Reproduce GrabCut

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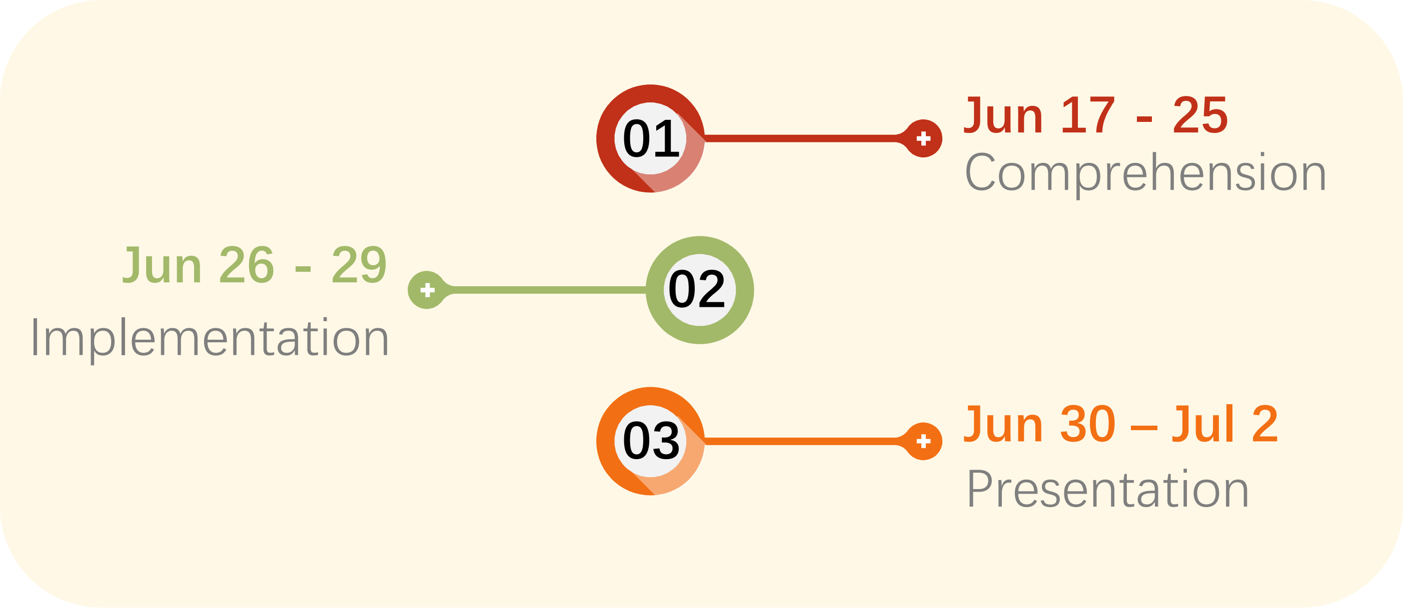
Outline

1. Time Overview
2. GrabCut Review
3. Implementation Detail
4. Results Analysis
5. Thoughts

1. Time Overview

- Comprehension
- Implementation
- Presentation



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2. GrabCut Review

"GrabCut" — Interactive Foreground Extraction using Iterated Graph Cuts [1]

Carsten Rother* Vladimir Kolmogorov† Andrew Blake‡
Microsoft Research Cambridge, UK

Figure 1: **Three examples of GrabCut.** The user drags a rectangle loosely around an object. The object is then extracted automatically.

[1] Rother, Carsten, Vladimir Kolmogorov, and Andrew Blake. "Grabcut: Interactive foreground extraction using iterated graph cuts." In *ACM transactions on graphics (TOG)*, vol. 23, no. 3, pp. 309-314. ACM, 2004.

2. GrabCut Review

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2. GrabCut Review

- What GrabCut does
  - Interactive foreground/background **segmentation**
  - i.e. extract a foreground element from a background image [1]

Segmentation vs **Matting**

$\alpha \in \{0,1\}$ $\alpha \in (0,1)$

opacity

[2]

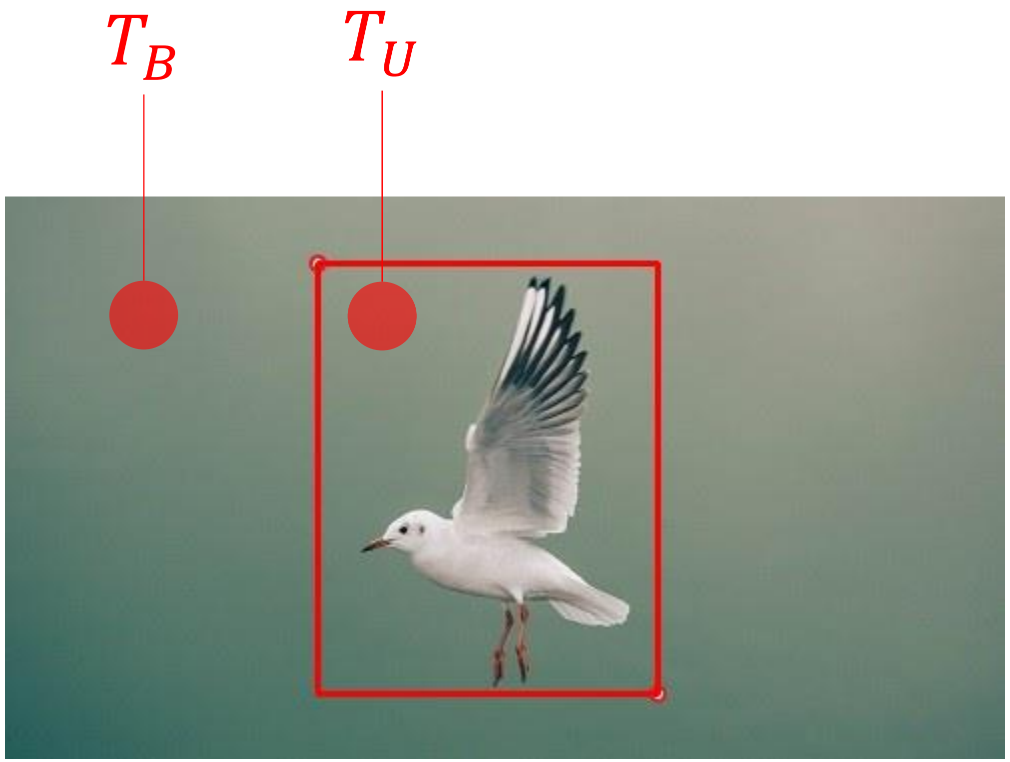
$$C = \alpha F + (1 - \alpha) B$$

composition foreground background

[1] Chuang, Yung-Yu, Brian Curless, David H. Salesin, and Richard Szeliski. "A bayesian approach to digital matting." In *CVPR (2)*, pp. 264-271. 2001.
[2] Zhu, Qingsong, Pheng Ann Heng, Ling Shao, and Xuelong Li. "What's the Role of Image Matting in Image Segmentation?." In *2013 IEEE International Conference on Robotics and Biomimetics (ROBIO)*, pp. 1695-1698. IEEE, 2013.

2. GrabCut Review

- What GrabCut bases
  - Bayes matting, Graph Cut, ……
- Keys:
  - trimap / seeds / hard constraints
    - T_F: $definitely\ foreground$
    - T_B: $definitely\ background$
    - T_U: $unknown\ region$
    - (note: in GrabCut, no T_F inputs.)



[1]

[1] Photo by janer zhang on Unsplash.

2. GrabCut Review

- What GrabCut bases
  - Bayes matting, Graph Cut, ……
- Keys:
  - energy function / cost function / soft constraints
    - find it expensive to assign a pixel to low-probability region.
    - find it expensive to separate similar parts.

In GrabCut:

$$E\left(\underline{\alpha},\vec{k},\ \underline{\theta},\ \vec{z}\right)=U\left(\underline{\alpha},\vec{k},\ \underline{\theta},\ \vec{z}\right)+V(\underline{\alpha},\vec{z})$$ [2]

regional penalty

$$E(A)=\lambda\cdot R(A)+B(A)$$ [1]

boundary penalty

[1] Boykov, Yuri Y., and M-P. Jolly. "Interactive graph cuts for optimal boundary & region segmentation of objects in ND images." In *Proceedings eighth IEEE international conference on computer vision. ICCV 2001*, vol. 1, pp. 105-112. IEEE, 2001.
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Where:

U: negative log-likelihoods
(entropy, the lower probability, the higher gain.)

V: gaussian form $\frac{1}{\mathrm{dis}} \cdot e\hat{}(-\frac{\mathrm{diff}^2}{2\sigma^2})$
(3σ rule, when difference between neighboring pixels exceeds σ, the penalty get small.)

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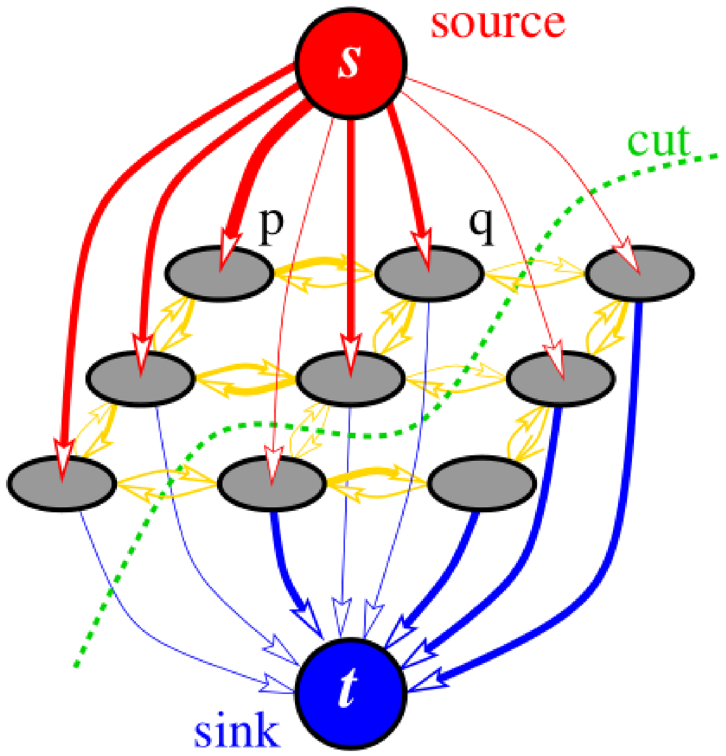
2. GrabCut Review

- What GrabCut bases
  - Bayes matting, Graph Cut, ……
- Keys:
  - energy minimization / min-cut / max-flow



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2. GrabCut Review

- What GrabCut makes
  - Color models
    - GMMs (Gaussian Mixture Models)
  - Iterative
    - Gaussian parameter estimation
  - Border matting
    - I didn't implement

3-D Gaussian probability distribution

$$\frac{1}{(2\pi)^{\frac{3}{2}}(\det \boldsymbol{C})^{\frac{1}{2}}}\exp\{-\frac{1}{2}(\boldsymbol{X}-\boldsymbol{\mu})^T\boldsymbol{C}^{-1}(\boldsymbol{X}-\boldsymbol{\mu})\}$$

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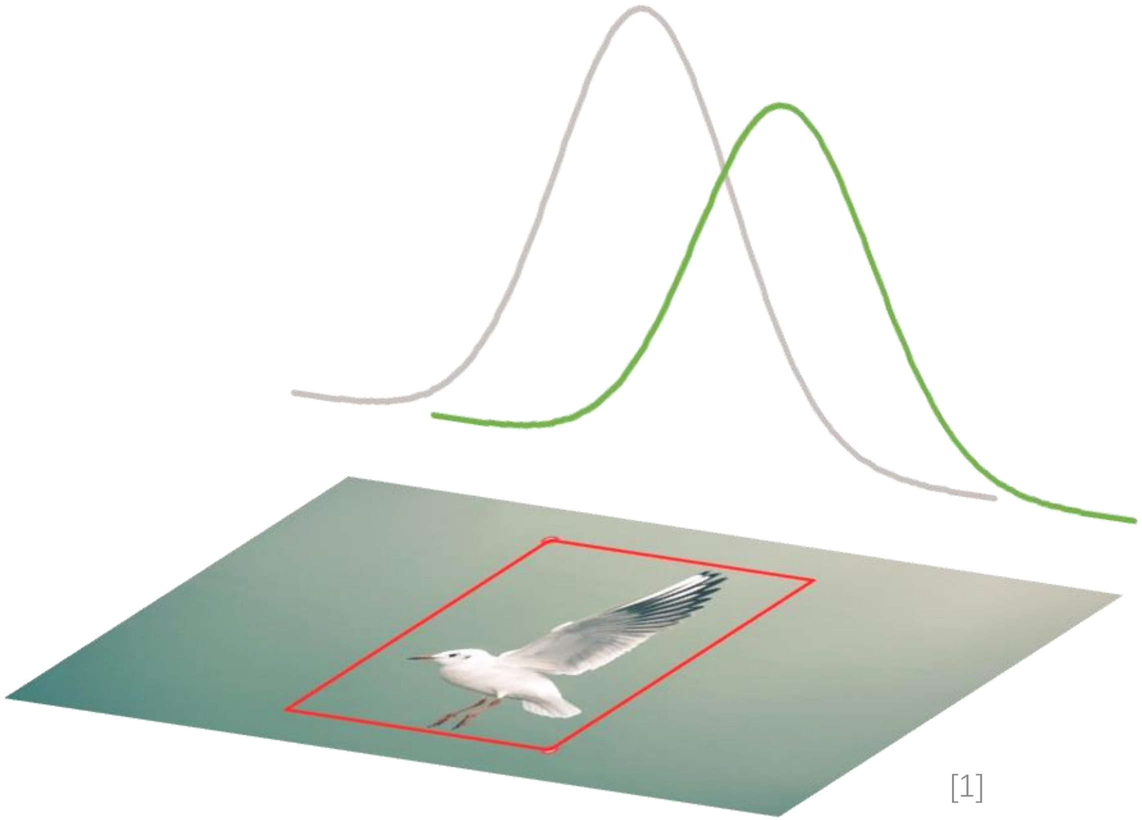

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[1] Photo by janer zhang on Unsplash.

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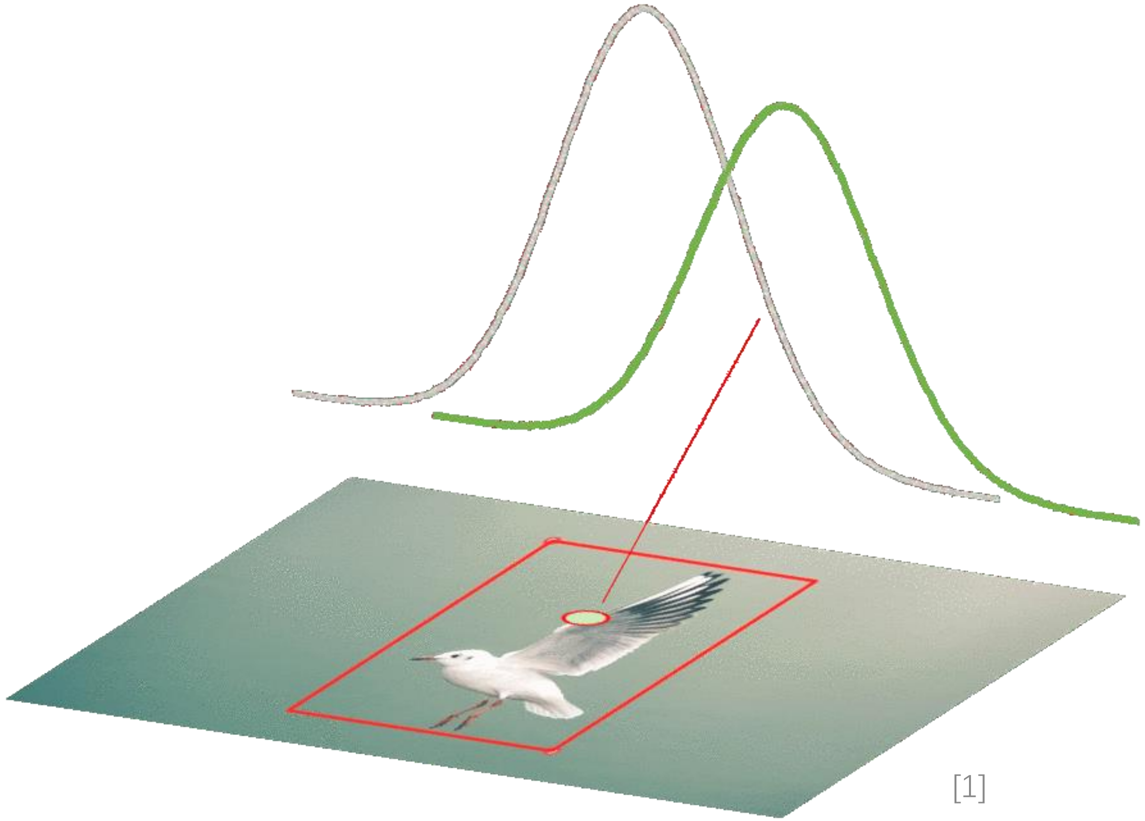

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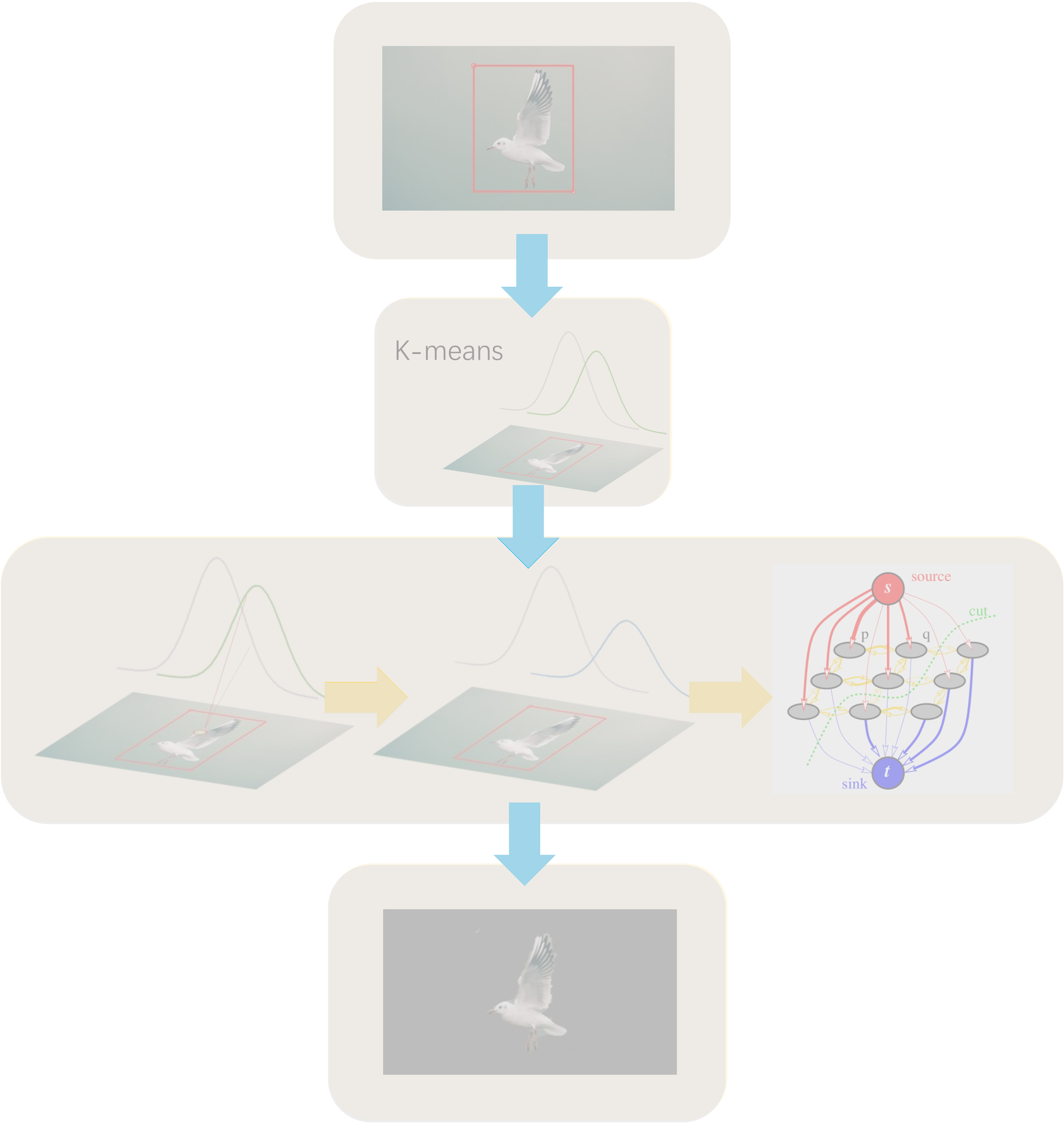
2. GrabCut Review

- Pipeline
- Initialization
  1. User initializes trimap
  2. Initialize alpha label
  3. Initialize GMM
- Iterative minimization
  4. Reassign GMM to pixels
  5. GMM learn from new clusters
  6. Build graph and cut
  7. Repeat 4-6 until convergence



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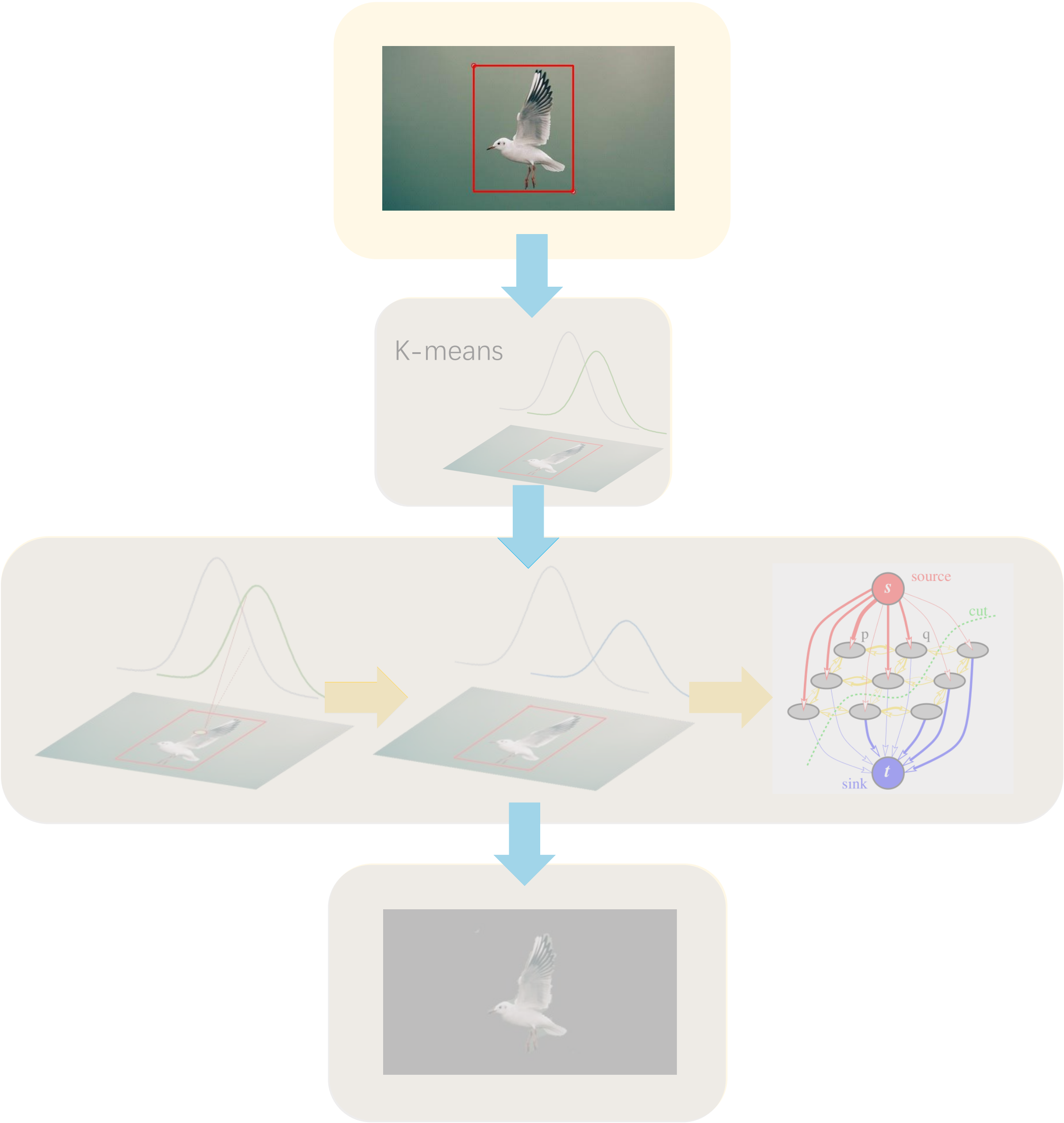

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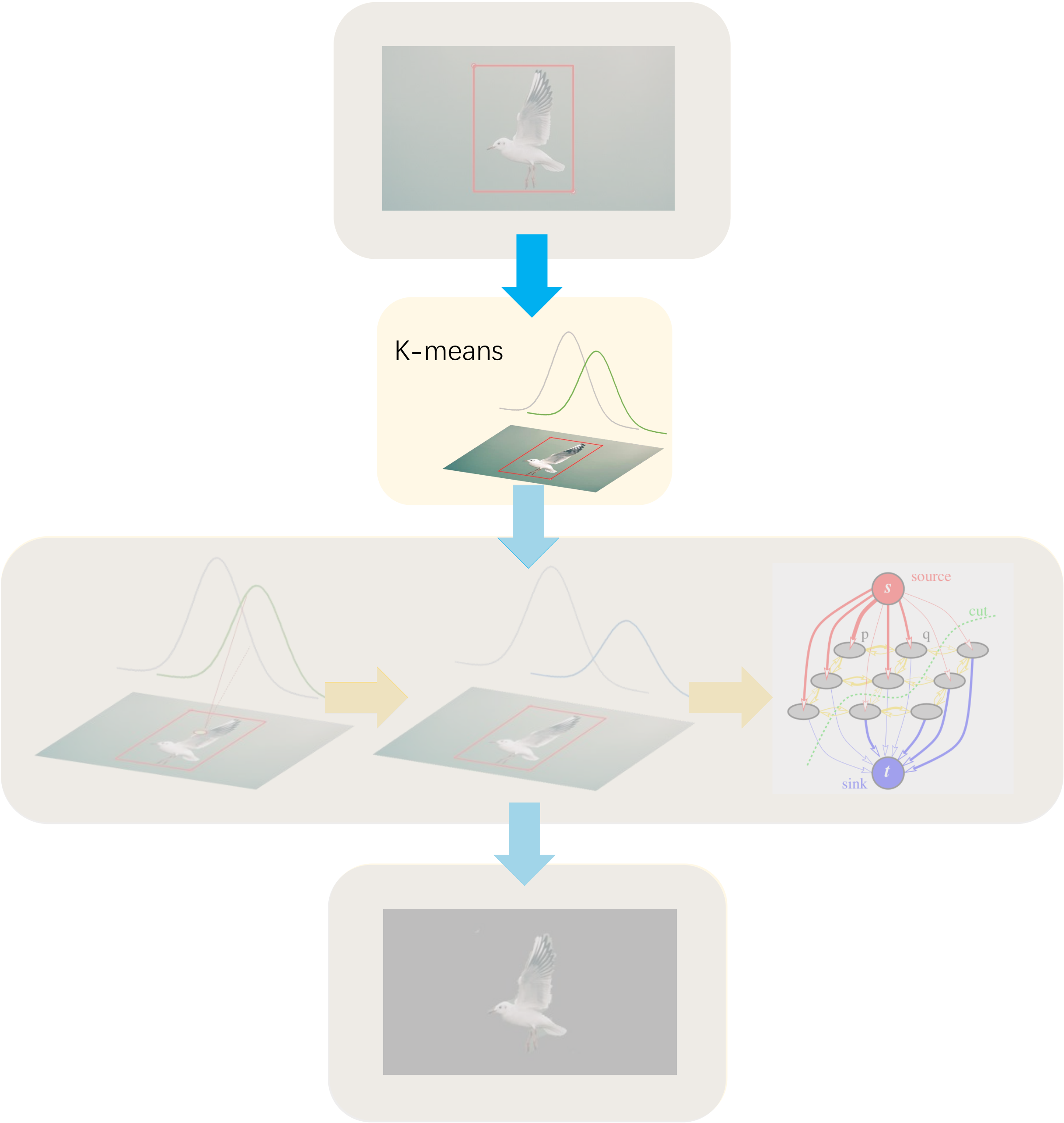

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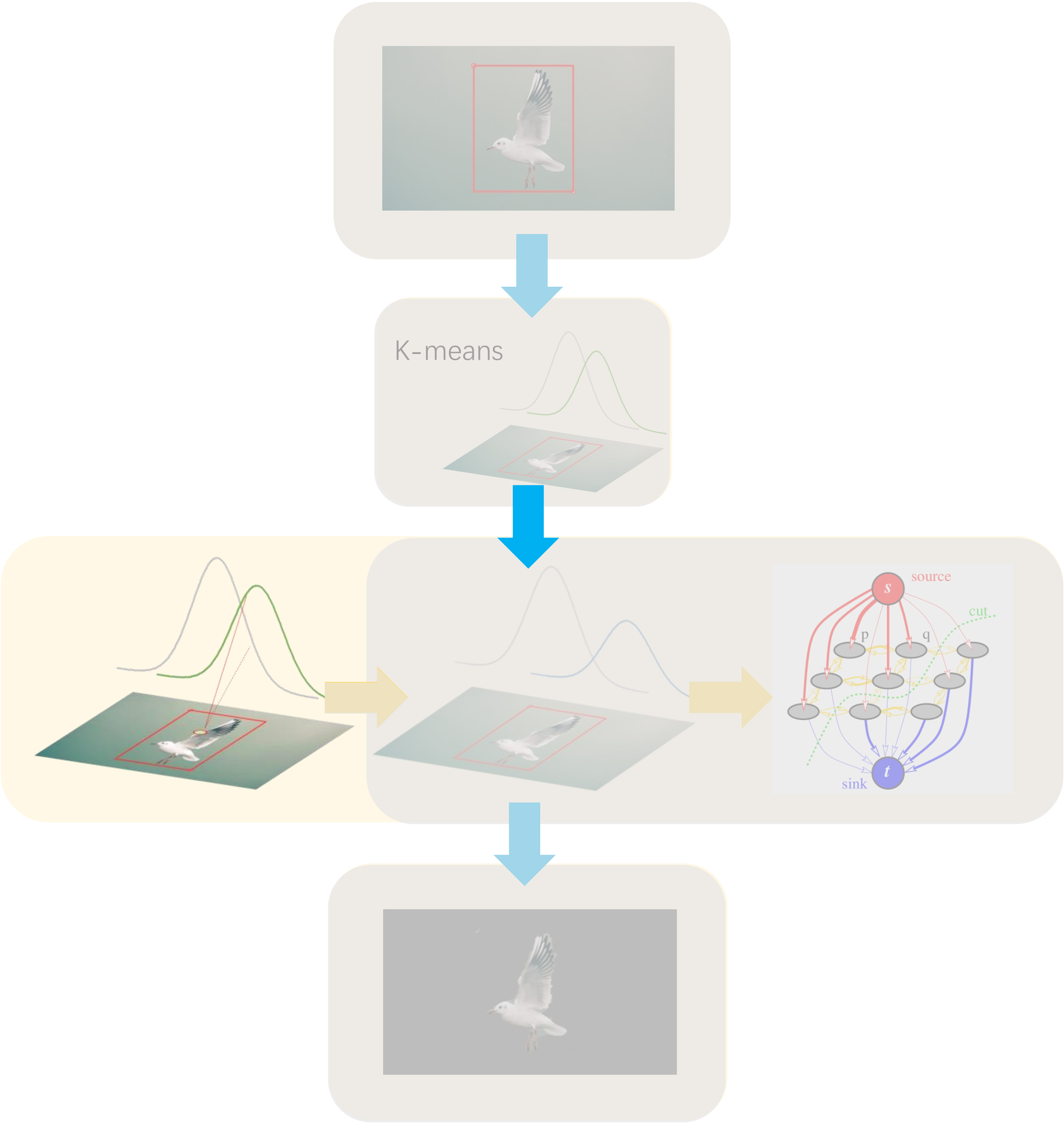

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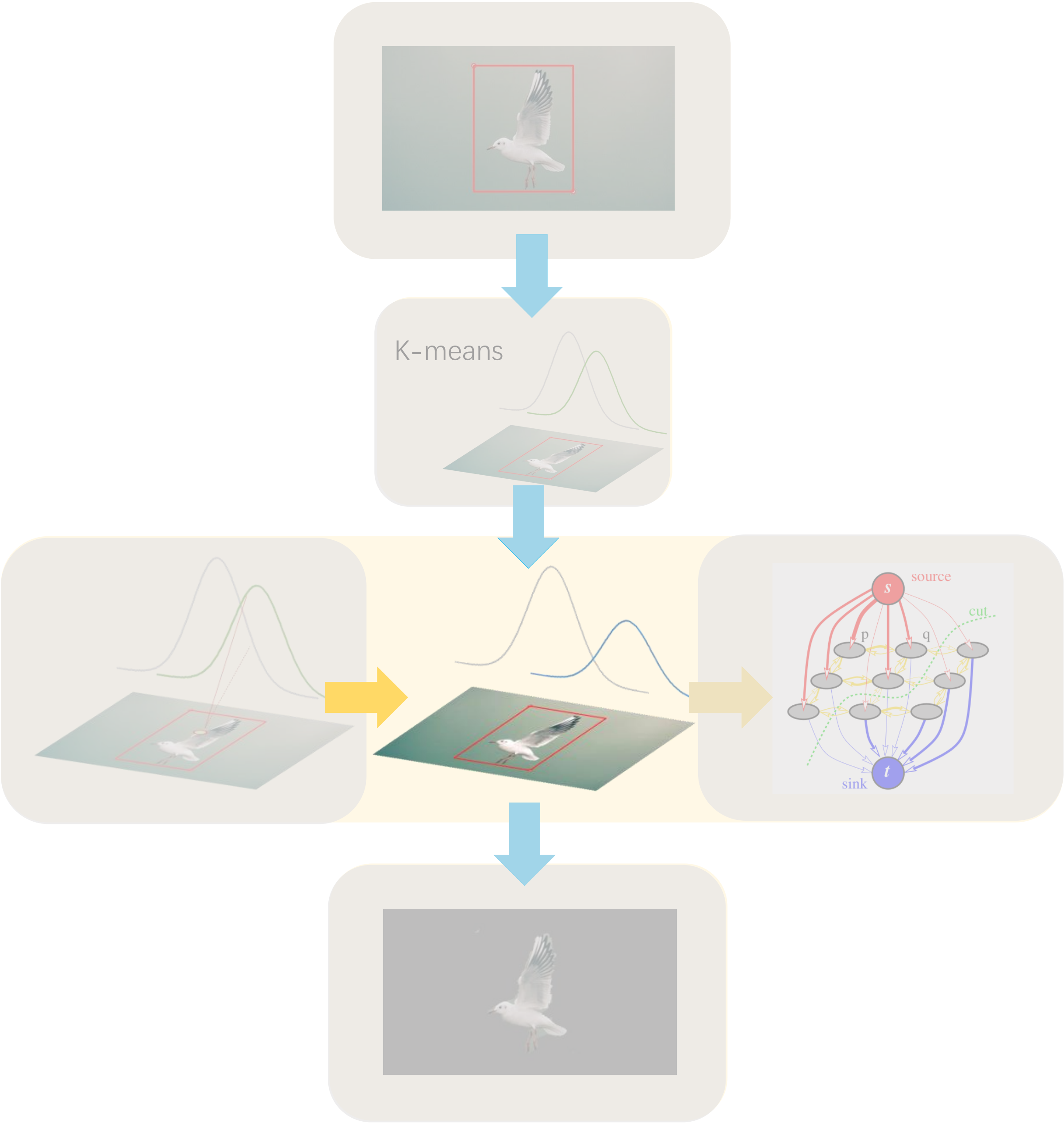

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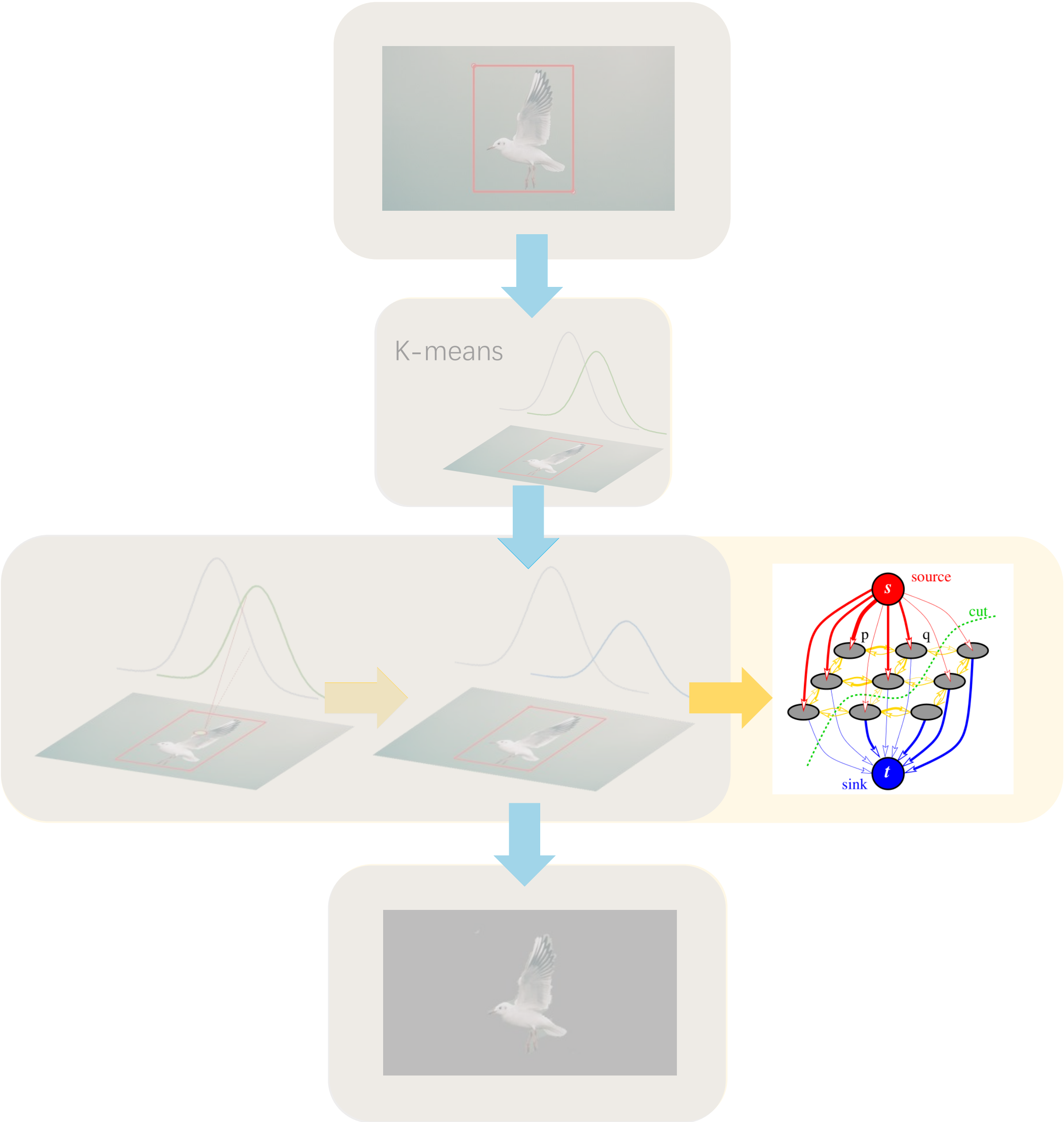

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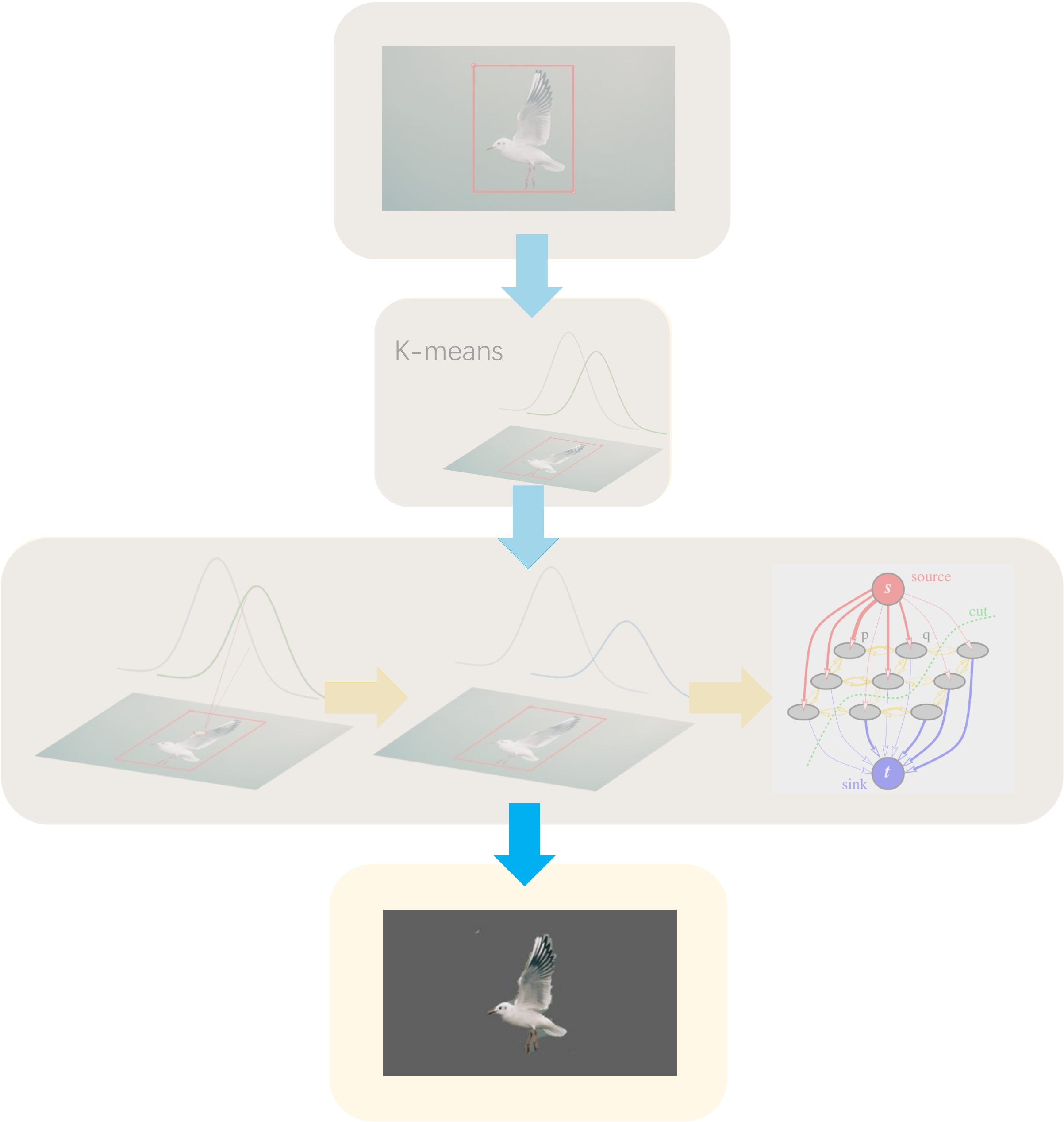

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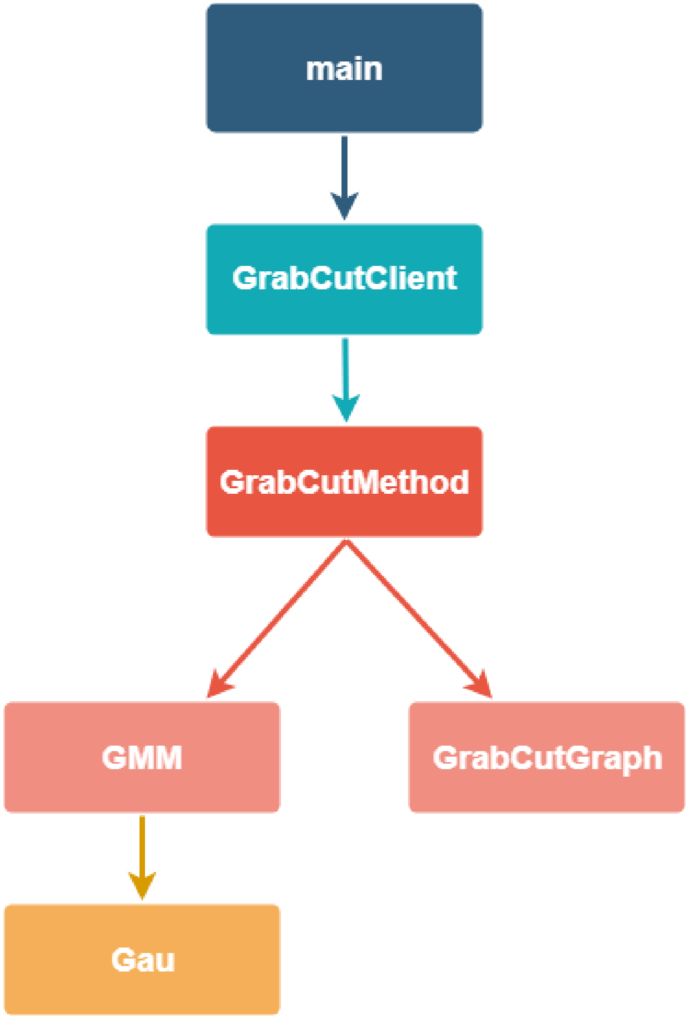
3. Implementation Detail

- GrabCutClient
- GrabCutMethod
- GrabCutGraph
- GMM, Gau
- cv::kmeans, cv::calcCovarMatrix,[1] maxflow[2]
- ……



[1] Opencv. "Opencv/opencv." GitHub. Accessed July 02, 2019. https://github.com/opencv/opencv/blob/master/modules/imgproc/src/grabcut.cpp.
[2] Boykov, Yuri, and Vladimir Kolmogorov. "An experimental comparison of min-cut/max-flow algorithms for energy minimization in vision." *IEEE Transactions on Pattern Analysis & Machine Intelligence* 9 (2004): 1124-1137.

3. Implementation Detail

```
GrabCutClient gc_client("images/white-bird-2-test.jpg", false ,
                        2 /*i_comp*/, 1 /*i_iterate*/);
```

Note: Algorithms were tested using a 4 cores 1.8 GHz machine with 8GB RAM.

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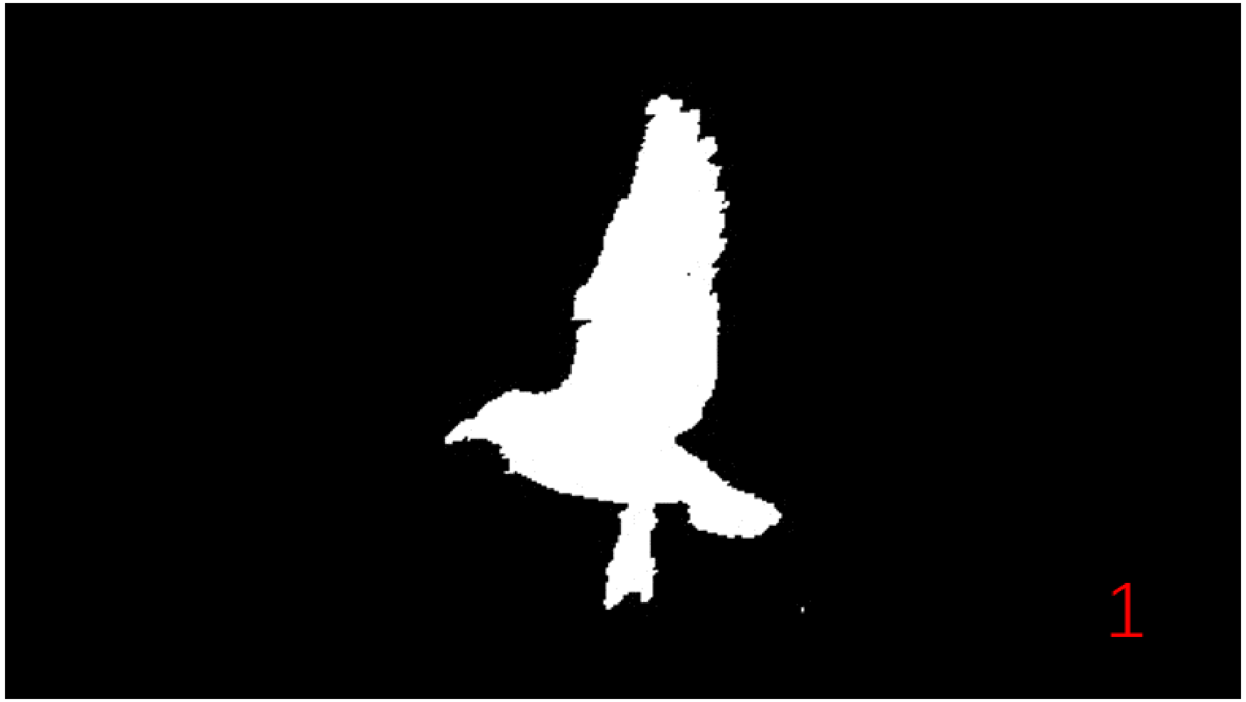
4. Results Analysis

Ground truth

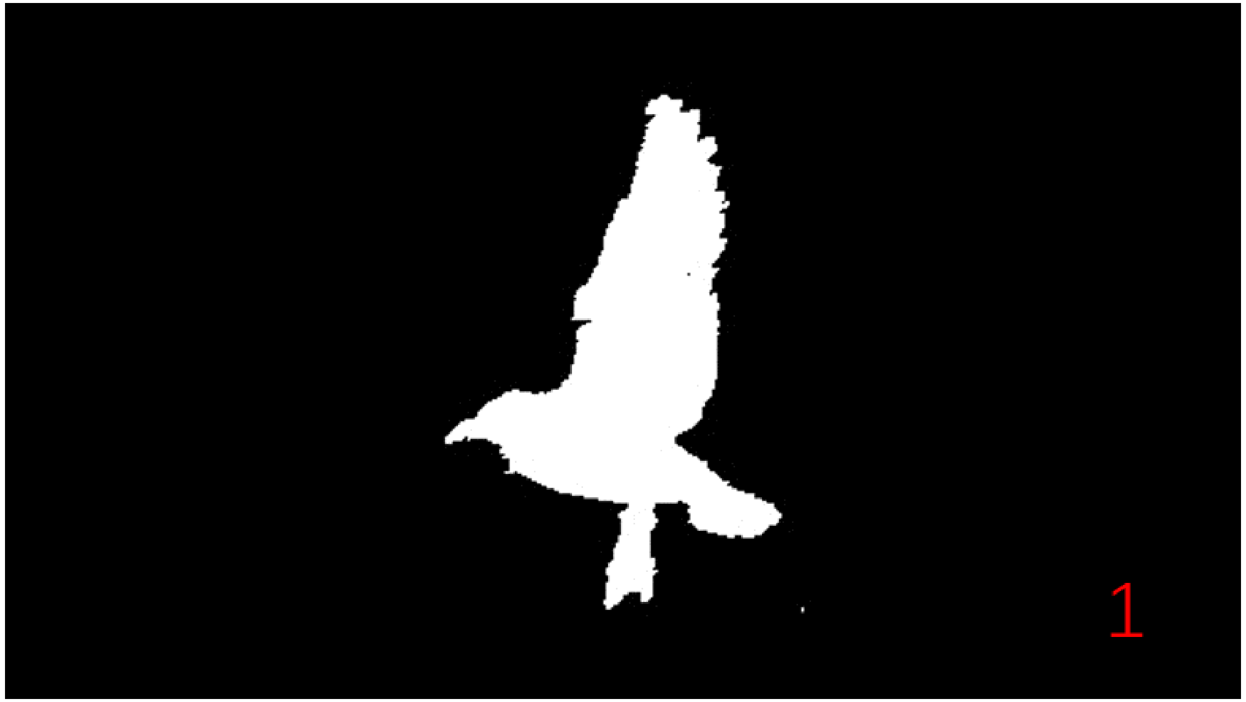
Components increases



4. Results Analysis

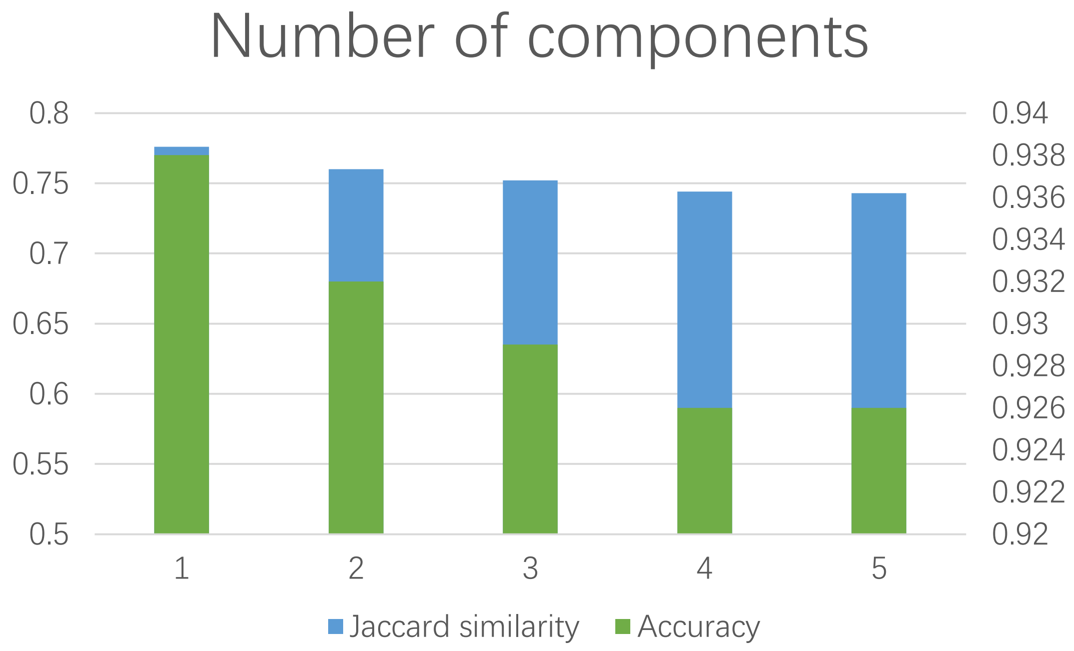
Ground truth

Iteration increases



4. Results Analysis

- Dependent variables:
    - Execution time
    - Error metrics
- Independent variables:
    - Number of components
    - Times of iteration
- Energy convergence……



Note: The chart shows the data tested under 1 iteration, and the number of components is incremented from 1 to 5.

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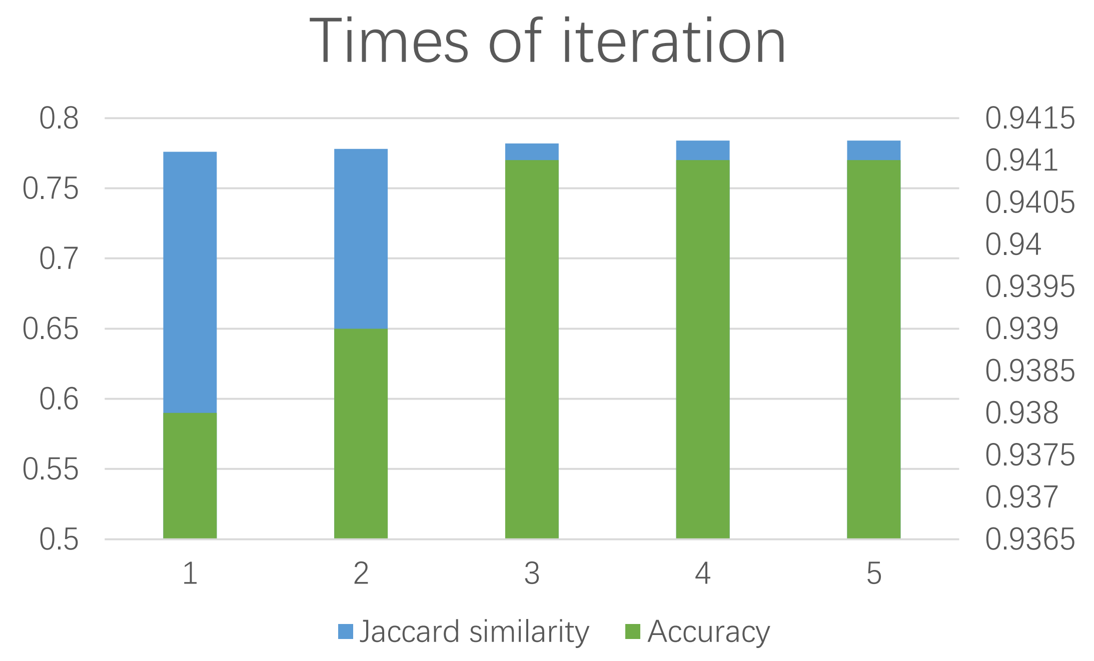

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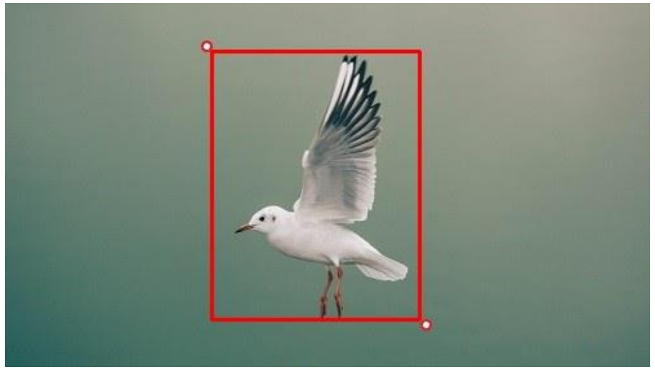
4. Results Analysis

Mine

OpenCV



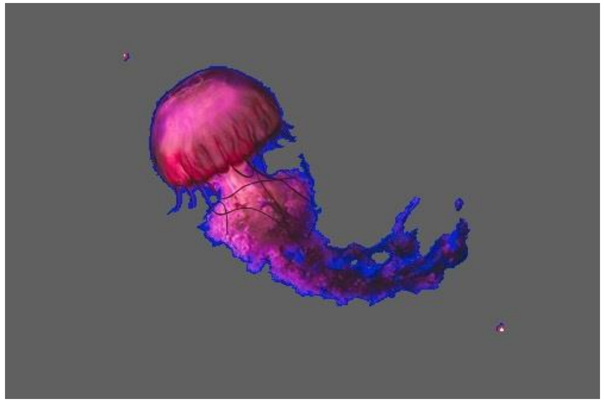
[1]

Note: Both are tested under 5 iterations, 5 components.
[1] Photo by janer zhang on Unsplash.

4. Results Analysis

Mine

Failed OpenCV



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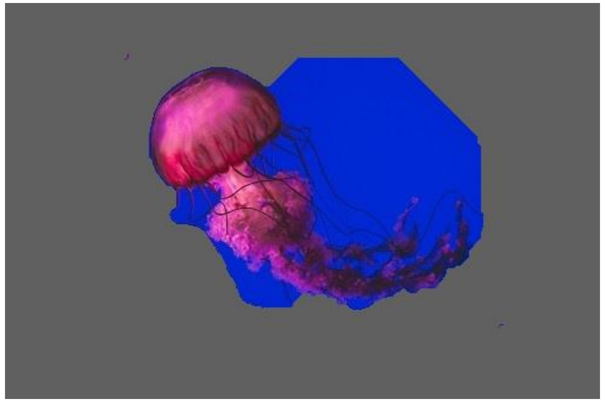

Note: Both are tested under 1 iterations. And my result is tested under 1 Gaussian component while OpenCV set 5 components as default.
[1] Photo by Chitbhanu Singh on Unsplash.

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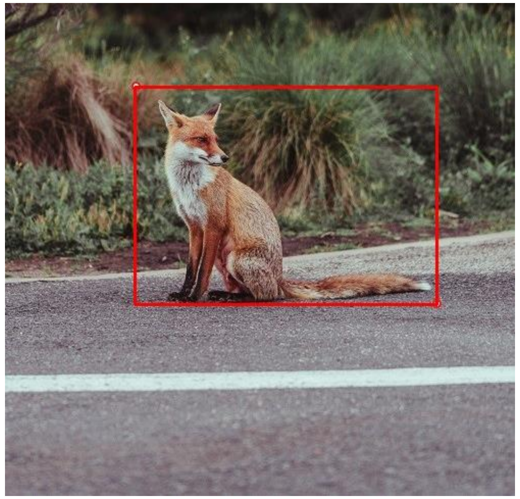

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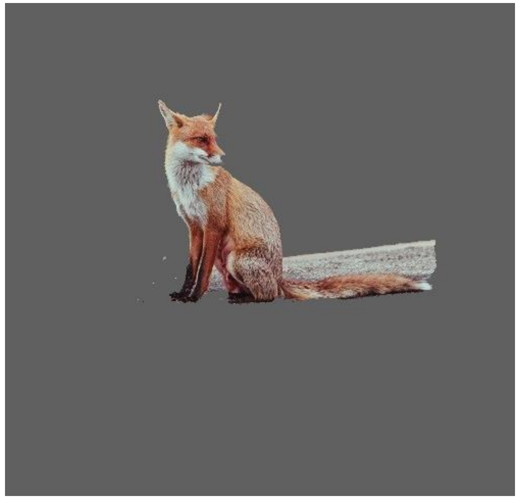

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5. Thoughts

- GrabCut is not that perfect, the point is what should be foreground elements?
- Reproducing is not simply copying, it helps to understand some background and will inspire you.
- Code writing needs more practice, knowledge about data structure and algorithm.
- Try to think problems in a different way.
- ……

Thank you!