# ON ITERATED INTEGRATED TAIL 

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Let $F$ be a distribution on $[0, \infty)$, with $\underline{F}(x):=F((x, \infty))$ its right tail. Suppose that $F$ has a finite first moment $\mu=\int_{0}^{\infty} \underline{F}(x) \mathrm{d} x$. The Lorenz curve of $F$ is the graph of $L(F):[0,1] \rightarrow[0,1]$ defined by $L(F)(y)=\frac{1}{\mu} \int_{0}^{y} F^{-1}(t) \mathrm{d} t$, where $F^{-1}(y)=\sup \{x: F(x) \leq y\}$ is the pseudoinverse of $F$. As $L(F)(0)=0$, $L(F)(1)=1$ and $L_{F}$ is increasing, it is the distribution function of some other measure $F_{1}$. Tzvetan Ignatov proved [5] that if we construct the sequence defined by the recurrence $F_{n+1}=L\left(F_{n}\right)$, this sequence has always a limit which does not depend on $F$. From a geometric point of view $L(F)(y)$ is the ratio $A(y) / A(0)$ where $A(y)$ is the area of the set $\{(x, z): y \leq z \leq \underline{F}(x)\}$. If we replace this ratio by $B(x) / B(0), B(x)$ being the area of the set $\{(t, z): 0 \leq z \leq \underline{F}(t), t \geq x\}$ we obtain the tail of another distribution which is denoted by $F_{I}$ and it is called the integrated tail of $F[1,3,8,13,14]$. Ignatov conjectured that if we construct the sequence defined by the recurrence $F_{n+1}=\left(F_{n}\right)$, this sequence has always a limit which is an exponential distribution. We prove that this is true in some cases if we agree to add Dirac's measure $\delta_{0}$ and the null measure $\delta_{\infty}$ to the family of exponential distributions under the name $\operatorname{Exp}(\infty)$ and $\operatorname{Exp}(0)$.

Key words: Weak convergence; Integrated tail; Hazard rate.

## 1. DEFINITIONS AND STATEMENT OF THE PROBLEM

Let $(\Omega, K, P)$ be a probability space and $\boldsymbol{L}=\bigcap L_{+}^{p}(\Omega, \boldsymbol{K}, P)$. So, $X \in \boldsymbol{L}$ iff $X \geq 0$ (a.s.) and $\mathrm{E} X^{p}<\infty$ for every $1 \leq p<\infty$. Let $\boldsymbol{M}$ be the set of the distribution of the random variables $X \in \boldsymbol{L}$. Thus $F \in \boldsymbol{M}$ iff $F([0, \infty))$ $=1$ and $\int x^{p} \mathrm{~d} F(x)<\infty \forall 1 \leq p<\infty$. The integral $\int x^{p} \mathrm{~d} F(x):=\mathrm{E} X^{p}$ will be denoted by $\mu_{p}(F)$. For $p=1$ it will be simply denoted $\mu(F)$. $\mu_{p}(F)$ is called the $p$ th moment of $X$. We shall denote by $F(x)$ the distribution function of $F$ and by $\underline{F}(x)$ its right tail. Precisely, $F(x)$ will stand for $F([0, x])$ and $\underline{F}(x)$ for $F((x, \infty))$.

Let $g:[0, \infty) \rightarrow \Re$ be a continuous function. Suppose that it is differentiable at almost all its points, with the possible exception of a discrete set. We shall often use the formula (integration by parts).

$$
\begin{equation*}
F \in \boldsymbol{M} \Rightarrow \int g \mathrm{~d} F=g(0)+\int_{0}^{\infty} g^{\prime}(x) \underline{F}(x) \mathrm{d} x . \tag{1.1}
\end{equation*}
$$

For instance, if $g(x)=(x-a)_{+}$we get $X \geq 0 \Rightarrow E(X-a)_{+}=\int_{a}^{\infty} \underline{F}(x) \mathrm{d} x \mathrm{E}(X-a)_{+}=\int_{a}^{\infty} \underline{F}(x) \mathrm{d} x$.
In renewal and ruin theories the following distribution is of interest: it is called the integrated tail. Its tail is defined by

$$
\begin{equation*}
\underline{F}_{I}(x)=\int_{x}^{\infty} \underline{F}(y) \mathrm{d} y / \int_{0}^{\infty} \underline{F}(y) \mathrm{d} y . \tag{1.2}
\end{equation*}
$$

We shall to study the mapping $T: \boldsymbol{M} \rightarrow \boldsymbol{M}$ defined by $T(F)=F_{I}$ and the sequence defined by

$$
\begin{equation*}
F_{0}=F, F_{n+1}=\left(F_{n}\right)_{I} . \tag{1.3}
\end{equation*}
$$

For the history of the operator "integrated tail" the reader can consult [1] or [3].

## 2. STRAIGHTFORWARD PROPERTIES

Let $\boldsymbol{M}_{\text {ac }}$ be the family of absolutely continuous (with respect to Lebesgue measure) distribution from $\boldsymbol{M}$. If $F \in \boldsymbol{M}_{\text {ac }}$ we denote by $f$ its density.

The first remark is that no matter $F \in \boldsymbol{M}, T(F)$ is absolutely continuous. Its density is

$$
\begin{equation*}
f_{I}(x)=\frac{\underline{F}(x)}{\mu_{1}(F)} \tag{2.1}
\end{equation*}
$$

Here are some simple properties of the operator $T$.

## Proposition 2.1.

(i) $F_{I}(x)=\frac{\mathrm{E}(X-x)_{+}}{\mathrm{E} X}=\frac{\mathrm{E}(X-x)_{+}}{\mu_{1}}$, where $X \sim F$.
(ii) $T(F) \in \boldsymbol{M}_{\text {ac }}$ for every $F \in \boldsymbol{M}$ and Range $(T)=\left\{G \in \boldsymbol{M}_{\text {ac }} \mid g\right.$ is non-increasing $\}$; the range consists of all absolutely continuous distribution with non-increasing densities.
(iii) Let $\varphi(t)=\int \mathrm{e}^{\mathrm{i} t x} \mathrm{~d} F(x)$ be the characteristic function of $F$ and $\varphi_{I}(t)=\int \mathrm{e}^{\mathrm{i} t x} \mathrm{~d} F_{I}(x)$ the characteristic function of $F_{I}$. Suppose that $\mu_{1}>0$. Then $\varphi_{I}(t)=\frac{\varphi(t)-1}{i t \mu_{1}}=\frac{\varphi(t)-1}{t \varphi^{\prime}(0)}$.
(iv) Let $\boldsymbol{m}(t)=\int \mathrm{e}^{t x} \mathrm{~d} F(x)$ be the m.g.f. of $F$ and $\boldsymbol{m}_{I}(t)=\int \mathrm{e}^{t x} \mathrm{~d} F_{I}(x)$ the m.g.f. of $F_{I}$. Suppose that $\mu_{1}>0$. Then $\boldsymbol{m}_{\boldsymbol{I}}(t)=\frac{\boldsymbol{m}(t)-1}{t \mu_{1}}=\frac{\boldsymbol{m}(t)-1}{t \boldsymbol{m}^{\prime}(0)}$.
(v) Unicity up to mixtures with $\boldsymbol{\delta}_{0}: F, G \in \boldsymbol{M} \Rightarrow F_{I}=G_{I}$ iff $G=(1-p) F+p \delta_{0}$ for some $p \in[0,1]$.
(vi) Let $\boldsymbol{M}_{0}=\{F \in \boldsymbol{M} \mid F((0, \infty))=1\}=\{F \in \boldsymbol{M} \mid F(0)=0\}$. The mapping $\boldsymbol{T}: \boldsymbol{M}_{0} \rightarrow \boldsymbol{M}_{\text {ac }}$ is one to one.

Proof. (i). Apply (1.1) for $g(t)=(t-x)_{+}$. (iii) and (iv) are consequences of (1.1) for $g_{t}(x)=\mathrm{e}^{i t x}$ and for $g(x)=\mathrm{e}^{t x}:$ for instance $\varphi_{I}(t)=\int_{0}^{\infty} \mathrm{e}^{\mathrm{i} t x} \mathrm{~d} F_{I}(x)=\int_{0}^{\infty} \mathrm{e}^{\mathrm{i} x x} \frac{F(x)}{\mu_{1}} \mathrm{~d} x=\frac{1}{\mu_{1}} \int_{0}^{\infty} \mathrm{e}^{\mathrm{i} t x} \underline{F}(x) \mathrm{d} x$.

By (1.1), $\varphi(t)=1+i t \int_{0}^{\infty} \mathrm{e}^{\mathrm{i} x x} \underline{F}(x) \mathrm{d} x$, hence $\int_{0}^{\infty} \mathrm{e}^{\mathrm{i} t x} \underline{F}(x) \mathrm{d} x=\frac{\varphi(t)-1}{i t}$ and (iii) follows. Equality (iv) has the same proof.
(ii) For the second assertion, let $G$ be an absolutely continuous distribution on $[0, \infty)$ such that its density $g$ is non-increasing and right-continuous. Then $\underline{F}(x)=\frac{g(x)}{g(0)}$ is the tail of some distribution $F$ and $G=F_{I}$. To prove the first assertion, we have to check that $F_{I}$ has finite moments or, which is the same thing, that $\varphi_{I}$ is indefinitely differentiable at 0 ; or, which is the same thing, that $\lim _{t \rightarrow 0} t^{-n}\left(\varphi_{I}(t)-1\right)$ does exist and is finite. But that is obvious, by Hospital's rule $\lim _{t \rightarrow 0} \frac{\varphi_{I}(t)-1}{t^{n}}=\lim _{t \rightarrow 0} \frac{\varphi(t)-1-t \mu_{1}}{i t^{n+1} \mu_{1}}=\frac{\varphi^{(n+1)}(0)}{i(n+1)!\mu_{1}}$,
and the last quantity does exist since $\varphi$ is indefinitely differentiable.
As a byproduct we have
Corollary 2. 2. The moments of $\boldsymbol{F}_{\mathbf{1}}$ are given by

$$
\begin{equation*}
\int x^{k} \mathrm{~d} F_{I}(x):=\mu_{k}\left(F_{I}\right)=\frac{\mu_{k+1}(F)}{(k+1) \mu_{1}(F)} \quad \forall k \geq 0 . \tag{2.2}
\end{equation*}
$$

Proof. $\mu_{k}\left(F_{I}\right)=\frac{\left(\varphi_{I}\right)^{(k)}(0)}{i^{k}}=\lim _{t \rightarrow 0} \frac{\varphi_{I}(t)-1}{i^{k} t^{k} / k!}=\lim _{t \rightarrow 0} \frac{k!\left(\varphi(t)-1-t \mu_{1}\right)}{i^{k+1} t^{k+1} \mu_{1}}=\frac{\mu_{k+1}(F)}{(k+1) \mu_{1}(F)}$.
Now, we study continuity properties of $T$. To begin with, notice that $T$ is not continuous in the weak topology since for any distribution $F$ the sequence $F_{n}=\left(1-n^{-1}\right) F+n^{-1} \delta_{0}$ obviously converges to $F$ but the tails $\left(\underline{F_{n}}\right)_{I}(x)=\frac{\left(1-\frac{1}{n}\right) \int_{x}^{\infty} \underline{F}(t) \mathrm{d} t+\frac{(n-x)_{+}}{n}}{\mu_{1}(F)+1}$ converge to $\frac{\int_{x}^{\infty} \underline{F}(t) \mathrm{d} t+1}{\mu_{1}(F)+1}$ as $n \rightarrow \infty$. The limit function does not vanish at infinity, hence it is not the tail of a distribution from $\boldsymbol{M}$.

However, $T$ is monotonously continuous.
Definition. Let $F$ and $G$ be two distribution on the real line. We say that $F$ is stochastically dominated by $G$, and write $F \prec_{\mathrm{st}} G$ iff $\underline{F} \leq \underline{G}$. (For a survey on stochastic orderings the reader may see [8, 12, 13] and the references therein). We write $F_{n} \uparrow F$ (respectively $\quad F_{n} \downarrow F$ ) iff $F_{n} \Rightarrow F$ and $n \leq n+1 \Rightarrow F_{n} \prec_{\text {st }} F_{n+1}$ (respectively $F_{n+1} \prec_{\mathrm{st}} F_{n}$ ).

Proposition 2.3. If $F_{n}, F \in \boldsymbol{M}$ and $F_{n} \uparrow F\left(\right.$ respectively $\left.F_{n} \downarrow F\right)$, then $T\left(F_{n}\right) \Rightarrow T(F)$.
Proof. Apply Beppo-Levi's theorem: if $\underline{E}_{\underline{-}} \uparrow \underline{F}$, then $\int_{x}^{\infty} \underline{F}_{n}(y) \mathrm{d} y \uparrow \int_{x}^{\infty} \underline{F}(y) \mathrm{d} y$ for any $x$. For $x=0$ we see that $\mu_{1}\left(F_{n}\right) \rightarrow \mu_{1}(F)$. Thus, $\left(F_{n}\right)_{I}$ converges weakly to $F_{I}$.

If we are interested in the possible limits of the sequence $\left(F_{n}\right)_{n}$ defined by (1.3), we should study the fixed points of $T$.

Proposition 2.4. Let $F \in \boldsymbol{M}$. Then $T(F)=F \Leftrightarrow F=\delta_{0}$ or if $F=\operatorname{Exp}(\lambda)$ for some $\lambda>0$.
( $\operatorname{By} \operatorname{Exp}(\lambda)$ we denote the distribution $F$ with tail $\underline{F}(x)=\mathrm{e}^{-\lambda x}$ ).
Proof. Let $F \in \boldsymbol{M}$ be such that $T(F)=F$ and let $\varphi$ be its characteristic function. Let $\mu$ be its expectation. If $\mu=0$, then $F=\delta_{0}$ and of course, $T(F)=F$. Suppose that $\mu>0$. According to Proposition 2.1(iii), $\varphi$ should satisfy the equation $\varphi(t)=\frac{\varphi(t)-1}{i t \mu_{1}} \Leftrightarrow \varphi(t)=\frac{1}{1-i t \mu_{1}}$. But this is the characteristic function of $\operatorname{Exp}(1 / \mu)$. The uniqueness theorem says that $F=\operatorname{Exp}(1 / \mu)$.

After that, we should study the monotonicity of $T$. Say that $T$ is increasing if $F \prec_{\mathrm{st}} G \Rightarrow F \prec_{\mathrm{st}} G$ and decreasing if $F \prec_{\mathrm{st}} G \Rightarrow G \prec_{\mathrm{st}} F$. The fact is that $T$ is not monotonous. Indeed, if $\underline{F}(x)=(1-x / 2)+$ and $\underline{G}(x)=$ $=1_{[0,1)}(x)+(1-x / 2)+$ then $\underline{F} \leq \underline{G}$, but there is no domination between $F_{I}$ and $G_{I}$ : indeed, $0<x<4 / 5 \Rightarrow \underline{F_{1}}(x)<$ $<\underline{G}_{l}(x)$ and $x \geq 4 / 5 \Rightarrow \underline{F}_{l}(x) \geq \underline{G}_{l}(x)$.

However, $T$ has a weaker monotonicity: it is HR - increasing.
Definitions. Suppose that $F \in \boldsymbol{M}$ is absolutely continuous. Then its tail can be written as

$$
\begin{equation*}
\underline{F}(x)=\mathrm{e}^{-\frac{\int_{0}^{x} \lambda(y) \mathrm{d} y}{0}} \tag{2.3}
\end{equation*}
$$

with $\lambda(x)=-\underline{F}^{\prime}(x) / \underline{F}(x)$.
The mapping $\lambda=\lambda_{F}:[0, \infty) \rightarrow[0, \infty]$ defined by (2.3) is called the hazard rate of $F$. We make the convention that if $\underline{F}(x)=0$ then $\lambda_{F}(x)=\infty$ (see [2] or [12]).

Let $F$ and $G \in \boldsymbol{M}_{\text {ac }}$. If $\lambda_{F} \geq \lambda_{G}$ we say that $F$ is HR-dominated by $G$ and write $F \prec_{\mathrm{HR}} G$. It is obvious that $F \prec_{\mathrm{HR}} G \Rightarrow F \prec_{\mathrm{st}} G$. (Indeed, $\underline{F}(x)=\mathrm{e}^{-\iint_{0}^{x} \lambda_{F}(y) \mathrm{d} y} \leq \mathrm{e}^{-\int \lambda^{-x} \lambda_{G}(y) \mathrm{d} y}=\underline{G}(x)!$ ).

If $T$ is an operator from $\boldsymbol{M}_{\text {ac }}$ to $\boldsymbol{M}_{\text {ac }}$ with the property that $F \prec_{\mathrm{HR}} G \Rightarrow T(F) \prec_{\mathrm{HR}} T(G)$, we say that $T$ is HR-increasing.

Proposition 2.5. (i) Let $F \in \boldsymbol{M}$ be have the hazard rate $\lambda$. Then the hazard rate of $F_{I}$ is

$$
\begin{equation*}
\lambda_{I}(x)=\underline{F}(x) / \int_{x}^{\infty} \underline{F}(y) \mathrm{d} y \tag{2.4}
\end{equation*}
$$

(ii). The mapping $T(F)=F_{I}$ is HR-increasing.

Proof. (i) The density of $F_{I}$ is $f_{I}(x)=\underline{F}(x) / \mu(F)$ and its tail is $\underline{F}_{I}(x)=\int_{x}^{\infty} \underline{F}(y) \mathrm{d} y / \mu(F)$. Thus, its hazard rate is their ratio, hence $\lambda_{I}(x)=\underline{F}(x) / \int_{x}^{\infty} \underline{F}(y) \mathrm{d} y$.
(ii) Notice that if $F, G \in \boldsymbol{M}$ are absolutely continuous, then

$$
\begin{equation*}
F \prec_{\mathrm{HR}} G \Leftrightarrow x \mapsto \frac{\underline{F}(x)}{\underline{G}(x)} \text { is non-increasing. } \tag{2.5}
\end{equation*}
$$

Indeed, let $\lambda_{F}$ and $\lambda_{G}$ be the hazard rates of $F$ and $G . F \prec_{H R} G \Leftrightarrow \lambda_{F} \geq \lambda_{G} \Rightarrow \frac{\underline{F}(x)}{\underline{G}(x)}=\int_{\mathrm{e}^{0}\left(\lambda_{G}-\lambda_{F}\right)(y) \mathrm{d} y}^{x}$ is obviously non-increasing. Conversely, if the mapping $x \mapsto \frac{\underline{F}(x)}{\underline{G}(x)}$ is non-increasing, then the mapping $h(x)=\int_{0}^{x}\left(\lambda_{F}-\lambda_{G}\right)(y) \mathrm{d} y$ is non-decreasing, hence its derivative should be non-negative: $\lambda_{F}-\lambda_{G} \geq 0$. So, (2.5) is true. To prove that $T$ is HR-monotonous, Let $F \prec_{H R} G$. According to (2.5) we can write $\underline{F}=\Lambda \underline{G}$ with $\Lambda$ non-increasing. Then $\lambda_{F_{I}}(x)=\underline{F}(x) / \int_{x}^{\infty} \underline{F}(y) \mathrm{d} y=\Lambda(x) \underline{G}(x) / \int_{x}^{\infty} \Lambda(y) \underline{G}(y) \mathrm{d} y$.

We claim that $\lambda_{F_{I}}(x) \geq \lambda_{G_{I}}(x)$. Indeed, the inequality $\Lambda(x) \underline{G}(x) / \int_{x}^{\infty} \Lambda(y) \underline{G}(y) \mathrm{d} y \geq \underline{G}(x) / \int_{x}^{\infty} \underline{G}(y) \mathrm{d} y$ is equivalent to $\int_{x}^{\infty} \Lambda(x) \underline{G}(y) \mathrm{d} y \geq \int_{x}^{\infty} \Lambda(y) \underline{G}(y) \mathrm{d} y$ and the last inequality is obvious.

From the point of view of the hazard rates, there are two interesting classes of distributions from $\boldsymbol{M}_{\mathrm{ac}}$ : the IFRs and the DFRs.

Definition. Let $F \in \boldsymbol{M}_{\mathbf{a c}}$. We write $F \in \mathrm{IFR}$ ( = Increasing Failure Rate) iff $\lambda_{\mathrm{F}}$ is non-decreasing. If $\lambda_{F}$ is non-increasing, then we write $F \in \operatorname{DFR}$ ( $=$ Decreasing Failure rate) [2, 6, 7, 9, 10 or 13].

It happens that the operator $T=(\cdot)_{I}$ preserves these two classes.
Proposition 2.6. $F \in \mathrm{IFR} \Rightarrow F_{I} \in \mathrm{IFR}$ while $F \in \mathrm{DFR} \Rightarrow F_{I} \in \mathrm{DFR}$.
Proof. Suppose that $F \in$ IFR. Let $\lambda$ be its hazard rate. By our assumption, $\lambda$ is non-decreasing. We want to show that the mapping $\lambda_{I}(x)=\underline{F}(x) / \int_{x}^{\infty} \underline{F}(y) \mathrm{d} y$ is increasing, too.

Write $\frac{1}{\lambda_{I}(x)}=\int_{x}^{\infty} \frac{\underline{F}(y)}{\underline{F}(x)} \mathrm{d} y=\int_{0}^{\infty} \frac{F(x+t)}{\underline{F}(x)} \mathrm{d} t=\int_{0}^{\infty} \mathrm{e}^{-\int_{0}^{t} \lambda(x+u) \mathrm{d} u} \mathrm{~d} t$. Let $a<b$ be positive. Then $\lambda(a+u) \leq \lambda(b+u) \forall u$ implies the inequality $\int_{0}^{t} \lambda(a+u) \mathrm{d} u \leq \int_{0}^{t} \lambda(b+u) \mathrm{d} u \quad \forall t>0 \Rightarrow \frac{1}{\lambda_{I}(a)} \geq \frac{1}{\lambda_{I}(b)}$. Thus, $\lambda_{I}$ is non-decreasing hence $F_{I} \in$ IFR. The proof for the DFRs is similar.

## 3. ITERATED INTEGRATED TAIL

Our problem is: when the sequence of measures defined by the recurrence

$$
\begin{equation*}
F_{0}=F, F_{n+1}=T\left(F_{n}\right) \tag{3.1}
\end{equation*}
$$

does have a weak limit? The main help will come from the HR-monotonicity of $T=(\cdot)_{I}$.
Proposition 3.1. If $F \in \mathrm{IFR}$ then $T(F) \prec_{\mathrm{HR}} F$ while if $F \in \mathrm{DFR}$ then $F \prec_{\mathrm{HR}} T(F)$.
$\operatorname{Proof}(\mathbf{i})$. Let $\lambda:[0, \infty) \rightarrow[0, \infty)$ be the hazard rate of $F$ and $\lambda_{I}$ be the hazard rate of $T(F):=F_{I}$. By the definition, we have to prove that if $\lambda$ is non-decreasing then $\lambda(x) \int_{x}^{\infty} \underline{F}(y) \mathrm{d} y \leq \underline{F}(x)$ and if $\lambda$ is non-increasing, then $\lambda(x) \int_{x}^{\infty} \underline{F}(y) \mathrm{d} y \geq \underline{F}(x) . \operatorname{As} \underline{F}(x)=\mathrm{e}^{-\iint_{0}^{x} \lambda(t) \mathrm{d} t}$, the claimed inequalities become $\lambda(x) \int_{x}^{\infty} \mathrm{e}^{-\int_{x}^{y} \lambda(t) \mathrm{d} t} \mathrm{~d} y \leq 1$ (if $\lambda$ is non-decreasing) and $\lambda(x) \int_{x}^{\infty} \mathrm{e}^{-\int_{x}^{y} \lambda(t) \mathrm{d} t} \mathrm{~d} y \geq 1$ (if $\lambda$ is non-increasing).

In the first case $\int_{x}^{y} \lambda(t) \mathrm{d} t \geq \lambda(x)(y-x)$ and in the second one $\int_{x}^{y} \lambda(t) \mathrm{d} t \geq \lambda(x)(y-x)$. Thus, in the first case $\lambda(x) \mathrm{e}^{-\int_{x}^{y} \lambda(t) \mathrm{d} t} \leq \lambda(x) \mathrm{e}^{-\lambda(x)(y-x)} \Rightarrow \lambda(x) \int_{x}^{\infty} \mathrm{e}^{-\int_{x}^{y} \lambda(t) \mathrm{d} t} \mathrm{~d} y \leq \int_{x}^{\infty} \lambda(x) \mathrm{e}^{-\lambda(x)(y-x)} \mathrm{d} y=\int_{0}^{\infty} \lambda(x) \mathrm{e}^{-\lambda(x) t} \mathrm{~d} t=1 \quad$ while in the second one the converse inequality holds.

Corollary 3.2. If $F \in \operatorname{IFR}$ then the sequence $F_{n}=T^{n}(F)$ is HR-decreasing while if $F \in \mathrm{DFR}$ the sequence is HR -increasing.

Proof. Obvious from Proposition 3.1.
Corollary 3.3. If $F \in \mathrm{IFR}$, then $T^{n}(F)$ has a limit, G. If $F \in \mathrm{DFR}$ then the sequence of non-increasing right continuous functions $\left(\underline{T^{n}(F)}\right)_{n}$ has a limit $\underline{G}$ too. If $\underline{G}(\infty)=0$, then $T^{n}(F)$ weakly converges to $G$.

Proof. Obvious. If $F_{n}=T^{n}(F)$ then the sequence of the tails $\left(\underline{F}_{n}\right)_{n}$ is monotonic - either increasing, or decreasing.

## Proposition 3.4.

I. (The IFR case). Let $F \in$ IFR have the hazard rate $\lambda$.
(i)If $\lambda(\infty)<\infty$ then $\lim _{n \rightarrow \infty} T^{n}(F)=\operatorname{Exp}(\lambda(\infty))$.
(ii) If $\lambda(\infty)=\infty$ then $\lim _{n \rightarrow \infty} T^{n}(F)=\delta_{0}$.
II. (The DFR case). Let $F \in$ DFR have the hazard rate $\lambda$.
(i)If $\lambda(\infty)>0$ then $\lim _{n \rightarrow \infty} T^{n}(F)=\operatorname{Exp}(\lambda(\infty))$.
(ii) If $\lambda(\infty)=0$ then the limit does not exist anymore.

Remark. In case II(ii) we could say that the limit is $\delta_{\infty}$, but that makes little sense for distribution.
Proof.
I. Let $\lambda_{n}$ be the hazard rate of $F_{n}=T^{n}(F)$. Then

$$
\begin{equation*}
\lambda_{n+1}(x)=\underline{F_{n}}(x) / \int_{x}^{\infty} F_{n}(y) \mathrm{d} y . \tag{3.2}
\end{equation*}
$$

(i). The sequence $\left(\lambda_{n}\right)_{n}$ is non-decreasing. Therefore, it has a limit, $\lambda^{*}$. Let $F^{*}$ be the distribution with tail $\underline{F}^{*}(x)=\mathrm{e}^{-\int_{0}^{x} \lambda^{*}(t) \mathrm{d} t}$. As $\lambda_{n} \rightarrow \lambda^{*}$ monotonously, $\underline{F}_{n}(x)$ converges to the tail $\underline{F^{*}}(x)$. We claim that $F^{*}=\operatorname{Exp}(\lambda(\infty))$. The first step is to check that $\lambda^{*}$ must be a constant. Anyway, the fact that $\lambda(0) \leq \lambda(x) \leq$ $\lambda(\infty)$ means that $\operatorname{Exp}(\lambda(\infty)) \prec_{H R} F \prec_{\mathrm{HR}} \operatorname{Exp}(\lambda(0))$. By Proposition 2.5, $T$ is HR-monotonic hence $\mathrm{T}(\operatorname{Exp}(\lambda(\infty))) \prec_{H R} T(F) \prec_{H R} T(\operatorname{Exp}(\lambda(0))$. By Proposition 2.4, the exponential distributions are fixed points for $T$. Therefore, $\operatorname{Exp}(\lambda(\infty)) \prec_{H R} F_{1} \prec_{H R} \operatorname{Exp}(\lambda(0)$. By induction, we see that

$$
\begin{equation*}
\operatorname{Exp}(\lambda(\infty)) \prec_{\mathrm{HR}} F_{n} \prec_{\mathrm{HR}} \operatorname{Exp}(\lambda(0) \tag{3.3}
\end{equation*}
$$

Letting $n \rightarrow \infty$, we get $\operatorname{Exp}(\lambda(\infty)) \prec_{\mathrm{HR}} F^{*} \prec_{\mathrm{HR}} \operatorname{Exp}(\lambda(0)$. Or, in terms of hazard rates,

$$
\begin{equation*}
\lambda(0) \leq \lambda^{*}(x) \leq \lambda(\infty) \forall x \geq 0 \tag{3.4}
\end{equation*}
$$

Proposition 2.3 says that $T$ is monotonically continuous: if $F_{n} \Rightarrow F^{*}$ monotonically, then $T\left(F_{n}\right) \Rightarrow$ $T\left(F^{*}\right)$. On the other hand, $T\left(F_{n}\right)=F_{n+1}$ converges to $F^{*}$ hence $F^{*}=T\left(F^{*}\right)$. According to Proposition 3(iii), the only fixed points of $T$ are the exponential distributions. Thus $\lambda^{*}=$ const. As $\lambda^{*} \geq \lambda$ (recall that the sequence $\left(\lambda_{n}\right)$ is increasing !), $\lambda^{*} \geq \lambda(x)$ for any $x \geq 0$. Letting $x \rightarrow \infty, \lambda^{*} \geq \lambda(\infty)$. On the other hand, inequality (3.4) points out that $\lambda^{*} \leq \lambda(\infty)$.
(ii). We reason as before: $\lambda^{*} \geq \lambda(x) \forall x \geq 0 \Rightarrow \lambda^{*} \geq \lambda(\infty)$ i.e. $\lambda^{*}=\infty$. The limit is $\delta_{0}$.

Proof for the DFR case. Now, the sequence $\left(\lambda_{n}\right)_{n}$ is decreasing. As in the proof of $\mathbf{I}$, the limit $\lambda^{*}$ must be a constant such that $\lambda(\infty) \leq \lambda^{*} \leq \lambda(0)$ and $\lambda^{*} \leq \lambda(x) \forall x$. If this constant is equal to 0 , there is no limit among distributions from $\boldsymbol{M}$ since all the mass vanishes. The limit, $G$, provided that it does exist, should dominate all the distributions $\operatorname{Exp}(\lambda)$, meaning that $\underline{G}(x) \geq e^{-\lambda x}$ for any $\lambda \Rightarrow \underline{G}(x)=1$ for any $x$, or $G=\delta_{\infty}$.

Now we prove our main result.
Theorem 3.5. Let $F \in \boldsymbol{M}_{\mathrm{ac}}$ be a distribution such that the limit $\lambda:=\lambda_{F}(\infty)$ does exist. Then

- if $\lambda \in(0, \infty)$ then $T^{n}(F) \Rightarrow \operatorname{Exp}(\lambda)$;
- if $\lambda=\infty$ then $T^{n}(F) \Rightarrow \delta_{0}$;
- if $\lambda=0$ then $T^{n}(F)$ diverges. Precisely, $\underline{T^{n}(F)}(x) \rightarrow 1$ as $n \rightarrow \infty$.

Proof. Let us define $\lambda_{*}(x)=\inf _{y \geq 0} \lambda_{F}(x+y)$ and $\lambda^{*}(x)=\sup _{y \geq 0} \lambda_{F}(x+y)$. Consider the first case, $\lambda \in(0, \infty)$.Then $\lambda_{*}$ is non-decreasing and $\lambda^{*}$ is non-decreasing. Moreover, $\lambda_{*}(\infty)=\lambda^{*}(\infty)=\lambda$ and

$$
\begin{equation*}
\lambda_{*}(x) \leq \lambda_{F}(x) \leq \lambda^{*}(x) \forall x \geq 0 \tag{3.5}
\end{equation*}
$$

Let $F^{*}, F_{*}$ be distributions from $\boldsymbol{M}_{\mathrm{ac}}$ such that $\lambda_{F^{*}}=\lambda^{*}$ and $\lambda_{F_{*}}=\lambda_{*}$. Then

$$
\begin{equation*}
F_{*} \in \mathrm{IFR}, F^{*} \in \mathrm{DFR} \text { and } F^{*} \prec_{\mathrm{HR}} F \prec_{\mathrm{HR}} F_{*} \tag{3.6}
\end{equation*}
$$

As $T$ is HR-increasing, we infer from (3.6) that

$$
\begin{equation*}
T^{n}\left(F^{*}\right) \prec_{\mathrm{HR}} T^{n}(F) \prec_{\mathrm{HR}} T^{n}\left(F_{*}\right) . \tag{3.7}
\end{equation*}
$$

According to Proposition (3.4), $T^{n}\left(F^{*}\right) \Rightarrow \operatorname{Exp}\left(\lambda^{*}(\infty)\right)=\operatorname{Exp}(\lambda)$. In the same way, $T^{n}\left(F_{*}\right) \Rightarrow \operatorname{Exp}\left(\lambda_{*}(\infty)\right)=$ $=\operatorname{Exp}(\lambda)$. Thus, both sequences $\left(T^{n}\left(F^{*}\right)\right)_{n}$ and $\left(T^{n}\left(F_{*}\right)\right)$ have the same limit. But clearly

$$
\begin{equation*}
G_{n} \prec_{\mathrm{st}} F_{n} \prec_{\mathrm{st}} H_{n}, G_{n} \Rightarrow F, H_{n} \Rightarrow F \tag{3.8}
\end{equation*}
$$

implies that $\left(F_{n}\right)_{n}$ is convergent and $F_{n} \Rightarrow F$. Indeed, (3.8) means $\underline{G}_{n} \leq \underline{F}_{\underline{n}} \leq \underline{H}_{\underline{n}}, \underline{G}_{\underline{n}} \rightarrow \underline{F}, \underline{H_{\underline{n}}} \rightarrow \underline{F}$ as $n \rightarrow \infty$.

Therefore, $\left(T^{n}(F)\right)_{n}$ must converge to the same limit, namely $\operatorname{Exp}(\lambda)$.
Consider now the case $\lambda=\infty$. Then $T^{n}\left(F_{*}\right) \Rightarrow \delta_{0} \Leftrightarrow$ the tails of $T^{n}\left(F_{*}\right)$ converge to 0 . The fact that $T^{n}(F) \prec_{\mathrm{st}} T^{n}\left(F_{*}\right)$ implies that the tails of $T^{n}(F)$ converge to 0 , too, hence $T^{n}(F) \Rightarrow \delta_{0}$.

The last case is $\lambda=0$. Then the distribution $T^{n}(F)$ dominates the DFR distributions $T^{n}\left(F^{*}\right)$. Their mass vanishes to infinity, so the same must happen with the mass of $T^{n}(F)$.

Do we have a clue to find the limit when we are not able to compute the hazard rate $\lambda_{F}$ ? The answer is YES, we have. If we are able to prove somehow that $\lambda_{F}(\infty)$ does exist. We should look at the mgf of $F$.

Proposition 3.6. Let $F \in \boldsymbol{M}_{\text {ac }}$ and $\boldsymbol{m}(t)=\int \mathrm{e}^{t x} \mathrm{~d} F(x)=1+t \int_{0}^{\infty} \mathrm{e}^{t x} \underline{F}(x) \mathrm{d} x$ be its $m g f$.
Let $t^{*}=\sup \{t \in \mathfrak{R}: \boldsymbol{m}(t)<\infty\}$. If $\lambda_{F}(\infty)$ does exist, then $\lambda_{F}(\infty)=t^{*}$.
Proof. If $t^{*}>0$, then $\boldsymbol{m}(t)<\infty \Leftrightarrow \int_{0}^{\infty} \mathrm{e}^{t x} \underline{F}(x) \mathrm{d} x<\infty$. Let $\lambda=\lambda_{F}$. Write $\underline{F}(x)=\mathrm{e}^{-\int_{0}^{x} \lambda(y) \mathrm{d} y}$. Then

$$
\int_{0}^{\infty} \mathrm{e}^{t x} \underline{F}(x) \mathrm{d} x=\int_{0}^{\infty} \mathrm{e}^{t x-\int_{0}^{x} \lambda(y) \mathrm{d} y} \mathrm{~d} x=\int_{0}^{\infty} \mathrm{e}^{0} \int^{x}(t-\lambda(y)) \mathrm{d} y \quad \mathrm{~d} x
$$

Suppose that $t<\lambda(\infty)$. There exists some $\varepsilon>0$ and some $a>0$ such that $y>a \Rightarrow \lambda(y)>t-\varepsilon \Leftrightarrow$ $t-\lambda(y) \leq-\varepsilon$. For $x>a$ we have

$$
\int_{0}^{x}(t-\lambda(y)) \mathrm{d} y=\int_{0}^{a}(t-\lambda(y)) \mathrm{d} y+\int_{a}^{x}(t-\lambda(y)) \mathrm{d} y=C(a)+\int_{a}^{x}(t-\lambda(y)) \leq C(a)-\varepsilon(x-a)=K-\varepsilon x
$$ It follows that $\underline{F}(x) \leq A \mathrm{e}^{-\varepsilon x}$ for some $A>0$ hence $\int_{0}^{\infty} \mathrm{e}^{t x} \underline{F}(x) \mathrm{d} x<\infty$.

We thus proved that $t<\lambda(\infty) \Rightarrow t \leq t^{*}$ hence $\lambda(\infty) \leq t^{*}$.
On the other hand, if $t>\lambda(\infty)$, we can find some $a>0$ and $\varepsilon>0$ such that $y>a \Rightarrow t-\lambda(y) \geq \varepsilon$ and the same reasoning as before yields $\mathrm{e}^{t x} \underline{F}(x) \geq B \mathrm{e}^{\varepsilon x}$ for some constant $B$. Obviously, this means that

$$
\int_{0}^{\infty} e^{t x} \underline{F}(x) \mathrm{d} x=\infty \Leftrightarrow t \geq t^{*}
$$

Thus, $t^{*}=\lambda(\infty)$.
In the same way one can proves the exception cases. If $\lambda(\infty)=\infty$ then $\int_{0}^{\infty} \mathrm{e}^{t x} \underline{F}(x) \mathrm{d} x<\infty$ for every $t$, hence $t^{*}=\infty$ and if $\lambda(\infty)=0$ then $t^{*}=0$.

If we agree to denote the measure $\delta_{\infty}$ by $\operatorname{Exp}(0)$ (the sense is that the tail of this measure is equal to 1 ), then we can restate Theorem 3.5. as

Corollary 3.7. Let Let $F \in \boldsymbol{M}_{\mathrm{ac}}$ and $\boldsymbol{m}(t)$ its mgf. Let $t^{*}$ defined as in Proposition 3.6. Suppose that the limit $\lambda(\infty)$ does exist. Then $T^{n}(F)$ converges to $\operatorname{Exp}\left(t^{*}\right)$.

Remark. We could call a distribution $F$ short tailed if $t^{*}=\infty$, medium tailed if $t^{*} \in(0, \infty)$ and long tailed if $t^{*}=0$. This agrees with the various definitions for long tailed distributions from [1, 4, 7].

Example 3.8. The Poisson distribution $F=\operatorname{Poisson}(\lambda)$ has the $\operatorname{mgf} \boldsymbol{m}(t)=\mathrm{e}^{\lambda\left(\mathrm{e}^{t}-1\right)}$. As $t^{*}=\infty, T^{n}(F)$ should converge to $\delta_{0}$. $F$ is not absolutely continuous, hence we cannot speak about its hazard rate. But $F_{1}$ has the density $f=\sum_{k=0}^{\infty} q_{k} 1_{[k, k+1)}$ with $q_{k}=\underline{F}(k) / \lambda=\sum_{j=k+1}^{\infty} \frac{\lambda^{j-1}}{j!} \mathrm{e}^{-\lambda}$ and the tail $\underline{F}_{1}(x)=\int_{x}^{\infty} f(y) \mathrm{d} y$.

The ratio $\lambda(x)=f(x) / \underline{F_{1}}(x)$ is increasing on $[k, k+1)$. We claim that $\lambda(\infty)=\infty$. Indeed, it is enough to prove that $\lambda(k) \rightarrow \infty$ as $k \rightarrow \infty$. We have

$$
\begin{gathered}
\lambda(k)=q_{k} /\left(q_{k+1}+q_{k+2}+\ldots\right)=\left(\frac{\lambda^{k}}{(k+1)!}+\frac{\lambda^{k+1}}{(k+2)!}+\ldots .\right) /\left(\frac{\lambda^{k+1}}{(k+2)!}+2 \frac{\lambda^{k+2}}{(k+3)!}+3 \frac{\lambda^{k+3}}{(k+4)!}+\ldots\right)= \\
=\frac{k+2}{\lambda}\left(1+\frac{\lambda}{k+2}+\frac{\lambda^{2}}{(k+2)(k+3)}+\ldots .\right)\left(1+\frac{2 \lambda}{(k+3)}+\frac{3 \lambda^{2}}{(k+3)(k+4)}+\ldots\right)
\end{gathered}
$$

which converges to $\infty$ as $k \rightarrow \infty$. Thus if $F=\operatorname{Poisson}(\lambda)$, then $T^{n}(F) \rightarrow \delta_{0}$.
Example 3.9. The lognormal distribution belongs to the class DFR and $t^{*}=0$. This means that the limit does not exist. The distribution $\operatorname{Gamma}(v, \lambda)$ are IFR distributions (see, for instance $[5,6,10]$ ) hence the limit is $\operatorname{Exp}(\lambda)$. An interesting example is the inverse Gaussian distribution $\operatorname{IG}(\mu, \lambda)$ which naturally arises from first passage problems for Brownian motion (see for instance[11]). This time the hazard rate $\lambda$ is not monotonous: these distributions are neither IFR nor DFR. Its density is $f(x)=\sqrt{\frac{\lambda}{2 \pi x^{3}}} \mathrm{e}^{-\frac{\lambda(x-\mu)^{2}}{2 x \mu^{2}}}$ and its tail is $\underline{F}(x)=1-\left(\Phi\left(-\frac{\sqrt{\lambda}}{\sqrt{x}}+\frac{\sqrt{\lambda}}{\mu} \sqrt{x}\right)+\mathrm{e}^{2 \frac{\lambda}{\mu}} \Phi\left(-\frac{\sqrt{\lambda}}{\sqrt{x}}-\frac{\sqrt{\lambda}}{\mu} \sqrt{x}\right)\right)$. Then $\lambda(\infty)=\lambda(\infty)=\frac{\lambda}{2 \mu^{2}}$ (use twice
L'Hospital rule).
Open problem. We still do not know at this stage if it is possible that $\left(T^{n}(F)\right)_{n}$ have no limit at all in other cases than the one stated in Proposition 3.4 II(ii). In the stated case it is true that the sequence of distributions $\left(T^{n}(F)\right)_{n}$ has no limit because all the mass vanishes; however the sequence of tails $\left(\underline{T^{n}(F)}\right)_{n}$ converges to 1 . Is it possible that this sequence of tails have no limit?

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