Neuroscience Applications of Dependent Mixtures

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Figure: Multiple target tracking (ANTS) [Neiswanger and Wood, http://arxiv.org/abs/1210.3288]
CHAPTER 2. SPIKE SORTING

Figure 2.2: Illustration of the stages employed by most current approaches to spike sorting. In order, these are: (a) spike detection, e.g. using some form of threshold detector as illustrated by the red line; (b) spike extraction by cutting a fixed-length window from the recording around the detected spike; (c) feature extraction, commonly done using principal components analysis (PCA); (d) spike clustering using some clustering technique.

Waveform Non-Stationarity

The fundamental assumption of spike sorting is that the action potentials generated by different neurons give rise to spike waveforms that have a characteristic shape, thus allowing them to be distinguished. While this assumption may generally be warranted, there is no reason to assume that the characteristic waveform stays fixed over time. As the characteristic waveform arises from several intrinsic and extrinsic parameters which can change over time, the waveforms will change.
Non-stationarity → Dependent Clustering

Figure 5.3: Subsampled scatter plot of the first two principal components of the HARRIS data set ignoring time (left) and across time (right). The red circles denote the spikes that were identified on the IC channel. It can be seen that the waveform of this neuron changes over time and in the end becomes indistinguishable from another neuron.

Hippocampus of anesthetized rats. Recordings from an extracellular tetrode and an intracellular electrode were made simultaneously, such that the cell recorded on the intracellular electrode was also recorded extracellularly by the tetrode. Spikes detected on the intracellular (IC) channel are an almost certain indicator that the cell being recorded fired an action potential. Spikes detected on the extracellular (EC) channels may include the action potentials generated by the intracellularly recorded cell but almost certainly include spiking activity from other cells as well. The intracellular recording therefore can be used to obtain a ground truth labeling for the spikes originating from one neuron that can be used to evaluate the performance of human sorters and automatic spike sorting algorithms that sort extracellular recordings [Harris et al., 2000]. However, by this method ground truth can only be determined for one of the neurons whose spikes are present in the extracellular recording, and this should be kept in mind when evaluating the performance of spike sorting algorithms on such a data set.

Neither the correct number of distinct neurons recorded from by the extracellular electrode nor the correct labeling for any spikes not originating from the neuron recorded intracellularly can be determined by this methodology.

The available data set consists of the raw waveforms (recorded at 10kHz) from several recordings sessions. A four-minute subset of the data was selected.

Data: [Harris, Henze, Csicsvari, Hirase, and Buzsáki, 2000]
Model:

- Time-varying cluster parameters
- Time-varying cluster strengths
- Cluster “birth”
- Cluster “death”

many variants exist.

GPUDDP: [Caron et al., 2007]
Spike Sort: [Gasthaus, Wood, Görür, and Teh, 2008]
Figure 5.6: Results on the HARRIS data set (subsampled). (a) shows the true labeling while (b) though (d) show the (MAP) labelings returned by the three algorithms. The GPUDPM algorithm successfully tracks the waveform change over time, while the DPM model splits the data from the IC channel into two clusters.

The transition kernel (specifying how the waveform shape is expected to change over time), the deletion probability $\pi$ and the DP concentration parameter $\nu$. Each parameter was varied in three discrete steps: The parameters used for the base distribution were a broad setting ($\nu = 1.1$, $\pi = 0.5$, $n_0 = 1$), a narrow setting ($\nu = 0.0$, $\pi = 4$, $n_0 = 0.01$), and an approximately correct setting ($\nu = 3.7$, $\pi = 0.65$, $n_0 = 0.05$). Illustrative draws from the resulting prior distributions are shown in figure 5.8. The number of auxiliary variables (per time step and active cluster) were chosen to be $M \in \{1, 30, 100\}$, and $\nu$ was chosen from a discrete set.

Data: [Harris, Henze, Csicsvari, Hirase, and Buzsáki, 2000]
Sorting Results (shown): [Gasthaus, Wood, Görür, and Teh, 2009]
Improvement (not shown): [Chen, Carlson, and Carin, 2012]
Results: Good

CHAPTER 5. EXPERIMENTS

Figure 5.6: Results on the HARRIS data set (subsampled). (a) shows the true labeling while (b) though (d) show the (MAP) labelings returned by the three algorithms. The GPUDPM algorithm successfully tracks the waveform change over time, while the DPM model splits the data from the IC channel into two clusters.

The transition kernel (specifying how the waveform shape is expected to change over time), the deletion probability $\alpha$ and the DP concentration parameter $\beta$.

Each parameter was varied in three discrete steps: The parameters used for the base distribution were a broad setting ($\beta = 1.1, \alpha = 0.5, n_0 = 1$), a narrow setting ($\beta = 8 0, \alpha = 4, n_0 = 0.01$), and an approximately correct setting ($\beta = 3.7, \alpha = 0.65, n_0 = 0.05$). Illustrative draws from the resulting prior distributions are shown in figure 5.8. The number of auxiliary variables (per time step and active cluster) were chosen to be $M \{1, 30, 100\}$, and $\beta$ was

Comments:
- Incremental Inference $\rightarrow$ Scalable
- Bayesian (nonparametric) $\rightarrow$ Interpretation Uncertainty Represented
 CHAPTER 3. TIME-VARYING DIRICHLET PROCESS MIXTURES

\[ k = 1, \ldots, K_t \]
\[ t = 1, \ldots, T \]

\[ \theta_{k,t} \]
\[ m_{k,t} \]
\[ c_t \]
\[ x_t \]

Figure 3.2: Graphical model of the GPU time-varying Dirichlet process mixture model [Caron et al., 2007].

\[ \theta_{k,t} \] denotes the parameters of mixture component \( k \) at time step \( t \), \[ \tilde{m}_{k,t} \] denotes the number of customers sitting at table \( k \) after the deletion step at \( t \), and \( c_t \) denotes the class label of data point \( x_t \). Furthermore, \( K_t \) refers to the number of mixture components that have had data associated with them within the first \( t \) time steps. While there in principle are an infinite number of mixture components, only a finite number will have data associated with them at any given \( t \).

\begin{align*}
\text{Data} & : \text{PETS2000} \\
\text{Model} & : \text{GPUDDP} \\
\text{Observations} & : \text{Features} \cup \text{Position} \\
\end{align*}

Figures: [Bock, Lee, Kerlin, Andermann, Hood, Wetzel, Yurgenson, Soucy, Kim, and Reid, 2011]
Steal Features Liberally from Literature


A feature vector $f$ is extracted for each superpixel $x_i$ in $I$. Each superpixel is assigned Ray, Rotational, and Histogram features.

2.4 Learning Object Boundaries

Most graph-cut approaches model object boundaries using a simple pairwise term

- [Venkataraju and Paiva, 2009]
- [Jurrus et al., 2009]
- ?
Plan

1. Steal Features Liberally from Literature
   - [Lucchi et al., 2010] (http://code.google.com/p/neurons/)
   - [Venkataraju and Paiva, 2009]
   - [Jurrus et al., 2009]
   - ?

2. Apply GPUPDDP
Plan

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2. Apply GPUDDP

3. Hack: Post hoc Track Joining

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Fig. 7: (a) Results for the PETS2009/2010 dataset, showing a sample from the posterior distribution of the state for frames 1-50, where the vertical axis denotes time, the horizontal axes represent spatial position, color represents assignment, and the mean and standard deviation are shown. (b) Performance metrics vs. covariance confidence interval threshold. Below (c-f) are four frames with one posterior sample mean and covariance matrix representation shown for each frame (and one sample mean shown for the previous 20 frames).

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Performance Metric
SFDA
ATA
Confidence Value

(a)

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   - ?

2. Apply GPUPDDP

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4. New Math: Dependent Mixture Model Prior with Cluster Splitting and Merging
   - GPUPDDP + Coagulation/Fragmentation [Ho et al., 2006, Teh et al., 2012]
Neuroscience: Infill or Test Hypotheses with Support of Posterior over Learned Tracks

- [Roberts, Jeong, Vázquez-Reina, Unger, Bischof, Lichtman, and Pfister, 2011]
Wrap-Up

- Strong Regularization is Imperative
  - Grouping Regions: [Kaynig, Fuchs, and Buhmann, 2010]

- Uncertainty in Interpretation should be Represented
  - Regularization in the form of a Prior
  - Bayesian

- Missing Mathematical Piece
  - Clustering Prior with Splitting and Merging


