## Note 1

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**Definition.** X is called  $\sigma^2$ -subgaussian if

$$\log E[e^{\lambda(X-EX)}] \leq \frac{1}{2}\lambda^2\sigma^2 = MGF(N(0,\delta^2))$$

Chernoff Bound. If X is  $\sigma^2$ -subgaussian, then,

$$Pr[X > EX + t] \le e^{-\frac{t^2}{2\sigma^2}}$$

Proof. Same.

**Hoeffding.** If  $a \le X \le b$  then X is  $\frac{1}{4}(b-a)^2$ -subgaussian.

*Proof.* Let  $\log E[e^{\lambda(X-EX)}] = \phi(\lambda)$ , then

$$\phi'(\lambda) = \frac{E[(X - EX)e^{\lambda(X - EX)}]}{E[e^{\lambda(X - EX)}]}$$

$$\phi''(\lambda) = \frac{E[(X - EX)^2e^{\lambda(X - EX)}]}{E[e^{\lambda(X - EX)}]} - \frac{E[(X - EX)e^{\lambda(X - EX)}]}{E[e^{\lambda(X - EX)}]^2}$$

$$\leq \frac{E[(X - EX)^2e^{\lambda(X - EX)}]}{E[e^{\lambda(X - EX)}]}$$

$$\leq \frac{1}{4}(a - b)^2$$

**Azuma.**  $X_t$  be r.v.  $E[X_t|\mathcal{F}_{t-1}] = X_{t-1}(martingale)$ ,  $\Delta_t = X_t - X_{t-1}$ . If  $a_t \leq \Delta_t \leq b_t$ , then  $X_t$  is  $\frac{1}{4} \sum_{i=1}^t (b_t - a_t)^2$ -subgaussian.

Proof.  $EX_t = 0$ 

$$\begin{split} & E e^{\lambda X_t} \\ &= E e^{\lambda (X_{t-1} + \Delta_t)} \\ &= E [E [e^{\lambda (X_{t-1} + \Delta_t)} | \mathcal{F}_{t-1}]] \\ &= E [e^{\lambda X_{t-1}} E [e^{\lambda \Delta_t} | \mathcal{F}_{t-1}]] \\ &\leq E [e^{\lambda X_{t-1}} ] e^{\frac{1}{8} \lambda^2 (b_t - a_t)^2} \end{split}$$

**McDiarmid.**  $X_1, X_2, ..., X_n$  independent r.v.  $f(x_1, x_2, ..., x_n)$ 

$$D_i f = \sup_{x_{-i}} \sup_{x,y} |f(x_{-i}, x) - f(x_{-i}, y)|$$

then  $f(X_1, X_2, ..., X_n)$  is  $\frac{1}{4} \sum_{i=1}^n D_i f^2$ -subgaussian.

<sup>&</sup>lt;sup>1</sup>Probability in High Dimension (Princeton).

Proof. Let 
$$Z_i = E[f(X_1, ..., X_n) | X_1, ..., X_i]$$
, then  $f - E[f] = \sum_{i=1}^n Z_i - Z_{i-1}$ , then 
$$E[Z_i | X_1, ..., X_{i-1}] = E[f(X_1, ..., X_n) | X_1, ..., X_{i-1}] = Z_{i-1}$$

 $Z_i$  is martingale (Doob martingale).

*Proof.* Taylor expansion: 
$$E[(X_1 + ... + X_n)^i] \leq E[(X_1' + ... + X_n')^i]$$