



**UiO : Matematisk institutt**

Det matematisk-naturvitenskapelige fakultet

## **STK-4051/9051 Computational Statistics Spring 2022**

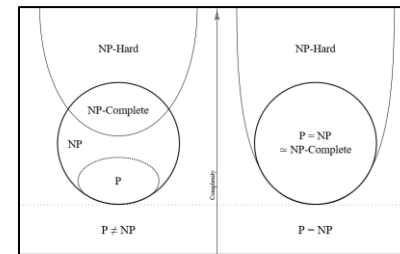
### **Tabu algorithm & Examples of Combinatorial optimization**

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# Last time

- Iterative reweighted least squares (IRLS)
- Method of moments (constrained optimization)
- Alternating Direction Method of Multipliers (ADMM)
- Decision vs Optimization
- Solving vs checking
- P, NP, NP-Hard, NP-Complete
- Heuristics:
  - Algorithms that find a good local optima within tolerable time
  - Genetic algorithm population
  - Local search = Neighborhood
    - Greedy
    - Simulated annealing
    - Tabu algorithm (today)



# Neighborhood

- We can't solve the full problem, i.e. not  $P$
- We look for refinement of our current best guess
- Limiting the search to a **local neighborhood**  $\mathcal{N}(\theta^{(t)})$  at any iteration

- Example model selection : (change only one component)

$$\mathcal{N}(\theta^{(t)}) = \{\theta : \exists l \text{ such that } \theta_j = \theta_j^{(t)} \text{ for } j \neq l\}$$

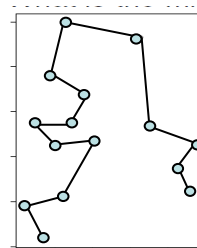
- Example traveling salesperson

$$\mathcal{N}(\theta^{(t)}) = \{\theta : \exists (k, l) \text{ such that } \theta_l = \theta_k^{(t)}, \theta_k = \theta_l^{(t)} \text{ and } \theta_j = \theta_j^{(t)} \text{ for } j \neq l, k\}$$

$$\theta = \gamma$$

$$Y_i = \beta_0 + \sum_{j=1}^p \gamma_j \beta_j x_{ij} + \varepsilon_i$$

$$\theta = \textit{ordering}$$



# Tabu algorithms

- Greedy gets stuck in local minima
- Simulated annealing
  - Next move may reverse previous move
- Is there a way to escape local minima in a controlled way?
- Tabu idea:
  - Allow downhill move when no uphill move is possible (i.e. local minima)
  - Make some moves temporarily forbidden or tabu (to avoid returning to local minima in next step)
  - Early form: steepest ascent /mildest decent
    - Move to least unfavorable when there is no uphill move

# Traveling salesperson Tabu

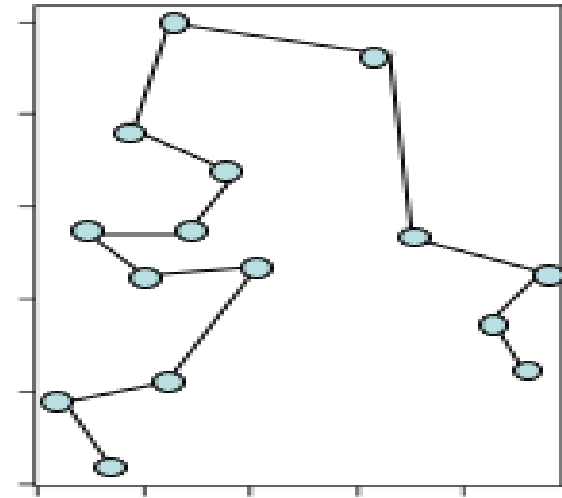
- **Neighborhood**: Swap the order of two components
- **Move**: To the best state in the neighborhood **even if it is worse**
- **Tabu**: Do not allow to pick two components that have been selected in the last  $k$  iterations
- **Implementation**:
  - Make a table of all possible pairs that can be picked, a  $p(p-1) \times 2$  table
  - Make a list  $H$  containing the last  $k$  pairs that have been picked (references to the rows in the table above)
  - When searching within neighborhood, do not consider those pairs contained in  $H$
  - When found the best pair, remove the first element of  $H$  and add the new pair to the end of  $H$
- `Travel_salesman_tabu.R`

# Tabu additional rules

- **Aspiration** criterion:
  - Allow a tabu move if it is **better than the best** found state so far
  - Allow a tabu move if it gives a **large change**
- **Diversification**
  - Penalize moves to a worse state if such a move has happened many times before
- **Intensification**
  - Reward moves that retain features that have shown to be important earlier
    - Variable selection: If inclusion of component  $j$  correspond to many good solutions, reward moves including this component

# R-Examples

- Baseball model selection
  - Genetic
- Travelling salesperson
  - Greedy
  - Simulated annealing
  - Tabu



- Question: Why do you think I do not show Traveling salesperson example for the genetic algorithm?

# Genetic algorithm baseball salaries

- Salaries for  $n = 337$  baseball players
- $p = 27$  possible covariates,  $2^{27} = 134\,217\,728$  possible models

Covariates are statistics collected during a season

- # runs scored
  - batting average
  - on pace percentage
  - ...
- Genetic algorithm (for model selection)
    - Starting with  $P = 100$  models selected randomly
    - Choose two parents with probabilities proportional to  $\exp(-AIC)$
    - For each component choose the state from one of the parents randomly
    - Allow mutation (change) with probability  $\mu = 0.01$
    - `Baseball_genetic.R`

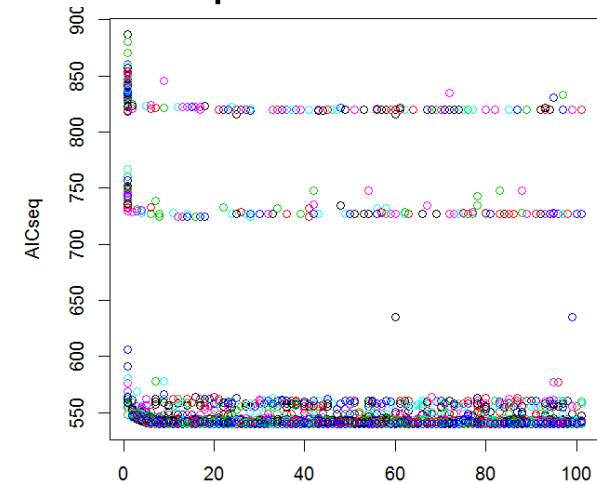


# Genetic algorithm, Baseball \$

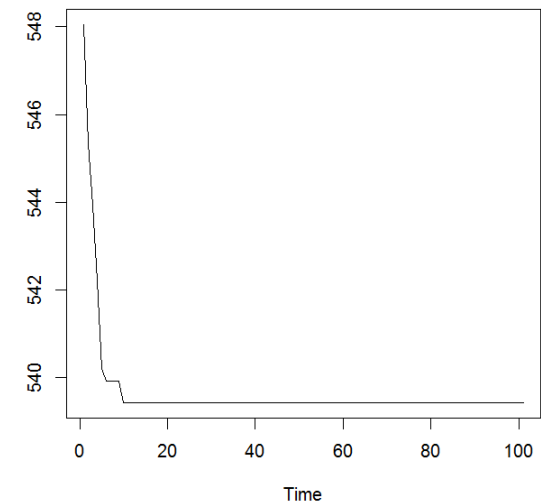
- `Baseball_genetic.R`
- Maximize:  $-AIC$  (model selection criteria)
- $P=100$  (population size)
- Chromosome length  $C=p=27$
- Random initialization
- Select individuals with probability  $\propto \exp(-AIC)$
- Mutation 1% (per locus and individual)
- 100 generations
- Best achieved (first run)
  - $\theta^* = [2 \ 3 \ 6 \ 8 \ 10 \ 13 \ 14 \ 15 \ 16 \ 24 \ 25 \ 26]$
  - $f(\theta^*) = 539.4174$

Other seeds 539.4174, 541.7527

Population fit



Best in generation



```

AICseq = AICfit
more = TRUE
Numit=100
pop.new = pop
AICfit.new = AICfit
mu = 0.01 #Probability for mutation
#Start iteration on updating populations
for(i in 1:Numit)
{
  for(k in 1:P)
  {
    #Selecting parents with probability proportional to exp(-AIC)
    phi1 = exp(-AICfit)
    phi2 = exp(-AICfit)

    #Selecting parents
    parent1 = sample(1:P,1,prob=phi1)
    parent2 = sample(1:P,1,prob=phi2)

    #Sampling independently which parent to inherit from
    bred = sample(1:2,p,replace=T)
    pop.new[k,bred==1] = pop[parent1,bred==1]
    pop.new[k,bred==2] = pop[parent2,bred==2]

    #Mutation
    ind2 = sample(0:1,p,replace=T,prob=c(1-mu,mu))
    if(sum(ind2)>0)
      pop.new[k,ind2==1] = 1-pop.new[k,ind2==1]

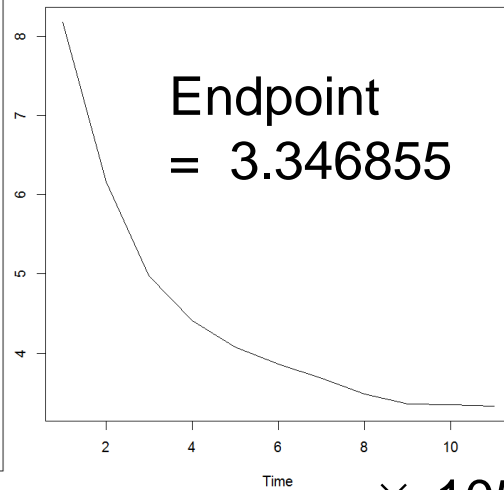
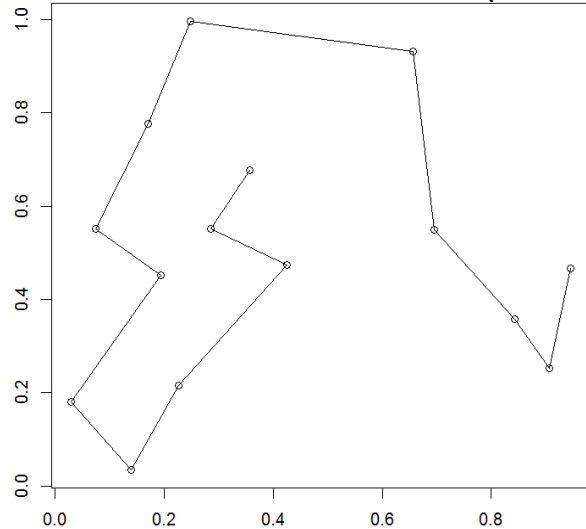
    #Extract only those components that are selected
    ind = c(1:p)[pop.new[k,]==1]
    base2 = baseball[,c(1,1+ind)]
    #Fit the new model
    AICfit.new[k] = AIC(lm(log(salary)~.,data=base2))
  }
  pop = pop.new
  AICfit = AICfit.new
  AICseq = rbind(AICseq,AICfit)
}

```

# Greedy TS

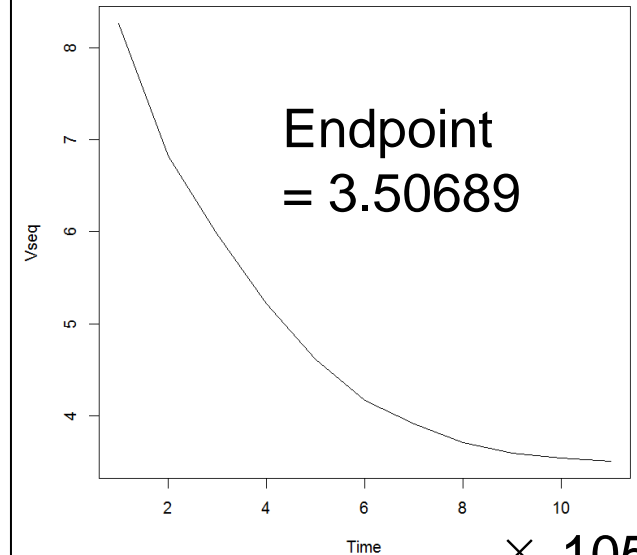
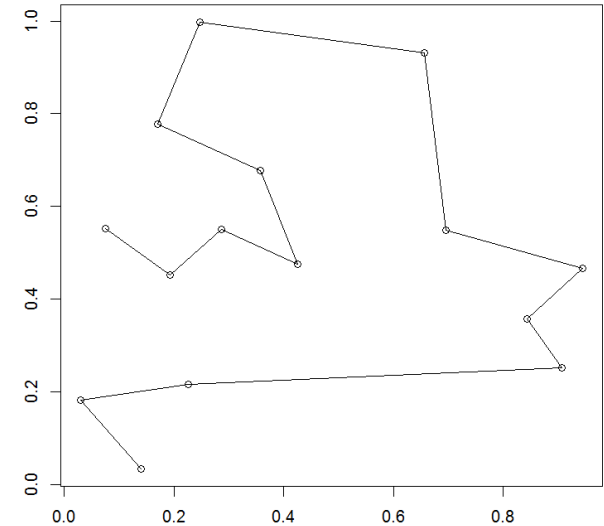
- Random initialization
- Compare all pairs of swap ( $\frac{p \cdot (p-1)}{2}$ )
- Select the best
- Continue until no improvement

Seed= 232323 (NB keep same points )



× 105

Seed=2323



× 105

# Greedy TS (Local search)

```

1 #Simulate positions for n=15 cities
2 set.seed(2323)
3 p = 15
4 pos = data.frame(x=runif(p),y=runif(p))
5
6 par(mfrow=c(1,1))
7 plot(pos)
8 #dev.copy2pdf(file="../doc/example_tra
9
10 #par(mfrow=c(3,1))
11 plot(pos)
12
13 #Calculate pairwise distances between
14 d = as.matrix((dist(pos,diag=TRUE,upper=TRUE)))
15 #image(d)
16
17 #Convert to vector in order to access
18 d = as.vector(d)
19
20 #Random order of visits
21 theta = sample(1:p,p)
22 #Convert sequential pairs into index
23 ind = (theta[-p]-1)*p+theta[-1] # local search
24 #Calculate total distance of order
25 v = sum(d[ind])
26 vseq = v

```

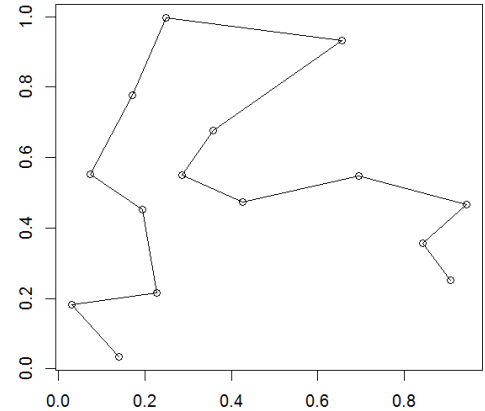
```

#Perform neighbor search, changing best two components
more = TRUE
while(more)
{
  v2opt = v
  i1opt = NA
  # loop below determines the best pair to swap
  for(i1 in 1:(p-1))
    for(i2 in (i1+1):p)
    {
      theta2 = theta
      theta2[i1] = theta[i2]
      theta2[i2] = theta[i1]
      ind2 = (theta2[-p]-1)*p+theta2[-1]
      v2 = sum(d[ind2])
      if(v2<v2opt)
      {
        v2opt = v2
        i1opt = i1
        i2opt = i2
      }
    }
  more = FALSE
  if(v2opt<v) ## if the best swap is better than current optimum update and continue
  {
    theta2 = theta
    theta2[i1opt] = theta[i2opt]
    theta2[i2opt] = theta[i1opt]
    theta = theta2
    v = v2opt
    vseq = c(vseq,v)
    more = TRUE
  }
}

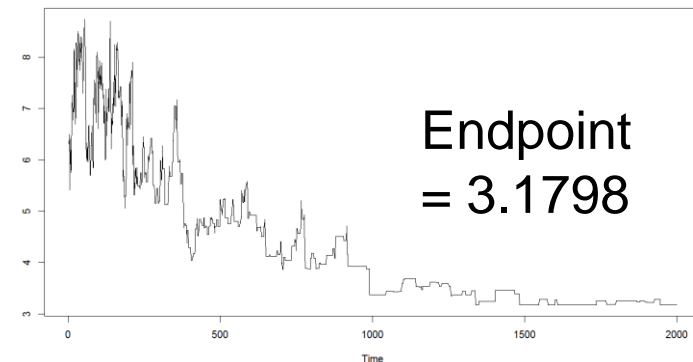
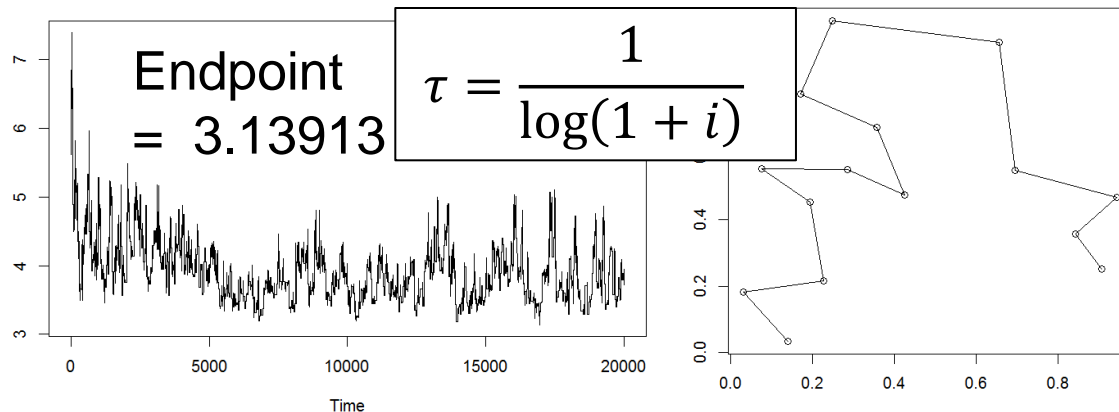
```

# Simulated annealing TS

- Random initialization , evaluate  $V^{(0)}$
- For each iteration draw a random pairs among  $\binom{p \cdot (p-1)}{2}$  possible
- Evaluate proposal gives value  $V^p$
- Temperature  $100/i$  or  $\frac{1}{\log(1+i)}$ ,  $m = 1$
- Accept if improvement or with probability  $\exp((V^{(t)} - V^p)/\tau)$
- Iterate a fixed number of times (50000) NB  
do not loop all pairs in one update



$$\tau = \frac{100}{i}$$



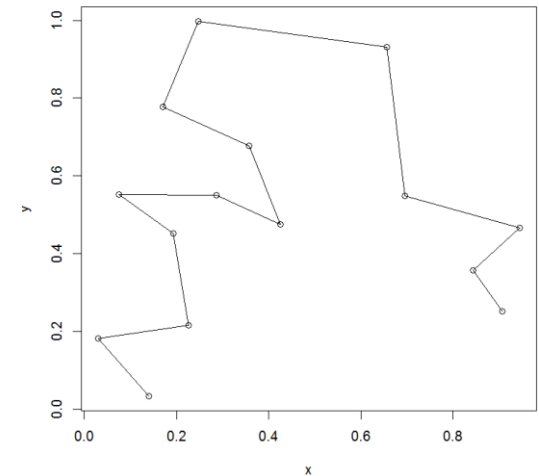
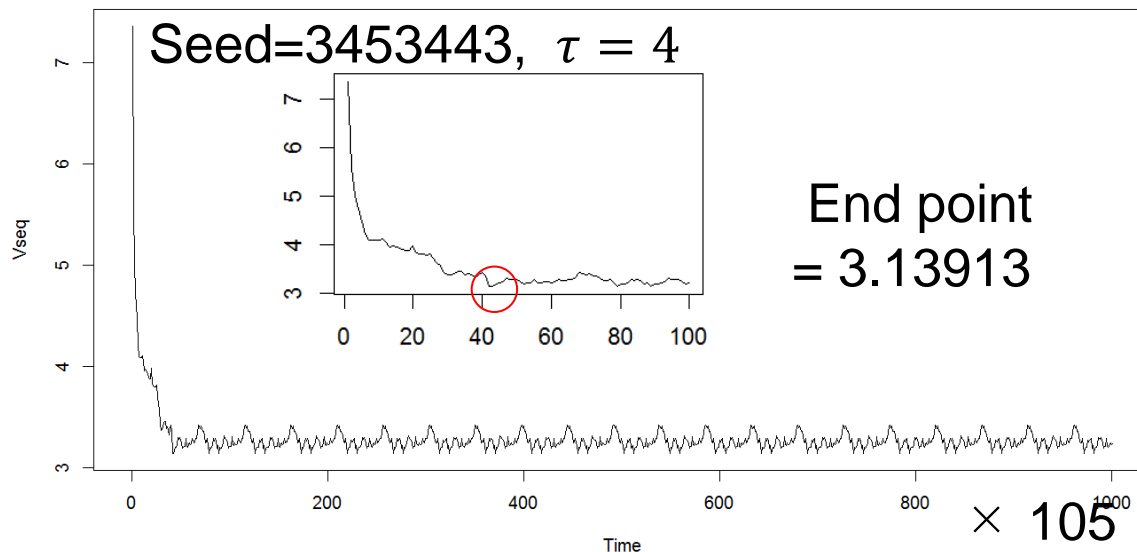
# Simulated annealing TS

```
28 Numit= 20000
29 for(i in 1:Numit)
30 {
31   tau = 100/i
32   #tau = 1/log(i+1)
33   ind2 = sample(1:p,2,replace=F)
34   theta2 = theta
35   theta2[ind2[1]] = theta[ind2[2]]
36   theta2[ind2[2]] = theta[ind2[1]]
37   ind2 = (theta2[-p]-1)*p+theta2[-1]
38   v2 = sum(d[ind2])
39   prob = exp((V-v2)/tau)
40   u = runif(1)
41   if(u<prob)
42   {
43     theta = theta2
44     V = v2
45   }
46   vseq = c(vseq,v)
47 }
```

# TABU TS

- Random initialization
- Compare all pairs of swap ( $\frac{p \cdot (p-1)}{2}$ ), except the four last  $\tau = 4$
- Build TABU list gradually to max size ( $\tau = 4$ ).
- Remove FIFO when exceeding max size
- Select the best on the list
- Store the best so far
- Iterate a fixed number of times (1000)

Seed	tau	Value	First occur.
2323	4	3.5068	11
2323	10	3.1391	359
232323	4	3.2979	10
232323	10	3.1391	915
3453443	4	3.1391	42
3453443	10	3.1391	22



× 10<sup>5</sup>

```
#Perform neighbor search, changing best two components
more = TRUE
tabu = NULL
H = NULL
tau = 10
#while(more)
for(it in 1:10000)
{
  v2opt = v+1000 #Just to get some initial value to beat
  i1opt = NA
  for(i in 1:num)
  {
    if(is.na(pmatch(i,H)))
    {
      #Find indices to swap
      i1 = searchtab[i,1]
      i2 = searchtab[i,2]
      #Swap components, put into theta2
      theta2 = theta
      theta2[i1] = theta[i2]
      theta2[i2] = theta[i1]
      #Calculate value for new configuration
      ind2 = (theta2[-p]-1)*p+theta2[-1]
      v2 = sum(d[ind2])
      #If best so far, store it
      if(v2<v2opt)
      {
        v2opt = v2
        iopt = i
        i1opt = i1
        i2opt = i2
      }
    }
  }
  #Change to best configuration found
  theta2 = theta
  theta2[i1opt] = theta[i2opt]
  theta2[i2opt] = theta[i1opt]
  theta = theta2
  v = v2opt
  vseq = c(vseq,v)
  #Include the swap in TABU table
  H = c(H,iopt)
  #If table is too large, remove first element (oldest swap)
  if(length(H)>tau)
    H = H[-1]
  #Check if better than best so far
  if(v < vopt)
  {
    theta.opt = theta
    vopt = v
  }
}
```