

the Chernoff Bound

X_1, X_2, \dots, X_n - independent Bernoulli trials s.t.

$$P_2(X_i = 1) = p \quad P_2(X_i = 0) = 1 - p$$

$X = \sum_1^n X_i \rightarrow X$ is binomial distribution

$$P_2(X_i = 1) = p_i$$

\hookrightarrow Poisson trials

Chance to not achieve some performance is small
to guarantee this we study $P_2[X > (1+\delta)\mu]$, where
 $E(X) = \mu$.

$E(e^{tX})$ - moment generating function ~~for~~ of X .

Chernoff bound idea — 1) Take moment generating function
2) Apply Markov inequality to it.

\hookrightarrow Sum of independent random variables appears in the exponent, this turns into the product of random variables whose expectation we then bound.

Theorem X_1, \dots, X_n - independent Poisson trials, $P_2[X_i = 1] = p_i$

$$P_2[X > (1+\delta)\mu] < \left(\frac{e^\delta}{(1+\delta)^{1+\delta}} \right)^\mu$$

Proof 1) Write moment generating function

2) Apply Markov inequality.

3) Expectation of Product is product of expectation

4) Pick desired value of t .

$$P_2 [X > (1+\delta)^M] = P_2 [\exp(tX) > \exp(t(1+\delta)^M)]$$

$$P_2 [X > (1+\delta)^M] < \frac{E(\exp(tX))}{\exp(t(1+\delta)^M)}$$

strict because $p_i \neq 0, 1$.

$$E(\exp(tX)) = E(\exp(t \sum_i X_i)) = E(\prod \exp(t X_i))$$

$$P_2 [X > (1+\delta)^M] < \frac{E(\prod (\exp(t X_i)))}{\exp(t(1+\delta)^M)} = \prod (E \exp(t X_i))$$

$$= \frac{\prod (p_i e^t + 1 - p_i)}{\exp(t(1+\delta)^M)}$$

$$1 + X < e^X \quad X = p_i(e^t - 1)$$

$$P_2 [X > (1+\delta)^M] < \frac{\prod \exp(p_i(e^t - 1))}{\exp(t(1+\delta)^M)} = \frac{\exp(\sum_i p_i(e^t - 1))}{e^{t(1+\delta)^M}} =$$

$$= \frac{\exp((e^t - 1) \mu)}{\exp(t(1+\delta)^M)}$$

$$t = \ln(1+\delta)$$

$$P_2 [X > (1+\delta)^M] = \left(\frac{e^\delta}{(1+\delta)(1+\delta)} \right)^M$$

Def $F^+(\mu, \delta) = \left(\frac{e^\delta}{(1+\delta)(1+\delta)} \right)^M$

✱

(2)

Example Arkansas tadpoles.

Вариантов \in бер $\frac{1}{3}$, бер. Вероятно больше вероятности

$$P_2(Y_n > \frac{n}{2}) < F^t(\frac{n}{3}, \frac{1}{2}) = (0.965)^n.$$

Theorem

$$P_2[X < (1-\delta)\mu] < \exp\left(-\frac{\mu\delta^2}{2}\right)$$

Proof Proof is similar to previous proof.

$$\begin{aligned} P_2[X < (1-\delta)\mu] &= P_2[-X > -(1-\delta)\mu] = P_2\left[e^{-tX} > e^{-t(1-\delta)\mu}\right] < \\ &< \frac{E(e^{-tX})}{e^{-t(1-\delta)\mu}} = \frac{E\left(\prod e^{-tx_i}\right)}{e^{-t(1-\delta)\mu}} = \frac{\prod (E e^{-tx_i})}{e^{-t(1-\delta)\mu}} = \\ &= \frac{\prod (p_i e^{-t} + (1-p_i))}{e^{-t(1-\delta)\mu}} \leq \frac{\prod (e^{p_i(-1+e^{-t})})}{e^{-t(1-\delta)\mu}} = \frac{e^{(e^{-t}-1)\mu}}{e^{-t(1-\delta)\mu}} \end{aligned}$$

$$\text{Let } t = \ln\left(\frac{1}{1-\delta}\right)$$

$$P_2[X < (1-\delta)\mu] < \left(\frac{e^{-\delta}}{(1-\delta)(1-\delta)}\right)^\mu$$

$$(1-\delta)^{1-\delta} > \exp\left(-\delta + \frac{\delta^2}{2}\right)$$

$$\Rightarrow P_2[X < (1-\delta)\mu] < e^{-\frac{\delta^2}{2}\mu},$$

Def $F^t(\mu, \delta) = \exp\left(-\frac{\mu\delta^2}{2}\right).$ *

Note: ① Apply Chernoff technique to $-X$, not to

$u-X$.

② $\ln(1-\delta)$ has good expansion while $\ln(1+\delta)$ not.

Ben Example Arkansas Adworks again

$$P_2[Y_n < \frac{\mu}{2}] < F^-(0, \pm 5\mu, \frac{1}{2}) < (0.9592)^n$$

Президентские выборы не зависят от n , только от μ и δ .
trials 1000, $P_i = 0.02 =$ trials 100 $P_i = 0.2$

Def $\Delta^+(\mu, \epsilon)$ is such value that

$$F^+(\mu, \Delta^+(\mu, \epsilon)) = \epsilon$$

Similarly $\Delta^-(\mu, \epsilon) : F^-(\mu, \Delta^-(\mu, \epsilon)) = \epsilon$

$$\Delta^-(\mu, \epsilon) = \sqrt{\frac{2 \ln(\frac{1}{\epsilon})}{\mu}}$$

$$e^{-\frac{\mu \delta^2}{2}} = \epsilon \Rightarrow \frac{\mu \delta^2}{2} = \ln \frac{1}{\epsilon} \Rightarrow \delta = \sqrt{\frac{2 \ln \frac{1}{\epsilon}}{\mu}}$$

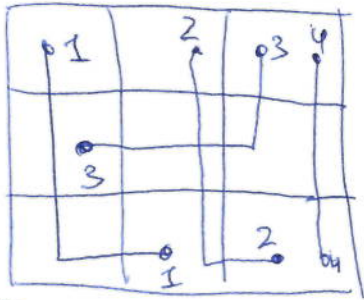
Theorem For $\delta \in [0, 2]$

$$F^+(\mu, \delta) \leq \exp(-c(u)\mu\delta^2), \text{ where } c(u) = \frac{[(1+u)\ln(1+u) - u]}{u^2}.$$

$$\text{For } u = 2e - 1 \quad F^+(\mu, \delta) < \exp\left(-\frac{\mu\delta^2}{4}\right)$$

$$\text{Given } \delta < 2e - 1 \Rightarrow \Delta^+(\mu, \epsilon) < \sqrt{\frac{4 \ln \frac{1}{\epsilon}}{\mu}}$$

Minimization problem



- Plan
- 1) Write ILP
 - 2) Relax to LP, and solve LP
 - 3) Round obtained solution.

ILP

$$\min w$$

$$x_{i0}, x_{i1} \in \{0, 1\}$$

$$x_{i0} + x_{i1} = 1$$

$$\sum_{i \in T_{b_0}} x_{i0} + \sum_{i \in T_{b_1}} x_{i1} \leq w$$

$$P_2 [x_{i0} = 1] = x_{i0} \quad P_2 [x_{i1} = 1] = x_{i1}$$

LP

$$0 \leq x_{i0}, x_{i1} \leq 1$$

$$\Rightarrow *$$

Theorem $\epsilon \in \mathbb{R}$, ϵ вероятностного $1-\epsilon$ решение для Minimization problem наименьше ϵ по сравнению вероятностного решения удовлетворяет:

$$w_\epsilon \leq \hat{w} \left(1 + \Delta^+ \left(\hat{w}, \frac{\epsilon}{2u} \right) \right) \leq w_0 \left(1 + \Delta^+ \left(w_0, \frac{\epsilon}{2u} \right) \right).$$

Доказ. Покажем, что вероятностное для конкретности

степени, что $w_\epsilon(b) > \hat{w} \left(1 + \Delta^+ \left(\hat{w}, \frac{\epsilon}{2u} \right) \right)$ не больше $\frac{\epsilon}{2u}$.

Мы знаем, что

$$\sum_{i \in T_{b_0}} x_{i0} + \sum_{i \in T_{b_1}} x_{i1} \leq \hat{w}$$

$$E(w_{\epsilon,b}) = \sum_i E(x_{i0}) + \sum_i E(x_{i1}) = \sum_i x_{i0} + \sum_i x_{i1} \leq \hat{w}$$

Since we expect by our theorem $\Delta^+(\hat{w}, \frac{\epsilon}{2n})$.

$$P_2 [w_s(b) > \hat{w} (1 + \Delta^+(\hat{w}, \frac{\epsilon}{2n}))] \leq \frac{\epsilon}{2n}$$

Since no dep. observed, we have some constant ϵ .



Congestion Minimization