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Finding Tiny Faces

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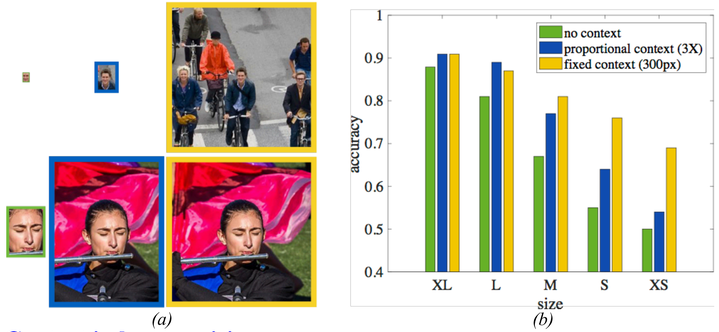
(a) (b) (c)

Core ideas

a) *How to model scale invariance:* Instead of an "one-size-fits-all" detector, we train separate detectors with each for a different scale in an multi-task fashion.
b) *How to generalize pre-trained networks*: We interpolate images to extend pre-trained features tuned for objects of a typical scale to ones of novel scales.
c) *How best to encode context:* We encode massively-large amount of context with "foveal" descriptors and demonstrate the "foveal" structure is crucial for detecting low-resolution faces.

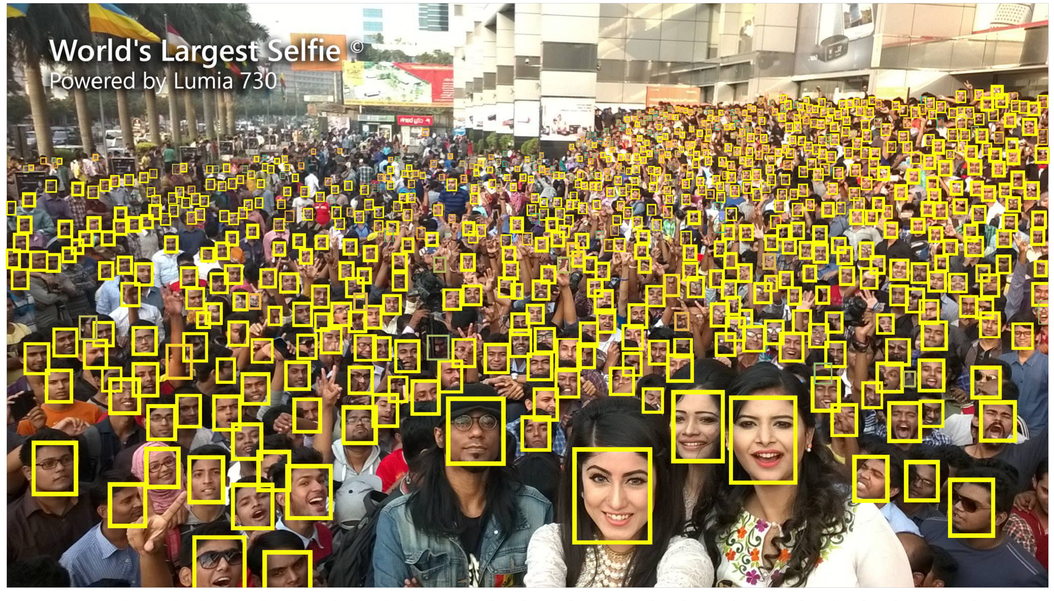


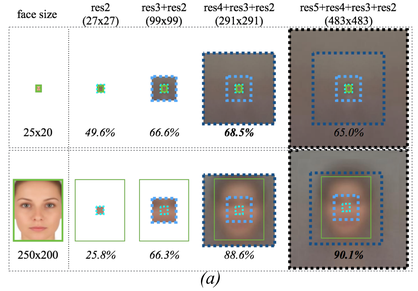
(a)

(b)

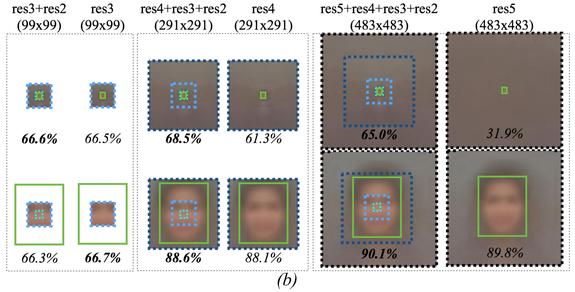
Context in human vision

a) We visualize a low-resolution (top) and an high-resolution (bottom) human face. *One does not need context to recognize the high-resolution face, while the low-resolution face is dramatically unrecognizable without its context.*
b) We quantify this observation with an human experiment, where users are asked to classify true and false positive faces generated by our proposed detector. Adding proportional context provides a small improvement on medium and large faces but insufficient for low-resolution (S and XS) faces. Adding a fixed contextual window of 300 pixels dramatically reduces error on low-resolution faces by 20%. This suggests that *context is crucial for human to recognize low-resolution faces and it can be modeled in a scale-variant manner.*





(a)

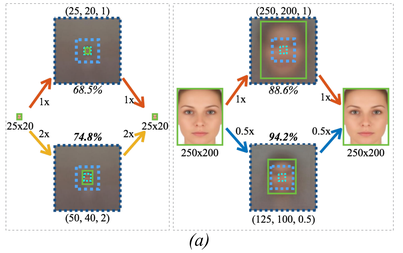


(b)

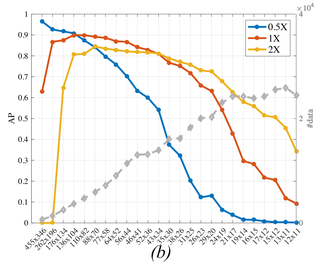
How best to encode context?

We factor out scale variation and focus on two fixed resolution. How do we encode context to build the best single-scale detector for each resolution?

a) *Modeling additional context helps, especially for finding low-resolution faces.* The improvement from adding context to a "tight-fitting" detector is much greater for low-res faces (+18.9%) than for high-res faces (+1.5%).
b) *Foveal descriptor is crucial for accurate detection on low-resolution faces.* The detector tuned for low-resolution faces performs 7%-33% worse without foveal structure. On the contrary, removing foveal structure does not hurt the detector tuned for high-resolution faces.



(a)



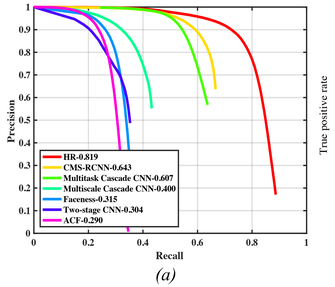
(b)

How to handle extreme scales?

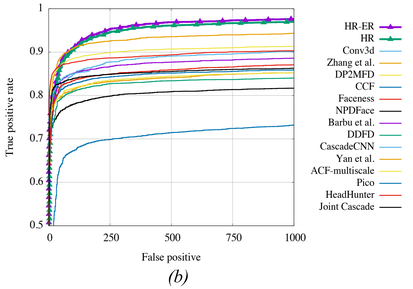
Since pre-trained networks are tuned for objects of characteristic scales, how do we extend them to extreme scales?

a) A detector tuned for 50x40 faces is 6.3% more accurate than one tuned for 25x20 on finding 25x20 faces when applied on 2X upsampled images; A detector tuned for 125x100 faces is 5.6% more accurate than one tuned for 250x200 on finding 250x200 faces when applied on 2X downsampled images.
b) *There exists a natural regime for picking which resolution to build a detector at given a target resolution.* For finding high-resolution faces (taller than 140px), build detectors at 0.5X resolution; for finding low-resolution (shorter than 40px) faces, build detectors at 2X resolution. For sizes in between, build at the original resolution.

State-of-the-art results on WIDER Face and FDDB



(a)



(b)

a) *Precision-recall curves on WIDER Face test set (hard only)*. Our approach achieves state-of-the-art performance on all subsets (easy, medium, hard). In particular, ours outperforms the prior art by ***17.6%*** on the hardest subset.

b) *ROC curves on FDDB test set*. Our out-of-the-box detector (HR) achieves state-of-the-art on discrete score. With post-hoc elliptical regression, our approach (HR-ER) achieves state-of-the-art on continuous score as well.