

# Descriptive Complexity: Part 2

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# Outline

*Lecture 1:* Introduction to Descriptive Complexity.

- Proving inexpressibility in Logics.
- Characterizing complexity classes.
- FPC and the Cai-Fürer-Immerman construction.

*Lecture 2:* FPC and its connections with:

- circuit complexity
- extension polytopes
- hardness of approximation

# Review

**Fagin:** ESO = NP

**Immerman-Vardi:** FP = P on *ordered* structures.

We are building up tools for proving inexpressibility in ever more powerful logics.

We used *Ehrenfeucht games* to show that first-order logic cannot define *Evenness*, *Connectivity*, *2-Colourability*.

We used *pebble games* to show that FP cannot define *Evenness*, *Perfect Matchings*, *Hamiltonicity*.

We want to use games to show that FPC cannot define  $\text{Solv}(\mathbb{Z}_2)$ .

# Constructing systems of equations

Take  $G$  a 4-regular, connected graph.

Define equations  $\mathbf{E}_G$  with two variables  $x_0^e, x_1^e$  for each edge  $e$ .

For each vertex  $v$  with edges  $e_1, e_2, e_3, e_4$  incident on it, we have 16 equations:

$$E_v : \quad x_a^{e_1} + x_b^{e_2} + x_c^{e_3} + x_d^{e_4} \equiv a + b + c + d \pmod{2}$$

$\tilde{\mathbf{E}}_G$  is obtained from  $\mathbf{E}_G$  by replacing, for exactly one vertex  $v$ ,  $E_v$  by:

$$E'_v : \quad x_a^{e_1} + x_b^{e_2} + x_c^{e_3} + x_d^{e_4} \equiv a + b + c + d + 1 \pmod{2}$$

*We can show:*  $\mathbf{E}_G$  is satisfiable;  $\tilde{\mathbf{E}}_G$  is unsatisfiable.

# Satisfiability

**Lemma  $\mathbf{E}_G$**  is satisfiable.

*by setting the variables  $x_i^e$  to  $i$ .*

**Lemma  $\tilde{\mathbf{E}}_G$**  is unsatisfiable.

*Consider the subsystem consisting of equations involving only the variables  $x_0^e$ .*

*The sum of all **left-hand sides** is*

$$2 \sum_e x_0^e \equiv 0 \pmod{2}$$

*However, the sum of **right-hand sides** is 1.*

Now we show that, for each  $k$ , we can find a graph  $G$  such that  $\mathbf{E}_G \equiv^{C^k} \tilde{\mathbf{E}}_G$ .

# Counting Game

**Immerman and Lander (1990)** defined a *pebble game* for  $C^k$ .

This is again played by *Spoiler* and *Duplicator* using  $k$  pairs of pebbles  $\{(a_1, b_1), \dots, (a_k, b_k)\}$  on a pair of structures  $\mathbb{A}$  and  $\mathbb{B}$

At each move, *Spoiler* picks  $i$  and a set of elements of one structure (say  $X \subseteq B$ )

*Duplicator* responds with a set of vertices of the other structure (say  $Y \subseteq A$ ) of the same *size*.

*Spoiler* then places  $a_i$  on an element of  $Y$  and *Duplicator* must place  $b_i$  on an element of  $X$ .

*Spoiler* wins at any stage if the partial map from  $\mathbb{A}$  to  $\mathbb{B}$  defined by the pebble pairs is not a partial isomorphism

If *Duplicator* has a winning strategy for  $p$  moves, then  $\mathbb{A}$  and  $\mathbb{B}$  agree on all sentences of  $C^k$  of quantifier rank at most  $p$ .

# Bijection Games

$\equiv^{C^k}$  is also characterised by a  $k$ -pebble *bijection game*. (Hella 96).

The game is played on graphs  $\mathbb{A}$  and  $\mathbb{B}$  with pebbles  $a_1, \dots, a_k$  on  $\mathbb{A}$  and  $b_1, \dots, b_k$  on  $\mathbb{B}$ .

- *Spoiler* chooses a pair of pebbles  $a_i$  and  $b_i$ ;
- *Duplicator* chooses a bijection  $h : A \rightarrow B$  such that for pebbles  $a_j$  and  $b_j (j \neq i)$ ,  $h(a_j) = b_j$ ;
- *Spoiler* chooses  $a \in A$  and places  $a_i$  on  $a$  and  $b_i$  on  $h(a)$ .

*Duplicator* loses if the partial map  $a_i \mapsto b_i$  is not a partial isomorphism.

*Duplicator* has a strategy to play forever if, and only if,  $\mathbb{A} \equiv^{C^k} \mathbb{B}$ .

# Equivalence of Games

It is easy to see that a winning strategy for *Duplicator* in the bijection game yields a winning strategy in the counting game:

*Respond to a set  $X \subseteq A$  (or  $Y \subseteq B$ ) with  $h(X)$  ( $h^{-1}(Y)$ ), respectively).*

For the other direction, consider the partition induced by the equivalence relation

$$\{(a, a') \mid (\mathbb{A}, \mathbf{a}[a/a_i]) \equiv^{C^k} (\mathbb{A}, \mathbf{a}[a'/a_i])\}$$

and for each of the parts  $X$ , take the response  $Y$  of *Duplicator* to a move where *Spoiler* would choose  $X$ .

Stitch these together to give the bijection  $h$ .



# Cops and Robbers

*A game played on an undirected graph  $G = (V, E)$  between a player controlling  $k$  cops and another player in charge of a robber.*

At any point, the cops are sitting on a set  $X \subseteq V$  of the nodes and the robber on a node  $r \in V$ .

A move consists in the cop player removing some cops from  $X' \subseteq X$  nodes and announcing a new position  $Y$  for them. The robber responds by moving along a path from  $r$  to some node  $s$  such that the path does not go through  $X \setminus X'$ .

The new position is  $(X \setminus X') \cup Y$  and  $s$ . If a cop and the robber are on the same node, the robber is caught and the game ends.

# Cops and Robbers on the Grid

If  $G$  is the  $k \times k$  toroidal grid, then the *robber* has a winning strategy in the *k-cops and robbers* game played on  $G$ .

To show this, we note that for any set  $X$  of at most  $k$  vertices, the graph  $G \setminus X$  contains a connected component with at least half the vertices of  $G$ .

If all vertices in  $X$  are in distinct rows then  $G \setminus X$  is connected. Otherwise,  $G \setminus X$  contains an entire row and in its connected component there are at least  $k - 1$  vertices from at least  $k/2$  columns.

Robber's strategy is to stay in the large component.

# Cops, Robbers and Treewidth

Actually, the cops and robbers game *characterizes tree-width*.

*A connected graph  $G$  has tree-width  $\geq k$  if, and only if, robber has a winning strategy against a team of  $k$  cops on  $G$ .*

# Cops, Robbers and Bijections

Suppose  $G$  is such that the *robber* has a winning strategy in the  $2k$ -cops and robbers game played on  $G$ .

We use this to construct a winning strategy for Duplicator in the  $k$ -pebble bijection game on  $\mathbf{E}_G$  and  $\tilde{\mathbf{E}}_G$ .

- A bijection  $h : \mathbf{E}_G \rightarrow \tilde{\mathbf{E}}_G$  is *good bar  $v$*  if it is an isomorphism everywhere except at the variables  $x_a^e$  for edges  $e$  incident on  $v$ .
- If  $h$  is good bar  $v$  and there is a path from  $v$  to  $u$ , then there is a bijection  $h'$  that is good bar  $u$  such that  $h$  and  $h'$  differ only at vertices corresponding to the path from  $v$  to  $u$ .
- Duplicator plays bijections that are good bar  $v$ , where  $v$  is the robber position in  $G$  when the cop position is given by the currently pebbled elements.

# Restricted Graph Classes

If we restrict the class of structures we consider, FPC may be powerful enough to express all polynomial-time decidable properties.

1. FPC captures P on *trees*. (Immerman and Lander 1990).
2. FPC captures P on any class of graphs of *bounded treewidth*. (Grohe and Mariño 1999).
3. FPC captures P on the class of *planar graphs*. (Grohe 1998).
4. FPC captures P on any *proper minor-closed class of graphs*. (Grohe 2010).

In each case, the proof proceeds by showing that for any  $G$  in the class, a *canonical, ordered* representation of  $G$  can be interpreted in  $G$  using FPC.

# Beyond FPC

How do we define logics extending FPC while remaining inside P?

FPrk is fixed-point logic with an operator for *matrix rank* over finite fields.  
(D., Grohe, Holm, Laubner, 2009)

*Choiceless Polynomial Time with counting* ( $\tilde{\text{CPT}}(\text{Card})$ ) is a class of computational problems defined by (Blass, Gurevich and Shelah 1999). It is based on a *machine model* (*Gurevich Abstract State Machines*) that works directly on a graph or relational structure (rather than on a string representation).

$\tilde{\text{CPT}}(\text{Card})$  is the polynomial time and space restriction of the machines.

Both of these have expressive power *strictly greater* than FPC.

Their relationship to each other and to P remains unknown.

We need new tools to analyze the *expressive power* of these logics.

# Circuit Complexity

A *language*  $L \subseteq \{0, 1\}^*$  can be described by a family of *Boolean functions*:

$$(f_n)_{n \in \omega} : \{0, 1\}^n \rightarrow \{0, 1\}.$$

Each  $f_n$  may be computed by a *circuit*  $C_n$  made up of

- Gates labeled by Boolean operators:  $\wedge, \vee, \neg$ ,
- Boolean inputs:  $x_1, \dots, x_n$ , and
- A distinguished gate determining the output.

If there is a polynomial  $p(n)$  bounding the *size* of  $C_n$ , i.e. the number of gates in  $C_n$ , the language  $L$  is in the class  $\mathbf{P/poly}$ .

If, in addition, the function  $n \mapsto C_n$  is computable in *polynomial time*,  $L$  is in  $\mathbf{P}$ .

*Note:* For these classes it makes no difference whether the circuits only use  $\{\wedge, \vee, \neg\}$  or a richer basis with *threshold* or *majority* gates.

# Circuits for Graph Properties

We want to study families of circuits that decide properties of *graphs* (or other relational structures—for simplicity of presentation we restrict ourselves to graphs).

We have a family of Boolean circuits  $(C_n)_{n \in \omega}$  where there are  $n^2$  inputs labelled  $(i, j) : i, j \in [n]$ , corresponding to the *potential edges*. Each input takes value 0 or 1;

Graph properties in  $\mathbf{P}$  are given by such families where:

- the size of  $C_n$  is bounded by a polynomial  $p(n)$ ; and
- the family is uniform, so the function  $n \mapsto C_n$  is in  $\mathbf{P}$  (or  $\mathbf{DLogTime}$ ).



# Invariant Circuits

$C_n$  is *invariant* if, for every input graph, the output is unchanged under a permutation of the inputs induced by a permutation of  $[n]$ .

That is, given any input  $G : [n]^2 \rightarrow \{0, 1\}$ , and a permutation  $\pi \in S_n$ ,

$C_n$  accepts  $G$  if, and only if,  $C_n$  accepts the input  $\pi G$  given

$$(\pi G)(i, j) = G(\pi(i), \pi(j)).$$

Note: this is not the same as requiring that the result is invariant under *all* permutations of the input. That would only allow us to define functions of the *number* of 1s in the input.

This requirement is simply that the circuit recognises an *encoding-invariant* graph property.

# Symmetric Circuits

Say  $C_n$  is *symmetric* if any permutation of  $[n]$  applied to its inputs can be extended to an automorphism of  $C_n$ .

*i.e., for each  $\pi \in S_n$ , there is an automorphism of  $C_n$  that takes input  $(i, j)$  to  $(\pi i, \pi j)$ .*

Any symmetric circuit is invariant, but *not* conversely.

*Consider the natural circuit for deciding whether the number of edges in an  $n$ -vertex graph is even.*

Any invariant circuit can be converted to a symmetric circuit, but with potentially *exponential blow-up*.

# Logic and Circuits

Any formula of  $\varphi$  *first-order logic* translates into a uniform family of circuits  $C_n$

*For each subformula  $\psi(\bar{x})$  and each assignment  $\bar{a}$  of values to the free variables, we have a gate.*

*Existential quantifiers translate to big disjunctions, etc.*

The circuit  $C_n$  is:

- of *constant* depth (given by the depth of  $\varphi$ );
- of size at most  $c \cdot n^k$  where  $c$  is the number of subformulas of  $\varphi$  and  $k$  is the *maximum number of free variables* in any subformula of  $\varphi$ .
- *symmetric* by the action of  $\pi \in S_n$  that takes  $\psi[\bar{a}]$  to  $\psi[\pi(\bar{a})]$ .

# FP and Circuits

For every sentence  $\varphi$  of FP there is a  $k$  such that for every  $n$ , there is a formula  $\varphi_n$  of  $L^k$  that is equivalent to  $\varphi$  on all graphs with at most  $n$  vertices.

The formula  $\varphi_n$  has

- *depth*  $n^c$  for some constant  $c$ ;
- at most  $k$  free variables in each sub-formula for some constant  $k$ .

It follows that every graph property definable in FP is given by a family of *polynomial-size, symmetric* circuits.

# FPC and Counting

For every sentence  $\varphi$  of **FP** there is a  $k$  such that for every  $n$ , there is a formula  $\varphi_n$  of  $C^k$  that is equivalent to  $\varphi$  on all graphs with at most  $n$  vertices.

The formula  $\varphi_n$  has

- *depth*  $n^c$  for some constant  $c$ ;
- at most  $k$  free variables in each sub-formula for some constant  $k$ .

It follows that every graph property definable in **FP** is given by a family of *polynomial-size, symmetric* circuits in a basis with *threshold gates*.

*Note:* we could also alternatively take a basis with *majority* gates.

# Main Result

The following is established in **(Anderson, D. 2017)**:

## Theorem

*A class of graphs is accepted by a  $P$ -uniform, polynomial-size, symmetric family of threshold circuits **if, and only if**, it is definable in FPC.*

We could just use *majority* instead of threshold gates. Or we could through in all *fully symmetric* Boolean functions.

We get a natural and purely circuit-based characterisation of FPC definability.

Inexpressibility results for FPC can be seen as lower bound results against a natural circuit class.

# Counting Width

For any class of structures  $\mathcal{C}$ , we define its *counting width*  $\nu_{\mathcal{C}} : \mathbb{N} \rightarrow \mathbb{N}$  so that

$\nu_{\mathcal{C}}(n)$  is the least  $k$  such that  $\mathcal{C}$  restricted to structures with at most  $n$  elements is closed under  $\equiv_{\mathcal{C}^k}$ .

Every class in **FPC** has counting width bounded by a *constant*.

*3-Sat*, *Hamiltonicity*, *3-Colourability* all have counting width  $\Omega(n)$ .

# FPC-Reductions

We can define a notion of one class  $\mathcal{C}$  being *FPC-reducible* to another  $\mathcal{D}$

If  $\mathcal{C} \leq_{\text{FPC}} \mathcal{D}$  then

$$\nu_{\mathcal{D}} = \Omega(\nu_{\mathcal{C}}^{1/d}).$$

If the reduction takes  $\mathcal{C}$ -instances to  $\mathcal{D}$ -instances of *linear size*, then

$$\nu_{\mathcal{D}} = \Omega(\nu_{\mathcal{C}}).$$

Known linear lower bounds follow from  $\nu_{\text{Solv}(\mathbb{Z}_2)} = \Omega(n)$ .



# Linear Programming

*Linear Programming* is an important algorithmic tool for solving a large variety of optimization problems.

It was shown by **(Khachiyan 1980)** that linear programming problems can be solved in polynomial time.

We have a set  $C$  of *constraints* over a set  $V$  of *variables*.

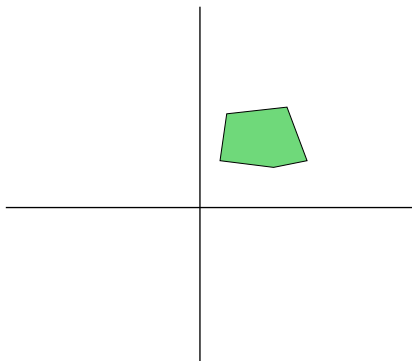
Each  $c \in C$  consists of  $a_c \in \mathbb{Q}^V$  and  $b_c \in \mathbb{Q}$ .

*Feasibility Problem*: Given a linear programming instance, determine if there is an  $x \in \mathbb{Q}^V$  such that:

$$a_c^T x \leq b_c \quad \text{for all } c \in C$$

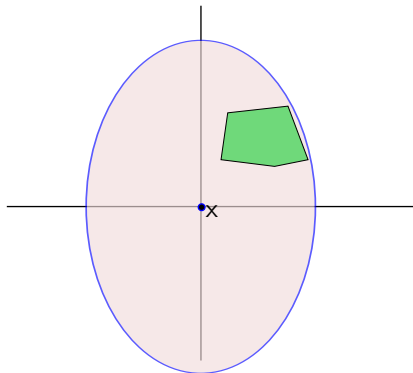
We can show that this, and the corresponding *optimization problem* are expressible in **FPC**.

# Ellipsoid Method



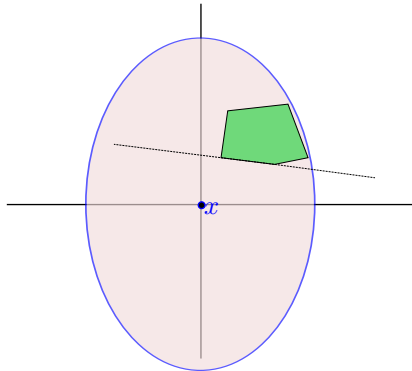
The set of constraints determines a *polytope*

# Ellipsoid Method



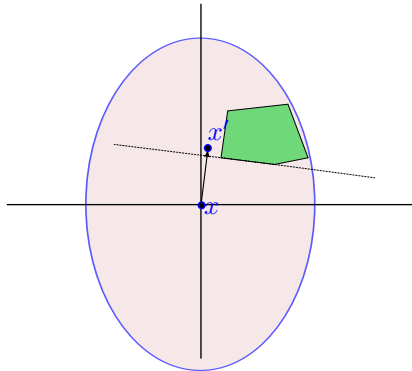
Start at the origin and calculate an *ellipsoid* enclosing it.

# Ellipsoid Method



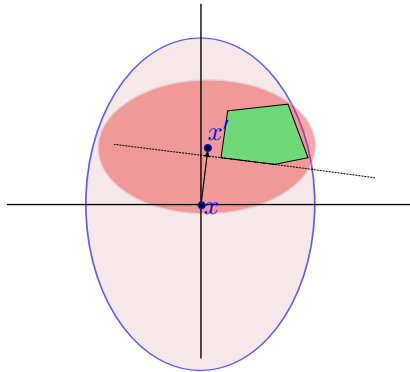
If the centre is not in the polytope, choose a constraint it *violates*.

# Ellipsoid Method



Calculate a new *centre*.

# Ellipsoid Method



And a new ellipsoid around the centre of at most *half* the volume.

# Ellipsoid Method in FPC

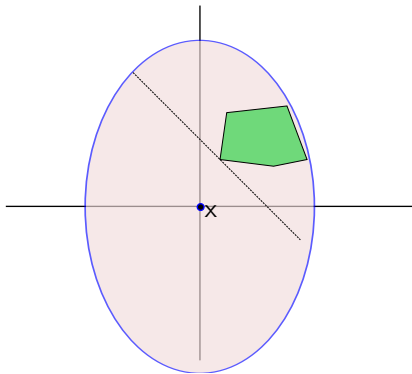
We can encode all the calculations involved in **FPC**.

This relies on expressing algebraic manipulations of *unordered* matrices.

What is not obvious is how to *choose* the violated constraint on which to project.

However, the ellipsoid method works as long as we can find, at each step, some *separating hyperplane*.

# Ellipsoid Method in FPC





# Ellipsoid Method in FPC

We can encode all the calculations involved in FPC.

This relies on expressing algebraic manipulations of *unordered* matrices.

What is not obvious is how to *choose* the violated constraint on which to project.

However, the ellipsoid method works as long as we can find, at each step, some *separating hyperplane*.

So, we can take:

$$\left(\sum_{c \in S} a_c\right)^T x \leq \sum_{c \in S} b_c$$

where  $S$  is the *set* of all violated constraints.

# Separation Oracle

More generally, the ellipsoid method can be used, even when the *constraint matrix* is not given explicitly, as long as we can always determine a *separating hyperplane*.

In particular, the polytope represented may have *exponentially many* facets.

We can show that as long as the *separation oracle* can be defined in FPC, the corresponding *optimization problem* can be solved in FPC.

# Graph Matching

Recall, in a *graph*  $G = (V, E)$  a matching  $M \subset E$  is a set of edges such that each vertex is incident on *at most* one edge in  $M$ .

(Edmonds 1965) showed that the problem of finding a *maximum weight matching* in  $G = (V, E)$ ,  $w : \mathbb{Q}_{\geq 0}^E$  can be expressed as an *exponential size* linear program.

We can show that a *separation oracle* for this polytope is definable by an **FPC** formula interpreted in the weighted graph  $G$ .

As a consequence, there is an **FPC** formula defining the *size* of the maximum matching in  $G$ .

Note that this does not allow us to define an *actual* matching.

# Lift and Project Hierarchies

Given a *polytope*  $\mathcal{K}$  for *integer* optimization problem, we can get a better approximation of the *convex hull* of the integer points by means of *lift-and-project* programs.

The general idea is to add new variables  $y_{x_1, \dots, x_t}$  to denote the product  $x_1 \cdots x_t$  and add linear (or semi-definite) constraints to try and force this meaning.

We get hierarchies as  $t$  increases:

- *Sherali-Adams*:  $SA_t(\mathcal{K})$
- *Lovasz-Schrijver*:  $LS_t(\mathcal{K})$
- *Lasserre*:  $Las_t(\mathcal{K})$

Of these, the last is the strongest.

For many cases, we can show that the number of levels  $t$  required to get an exact solution can be bounded by  $\Omega(\nu_c)$ .

# Hardness of Approximation

## MAX 3SAT:

We are given a *Boolean formula*  $\varphi$  in 3CNF, i.e. a conjunction of clauses with three literals per clause.

Say  $\varphi$  has  $n$  Boolean variables and  $m$  clauses.

Let  $m^*$  denote the *maximum* number such that some assignment of values to the Boolean variables makes  $m^*$  clauses of  $\varphi$  true.

## Algorithmic Problems:

- *Find* an assignment of values to the variables that makes  $m^*$  clauses of  $\varphi$  true;
- *Determine* the value of  $m^*$ ;
- *c-approximate*  $m^*$  for some constant  $0 < c < 1$ , i.e. give a value  $m'$  with a guarantee that  $cm^* < m' \leq m^*$ .

# Lower Bounds

## NP-completeness (Cook; Levin 1973):

Unless  $P = NP$ , there is no *polynomial-time algorithm* that can determine  $m^*$ .

## PCP Theorem (Arora et al. 1998):

There is a constant  $c < 1$  such that, unless  $P = NP$ , there is no *polynomial-time algorithm* that can  $c$ -approximate  $m^*$ .

## (Håstad 2001):

Unless  $P = NP$ , for every  $\epsilon > 0$  there is no *polynomial-time algorithm* that can  $(\frac{7}{8} + \epsilon)$ -approximate  $m^*$ .

*Note: This is optimal since there is a trivial algorithm that can  $\frac{7}{8}$ -approximate  $m^*$ .*

# MAX SNP

(Papadimitriou-Yannakakis 1991) define (in *syntactic terms*) a class MAX SNP of *NP optimization problems*.

For every problem in MAX SNP, there is a constant  $d$  such that there is a polynomial-time  $d$ -approximation algorithm.

They also define a notion of *approximation preserving reduction* under which MAX 3SAT is MAX SNP-*complete*.

It is a consequence of the PCP theorem that for every MAX SNP-*complete* problem, there is a constant  $c < 1$  such that, unless  $P = NP$ , there is no polynomial-time  $c$ -approximation algorithm.

This poses a challenge for each problem in MAX SNP, to determine the best possible value of  $d$ .

# MAX 3XOR

We are given a Boolean formula  $\varphi$  in 3XOR, i.e. a conjunction of clauses each of which is the *exclusive or* ( $\oplus$ ) of three literals.

Say  $\varphi$  has  $n$  Boolean variables and  $m$  clauses.

Let  $m^*$  denote the *maximum* number such that some assignment of values to the Boolean variables makes  $m^*$  clauses of  $\varphi$  true.

- determining whether  $m^* = m$  can be done in polynomial-time, by Gaussian elimination;
- determining the exact value of  $m^*$  is MAX SNP-complete.

**(Håstad 2001):**

Unless  $P = NP$ , for every  $\epsilon > 0$  there is no *polynomial-time algorithm* that can  $(\frac{1}{2} + \epsilon)$ -approximate  $m^*$ .

*This is optimal since there is a trivial algorithm that can  $\frac{1}{2}$ -approximate  $m^*$ .*



# Vertex Cover

In a graph  $G = (V, E)$ ,  $S \subseteq V$  is a *vertex cover* if each edge in  $E$  has at least one endpoint in  $S$ .

$vc(G)$  is the *size* of the smallest vertex cover in  $G$ .

**(Dinur-Safra 2005):**

Unless  $P = NP$ , there is no polynomial-time algorithm that can approximate  $vc(G)$  up to a factor of 1.36.

*Note 1: Since this is a minimization problem, the approximation ratio is a constant  $c > 1$ .*

*Note 2: This has recently been improved to  $\sqrt{2}$  (Khot, Minzer, Safra 2018+).*

There are polynomial-time algorithms that can approximate  $vc(G)$  up to a factor of 2.

**Conjecture:**

Unless  $P = NP$ , for every  $\epsilon > 0$  there is no polynomial-time algorithm that can approximate  $vc(G)$  up to a factor of  $2 - \epsilon$ .

# Methods

Say that a 3CNF formula is *c-satisfiable* if  $m^* > cm$ .

The proof of the PCP theorem gives (for some constant  $c$ ) a reduction from 3SAT to itself which:

- maps a satisfiable formula to a satisfiable formula; and
- maps an unsatisfiable formula to one that is not  $c$ -satisfiable.

As a consequence, any class  $\mathcal{C}$  of formulas that includes the satisfiable ones and excludes the ones that are *not*  $c$ -satisfiable, is NP-hard to decide.

The gap is amplified by further reductions, such as Håstad's long-code reductions.

In the case of 3XOR:

*For any  $\epsilon > 0$ , any class  $\mathcal{C}$  of formulas that includes the  $(1 - \epsilon)$ -satisfiable ones and excludes the ones that are *not*  $(\frac{1}{2} + \epsilon)$ -satisfiable, is NP-hard to decide.*

# Results

For any  $\epsilon > 0$  there is no term of FPC which, interpreted in a 3CNF formula  $\varphi$ , defines a number guaranteed to be within  $\frac{7}{8} + \epsilon$  of  $m^*(\varphi)$ .

For any  $\epsilon > 0$  there is no term of FPC which, interpreted in a 3XOR formula  $\varphi$ , defines a number guaranteed to be within  $\frac{1}{2} + \epsilon$  of  $m^*(\varphi)$ .

There is no term of FPC which, interpreted in a graph  $G$ , defines a value guaranteed to be within a factor 1.36 of  $vc(G)$ .

# New Challenges for Duplicator

The results are established by showing *definability gaps*:

*If  $\mathcal{C}$  is any class of 3CNF formulas that includes the satisfiable ones and excludes those that are not  $(\frac{7}{8} + \epsilon)$ -satisfiable, then  $\mathcal{C}$  has counting width  $\Omega(n^\delta)$  for some  $\delta > 0$ .*

*If  $\mathcal{C}$  is any class of 3XOR formulas that includes the satisfiable ones and excludes those that are not  $(\frac{1}{2} + \epsilon)$ -satisfiable, then  $\mathcal{C}$  has counting width  $\Omega(n^\delta)$  for some  $\delta > 0$ .*

# Initial Gap

Unlike the PCP theorem, we establish an initial gap for **3XOR**:

*If  $\mathcal{C}$  is any class of **3XOR** formulas that includes the satisfiable ones and excludes those that are not  $(\frac{1}{2} + \epsilon)$ -satisfiable, then  $\mathcal{C}$  has counting width  $\Omega(n)$ .*

We then *amplify the gap*, and extend it to **3SAT** and *vertex cover* by means of *reductions* definable in *first-order logic*.

This involves showing that known polynomial-time reductions in the literature can be done in first-order logic.

# Gap Construction

The initial gap is established by a variant of the *Cai-Fürer-Immerman* construction.

For a set  $V$  of  $n$  variables, choose uniformly at random, a collection of  $m > n$  subsets  $\{x_1, x_2, x_3\}$  of  $V$  of three elements.

*With high probability, the resulting bipartite graph has certain expansion properties.*

Construct a system of equations  $x_1 + x_2 + x_3 = b$  where the left-hand sides are the chosen sets and  $b$  is 0 or 1 based on the toss of a coin.

*With high probability, the system is not  $(\frac{1}{2} + \epsilon)$ -satisfiable.*

*The expansion properties guarantee that it is  $k$ -locally consistent for  $k = \Omega(n)$ .*

A *CFI* construction on this then gives a system that is not  $(\frac{1}{2} + \epsilon)$ -satisfiable but  $\equiv^{C^k}$ -equivalent to a satisfiable one.

# Perspectives

FPC is a *subclass* of P that captures a natural notion of *symmetric algorithm*.

We are able to show both

- that powerful algorithmic techniques are expressible in FPC; and
- *unconditional* inexpressibility results for many problems.

The lower bound results reveal

- fundamental *structural* properties of the problems; and
- lower bounds on important algorithmic techniques.

## Pointers

For the classical material in Lecture 1, you may consult a textbook such as: L. Libkin, *Elements of Finite Model Theory*.

The recent work in Lecture 2 may be found in the following papers:

M. Anderson, A. Dawar:

*On Symmetric Circuits and Fixed-Point Logics*. Theory Comput. Syst. (2017)

M. Anderson, A. Dawar, B. Holm:

*Solving Linear Programs without Breaking Abstractions*. J. ACM (2015)

A. Dawar, P. Wang:

*Definability of Semidefinite Programming and Lasserre Lower Bounds for CSPs*. LICS 2017

A. Atserias, A. Dawar:

*Definable Inapproximability: New Challenges for Duplicator*. CSL 2018

A. Atserias, A. Dawar, J. Ochremiak:

*On the Power of Symmetric Linear Programs*. LICS 2019