

Laboratorium 3

```
In [31]: #tablice wielowymiarowe w Julii
Asmall=[[1.0 0.0 10]; [0.0 1.0 10]]
Bsmall=Asmall
Asmall
C = zeros(Float64, size(Asmall,1), size(Asmall,2))
```

```
Out[31]: 2×3 Array{Float64,2}:
 0.0  0.0  0.0
 0.0  0.0  0.0
```

```
In [26]: size(Asmall)
```

```
Out[26]: (2, 3)
```

```
In [14]: # mnożenie macierzy - wersja naiwna, naiwna przez sposob dostępu do
          # pamięci
          # najlepiej zeby dane byly blisko siebie w pamieci, przez sposob dzia
          # lania pamieci cache, ktora odczytuje dane
          # blokami zwanymi liniami cache. Odczytywanie obok siebie jest duzo s
          # zybsze.
          # Pytniem jest jak jest tablica przechowywana w pamieci, zazwyczaj wi
          # erszami (C) ale w julli sa przechowywane
          # kolumnami
          function naive_multiplication(A,B)
            C=zeros(Float64,size(A,1),size(B,2))
            for i=1:size(A,1)
              for j=1:size(B,2)
                for k=1:size(A,2)
                  C[i,j]=C[i,j]+A[i,k]*B[k,j]
                end
              end
            end
          end
          C
          end
```

```
Out[14]: naive_multiplication (generic function with 1 method)
```

```
In [4]: #kompilacja
naive_multiplication(Asmall,Bsmall)
```

```
Out[4]: 2×2 Array{Float64,2}:
 1.0  0.0
 0.0  1.0
```

```
In [5]: #kompilacja funkcji BLASowej do mnożenia macierzy
#https://docs.julialang.org/en/stable/stdlib/linalg/#BLAS-Functions-1
#to też jest mnożenie macierzy ale zoptymalizowanymi funkcjami BLAS
Asmall*Bsmall
```

```
Out[5]: 2×2 Array{Float64,2}:
 1.0  0.0
 0.0  1.0
```

```
In [6]: A=rand(1000,1000); #tworzenie macierzy 1000 x 1000 z losowymi wartosciami
B=rand(1000,1000);
```

```
In [7]: # Należy pamiętać o "column-major" dostępie do tablic -
# pierwszy indeks zmienia się szybciej
# tak jak Matlab, R, Fortran
# inaczej niż C, Python
A1 = [[1 2]; [3 4]]
vec(A1)
```

```
Out[7]: 4-element Array{Int64,1}:
 1
 3
 2
 4
```

```
In [15]: # poprawiona funkcja korzystająca z powyższego oraz z faktu, że
#można zmieniać kolejność operacji dodawania (a co za tym idzie kolejność
# jest lepsza przez zamienienie kolejności petli i częściej odczytuje
# elementy będące bliżej siebie
function better_multiplication( A,B )
C=zeros(Float64,size(A,1),size(B,2))
    for j=1:size(B,2)
        for k=1:size(A,2)
            for i=1:size(A,1)
                C[i,j]=C[i,j]+A[i,k]*B[k,j]
            end
        end
    end
end
C
end
```

```
Out[15]: better_multiplication (generic function with 1 method)
```

```
In [9]: better_multiplication(Asmall, Bsmall)
```

```
Out[9]: 2×2 Array{Float64,2}:
 1.0  0.0
 0.0  1.0
```

```
In [10]: @elapsed naive_multiplication(A,B) #mierzenie czasu
```

```
Out[10]: 3.69591414
```

```
In [11]: @elapsed better_multiplication(A,B)
```

```
Out[11]: 1.600793835
```

```
In [12]: @elapsed A*B #blas
```

```
Out[12]: 0.016316159
```

```
In [59]: # aproksymacja sredniokwadratowa wielomianem - tutaj przyklad dla wie  
lomianu 3 stopnia  
# pakiet Polynomials jest mozliwy do instalacji pod Juliabox  
# https://github.com/JuliaMath/Polynomials.jl
```

```
using Polynomials  
xs = 0:3; ys = [1,3,4,5]  
fit1=polyfit(xs, ys,3)
```

```
# po prostu za xs podstawic to co mam za wielkosc macierzy a za ys po  
dstawiac po kolei te zmienne dla których  
# chce wyliczyc wielomian
```

```
Out[59]: 1.0 + 2.8333333333333335·x - 0.9999999999999999·x^2 + 0.16666666666666663·x^3
```

```
In [14]: # obliczanie wartosci wielomianu  
fit1(1)
```

```
Out[14]: 836.4071935534389
```

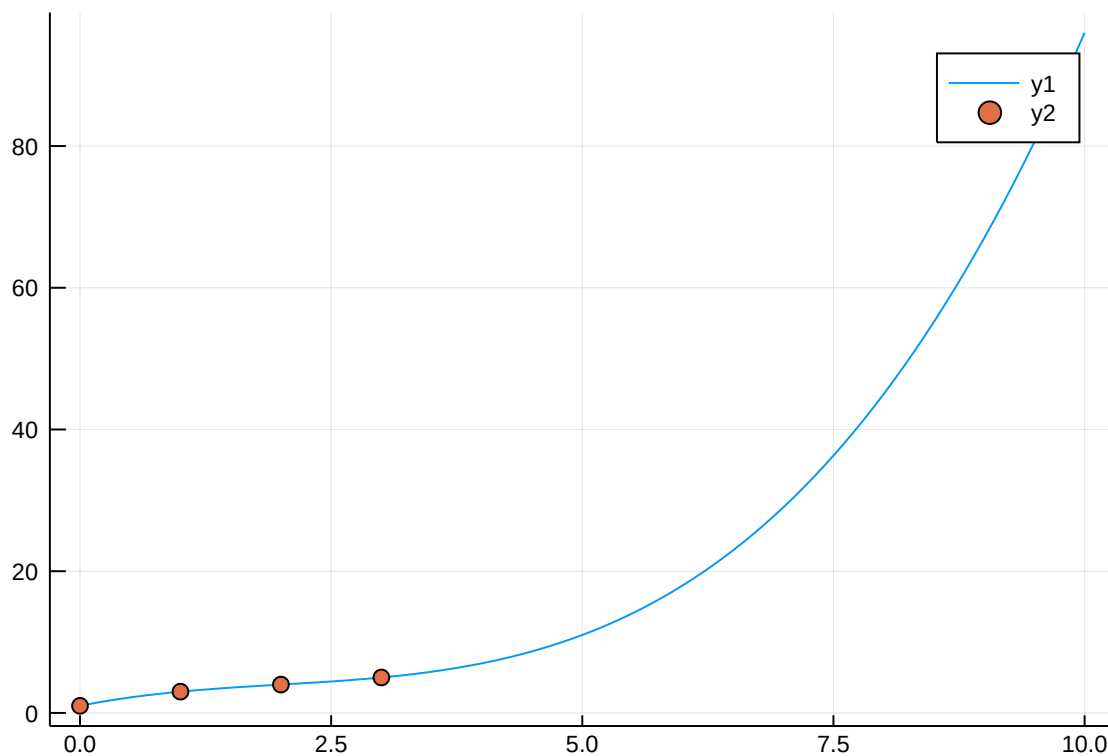
```
In [15]: # obliczanie wartosci wielomianu (drugi sposob)  
polyval(fit1, 1)
```

```
Out[15]: 836.4071935534389
```

In [60]: **using** Plots

```
# geste punkty do wyliczenia wartosci wielomianu aproksymujacego:  
xd=0:0.1:10  
# wykres wartosci wielomianu dla gestych punktow:  
plot(xd,polyval(fit1, xd))  
  
# ! -dodanie do tego samego wykresu punktów wg których aproksymowalis  
my  
scatter!(xs,ys)
```

Out[60]:



Zadania

1. Uruchomić

- `naive_multiplication(A,B)`,
- `better_multiplication(A,B)`
- mnożenie BLAS w Julii ($A*B$)

dla coraz większych macierzy i zmierzyć czasy. Narysować wykres zależności czasu od rozmiaru macierzy wraz z słupkami błędów, tak jak na poprzednim laboratorium. Wszystkie trzy metody powinny być na jednym wykresie.

2. Napisać w języku C:

- naiwną metodę mnożenia macierzy (wersja 1)
- ulepszoną za pomocą zamiany pętli metodę mnożenia macierzy (wersja 2), pamiętając, że w C macierz przechowywana jest wierszami (row major order tzn $A_{11}, A_{12}, \dots, A_{1m}, A_{21}, A_{22}, \dots, A_{2m}, \dots, A_{nm}$), inaczej niż w Julii !
- skorzystać z możliwości BLAS dostępnego w GSL (wersja 3).

Należy porównywać działanie tych trzech algorytmów bez włączonej opcji optymalizacji kompilatora. Przedstawić wyniki na jednym wykresie tak jak w p.1. (osobno niż p.1). (Dla chętnych) sprawdzić, co się dzieje, jak włączymy optymalizację kompilatora i dodać do wykresu.

3. Użyć funkcji `polyfit` z pakietu `Polynomials` do znalezienia odpowiednich wielomianów, które najlepiej pasują do zależności czasowych każdego z algorytmów. Stopień wielomianu powinien zgadzać się z teoretyczną złożonością. Dodać wykresy uzyskanych wielomianów do wcześniejszych wykresów.

```
In [16]: columns_and_rows = Int64[]
naive_time = Float64[]
better_time = Float64[]
blas_time = Float64[]

nb_of_tests = 10
i = 50
while(i <= 1000)
    for k=0:nb_of_tests
        A = rand(i,i)
        B = rand(i,i)
        push!(columns_and_rows, i)
        push!(naive_time,@elapsed naive_multiplication(A,B))
        push!(better_time,@elapsed better_multiplication(A,B))
        push!(blas_time,@elapsed A * B)
    end
    i += 50
end
columns_and_rows
```

Out[16]: 220-element Array{Int64,1}:

```
50
50
50
50
50
50
50
50
50
50
50
50
100
100
:
950
1000
1000
1000
1000
1000
1000
1000
1000
1000
1000
1000
1000
```

In [18]: **using** DataFrames

```
df = DataFrame()
df[:columns_and_rows]= columns_and_rows
df[:naive_time] = naive_time
df[:better_time] = better_time
df[:blas_time] = blas_time
```

Out[18]: 220-element Array{Float64,1}:

| |
|-------------|
| 0.445678423 |
| 2.42e-5 |
| 1.8701e-5 |
| 2.19e-5 |
| 2.24e-5 |
| 1.99e-5 |
| 2.24e-5 |
| 2.21e-5 |
| 4.9201e-5 |
| 2.08e-5 |
| 2.22e-5 |
| 0.000635004 |
| 8.0501e-5 |
| ⋮ |
| 0.011140474 |
| 0.017180114 |
| 0.015388102 |
| 0.013482489 |
| 0.021169041 |
| 0.013324388 |
| 0.013693191 |
| 0.016768711 |
| 0.013379489 |
| 0.014136793 |
| 0.01671251 |
| 0.01357489 |

```
In [19]: using Statistics
df2 = DataFrame(by(df, [:columns_and_rows],
    :naive_time => mean,
    :naive_time => std,
    :better_time => mean,
    :better_time => std,
    :blas_time => mean,
    :blas_time => std))
```

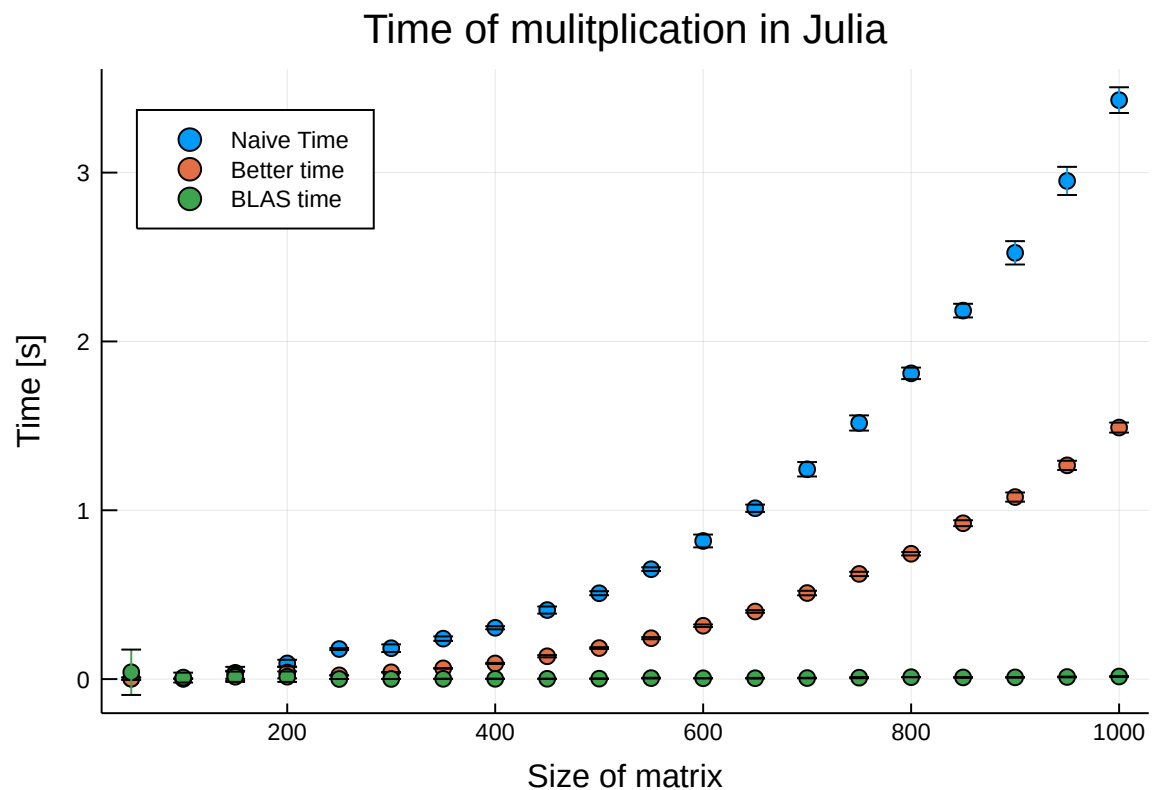
Out[19]: 20 rows × 7 columns

| | columns_and_rows | naive_time_mean | naive_time_std | better_time_mean | better_time_std | b |
|----|------------------|-----------------|----------------|------------------|-----------------|---|
| | Int64 | Float64 | Float64 | Float64 | Float64 | |
| 1 | 50 | 0.00258037 | 0.00713601 | 0.00233655 | 0.00696521 | |
| 2 | 100 | 0.00333974 | 9.22051e-5 | 0.00157779 | 6.40788e-5 | |
| 3 | 150 | 0.0371351 | 0.0355213 | 0.0191812 | 0.0298498 | |
| 4 | 200 | 0.0928441 | 0.0216986 | 0.0392809 | 0.0352772 | |
| 5 | 250 | 0.178135 | 0.00578942 | 0.0223672 | 0.000658748 | |
| 6 | 300 | 0.18299 | 0.0225436 | 0.0402549 | 0.00198967 | |
| 7 | 350 | 0.239635 | 0.0131353 | 0.0637023 | 0.00196339 | |
| 8 | 400 | 0.30382 | 0.00926658 | 0.0926878 | 0.00341562 | |
| 9 | 450 | 0.408957 | 0.0209303 | 0.135173 | 0.00649957 | |
| 10 | 500 | 0.508545 | 0.0118891 | 0.183753 | 0.00489786 | |
| 11 | 550 | 0.65091 | 0.0111029 | 0.242095 | 0.00608552 | |
| 12 | 600 | 0.818139 | 0.0380825 | 0.315904 | 0.00763555 | |
| 13 | 650 | 1.01197 | 0.0216512 | 0.400414 | 0.00730541 | |
| 14 | 700 | 1.24273 | 0.0426229 | 0.509718 | 0.0136065 | |
| 15 | 750 | 1.517 | 0.0448517 | 0.622955 | 0.0129383 | |
| 16 | 800 | 1.81098 | 0.0342295 | 0.742372 | 0.0100373 | |
| 17 | 850 | 2.18262 | 0.0405781 | 0.923156 | 0.0174981 | |
| 18 | 900 | 2.52477 | 0.0691341 | 1.07829 | 0.0271135 | |
| 19 | 950 | 2.95079 | 0.0834888 | 1.2661 | 0.0274116 | |
| 20 | 1000 | 3.4293 | 0.076056 | 1.48992 | 0.0295836 | |

In [20]: using Plots

```
ydata = scatter(df2[:columns_and_rows],
    [df2[:naive_time_mean] df2[:better_time_mean] df2[:blas_time_mean]
]),
yerr = [df2[:naive_time_std] df2[:better_time_std] df2[:blas_time_std]],
labels = ["Naive Time" "Better time" "BLAS time"],
title = "Time of mulitplication in Julia",
legend=:topleft,
xlabel = "Size of matrix",
ylabel = "Time [s]",)
```

Out[20]:



```
In [21]: using CSV
input0="result00.csv"
mydata0=CSV.read(input0, delim=";")
input1="result01.csv"
mydata1=CSV.read(input1, delim=";")
input2="result02.csv"
mydata2=CSV.read(input2, delim=";")
input3="result03.csv"
mydata3=CSV.read(input3, delim=";")
```

Out[21]: 200 rows × 4 columns

| | columns_and_rows | naive_time | better_time | blas_time |
|----|------------------|------------|-------------|------------|
| | Int64[?] | Float64[?] | Float64[?] | Float64[?] |
| 1 | 50 | 9.8e-5 | 6.7e-5 | 9.7e-5 |
| 2 | 50 | 9.4e-5 | 6.3e-5 | 0.000103 |
| 3 | 50 | 9.3e-5 | 7.3e-5 | 9.5e-5 |
| 4 | 50 | 0.000104 | 6.2e-5 | 9.2e-5 |
| 5 | 50 | 9.3e-5 | 6.3e-5 | 0.000129 |
| 6 | 50 | 9.3e-5 | 6.2e-5 | 9.2e-5 |
| 7 | 50 | 9.3e-5 | 6.1e-5 | 9.1e-5 |
| 8 | 50 | 9.3e-5 | 6.4e-5 | 0.000112 |
| 9 | 50 | 9.3e-5 | 6.2e-5 | 0.000124 |
| 10 | 50 | 0.000154 | 7.6e-5 | 0.000114 |
| 11 | 100 | 0.000944 | 0.00047 | 0.000702 |
| 12 | 100 | 0.000847 | 0.000632 | 0.00102 |
| 13 | 100 | 0.001298 | 0.000695 | 0.001074 |
| 14 | 100 | 0.000966 | 0.000449 | 0.000664 |
| 15 | 100 | 0.000819 | 0.000472 | 0.000645 |
| 16 | 100 | 0.000816 | 0.000448 | 0.000669 |
| 17 | 100 | 0.000814 | 0.000437 | 0.00071 |
| 18 | 100 | 0.000896 | 0.000475 | 0.000754 |
| 19 | 100 | 0.000805 | 0.000504 | 0.000652 |
| 20 | 100 | 0.000813 | 0.000437 | 0.00067 |
| 21 | 150 | 0.002834 | 0.001525 | 0.002231 |
| 22 | 150 | 0.002914 | 0.001524 | 0.002104 |
| 23 | 150 | 0.002866 | 0.001468 | 0.002066 |
| 24 | 150 | 0.002745 | 0.00143 | 0.002067 |
| 25 | 150 | 0.00279 | 0.001467 | 0.002049 |
| 26 | 150 | 0.002752 | 0.001416 | 0.002069 |
| 27 | 150 | 0.002769 | 0.001419 | 0.002067 |
| 28 | 150 | 0.002757 | 0.001409 | 0.002065 |
| 29 | 150 | 0.002768 | 0.001419 | 0.002056 |
| 30 | 150 | 0.002798 | 0.001433 | 0.002046 |
| ⋮ | ⋮ | ⋮ | ⋮ | ⋮ |

```
In [23]: using Statistics, DataFrames, Plots
data0 = DataFrame(by(mydata0, [:columns_and_rows],
    :naive_time => mean,
    :naive_time => std,
    :better_time => mean,
    :better_time => std,
    :blas_time => mean,
    :blas_time => std))
data1 = DataFrame(by(mydata1, [:columns_and_rows],
    :naive_time => mean,
    :naive_time => std,
    :better_time => mean,
    :better_time => std,
    :blas_time => mean,
    :blas_time => std))
data2 = DataFrame(by(mydata2, [:columns_and_rows],
    :naive_time => mean,
    :naive_time => std,
    :better_time => mean,
    :better_time => std,
    :blas_time => mean,
    :blas_time => std))
data3 = DataFrame(by(mydata3, [:columns_and_rows],
    :naive_time => mean,
    :naive_time => std,
    :better_time => mean,
    :better_time => std,
    :blas_time => mean,
    :blas_time => std))
```

Out[23]: 20 rows × 7 columns

| | columns_and_rows | naive_time_mean | naive_time_std | better_time_mean | better_time_std | b |
|----|------------------|-----------------|----------------|------------------|-----------------|---|
| | Int64[2] | Float64 | Float64 | Float64 | Float64 | |
| 1 | 50 | 0.0001008 | 1.9031e-5 | 6.53e-5 | 5.16505e-6 | |
| 2 | 100 | 0.0009018 | 0.000150958 | 0.0005019 | 8.88075e-5 | |
| 3 | 150 | 0.0027993 | 5.55479e-5 | 0.001451 | 4.36552e-5 | |
| 4 | 200 | 0.0070292 | 6.93282e-5 | 0.0033728 | 1.62535e-5 | |
| 5 | 250 | 0.0138767 | 8.9614e-5 | 0.0065372 | 6.45838e-5 | |
| 6 | 300 | 0.0242617 | 0.0001352 | 0.0111669 | 8.02641e-5 | |
| 7 | 350 | 0.0434019 | 0.000519811 | 0.0176253 | 0.000202312 | |
| 8 | 400 | 0.059222 | 0.000271867 | 0.0258232 | 0.000176843 | |
| 9 | 450 | 0.0897198 | 0.00298483 | 0.0365432 | 0.000374439 | |
| 10 | 500 | 0.132688 | 0.000173886 | 0.050158 | 0.000104083 | |
| 11 | 550 | 0.189049 | 0.0218715 | 0.0663637 | 0.000542822 | |
| 12 | 600 | 0.239029 | 0.0207561 | 0.086083 | 0.00118062 | |
| 13 | 650 | 0.296271 | 0.00397298 | 0.109232 | 0.000735391 | |
| 14 | 700 | 0.407073 | 0.0560403 | 0.141404 | 0.00580082 | |
| 15 | 750 | 0.463916 | 0.0712514 | 0.173345 | 0.00794257 | |
| 16 | 800 | 0.562829 | 0.00434685 | 0.207849 | 0.000872308 | |
| 17 | 850 | 0.738729 | 0.0305803 | 0.266075 | 0.00505022 | |
| 18 | 900 | 1.54044 | 0.0614094 | 0.351571 | 0.00353188 | |
| 19 | 950 | 1.44931 | 0.11367 | 0.441002 | 0.00383281 | |
| 20 | 1000 | 3.43011 | 0.0996768 | 0.513976 | 0.00112116 | |

```

In [24]: plot00 = scatter(data0[:columns_and_rows],
    [data0[:naive_time_mean] data0[:better_time_mean] data0[:blas_time_mean]],
    yerr = [data0[:naive_time_std] data0[:better_time_std] data0[:blas_time_std]],
    labels = ["Naive Time" "Better time" "BLAS time"],
    title = "Time of mulitplication in C, with 00 optim",
    legend=:topleft,
    xlabel = "Size of matrix",
    ylabel = "Time [s]")
plot01 = scatter(data1[:columns_and_rows],
    [data1[:naive_time_mean] data1[:better_time_mean] data1[:blas_time_mean]],
    yerr = [data1[:naive_time_std] data1[:better_time_std] data1[:blas_time_std]],
    labels = ["Naive Time" "Better time" "BLAS time"],
    title = "Time of mulitplication in C, with 01 optim",
    legend=:topleft,
    xlabel = "Size of matrix",
    ylabel = "Time [s]")
plot02 = scatter(data2[:columns_and_rows],
    [data2[:naive_time_mean] data2[:better_time_mean] data2[:blas_time_mean]],
    yerr = [data2[:naive_time_std] data2[:better_time_std] data2[:blas_time_std]],
    labels = ["Naive Time" "Better time" "BLAS time"],
    title = "Time of mulitplication in C, with 02 optim",
    legend=:topleft,
    xlabel = "Size of matrix",
    ylabel = "Time [s]")

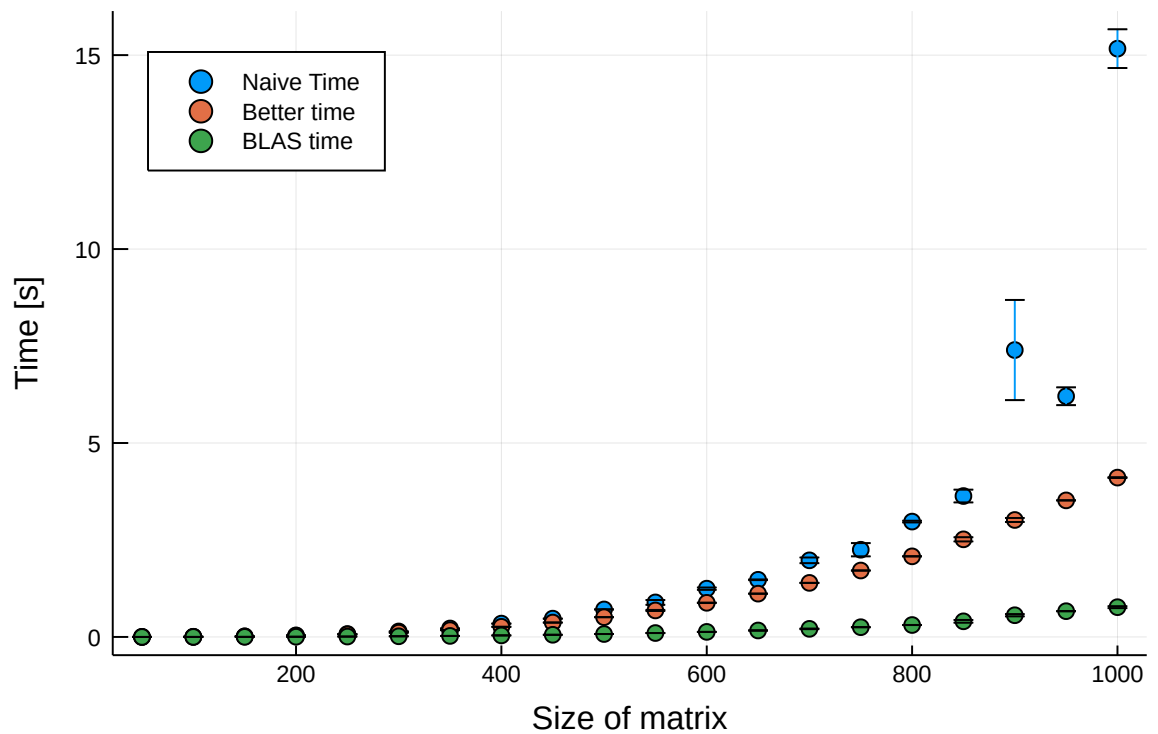
plot03 = scatter(data3[:columns_and_rows],
    [data3[:naive_time_mean] data3[:better_time_mean] data3[:blas_time_mean]],
    yerr = [data3[:naive_time_std] data0[:better_time_std] data3[:blas_time_std]],
    labels = ["Naive Time" "Better time" "BLAS time"],
    title = "Time of mulitplication in C, with 03 optim",
    legend=:topleft,
    xlabel = "Size of matrix",
    ylabel = "Time [s]")

naive_compare = scatter([data0[:columns_and_rows] data1[:columns_and_rows] data2[:columns_and_rows]],
    [data0[:naive_time_mean]
    data1[:naive_time_mean]
    data2[:naive_time_mean] ],
    yerr =
    [data0[:naive_time_std]
    data1[:naive_time_std]
    data2[:naive_time_std] ],
    labels = ["Naive Time 00" "Naive Time 01" "Naive Time 02"],
    title = "naive in optimalization dependency",
    legend=:topleft,
    xlabel = "Size of matrix",

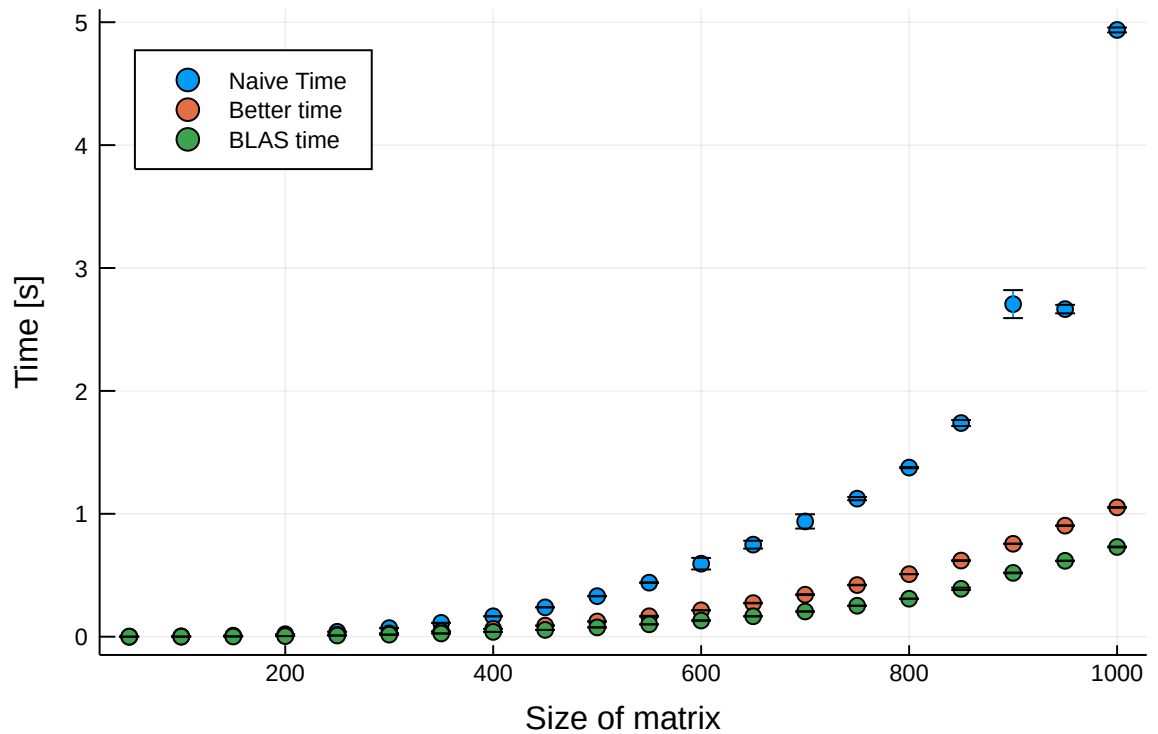
```

```
        ylabel = "Time [s]",)  
  
display(plot00)  
display(plot01)  
display(plot02)  
display(plot03)  
  
display(naive_compare)
```

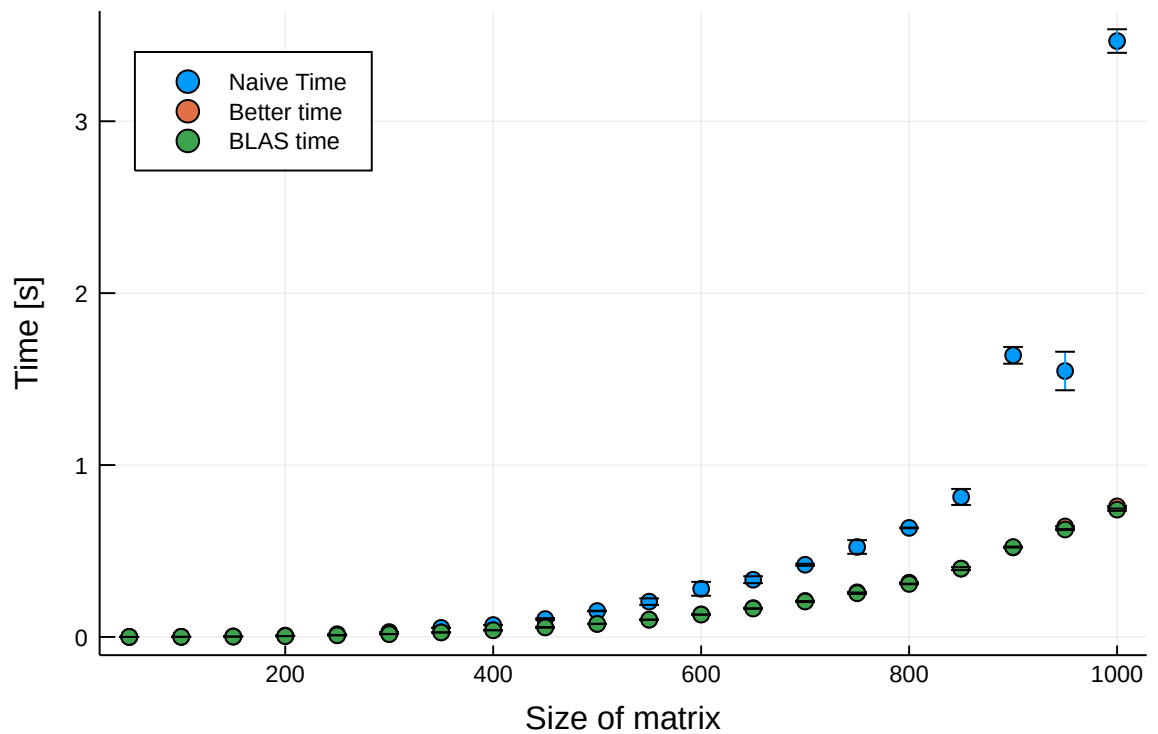
Time of mulitplication in C, with O0 optim



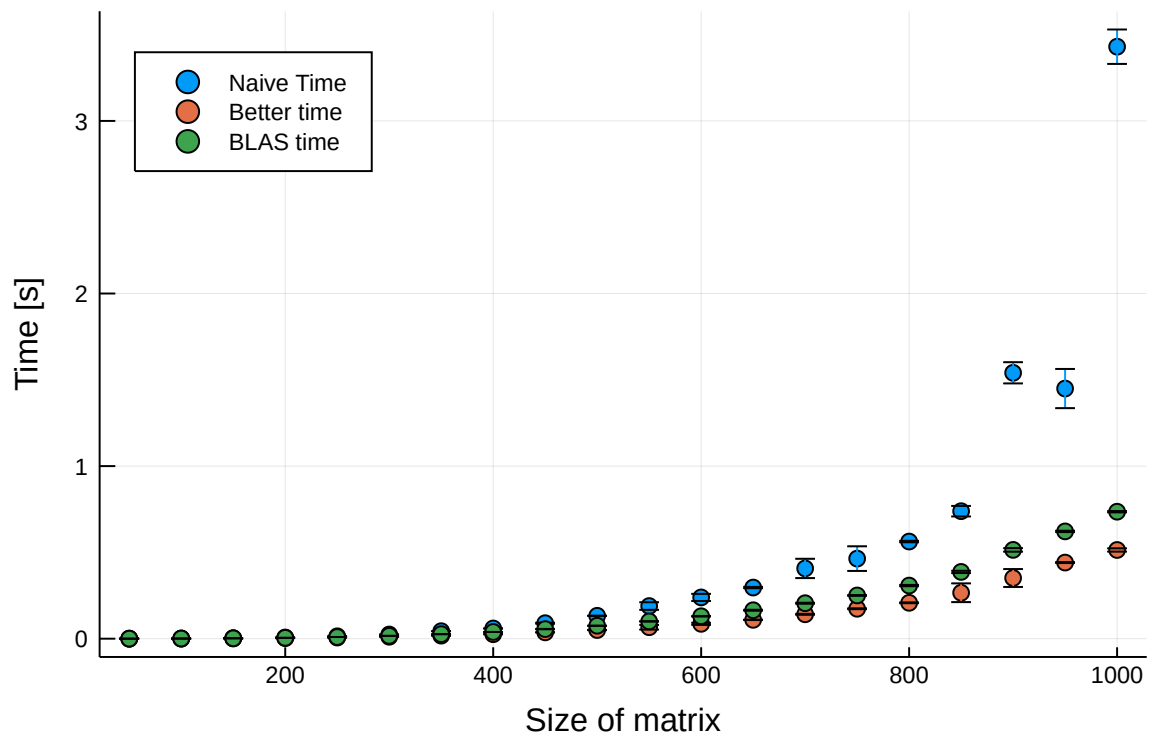
Time of mulitplication in C, with O1 optim

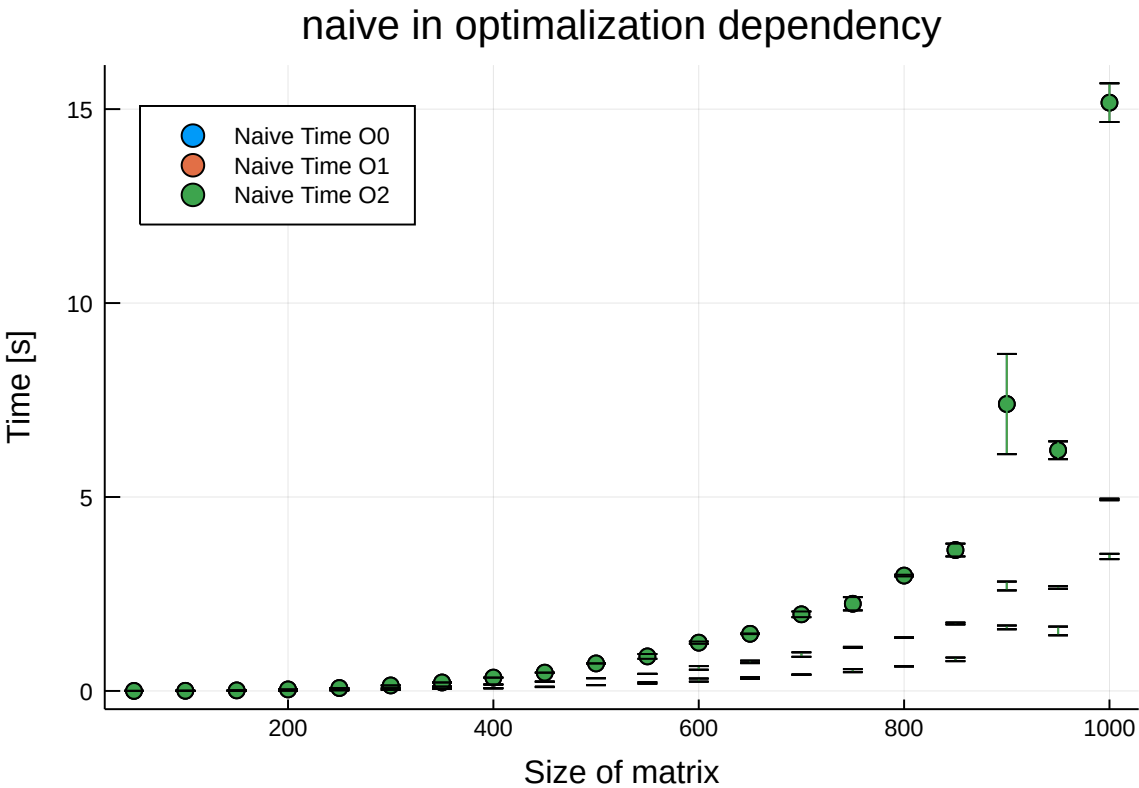


Time of mulitplication in C, with O2 optim



Time of mulitplication in C, with O3 optim



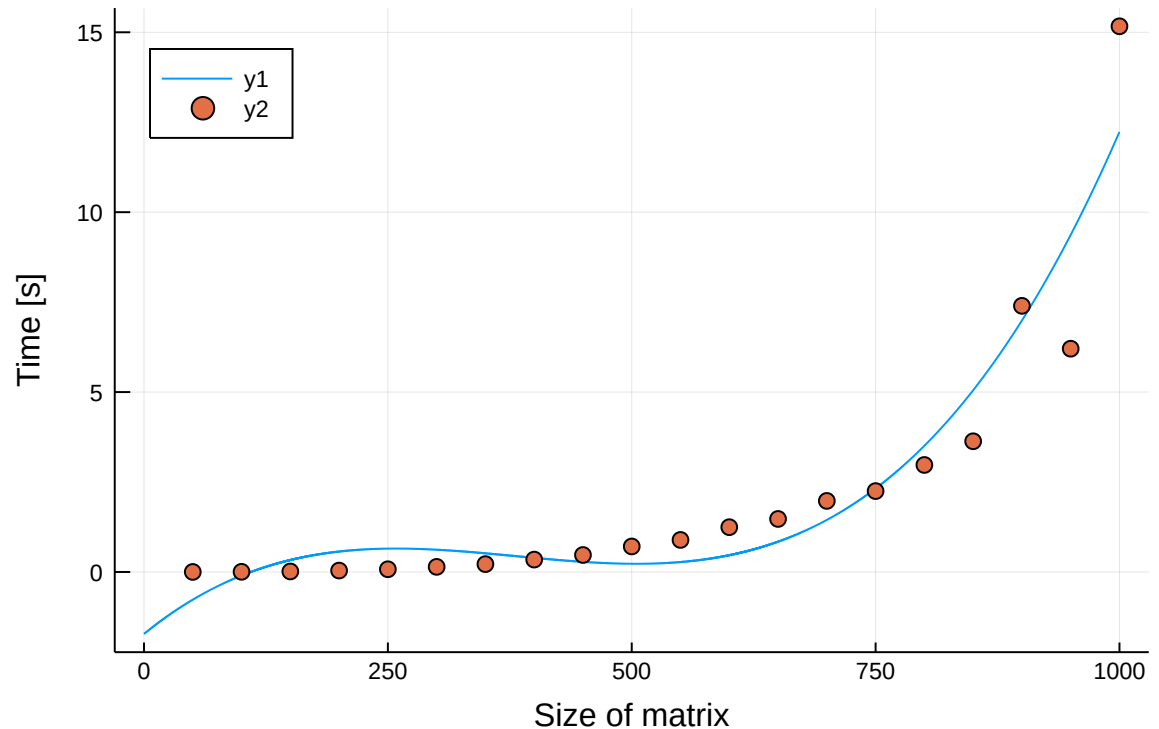


In [75]: **using** Polynomials, Plots

```
fit_data0_naive=polyfit(data0[:columns_and_rows],data0[:naive_time_mean],3)
xd=0:0.01:1000
plot(xd,polyval(fit_data0_naive, xd))
scatter!(data0[:columns_and_rows],data0[:naive_time_mean])
scatter!(labels = ["Naive Time 00" "Polynomial approximation"],
legend=:topleft,xlabel = "Size of matrix", ylabel = "Time [s]", title
= "Naive in C")
#print(fit_data0_naive)
```

Out[75]:

Naive in C

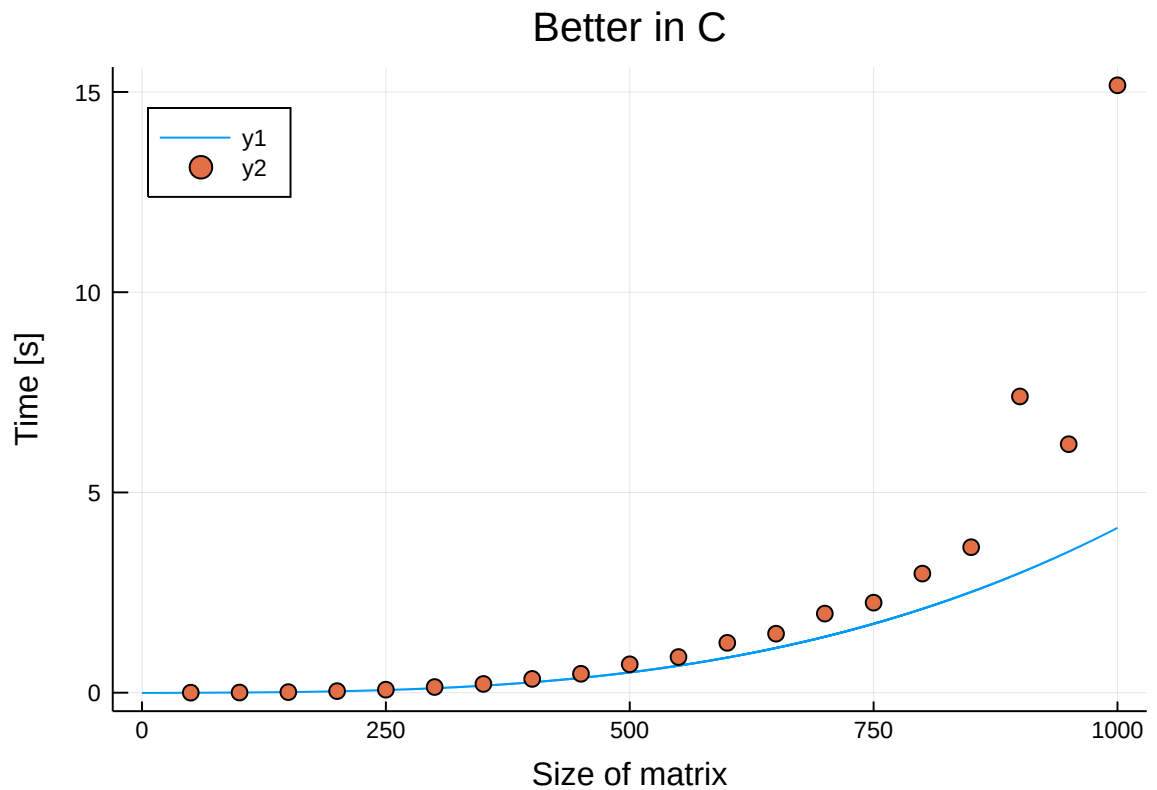


```

In [81]: fit_data0_better=polyfit(data0[:columns_and_rows],data0[:better_time_
mean],3)
xd=0:0.01:1000
plot(xd,polyval(fit_data0_better, xd))
scatter!(data0[:columns_and_rows],data0[:naive_time_mean])
scatter!(labels = ["Naive Time 00" "Polynomial approximation"],
legend=:topleft,xlabel = "Size of matrix", ylabel = "Time [s]", title
= "Better in C")
#print(fit_data0_better)

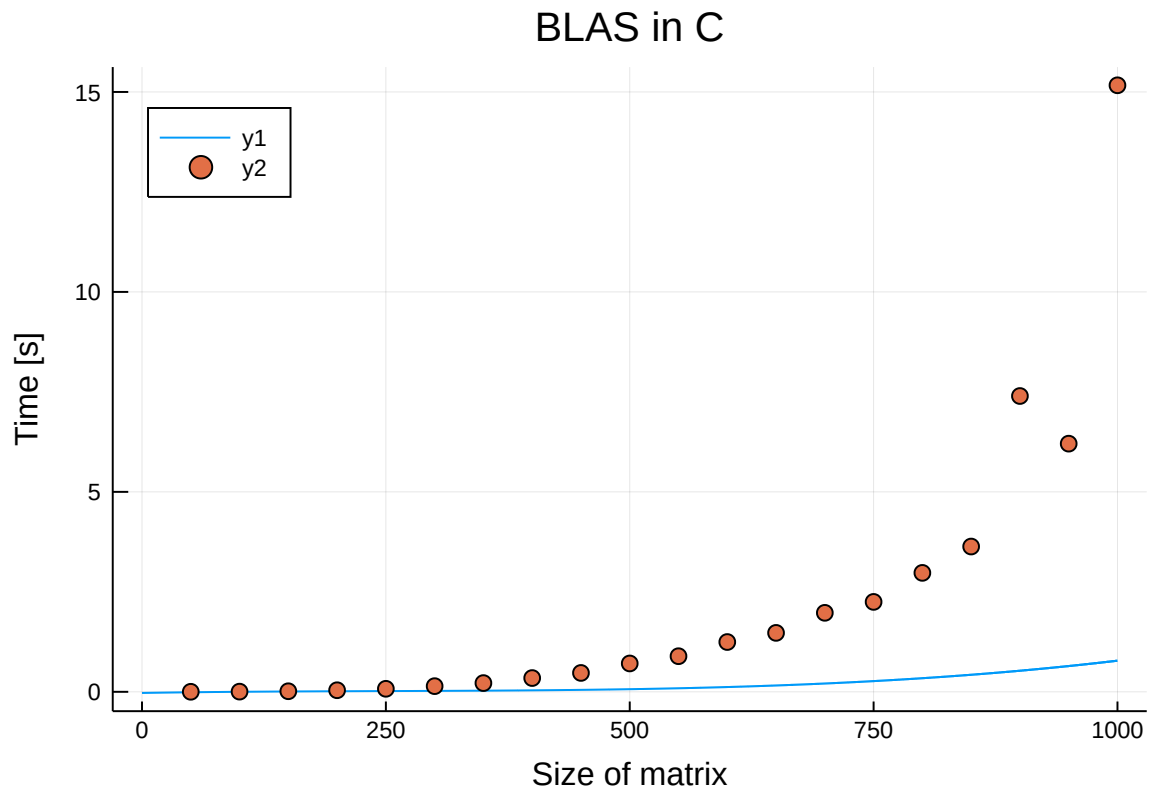
```

Out[81]:



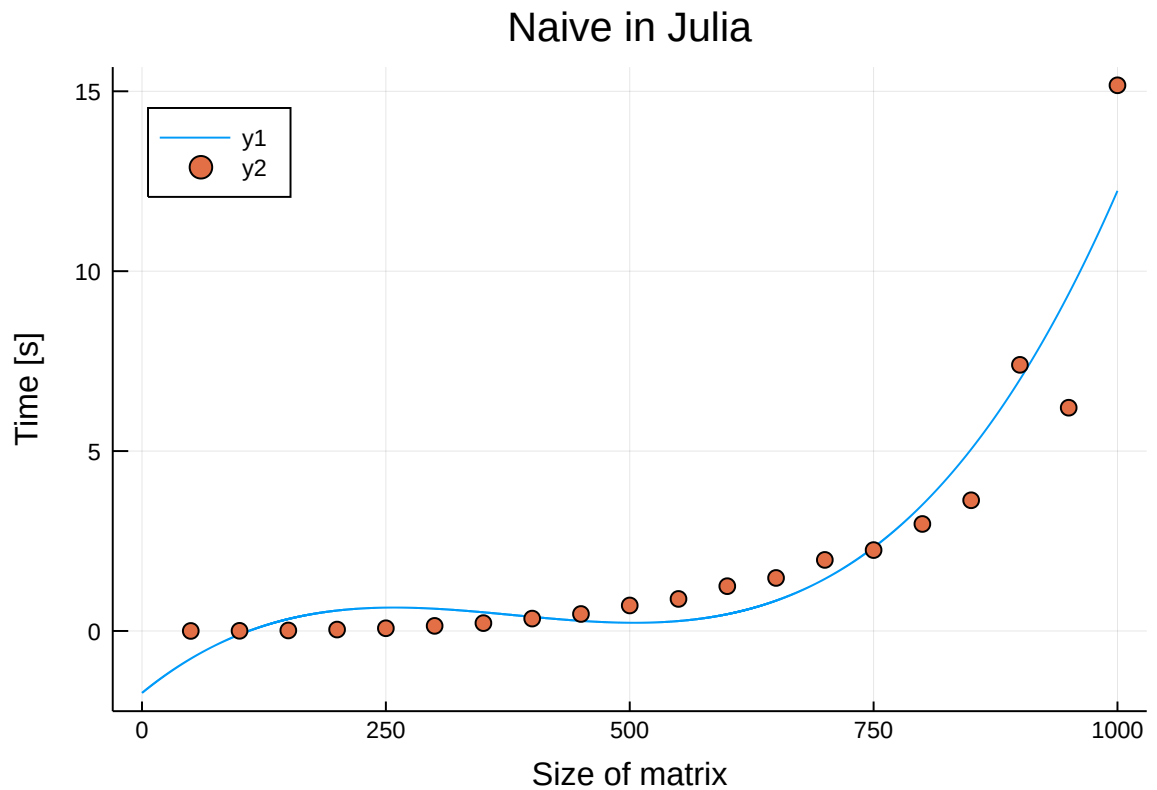
```
In [76]: fit_data0_blas=polyfit(data0[:columns_and_rows],data0[:blas_time_mean],3)
xd=0:0.01:1000
plot(xd,polyval(fit_data0_blas, xd))
scatter!(data0[:columns_and_rows],data0[:naive_time_mean])
scatter!(labels = ["Naive Time 00" "Polynomial approximation"],
legend=:topleft,xlabel = "Size of matrix", ylabel = "Time [s]", title
= "BLAS in C")
#print(fit_data0_blas)
```

Out[76]:



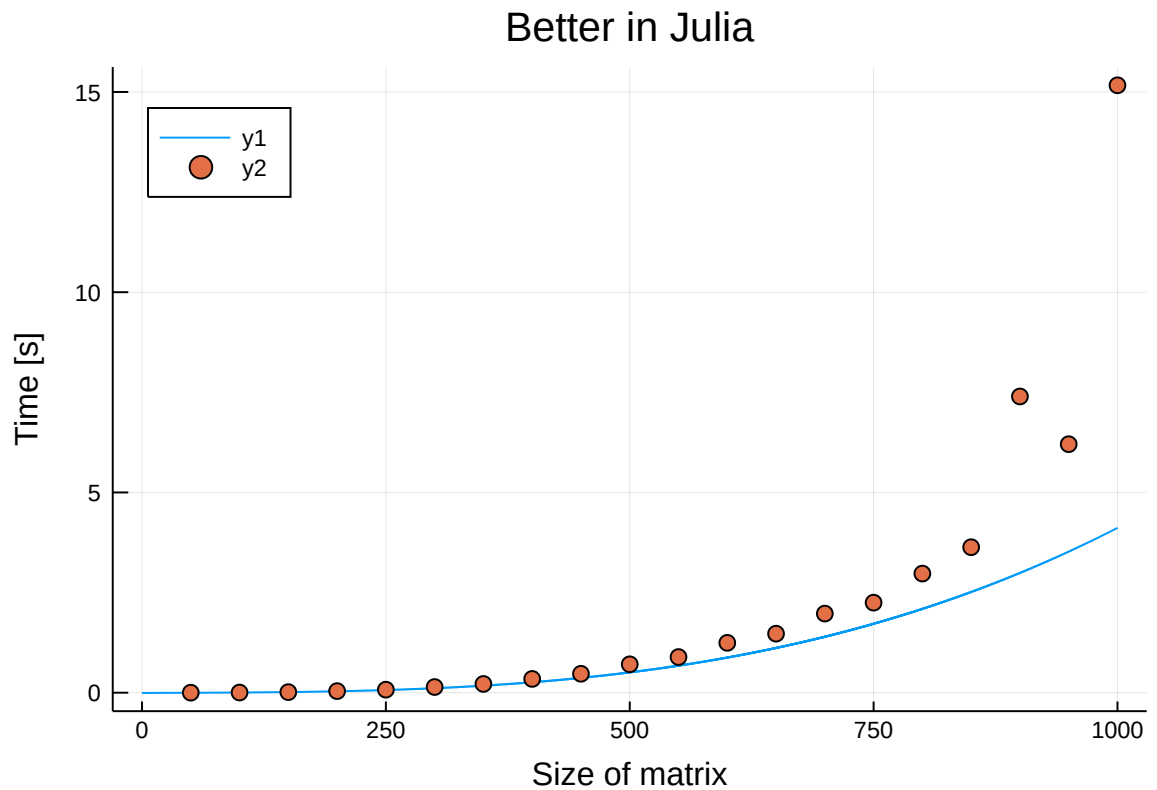
```
In [77]: fit_julia_naive=polyfit(df2[:columns_and_rows],df2[:naive_time_mean],
3)
xd=0:0.01:1000
plot(xd,polyval(fit_data0_naive, xd))
scatter!(data0[:columns_and_rows],data0[:naive_time_mean])
scatter!(labels = ["Naive Time 00" "Polynomial approximation"],
legend=:topleft,xlabel = "Size of matrix", ylabel = "Time [s]", title
= "Naive in Julia")
#print(fit_julia_naive)
```

Out[77]:



```
In [78]: fit_julia_better=polyfit(df2[:columns_and_rows],df2[:better_time_mean],3)
xd=0:0.01:1000
plot(xd,polyval(fit_data0_better, xd))
scatter!(data0[:columns_and_rows],data0[:naive_time_mean])
scatter!(labels = ["Naive Time 00" "Polynomial approximation"],
legend=:topleft,xlabel = "Size of matrix", ylabel = "Time [s]", title
= "Better in Julia")
#print(fit_julia_better)
```

Out[78]:



```
In [79]: fit_julia_blas=polyfit(df2[:columns_and_rows],df2[:blas_time_mean],3)
xd=0:0.01:1000
plot(xd,polyval(fit_data0_blas, xd))
scatter!(data0[:columns_and_rows],data0[:naive_time_mean])
scatter!(labels = ["Naive Time 00" "Polynomial approximation"],
legend=:topleft,xlabel = "Size of matrix", ylabel = "Time [s]", title
= "BLAS in Julia")
#print(fit_julia_blas)
```

Out[79]:

