Application:
Occupancy Problem Drop $m$ balls into $n$ bins independently at random. What is the distribution of the fraction of empty bins?

- \#(cmpty bins $): S_{n}=X_{1}+\cdots+X_{n}$ where $x_{i}=\left\{\begin{array}{l}1 \\ 0,\end{array}\right.$ if bin $i$ is empty $X_{i} \sim \operatorname{Ber}\left((1-1 / n)^{m}\right)$ NOT independent, but

$$
\text { - } \mathbb{E} S_{n}=\sum_{i=1}^{n} \mathbb{E} X_{i}=n \mathbb{P}\left\{X_{1}=1\right\}=n\left(\frac{n-1}{n}\right)^{m}
$$



Asymptotic behavior? let $m=m(n), \quad \frac{m}{n} \rightarrow \lambda$ as $n \rightarrow \infty$

$$
\Rightarrow \frac{\mathbb{E} S_{n}}{n}=\left(1-\frac{1}{n}\right)^{\lambda n} \rightarrow e^{-\lambda} . \quad(\text { decays fast! })
$$ "Oversampling factor"

$\xrightarrow{\text { TH }} \quad \frac{S_{n}}{n} \rightarrow e^{-\lambda}$ in probability
Prof: By WLLN (remark P.78), it suffices to check that $x_{i}$ are negatively correlated Heuristically, this is true: an empty bin increases other bins to be full. Formally:

$$
\begin{aligned}
\operatorname{Cov}\left(x_{i}, x_{j}\right)= & \underbrace{\mathbb{E}\left[x_{i} x_{j}\right]}_{\|}- \\
& -\underbrace{\left(\frac{n-2}{n}\right)^{m}}_{\|} \stackrel{?}{\left.\stackrel{E}{<}\left(\frac{n-1}{n}\right)^{2 m}\right] \cdot \mathbb{E}}\left[x_{j}\right] \\
& 1-\frac{2}{n}<\stackrel{1}{<}\left(1-\frac{1}{n}\right)^{2}=1-\frac{2}{n}+\frac{1}{n^{2}} \text {. True! }
\end{aligned}
$$

Remark The wIN does not apply directly since the distributions of each $x_{\text {: }}$ depend on $n \quad\left(\Rightarrow\right.$ we have a "triangular array" of $X_{i}^{(n)}$ ) But the proof of WLCN works fine. $\longrightarrow \mathrm{KW}$.

Example: Approximate Caratheodory Theorem. [see my HDD book]
Def The convex hull of a set $T \subset \mathbb{R}^{d}$, denoted $\operatorname{conv}(T)$, is the smallest convex set that contains $T$. Equivalently,

$$
x \in \operatorname{comv}(T) \Leftrightarrow x=\sum_{i=1}^{m} \lambda_{i} z_{i} \text { for some } \lambda_{i} \geq 0, \sum_{i=1}^{m} \lambda_{i}=1, z_{i} \in T
$$

Convex combination
The (Caratheodory) $m=d+1$ suffices
and is optimal in general


But if we allow to approximate $x$, we get a dramatic improvement:


Thu (Approximate Caratheodory) let $T$ cunit ball of $\mathbb{R}^{d}$ Then $\forall x \in \operatorname{cons}(T), \forall k \in \mathbb{N} \quad \exists z_{1}, \ldots, z_{n} \in T$ :

$$
\left\|x-\frac{1}{n} \sum_{i=1}^{n} z_{i}\right\|_{2} \leq \frac{1}{\sqrt{n}}
$$

- Dimension-free; does not depend on geometry of $T$ !

Proof ("Empirical method", B. Maurey)

- Fix $x \in \operatorname{com}(T)$ express it as a convex combination

$$
x=\sum_{i=1}^{m^{\text {op}}} \lambda_{i} z_{i}, \lambda_{i} \geq 0, \sum_{i=1}^{m} \lambda_{i}=1, \quad z_{i} \in T
$$

- Interpret $\lambda_{i}$ as probabilities, the sum as expectation let r.vector $Z$ take value $z_{i}$ with prob. $\lambda_{i}$

$$
\Rightarrow \quad x=\mathbb{E} Z
$$

- Consider indep copies $Z_{1}, Z_{2}, \ldots$ of $Z$.

$$
\text { SLLN: } \frac{1}{n} \sum_{i=1}^{n} Z_{i} \rightarrow \mathbb{E} Z=x \quad \text { ass. }
$$

- Error:

Analog of $\operatorname{Var}($ sum $)=\operatorname{sum}(\operatorname{Variances})$ in $R^{d}(D \mid r)$

$$
\begin{aligned}
& \stackrel{\downarrow}{n^{2}} \sum_{i=1}^{\mathbb{E}\left\|Z_{i}-\mathbb{E} Z\right\|_{1}^{2} \|_{2}^{2}} \\
& =\frac{1}{n} \mathbb{E} \| Z-\mathbb{E} Z_{2}^{2} \\
& \text { analog of } \operatorname{Var}(z)=\mathbb{E} Z \|^{2}-c=\frac{1}{n}(\underbrace{-\|}_{\hat{1}_{\text {(arm.) }}^{\mathbb{E}\|z\|^{2}}-\|\mathbb{E} z\|_{2}^{2}}) \leq \frac{1}{n}
\end{aligned}
$$

$$
{ }^{\mathbb{E}}\|Z-\mathbb{E} Z\|_{2}^{2} \text { analog of } \operatorname{Var}(Z)=\mathbb{E} Z^{2}-(\mathbb{E} Z)^{2} \quad \text { (D rI) }
$$

- $\Rightarrow \exists$ realization of the riv's $z_{1}, \ldots, z_{n}$ s.t.

$$
\left\|x-\frac{1}{n} \sum_{i=1}^{n} z_{i}\right\|_{2}^{2} \leq \frac{1}{n} \quad \text { since } z_{i} \in T, \quad Q E D
$$

Application: polytopes with few vertices have exponentially small volume:
TuM [Carl-Pajor'88] unit Euclidean Pall Let $P \subset B$ polytope with $m$ vertices
Then $\frac{\operatorname{Vol}(P)}{\operatorname{Vol}(B)} \leq\left(3 \sqrt{\frac{\log m}{d}}\right)^{d}$.

$$
2^{-d} \text { if } m<\exp (c d)
$$



Proof

- $P \subset \operatorname{conv}(T)$ where $T=\{$ vertices of $P\}<B$.
- A.C.T $\Rightarrow$
$\forall x \in P<\operatorname{con}(T)$ is within distance $\frac{1}{\sqrt{n}}$
from some point in the set

$$
\mathcal{N}:=\left\{\frac{1}{n} \sum_{i=1}^{n} x_{i}: x_{i} \in T\right\}
$$

$\Rightarrow \forall x \in P$ is covered $B$ a ball of radius $\frac{1}{\sqrt{n}}$ and center $\in \mathbb{N}$. The number of such balls is

$$
|\mathcal{N}| \leq m^{n} \quad\left(\begin{array}{l}
\text { \#ays to choose } n \text { elements } x_{i} \\
\text { from the set } T \text { of } m \text { elements, } \\
\text { with repetition }
\end{array}\right)
$$

$\Rightarrow \underline{P}$ can be covered by $m^{n}$ upies of $\frac{1}{\sqrt{n}} B$.

- Comparing volumes $\Rightarrow v_{0 l}(P) \leq m^{n} V_{0} l\left(\frac{1}{\sqrt{n}} B\right)=m^{n}\left(\frac{1}{\sqrt{n}}\right)^{d} V_{0} l(B)$

$$
\frac{V_{d}(P)}{V_{d}(B)} \leq \frac{m^{n}}{n^{d / 2}} \leq\left(\sqrt[3]{\frac{\log m}{d}}\right)^{d}
$$

(optinize $n$ : choose $n=\frac{d}{2 \log m}$ )

Remarks
(1) A slightly more accurate count yields the bound $\left(C \sqrt{\frac{\log (m / d)}{d}}\right)^{d}$.
(2) It is optimal, attained by a candom poly tope $p=\operatorname{conv}\left\{x_{1}, \ldots, x_{m}\right\}$
where $x_{i}=$ indep. random pts on the unit sphere [Datnis-Giannopoulos-Tsolomitis'2003, 2009]

- see next page
(3) "Hyperbolic intuition"
for $\delta:=3 \sqrt{\frac{\log m}{d}}$, Thu says: ting ball!


$$
\operatorname{Vol}(P) \leq \delta^{d} \operatorname{Vol}(B)=\operatorname{Vol}(\delta B)
$$

Thus the picture "actually" looks like this, even though it violates convexity.
V.Milman's "hyperbolic intuition"

(4) A "blind spider" experiment:

- A random walk will stay in the "core" $\delta B$, will not find the "tentacles".
- The spider can't tell the polytgpe from the ball $\delta B$.
- Bad for algorithms (MCMC)

