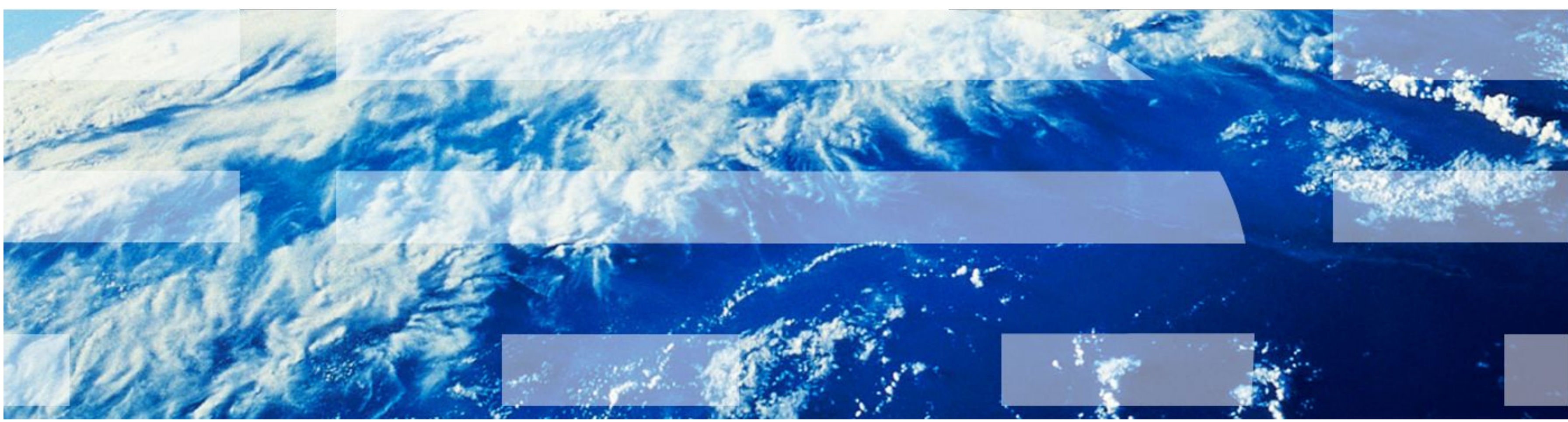
E6895 Advanced Big Data Analytics Task Milestone 3:

Authenticating Chinese Painting

Leying Hu and Mason Lin



April 5th, 2018

Schedules of the 3 milestones

Milestone 1:
- History of Art Authentication
- Why do we care about art authentication using computational techniques
- Current state-of-the-art approaches
- Our approach to the problem

Milestone 2:
- Discuss our approach and implementation
    - Architecture
- What we discovered during the process
- Challenges and how we are dealing with them

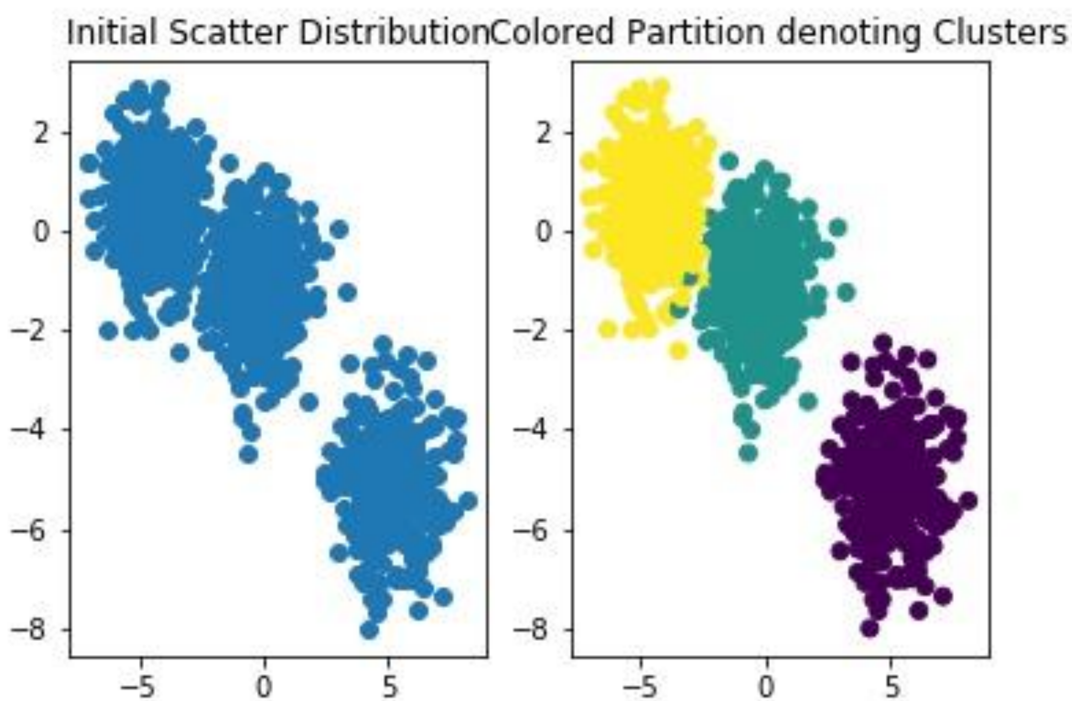
Milestone 3:
- Present (some) results
- Compare with other models

Bag of Visual Words Model

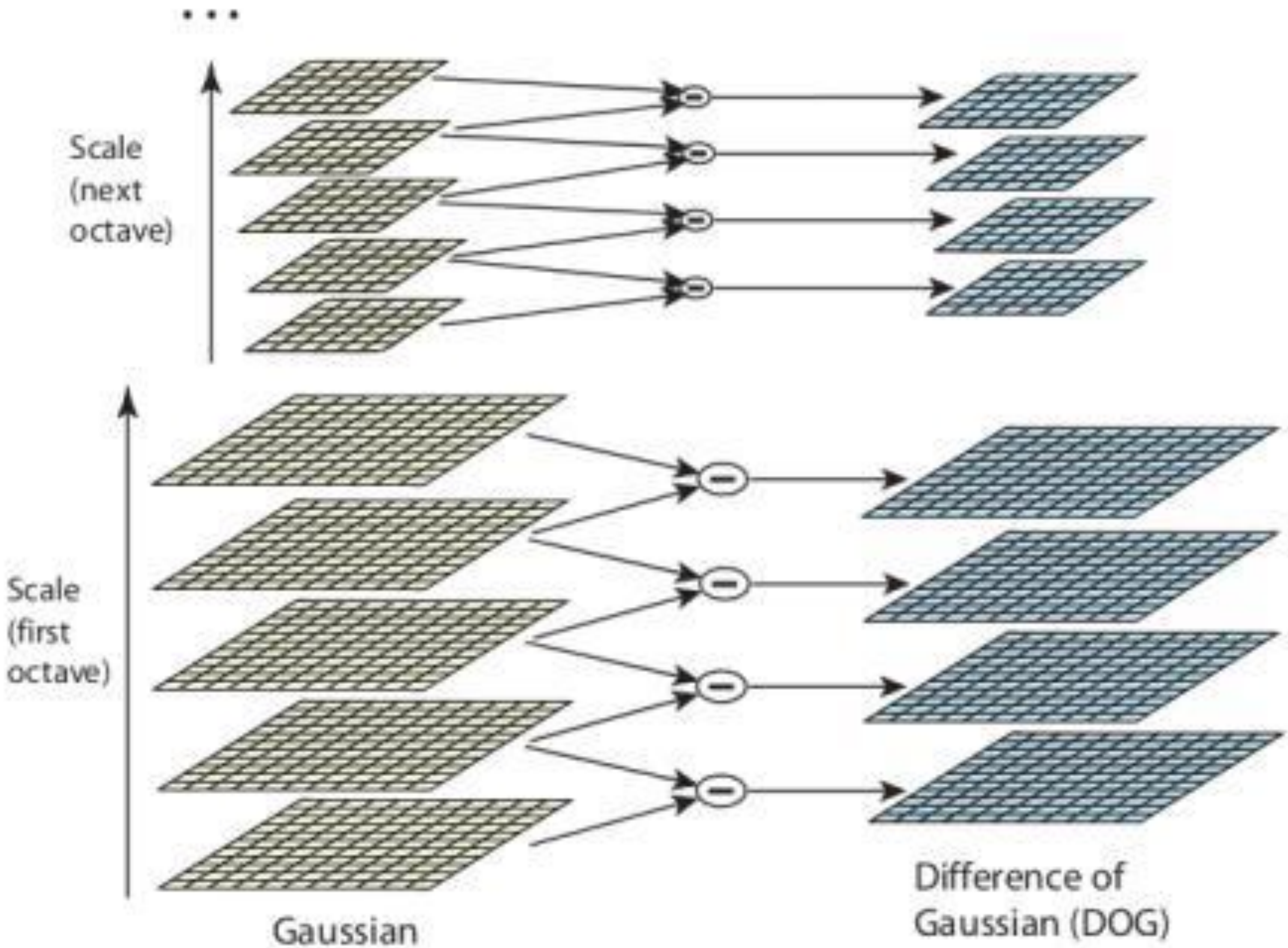
- Clustering
- Scale-invariant Feature Transform (SIFT)
- Support Vector Machines (SVM)

Clustering

$$\underset{\mathbf{S}}{\arg\min} \sum_{i=1}^{k} \sum_{\mathbf{x}\in S_i} \left\| \mathbf{x} - \boldsymbol{\mu}_i \right\|^2$$



Scale-invariant Feature Transform (SIFT)

- 

Scale-invariant Feature Transform (SIFT)

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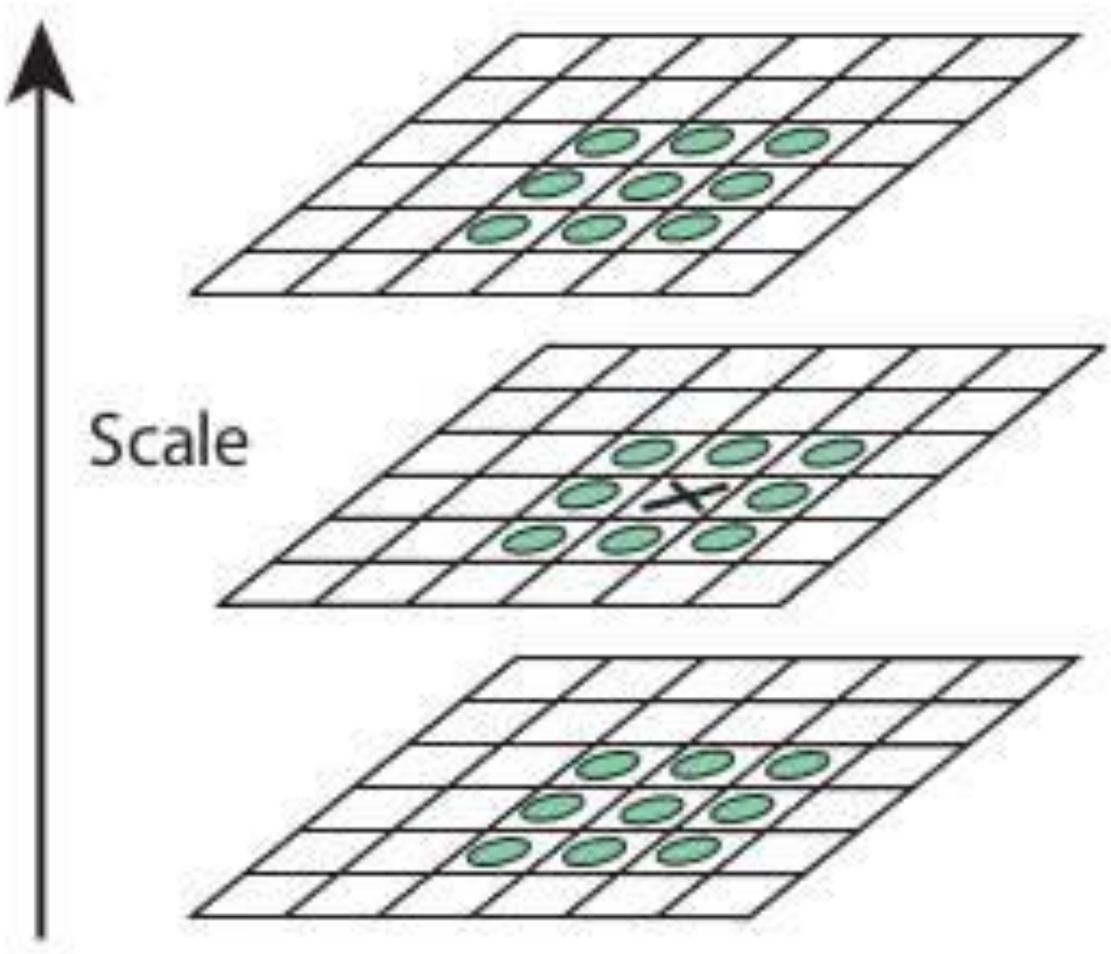

Scale-invariant Feature Transform (SIFT)

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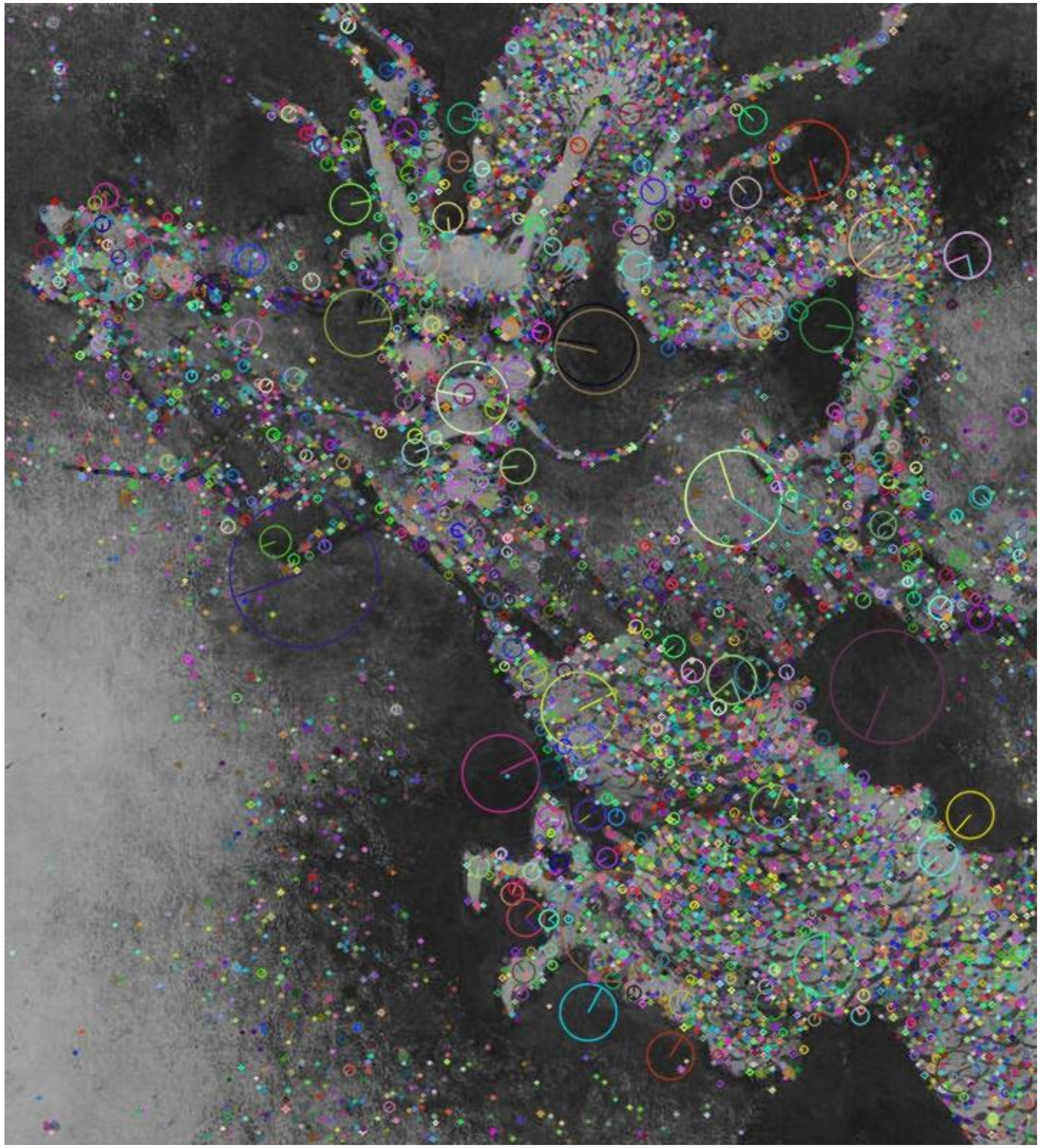
$$\begin{bmatrix} features_0 \\ features_1 \\ \cdots\cdot \\ \cdots\cdot \\ \cdots\cdot \\ features_n \end{bmatrix}$$

$$where\ features_i \ \ is \ \ a \ \ array\ of \ \ dimension \ \ m \times 128$$



Bag of Visual Words Training Model

https://en.wikipedia.org/wiki/Cui_Bai
https://www.zhihu.com/question/50062262/answer/123734810

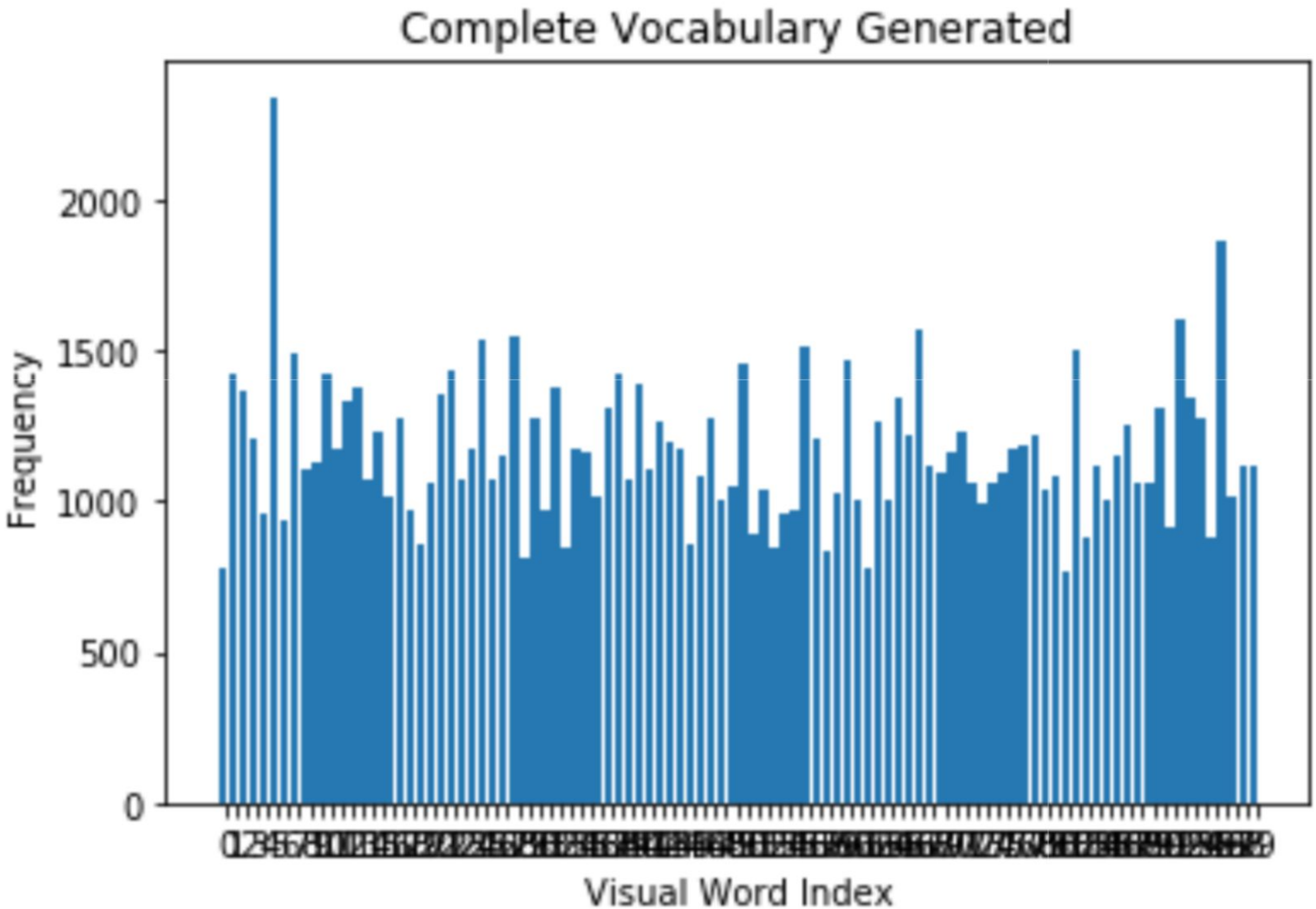
Bag of Visual Words Training Model

http://www.pwq4129.com/shufa/aritcle1341.html

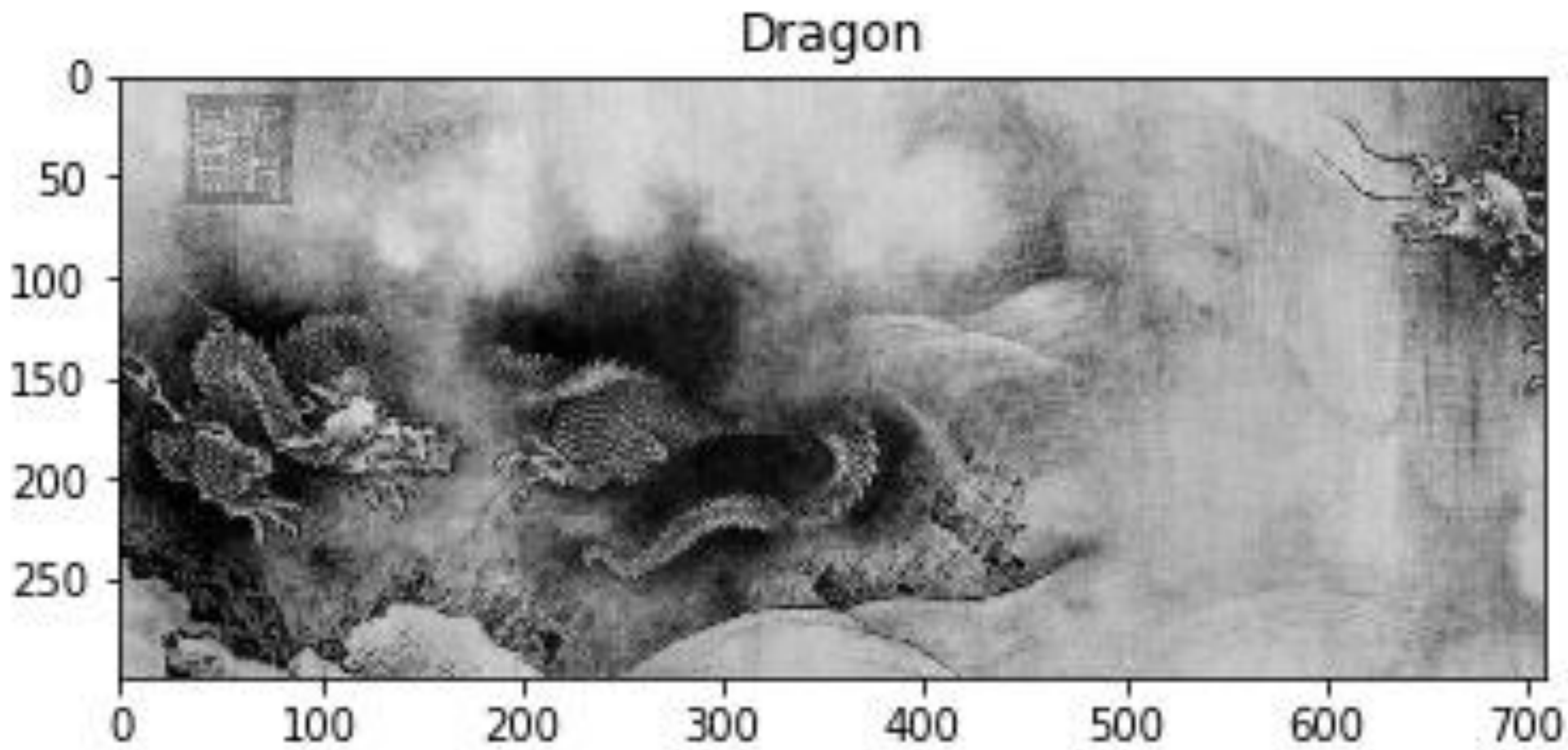
Bag of Visual Words Training Model

http://vr.theatre.ntu.edu.tw/fineart/painter.htm#painter-ch

Bag of Visual Words Training Vocabulary



Bag of Visual Words Testing Result



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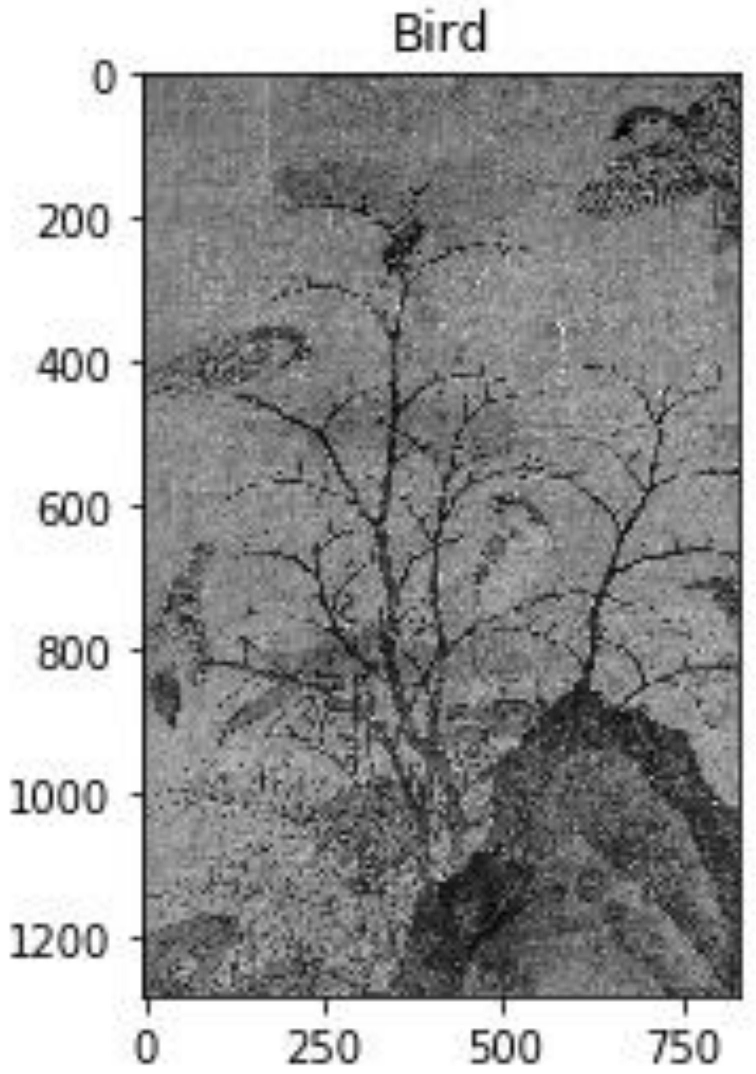
Bag of Visual Words Testing Result



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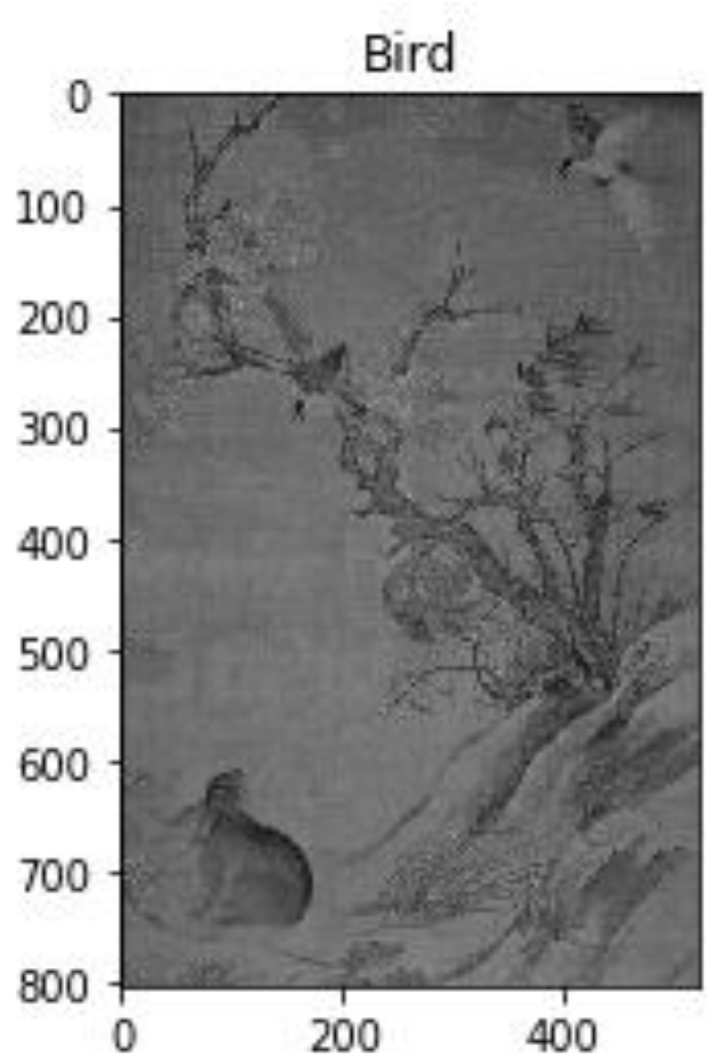
Bag of Visual Words Testing Result



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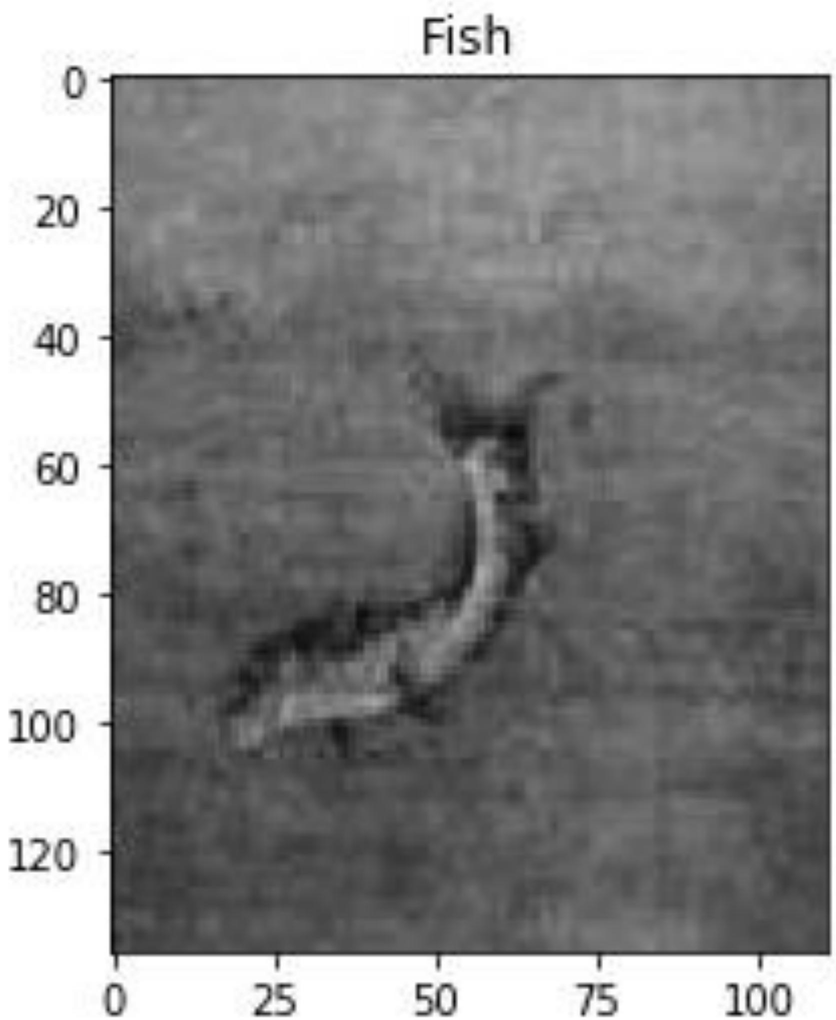

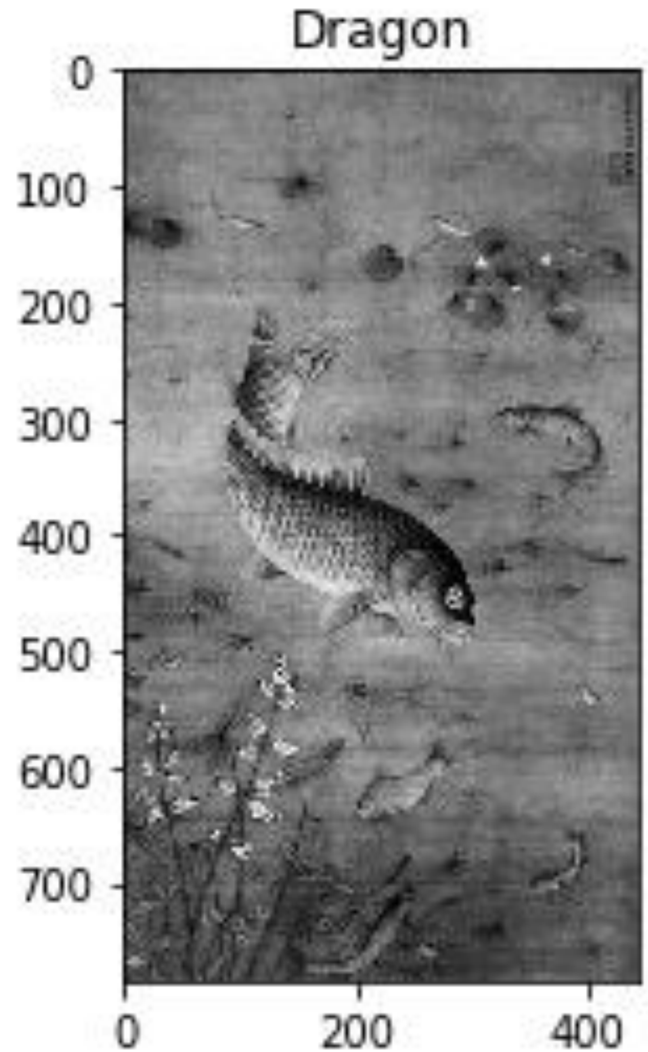

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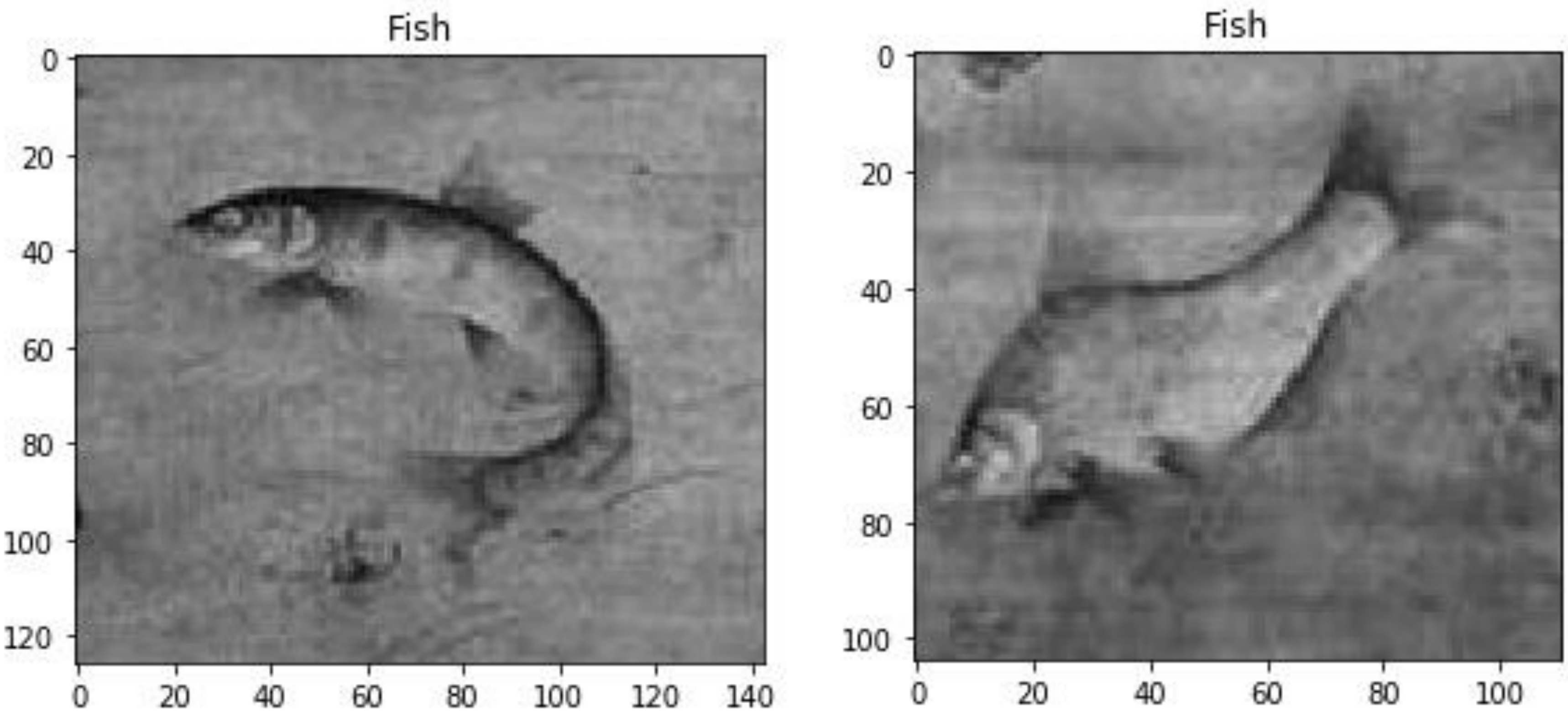

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Kernel Feature Descriptors [Bo, Ren, Fox 2010]

- Extension from SIFT
- Kernel descriptor for gradient, shape, color
  - Derived from kernel representation of histogram features

Kernel Descriptor for Histogram

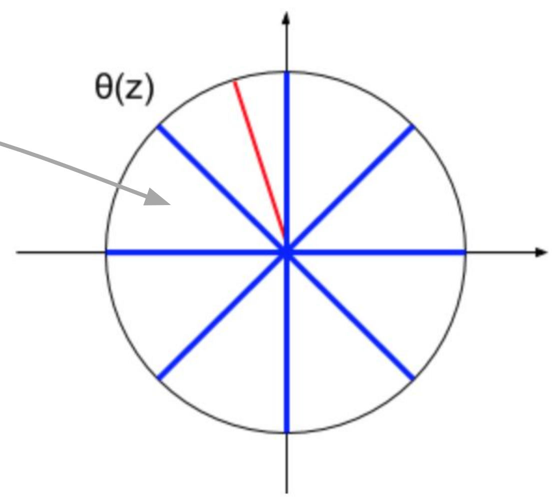
$$F_h(P) = \sum_{z \in P} \widetilde{m}(z)\delta(z)$$

Kernel Function for Histogram

$$K_h(P,Q) = F_h(P)^\top F_h(Q) = \sum_{z \in P} \sum_{z' \in Q} \widetilde{m}(z)\widetilde{m}(z')\delta(z)^\top \delta(z')$$

Binning (hard or soft)

$$\delta(z) = [\delta_1(z), \cdots, \delta_d(z)]$$



Kernel Feature Descriptors [Bo, Ren, Fox 2010]

Gradient Kernel

$$K_{\text{grad}}(P,Q) = \sum_{z\in P}\sum_{z'\in Q} \widetilde{m}(z)\widetilde{m}(z')k_o(\widetilde{\theta}(z),\widetilde{\theta}(z'))k_p(z,z')$$

Gradient Kernel Descriptor

$$F_{\text{grad}}(P) = \sum_{z\in P} \widetilde{m}(z)\phi_o(\widetilde{\theta}(z)) \otimes \phi_p(z)$$

Gaussian Kernel Over (normalize) Orientation

$$k_o(\widetilde{\theta}(z),\widetilde{\theta}(z')) = \exp(-\gamma_o\|\widetilde{\theta}(z) - \widetilde{\theta}(z')\|^2)$$

Normalized Orientation

$$\widetilde{\theta}(z) = [\sin(\theta(z))\cos(\theta(z))]$$

Kernel Feature Descriptors [Bo, Ren, Fox 2010]

Color Kernel

$$K_{\text{col}}(P,Q) = \sum_{z \in P} \sum_{z' \in Q} k_c(c(z), c(z'))k_p(z, z')$$

Shape Kernel

$$K_{\text{shape}}(P,Q) = \sum_{z \in P} \sum_{z' \in Q} \widetilde{s}(z)\widetilde{s}(z')k_b(b(z), b(z'))k_p(z, z')$$

Kernel Feature Descriptors [Bo, Ren, Fox 2010]

Color at pixel

Color Kernel

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Variance around 3x3 neighborhood

163	155	124
168	139	187
171	135	130

→

1	1	0
1		1
1	0	0

Kernel Feature Descriptors [Bo, Ren, Fox 2010]

Gradient Kernel

$$K_{\text{grad}}(P,Q) = \sum_{z \in P} \sum_{z' \in Q} \widetilde{m}(z)\widetilde{m}(z') k_o(\widetilde{\theta}(z), \widetilde{\theta}(z')) k_p(z, z')$$

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Kernel Feature Descriptors [Bo, Ren, Fox 2010]

Feature map has infinite dimension

Gradient Kernel Descriptor

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Orthogonal Random Features [Yu, Suresh, Choromanski 2016]

- Approximating the Gaussian Kernel

$$K(\mathbf{x}, \mathbf{y}) \approx \hat{K}(\mathbf{x}, \mathbf{y}) = \phi(\mathbf{x})^T \phi(\mathbf{y}).$$

Gaussian Kernel

$$K(\mathbf{x}, \mathbf{y}) = e^{-||\mathbf{x}-\mathbf{y}||^2/2\sigma^2}.$$

Random Feature Map

$$\phi(\mathbf{x}) = \sqrt{1/D}\left[\sin(\mathbf{w}_1^T\mathbf{x}), \cdots, \sin(\mathbf{w}_D^T\mathbf{x}), \cos(\mathbf{w}_1^T\mathbf{x}), \cdots, \cos(\mathbf{w}_D^T\mathbf{x})\right]^T,$$

Orthogonal Random Features [Yu, Suresh, Choromanski 2016]

- Orthogonality gives better concentration result (lower variance)
- Remains as an unbiased estimator of kernel

$$\mathbf{W}_{\mathrm{ORF}} = \frac{1}{\sigma}\mathbf{S}\mathbf{Q},$$

Orthogonal Random Features [Yu, Suresh, Choromanski 2016]

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Sampled from χ2-distribution

Orthogonal Gaussian Matrix

Tamura Texture As Kernel Descriptor

- Human perception
  - Coarseness, Directionality, Contrast
- Represented as kernel descriptor

$$K_{coarse}(A, B) = \sum_{z \in A} \sum_{z' \in B} k_s(s(z), s(z')) k_p(z, z')$$

$$\tilde{F}_{coarse}(A) = \sum_{z \in A} \tilde{\phi}_s(s(z)) \otimes \tilde{\phi}_p(z)$$

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