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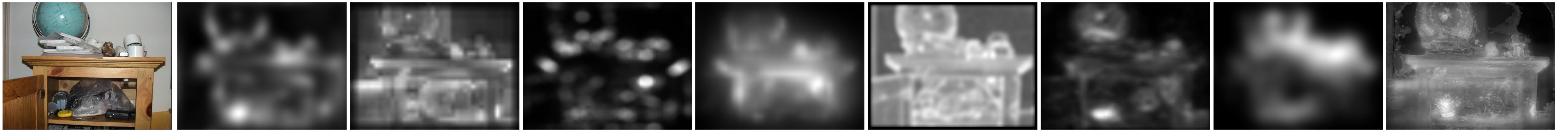
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Saliency aggregation: Does unity make strength?

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Motivation: we investigate whether we could improve on the saliency quality by aggregating a set of predicted saliency maps.



Does the linear combination improve the prediction?

$$p(x|M_1, \dots, M_K) = \sum_{k=1}^K w_k \times p(x|M_k)$$

$p(x|M_k)$ is the probability of an image pixel x from the saliency map M_k to be salient,
 $\sum_{k=1}^K w_k = 1$

Unsupervised methods to compute the weights

- **Uniform:** weights w are uniform and spatially invariant, $w_k = 1/K$
- **Median**
- **M-estimators:**

$$g_{Welsh}(e(x|M_k)) = \exp\left(-\frac{e(x|M_k)^2}{\sigma^2}\right)$$

$$g_{L1L2}(e(x|M_k)) = \frac{1}{\sqrt{1 + e(x|M_k)^2}}$$

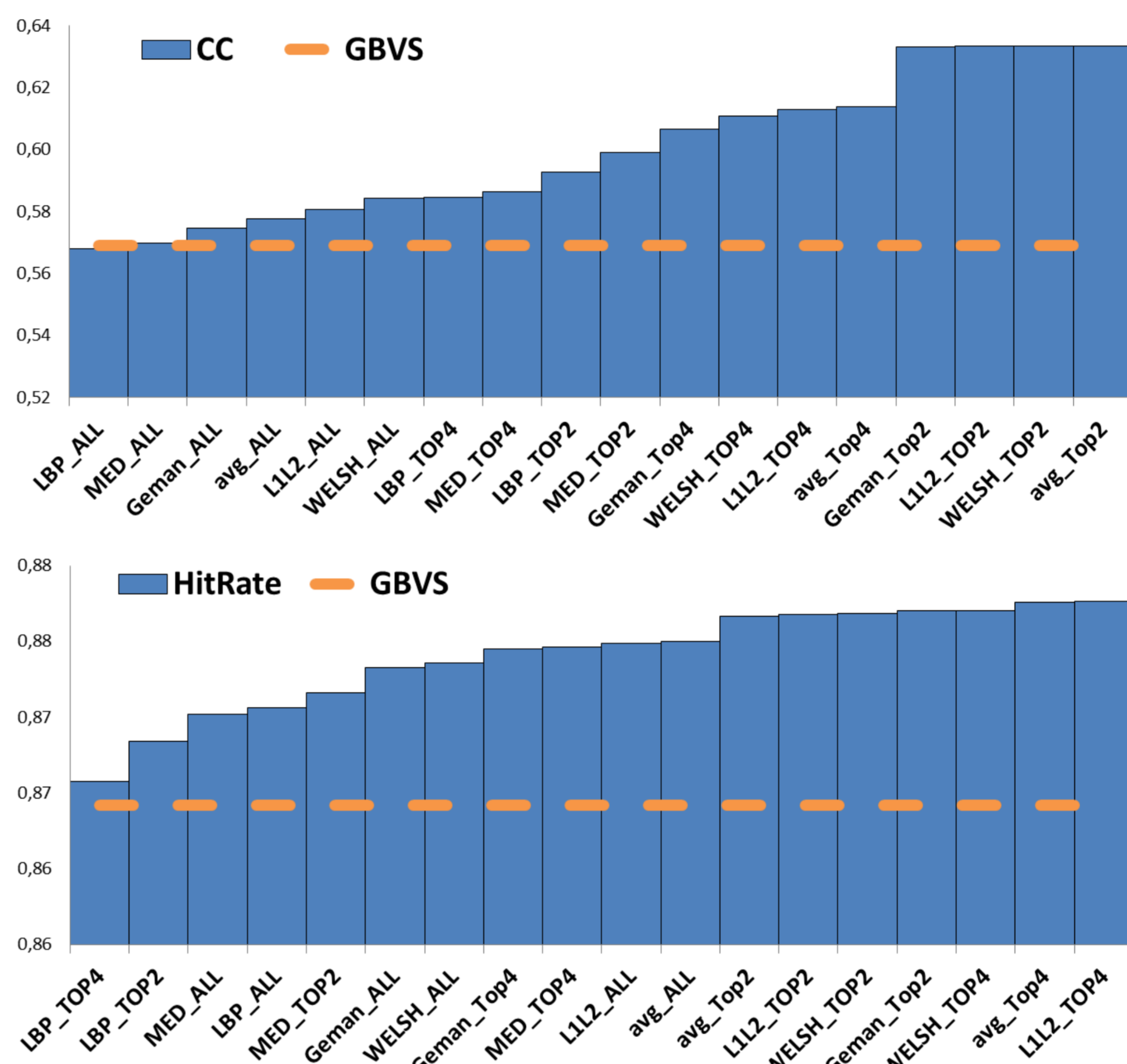
$$g_{Geman}(e(x|M_k)) = \frac{1}{1 + e(x|M_k)^2}$$

- **Global minimization of an energy function (Loopy Belief Propagation)**

TOP 2 : GBVS and RARE2012

TOP 4 : GBVS, RARE2012, Judd and AWS

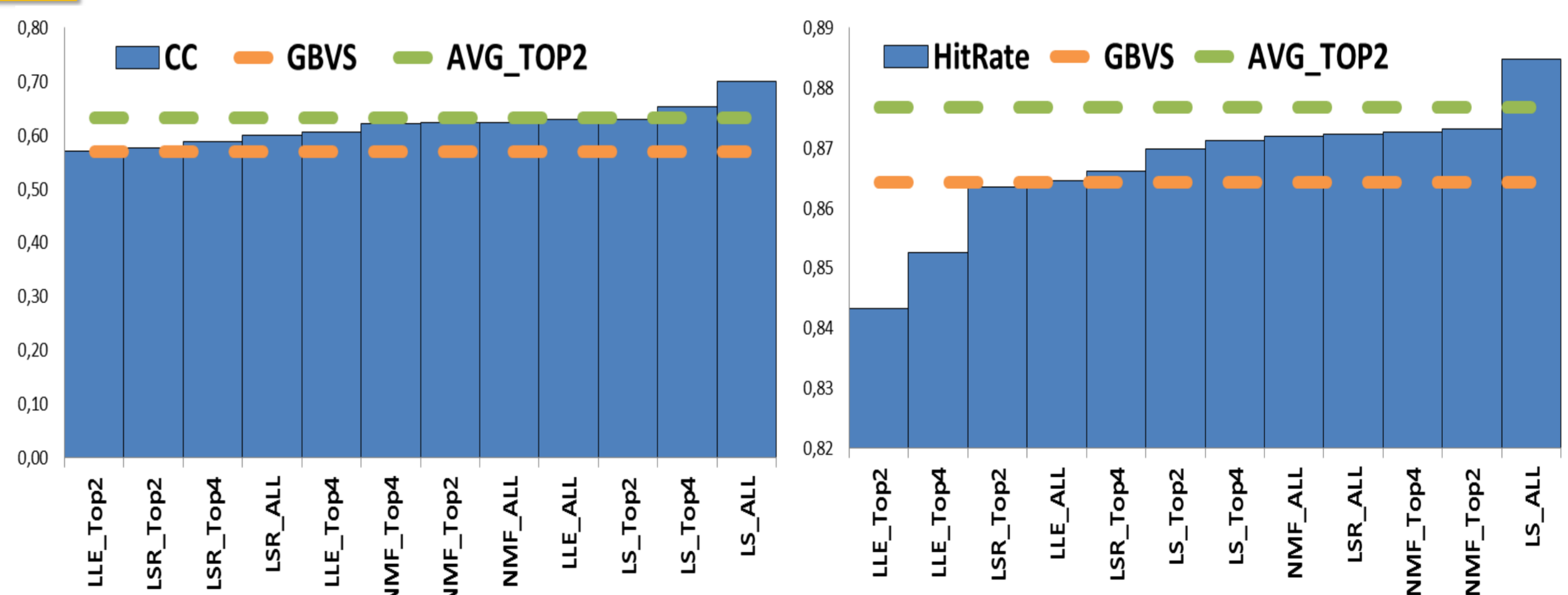
ALL: GBVS, RARE2012, Judd, AWS, Le Meur, Hou, Itti, Bruce.



A simple aggregation function, such as the average function, operating on the top 4 or top 2 models is a good candidate to improve significantly the performance of saliency models.

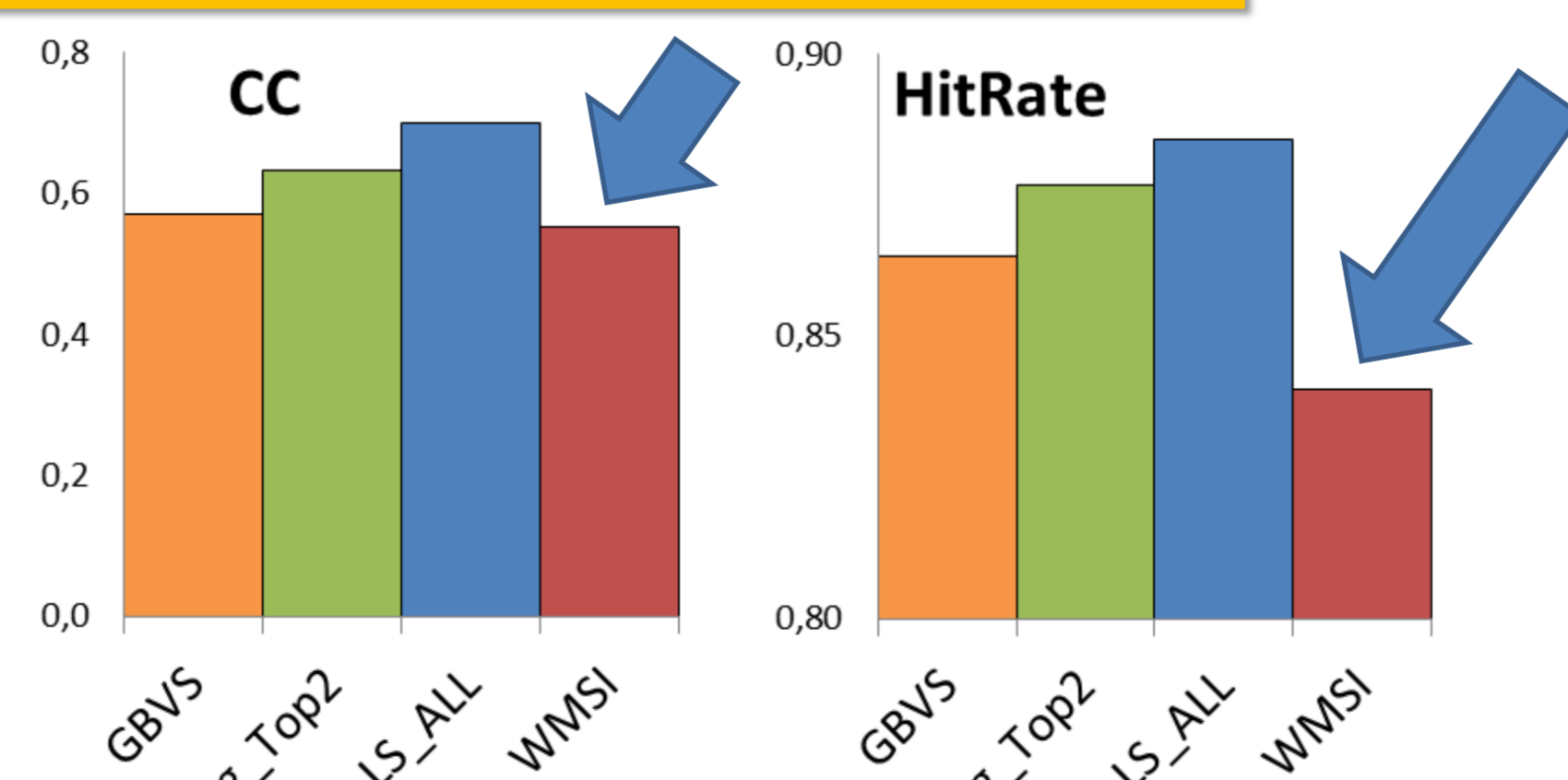
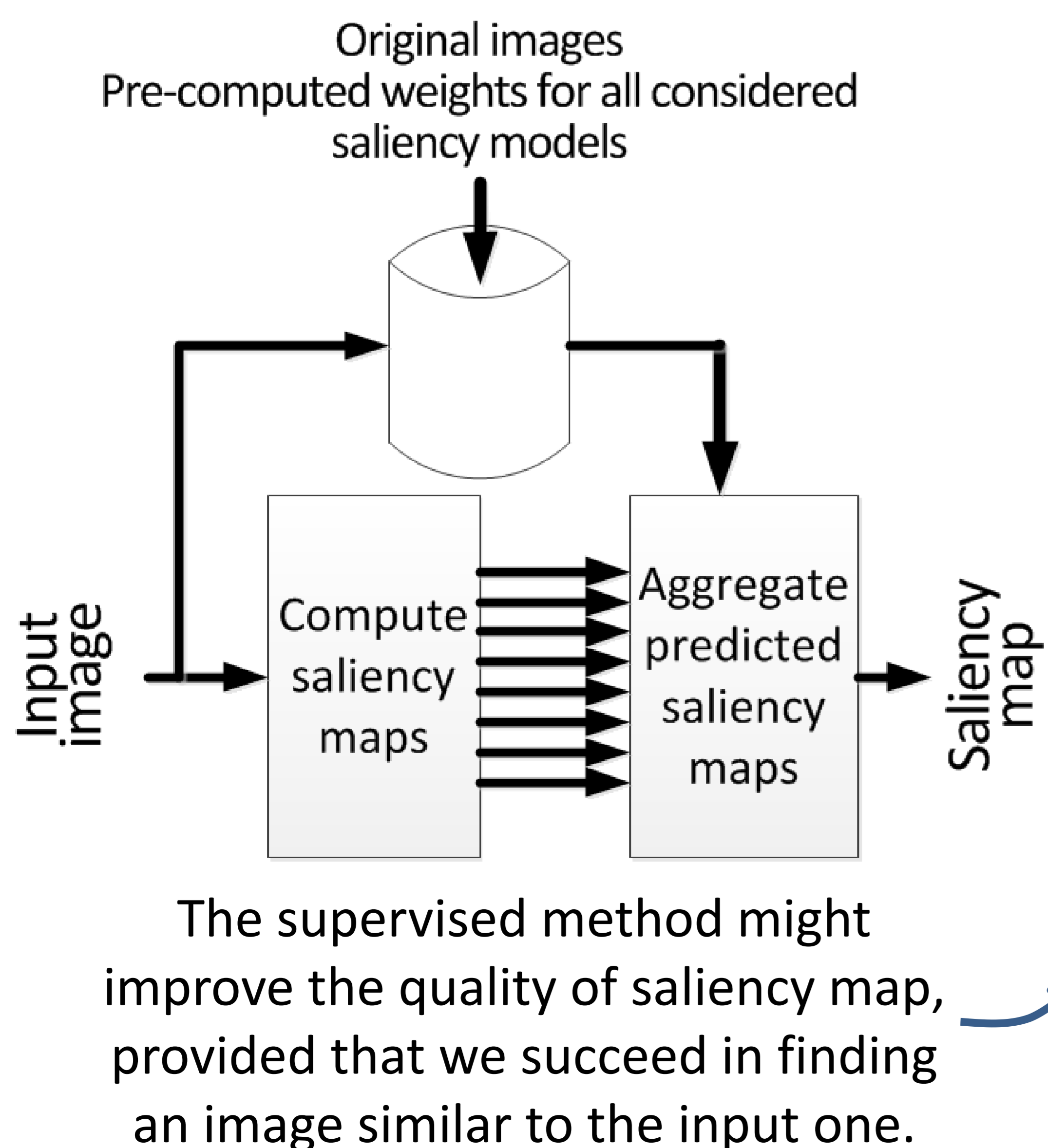
Least-squares estimation of the weights

- The classical least-squares method (LS)
- LS with the sum-to-one constraint of the weights (LLE)
- LS with positive weights (NMF)
- Robust least-squares (LSR)



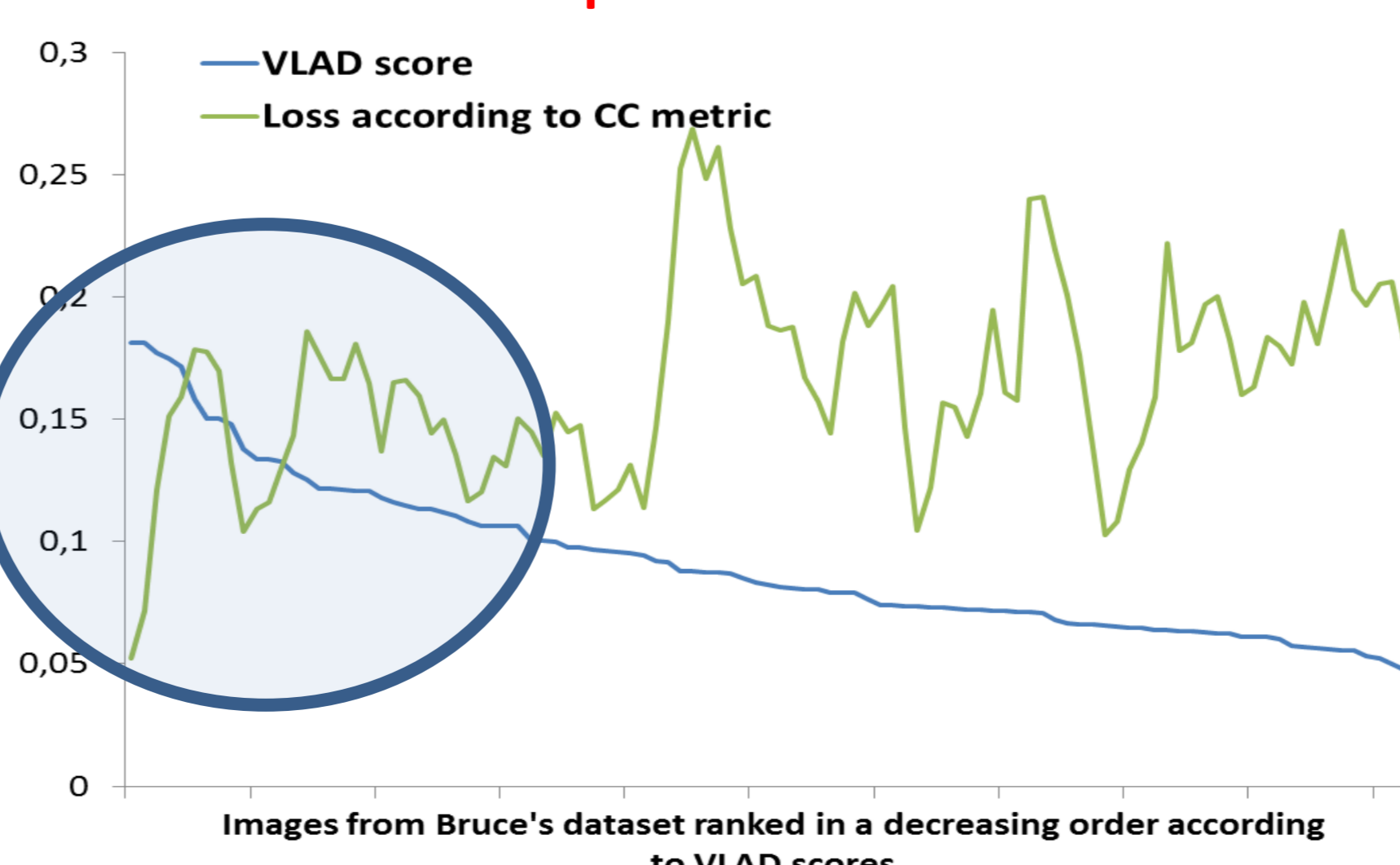
The best learning function is the simple least-squares method involving all saliency maps.

The use of the learned weights of the most similar image



WMSI = Weights of the Most similar Image

The WMSI method gets the lowest performance



Conclusion

The robustness of the prediction can be enhanced by:

- ✓ averaging the saliency maps of the top 2 models;
- ✓ considering a **dedicated training dataset**.

Acknowledgment

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