Visualization for Analyzing Trajectory-Based Metaheuristic Search Algorithms

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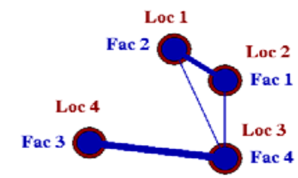
Introduction

- Combinatorial Optimization Problems (COPs)
  - **Practical usage** in various fields
  - Usually **NP-hard**, e.g. TSP, QAP
- Metaheuristics/Local Search algorithms for attacking COP
  - **Metaheuristic Tuning Problem**



Tabu Search Basic Algorithmic Template M

```
CurrentSolution = OverallBest = InitialSolution
while (terminating-condition-not-satisfied)
  BestMove = Best([Neighborhood],[TabuList],[AspirationCriteria],CurrentSolution)
  CurrentSolution = BestMove(CurrentSolution)
  [TabuList].SetTabu(CurrentSolution,BestMove,TabuTenure)
  if (Better(CurrentSolution,OverallBest))
    OverallBest = CurrentSolution
  if (Something_Happens())
    Do_A_Strategy()
return OverallBest
```

Tunable parts of Tabu Search Φ:

Setting the length of Tabu Tenure:
- By Guessing ??
- By Trial and Error ??
- By using past experience as a guide ??

Selecting Local Neighborhood:
- 2/3/k-opt ??
- Very Large Scale Neighborhood (VLSN) ??

Selecting Tabu List:
- Tabu moves/attributes/solutions ??

Adding Search Strategies:
- Intensification ??
- Diversification ??
- Hybridization ??
- **When** & **How** to apply these strategies ??

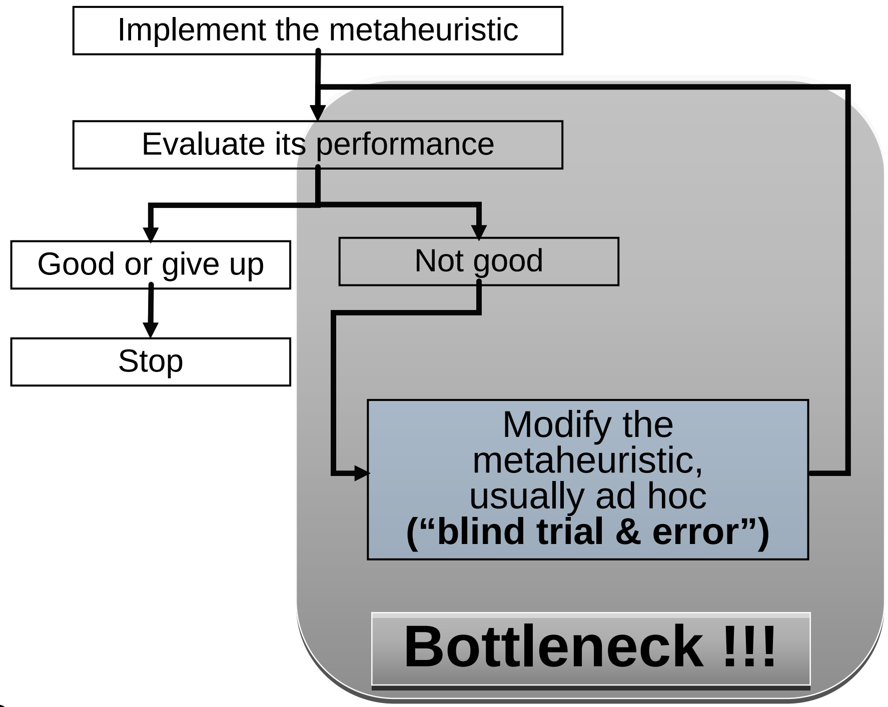
- Different M+Φ yields **different performance!!**
- The behavior of M+Φ is not well understood…
- Finding the best Φ for a given M and a COP instance *within limited time* is **difficult…**

Approaches to Address Metaheuristic Tuning Problem

- Common Practice:
  Ad Hoc (Blind) Tuning…
  - (Very) Slow

Addressing Tuning Problem is not easy…

1. **Barr *et al.*** says: "The selection of parameter values that drive heuristics (Type-1) is itself a scientific endeavor, and deserves more attention than it has received in the Operations Research literature."
2. **Birattari** says: "For obtaining a fully functioning algorithm, a metaheuristic needs to be configured: typically some modules need to be instantiated (Type-2) and some parameters (Type-1) need to be tuned."
3. **Adenso Diaz & Laguna** says: "There is anecdotal evidence that about 10% of the total time dedicated to designing and testing of a new heuristic or metaheuristic is spent on development, and the remaining 90% is consumed (by) fine-tuning (its) parameters."
4. And so on…



- Emerging Trend: Various Tuning Methods
  - Black-Box --- Auto Configurator
    - CALIBRA (Adenso-Diaz & Laguna, 2006)
    - F-Race (Birattari, 2004), (Yuan & Gallagher, 2005),
    - +CARPS (Monett-Diaz, 2004)
  - White-Box --- Involving Human
    - Statistical Analysis (Jones & Forrest, 1995), (Fonlupt *et al.*, 1997), (Merz, 2000), etc;
    - Human-Guided Search (Klau *et al.*, 2002);
    - Visualization of Search (Syrjakow & Szczerbicka, 1999), (Kadluzdka *et al.*, 2004)

- Despite various approaches, there is still a need for a better solution for Tuning Problem!!

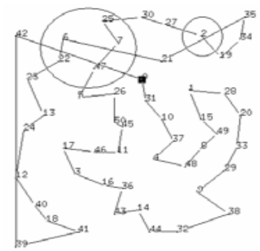
Visual Diagnosis Tuning: Human + Computer

Exploit humans!

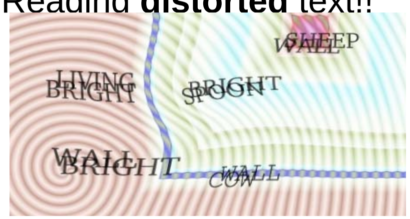
Olny srmat poelpe can raed tihs. cdnuolt blveiee taht I cluod aulaclty uesdnatnrd waht I was rdanieg. The phaonmneal pweor of the hmuan mnid, aoccdrnig to a rscheearch at Cmabrigde Uinervtisy, it deosn't mttaer in waht oredr the ltteers in a wrod are, the olny iprmoatnt tihng is taht the frist and lsat ltteer be in the rghit pclae. The rset can be a taotl mses and you can sitll raed it wouthit a porbelm. Tihs is bcuseae the huamn mnid deos not raed ervey lteter by istlef, but the wrod as a wlohe. Amzanig huh? yaeh and I awlyas tghuhot slpeling was ipmorantt! if you can raed tihs psas it on !!

Human is good in visualization!!

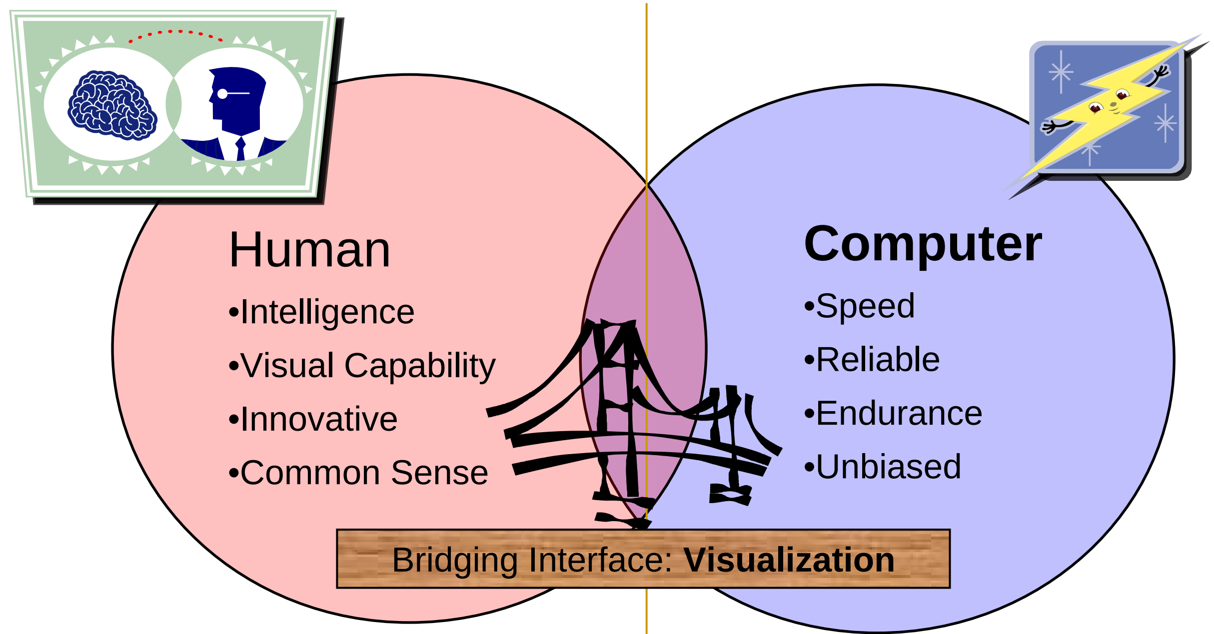
*. Aware of crossings in TSP tour **in a glance!!**



*. Reading **distorted** text!!



*. Identifying **similarities/patterns** across seemingly disparate pictures.



Task:
Understanding and **Tuning** the Local Search

Task:
Run Local Search and **Visualize** Search Information

- How to understand the behavior of heuristic and stochastic local search??

Explaining Local Search Behavior

There are several interesting questions about local search behavior:

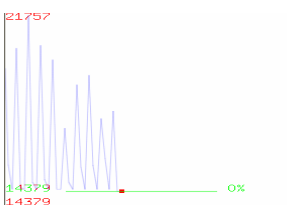
1. Does it behave like as what we intended?
2. How good is the local search in intensification?
3. How good is the local search in diversification?
4. Is there any sign of cycling behavior?
5. How does the local search algorithm make progress?
6. Where in the search space does the search spend most of its time?
7. What is the effect of modifying a certain search parameter/component/strategy w.r.t the search behavior?
8. How far is the starting (initial) solution to the global optima/best found solution?
9. Does the search quickly find the global optima/best found solution region or does it wander around in other regions?
10. How wide is the local search coverage?
11. How do two different algorithms compare?

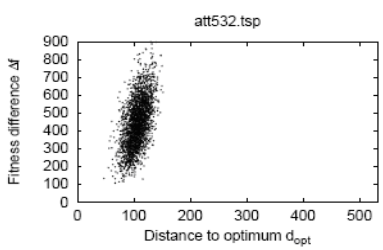
Advantages for understanding local search behavior:

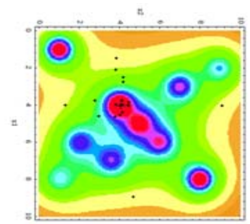
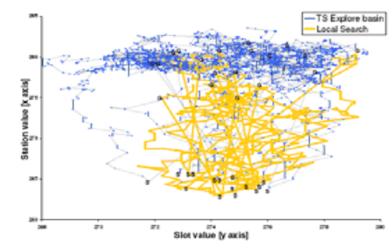
- Better equipped for addressing the Tuning Problem
- Can spot and debug the incorrect behavior
- Improving the underlying local search algorithm.

Existing approaches for explaining Local Search behavior:

- Objective Value/Solution Quality/Robustness
- Run Time/Length Distribution [Hoos, 1998]
- Fitness Distance Correlation [Jones, 1995]
- Problem Specific, e.g. TSP [Klau *et al.*, 2002]
- N-to-2-Space Mapping [Kadluczka, 2004]
- 2-D Animation [Syrjakow & Szczerbicka, 1999]
- Search Trajectory Visualization [this work]



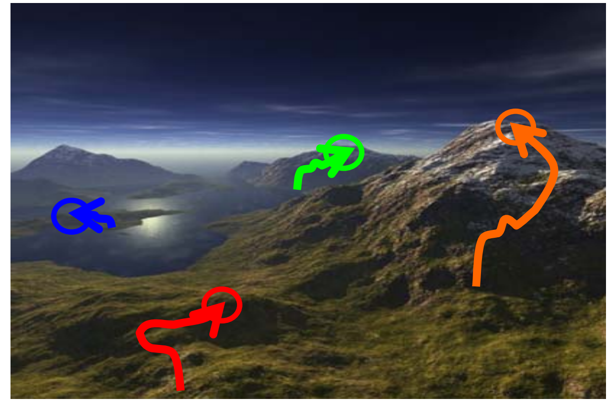


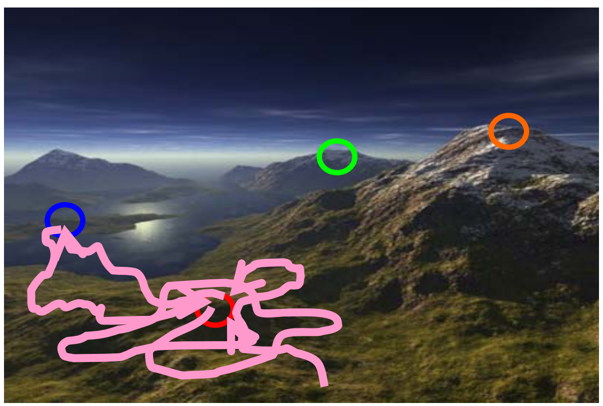
Search Trajectory Visualization – Main Concepts

- Analogy: Mountainous Landscape ~ Fitness Landscape of an instance of combinatorial optimization problem.
- Objective: Explaining the local search trajectory using **anchor points**, **distance** metric and **fitness** function!!

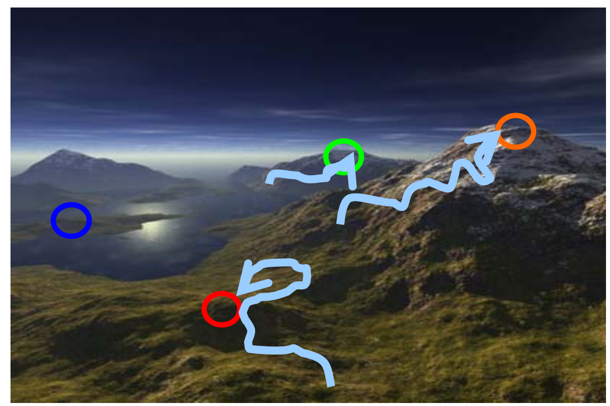
1. Without anchor points, the behavior of the **pink trajectory** is hard to be explained.



2. Do several local search runs with different **configurations**, record diverse local optima/anchor points **(circled)**.



3. With anchor points, the behavior of the **pink trajectory** is as follows: trapped in region that contains **red**/**blue** anchor points, thus failed to visit good solutions, the **green**/**orange** anchor points.



4. The behavior of the **pale blue trajectory** is as follows: after reaching a local optima, it diversifies to another place. It manages to reach **green** and **orange** anchor points, and thus its performance is better than the **pink trajectory** in Figure 3.

Laying Out Points in Abstract 2-D Space

Search Trajectory Visualization
In Practice

Layout the points in Abstract 2-D Space

- Points that are close in N-dimensional space in terms of distance metric (hamming, permutation distance, etc) are laid out close to each other in the abstract 2-D space and vice versa.
- This utilizes human strength in discerning *2-D spatial information*.

Layout First Phase:

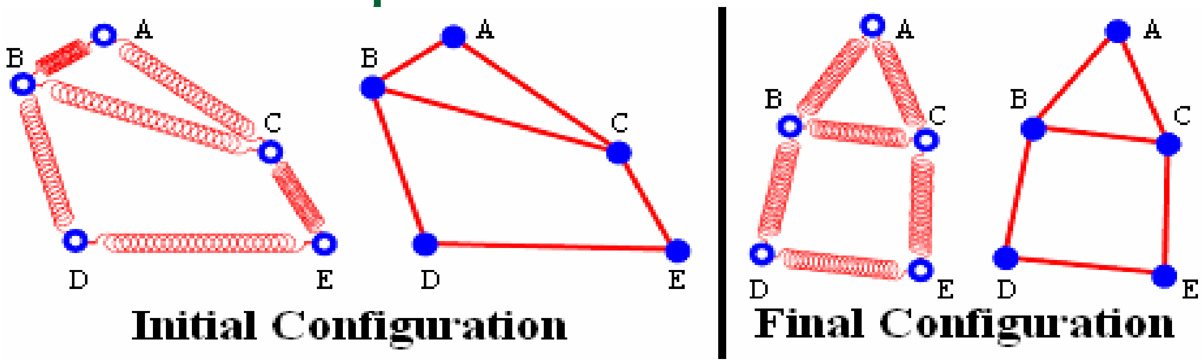
- The anchor points are measured with each other using distance metric.
- The anchor points are installed greedily in abstract 2-D space
- Re-optimize using the Spring Model layout algorithm.

Layout Second Phase:

- Again, using Spring Model algorithm, the points along search trajectory are aid out in abstract 2-D space using these anchor points as reference.

Presentation Aspects:

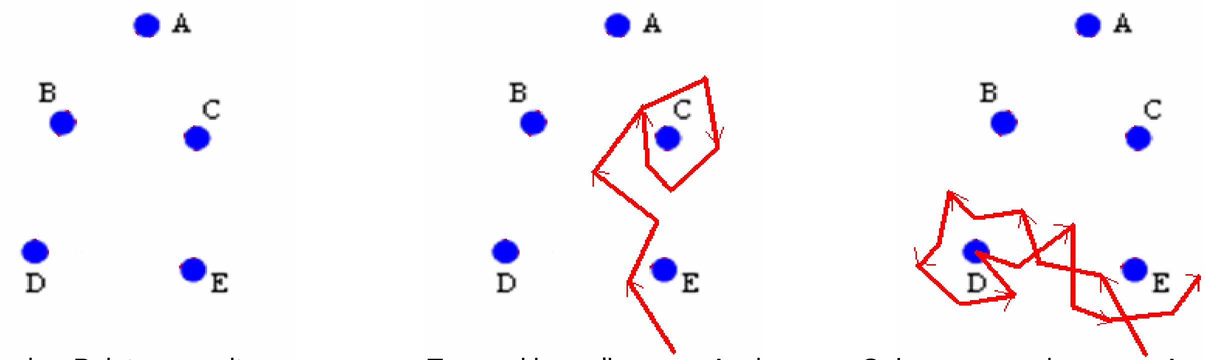
- Color coding is used to enhance our understanding: blue: good, green: medium, brown: poor anchor points.
- The search trajectory is animated over time.



Anchor Points are quite close to each other.

Trapped in cycling near Anchor Point C

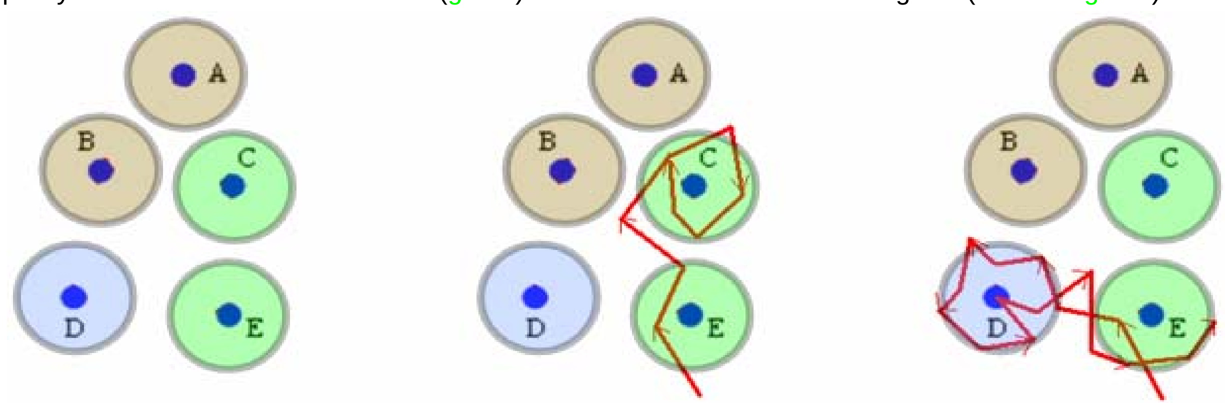
Only covers regions near Anchor Point D and E



Anchor Points are quite close to each other, but their quality are different.

Trapped in cycling near Anchor Point C because it is attractive (green)

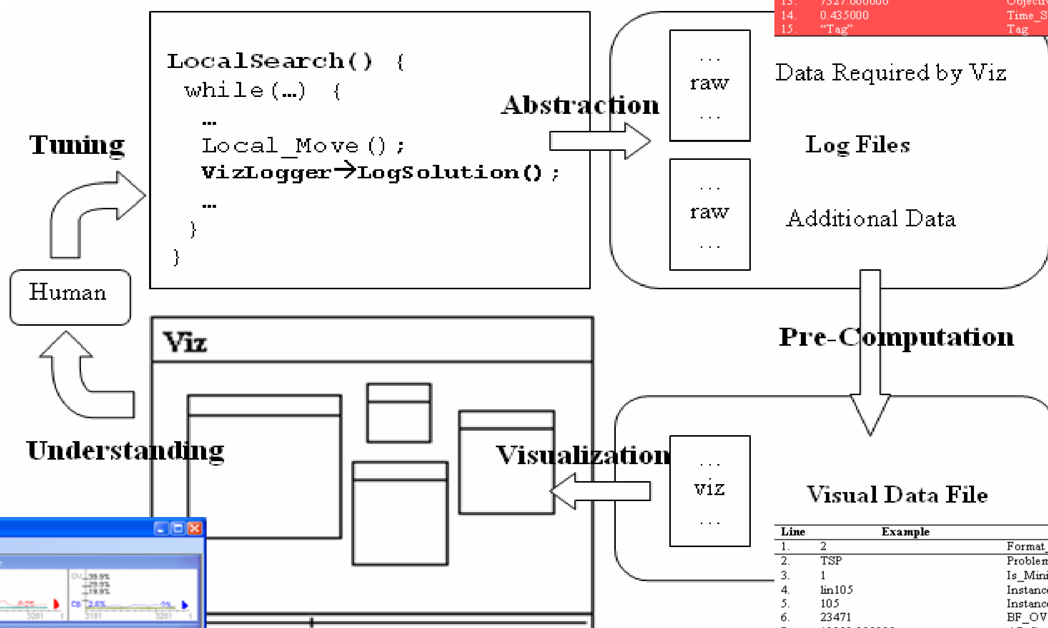
Only covers regions near Anchor Point D and E, which are good regions (blue and green)



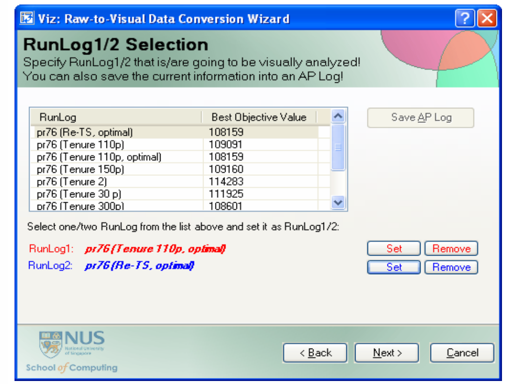
Viz: Local Search Visual Analysis Suite

Features:

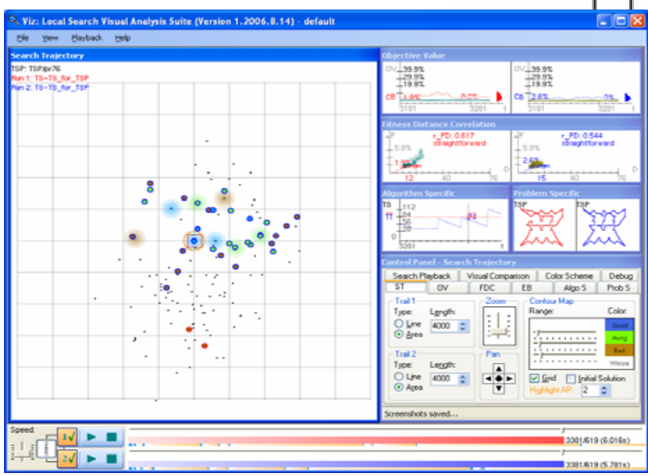
- Can answer all questions of local search behavior shown previously
- Multi Visualization
- **Animation**
- Color & Highlighting
- Visual Comparison
- Customize-able GUI



Line	Example	Field Name
1.	1	Format_Version
2.	TSP	Problem_Name
3.	1	Is_Minimizing
4.	lin105	Instance_Name
5.	105	Instance_Size
6.	TS	Solver_Name
7.	Strict TS with Tabu Tenure = 40	Run_Description
8.	"FileName"	Algorithm_Specific_Log_File
9.	"FileName"	Problem_Specific_Log_File
10.	1500	Number_of_Entries
11.	0,1,2,…,104,	Solution
12.	1	Is_Feasible
13.	7327.000000	Objective_Value
14.	0.435000	Time_Stamp
15.	"Tag"	Tag



Line	Example	Field Name
1.	2	Format_Version
2.	TSP	Problem_Name
3.	1	Is_Minimizing
4.	lin105	Instance_Name
5.	105	Instance_Size
6.	23471	BF_OV
7.	10000.000000	AP_Spring_Tension
8.	100	AP_Size
9.	0,1,2,…,104,	AP_Solution
10.	AP_Size columns entries	AP_Distance
11.	10,20	AP_Coordinate[]
12.	1	AP_Is_Feasible
13.	7327.000000	AP_OV
14.	"0"	AP_Tag
15.	2	AP_D_wrt_BF
16.	TS	Solver_Name[0]
17.	Strict TS with Tabu Tenure = 40	Run_Description[0]
18.	"FileName"	Algorithm_Specific_Log_File[0]
19.	"FileName"	Problem_Specific_Log_File[0]
20.	2000	Max_OV[0]
21.	650	Average_OV[0]
22.	100	Min_OV[0]
23.	200	Best_Iteration[0]
24.	8	Total_New_BF_Steps[0]
25.	10,20,40,50,60,100,200,150	New_BF_Iteration[0][]
26.	0.567	R_FD[0]
27.	0	Current_Iteration[0]



Off-line Analysis Tools:

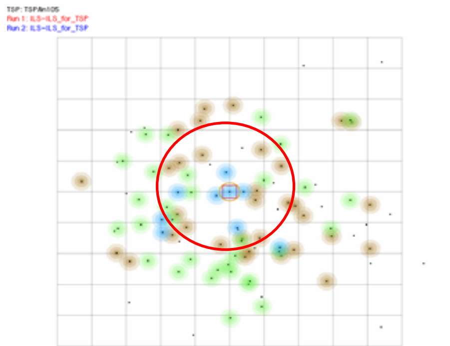
- Analyze Local Search RunLogs

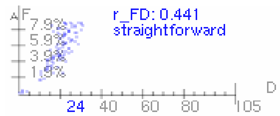
Technologies used:

- Visual C#.NET 2005
- .NET Framework 2.0
- OpenGL/CsGL

A TSP Example

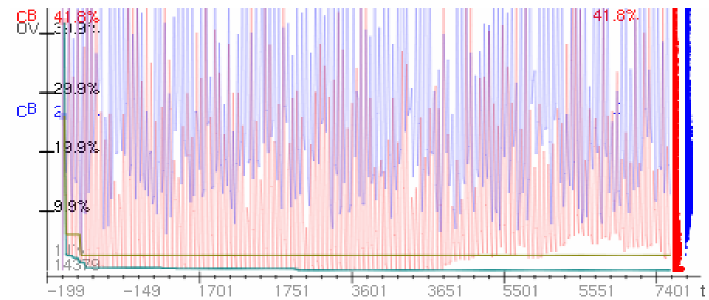
Explaining 2 Iterated Local Search (ILS) performance and behavior for Traveling Salesman Problem (TSP)!!



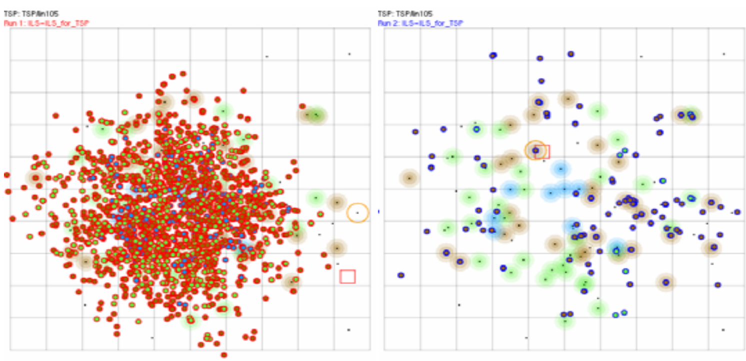


Fitness Distance Correlation analysis confirmed the presence of `Big Valley': the distance of most local optima w.r.t best found are only 1/4 of the diameter and the FDC coefficient is high.

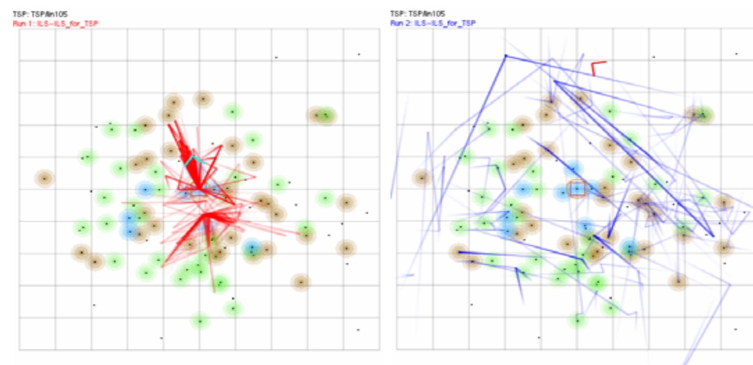
TSP Fitness Landscape: `Big Valley' (**circled**) - a cluster of good anchor points (**blue**) are located in the middle of the screen and are close to each other…



Objective Value chart: In overall, ILS_A (**red**) seems to find better solutions than ILS_B (**blue**). Eventually, the best solution found by ILS_A is better than ILS_B.



After filtering the points above 7.5%-off from best found value, ILS_A (**red**) covers a lot more good points, which are near to the `Big Valley' (center of the screen) than ILS_B (**blue**).



When the search trajectory is played back iteratively, the trajectory of ILS_A (**red**) is concentrated in the region near `Big Valley' whereas the trajectory of ILS_B (**blue**) is more erratic.

Conclusion: *Viz can be used to explain local search behaviors, which is a* ***necessary*** *step before tuning the local search algorithm.*

For more details, please visit: **http://www.comp.nus.edu.sg/~stevenha/viz**