

# Optimization and mathematical programming in Julia with applications to spatial data

**Przemysław Szufel**  
**<https://szufel.pl/>**

Basics...

# Linear optimization

```
using JuMP, HiGHS
m = Model(optimizer_with_attributes(HiGHS.Optimizer))
@variable(m,      x1 >= 0)
@variable(m,      x2 >= 0)
@objective(m,     Min, 50x1 + 70x2)
@constraint(m,    200x1 + 2000x2 >= 9000    )
@constraint(m,    100x1 +    30x2 >=    300    )
@constraint(m,     9x1    +   11x2 >=     60    )
optimize!(m)
JuMP.value.([x1, x2])
```

# Note – how to type indexes in Julia

- `julia> x`
- `julia> x\_`
- `julia> x\_1`
- `julia> x\_1<TAB>`
- `julia> x1`

## ... and Integer programming

```
using JuMP, HiGHS
m = Model(optimizer_with_attributes(HiGHS.Optimizer))
@variable(m, x1 >= 0, Int)
@variable(m, x2 >= 0)
@objective(m, Min, 50x1 + 70x2)
@constraint(m, 200x1 + 2000x2 >= 9000)
@constraint(m, 100x1 + 30x2 >= 300)
@constraint(m, 9x1 + 11x2 >= 60)
optimize!(m)
```

# How it works - metaprogramming

```
julia> code = Meta.parse("x=5")  
:(x = 5)
```

```
julia> dump(code)  
Expr  
  head: Symbol =  
  args: Array{Any}((2,))  
    1: Symbol x  
    2: Int64 5
```

```
julia> eval(code)  
5
```

```
julia> x  
5
```

# Macros – hello world...

```
macro sayhello(name)  
    return :( println("Hello, ", $name) )  
end
```

```
julia> macroexpand(Main,:(@sayhello("aa")))  
:((Main.println)("Hello, ", "aa"))
```

```
julia> @sayhello "world!"  
Hello, world!
```

# Macro @variable

```
julia> @macroexpand @variable(m, x₁ >= 0)
quote
  (JuMP.validmodel)(m, :m)
  begin
    #1###361 = begin
      let
        #1###361 = (JuMP.constructvariable!)(m, getfield(JuMP, Symbol("#_error#107")){Tuple{Symbol,Expr}}{(:m, :(x₁ >= 0))}, 0,
        Inf, :Default, (JuMP.string)(:x₁), NaN)
        #1###361
      end
    end
    (JuMP.registervar)(m, :x₁, #1###361)
    x₁ = #1###361
  end
end
```



# Some of JuMP Solvers (over 40 as of today)

Solver	Julia Package	License	LP	SOCP	MILP	NLP	MINLP	SDP
<u>Artelys Knitro</u>	<u>KNITRO.jl</u>	Comm.				X	X	
<u>BARON</u>	<u>BARON.jl</u>	Comm.				X	X	
<u>Bonmin</u>	<u>AmpNLWriter.jl</u>	EPL	X		X	X	X	
	<u>CoinOptServices.jl</u>							
<b><u>Cbc</u></b>	<b><u>Cbc.jl</u></b>	<b>EPL</b>			<b>X</b>			
<u>Clp</u>	<u>Clp.jl</u>	EPL	X					
<u>Couenne</u>	<u>AmpNLWriter.jl</u>	EPL	X		X	X	X	
	<u>CoinOptServices.jl</u>							
<b><u>CPLEX</u></b>	<b><u>CPLEX.jl</u></b>	Comm.	X	X	X			
<u>ECOS</u>	<u>ECOS.jl</u>	GPL	X	X				
<u>FICO Xpress</u>	<u>Xpress.jl</u>	Comm.	X	X	X			
<u>HiGHS</u>	<u>HiGHSMathProgInterfac e</u>	GPL	X		X			
<b><u>Gurobi</u></b>	<b><u>Gurobi.jl</u></b>	Comm.	X	X	X			
<b><u>Ipopt</u></b>	<b><u>Ipopt.jl</u></b>	<b>EPL</b>	X			X		
<u>MOSEK</u>	<u>Mosek.jl</u>	Comm.	X	X	X	X		X
<u>NLopt</u>	<u>NLopt.jl</u>	LGPL				X		
<u>QSOQ</u>	<u>QSOQ.jl</u>	MIT	X	X				X

JuMP

Transportation of good among  
branches

# Use case scenario

The Subway restaurant chain in Las Vegas has a total of 118 restaurants in different parts of the city.

18 restaurants have adjacent huge product warehouses that keep ingredients cool and fresh, moreover fresh vegetables are delivered only to those warehouses (rather than to every restaurant) daily at 3am.

Subway has signed a contract with a transportation agency and is billed by the multiple of the weight of transported goods and the distance.

Knowing the amount of available stock at each warehouse and the expected demand at each restaurant (measured in kg), the company needs to decide how the goods should be distributed among warehouses.

# Transportation problem statement

- Variables

- $x_{ij}$  – number of units transported for  $i$ -th supplier to  $j$ -th requester
- $c_{ij}$  – unit transportation cost between  $i$ -th supplier to  $j$ -th requester

- Cost function  $C$

$$C = \sum_{i=1}^m \sum_{j=1}^n c_{ij} x_{ij}$$

- Constraints:

suppliers have maximum capacity  $S_i$

$$\sum_{j=1}^n x_{ij} \leq S_i$$

demand  $D_j$  must be met

$$\sum_{i=1}^m x_{ij} \geq D_j$$

# Implementation in JuMP

```
m = Model(optimizer_with_attributes(HiGHS.Optimizer));
@variable(m, x[i=1:S, j=1:D])
@objective(m, Min, sum( x[i, j]*distance_mx[i, j] for i=1:S, j=1:D))
@constraint(m, x .>= 0)
for j=1:D
    @constraint(m, sum( x[i, j] for i=1:S) >= demand[j] )
end
for i=1:S
    @constraint(m, sum( x[i, j] for j=1:D) <= supply[i] )
end
optimize!(m)
termination_status(m)
```

# Use case scenario

A tourist in San Francisco and plans to visit all McDonald's restaurant in one day  
Let's help him!

# Spatial data

OpenStreetMap - <https://www.openstreetmap.org>

- Open project – “Wikipedia for maps”
- Lots, lots of data
  - Roads, Buildings, trees, ...
  - Transportation systems
  - Point-of-interests (POIs) – businesses, restaurants, schools, universities...
- Formats: XML, PBF
- Multilayered structure
  - Nodes (points) ← <tag/>
  - Ways (lines, shapes) ← <tag/>
  - Relations (wider concepts) ← <tag/>

```

<osm>
  <bounds minlat="42.3609500" minlon="-71.0914900" maxlat="42.3621500" maxlon="-71.0898000"/>
  <node id="61317286" lat="42.3611637" lon="-71.0927647"/>
  <node id="61317287" lat="42.3607193" lon="-71.0937014"/>
  <node id="6898815038" lat="42.3608365" lon="-71.0894651">
    <tag k="entrance" v="yes"/>
  </node>
  ....
  <way id="17660188">
    <nd ref="182893079"/>
    <nd ref="182893081"/>
    <tag k="addr:city" v="Cambridge"/>
    <tag k="addr:housenumber" v="43"/>
    ....
  </way>
  ....
  <relation id="1590059">
    <member type="node" ref="9124611329" role=""/>
    <member type="way" ref="426493700" role=""/>
    <member type="way" ref="8605061" role=""/>

    <tag k="network:wikipedia" v="en:Massachusetts Bay Transp
    <tag k="operator" v="Massachusetts Bay Transportation Aut
    <tag k="public_transport:version" v="2"/>
    <tag k="ref" v="CT2"/>
    <tag k="route" v="bus"/>
    <tag k="to" v="Ruggles Station"/>
    <tag k="type" v="route"/>
  </relation>

```





# Libraries for OSM data

**OpenStreetMapX.jl** – mainly oriented on road system

- Road system extracted as a directed graph (Graphs.jl) along with separate metadata
- Supports routing, road classes, vehicle speeds etc.
- Spatial algebra (ENU, LLA, ECEF), overlap with Geodesy.jl

**OpenStreetMapXPlots.jl**

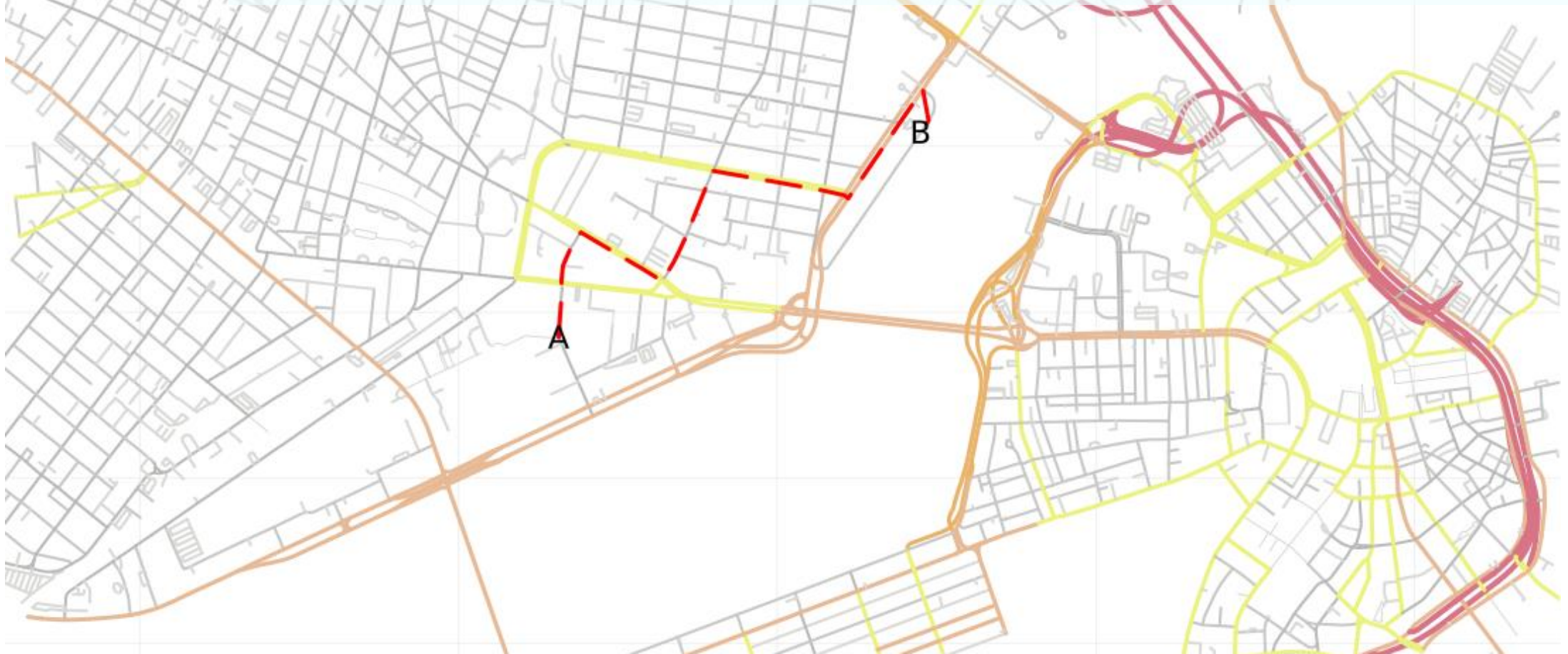
- Plotting maps with Plots.jl and PyPlot.jl .

**OSMtoolset.jl** – <https://github.com/pszufe/OSMToolset.jl>

- Spatial indexes on maps
- Mass extraction of points-of-interests (POIs) from maps
- Tools for slicing/tiling large OSM \*.xml files

(developed under grant National Science Centre, Poland 2021/41/B/HS4/03349)

```
using OpenStreetMapX, OpenStreetMapXPlot
m = get_map_data("boston.osm"); # or *.pbf
p = plotmap(m; width=900, height=600)
r = shortest_route(m, 436587028, 5235225267)[1]
addroute!(p,m,r; route_color="red");
```



# OSMToolset.jl – point of interest extraction

```
julia> df[end-2:end,:]
```

```
3x5 DataFrame
```

Row	class String15	key String31	influence Int64	range Int64	values String
1	leisure	sport	5	800	fitness
2	leisure	landuse	5	1500	recreation_ground,winter_sports
3	leisure	tourism	5	1500	*



**Throughput ~ 2GB/min**

```
julia> poidf = find_poi("boston.osm"; attract_config=AttractivenessConfig(df))
```

```
2576x10 DataFrame
```

Row	elemtype Symbol	elemid Int64	nodeid Int64	lat Float64	lon Float64	key String	value String	class String	influence Int64	range Int64
1	node	69480814	69480814	42.357	-71.0588	public_transport	stop_position	transport	5	300
2	node	69482188	69482188	42.3599	-71.06	public_transport	stop_position	transport	5	300
3	node	69482993	69482993	42.3525	-71.0549	public_transport	stop_position	transport	5	300
4	node	69487423	69487423	42.3736	-71.0697	railway	station	transport	10	700
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
2574	relation	14205406	9784109000	42.38	-71.0934	amenity	parking	parking	5	250
2575	relation	14205408	327175969	42.38	-71.0956	amenity	parking	parking	5	250
2576	relation	15704864	10800012568	42.3551	-71.1022	leisure	garden	leisure	5	500

2569 rows omitted

# McDonald's in SF

```
In [48]: using DataFrames, OSMToolset
         config = DataFrame(key="brand", values="McDonald's")
         dfpoi = find_poi("SF.osm"; scrape_config=ScrapePOIConfig{NoneMetaPOI}(config))
```

Out[48]: 18×7 DataFrame

Row	elemtype	elemid	nodeid	lat	lon	key	value
	Symbol	Int64	Int64	Float64	Float64	String	String
1	node	358116917	358116917	37.7264	-122.476	brand	McDonald's
2	node	597382133	597382133	37.7066	-122.415	brand	McDonald's
3	node	1229920544	1229920544	37.7131	-122.445	brand	McDonald's
4	node	2365742146	2365742146	37.789	-122.401	brand	McDonald's
5	node	3455025884	3455025884	37.6522	-122.491	brand	McDonald's
6	node	4626983989	4626983989	37.7892	-122.408	brand	McDonald's
7	node	6959355927	6959355927	37.644	-122.404	brand	McDonald's
8	node	9980865058	9980865058	37.6438	-122.454	brand	McDonald's
9	node	11338930625	11338930625	37.6747	-122.47	brand	McDonald's
10	way	143811393	1573722786	37.669	-122.47	brand	McDonald's
11	way	159024983	1711296799	37.7236	-122.455	brand	McDonald's
12	way	231047897	2394660225	37.752	-122.418	brand	McDonald's
13	way	256462436	2621272506	37.7653	-122.408	brand	McDonald's

JuMP

Travelling salesman problem

# Use case scenario

A tourist in San Francisco and plans to visit all McDonald's restaurant in one day  
Let's help him!

# Traveling salesman problem (TSP)

- Variables:

- $c_{ft}$  – cost of travel from “ $f$ ” to “ $t$ ”
- $x_{ft}$  – binary variable indicating 1 when agent travels from “ $f$ ” to “ $t$ ”

$$\text{Min} \sum_{f=1}^N \sum_{t=1}^N c_{ft} x_{ft}$$



# TSP

$$\text{Min} \sum_{f=1}^N \sum_{t=1}^N c_{ft} x_{ft}$$

Each city visited once

$$\sum_{t=1}^N x_{ft} = 1 \quad \forall f \in \{1, \dots, N\}$$

$$\sum_{f=1}^N x_{ft} = 1 \quad \forall t \in \{1, \dots, N\}$$

City cannot visit itself

$$x_{ff} = 0 \quad \forall f \in \{1, \dots, N\}$$

Avoid two-city cycles

$$x_{ft} + x_{tf} \leq 1 \quad \forall f, t \in \{1, \dots, N\}$$

Other cycles:

/dynamically add a constraint whenever a cycle occurs/

Variables:

- $c_{ft}$  – cost of travel from “ $f$ ” to “ $t$ ”
- $x_{ft}$  – binary variable indicating 1 when agent travels from “ $f$ ” to “ $t$ ”

For more details see: <http://opensourc.es/blog/mip-tsp>



# JuMP implementation

```
m = Model(optimizer_with_attributes(HiGHS.Optimizer));
@variable(m, x[f=1:N, t=1:N], Bin)
@objective(m, Min, sum( x[i, j]*distance_mx[i,j] for i=1:N,j=1:N))
@constraint(m, notself[i=1:N], x[i, i] == 0)
@constraint(m, oneout[i=1:N], sum(x[i, 1:N]) == 1)
@constraint(m, onein[j=1:N], sum(x[1:N, j]) == 1)
for f=1:N, t=1:N
    @constraint(m, x[f, t]+x[t, f] <= 1)
end
```

# Getting a cycle

```
function getcycle(m, N)
    x_val = getvalue(x)
    cycle_idx = Vector{Int}()
    push!(cycle_idx, 1)
    while true
        v, idx = findmax(x_val[cycle_idx[end], 1:N])
        if idx == cycle_idx[1]
            break
        else
            push!(cycle_idx, idx)
        end
    end
    cycle_idx
end
```

# Adding a constraint...

```
function solved(m, cycle_idx, N)
    println("cycle_idx: ", cycle_idx)
    println("Length: ", length(cycle_idx))
    if length(cycle_idx) < N
        cc = @constraint(m, sum(x[cycle_idx,cycle_idx])
            <= length(cycle_idx)-1)
        println("added a constraint")
        return false
    end
    return true
end
```

# Iterating over the model

```
while true
    status = solve(m)
    println(status)
    cycle_idx = getcycle(m, N)
    if solved(m, cycle_idx, N)
        break;
    end
end
```

# Gurobi.jl

- Commercial software
- Free for academic use
- Integrates with JuMP via Gurobi.jl
- Supports JuMP Lazy constraints (<http://www.juliaopt.org/JuMP.jl/0.18/callbacks.html>)

# Gurobi callbacks

```
function getcycle(cb, N)
    x_val = callback_value.(Ref(cb), x)
    getcycle(x_val)
end
function callbackhandle(cb)
    cycle_idx = getcycle(cb, N)
    println("Callback! N= $N cycle_idx: ", cycle_idx)
    println("Length: ", length(cycle_idx))
    if length(cycle_idx) < N
        con = @build_constraint(sum(x[cycle_idx,cycle_idx]) <= length(cycle_idx)-1)
        MOI.submit(m, MOI.LazyConstraint(cb), con)
        println("added a lazy constraint")
    end
end
MOI.set(m, MOI.LazyConstraintCallback(), callbackhandle)
```

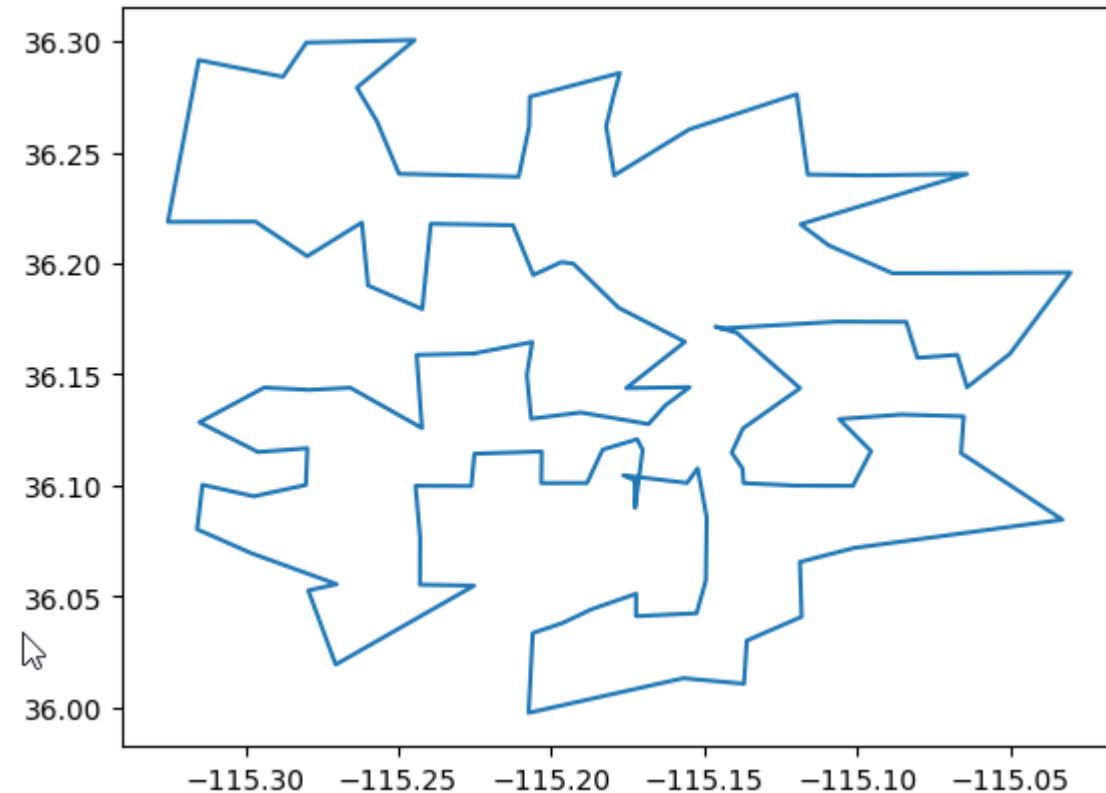
# TravelingSalesmanHeuristics.jl

using TravelingSalesmanHeuristics

```
sol = TravelingSalesmanHeuristics.solve_tsp(  
distance_mx, quality_factor = 100)
```

More info:

<http://evanfields.github.io/TravelingSalesmanHeuristics.jl/latest/heuristics.html>



JuMP

Non-Linear Programming



# Simple scenario

Estimate parameters of a quadratic form

$$y(\mathbf{x}_i) = \mathbf{x}_i^T \begin{bmatrix} a & b/2 \\ b/2 & c \end{bmatrix} \mathbf{x}_i, \text{ where } \mathbf{x}_i = \begin{bmatrix} x_i^1 \\ x_i^2 \end{bmatrix}$$

for a vector of observed values  $\mathbf{y}$  to minimize the observed error function

$$\sum_{i=1}^N (y(\mathbf{x}_i) - y_i)^2$$

# Nonlinear optimization Julia

```
m = Model(optimizer_with_attributes(Ipopt.Optimizer));

@variable(m, aa[1:2,1:2])

function errs(aa)
    sum((y .- (x * aa) ) .* x * [1;1]) .^ 2)
end

@objective(m, Min, errs(aa))

optimize!(m)
```

# Use case scenario

(source: Hart et al, Pyomo-optimization modeling in python, 2017)

Simulate dynamics of disease outbreak in a small community of 300 individuals (e.g. children at school)

Three possible states of a patient:

- susceptible ( $S$ )
- infected ( $I$ )
- recovered ( $R$ )

Infection spread model :

- $N$  – population size
- $\alpha, \beta$  – model parameters

$$I_i = \frac{\beta I_{i-1}^\alpha S_{i-1}}{N}$$

$$S_i = S_{i-1} - I_i$$

# Optimization problem for finding parameters $\alpha$ and $\beta$

$S$  - susceptible

$I$  - infected

$N$  – population size

$\alpha, \beta$  – model parameters

$SI$  - time indices  $\{1, 2, 3, \dots\}$

$C_i$  - known input (the actual  
number of infected patients)

$$\min \sum_{i \in SI} (\varepsilon_i^I)^2$$

$$I_i = \frac{\beta I_{i-1}^\alpha S_{i-1}}{N} \quad \forall i \in SI \setminus \{1\}$$

$$S_i = S_{i-1} - I_i \quad \forall i \in SI \setminus \{1\}$$

$$C_i = I_i + \varepsilon_i^I$$

$$0 \leq I_i, S_i \leq N$$

$$0.5 \leq \beta \leq 70$$

$$0.5 \leq \alpha \leq 1.5$$

# Model implementation in JuMP

- Input data (disease dynamics)

```
obs_cases = vcat(1,2,4,8,15,27,44,58,55,32,12,3,1,zeros(13))
```

# Full model specification in JuMP

```
m = Model(optimizer_with_attributes(Ipopt.Optimizer));
@variable(m, 0.5 <= α <= 1.5)
@variable(m, 0.05 <= β <= 70)
@variable(m, 0 <= I_[1:SI_max] <= N)
@variable(m, 0 <= S[1:SI_max] <= N)
@variable(m, ε[1:SI_max])
@constraint(m, ε .== I_ .- obs_cases )
@constraint(m, I_[1] == 1)
for i=2:SI_max
    @NLconstraint(m, I_[i] == β*(I_[i-1]^α)*S[i-1]/N)
end
@constraint(m, S[1] == N)
for i=2:SI_max
    @constraint(m, S[i] == S[i-1]-I_[i])
end
@NLobjective(m, Min, sum(ε[i]^2 for i in 1:SI_max))
```

JuMP

Non-Linear Programming  
for estimation of model parameters

# Simple scenario

Estimate parameters of a quadratic form

$$y(\mathbf{x}_i) = \mathbf{x}_i^T \begin{bmatrix} a & b/2 \\ b/2 & c \end{bmatrix} \mathbf{x}_i, \text{ where } \mathbf{x}_i = \begin{bmatrix} x_i^1 \\ x_i^2 \end{bmatrix}$$

for a vector of observed values  $\mathbf{y}$  to minimize the observed error function

$$\sum_{i=1}^N (y(\mathbf{x}_i) - y_i)^2$$



# Nonlinear optimization Julia

```
m = Model(optimizer_with_attributes(Ipopt.Optimizer));

@variable(m, aa[1:2,1:2])

function errs(aa)
    sum((y .- (x * aa) ) .* x * [1;1]) .^ 2)
end

@objective(m, Min, errs(aa))

optimize!(m)
```

# Use case scenario

(source: Hart et al, Pyomo-optimization modeling in python, 2017)

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- $N$  – population size
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$$I_i = \frac{\beta I_{i-1}^\alpha S_{i-1}}{N}$$

$$S_i = S_{i-1} - I_i$$

# Optimization problem for finding parameters $\alpha$ and $\beta$

$S$  - susceptible

$I$  - infected

$N$  – population size

$\alpha, \beta$  – model parameters

$SI$  - time indices  $\{1, 2, 3, \dots\}$

$C_i$  - known input (the actual  
number of infected patients)

$$\min \sum_{i \in SI} (\varepsilon_i^I)^2$$

$$I_i = \frac{\beta I_{i-1}^\alpha S_{i-1}}{N} \quad \forall i \in SI \setminus \{1\}$$

$$S_i = S_{i-1} - I_i \quad \forall i \in SI \setminus \{1\}$$

$$C_i = I_i + \varepsilon_i^I$$

$$0 \leq I_i, S_i \leq N$$

$$0.5 \leq \beta \leq 70$$

$$0.5 \leq \alpha \leq 1.5$$

# Model implementation in JuMP

- Input data (disease dynamics)

```
obs_cases = vcat(1,2,4,8,15,27,44,58,55,32,12,3,1,zeros(13))
```

# Full model specification in JuMP

```
m = Model(optimizer_with_attributes(Ipopt.Optimizer));
@variable(m, 0.5 <= α <= 1.5)
@variable(m, 0.05 <= β <= 70)
@variable(m, 0 <= I_[1:SI_max] <= N)
@variable(m, 0 <= S[1:SI_max] <= N)
@variable(m, ε[1:SI_max])
@constraint(m, ε .== I_ .- obs_cases )
@constraint(m, I_[1] == 1)
for i=2:SI_max
    @NLconstraint(m, I_[i] == β*(I_[i-1]^α)*S[i-1]/N)
end
@constraint(m, S[1] == N)
for i=2:SI_max
    @constraint(m, S[i] == S[i-1]-I_[i])
end
@NLobjective(m, Min, sum(ε[i]^2 for i in 1:SI_max))
```