In-Depth DCT Coefficient Distribution Analysis for First Quantization Estimation

S. Battiato[1], O. Giudice[1], F. Guarnera[1], **G. Puglisi**[2]

[1]University of Catania, [2]University of Cagliari

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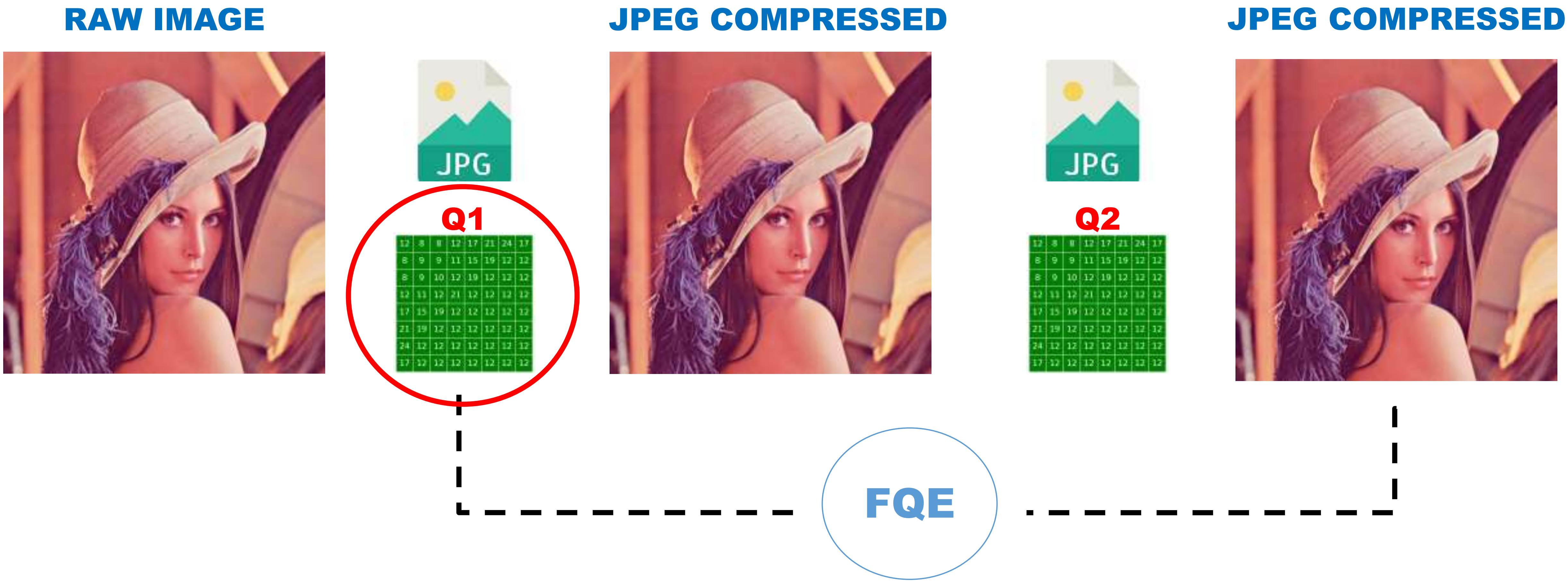
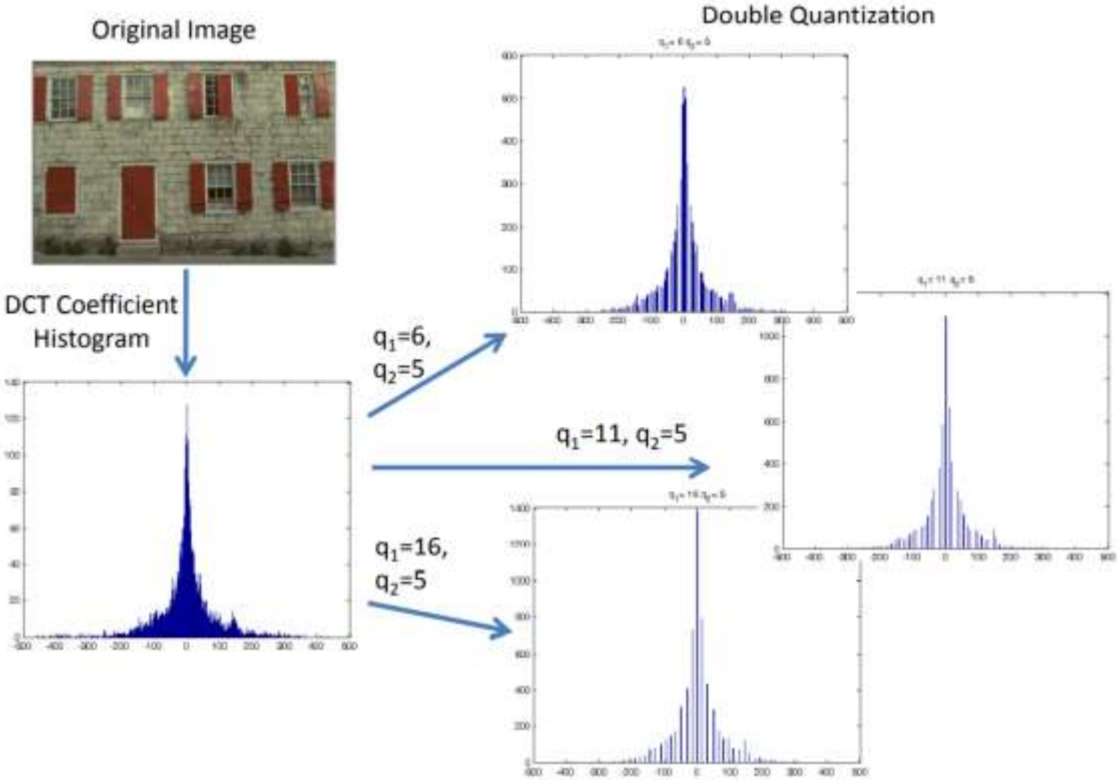
iCtLab Digital Forensics

FQE: First Quantization Estimation



State-of-the-art



Consecutive quantizations introduced periodic artifacts into the histogram of DCT coefficients.

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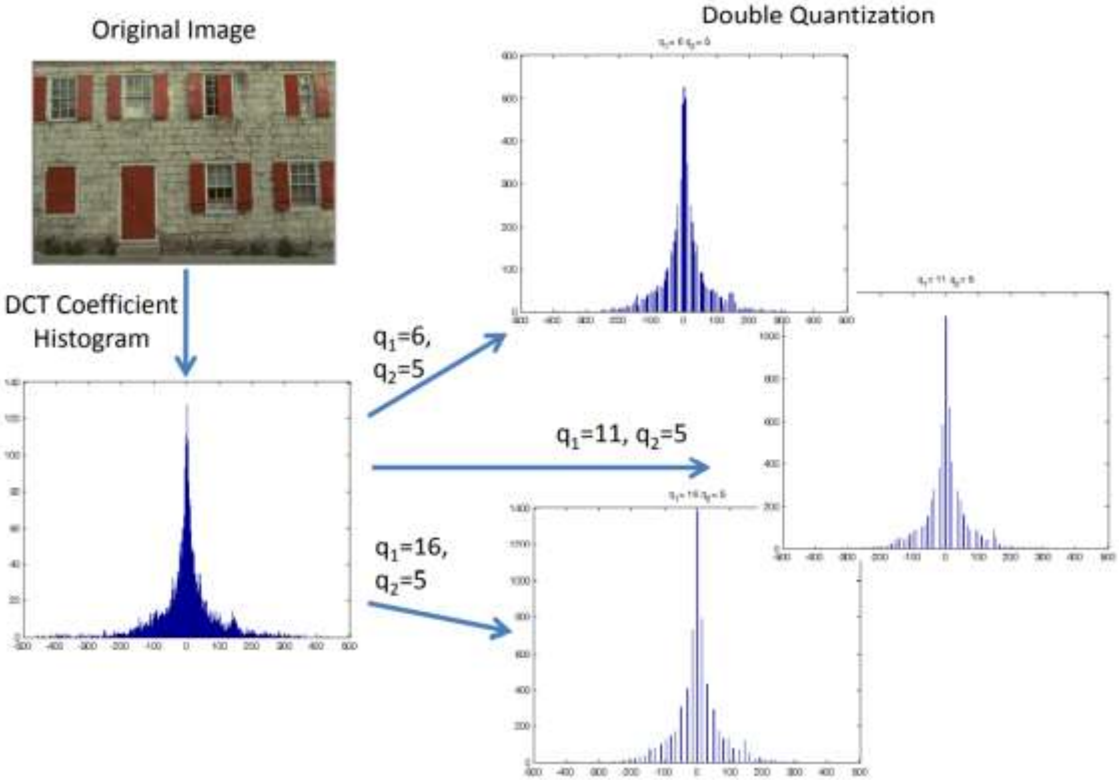

Statistical approaches

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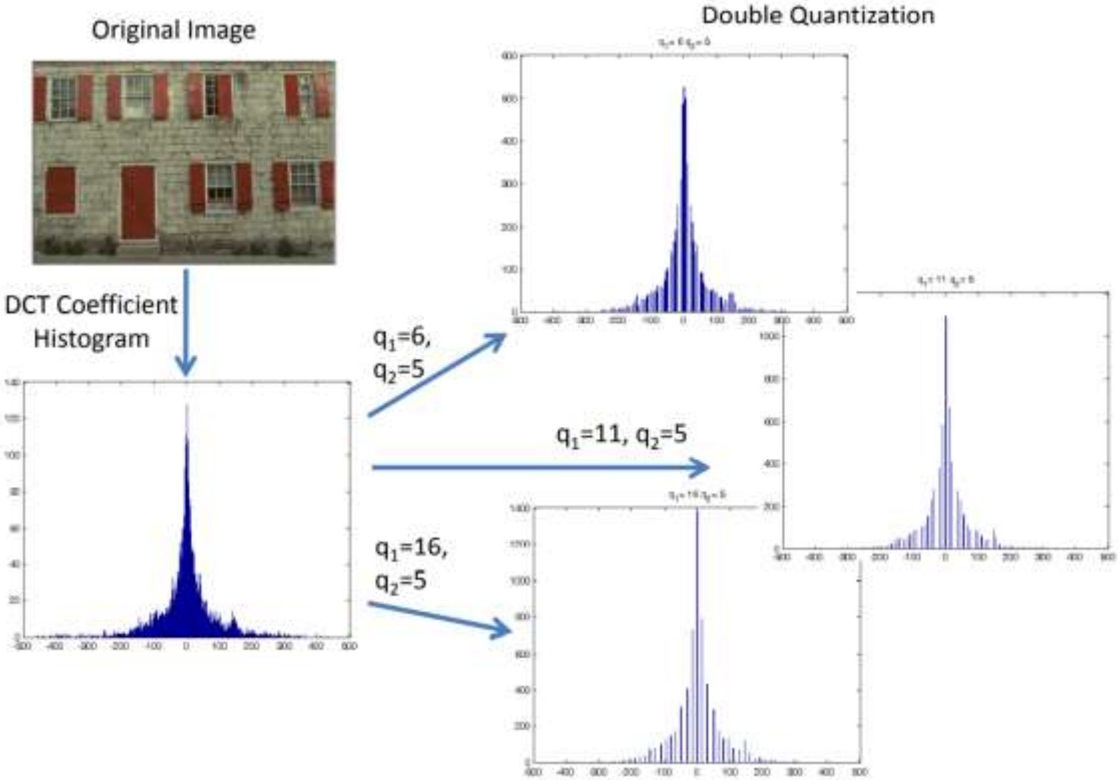

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They usually provide satisfactory results only at specific combinations between first and second compression factors.

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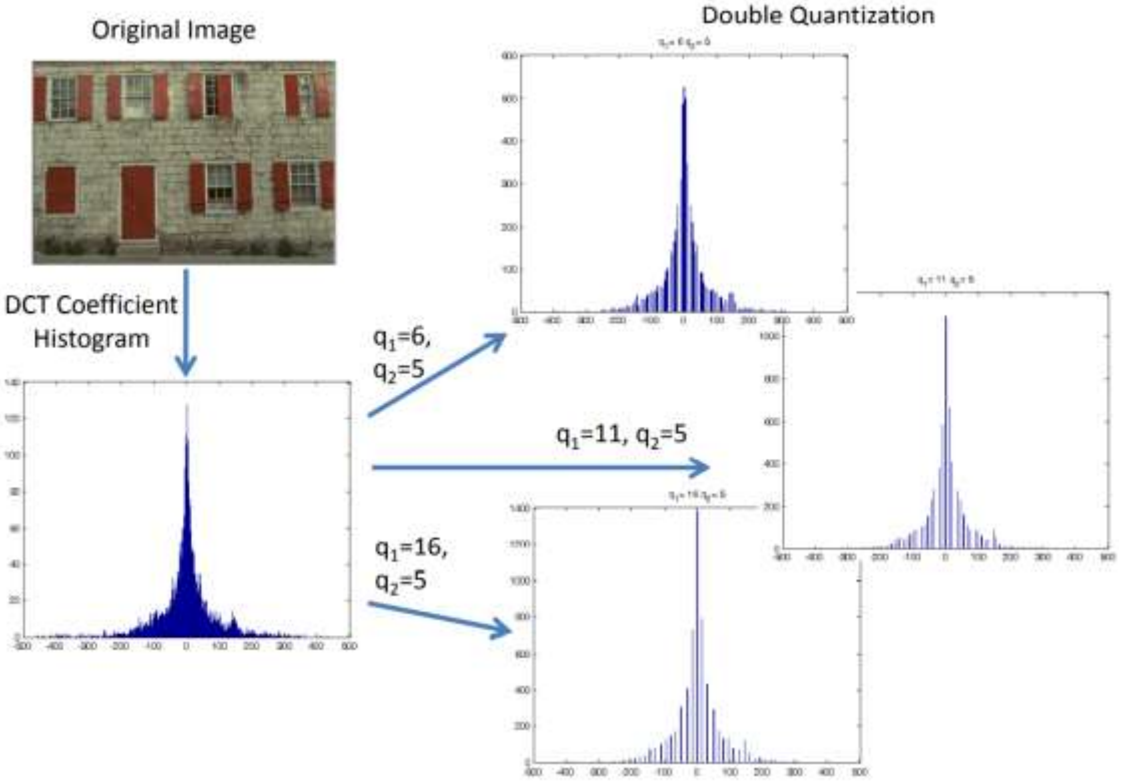

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Statistical approaches

Machine learning approaches

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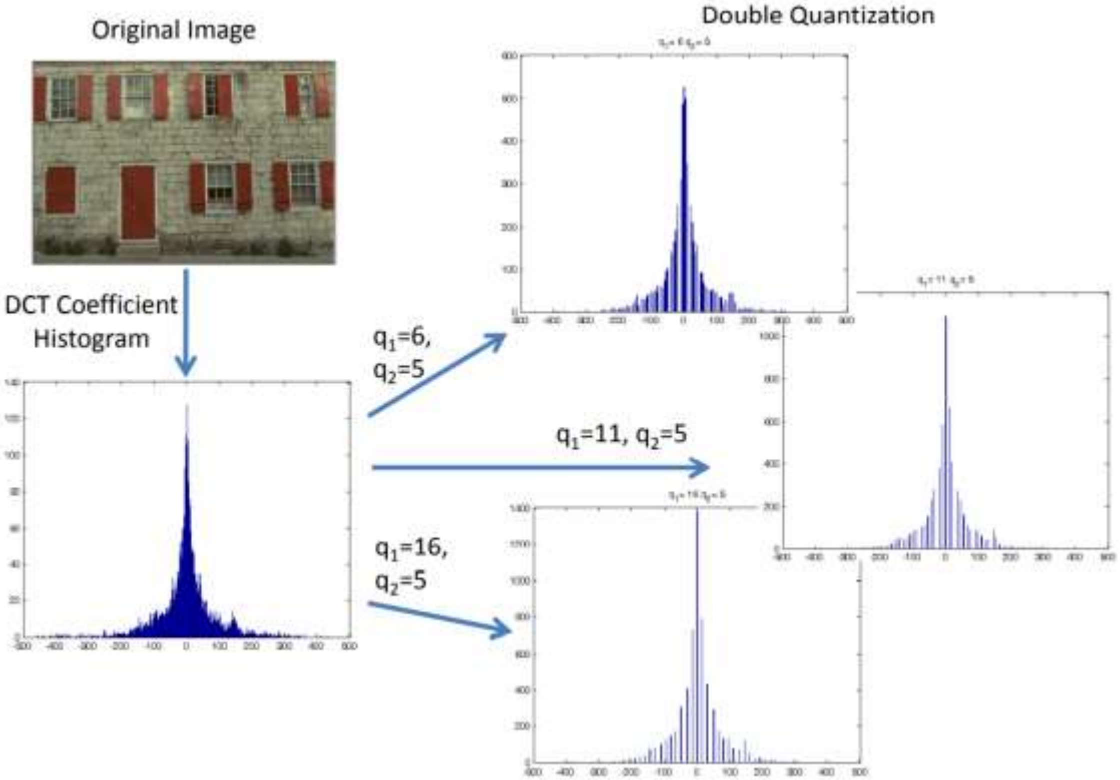

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Statistical approaches

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Machine learning approaches

They could suffer from overfitting.

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Training Dataset Generation

D. Dang-Nguyen, C. Pasquini, V. Conotter, and G. Boato, “Raise: a raw images dataset for digital image forensics,” in Proc. of the 6th ACM Multimedia Systems Conference, 2015, pp. 219–224.

Training Dataset Generation

I

8156 high resolution
images in TIFF format
(RAISE dataset)

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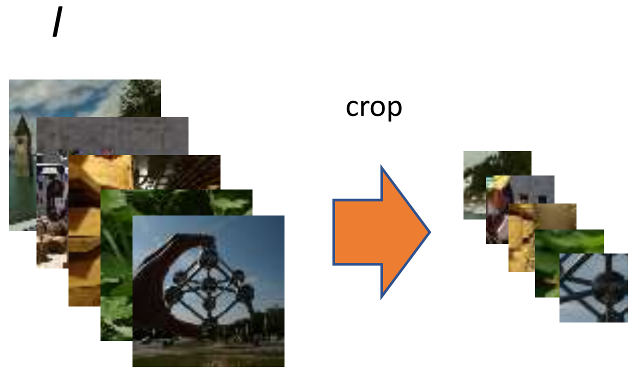

8156 high resolution images in TIFF format (RAISE dataset)

64×64 patches extracted from the center

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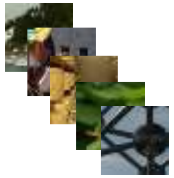
Training Dataset Generation

$$\begin{bmatrix} 1 & \cdots & 1 \\ \vdots & \ddots & \vdots \\ 1 & \cdots & 1 \end{bmatrix} \begin{bmatrix} 2 & \cdots & 2 \\ \vdots & \ddots & \vdots \\ 2 & \cdots & 2 \end{bmatrix} \begin{bmatrix} 3 & \cdots & 3 \\ \vdots & \ddots & \vdots \\ 3 & \cdots & 3 \end{bmatrix} \begin{bmatrix} 4 & \cdots & 4 \\ \vdots & \ddots & \vdots \\ 4 & \cdots & 4 \end{bmatrix} \cdots \begin{bmatrix} q1_{max} & \cdots & q1_{max} \\ \vdots & \ddots & \vdots \\ q1_{max} & \cdots & q1_{max} \end{bmatrix}$$

Fist JPEG compression with constant matrices

I

crop



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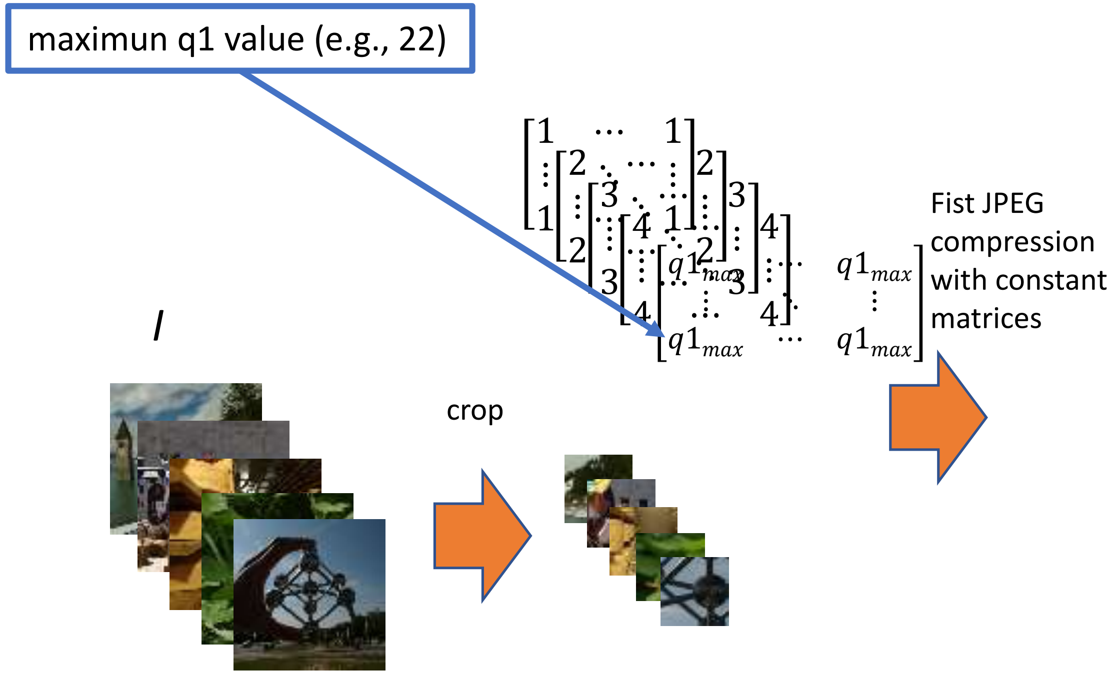

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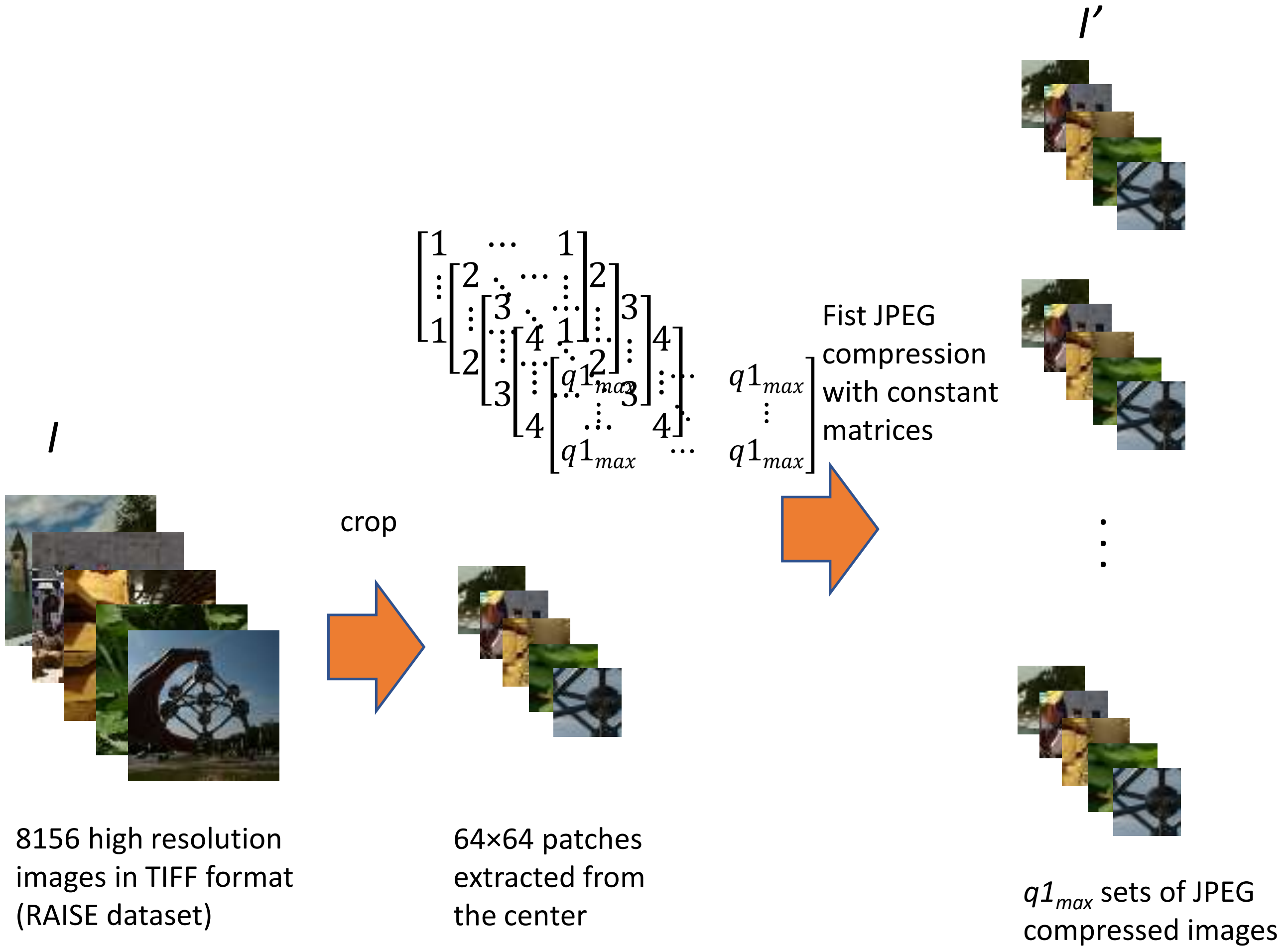

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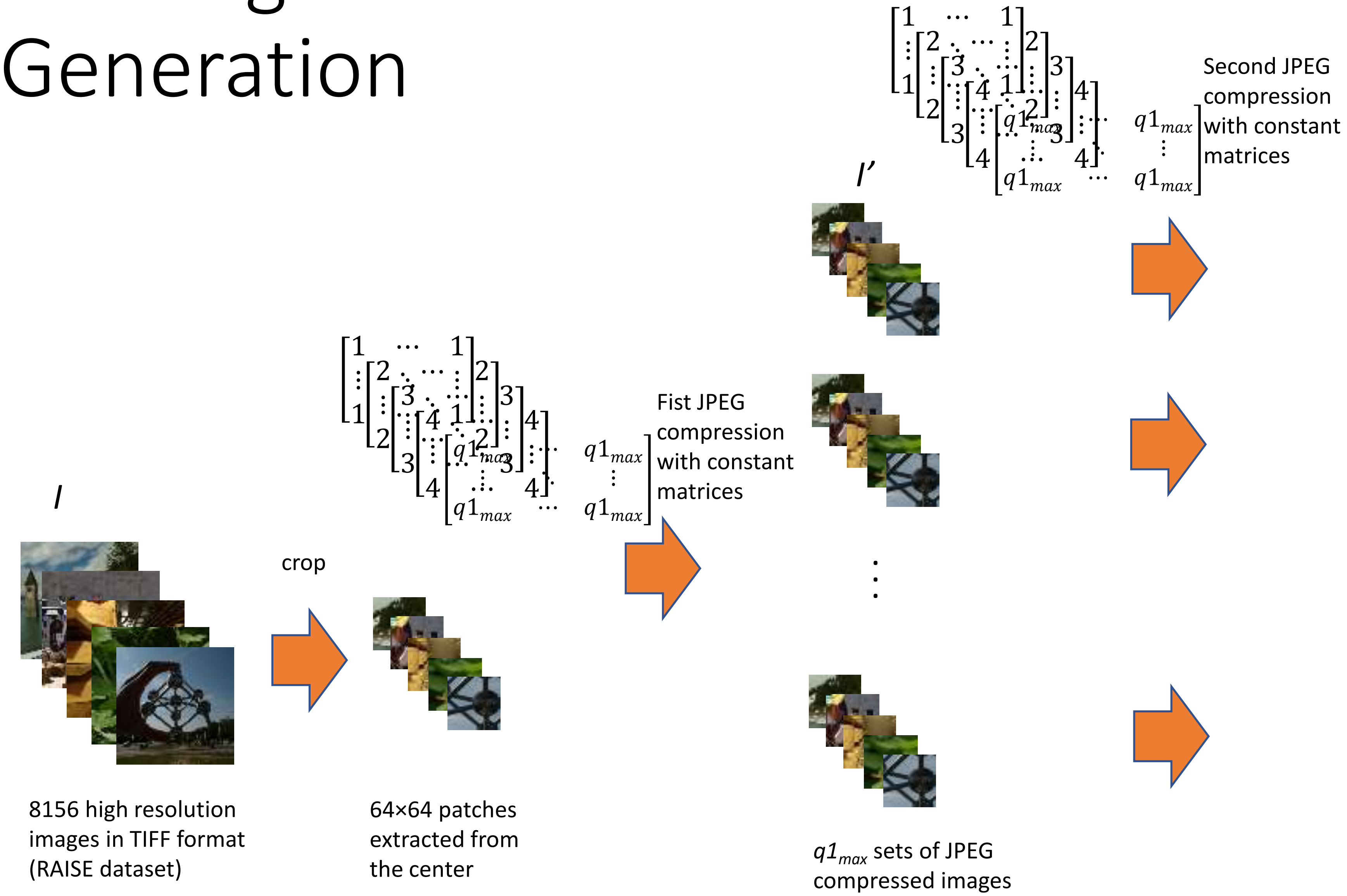

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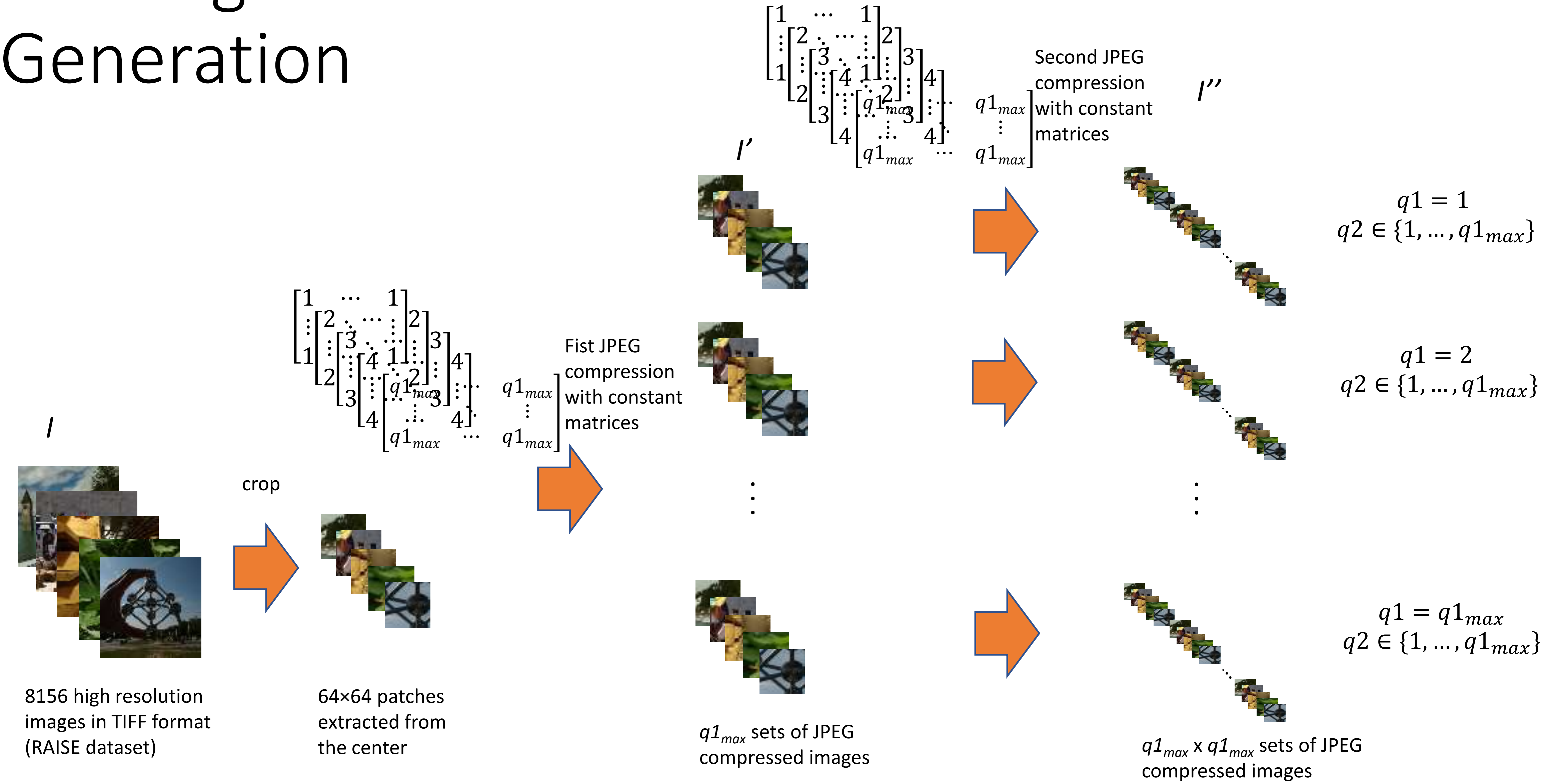

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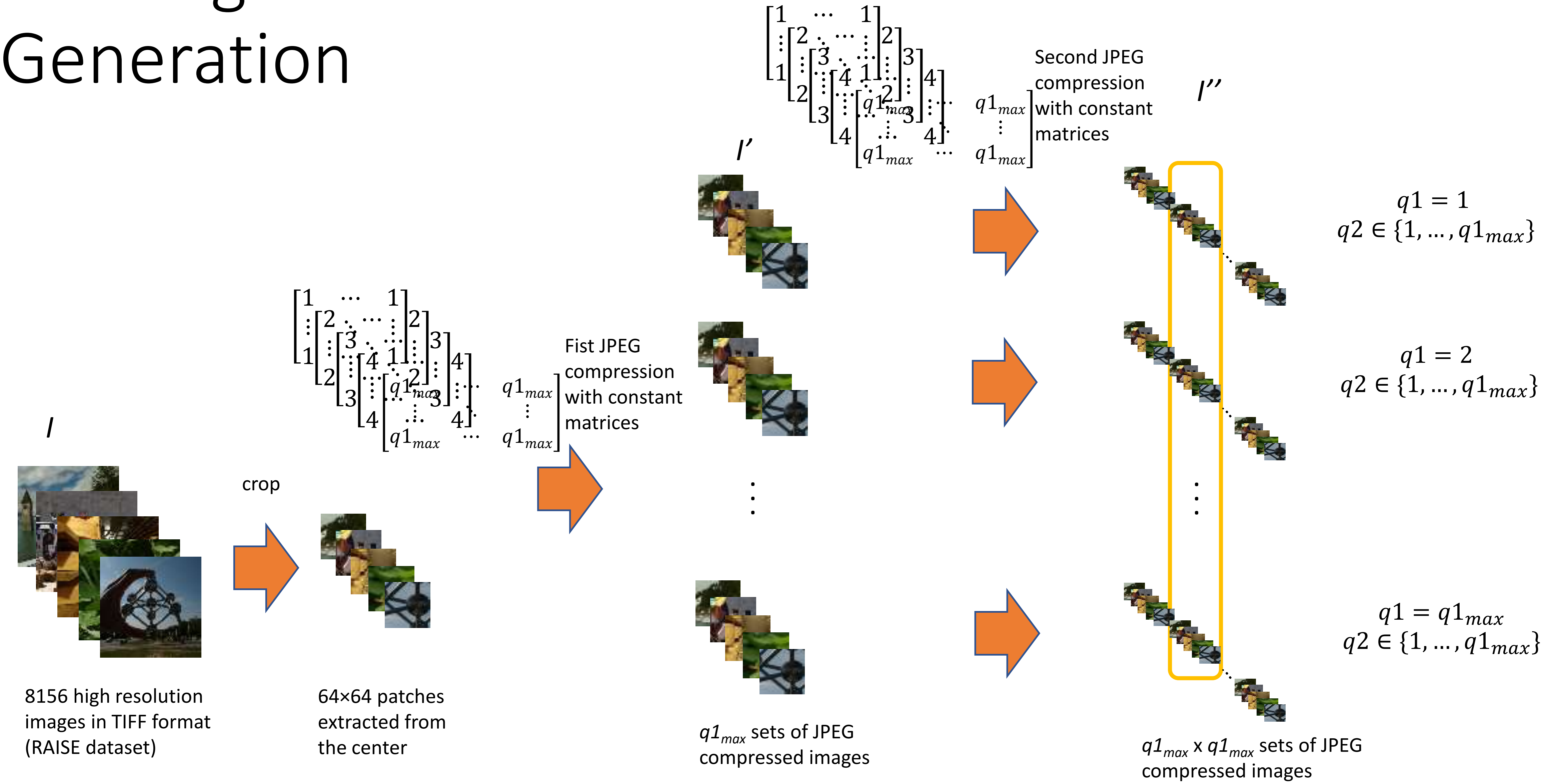

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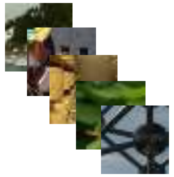
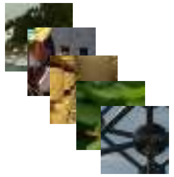
Training Dataset Generation

I''





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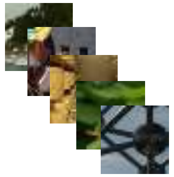
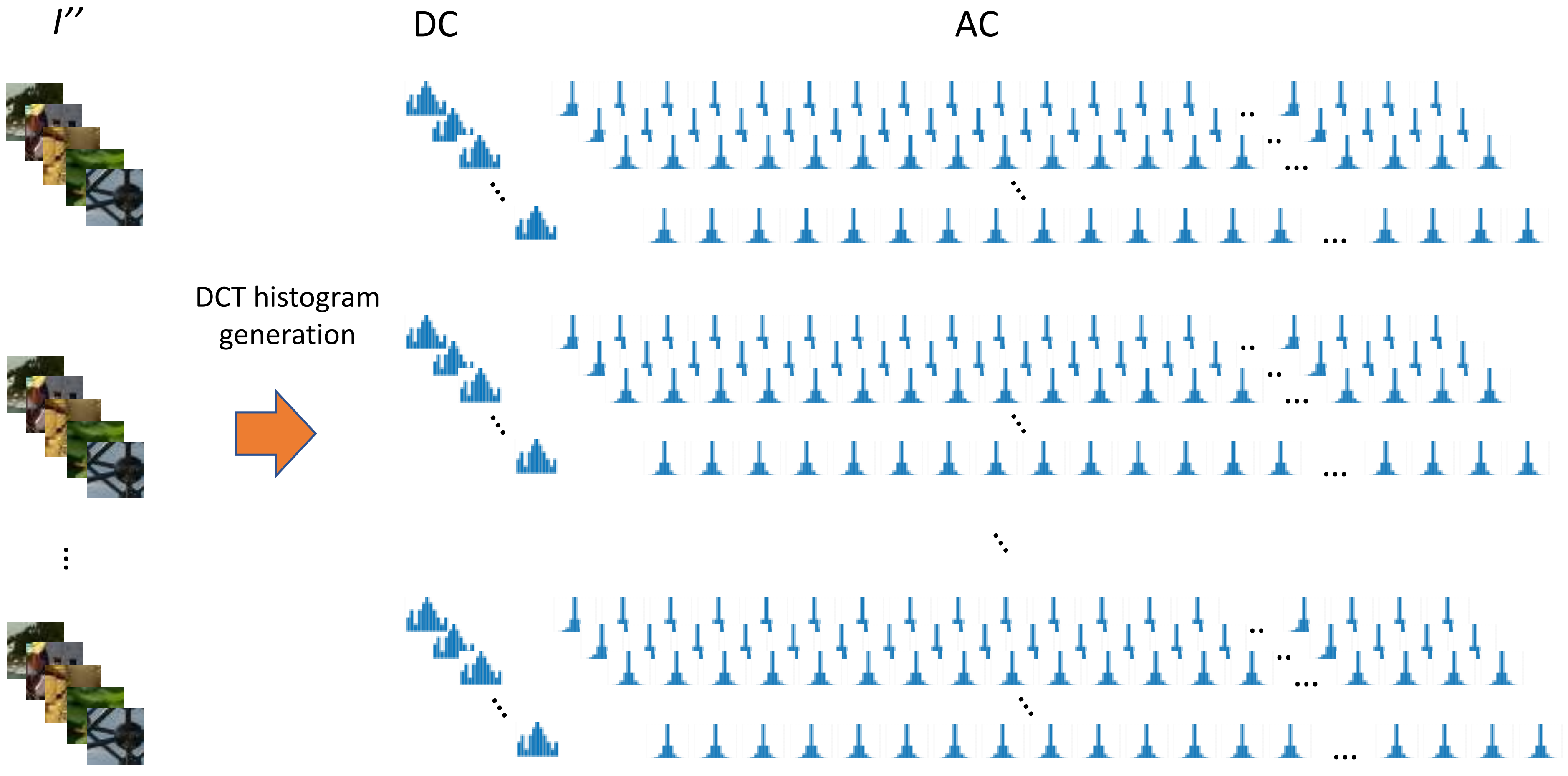


Double compressed images with
$q1 \in \{1, \dots, q1_{max}\}$
$q2 = q2_i$

Training Dataset Generation



Double compressed images with
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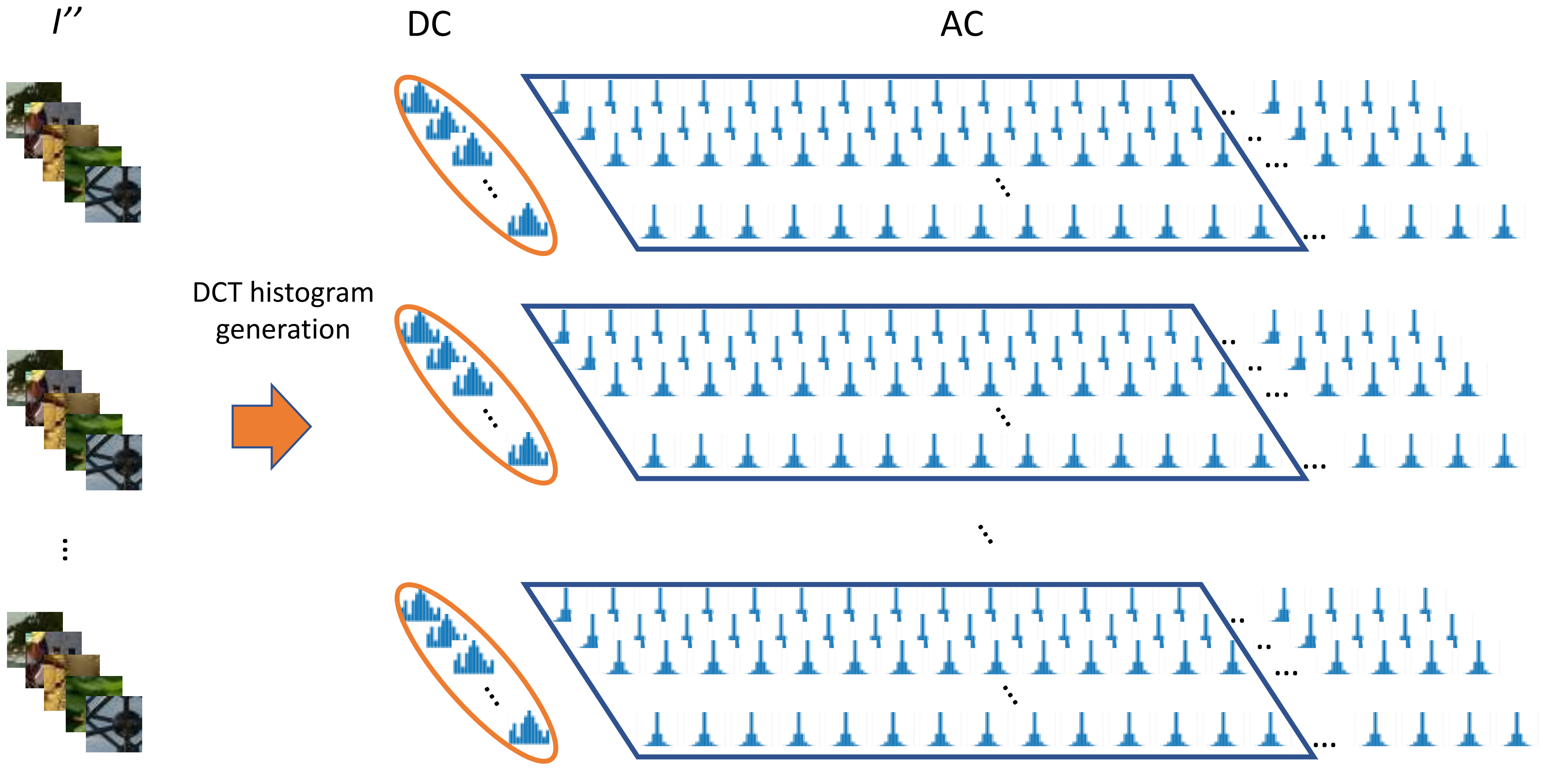
DCT histograms

Training Dataset Generation



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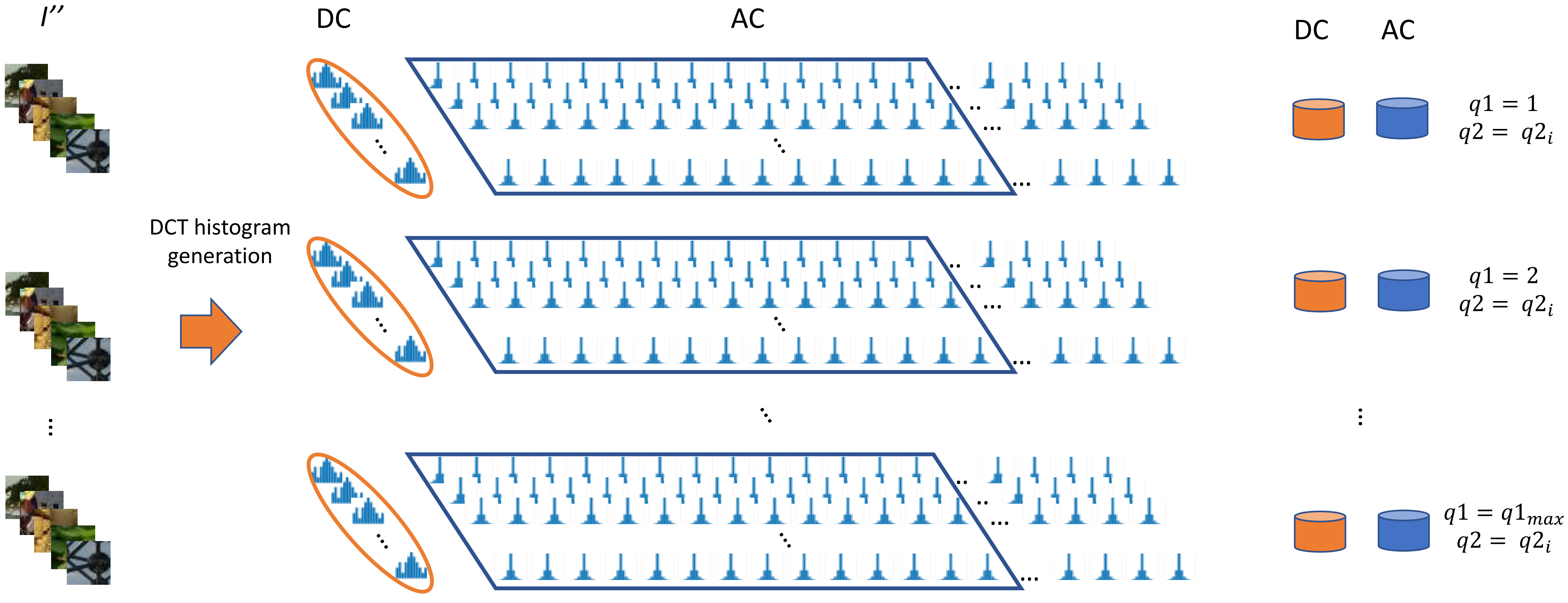

Double compressed images with
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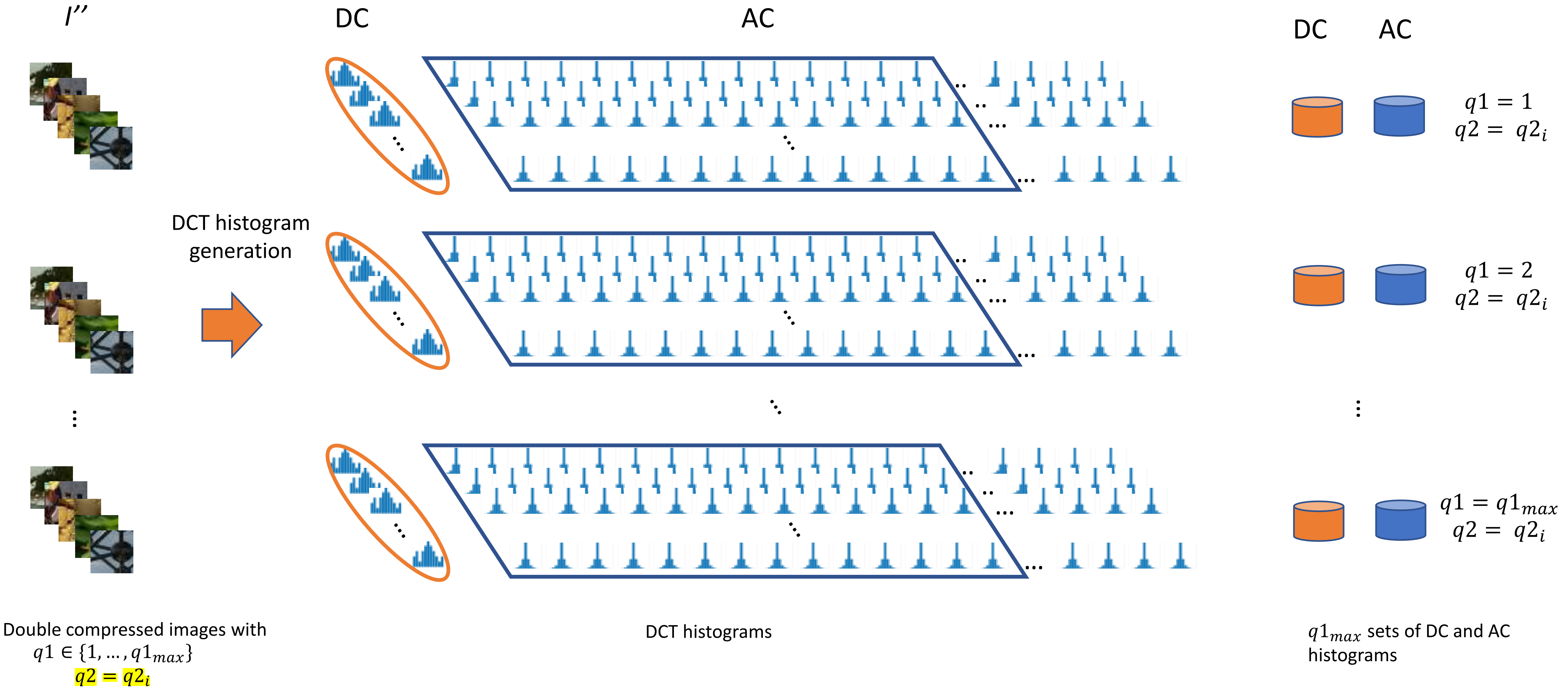
DCT histograms

$q1_{max}$ sets of DC and AC histograms

Training Dataset Generation

Considering all the q2 in the range $\{1, \ldots, q1_{max}\}$, $q1_{max} \times q1_{max}$ sets of DC and AC histograms are generated.



Algorithm 1 The Proposed FQE Technique

Input: double compressed image I''
Output: $\{q1_1, q1_2, \ldots, q1_k\}$

Initialization : k, $q1_{max}$

for $i = 1$ to k **do**
  h_i : distribution of i-th DCT coefficient
  if $(i = 1)$ **then**
    $D : DC_{dset}$
    m : median value of h_i
  else
    $D : AC_{dset}$
    β : β fitted on Laplacian h_i
  end if
  $q2_i$: quantization factor of Q_2 for i-th DCT
  for $j = 1$ to $q1_{max}$ **do**
    $D_{j,q2_i}$: sub-dataset $(q1, q2)$ with $q1 = j$, $q2 = q2_i$
    $D_{j,q2_i}(m, \beta)$: sub-range with most similar m, β
    $d_{i,j}$: lower χ^2 distance between h_i and $D_{j,q2_i}$
  end for
  $q1_i : \arg\min_{\{d_{i,j}\}}$, $j \in \{1, 2, \ldots, q1_{max}\}$
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regularize($\{q1_1, q1_2, \ldots, q1_k\}$)
return $\{q1_1, q1_2, \ldots, q1_k\}$

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$$\begin{bmatrix} & \cdots & \\ \vdots & \ddots & \vdots \\ & \cdots & \end{bmatrix}$$

First quantization matrix Q_1

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number of quantization factors to be estimated (e.g., 15)

maximun q1 value (e.g., 22)

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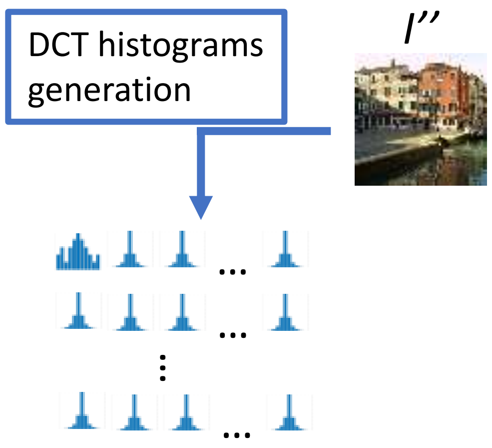

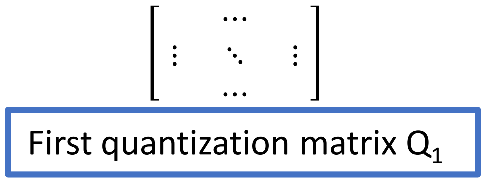

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    for j = 1 to q1_max do
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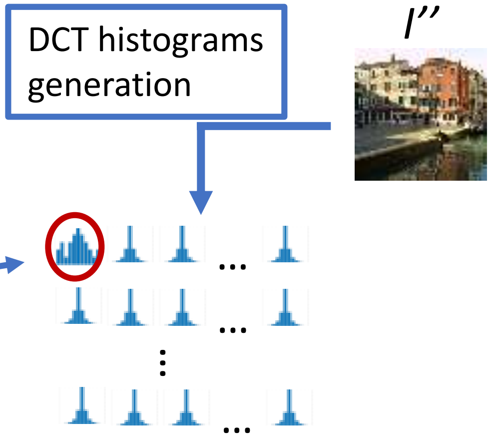
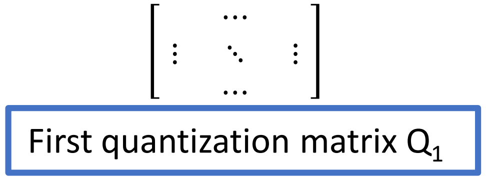
        D_{j,q2_i}(m, β) : sub-range with most similar m, β
        d_{i,j} : lower χ^2 distance between h_i and D_{j,q2_i}
    end for
    q1_i : arg min_{d_{i,j}}, j ∈ {1, 2, ..., q1_max}
end for
regularize({q1_1, q1_2, ..., q1_k})
return {q1_1, q1_2, ..., q1_k}
```





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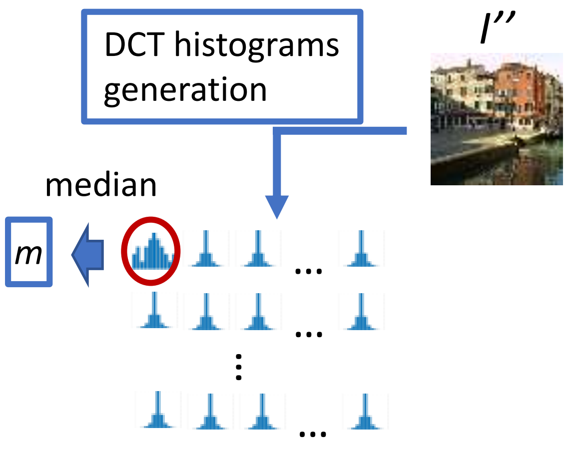

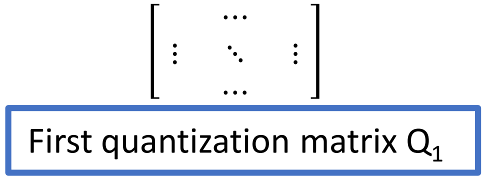

Algorithm 1 The Proposed FQE Technique

Input: double compressed image I''
Output: $\{q1_1, q1_2, \ldots, q1_k\}$
Initialization : k, $q1_{max}$

for $i = 1$ to k **do**
  h_i : distribution of i-th DCT coefficient
  if $(i = 1)$ **then**
    $D : DC_{dset}$
    m : median value of h_i
  else
    $D : AC_{dset}$
    β : β fitted on Laplacian h_i
  end if
  $q2_i$: quantization factor of Q_2 for i-th DCT
  for $j = 1$ to $q1_{max}$ **do**
    $D_{j,q2_i}$: sub-dataset $(q1, q2)$ with $q1 = j$, $q2 = q2_i$
    $D_{j,q2_i}(m, \beta)$: sub-range with most similar m, β
    $d_{i,j}$: lower χ^2 distance between h_i and $D_{j,q2_i}$
  end for
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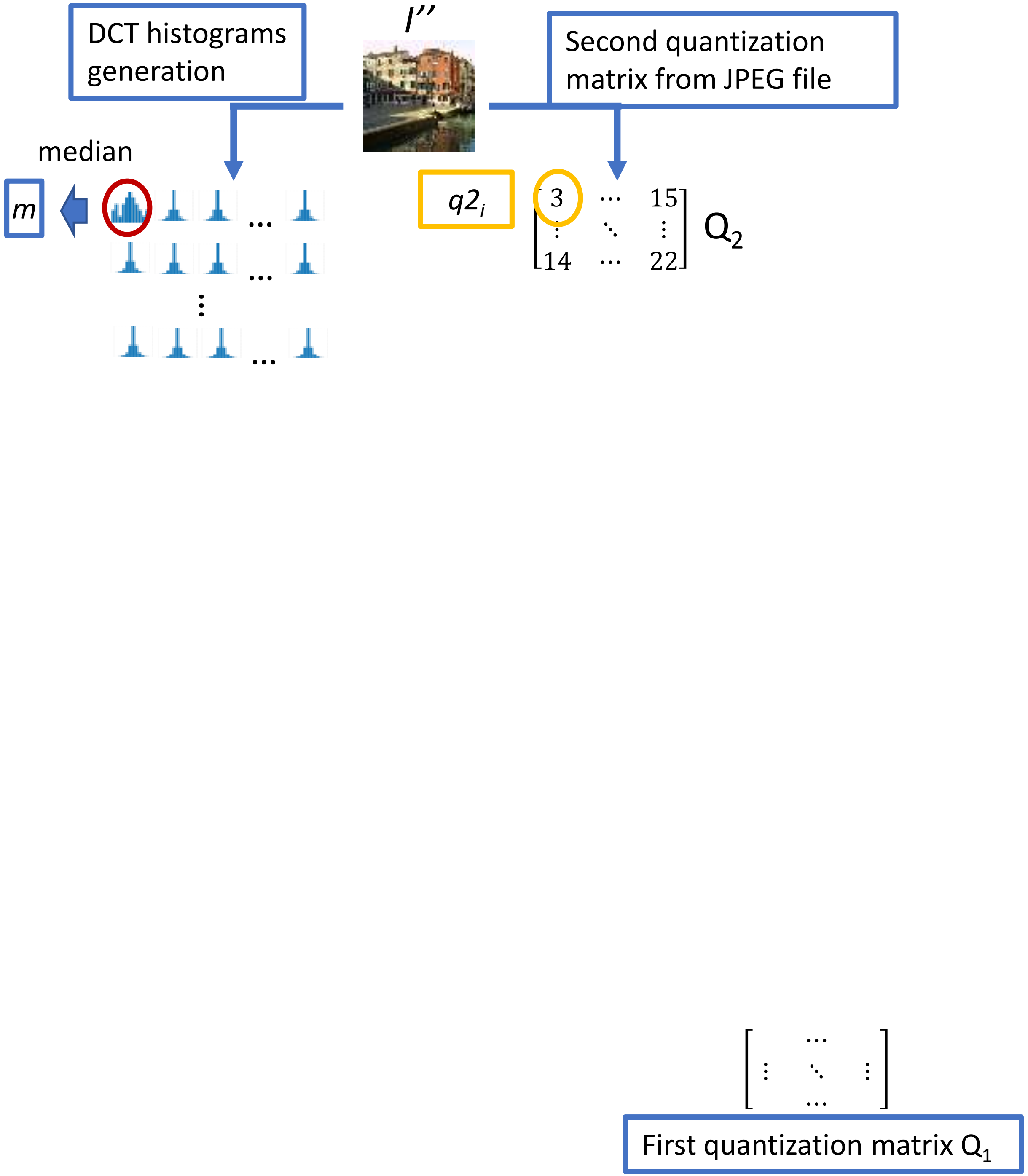

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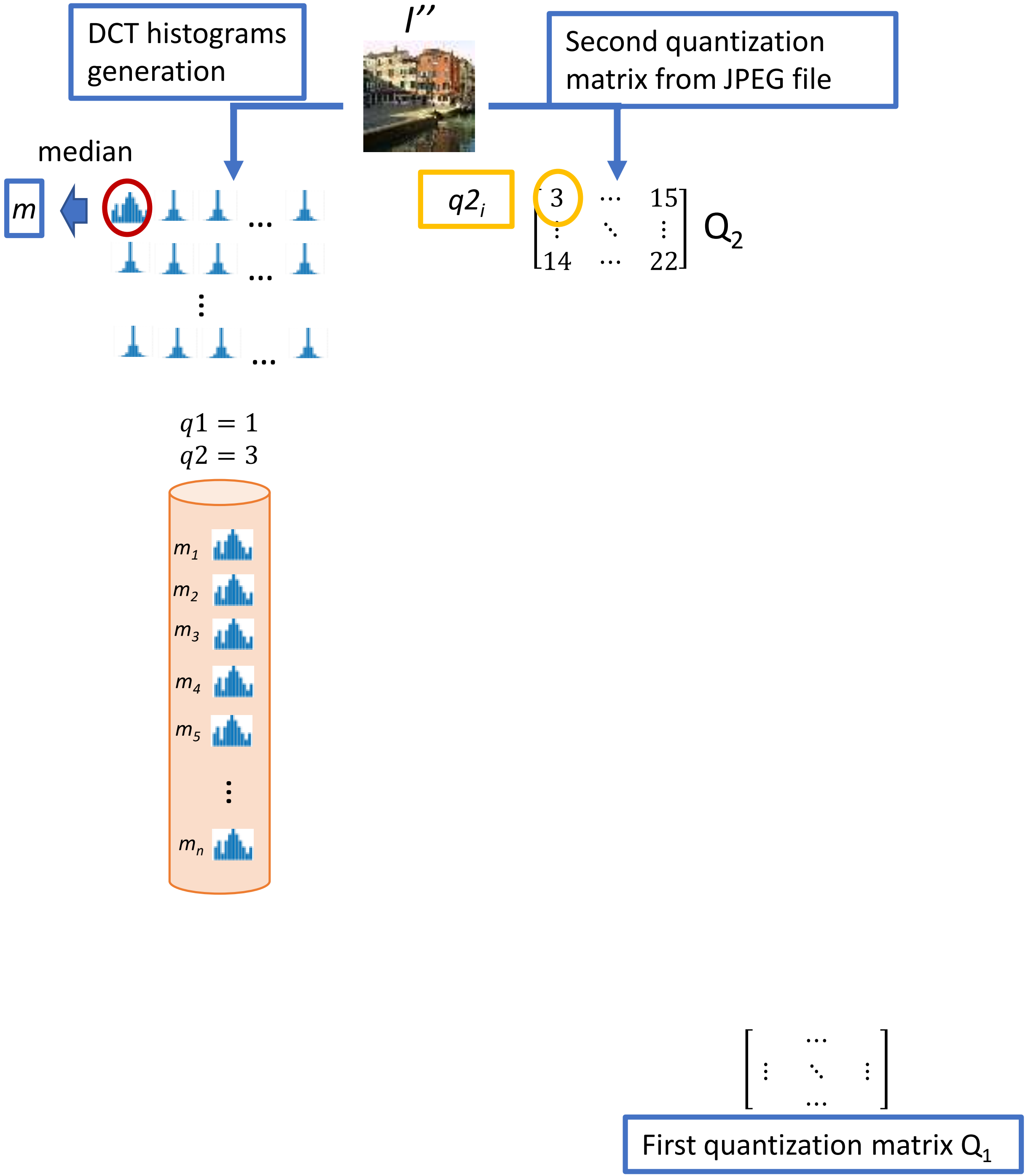

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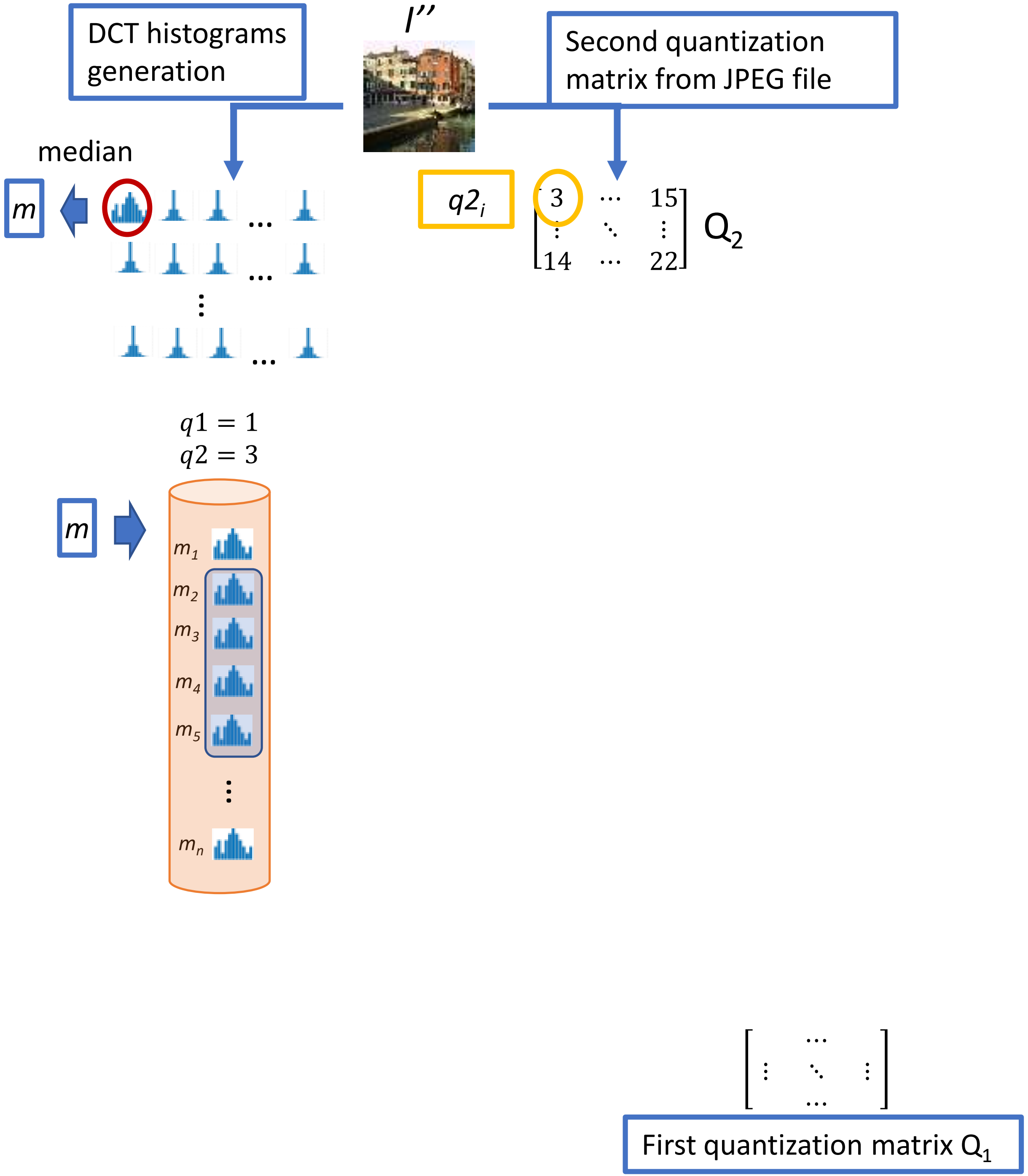

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        D_{j,q2_i}(m, β) : sub-range with most similar m, β
        d_{i,j} : lower χ^2 distance between h_i and D_{j,q2_i}
    end for
    q1_i : arg min_{d_{i,j}}, j ∈ {1, 2, ..., q1_max}
end for
regularize({q1_1, q1_2, ..., q1_k})
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```

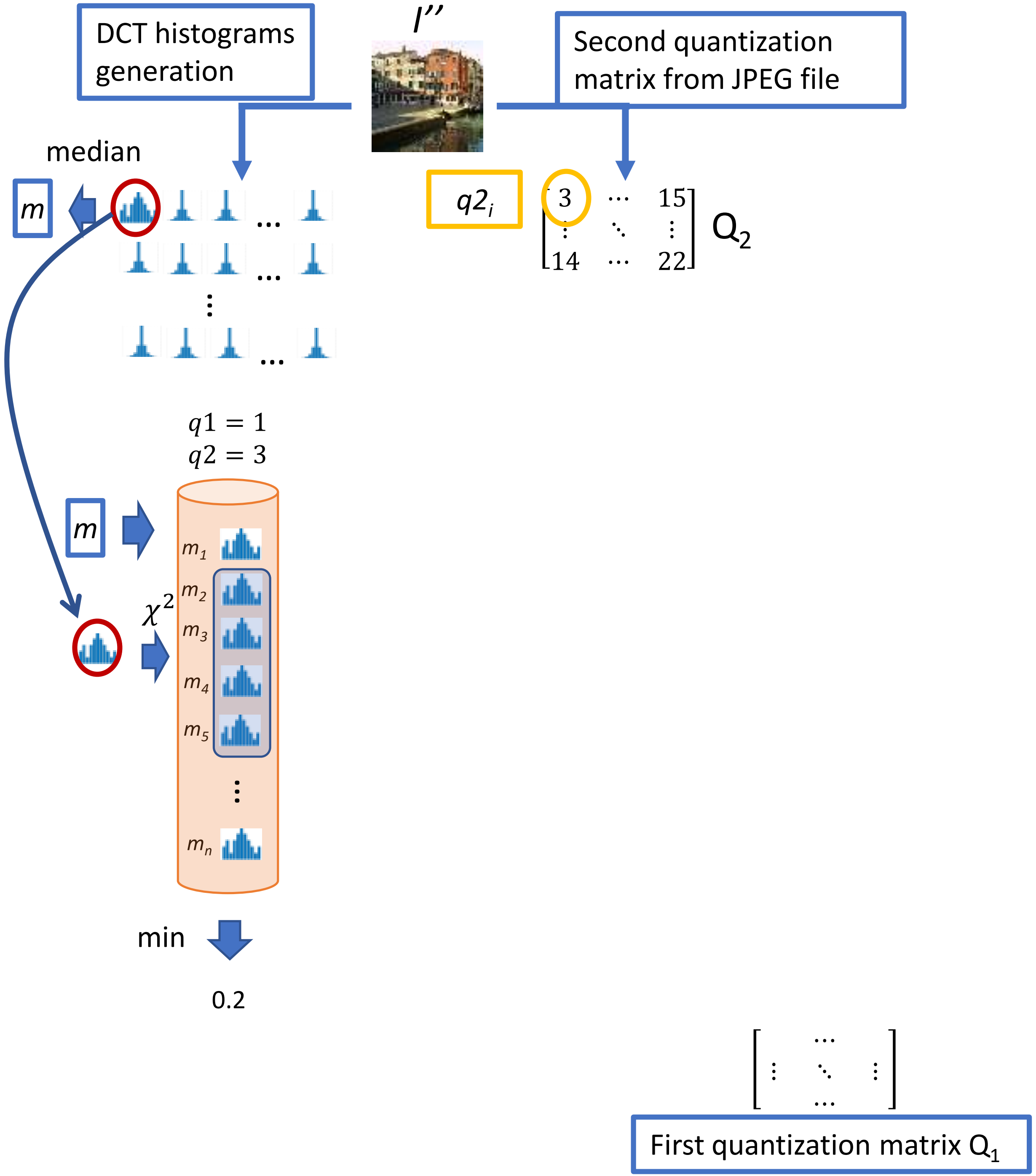

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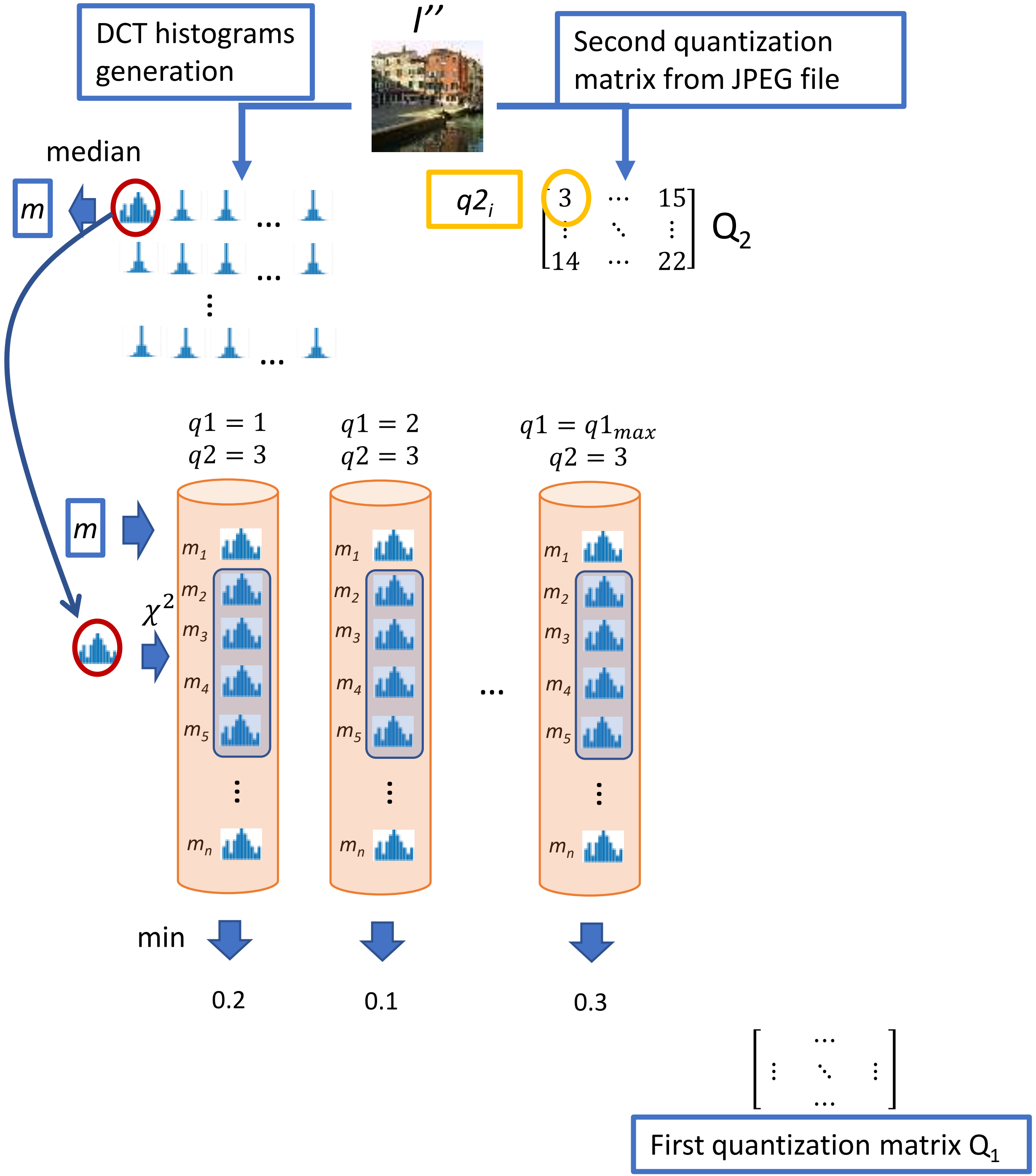

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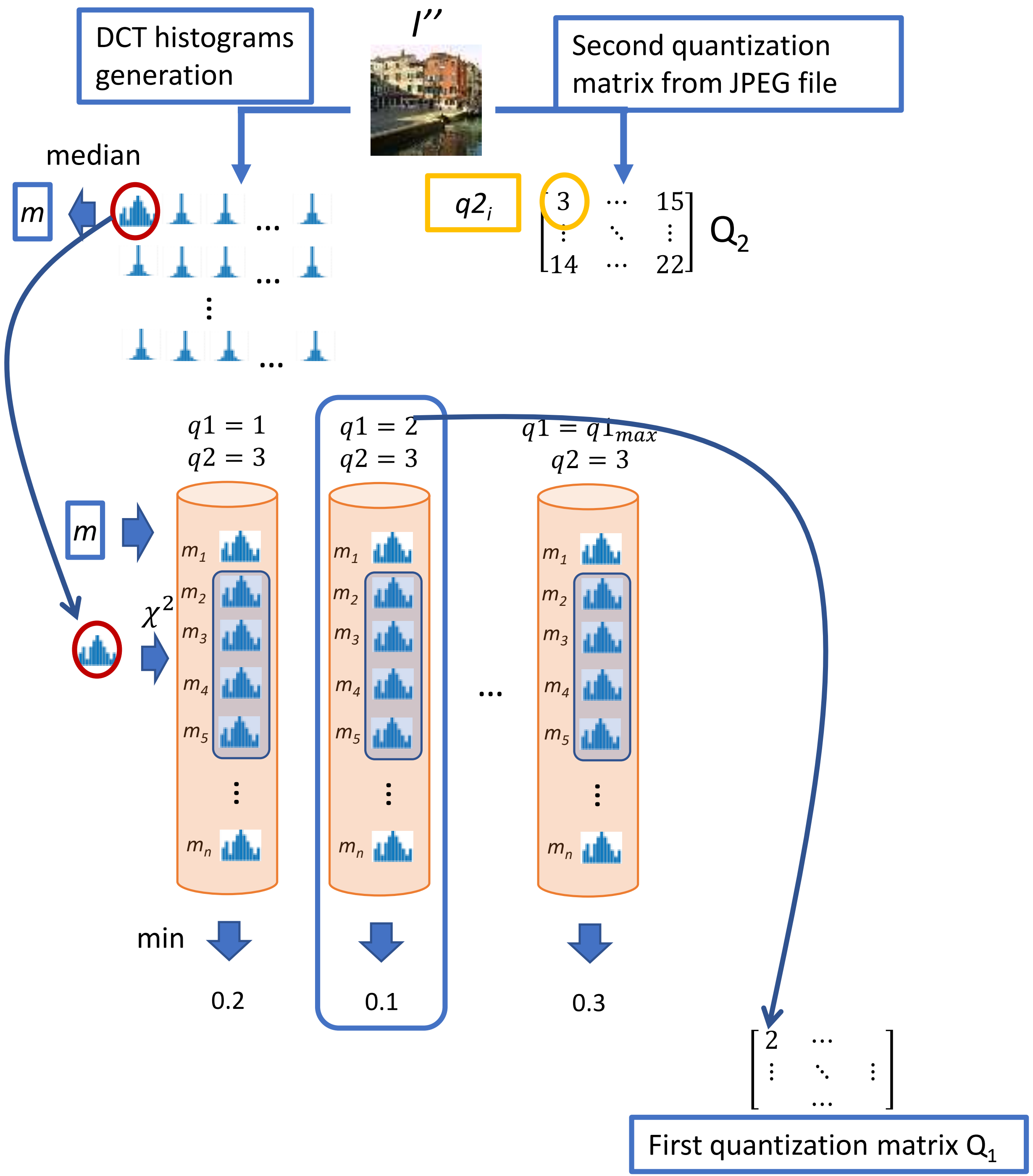

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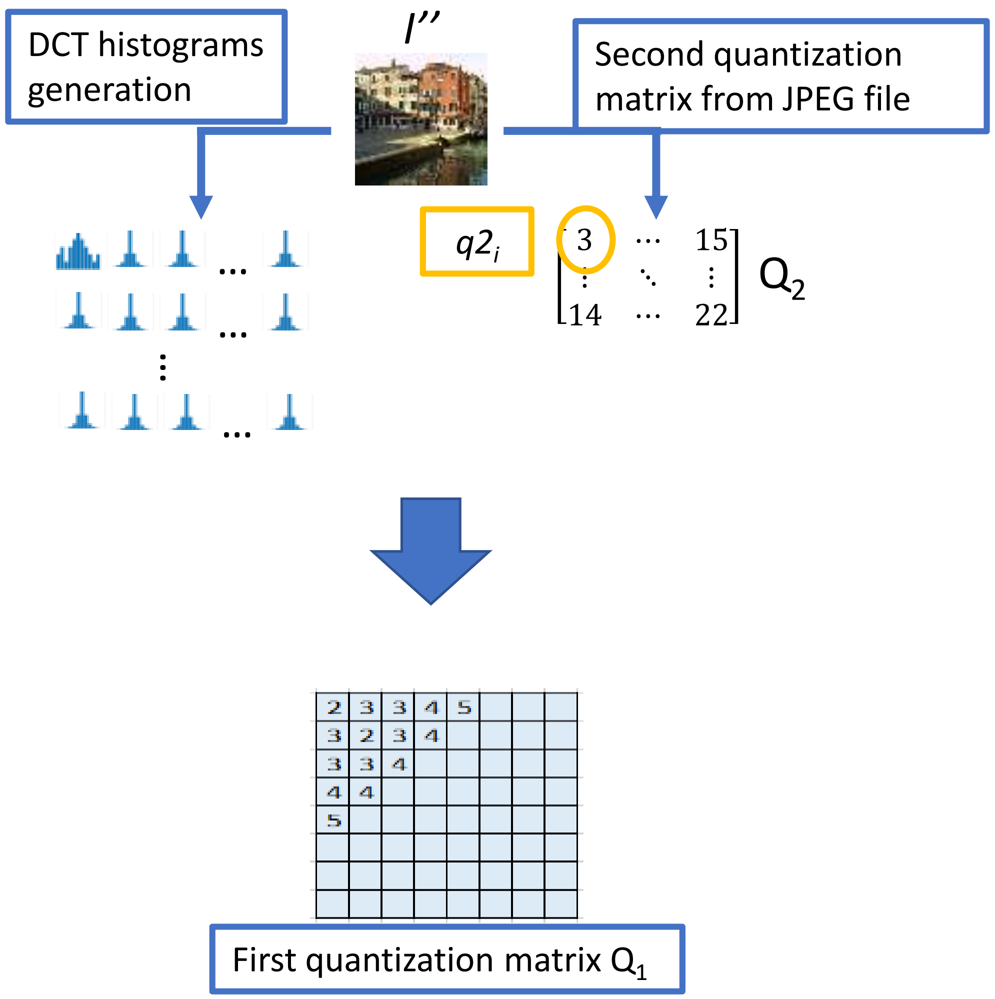

Regularization

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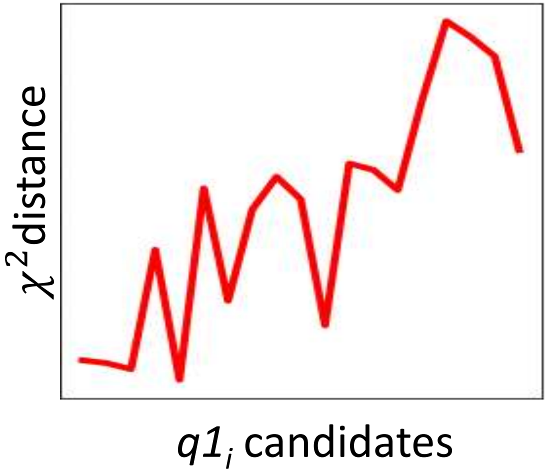

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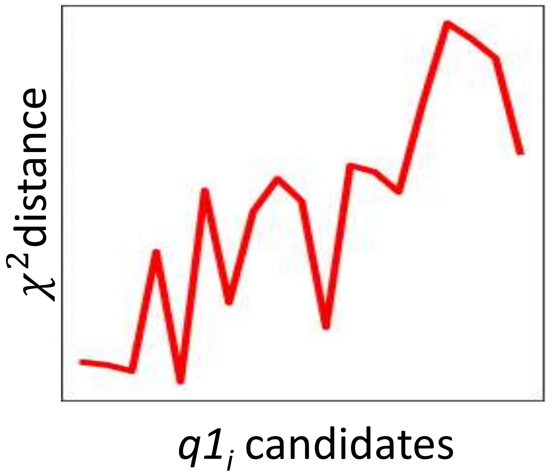

- A strong minimum is not always present at varying of $q1_i$ candidates.

Regularization

- Data coming from neighbors DCT coefficients can be exploited.

J. Park, D. Cho, W. Ahn, and H. Lee, “Double JPEG detection in mixed JPEG quality factors using deep convolutional neural network,” in The European Conference on Computer Vision (ECCV), September 2018.

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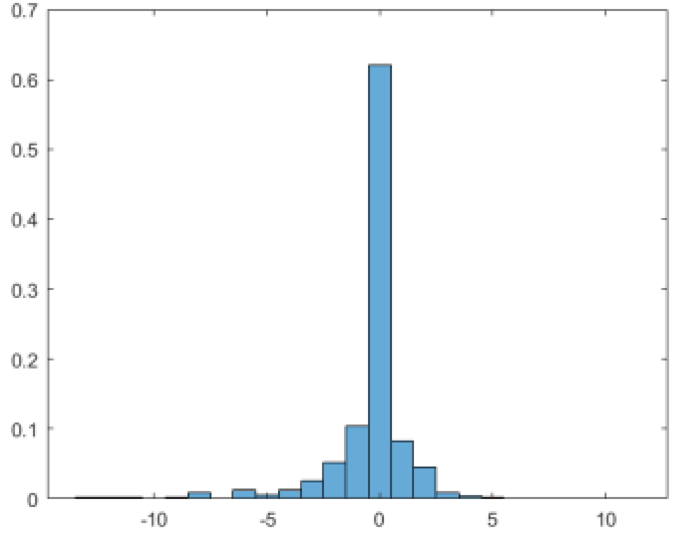
Distribution of $q1_i$-$q1_{i+1}$built considering custom tables from Park et al. and $q1_{max}$<22.



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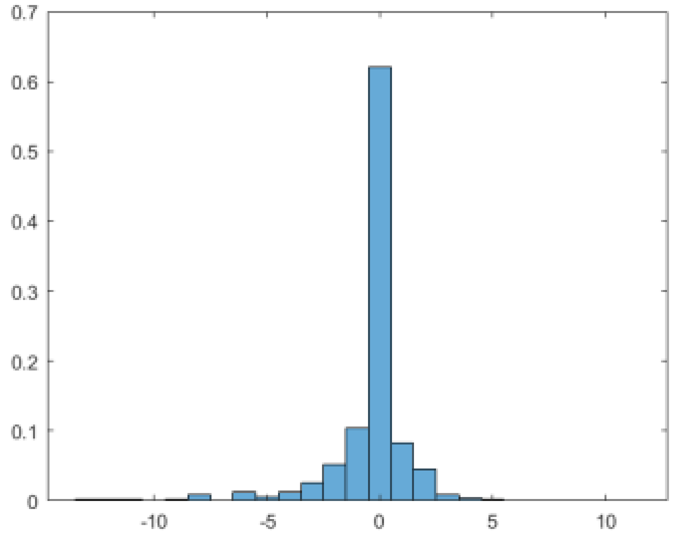
- Instead of estimating each coefficient independently, three consecutive elements in zig-zag order are considered.

Distribution of $q1_i$-$q1_{i+1}$built considering custom tables from Park et al. and $q1_{max}$<22.



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$$S = wC_{data} + (1 - w)C_{reg} \quad w \epsilon [0,1]$$

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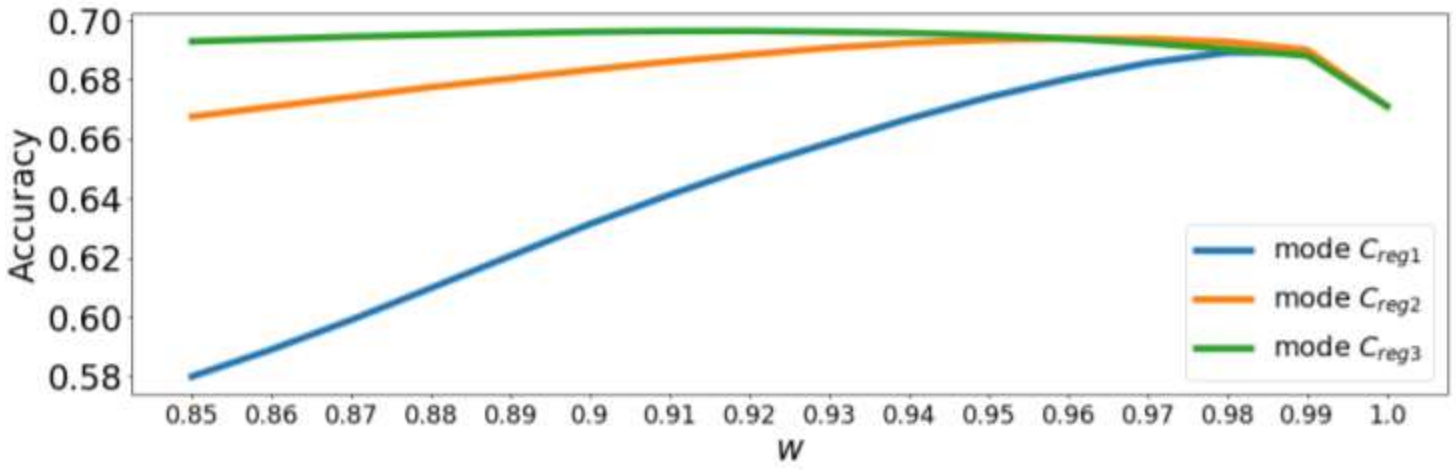

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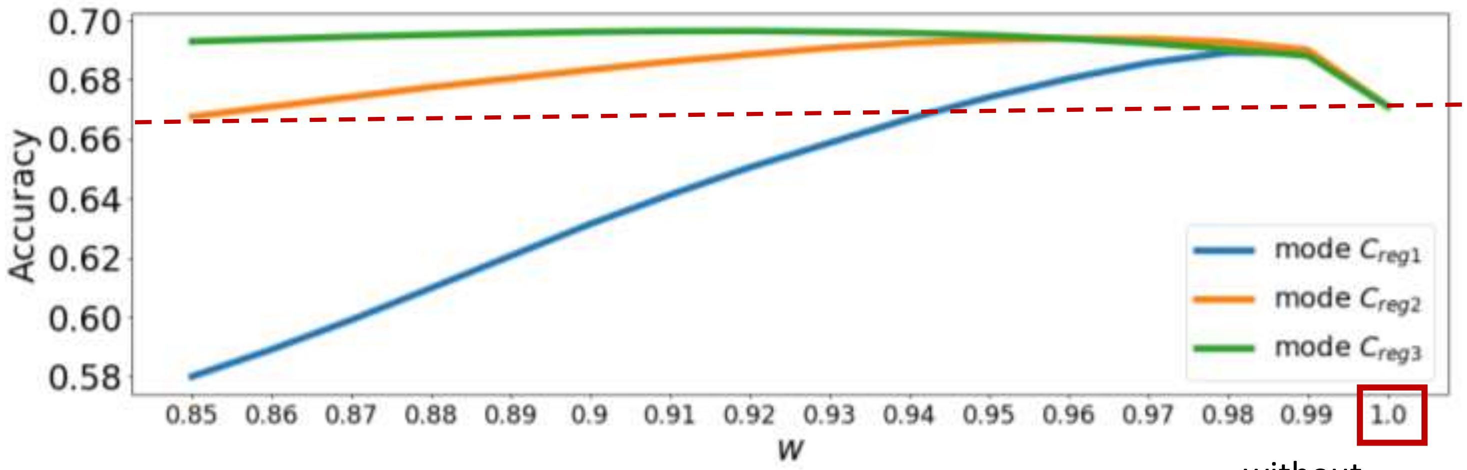

without regularization

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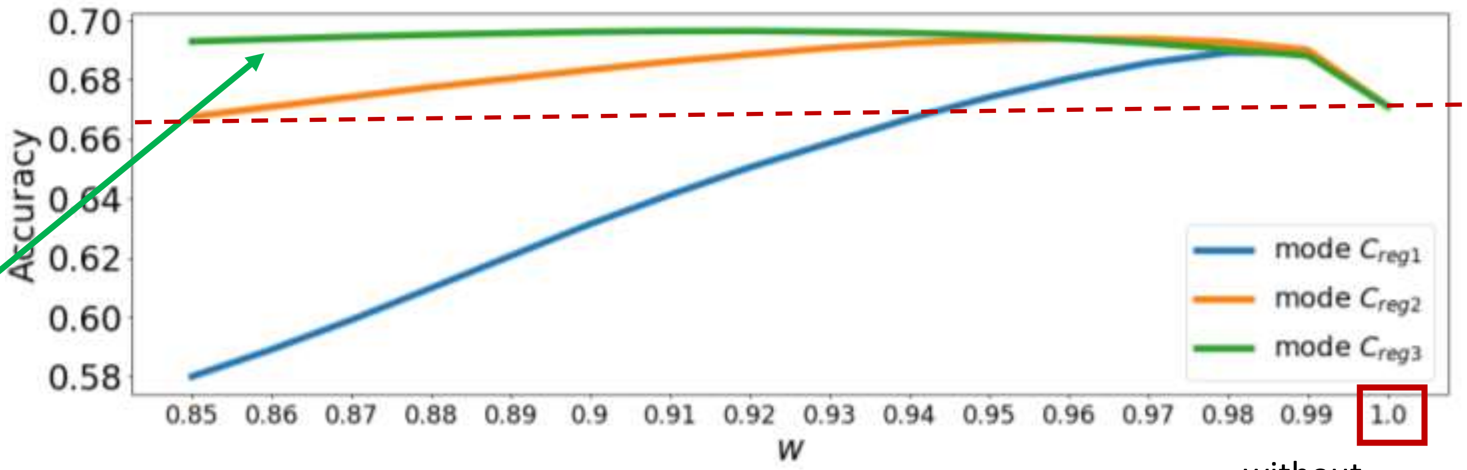
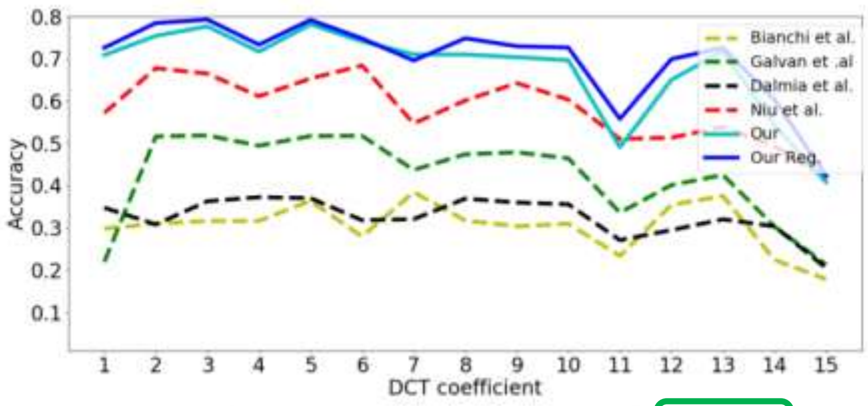


without regularization

Experimental results (comparisons)

Standard Matrices



a. $QF_1 \in \{55, 60, 65, 70, 75, 80, 85, 90, 95, 98\}$, $\boxed{QF_2 = 90}$

T. Bianchi and A. Piva, "Image forgery localization via block-grained analysis of JPEG artifacts," Proc. of IEEE Trans. on Information Forensics and Security, vol. 7, no. 3, p. 1003, 2012.
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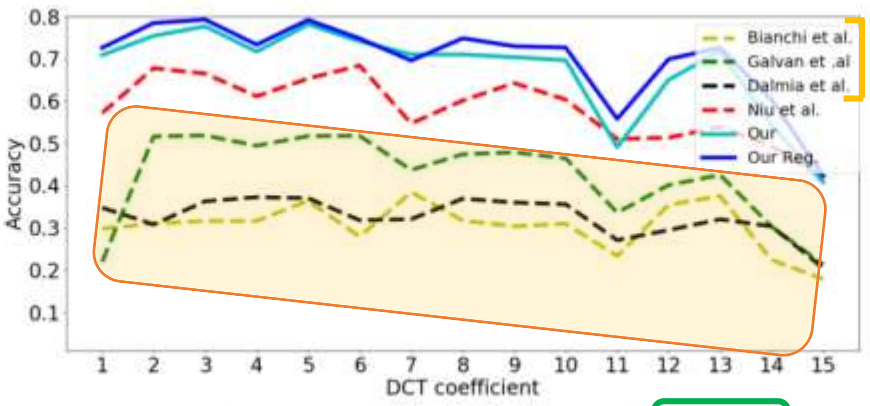

Classical approaches

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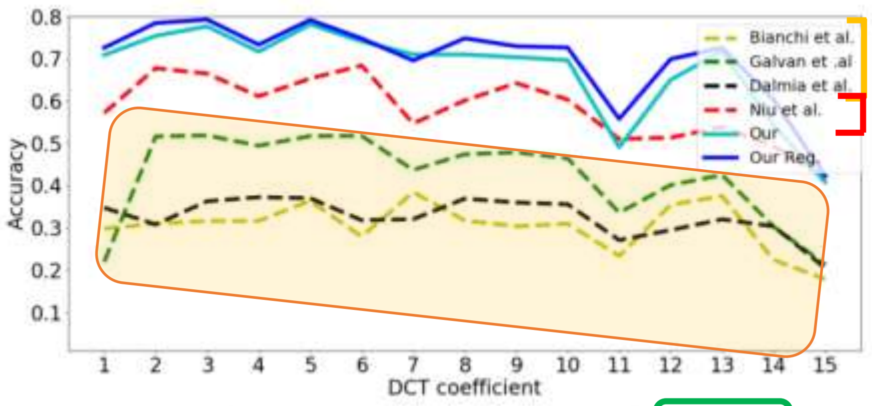

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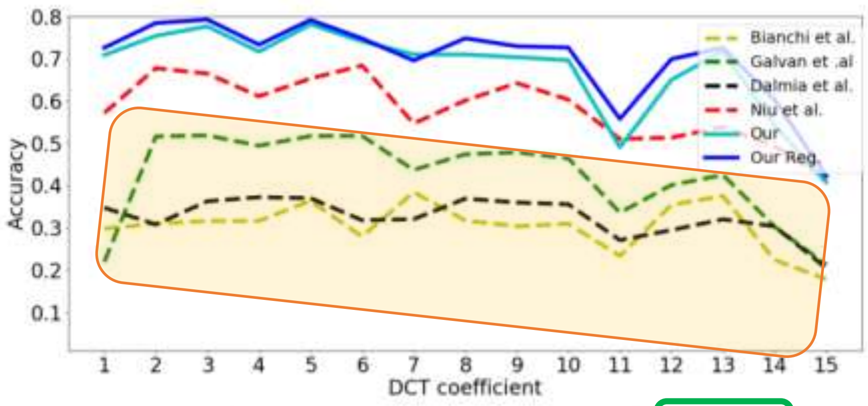

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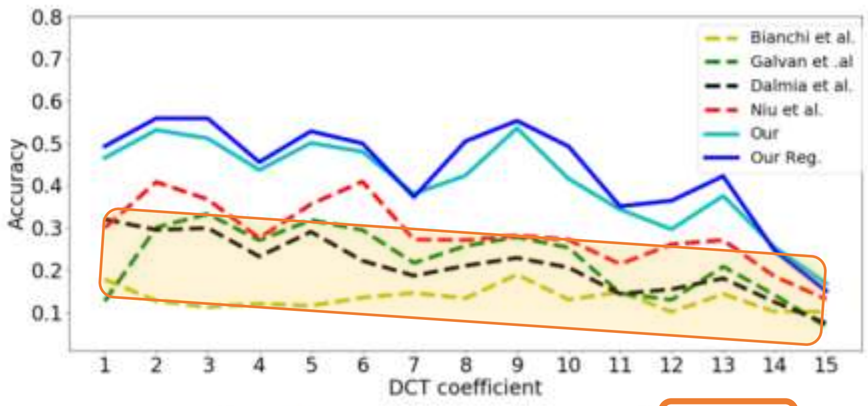

b. $QF_1 \in \{55, 60, 65, 70, 75, 80, 85, 90, 95, 98\}$, $\boxed{QF_2 = 80}$

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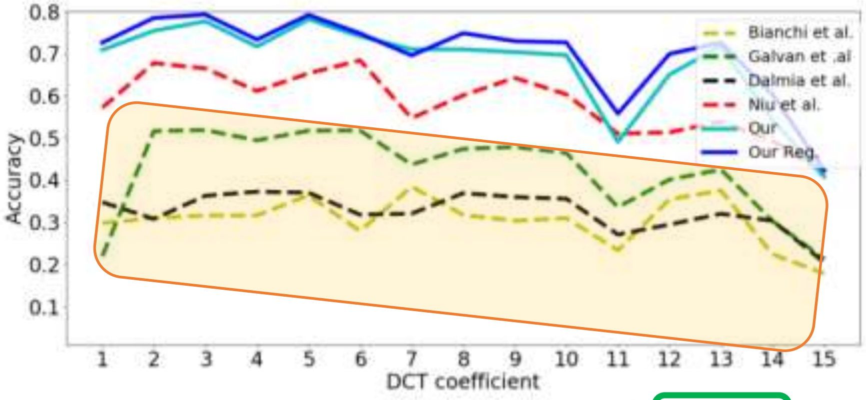

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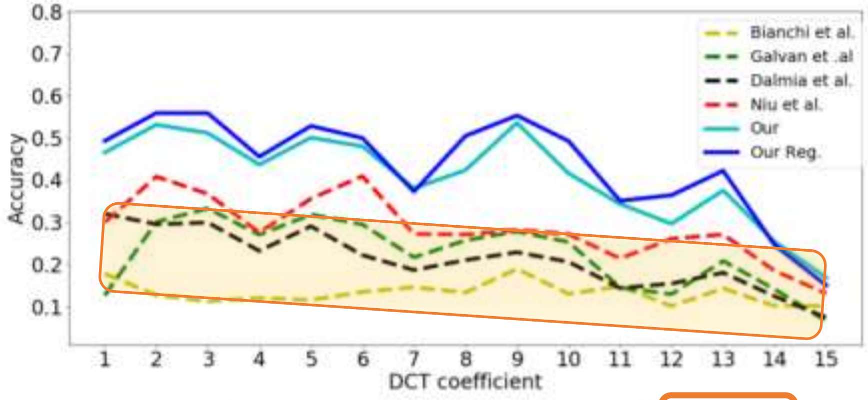
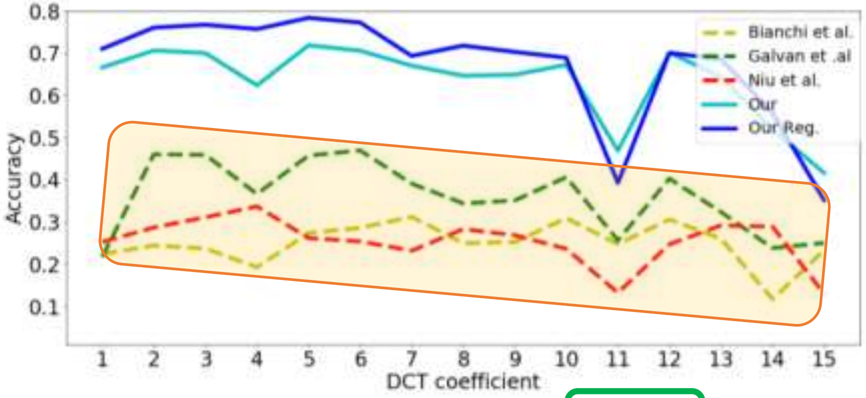
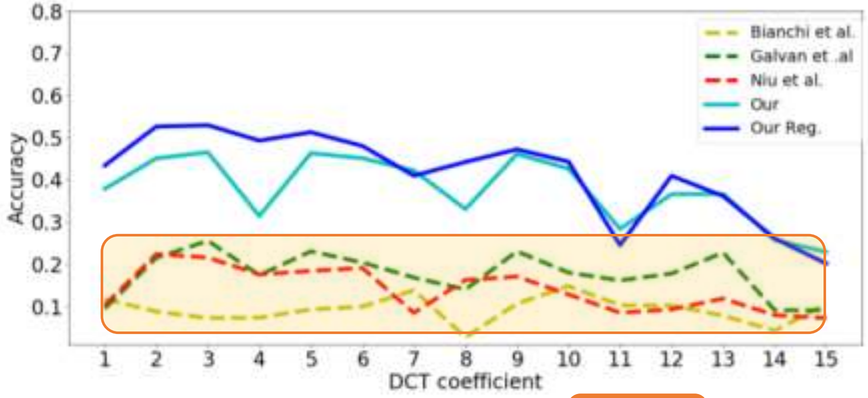


b. $QF_1 \in \{55, 60, 65, 70, 75, 80, 85, 90, 95, 98\}$, $\boxed{QF_2 = 80}$

Photoshop Custom Matrices



c. $Q_1 \in \{5, 6, 7, 8, 9, 10, 11, 12\}$, $\boxed{QF_2 = 90}$



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Method	Dataset	Cropped Patch	Low/Low	Low/Mid	Low/High	Mid/Low	Mid/Mid	Mid/High	High/Low	High/Mid	High/High	Mean
Our	RAISE	64 × 64	0.25	0.47	0.79	0.17	0.32	0.82	**0.27**	0.31	0.70	0.46
Our Reg.			**0.30**	**0.53**	**0.81**	**0.22**	**0.37**	**0.84**	0.25	**0.33**	**0.75**	**0.49**
Our	UCID	64 × 64	0.33	0.63	0.93	0.20	0.39	0.90	**0.15**	0.21	0.66	0.49
Our Reg.			**0.36**	**0.65**	**0.96**	**0.23**	**0.42**	**0.91**	0.13	**0.23**	**0.73**	**0.51**
Our	RAISE	128 × 128	0.36	**0.60**	0.85	0.29	0.44	0.87	**0.25**	0.32	0.74	0.52
Our Reg.			**0.41**	0.55	**0.88**	**0.34**	**0.48**	**0.89**	**0.25**	**0.38**	**0.79**	**0.55**
Our	UCID	128 × 128	0.47	0.76	0.96	0.31	0.49	**0.94**	0.18	0.29	0.74	0.57
Our Reg.			**0.50**	**0.79**	**0.96**	**0.35**	**0.51**	0.93	**0.20**	**0.34**	**0.79**	**0.60**
Our	RAISE	256 × 256	0.45	0.69	0.88	0.38	0.52	0.89	0.25	0.36	0.77	0.58
Our Reg.			**0.49**	**0.73**	**0.90**	**0.40**	**0.55**	**0.90**	**0.30**	**0.45**	**0.82**	**0.62**
Our	UCID	256 × 256	0.56	0.83	**0.98**	0.44	0.57	**0.96**	0.23	0.34	0.77	0.63
Our Reg.			**0.60**	**0.85**	0.97	**0.48**	**0.60**	**0.96**	**0.28**	**0.43**	**0.82**	**0.67**
Our	RAISE	512 × 512	**0.50**	0.74	0.91	0.44	0.57	0.91	0.26	0.38	0.77	0.61
Our Reg.			**0.50**	**0.78**	**0.92**	**0.48**	**0.59**	**0.92**	**0.32**	**0.48**	**0.83**	**0.65**
Our	UCID	Full size	0.63	0.86	**0.98**	0.51	**0.62**	**0.96**	0.27	0.39	0.80	0.66
Our Reg.			**0.67**	**0.87**	0.97	**0.56**	**0.62**	**0.96**	**0.37**	**0.49**	**0.85**	**0.71**

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[0,0.33[
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- Finally, the use of 1-nn to learn the distribution underlines rooms for improvement of the proposed method.

Thank you!

In-Depth DCT Coefficient Distribution Analysis for First Quantization Estimation

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