

Algorithms and Data Structures

Amortized Analysis

Ulf Leser

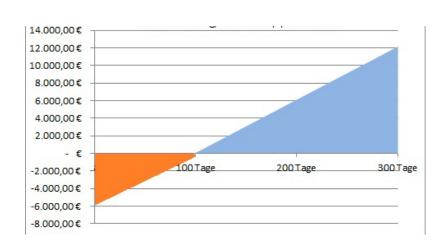
- Two Examples
- Two Analysis Methods
- Dynamic Tables
- SOL Analysis
- This lecture is not covered in [OW93] but, for instance, in [Cor03]

Setting

- SOL: Sequences of operations influencing each other
 - We have a sequence Q of operations on a data structure
 - Searching SOL and rearranging a SOL
 - Operations are not independent by changing the data structure, costs of subsequent operations are influenced
- Conventional WC-analysis produces misleading results
 - Assumes all operations to be independent
 - Changing search order in a workload does not influence WC result
- Amortized analysis analyzes the complexity of a sequence of dependent operations
 - In other terms: We seek the worst average cost of each operation in any sequence

"Amortizing"

- Economics: How long does it take until a (high) initial investment pays off because it leads to continuous business improvements (less costs, more revenue)?
- Example:
 - Investment of 6000€ leads to daily rev. increase from 500 to 560€
 - Investment is amortized after 100 days
- WC: Look at all days independently
 - Look at ratio cost / revenue
 - Compare 560-6000 to 500-0
 - Do not invest! Never!



Algorithmic Example 1: Multi-Pop

- Assume a stack S with a special operation: mpop(k)
 - mpop(k) pops min(k, |S|) elements from S
 - Implementation: mpop calls pop k times
- Assume any sequence Q of operations push, pop, mpop
 - E.g. Q={push,push,mpop(k),push,pop,push,mpop(k),...}
- Assume costs c(push)=1, c(pop)=1, c(mpop(k))=k
- : What cost do we expect for a given Q?
 - Every op in Q costs 1 (push) or 1 (pop) or k (mpop)
 - In the worst case, k can be $\sim |Q| = n$
 - n times push, then one mpop(n) <
 - Thus: Worst case of a single operation is O(n)
 - Total worst-case cost: O(n²)

Note: Costs only ~2*n

Problem

- Clearly, the cost of Q is in O(n²), but this is not tight
- A simple thought shows: The cost of Q is in O(n)
 - Every element can be popped only once
 - No matter if this happens through a pop or a mpop
 - Pushing an element costs 1, popping it costs 1
 - For any |Q|, we can at most push n elements and pop n elements
 - Thus, the total cost is in O(n)
 - It is maximally ~2n
- We want to derive such a result in a systematic manner
 - Analyzing SOLs is not that easy we do not always take from the front

Example 2: Bit-Counter

- We want to generate bitstrings by iteratively adding 1
 - Starting from 0
 - Assume bitstrings of length k
 - Roll-over counter if we exceed 2^k-1
- Q is a sequence of "+1"
- We count as cost of an operation the number of bits we have to flip
- Classical WC analysis
 - A single operation can flip up to k bits
 - "1111111" +1
 - Worst case cost for Q: O(k*n)

00000000		
0000001	1	1
0000010	2	3
0000011	1	4
00000100	3	7
00000101	1	8
00000110	2	10
00000111	1	11
00001000	4	15
00001001	1	16
00001010	2	18
	_	

Problem

- Again, this complexity is overly pessimistic / not tight
- Cost actually is in O(n)
 - The right-most bit is flipped in every operation: cost=n
 - The second-rightmost bit is flipped every second time: n/2
 - The third ...: n/4
 - **–** ...
 - Together

$$\sum_{i=0}^{k-1} \frac{n}{2^i} < n * \sum_{i=0}^{\infty} \frac{1}{2^i} = 2 * n$$

- Two Examples
- Two Analysis Methods
 - Accounting Method
 - Potential Method
- Dynamic Tables
- SOL Analysis

Accounting Analysis

- Idea: We create an account for Q
- Operations put / withdraw some amounts of "money"
- We choose these amounts such that the current state of the account is always (throughout Q) an upper bound of the actual cost incurred by Q
 - Let c_i be the true cost of operation i, d_i its effect on the account
 - We require $\forall 1 \le k \le n : \sum_{i=1}^{k} c_i \le \sum_{i=1}^{k} d_i$
 - The account must never become negative
 - "≤" gives us more freedom in analysis than "="
- It follows: An upper bound for the account (d) after Q is also an upper bound for the true cost (c) of Q

Application to mpop

- Assume $d_{push}=2$, $d_{pop}=0$, $d_{mpop}=0$
- Upper bounds?
 - Clearly, d_{push} is an upper bound on c_{push} (which is 1)
 - But neither d_{pop} nor d_{mpop} are upper bounds for c_{pop} / c_{mpop}
- Let's try: d_{push}=2, d_{pop}=1, d_{mpop}=n
 - Now all individual d's are upper bounds for their c's
 - But this doesn't help (worst-case analysis)

$$\sum_{i=1}^{n} c_{i} \leq \sum_{i=1}^{n} d_{i} \leq n * n \in O(n^{2})$$

 But: We only have to show that the sum of d's for any prefix of Q is higher than the sum of c's

Application to mpop

- Assume again: d_{push}=2, d_{pop}=0, d_{mpop}=0
- Summing these up yields an upper bound on the real cost
 - Idea: Whenever we push an element, we pay 1 for the push and 1 for the operation that will (sometime later) pop exactly this element
 - It doesn't matter whether this will be through a pop or a mpop
 - Note: For every pop, there must have been a corresponding push before
 - Thus, when it comes to a pop or mpop, there is always enough money on the account
 - Deposited by previous push's
 - "enough": Enough such that the sum remains an upper bound
- This proves:

$$\sum_{i=1}^{n} c_i \le \sum_{i=1}^{n} d_i \le 2 * n \in O(n)$$

Choose d's carefully

- Assume d_{push}=1, d_{pop}=1, d_{mpop}=1
 - Assume Q={push,push,mpop(3)}
 - $-\Sigma c=6 > \Sigma d = 4$
- Assume d_{push}=1, d_{pop}=0, d_{mpop}=0
 - Assume Q={push,push,mpop(2)}
 - $-\Sigma c=4 > \Sigma d=2$
- Assume $d_{push}=3$, $d_{pop}=0$, $d_{mpop}=0$
 - Fine as well, but not as tight (but also leads to O(n))

Application to Bit-Counter

- Look at the sequence Q' of flips generated by a sequence Q
 - Every +1 creates a sequence of [0,k] flip-to-0 and [0,1] flip-to-1
 - There is no "flip to 1" if we roll-over
 - Since only flips cost, the cost of Q' is the same as the cost of Q
- Let's try $d_{\text{flip-to-1}}=2$ and $d_{\text{flip-to-0}}=0$
 - Clearly, d_{flip-to-1} is an upper bound to c_{flip-to-1}
 - Note: We start with only 0 and can flip-to-0 any 1 only once
 - Before we flip-to-1 again, again enabling one flip-to-0 etc.
 - Idea: When we flip-to-1, we pay 1 for flipping and 1 for the backflip-to-0 that might happen at some later time in Q'
 - There can be only one flip-to-0 per single flip-to-1
 - Thus, the account is always an upper bound on the actual cost

Application to Bit-Counter -2-

- We know that the account is always an upper bound on the actual cost for any prefix of Q
- Every step of Q creates a sequence of flip-to-1 (at most one) and flip-to-0 in Q'
- This sequence costs at most 2
 - There can be only on flip-to-1, and all flip-to-0 are free
- Every step in Q costs at most 2
- Thus, Q is bound by O(n)
- qed.

- Two Examples
- Two Analysis Methods
 - Accounting Method
 - Potential Method
- Dynamic Tables
- SOL Analysis

Potential Method: Idea

- In the accounting method, we assign a cost to every operation and compare aggregated accounting costs of ops with aggregated real costs of ops
- In the potential method, we assign a potential Φ(D) to the data structure D manipulated by Q
 - Think of the potential as potential future cost
- As ops from Q change D, also change D's potential
- The trick is to design Φ such that we can use it to derive an upper bound on the real cost of Q
- "Accounting" and "potential" methods are quite similar use whatever is easier to apply for a given problem

Potential Function

- Let D₀, D₁, ... D_n be the states of D when applying Q
- We define the amortized cost d_i of the i'th operation as $d_i = c_i + \Phi(D_i) \Phi(D_{i-1})$
- We derive the amortized cost of Q as

$$\sum_{i=1}^{n} d_i = \sum_{i=1}^{n} (c_i + \phi(D_i) - \phi(D_{i-1})) = \sum_{i=1}^{n} c_i + \phi(D_n) - \phi(D_0)$$

- Rough idea: If we find a Φ such that (a) we can obtain formulas for the amortized costs for all individual d_i and (b) Φ(D_n)≥Φ(D₀), we have an upper bound for the real costs
 - Because then: $\sum_{i=1}^{n} d_{i} = \sum_{i=1}^{n} c_{i} + \phi(D_{n}) \phi(D_{0}) \ge \sum_{i=1}^{n} c_{i}$

Details: Always Pay in Advance

- Operations raise or lower the potential of D
- We need to find a function Φ such that
 - Req. 1: $\Phi(D_i)$ depends on a property of D_i (future cost)
 - Req. 2: $\Phi(D_n)$ ≥ $\Phi(D_0)$ [and we will always have $\Phi(D_0)$ =0]
 - Req. 3: We can compute $d_i = c_i + \Phi(D_i) \Phi(D_{i-1})$
- As within a sequence we do not know its future, we also have to require that Φ(D_i) never is negative
 - Otherwise, the amortized cost of the prefix Q[1...i] would not be an upper bound of the real costs at step i
- Idea: Always pay in advance

Example: mpop

- We use the number of objects on the stack as its potential
- Then
 - Req. 1: Φ(D_i) depends on a property of D_i
 - Future cost: To empty a stack with n elements, we need cost n
 - Req. 2: $\Phi(D_n) \ge \Phi(D_0)$ and $\Phi(D_0) = 0$
 - Req. 3: Compute $d_i = c_i + \Phi(D_i) \Phi(D_{i-1})$ for all ops:
 - If op is push: $d_i = c_i + (x (x-1)) = 1 + 1 = 2$
 - If op is pop: $d_i = c_i + (x (x+1)) = 1 1 = 0$
 - If op is mpop(k): $d_i = c_i + (x (x+k)) = k k = 0$
- Thus, $2*n \ge \Sigma d_i \ge \Sigma c_i$ and Q is in O(n)

Example: Bit-Counter

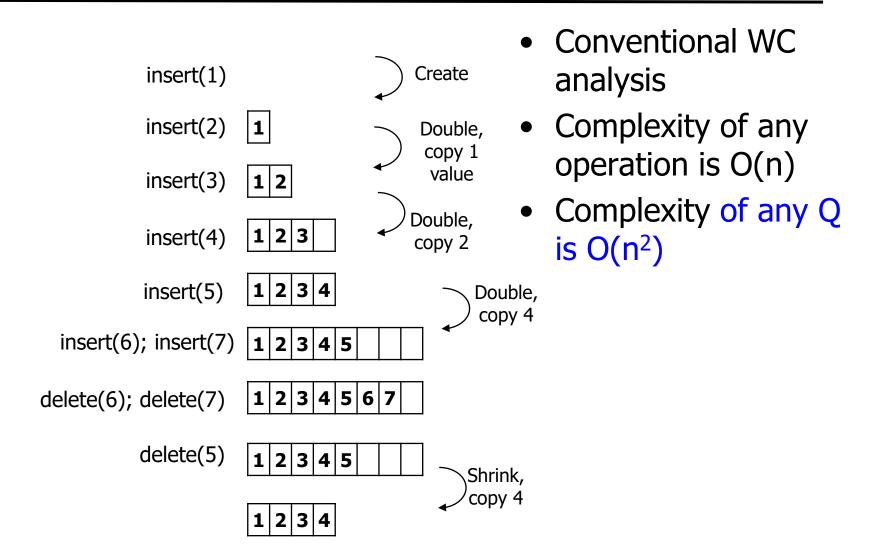
- We use the number of "1" in the bitstring as its potential
- Then
 - Req. 1: $\Phi(D_i)$ depends on a property of D_i
 - Req. 2: $\Phi(D_n) \ge \Phi(D_0)$ and $\Phi(D_0) = 0$
 - Req. 3: We compute $d_i = c_i + \Phi(D_i) \Phi(D_{i-1})$ for all ops
 - Let the i'th operation incur t_i flip-to-0 and 0 or 1 flip-to-1
 - Thus, $c_i \le t_i + 1$
 - If $\Phi(D_i)=0$, then operation i has flipped all positions to 0; this implies that previously they were all 1, which means that $\Phi(D_{i-1})=k$
 - If $\Phi(D_i) > 0$, then $\Phi(D_i) = \Phi(D_{i-1}) t_i + 1$
 - In both cases, we have $\Phi(D_i) \leq \Phi(D_{i-1}) t_i + 1$
 - Thus, $d_i = c_i + \Phi(D_i) \Phi(D_{i-1}) \le (t_i+1) + (\Phi(D_{i-1})-t_i+1) \Phi(D_{i-1}) \le 2$
- Thus, $2*n \ge \Sigma d_i \ge \Sigma c_i$ and Q is in O(n)

- Two Examples
- Two Analysis Methods
- Dynamic Tables
 - SOL will be complicated ... we still try to get familiar with the analysis method using simpler problems ...
- SOL Analysis

Dynamic Tables

- We use amortized analysis for something more useful: Complexity of operations on a dynamic table
- Assume an array T and a sequence Q of inserts/deletes
- Dynamic Tables: Keep the array small, yet avoid overflows
 - Start with a table T of size 1
 - When inserting and T is full, we double |T|; upon deleting and T is only half-full, we reduce |T| by 50%
 - "Doubling", "reducing" means: Copying data to a new array
 - Assumption: Copying an element of an array costs 1
- Thus, any operation costs either 1 or |T|

Example



With Potential Method

```
1: \Phi(D_i) depends on a property of D_i
2: \Phi(D_n) \ge \Phi(D_0)
3: d_i = c_i + \Phi(D_i) - \Phi(D_{i-1})
```

- Let num(T) be the current number of elements in T
- We use potential $\Phi(T) = 2*num(T) |T|$
 - Intuitively a "potential"
 - Immediately before an expansion, num(T)=|T| and $\Phi(T)=|T|$, so there is much potential in T (we saved for the expansion to come)
 - Immediately after an expansion, num(T)=|T|/2+1 and $\Phi(T)=2$; almost all potential has been used, we need to save again for next expansion
 - Formally
 - Requirement 1: Of course
 - Requirement 2: As T is always at least half-full, $\Phi(T)$ is always ≥ 0 ; we start with |T|=0, and thus $\Phi(T_n)-\Phi(T_0)\geq 0$

Continuation

```
1: \Phi(D_i) depends on a property of D_i
2: \Phi(D_n) \ge \Phi(D_0)
3: d_i = c_i + \Phi(D_i) - \Phi(D_{i-1})
```

- Req. 3: Let's look at $d_i = c_i + \Phi(T_i) \Phi(T_{i-1})$ for insertions
- Without expansion

```
d_{i} = 1 + (2*num(T_{i})-|T_{i}|) - (2*num(T_{i-1})-|T_{i-1}|)
= 1 + 2*num(T_{i})-2*num(T_{i-1}) - |T_{i}| + |T_{i-1}|
= 1 + 2 + 0
= 3
```

With expansion

```
\begin{array}{llll} d_i &= num(T_i) + & (2*num(T_i)-|T_i|) & - & (2*num(T_{i-1})-|T_{i-1}|) \\ &= num(T_i) + & 2*num(T_i) - |T_i| & - & 2*num(T_{i-1}) + |T_{i-1}| \\ &= num(T_i) + 2*num(T_i) - 2*(num(T_i)-1) - 2*(num(T_i)-1) + num(T_i)-1 \\ &= 3*num(T_i) - 2*num(T_i) + 2 - 2*num(T_i) + 2 + num(T_i) - 1 \\ &= 3 \end{array}
```

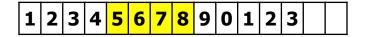
• Thus, $3*n \ge \Sigma d_i \ge \Sigma c_i$ and Q is in O(n) (for only insertions)

Intuition

- Think accounting method
- For inserts, we deposit 3 because
 - 1 for the insertion (the real cost)
 - 1 for the time when we need to copy this new element at the next expansion
 - These 1's fill the account with |T_i|/2 before the next expansion
 - 1 for one of the |T_i|/2 elements
 already in A after the last expansion
 - These fill the account with another |T_i|/2 before the next expansion
- Thus, we have enough credit at the next expansion









Problem: Deletions

- Our strategy for deletions so far is not very clever
 - Assume a table with num(T)=|T|
 - Assume a sequence $Q = \{I,D,I,D,I,D,I...\}$
 - This sequence will perform |T|+|T|/2+|T|+|T|/2+... real ops
 - As |T| is O(n), Q is in $O(n^2)$ and not in O(n)
- Simple trick: Do only contract when num(T)=|T|/4
 - Leads to amortized cost of O(n) for any sequence of operations
 - We omit the proof (see [Cor03])

- Two Examples
- Two Analysis Methods
- Dynamic Tables
- SOL Analysis
 - Goal and idea
 - Preliminaries
 - A short proof

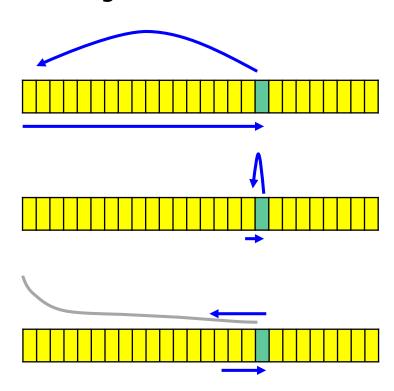
Re-Organization Strategies

- Recall self-organizing lists (SOL)
 - Accessing the i'th element costs i
 - After searching an element, we change the list L
- Three strategies

– MF, move-to-front:

- T, transpose:

– FC, frequency count:



Notation

- Assume we have a strategy A and a workload S on list L
- After accessing element i, A may move i by swapping
 - Swap with predecessor (to-front) or successor (to-back)
 - Let $F_A(I)$ be the number of front-swaps and $X_A(I)$ the number of back-swaps of step I when using strategy A
 - This means: F_{MF}/X_{MF} for strategy MF, F_T/X_T ... F_{FC}/X_{FC}
 - Note: Our three strategies never back-swap: ∀I: X_{MF}(I)=X_T(I)=X_{FC}(I)=0
 But strategy A could
- Let C_A(S) be the total access cost of A incurred by S
 - Again: C_{MF} for strategy MF, C_{T} for T, C_{FC} for FC
- With conventional worst-case analysis, we can only derive that $C_A(S)$ is in O(|S|*|L|) for any A
 - Searched element always at last positions, swaps ignored

Theorem

Theorem (Amortized costs)
 Let A be any self-organizing strategy for a SOL L, MF be the move-to-front strategy, and S be a sequence of accesses to L. Then

$$C_{MF}(S) \le 2*C_{A}(S) + X_{A}(S) - F_{A}(S) - |S|$$

- What does this mean?
 - We don't learn more about the absolute complexity of SOLs
 - But we learn that MF is quite good
 - Any strategy with the same constraints (only series of swaps) will at best be roughly twice as good as MF
 - Assuming $C_A(S) >> |S|$ and for $|S| \to \infty$: $X(S) \sim F(S)$ for any strategy
 - Despite its simplicity, MF is a fairly safe bet for all workloads

Idea of the Proof

- We will compare access costs in L between MF and any A
- Think of both strategies (MF, A) running S on two copies of the same initial list L
 - After each step, A and MF perform different swaps, so all list states except the first very likely are different
- We will compare list states by looking at the number of inversions ("Fehlstellungen")
 - Actually, we only analyze how the number of inversions changes
- We will show that the number of inversions defines a potential of a pair of lists that helps to derive an upper bound on the differences in real costs

Content of this Lecture

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Inversions

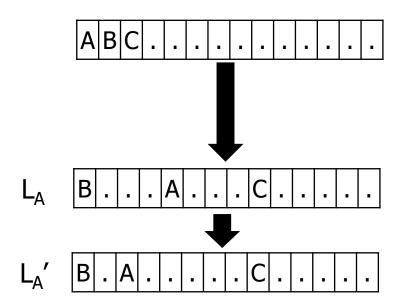
- Let L and L' be permutation of the set {1, 2, ..., n}
- Definition
 - A pair (i,j) is called an inversion of L and L' iff i and j are in different order in L than in L' (for $1 \le i,j \le n$ and $i\ne j$)
 - The number of inversions between L and L' is denoted by inv(L, L')

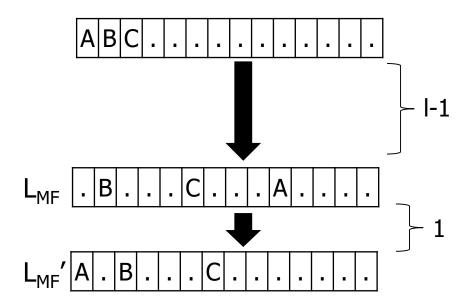
Remarks

- Different order: Once i before j, once i after j
- Obviously, inv(L, L') = inv(L', L)
- Example: inv($\{4,3,1,5,7,2,6\}$, $\{3,6,2,5,1,4,7\}$) = 12
- Without loss of generality, we assume that L={1,...,n}
 - Because we only look at changes in number of inversions and not at the actual set of inversions

Sequences of Changes

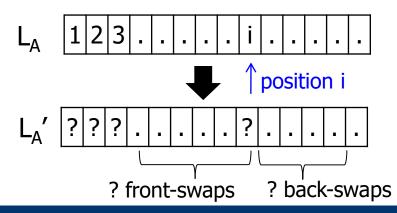
- Assume we applied I-1 steps of S on L, creating L_{MF} using MF and L_{A} using A
- Let us consider the next step I, creating L_{MF}' and L_A'

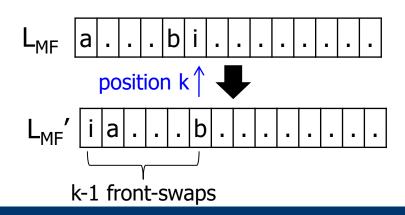




Inversion Changes

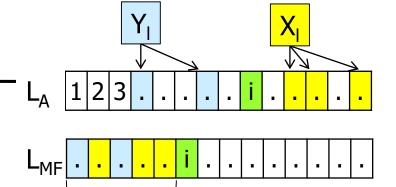
- How does I change the number of inv's between L_{MF} / L_A?
- Can we compute inv(L_{MF}', L_A') from inv(L_{MF}, L_A)?
 - Assume step I accesses element i from L_A
 - We may assume it is at position i
 - Let this element i be at position k in L_{MF}
 - Access in L_A costs i, access in L_{MF} costs k
 - After step I, A performs an unknown number of swaps; MF performs exactly k-1 front-swaps





Counting Inversion Changes 1

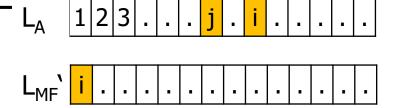
 Let X_I be the set of values that are before position k in L_{MF} and after position i in L_A



- Let Y_i be the values before pos. k in L_{MF} and before i in L_A
 - Clearly, $|X_1| + |Y_1| = k-1$
- All pairs (i,c) with $c \in X_I$ are inversions between L_A and L_{MF}
 - There may be more; but only those with i are affected in this step
- After step I, MF moves element i to the front
 - Assume first that A does simply nothing
 - All inversions (i,c) with $c \in X_1$ disappear (there are $|X_1|$ many)
 - But $|Y_1| = k-1-|X_1|$ new inversions appear
 - Thus: $inv(L_{MF}', L_{A}') = inv(L_{MF}, L_{A}) |X_{I}| + k-1-|X_{I}|$
 - But A does something

Counting Inversion Changes 2

In step I, let A perform
 F_A(I) front-swaps and
 X_A(I) back-swaps



- Every front-swap (swapping i before any j) in L_A decreases inv(L_{MF}', L_A') by 1
 - Before step I, j must be before i in L_A (it is a front-swap), but after i in L_{MF} (because i now is the first element in L_{MF})
 - After step I, i is before j in both L_A' and L_{MF}' inversion removed
- Equally, every back-swap increases inv(L_{MF}',L_A') by 1
- Together: After step I, we have

$$\operatorname{inv}(L_{MF}', L_{A}') = \operatorname{inv}(L_{MF}, L_{A}) - |X_{I}| + k-1-|X_{I}| - F_{A}(I) + X_{A}(I)$$

Before step I through MF through A

Amortized Costs

Was c_1 ... was d_1 ... we switch to Cor notation

- Let t_{MF}(I) be the real cost of strategy MF for step I
- We use the number of inversions as potential function $\Phi(L_A, L_{MF}) = inv(L_A, L_{MF})$ on the pair L_A , L_{MF}
- Definition
 - The amortized costs of step I, called a_i, are

$$a_{l} = t_{MF}(l) + inv(L_{A}(l), L_{MF}(l)) - inv(L_{A}(l-1), L_{MF}(l-1))$$

- Accordingly, the amortized costs of sequence S, |S|=m, are $\Sigma a_l = \Sigma t_{MF}(l) + inv(L_A(m), L_{MF}(m)) - inv(L_A(0), L_{MF}(0))$

- This is a proper potential function
 - 1: Φ depends on a property of the pair L_A, L_{MF}
 - 2: inv() can never be negative, so \forall 1: $\Phi(L_A(I), L_{MF}(I)) \ge \Phi(L,L)=0$
- Let's look at how operations change the potential

Content of this Lecture

- Two Examples
- Two Analysis Methods
- Dynamic Tables
- SOL Analysis
 - Goal and idea
 - Preliminaries
 - A short proof (after much preparatory work)

Putting it Together

• We know for every step I from S accessing some i: $inv(L_{MF}',L_{A}') = inv(L_{MF},L_{A}) - |X_{I}| + k-1-|X_{I}| - F_{A}(I) + X_{A}(I)$ and thus

$$inv(L_{MF}', L_{A}') - inv(L_{MF}, L_{A}) = -|X_{I}| + k - 1 - |X_{I}| - F_{A}(I) + X_{A}(I)$$

Since t_{MF}(I)=k, we get amortized costs of

$$a_{l} = t_{MF}(I) + inv(L_{A}', L_{MF}') - inv(L_{A}, L_{MF})$$

= $k - |X_{l}| + k - 1 - |X_{l}| - F_{A}(I) + X_{A}(I)$
= $2(k - |X_{l}|) - 1 - F_{A}(I) + X_{A}(I)$

- Recall that $Y_l(|Y_l|=k-1-|X_l|)$ are those elements before i in both lists. This implies that $k-1-|X_l| \le i-1$ or $k-|X_l| \le i$
 - There can be at most i-1 elements before position i in L_A
- Therefore: $a_1 \le 2i 1 F_A(I) + X_A(I)$

Putting it Together

- This is the central trick!
- Because we only looked at inversions (and hence the sequence of values), we can draw a connection between the value that is accessed and the number of inversions that are affected

- Recall that $Y_i(|Y_i|=k-1-|X_i|)$ are those elements before i in both lists. This implies that $k-1-|X_i| \le i-1$ of $k-|X_i| \le i$
 - There can be at most i-1 elements before position in L_A
- Therefore: $a_1 \le 2i 1 F_A(I) + X_A(I)$

Aggregating

- We also know the real cost of accessing i using A: t_A(I)=i
- Together: $a_l \le 2t_A(l) 1 F_A(l) + X_A(l)$
- Aggregating this inequality over all a₁ in S, we get

$$\sum a_1 \le 2 * C_A(S) - |S| - F_A(S) + X_A(S)$$

By definition, we also have

$$\Sigma a_{l} = \Sigma t_{MF}(l) + inv(L_{A}^{m}, L_{MF}^{m}) - inv(L_{A}^{0}, L_{MF}^{0})$$

- Since $\sum t_{MF}(I) = C_{MF}(S)$ and $inv(L_A{}^0, L_{MF}{}^0) = 0$, we get $C_{MF}(S) + inv(L_A{}^m, L_{MF}{}^m) \le 2*C_A(S) |S| F_A(S) + X_A(S)$
- It finally follows (inv()≥0)

$$C_{MF}(S) \le 2*C_{A}(S) - |S| - F_{A}(S) + X_{A}(S)$$

Summary

- Looking at sequences of operations with self-organization creates a new class of problem
 - Things change during a workload
 - These changes (positively) influence future costs of operations
 - Not at random we follow a strategy
- Analysis is none-trivial, but
 - Helped to find a elegant and surprising conjecture
 - Very interesting in itself: We showed relationships between measures we never counted (and could not count easily)
 - But beware the assumptions (e.g., only single swaps)
 - Original work: Sleator, D. D. and Tarjan, R. E. (1985). "Amortized efficiency of list update and paging rules." Communications of the ACM 28(2): 202-208.