

# Computer Course Linear Programming Introduction to Gurobipy



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Technical University of Munich



# **Organizational Things**



#### What to expect

#### What this course offers:

- praxis-oriented introduction to python and gurobipy
- lots of examples
- preparation for further lectures, case studies and theses

#### What this course does not offer:

- detailed installation instructions
- ▶ the time needed to become an expert in python and gurobipy



#### Schedule

- ► Wednesday:
  - ► Introduction to Python
  - ► Introduction to Gurobi
- ► Thursday:
  - Features Python (advanced input and output methods)
  - Features Gurobi (advanced variable types and output interpretation)



#### **Schedule**

- 10:15 first slot
- 11:45 lunch break
- 13:15 second slot
- 14:45 coffee break
- 15:15 third slot



#### Work in teams!



#### **Outlook**



Structure of Gurobi

Basics

Linear Programming

Modelling

Output Interpretation

Advanced Input Methods

Advanced Gurobi Datatypes

Visualization



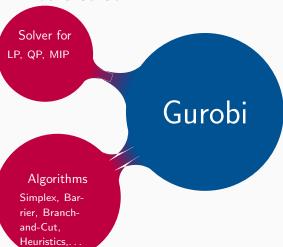
# Structure of Gurobi



# What is Gurobi? Solver for LP, QP, MIP Gurobi



#### What is Gurobi?





#### What is Gurobi?

Solver for LP, QP, MIP

# Gurobi

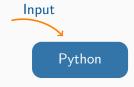
Algorithms

Simplex, Barrier, Branchand-Cut, Heuristics,... Features
Parameters,
Datatypes, . . .



# What is Gurobi? Solver for Interfaces LP, QP, MIP Python, c++, Java, matlab, Gurobi Algorithms **Features** Simplex, Bar-Parameters, rier, Branch-Datatypes, ... and-Cut, Heuristics,...





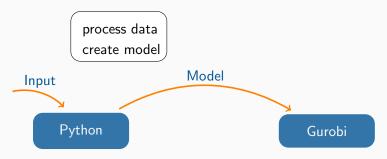


process data create model

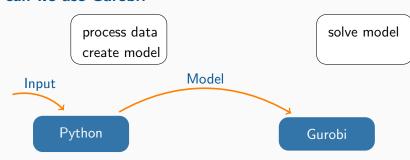
Input

Python

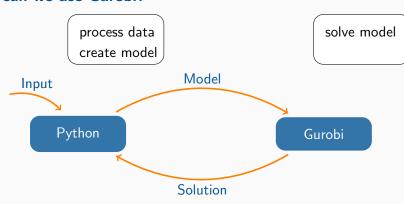




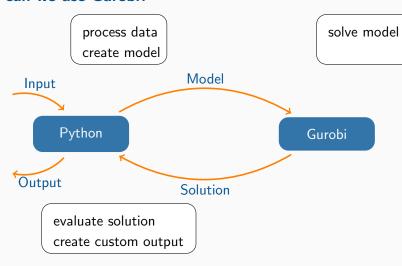




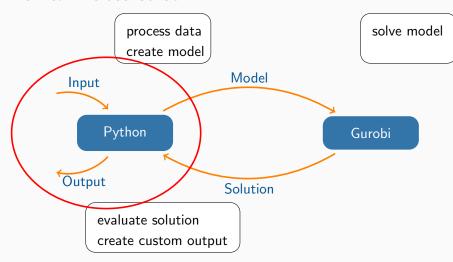














#### **Credits**

The materials used in this course have been developed and improved by

- ▶ Melanie Herzog
- Anja Kirschbaum
- ► Fabian Klemm
- ► Michael Ritter
- Matthias Silbernagel
- Paul Stursberg
- Stefan Kober



# **Basics**



## **Python**

- open source
- most popular programming language
- object-oriented, procedural, functional
- ▶ interactive
- easy to learn



# **Advantages**

- high-level
  - direct interpretation of objects
  - readable and accessible
- many useful libraries (graphs, visualization, computations, data management,...)



#### Limits

- ► slow running times
- somewhat restricted
- possibly not best choice for large object oriented project



# **Basic Knowledge**

- Datatypes
  - ▶ integer, float, string
  - ▶ list, tuple, dict, set
- ► Indentation
- ► Output
  - print
  - ▶ formatted print
- Imports



# **Linear Programming**



$$\min c^{\top} x$$
 s.t.  $Ax < b$ 

$$A = \begin{pmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \\ 2 & 1 & 1 \\ -2 & -2 & 0 \\ -2 & 0 & -3 \end{pmatrix}, \quad b = \begin{pmatrix} 4 \\ 7 \\ 1 \\ -1 \\ -1 \end{pmatrix}, \quad c = \begin{pmatrix} -1 \\ -1 \\ -1 \end{pmatrix}$$

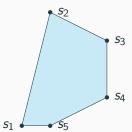


$$\min c^{\top} x \quad \text{s.t.}$$
$$Ax \le b$$

- set of variables x
- ightharpoonup set of linear constraints Ax < b
- ▶ linear objective function min  $c^{\top}x$

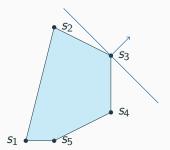


$$\min c^{\top} x \quad \text{s.t.}$$
$$Ax \le b$$



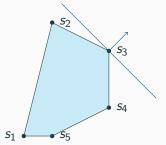


$$\min c^{\top} x \quad \text{s.t.}$$
$$Ax \le b$$



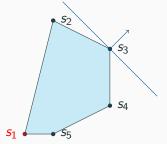


- ► Find a feasible solution
- Travel along improving edge
- ► Terminate at optimal solution



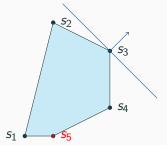


- ► Find a feasible solution



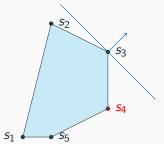


- ► Find a feasible solution
- ► Travel along improving edges



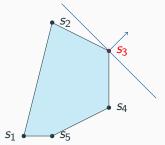


- ► Find a feasible solution
- ► Travel along improving edges





- ► Find a feasible solution
- ► Travel along improving edges
- ► Terminate at optimal solution





#### The Simplex Algorithm

- ► Find a feasible solution
- ► Travel along improving edges
- ► Terminate at optimal solution

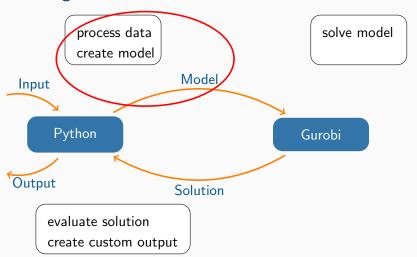
Good News: Gurobi does that for us



# **Modelling**



## Modelling

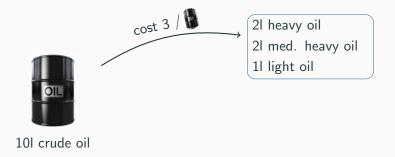




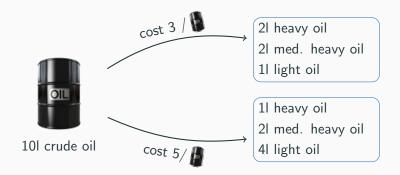


10l crude oil

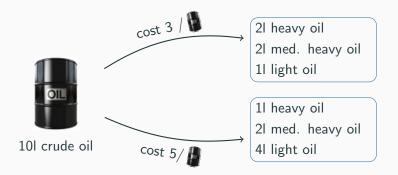






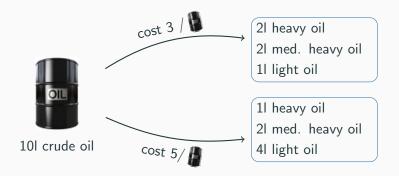






demand: 3I heavy oil, 5I med. heavy oil, 4I light oil





demand: 3l heavy oil, 5l med. heavy oil, 4l light oil

objective: minimize cost





$$min 3x_1 + 5x_2$$



$$min 3x_1 + 5x_2$$

$$2x_1+1x_2\geq 3$$



$$min 3x_1 + 5x_2$$

$$2x_1+1x_2\geq 3$$

$$2x_1+2x_2\geq 5$$



$$min 3x_1 + 5x_2$$

$$2x_1+1x_2\geq 3$$

$$2x_1+2x_2\geq 5$$

$$1x_1+4x_2\geq 4$$



$$min 3x_1 + 5x_2$$

s.t.

$$2x_1 + 1x_2 \ge 3$$
$$2x_1 + 2x_2 \ge 5$$
$$1x_1 + 4x_2 \ge 4$$

 $x_1, x_2 > 0$ 



# Initialize gurobipy and create set of variables x

```
# Create a new model
m = Model()

# Create variables
x = m.addVar(vtype=GRB.CONTINUOUS)
y = m.addVar(vtype=GRB.CONTINUOUS)
```

from gurobipy import \*



# Initialize gurobipy and create set of variables x

```
from gurobipy import *

# Create a new model
m = Model()

# Create variables
x = m. addVar(vtype=GRB.CONTINUOUS)
y = m. addVar(vtype=GRB.CONTINUOUS)
```



- ► GRB.CONTINUOUS
- ► GRB.BINARY
- ► GRB.INTEGER
- ▶ GRB.SEMICONT
- ► GRB.SEMIINT



- ▶ GRB.CONTINUOUS  $(-\infty, \infty)$
- ► GRB.BINARY
- GRB.INTEGER
- ► GRB.SEMICONT
- ▶ GRB.SEMIINT



- ▶ GRB.CONTINUOUS  $(-\infty, \infty)$
- ► GRB.BINARY {0,1}
- ► GRB.INTEGER
- ► GRB.SEMICONT
- ▶ GRB.SEMIINT



- ▶ GRB.CONTINUOUS  $(-\infty, \infty)$
- ► GRB.BINARY {0,1}
- ► GRB.INTEGER {0, 1, 2, ...}
- ▶ GRB.SEMICONT
- ► GRB.SEMIINT



- ▶ GRB.CONTINUOUS  $(-\infty, \infty)$
- ► GRB.BINARY {0,1}
- ► GRB.INTEGER {0, 1, 2, ...}
- ▶ GRB.SEMICONT  $\{0\} \cup (a, b)$
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- ▶ GRB.CONTINUOUS  $(-\infty, \infty)$
- ► GRB.BINARY {0, 1}
- ► GRB.INTEGER {0, 1, 2, ...}
- ▶ GRB.SEMICONT  $\{0\} \cup (a, b)$
- ▶ GRB.SEMIINT  $\{0\} \cup (a, b) \cap \mathbb{Z}$



# Initialize gurobipy and create set of variables x

```
from gurobipy import *

# Create a new model
m = Model()

# Create variables
x = m.addVar(vtype=GRB.CONTINUOUS)
y = m.addVar(vtype=GRB.CONTINUOUS)
```



### **Add Variables**

```
addVar(lb=0,ub=GRB.INFINITY,obj=0.0,vtype=GRB.CONTINUOUS,name="""
```

- ▶ *lb*, *ub*: variable lower and upper bound
- ▶ *obj*: coefficient of the linear objective function
- vtype: variable type
- name: name for further referencing



### **Add Variables**

```
addVars(indices, lb = 0, ub = GRB. INFINITY, obj = 0.0, vtype = GRB. CONTINUOUS, name = "")
```

- Ib, ub: variable lower and upper bound
- ▶ *obj*: coefficient of the linear objective function
- vtype: variable type
- name: name for further referencing
- indices: integer, range, list or dictionary used to generate set of variables



### Create set of linear constraints $Ax \ge b$

```
# Add constraints

c1 = m.addConstr(2*x+y>=3)

c2 = m.addConstr(2*x+2*y>=5)

c3 = m.addConstr(x+4*y>=4)

c4 = m.addConstr(x>=0)

c5 = m.addConstr(y>=0)
```



### Create set of linear constraints $Ax \ge b$

```
# Add constraints
c1 = m.addConstr(2*x+y>=3)
c2 = m.addConstr(2*x+2*y>=5)
c3 = m.addConstr(x+4*y>=4)
c4 = m.addConstr(x>=0)
c5 = m.addConstr(y>=0)
```



### **Add Constraints**

Basic form:

m.addConstr(LinExpr>=a)



### **Add Constraints**

### Basic form:

Linear expressions can be created by:

- ightharpoonup 1e = 2 \* x + 3 \* y
- ▶ le = x.prod([2, 3])
- ightharpoonup le = x.sum()
- le = quicksum([2 \* x, 3 \* y])



# Set linear objective function $\min c^{\top}x$ and optimize the model

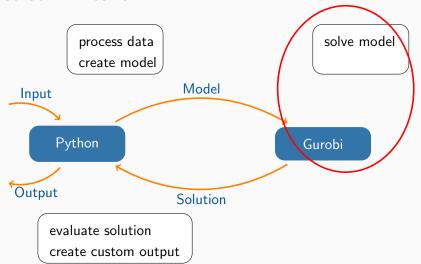
```
# Set objective function
m. setObjective (3*x+5*y, GRB. MINIMIZE)
# Optimize model
m. optimize()
```



# **Output Interpretation**



### Gurobi - LP solver





#### **Presolve**

```
Optimize a model with 1500 rows,
   2250000 columns and 4497000 nonzeros

Coefficient statistics:
   Matrix range [le+00, le+00]
   Objective range [le+00, le+02]
   Bounds range [0e+00, 0e+00]
   RHS range [le+00, 2e+01]

Presolve removed 0 rows and 1611 columns

Presolve time: 4.37s

Presolved: 1500 rows, 2248389 columns, 4496778 nonzeros
```



# **Presolve - Example**

$$x_1 + x_2 + x_3 \ge 15$$

$$x_1 \le 7$$

$$x_2 \le 3$$

$$x_3 \le 5$$



# **Presolve - Example**

$$x_1 + x_2 + x_3 \ge 15$$

$$x_1 \le 7$$

$$x_2 \le 3$$

$$x_3 \le 5$$

delete constraint and variables in order to reduce the problem



### LP methods

- ▶ 3 different methods
  - primal/dual simplex
    - robust
    - easy to restart after model modification
  - barrier
    - can be run on multiple cores
- concurrent optimization

## **Concurrent Optimization**

- run simplex and barrier at the same time
- ▶ first one to finish reports solution
- use multiple cores
- ► fastest choice for general model

Iteration		Objective	Primal Inf.	Dual Inf.	Time				
		-1.2573140e+02	2.968000e+03	5.593346e+11	7s				
	3297	1.2166285e+05	0.000000e+00	6.532640e+07	10s				
	4619	8.3232592e+04	0.000000e+00	1.162234e+08	15s				
	7000	5.2154173e+04	0.000000e+00	4.234078e+06	25s				
	9189	3.7601369e+04	0.000000e+00	1.177763e+07	35s				
	10706	3.0986489e+04	0.000000e+00	2.645246e+06	45s				
	12019	2.7488411e+04	0.000000e+00	4.758955e+06	56s				
	13844	2.3646778e+04	0.000000e+00	3.840044e+05	65s				
	15403	2.1713789e+04	0.000000e+00	3.055039e+04	75s				
	17347	2.1105977e+04	0.000000e+00	1.777696e+01	85s				
	17419	2.1108270e+04	0.000000e+00	0.000000e+00	91s				
Solved in 17419 iterations and 90.82 seconds									
Optimal objective 2.110826998e+04									

```
Primal Inf.
                                             Dual Inf.
Iteration
             Objective
                                                             Time
           -1.2573140e+02
                             2.968000e+03
                                            5.593346e+11
                                                               7s
    3297
            1.2166285e+05
                             0.000000e+00
                                            6.532640e+07
                                                              10s
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            8.3232592e+04
                             0.000000e+00
                                            1.162234e+08
                                                              15s
    7000
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                             0.000000e+00
                                            4.234078e+06
                                                              25s
    9189
            3.7601369e+04
                             0.000000e+00
                                                              35s
                                            1.177763e+07
                                            2.645246e+06
   10706
            3.0986489e+04
                             0.000000e+00
                                                              458
   12019
            2.7488411e+04
                             0.000000e+00
                                            4.758955e+06
                                                              56s
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            2.3646778e+04
                             0.000000e+00
                                            3.840044e+05
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                                                              568
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                             0.000000e+00
                                                              65s
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                             0.000000e+00
                                            3.055039e+04
                                                              75s
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Solved in 17419 iterations and 90.82 seconds							
Optimal objective 2.110826998e+04							

Primal:

Dual:

 $\min c^{\top}x$  s.t.

 $Ax \leq b$ 

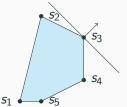
 $\max_{x} b^{\top} y$  s.t.

 $A^\top y = c$ 

 $y \ge 0$ 

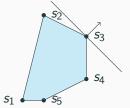
$$\min c^{\top}x$$
 s.t.

$$Ax \leq b$$



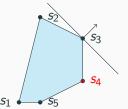
$$\max b^{\top} y \quad \text{s.t.}$$
$$A^{\top} y = c$$

$$A \quad y = c$$
$$y \ge 0$$



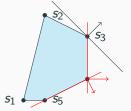
$$\min c^\top x \quad \text{s.t.}$$

$$Ax \leq b$$



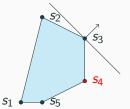
$$\max_{z} b^{\top} y$$
 s.t.

$$A^{\top}y = c$$
$$y \ge 0$$



$$\min c^{\top}x$$
 s.t.

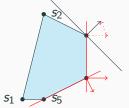
$$Ax \leq b$$



$$\max b^{\top} y$$
 s.t.

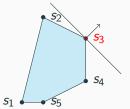
$$A^{\mathsf{T}}y = c$$

$$y \ge 0$$



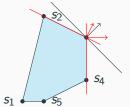
$$\min c^{\top}x$$
 s.t.

$$Ax \leq b$$



$$\max_{x} b^{\top} y$$
 s.t.

$$A^{\top}y = c$$
$$y \ge 0$$

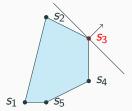




# Primal:

$$\min c^{\top}x \quad \text{s.t.}$$

$$Ax \leq b$$

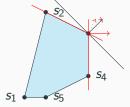


# Dual:

$$\max b^{\top} y$$
 s.t.

$$A^\top y = c$$

$$y \ge 0$$





Primal: Dual:

$$\min c^{\top}x$$
 s.t.  $\max b^{\top}y$  s.t. 
$$Ax \le b \qquad \qquad A^{\top}y = c \qquad \qquad y \ge 0$$

$$c^{\top}\bar{x} = \bar{y}^{\top}A\bar{x} = (*) \bar{y}^{\top}b$$



# **Dual Simplex**

- ► simplex on dual problem
- obtain primal solution as discussed before
- dominant algorithm used in MIP solving



Idea:

$$\min c^\top x \quad \text{s.t.}$$

$$Ax \leq b$$



Idea:

$$\min f(x)$$
 s.t.  $c_i(x) \le 0$ 

with f and  $c_i$  linear



Idea:

$$\min f(x)$$
 s.t.  $c_i(x) \le 0$ 

with f and  $c_i$  linear

$$\Downarrow$$

$$\min f(x) - \mu \sum_{i} log(c_{i}(x))$$

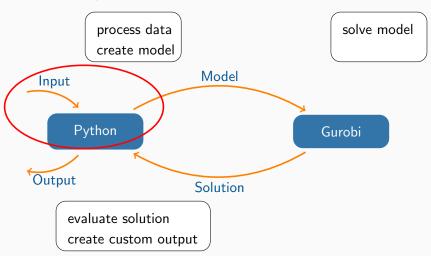
$$\min f(x) - \mu \sum_{i} log(c_{i}(x))$$

- $\blacktriangleright$   $\mu \to 0$  and solve as nonlinear optimization problem
- also known as Interior Point Method
- ► few, but expensive calculations
- not clear whether warm start is doable

# **Advanced Input Methods**



# **Advanced Input**





# **Reading Data from Files**

### Advantages:

- separation between data and code
- ► faster replacement and sharing of data
- more flexible code
- clearer code



#### **File Formats**

- excel (pandas, xlrd)
- csv (csv)
- ▶ json (json)
- basically any text-file of some custom format (write parser)



#### The JSON File Format

```
{
    "oil_types":[
        "heavy","medium","light"
    "processes": [0,1],
    "production":{
        "heavy": [2,1], "medium": [2,2], "light": [1,4]
    " demand" : {
        "heavy":3,"medium":5,"light":4
    "process_cost":[3,5]
```



# **Data Types**

- Boolean
- Number (integer or floating point)
- String
- Array [] (ordered list of elements of arbitrary type)
- Object {} (unordered collection of name-value pairs)



# **Data Types**

- Boolean
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Translates straight-forward to Python!



# Reading JSON files in Python

#### import json

```
with open("data.json") as json_file:
data = json.load(json_file)
```



#### Read text files

- ▶ generally, input files not given as *json* or *csv* or *xslx*
- any custom format
- solution: read file line by line according to its syntax and create list/dictionary/object



### Reading general textfiles in Python

```
filename = 'data.txt'
with open(filename, "r") as file:
    line = file.readline()
    while line:
        print(line.split("separator"))
```



#### Write text files

- generate different datasets to have stable collection of example data
- straightforward in python (very similar to print())

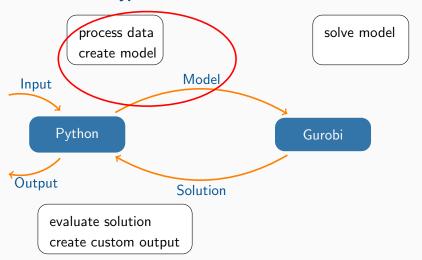
# Writing textfiles in Python

```
filename = 'data.txt'
with open(filename, "w") as file:
    file.write("sometext\n")
    file.close()
```

# **Advanced Gurobi Datatypes**



### **Advanced Datatypes**





# **Tuplelist**

- subclass of python list
- ▶ list of tuples of same size
- easy notation to find specific subsets
- ▶ same is doable with list comprehension *but* tuplelist is faster



# **Tuplelist**

#### Creation

```
l = tuplelist([(1, 2), (1, 3), (2, 3), (2, 4)])
```



### **Tuplelist**

#### Creation

```
I = tuplelist([(1, 2), (1, 3), (2, 3), (2, 4)])
```

# Queries ('\*' is wildcard character)

```
I.select(1, '*')
I.select('*', [2, 4])
I.select('*', '*')
```



# **Tupledict**

- subclass of python dictionary
- dictionary with tuplelist as keys
- usually used for variables of complex systems
- easy access via select
- easy constraint generation via sum and prod



### **Tupledict**

#### Creation

#### **Tupledict**

#### Creation

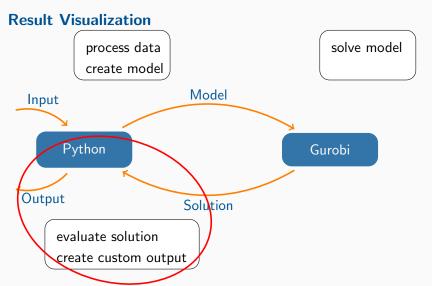
```
I = tuplelist([(1, 2), (1, 3), (2, 3), (2, 4)])
d=model.addVars(I)
```

#### Queries and creation of expressions

```
d.select(1, '*')
d.sum(1, '*')
coeff = [2,5]
d.prod(coeff, 1, '*')
```

# **Visualization**







# **Visualization of Graphs**

- natural connection between many LPs and graphs
- visualizing graphs improves understanding
- matplotlib



### Visualizing graphs

```
import networkx as nx
from random import randint
n = 10
position = [[randint(0,100), randint(0,100)]]
    for i in range(n)]
edges = [(randint(0,n-1),randint(0,n-1))]
    for i in range (3*n)
G = nx.Graph()
G.add_nodes_from([(i, {'x': coord[0], 'y': coord[1]}))
    for i, coord in enumerate(position)])
G.add\_edges\_from([(e[0], e[1]) for e in edges])
nx.draw_networkx_nodes(G, position, node_color="black")
nx.draw_networkx_edges(G, position,edge_color="black")
```

