Event Outlier Detection in Continuous Time

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A. Continuous-Time LSTM with Context

The input to the continuous-time LSTM consists of the marked events in the combined sequence, $(t_i, u_i) \in S_{\mathcal{M}}$. That is, we not only use the target events but also the context events as input, although we only model the CIF of the target events, $\lambda(t)$. The output consists of the hidden states $\boldsymbol{h}(t_i)$ corresponding to the input. It is a nonlinear mapping from the content in the memory cell $\boldsymbol{c}(t_i)$ of the LSTM at time t_i. As in a traditional LSTM, each continuous-time LSTM unit also has an input gate $\boldsymbol{i}$, an output gate $\boldsymbol{o}$, and a forget gate $\boldsymbol{f}$. The relations between the memory cells, the hidden states, the input, and these gates are summarized as follows.

Let $\boldsymbol{u}_i$ be a vector representation of the mark u_i, which is a learnable embedding. For $t \in (t_{i-1}, t_i]$, $\boldsymbol{c}(t)$ is a continuous function changing over time from $\boldsymbol{c}_i$ to $\bar{\boldsymbol{c}}_i$, and for $\boldsymbol{c}_i$ and $\bar{\boldsymbol{c}}_i$ there are separate input gates and forget gates:

$$\boldsymbol{h}(t) = \boldsymbol{o}_i \odot \tanh(\boldsymbol{c}(t)) \quad \text{(A.1)}$$

$$\boldsymbol{c}(t) = \bar{\boldsymbol{c}}_i + (\boldsymbol{c}_i - \bar{\boldsymbol{c}}_i) \exp\left(-\boldsymbol{\delta}_i (t - t_{i-1})\right) \quad \text{(A.2)}$$

$$[\boldsymbol{i}_{i+1}; \boldsymbol{o}_{i+1}; \boldsymbol{f}_{i+1}] = \sigma(\boldsymbol{W}\boldsymbol{u}_i + \boldsymbol{U}\boldsymbol{h}(t_i) + \boldsymbol{d}) \quad \text{(A.3)}$$

$$[\bar{\boldsymbol{i}}_{i+i}; \bar{\boldsymbol{f}}_{i+1}] = \sigma(\bar{\boldsymbol{W}}\boldsymbol{u}_i + \bar{\boldsymbol{U}}\boldsymbol{h}(t_i) + \bar{\boldsymbol{d}}) \quad \text{(A.4)}$$

$$\boldsymbol{z}_{i+1} = \tanh(\boldsymbol{W}_z\boldsymbol{u}_i + \boldsymbol{U}_z\boldsymbol{h}(t_i) + \boldsymbol{d}_z) \quad \text{(A.5)}$$

$$\boldsymbol{c}_{i+1} = \boldsymbol{f}_{i+1} \odot \boldsymbol{c}(t_i) + \boldsymbol{i}_{i+1} \odot \boldsymbol{z}_{i+1} \quad \text{(A.6)}$$

$$\bar{\boldsymbol{c}}_{i+1} = \bar{\boldsymbol{f}}_{i+1} \odot \bar{\boldsymbol{c}}_i + \bar{\boldsymbol{i}}_{i+1} \odot \boldsymbol{z}_{i+1} \quad \text{(A.7)}$$

$$\boldsymbol{\delta}_{i+1} = g(\boldsymbol{W}_\delta\boldsymbol{u}_i + \boldsymbol{U}_\delta\boldsymbol{h}(t_i) + \boldsymbol{d}_\delta, 1) \quad \text{(A.8)}$$

where $[\boldsymbol{a}; \boldsymbol{b}]$ denotes the concatenation of the vectors $\boldsymbol{a}$ and $\boldsymbol{b}$, $\odot$ is the elementwise product, $\sigma(\cdot)$ is the logistic function, and $g(x, s) = s \log(1 + \exp(x/s))$ is the scaled softplus function with parameter s. All the $\boldsymbol{W}$, $\boldsymbol{U}$ and $\boldsymbol{d}$ with/without different subscripts and bars are learnable parameters of the continuous-time LSTM.

Finally, to convert the output of the continuous-time LSTM to the CIF of the target events, $\lambda(t)$, we have $\lambda(t) = g(\boldsymbol{w}_\lambda^T \boldsymbol{h}(t), s)$ where $\boldsymbol{w}_\lambda$ and s are learnable parameters. The model is learned by maximizing the likelihood (Eq. 1) for all sequences in the training data. Monte-Carlo integration is used to evaluate $\int \lambda(s) ds$.

B. Generalization to Nonconstant Commission

We generalize the method we have developed in Section 3.3 to cases when the rate of commission is not a constant. Treating $\lambda_1(t_n)$ as a random variable, based on what we have already developed, we have

$$\begin{aligned} p(Z_n = 1 | t_n, \lambda_1(t_n)) &= 1 - \frac{\lambda_0(t_n)}{\lambda_g(t_n)} \\ &= 1 - \frac{\lambda_0(t_n)}{\lambda_0(t_n) + \lambda_1(t_n)} \\ &= 1 + \frac{s_c(t_n)}{\lambda_1(t_n) - s_c(t_n)} \end{aligned}$$

To avoid cluttering, we omit t_n in λ_0, λ_1, and s_c from now. By marginalizing out λ_1, we get

$$\begin{aligned} p(Z_n = 1 | t_n) &= \mathbb{E}_{\lambda_1}\left[p(Z_n = 1 | t_n, \lambda_1)\right] \\ &= 1 + \mathbb{E}_{\lambda_1}\left[\frac{s_c}{\lambda_1 - s_c}\right] \\ &= 1 + \mathbb{E}_{\lambda_1}\left[f(s_c, \lambda_1)\right] \end{aligned}$$

where we defined

$$f(s_c, \lambda_1) = \frac{s_c}{\lambda_1 - s_c}$$

We assume

$$\mathbb{E}_{\lambda_1}\left[\frac{1}{\lambda_1}\right] < \infty$$

which is easy to satisfy, since it is sufficient that either $\lambda_1 \geq \epsilon$ for some $\epsilon > 0$ or the distribution of λ_1 is one of the common distributions including any finite discrete distribution, Gamma distribution, etc.

It is not hard to see that f is an increasing function of s_c for any given λ_1, as $s_c \in (-\infty, 0)$, $\lambda_1 \in (0, \infty)$, and

$$\frac{\partial f}{\partial s_c} = \frac{\lambda_1 - 2s_c}{(\lambda_1 - s_c)^2} > 0$$

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Meanwhile,

$$\left|\frac{\partial f}{\partial s_c}\right| = \left|\frac{\lambda_1 - 2s_c}{(\lambda_1 - s_c)^2}\right| < \frac{1}{\lambda_1}$$

Therefore, we can show that

$$\frac{\partial \mathbb{E}_{\lambda_1}\left[f(s_c, \lambda_1)\right]}{\partial s_c} = \mathbb{E}_{\lambda_1}\left[\frac{\partial f(s_c, \lambda_1)}{\partial s_c}\right] > 0$$

using the Dominated Convergence Theorem. This implies that $p(Z_n = 1|t_n)$ is an increasing function of s_c.

C. Generalization to Nonconstant Omission

Similar to commission outliers, we generalize the method we have developed in Section 3.4 to cases when the probability of omission is not a constant and the normal point process is an inhomogeneous Poisson process. Treating p_1 as a random variable, based on what we have already developed, we have

$$\begin{aligned} p(Z_B = 1|N(B) = 0, p_1) &= 1 - \exp\left(-p_1 \int_B \lambda_0(s) ds\right) \\ &= 1 - \exp\left(-p_1 s_o(B)\right) \end{aligned}$$

To avoid cluttering, we omit B in s_o from now. By marginalizing out p_1, we get

$$\begin{aligned} p(Z_B = 1|N(B) = 0) &= 1 - \mathbb{E}_{p_1}\left[\exp\left(-p_1 s_o\right)\right] \\ &= 1 - \mathbb{E}_{p_1}\left[g(s_o, p_1)\right] \end{aligned}$$

where we defined

$$g(s_o, p_1) = \exp\left(-p_1 s_o\right)$$

Apparently g is an decreasing function of s_c for any given p_1, as $s_o \in (0, \infty)$, $p_1 \in [0, 1]$, and

$$\frac{\partial g}{\partial s_o} = (-p_1)\exp\left(-p_1 s_o\right) \leq 0$$

Meanwhile,

$$\left|\frac{\partial g}{\partial s_o}\right| = \left|(-p_1)\exp\left(-p_1 s_o\right)\right| \leq 1$$

Therefore, we can show that

$$\frac{\partial \mathbb{E}_{p_1}\left[g(s_o, p_1)\right]}{\partial s_o} = \mathbb{E}_{p_1}\left[\frac{\partial g(s_o, p_1)}{\partial s_o}\right] \leq 0$$

using the Dominated Convergence Theorem. This implies that $p(Z_B = 1|N(B) = 0)$ is an increasing function of s_o.

D. Proofs of the Theorems

D.1. Theorem 3.1

Proof. From Eq. 4 and implicitly conditioned on the event t_n and the history

$$p(y_c(t_n) = 0) = p(Z_n = 0) = \frac{\lambda_0(t_n)}{\lambda_0(t_n) + \lambda_1}$$

Given that $\hat{y}_c(t_n) = 1$, i.e., $-\lambda_0(t_n) > \theta_c$, we get

$$p(y_c(t_n) = 0|\hat{y}_c(t_n) = 1) < \frac{-\theta_c}{-\theta_c + \lambda_1}$$

□

D.2. Theorem 3.2

Proof. Let T_n be the random variable for the inter-event time corresponding to the observed inter-event interval B, assuming it is generated from the normal point process. From Eq. 18

$$\begin{aligned} & p(\hat{y}_o(B) = 1|y_o(B) = 0) \\ =& p\left(\int_B \lambda_0(s) ds > \theta_o \middle| y_o(B) = 0\right) \\ =& p\left(\exp\left(-\int_B \lambda_0(s) ds\right) < \exp\left(-\theta_o\right) \middle| y_o(B) = 0\right) \\ =& p\left(p(T_n > |B|) < \exp\left(-\theta_o\right)\right) \\ =& \exp\left(-\theta_o\right) \end{aligned}$$

The last equality is because $p(T_n > |B|) = 1 - p(T_n \leq |B|)$, and $p(T_n \leq |B|)$ is the cumulative distribution function of T_n, implying it follows a uniform distribution. □

D.3. Theorem 3.3

Proof. From Eq. 17 and implicitly conditioned on $N(B) = 0$ and the history

$$p(y_o(B) = 0) = p(K_B = 0) = \exp\left(-p_1 \int_B \lambda_0(s) ds\right)$$

Given that $\hat{y}_o(B) = 1$, i.e., $\int_B \lambda_0(s) ds > \theta_o$, we get

$$p(y_o(B) = 0|\hat{y}_o(B) = 1) < \exp\left(-p_1 \theta_o\right)$$

□

E. Simulation of Commission and Omission Outliers

To define outliers, we simulate commission and omission outliers on top of the existing data. In this way, we can obtain ground-truth labels for testing.

To define commission outliers, we simulate a new sequence of target events independently from the existing data, and then merge the new events with the existing events. We use an (inhomogeneous) Poisson process with an intensity $\lambda_c(t)$ to generate the outliers. λ_c controls the rate of such outliers. In the experiments, for each dataset, we set $\lambda_c(t) = \alpha(t)\hat{\lambda}_{test}$, where $\alpha(t)$ is either a constant or a function over time depending on the settings, and $\hat{\lambda}_{test}$ is the empirical rate of the target events calculated from the original test data.

To define omission outliers, we randomly remove target events in the original sequences according to independent Bernoulli trials. That is, each event is removed with probability p_1 and kept with probability $1 - p_1$. We always keep the event if it marks the start time of the sequence. In the experiments, we set $p_1 = \alpha(t)$, where, similar to commission, $\alpha(t)$ is either a constant or a function over time depending on the settings.

F. Detection of Commission and Omission Outliers

We detect the presence of commission and omission outliers differently. To test for commission outliers, each method outputs an outlier score at the time of each target event. That is, whenever there is a new target event, we ask the question: is this event a commission outlier or not?

Testing for omission outliers is trickier, because we need to decide the checkpoints more carefully, i.e., when to ask for outlier scores. The simplest thing to do is to only check at the target event times. That is, whenever there is a new target event, we ask the question: is there any omission outlier since the previous target event till now?

However, this may become unsatisfactory in real-world applications, because there could be cases when the target events just stop occurring for a long period of time or even forever (potentially due to malfunctions of the underlying system). These are interesting and important cases we are supposed to detect, but the above testing method will not work. Therefore, we use a combined approach. We still have a checkpoint at each target event time, but on top of that, we also randomly generate checkpoints in long blank intervals.

Specifically, we have a parameter w set to $2/\hat{\lambda}_{train}$, where $\hat{\lambda}_{train}$ is the empirical rate of the target events estimated from the training data for each dataset, so within w, on average, we should see two events normally. Then, whenever the blank interval from the previous checkpoint till now is longer than w, we generate a new checkpoint within the interval by uniform sampling, and set the previous checkpoint to the generated checkpoint. We keep generating checkpoints until we reach the next target event or the end of the sequence.

G. Outlier Ratios

The outlier ratio, i.e., the number of outliers divided by the total number of test points, for each dataset is summarized in Table G.1.

Table G.1. Outlier ratios of the datasets. Dataset: name abbreviation (C=commission, O=omission) [α].

Dataset			Ratio	Dataset			Ratio
Gam	(C)	[0.05]	0.047	Gam	(O)	[0.05]	0.034
Gam	(C)	[0.1]	0.095	Gam	(O)	[0.1]	0.072
Gam	(C)	[sin]	0.089	Gam	(O)	[sin]	0.069
Gam	(C)	[pc]	0.088	Gam	(O)	[pc]	0.067
Poi	(C)	[0.05]	0.046	Poi	(O)	[0.05]	0.033
Poi	(C)	[0.1]	0.092	Poi	(O)	[0.1]	0.070
Poi	(C)	[sin]	0.088	Poi	(O)	[sin]	0.066
Poi	(C)	[pc]	0.086	Poi	(O)	[pc]	0.065
INR	(C)	[0.05]	0.057	INR	(O)	[0.05]	0.033
INR	(C)	[0.1]	0.102	INR	(O)	[0.1]	0.065
INR	(C)	[sin]	0.111	INR	(O)	[sin]	0.072
INR	(C)	[pc]	0.096	INR	(O)	[pc]	0.063
Cal	(C)	[0.05]	0.048	Cal	(O)	[0.05]	0.028
Cal	(C)	[0.1]	0.092	Cal	(O)	[0.1]	0.054
Cal	(C)	[sin]	0.099	Cal	(O)	[sin]	0.061
Cal	(C)	[pc]	0.096	Cal	(O)	[pc]	0.050
Pot	(C)	[0.05]	0.049	Pot	(O)	[0.05]	0.030
Pot	(C)	[0.1]	0.095	Pot	(O)	[0.1]	0.059
Pot	(C)	[sin]	0.102	Pot	(O)	[sin]	0.067
Pot	(C)	[pc]	0.089	Pot	(O)	[pc]	0.059
Nor	(C)	[0.05]	0.052	Nor	(O)	[0.05]	0.023
Nor	(C)	[0.1]	0.086	Nor	(O)	[0.1]	0.047
Nor	(C)	[sin]	0.100	Nor	(O)	[sin]	0.058
Nor	(C)	[pc]	0.098	Nor	(O)	[pc]	0.050

H. Empirical Verification of the Bounds on FDR and FPR

We show the results of empirically verifying the bounds proved in Section 3.5, continuing the results in Section 4.2. We use GT (Ground Truth): our outlier scoring methods combined with the *ground-truth* point-process model, which is only available on synthetic data. Figure H.1 shows the empirical FDR (commission outlier), FDR (omission outlier), and FPR (omission outlier) with means and standard deviations on data simulated from inhomogeneous Poisson processes along with the theoretical bounds. As we can see, the empirical FDRs have high variance when the threshold is high, because there are smaller number of samples above a higher threshold. Nonetheless, the empirical FDRs conform with the theoretical bounds, and so does the empirical FPR.

I. Additional Experiment Results

Using Ground-Truth Model We also compared with GT (Ground Truth): our outlier scoring methods combined with the *ground-truth* point-process model (only available on synthetic data). Figure I.1 and I.2 show the receiver operating characteristic (ROC) curves of the outlier detection methods on the synthetic data generated from inhomogeneous Poisson processes and Gamma processes with $\alpha = 0.1$. We note that the curves of GT and CPPOD are almost identical. The fact that CPPOD almost has the same performance as GT is an evidence that the model based on the continuous-time LSTM is flexible enough to represent these context-dependent point processes.

Varying Outlier Rate We also experimented with changing $\alpha_0 = 0.05$ for the constant rate to see its effect. Table I.1 and Table I.2 show the full AUROC results for synthetic and MIMIC data respectively. As we can see, the relative performance for each method does not change in almost all cases.

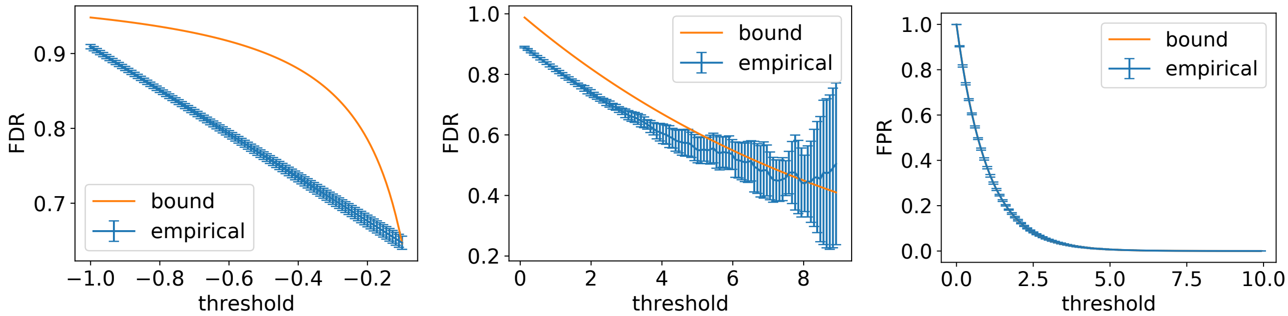

Figure H.1. From left to right: FDR (commission outlier), FDR (omission outlier), and FPR (omission outlier) on synthetic data (Poisson process).

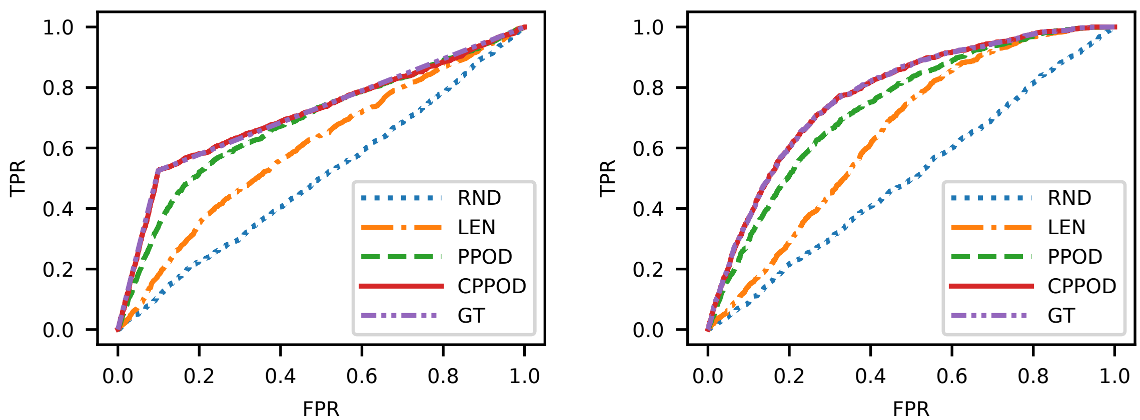

Figure I.1. ROC curves on synthetic data (Poisson process). Left: commission. Right: omission.

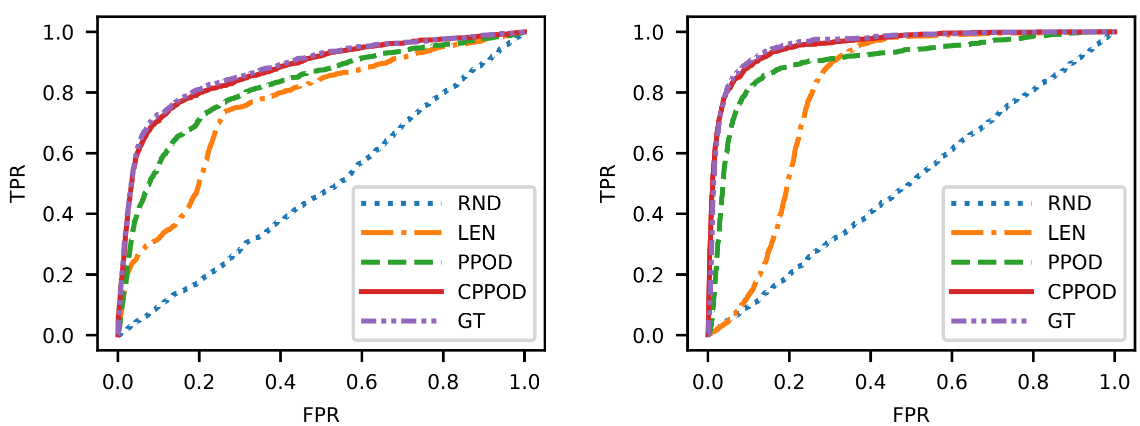

Figure I.2. ROC curves on synthetic data (Gamma process). Left: commission. Right: omission.

Table I.1. AUROC on synthetic data. Dataset: name abbreviation (C=commission, O=omission) [α].

Dataset			RND	LEN	PPOD	CPPOD
Poi	(C)	[0.05]	0.493 (± 0.011)	0.627 (± 0.011)	0.684 (± 0.014)	**0.716** (± 0.019)
Poi	(C)	[0.1]	0.500 (± 0.010)	0.601 (± 0.008)	0.684 (± 0.010)	**0.711** (± 0.012)
Poi	(C)	[sin]	0.493 (± 0.007)	0.575 (± 0.006)	0.661 (± 0.016)	**0.707** (± 0.017)
Poi	(C)	[pc]	0.512 (± 0.009)	0.584 (± 0.011)	0.664 (± 0.009)	**0.697** (± 0.014)
Poi	(O)	[0.05]	0.491 (± 0.018)	0.650 (± 0.008)	0.736 (± 0.007)	**0.776** (± 0.009)
Poi	(O)	[0.1]	0.503 (± 0.008)	0.650 (± 0.006)	0.737 (± 0.006)	**0.778** (± 0.005)
Poi	(O)	[sin]	0.498 (± 0.013)	0.659 (± 0.007)	0.741 (± 0.012)	**0.791** (± 0.010)
Poi	(O)	[pc]	0.491 (± 0.007)	0.652 (± 0.011)	0.734 (± 0.013)	**0.784** (± 0.010)
Gam	(C)	[0.05]	0.479 (± 0.018)	0.776 (± 0.011)	0.840 (± 0.010)	**0.897** (± 0.006)
Gam	(C)	[0.1]	0.485 (± 0.007)	0.754 (± 0.006)	0.816 (± 0.008)	**0.871** (± 0.006)
Gam	(C)	[sin]	0.493 (± 0.008)	0.762 (± 0.008)	0.817 (± 0.006)	**0.886** (± 0.004)
Gam	(C)	[pc]	0.506 (± 0.007)	0.757 (± 0.005)	0.813 (± 0.005)	**0.870** (± 0.007)
Gam	(O)	[0.05]	0.503 (± 0.013)	0.803 (± 0.009)	0.919 (± 0.008)	**0.960** (± 0.007)
Gam	(O)	[0.1]	0.505 (± 0.012)	0.799 (± 0.005)	0.901 (± 0.007)	**0.956** (± 0.003)
Gam	(O)	[sin]	0.503 (± 0.010)	0.809 (± 0.006)	0.902 (± 0.006)	**0.956** (± 0.004)
Gam	(O)	[pc]	0.515 (± 0.010)	0.813 (± 0.005)	0.905 (± 0.006)	**0.955** (± 0.004)

Table I.2. AUROC on MIMIC data. Dataset: name abbreviation (C=commission, O=omission) [α].

Dataset			RND	LEN	PPOD	CPPOD
INR	(C)	[0.05]	0.486 (± 0.014)	0.613 (± 0.018)	**0.702** (± 0.014)	0.701 (± 0.018)
INR	(C)	[0.1]	0.496 (± 0.010)	0.596 (± 0.009)	0.682 (± 0.010)	**0.687** (± 0.009)
INR	(C)	[sin]	0.508 (± 0.009)	0.588 (± 0.010)	0.675 (± 0.009)	**0.680** (± 0.009)
INR	(C)	[pc]	0.488 (± 0.010)	0.607 (± 0.010)	0.673 (± 0.008)	**0.681** (± 0.010)
INR	(O)	[0.05]	0.487 (± 0.013)	0.736 (± 0.011)	0.779 (± 0.012)	**0.782** (± 0.012)
INR	(O)	[0.1]	0.498 (± 0.011)	0.726 (± 0.008)	**0.748** (± 0.009)	0.746 (± 0.010)
INR	(O)	[sin]	0.516 (± 0.012)	0.717 (± 0.011)	0.760 (± 0.010)	**0.764** (± 0.009)
INR	(O)	[pc]	0.508 (± 0.009)	0.720 (± 0.011)	**0.773** (± 0.009)	0.770 (± 0.009)
Cal	(C)	[0.05]	0.470 (± 0.020)	0.753 (± 0.017)	0.843 (± 0.012)	**0.885** (± 0.010)
Cal	(C)	[0.1]	0.504 (± 0.013)	0.739 (± 0.012)	0.830 (± 0.010)	**0.866** (± 0.006)
Cal	(C)	[sin]	0.502 (± 0.016)	0.688 (± 0.015)	0.797 (± 0.010)	**0.835** (± 0.009)
Cal	(C)	[pc]	0.508 (± 0.011)	0.742 (± 0.011)	0.837 (± 0.009)	**0.860** (± 0.011)
Cal	(O)	[0.05]	0.513 (± 0.021)	0.531 (± 0.014)	0.760 (± 0.014)	**0.761** (± 0.014)
Cal	(O)	[0.1]	0.493 (± 0.016)	0.526 (± 0.009)	0.759 (± 0.008)	**0.775** (± 0.008)
Cal	(O)	[sin]	0.518 (± 0.017)	0.529 (± 0.012)	0.758 (± 0.009)	**0.777** (± 0.010)
Cal	(O)	[pc]	0.496 (± 0.017)	0.541 (± 0.010)	0.759 (± 0.011)	**0.780** (± 0.009)
Pot	(C)	[0.05]	0.488 (± 0.020)	0.707 (± 0.016)	0.827 (± 0.012)	**0.878** (± 0.009)
Pot	(C)	[0.1]	0.498 (± 0.012)	0.733 (± 0.013)	0.839 (± 0.009)	**0.878** (± 0.009)
Pot	(C)	[sin]	0.503 (± 0.010)	0.691 (± 0.009)	0.813 (± 0.011)	**0.857** (± 0.007)
Pot	(C)	[pc]	0.511 (± 0.010)	0.718 (± 0.013)	0.831 (± 0.008)	**0.874** (± 0.010)
Pot	(O)	[0.05]	0.503 (± 0.015)	0.539 (± 0.014)	0.727 (± 0.015)	**0.744** (± 0.014)
Pot	(O)	[0.1]	0.495 (± 0.017)	0.533 (± 0.012)	0.736 (± 0.011)	**0.748** (± 0.011)
Pot	(O)	[sin]	0.508 (± 0.011)	0.536 (± 0.014)	0.744 (± 0.011)	**0.759** (± 0.012)
Pot	(O)	[pc]	0.524 (± 0.010)	0.552 (± 0.011)	0.746 (± 0.011)	**0.761** (± 0.011)
Nor	(C)	[0.05]	0.506 (± 0.013)	0.868 (± 0.014)	0.899 (± 0.013)	**0.899** (± 0.013)
Nor	(C)	[0.1]	0.494 (± 0.014)	0.864 (± 0.010)	0.890 (± 0.012)	**0.897** (± 0.013)
Nor	(C)	[sin]	0.536 (± 0.012)	0.837 (± 0.012)	0.858 (± 0.014)	**0.871** (± 0.014)
Nor	(C)	[pc]	0.524 (± 0.012)	0.844 (± 0.016)	**0.884** (± 0.014)	0.882 (± 0.013)
Nor	(O)	[0.05]	0.506 (± 0.023)	0.489 (± 0.018)	**0.829** (± 0.013)	0.826 (± 0.012)
Nor	(O)	[0.1]	0.510 (± 0.010)	0.468 (± 0.016)	**0.835** (± 0.010)	0.832 (± 0.009)
Nor	(O)	[sin]	0.488 (± 0.014)	0.462 (± 0.013)	**0.842** (± 0.011)	0.837 (± 0.011)
Nor	(O)	[pc]	0.503 (± 0.012)	0.476 (± 0.014)	**0.851** (± 0.011)	0.848 (± 0.010)