

Prof. Dr. Sebastian Wild

Outline

4 Fixed-Parameter Algorithms

- 4.1 Fixed-Parameter Tractability
- 4.2 Depth-Bounded Exhaustive Search I
- 4.3 Problem Kernels
- 4.4 Depth-Bounded Search II: Planar Independent Set
- 4.5 Depth-Bounded Search III: Closest String
- 4.6 Linear Recurrences & Better Vertex Cover
- 4.7 Interleaving

Philosophy of FPT

- ▶ **Goal:** Principled theory for studying complexity based on two dimensions: input size n = |x| (encoding length) and *some additional parameter* k
 - generalize ideas from k = MaxInt(x)
 - ightharpoonup investigate influence of k (and n) on running time
 - \rightarrow Try to find a parameter k such that
 - (1) the problem can be solved efficiently as long as k is small, and
 - (2) practical instances have small values of k (even where n gets big).

Motivation: Satisfiability

Consider Satisfiability of CNF formula

the drosophila melanogaster of complexity theory

- general worst case: NP-complete
- ightharpoonup k = #literals per clause
 - ▶ $k \le 2 \rightsquigarrow \text{in P}$
 - ▶ $k \ge 3$ NP-complete
- \triangleright k = #variables
 - $ightharpoonup O(2^k \cdot n)$ time possible (try all assignments)
- \triangleright k = #clauses?
- \triangleright k = #literals?
- ightharpoonup k = #ones in satisfying assignment
- \blacktriangleright k =structural property of formula
- for Max-SAT, k = #optimal clauses to satisfy

Parameters

Definition 4.1 (Parameterization)

Let Σ a (finite) alphabet. A *parameterization* (of Σ^*) is a mapping $\kappa : \Sigma^* \to \mathbb{N}$ that is polytime computable.

Definition 4.2 (Parameterized problem)

A *parameterized (decision) problem* is a pair (L, κ) of a language $L \subset \Sigma^*$ and a parameterization κ of Σ^* .

Definition 4.3 (Canonical Parameterizations)

We can often specify a parameterized problem conveniently as a language of *pairs* $L \subset \Sigma^* \times \mathbb{N}$ with

$$(x,k) \in L \land (x,k') \in L \rightarrow k = k'$$

using the *canonical parameterization* $\kappa(x, k) = k$.

3

Examples

As before: Typically leave encoding implicit.

Definition 4.4 (p-variables-SAT)

Given: formula boolean ϕ (same as before)

Parameter: number of variables

Question: Is there a satisfying assignment $v : [n] \rightarrow \{0, 1\}$?

Definition 4.5 (p-Clique)

Given: graph G = (V, E) and $k \in \mathbb{N}$

Parameter: k

Question: $\exists V' \subset V : |V'| \ge k \land \forall u, v \in V' : \{u, v\} \in E$?

Canonical Parameterization

Definition 4.6 (Canonically Parameterized Optimization Problems)

Let $U = (\Sigma_I, \Sigma_O, L, L_I, M, cost, goal)$ be an optimization problem.

Then p-U denotes the (canonically) parameterized (decision) problem given by the threshold problem $Lang_U$.

Recall: $Lang_U$ is the set of pairs (x, k) of all instances $x \in L_I$ that have solutions that are weakly "better" than k.

Examples:

- ▶ *p*-Clique
- ▶ *p*-Vertex-Cover
- ▶ p-Graph-Coloring
- ▶ ..

Naming convention for other parameters:

*p-clause-*CNF-SAT: CNF-SAT with parameter "number of *clauses*"

4.1 Fixed-Parameter Tractability

Exemplary Running Times of Parameterized Problems

▶ *p-variables-*SAT

(consider simplest brute-force methods for problems)

- \blacktriangleright *k* variables, *n* length of formula
- \rightarrow $O(2^k \cdot n)$ running time
- ▶ *p*-Clique
 - ▶ *k* threshold (clique size); *n* vertices, *m* edges in graph
 - \rightsquigarrow $\binom{n}{k}$ candidates to check, each takes time $O(k^2)$ to check
 - \rightarrow Total time $O(n^k \cdot k^2)$
- ▶ *p*-VertexCover
 - ▶ *k* threshold (VC size); *n* vertices, *m* edges in graph
 - \rightsquigarrow $\binom{n}{k}$ candidates to check, each takes time O(m) to check
 - \rightarrow Total time $O(n^k \cdot m)$
- ▶ p-GraphColoring
 - ▶ *k* threshold (#colors); *n* vertices, *m* edges in graph
 - \rightsquigarrow k^n candidates to check, each takes time O(m)
 - \rightsquigarrow Total time $O(k^n \cdot m)$

FPT Running Time

Definition 4.7 (fpt-algorithm)

Let κ be a parameterization for Σ^* .

A (deterministic) algorithm A (with input alphabet Σ) is a *fixed-parameter tractable algorithm* (*fpt-algorithm*) w.r.t. κ if its running time on $x \in \Sigma^*$ with $\kappa(x) = k$ is at most

$$f(k) \cdot p(|x|) = O(f(k) \cdot |x|^c)$$

where p is a polynomial of degree c and f is an **arbitrary** computable function.

Definition 4.8 (FPT)

A parameterized problem (L, κ) is *fixed-parameter tractable* if there is an fpt-algorithm that decides it.

The complexity class of all such problems is denoted by FPT.

Intuitively, FPT plays the role of P.

A First FPT Example

Theorem 4.9 (p-variables-SAT is FPT)

```
p-variables-SAT \in FPT.
```

Proof:

Suffices to use brute force satisfiability for *p-variables*-SAT

```
1 procedure bruteForceSat(\varphi, \mathcal{X} = \{x_1, \dots, x_k\})

2 if k = 0

3 if \varphi = true return \emptyset else UNSATISFIABLE

4 for value in \{true, false\} do

5 A := \{x_1 \mapsto value\}

6 \psi := \varphi[x_1/value] // Substitute value for x_1

7 B := bruteForceSat(\psi, \{x_2, \dots, x_k\})

8 if B \neq UNSATISFIABLE

9 return A \cup B
```

Worst case running time: $O(2^k n)$ for $n = |\varphi|$.

 2^k recursive calls;

base case needs time $O(|\phi|)$ to check whether formula evaluates to true

... but #variables not usually small

Aren't we all FPT?

Theorem 4.10 (k never decreases \rightarrow FPT)

Let $g: \mathbb{N} \to \mathbb{N}$ weakly increasing, unbounded and computable, and κ a parameterization with

$$\forall x \in \Sigma^* : \kappa(x) \ge g(|x|).$$

Then $(L, \kappa) \in \mathsf{FPT}$ for *any* decidable L.

g weakly increasing: $n \le m \to g(n) \le g(m)$

g unbounded: $\forall t \ \exists n : g(n) \ge t$

Proof:

Aren't we all FPT? - Proof

Proof (cont.):

Back to "sensible" parameters

- → always check if parameter is reasonable (can be expected to be small)
 - ▶ if not, FPT might not even mean in NP!
- ▶ but now, for some positive examples!

4.2 Depth-Bounded Exhaustive Search I

FPT Design Pattern

- ► The simplest FPT algorithms use exhaustive search
- \blacktriangleright but with a search tree bounded by f(k)
- bruteforceSat was a typical example!
- does this work on other problems?

Depth-Bounded Search for Vertex Cover

Let's try *p*-VertexCover.

Key insight: for every edge $\{v, w\}$, any vertex cover must contain v or w

```
procedure simpleFptVertexCover(G = (V, E), k):

if E = \emptyset then return \emptyset

if k = 0 then return NOT_POSSIBLE // truncate search

Choose \{v, w\} \in E (arbitrarily)

for u in \{v, w\} do:

Gu := (V \setminus \{u\}, E \setminus \{\{u, x\} \in E\}) // Remove u from G

Cu := \text{simpleFptVertexCover}(G_u, k - 1)

if C_v = \text{NOT_POSSIBLE} then return C_v \cup \{w\}

if C_w = \text{NOT_POSSIBLE} then return C_v \cup \{v\}

if |C_v| \le |C_w| then return |C_v| \le |C_v| else return |C_v| \le |C_v|
```

- ▶ Does not need explicit checks of solution candidates!
- ▶ runs in time $O(2^k(n+m))$ \leadsto fpt-algorithm for p-Vertex-Cover

Guessing the parameter

- ▶ Note: Previous algorithm only uses *k* to *truncate* branches.
- \rightsquigarrow We can *guess* a k and it still works

```
\rightsquigarrow Try all k!
```

```
1 procedure vertexCoverBfs(G = (V, E))

2 for k := 0, 1, ..., |V| do

3 C := \text{simpleFptVertexCover}(G, k)

4 if C \neq \text{NOT\_POSSIBLE} return C
```

- ► Running time: $\sum_{k'=0}^{k} O(2^{k'}(n+m)) = O(2^{k}(n+m))$
- \rightarrow For exponentially growing cost, trying all values up to k costs only constant factor more

4.3 Problem Kernels

Preprocessing

- Second key fpt technique are reduction rules
- ► **Idea:** Reduce the size of the instance (in polytime) without changing its outcome
- ► Trivial example for SAT:

If a CNF formula contains a single-literal clause $\{x\}$ resp. $\{\neg x\}$, set x to *true* resp. *false* and remove the clause.

- doesn't do anything in the worst case . . .
- ▶ special case of resolution calculus rule $\frac{a_1 \lor a_2 \lor \cdots \lor x, b_1 \lor b_2 \lor \cdots \lor \neg x}{a_1 \lor a_2 \lor \cdots \lor b_1 \lor b_2 \lor \cdots}$
- basis of practical SAT solvers
- ► Trivial example for VertexCover

Remove vertices of degree 0 or 1.

(never needed as part of optimal VC)

▶ Here: reduction rules that provably shrink an instance to size g(k)

Buss's Reduction Rule for VC

▶ Given a p-VertexCover instance (G, k)

"deg > k" Rule: If G contains vertex v of degree deg(v) > k, include v in potential solution and remove it from the graph.

- ightharpoonup Can apply this simultaneously to degree > k vertices.
- ► Either rule applies, or all vertices bounded degree(!)

Kernels

Definition 4.11 (Kernelization)

Let (L, κ) be a parameterized problem. A function $K : \Sigma^* \to \Sigma^*$ is *kernelization* of L w.r.t. κ if it maps any $x \in L$ to an instance x' = K(x) with $k' = \kappa(x')$ so that

- 1. (self-reduction) $x \in L \iff x' \in L$
- **2.** (polytime) *K* is computable in polytime.
- **3.** (kernel-size) $|x'| \le g(k)$ for some computable function g

We call x' the (problem) kernel of x and g the size of the problem kernel.

17

Buss's Kernel

Buss's Reduction for Vertex Cover: (repeatedly apply until no more changes)

- ightharpoonup deg > k rule
- ► Remove degree 0 and 1 vertices

Theorem 4.12 (Buss's Reduction is Kernelization)

Buss' reduction yields a kernelization for p-Vertex-Cover with kernel size $O(k^2)$.

Proof:

After repeatedly applying Buss's rule as well as the isolated/leaf rule until neither applies further, we have $\forall v \in V : 2 \leq \deg(v) \leq k$.

(Note that the rule might reduce the parameter k).

In the resulting graph, any VC of size $\leq k$ covers $\leq k^2$ edges.

If $m > k^2$, we output a trivial No-instance (e. g., a K_{k+1} a complete graph on k+1 vertices).

If $m \le k^2$, then the input size is now bounded by $g(k) = 2k^2$.

FPT iff Kernelization

Theorem 4.13 (FPT \leftrightarrow kernel)

A computable, parameterized problem (L, κ) is fixed-parameter tractable if and only if there is a kernelization for L w.r.t. κ .

Proof:

FPT iff Kernelization [2]

Proof (cont.):

Max-SAT Kernel

Theorem 4.14 (Kernel for Max-SAT)

p-Max-SAT has a problem kernel of size $O(k^2)$ which can be constructed in linear time.

Proof:

Max-SAT Kernel [2]

Proof (cont.):

Max-SAT Kernel [3]

Proof (cont.):

Corollary 4.15 p-Max-SAT \in FPT

4.4 Depth-Bounded Search II: Planar Independent

Set

Deeper results (towards more shallow trees)

- Our previous examples of depth-bounded search were basically brute force
- ► Here we will see two more examples that exploit the problem structure in more interesting ways

Independent Set on Planar Graphs

Recall: general problem p-Independent-Set is $\mathcal{W}[1]$ -hard.

Definition 4.16 (p-Planar-Independent-Set)

Given: a *planar* graph G = (V, E) and $k \in \mathbb{N}$

Parameter: *k*

Question: $\exists V' \subset V : |V'| \ge k \land \forall u, v \in V' : \{u, v\} \notin E$?

Theorem 4.17 (Depth-Bounded Search for Planar Independent Set)

p-Planar-Independent-Set is in FPT and can be solved in time $O(6^k n)$.

25

Elementary Knowledge on Planar Graphs

Theorem 4.18 (Euler's formula)

In any finite, connected planar graph G with n nodes, m edges f holds n - m + f = 2.

 \triangleleft

Corollary 4.19

A simple planar graph G on $n \ge 3$ nodes has $m \le 3n - 6$ edges.

The average degree in G is < 6.

4

Depth-Bounded Search for Planar Independent Set

```
procedure planarIndependentSet(G = (V, E), k):

if k = 0 then return \emptyset

if k > |V| then return NOT_POSSIBLE // truncate search

Choose v \in V with minimal degree; let w_1, \ldots, w_d be v's neighbors

// By planarity, we know d \le 5.

for u in \{v, w_1, \ldots, w_d\} do

D := \{u\} \cup N(u)

G_u := \{v\} \cup P(x) \cup P(x) \cup P(x)

G_u := \{u\} \cup P(x) \cup P(x)

return largest G_u \in S_u none exists
```

Summary Planar Independent Set

- ▶ Note: IndependentSet is NP-hard on planar graphs even with vertex degrees at most 3
- ▶ planarIndependentSet will often be faster than $O(6^k n)$
- works unchanged in $O((d+1)^k n)$ time for any degeneracy-d graph every (induced) subgraph has vertex of degree at most d

4.5 Depth-Bounded Search III: Closest String

Closest String

Definition 4.20 (*p***-CLOSEST-STRING)**

Given: S set of m strings s_1, s_2, \ldots, s_m of length L over alphabet Σ and a $k \in \mathbb{N}$.

Parameter: *k*

Question: Is there a string *s* for which $d_H(s, s_i) \le k$ holds for all i = 1, ..., m?

Dirty Columns

Definition 4.21 (Dirty Column)

A column of the $m \times L$ matrix corresponding to m strings of length L is called *dirty* if it contains at least 2 different symbols.

Lemma 4.22 (Many Dirty Columns → No)

Let an instance to Closest-String with m strings of length L and parameter k be given. If the corresponding $m \times L$ matrix contains more than $m \cdot k$ dirty columns, then no solution for the given instance exists.

Depth-Bounded Search for Closest String

```
procedure closestStringFpt(s, d):
        if d < 0 then return NOT POSSIBLE
        if d_H(s, s_i) > k + d for an i \in \{1, ..., m\} then
            return NOT POSSIBLE
       if d_H(s, s_i) \le k for all i = 1, ..., m then return s
        Choose i \in \{1, ..., m\} arbitrarily with d_H(s, s_i) > k
            P := \{p : s[p] \neq s_i[p]\}
            Choose arbitrary P' \subseteq P with |P'| = k + 1
            for p in P' do
                 s' := s
10
                s'[p] := s_i[p]
11
                s_{ret} := closestStringFpt(s', d-1)
12
                if s_{ret} \neq NOT POSSIBLE then return s_{ret}
13
        return NOT POSSIBLE
14
```

▶ initial call closestStringFpt(*s*₁, *k*)

Too Much Dirt

Lemma 4.23 (Pair Too Different \rightarrow No)

Let $S = \{s_1, s_2, \dots, s_m\}$ a set of strings and $k \in \mathbb{N}$. If there are $i, j \in \{1, \dots, m\}$ with $d_H(s_i, s_j) > 2k$, then there is no string s with $\max_{1 \le i \le m} d_H(s, s_i) \le k$.

32

Depth-Bounded Search for Closest String

Theorem 4.24 (Search Tree for Closest String)

There is a search tree of size $O(k^k)$ for problem *p*-Closest-String.

Corollary 4.25 (Closest String is FPT)

p-Closest-String can be solved in time $O(mL + mk \cdot k^k)$.

- ightharpoonup preprocessing (O(mL) time)
 - ▶ ignore any clean columns
 - reject if more than *mk* dirty columns
- \rightsquigarrow effective string length after preprocessing is $L' \leq mk$
- ightharpoonup call closestStringFpt(s_1, k)
 - ightharpoonup maintain $d_H(s,s_i)$ in an array
 - \rightsquigarrow checking any distance $d_H(s, s_i)$ takes O(1) time
 - before and after recursive call, update array to reflect $d_H(s', s_i)$ Single character changed, so update only needs to check single position
 - \rightsquigarrow Can maintain distances in O(m) time per recursive call
 - ightharpoonup P' can be computed in O(mk) time

4.6 Linear Recurrences & Better Vertex Cover

A Better Algorithm for Vertex Cover

Recall: Branching on endpoints of k edges gives search space of size 2^k for Vertex-Cover. Can we do better?

Idea: Enlarge base case with "easy inputs"

Here: Consider graphs G with $deg(v) \le 2$ for all $v \in V(G)$.

Depth-Bounded Search for Vertex Cover

```
procedure betterFptVertexCover(G = (V, E), k):
       if E = \emptyset then return \emptyset
       if k = 0 then return NOT POSSIBLE // truncate search
       if all node have degree \leq 2 then
            Find connected components of G
            for each component G_i do
                Fill C_i by picking every other node,
                starting with the neighbor of a degree-one node if one exists
            C := \bigcup C_i
            if |C| \le k then return C else return NOT POSSIBLE
       Choose v with maximal degree, let w_1, \ldots, w_d be its neighbors //d \ge 3
11
       For D in \{\{v\}, \{w_1, \dots, w_d\}\} do:
12
            G_D := (V \setminus D, E \setminus \{\{x,y\} \in E : x \in D\}) // Remove D from G
13
            C_D := D \cup \text{betterFptVertexCover}(G_u, k - |D|)
14
       return smallest C_D or NOT POSSIBLE if none exists
15
```

How to analyze running time of betterFptVertexCover?

Analysis of betterFptVertexCover

worst case running time

- ▶ never have all degrees ≤ 2
- always need both recursive calls (until base case)
- ignore that graph gets smaller

$$T_0 = \Theta(1)$$

 $T_k = \Theta(|V| + |E|) + T_{k-3} + T_{k-1}$

If we only number of base cases B_n , we obtain $T_n = O(B_n n^2)$

$$B_0 = 1$$
, $B_1 = 1$, $B_2 = 1$
 $B_k = B_{k-3} + B_{k-1}$ $(k \ge 3)$

Solving Linear Recurrences

Solving Linear Recurrences – Result

Theorem 4.26 (Linear Recurrences)

Let $d_1, \ldots, d_i \in \mathbb{N}$ and $d = \max d_j$.

The solution to the homogeneous linear recurrence equation

$$T_n = T_{n-d_1} + T_{n-d_2} + \dots + T_{n-d_i}, \qquad (n \ge d)$$

is always given by

$$T_n = \sum_{\ell} \sum_{j=0}^{\mu_{\ell}-1} c_{\ell,j} z_{\ell}^n n^j$$

where we sum over all roots z_{ℓ} of multiplicity μ_{ℓ} of the so-called *characteristic polynomial* $z^{d} - z^{d-d_{1}} - z^{d-d_{2}} \cdots - z^{d-d_{i}}$.

The *d* coefficients $c_{\ell,i}$ are determined by the *d* initial values $T_0, T_1, \ldots, T_{d-1}$.

Corollary 4.27

 $T_n = O(z_0^n n^d)$ for z_0 the root of the characteristic polynomial with *largest absolute value*.

38

Analysis of betterFptVertexCover [2]

$$T_0 = \Theta(1)$$

 $T_k = \Theta(|V| + |E|) + T_{k-3} + T_{k-1}$

If we only number of base cases B_n , we obtain $T_n = O(B_n n^2)$

$$B_0 = 1, \ B_1 = 1, \ B_2 = 1$$

 $B_k = B_{k-3} + B_{k-1} \qquad (k \ge 3)$

 \rightarrow $\vec{d} = (1,3)$; characteristic polynomial $z^3 - z^2 - 1$ roots at $z_0 \approx 1.4656$ and $z_{1,2} \approx -0.2328 \pm 0.7926i$

Theorem 4.28 (Depth-Bounded Search for Vertex Cover)

p-Vertex-Cover can be solved in time $O(1.4656^k n^2)$.

39

4.7 Interleaving

Motivation

Up to now, considered two-phase algorithms

- 1. Reduction to problem kernel
- 2. Solve kernel by depth-bounded exhaustive search

Idea: Apply kernelization in each recursive step.

(Extreme) Example: Vertex Cover with large-degree rule

► As a (slightly artificial) example, consider only using the simple reduction rule

```
"deg > k" Rule: If G contains vertex v of degree deg(v) > k, include v in potential solution and remove it from the graph.
```

► Algorithm A:

- **1.** Apply deg > k rule until saturation
- 2. Call simpleFptVertexCover (recursively branch over arbitrary edge)
- ► **Algorithm B:** Same, interleaved:
 - Modified simpleFptVertexCover
 - Before choosing each new edge to branch on, apply deg > k rule.

SimpleFptVertexCover Interleaved

```
procedure simpleFptVertexCover(G = (V, E), k):
        if E == \emptyset then return \emptyset
       if k == 0 then return NOT_POSSIBLE
       // nothing
       // new
       // on
       // this
       // side
       Choose \{v, w\} \in E (arbitrarily)
        for u in \{v, w\} do:
10
            G_u := G[V \setminus \{u\}]
11
            C_u := simpleFptVertexCover(G_u, k - 1)
12
        if C_v == NOT_POSSIBLE then return C_w \cup \{w\}
13
        if C_w == NOT_POSSIBLE then return C_v \cup \{v\}
14
        if |C_v| \leq |C_w| then
15
            return C_v \cup \{v\}
16
       else
17
            return C_w \cup \{w\}
18
```

```
1 procedure simpleInterleavedVC(G = (V, E), k):
        if E == \emptyset then return \emptyset
       if k == 0 then return NOT_POSSIBLE
        C := \emptyset
        while \exists v \in V : \deg(v) > k
             G := G[V \setminus \{v\}] // Remove v
           C := C \cup \{v\}
            k := k - 1
        Choose \{v, w\} \in E (arbitrarily)
        for u in \{v, w\} do:
10
             G_u := G[V \setminus \{u\}]
11
             C_u := \mathbf{C} \cup \text{simpleInterleavedVC}(G_u, k-1)
12
        if C_v == NOT_POSSIBLE then return C_w \cup \{w\}
13
        if C_w == NOT_POSSIBLE then return C_v \cup \{v\}
14
        if |C_v| \leq |C_w| then
15
             return C_v \cup \{v\}
16
        else
17
             return C_w \cup \{w\}
18
```

Comparison on Lollipop Flowers

Consider family of graphs G_k "Lollipop Flowers": "head" vertex with k-2 stars of k-2 leaves each attached + "tail" of 3k+1 vertex path

$$n = |V(G_k)| = (k-2)(k-1) + 1 + 3k + 1 = k^2 + 4$$

Algorithm A

deg > k rule does nothing search space remains 2^k Answer No after exploring all branches

 \rightarrow time $\Theta(2^k k^2)$

Algorithm B

initially same (no reduction) after 2 edges removed from tail, parameter k-2 vertices in head have degree k-1 Output No (parameter 0, but tail edges left) \rightarrow time $\Theta(k^2)$

Setting for Interleaving

Can we prove a general speedup?

Assumptions: (more restrictive than general kernelization!)

- ► *K* kernelization that
 - ▶ produces *kernel of size* $\leq q(k)$ for q a *polynomial*
 - ▶ in time $\leq p(n)$ for p a polynomial
- ▶ Branch in depth-bounded search tree
 - into *i* subproblems with branching vector $\vec{d} = (d_1, \dots, d_i)$ (i. e., parameter in subproblems $k d_1, \dots, k d_i$)
 - ▶ Branching is computed in time $\leq r(n)$ for r a polynomial
- \rightsquigarrow search space has size $O(\alpha^k)$.

 \sim Running time of two-phase approach on input x with n = |x| and $k = \kappa(x)$:

$$O(p(n) + r(q(k)) \cdot \alpha^k)$$

With Interleaving

Generic interleaving:

```
if |I| > c \cdot q(k) then
(I,k) := (I',k') \text{ where } (I',k') \text{ forms a problem kernel } // \text{ Conditional Reduction}
a end
\text{replace } (I,k) \text{ with } (I_1,k-d_1), (I_2,k-d_2), \dots, (I_i,k-d_i) \text{ } // \text{ Branching}
```

 \sim Running time of interleaved approach on input x with n = |x| and $k = \kappa(x)$ is at most T_k :

$$T_{\ell} = T_{\ell-d_1} + \cdots + T_{\ell-d_i} + p(q(\ell)) + r(q(\ell))$$

Compare to non-interleaved version:

$$T_{\ell} = T_{\ell-d_1} + \cdots + T_{\ell-d_i} + r(q(k))$$

Here the inhomogeneous term is constant w.r.t. ℓ , but depends on $k \rightsquigarrow$ cannot ignore constant factors

Analysis of interleaved betterFptVertexCover [1]

Consider betterFptVertexCover from before, but with deg > k rule added.

- ► Initial call has unbounded n and m; after applying degree 0, 1, > k rules (in O(n + m) time) size of graph $n + m = O(k^2)$
- ▶ interleaving \rightsquigarrow graph also bounded recursively (in terms of new k)
- ► Recursive worst-case time after first reduction:

$$T_0 = \Theta(1)$$

 $T_k = O(k^2) + T_{k-3} + T_{k-1}$

Inhomogenous Linear Recurrences

Inhomogenous Linear Recurrences Summary

Theorem 4.29 (Linear Recurrences II)

Let $d_1, \ldots, d_i \in \mathbb{N}$ and $d = \max d_j$.

Consider the *inhomogeneous linear recurrence equation*

$$T_n = T_{n-d_1} + T_{n-d_2} + \dots + T_{n-d_i} + f_n, \qquad (n \ge d)$$

with $(f_n)_{n \in \mathbb{R}_{>0}}$ a known sequence of positive numbers, satisfying $f_n = O(n^c)$ and d initial values $T_0, \ldots, T_{d-1} \in \mathbb{R}_{>0}$.

Let z_0 be the root with largest absolute value of $z^d - \sum_{j=1}^i z^{d-d_j}$ and assume $f_n = O((z-\varepsilon)^n)$ for some fixed $\varepsilon > 0$.

Then $T_n = O(T_n^0)$ where T_n^0 is defined as T_n with $f_n \equiv 0$.

A Little Excursion: Singularity Analysis

General strategy: use generating functions for asymptotic approximations

Sequence Land

Generating Function Land

- ▶ number sequence $(a_n)_{n>0}$
- (ordinary) generating function $A(z) = \sum_{n=1}^{\infty} a_n z^n$

recurrence equation

- \blacktriangleright (functional) equation for A(z)
- ↓ solve, simplify (e.g., partial fractions)
- \rightsquigarrow closed form for A(z)

 \triangleright closed form for a_n

- \blacktriangleright exact coefficients $[z^n]A(z)$
- OR approximate A(z)near its dominant singularity

- asymptotic approximation $a_n = z_0^{-n} n^{\alpha - 1} (1 \pm O(n^{-1}))$
- \leftarrow transfer thms
 - \rightsquigarrow singular expansion at $z = z_0$ $A(z) = f(z) \pm O((1 - z/z_0)^{-\alpha})$

O-Transfer

Theorem 4.30 (Transfer-Theorem of Singularity Analysis)

Assume f(z) is Δ -analytic and admits the singular expansion

$$f(z) = g(z) \pm O((1-z)^{-\alpha}) \qquad (z \to 1)$$

with $\alpha \in \mathbb{R}$. Then

$$[z^n] f(z) = [z^n] g(z) \pm O(n^{\alpha - 1}) \qquad (n \to \infty).$$

Possible Extensions

- ▶ (constant) coefficients $c_j \cdot T_{n-d_j}$ in recurrence \rightsquigarrow different characteristic polynomial, same ideas
- any recurrence that leads to a representation of the generating function as a singular expansion around the dominant singularity.

$$f(z) = c(1 - z/z_0)^{-m} \pm O((1 - z/z_0)^{-m+1}) \qquad (z \to z_0)$$

$$\leadsto [z^n] f(z) = \frac{c}{(m-1)!} z_0^{-n} n^{m-1} \cdot \left(1 \pm O(n^{-1})\right) \qquad (n \to \infty)$$

• other powers α in $1/(1-z)^{\alpha}$:

$$[z^n] \frac{1}{(1 - \frac{z}{z_0})^{\alpha}} = \frac{z_0^{-n} n^{\alpha - 1}}{\Gamma(\alpha)} \left(1 \pm O(n^{-1}) \right) \qquad (n \to \infty) \qquad \frac{-\alpha \notin \mathbb{N}_0}{z_0 > 0}$$

► much more! → analytic combinatorics

Analysis of interleaved betterFptVertexCover [2]

- ► $T_0 = \Theta(1)$ $T_k = O(k^2) + T_{k-3} + T_{k-1}$ $T_k = O(1.4656^k)$ (same characteristic polynomial)
- ► Total time: $O(1.4656^k + n + m)$
- ► The current record is $O(1.2738^k + kn)$ time

Summary

- Strategies for fpt algorithms
 - Use parameter to bound depth of exhaustive search
 - ► Use problem specific reduction rules to shrink input → kernel(ization)s
- analysis of exact exponential searches often reduces to linear recurrences
 - generating functions!
- more clever branching reduces exponent of search space
- interleaving kernelization and exhaustive search improves polynomial parts