Algorithm for Optimization

Practical No. 6

AIM: Apply Random Forest in surrogate Model.

Random forests is a supervised learning algorithm that randomly creates and merges multiple decision trees into one forest.

We are going to use a Random forests surrogate to optimize $f(x)=\sin(x)+\sin(10/3*x)$.

First of all import Surrogates and Plots.

Code:

using Surrogates using SurrogatesRandomForest using Plots default()

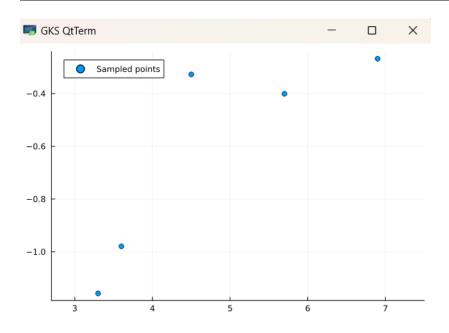
```
julia> using Surrogates
julia> using SurrogatesRandomForest
julia> using Plots
julia> default()
```

Sampling:

We choose to sample f in 4 points between 0 and 1 using the sample function. The sampling points are chosen using a Sobol sequence, this can be done by passing SobolSample() to the sample function.

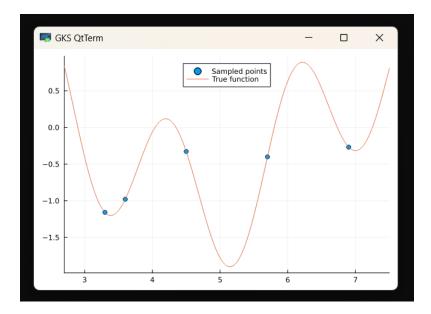
```
f(x) = sin(x) + sin(10/3 * x)
n_samples = 5
lower_bound = 2.7
upper_bound = 7.5
x = sample(n_samples, lower_bound, upper_bound, SobolSample())
y = f.(x)
scatter(x, y, label="Sampled points", xlims=(lower_bound, upper_bound))
```

```
julia> f(x) = sin(x) + sin(10/3 * x)
f (generic function with 1 method)
julia> n_samples = 5
julia> lower_bound = 2.7
2.7
julia> upper_bound = 7.5
julia> x = sample(n_samples, lower_bound, upper_bound, SobolSample())
5-element Vector{Float64}:
6.9
5.7
3.3000000000000003
3.6
julia> y = f.(x)
5-element Vector{Float64}:
-0.3272422775079802
-0.2677806397869723
-0.4008083329346852
-1.157735900693952
-0.9790933612952875
julia> scatter(x, y, label="Sampled points", xlims=(lower_bound, upper_bound))
```



plot!(f, label="True function", xlims=(lower_bound, upper_bound),legend=:top)

```
julia> plot!(f, label="True function", xlims=(lower_bound, upper_bound), legend=:top)
```



Building a surrogate:

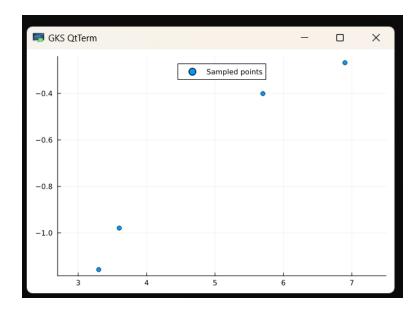
With our sampled points we can build the Random forests surrogate using the RandomForestSurrogate function.

randomforest_surrogate behaves like an ordinary function which we can simply plot. Additionally, you can specify the number of trees created using the parameter num_round

```
num round = 2
```

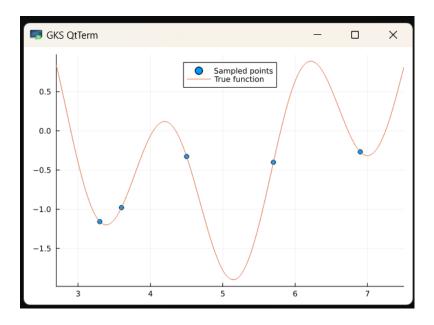
 $randomforest_surrogate = RandomForestSurrogate(x \ ,y \ ,lower_bound, upper_bound, num_round = 2)$

plot(x, y, seriestype=:scatter, label="Sampled points", xlims=(lower_bound, upper_bound), legend=:top)



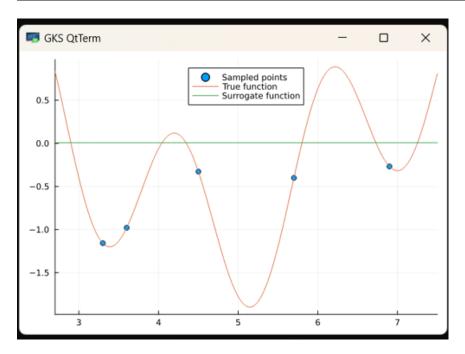
plot!(f, label="True function", xlims=(lower_bound, upper_bound), legend=:top)

julia> plot!(f, label="True function", xlims=(lower_bound, upper_bound), legend=:top)



plot!(randomforest_surrogate, label="Surrogate function", xlims=(lower_bound, upper_bound), legend=:top)

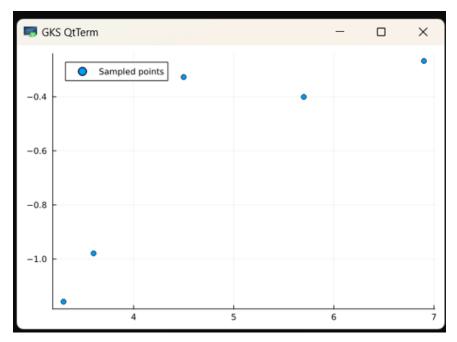
julia> plot!(randomforest_surrogate, label="Surrogate function", xlims=(lower_bound, upper_bound), legend=:top)



Optimizing:

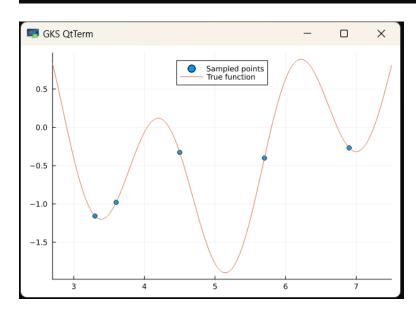
Having built a surrogate, we can now use it to search for minima in our original function f. To optimize using our surrogate we call surrogate_optimize method. We choose to use Stochastic RBF as optimization technique and again Sobol sampling as sampling technique.

@show surrogate_optimize(f, SRBF(), lower_bound, upper_bound, randomforest_surrogate,
SobolSample())
scatter(x, y, label="Sampled points")



plot!(f, label="True function", xlims=(lower_bound, upper_bound), legend=:top)





plot!(randomforest_surrogate, label="Surrogate function", xlims=(lower_bound, upper_bound), legend=:top)

julia> plot!(randomforest_surrogate, label="Surrogate function", xlims=(lower_bound, upper_bound), legend=:top)

