Recall: Exponential distribution: $X \sim \varepsilon_{x p}(x)$

$$
p d f \quad p(x)= \begin{cases}\lambda e^{-\lambda x}, & x \geq 0 \\ 0, & x<0\end{cases}
$$

$$
C D F \quad F(x)=\left\{\begin{array}{cc}
1-e^{\lambda x}, & x \geq 0 \\
0, & x<0 .
\end{array}\right.
$$

Properties: anevoryless: only real $\geq 0$ 1.v. with this property

- failure rate function is constant $=\lambda$
- Minimuen of 2 independent Exp riv.
$X_{1} \sim \varepsilon_{x p}\left(\lambda_{1}\right), \quad X_{2} \sim \varepsilon_{x p}\left(\lambda_{2}\right) \quad$ independent

$$
x=\min \left(x_{1}, x_{2}\right), \quad x \sim ?
$$

(Remark: in the example with the 2 tellers, $X$ would bethe $1^{\text {st }}$ time one of the 2 customers to leave).
Idea: look at the event $E=\{X>x\}$.
One can show $X>x \Leftrightarrow X_{1}>x$ and $X_{2}>x$

$$
\Rightarrow E=\left\{x_{1}>x_{1} x_{2}>x\right\} \quad(x \geq 0) .
$$

So, $\quad P(X>x)=P\left(X_{1}>x, X_{2}>x\right)=P\left(X_{1}>x\right) P\left(X_{2}>x\right)$

$$
x_{1} \text { index. of } x_{2}
$$

$$
\begin{aligned}
& =e^{-\lambda_{1} x} e^{-\lambda_{2} x}=e^{-\left(\lambda_{1}+\lambda_{2}\right) x} . \\
& \Rightarrow F_{x}(x)=1-e^{-\left(\lambda_{1}+\lambda_{2}\right) x} \quad \text { and } \quad X \sim \varepsilon_{x p}\left(\lambda_{1}+\lambda_{2}\right)!
\end{aligned}
$$

We can easily generalize.
Proposition: Let $X_{1}, \ldots, X_{n}$ be $n$ independent riv. $X_{i} \sim \varepsilon_{x_{p}}\left(\lambda_{i}\right)$.
Then, $X=\min \left(X_{1}, \ldots, X_{n}\right) \sim \operatorname{Exp}\left(\lambda_{1}+\cdots+\lambda_{n}\right)$.

Example: Recall the previous example, with 3 customers at the bank, and 2 tellers. What is the expected time suit all 3 customers have left?
Solution: Time until $1^{\text {st }}$ leaves is min of 2 indep Exp $(\lambda)$, so is $E_{x p}(2 \lambda)$ with mean $\frac{1}{2 \lambda}$.

- Then, dock effectively restarts, but now theure are 2 customers, so first leaves after mean time $\frac{1}{2 \lambda}$
- Clock zostarts, and last customer leaves after mean tine $\frac{1}{\lambda}$.
$\Rightarrow$ Total mean fine is: $\frac{1}{2 \lambda}+\frac{1}{2 \lambda}+\frac{1}{\lambda}=\frac{2}{\lambda}$.
- Probability that $X_{1}<X_{2}$, where $X_{i} \sim \varepsilon_{x p}\left(\lambda_{i}\right)$.

Proposition: If $x_{1}, x_{2}$ are ndependont $\varepsilon_{x p}\left(\lambda_{i}\right)$, then

$$
P\left(X_{1}<x_{2}\right)=\frac{\lambda_{1}}{\lambda_{1}+\lambda_{2}} .
$$

Prog f: $P\left(x_{1}<x_{2}\right)=\iint_{x_{1}<x_{2}} \lambda_{1} e^{-\lambda_{1} x_{1}} \lambda_{2} e^{-\lambda_{2} x_{2}} d x d x_{2}$

$$
\begin{aligned}
& =\int_{0}^{+\infty} \int_{0}^{x_{2}} \lambda_{1} \lambda_{2} e^{-\lambda_{1} x_{1}} e^{-\lambda_{2} x_{2}} d x_{2} d x_{2} \\
& =\int_{0}^{+\infty} \lambda_{2} e^{-\lambda_{2} x_{2}} \underbrace{\int_{0}^{x_{2}} \lambda^{-\lambda_{1} x_{1}} d x_{1} d x_{2}}_{=p\left(x_{1} \leq x_{2}\right)}=1-e^{-\lambda_{1} x_{2}} \\
& =\int_{0}^{+\infty} \lambda_{2} e^{-\lambda_{2} x_{2}}\left(1-e^{-\lambda_{1} x_{2}}\right) d x_{2} \\
& =\int_{0}^{+\infty} \lambda_{2} e^{-\lambda_{2} x_{2}}-\int_{0}^{+\infty} \lambda_{2} e^{-\left(\lambda_{1}+\lambda_{2}\right) x_{2}} d x_{2}
\end{aligned}
$$

$$
=1-\frac{\lambda_{2}}{\lambda_{1}+\lambda_{2}}=\frac{\lambda_{1}}{\lambda_{1}+\lambda_{2}} .
$$

- Sum of independent exponential riv.

Suppose that $X, Y$ are independent contimons $v, v$, and let $z=x+y$. Then, $F_{z}(z)=P(z \leq z)=\iint_{x+y \leqslant z} f_{x, y}(x, y) d x d y$

$$
\begin{aligned}
& =\iint_{x+y \leq z} f_{x}(x) f_{y}(y) d x d y \\
& =\int_{-\infty}^{+\infty} f_{y}(y) \underbrace{\left.\int_{-\infty}^{z-y} f_{x}(x) d x\right)}_{F_{x}(z-y)} d y \\
& =\int_{-\infty}^{\infty} f_{y}(y) F_{x}(z-y) d y \\
& \Rightarrow f_{z}(z)=F_{z}^{\prime}(z)=\int_{-\infty}^{\infty} f_{x}(z-y) f_{y}(y) d y
\end{aligned}
$$

$$
=\text { " } f_{x} * f_{y} \text { " the convolution of } f_{x}
$$ and $f_{y}$

$\rightarrow$ let $X_{1} \sim \operatorname{Exp}_{p}\left(\lambda_{1}\right)$ and $X_{2} \sim \varepsilon_{x p}\left(\lambda_{2}\right)$.
Then, $f_{x_{1}+x_{2}}(t)=\left(f_{x_{1}}+f_{x_{2}}\right)(t)=\int_{-\infty}^{\infty} f_{x_{1}}(t-s) f_{x_{2}}(s) d s$

$$
=\int_{0}^{t} f_{x_{1}}(t-s) f_{x_{2}}(s) d s \quad\left(\text { because } f_{x_{i}}(u)=0 \text { for } u \leq 0\right)
$$

$$
\begin{aligned}
& =\int_{0}^{t} \lambda_{1} e^{-\lambda_{1}(t-s)} \lambda_{2} e^{-\lambda_{2} s} d s \\
& =\lambda_{1} \lambda_{2} e^{-\lambda_{1} t} \int_{0}^{t} e^{-\left(\lambda_{2}-\lambda_{1}\right) s} d s \\
& =\lambda_{1} \lambda_{2} e^{-\lambda_{1} t} \frac{\left(1-e^{-\left(\lambda_{2}-\lambda_{1}\right) t}\right)}{\lambda_{2}-\lambda_{1}} \text { with } \lambda_{2} \neq \lambda_{1} \\
& \Rightarrow f_{x_{1}+x_{2}}(t)=\frac{\lambda_{1}}{\lambda_{1}-\lambda_{2}} \lambda_{2} e^{-\lambda_{2} t}+\frac{\lambda_{2}}{\lambda_{2}-\lambda_{1}} e^{-\lambda_{1} t}
\end{aligned}
$$

$\rightarrow$ This generalizes by induction (see Ross 5.2.4) to

$$
f_{x_{1}+\cdots+x_{n}}(t)=\sum_{i=1}^{n} c_{i, n} \lambda_{i} e^{-\lambda_{i} t}
$$

where $\quad C_{i, n}=\underset{j \neq i}{\pi} \frac{\lambda_{j}}{\lambda_{j}-\lambda_{i}}$

