# PCP - Huji Course, Ex 1.

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#### 1 Ex 1.

Claim 1. Let A be a random matrix in  $M(\mathbb{F}_2^{k\times n})$ then for any non zero  $x \in \mathbb{F}$  we have that Ax distributed uniformly.

*Proof.* By the fact that  $x \neq 0$  there exists at least one coordinate  $i \in [k]$  such that  $x_i \neq 0$ . Thus we

$$(Ax)_j = \sum_k A_{jk} x_k = \sum_{i \ neak} A_{jk} x_k - \sum_{i \ neak} A_{$$

$$= \sum_{i \ negk} A_{jk} x_k + A_{ji}$$

Notice that due to the fact that  $\mathbb{F}_2$  is a field, there is exactly one assignment that satisfies the equation conditioned on all the values  $A_{ik}$  where  $j \neq k$ .

$$\mathbf{Pr}\left[\left(Ax\right)_{j}=1\right]=\sum_{A_{jk}:k\neq i}\mathbf{Pr}\left[\left(Ax\right)_{j}=1|A_{jk};k\neq i\right]\mathbf{Pr}\left[A_{jk};k\neq i\right]//=\frac{1}{2}$$

therefore any coordinate of Ax distributed uniformly  $\Rightarrow Ax$  distributed uniformly.

By the uniformity of Ax we obtain that the expected Hamming wight of Ax is:

$$\mathbf{E}[|Ax|] = \mathbf{E}\left[\sum_{i=1}^{n} (Ax)_{i}\right] = \frac{1}{2}n$$

As the coordinates of  $A_x$  are independent (each row of A is sampled separately) we can use the Hoff' bound to conclude that:

$$\mathbf{Pr}\left[||Ax| - \mathbf{E}\left[|Ax|\right]| \ge \left(\frac{1}{2} - \delta\right)n\right] \le e^{-n\left(\frac{1}{2} - \delta\right)^2} \Rightarrow$$

Now we will use the union bound to show that any  $x \in \mathbb{F}_2^k$ , Ax is at weight at least  $\delta$ .

$$\mathbf{Pr}\left[|Ax| \ge \delta : \forall x \in \mathbb{F}_2^k\right] \ge 1 - |\mathbb{F}_2^k| \cdot e^{-n\left(\frac{1}{2} - \delta\right)^2}$$

Denote  $k = \rho n$  and notice that the above holds when  $\rho \geq \left(\frac{1}{2} - \delta\right)^2$ 

### Ex 2. $\mathbf{2}$

Claim 2. Let  $v_1, v_2..v_m$  unit vectors in an innerproduct space such that  $\langle v_i, v_j \rangle \leq -2\varepsilon$  for all  $i \neq j$ , then  $m \leq \frac{1}{2\varepsilon} + 1$ .

Proof. Let's us bound form both sides the norm of the summation  $|\sum_i v_i|$ . As the norm is by def- $(Ax)_j = \sum_k A_{jk} x_k = \sum_{i \ neqk} A_{jk} x_k + \text{for inition (construction) non-negative we are going from the left by 0, on the other hand$ we have that:

$$0 \le |\sum_{v_i} v_i| = m + 2\sum_{i,j} \langle v_i, v_j \rangle \le m - 2 \cdot \frac{m(m-1)}{2} \cdot 2\varepsilon$$

Thus we obtain  $m\left(2(m-1)\varepsilon-1\right)\leq 0$  namely,  $m\leq \frac{1}{2\varepsilon}+1$ 

Now, define the following product for  $u, v \in$  $\mathbb{F}_2^n$ ,  $\langle v, u \rangle = \sum_i (-1)^{v_i} (-1)^{\bar{u}_i}$  observes that:

1. 
$$\langle v, v \rangle = \sum_{i} 1 = n \ge 0$$
.

$$2. \langle v, u \rangle = \langle u, v \rangle.$$

3. 
$$\langle ax + by, z \rangle = (-1)^a \langle x, z \rangle + (-1)^b \langle y, z \rangle$$
.

Now the v's corresponds to code with distance at least d then, i.e for any codewords v and udisagree on at least d coordinates, and therefore  $\langle v,u \rangle \leq \text{agree-disagree} = n - 2 \text{ disagree}$ = n - 2d. Now consider the normal codewords  $\tilde{v_1}..\tilde{v_n}$  and assume that  $\langle \tilde{v_i}, \tilde{v_j} \rangle = (1-2\delta) =$  $\frac{1}{n}(n-2d(v_i,v_j)) \le \varepsilon$ . So if  $d \ge \frac{1}{2} + \varepsilon$  we obtain the condition of the above claim.

### 3 Ex 3.

Consider the following process for decoding a, first we sample uniformly random  $x \in \mathbb{F}_2^n$  and assign:  $\hat{a}_i \leftarrow w(x) + w(\sigma_i(x))$ .

Claim 3. The above decoding returns the correct i'th in probability grater than  $\frac{1}{2}$ .

*Proof.* In this question we will say that w agree on  $x, \sigma_i(x)$  if both  $x, \sigma_i(x)$  were either filliped or unfliped. Clearly if w(x) agree with  $w(\sigma_i(x))$  than

$$\begin{split} w\left(x\right) + w\left(\sigma_i(x)\right) &= H_a(x) + H_a(\sigma_i(x)) = \sum_{i \neq j} a_j(x_j + x_j) + a_i(x_j + 1 + x_j) = a_j \text{neither of them were flipped.} \\ &= 1 + H_a(x) + 1 + H_a(\sigma_i(x)) = a_i \text{both flipped.} \end{split}$$

Also if w disagree on  $x, \sigma_i(x)$  then  $w(x) + w(\sigma_i(x)) = 1 + a_i$ . Now consider the inner product from the above section, and observes that  $\langle w(x), w(\sigma_i(x)) \rangle = 1 - (-1)^{a_i}$