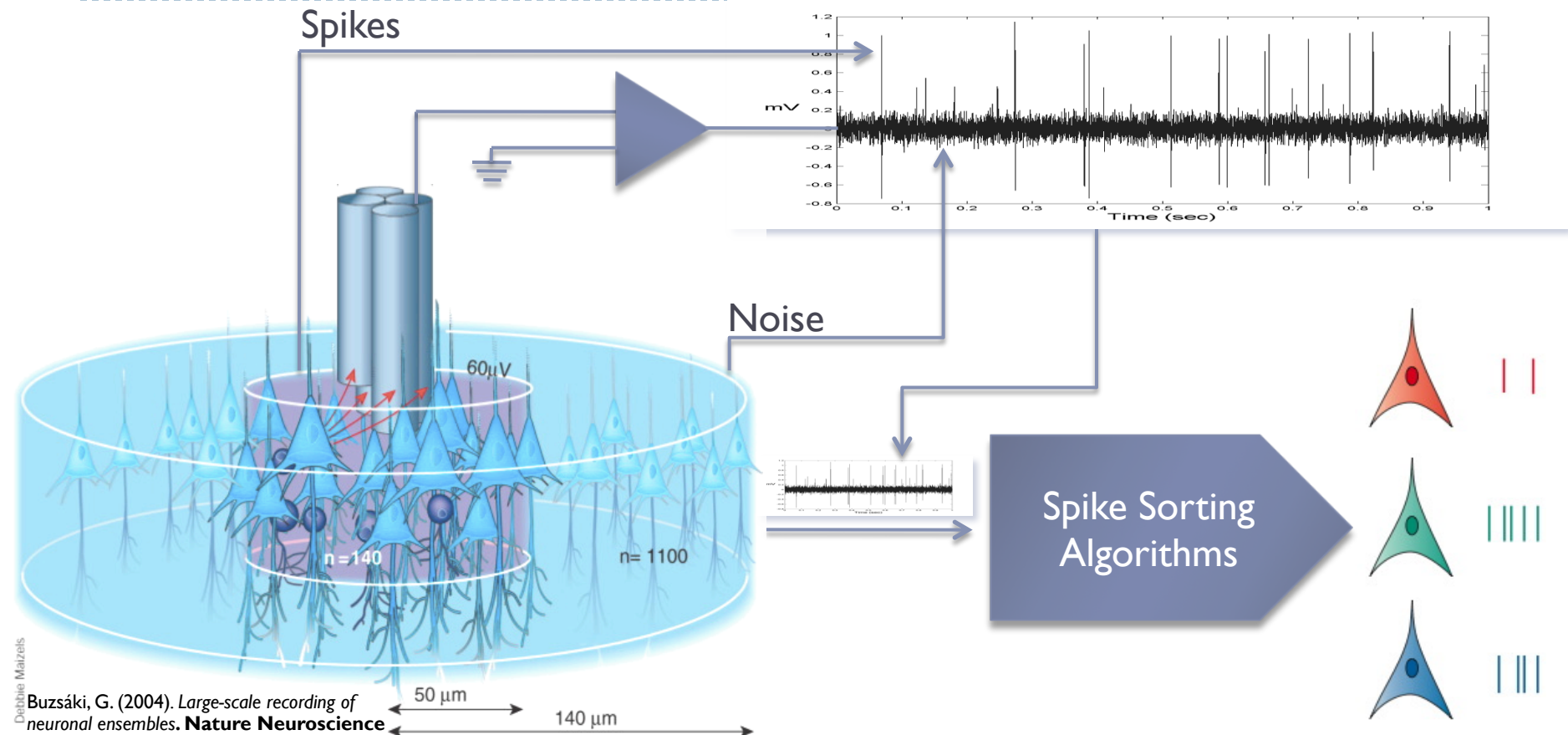


Spike Sorting based on Dominant-Sets clustering

Dimitrios A. Adamos PhD



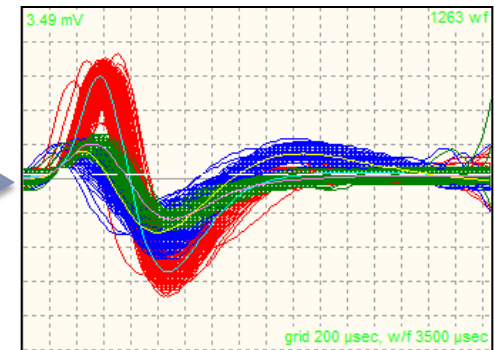
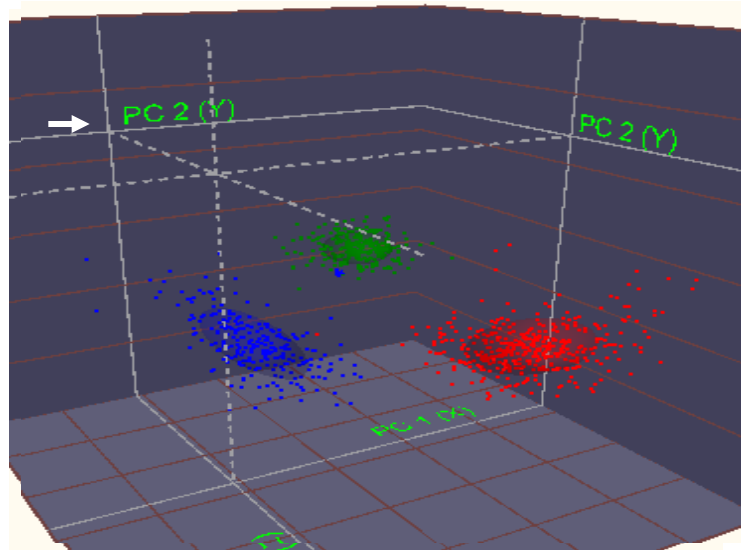
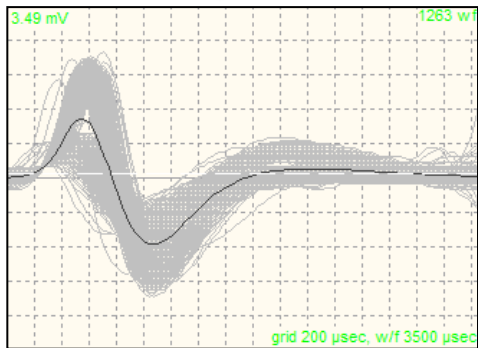
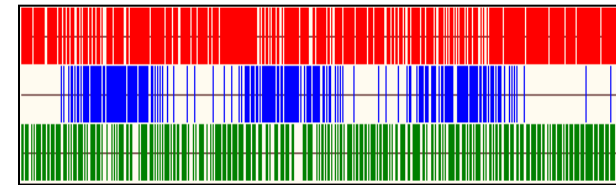
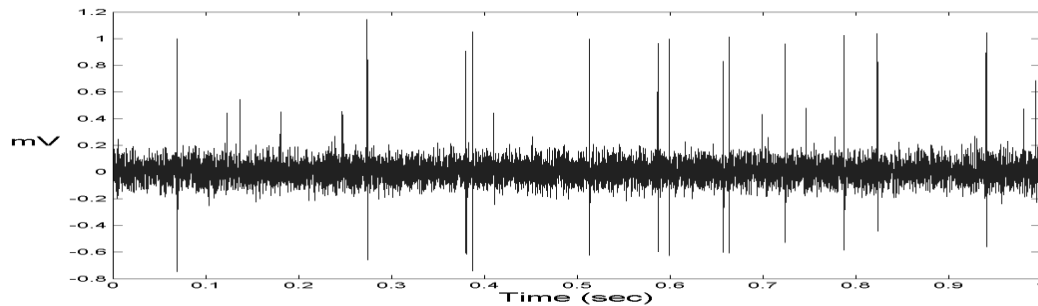
What is spike sorting?



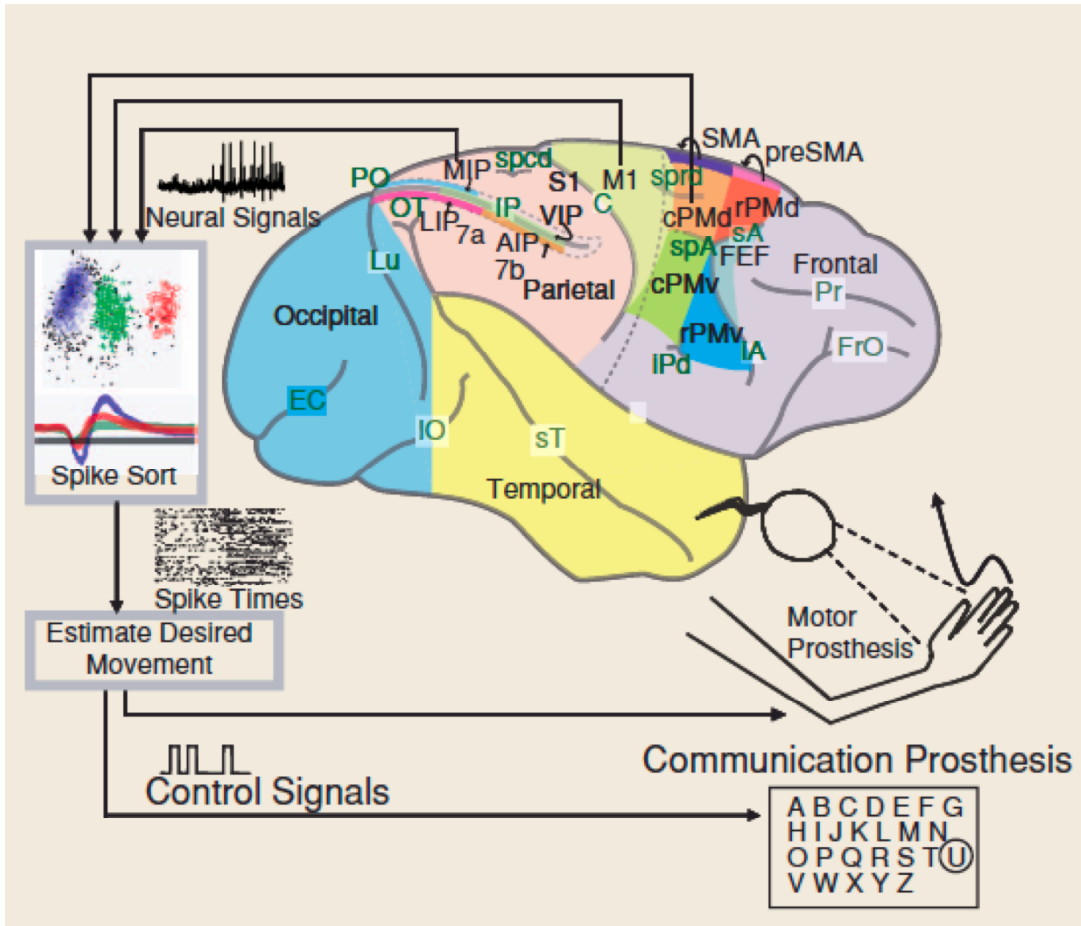
Debbie Malzev
Buzsáki, G. (2004). Large-scale recording of neuronal ensembles. **Nature Neuroscience**



Spike sorting in a nutshell

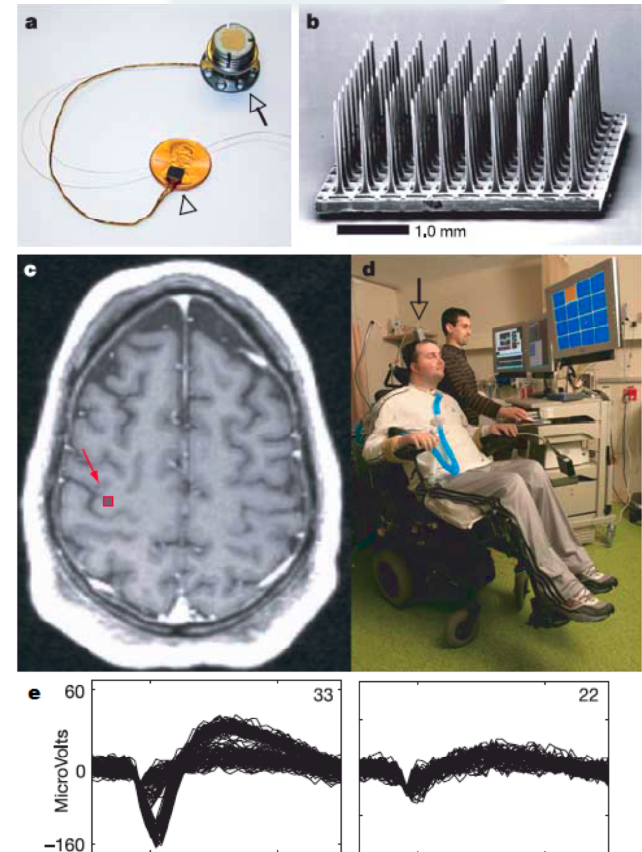


Spike sorting applications



Linderman et al. (2008). Signal processing challenges for neural prostheses. **IEEE Signal Processing Magazine**

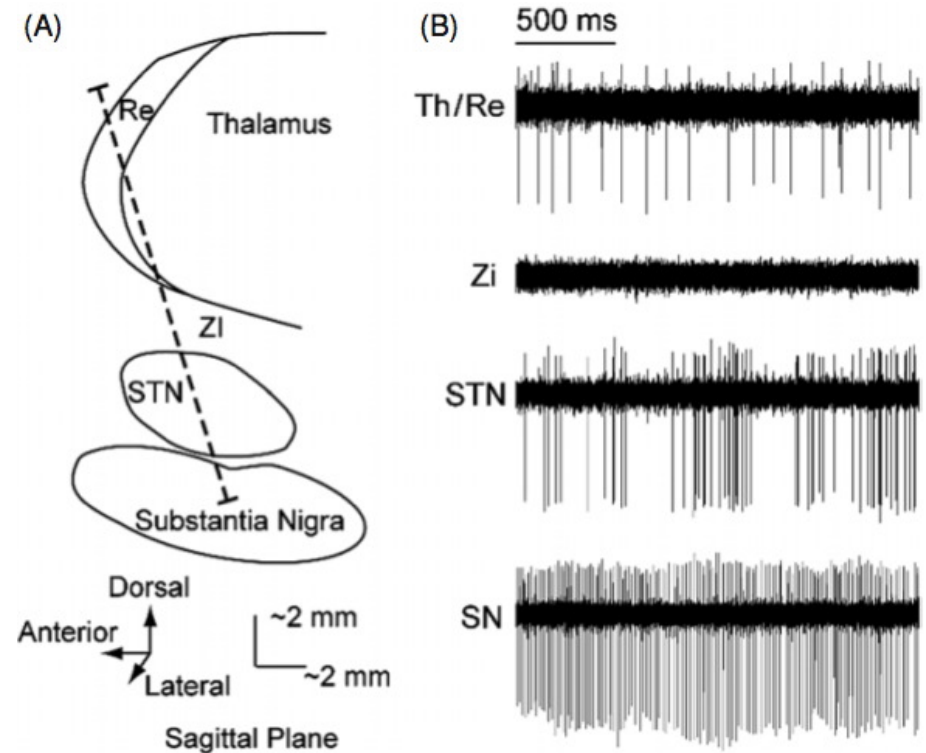
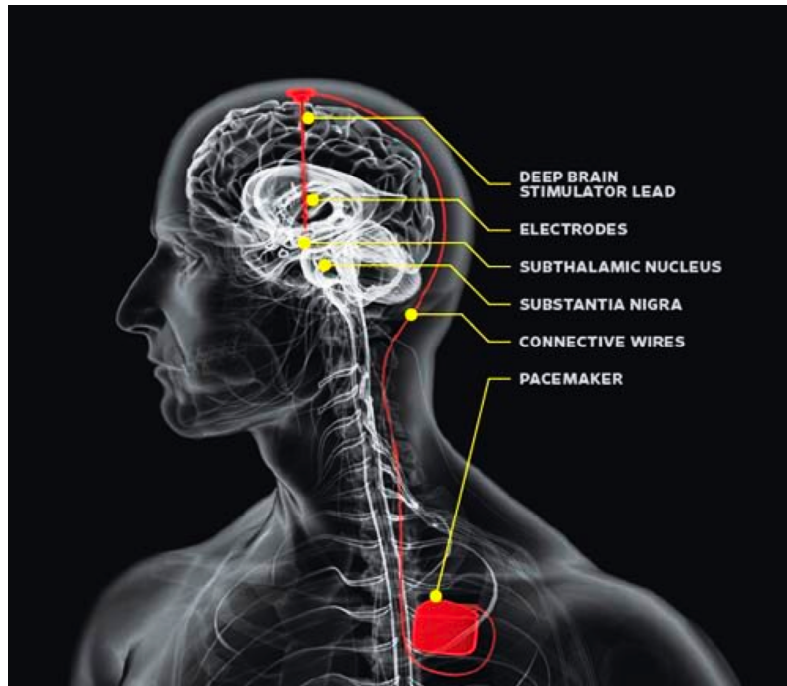
BrainGate



Hochberg et al. (2006). Neuronal ensemble control of prosthetic devices by a human with tetraplegia. **Nature**



Spike sorting applications



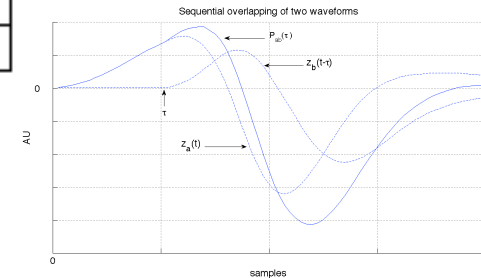
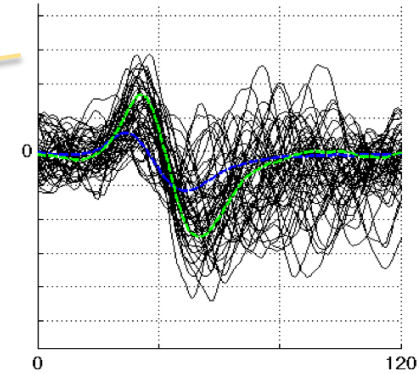
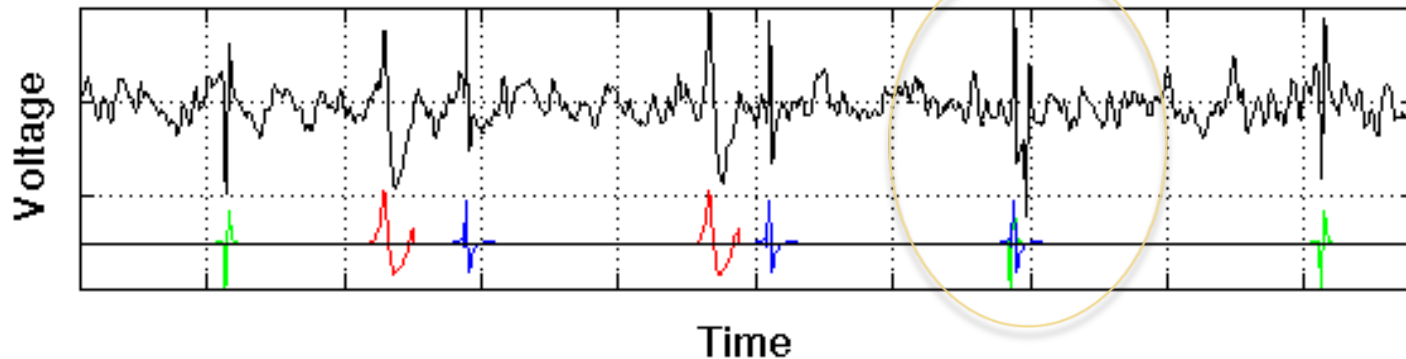
► Functional STN Targeting during DBS surgery

Wong et al. (2009). *Functional localization and visualization of the STN from microelectrode recordings acquired during DBS surgery with unsupervised machine learning.* **J Neural Eng**



Open problems in spike sorting #1

► Resolution of **overlapping** spikes



Adamos DA, Laskaris NA , Kosmidis EK and Theophilidis G.

NASS: *An empirical approach to **S**pike **S**orting with overlap resolution based on a hybrid **N**oise-**A**ssisted methodology*

(2010) **Journal of Neuroscience Methods** Article in Press doi:10.1016/j.jneumeth.2010.04.018



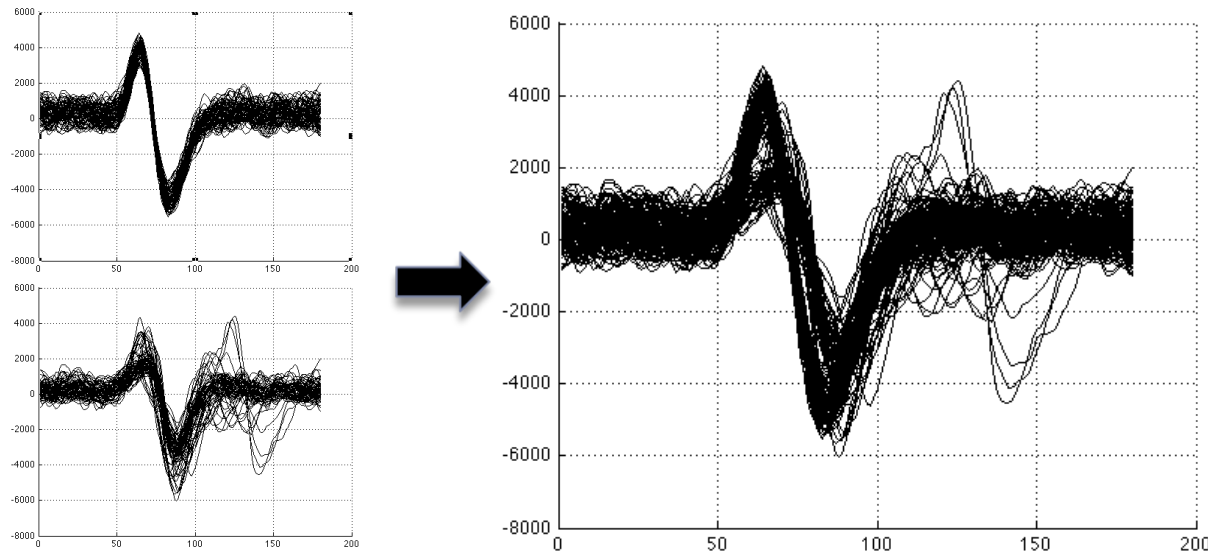
Open problems in spike sorting #2

- ▶ Goal of this study: Correct estimation of **active** neurons

Challenges: **Noise** & **Sparsely firing neurons**

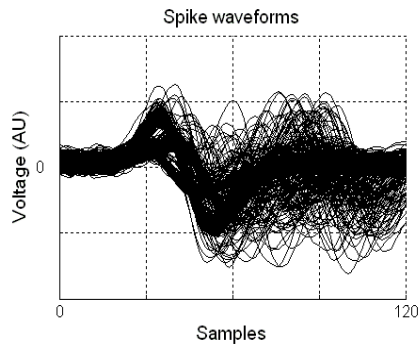
Common clustering errors: *Under-clustering* & *over-clustering*

Under-clustering example

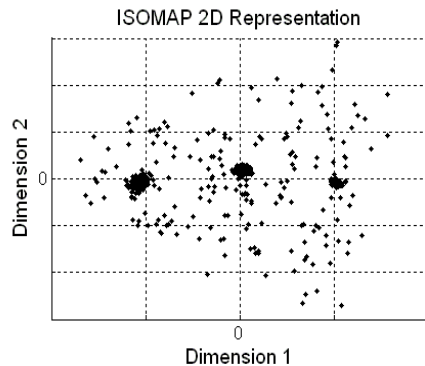
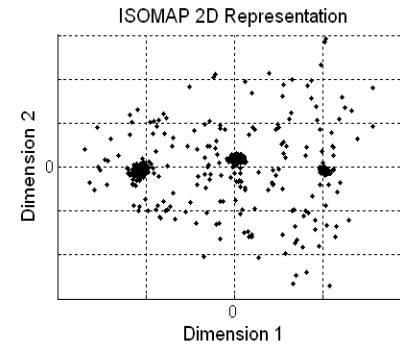


Methods

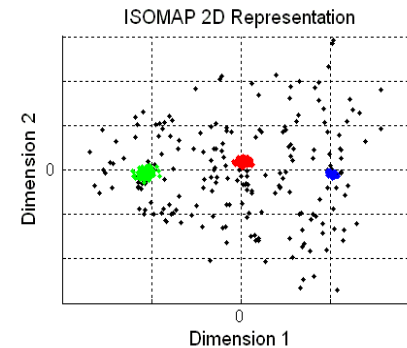
► Combination of two methods from the graph-theoretic domain



#1 ISOMAP
Graph-theoretic
feature extraction

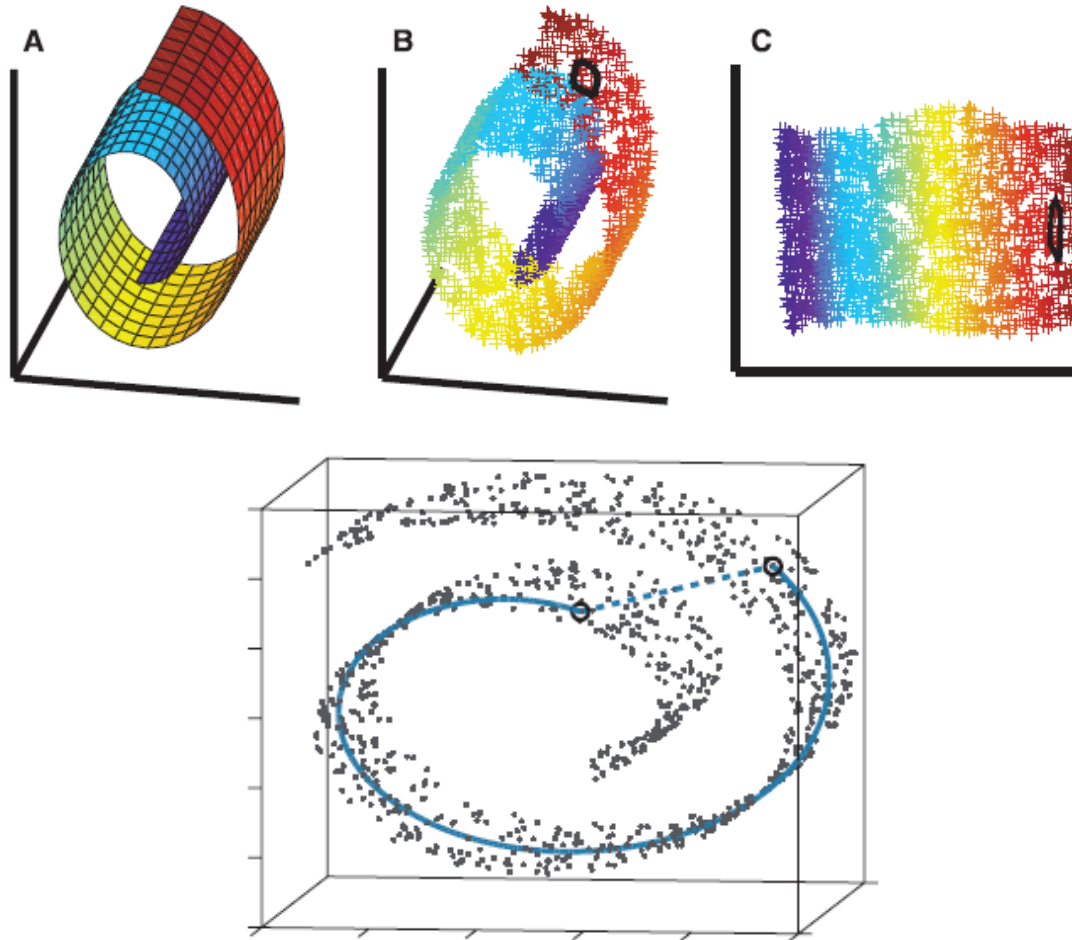


#2 Dominant-sets
Graph-theoretic
clustering



Methods #1: Non-linear low-dimensional representation

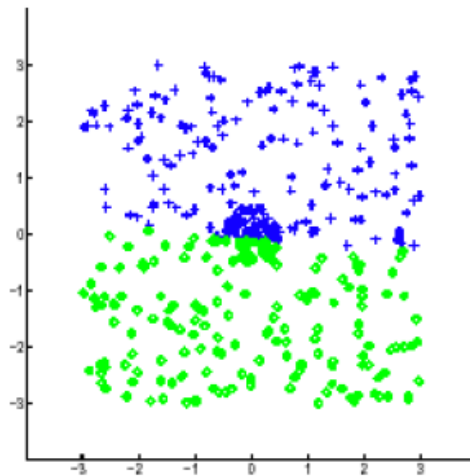
► Manifold learning: Isometric Feature Mapping (ISOMAP)



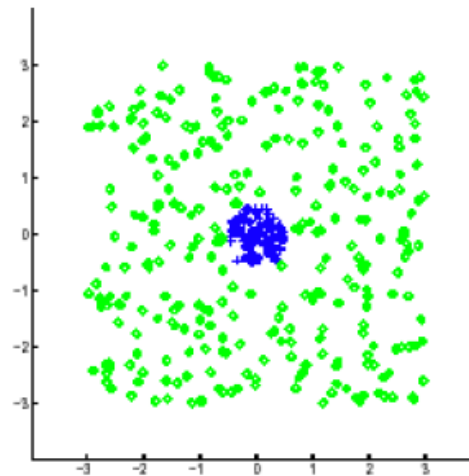
Methods #2: Graph-Theoretic Clustering

► Dominant-Sets clustering

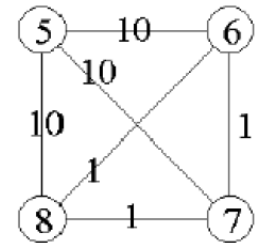
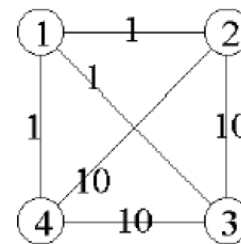
- **Internal criterion:** all objects *inside* a cluster should be highly similar to each other
- **External criterion:** all objects *outside* a cluster should be highly dissimilar to the ones inside
- **Similarity** is represented by weights:



K-means



Dominant-Sets

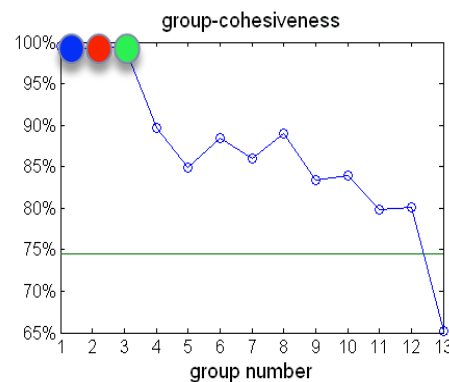
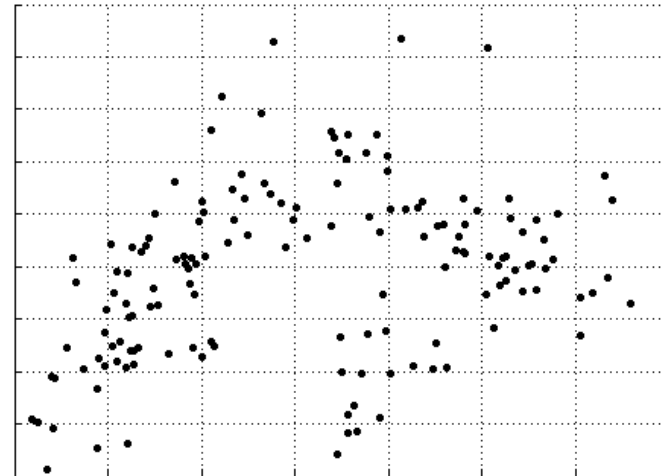
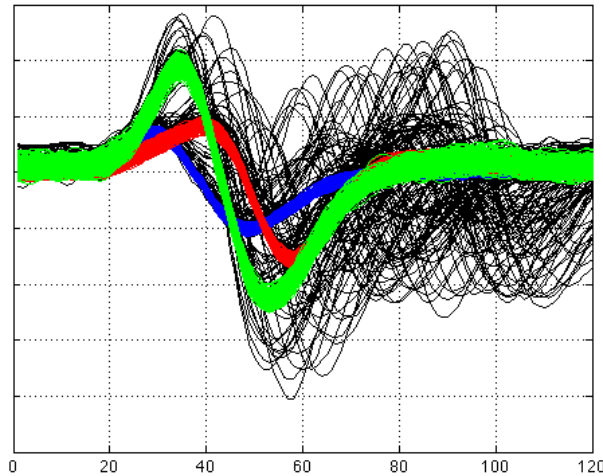


Pavan M and Pelillo M (2007) Dominant Sets and Pairwise Cluster-ing. IEEE Trans. Pattern Anal. Mach. Intell. 29(1): 167-172



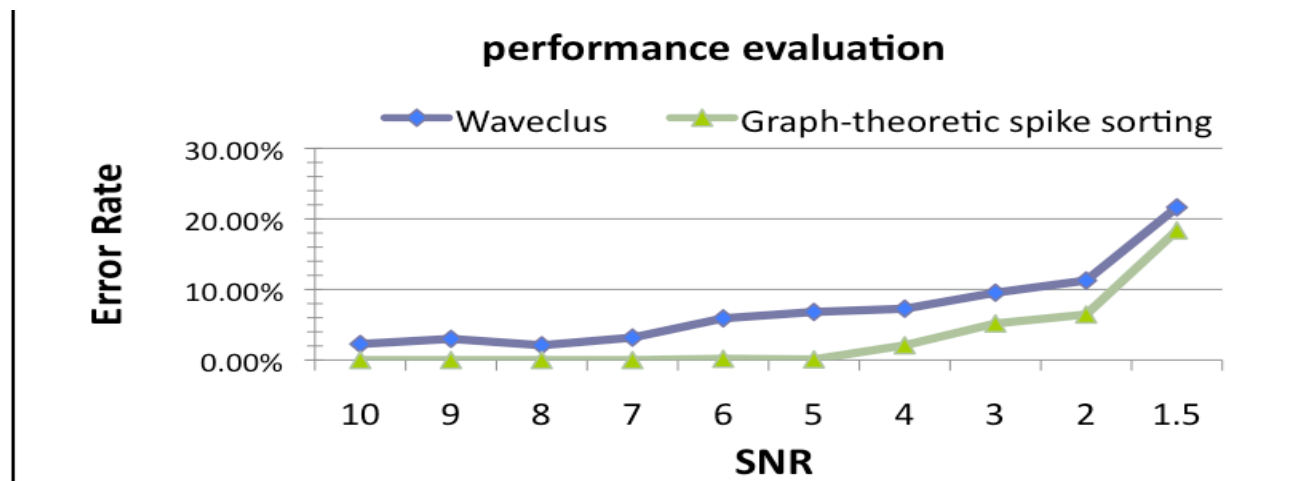
Algorithm

► Replicator Dynamics approach



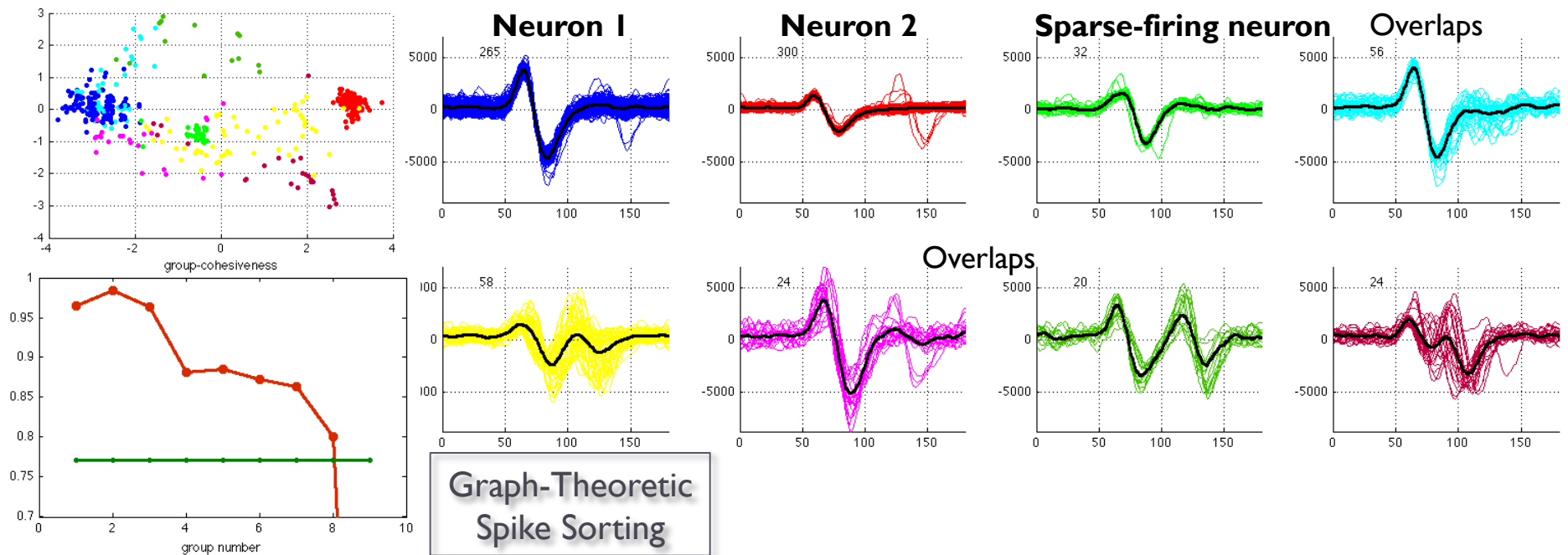
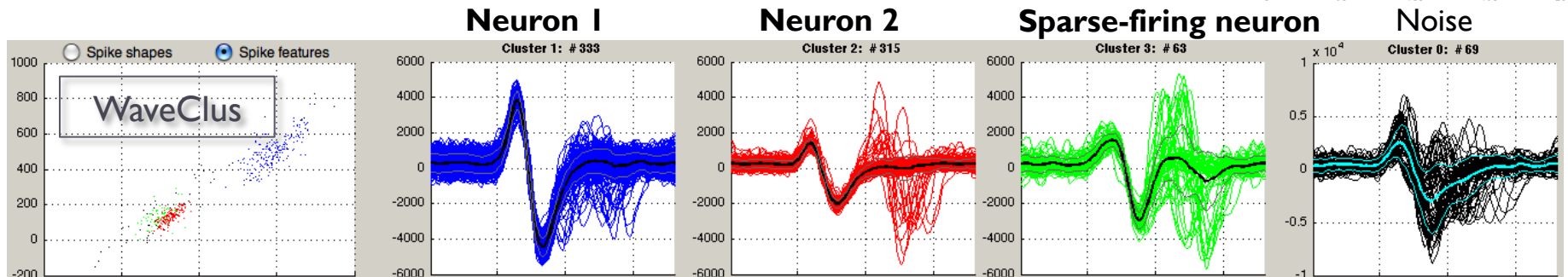
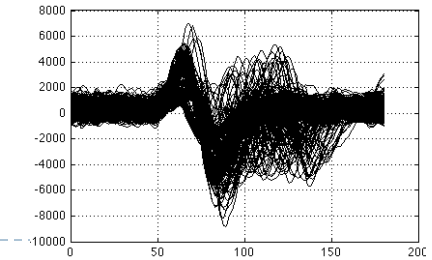
Comparative evaluation

- ▶ 3 neurons (3 x 300 spikes)
- ▶ 150 random double-overlaps (3 x 50 spikes)
- ▶ 50 random triple-overlaps
- ▶ Variable SNR



Low SNR example

2 firing neurons (2 × 300 spikes) +
+ 1 sparse-firing neuron (30 spikes) + overlaps (150 spikes)



Conclusions

- ▶ **Problem:**

- ▶ Estimating the number of active neurons

- ▶ **Methods**

- ▶ Methods from the graph-theoretic domain
 - ▶ Replicator dynamics approach

- ▶ **Results**

- ▶ Semi-supervised spike-sorting approach with relative ranking of groups
 - ▶ High ranking: active neurons
 - ▶ Medium ranking: overlapping and noisy spikes that need further processing
 - ▶ Low ranking: noise



Thank you

