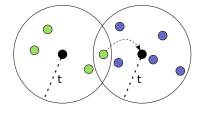
Bachelor's thesis defense

Nikolaj Dybdahl Rathcke



# Background

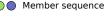
- Inexpensive sequencing data
- Centroid-based clustering
- What does klust solve?



t: Threshold similarity









#### Distance metric

- Sequence alignment is expensive
- *k*-mer is cheap to compute
- The Manhattan distance

- Windows ensures that string of different length are still comparable
- K-Dist

k-mer	AA	AC	AG	AT	CA	СС	CG	СТ	GA	GC	GG	GT	TA	TC	TG	П
s1				2			1	1					1	2		
s2				2			1	1					2	2		1



K-DIST example with k = 2

Manhattan distance: 4

ATCTATCG TTATCTATCG



## K-DIST example with k = 2

# Manhattan distance: 2

ATCTATCG TTATCTATCG



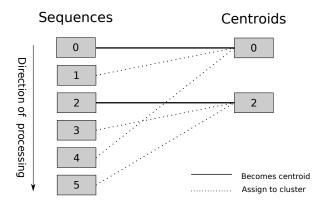
K-DIST example with k = 2

Manhattan distance: 0

A T C T A T C G T T A T C T A T C G



• Greedy algorithm improves time complexity





- Greedy algorithm improves time complexity
- Intersection criterion to quickly dismiss sequences that are not likely to belong to a cluster

#### Intersection criterion

$$|K(s) \cap K(c)| \ge |K(c)| \cdot id$$

k-mer	АА	AC	AG	AT	CA	СС	CG	СТ	GA	GC	GG	GT	TA	TC	TG	тт
s1				2			1	1					1	2		
s2				2			1	1					2	2		1



- Greedy algorithm improves time complexity
- Intersection criterion to quickly dismiss sequences that are not likely to belong to a cluster

#### Intersection criterion

$$|K(s) \cap K(c)| \ge |K(c)| \cdot id$$

k-mer	AA	AC	AG	AT	CA	СС	CG	СТ	GA	GC	GG	GT	TA	TC	TG	TT
K(s1)				1			1	1					1	1		
K(s2)				1			1	1					1	1		1



- Greedy algorithm improves time complexity
- Intersection criteria to quickly dismiss sequences that are not likely to belong to a cluster
- Ordering centroids can improve performance

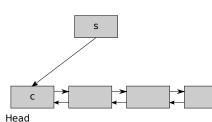


- Greedy algorithm improves time complexity
- Intersection criteria to quickly dismiss sequences that are not likely to belong to a cluster
- Ordering centroids can improve performance
- The centroid structure



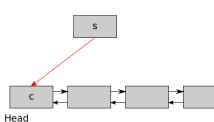
- Greedy algorithm improves time complexity
- Intersection criteria to quickly dismiss sequences that are not likely to belong to a cluster
- Ordering centroids can improve performance
- The centroid structure
- K-Clust





Intersection criteria
Distance(s,c) >= id?
Distance(s,c.link) >= id?
Update centroid list

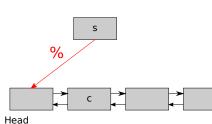




#### Intersection criteria

Distance(s,c) >= id? Distance(s,c.link) >= id? Update centroid list

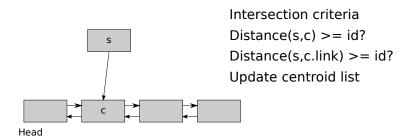




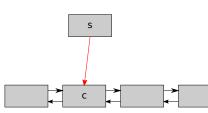
#### Intersection criteria

Distance(s,c) >= id? Distance(s,c.link) >= id? Update centroid list







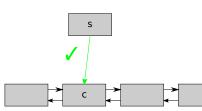


#### Intersection criteria

Distance(s,c) >= id?Distance(s,c.link) >= id?Update centroid list

Head



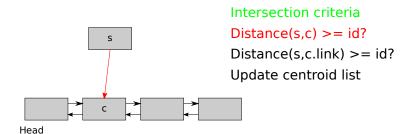


#### Intersection criteria

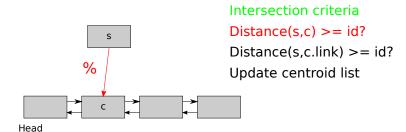
Distance(s,c) >= id? Distance(s,c.link) >= id? Update centroid list



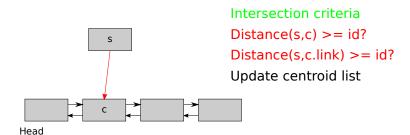




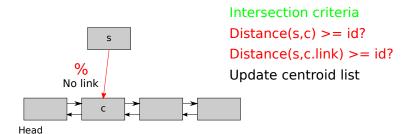




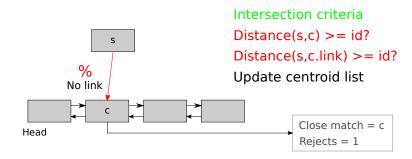




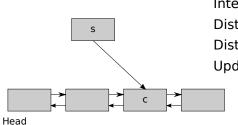






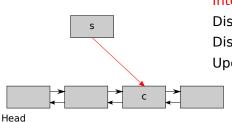






Intersection criteria
Distance(s,c) >= id?
Distance(s,c.link) >= id?
Update centroid list

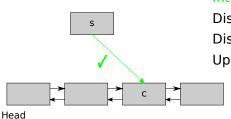




#### Intersection criteria

Distance(s,c) >= id? Distance(s,c.link) >= id? Update centroid list

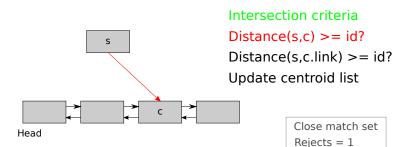




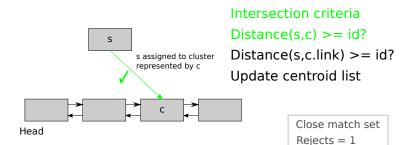
#### Intersection criteria

Distance(s,c) >= id? Distance(s,c.link) >= id? Update centroid list

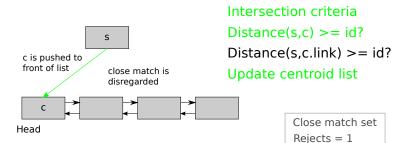




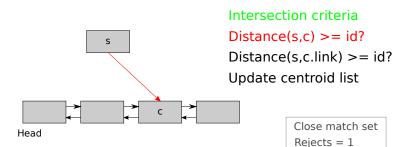




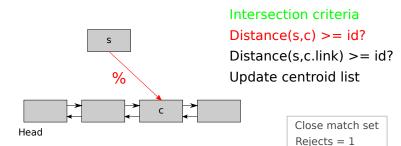




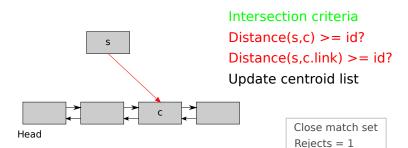




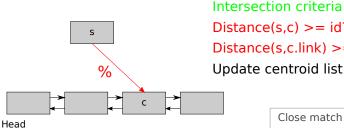








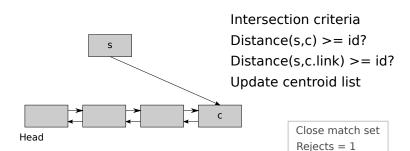




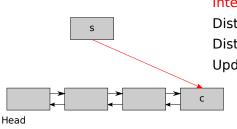
Distance(s,c) >= id?Distance(s,c.link) >= id?

Update centroid list





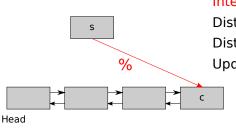




#### Intersection criteria

Distance(s,c) >= id? Distance(s,c.link) >= id? Update centroid list

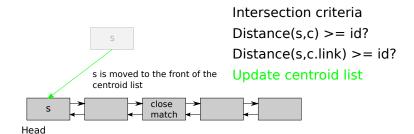




#### Intersection criteria

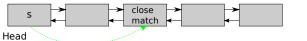
Distance(s,c) >= id? Distance(s,c.link) >= id? Update centroid list







Intersection criteria
Distance(s,c) >= id?
Distance(s,c.link) >= id?
Update centroid list



s has a link to the centroid it was close to matching



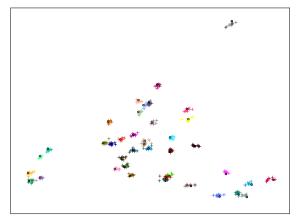
#### Results

- ullet Evaluation of K-CLUST with synthetic data
- Evaluation of klust on real data



# Multi-dimensional scaling of clustering output from SILVA

Clustering on 40 very different sequences with 9 copies of each that has been altered.





# Comparison of klust and USEARCH on RDP

Clustering algorithm	Time (sec.)	Throughput (seqs./sec.)	Clusters	Clus	ter sizes	Max memory
K-Clust, k = 5, id = 0.85, m = 8, incr. sort	5420.8	557.10	220 982	Max. Avg. Min.	100 832 13.67 1	≈ 2031 MB
K-CLUST, k = 5, $id = 0.9$ , $m = 8$ , incr. sort	11 948.7	252.74	344 122	Max. Avg. Min.	55 992 8.78 1	≈ 2031 MB
USEARCH,  id = 0.95, decr. sort -cluster_smallmem	6874.0	439.20	261 880	Max. Avg. Min.	65 654 11.50 1	≈ 1433 MB
USEARCH,  id = 0.97, decr. sort -cluster_smallmem	11 980.0	252.00	471 982	Max. Avg. Min.	56 279 6.40 1	≈ 2560 MB



#### Future work

- Link optimization effectively using max rejects
- Optimizing distance metric to better recognize mutations
- A better merge strategy for a solution using parallelization

