

DERIVATIVE FREE OPTIMIZATION

CLASS 4

2025/2026

On the scientific project:

Do

Allowed to copy paste but
put into " " and cite source

Borrow figures but cite the
source

Presenting numerical results:

1/ compare to state of
the art $\rightarrow$ if you want to
prove that a new approach is competitive

Don't

$\rightarrow$ Plagiarism

2/ → report experimental setup to be able to redo experiments

→ quantify error

When describing results:

1/ Describe what is displayed on a graph

↳ on the y axis we have...

↳ ——— x ——— ...

2/ Describe what you observe

3/ Interpret the observation.

Use the right scale to present graphs

↳ don't hesitate to use log scale or log-log scale

Last time we have motivated that to solve ill-conditioned problems, we need to sample with

$$U^P(\mathbf{m}_t, \mathbf{s}_t; C_t)$$

where C_t is adapted.

Ideally we would like $C_t \propto H^{-1}$.

Covariance Matrix Adaptation

Covariance Matrix Adaptation

Evolution Strategies

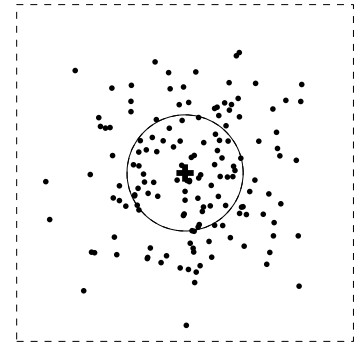
Recalling

New search points are sampled normally distributed

$$\mathbf{x}_i \sim \mathbf{m} + \sigma \mathcal{N}_i(\mathbf{0}, \mathbf{C}) \quad \text{for } i = 1, \dots, \lambda$$

as perturbations of $\mathbf{m}$,

where $\mathbf{x}_i, \mathbf{m} \in \mathbb{R}^n$, $\sigma \in \mathbb{R}_+$,
 $\mathbf{C} \in \mathbb{R}^{n \times n}$



where

- ▶ the **mean** vector $\mathbf{m} \in \mathbb{R}^n$ represents the favorite solution
- ▶ the so-called **step-size** $\sigma \in \mathbb{R}_+$ controls the *step length*
- ▶ the **covariance matrix** $\mathbf{C} \in \mathbb{R}^{n \times n}$ determines the **shape** of the distribution ellipsoid

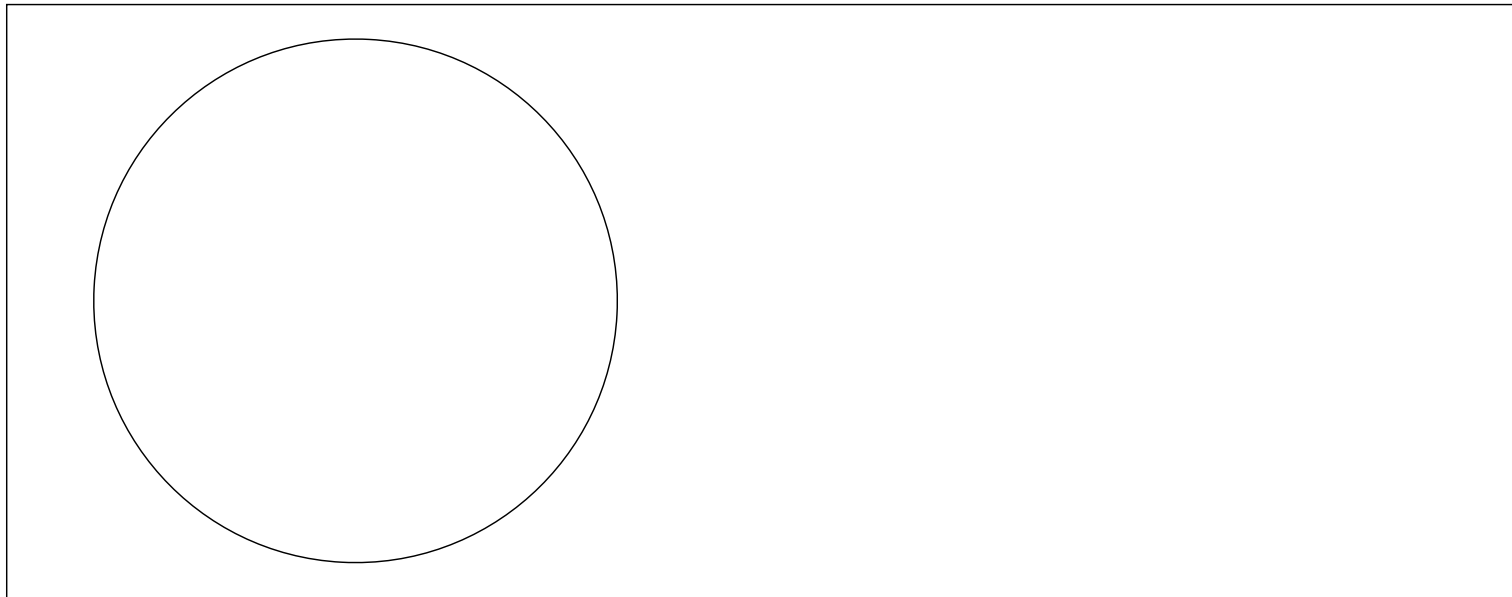
The remaining question is how to update $\mathbf{C}$.

Covariance Matrix Adaptation

Rank-One Update

[Hansen, Ostermair, 2001]

$$\mathbf{m} \leftarrow \mathbf{m} + \sigma \mathbf{y}_w, \quad \mathbf{y}_w = \sum_{i=1}^{\mu} w_i \mathbf{y}_{i:\lambda}, \quad \mathbf{y}_i \sim \mathcal{N}_i(\mathbf{0}, \mathbf{C})$$

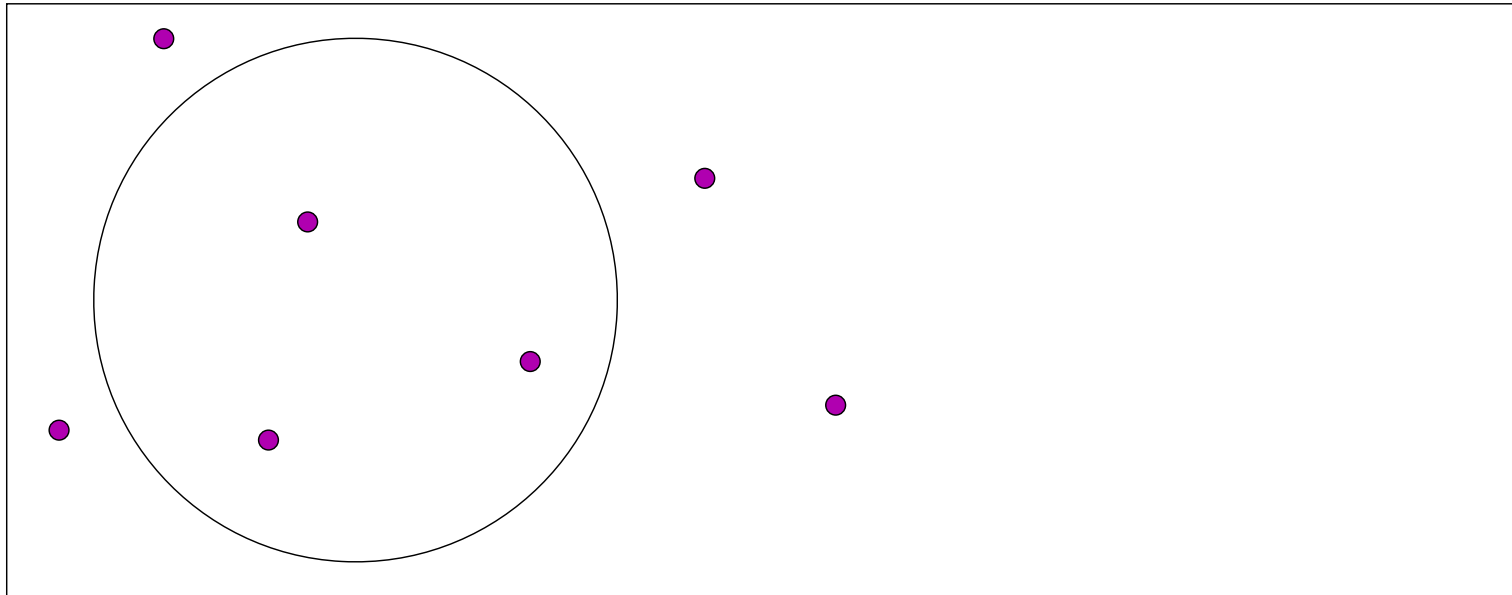


initial distribution, $\mathbf{C} = \mathbf{I}$

Covariance Matrix Adaptation

Rank-One Update

$$\mathbf{m} \leftarrow \mathbf{m} + \sigma \mathbf{y}_w, \quad \mathbf{y}_w = \sum_{i=1}^{\mu} w_i \mathbf{y}_{i:\lambda}, \quad \mathbf{y}_i \sim \mathcal{N}_i(\mathbf{0}, \mathbf{C})$$

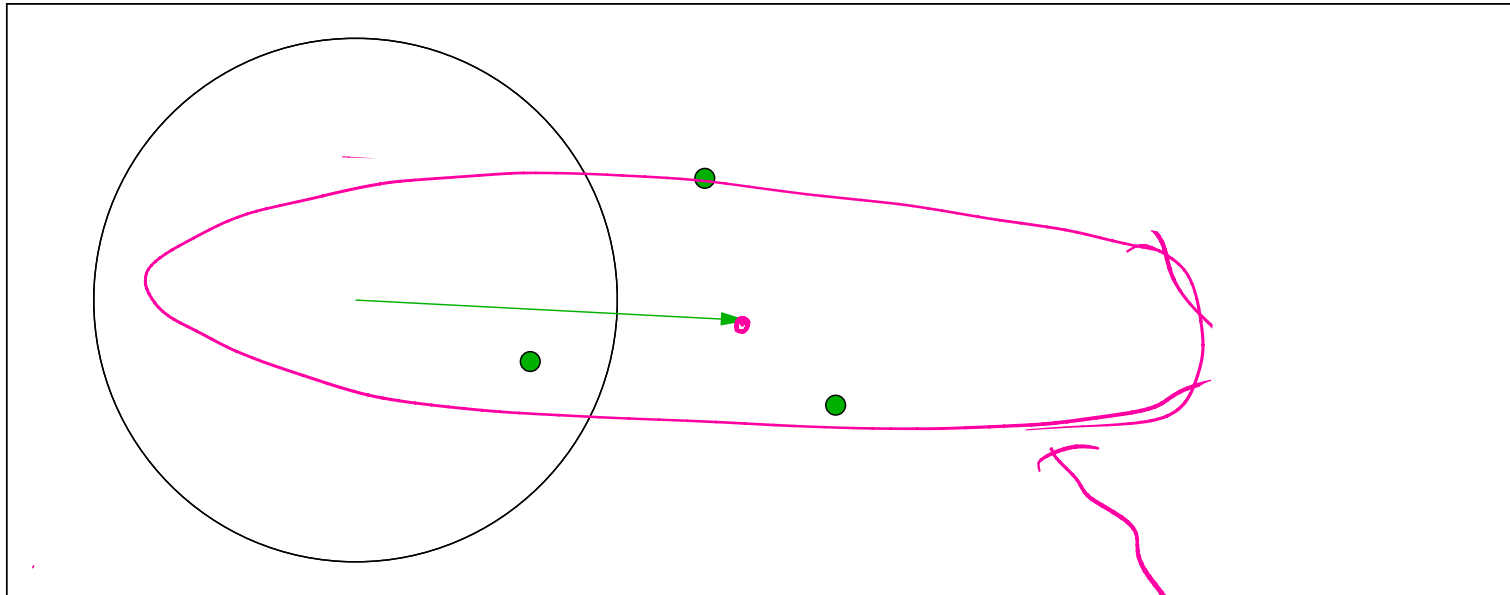


initial distribution, $\mathbf{C} = \mathbf{I}$

Covariance Matrix Adaptation

Rank-One Update

$$\mathbf{m} \leftarrow \mathbf{m} + \sigma \mathbf{y}_w, \quad \mathbf{y}_w = \sum_{i=1}^{\mu} w_i \mathbf{y}_{i:\lambda}, \quad \mathbf{y}_i \sim \mathcal{N}_i(\mathbf{0}, \mathbf{C})$$



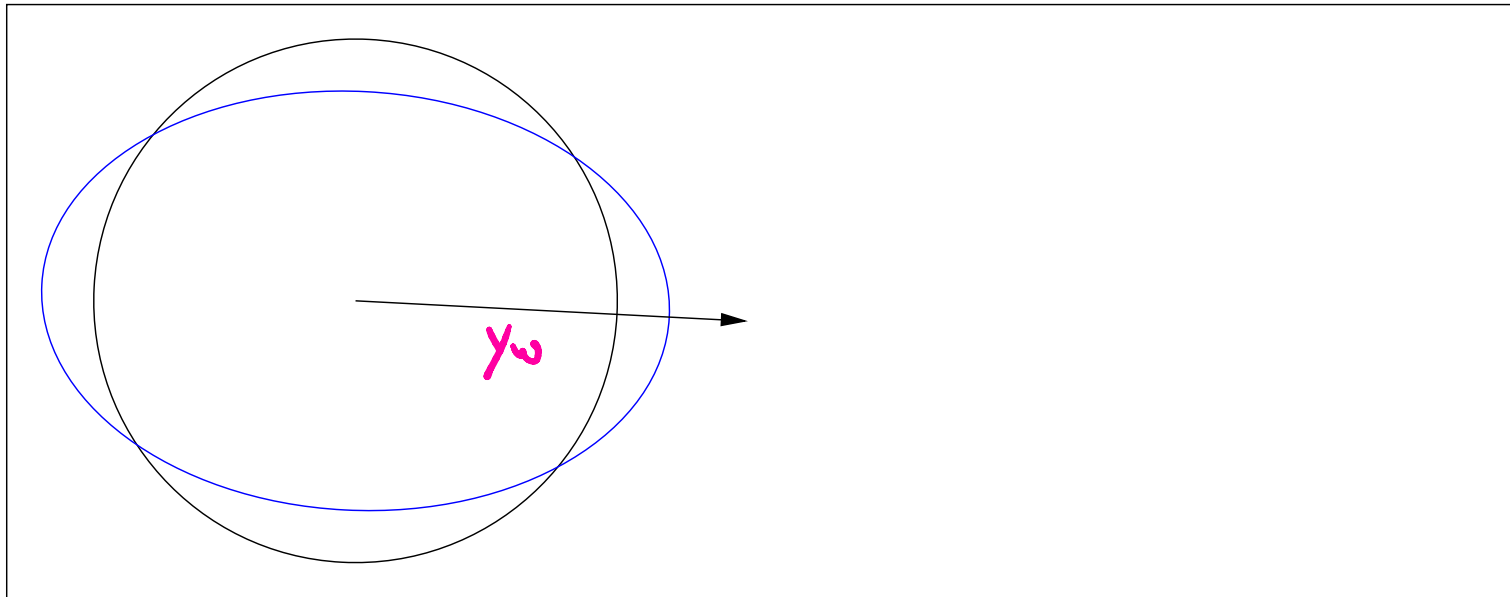
$\mathbf{y}_w$, movement of the population mean $\mathbf{m}$ (disregarding σ)

I would like to have this

Covariance Matrix Adaptation

Rank-One Update

$$\mathbf{m} \leftarrow \mathbf{m} + \sigma \mathbf{y}_w, \quad \mathbf{y}_w = \sum_{i=1}^{\mu} w_i \mathbf{y}_{i:\lambda}, \quad \mathbf{y}_i \sim \mathcal{N}_i(\mathbf{0}, \mathbf{C})$$



mixture of distribution $\mathbf{C}$ and step $\mathbf{y}_w$,

$$\mathbf{C} \leftarrow 0.8 \times \mathbf{C} + 0.2 \times \underbrace{\mathbf{y}_w \mathbf{y}_w^T}_{\text{semi-definite symmetric}}$$

$y_w y_w^T$ is a rank-one matrix

$$\begin{pmatrix} y_w \end{pmatrix} \begin{pmatrix} y_w^T \end{pmatrix} = \begin{pmatrix} (y_w)_1 y_w, (y_w)_2 y_w, \dots, (y_w)_n y_w \end{pmatrix}$$

$$\text{Vect}((y_w)_1 y_w, \dots, (y_w)_n y_w) = \text{Vect}(y_w)$$

$$\text{rank}(y_w y_w^T) = 1$$

$\text{Ker}(y_w y_w^T)$ has dimension $n-1$.

Check that y_w is eigenvector associated to non-zero eigenvalue:

$$y_w \underbrace{y_w^T y_w}_{\|y_w\|^2} = \|y_w\|^2 y_w$$

$\rightarrow y_w$ is eigenvector associated to the eigenvalue $\|y_w\|^2$.

Deduce eigenvectors and eigenvalue of :
 $(1-\alpha)\text{Id} + \alpha V y_w y_w^T$

1/ y_w is also eigenvector of $(1-\alpha)\text{Id} + \alpha V y_w y_w^T$:

$$\begin{aligned} \left[(1-\alpha)\text{Id} + \alpha V y_w y_w^T \right] y_w &= (1-\alpha) y_w + \alpha \|y_w\|^2 y_w \\ &= (1-\alpha + \alpha \|y_w\|^2) y_w \end{aligned}$$

I can complement $(y_w, \underbrace{y_2, \dots, y_m}_{\text{Ker}(y_w y_w^T)})$ into orthogonal basis.

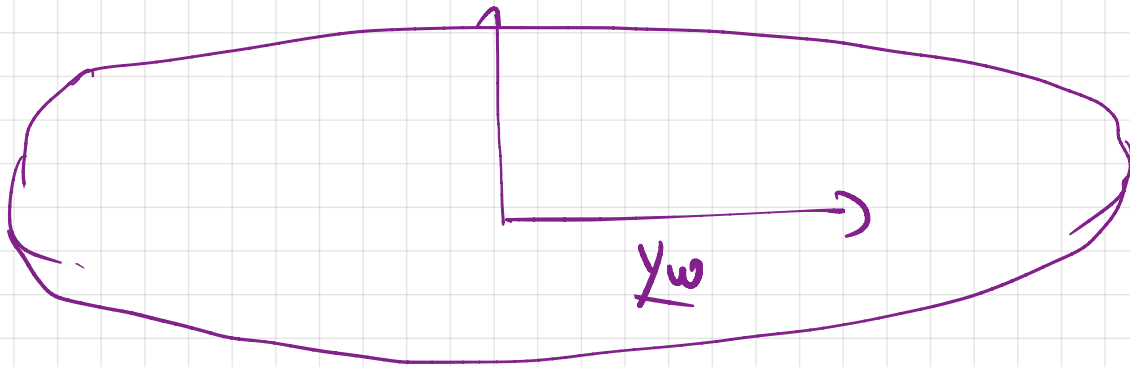
For y_i vector $(y_w y_w^T) y_i = 0$

$$\left[(1-\alpha)\text{Id} + \alpha (y_w y_w^T) \right] y_i = (1-\alpha) y_i$$

$(y_1, y_2, \dots, y_m)$ forms an orthogonal basis of eigenvectors
 $(1 - \text{cov}) \text{Id} + \text{cov}(y_1 y_1^T)$ associated to the
eigenvalue:

$$((1 - \text{cov}) + \text{cov} \|y_1\|^2, (1 - \text{cov}), \dots, (1 - \text{cov}))$$

The ellipsoid associated to the density related to $C = (1 - \text{cov}) \text{Id} + \text{cov}(y_1 y_1^T)$

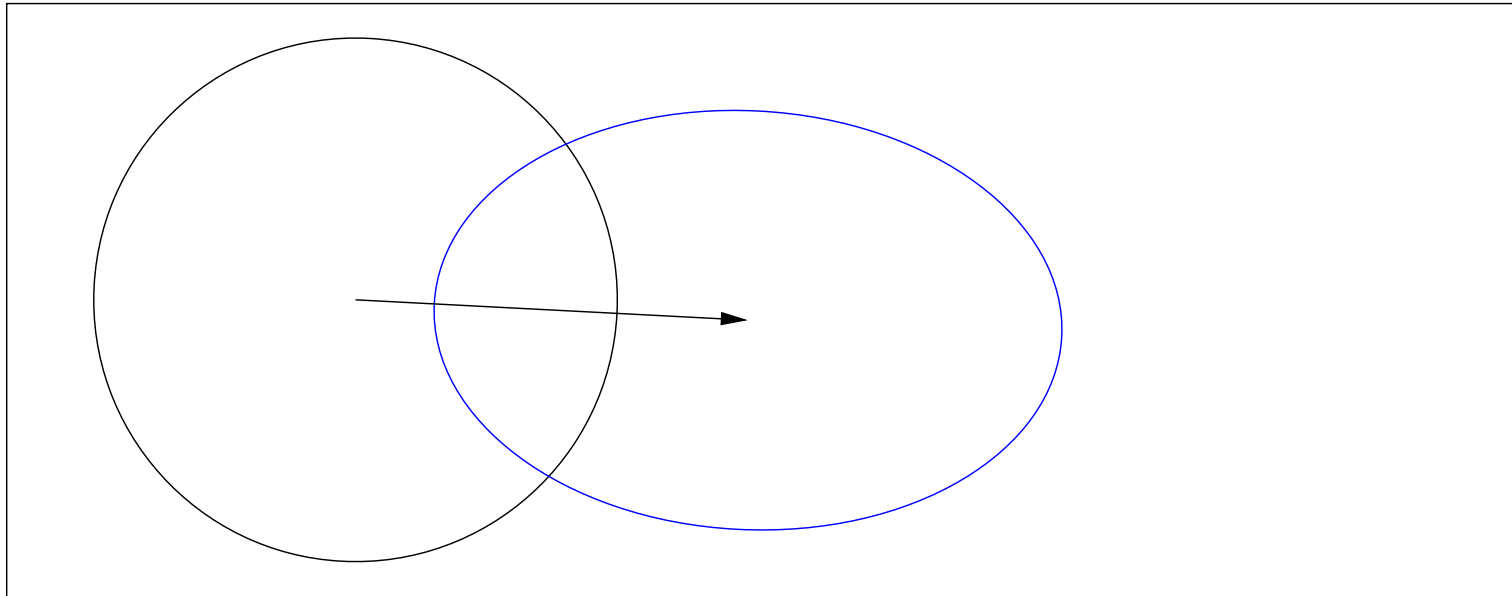


Conclusion: The rank-one update elongates the iso-density
ellipsoid in the direction y_1 .

Covariance Matrix Adaptation

Rank-One Update

$$\mathbf{m} \leftarrow \mathbf{m} + \sigma \mathbf{y}_w, \quad \mathbf{y}_w = \sum_{i=1}^{\mu} w_i \mathbf{y}_{i:\lambda}, \quad \mathbf{y}_i \sim \mathcal{N}_i(\mathbf{0}, \mathbf{C})$$

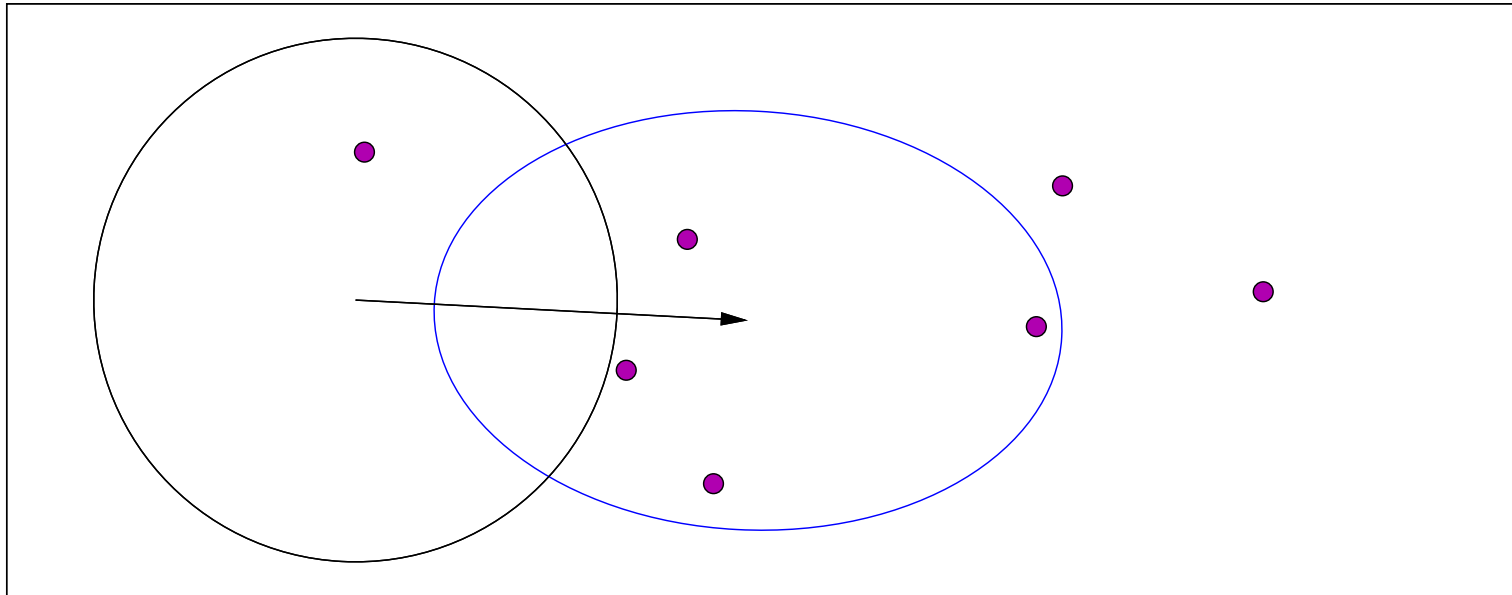


new distribution (disregarding σ)

Covariance Matrix Adaptation

Rank-One Update

$$\mathbf{m} \leftarrow \mathbf{m} + \sigma \mathbf{y}_w, \quad \mathbf{y}_w = \sum_{i=1}^{\mu} w_i \mathbf{y}_{i:\lambda}, \quad \mathbf{y}_i \sim \mathcal{N}_i(\mathbf{0}, \mathbf{C})$$

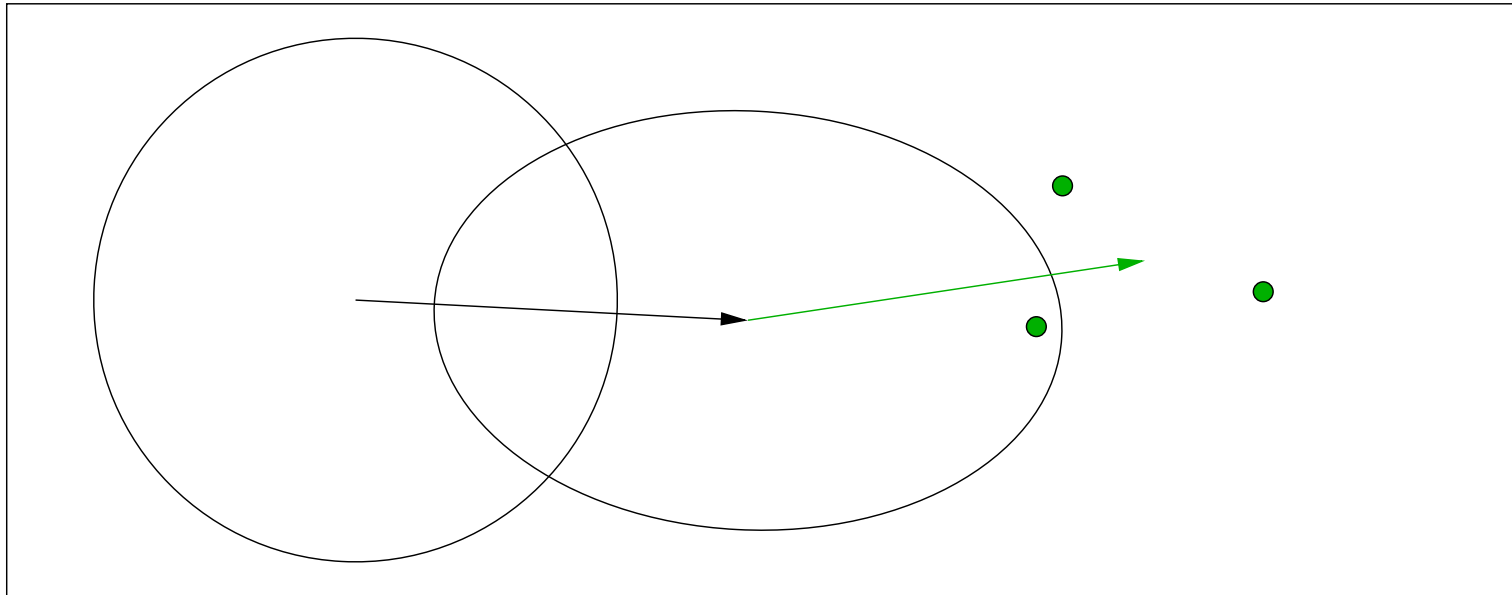


new distribution (disregarding σ)

Covariance Matrix Adaptation

Rank-One Update

$$\mathbf{m} \leftarrow \mathbf{m} + \sigma \mathbf{y}_w, \quad \mathbf{y}_w = \sum_{i=1}^{\mu} w_i \mathbf{y}_{i:\lambda}, \quad \mathbf{y}_i \sim \mathcal{N}_i(\mathbf{0}, \mathbf{C})$$

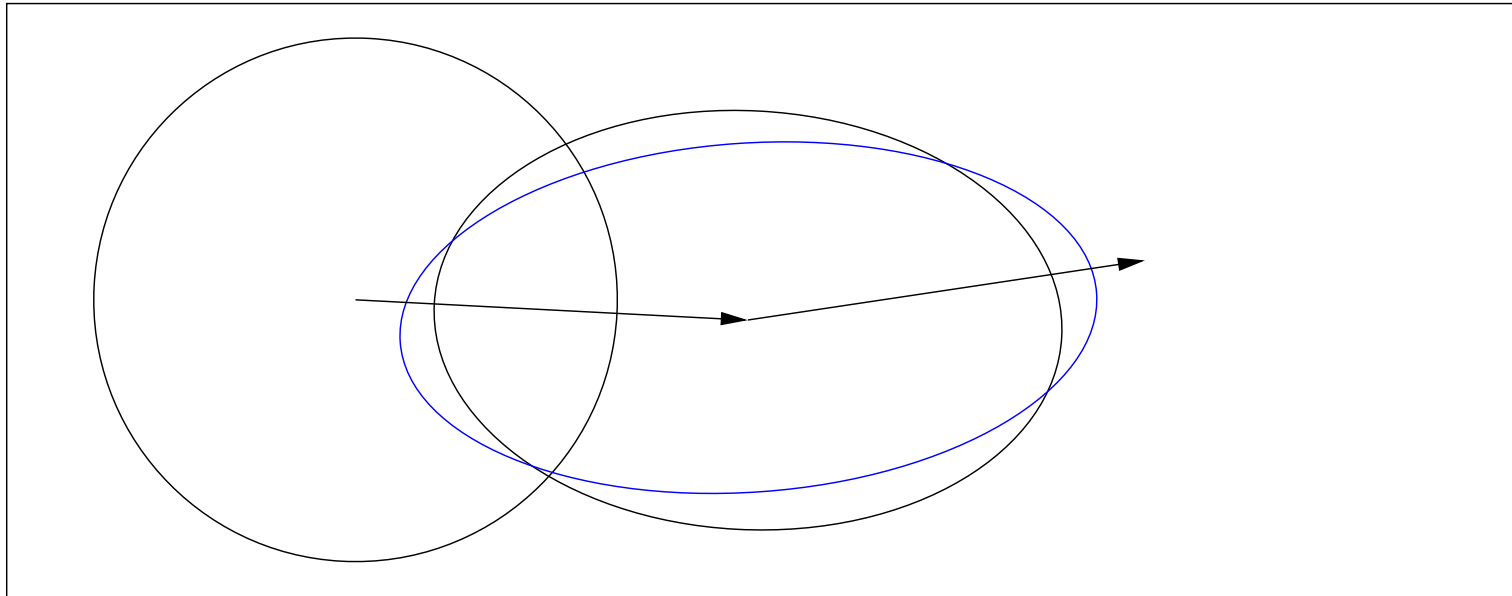


movement of the population mean $\mathbf{m}$

Covariance Matrix Adaptation

Rank-One Update

$$\mathbf{m} \leftarrow \mathbf{m} + \sigma \mathbf{y}_w, \quad \mathbf{y}_w = \sum_{i=1}^{\mu} w_i \mathbf{y}_{i:\lambda}, \quad \mathbf{y}_i \sim \mathcal{N}_i(\mathbf{0}, \mathbf{C})$$



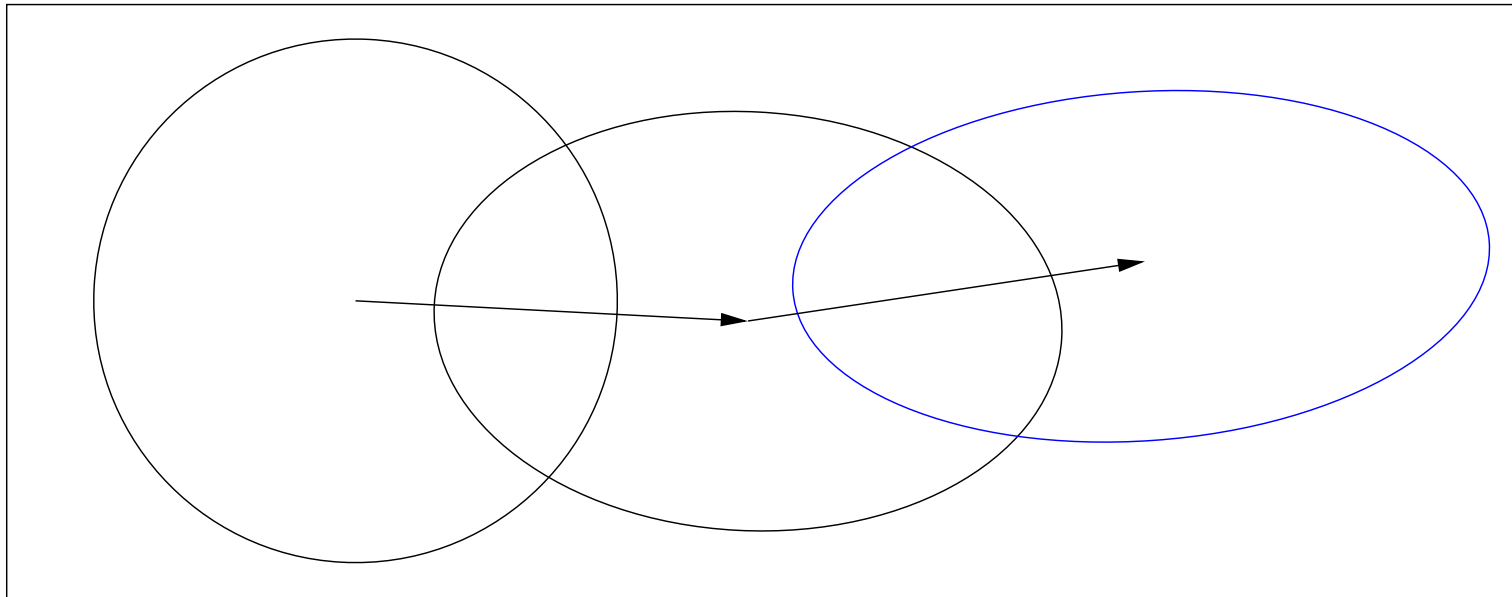
mixture of distribution $\mathbf{C}$ and step $\mathbf{y}_w$,

$$\mathbf{C} \leftarrow 0.8 \times \mathbf{C} + 0.2 \times \mathbf{y}_w \mathbf{y}_w^T$$

Covariance Matrix Adaptation

Rank-One Update

$$\mathbf{m} \leftarrow \mathbf{m} + \sigma \mathbf{y}_w, \quad \mathbf{y}_w = \sum_{i=1}^{\mu} w_i \mathbf{y}_{i:\lambda}, \quad \mathbf{y}_i \sim \mathcal{N}_i(\mathbf{0}, \mathbf{C})$$



new distribution,

$$\mathbf{C} \leftarrow 0.8 \times \mathbf{C} + 0.2 \times \mathbf{y}_w \mathbf{y}_w^T$$

the ruling principle: the adaptation **increases the likelihood of successful steps**, $\mathbf{y}_w$, to appear again

Covariance Matrix Adaptation

Rank-One Update

Initialize $\mathbf{m} \in \mathbb{R}^n$, and $\mathbf{C} = \mathbf{I}$, set $\sigma = 1$, learning rate $c_{\text{cov}} \approx 2/n^2$

While not terminate

$$\mathbf{x}_i = \mathbf{m} + \sigma \mathbf{y}_i, \quad \mathbf{y}_i \sim \mathcal{N}_i(\mathbf{0}, \mathbf{C}),$$

$$\mathbf{m} \leftarrow \mathbf{m} + \sigma \mathbf{y}_w \quad \text{where } \mathbf{y}_w = \sum_{i=1}^{\mu} w_i \mathbf{y}_{i:\lambda}$$

$$\mathbf{C} \leftarrow (1 - c_{\text{cov}})\mathbf{C} + c_{\text{cov}} \underbrace{\mu_w \mathbf{y}_w \mathbf{y}_w^T}_{\text{rank-one}} \quad \text{where } \mu_w = \frac{1}{\sum_{i=1}^{\mu} w_i^2} \geq 1$$

REST OF THE CLASS: Exercise "Running and Understanding CNA-ES" (see exercise sheet)