julia for Data Science

Julia is a high-level and general-purpose language that can be used to write code that is fast to execute and easy to implement for scientific calculations. The language is designed to keep all the needs of scientific researchers and data scientists to optimize the experimentation and design implementation. Julia (programming language). Python is still famous among data science enthusiasts as they get an ecosystem with loaded libraries to makes the work of data science and analysis faster and more convenient. "Julia was built for scientific computing, machine learning, data mining, large-scale linear algebra, distributed and parallel computing"—developers behind the Julia language.

Python isn't fast or convenient *enough and it comes with securities variabilities as most of the libraries are built from other languages such a JavaScript, Java, C, and C++*. The fast execution and convenient development make it quite attractive among the data science community and the majority of libraries are directly written in Julia to provide an extra layer of security. InfoWorld.

According to Jeremy Howard "Python is not the future of machine learning".

In his recent video, he talks about how Python is frustrating when it comes to running machine learning models as you have to use other languages libraries such as CUDA and to run parallel computing you must use other libraries which makes it quite difficult. He also suggests how Julia is going to be the future of machine learning and if you want to become future-proof and have free time to learn a new language I will suggest you start with Julia.

Simple examples and a few lines of code to demonstrate data manipulation and data visualization will be using the famous Heart Disease UCI | Kaggle Dataset which has a binary classification of Heart Disease based on multiple factors. The dataset is small and clean so it's the best example we can use to see how simple Julia has become.

Julia

While comparing with Python, Julia takes lead in multiple fields as mentioned below.

Julia is fast

Python can be made optimized by using external libraries and optimization tools, but Julia is faster by default as it comes with JIT compilation and type declarations.

Math-friendly syntax

Julia attracts non-programmer scientists by providing simple syntax for math operations which are similar to the non-computing world.

Automatic memory management

Julia is better than Python in terms of memory allocation, and it provides you more freedom to manually control garbage collection. Whereas in python you are constantly freeing memory and collecting information about memory usage which can be daunting in some cases.

Superior parallelism

It’s necessary to use all available resources while running scientific algorithms such as running it on parallels computing with a multi-core processor. For Python, you need to use external packages for parallel computing or serialized and deserialized operations between threads which can be hard to use. For Julia, it’s much simpler in implementation as it inherently comes with parallelism.

Native machine learning libraries

Flux is a machine learning library for Julia and there are other deep learning frameworks under development that are entirely written in Julia and can be modified as needed by the user. These libraries come with GPU acceleration, so you don’t need to worry about the slow training of deep learning models.

Exploring Heart Disease Dataset

Before you follow my code, I want to look into A tutorial on DataFrames.jl prepared for JuliaCon2021 as most of my code is inspired by the live conference.

Before you start coding you need to set up your Julia repl, either use JuliaPro or set up your **VS code** for Julia and if you are using a cloud notebook just like me, I will suggest you add the below code into your docker file and build it. **Docker** code below only works for Deepnote only.

The output of the code shows a limited number of columns for the compact view but in reality, it has 14 columns.

```
FROM gcr.io/deepnote-200602/templates/deepnote

RUN wget https://julialang-s3.julialang.org/bin/linux/x64/1.6/julia-1.6.2-linux-
x86_64.tar.gz &&
    tar -xvzf julia-1.6.2-linux-x86_64.tar.gz &&
    sudo mv julia-1.6.2 /usr/lib/ &&
    sudo ln -s /usr/lib/julia-1.6.2/bin/julia /usr/bin/julia &&
    rm julia-1.6.2-linux-x86_64.tar.gz &&
    julia  -e "using Pkg;pkg"add IJulia LinearAlgebra SparseArrays Images MAT""
ENV DEFAULT_KERNEL_NAME "julia-1.6.2"
```

Installing Julia packages

The method below will help you download and install all multiple libraries at once.

```
import Pkg; Pkg.add(["CSV","CategoricalArrays",
"Chain", "DataFrames", "GLM", "Plots", "Random", "StatsPlots",
"Statistics","Interact", "Blink"])
```

Importing Packages

We will be focusing more on loading CVS files, data manipulation, and visualization.

```
using CSV
using CategoricalArrays
using Chain
using DataFrames
using GLM
using Plots
using Random
using StatsPlots
using Statistics

ENV["LINES"] = 20 # to limit number of rows.
ENV["COLUMNS"] = 20 # to limit number of columns
```

Loading Data

We are using the famous Heart Disease UCI | Kaggle dataset for our beginner-level code for data analysis. We will be focusing on the coding part.

Features:

1. age
2. sex
3. chest pain type (4 values)
4. resting blood pressure
5. serum cholesterol in mg/dl
6. fasting blood sugar > 120 mg/dl
7. resting electrocardiographic results (values 0,1,2)
8. maximum heart rate achieved
9. exercise-induced angina
10. oldpeak
11. the slope of the peak exercise ST segment
12. number of major vessels
13. thal: 3 to 7 where 5 is normal.

Simply Use `CSV.read()` just like pandas `pd.read_csv()` and your data will be loaded as data frame.

```
df_raw = CSV.read("/work/Data/Heart Disease Dataset.csv", DataFrame)
```

303 rows × 14 columns

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
	Int64	Int64	Int64	Int64	Int64	Int64	Int64	Int64	Int64	Float64	Int64	Int64	Int64	Int64
1	63	1	3	145	233	1	0	150	0	2.3	0	0	1	1
2	37	1	2	130	250	0	1	187	0	3.5	0	0	2	1
3	41	0	1	130	204	0	0	172	0	1.4	2	0	2	1
4	56	1	1	120	236	0	1	178	0	0.8	2	0	2	1
5	57	0	0	120	354	0	1	163	1	0.6	2	0	2	1

Operation	pandas	DataFrames.jl
Cell indexing by location	`df.iloc[1, 1]`	`df[2, 2]`
Row slicing by location	`df.iloc[1:3]`	`df[2:3, :]`
Column slicing by location	`df.iloc[:, 1:]`	`df[:, 2:end]`
Row indexing by label	`df.loc['c']`	`df[findfirst(==('c'), df.id), :]`
Column indexing by	`df.loc[:, 'x']`	`df[:, :x]`

label		
Column slicing by label	`df.loc[:, ['x', 'z']]`	`df[:, [:x, :z]]`
	`df.loc[:, 'x':'z']`	`df[:, Between(:x, :z)]`
Mixed indexing	`df.loc['c'][1]`	`df[findfirst(==('c'), df.id), 2]`

For more Information on [Comparison with Python/R/Stata · DataFrames.jl (juliadata.org)]

Checking the shape of the Dataframe

```
size(df_raw)
```

output

```
(303, 14)
```

Checking Multiple features distributions. We can observe mean, min, max, and missing all in one, using `describe()`

```
describe(df_raw)
```

	variable	mean	min	median	max	nmissing	eltype
	Symbol	Float64	Real	Float64	Real	Int64	DataType
1	age	54.2013	34	55.0	77	0	Int64
2	sex	0.660066	0	1.0	1	0	Int64
3	cp	0.874587	0	1.0	3	0	Int64
4	trestbps	131.007	94	130.0	200	0	Int64
5	chol	251.627	141	248.0	564	0	Int64
6	fbs	0.128713	0	0.0	1	0	Int64
7	restecg	0.547855	0	1.0	2	0	Int64
8	thalach	150.29	71	155.0	192	0	Int64
9	exang	0.330033	0	0.0	1	0	Int64
10	oldpeak	1.06337	0.0	0.8	5.6	0	Float64

	variable	mean	min	median	max	nmissing	eltype
	Symbol	Float64	Real	Float64	Real	Int64	DataType
11	slope	1.40924	0	1.0	2	0	Int64
12	ca	0.70297	0	0.0	4	0	Int64
13	thal	2.30033	0	2.0	3	0	Int64
14	target	0.547855	0	1.0	1	0	Int64

Data select

we can convert columns into categorical types by using `:fbs => categorical => :fbs` and we have used between to select multiple columns at once. The select function is simple, for selecting columns and manipulating the types.

```
df = select(df_raw,:age,:sex => categorical => :sex,
            Between(:cp, :chol),
            :fbs => categorical => :fbs,:restecg,:thalach,
            :exang => categorical => :exang,
            Between(:oldpeak,:thal),
            :target => categorical => :target
            )
```

303 rows × 14 columns

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
	Int64	Cat…	Int64	Int64	Int64	Cat…	Int64	Int64	Cat…	Float64	Int64	Int64	Int64	Cat…
1	47	1	2	108	243	0	1	152	0	0.0	2	0	2	0
2	35	1	0	126	282	0	0	156	1	0.0	2	0	3	0
3	68	1	0	144	193	1	1	141	0	3.4	1	2	3	0
4	50	0	0	110	254	0	0	159	0	0.0	2	0	2	1
5	49	0	1	134	271	0	1	162	0	0.0	1	0	2	1
6	40	1	0	110	167	0	0	114	1	2.0	1	0	3	0
7	45	1	0	142	309	0	0	147	1	0.0	1	3	3	0
8	57	0	0	120	354	0	1	163	1	0.6	2	0	2	1

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
	Int64	**Cat…**	**Int64**	**Int64**	**Int64**	**Cat…**	**Int64**	**Int64**	**Cat…**	**Float64**	**Int64**	**Int64**	**Int64**	**Cat…**
9	62	0	0	140	394	0	0	157	0	1.2	1	0	2	1
10	34	1	3	118	182	0	0	174	0	0.0	2	0	2	1

Using Chain

if you want to apply multiple operations on your datasets all at once, I will suggest you use chain, in R it’s equivalent to `%>%`.

- the `dropmissing` will drop missing values from the database, we don’t have any missing, so this is simply for a showcase.
- the `groupby` function groups the data frame by the passed column
- the `combine` function that combines the rows of a data frame by some function

you can see the results of how I have grouped the data frame by target and then combine 5 columns to get the mean values.

```
@chain df_raw begin
    dropmissing
    groupby(:target)
    combine([:age, :sex, :chol, :restecg, :slope] .=> mean)
end
```

	target	age_mean	sex_mean	chol_mean	restecg_mean	slope_mean
	Int64	**Float64**	**Float64**	**Float64**	**Float64**	**Float64**
1	0	56.6277	0.824818	254.073	0.489051	1.14599
2	1	52.1988	0.524096	249.608	0.596386	1.62651

another simple way to use group by and combine is by using names(df, Real) which returns all the columns with real values, which mean not integers or categorical columns.

```
@chain df_raw begin
    groupby(:target)
    combine(names(df, Real) .=> mean)
end
```

	target	age_mean	cp_mean	trestbps_mean	chol_mean	restecg_mean	thalach_mean	oldpeak_mean	slope_mean	ca_mean	thal_mean
	Int64	Float64	Float64	Float64	Float64	Float64	Float64	Float64	Float64	Float64	Float64
1	0	56.6277	0.518248	133.73	254.073	0.489051	138.65	1.68686	1.14599	1.16788	2.58394
2	1	52.1988	1.16867	128.759	249.608	0.596386	159.898	0.548795	1.62651	0.319277	2.06627

You can also add multiple columns using groupby and combine them by nrows which will display a number of rows for each sub-group.

```
@chain df_raw begin
    groupby([:target, :sex])
    combine(nrow)
end
```

	target	sex	nrow
	Int64	Int64	Int64
1	0	0	24
2	0	1	113
3	1	0	79
4	1	1	87

You can also combine it and then unstack as shown below. So that one category becomes an index and another becomes a column.

```
@chain df_raw begin
    groupby([:target, :sex])
    combine(nrow)
    unstack(:target, :sex, :nrow)
end
```

	target	0	1
	Int64	Int64?	Int64?
1	0	24	113
2	1	79	87

Groupby

The simple group by the function will show all groups at a time and access the specific group you need to hack it.

```
gd = groupby(df_raw, :target)
```

First Group (137 rows): target = 0

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
	Int64	Int64	Int64	Int64	Int64	Int64	Int64	Int64	Int64	Float64	Int64	Int64	Int64	Int64
1	47	1	2	108	243	0	1	152	0	0.0	2	0	2	0
2	35	1	0	126	282	0	0	156	1	0.0	2	0	3	0
3	68	1	0	144	193	1	1	141	0	3.4	1	2	3	0
4	40	1	0	110	167	0	0	114	1	2.0	1	0	3	0
5	45	1	0	142	309	0	0	147	1	0.0	1	3	3	0

Last Group (166 rows): target = 1

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
	Int64	Int64	Int64	Int64	Int64	Int64	Int64	Int64	Int64	Float64	Int64	Int64	Int64	Int64
1	50	0	0	110	254	0	0	159	0	0.0	2	0	2	1
2	49	0	1	134	271	0	1	162	0	0.0	1	0	2	1
3	57	0	0	120	354	0	1	163	1	0.6	2	0	2	1
4	62	0	0	140	394	0	0	157	0	1.2	1	0	2	1

we can use :

```
gd[(target=0,)] | gd[Dict(:target => 0)] | gd[(0,)]
```

to get a specific group that we are focusing on, this helps us a lot in the long run. gd[1] will be shown the first group which is target =0.

```
gd[1]
```

age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target

	Int64	Int64	Int64	Int64	Int64	Int64	Int64	Int64	Int64	Float64	Int64	Int64	Int64	Int64
1	47	1	2	108	243	0	1	152	0	0.0	2	0	2	0
2	35	1	0	126	282	0	0	156	1	0.0	2	0	3	0
3	68	1	0	144	193	1	1	141	0	3.4	1	2	3	0
4	40	1	0	110	167	0	0	114	1	2.0	1	0	3	0

Density Plot

For this, we use a density plot from the StatsPlots.jl package. This package contains statistical recipes that extend the Plots.jl functionality. Just like seaborn with simple code, we can get our density plot with the separate groups are defined by colors.

We are going to group it by target columns and display cholesterol.

```
@df df density(:chol, group=:target)
```

```
Output:
```

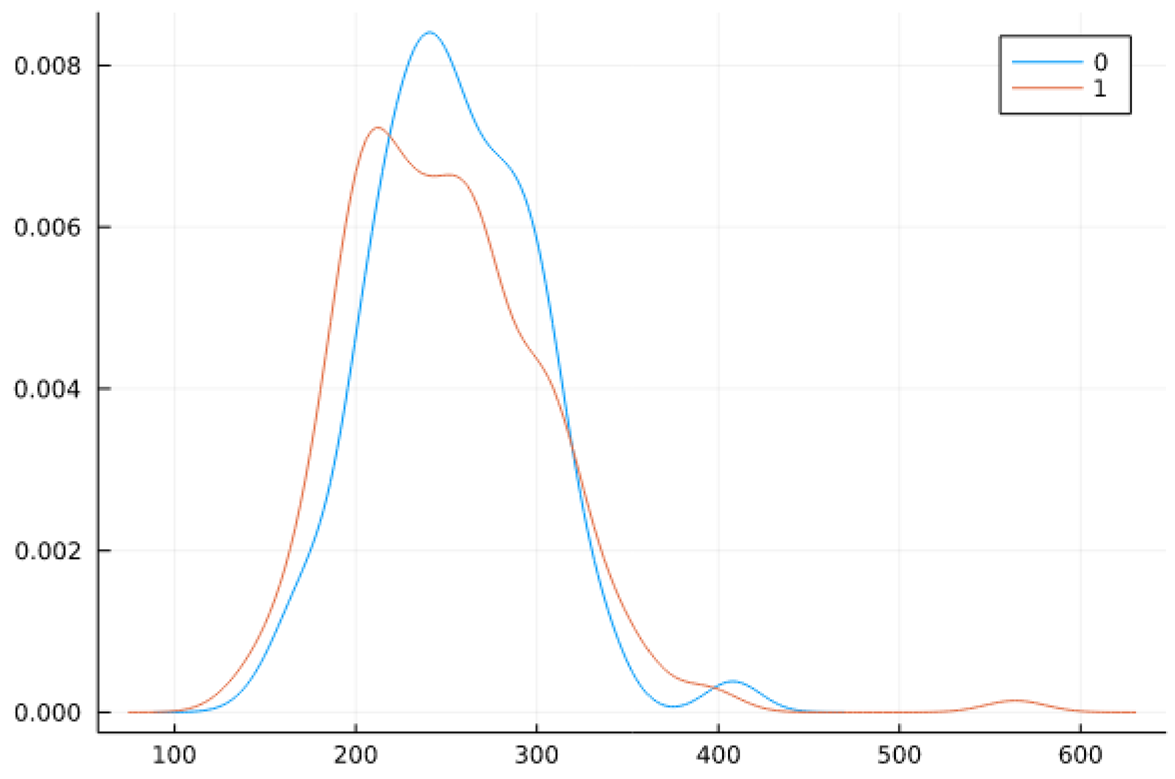
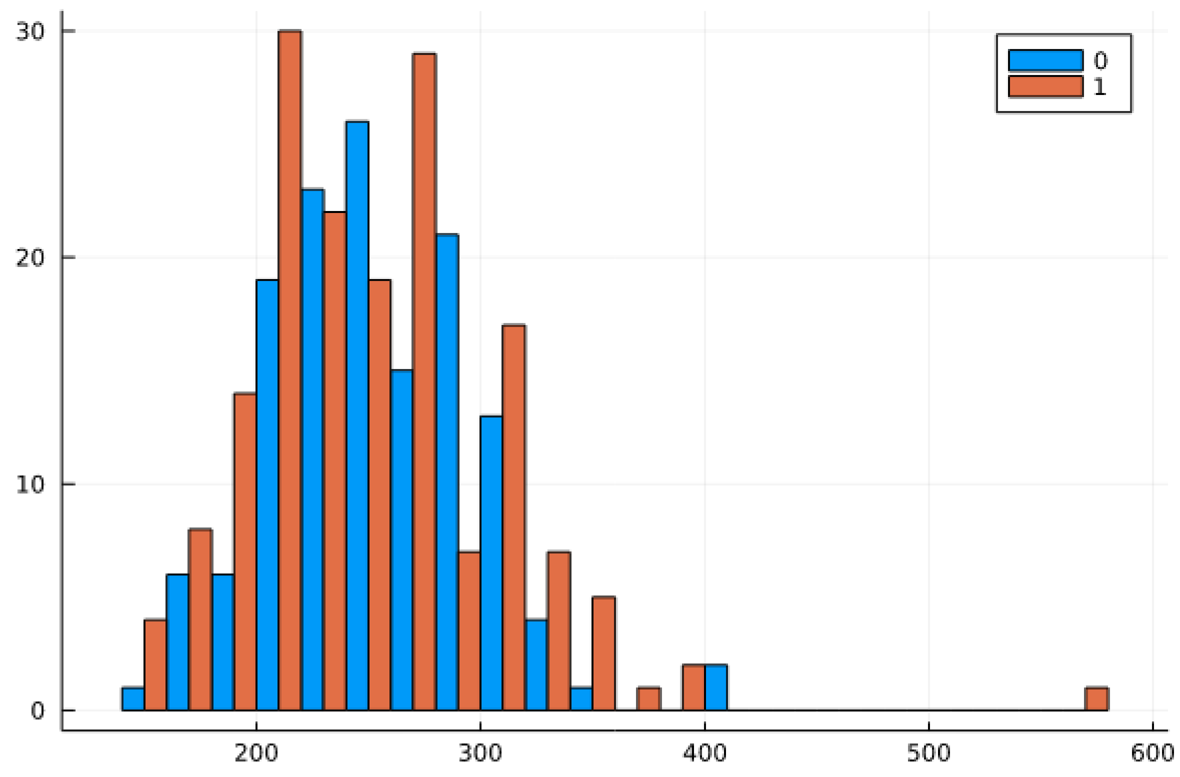


Image By Author

Group Histogram

Similar to density plot you can plot grouphist which is grouped by target and display cholesterols.

```
@df df_raw groupedhist(:chol, group = :target, bar_position = :dodge)
```



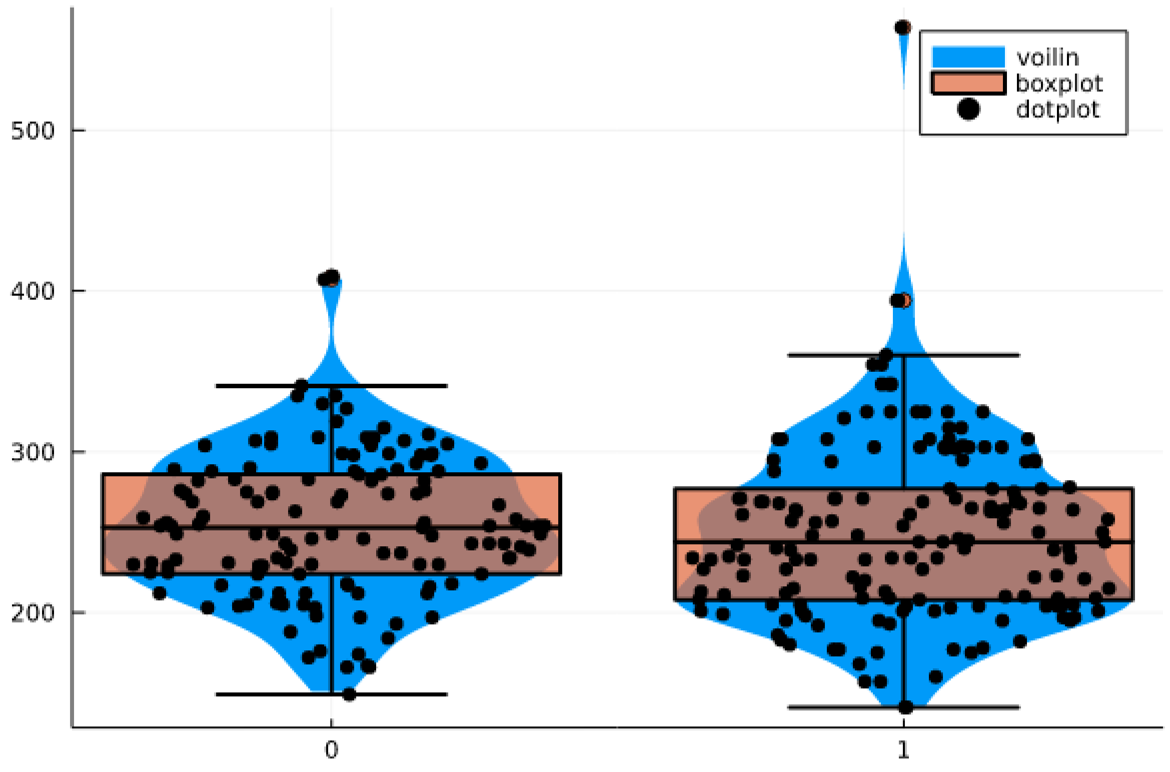
Histplot by Author

You can plot multiple graphs on the same figure by using **!** at the end of the function name for example `boxplot!()`. I have shown the example below of violin plot, boxplot, and dotplot on cholesterol which is grouped by the target.

```
@df df_raw violin(string.(:target), :chol, linewidth=0,label = "voilin")

@df df_raw boxplot!(string.(:target), :chol, fillalpha=0.75, linewidth=2,label =
"boxplot")

@df df_raw dotplot!(string.(:target), :chol, marker=(:black, stroke(0)),label =
"dotplot")
```



Violin Plot by Author

Predictive Model

I have used the glm model just like in R you can use y~x to train the model. The example below has **x= trestbps, age, chol, thalach, oldpeak, slope, ca,** and **y= target** which is binary. We are going to train our generalized linear model on binomial distribution to predict heart disease which is the target.

```
probit = glm(@formula(target ~ trestbps    + age + chol + thalach + oldpeak +
slope + ca),
             df_raw, Binomial(), ProbitLink())
```

Output:

```
StatsModels.TableRegressionModel{GeneralizedLinearModel{GLM.GlmResp{Vector{Float64}, Binomial{Float64}, ProbitLink}, GLM.DensePredChol{Float64, LinearAlgebra.Cholesky{Float64, Matrix{Float64}}}}, Matrix{Float64}}
```

```
target ~ 1 + trestbps + age + chol + thalach + oldpeak + slope + ca

Coefficients:
────────────────────────────────────────────────────────────────────────
────────────────────────────────────────────────
Coef. Std. Error z Pr(>|z|) Lower 95% Upper 95%
────────────────────────────────────────────────────────────────────────
────────────────────────────────────────────────
(Intercept) -1.64186 1.18724 -1.38 0.1667 -3.9688 0.685081
trestbps -0.00613815 0.00584914 -1.05 0.2940 -0.0176022 0.00532595
age 0.00630188 0.0122988 0.51 0.6084 -0.0178034 0.0304071
chol -0.00082276 0.00176583 -0.47 0.6413 -0.00428373 0.00263821
thalach 0.018028 0.00457232 3.94 <1e-04 0.00906645 0.0269896
oldpeak -0.421474 0.102024 -4.13 <1e-04 -0.621438 -0.221511
slope 0.37985 0.166509 2.28 0.0225 0.0534989 0.706202
ca -0.543177 0.110141 -4.93 <1e-06 -0.759049 -0.327304
────────────────────────────────────────────────────────────────────────
────────────────────────────────────────────────
```