

1 Technical Details

In this appendix we provide additional details to our arguments.

1.1 Quadrant Probabilities for the Bivariate Normal Distribution

In order to derive a formula for the quadrant probabilities of $\mathcal{N}\left(\mathbf{0}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}\right)$, we first have to prove an auxiliary lemma:

Lemma 1.1.1. *Let X and Y have a bivariate normal distribution where X and Y are standard normal variables, $X, Y \sim \mathcal{N}(0, 1)$, with correlation ρ . The variable $Z = \frac{Y - \rho X}{\sqrt{1 - \rho^2}}$ is a standard normal variable, and X and Z are independent.*

Proof. First, we show that Z is a standard normal variable. Since Z is a linear combination of the jointly normal variables X and Y , Z is also a normal variable. We compute its mean and variance.

The mean of Z is:

$$E[Z] = E\left[\frac{Y - \rho X}{\sqrt{1 - \rho^2}}\right] = \frac{E[Y] - \rho E[X]}{\sqrt{1 - \rho^2}} = \frac{0 - \rho \cdot 0}{\sqrt{1 - \rho^2}} = 0 \quad .$$

The variance of Z is:

$$\begin{aligned} \text{Var}(Z) &= \text{Var}\left(\frac{Y - \rho X}{\sqrt{1 - \rho^2}}\right) = \frac{1}{1 - \rho^2} \text{Var}(Y - \rho X) \\ &= \frac{1}{1 - \rho^2} (\text{Var}(Y) + \rho^2 \text{Var}(X) - 2\rho \text{Cov}(X, Y)) \quad . \end{aligned}$$

Since X and Y are standard normal variables, $\text{Var}(X) = 1$, $\text{Var}(Y) = 1$, and their covariance $\text{Cov}(X, Y)$ is equal to their correlation ρ . Hence:

$$\text{Var}(Z) = \frac{1}{1 - \rho^2} (1 + \rho^2(1) - 2\rho(\rho)) = \frac{1 - \rho^2}{1 - \rho^2} = 1 \quad .$$

Thus, Z is a standard normal variable, $Z \sim \mathcal{N}(0, 1)$.

To show that X and Z are independent, we compute their covariance. Since they are jointly normal, zero covariance implies independence.

$$\begin{aligned} \text{Cov}(X, Z) &= \text{Cov}\left(X, \frac{Y - \rho X}{\sqrt{1 - \rho^2}}\right) = \frac{1}{\sqrt{1 - \rho^2}} \text{Cov}(X, Y - \rho X) \\ &= \frac{1}{\sqrt{1 - \rho^2}} (\text{Cov}(X, Y) - \rho \text{Cov}(X, X)) \\ &= \frac{1}{\sqrt{1 - \rho^2}} (\rho - \rho \text{Var}(X)) = \frac{1}{\sqrt{1 - \rho^2}} (\rho - \rho \cdot 1) = 0 \quad . \end{aligned}$$

Since $\text{Cov}(X, Z) = 0$ and they are jointly normal, X and Z are independent. \square

Now we can prove our proposition of interest:

Proposition 1.1.1. *For bivariate standard normal variables X and Y with correlation ρ ,*

$$P(X > 0, Y > 0) = \frac{1}{4} + \frac{1}{2\pi} \arcsin(\rho) \quad .$$

Proof. Define the random variable Z like in the previous lemma. Then, the event $\{X > 0, Y > 0\}$ is the same as the event $\{X > 0, Z > \frac{-\rho}{\sqrt{1-\rho^2}}X\}$, where X and Z are independent standard normal variables as shown above. Writing $a := \frac{-\rho}{\sqrt{1-\rho^2}}$ for brevity, the desired probability is expressible as a double integral involving the joint density of (X, Z) :

$$\begin{aligned} P(X > 0, Y > 0) &= P(X > 0, Z > aX) \\ &= \int_{x=0}^{\infty} \int_{z=ax}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-x^2/2} \frac{1}{\sqrt{2\pi}} e^{-z^2/2} dz dx \quad . \end{aligned}$$

Switching to polar coordinates ($x = r \cos \theta, z = r \sin \theta$), the integral becomes:

$$\int_{\theta=\arctan(a)}^{\pi/2} \int_{r=0}^{\infty} \frac{1}{2\pi} e^{-r^2/2} r dr d\theta = \int_{\theta=\arctan(a)}^{\pi/2} \frac{1}{2\pi} \left[-e^{-r^2/2} \right]_0^{\infty} d\theta \quad .$$

This equals:

$$\int_{\theta=\arctan(a)}^{\pi/2} \frac{1}{2\pi} d\theta = \frac{1}{2\pi} \left(\frac{\pi}{2} - \arctan(a) \right) = \frac{1}{4} - \frac{1}{2\pi} \arctan\left(\frac{-\rho}{\sqrt{1-\rho^2}}\right) \quad .$$

Using the fact that the arctan function is odd, i.e. $\arctan(-u) = -\arctan(u)$, we get:

$$\frac{1}{4} + \frac{1}{2\pi} \arctan\left(\frac{\rho}{\sqrt{1-\rho^2}}\right) \quad .$$

To finish, we use the identity $\arcsin(\rho) = \arctan\left(\frac{\rho}{\sqrt{1-\rho^2}}\right)$. To see this, let $\phi = \arcsin(\rho)$ for $\phi \in [-\pi/2, \pi/2]$. Then $\sin(\phi) = \rho$ and $\cos(\phi) = \sqrt{1-\rho^2}$. Thus, $\tan(\phi) = \frac{\sin(\phi)}{\cos(\phi)} = \frac{\rho}{\sqrt{1-\rho^2}}$, which implies $\phi = \arctan\left(\frac{\rho}{\sqrt{1-\rho^2}}\right)$. Substituting this into our expression gives the final result:

$$P(X > 0, Y > 0) = \frac{1}{4} + \frac{1}{2\pi} \arcsin(\rho) \quad .$$

□

1.2 Prerequisites for Theorem ??

Lemma 1.2.1. *Let*

$$\mathbf{M} := \begin{bmatrix} \mathbf{A} & \mathbf{B} \\ \mathbf{0} & \mathbf{C} \end{bmatrix}$$

be a matrix consisting of submatrices $\mathbf{A} \in \mathbb{R}^{k \times k}$, $\mathbf{B} \in \mathbb{R}^{k \times \ell}$, and $\mathbf{C} \in \mathbb{R}^{\ell \times \ell}$. Let \mathbf{A} be an irreducible aperiodic Markov transition matrix, and let $\mathbf{C}^n \xrightarrow{n \rightarrow \infty} \mathbf{0}$ with exponential decay. Then, \mathbf{M}^n decays exponentially in n towards a matrix \mathbf{M}' .

Proof. The proof proceeds in three steps. First, we establish a closed-form expression for \mathbf{M}^n . Second, we determine the limit matrix \mathbf{M}' . Third, we prove that the convergence to this limit is exponential.

1. The Form of \mathbf{M}^n Since \mathbf{M} is a block upper triangular matrix, its powers take a specific form. By induction, we can show that:

$$\mathbf{M}^n = \begin{bmatrix} \mathbf{A}^n & \mathbf{X}_n \\ \mathbf{0} & \mathbf{C}^n \end{bmatrix} \quad \text{where} \quad \mathbf{X}_n = \sum_{j=0}^{n-1} \mathbf{A}^{n-1-j} \mathbf{B} \mathbf{C}^j \quad .$$

2. The Limit Matrix \mathbf{M}' We analyze the limit of each block of \mathbf{M}^n as $n \rightarrow \infty$.

- **Block \mathbf{A}^n :** Since \mathbf{A} is an irreducible aperiodic Markov transition matrix, the Perron-Frobenius theorem for stochastic matrices guarantees that \mathbf{A}^n converges to a rank-one matrix $\mathbf{A}' = \boldsymbol{\pi} \mathbf{1}^T$, where $\boldsymbol{\pi}$ is the unique stationary distribution. The convergence is exponential, so there exist constants $K_A > 0$ and $0 \leq \lambda < 1$ such that $\|\mathbf{A}^n - \mathbf{A}'\| \leq K_A \lambda^n$.
- **Block \mathbf{C}^n :** By hypothesis, $\mathbf{C}^n \rightarrow \mathbf{0}$ with exponential decay. This is equivalent to its spectral radius being less than one, $\rho(\mathbf{C}) < 1$. Thus, there exist constants $K_C > 0$ and $0 \leq \gamma < 1$ such that $\|\mathbf{C}^n\| \leq K_C \gamma^n$.

- **Block \mathbf{X}_n :** Let $\mathbf{E}_k = \mathbf{A}^k - \mathbf{A}'$. We have $\|\mathbf{E}_k\| \leq K_A \lambda^k$. We can rewrite \mathbf{X}_n as:

$$\mathbf{X}_n = \sum_{j=0}^{n-1} (\mathbf{A}' + \mathbf{E}_{n-1-j}) \mathbf{B} \mathbf{C}^j = \mathbf{A}' \mathbf{B} \left(\sum_{j=0}^{n-1} \mathbf{C}^j \right) + \sum_{j=0}^{n-1} \mathbf{E}_{n-1-j} \mathbf{B} \mathbf{C}^j \quad .$$

As $n \rightarrow \infty$, the first term converges to $\mathbf{A}' \mathbf{B} (\mathbf{I} - \mathbf{C})^{-1}$, since the series $\sum_{j=0}^{\infty} \mathbf{C}^j$ converges to $(\mathbf{I} - \mathbf{C})^{-1}$. The second term converges to $\mathbf{0}$ because its norm is bounded by a vanishing convolution sum. Thus, the limit of \mathbf{X}_n is $\mathbf{X}' = \mathbf{A}' \mathbf{B} (\mathbf{I} - \mathbf{C})^{-1}$.

Combining these limits, the limit matrix is $\mathbf{M}' = \begin{bmatrix} \mathbf{A}' & \mathbf{X}' \\ \mathbf{0} & \mathbf{0} \end{bmatrix}$.

3. Exponential Rate of Convergence We analyze the norm of the difference matrix $\mathbf{M}^n - \mathbf{M}'$:

$$\mathbf{M}^n - \mathbf{M}' = \begin{bmatrix} \mathbf{A}^n - \mathbf{A}' & \mathbf{X}_n - \mathbf{X}' \\ \mathbf{0} & \mathbf{C}^n \end{bmatrix} \quad .$$

The blocks $\|\mathbf{A}^n - \mathbf{A}'\|$ and $\|\mathbf{C}^n\|$ decay exponentially by definition. We examine the convergence of the off-diagonal block:

$$\mathbf{X}_n - \mathbf{X}' = -\mathbf{A}' \mathbf{B} \left(\sum_{j=n}^{\infty} \mathbf{C}^j \right) + \sum_{j=0}^{n-1} \mathbf{E}_{n-1-j} \mathbf{B} \mathbf{C}^j \quad .$$

The norm of each part is bounded by an exponentially decaying function:

- $\left\| -\mathbf{A}' \mathbf{B} \left(\sum_{j=n}^{\infty} \mathbf{C}^j \right) \right\| \leq \|\mathbf{A}'\| \|\mathbf{B}\| \sum_{j=n}^{\infty} \|\mathbf{C}^j\| \leq \|\mathbf{A}'\| \|\mathbf{B}\| K_C \frac{\gamma^n}{1-\gamma}$. This decays with rate γ .
- $\left\| \sum_{j=0}^{n-1} \mathbf{E}_{n-1-j} \mathbf{B} \mathbf{C}^j \right\| \leq \sum_{j=0}^{n-1} K_A \lambda^{n-1-j} \|\mathbf{B}\| K_C \gamma^j = K_A \|\mathbf{B}\| K_C \sum_{j=0}^{n-1} \lambda^{n-1-j} \gamma^j$. This convolution sum is bounded by $K' n \mu^n$ where $\mu = \max(\lambda, \gamma)$, which decays exponentially.

Since $\|\mathbf{X}_n - \mathbf{X}'\|$ is bounded by a sum of exponentially decaying terms, it also decays exponentially. As all blocks of $\mathbf{M}^n - \mathbf{M}'$ converge to zero exponentially, the norm $\|\mathbf{M}^n - \mathbf{M}'\|$ does as well. This completes the proof. \square

1.2.1 Convergence of Mutual Information

Theorem 1.2.1 (Element-Wise Exponential Convergence Implies Exponential Convergence). *Let $f : \mathcal{D} \rightarrow \mathbb{R}^m$ be a function defined on a convex domain $\mathcal{D} \subseteq \mathbb{R}^n$ that is a Cartesian product of real intervals, i.e., $\mathcal{D} = \mathcal{D}_1 \times \mathcal{D}_2 \times \dots \times \mathcal{D}_n$ where each $\mathcal{D}_i \subseteq \mathbb{R}$ is an interval. Let $\{\mathbf{x}_k\}_{k=1}^\infty \subset \mathcal{D}$ be a sequence converging exponentially fast to $\mathbf{x}_\infty \in \mathcal{D}$.*

Let \mathbf{e}_j denote the j -th standard basis vector in \mathbb{R}^n . Suppose that for each input coordinate $j \in \{1, 2, \dots, n\}$ there exist functions $K_j(C', \rho)$, $C_j(C', \rho)$, $P_j(C', \rho)$ s.t. for every sequence $\{\mathbf{u}_k\}_{k=1}^\infty \subset \mathcal{D}$ converging to \mathbf{u}_∞ where the difference $\mathbf{u}_\ell - \mathbf{u}_{\ell'}$ is parallel to \mathbf{e}_j (i.e., they only differ in the j -th coordinate) that satisfies $|\mathbf{u}_\infty - \mathbf{u}_k| \leq C' \rho^k$ for all k and some $\rho \in [0, 1)$, $C' > 0$, we have for all $k \geq K_j(C', \rho)$:

$$\|f(\mathbf{u}_\infty) - f(\mathbf{u}_k)\| \leq C_j(C', \rho) \rho^k k^{P_j(C', \rho)} \quad .$$

Then, there exist constants $C > 0$ and $\sigma \in [0, 1)$ such that for all sufficiently large k :

$$\|f(\mathbf{x}_\infty) - f(\mathbf{x}_k)\| \leq C \sigma^k \quad .$$

Proof. Let the sequence $\{\mathbf{x}_k\}_{k=1}^\infty \subset \mathcal{D}$ converge exponentially to $\mathbf{x}_\infty \in \mathcal{D}$. By definition, there exist constants $C_x > 0$ and $\rho \in [0, 1)$ such that for all k ,

$$\|\mathbf{x}_k - \mathbf{x}_\infty\| \leq C_x \rho^k \quad .$$

Let $\mathbf{x}_k = (x_{k,1}, \dots, x_{k,n})^T$ and $\mathbf{x}_\infty = (x_{\infty,1}, \dots, x_{\infty,n})^T$. An immediate consequence is that each coordinate also converges exponentially, i.e., for each $j \in \{1, \dots, n\}$:

$$|x_{k,j} - x_{\infty,j}| \leq \|\mathbf{x}_k - \mathbf{x}_\infty\|_\infty \leq \|\mathbf{x}_k - \mathbf{x}_\infty\| \leq C_x \rho^k \quad ,$$

where we use the equivalence of norms in \mathbb{R}^n .

To bound $\|f(\mathbf{x}_\infty) - f(\mathbf{x}_k)\|$, we define a sequence of $n + 1$ intermediate points that form a path from \mathbf{x}_k to \mathbf{x}_∞ by changing one coordinate at a time. For each k , let:

$$\begin{aligned} \mathbf{z}_{k,0} &:= \mathbf{x}_k = (x_{k,1}, x_{k,2}, \dots, x_{k,n}) \\ \mathbf{z}_{k,1} &:= (x_{\infty,1}, x_{k,2}, \dots, x_{k,n}) \\ &\vdots \\ \mathbf{z}_{k,j} &:= (x_{\infty,1}, \dots, x_{\infty,j}, x_{k,j+1}, \dots, x_{k,n}) \\ &\vdots \\ \mathbf{z}_{k,n} &:= (x_{\infty,1}, \dots, x_{\infty,n}) = \mathbf{x}_\infty \quad . \end{aligned}$$

Since \mathcal{D} is a cartesian product of intervals and both \mathbf{x}_k and \mathbf{x}_∞ are in \mathcal{D} , all intermediate points $\mathbf{z}_{k,j}$ are also contained in \mathcal{D} . We can express the total difference $f(\mathbf{x}_\infty) - f(\mathbf{x}_k)$ as a telescoping sum:

$$f(\mathbf{x}_\infty) - f(\mathbf{x}_k) = f(\mathbf{z}_{k,n}) - f(\mathbf{z}_{k,0}) = \sum_{j=1}^n (f(\mathbf{z}_{k,j}) - f(\mathbf{z}_{k,j-1})) \quad .$$

By the triangle inequality, we have:

$$\|f(\mathbf{x}_\infty) - f(\mathbf{x}_k)\| \leq \sum_{j=1}^n \|f(\mathbf{z}_{k,j}) - f(\mathbf{z}_{k,j-1})\| \quad .$$

Now, we analyze each term $\|f(\mathbf{z}_{k,j}) - f(\mathbf{z}_{k,j-1})\|$ for a fixed $j \in \{1, \dots, n\}$. The points $\mathbf{z}_{k,j}$ and $\mathbf{z}_{k,j-1}$ differ only in their j -th coordinate.

Let us define a sequence $\{\mathbf{u}_m\}_{m=1}^\infty$ and a limit point \mathbf{u}_∞ that fit the condition in the theorem's hypothesis. For the given j and k , let

$$\begin{aligned} \mathbf{u}_m &:= (x_{\infty,1}, \dots, x_{\infty,j-1}, x_{m,j}, x_{k,j+1}, \dots, x_{k,n}) \\ \mathbf{u}_\infty &:= (x_{\infty,1}, \dots, x_{\infty,j-1}, x_{\infty,j}, x_{k,j+1}, \dots, x_{k,n}) \quad . \end{aligned}$$

Note that $\mathbf{u}_\infty = \mathbf{z}_{k,j}$ and by setting $m = k$, we get $\mathbf{u}_k = \mathbf{z}_{k,j-1}$. The sequence $\{\mathbf{u}_m\}$ lies on a line parallel to the j -th coordinate axis. As $m \rightarrow \infty$, $\mathbf{u}_m \rightarrow \mathbf{u}_\infty$ because $x_{m,j} \rightarrow x_{\infty,j}$. The convergence is exponential:

$$\|\mathbf{u}_m - \mathbf{u}_\infty\| = |x_{m,j} - x_{\infty,j}| \leq C_x \rho^m \quad .$$

The hypothesis states that for any such sequence, there exist constants $K_j(C_x, \rho)$, $C_j(C_x, \rho)$, $P_j(C_x, \rho)$ which are independent of the specific line, such that for all $k \geq K_j(C_x, \rho)$ we have $\|f(\mathbf{u}_\infty) - f(\mathbf{u}_m)\| \leq C_j(C_x, \rho) \rho^m m^{P_j(C_x, \rho)}$. Applying this for $m = k$:

$$\|f(\mathbf{z}_{k,j}) - f(\mathbf{z}_{k,j-1})\| = \|f(\mathbf{u}_\infty) - f(\mathbf{u}_k)\| \leq C_j(C_x, \rho) \rho^k k^{P_j(C_x, \rho)} \quad .$$

This inequality holds for each $j = 1, \dots, n$. Substituting these bounds back into the sum:

$$\|f(\mathbf{x}_\infty) - f(\mathbf{x}_k)\| \leq \sum_{j=1}^n C_j(C_x, \rho) \rho^k k^{P_j(C_x, \rho)} \quad .$$

Let $K := \max_{j \in \{1, \dots, n\}} \{K_j(C_x, \rho)\}$, $C := \sum_{j=1}^n C_j(C_x, \rho)$ and $P := \max_{j \in \{1, \dots, n\}} \{P_j(C_x, \rho)\}$. Hence, for all $k \geq K$:

$$\|f(\mathbf{x}_\infty) - f(\mathbf{x}_k)\| \leq \sum_{j=1}^n C_j(C_x, \rho) \rho^k k^P = \left(\sum_{j=1}^n C_j(C_x, \rho) \right) \rho^k k^P = C \rho^k k^P \quad .$$

This shows that $\{f(\mathbf{x}_k)\}$ converges exponentially to $f(\mathbf{x}_\infty)$ with a rate of σ s.t. $\rho < \sigma < 1$ (like $\sigma := \sqrt{\rho}$). This completes the proof. \square

Lemma 1.2.2. *Let the function $f : [0, \infty) \rightarrow \mathbb{R}$ be defined as $f(x) = x \log x$ for $x \in (0, 1)$, and $f(x) = 0$ everywhere else. If a sequence $\{x_k\}_{k=1}^\infty \subset [0, 1]$ converging to a limit $x_\infty \in [0, 1]$ satisfies $|x_k - x_\infty| \leq C\rho^k$ for some $C \in \mathbb{R}_{>0}$, $\rho \in [0, 1)$, then the sequence $\{f(x_k)\}$ converges to $f(x_\infty)$ with $|f(x_k) - f(x_\infty)| \leq C\rho^k |\log C + k \log \rho|$ for $k \geq \log_\rho \left(\frac{e^{-1}}{C} \right) =: K$.*

Proof. We consider two cases for the limit x_∞ :

Case 1: $x_\infty = 0$

In this case, $|x_k - 0| = x_k \leq C\rho^k$. We want to bound the difference $|f(x_k) - f(0)| = |f(x_k)|$. Note that $|f(x)|$ is monotonically increasing on $[0, e^{-1}]$. For $k \geq K$ we have $x_k \leq C\rho^k \leq e^{-1}$. Thus, for all $k \geq K$:

$$|f(x_k)| \leq |f(C\rho^k)| = |C\rho^k \log(C\rho^k)| = C\rho^k |\log C + k \log \rho| \quad .$$

Case 2: $x_\infty > 0$

Similarly, for $k \geq K$ we have $|x_k - x_\infty| \leq C\rho^k \leq e^{-1}$. Based on the function graph, it follows that for $k \geq K$ we have:

$$|f(x_k) - f(x_\infty)| \leq |f(C\rho^k) - f(0)| = |f(C\rho^k)| = C\rho^k |\log C + k \log \rho| \quad .$$

□

Theorem 1.2.2 (Element-Wise Exponential Convergence Property of Mutual Information). *Let the function $f : [0, \infty) \rightarrow \mathbb{R}$ be defined as $f(x) = x \log x$ for $x \in (0, 1)$, and $f(x) = 0$ everywhere else. Define the function $I : [0, 1]^{m \times n} \rightarrow \mathbb{R}$ for a matrix $\mathbf{M} \in [0, 1]^{m \times n}$ as:*

$$I(\mathbf{M}) = \sum_{i=1}^m \sum_{j=1}^n f(M_{ij}) - \sum_{i=1}^m f\left(\sum_{j=1}^n M_{ij}\right) - \sum_{j=1}^n f\left(\sum_{i=1}^m M_{ij}\right) \quad .$$

This function exhibits element-wise exponential convergence. That is, for any single component (i_0, j_0) , if a sequence of matrices $\{\mathbf{U}_k\}_{k=1}^\infty \subset [0, 1]^{m \times n}$ converges to a limit \mathbf{U}_∞ , varies only in the (i_0, j_0) -th component and satisfies $\|\mathbf{U}_k - \mathbf{U}_\infty\| \leq C\rho^k$ for some $C > 0$, $\rho \in [0, 1)$ and all k , then the sequence of values $\{I(\mathbf{U}_k)\}$ converges to $I(\mathbf{U}_\infty)$ with $|I(\mathbf{U}_k) - I(\mathbf{U}_\infty)| \leq C'(C, \rho)\rho^k k^{P(C, \rho)}$ for all $k \geq K(C, \rho)$.

Proof. The function $I(\mathbf{M})$ is a sum of terms involving f applied to the matrix entries and their row and column sums. Let $m_i(\mathbf{M}) = \sum_j M_{ij}$ and $m'_j(\mathbf{M}) = \sum_i M_{ij}$. We have:

$$I(\mathbf{M}) = \sum_{i,j} f(M_{ij}) - \sum_i f(m_i(\mathbf{M})) - \sum_j f(m'_j(\mathbf{M})) \quad .$$

We are given a sequence $\{\mathbf{U}_k\}$ that varies only in the (i_0, j_0) -th component, $u_k = \mathbf{U}_k(i_0, j_0)$. All other components are constant. The exponential convergence of $\{\mathbf{U}_k\}$ means $|u_k - u_\infty| \leq C\rho^k$.

The difference $I(\mathbf{U}_k) - I(\mathbf{U}_\infty)$ consists only of terms whose arguments change with k . These are:

1. The entry term: $f(u_k)$.
2. The row-sum term: $f(m_{i_0}(\mathbf{U}_k))$, where $m_{i_0}(\mathbf{U}_k) = u_k + \text{const.}$
3. The column-sum term: $f(m'_{j_0}(\mathbf{U}_k))$, where $m'_{j_0}(\mathbf{U}_k) = u_k + \text{const.}$

By the triangle inequality, the total error is bounded by the sum of the absolute errors of these three terms:

$$\begin{aligned} |I(\mathbf{U}_k) - I(\mathbf{U}_\infty)| &\leq |f(u_k) - f(u_\infty)| \\ &\quad + |f(m_{i_0}(\mathbf{U}_k)) - f(m_{i_0}(\mathbf{U}_\infty))| \\ &\quad + |f(m'_{j_0}(\mathbf{U}_k)) - f(m'_{j_0}(\mathbf{U}_\infty))| \quad . \end{aligned}$$

The arguments to the function f in each of these three terms converge exponentially to their limits with rate ρ and constant C , since $|m_{i_0}(\mathbf{U}_k) - m_{i_0}(\mathbf{U}_\infty)| = |u_k - u_\infty|$ and $|m'_{j_0}(\mathbf{U}_k) - m'_{j_0}(\mathbf{U}_\infty)| = |u_k - u_\infty|$.

Hence, by lemma 1.2.2, we have:

$$\begin{aligned} |I(\mathbf{U}_k) - I(\mathbf{U}_\infty)| &\leq 3C\rho^k |\log C + k \log \rho| \\ &\leq 3C\rho^k k (|\log C| + |\log \rho|) \\ &= C'\rho^k k \quad , \end{aligned}$$

with $C' := 3C(|\log C| + |\log \rho|)$ and for all $k \geq K(C, \rho)$. Note that K , C' and P only depend on C and ρ . \square

Corollary 1.2.1. *Using theorem 1.2.1, we see that if a sequence $\{\mathbf{P}_k\}$ of joint probability distributions converges exponentially fast, then $\{I(\mathbf{P}_k)\}$ converges exponentially fast as well.*

Corollary 1.2.2. *A joint probability matrix $\mathbf{P}_{X,Y}$ can be calculated from the conditional probability matrix $\mathbf{P}_{Y|X}$ and the diagonal matrix \mathbf{P}_X with the probabilities for X on its diagonal using $\mathbf{P}_{X,Y} = \mathbf{P}_{Y|X}\mathbf{P}_X$. Hence, if $\mathbf{P}_{Y|X}$ converges exponentially fast while \mathbf{P}_X stays constant, the mutual information $I(X;Y)$ will converge exponentially fast as well.*