## 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 have

$$(Ax)_{j} = \sum_{k} A_{jk} x_{k} = \sum_{i \text{ neq}k} A_{jk} x_{k} + A_{ji} x_{i}$$
$$= \sum_{i \text{ neq}k} A_{jk} x_{k} + A_{ji}$$

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  $A_{jk}$  where  $j \neq k$ .

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

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:

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

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  $\rho \ge \left(\frac{1}{2} - \delta\right)^2$ 

## 2 Ex 2.

Claim 2. Let  $v_1, v_2..v_m$  unit vectors in an inner-product 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 definition (construction) non-negative we are going to bound 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 u disagree on at least d coordinates, and therefore  $\langle v,u\rangle \leq \texttt{agree}-\texttt{disagree}=\texttt{n}-2$  disagree =n-2d. Now consider the normal codewords  $\tilde{v_1}..\tilde{v_n}$  and assume that  $\langle \tilde{v_i}, \tilde{v_j} \rangle = (1-2\delta) = \frac{1}{n} \left(n-2d(v_i,v_j)\right) \leq \varepsilon$ . So if  $d \geq \frac{1}{2} + \varepsilon$  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 unflipped. Clearly if w(x) agree with  $w(\sigma_i(x))$  than

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

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  $\langle w(x), w(\sigma_i(x)) \rangle = 1 - (-1)^{a_i}$