# Prediction Target and Loss Function for Competition

April 12, 2007

## "Quantitative Neuron Modeling: Predicting every spike?"

A workshop with this title will be organized by EPFL and UCL London on
June 25-26 , 2007
in Lausanne, Switzerland.
Results of the competition will be presented at this workshop.

The Competition is is organized in four challenges.

- A: Single-electrode data from cortical neurons under random current injection. Stimulation is done with currents of different means and fluctation amplitudes.
- B: Single-electrode data from cortical neurons under various current injection paradimgs. Stimulation is done by combination of various step and current pulses.
- C: Two electrode data from cortical neurons under random current injection at soma and/or dendrite. Stimulation is done with currents of different means and fluctuation amplitudes.
- D: More multi-electrode data including subthreshold stimulation. Challenge D has opened beginning of April.

**The aim of each challenge is described in this document.**

Changes compared to previous document:
(a) The definition of function $F_1$ in paragraph 2.1 includes now a factor $1/n$ that was obviously missing.
(b) The details of Challenge D have been added.

# 1 Challenge A

Single-electrode data from cortical neurons under random current injection. Data courtesy of A. Rauch et al., J. Neurophysology, 90, 1598–1612 (2004)) Stimulation is done with currents of different means and fluctuation amplitudes. Currents are generated by an Ornstein-Uhlenbeck process with time constant $\tau = 1$ms. That is, the input is colored noise with a frequency cutoff of 1 kHz.
For each input, 4 repetitions of the same stimulus are available so as to estimate the intrinsic reliability of neurons. Several stimulation sets are set apart for the prediction.

## 1.1 Evaluation criteria for dataset A

The aim is to predict spike times with a precision of $\pm$2ms. To evaluate the quality, we calculate the number of coincidences $N_{coinc}$ between the spikes in the data spike train (target) and the spike train of the model submitted by a participant. We subtract the expected number of coincidences $\langle N_{coinc} \rangle$ that a Poisson spike train would give and we divide by the number of spikes in the two spike trains:

$$\Gamma = \alpha \frac{N_{coinc} - \langle N_{coinc} \rangle}{N_{data} + N_{model}} \tag{1}$$

where $N_{data}$ and $N_{model}$ denote the number of spikes in the data and model spike trains and $\alpha$ is a factor that normalises the coincidence factor $\Gamma$ to a maximum of 1. For details see Kistler et al. Neural Comput. 9:1069-1100 (1997) and Jolivet et al., J. Comput. Neurosci. 21:35-49 (2006).

$\Gamma = 0$ implies that the prediction is not better than chance level. $\Gamma$=1 implies that the prediction by the model is optimal.

## 1.2 Overall Aim

**Maximize $\Gamma$ averaged across all test sets.**
Procedure:
Step (i). If your model is deterministic, you send us for each input in the test set ONE spike train (set of spike times). If your model is stochastic, you send us for each input in the test set 25 spike trains (25 sets of spike times).
Step (ii). For each input, we have four responses of the neuron (the same input was repeated four times). We calculate $\Gamma(k)$ for all $n$ combinations of model response and neuron response $1 \leq k \leq n$. We also calculate the intrinsic reliability $\Gamma_{int}$ (same formula as above, but comparing the response to different repetitions of the same input). Overall we return

$$\Gamma_A = \frac{1}{n} \sum_{k=1}^{n} \frac{\Gamma(k)}{\Gamma_{int}} \tag{2}$$

**The winner is the submission with maximal value of $\Gamma_A$ averaged over all stimulations in the test set.**

# 2 Challenge B

Several input samples (steps of various duration and amplitude) will given as training data together with the electrophysiological measurements. Other input samples (e.g., step currents of a different amplitude or duration) will be given for test/prediction (without the measurement). Data courtesy of the Blue Brain Project (http://bluebrainproject.epfl.ch). Please contact Felix Schuermann (felix.schuermann@epfl.ch) regarding correct referencing of the data in case of publication.

**Training input**

(i) hyperpolarizing and depolarizing subthreshold current steps.

(ii) Superthreshold step currents of about 0.1 second duration. Cells respond with a few spikes.

(iii) Superthreshold step currents of about 2 second duration. One cell responds with spike trains that show adaptation; another cells exhibits initial bursting without further adaptation.

(iv) Pairs of strongly depolarizing pulses that allow to study spike-afterpolarizing potentials, spike triggered adaptation, and refractoriness.

**Test input**

(i) Two sequences of different subthreshold steps, one depolarizing, the other hyperpolarizing.

(iii) Superthreshold step currents of about 0.2 second duration, similar to the one in the training set, but starting from a depolarized background.

(iii) A slow ramp current, leading to neuronal firing

## 2.1 Evaluation criteria for data set B

The aim is to predict the subthreshold voltage trace, the timing of the first spike, as well as the firing frequency at the beginning and the end of a step current.

Model quality will be measured first separately for each criterion, and then the overall rating will be determined by appropriate mixing of the criteria. Each criterion will be evaluated on a scale between zero and 1 where 1 is the optimal solution. In addition to the coincidence factor $\Gamma$ used above, we will use a function

$$g(x) = \frac{1}{1+x^2} \tag{3}$$

which is bounded between 0 and 1.

This function will be used as follows on the different test sets mentioned above:

(i) Two sequences of different subthreshold steps, one depolarizing, the other hyperpolarizing.

**Aim: predict the subthreshold voltage with a precision of 2 mV.**

Criterion:
We define difference between the voltage of the experimental trace and that of the model neuron in data set $k$ as $x_k(t) = (u_{data,k}(t) - u_{model,k}(t))/2mV$ and use the criterion

$$F_1 = \frac{1}{n}\sum_{k=1}^{n}\frac{1}{T}\int_0^T g(x_k(t))dt \tag{4}$$

where $k$ runs over all $n$ sequences of subthreshold steps and $T$ is the duration of the stimulation. *To be submitted*: You send us for each input trace $k$ a two-column ascii file (time, model voltage at this time).

(ii) Superthreshold step currents of about 0.2 second duration, similar to those in the training set, but from a depolarizing background.

**Aim 1: predict the timing of the first spike with a precision of 2 ms.**

Criterion:
We define difference between the timing of the first spike of the experimental neuron and that of the model neuron as $x^{first} = (t^{first}_{data} - t^{first}_{model})/2ms$ and use the criterion

$$F_2 = \frac{1}{n}\sum_{k=1}^{n} g(x^{first}_n)$$

The lower index refers to the $n$ different data sets (step currents of different amplitudes).

**Aim 2: predict the firing frequency in the first interval with a precision of 5 Hz.**

Criterion:
The frequency is the inverse of the first interspike interval $f^{first} = 1/(t^{second} - t^{first})$. We define difference between the frequency of the experimental neuron and that of the model neuron as $x^{f1} = (f^{first}_{data} - f^{first}_{model})/5Hz$ and use the criterion

$$F_3 = \frac{1}{n}\sum_{k=1}^{n} g(x^{f1}_k)$$

**Aim 3: predict the firing frequency in the second interval with a precision of 5 Hz.**

Criterion:
We search for the second and third spike in the spike train under step current injection. The frequency is the inverse of the interspike interval $f^2 = 1/(t^{third} - t^{second})$. We define difference between the frequency of the experimental neuron and that of the model neuron as $x^{f2} = (f^2_{data} - f^2_{model})/5Hz$ and use the criterion

$$F_4 = \frac{1}{n}\sum_{k=1}^{n} g(x^{f2}_1)$$

**Aim 4: predict the firing frequency in the last interval with a precision of 5 Hz.**

Criterion:
We search for the two last spikes in the spike train under step current injection. The frequency is the inverse of the interspike interval $f^{last} = 1/(t^{last} - t^{secondlast})$. We define difference between the frequency of the experimental neuron and that of the model neuron as $x^{flast} = (f^{last}_{data} - f^{last}_{model})/5Hz$ and use the criterion

$$F_5 = \frac{1}{n}\sum_{k=1}^{n} g(x_1^{flast})$$

*To be submitted*: You send us for each input in the test set ONE somatic spike train (set of somatic spike times).

(iii) A slow ramp current, leading to neuronal firing

**Aim: predict the timing of the first spike with a precision of 10 ms.**

Criterion:
We define the difference between the timing of the first spike of the experimental neuron and that of the model neuron as $x^{first} = (t^{first}_{data} - t^{first}_{model})/10ms$ and use the criterion

$$F_6 = g(x^{first})$$

*To be submitted*: You send us a single number, i.e., the timing of the first spike in your model.

## 2.2 Overall Aim

**Maximize criteria $F_1, ..., F_6$ for each of the two different neurons**.

Since we have two neurons (Regular spiking with adaptation AND Non-adapting neuron with an initial burst) we have a total of 12 criteria. We use the labels $F_1, ..., F_6$ for the first neuron and $F_7, ..., F_{12}$ for the second neuron.

In the literature of multi-criteria optimization several possibilities of combining the differen 'targets' are discusssed. A particularly severe one is to look only at the **worst performance**, i.e., $\min_k F_k$ for $1 \leq k \leq 12$. An alternative would be to look at the **mean** performance $\sum_k F_k/12$.

We will use a compromise between both approaches and average over all 12 criteria but give more importance to the worst performing criteria. Specifically, we will use the following

**two-step procedure:**

(i) Rank the indices according to performance. The criteria that performs worst gets an upper index (1): $C^{(1)} = \min_k\{F_k\}$ the second worst and upper index (2) $C^{(2)} = \min_k\{F_k|worstremoved\}$ etc.

(ii) Evaluate the weighted mean

$$\Gamma_B = 0.5C^{(1)} + 0.25C^{(2)} + ... = \sum_{k=1}^{12} \frac{1}{2^k} C^{(k)} \tag{5}$$

**The winner is the submission with maximal value of $\Gamma_B$.**

# 3 Challenge C

Simultaneous whole-cell voltage recordings from the soma and apical dendrite of neocortical layer 5 pyramidal neurons under random current injection via the somatic and/or dendritic recording pipette. Data courtesy of Matthew Larkum, Walter Senn and Hans-Rudolf Lüscher (Larkum et al., Cereb. Cortex 14, 1059-1070 (2004))

Stimulation is done with currents of different means and fluctuation amplitudes. Currents are generated by an Ornstein-Uhlenbeck process with time constant $\tau = 3$ms. That is, the input is colored noise with a frequency cutoff of 333 Hz. For each combination of somatic and dendritic inputs, only a single trial is available. Several stimulation sets are set apart for the prediction.

## 3.1 Evaluation criteria for data set C

The aim is to predict spike times with a precision of $\pm 2$ms. Spike time is defined by the time of the peak of the somatic action potential waveform. To evaluate the quality, we calculate the number of conincidences $N_{coinc}$ between the spikes in the data spike train (target) and the model spike train submitted by participants in challenge C. We subtract the expected number of coincidences $\langle N_{coinc} \rangle$ that a Poisson spike train would give and we divide by the number of spikes in the two spike trains:

$$\Gamma = \alpha \frac{N_{coinc} - \langle N_{coinc} \rangle}{N_{data} + N_{model}} \tag{6}$$

where $N_{data}$ and $N_{model}$ denote the number of spikes in the data and model spike trains and $\alpha$ is a factor that normalises the coincidence factor $\Gamma$ to a maximum of 1. For details see Kistler et al. Neural Comput. 9:1069-1100 (1997) and Jolivet et al., J. Comput. Neurosci. 21:35-49 (2006).

$\Gamma = 0$ implies that the prediction is not better than chance level. $\Gamma$=1 implies that the prediction by the model is optimal.

## 3.2 Overall Aim

**Maximize $\Gamma$ averaged across all test sets.**

Procedure:

Step (i) If your model is deterministic, you send us for each input in the test set ONE somatic spike train (set of somatic spike times). If your model is stochastic, you send us for each input in the test set 25 somatic spike trains (set of somatic spike times).

Step (ii) We calculate $\Gamma(k)$ for all $n$ combinations of model response and neuron response $1 \leq k \leq n$ and return

$$\Gamma_C = \frac{1}{n} \sum_k \Gamma(k). \tag{7}$$

**The winner is the submission with maximal value of $\Gamma_C$ averaged across all different stimuli in the test set.**

# 4 Challenge D

Challenge D combines features of Challenges B and C and focuses on voltage traces obtained by triple whole-cell recordings from neocortical layer 5 pyramidal neurons. Data courtesy of Matthew Larkum, Walter Senn and Hans-Rudolf Lüscher (Larkum et al., Cereb. Cortex 14, 1059-1070 (2004)).

## 4.1 Aim 1: predict the subthreshold voltage with a precision of 2 mV.

We define difference between the voltage of the experimental trace and that of the model neuron in data set $k$ as $x_k(t) = (u_{data,k}(t) - u_{model,k}(t))/2mV$ and use the criterion

$$F_1 = \frac{1}{n} \sum_{k=1}^{n} \frac{1}{T} \int_0^T g(x_k(t))dt$$

where $k$ runs over all $n$ sequences of subthreshold steps and $T$ is the duration of the stimulation. Similar to challenge B, the function $g$ is bounded between 0 and 1 and given by $g(x) = 1/(1 + x^2)$.

*To be submitted*: You send us for each of the second, fourth, ..., and sixteenth trial in experiment no. 19 a two-column ascii file (time, model voltage at the proximal dendritic pipette D2 at this time)

## 4.2 Aim 2: predict the timing of spikes with a precision of 2 ms.

Spike time is defined by the time of the peak of the somatic action potential waveform. To evaluate the quality, we calculate the number of conincidences $N_{coinc}$ between the spikes in the data spike train (target) and the model spike train submitted by participants in challenge D. We subtract the expected number of coincidences $\langle N_{coinc} \rangle$ that a Poisson spike train would give and we divide by the number of spikes in the two spike trains:

$$\Gamma = \alpha \frac{N_{coinc} - \langle N_{coinc} \rangle}{N_{data} + N_{model}}$$

where $N_{data}$ and $N_{model}$ denote the number of spikes in the data and model spike trains and $\alpha$ is a factor that normalises the coincidence factor $\Gamma$ to a maximum of 1. For details see Jolivet et al., J. Comput. Neurosci. 21:35-49 (2006). $\Gamma = 0$ implies that the prediction is not better than chance level. Optimal prediction yields $\Gamma$=1.

The factor $\Gamma$ is calculated for all spike trains in the test set, i.e. experiments no. 11, 12, 14, 15 and 19, and $F_2$ will be taken as the average value

$$F_2 = \frac{1}{5} (\Gamma(11) + \Gamma(12) + \Gamma(14) + \Gamma(15) + \Gamma(19)) \tag{8}$$

The eight spike trains to be predicted for experiment no. 19 will count as one spike train for this purpose, since they contain only a very small number of spikes.

*To be submitted*: If your model is deterministic, you send us for each input in the test set ONE spike train (set of spike times). If your model is stochastic, you send us for each input in the test set 25 spike trains (25 sets of spike times).

### 4.3 Overall Aim

Both the subthreshold criterion $F_1$ and the spike precision criterion $F_2 = \Gamma$ will be given equal weight:

$$\Gamma_D = 0.5F_1 + 0.5F_2 \tag{9}$$

**The winner is the submission with maximal value of $\Gamma_D$.**