Transfer of $x^{2}$-contraction to $D_{k c}$ contraction

- Two approaches:
* Entropic Independence " "tight" transfer
* Entropy Factorization a "loose" transfer which ends up OK in many apps
[A-Sain-Koehter-Pham-Vworg' 21]
- Entropic Independence Approach:

If $\lambda * \mu$ has $\lambda_{2}\left(D_{k \rightarrow 1} U_{1 \rightarrow k}\right) \leqslant \frac{C}{k}$ for every $\lambda \in \mathbb{R}_{>0}^{n}$, then

$$
\begin{aligned}
& \qquad D_{k L}\left(\nu D_{k \rightarrow 1} \| \mu D_{k \rightarrow 1}\right) \leqslant \frac{C}{k} \\
& \text { external } \rightarrow \lambda * \mu(S):=\mu(S) \prod_{i \in S} \lambda_{i} \\
& \text { field } \rightarrow \lambda, 0 \text { then }
\end{aligned}
$$

[Chen-Liu-vigoda 121]

- Entropy Factorization Approach:

If $\mu$ comes from product space $\Omega_{1} \times \ldots \Omega_{k}$ that we look at as $\left(\Omega_{k} \omega_{k}\right)$, and $\mu$ and its links are spectrally independent and have marginals $\geqslant \Omega(1)$ :

$$
\underset{x \sim \mu_{T}}{\mathbb{P}}\left[x_{i}=\omega_{i}\right] \geqslant \Omega(1)
$$

then

$$
D_{k l}\left(\nu D_{k \rightarrow l} \| \mu D_{k \rightarrow l}\right) \leqslant[1-\underbrace{\left.-\frac{k-l}{k}\right)}] D_{r L}^{(\nu)}(\nu \| \mu)
$$

a constant for

$$
k-l=\Omega(k)
$$

Lemma [A-Jain-Koehter-Phar-Unong]
We have $D_{k L}\left(\nu D_{k \rightarrow 1} \| \mu D_{k \rightarrow 1}\right) \leqslant \frac{C}{k} D_{k L}(\nu \| \mu)$ if and only if $\lg _{g_{\mu}\left(\frac{1}{c}\right)}$ is upperbounded by its tangent at $z=1: \quad \forall z \in \mathbb{R} \geqslant 0$

$$
\lg _{\mu}\left(z^{\frac{1}{2}} \leqslant \lg _{\mu}(1)+\nabla \lg _{\mu}(1) \cdot\left(2^{\frac{1}{2}}-1\right)\right.
$$

Bounded by tangent:
$x^{2}$ : Locally around $z=1$
$P_{k L}$ : Gbbally at all $z$.
Corollary: If $\mathrm{C}-\lg$-concave $\Rightarrow$ $D_{u L}$ contracts by $C / k$

Note: C-y-concave means spectral independence under all external fields $\xrightarrow{\lambda * \mu}$ move 1 to any other point.

Lemma: if $f^{k} d^{g \mu(h o m}\left(\frac{1}{c}\right)$ over $\mathbb{R}_{>0}^{n}$ TFAE
[folklore] $\lg f$ concave
-f quasi-concave $\equiv\{21 f(2)>1\}$ convex

- $f^{\frac{1}{d}}$ concave
and TFAE:
- $\lg f$ upperbounded by tangent
$-\{2 \mid f(2) \geqslant 1\}$ lowerbounded by tangent
- $f^{\frac{1}{d}}$ upperbouided by tangent


Proof of Folklore Lemmas
19-concave $\Rightarrow$ quasi-concuve
Now assume quasi-concave:
We want to show

$$
f(\lambda x+(1-\lambda) y)^{\frac{1}{d}} \geqslant \lambda f(x)^{\frac{1}{d}}+(1-\lambda) f(y)^{\frac{1}{d}}
$$

Let $x^{\prime}=\alpha x, y^{\prime}=\beta y$ such that $f\left(x^{\prime}\right)=f\left(y^{\prime}\right)=1$
$\alpha=\frac{1}{f_{(x)}^{\frac{1}{d}}} \quad \beta=\frac{1}{f_{(y)^{\frac{1}{d}}}}$
Then $f(z) \geqslant 1$ for $z$ any convex combination of $x^{\prime}$ and $y^{\prime}$. In particular

$$
z:=\underbrace{\left(\frac{\lambda}{\alpha} x^{\prime}+\frac{(1-\lambda)}{\beta} y^{\prime}\right)}_{\lambda x+(1-\lambda) y} /\left(\frac{\lambda}{\alpha}+\frac{1-\lambda}{\beta}\right)
$$

But this means

$$
\begin{gathered}
f\left(\frac{\lambda}{\alpha} x^{\prime}+\frac{1-\lambda}{\beta} y^{\prime}\right) \geqslant\left(\frac{\lambda}{\alpha}+\frac{1-\lambda}{\beta}\right)^{d} \Rightarrow \\
f\left(\lambda x+((1-\lambda) y)^{\frac{1}{d}} \geqslant \lambda f(x)^{\frac{1}{d}}+(1-\lambda) f(y)^{\frac{1}{d^{\prime}}}\right. \\
f^{\frac{1}{d}} \text { concave } \Rightarrow \\
\begin{array}{l}
1 g-c o n c a v e \\
\text { tare } \lg \text { from above } \\
\text { use concavity of } l y
\end{array}
\end{gathered}
$$

The arguments for tangent versions are very similar

Essentially because of athom all info about $f$ is captured in its level set $\{z \mid f(z) \geqslant 1\}$.

Equivalence of Entropy Contraction and Tangent Bound

We want

$$
D_{k c}\left(\nu D_{k \rightarrow 1} \| \mu D_{k \rightarrow 1}\right) \leqslant \frac{C}{k} D_{k c}(\nu \| \mu)
$$

Main Idea: For a fixed $q=\nu D_{k \rightarrow 1}$, which $\nu$ minimizes $D_{k L}(\nu \| \mu)$ ? It turns out the answer is always some $\lambda * \mu$ for some $x \in \mathbb{R}_{>0}^{n}$. Moreover

$$
\begin{aligned}
& \min \left\{D_{k L}(\nu \| \mu) \mid \nu D_{k \rightarrow 1}=q\right\}=\lg (\sup _{z>0} \frac{\underbrace{\frac{\pi}{i} z_{i}^{k q_{i}}}}{g_{\mu}(z)}) \\
& \text { enough to upperbound }
\end{aligned}
$$

Now if we have C-lg-concavity then

$$
\begin{aligned}
& \nabla g_{\mu}(1)=\left(k p_{1} 1-, k p_{n}\right) \text { where } p=\mu D_{k \rightarrow 1} \\
\Rightarrow & \left.\nabla\left(g_{\mu}\left(2^{\frac{1}{c}}\right)^{\frac{C}{k}}\right)\right|_{2=1}=p
\end{aligned}
$$

So

$$
\begin{gathered}
g_{\mu}\left(2^{\frac{1}{c}}\right)^{\frac{c}{k}} \leqslant g_{\mu} n^{\prime}(1)+p \cdot(z-k)=p \cdot z \\
\downarrow \downarrow \\
\underbrace{g_{\mu}(z) \leqslant\left(\sum p_{i} z_{i}^{c}\right)^{\frac{1}{c}}}_{\text {the upperbound we want }}
\end{gathered}
$$

This means $\min \left\{D_{k L}(\nu \| \mu) \mid \nu D_{k \rightarrow 1}=q\right\}$ is at least $\lg \left(\sup _{z>0} \pi z_{i}^{k q_{i}} /\left(\sum p_{i} z_{i}^{c}\right)^{\frac{k}{c}}\right)$. Plug in $z_{i}=\left(\frac{q_{i}}{p_{i}}\right)^{\frac{1}{c}}$ z>0 ge get

$$
\left.D_{k L}(\nu \| \mu) \geqslant \frac{k}{C} \sum_{i} q_{i} \lg \frac{q_{i}}{P_{i}}=\frac{k}{C} D_{c}(\nu)_{k \rightarrow 1} \| \mu P_{k \rightarrow 1}\right)
$$

It remains to show formula for $D_{k i}$ this is just convex duality

$$
\min \left\{D_{k L}(\nu \| \mu) \mid \nu D_{k \rightarrow 1}=p\right\}
$$

$\widetilde{\Sigma}_{\text {convex objective }}$ linear canst.

Note that at optimum we have

$$
\nabla_{\nu} D_{k L}(\nu \| \mu)=\sum_{i} \alpha_{i} v_{i} \text { where }
$$

vi's are the constraint gradients, namely $v_{i} \in \mathbb{R}^{\binom{n}{k}}$ and

$$
v_{i}^{\prime}(s)=\frac{1}{k} 1[i \epsilon s]
$$

But $\partial_{\nu(s)} D_{n c}(\nu \| \mu)=\lg \frac{\nu(s)}{\mu(s)}-\lg \frac{\sum \nu(T)}{\sum \mu(T)}$.
This means

$$
\frac{\nu(s)}{\sum_{T} \nu(T)}=\frac{\mu(s)}{\sum_{T} \mu(T)} \cdot \prod_{i \in s} e^{\alpha_{i} / k}
$$

In other words, $\nu=\lambda * \mu$.
So OPT is found by the external field that achieves the correct marginals $q$.
We show the "dual" also has the same optimality condition. First we mare the dual concave:

OPT achieved when

$$
\underbrace{\nabla_{w} \lg g_{\mu}\left(e^{w}\right)}_{\text {marginals of } e^{w} * \mu}=k q
$$

So the primal and dual have the same conditions of optimality. We show their values are equal: Suppose $\lambda=e^{\omega}$ is the external field (we can assume $g_{\mu}(\lambda): \sum \lambda^{s} \mu(s)=1$, ie., already normalized)

$$
\begin{gathered}
\left.D_{k L}(\lambda * \mu \| \mu)=\sum_{S}(\lambda * \mu) \mid s\right) \lg \prod_{i=s} \lambda_{i}= \\
\sum_{i}^{k} q_{i} \lg \lambda_{i} \quad \text { primal } \\
\lg \frac{\prod_{i} \lambda_{i}^{k q_{i}}}{g_{\mu}(\lambda)}=\lg \prod_{i} \lambda_{i}^{k q_{i}}=\sum_{i}^{k q_{i} \lg \lambda_{i}} \begin{array}{l}
\text { dual }
\end{array}
\end{gathered}
$$

Entropy Factorization
Main Ideas:
(1) $D_{2 \rightarrow 1}$ instead of $D_{k \rightarrow 1}$
${ }^{\wedge}$ because quadratic polynomial we use spin system + marginal bounds here
(2) Alternate local-to-global the: Stitch $D_{2 \rightarrow 1}$ 's together
(3) Either use big-step DU or try harder and compare!
(1) Suppose $\mu$ is a spin System with marginals $\geqslant \Omega(1)$. Then for any other $\nu$ we have

$$
\frac{\nu D_{k \rightarrow 1}(i)}{\mu D_{k \rightarrow 1}(i)}=O(1)
$$

because marginals of $\nu$ are $\leqslant 1$

This makes $x^{2}$ and $D_{k l}$ comparable.
Lemma) With the above assumptions

$$
\begin{array}{r}
D_{k L}\left(\nu D_{k \rightarrow 1} \| \mu D_{k \rightarrow 1}\right) \leqslant\left(\frac{1}{2}+\delta^{\left.c^{\text {spectral }}\left(\frac{1}{k}\right)\right)}\right. \text { ir } \\
D_{k L}\left(\nu D_{k \rightarrow 2} \| \mu D_{k \rightarrow 2}\right)
\end{array}
$$

(2) Alternative local-to-global:

Let $z_{i}=D_{k l}\left(\nu D_{k \rightarrow i} \| \mu D_{k \rightarrow i}\right)$.
Previous bcal-to-global would proceed:

$$
\begin{aligned}
& \left(z_{1}-z_{0}\right) \leqslant 0 \cdot\left(z_{k}-z_{0}\right) \Rightarrow\left(z_{k}-z_{1}\right) \geqslant \square \cdot\left(z_{2}-z_{0}\right) \\
& \prod_{1}\left(z_{2}-z_{1}\right) \leqslant \Delta \cdot\left(z_{k}-z_{1}\right) \Rightarrow\left(z_{k}-z_{2}\right) \geqslant \Delta\left(z_{k}-z_{1}\right) \\
& \text { we don't have } \\
& \text { these anymore } \\
& \left(z_{k}-z_{l}\right) \geqslant \square \cdot \rrbracket \cdot \cdots \cdot\left(z_{k}-z_{0}\right) \\
& \Downarrow \\
& \left(z_{l}-z_{0}\right) \leqslant(1-\square \searrow-)\left(z_{k}-z_{0}\right)
\end{aligned}
$$

Instead now we know

$$
\left(z_{i+1}-z_{i}\right) \leqslant\left(\frac{1}{2}+O\left(\frac{1}{k-i}\right)\right)\left(z_{i+2}-z_{i}\right)
$$

apply (1) to $\mu_{T}$ for $|T|=i$ and average over $T$.

Note that this can be rewritten as

$$
\underbrace{\left(z_{i+1}-z_{i}\right)}_{A_{i}} \leqslant \underbrace{\left(1+O\left(\frac{1}{k-i}\right)\right)}_{\alpha_{i}} \underbrace{\left(z_{i+2}-z_{i+1}\right)}_{A_{i+1}}
$$

Question: $A_{i} \leqslant \alpha_{i} \cdot A_{i+1} \quad \forall i$.

$$
\max \frac{A_{0}+A_{1}+-A_{l-1}^{n_{n c}}\left(\nu D_{k+l} \| \mu D_{k+l}\right)}{A_{0}+\frac{A_{i l}}{A_{k-1}(\nu \| \mu)}}=?
$$

Answer: When $A_{i}=\alpha_{i} A_{i+1}$ !

$$
\begin{aligned}
\frac{A_{i}}{A_{k-1}} & =\left(1+\frac{d(1)}{k-i}\right)\left(1+\frac{O(1)}{k-i-1}\right) \cdots\left(1+\frac{O(1)}{k-j+1}\right) \\
& \simeq(k-i)
\end{aligned}
$$

So we have

$$
\begin{aligned}
& 1-\frac{A_{0}+\cdots+A_{l-1}}{A_{0}+\cdots A_{k-1}} \simeq \frac{1+2^{O(1)}-+(k-l)^{O(1)}}{1+2^{O(1)}+\cdots+k^{O(1)}} \\
& \simeq \frac{k-l}{k} \cdot \frac{(k-l)^{O(1)}}{k O(1)}=\left(\frac{k-l}{k}\right)^{O(1)}
\end{aligned}
$$

This proves that

$$
D_{k l}\left(\nu D_{k \rightarrow l} \| \mu D_{k \rightarrow l}\right) \leqslant\left(1-\left(\frac{k-l}{k}\right)^{0(1)}\right) D_{k l}(\nu \| \mu)
$$

(3) For $l$ close to $k$, the factor 1 - $\left(\frac{k-l}{k}\right)^{o(1)}$ becomes very bad! However if $k-l=\Omega(k)$, this factor is always $1-\Omega(1) \quad \ddot{ }$

Ideal: Use the $D_{k \rightarrow l} U_{l \rightarrow k}$ walk for $k-l=\Omega(u)!$ it has $\Omega(1)$ MLSI and mixes in just $\tilde{O}(1)$ steps.

Idea 2: [Chen-Liu-Vigoda] Showed that for bounded degree spin systems, we can translate above to $\Omega\left(\frac{1}{k}\right)$ MLSI for $D_{k \rightarrow k-1} U_{k-1+k}$, a.k.a. Glauber dynamics.
let us expand Idea 1. Main problem. is how to implement $U_{l \rightarrow k}$ step.

now we need to resample the erased

Lem: If degs bounded by $\Delta$, there is threshold $l_{0}=k-\Omega_{\Delta}(k)$ s.t. for $l \geqslant l_{0}$ ' the "erased" vertices will be in islands of size $O_{\Delta}(\lg n)$ w.h.p.

We an sample each island separately!

Proof: -If we erase $<\frac{1}{\Delta}$ fraction of vertices, then bal neighborhood of any $u$ grows at most lice a tree with arg. branching factor $<\Delta \frac{1}{\Delta}=1$ These trees die off quickly.

- Here is a loose argument: tet $u$ be some vertex. We know \#connected subgraphs containing $u$ of size $t$ is at most $\Delta^{2(t-1)} \leqslant \Delta^{2 t}$ Remember Euler tour argument from Patel-Rears?

Suppose $l=p k, \quad p \in[0,1]$.

Any such conn. neighborhood gets fully $\begin{aligned} \text { erased w.p. } & \leqslant(1-p)^{t} \\ & \uparrow \text { easy exercise }\end{aligned}$

Thus by union bound, $\mathbb{P}\left[\mid v^{\prime}\right.$ s island $\left.\mid \geqslant t\right] \leqslant \Delta^{2 t}(1-P)^{t}$.
So if $1-P \leqslant \frac{1}{2 \Delta^{2}}$ and $t \geqslant C \cdot 1, n$, th's is at mort $n^{-C}$. Union bounding over all $v$ gives us

$$
\mathbb{P} \cdot[\text { any is land } \geqslant C \cdot 19 n] \leqslant n^{1-C}
$$

Note that we could set $p=1-\frac{1}{2 A^{2}}$, which means $k-l=\Omega(k)$.

It remains to prove (1): $\left\lvert\, \begin{aligned} & \nu^{(i)}=\nu D_{k \rightarrow i} \\ & \mu^{(i)}=\mu D_{k \rightarrow i}\end{aligned}\right.$

$$
D_{k L}\left(\nu^{(1)} \| \mu^{(1)}\right) \leqslant\left(\frac{1}{2}+\partial\left(\frac{1}{k}\right)\right) D_{n c}\left(\nu^{(2)} \| \mu(2)\right)
$$

Proof: We can use an upperbound for $g_{\mu}(2)$ :

$$
g_{\mu}(2)(2) \leqslant \lambda\left(\sum p_{i} z_{i}^{2}\right)+(1-\lambda)\left(\sum p_{i} z_{i}^{1}\right)^{2}
$$

where $\lambda=O\left(\frac{1}{k}\right), \quad P=\mu^{(1)}$.
This follows because $g_{\mu(2)}$ is a quadratic, ie., $2^{t} A_{2}$ and $A$ can be bounded by spectral independence as diagonal $+\operatorname{rank} 1$.

Now again if $q=\nu^{(1)}$, then

$$
\begin{aligned}
& \left.D_{k( }\left(\nu^{(2)} \| \mu^{(2)}\right) \geqslant \operatorname{lgsup}_{2)_{0}} \frac{z_{1}^{2 q_{1}}-z_{n}^{2 q_{n}}}{g_{\mu^{(2)}}(z)}\right\} \geqslant \\
& \lg \sup _{z>0}\left\{\frac{z_{1}^{2 q_{1}}-z_{n}^{2 q_{n}}}{\lambda\left(\sum p_{i} z_{i}^{2}\right)+(1-\lambda)\left(\sum p_{i} z_{i}\right)^{2}}\right\}
\end{aligned}
$$

If we plug in $z_{i}=\frac{q_{i}}{p_{i}}$ we get

$$
\begin{aligned}
& D_{k L}\left(\nu^{(2)} \| p^{(2)}\right) \geqslant \lg \left(\frac{e^{2 D_{k L}(q \| p)}}{1+\lambda x^{2}(q \| p)}\right) \geqslant \\
& \lg \left(\frac{e^{2 D_{k L}(q \| p)}}{e^{\lambda x^{2}(q \| p)}}\right)=2 D_{k c}(q \| p)-\lambda x^{2}(q \| p) .
\end{aligned}
$$

Lemma: If $q<O(1) \cdot p$ everywhere, and $q, p$ are prob lists, then $x^{2}(q \| p)=O\left(\sigma_{k}(q \| p)\right)$. Exercise: Pave this.

