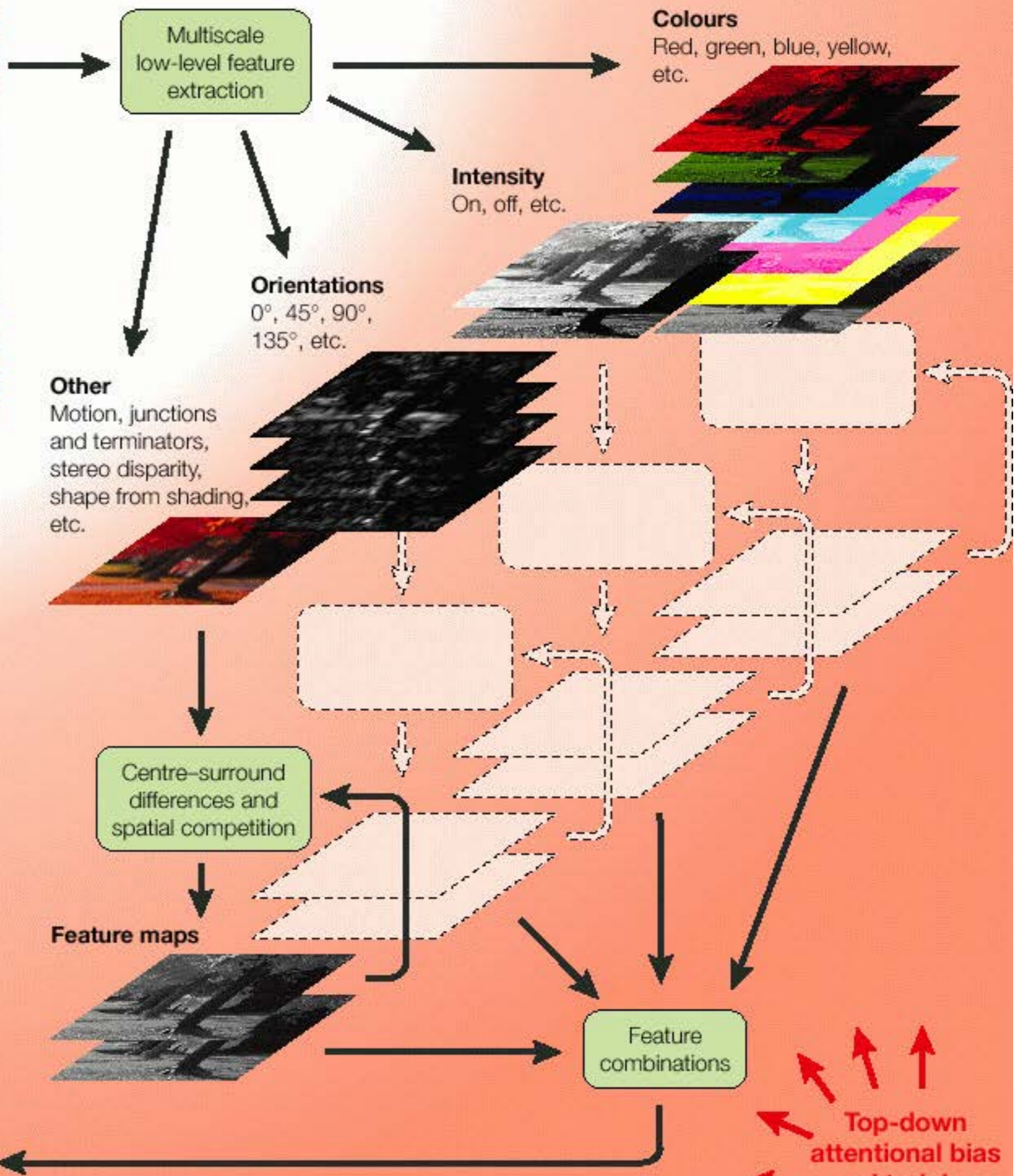


Temporal outliers – Novelty

E.g., Mueller et al. '99; Markou & Singh '01;
Theeuwes '95; Fecteau & Munoz '04

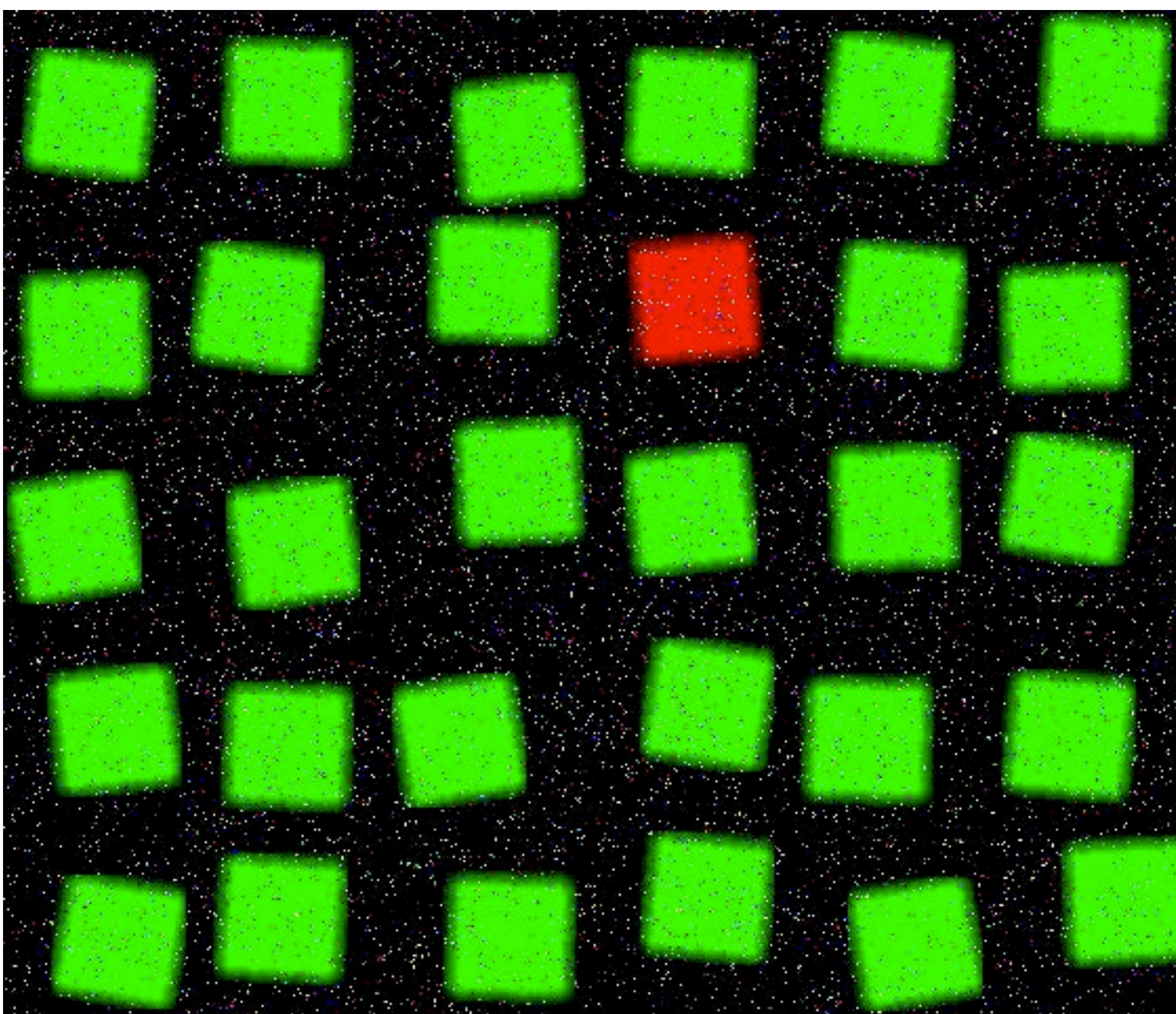


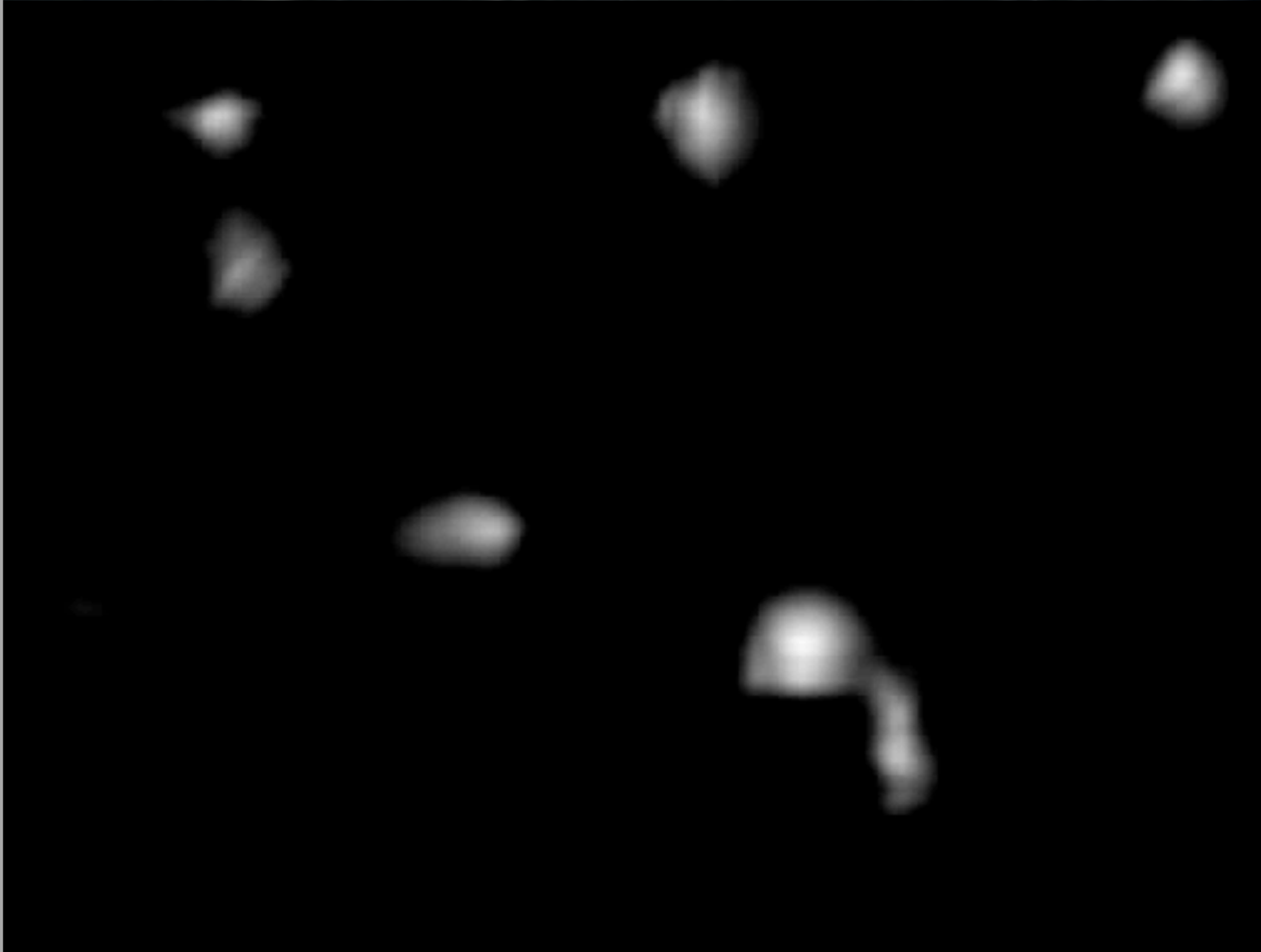
Input image



Saliency map







Itti, Koch & Niebur, 1998

Also see:

Treisman & Gelade, 1980
Wolfe, Cave & Franzel, 1989
Tsotsos et al., 1995
Hamker, 1999
Heinke & Humphreys, 1997
Zhaoping, 1999
Krummenacher et al., 2001
Paletta et al., 2005
Tatler et al., 2005
Torralba, Oliva et al., 2006
Underwood et al., 2007
Zhang et al., 2008
Kanan, Tong, Zhang &
Cottrell, 2009
Borji & Itti, 2012

Which cues attract BU visual attention?

- Color contrast
- Intensity contrast
- Orientation contrast
- Motion
- Flicker
- Context
- Scene layout
- Text
- Face
- Human body
- Animals
- Depth
- Gaze direction
- Focus of expansion
- Surprise
- Vanishing point

- Center-bias
- Object center-bias
- Symmetry
- Semantic object distance
- ...

free viewing task usually 3-5 seconds

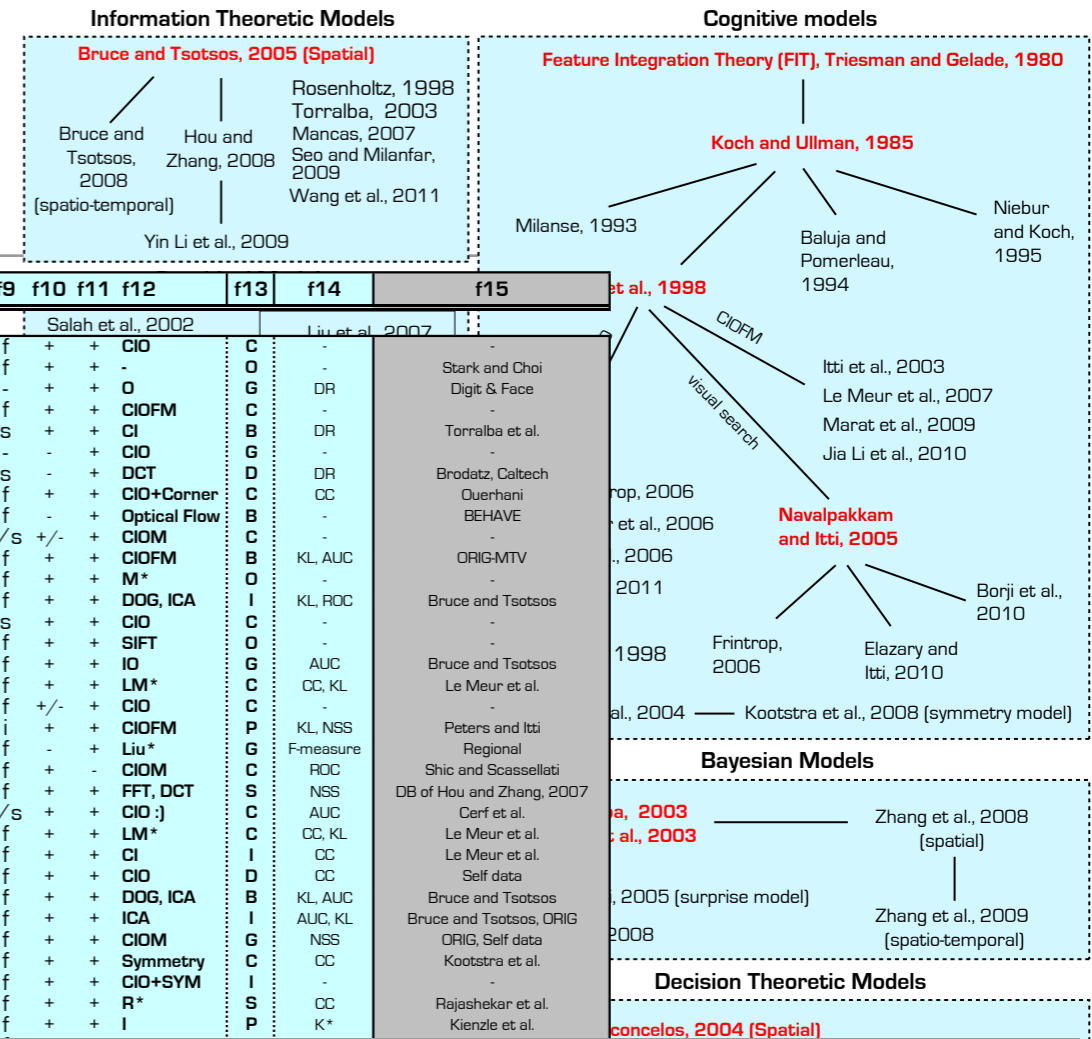


To pinpoint BU attention

Attention Models

As of Nov. 2012

A hierarchical illustration of saliency models.



• Bottom-up models

- Cognitive models
- Information-theoretic models
- Graphical models
- Spectral-analysis models
- Decision-theoretic models
- Pattern classification models

No	Model	Year	f1	f2	f3	f4	f5	f6	f7	f8	f9	f10	f11	f12	f13	f14	f15
Bottom-up (saliency models)																	
1	Itti et al. [15]	1998	+	-	+	-	+	-	+	-	f	+	+	CIO	C	-	-
2	Privitera & Stark [127]	2000	+	-	+	-	+	-	+	-	f	+	+	O	G	DR	-
3	Salah et al. [53]	2002	+	+	+	-	+	-	+	-	-	+	+	O	G	DR	-
4	Itti et al. [118]	2003	+	-	+	+	+	+	+	+	-	+	+	CIOFM	C	-	-
5	Torralba [93]	2003	-	+	+	-	+	-	+	+	s	+	+	CI	B	DR	-
6	Sun & Fisher [116]	2003	+	-	+	-	+	-	+	-	-	-	+	CIO	G	-	-
7	Gao & Vasconcelos [146]	2004	-	+	+	-	+	-	+	-	s	-	+	DCT	D	DR	-
8	Ouerhani et al. [209]	2004	+	-	+	-	+	-	+	-	f	+	+	CIO+Corner	C	CC	-
9	Boccignone & Ferraro [175]	2004	+	-	+	+	-	+	-	+	f	-	+	Optical Flow	B	-	-
10	Frintrop [51]	2005	+	+	+	+	+	+	+	+	f/s	+/-	+	CIO	C	-	-
11	Itti & Baldi [145]	2005	+	-	+	+	+	+	+	-	f	+	+	CIOFM	B	KL, AUC	-
12	Ma et al. [34]	2005	+	-	+	+	+	-	+	+	f	+	+	M*	O	-	-
13	Bruce & Tsotsos [144]	2006	+	-	+	-	+	-	+	+	f	+	+	DOG, ICA	I	KL, ROC	-
14	Navalpakkam & Itti [52]	2006	-	+	+	-	+	-	+	+	s	+	+	CIO	C	-	-
15	Zhai & Shah [104]	2006	+	-	+	+	+	-	+	+	f	+	+	SIFT	O	-	-
16	Harel et al. [120]	2006	+	-	+	-	+	-	+	-	f	+	+	IO	G	AUC	-
17	Le Meur et al. [42]	2006	+	-	+	-	+	-	+	+	f	+	+	LM*	C	CC, KL	-
18	Walther & Koch [36]	2006	+	-	+	-	+	-	+	+	f	+/-	+	CIO	C	-	-
19	Peters & Itti [102]	2007	+	+	+	+	+	+	+	+	i	+	+	CIOFM	P	KL, NSS	-
20	Liu et al. [44]	2007	+	-	+	-	+	-	+	-	f	-	+	Liu*	G	F-measure	-
21	Shic & Scassellati [75]	2007	+	-	+	+	+	+	+	+	f	+	-	CIO	C	ROC	-
22	Hou & Zhang [150]	2007	+	-	+	-	+	-	+	+	f	+	+	FFT, DCT	S	NSS	DB of Hou and Zhang, 2007
23	Cerf et al. [156]	2007	+	+	+	-	+	-	+	+	f/s	+	+	CIO :)	C	AUC	-
24	Le Meur et al. [138]	2007	+	-	+	+	+	-	+	+	f	+	+	LM*	C	CC, KL	-
25	Mancas [152]	2007	+	-	+	+	+	+	+	+	f	+	+	CI	I	CC	-
26	Guo et al. [156]	2008	+	-	+	-	+	-	+	+	f	+	+	CIO	D	CC	-
27	Zhang et al. [141]	2008	+	-	+	-	+	-	+	+	f	+	+	DOG, ICA	B	KL, AUC	-
28	Hou & Zhang [151]	2008	+	-	+	+	+	+	+	+	f	+	+	ICA	I	AUC, KL	-
29	Pang et al. [103]	2008	+	+	+	+	+	+	+	+	f	+	+	CIO	G	NSS	-
30	Kootstra et al. [136]	2008	+	-	+	-	+	-	+	+	f	+	+	Symmetry	C	CC	-
31	Ban et al. [172]	2008	+	-	+	+	+	+	+	+	f	+	+	CIO+SYM	I	-	-
32	Rajashekar et al. [174]	2008	+	-	+	-	+	-	+	+	f	+	+	R*	S	CC	-
33	Kienzle et al. [165]	2009	+	-	+	-	+	-	+	+	f	+	+	I	P	K*	-
34	Marat et al. [50]	2009	+	-	+	+	+	+	+	+	f	+	+	-	-	-	-
35	Judd et al. [166]	2009	+	-	+	-	+	-	+	+	f	+	+	-	-	-	-
36	Seo & Milanfar [107]	2009	+	-	+	+	+	+	+	+	f	+	+	-	-	-	-
37	Rosin [169]	2009	+	-	+	-	+	-	+	+	f	+	+	-	-	-	-
38	Yin Li et al. [171]	2009	-	+	+	+	+	+	+	+	f	+	+	-	-	-	-
39	Bian & Zhang [159]	2009	+	-	+	+	+	+	+	+	f	+	+	-	-	-	-
40	Diaz et al. [160]	2009	+	-	+	-	+	-	+	+	f	+	+	-	-	-	-
41	Zhang et al. [142]	2009	+	-	+	+	+	+	+	+	f	+	+	-	-	-	-
42	Achanta et al. [158]	2009	+	-	+	-	+	-	+	+	f	+	+	-	-	-	-
43	Gao et al. [147]	2009	+	-	+	+	+	+	+	+	f	+	+	-	-	-	-
44	Chikkerur et al. [154]	2010	+	+	+	-	+	-	+	+	f	+	+	-	-	-	-
45	Mahadaven & Vasconcelos [106]	2010	+	-	+	+	+	-	+	+	f	+	+	-	-	-	-
46	Avraham & Lindenbaum [153]	2010	+	+	+	-	+	-	+	+	f	+	+	-	-	-	-
47	Jia Li et al. [133]	2010	-	+	+	+	+	+	+	+	f	+	+	-	-	-	-
48	Guo et al. [157]	2008	+	-	+	+	+	+	+	+	f	+	+	-	-	-	-
49	Borji et al. [90]	2010	-	+	+	-	+	-	+	+	f	+	+	-	-	-	-
50	Goferman et al. [47]	2010	+	-	+	-	+	-	+	+	f	+	+	-	-	-	-
51	Murray et al. [199]	2011	+	-	+	-	+	-	+	+	f	+	+	-	-	-	-
52	Wang et al. [200]	2011	+	-	+	-	+	-	+	+	f	+	+	-	-	-	-
Top-down (general attention models)																	
53	McCallum [163]	1995	-	+	+	-	+	-	+	-	f	+	+	-	-	-	-
54	Rao et al. [24]	1995	-	+	+	-	+	-	+	-	f	+	+	-	-	-	-
55	Ramstrom & Christiansen [168]	2002	-	+	+	-	+	-	+	-	f	+	+	-	-	-	-
56	Sprague & Ballard [108]	2003	-	+	+	+	+	+	+	+	f	+	+	-	-	-	-
57	Renninger et al. [95]	2004	-	+	+	-	+	-	+	-	f	+	+	-	-	-	-
58	Navalpakkam & Itti [81]	2005	-	+	+	-	+	-	+	-	f	+	+	-	-	-	-
59	Palleta et al. [164]	2005	-	+	+	-	+	-	+	-	f	+	+	-	-	-	-
60	Jodogne & Piater [162]	2007	-	+	+	-	+	-	+	-	f	+	+	-	-	-	-
61	Butko & Movellan [161]	2009	-	+	+	-	+	-	+	-	f	+	+	-	-	-	-
62	Verma & McOwan [213]	2009	+	-	+	-	+	-	+	-	f	+	+	-	-	-	-
63	Borji et al. [89]	2010	-	+	+	-	+	-	+	-	f	+	+	-	-	-	-

• Top-down models

Yet, few top-down models!?

mit saliency benchmark



[home](#)

[results](#)

[datasets](#)

[submission](#)

[downloads](#)

The goal of this website is to be the most up-to-date, online source of saliency **model performances** and **datasets**. We believe that a continuous effort should serve as an essential resource to document and promote progress in the field of saliency modeling.

On this site, our contribution is twofold:

(1) We score and report performances for the latest saliency models on our saliency benchmark: the only data sets where human eye movements and fixations are fitted to the datasets. [Go to model performances](#) or [submit a new model](#).

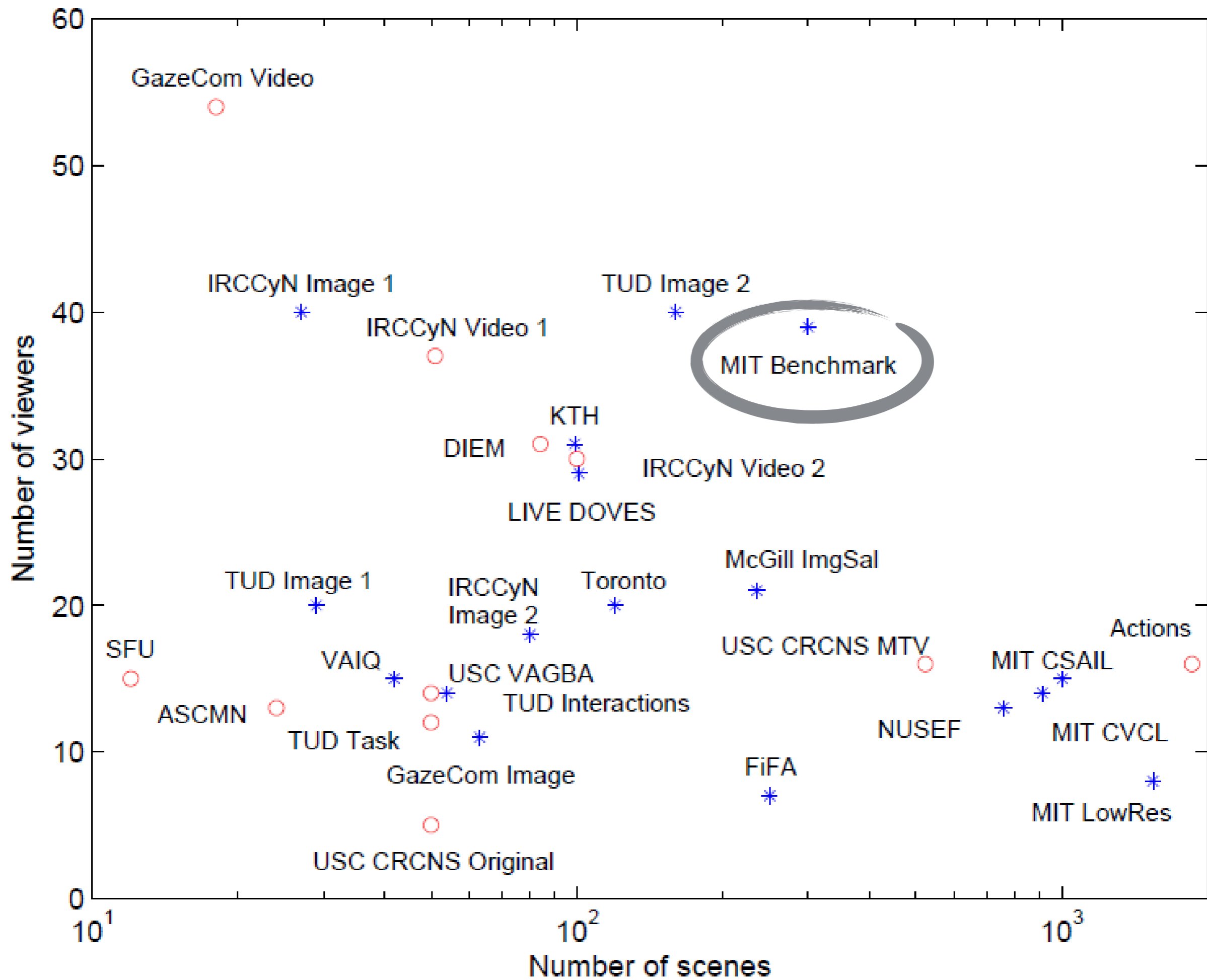
(2) We maintain an up-to-date listing of other saliency datasets and collection procedures, along with all relevant links in order to have a one-stop shop for saliency datasets. [Go to datasets](#).

We continuously **update** this page with the latest developments in saliency modeling. Please browse around.

citation

If you use any of the results or data on this page, please cite the following:

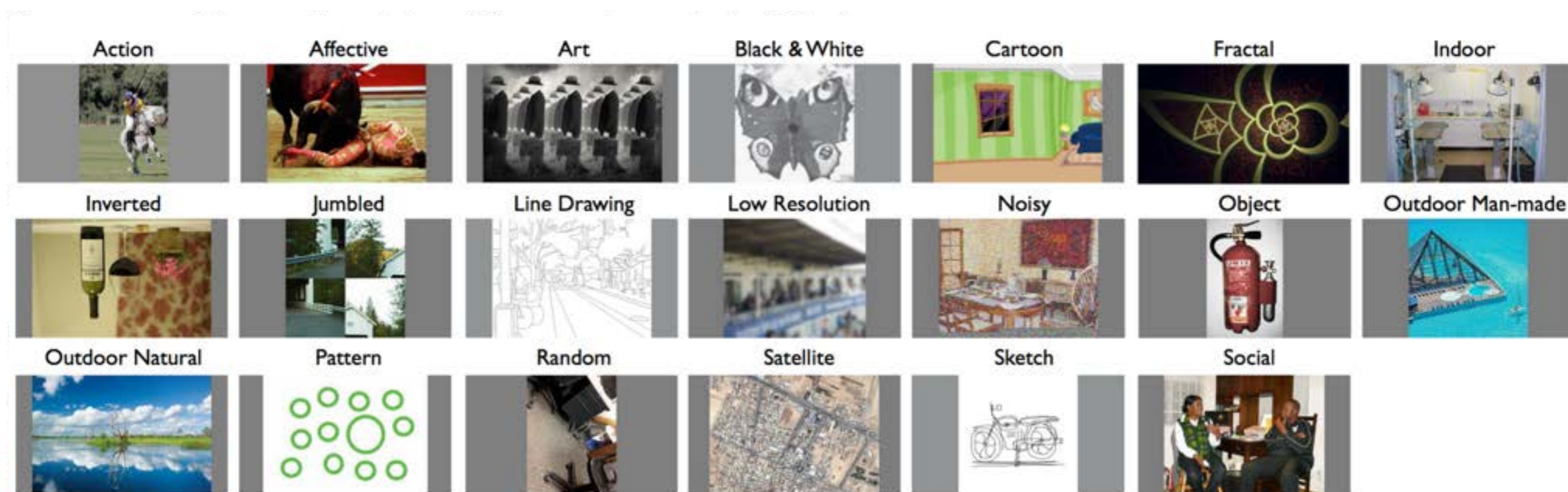
```
@misc{mit-saliency-benchmark,  
  author      = {Zoya Bylinskii and Tilke Judd and Ali Borji and Laurent Itti and Fr{e}do Durand and Aude Oliva and Antonio Torralba},  
  title       = {MIT Saliency Benchmark},  
  url         = {http://saliency.mit.edu/}  
}
```



mit saliency benchmark results: cat2000

The following are results of models evaluated on their ability to predict ground truth human fixations on our **benchmark data set** **categories** with eye tracking data from 24 observers. We post the results here and provide a way for people to submit new model

citations



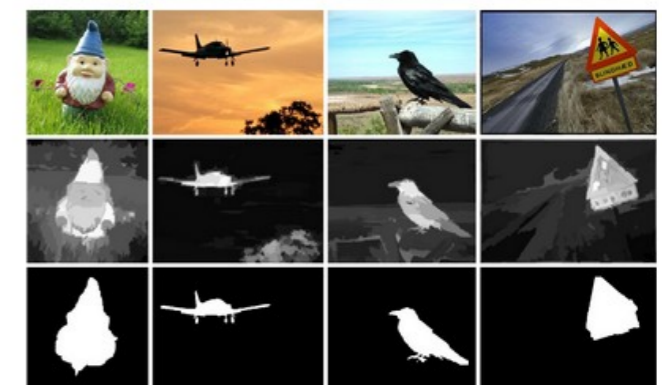
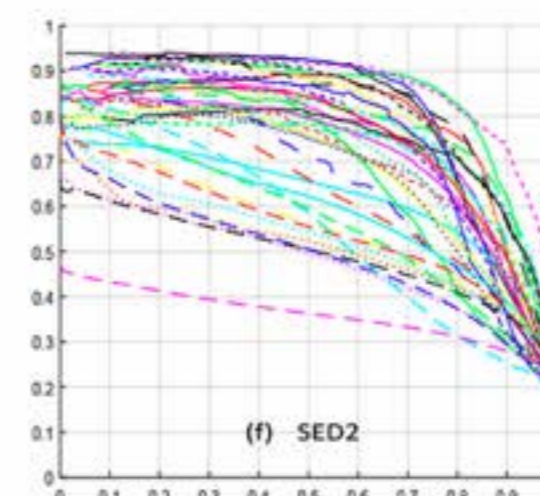
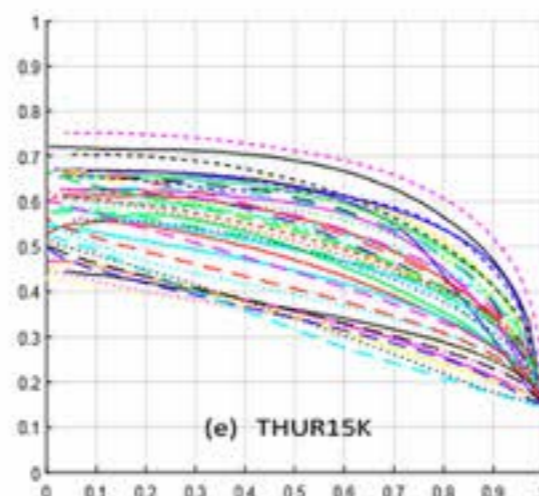
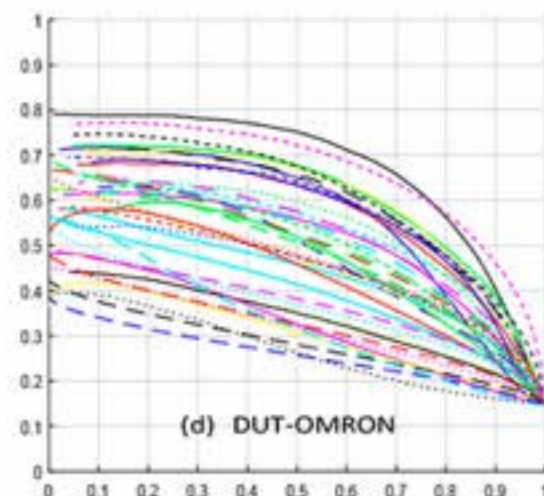
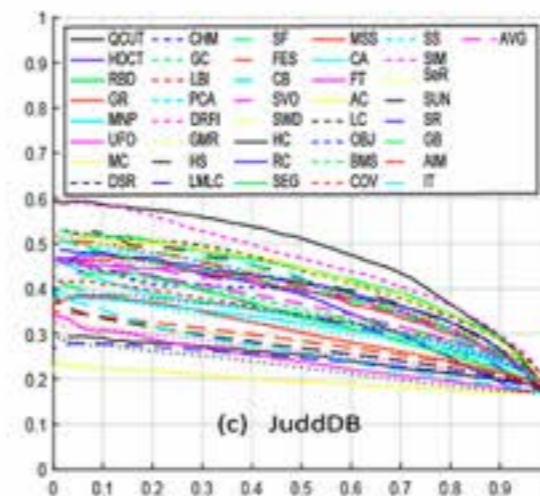
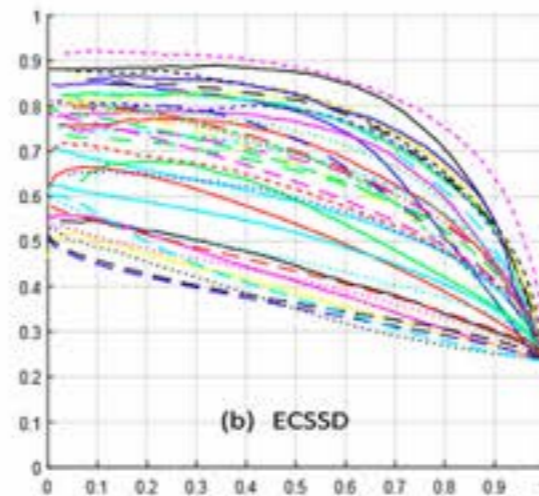
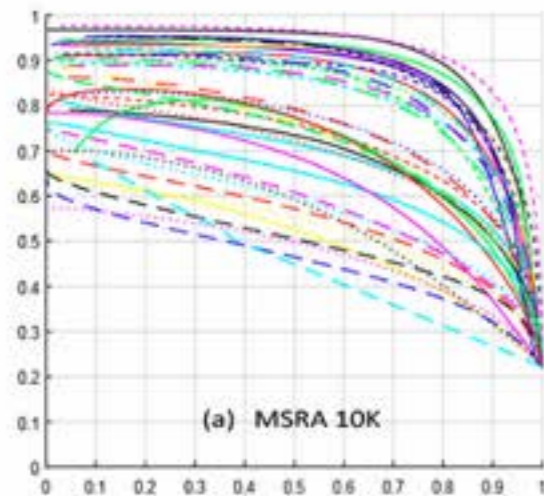
model performances

12 models, 4 baselines, 7 metrics, and counting...

24 people , 4000 images,
20 categories, 32 Billion saccades

Salient Object Detection: A Benchmark

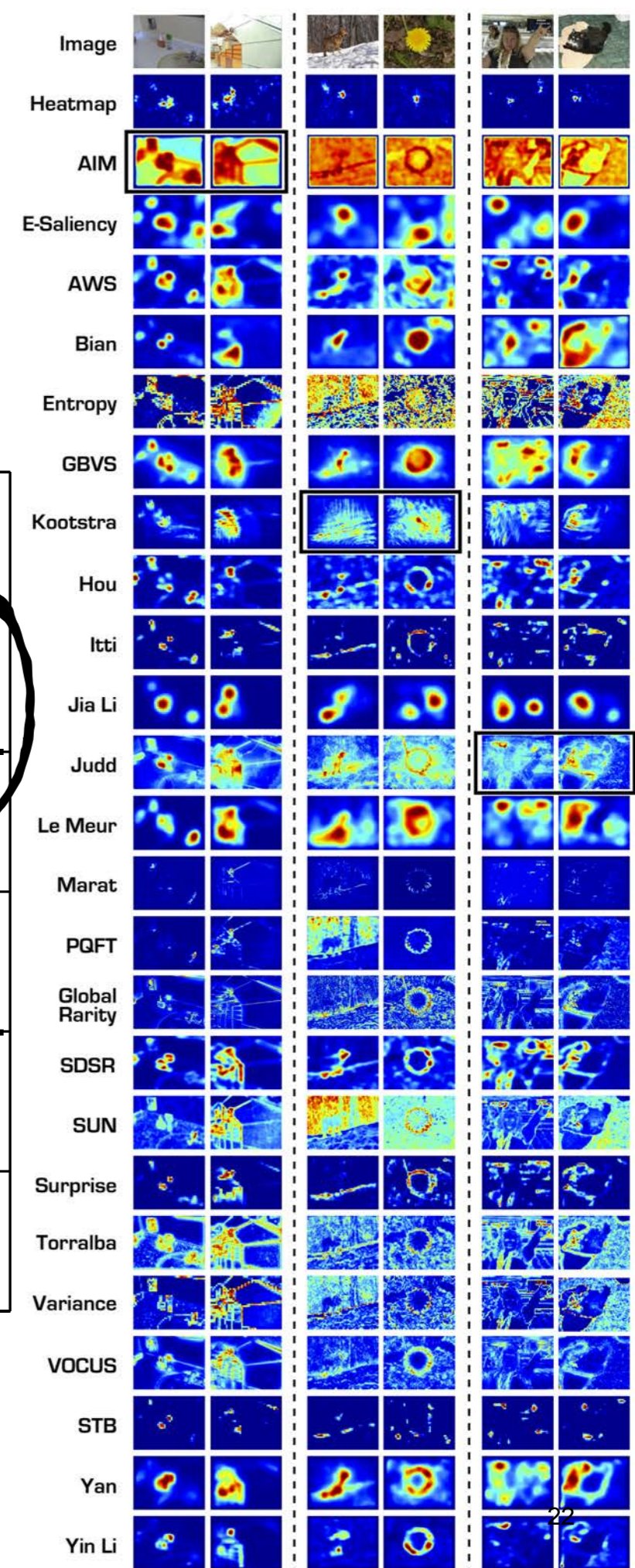
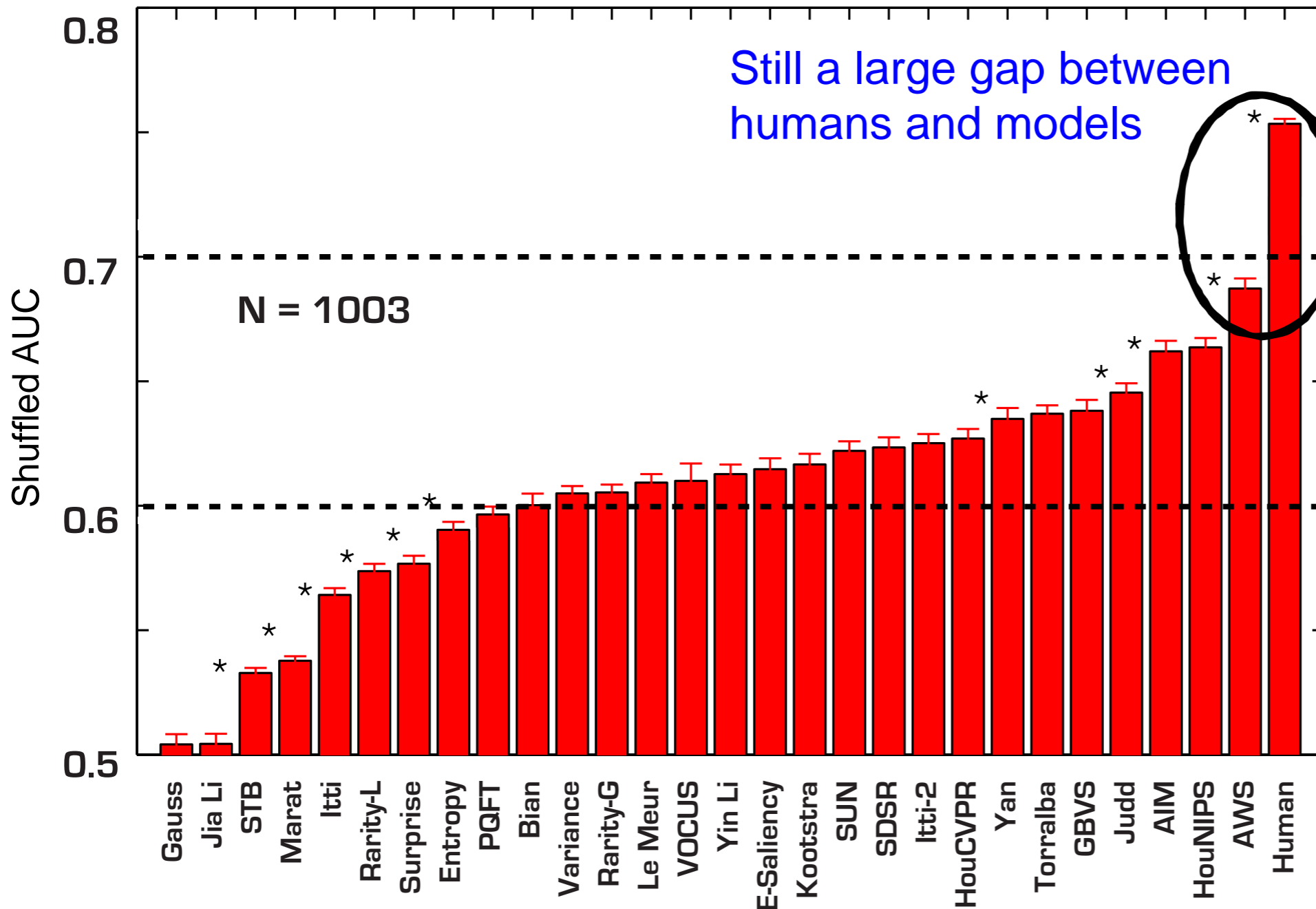
[Ali Borji](#), [Ming-Ming Cheng](#), [Huaizu Jiang](#), [Jia Li](#)



Precision (vertical axis) and recall (horizontal axis) curves of saliency methods on 6 popular benchmark datasets.

Model Benchmarking over Judd et al. 2009 dataset using shuffled AUC score

Borji et al., IEEE TIP 2012



model performances

46 models, 5 baselines, 7 metrics, and counting...

Performance numbers prior to September 25, 2014.

Matlab code for the metrics we use.

Sorted by:

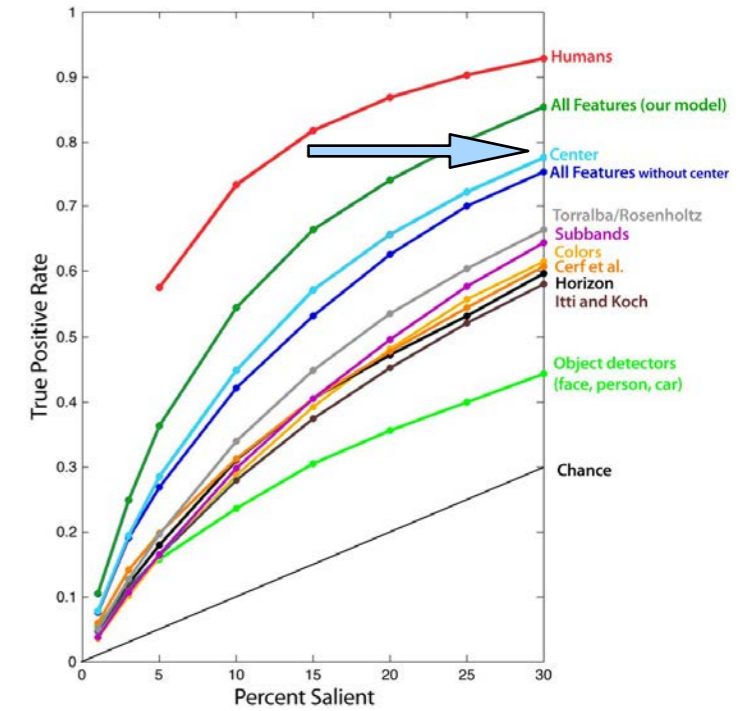


Model Name	Published	Code	AUC-Judd [?]	SIM [?]	EMD [?]	AUC-Borji [?]	sAUC [?]	CC [?]	NSS [?]	Date tested [key]	Sample [img]
Baseline: infinite humans [?]			0.91	1	0	0.87	0.80	1	3.18		
SALICON	Xun Huang, Chengyao Shen, Xavier Boix, Qi Zhao		0.87	0.60	2.62	0.85	0.74	0.74	2.12	first tested: 19/11/2014 last tested: 20/03/2015 maps from authors	
SalNet	Kevin McGuinness. Unpublished work.		0.83	0.52	3.31	0.82	0.69	0.58	1.51	first tested: 17/06/2015 last tested: 17/06/2015 maps from authors	
Multiresolution CNN (Mr-CNN)	Nian Liu, Junwei Han, Dingwen Zhang, Shifeng Wen, Tianming Liu. Predicting Eye Fixations using Convolutional Neural Networks [CVPR 2015]		0.77	0.45	4.33	0.76	0.69	0.41	1.13	first tested: 11/08/2015 last tested: 11/08/2015 maps from authors	
Adaptive Whitening Saliency Model (AWS)	Anton Garcia-Diaz, Victor Leboran, Xose R. Fdez-Vidal, Xose M. Pardo. On the relationship between optical variability, visual saliency, and eye fixations: A computational approach [JoV 2012]	matlab	0.74	0.43	4.62	0.73	0.68	0.37	1.01	last tested: 23/09/2014 maps from code (DL:17/01/2014) with params: rescale=0.5	
RARE2012	Nicolas Riche, Matei Mancas, Matthieu Duvinage, Makiese Mibulumukini, Bernard Gosselin, Thierry Dutoit. RARE2012: A multi-scale rarity-based saliency detection with its comparative statistical analysis [Signal Processing: Image Communication, 2013]	matlab	0.77	0.46	4.11	0.75	0.67	0.42	1.15	first tested: 31/08/2012 last tested: 23/09/2014 maps from authors	
Deep Gaze 1	Matthias Kümmerer, Lucas Theis, Matthias Bethge. Deep Gaze I: Boosting Saliency Prediction with Feature Maps Trained on ImageNet [arxiv 2014]		0.84	0.39	4.97	0.83	0.66	0.48	1.22	first tested: 02/10/2014 last tested: 22/10/2014 maps from authors	
AIM	Neil Bruce, John Tsotsos. Attention based on information maximization [JoV 2007]	matlab	0.77	0.40	4.73	0.75	0.66	0.31	0.79	last tested: 23/09/2014 maps from code (DL:15/01/2014) with params: resize=0.5, convolve=1, thebasis='31infomax975'	
Image Signature	Xiaodi Hou, Jonathan Harel, Christof Koch. Image Signature: Highlighting Sparse Salient Regions [PAMI 2011]	matlab	0.75	0.43	4.49	0.74	0.66	0.38	1.01	first tested: 19/06/2014 last tested: 23/09/2014 maps from authors	

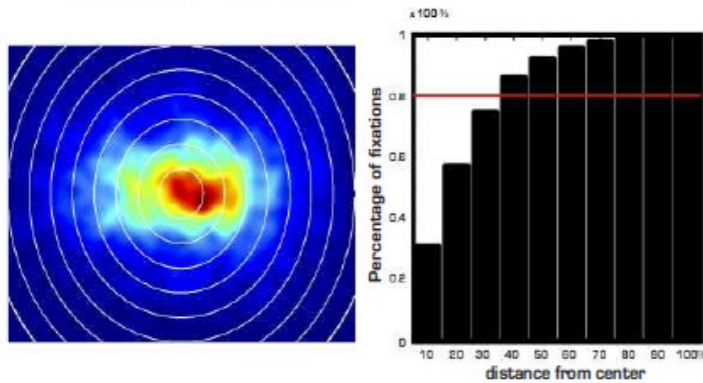
Center-bias

- Observers tend to look at the center of objects for two reasons:

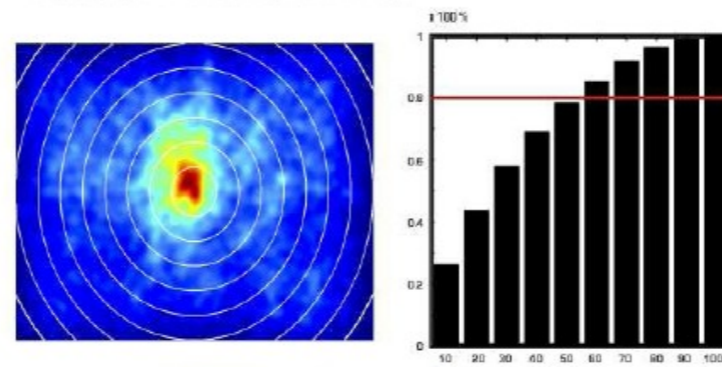
- Viewing strategy
- Photographer bias



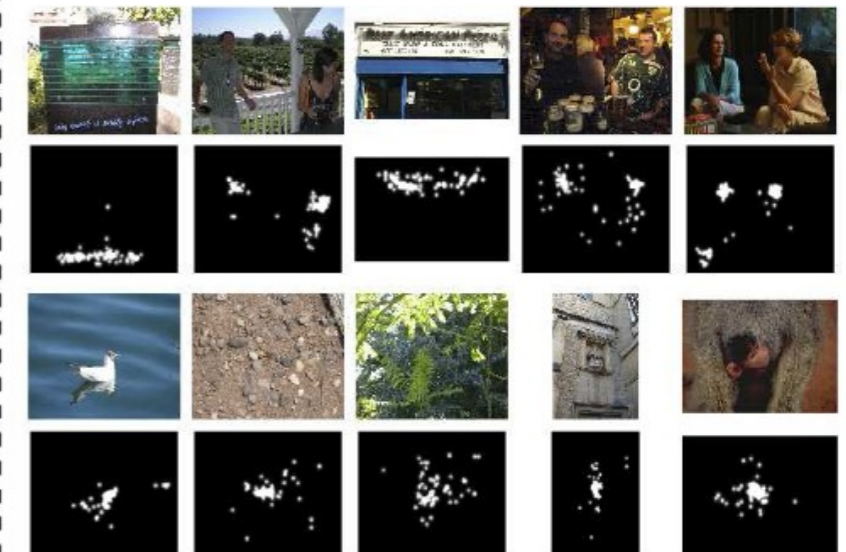
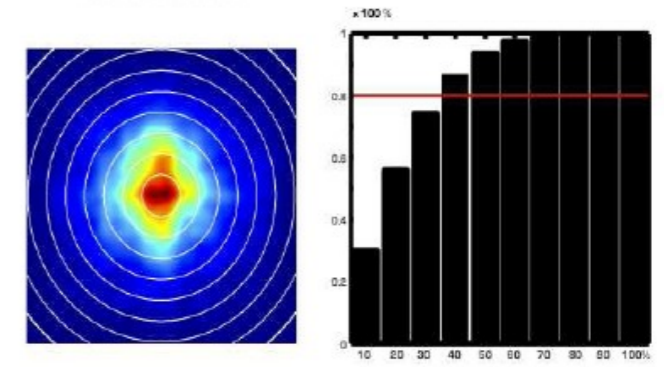
Bruce and Tsotsos



Kootstra and Shomaker



Judd et al.



Scores

- **Fixation Prediction**

- AUC (I spotted 4 types of AUC)
- NSS
- CC
- KL
- EMD
- Percentile
- Fixation Saliency Method (FS)
- String Editing Distances
- Average Accuracy Score (AAS)
- Similarity score

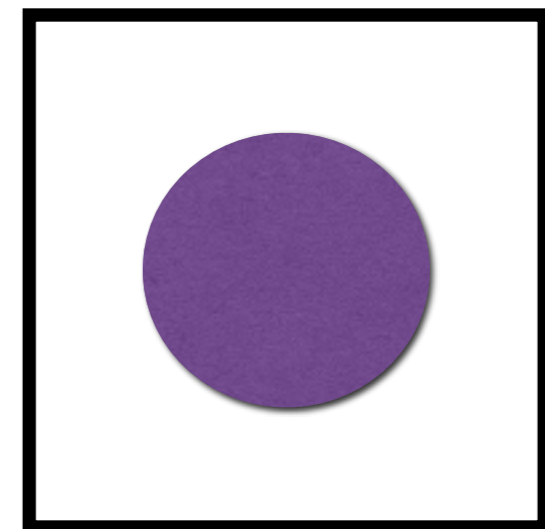
- **Saliency Detection**

- AUC
- Precision-Recall
- Mean Error Rate

Refs:

- Borji and Itti, PAMI 2013
- Peters and Itti, TAP 2008
- Alsam and Sharma, SCIA 2013

Problem with sAUC



Effect of gaze direction



- Do observers follow the gaze direction in viewing natural scenes?
- How are gaze direction and BU saliency related?
- How can gaze direction help fixation prediction?



Complementary effects of gaze direction and saliency in free viewing of natural scenes,

Borji et al., JOV 2014

Augmented saliency model using automatic 3D head pose detection and learned gaze following in natural scenes

Parks, Borji and Itti, VR 2015

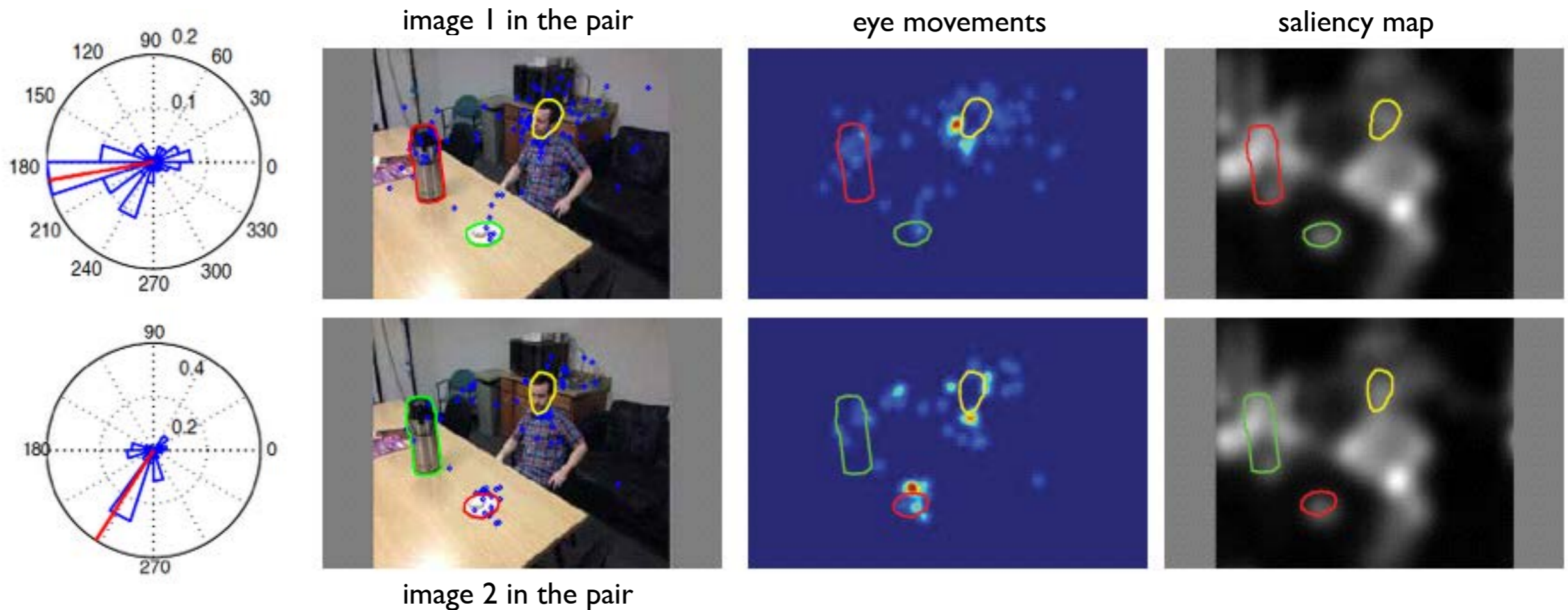
See for example

- Frischen et al., *Psychological bulletin*, 2007

- Morales et al., *Infant Behavior and Development*, 1998

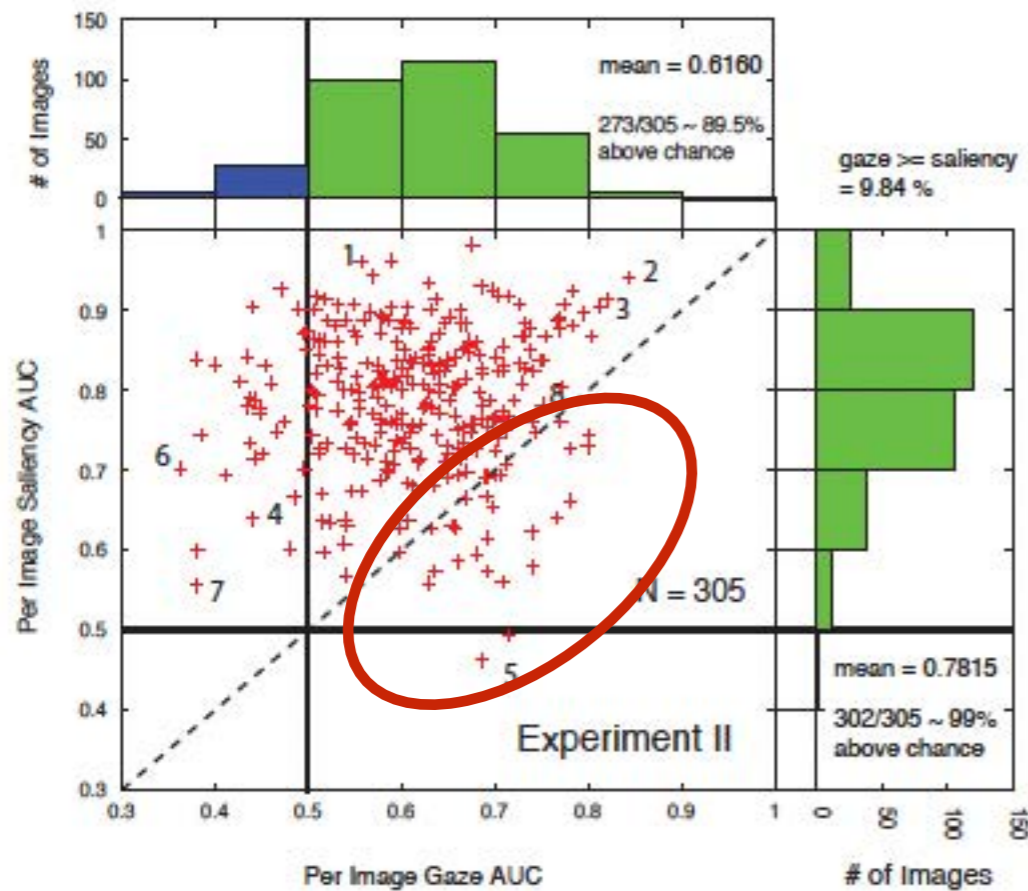
Predicting saccade direction

- Do observers saccade at the direction of the gaze more than random (chance) and max saliency directions?
- Analysis is done over all saccades that leave the head region



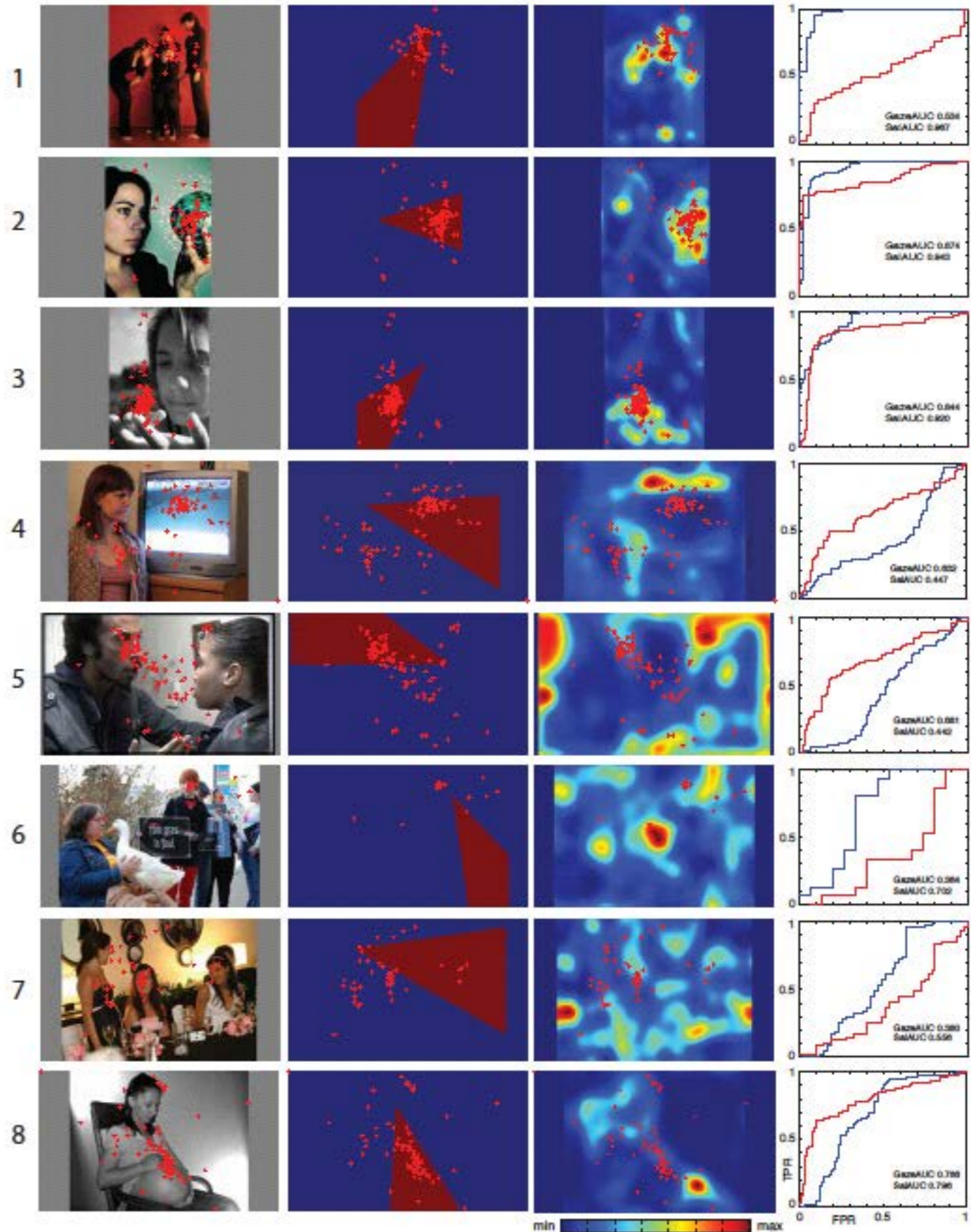
Predicting fixation location

- Building a cone model
- Sometimes this simple model outperforms the best saliency model

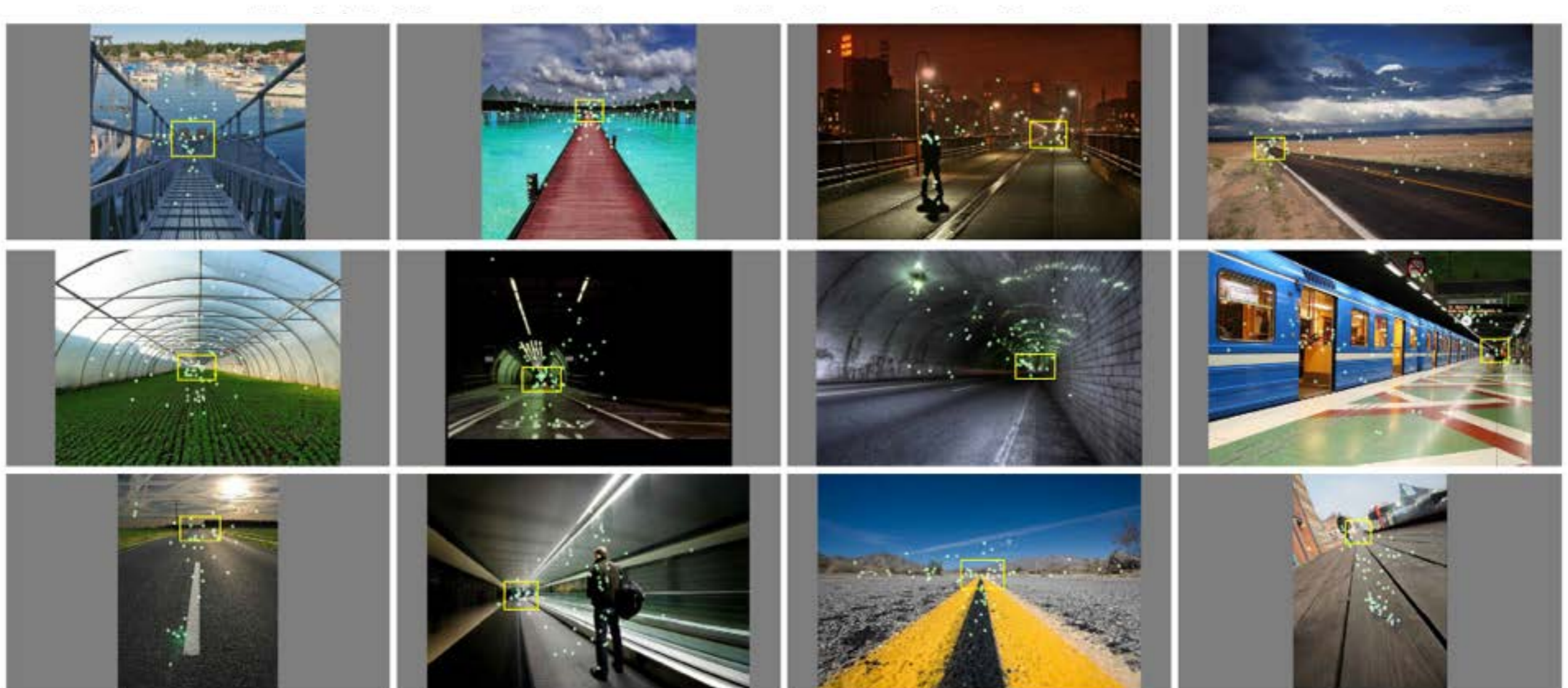


- How about a combined model of saliency and gaze direction?

Parks, Borji and Itti, VR 2015



Effect of vanishing point



Vanishing Point Attracts Eye Movements in Scene Free-viewing

A Borji, M Feng, H Lu

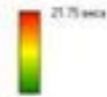
arXiv preprint arXiv:1505.03578

Fixation prediction with a combined model of bottom-up saliency and vanishing point

M Feng, A Borji, H Lu

Submitted.

Media: Diapers (7) .log
Time: 02/01/2008 - 02/02/08 033
Participant ID: 20



Example for the most sensitive skin.

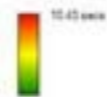
For the most sensitive skin, add the chemicals and moisture to the diaper. If you have diaper rash.

Baby's unique high-absorbency natural-blend cotton provides cotton-soft, extra thick, gel-free protection for your baby's sensitive skin. The chlorine-free materials and absorbent polymers is non-toxic and non-irritating. Clinically tested and pediatrician recommended for babies with allergies and sensitive skin.



If you are not satisfied with the baby leakage protection, you will get your money back. Read more about our leakfree guarantee at www.baby.com

Participant ID: 20



Example for the most sensitive skin.

For the most sensitive skin, add the chemicals and moisture to the diaper. If you have diaper rash.

Baby's unique high-absorbency natural-blend cotton provides cotton-soft, extra thick, gel-free protection for your baby's sensitive skin. The chlorine-free materials and absorbent polymers is non-toxic and non-irritating. Clinically tested and pediatrician recommended for babies with allergies and sensitive skin.



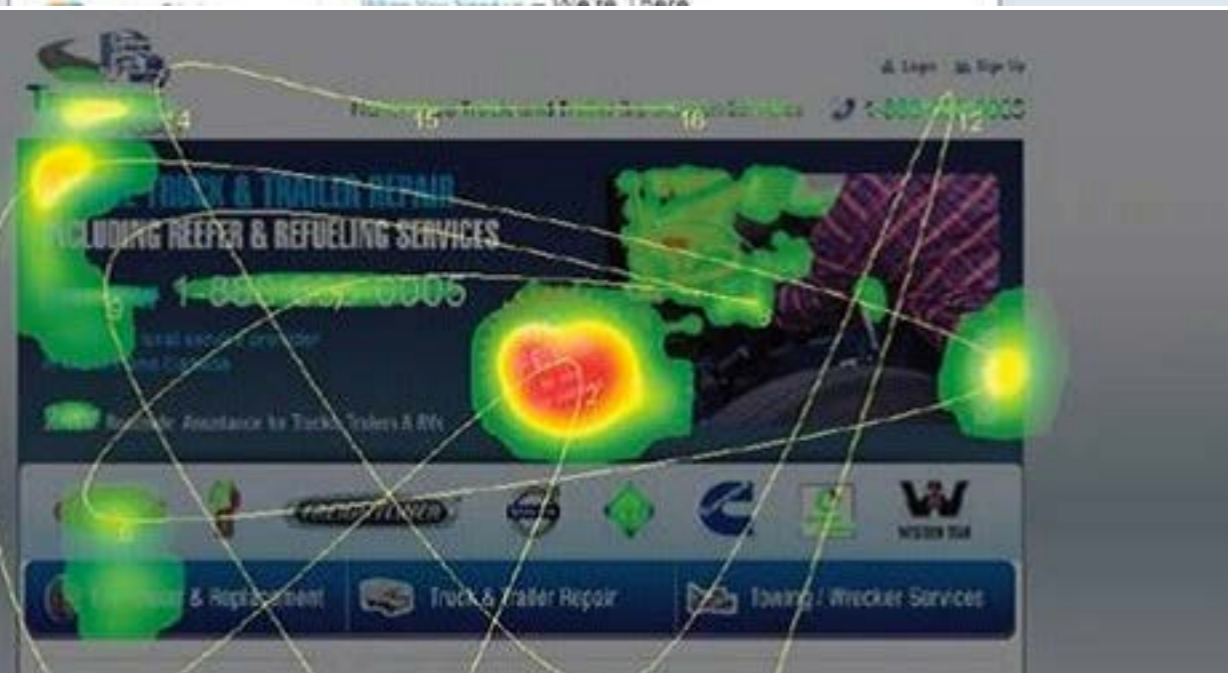
If you are not satisfied with the baby leakage protection, you will get your money back. Read more about our leakfree guarantee at www.baby.com

Beware of “Dead Weight” with Visuals

Before



After



Lesson learned: When you are assembling a persuasive landing page, be sure the elements that “pop” are the ones that matter, and that you aren’t giving too much weight to visuals that don’t encourage customers to take action.

The F-Pattern Works Across the Board

amazon
Join Prime

Your Amazon.com | Today's Deals | Gift Cards | Sell | Help

Shop by
Department

Search All ▼

- Unlimited Instant Videos
- MP3s & Cloud Player
20 million songs, play anywhere
- Amazon Cloud Drive
5 GB of free storage
- Kindle
- Appstore for Android
Monster Mouth DDS free today
- Digital Games & Software
- Audible Audiobooks

- Books
- Movies, Music & Games
- Electronics & Computers

Instant Video MP3 Store Cloud Player

The Perfect Gift for

kindle fire HD

From ~~\$199~~ From \$179

Enter **DADSFIRE** at checkout
Limited-time offer

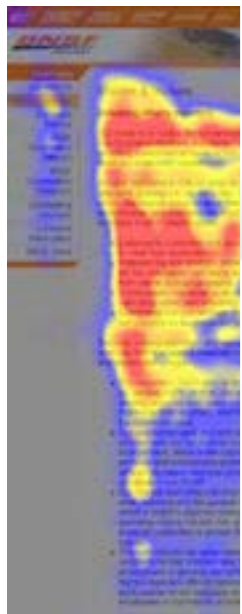


www.usatoday.com

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A Good Night



People al
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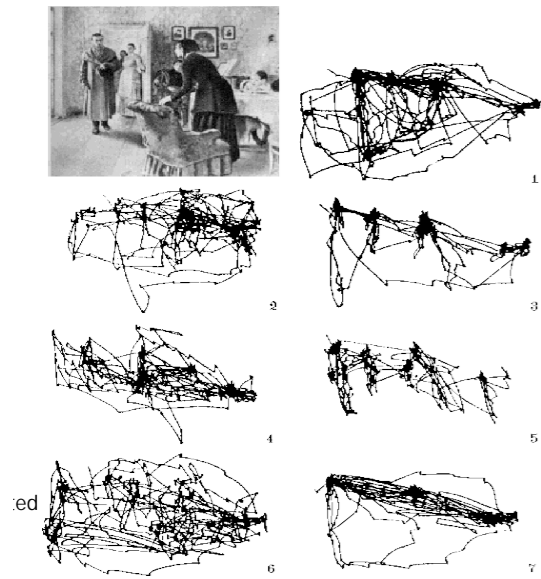
Lessor
For Eng
left side
F-pattern.

Note: It is important to note all of these studies were conducted with **English speaking (and reading)** participants. The opposite was true for those users whose languages read from right to left.

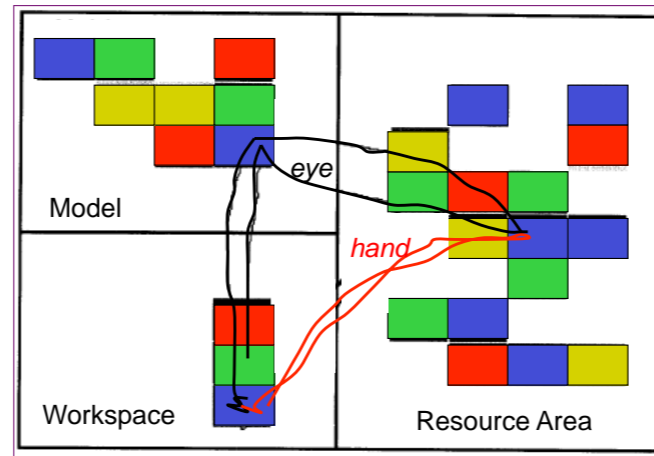
Top-down (TD) Attention



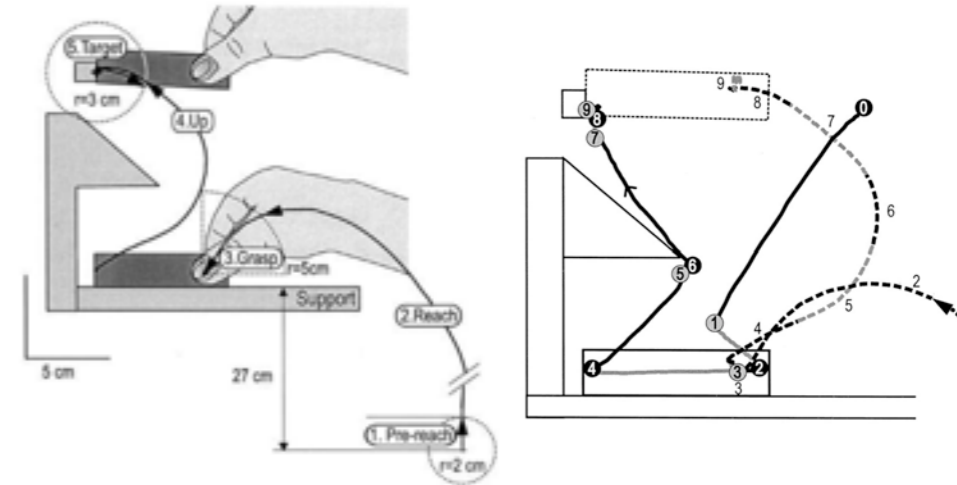
Eye movements during natural behavior



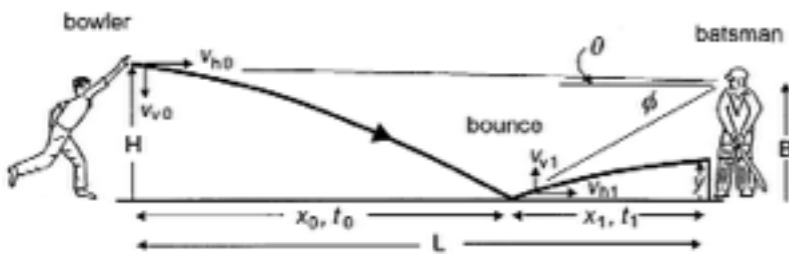
Yarbus 1967



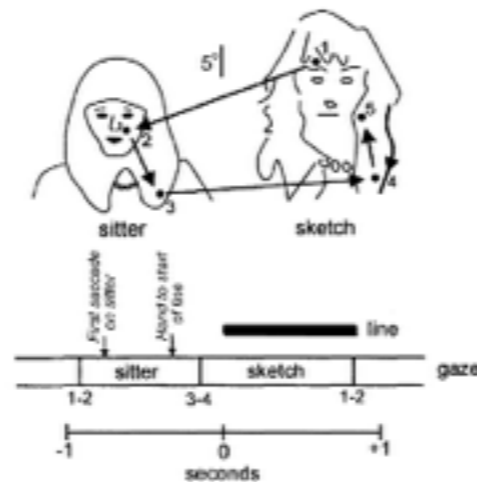
Block copying
(Ballard et al. 1995)



Picking and moving a bar
(Johanssen et al 2001)



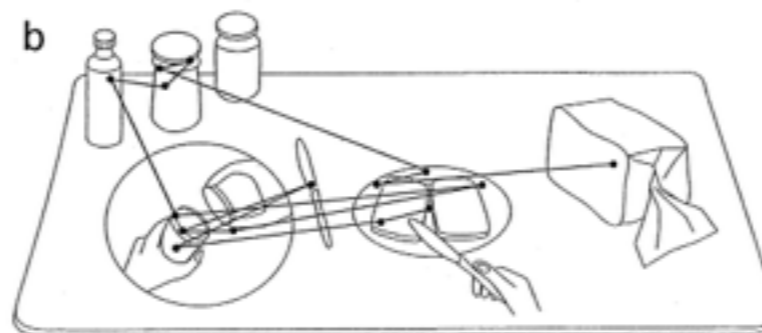
Cricket
(Land and Macleod, 2000)



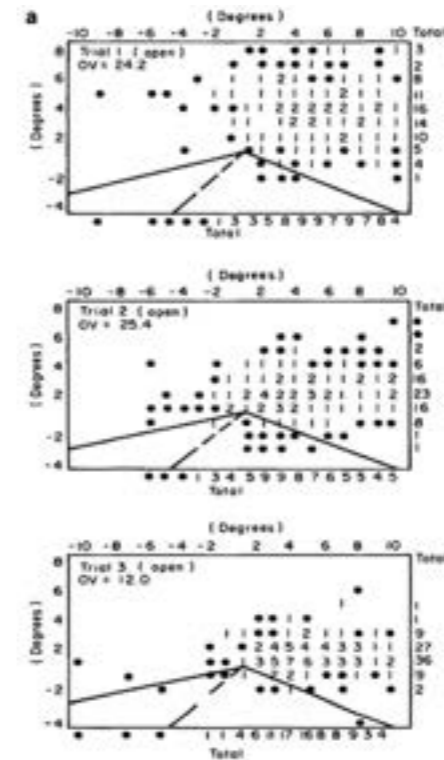
Drawing
Miall and Tchalenko (2001)



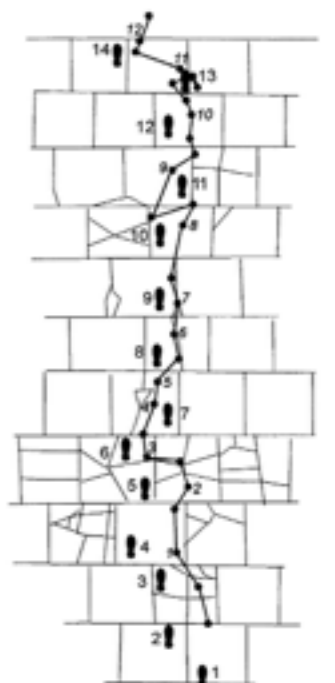
Tea making
(Ballard et al. 1995)



Sandwich making
(Ballard et al. 1995)



Driving
Mourant & Rockwell 1970
Land 2001



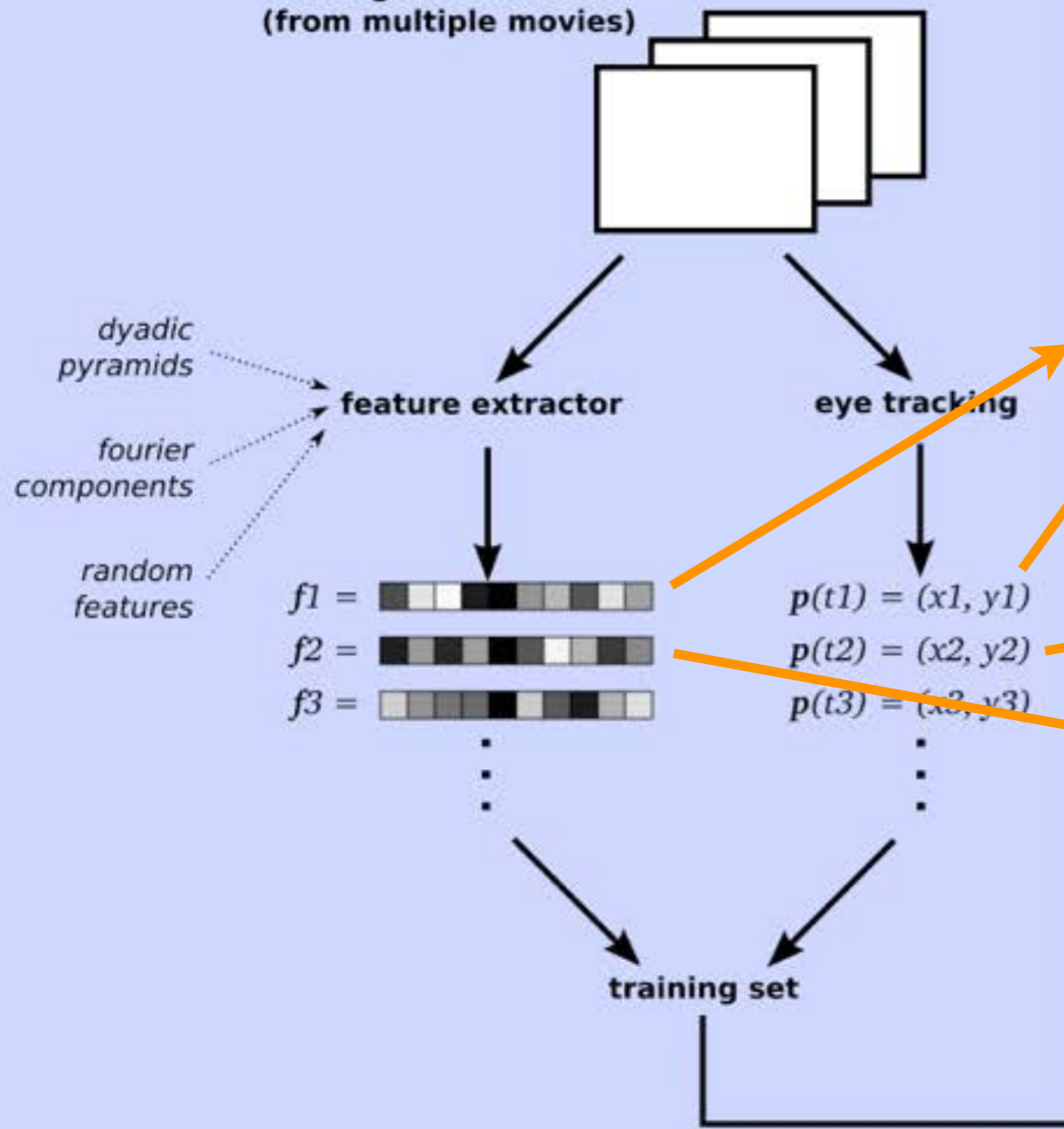
Walking
Palta and Vickers 1997,
Turano et al., 2003

STIMULUS TYPE	MODEL TYPE	
	qualitative/descriptive	quantitative/predictive
artificial <i>(gabor patches, search arrays)</i>	Treisman & Gelade 1980; Wolfe & Horowitz 2004	Rao et al 2002; Najemnik & Geisler 2005; Navalpakkam & Itti 2006
static, natural <i>(photographs)</i>	Yarbus 1967 Greene et al 2012 Henderson et al 2012 Borji and Itti, 2014	Privitera & Stark 1998; Reinagel & Zador 1999; Parkhurst et al 2002; Torralba 2003; Peters et al 2005; Navalpakkam & Itti 2005; Pomplun 2006 Tatler et al., 2005, 2007
dynamic, natural <i>(movies, cartoons)</i>	Tosi, Mecacci & Pasqual 1997; May, Dean & Barnard 2003; Peli, Goldstein & Woods 2005	Carmi & Itti 2004; Itti & Baldi 2005
interactive, natural <i>(video games, virtual reality flying/driving simulators)</i>	Land & Hayhoe 2001; Hayhoe et al 2002; Hayhoe et al 2003	Peters and Itti, 2007 Borji et al., 2011, 2012



train

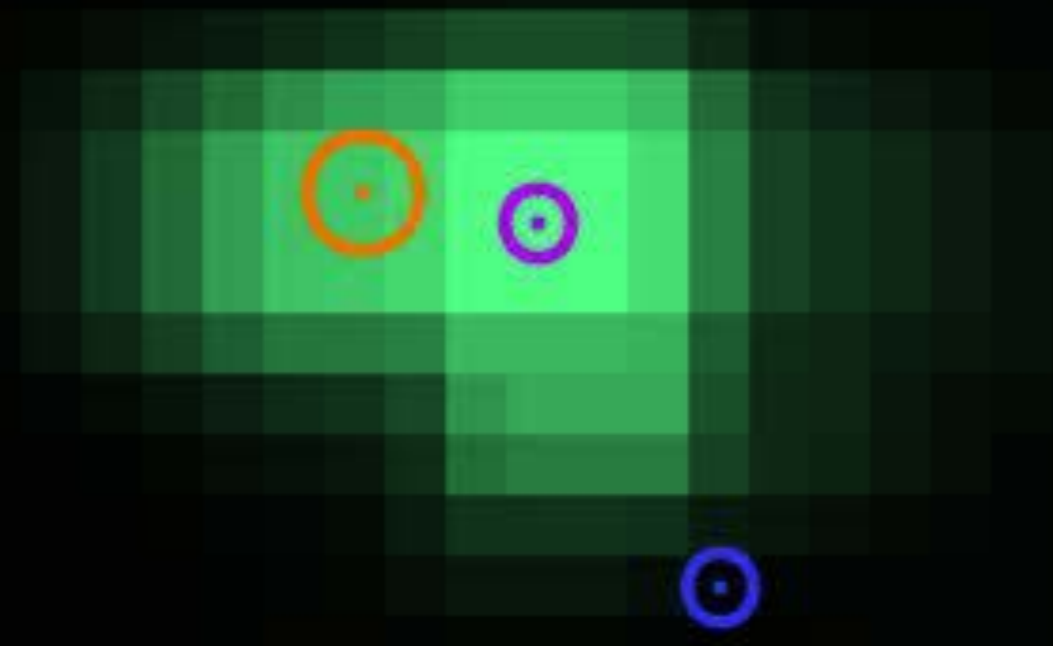
training movie frames
(from multiple movies)



test



Peters & Itti, IEEE CVPR 2007;
Borji et al., IEEE CVPR 2012;
Borji et al., IEEE T. SMC-A 2014

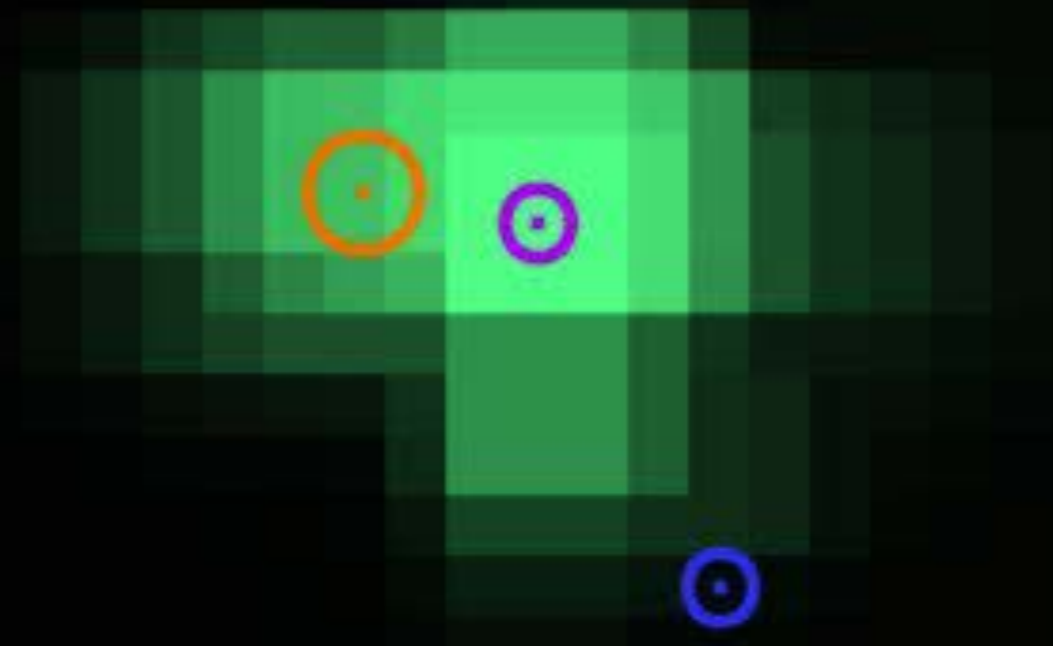


input

top-down

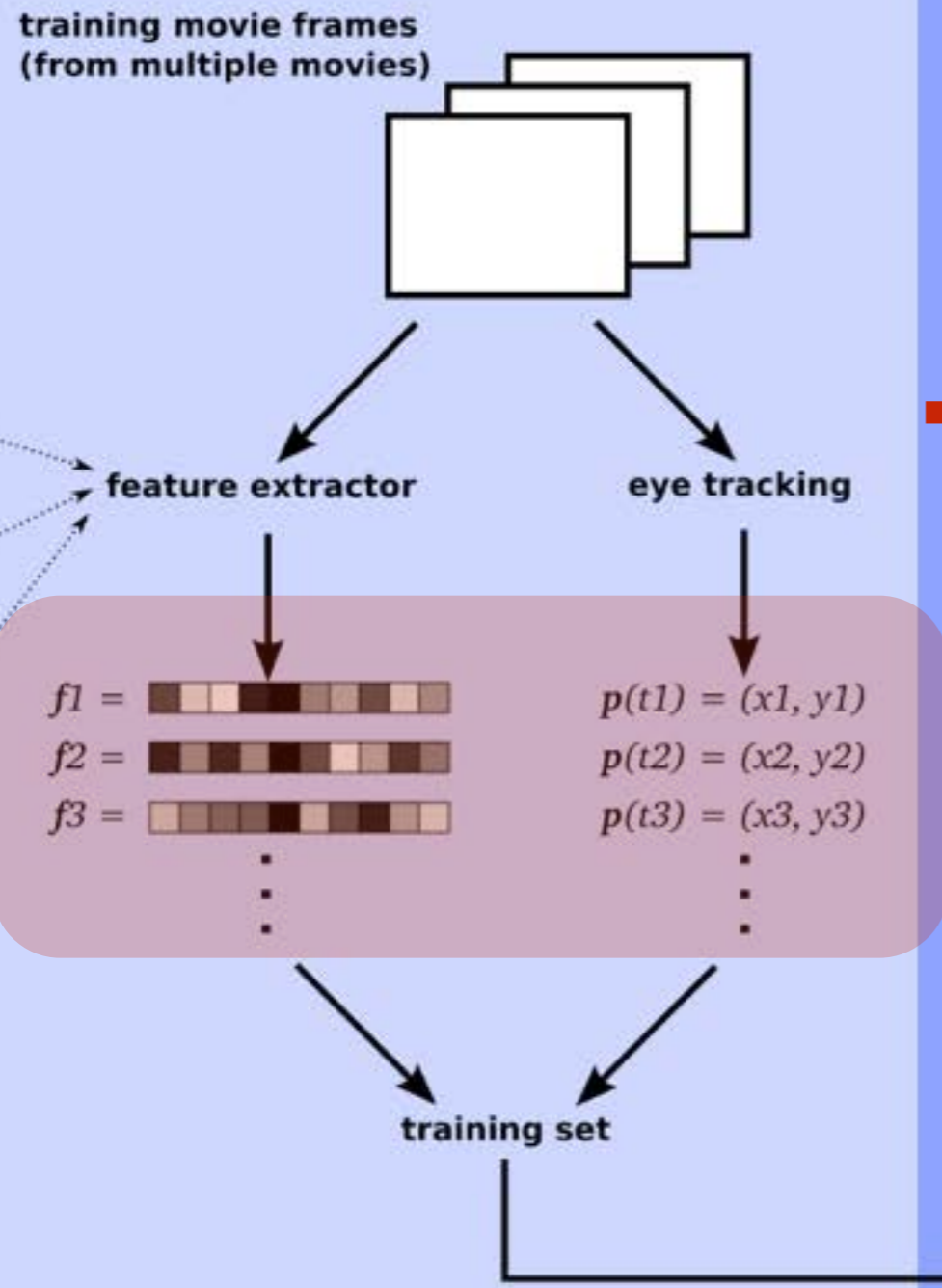


bottom-up



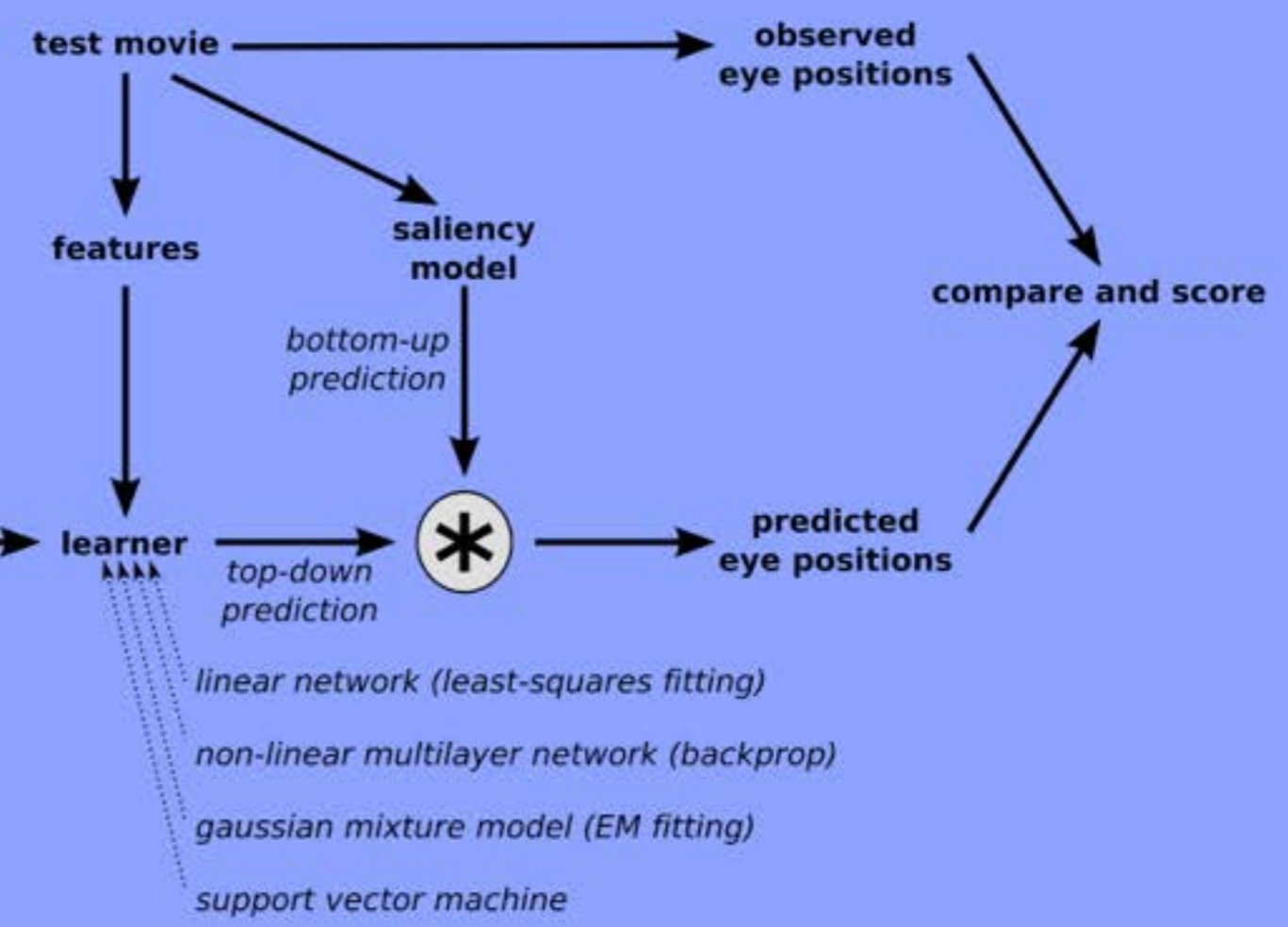
bottom-up + top-down

train



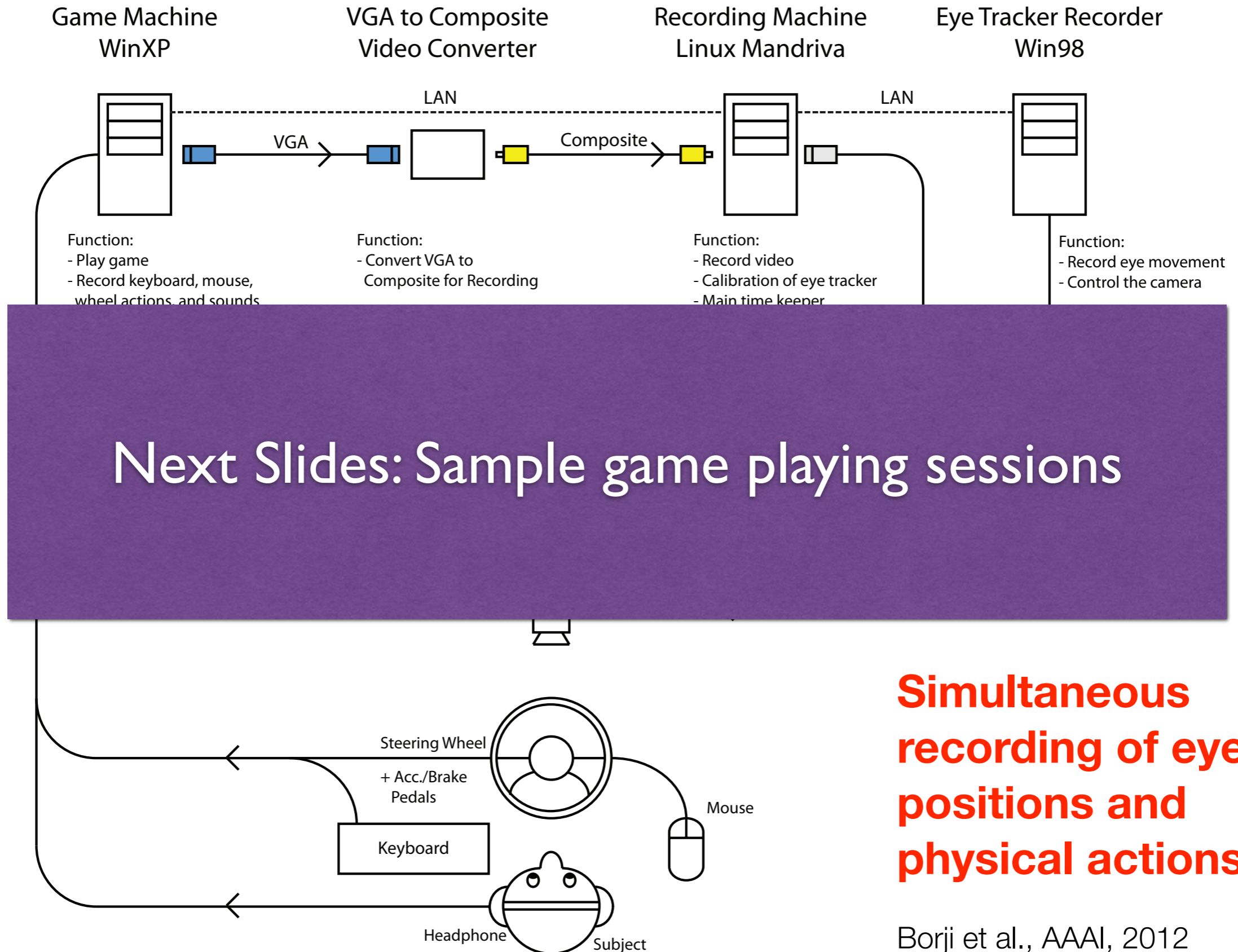
test

TASK



Peters & Itti, IEEE CVPR 2007;
Borji et al., IEEE CVPR 2012;
Borji et al., IEEE T. SMC-A 2014

Experimental setup



Borji et al., AAAI, 2012
Borji et al., IEEE SMC, 2014



1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20

5 (4) 7
Goal (Goal Reached?)

LEVEL 5 MENU



Mouse: L M R Key:



Mouse: n/a

Key:

1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20



 **PLAY**



\$0

Goal: \$150

Pause

Bayesian object-based Model

- In general we are interested in: $P(R_{t+1} | S_t)$
 - No direct access to S_t , therefore estimate it from observables

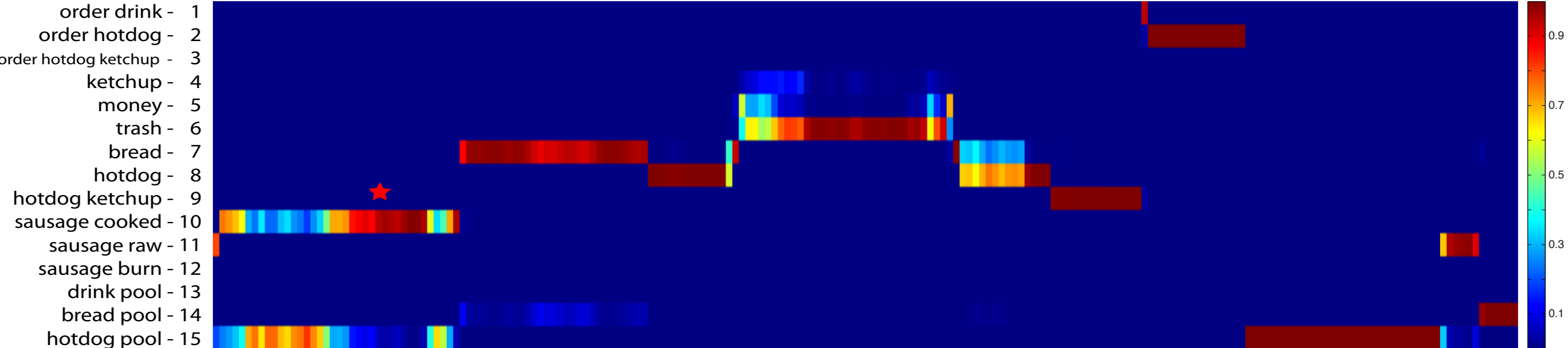
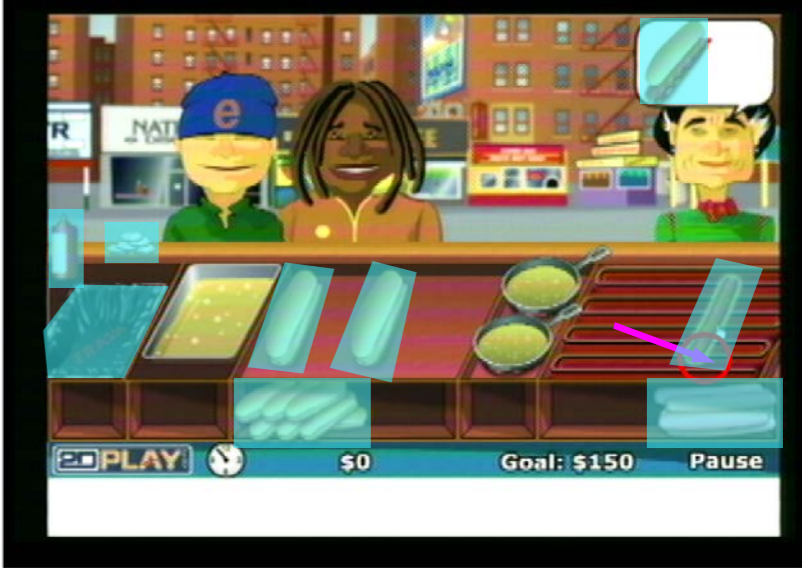
- A pdf over scene objects being attended:

Euclidean distance fixation location center of the j-th object
 spatial decay

$$z(o^j) = 1 / e^{\alpha d(X, C(o^j))}$$

$$P(o^j) = z(o^j) / \sum_{i=1}^N z(o^i)$$

sample frame



Bayesian object-based Model

$O_t = [o_t^1, o_t^2, \dots, o_t^N]$ Object-based representation of the scene at time t

Define some functions encoding properties of objects: $F_t = \{f^i(o_t^j)\}$

$X_{1:T} = [X_1, X_2, \dots, X_T]$ Sequence of attended spatial locations

$Y_{1:T} = [Y_1, Y_2, \dots, Y_T]$ Sequence of attended objects

$C_{1:T} = [C_1, C_2, \dots, C_T]$ Sequence of selected actions

$F_{1:T}^{1:N} = [F_1^{1:N}, F_2^{1:N}, \dots, F_T^{1:N}]$ Sequence of object-level scene representations

Full task-dependent joint probability:

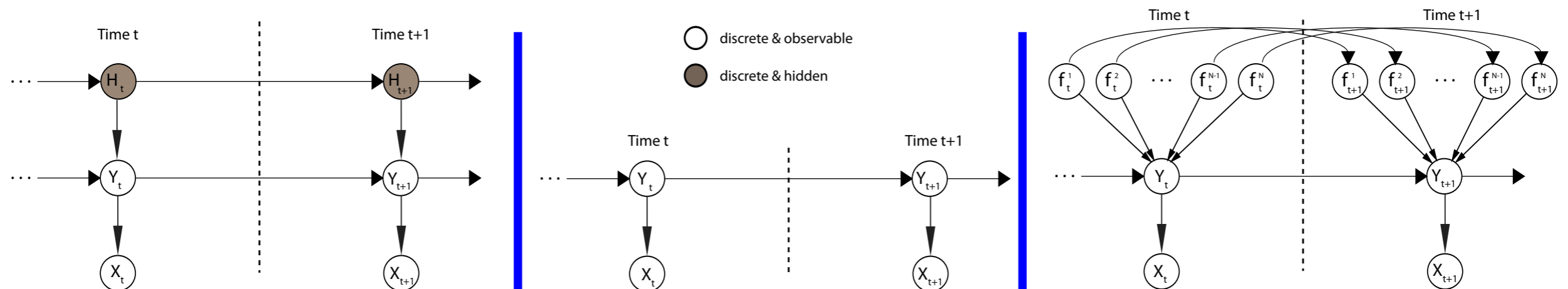
$$P(X_{1:T}, Y_{1:T}, F_{1:T}^{1:N}) = P(X_{1:T}, Y_{1:T} | F_{1:T}^{1:N}) P(F_{1:T}^{1:N}) = P(X_{1:T} | Y_{1:T}) P(Y_{1:T} | F_{1:T}^{1:N}) P(F_{1:T}^{1:N}) = \\ \prod_{j=1}^N P(F_1^j) P(Y_1 | F_1^j) P(X_1 | Y_1) \times \prod_{t=2}^T \prod_{j=1}^N P(Y_t | F_t^j) P(Y_t | Y_{t-1}) \times \prod_{t=2}^T P(X_t | Y_t)$$

Bayesian object-based Model

Conditional independence assumptions:

- 1) $X_t \perp\!\!\!\perp F_t^i | Y_t$ Gaze position is independent of scene given attended object
- 2) $F_t^i \perp\!\!\!\perp F_t^j$ No interaction between objects (assuming a general structure)
- 3) $F_{t+1}^i \perp\!\!\!\perp F_t^i$ Property of an object is independent of its property at previous time (given annotated data hence 100% accuracy in labeling)
- 4) $X_{t+1} \perp\!\!\!\perp X_t | Y_{t+1}$ Gaze positions are independent through time given attended object

Graphical representation of DBN models



You failed to meet the target...

Tip: Customers will give you less money if you serve them undercooked or overcooked hot dogs.

Needed: \$150

Earned: \$105

Total: \$0

Try Day Again

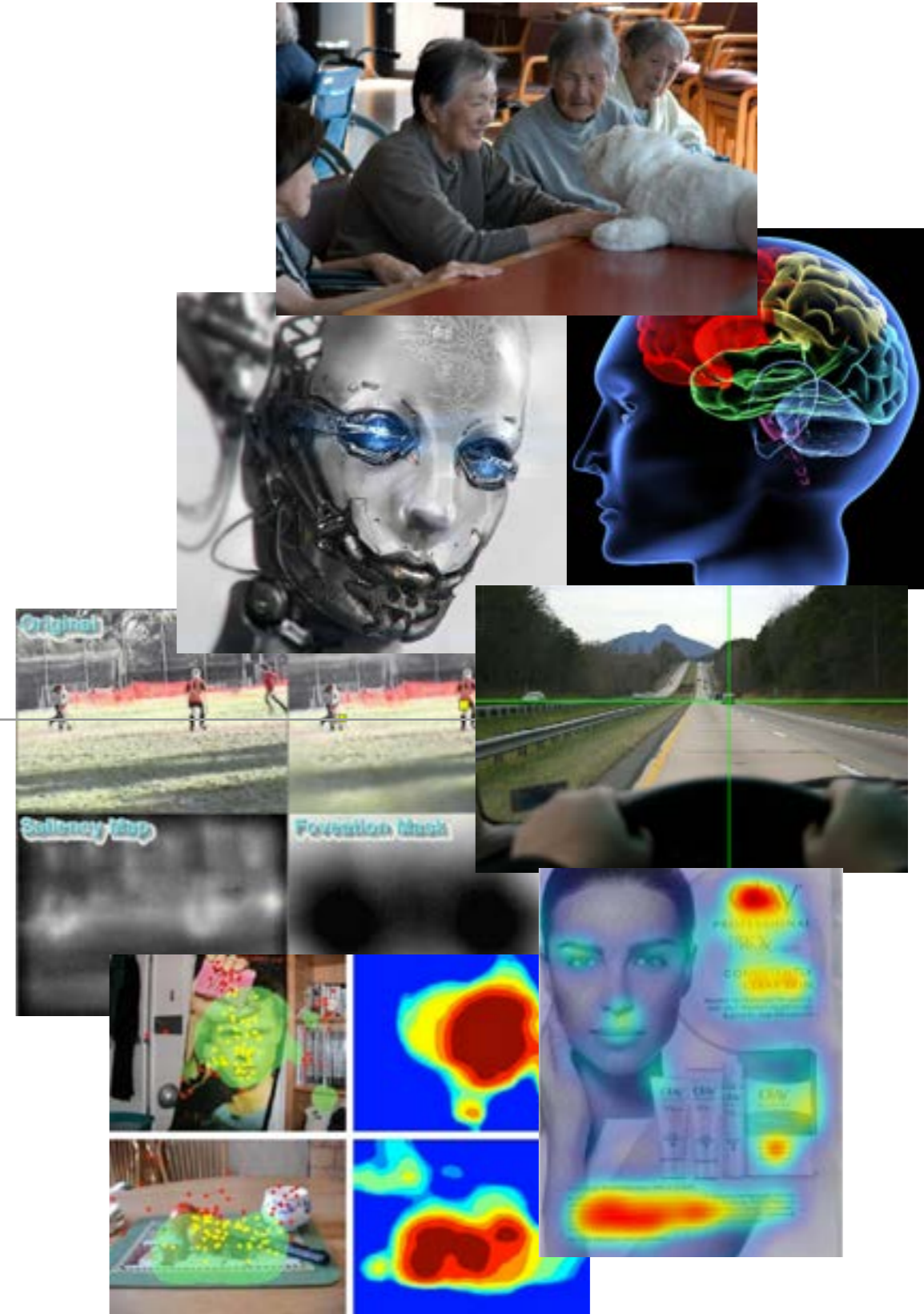
Submit Your Score

Main Menu



Applications

- Engineering
- Societal & Clinical

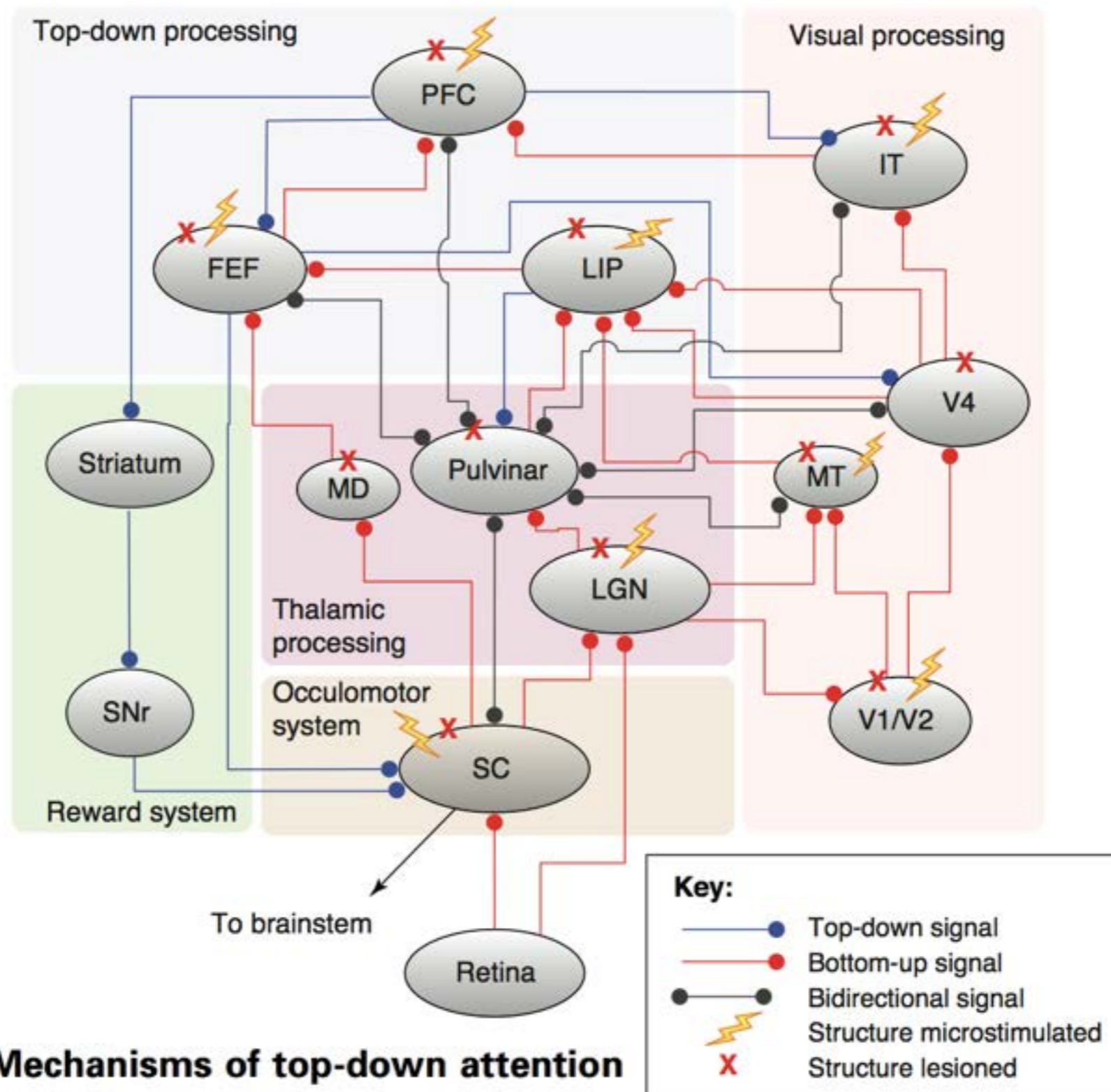


Applications

- Marketing and Advertisement
- Intent decoding / Mind reading
 - Patient vs. normal observer
- computer vision
 - Image re-targeting, segmentation,
 - compression, detection, recognition,
 - enhancement, etc.
- Robotics
 - Localization and Navigation
 - Human robot interaction, etc.



cognition ↔ attention

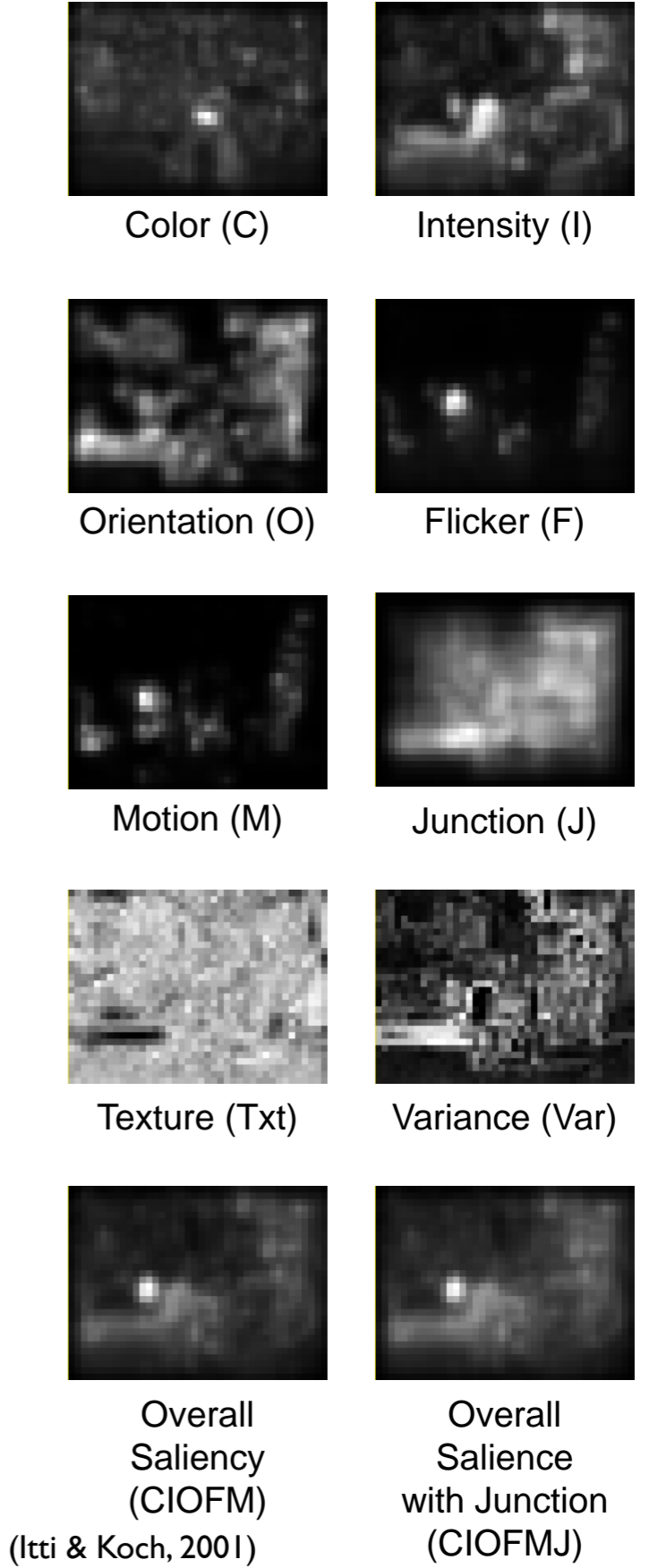
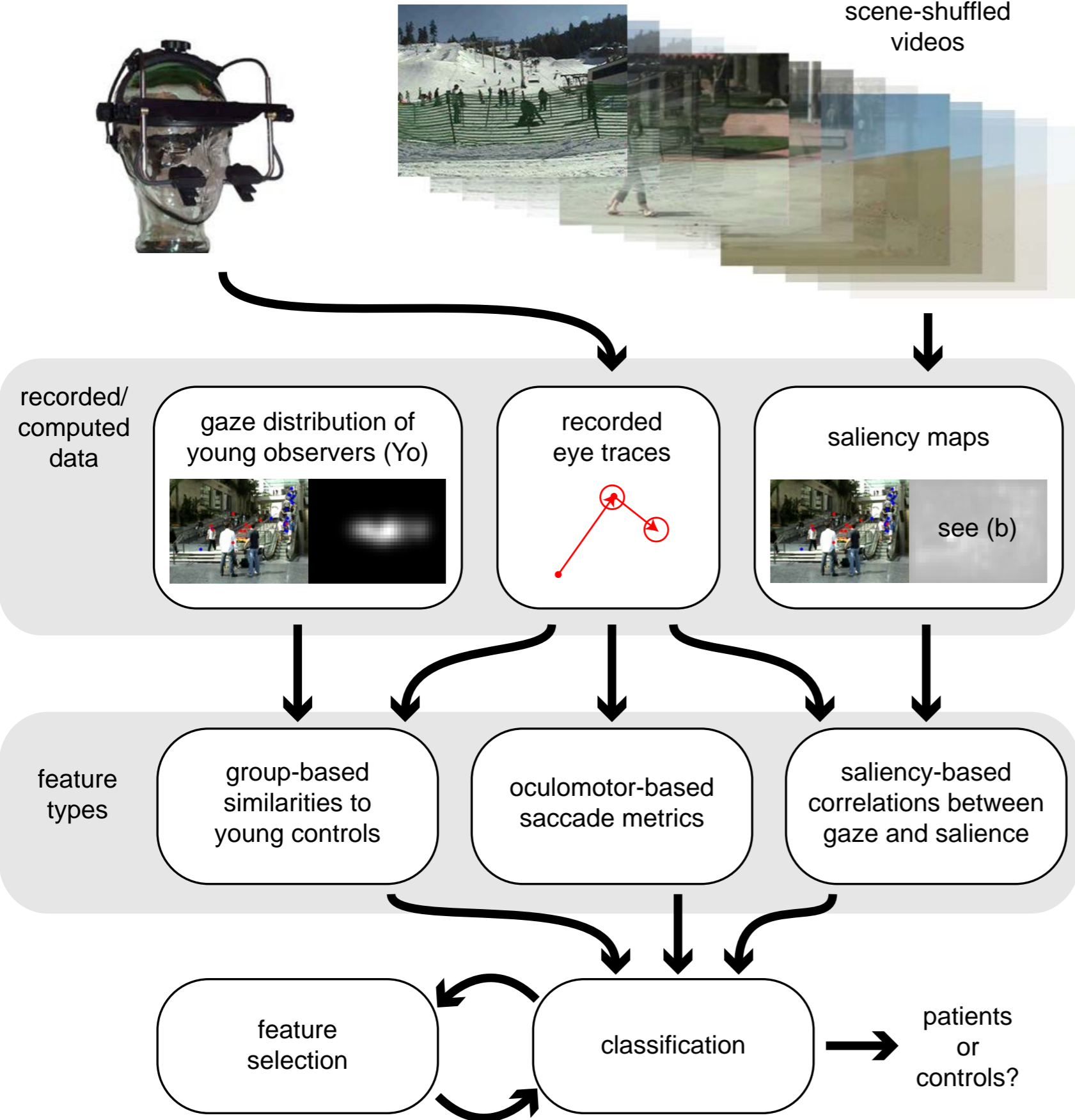


Mechanisms of top-down attention

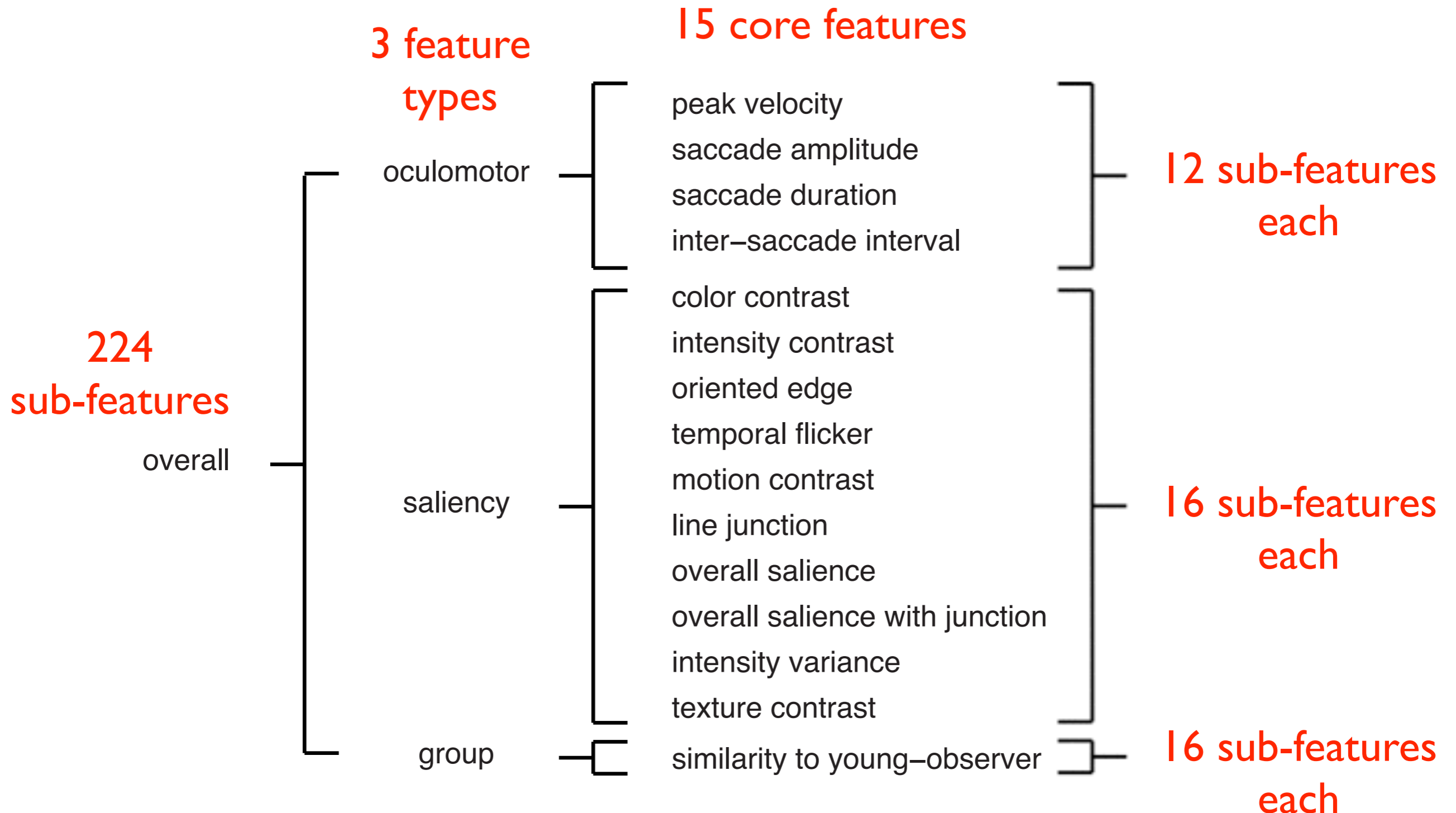
Farhan Baluch¹ and Laurent Itti^{1,2}

¹Neuroscience Graduate Program, University of Southern California, Los Angeles, CA, USA
²Department of Computer Science, University of Southern California, Los Angeles, CA, USA

saliency-based feature type

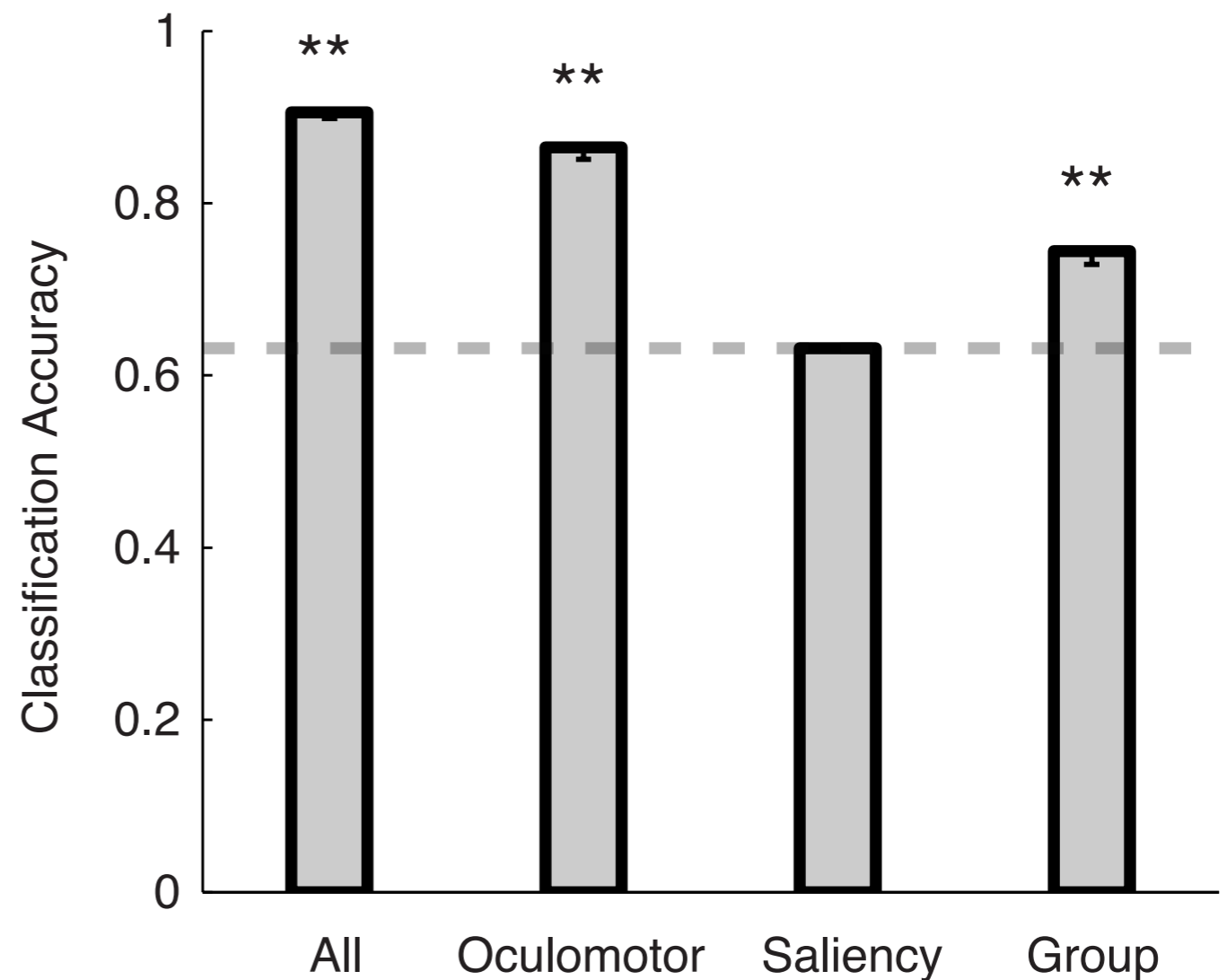
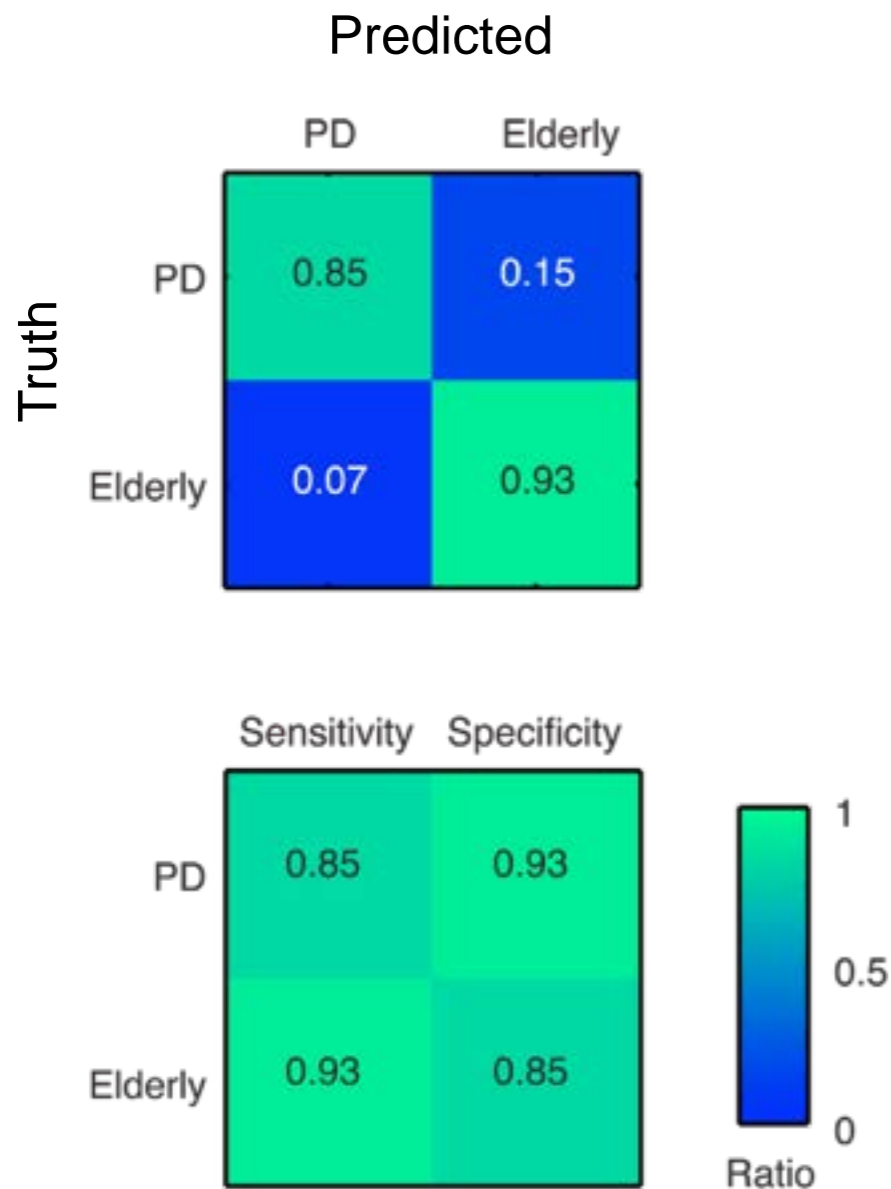


summary of classification features



Results (PD vs. Controls)

Classification Accuracy: 89.6% (5 sub-features)
(63.2% chance)



1280 (2,000 ± 0.001) × 10⁶
New test detects autism and ADHD as young as 6 months, can also diagnose Parkinson's early in elderly.
(queensu.ca)
submitted 11 days ago by robomonkeyscat
865 comments share

top 500 comments

[-] refanius 2 points 11 days ago
My excitement is founded on the versatility of this testing procedure and the potential accuracy which may be developed in the future. It is possible that this method will become more accurate and perform more quickly due to the deterministic nature of the problem. The trait measurements which are being used in this study were mostly ineffective at measuring PD. "Only 5 of 224 sub-features selected as most discriminative" for PD identification, indicating that substantial improvements in accuracy certainly room for improvement, as always accuracy.
If you read the study, you'll see that they "controls". Given the sizes of feature and p a bit more before taken as proof of a new focused feature selection and still found 9 improving for time efficiency.
As a first foray into this method for diagnosing looking at one method which can diagnose 10% of the subfeatures which are being measured only measured the 5 relevant subfeatures against. Remember that the data for this time, this method could outpace human eye. In addition, only 5 subfeatures were relevant of a total 224 subfeatures being measured with the other 90% of subfeatures which r
With appropriate development, I think the improved ability to detect neurological disorders diagnoses efficiency, but certainly producing
permalink parent

search reddit

this post was submitted on 15 Sep 2012
1,280 points (63% like it)
2,931 up votes 1,651 down votes
shortlink: <http://redd.it/zy9ur>

username password
 remember me reset password login

SCIENTIFIC AMERICAN™

Permanent Address: <http://www.scientificamerican.com/article.cfm?id=eye-tracking-software-may-reveal-autism-and-other-brain-disorders>

Eye-Tracking Software May Reveal Autism and other Brain Disorders

The eyes of people with neurological conditions, including ADHD and Parkinson's, have a distinctive motion that could form the basis of clinical diagnosis
By Nadja Popovich | Tuesday, June 18, 2013 | 3 comments

Eye-tracking has become the tech trend du jour. Advertisers use data on where you look and when to better capture your attention. Designers employ it to improve products. Game and phone developers utilize it to offer the latest in hands-free interaction.

But eye-tracking can do more than help sell products or give your finger a rest while playing Fruit Ninja. Years of research have found that our tiny, rapid eye movements called saccades serve as a window into the brain for psychologists just as for advertisers—but instead of giving clues about our preferred cookie brands (pdf), they elucidate our inner mental functioning. The question is, can capturing

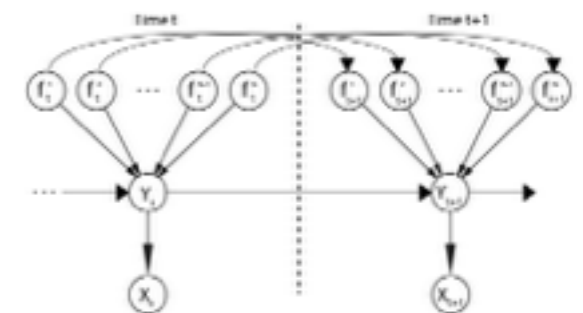
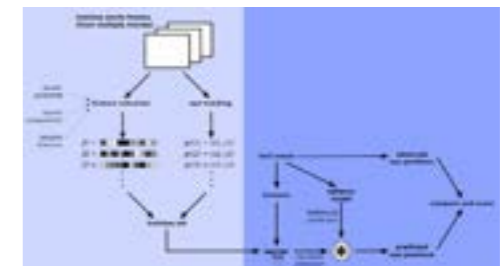
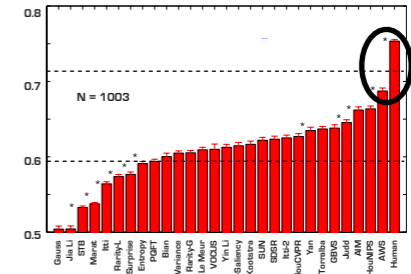


Related Topics

- 1 - Insight problem solving/ Theory of mind
- 2 - Mind reading/ Intent decoding
- 3 - Category and feature learning
- 4 - Visual Search/ Search games/ Foraging
- 5 - Active learning/ Online learning
- 6 - Scene understanding and perception
- ...

Summary, discussion and conclusions

- In spite of recent progress, there is still a gap between BU models and inter-observer model in fixation prediction
- Modeling top-down attention is a hard problem since different tasks need different attentional behaviors
- Most previous studies on TD attention are devoted to simple laboratory scale tasks and stimuli
- We proposed several models which capture task demands better than all previous models, using combined information from saliency, gist, actions, and objects
- These models can be used to assess internal mental state of controls and patients with neurological disorders



Credits:



Dicky N. Sihite



Daniel Parks



Laurent Itti

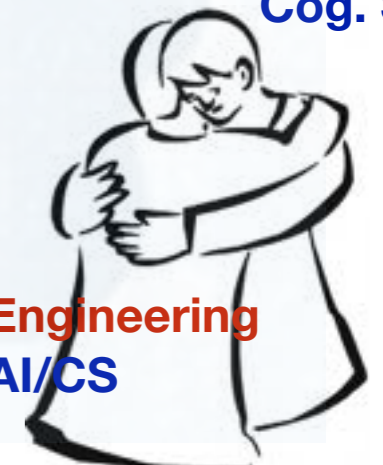
Sponsors:



Thanks for your attention



Science
Cog. Sci



Engineering
AI/CS

