http://bit.ly/dlcv2018

#DLUPC

Day 3 Lecture 5

Saliency Prediction

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The importance of visual attention

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Why don’t we see the changes?

We don’t really see the whole image

We only focus on small specific regions: the **salient** parts

Human beings reliably attend to the same regions of images when shown

What we perceive

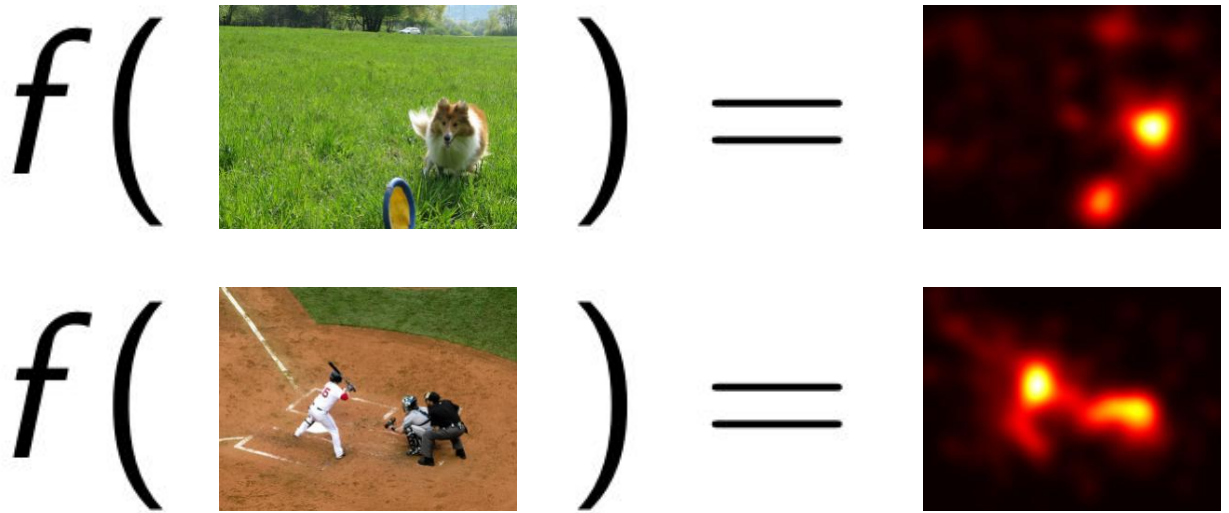
Where we look

What we actually see

Saliency prediction

Produce a **computational model of visual attention**: predict where humans will look.

Often want to map an image to a **heatmap** (saliency map).



Salient object detection?

Often confused with saliency prediction, but a different task.

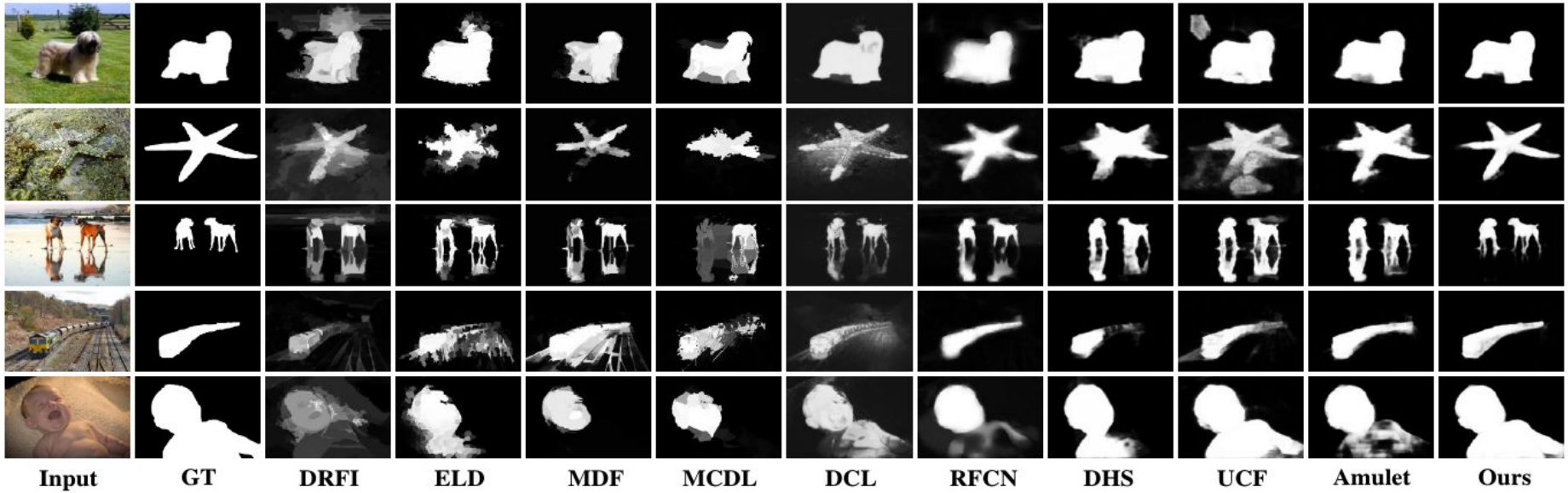


Figure from: Progressive Attention Guided Recurrent Network for Salient Object Detection, CVPR 2018

Datasets

MIT 300

300 natural indoor and outdoor scenes.

39 observers. 3 sec free view.

ETL 400 ISCAN eye tracker

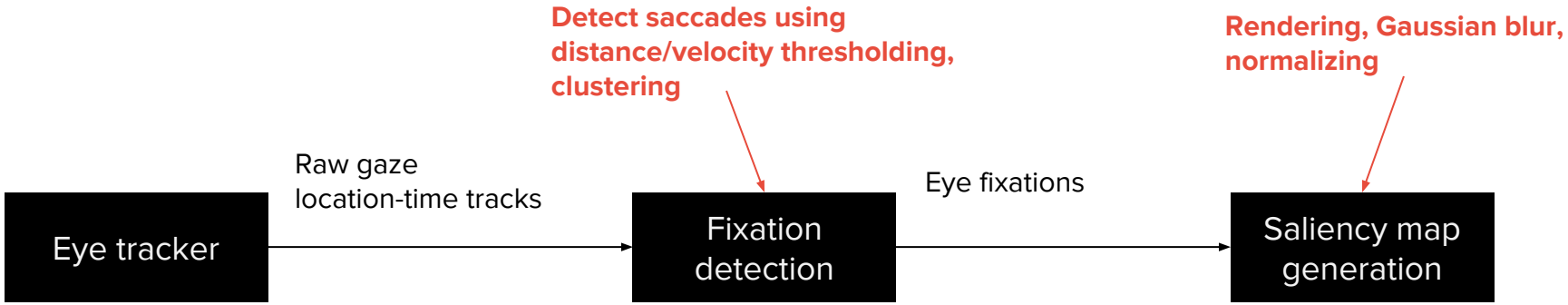
Test set only: no training data or public ground truth

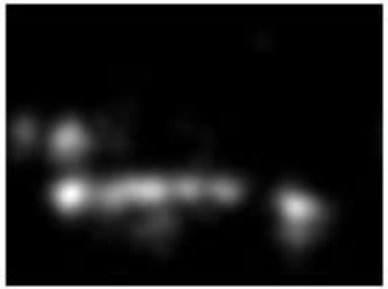
http://saliency.mit.edu/results_mit300.html

A Benchmark of Computational Models of Saliency to Predict Human Fixations [MIT tech report 2012]

Fixations and saliency maps

Raw eye tracker data needs to be processed to produce saliency maps





MIT 1003

1003 natural indoor and outdoor scenes.

15 observers. 3 sec free view.

ETL 400 ISCAN eye tracker

Training dataset for MIT 300

Learning to Predict where Humans Look [ICCV 2009]

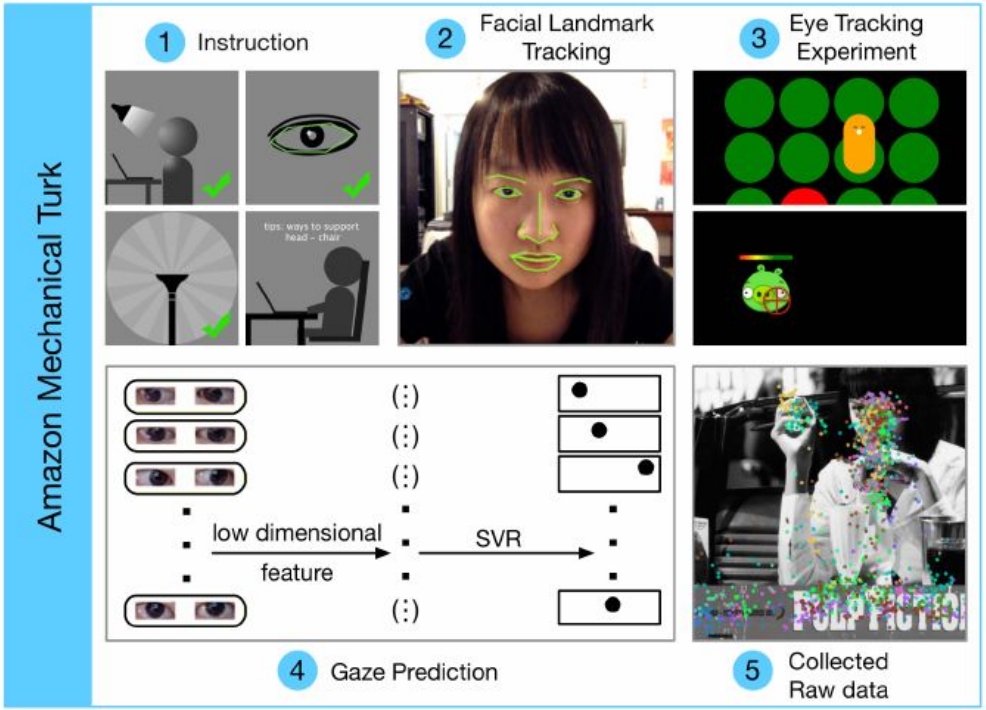
iSUN

Large scale dataset of natural scenes

20,608 images with avg. 3 observers each

Collected using webcams and Amazon Mechanical Turk

Used in LSUN challenge 2015/2016



Xu et al. TurkerGaze: Crowdsourcing Saliency with Webcam based Eye Tracking arXiv 2015.

SALICON

Another large scaled dataset of images from MS COCO dataset

10K train, 5K val, 5K test

Simulated crowdsourced attention using **mouse** movements and **simulated artificial foveation**.

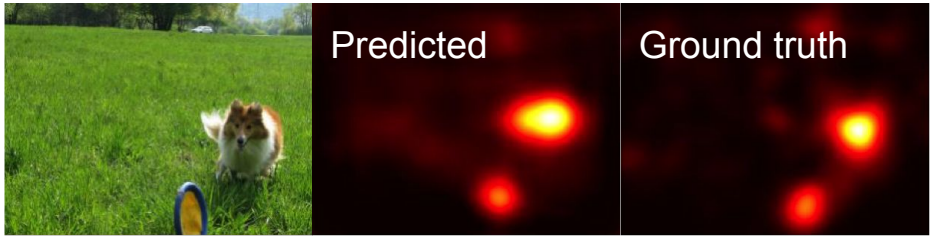
Jiang et al. SALICON: Saliency in Context, CVPR 2015

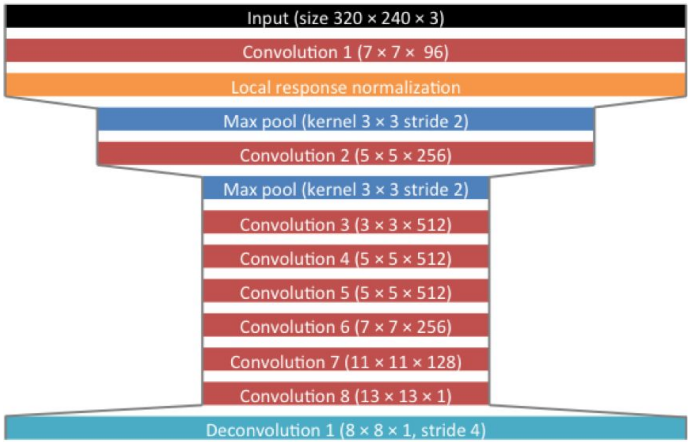
Models

SalNet: deep visual saliency model

Predict map of visual attention from image pixels (find the parts of the image that stand out)

- Feedforward 8 layer “fully convolutional” architecture
- Transfer learning in bottom 3 layers from pretrained VGG-M model on ImageNet
- Trained on SALICON dataset





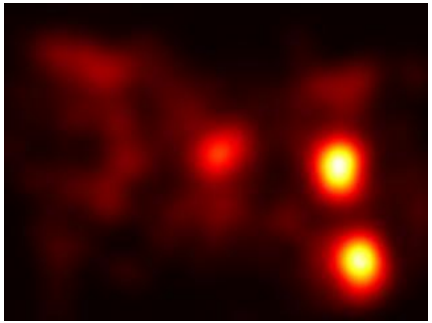
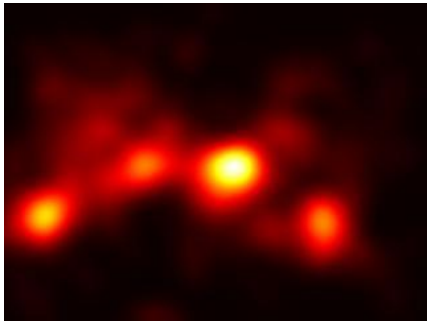
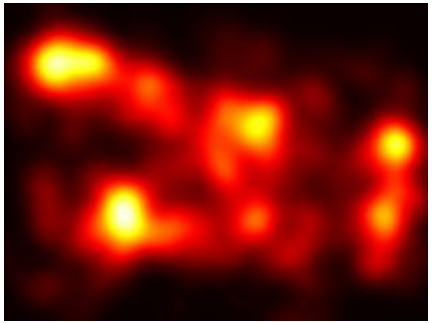
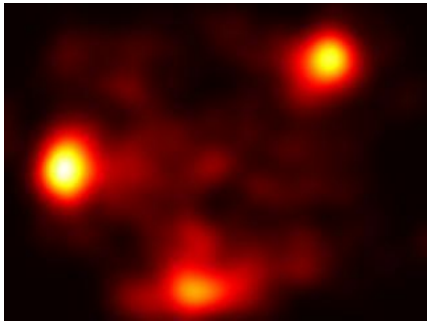
Pan, McGuinness, et al. **Shallow and Deep Convolutional Networks for Saliency Prediction**, CVPR 2016 http://arxiv.org/abs/1603.00845


Image
Ground truth
Prediction

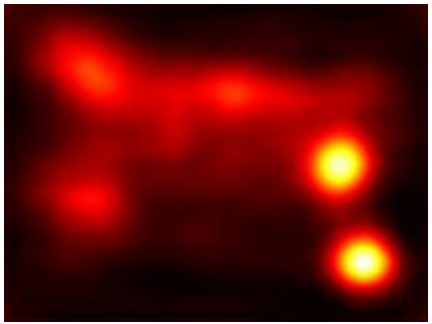
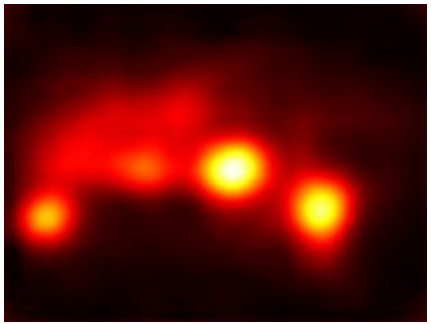
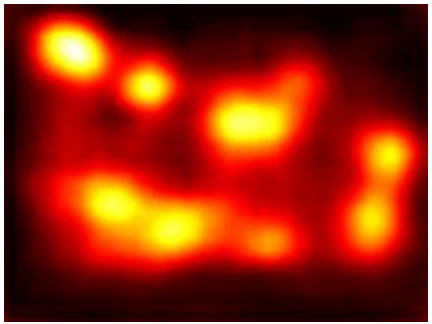
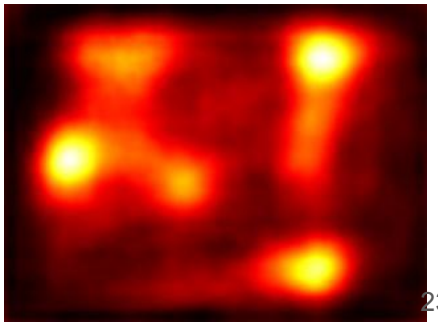
Image




Ground truth

Prediction

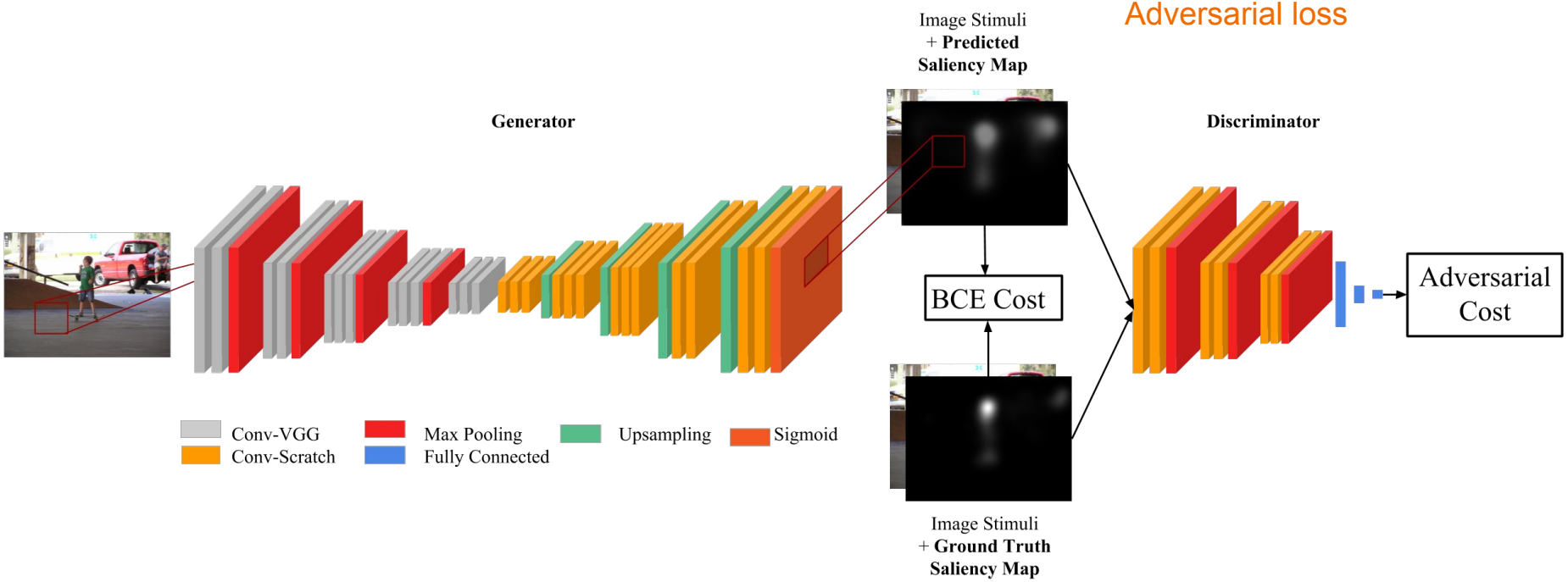





SalGAN

Data loss

$$\alpha \cdot \mathcal{L}_{BCE} - \log D(I, \hat{S}),$$

Adversarial loss



Junting Pan, Cristian Canton, Kevin McGuinness, Noel E. O'Connor, Jordi Torres, Elisa Sayrol and Xavier Giro-i-Nieto. "SalGAN: Visual Saliency Prediction with Generative Adversarial Networks." arXiv. 2017.

SalNet and SalGAN benchmarks

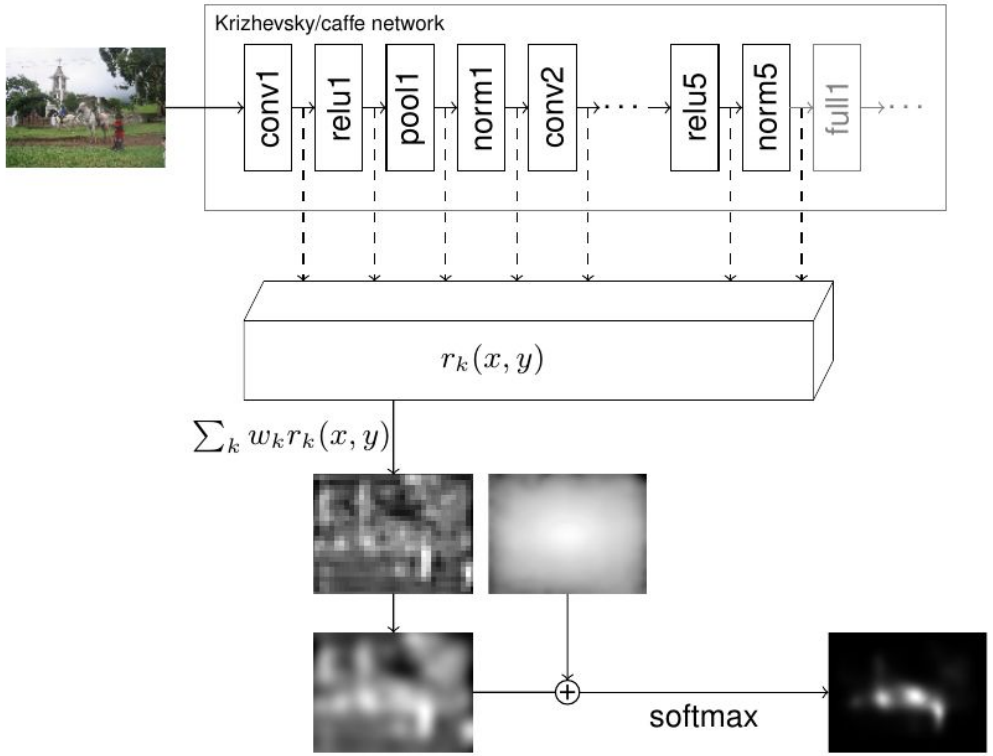
SALICON (test)	AUC-J ↑	Sim ↑	EMD ↓	AUC-B ↑	sAUC ↑	CC ↑	NSS ↑	KL ↓
DSCLRCN [24](*)	-	-	-	0.884	0.776	0.831	3.157	-
SalGAN	-	-	-	**0.884**	**0.772**	**0.781**	**2.459**	-
ML-NET [5]	-	-	-	(0.866)	(0.768)	(0.743)	2.789	-
SalNet [25]	-	-	-	(0.858)	(0.724)	(0.609)	(1.859)	-
MIT300	AUC-J ↑	Sim ↑	EMD ↓	AUC-B ↑	sAUC ↑	CC ↑	NSS ↑	KL ↓
Humans	0.92	1.00	0.00	0.88	0.81	1.0	3.29	0.00
Deep Gaze II [21](*)	0.88	(0.46)	(3.98)	0.86	0.72	(0.52)	(1.29)	(0.96)
DSCLRCN [24](*)	0.87	0.68	2.17	(0.79)	0.72	0.80	2.35	0.95
DeepFix [17](*)	0.87	0.67	2.04	(0.80)	(0.71)	0.78	2.26	0.63
SALICON [9]	0.87	(0.60)	(2.62)	0.85	0.74	0.74	2.12	0.54
SalGAN	**0.86**	**0.63**	**2.29**	**0.81**	**0.72**	**0.73**	**2.04**	**1.07**
PDP [11]	(0.85)	(0.60)	(2.58)	(0.80)	0.73	(0.70)	2.05	0.92
ML-NET [5]	(0.85)	(0.59)	(2.63)	(0.75)	(0.70)	(0.67)	2.05	(1.10)
Deep Gaze I [19]	(0.84)	(0.39)	(4.97)	0.83	(0.66)	(0.48)	(1.22)	(1.23)
iSEEL [29](*)	(0.84)	(0.57)	(2.72)	0.81	(0.68)	(0.65)	(1.78)	0.65
SalNet [25]	(0.83)	(0.52)	(3.31)	0.82	(0.69)	(0.58)	(1.51)	0.81
BMS [31]	(0.83)	(0.51)	(3.35)	0.82	(0.65)	(0.55)	(1.41)	0.81

Deep Gaze

Simple linear model trained on activations of all conv layers (upsampled) from AlexNet

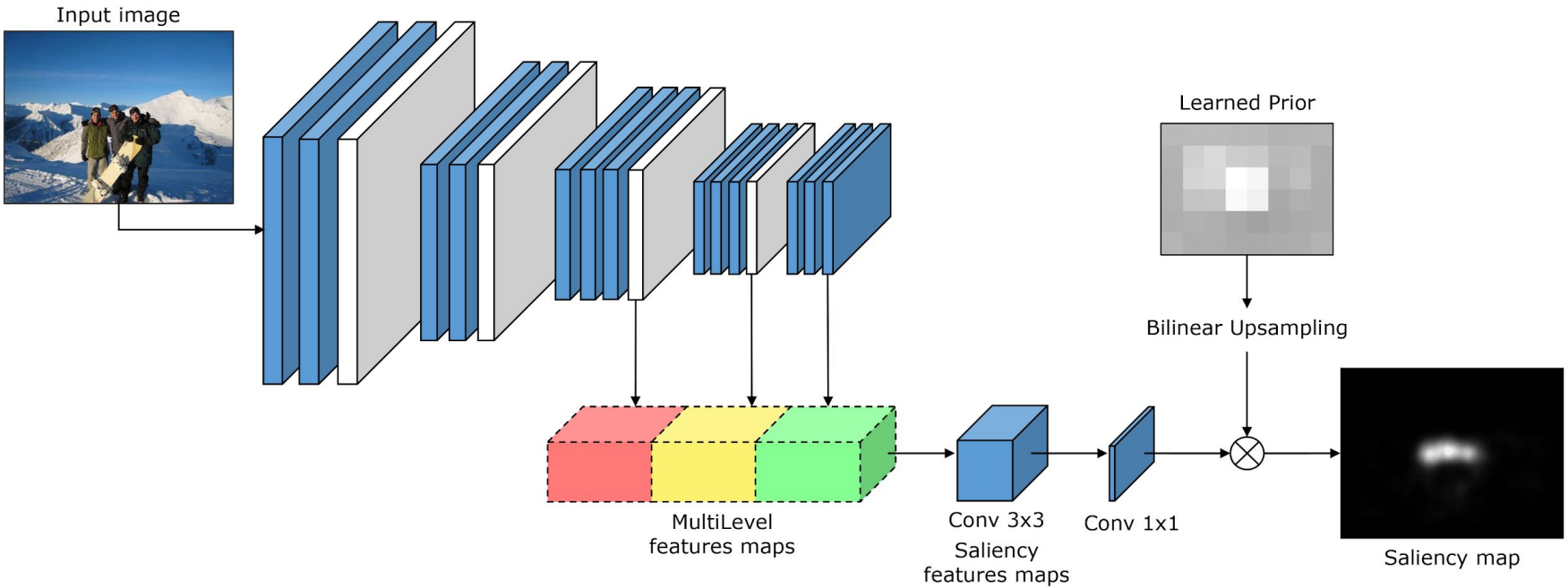
Softmax output over full image, categorical cross entropy.

L_1 regularization used to encourage sparsity.



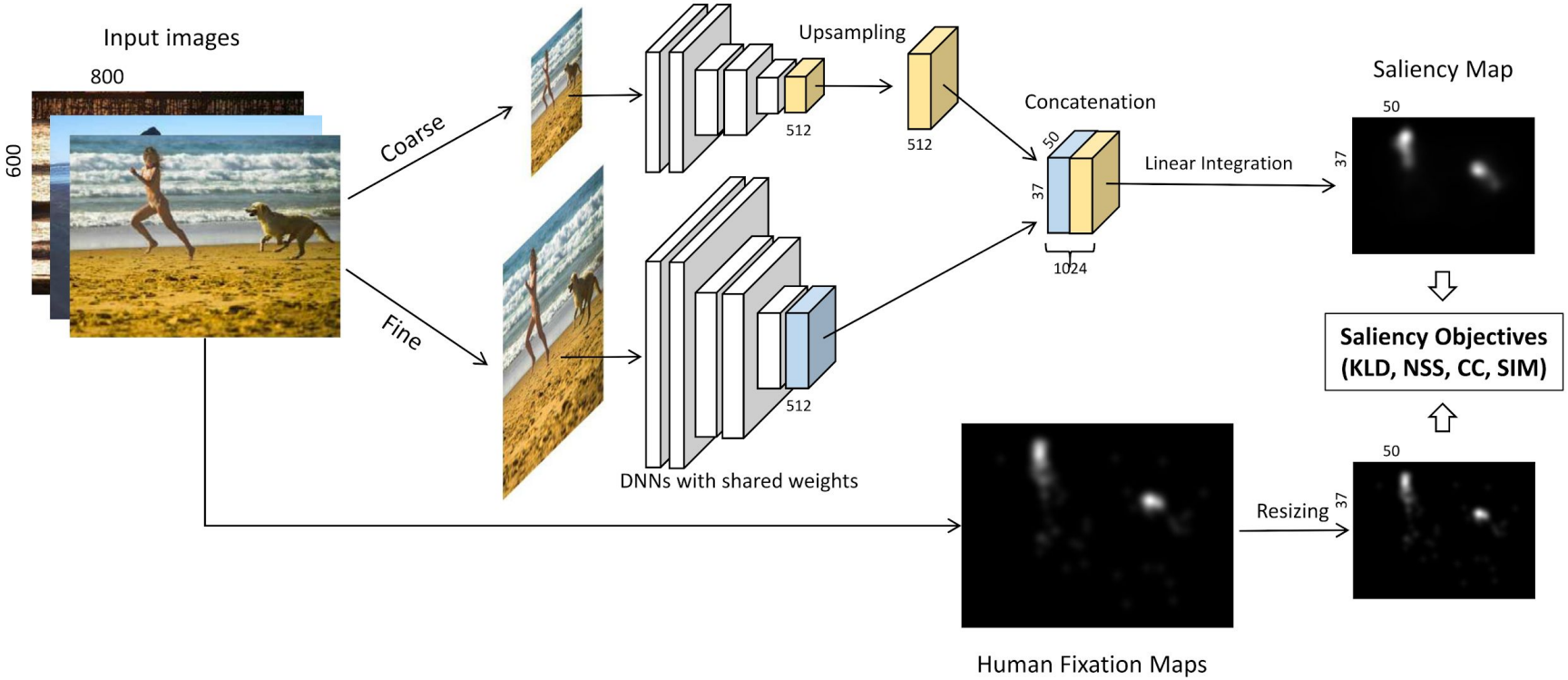
Kümmerer et al. Deep gaze 1: Boosting saliency prediction with feature maps trained on imagenet. ICLR workshops 2015

MLNet



Cornia et al. A Deep Multi-Level Network for Saliency Prediction. ICPR 2016.

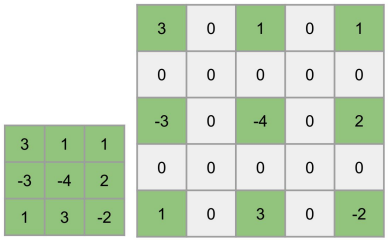
SALICON



Huang et al., SALICON: Reducing the Semantic Gap in Saliency Prediction by Adapting Deep Neural Networks, ICCV 2015

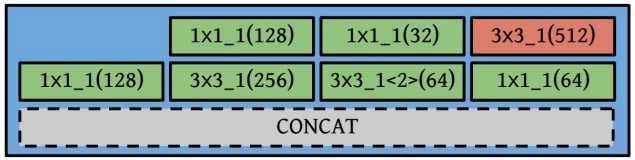
DeepFix

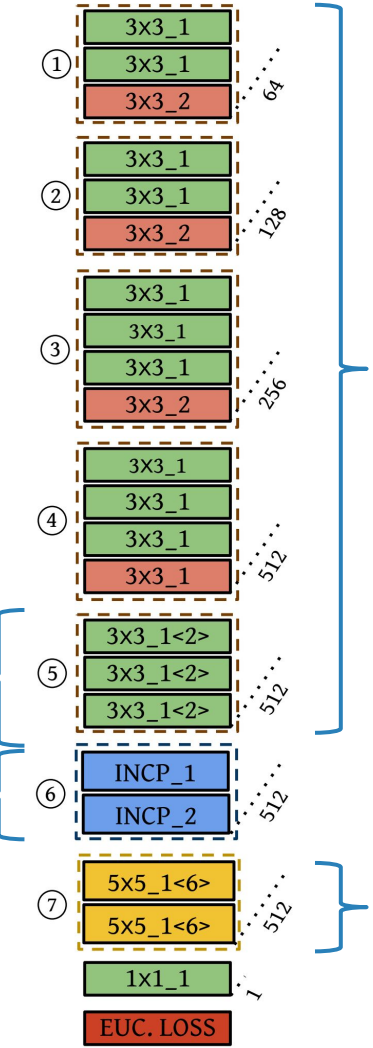
Kruthiventi et al. **DeepFix: A Fully Convolutional Neural Network for predicting Human Eye Fixations**
https://arxiv.org/abs/1510.02927



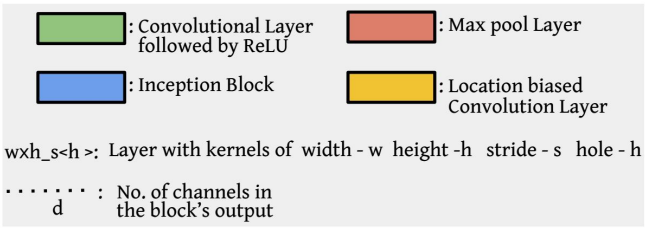
Dilated convolutions

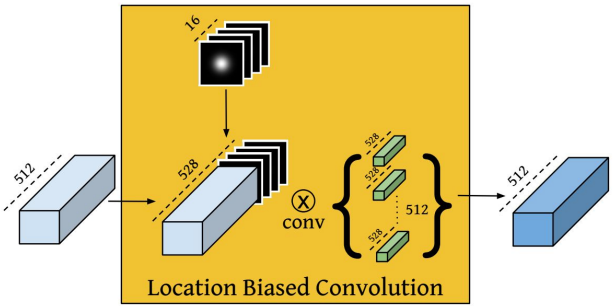
Inception layers





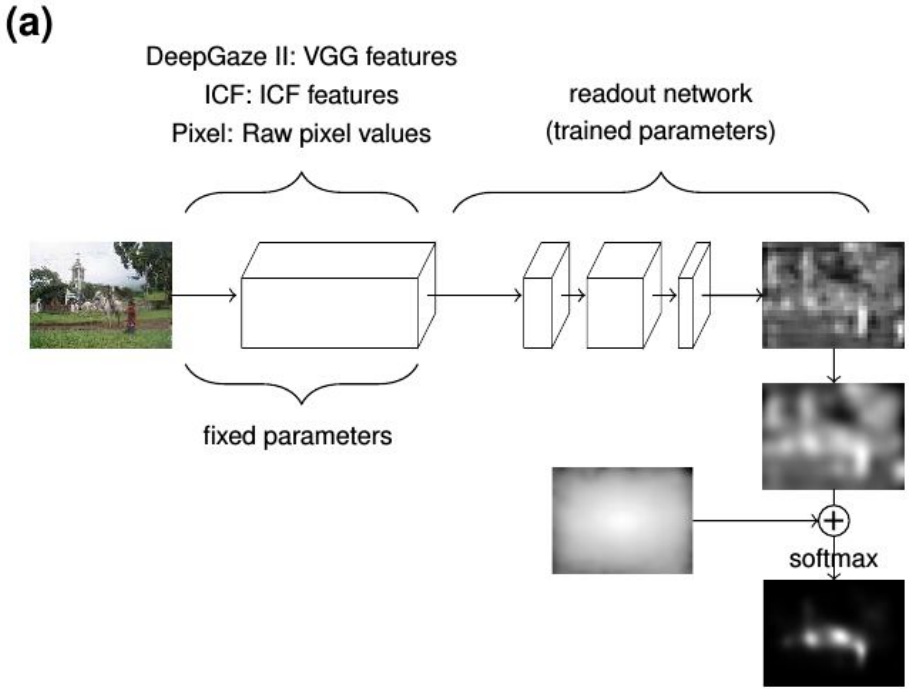
Weights initialized from VGG16 trained on ImageNet

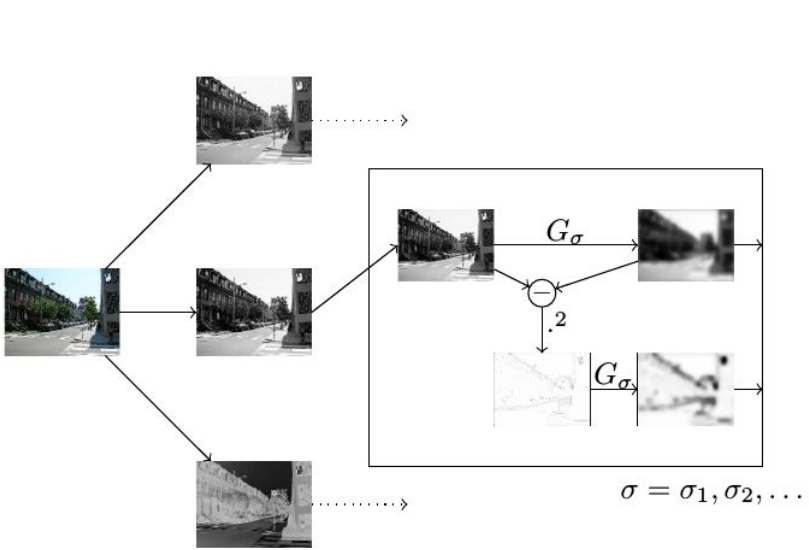




Location biased convolutions

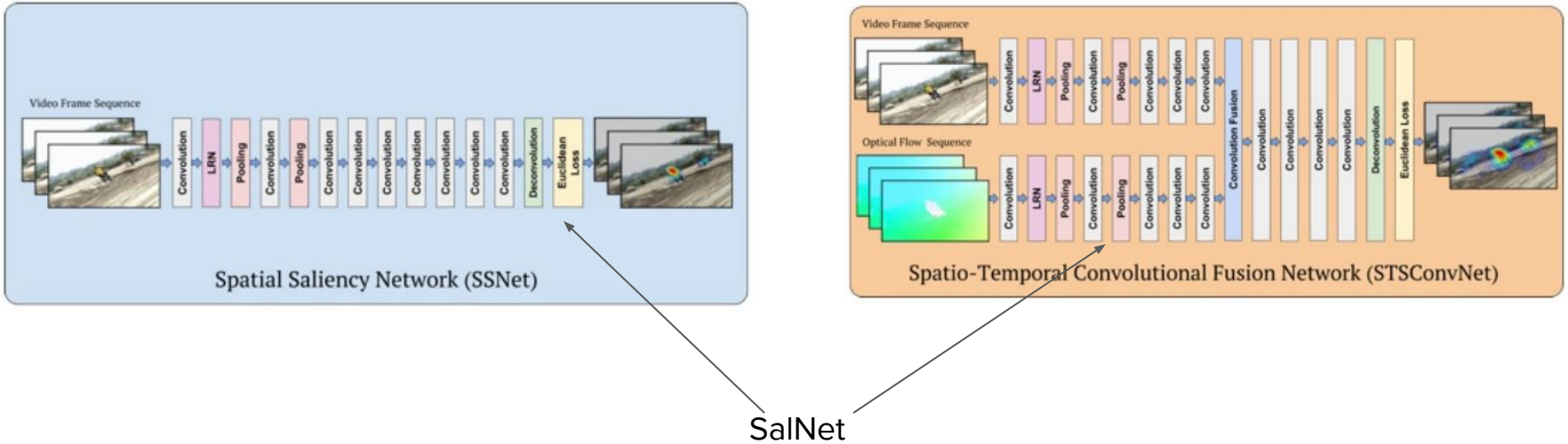
Deep Gaze II





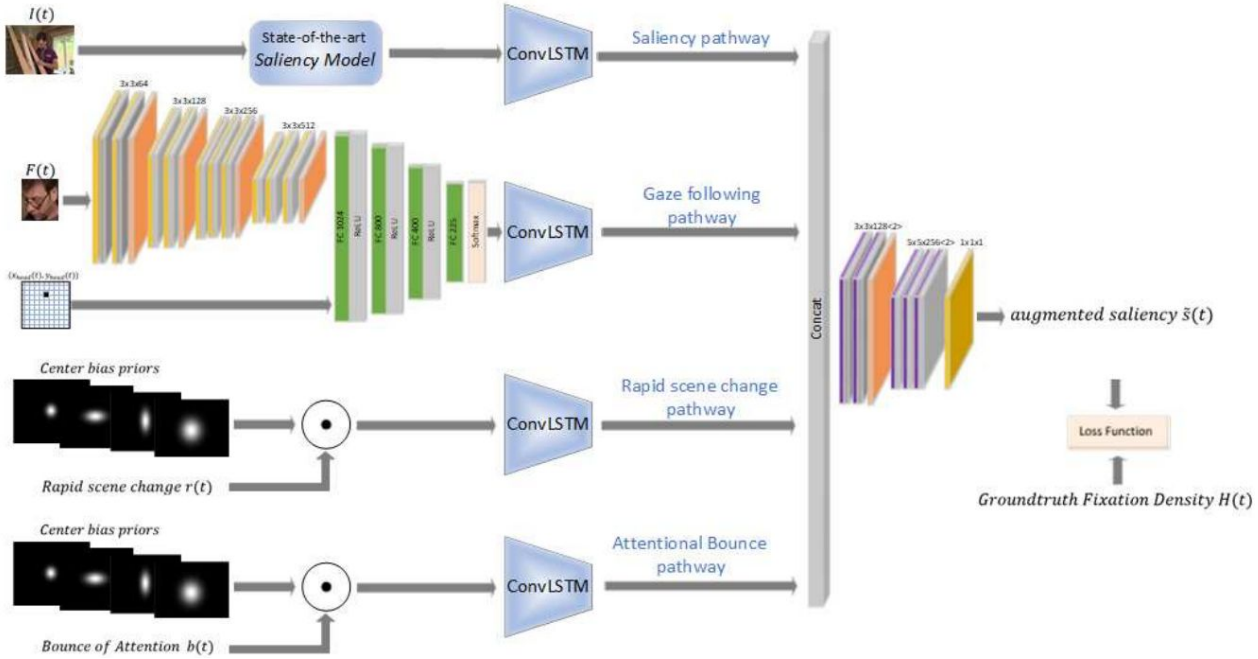
Kümmerer, et al. Understanding low-and high-level contributions to fixation prediction. ICCV 2017

From image to video saliency?



Bak et al. Spatio-temporal saliency networks for dynamic saliency prediction. IEEE Trans. Multimedia 2017

From image to video saliency



Gorji and Clark, Going From Image to Video Saliency: Augmenting Image Salience With Dynamic Attentional Push, CVPR 2018

Questions?