



Computational models for predicting gaze direction in interactive virtual environments



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introduction

We use *fully-computational, autonomous* models to predict eye movements in a *dynamic and interactive* visual task with *naturalistic stimuli*.

We move beyond purely stimulus-driven bottom-up models, and introduce a simple model that captures task-dependent top-down influences on eye movements.

Previous studies have either relied on qualitative/descriptive models, or have not used naturalistic interactive stimuli.

conclusions

- Purely bottom-up models are able to predict eye position significantly better than chance, but not as well as in passive-viewing conditions
- Combining the bottom-up model with a simple model of top-down, task-dependent influences leads to significantly improved eye position prediction
- This kind of model could be used in autonomous machine vision situations, such as interactive virtual environments

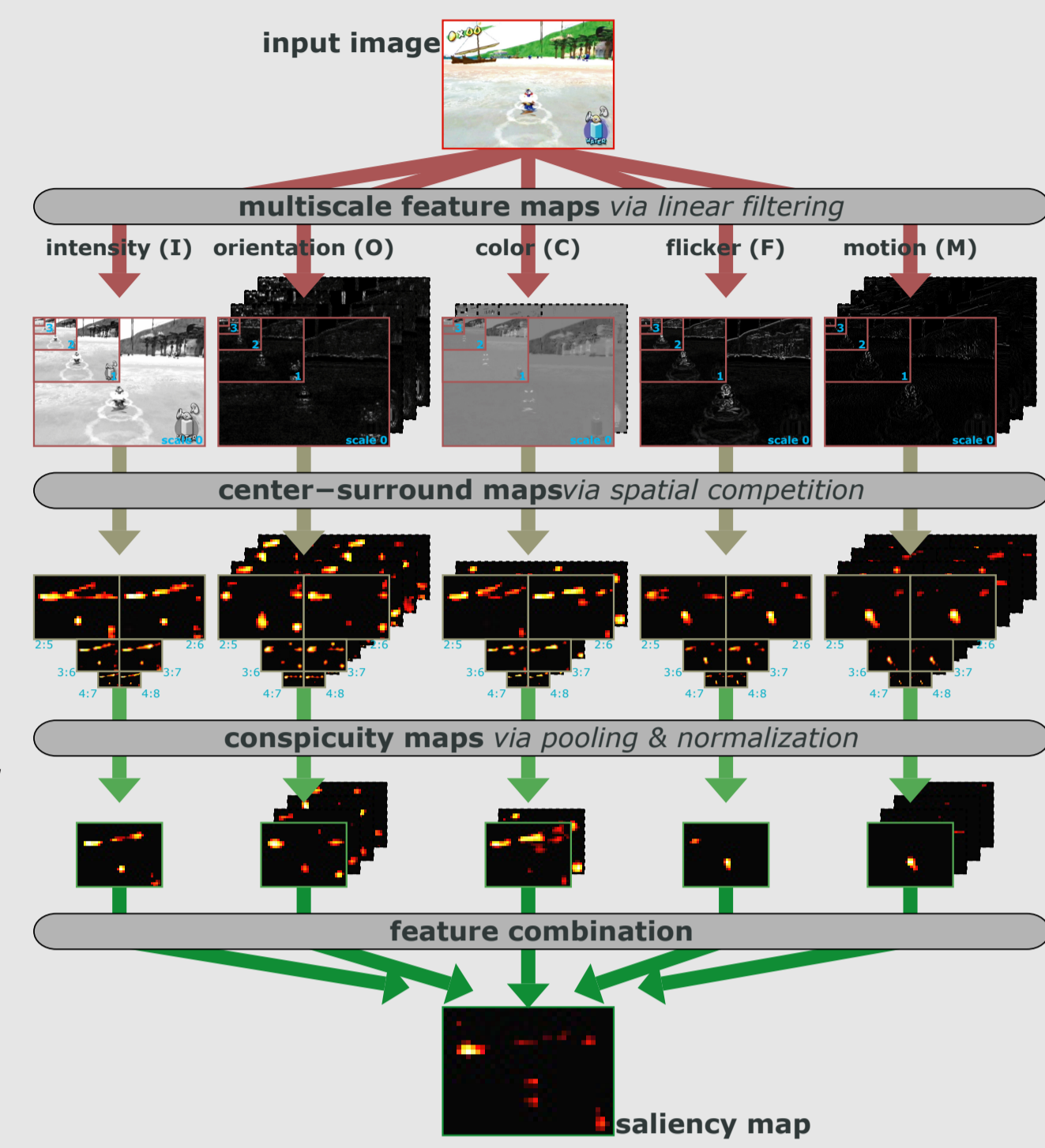
videogame stimuli

- Nintendo GameCube games
- 24 sessions, 5 minutes each
- eye movements recorded during game play



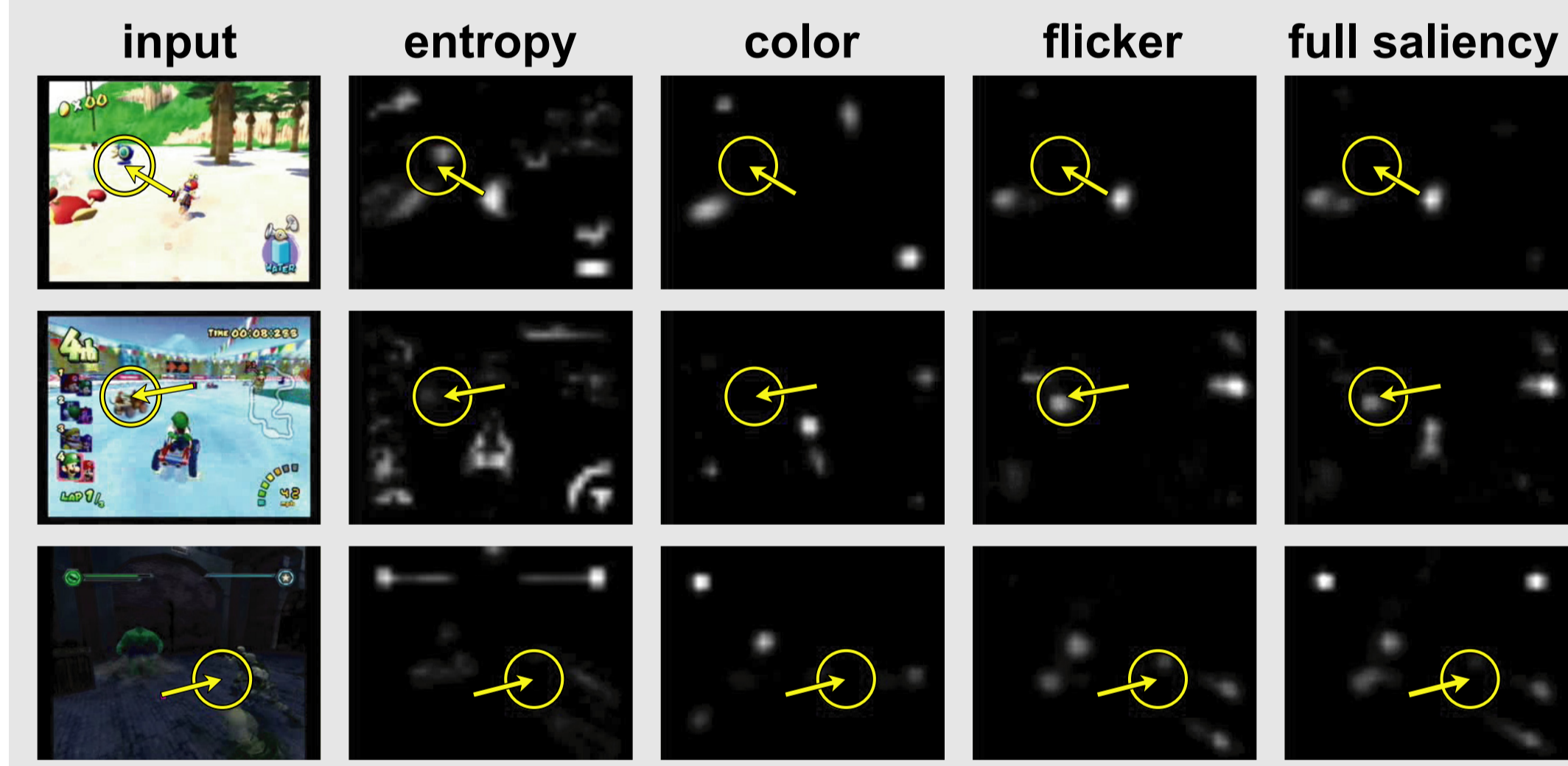
bottom-up model

- input processed through as many as 5 multi-scale feature channels
- different versions of the model include different combinations of features
- *saliency is a global property*: outliers detected through coarse global competition



bottom-up predictions

- sample frames illustrate the output of the models
- for illustration, these frames are selected at the time when a saccade is just beginning
- yellow arrows indicate the saccade path



metrics: model scoring

- two different metrics used to test how well the models predict human eye movements

normalized scanpath saliency (NSS)

- each saliency map (or control map) is normalized to have mean=0 and stdev=1
- human scanpath is overlaid on normalized saliency map
- normalized saliency value is extracted at each fixation location
- these values are summed to give the normalized scanpath saliency (NSS)
- NSS can be compared with the distribution of random saliency values

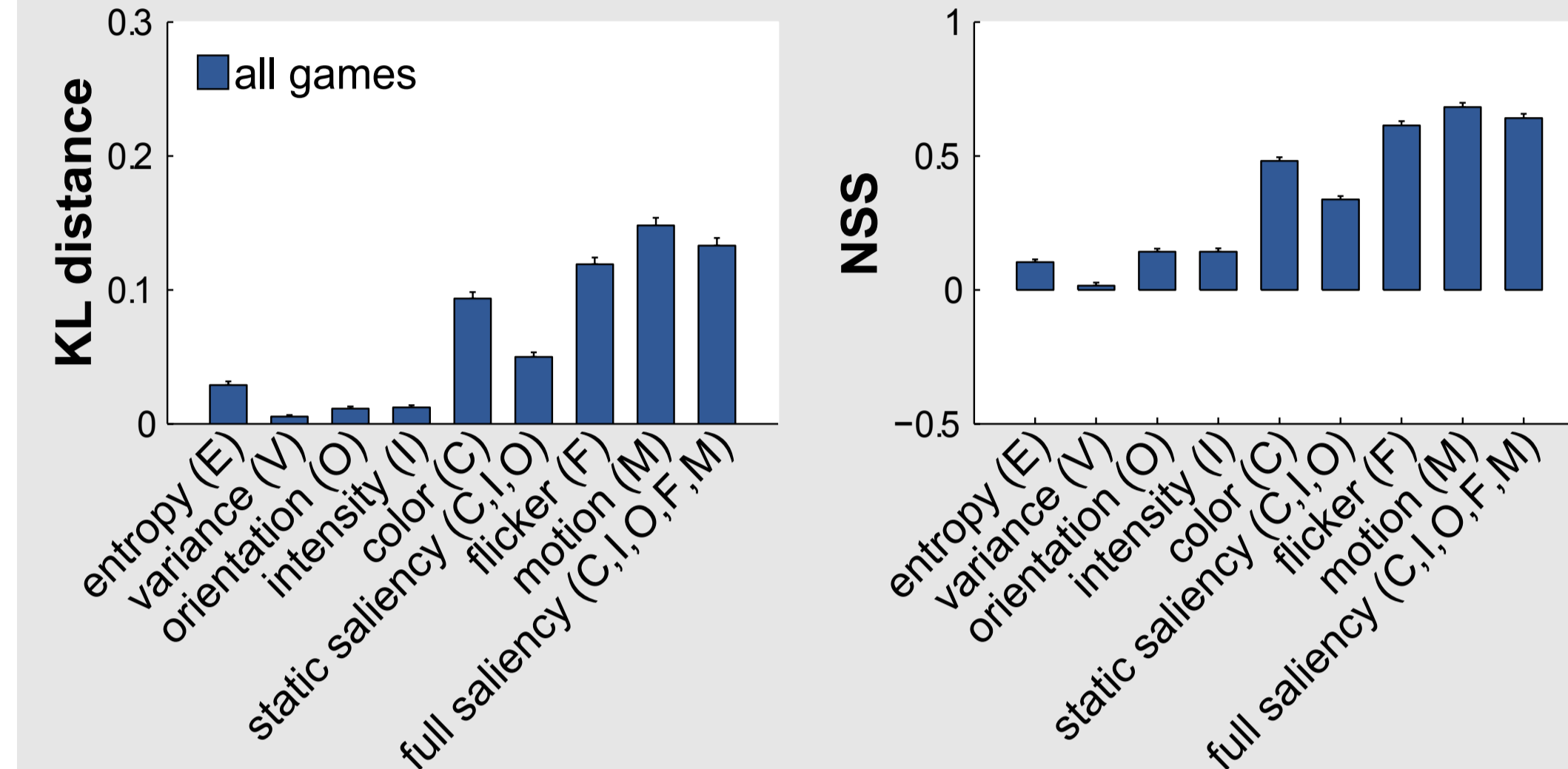
Kullback-Leibler (KL) distance

- how well can fixated and non-fixated locations be distinguished, with no assumptions about decision criteria?

$$KL = 0.5 \cdot \sum_i p_i(f) \cdot \log(p_i(f)/p_i(nf)) + 0.5 \cdot \sum_i p_i(nf) \cdot \log(p_i(nf)/p_i(f))$$

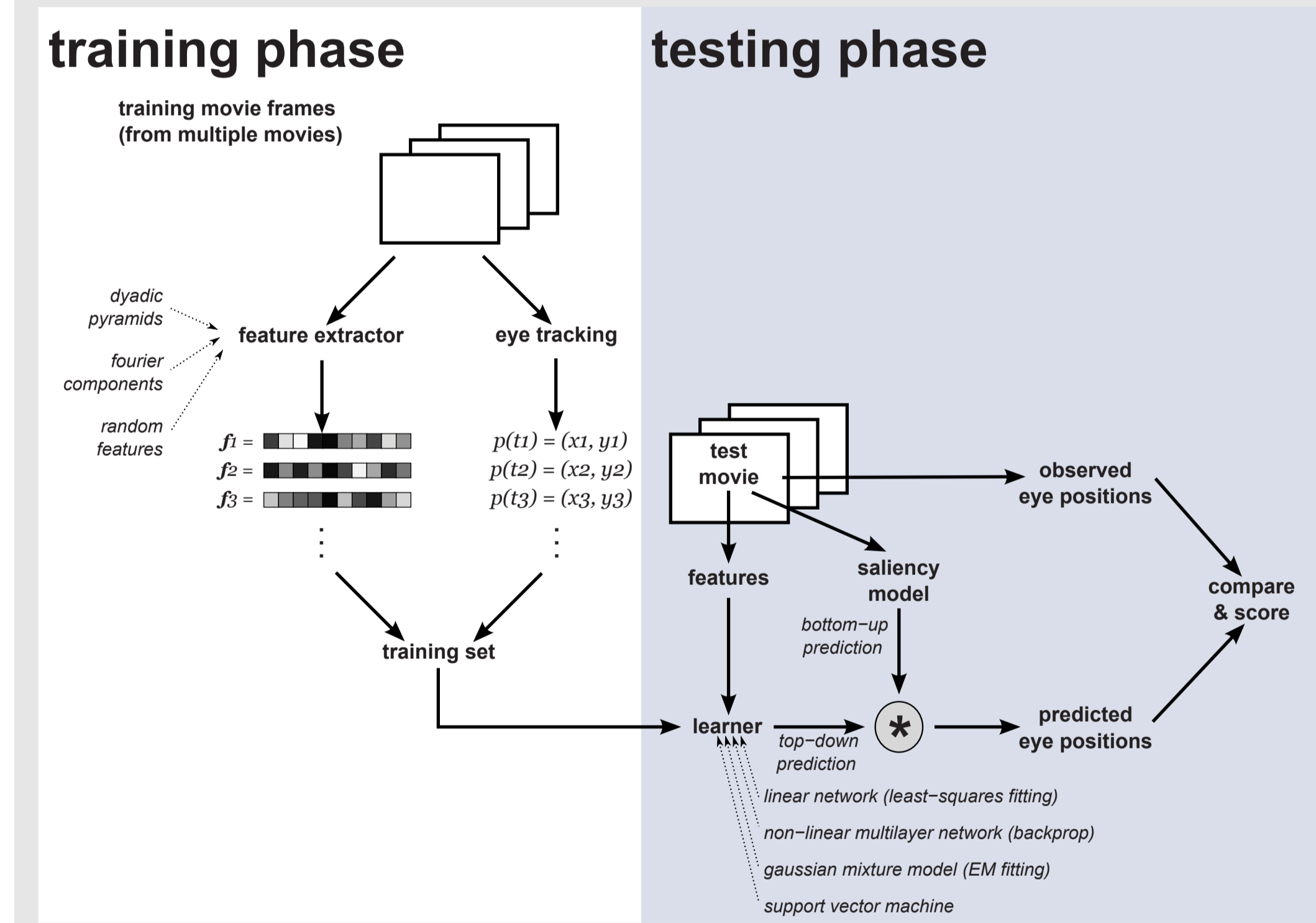
bottom-up results

- models score significantly above chance
- dynamic, global features work best
- but, scores in this *interactive task* are lower than in previous *passive-viewing* experiments



top-down model

- model learns to associate *image "gist" signatures* with corresponding *eye position density maps*
- in testing, a leave-one-out approach is used: for each test clip, the remaining 23 clips are used for training
- therefore, the model must be able to *generalize across game types* in order to successfully predict eye positions



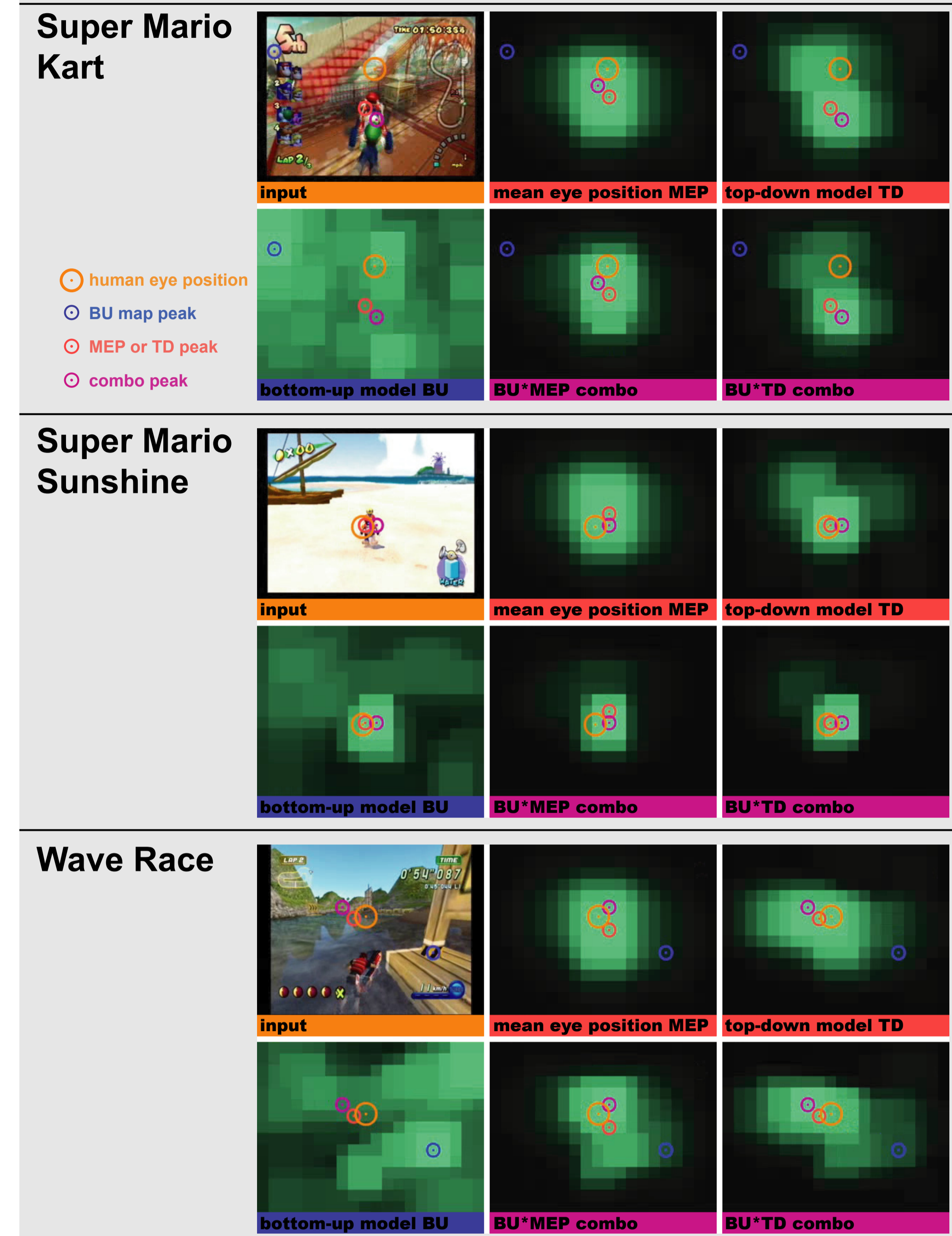
dyadic pyramid features

- **7 pyramids**
 - 1 luminance
 - 2 color
 - 4 orientation
- **2 scales per pyramid**
 - coarse
 - fine
- **32 features per scale**
 - 4x4 array of local mean
 - 4x4 array of local var.

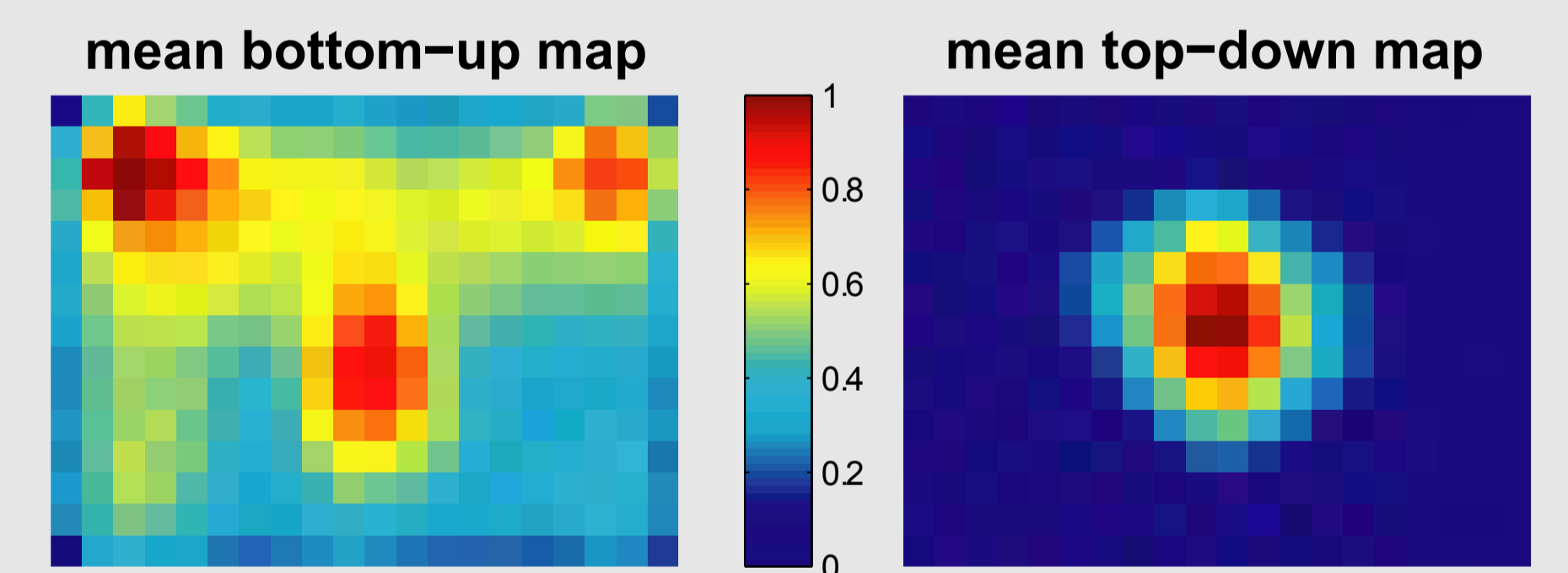


top-down predictions

- sample frames illustrating output of
 - bottom-up (BU) model alone
 - mean eye position (MEP) (a control condition)
 - BU combined with MEP
 - top-down model (TD) based on pyramid features
 - BU combined with TD

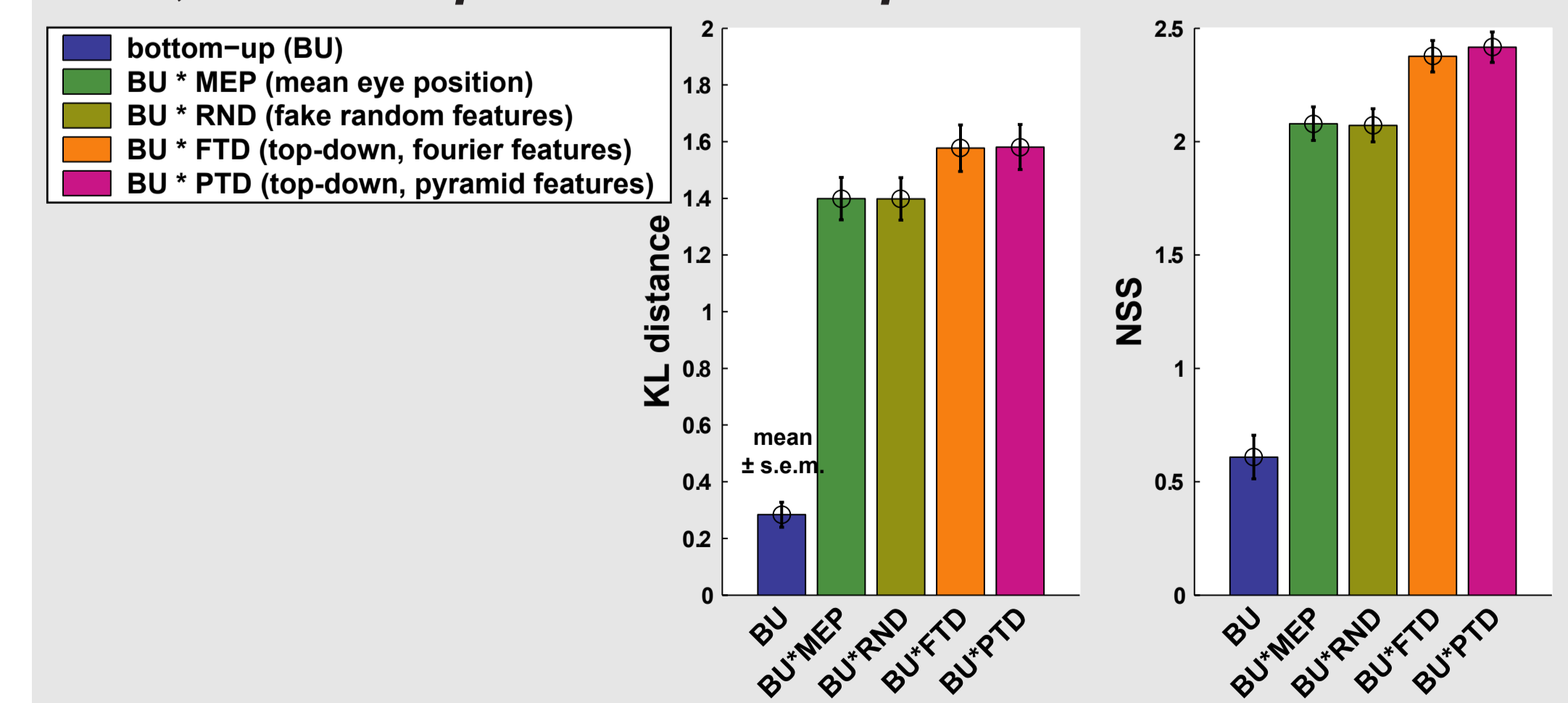


- average bottom-up and top-down maps across all frames
- bottom-up map reflects activity in the screen corners (game score, time counter, etc.) that is largely ignored by observers



top-down results

- a simple mean-eye-position control improves upon purely bottom-up performance by a factor of 3-4x
- but, *the full top-down models perform best*



acknowledgments

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