Gaussianization–PCA for One-Class Remote Sensing Image Classification

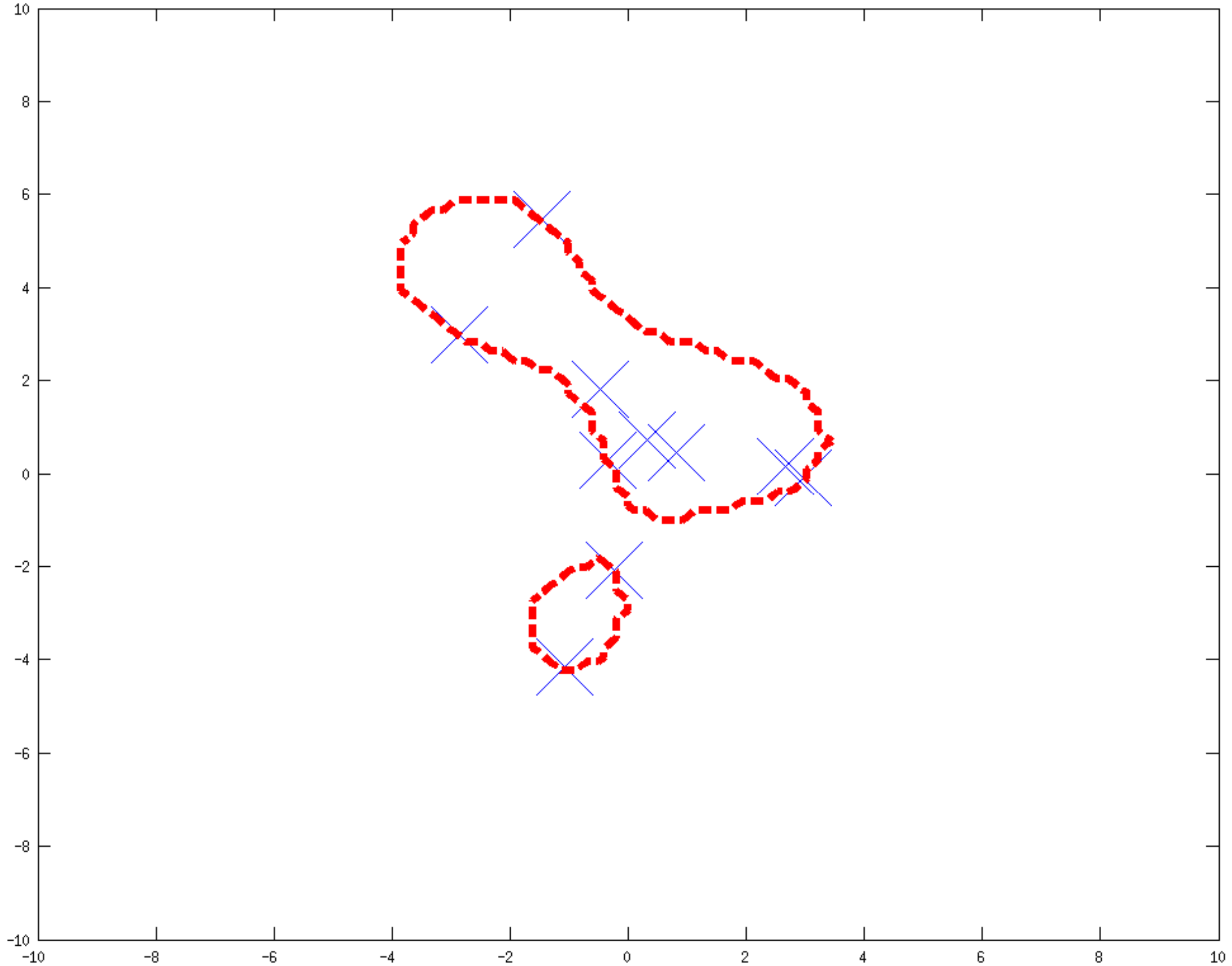
Valero Laparra, Jordi Muñoz-Marí,
Gustavo Camps-Valls and Jesús Malo

Image Processing Laboratory (IPL)
Universitat de València, Spain

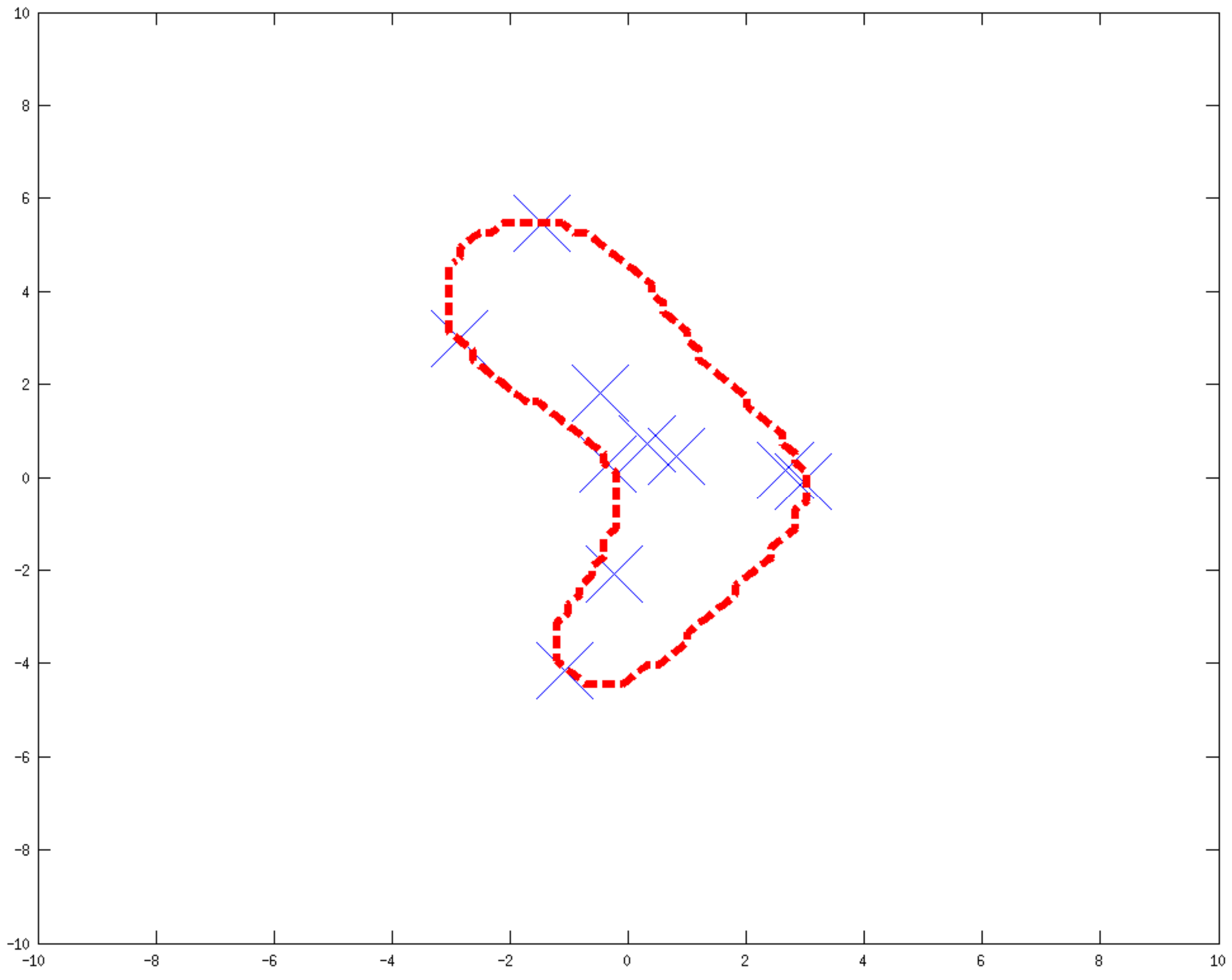
ONE CLASS classification

- **One-class classification** tries to distinguish one class of objects from **all** other possible objects, by learning from a training set containing **only** the objects of that class.

ONE CLASS classification



ONE CLASS classification



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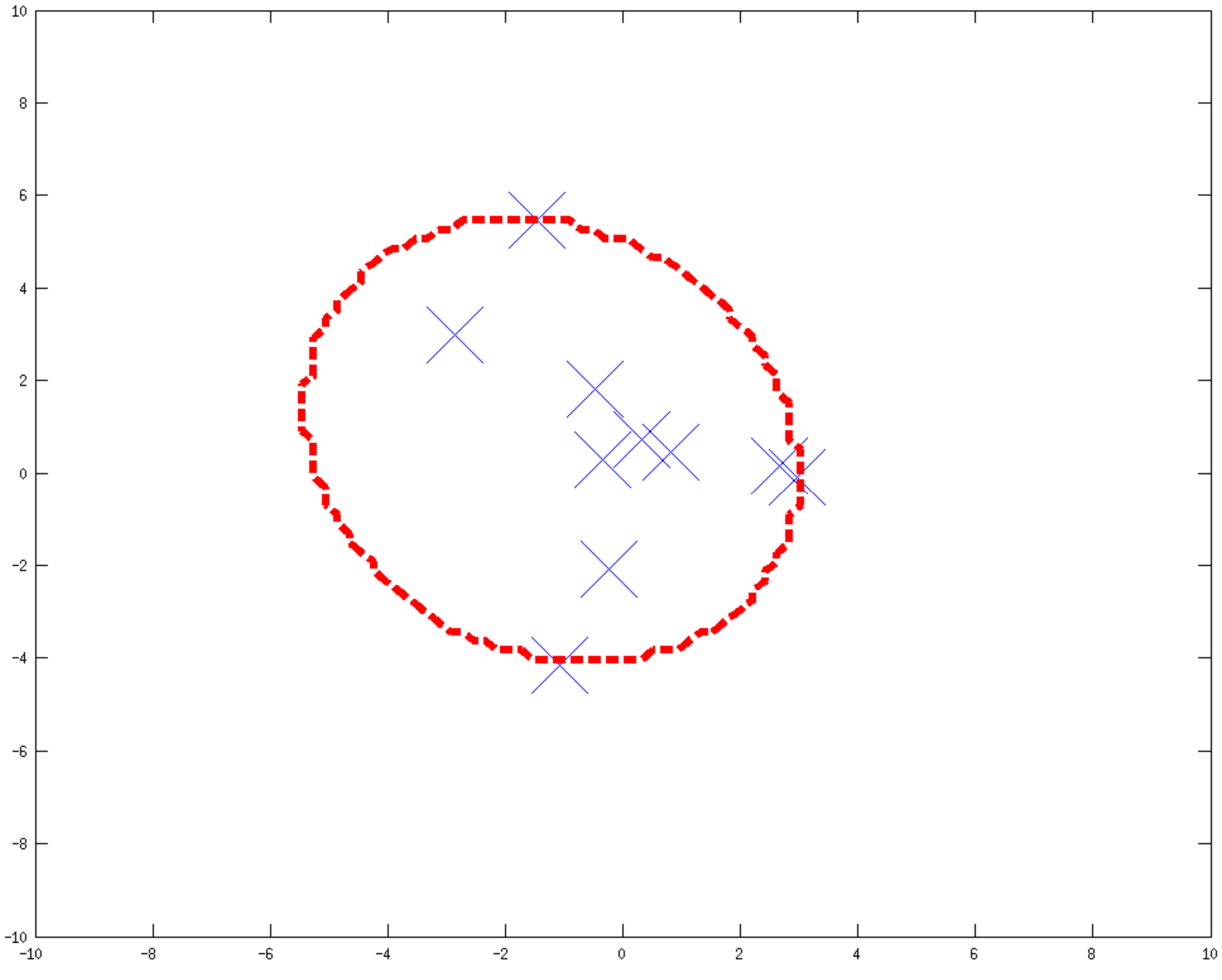

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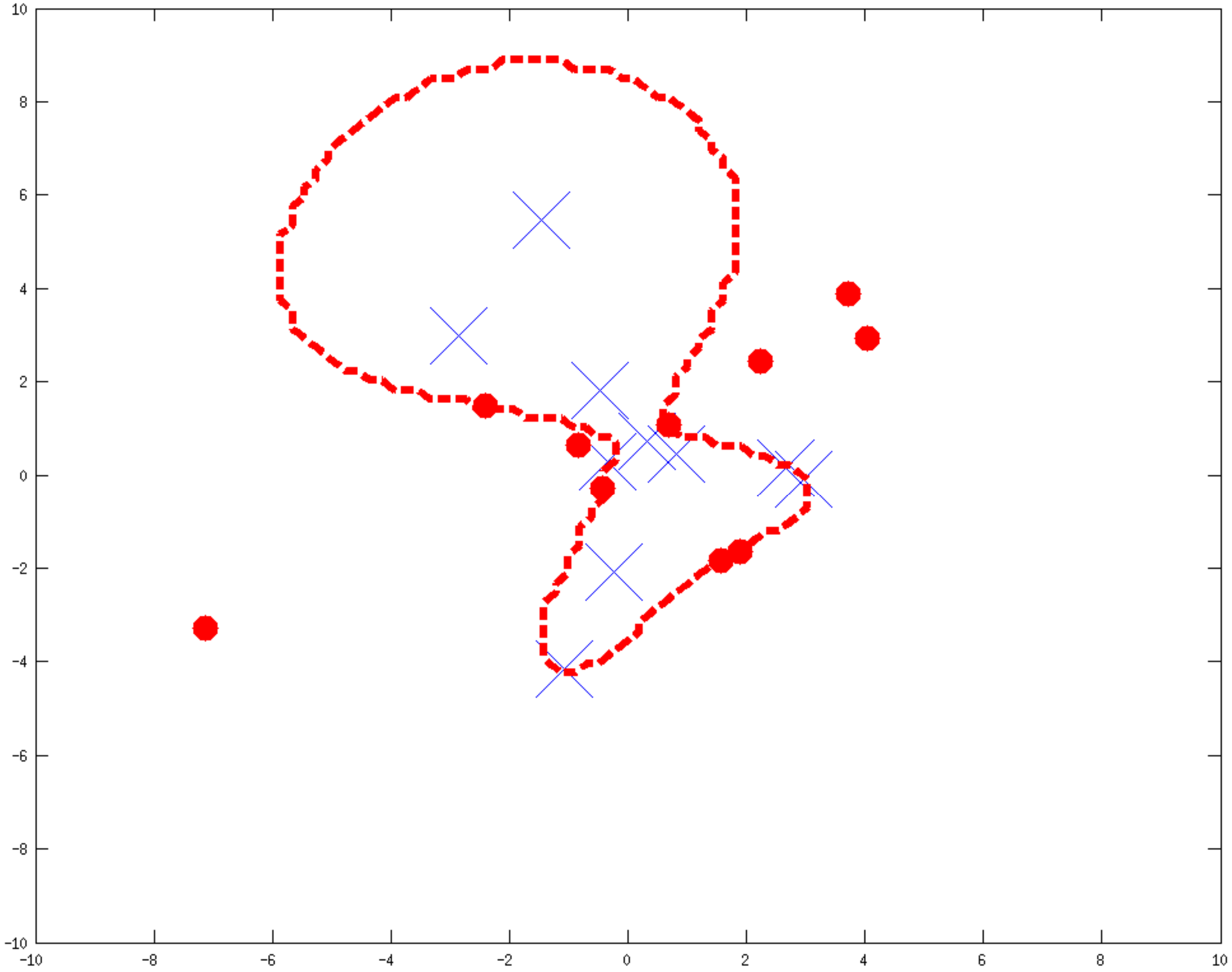

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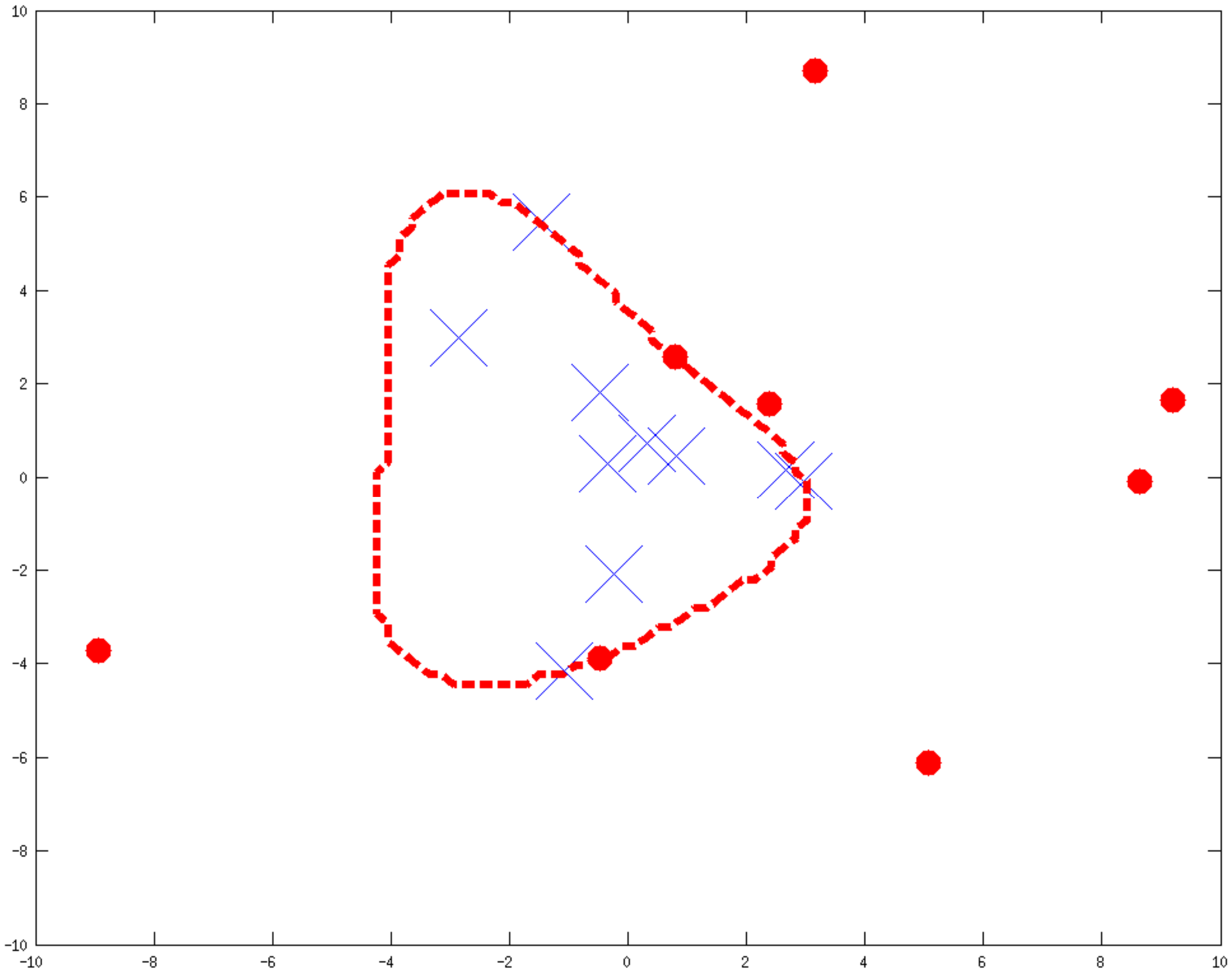

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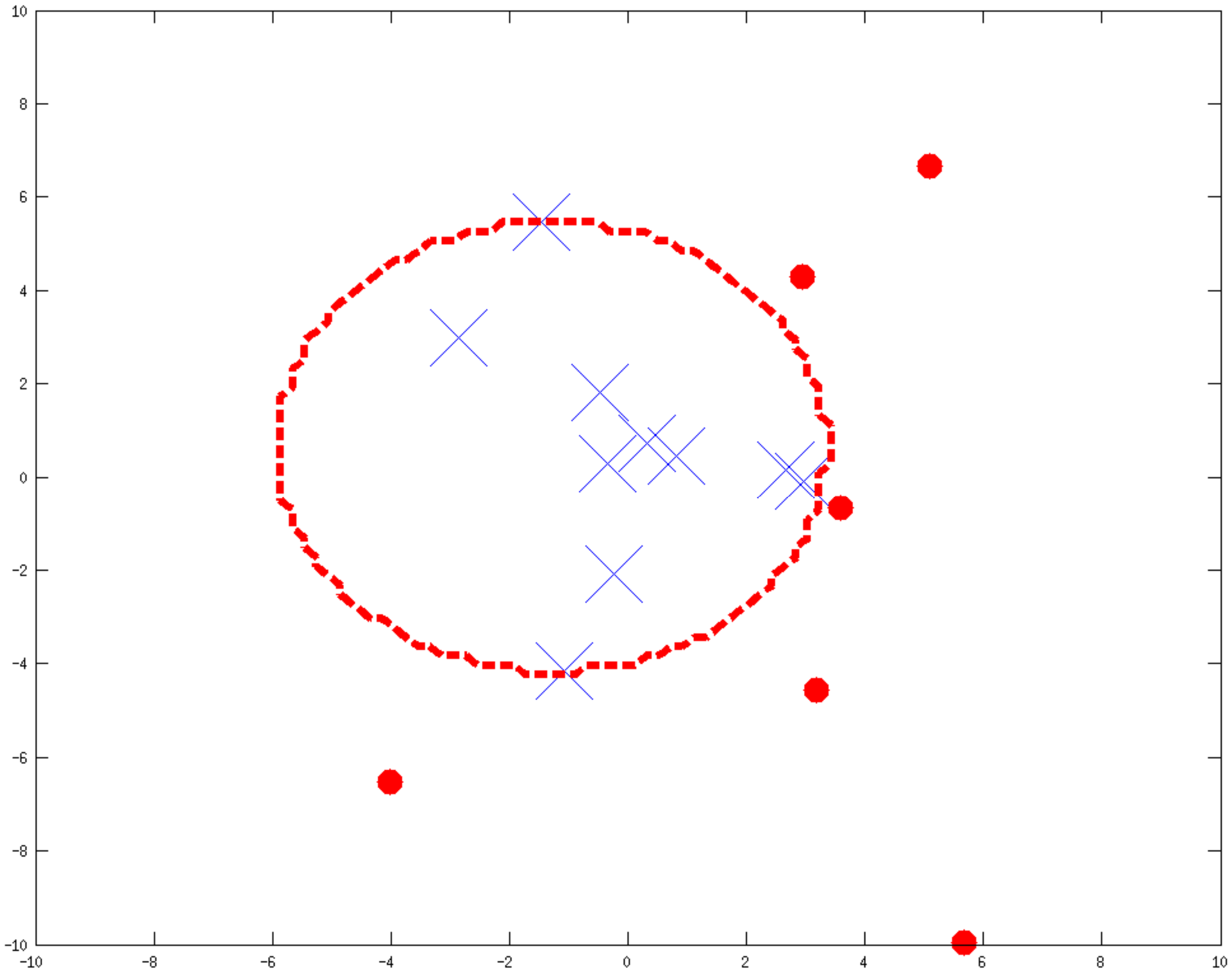

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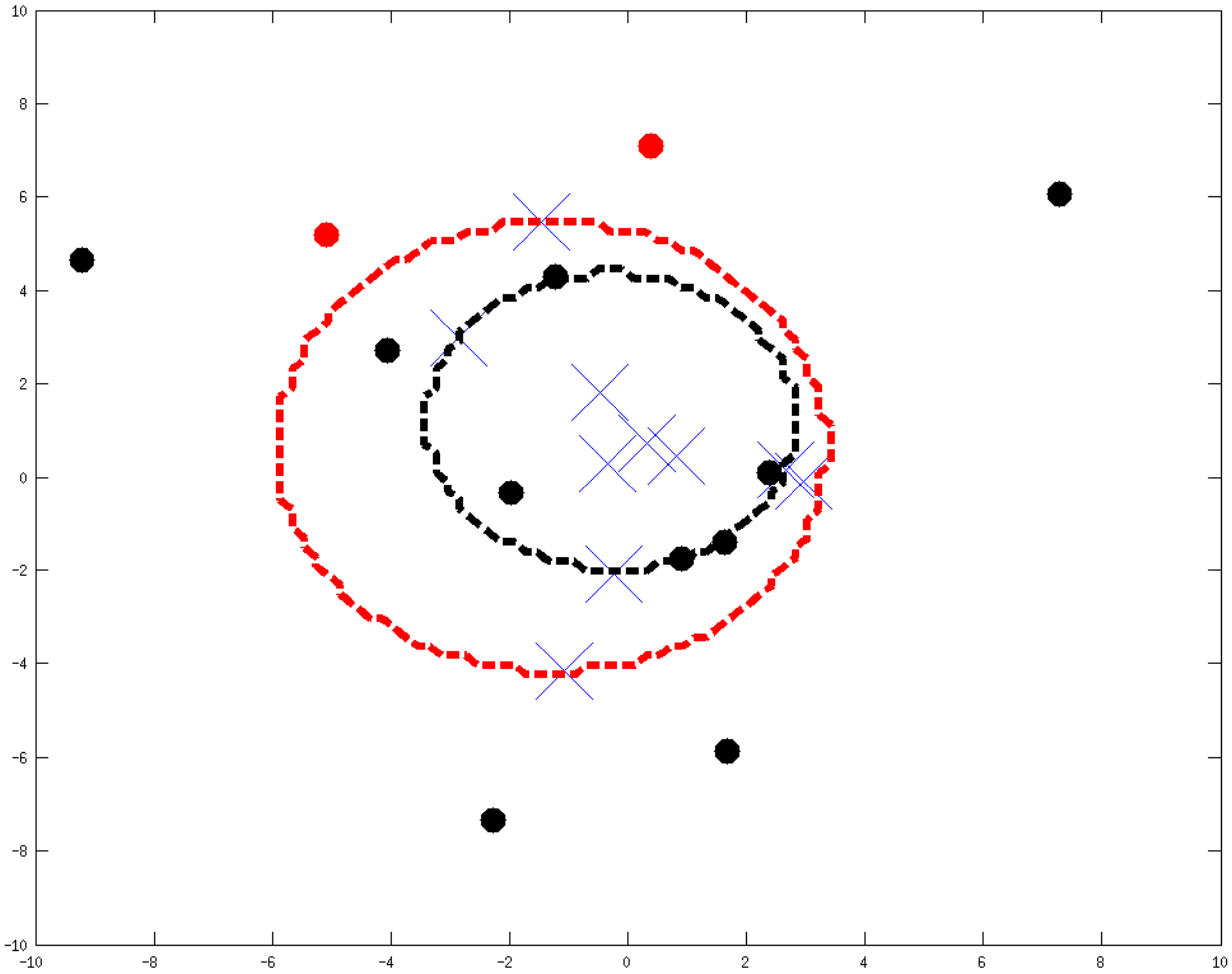

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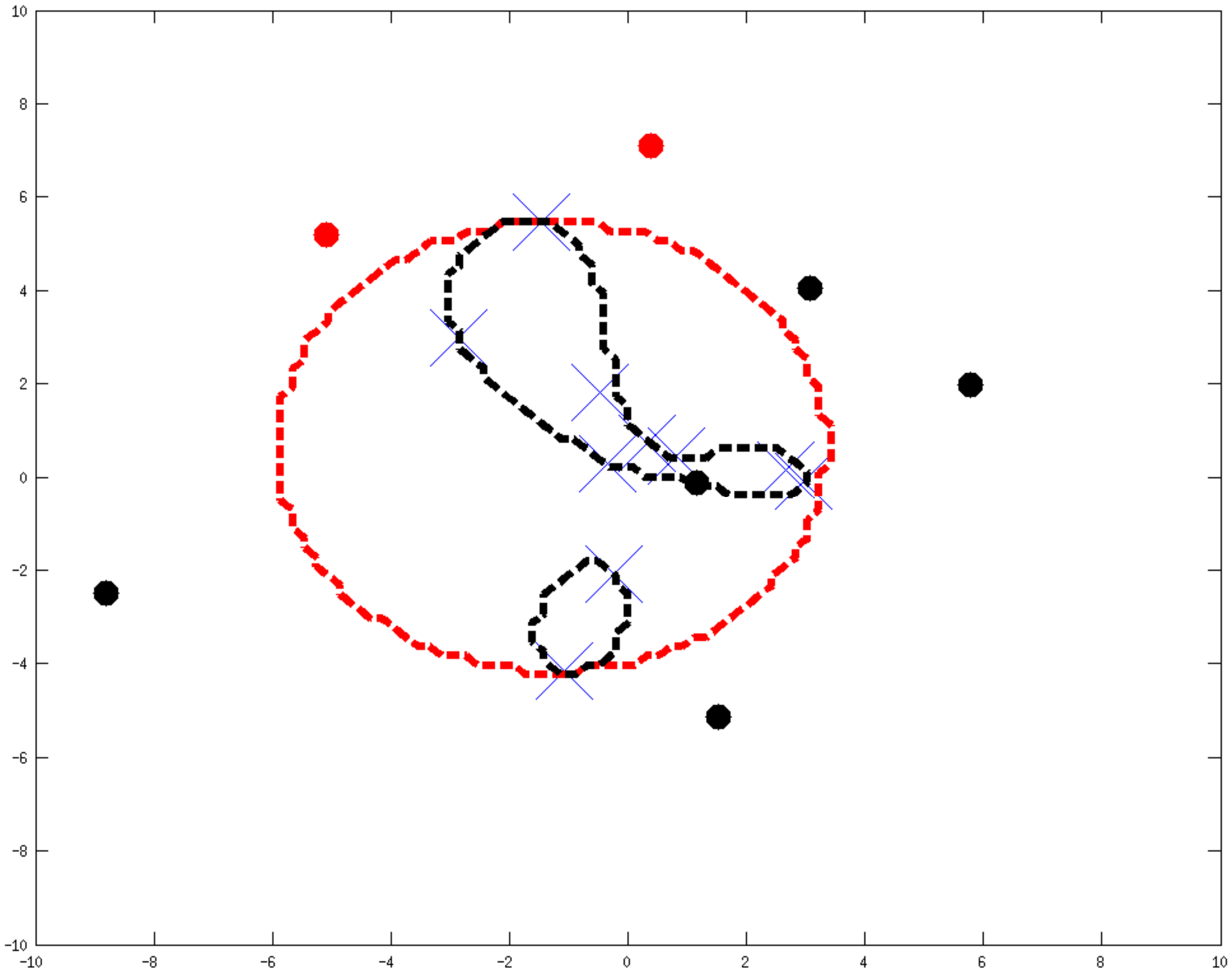

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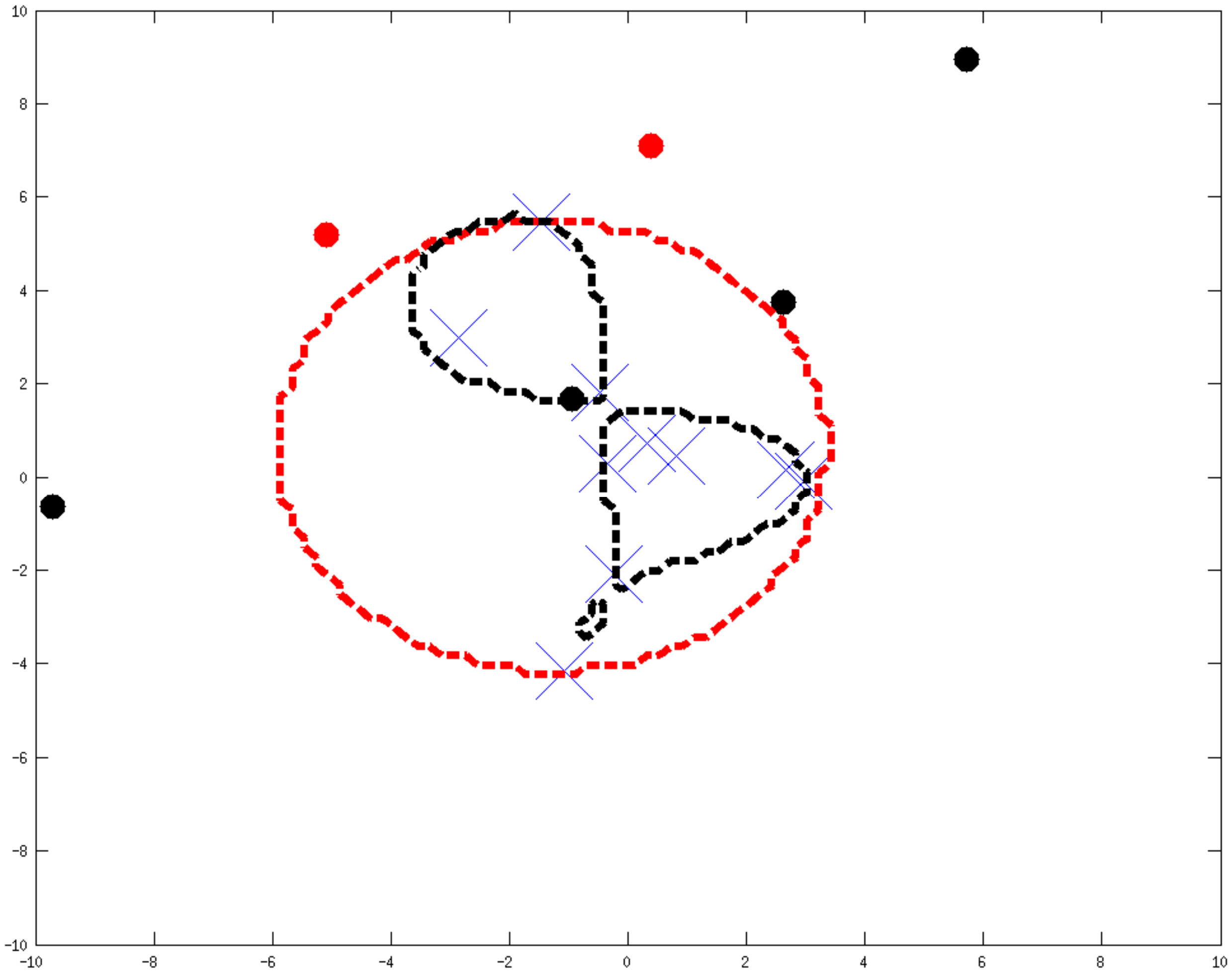


SUMMARY

- One-class classification
- G-PCA
  - Convergence
  - PDF estimation
- Experiments
  - 2D example
  - 10D experiment with real data
- Conclusions & Further work

ONE CLASS classification

Trade-off problem

- General
- Specific

2 approaches

- Boundary

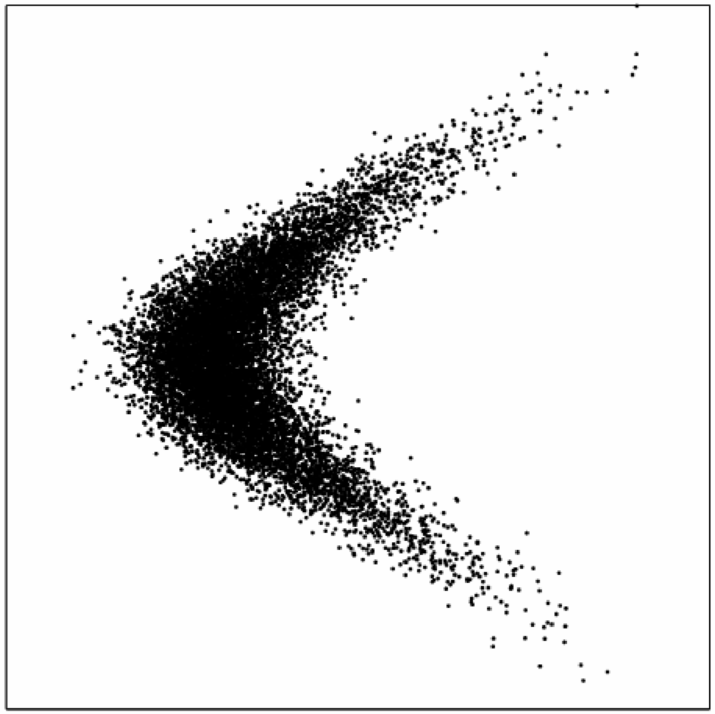
  Support Vector Domain Description SVDD

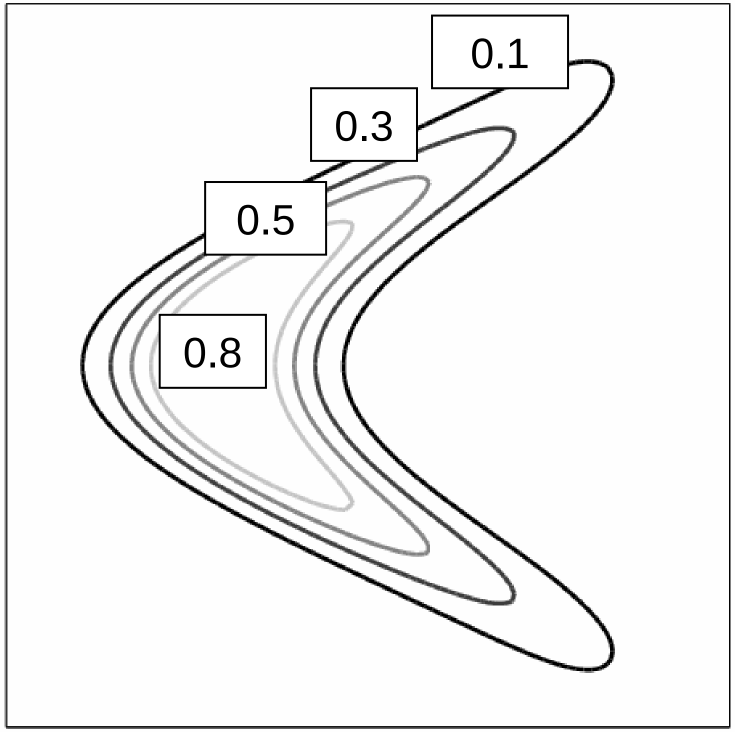
- Probability Density Function (PDF)

  Gaussianization PCA

ONE CLASS - PDF solution

- $P_{cl1}(x_0) >$ THRESHOLD $\rightarrow$ $Class(x_0) = 1$
- $P_{cl1}(x_0) <$ THRESHOLD $\rightarrow$ $Class(x_0) = 0$





ONE CLASS - PDF solution

- PROBLEM: PDF estimation!!
  - Assuming a parametric model (Gaussian, GSM…)
    - Problem: Previous knowledge about the PDF
  - Non assuming a parametric model (histogram…)
    - Problem: number of samples

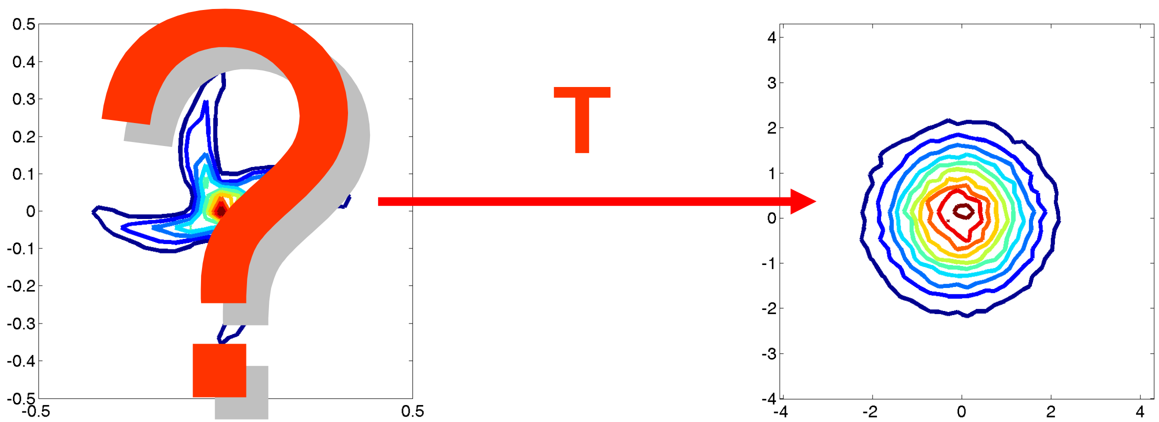
      "curse of dimensionality"

OUR APPROACH

$$Y = T(X)$$

$$P_X = P_Y * |J_T|$$

- From P(x) to P(y) (Gaussian)

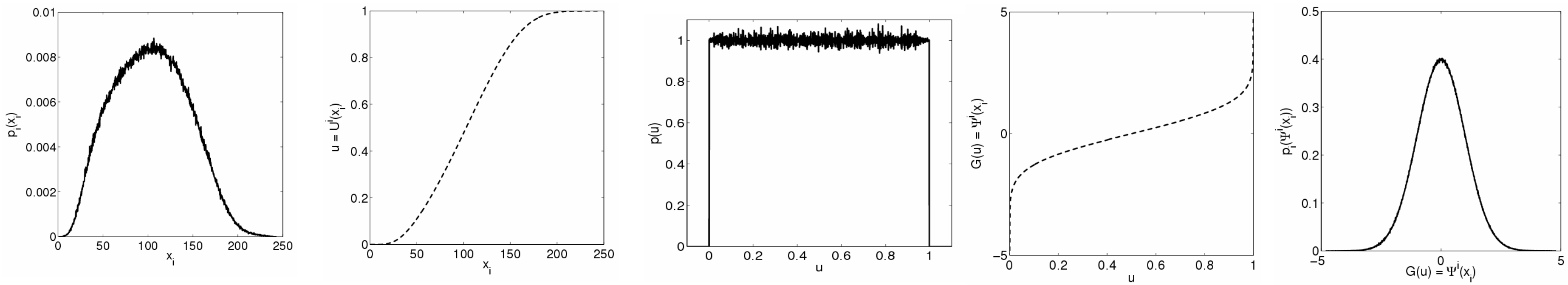


Gaussianization - PCA

$$Y = X^{n+1} = B^T \Psi(X^n)$$

- Gaussianization-PCA 2 steps:

(1) Marginal gaussianization



(2) PCA Rotation

Theoretical convergence Proof

$$Y = X^{n+1} = B^T \Psi(X^n)$$

- Negentropy:

$$J(X) = \int_{-\infty}^{\infty} p(X) log \frac{p(X)}{\mathcal{N}(X)} dX$$

- Difference in Negentropy:

$$\Delta J = J(X^n) - J(X^{n+1}) = \sum_{k=1}^{d} J(X_i^n) + 2_{ord}^{nd}(\Psi(X^n))$$

G-PCA

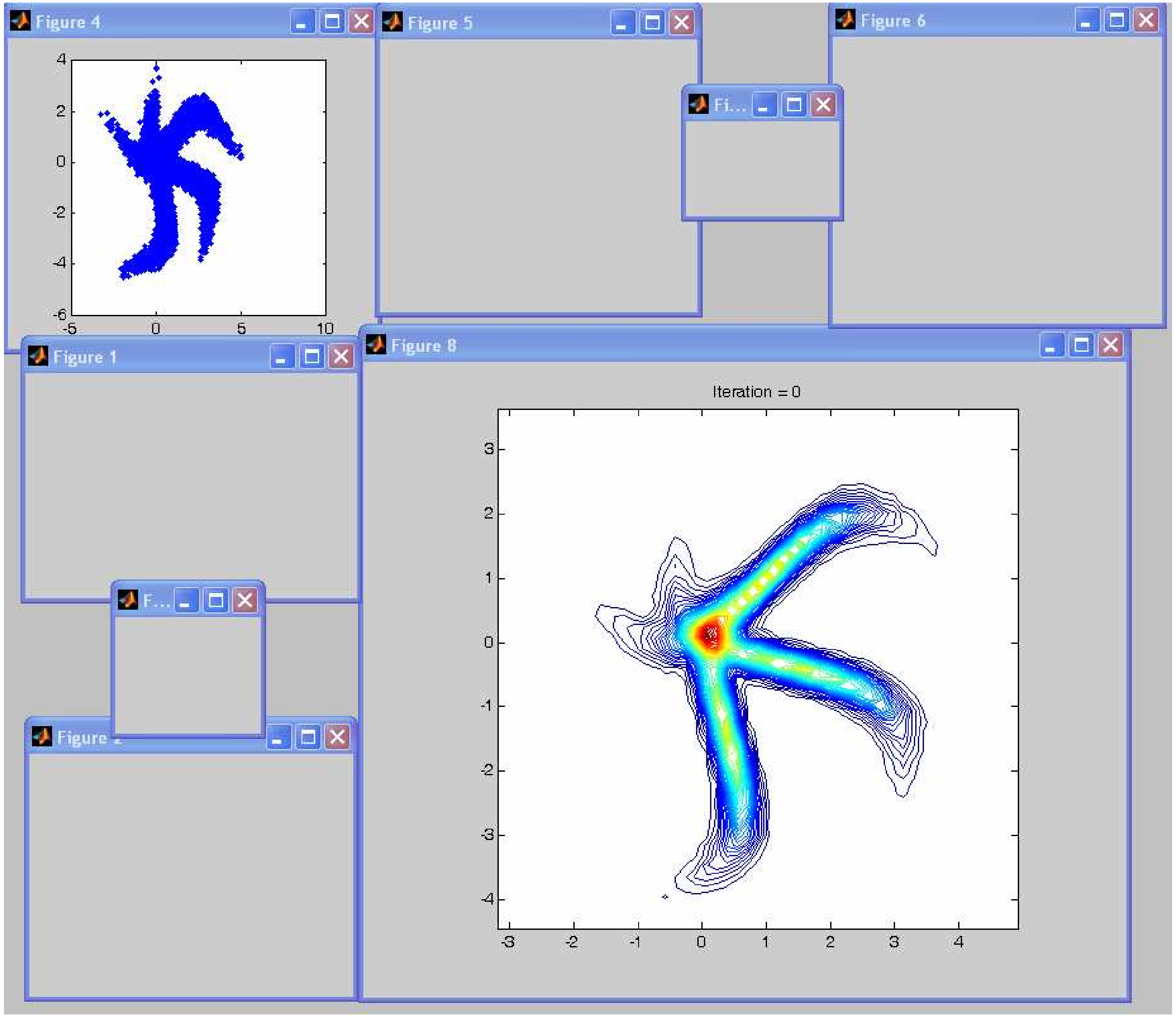


Figure 4
Figure 5
Figure 6
Fi...
Figure 1
F...
Figure 2
Figure 8
Iteration = 0

G-PCA

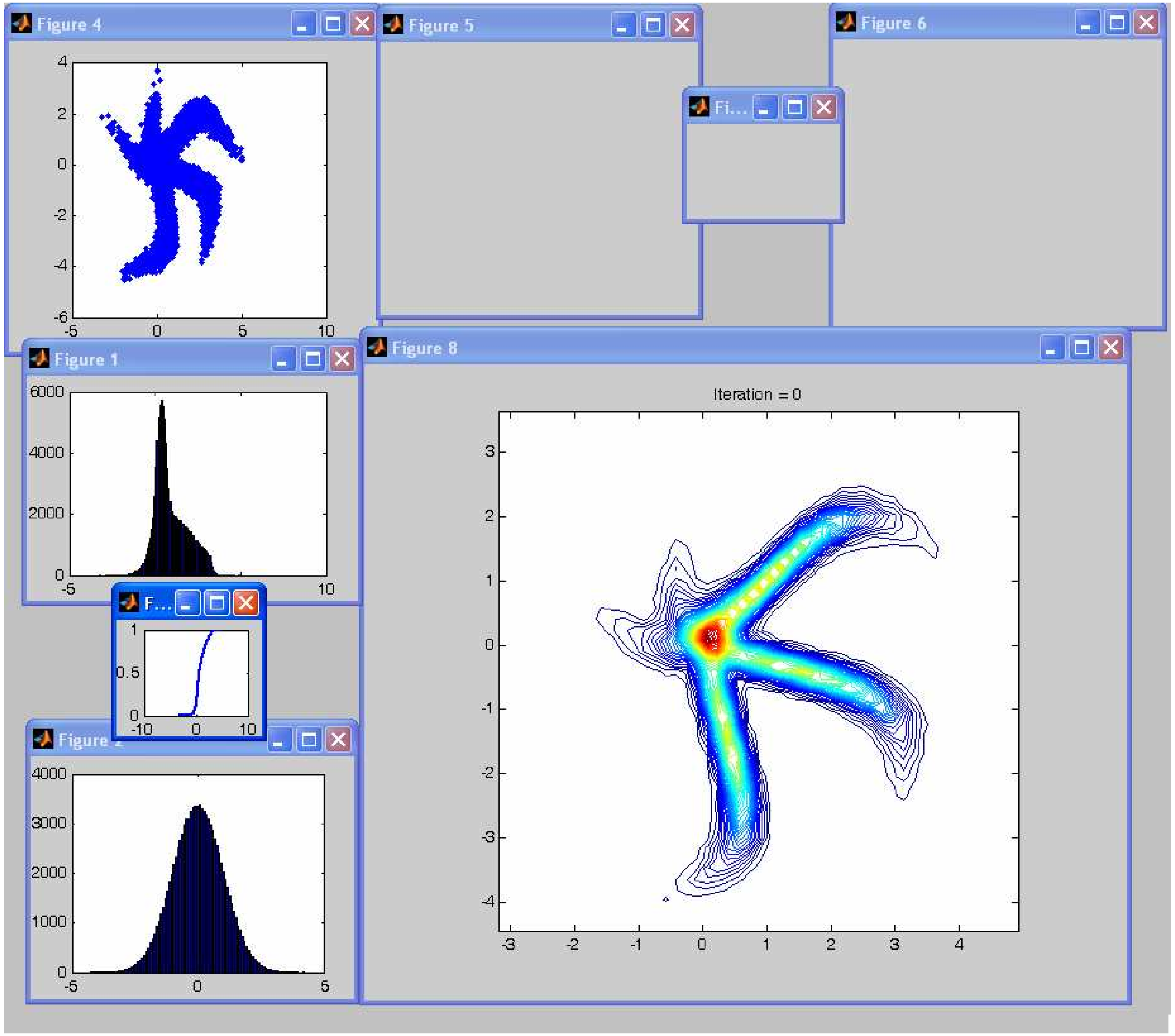

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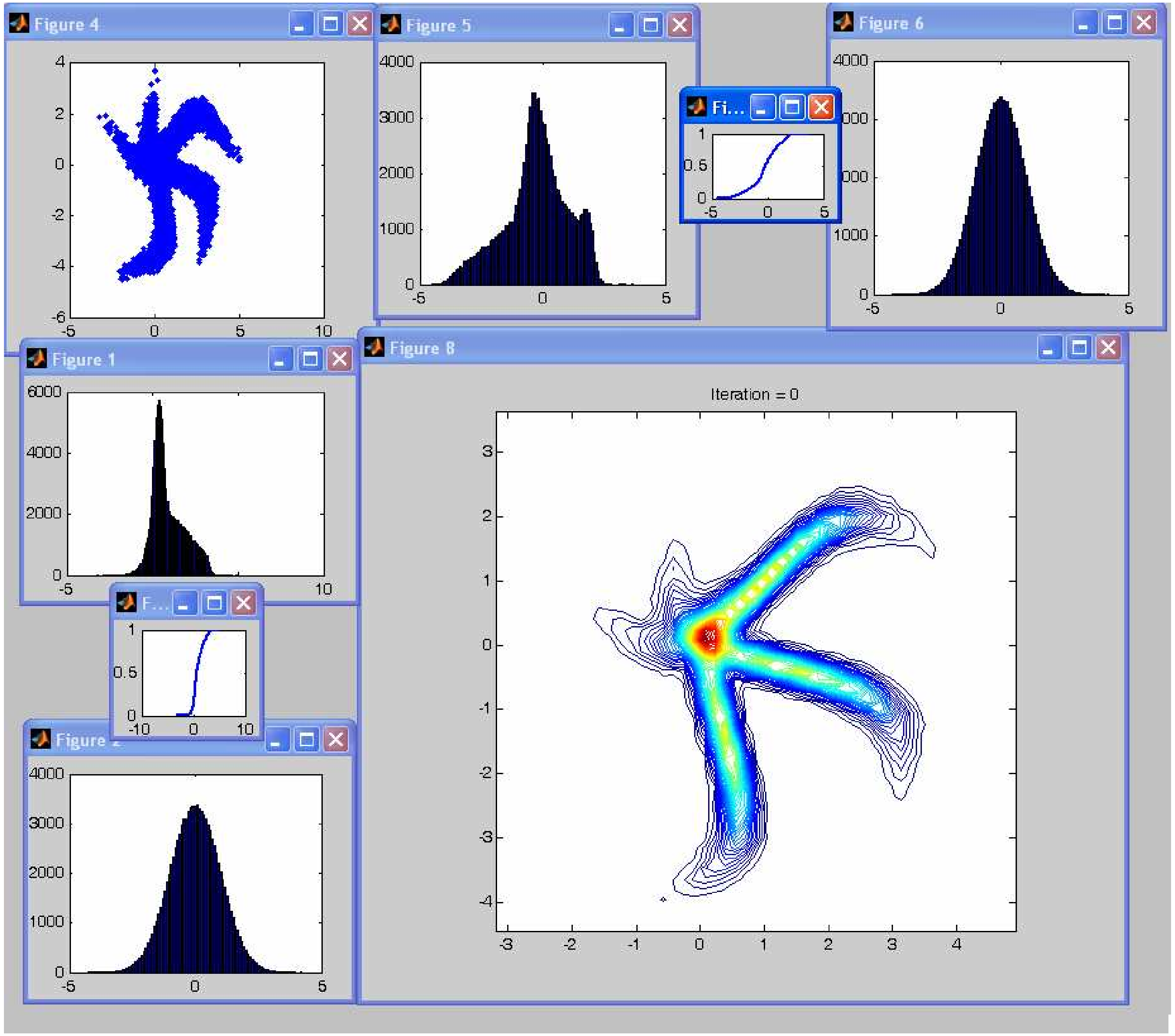
Figure 2

G-PCA



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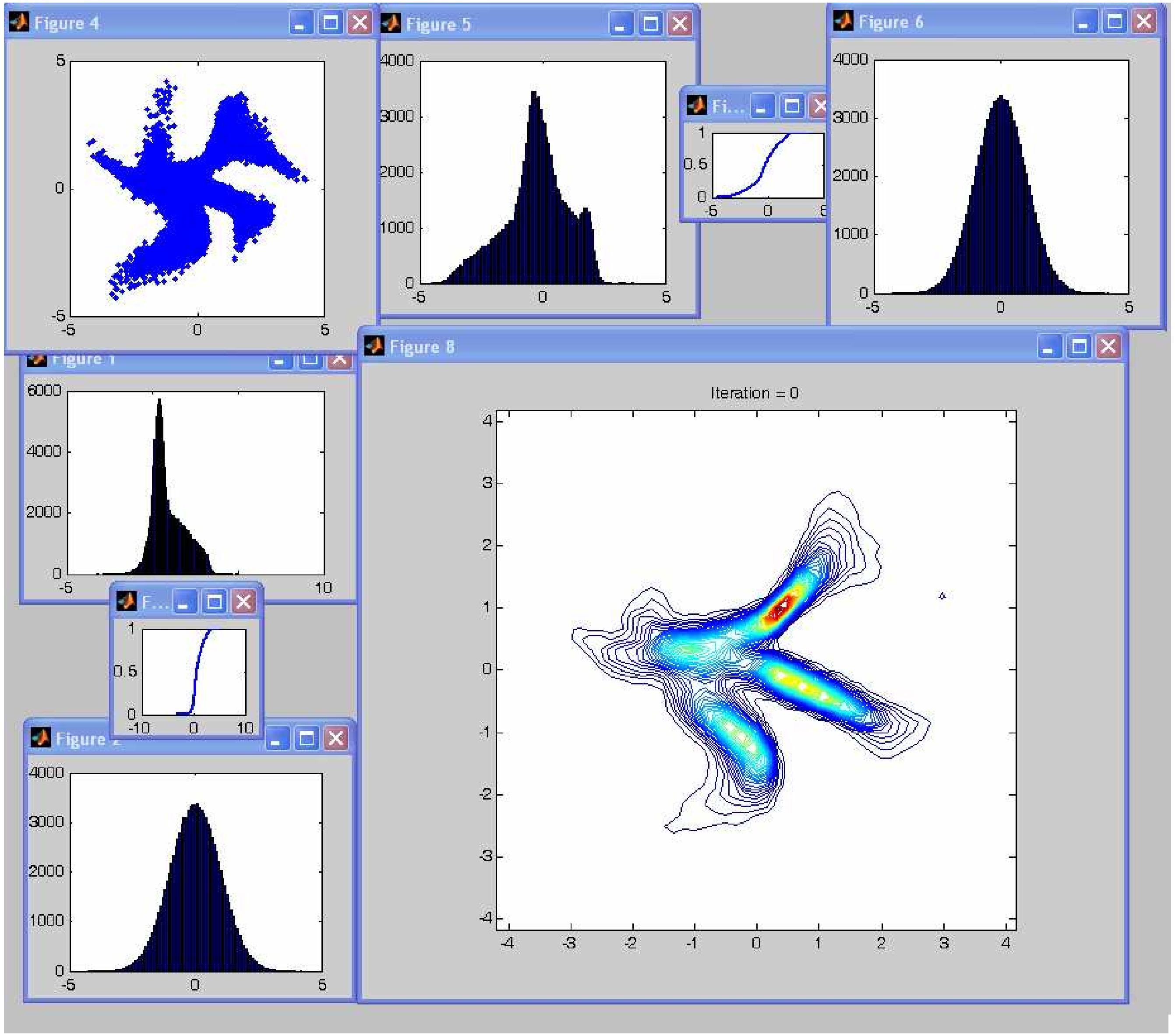
G-PCA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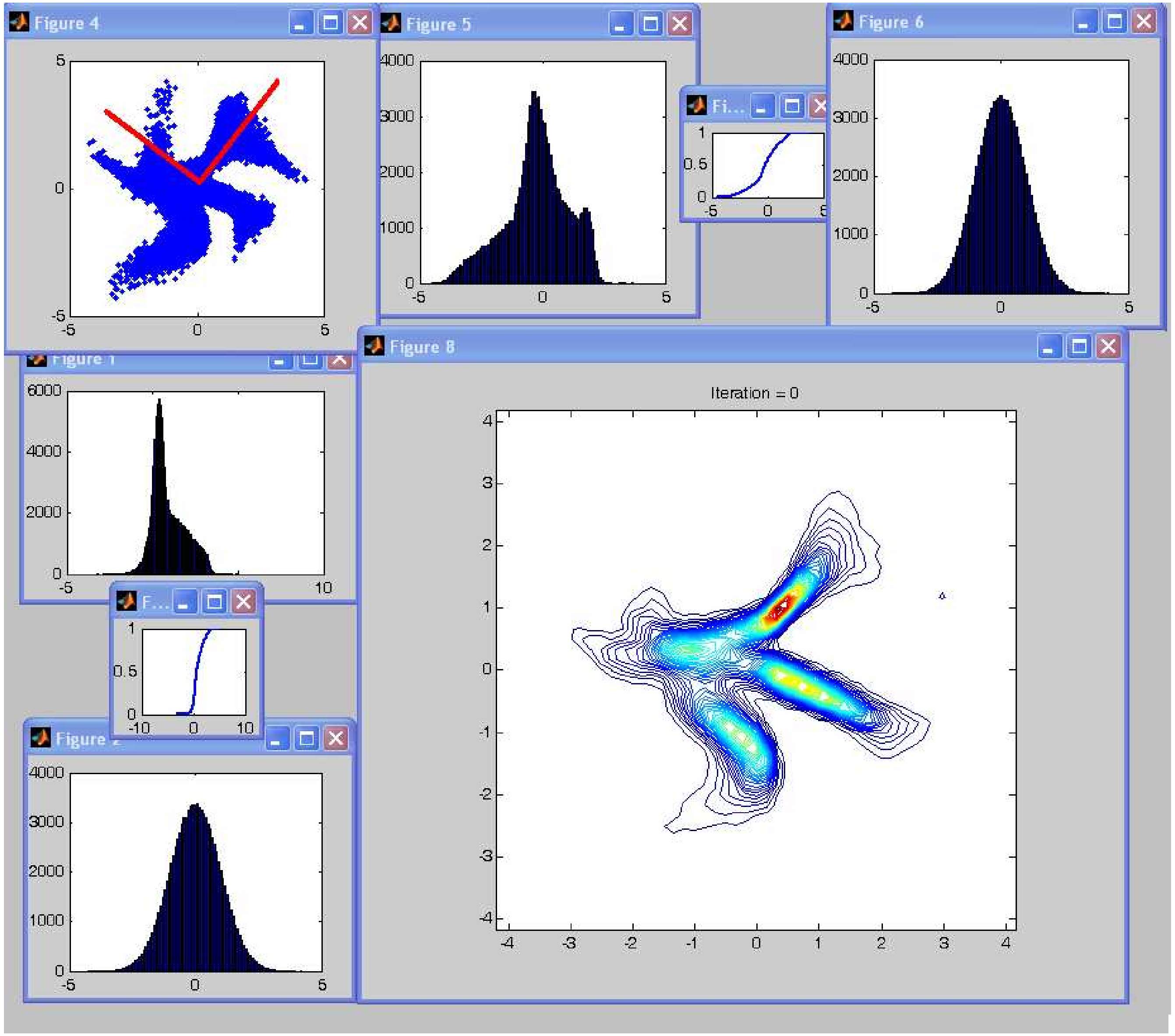

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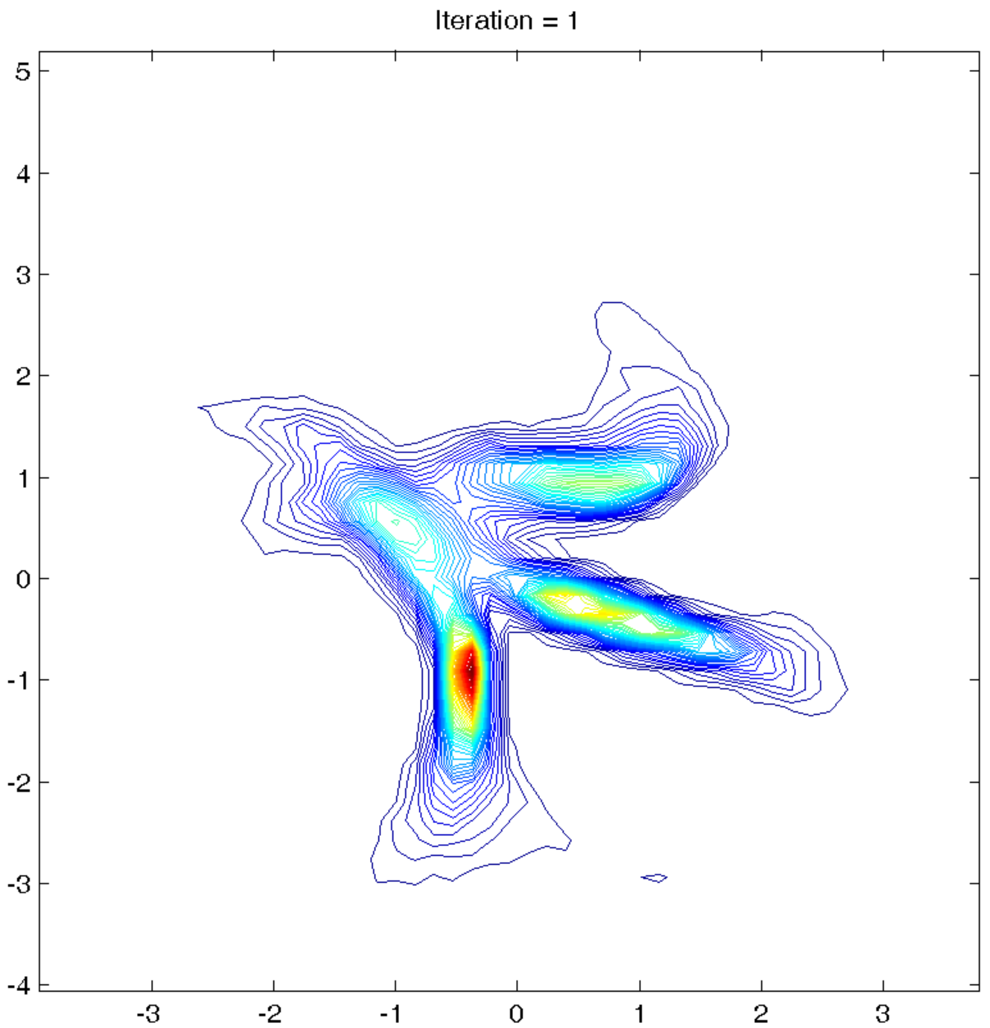

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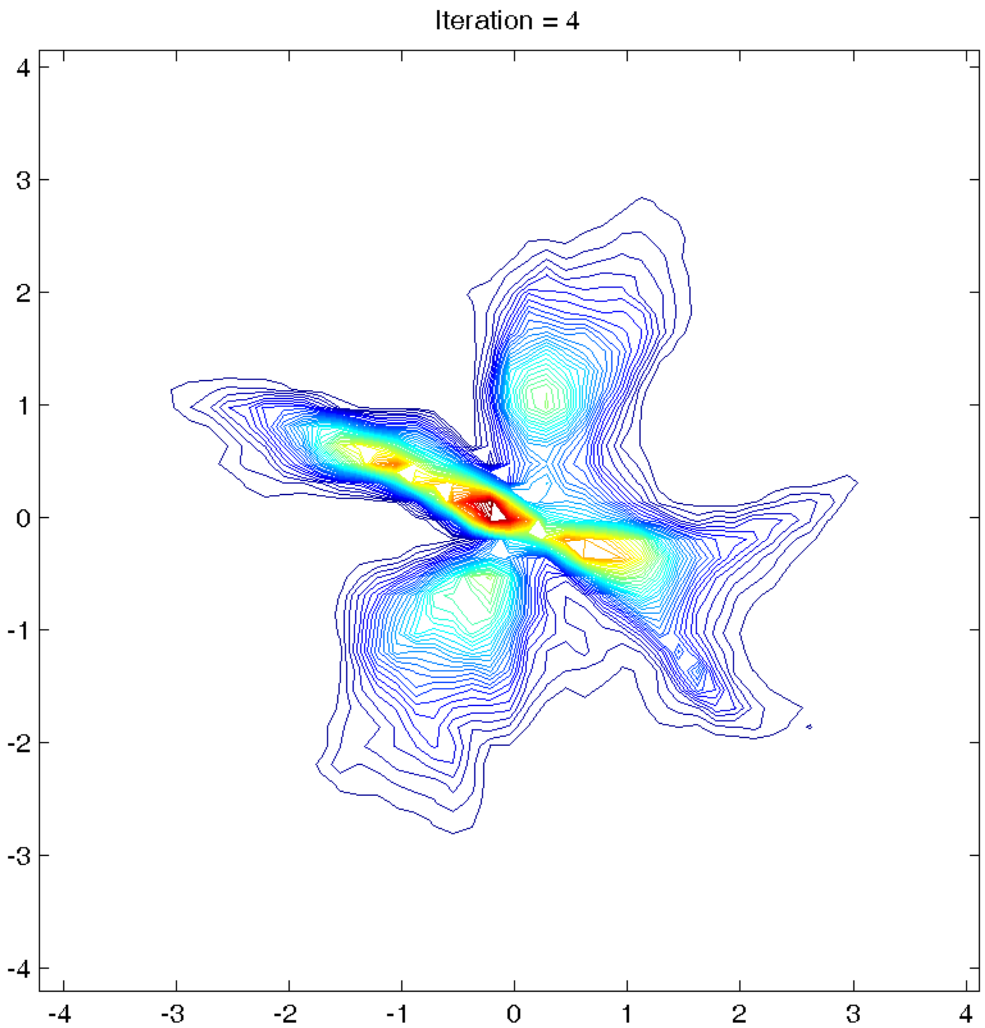

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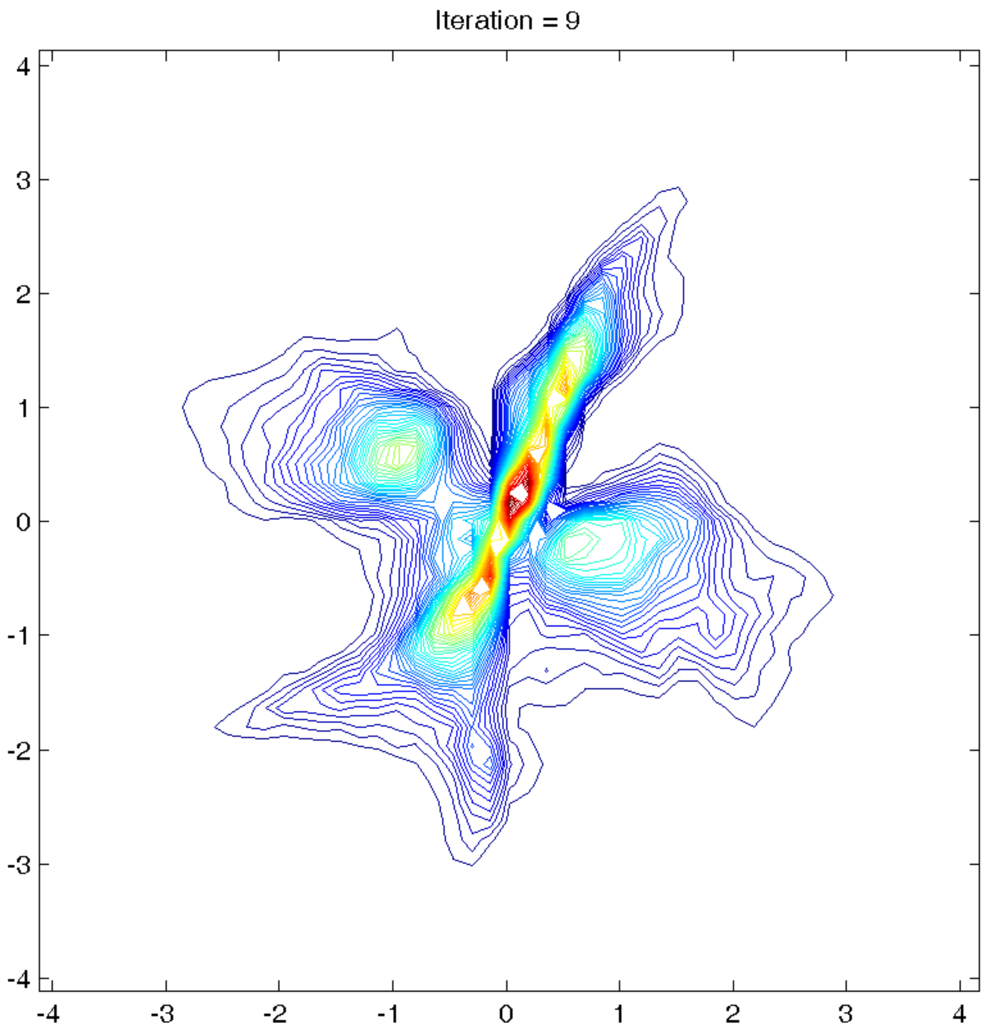

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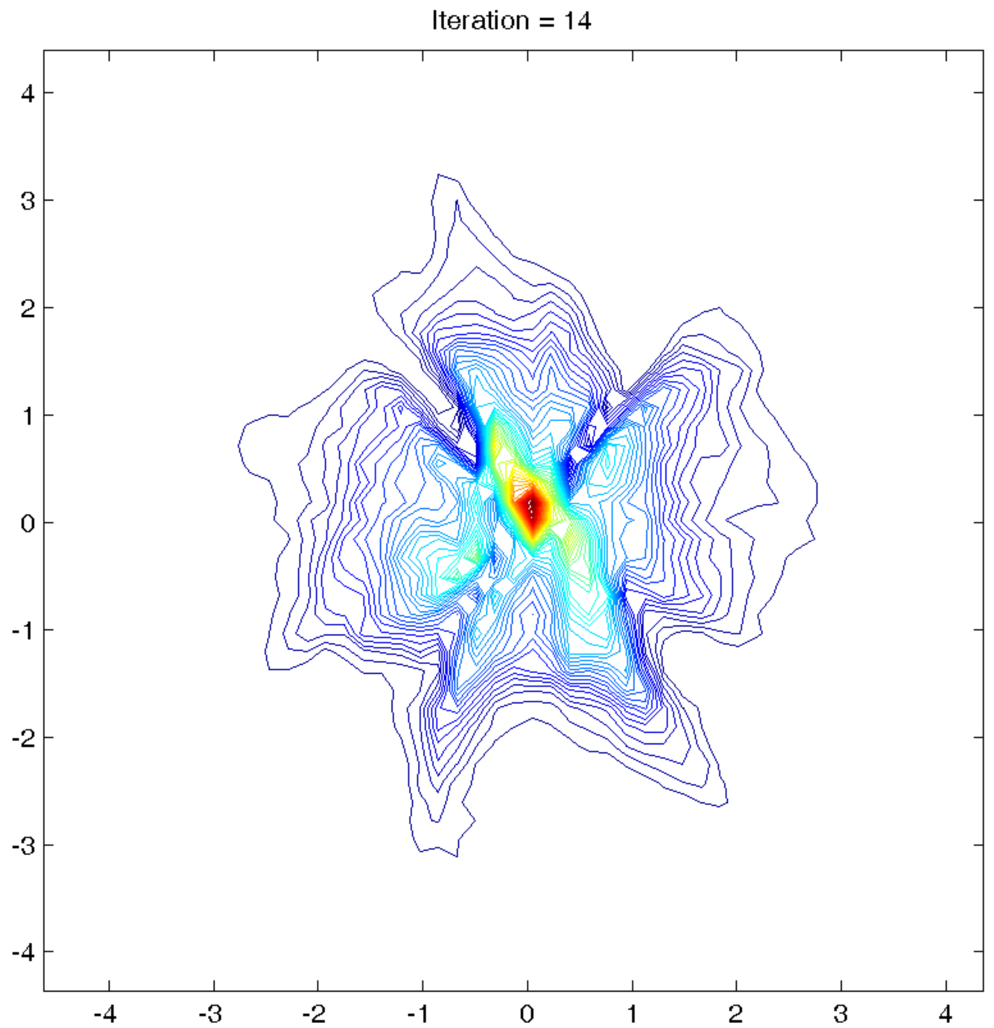

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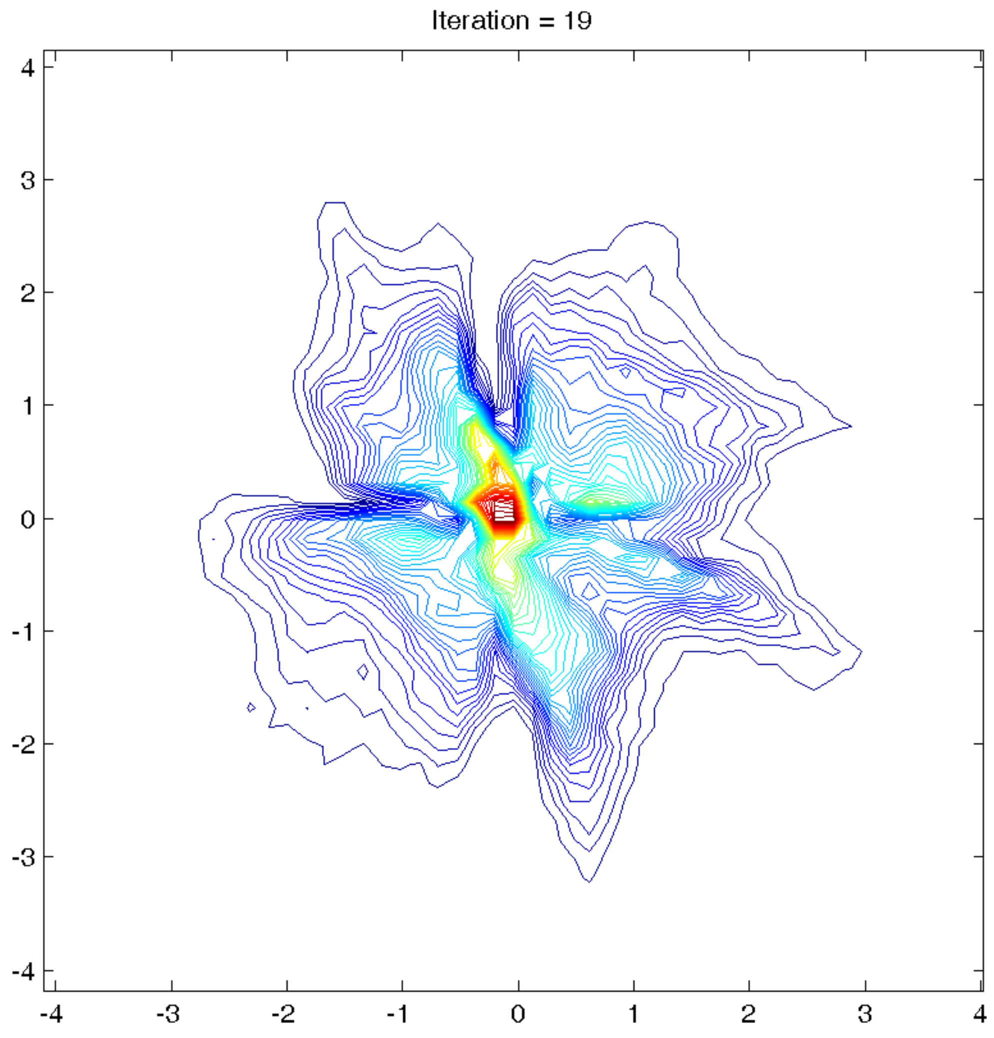

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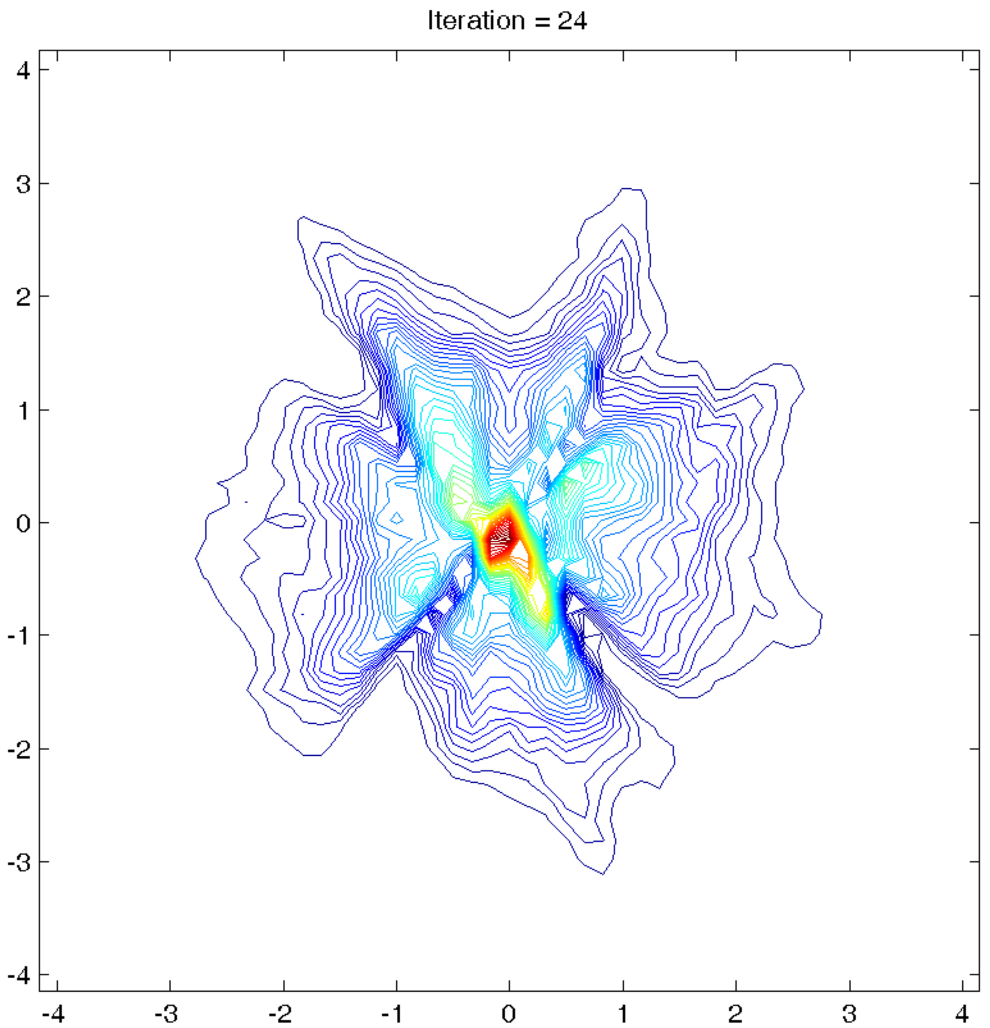

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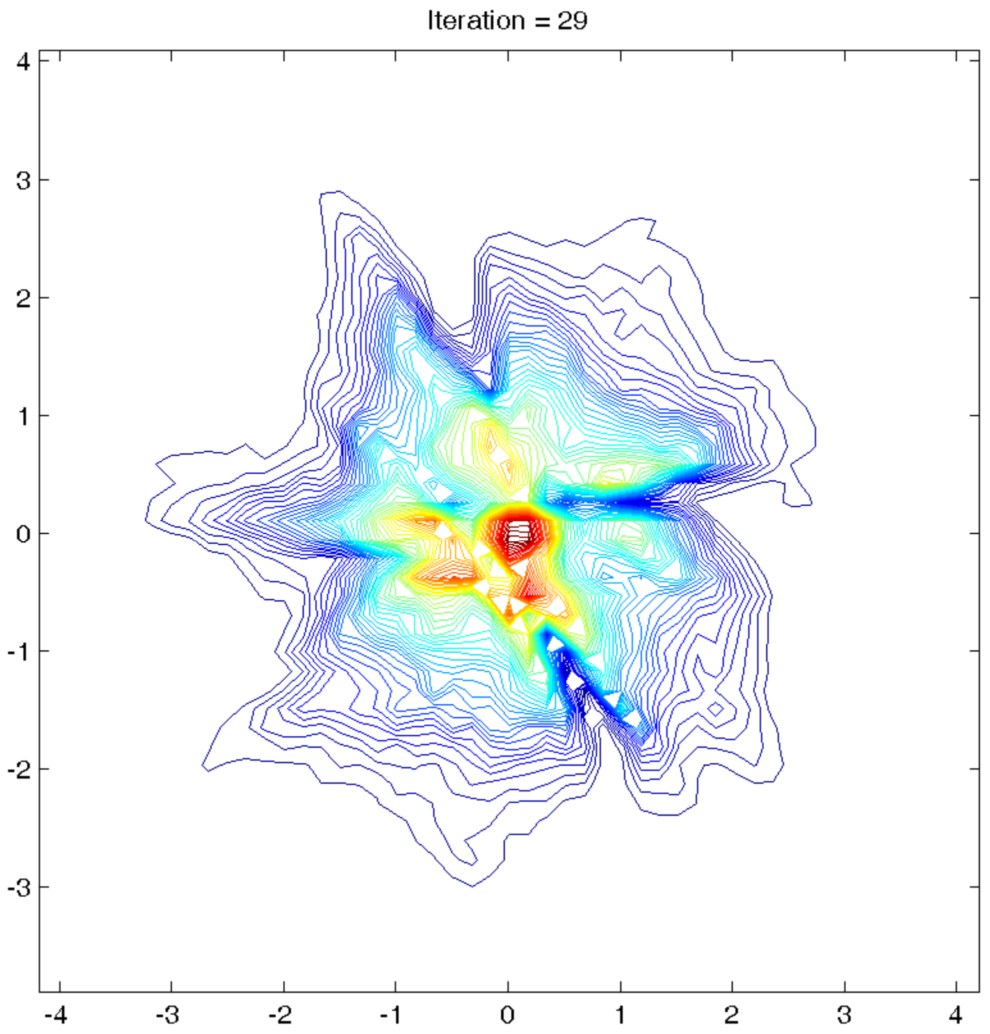

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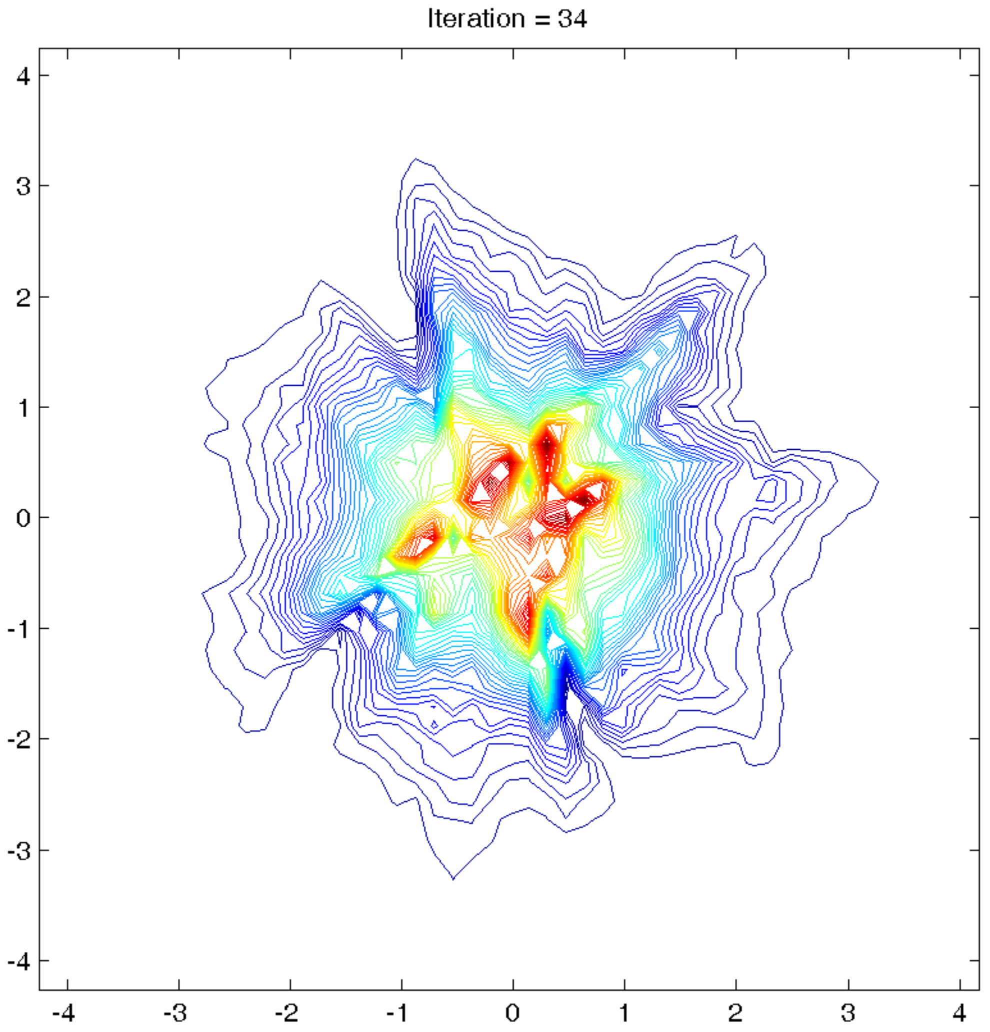

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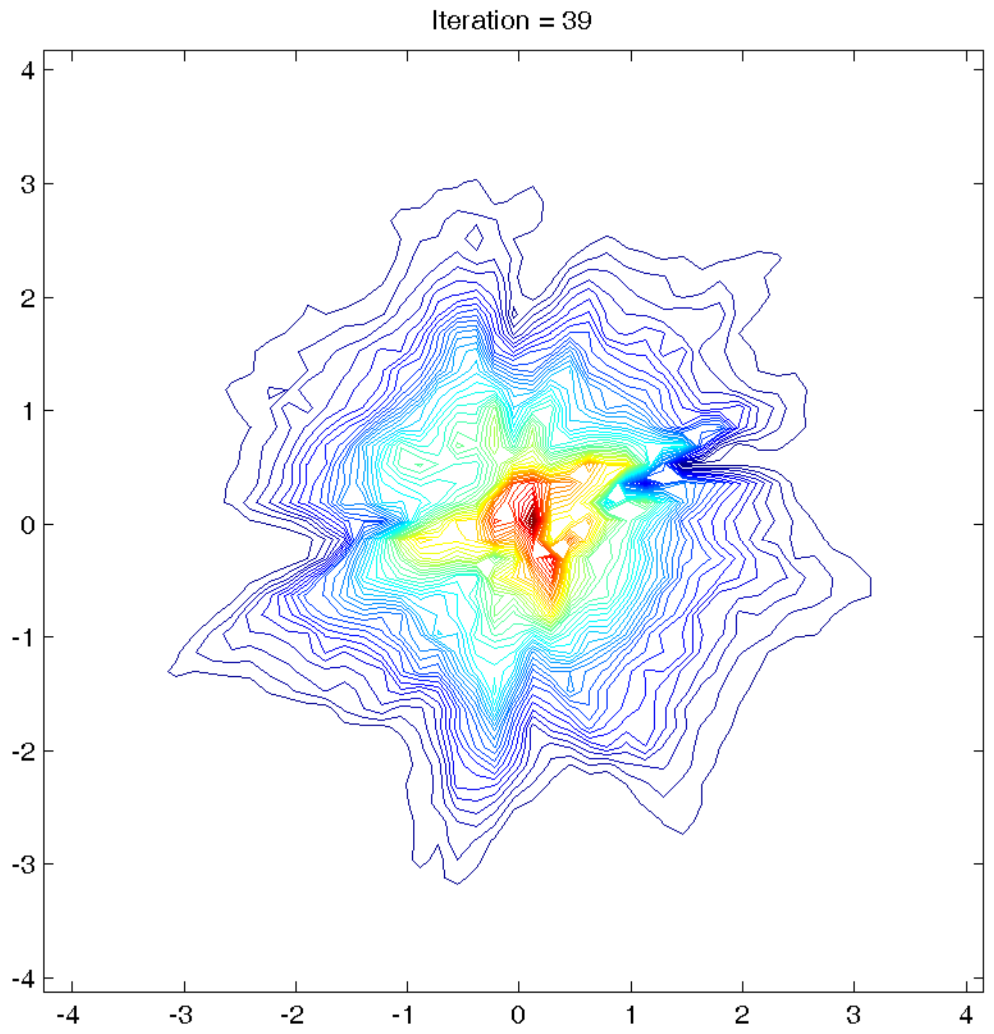

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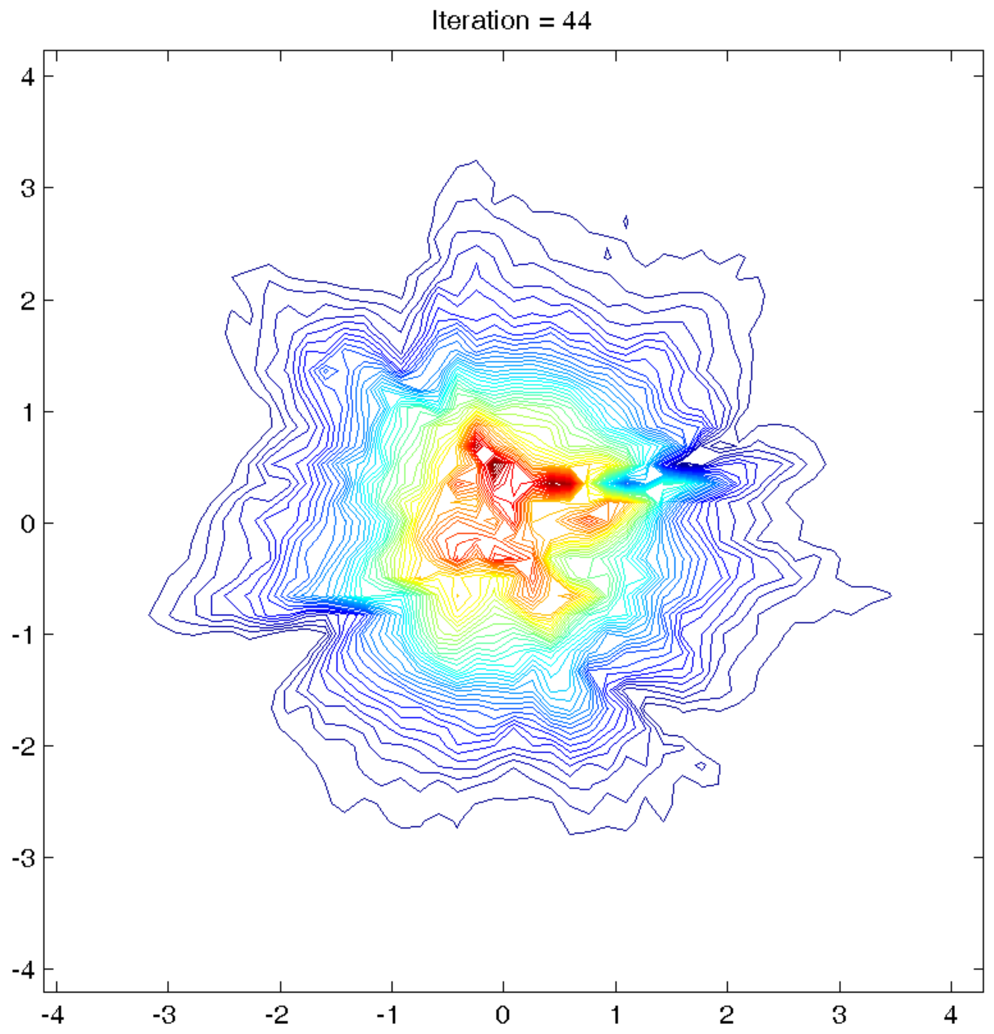

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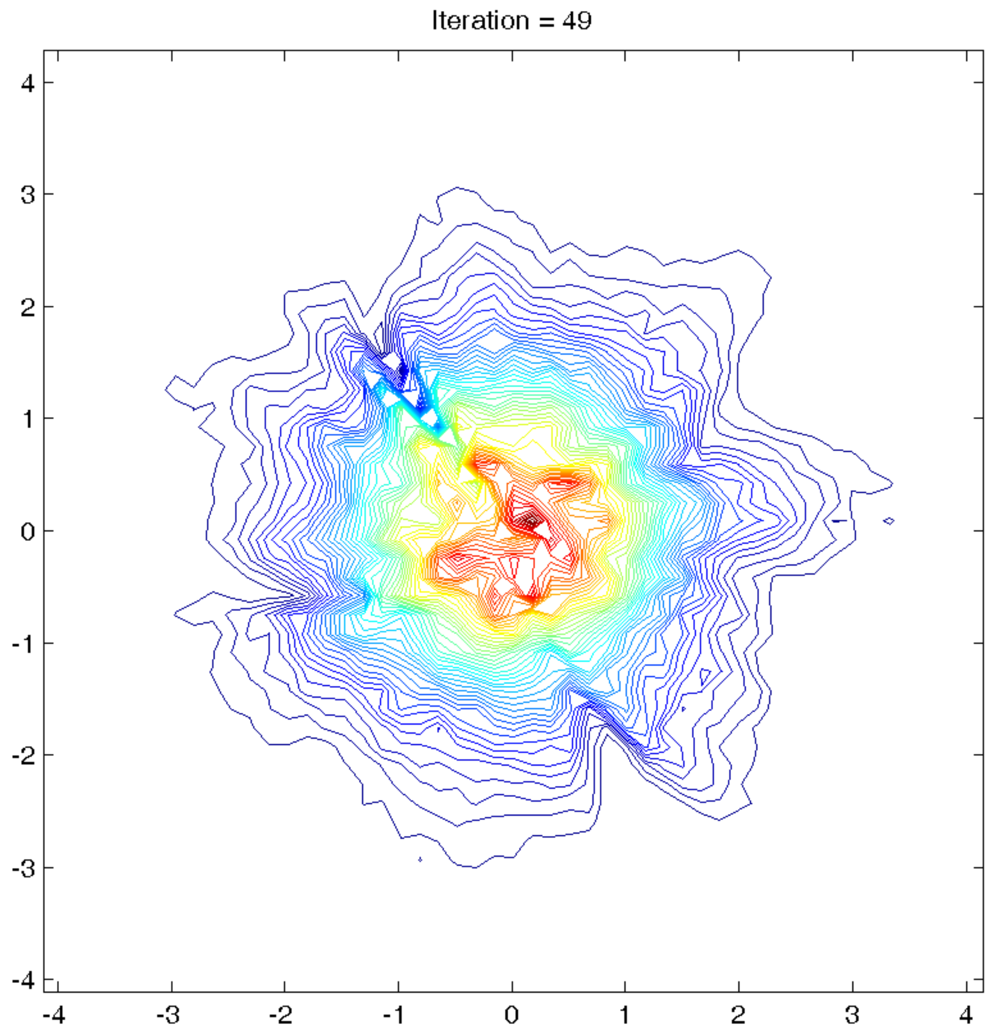

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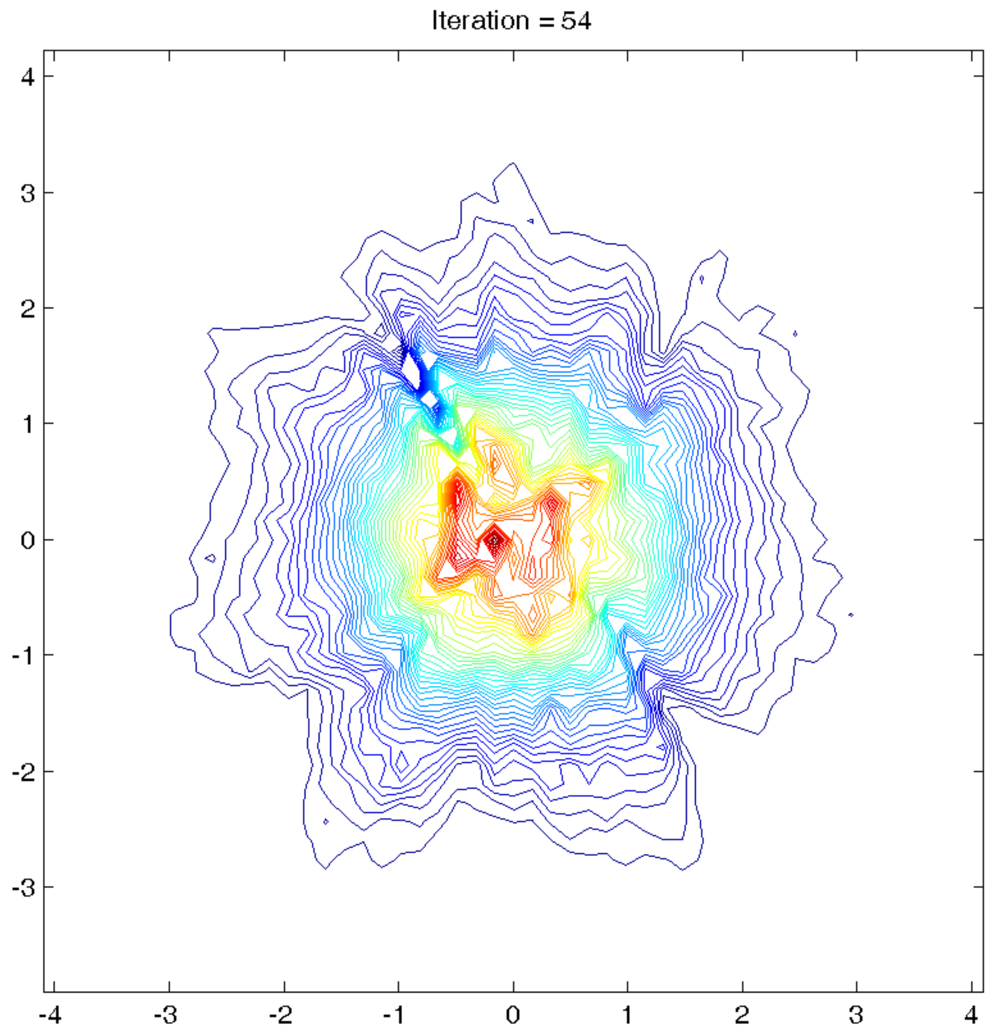

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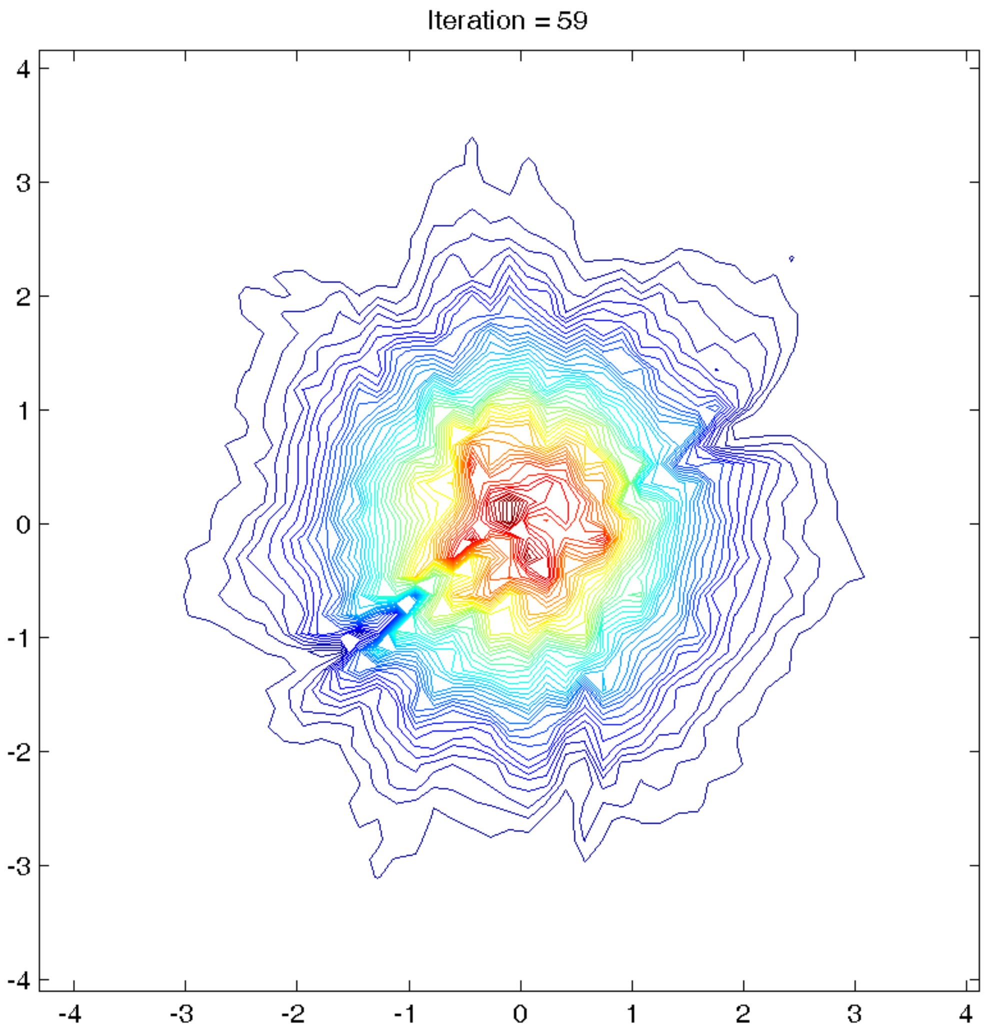

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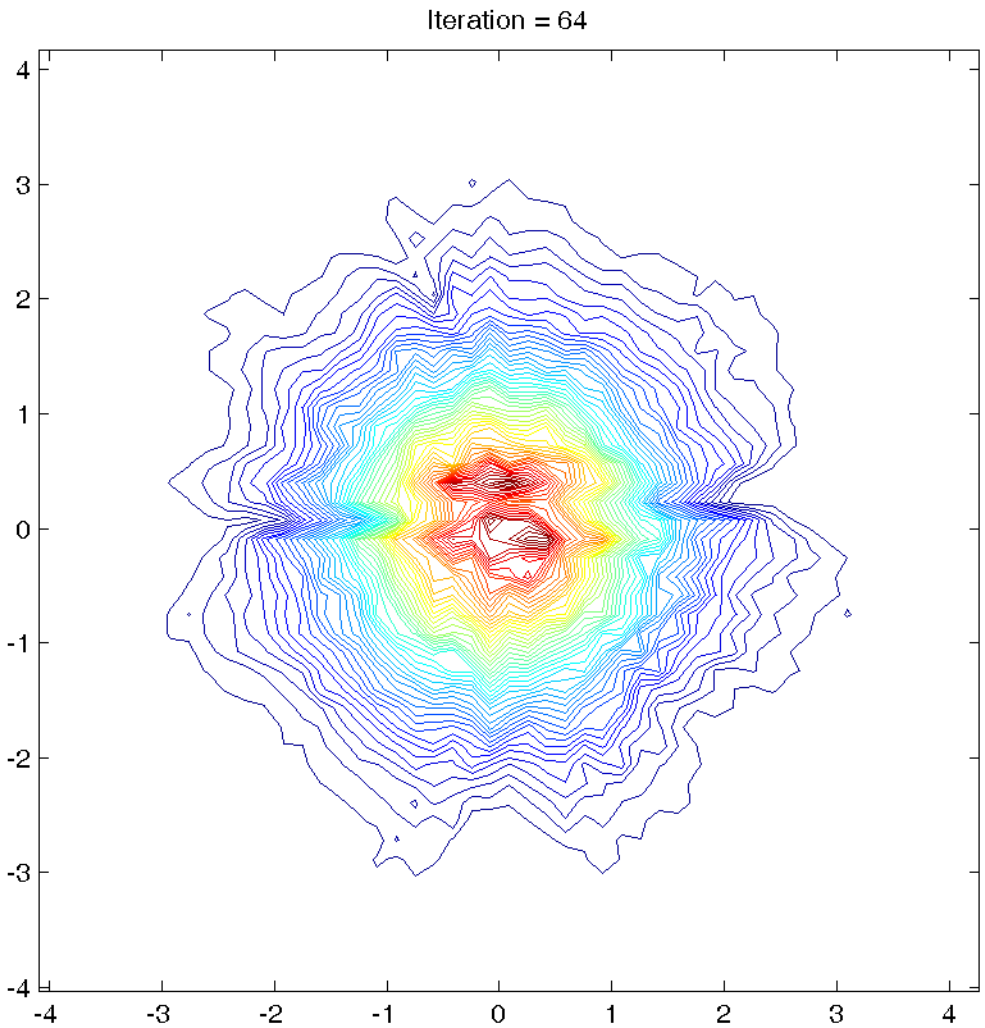

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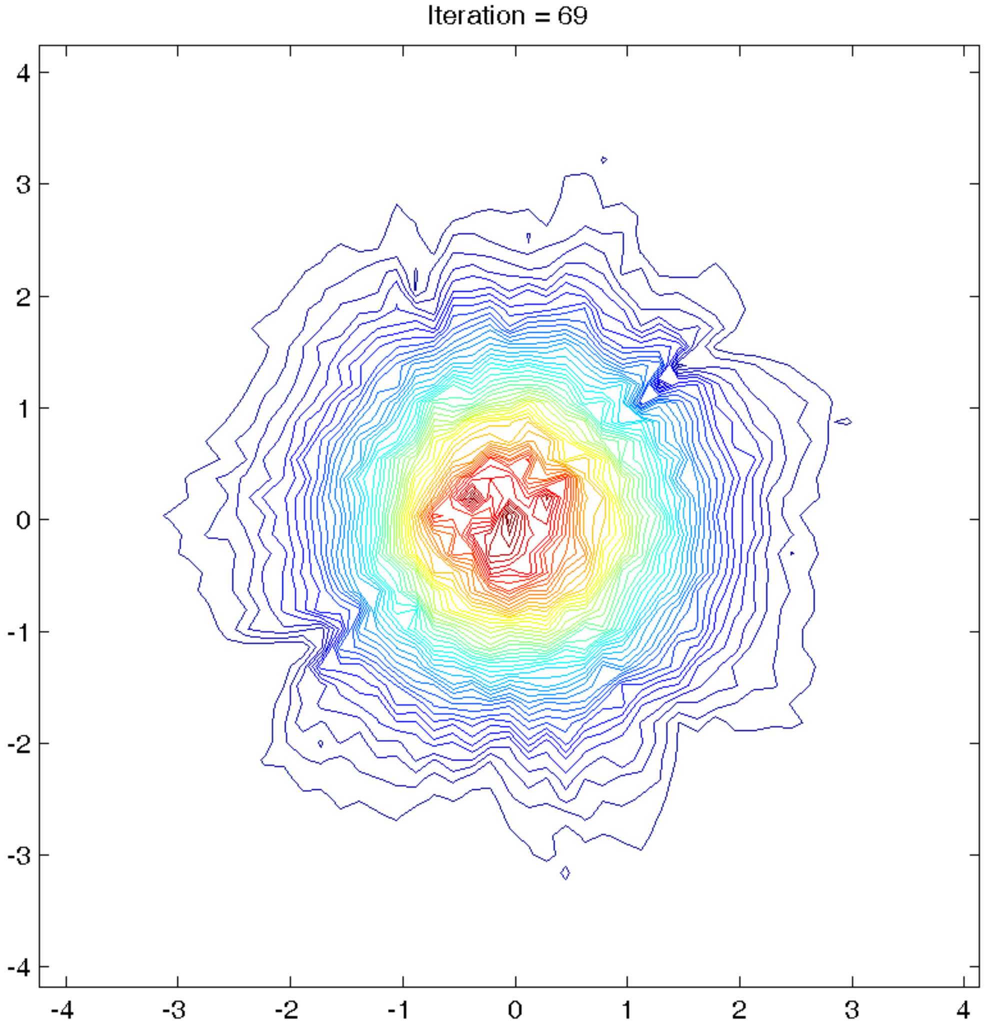

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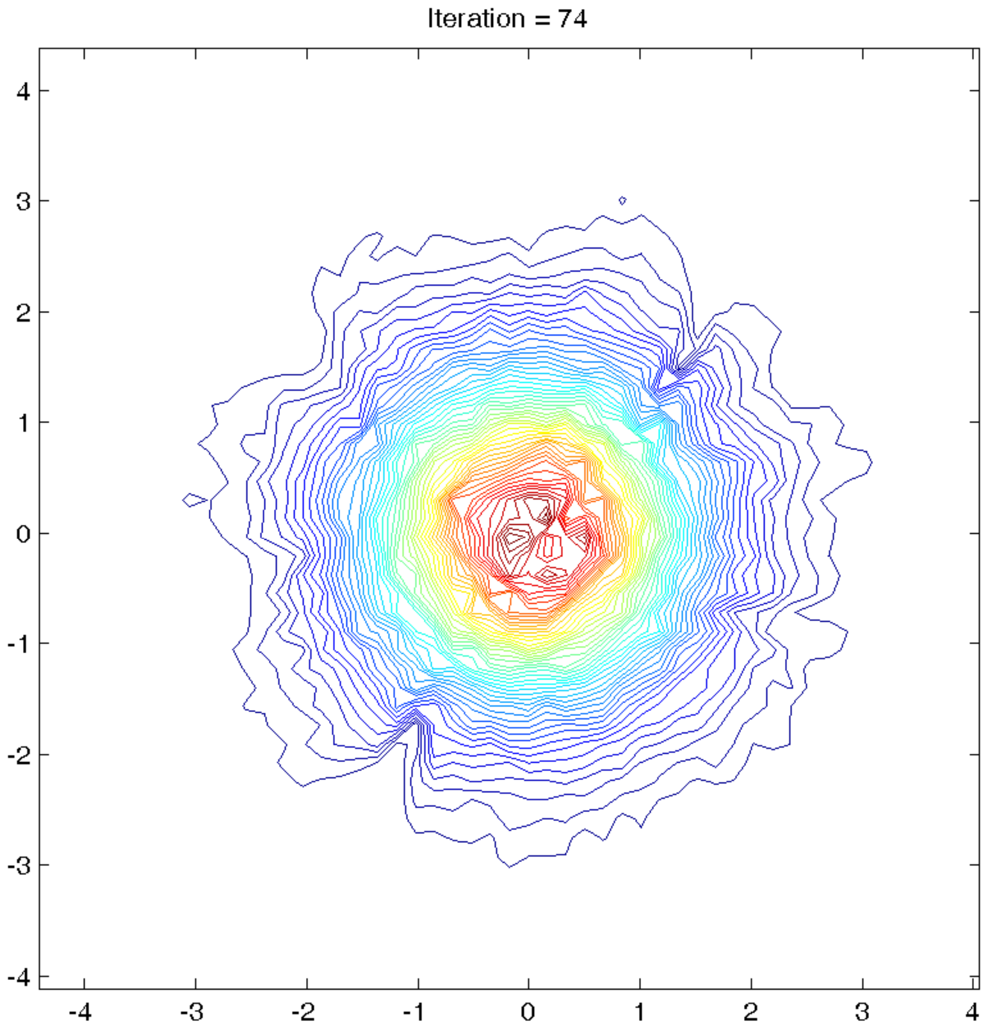

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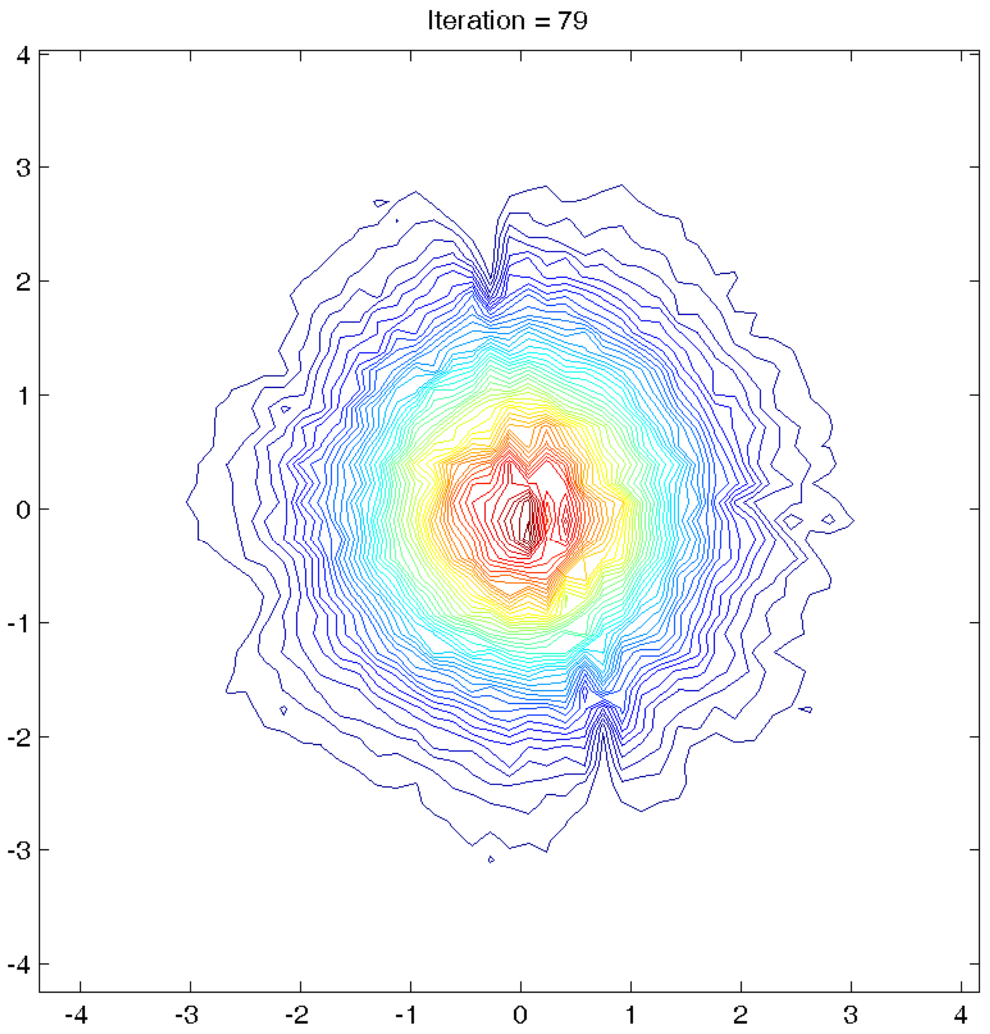

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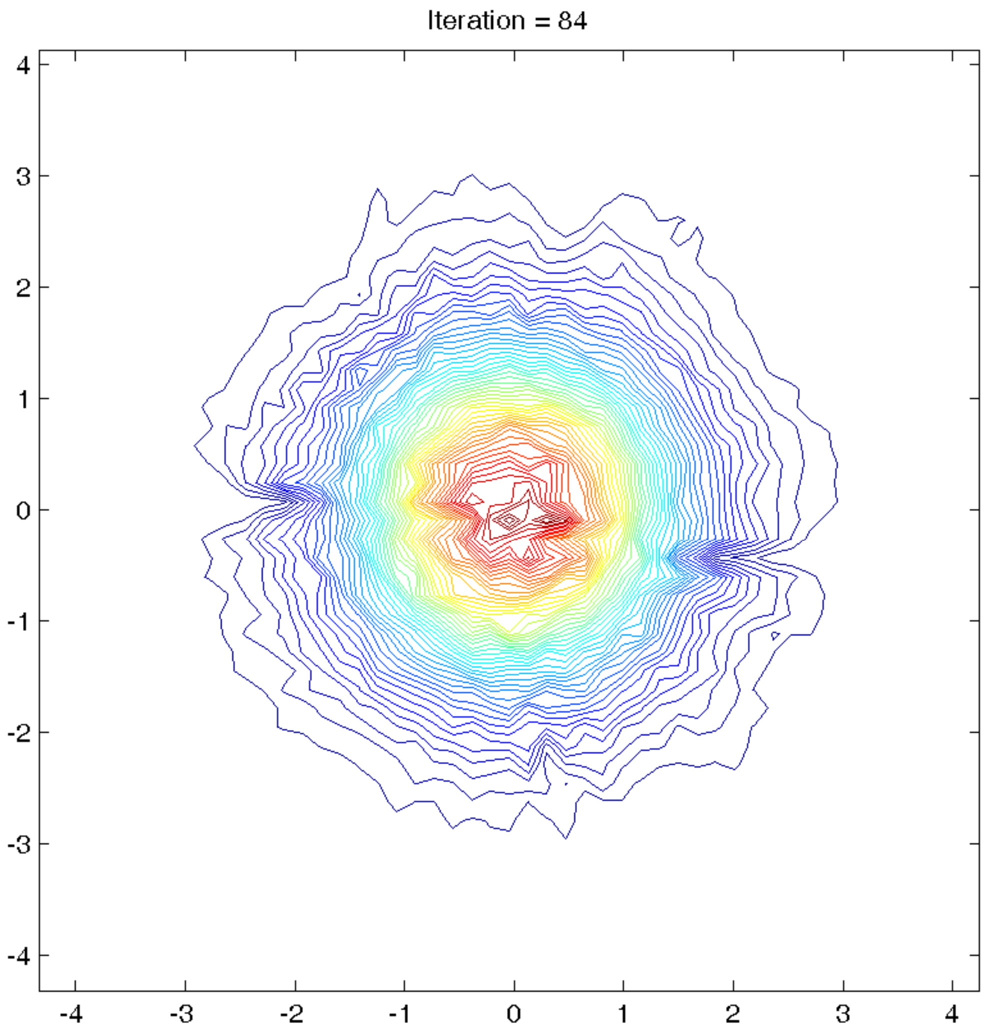

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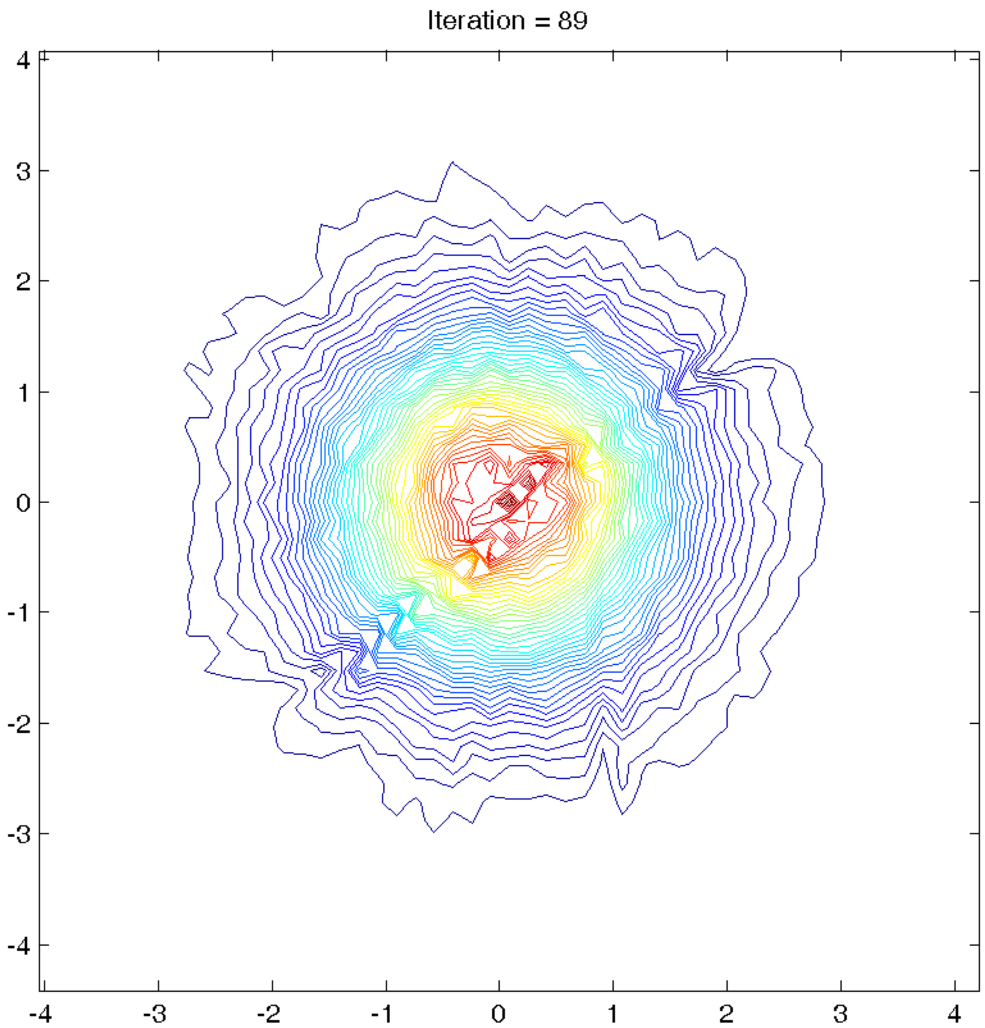

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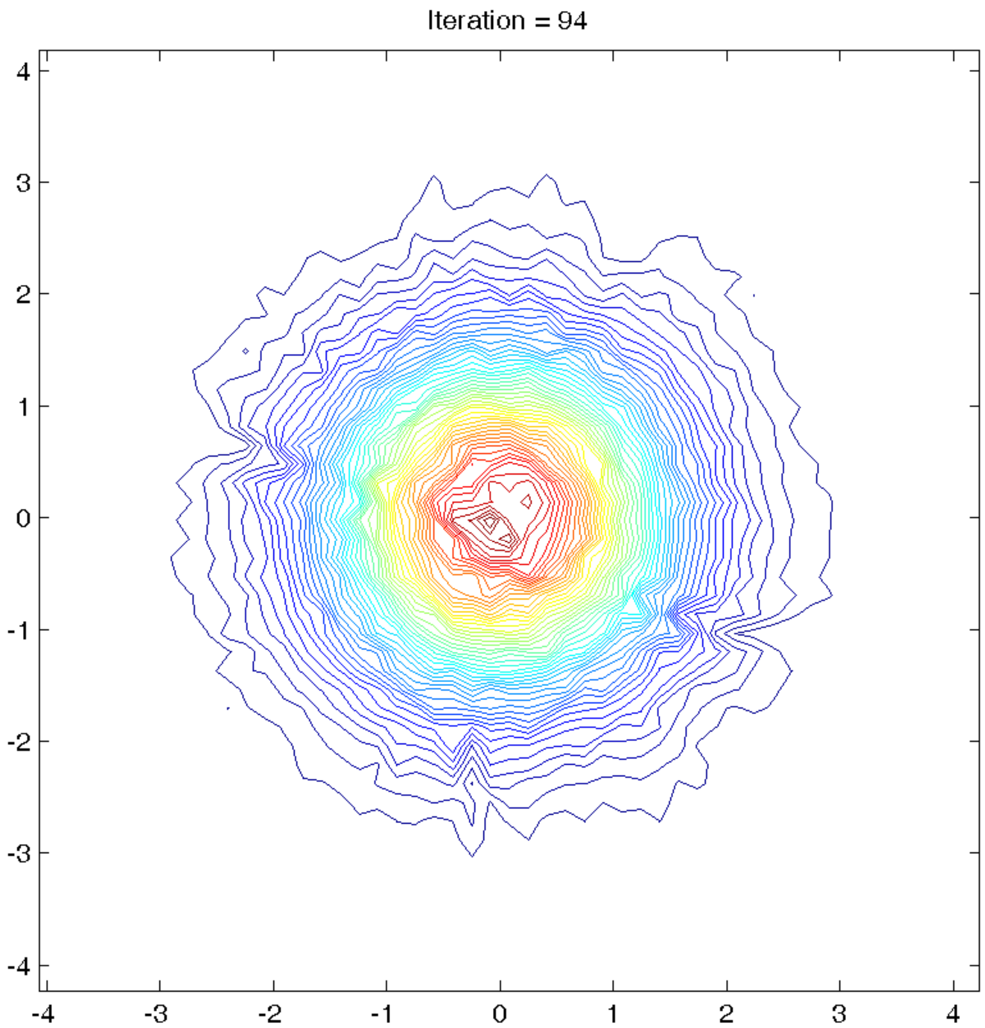

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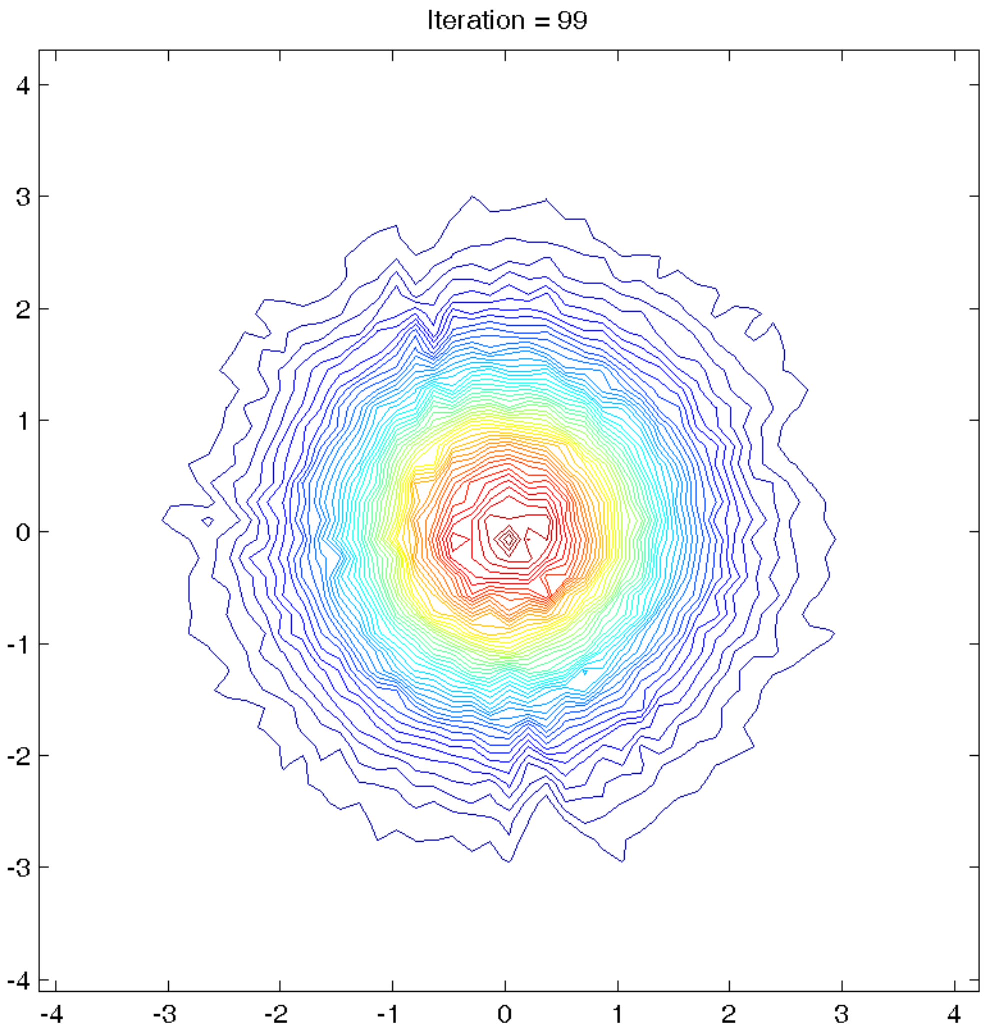

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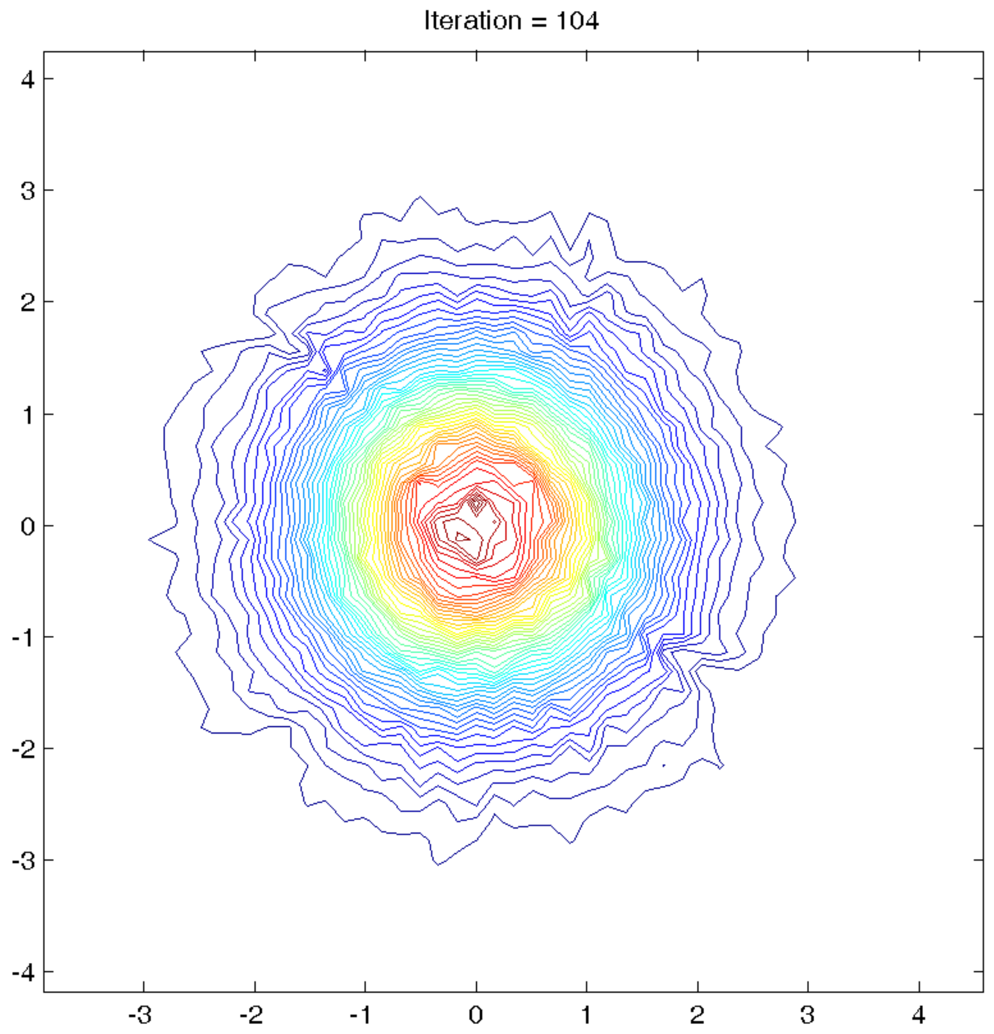

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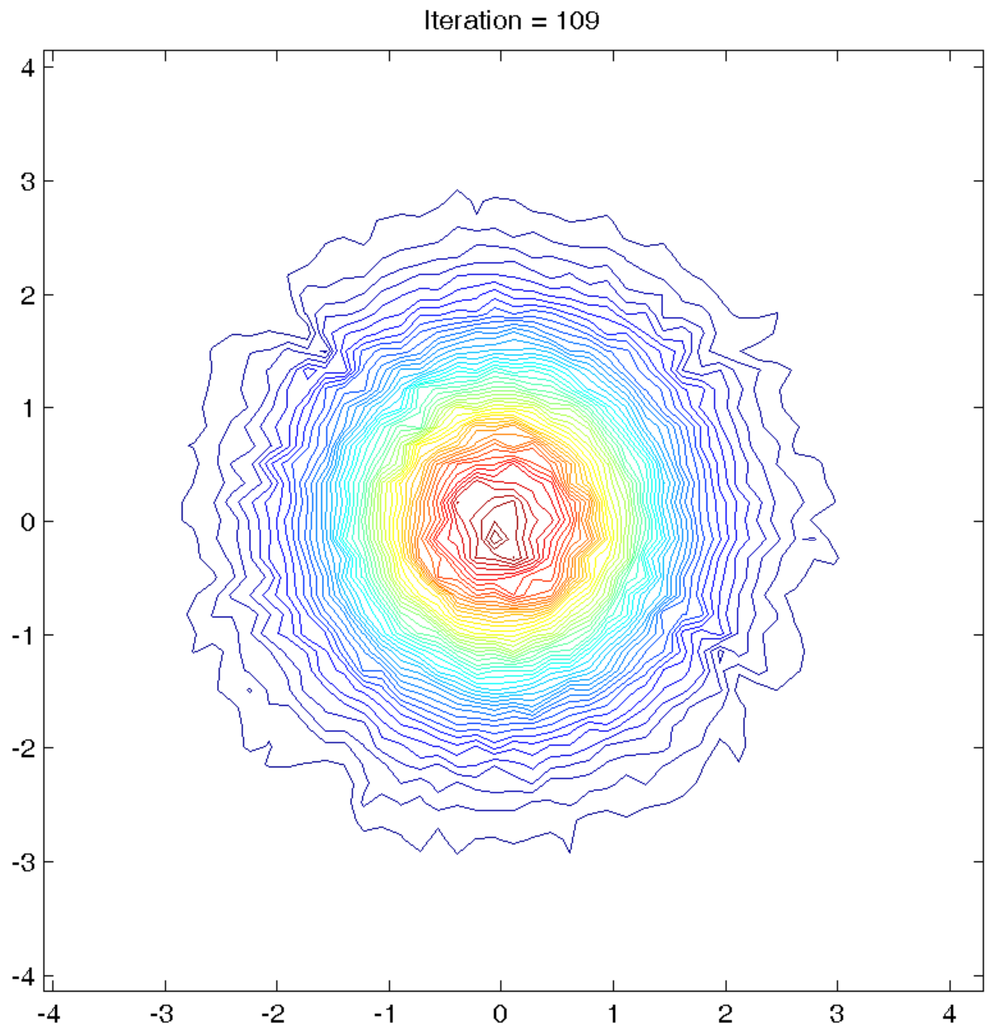

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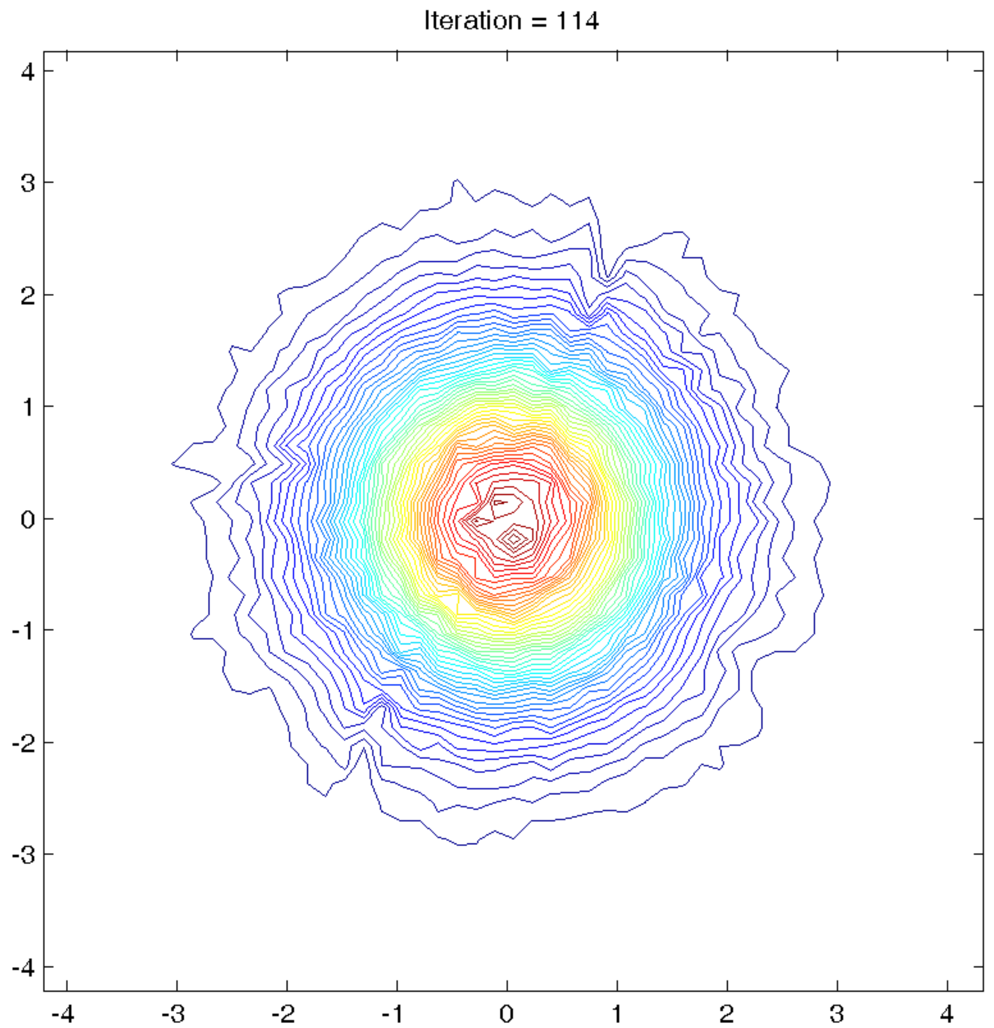

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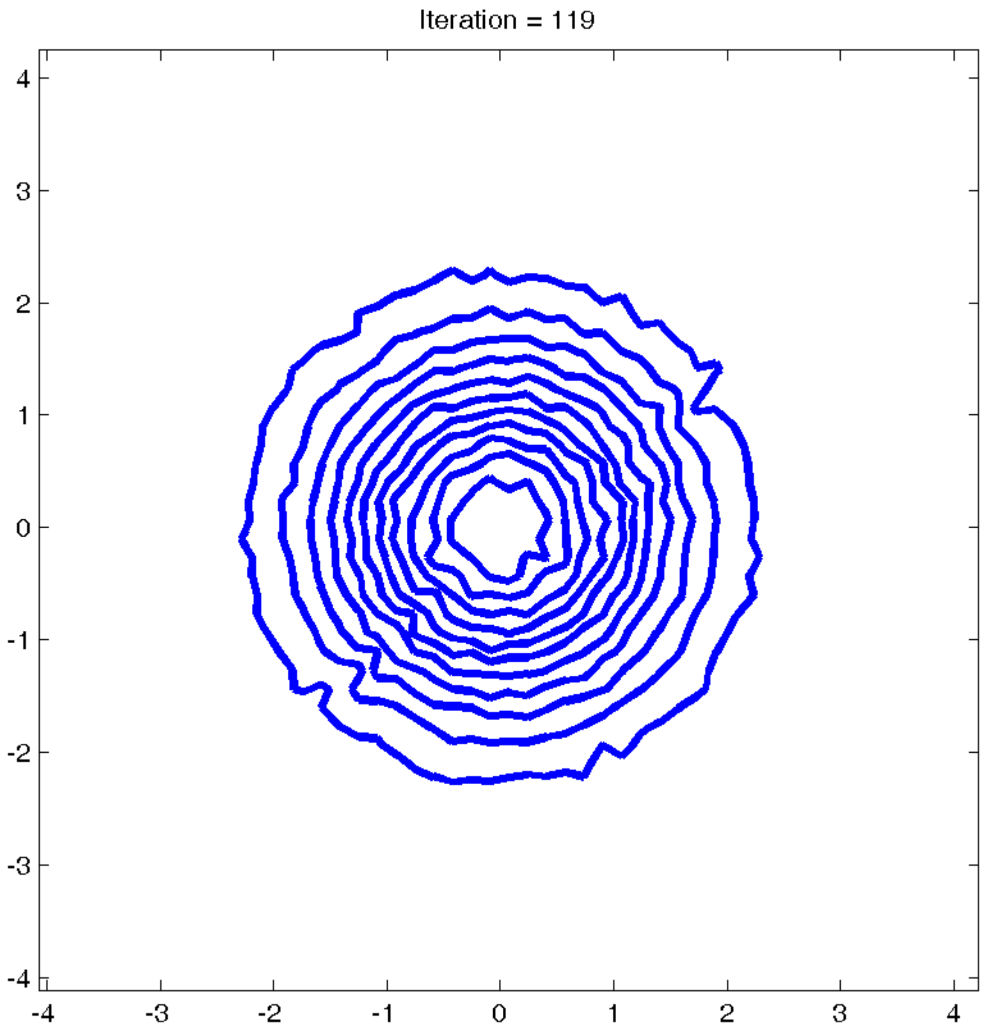

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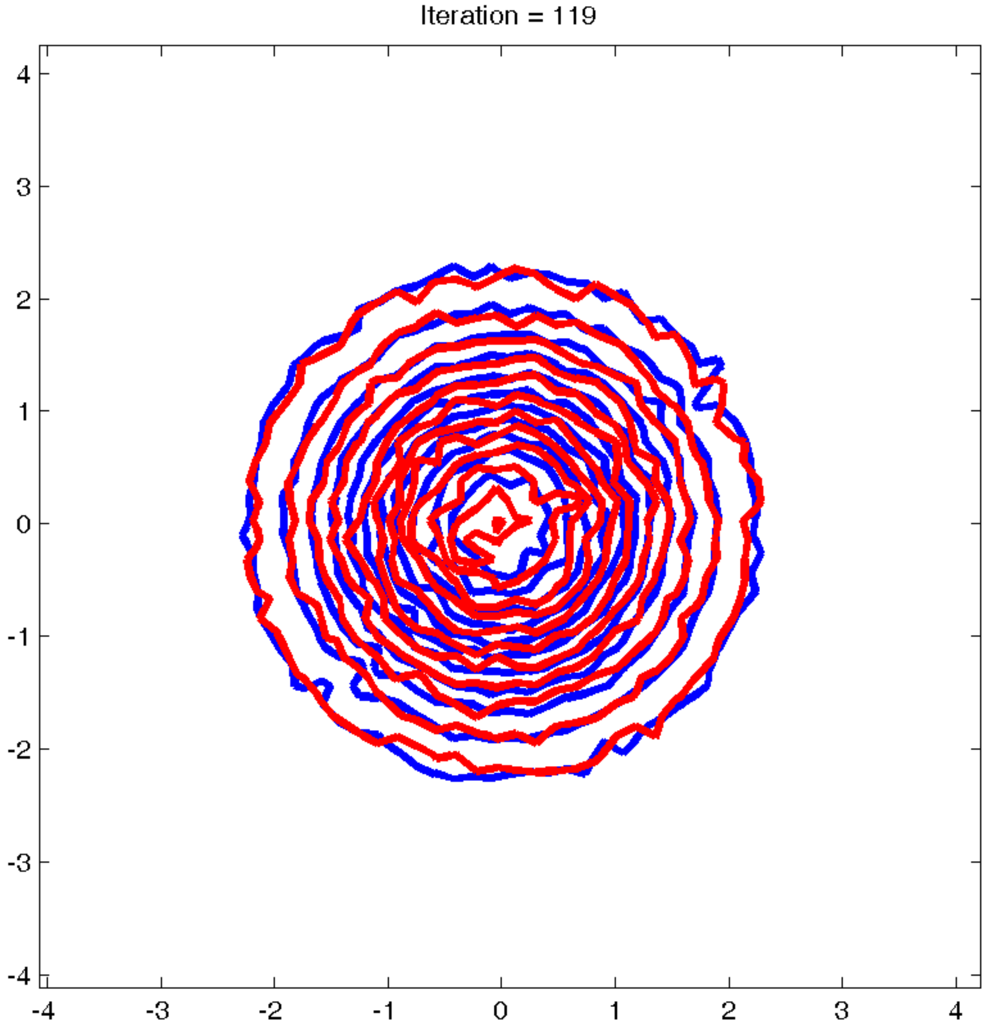
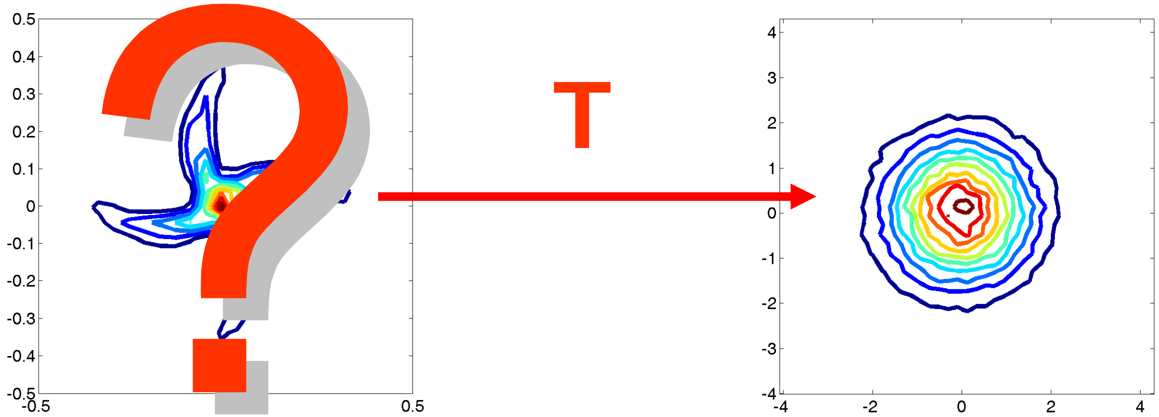


OUR APPROACH

$$Y = T(X)$$

$$P_X = P_Y * |J_T|$$

- From P(x) to P(y) (Gaussian)



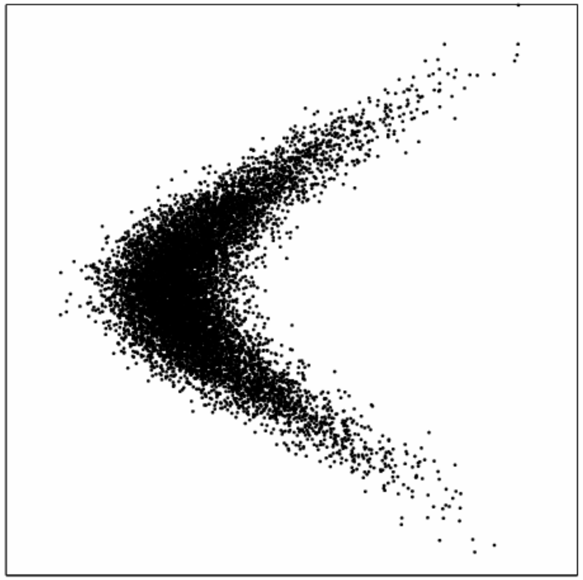
GPCA Jacobian

$$\nabla_{\mathbf{x}} \mathcal{G} = \prod_{k=1}^{N} \mathbf{B}_{(k)} \cdot \nabla_{\mathbf{x}^{(k)}} \Psi_{(k)}$$

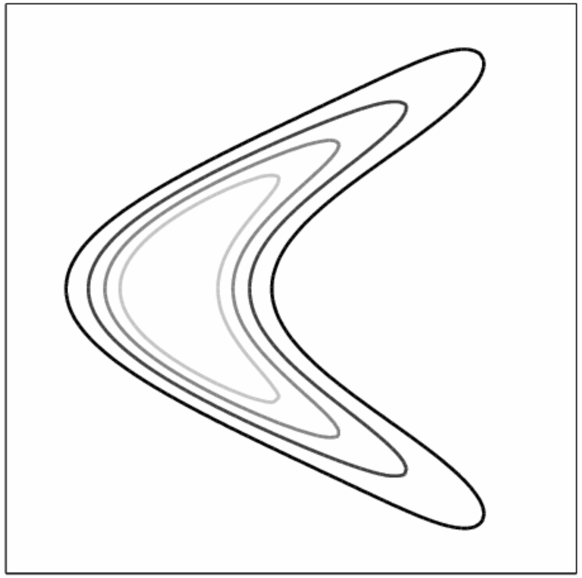
$$\nabla_{\mathbf{x}^{(k)}} \Psi_{(k)} = \begin{pmatrix} \frac{\partial \Psi^1_{(k)}}{\partial x^{(k)}_1} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \frac{\partial \Psi^d_{(k)}}{\partial x^{(k)}_d} \end{pmatrix}$$

$$\frac{\partial \Psi^i_{(k)}}{\partial x^{(k)}_i} = \frac{\partial G}{\partial u} \cdot \frac{\partial u}{\partial x^{(k)}_i} = \left(\frac{\partial G^{-1}}{\partial x_i} \right)^{-1} \cdot p_i(x^{(k)}_i) = g(\Psi^i_{(k)}(x^{(k)}_i))^{-1} \cdot p_i(x^{(k)}_i)$$

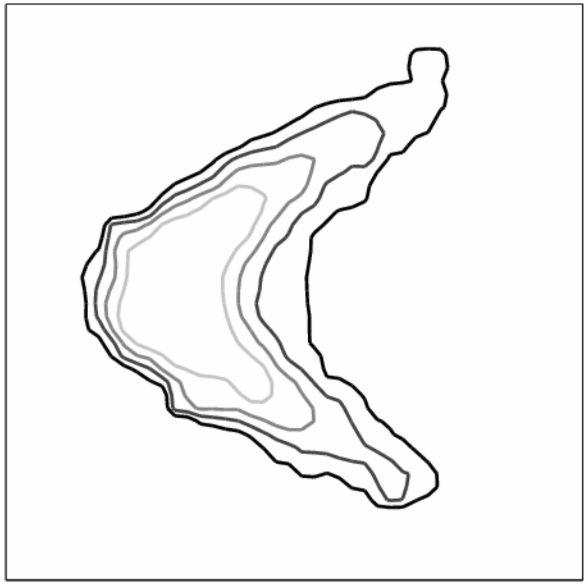
G-PCA – PDF estimation



DATA



ANALYTICAL PDF



G-PCA APPROACH

EXPERIMENTS

Gaussianization-PCA	**vs**	**SVDD**
(PDF)		**(Boundary)**

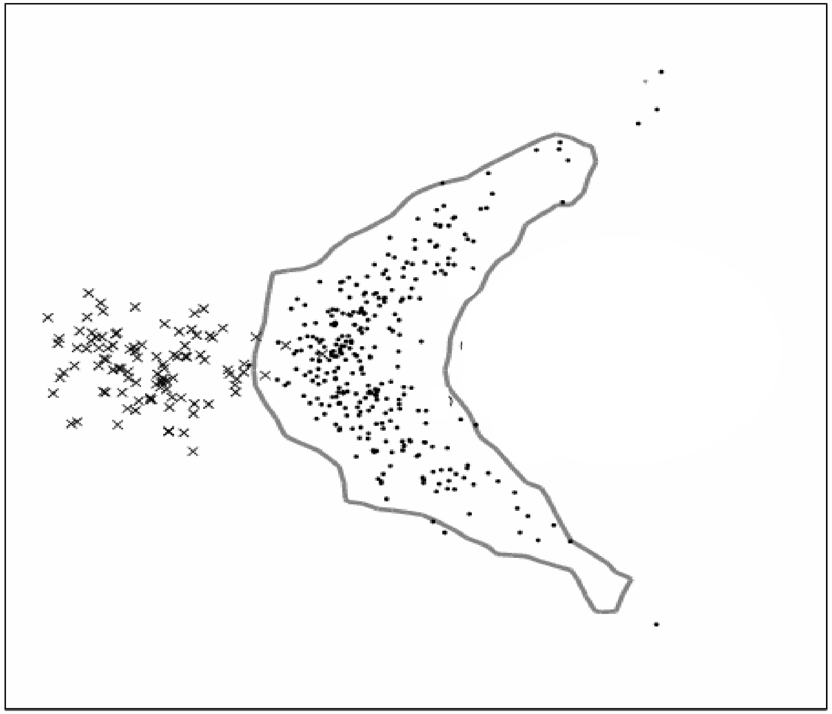
- 2D EXAMPLE (TOY EXAMPLE)

- 10D EXPERIMENT (REAL DATA EXAMPLE)

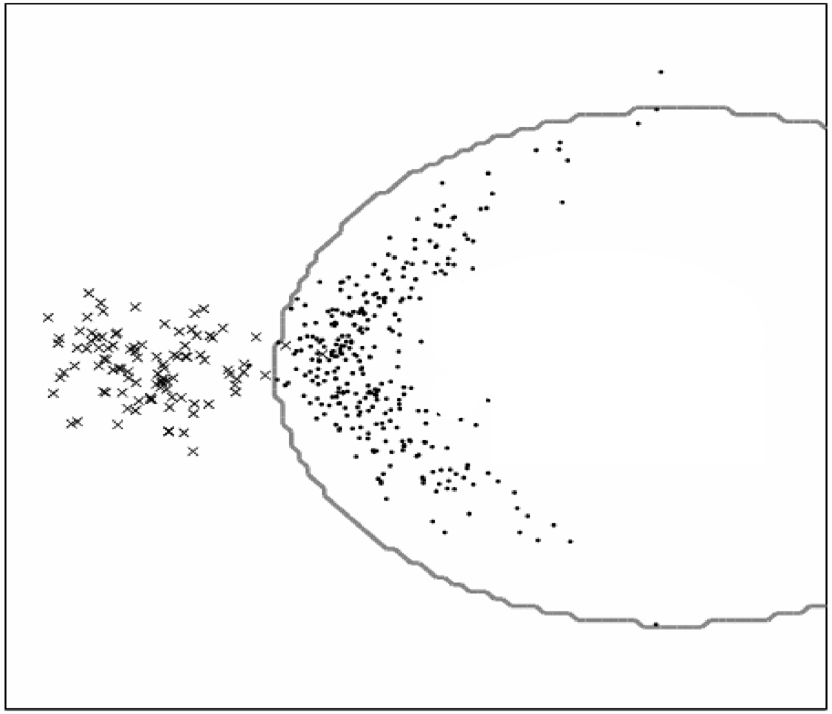
- TRAINING

Parameters: obtained to maximizing Kappa

TOY EXAMPLE GPCA vs SVDD



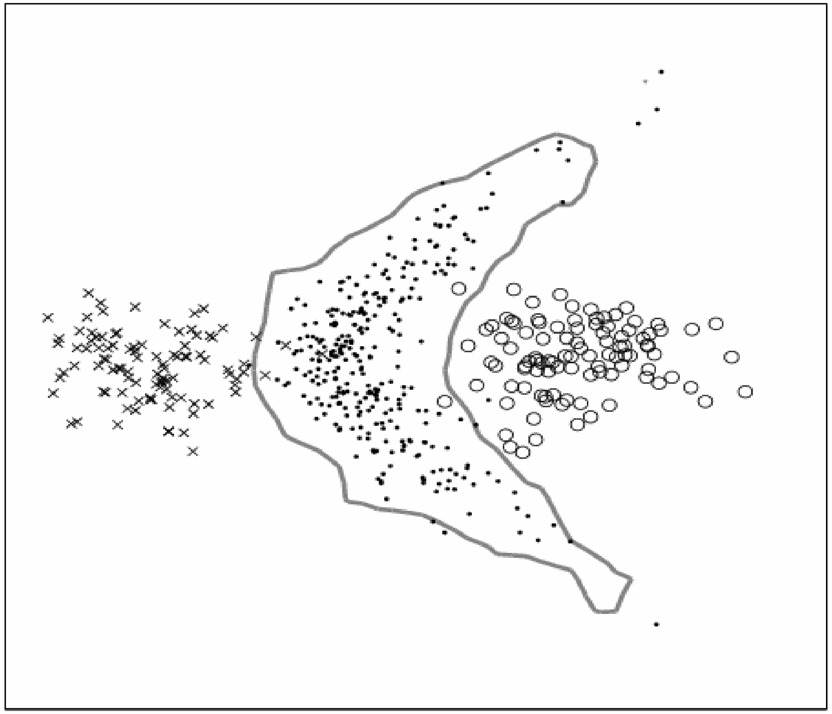
G-PCA



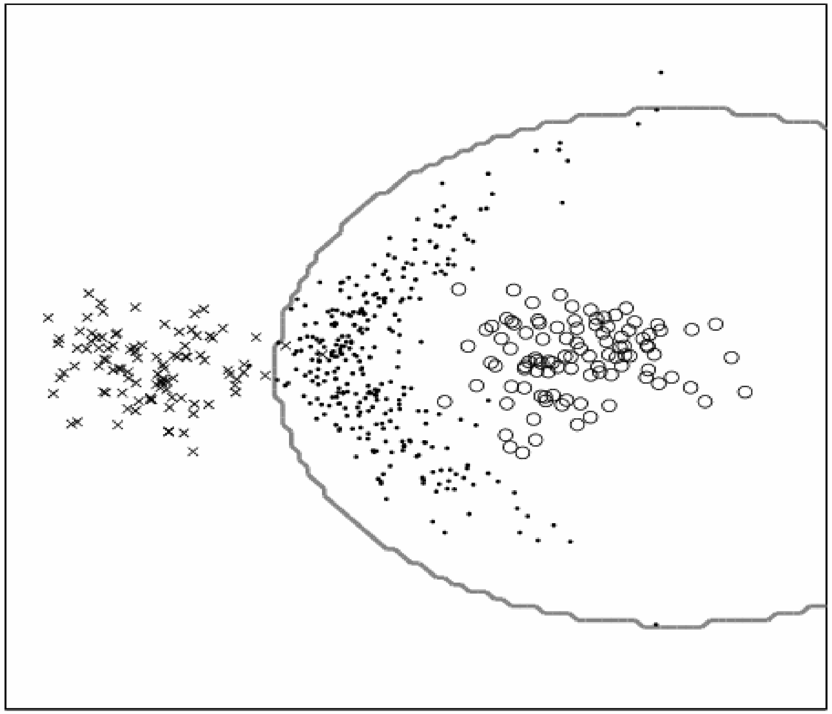
SVDD

- PROBLEM WITH NO TARGET SAMPLES
- PROBLEM WITH THE REPRESENTATIVITY OF NO TARGET SAMPLES

TOY EXAMPLE GPCA vs SVDD



G-PCA



SVDD

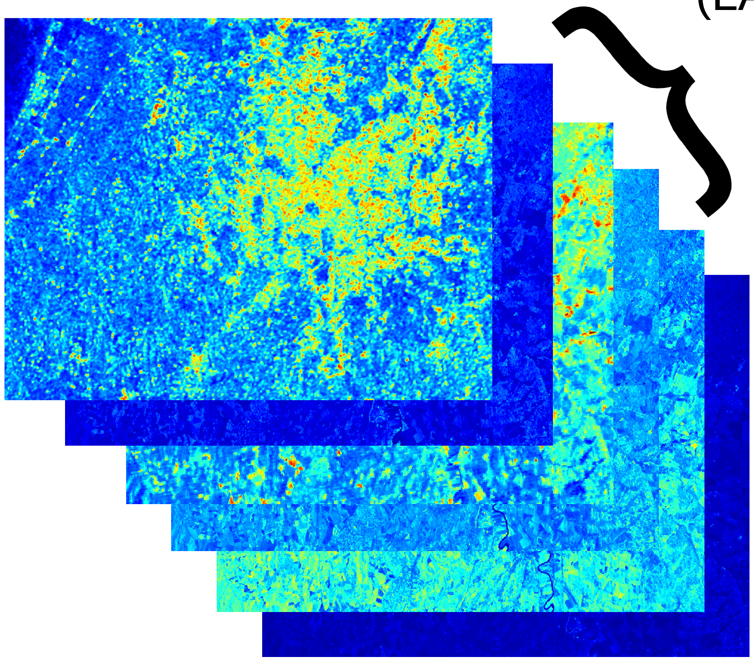
- PROBLEM WITH NO TARGET SAMPLES
- PROBLEM WITH THE REPRESENTATIVITY OF NO TARGET SAMPLES

10D EXPERIMENT RESULTS

- REAL DATA: 3 MULTISOURCE IMAGES

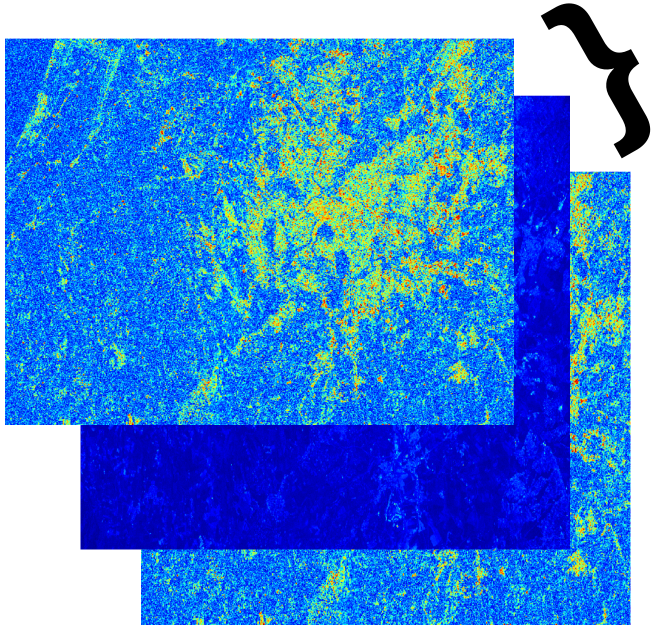
7 OPTIC BANDS

(LANDSAT)

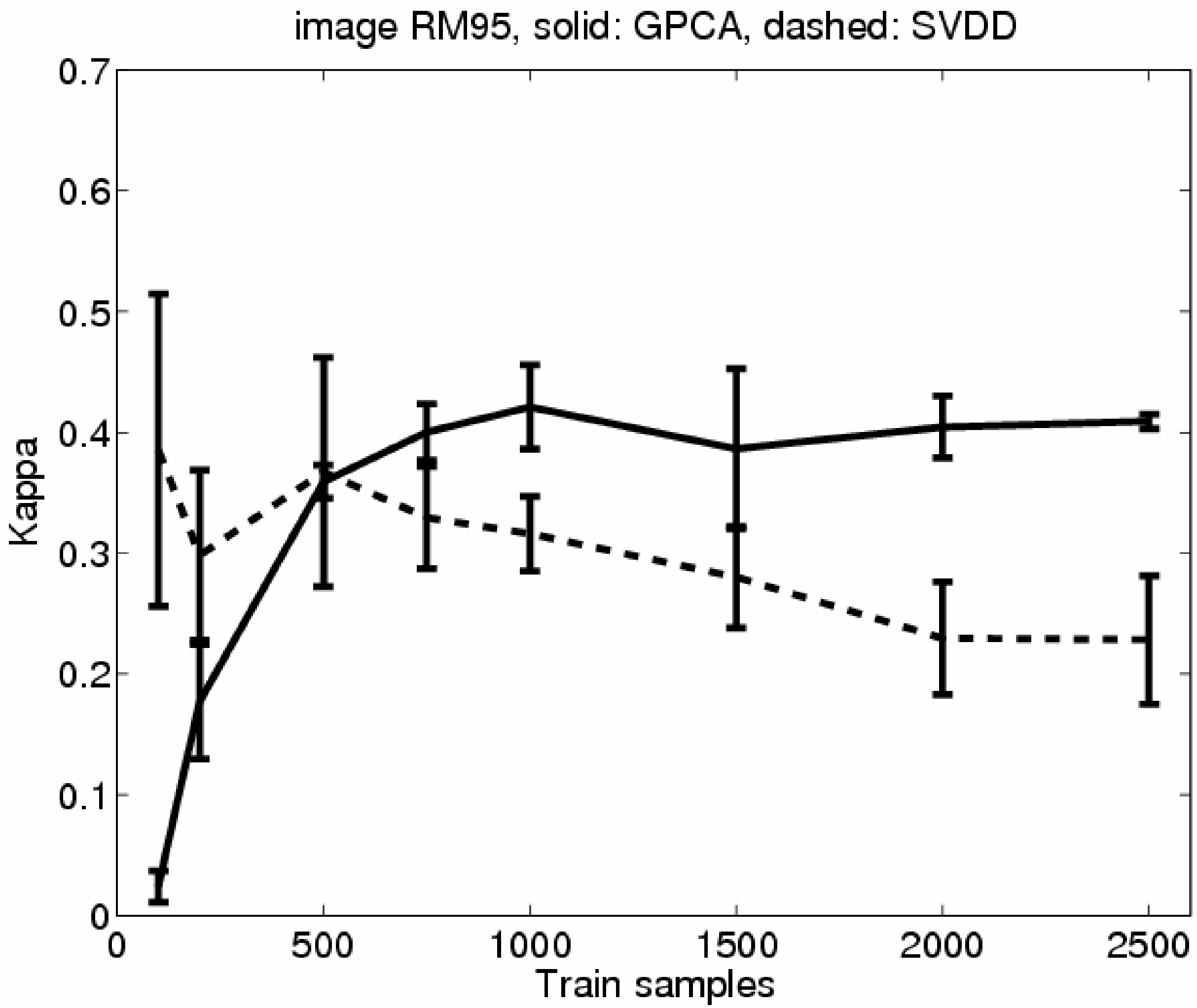


3 SAR BANDS

(ERS)



10D EXAMPLE RESULTS



Test region:

930 x 1440 pixels

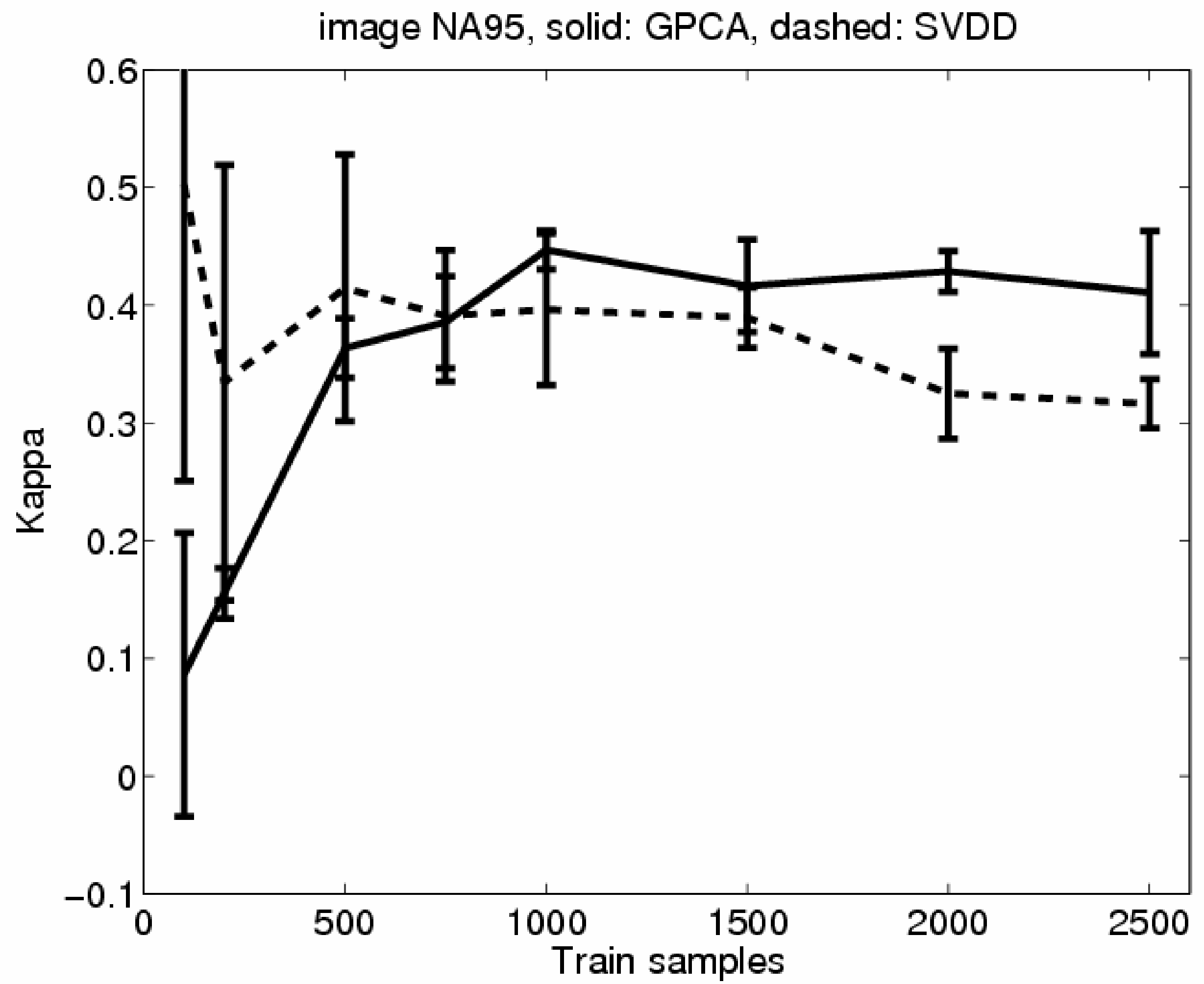
Test samples:

100.000

No-target samples:

10

10D EXAMPLE RESULTS



Test region:

930 x 1440 pixels

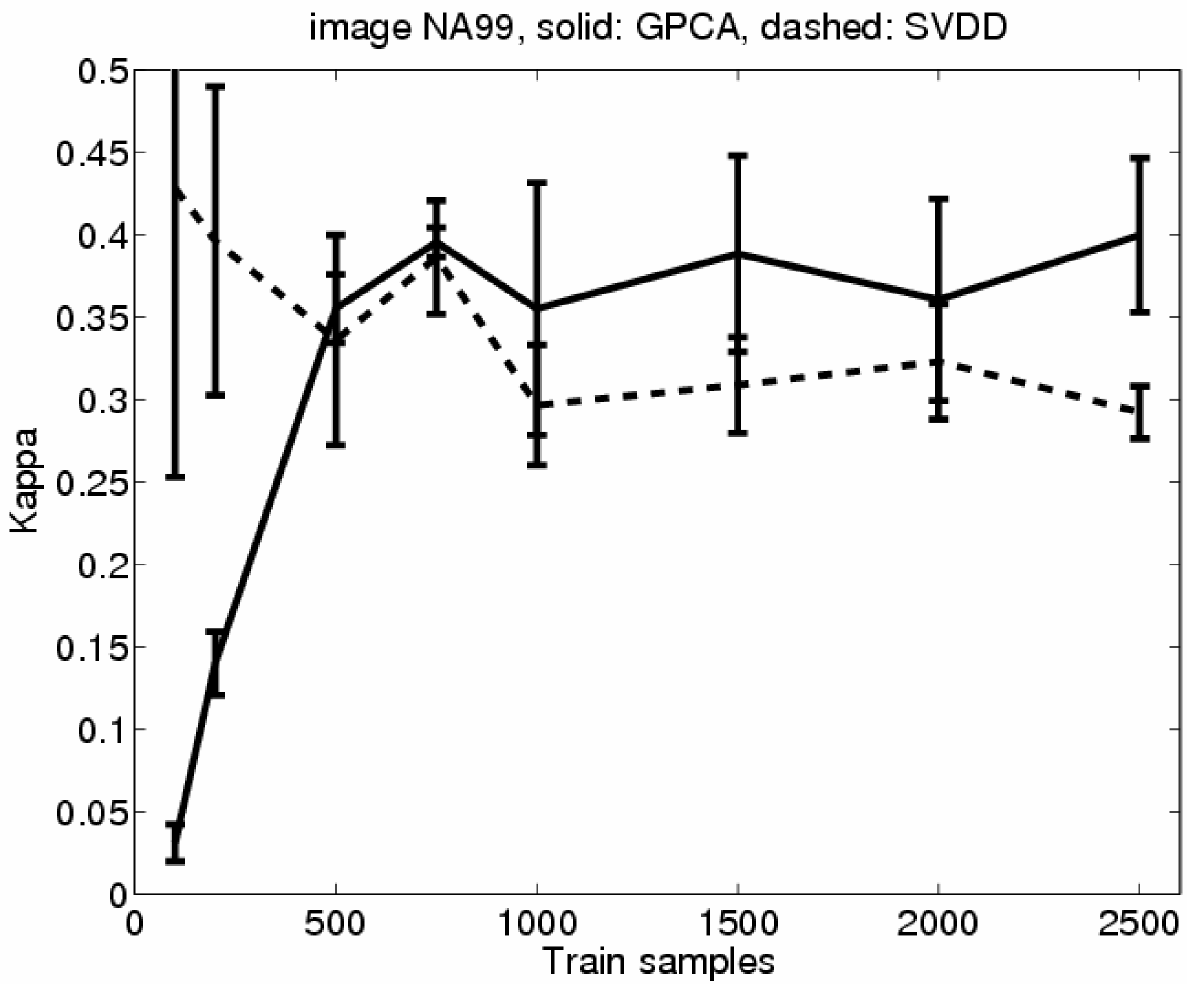
Test samples:

100.000

No-target samples:

10

10D EXAMPLE RESULTS



Test region:

930 x 1440 pixels

Test samples:

100.000

No-target samples:

10

10D EXAMPLE RESULTS

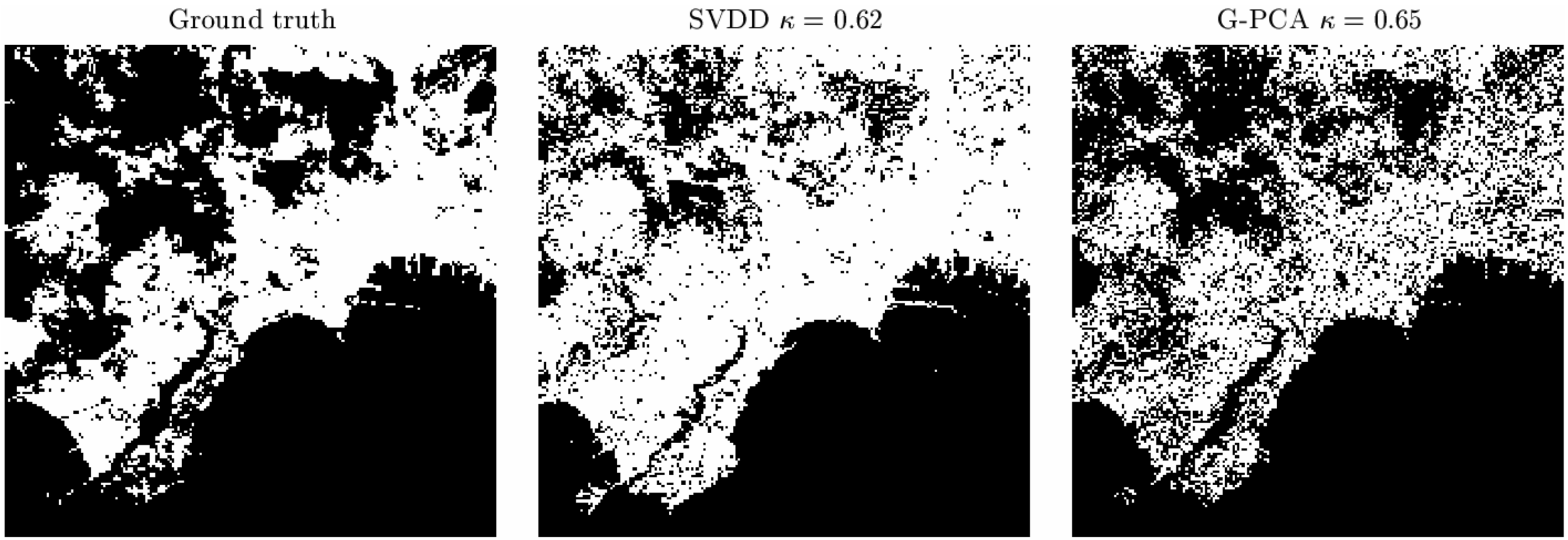
Test region: 200 x 200 pixels

Test samples: 40.000

No-target samples: 10

Target samples: 2.000

Image NA99



CONCLUSIONS

- Gaussianization-PCA can be used to characterize the PDF of a data without assuming a explicit model.
- Boundary estimation (SVDD) vs PDF estimation (GPCA):
  - Boundary estimation method works better with few samples, however it needs samples of non-target class.
  - PDF estimation characterizes better the target class without non-target class information.

FURTHER WORK

- Include spatial information.
- Test the performance of the algorithms with different number of non-target samples.
- Compare with other one-class methods (Boundary and PDF).