

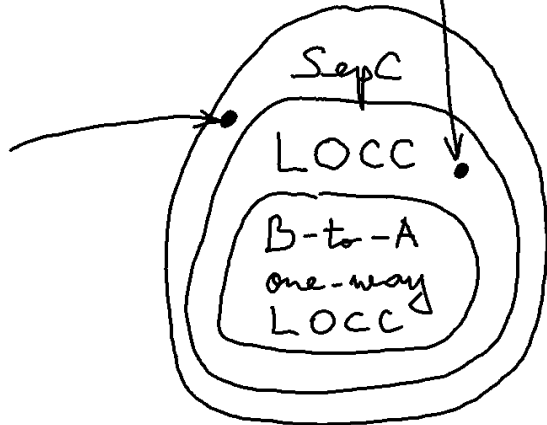
Lecture 11: Majorization and Nielsen's theorem

Remark: you saw in Problem 10.2 a set of orthogonal product states that can be perfectly discriminated by a separable measurement or a one-way LOCC from Alice to Bob, but not by one-way LOCC from Bob to Alice:

		Alice	
		0	1
Bob	0		+
	1		-

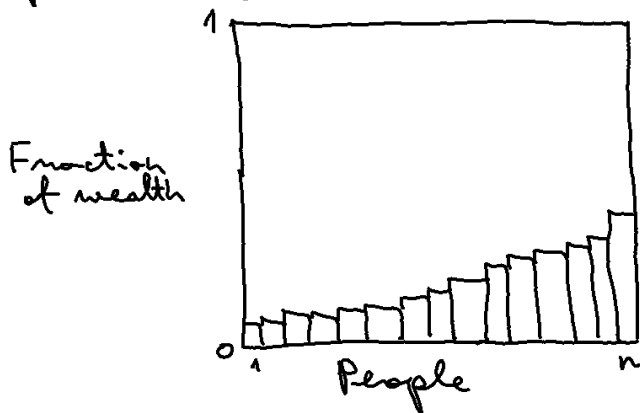
This idea can be extended to orthogonal product states that cannot be perfectly discriminated even by two-way LOCC:

		Alice		
		0	1	2
Bob	0	+		+
	1	+		-
	2	-		+



How to measure wealth inequality?

We can model the distribution of wealth by a probability distribution:



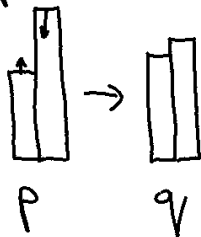
$$p(i) \geq 0$$

$$\sum_{i=1}^n p(i) = 1$$

Given two distributions p and q , how we tell which one is more equal?

Clearly, $p = (\frac{1}{n}, \frac{1}{n}, \dots, \frac{1}{n})$ is the most equal and $q = (0, 0, \dots, 0, 1)$ is the least equal. What about the rest?

Robin Hood transfer: if a richer person gives to a poorer one, the distribution becomes more equal:



$$p = Mq$$

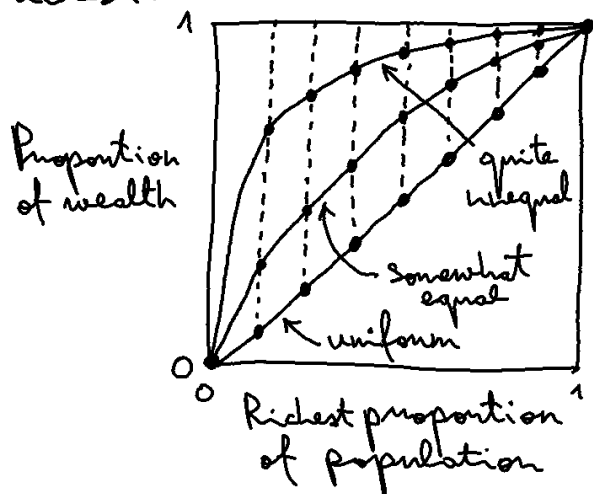
$$\text{where } M = cI + (1-c)X$$

$$= \begin{pmatrix} c & 1-c \\ 1-c & c \end{pmatrix}$$

for some $0 < c < 1$.

Any sequence of such moves makes the distribution more equal. Note that the overall transformation is a convex combination of permutations.

Another way to compare wealth distributions is to look at what proportion of wealth is owned by the richest:



We are plotting the cumulative wealth of the richest fraction of population:

$$p(1) \geq p(2) \geq \dots \geq p(n)$$

$$f(k) = \sum_{i=1}^k p(i)$$

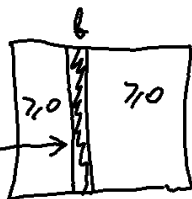
If one curve is point-wise below another, the wealth distribution is more equal. Robin Hood pushes the curve downwards and makes the distribution more equal.

Stochastic and doubly stochastic operators

Def (p. 233) $A \in L(\mathbb{R}^{\Sigma})$ is stochastic if

- $A(a, b) \geq 0, \forall a, b \in \Sigma$

- $\sum_{a \in \Sigma} A(a, b) = 1, \forall b \in \Sigma$ (columns sum to 1)



A is doubly stochastic if 1., 2., and

- $\sum_{b \in \Sigma} A(a, b) = 1, \forall a \in \Sigma$ (rows sum to 1)

A is a permutation if 1., 2., 3., and $A(a, b) \in \{0, 1\}, \forall a, b \in \Sigma$. So each row and column of a permutation operator contains exactly one entry equal to 1 and the rest are 0.

Note that any convex combination of permutations is doubly stochastic since each row and column is a convex combination of the standard basis vectors. Surprisingly, the converse is also true.

Thm 4.28 (Birkhoff - von Neumann):

$A \in L(\mathbb{R}^\Sigma)$ is doubly stochastic iff there exists a probability vector $p \in P(\text{Sym}(\Sigma))$ such that

$$A = \sum_{\pi \in \text{Sym}(\Sigma)} p(\pi) V_\pi$$

where $\text{Sym}(\Sigma)$ is the set of all permutations acting on Σ and $V_\pi(a, b) = \delta_{a, \pi(b)}$.

Majorization for real vectors

Def 4.29: Let $u, v \in \mathbb{R}^\Sigma$. Then u majorizes v , $v \prec u$, if $v = Au$, for some doubly stochastic $A \in L(\mathbb{R}^\Sigma)$.

Let $r(u)$ denote the reverse sorting of u :

$$r_1(u) \geq r_2(u) \geq \dots \geq r_n(u)$$

$$\text{and } \{r_1(u), r_2(u), \dots, r_n(u)\} = \{u(a) : a = 1, \dots, n\}.$$

Thm 4.30: Let $u, v \in \mathbb{R}^\Sigma$. Then these are equivalent:

1. $v \prec u$

2. $\sum_{i=1}^m r_i(v) \leq \sum_{i=1}^m r_i(u)$, for all $m \in \{1, \dots, n-1\}$ and

$$\sum_{i=1}^n r_i(v) = \sum_{i=1}^n r_i(u).$$

Majorization for Hermitian operators

For probability distributions, permutations are precisely the reversible transformations. Similarly, for quantum states they correspond to unitary change of basis.

Def 4.2: $\Phi \in \mathcal{C}(\mathcal{X})$ is a mixed-unitary channel if

$$\Phi(X) = \sum_{\alpha \in \Sigma} p(\alpha) U_{\alpha} X U_{\alpha}^*,$$

for some $p \in \mathcal{P}(\Sigma)$ and $U_{\alpha} \in \mathcal{U}(\mathcal{X})$.

Def 4.31: Let $X, Y \in \text{Herm}(\mathcal{X})$. Then X majorizes Y , $Y < X$, if $Y = \Phi(X)$, for some mixed-unitary $\Phi \in \mathcal{C}(\mathcal{X})$.

Thm 4.32 (Uhlmann): Let $X, Y \in \text{Herm}(\mathcal{X})$. Then the following are equivalent:

1. $Y < X$

2. $\lambda(Y) < \lambda(X)$,

where $\lambda(X)$ denotes the spectrum of X .

Note that for diagonal matrices X , the spectrum $\lambda(X)$ is just the set of diagonal entries of X . Hence, majorization for diagonal matrices reduces to majorization for vectors.

If $\text{vec}(X) = |u\rangle_{AB}$ and $\text{vec}(Y) = |v\rangle_{AB}$, can we use the mixed-unitary channel Φ s.t. $Y = \Phi(X)$ to devise a one-way LOCC protocol for transforming $|u\rangle_{AB}$ to $|v\rangle_{AB}$? This is what Nielsen's thm is about!

Theorem 6.33 (Nielsen) Let $|u\rangle, |v\rangle \in S(X \otimes Y)$.

The following are equivalent:

1. $\text{Tr}_Y[|u\rangle\langle u|] \prec \text{Tr}_Y[|v\rangle\langle v|]$.
2. There exists a one-way LOCC protocol $\mathbb{H} \in \text{LOCC}(X:Y)$ from Bob to Alice such that $\mathbb{H}(|u\rangle\langle u|) = |v\rangle\langle v|$.
3. Same, but one-way LOCC from Alice to Bob.
4. Same, but $\mathbb{H} \in \text{SepC}(X:Y)$.

Proof: $(1 \Rightarrow 2)$ Recall that, for any $A, B \in L(Y, X)$,

$$\text{Tr}_Y[\text{vec}(A) \text{vec}(B)^*] = AB^* \quad (\text{Exercise})$$

In particular, if $X, Y \in L(Y, X)$ are such that $\text{vec}(X) = |u\rangle$ and $\text{vec}(Y) = |v\rangle$ then 1. is equivalent to

$$XX^* \prec YY^*$$

By Def. 4.31 of majorization for Hermitian operators,

$$XX^* = \sum_{\alpha \in \Sigma} p(\alpha) W_\alpha YY^* W_\alpha$$

where $p \in \mathcal{P}(\Sigma)$ is a probability distribution and $W_\alpha \in U(X)$. We need to convert this somehow into a one-way LOCC protocol. Note that we can write

$$XX^* = \underbrace{\left(\sum_{\alpha \in \Sigma} \sqrt{p(\alpha)} (W_\alpha Y) \otimes |\alpha\rangle \right)}_{Z \in L(Y \otimes Z, X)} \cdot \underbrace{\left(\sum_{\alpha \in \Sigma} \sqrt{p(\alpha)} (Y^* W_\alpha^*) \otimes \langle \alpha| \right)}_{Z^*}$$

Given that $XX^* = ZZ^*$, how are X and Z related? Let

$$X = \sum_{k=1}^r s_k |x_k\rangle\langle y_k|$$

be the singular value decomposition of X where $r = \text{rank}(X)$, $s_k > 0$, and $|x_k\rangle \in S(X)$ and $|y_k\rangle \in S(Y)$ are orthonormal sets in X and Y . Note that

$$XX^* = \sum_{j,k=1}^r s_j s_k |x_j\rangle\langle y_j| \langle y_k| \langle x_k| = \sum_{k=1}^r s_k^2 |x_k\rangle\langle x_k| = ZZ^*,$$

so XX^* and ZZ^* have eigenvalues s_k^2 with eigenvectors $|x_k\rangle$. Hence, Z has singular value decomposition

$$Z = \sum_{k=1}^r s_k |x_k\rangle\langle w_k|$$

for some orthonormal basis $\{|w_k\rangle, \dots, |w_r\rangle\}$ of $Y \otimes Z$.

Let $V \in U(Y, Y \otimes Z)$ be an isometry such that $V|y_k\rangle = |w_k\rangle$, for all k . Then

$$XV^* = Z = \sum_{\alpha \in \Sigma} \sqrt{p(\alpha)} (W_\alpha Y) \otimes \langle \alpha|.$$

Let us use this observation to devise a one-way LOCC protocol from Bob to Alice. Let

$$\{B_\alpha : \alpha \in \Sigma\} \subset L(Y) \text{ and } \{U_\alpha : \alpha \in \Sigma\} \subset U(X)$$

be Bob's measurement and Alice's basis change. Note that

$$\begin{aligned} (U_\alpha \otimes B_\alpha) |u\rangle &= (U_\alpha \otimes B_\alpha) \text{vec}(X) \\ &= \text{vec}(U_\alpha X B_\alpha^T). \end{aligned}$$

We would like this to be $\sqrt{p(\alpha)} \text{vec}(Y)$ since then

$$\begin{aligned} \sum_{\alpha \in \Sigma} (U_\alpha \otimes B_\alpha) |u\rangle\langle u| (U_\alpha \otimes B_\alpha)^* &= \sum_{\alpha \in \Sigma} p(\alpha) \text{vec}(Y) \text{vec}(Y)^* \\ &= \text{vec}(Y) \text{vec}(Y)^* \\ &= |u\rangle\langle u|. \end{aligned}$$

So what we want is that

$$U_a X B_a^T = \sqrt{p(a)} Y.$$

Recall that

$$X V^* = \sum_{a \in \Sigma} \sqrt{p(a)} (W_a Y) \otimes \langle a |,$$

hence

$$\underbrace{W_a^*}_{U_a} X \underbrace{V^*}_{B_a^T} (I_Y \otimes |a\rangle\langle z|) = \sqrt{p(a)} Y.$$

So we take $U_a := W_a^*$ and $B_a := (I_Y \otimes \langle a | z \rangle) \bar{V}$.

Note that $\sum_{a \in \Sigma} B_a^* B_a = V^T \sum_{a \in \Sigma} (I_Y \otimes |a\rangle\langle a|) \bar{V} = V^T \bar{V} = I_Y$,

so $\{B_a : a \in \Sigma\}$ is a valid measurement.

2 \Rightarrow 3 Same, but exchange Alice and Bob.

3 \Rightarrow 4 Every LOCC channel is separable.

4 \Rightarrow 1 Let $\mathbb{H} \in \text{Sep } C(X:Y)$ with Kraus operators

$\{A_a : a \in \Sigma\} \subset L(X)$ and $\{B_a : a \in \Sigma\} \subset L(Y)$ such that

$$\mathbb{H}(|ux\rangle\langle u|) = \sum_{a \in \Sigma} (A_a \otimes B_a) |ux\rangle\langle u| (A_a \otimes B_a)^* = |vx\rangle\langle v|.$$

Since $|vx\rangle\langle v|$ is rank-one, each term must be of the form $p(a) |vx\rangle\langle v|$, for some probability distr. $p \in P(\Sigma)$.

Equivalently,

$$\text{vec}(A_a X B_a^T) \text{vec}(A_a X B_a^T)^* = p(a) \text{vec}(Y) \text{vec}(Y)^*.$$

Taking partial trace over Y ,

$$A_a X B_a^T \bar{B}_a X^* A_a^* = p(a) Y Y^*$$

What we want to show is $XX^* \prec YY^*$, which by Theorem 4.32 is equivalent to

$$\lambda(XX^*) \prec \lambda(YY^*).$$

Note that $\sum_{k=1}^n \lambda_k(XX^*) = \text{Tr}[XX^*] = 1 = \text{Tr}[YY^*] = \sum_{k=1}^n \lambda_k(YY^*)$, since $|u\rangle$ and $|v\rangle$ are unit vectors. What remains to show is that, for all $m \in \{1, \dots, n\}$,

$$\sum_{k=m}^n \lambda_k(YY^*) \leq \sum_{k=1}^m \lambda_k(XX^*).$$

Note that $\lambda_k(cM) = c \lambda_k(M)$ for any $c > 0$ and $M \in L(\mathcal{X})$, so

$$\begin{aligned} \sum_{k=m}^n \lambda_k(YY^*) &= \sum_{k=m}^n \sum_{a \in \Sigma} \lambda_k(p(a) Y Y^*) \\ &= \sum_{a \in \Sigma} \sum_{k=m}^n \lambda_k \left(\underbrace{A_a X B_a^T \bar{B}_a X^* A_a^*}_{P_a \in \text{Pos}(\mathcal{X})} \right). \end{aligned}$$

Since we are summing over the $n-m+1$ smallest eigenvalues of P_a , for any projector $\Pi_{a,m} \in \text{Pos}(\mathcal{X})$ such that $\text{rank}(\Pi_{a,m}) \geq n-m+1$,

$$\sum_{k=m}^n \lambda_k(P_a) \leq \text{Tr}[\Pi_{a,m} \cdot P_a].$$

Let us choose $\Pi_{a,m}$ so that $\Pi_{a,m} A_a |x_i\rangle = 0$, for all $i \in \{1, \dots, m-1\}$, where $|x_i\rangle$ is the i -th left singular vector of X (or 0 if $i > r = \text{rank}(X)$).

Let us truncate the singular value decomposition of X and define

$$X_m := \sum_{k=m}^r s_k |x_k\rangle \langle y_k|.$$

By the definition of $\Pi_{a,m}$,

$$\text{Tr}[\Pi_{a,m} \cdot P_a] = \text{Tr}[\Pi_{a,m} \cdot P_{a,m}]$$

where $P_{a,m} := A_a X_m B_a^T \bar{B}_a X_m^* A_a^*$.

So far we have $\sum_{\kappa=m}^n \lambda_{\kappa}(YY^*) = \sum_{a \in \Sigma} \lambda_{\kappa}(P_a)$, where

$$\lambda_{\kappa}(P_a) \leq \text{Tr}[\Pi_{a,m} \cdot P_{a,m}] \leq \text{Tr}[P_{a,m}]$$

Note that

$$\sum_{a \in \Sigma} \text{Tr}[P_{a,m}] = \sum_{a \in \Sigma} \text{Tr}[A_a X_m B_a^T \bar{B}_a X_m^* A_a^*] \quad \left. \begin{array}{l} \text{Exercise} \\ \downarrow \end{array} \right\}$$

$$= \text{Tr} \left[\sum_{a \in \Sigma} (A_a \otimes B_a) \text{vec}(X_m) \text{vec}(X_m)^* (A_a \otimes B_a) \right]$$

$$= \text{Tr} \left[\mathbb{H}(\text{vec}(X_m) \text{vec}(X_m)^*) \right]$$

Since \mathbb{H} is trace-preserving

$$= \text{Tr}[\text{vec}(X_m) \text{vec}(X_m)^*]$$

$$= \text{Tr}[X_m X_m^*]$$

$$= \text{Tr} \left[\sum_{j,k=m}^r s_j |x_j X y_j| \cdot s_k |y_k X x_k| \right] = \sum_{\kappa=m}^r s_{\kappa}^2$$

Note that $XX^* = \sum_{i,j=1}^n s_i |x_i X y_i| \cdot s_j |y_j X x_j|$

$$= \sum_{i=1}^n s_i^2 |x_i X x_i|,$$

Since $\text{rank}(X) = r$

so $s_{\kappa}^2 = \lambda_{\kappa}(XX^*)$ and $\sum_{\kappa=m}^r s_{\kappa}^2 = \sum_{\kappa=m}^n s_{\kappa}^2 = \sum_{\kappa=m}^n \lambda_{\kappa}(XX^*)$.

Hence $\sum_{\kappa=m}^n \lambda_{\kappa}(YY^*) \leq \sum_{\kappa=m}^n \lambda_{\kappa}(XX^*)$. □