

Portfolio Optimization

Import packages, read the stock data, and print the stocks curves

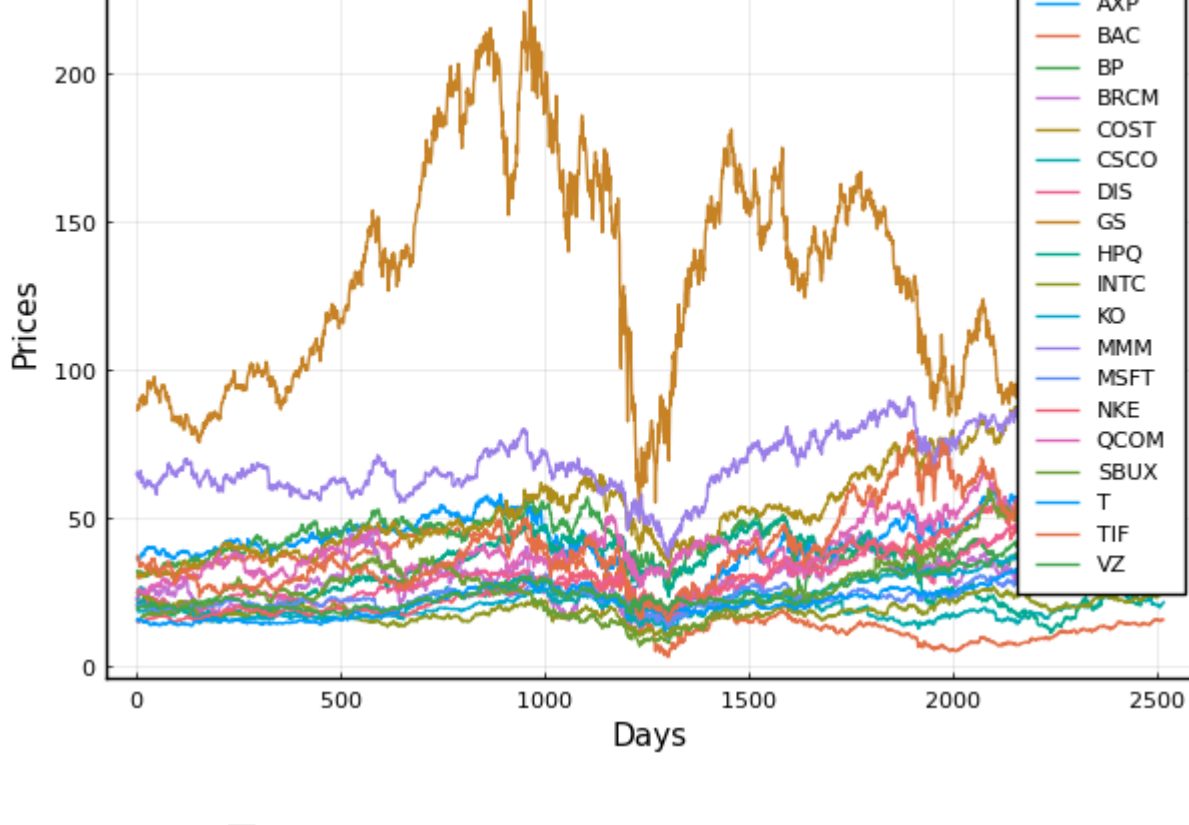
```
In [31]: using Plots
using CSV
using DataFrames
using Statistics # For computing  $\mu$ ,  $\Sigma$ ,  $\rho$ ,  $\sigma$ 
using LinearAlgebra # Needed by some function in Statistics

pyplot()

data = CSV.read("prices.csv", DataFrame) # Read the daily prices data from a .csv file and create a DataFrame.
nametags = names(data[:, 1:end-2]) # Get names of the stocks from first row
nametags = reshape(nametags, 1, length(nametags)) # and convert them into columns
prices = Matrix{Float64}(data[1:end, 1:end-2]) # Last two columns have data and US$ rate

## Plot the stock data + add labels
plot(prices,
     label = nametags,
     grid = :on,
     xlabel = "Days",
     ylabel = "Prices")

savefig("stockdata.pdf")
```



Compute μ , Σ , ρ , and σ . Sort stocks in increasing order by their expected values μ . Using this order, plot μ and σ as functions of their corresponding stocks.

```
In [32]: ## Relative returns are computed as 100% * (p(t+1) - p(t))/p(t)
returns = diff(prices, dims = 1) ./ prices[1:end-1,:]

(T, n) = size(returns) # Number of days T and stocks n
 $\mu$  = vec(mean(returns, dims = 1)) # Expected returns
 $\Sigma$  = cov(returns) # Covariance matrix
 $\rho$  = cor(returns) # Correlation matrix
 $\sigma$  = sqrt.(diag( $\Sigma$ )) # Standard deviation

print( $\mu$ )

## Sort stocks by expected return:
ix = sortperm( $\mu$ ) # ix = index ordering (increasing order)
x = 1:1:n # x = range of all stocks (for plotting)

## Plot expected return (increasing order)
p1 = plot(x,  $\mu$ [ix],
     lab = "",
     xticks = ix,
     ylabel = "\$ \\\mu \$",
     series_annotations = string.(ix),
     title = "Expected return \$\ \\\mu \$")

## Plot the points separately
scatter!(x,  $\mu$ [ix], color = :orange, lab = "\$ \\\mu \$")

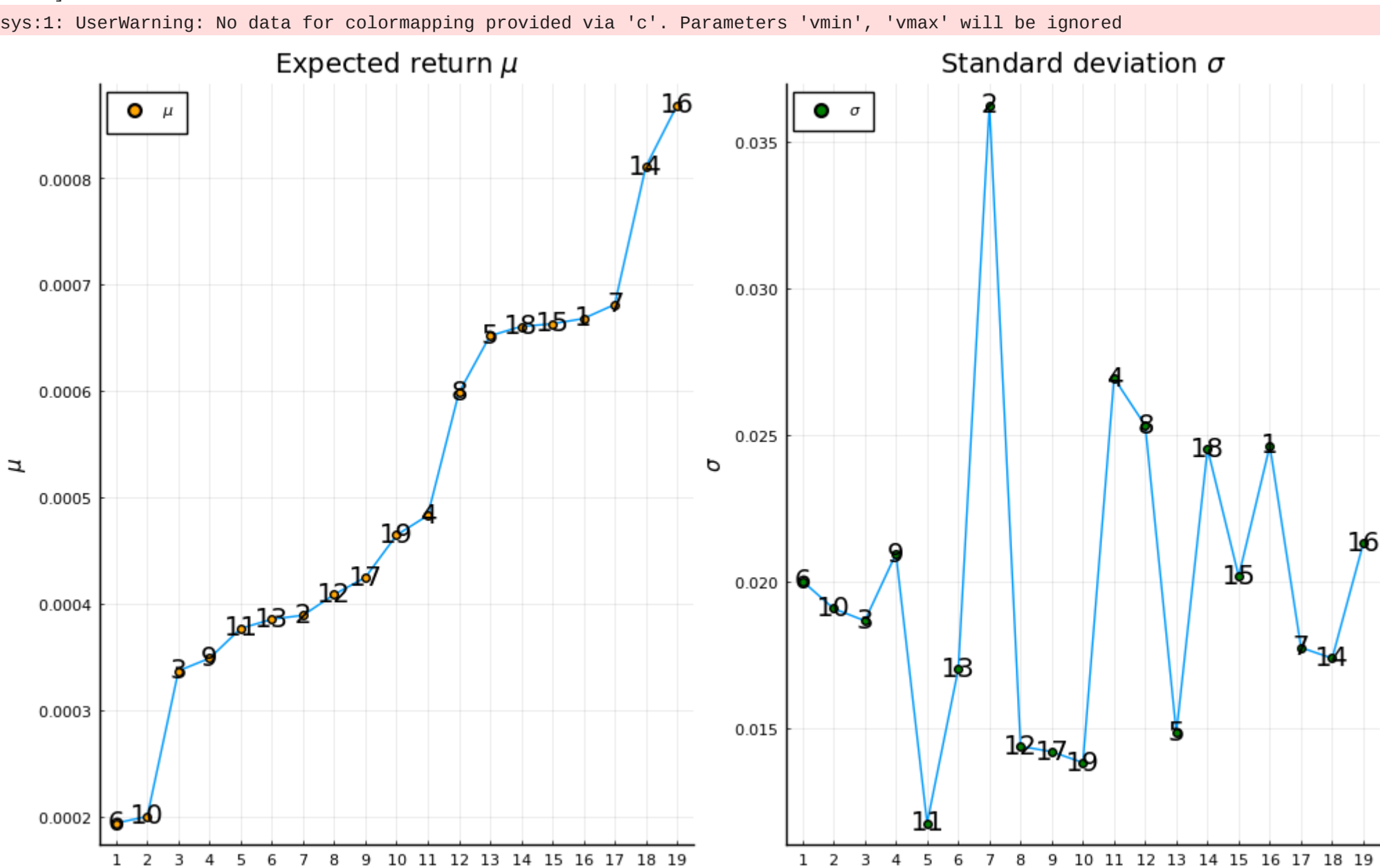
## Plot standard deviation (increasing order w.r.t.  $\mu$ )
p2 = plot(x,  $\sigma$ [ix],
     lab = "",
     xticks = 1:1:n,
     ylabel = "\$ \\\sigma \$",
     series_annotations = string.(ix),
     title = "Standard deviation \$\ \\\sigma \$")

## Plot the points separately
scatter!(x,  $\sigma$ [ix], color = :green, lab = "\$ \\\sigma \$")

## Plot both in the same figure
plot(p1, p2, size = (1000, 600), legend = :topleft)
savefig("mean_std.pdf")

[0.0006681127397809204, 0.0003890411410037511, 0.0003676148028278515, 0.0004828824677873152, 0.0006518453489625798, 0.00019357680091489332, 0.000681248403764681, 0.0005982922835665234, 0.00034865581180055627, 0.000199
87664352140178, 0.0003766516553252695, 0.0004086180439341079, 0.0003853376544840659, 0.0008188370322505913, 0.0006631399290369607, 0.0008684918812743542, 0.00042469895326322676, 0.0006606785621456304, 0.00046442225930
8299]
```

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Visualize the correlation matrix ρ and make a scatterplot of (μ_i, σ_i) , for all $i \in N$.

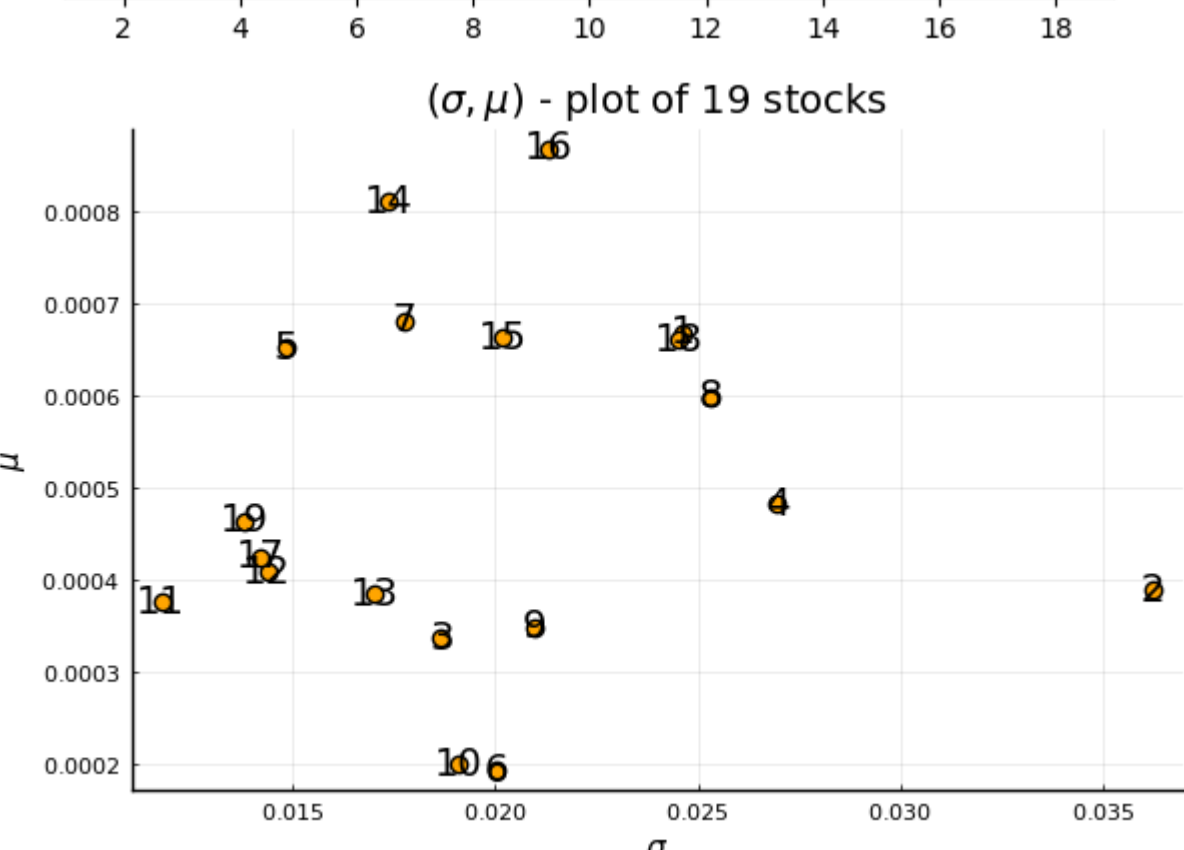
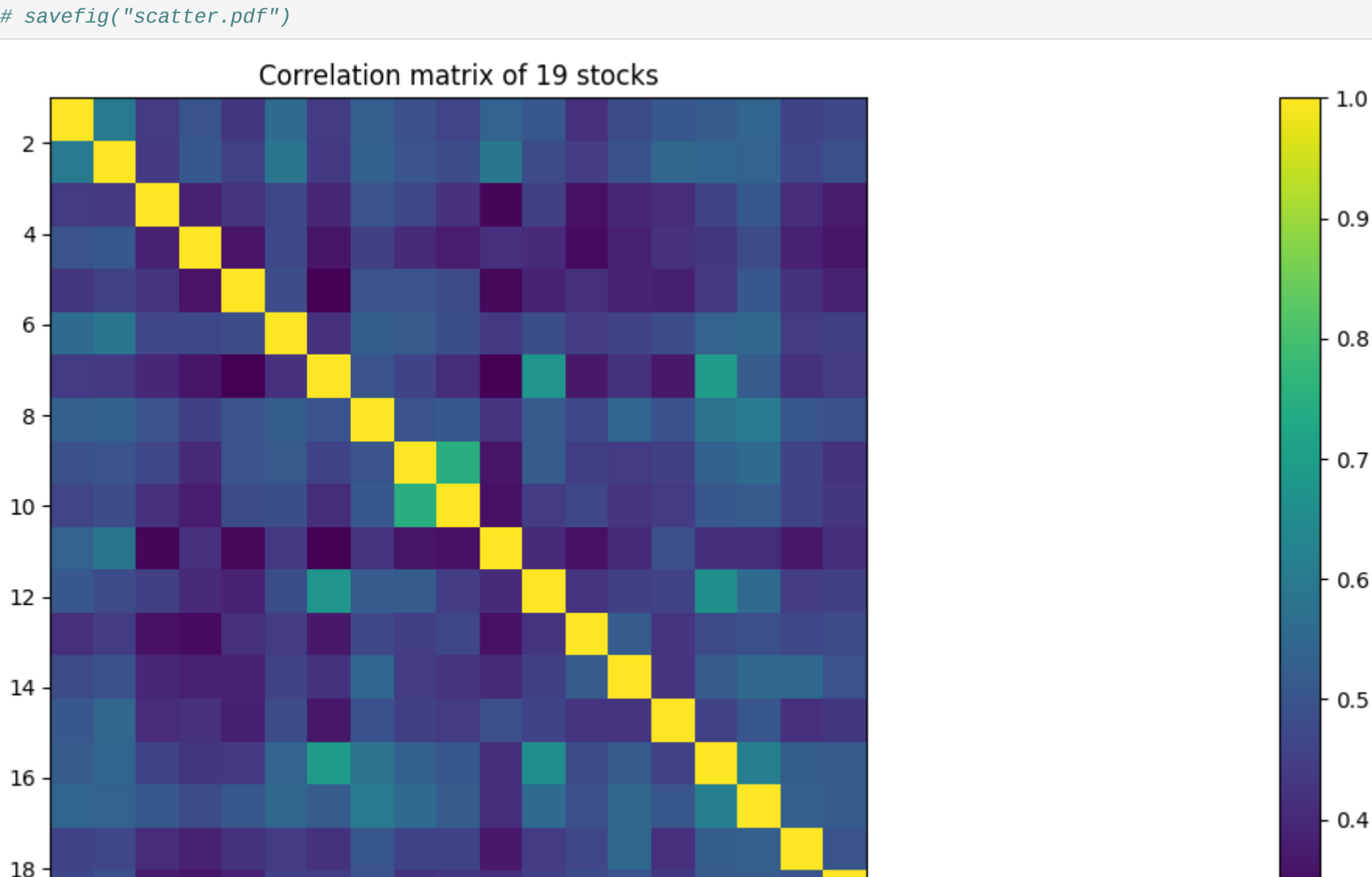
```
In [33]: using PyPlot # We will use PyPlot temporary to plot the correlation Matrix
## To refresh memory: ix = index ordering of value of  $\mu$  (in increasing order)
ix = sortperm( $\mu$ )

## We will visualize the correlation matrix with PyPlot function 'imshow'
figure(figsize = (12,6))
imshow( $\rho$ [ix,ix], extent = [1,19,1,1]);
colorbar(); axis("image")
title("Correlation matrix of $n$ stocks")
tight_layout()

## We must call PyPlot.savefig() explicitly since we used PyPlot for plotting
PyPlot.savefig("corrat.pdf")

### Plot the points  $(\sigma_i, \mu_i) \forall i \in N$ .
Plots.scatter( $\sigma$ ,  $\mu$ ,
     color = :orange,
     markersize = 6,
     xlabel = L"\$\\sigma\$",
     ylabel = L"\$\\mu\$",
     lab = "",
     series_annotations = string.(1:n),
     title = L"\$(\\sigma, \\mu)\$" * " - plot of $(n)$ stocks"
)

# savefig("scatter.pdf")
```



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Solve the portfolio optimization problem

$$\begin{aligned} & \text{minimize} && x^T \Sigma x \\ & \text{subject to} && \mu^T x \geq \mu_{\min} \\ & && \sum_{i \in N} x_i = 1 \\ & && x \geq 0 \end{aligned}$$

with different values of $0 \leq \mu_{\min} \leq 0.000869$.

```
In [34]: ## Compute the minimum risk portfolio with different average returns
 $\mu_{\min}$  = 0.000350 # Minimum expected average return

model = Model(optimizer_with_attributes(Ipopt.Optimizer, "print_level" => 0))

## Variables
@variable(model, x[1:n] >= 0) # Stock positions

## Objective
@objective(model, Min, dot(x,  $\Sigma$ x)) # Minimize variance

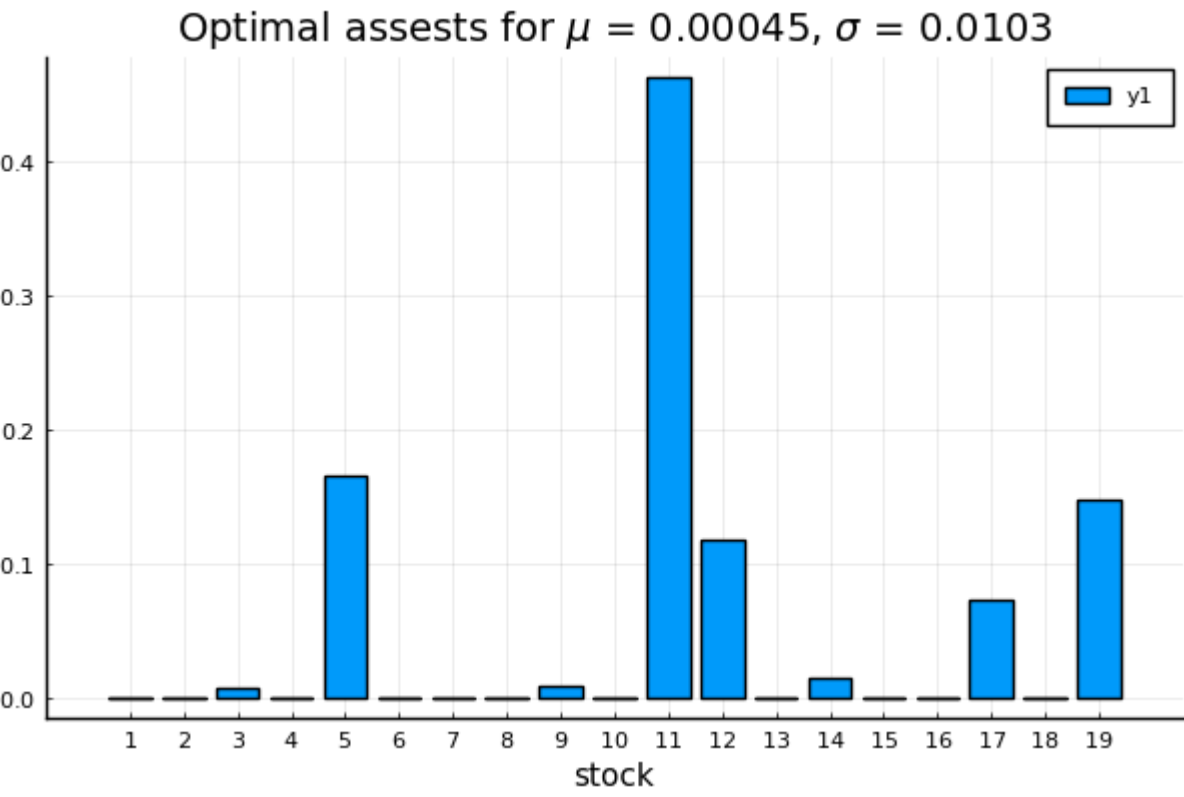
## Constraints
@constraint(model, dot(x,  $\mu$ ) >=  $\mu_{\min}$ ) # Expected average return bound
@constraint(model, sum(x) == 1) # Scaling of stock positions

## Solve the problem and get solution
optimize!(model)
status = termination_status(model)
# println(status)

x = value.(x) # Stock positions
ret = dot( $\mu$ , x) # Return
std = sqrt(dot(x,  $\Sigma$ x)) # Risk: std. deviation of returns

## Plot optimal asset selection
Plots.bar(1:n, x,
     xticks = 1:1:n,
     title = string("Optimal assets for \$\ \\\mu \$ = ", round(ret, digits = 5), ", ", "\$ \\\sigma \$ = ", round(std, digits = 5)),
     xlabel = "stock")
```

Out[34]:



Compute optimal tradeoff curve for 50 equidistant points $\mu_{\min} \in [0, 0.000869]$ for the problem

$$\begin{aligned} & \text{minimize} && x^T \Sigma x \\ & \text{subject to} && \mu^T x \geq \mu_{\min} \\ & && \sum_{i \in N} x_i = 1 \\ & && x \geq 0 \end{aligned}$$

```
In [36]: N = 50 # Number of points to compute
ret = zeros(N) # Array to save values of  $\mu$ 
std = zeros(N) # Array to save values of  $\sigma$ 
 $\mu_{\min}$  values = LinRange(0,0.000869,N) # Range of 50 values  $\mu_{\min} \in [0, 0.000869]$ 

for (i,  $\mu_{\min}$ ) in enumerate( $\mu_{\min}$  values)
    model = Model(optimizer_with_attributes(Ipopt.Optimizer, "print_level" => 0))
    @variable(model, x[1:n] >= 0) # Stock positions
    @objective(model, Min, dot(x,  $\Sigma$ x)) # Minimize variance
    @constraint(model, dot(x,  $\mu$ ) >=  $\mu_{\min}$ ) # Expected average return bound
    @constraint(model, sum(x) == 1) # Scaling of stock positions

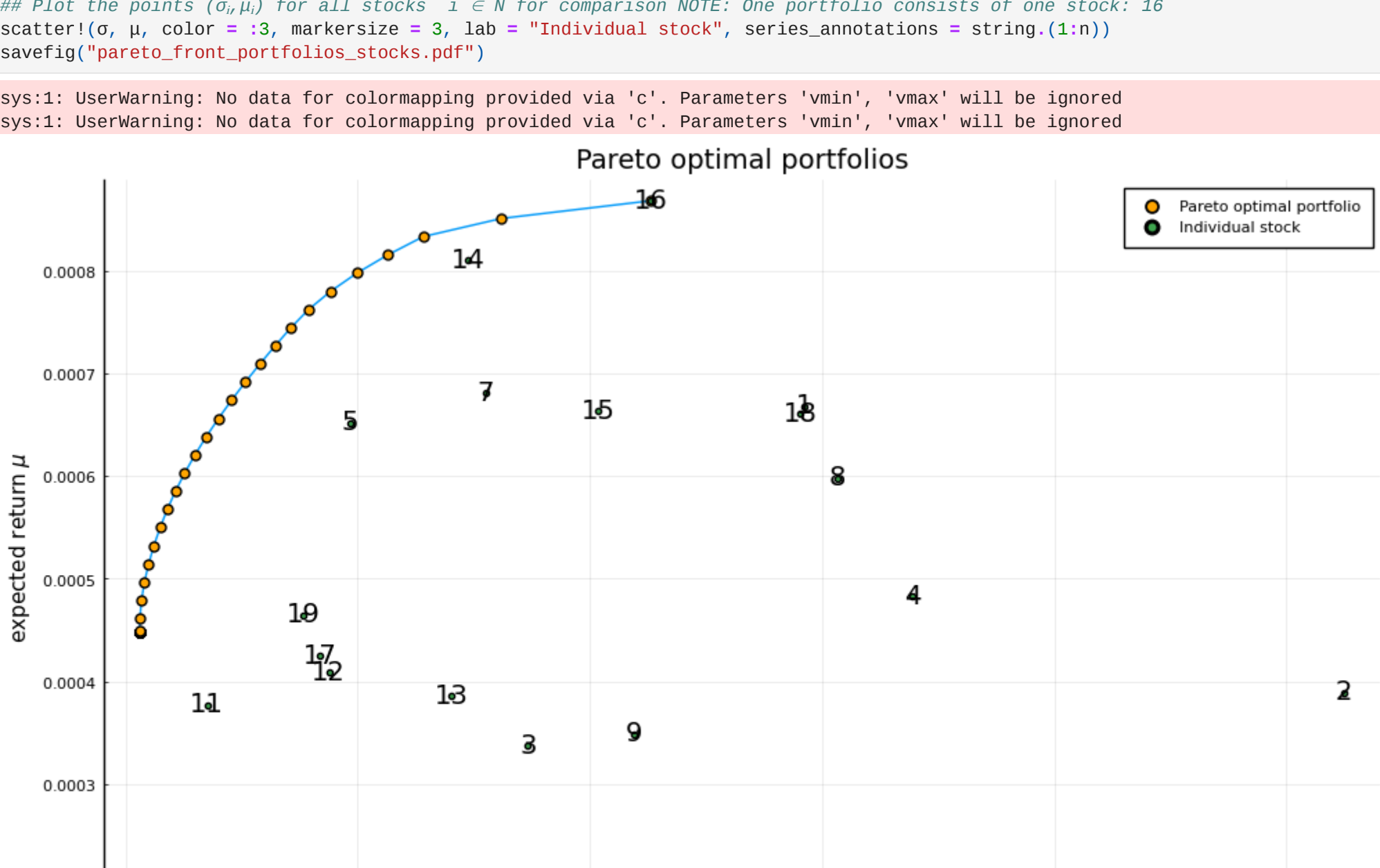
    ## Solve the problem and compute ret[i] and std[i] for the current  $\mu_{\min}$  value
    optimize!(model)
    x = value.(x) # Get stock positions
    ret[i] = dot( $\mu$ , x) # Compute return
    std[i] = sqrt(dot(x,  $\Sigma$ x)) # Compute risk (standard deviation)
end

## Plot the tradeoff curve (Pareto front)
plot(std, ret,
     xlabel = "standard deviation \$\ \\\sigma \$",
     ylabel = "expected return \$\ \\\mu \$",
     title = "Pareto optimal portfolios",
     grid = :on,
     lab = "",
     size = (1000, 600))

## Plot the individual portfolio points
scatter!(std, ret, color = :orange, markersize = 5, lab = "Pareto optimal portfolio")
savefig("pareto_front_portfolios.pdf")

## Plot the points  $(\sigma_i, \mu_i)$  for all stocks 1  $\leq i \leq N$  for comparison NOTE: One portfolio consists of one stock: 16
scatter!( $\sigma$ ,  $\mu$ , color = :3, markersize = 3, lab = "Individual stock", series_annotations = string.(1:n))
savefig("pareto_front_portfolios_stocks.pdf")

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In []: