A Practical Approximation Method for Firing Rate Models of Coupled Neural Networks with Correlated Inputs

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Rapid experimental advances now enable simultaneous electrophysiological recording of neural activity at single-cell resolution across large regions of the nervous system. Models of this neural network activity will necessarily increase in size and complexity, thus increasing the computational cost of simulating them and new challenges in analyzing them. Here we present a novel approximation method to approximate the activity and firing statistics of a general firing rate network model (of Wilson-Cowan type) subject to noisy correlated background inputs. The method requires solving a system of algebraic equations and is fast compared to Monte Carlo simulations of coupled stochastic differential equations. We implement the method with several examples of coupled neural networks and show that the results are quantitatively accurate even with moderate coupling strengths and an appreciable amount of heterogeneity in many parameters. This work should be useful for investigating how various neural attributes qualitatively effect the spiking statistics of coupled neural networks. Matlab code implementing the method is freely available at xxx.

I. INTRODUCTION

With advances in neural recording technologies, experimenters can now record simultaneous activity across multiple brain regions at single cell resolution [1–4]. However, it is still a technical challenge to measure the interactions within and across brain regions that govern this multi-region activity. This challenge is heightened by the fact that cortical neurons are heterogeneous and show substantial trial-to-trial variability [5]. Numerous theoretical studies have examined how neural networks can lead to cortex-like dynamics [6–14]; however, most have been limited to a single region, leaving open the question of how inter-region connection strengths contribute to network processing.

One challenge presented by analyzing multi-region neural networks, is the increased number of parameters which must be specified. To survey a high-dimensional parameter space, one must have a way to efficiently simulate (as in [15]) or approximate network statistics (as in [16]). Here we present a novel approximation method for calculating the statistics of a general coupled firing rate model (based on [17]) of neural networks where we: i) assume the activity (not the firing) is pairwise normally distributed, ii) take the entire probability distribution of the presynaptic neurons/populations (providing input) into account. Our method is fast, requiring only solving algebraic equations self-consistently rather than simulating stochastic differential equations. Several example neural networks are considered and compared with Monte Carlo simulations. A specific version of this method was presented in [18] to model the olfactory sensory pathway; here, we derive formulas in a general way which is easy to evaluate and can accommodate heterogeneous networks. We also demonstrate the method’s efficacy on several example networks with much larger dimension (than the networks examined in the previous work).

II. NEURAL NETWORK MODEL

Each cell (or homogeneous population) has a prescribed activity $x_j$ that is modeled by the following equation [17] for $j = 1, 2, \ldots, N_c$:

$$
\tau_j \frac{dx_j}{dt} = -x_j + \mu_j + \sigma_j \eta_j(t) + \sum_k g_{jk} F_k(x_k(t)) \quad (1)
$$

where $F_k(\cdot)$ is a transfer function mapping activity to firing rate (related to the so-called F-I curve) for the $k^{th}$ cell/population. Thus, the instantaneous firing rate of the $j^{th}$ neuron is:

$$
F_j(x_j(t)). \quad (2)
$$

This type of equation has historically been used to capture the average activity of a population of neurons but from here on out we will use the term “cell” for exposition purposes. All cells receive background noise $\eta_j$, the increment of a Weiner process, uncorrelated in time but potentially correlated at each instant: $\langle \eta_j(t) \rangle = 0$, $\langle \eta_j(t) \eta_k(t') \rangle = \rho_j \delta_{jk} \delta(t-t')$. 

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\[ \langle \eta_j(t) \eta_j(t') \rangle = \delta(t - t'), \quad \text{and} \quad \langle \eta_j(t) \eta_k(t') \rangle = c_{jk} \delta(s) \text{ for } j \neq k \text{ with } c_{jk} \in (-1, 1). \] The parameters \( \mu_j \) and \( \sigma_j \) are constants that give the background input mean and input standard deviation, respectively. The parameter \( g_{jk} \) represents coupling strength from the presynaptic \( k^{th} \) cell and is a signed quantity; \( g_{jk} < 0 \) represents inhibitory coupling.

We would like to compute the following statistics:

1. \( \mu(j) := \langle x_j \rangle \), mean activity
2. \( \sigma^2(j) := \langle x_j^2 \rangle - \mu^2(j) \), variance of activity
3. \( \text{Cov}(j, k) := \langle x_j x_k \rangle - \mu(j) \mu(k) \), covariance of activity
4. \( \nu_j := \langle F_j(x_j(t)) \rangle \), firing rate
5. \( \text{Var}(\nu_j) := \langle F_j^2(x_j) \rangle - \nu_j^2 \), variance of spiking
6. \( \text{Cov}(\nu_j, \nu_k) := \langle F_j(x_j(t)) F_k(x_k(t)) \rangle - \nu_j \nu_k \), covariance of spiking
7. \( \rho(\nu_j, \nu_k) := \frac{\text{Cov}(\nu_j, \nu_k)}{\sqrt{\text{Var}(\nu_j) \text{Var}(\nu_k)}} \), correlation of spiking

where the angular brackets \( \langle \cdot \rangle \) denote averaging over time and realizations [19].

To simplify the calculation(s) as follows:

\[
\sigma^2(j) \equiv \langle (x_j - \mu(j))^2 \rangle = \frac{\sigma_j^2}{\tau_j} \int_0^t \int_0^t e^{-(t-u)/\tau_j} \eta_j(u) e^{-(t-v)/\tau_j} \eta_j(v) \, du \, dv
\]

\[
\frac{\sigma_j^2}{\tau_j} \lim_{t \to \infty} \int_0^t e^{-(t-u)/\tau_j} \eta_j(u) \, du = \frac{\sigma_j^2}{2\tau_j}
\]

A similar calculation shows in general we have:

\[
\text{Cov}(j, k) = \frac{c_{jk}}{\tau_j + \tau_k} \sigma_j \sigma_k
\]

Thus, \( (x_j, x_k) \sim \mathcal{N} \left( (\mu_j, \mu_k), \left( \begin{array}{cc} \sigma_j^2 / \tau_j & c_{jk} / \tau_j \sigma_j \\ c_{jk} / \tau_j \sigma_j & \sigma_k^2 / \tau_k \end{array} \right) \right) \).

Statistics for the firing rates, \( F(x_j) \), are inherited from this normal distribution, since the firing rate \( F(x_j) \) is simply a nonlinear function of the activity \( x_j \).

**When coupling is included**, i.e. \( g_{jk} \neq 0 \) for some indices \( j \) and \( k \), it may no longer be true that the activity variables \( x_j \) remain normally distributed. However, it is reasonable to suppose that, for sufficiently weak coupling, the deviations from a normal distribution will be small. Furthermore, if the firing rate function \( F \) has thresholding and saturating behavior (as does a sigmoidal function), then higher moments of \( x_j \) have limited impact on statistics of \( F(x_j) \). Thus, our first assumption will be that each pair of activity variables \( (x_j, x_k) \), can be approximated by a bivariate normal, even when coupling is present. We can think of this as a weak coupling assumption, as it holds exactly only with no coupling.

## III. REDUCTION METHOD

To compute statistics, we start by writing Eq. (1) as a low-pass filter of the right-hand-side:

\[
x_j(t) = \frac{1}{\tau_j} \int_0^t e^{-(t-u)/\tau_j} \left[ \mu_j + \sigma_j \eta_j(u) \sum_k g_{jk} F_k(x_k(u)) \right] du,
\]

used as the basis for calculating the desired moments of \( x_j \). For example, when \( (x_j, x_k) \) is desired, we use the previous equation for \( j \) and \( k \), multiply, then take the expected value \( \langle \cdot \rangle \) while letting \( t \to \infty \). The exact statistic is complicated because of the network coupling, so we simplify the calculation(s) as follows:

We only account for direct connections in the formulas for the first and second order statistics, assuming the terms from the indirect connections are either small or already accounted for in the direct connections. For example, although \( F_k(x_k(u)) \) on the RHS of Eq. (16) itself depends on coupling terms of the form \( g_{kl} F_l(x_l) \), etc... we will neglect such terms. We further make the following assumptions:
that over realizations is the same as averaging over time; e.g., we make the assumption of ergodicity, that averaging functions explicitly. The first assumption, Eq (17), states that \( E \) and \( V \) are \( \delta \)-correlated with itself; the second, Eq (18), addresses \( N \) and \( F \), where \( N \) denotes the random variable \( \int_0^t \sigma_j y_j(u)e^{-(t-u)/\tau_m} du \), which is by itself normally distributed with mean 0 and variance \( \sigma^2_j \tau_j/2 \). The final assumption, Eq (19), states that \( F(x_j(t)) \) and \( F(x_k(t)) \) are \( \delta \)-correlated. Finally, we make the assumption of ergodicity, that averaging over realizations is the same as averaging over time; e.g., \( \langle x_j \rangle = \lim_{T \to \infty} \frac{1}{T} \int_0^T x_j(t) dt \).

We arrive at the following (approximation) formulas for the statistics of the activity: \( \mu(j) = \mu_j + \sum_k g_{jk} E_1(k) \), \( \sigma^2(j) \tau_j = \frac{\sigma^2_j}{2} + \sum_k g_{jk} N_F(j,k) + \frac{1}{2} \sum_k g_{lk} V(k) \), \( \text{Cov}(j,k) \tau_{j+k} = \frac{1}{2} \sum_l g_{jl} \text{Cov}(j,l) \), and \( \text{Cov}(j,l) \tau_{j+l} = \frac{1}{2} \sum_k g_{jk} g_{lk} N_F(k,l) + \frac{1}{2} \sum_{l_1,l_2} g_{j,l_1} g_{k,l_2} \text{Cov}(l_1,l_2) \).

See Table I for the definition of the symbols: \( E_2(k), N_F(j,k), S(j,k) \).

### Table I. For readability, we define the following quantities. Whenever \( j = k \) in the double integrals (e.g., in \( N_F, \mathcal{S} \)), the bivariate normal distribution \( \varrho_{j,k} \) is replaced with the standard normal distribution \( \varrho \). Note that order of the arguments matters in \( N_F \): \( N_F(j,k) \neq N_F(k,j) \) in general; all of these quantities depend on the statistics of the activity \( \mu(\cdot), \sigma(\cdot) \).

| Abbreviation | Definition |
|--------------|------------|
| \( E_1(k) \) | \( F_k(\sigma(k)y + \mu(k)) \varrho_1(y) dy \) |
| \( E_2(k) \) | \( F_k^2(\sigma(k)y + \mu(k)) \varrho_1(y) dy \) |
| \( V(k) \) | \( F_k^2(\sigma(k)y + \mu(k)) \varrho_1(y) dy - \left( \int F_k(\sigma(k)y + \mu(k)) \varrho_1(y) dy \right)^2 = E_2(k) - [E_1(k)]^2 \) |
| \( N_F(j,k) \) | \( \int F_j(\sigma(j)y_1 + \mu(j)) \varrho_{j,k}(y_1,y_2) dy_1 dy_2, \text{if } j \neq k \) |
| \( S(j,k) \) | \( S(j,k) - E_1(j)E_1(k) \) |
| \( C_V(j,k) \) | \( \sum_{l \neq j,k} \text{Cov}(j,l) \) |

Each assumption is equivalent to the assumption that two of the random variables of interest are \( \delta \)-correlated in time; thus avoiding the need to compute autocorrelation functions explicitly. The first assumption, Eq (17), states that \( F(x_j(t)) \) is \( \delta \)-correlated with itself; the second, Eq (18), addresses \( N \) and \( F(x_k(t)) \), where \( N \) denotes the random variable \( \int_0^t \sigma_j y_j(u)e^{-(t-u)/\tau_m} du \), which is by itself normally distributed with mean 0 and variance \( \sigma^2_j \tau_j/2 \). The final assumption, Eq (19), states that \( F(x_j(t)) \) and \( F(x_k(t)) \) are \( \delta \)-correlated. Finally, we make the assumption of ergodicity, that averaging over realizations is the same as averaging over time; e.g., \( \langle x_j \rangle = \lim_{T \to \infty} \frac{1}{T} \int_0^T x_j(t) dt \).
We first consider two cells. We next consider an all-to-all coupled covariance of the activity (Fig. 1c) is also accurate. Even when the magnitude of the coupling $g$ (Fig. 1b) shows the variance of this statistic is independent of background correlation. The resulting formulas can be written compactly with matrices; Eq. (20) for the mean activity $\mu(j)$ can easily be written as a matrix-vector equation and is thus omitted. Let $\text{Cov}$ denote the $N_c \times N_c$ covariance matrix of the activity with $\text{Cov}(j, k) = \text{Cov}(j, k)$. $G$ represent the coupling strengths $G(j, k) = g_{jk}$, and $\text{Cr}$ denote the correlation matrix of the background noise (i.e. $\text{Cr}(j, k) = \delta_{jk} + c_{jk}(1 - \delta_{jk})$). Then we have

$$\text{Cov} = IT \ast \left( \text{Cov}_0 + G \text{M}_{\text{NF}} + M'_{\text{NF}} G' + G \text{M}_{\text{FSq}} G' \right)$$

where $\ast$ represents element-wise multiplication, $'$ denotes matrix transposition, and

$$IT(j, k) = \frac{1}{\tau_j + \tau_k}$$

$\text{Cov}_0(j, k) = \sigma_j \sigma_k [\delta_{jk} + (1 - \delta_{jk})c_{jk}]$ \quad (24)

$M_{\text{NF}}(j, k) = \sigma_k N_F(k, j)$ \quad (25)

$M_{\text{FSq}}(j, k) = C_V(j, k)$ \quad (26)

$\text{Cov}(\nu_j, \nu_k) = \int \int F_j(\sigma(j)y_1 + \mu(j))F_k(\sigma(k)y_2 + \mu(k)) \mathcal{P}_{j,k}(y_1, y_2) dy_1 dy_2 - \nu_j \nu_k$ \quad (30)

where $\mathcal{P}_{j,k}$ is a bivariate normal PDF with zero mean and covariance: \left( \begin{array}{cc} 1 & \text{Cov}(j, k) \\ \text{Cov}(k, j) & 1 \end{array} \right).$ The off-diagonal terms are obtained from the second order statistics of the activity, Eq. (21)–(22).

**IV. EXAMPLE NETWORKS AND RESULTS**

**Network I.** We first consider two cells ($N_c = 2$) that are reciprocally coupled without autaptic coupling. For simplicity, we set the intrinsic parameters in the two equations to be identical, with $\tau_j = 1$, $F_j(x) = 0.5(1 + \tanh((x - 0.5)/0.1)) \in [0, 1]$, but the mean and variance of the background input differ: $\mu_1 = 0.15$, $\mu_2 = 4/15 \approx 0.2667$, $\sigma_1 = 2$, $\sigma_2 = 3$. To illustrate the accuracy of our method, we vary two parameters: $g_{12} \in [-2, 2]$ (input strength from $x_2$ to $x_1$), and $c_{12} = c_{21} \in [0.05, 0.8]$, with $g_{21} = 0.4$ fixed.

In Fig. 1, we see that all of the activity and firing statistics are accurate compared to Monte Carlo simulations. Fig. 1a shows the mean of $x_1$ as the input strength $g_{12}$ varies from negative (inhibitory) to positive (excitatory); this statistic is independent of background correlation. Fig. 1b shows the variance of $x_1$; deviations are apparent when the magnitude of the coupling $g_{12}$ is large. The covariance of the activity (Fig. 1c) is also accurate. Even the statistics of the firing rate are relatively accurate; the mean firing rate $F(x_1)$ (Fig. 1d) is only weakly dependent on background correlation whereas the variance of $F(x_1)$ (Fig. 1e) appears to vary more with background correlation. In Fig. 1f, the strong dependence of the covariance on background correlation is captured by our method. For brevity, we omit the corresponding statistics for $x_2$; the method performs equally well there.

**Network II.** We next consider an all-to-all coupled network of $N_c = 50$ neurons with heterogeneity in all parameters. The parameter values were selected from specific distributions and gave rise to quenched variability. The transfer function was set to $F_j(\bullet) = 0.5(1 + \tanh((\bullet - x_{\text{rev},j})/x_{\text{sp},j})) \in [0, 1]$, where $x_{\text{rev},j}$ and $x_{\text{sp},j}$ are fixed parameters that depend on the the $j^{th}$ neuron. The distributions of the parameters for this network are:

$$\tau_j \sim \mathcal{N}(1, 0.05^2) \quad (31)$$

$$\mu_j \sim 2U - 1 \quad (32)$$

$$\sigma_j \sim U + 1 \quad (33)$$

$$x_{\text{rev},j} \sim \mathcal{N}(0.01^2) \quad (34)$$

$$x_{\text{sp},j} \sim 0.35U + 0.05 \quad (35)$$

where $U \in [0, 1]$ is a uniform random variable, and $\mathcal{N}$ is normally distributed with the mean and variance as the arguments. The covariance matrix $\text{Cr}$ of the background

$$\text{Cov}_0 = (I\bar{\sigma})\text{Cr}(I\bar{\sigma})$$

Once the statistics of the activity: $\mu(j)$, $\sigma^2(j)$, and $\text{Cov}(j, k)$ are solved for self-consistently, the firing statistics are solved as follows.

$$\nu_j = \int F_j(\sigma(j)y + \mu(j))g_1(y) dy \quad (28)$$

$$\text{Var}(\nu_j) = \int F_j^2(\sigma(j)y + \mu(j))g_1(y) dy - \nu_j^2 \quad (29)$$

The matrix $I$ is the $N_c \times N_c$ identity matrix. Note that the matrices $\text{M}_{\text{NF}}$ and $\text{M}_{\text{FSq}}$ have the same nonzero entries as $\text{Cr}$. The unperturbed covariance (Eq. (25)) can also be expressed in matrix form as:

$$\text{Cov} = (I\bar{\sigma})\text{Cr}(I\bar{\sigma})$$

grals with respect to standard normal distributions but with shifted integrands, which leads to faster calculations because one does not have to calculate new probability density functions at each step of the iteration.
noise was randomly selected as follows:

\[
\mathbf{C}_r = (\mathbf{I}d_s^2)\mathbf{A}'\mathbf{A}(\mathbf{I}d_s^2)
\]

(36)

where the entries of the \(N_c \times N_c\) matrix \(\mathbf{A}\) are independently chosen from a normal distribution: \(a_{j,k} \sim N(0, 0.8^2)\) and \(d_s\) is the inverse square-root of the diagonal of \(\mathbf{A}'\mathbf{A}\); i.e., if we set \(\mathbf{B} := \mathbf{A}'\mathbf{A}\) with entries \(b_{j,k}\), then \(d_s(j) = 1/\sqrt{b_{j,j}}\). By construction, \(\mathbf{C}_r\) is symmetric positive semi-definite with 1’s on the diagonal.

Finally, the entries of the coupling matrix \(\mathbf{G}_m\) is randomly chosen, but the parameters of the distribution were varied:

\[
\mathbf{G}_m(j,k) \sim N(0, \nu_l)
\]

(37)

where \(\nu_l = (l/10)^2\) for \(l = 1, 2, 3, 4\). There are no zero entries in \(\mathbf{G}_m\) (i.e. coupling is all-to-all), with both inhibition, excitation, and autaptic (self) coupling.

For each of the four values for the variance of the normal distribution, we chose a single realization of a coupling matrix \(\mathbf{G}_m\) and computed first and second-order statistics of \(x_k\) and \(F(x_k)\). In Fig. 2 we compared analytic vs. Monte Carlo results for each cell or cell pair. Each realization is identified by a different color; in Fig. 2a for example, there are \(N_c\) red data points, corresponding to each \(\mu(j)\) for \(j = 1, \ldots, N_c\). Points that are on the black diagonal line represent perfect matching between Monte Carlo simulations and our method.

First-order statistics \(\mu(j)\) and \(\nu_l\) are well-captured by the analytic method, even for the largest coupling strength (Fig. 2a,b). This excellent agreement is present despite the substantial amount of heterogeneity in these networks: note that \(x_j = \mathcal{O}(1)\) and that \(F_j \in [0, 1]\), and thus that single-cell firing rates in Fig. 2b have a relatively large range. Second-order statistics (variances and covariances: Fig. 2c-f) are captured well for smaller coupling values (blue and cyan) but become less accurate for the largest coupling value (red). In particular, the analytic method appears to overestimate variance for the largest coupling strength (Fig. 2c).

**Network III**. Finally we consider a moderately sized network of \(N_c = 100\) neurons with quenched heterogeneity in all of the intrinsic parameters, but with more physiological connectivity structure (than Network II). The first 50 neurons are excitatory (E) \((g_{jk} \geq 0\) for \(k = 1, 2, \ldots, 50\)) and the last 50 are inhibitory (I) \((g_{jk} \leq 0\) for \(k = 51, 52, \ldots, 100\)). We choose a sparse (random)
The background correlation matrix is tridiagonal with another diagonal within E or I (second and third lines respectively). The average background E-I correlation \( \langle \nu \rangle \), so we set the and I neurons are positively correlated (i.e., the synaptic \( N \) to \( N \) with a wide distribution \([21–23]\); thus we set the distribution of the coupling matrix entries are shown, while the other parameters are held fixed. (a) Comparison of the mean activity \( \mu(j) \) calculated via Monte Carlo simulations (horizontal axis) and our reduction method (vertical axis), showing all 50 values for each color (coupling matrix distribution). (b) Similar to (a) but for mean firing rate \( \nu_j \). (c) Variance of activity \( \sigma^2_j \). (d) Variance of firing rate \( \text{Var}(\nu_j) \). (e) Covariance of activity \( \text{Cov}(j,k) \), showing all 50*49/2=1225 values for each coupling matrix. (f) Covariance of the firing rate \( \text{Cov}(\nu_j,\nu_k) \). The method is accurate but starts to deviate as the overall coupling strength \( \|\mathbf{G}_m\| \) increases (from blue to red, more deviations from diagonal line).

In order to capture some realistic features of cortical neural networks, we impose sparse but clustered connectivity. Specifically, we have 5 clusters of E cells of size 10 with all-to-all connectivity and no autaptic (self-coupling) connections, and sparse random coupling within the I population (no autaptic connections) and between E and I cells (35% connection probability). See Fig.3(b) for the sparsity structure of \( \mathbf{G}_m \). This is motivated by experimental evidence that E cells show clustered connectivity \([27–29]\), while inhibitory connections have less structure \([30]\).

Synaptic connection strengths were chosen randomly for each realization with the following distributions:

\[
g_{EE} = U/10, \\
g_{EI} = -\frac{12}{35} U - \frac{4}{35}, \\
g_{IE} = \frac{12}{35} U + \frac{4}{35}, \\
g_{II} = -\frac{12}{35} U - \frac{4}{35},
\]

where again \( U \in [0,1] \) is a uniform random variable. The value \( g_{EE} \) is used for all nonzero E to E connections: \( g_{jk} \) with \( j,k \in \{1,\ldots,50\} \); \( g_{EI} \) is used for all nonzero I to E connections: \( g_{jk} \) with \( j \in \{1,\ldots,50\} \)

background correlation matrix via:

\[
c_{jk} = \begin{cases} 
1, & \text{if } j = k \\
\mathbb{N}(0.1,0.1^2), & \text{if } k = j + 1 \text{ and } j = 1,\ldots,49 \\
\mathbb{N}(0.12,0.1^2), & \text{if } k = j + 1 \text{ and } j = 51,\ldots,99 \\
\mathbb{N}(0.3,0.1^2), & \text{if } k = 101 - j \text{ and } j = 1,\ldots,100 \\
0, & \text{otherwise}
\end{cases}
\]

(38)
and \(k \in \{51, \ldots, 100\}\); \(g_{IE}\) for all nonzero E to I; \(j \in \{51, \ldots, 100\}\) and \(k \in \{1, \ldots, 50\}\); similarly for \(g_{II}\).

The distributions for the rest of the parameters were similar to Network II, with only inconsequential differences:

\[
\tau_j \sim N(1, 0.075^2) \quad (40)
\]

\[
\mu_j \sim 2U - 1 \quad (41)
\]

\[
\sigma_j \sim U + 1 \quad (42)
\]

\[
x_{rev,j} \sim N(0, 0.1^2) \quad (43)
\]

\[
x_{sp,j} \sim 0.4U + 0.05 \quad (44)
\]

In Fig. 3(c) and (d) we show the results of the analytic approximation compared to Monte Carlo simulations for both the activity and firing rates, respectively. In each panel, we have combined the mean, variance and covariance and, as in Fig. 2, a data point is plotted for each cell (for means and variances) or cell pair (for covariances). Also, we show data from two (2) instances of the network, labeled A and B; for each instance a new realization of the coupling matrix \(G_m\) and the coupling parameters (Eq. (39)) are generated (see Fig. 3 caption for values), but each of the other randomly selected parameters were kept fixed. Points that are on the black diagonal line represent a perfect match between Monte Carlo simulations and our method. As with Network II, the analytic method accurately captures the statistics cell-by-cell, despite an appreciable degree of heterogeneity.

Finally, we test how well our method approximates firing rate correlation, which is an important normalized measure of trial-to-trial variability (or noise correlations). The Pearson’s correlation coefficient is the predominant measure: \(\rho_{\nu_j, \nu_k} = \frac{\text{Cov}(\nu_j, \nu_k)}{\sqrt{\text{Var}(\nu_j)\text{Var}(\nu_k)}}\), i.e. the ratio of two quantities which we must estimate using the analytic method. In Fig. 4, we show comparisons between the analytic method and Monte Carlo simulations for Network II and Network III. The method is accurate for a wide range of correlations; Fig. 4a shows correlations as low as \(-0.3\) and as high as \(0.3\). Thus, the viability of our approximation is not limited to small correlation values, but can robustly capture the full range of correlation values observed in cortical neurons [5, 31].

V. DISCUSSION

There has been a long history of analytic reduction methods for neural network models, both to enhance efficiency in simulation and to aid mathematical analyses. Here, we summarize some of this literature and its relationship to the work presented here.

Many authors have analyzed mean-field equations, in which they derive equations for population-averaged activity, usually in the limit of large system size. The dynamics of single neurons within such a population may be described either by master equations [12, 32, 33], stochastic differential equations [14, 34], or generalized linear models [35]. We have not attempted that here, in that we have made no attempt to reduce the number of degrees of freedom. Rather, we start with a system of coupled stochastic differential equations, each of which may represent either a single neuron or a population, and sought to quickly and accurately estimate statistics of the coupled system. Importantly, the unperturbed state in our system is not one in which all neurons are independent; instead we perturb from a state with background noise correlations. Thus, we anticipate this approximation can be used to probe a range of neural networks, in which correlations can be significant and activity-modulated.

While the coupled firing rate models we study here were not derived as a mean field limit of a spiking network, our results presented can still yield insight into spiking networks. Our previous work [18] used the qualitative principles and intuitions gained from a simple firing rate model to characterize relationships between the analogous parameters in a full spiking model of a multi-region olfactory network. In that paper, a small system with simple coupling and background correlations was studied, whereas this paper treats networks of arbitrary size, and arbitrary coupling and input correlation structures. The work here is thus a generalization of the calculations in [18].
In other models, $F(\cdot)$ represents the function that maps firing rate to synaptic input. Here, we assume that the effective synaptic input $q_{jk} F_j$ is a fixed scaling of the firing rate $F_j$. In other biophysical models the effective synaptic input may be a more complex transformation of the firing rate (e.g., an alpha function convolved with firing rate): the methods presented here can easily be altered to account for this. To do this, the only change would be to use $S_j(F_j)$ in Eq. (1) instead of $F_j$.

Our method relies on the assumption that statistics are stationary in time; this assumption allows a set of statistics to be solved self-consistently. Thus we have not addressed complex network dynamics, such as oscillations. However, this limitation is not specific to our method, but is also in related work. Previously developed approximation methods may fail when the system undergoes a bifurcation [32, 33], and truncation methods (or moment closure methods) are known to fail in certain parameter regimes [36]. When the set of self-consistent equations cannot be solved, there may be other methods available to characterize the oscillatory dynamics (see [37] where this is done for the adaptive quadratic integrate-and-fire model). Considering how to accurately and quickly capture firing statistics when in this regime is an important topic of future work.

Time-varying statistics are not considered here and is beyond the scope of this study. Such an approach often requires deriving an ODE of the desired quantities [33–35, 38] or some other dynamical equation(s) [39] that must be solved numerically.

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