

# Arthur Charpentier

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<https://freakonometrics.github.io/>

Université Rennes 1, 2017

# Graphs, Networks & Flows # 1



## Travelling Salesman Problem

Consider 5 cities,

```

1 > v=c("Rennes","Paris","Lyon","Marseille",
      "Toulouse")
2 > x=c(-1.6742900,2.348800,4.846710,
      5.38107,1.443670)
3 > y=c(48.1119800,48.853410,45.748460,
      43.29695,43.604260)
4 > library(maps)
5 > france<-map(database="france",col="grey")
6 > points(x,y,pch=19,cex=2,col="red")
7 > text(x,y,v,pos=3,col="red")

```



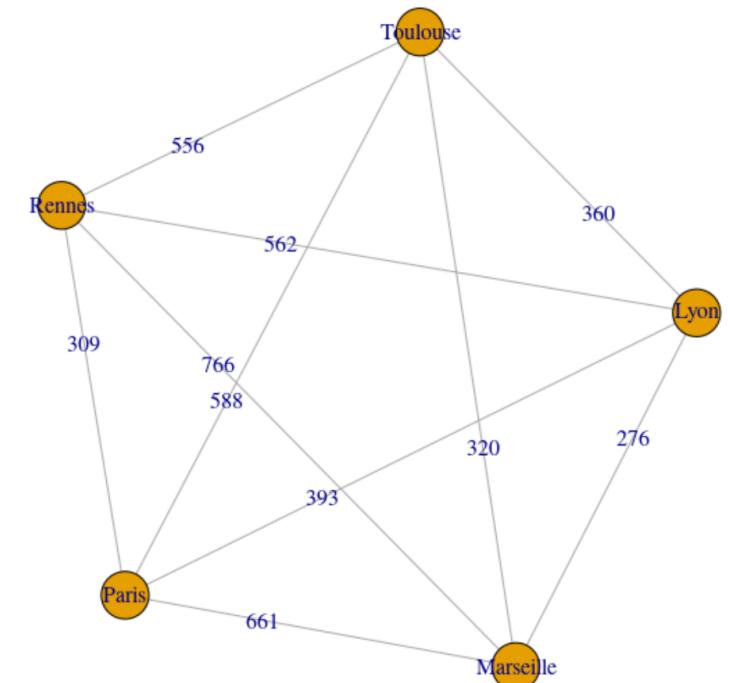
It can also be seen as a complete weighted graph.

## Travelling Salesman Problem

```

1 > df=data.frame(name=v,lat=y,lon=x,index
=1:5)
2 > D=round(GeoDistanceInMetresMatrix(df) /
1000)
3 > library(igraph)
4 > i=c(rep(1,4),rep(2,3),rep(3,2),4)
5 > j=c(2:5,3:5,4:5,5)
6 > df=data.frame(a = i, b=j, w=diag(D[i,j]))
7 > g=graph.data.frame(df, directed=FALSE)
8 > V(g)$label=v
9 > plot(g, edge.label=E(g)$w)

```



What is the path with minimal cost (length) that goes through all cities (and returns back home) ?

## Travelling Salesman Problem

Can be formulated as an [integer linear programming](#) problem. Set  $x_{ij}$  be the dummy variable with value 1 if the path goes from city  $i$  to city  $j$ ,  $u_i$  be some dummy variable, and  $c_{ij}$  denote the distance from city  $i$  to city  $j$ . Consider

$$\begin{aligned}
 & \min \sum_{i=1}^n \sum_{j \neq i, j=1}^n c_{ij} x_{ij} \\
 & 0 \leq x_{ij} \leq 1 \quad i, j = 1, \dots, n; \\
 & u_i \in \mathbf{Z} \quad i = 1, \dots, n; \\
 & \sum_{i=1, i \neq j}^n x_{ij} = 1 \quad j = 1, \dots, n; \\
 & \sum_{j=1, j \neq i}^n x_{ij} = 1 \quad i = 1, \dots, n; \\
 & u_i - u_j + nx_{ij} \leq n - 1 \quad 2 \leq i \neq j \leq n.
 \end{aligned}$$

## Travelling Salesman Problem

Let  $D = [D_{i,j}]$  denote the distance matrix, with  $D_{i,i} = \infty$ ,  $c_{i,j}$  otherwise

	Rennes	Paris	Lyon	Marseille	Toulouse
Rennes	$\infty$	309	562	766	556
Paris	309	$\infty$	393	661	588
Lyon	562	393	$\infty$	276	360
Marseille	766	661	276	$\infty$	320
Toulouse	556	588	360	320	$\infty$

5 cities,  $5! = 24$  possibilities (with assymmetric costs, otherwise 12).

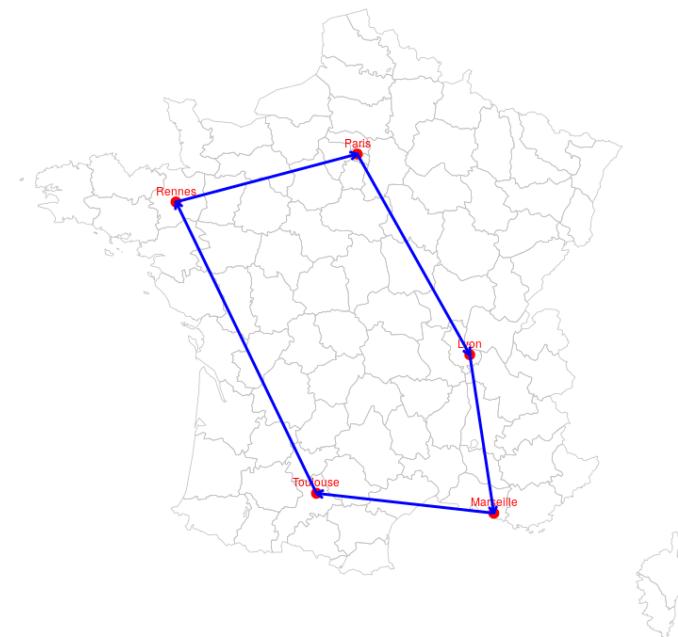
# Travelling Salesman Problem

One can use brute force search

```

1 > library(combinat)
2 > M=matrix(unlist(permn(1:5)), nrow=5)
3 > sM=M[,M[1,]==1]
4 > sM=rbind(sM,1)
5 > traj=function(vi){
6 +   s=0
7 +   for(i in 1:(length(vi)-1)) s=s+D[vi[i],
8 +     vi[i+1]]
8 +   return(s) }
9 > d=unlist(lapply(1:ncol(sM), function(x)
10    traj(sM[,x])))
10 > sM=rbind(sM,d)
11 > sM[,which.min(d)]
12
13      d
14      1      2      3      4      5      1 1854

```



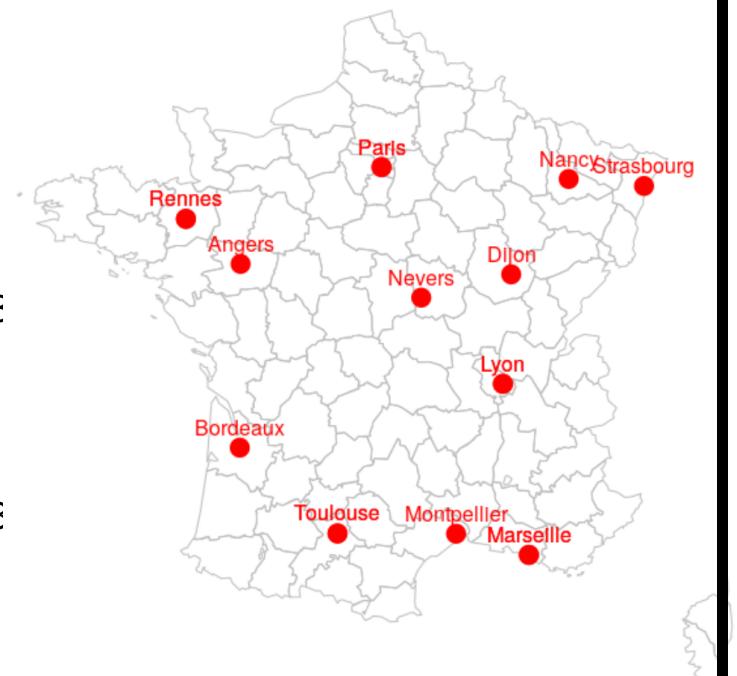
## Travelling Salesman Problem

12 cities,  $12! = 39916800$  possibilities (with assymmetric costs, otherwise 2 millions).

```

1 > v2=c(v,"Strasbourg","Angers","Bordeaux",
  + "Dijon","Nancy","Montpellier", "Nevers")
2 > x2=c(x
  + ,7.75,-0.55,-0.566667,5.016667,6.2,3.883333
3 > y2=c(y
  + ,48.583333,47.466667,44.833333,47.316667,48
  + )

```



## Little Algorithm

Branch and bound, [Little algorithm](#), from Little, Murty, Sweeney & Karel (1963)

An algorithm for the traveling salesman problem

**Step 1** find a lower bound for the total cost

Derive reduced matrix  $\tilde{D}$  by removing to each raw the smallest element

	Rennes	Paris	Lyon	Marseille	Toulouse	
Rennes	$\infty$	0	253	457	247	(-309)
Paris	0	$\infty$	84	352	279	(-309)
Lyon	286	117	$\infty$	0	84	(-276)
Marseille	490	385	0	$\infty$	44	(-276)
Toulouse	236	268	40	0	$\infty$	(-320)

## Little Algorithm

and by removing to each column the smallest element

	Rennes	Paris	Lyon	Marseille	Toulouse	
Rennes	$\infty$	0	253	457	203	(-309)
Paris	0	$\infty$	84	352	235	(-309)
Lyon	286	117	$\infty$	0	40	(-276)
Marseille	490	385	0	$\infty$	0	(-276)
Toulouse	236	268	40	0	$\infty$	(-320)
						(-44)

Again  $D$  can be non-symmetric (and it will be afterwards).

Starting value for the cost:  $309+309+276+276+320+44=1534$

## Little Algorithm

**Step 2:** compute regrets (min on rows and columns)

	Rennes	Paris	Lyon	Marseille	Toulouse	
Rennes	$\infty$	0	253	457	203	(203)
Paris	0	$\infty$	84	352	235	
Lyon	286	117	$\infty$	0	40	
Marseille	490	385	0	$\infty$	0	
Toulouse	236	268	40	0	$\infty$	
		(117)				(320)

## Little Algorithm

	Rennes	Paris	Lyon	Marseille	Toulouse	
Rennes	$\infty$	0 (320)	253	457	203	
Paris	0	$\infty$	84	352	235	(84)
Lyon	286	117	$\infty$	0	40	
Marseille	490	385	0	$\infty$	0	
Toulouse	236	268	40	0	$\infty$	
	(236)					(320)

## Little Algorithm

	Rennes	Paris	Lyon	Marseille	Toulouse	
Rennes	$\infty$	0 (320)	253	457	203	
Paris	0 (320)	$\infty$	84	352	235	
Lyon	286	117	$\infty$	0	40	(40)
Marseille	490	385	0	$\infty$	0	
Toulouse	236	268	40	0	$\infty$	
				(0)		(40)

## Little Algorithm

	Rennes	Paris	Lyon	Marseille	Toulouse
Rennes	$\infty$	0 (320)	253	457	203
Paris	0 (320)	$\infty$	84	352	235
Lyon	286	117	$\infty$	0 (40)	40
Marseille	490	385	0 (40)	$\infty$	0 (40)
Toulouse	236	268	40	0 (40)	$\infty$

Select the maximal regret path (arbitrarily if not unique) : Rennes  $\rightarrow$  Paris (RP).

Consider now two alternatives:

- either we keep (RP)
- either we remove (RP)

## Little Algorithm

If we exclude (RP), the cost is known :  $1534+320=1854$ .

If we include, consider the simplified matrix

	Rennes	Lyon	Marseille	Toulouse
Paris	$\infty$	84	352	235
Lyon	286	$\infty$	0	40
Marseille	490	0	$\infty$	0
Toulouse	236	40	0	$\infty$

Here (PR) is  $\infty$  otherwise, it will be a round trip.

## Little Algorithm

Then derive the reduced matrix

	Rennes	Lyon	Marseille	Toulouse	
Paris	$\infty$	0	268	151	(-84)
Lyon	50	$\infty$	0	40	(0)
Marseille	254	0	$\infty$	0	(0)
Toulouse	0	40	0	$\infty$	(0)
					(-236)

Total (reduction) cost is  $84+236=320$ .

## Little Algorithm

And again, compute regrets

	Rennes	Lyon	Marseille	Toulouse
Paris	$\infty$	0 (151)	268	151
Lyon	50	$\infty$	0 (40)	40
Marseille	254	0 (0)	$\infty$	0 (40)
Toulouse	0 (50)	40	0 (0)	$\infty$

The maximal regret path is Paris → Lyon (PL). Consider now two alternatives:

- either we keep (PL)
- either we remove (PL) : cost will be  $1534+320+151=1725$

If we include, consider the simplified matrix (with possibly  $\infty$  for (LP))

## Little Algorithm

	Rennes	Marseille	Toulouse
Lyon	50	0	40
Marseille	254	$\infty$	0
Toulouse	0	0	$\infty$

Note that this matrix cannot be simplified, here.

	Rennes	Marseille	Toulouse	
Lyon	50	0	40	(0)
Marseille	254	$\infty$	0	(0)
Toulouse	0	0	$\infty$	(0)
	(0)	(0)	(0)	

So the total cost if we keep (RL) is  $1534+320=1584$

## Little Algorithm

Then compute regrets

	Rennes	Marseille	Toulouse
Lyon	50	0 (40)	40
Marseille	254	$\infty$	0 (294)
Toulouse	0 (50)	0 (0)	$\infty$

The maximal regret path is Marseille → Toulouse (MT)

Consider now two alternatives:

- either we keep (MT)
- either we remove (MT) : cost will be 1854+294

If we include, consider the simplified matrix (with  $\infty$  for (TM))

	Rennes	Marseille
Lyon	50	0
Toulouse	0	$\infty$

Here again no simplification. The regret matrix is

	Rennes	Marseille
Lyon	50	0 (50)
Toulouse	0 (50)	$\infty$

The maximal regret path is Lyon → Marseille (LM)

Consider now two alternatives:

- either we keep (MT): cost will be 1854+0
- either we remove (MT) : cost will be 1854+50

## Little Algorithm

Here we have constructed a [search tree](#).

[click to visualize the construction](#)

[click to visualize the construction](#)

**Remark** This is an exact algorithm

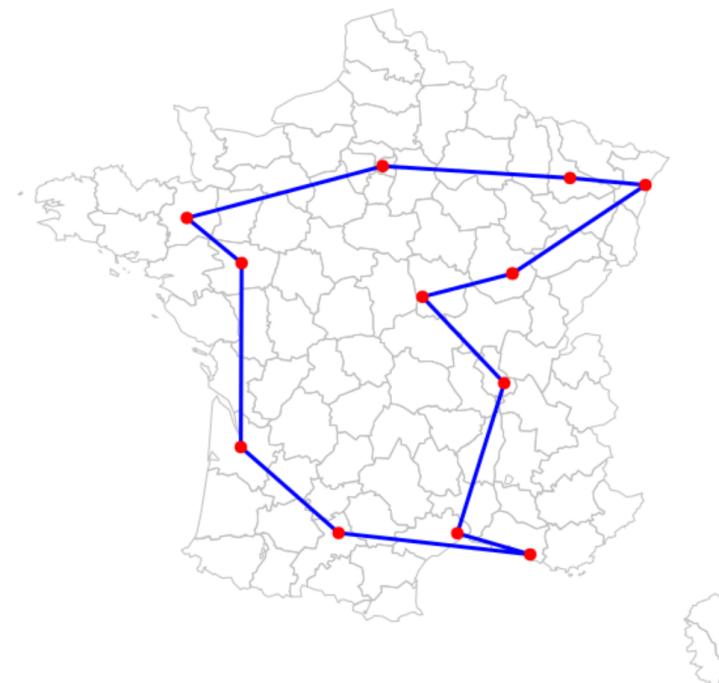
## Travelling Salesman

Exact algorithms are usually extremely slow. For Little Algorithm, the maximal number of nodes, with  $n$  cities, is of order  $N_n$  with  $N_n = (n - 1)[1 + N_{n-1}]$  (with is of order  $n!$ ).

```

1 > library(TSP)
2 > df2=data.frame(name=v2,lat=y2,lon=x2,index
   =1:12)
3 > D2=round(GeoDistanceInMetresMatrix(df2) /
   1000)
4 > listeFR=TSP(D2,v2)
5 > tour=solve_TSP(listeFR, method = "nn")
6 > COORD=df2[,as.numeric(tour),]
7 > COORD=rbind(COORD,COORD[1,])
8 > france<-map(database="france",col="grey")
9 > lines(COORD$lon,COORD$lat,lwd=3,col="blue"
   )

```



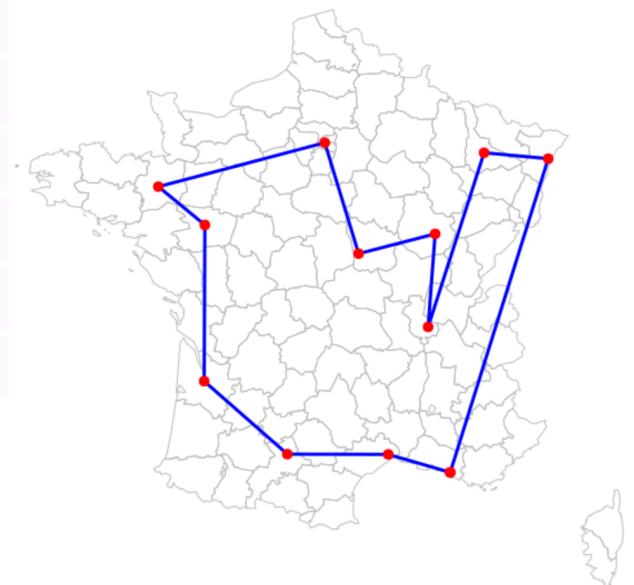
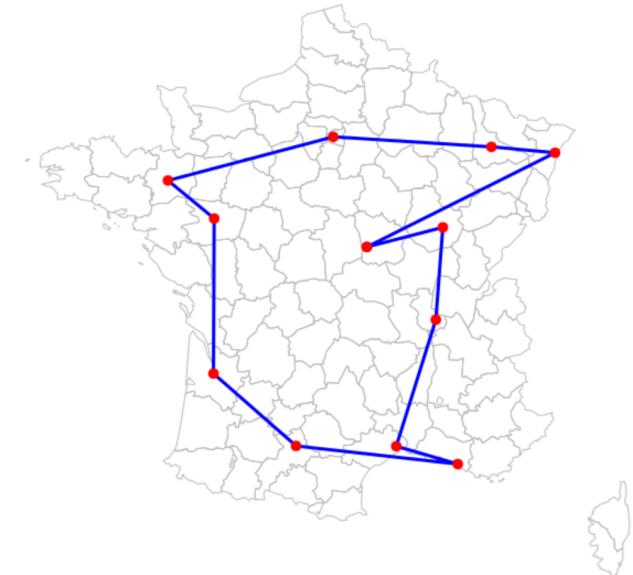
## Travelling Salesman

```

1 > tour=solve_TSP(listeFR, method = "nn")
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7 > tour=solve_TSP(listeFR, method = "nn")
8 > COORD=df2[,as.numeric(tour),]
9 > COORD=rbind(COORD,COORD[1,])
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```

It is not stable... local optimization?

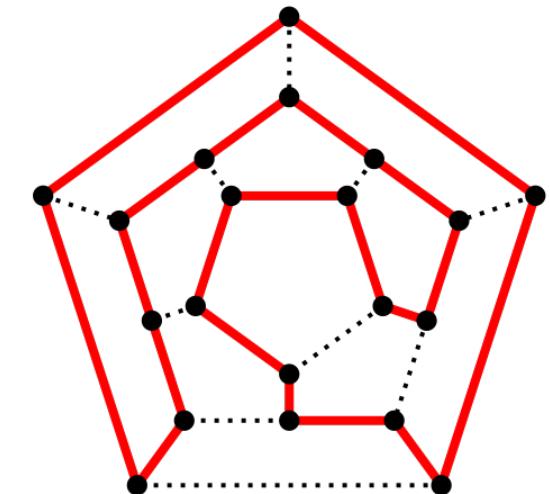


## Travelling Salesman

Historically, introduced by William Rowan Hamilton in the context of dodecahedrons.

A [Hamiltonian path](#) is a path in a graph that visits each vertex exactly once

Done with  $n = 20$  cities (regular algebraic structure)



Dantzig, Fulkerson & Johnson (1954) [Solution of a large-scale traveling-salesman problem](#) with  $n = 49$  cities (US State capitals)

In 2000, it was performed on  $n = 15,000$  cities, nowadays close to 2 million.

See also Applegate *et al.* (2006) [The traveling salesman problem: a computational study](#).

## Stochastic Algorithm

One can use a [Greedy Algorithm](#)

Heuristically, makes locally optimal choices at each stage with the hope of finding a global optimum.

[nearest neighbour](#), “*at each stage visit an unvisited city nearest to the current city*”

- (1) start on an arbitrary vertex as current vertice.
- (2) find out the shortest edge connecting current vertice and an unvisited vertice  $v$ .
- (3) set current vertice to  $v$ .
- (4) mark  $v$  as visited.
- (5) if all the vertices in domain are visited, then terminate.
- (6) Go to step 2.

[click to visualize the construction](#)

## Stochastic Algorithm

E.g. descent algorithm, where we start from an initial guess, then consider at each step one vertex  $s$ , and in the neighborhood of  $s$ , denoted  $V(s)$  search

$$f(s^*) = \min_{s' \in V(s)} \{f(s')\}$$

If  $f(s^*) < f(s)$  then  $s = s^*$ .

See Lin (1965) with 2 opt or 3 opt, see also Lin & Kernighan (1973) An Effective Heuristic Algorithm for the Traveling-Salesman Problem

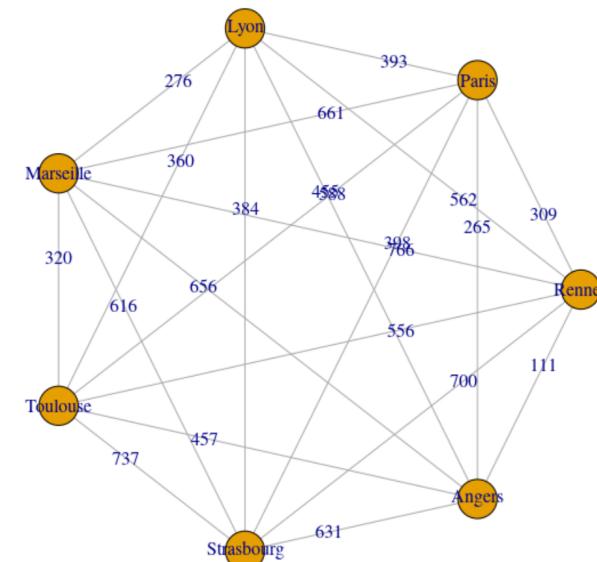
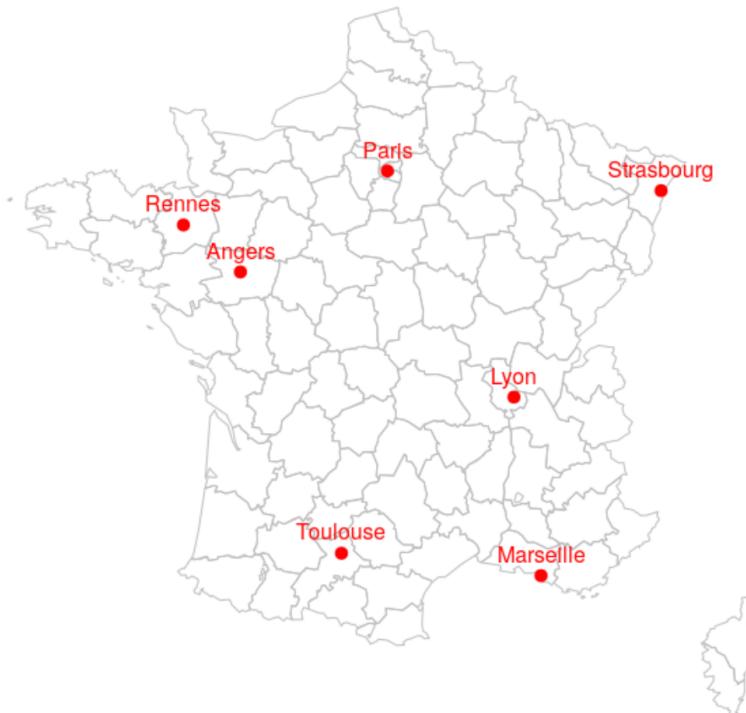
The pairwise exchange or 2-opt technique involves iteratively removing two edges and replacing these with two different edges that reconnect the fragments created by edge removal into a new and shorter tour.

[click to visualize the construction](#)

## Spanning Algorithm

Kruskal's algorithm is a minimum-spanning-tree algorithm, see Kruskal (1956)

On the shortest spanning subtree of a graph and the traveling salesman problem



## Spanning Algorithm

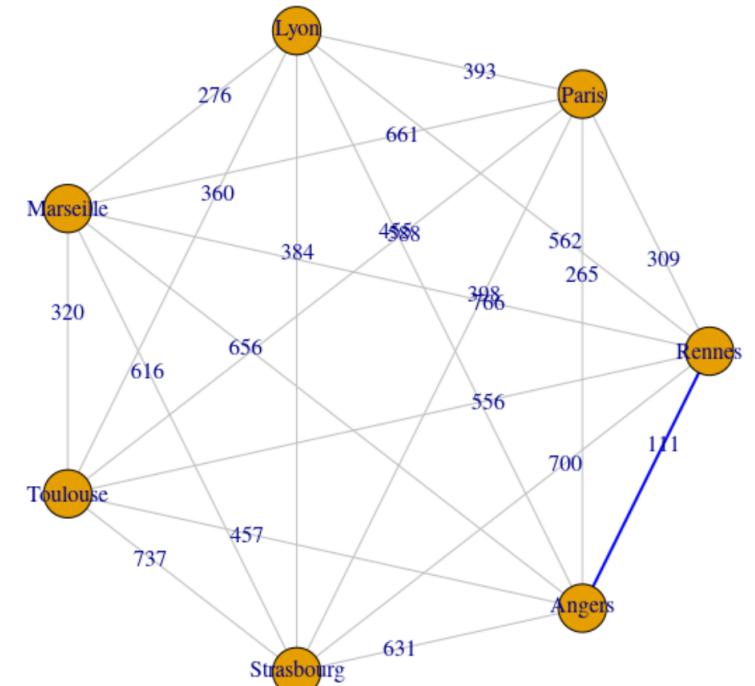
Select edge  $e = (u, v) \in E$  which minimizes  $\omega_\epsilon$ ,

$$e = \operatorname{argmin}_{\epsilon \in E} \{\omega_\epsilon\}$$

Then remove  $e$  from the set of electible edges

$$\mathcal{E} = E \setminus \{e\}$$

and mark that edge  $\mathcal{F} = \{e\}$



## Spanning Algorithm

Select edge  $e = (u, v) \in \mathcal{E}$  which minimizes  $\omega_e$ ,

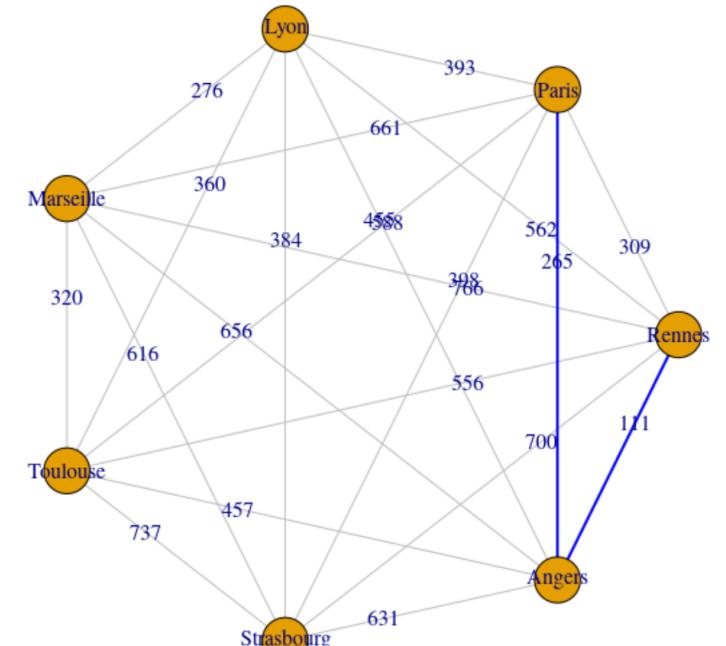
$$e = \operatorname{argmin}_{\epsilon \in \mathcal{E}} \{\omega_\epsilon\}$$

Then remove  $e$  from the set of electible edges

$$\mathcal{E} = \mathcal{E} \setminus \{e\}$$

and mark that edge  $\mathcal{F} = \mathcal{F} \cup \{e\}$

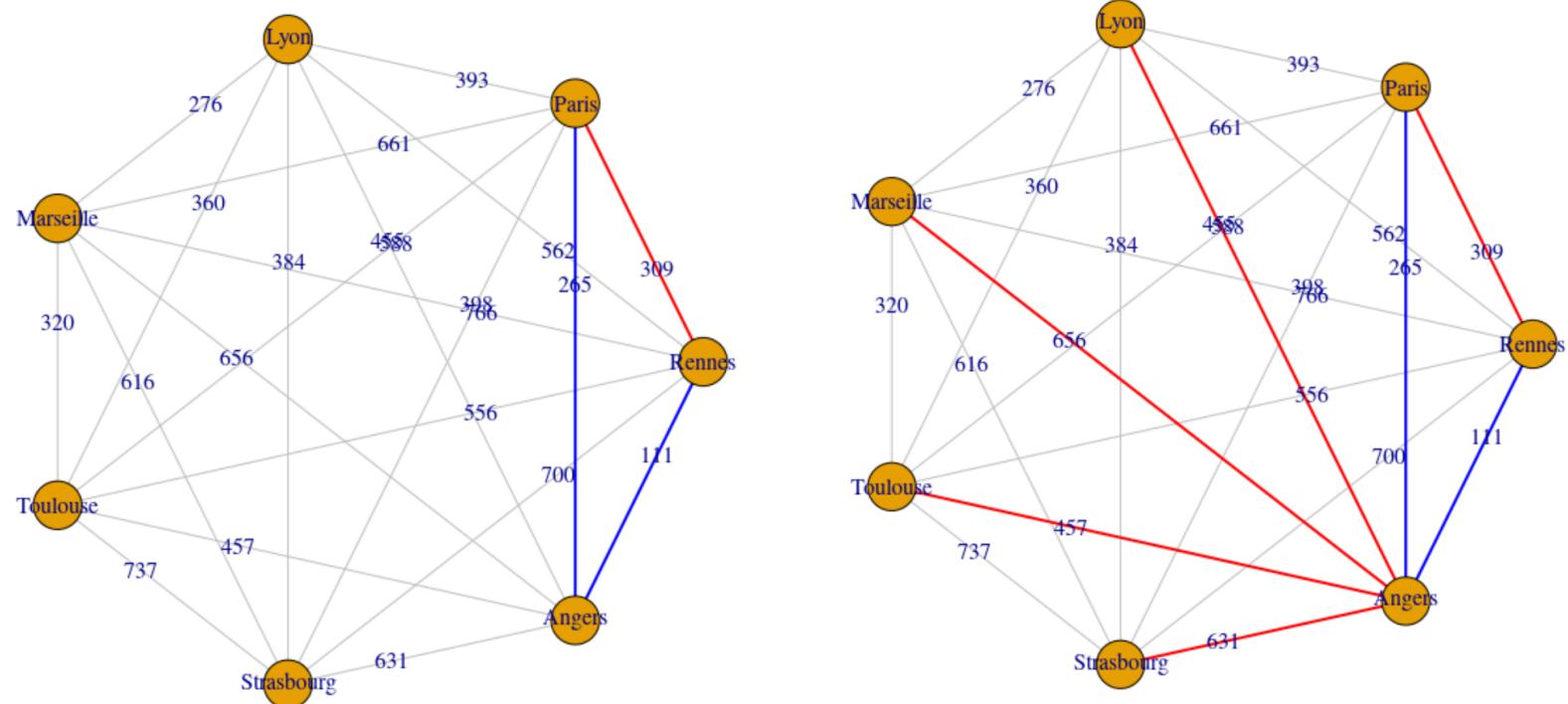
If the minima is not unique, choose randomly



## Spanning Algorithm

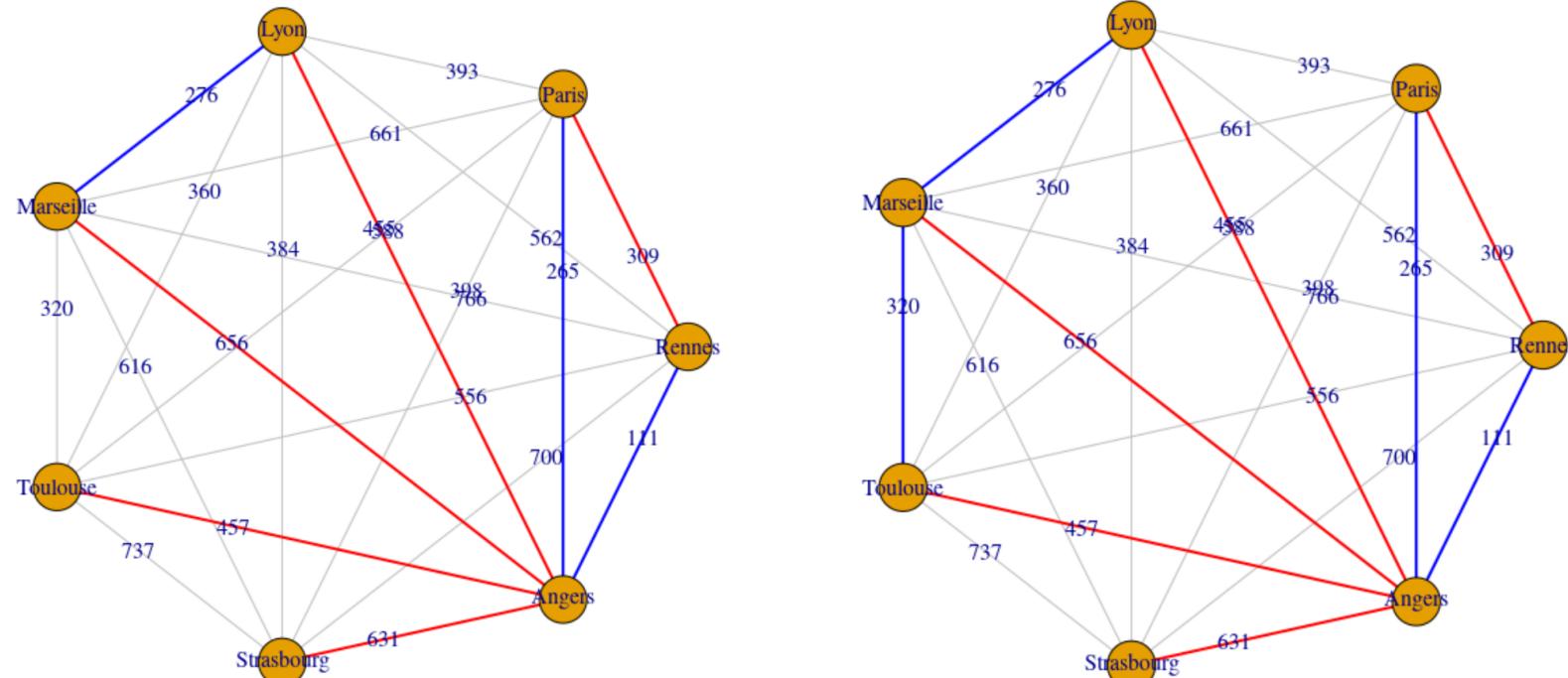
$\mathcal{E} = \mathcal{E} \setminus \{E_1 \cup E_2\}$  where we remove

- all edges  $E_1$  such that  $\mathcal{E} \cup E_1$  contains a cycle (here Rennes-Paris)
- all edges from a node that appears twice in  $\mathcal{E}$  (here all edges connected to Angers)



## Spanning Algorithm

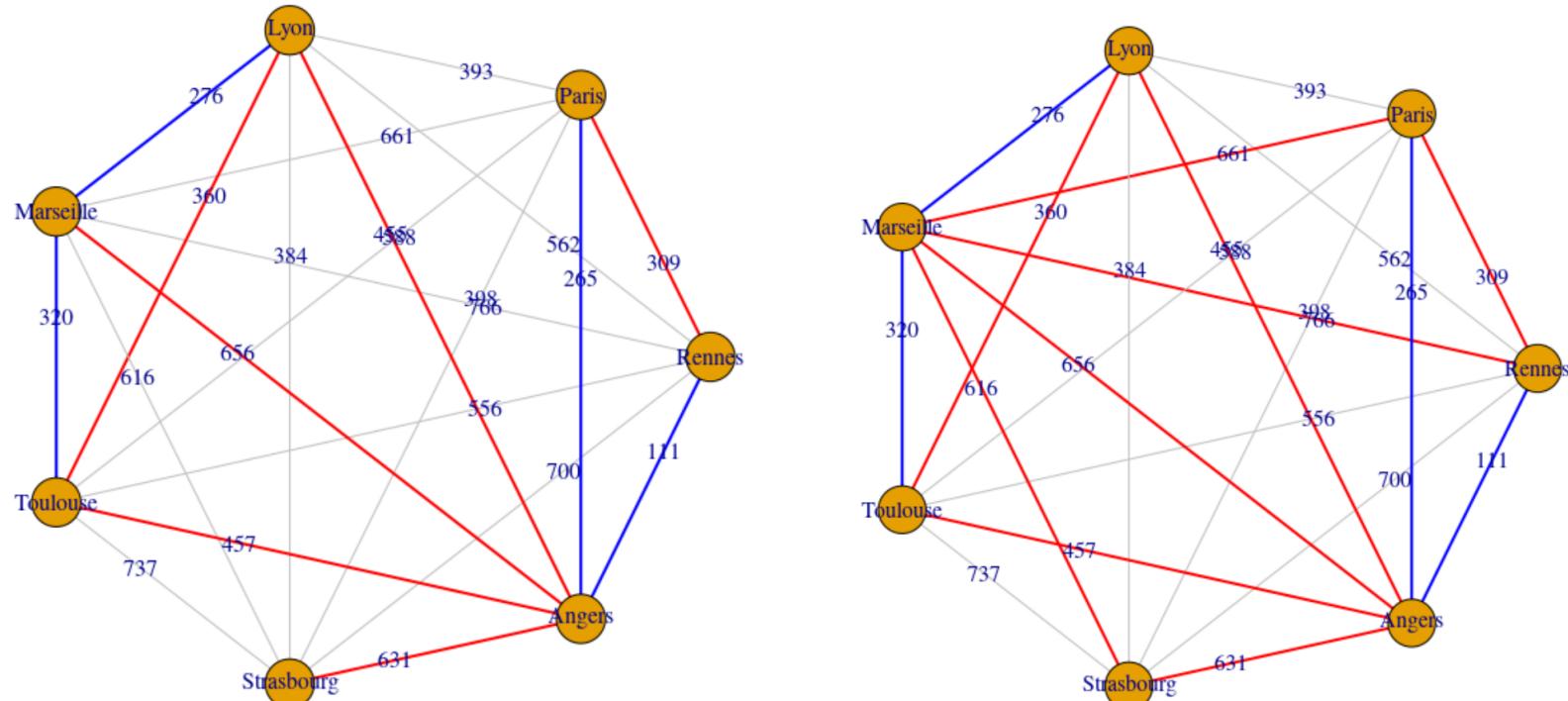
As long as there are no cycle, set  $e = \operatorname{argmin}_{e \in \mathcal{E}} \{\omega_e\}$  and then remove  $e$  from the set of electible edges  $\mathcal{E} = \mathcal{E} \setminus \{e\}$ , and mark those  $\mathcal{F} = \mathcal{F} \cup \{e\}$



# Spanning Algorithm

Here again remove

- all edges  $E_1$  such that  $\mathcal{E} \cup E_1$  contains a cycle (here Rennes-Paris)
- all edges from a node that appears twice in  $\mathcal{E}$  (here all edges connected to Angers)



## Spanning Algorithm

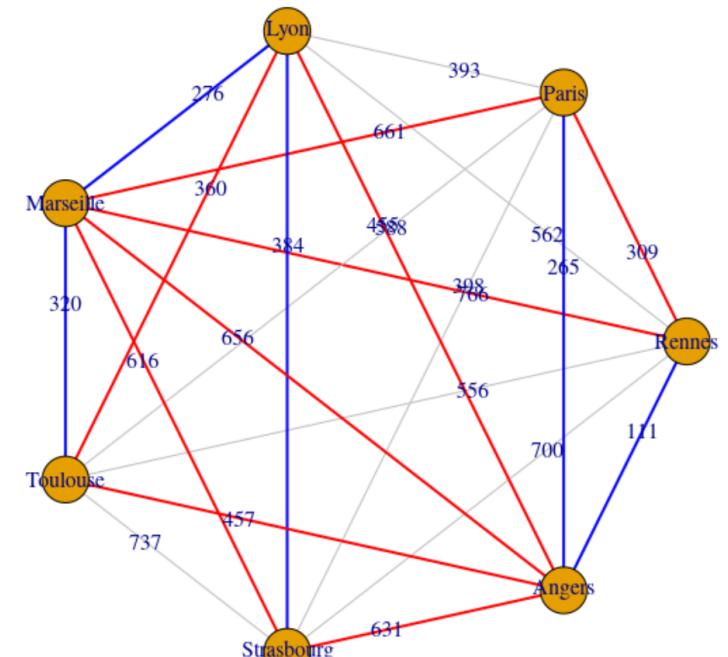
Select edge  $e = (u, v) \in \mathcal{E}$  which minimizes  $\omega_e$ ,

$$e = \operatorname{argmin}_{\epsilon \in \mathcal{E}} \{\omega_\epsilon\}$$

Then remove  $e$  from the set of electible edges

$$\mathcal{E} = \mathcal{E} \setminus \{e\}$$

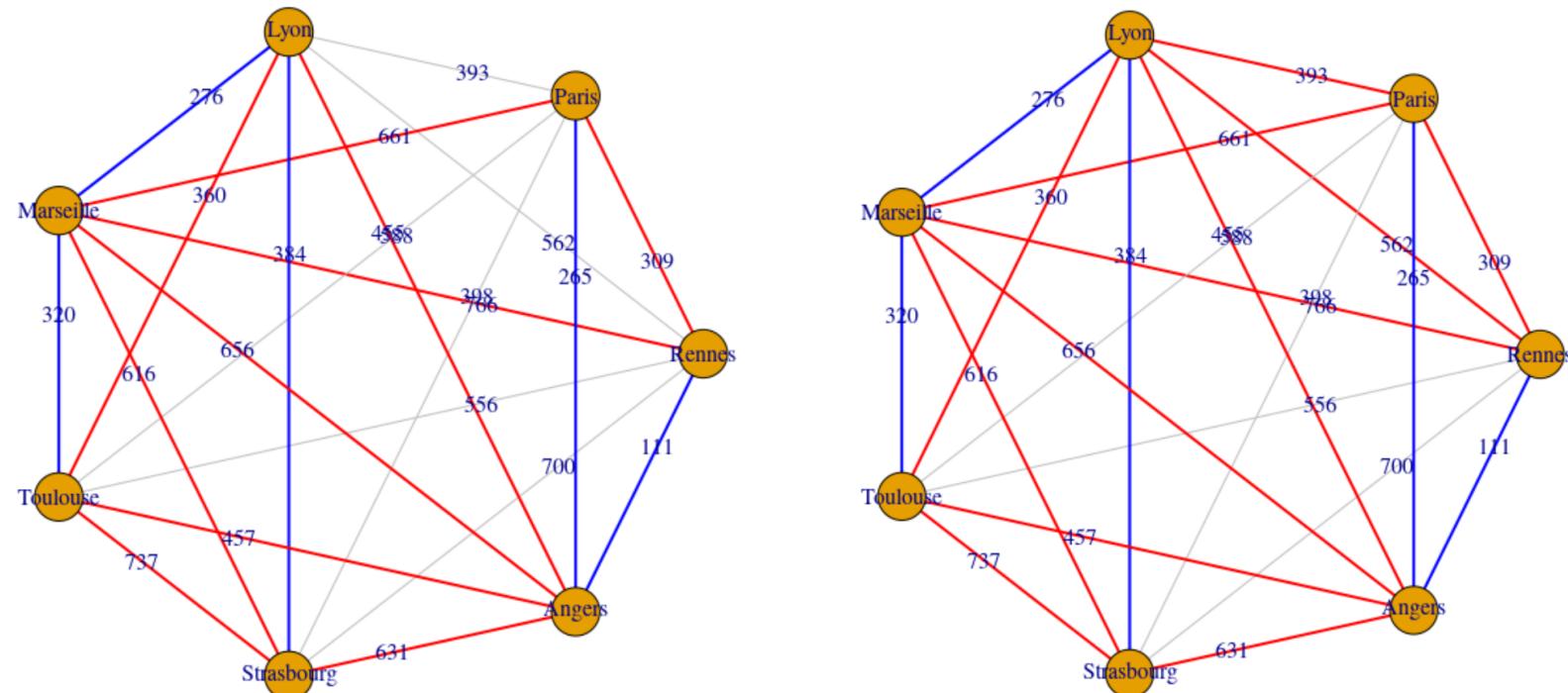
and mark it  $\mathcal{F} = \mathcal{F} \cup \{e\}$



# Spanning Algorithm

Remove

- all edges  $E_1$  such that  $\mathcal{E} \cup E_1$  contains a cycle (here Rennes-Paris)
- all edges from a node that appears twice in  $\mathcal{E}$  (here all edges connected to Angers)



## Spanning Algorithm

Select edge  $e = (u, v) \in \mathcal{E}$  which minimizes  $\omega_\epsilon$ ,

$$e = \operatorname{argmin}_{\epsilon \in \mathcal{E}} \{\omega_\epsilon\}$$

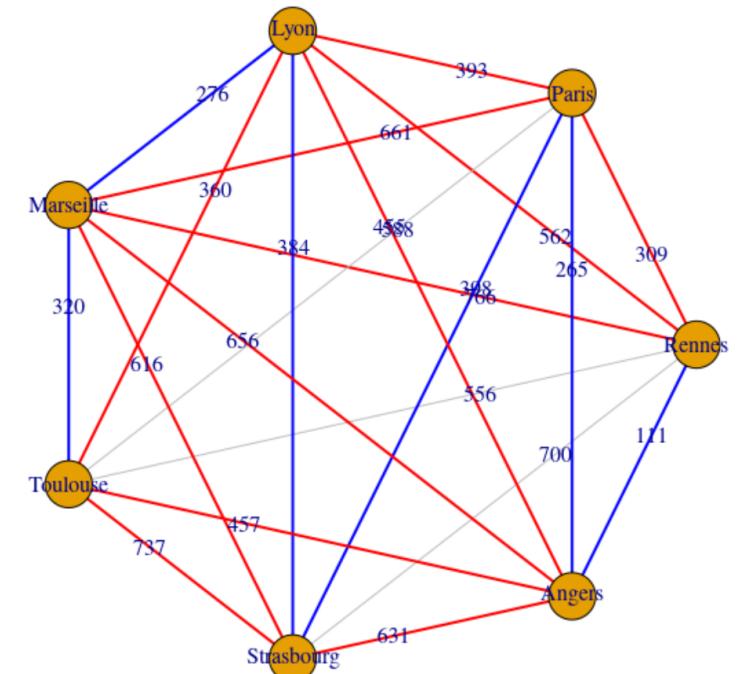
Then remove  $e$  from the set of electible edges

$$\mathcal{E} = \mathcal{E} \setminus \{e\}$$

and mark it  $\mathcal{F} = \mathcal{F} \cup \{e\}$

Here  $e = \text{Strasbourg-Paris}$

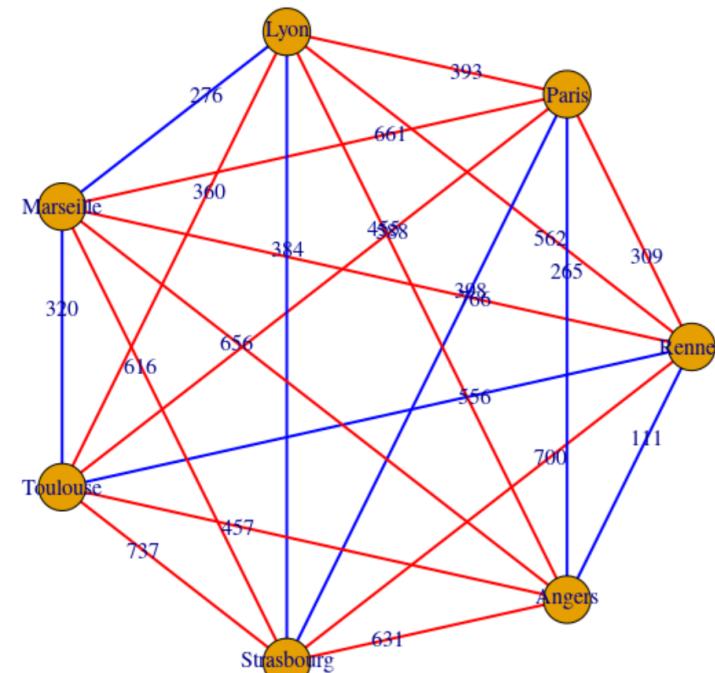
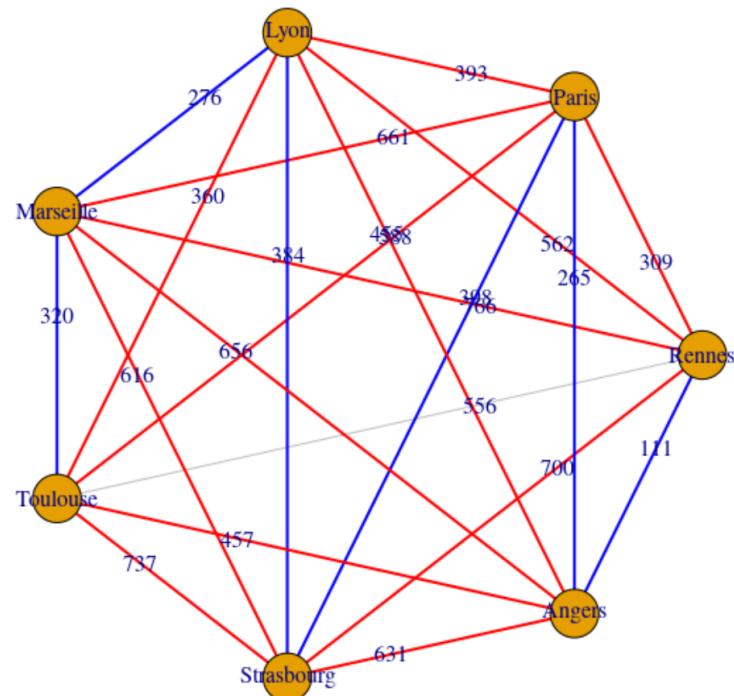
If the minima is not unique, choose randomly



# Spanning Algorithm

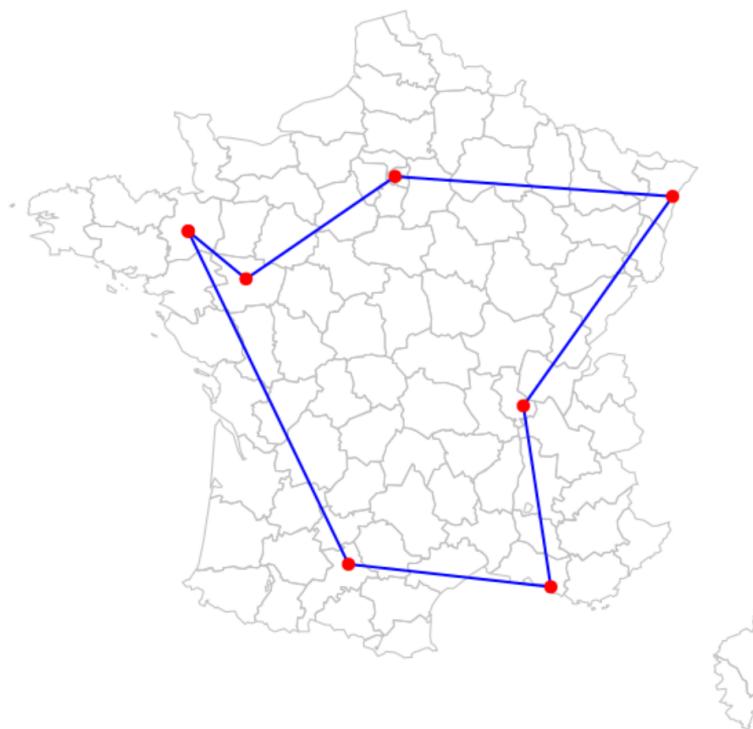
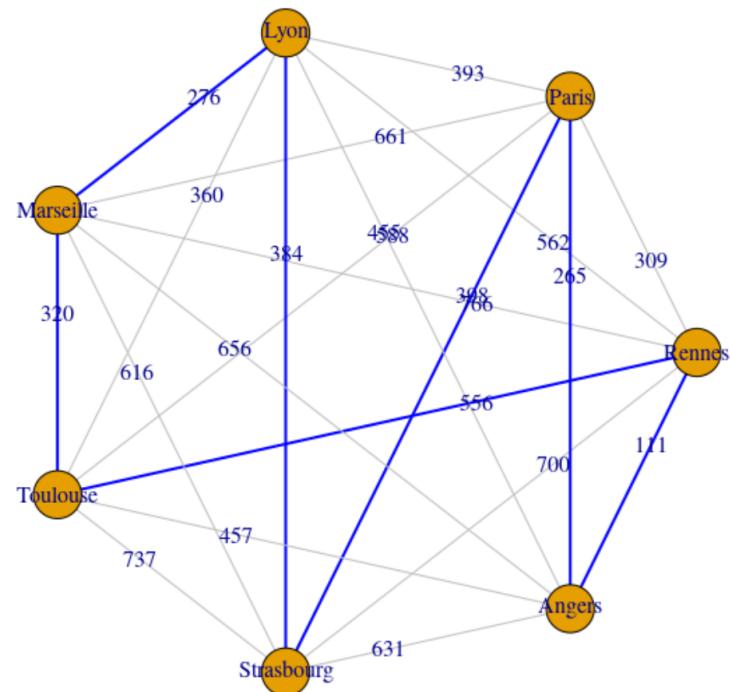
Last but not least, remove

- all edges  $E_1$  such that  $\mathcal{E} \cup E_1$  contains a cycle (here Rennes-Paris)
- all edges from a node that appears twice in  $\mathcal{E}$  (here all edges connected to Angers)



## Spanning Algorithm

The collection of edges that were marked in  $\mathcal{F}$  is our best cycle.



## Christofides Algorithm

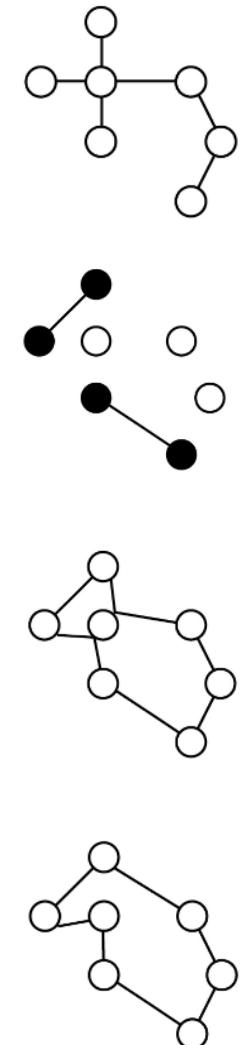
Use a spanning algorithm (as in Kruskal algorithm)  $G = (V, E)$  but allow for vertices to have more than 2 incident edges.

Let  $V_1$  denote the set of vertices with **odd degree**, and let  $G_1 = (V_1, E_1)$  denote the induced subgraph of  $G = (V, E)$ .

Find a **perfect coupling**  $G'_1$  of  $G_1$  (discussed in the next course).

Consider graph  $G'$  with vertices  $V$  and edges  $E \cup E'_1$ .

If there are still vertices  $v$  with degree exceeding 2, consider shortcuts i.e.  $(u, v)$  and  $(v, w)$  becomes  $(u, w)$ .

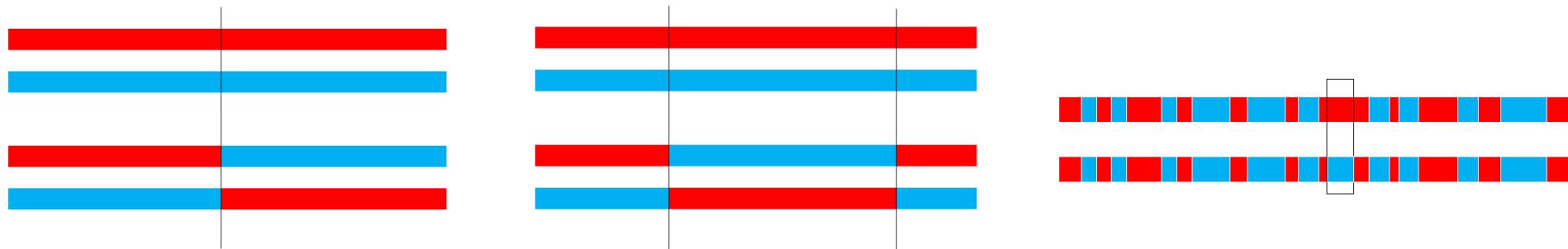


## Genetic Algorithm

See Potvin (1996) Genetic algorithms for the traveling salesman problem

Mutation can be used to diversify solutions by alteringating (randomly) an individual (possibly bit string)

Cross-Over is obtained by mixing two individuals (single point or two points)



## Travelling Salesman

Can be performed on a (much) larger scale  
e.g. 48 State capitals in mainland U.S.

see Cook (2011) [In Pursuit of the Traveling Salesman](#)  
for a survey.

