# The asymptotic distribution of the length of Beta-coalescent trees 

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#### Abstract

We derive the asymptotic distribution of the total length $L_{n}$ of a $\operatorname{Beta}(2-\alpha, \alpha)$-coalescent tree for $1<\alpha<2$, starting from $n$ individuals. There are two regimes: If $\alpha \leq \frac{1}{2}(1+\sqrt{5})$, then $L_{n}$ suitably rescaled has a stable limit distribution of index $\alpha$. Otherwise $L_{n}$ just has to be shifted by a constant (depending on $n$ ) to get convergence to a non-degenerate limit distribution. As a consequence we obtain the limit distribution of the number $S_{n}$ of segregation sites.


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## 1 Introduction and result

In this paper we investigate the asymptotic distribution of the suitably normalized length $L_{n}$ of a $n$-coalescent of the $\operatorname{Beta}(2-\alpha, \alpha)$-type with $1<\alpha<2$. As a corollary we obtain the asymptotic distribution of the associated number $S_{n}$ of segregating sites, which is the basis of the Watterson estimator [18] for the rate $\theta$ of mutation of the DNA. Here we recall that coalescents with multiple merging such as Beta-coalescents have been considered in the

[^0]literature as model for the genealogical relationship within certain maritime species [6, 9].

Beta-coalescents (and more generally $\Lambda$-coalescents, as introduced by Pitman [15] and Sagitov [16]) possess a rich underlying partition structure, which is nicely presented in detail in N. Berestycki [3]. For our purposes it is not necessary to recall all these details, we refer to the following condensed description of a $n$-coalescent:

Imagine $n$ particles (blocks in a partition), which coalesce into a single particle within a random number of steps. This happens in the manner of a continuous time Markov chain. Namely, if there are currently $m>1$ particles, then they merge to $l$ particles at a rate $\rho_{m, l}$ with $1 \leq l \leq m-1$. Thus

$$
\rho_{m}=\rho_{m, 1}+\cdots+\rho_{m, m-1}
$$

is the total merging rate and

$$
P_{m, l}=\frac{\rho_{m, l}}{\rho_{m}}, \quad 1 \leq l \leq m-1
$$

gives the probability of a jump from $m$ to $l$.
In these models the rates $\rho_{m, l}$ have a specific consistency structure arising from the merging mechanism. As follows from Pitman [15] they are in general of the form

$$
\rho_{m, m-k+1}=\binom{m}{k} \int_{0}^{1} t^{k-2}(1-t)^{m-k} \Lambda(d t), \quad 2 \leq k \leq m
$$

where $\Lambda(d t)$ is a finite measure on $[0,1]$. The choice $\Lambda=\delta_{0}$ corresponds to the original model due to Kingman [12], then $\rho_{m, l}=0$ for $l \neq m-1$. In this paper we assume

$$
\Lambda(d t)=\frac{1}{\Gamma(2-\alpha) \Gamma(\alpha)} t^{1-\alpha}(1-t)^{\alpha-1} d t
$$

thus

$$
\rho_{m, m-k+1}=\frac{1}{\Gamma(2-\alpha) \Gamma(\alpha)}\binom{m}{k} B(k-\alpha, m-k+\alpha),
$$

where $B(a, b)$ denotes the ordinary Beta-function. Then the underlying coalescent is called the $\operatorname{Beta}(2-\alpha, \alpha)$-coalescent. For $\alpha=1$ it is the BolthausenSznitman coalescent [5] and the case $\alpha=2$ can be linked with Kingman's coalescent.

The situation can be descriped as follows: There are the merging times $0=T_{0}<T_{1}<\cdots<T_{\tau_{n}}$ and there is the imbedded time discrete Markov chain $n=X_{0}>X_{1}>\cdots>X_{\tau_{n}}=1$, where $X_{i}$ is the number of particles (partition blocks) after $i$ merging events. This Markov chain has transition probabilities $P_{m, l}$ and, given the event $X_{i}=m$ with $m>1$, the waiting time $T_{i+1}-T_{i}$ to the next jump is exponential with expectation $1 / \rho_{m}$. Since a point process description is convenient later, we name the point process

$$
\begin{equation*}
\mu_{n}=\sum_{i=0}^{\tau_{n}-1} \delta_{X_{i}} \tag{1}
\end{equation*}
$$

on $\{2,3, \ldots\}$ the coalescent's point process downwards from $n$, shortly the $\operatorname{CPP}(n)$.

This dynamics can be vizualised by a coalescent tree with a root and $n$ leaves. The leaves are located at height $T_{0}=0$ and the root at height $T_{\tau_{n}}$ above. At height $T_{i}$ there are $X_{i}$ nodes representing the particles after $i$ coalescing events. The total branch length of this tree is given by

$$
\begin{equation*}
L_{n}=\sum_{i=0}^{\tau_{n}-1} X_{i}\left(T_{i+1}-T_{i}\right) \tag{2}
\end{equation*}
$$

For $1<\alpha<2$ the asymptotic magnitude of $L_{n}$ is obtained by Berestycki et al in [2], it is proportional to $n^{2-\alpha}$. The asymptotic distribution of $L_{n}$ is easily derived for the Kingman coalescent, see [7], it is Gumbel. The case of a Bolthausen-Sznitman coalescent is treated by Drmota et al [8], here $L_{n}$ properly normalized is asymptotically stable. The case $0<\alpha<1$ of a Betacoalescent is contained in more general results of Möhle [13]. Partial results for the Beta-coalescent with $1<\alpha<2$ have been obtained by Delmas et al [7].

In this paper we derive the asymptotic distribution of the Beta-coalescent for $1<\alpha<2$. Let $\varsigma$ denote a real-valued random variable with a distribution, which is stable of index $\alpha$ and normalized by the properties

$$
\begin{equation*}
\mathbf{E}(\varsigma)=0, \quad \mathbf{P}(\varsigma>x)=o\left(x^{-\alpha}\right), \quad \mathbf{P}(\varsigma<-x) \sim x^{-\alpha} \tag{3}
\end{equation*}
$$

for $x \rightarrow \infty$. Thus it is maximally skewed among the stable distributions of index $\alpha$.

Also let

$$
c_{1}=\frac{\Gamma(\alpha) \alpha(\alpha-1)}{2-\alpha}, \quad c_{2}=\frac{\Gamma(\alpha) \alpha(\alpha-1)^{1+\frac{1}{\alpha}}}{\Gamma(2-\alpha)^{\frac{1}{\alpha}}} .
$$

Theorem 1. For the Beta-coalescent with $1<\alpha<2$ :
(i) If $1<\alpha<\frac{1}{2}(1+\sqrt{5})$ (thus $\left.1+\alpha-\alpha^{2}>0\right)$, then

$$
\frac{L_{n}-c_{1} n^{2-\alpha}}{n^{\frac{1}{\alpha}+1-\alpha}} \xrightarrow{d} \frac{c_{2} \varsigma}{\left(1+\alpha-\alpha^{2}\right)^{\frac{1}{\alpha}}} .
$$

(ii) If $\alpha=\frac{1}{2}(1+\sqrt{5})$, then

$$
\frac{L_{n}-c_{1} n^{2-\alpha}}{(\log n)^{\frac{1}{\alpha}}} \xrightarrow{d} c_{2} \varsigma .
$$

(iii) If $\frac{1}{2}(1+\sqrt{5})<\alpha<2$, then

$$
L_{n}-c_{1} n^{2-\alpha} \xrightarrow{d} \eta,
$$

where $\eta$ is a non-degenerate random variable.
In fact it is not difficult to see from the proof that $\eta$ has a density with respect to Lebesgue measure.

This transition at the golden ratio $\frac{1}{2}(1+\sqrt{5})$ gets manifest already in the results of Delmas et al [7]. They also show that the number $\tau_{n}$ of collisions, properly rescaled, has asymptotically a stable distribution. This latter result has been independently obtained by Gnedin and Yakubovitch [11].

The region within the coalescent tree, where the random fluctuations of $L_{n}$ asymptotically arise, are different in the three cases. In case (i) fluctuations come from everywhere between root and leaves, whereas in case (iii) they mainly originate at the neighborhood of the root. Then we have to take care of those summands $X_{i}\left(T_{i+1}-T_{i}\right)$ within $L_{n}$, which have an index $i$ close to $\tau_{n}$. In the intermediate case (ii) the primary contribution stems from summands with index $i$ such that $\tau_{n}-n^{1-\varepsilon} \leq i \leq \tau_{n}-n^{\varepsilon}$ with $0<\varepsilon<\frac{1}{2}$.

To get hold of the these fluctuations, in proving the theorem we loosely speaking turn around the order of summation in $L_{n}=\sum_{i=0}^{\tau_{n}-1} X_{i}\left(T_{i+1}-T_{i}\right)$. We shall handle the reversed order by means of two point processes $\mu$ and $\nu$ on $\{2,3, \ldots\}$. The first one gives the asymptotic particle numbers seen from the root of the tree. Here we use Schweinsberg's result [17] implying that the Beta-coalescent comes down from infinity for $1<\alpha<2$, see [3], Corollary 3.2. (Therefore our method of proof does not apply to the case of the BolthausenSznitman coalescent.) The second one is a classical stationary renewal point
process, which can be reversed without difficulty. Two different couplings establish the links. Thereby the exponential holding times are left aside at first stage. In this respect our approach to the Beta-coalescent differs from others as in Birkner et al [4] or Berestyki et al [1].

Coalescent trees are used as a model for the genealogical relationship of $n$ individuals backwards to their most recent ancestor. Then one imagines that mutations are assigned to positions on the tree's branches in the manner of a Poisson point process with rate $\theta$. Let $S_{n}$ be the number of these segregation sites (see [3], section 2.3.4). Given $L_{n}$ the distribution of $S_{n}$ is Poisson with mean $\theta L_{n}$. To get the asymptotic distribution one splits $S_{n}$ into parts:

$$
S_{n}-\theta c_{1} n^{2-\alpha}=\left(S_{n}-\theta L_{n}\right)+\theta\left(L_{n}-c_{1} n^{2-\alpha}\right) .
$$

Since $L_{n} / c_{1} n^{2-\alpha}$ converges to 1 in probability, the first summand is asymptotically normal and also asymptotically independent from the second one. Its normalizing constant is $\left(\theta L_{n}\right)^{-\frac{1}{2}} \sim\left(\theta c_{1}\right)^{-\frac{1}{2}} n^{\frac{\alpha}{2}-1}$. Again there are two regimes: $n^{1-\frac{\alpha}{2}}=o\left(n^{\frac{1}{\alpha}+1-\alpha}\right)$, iff $\alpha<\sqrt{2}$. Partial results are contained in Delmas et al [7]. We obtain:
Corollary 2. Let $\zeta$ denote a standard normal random variable, which is independent from $\varsigma$.
(i) If $1<\alpha<\sqrt{2}$, then

$$
\frac{S_{n}-\theta c_{1} n^{2-\alpha}}{n^{\frac{1}{\alpha}+1-\alpha}} \xrightarrow{d} \frac{\theta c_{2} \varsigma}{\left(1+\alpha-\alpha^{2}\right)^{\frac{1}{\alpha}}} .
$$

(ii) If $\alpha=\sqrt{2}$, then

$$
\frac{S_{n}-\theta c_{1} n^{2-\alpha}}{n^{1-\frac{\alpha}{2}}} \xrightarrow{d} \sqrt{\theta c_{1}} \zeta+\frac{\theta c_{2} \varsigma}{\left(1+\alpha-\alpha^{2}\right)^{\frac{1}{\alpha}}} .
$$

(iii) If $\sqrt{2}<\alpha<2$, then

$$
\frac{S_{n}-\theta c_{1} n^{2-\alpha}}{n^{1-\frac{\alpha}{2}}} \xrightarrow{d} \sqrt{\theta c_{1}} \zeta .
$$

This is the organisation of the paper: Section 2 contains an elementary coupling of two $\mathbb{N}$-valued random variables. It is used in section 3 , where we introduce and analyse coalescent's point processes, and in section 4, where we couple these point processes to stationary point processes. Section 5 assembles two auxiliary results on sums of independent random variables. Finally the proof of Theorem 1 is given in section 6.

## 2 A coupling

In this section let the natural number $m$ be fixed. We introduce a coupling of the transition probabilities $P_{m, l}$ and a distribution, which does not depend on $m$. From the representation of the Beta-function by means of the $\Gamma$-function and its functional equation we have

$$
\begin{aligned}
& \rho_{m, m-k+1}=\frac{1}{\Gamma(2-\alpha) \Gamma(\alpha)} \frac{m!}{\Gamma(m)} \frac{\Gamma(k-\alpha)}{k!} \frac{\Gamma(m-k+\alpha)}{(m-k)!} \\
& \quad=\frac{1}{\Gamma(2-\alpha) \Gamma(\alpha)} \frac{\Gamma(k-\alpha)}{\Gamma(k+1)} \frac{(m-k+1) \cdots m}{(m-k+\alpha) \cdots(m-1+\alpha)} \frac{\Gamma(m+\alpha)}{\Gamma(m)},
\end{aligned}
$$

thus

$$
P_{m, m-k}=d_{m k} \frac{\Gamma(k+1-\alpha)}{\Gamma(k+2)}, \quad k \geq 1
$$

with

$$
d_{m k}=d_{m} \frac{(m-k) \cdots(m-1)}{(m+\alpha-k-1) \cdots(m+\alpha-2)}
$$

and a normalizing constant $d_{m}>0$ (also dependent on $\alpha$ ). Recall from the introduction that given $X_{0}=m$ the quantities $P_{m, m-k}$ are the weights of the distribution of the downward jump $U=X_{0}-X_{1}$. For a more detailed discussion of this 'law of first jump' we refer to Delmas et al [7].

It is natural to relate this distribution to the distribution of some random variable $V$ with values in $\mathbb{N}$ and distribution given by

$$
\begin{equation*}
\mathbf{P}(V=k)=\frac{\alpha}{\Gamma(2-\alpha)} \frac{\Gamma(k+1-\alpha)}{\Gamma(k+2)}, \quad k \geq 1 . \tag{4}
\end{equation*}
$$

This kind of distribution appears for Beta-coalescents already in Berestycki et al [1] (in the context of frequency spectra) as well as in Delmas et al [7]. There the normalizing constant is determined and the following formulas derived:

$$
\begin{equation*}
\mathbf{E}(V)=\frac{1}{\alpha-1} \quad \text { and } \quad \mathbf{P}(V \geq k)=\frac{1}{\Gamma(2-\alpha)} \frac{\Gamma(k+1-\alpha)}{\Gamma(k+1)} \tag{5}
\end{equation*}
$$

From Stirling's approximation

$$
\begin{equation*}
\mathbf{P}(V=k) \sim \frac{\alpha}{\Gamma(2-\alpha)} k^{-\alpha-1} \quad \text { and } \quad \mathbf{P}(V \geq k) \sim \frac{1}{\Gamma(2-\alpha)} k^{-\alpha} \tag{6}
\end{equation*}
$$

The sequence $d_{m k}$ is decreasing in $k$ for fixed $m$, thus the same is true for $P_{m, m-k} / \mathbf{P}(V=k)$. Therefore $V$ stochastically dominates the jump size $U$, that is for all $k \geq 1$

$$
\begin{equation*}
\mathbf{P}\left(U \geq k \mid X_{0}=m\right) \leq \mathbf{P}(V \geq k) \tag{7}
\end{equation*}
$$

We like to investigate a coupling of $U$ and $V$, where $U \leq V$ a.s. It is fairly obvious that this can be achieved in such a way that

$$
\begin{equation*}
\mathbf{P}(U=k \mid V=k)=1 \wedge \frac{P_{m, m-k}}{\mathbf{P}(V=k)}=1 \wedge \frac{d_{m k}}{d} \tag{8}
\end{equation*}
$$

(Indeed one may put

$$
\mathbf{P}(U=j \mid V=k)=\left(1-\frac{P_{m, m-k}}{\mathbf{P}(V=k)}\right)^{+} \frac{\left(P_{m, m-j}-\mathbf{P}(V=j)\right)^{+}}{\mathbf{P}\left(U<k_{m}\right)-\mathbf{P}\left(V<k_{m}\right)}
$$

for $j \neq k$ with $k_{m}=\min \left\{k \geq 1: P_{m, m-k} \leq \mathbf{P}(V=k)\right\}$. There are other possibilities, later it will be only important that we commit to one of them.)

Lemma 3. For a coupling ( $U, V$ ) fulfilling (8) it holds

$$
\mathbf{P}(U \neq V) \leq \frac{1}{(\alpha-1) m} \quad \text { and } \quad \mathbf{P}(V \geq k \mid U \neq V) \leq c k^{1-\alpha}
$$

for all $k \geq 1$ and some $c<\infty$, which does not depend on $m$.
Proof. Because of $\alpha<2$

$$
\frac{(m-k) \cdots(m-1)}{(m+\alpha-k-1) \cdots(m+\alpha-2)} \geq \frac{(m-k) \cdots(m-1)}{(m-k+1) \cdots m}=\frac{m-k}{m}
$$

and because of $\alpha>1$

$$
\frac{(m+\alpha-k-1) \cdots(m+\alpha-2)}{(m-k) \cdots(m-1)} \geq\left(\frac{m+\alpha-1}{m}\right)^{k} \geq 1+k \frac{\alpha-1}{m}
$$

consequently

$$
1-\frac{k}{m} \leq \frac{d_{m k}}{d_{m}} \leq \frac{1}{1+(\alpha-1) \frac{k}{m}}
$$

It follows

$$
\left(1-\frac{k}{m}\right) \mathbf{P}(V=k) \leq \frac{d}{d_{m}} P_{m, m-k} \leq \mathbf{P}(V=k)
$$

for all $k \geq 1$ with $d=\alpha / \Gamma(2-\alpha)$. Summing over $k$ yields

$$
1-\frac{1}{m} \mathbf{E}(V) \leq \frac{d}{d_{m}} \leq 1 \quad \text { or } \quad 1 \leq \frac{d_{m}}{d} \leq \frac{1}{\left(1-\frac{1}{(\alpha-1) m}\right)^{+}}
$$

Combining the estimates we end up with

$$
\begin{equation*}
1-\frac{k}{m} \leq \frac{d_{m k}}{d} \leq \frac{1}{\left(1+(\alpha-1) \frac{k}{m}\right)\left(1-\frac{1}{(\alpha-1) m}\right)^{+}} \tag{9}
\end{equation*}
$$

for all $k \geq 1$.
Now from (8), (9)

$$
\begin{aligned}
\mathbf{P}(U \neq V) & =\sum_{k \geq 1}\left(\mathbf{P}(V=k)-P_{m, m-k}\right)^{+} \\
& =\sum_{k \geq 1} \mathbf{P}(V=k)\left(1-\frac{d_{m k}}{d}\right)^{+} \leq \sum_{k \geq 1} \mathbf{P}(V=k) \frac{k}{m},
\end{aligned}
$$

thus from (5)

$$
\mathbf{P}(U \neq V) \leq \frac{1}{(\alpha-1) m}
$$

which is our first claim.
Also, letting $m \geq 2 /(\alpha-1)$ and $k^{\prime}=2\left\lceil(\alpha-1)^{-2}+(\alpha-1)^{-1}\right\rceil$ then

$$
\begin{gathered}
\left(1+(\alpha-1) \frac{k^{\prime}}{m}\right)\left(1-\frac{1}{(\alpha-1) m}\right)^{+}=1+(\alpha-1) \frac{k^{\prime}}{m}-\frac{1}{(\alpha-1) m}-\frac{k^{\prime}}{m^{2}} \\
\geq 1+\frac{\alpha-1}{2} \frac{k^{\prime}}{m}-\frac{1}{(\alpha-1) m} \geq 1+\frac{1}{m}
\end{gathered}
$$

From (9)

$$
1-\frac{d_{m k^{\prime}}}{d} \geq 1-\frac{1}{1+\frac{1}{m}} \geq \frac{1}{2 m}
$$

and from (8)

$$
\mathbf{P}(U \neq V) \geq \mathbf{P}\left(U \neq k^{\prime}, V=k^{\prime}\right)=\left(1-\frac{d_{m k^{\prime}}}{d}\right)^{+} \mathbf{P}\left(V=k^{\prime}\right) \geq \frac{1}{2 m} \mathbf{P}\left(V=k^{\prime}\right)
$$

for $m \geq 2 /(\alpha-1)$. It follows that there is a $\eta>0$ such that for all $m \geq 1$

$$
\mathbf{P}(U \neq V) \geq \frac{1}{\eta m}
$$

Now from (8) and (9)

$$
\begin{aligned}
\mathbf{P}(V=k \mid U \neq V) & =\frac{\mathbf{P}(U \neq k, V=k)}{\mathbf{P}(U \neq V)} \\
& =\frac{\left(1-\frac{d_{m k}}{d}\right)^{+}}{\mathbf{P}(U \neq V)} \mathbf{P}(V=k) \leq \eta k \mathbf{P}(V=k),
\end{aligned}
$$

and the second claim follows from (6).

## 3 The coalescent's point process

Let $\mu$ denote a point process on $\{2,3, \ldots\}$. For any interval $I$ let $\mu_{I}$ be the point process on $\{2,3, \ldots\}$ given by

$$
\mu_{I}(B)=\mu(B \cap I), \quad B \subset\{2,3, \ldots\}
$$

We call $\mu$ a coalescent's point process downwards from $\infty$, shortly a $\operatorname{CPP}(\infty)$, if the following properties hold:

- $\mu(\{2,3, \ldots\})=\infty$ and $\mu(\{n\})=0$ or 1 for any $n \geq 2$ a.s.
- For $n \geq 2$ we have: Given the event $\mu(\{n\})=1$ and given $\mu_{[n+1, \infty)}$ the point process $\mu_{[2, n]}$ is a $\operatorname{CPP}(n)$ a.s.

Recall that a point process is called a $\operatorname{CPP}(n)$, if it can be represented as in (1).

Theorem 4. Let $1<\alpha<2$. Then the $\operatorname{CPP}(\infty)$ exists and is unique in distribution.

We prepare the proof by two lemmas.
Lemma 5. Let $\mu$ be a $\operatorname{CPP}(n)$ with $1<n \leq \infty$. Then for any $\varepsilon>0$ there is a natural number $r$ such that for any interval $I=[a, b]$ with $2 \leq a<b<n$ and $b-a \geq r$ we have

$$
\mathbf{P}(\mu(I)=0) \leq \varepsilon
$$

Proof. For $I=[a, b]$

$$
\{\mu(I)=0\}=\bigcup_{m=b+1}^{n}\{\mu(\{m\})=1, \mu([a, m-1])=0\} \text { a.s. }
$$

since $\mu(\{n\})=1$ for $n<\infty$ and $\mu(\{2,3, \ldots\})=\infty$ a.s. for $n=\infty$. Thus from (1)

$$
\mathbf{P}(\mu(I)=0) \leq \sum_{m=b+1}^{n} \mathbf{P}\left(X_{1}<a \mid X_{0}=m\right)
$$

Applying (7) to $U=X_{0}-X_{1}$ it follows that

$$
\begin{equation*}
\mathbf{P}(\mu(I)=0) \leq \sum_{m=b+1}^{n} \mathbf{P}(V>m-a) \leq \sum_{k=1}^{\infty} \mathbf{P}(V>b-a+k) \tag{10}
\end{equation*}
$$

Since $\mathbf{E}(V)<\infty$, this series is convergent and the claim follows.
The next lemma prepares coupling of CPPs.
Lemma 6. Let $\mu, \mu^{\prime}$ be two independent CPPs coming down from $n, n^{\prime} \leq \infty$. Then for any $\varepsilon>0$ there is a natural number s such that for any $b$ sufficiently large and $n, n^{\prime}>b$ we have

$$
\left.\mathbf{P}\left(\mu(\{j\})=\mu^{\prime}(\{j\})=1 \text { for some } j=b-s, \ldots, b\right]\right) \geq 1-\varepsilon .
$$

Proof. First let $n<\infty$. We construct a coupling of a $\operatorname{CCP}(n) \mu$ to an i.i.d. random sequence. Consider random variables $U_{1}, V_{1}, U_{2}, V_{2}, \ldots$ and $n=X_{0}, X_{1}, \ldots$ with $X_{i}=n-U_{1}-\cdots-U_{i}$, which are constructed inductively as follows: If $U_{1}, V_{1}, \ldots, U_{i}, V_{i}$ are already gotten, then given the values of these random variables let $V_{i+1}$ be a copy of the random variable $V$ from section 2 and couple $U_{i+1}$ to $V_{i+1}$ as in section 2, with $m=X_{i}$. For definitness put $U_{i+1}=0$ if $X_{i}=1$. Then $V_{1}, V_{2}, \ldots$ are i.i.d. random variables with distribution (4) and $X_{0}>X_{1}>\ldots>X_{\tau_{n}-1}$ are the points of a $\operatorname{CPP}(n) \mu$ down from $n$, where $\tau_{n}$ is the natural number $i$ such that $X_{i}=1$ for the first time.

Now let $k$ be a natural number. Then $X_{i-1} \geq n-U_{1}-\cdots-U_{k}$ for $i \leq k$. Thus for any $\eta>0$ and $n \geq 6 k \eta^{-1} \mathbf{E}(V)+2$ from Lemma 3

$$
\begin{aligned}
& \mathbf{P}\left(U_{i} \neq V_{i} \text { for some } i \leq k, U_{1}+\cdots+U_{k} \leq 6 k \eta^{-1} \mathbf{E}(V)\right) \\
& \quad \leq \sum_{i=1}^{k} \mathbf{P}\left(U_{i} \neq V_{i}, X_{i-1} \geq n-6 k \eta^{-1} \mathbf{E}(V)\right) \leq \frac{k}{(\alpha-1)\left(n-6 k \eta^{-1} \mathbf{E}(V)\right)},
\end{aligned}
$$

thus

$$
\mathbf{P}\left(U_{i} \neq V_{i} \text { for some } i \leq k, U_{1}+\cdots+U_{k} \leq 6 k \eta^{-1} \mathbf{E}(V)\right) \leq \frac{\eta}{6}
$$

if $n$ is large enough. Also $\mathbf{E}\left(U_{i}\right) \leq \mathbf{E}(V)$ because of (7), thus from Markov's inequality

$$
\begin{equation*}
\mathbf{P}\left(U_{1}+\cdots+U_{k}>6 k \eta^{-1} \mathbf{E}(V)\right) \leq \frac{\eta}{6} \tag{11}
\end{equation*}
$$

and consequently

$$
\mathbf{P}\left(U_{i} \neq V_{i} \text { for some } i \leq k\right) \leq \frac{\eta}{3}
$$

if $n$ is sufficiently large (depending on $\eta$ and $k$ ).
Next let $l$ be a natural number and $n^{\prime}=n+l$. Let $U_{1}^{\prime}, V_{1}^{\prime}, U_{2}^{\prime}, V_{2}^{\prime}, \ldots$ and $n^{\prime}=X_{0}^{\prime}, X_{1}^{\prime}, \ldots$ an analogue construction with random variables, which are independent of $U_{1}, V_{1}, U_{2}, V_{2}, \ldots$ Then also

$$
\mathbf{P}\left(U_{i}^{\prime} \neq V_{i}^{\prime} \text { for some } i \leq k\right) \leq \frac{\eta}{3} .
$$

Moreover because $V$ has finite expectation and because of independence from classical results on recurrent random walks

$$
\mathbf{P}\left(\sum_{i=1}^{j} V_{i} \neq \sum_{i=1}^{j} V_{i}^{\prime}-l \text { for all } j \leq k\right) \leq \frac{\eta}{6}
$$

if only $k$ is sufficiently large (depending on $l$ ). Combining the estimates we obtain

$$
\mathbf{P}\left(\sum_{i=1}^{j} U_{i} \neq \sum_{i=1}^{j} U_{i}^{\prime}-l \text { for all } j \leq k\right) \leq \frac{5 \eta}{6}
$$

For the corresponding independent $\operatorname{CPPs} \mu$ and $\mu^{\prime}$ coming down from $n$ and $n^{\prime}=n+l$ this implies together with (11)

$$
\mathbf{P}\left(\mu(\{j\})=\mu^{\prime}(\{j\})=1 \text { for some } j \in\left[n-6 k \eta^{-1} \mathbf{E}(V), n\right]\right) \geq 1-\eta
$$

Leaving aside the coupling procedure we have proved: Let $\eta>0$, let $l$ be a natural number and let $\mu$ and $\mu^{\prime}$ denote independent CPPs coming down from $n<\infty$ and $n^{\prime}=n+l$. Then there is a natural number $r^{\prime}$ such that

$$
\begin{equation*}
\mathbf{P}\left(\mu(\{j\})=\mu^{\prime}(\{j\})=1 \text { for some } j=n-r^{\prime}, \ldots, n\right) \geq 1-\eta, \tag{12}
\end{equation*}
$$

if only $n$ is large enough.

With this preparation we come to the proof of the lemma. Let $\varepsilon>0$, $b \geq 2$ and let $n, n^{\prime}>b$. Denote

$$
M=\max \{k \leq b: \mu(\{k\})=1\}, \quad M^{\prime}=\max \left\{k \leq b: \mu^{\prime}(\{k\})=1\right\}
$$

(with the convention $M=1$, if $\mu([2, b])=0$ ). From Lemma 5

$$
\mathbf{P}\left(M, M^{\prime} \in[b-r, b]\right) \geq 1-\frac{\varepsilon}{2}
$$

for some $r$ and $b>r+2$. Then

$$
\begin{aligned}
& \mathbf{P}\left(\mu(\{j\})=\mu^{\prime}(\{j\})=1 \text { for no } j \in\left[b-r^{\prime}-r, b\right]\right) \\
& \leq \frac{\varepsilon}{2}+\mathbf{P}\left(\mu(\{j\})=\mu^{\prime}(\{j\})=1 \text { for no } j \in\left[b-r^{\prime}-r, b\right] ; b-r \leq M, M^{\prime} \leq b\right) \\
& \leq \frac{\varepsilon}{2}+2 \sum_{b-r \leq m<m^{\prime} \leq b} \mathbf{P}\left(\mu(\{j\})=\mu^{\prime}(\{j\})=1\right. \\
& \left.\quad \text { for no } j=m-r^{\prime}, \ldots, m \mid X_{0}=m, X_{0}^{\prime}=m^{\prime}\right)
\end{aligned}
$$

From (12) it follows that the right-hand probabilities are bounded by $\eta=$ $\varepsilon / 4 r^{2}$, if $b$ is only sufficiently large. Then

$$
\mathbf{P}\left(\mu(\{j\})=\mu^{\prime}(\{j\})=1 \text { for no } j \in\left[b-r^{\prime}-r, b\right]\right) \leq \varepsilon,
$$

which is our claim with $s=r+r^{\prime}$.
As a corollary we note:
Lemma 7. Let $\mu$ and $\mu^{\prime}$ be two independent $C P P(\infty)$. Then a.s. $\mu(\{j\})=$ $\mu^{\prime}(\{j\})=1$ for infinitely many $j \in \mathbb{N}$.

Proof. From the preceding lemma there are numbers numbers $b_{1}<b_{2}<\cdots$ such that

$$
\left.\mathbf{P}\left(\mu(\{j\})=\mu^{\prime}(\{j\})=1 \text { for no } j=b_{k}, \ldots, b_{k+1}\right]\right) \leq 2^{-k} .
$$

Now an application of the Borel-Cantelli Lemma gives the claim.
Proof of Theorem [4. The existence follows from the fact that for $\alpha>1$ the corresponding Beta-coalescent $\left(\Pi_{t}\right)_{t \geq 0}$ comes down from infinity [17], which means that the number of blocks in $\Pi_{t}$ is a finite number $N_{t}$ for each $t>0$. Put $\mu(\{k\})=1$, iff $N_{t}=k$ for some $t>0$.

Uniqueness follows from the last lemma and a standard coupling argument.

## 4 A bigger coupling

Now let $\nu$ a stationary renewal point process on $\{2,3, \ldots\}$, that is, if we denote the points of $\nu$ by $2 \leq R_{1}<R_{2}<\cdots$, then the increments $R_{i+1}-R_{i}$ are independent for $i \geq 0$ (with $R_{0}=1$ ) and $R_{i+1}-R_{i}$ has for $i \geq 1$ the distribution (4). A stationary version of the process exists, since $\mathbf{E}(V)<\infty$, such that the distribution of $R_{1}$ may be adjusted in the usual way to obtain stationarity:

$$
\begin{equation*}
\mathbf{P}\left(R_{1}=r\right)=\frac{\mathbf{P}(V \geq r-1)}{\mathbf{E}(V)}, \quad r=2,3, \ldots \tag{13}
\end{equation*}
$$

Stationarity is of advantage for us. Then $\nu$ may be considered as restriction of a stationary point process on $\mathbb{Z}$. Such a process is invariant in distribution under the transformation $z \mapsto z_{0}-z, z \in \mathbb{Z}$ with $z_{0} \in \mathbb{Z}$. Therefore $\nu$, restricted to $\{2, \ldots, n\}$ looks the same, when considered upwards or downwards.

In this section we introduce a coupling between $\nu$ and the $\operatorname{CPP}(\infty) \mu$, which allows us later to replace $\mu$ by $\nu$. Given $b \geq 2$ let as above

$$
M=\max \{k \leq b: \mu(\{k\})=1\}, \quad M^{\prime}=\max \{k \leq b: \nu(\{k\})=1\} .
$$

Again, if there is no $k \leq b$ such that $\mu(\{k\})=1$, we put $M=1$, and similary for $M^{\prime}$. Let $\lambda_{b}$ and $\lambda_{b}^{\prime}$ denote the distributions of $M$ and $M^{\prime}$ (both dependent on $b$ ).

Now for $r \in \mathbb{N}$ we consider the following construction of $\mu$ and $\nu$, restricted to $\left[2^{r-1}+1,2^{r}\right]$. Take any coupling $\left(M, M^{\prime}\right)$ of $\lambda_{2^{r}}$ and $\lambda_{2^{r}}^{\prime}$. Given $\left(M, M^{\prime}\right)$ construct random variables $U_{1}, V_{1}, U_{2}, V_{2}, \ldots$ inductively as in the proof of Lemma 6, using the coupling of section 2. Here we start with $X_{0}=M$. Also let $Y_{0}=M^{\prime}$,

$$
\begin{equation*}
X_{i}=M-U_{1}-\cdots-U_{i}, \quad Y_{i}=M^{\prime}-V_{1}-\cdots-V_{i}, \quad i \geq 1 \tag{14}
\end{equation*}
$$

and

$$
\begin{equation*}
N=\min \left\{i \geq 0: X_{i} \leq 2^{r-1}\right\}, \quad N^{\prime}=\min \left\{i \geq 0: Y_{i} \leq 2^{r-1}\right\} . \tag{15}
\end{equation*}
$$

The whole construction is interrupted at the moment $N \vee N^{\prime}$. Maybe $M, M^{\prime} \leq 2^{r-1}$, then no step of the construction is required. Clearly the following statements are true:

- The point process $\sum_{i=0}^{N-1} \delta_{X_{i}}$ is equal in distribution to $\mu$, restricted to $\left[2^{r-1}+1,2^{r}\right]$.
- The point process $\sum_{i=0}^{N^{\prime}-1} \delta_{Y_{i}}$ is equal in distribution to $\nu$, restricted to $\left[2^{r-1}+1,2^{r}\right]$.
- $X_{N}$ and $Y_{N^{\prime}} \vee 1$ have the distributions $\lambda_{2^{r-1}}$ and $\lambda_{2^{r-1}}^{\prime}$.

The complete coupling is

$$
\begin{align*}
\Phi^{r}\left(M, M^{\prime}\right) & =\left(\sum_{i=0}^{N-1} \delta_{X_{i}}, \sum_{i=0}^{N^{\prime}-1} \delta_{Y_{i}}, X_{N}, Y_{N^{\prime}} \vee 1\right)  \tag{16}\\
& =\left(\phi_{1}^{r}, \phi_{2}^{r}, \phi_{3}^{r}, \phi_{4}^{r}\right) \quad \text { (say) }
\end{align*}
$$

Its distribution is uniquely determined by the distribution of the coupling ( $U, V$ ) from section 2 . The following continuity property is obvious:

- If we have a sequence $\left(M_{n}, M_{n}^{\prime}\right)$ of couplings of $\lambda_{2^{r}}$ and $\lambda_{2^{r}}^{\prime}$ such that $\left(M_{n}, M_{n}^{\prime}\right) \xrightarrow{d}\left(M, M^{\prime}\right)$, then $\left(M, M^{\prime}\right)$ is also a coupling of $\lambda_{2^{r}}$ and $\lambda_{2^{r}}^{\prime}$ and

$$
\Phi^{r}\left(M_{n}, M_{n}^{\prime}\right) \xrightarrow{d} \Phi^{r}\left(M, M^{\prime}\right) .
$$

Another obvious fact is that this construction can be iterated: Given $\Phi^{r}\left(M, M^{\prime}\right)$ we construct $\Phi^{r-1}\left(\phi_{3}^{r}, \phi_{4}^{r}\right)$ and so forth. Thus starting with the independent coupling $\left(M, M^{\prime}\right)$ (i.e. $M$ and $M^{\prime}$ are independent) we obtain the tupel

$$
\Psi^{r}=\left(\Phi^{1, r}\left(M_{1, r}, M_{1, r}^{\prime}\right), \Phi^{2, r}\left(M_{2, r}, M_{2, r}^{\prime}\right), \ldots, \Phi^{r, r}\left(M_{r, r}, M_{r, r}^{\prime}\right)\right)
$$

where $\left(M_{r, r}, M_{r, r}^{\prime}\right)=\left(M, M^{\prime}\right)$ and $\left(M_{s, r}, M_{s, r}^{\prime}\right)=\left(\phi_{3}^{s+1, r}, \phi_{4}^{s+1, r}\right)$ for $s<r$. Since $M_{s, r}$ and $M_{s, r}^{\prime}$ are no longer independent in general, the tupels $\Psi^{r}$ are initially not consistent for different $r$. To enforce consistency note that for fixed $s$ the distributions of $\left(M_{s, r}, M_{s, r}^{\prime}\right)$ are tight for $r \geq s$, since they take values in the finite set $\left\{1, \ldots, 2^{s}\right\} \times\left\{1, \ldots, 2^{s}\right\}$. Thus by a diagonalisation argument we may obtain a sequence $1 \leq r_{1}<r_{2}<\cdots$ such that

$$
\left(M_{s, r_{n}}, M_{s, r_{n}}\right) \xrightarrow{d}\left(M_{s, \infty}, M_{s, \infty}^{\prime}\right)
$$

for certain couplings $\left(M_{s, \infty}, M_{s, \infty}^{\prime}\right)$ of $\lambda_{2^{s}}$ and $\lambda_{2^{s}}^{\prime}$.

If we use instead of the independent coupling $\left(M, M^{\prime}\right)$ now $\left(M_{r, \infty}, M_{r, \infty}^{\prime}\right)$ as starting configuration in the construction of $\Psi^{r}$, then we gain consistency in the sence that

$$
\Psi^{r-1} \stackrel{d}{=}\left(\Phi^{1, r}\left(M_{1, r}, M_{1, r}^{\prime}\right), \Phi^{2, r}\left(M_{2, r}, M_{2, r}^{\prime}\right), \ldots, \Phi^{r-1, r}\left(M_{r-1, r}, M_{r-1, r}^{\prime}\right)\right) .
$$

Proceeding to the projective limit we obtain the 'big coupling'

$$
\begin{equation*}
\Psi^{\infty}=\left(\Phi^{1, \infty}\left(M_{1, \infty}, M_{1, \infty}^{\prime}\right), \Phi^{2, \infty}\left(M_{2, \infty}, M_{2, \infty}^{\prime}\right), \ldots\right) \tag{17}
\end{equation*}
$$

It has the property that

$$
\begin{equation*}
\mu=\sum_{r=1}^{\infty} \phi_{1}^{r, \infty} \text { and } \nu=\sum_{r=1}^{\infty} \phi_{2}^{r, \infty} \tag{18}
\end{equation*}
$$

are coupled copies of our $\operatorname{CPP}(\infty)$ and stationary point process.
In order to estimate the difference between both point processes we go back to (14), (15) and estimate the tail of the distribution of

$$
\begin{equation*}
D_{r}=\max _{i \leq N \wedge N^{\prime}}\left|X_{i}-Y_{i}\right| \tag{19}
\end{equation*}
$$

Lemma 8. There is a constant $c>0$ such that for all $r \geq 1$ and all $t>0$

$$
\mathbf{P}\left(D_{r}>t\right) \leq c t^{1-\alpha}
$$

Proof. For $i \leq N \wedge N^{\prime}$ we have

$$
\begin{align*}
\left|X_{i}-Y_{i}\right| & \leq \sum_{j \leq N \wedge N^{\prime}}\left|U_{j}-V_{j}\right|+\left|X_{0}-Y_{0}\right| \\
& \leq \sum_{j \leq N \wedge N^{\prime}}\left|U_{j}-V_{j}\right|+\left(2^{r}-M\right)+\left(2^{r}-M^{\prime}\right) \tag{20}
\end{align*}
$$

From (6), (10)

$$
\begin{equation*}
\mathbf{P}\left(2^{r}-M>t\right) \leq \sum_{k \geq t} \mathbf{P}(V \geq k) \leq c t^{1-\alpha} \tag{21}
\end{equation*}
$$

for a suitable $c>0$.

Because of stationarity $2^{r}-M^{\prime}$ and $\left(R_{1}-2\right) \wedge\left(2^{r}-1\right)$ are equal in distribution, therefore because of (6), (13)

$$
\begin{equation*}
\mathbf{P}\left(2^{r}-M^{\prime}>t\right) \leq\left(R_{1}>t\right) \leq c t^{1-\alpha} \tag{22}
\end{equation*}
$$

for a suitable $c>0$.
Finally from Lemma $3 U_{j} \neq V_{j}$ occurs for $j \leq N$ at most with probability $p=2^{1-r} /(\alpha-1)$ and then $\left|U_{j}-V_{j}\right| \leq V_{j}$ a.s. Also because of Lemma 3 these $V_{j}$ can be stochastically dominated by random variables $a+b \zeta_{j}$ with constants $a, b>0$ and positive i.i.d. random variables $\zeta_{j}$, which possess a stable distribution of index $\alpha-1$ and Laplace transform $\exp \left(-\lambda^{\alpha-1}\right)$. Also $N \wedge N^{\prime} \leq 2^{r-1}=w$ (say). Thus $\sum_{j \leq N \wedge N^{\prime}}\left|U_{j}-V_{j}\right|$ is stochastically dominated by the random variable

$$
W=\sum_{j=0}^{w}\left(a+b \zeta_{j}\right) I_{j}
$$

where $I_{j}$ are i.i.d. Bernoulli with success probability $p$. Let $\varphi(\lambda)=$ $\exp \left(-a \lambda-(b \lambda)^{\alpha-1}\right)$ be the Laplace transform of $a+b \zeta_{j}$. Then $W$ has the Laplace transform

$$
\sigma(\lambda)=(1-p(1-\varphi(\lambda)))^{w}
$$

It follows $1-\sigma(\lambda) \leq w p(1-\varphi(\lambda)) \leq(1-\varphi(\lambda)) /(\alpha-1)$. From the well-known identity $\lambda \int_{0}^{\infty} e^{-\lambda x} \mathbf{P}(W>x) d x=1-\sigma(\lambda)$ it follows that

$$
\begin{aligned}
e^{-1} \mathbf{P}(W>t) & \leq t^{-1} \int_{0}^{\infty} e^{-x / t} \mathbf{P}(W>x) d x \\
& =1-\sigma(1 / t) \leq \frac{1}{\alpha-1}\left(1-\exp \left(-a t^{-1}-(b t)^{1-\alpha}\right)\right)
\end{aligned}
$$

Thus

$$
\begin{equation*}
\mathbf{P}\left(\sum_{j \leq N \wedge N^{\prime}}\left|U_{j}-V_{j}\right|>t\right) \leq \mathbf{P}(W>t) \leq c t^{1-\alpha} \tag{23}
\end{equation*}
$$

for a suitable $c>0$. Using the estimates (21) to (23) in (20) yields our claim.

Additionally we note that

$$
\begin{equation*}
\left|N-N^{\prime}\right| \leq D_{r} \tag{24}
\end{equation*}
$$

Indeed, if $N<N^{\prime}$, then $X_{N} \leq 2^{r-1}$, thus $Y_{N} \leq 2^{r-1}+D_{r}$. Further $Y_{N^{\prime}-1}>$ $2^{r-1}$, which implies $N^{\prime}-1-N \leq Y_{N}-Y_{N^{\prime}-1} \leq D_{r}-1$. The case $N^{\prime}<N$ is treated in the same way.

## 5 On sums of independent random variables

The following lemma can be deduced from well-known results (see f.e. Petrov [14]), but a direct proof seems more convenient. Let

$$
\gamma=\frac{1}{\alpha-1} .
$$

Lemma 9. Let $V_{1}, V_{2}, \ldots$ be i.i.d. copies of the random variable (4). Then for any $\beta \in \mathbb{R}$ and any $\varepsilon>0$ a.s.

$$
\sum_{k=1}^{n} k^{-\beta}\left(V_{k}-\gamma\right)=\eta_{n}+o\left(n^{\frac{1}{\alpha}-\beta+\varepsilon}\right)
$$

where $\eta_{n}$ is a.s. convergent.
Proof. Let $\varepsilon>0$. A short calculation gives that $\mathbf{E}\left(V_{k}^{2} ; V_{k} \leq k^{\frac{1}{\alpha}+\varepsilon}\right)$ is of order $k^{\frac{2}{\alpha}-1+(2-\alpha) \varepsilon}$, thus

$$
\sum_{k=1}^{\infty} k^{-\frac{1}{\alpha}-\varepsilon}\left(V_{k} 1_{V_{k} \leq k} \frac{\frac{1}{\alpha}+\varepsilon}{}-\mathbf{E}\left(V_{k} ; V_{k} \leq k^{\frac{1}{\alpha}+\varepsilon}\right)\right)
$$

is a.s. convergent. Also $\mathbf{E}\left(V_{k} ; V_{k}>k^{\frac{1}{\alpha}+\varepsilon}\right)$ is of order less than $k^{\frac{1}{\alpha}-1}$ and $\mathbf{P}\left(V_{k}>k^{\frac{1}{\alpha}+\varepsilon}\right)$ is of order $k^{-1-\alpha \varepsilon}$ such that $V_{k}>k^{\frac{1}{\alpha}+\varepsilon}$ occurs only finitely often a.s. Thus

$$
\sum_{k=1}^{\infty} k^{-\frac{1}{\alpha}-\varepsilon}\left(V_{k}-\gamma\right)
$$

is a.s. convergent for all $\varepsilon>0$.
For $\beta>\frac{1}{\alpha}$ it follows that the sum $\sum_{k=1}^{n} k^{-\beta}\left(V_{k}-\gamma\right)$ is a.s. convergent, which is our claim (then the term $o\left(n^{\frac{1}{\alpha}-\beta+\varepsilon}\right)$ is superfluous). In the case $\beta \leq \frac{1}{\alpha}$ by Kronecker's Lemma a.s.

$$
\sum_{k=1}^{n} k^{-\beta}\left(V_{k}-\gamma\right)=o\left(n^{\frac{1}{\alpha}-\beta+\varepsilon}\right)
$$

which again is our claim (now $\eta_{n}$ is superfluous).
Next recall that $\varsigma$ denotes a random variable with maximally skewed stable distribution of index $\alpha$ as in (3). The following result can be deduced from a general statement on triangular arrays of independent random variables (see [10], chapter XVII, section 7), however a direct proof seems easier.

Lemma 10. Let $V_{1}, V_{2}, \ldots$ be independent copies of the random variable (4). Then the following holds true:
(i) Let $1<\alpha<\frac{1}{2}(1+\sqrt{5})$. Then

$$
n^{\alpha-1-\frac{1}{\alpha}} \sum_{k=1}^{n} k^{1-\alpha}\left(V_{k}-\gamma\right) \xrightarrow{d}-c \varsigma,
$$

where

$$
c=\left(\left(1+\alpha-\alpha^{2}\right) \Gamma(2-\alpha)\right)^{-\frac{1}{\alpha}} .
$$

(ii) For $\alpha=\frac{1}{2}(1+\sqrt{5})$

$$
(\log n)^{-\frac{1}{\alpha}} \sum_{k=1}^{n} k^{1-\alpha}\left(V_{k}-\gamma\right) \xrightarrow{d} \frac{-\varsigma}{\Gamma(2-\alpha)^{\frac{1}{\alpha}}} .
$$

Proof. (i): From (5), (6) and the theory of stable laws it follows that

$$
n^{-\frac{1}{\alpha}}\left(V_{1}+\cdots+V_{n}-\gamma n\right) \xrightarrow{d} \frac{-\varsigma}{\Gamma(2-\alpha)^{\frac{1}{\alpha}}} .
$$

We express this relation by means of the characteristic functions $\varphi(u)$ and $e^{\psi(u)}$ of $V-\gamma$ and $-\varsigma / \Gamma(2-\alpha)^{1 / \alpha}: \varphi\left(n^{-\frac{1}{\alpha}} u\right)^{n} \rightarrow e^{\psi(u)}$ for all $u \in \mathbb{R}$ or slightly more general

$$
\varphi\left(v_{n} n^{-\frac{1}{\alpha}} u\right)^{n} \rightarrow e^{\psi(u)}
$$

if $v_{n} \rightarrow 1$. Since $\varphi_{n}(u)=\varphi\left(v_{n} n^{-\frac{1}{\alpha}} u\right)$ is again a characteristic function, it follows from Feller [10], chapter XVII. 1 Theorem 1, that for $n \rightarrow \infty$

$$
n\left(\varphi\left(v_{n} n^{-\frac{1}{\alpha}} u\right)-1\right) \rightarrow \psi(u)
$$

or

$$
\varphi(s u)-1 \sim s^{\alpha} \psi(u), \quad \text { as } s \rightarrow 0
$$

for all real $u$. Since $\alpha-\alpha^{2}>-1$ for $\alpha<\frac{1}{2}(1+\sqrt{5})$, it follows that with $\zeta=\left(1+\alpha-\alpha^{2}\right)^{\frac{1}{\alpha}}$

$$
\begin{aligned}
& \sum_{k=1}^{n}\left(\varphi\left(\frac{\zeta k^{1-\alpha}}{n^{1-\alpha+\frac{1}{\alpha}}} u\right)-1\right) \\
& \quad \sim \psi(u) \sum_{k=1}^{n}\left(\frac{\zeta k^{1-\alpha}}{n^{1-\alpha+\frac{1}{\alpha}}}\right)^{\alpha} \rightarrow \psi(u) .
\end{aligned}
$$

Similarly

$$
\sum_{k=1}^{n}\left|\varphi\left(\frac{\zeta k^{1-\alpha}}{n^{1-\alpha+\frac{1}{\alpha}}} u\right)-1\right| \rightarrow|\psi(u)|
$$

and consequently

$$
\begin{aligned}
& \sum_{k=1}^{n}\left|\varphi\left(\frac{\zeta k^{1-\alpha}}{n^{1-\alpha+\frac{1}{\alpha}}} u\right)-1\right|^{2} \\
& \quad \leq \max _{k=1, \ldots, n}\left|\varphi\left(\frac{\zeta k^{1-\alpha}}{n^{1-\alpha+\frac{1}{\alpha}}} u\right)-1\right| \sum_{k=1}^{n}\left|\varphi\left(\frac{\zeta k^{1-\alpha}}{n^{1-\alpha+\frac{1}{\alpha}}} u\right)-1\right| \rightarrow 0
\end{aligned}
$$

for $n \rightarrow \infty$.
In order to transfer these limit results to characteristic functions we use that for all complex numbers $z$ with $|z| \leq 1$

$$
\left|z-e^{z-1}\right| \leq c|z-1|^{2}
$$

for some $c>0$. Therefore, if $\left|z_{1}\right|, \ldots,\left|z_{n}\right| \leq 1$,

$$
\left|z_{1} \cdots z_{n}-e^{\left(z_{1}-1\right)+\cdots+\left(z_{n}-1\right)}\right| \leq \sum_{k=1}^{n}\left|z_{k}-e^{z_{k}-1}\right| \leq c \sum_{k=1}^{n}\left|z_{k}-1\right|^{2}
$$

We put $z_{k}=z_{k n}(u)=\varphi\left(\frac{\zeta k^{1-\alpha}}{n^{1-\alpha+\frac{1}{\alpha}}} u\right)$. Then the right-hand side goes to zero and we obtain

$$
z_{1 n}(u) \cdots z_{n n}(u) \rightarrow e^{\psi(u)}
$$

Since the product on the left-hand side is the characteristic function of $\zeta n^{\alpha-1-\frac{1}{\alpha}} \sum_{k=1}^{n} k^{1-\alpha}\left(V_{k}-\frac{1}{\alpha-1}\right)$ the claim follows.
(ii): This proof goes along the same lines using

$$
\sum_{k=1}^{n}\left(\varphi\left(\frac{k^{1-\alpha}}{(\log n)^{\frac{1}{\alpha}}} u\right)-1\right) \sim \psi(u) \sum_{k=1}^{n}\left(\frac{k^{1-\alpha}}{(\log n)^{\frac{1}{\alpha}}}\right)^{\alpha}
$$

Now $\alpha-\alpha^{2}=-1$, thus

$$
\sum_{k=1}^{n}\left(\varphi\left(\frac{k^{1-\alpha}}{(\log n)^{\frac{1}{\alpha}}} u\right)-1\right) \sim \psi(u) \frac{1}{\log n} \sum_{k=1}^{n} \frac{1}{k} \sim \psi(u)
$$

and the claim follows.

## 6 Proof of Theorem 1

Again let $2 \leq R_{1}<R_{2}<\cdots$ be the points of the stationary point process $\nu$ and denote

$$
V_{j}=R_{j+1}-R_{j}, j \geq 1
$$

The random variables $V_{1}, V_{2}, \ldots$ are i.i.d. with distribution (4).
Lemma 11. We have

$$
\int_{[2, n]} x^{1-\alpha} \nu(d x)=\frac{n^{2-\alpha}}{\gamma(2-\alpha)}-\gamma^{-\alpha} \sum_{k \leq \frac{n}{\gamma}} k^{1-\alpha}\left(V_{k}-\gamma\right)+\delta_{n}
$$

with

$$
\delta_{n}=\eta_{n}+o_{P}\left(n^{\frac{1}{\alpha^{2}}+1-\alpha+\varepsilon}\right)
$$

for any $\varepsilon>0$, where the random variables $\eta_{n}$ are convergent in probability.
Proof. Our starting point is

$$
\int_{[2, n]} x^{1-\alpha} \nu(d x)=\sum_{i=1}^{r_{n}} R_{i}^{1-\alpha},
$$

where $r_{n}$ is such that $R_{r_{n}} \leq n<R_{r_{n}+1}$. From Lemma 9 we have $R_{n}-\gamma n=$ $o\left(n^{\frac{1}{\alpha}+\varepsilon}\right)$ a.s., which implies $r_{n}-\frac{n}{\gamma}=o\left(n^{\frac{1}{\alpha}+\varepsilon}\right)$ a.s.

By a Taylor expansion

$$
\begin{align*}
R_{i}^{1-\alpha} & =(\gamma i)^{1-\alpha}+(1-\alpha)(\gamma i)^{-\alpha}\left(R_{i}-\gamma i\right)+\delta_{i}^{\prime} \\
& =(\gamma i)^{1-\alpha}+(1-\alpha)(\gamma i)^{-\alpha} \sum_{j=1}^{i-1}\left(V_{j}-\gamma\right)+\delta_{i}^{\prime \prime} \tag{25}
\end{align*}
$$

where the remainder is a.s. of the order

$$
\delta_{i}^{\prime \prime}=O\left(i^{-\alpha-1}\left(R_{i}-\gamma i\right)^{2}\right)+O\left(i^{-\alpha}\right)=o\left(i^{\frac{2}{\alpha}-\alpha-1+\varepsilon}\right) .
$$

We consider now the sums of the different terms in (25):

$$
\begin{equation*}
\sum_{i=1}^{r_{n}}(\gamma i)^{1-\alpha}=\frac{\gamma^{1-\alpha}}{2-\alpha} r_{n}^{2-\alpha}+\eta_{n}^{\prime} \tag{26}
\end{equation*}
$$

where $\eta_{n}^{\prime}$ is a.s. convergent. Further, putting $a_{n}=(\alpha-1) \sum_{i>n} i^{-\alpha}$,

$$
\begin{aligned}
(1-\alpha) \sum_{i=1}^{r_{n}} i^{-\alpha} \sum_{j=1}^{i-1}\left(V_{j}-\gamma\right) & =(1-\alpha) \sum_{j=1}^{r_{n}}\left(V_{j}-\gamma\right) \sum_{i=j+1}^{r_{n}} i^{-\alpha} \\
& =a_{r_{n}}\left(R_{r_{n}+1}-R_{1}-\gamma r_{n}\right)-\sum_{j=1}^{r_{n}} a_{j}\left(V_{j}-\gamma\right) .
\end{aligned}
$$

The distribution of $R_{r_{n}+1}-n$ does not depend on $n$ because of stationarity, thus $a_{r_{n}}\left(R_{r_{n}+1}-R_{1}-n\right)=O_{P}\left(n^{1-\alpha}\right)$. Also $\sum_{j=1}^{n}\left(a_{j}-j^{1-\alpha}\right)\left(V_{j}-\gamma\right)$ is a.s. convergent for $\alpha>1$, since $a_{n}-n^{1-\alpha}=O\left(n^{-\alpha}\right)$ and since $V$ has finite expectation. It follows

$$
\begin{align*}
& (1-\alpha) \sum_{i=1}^{r_{n}} i^{-\alpha} \sum_{j=1}^{i-1}\left(V_{j}-\gamma\right) \\
& \quad=r_{n}^{1-\alpha}\left(n-\gamma r_{n}\right)-\sum_{j=1}^{r_{n}} j^{1-\alpha}\left(V_{j}-\gamma\right)+\eta_{n}^{\prime \prime}+O_{P}\left(n^{1-\alpha}\right) \tag{27}
\end{align*}
$$

where $\eta_{n}^{\prime \prime}$ is a.s. convergent. Next

$$
\begin{equation*}
\sum_{i=1}^{r_{n}} \delta_{i}^{\prime \prime}=\eta_{n}^{\prime \prime \prime}+o\left(n^{\frac{2}{\alpha}-\alpha+\varepsilon}\right) \text { a.s. } \tag{28}
\end{equation*}
$$

for all $\varepsilon>0$, where $\eta_{n}^{\prime \prime \prime}$ is a.s. convergent. Note that this formula covers two cases: If $\frac{2}{\alpha}<\alpha$, then the sum is a.s. convergent and the right-hand term is superfluous. Otherwise the term $\eta_{n}^{\prime \prime \prime}$ can be neglected.

Furthermore another Taylor expansion gives

$$
\begin{equation*}
\frac{n^{2-\alpha}}{2-\alpha}=\frac{\left(\gamma r_{n}\right)^{2-\alpha}}{2-\alpha}+\left(\gamma r_{n}\right)^{1-\alpha}\left(n-\gamma r_{n}\right)+o\left(n^{\frac{2}{\alpha}-\alpha+\varepsilon}\right) \text { a.s. } \tag{29}
\end{equation*}
$$

Combining (25) to (29) gives

$$
\begin{equation*}
\sum_{i=1}^{r_{n}} R_{i}^{1-\alpha}=\frac{n^{2-\alpha}}{\gamma(2-\alpha)}-\gamma^{-\alpha} \sum_{j=1}^{r_{n}} j^{1-\alpha}\left(V_{j}-\gamma\right)+\eta_{n}+o\left(n^{\frac{2}{\alpha}-\alpha+\varepsilon}\right) \text { a.s. } \tag{30}
\end{equation*}
$$

where $\eta_{n}$ is convergent in probability.

Finally we consider the (loosely notated) difference

$$
\sum_{j=r_{n}+1}^{n / \gamma} j^{1-\alpha}\left(V_{j}-\gamma\right)=\sum_{j \leq n / \gamma} j^{1-\alpha}\left(V_{j}-\gamma\right)-\sum_{j=1}^{r_{n}} j^{1-\alpha}\left(V_{j}-\gamma\right)
$$

For any random sequence of natural numbers $s_{n}$ such that $s_{n}=o\left(n^{\frac{1}{\alpha}+\varepsilon}\right)$ a.s. for all $\varepsilon>0$

$$
\sum_{i \leq s_{n}}\left(V_{i}-\gamma\right)=R_{s_{n}+1}-R_{1}-\gamma s_{n}=o\left(s_{n}^{\frac{1}{\alpha}+\varepsilon}\right)=o\left(n^{\frac{1}{\alpha^{2}}+2 \varepsilon+\varepsilon^{2}}\right) \text { a.s. }
$$

Since $r_{n}-n / \gamma=o\left(n^{\frac{1}{\alpha}+\varepsilon}\right)$ a.s. for any $\varepsilon>0$, this implies for any $\varepsilon>0$ in probability

$$
\sum_{j=r_{n}+1}^{n / \gamma}\left(V_{j}-\gamma\right)=o_{P}\left(n^{\frac{1}{\alpha^{2}}+\varepsilon}\right)
$$

This implies $\sum_{j=r_{n}+1}^{n / \gamma}\left(V_{j}+\gamma\right)=o_{P}\left(n^{\frac{1}{\alpha}+\varepsilon}\right)$. Therefore

$$
\begin{aligned}
& \left|\sum_{j=r_{n}+1}^{n / \gamma} j^{1-\alpha}\left(V_{j}-\gamma\right)\right| \\
& \quad \leq r_{n}^{1-\alpha}\left|\sum_{j=r_{n}+1}^{n / \gamma}\left(V_{j}-\gamma\right)\right|+\left|\left(\frac{n}{\gamma}\right)^{1-\alpha}-r_{n}^{1-\alpha}\right| \sum_{j=r_{n}+1}^{n / \gamma}\left(V_{j}+\gamma\right) \\
& \quad=o_{P}\left(n^{\frac{1}{\alpha^{2}}+1-\alpha+\varepsilon}\right)+O\left(n^{-\alpha}\left(n-\gamma r_{n}\right)\right) o_{P}\left(n^{\frac{1}{\alpha}+\varepsilon}\right) \\
& \quad=o_{P}\left(n^{\frac{1}{\alpha^{2}}+1-\alpha+\varepsilon}\right)+o_{P}\left(n^{\frac{2}{\alpha}-\alpha+2 \varepsilon}\right) .
\end{aligned}
$$

Since $\frac{1}{\alpha^{2}}+1 \geq \frac{2}{\alpha}$, we end up with

$$
\sum_{j=r_{n}+1}^{n / \gamma} j^{1-\alpha}\left(V_{j}-\gamma\right)=o_{P}\left(n^{\frac{1}{\alpha^{2}}+1-\alpha+\varepsilon}\right) .
$$

Combining this estimate with (30) gives the claim.

Proof of Theorem 1. The total length (2) of the $n$-coalescent can be rewritten as

$$
L_{n}=\sum_{i=0}^{\tau_{n}-1} \frac{X_{i}}{\rho_{X_{i}}} E_{i}
$$

where $E_{0}, E_{1}, \ldots$ denote exponential random variables with expectation 1 , independent among themselves and from the $X_{i}$.

From Lemma 2.2 in Delmas et al [7] we have for $m \rightarrow \infty$

$$
\begin{equation*}
\rho_{m}=\frac{1}{\alpha \Gamma(\alpha)} m^{\alpha}+O\left(m^{\alpha-1}\right) . \tag{31}
\end{equation*}
$$

In the first step we replace the points $n=X_{0}>X_{1}>\cdots$ of a $\operatorname{CPP}(n)$ by points of a $\operatorname{CPP}(\infty)$ : If we take independent versions of both then for given $\varepsilon>0$ by Lemma 6 there is a natural number $s \geq 1$ such that with probability at least $1-\varepsilon$ they meet before $n-s$. From this moment both CPPs can be coupled. Thus, letting $n \geq X_{0}^{\prime}>X_{1}^{\prime}>\cdots$ be the points of the coupled $\operatorname{CPP}(\infty)$ within $[2, n]$, independent of $E_{0}, E_{1}, \ldots$, and

$$
L_{n}^{\prime}=\sum_{i=0}^{\tau_{n}^{\prime}-1} \frac{X_{i}^{\prime}}{\rho_{X_{i}^{\prime}}} E_{i}
$$

then due to the the coupling and (31) for $n$ sufficiently big

$$
\mathbf{P}\left(\left|L_{n}-L_{n}^{\prime}\right|>3 \alpha \Gamma(\alpha) n^{1-\alpha}\left(E_{0}+\cdots+E_{s}\right)\right) \leq \varepsilon
$$

Since $\alpha>1, L_{n}-L_{n}^{\prime}=o_{P}(1)$, thus we may replace $L_{n}$ by $L_{n}^{\prime}$ in our asymptotic considerations.

Thus we work now with a $\operatorname{CPP}(\infty) \mu$, which we couple to a stationary point process $\nu$ according to (17) and (18). Also let $E_{0}, E_{1}, \ldots$ be independent of the whole coupling. We use the formula

$$
\begin{equation*}
L_{n}^{\prime}=\int_{[2, n]} \frac{x E_{x}}{\rho_{x}} \mu(d x) \tag{32}
\end{equation*}
$$

in which the exponential random variables now are ordered differently. Since $\sum_{x \geq 1} x^{-\alpha} E_{x}<\infty$ a.s., it follows from (31) that

$$
L_{n}^{\prime}=\alpha \Gamma(\alpha) \int_{[2, n]} \frac{E_{x}}{x^{\alpha-1}} \mu(d x)+\eta_{1, n},
$$

where $\eta_{1, n}$ is a.s. convergent.
Next $\sum_{x>2} x^{-1 / 2-\varepsilon}\left(E_{x}-1\right)$ is a.s. convergent for any $\varepsilon>0$. It follows that $\sum_{x \geq 2} x^{1-\alpha}\left(E_{x}-1\right)$ is a.s. convergent for $\alpha>\frac{3}{2}$ and else a.s. of order $O\left(n^{\frac{3}{2}-\alpha+\varepsilon}\right)$. Given $\mu$ the same holds true for $\int_{[2, n]} \frac{E_{x}-1}{x^{\alpha-1}} \mu(d x)$, thus

$$
L_{n}^{\prime}=\alpha \Gamma(\alpha) \int_{[2, n]} x^{1-\alpha} \mu(d x)+\eta_{2, n}+o\left(n^{3 / 2-\alpha+\varepsilon}\right) \text { a.s. },
$$

where again $\eta_{2, n}$ is a.s. convergent.
Next from (18) with $2^{s}<n \leq 2^{s+1}$

$$
\begin{aligned}
\int_{[2, n]} x^{1-\alpha} \mu(d x) & =\int_{[2, n]} x^{1-\alpha} \nu(d x) \\
& +\sum_{r=1}^{s} \int_{\left[2^{r-1}+1,2^{r}\right]} x^{1-\alpha}\left(\phi_{1}^{r, \infty}(d x)-\phi_{2}^{r, \infty}(d x)\right) \\
& +\int_{\left[2^{s}+1, n\right]} x^{1-\alpha}\left(\phi_{1}^{s, \infty}(d x)-\phi_{2}^{s, \infty}(d x)\right)
\end{aligned}
$$

From (19) and (24) we see that

$$
\begin{aligned}
& \left|\int_{\left[2^{r-1}+1,2^{r}\right]} x^{1-\alpha}\left(\phi_{1}^{r, \infty}(d x)-\phi_{2}^{r, \infty}(d x)\right)\right| \\
& \leq 2^{r-1}(\alpha-1)\left(2^{r-1}\right)^{-\alpha} D_{r}+2\left(2^{r-1}\right)^{1-\alpha} D_{r}
\end{aligned}
$$

and the same estimate holds for the last term above. In view of Lemma 8 and the Borel-Cantelli Lemma we conclude that

$$
\int_{[2, n]} x^{1-\alpha} \mu(d x)=\int_{[2, n]} x^{1-\alpha} \nu(d x)+\eta_{3, n}
$$

with $\eta_{3, n}$ a.s. convergent. Altogether

$$
L_{n}^{\prime}=\alpha \Gamma(\alpha) \int_{[2, n]} x^{1-\alpha} \nu(d x)+\eta_{4, n}+o\left(n^{3 / 2-\alpha+\varepsilon}\right)
$$

where $\eta_{4, n}$ is a.s. convergent. Finally Lemma 11 gives a.s.

$$
\begin{gather*}
L_{n}^{\prime}=\frac{\Gamma(\alpha) \alpha(\alpha-1)}{(2-\alpha)} n^{2-\alpha}-\Gamma(\alpha) \alpha(\alpha-1)^{\alpha} \sum_{k \leq \frac{n}{\gamma}} k^{1-\alpha}\left(V_{k}-\gamma\right) \\
+\eta_{n}+o_{P}\left(n^{\frac{1}{\alpha^{2}}+1-\alpha+\varepsilon}\right)+o\left(n^{3 / 2-\alpha+\varepsilon}\right) \tag{33}
\end{gather*}
$$

for all $\varepsilon>0$, where $\eta_{n}$ now is convergent in probability.
We are ready to treat the different cases of Theorem [1:
If $1<\alpha<(1+\sqrt{5}) / 2$, then we use that $1 / \alpha>1 / \alpha^{2}$ and $1 / \alpha>1 / 2$. Therefore the three remainder terms in (33) are all of order $o_{P}\left(n^{\frac{1}{\alpha}+1-\alpha}\right)$ and thus may be neglected. The result follows from an application of Lemma 10. The case $\alpha=(1+\sqrt{5}) / 2$ is treated in the same way.

If $\alpha>(1+\sqrt{5}) / 2$, then $\frac{1}{\alpha^{2}}+1-\alpha<0$ and $3 / 2-\alpha<0$. Also from Lemma 9 it follows that $\sum_{k \leq \frac{n}{\gamma}} k^{1-\alpha}\left(V_{k}-\gamma\right)$ is a.s. convergent. Thus it follows from (33) that $L_{n}^{\prime}-\frac{\Gamma(\alpha) \alpha(\alpha-1)}{(2-\alpha)} n^{2-\alpha}$ is convergent in probability. To see that the limit of $L_{n}^{\prime}$ (and thus $L_{n}$ ) is nondegenerate, we go back to (32) resp.

$$
\begin{aligned}
L_{n}^{\prime}- & \frac{\Gamma(\alpha) \alpha(\alpha-1)}{(2-\alpha)} n^{2-\alpha} \\
& =\frac{2 \alpha \Gamma(\alpha)}{\rho_{2}} \mu(\{2\}) E_{2}+\left(\alpha \Gamma(\alpha) \int_{[3, n]} \frac{x E_{x}}{\rho_{x}} \mu(d x)-\frac{\Gamma(\alpha) \alpha(\alpha-1)}{(2-\alpha)} n^{2-\alpha}\right)
\end{aligned}
$$

As shown the term in brackets in convergent in probability. Also $\mu(\{2\})=1$ with positive probability. Since the exponential variable $E_{2}$ is independent from the rest on the right-hand side, the whole limit has to be non-degenerate. This finishes the proof.

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