

Developing a population PK model using Pumas

```
using AlgebraOfGraphics
using CSV
using CairoMakie
using Loess
using Pumas
using PumasUtilities
using Random
```

Read data

```
pkdata = CSV.read("iv_sd.csv", DataFrame, missingstring=".");
```

Coverting the DataFrame to a collection of Subjects

```
population = read_pumas(pkdata;
    id           = :ID,
    time         = :TIME,
    observations = [:CONC],
    evid         = :EVID,
    amt          = :AMT,
    cmt          = :CMT,
    covariates   = [:WEIGHT, :eGFR],
)
```

```
Population
Subjects: 100
Covariates: WEIGHT, eGFR
Observations: CONC
```

Model definition

```
iv1cmt = @model begin
    @param begin
        θcl ∈ RealDomain(lower=0.1)
        θvc ∈ RealDomain(lower=1.0)
        Ω ∈ PDiagDomain(2)
        σ_add ∈ RealDomain(lower=0.0)
        σ_prop ∈ RealDomain(lower=0.0)
```

```

end
@random begin
   $\eta \sim \text{MvNormal}(\Omega)$ 
end
@covariates WEIGHT eGFR
@pre begin
  CL =  $\theta_{cl}$  *  $\exp(\eta[1])$ 
  Vc =  $\theta_{vc}$  *  $\exp(\eta[2])$ 
end
@dynamics Central1
@derived begin
  conc_model := @. Central / Vc
  CONC ~ @.  $\text{Normal}(\text{conc\_model}, \sqrt{\sigma_{\text{add}}^2 + (\text{conc\_model} * \sigma_{\text{prop}})^2})$ 
end
end

```

PumasModel
 Parameters: θ_{cl} , θ_{vc} , Ω , σ_{add} , σ_{prop}
 Random effects: η
 Covariates: WEIGHT, eGFR
 Dynamical variables: Central
 Derived: CONC
 Observed: CONC

Initial parameters

```

initial_est_iv1cmt = ( $\theta_{cl} = 1.0$ ,
                      $\theta_{vc} = 10.0$ ,
                      $\Omega = \text{Diagonal}([0.09, 0.09])$ ,
                      $\sigma_{\text{add}} = \sqrt{10.0}$ ,
                      $\sigma_{\text{prop}} = \sqrt{0.01}$ ,
                     )

```

```

( $\theta_{cl} = 1.0$ ,
  $\theta_{vc} = 10.0$ ,
  $\Omega = [0.09 \ 0.0; 0.0 \ 0.09]$ ,
  $\sigma_{\text{add}} = 3.1622776601683795$ ,
  $\sigma_{\text{prop}} = 0.1$ ,)

```

Fit base model

```

@time iv1cmt_results = fit(iv1cmt, population, initial_est_iv1cmt, Pumas

```

Iter	Function value	Gradient norm	
0	4.793467e+03	6.038857e+02	
* time:	3.886222839355469e-5		
1	4.452849e+03	2.701932e+02	
* time:	0.004850864410400391		
2	4.444815e+03	3.023106e+02	
* time:	0.008612871170043945		
3	4.408458e+03	2.733233e+01	
* time:	0.012093067169189453		
4	4.406848e+03	2.393277e+01	
* time:	0.015462875366210938		
5	4.403159e+03	1.912437e+01	
* time:	0.018949031829833984		
6	4.402384e+03	1.522726e+01	
* time:	0.0222928524017334		
7	4.401749e+03	4.543511e+00	
* time:	0.025703907012939453		
8	4.401666e+03	1.522852e+00	
* time:	0.028828859329223633		
9	4.401656e+03	9.513180e-01	
* time:	0.0319209098815918		
10	4.401653e+03	8.885659e-01	
* time:	0.03486990928649902		
11	4.401649e+03	7.376923e-01	
* time:	0.02514309883117676		
12	4.401644e+03	6.903798e-01	
* time:	0.02555508613586426		
13	4.401640e+03	5.160329e-01	
* time:	0.0259458065032959		
14	4.401639e+03	1.943664e-01	
* time:	0.026360297203063965		
15	4.401639e+03	4.342882e-02	
* time:	0.026775693893432617		
16	4.401639e+03	1.590737e-02	
* time:	0.027225685119628906		
17	4.401639e+03	1.484691e-02	
* time:	0.02783169746398926		
18	4.401639e+03	1.470245e-02	
* time:	0.02885880470275879		
19	4.401639e+03	1.468561e-02	
* time:	0.0296314001083374		
20	4.401639e+03	1.467079e-02	
* time:	0.03054800033569336		
21	4.401639e+03	1.467064e-02	
* time:	0.03150289058685303		
22	4.401639e+03	1.467049e-02	
* time:	0.032541799545288086		
23	4.401639e+03	1.467035e-02	
* time:	0.033480000495910645		
24	4.401639e+03	1.467033e-02	

```
* time: 0.34432005882263184
  25    4.401639e+03    1.467032e-02
* time: 0.3501319885253906
  26    4.401639e+03    1.467031e-02
* time: 0.3561398983001709
  27    4.401639e+03    1.467031e-02
* time: 0.3622109889984131
  28    4.401639e+03    1.467031e-02
* time: 0.36820292472839355
  29    4.401639e+03    1.467031e-02
* time: 0.3742818832397461
  30    4.401639e+03    1.467031e-02
* time: 0.38030195236206055
  31    4.401639e+03    1.467031e-02
* time: 0.3863818645477295
  32    4.401639e+03    1.467031e-02
* time: 0.3935699462890625
  33    4.401639e+03    1.467031e-02
* time: 0.4007558822631836
  3.049752 seconds (9.31 M allocations: 1.013 GiB, 9.56% gc time, 86.51%
mpilation time)
FittedPumasModel

Successful minimization:                                true

Likelihood approximation:                                FOCE
Log-likelihood value:                                    -4401.639
Number of subjects:                                      100
Number of parameters:      Fixed      Optimized
                                0              6
Observation records:      Active      Missing
  CONC:                    1500        0
  Total:                   1500        0

-----
              Estimate
-----
0cl           0.41706
0vc           7.1608
Ω1,1       0.17141
Ω2,2       0.19818
σadd       2.9282
σprop      0.12114
-----
```

Inspection

```
iv1cmt_inspect = inspect(iv1cmt_results)
iv1cmt_inspect_df = DataFrame(iv1cmt_inspect)
iv1cmt_inspect_df_plot = dropmissing(iv1cmt_inspect_df, :CONC);
```

Observed vs Population predicted plot

```
pred_vs_obs_loess_model = loess(Float64.(iv1cmt_inspect_df_plot.CONC_pred),
                                Float64.(iv1cmt_inspect_df_plot.CONC),

range_x_axis = range(extrema(Float64.(iv1cmt_inspect_df_plot.CONC_pred))
loess_pred = predict(pred_vs_obs_loess_model, range_x_axis)
loess_pred_df = DataFrame(x_axis = range_x_axis, y_axis = loess_pred)

pred_vs_obs_iv_sd = Figure(fontsize=30,resolution=(800,800))

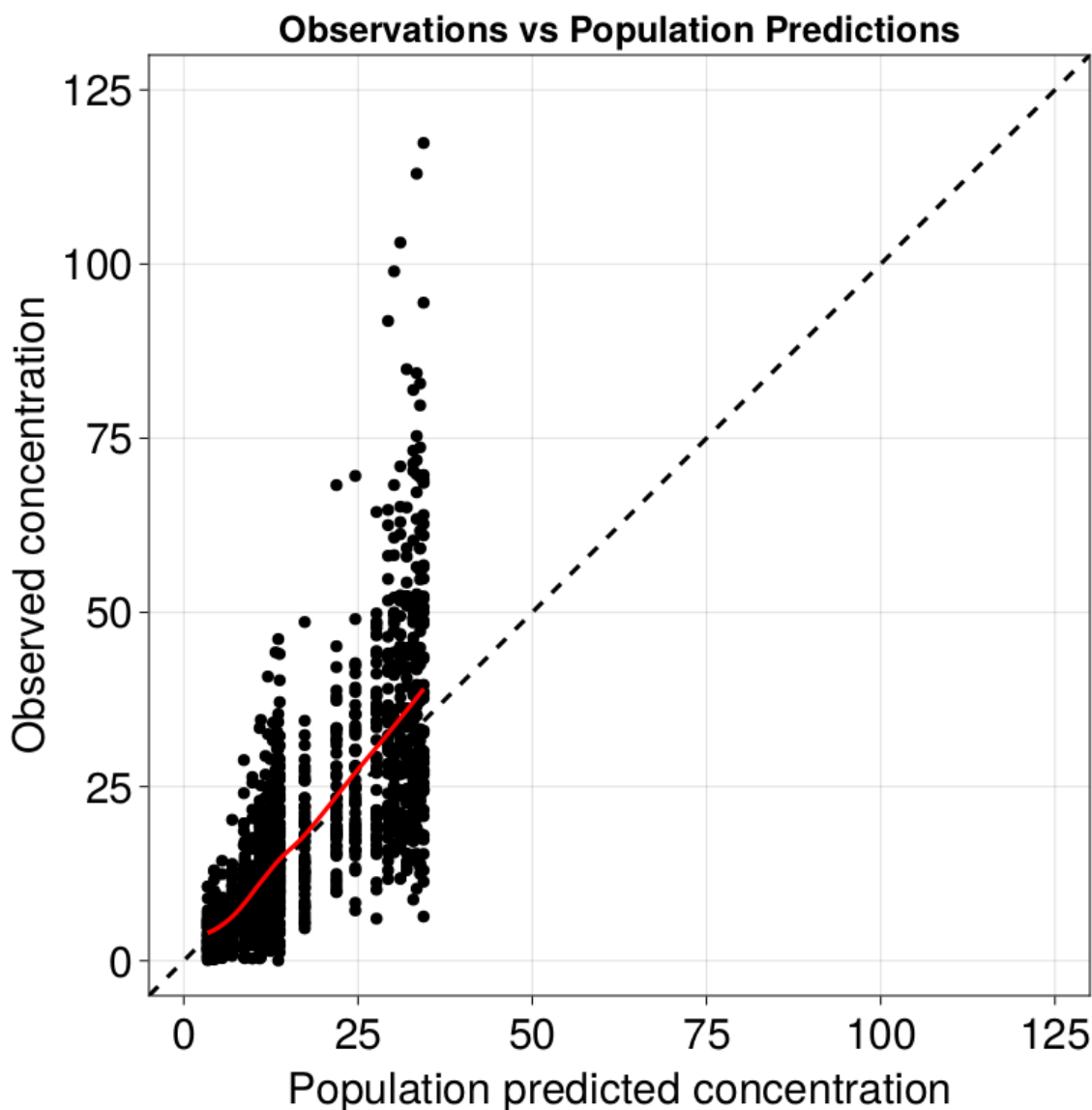
pred_vs_obs_plt=
    data(iv1cmt_inspect_df_plot) *
    mapping(:CONC_pred => "Population predicted concentration",
           :CONC => "Observed concentration") *
    (visual(Scatter))

plt_ablines = mapping([0], [1]) * visual(ABLines; linewidth = 3 ,linesty

plt_loessline = data(loess_pred_df) *
    mapping(:x_axis => "Population predicted concentration",
           :y_axis => "Observed concentration") *
    visual(Lines; linewidth = 3, color=(red,1.5));

draw!(pred_vs_obs_iv_sd[1,1],pred_vs_obs_plt + plt_ablines + plt_loessli
    axis=(; aspect=1,
    title=("Observations vs Population Predictions"),
    titlesize =25,xticks = 0:25:125,yticks=0:25:125,limits=(-5,130),(-5

pred_vs_obs_iv_sd
```



Population predicted vs Observed plot

```
obs_vs_pred_loess_model = loess(Float64.(iv1cmt_inspect_df_plot.CONC),
                                Float64.(iv1cmt_inspect_df_plot.CONC_pred))

range_x_axis = range(extrema(Float64.(iv1cmt_inspect_df_plot.CONC))...;
loess_pred = predict(obs_vs_pred_loess_model, range_x_axis)
loess_pred_df = DataFrame(x_axis = range_x_axis, y_axis = loess_pred)

obs_vs_pred_iv_sd = Figure(fontsize=30,resolution=(800,800))

obs_vs_pred_plt=
    data(iv1cmt_inspect_df_plot) *
    mapping(:CONC => "Observed concentration",
            :CONC_pred => "Population predicted concentration") *
    (visual(Scatter))

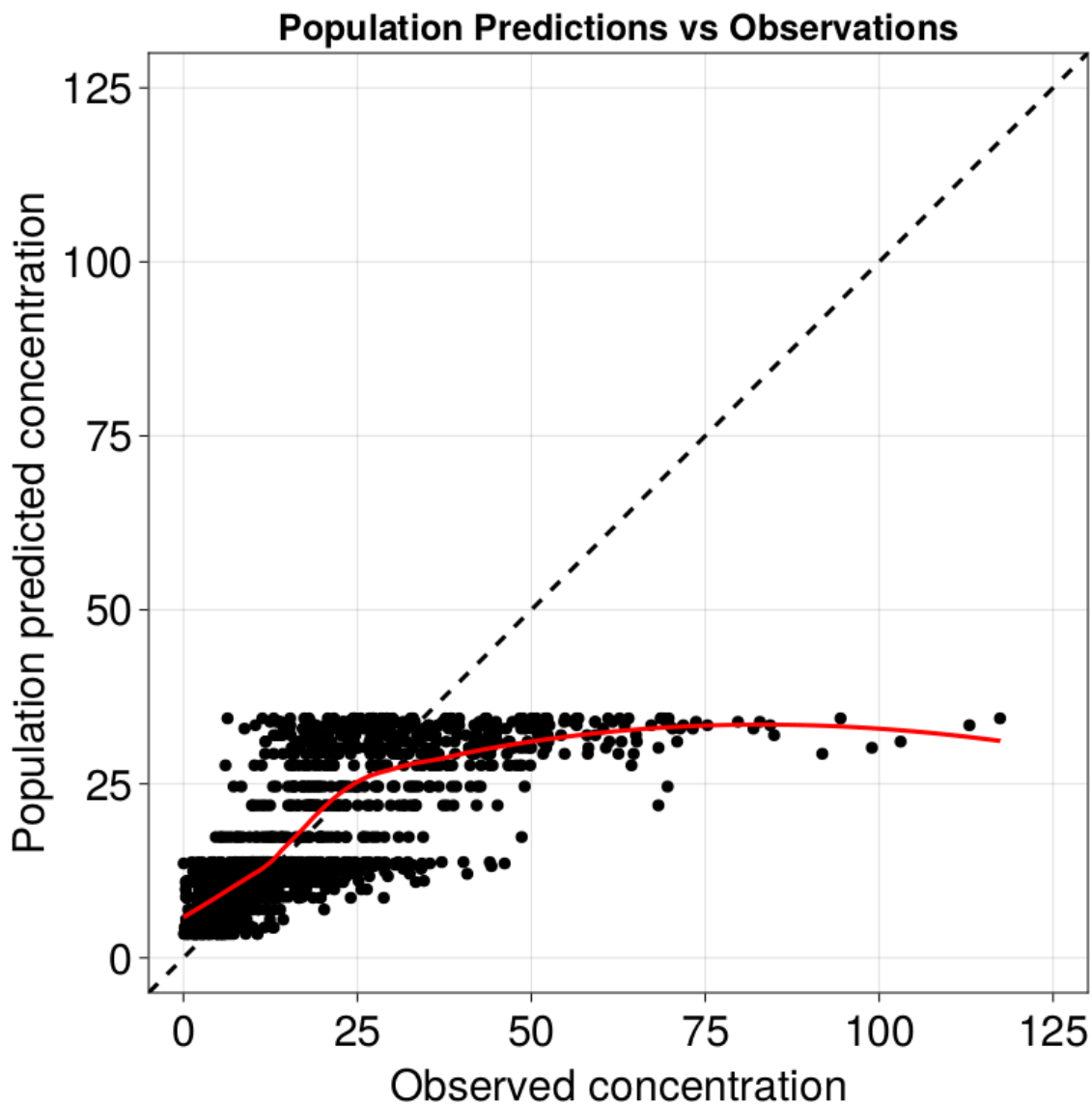
plt_ablines = mapping([0], [1]) * visual(ABLines; linewidth = 3 ,linesty
```

```

plt_loessline = data(loess_pred_df) *
  mapping(:x_axis => "Observed concentration",
    :y_axis => "Population predicted concentration")
  visual(Lines; linewidth = 3, color=(red,1.5));

draw!(obs_vs_pred_iv_sd[1,1],obs_vs_pred_plt + plt_ablines + plt_loessli
  axis=(); aspect=1,
  title=("Population Predictions vs Observations"),
  titlesize =25,xticks = 0:25:125,yticks=0:25:125,limits=((-5,130),(-5
obs_vs_pred_iv_sd

```



Diagnostic check

```
icoef_result_iv1cmt = reduce(vcat, DataFrame.(icoef(iv1cmt_results)))  
  
app1 = evaluate_diagnostics(iv1cmt_inspect)  
close(app1)
```

Save report

```
report(iv1cmt_inspect; output="reports/base_model")
```

```
note: Running TeX ...  
note: Rerunning TeX because "main.out" changed ...  
note: Rerunning TeX because "main.out" changed ...  
note: Rerunning TeX because "main.toc" changed ...  
note: Running xdvipdfmx ...  
note: Writing `/tmp/jl_IZ2XR5/main.pdf` (959.78 KiB)  
note: Skipped writing 5 intermediate files (use --keep-intermediates to  
p them)  
"reports/base_model/Report.pdf"
```

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