Elevating Your Streaming Experience with Just Noticeable Difference (JND)-based Encoding

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Outlines

1. Context
   - What is JND
   - What is SUR
   - Motivation
2. Solutions
   1. VMAF proxy for JND
   2. SUR modeling and prediction
3. Work in progress

1.1. What is Just Noticeable Difference (JND) ?

The scope of research:

- **JND type**: video wise
- **Distortion** : video compression
- **Proxy of JND** : encoding parameters, VMAF, bitrate …

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SRC ... QP=N-1 QP=N QP=N+1 ...

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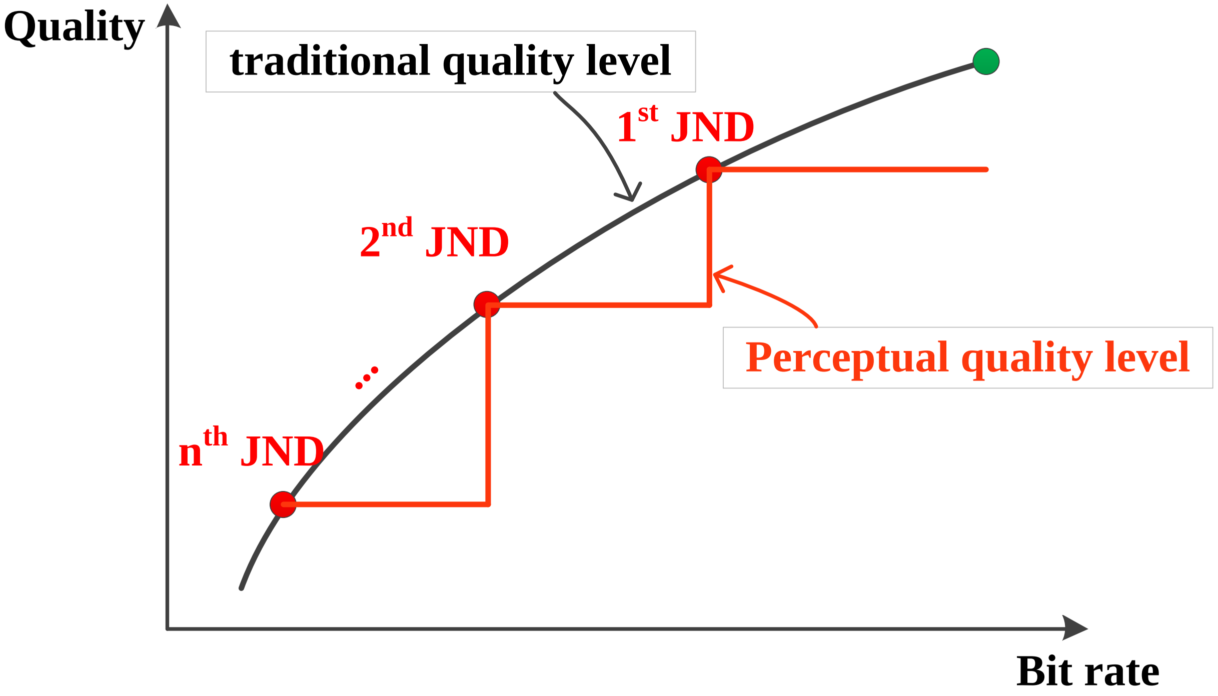

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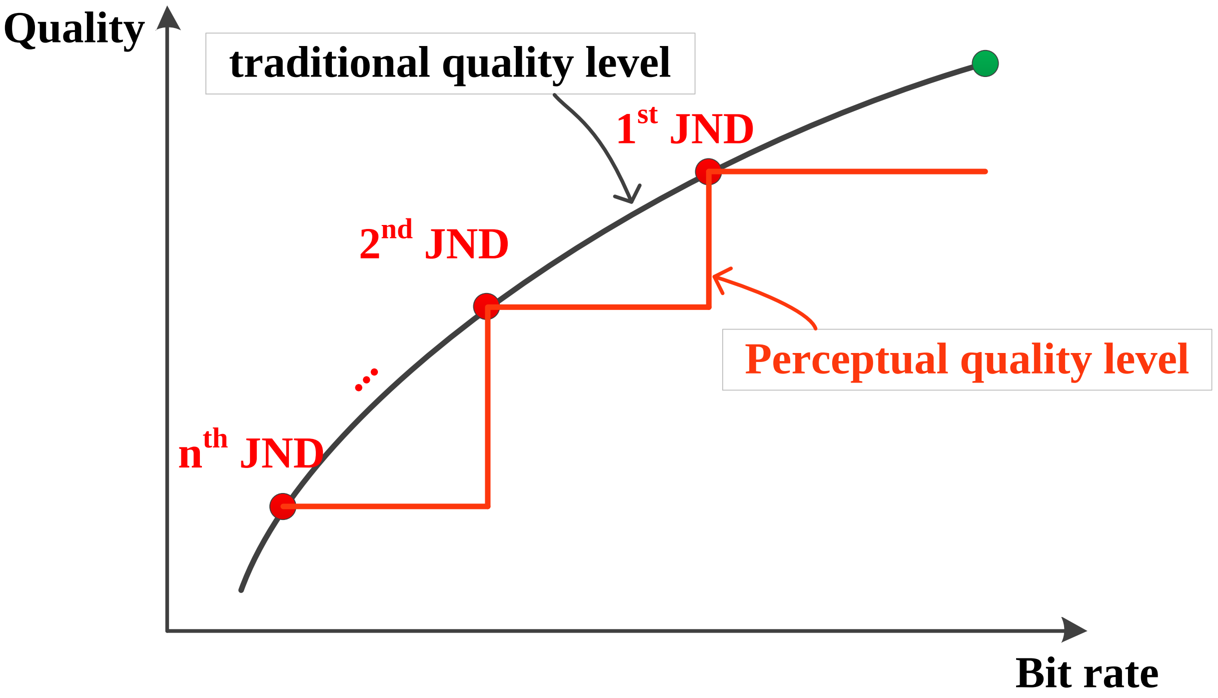

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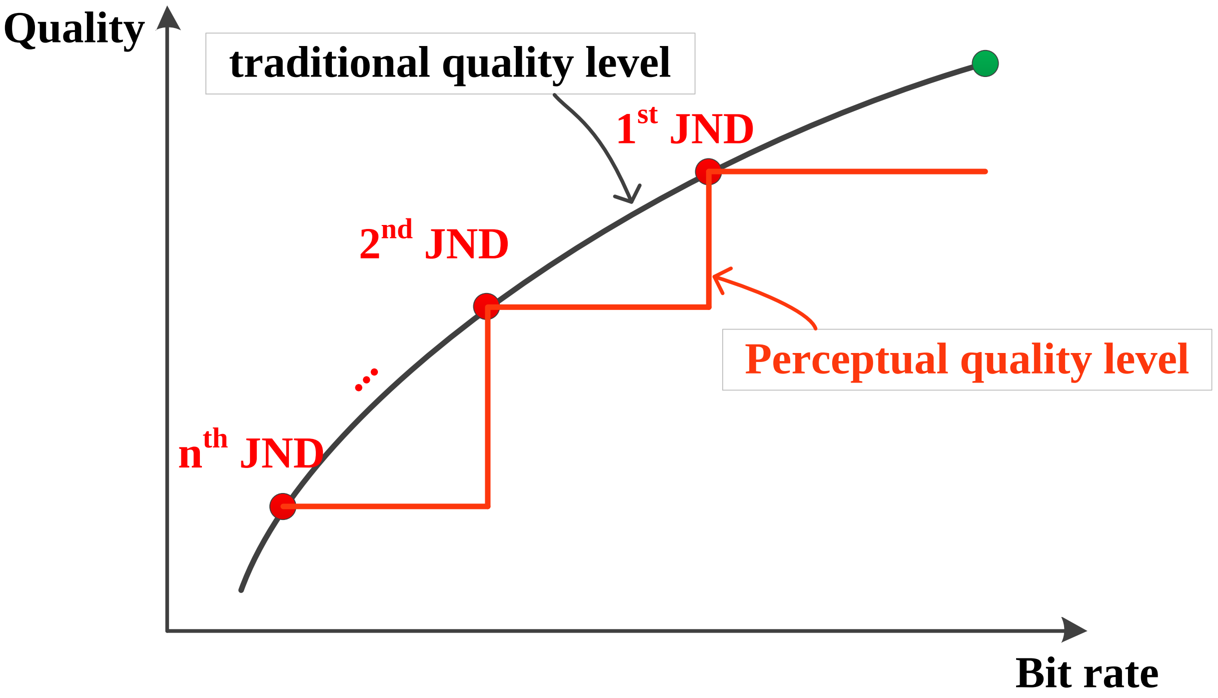

Determinants:

1. **Display setting** (e.g. viewing distance, monitor profiling, etc.)
2. **Subjects/viewers/observers**
3. **Video content**

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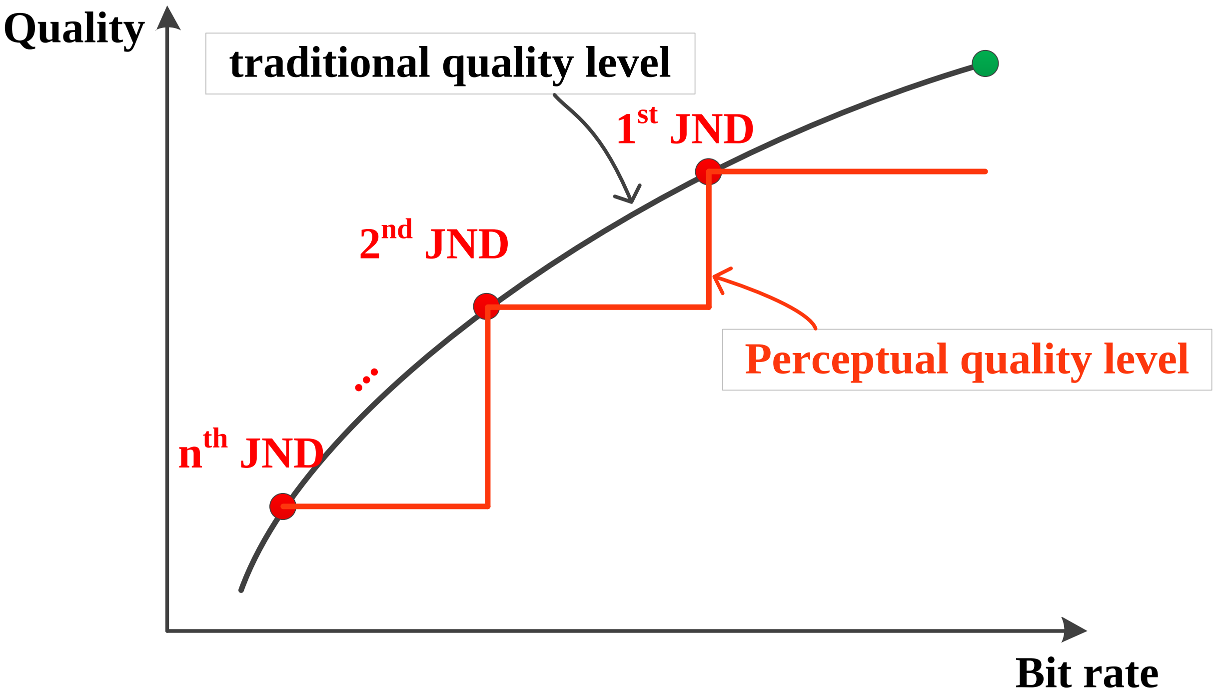

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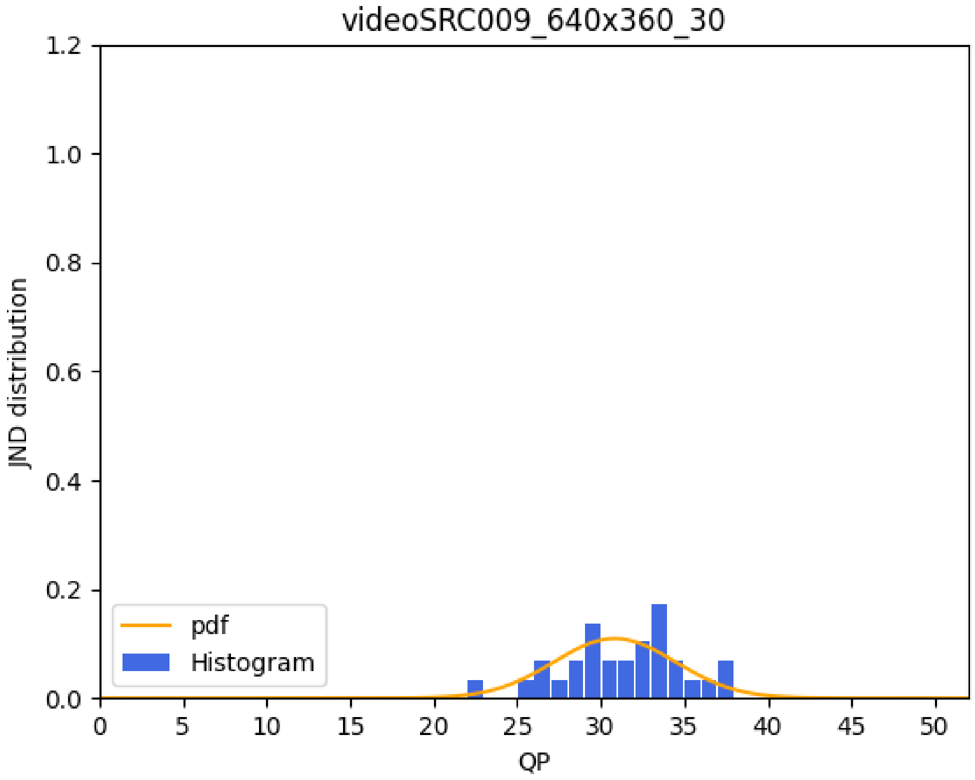

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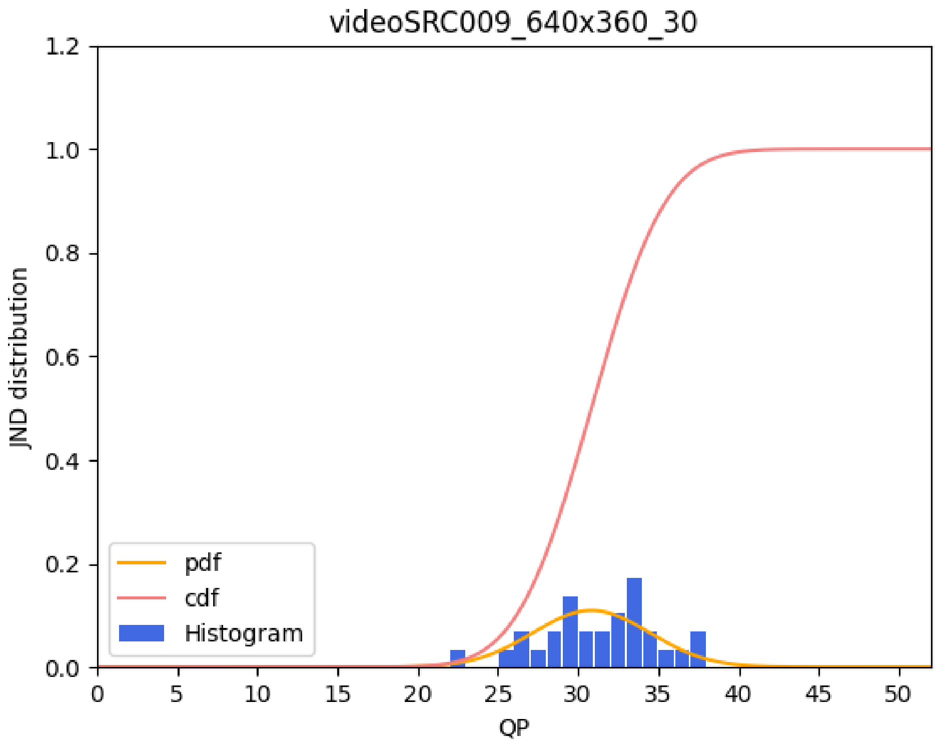
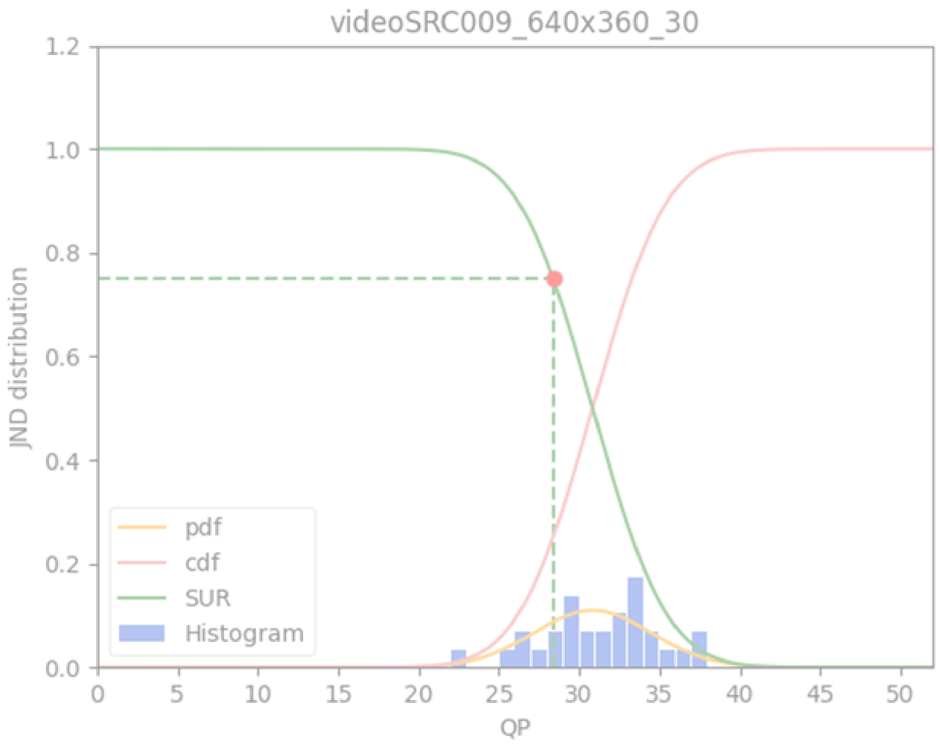


$$F_{cdf}(x) = \int_{-\infty}^{x} f_{pdf}(x)dx$$



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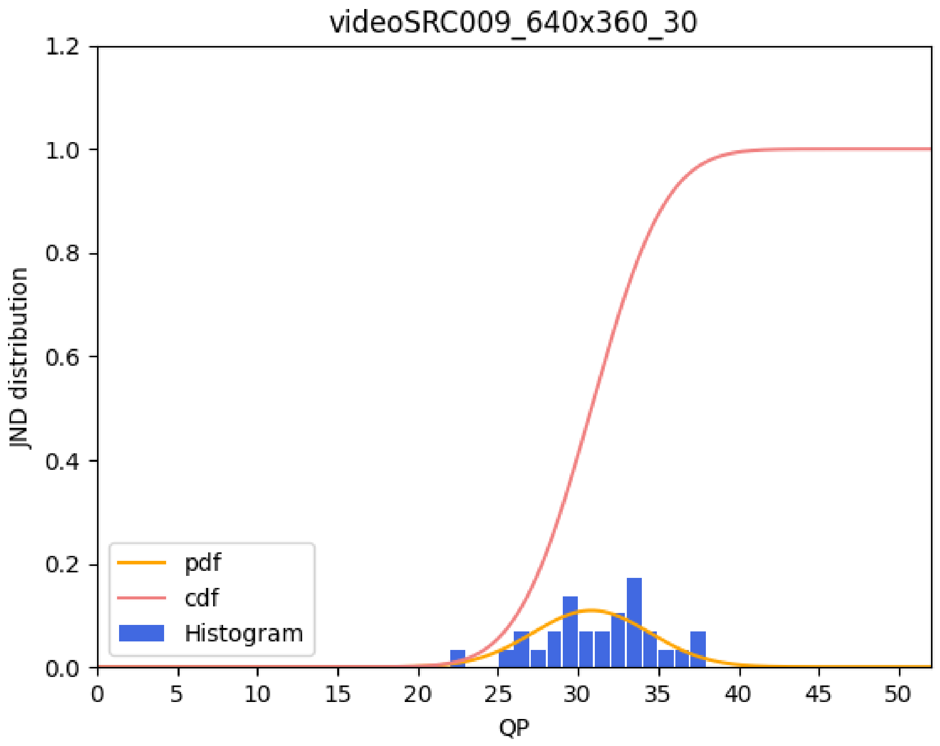

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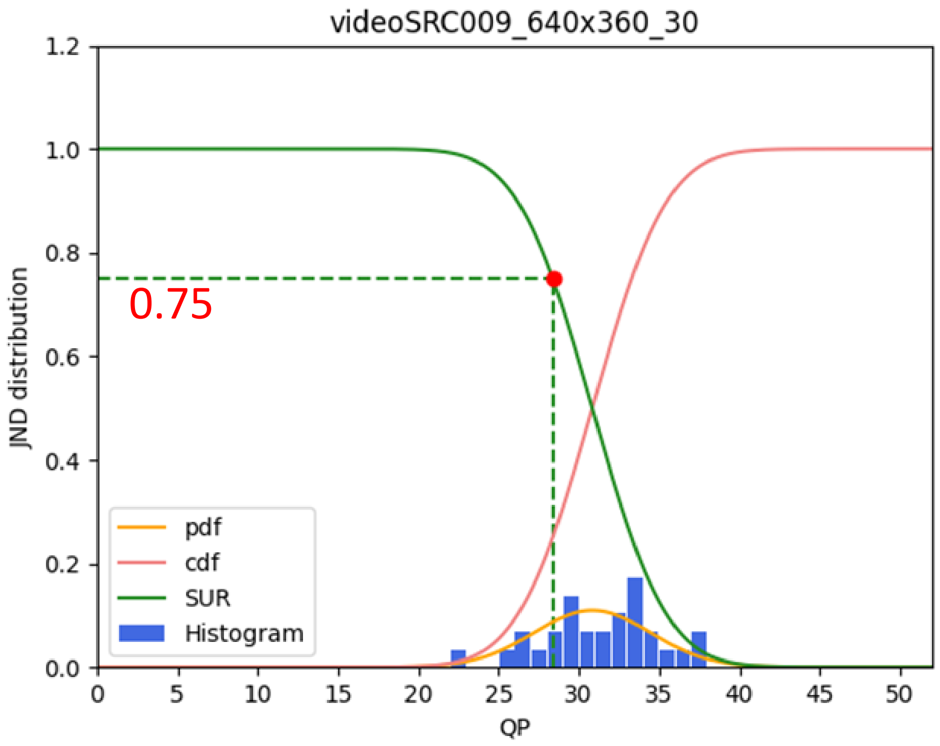

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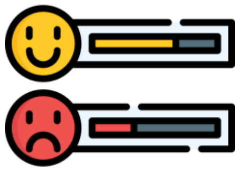
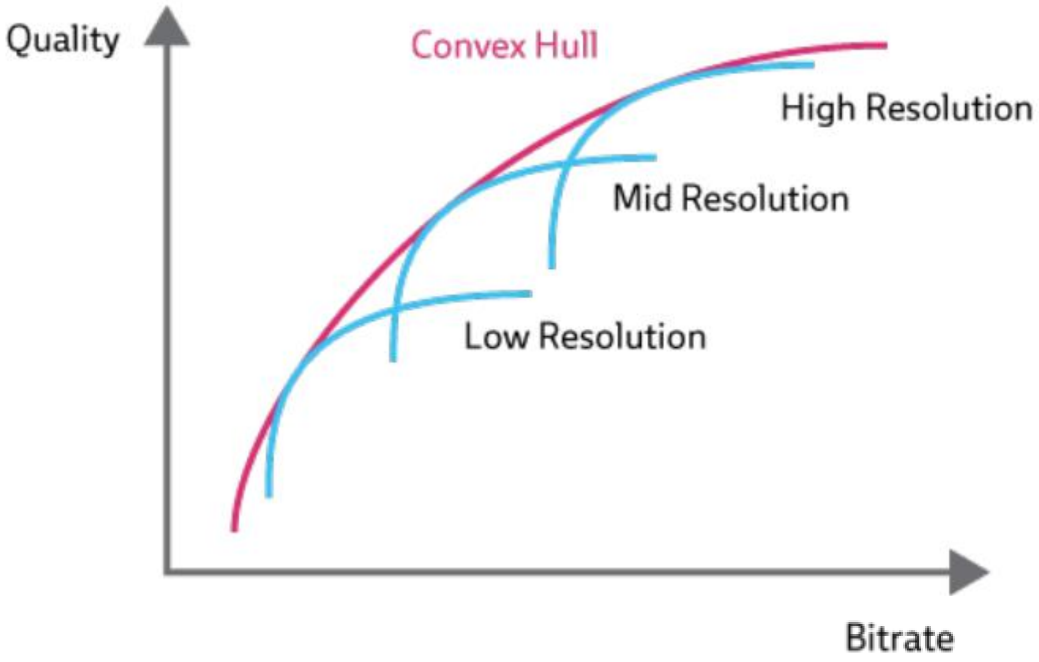


- Satisfied: didn’t perceive difference
- Not satisfied: perceived a difference

1.3. Motivation of JND and SUR

- Each video content is encoded at multiple bitrates and resolutions and a convex hull is formed based on the quality of encodings



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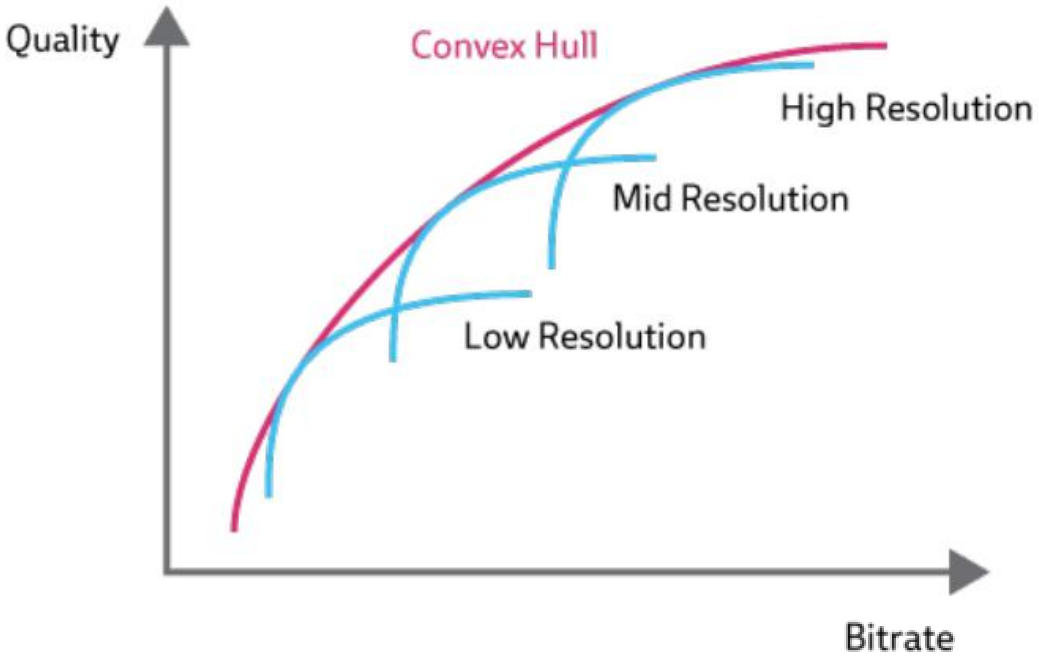

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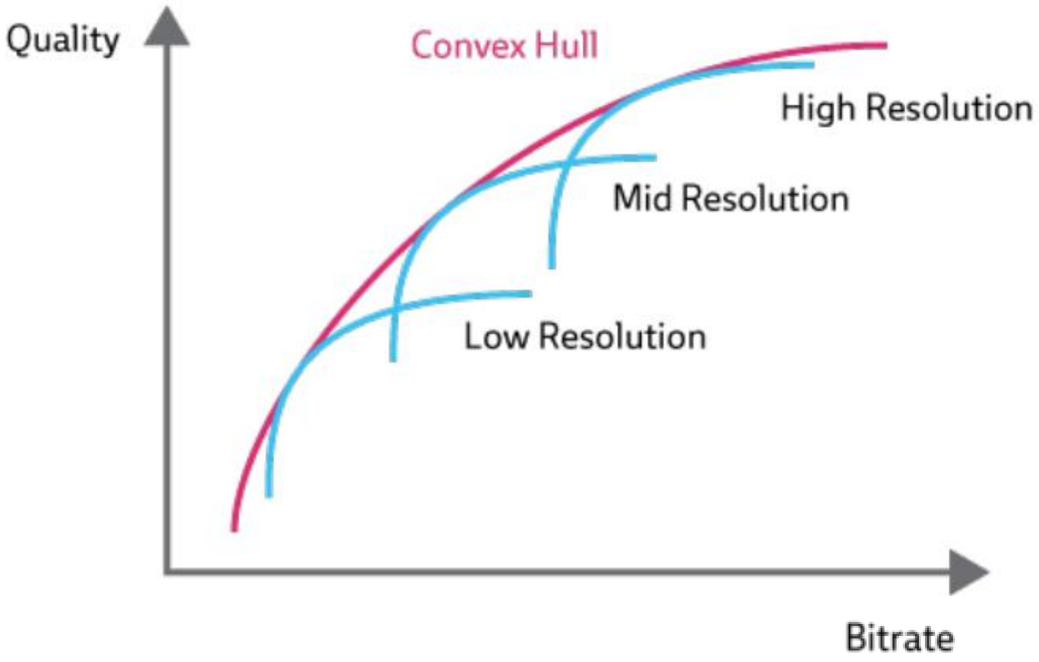

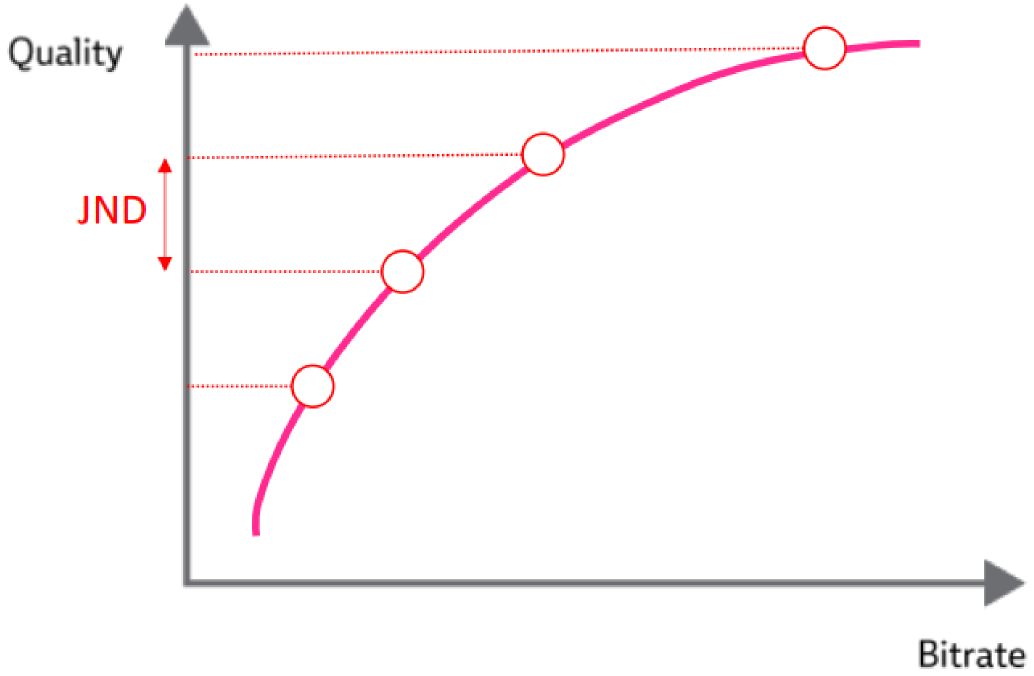

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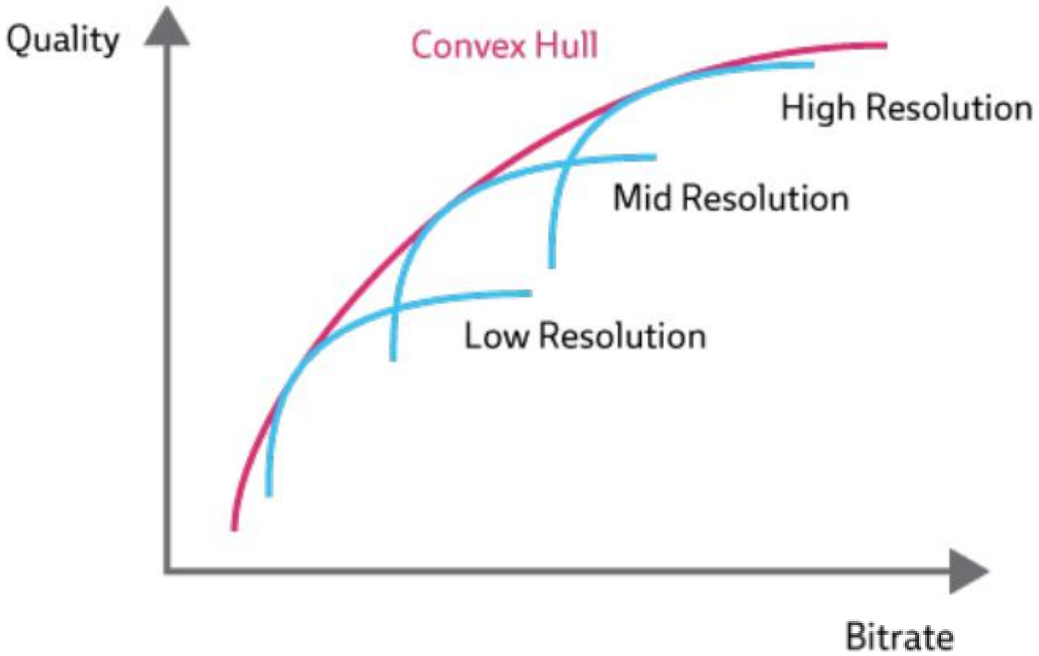

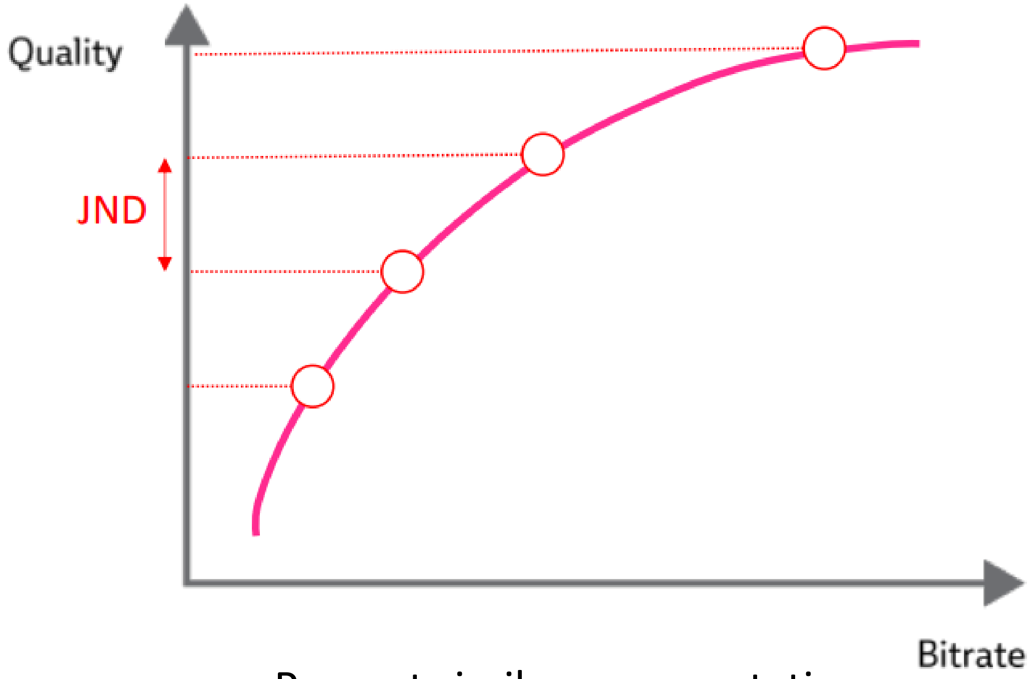

- Prevent similar representations
- Use least resources for the same quality

2.1. VMAF proxy for JND

Large scale JND datasets VideoSet[1]:
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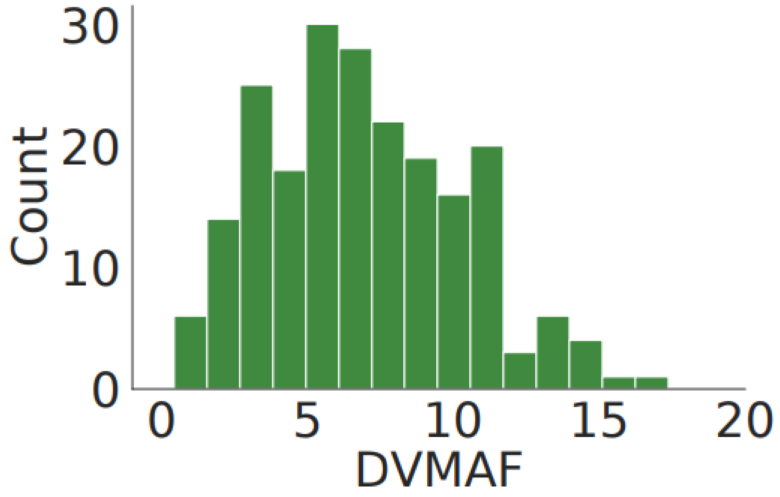

- **Method 1**: Anchor quality dependent JND:
  - A framework to map vmaf with the probability of just noticeable difference between video encoding recipes. Zhu et al. IVMSP 2022
- **Method 2:** Content dependent JND:
  - Between Two and Six? Towards Correct Estimation of JND Step Sizes for VMAF-based Bitrate Laddering. Amirpour et al. Qomex 2022

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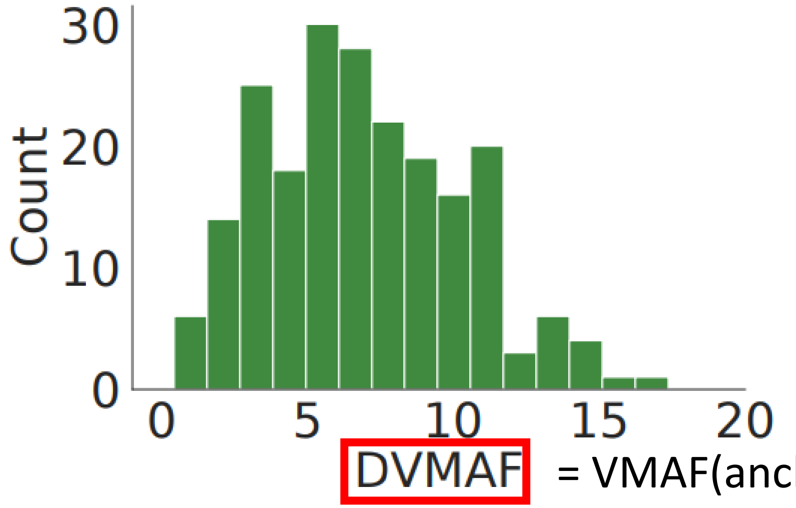

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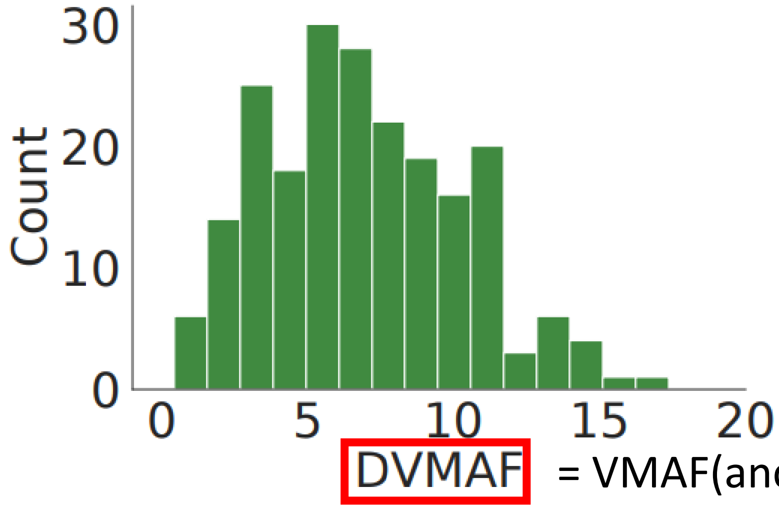

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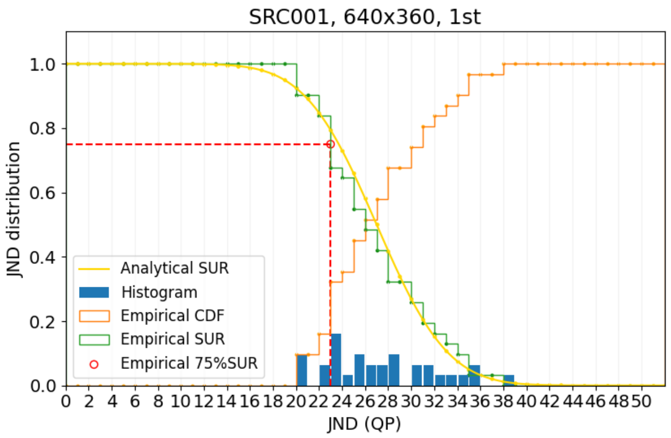
2.1. VMAF proxy: optimization for subjective test

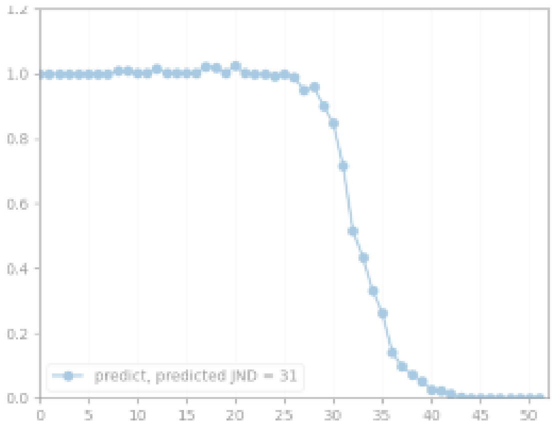
- Binary search [1]
  - $Nb\_comparison = \log_{(3/4)}\left(1/len\left(JCP\right)\right)$
  - ***JCP***: JND Candidate Playlist, e.g., QP (1~51)
- Pre-processing: reduce ***JCP***
  - Reduce 7.14% subjective test duration [2]

[1] Wang et al. VideoSet: A Large-Scale Compressed Video Quality Dataset Based on JND Measurement.
[2] Subjective test methodology optimization and prediction framework for Just Noticeable Difference and Satisfied User Ratio for compressed HD video. Zhu et al. PCS 2022

2.2. SUR modeling and prediction: drawbacks in current work

- Gaussian assumption [1-5]
- Point-by-point prediction in SUR curve [1-4]





[1] Wang et al. Prediction of Satisfied User Ratio for Compressed Video.
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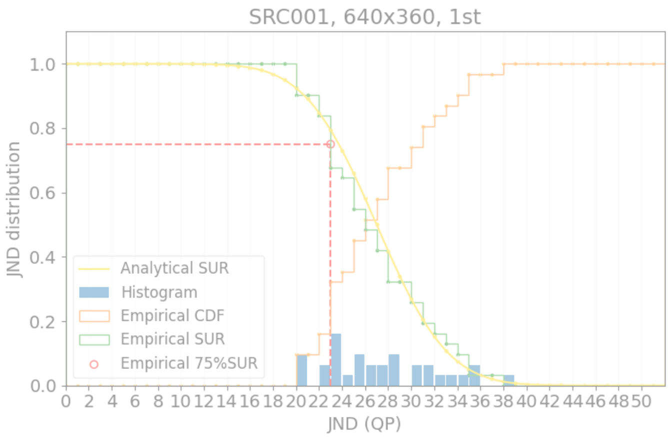

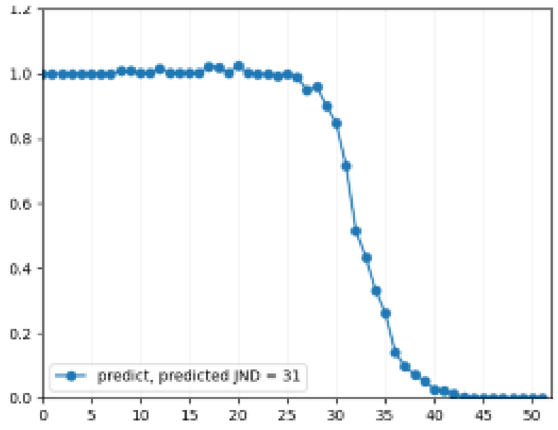

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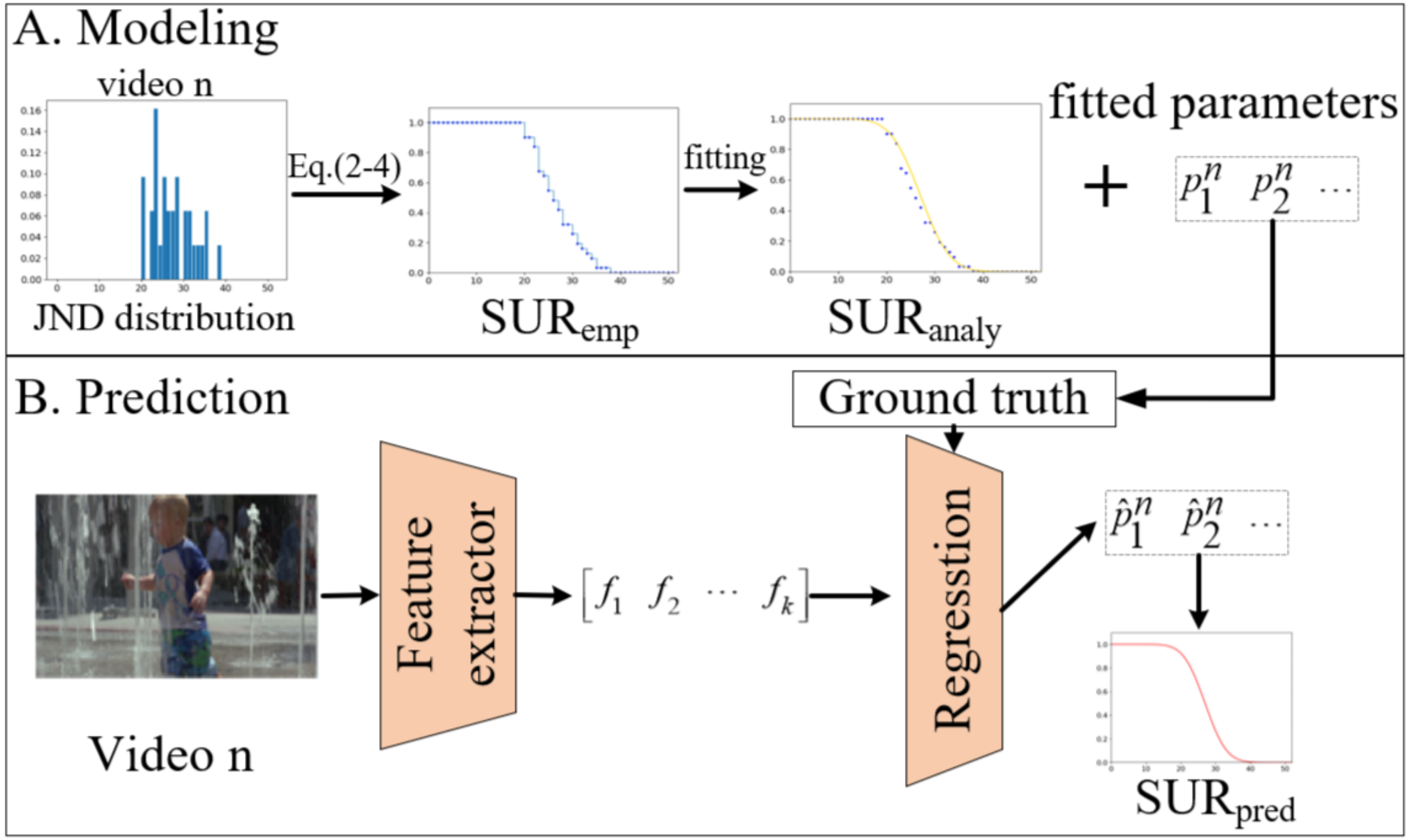
2. Pipeline of SUR and JND modeling and prediction



- **Gaussian** distributions are not the best option for JND modeling
- For SUR curve prediction, **parameter-driven** approaches are much less complex than **point-by-point**

On the benefit of parameter-driven approaches for the modeling and the prediction of satisfied user ratio for compressed video. Zhu et al. ICIP2022

3. Work in progress

- Improve accuracy and reduce complexity
- SUR and JND modeling and prediction through different proxies: VMAF, Bitrate, QP, CRF …

Thank you for your questions

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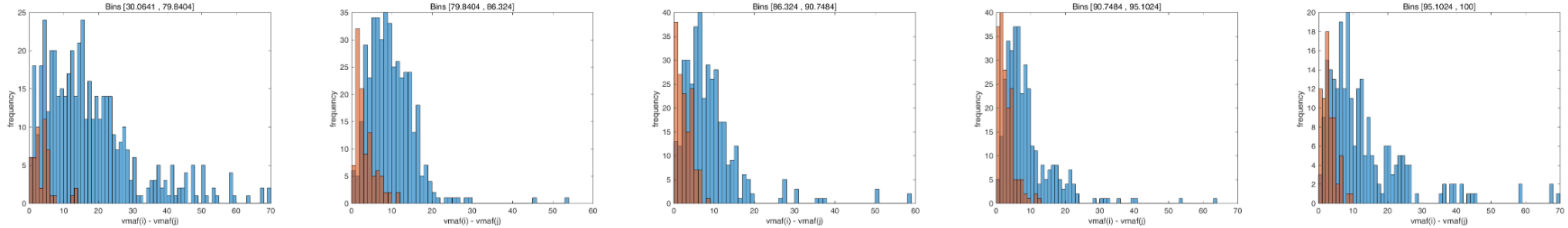
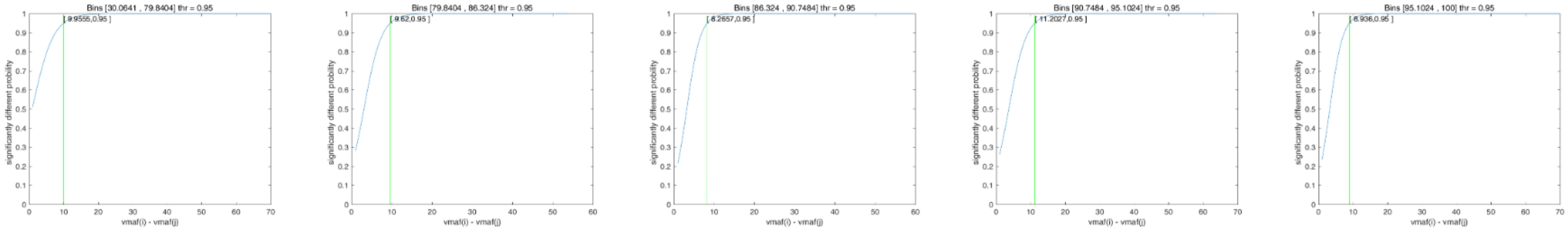
Annex

HD JND VMAF lookup table



(a) $vmaf_{(anc)} \in \lfloor 30, 79 \rfloor$ (b) $vmaf_{(anc)} \in \lfloor 79, 86 \rfloor$ (c) $vmaf_{(anc)} \in \lfloor 86, 90 \rfloor$ (d) $vmaf_{(anc)} \in \lfloor 90, 95 \rfloor$ (e) $vmaf_{(anc)} \in \lfloor 95, 100 \rfloor$



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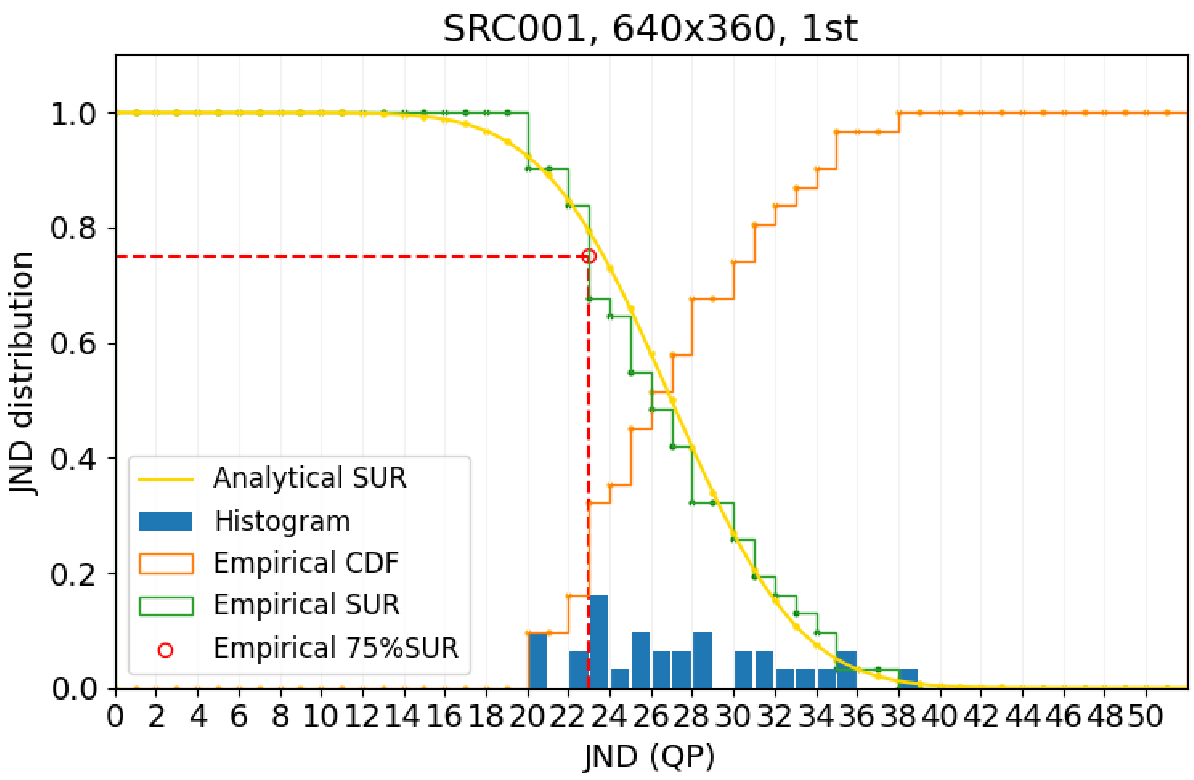

Step 1: Compute empirical SUR:

$$p(x) = P(\mathrm{JND} = \mathrm{x}) = \frac{1}{N}\sum_{i=1}^{N} \mathbf{1}\,(j_i = x),$$

$$\mathrm{CDF_{emp}}(x) = P(\mathrm{JND} \le \mathrm{x}) = \sum_{\omega < \mathrm{x}} \mathrm{p}(\omega).$$

$$\mathrm{SUR_{emp}}(x) = 1 - \mathrm{CDF_{emp}}(\mathrm{x}).$$

2.1. Modeling of SUR

Step 2: find the best fit of $\mathrm{SUR}_{\mathbf{emp}}(x)$

Table 1: Summary of candidate model functions. (NB para is the number of parameters in model function)

Name	Model function	NB para
Polynomial-3	$f(x) = \sum_{k=0}^{n} a_k x^k$	4
Polynomial-4		5
Gaussian	$1 - \frac{1}{2}\left(1 + erf\left(\frac{x-\mu}{\sigma\sqrt{2}}\right)\right)$	2
2-para-logistic	$1 - \frac{1}{1+e^{-(x-\mu)/s}}$	2
4-para-logistic	$f(x) = b + \frac{L}{1+e^{-k(x-x_0)}}$	4
Weibull	$e^{-\left(\frac{x}{\lambda}\right)^k}$	2
Gumbel	$1 - e^{-e^{-(x-\mu)/\beta}}$	2
Rayleigh	$e^{\frac{-x^2}{(2\sigma^2)}}$	1

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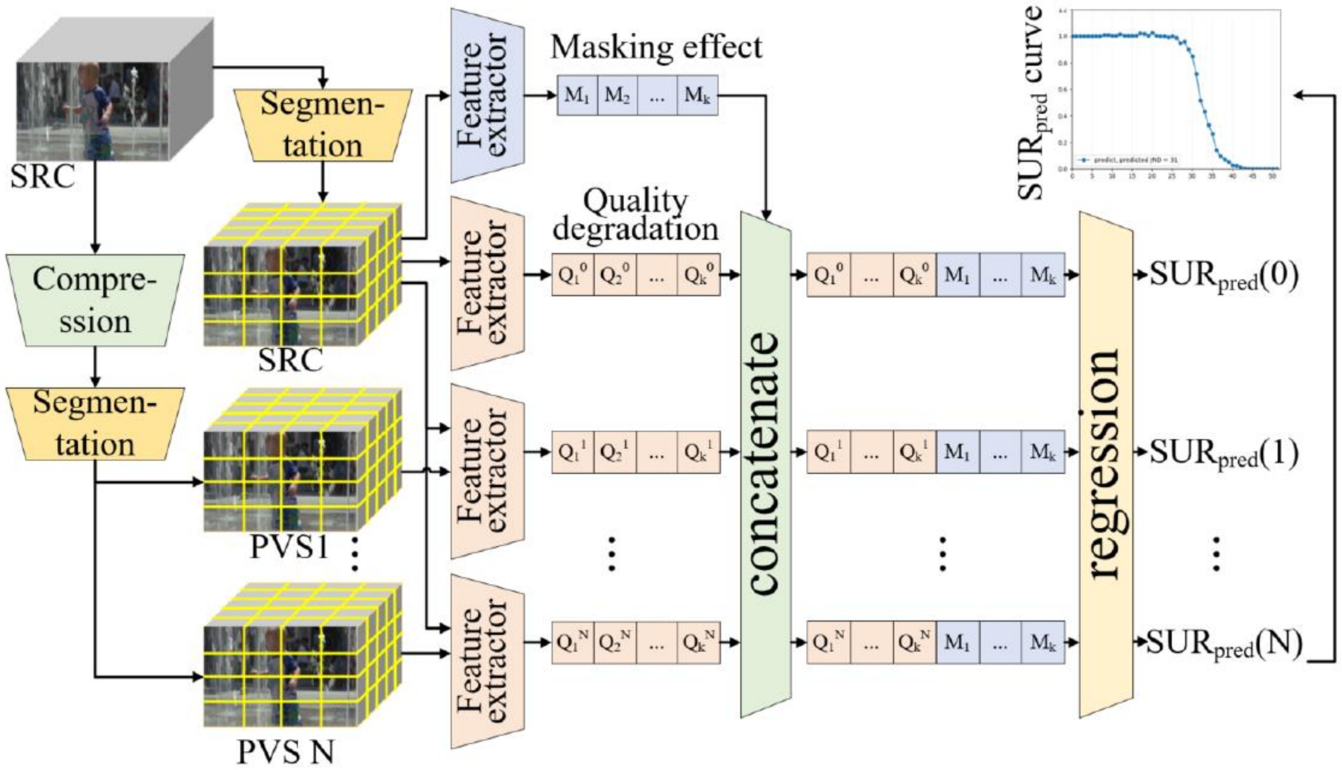
Linear regression
Monotonic constraint

Non-linear least square

2.2. Prediction of SUR



Baseline model (Wang et al. PREDICTION OF SATISFIED USER RATIO FOR COMPRESSED VIDEO)

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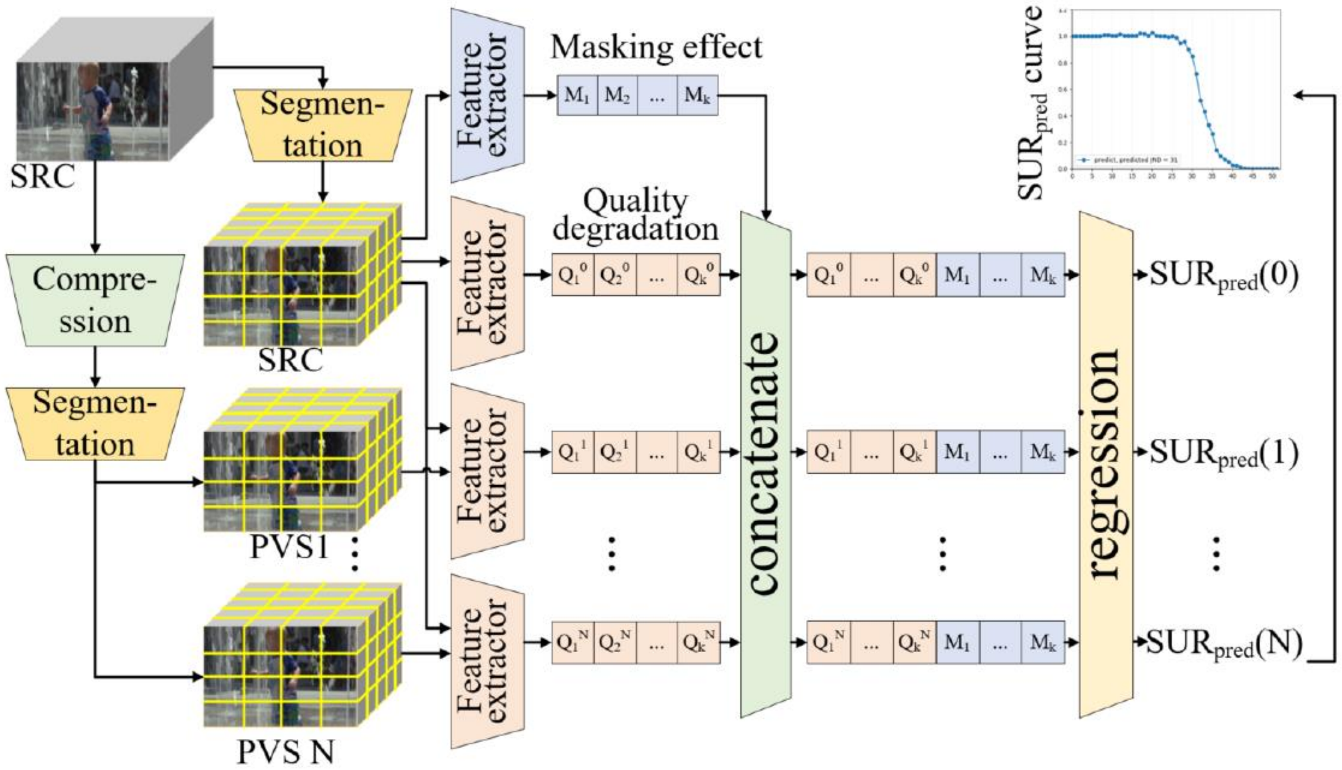

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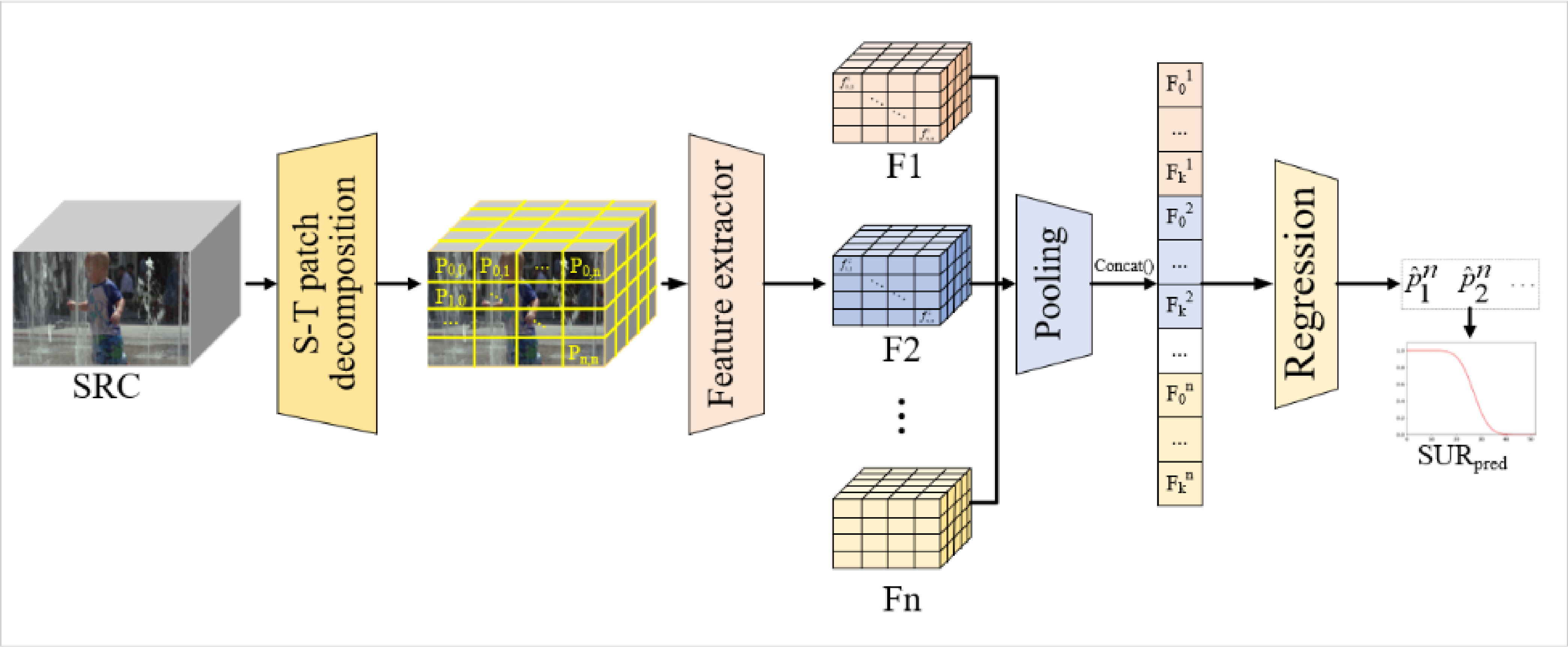

3.1. Results of modeling

Large scale JND datasets VideoSet:
- 220 5-second SRCs
- H.264 (QP 1 to 51)
- 4 resolution (1080p, 720p, 540p, 360p)

Table 2: Mean of MAE, RMSE and $\Delta 75\%\mathrm{SUR}_{|E-A|}$ for different model functions with VideoSet [12]

Name	MAE	RMSE	$\Delta 75\%\mathrm{SUR}_{|E-A|}$
Polynomial-3	0.1204	0.1466	5.0614
Polynomial-4	0.1085	0.1338	4.7420
Gaussian	0.0147	0.0253	0.6625
2-para-logistic	0.0156	0.0250	0.5875
4-para-logistic	0.0164	**0.0236**	**0.5761**
Weibull	**0.0138**	0.0240	0.6761
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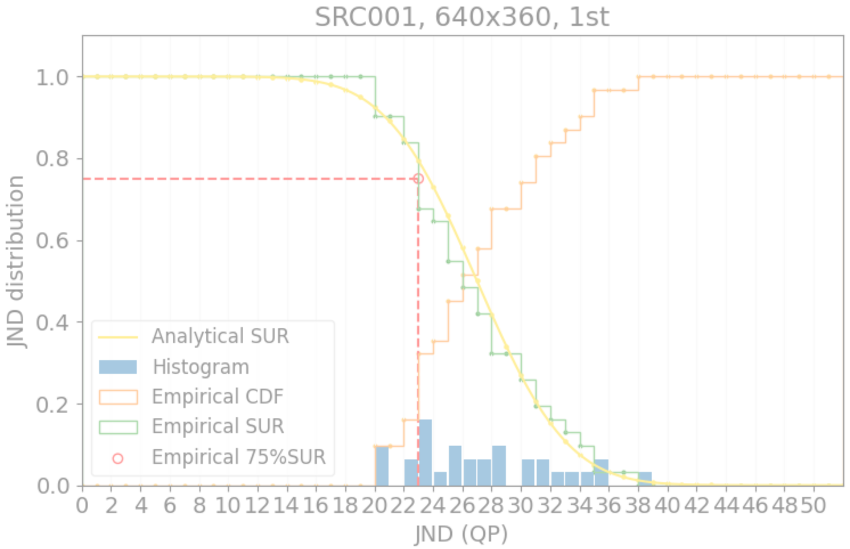

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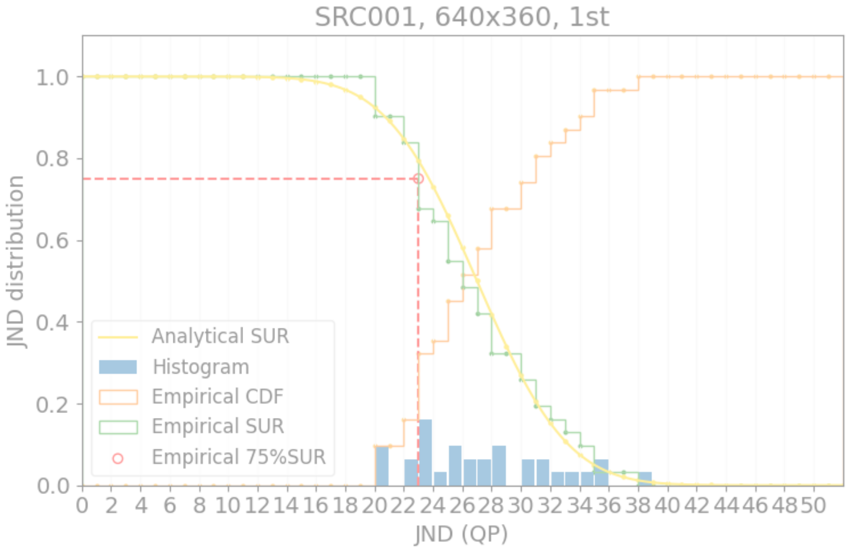

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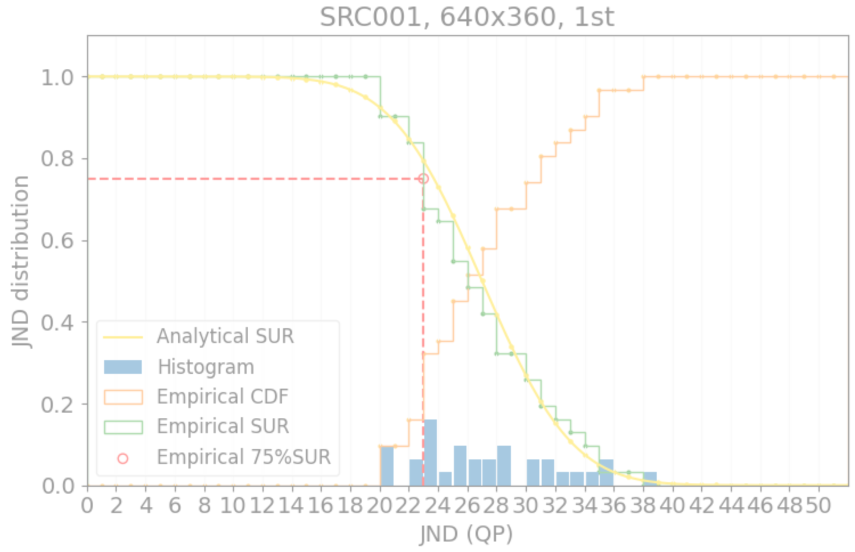

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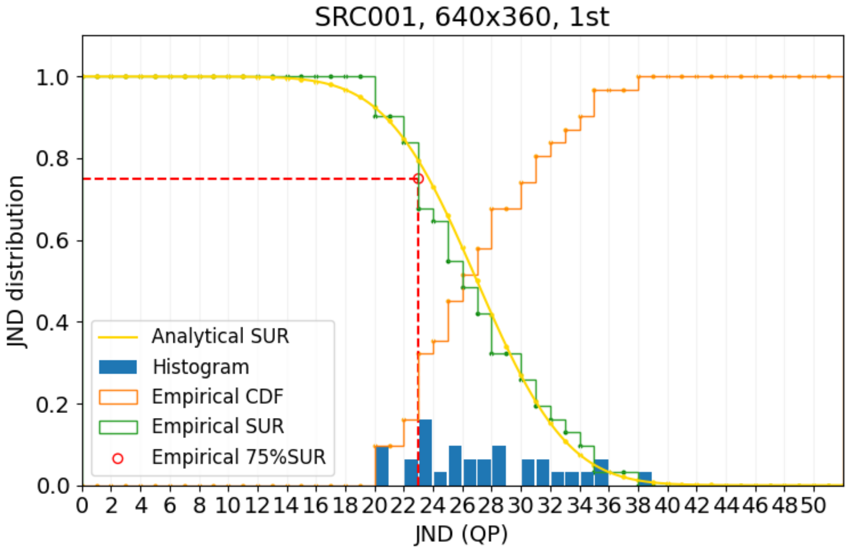


$$\boxed{\Delta p\%\mathrm{SUR}_{|\mathrm{E-A}|} = |p\%\mathrm{SUR}_{\mathrm{emp}} - p\%\mathrm{SUR}_{\mathrm{analy}}|}$$

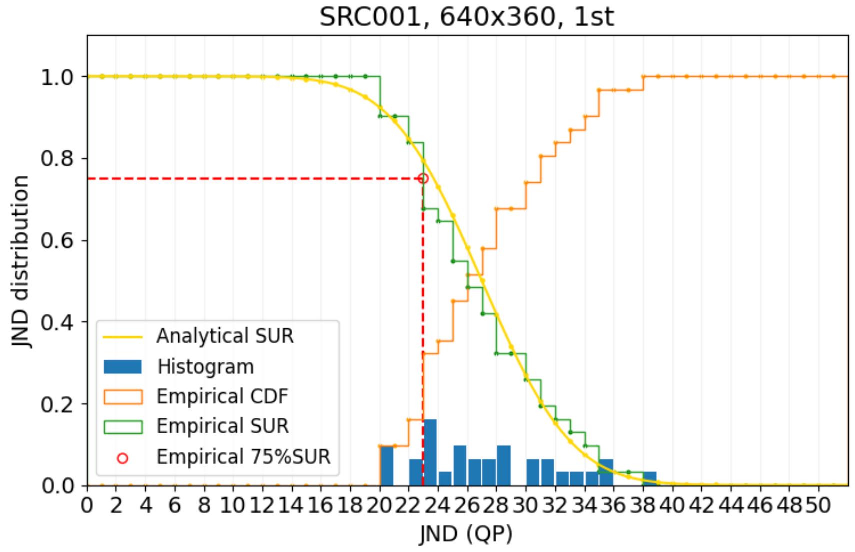
3.1. Results of modeling

Large scale JND datasets VideoSet:

- 220 5-second SRCs
- H.264 (QP 1 to 51)
- 4 resolution (1080p, 720p, 540p, 360p)

Table 2: Mean of MAE, RMSE and $\Delta 75\%\mathrm{SUR}_{|E-A|}$ for different model functions with VideoSet [12]

Name	MAE	RMSE	$\Delta 75\%\mathrm{SUR}_{|E-A|}$
Polynomial-3	0.1204	0.1466	5.0614
Polynomial-4	0.1085	0.1338	4.7420
Gaussian	0.0147	0.0253	0.6625
2-para-logistic	0.0156	0.0250	0.5875
4-para-logistic	0.0164	**0.0236**	**0.5761**
Weibull	**0.0138**	0.0240	0.6761
Gumbel	0.0220	0.0343	0.5977
Rayleigh	0.1451	0.1703	8.9114



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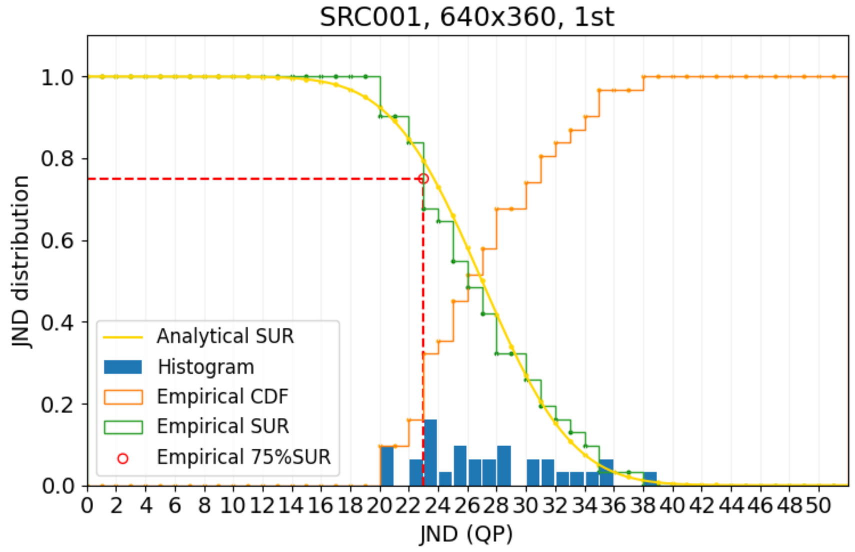

3.2. Results of prediction

Table 3: Averaged prediction error comparison between baseline model and 3 SRC-based parameter-driven models.

RES	Model name	ΔSUR		Δ75%SUR	
		|P − A|	|P − E|	|P − A|	|P − E|
360p	baseline	0.0769	0.0799	4.3682	4.3773
	2-p-Gaussian	**0.0459**	**0.0480**	2.4773	2.5864
	2-p-Logistic	0.0462	0.0489	**2.4455**	**2.5682**
	4-p-Logistic	0.0496	0.0515	2.4591	2.5909
540p	baseline	0.0786	0.0812	4.3182	4.2909
	2-p-Gaussian	**0.0397**	**0.0428**	2.1182	2.1045
	2-p-Logistic	0.0398	0.0437	**1.9727**	**2.0955**
	4-p-Logistic	0.0435	0.0458	2.0045	2.1000
720p	baseline	0.0783	0.0820	4.2864	4.2909
	2-p-Gaussian	**0.0433**	**0.0447**	**2.1636**	**2.2045**
	2-p-Logistic	0.0435	0.0459	**2.1636**	2.2364
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1080p	baseline	0.0801	0.0834	4.6000	4.5591
	2-p-Gaussian	0.0412	**0.0431**	2.3455	2.2136
	2-p-Logistic	**0.0409**	0.0440	**2.1182**	**2.1773**
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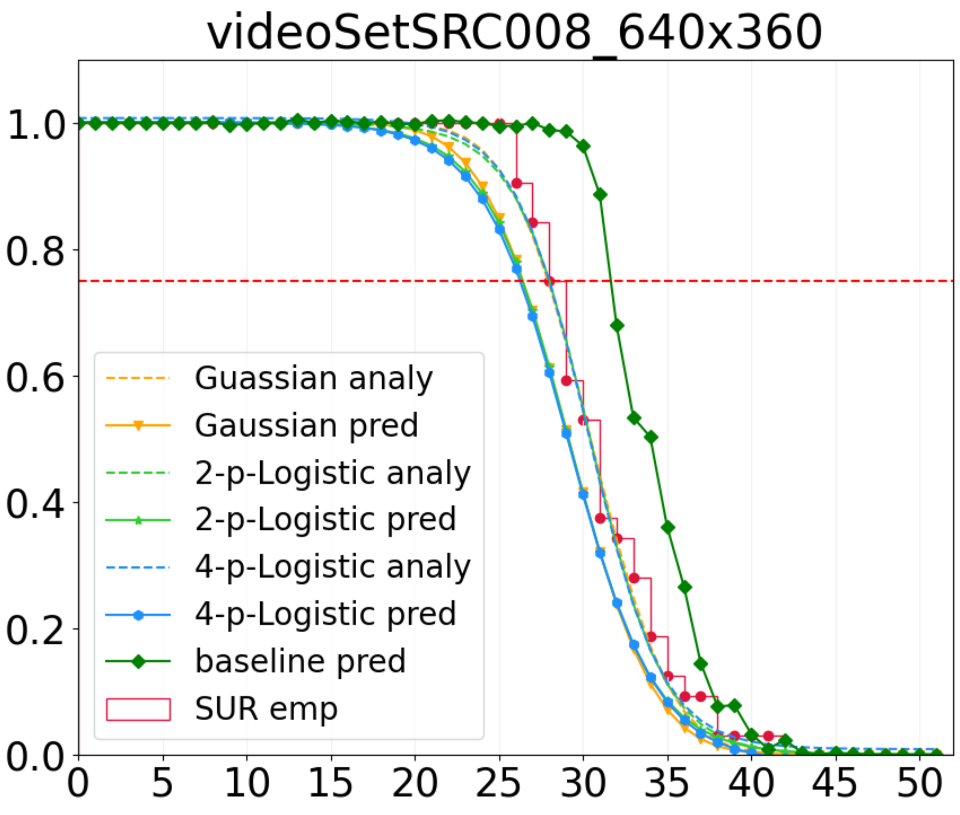

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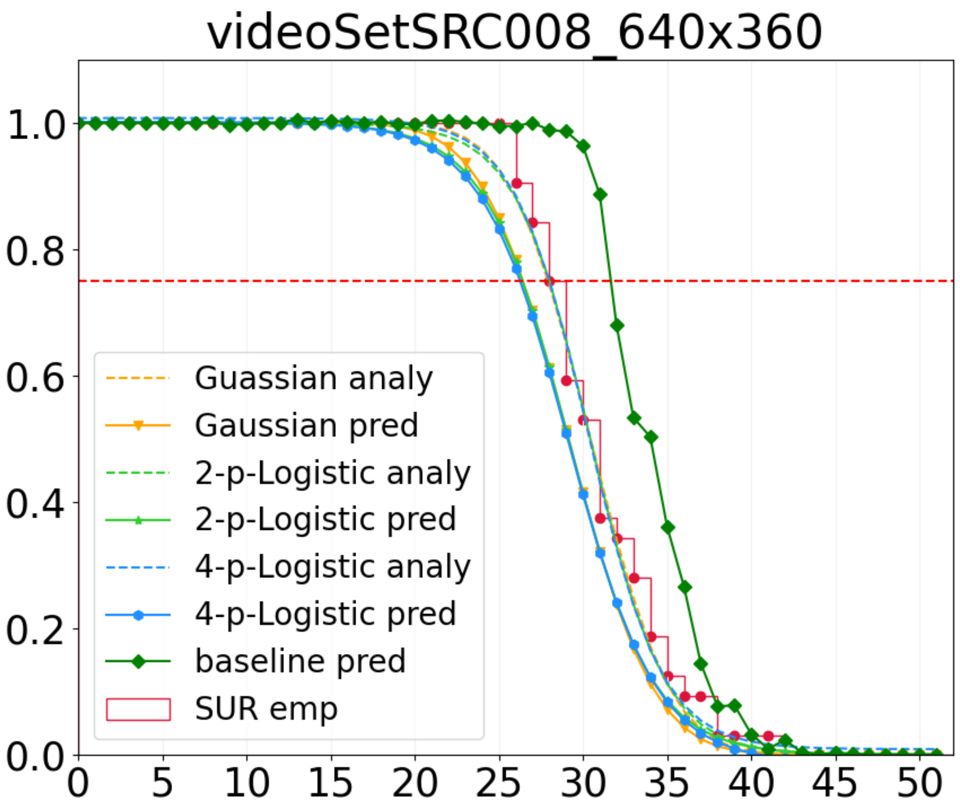

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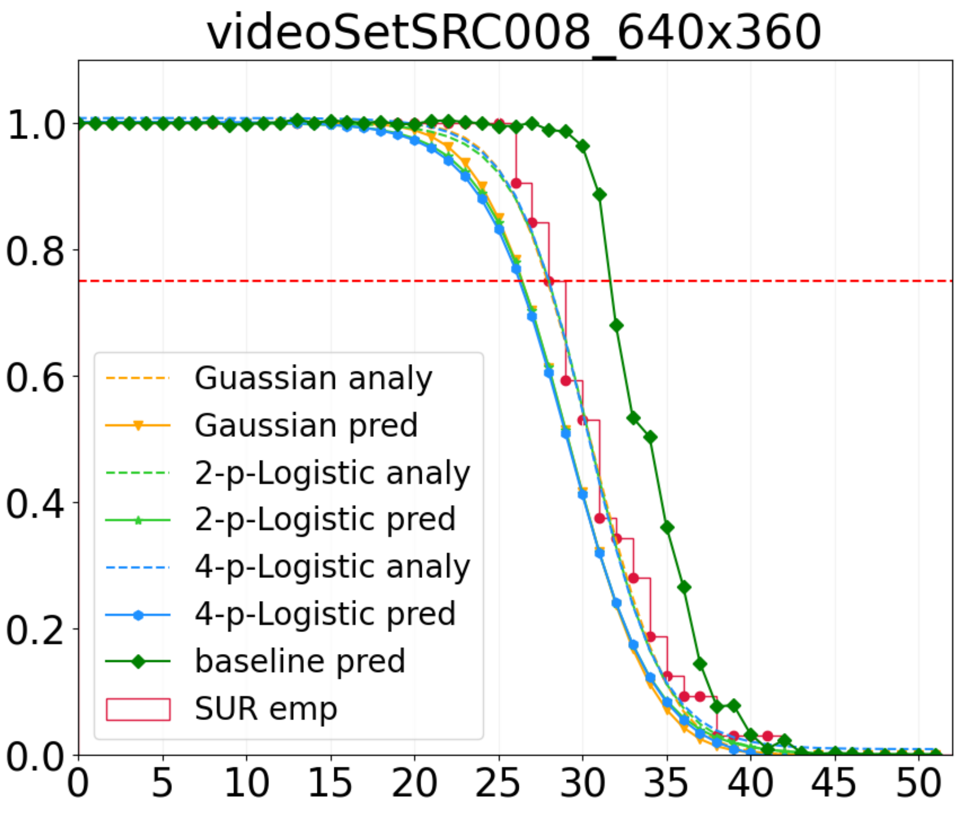

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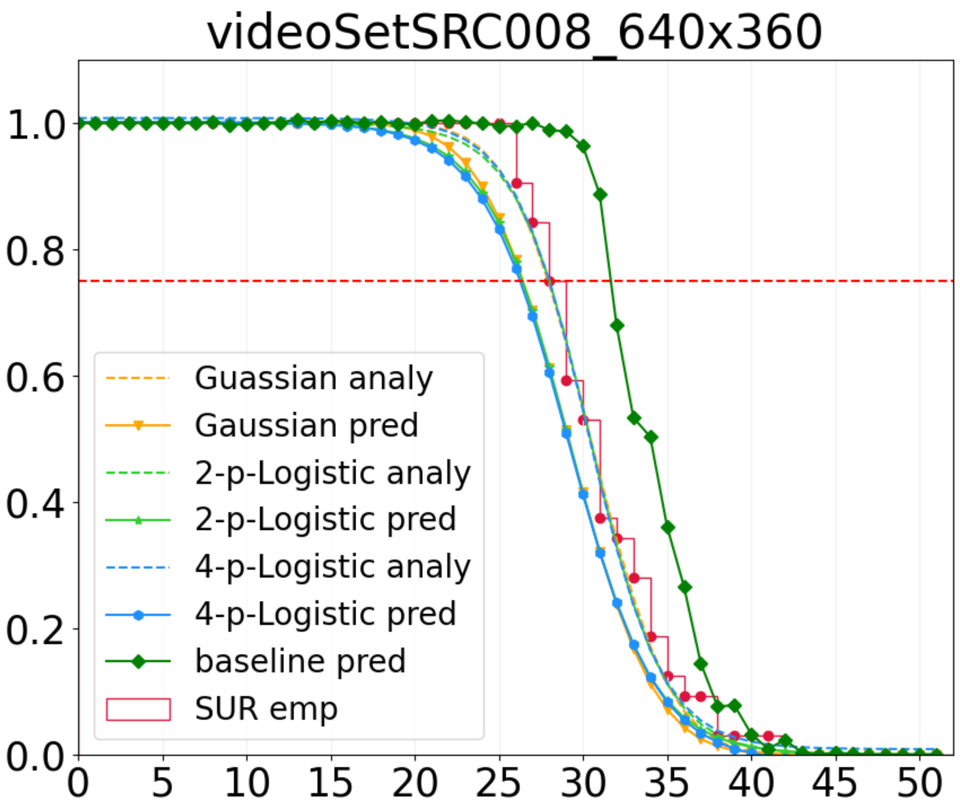

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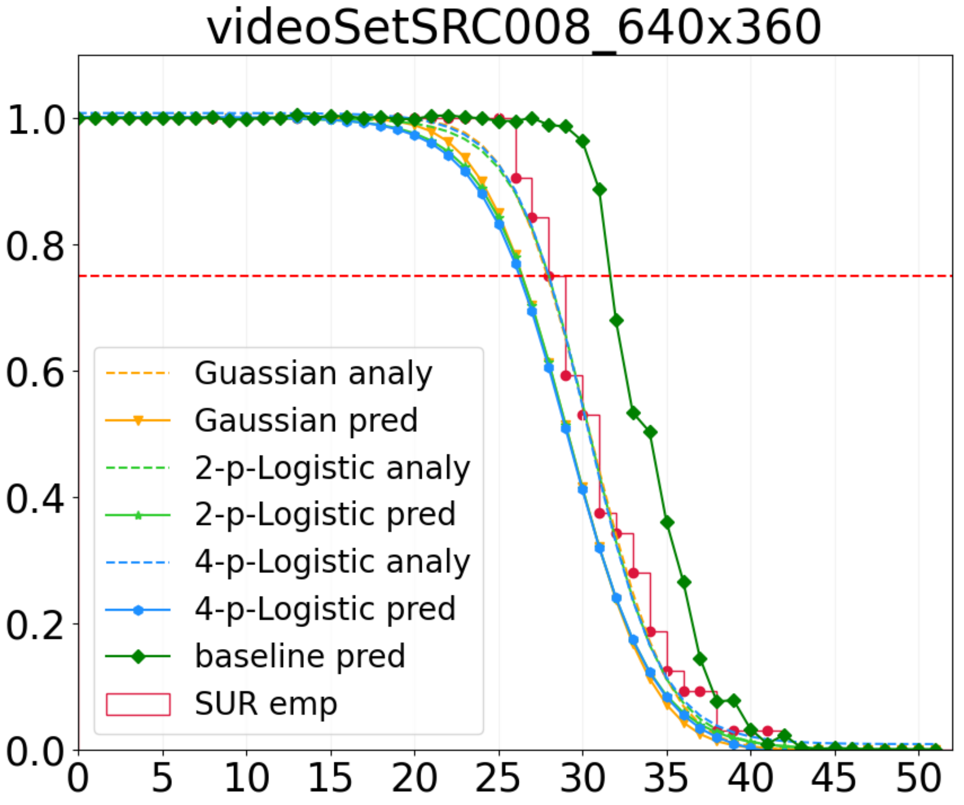

3.2. results of prediction

Table 4: Averaged prediction error comparison between SRC-based and SRC+PVS based model on 1080p with Guassian modeling.

Model	ΔSUR		Δ75%SUR	
	$\lvert P - A \rvert$	$\lvert P - E \rvert$	$\lvert P - A \rvert$	$\lvert P - E \rvert$
SRC-based	0.0412	0.0431	2.3455	2.2136
SRC+PVS-based	**0.0377**	**0.0412**	**2.0727**	**2.1409**

4. Main takes away

- **Gaussian** is not the best modeling for JND
- **Parameter-driven** is better than **point-by-point** for SUR curve prediction
- the quality degradation features from **PVSs** can improve but are not crucial to SUR prediction

5. Work in progress

- VMAF as proxy of JND:
  - Zhu, J., Ling, S., Baveye, Y., & Le Callet, P. (2022, June). A Framework to Map VMAF with the Probability of Just Noticeable Difference between Video Encoding Recipes. In *2022 IEEE 14th Image, Video, and Multidimensional Signal Processing Workshop (IVMSP)* (pp. 1-5). IEEE.
  - improvement
- New VW-JND datasets for HD, HDR videos:
  - Zhu, J., Perrin, A. F., & Le Callet, P. (2022, December). Subjective test methodology optimization and prediction framework for Just Noticeable Difference and Satisfied User Ratio for compressed HD video. In *2022 Picture Coding Symposium*.
  - Improvement of prediction