

# Algebraic cryptanalysis and multivariate cryptography

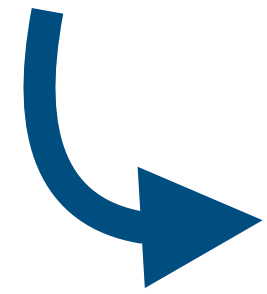
Monika Trimoska

PQSCA summer school  
June 17, Albena, Bulgaria



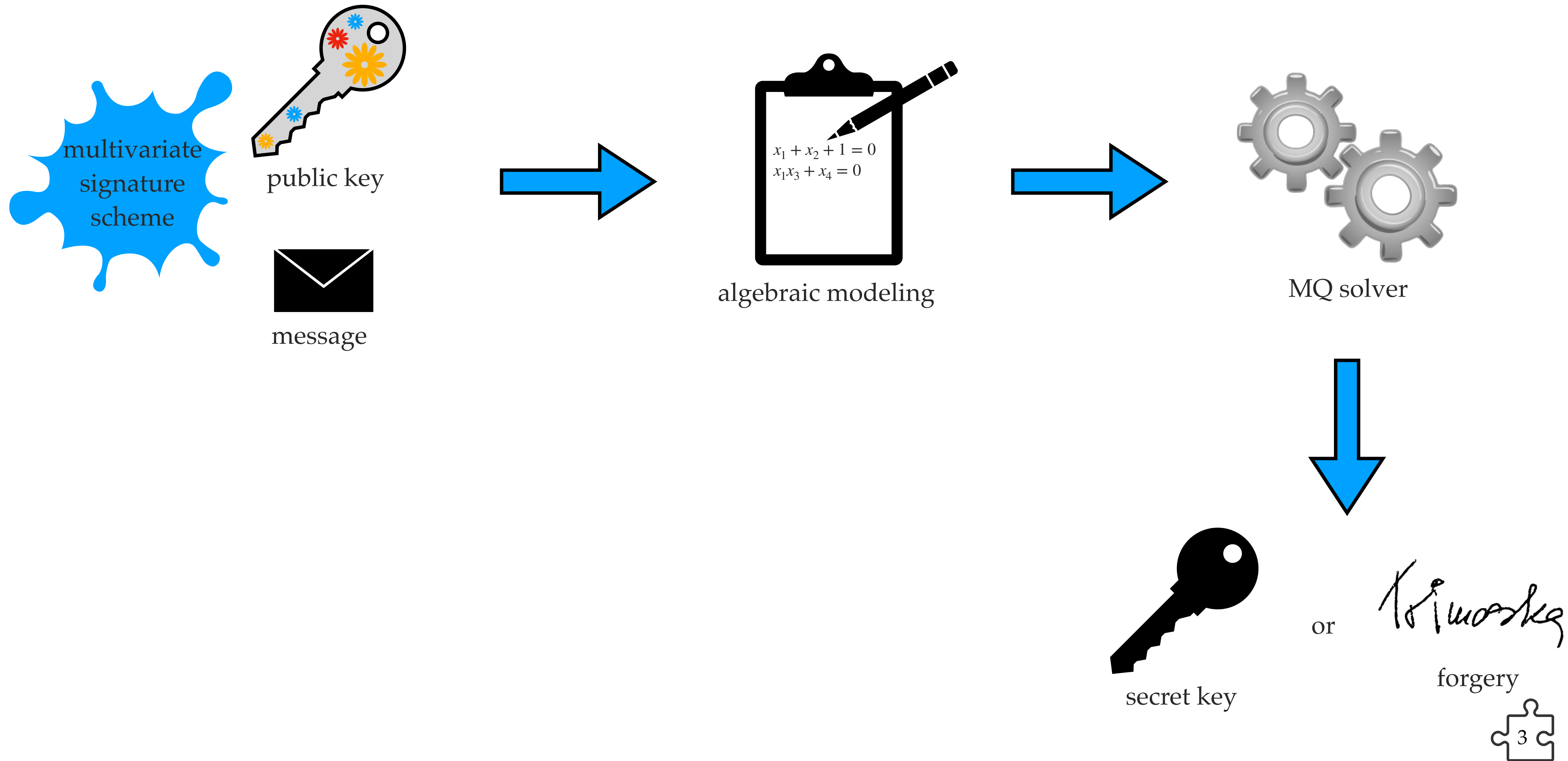
# Algebraic cryptanalysis

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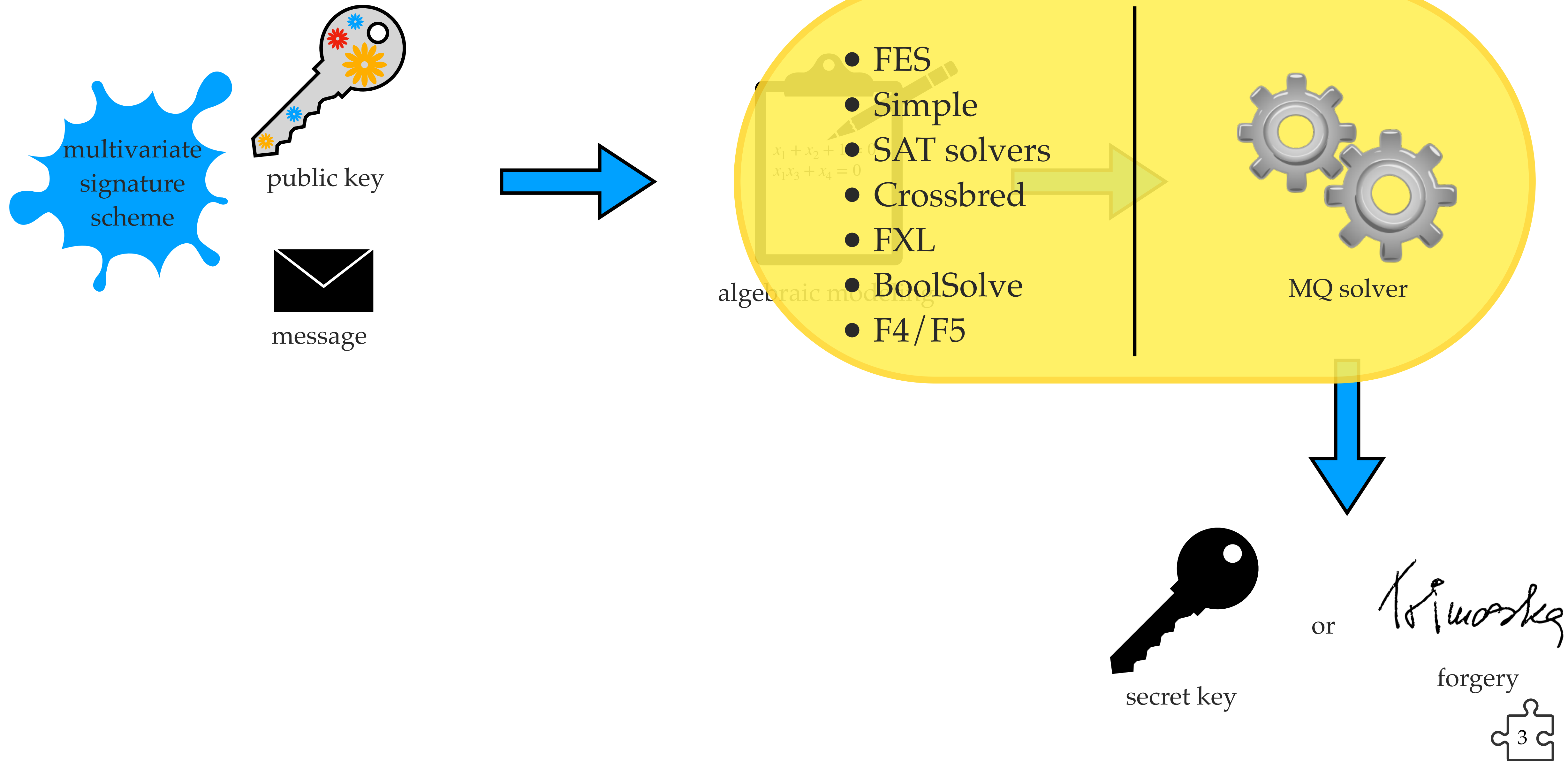


A type of cryptanalytic methods where the problem of finding the secret key (or any attack goal) is **reduced** to the problem of finding a solution to a **nonlinear multivariate polynomial system of equations**.

# Algebraic cryptanalysis

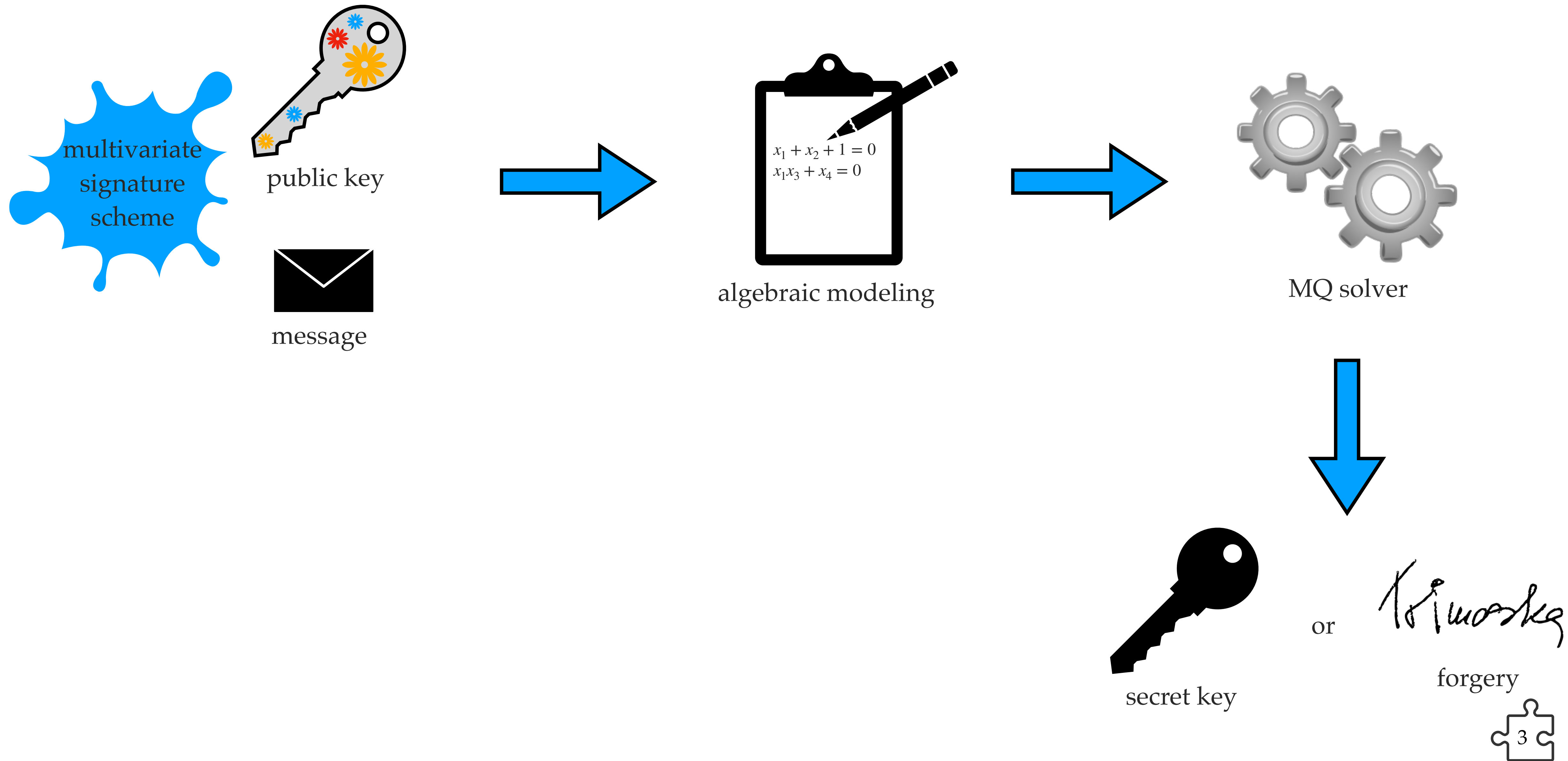


# Algebraic cryptanalysis

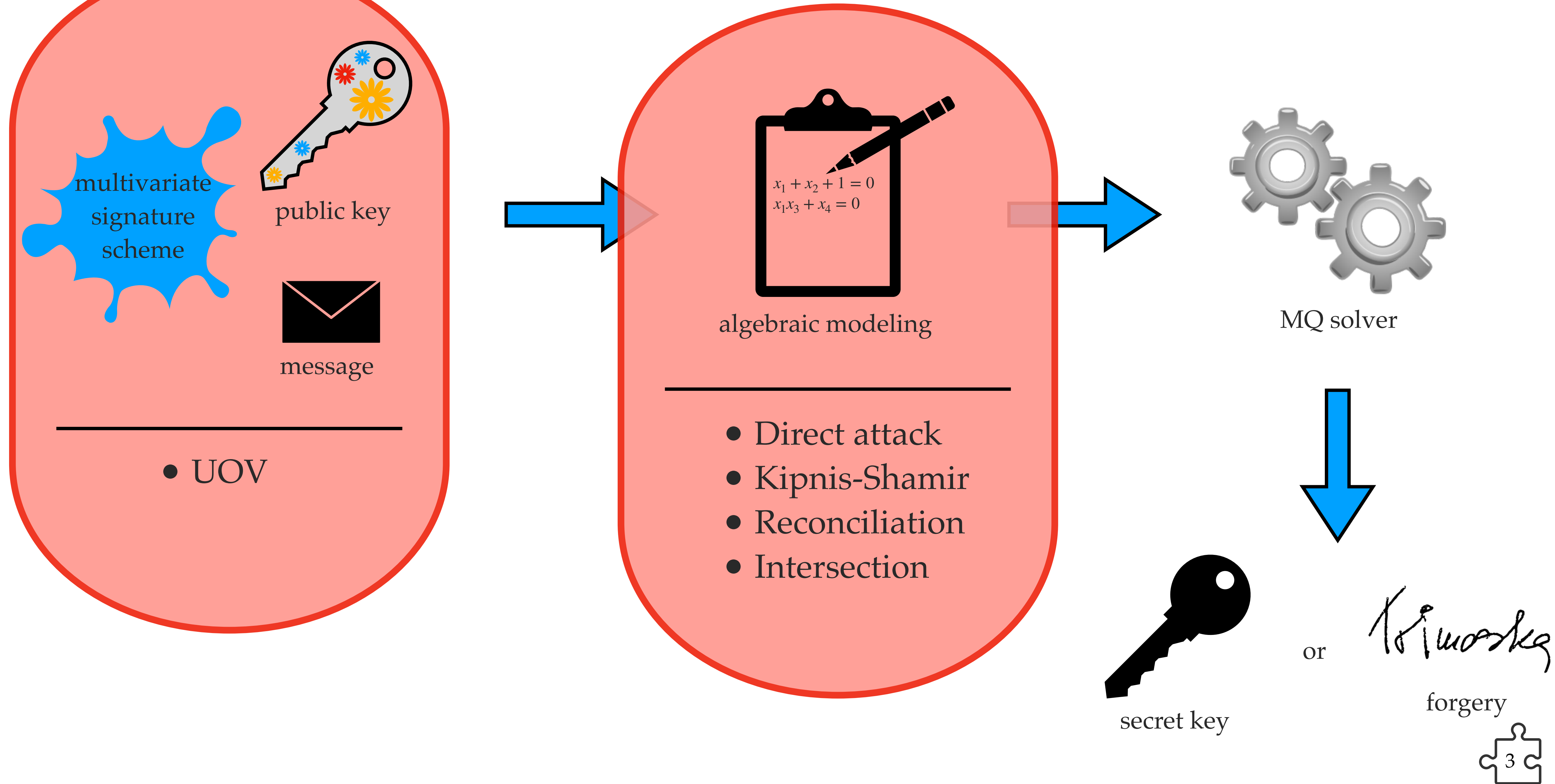


# Algebraic cryptanalysis

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# Algebraic cryptanalysis



# The MQ problem (recall)

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## The MQ problem

Given  $m$  multivariate quadratic polynomials  $f_1, \dots, f_m$  of  $n$  variables over a finite field  $\mathbb{F}_q$ , find a tuple  $\mathbf{x} = (x_1, \dots, x_n)$  in  $\mathbb{F}_q^n$ , such that  $f_1(\mathbf{x}) = \dots = f_m(\mathbf{x}) = 0$ .

**Example.**

$$f_1 : x_1x_3 + x_2x_4 + x_1 + x_3 + x_4 = 0$$

$$f_2 : x_2x_3 + x_1x_4 + x_3x_4 + x_1 + x_2 + x_4 = 0$$

$$f_3 : x_2x_4 + x_3x_4 + x_1 + x_3 + 1 = 0$$

$$f_4 : x_1x_2 + x_1x_3 + x_2x_3 + x_3 + x_4 + 1 = 0$$

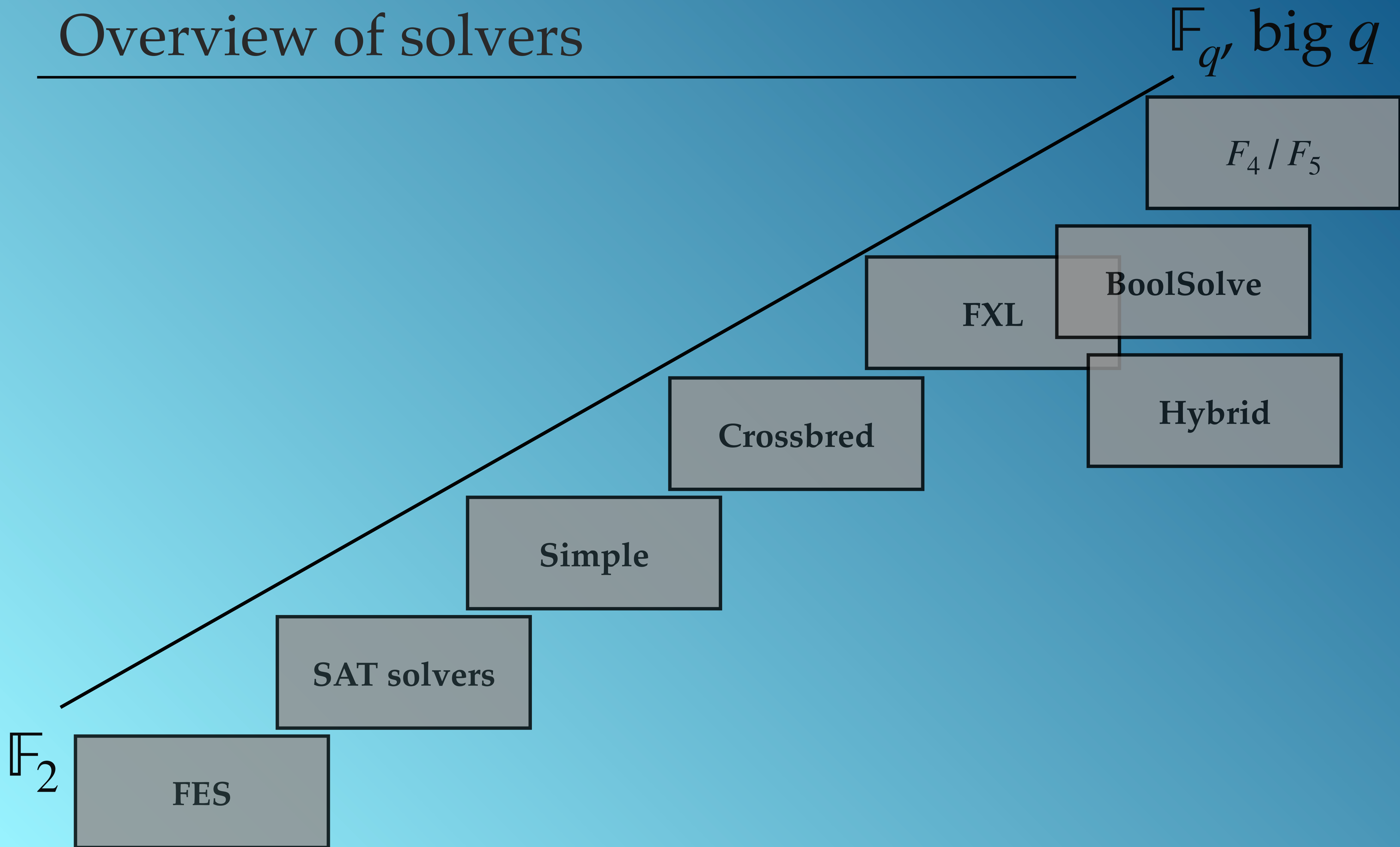
$$f_5 : x_1x_2 + x_2x_3 + x_1x_4 + x_3 = 0$$

$$f_6 : x_1x_3 + x_1x_4 + x_3x_4 + x_1 + x_2 + x_3 + x_4 = 0$$



# Overview of solvers

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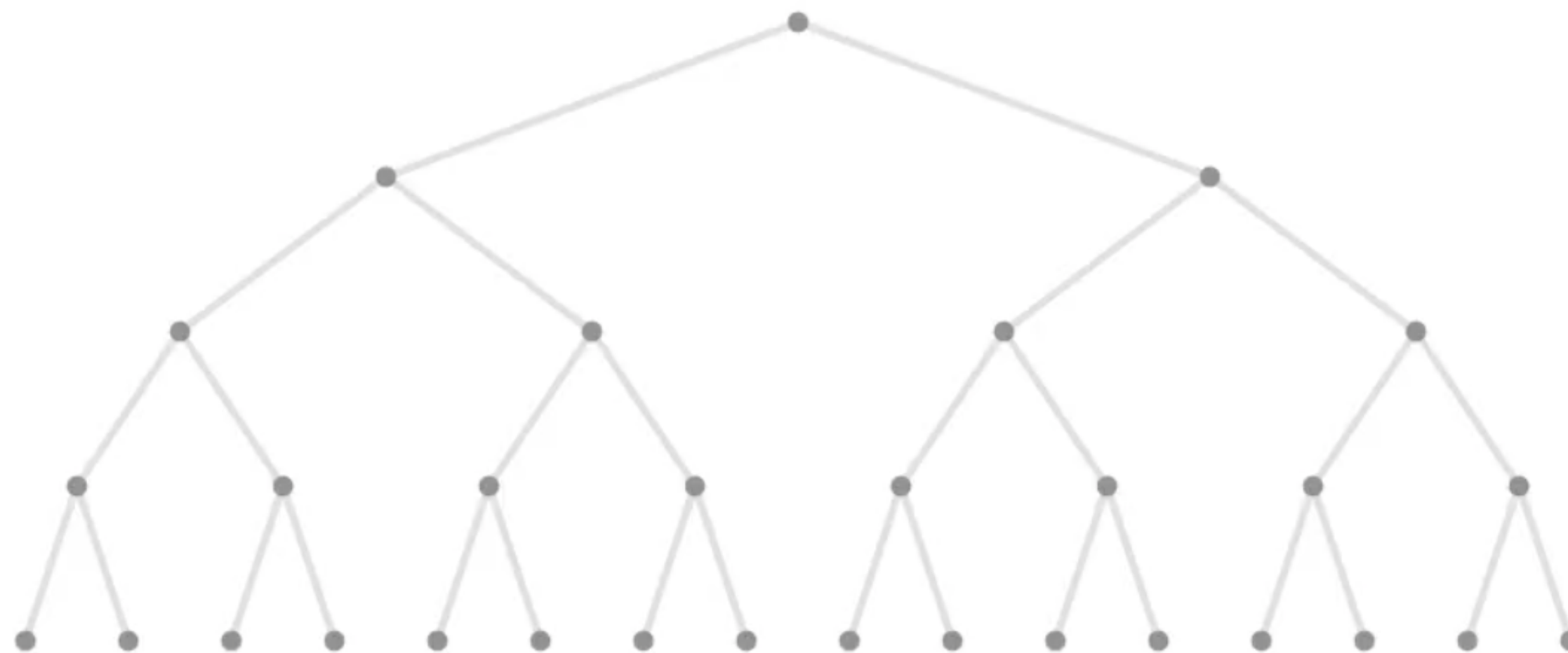
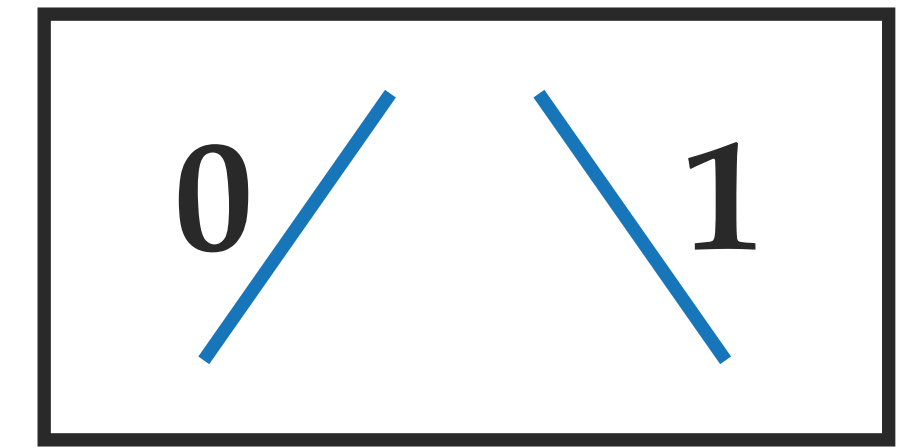


# (Fast) Exhaustive Search

[Bouillaguet, Chen, Cheng, Chou, Niederhagen, Shamir, Yang, 2010]

# Exhaustive Search

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$$x_1 \cdot x_2 + x_1 \cdot x_3 + x_3 \cdot x_4 + x_3 = 0$$

$$x_2 \cdot x_3 + x_2 \cdot x_4 + x_1 + x_2 + 1 = 0$$

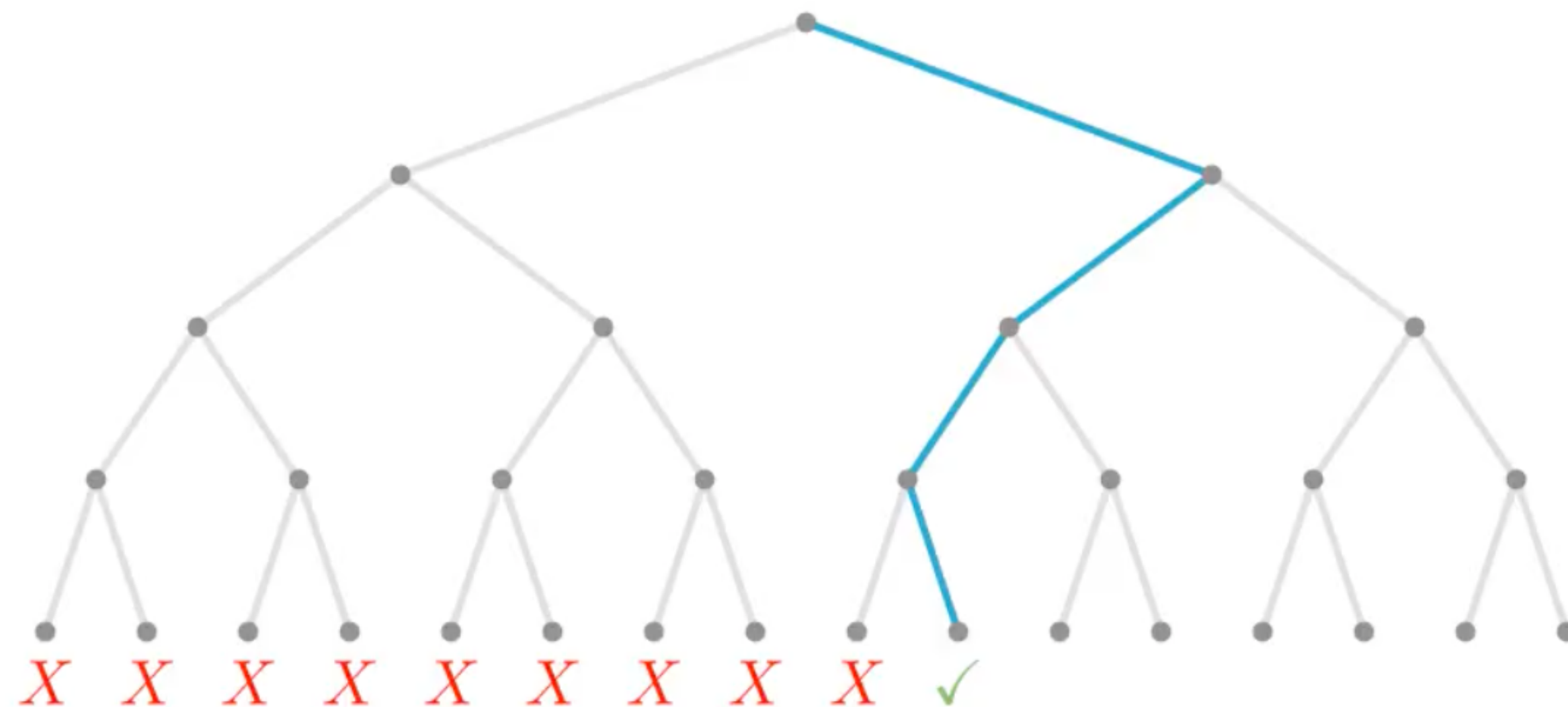
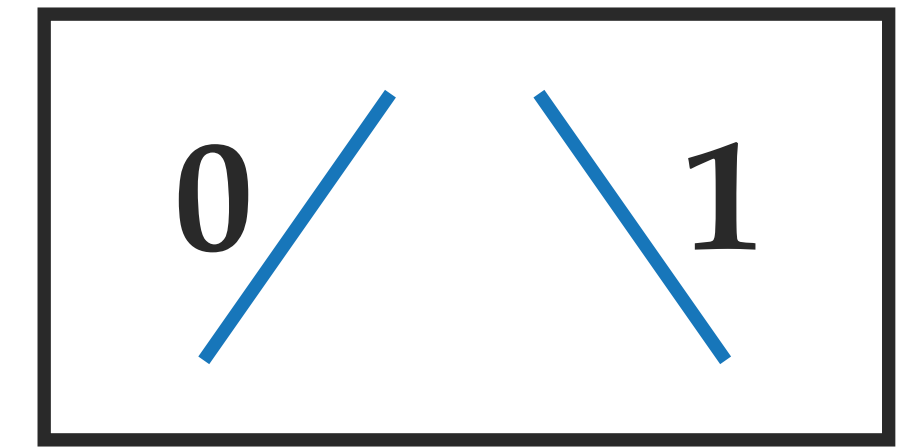
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Binary search tree

# Exhaustive Search

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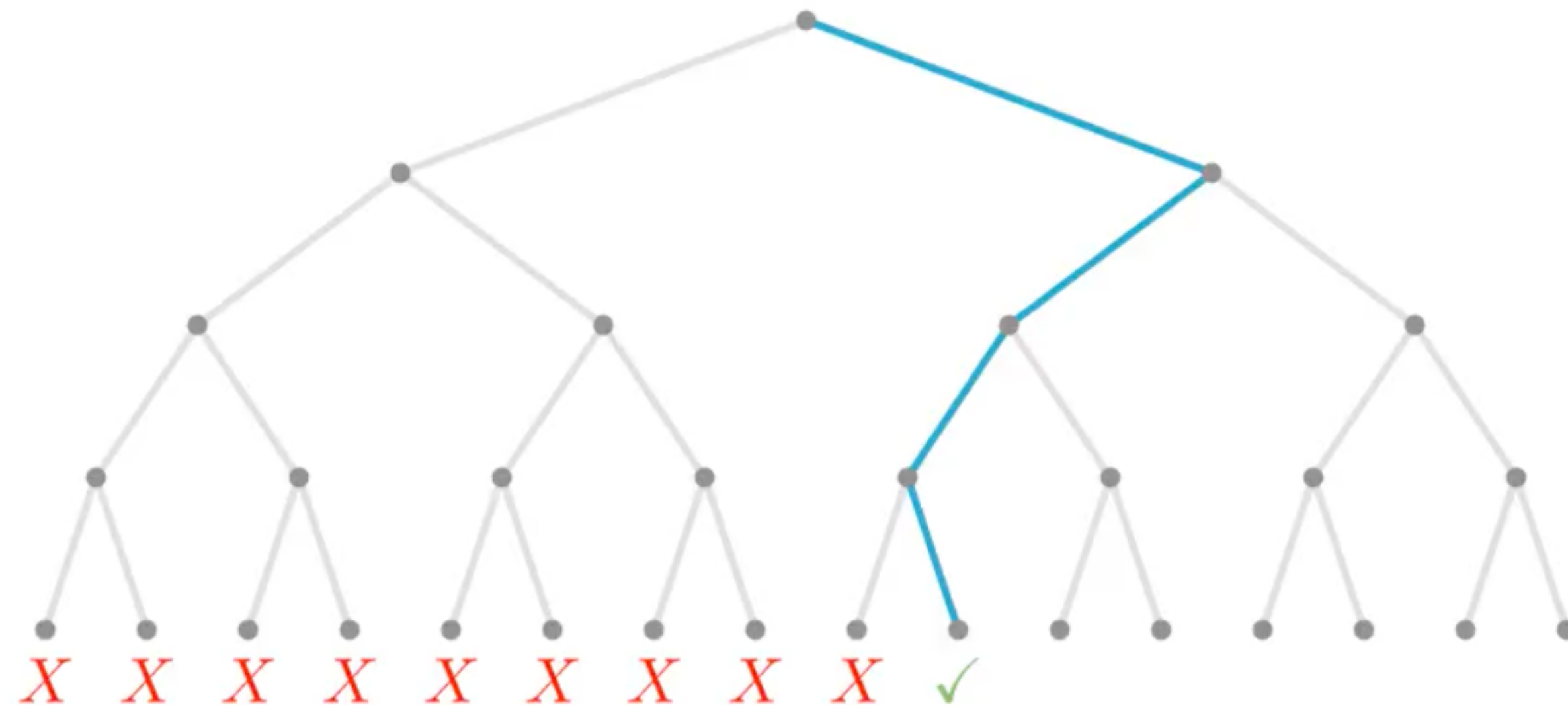
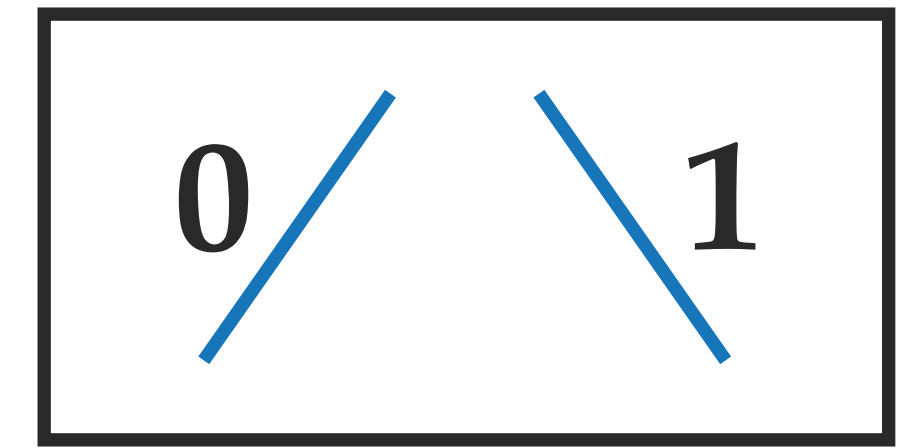


Binary search tree

$$\begin{aligned}1 \cdot 0 + 1 \cdot 0 + 0 \cdot 1 + 0 &= 0 \\0 \cdot 0 + 0 \cdot 1 + 1 + 0 + 1 &= 0 \\1 \cdot 0 + 0 \cdot 0 + 0 \cdot 1 + 1 + 1 &= 0 \\1 \cdot 1 + 0 \cdot 0 + 0 + 0 + 1 &= 0\end{aligned}$$

# Exhaustive Search

Worst-case complexity:  $\mathcal{O}(2^n)$



Binary search tree

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# Fast Exhaustive Search

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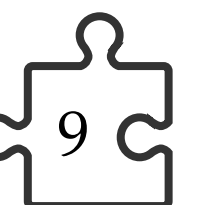
\* The libFES solver

## Gray code

- An ordering of the binary system where two successive values **differ in only one bit**.

*Example.  $n = 4$*

0000	1100
0001	1101
0011	1111
0010	1110
0110	1010
0111	1011
0101	1001
0100	1000

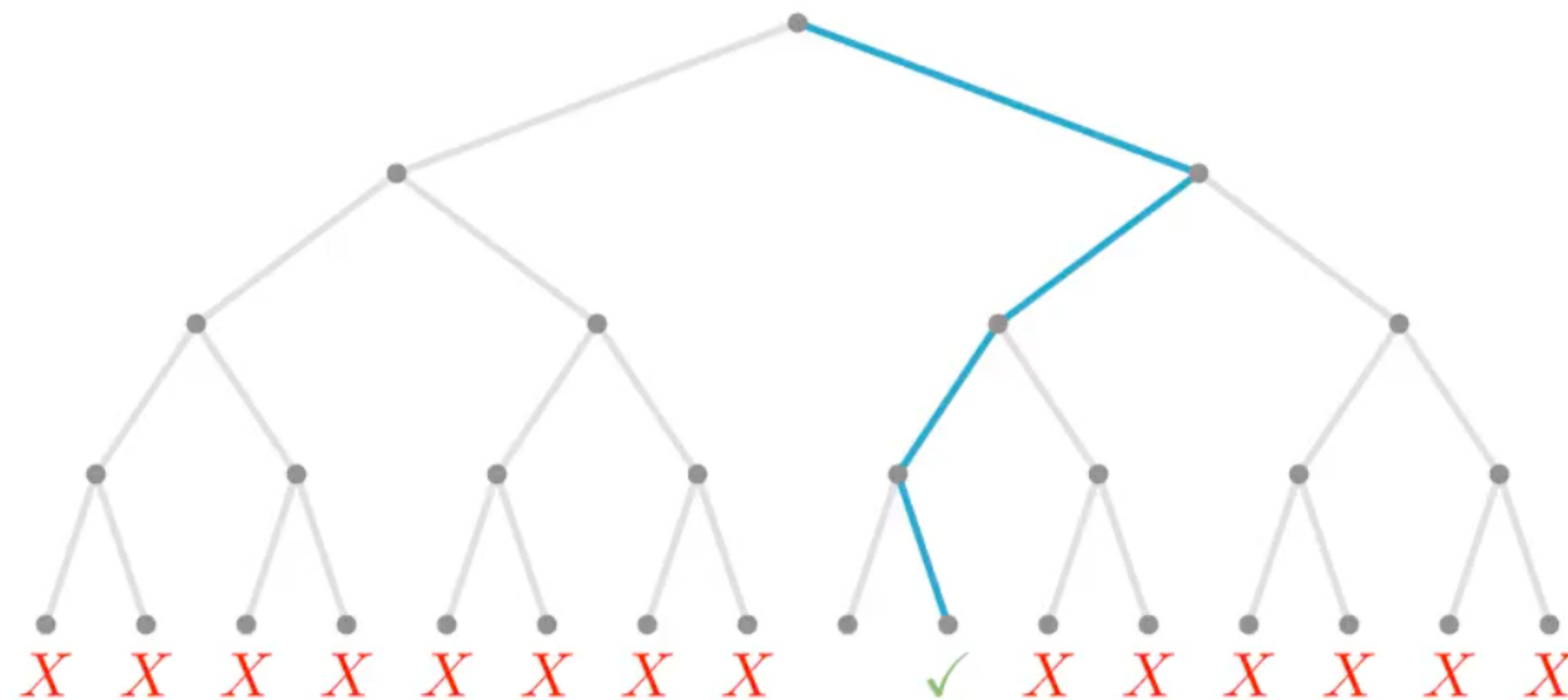


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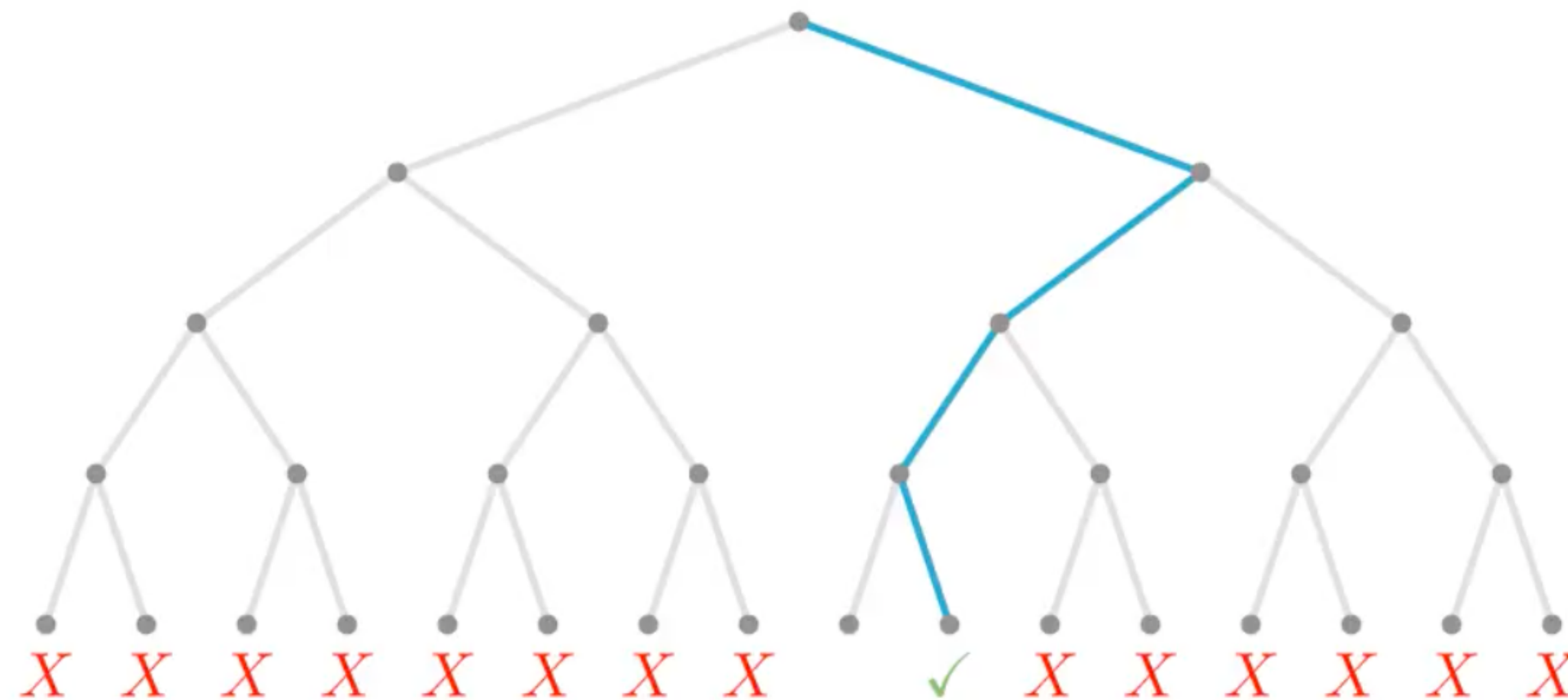


Worst-case complexity:  $\mathcal{O}(2^n)$

! But, it differs from the depth-first traversal in the polynomial factors

Gray code

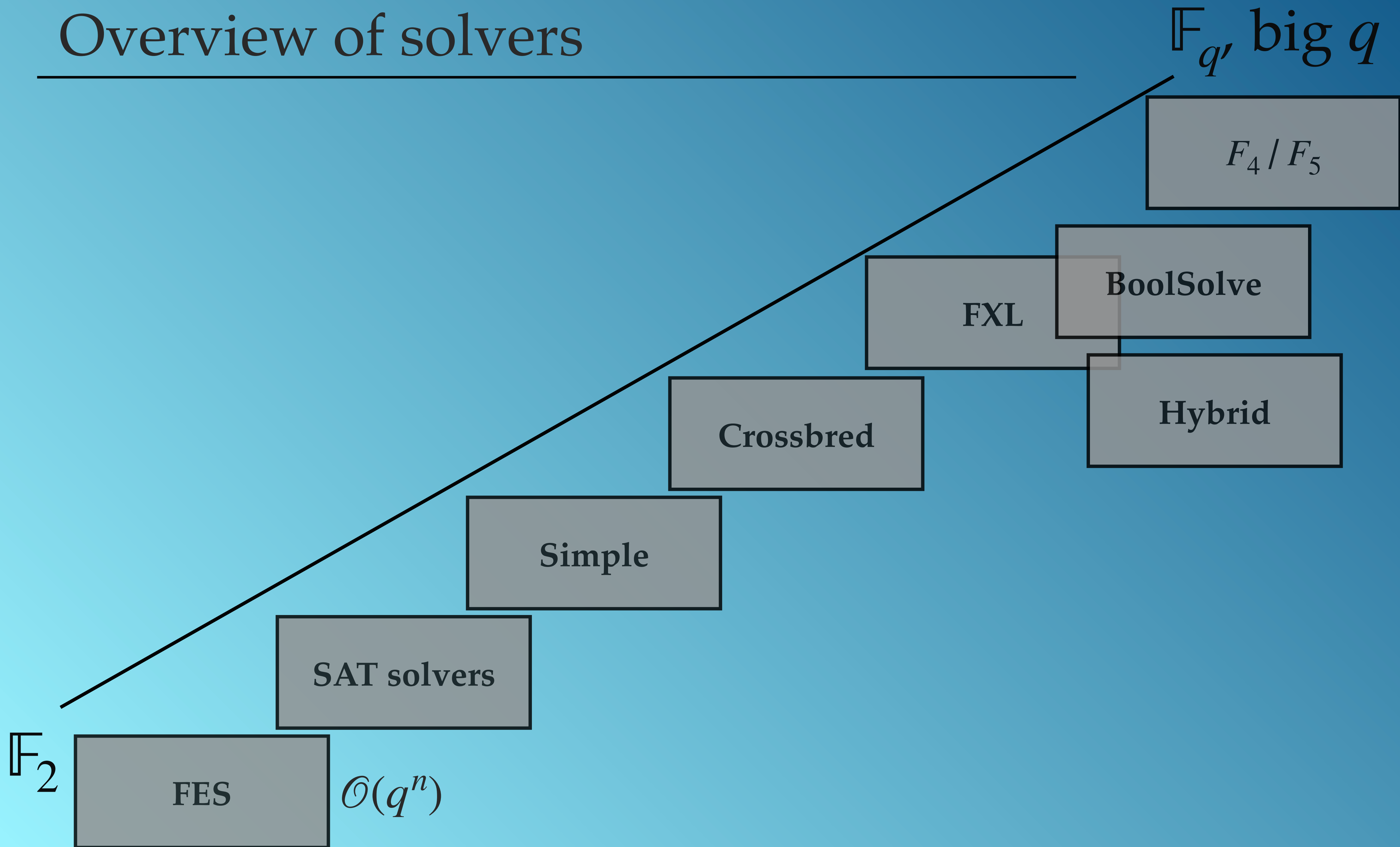
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0001	1101
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# Overview of solvers



The background of the slide features three interlocking gears of different sizes, rendered in a light red color against a dark red background. The gears are positioned such that they appear to be meshing together, with one gear at the top and two at the bottom.

# SAT solvers

CryptoMiniSat [Soos, Nohl, Castelluccia, 2009], WDSat [T., Dequen, Ionica, 2020]

## *Simple* algorithm

[Bouillaguet, Delaplace, T., 2021]

# (SAT solvers)

---

- **Propositional formula** in Conjunctive Normal Form (**CNF**): a **conjunction of clauses** where each clause is a **disjunction of literals** and where each **literal** is a variable or a negated variable.

**Example.**  $(x_1 \vee \neg x_2) \wedge$   
 $(x_2 \vee x_3 \vee x_4) \wedge$   
 $(\neg x_1 \vee x_4)$

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## The SATisfiability problem

Given a propositional formula, determine whether there exists an interpretation (assignment of all variables) such that the formula is satisfied (evaluates to TRUE).

# (SAT solvers)

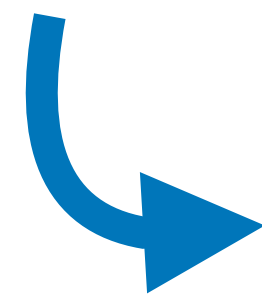
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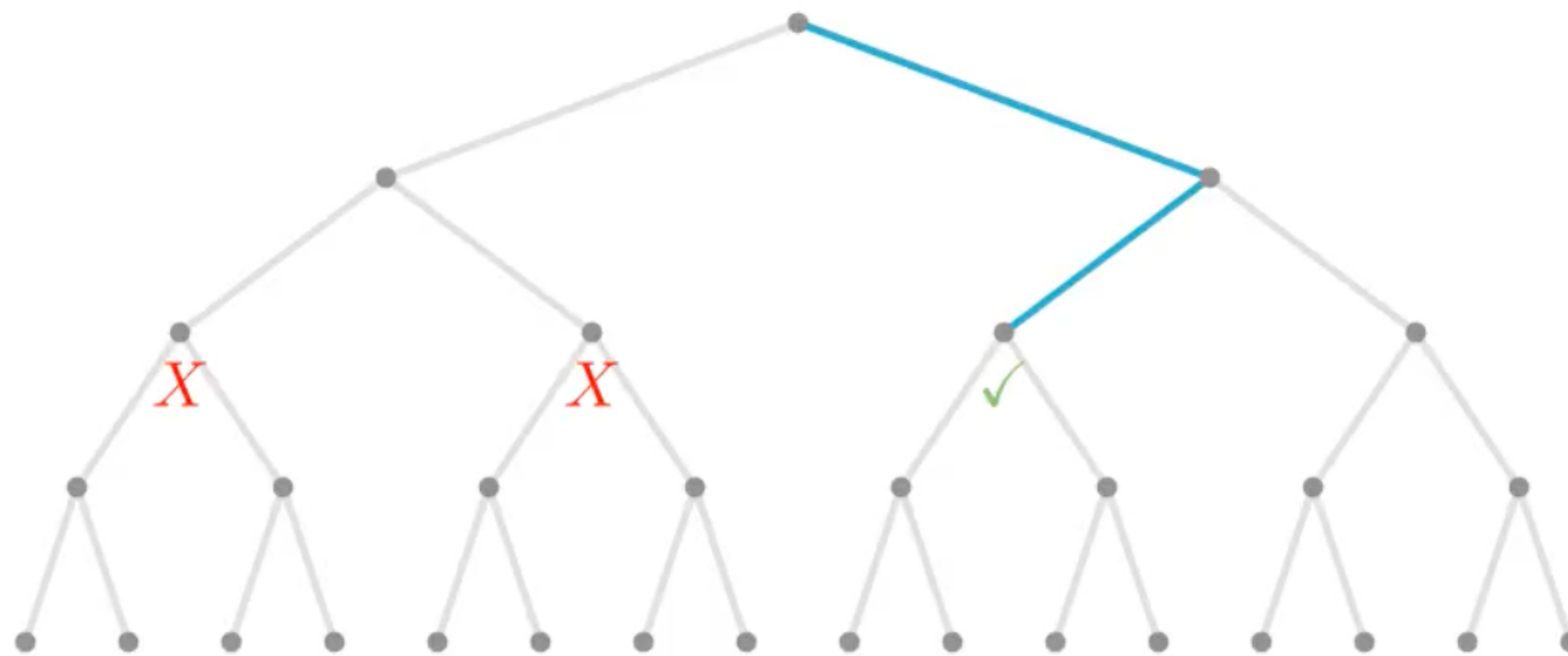
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SAT solver: a tool for solving the SAT problem.

# Partial assignment and conflicts

---



$$1 \cdot 0 + 1 \cdot x_3 + x_3 \cdot x_4 + x_3 = 0$$

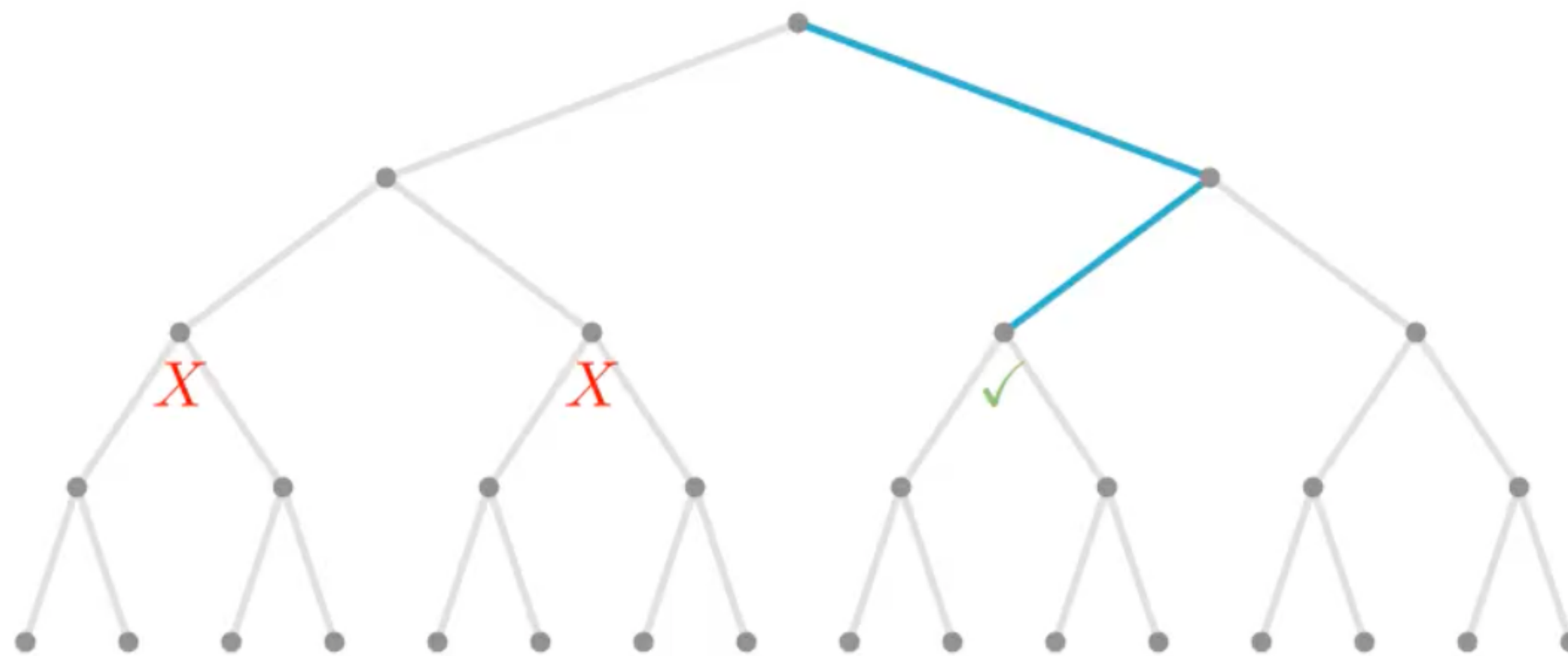
$$0 \cdot x_3 + 0 \cdot x_4 + 1 + 0 + 1 = 0$$

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# Partial assignment and conflicts

Which (portion of) branches are missing ??



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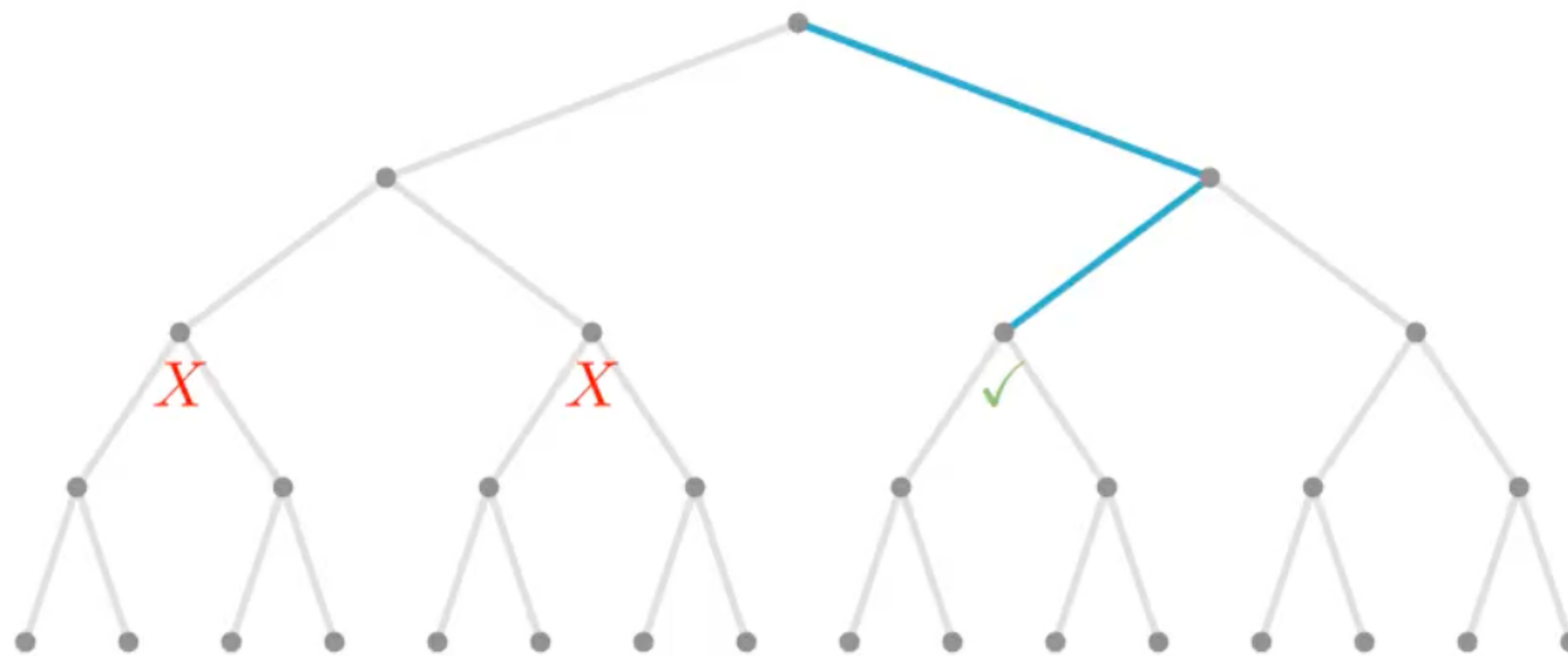
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Worst-case complexity:  $\mathcal{O}(2^n)$



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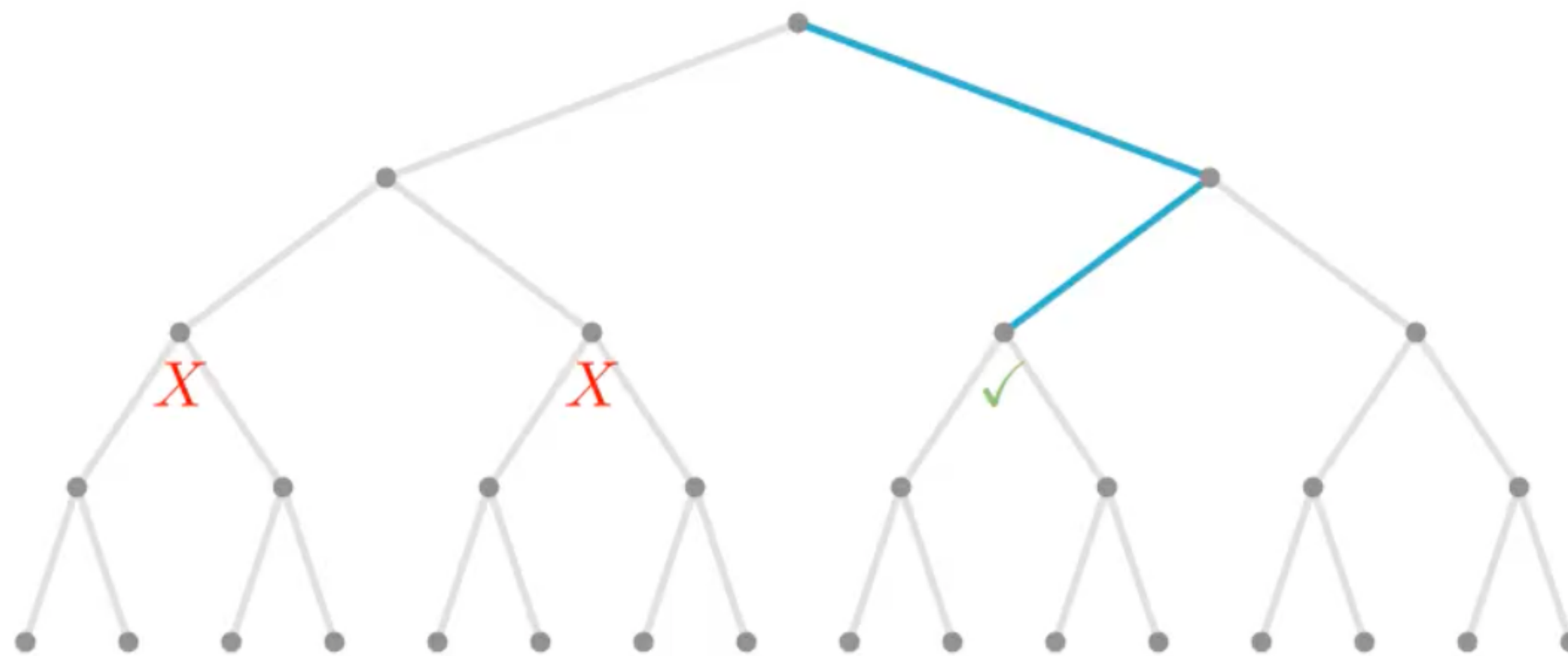
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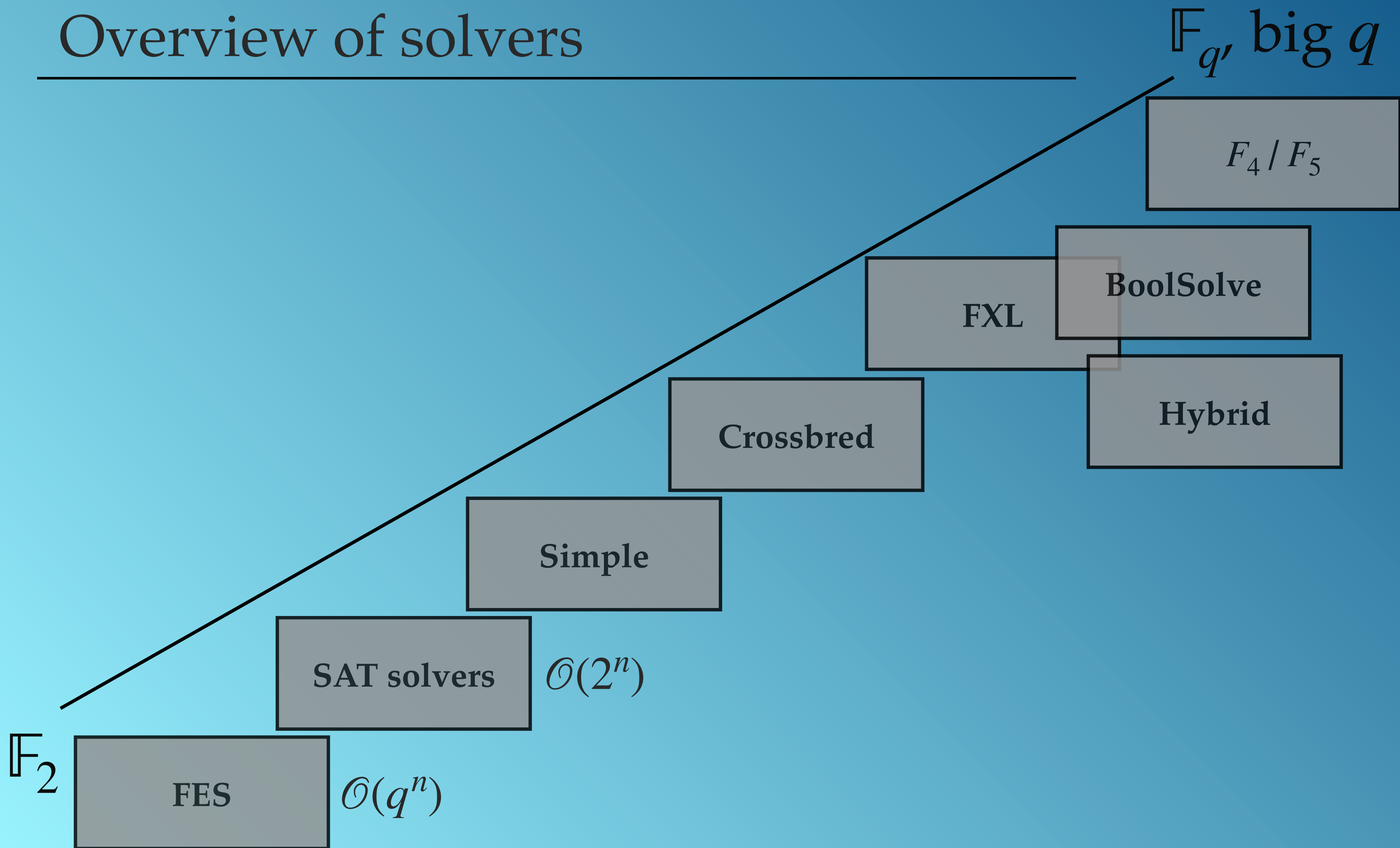
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XOR-enabled SAT solvers: take as input XOR constraints as well; perform Gaussian elimination;  
\*CryptoMiniSat, WDSat

# Overview of solvers



Macaulay matrix

# Linearisation

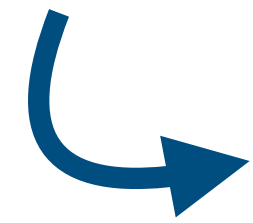
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Linear systems are easy to solve, nonlinear systems are hard.

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$$f_3 : x_2x_4 + x_3x_4 + x_1 + x_3 + 1 = 0$$

$$f_4 : x_1x_2 + x_1x_3 + x_2x_3 + x_3 + x_4 + 1 = 0$$

$$f_5 : x_1x_2 + x_2x_3 + x_1x_4 + x_3 = 0$$

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$$f_1 : y_2 + y_5 + x_1 + x_3 + x_4 = 0$$

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$$f_3 : y_5 + y_6 + x_1 + x_3 + 1 = 0$$

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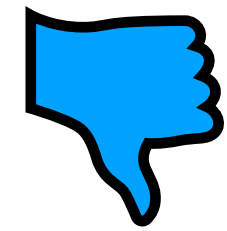
$$f_4 : y_1 + y_2 + y_4 + x_3 + x_4 + 1 = 0$$

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# Linearisation

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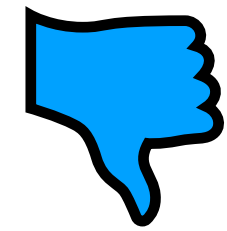


Linearisation adds solutions: a *random* quadratic system of  $m$  equations in  $n$  variables, when  $n = m$ , is expected to have one solution (probability is  $\sim \frac{1}{q}$  for systems over  $\mathbb{F}_q$ ). The corresponding linearised system has a solution space of dimension  $\binom{n+1}{2} - m$ .

  $\binom{n}{2}$  quadratic plus  $n$  linear monomials

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Loss of information: e.g. assignment  $x_1 = 1; x_2 = 0; y_1 = 1$ ; is part of a valid solution to the linearised system, but  $x_1 x_2 \neq y_1$ .

# Macaulay matrix

Equations  
↓

Monomials  
→

	$x_1x_2$	$x_1x_3$	$x_1x_4$	$x_1$	$x_2x_3$	$x_2x_4$	$x_2$	$x_3x_4$	$x_3$	$x_4$	1
$f_1$											
$f_2$											
$f_3$											
$f_4$											
$f_5$											
$f_6$											

$f_1 : x_1x_3 + x_2x_4 + x_1 + x_3 + x_4 = 0$  $f_2 : x_2x_3 + x_1x_4 + x_3x_4 + x_1 + x_2 + x_4 = 0$  $f_3 : x_2x_4 + x_3x_4 + x_1 + x_3 + 1 = 0$  $f_4 : x_1x_2 + x_1x_3 + x_2x_3 + x_3 + x_4 + 1 = 0$  $f_5 : x_1x_2 + x_2x_3 + x_1x_4 + x_3 = 0$  $f_6 : x_1x_3 + x_1x_4 + x_3x_4 + x_1 + x_2 + x_3 + x_4 = 0$

# Macaulay matrix

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	Monomials →										
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$f_1$	0	1	0	1	0	1	0	0	1	1	0
$f_2$	0	0	1	1	1	0	1	1	0	1	0
$f_3$	0	0	0	1	0	1	0	1	1	0	1
$f_4$	1	1	0	1	1	0	0	0	1	1	1
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$f_6$	0	1	1	1	0	0	1	1	1	1	0

$f_1 : x_1x_3 + x_2x_4 + x_1 + x_3 + x_4 = 0$  $f_2 : x_2x_3 + x_1x_4 + x_3x_4 + x_1 + x_2 + x_4 = 0$  $f_3 : x_2x_4 + x_3x_4 + x_1 + x_3 + 1 = 0$  $f_4 : x_1x_2 + x_1x_3 + x_2x_3 + x_3 + x_4 + 1 = 0$  $f_5 : x_1x_2 + x_2x_3 + x_1x_4 + x_3 = 0$  $f_6 : x_1x_3 + x_1x_4 + x_3x_4 + x_1 + x_2 + x_3 + x_4 = 0$

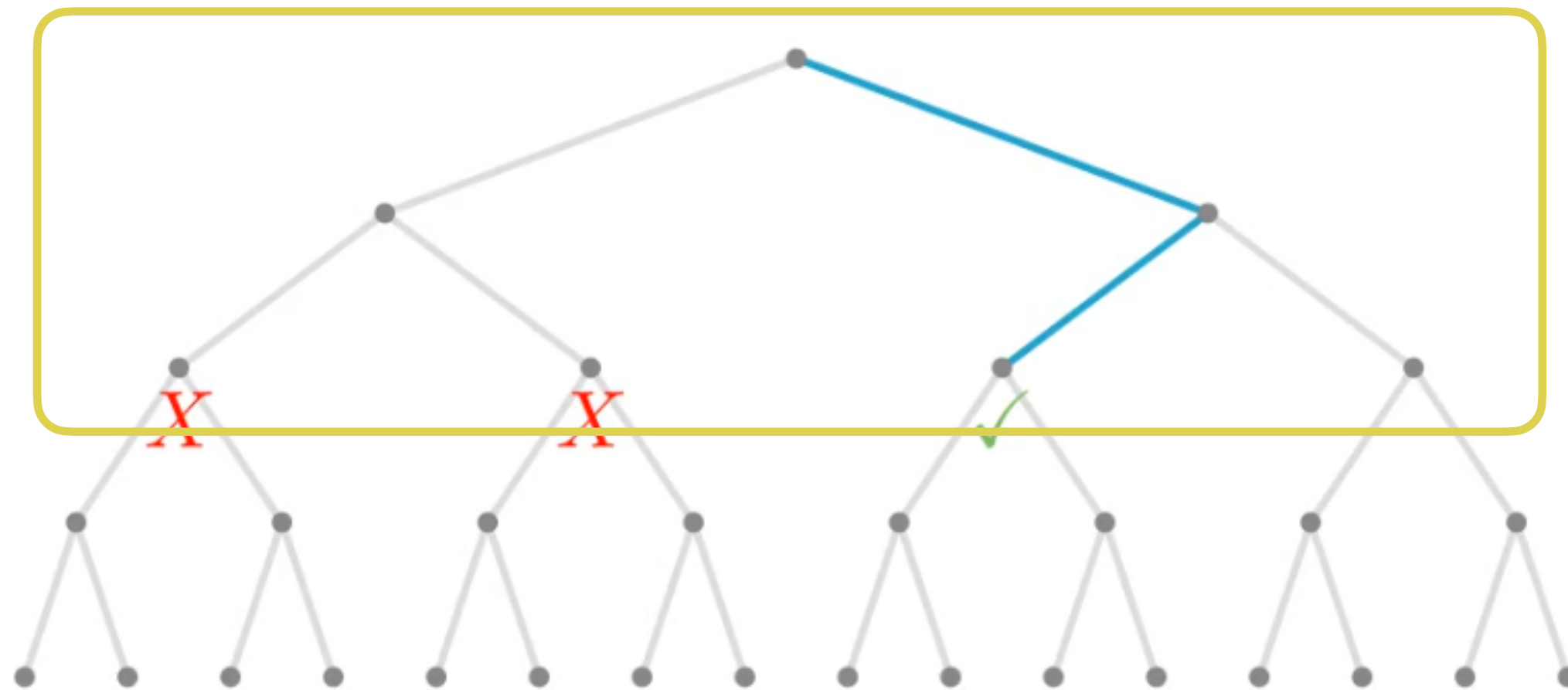


# *Simple* algorithm

[Bouillaguet, Delaplace, T., 2021]

# Simple algorithm

- Partial assignment
- Gaussian elimination



$$1 \cdot 0 + 1 \cdot x_3 + x_3 \cdot x_4 + x_3 = 0$$

$$0 \cdot x_3 + 0 \cdot x_4 + 1 + 0 + 1 = 0$$

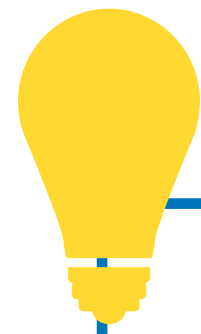
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# *Simple* algorithm

---



Guess sufficiently many variables so that the remaining polynomial system can be solved by linearization.

# *Simple* algorithm: complexity

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- $n$  - number of variables
- $m$  - number of equations

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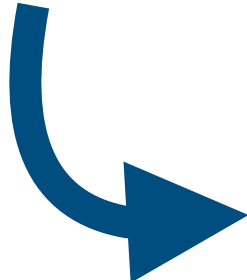
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  $\mathcal{O}(2^{n-\sqrt{2m}})$

# Simple algorithm: complexity

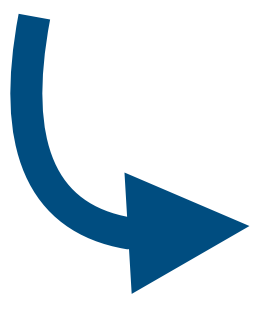
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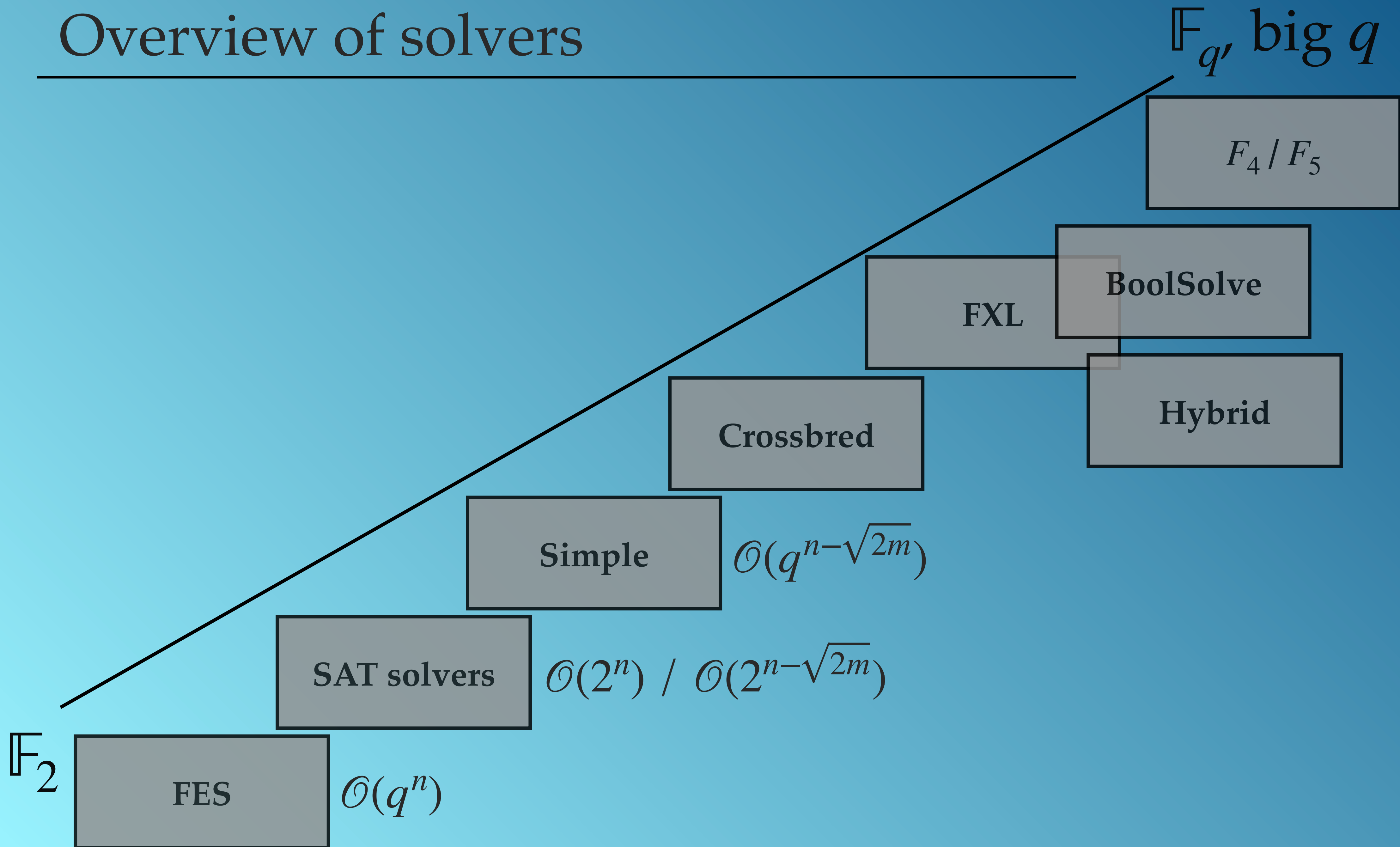
number of **monomials**  $\leq$  number of **equations**

$$\binom{n-?}{2} \leq m$$

  $\mathcal{O}(2^{n-\sqrt{2m}})$

 See also: Quantum BDT [Edme, Fouque, Schrottenloher]

# Overview of solvers







# Gröbner basis algorithms

[Buchberger, 1965]

[Lazard, 1983]

$F_4/F_5$  [Faugère, 1999/2002]

(XL [Courtois, Klimov, Patarin, Shamir, 2000])

# Gröbner basis algorithms (intuition)

---

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$f_1$	0	1	0	1	0	1	0	0	1	1	0
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# Gröbner basis algorithms (intuition)

\*We are essentially describing the XL algorithm.

$f_1 : x_1x_3 + x_2x_4 + x_1 + x_3 + x_4 = 0$  $f_2 : x_2x_3 + x_1x_4 + x_3x_4 + x_1 + x_2 + x_4 = 0$  $f_3 : x_2x_4 + x_3x_4 + x_1 + x_3 + 1 = 0$  $f_4 : x_1x_2 + x_1x_3 + x_2x_3 + x_3 + x_4 + 1 = 0$  $f_5 : x_1x_2 + x_2x_3 + x_1x_4 + x_3 = 0$  $f_6 : x_1x_3 + x_1x_4 + x_3x_4 + x_1 + x_2 + x_3 + x_4 = 0$

	$x_1x_2$	$x_1x_3$	$x_1x_4$	$x_1$	$x_2x_3$	$x_2x_4$	$x_2$	$x_3x_4$	$x_3$	$x_4$	1
$f_1$	0	1	0	1	0	1	0	0	1	1	0
$f_2$	0	0	1	1	1	0	1	1	0	1	0
$f_3$	0	0	0	1	0	1	0	1	1	0	1
$f_4$	1	1	0	1	1	0	0	0	1	1	1
$f_5$	1	0	1	1	1	0	0	0	1	0	0
$f_6$	0	1	1	1	0	0	1	1	1	1	0

# Gröbner basis algorithms (intuition)

\*We are essentially describing the XL algorithm.

$D = 3$

$$\begin{aligned} f_1 &: x_1x_3 + x_2x_4 + x_1 + x_3 + x_4 = 0 \\ f_2 &: x_2x_3 + x_1x_4 + x_3x_4 + x_1 + x_2 + x_4 = 0 \\ f_3 &: x_2x_4 + x_3x_4 + x_1 + x_3 + 1 = 0 \\ f_4 &: x_1x_2 + x_1x_3 + x_2x_3 + x_3 + x_4 + 1 = 0 \\ f_5 &: x_1x_2 + x_2x_3 + x_1x_4 + x_3 = 0 \\ f_6 &: x_1x_3 + x_1x_4 + x_3x_4 + x_1 + x_2 + x_3 + x_4 = 0 \end{aligned}$$

	$x_1x_2$	$x_1x_3$	$x_1x_4$	$x_1$	$x_2x_3$	$x_2x_4$	$x_2$	$x_3x_4$	$x_3$	$x_4$	1	$x_1x_2x_3$	$x_1x_2x_4$	$x_1x_3x_4$	$x_2x_3x_4$
$f_1$	0	1	0	1	0	1	0	0	1	1	0				
$f_2$	0	0	1	1	1	0	1	1	0	1	0				
$f_3$	0	0	0	1	0	1	0	1	1	0	1				
$f_4$	1	1	0	1	1	0	0	0	1	1	1				
$f_5$	1	0	1	1	1	0	0	0	1	0	0				
$f_6$	0	1	1	1	0	0	1	1	1	1	0				
$x_1f_1$															
$x_2f_1$															
...															

# Gröbner basis algorithms (intuition)

\*We are essentially describing the XL algorithm.

$D = 4$

$$\begin{aligned} f_1 &: x_1x_3 + x_2x_4 + x_1 + x_3 + x_4 = 0 \\ f_2 &: x_2x_3 + x_1x_4 + x_3x_4 + x_1 + x_2 + x_4 = 0 \\ f_3 &: x_2x_4 + x_3x_4 + x_1 + x_3 + 1 = 0 \\ f_4 &: x_1x_2 + x_1x_3 + x_2x_3 + x_3 + x_4 + 1 = 0 \\ f_5 &: x_1x_2 + x_2x_3 + x_1x_4 + x_3 = 0 \\ f_6 &: x_1x_3 + x_1x_4 + x_3x_4 + x_1 + x_2 + x_3 + x_4 = 0 \end{aligned}$$

	$x_1x_2$	$x_1x_3$	$x_1x_4$	$x_1$	$x_2x_3$	$x_2x_4$	$x_2$	$x_3x_4$	$x_3$	$x_4$	$1$	$x_1x_2x_3$	$x_1x_2x_4$	$x_1x_3x_4$	$x_2x_3x_4$	$x_1x_2x_3x_4$
$f_1$	0	1	0	1	0	1	0	0	1	1	0					
$f_2$	0	0	1	1	1	0	1	1	0	1	0					
$f_3$	0	0	0	1	0	1	0	1	1	0	1					
$f_4$	1	1	0	1	1	0	0	0	1	1	1					
$f_5$	1	0	1	1	1	0	0	0	1	0	0					
$f_6$	0	1	1	1	0	0	1	1	1	1	0					
$x_1f_1$																
$x_2f_1$																
...																
$x_1x_2f_1$																
$x_1x_3f_1$																

# Gröbner basis

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# Gröbner basis

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- Let  $R = \mathbb{F}_q[x_1, \dots, x_n]$  be the **polynomial ring** in  $n$  variables.



# Gröbner basis

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- Let  $R = \mathbb{F}_q[x_1, \dots, x_n]$  be the **polynomial ring** in  $n$  variables.
- An **ideal** in  $R$  is an additive subgroup  $I$  such that if  $g \in R$  and  $f \in I$ , then  $gf \in I$ .

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- The subset  $\{f_1, \dots, f_m\} \subset R$  is a **set of generators** for an ideal  $I$  if every element  $t \in I$  can be written in the form
$$t = \sum_1^n \text{ with } g_i \in R.$$

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$$t = \sum_{i=1}^n g_i$$
with  $g_i \in R$ .
- By the **Hilbert basis theorem**: every ideal in  $R$  has a **finite** set of generators.
- The subset of  $R$  defined as  $V(I) = \{(a_1, \dots, a_n) \in \mathbb{F}_q^n \mid f(a_1, \dots, a_n) = 0 \text{ for all } f \in I\}$  is called an **algebraic variety**. It is the set of all solutions to the system of equations  $f_1(x_1, \dots, x_n) = \dots = f_m(x_1, \dots, x_n) = 0$ .

# Gröbner basis

---

- Let  $R = \mathbb{F}_q[x_1, \dots, x_n]$  be the **polynomial ring** in  $n$  variables.
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$$f_1(x_1, \dots, x_n) = \dots = f_m(x_1, \dots, x_n) = 0.$$
- By the **Nullstellensatz**:  $\mathbf{I}(V(I)) = I$ , where  $\mathbf{I}(V)$  denotes the ideal of  $V$ , i.e.  $\mathbf{I}(V) = \{f \in R \mid f(a) = 0 \text{ for all } a \in V\}$  (Similar to Gauss' fundamental theorem, but for polynomials in many variables).

# Gröbner basis

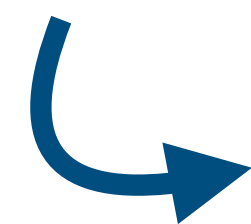
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- A **Gröbner basis** of an ideal  $I$  is a set of generators with some **nice** (useful) property.

# Gröbner basis

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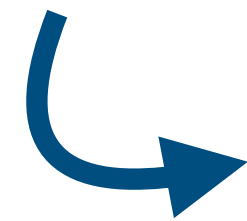
For our case, the nice property is that a solution can be extracted easily from the Gröbner basis.



# Gröbner basis

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- A **Gröbner basis** of an ideal  $I$  is a set of generators with some **nice** (useful) property.



For our case, the nice property is that a solution can be extracted easily from the Gröbner basis.

**Example.** The **shape** of a GB with respect to the lexicographic order

$$f_1 : x_1x_3 + x_1 + x_2x_4 + x_5 + x_6 + 1 = 0$$

$$f_2 : x_1x_4 + x_1 + x_2x_3 + x_2 + x_3x_4 + x_3x_6 + x_4 + x_5 = 0$$

$$f_3 : x_1x_5 + x_1 + x_2 + x_3x_4 + x_6 + 1 = 0$$

$$f_4 : x_1x_2 + x_1x_3 + x_2x_5 + x_3 + x_4 + x_6 + 1 = 0$$

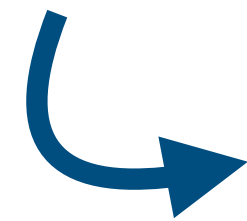
$$f_5 : x_1x_4 + x_2x_3 + x_2x_5 + x_5x_6 + 1 = 0$$

$$f_6 : x_1x_3 + x_1x_4 + x_1 + x_2 + x_3x_6 + x_3 + x_5 = 0$$

# Gröbner basis

---

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$$\begin{aligned}f'_1 &: x_1 + x_6 = 0 \\f'_2 &: x_2 + x_6 = 0 \\f'_3 &: x_3 + x_6 = 0 \\f'_4 &: x_4 + x_6 + 1 = 0 \\f'_5 &: x_5 = 0\end{aligned}$$

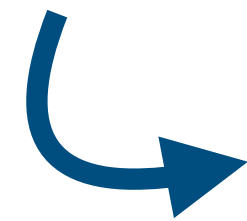
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# Gröbner basis

---

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$$\begin{aligned} f'_1 &: x_1 + x_6 = 0 \\ f'_2 &: x_2 + x_6 = 0 \\ f'_3 &: x_3 + x_6 = 0 \\ f'_4 &: x_4 + x_6 + 1 = 0 \\ f'_5 &: x_5 = 0 \end{aligned}$$

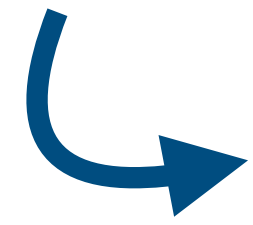
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$$V( \langle f_1, \dots, f_6 \rangle ) = \{ (0,0,0,1,0,0), (1,1,1,0,0,1) \}$$

# Gröbner basis algorithms:

---

Buchberger, Lazard, F4, F5



Follow the core idea that we described, but combine the equations in an organised way, rather than multiplying them by all possible monomials.

Not covered in this talk:

- Monomial orders
- S-polynomials
- Polynomial long division
- Row reduction in parallel
- Reductions to zero
- Syzygy criterion
- ...

# XL / Gröbner basis algorithms: complexity

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$$\mathcal{O} \left( m D_{reg} \binom{n + D_{reg} - 1}{D_{reg}}^{\omega} \right)$$

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$$\mathcal{O} \left( m D_{reg} \binom{n + D_{reg} - 1}{D_{reg}}^{\omega} \right)$$

$D_{reg}$ : degree of regularity

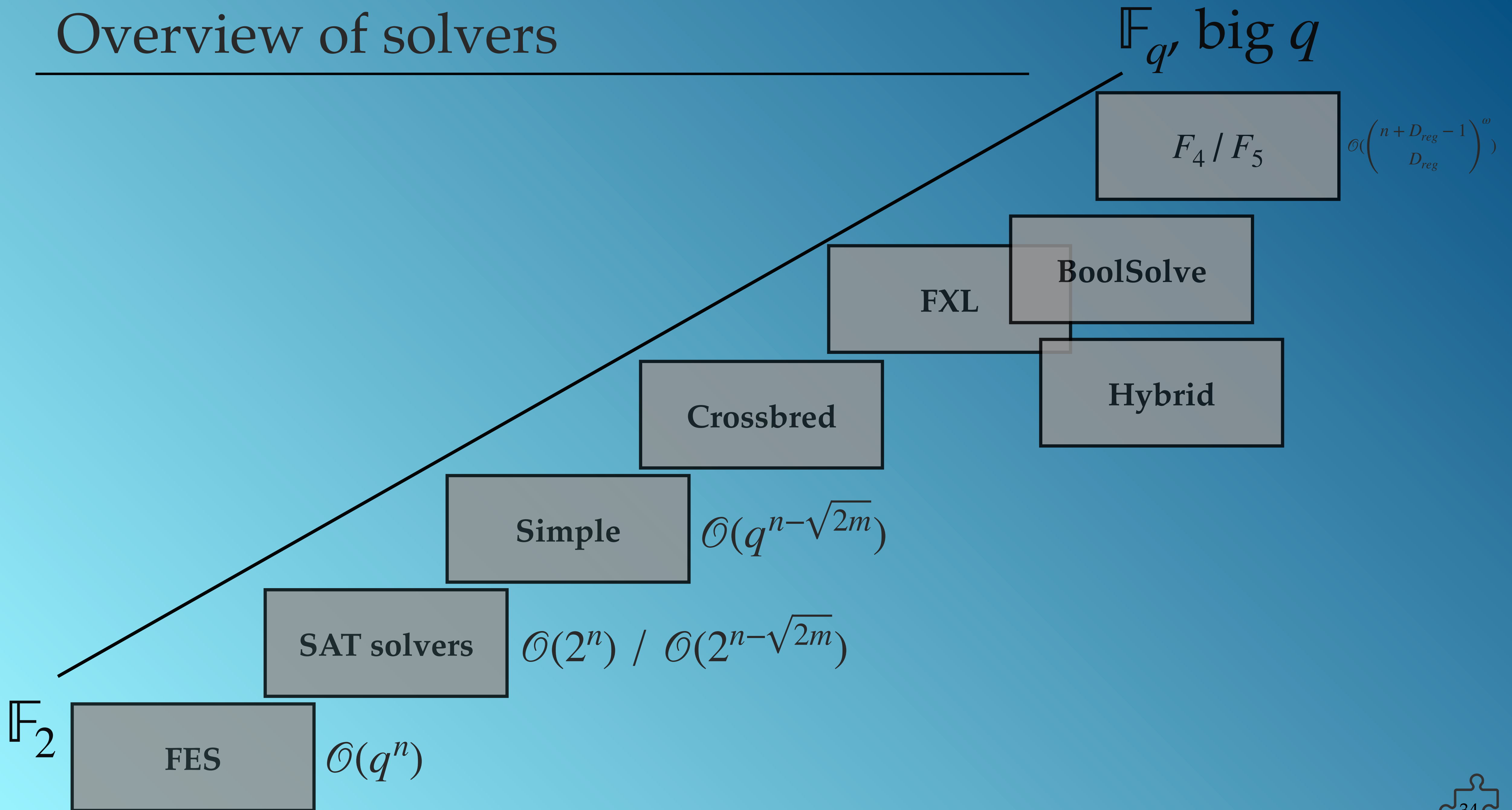


the power of the first non-positive coefficient in the expansion of

$$\frac{(1 - t^2)^m}{(1 - t)^n}$$



# Overview of solvers





FXL

[Courtois, Klimov, Patarin, Shamir, 2000]

Hybrid

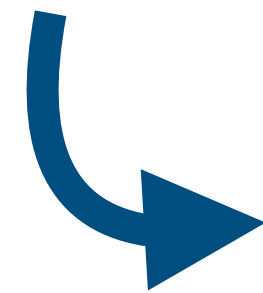
[Bettale, Faugère, Perret, 2009]

BoolSolve

[Bardet, Faugère, Salvy, Spaenlehauer, 2013]

# FXL, Hybrid, BoolSolve

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Techniques are already covered in the previous section.

Algorithms will be explained in the summary.



# The crossbred algorithm

[Joux, Vitse, 2017]

# Crossbred algorithm

$f_1 : x_1x_3 + x_2x_4 + x_1 + x_3 + x_4 = 0$  $f_2 : x_2x_3 + x_1x_4 + x_3x_4 + x_1 + x_2 + x_4 = 0$  $f_3 : x_2x_4 + x_3x_4 + x_1 + x_3 + 1 = 0$  $f_4 : x_1x_2 + x_1x_3 + x_2x_3 + x_3 + x_4 + 1 = 0$  $f_5 : x_1x_2 + x_2x_3 + x_1x_4 + x_3 = 0$  $f_6 : x_1x_3 + x_1x_4 + x_3x_4 + x_1 + x_2 + x_3 + x_4 = 0$

	$x_1x_2$	$x_1x_3$	$x_1x_4$	$x_1$	$x_2x_3$	$x_2x_4$	$x_2$	$x_3x_4$	$x_3$	$x_4$	1
$f_1$	0	1	0	1	0	1	0	0	1	1	0
$f_2$	0	0	1	1	1	0	1	1	0	1	0
$f_3$	0	0	0	1	0	1	0	1	1	0	1
$f_4$	1	1	0	1	1	0	0	0	1	1	1
$f_5$	1	0	1	1	1	0	0	0	1	0	0
$f_6$	0	1	1	1	0	0	1	1	1	1	0

# Crossbred algorithm

→ Put matrix in reduced row echelon form

$f_1 : x_1x_3 + x_2x_4 + x_1 + x_3 + x_4 = 0$  $f_2 : x_2x_3 + x_1x_4 + x_3x_4 + x_1 + x_2 + x_4 = 0$  $f_3 : x_2x_4 + x_3x_4 + x_1 + x_3 + 1 = 0$  $f_4 : x_1x_2 + x_1x_3 + x_2x_3 + x_3 + x_4 + 1 = 0$  $f_5 : x_1x_2 + x_2x_3 + x_1x_4 + x_3 = 0$  $f_6 : x_1x_3 + x_1x_4 + x_3x_4 + x_1 + x_2 + x_3 + x_4 = 0$

	$x_1x_2$	$x_1x_3$	$x_2x_3$	$x_1x_4$	$x_2x_4$	$x_3x_4$	$x_1$	$x_2$	$x_3$	$x_4$	1
$f_1$	1	0	0	0	0	0	0	0	0	1	1
$f_2$	0	1	0	0	0	0	1	1	1	1	0
$f_3$	0	0	1	0	0	0	1	1	0	1	0
$f_4$	0	0	0	1	0	0	1	1	1	0	1
$f_5$	0	0	0	0	1	0	0	1	0	0	0
$f_6$	0	0	0	0	0	1	1	1	1	0	1

...

# Crossbred algorithm

→ Take linear subsystem

	$x_1x_2$	$x_1x_3$	$x_2x_3$	$x_1x_4$	$x_2x_4$	$x_3x_4$	$x_1$	$x_2$	$x_3$	$x_4$	1
$f_1$	1	0	0	0	0	0	0	0	0	1	1
$f_2$	0	1	0	0	0	0	1	1	1	1	0
$f_3$	0	0	1	0	0	0	1	1	0	1	0
$f_4$	0	0	0	1	0	0	1	1	1	0	1
$f_5$	0	0	0	0	1	0	0	1	0	0	0
$f_6$	0	0	0	0	0	1	1	1	1	0	1

...



...if we had another 4 equations

$f_1 : x_1x_3 + x_2x_4 + x_1 + x_3 + x_4 = 0$  $f_2 : x_2x_3 + x_1x_4 + x_3x_4 + x_1 + x_2 + x_4 = 0$  $f_3 : x_2x_4 + x_3x_4 + x_1 + x_3 + 1 = 0$  $f_4 : x_1x_2 + x_1x_3 + x_2x_3 + x_3 + x_4 + 1 = 0$  $f_5 : x_1x_2 + x_2x_3 + x_1x_4 + x_3 = 0$  $f_6 : x_1x_3 + x_1x_4 + x_3x_4 + x_1 + x_2 + x_3 + x_4 = 0$

# Crossbred algorithm

$f_1 : x_1x_3 + x_2x_4 + x_1 + x_3 + x_4 = 0$  $f_2 : x_2x_3 + x_1x_4 + x_3x_4 + x_1 + x_2 + x_4 = 0$  $f_3 : x_2x_4 + x_3x_4 + x_1 + x_3 + 1 = 0$  $f_4 : x_1x_2 + x_1x_3 + x_2x_3 + x_3 + x_4 + 1 = 0$  $f_5 : x_1x_2 + x_2x_3 + x_1x_4 + x_3 = 0$  $f_6 : x_1x_3 + x_1x_4 + x_3x_4 + x_1 + x_2 + x_3 + x_4 = 0$

	$x_1x_2$	$x_1x_3$	$x_2x_3$	$x_1x_4$	$x_2x_4$	$x_3x_4$	$x_1$	$x_2$	$x_3$	$x_4$	1
$f_1$	1	0	0	0	0	0	0	0	0	1	1
$f_2$	0	1	0	0	0	0	1	1	1	1	0
$f_3$	0	0	1	0	0	0	1	1	0	1	0
$f_4$	0	0	0	1	0	0	1	1	1	0	1
$f_5$	0	0	0	0	1	0	0	1	0	0	0
$f_6$	0	0	0	0	0	1	1	1	1	0	1
...											



# Crossbred algorithm

- Subsystem is linear in variables  $\{x_1, x_2, x_3\}$ .
- Enumerating  $x_4$  will result in a linear subsystem.

$f_1 : x_1x_3 + x_2x_4 + x_1 + x_3 + x_4 = 0$  $f_2 : x_2x_3 + x_1x_4 + x_3x_4 + x_1 + x_2 + x_4 = 0$  $f_3 : x_2x_4 + x_3x_4 + x_1 + x_3 + 1 = 0$  $f_4 : x_1x_2 + x_1x_3 + x_2x_3 + x_3 + x_4 + 1 = 0$  $f_5 : x_1x_2 + x_2x_3 + x_1x_4 + x_3 = 0$  $f_6 : x_1x_3 + x_1x_4 + x_3x_4 + x_1 + x_2 + x_3 + x_4 = 0$

	$x_1x_2$	$x_1x_3$	$x_2x_3$	$x_1x_4$	$x_2x_4$	$x_3x_4$	$x_1$	$x_2$	$x_3$	$x_4$	1
$f_1$	1	0	0	0	0	0	0	0	0	1	1
$f_2$	0	1	0	0	0	0	1	1	1	1	0
$f_3$	0	0	1	0	0	0	1	1	0	1	0
$f_4$	0	0	0	1	0	0	1	1	1	0	1
$f_5$	0	0	0	0	1	0	0	1	0	0	0
$f_6$	0	0	0	0	0	1	1	1	1	0	1
...											

# Crossbred algorithm

	$x_1x_2$	$x_1x_3$	$x_2x_3$	$x_1x_4$	$x_2x_4$	$x_3x_4$	$x_1$	$x_2$	$x_3$	$x_4$	1
$f_1$	1	0	0	0	0	0	0	0	0	1	1
$f_2$	0	1	0	0	0	0	1	1	1	1	0
$f_3$	0	0	1	0	0	0	1	1	0	1	0
$f_4$	0	0	0	1	0	0	1	1	1	0	1
$f_5$	0	0	0	0	1	0	0	1	0	0	0
$f_6$	0	0	0	0	0	1	1	1	1	0	1
...											

$f_1 : x_1x_3 + x_2x_4 + x_1 + x_3 + x_4 = 0$  $f_2 : x_2x_3 + x_1x_4 + x_3x_4 + x_1 + x_2 + x_4 = 0$  $f_3 : x_2x_4 + x_3x_4 + x_1 + x_3 + 1 = 0$  $f_4 : x_1x_2 + x_1x_3 + x_2x_3 + x_3 + x_4 + 1 = 0$  $f_5 : x_1x_2 + x_2x_3 + x_1x_4 + x_3 = 0$  $f_6 : x_1x_3 + x_1x_4 + x_3x_4 + x_1 + x_2 + x_3 + x_4 = 0$

# Crossbred algorithm

→ Subsystem can be linearised

	$x_1x_2$	$x_1x_3$	$x_2x_3$	$x_1x_4$	$x_2x_4$	$x_3x_4$	$x_1$	$x_2$	$x_3$	$x_4$	1
$f_1$	1	0	0	0	0	0	0	0	0	1	1
$f_2$	0	1	0	0	0	0	1	1	1	1	0
$f_3$	0	0	1	0	0	0	1	1	0	1	0
$f_4$	0	0	0	1	0	0	1	1	1	0	1
$f_5$	0	0	0	0	1	0	0	1	0	0	0
$f_6$	0	0	0	0	0	1	1	1	1	0	1
...											

$f_1 : x_1x_3 + x_2x_4 + x_1 + x_3 + x_4 = 0$  $f_2 : x_2x_3 + x_1x_4 + x_3x_4 + x_1 + x_2 + x_4 = 0$  $f_3 : x_2x_4 + x_3x_4 + x_1 + x_3 + 1 = 0$  $f_4 : x_1x_2 + x_1x_3 + x_2x_3 + x_3 + x_4 + 1 = 0$  $f_5 : x_1x_2 + x_2x_3 + x_1x_4 + x_3 = 0$  $f_6 : x_1x_3 + x_1x_4 + x_3x_4 + x_1 + x_2 + x_3 + x_4 = 0$

# Crossbred algorithm

→ Subsystem can be linearised

	$x_1x_2$	$x_1x_3$	$x_2x_3$	$x_1x_4$	$x_2x_4$	$x_3x_4$	$x_1$	$x_2$	$x_3$	$x_4$	1
$f_1$	1	0	0	0	0	0	0	0	0	1	1
$f_2$	0	1	0	0	0	0	1	1	1	1	0
$f_3$	0	0	1	0	0	0	1	1	0	1	0
$f_4$	0	0	0	1	0	0	1	1	1	0	1
$f_5$	0	0	0	0	1	0	0	1	0	0	0
$f_6$	0	0	0	0	0	1	1	1	1	0	1
...											

$f_1 : x_1x_3 + x_2x_4 + x_1 + x_3 + x_4 = 0$  $f_2 : x_2x_3 + x_1x_4 + x_3x_4 + x_1 + x_2 + x_4 = 0$  $f_3 : x_2x_4 + x_3x_4 + x_1 + x_3 + 1 = 0$  $f_4 : x_1x_2 + x_1x_3 + x_2x_3 + x_3 + x_4 + 1 = 0$  $f_5 : x_1x_2 + x_2x_3 + x_1x_4 + x_3 = 0$  $f_6 : x_1x_3 + x_1x_4 + x_3x_4 + x_1 + x_2 + x_3 + x_4 = 0$

...if we had another 4 equations, the subsystem would have a unique solution.

Otherwise: check candidate solutions against the other equations.

# Crossbred algorithm

---

Parameters of the algorithm:  $D, k, d, h$


- Enumerate  $h$  variables.
- Choose  $k$  of the remaining variables.
- Augment system up to degree  $D$  (compute degree- $D$  Macaulay matrix).
- Take the subsystem that is at most degree  $d$  in the  $k$  chosen variables.
- Enumerate all but the  $k$  chosen variables.
- Linearise the subsystem and solve it.
- Check if candidate solutions are consistent with the rest of the system.

# Crossbred algorithm

---

Parameters of the algorithm:  $D, k, d, h$

- Enumerate  $h$  variables.
- Choose  $k$  of the remaining variables.
- Augment system up to degree  $D$  (compute degree- $D$  Macaulay matrix).
- Take the subsystem that is at most degree  $d$  in the  $k$  chosen variables.
- Enumerate all but the  $k$  chosen variables.
- Linearise the subsystem and solve it.
- Check if candidate solutions are consistent with the rest of the system.

 The complexity is calculated as the best trade-off between the four parameters.

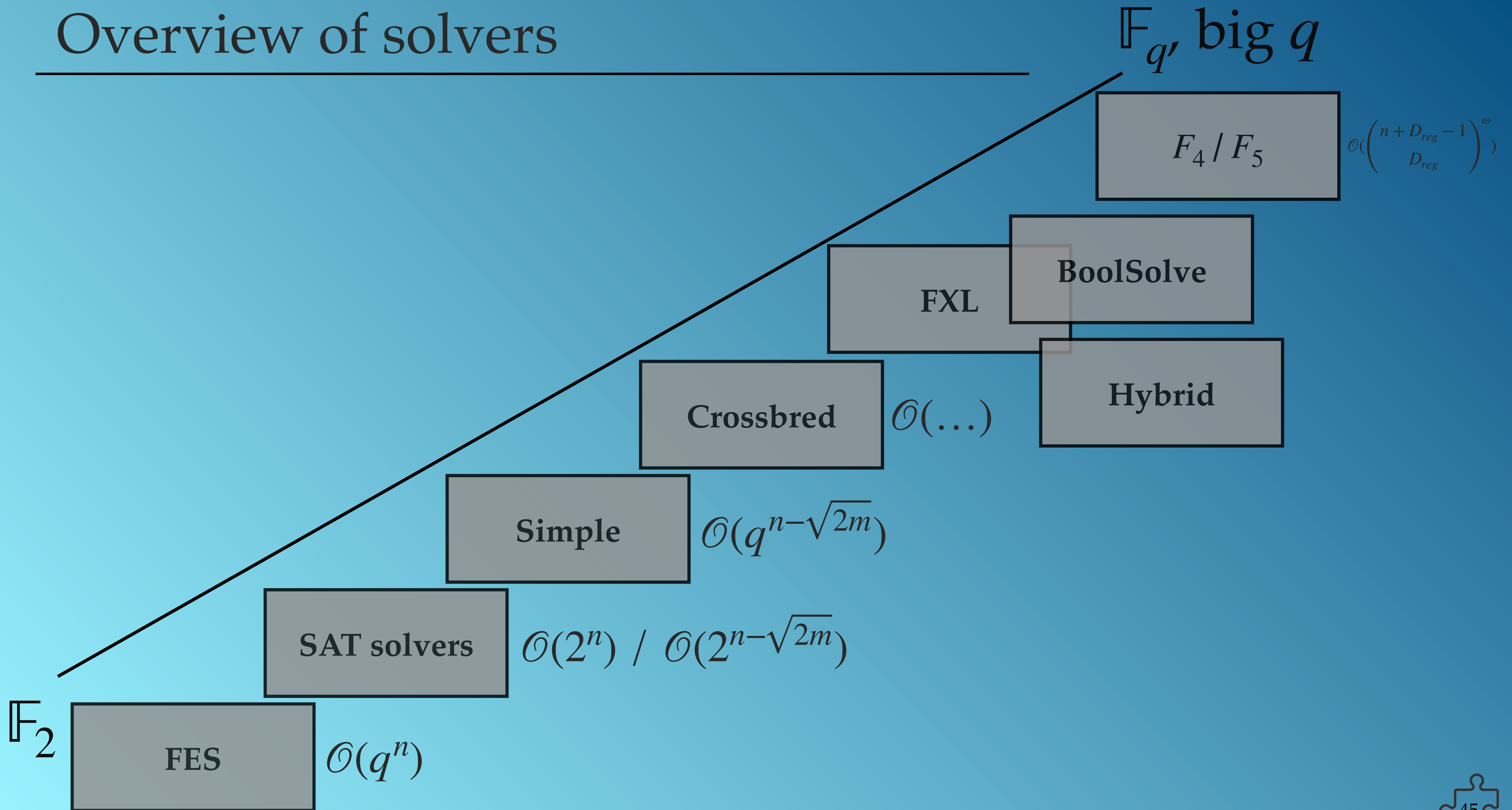
# Crossbred algorithm

	Number of Variables (n)	Seed (0,1,2,3,4)	Date	Contestants	Computational Resource	Data
1	83	0	2023/09/16	Charles Bouillaguet and Julia Sauvage	<a href="https://gitlab.lip6.fr/almasty/hpXbred">https://gitlab.lip6.fr/almasty/hpXbred</a> , 3488 AMD EPYC 7J13 cores on the Oracle public cloud	<a href="#">Details</a>
6	74	0	2016/12/17	Antoine Joux	New hybridized XL related algorithm, Heterogeneous cluster of Intel Xeon @ 2.7-3.5 Ghz	<a href="#">Details</a>
7	74	4	2017/11/15	Kai-Chun Ning, Ruben Niederhagen	Parallel Crossbred, 54 GPUs in the Saber cluster	<a href="#">Details</a>
25	66	0	2016/01/22	Tung Chou, Ruben Niederhagen, Bo-Yin Yang	Gray Code enumeration, Rivyera, 128 Spartan 6 FPGAs	<a href="#">Details</a>

Fukuoka MQ challenge record computations ( $m = 2n$ )



# Overview of solvers





# Summary

---

(Partial)  
enumeration

Candidate  
solutions  
(subsystem)

Conflict search

Extending to  
higher degrees

Computing a  
Gröbner Basis

FES

Simple

FXL

$F_4 / F_5$

SAT solvers

Crossbred

BoolSolve

Hybrid

# Summary

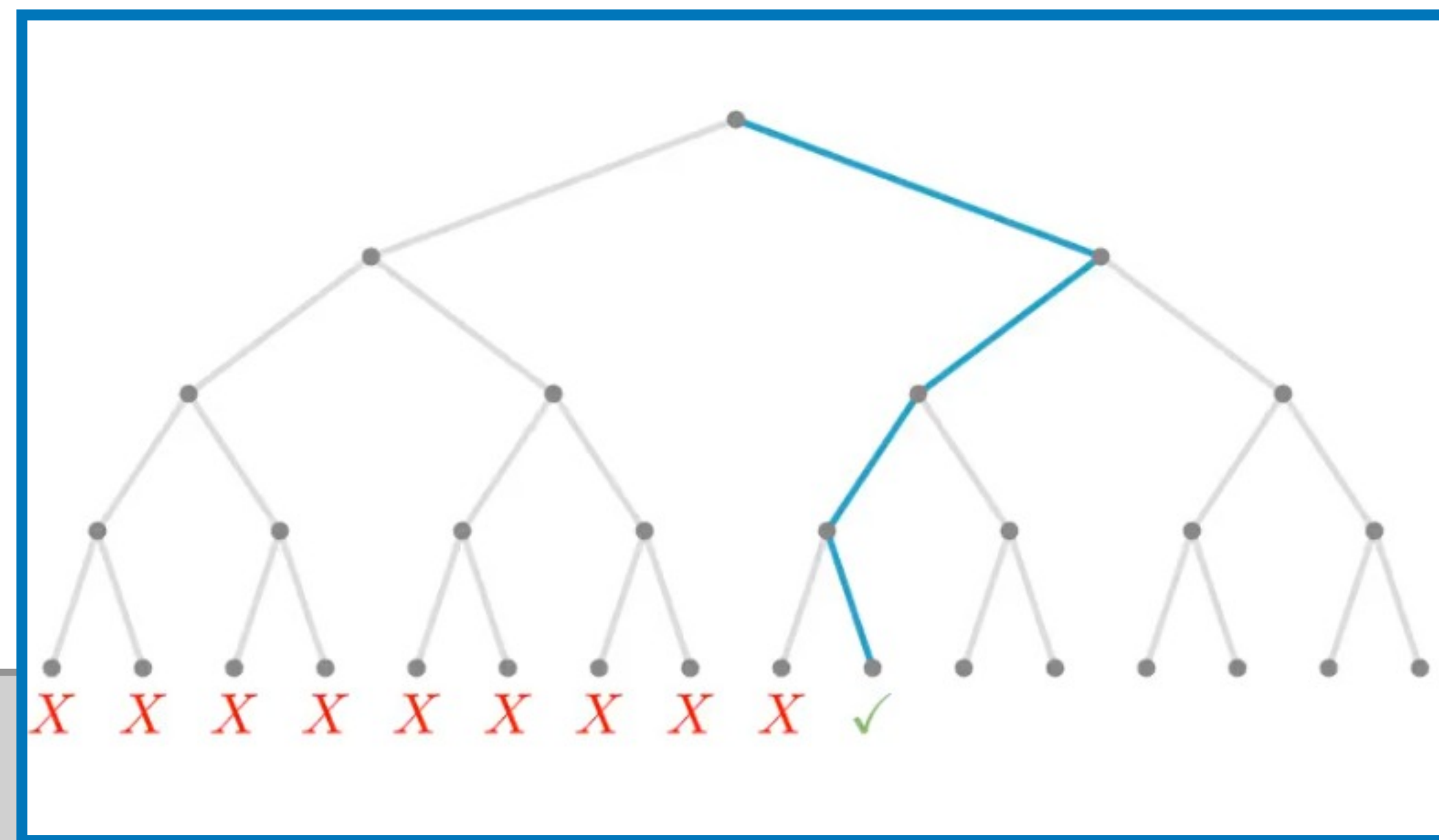
(Partial)  
enumeration

Candidate  
solutions  
(subsystem)

Conflict search

Extending to  
higher degrees

Computing a  
Gröbner Basis



FES

KL

$F_4 / F_5$

SAT solvers

Crossbred

BoolSolve

Hybrid

# Summary

---

(Partial)  
enumeration

Candidate  
solutions  
(subsystem)

Conflict search

Extending to  
higher degrees

Computing a  
Gröbner Basis

FES

Simple

FXL

$F_4 / F_5$

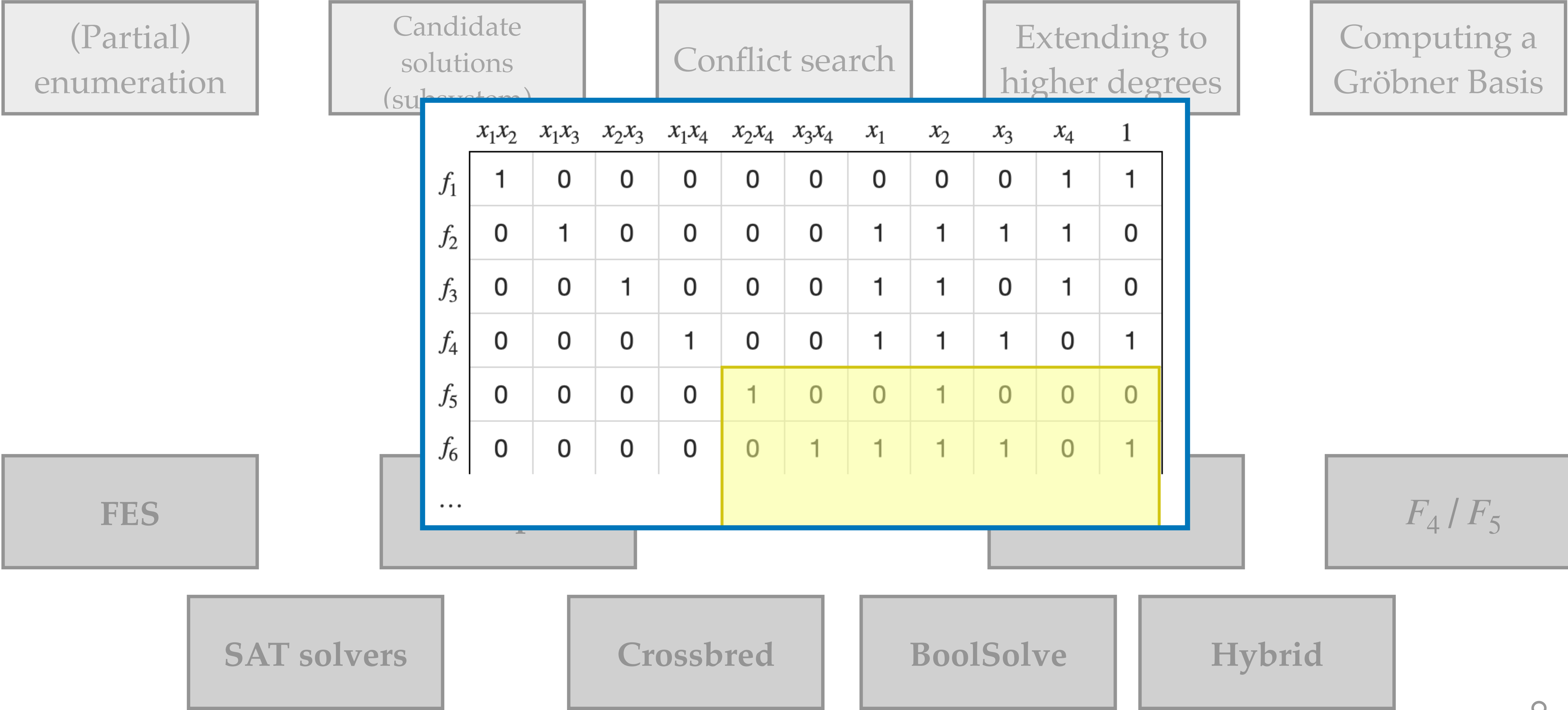
SAT solvers

Crossbred

BoolSolve

Hybrid

# Summary



# Summary

---

(Partial)  
enumeration

Candidate  
solutions  
(subsystem)

Conflict search

Extending to  
higher degrees

Computing a  
Gröbner Basis

FES

Simple

FXL

$F_4 / F_5$

SAT solvers

Crossbred

BoolSolve

Hybrid

# Summary

(Partial)  
enumeration

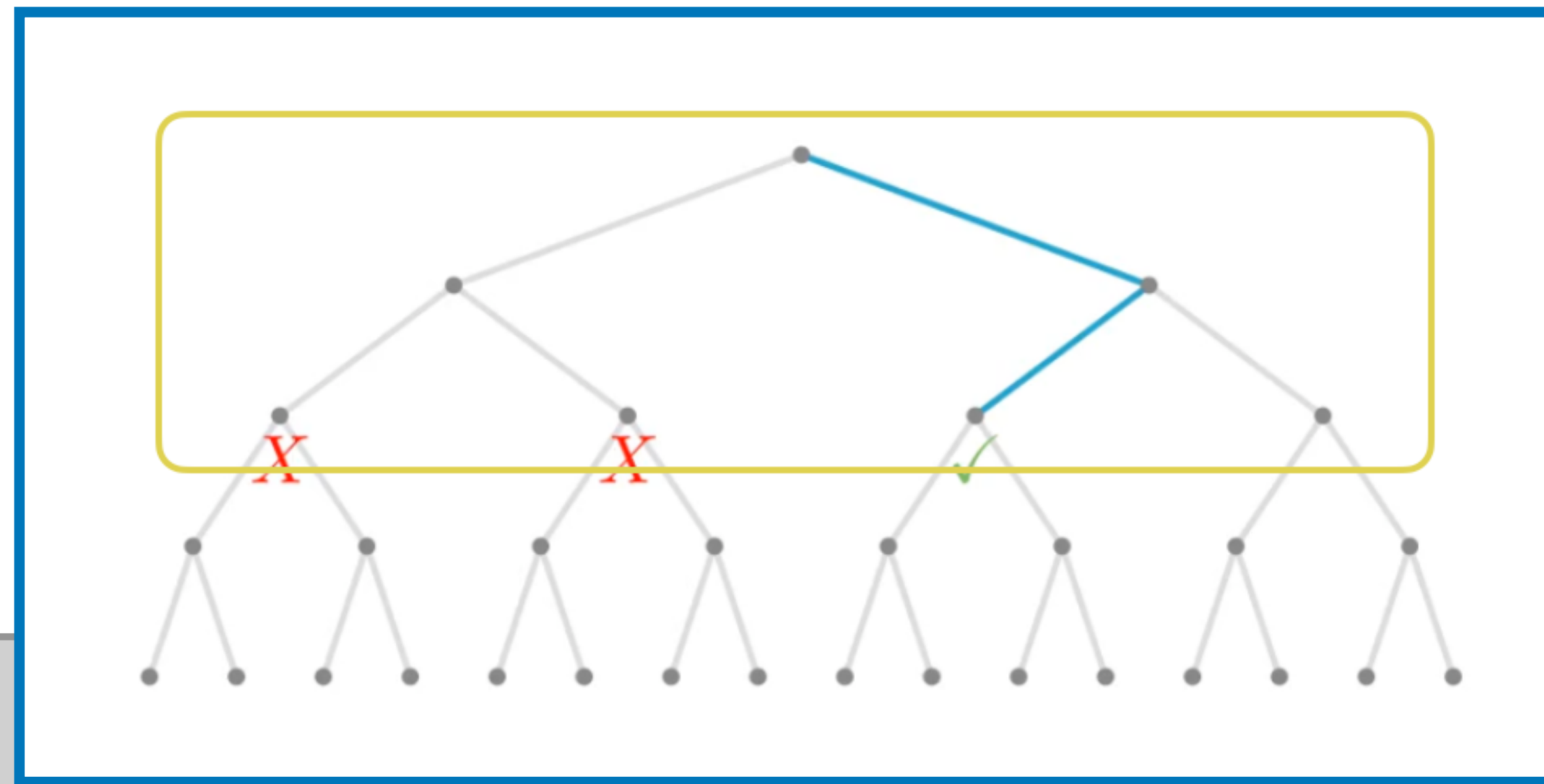
Candidate  
solutions  
(subsystem)

Conflict search

Extending to  
higher degrees

Computing a  
Gröbner Basis

FES



$F_4 / F_5$

SAT solvers

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$F_4 / F_5$

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# Summary

(Partial)  
enumeration

Candidate  
solutions

Conflict search

Extending to  
higher degrees

Computing a  
Gröbner Basis

	$x_1x_2$	$x_1x_3$	$x_1x_4$	$x_1$	$x_2x_3$	$x_2x_4$	$x_2$	$x_3x_4$	$x_3$	$x_4$	1	$x_1x_2x_3$	$x_1x_2x_4$	$x_1x_3x_4$	$x_2x_3x_4$	$x_1x_2x_3x_4$
$f_1$	0	1	0	1	0	1	0	0	1	1	0					
$f_2$	0	0	1	1	1	0	1	1	0	1	0					
$f_3$	0	0	0	1	0	1	0	1	1	0	1					
$f_4$	1	1	0	1	1	0	0	0	1	1	1					
$f_5$	1	0	1	1	1	0	0	0	1	0	0					
$f_6$	0	1	1	1	0	0	1	1	1	1	0					
$x_1f_1$																
$x_2f_1$																
...																
$x_1x_2f_1$																
$x_1x_3f_1$																

FES

$F_4 / F_5$

SAT solvers

Crossbred

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# Summary

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---

(Partial)  
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Candidate  
solutions  
(subsystem)

Conflict search

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higher degrees

Computing a  
Gröbner Basis

$$\begin{aligned}f'_1 &: x_1 + x_6 = 0 \\f'_2 &: x_2 + x_6 = 0 \\f'_3 &: x_3 + x_6 = 0 \\f'_4 &: x_4 + x_6 + 1 = 0 \\f'_5 &: x_5 = 0\end{aligned}$$

\*\*\*\*\*  
\*\*\*\*\*  
\*\*\*  
\*\*  
\*



FES

Simple

FXL

$F_4 / F_5$

SAT solvers

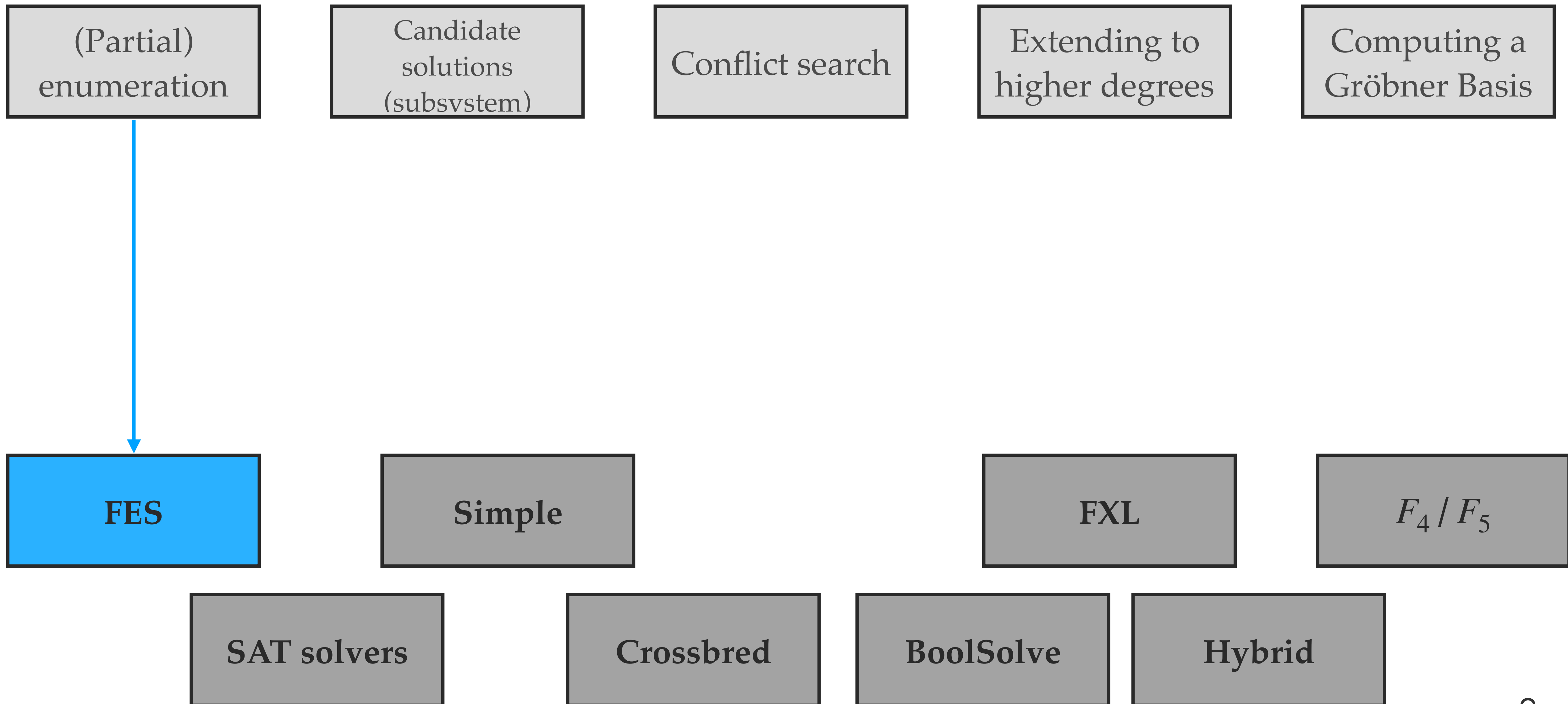
Crossbred

BoolSolve

Hybrid

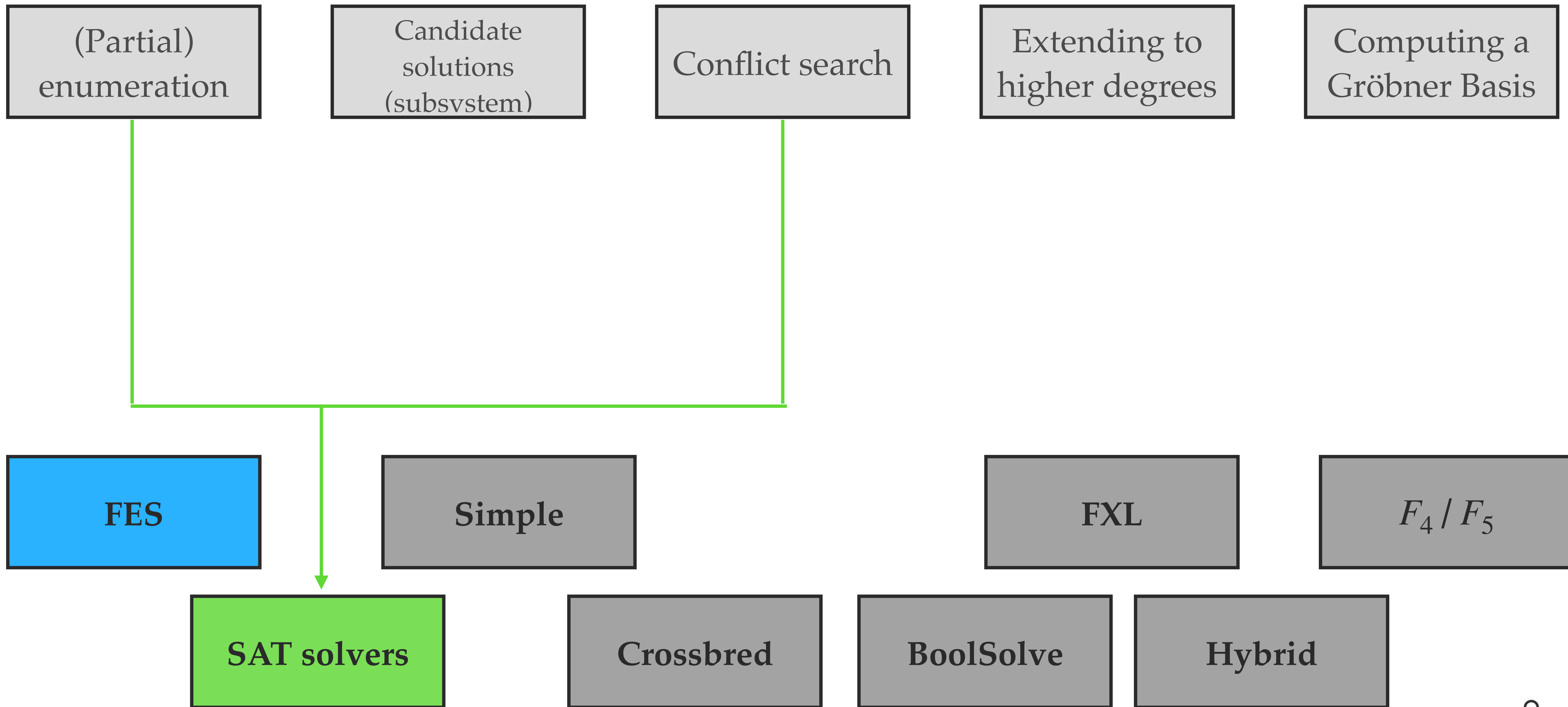
# Summary

---



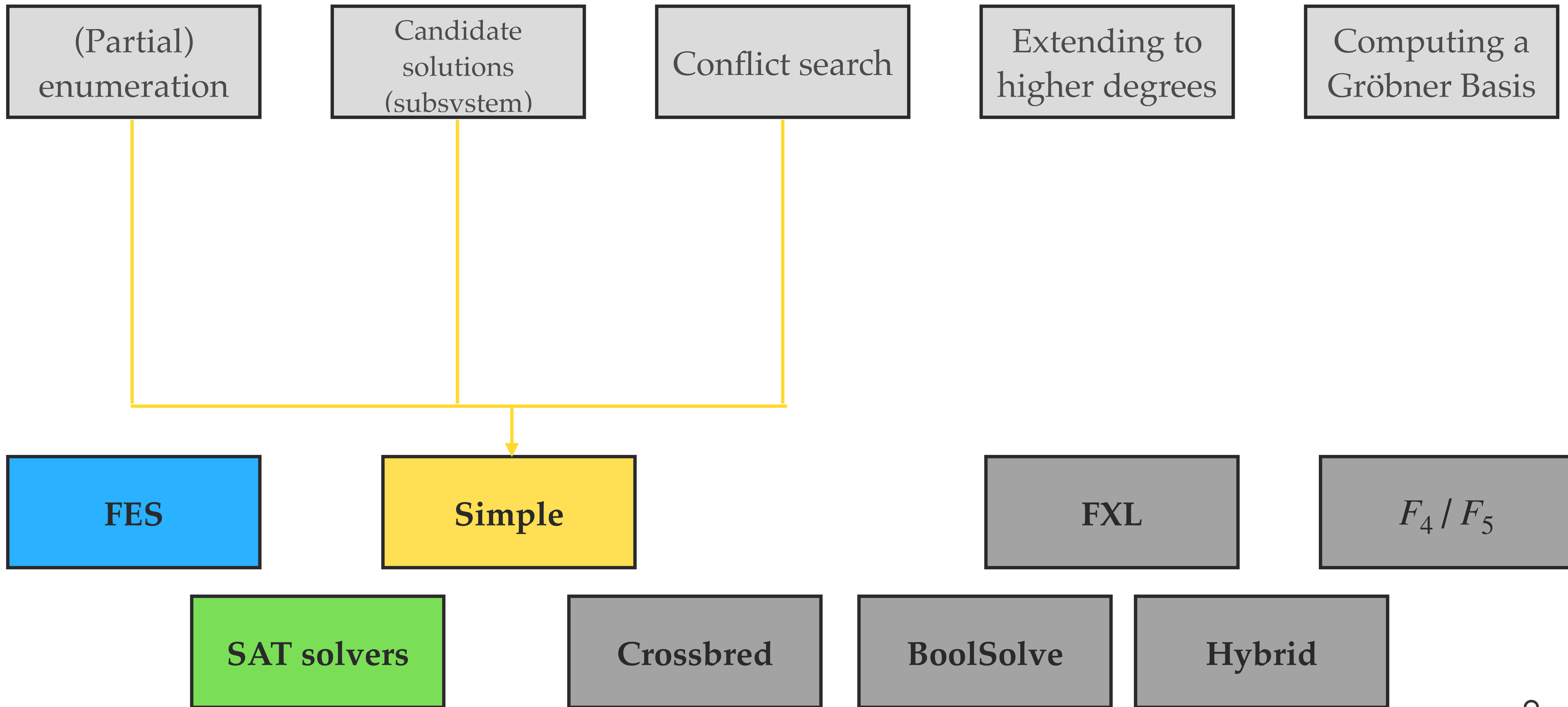
# Summary

---



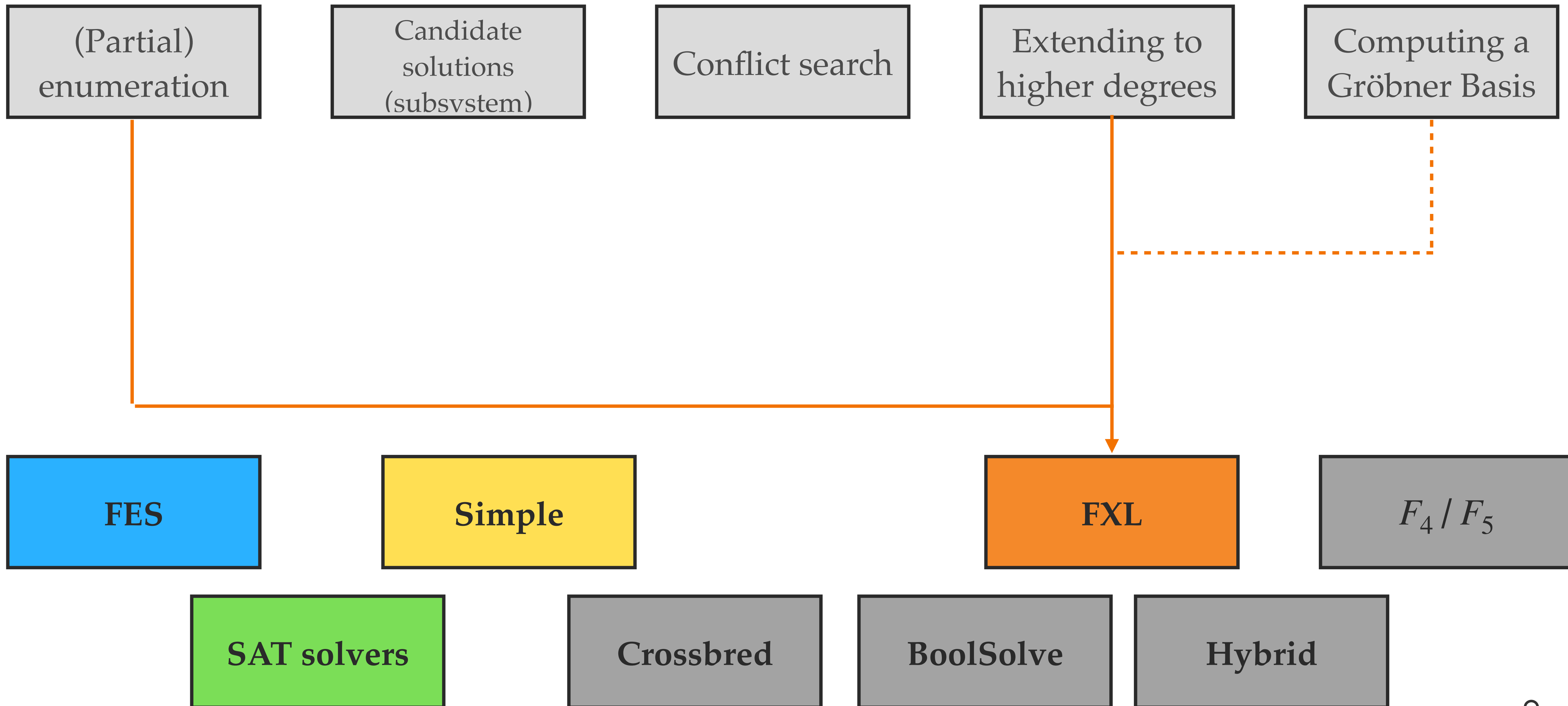
# Summary

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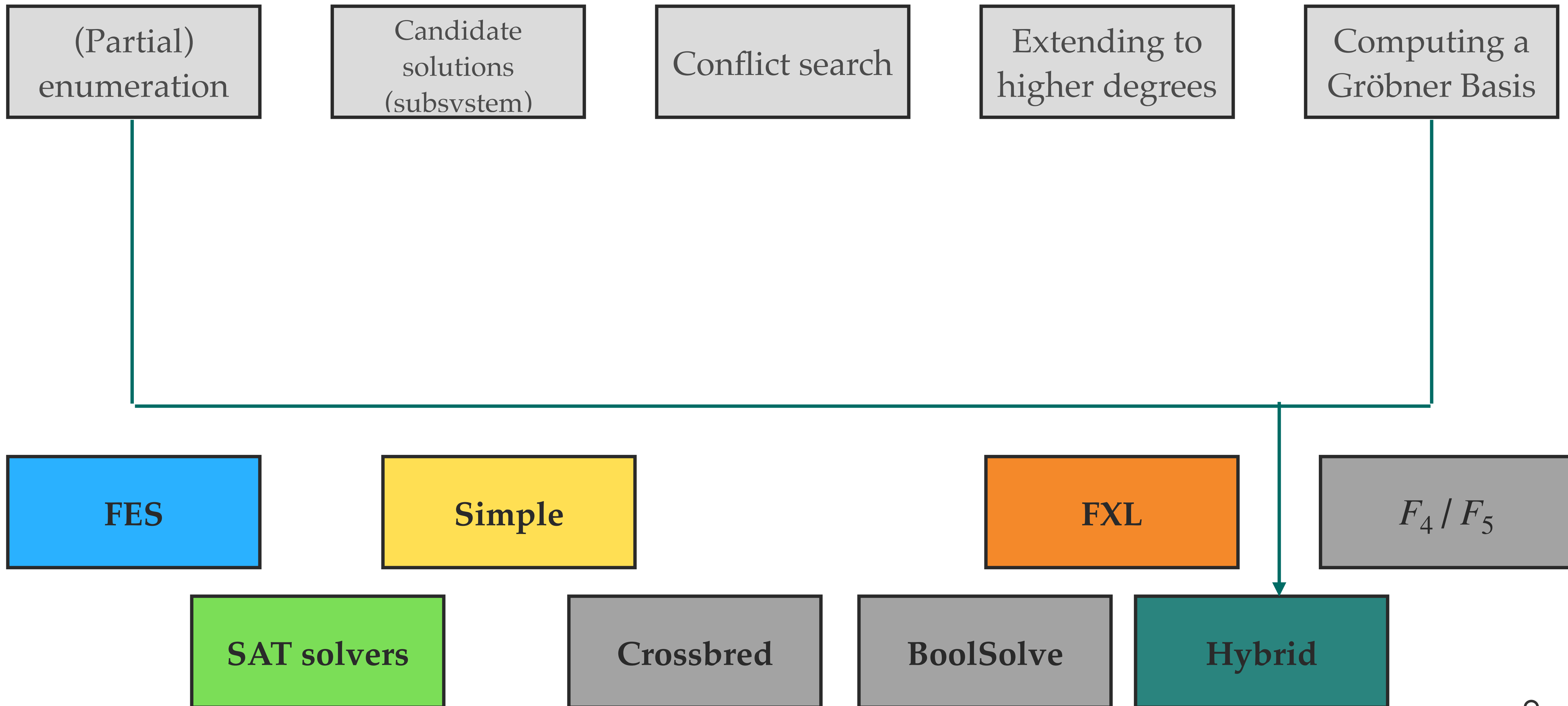
# Summary

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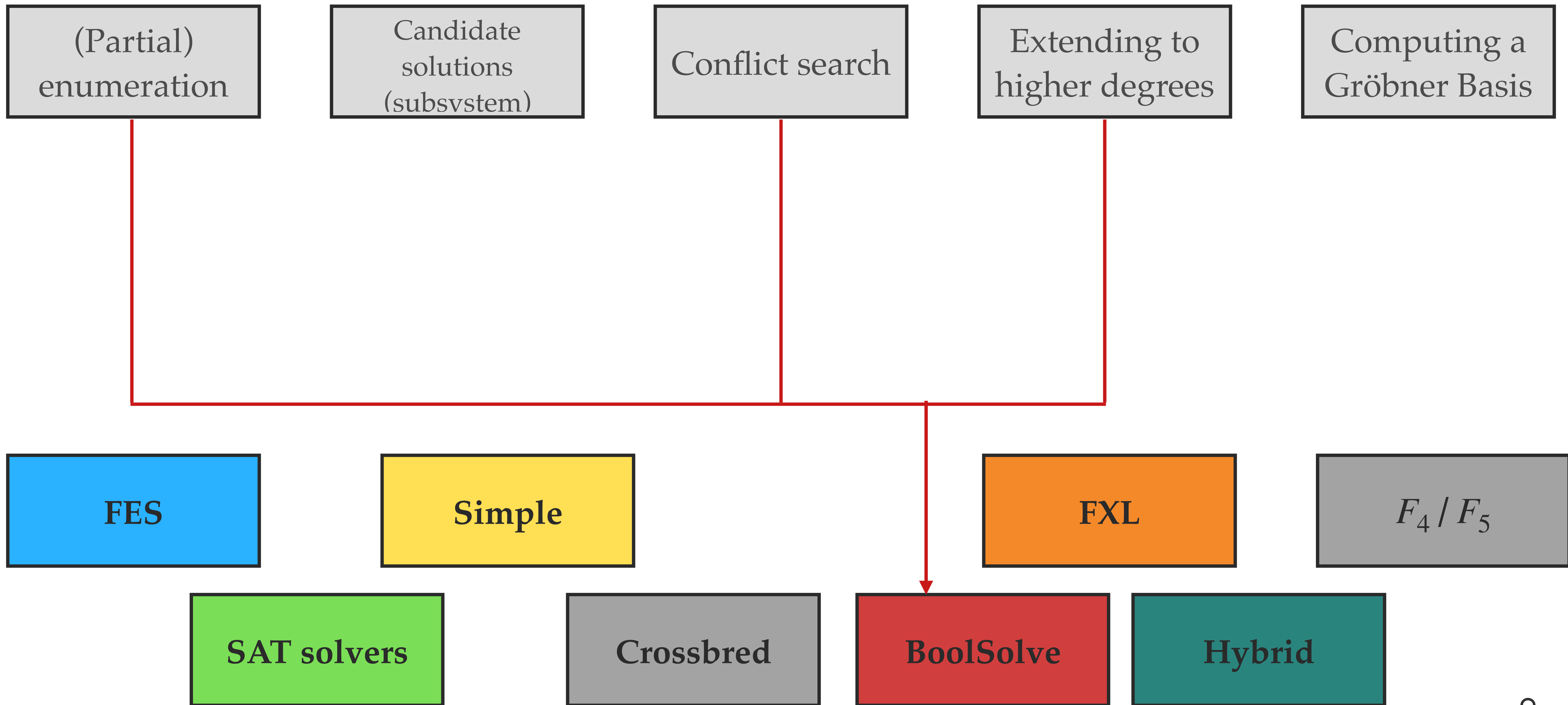
# Summary

---



# Summary

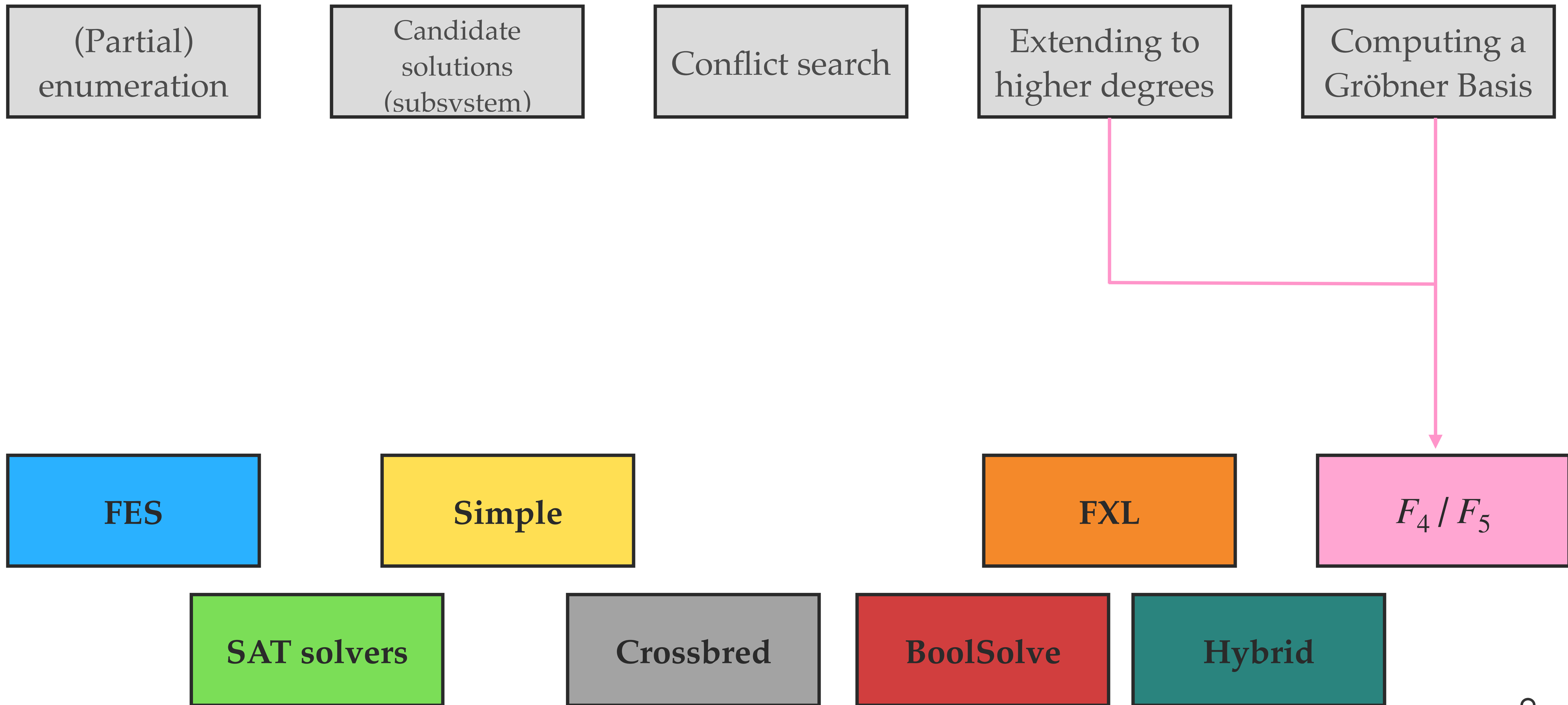
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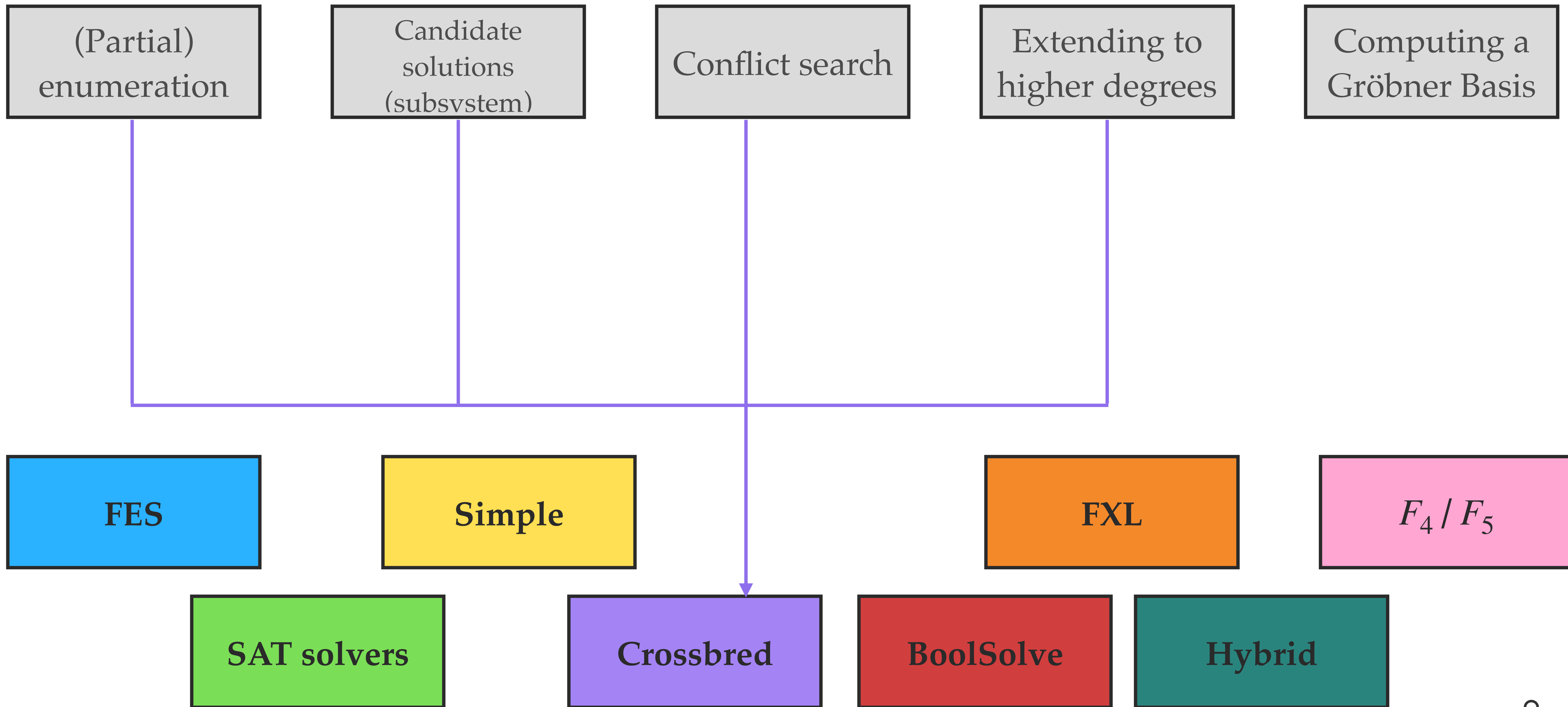
# Summary

---



# Summary

---

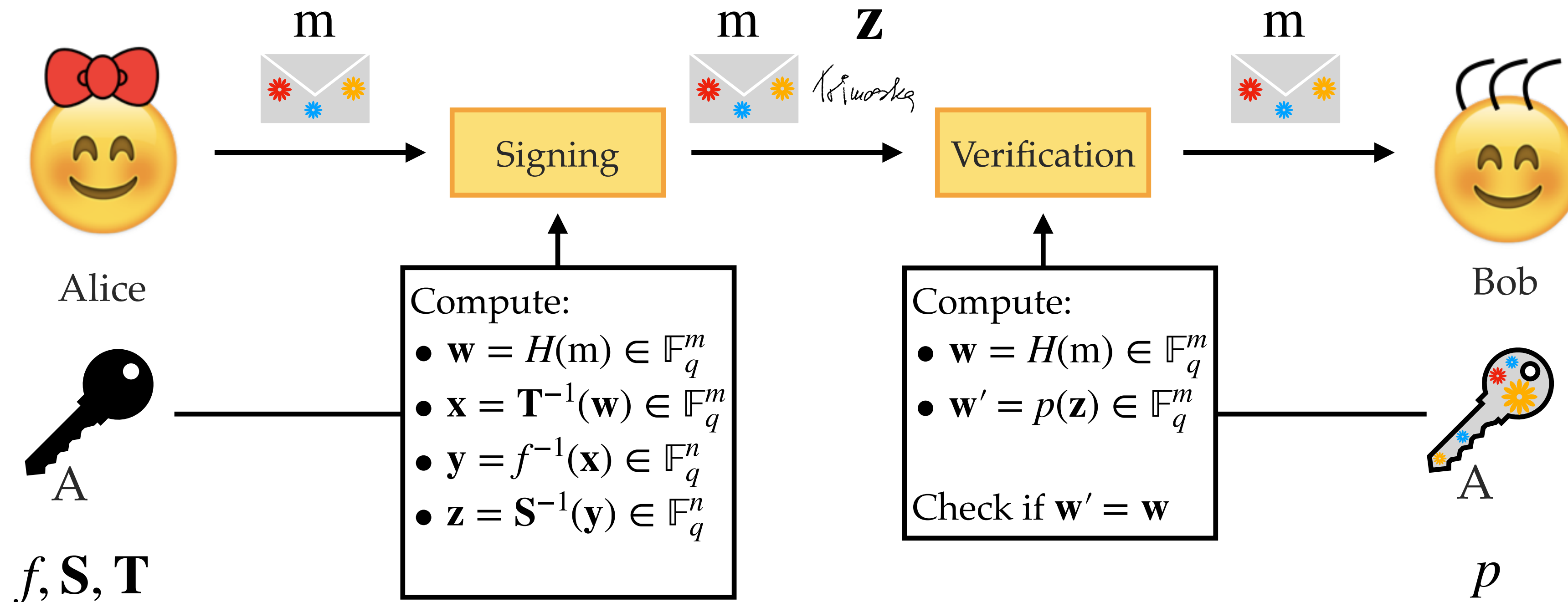


Modelisation: Attacks on UOV

*O*

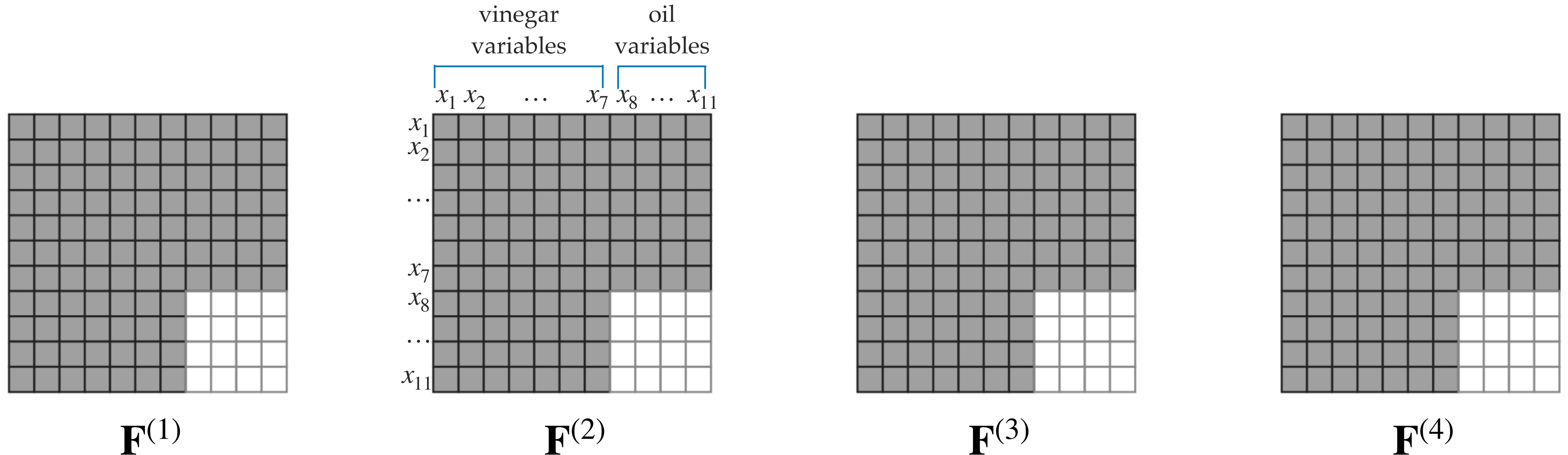
*v*

# The trapdoor construction (recall)



# The UOV central map (recall)

Toy example:  $v = 7, m = 4$



\*Grayed areas represent the entries that are possibly nonzero; blank areas denote the zero entries;

# Attacks on UOV

---

- Direct attack
- Reconciliation attack
- Kipnis-Shamir attack
- Intersection attack



# Direct attack

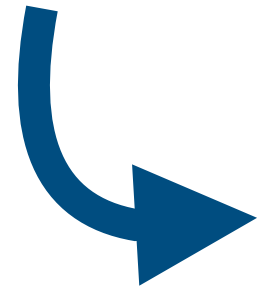
---

 Try to forge a signature with only the knowledge of the public key.



# Direct attack

---



Try to forge a signature with only the knowledge of the public key.

## Constraint for modelisation

For a target  $\mathbf{w}$ , find  $\mathbf{z}$  such that  $p(\mathbf{z}) = \mathbf{w}$ .

# Direct attack

---

 Try to forge a signature with only the knowledge of the public key.

## Constraint for modelisation

For a target  $\mathbf{w}$ , find  $\mathbf{z}$  such that  $p(\mathbf{z}) = \mathbf{w}$ .

 Equations:

$$\mathbf{z}^\top \mathbf{P}^{(1)} \mathbf{z} = w_1$$

$$\mathbf{z}^\top \mathbf{P}^{(2)} \mathbf{z} = w_2$$

...

$$\mathbf{z}^\top \mathbf{P}^{(m)} \mathbf{z} = w_m$$

# Direct attack

---

 Try to forge a signature with only the knowledge of the public key.

## Constraint for modelisation

For a target  $\mathbf{w}$ , find  $\mathbf{z}$  such that  $p(\mathbf{z}) = \mathbf{w}$ .

 Equations:

$$\mathbf{z}^\top \mathbf{P}^{(1)} \mathbf{z} = w_1$$

$$\mathbf{z}^\top \mathbf{P}^{(2)} \mathbf{z} = w_1$$

...

$$\mathbf{z}^\top \mathbf{P}^{(m)} \mathbf{z} = w_m$$



# Reconciliation attack

[Ding, Yang, Chen, Chen, Cheng, 2008]

# The secret subspace $\mathcal{O}$

---

The map  $p$  with a UOV trapdoor vanishes on a linear subspace  $\mathcal{O} \subset \mathbb{F}_q^n$  of  $\dim(\mathcal{O}) = m$  :

$$p(\mathbf{o}) = 0, \text{ for all } \mathbf{o} \in \mathcal{O}.$$

# The secret subspace $\mathcal{O}$

---

The map  $p$  with a UOV trapdoor vanishes on a linear subspace  $\mathcal{O} \subset \mathbb{F}_q^n$  of  $\dim(\mathcal{O}) = m$  :

$$p(\mathbf{o}) = 0, \text{ for all } \mathbf{o} \in \mathcal{O}.$$

Why ?

# The secret subspace $O$

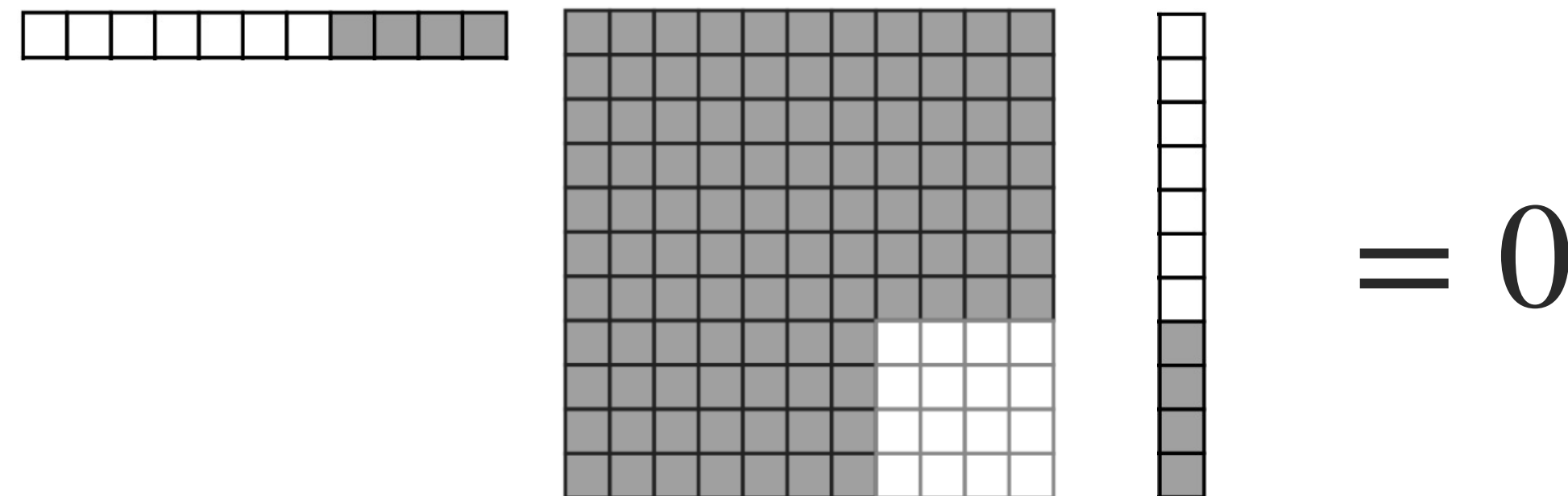
---

The map  $p$  with a UOV trapdoor vanishes on a linear subspace  $O \subset \mathbb{F}_q^n$  of  $\dim(O) = m$  :

$$p(\mathbf{o}) = 0, \text{ for all } \mathbf{o} \in O.$$

Why ?

Let  $O' \in \mathbb{F}_q^n$  be the  $m$ -dimensional space that consists of all the vectors whose first  $n - m$  entries (corresponding to the vinegar variables) are zero:  $O' = \{\mathbf{v} \mid v_i = 0 \text{ for all } i \leq n - m\}$ .



The diagram illustrates the map  $p$  applied to a vector from the secret subspace  $O'$ . It shows three components: a horizontal row of 10 boxes (5 white, 5 gray), a 10x10 grid (9x9 gray, 1x1 white at the bottom right), and a vertical column of 10 boxes (5 white, 5 gray). These are followed by an equals sign and a zero, representing the result of the map.

$$= 0$$

# The secret subspace $O$

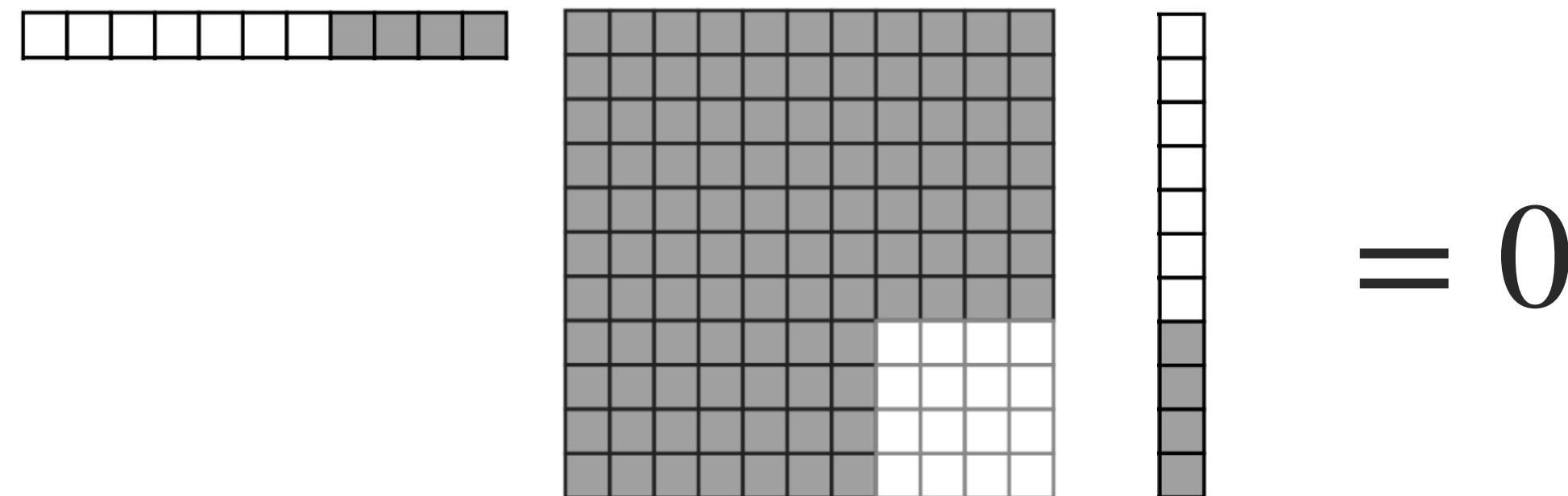
---

The map  $p$  with a UOV trapdoor vanishes on a linear subspace  $O \subset \mathbb{F}_q^n$  of  $\dim(O) = m$  :

$$p(\mathbf{o}) = 0, \text{ for all } \mathbf{o} \in O.$$

Why ?

Let  $O' \in \mathbb{F}_q^n$  be the  $m$ -dimensional space that consists of all the vectors whose first  $n - m$  entries (corresponding to the vinegar variables) are zero:  $O' = \{\mathbf{v} \mid v_i = 0 \text{ for all } i \leq n - m\}$ .



The diagram illustrates the vanishing of the map  $p$  on the subspace  $O'$ . It shows a horizontal row of 10 boxes, where the first 6 are white and the last 4 are gray. To the right of this row is a large grid of 10 columns and 10 rows. The first 6 columns of this grid are gray, and the last 4 columns are white. To the right of the grid is a vertical column of 10 boxes, where the top 6 are white and the bottom 4 are gray. To the right of this column is the expression  $= 0$ .

  $f$  vanishes on  $O'$ .



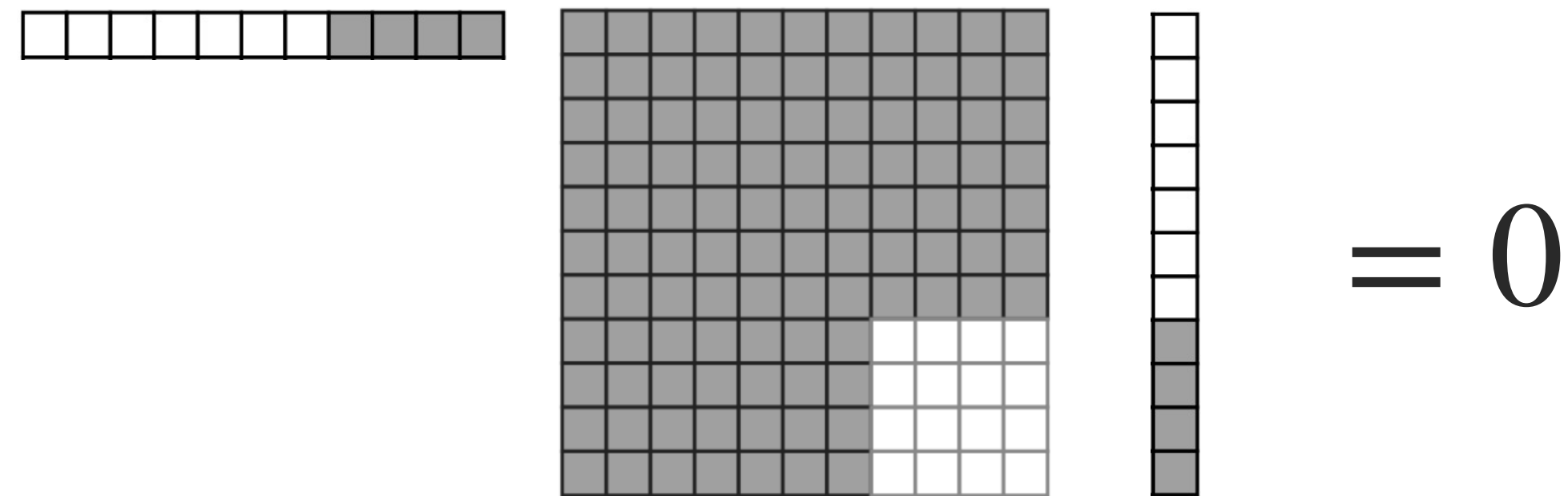
# The secret subspace $O$

The map  $p$  with a UOV trapdoor vanishes on a linear subspace  $O \subset \mathbb{F}_q^n$  of  $\dim(O) = m$  :

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Why ?

Let  $O' \in \mathbb{F}_q^n$  be the  $m$ -dimensional space that consists of all the vectors whose first  $n - m$  entries (corresponding to the vinegar variables) are zero:  $O' = \{\mathbf{v} \mid v_i = 0 \text{ for all } i \leq n - m\}$ .



$$\begin{bmatrix} \square & \square & \square & \square & \square & \square & \square & \square & \square & \square \end{bmatrix} \begin{bmatrix} \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} \\ \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} \\ \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} \\ \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} \\ \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} \\ \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} \\ \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} \\ \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} \\ \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} \\ \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} & \text{gray} \end{bmatrix} \begin{bmatrix} \square \\ \square \\ \square \\ \square \\ \square \\ \square \\ \square \\ \square \\ \square \\ \square \end{bmatrix} = 0$$

  $f$  vanishes on  $O'$ .

Let  $O = \mathbf{S}^{-1}(O')$ .

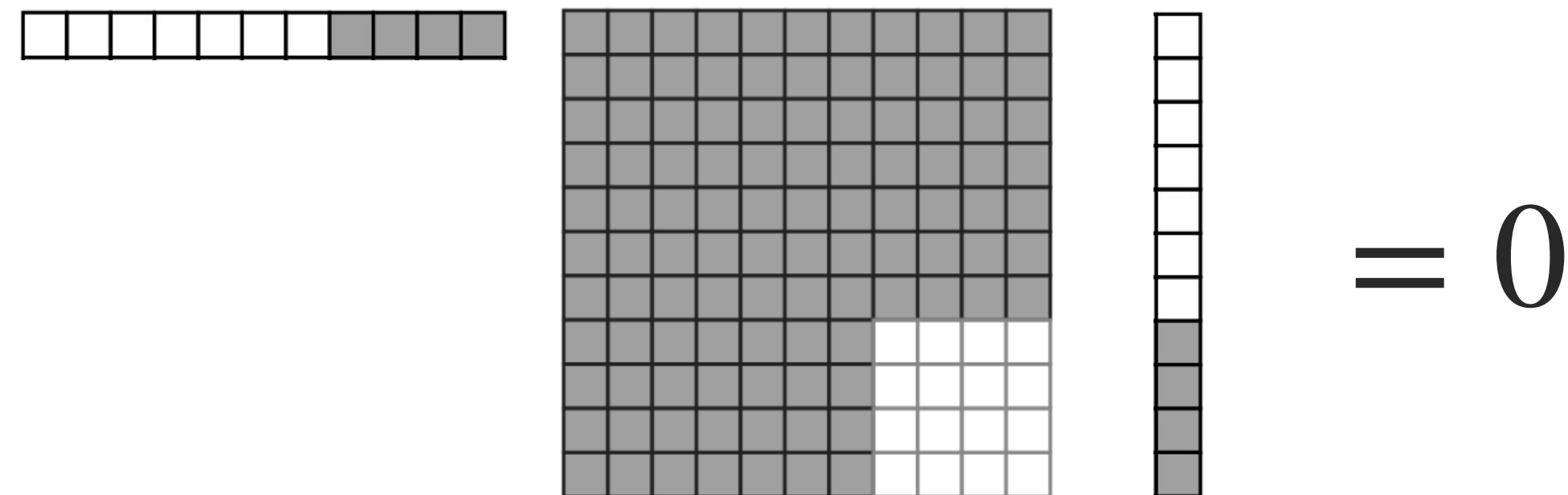
# The secret subspace $O$

The map  $p$  with a UOV trapdoor vanishes on a linear subspace  $O \subset \mathbb{F}_q^n$  of  $\dim(O) = m$  :

$$p(\mathbf{o}) = 0, \text{ for all } \mathbf{o} \in O.$$

Why ?

Let  $O' \in \mathbb{F}_q^n$  be the  $m$ -dimensional space that consists of all the vectors whose first  $n - m$  entries (corresponding to the vinegar variables) are zero:  $O' = \{\mathbf{v} \mid v_i = 0 \text{ for all } i \leq n - m\}$ .



The diagram illustrates the vanishing of a function  $f$  on a subspace  $O'$ . It shows a 1x10 vector of white and grey cells, a 10x10 grid with a 6x6 white block at the bottom right, and a 10x1 vector of white and grey cells, followed by  $= 0$ .

↪  $f$  vanishes on  $O'$ .

Let  $O = \mathbf{S}^{-1}(O')$ .

↪  $p$  vanishes on  $O$ .

# Reconciliation attack

---

 Find the secret oil subspace  $O$  : find  $m$  linearly independent vectors in  $O$ .

# The polar form

---

The **polar form** of a quadratic map  $p = (p^{(1)}, \dots, p^{(m)})$  is the bilinear form  $p' = (p'^{(1)}, \dots, p'^{(m)})$  such that

$$p'^{(k)}(\mathbf{x}, \mathbf{y}) = p^{(k)}(\mathbf{x} + \mathbf{y}) - p^{(k)}(\mathbf{x}) - p^{(k)}(\mathbf{y}), \text{ for all } k \in \{1, \dots, m\}.$$

# The polar form

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The **polar form** of a quadratic map  $p = (p^{(1)}, \dots, p^{(m)})$  is the bilinear form  $p' = (p'^{(1)}, \dots, p'^{(m)})$  such that

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What does  $p'^{(k)}(\mathbf{x}, \mathbf{y})$  look like ?

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$$p'^{(k)}(\mathbf{x}, \mathbf{y}) = p^{(k)}(\mathbf{x} + \mathbf{y}) - p^{(k)}(\mathbf{x}) - p^{(k)}(\mathbf{y}), \text{ for all } k \in \{1, \dots, m\}.$$

What does  $p'^{(k)}(\mathbf{x}, \mathbf{y})$  look like ?

Let  $\tilde{\mathbf{P}}^{(k)}$  be the upper triangular representation of  $p^{(k)}$ .

# The polar form

---

The **polar form** of a quadratic map  $p = (p^{(1)}, \dots, p^{(m)})$  is the bilinear form  $p' = (p'^{(1)}, \dots, p'^{(m)})$  such that

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→ So,  $p'$  is bilinear and symmetric.



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 Equations:

**For**  $i \in \{1, \dots, m\}$  **do**

$$\mathbf{o}_i = (o_1, \dots, o_v, 0, \dots, 1_{n-i+1}, 0, \dots, 0)$$

**Model:**

$$\mathbf{o}_i^\top \mathbf{B}^{(k)} \mathbf{o}_j = 0, \text{ for } k \in \{1, \dots, m\} \text{ and } j < i$$

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# Kipnis-Shamir attack

[Kipnis, Shamir, 1998]

*O*

*v*

# The orthogonal complement of a subspace

Let  $V \subset \mathbb{F}_q^n$ . The orthogonal complement of  $V$  is  $V^\perp$  such that

$$V^\perp = \{\tilde{\mathbf{v}}_i \in \mathbb{F}_q^n \mid \langle \mathbf{v}_j, \tilde{\mathbf{v}}_i \rangle = 0, \text{ for all } \mathbf{v}_j \in V\}.$$

If  $V$  is  $m$ -dimensional, then  $V^\perp$  is  $(n - m)$ -dimensional.

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Finding a common invariant subspace of a large number of linear maps is easy.

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→ Finding a common invariant subspace of a large number of linear maps is easy.

→ Oil and Vinegar becomes **Unbalanced** Oil and Vinegar because of this attack.

# Intersection attack

[Beullens, 2021]



O



V



# Intersection attack

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 Find the secret oil subspace  $\mathcal{O}$ . Use the ideas of the Kipnis-Shamir attack, but for the unbalanced case ( $n > 2m$ ).

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Since  $n > 2m$ ,  $\dim(O^\perp) > m$ . We still have  $\mathbf{B}^{(k_1)}O \subset O^\perp$  and  $\mathbf{B}^{(k_2)}O \subset O^\perp$ , but they are not (necessarily) the same subspace.

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→ The attack can be generalised to find a vector in the intersection of more than two subspaces.

# Recap

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- ▶ The MQ problem can be easy for some **structured** systems. We use this to build **trapdoors** in crypto.
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