A UNIFIED DIVERSITY MEASURE FOR DISTRIBUTED INFERENCE

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ABSTRACT

Present day distributed inference systems consist of sensors with different modalities working as a system to perform specific tasks. With multiple sensors sensing heterogeneous data over multiple time instants, diversity is an inherent aspect of such systems. In this work, we take the first step to characterize the diversity of a general heterogeneous sensing system performing inference tasks. We provide a unified definition for diversity which can be customized for the system in use. The use of the definition is illustrated by applying it to a specific detection system where the sensors collect data over heterogeneous sensing channels. We assume the data to be both temporally and spatially correlated and analyze the effect of dependence on the diversity of the detection system.

Index Terms— diversity, heterogeneous sensing, spatio-temporal data, internet of things, distributed inference

1. INTRODUCTION

In typical multi-sensor inference systems, nodes often observe different instantiations of the same process before forwarding either quantized or unquantized data to a fusion center (FC) [1–4]. The FC then processes this data to perform the inference task. With the evolution of novel sensing technologies, often sensors of different modalities collaborate to make a combined decision. Such systems often deal with heterogeneity in data and sensors, e.g., Internet of Things (IoT) [5–8]. Analysis of such distributed inference systems is difficult because computation of their corresponding performance measures is often intractable. This has motivated the researchers to perform analysis under certain simplifying assumptions including asymptotic analyses. While performing such analyses, diversity arises as a natural surrogate to system performance [9–13]. Many researchers have defined diversity measures in the context of specific problems [9–17]. We aim to bring all these definitions together into a single definition. Our major contributions in this work are summarized as follows.

We present a unified definition of diversity for a general inference system. We show that our definition is fairly general and is applicable to many systems performing inference and communication tasks [9–17]. We make use of our definition to derive the diversity of a heterogeneous system performing a detection task. We present a simple model which captures spatial and temporal dependence among sensors and data respectively. We also study the effect of dependence on the diversity of the system.

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2. DIVERSITY OF INFERENCE SYSTEMS

Consider an inference system performing a task T, where the performance metric is utility U and the signal quality is Q. The goal of any inference system is to perform T as efficiently as possible, i.e, optimize U which in effect depends on Q. A simple example of T is a binary hypothesis test, U in this case can be the error probability whereas Q can be the signal to noise ratio (SNR). Next, we give a unified definition of diversity using the above metrics which can be used for several tasks in inference networks.

Definition 1. *We define the diversity of an inference network performing an inference task T with utility U and signal quality Q at a specific point of target utility U_o as,*

$$D = \frac{\partial F(U)}{\partial G(Q)}\bigg|_{U=U_0} \tag{1}$$

where, $F : \mathbb{R} \to \mathbb{R}$ and $G : \mathbb{R} \to \mathbb{R}$ are monotonic functions of task utility U and signal quality Q, respectively.

Hence, diversity measures how U (function F) varies at the point of interest with Q (function G). In particular, high diversity implies that we can get higher returns in performance gain with only a little improvement in signal quality. In most applications of interest, U and Q have a one-to-one mapping. Therefore, one can use $U = U_0$ or $Q = Q_0$ in Definition 1 based on the context. Unless some simplifying assumptions are made, the performance analysis of many systems is intractable, i.e., U cannot be computed in closed form. Moreover, in many cases, numerical evaluation of performance does not offer insights into the system behavior. Sometimes, even in the cases when U can be evaluated analytically, the expressions might be too cumbersome to be used as a design criterion [17]. In such systems, diversity can be used as a surrogate to the system utility as a measure of performance. In the following, we show how Definition 1 can be used to represent diversity presented in the literature for various tasks by an appropriate choice of U, Q, F and G. [1]

Table 1 details how different definitions of diversity used in the literature are encompassed by our unified definition in Definition 1. MIMO based communication systems [9, 18, 19], have defined diversity by using the error probability as the utility for a fast-fading system and outage probability for slow-fading systems. For distributed estimation systems in [10], utility $\mathcal{P}_{D_0}$ is the probability that the mean square error (MSE) variance is above some threshold. Similarly for distributed detection systems, utility is p_{J_0} which is the probability of J-divergence being less than some threshold. Most of these works, because of the intractability of the corresponding utilities, perform an

[1] Notations from corresponding works are adopted for consistency.

Table 1. Different definitions of diversity in inference tasks.

Task (T)	Diversity (D)	Utility (U)	Quality (Q)	Q_0 or U_0
MIMO communication [9]	$-\lim_{\text{SNR}\to\infty} \frac{\log p_e}{\log \text{SNR}}$	Error probability	SNR	$\text{SNR} \to \infty$
Distributed estimation [10]	$-\lim_{P_{\text{tot}}\to\infty} \frac{\log \mathcal{P}_{D_0}}{\log P_{\text{tot}}}$	Outage probability	Total transmit power	$P_{\text{tot}} \to \infty$
Distributed detection [11]	$-\lim_{P_{\text{tot}}\to\infty} \frac{\log p_{J_0}}{\log P_{\text{tot}}}$	Outage probability	Total transmit power	$P_{\text{tot}} \to \infty$
Radar network [12]	$\left.\frac{\partial P_D}{\partial \text{SNR}}\right\rvert_{P_D=0.5}$	Detection probability	SNR	$P_D = 0.5$
Spectrum sensing [13]	$-\lim_{\text{SNR}\to\infty} \frac{\log P_*}{\log \text{SNR}}$	Type-I, II, avg. error probability	SNR	$\text{SNR} \to \infty$
Spectrum sensing [14]	$\max \frac{\partial P_D}{\partial \text{SNR}_{\text{dB}}}$	Detection probability	SNR_{dB} (in dB)	$\arg\max_{P_D, \text{SNR}_{\text{dB}}} \frac{\partial P_D}{\partial \text{SNR}_{\text{dB}}}$

asymptotic error exponent analysis, which yields a linear relationship between utility and signal quality in log-log domain. This eliminates the need to use partial derivative in Definition 1.

While most definitions consider asymptotically high SNRs or high signal quality Q, it is often desirable for the inference systems to perform satisfactorily under severe network and resource constraints. Daher and Adve in [12] provide a definition of diversity under these conditions (Table 1). Notice that this definition has the slope in the linear scale as opposed to other definitions. Also slope is evaluated at $P_D = 0.5$ which is the rising part of the P_D vs SNR curve, where SNRs are typically low.

Having shown the universal applicability of the generalized definition of diversity, in the following, we consider a specific inference system and derive the diversity for this system. We also describe the benefits associated with the notion of diversity in the design and analysis of inference systems.

3. DETECTION USING HETEROGENEOUS SENSORS WITH SPATIO-TEMPORALLY DEPENDENT DATA

Consider an inference system performing a binary hypothesis test, where multiple heterogeneous sensors collect multiple observations [1,2]. We model heterogeneity using a simple model where the conditional probability density function corresponding to each sensor is different. Specifically, we consider all the sensors to be observing the phenomenon over a Gaussian channel but with different channel variances. We derive the diversity for this system based on Definition 1 that captures the effect of heterogeneity. Moreover, dependence across space and time dimensions can have a major impact on the diversity of an inference system. Most of the previous works ignore this dependence for the sake of mathematical tractability. However, we investigate the effect of this dependence on the diversity of an inference system by presenting a relatively simple model with only a few parameters that models spatio-temporal dependence.

3.1. System model

Consider a sensor network with K spatially distributed sensors collecting N observations. The observation at the kth sensor at the nth time instant is $x_k[n]$ for $k \in \{1, 2, \ldots, K\}$ and $n \in \{1, 2, \ldots, N\}$. The binary hypothesis test is:

$$\begin{aligned} H_0 &: \quad x_k[n] = w_k[n], \\ H_1 &: \quad x_k[n] = A + w_k[n], \end{aligned} \tag{2}$$

where, A is a deterministic known signal and $w_k[n]$ is the additive Gaussian noise. Dependence of $x_k[n]$ across space and time is due to the dependence structure of noise described below.

3.1.1. *Time Dependence*

Across time, we assume the noise to follow an autoregressive model of order 1 (AR(1)) [18]. For the kth sensor, noise evolves as

$$w_k[n] = \rho_t w_k[n-1] + \epsilon_k[n], \quad \text{for} \quad n = 1, 2, \ldots, N, \tag{3}$$

where, $w_k[0] = 0$, $|\rho_t| < 1$ is the AR correlation parameter, and $\epsilon_k[n] \sim \mathcal{N}(0, \sigma_k^2)$ is independent (across n) Gaussian white noise. Note that although the noise follows the same AR(1) model across K sensors, the heterogeneity of the sensing model is captured by different noise variances σ_k^2.

3.1.2. *Spatial Dependence*

For spatial dependence, we assume that the component $\epsilon_k[n]$, for any two given sensors k and k' at any fixed time instant n, is bivariate Gaussian with correlation parameter ρ_s. Therefore, at the nth time instant, the noise correlation across space is

$$(\epsilon_k[n], \epsilon_{k'}[n]) \sim \mathcal{N}(0, 0, \sigma_k^2, \sigma_{k'}^2, \rho_s) \ \text{ for } k \neq k'. \tag{4}$$

Therefore, the correlation between $\epsilon_k[n]$ and $\epsilon_{k'}[n]$ is

$$\mathbf{\Sigma}_K(k, k') = \begin{cases} \sigma_k \sigma_{k'} \rho_s, & \text{if} \quad k \neq k' \\ \sigma_k^2, & \text{else} \end{cases} \tag{5}$$

where, $\mathbf{\Sigma}_K(k, k')$ represents the element corresponding to kth row and k'th column of the matrix $\mathbf{\Sigma}_K$. The correlation between kth and k'th sensor data at lth and mth time instants for $k, k' \in \{1, 2, \cdots, K\}$ and $l, m \in \{1, 2, \cdots, N\}$ is

$$\begin{aligned} &\mathbf{\Sigma}_{NK}(kl, k'm) \\ &= \begin{cases} \sigma_k \sigma_{k'} \rho_s \frac{\rho_t^{l+m-2\min\{l,m\}}(1-\rho_t^{2\min\{l,m\}})}{1-\rho_t^2}, \text{if } k \neq k' \\ \sigma_k^2 \frac{\rho_t^{l+m-2\min\{l,m\}}(1-\rho_t^{2\min\{l,m\}})}{1-\rho_t^2}, \text{if } k = k'. \end{cases} \end{aligned} \tag{6}$$

Here $\mathbf{\Sigma}_{NK}$ is an $NK \times NK$ matrix whose klth and $k'm$th element is the correlation between the lth observation of the kth sensor and the mth observation of the k'th sensor. We define a matrix $\mathbf{\Sigma}_N \in \mathbb{R}^{N \times N}$ with lth and mth element as

$$\mathbf{\Sigma}_N(l, m) = \frac{\rho_t^{l+m-2\min\{l,m\}}(1 - \rho_t^{2\min\{l,m\}})}{1 - \rho_t^2}, \tag{7}$$

then $\mathbf{\Sigma}_{NK}$ can be represented in a compact matrix form as

$$\mathbf{\Sigma}_{NK} = \mathbf{\Sigma}_K \otimes \mathbf{\Sigma}_N, \tag{8}$$

where, $\otimes$ is the Kronecker product and $\mathbf{\Sigma}_K$ is defined in (5). Sensors collect N samples and forward the samples to the FC over noiseless orthogonal Multiple Access Channels (MAC). For this particular detection task, we assume a Neyman-Pearson framework where the detection probability ($P_{d,fc}$) is maximized under a constraint on the false alarm probability at the FC ($P_{f,fc}$). The FC performs the Likelihood Ratio Test (LRT) and compares the test statistic to a threshold.

3.2. Heterogeneous System Characterization

We denote the kth sensor's observations as $\mathbf{x_k} = [x_k[1], x_k[2], \cdots, x_k[N]]^T$ and $\mathbf{x} = [\mathbf{x_1}^T, \mathbf{x_2}^T, \cdots, \mathbf{x_K}^T]^T$. Here $\mathbf{x}$ is multivariate Gaussian with covariance matrix $\mathbf{\Sigma}_{NK}$, given as in (6) and (8). Application of LRT yields $P_{f,fc}$ as

$$P_{f,fc} = \mathcal{Q}\left(\frac{\tau_{fc}}{\sqrt{A^2\, \underline{\mathbf{1}}_{NK}^T \mathbf{\Sigma}_{NK}^{-1} \underline{\mathbf{1}}_{NK}}}\right), \tag{9}$$

where τ_{fc} is the decision threshold and $\underline{\mathbf{1}}_{NK}$ is a NK dimensional vector with all ones. $\mathcal{Q}(x) = \int_x^\infty \frac{1}{\sqrt{2\pi}} \mathrm{e}^{-\frac{z_k^2}{2}} dz_k$ is the complementary cumulative distribution function of the standard Gaussian random variable. Similarly $P_{d,fc}$ is given as

$$P_{d,fc} = \mathcal{Q}\left(\mathcal{Q}^{-1}(P_{f,fc}) - \sqrt{A^2\, \underline{\mathbf{1}}_{NK}^T \mathbf{\Sigma}_{NK}^{-1} \underline{\mathbf{1}}_{NK}}\right). \tag{10}$$

We now state an important lemma and a couple of propositions which are used to derive diversity. The proofs are omitted due to space constraints.

Lemma 1.

$$\underline{\mathbf{1}}_{NK}^T \mathbf{\Sigma}_{NK}^{-1} \underline{\mathbf{1}}_{NK} = \underline{\mathbf{1}}_{K}^T \mathbf{\Sigma}_{K}^{-1} \underline{\mathbf{1}}_{K} \times \underline{\mathbf{1}}_{N}^T \mathbf{\Sigma}_{N}^{-1} \underline{\mathbf{1}}_{N}$$

where $\underline{\mathbf{1}}_{NK} \in \mathbb{R}^{NK}$, $\underline{\mathbf{1}}_{K} \in \mathbb{R}^{K}$ and $\underline{\mathbf{1}}_{N} \in \mathbb{R}^{N}$ represent vectors containing all ones of respective lengths.

Proposition 1.

$$\underline{\mathbf{1}}_{K}^T \mathbf{\Sigma}_{k}^{-1} \underline{\mathbf{1}}_{K} = \frac{\left[((K-2)\rho_s + 1)\sum_{i=1}^K \frac{1}{\sigma_i^2} - 2\rho_s \sum_{k \neq k'} \frac{1}{\sigma_k \sigma_{k'}}\right]}{1 + (K-2)\rho_s - (K-1)\rho_s^2}$$

where $\underline{\mathbf{1}}_{K} \in \mathbb{R}^{K}$ is the vector of all ones and $\mathbf{\Sigma}_K$ is given in (5).

Proposition 2.

$$\underline{\mathbf{1}}_{N}^T \mathbf{\Sigma}_{N}^{-1} \underline{\mathbf{1}}_{N} = (N-1)(\rho_t^2 - 2\rho_t) + N \tag{11}$$

where $\underline{\mathbf{1}} \in \mathbb{R}^{N}$ is the vector of all ones and $\mathbf{\Sigma}_N$ is given in (7).

For the system considered, U is the detection probability $P_{d,fc}$ and $U_0 = P_{d,fc} = 0.5$ is the point which captures the diversity of the system. Q is the SNR of the heterogeneous system,

$$\text{SNR} = \frac{1}{K}\sum_{k=1}^K \frac{A^2}{\sigma_k^2}, \tag{12}$$

which is the average SNR as seen by each channel at a given time instant. This is a generalized version of the definition used in [12], as it can handle heterogeneous channels (different channel variances). Using the definition of diversity in Definition 1, we have Theorem 1.

Theorem 1. *Diversity of an inference system performing a detection task using a distributed sensor network with spatio-temporally dependent data following* (3) *and* (4)*, is given by*

$$D(N, K, \rho_s, \rho_t) = \frac{1}{2\sqrt{2\pi}} \sqrt{\frac{\underline{\mathbf{1}}_{N}^T \mathbf{\Sigma}_{N}^{-1} \underline{\mathbf{1}}_{N} \times \underline{\mathbf{1}}_{K}^T \mathbf{\Sigma}_{K}^{-1} \underline{\mathbf{1}}_{K}}{A^2}} \frac{K}{\sum_{k=1}^K \frac{1}{\sigma_k^2}}, \tag{13}$$

where $\underline{\mathbf{1}}_{N}^T \mathbf{\Sigma}_{N}^{-1} \underline{\mathbf{1}}_{N}$ and $\underline{\mathbf{1}}_{K}^T \mathbf{\Sigma}_{K}^{-1} \underline{\mathbf{1}}_{K}$ are given by Propositions 1 and 2 respectively.

Proof. Defining $t = \mathcal{Q}^{-1}(P_{f,fc}) - \sqrt{A^2\, \underline{\mathbf{1}}_{NK}^T \mathbf{\Sigma}_{NK}^{-1} \underline{\mathbf{1}}_{NK}}$ and using the chain rule for differentiation,

$$\frac{\partial P_{d,fc}}{\partial \text{SNR}} = \frac{\partial P_{d,fc}}{\partial t} \frac{\partial t}{\partial \text{SNR}}. \tag{14}$$

Using Lemma 1, the second term of (14) is

$$\frac{\partial t}{\partial \text{SNR}} == -\frac{1}{2}\sqrt{\frac{\underline{\mathbf{1}}_{N}^T \mathbf{\Sigma}_{N}^{-1} \underline{\mathbf{1}}_{N} \times \underline{\mathbf{1}}_{K}^T \mathbf{\Sigma}_{K}^{-1} \underline{\mathbf{1}}_{K}}{A^2}} \frac{K}{\sum_{k=1}^K \frac{1}{\sigma_k^2}}.$$

Now, using Q function, $\frac{\partial P_{d,fc}}{\partial t} = -\frac{1}{\sqrt{2\pi}} \mathrm{e}^{-\frac{t^2}{2}}$. Therefore,

$$\left.\frac{\partial P_{d,fc}}{\partial \text{SNR}}\right|_{P_{d,fc}=0.5} = \frac{1}{2\sqrt{2\pi}} \sqrt{\frac{\underline{\mathbf{1}}_{N}^T \mathbf{\Sigma}_{N}^{-1} \underline{\mathbf{1}}_{N} \times \underline{\mathbf{1}}_{K}^T \mathbf{\Sigma}_{K}^{-1} \underline{\mathbf{1}}_{K}}{A^2}} \left.\frac{K}{\sum_{k=1}^K \frac{1}{\sigma_k^2}} \mathrm{e}^{-\frac{\left(\mathcal{Q}^{-1}(P_{fa,fc}) - \sqrt{A^2\, \underline{\mathbf{1}}_{NK}^T \mathbf{\Sigma}_{NK}^{-1} \underline{\mathbf{1}}_{NK}}\right)^2}{2}}\right|_{P_{d,fc}=0.5}. \tag{15}$$

With $U_0 = Q\left[\mathcal{Q}^{-1}(P_{fa,fc}) - \sqrt{A^2\, \underline{\mathbf{1}}_{NK}^T \mathbf{\Sigma}_{NK}^{-1} \underline{\mathbf{1}}_{NK}}\right] = 0.5$,

$$D = \frac{1}{2\sqrt{2\pi}} \sqrt{\frac{\underline{\mathbf{1}}_{N}^T \mathbf{\Sigma}_{N}^{-1} \underline{\mathbf{1}}_{N} \times \underline{\mathbf{1}}_{K}^T \mathbf{\Sigma}_{K}^{-1} \underline{\mathbf{1}}_{K}}{A^2}} \frac{K}{\sum_{k=1}^K \frac{1}{\sigma_k^2}}.$$

□

The above derivation used the fact that the overall covariance matrix could be decomposed as the Kronecker product of temporal and spatial covariance matrices. As a consequence, system diversity can be decomposed into temporal and spatial diversity. Therefore, for systems where the covariance matrix can be decomposed as above, system diversity using this particular definition [12] can also be decomposed into temporal and spatial diversity.

Following corollaries are the results for special cases of systems arising from Theorem 1.

Corollary 1. *For the inference system given in Theorem 1 with homogeneous channels, i.e., $\sigma_k^2 = \sigma^2$, diversity grows as* $D(N, K, \rho_s, \rho_t) \sim \mathcal{O}\left(\left(\frac{K(1-\rho_s)}{1+(K-2)\rho_s-(K-1)\rho_s^2}\right)\left((N-1)(\rho_t^2 - 2\rho_t) + N\right)\right)$, *where the notation $\mathcal{O}(\cdot)$ refers to diversity order and indicates that the diversity is proportional to the argument of $\mathcal{O}(\cdot)$.*

Corollary 2. *For the inference system given in Theorem 1 with only time-dependent data and data independence across space,*

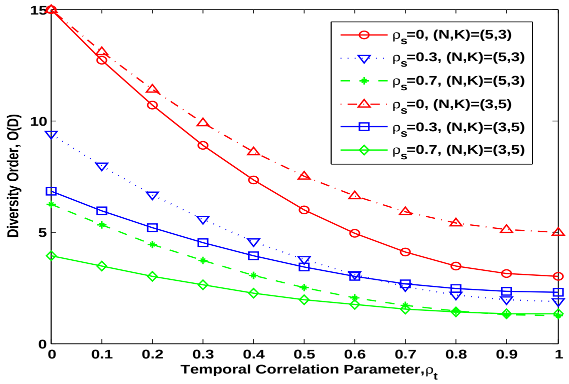

Fig. 1. Diversity order vs ρ_t for different ρ_s and (N, K) pairs.

the diversity is of order $D(N, K, 0, \rho_t) \sim \mathcal{O}\left(K\left((N-1)(\rho_t^2 - 2\rho_t) + N\right)\right)$.

Corollary 3. *For the inference system given in Theorem 1 with only spatially-dependent data and temporal independence, diversity grows as* $D(N, K, \rho_s, 0) \sim \mathcal{O}\left(\frac{K(1-\rho_s)}{1+(K-2)\rho_s-(K-1)\rho_s^2} N\right)$.

Corollary 4. *For the inference system given in Theorem 1 with data independence across both time and space, diversity is of order* $D(N, K, 0, 0) \sim \mathcal{O}(KN)$ *[12].*

3.3. Simulation Results

We illustrate the analytical results derived in the previous section via simulations. In order to study and highlight the effect of temporal and spatial dependence, we assume $\sigma_k^2 = \sigma^2$. In Fig. 1, we plot the diversity order as a function of ρ_t. Notice that the diversity order falls as dependence increases. It is interesting to note that the rate of fall of diversity order is different for different pairs of (N, K). We observe a similar degradation of performance as ρ_s increases when we plot the diversity order with ρ_s in Fig. 2. In Fig. 3, we plot the diversity order with N for $K = 3$. As evident from Corollary 2, the diversity order is a linear function of N and performance degrades with increasing ρ_t. Finally, in Fig. 4, we plot the diversity order with varying K for $N = 5$. Here the effect of increasing K is not linear on the diversity order if $\rho_s \neq 0$. From Fig. 3, we notice that the diversity order increases with N but it decreases rapidly with increasing ρ_t. On comparison with Fig. 4, we see that the diversity order still increases with increasing K but it falls with increasing ρ_s. Although the degradation in diversity order is more, the fall is gradual compared to Fig. 3 as also evident from Figs. 1 and 2.

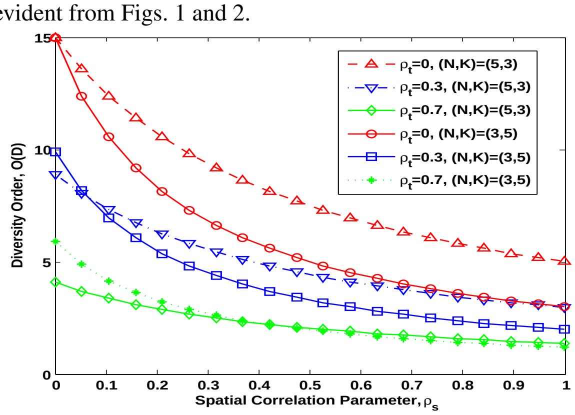

Fig. 2. Diversity order vs ρ_s for different ρ_t and (N, K) pairs.

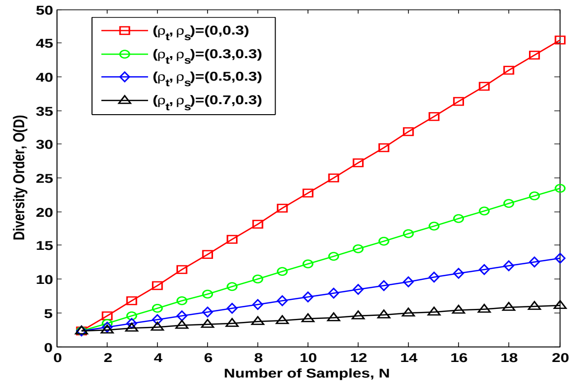

Fig. 3. Diversity order vs N for different (ρ_t, ρ_s) pairs.

4. DISCUSSION

As evident from earlier discussions, diversity is governed by the system parameters, for example, the inference system discussed above has two design parameters that affect the performance of the system, number of sensors K and number of observations N per sensor. However, both these resources come at a cost. For a system with spatio-temporal independence, the task of choosing N and K is straightforward. For a centralized detection system, choosing (N, K) pairs is symmetric when data is independent. However, when there is spatio-temporal dependence in the system, there exists an interplay between the choice of (N, K) pairs for different (ρ_t, ρ_s) pairs (refer to Sec. 3.3). Therefore, as a stepping stone for future work, we propose to divide such inference systems into categories based on the amount of spatial and temporal dependence present in the system. This will make the job of a system designer easier in choosing the (N, K) pairs. For example, the systems can be divided into four main categories as: (low ρ_t, low ρ_s), (low ρ_t, high ρ_s), (high ρ_t, low ρ_s) and finally (high ρ_t, high ρ_s). The system designer can choose N and K based on these 4 categories, to have the best performance.

In this work, we proposed a unified definition of diversity for a general inference system and showed it's applicability for systems performing various tasks. Moreover, as an example of its use, we provided a thorough analysis of an inference system performing a detection task with heterogeneous and dependent data. To the best of our knowledge this work is the first to characterize the notion of diversity in IoT systems. A major application of the proposed framework is in IoT framework as they are composed of heterogeneous sensors collecting correlated data for various tasks.

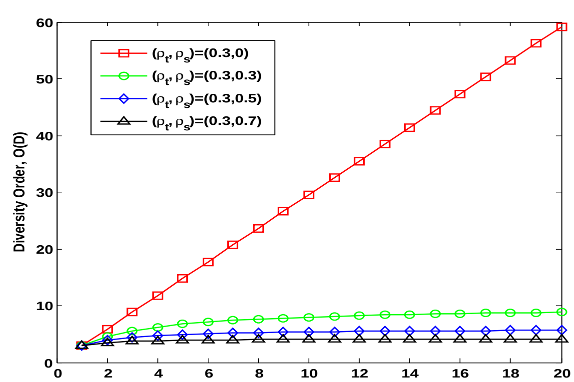

Fig. 4. Diversity order vs K for different (ρ_t, ρ_s) pairs.

5. REFERENCES

[1] P. K. Varshney, "Distributed detection and data fusion." NewYork: Springer, 1997.

[2] J. N. Tsitsiklis, "Decentralized detection," *in Advances in Statistical Signal Processing*, 1993.

[3] D. Ciuonzo and P. S. Rossi, "Decision fusion with unknown sensor detection probability," *IEEE Signal Processing Letters*, vol. 21, no. 2, pp. 208–212, Feb 2014.

[4] D. Ciuonzo, A. D. Maio, and P. S. Rossi, "A systematic framework for composite hypothesis testing of independent bernoulli trials," *IEEE Signal Processing Letters*, vol. 22, no. 9, pp. 1249–1253, Sept 2015.

[5] L. Atzori, A. Iera, and G. Morabito, "The internet of things: A survey," *Computer Networks*, vol. 54, no. 15, pp. 2787 – 2805, 2010.

[6] A. Al-Fuqaha, M. Guizani, M. Mohammadi, M. Aledhari, and M. Ayyash, "Internet of things: A survey on enabling technologies, protocols, and applications," *IEEE Communications Surveys Tutorials*, vol. 17, no. 4, pp. 2347–2376, 2015.

[7] J. Gubbi, R. Buyya, S. Marusic, and M. Palaniswami, "Internet of things (IoT): A vision, architectural elements, and future directions," *Future Generation Computer Systems*, vol. 29, no. 7, pp. 1645 – 1660, 2013.

[8] D. Miorandi, S. Sicari, F. De Pellegrini, and I. Chlamtac, "Internet of things," *Ad Hoc Netw.*, vol. 10, no. 7, pp. 1497–1516, Sep. 2012.

[9] L. Zheng and D. N. C. Tse, "Diversity and multiplexing: A fundamental tradeoff in multiple-antenna channels," *IEEE Trans. Inf. Theory*, vol. 49, no. 5, pp. 1073–1095, May 2003.

[10] S. Cui, J. J. Xiao, A. J. Goldsmith, Z. Q. Luo, and H. V. Poor, "Estimation diversity and energy efficiency in distributed sensing," *IEEE Transactions on Signal Processing*, vol. 55, no. 9, pp. 4683–4695, Sept 2007.

[11] H.-S. Kim, J. Wang, P. Cai, and S. Cui, "Detection outage and detection diversity in a homogeneous distributed sensor network," *IEEE Trans. Signal Process*, vol. 57, no. 7, pp. 2875–2881, June 2009.

[12] R. Daher and R. Adve, "Notion of diversity order in distributed radar networks," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 46, no. 2, pp. 818–831, Apr. 2010.

[13] D. Duan, L. Yang, and J. C. Principe, "Cooperative diversity of spectrum sensing for cognitive radio systems," *IEEE Transactions on Signal Processing*, vol. 58, no. 6, pp. 3218–3227, June 2010.

[14] J. Oksanen, J. Lunden, and V. Koivunen, "Characterization of spatial diversity in cooperative spectrum sensing," in *Communications, Control and Signal Processing (ISCCSP), 2010 4th International Symposium on*. IEEE, March 2010, pp. 1–5.

[15] J. Tang, N. Li, Y. Wu, and Y. Peng, "On detection performance of mimo radar: A relative entropy-based study," *IEEE Signal Processing Letters*, vol. 16, no. 3, pp. 184–187, March 2009.

[16] D. P. Bruyere and N. A. Goodman, "Adaptive detection and diversity order in multistatic radar," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 44, no. 4, pp. 1615–1623, Oct 2008.

[17] Z. Wang and G. B. Giannakis, "A simple and general parameterization quantifying performance in fading channels," *IEEE Transactions on Communications*, vol. 51, no. 8, pp. 1389–1398, Aug 2003.

[18] R. S. Tsay, "Analysis of financial time series." Wiley-Interciencel, 2005.

[19] E. T. Ar and I. E. Telatar, "Capacity of multi-antenna gaussian channels," *European Transactions on Telecommunications*, vol. 10, pp. 585–595, 1999.