Illustration for Combining Sorting Results from Multiple Sorters

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In this document, I would give a brief illustration of the current derivation and implementation of how I combine different sorting results from different sorters. The Github repo of this algorithm is https://github.com/Shawn-Guo-CN/spikecombine.

1 Derivation of the Algorithm

1.1 Preliminary

Assume that we first have the following things:

- K sorters, i.e. $\{s_1, s_2, \dots, s_K\}$;
- $N^{(k)}$ units from with their metric values $\mathbf{m}_i^{(k)} = \left\{m_{i,1}^{(k)}, m_{i,2}^{(k)}, \dots, m_{i,D}^{(k)}\right\}, \ \forall i \in \{1, 2, \dots, N^{(k)}\}$ for every sorting s_k , where D is the number of metrics we have.

Then, we task is: for a specific sorter s_k , decide whether unit $u_i^{(k)}$ it detected is a true positive (TP) unit (i.e. $u_i^{(k)}=1$) or false positive (FP) one (i.e. $u_i^{(k)}=0$), based on their corresponding metric values. As we would only curate the sortings from one sorter, from then on, I will ignore the serial number (k) of different sorters.

1.2 Derivation

Based on the Bayesian theorem and the task, I could derive the posterior probability of some unit u_i being a TP as follow:

$$p(u_{i} = 1 | \mathbf{m}_{i}) = \sum_{k=1}^{K} p(u_{i} = 1, s_{k} | \mathbf{m}_{i})$$

$$= \sum_{k=1}^{K} \frac{p(u_{i} = 1, s_{k}, \mathbf{m}_{i})}{\sum_{k'=1}^{K} \sum_{i'=1}^{N^{(k')}} p(u_{i'}, s_{k'}, \mathbf{m}_{i'})}$$

$$\propto p(u_{i} = 1, s_{k}, \mathbf{m}_{i})$$

$$= p(\mathbf{m}_{i} | u_{i} = 1, s_{k}) p(u_{i} = 1 | s_{k}) p(s_{k})$$
(1)

Similarly, we could have:

$$p(u_i = 0|\mathbf{m}_i) \propto p(\mathbf{m}_i|u_i = 0, s_k)p(u_i = 0|s_k)p(s_k)$$
(2)

Note: $p(u_i|s_k)$ is a delta distribution whose value is decided by $spikecomparison.compare_two_sorters()$. So, it doesn't have a probabilistic explanation.

Then, take $p(u_i = 1 | \mathbf{m}_i)$ for example, what we need to estimate is only $p(\mathbf{m}_i | u_i = 1, s_k)$, i.e. the posterior distribution of metric values on TP units from sorter s_k . As for the prior distribution $p(s_k)$, we can set it to uniform. And $p(u_i = 1 | s_k)$ could be estimated by: i) the agreement score between s_k and ground-truth during learning; ii) the agreement score between s_k and other sorter $s_{k'}$ during inference.

2 Implementation of the Algorithm

2.1 Hierarchy of Classes

In the project, all the classes and their brief descriptions are given as follows:

- **SpikeSortersCombiner**, the class implementing the algorithm with a function *fit* for fitting $p(\mathbf{m}_i|u_i=1,s_k)$ and a function *predict* for performing the inference in Equation(1) and Equation (2).
- **DataGenerator**, the class is to load a folder containing lots of *MEArecRecordingExtractor* in .h format, and (more importantly) generate a folder that is specifically organised to be taken as the input for *DataLoader*.
- **DataLoader**, the class is to take the folder generated by *DataGenerator* as the input, and provide *SpikeSortersCombiner* APIs to get access the *sortings* from different sorters with the corresponding *ground-truth sorting* and *original recording*.

2.2 Descriptions of Key Steps

Here, I did not provide pseudocodes for the key steps, as the codes themselves are all very straightforward.

2.2.1 For Fitting

The steps of fitting parameters of $p(\mathbf{m}_i|u_i=1,s_k)$ of **every sorter** s_k are given as follows:

- 1. by comparing with the corresponding ground-truth sorting, classify the units to TP U_k^{TP} ones and FP ones U_k^{FP} for every sorter s_k , based on the agreement scores between s_k and ground-truth;
- 2. estimate the mean and covariance matrix on: i) U_k^{TP} , which gives μ_k^{TP} and σ_k^{TP} ; ii) U_k^{FP} , which gives μ_k^{FP} and σ_k^{FP} .

2.2.2 For Inference

The steps to do inference on sortings from s_k are exactly following Equation (1) and (2):

- 1. compare s_k with sortings from all other different sorters, and store the agreement scores between them;
- 2. calculate the metric $\mathbf{m}_{i}^{(k)}$ for every detected unit $u_{i}^{(k)}$;
- 3. for every $u_i^{(k)}$, calculate $p(u_i = 1|\mathbf{m}_i)$ and $p(u_i = 1|\mathbf{m}_i)$ following Equation (1) and (2) respectively;
- 4. if $p(u_i = 1 | \mathbf{m}_i) < p(u_i = 1 | \mathbf{m}_i)$, then exclude $u_i^{(k)}$ from the output of s_k .