Max-Planck-Institut
für Biochemie

# Machine learning for <br> <br> single particles 

 <br> <br> single particles}

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## Particle picking

$\triangleright$ Problem:
$\triangleright$ Views are randomly distributed on images
$\triangleright$ Must pick regions with particles from image
$\triangleright$ Difficulty: high noise $\rightarrow$ simple template matching does not work
$\triangleright$ Approach:
Initial picks by linear correlation
Use a Support Vector Machine (SVM) to select for correct particles according to a manually chosen data set

## Picking by template matching



Picking by
linear correlation
many
mis-picks
Apply SVM
to pixel vector (reduced) of the images

Coloring: training data set

## Support Vector Machines



From Duda et al., Pattern Classification

Machine Learning:

- Training (vs rules)

Support Vector Machine:

- Linear classifier
- Extended to higher polynomials
- Efficient calculation of the separating hyperplane by duality transform


## Non-linearity

Linearly inseperable


Linearly separable
after introduction of pseudo-variable


## Improving picking using SVMs



Receiver operating characteristics for different feature set sizes
M. Tacke, C. Best 2006

## Improving picking using SVMs



Receiver operating characteristics for different feature set sizes
[Logarithmic scale]
M. Tacke, C. Best 2006

## Picking result



## Sorting views into angles



Tripeptidyl-peptidase II (TPP II)
courtesy of B. Rockel, Martinsried


## Sorting views into angles

$\triangleright$ Problem:
How can we sort the views of a particle according to the viewing angle (elevation, azimuth) ?
$\triangleright$ Answer:

## Similar angles $\rightarrow$ similar images

$\triangleright$ Does not require any knowledge about the actual 3D model!
$\triangleright$ HOW?
Parameter estimation in a probabilistic model

## What are Bayesian models?

$\triangleright$ Probability distribution $\leftrightarrow$ Belief about reality
$\triangleright$ What do we know?
Images that correspond to nearby viewing angles should be similar
$\triangleright$ This can be expressed by a probability distribution

$$
P(M \mid \phi)
$$

"Belief that images $M$ are compatible with the angular assignments $\phi^{\prime \prime}$

- Building block:

$$
P\left(M \mid \phi ; M_{0,} \phi_{0}\right)
$$

"Belief that two images are compatible with each other given their angular assignment"

## Model-free particle classification

$\triangleright$ Probabilistic model:

$$
\begin{aligned}
& P\left(M \mid \phi ; M_{0}, \phi_{0}\right)= \\
& \quad\left(\frac{1}{2 \pi \kappa\left(\left|\phi-\phi_{0}\right|\right)}\right)^{D / 2} \exp \left(-\frac{\left|M-M_{0}\right|^{2}}{2 \kappa\left(\left|\phi-\phi_{0}\right|\right)^{2}}\right)
\end{aligned}
$$

Angular distance-to-similarity kernel
$\triangleright$ Probability for an image $M$ given an assigned angle $\phi$, a reference image $M^{(0)}$, and a reference angle $\phi^{(0)}$ :

Gaussian with a width that gets wider when the images are farther apart.

## Parameter estimation

$\triangleright$ Problem:
We do know the images - why would we care about their probability distribution?
$\triangleright$ Bayesian parameter estimation:

$$
\mathrm{P}(M \mid \phi) \Leftrightarrow \mathrm{P}(\phi \mid \underset{)}{\text { Images }}
$$

$\triangleright$ This is done using Bayes' formula
$\triangleright$ Simplified version: Maximum-likelihood estimation

$$
\phi=\max \mathrm{P}(M \mid \phi)
$$

The best angular assignments are those which make the images most probable

## Self-organizing point map

$\triangleright$ Joint probability distribution:

$$
P\left(\left\{M^{(n)}\right\} \mid\left\{\phi^{(n)}\right\}\right)=\prod_{i=1}^{N} P\left(M^{(i)} \mid\left\{M^{\left(i^{\prime}\right)}, \phi^{\left(i^{\prime}\right)}\right\}\right)
$$

$\triangleright$ Maximum-likelihood principle $\rightarrow$ Hamiltonian:

$$
\begin{aligned}
& -\ln L(\phi)= \\
& \quad \sum_{n, m}\left(\frac{D}{2} \ln 2 \pi \kappa\left(\left|\phi^{(n)}-\phi^{(m)}\right|\right)+\frac{\left|M^{(n)}-M^{(m)}\right|^{2}}{2 \kappa\left(\left.\left|\phi^{(n)}-\phi^{(m)}\right|\right|^{2}\right.}\right) \\
& \text { Attractive force } \quad \text { Repulsive force }
\end{aligned}
$$

Point-to-point potential $\rightarrow$ multidimensional scaling
$\triangleright$ Gradient descent solution

## Optimization process


"Spring embedding"
Attractive and repulsive "force" between points (=images)

Minimum (=optimum) is determined by how similar the images appear

Abstract coordinate 1

## Similarity matrix

| \%-3 | +2m | *** | ms. | -3. | ** | ** | ** | $\cdots$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $\cdots$ | \%* | *** | -s. | *) | * | * | * | ** |
| \% | ma | 2. | 2m | - | - | - | * | -* |
| 2 | n* | mis | ns | 2m | $\cdots$ | $\pm$ | \% | ** |
| n* | nm | Am | $\cdots$ | $\cdots$ | $\cdots$ | $\cdots$ | $\cdots$ | \% |
| $\infty$ | $\cdots$ | $\wedge$ | $\pm$ | $\bullet$ | $\cdots$ | $\pm$ | $\cdots$ | $\pm$ |
| 0 | $\cdots$ | $\omega$ | $\omega$ | $\omega$ | $\omega$ | $\cdots$ | $\checkmark$ | $\cdots$ |
| $\bullet$ | - | - | $\bullet$ | $\bigcirc$ | - | - | $\bullet$ | $\bigcirc$ |
| $\bullet$ | $\bullet$ | $\bullet$ | $\bullet$ | $\bigcirc$ | $\bullet$ | $\bigcirc$ | $\bigcirc$ | $\bigcirc$ |

9x9 projections of TPP2

Pairwise correlation max. over translations and rotations

Correlation matrix:


## Result



Good representation of original distribution of viewing angles

Good as an initial model for iterative refinement

## Tomographic classification



