A Probabilistic Graphical Model for Analyzing the Subjective Visual Quality Assessment Data from Crowdsourcing

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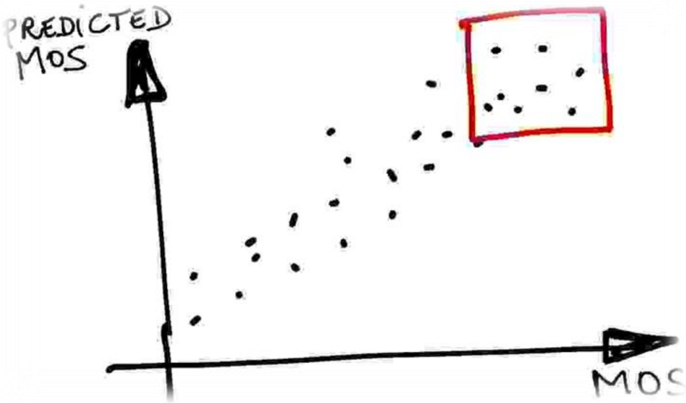
Visual Quality Assessment

Subjective Quality: ratings from observers using scale (ACR, DSIS, SSQE, DSCQS, SAMVIQ …)
Averaged across observers => A.K.A MOS (Mean Opinion Score)

Objective Quality: predict a quality score

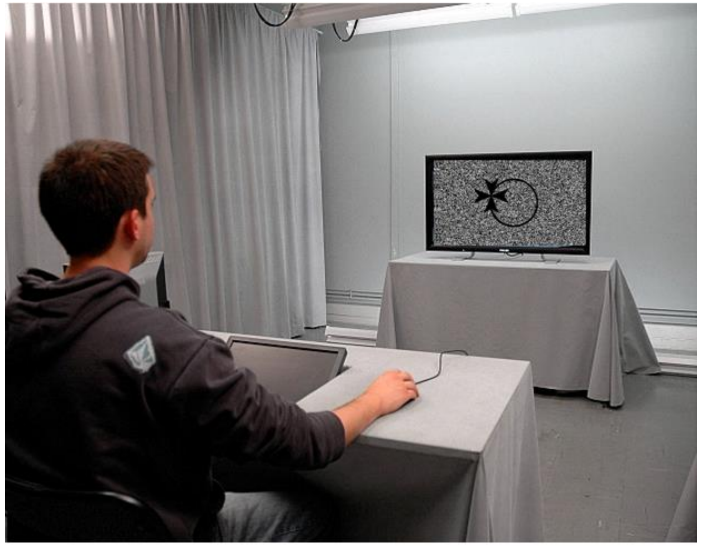


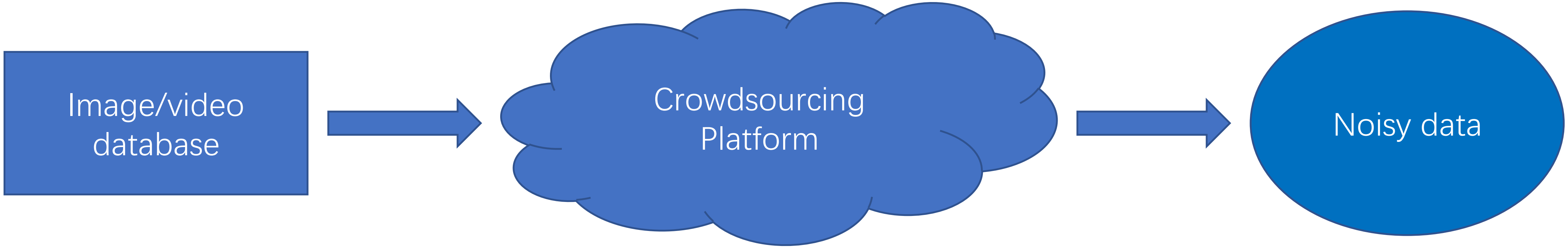
Deep Learning needs big data

- Traditional way to get quality data:
  Everything is in ITU standard
  - well control
  - time consuming

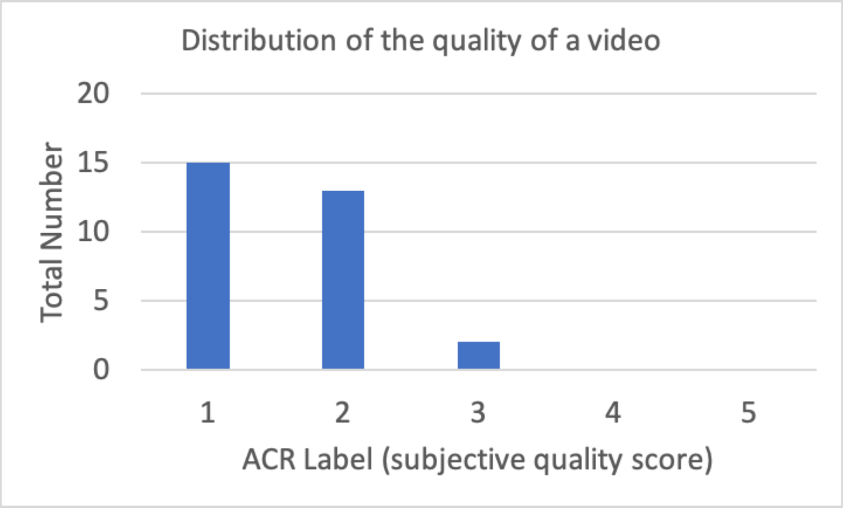
- Solution: Crowdsourcing

ITU standard test room





A model to recover ground truth



- Regarding subjective quality data
  - The distribution is not gaussian

But an ordinal categorical distribution

- Regarding annotator's behavior
  - he/she does not always give wrong/random answer

Should count on probability of abnormal behavior

The Proposed Annotation Model: GPM

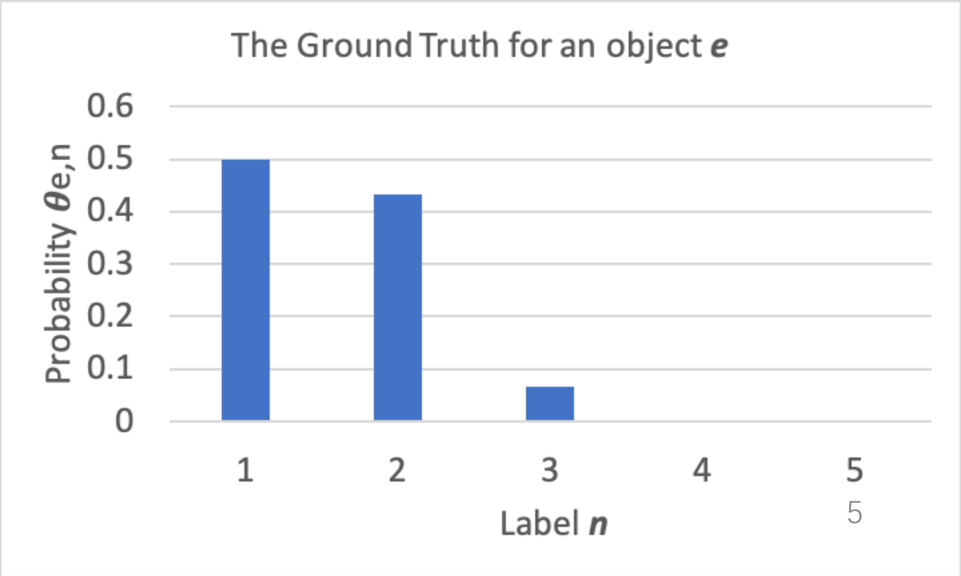
- Ground truth is an ordinal categorical distribution
    - For example, in ACR test, N = 5

$$Cat(y|\theta_{\mathbf{e}}) = \prod_{n=1}^{N} \theta_{e,n}^{[y=n]}$$

$\theta_{e,n}$ the probability of obtaining label *n* in one trial for object *e*

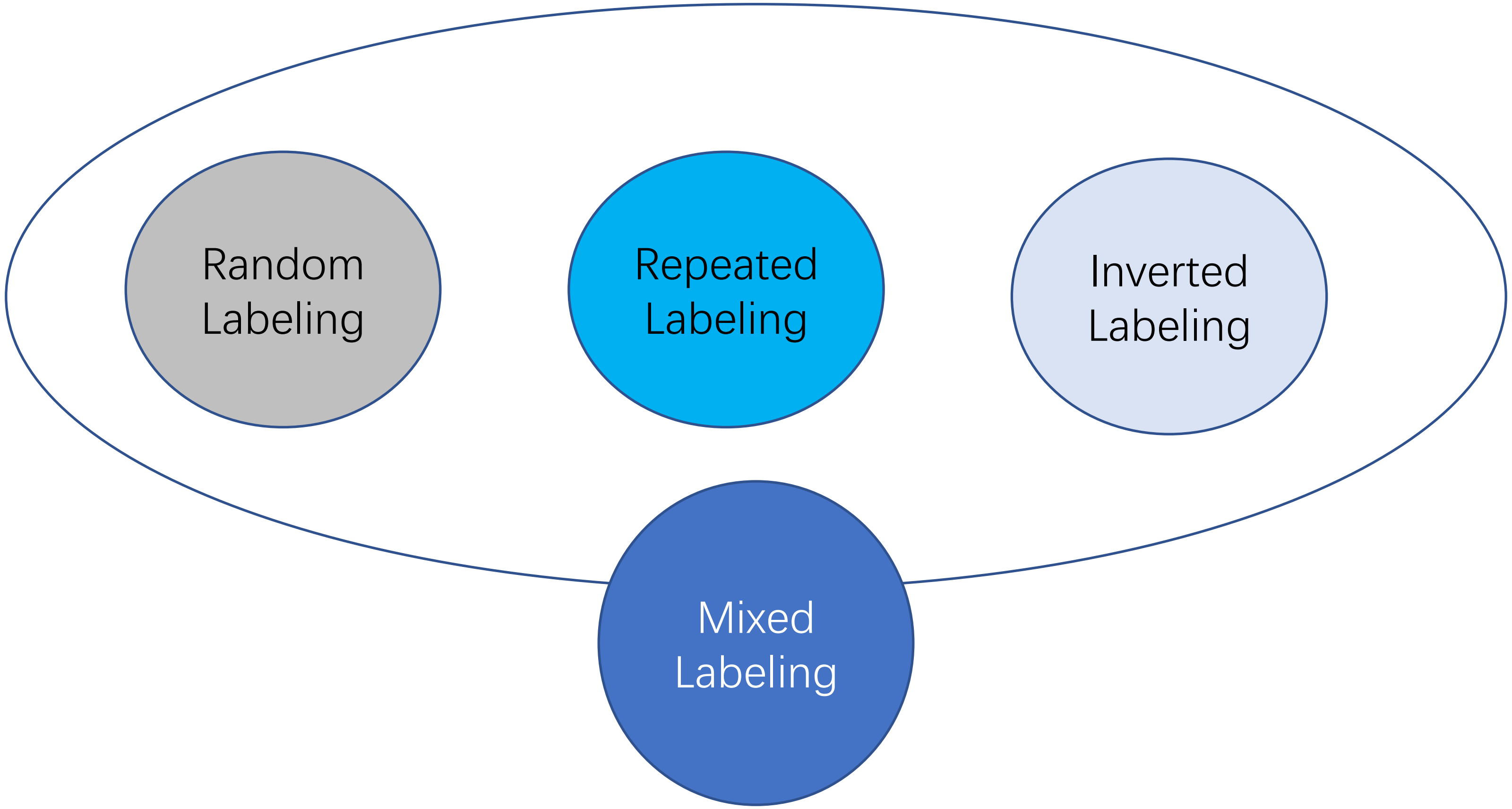
$$\sum_{n=1}^{N} \theta_{e,n} = 1$$

$[y = n]$ equals to 1 if $y = n$



The Proposed Annotation Model: GPM

- Annotators behavior classification

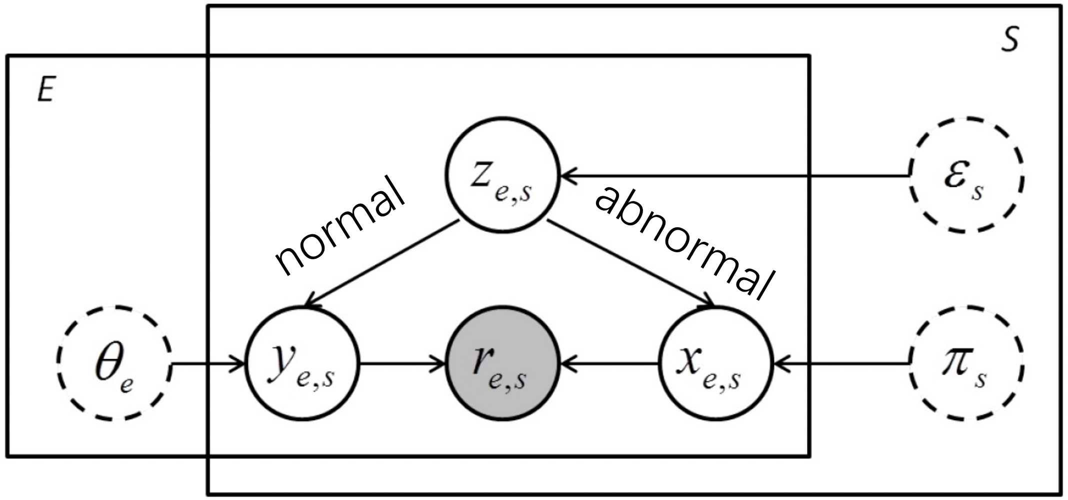


Yunus Emre Kara, Gaye Genc, Oya Aran, and Lale Akarun. 2015. Modeling annotator behaviors for crowd labeling. Neurocomputing 160 (2015), 141–156.

The Proposed Annotation Model: GPM

- For an annotator *s*
- Given an quality assessment task on object (image/video) *e*
- Using 1-5 Likert scale

$r_{e,s}$ *is the provided label for e by annotator s*



Using latent variable $z_{e,s}$ to control whether or not the annotator is in abnormal behavior

θ_e, ϵ_s and π_s are parameters, $y_{e,s}$, $x_{e,s}$ and $z_{e,s}$ are latent variables, $r_{e,s}$ is the provided label by annotator s.

$$p(Z|\epsilon) = \prod_{e,s \in A} B(z_{e,s}|\epsilon_s)$$

$$p(X|\pi) = \prod_{e,s \in A} D(x_{e,s}|\pi_s)$$

$$p(Y|\theta) = \prod_{e,s \in A} Cat(y_{e,s}|\theta_e)$$

$$p(R|X,Y,Z) = \prod_{e,s \in A} p(x_{e,s})^{[z_{e,s}=0]} p(y_{e,s})^{[z_{e,s}=1]},$$

A represents the set of all possible combinations of labelled objects and annotators

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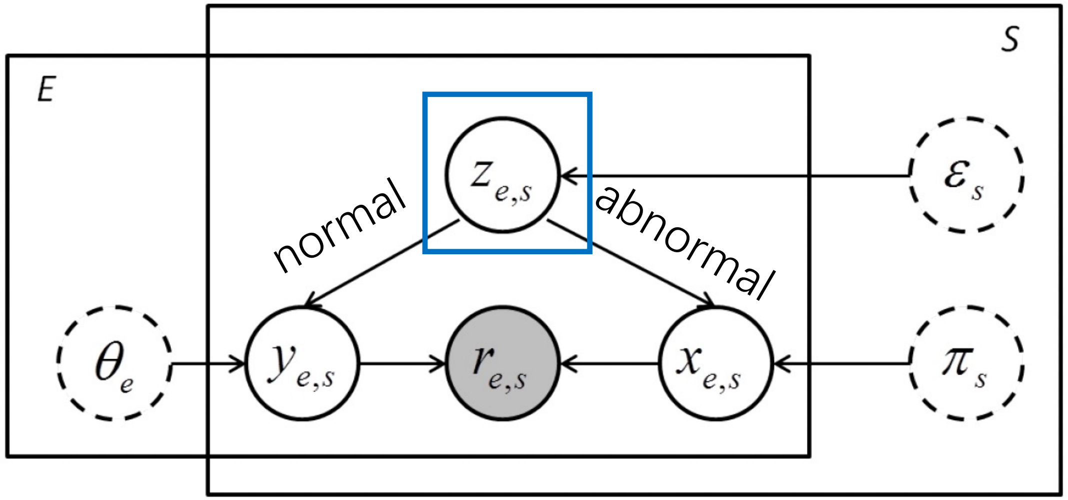

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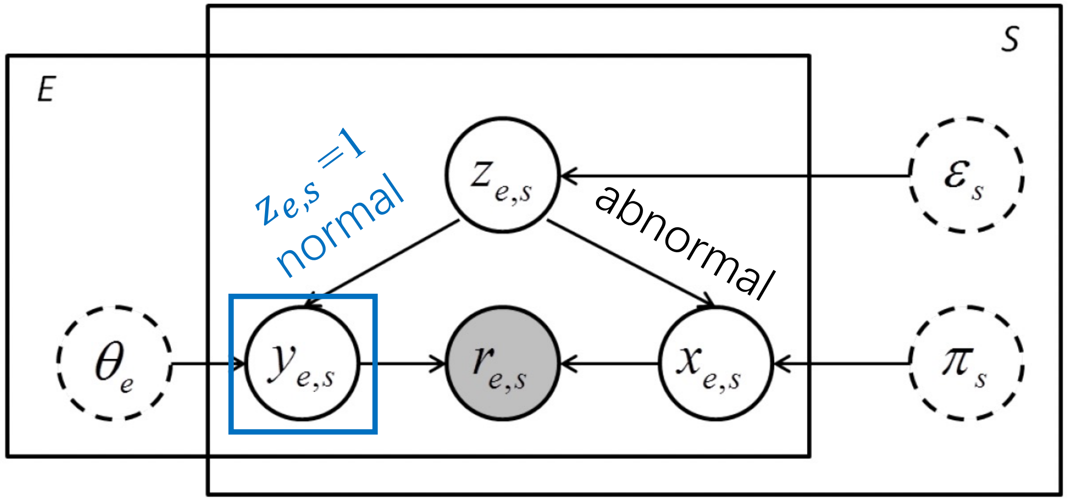

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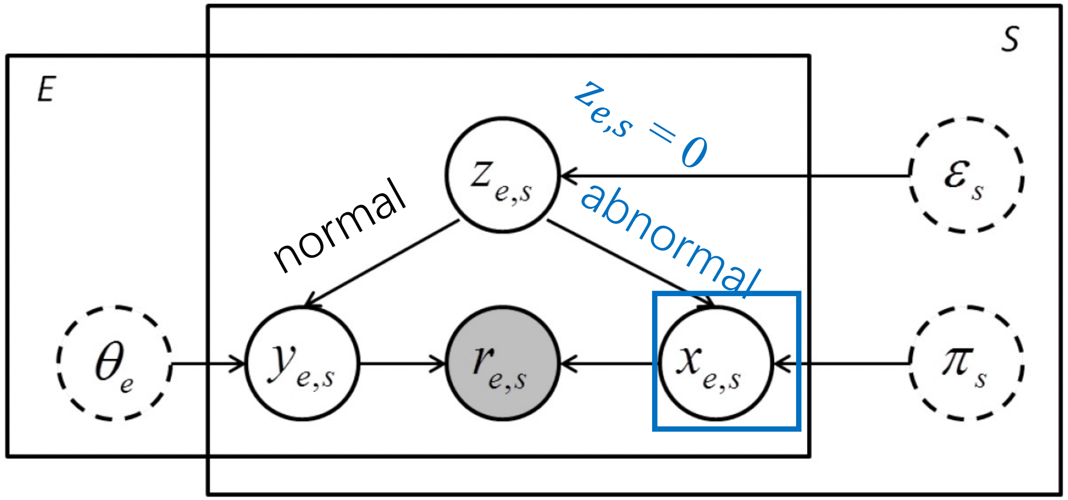

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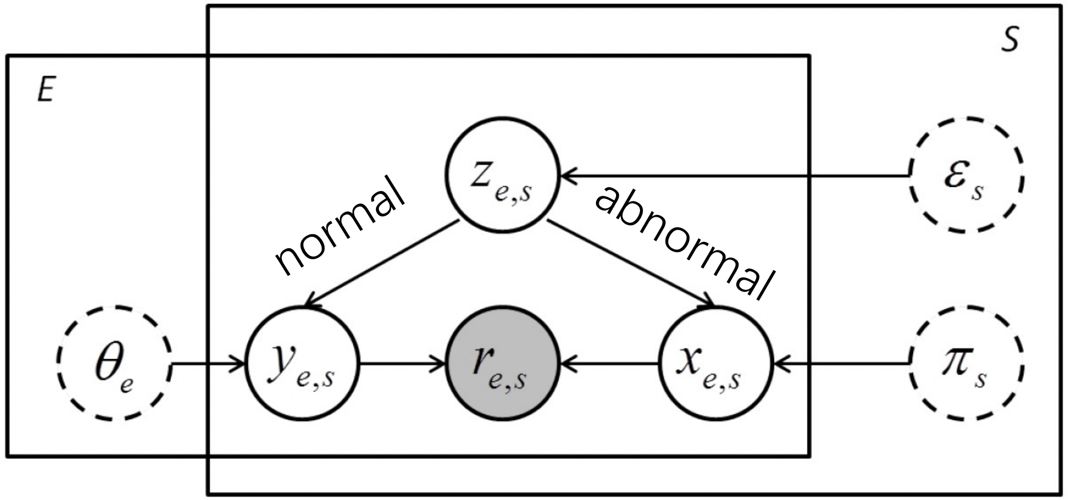

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the complete conditional density

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The Proposed Annotation Model: GPM

$$
\begin{aligned}
p(R|Y, X, Z, \pi, \epsilon, \theta) &= \sum_{Z} p(R|X, Y, Z) p(Z|\epsilon) \\
&= p(Z = 1|\epsilon) p(Y|\theta) \\
&+ p(Z = 0|\epsilon) p(X|\pi) \\
&= \prod_{e,s \in A} [\epsilon_s (\prod_{n=1}^{N} \theta_{e,n}^{[r_{e,s}=n]}) \\
&+ (1 - \epsilon_s)(\prod_{n=1}^{N} \pi_{s,n}^{[r_{e,s}=n]})]
\end{aligned}
$$

$r_{e,s}$ is the provided label by annotator s

Parameter Estimation Using EM algorithm

Prediction of Ground Truth

$$\hat{v}_e = \sum_{n=1}^{N} n \cdot \theta_{e,n}$$

Subject to:

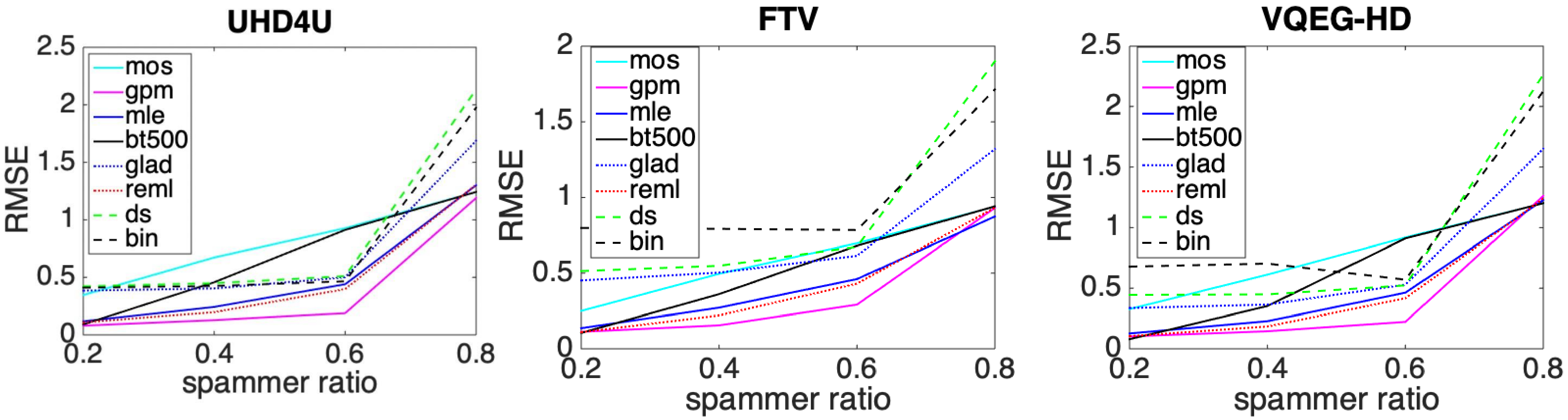
$$1 \geq \theta_{e,n} \geq 0, \sum_{n=1}^{N} \theta_{e,n} = 1$$

$$1 \geq \pi_{s,n} \geq 0, \sum_{n=1}^{N} \pi_{s,n} = 1$$

Experimental results

- Random selection of the spammer
- Simulate mixed abnormal behavior
- Replace the real data by error data
- Simulate 100 times

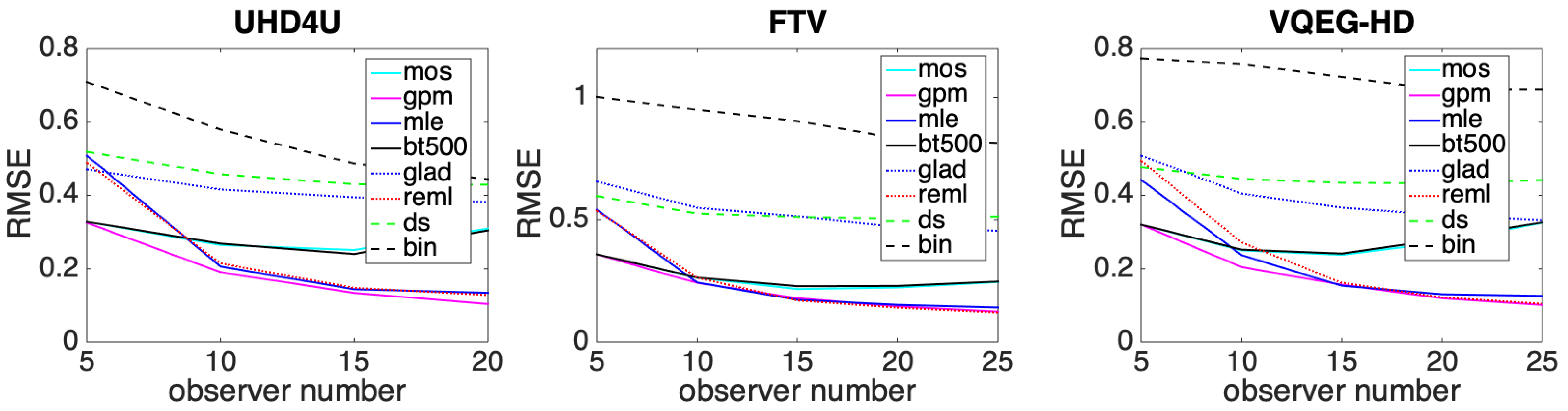
1) The influence of spammer ratio on recovered ground truth



Experimental Results

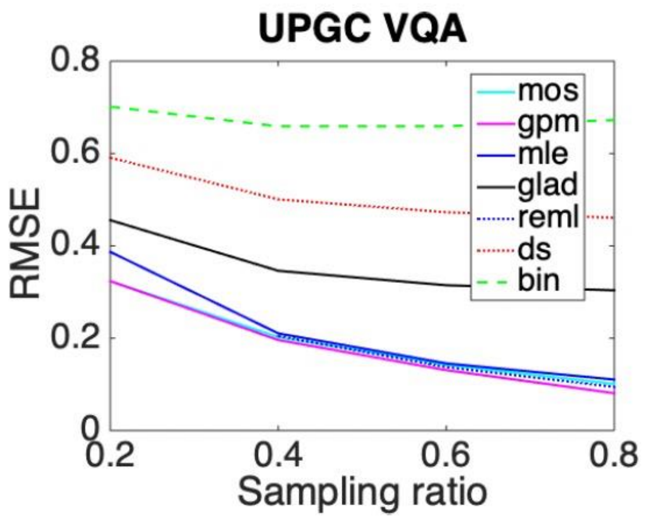
- Random sampling annotators
- Simulate mixed abnormal behavior
- Fix ‘mixed’ behavior = 20%
- Replace the real data by error data

2) Influence of annotator number on inferring the ground truth



Experiment on real crowdsourcing data

- **UPGC crowdsourcing data**
  - -1074 UPGC video sequences
  - -181 annotators
  - -23962 collected labels
  - -22 annotators/video



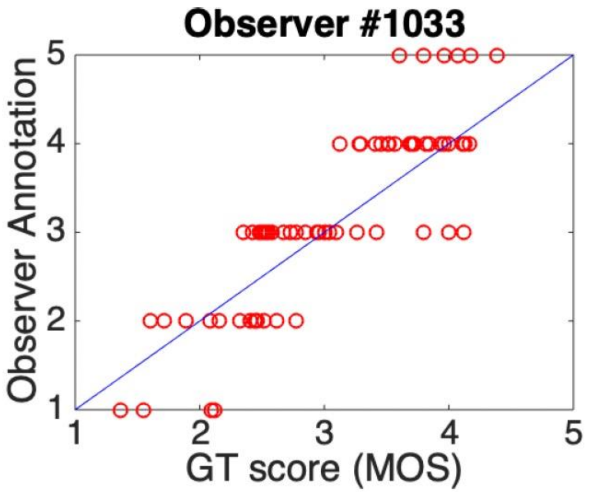
- **MovieLens 20M review data**
  - - 174 movies
  - - 69 annotators
  - - 2833 ratings
  - - 16 annotators/movie

GT: 5662 movies labeled by 15147 annotators

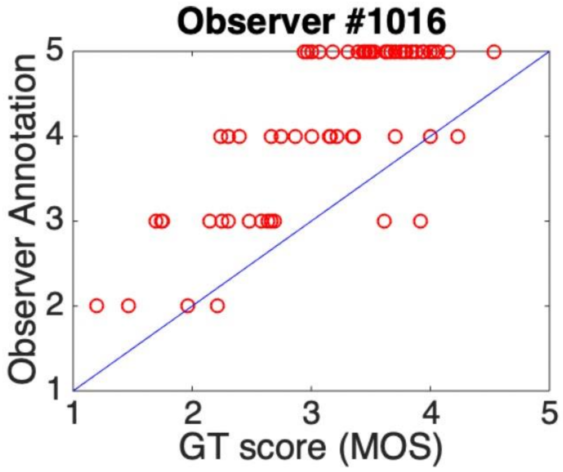
Model	PLCC ↑	ROCC ↑	RMSE ↓
D&S [6]	0.4073	0.4957	1.2287
GLAD [33]	0.5347	0.6029	0.6361
Bin [25]	0.7122	0.7166	0.5849
REML[26]	0.7066	0.7282	0.4292
MLE [18]	0.8369	0.8219	0.2483
Proposed	**0.8620**	**0.8420**	**0.2228**

Detected abnormal behavior

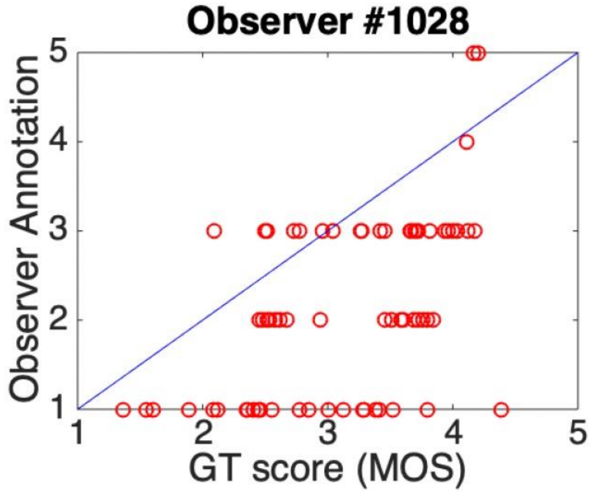
- In UPGC crowdsourcing video database



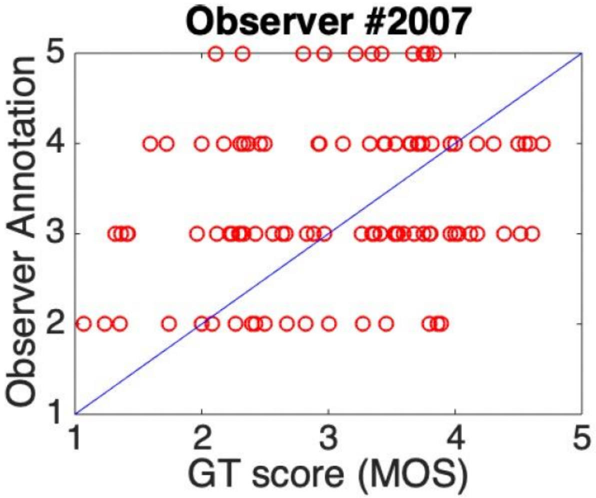
Normal annotation



Optimistic annotation



Picky annotation



Random annotation

Conclusion

- A probabilistic graphic model is proposed to recover ground truth and detect abnormal behavior
- The ground truth of the visual quality is a distribution
  - Not Gaussian
  - But an ordinal categorical distribution → more general
- Each annotator has a probability to make a mistake
  - If this probability smaller than 0.5 → spammer
  - Data is expensive, using model to denoise
- The proposed model outperforms the other SOTA methods.