

SAMPLING TECHNIQUES FOR
APPROXIMATING **CSP** PROBLEMS.

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GENERAL FRAMEWORK:

- PROBLEM WITH **MASSIVE** DATA.
TOO LARGE TO BE STORED IN RAM,
MUST READ FROM EXTERNAL MEMORY.
- NATURAL APPROACH:
DRAW A **SMALL** SAMPLE STORABLE IN RAM.
A SPECIAL APPROXIMATION ALGORITHM
PROCESSES SAMPLE AND YIELD A GOOD ESTIMATE
OF AN ANSWER TO THE WHOLE PROBLEM.

OPT. PROBLEM P

(MAX-CUT, MAX-3SAT,
....)



CONSTANT SIZE (VERY TINY)

SAMPLE, DOES OPT_IS

TELLS YOU "SOMETHING"

ABOUT OPT_I ??

BASIC QUESTION
OF PROPERTY TESTING
OR EQUIVALENTLY
ABSOLUTE APPROX.

HISTORICALLY,
THE FIRST RESULTS
WERE DISCOVERED
FOR DENSE GRAPHS
(AT FIRST LACKING
THE **HARD CORE**
ESTIMATES)

- FIRST-CONNECTION TO
THE DENSE INSTANCES
OF OPTIMIZATION PROBLEMS
- SUBDENSE AND NONDENSE INSTANCES
- SAMPLE SIZES
- METRIC & QUASIMETRIC INSTANCES

PART I:

FIRST-TRY:

DENSE MAX-CSP INSTANCES AND
SMOOTH INTEGER PROGRAMS

PART II:

MIN-CSP INSTANCES

PART III:

APPLICATIONS:

METRIC AND
QUASI-METRIC PROBLEMS

MAX/MIN

r -CSP

EQUIVALENT

TO THE FOLLOWING:

GIVEN A SET OF

r -ARY **BOOLEAN** FNCT.'s

f_1, f_2, \dots, f_m . CONSTRUCT

AN ASSIGNMENT

$x \in \{0,1\}^n$ SO AS TO

MAXIMIZE/MINIMIZE

THE NUMBER OF

SATISFIED FNCT.'s f_i .

PRELIMINARIES:

COPING WITH
COMPUTATIONAL
HARDNESS

- NEW APPROX.
METHODS (U.B.'s.)
- NEW PCP-TECHN.
(L.B.'s.)

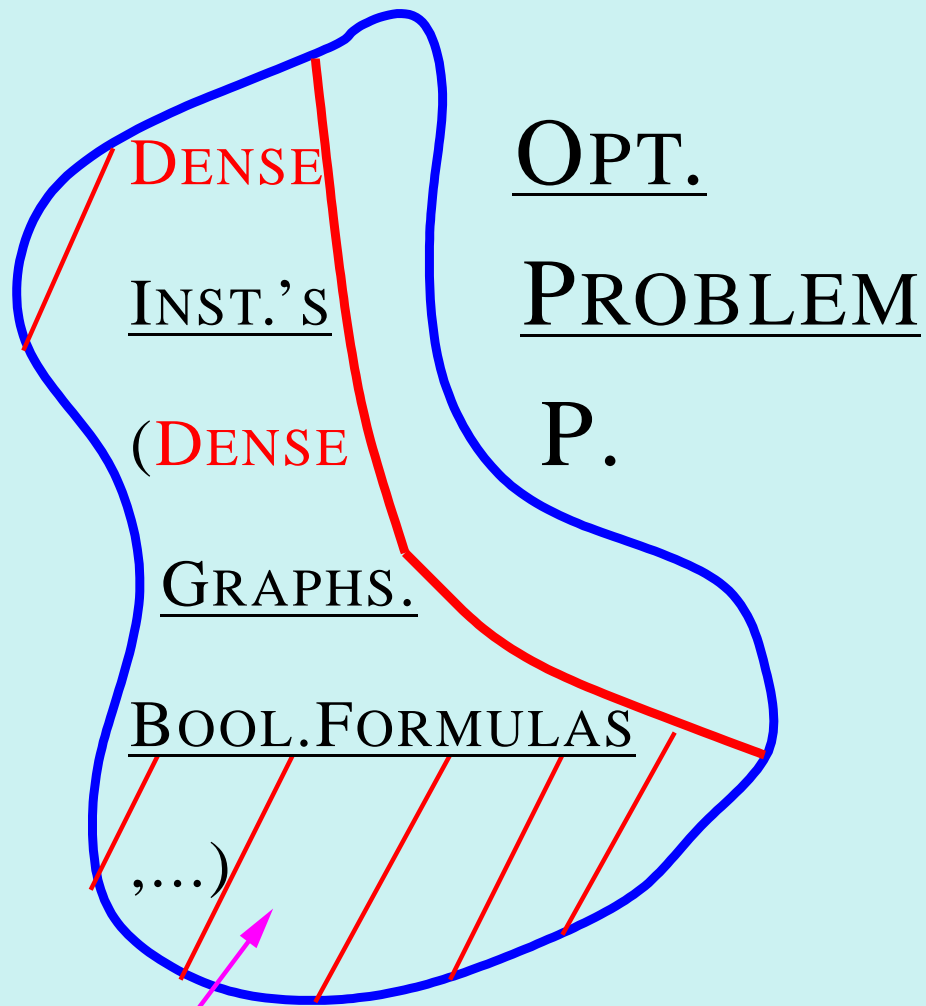
DENSE INSTANCES

ARE IN MANY

CASES -**VERY**-

“NATURAL” INSTANCES.

⇒ (**DENSITY** IN MANY CASES-
A SENSIBLE PARAMETER)



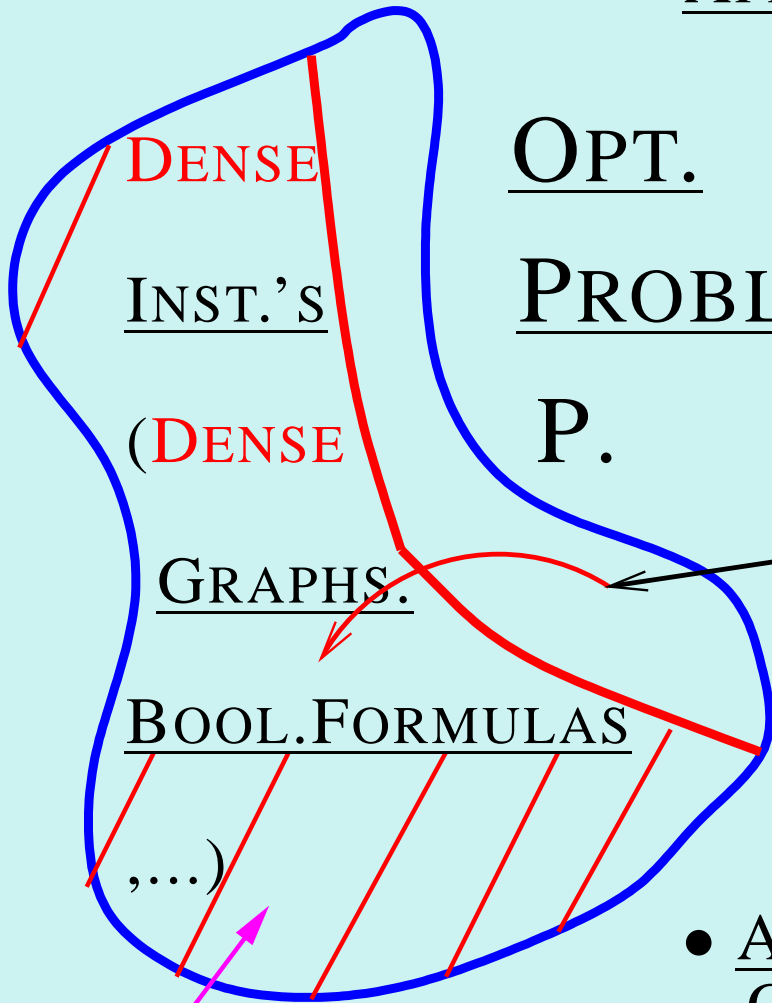
'ALMOST ALL' GRAPHS , k-SAT FORMULAS ,...

APPROX.HARDNESS?
(**DENSE** PCP??)

OPT.
PROBLEM

P.

CLASSIC.NP-H.



- AVOIDING PATHOLOGIES
OF **NON-DENSE HARDNESS.**

'ALMOST ALL' GRAPHS , k-SAT FORMULAS ,...

DENSITY

IN OPT. :

• $\Omega(n^2)$ EDGES

• $\Omega(n^k)$ CLAUSES

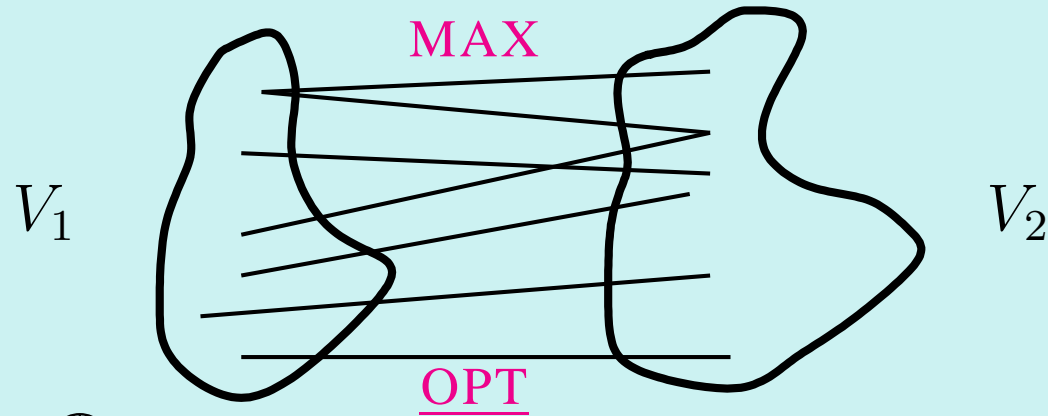
IN k-SAT FORM.'S

⋮

⇒ EXAMPLE:

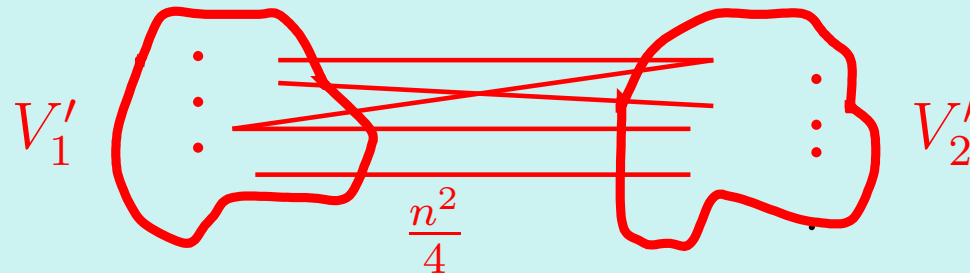
MAX-CUT.

G::



\oplus

K_n



$$\text{MAX-CUT } (G) = \text{OPT}$$

$$\text{MAX-CUT } (G \oplus K_n) = \text{OPT} + \frac{n^2}{4}$$

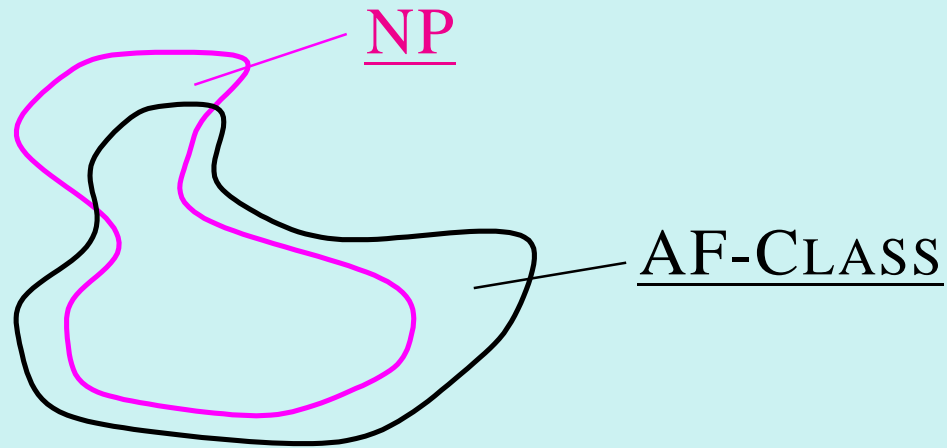
$G \oplus K_n$ HAS
 $\Omega(n^2)$ EDGES

⇒ BEYOND
DENSITY.

⇒ ”METRIC / GEOMETRIC
SITUATIONS”

⇒ [APPROXIMATION FEASIBILITY]

VS. NP.



APPROX. ANALOG TO
THE NP-CLASS: MAX-SNP

TWO NOTIONS OF APPROX.'S:

- ABSOLUTE:

$$| \underline{\text{OPT}} - Y | \leq \tau$$

- RELATIVE:

$$\text{MAX} \left\{ \frac{Y}{\underline{\text{OPT}}}, \frac{\underline{\text{OPT}}}{Y} \right\} \leq \tau$$

$Y = \underline{\text{COSTS OF SOLUTION } S}$

⇒ PTAS:

• A IS CALLED A
PTAS FOR π IF
FOR EVERY FIXED
 $\epsilon > 0$, A IS A POLY
TIME ALGORITHM IN
THE SIZE OF I (AN
INSTANCE OF π) WITH
APPROX. RATIO $1 + \epsilon$
(MEANING A OUTPUTS
A SOLUTION S TO
I S.T. $\text{MAX} \left\{ \frac{S}{\text{OPT}(I)}, \frac{\text{OPT}(I)}{S} \right\}$
 $\leq 1 + \epsilon$)

AF-CLASS

|||

EPTAS

- \mathcal{A} IS CALLED AN
EFFICIENT PTAS (EPTAS)

IF ITS RUNNING TIME IS

$$\underbrace{f(1/\varepsilon)} \cdot n^{O(1)}.$$

[OUGHT TO BE “SMALL”
GROWTH FUNCTION.]

AN EPTAS
IS CONSTANT
TIME AS (CTAS)
IF ITS RUNNING
TIME IS

$$f\left(\frac{1}{\epsilon}\right)$$

ρ -ABSOLUTE

PTAS (ρ -APTAS)

CONDITION:

$$|\underline{OPT} - \gamma| \leq \epsilon \rho,$$

FOR ALL $\epsilon > 0$.

IF OPT IS OF
ORDER ρ (OPT = $\Theta(\rho)$)

(\rightarrow DENSE INSTANCES),

EXIST. OF ρ -APTAS \Rightarrow
EXIST. OF PTAS)

• DENSE MAX-CSP

HAS PTAS_s

[AKK95] .
REF. [2]

• SUBDENSE MAX-CSP

HAS PTAS_s

[FK05]

REF. [4]

$\left(\frac{n^k}{\log n} \right)$ - CLAUSES.

RUNNING TIME

IMPROVEMENTS

FOR MAX-CSP:

'95 -----> 2003.
↑ [AFKK03]

- ABSOLUTE CTASs

($O^{\sim}(\frac{1}{\epsilon^4})$ SAMPLE,

$2^{O^{\sim}(\frac{1}{\epsilon^2})}$ TIME)

(THAT AREA BECAME
TO BE KNOWN AS THE
PROPERTY TESTING)

(\Downarrow)

- DENSE INST. OF MAX-CSP HAVE CTASs ($O^{\sim}(\frac{1}{\epsilon^4})$ SAMPLE, $2^{O^{\sim}(\frac{1}{\epsilon^2})}$ TIME)

- APPROXIMATION HARDNESS

(WITH RESPECT TO APPROX. RATIO r):

ACHIEVING A.R. r

IN (RANDOMIZED) POLY TIME

\Rightarrow NP = P (NP = **RP**, NP = co**RP**, ...)

- APPROXIMATION HARDNESS

(WITH RESPECT TO APPROX. RATIO r):

ACHIEVING A.R. r

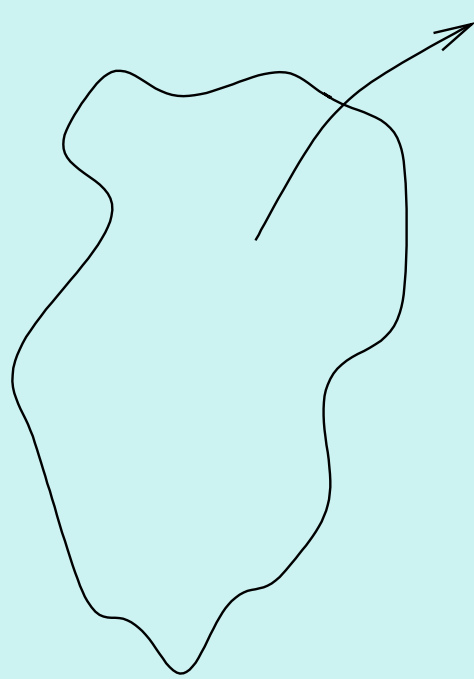
IN (RANDOMIZED) POLY TIME

\Rightarrow NP = P (NP = RP, NP = coRP, ...)

(PCP-TH. $\Rightarrow \forall X$ MAX-SNP-HARD

$\exists \varepsilon > 0$ [X IS APPROX. HARD WITHIN $1 + \varepsilon$].)

“WORLDS” OF MAX-OPT. APPROXIMATION:

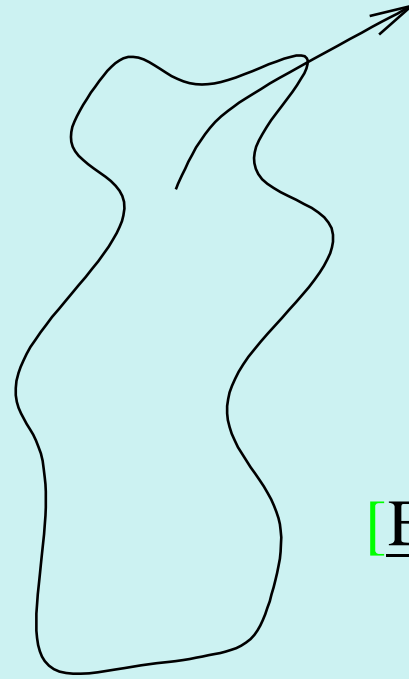
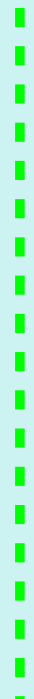


PTAS
(SPIPs
PROGR.,
..., '95)

[● DENSE]

MIN. DEG.

$= \Theta(n)$ ($\Theta(n^2)$ -EDGES)



No PTAS
(MAX-SNP-
HARD FOR
 $b = 3$,
'91, '92)

[EXPL. CONST.]

[● SPARSE]

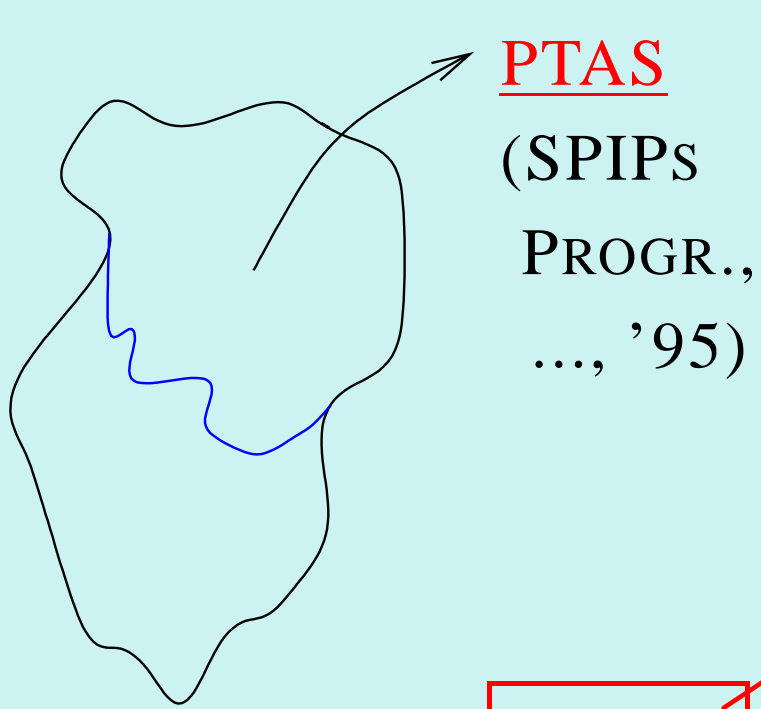
MAX. DEG

$\leq b$ (CONST.)

'95 \Rightarrow 2000/'01

MIN

“WORLDS” OF ~~MAX-OPT.~~ APPROXIMATION:



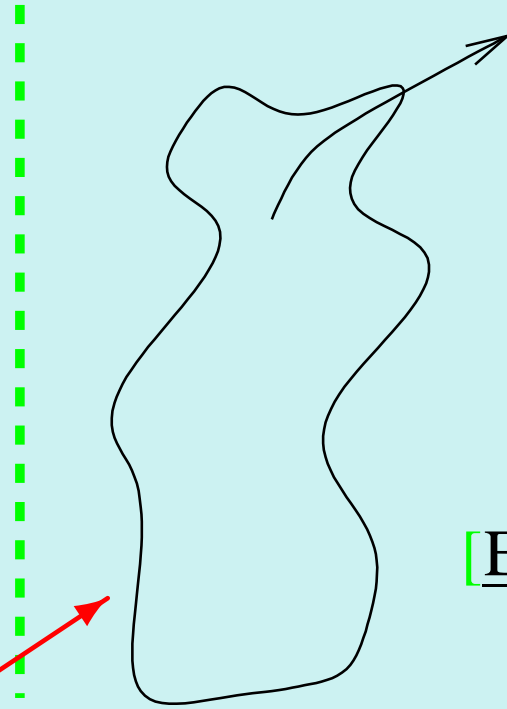
PTAS
(SIPs
PROGR.,
..., '95)

[● DENSE]

MIN. DEG.

$$= \Theta(n) (\cancel{\Theta(n^2)} \text{ EDGES})$$

$\Theta(n^2)$ -
EDGES



No PTAS
(MAX-SNP-
HARD FOR
 $b=3$,
'91, '92)

[EXPL. CONST.]

[● SPARSE]

MAX. DEG

$$\leq b \text{ (CONST.)}$$

- **DENSE** INSTANCES:

α -DENSE GRAPHS

(MIN DEGREE OF $G = (V, E)$ IS $\geq \alpha|V|$)

- A GRAPH IS DENSE

IF ITS MIN DEGREE IS $\Theta(n)$

- (A GRAPH IS DENSE IN AVERAGE

IF IT HAS $\Theta(n^2)$ EDGES)

⇒ OPTIMIZATION CLASSES:

0-CLASS:

- LONGEST PATH
- TSP

1ST CLASS: (LOCAL CONSTR.)

- MAX-CUT
- BISECTION

2ND CLASS:

- SET COVER
- STEINER TREE

3RD CLASS:

- BANDWIDTH

REF. [7]

A MAP OF
"DENSE" (ABSOLUTE)
APPROXIMATIONS:

PROBLEM	APPROX. RATIO	APPROX. HARDNESS	REF.
DENSE MAX-SNP	PTAS	—	[AKK95]
DENSE MAX-CUT	PTAS	—	[AKK95],[FV96]
DENSE MAX-DCUT	PTAS	—	[AKK95]
DENSE MAX-HYPERCUT(d)	PTAS	—	[AKK95]
DENSE DENSE-K-SUBGRAPH	PTAS	—	[AKK95]
EVERYWHERE DENSE SEPERATOR	PTAS	—	[AKK95]
EVERYWHERE DENSE BISECTION	PTAS	—	[AKK95]
EVERYWHERE DENSE MIN-K-CUT	PTAS	—	[AKK95]

PROBLEM	APPROX. RATIO	APPROX. HARDNESS	REF.
DENSE MIN-LINEAR-ARRANGEMENT	PTAS	—	[AFK96]
DENSE d-DIMENSIONAL-ARRANGEMENT	PTAS	—	[AFK96]
DENSE MIN-CUT-LINEAR-ARRANGEMENT	PTAS	—	[AFK96]
DENSE SET COVER	$\bigcap_c c \cdot \ln n$	OPEN	[KZ97b]
DENSE STEINER TREE	PTAS	—	[KZ97b]
DENSE VERTEX COVER	$\frac{2}{2-\sqrt{1-\varepsilon}}$	MAX-SNP-hard	[KZ97b]
EVERYWHERE DENSE VERTEX COVER	$\frac{2}{1+\varepsilon}$	MAX-SNP-hard	[KZ97b]
EVERYWHERE DENSE BANDWIDTH	3	OPEN	[KWZ97]
EVERYWHERE DENSE DBANDWIDTH	2	OPEN	[KWZ97]

(\Rightarrow 4TH CLASS:
(METRIC PROBLEMS)
• METRIC MAX-CUT)

\Rightarrow 4*TH CLASS:
(GEOMETRIC AND METRIC
GRAPH PROBLEMS)
• PARTITIONING PROBLEMS



(\Rightarrow '0'-CLASS

DENSE 'METRIC' TSP,

LONGEST PATH.)

QUALITATIVE RESULTS CONNECTED

TO BOTH

DENSE AND VERY

SPARSE SITUATIONS (!)

NP-HARDNESS AND DENSITY

α -DENSE GRAPHS

(MIN DEGREE OF $G = (V, E)$ IS $\geq \alpha|V|$)

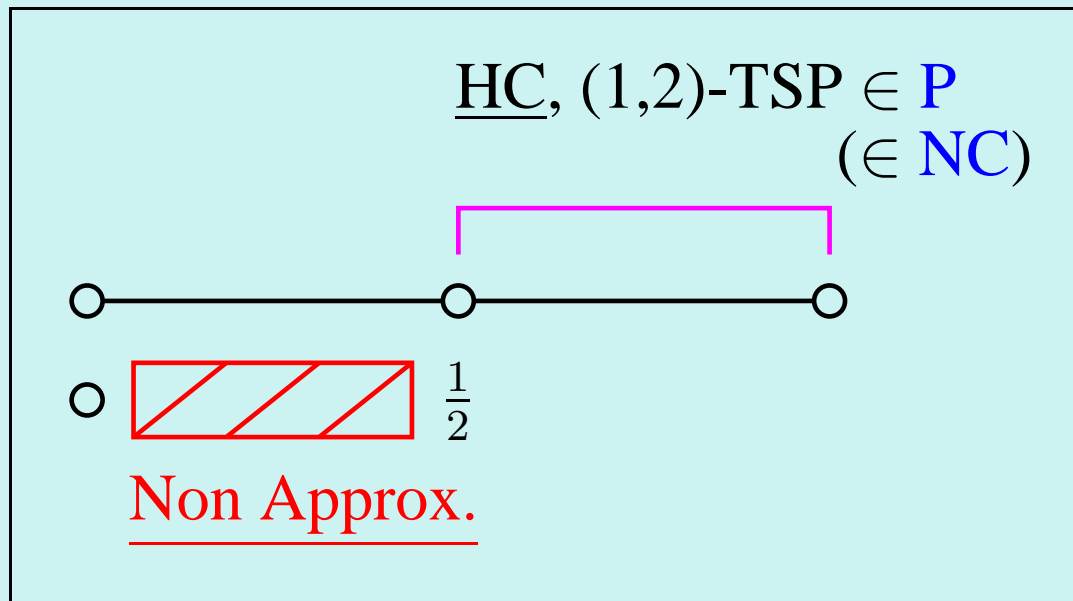
- HC (HAMILTONIAN CYCLE PROBLEM)
IS IN P FOR $\alpha \geq 1/2$,
- HC IS NP-HARD FOR $\alpha < 1/2$.

- LONGEST-PATH IS APPROX. HARD

FOR $\alpha < 1/2$ ([FVK98]).

- (1,2)-TSP IS APPROX. HARD

FOR $\alpha < 1/2$ ([FVK98]).



⇒ ANOTHER 'METRIC' PROBLEM

DENSE (1,2)-TSP

↑

SUBGRAPH SPANNED BY THE EDGES OF
LENGTH 1 IS DENSE

THEOREM ([FVK98],[FS98]).

FOR EVERY $0 < d < 1/2$,

(1,2)-TSP | INST. OF MIN. DEG. $\geq dn$

HAS A PTAS ⇒ (1,2)-TSP HAS A PTAS.

● APPROX. HARDNESS OF (1,2)-TSP:

$$r^* \cong 1 + 1.34 \cdot 10^{-3} \quad (743/742) \quad [\text{EK00}]$$



1/4-DENSE-TSP:

$$r^* = 1 + 1.07 \cdot 10^{-3} \quad [\text{FVK98}]$$

(BEST UPPER BOUND:

$$1.1429 \quad (8/7), [\text{BK06}].)$$

3-OCC-E3-LIN2

LOWER B.:

1.0163 [BK99]

$$r_d^* = 1 + \varepsilon^* \cdot \frac{1}{1+d}$$

FOR

$$r^* = 1 + \varepsilon^* .$$

CLASSES OF DENSE OPT. PROBLEMS

⇒ 1ST CLASS (LOCAL-CONSTRAINT)

- MAX-CUT
- BISECTION
- MAX-SNP

⇒ 2ND CLASS (COVERING PROBLEMS)

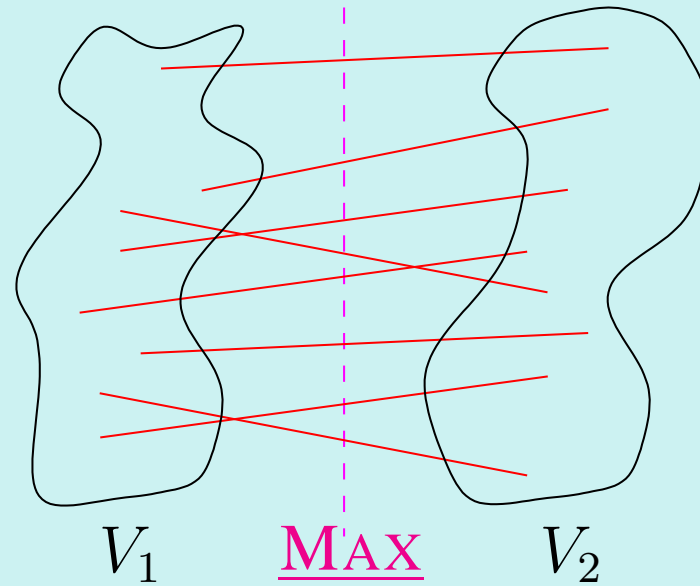
- SET COVER
- STEINER TREE
- VERTEX COVER

⇒ 3RD CLASS (BANDWIDTH PROBLEMS)

- BANDWIDTH
- DBANDWIDTH

\Rightarrow 1ST CLASS
([AKK95],
[FV96].)

- MAX-CUT

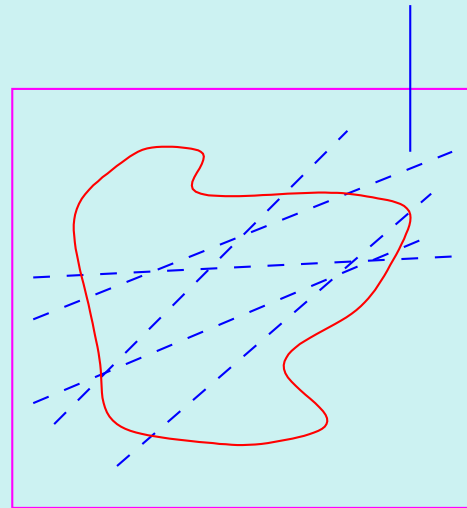


- BISECTION

MIN IN “50/50”-CUT
(EQUI-CUT) $|V_1| = |V_2|$
(“STATUS” WIDE OPEN!)

[“DENSE”-IDEA::]

SAMPLE CUTS



EXHAUSTIVE
SAMPLING

$O(\log n)$ -SAMPLE

PLACEMENT METHOD

BY EXHAUSTIVE SAMPLING:

- TAKE A SAMPLE OF
 $O(\log n)$ VERTICES.
- EXHAUSTIVELY TRY ALL
POSSIBLE PLACEMENTS (IN L, R),
 $2^{O(\log n)}$ -MANY DECIDE
WHERE EACH VERTEX OF THE
SAMPLE BELONGS IN OPT CUT.

DENSITY \Rightarrow WITH HIGH
PROBABILITY $(1 - n^{-\beta}, \beta \text{ CONST.})$
SOME OF THE NEIGHBORS
OF V WHERE SAMPLED.

EASY DECISIONS

IF $|\Gamma_L(V)| \ll |\Gamma_R(V)|$

OR $|\Gamma_L(V)| \gg |\Gamma_R(V)|$

“DIFFICULTY”

IF

$$|\Gamma_L(V)| \approx |\Gamma_R(V)|$$

(\Rightarrow SPIPs)

Smooth-
-Programming

\oplus Global
Method

①

SPIP-

PROGRAMS.

①

SPIP-

PROGRAMS.

SMOOTH POLYNOMIAL
INTEGER PROGRAMS.

SPIPS.

LET $P \in \mathbb{Z}[x_1, x_2, \dots, x_n]$
BE A DEGREE K
POLYNOMIAL WITH
INTEGER COEFF.'S.

LET

$$P = \sum_{i=1}^m \underbrace{a_i}_{\text{COEFF.}} \underbrace{M_i}_{\text{MONOMIAL.}}$$

P IS CALLED

C -SMOOTH, FOR A

CONSTANT $C > 0$, IFF

$$|a_i| \leq C \cdot n^{k - \text{DEG}(M_i)}$$

FOR ALL $1 \leq i \leq n$.

DEF. A POLYNOMIAL
INTEGER PROGRAM

OF DEGREE K

IS A SPIP

(OF DEGREE K)

IF BOTH

"OBJECTIVE" AND

"CONSTRAINT"

POLYNOMIALS ARE

C -SMOOTH FOR

SOME CONSTANT $C > 0$.

$$\text{MAX}_x / \text{MIN}_x P(x),$$

$$P \in \mathbb{Z}[x_1, \dots, x_n],$$

C-SMOOTH,

$$\text{DEG}(P) \leq k,$$

$$x_i \in \{0, 1\};$$

$$q_j(x) \geq 0$$

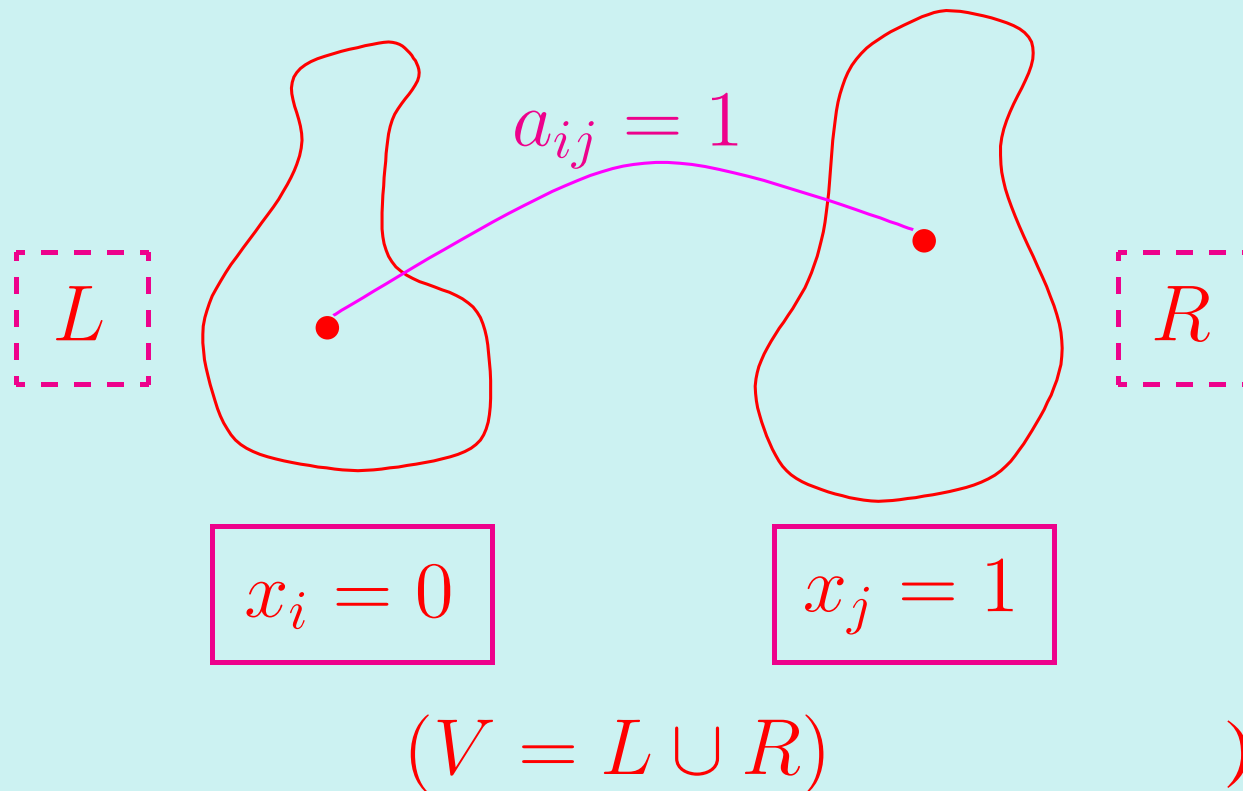
FOR $q_j \in \mathbb{Z}[x_1, \dots, x_n]$

C-SMOOTH, AND
OF DEG. $\leq k$.

EXAMPLE :

[“SMOOTH” PROGRAMS]

(MAX-CUT:



⇒ WRITE A

QUADRATIC INT. PROGRAM:

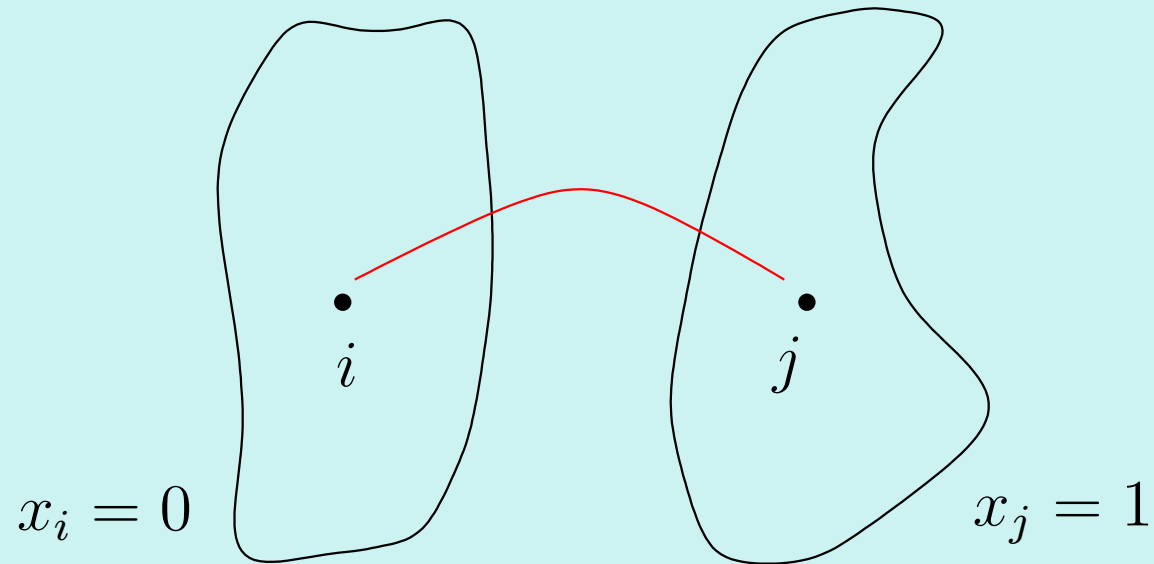
P::

$$\max_{x_i} \left\{ \sum_{i < j} (a_{ij} \cdot (x_i(1 - x_j) + x_j(1 - x_i))) \right\}$$

- $x_i \in \{0, 1\}$

($A = [a_{ij}]$ IS THE
ADJ. MATRIX OF G)

$$\underline{\text{MAX-CUT}}(G) = \underline{OPT}_P$$



$$s_{ij} = x_i(1 - x_j) + x_j(1 - x_i)$$

$$s_{ij} = 1 \iff x_i \neq x_j, \quad (x_i, x_j \in \{0, 1\})$$

$$(s_{ij} = x_i + x_j - 2x_i x_j)$$

$$\begin{aligned} Q &= \sum_{i < j} a_{ij} s_{ij} \\ &= \sum_{i < j} -2a_{ij} x_i x_j + \sum_i b_i x_i \end{aligned}$$

- COEFFICIENTS OF DEG. 2
MONOMIALS $\in \{0, -2\}$
- COEFFICIENTS OF DEG. 1
MONOMIALS $= O(n)$

DEF.

A POLYNOMIAL $P \in \mathbb{Q}[x_1, \dots, x_n]$ OF
DEG. d IS c -SMOOTH (c -CONST)

IF

$$P = \sum_{i=1}^m a_i M_i$$

AND

$$|a_i| \leq c \cdot n^{d - \text{DEG}(M_i)}$$

FOR ALL $1 \leq i \leq m$.

$$\Rightarrow Q = \sum_{i < j} a_{ij} s_{ij}$$

FOR MAX-CUT

IS 2-SMOOTH.

- (• $| - 2 | \leq 2n^0$ FOR DEG = 2 ;
• $|cn| \leq 2n^{2-1}$ FOR DEG = 1
($c \leq 1$)).

DEF.

A POLYNOMIAL INTEGER PROGRAM

(PIP) OF DEG. d IS c -SMOOTH

IF ITS OBJECTIVE FNCT. P IS A

c -SMOOTH POLYNOMIAL OF DEG. d .

ABS. APPROX. OF SPIPs NEEDED

FOR BOTH MAX- & MIN-CSP.

SPIP-THEOREM

(ARORA, KARGER, KARPINSKI '95)

LET P BE AN SPIP OF DEG. d .

LET OPT BE THE OPT-VALUE OF P .

THEN FOR EVERY $\varepsilon > 0$ THERE IS A

POLY TIME APPROX. ALG. PRODUCING

AN ASSIGNMENT $s \in \{0, 1\}^n$,

S.T.

$$P(s) \geq \underline{\text{OPT}} - \varepsilon n^d$$

- RUNNING TIME: $n^{O(1/\varepsilon^2)}$ (AS OF '95)

Π.

• RUNING TIME: $O^{\sim}(\frac{1}{\epsilon^4})$,
[AFKK'03], REF [1].

II'

IMPROVEMENT
OF ABSOLUTE

APPROX. RATIO

To $\boxed{\varepsilon n^d / \text{LOG} n}$:

$$|P(s) - \text{OPT}| \leq \varepsilon n^d / \text{LOG} n$$

(DE LA VEGA, KARPINSKI,
2006)

→ cf. REF. [4].

WORKS FOR

BOTH MAX- & MIN-OBJ.



YIELDS PTASs FOF “LARGE”-VALUES
OF OBJ. FNCTS. FOR ’MAX/MIN’.



DENSE MAX-SNP

DOES HAVE A PTAS.

SO, ’CONSTRUCTIVELY’





DENSE

MAX-CUT \in PTAS

■ (1ST CLASS).

PART II.

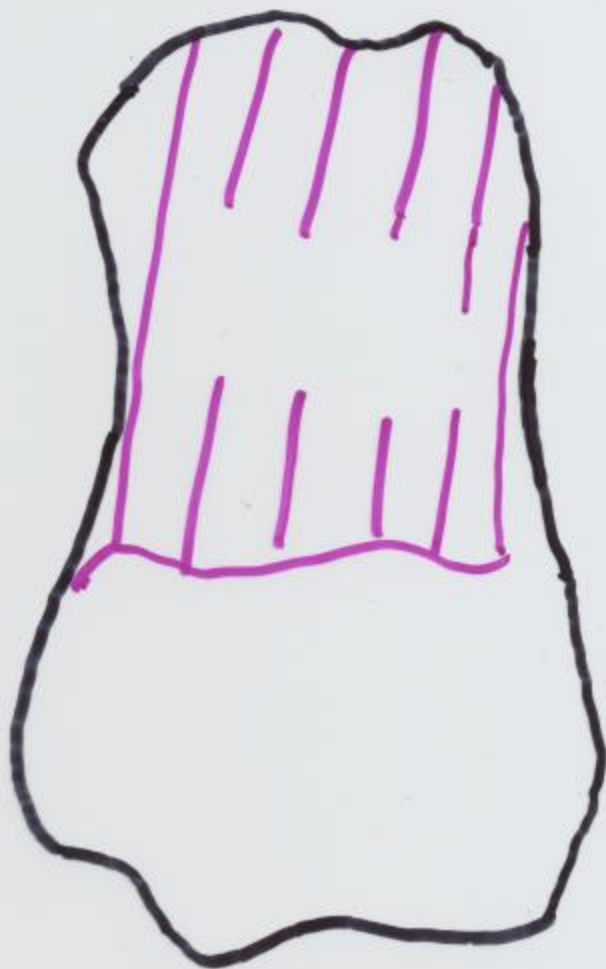
MIN -

OPTIMIZATION

(MIN-CSP).

CSP:

DENSE
INSTANCES



CSP:

DENSE
INSTANCES



SPARSE

INSTANCES

CSP:

DENSE
INSTANCES



SPARSE
INSTANCES

PTASs

[AKK '95]

SMOOTH POLY. INTEGER
PROGRAMS.

No
PTASs

(→ E.G. -
MIN-2DNF)

SPARSITY

(vs. DENSITY)

TAKE

2DNF-CONJ.

*)

MIN-CSP ($x \wedge y, \neg x \wedge \neg y$)

MIN-2CNF-DELETION

KNOWN TO BE MAX-SNP-HARD ([KPRT'96]).

FOR f AN INSTANCE
OF *) WITH n VAR'S x_1, \dots, x_n ,
CONSTRUCT A DENSE INST.
 f' BY ADDING ALL CLAUSES
 $x_i \wedge y_j$ FOR $1 \leq i, j \leq n$. WE
HAVE CLEARLY $OPT(f') = OPT(f)$.

NEW VAR'S

$$f' = f \bigwedge_{i,j} (x_i \wedge y_j)$$

IN OPT(f')
SET TO 0.

f' IS "EVERYWHERE"

DENSE \Rightarrow DENSE

MIN-2 DNF IS

MAX-SNP-HARD.

Two

OUTSTANDING

PROBLEMS:

MIN-kSAT

AND

MIN-kLIN

≡ kNCP

↑
NEAREST CODEWORD
PROBLEM

HERE

"DENSE"

MEANS

"EVERYWHERE

DENSE"

(EVERY VAR. x_i)

OR ITS NEGATION

OCCURS $\Theta(n^{k-1})$

TIMES).

MIN-kSAT

IS

MAX-SNP - HARD ✓

AND

APPROX. WITHIN

$$2(1 - 1/2^k)$$

FOR EVERY $k \geq 2$

([BTV 96], [KKM 94]).

⇒ OB:

APPROX.

UPPER : $O(n/\log n)$

APPROX.

LOWER : $n^{\Omega(1/\log \log n)}$

3NCP =

MIN-CSP ($x \oplus y \oplus z = 0,$
 $x \oplus y \oplus z = 1$)

↑

SET OF CONSTRAINT
APPLICATIONS IS
A SYSTEM OF LIN.
EQUATIONS WITH
EXACTLY 3 VAR'S
PER EQUATION.

→ REF. [7].

How

ABOUT

DENSE

MIN-KSAT ?

(MAX-SNP-HARD OR

EXISTENCE OF PTAS?)

(IT IS NP-HARD IN
EXACT SETTING)

• "OPTIMALITY"
OF PTAS ($\forall \epsilon > 0$)

How

ABOUT

DENSE

MIN-KSAT ?

(MAX-SNP-HARD OR

EXISTENCE OF PTAS?)

ALIKE
MIN-KDNF
??

(IT IS NP-HARD IN
EXACT SETTING)

• "OPTIMALITY"
OF PTAS ($\forall \epsilon > 0$)

TI.



SUGGESTS

A PARTITION
OF INSTANCES
OF MIN-kSAT
INTO INSTANCES
f WITH

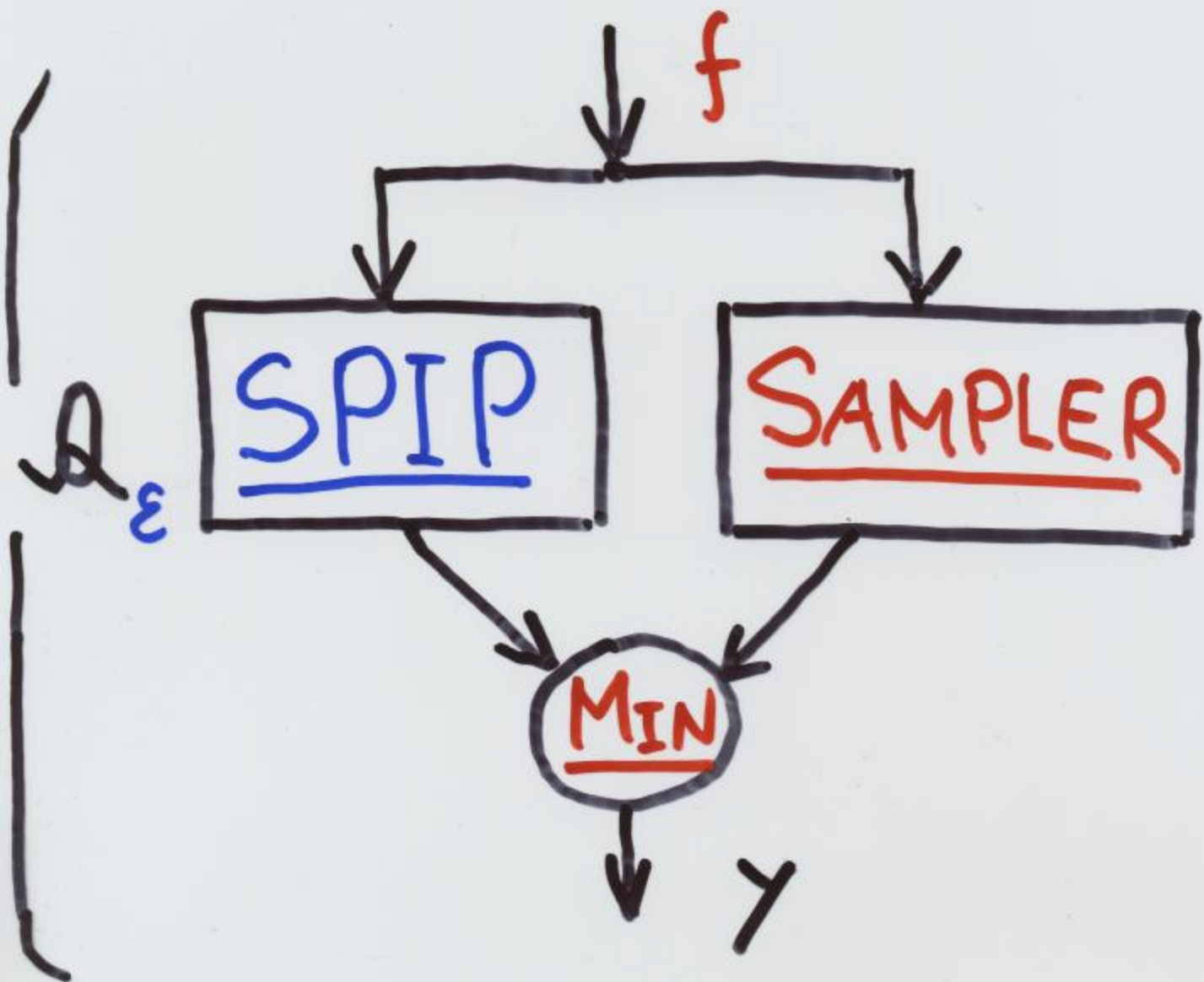
• OPT(f) $\geq \alpha n^k$,

AND

• OPT(f) $< \alpha n^k$.

ALGORITHMS

A_ϵ OF THE FORM:



METHOD:

SAMPLER

DESIGN FOR

'RETRACT DENSITY'

OF (k-1)-UNIFORM

HYPERGRAPHS.

OBJ.

FNCT. $\leq \alpha n^k$

THEOREM.

DENSE

MIN-K SAT

AND

K NCP

PROBLEMS

HAVE

PTASs

(FOR EVERY $k \geq 2$)

A PTAS

FOR DENSE

NEAREST

CODEWORD

PROBLEM.

A PTAS BASED
ON SAMPLERS FOR 3NCP.

I.: A δ -DENSE INSTANCE
OF MIN-E3-LIN-2, AND $\epsilon > 0$.

1. APPLY SPIP-ALG. OF [AKK95]

OUTPUT = $\bar{x}_i^* \in \{0, 1\}^n$

(START NOW A NEW ALG.
BASED ON SAMPLERS)

▶ 2. PICK 2 RANDOM SUBSETS
 S_1, S_2 OF THE SET $X = \{x_1, \dots, x_n\}$
OF VAR'S OF SIZE $\Theta\left(\frac{1}{\delta\epsilon^2} \log n\right)$
($S_1 \cap S_2 = \emptyset$).

3. FOR ALL POSSIBLE ASSIGN'S
 $a \in \{0, 1\}^{S_1 \cup S_2}$ DO: SAMPLER

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I.: A δ -DENSE INSTANCE
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OBJ. 1. APPLY SPIP-ALG. OF [AKK95]

FNCT.: OUTPUT = $\bar{x}_1^* \in \{0,1\}^n$

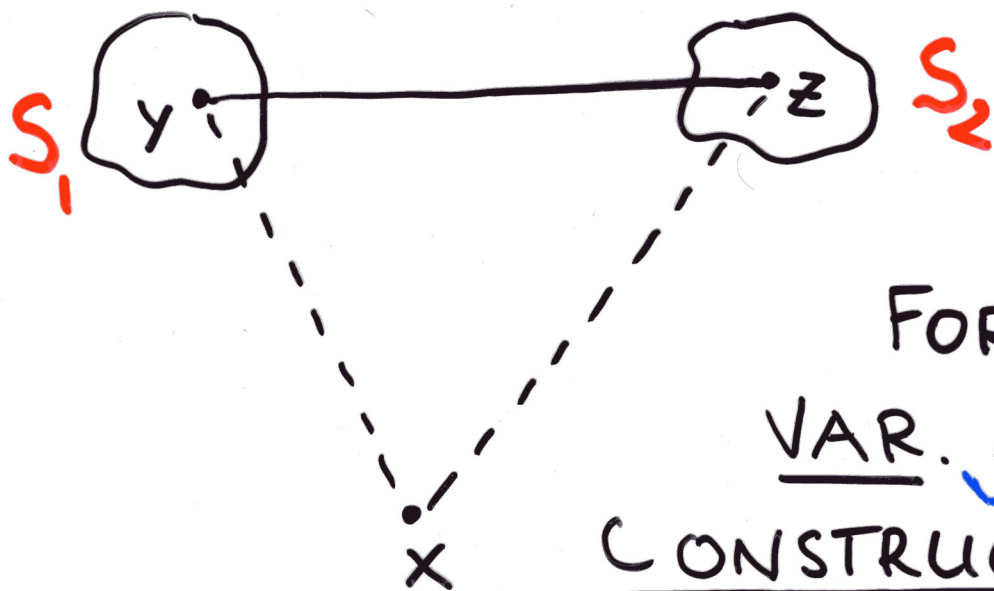
$\geq \alpha n^3$ (START NOW A NEW ALG.
BASED ON SAMPLERS)

▶ 2. PICK 2 RANDOM SUBSETS
 $\leq \alpha n^3$ S_1, S_2 OF THE SET $X = \{x_1, \dots, x_n\}$
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SAMPLER:

(FOR $a \in \{0,1\}^{|S_1 \cup S_2|}$)



FOR EACH
VAR. $x \in S_1 \cup S_2$

CONSTRUCT

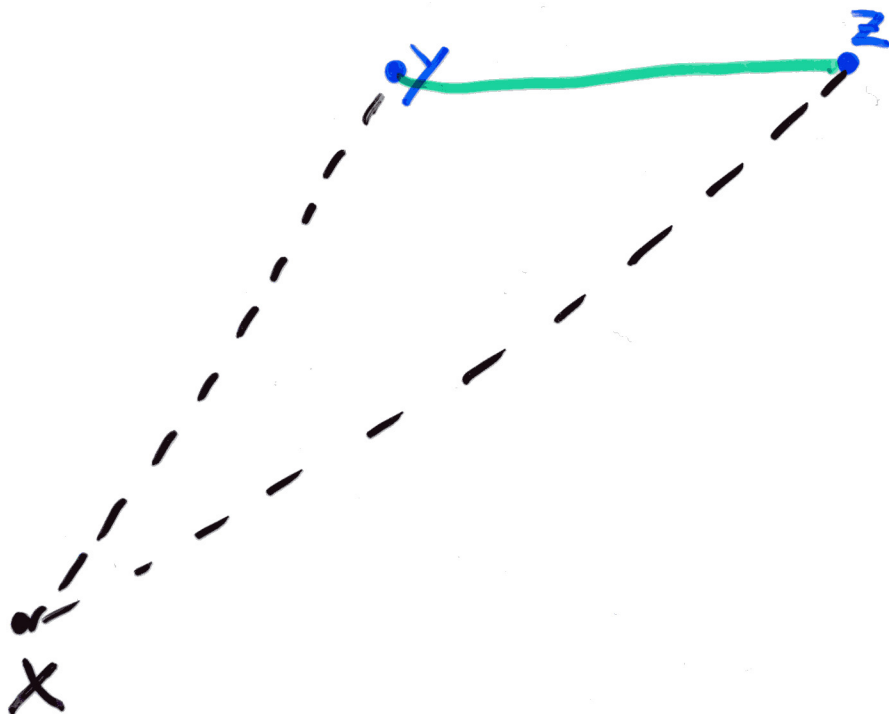
A GRAPH

$$G_x = (S_1 \cup S_2, E_x),$$

$$E_x = \left\{ \{y, z\} \mid x \oplus y \oplus z = a \right. \\ \left. \text{IS AN EQ. , } y \in S_1 \text{ AND } z \in S_2, \text{ OR } y \in S_2 \text{ AND } z \in S_1 \right\}$$

$$\left(\begin{array}{l} m_a \\ m_{-a} \end{array} \right) = \# \text{ OF EDG'S IN } E_x \frac{\text{SAT. BY } x=0}{x=1}$$

FOR ALL $a \in \{0,1\}^{|S_1 \cup S_2|}$ DO:



(DEC.
WHETHER
 $x := 0$
OR
 $x := 1$)

• TEST

• IF $m_0^a \geq \frac{2}{3}(m_0^a + m_1^a)$

THEN SET $x := 1;$

• IF $m_1^a \geq \frac{2}{3}(m_0^a + m_1^a)$

THEN SET $x := 0;$

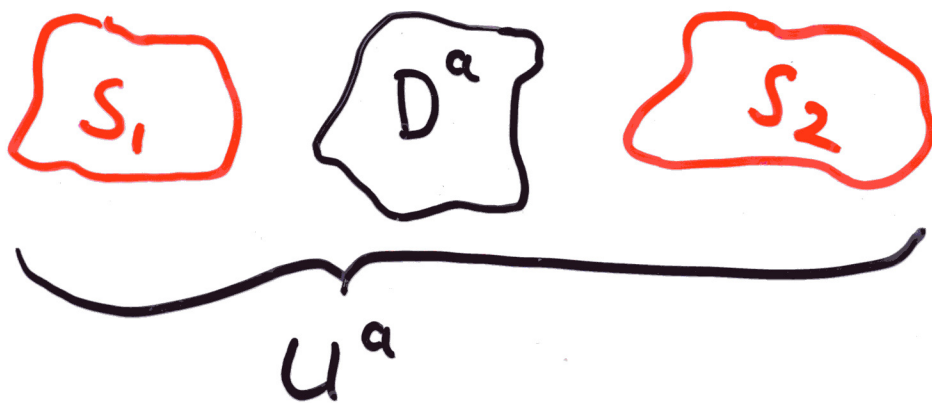
OTHERWISE SET

$x := \underline{\text{UNDEFINED}}$.

• PLACEMENT OF UNDEFINED VAR'S.

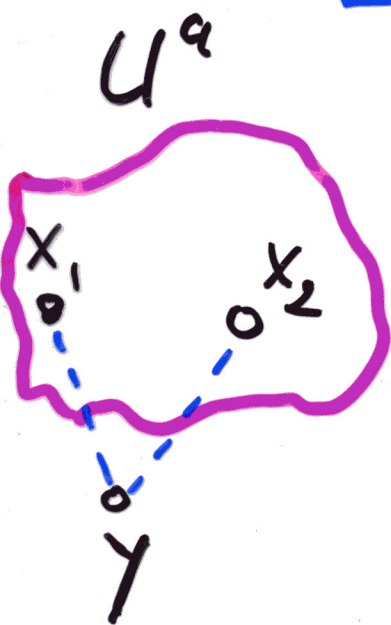
$$U^a = S_1 \cup S_2 \cup D^a$$

VAR'S WHICH ARE ALREADY DEFINED.



SUPPOSE

$y \in X \setminus U^a$ (y IS UNDEF.)



CONSTRUCT

A SET OF EQ.'S \mathcal{S}_y
WITH y AS A VARIABLE

IF $\mathcal{S}_y = \emptyset$ WE SET

y TO 0 (OR 1 ARBITR.)

$\left\{ \begin{array}{l} n_0^a = \# \text{ OF EQ.'S SAT. IN } \mathcal{S}_y \text{ FOR } y=0; \\ n_1^a = \# \text{ " " " " } y=1 \end{array} \right.$

• IF $n_0^a \geq n_1^a$ THEN

SET $y := 1$ ELSE

SET $y := 0$.

DENOTE THE RESULTING
ASSIGNMENT BY $\bar{x}_a^* (\in \{0,1\}^n)$.

4.

OUTPUT \bar{x}^* S.T. $N^* =$

$\text{MIN}(\bar{x}_1^*, \underbrace{\text{MIN}_a(\bar{x}_a^*)}_{\bar{x}_2^*})$

$N^* = \#$ OF EQ.'S SAT.
BY \bar{x}^* .

CLAIM:

$N^* \leq (1 + \epsilon) \cdot \text{OPT.} (\forall \epsilon > 0)$

PART III.

CONSTANT TIME

ALGORITHMS

&

APPLICATIONS,

GETTING BEYOND

ABSOLUTE APPROX.

BOUNDS.

GETTING THE
RUNNING TIME
OF SPIP-THEOREM
DOWN TO
 $O^{\sim}(\frac{1}{\epsilon^4})$.

SEE FOR THE
INTERMEDIATE
RESULTS, AND
THEIR APPLIC'S REF[1]

SPECIAL

LINEAR ALGEBRAIC

TECHNIQUES NEEDED-

COMBINED WITH

SOME CONSTANT

TIME SAMPLING

METHOD FOR LPs

(LINEAR PROGRAMS).

// FIRST A LOOK

AT THE METHOD
OF SPIP-THEOREM:

LINEARIZING

QUADRATIC PROGRAM

P FOR MAX-CUT

$$P: \text{MAX}_{x_i} \left\{ \sum_i x_i - \sum_{(i,j) \in E} a_{ij} (1 - x_j) \right\},$$

$$x_i, x_j \in \{0, 1\}.$$

LET x^* BE OPT.

ASSIGNMENT OF P.

LINEARIZE P BY

ESTIMATING

$$z_i - \epsilon n \leq \sum_{(i,j) \in E} (1 - x_j^*) \leq z_i + \epsilon n$$

BY TAKING A
RANDOM SAMPLES OF
SIZE $\Theta(\log n / \epsilon^2)$ AND
SETTING $z_i = \frac{n}{|S|} \sum_{(i,j) \in E, j \in S} (1 - x_j^*)$

SOLVE LINEARIZED
LP AND ROUND
FRACTIONAL SOLUTION
(BY RANDOMIZED
ROUNDING).

FOR HIGHER DEGREES
USE RECURSION BASED
ON POLYN. DECOMPOSITION

$$P(x) = T + \sum x_i P_i(x_i, \dots, x_n)$$

CONST.

SMOOTH,
DEG = d-1.

GETTING

DOWN TO

CONSTANT TIME.



NOTATION:

GIVEN FINITE

SETS $V_1, V_2, \dots, V_r,$

AN r-DIMENSIONAL

ARRAY A ON V_1, \dots, V_r

IS A FUNCTION

$$A: V_1 \times V_2 \times \dots \times V_r \rightarrow \mathbb{R}$$

($A(i_1, i_2, \dots, i_r)$ IS AN
ENTRY OF A).

FROBENIUS

NORM OF A :

$$\|A\|_F = \underline{\text{SQUARE}}$$

ROOT OF THE **SUM**

OF SQUARES OF

ALL ENTRIES.

LET $S_1 \subseteq V_1, S_2 \subseteq V_2,$
 $\dots, S_r \subseteq V_r,$ DEFINE
THE QUANTITY:

$$A(S_1, S_2, \dots, S_r) = \sum_{(i_1, \dots, i_r) \in S_1 \times S_2 \times \dots \times S_r} A(i_1, i_2, \dots, i_r).$$

A CUT-NORM OF A:

$$\|A\|_c = \text{MAX}_{S_1 \subseteq V_1, \dots, S_r \subseteq V_r} |A(S_1, \dots, S_r)|$$

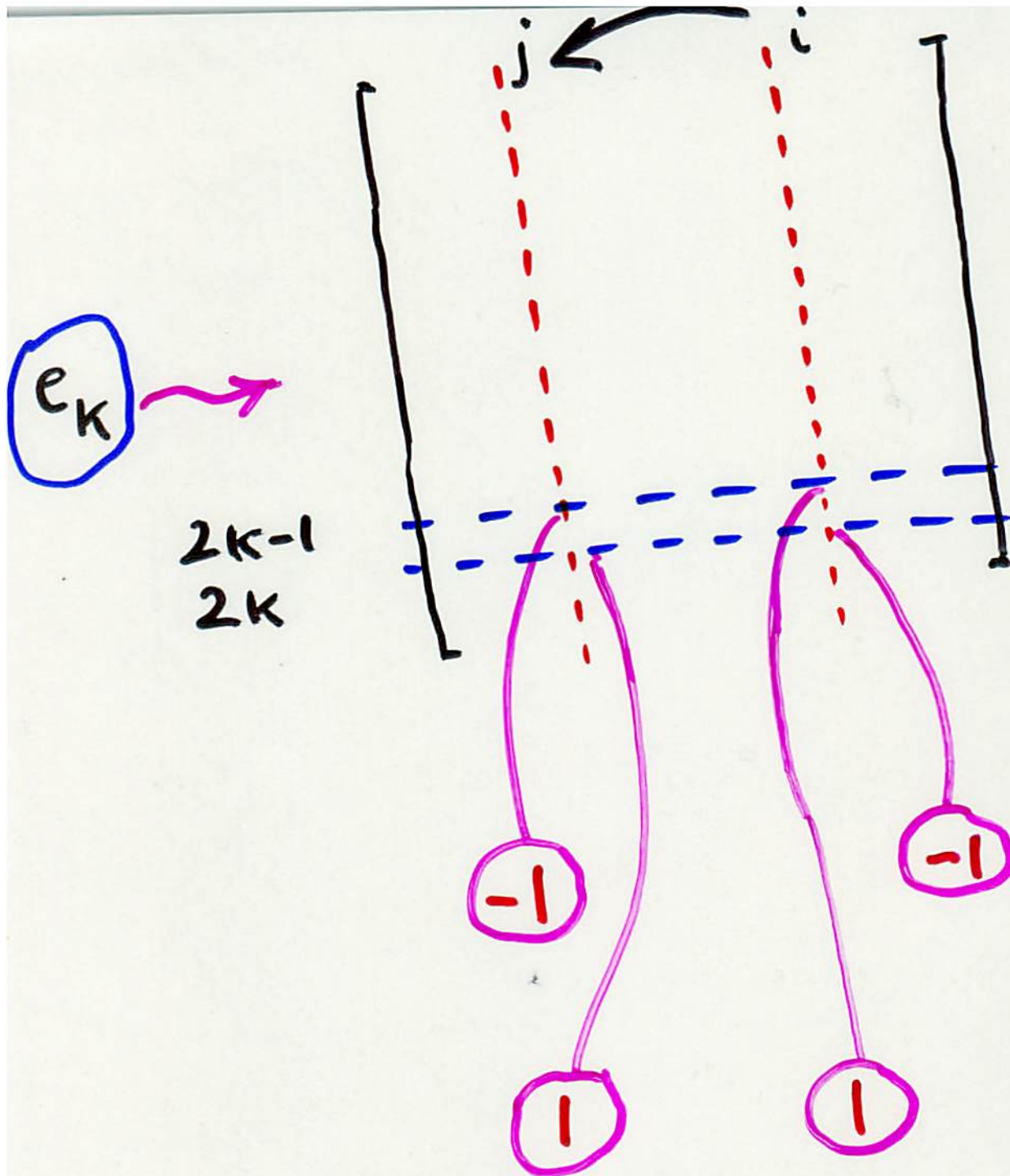
EXAMPLE:

$r=2$, A IS A MATRIX
WITH A SET OF
ROWS INDEXED BY
 E' AND A SET OF
COLUMNS INDEXED
BY V , FOR A GIVEN
GRAPH $G=(V, E)$,

$$V = \{v_1, v_2, \dots, v_n\},$$

$$E = \{e_1, e_2, \dots, e_m\}, \text{ AND}$$

$$E' = \{e_1, \dots, e_m, e'_1, \dots, e'_m\}.$$



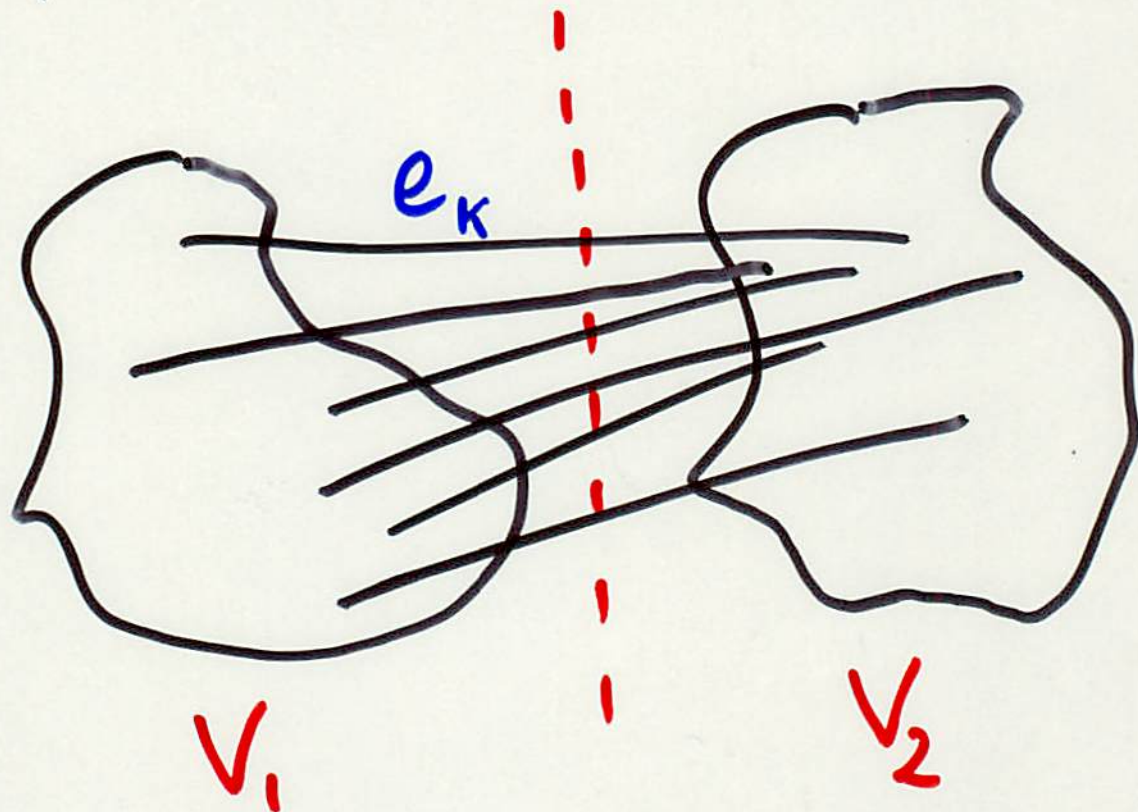
THE REST OF
ENTRIES ARE ALL
SET TO 0.

ANY

CUT

OF

G :



INDUCES A SET
OF EDGES e_k IN A CUT,
AND THE SET OF 1-
ENTRIES IN A. THUS,

$$\|A\|_c = \underline{\text{MAX-CUT}}(G).$$

MAX- τ CSP CAN

BE REDUCED TO

THE PROBLEMS OF

MAXIMIZING

POLYNOMIALS OF

DEGREE τ OVER

THE BOOLEAN CUBE

(AS WE DID USING

AN SPIP FOR

MAX-CUT PROBLEM),

AND COMPUT. OF $\|A\|_c$
FOR τ -DIM. ARRAYS A .

APPROXIMATION

OF $\|A\|_c$.

ON A **RANDOM**
SUBSET OF SIZE
 $\Theta(\log(1/\epsilon)/\epsilon^4)$ ($= q$).

ASSUMPTIONS (*)

ON A :

$$\|A\|_c \leq \epsilon n^\tau, \quad \|A\|_\infty \leq \frac{1}{\epsilon} B(\tau),$$

$$\|A\|_F \leq 2^{2\tau} n^{\tau/2}.$$

THEN, A **RANDOM**
INDUCED SUBARRAY
H OF A SATISFIES

$$\|H\|_c \leq C(\tau) \cdot q^\tau$$

W.H.P.

THE OTHER DIRECTION
IS EASY:

IF $\|A\|_c$ IS **HIGH**,

THEN SO IS $\|H\|_c$.

THE COMPUTATION

OF $\|H\|_c$ (WE NEED

ONLY ABS. APPROX.)

ON A SMALL SAMPLE

CAN BE DONE BY

KNOWN METHOD

OF CUT-ARRAY

DECOMPOSITION.

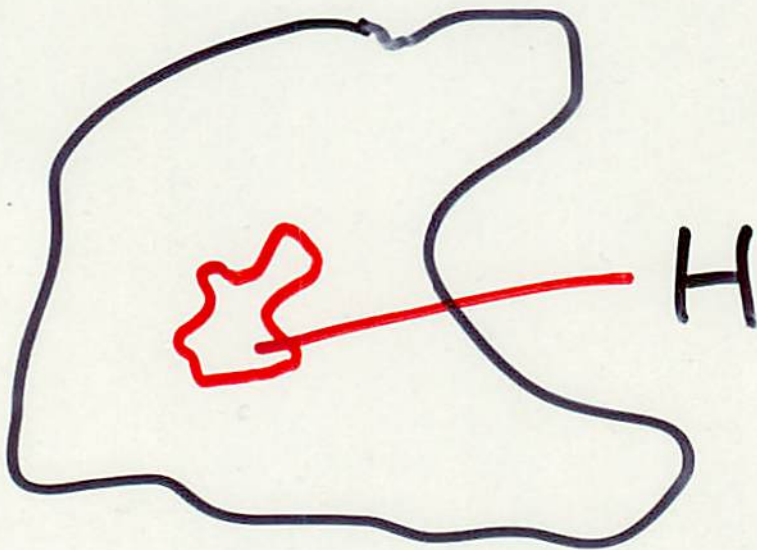
RESULTING TIME:

$$2^{O(\frac{1}{\epsilon^2})}$$

SO FAR, WE
WERE ABLE TO
DEAL WITH

"DOWN-STAIRS"

SITATION FROM THE
WHOLE ARRAY TO
THE SMALL **RANDOM**
SUBARRAY H.



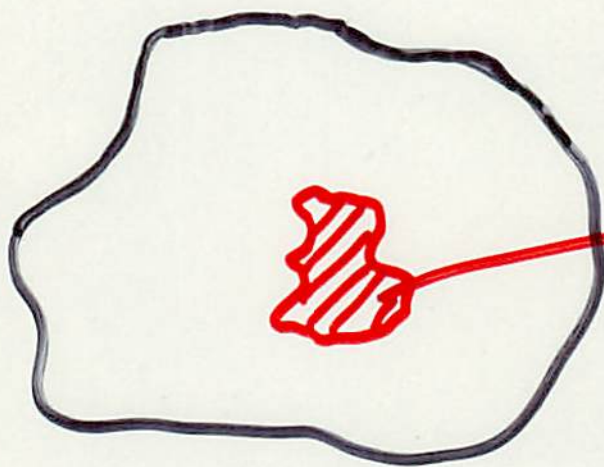
How ABOUT
REVERSED
("UP-STAIRS")
DIRECTION?

To RELATE
 $\|H\|_c$ WITH THE
 $\|A\|_c$ (OPT OF
AN INSTANCE).

LP PART:

TAKE A LINEARIZED
SPIP FOR AN INST.
F WHICH IS AN ILP,
CALL IT P.

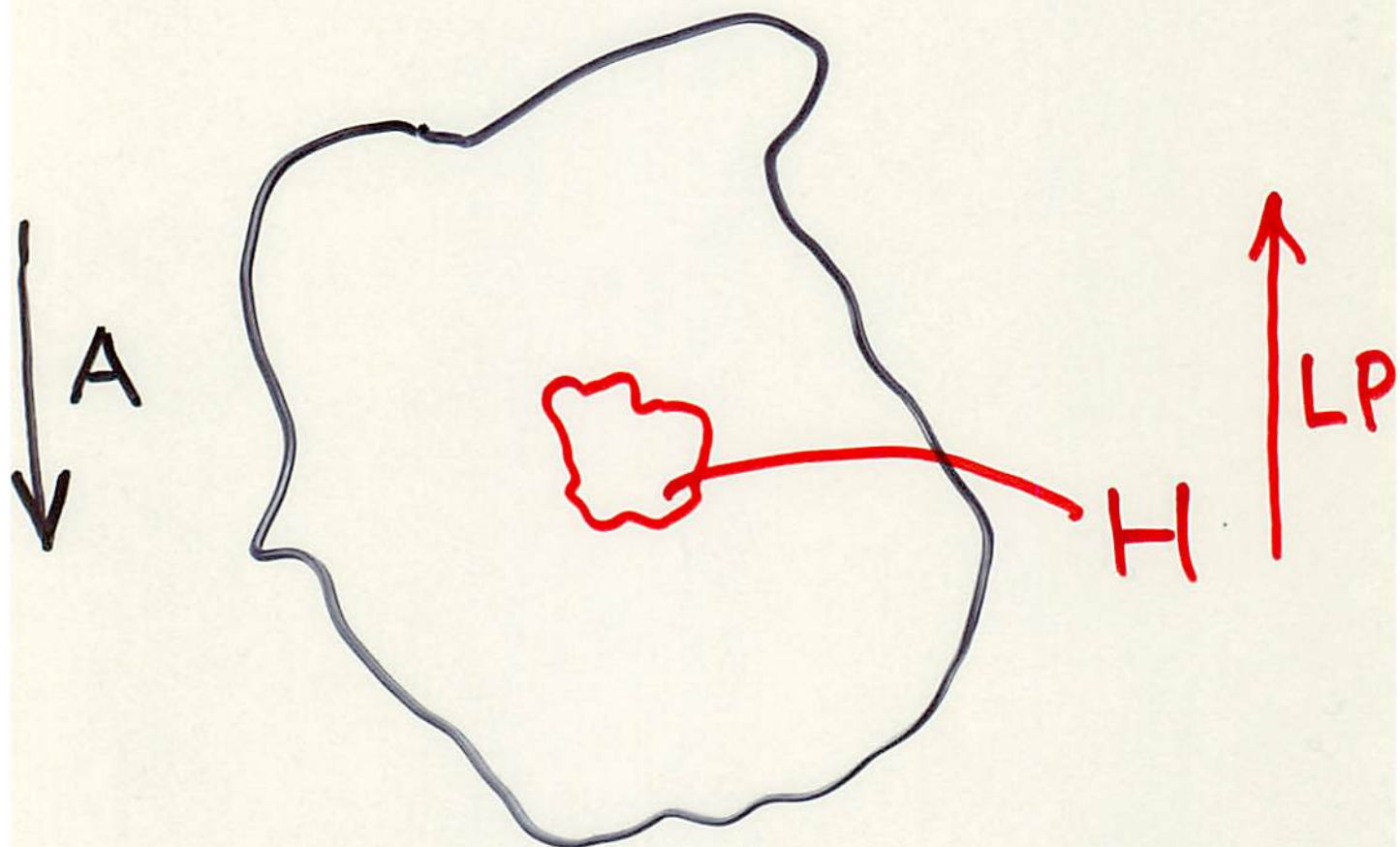
$|S| =$
 $\approx (\frac{1}{\epsilon^4})$



P
S (~H)
↑
SUBARRAY

IF $\alpha \geq \underline{OPT}_P$, THEN
 $\alpha' \geq \underline{OPT}_{P^S}$.

A SITUATION:



$$\beta \leq \|A\|_c \leq \epsilon n^r$$



$$\beta' \leq \|H\| \leq \alpha'$$



[ILP P GIVES
NORMAL. FACTOR $\frac{\beta}{\alpha^r}$]

MAIN RESULT:

LET F BE AN INST.
 OF MAX- r CSP WITH
 n VAR.'S. FOR A RANDOM
SAMPLE Q OF THE
 SET OF VAR.'S $\{x_1, \dots, x_n\}$
LET F^Q BE A RANDOM
SUB-INST. INDUCED BY
 Q .

MAIN RESULT:

$$\left| \frac{n^r}{q^r} \text{OPT}_{F^Q} - \text{OPT}_F \right| \leq \epsilon n^r$$

FOR $|Q| = q = O(\text{LOG}(1/\epsilon) / \epsilon^4)$

VERY RECENT

IMPROVEMENT OF

A-PART

TO

HARD CORE

SIZE

$\sim (\frac{1}{\epsilon^2})$ BY

RUDELSON AND

VERSHYNIN USING

SOME NEW TECHNIQUES

OF BOURGAIN AND
TZAFRIRI.

RECENT EXT.'S

TO **UNBOUNDED**
WEIGHT CLASSES,

INCLUDING

METRIC AND

QUASIMETRIC

CASES.

[FKKV05]

(REF. [3])

• THERE ARE PTASs
FOR GENERAL
QUASIMETRIC
K-CLUSTERING
PROBLEMS.

(BY "NON-HARD-CORE"
METHOD)
[FKKRO3]

NO GENERAL
SUBLINEAR PTASs
KNOWN.

$$\sum_{i=1}^k \sum_{\{u,v\} \in C_i} d(u,v)$$



INTRA-CLUSTER
DISTANCES



C_1



C_2

...



C_k

$$\text{MIN} \sum_{i=1}^k \sum_{\{u,v\} \in C_i} d(u,v)$$



INTRA-CLUSTER
DISTANCES



C_1



C_2

...



C_k

MIN-SUM
CLUSTERING

GETTING BEYOND
THE ABSOLUTE
BOUNDS.

GIVEN A $\Theta\left(\frac{n^r}{\Delta}\right)$ -DENSE

INST. OF MAX-rCSP,

THERE EXISTS

$2^{O(\Delta)}$ -TAS WITH

$\Theta(\Delta)$ SAMPLE SIZE.

(FOR SUBDENSE CLASS,

$\Delta = \log n$, WE HAVE

PTAS).

PROOF METHOD

BASED ON

NEW ANALYSIS

OF SPECIAL

SPIPs FOR THAT

PROBLEMS.

[FK05]

(cf. REF. [4])

FURTHER
RESEARCH:

IMPROVING THE
HARD CORE COMPLEXITY
OF THE ALGORITHMS.

ARE THERE ANY
"MYSTERIOUS"
INTRACTABILITY
BARRIERS FOR GETTING
DOWN TO, SAY, $\Theta(\frac{1}{\epsilon^2})$
HARD CORE BOUNDS?

ANY **SUBLINEAR**

HARD CORE PTASs

(CTASs WITH METRIC
PREPROCESSING) FOR

K-CLUSTERING

PROBLEMS?