Advanced Graphics & Image Processing

Assessing Image Quality

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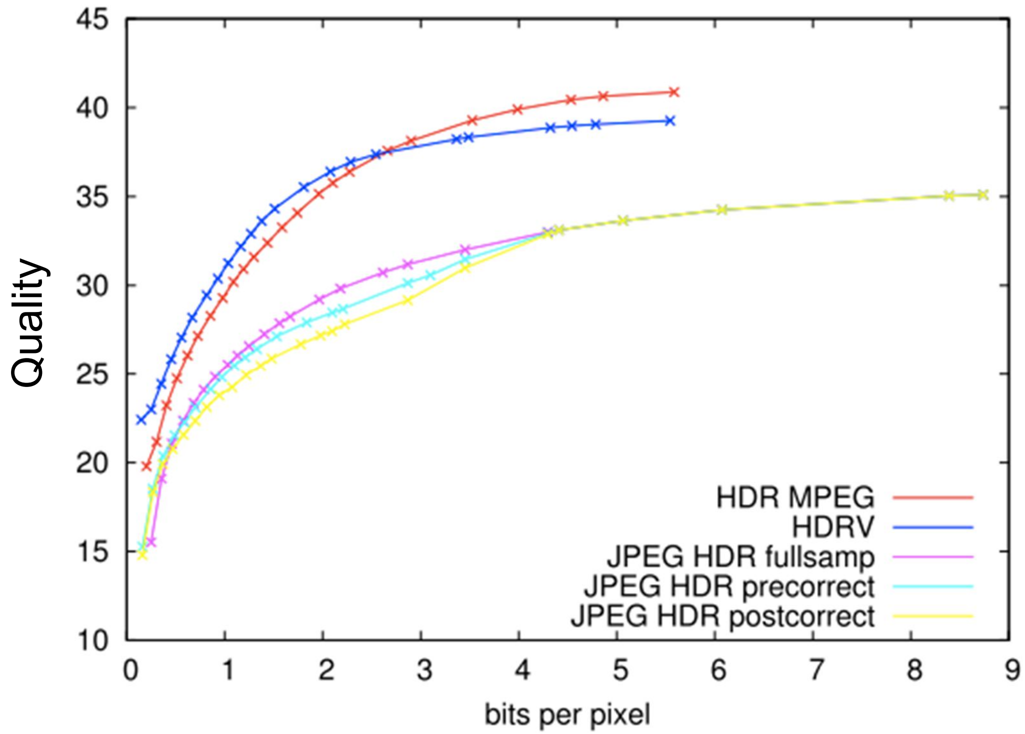
The purpose of image quality assessment

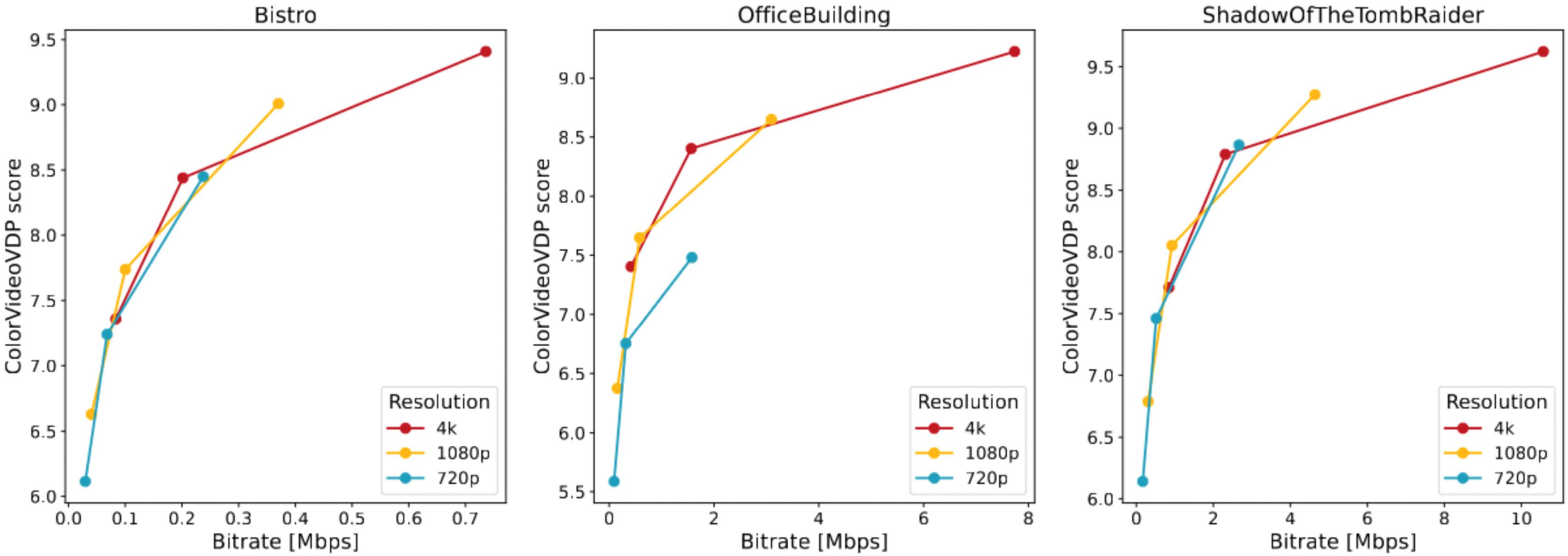
- To compare algorithms in terms of image or video quality



Rate-Distortion (RD) curves

The purpose of image quality assessment

- To optimize application parameters – e.g. resolution and bit-rate



The purpose of image quality assessment

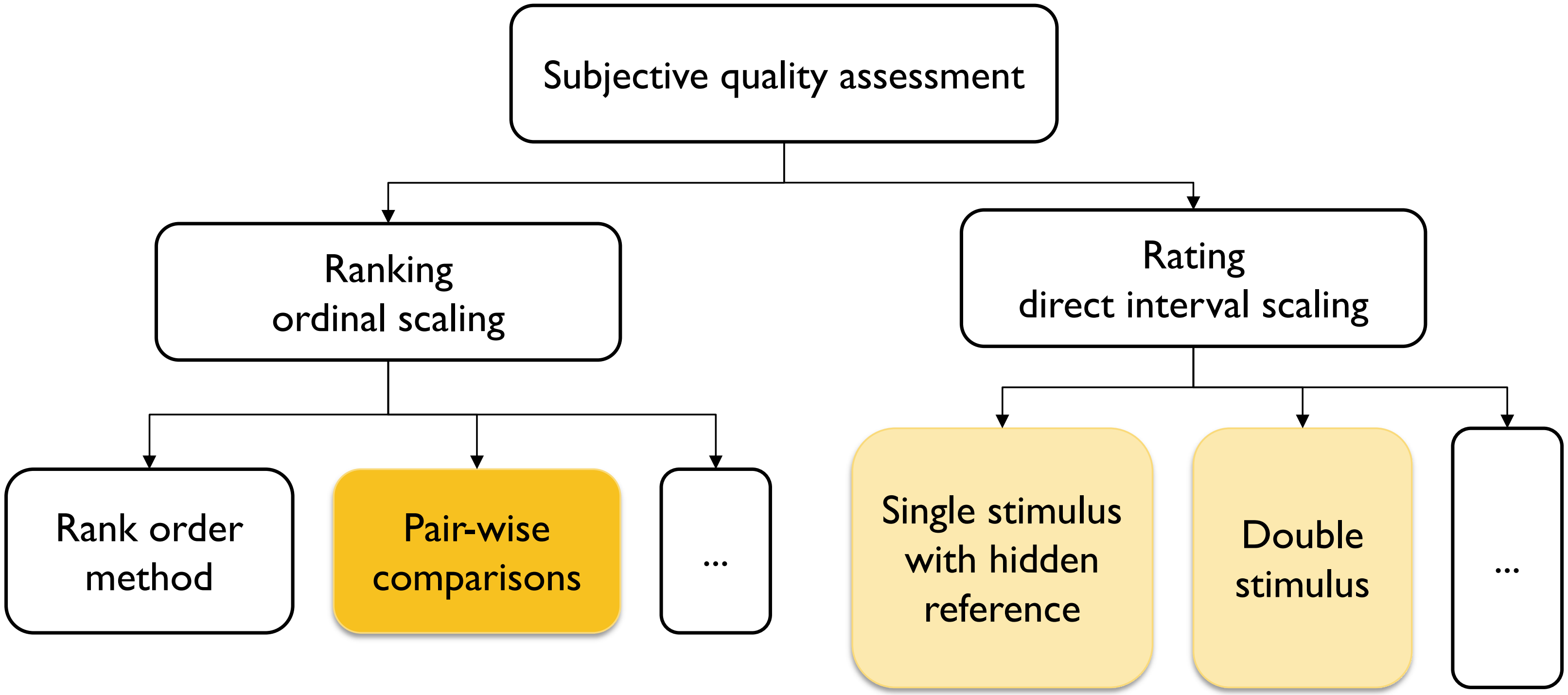
- To provide evidence of improvement over the state-of-the-art

Algorithm A　　Algorithm B　　Algorithm C

Other application domains

- Recommendation systems
  - Which movie to watch? (Netflix)
  - Which product to buy? (Amazon)
- Product acceptance / rating
  - Food
  - Clothing
  - Consumer electronics, …
- Similar techniques used for
  - Ranking of the players/gamers to match their skills in the game (TrueSkill on Xbox)

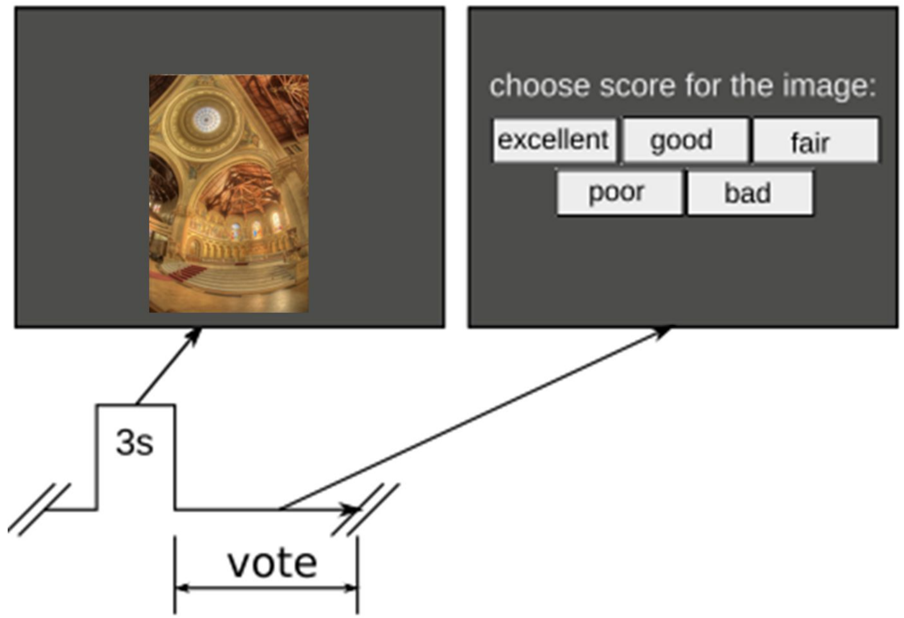
Subjective image/video quality assessment methods



Rating: Single stimulus + hidden reference

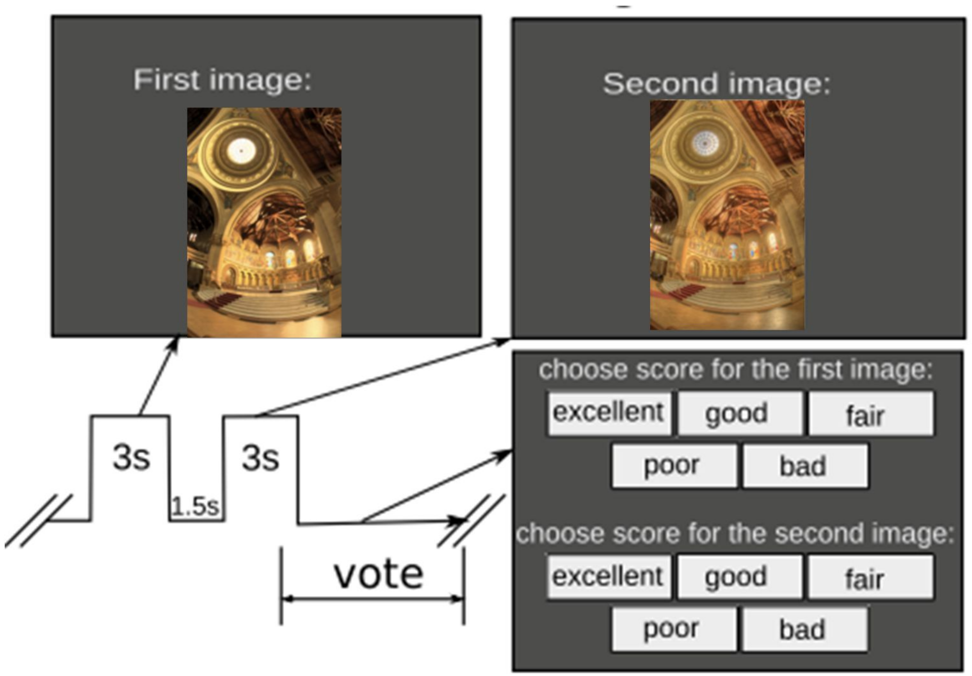
- With a hidden reference
- Task: **Rate** the quality of the image
- The categorical variables (excellent, good, …) are converted into scores 1-5
- Then those are averaged across all observers to get Mean-Opinion-Scores (MOS)
- To remove the effect of reference content, we often calculate DMOS:

$$Q_{DMOS} = Q_{MOS}^{reference} - Q_{MOS}^{test}$$



Rating: Double stimulus

- Task: Rate the quality of the first and the second image
- The second image is typically the reference
- Potentially better accuracy of DMOS
- But takes more time
  - The reference shown after each test image



Pair-wise comparison method

- Example: video quality
- Task: Select the video sequence that has a higher quality

Comparison matrix

- Results of pairwise comparisons can be stored in a comparison matrix

$$
\begin{array}{cc}
 & \begin{array}{ccc} C1 & C2 & C3 \end{array} \\
C = & \begin{bmatrix} 0 & 3 & 1 \\ 3 & 0 & 2 \\ 5 & 4 & 0 \end{bmatrix}
\end{array}
\begin{array}{c} C1 \\ C2 \\ C3 \end{array}
$$

- In this example: 3 compared conditions: C1, C2, C3
- $C_{ij} = n$ means that condition Ci was preferred over Cj n times

Full and reduced designs

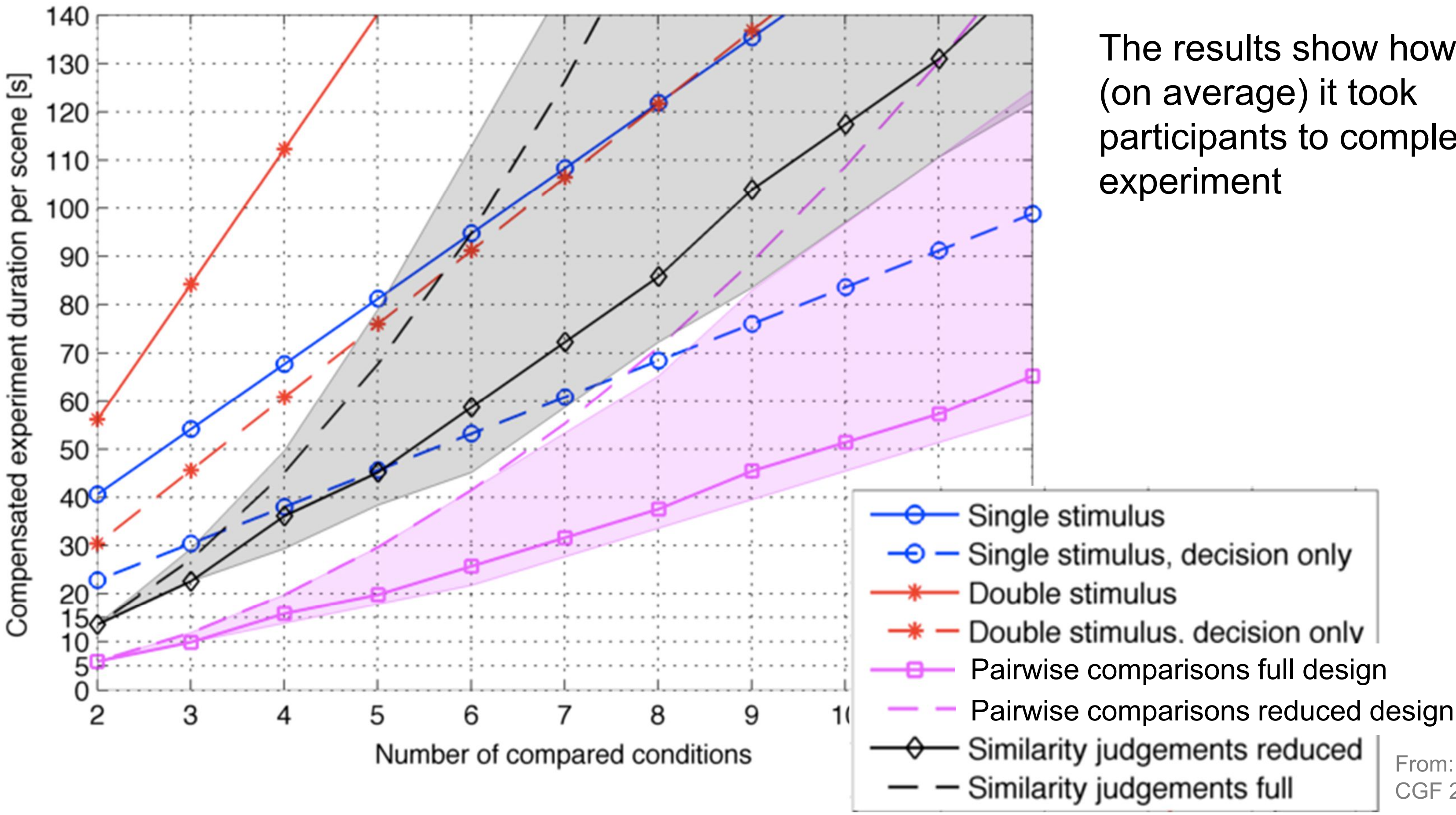
- Full design
  - Compare all pairs of conditions
  - This requires $\binom{n}{2} = \frac{n(n-1)}{2}$ comparisons for *n* conditions
  - Tedious if *n* is large
- Reduced design
  - We assume transitivity
    - If C1 > C2 and C2 > C3 then C1 > C3
      - no need to do all comparisons
  - There are numerous "block designs" (before computers)
  - But the task is also a sorting problem
    - The number comparison can be reduced to $n\log(\mathrm{n})$ for a "human quick-sort"
  - And many others: Swiss chess system, active sampling ...

$$C = \begin{array}{c} \\ \\ \end{array} \begin{array}{cc} & \begin{array}{ccc} \mathrm{C1} & \mathrm{C2} & \mathrm{C3} \end{array} \\ & \begin{bmatrix} 0 & 3 & 1 \\ 3 & 0 & 2 \\ 5 & 4 & 0 \end{bmatrix} \end{array} \begin{array}{c} \\ \mathrm{C1} \\ \mathrm{C2} \\ \mathrm{C3} \end{array}$$

Pairwise comparisons vs. rating (e.g. single stimulus)

- The method of pairwise comparisons is **fast**
  - More comparisons, but
  - It takes less time to achieve the same sensitivity as for direct rating methods
- Has a higher sensitivity
  - Less "external" variance between and within observers
- Provides a unified quality scale
  - The scale (of JOD/JND) is transferrable between experiments
- Simple procedure
  - Training is much easier
  - Less affected by learnining effects
- Especially suitable for non-expert participants
  - E.g. Crowdsourcing experiments

Time-efficiency

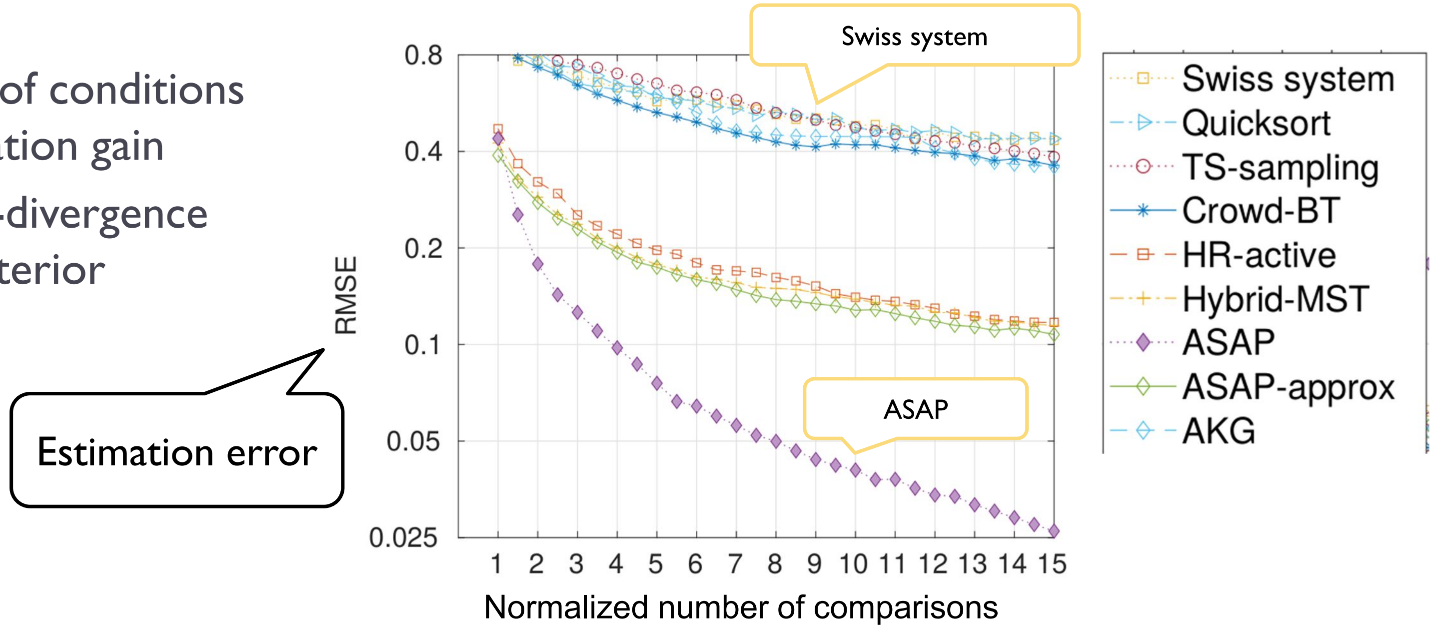


The results show how long (on average) it took participants to complete the experiment

From: Mantiuk et al. CGF 2012

Active sampling can make the experiments even faster

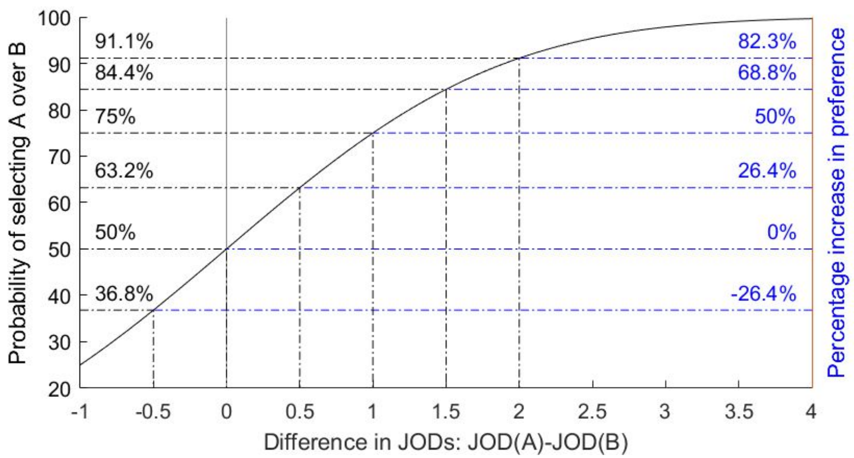
- Active sampling
  - For each trial, select a pair of conditions that maximizes the information gain
  - Information gain is the DK-divergence between the prior and posterior distributions

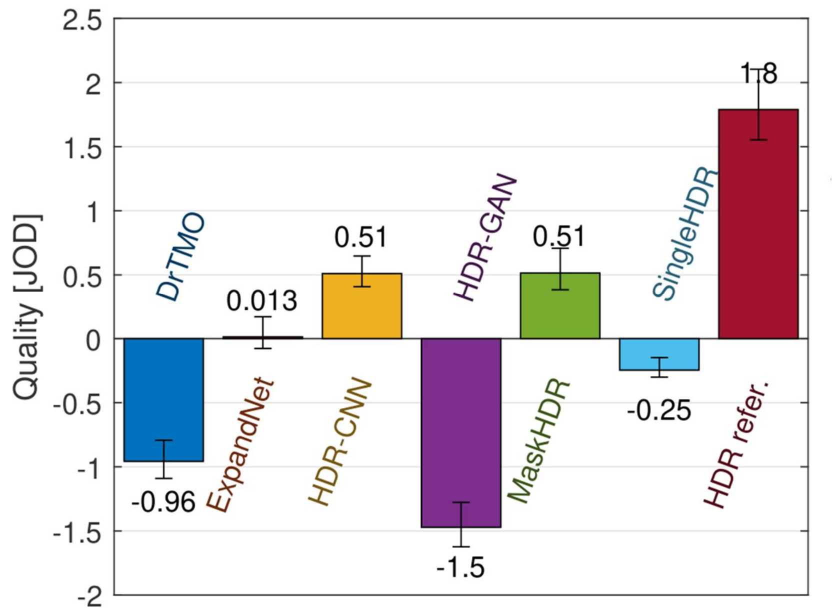


- Mikhailiuk, A., C. Wilmot, M. Perez-Ortiz, D. Yue, and R.K. Mantiuk. "ASAP: Active Sampling for Pairwise Comparisons via Approximate Message Passing and Information Gain Maximization." In *International Conference on Patter Recognition*, 2020.

Practical significance - scaling

- Scaling: to map user judgments into meaningful interval scale
- Typically that scale is in just-noticeable-difference units
  - The difference of 1 JND means that 75% of observers would choose one condition over another
  - Useful to show "practical" significance





Scaling pairwise comparison data

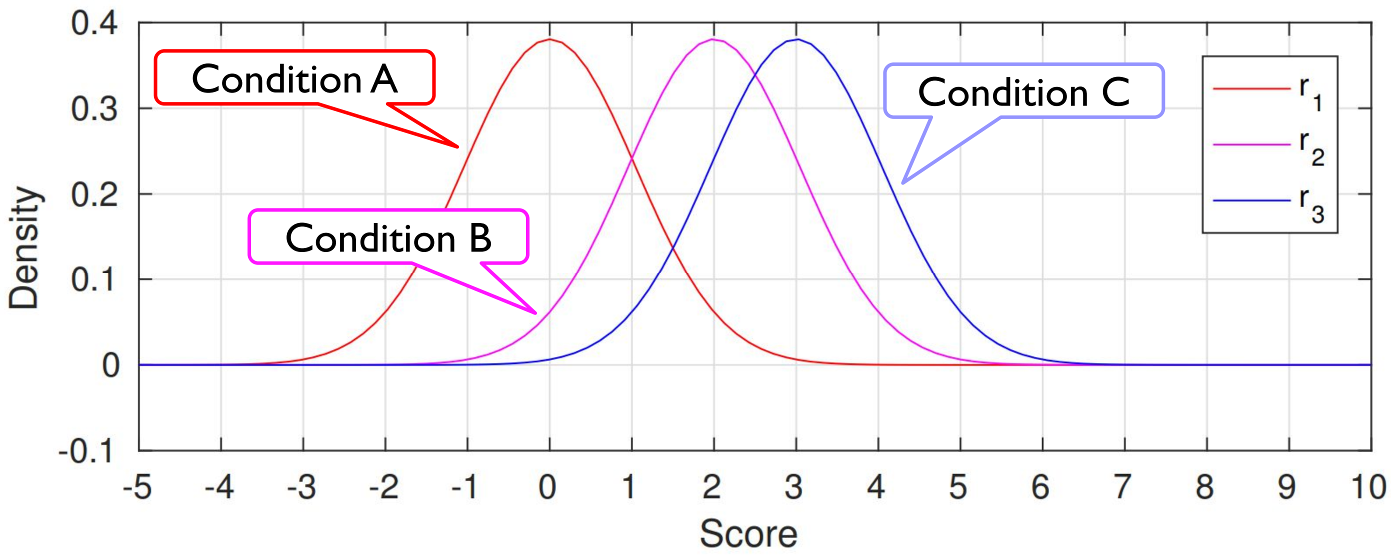
- Given a matrix of comparisons, for example

$$\mathbf{C} = \begin{bmatrix} 0 & 3 & 0 \\ 27 & 0 & 7 \\ 30 & 23 & 0 \end{bmatrix}$$

- Infer the quality scores for all compared conditions
  - Using Maximum Likelihood Estimation (MLE)
- We start from an observer model, then link it to the observations

Thurstone (observer) model - Case V

- Two assumptions:
  - Quality scores for a given condition are normally distributed across the population
  - The variance of that distribution is the same for each condition and the judgements are independent



From the observer model to probabilities

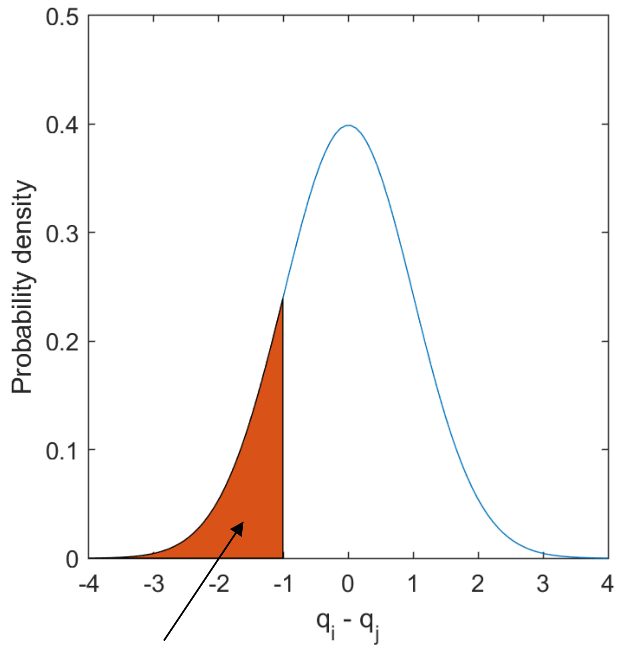
- Given the observer model for two conditions:

$$r_i = N(q_i, \sigma^2) \qquad r_j = N(q_j, \sigma^2)$$

- The difference between two quality scores is:

$$r_i - r_j = N(q_i - q_j, 2\sigma^2)$$

- Then, the probability of the judgment is explained by the cumulative normal distribution



$$P(r_i > r_j | q_i - q_j = -1)$$

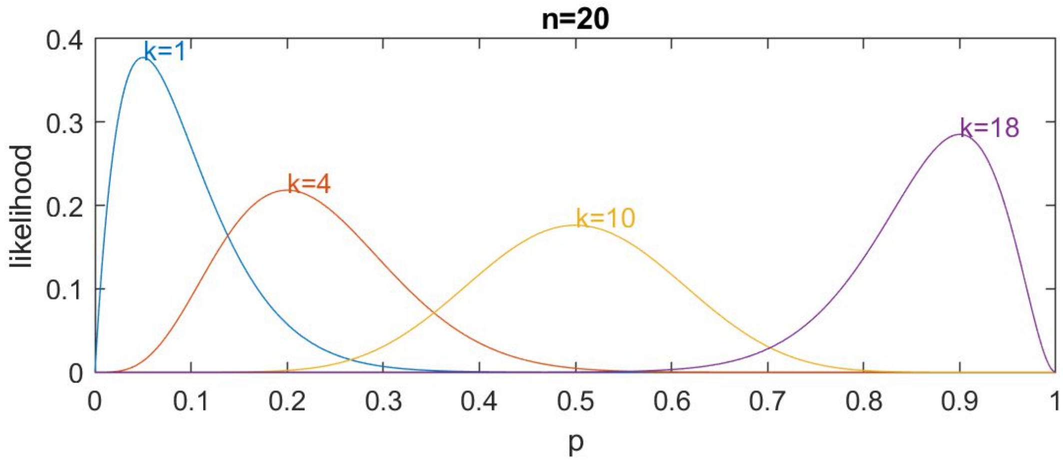
$$P(r_i > r_j) = P(r_i - r_j > 0) = \Phi\left(\frac{q_i - q_j}{\sigma_{ij}}\right)$$

$$= \frac{1}{\sigma_{ij}\sqrt{2\pi}} \int_{-\infty}^{q_i - q_j} e^{\left(\frac{-x^2}{2\,\sigma_{ij}{}^2}\right)} dx \,.$$

where $\sigma_{ij} = \sqrt{2}\sigma$

Binomial distribution

- Given that *k* out of *n* observers selected A over B, what is the probability distribution of selecting A over B



$$P\left(r_i > r_j | n, k\right) = \binom{n}{k} p^k (1-p)^{n-k}$$

Maximum Likelihood Estimation

- Given our observations (comparison matrix) what is the likelihood of the quality values q_i:

$$
\begin{aligned}
L(\hat{q}_i - \hat{q}_j | c_{ij}, n_{ij}) &= \binom{n_{ij}}{c_{ij}} P(r_i > r_j)^{c_{ij}} \left(1 - P(r_i > r_j)\right)^{n_{ij} - c_{ij}} \\
&= \binom{n_{ij}}{c_{ij}} \Phi\left(\frac{\hat{q}_i - \hat{q}_j}{\sigma_{ij}}\right)^{c_{ij}} \left(1 - \Phi\left(\frac{\hat{q}_i - \hat{q}_j}{\sigma_{ij}}\right)\right)^{n_{ij} - c_{ij}}
\end{aligned}
$$

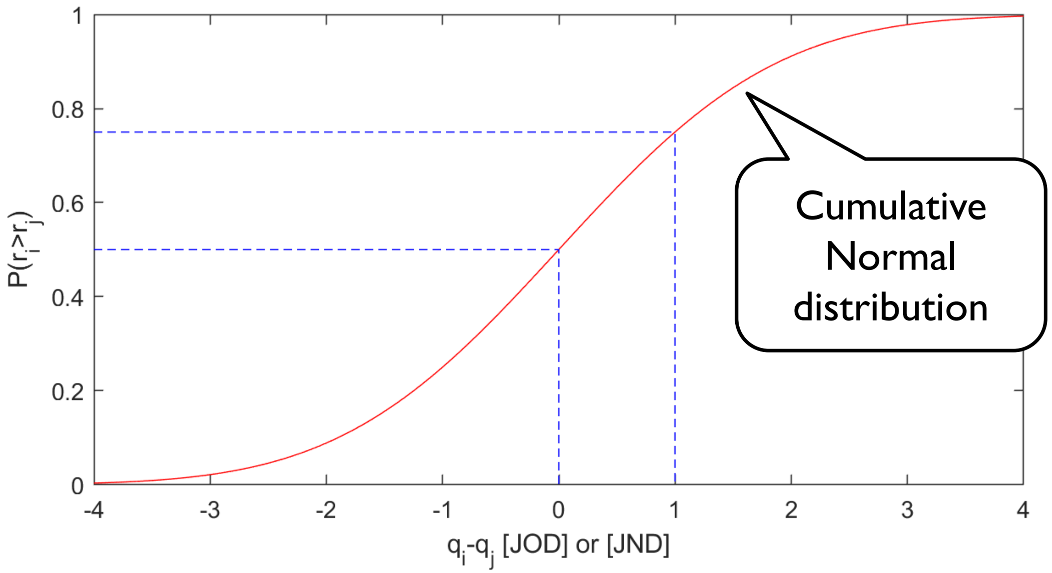
Cumulative Normal

  - where $n_{ij} = c_{ij} + c_{ji}$
- To estimate the values of q_i, we maximize:

$$
\underset{\hat{q}_2, \ldots, \hat{q}_n}{\arg\max} \prod_{i,j \in \Omega} L(\hat{q}_i - \hat{q}_j | c_{ij}, n_{ij})
$$

JND/JOD = 1

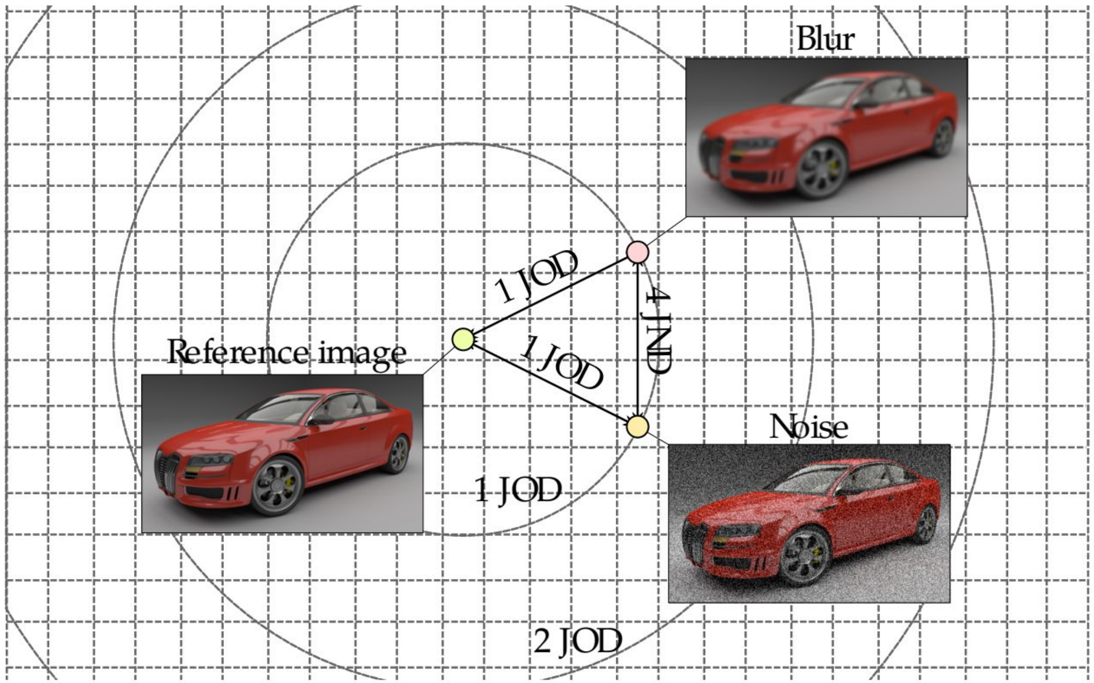
- Just Noticeable Differences
- Just Objectionable Differences
- We want $q_i - q_j = 1$ when 75% of observers prefer condition "i" over "j"



- This happens when $\sigma_{ij} = 1.4826$
- This is arbitrary selected scaling, made for easier interpretation of the results

JND vs JOD

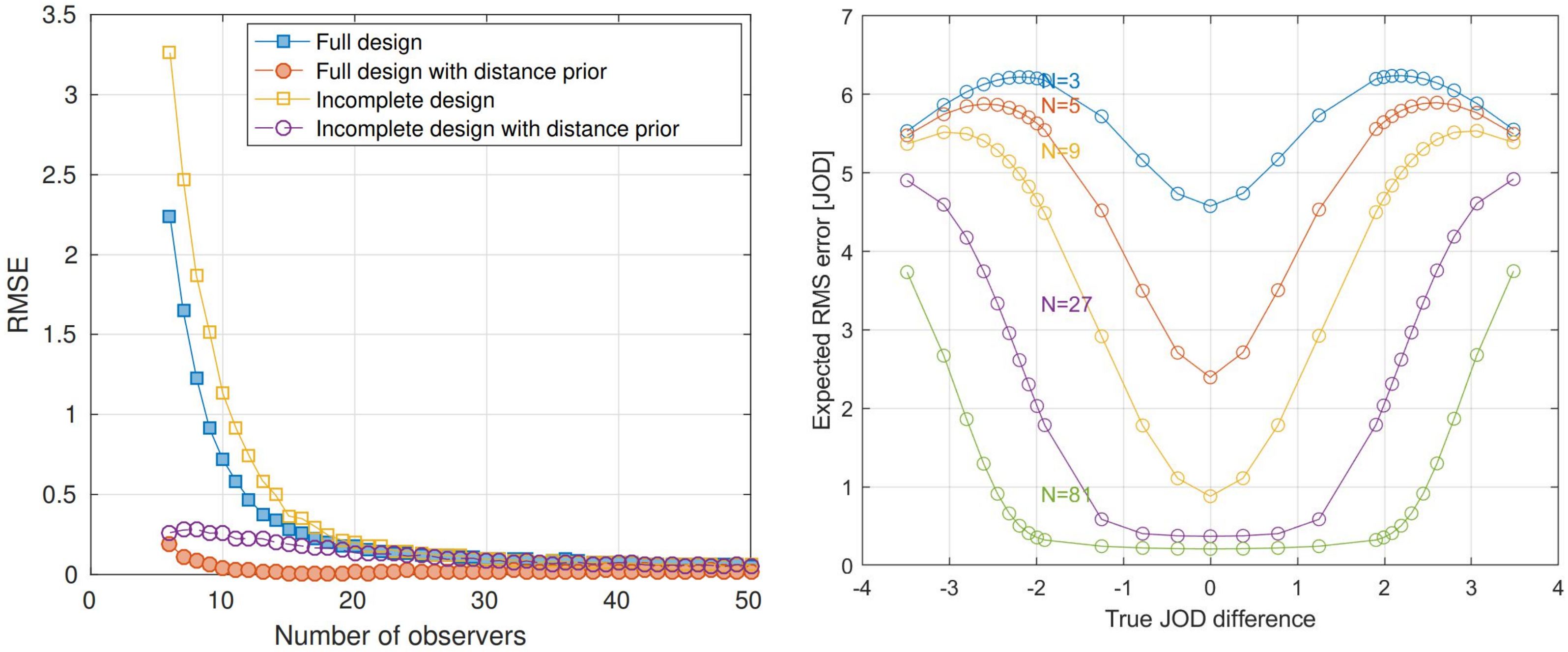
- Just Noticeable Differences
- Just Objectionable Differences



- JND – is one visually different from another
- JOD – is the **quality** of one different from the quality of another (relative to the reference)

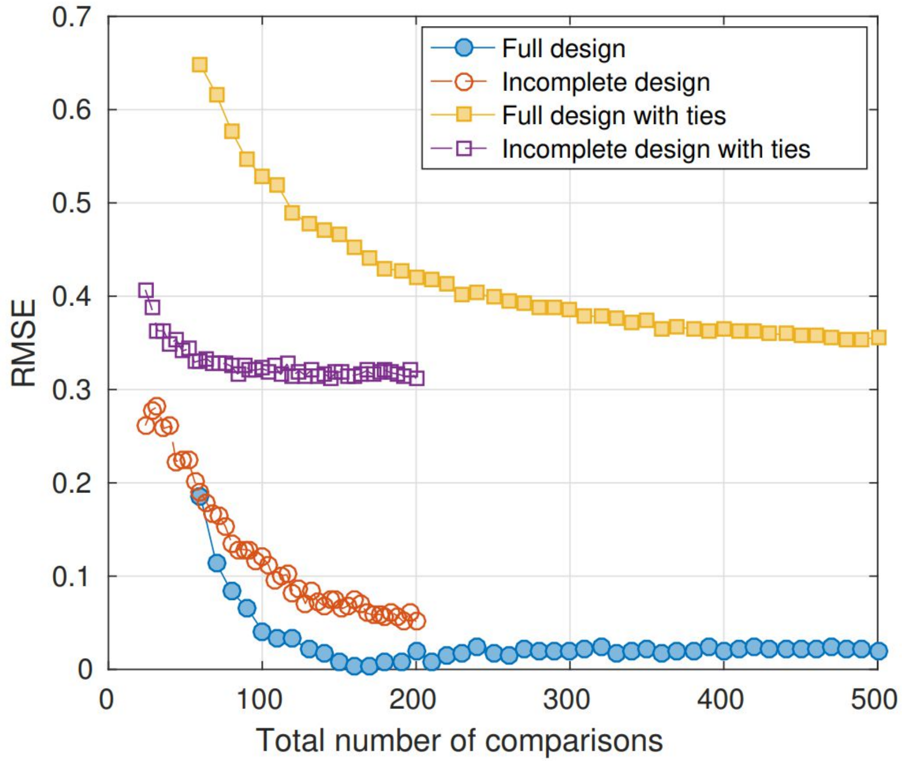
Practicalities of MLE scaling

- At least 15-20 comparisons per each pair are needed to obtain stable results (prior helps)



Forced choice vs. comparison with ties

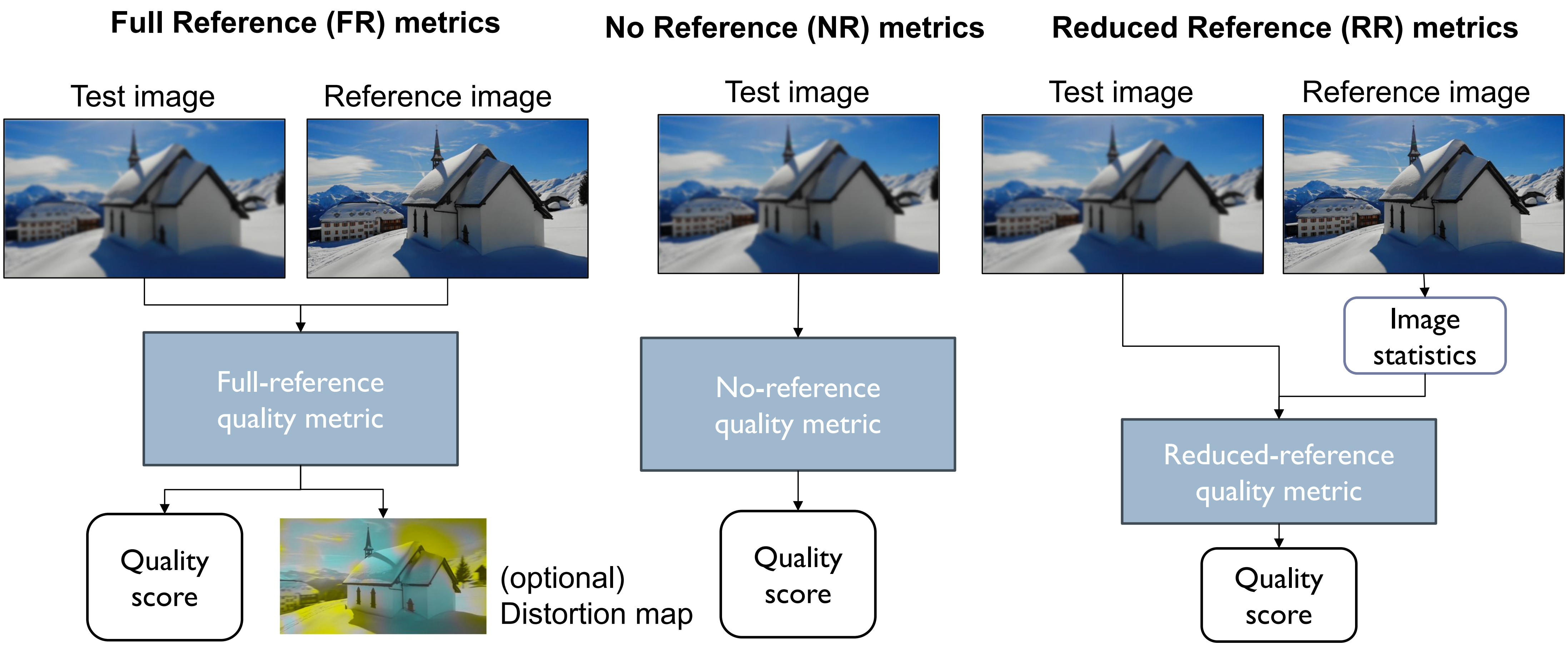
- Giving a "tie" option is usually a bad idea



- Scaling the results with ties requires a more complex observer model with more parameters to estimate

Objective (image/video) quality metrics

Types of objective (image/video) quality metrics



Main use cases of objective quality metrics

(I) Evaluation

Which method is the best?

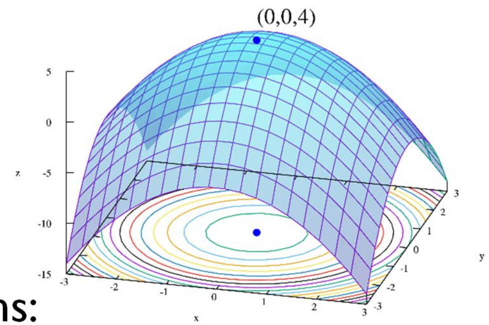
Dataset	Scale	Bicubic	A+ [27]	SRCNN [4]	VDSR [11]
Set5	×2	33.66 / 0.9299	36.54 / 0.9544	36.66 / 0.9542	37.53 / 0.9587
	×3	30.39 / 0.8682	32.58 / 0.9088	32.75 / 0.9090	33.66 / 0.9213
	×4	28.42 / 0.8104	30.28 / 0.8603	30.48 / 0.8628	31.35 / 0.8838
Set14	×2	30.24 / 0.8688	32.28 / 0.9056	32.42 / 0.9063	33.03 / 0.9124
	×3	27.55 / 0.7742	29.13 / 0.8188	29.28 / 0.8209	29.77 / 0.8314
	×4	26.00 / 0.7027	27.32 / 0.7491	27.49 / 0.7503	28.01 / 0.7674
B100	×2	29.56 / 0.8431	31.21 / 0.8863	31.36 / 0.8879	31.90 / 0.8960
	×3	27.21 / 0.7385	28.29 / 0.7835	28.41 / 0.7863	28.82 / 0.7976
	×4	25.96 / 0.6675	26.82 / 0.7087	26.90 / 0.7101	27.29 / 0.7251
Urban100	×2	26.88 / 0.8403	29.20 / 0.8938	29.50 / 0.8946	30.76 / 0.9140
	×3	24.46 / 0.7349	26.03 / 0.7973	26.24 / 0.7989	27.14 / 0.8279
	×4	23.14 / 0.6577	24.32 / 0.7183	24.52 / 0.7221	25.18 / 0.7524

Aims:

- To demonstrate the difference in quality
- To replace subjective experiments

(II) Optimization

What are the best parameter values?



Aims:

- To replace manual parameter tweaking
- Especially in multi-dimensional problems

Pixel-wise quality metrics

- Root Mean Square Error (RMSE)

$$E_{RMSE} = \sqrt{\frac{1}{w \cdot h}\sum_{x,y}\left(t(x,y) - r(x,y)\right)^2}$$

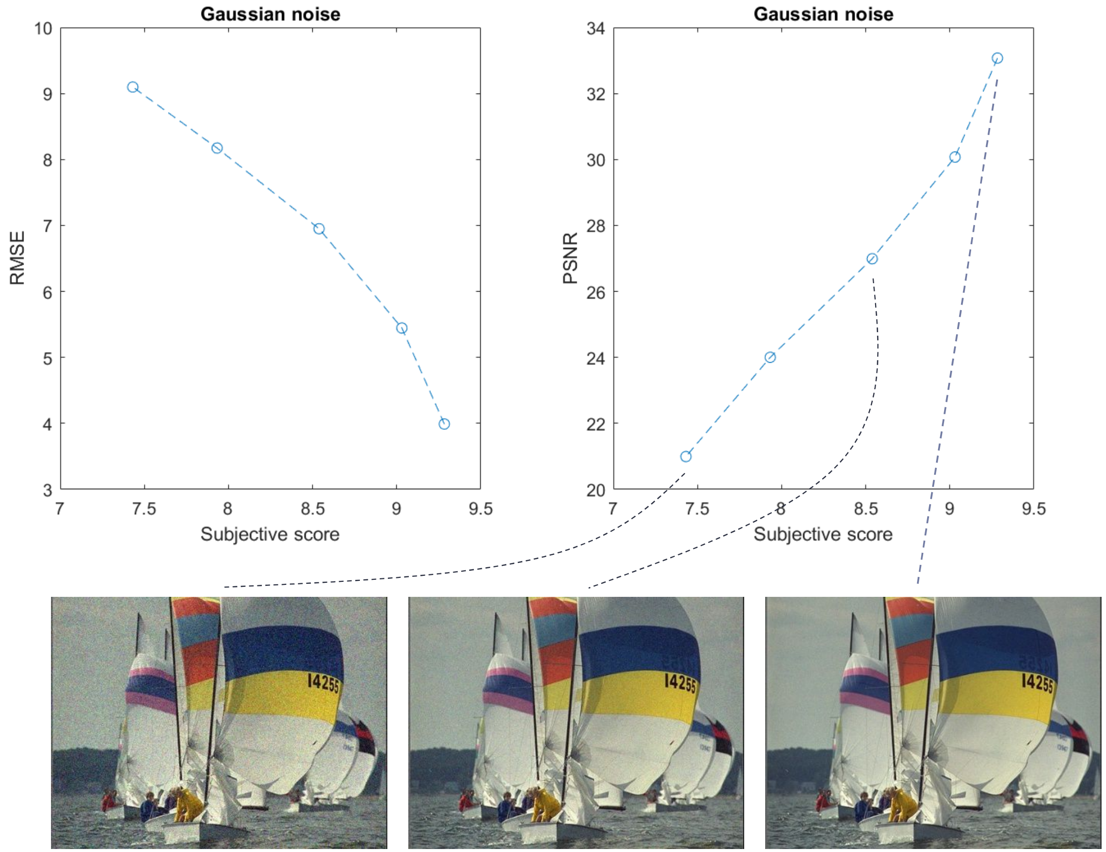
Test image

Reference image

- Peak Signal to Noise Ratio

$$E_{PSNR} = 20\,\frac{I_{peak}}{E_{RMSE}}\ [dB]$$

  - I_{peak} - the peak pixel value (e.g. 255 or 1)
  - If the error is normally distributed and its mean is 0, E_{RMSE} is the standard deviation of the distortion (noise)



The shortcomings of pixel-wise metrics

Reference

JPEG-encoded
PSNR=24.7

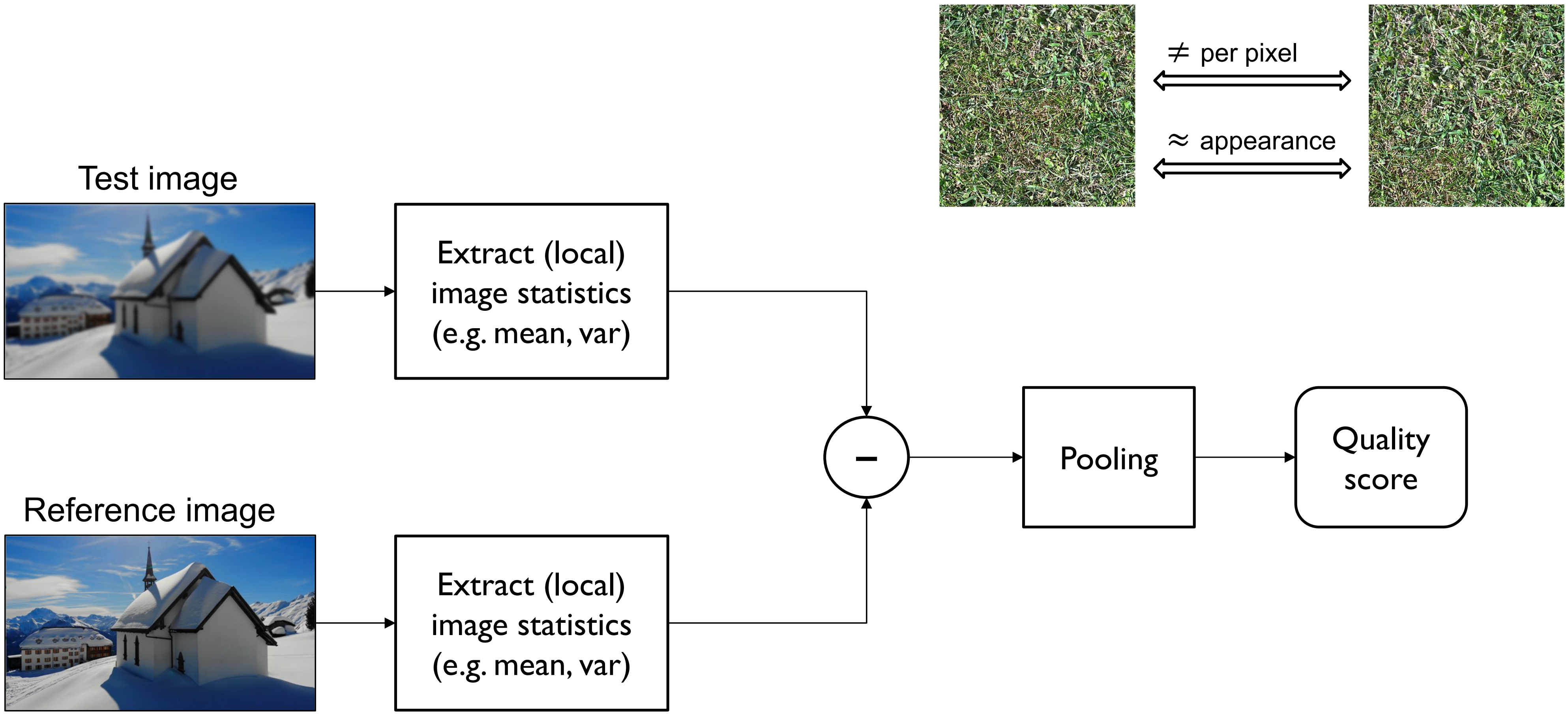
Blur
PSNR=24.8

Noise
PSNR=24.8

Rotation (1.3 deg)
PSNR=23.4

[Examples from: 10.1109/TIP.2008.926161]

Texture quality metrics

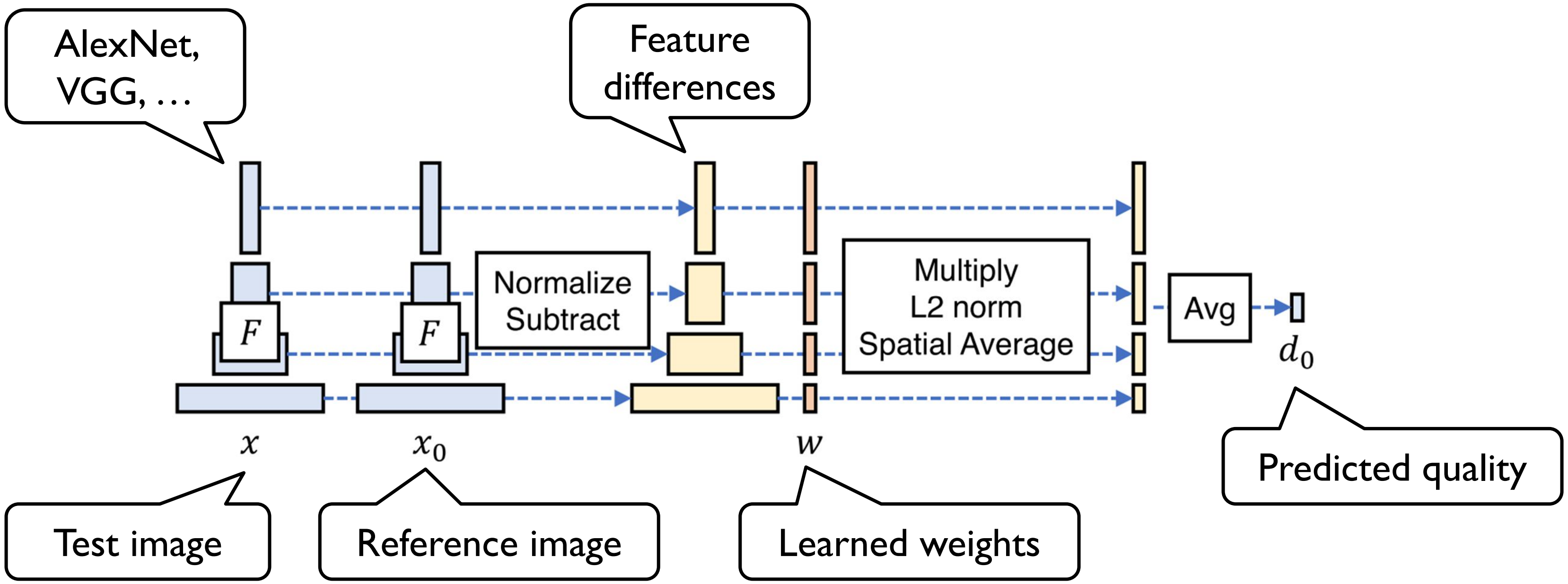


Structural Similarity Index (SSIM)

- Split test and reference images into 11×11 px overlapping patches
- For each patch, calculate mean μ_T, μ_R, std $\sigma_T \sigma_R$ and covariance σ_{TR}
  - of each patch, weighted by a Gaussian window
- Calculate three terms (per patch)
  - "Luminance": $\mathrm{l}_{\boldsymbol{x}} = \frac{2\mu_T\mu_R + C_0}{\mu_T^2 + \mu_R^2 + C_0}$
  - Contrast: $c_{\boldsymbol{x}} = \frac{2\sigma_T\sigma_R + C_1}{\sigma_T^2 + \sigma_R^2 + C_1}$
  - Structure: $s_{\boldsymbol{x}} = \frac{\sigma_{TR} + C_2}{\sigma_T\sigma_R + C_2}$ (cross-correlation)
- Multiply them together: $q_{\boldsymbol{x}} = l_{\boldsymbol{x}} \cdot \mathrm{c}_{\boldsymbol{x}} \cdot \mathrm{s}_{\boldsymbol{x}}$
- And pool: $q_{SSIM} = \frac{1}{N} \sum_{\boldsymbol{x}} q_{\boldsymbol{x}}$

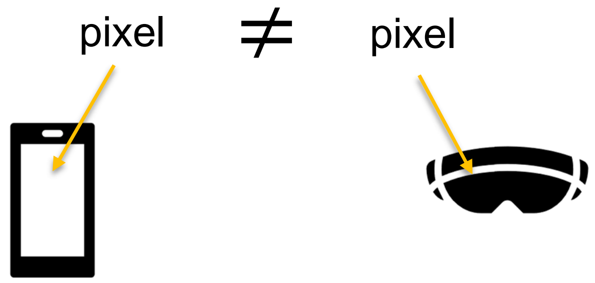
Learned Perceptual Image Patch Similarity (LPIPS)

- Use a pre-trained CNN as a feature extractor

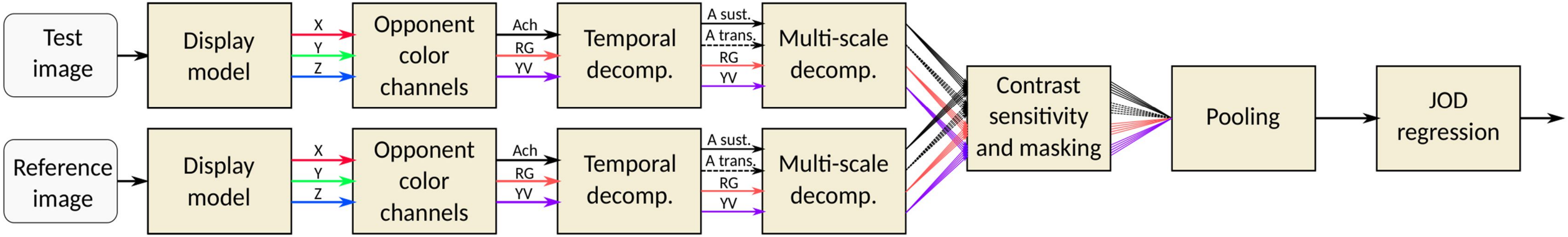


Metrics and viewing conditions

- Majority of image/video metrics disregard viewing conditions
  - Display size
  - Display resolution
  - Viewing distance
  - Display peak luminance
  - Colour gamut
- PSNR, SSIM, LPIPS operate on 0-255 pixel values
  - Cannot handle HDR images/video
- To account for the viewing conditions, we need metrics based on psychophysical models
  - known as visual difference predictors (VDPs)

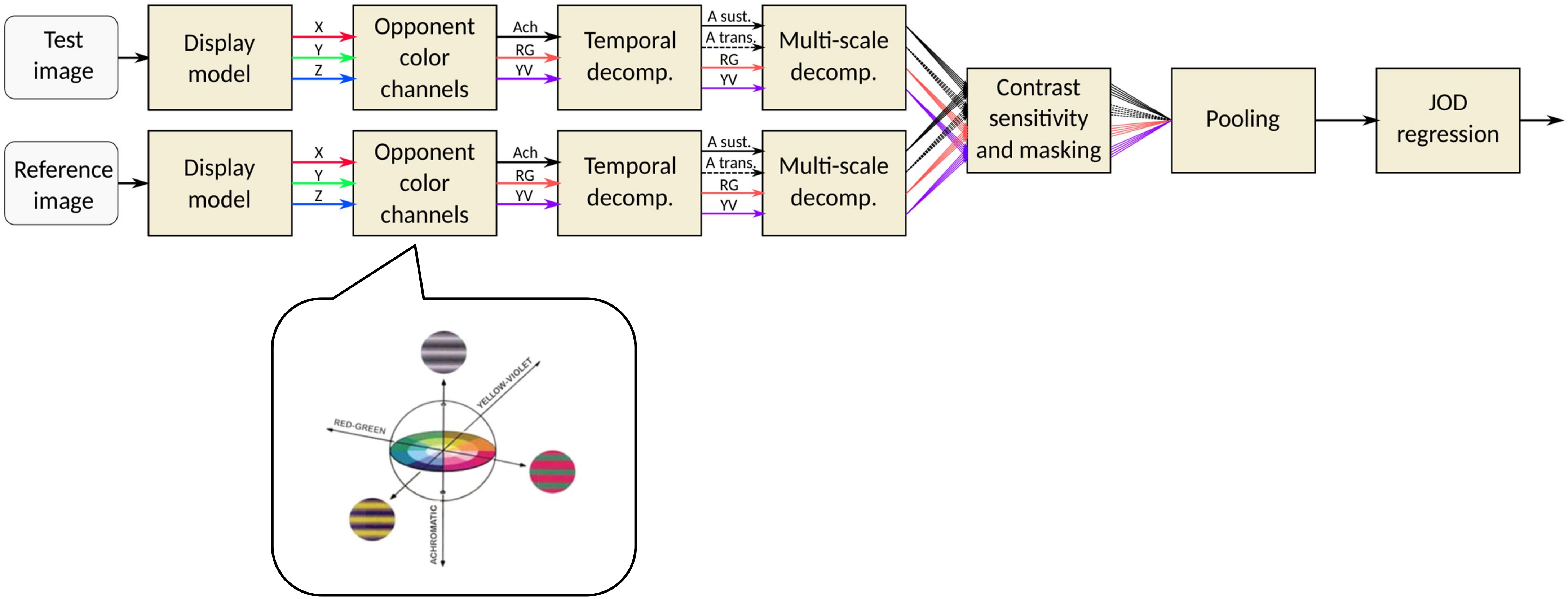


Perceptual metrics (Visual Difference Predictors)




```
"standard_4k": {
  "resolution": [3840, 2160],
  "viewing_distance_meters":  0.7472,
  "diagonal_size_inches": 30,
  "max_luminance": 200,
  "contrast": 1000,
  "E_ambient": 250,
}
```

Perceptual metrics (Visual Difference Predictors)



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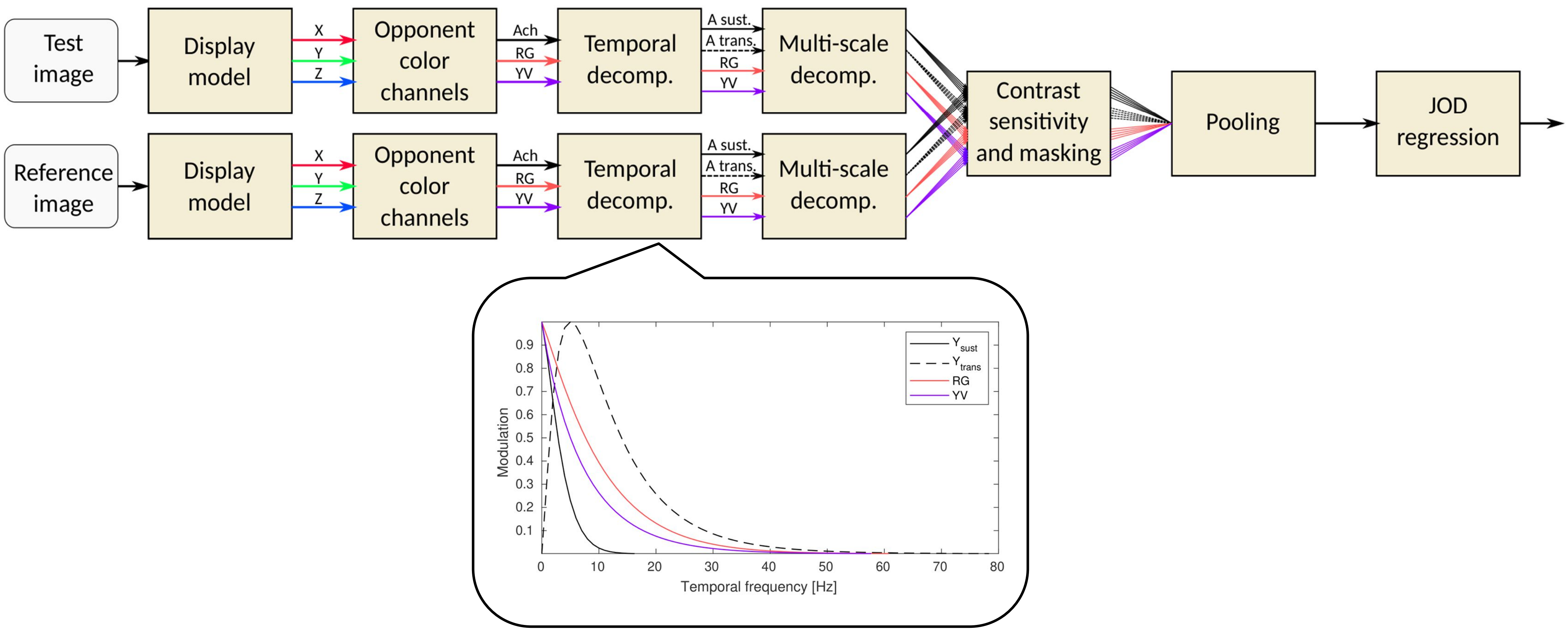

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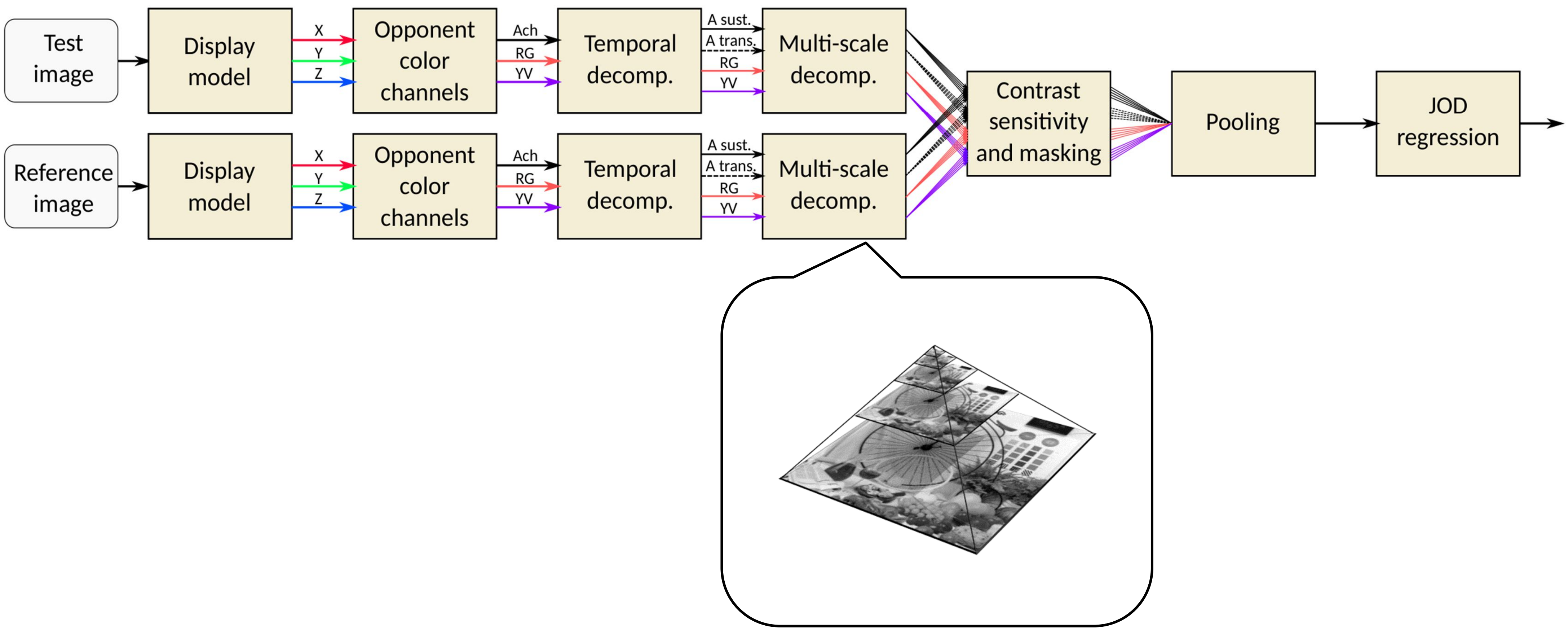
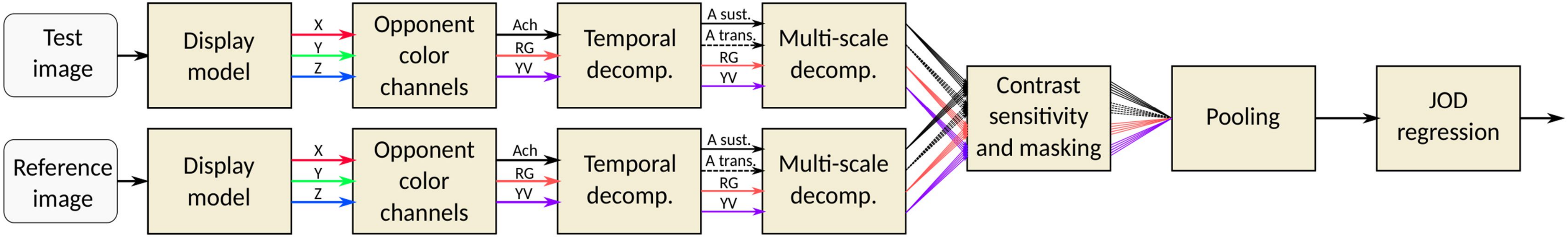
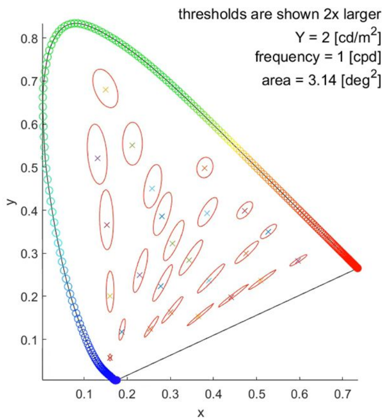


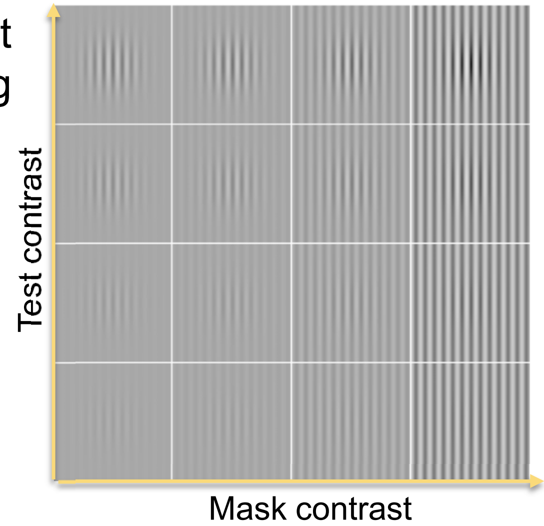
Perceptual metrics (Visual Difference Predictors)



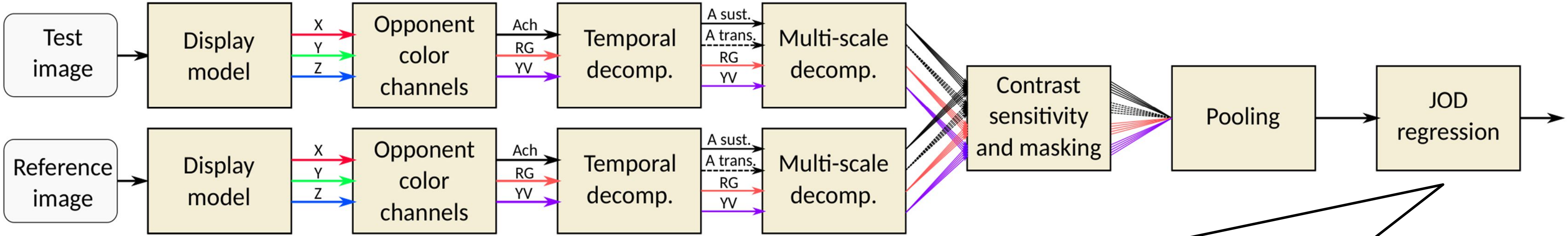
castle**CSF**
minimum
detectable
contrast
difference



Contrast
masking

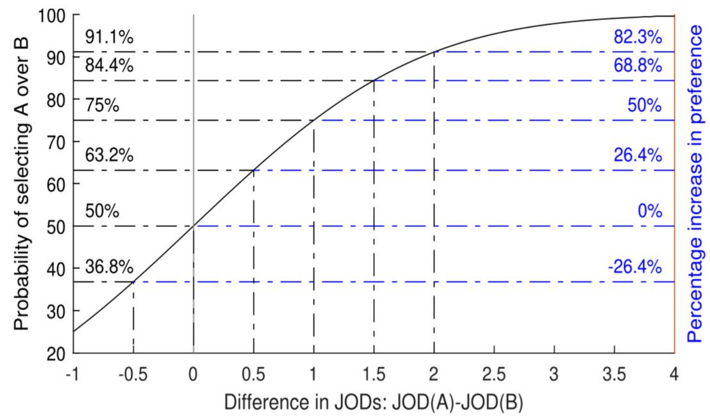


Perceptual metrics (Visual Difference Predictors)

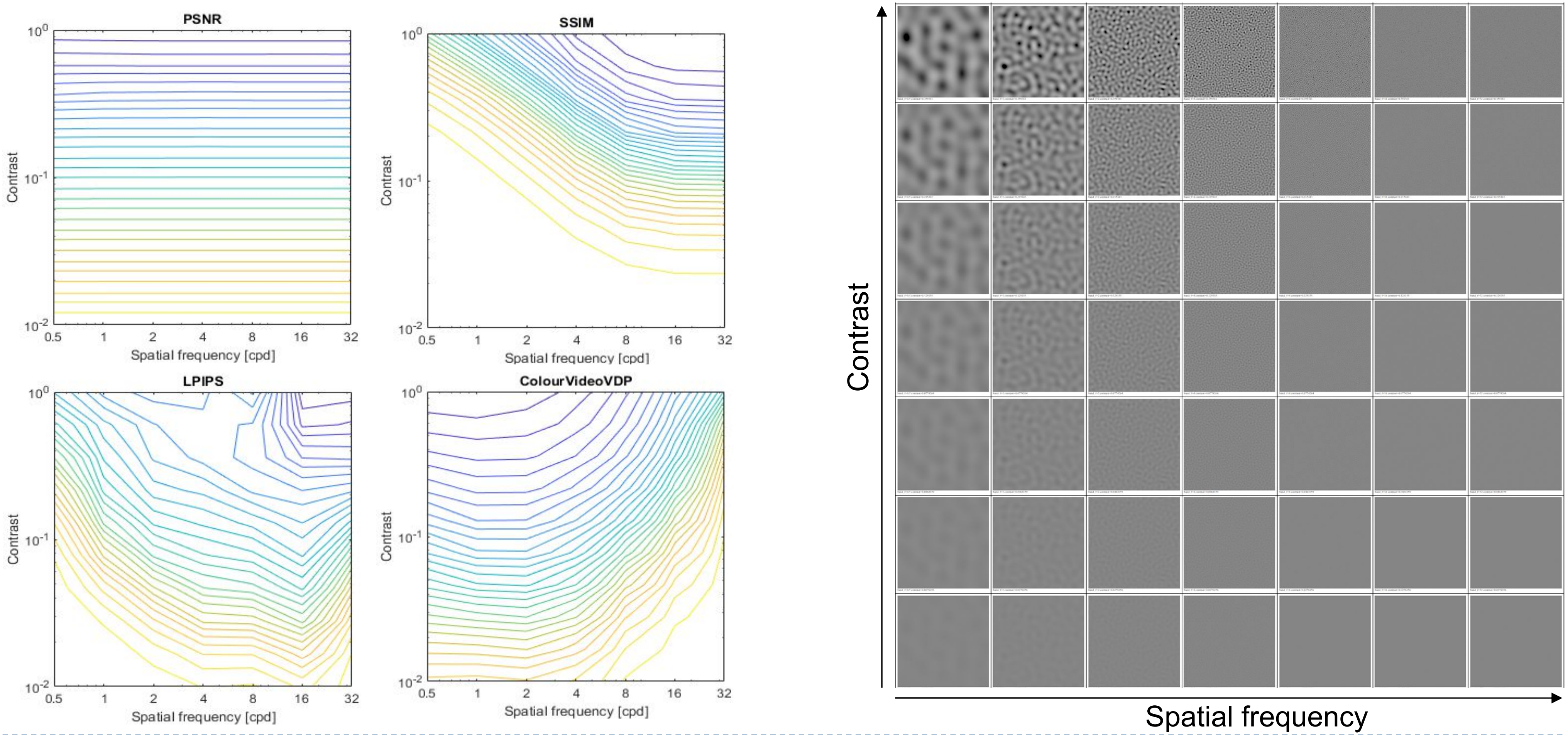


The quality is scaled in the units of
Just Objectionable Differences [JOD]
1 JOD difference ≈ 50% increase in preference

Can express supra-threshold (well-visible) differences

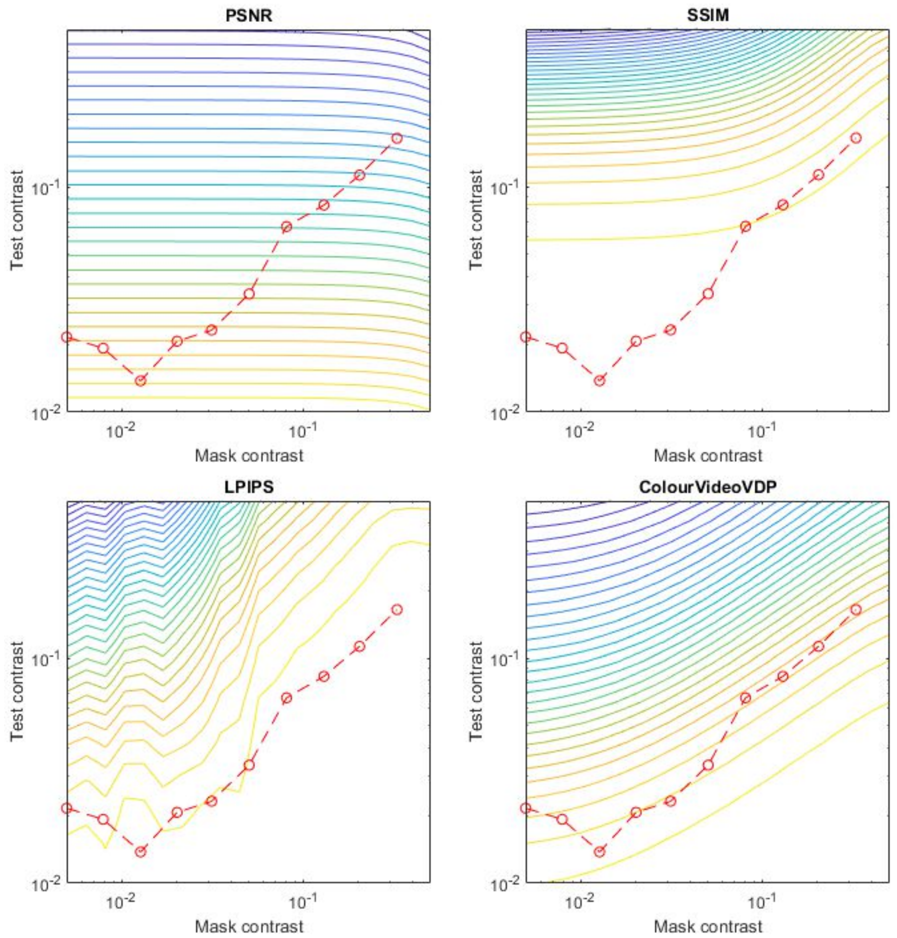


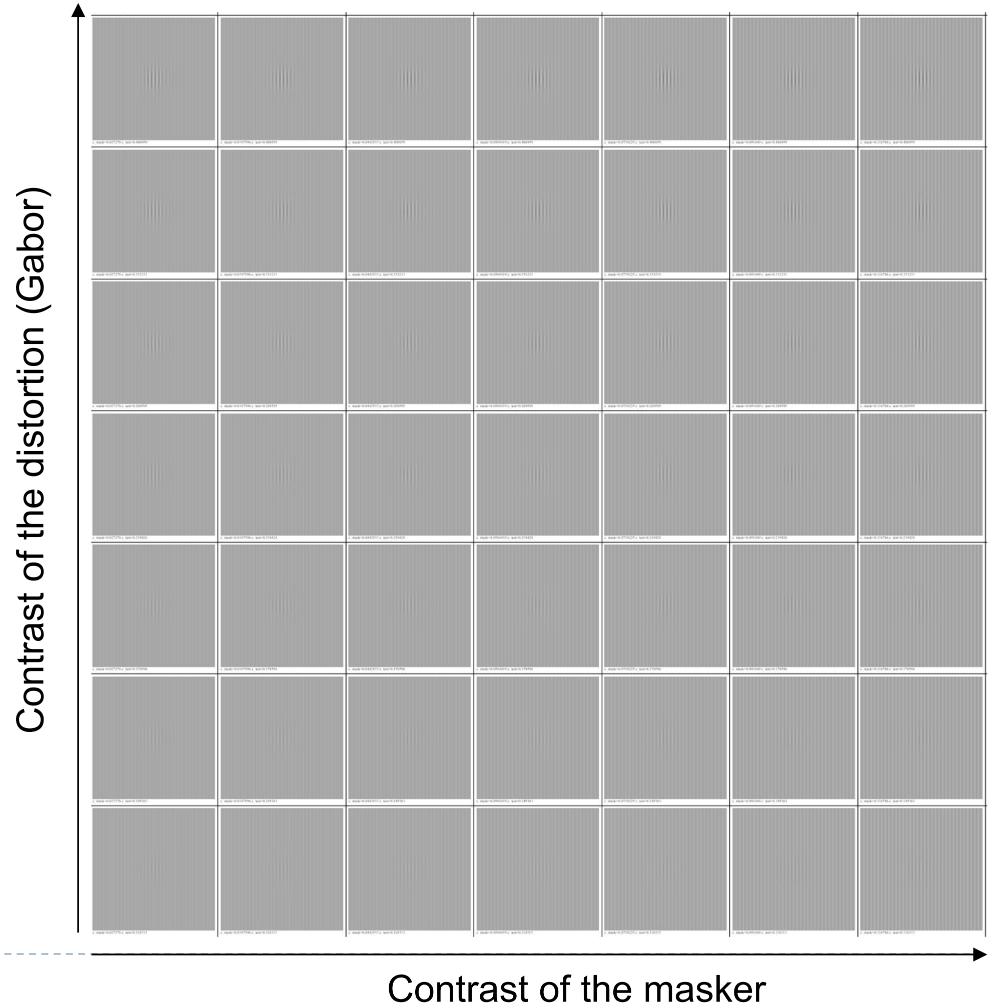
Metric performance on band-limited noise



 Violet – large difference; Orange – small difference

Metric performance on masking patterns





Violet – large difference; Orange – small difference

References

- Scaling of pairwise comparison data
  - pwcmp - https://github.com/mantiuk/pwcmp
  - A practical guide and software for analysing pairwise comparison experiments - https://arxiv.org/abs/1712.03686
- Active sampling
  - ASAP - https://github.com/gfxdisp/asap
- SSIM
  - A Hitchhiker's Guide to Structural Similarity - https://doi.org/10.1109/ACCESS.2021.3056504
- VDP metrics
  - HDR-VDP – https://hdrvdp.sourceforge.net/
  - FovVideoVDP - https://github.com/gfxdisp/FovVideoVDP
  - ColorVideoVDP - https://github.com/gfxdisp/ColorVideoVDP