METRICS ON COMPOSITIONS AND COINCIDENCES
AMONG RENEWAL SEQUENCES

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METRICS ON COMPOSITIONS AND COINCIDENCES AMONG RENEWAL SEQUENCES

PERSI DIACONIS*, SUSAN HOLMES†, SVANTE JANSON‡, STEVEN P. LALLEY§, AND ROBIN PEMANTLE¶

Abstract. We study several metrics on the space \( C(m, n) \) of compositions of \( m \) into at most \( n \) parts. Understanding the geometry of these spaces leads to the study of the distribution of the distance between randomly chosen compositions. This in turn leads to some non-standard probability problems. One involves pinned Weiner processes. A second leads to the following renewal theory problem: Let \( X_1, Y_1, \ldots, X_n, Y_1, Y_2, \ldots, Y_n \) be positive integer valued random variables. Let \( C_n = |\{(i, j) \leq n : X_1 + \ldots + X_i = Y_1 + \ldots + Y_j\}| \) be the number of coincidences among the partial sums. We determine limiting approximations to the distribution of \( C_n \). When \( X_1 \) and \( Y_1 \) are jointly independent and identically distributed; the limit is non normal. When \( X_1 + \ldots + X_n = Y_1 + \ldots + Y_n \) is tied down (as in the application to compositions) the limit is normal. Our study was motivated by algorithms for careful approximation of the bootstrap.

1. Introduction. Let \( C(m, n) \) be the set of compositions of \( m \) into at most \( n \) parts. Thus

\[
C(m, n) = \{(h_1, h_2, \ldots, h_n) : h_i \geq 0, \text{ integer, } h_1 + \cdots + h_n = m\}
\]

The familiar stars and bars argument shows \( |C(m, n)| = \binom{m+n-1}{n-1} \).

For example, when \( m = 4, n = 3 \) the 15 compositions in \( C(4,3) \) are

112 400 013 130 220
121 040 031 301 202
211 004 103 103 022

Compositions are a basic combinatorial object which arise in several statistical applications. For example, a class of \( m \) students given grades in \{A, B, C, D, E\} give rise to a point in \( C(m, 5) \). Aitchison [1] gives a comprehensive treatment of compositional data.

Our motivation for careful study of compositions arose from analysis of the statistical tool known as the bootstrap. This is based on repeated samples of \( n \) items chosen with replacement from a list of \( n \). Each sample can be associated to a point in \( C(n, n) \), with \( h_i \) being the number of times item \( i \) appears in the sample. We were seeking “well distributed” points in \( C(n, n) \) this required natural motions of distance. See Diaconis and Holmes [7] for further discussion.

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In Section 2 we introduce and study a number of metrics on $C(m, n)$. As explained below, this is closely related to the study of metrics on the space of probability measures. We study the size of the balls in a given metric by studying the following problem: Pick $h, h'$ at random in $C(m, n)$. What is the distribution of $d(h, h')$? We give fairly complete answers on $C(n, n)$. The results lead to some non-standard probability problems.

The final two sections focus on some renewal theory problems arising from the study of our subset metric. Let $X_1, X_2, \ldots, Y_1, Y_2, \ldots$ be positive integer valued random variables. Let $S_i^X$ and $S_j^Y$ be the corresponding partial sums. Define the coincidence number

$$C_n = \{|(i, j); 1 \leq i, j \leq n : S_i^X = S_j^Y\}|$$

That is, the number of common values between the sets

$$\{S_1^X, S_2^X, \ldots, S_n^X\} \text{ and } \{S_1^Y, S_2^Y, \ldots, S_n^Y\}.$$ 

We study the limit distribution of $C_n$ under two distributional assumptions. We first treat the independent and identically distributed case. In Section 3 we prove

**Theorem 1.1.** Let $\{X_i\}_{i=1}^\infty, \{Y_j\}_{j=1}^\infty$ be jointly independent and identically distributed positive integer valued random variables. Suppose that $g.c.d.\{h : P\{X_1 = h\} > 0\} = 1$ and that $X_1$ has finite mean $\mu$ and finite positive variance $\sigma^2$. Then, as $n \to \infty$

$$\frac{C_n - n\mu^{-1}}{\sqrt{n}} \Rightarrow \min(Z_1, Z_2)$$

where the vector $(Z_1, Z_2)$ has a bivariate normal distribution with mean zero and non-degenerate (rank 2) covariance matrix. The limit is thus non-normal.

In Section 4 we prove

**Theorem 1.2.** Let $\{W_i\}_{i=1}^n$ be the cell counts when $n$ balls are dropped into $n$ boxes. Let $X_i = W_i + 1$. Let $\{Y_i\}_{i=1}^n$ be an independent copy of $\{X_i\}_{i=1}^n$. As $n \to \infty$, the $C_n$ of (1.2) satisfies

$$\frac{C_n - n/2}{\sqrt{n}} \Rightarrow Z$$

where $Z$ is normal with mean 0 and positive, finite variance.

The connection between Theorems 1.1 and 1.2 and the metrics of Section 2 is explained in the introduction to Section 3.

**2. Metrics on compositions.** Let $C(m, n)$ be the set of compositions of $m$ into at most $n$ parts. In this section we define and study several metrics on $C(m, n)$: total variation (Section 2.1), the subset metric
(Section 2.2), and Vaserstein metric (Section 2.3). Basic properties and sampling distributions are developed. The sampling distributions are derived for both the uniform and multinomial distributions. The first gives a geometric feeling for the space. The second is natural for the bootstrap applications: the measure induced on $C(n,n)$ by bootstrap sampling is exactly the multinomial distribution of $n$ balls dropped randomly into $n$ boxes.

Compositions may be regarded as measures on $\{1,2,\ldots,n\}$ with total mass $m$. This allows any distance on probabilities to be adapted to a metric on $C(m,n)$. Section 2.4 gives pointers to the relevant literature and some further examples.

Total variation emerges as our favorite metric. The others are developed because they have natural invariance properties or lead to interesting math problems.

2.1. **Total variation.** For $x, y \in C(m,n)$ define

$$d_{TV}(x, y) = \begin{cases} \text{minimum number of } \pm 1 \text{ switches} \\ \text{needed to bring } x \text{ to } y. \end{cases}$$

For example, take $m = 4$, $n = 3$, $x = (4, 0, 0)$, $y = (1, 1, 2)$. We bring $x$ to $y$ by $400 \rightarrow 301 \rightarrow 202 \rightarrow 112$ so $d_{TV}(x, y) = 3$.

The standard properties of the total variation distance between two probability measures (see e.g. Diaconis [6, Chapter 3]) can be translated to give the following equivalences.

**Lemma 2.1.** The total variation distance on $C(m,n)$ defined in (3.1) satisfies

$$d_{TV}(x, y) = \frac{1}{2} \sum_{i=1}^{n} |x_i - y_i| = \frac{1}{2} \max_{1 \leq i \leq l} \sum_{i=1}^{n} x_i f_i - y_i f_i = m - \sum_{i=1}^{n} \min(x_i, y_i)$$

**Remark 2.2.**

1. The first equality gives an easy way to calculate $d_{TV}$. The second equality shows that if two compositions are close then linear combinations of them are uniformly close. The third equality gives a statistically natural property of $d_{TV}$. In the bootstrap application, $\min(x_i, y_i)$ is the amount of overlap or redundancy between the two samples. For $m = n$, the distance is largest (equal to $n$) if the two compositions come from disjoint bootstrap replications.

2. The distance $d_{TV}$ is invariant under coordinate permutations. On the other hand the number of points in a metric ball can depend on where the ball is centered. For example, when $m = 4$ and $n = 3$, there are two points at distance 1 from (004) and 6 points at distance 1 from (112). Generic $x$ have $n(n-1)$ points at distance 1 but for larger balls, all depends on how close $x$ is to the corner of the simplex $C(m,n)$. This becomes more pronounced for larger
n. For example, on $C(n, n)$, if $Y$ has a multinomial distribution
and $x = (n, 0, \cdots 0)$, $d_{TV}(x, Y)$ is essentially constant at $n$ while if
$x = (1, 1, \cdots 1)$ $d_{TV}(x, Y)$ has an approximate normal distribution
centered at $n/e$. This can be proved using the argument of Lemma
2.3 which interpolates between these extremes by choosing $x$ at
random.

The next two lemmas give the approximate sampling distributions of
$d_{TV}(X, Y)$ where $X$ and $Y$ are randomly chosen compositions. We derive
limiting approximations when $m$ and $n$ are large with $m/n \to \lambda$. This
is the domain of interest for bootstrap applications. The answers can be
quite different in other zones ($m$ small $n$ large or vice-versa). Nowadays,
one can easily simulate this distribution for any specific $m, n$ of interest.

**Lemma 2.3.** Let $X$ and $Y$ be independently chosen from the multino-
mial distribution on $C(m, n)$. Then, for $m, n \not\sim \infty$ with $m/n \to \lambda$, $0 < \lambda < \infty$, $d_{TV}(X, Y)$ is approximately normally distributed with

$$\text{mean} \sim \frac{n}{2} E|W - W'|,$$

with $W, W'$ independent Poisson ($\lambda$)

$$\text{var} \sim \frac{n}{4} [2\lambda - \{E|W - W'|\}^2]$$

**Proof.** Under the multinomial distribution, $X = (X_1, \cdots X_n)$ with
$X_i$ having a binomial ($\frac{1}{n}, m$) distribution which is well approximated by
Poisson ($\lambda$). Thus, $|X_i - Y_i|$ is approximately distributed as the absolute
difference between independent Poisson ($\lambda$) variates. The distribution of the
sum is approximately normal by standard Poissonization arguments
(see e.g. Holst [11]). \(\Box\)

**Remark 2.4.** Ramasubban [18,19] studied $\Delta_r = E|W - W'|^r$. He gives
$\Delta_1 = 2\lambda e^{-2\lambda} [I_0(2\lambda) + I_1(2\lambda)]$ with $I_n(x)$ the $n^{th}$ order modified Bessel
function of the first kind. He also gives expressions for higher moments.
For example,

<table>
<thead>
<tr>
<th>$\lambda$</th>
<th>0.5</th>
<th>1.0</th>
<th>1.5</th>
<th>2.0</th>
<th>2.5</th>
<th>3.0</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta_1$</td>
<td>0.674</td>
<td>1.048</td>
<td>1.319</td>
<td>1.543</td>
<td>1.738</td>
<td>1.912</td>
</tr>
</tbody>
</table>

Feller [8] relates Poisson differences and Bessel functions.

**Lemma 2.5.** Let $X$ and $Y$ be independently chosen from the uniform
distribution on $C(m, n)$. Then, for $m, n \not\to \infty$ with $m/n \to \lambda$, $0 < \lambda < \infty$, $d_{TV}(X, Y)$ is approximately normally distributed with

$$\text{mean} \sim \frac{n}{2} \frac{2\lambda(1 + \lambda)}{1 + 2\lambda}$$

$$\text{var} \sim \frac{n}{2} \left[ \lambda(\lambda + 1) - 2\frac{\lambda^2(1 + \lambda)^2}{(1 + 2\lambda)^2} \right]$$
Proof. Under the uniform distribution, $X = (X_1, \ldots, X_n)$ has a Bose-Einstein distribution with $P\{X_i = k\} = \binom{n-1}{n+k-1} \left( \frac{1}{\lambda+1} \right)^k$. Thus $|X_1 - Y_1|$ is approximately distributed as the absolute difference between independent geometric $\left( \frac{1}{\lambda+1} \right)$ variables; $V$ and $V'$ say. Then $E|V - V'| = 2\lambda(1+\lambda)/(1+2\lambda)$. The Bose-Einstein distribution on $C(m, n)$ may be represented as the law of $n$ independent geometric random variables conditional on their sum being $m$. The limiting normality follows from standard conditional limit theorems as in Holst [11].

Remark 2.6. If $\delta_1 = 2\lambda(1+\lambda)/(1+2\lambda)$ we compute

<table>
<thead>
<tr>
<th>$\lambda$</th>
<th>.5</th>
<th>1</th>
<th>1.5</th>
<th>2</th>
<th>2.5</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\delta_1$</td>
<td>0.75</td>
<td>1.333</td>
<td>1.875</td>
<td>2.4</td>
<td>2.92</td>
<td>3.43</td>
</tr>
</tbody>
</table>

Thus, typical pairs $X, Y$ tend to be further apart under the uniform as compared with the multinomial distribution.

2.2. Subset distance. Compositions are in $1-1$ correspondence with subsets of size $n-1$ in a set of $m+n-1$ elements: arrange $1, 2, \ldots, m+n-1$ in a row and circle the elements in the subset. The associated composition has $n$ parts corresponding to the number of elements between the circles. Thus, with $m = 4, n = 3$, the composition (400) corresponds to $1 \ 2 \ 3 \ 4 \ \overset{5}{\otimes}$ \overset{6}{\otimes}$; (013) corresponds to $1 \ 2 \ 3 \ 4 \ 5 \ 6$. The composition $(k_1, k_2, \ldots, k_n)$ corresponds to the subset $\{k_1 + 1, k_2 + 2, \ldots, k_1 + \ldots + k_{n-1} + n - 1\}$. Write $s(x)$ for the subset corresponding to the composition $x$.

There is a natural metric on subsets which induces a metric on compositions. For $x, y \in C(m, n)$ define

$$d_s(x, y) = (n - 1) - |s(x) \cap s(y)|$$

Thus for $x = (400), y = (013); s(x) = \{5, 6\}, s(y) = \{1, 3\}, d(x, y) = 2$.

The metric $d_s$ depends on the ordering: $d_s(50000, 11111) = 2$, $d_s(05000, 11111) = 3$. On the other hand the metric $d_s$ has the following invariance property: the number of points in the ball $\{y : d_s(x, y) \leq \omega\}$ does not depend on $x$. This follows from the invariance of the metric $(n - 1) - |s \cap t|$ on subsets under the action of the permutation group $S_{n+m-1}$. The main reason for studying $d_s$ is because of the frequent interplay between subsets and compositions in the combinatorial literature.

The following two results give the limiting distribution of $d_s(X, Y)$ under the two distributions on $C(m, n)$.

Lemma 2.7. Let $X$ and $Y$ be independently chosen from the uniform distribution on $C(m, n)$. Then, for $m, n \to \infty$ with $m/n \to \lambda$,
0 < \lambda < \infty, d_\nu has a hypergeometric distribution. It is approximately normally distributed with

\[
\text{mean} = (n-1) - \frac{(n-1)^2}{n+m-1} \sim n\lambda/(1+\lambda)
\]

\[
\text{var} = \frac{(n-1)^2m^2}{(m+\lambda-1)^2(m+n-2)} \sim n\lambda^2/(1+\lambda)^3
\]

Proof. Using the correspondence, \(d_\nu(X, Y)\) has the same distribution as \(n-1 - |S \cap T|\) where \(S\) and \(T\) are randomly chosen subsets of size \((n-1)\) from \(\{1, 2, \cdots, m+n-1\}\). By invariance, \(S\) may be fixed at \(\{1, 2, \cdots, n-1\}\). Now, the distribution of \(|S \cap T|\) is hypergeometric and the result stated is classical. \(\square\)

**Lemma 2.8.** Let \(X\) and \(Y\) be independently chosen from the multinomial distribution on \(C(n, n)\). Then, as \(n \rightarrow \infty\), \(d_\nu(X, Y)\) is approximately normally distributed with

\[
\text{mean} \sim n/2
\]

\[
\text{var} \sim \sigma^2 n \text{ for some } \sigma^2, 0 < \sigma^2 < \infty.
\]

Proof. Choosing \(X = (X_1, X_2, \cdots, X_n) \in C(n, n)\) from the multinomial distribution amounts to dropping \(n\) balls into \(n\) boxes with \(X_i\) the number of balls in box \(i\). With \(Y\) similarly distributed. Now \(|S(X) \cap S(Y)| = C_\nu(n)\) as defined in (1.1). The result now follows from Theorem 1.2. See Section 4 below. \(\square\)

**Remark 2.9.** Very similar arguments give results similar to Lemma 2.8 for general \(m, n\).

### 2.3. Vaserstein distance.

The final metric considered in detail is the analog of a standard metrization of the weak star topology. For \(x, y \in C(m, n)\) define

\[
(2.2) \quad d_\nu(x, y) = \text{minimum number of adjacent } \pm 1
\]

switches need to bring \(x\) to \(y\).

Thus \(d_\nu(400, 112) = 5\) from \(400 \rightarrow 310 \rightarrow 301 \rightarrow 211 \rightarrow 202 \rightarrow 112\). Rachev [17] discusses the history and literature for this distance on probability measures. From results proved there we have the following equivalent versions:

**Lemma 2.10.** The Vaserstein distance \(d_\nu\) on \(C(m, n)\) defined by (2.2) satisfies

\[
\begin{align*}
&d_\nu(x, y) = \sum_{i=1}^n |x_i^+ - y_i^+|; \quad x_i^+ = x_1 + \cdots + x_i \\
&= \max_{f \in \text{Lip}_1} |\sum x_i f_i - y_i f_i|, \quad \text{Lip}_1 = \{f_1|f_i - f_{i+1}| \leq 1, 1 \leq i < n\}.
\end{align*}
\]
Remark 2.11. Note that \( dv \) depends on the coordinate ordering: \( dv(300, 030) = 3, dv(300, 003) = 6 \). However, in the bootstrap application, if the original sample values are ordered real numbers then adjacency has a natural meaning and the Vasserstein distance becomes interesting.

We have not studied the distribution of \( dv(X, Y) \) under the uniform distribution. We believe the limit theory is essentially the same as the following:

**Lemma 2.12.** Let \( X \) and \( Y \) be chosen independently from the multinomial distribution on \( C(n, n) \). Then, as \( n \to \infty \), \( dv(X, Y)/n^{\frac{1}{2}} \) converges in distribution to \( \int_0^1 |B_0(t)| dt \) with \( B_0(t) \) the standard Brownian bridge on [0, 1].

**Proof.** Under the multinomial distribution

\[
dv(X, Y) \overset{d}{=} \sum_{n=1}^{n} |X_i^+ - Y_i^+|
\]

with \( X_i^+ \) and \( Y_i^+ \) independent binomial \( (n, \frac{1}{n}) \). Thus, for \( i = \theta n, 0 < \theta < 1 \) fixed, \( (X_i^+ - Y_i^+)/\sqrt{n} \) has a normal limit with mean 0 and variance \( \theta(1-\theta) \). Checking the covariances, we see that the increments have the covariances of a Brownian bridge. To make the convergence argument rigorous, we may appeal to Billingsley [3, Theorem 24.2]. This asserts that if \( \xi_1, \xi_2, \cdots, \xi_n \) are exchangeable random variables with sum zero, sum of squares 1, and max tending to 0, then the associated random function converges to a Brownian bridge.

Multiplying and dividing the expression for \( dv(X, Y) \) by \( n \) we get a Riemann sum for the integral. The result follows from the continuous mapping theorem.

**Remark 2.13.** Following work of Cifarelli and Regazzini [4], Shepp [21] and Rice [20] carried out a careful investigation of the law of \( \int_0^1 |B_0(t)| dt \). Shepp gives an elegant derivation of the Fourier transform in terms of Airy functions and a recursion for moments. Rice managed to numerically invert the Fourier transform to give highly accurate percentage points and the following graph of the density.
2.4. Other metrics. Compositions in $C(m, n)$ can be identified with probability vectors of length $n$ by dividing by $m$. Thus any metric on probabilities can be carried over to compositions. Rachev [17] gives an encyclopedic survey of metrics on probabilities. Two simple metrics are the Hellinger and $\ell_2$ distances

$$d_H(x, y) = \sum_{i=1}^{n} (x_i^{\frac{1}{2}} - y_i^{\frac{1}{2}})^2 \quad d_2(x, y) = \sum_{i=1}^{n} (x_i - y_i)^2$$

The first represents compositions as points on a sphere. The second has all of the advantages of Euclidian space. Each has an easily derived normal approximation using the techniques of Section 2.1.

We conclude by mentioning two further metrics which do not have natural versions on probabilities. The first is Hamming distance:

$$d_H(x, y) = |\{i : x_i \neq y_i\}|$$
This is invariant under permuting coordinates. It also has the following invariance property: \(|\{y : d_H(x, y) \leq k\}|| does not depend on \(x\). Under both uniform distribution \(w\) and multinomial distribution \(m\), \(d_H(X, Y)\) has an approximate normal limiting distribution, when \(m = n\), the means and variances are
\[
E_w\{d_H(X, Y)\} = \frac{2}{3}n \quad E_m\{d_H(X, Y)\} = \theta n,
\]
\[
1 - \theta = e^{-2} \sum_{j=0}^{\infty} \frac{1}{(j!)^2} \approx .3085^+
\]
\[
\text{var}_w\{d_H(X, Y)\} = \frac{2}{3}n \quad \text{var}_m\{d_H(X, Y)\} = \theta(1 - \theta)n
\]

Our second metric may be called the child’s metric
\[
d_e(x, y) = \begin{cases} \text{minimum number of moves} & \text{required to bring } X \text{ to } Y \\ \end{cases}
\]
where a move takes \((x_1, \ldots, x_n) \rightarrow (x_1 \cdots x_i - a, \ldots x_j + a, \ldots x_n)\) for any pair of coordinates \(i \neq j\) and any integer \(a\) chosen so all coordinates are non-negative. Thus \(d_e(50000, 02300) = 2\) from \((50000) \rightarrow (32000) \rightarrow (02300)\).

If a composition is thought of as \(n\) piles of blocks, a move consists of picking any number of blocks from a pile and depositing them on any other pile. This metric has good invariance properties. Alas, R.L. Graham (personal communication) has shown that computing \(d_e\) is \# - \(p\) complete. Indeed, given \(x, y \in C(m, n)\) form \(z_i = x_i - y_i\). Let \(t\) be the maximum number of blocks in a partition such that \(z_i\), summed over each block, gives zero. The \(d_e(x, y) = n - t\). However, deciding if \(d_e(x, y) \leq n - 2\) involves computing if some non-trivial subset sum of \(z_i\) is zero. This is a well known NP complete problem.

**Final Remark 2.14.** Metrics on combinatorial objects offer a rich area of study and application. See Critchlow [5] and Diaconis [6, Chapter 6] for examples in the space of permutations. We hope that some of the present results will be found similarly useful for analyzing compositional data.

### 3. Coincidences for independent renewal sequences

This section studies the number of coincidences between independent renewal sequences. Throughout we assume that \(\{X_i\}_{i=1}^{\infty}\) and \(\{Y_i\}_{i=1}^{\infty}\) are each independent and identically distributed random variables. With \(\{X_i\}\) independent of \(\{Y_i\}\). We do not assume \(X_i\) and \(Y_i\) have the same distribution. Assume further that all variables are strictly positive, integer valued, non-arithmetic (g.c.d. \(\{h : P(X_1 = h) > 0\} = 1\)), non degenerate (not almost surely equal to 1), and have finite second moments.

We let \(S_i^X = X_1 + \cdots + X_i\) and \(S_j^Y\) be the partial sums. The object of study is the number of coincidences
\[
C_n = |\{i, j \leq n : S_i^X = S_j^Y\}|
\]
We will prove a limit theorem for $C_n$ when $X_t$ and $Y_t$ have the same law in Section 3.1. We explain what happens when $X_t$ and $Y_t$ have different laws in Section 3.2, which also contains a review of relevant literature.

Our motivation came from studying the metric $d_*$ explained in Section 2.2 above. Under the multinomial distribution on $C(n, n)$, this has the same distribution as the number of coincidences between the two sequences $\{W_1 + 1, W_1 + W_2 + 2, \ldots, W_1 + \cdots + W_{n-1} + (n-1)\} \{Z_1 + 1, Z_1 + Z_2 + 2, \ldots, Z_1 + \cdots + Z_{n-1} + (n-1)\}$ where $\{W_i\}_{i=1}^n$ are the number of balls in box $i$ when $n$ balls are dropped into $n$ boxes according to the multinomial distribution and $\{Z_i\}_{i=1}^n$ are independent with the same distribution. Heuristically, $W_i$ are approximately independent Poisson (1).

The limit theory in this section was developed to study such coincidences. It turns out that the heuristic is wrong: the multinomial counts are tied down and this matters, the correct results for the balls in boxes case are explained in Section 4. The present results seem of independent interest. We found a rigorous development under minimal conditions challenging.

We conclude this introduction with an overview of the argument. With notation as above, for the remainder of this introduction take $X_t$ and $Y_t$ with a common law. Define

$$(3.1) \quad R_X = \{S_1^X, S_2^X, \ldots\} \quad R_Y = \{S_1^Y, S_2^Y, \ldots\}.$$ 

Let the common points of $R_X$ and $R_Y$ be $T_1 < T_2 < T_3 < \cdots$. There are infinitely many common points from the renewal theorem (condition on the set $R_X$ and use the renewal theorem on the renewal process $S_n^X$). The $T_i$ form a renewal processes. Moreover, the $X$ and $Y$ excursions between successive $T_i$ are independent and identically distributed. Consequently, if we define $U_n, V_n$ by

$$(3.2) \quad S_{U_n}^X = S_{V_n}^Y = T_n$$

The successive (vector) increments of the two dimensional process

$$(3.3) \quad (U_n, V_n)$$

are iid so that $(U_n, V_n)$ is a random walk which is strictly increasing in both coordinates. Theorem 1.1 of the introduction follows from a study of this walk. Indeed, $C_n$ is just the number of points of the walk $(U_j, V_j)$ that lie in the square $[0, n] \times [0, n]$. This is because each point of the walk corresponds to a coincidence of partial sums with $(U_j, V_j)$ giving the times when the partial sums are equal. This coincidence is counted in $C_n$ if and only if $U_t, V_t \leq n$.

We next explain (heuristically) why the limit law is the minimum of two correlated normal variables. The argument is based on a useful fact from renewal theory. Let $Z_1, Z_2, \ldots$ be independent and identically distributed, integer valued random variables with $E(Z_t) = \beta$, $\text{var}(Z_t) = \sigma^2$, $0 < \sigma^2 < \ldots$
Let $S_n^Z$ be the partial sum process. Define $W_h = \{n : S_n^Z \leq h\}$. Then, as $h \to \infty$,

$$
\frac{W_h - h\beta^{-1}}{\sqrt{h\beta^{-3}\sigma^2}} \Rightarrow \xi
$$

where $\xi$ has a standard normal distribution. This is an immediate consequence of the ordinary central limit theorem since $P\{N_h \leq n\} = P\{S_n^Z \leq h\}$.

Now consider the renewal process $(U_j, V_j)$ defined above. As noted, $C_n$ is the number of points of this sequence in the square $[0, n] \times [0, n]$. This is clearly the same as the minimum of $N_U, N_V$ where these are respectively the number of points in the renewal sequences $U_j, V_j$ in $[0, n]$. Now Hunter [12] showed $(N_U - n\mu^{-1})/\sqrt{n}, (N_V - n\mu^{-1})/\sqrt{n}$ has a bivariate limiting normal distribution.

Thus $C_n$ suitably normalized converges to the minimum of two normals.

To make the argument rigorous, we must study the distribution of $(U_1, V_1)$. We show this has a non-degenerate covariance matrix in Section 3.2 which also contains further remarks and references.

### 3.1. Time between coincidences

Throughout we assume $\{X_i\}, \{Y_i\}$ satisfy the assumptions of the first paragraph of Section 3. We study the moments of $T_n$ and $(U_i, V_i)$ defined in (3.1, 3.2). We need a preliminary lemma for which we introduce notation.

Let $F(z) = \sum_{h=0}^{\infty} P_h z^h, |z| < 1$, be the probability generating function of the increments of a renewal process $S_n$. Let $U(z) = \sum_{h=0}^{\infty} u_h z^h$, where

$$
(3.4) \quad u_h = \sum_{n=0}^{\infty} P\{S_n = h\}
$$

is the renewal measure. Then $U(z) = 1/(1 - F(z))$.

**Lemma 3.1.** Assume $\mu = F'(1) < \infty$. Then, the increments have finite variance if and only if

$$
U(z) - \frac{1}{\mu(1-z)} = \sum_{h=0}^{\infty} \left( u_h - \frac{1}{\mu} \right) z^h
$$

stays bounded as $z \to 1$. In this case, $U(z) - \frac{1}{\mu(1-z)} \to \frac{\sigma^2 + \mu \sigma^2 - \mu}{2\mu^2}$ with $\sigma^2$ the variance of the increment.

**Proof.**

\[
U(z) - \frac{1}{\mu(1-z)} = \frac{1}{1 - F(z)} - \frac{1}{\mu(1-z)} = \frac{\mu(1-z) - (1-F(z))}{\mu(1-z)(1-F(z))} = \frac{F(z) - 1 - (z - 1)F'(1)}{\mu(1-z)(1-F(z))}.
\]

Since $\frac{1}{1 - F(z)} \to F'(1) = \mu$ as $z \to 1$, \sup_{0 \leq z < 1} |U(z) - \frac{1}{\mu(1-z)}| < \infty if and only if $F(z) - 1 - (z - 1)F'(1) = O\left((1-z)^2\right)$ as $z \to 1$. Now

\[
F(z) - 1 - (z - 1)F'(1) = \int_0^1 F''(1 - t(1-z))(1-t)\,dt
\]
Hence $F''(1-) < \infty$ if and only if the increments have finite variance. \(\square\)

The next result shows that the increments of the renewal process $T_i$ defined at (3.1, 3.2) have finite variance.

**Proposition 3.2.** Let $\{X_i\}_{i=1}^\infty$, $\{Y_i\}_{i=1}^\infty$, be independent and identically distributed non-arithmetic, integer valued random variables with finite means $\mu_X, \mu_Y$ and finite, positive variances $\sigma_X^2, \sigma_Y^2$. Let $\{T_i\}_{i=1}^\infty$ be the intersection places (cf. 3.2) of the partial sum processes. Then, $\{T_i\}$ is a renewal process with iid increments $Z_i = T_{i+1} - T_i$ having $E(Z_i) = \mu_X \mu_Y$ and $\text{var}(Z_i) = \sigma^2(Z_i) < \infty$.

**Proof.** Let $U^X_h$ be the renewal measure defined at (3.4). Clearly $\mu^Z = U^X_h \mu^Y_h$. Hence $U_h \mu \mu < \infty$. So $\mu_Z = \mu_X \mu_Y < \infty$. Now, with notation as in Lemma 3.1,

$$U^X_h - \frac{1}{\mu_Z} = U^X_h U^Y_h - \frac{1}{\mu_X \mu_Y} = \frac{1}{\mu_Y} (U^X_h - \frac{1}{\mu_X}) + \frac{1}{\mu_X} (U^Y_h - \frac{1}{\mu_Y}) + (U^X_h - \frac{1}{\mu_X}) (U^Y_h - \frac{1}{\mu_Y}).$$

Thus

$$U^Z(z) - \frac{1}{\mu_Z(1-z)} = \frac{1}{\mu_Y} [U^X(z) - \frac{1}{\mu_X(1-z)}] + \frac{1}{\mu_X} [U^Y(z) - \frac{1}{\mu_Y(1-z)}]$$

$$+ \sum_{h=0}^{\infty} (U^X_h - \frac{1}{\mu_X}) (U^Y_h - \frac{1}{\mu_Y}) z^h.$$

By Lemma 3.1, the first two terms on the right hand side stay bounded as $z \nearrow 1$. So, using Lemma 3.1 again, it suffices to show that the third term stays bounded.

Using the Cauchy-Schwartz inequality it suffices to show

$$\lim_{r \searrow 1} \sum_{h=0}^{\infty} \left( U^X_h - \frac{1}{\mu_X} \right) r^{2h} = \sum_{h=0}^{\infty} \left( \frac{\mu^X_h - 1}{\mu_X} \right)^2 < \infty$$

and the same with $Y$ replacing $X$. Using the Plancherel Theorem, the first sum in (3.5) equals

$$\frac{1}{2\pi} \int_0^{2\pi} \left| U^X(re^{it}) - \frac{1}{\mu_X(1-re^{it})} \right|^2 dt \leq \sup_{|z|<1} \left| U^X(z) - \frac{1}{\mu_X(1-z)} \right|^2$$

This last is finite since

$$U^X(z) - \frac{1}{\mu_X(1-z)} = \frac{1}{1-F(z)} - \frac{1}{\mu_X(1-z)}$$

is continuous on $|z| \leq 1$: The only singularity could be at $z = 1$ but the argument in Lemma 3.1 shows convergence for $z \to 1$ as long as $|z| \leq 1$. \(\square\)

**Remark 3.3.** We do not know how to relate higher moments of $X$ and $Y$ to those of $Z$. We have shown that if $X$ and $Y$ have finite moment generating functions then $Z$ does as well.
The next result of this section shows that the bivariate vector \((U_1, W_1)\) of (3.2) has a finite, nondegenerate covariance matrix.

**Proposition 3.4.** Let \(\{X_i\}_{i=1}^{\infty}, \{Y_i\}_{i=1}^{\infty}\) satisfy the assumptions of Proposition 3.2. Let \((U_i, V_i)\) be the times of intersection of the two partial sum processes (cf. 3.2). Then \((U_i, V_i)\) are iid with finite, rank two covariance matrix and \(E(U_i) = \mu_X, E(V_i) = \mu_Y\).

**Proof.** By Proposition 3.2, \(ET_1^2 < \infty\). But \(U_1 \leq T_1 \) and \(V_1 \leq T_1\). Thus the second moments are finite. For the means, condition on \(\{Y_i\}_{i=1}^{\infty}\). Then, \(U_1\) is a stopping time relative to \(\{X_i\}_{i=1}^{\infty}\). Since \(T_1 = \sum_{i=1}^{U_1} X_i\), \(E(T_1 | \{Y_i\}) = E(U_1 | \{Y_i\}) \mu_X\) by Wald's Lemma (see e.g. Gut [10, Theorem 1.5.3(i)]). Hence \(E(T_1) = E(U_1) \mu_X\) but \(E(T_1) = \mu_X \mu_Y\) by Proposition 3.2 so \(E(U_1) = \mu_X\). A parallel argument gives \(E(V_1) = \mu_Y\).

The difficult part of the argument is showing that the covariance matrix of \((U_1, V_1)\) is rank 2. If the covariance matrix is singular, then \(aU_1 + bV_1 + c = 0\) a.s. for some \(a, b, c\) not all zero. We may take \(a, b, c\) integral. Now \(a = b = 0\) implies \(c = 0\) which is excluded. Hence without loss \(a \neq 0\). We may further assume \(a > 0\) and that \(a\) and \(b\) have no common divisors > 1.

The argument proceeds in two cases:

**Case 3.5.** \(b \geq 0\). Then, \(aU_1 \leq -c\) so \(U_1 \leq -c/a\) almost surely. This is impossible since \(P\{U_1 > M\} > 0\) for any integer \(M\) by the following argument. We will assign values to \(X_1, X_2, \ldots, X_M\) and \(Y_1, Y_2, \ldots, Y_n\) (for some \(n\)) which are taken with positive probabilities and are such that \(S^X_i \neq S^Y_j\) for all \(i \leq M, j \leq n\) and \(S^X_i < S^Y_j\). Thus \(S^X_i \neq S^Y_j\) for all \(i \leq M, j \leq n\) and so \(U_1 > M\). To do the assignment, start with any \(X_1\) and \(Y_1 \neq X_1\). If \(Y_1 < X_1\), choose \(Y_2\) such that \(S^Y_1 \neq S^X_1\). If \(S^Y_1 < S^X_1\), choose \(Y_3\) but if \(S^Y_1 > S^X_1\), choose \(X_2\). Continue, always choosing the next value in the sequence with the smallest sum. This is always possible since there are at least two allowed values for each variable and only one of these is excluded by the construction. The construction stops when \(X_{M+1}\) is to be chosen.

**Case 3.6.** \(b < 0\). Let \(\beta = -b > 0\). The solutions to the diophantine equation \(aU + bV + c = 0\) are of the form \(U = U_h = U_0 + \beta h, V = V_h = V_0 + ah\) for some \(u_0, v_0 > 0\) and \(h = 0, 1, 2, \ldots\). Consider the sequence \(\{S^X_{U_h} - S^Y_{V_h}\}_{h \geq 0}\). This is a random walk (starting at \(S^X_{U_0} - S^Y_{V_0}\)) with increments distributed as \(S^X_h - S^Y_h\). Since the starting point and the increments take on at least three possible values with positive probability, there exists, for each \(M > 0\), a possible realization of \(\{S^X_{U_h} - S^Y_{V_h}\}_{h \geq 0}\) for some \(n \geq 0\), with all terms \(\neq 0\) and \(|S^X_{U_h} - S^Y_{V_h}| > M\). This corresponds to a realization of \(\{X_i\}_{i=1}^n\) and \(\{Y_i\}_{i=1}^n\) such that \((U_1, V_1) \neq (U_h, V_h)\) for every \(h \leq n\). Thus, by the assumption \(aU_1 + bV_1 + c = 0\), \(U_1 \geq U_{n+1}\) and \(V_1 \geq V_{n+1}\) for a.e. continuation of \(\{X_i\}, \{Y_i\}\). If \(M\) is chosen large enough, every integer larger than \(M\) is a sum of possible values of \(X_i\) and a sum of possible values of \(Y_i\). Hence if \(S^X_{U_h} - S^Y_{V_h} < -M\), there are
possible continuations \( \{X_i\}_{i=U_n+1}^{U_{n+1}}, \) with \( b \geq 1, \) and \( X_{U_n+1} + \cdots + X_{U_{n+b}} = S_{V_n} - S_{U_n}X. \) This gives a realization \( \{X_i\}_{i=1}^{U_{n+b}}, \{Y_i\}_{i=1}^{V_n}. \) with \( S_{U_{n+b}} = S_{V_n}, \) and thus \( V_1 \leq V_n \) which is a contradiction.

**Remark 3.7.** It is the nondegeneracy of the covariance matrix which gives a non-normal limit in Theorem 1.1. We have no real hold on any of the elements of the covariance matrix.

**Proof of Theorem 1.1.** Suppose now that \( \{X_i\}, \{Y_j\} \) have common distributions. From Proposition 3.4, the bivariate random walk \((U_i, V_i)\) has \( E(U_1) = E(V_1) = \mu = E(X_1) \) and finite rank two covariance matrix

\[
\Sigma = \begin{pmatrix}
\sigma^2 & \rho \sigma^2 \\
\rho \sigma^2 & \sigma^2
\end{pmatrix}
\]

Hunter [12] shows

\[
\lim_{n \to \infty} P \left\{ \frac{N_n^U - n \mu^{-1}}{\sigma(n/\mu^3)^{1/2}} \leq \alpha, \frac{N_n^V - n \mu^{-1}}{\sigma(n/\mu^3)^{1/2}} \leq \beta \right\} = \Phi_\rho(\alpha, \beta)
\]

with \( \Phi_\rho \) a bivariate normal distribution with mean 0, variances 1, and correlation \( \rho. \)

From this, \((C_n - n \mu^{-1})/\sqrt{n}\) converges to \( \min(Z_1, Z_2) \) where \((Z_1, Z_2)\) is bivariate normal with mean 0 and covariance matrix

\[
\begin{pmatrix}
\sigma^2 \mu^3 & \rho \sigma^2 \mu^3 \\
\rho \sigma^2 \mu^3 & \sigma^2 \mu^3
\end{pmatrix}
\]

\( \square \)

**Remark 3.8.** Under the assumptions of Theorem 1.1, standard renewal theory (e.g. [10, Theorem II.5.1]) shows \( \frac{1}{n} N_n^U \to \mu^{-1} \) a.s. \( \frac{1}{n} N_n^V \to \mu^{-1} \) a.s. hence \( \frac{1}{n} C_n \to \mu^{-1} \) a.s.

### 3.2. Remarks and related literature.

1. Consider the number of coincidences under the conditions of Theorem 1.1 when \( X_1 \) and \( Y_1 \) have different distributions. Proposition 3.4 and Hunter's Central Limit Theorem [12] can be used to show that if the means differ then \( C_n \) has a normal limit. If the means are equal, then \( C_n \) has a non-normal limit as above.

2. Under the assumptions of Theorem 1.1 the number of coincidences among the partial sums of \( j \) iid random walks is distributed as the minimum of a \( j \)-variate normal (with suitable normalizing).

3. Things change radically if the increments are allowed to take negative values. Then, the sequence of partial sums will tend to fill out an interval and stochastic fluctuations take place at the fringes.
4. Proposition 3.2 of Section 3 is closely related to the regenerative phenomena studied by Kendall and Kingman [13] [15]. They study the Abelian semi-group of renewal sequences \( \{u_n\}_{n=1}^\infty \) under the coordinate wise product. A masterful summary of this work is in Kingman [15]. Fristedt [9] gives recent developments. A survey of its extensions to the theory of delphic semi-groups can be found in the work of Kendall and Harding [14]. This includes a survey of the work of Rollo Davidson which has connections to several of the authors of the present paper.

Specialize the set up of Proposition 4.2 to the case where \( X_1 \) and \( Y_1 \) have the same distribution. There is then a map from measures to measures (from the Law of \( X_1 \) to the Law of \( Z_1 \)) this corresponds to squaring the renewal measure: \( u_n^2 = (u_n^X)^2 \).

Evidently this map is one to one and continuous. To see that it is not onto, we observe that if \( P(Y = 1) = P(Y = 2) = \frac{1}{2} \), the corresponding renewal sequence does not have a square-root. Kendall [13] classified the infinitely divisible renewal sequences, showing they form a convex set with a countable set of extreme points.

5. The problem of coincidences among renewal sequences arises in the analysis of coupling arguments (see e.g. Lindvall [16]). Here the focus is on the occurrence of the first coincidence.

4. Coincidences with tied down sequences. This section gives a proof of Theorem 1.2, restated here for the readers convenience. Consider \( n \) balls, placed uniformly and independently in \( n \) boxes. For \( 1 \leq j \leq n \), let \( S_j \) equal \( j \) plus the number of balls in boxes \( 1, \ldots, j \). Let \( \{S_j^X : 1 \leq j \leq n\} \) and \( \{S_j^Y : 1 \leq j \leq n\} \) each be jointly distributed as \( \{S_j : 1 \leq j \leq n\} \) and be independent of each other. Define

\[
C_n = C_n (\{S_j^X\}, \{S_j^Y\}) = \# \{(i, j) : S_i^X = S_j^Y\}
\]

to be the number of coincidences among the partial sums.

**Theorem 4.1.**

\[
\frac{C_n - (n/2)}{\sqrt{n}} \overset{\mathcal{D}}{\to} Z \quad \text{as } n \to \infty,
\]

where \( Z \) is normal with zero mean and positive finite variance.

The steps in proving Theorem 4.1 are:

1. reduce to a one-sided local Central Limit Theorem (CLT);
2. Poissonize;
3. use the Poisson representation to embed in a renewal problem;
4. apply a known local CLT to the renewal problem to prove the one-sided local CLT.
We begin with step 1, a reduction to Theorem 4.1'.

**Theorem 4.1'** There exist $\sigma > 0$ and $\phi$ satisfying $\sup_k \phi(n, k) \to 0$ as $n \to \infty$, such that for all integers $n$ and $k$,

\[
(4.3) \quad P(C_n = k) \geq \frac{1}{\sigma \sqrt{2\pi n}} \left( e^{-(n-2k)^2/(2n\sigma^2)} - \phi(n, k) \right) .
\]

To see that this implies Theorem 4.1, let $f : \mathbb{R} \to [0, 1]$ be any continuous function, and let $W_n = (C_n - n/2) / \sqrt{n}$. Then

\[
\lim_{n \to \infty} \mathbb{E}f(W_n) \geq \lim_{n \to \infty} \lim_{A \to \infty} \sum_{k : |k - n/2| < A \sqrt{n}} \frac{1}{\sigma \sqrt{2\pi n}} e^{-(n-2k)^2/(2n\sigma^2)} f((k - n/2)/\sqrt{n})
\]

\[
= \lim_{A \to \infty} \int_{-A}^{A} f(x) dG(x)
\]

\[
= \int f(x) dG(x)
\]

where $G$ is the distribution of $\sigma$ times a standard normal. Replacing $f$ by $1 - f$ shows that $\mathbb{E}f(W_n) \to \int f(x) dG(x)$ for all bounded continuous $f$, establishing the implication.

For step 2, we construct a version of the process $\{S_j\}$ from a Poisson point process.

**Proposition 4.2.** Let $\{N_t : t \geq 0\}$ be a rate 1 Poisson point process.
Then the conditional law of the process $\{N_j + j : j = 1, 2, 3, \ldots\}$ given $N_n = n$ is the same as the law of the process $\{S_j\}$ above.

**Proof.** One way to assign $n$ balls uniformly and independently into $n$ boxes is to generate $n$ IID random variables $\{T_j\}$, uniform on the real interval $[0, n)$, and then to place ball $j$ in box $[T_j]$. The values of $\{S_j\}$ arising in this way will be unaffected if the sequence $T_1, \ldots, T_n$ is replaced by its ascending rearrangement, $T_{(1)}, \ldots, T_{(n)}$. But the times of the Poisson process $\{N_t\}$ conditioned on $N_n = n$ are distributed as the order statistics of $n$ independent draws from $[0, n)$, and therefore $\{N_j + j\} \xrightarrow{d} \{S_j\}$.

Step 3 is to construct a version of $C_n$ via the Poisson representation. Let $\{N^X_i\}$ and $\{N^Y_j\}$ be independent rate 1 Poisson processes. Let $T_0 = 0$ and inductively define $T_n$ to be the least integer $k > T_{n-1}$ such that

\[
N^X_i + i = N^Y_j + j = k \quad \text{for some integers } i \text{ and } j .
\]

In other words, $T_1, T_2, \ldots$ are the joint renewal times of the independent renewal processes $\{N^X_j + j\}$ and $\{N^Y_j + j\}$, whose increments are each 1 plus a Poisson of mean 1. Let $R^X_0 = R^Y_0 = 0$ and define $R^X_k$ (respectively
$$R_k^X$$ to be the integer \(i\) for which \(N_{i+1}^X = T_k\) (respectively \(N_{i+1}^Y = T_k\)). Then the triples \(\{(U_k, V_k, Z_k) : k \geq 1\}\) defined by

\[
(4.4) \quad (U_k, V_k, Z_k) = (R_k^X - R_{k-1}^X, R_k^Y - R_{k-1}^Y, T_k - T_{k-1})
\]

are IID. In words, the blocks between joint renewals are IID, and these blocks contain the information: number of renewals in first process, number of renewals in second process, total time from last joint renewal.

Let \(\bar{C}_n = \sup\{k : T_k \leq 2n\}\) denote the number of joint renewals before time \(2n\). Let \(G\) denote the event \(\{N_k^X = N_k^Y = n\}\). Proposition 4.2 implies that the conditional law of \(\{N_{i}^X + i, N_{j}^Y + j : 1 \leq i, j \leq n\}\) given \(G\) is the same as the law of \(\{S_i^X, S_j^Y : 1 \leq i, j \leq n\}\). Observe that on the intersection of \(G\) and \(\{\bar{C}_n = k\}\), one has \(R_k^X = R_k^Y = n\). Denoting

\[
p_{n,k} = P(R_k^X = R_k^Y = n, T_k = 2n),
\]

we then have

\[
(4.5) \quad P(C_n = k) = P(\bar{C}_n = k | G) = \frac{p_{n,k}}{\sum_j p_{n,j}},
\]

Finally, step 4 consists of applying a local CLT to \(\{(U_j, V_j, Z_j)\}\) to derive Theorem 4.1' from (4.5). This is done in three substeps. First we show that

\[
(4.6) \quad p_{n,k} = c n^{-3/2} \exp \left(-\frac{Q(n-2k, n-2k, 2n-4k)}{2k}\right) + g(n, k),
\]

where \(Q\) is the quadratic form obtained by inverting the covariance matrix of the triple \((U_1, V_1, Z_1)\) and

\[
\lim_{k \to \infty} \sup_n k^{3/2} \left(1 + \frac{(n-2k)^2}{k}\right) |g(n, k)| = 0.
\]

Secondly we show that

\[
(4.7) \quad p_{n,k} = cn^{-3/2} \exp \left(-\frac{(n-2k)^2}{2n\sigma^2}\right) + h(n, k),
\]

where

\[
(4.8) \quad \lim_{k \to \infty} \sup_n k^{3/2} \left(1 + \frac{(n-2k)^2}{k}\right) |h(n, k)| = 0.
\]

Thirdly, we show that (4.7), (4.8) and (4.5) imply Theorem 4.1'.

Step 4a is an application of the local CLT from Bhattacharya and Rao [2, Theorem 22.1]. The conclusion (4.6) follows immediately once the following hypotheses are verified:
(i) \( \mathbb{E}(U_1, V_1, Z_1) = (2, 2, 4) \);
(ii) \( \mathbb{E}(U_1^2 + V_1^2 + Z_1^2) < \infty \);
(iii) \( P(Z_1 > t) < C_1 e^{-C_2 t} \) for some \( C_1, C_2 > 0 \);
(iv) \( (U_1, V_1, Z_1) \) generates a truly 3-dimensional lattice.

Of these, (iv) is obvious, (iii) is a consequence of an easy coupling argument, and (ii) follows from (iii) since \( U_j, V_j \leq Z_j \). To prove (i), observe that for any independent renewal processes with means \( m_1 \) and \( m_2 \), the mean joint renewal time is \( m_1 m_2 \) since the probability of a joint renewal at zero in the stationary process is \( 1/(m_1 m_2) \). This implies that the mean number of renewals of the first (respectively second) process in a joint renewal block is \( m_2 \) (respectively \( m_1 \)). Since the increments of the renewal process \( \{N_j + j\} \) have mean 2, this proves (i) and establishes (4.6).

Step 4b, the derivation of (4.7) from (4.6), begins with the easy observation that \( Q(x, x, 2x) \) is nondegenerate, and can be written as \( x^2/(2\sigma^2) \) for some positive finite \( \sigma \). [For if this fails, summing (4.6) in \( k \) contradicts \( \lim_{n \to \infty} P(R_n^X = R_n^Y = n) \to 0 \).] Letting (4.7) define the quantity \( h(n, k) \), it remains to establish (4.8). In other words, we must show that

\[
(4.9) \quad \varepsilon(n, k) := \left| k^{-3/2} \exp \left( -\frac{(n - 2k)^2}{4k\sigma^2} \right) - n^{-3/2} \exp \left( -\frac{(n - 2k)^2}{2n\sigma^2} \right) \right|
\]

satisfies \( \sup_n \varepsilon(n, k) k^{3/2}(1 + (n - 2k)^2/k) \to 0 \). Fix \( k \), and consider first the case \( |n - 2k| > k^{0.6} \). The exponential terms in (4.9) are then at most \( e^{-ck^{0.3}} \), which establishes (4.8). On the other hand, when \( |n - 2k| \leq k^{0.6} \), then the mean value theorem gives

\[
|n^{-3/2} - k^{-3/2}| \leq Ck^{-5/2}|n - 2k| \leq Ck^{-1.8}.
\]

Also, for sufficiently large \( k \),

\[
|\exp \left( -\frac{(n - 2k)^2}{2n\sigma^2} \right) - \exp \left( -\frac{(n - 2k)^2}{4k\sigma^2} \right)| \leq 2 \exp \left( -\frac{(n - 2k)^2}{1.5n\sigma^2} \right) \leq \min \left\{ 2, \frac{k\sigma^2}{(n - 2k)^2} \right\}.
\]

Since

\[
\varepsilon(n, k) \leq |n^{-3/2} - k^{-3/2}| + k^{-3/2} \left| \exp \left( -\frac{(n - 2k)^2}{2n\sigma^2} \right) - \exp \left( -\frac{(n - 2k)^2}{4k\sigma^2} \right) \right|,
\]

this yields (4.8) in the case \( |n - 2k| \leq k^{0.6} \).

The final substep, 4c, is accomplished by showing

\[
(4.10) \quad \lim_{A \to \infty} \limsup_{n \to \infty} \frac{\sum_{k : |k - n/2| > A\sqrt{n}} P_{n,k}}{\sum_{k} P_{n,k}} = 0.
\]

For this shows that given \( \epsilon > 0 \), we can choose \( A \) such that for sufficiently large \( n \), all but mass \( \epsilon \) of the conditional law of \( \hat{C}_n \) given \( G \) is contained in
the range \([-A\sqrt{n}, A\sqrt{n}]\), from which it is immediate that (4.7) and (4.5) imply Theorem 4.1'.

Firstly, from (4.7),

\[
\sum_k p_{n,k} \geq \sum_{k:|k-n/2| \leq \sqrt{n}} p_{n,k} \geq 2\sqrt{n} \left[ cn^{-3/2} \exp\left(-1/(1.9\sigma^2)\right) - \sup_k h(n, k) \right],
\]

and this is at least \(c'n^{-1}\) for some constant \(c'\) and sufficiently large \(n\). Secondly, let \(c_0 = \sup_{n,k} |h(n, k)k^{3/2}(1 + (n - 2k)^2/k)|\). Thus \(|h(n, k)| < c_0 k^{-1/2}(n - 2k)^{-2}\). Estimating the numerator of (4.10) gives

\[
\sum_{k:|k-n/2| > A\sqrt{n}} p_{n,k} = \sum_{k:|k-n/2| > A\sqrt{n}} cn^{-3/2} \exp\left(-\frac{(n - 2k)^2}{2n\sigma^2}\right) + h(n, k) + \sum_{k \geq n/3, |k-n/2| > A\sqrt{n}} h(n, k).
\]

The first of these terms is \(2n^{-1}(1 - \Phi(2A/\sigma))\) plus an error term going to zero as \(n \to \infty\) (uniformly in \(A\), though we don’t need the uniformity). The second term is at most

\[
c_0 \sum_{k < n/3} k^{-1/2}(n - 2k)^{-2} \leq 9c_0 n^{-3/2}.
\]

And the third term is at most

\[
2c_0 \sum_{j > A\sqrt{n}} (n/3)^{-1/2}(2j)^{-2} \leq 6c_0 n^{-3/2}.
\]

These three estimates establish (4.10), thus finishing step 4 and the proof of Theorem 4.1'.

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