

The vector version of the theorem

Theorem 4.1 (Contraction Mapping Theorem) Suppose that D is a closed subset of \mathbb{R}^n , $g: \mathbb{R}^n \rightarrow \mathbb{R}^n$ is defined on D , and $g(D) \subset D$. Suppose further that g is a contraction on D in the ∞ -norm. Then, g has a unique fixed point ξ in D , and the sequence $(\mathbf{x}^{(k)})$ defined by (4.3) converges to ξ for any starting value $\mathbf{x}^{(0)} \in D$.

Theorem 1.3 (Contraction Mapping Theorem) Let g be a real-valued function, defined and continuous on a bounded closed interval $[a, b]$ of the real line, and assume that $g(x) \in [a, b]$ for all $x \in [a, b]$. Suppose, further, that g is a contraction on $[a, b]$. Then, g has a unique fixed point ξ in the interval $[a, b]$. Moreover, the sequence (x_k) defined by (1.3) converges to ξ as $k \rightarrow \infty$ for any starting value x_0 in $[a, b]$.

- Use of Gerschgorin algorithm to estimate eigenvalues.

Theorem

Theorem 5.4 (Gerschgorin's Theorem) Let $n \geq 2$ and $A \in \mathbb{C}^{n \times n}$. All eigenvalues of the matrix A lie in the region $D = \bigcup_{i=1}^n D_i$, where D_i , $i = 1, 2, \dots, n$, are the Gerschgorin discs of A defined by (5.17), (5.18).

Theorem 5.5 (Gerschgorin's Second Theorem) Let $n \geq 2$. Suppose that $1 \leq p \leq n - 1$ and that the Gerschgorin discs of the matrix $A \in \mathbb{C}^{n \times n}$ can be divided into two disjoint subsets $D^{(p)}$ and $D^{(q)}$, containing p and $q = n - p$ discs respectively. Then, the union of the discs in $D^{(p)}$ contains p of the eigenvalues, and the union of the discs in $D^{(q)}$ contains $n - p$ eigenvalues. In particular, if one disc is disjoint from all the others, it contains exactly one eigenvalue, and if all the discs are disjoint then each disc contains exactly one eigenvalue.

Computation example of least squares.

$$F_c(x) = C_1 \phi_1(x) + C_2 \phi_2(x) + C_3 \phi_3(x)$$

$$\phi_1(x) = 1, \quad \phi_2(x) = \cos x, \quad \phi_3(x) = \sin x$$

First we need data to fit.

Suppose some data

| x | y |
|----------|----------|
| x_1 | y_1 |
| x_2 | y_2 |
| x_3 | y_3 |
| \vdots | \vdots |
| x_m | y_m |

```
julia> phi1(x)=1.0
phi1 (generic function with 1 method)

julia> phi2(x)=cos(x)
phi2 (generic function with 1 method)

julia> phi3(x)=sin(x)
phi3 (generic function with 1 method)

julia> F(c,x)=[phi1(x),phi2(x),phi3(x)]'*c
F (generic function with 1 method)
```

```
julia> xs=4*pi*rand(20)
20-element Vector{Float64}:
 9.547753029274727
 1.8217677360589428
 1.6031398306494404
 5.394043776740737
 6.480271494426944
 3.8525145941307812
 9.921444466433005
10.442139736363245
 7.665549800539033
 6.767274193989993
 2.7794758027289386
 3.5155382491311022
 2.6123880141058966
 0.8751636047303569
 4.789863806635315
11.718128975781715
 3.9460628804491304
 4.603146170508093
 1.067992793231892
 0.8460986170500502
```

← randomly create 20 values of x for testing...

```
julia> c=[2,3,4]
3-element Vector{Int64}:
 2
 3
 4
```

← actual values of c that the data comes from.

After generating the data we'll try to solve for c pretending that we didn't already know it.

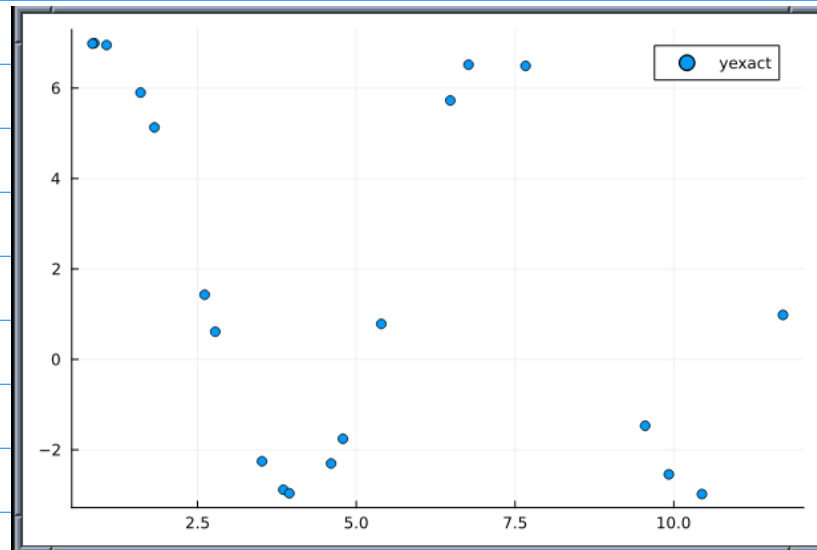
Turns the function of 2 variables into a function of one holding c constant

```
julia> yexact=(t->F(c,t)).(xs)
20-element Vector{Float64}:
-1.4680056594149251
 5.129651377762678
 5.900894382756249
 0.7841121402641238
 5.725174949016598
-2.883412439245213
-2.5435173911384745
-2.9797337435308844
 6.491152910570654
 6.5169065594741244
 0.6115713400946239
-2.253844689030923
 1.4297611183229493
 6.9932072758385
-1.7558092730294792
 0.9834344205494525
-2.9623324439462015
-2.3032327113282696
 6.950592067375558
 6.9835268334475185
```

apply that function pointwise to each of the xs.

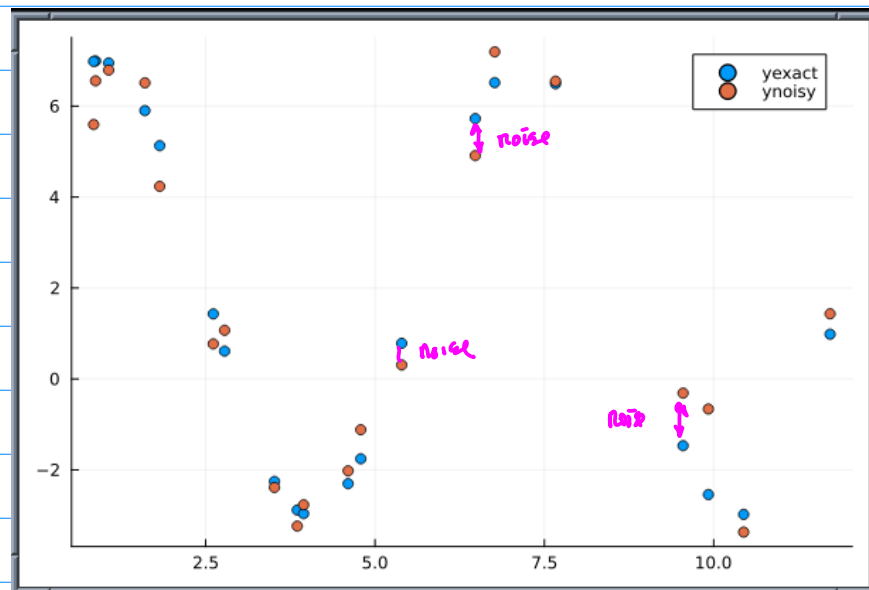
```
julia> using Plots
```

```
julia> scatter(xs,yexact,label="yexact")
```



```
julia> ynoisy=yexact+0.5*randn(20);
```

```
julia> scatter!(xs,ynoisyl, label="ynoisyl")
```



The Vandermonde Matrix .

$$V = \begin{bmatrix} \phi_1(x_1) & \phi_2(x_1) & \dots & \phi_n(x_1) \\ \phi_1(x_2) & \phi_2(x_2) & \dots & \phi_n(x_2) \\ \vdots & \vdots & \ddots & \vdots \\ \phi_1(x_m) & \phi_2(x_m) & \dots & \phi_n(x_m) \end{bmatrix}$$

$$[\phi_j(x_i)]_{i,j}$$

↑ column
↑ row

Try to minimize

$$\|Vc - y_{\text{noisy}}\|$$

```
julia> cnoisy=V\ynoisy
3-element Vector{Float64}:
 2.009960548979548
 2.6944678358542005
 3.773818116138601
```

The value of c for which the noisy data was most likely to have come from Fc .

Check by drawing a graph

```
julia> xdom=0:0.01:4*pi
0.0:0.01:12.56

julia> yrange=(t->F(cnoisy,t)).(xdom);

julia> plot!(xdom,yrange)
```

```
julia> phi=[phi1,phi2,phi3]
3-element Vector{Function}:
 phi1 (generic function with 1 method)
 phi2 (generic function with 1 method)
 phi3 (generic function with 1 method)

julia> V=[phi[j](xs[i]) for i=1:20,j=1:3]
20x3 Matrix{Float64}:
 1.0 -0.992448 -0.122665
 1.0 -0.248345  0.968672
 1.0 -0.0323379 0.999477
 1.0  0.630079 -0.776531
 1.0  0.980641  0.195813
 1.0 -0.757761 -0.652533
 1.0 -0.879176 -0.476497
 1.0 -0.525612 -0.850724
 1.0  0.187319  0.982299
 1.0  0.885099  0.465402
 1.0 -0.935149  0.354255
 1.0 -0.930893 -0.365291
 1.0 -0.863209  0.504847
 1.0  0.640871  0.767648
 1.0  0.0773973 -0.997
 1.0  0.661303 -0.750119
 1.0 -0.693493 -0.720463
 1.0 -0.109026 -0.994039
 1.0  0.481884  0.876235
 1.0  0.662909  0.7487
```

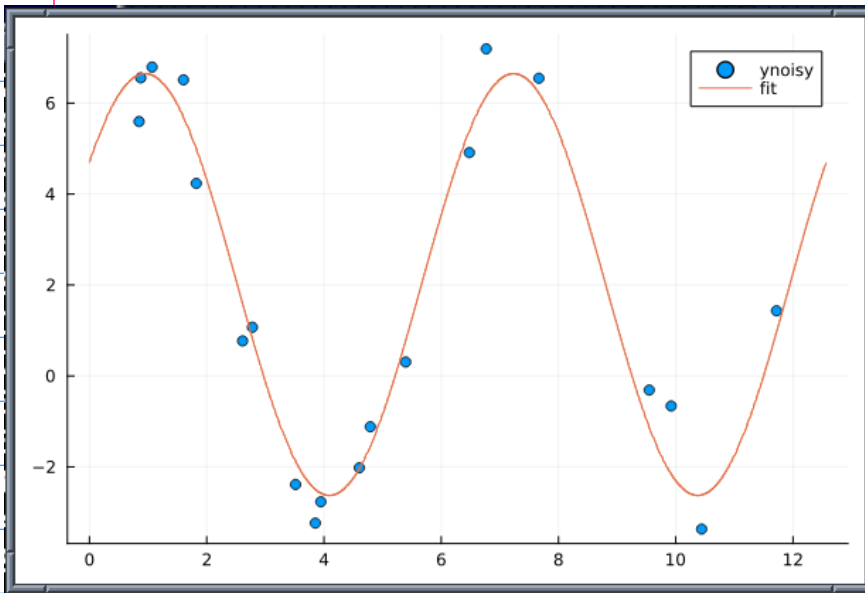
behind the scenes uses QR factorization to solve the least squares problem

$$A = \tilde{Q}\tilde{R}$$

$$\tilde{R}c = \tilde{Q}^T y$$

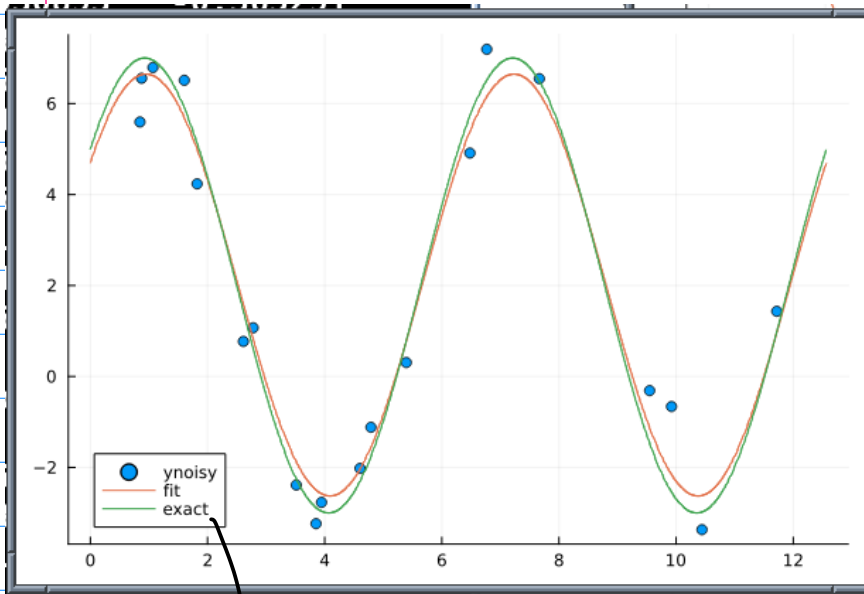
Hausholder reflectors to find \tilde{Q}

↑ solve by backsubstitution since \tilde{R} is triangular



approximate linear model

How did \bar{I} do in comparison to the actual models



Note the data was generated by the green model but is actually closer to the red one.

$F_{(2,3,1)}(x)$

What happens without the noise?

$Vc = y_{\text{exact}}$ over determined system..
 $y_{\text{exact}} \in C(V)$.

noisy data

```

julia> cnoisy=V\ynoisy
3-element Vector{Float64}:
 2.009960548979548
 2.6944678358542005
 3.773818116138601
  
```

```

julia> cexact=V\yexact
3-element Vector{Float64}:
 1.9999999999999996
 3.0000000000000004
 3.9999999999999999
  
```

up to rounding.

How good is the fit. I.e. what is the minimum

$$\|Vc - y_{\text{noisy}}\| \approx 3.07 \dots$$

Check

```
julia> using LinearAlgebra
julia> norm(V*cnoisy - ynoisy)
3.0717214650120424
```

Small it is the better the fit... but we don't expect it to fit exactly because of the noise

HW 5 will be about least squares ... please check in a day for the assignment...