

Blur-Aware Image Downsampling

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Is the photograph blurry?



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Motivation

- Sensors higher resolution than displays
- Image display implies image downsizing
- Conventional downsizing doesn't accurately represent image appearance and perception of the image changes
- Users can make inaccurate quality assessments when not viewing image pixels 1-to-1 with display pixels



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2 Mp

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2 Mp



3-22 Mp

Motivation

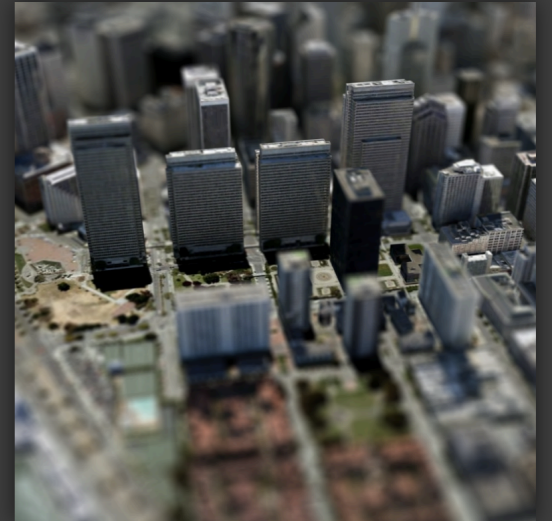
- Want to preserve appearance of blur when downsampling
- Perceptual experiment: relation between blur present and perception at different sizes
- New resizing operator that amplifies blur present to ensure the result is perceived the same as the original

Organization

- Related work
- Experiment design + results
- Model of perceived blur
- Blur estimation
- Accurate blur synthesis
- Evaluation + conclusion

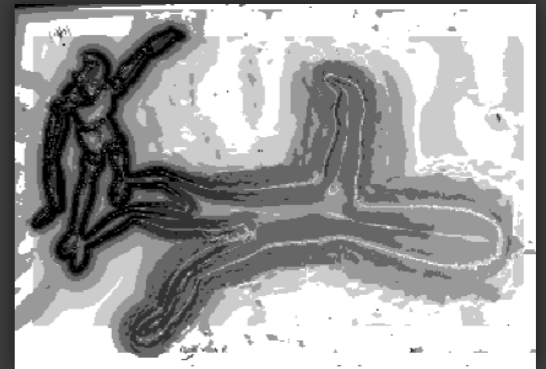
Related work

- Blur perception
[Cufflin 2007][Chen 2009]
[Mather 2002][Held 2010]
- Intelligent upsampling
[Fattal 2007][Kopf 2007][Shan 2008]
- Seam carving
[Avidan 2007]
[Rubenstein 2009,2010]



Related work

- Blind deconvolution
[Lam 2000][Fergus 2006]
- Spatially-variant blur estimation
[Elder 1998][Liu 2008]
- Blur magnification
[Bae 2007][Samadani 2007]

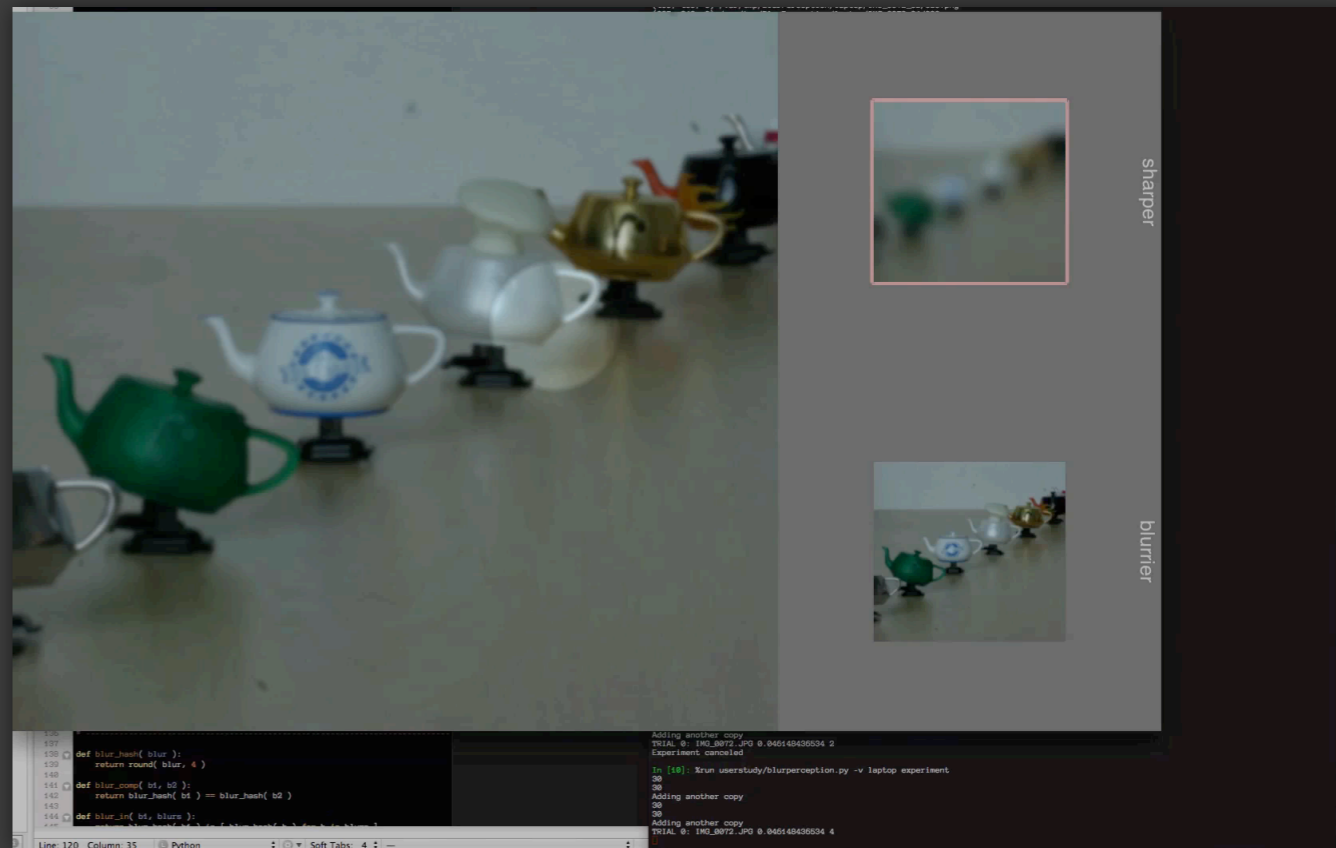


Perceptual study

- Blur-matching experiment
- Given large image with reference amount of blur present ζ_r
- Need to adjust blur in smaller images to match appearance of large
- Repeated for between 0 and .26 visual degrees and downsamples of 2x 4x 8x

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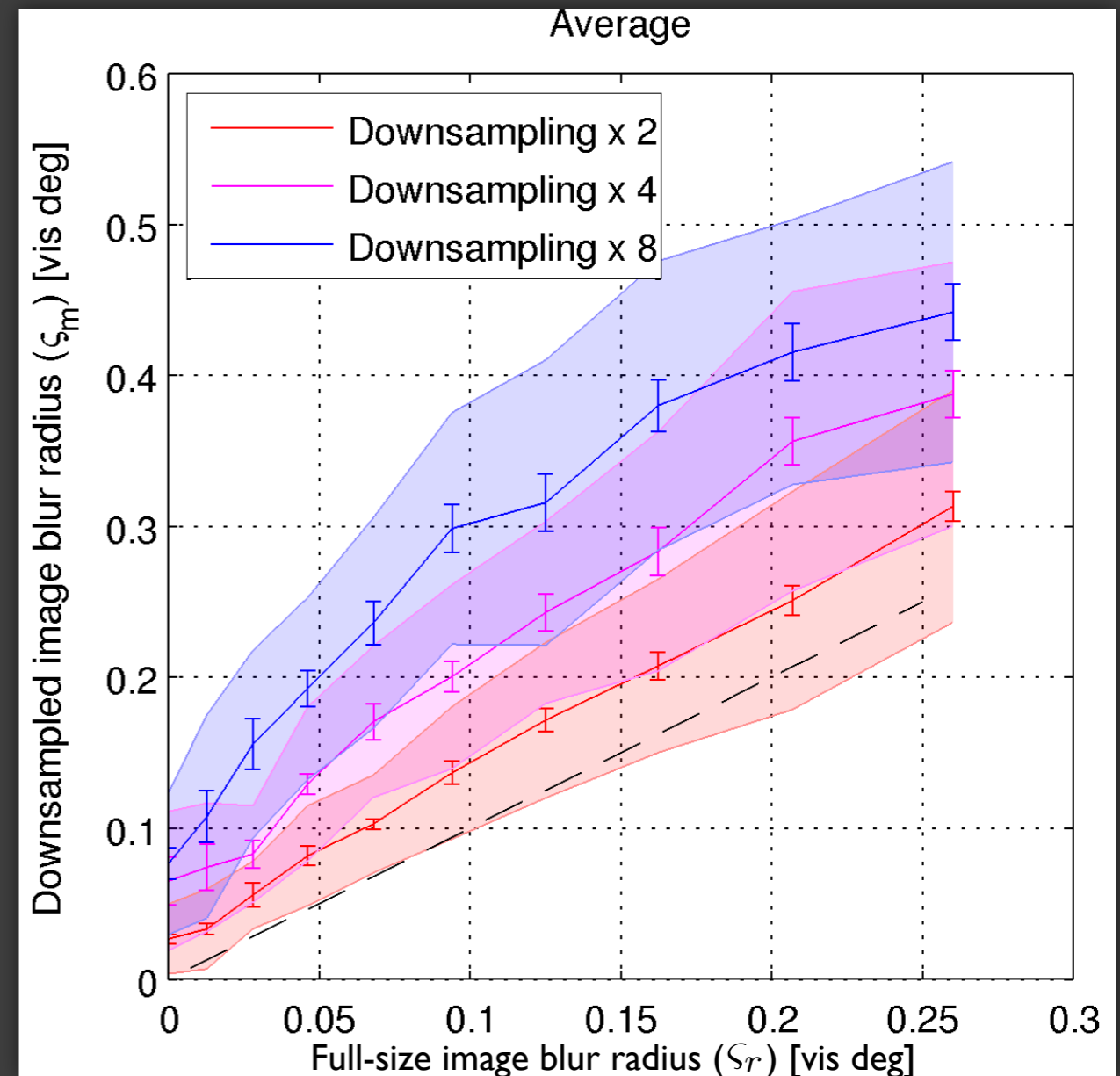
Perceptual study

- Add uniform synthetic blur to full-size images with no noticeable blur present
- Same process for thumbnails, with nearest neighbor sampling
- 5 images selected from pre-study of 20 -- 150 conditions, trial subset of 30, 3x each
- 24 observers participated in over 2100 trials



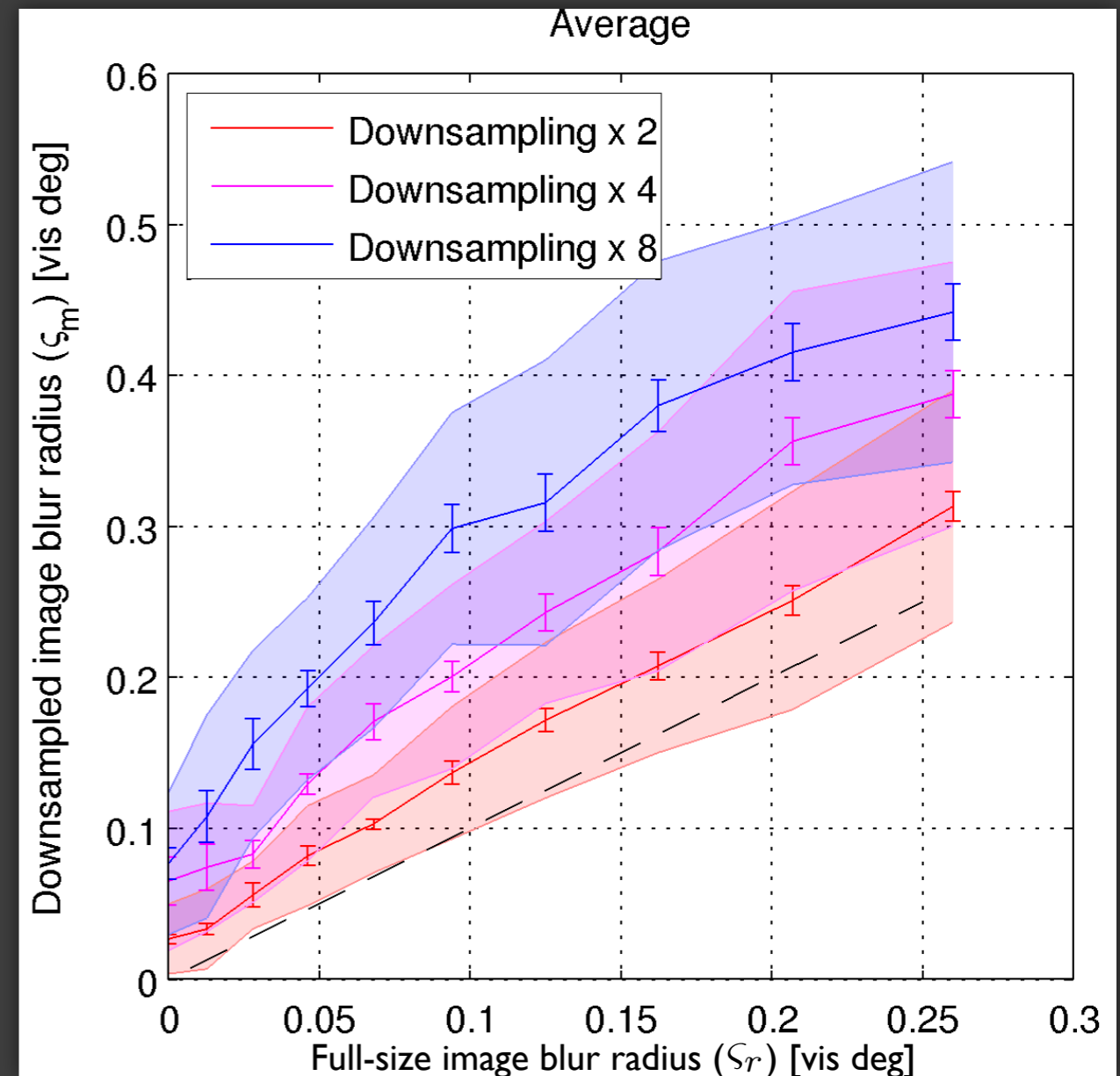
Matching results

- Matching blur larger than reference blur, smaller images appear sharper
- Curves level off with larger blur, downsample -- blur sufficient to convey appearance
- Reported values include any blur needed to remove aliasing artifacts
- Viewing setup had Nyquist limit of 30 cpd - results not due to limited resolution in terms of pixels, but visual angle



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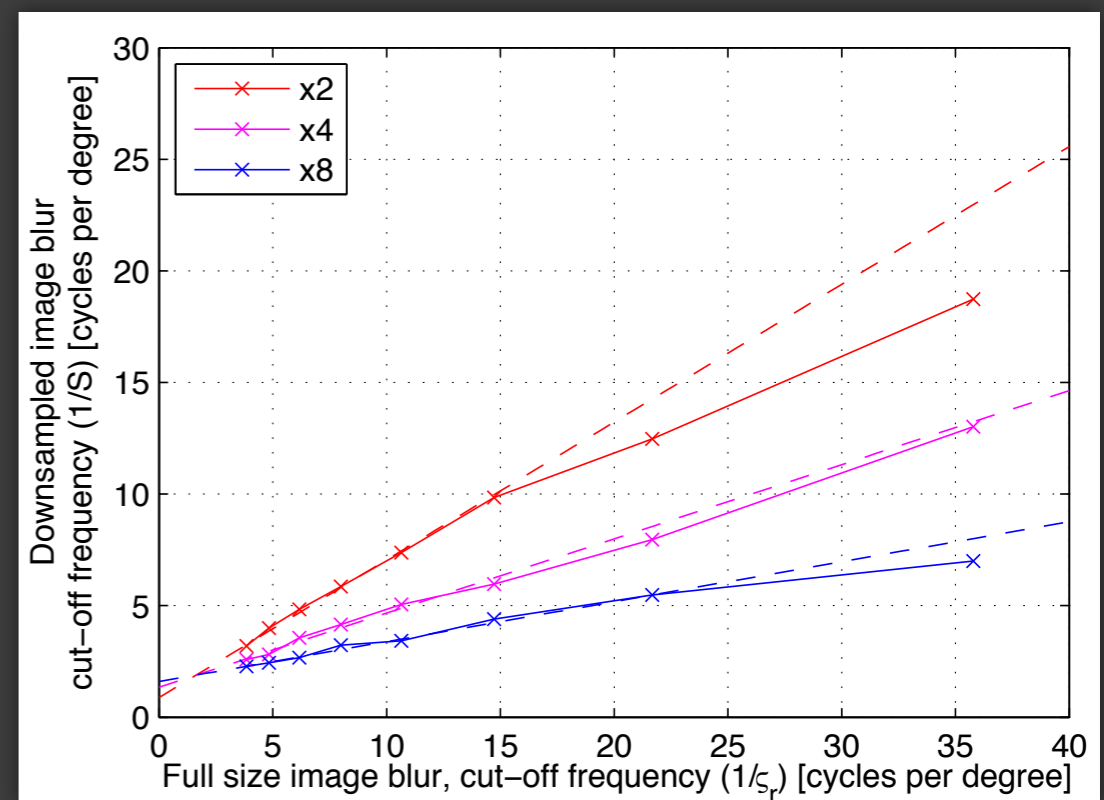


Blur appearance model

- Measured data ζ_m well predicted by anti-aliasing filter ζ_d and model \mathcal{S} in spatial frequencies

$$\hat{\zeta}_m = \sqrt{\zeta_d^2 + \mathcal{S}^2}$$

- After removing ζ_d , we model \mathcal{S} as a linear function in $1/\zeta$ spatial frequencies
- Full model provides accurate and plausible fit of the measured data in the spatial domain

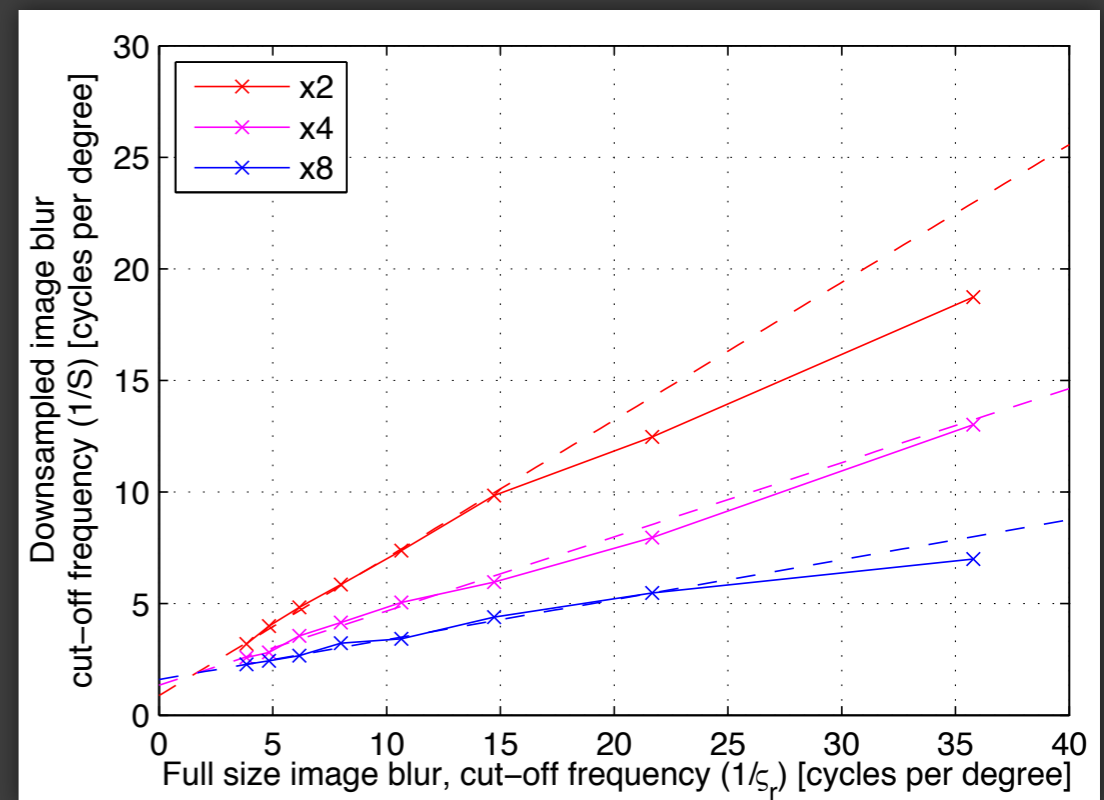


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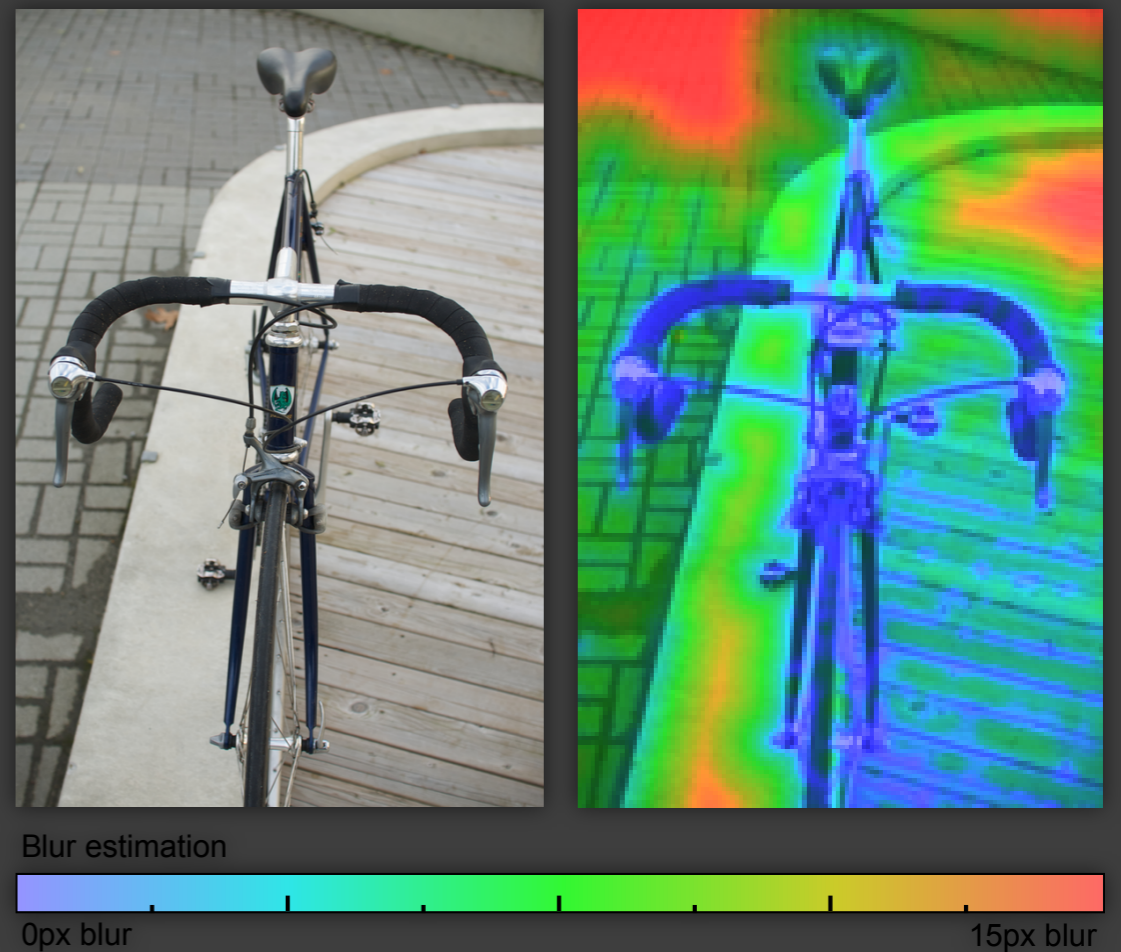
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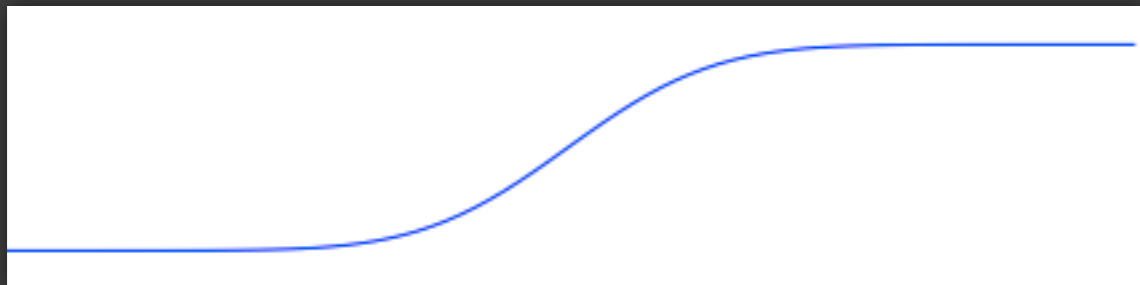
Blur estimation

- Spatially-variant estimate of the blur present at each pixel of image
- Calibrate method of Samadani *et al.* to provide estimate of blur in absolute units
- Downsampling approximates a blur-free image
- Relation between width of a Gaussian profile and the peak value of its derivative

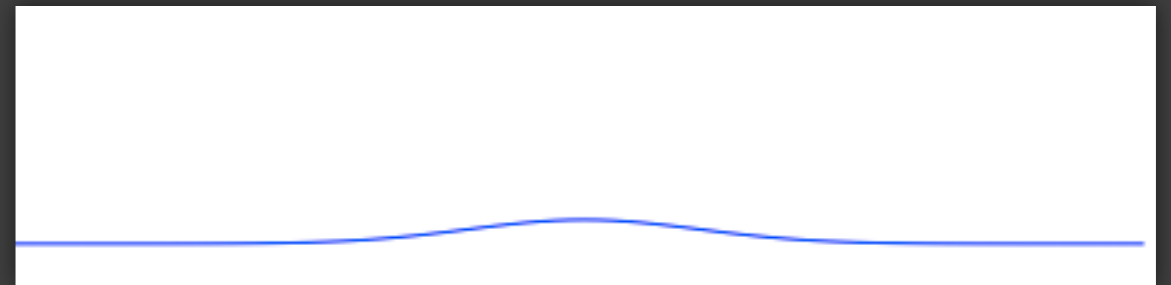


Blur estimation

Edge

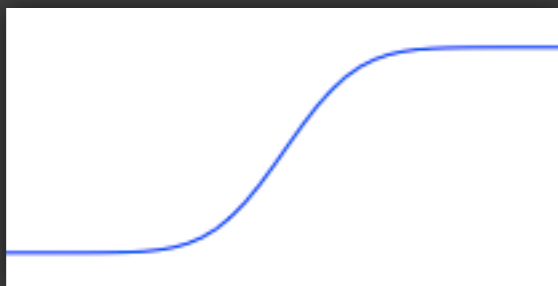
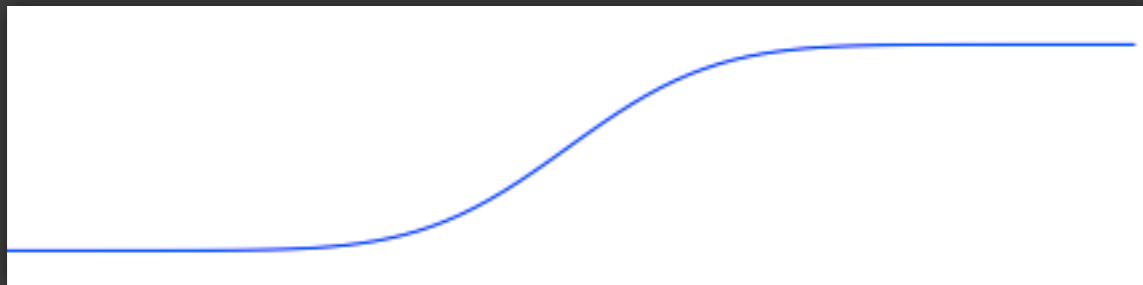


Derivative



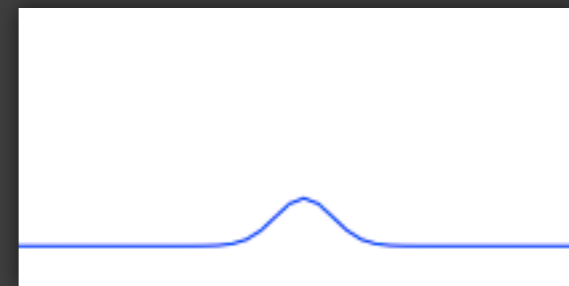
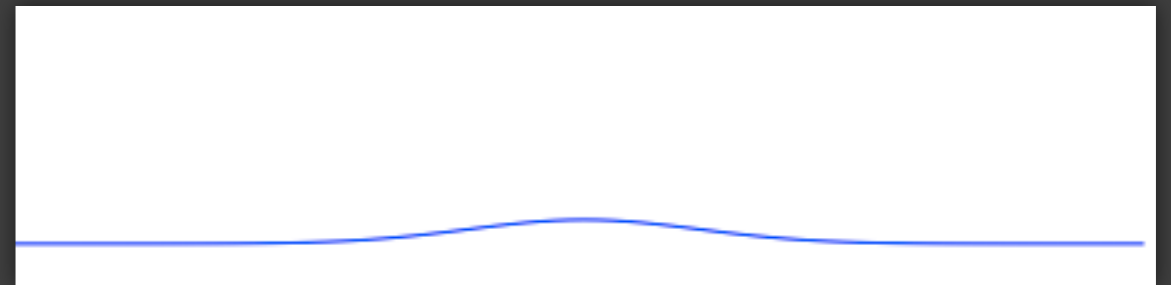
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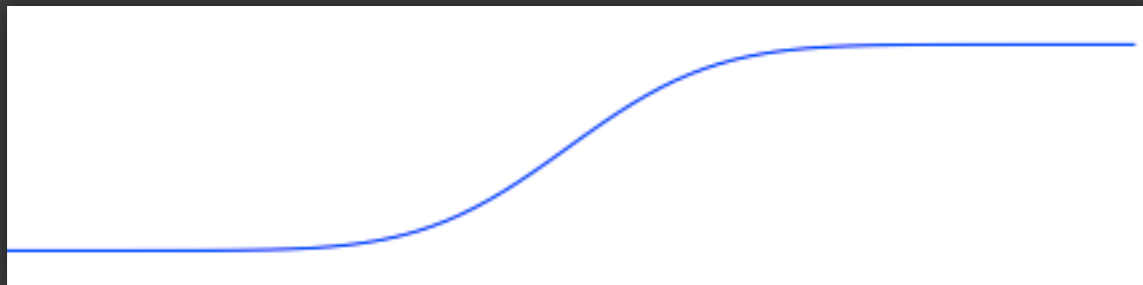
2x

Derivative

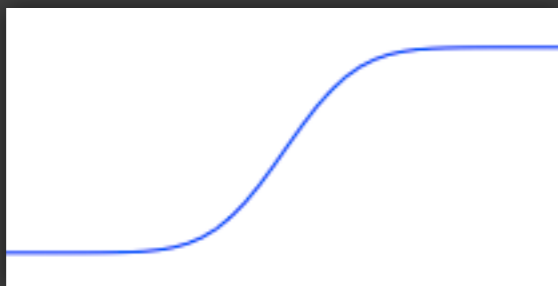
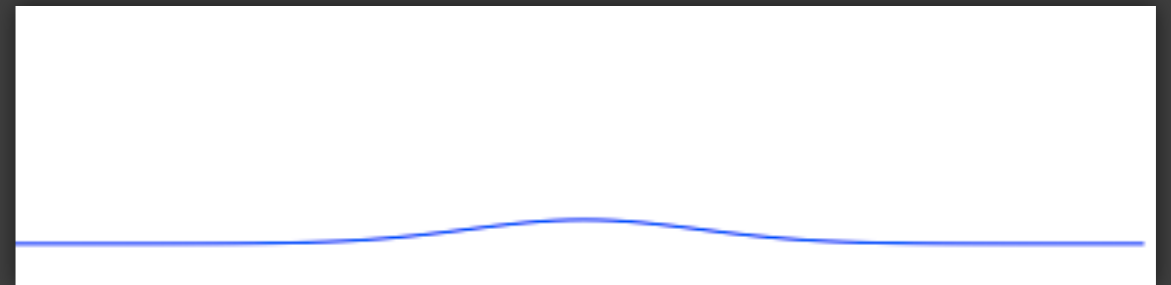


Blur estimation

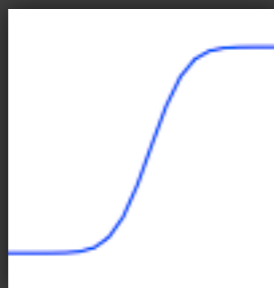
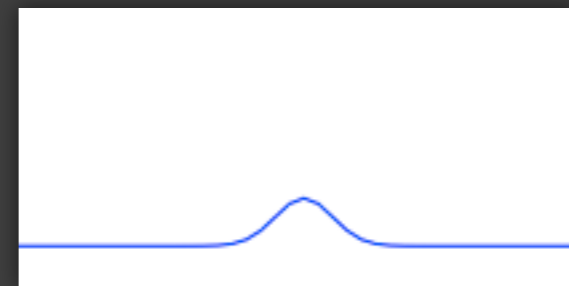
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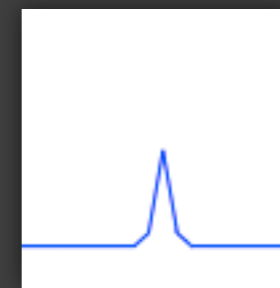
Derivative



2x

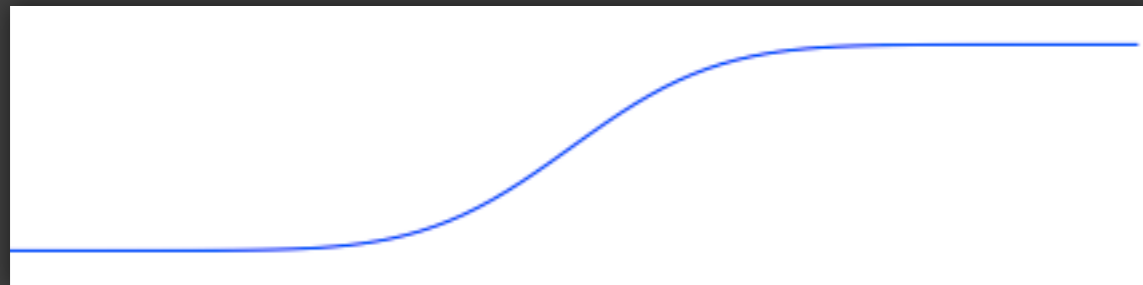


4x

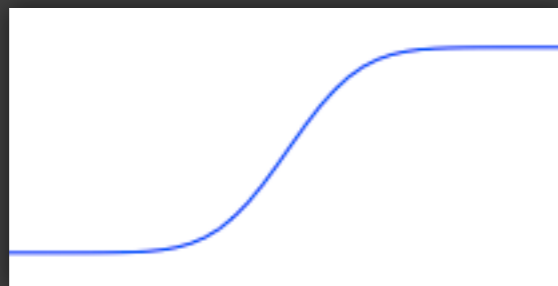
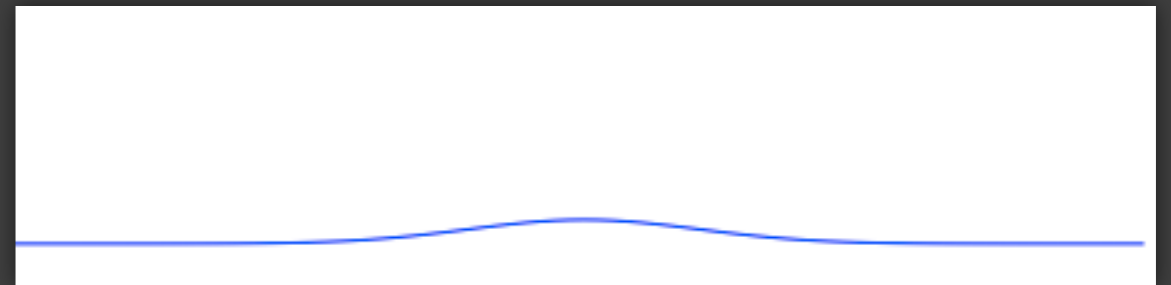


Blur estimation

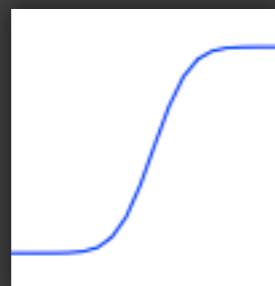
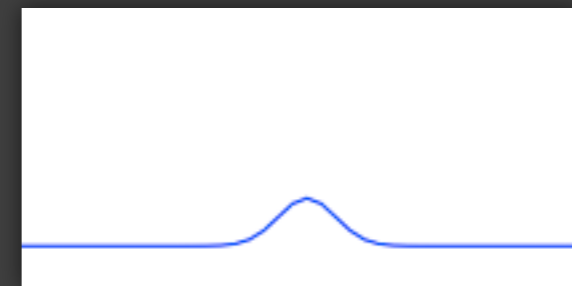
Edge



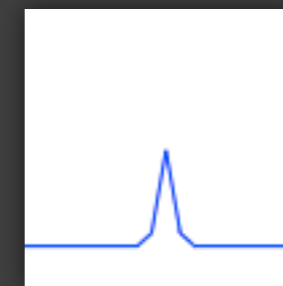
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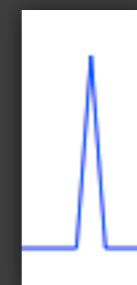
2x



4x

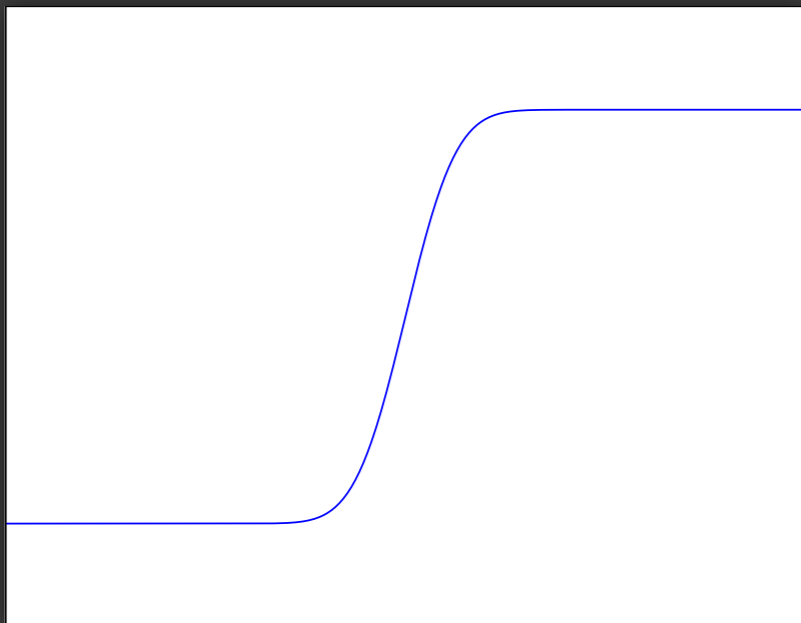


8x



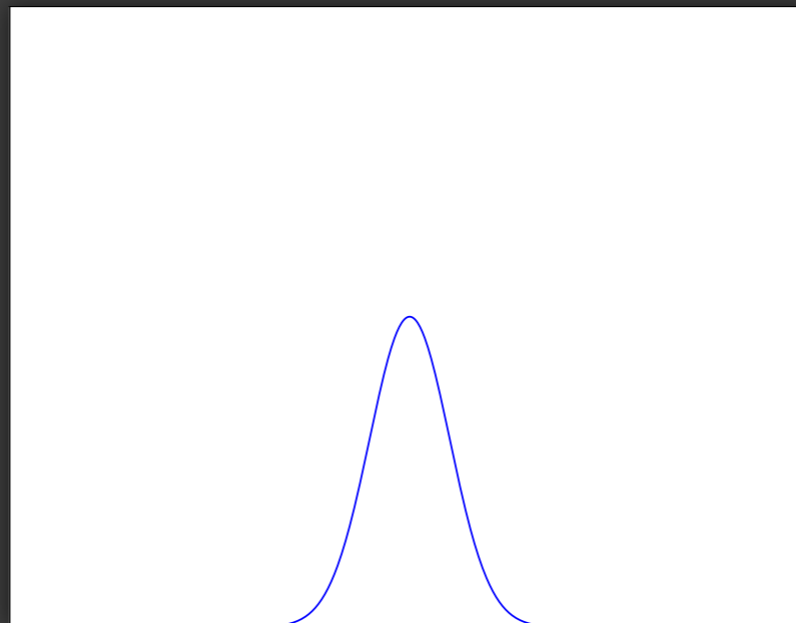
Blur estimation

Edge



width: σ

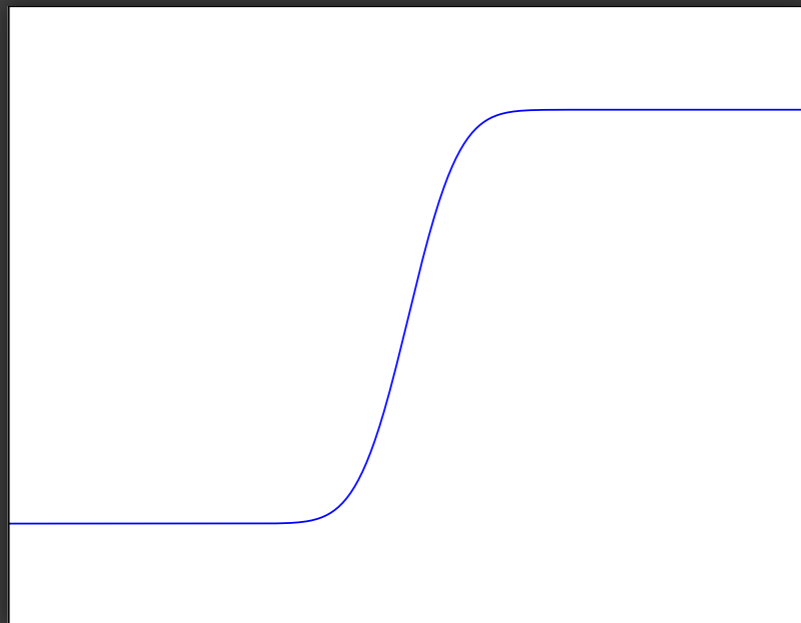
Gradient magnitude



$$g(x, \sigma) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{x^2}{2\sigma^2}}$$

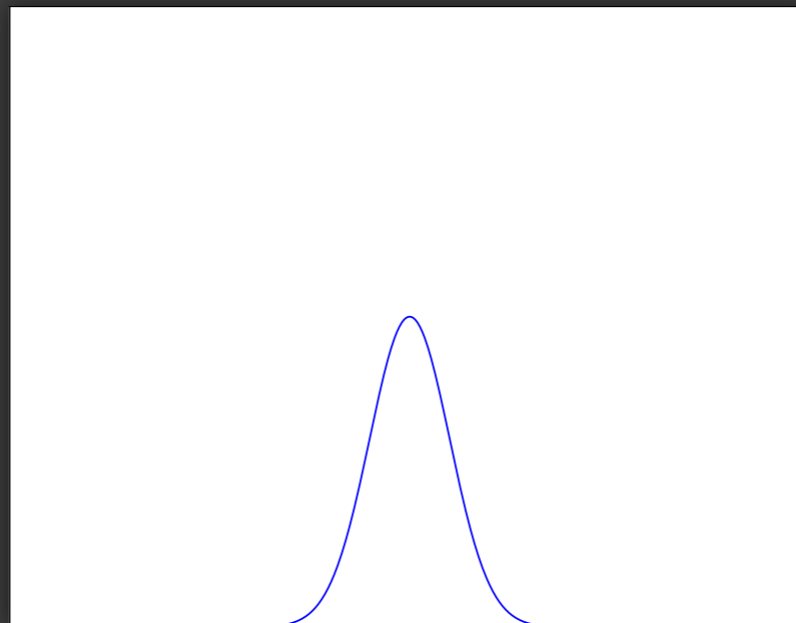
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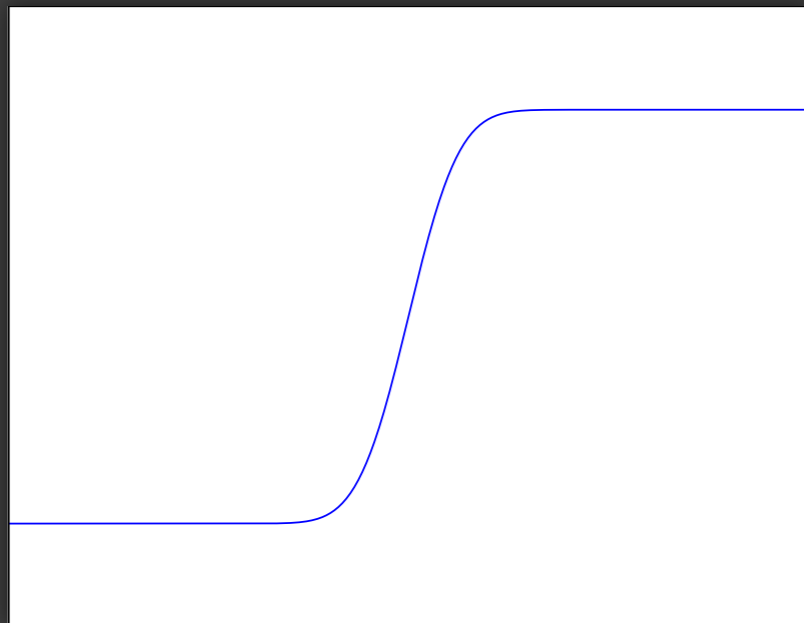
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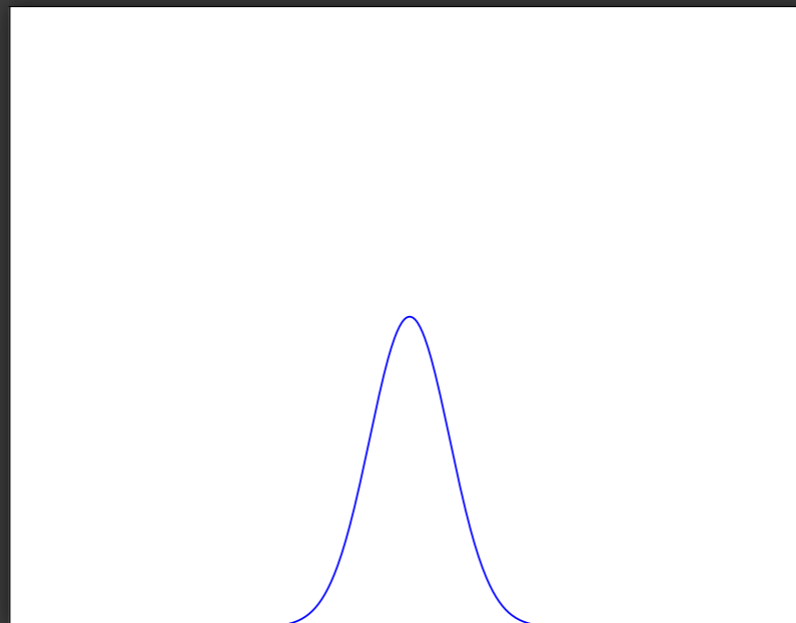
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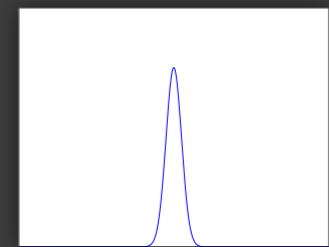
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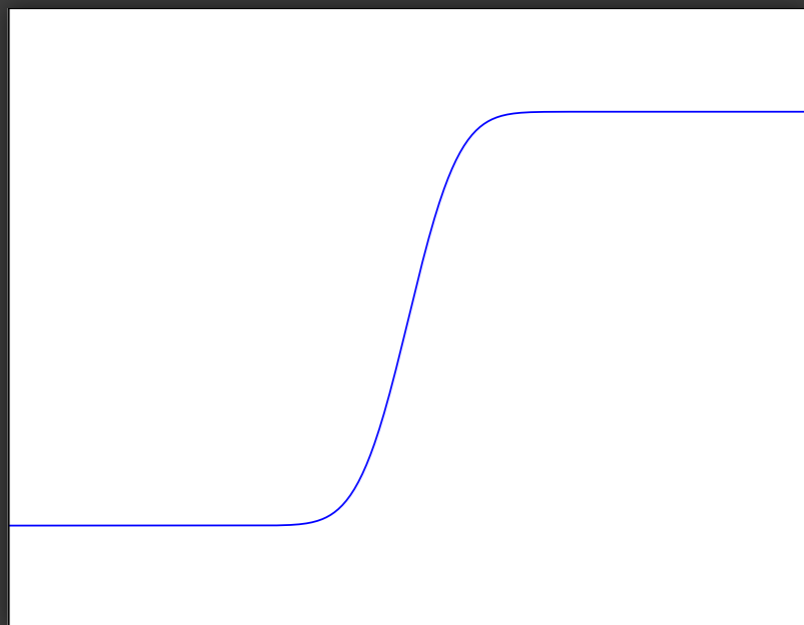
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Downsampled
scale space



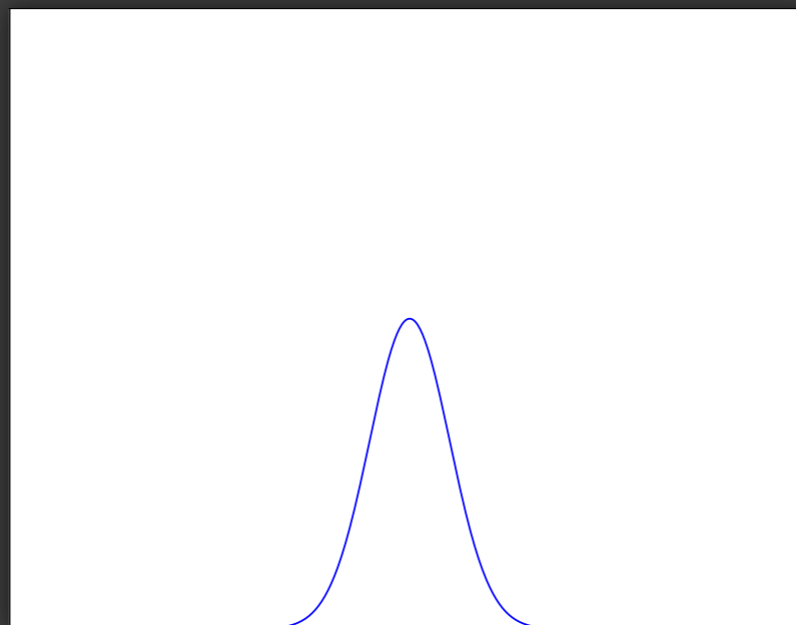
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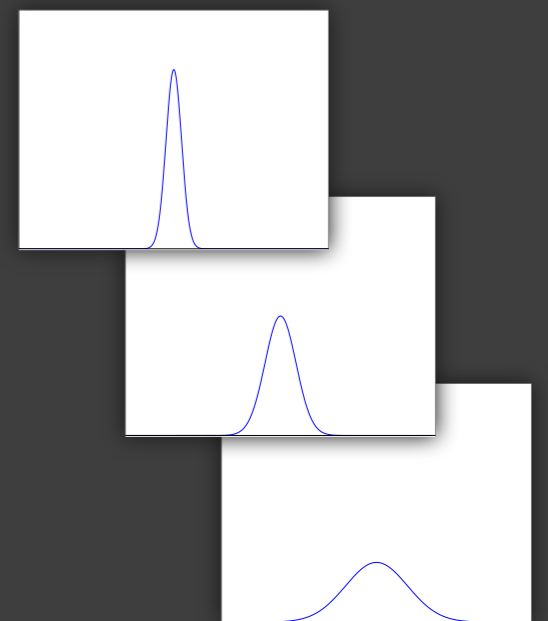
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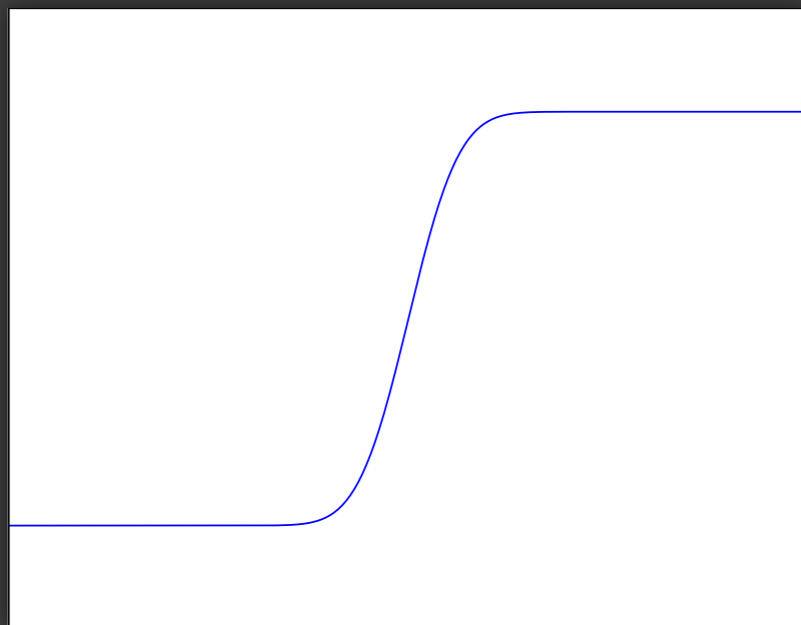
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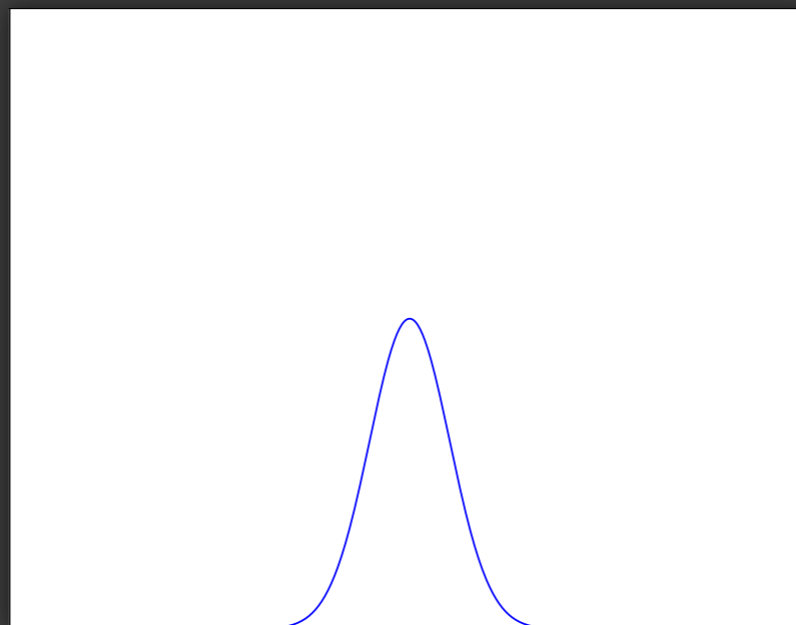
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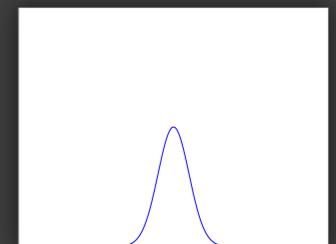
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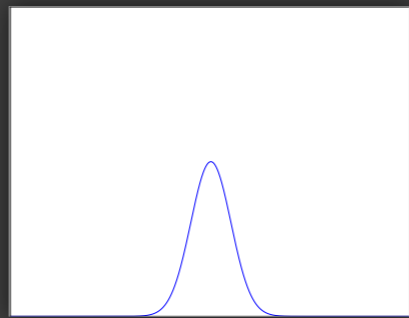
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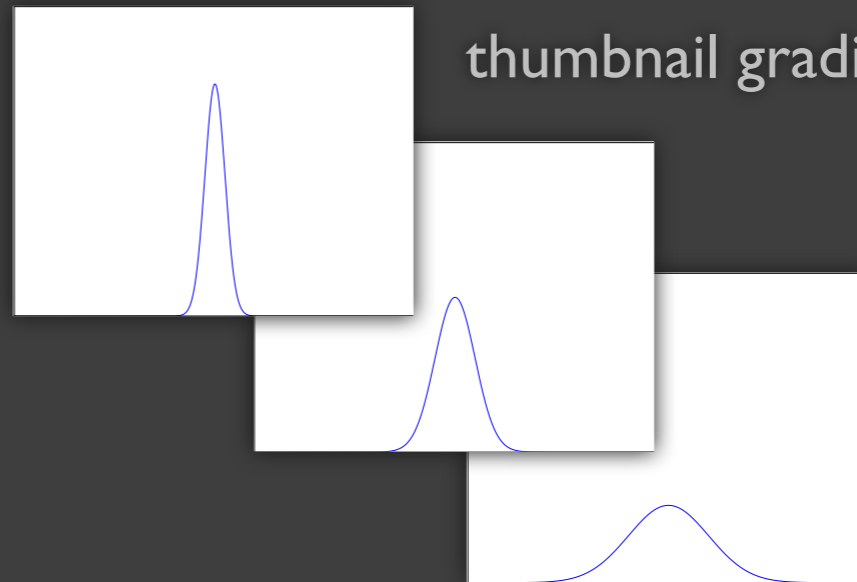


Blur estimation

original gradients



thumbnail gradients



$$\frac{1}{\sqrt{2\pi\sigma_o^2}}$$

\approx

$$\frac{1}{\sqrt{2\pi \left[\left(\frac{\sigma_o^2}{d} \right) + (\beta j)^2 \right]}}$$

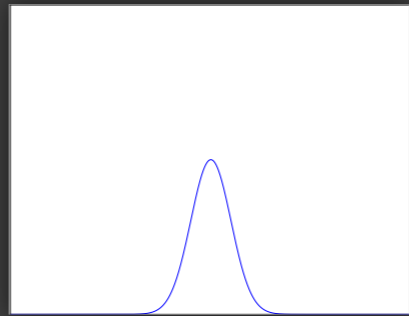
d downsample

j scale space level

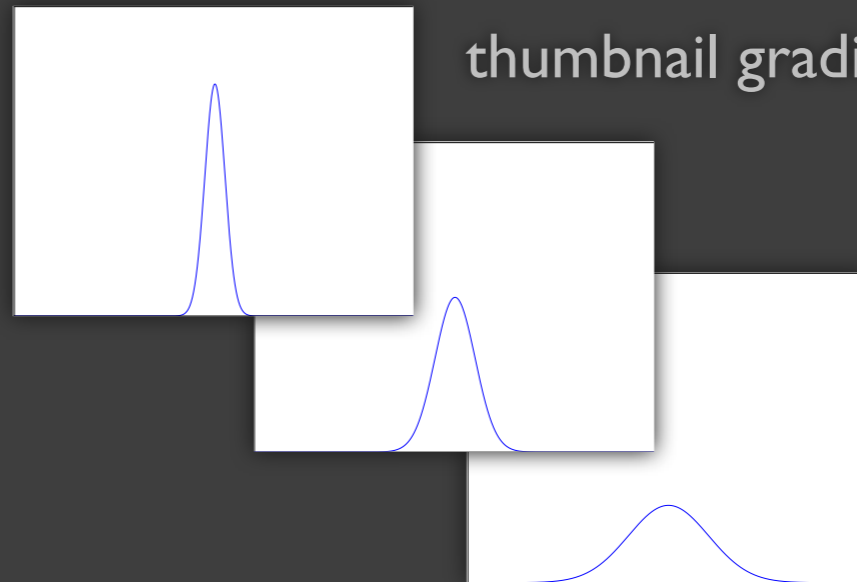
β quantization term

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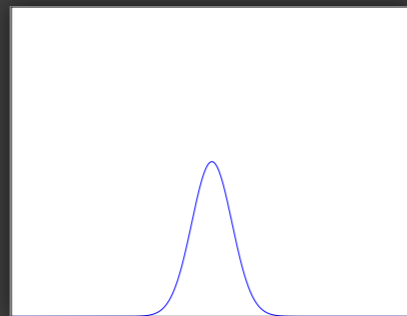
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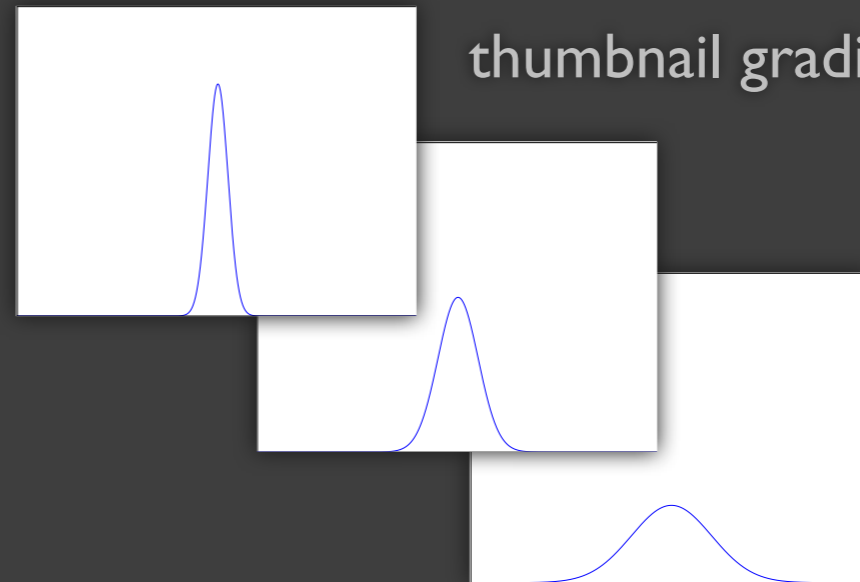
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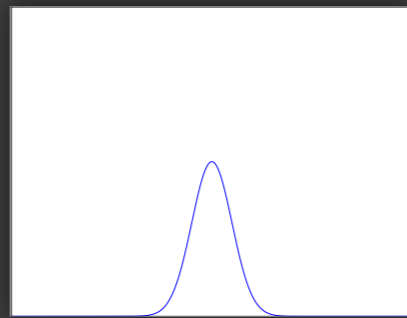
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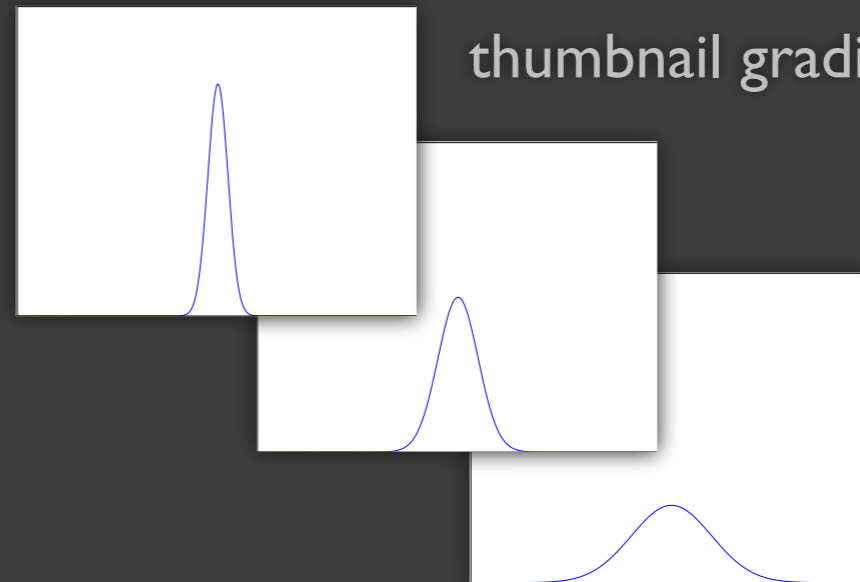
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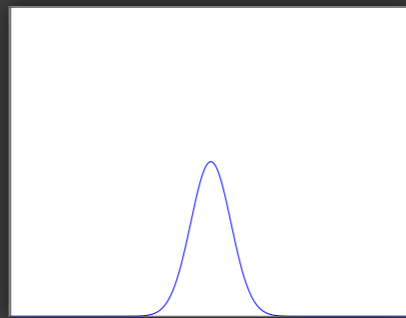
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- d downsample
- j scale space level
- β quantization term

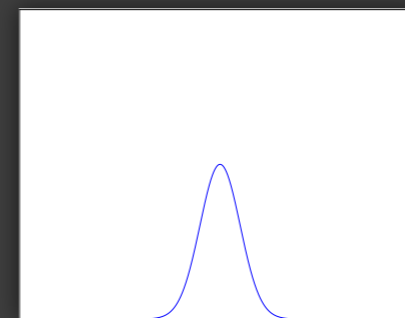
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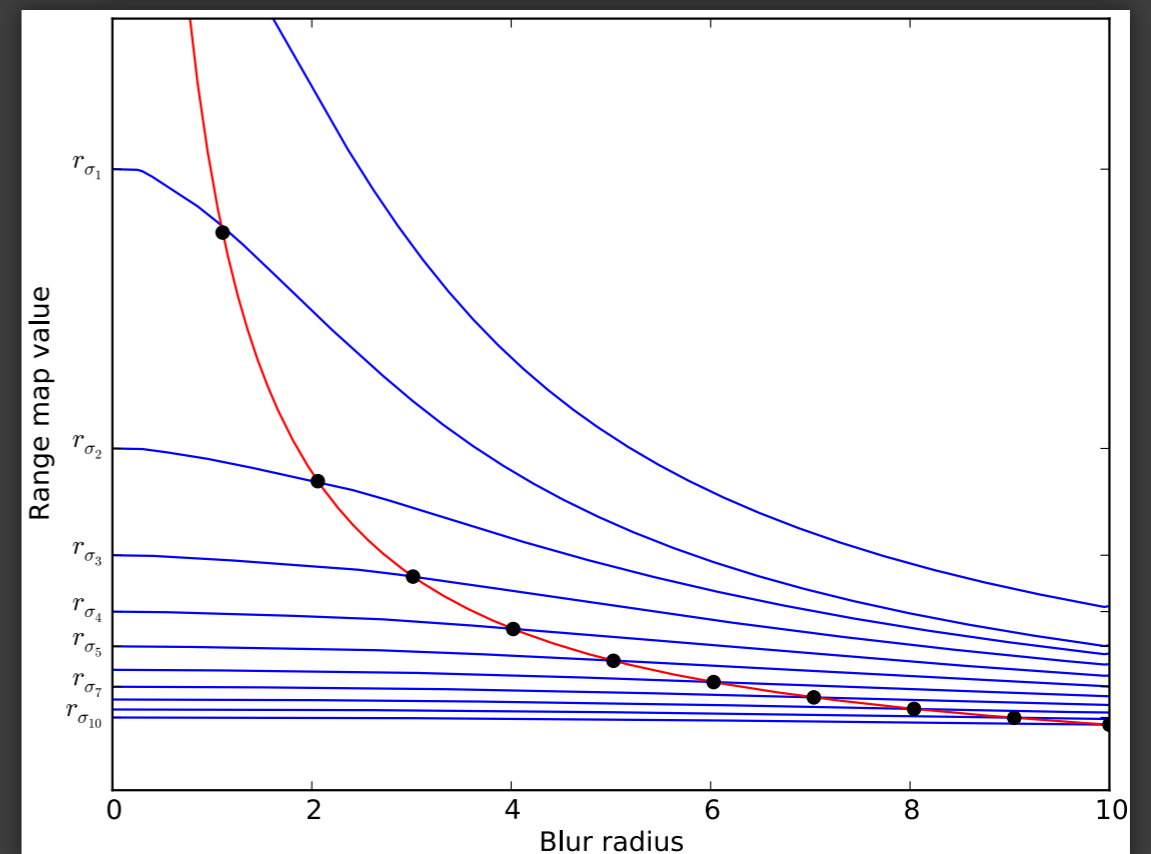
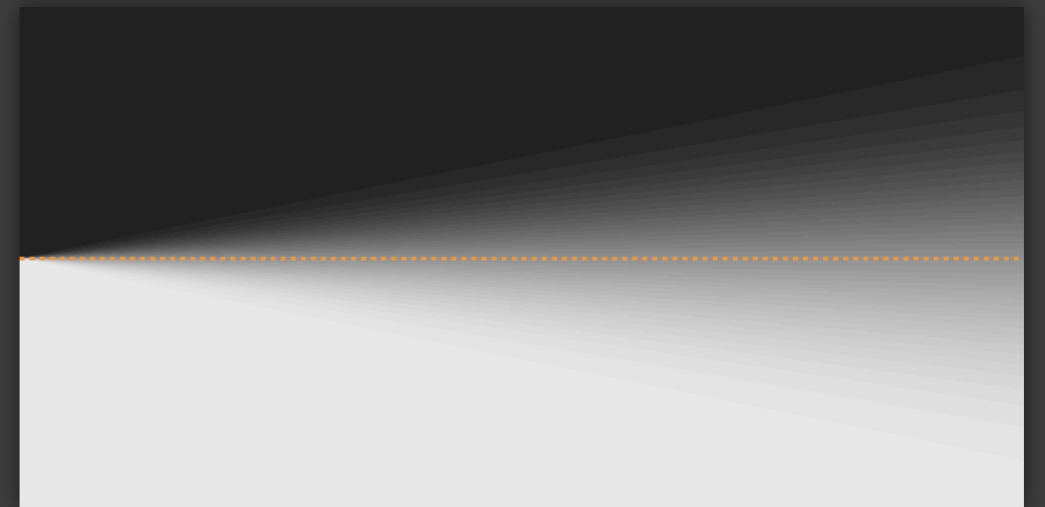
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d downsample
j scale space level
 β quantization term

$$\gamma = \frac{1}{\sqrt{\left(\frac{1}{d} \right)^2 + \beta^2}}$$

Blur estimation

- Scaled original image gradients by gamma to align with scalespace
- If j th level is the closest match to r_o , implies a blur of j pixels in the original image
- Thus ensuring the estimate blur corresponds to some absolute measure of pixels



Blur synthesis

- Model specifies desired blur, give blur present determine how much to add
- Created thumbnail by standard downsample -- already includes anti-aliasing, so use model \mathcal{S} instead of $\hat{\zeta}_m$

- Given existing blur σ_o
compute blur to add σ_a

$$\sigma_a = \sqrt{\left(\frac{\mathcal{S}(\sigma_o \cdot p^{-1}, d) \cdot p}{d}\right)^2 - \sigma_o^2}$$

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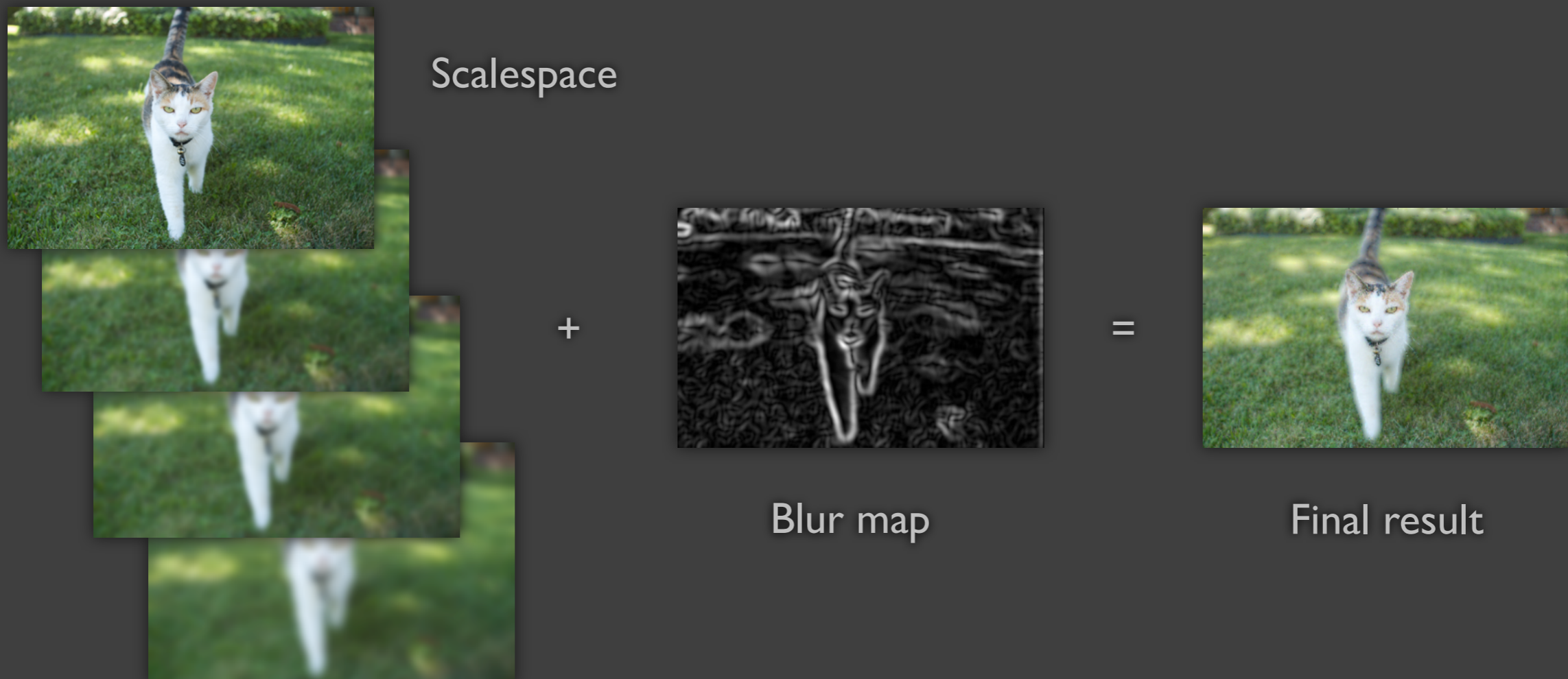
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Blur synthesis

- To produce final image blur each level scalespace l_{σ_j} by corresponding σ_a , linearly blend for non-integer σ_a



Evaluation



Naive



Samadani
 $\gamma=4$



Samadani
 $\gamma=.5$



Blur-Aware



Evaluation



Naive



Blur-Aware

Naive



Blur-Aware



Evaluation

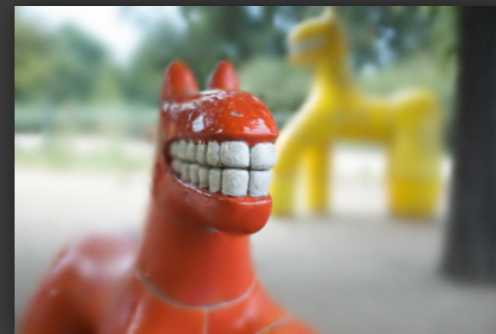
Original



2x naive



2x blur-aware



4x naive



4x aware



4x naive

4x aware



2x naive



2x blur-aware



Original

Conclusion

- Fully automatic image resizing operator that uses a perceptual metric to preserve image appearance
- Effect due to HVS:
The same metric can account for changes in appearance due to viewing distance
- Future work:
Other models like camera optics to enhance blur
Extending principle to other attributes such as noise or contrast



Thanks!
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