## Lemma 2 (Chernoff Bounds)

*Let $X_1, \ldots, X_n$ be $n$ independent 0-1 random variables, not necessarily identically distributed. Then for $X = \sum_{i=1}^{n} X_i$ and $\mu = E[X]$, $L \leq \mu \leq U$, and $\delta > 0$*

$$\Pr[X \geq (1+\delta)U] < \left(\frac{e^{\delta}}{(1+\delta)^{1+\delta}}\right)^{U} ,$$

*and*

$$\Pr[X \leq (1-\delta)L] < \left(\frac{e^{-\delta}}{(1-\delta)^{1-\delta}}\right)^{L} ,$$

## Lemma 3

*For* $0 \leq \delta \leq 1$ *we have that*

$$\left(\frac{e^{\delta}}{(1+\delta)^{1+\delta}}\right)^U \leq e^{-U\delta^2/3}$$

*and*

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# Proof of Chernoff Bounds

**Markovs Inequality**:

Let $X$ be random variable taking non-negative values.

Then

$$\Pr[X \geq a] \leq \mathrm{E}[X]/a$$

Trivial!

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**That's awfully weak :(**

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**This may be a lot better (!?)**

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$$\prod_i \mathrm{E}\left[e^{tX_i}\right] \le \prod_i e^{p_i(e^t-1)} = e^{\sum p_i(e^t-1)} = e^{(e^t-1)U}$$

Now, we apply Markov:

$$
\begin{aligned}
\Pr[X \geq (1+\delta)U] &= \Pr[e^{tX} \geq e^{t(1+\delta)U}] \\
&\leq \frac{\mathrm{E}[e^{tX}]}{e^{t(1+\delta)U}}
\end{aligned}
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We choose $t = \ln(1+\delta)$.

## Lemma 4

*For $0 \leq \delta \leq 1$ we have that*

$$\left(\frac{e^{\delta}}{(1+\delta)^{1+\delta}}\right)^{U} \leq e^{-U\delta^2/3}$$

*and*

$$\left(\frac{e^{-\delta}}{(1-\delta)^{1-\delta}}\right)^{L} \leq e^{-L\delta^2/2}$$

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True for $\delta = 0$.

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Take logarithms:

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True for $\delta = 0$. Divide by $U$ and take derivatives:

$$-\ln(1+\delta) \le -2\delta/3$$

**Reason:**
As long as derivative of left side is smaller than derivative of right side the inequality holds.

$$f(\delta) := -\ln(1+\delta) + 2\delta/3 \le 0$$

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$f(0) = 0$ and $f(1) = -\ln(2) + 2/3 < 0$

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$$U(\delta - (1+\delta)\ln(1+\delta)) \leq -U\delta/3$$

True for $\delta = 0$. Divide by $U$ and take derivatives:

$$-\ln(1+\delta) \leq -1/3 \iff \ln(1+\delta) \geq 1/3 \quad \text{(true)}$$

**Reason:**
As long as derivative of left side is smaller than derivative of right side the inequality holds.

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This holds for $0 \le \delta < 1$.

# Integer Multicommodity Flows

- Given $s_i$-$t_i$ pairs in a graph.
- Connect each pair by a path such that not too many path use any given edge.

$$
\begin{array}{llrcl}
\min & & & & W \\
\text{s.t.} & \forall i & \sum_{p\in\mathcal{P}_i} x_p & = & 1 \\
& & \sum_{p:e\in p} x_p & \le & W \\
& & x_p & \in & \{0,1\}
\end{array}
$$

# Integer Multicommodity Flows

**Randomized Rounding:**
For each $i$ choose one path from the set $\mathcal{P}_i$ at random according to the probability distribution given by the Linear Programming solution.

## Theorem 5

*If* $W^* \geq c \ln n$ *for some constant* $c$, *then with probability at least* $n^{-c/3}$ *the total number of paths using any edge is at most* $W^* + \sqrt{cW^* \ln n}$.

## Theorem 6

*With probability at least* $n^{-c/3}$ *the total number of paths using any edge is at most* $W^* + c \ln n$.

# Integer Multicommodity Flows

Let $X_e^i$ be a random variable that indicates whether the path for $s_i$-$t_i$ uses edge $e$.

Then the number of paths using edge $e$ is $Y_e = \sum_i X_e^i$.

$$E[Y_e] = \sum_i \sum_{p \in \mathcal{P}_i : e \in p} x_p^* = \sum_{p : e \in P} x_p^* \le W^*$$

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# Integer Multicommodity Flows

Choose $\delta = \sqrt{(c \ln n)/W^*}$.

Then

$$\Pr[Y_e \geq (1+\delta)W^*] < e^{-W^*\delta^2/3} = \frac{1}{n^{c/3}}$$

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# 18 MAXSAT

**Problem definition:**

- $n$ Boolean variables
- $m$ clauses $C_1, \ldots, C_m$. For example

$$C_7 = x_3 \vee \bar{x}_5 \vee \bar{x}_9$$

- Non-negative weight $w_j$ for each clause $C_j$.
- Find an assignment of true/false to the variables sucht that the total weight of clauses that are satisfied is maximum.

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**Terminology:**

- A variable $x_i$ and its negation $\bar{x}_i$ are called literals.
- Hence, each clause consists of a set of literals (i.e., no duplications: $x_i \vee x_i \vee \bar{x}_j$ is **not** a clause).
- We assume a clause does not contain $x_i$ and $\bar{x}_i$ for any $i$.
- $x_i$ is called a positive literal while the negation $\bar{x}_i$ is called a negative literal.
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- Clauses of length one are called unit clauses.

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# MAXSAT: Flipping Coins

Set each $x_i$ independently to true with probability $\frac{1}{2}$ (and, hence, to false with probability $\frac{1}{2}$, as well).

Define random variable $X_j$ with

$$X_j = \begin{cases} 1 & \text{if } C_j \text{ satisfied} \\ 0 & \text{otw.} \end{cases}$$

Then the total weight $W$ of satisfied clauses is given by

$$W = \sum_j w_j X_j$$

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$$E[W]$$

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$$= \sum_j w_j \Pr[C_j \text{ is satisified}]$$

$$
\begin{aligned}
E[W] &= \sum_j w_j E[X_j] \\
&= \sum_j w_j \Pr[C_j \text{ is satisified}] \\
&= \sum_j w_j \left(1 - \left(\frac{1}{2}\right)^{\ell_j}\right)
\end{aligned}
$$

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&= \sum_j w_j \left(1 - \left(\frac{1}{2}\right)^{\ell_j}\right) \\
&\geq \frac{1}{2} \sum_j w_j \\
&\geq \frac{1}{2} \mathrm{OPT}
\end{aligned}
$$

# MAXSAT: LP formulation

- Let for a clause $C_j$, $P_j$ be the set of positive literals and $N_j$ the set of negative literals.

$$C_j = \bigvee_{j \in P_j} x_i \vee \bigvee_{j \in N_j} \bar{x}_i$$

$$\begin{array}{llrcl}
\max & & \multicolumn{3}{c}{\sum_j w_j z_j} \\
\text{s.t.} & \forall j & \sum_{i \in P_j} y_i + \sum_{i \in N_j} (1 - y_i) & \geq & z_j \\
 & \forall i & y_i & \in & \{0,1\} \\
 & \forall j & z_j & \leq & 1
\end{array}$$

# MAXSAT: LP formulation

- Let for a clause $C_j$, $P_j$ be the set of positive literals and $N_j$ the set of negative literals.

$$C_j = \bigvee_{j \in P_j} x_i \vee \bigvee_{j \in N_j} \bar{x}_i$$

$$\begin{array}{llrcl} \max & & \sum_j w_j z_j & & \\ \text{s.t.} & \forall j & \sum_{i \in P_j} y_i + \sum_{i \in N_j} (1 - y_i) & \geq & z_j \\ & \forall i & y_i & \in & \{0,1\} \\ & \forall j & z_j & \leq & 1 \end{array}$$

# MAXSAT: Randomized Rounding

Set each $x_i$ independently to true with probability $y_i$ (and, hence, to false with probability $(1 - y_i)$).

**Lemma 7 (Geometric Mean $\leq$ Arithmetic Mean)**

*For any nonnegative* $a_1, \dots, a_k$

$$\left(\prod_{i=1}^{k} a_i\right)^{1/k} \leq \frac{1}{k}\sum_{i=1}^{k} a_i$$

## Definition 8

A function $f$ on an interval $I$ is concave if for any two points $s$ and $r$ from $I$ and any $\lambda \in [0,1]$ we have

$$f(\lambda s + (1-\lambda)r) \geq \lambda f(s) + (1-\lambda)f(r)$$

## Lemma 9

*Let $f$ be a concave function on the interval $[0,1]$, with $f(0) = a$ and $f(1) = a + b$. Then*

$$\begin{aligned} f(\lambda) &= f((1-\lambda)0 + \lambda 1) \\ &\geq (1-\lambda)f(0) + \lambda f(1) \\ &= a + \lambda b \end{aligned}$$

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$\Pr[C_j \text{ not satisfied}]$

$$\Pr[C_j \text{ not satisfied}] = \prod_{i \in P_j} (1 - y_i) \prod_{i \in N_j} y_i$$

$$\Pr[C_j \text{ not satisfied}] = \prod_{i\in P_j}(1-y_i)\prod_{i\in N_j} y_i$$

$$\le \left[\frac{1}{\ell_j}\left(\sum_{i\in P_j}(1-y_i) + \sum_{i\in N_j} y_i\right)\right]^{\ell_j}$$

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\Pr[C_j \text{ not satisfied}] &= \prod_{i\in P_j}(1-y_i)\prod_{i\in N_j} y_i \\
&\le \left[\frac{1}{\ell_j}\left(\sum_{i\in P_j}(1-y_i)+\sum_{i\in N_j} y_i\right)\right]^{\ell_j} \\
&= \left[1-\frac{1}{\ell_j}\left(\sum_{i\in P_j} y_i+\sum_{i\in N_j}(1-y_i)\right)\right]^{\ell_j}
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&= \left[ 1 - \frac{1}{\ell_j} \left( \sum_{i \in P_j} y_i + \sum_{i \in N_j} (1 - y_i) \right) \right]^{\ell_j} \\
&\le \left( 1 - \frac{z_j}{\ell_j} \right)^{\ell_j} .
\end{aligned}
$$

The function $f(z) = 1 - (1 - \frac{z}{\ell})^{\ell}$ is concave. Hence,

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$$\geq \left[1 - \left(1 - \frac{1}{\ell_j}\right)^{\ell_j}\right] \cdot z_j \ .$$

$f''(z) = -\frac{\ell-1}{\ell}\left[1 - \frac{z}{\ell}\right]^{\ell-2} \leq 0$ for $z \in [0, 1]$. Therefore, $f$ is concave.

$$E[W]$$

$$E[W] = \sum_j w_j \Pr[C_j \text{ is satisfied}]$$

$$
\begin{aligned}
E[W] &= \sum_j w_j \Pr[C_j \text{ is satisfied}] \\
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&\geq \left(1 - \frac{1}{e}\right) \mathrm{OPT} \ .
\end{aligned}
$$

# MAXSAT: The better of two

**Theorem 10**
*Choosing the better of the two solutions given by randomized rounding and coin flipping yields a $\frac{3}{4}$-approximation.*

Let $W_1$ be the value of randomized rounding and $W_2$ the value obtained by coin flipping.

$$E[\max\{W_1, W_2\}]$$

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E[\max\{W_1, W_2\}] \\
&\geq E[\tfrac{1}{2}W_1 + \tfrac{1}{2}W_2]
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$$
\begin{aligned}
E[\max\{W_1, W_2\}]& \\
&\geq E[\tfrac{1}{2}W_1 + \tfrac{1}{2}W_2] \\
&\geq \frac{1}{2}\sum_j w_j z_j \left[1 - \left(1 - \frac{1}{\ell_j}\right)^{\ell_j}\right] + \frac{1}{2}\sum_j w_j \left(1 - \left(\frac{1}{2}\right)^{\ell_j}\right)
\end{aligned}
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&\geq \sum_j w_j z_j \Bigg[\underbrace{\frac{1}{2}\left(1 - \left(1 - \frac{1}{\ell_j}\right)^{\ell_j}\right) + \frac{1}{2}\left(1 - \left(\frac{1}{2}\right)^{\ell_j}\right)}_{\geq \frac{3}{4} \text{ for all integers}}\Bigg]
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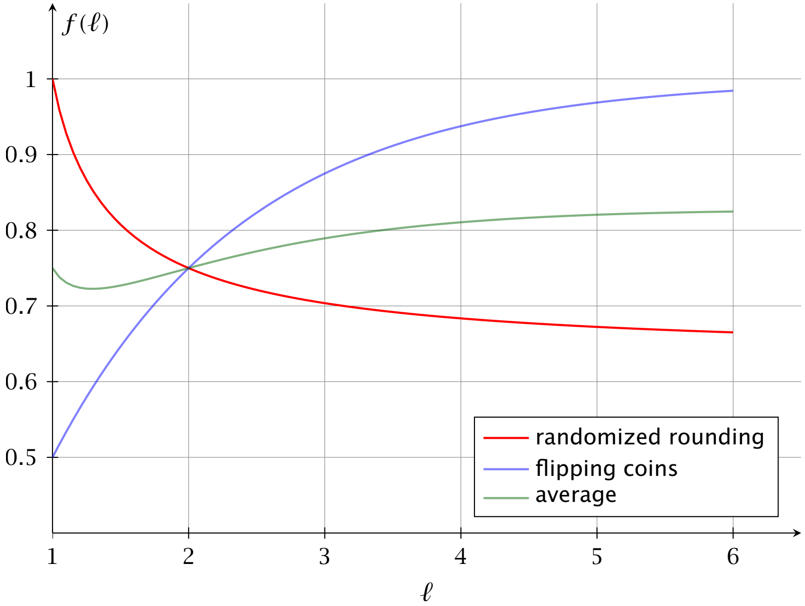
&\geq \frac{3}{4}\text{OPT}
\end{aligned}
$$



$f(\ell)$
1
0.9
0.8
0.7
0.6
0.5
1
2
3
4
5
6
$\ell$
randomized rounding
flipping coins
average

# MAXSAT: Nonlinear Randomized Rounding

So far we used linear randomized rounding, i.e., the probability that a variable is set to $1$/true was exactly the value of the corresponding variable in the linear program.

We could define a function $f : [0,1] \to [0,1]$ and set $x_i$ to true with probability $f(y_i)$.

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Let $f : [0,1] \to [0,1]$ be a function with

$$1 - 4^{-x} \le f(x) \le 4^{x-1}$$

**Theorem 11**

*Rounding the LP-solution with a function $f$ of the above form gives a $\frac{3}{4}$-approximation.*

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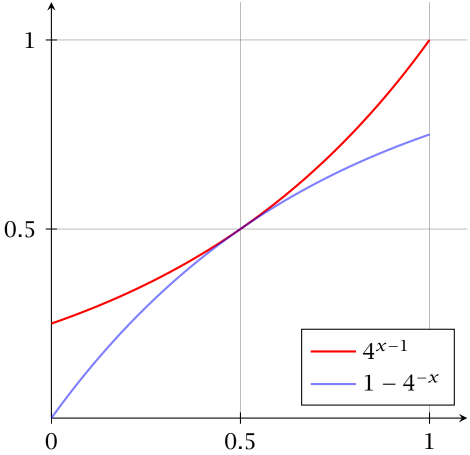
1
0.5
0
0.5
1
$4^{x-1}$
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## Can we do better?

Not if we compare ourselves to the value of an optimum LP-solution.

**Definition 12 (Integrality Gap)**

The integrality gap for an ILP is the worst-case ratio over all instances of the problem of the value of an optimal IP-solution to the value of an optimal solution to its linear programming relaxation.

Note that the integrality is less than one for maximization problems and larger than one for minimization problems (of course, equality is possible).

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## Lemma 13

*Our ILP-formulation for the MAXSAT problem has integrality gap at most* $\frac{3}{4}$.

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\begin{array}{llrcl}
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\end{array}
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Consider: $(x_1 \vee x_2) \wedge (\bar{x}_1 \vee x_2) \wedge (x_1 \vee \bar{x}_2) \wedge (\bar{x}_1 \vee \bar{x}_2)$

- any solution can satisfy at most 3 clauses
- we can set $y_1 = y_2 = 1/2$ in the LP; this allows to set $z_1 = z_2 = z_3 = z_4 = 1$
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