

Machine Learning the Ising Transition

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```
const IsingTc = 1/(1/2*log(1+sqrt(2))) # Exact Onsager solution
2.269185314213022
```

1 Monte Carlo simulation

```
using Printf, Dates

up(neighs, i) = neighs[1, i]
right(neighs, i) = neighs[2, i]
down(neighs, i) = neighs[3, i]
left(neighs, i) = neighs[4, i]

function montecarlo(; L, T)
    # set parameters & initialize
    nsweeps = 10^7
    measure_rate = 5_000
    beta = 1/T
    conf = rand([-1, 1], L, L)
    confs = Matrix{Int64}[] # storing intermediate configurations
    # build nearest neighbor lookup table
    lattice = reshape(1:L^2, (L, L))
    ups = circshift(lattice, (-1,0))
    rights = circshift(lattice, (0,-1))
    downs = circshift(lattice, (1,0))
    lefts = circshift(lattice, (0,1))
    neighs = vcat(ups[:, :], rights[:, :], downs[:, :], lefts[:, :])

    start_time = now()
    println("Started: ", Dates.format(start_time, "d.u yyyy HH:MM"))

    for i in 1:nsweeps
        # sweep
        for i in eachindex(conf)
            # local update
            ΔE = 2.0 * conf[i] * (conf[up(neighs, i)] + conf[right(neighs, i)] +
                                   + conf[down(neighs, i)] + conf[left(neighs, i)])

            # Metropolis
            if ΔE <= 0 || rand() < exp(- beta*ΔE)
                conf[i] *= -1 # flip spin
            end
        end
    end
end
```

```

        # measure
        iszero(mod(i, measure_rate)) && push!(confs, copy(conf))
    end

    end_time = now()
    println("Ended: ", Dates.format(end_time, "d.u yyyy HH:MM"))
    @printf("Duration: %.2f minutes", (end_time - start_time).value / 1000. /60.)
    return confs
end

montecarlo (generic function with 1 method)

montecarlo(L=8, T=5)

```

Started: 5.Aug 2019 11:33

Ended: 5.Aug 2019 11:33

Duration: 0.24 minutes2000-element Array{Array{Int64,2},1}:

```

[-1 -1 ... 1 -1; -1 -1 ... -1 1; ... ; -1 -1 ... -1 -1; -1 1 ... -1 -1]
[-1 1 ... -1 -1; 1 -1 ... -1 -1; ... ; 1 1 ... -1 -1; 1 1 ... 1 1]
[-1 1 ... -1 -1; -1 1 ... 1 1; ... ; 1 1 ... 1 1; 1 1 ... 1 1]
[-1 1 ... 1 1; -1 -1 ... -1 1; ... ; 1 -1 ... 1 1; 1 1 ... 1 -1]
[-1 1 ... -1 -1; 1 1 ... 1 1; ... ; 1 -1 ... -1 1; -1 1 ... -1 -1]
[1 1 ... 1 1; 1 -1 ... 1 1; ... ; 1 1 ... 1 1; 1 -1 ... -1 1]
[1 -1 ... -1 1; 1 1 ... -1 1; ... ; 1 1 ... 1 1; 1 1 ... -1 1]
[-1 1 ... 1 1; 1 1 ... 1 1; ... ; 1 -1 ... 1 -1; 1 1 ... 1 1]
[1 -1 ... 1 1; 1 1 ... 1 1; ... ; 1 -1 ... 1 1; 1 -1 ... 1 1]
[-1 1 ... -1 -1; 1 1 ... -1 1; ... ; 1 1 ... -1 1; 1 1 ... -1 -1]
⋮
[-1 -1 ... 1 1; -1 1 ... 1 -1; ... ; -1 1 ... -1 -1; -1 -1 ... 1 1]
[-1 1 ... 1 -1; -1 1 ... 1 -1; ... ; -1 1 ... 1 1; -1 -1 ... 1 1]
[-1 -1 ... -1 -1; -1 -1 ... -1 1; ... ; -1 -1 ... -1 -1; 1 -1 ... -1 1]
[-1 1 ... 1 -1; 1 -1 ... -1 -1; ... ; 1 1 ... 1 1; -1 -1 ... 1 -1]
[-1 -1 ... 1 -1; -1 -1 ... 1 -1; ... ; 1 -1 ... 1 -1; -1 1 ... 1 -1]
[-1 1 ... 1 1; -1 -1 ... -1 -1; ... ; 1 -1 ... 1 1; 1 1 ... 1 1]
[-1 -1 ... 1 -1; -1 -1 ... -1 -1; ... ; -1 1 ... 1 -1; -1 -1 ... 1 -1]
[1 1 ... 1 1; 1 1 ... 1 1; ... ; -1 -1 ... 1 1; -1 -1 ... -1 1]
[1 1 ... 1 1; -1 1 ... 1 -1; ... ; 1 -1 ... 1 1; 1 1 ... 1 -1]

```

1.0.1 Simulate an $L = 8$ system at a couple of temperatures

Ts = [1.189, 1.733, 2.069, 2.269, 2.278, 2.469, 2.822, 3.367]

8-element Array{Float64,1}:

```

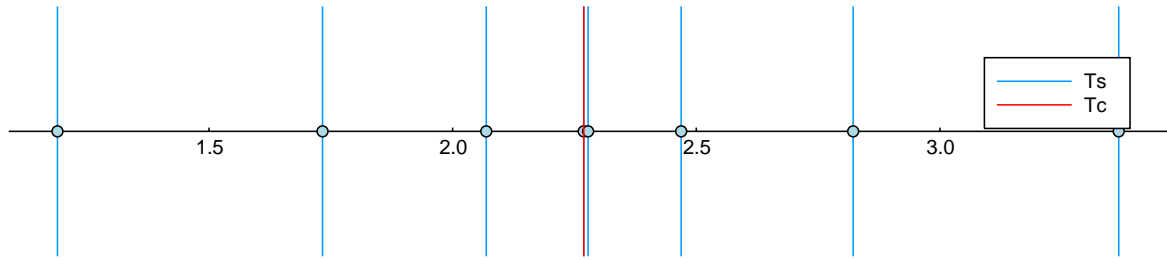
1.189
1.733
2.069
2.269
2.278
2.469
2.822
3.367

```

```

# visualize temperatures
using Plots
vline(Ts, grid=false, axis=:x, framestyle=:origin, xlim=(minimum(Ts)-0.1,
    maximum(Ts)+0.1), size=(800,200), label="Ts")
scatter!(Ts, fill(0, length(Ts)), color=:lightblue, label="")
vline!([IsingTc], color=:red, label="Tc")

```



```

confs = Dict{Float64, Array{Float64,3}}{ } # key: T, value: confs
for T in Ts
    println("T = $T"); flush(stdout);
    c = montecarlo(L=8, T=T)
    confs[T] = cat(c..., dims=3)
    println("Done.\n")
end

```

```

T = 1.189
Started: 5.Aug 2019 11:33
Ended: 5.Aug 2019 11:33
Duration: 0.28 minutesDone.

```

```

T = 1.733
Started: 5.Aug 2019 11:33
Ended: 5.Aug 2019 11:34
Duration: 0.30 minutesDone.

```

```

T = 2.069
Started: 5.Aug 2019 11:34
Ended: 5.Aug 2019 11:34
Duration: 0.31 minutesDone.

```

```

T = 2.269
Started: 5.Aug 2019 11:34
Ended: 5.Aug 2019 11:34
Duration: 0.30 minutesDone.

```

```

T = 2.278
Started: 5.Aug 2019 11:34
Ended: 5.Aug 2019 11:35
Duration: 0.30 minutesDone.

```

```

T = 2.469
Started: 5.Aug 2019 11:35
Ended: 5.Aug 2019 11:35
Duration: 0.29 minutesDone.

```

```

T = 2.822
Started: 5.Aug 2019 11:35
Ended: 5.Aug 2019 11:35
Duration: 0.27 minutesDone.

```

```

T = 3.367
Started: 5.Aug 2019 11:35
Ended: 5.Aug 2019 11:35
Duration: 0.26 minutesDone.

```

2 Machine learning the magnetic phase transition

```
using Flux
using Flux: crossentropy, onecold, onehotbatch, params, throttle, @epochs
using Statistics, Random

function flatten_and_Z2(confs, T)
    c = confs[T]
    cs = Float64.(reshape(c, (64,:))) # flatten space dimension
    cs = hcat(cs, -one(eltype(cs)) .* cs) # concatenate Z2 (spin flip) symmetry partners
    return cs
end

flatten_and_Z2 (generic function with 1 method)

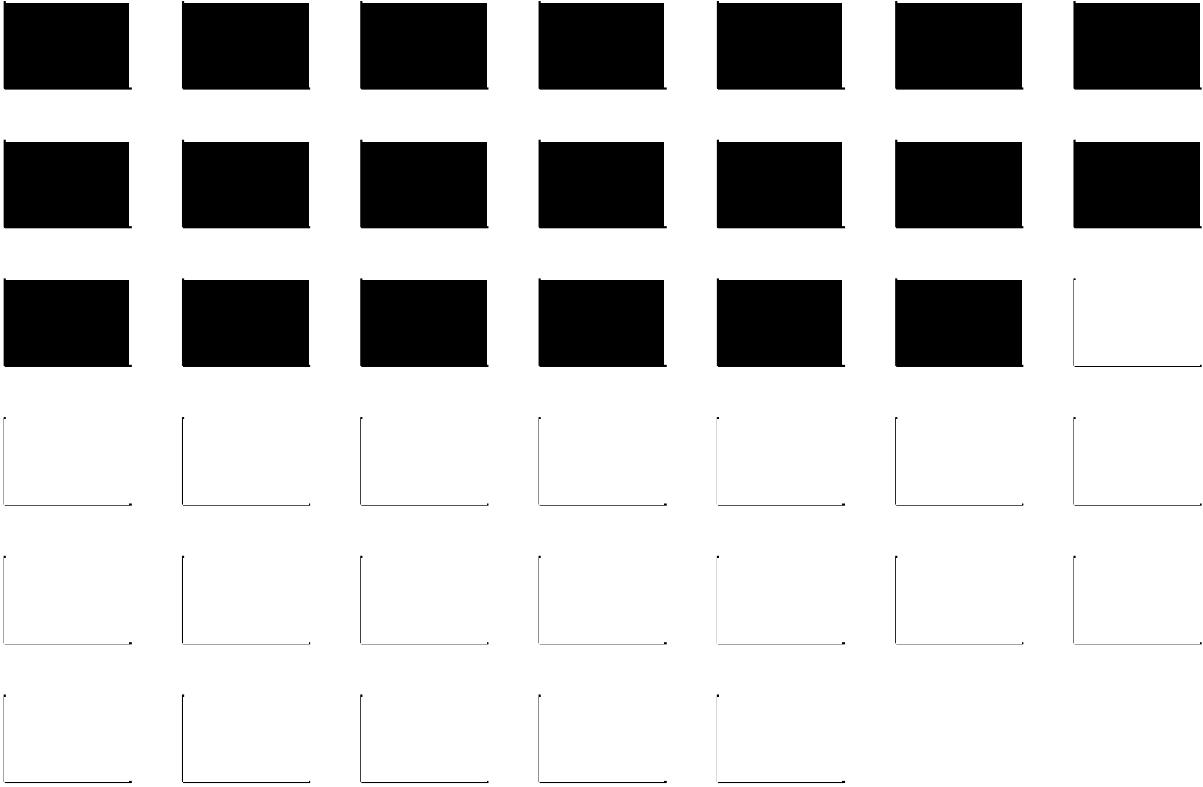
L = 8
Tleft = 1.189
Tright = 3.367

confs_left = flatten_and_Z2(confs, Tleft)
confs_right = flatten_and_Z2(confs, Tright);

# visualize configurations
printconfs(confs) = plot([heatmap(Gray.(reshape(confs[:,i], (L,L))), ticks=false) for i
    in 1:100:size(confs, 2)]...)

printconfs (generic function with 1 method)

printconfs(confs_left)
```



```
printconfs(confs_right)
```



```

# set up as training data
neach = size(confs_left, 2)
X = hcat(confs_left, confs_right)
labels = vcat(fill(1, neach), fill(0, neach))
Y = onehotbatch(labels, 0:1)
dataset = Base.Iterators.repeated((X, Y), 10); # repeat dataset 10 times

# create neural network with 10 hidden units and 2 output neurons
Random.seed!(123)

m = Chain(
  Dense(L^2, 10, relu),
  Dense(10, 2),
  softmax)

Chain(Dense(64, 10, NNlib.relu), Dense(10, 2), NNlib.softmax)

# classify phases at all intermediate temperatures
function confidence_plot()
  results = Dict{Float64, Vector{Float32}}{ }
  for T in Ts
    c = flatten_and_Z2(confs, T);
    results[T] = vec(mean(m(c), dims=2).data)
  end
  results = sort(results)

  p = plot(keys(results) |> collect, reduce(hcat, values(results))',
    marker=:circle,
    xlabel="temperature",
    ylabel="CNN confidence",
    labels=["paramagnet", "ferromagnet"],
    frame=:box)
  plot!(p, [IsingTc, IsingTc], [0, 1], ls=:dash, color=:black, label="IsingTc")

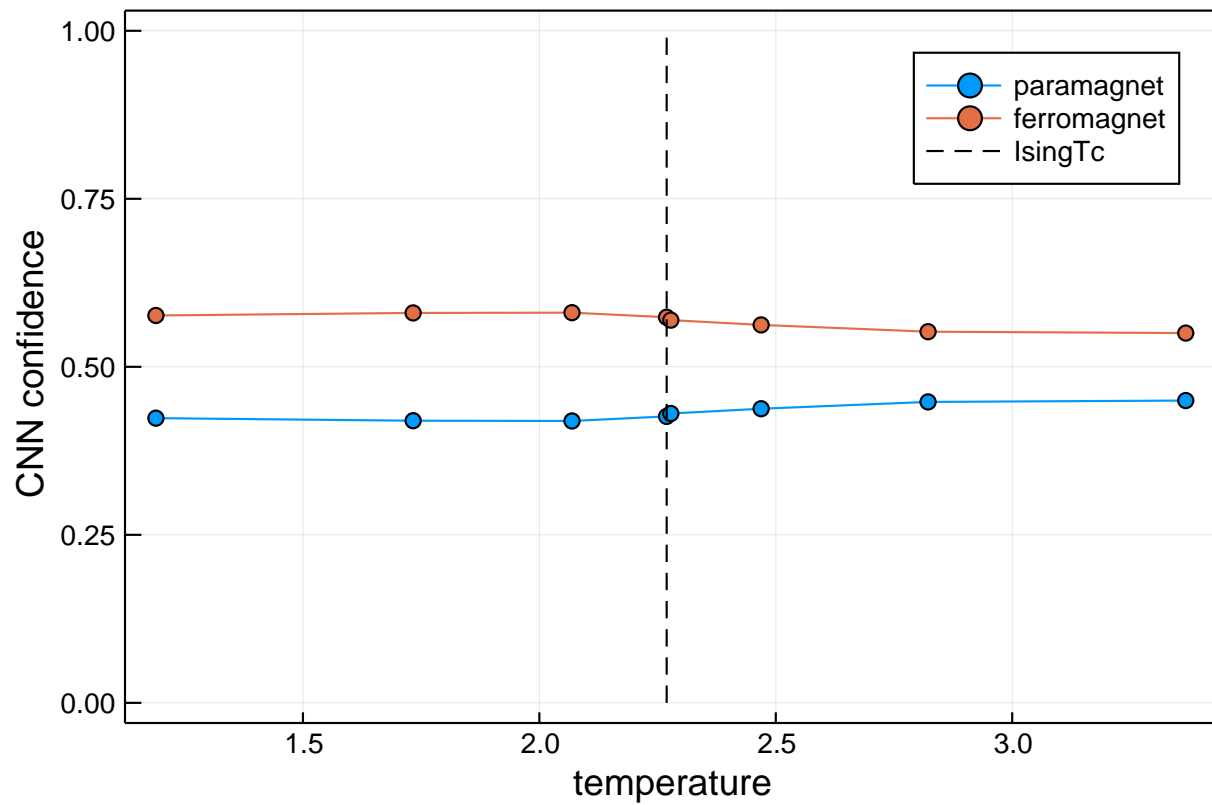
```

```

if (@isdefined IJulia)
    # "animation" in jupyter
    IJulia.clear_output(true)
end
display(p)
end

confidence_plot()

```



```

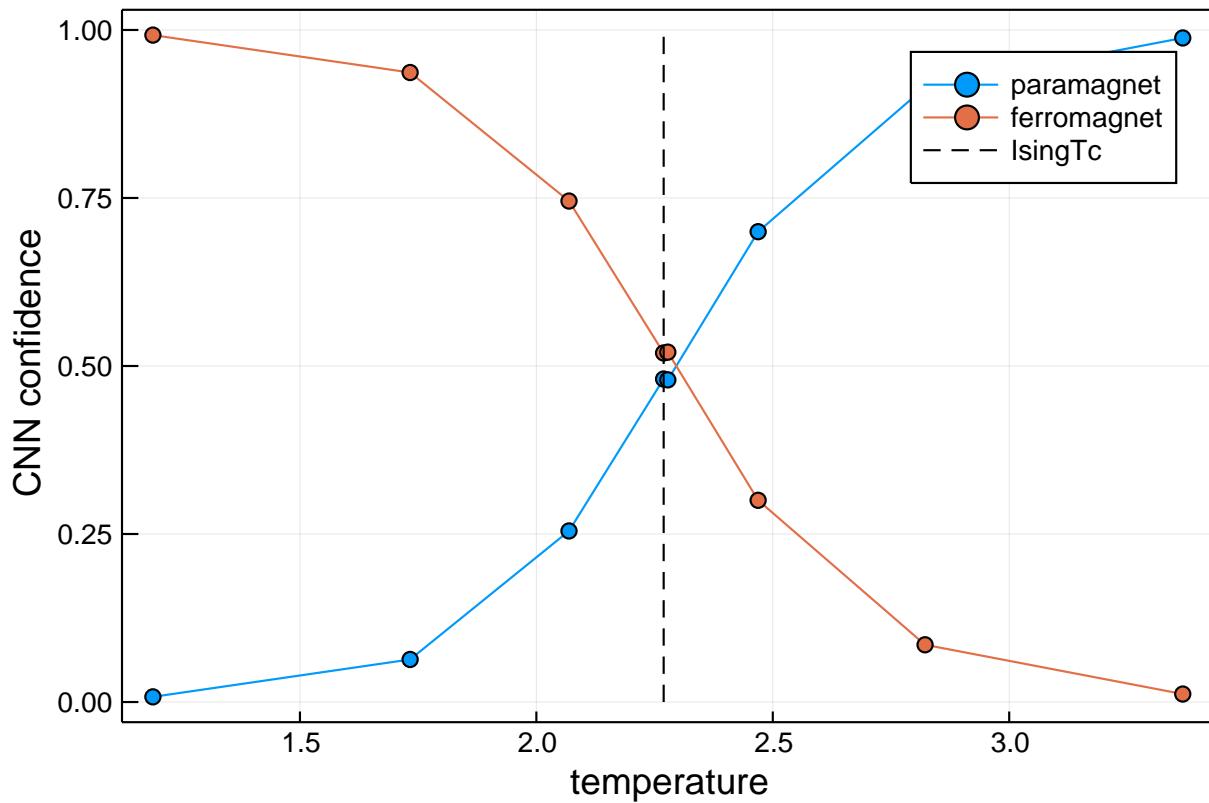
# define cost-function
loss(x, y) = crossentropy(m(x), y)

# define optimizer
opt = ADAM()

# train for 100 epochs
for i in 1:100
    Flux.train!(loss, params(m), dataset, opt)
end

#
confidence_plot()

```

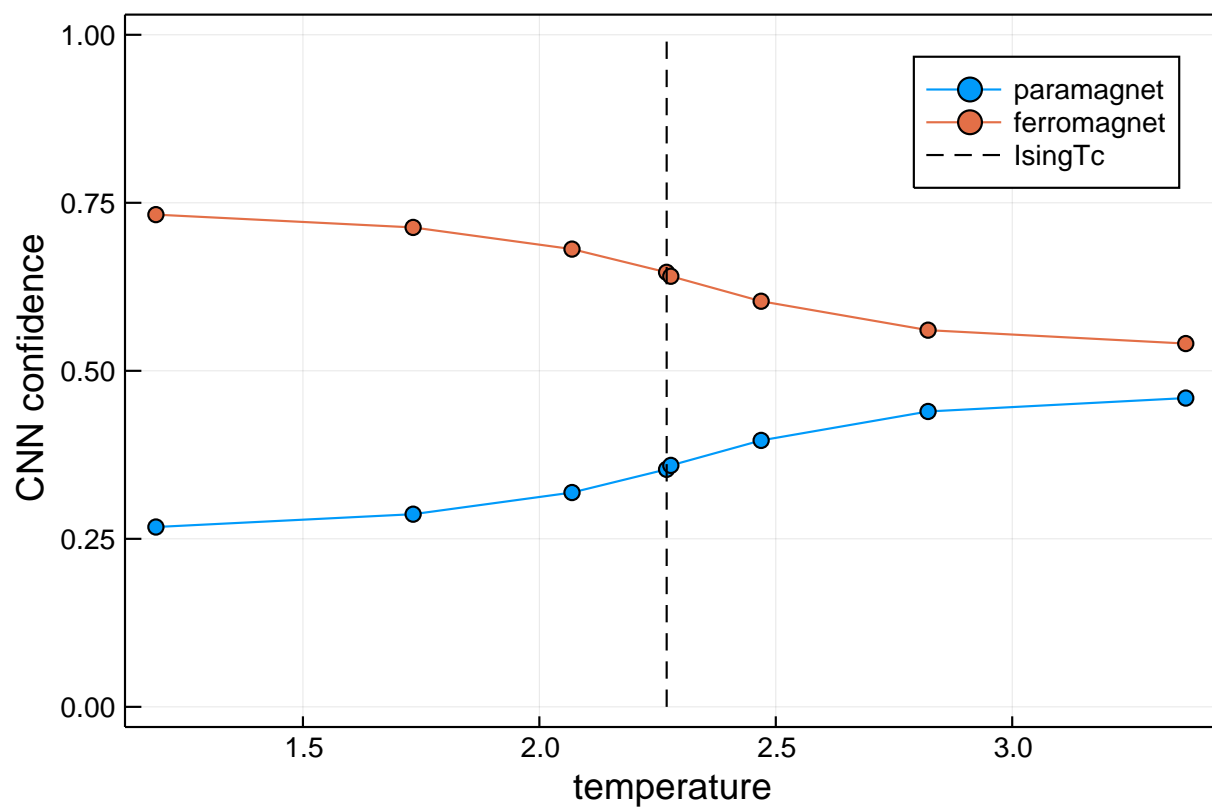
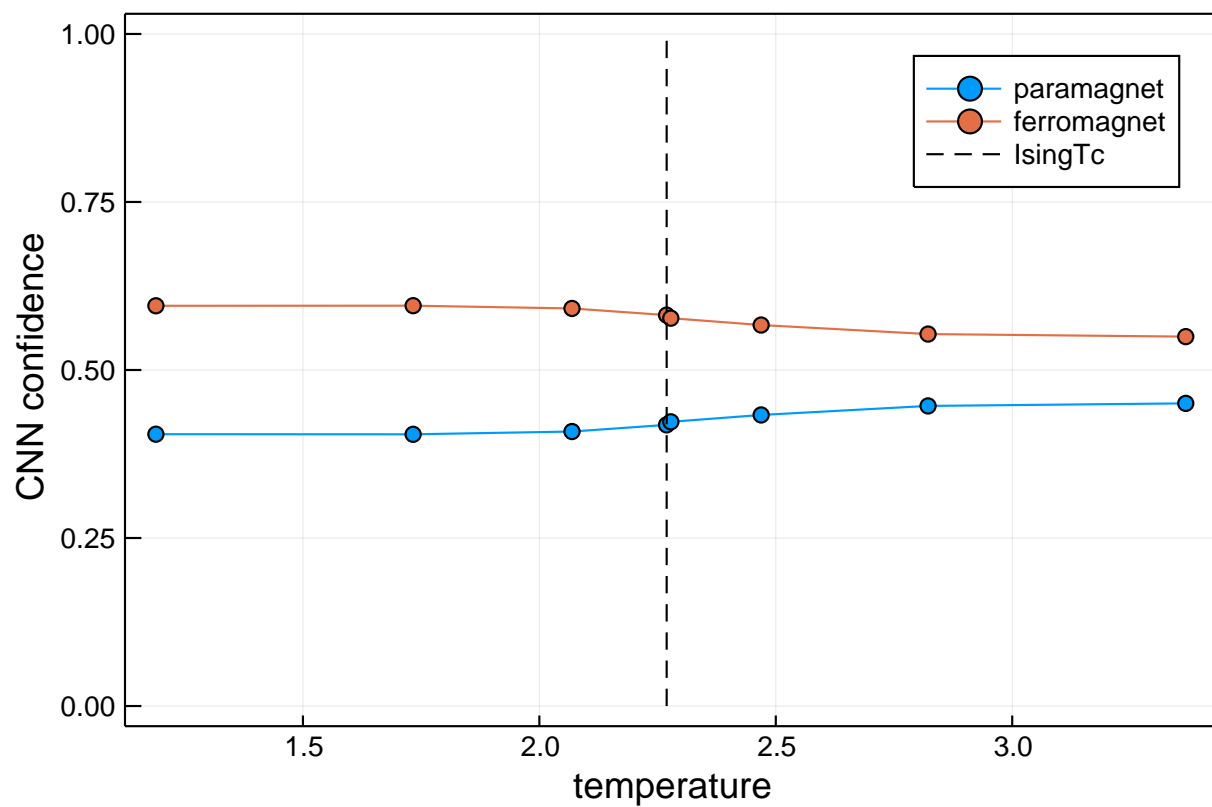


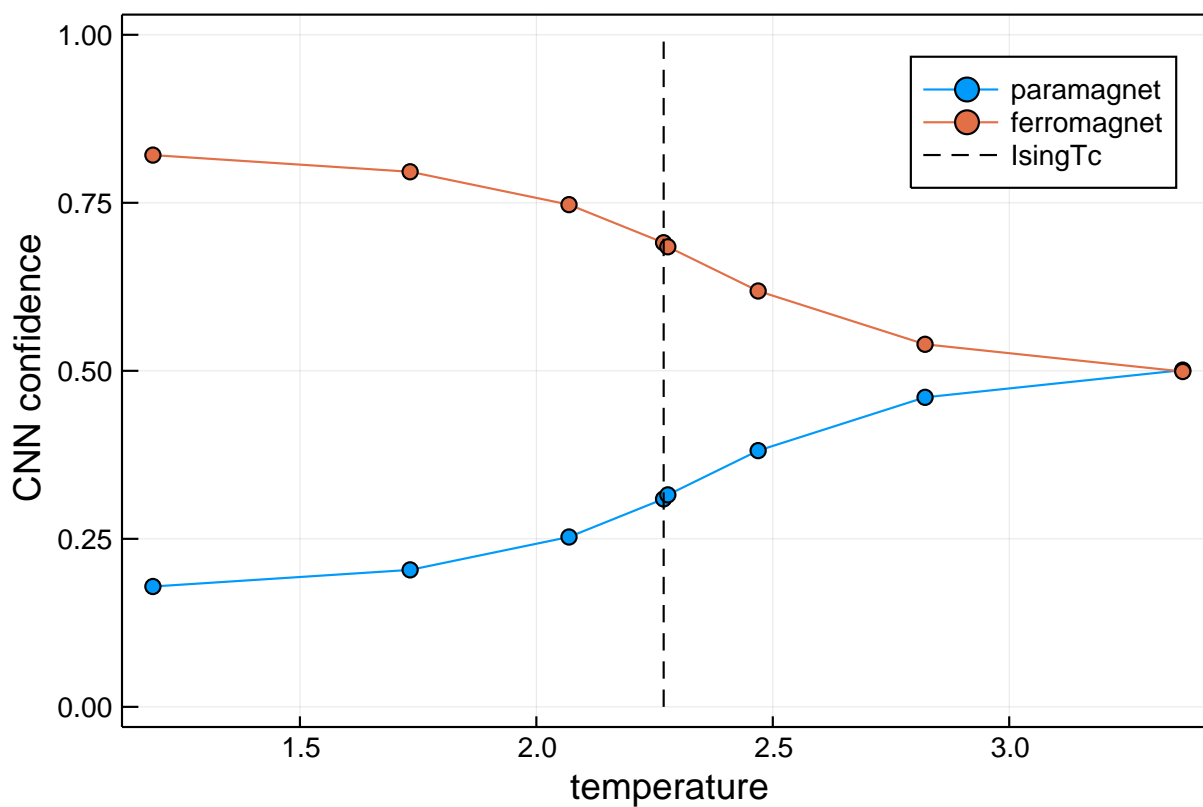
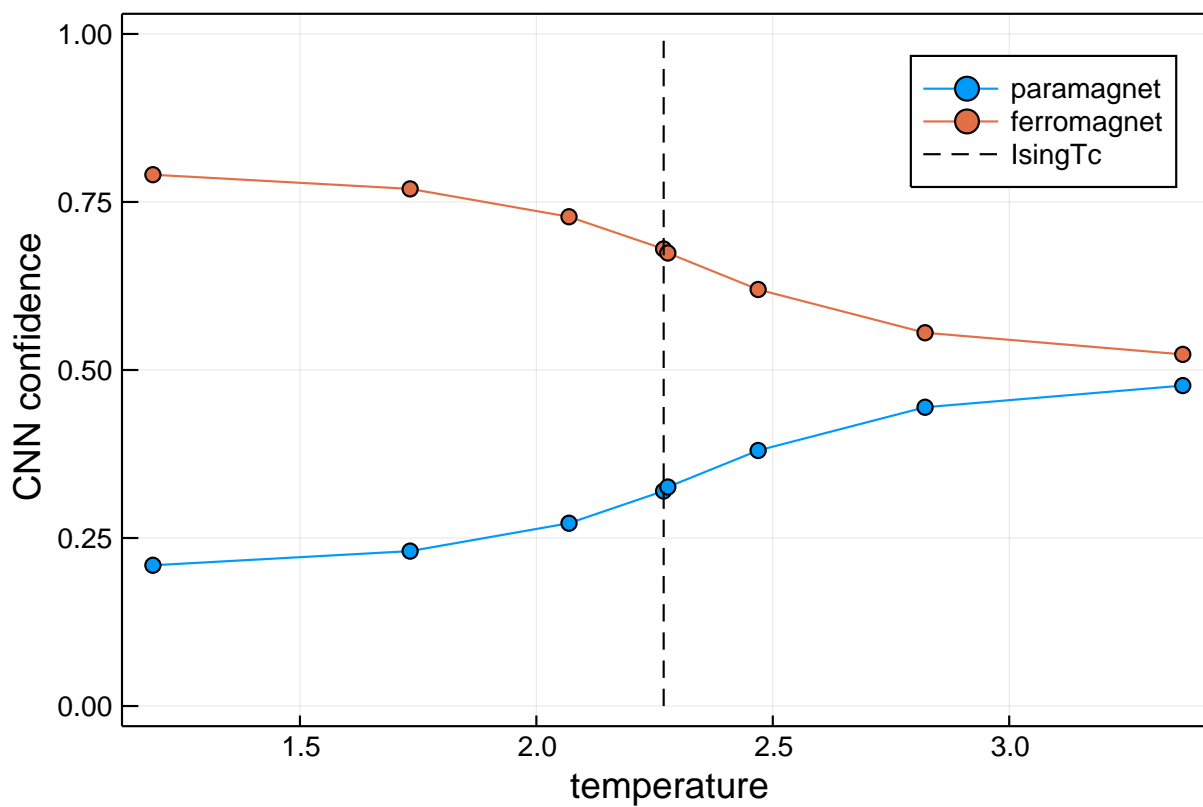
In Jupyter notebooks or Juno you should see an "animation" of the confidence plot across training.

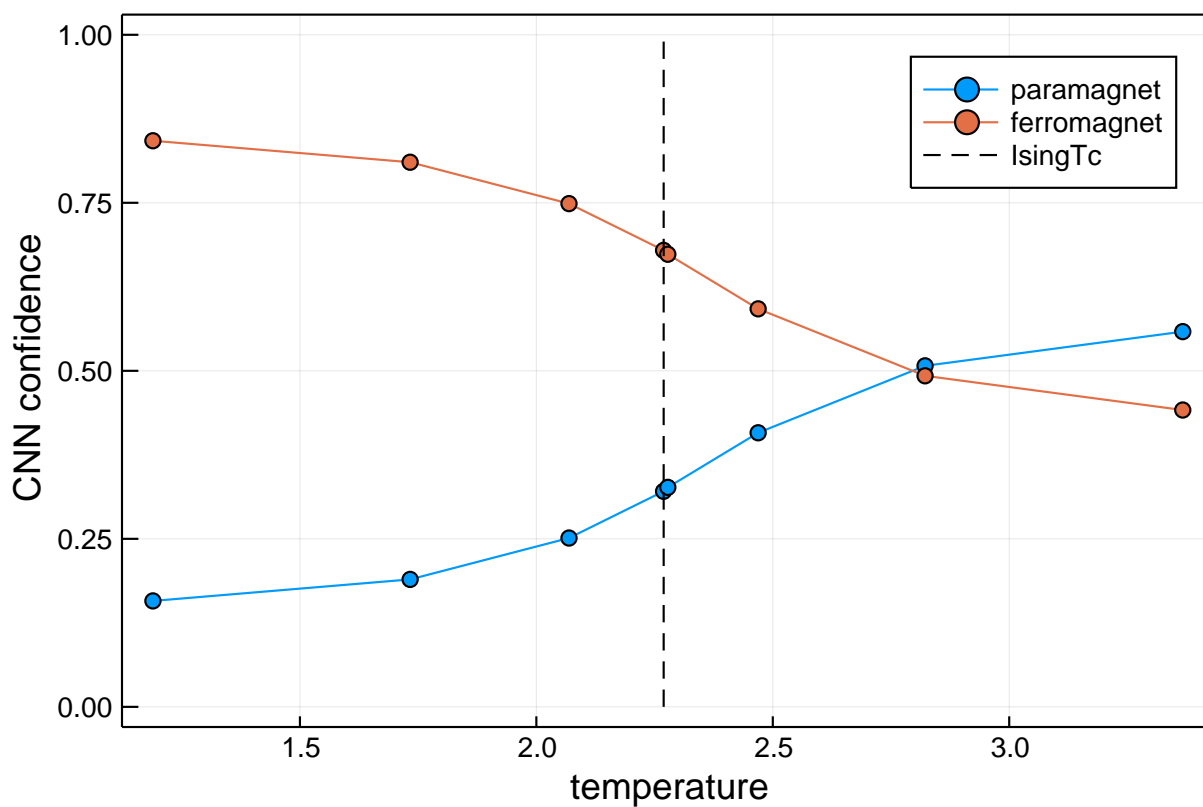
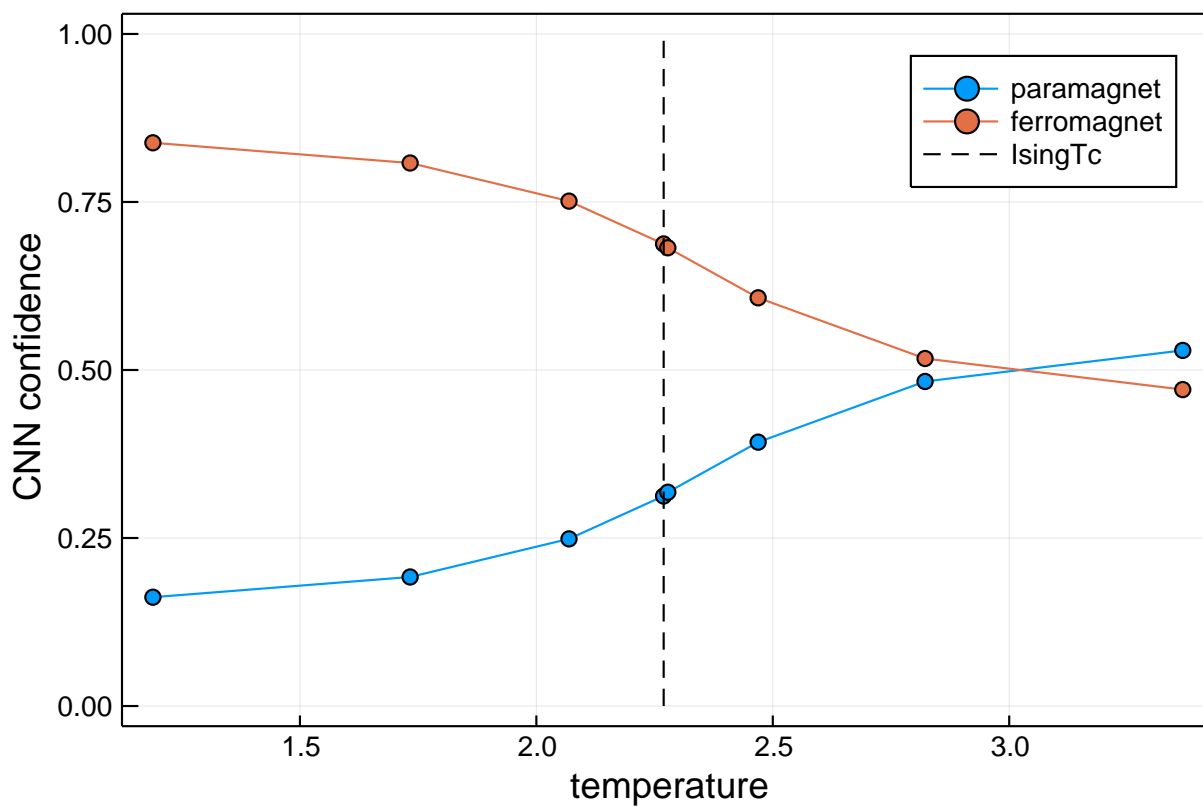
```
# Define a callback
evalcb = () -> begin
# @show(loss(X, Y))
# @show(accuracy(X, Y))
    confidence_plot()
end

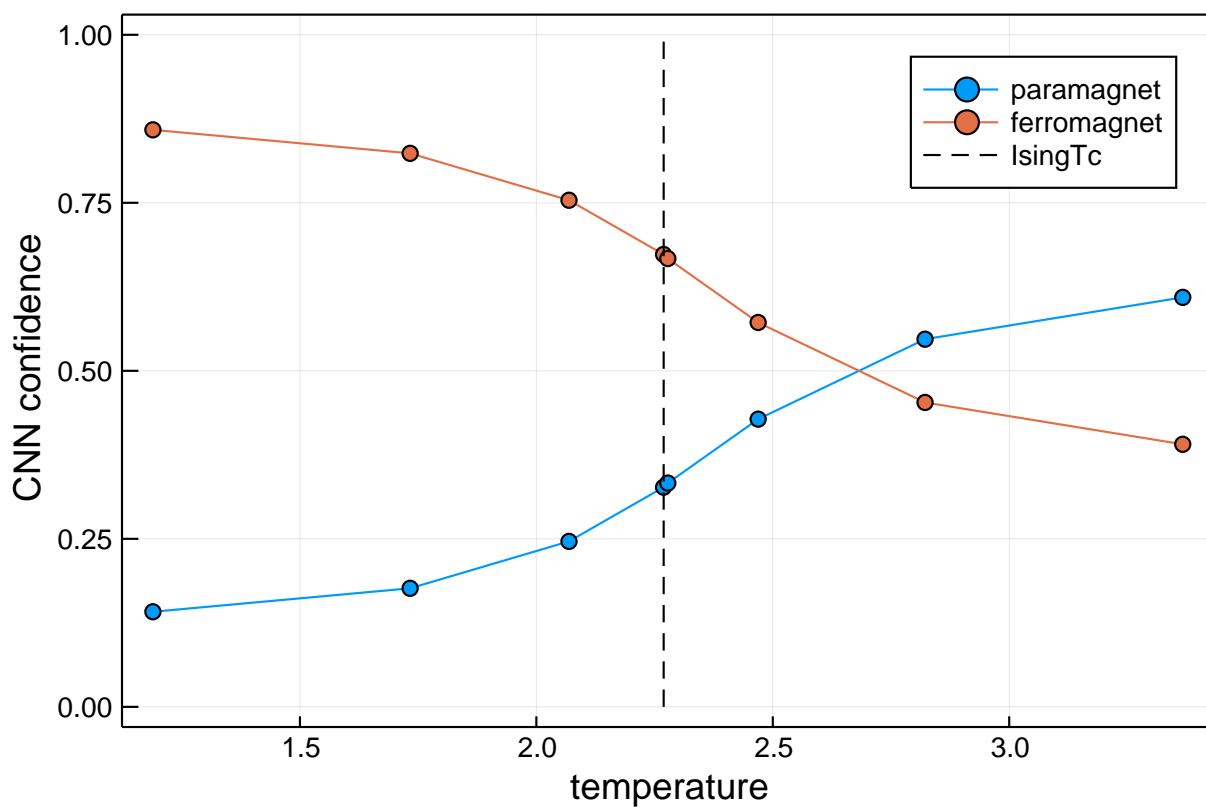
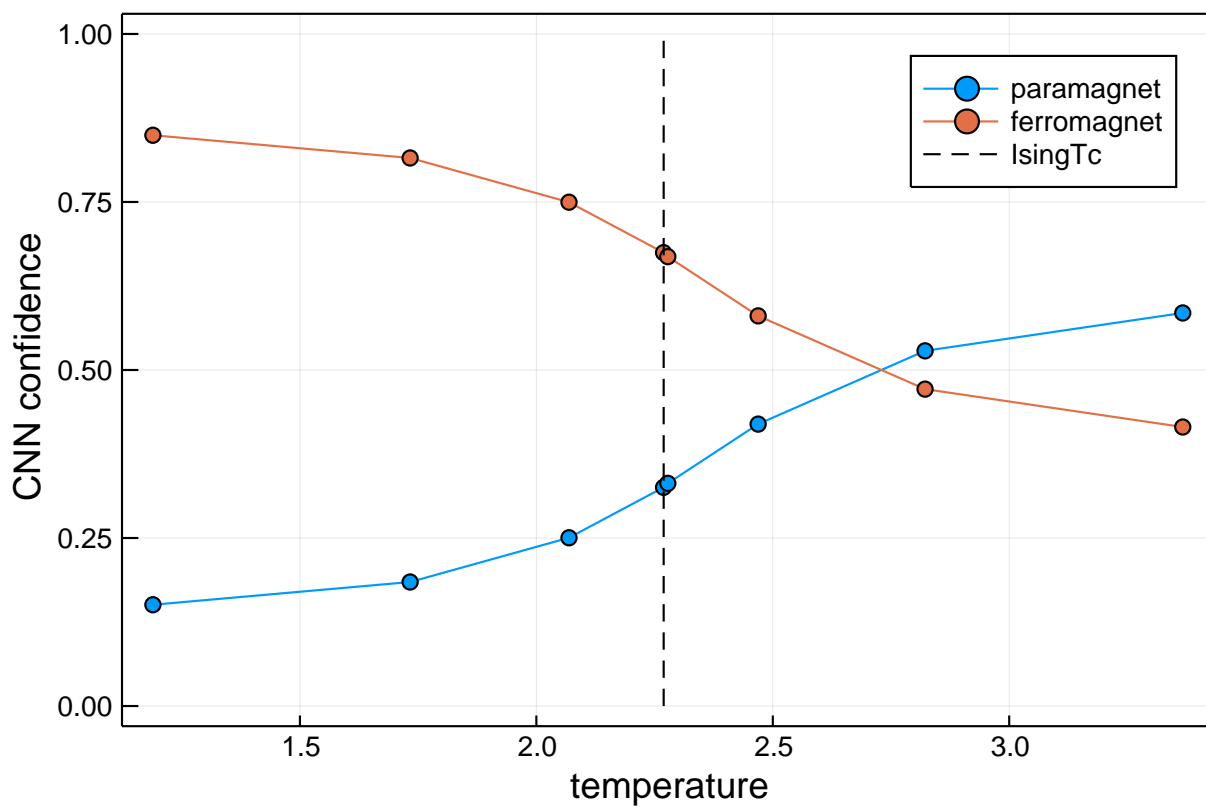
# Reset the network and the optimizer
Random.seed!(123)
m = Chain(
    Dense(L^2, 10, relu),
    Dense(10, 2),
    softmax)
opt = ADAM()

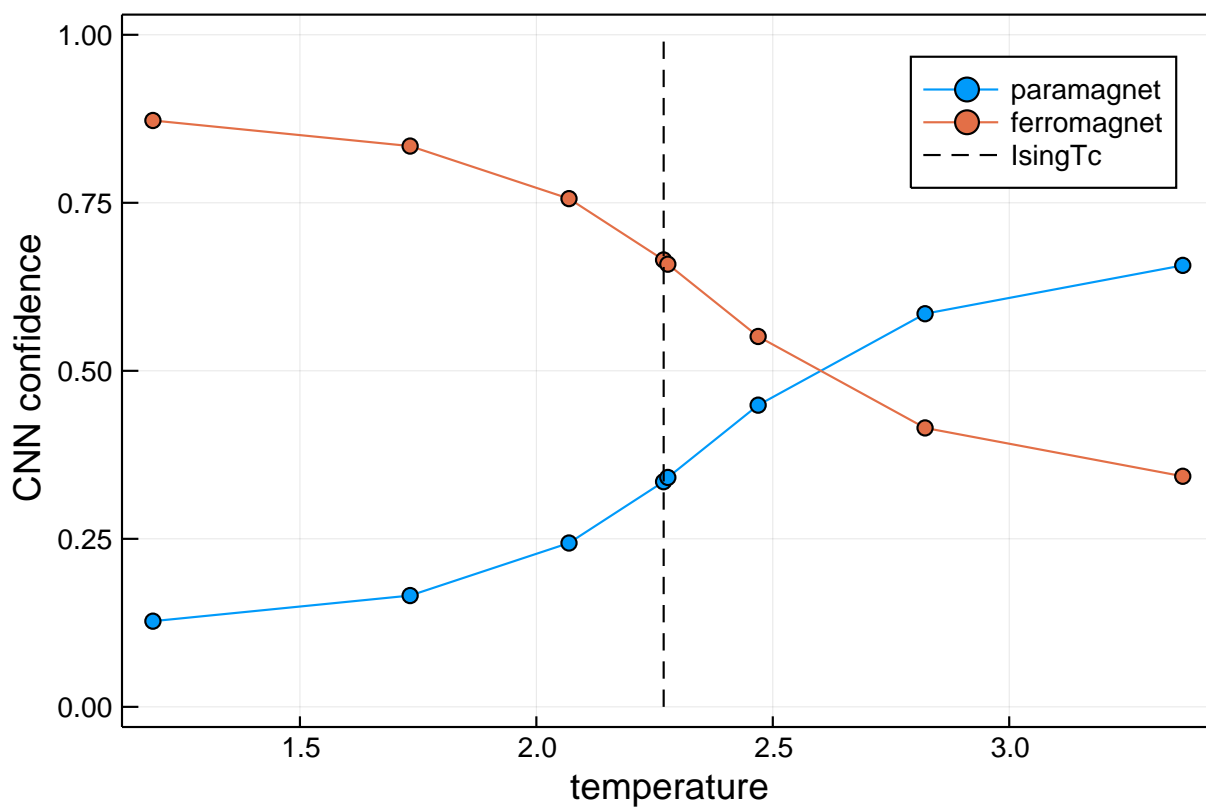
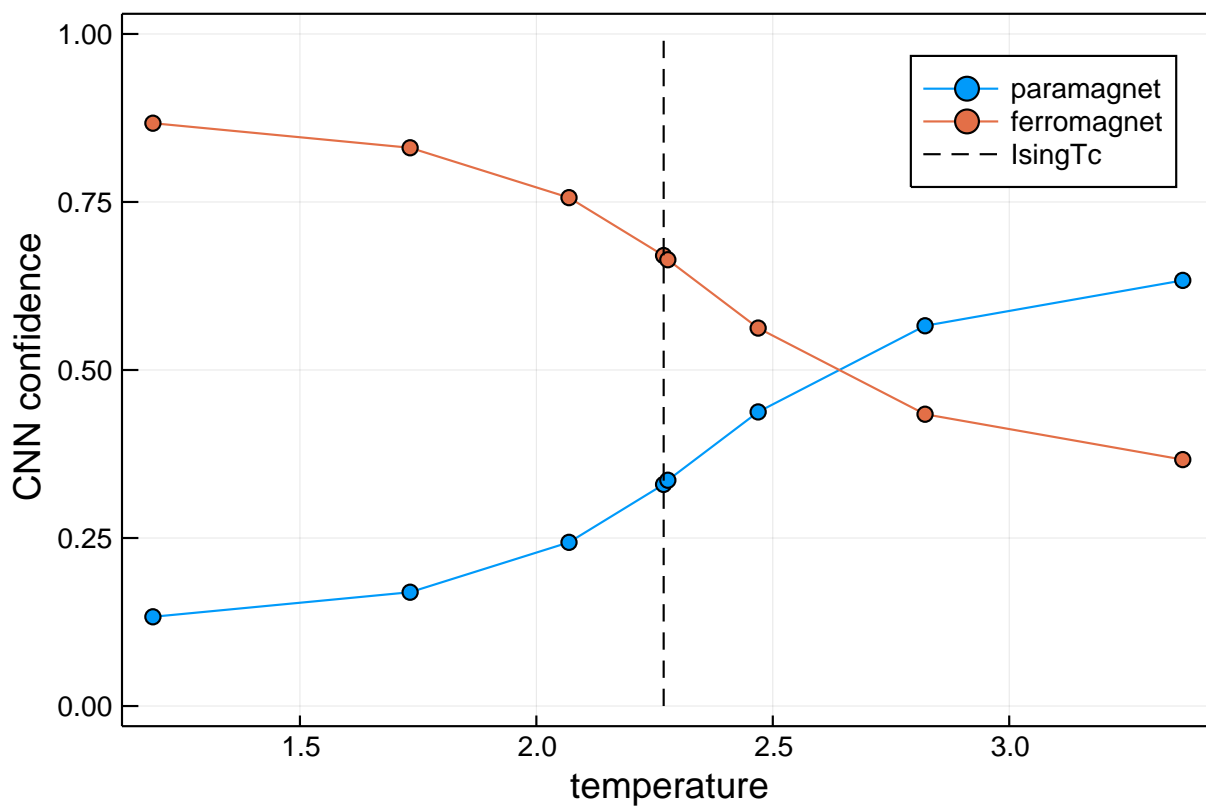
# Train for 100 epochs (with "animation")
for i in 1:100
    Flux.train!(loss, params(m), dataset, opt, cb = throttle(evalcb, 50))
end
```

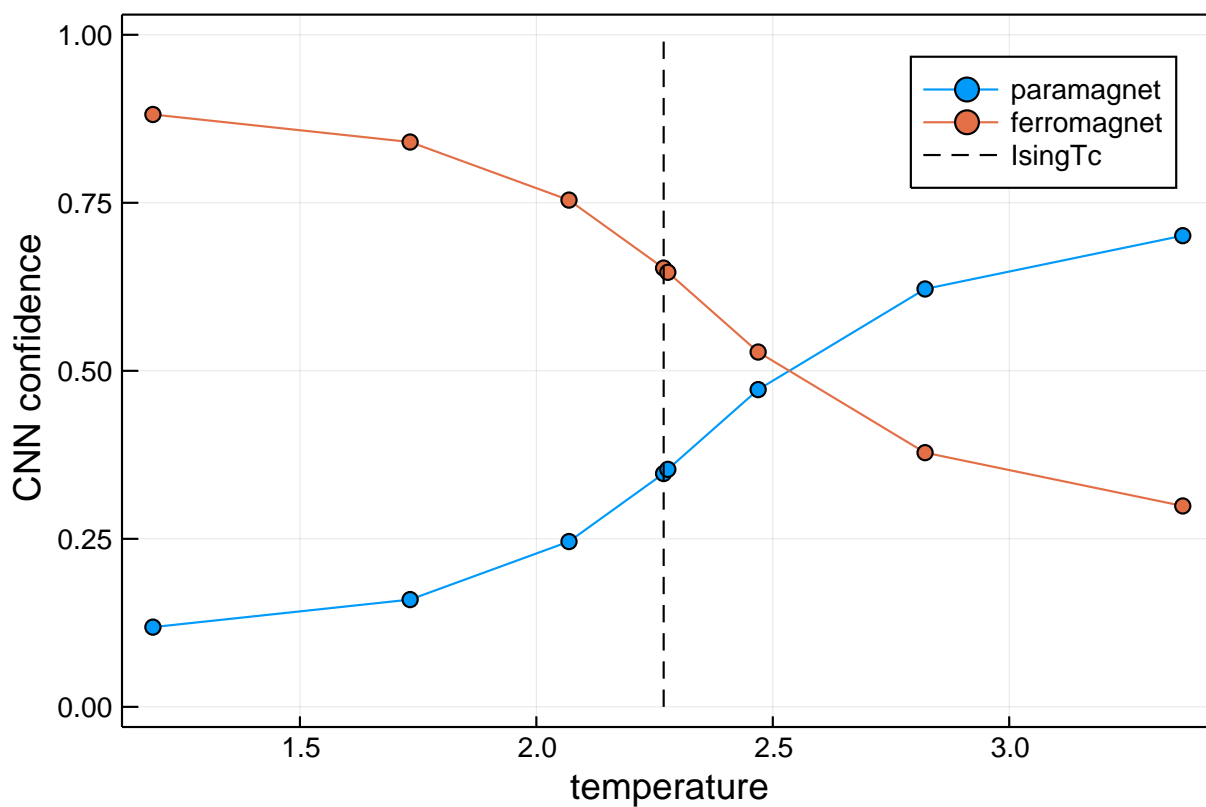
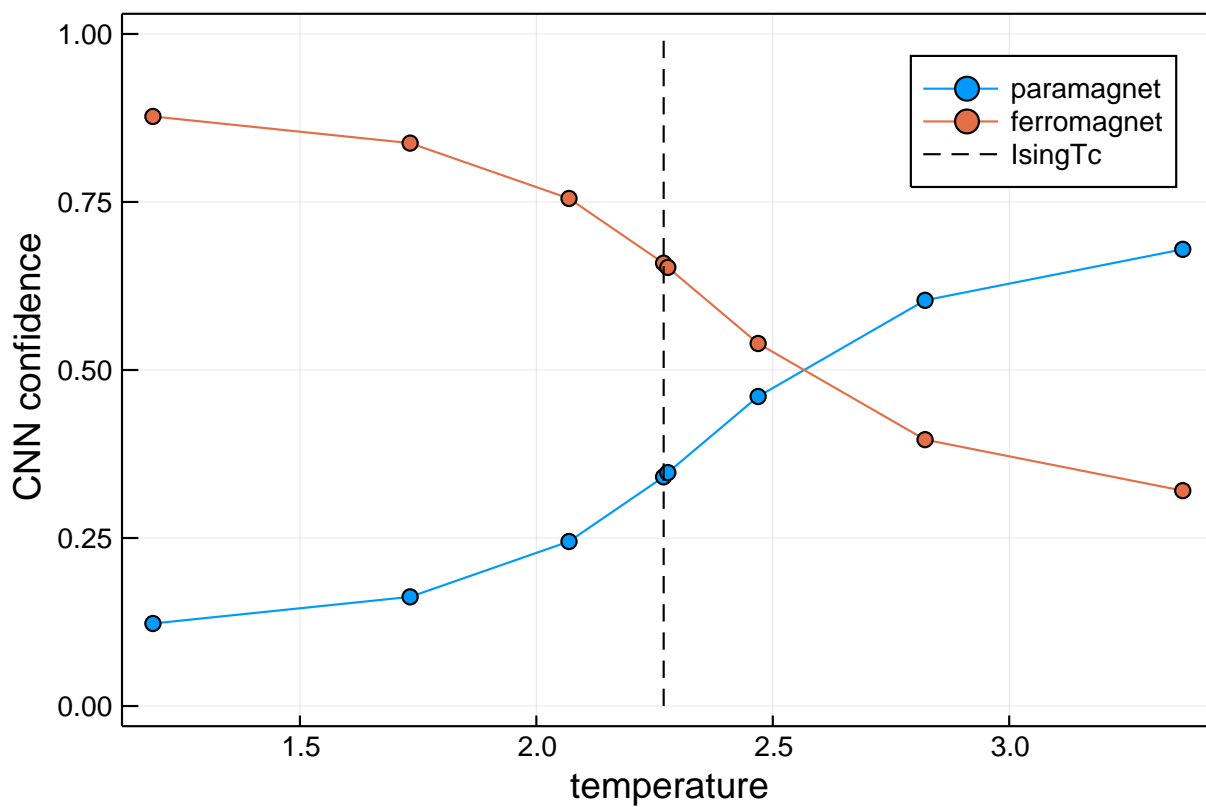


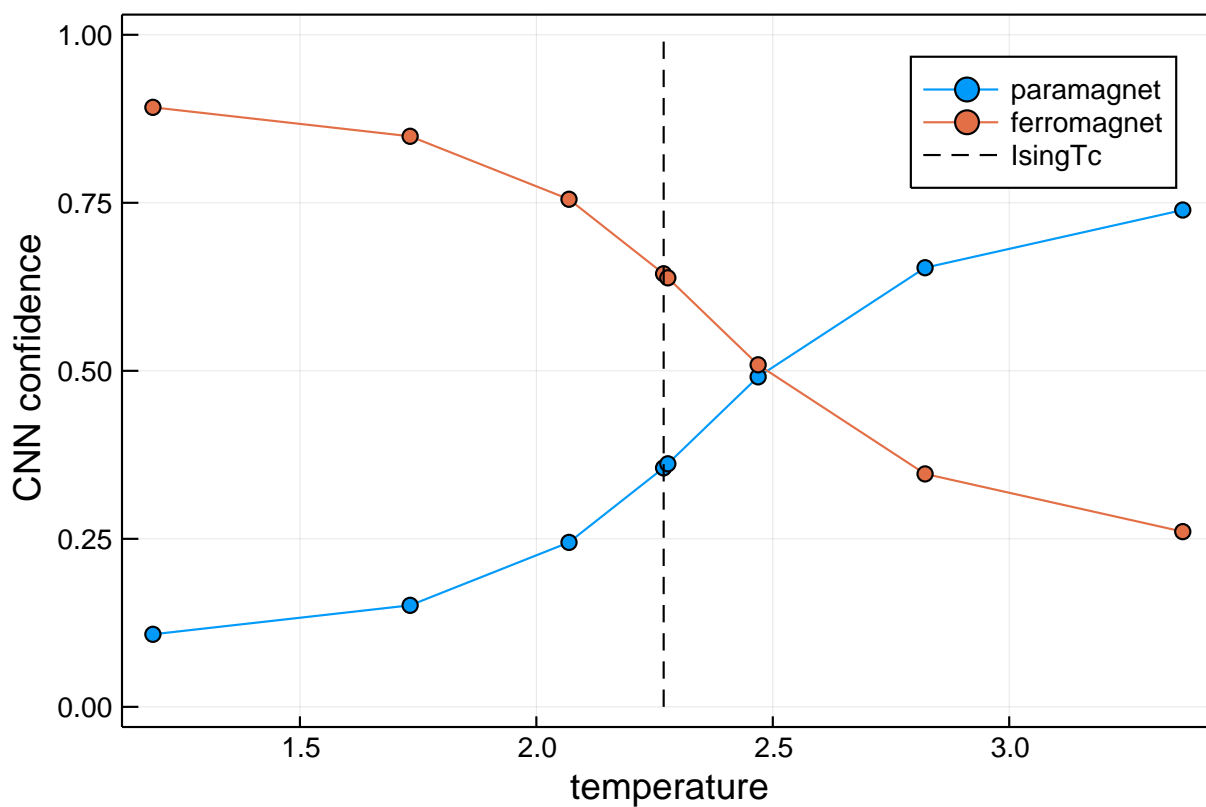
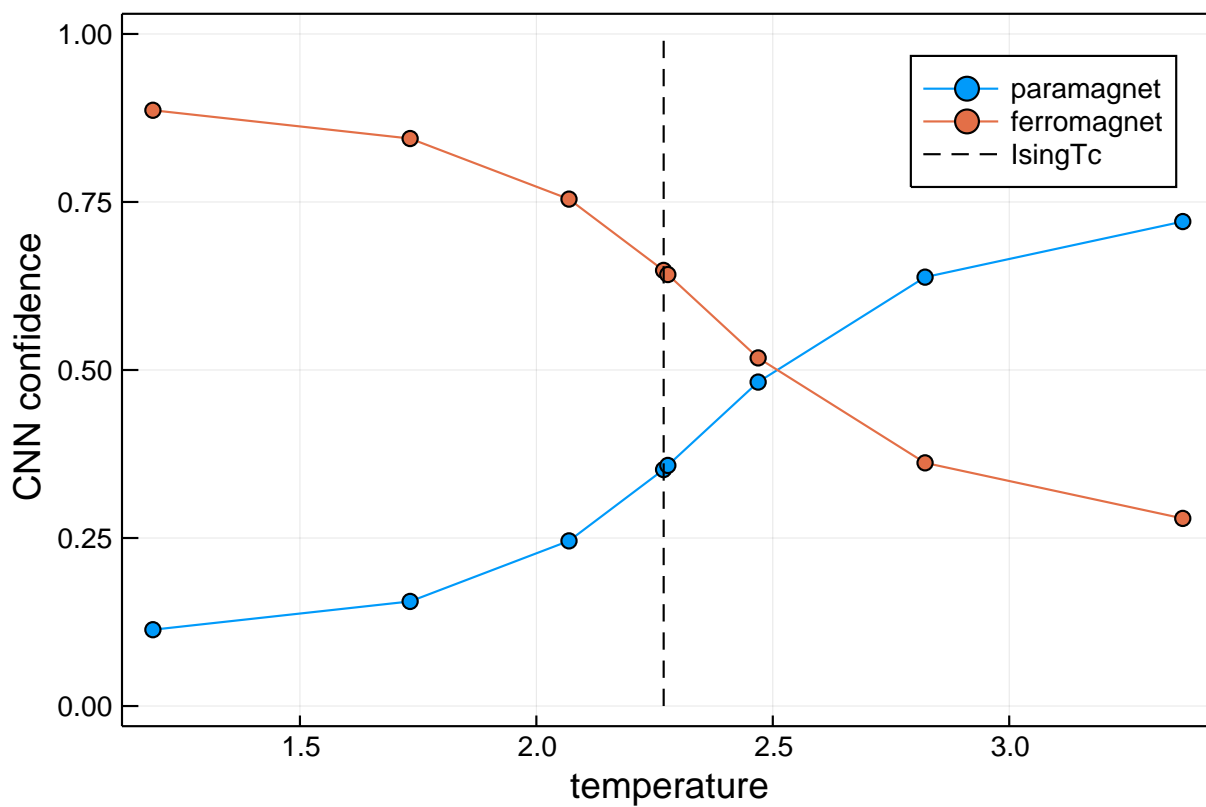


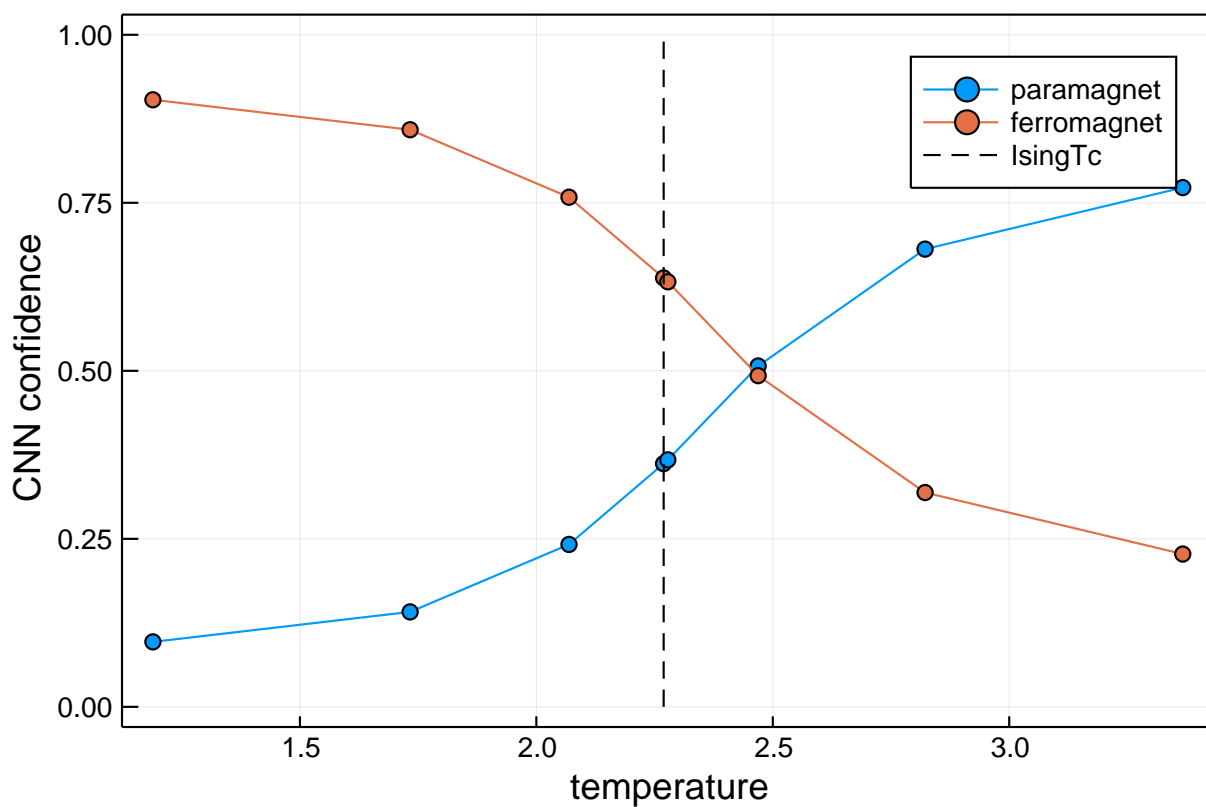
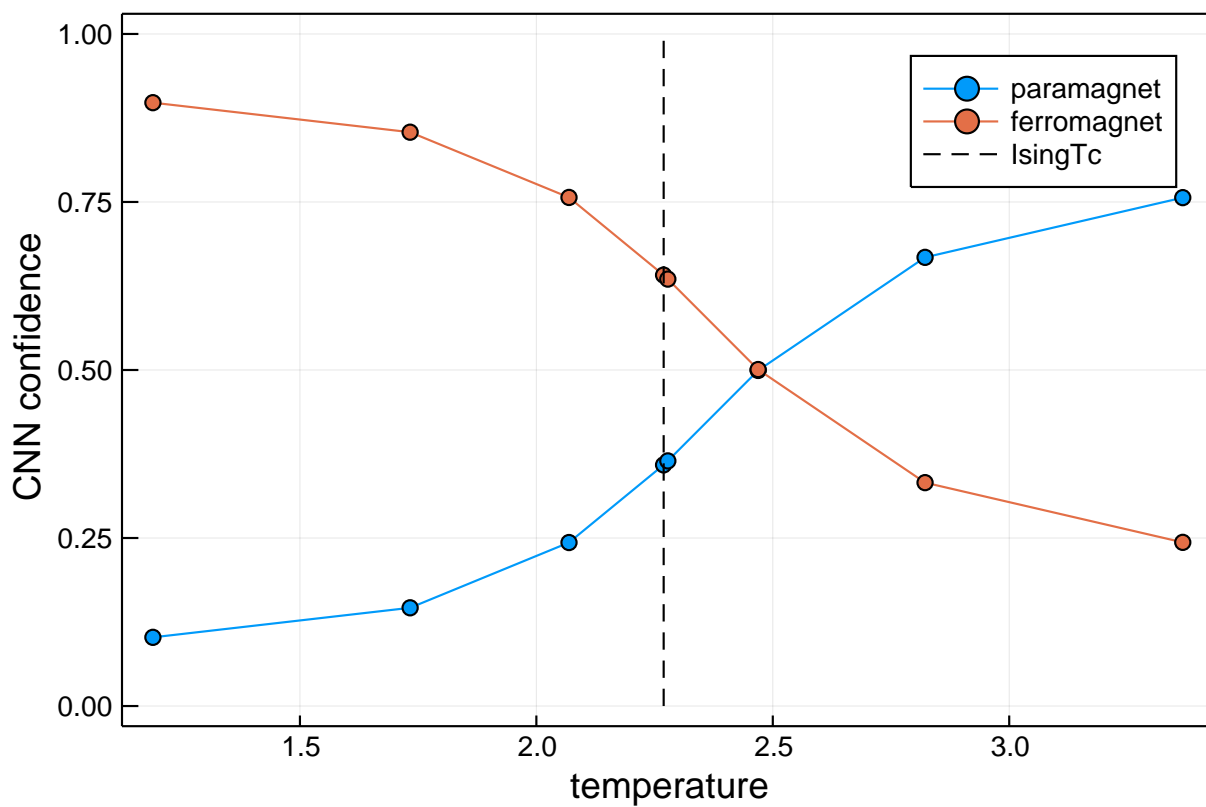


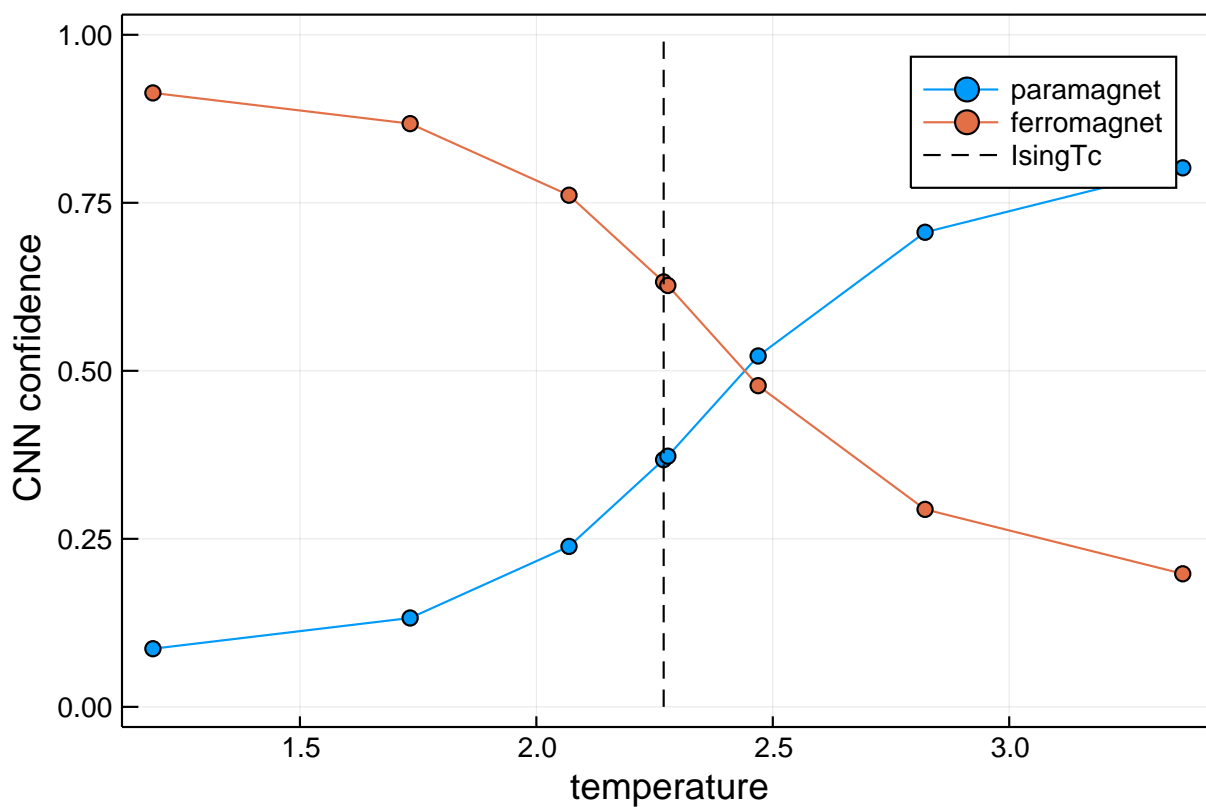
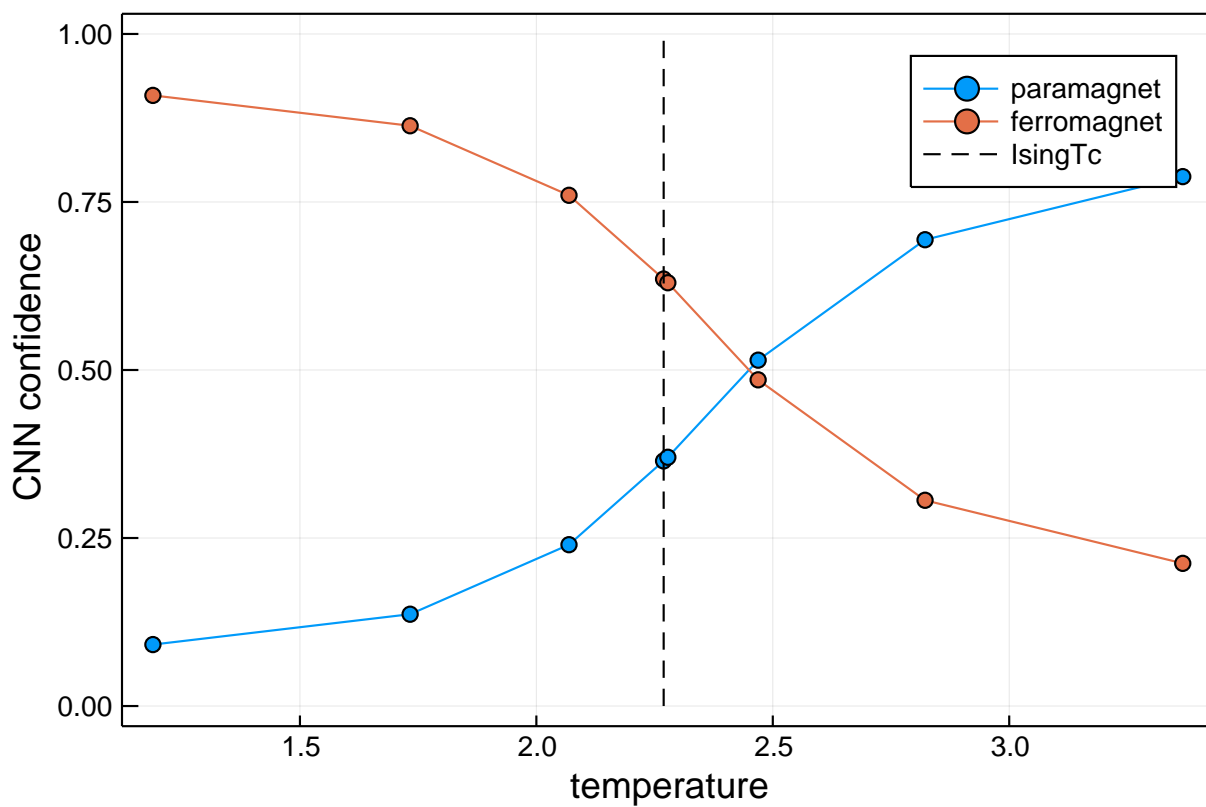


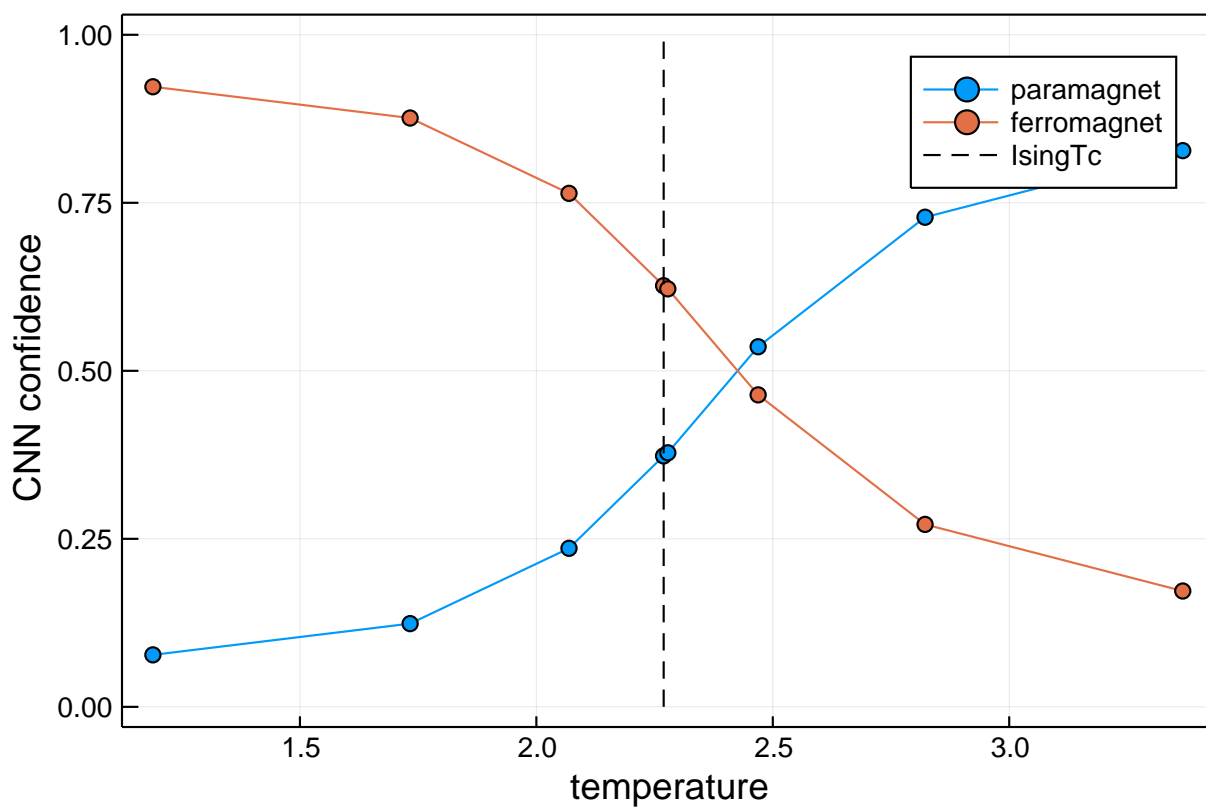
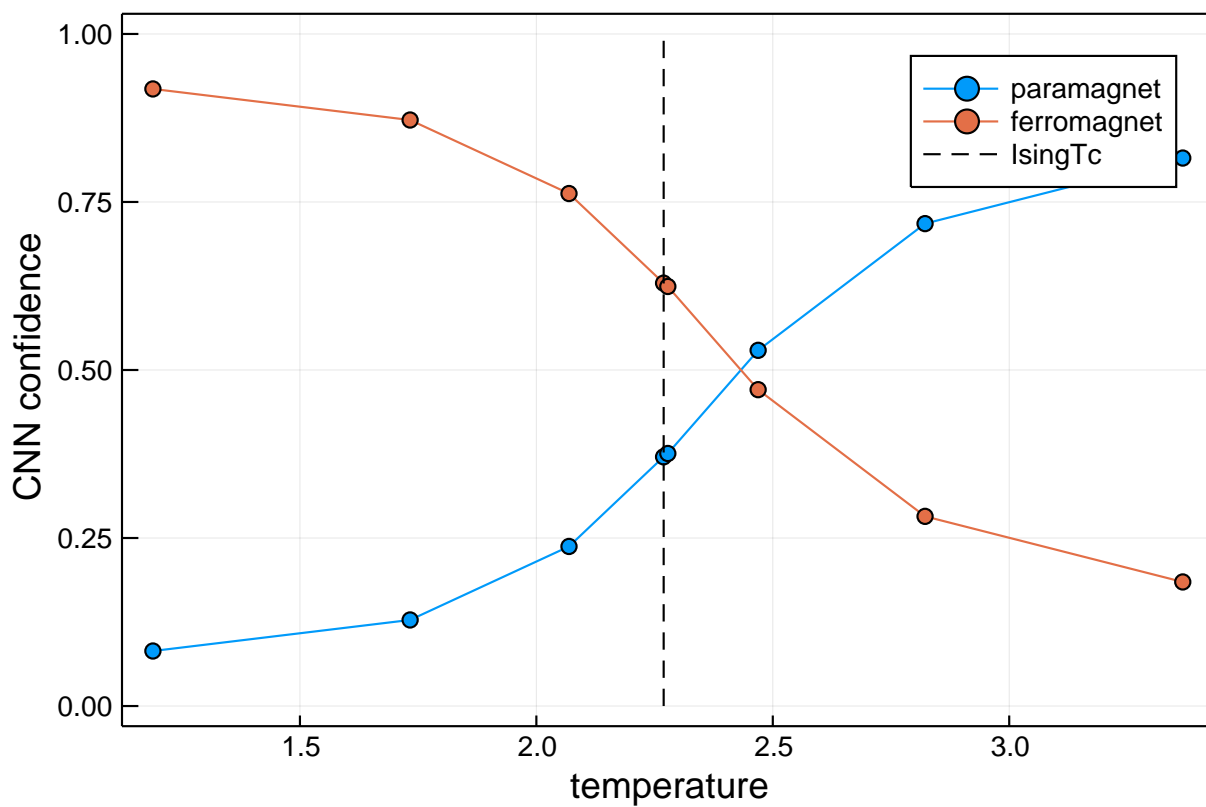


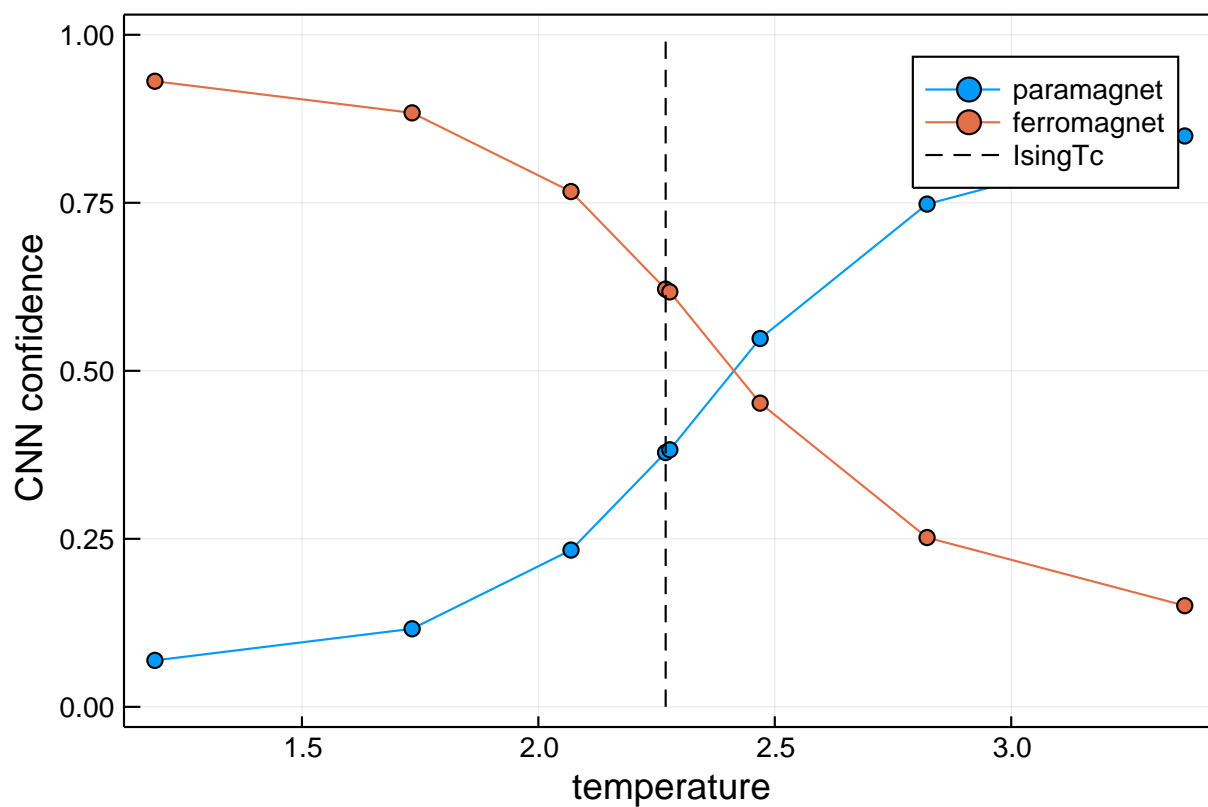
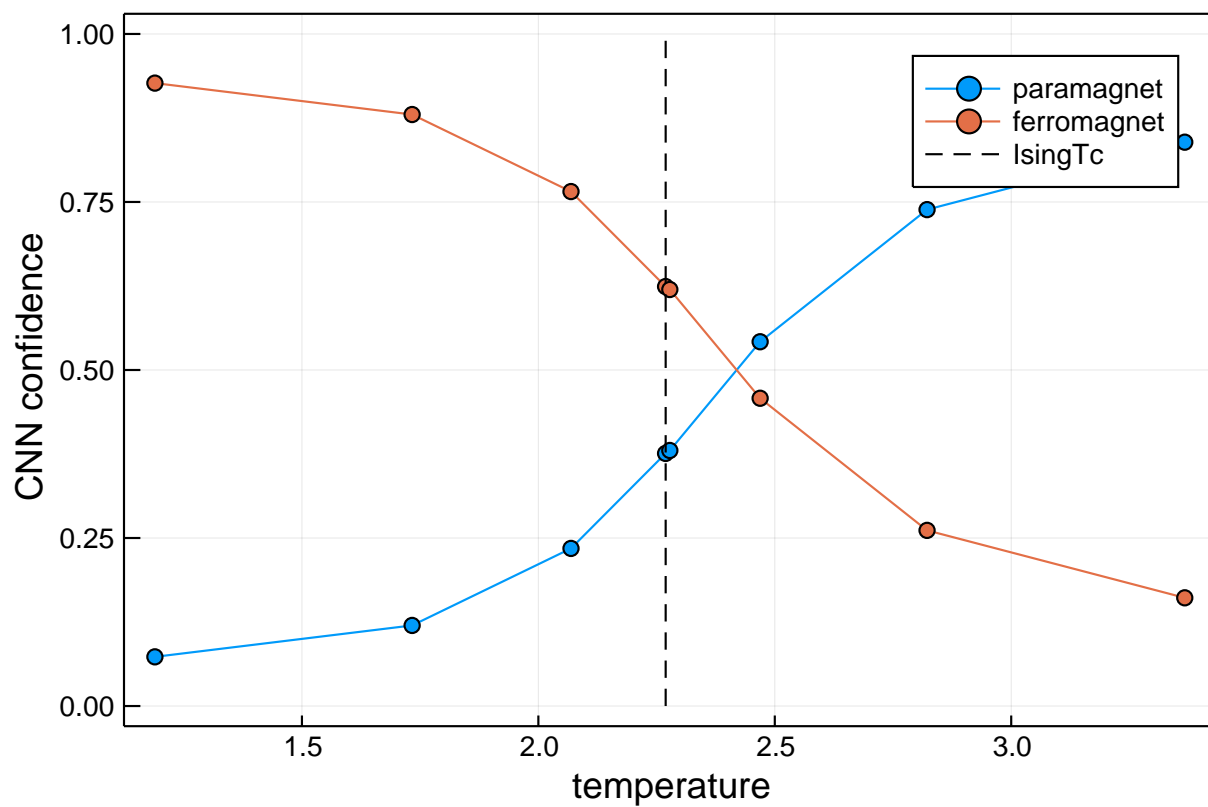


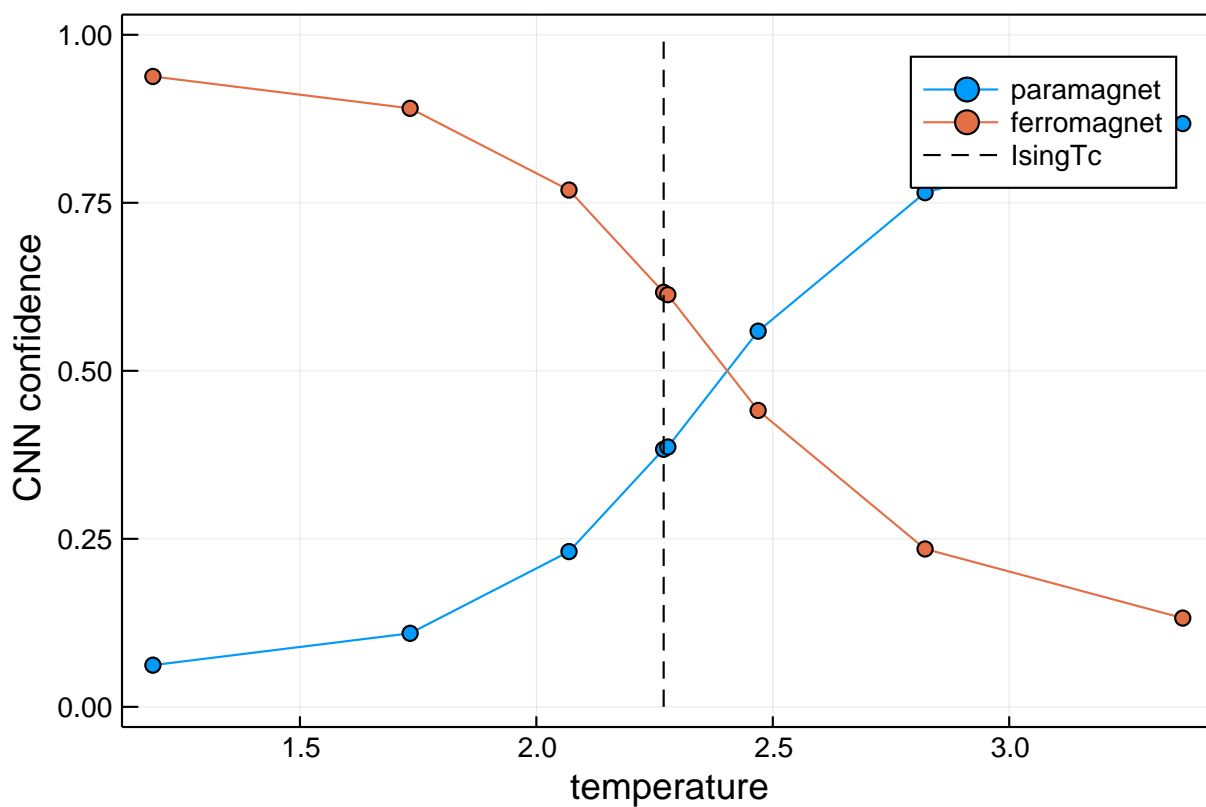
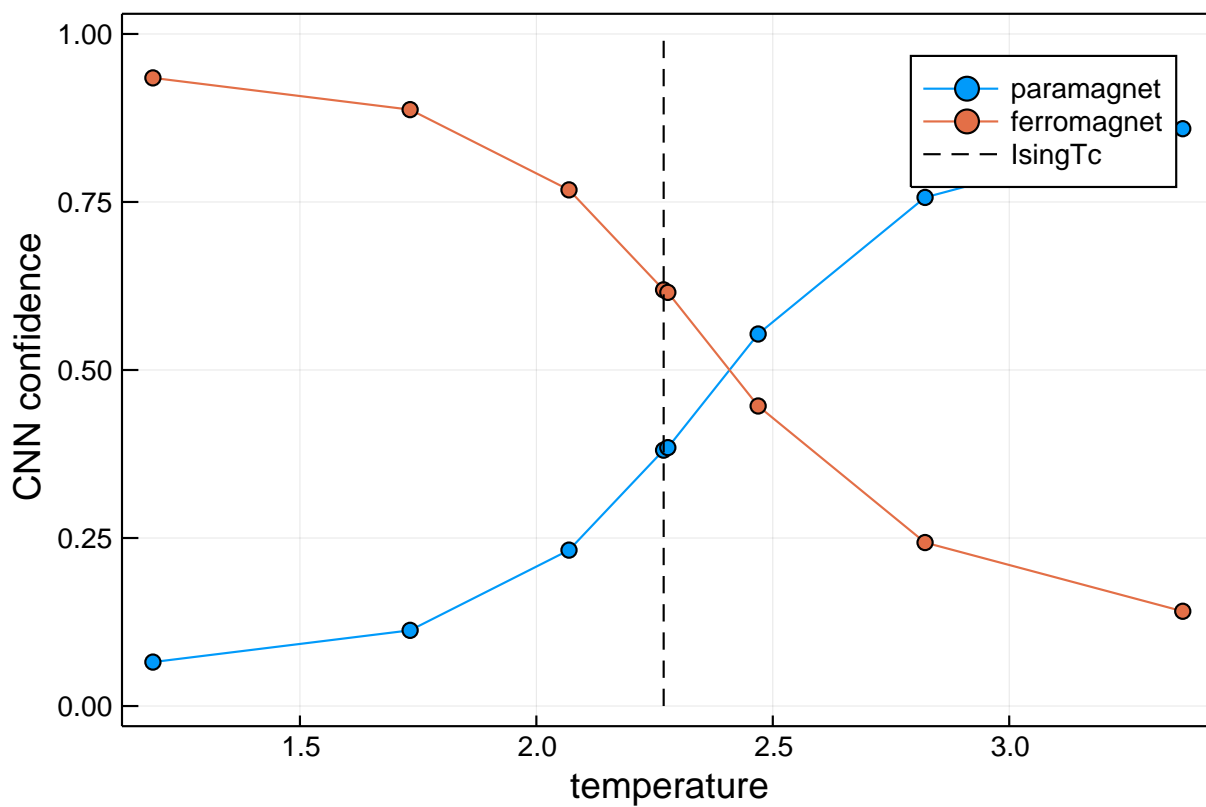


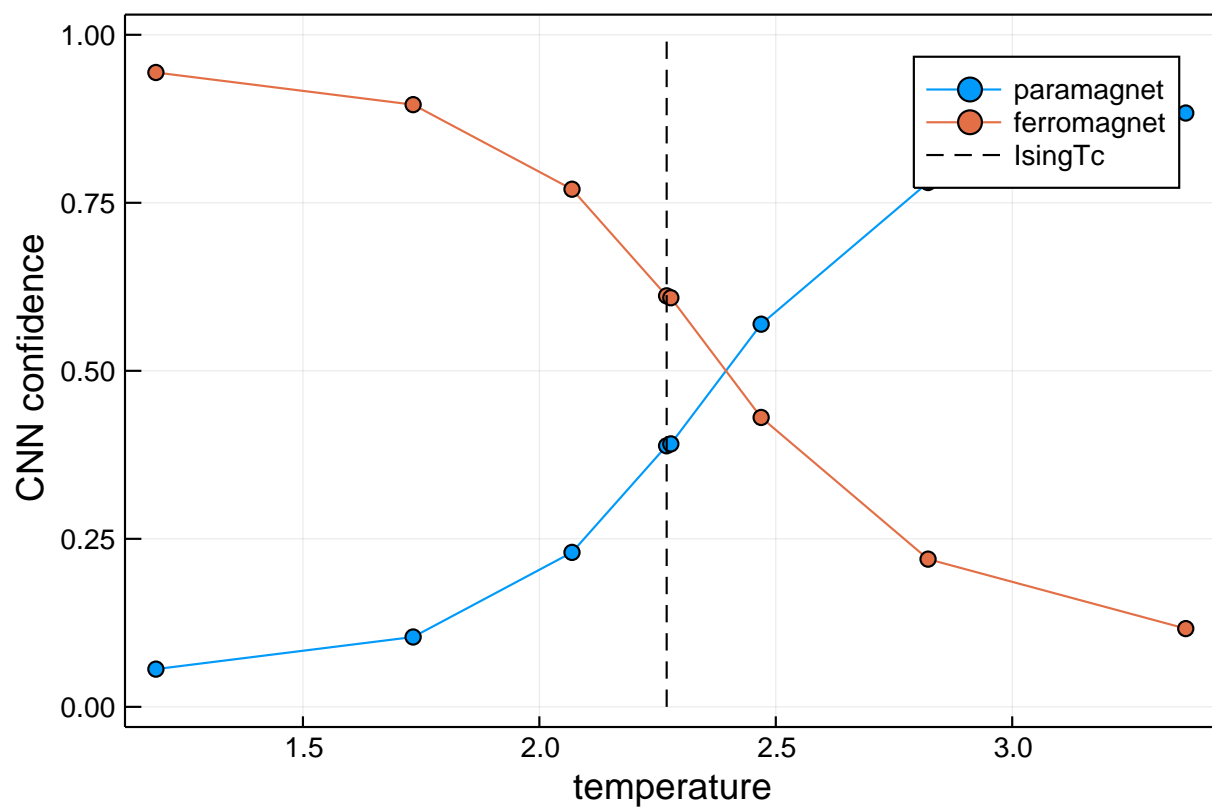
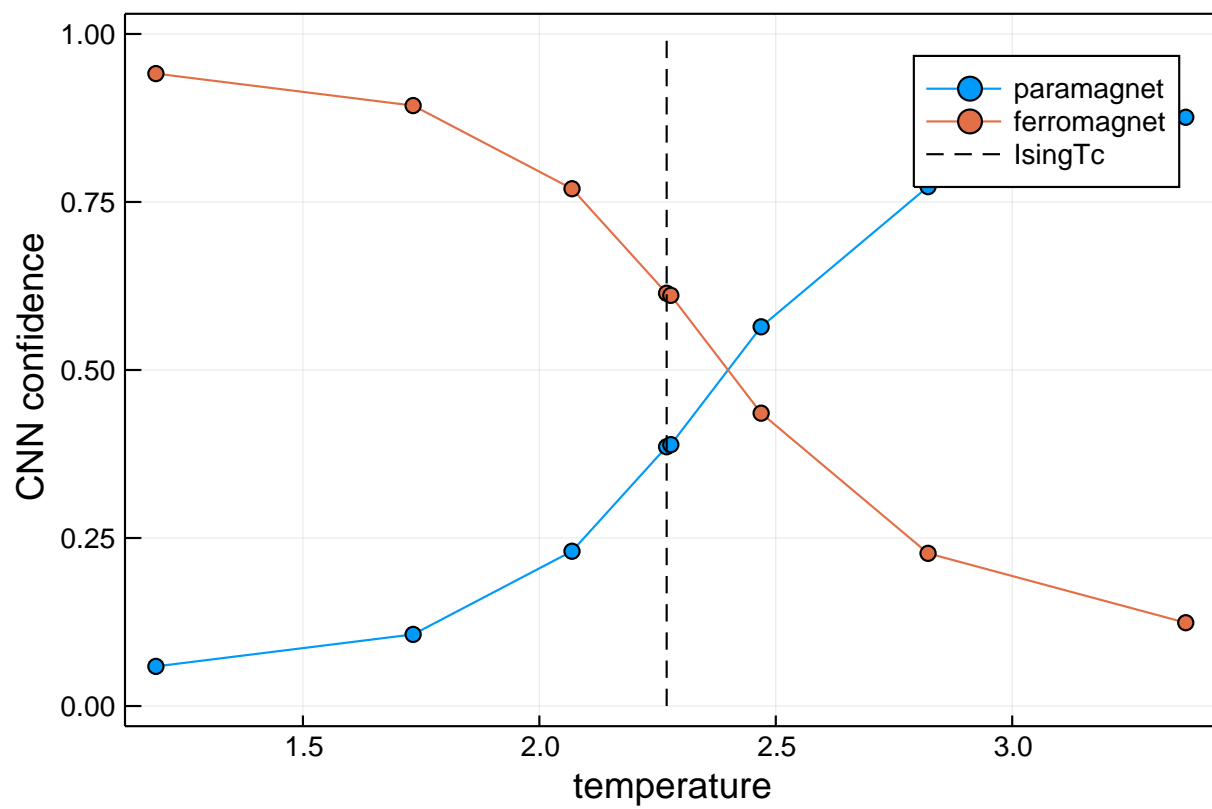


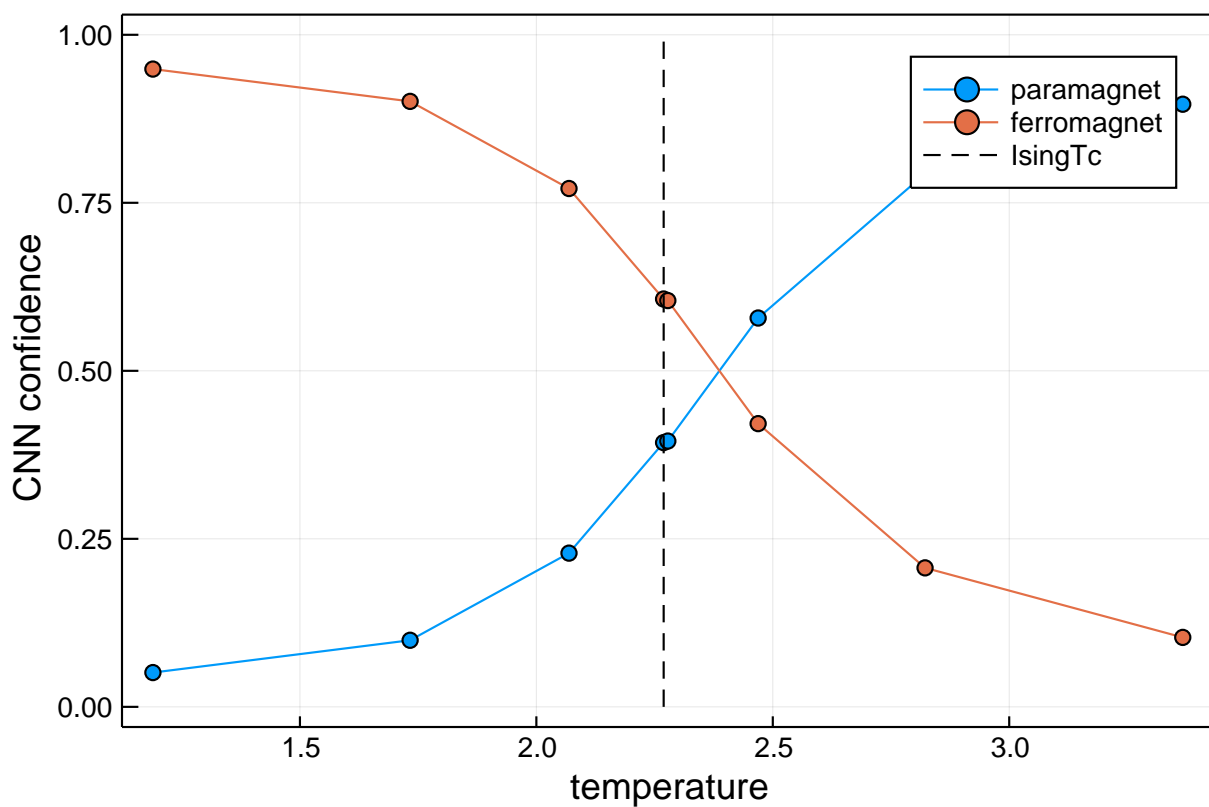
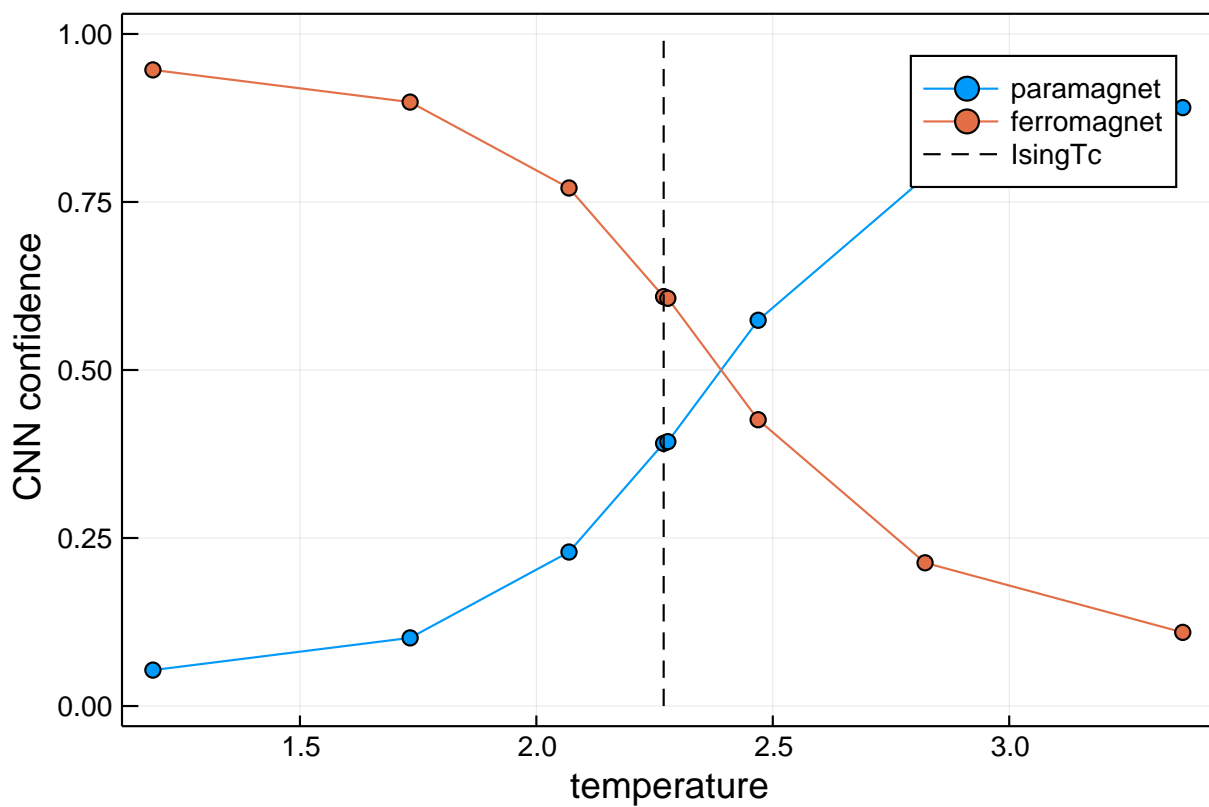


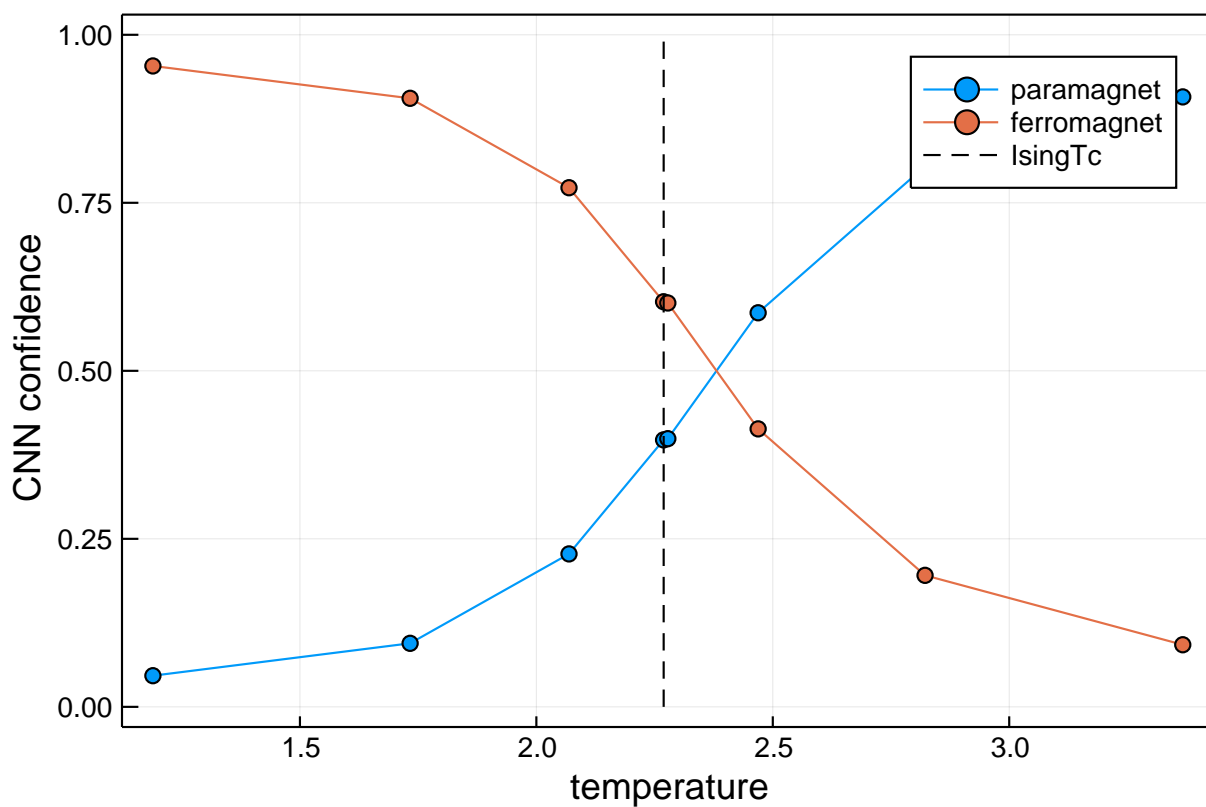
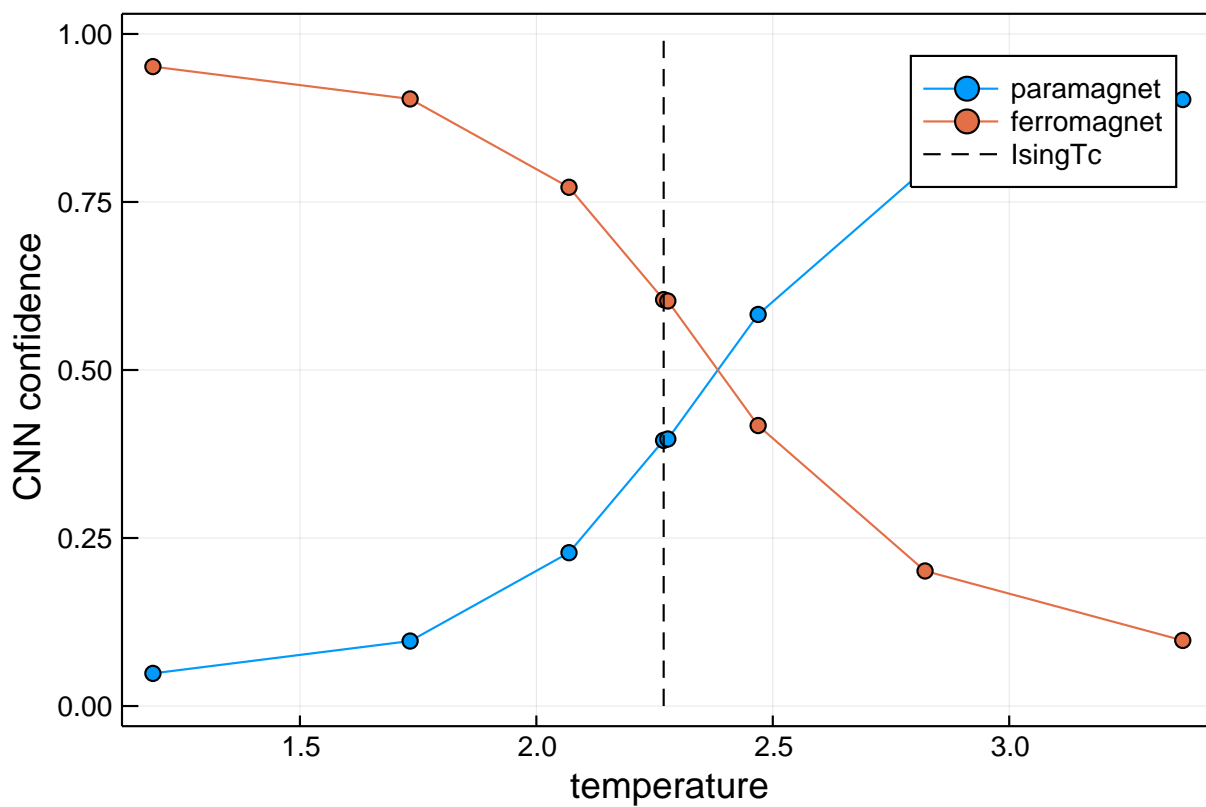


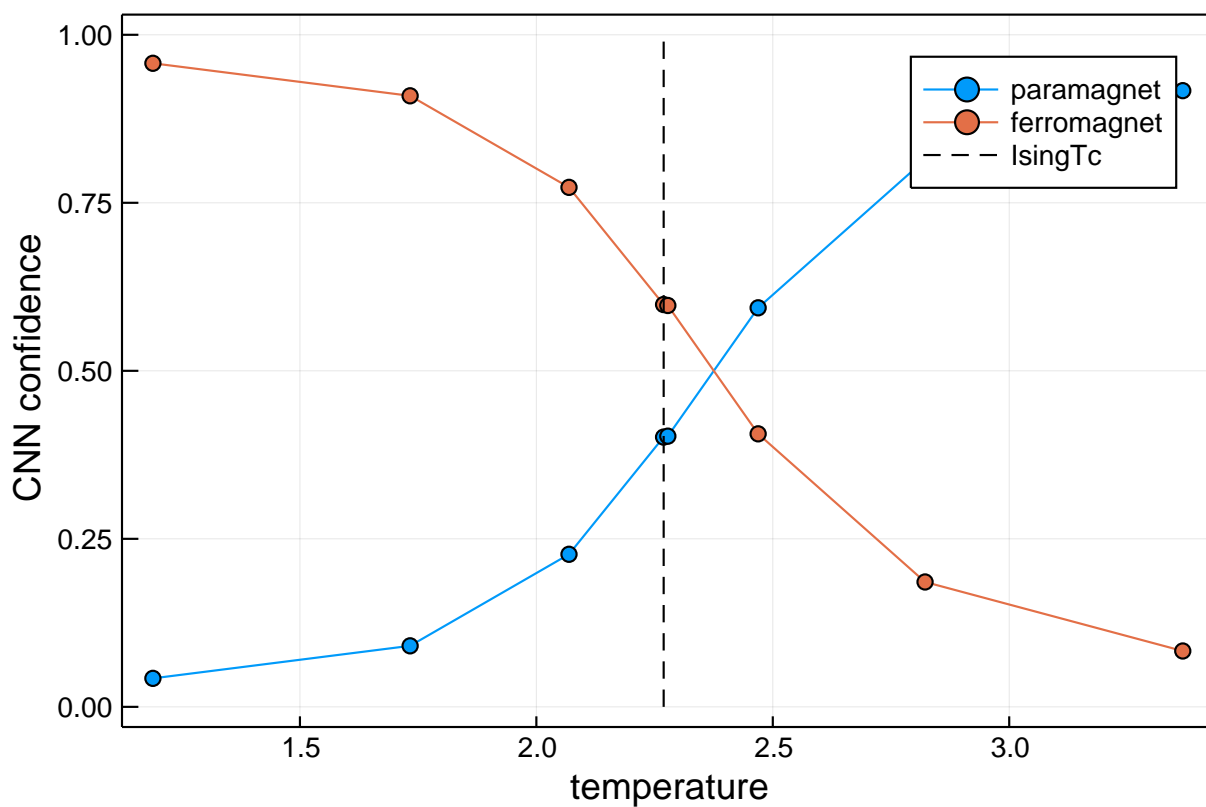
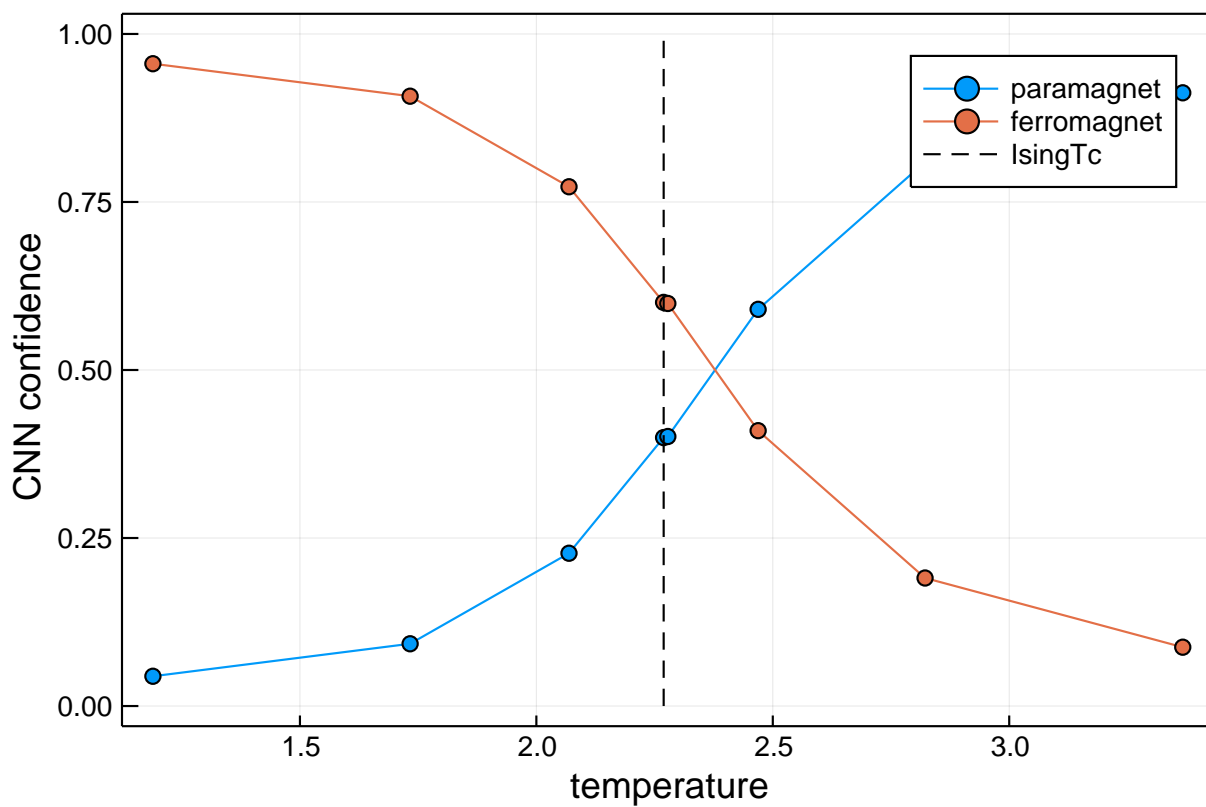


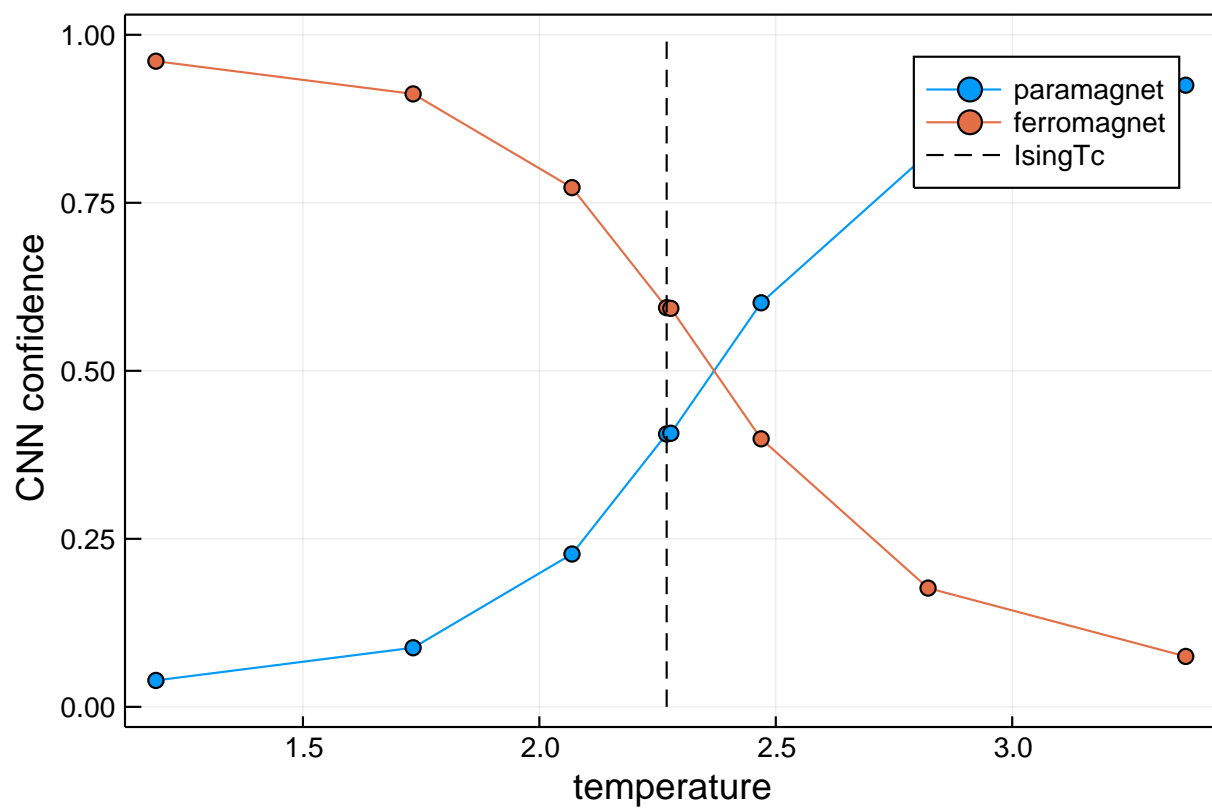
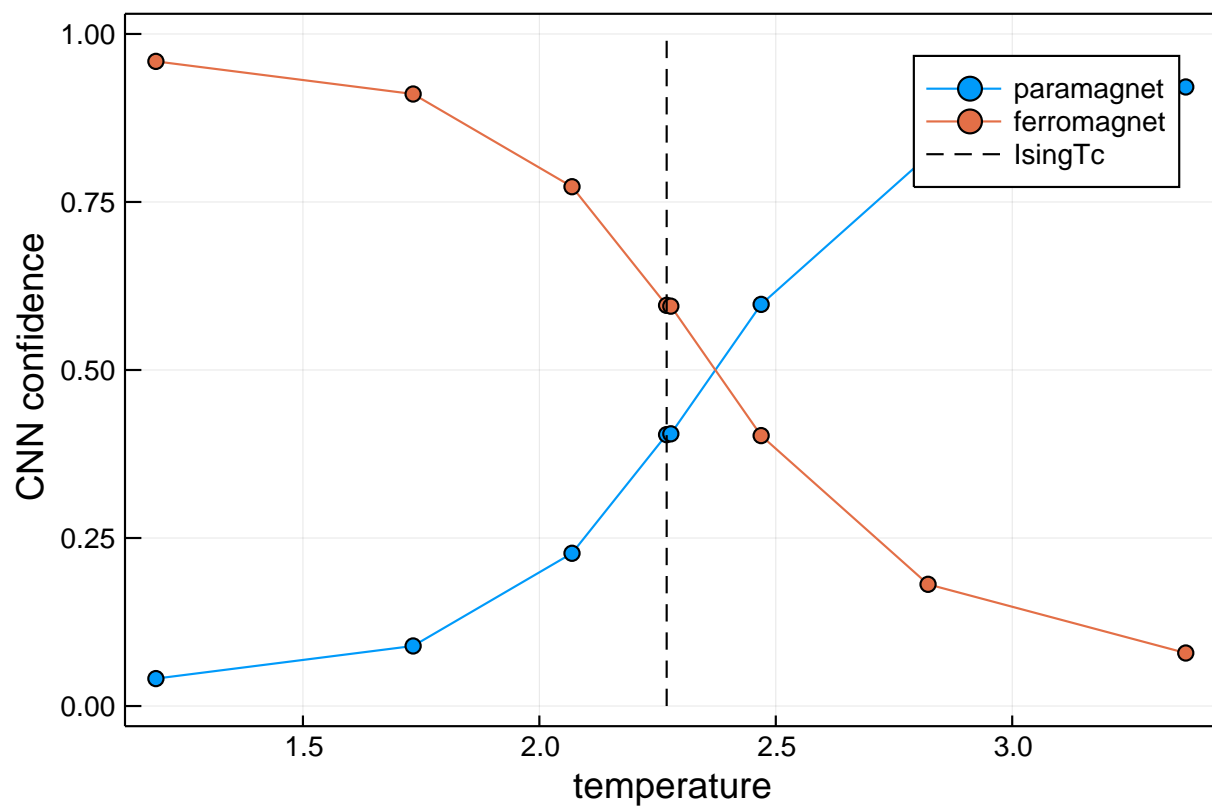


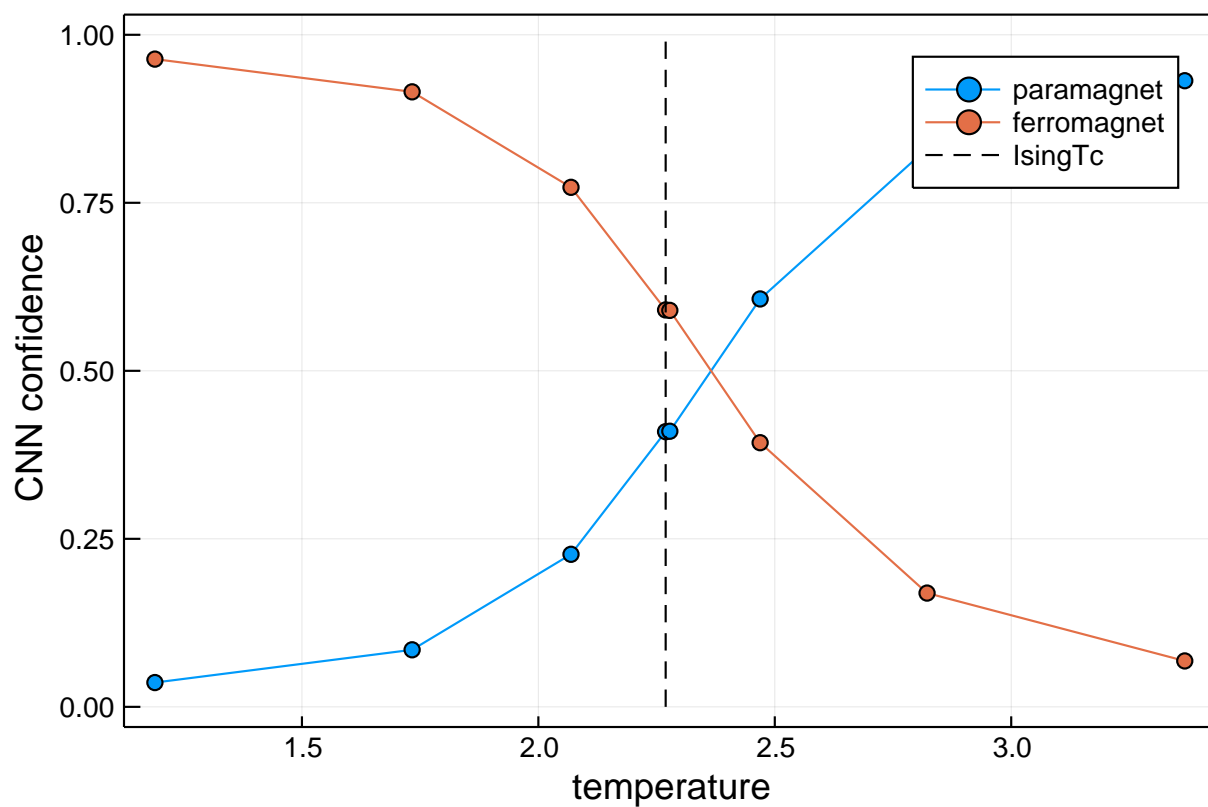
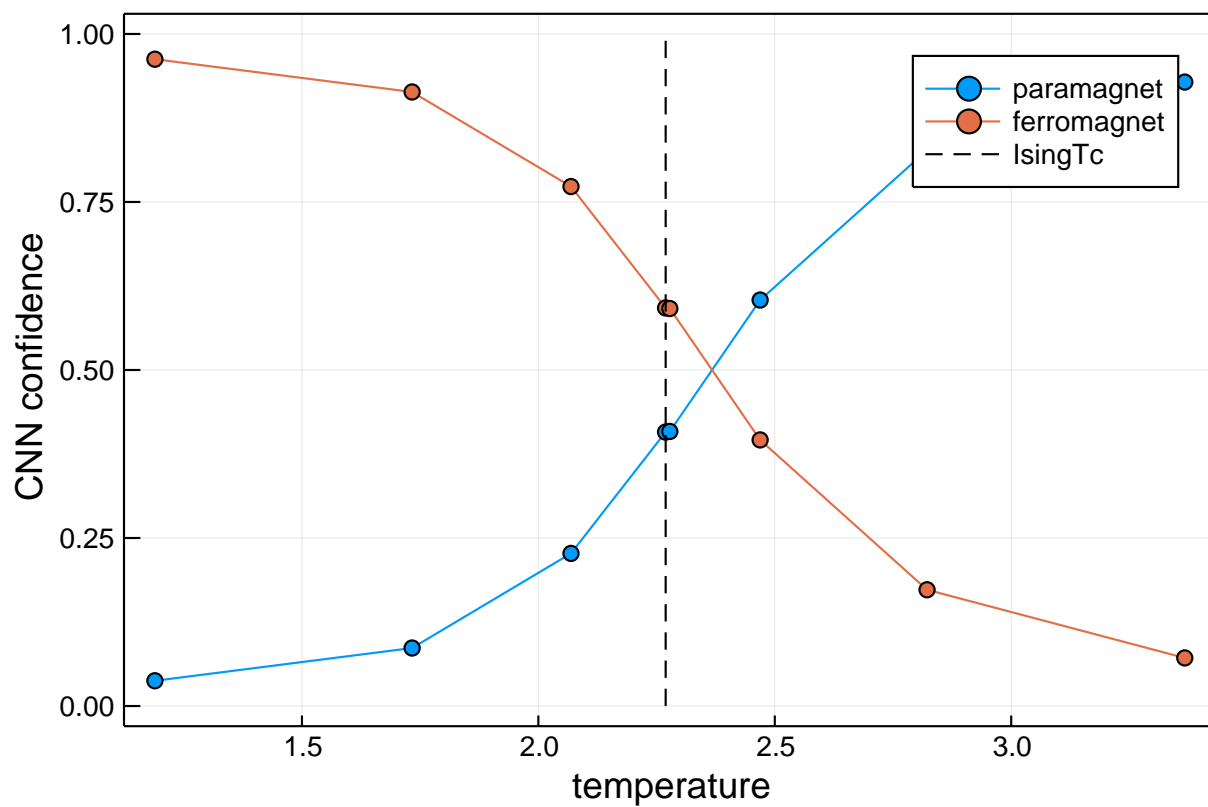


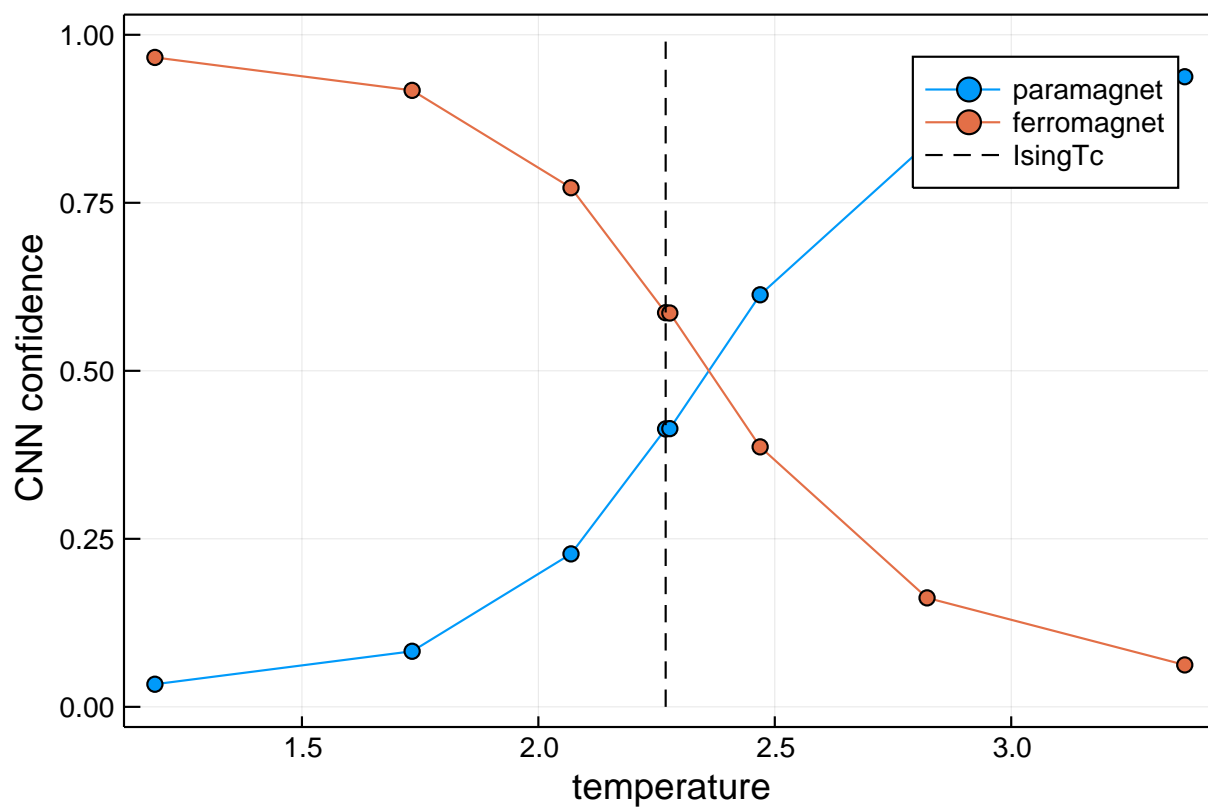
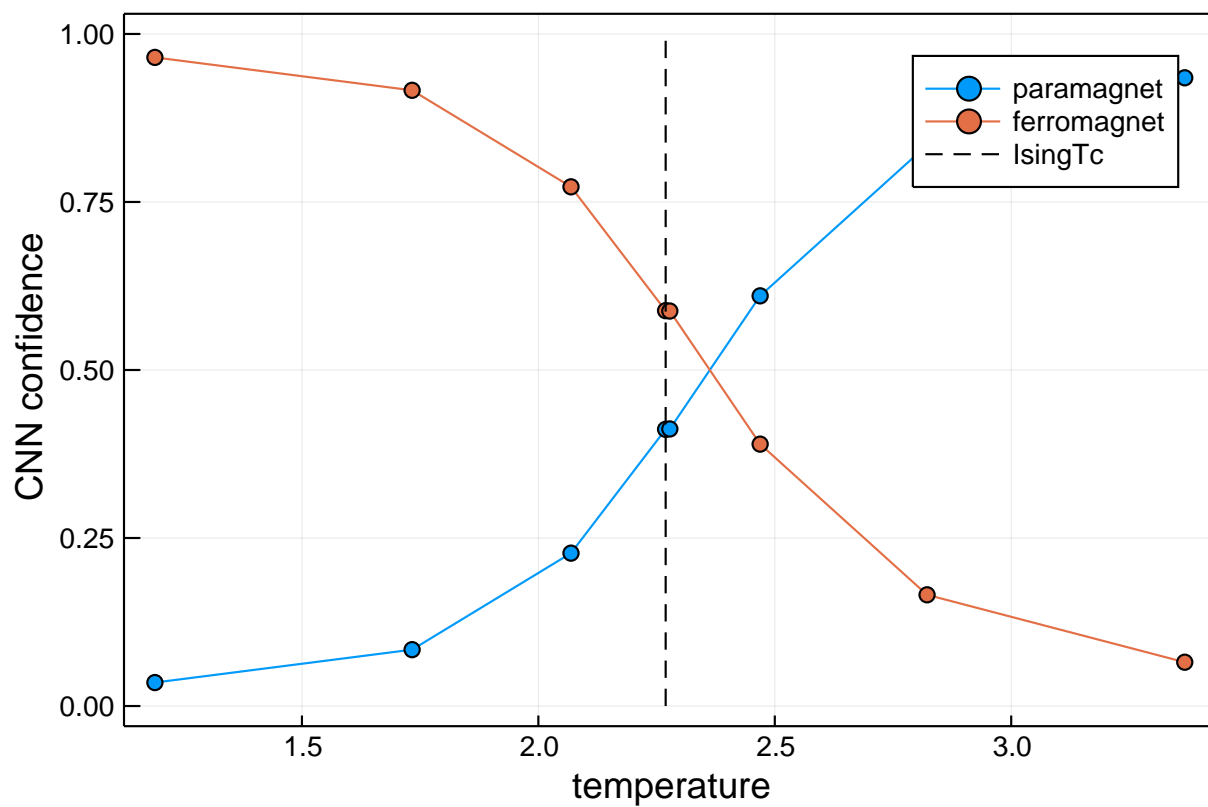


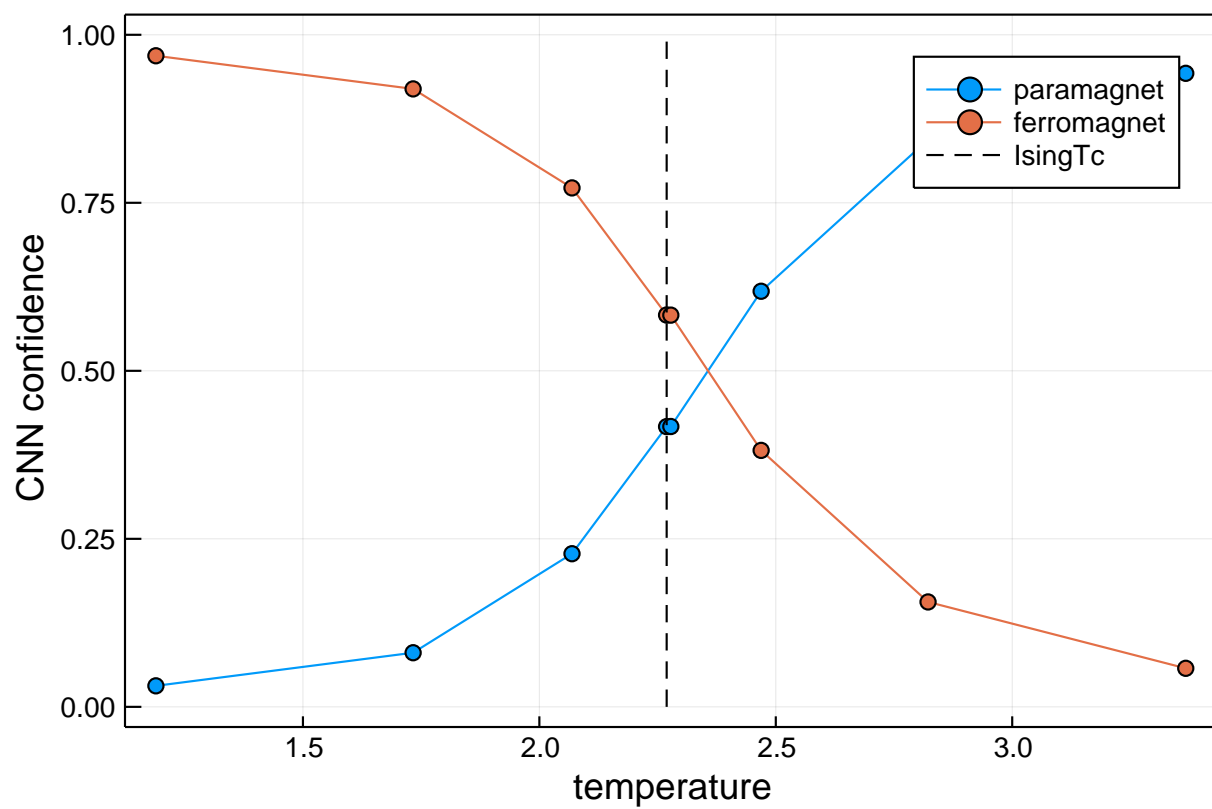
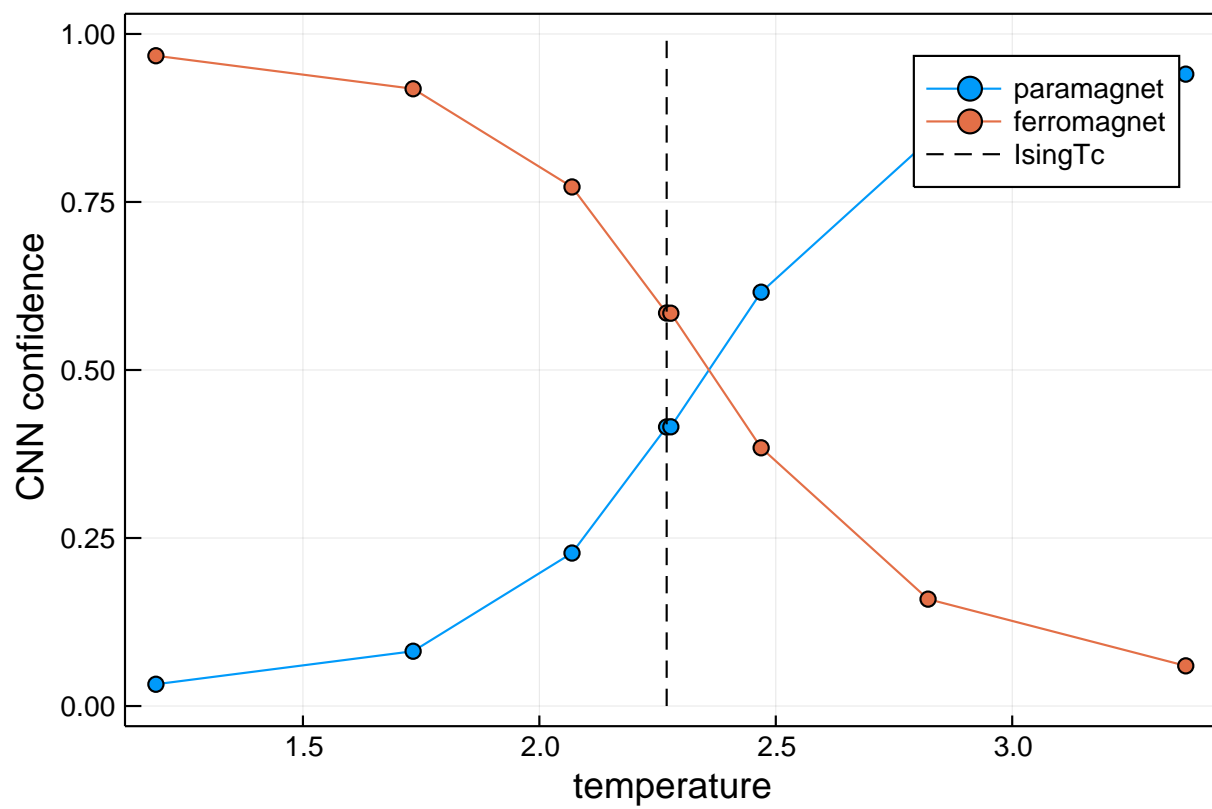


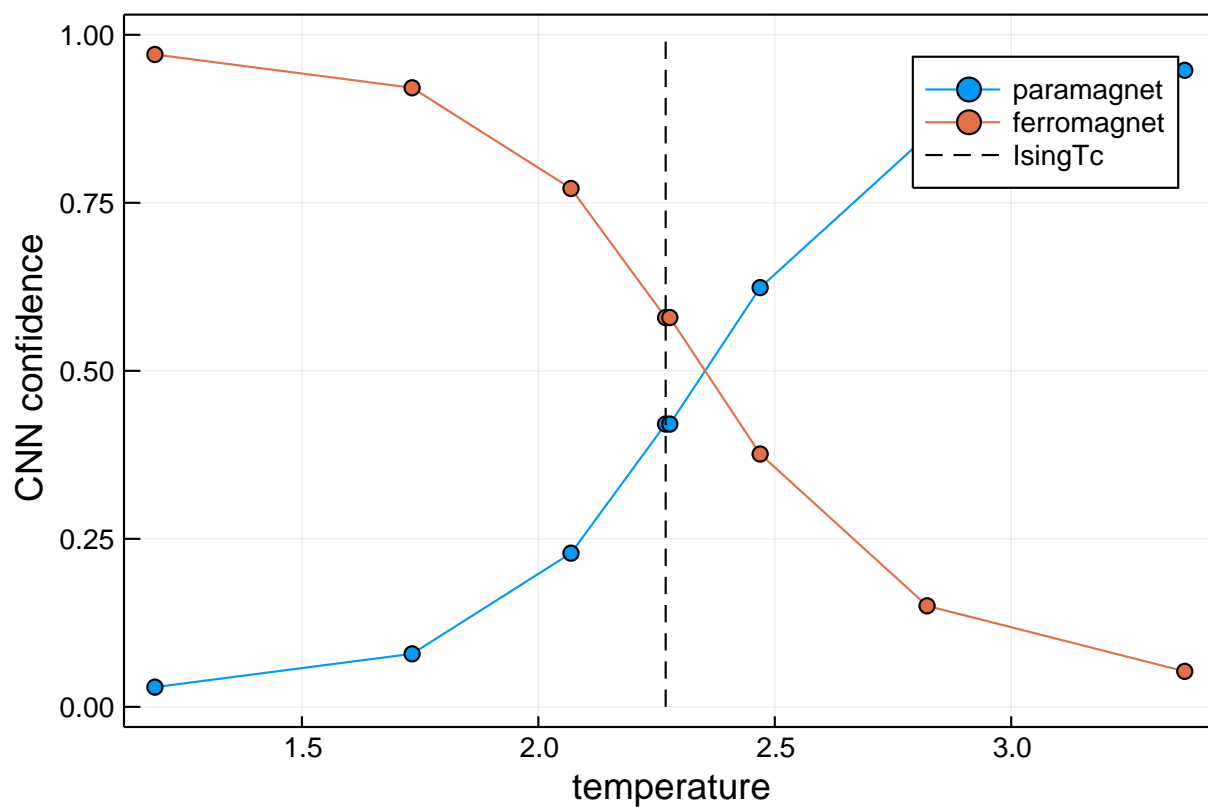
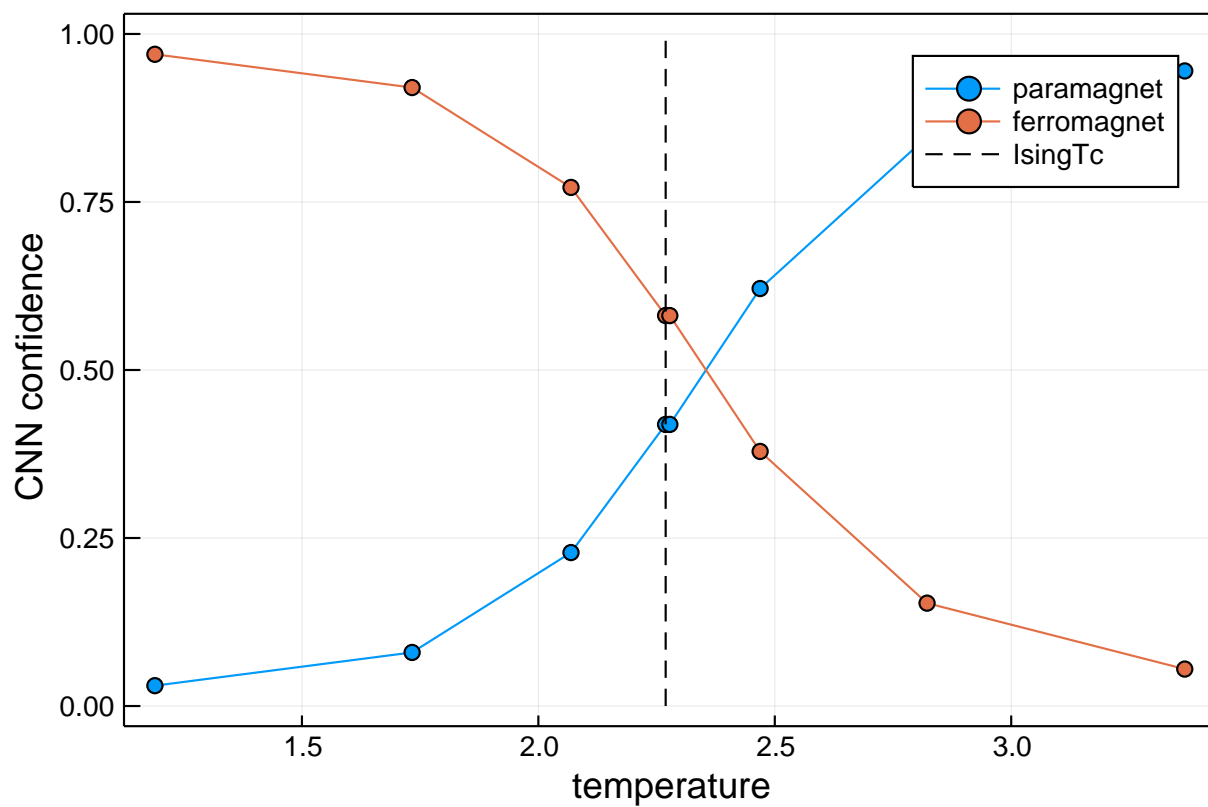


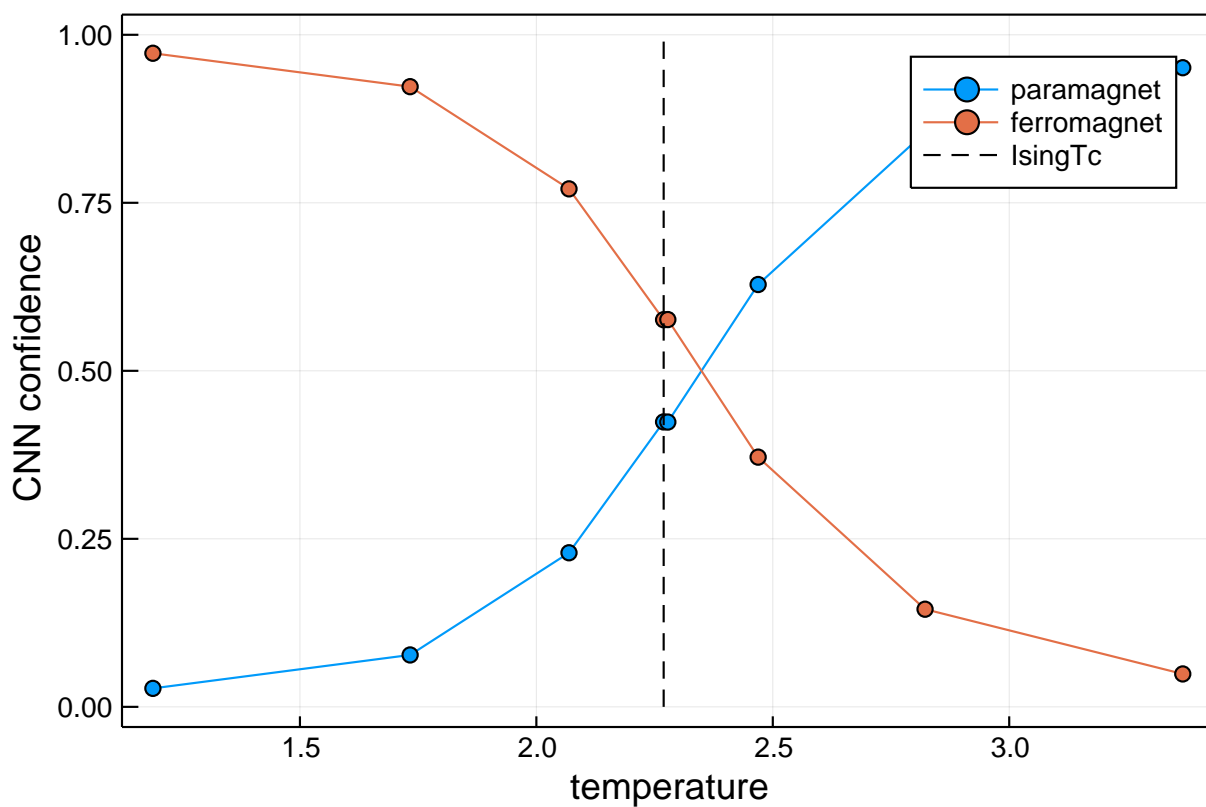
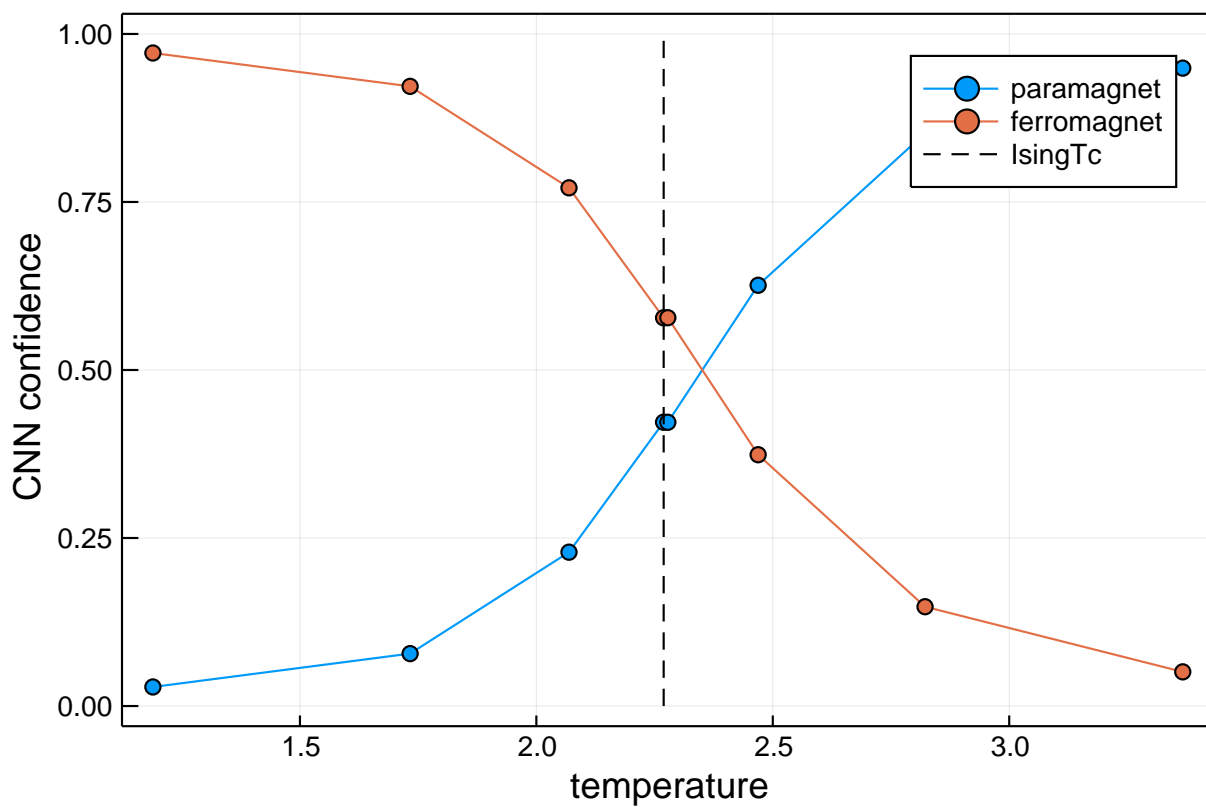


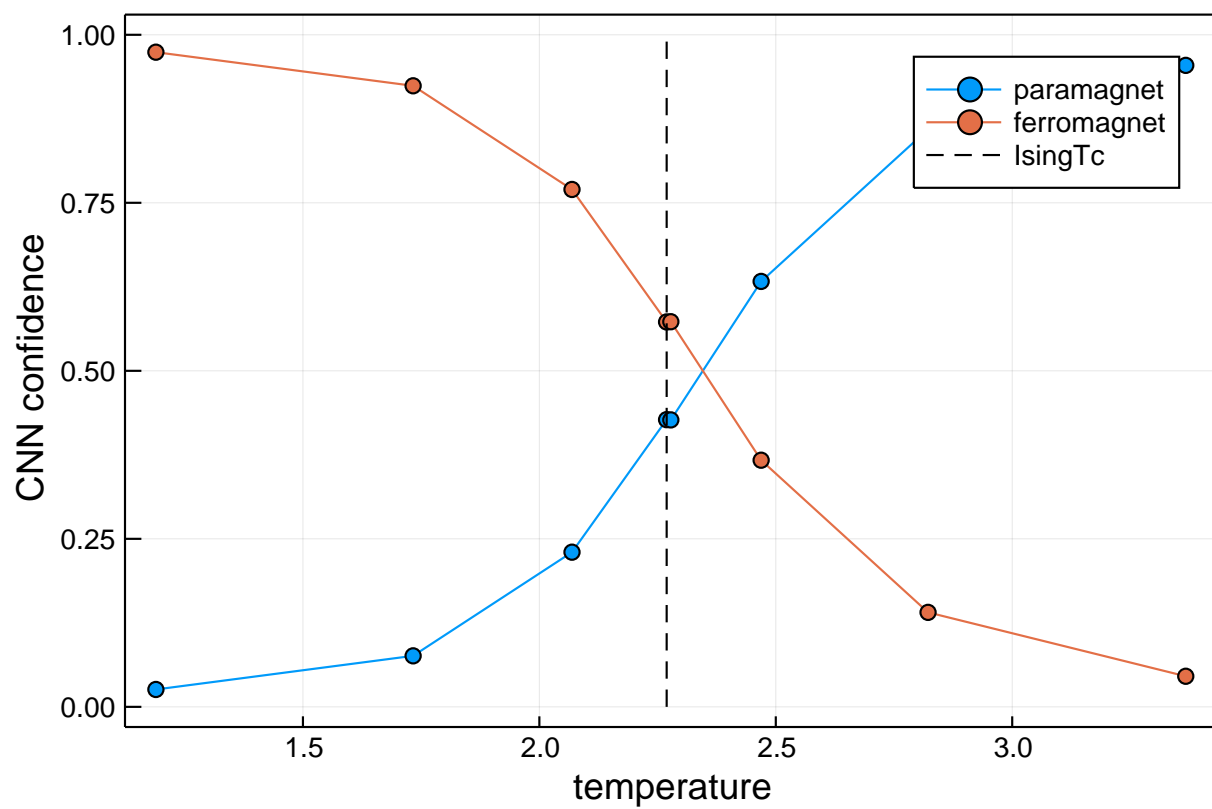
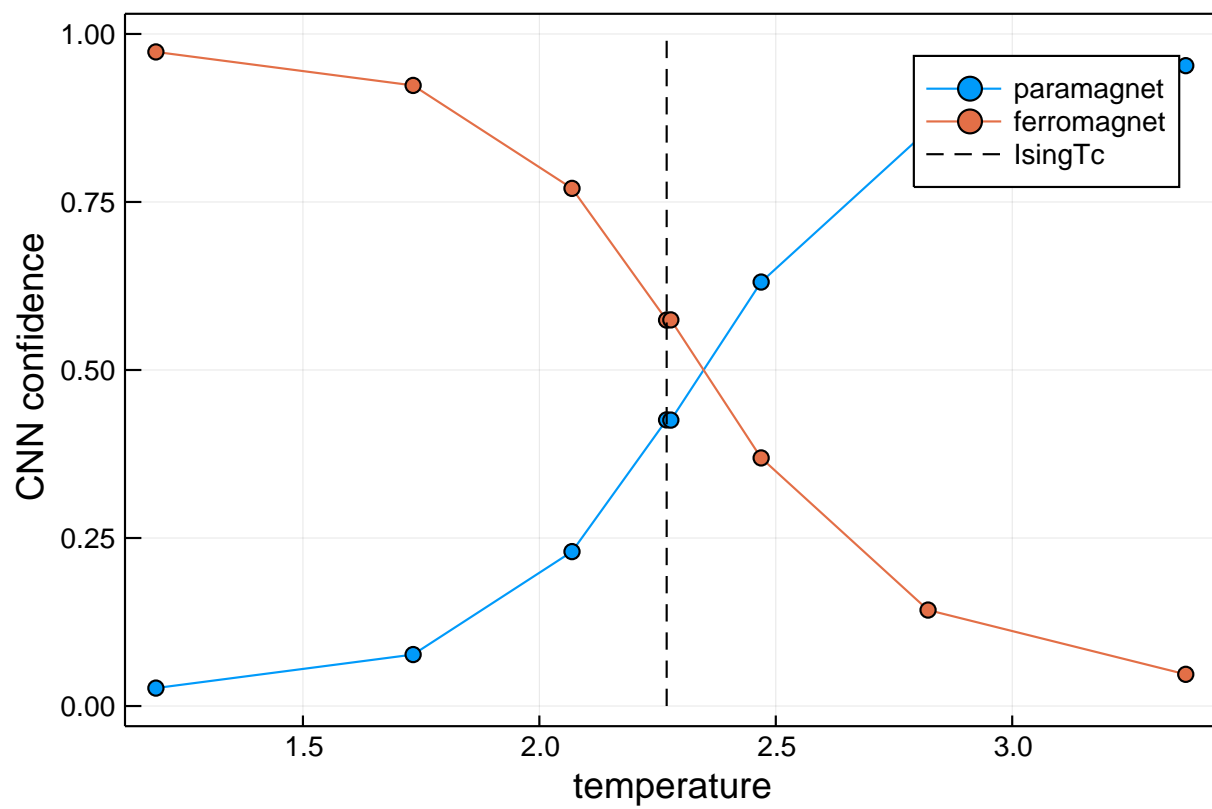


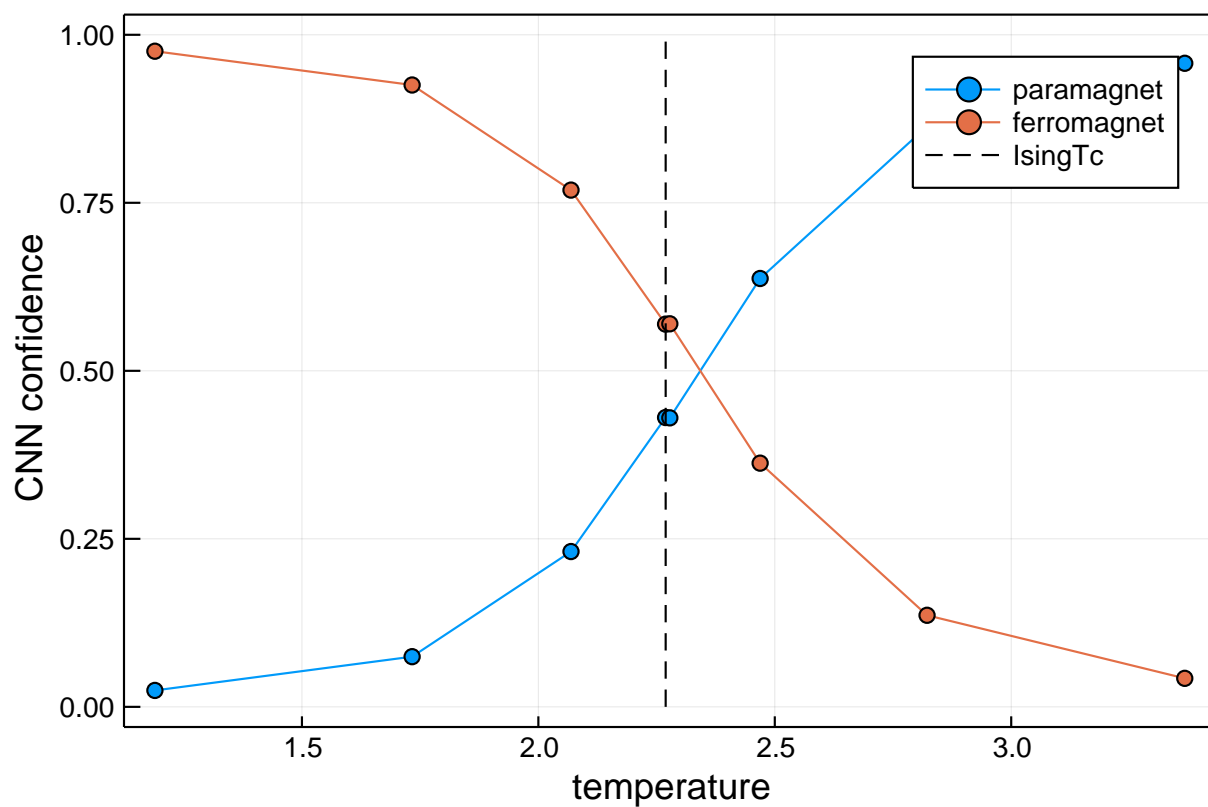
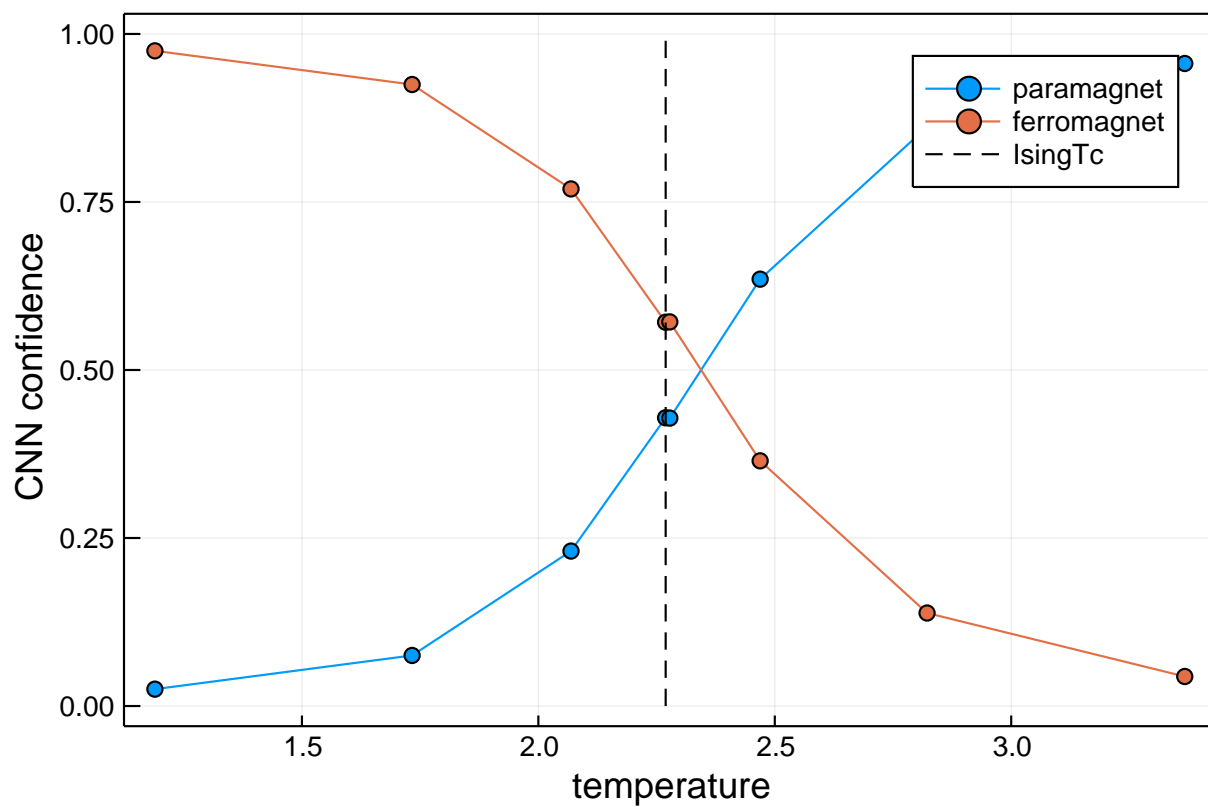


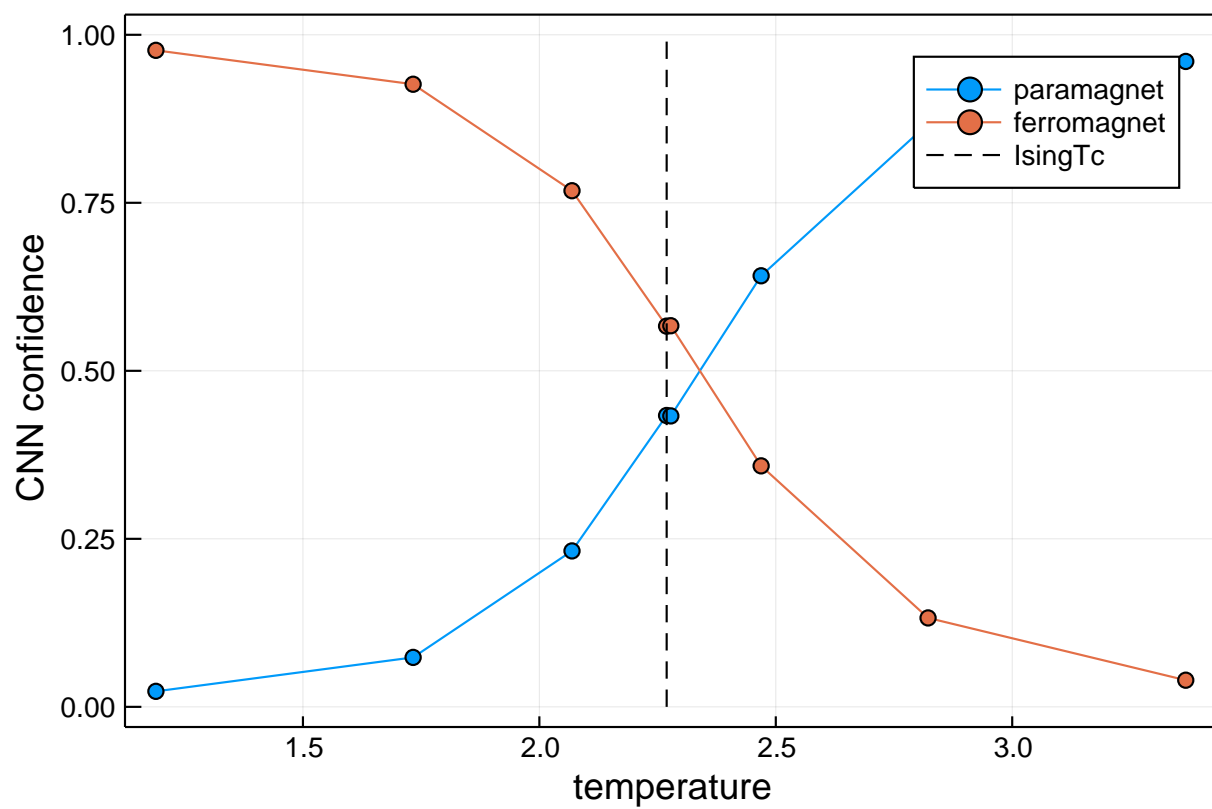
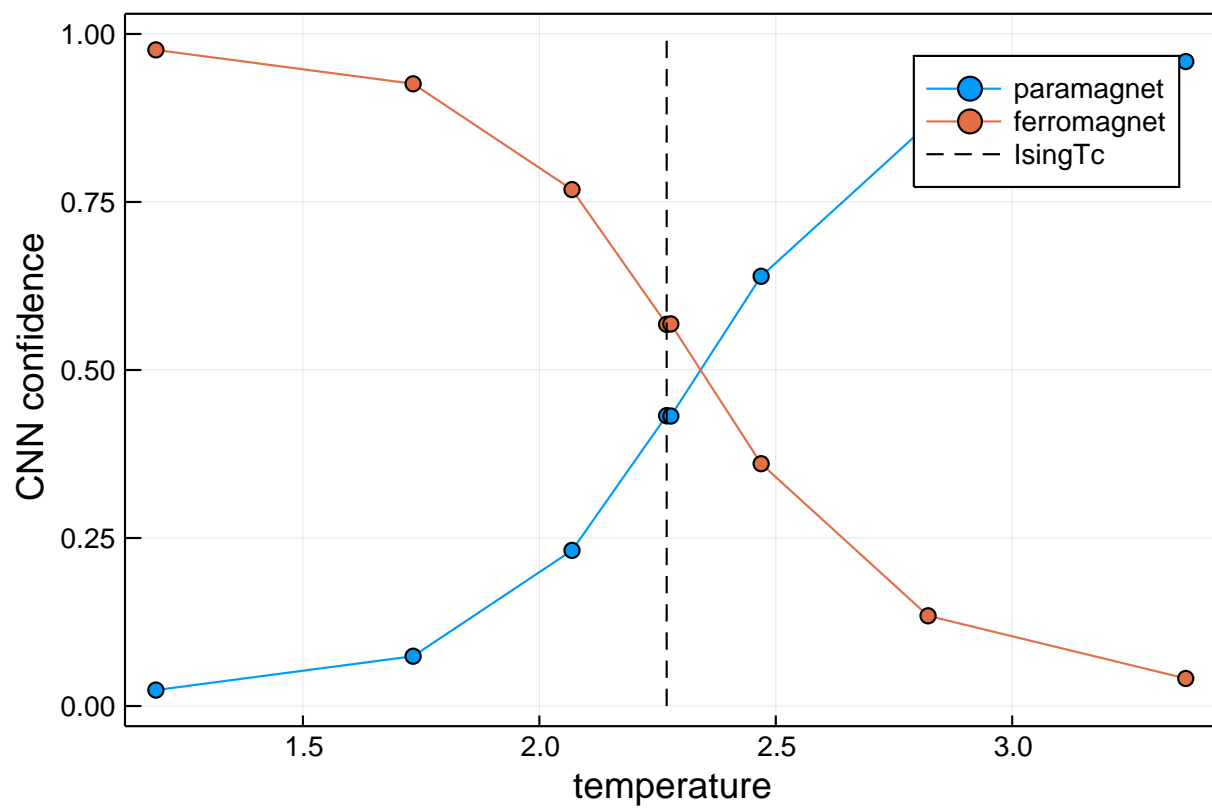


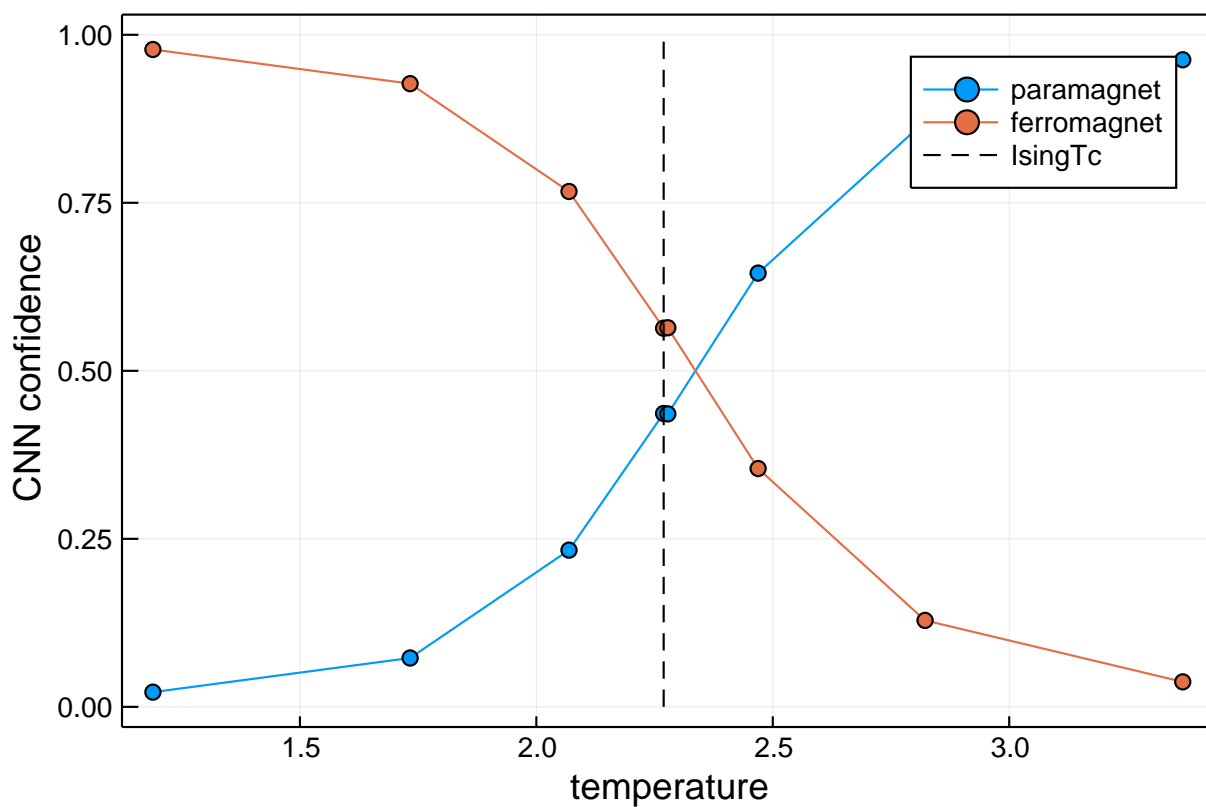
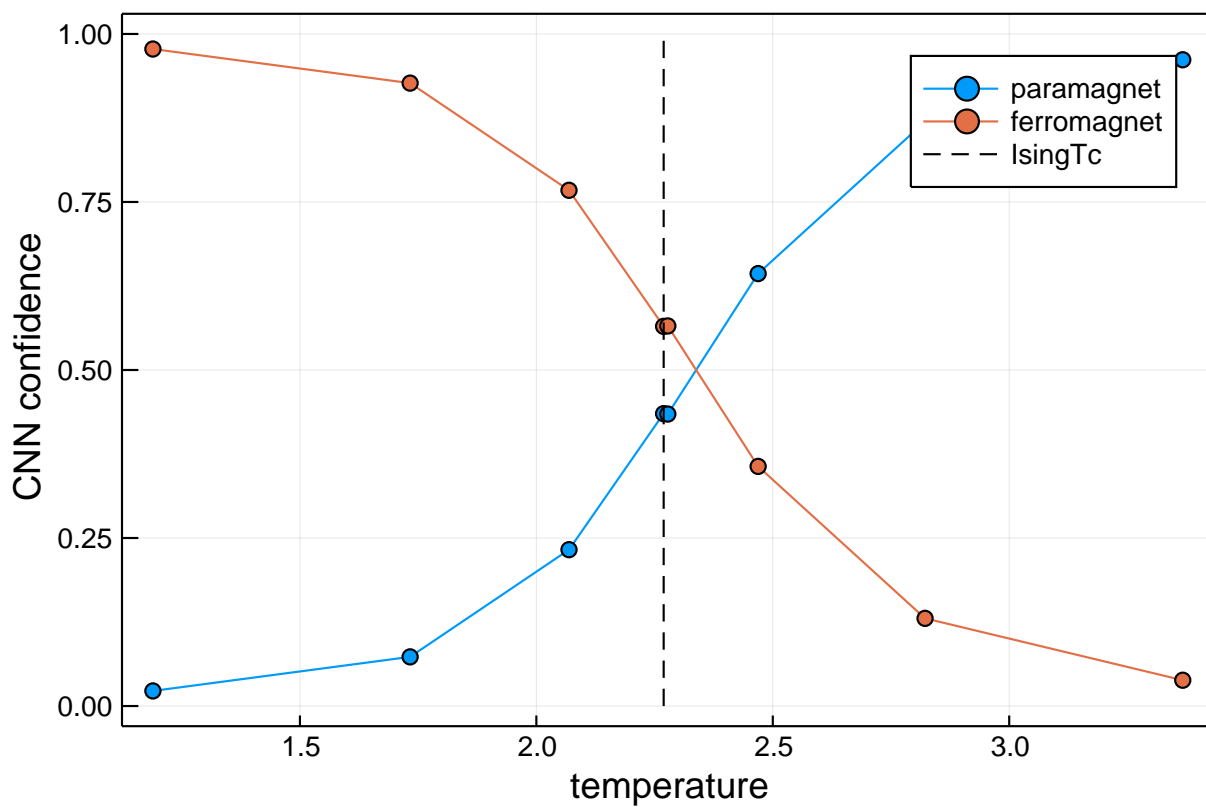


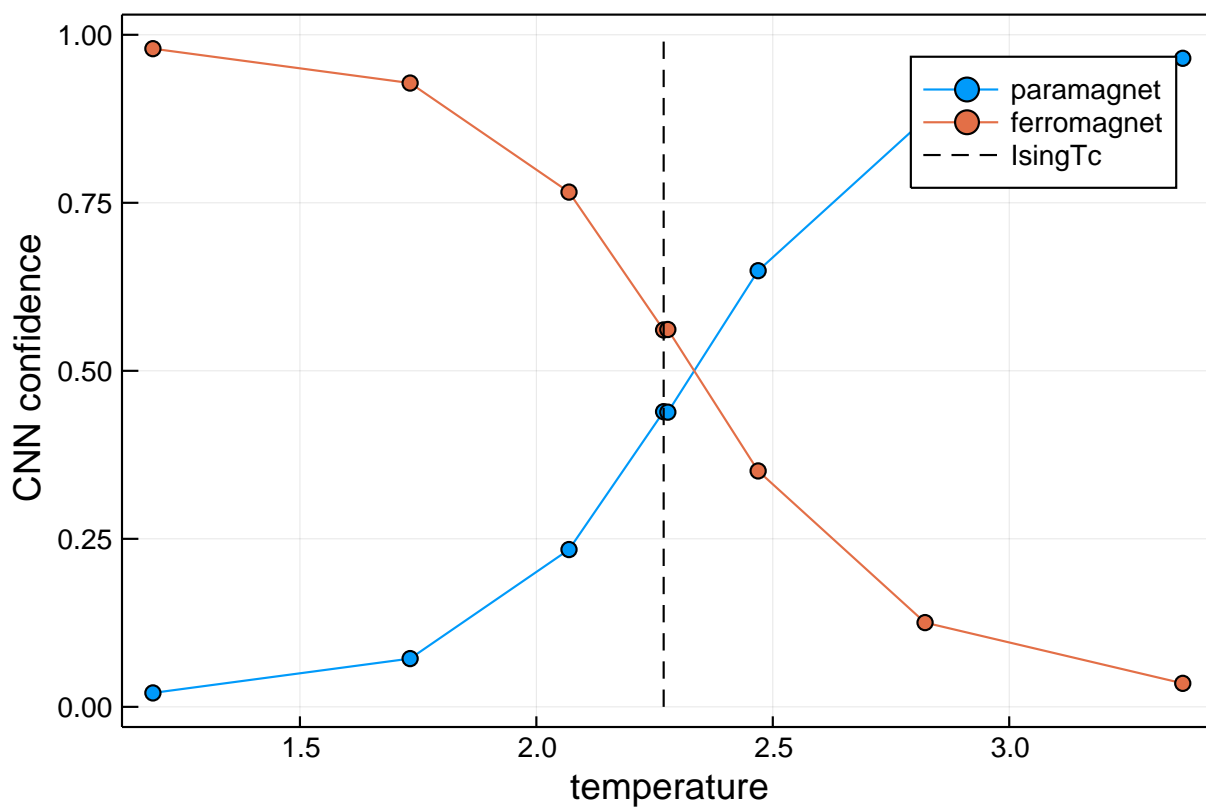
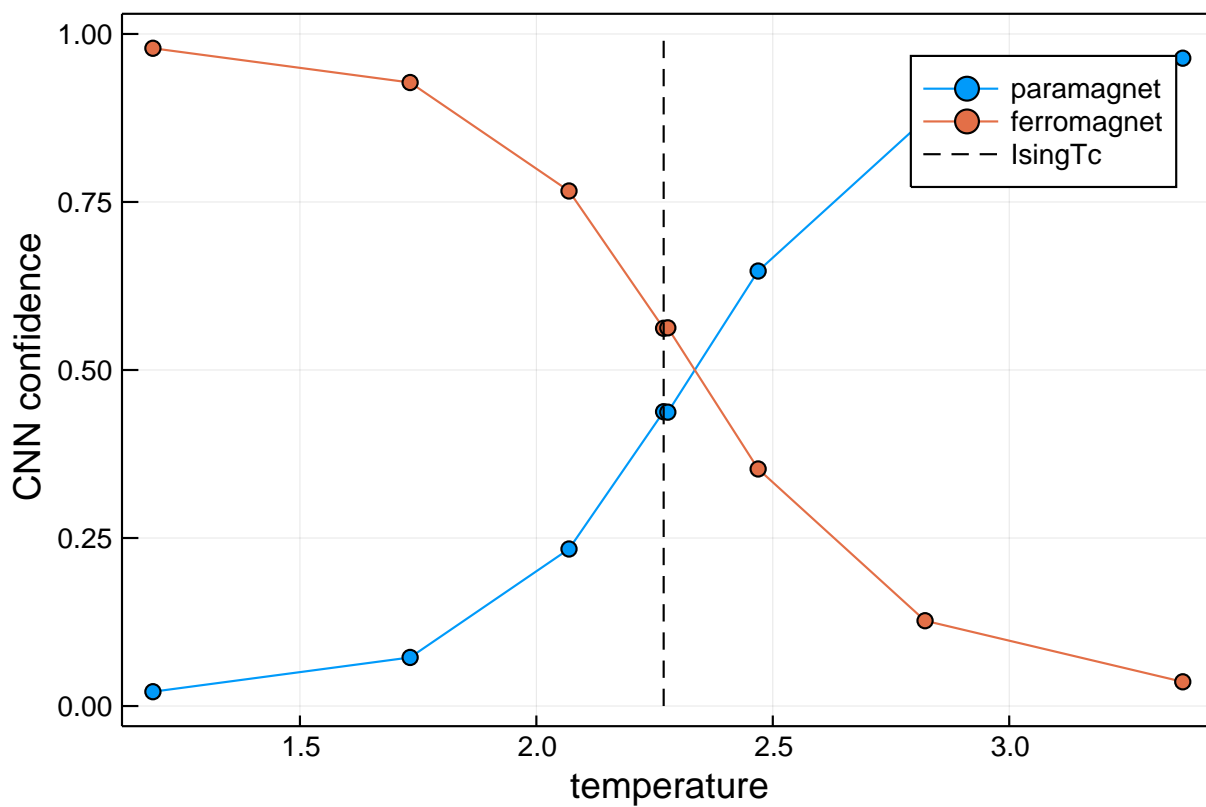


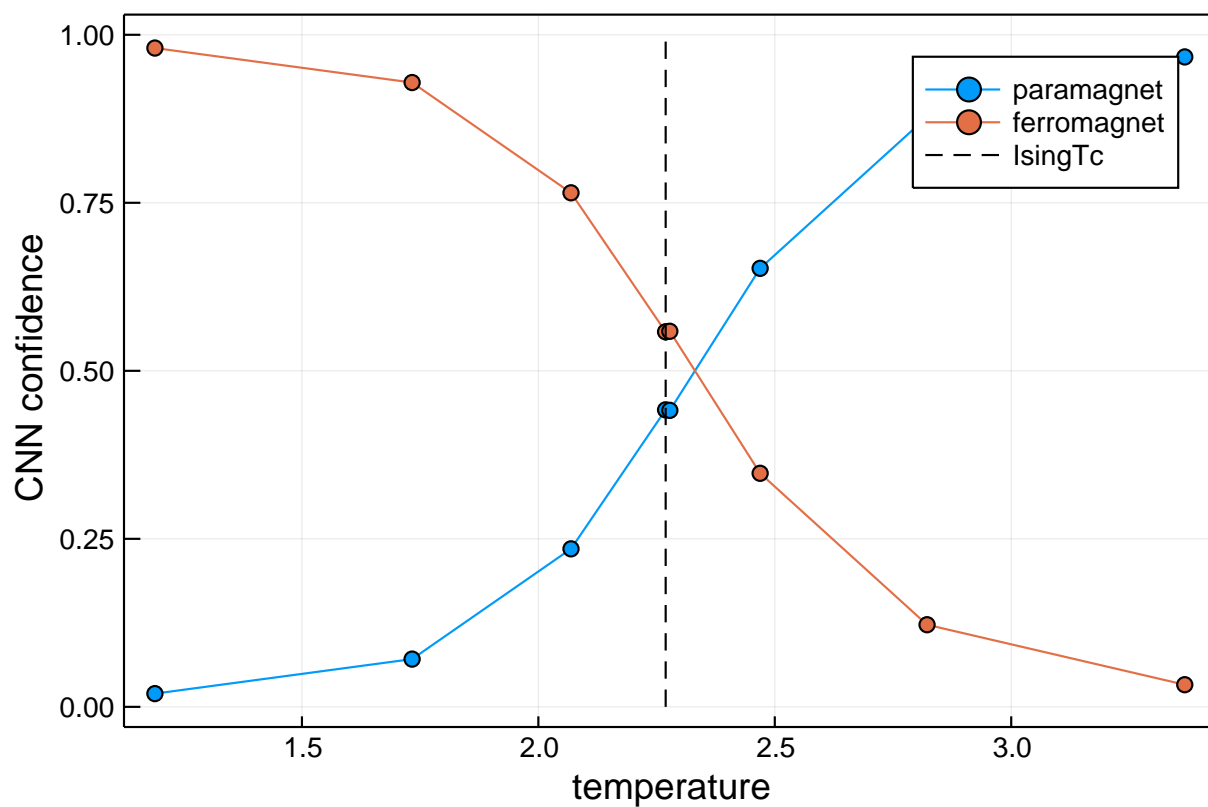
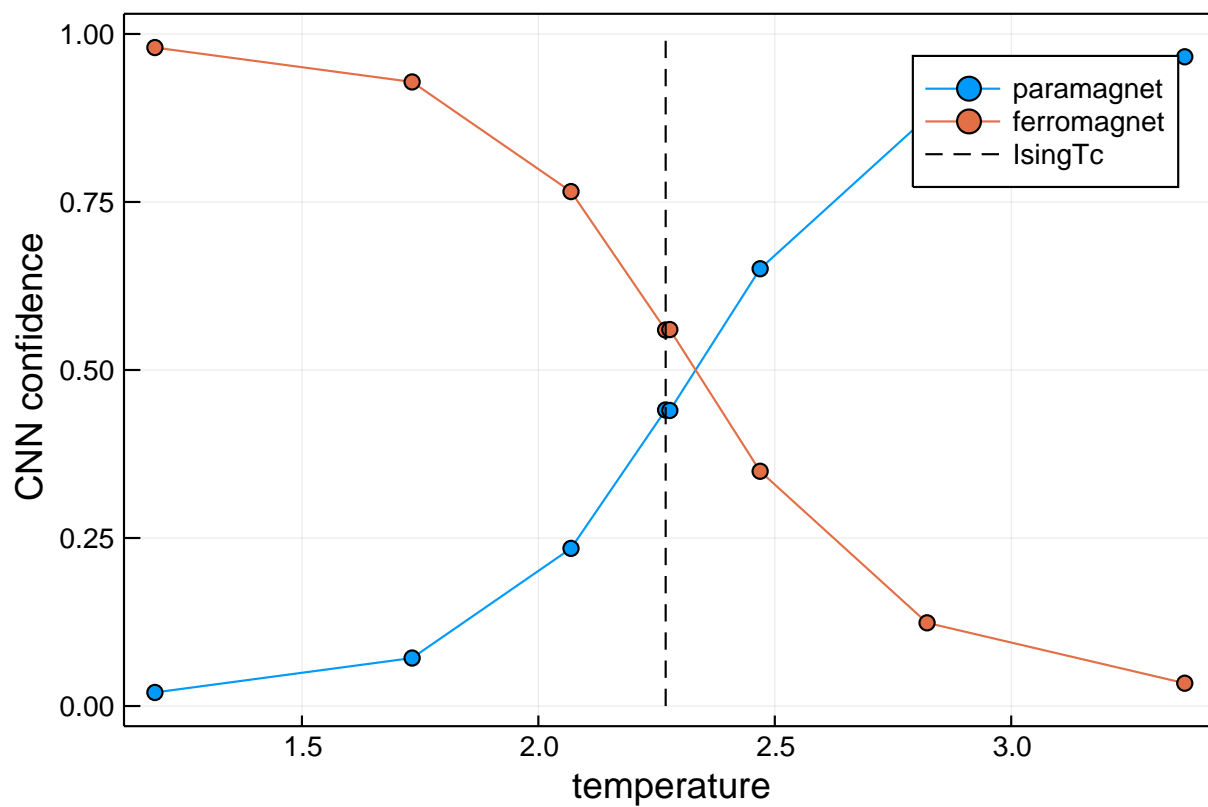


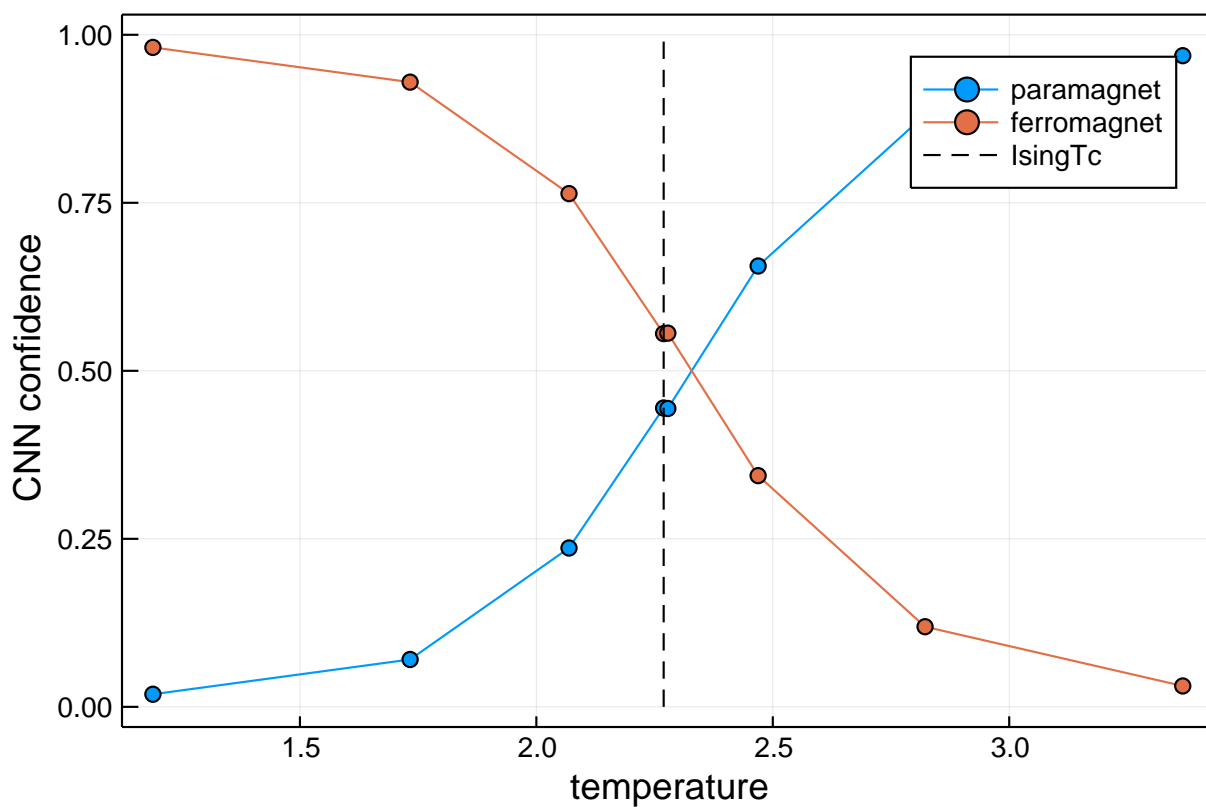
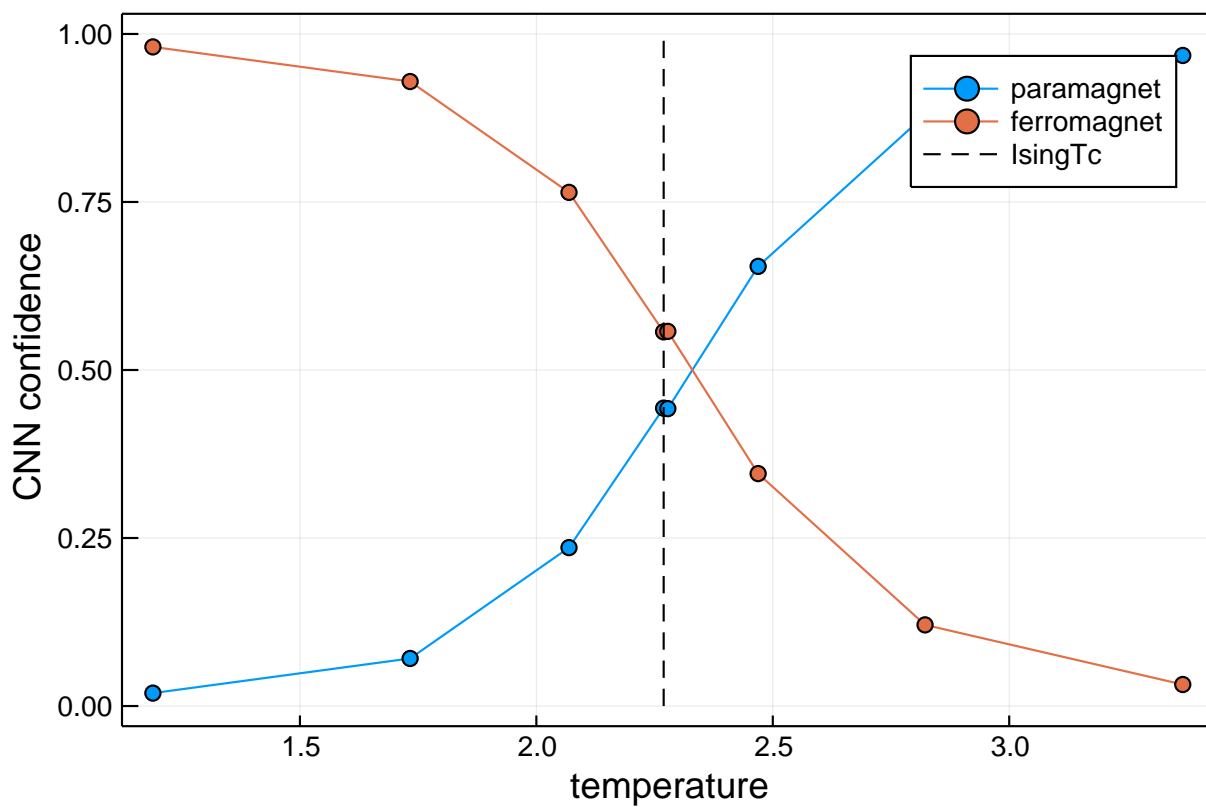


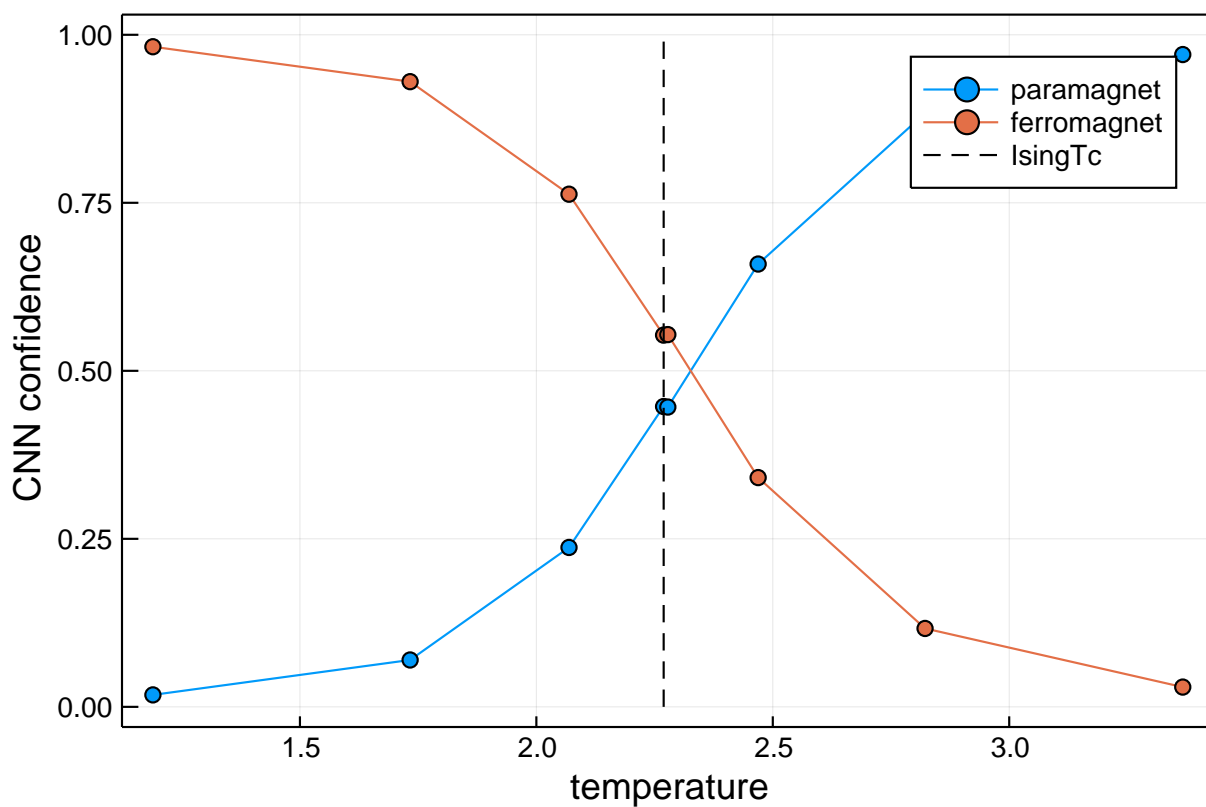
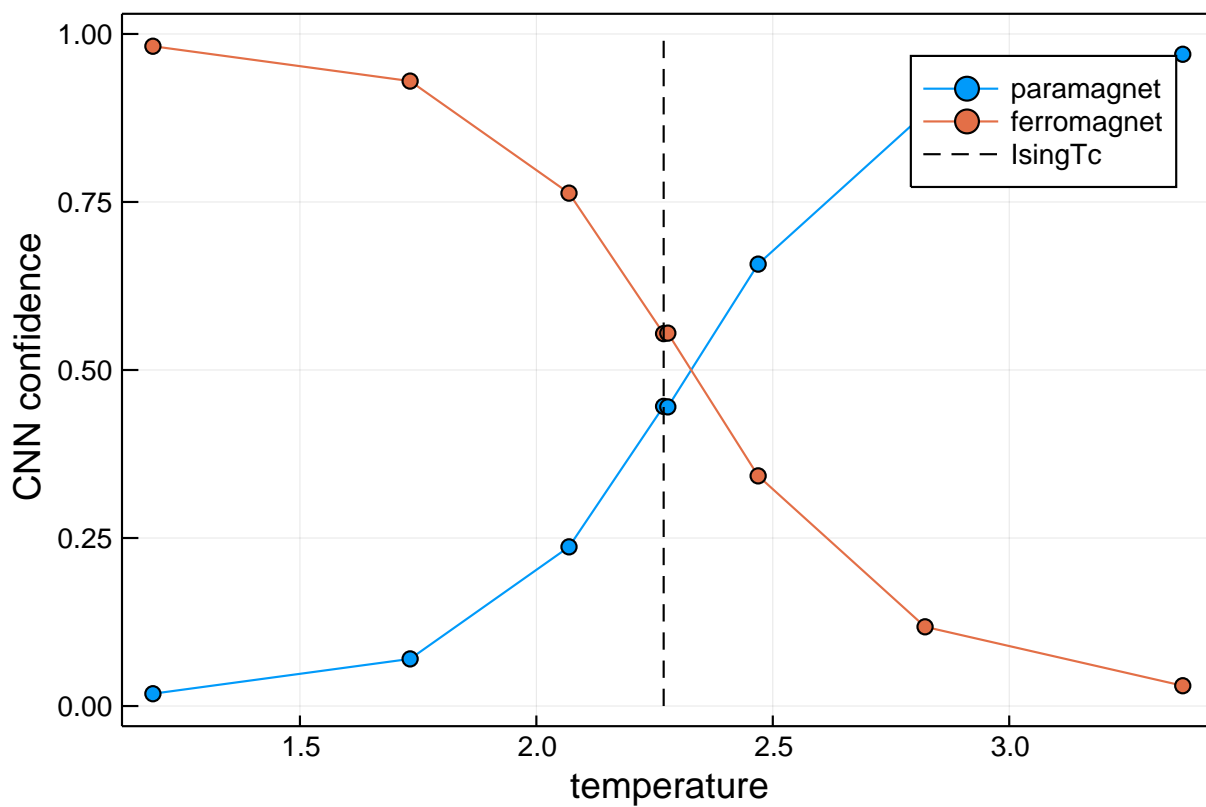


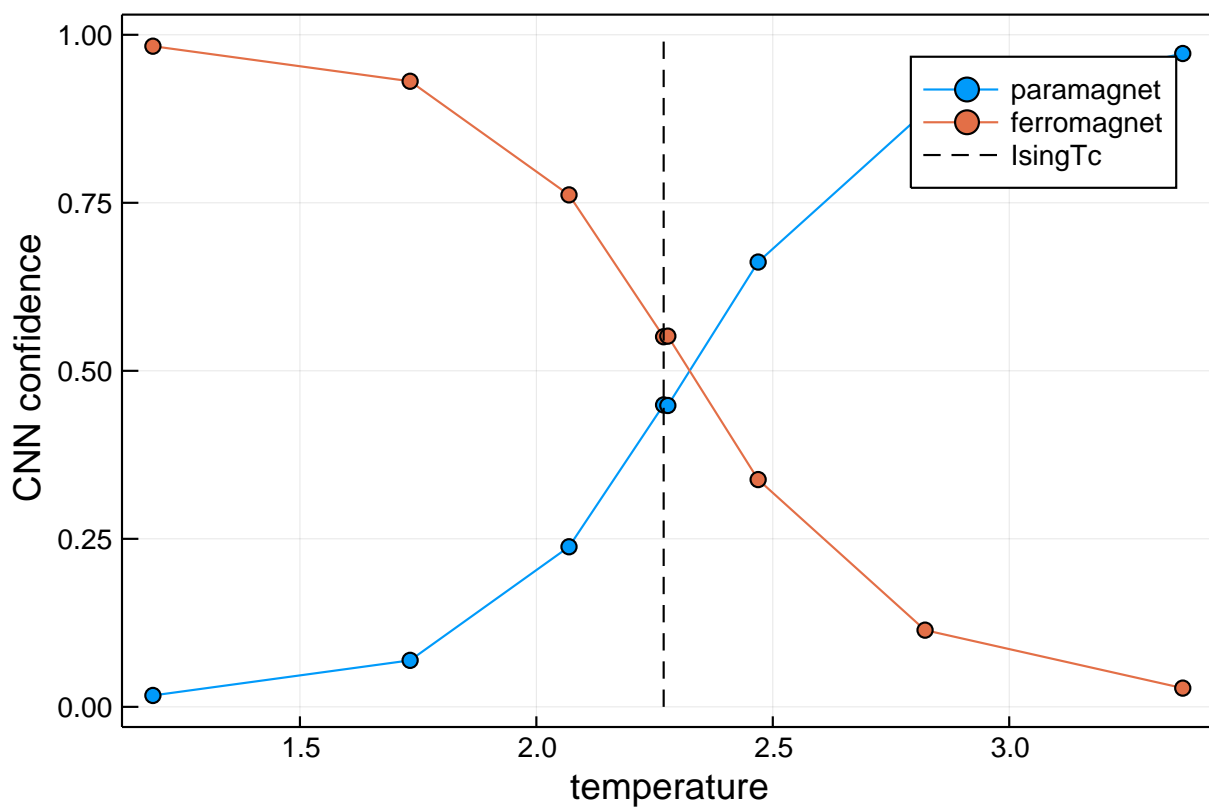
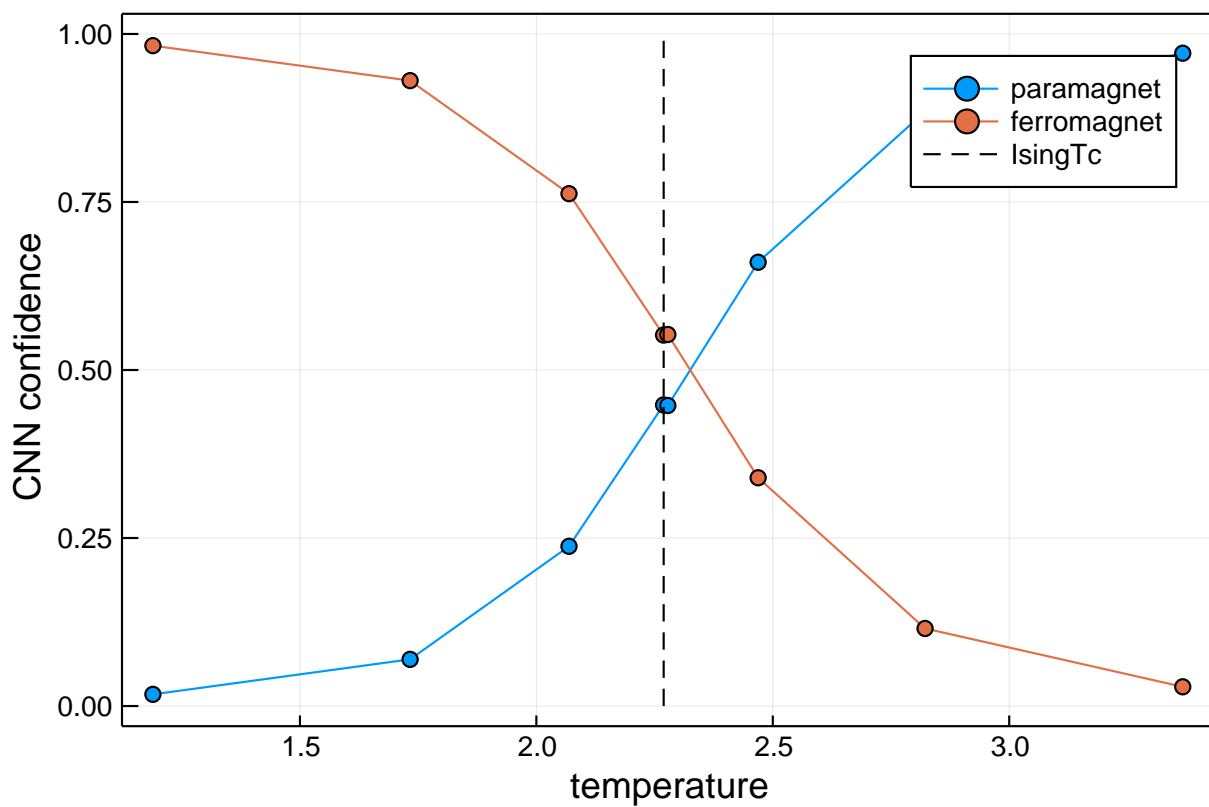


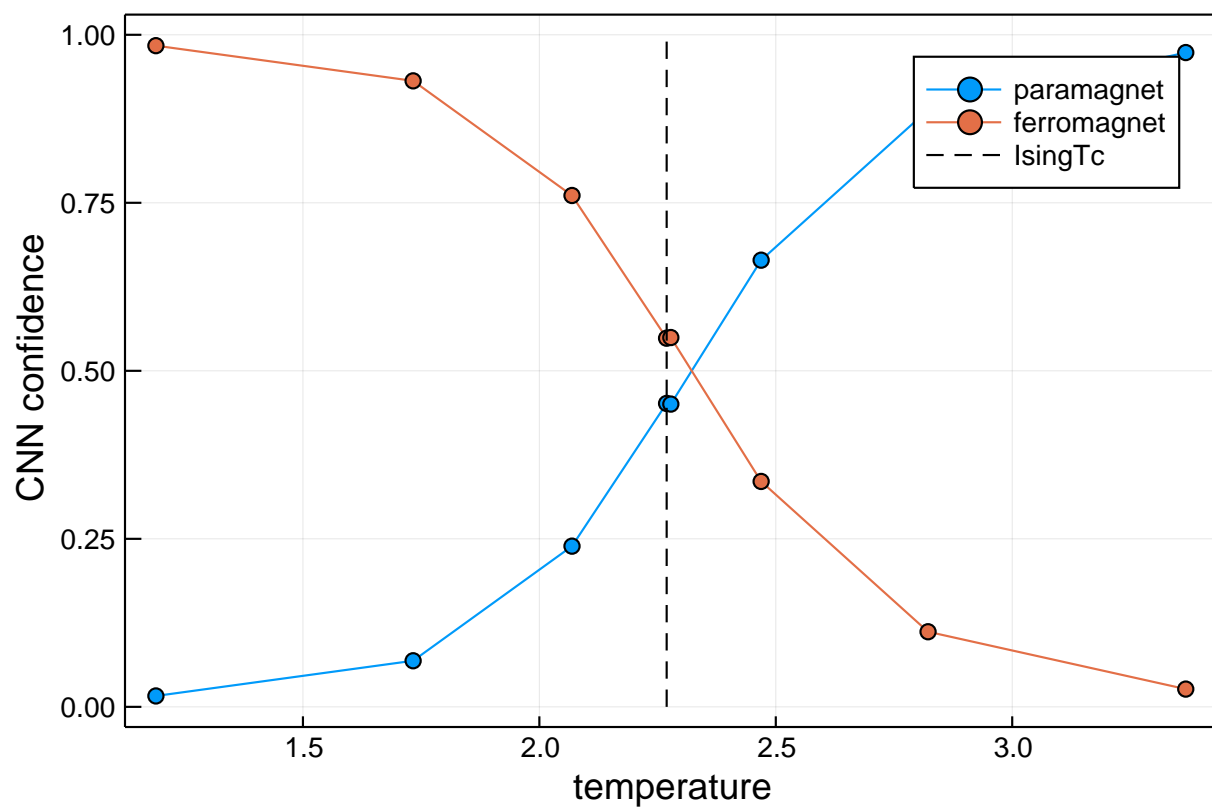
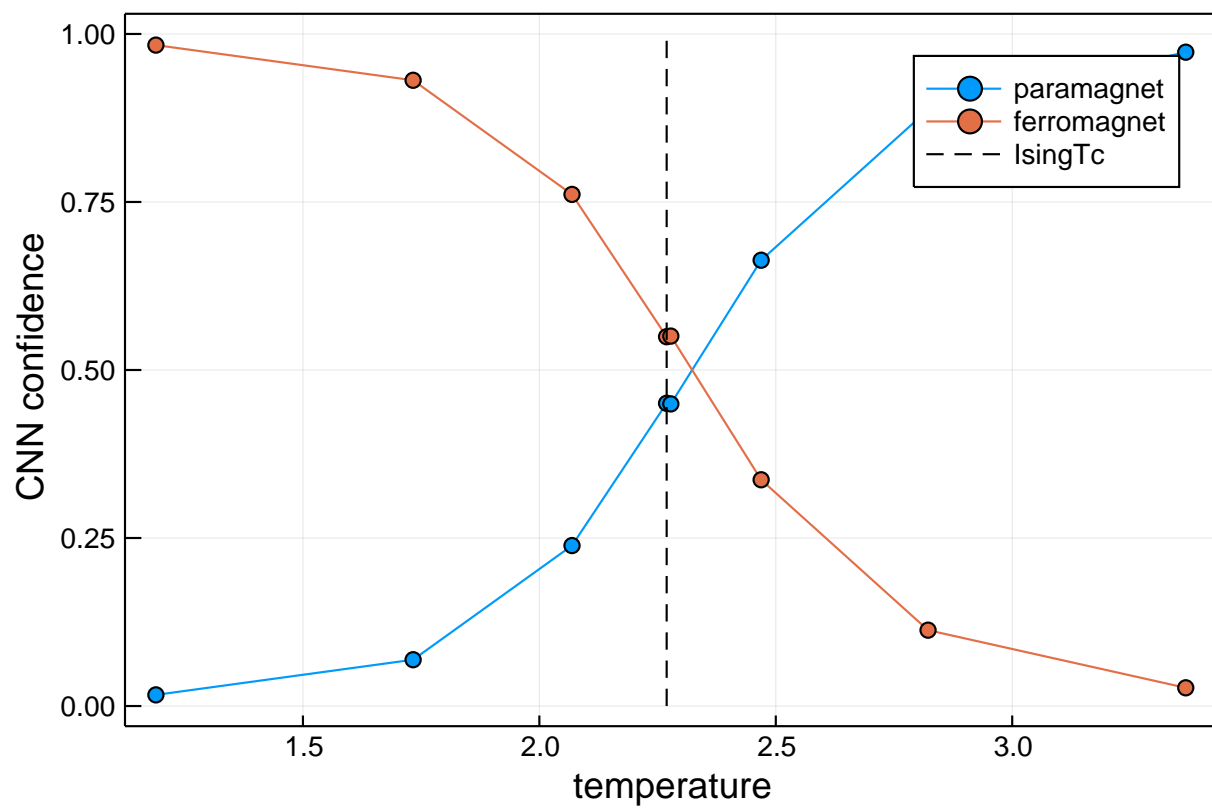


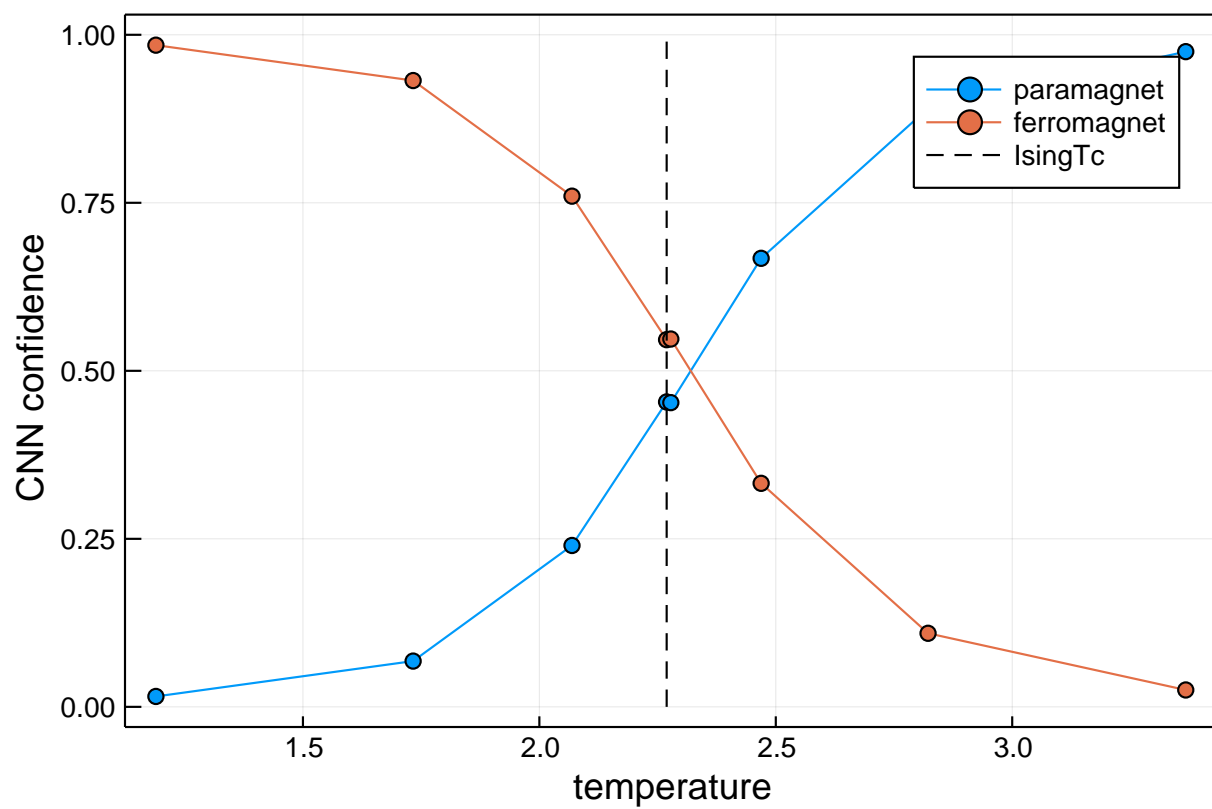
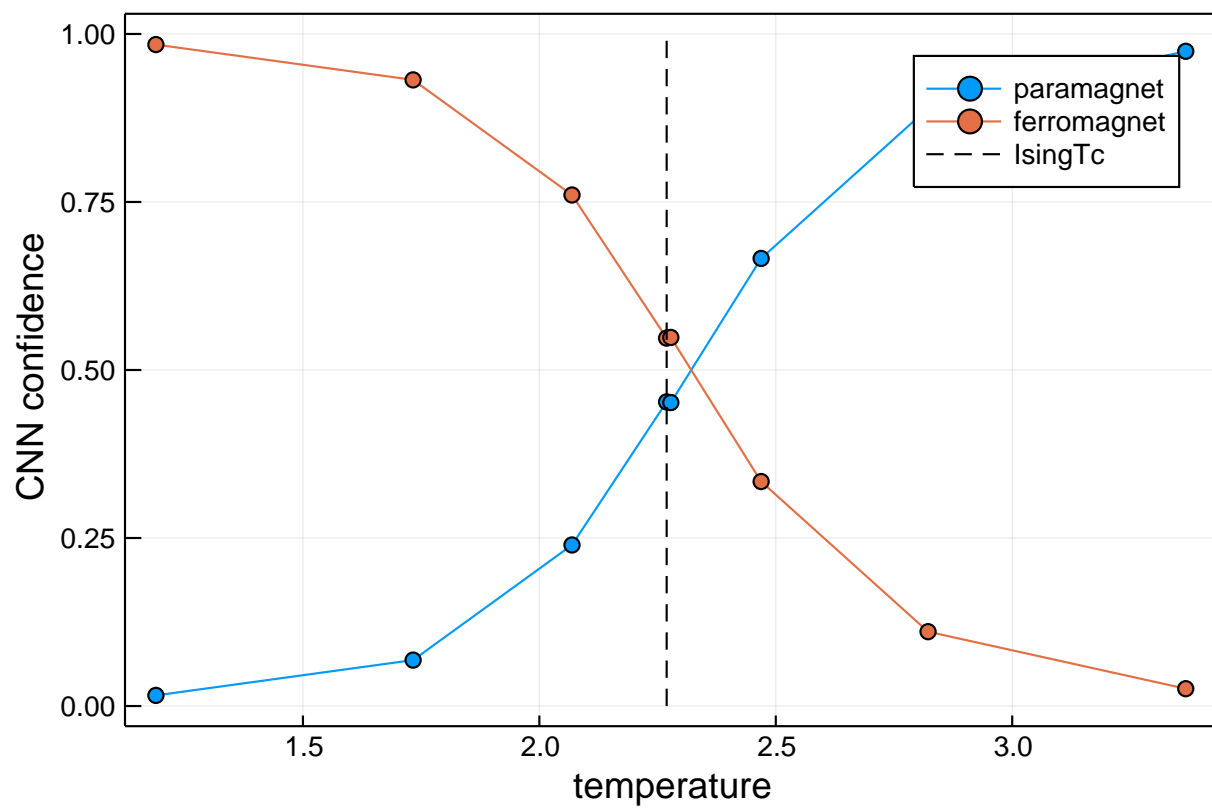


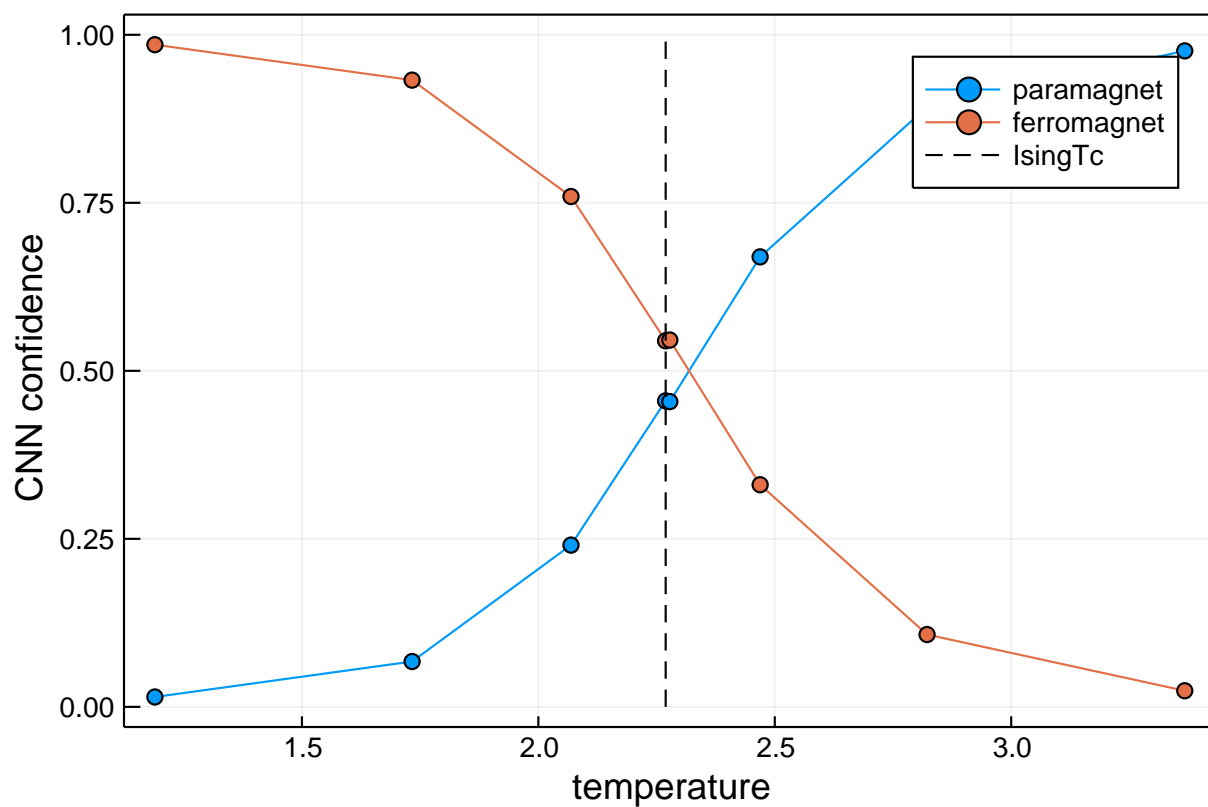
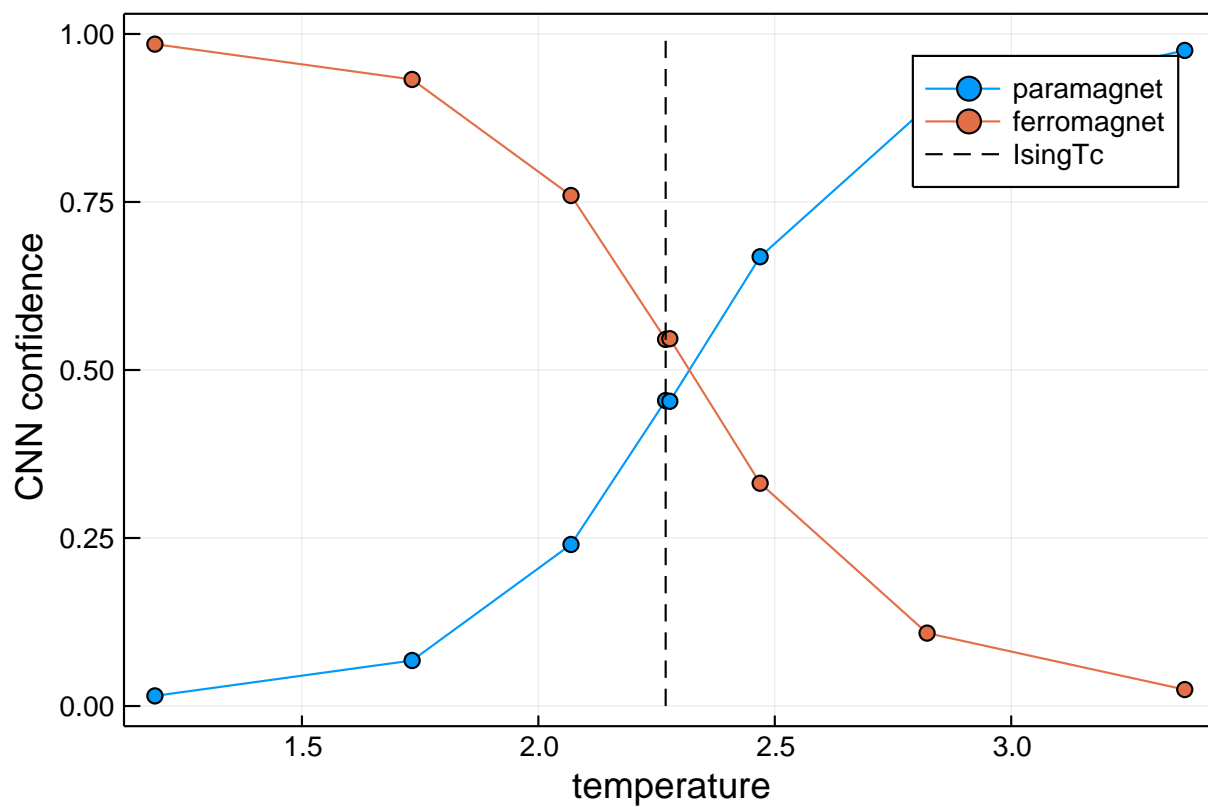


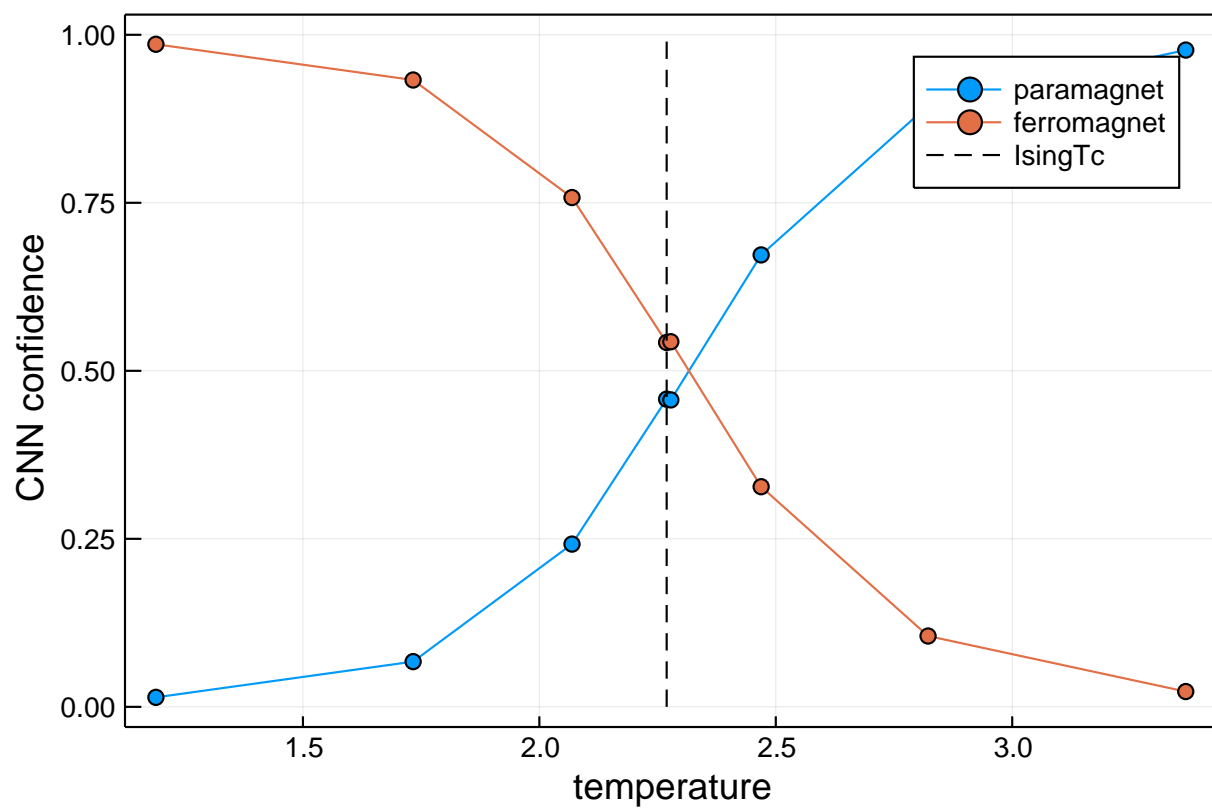
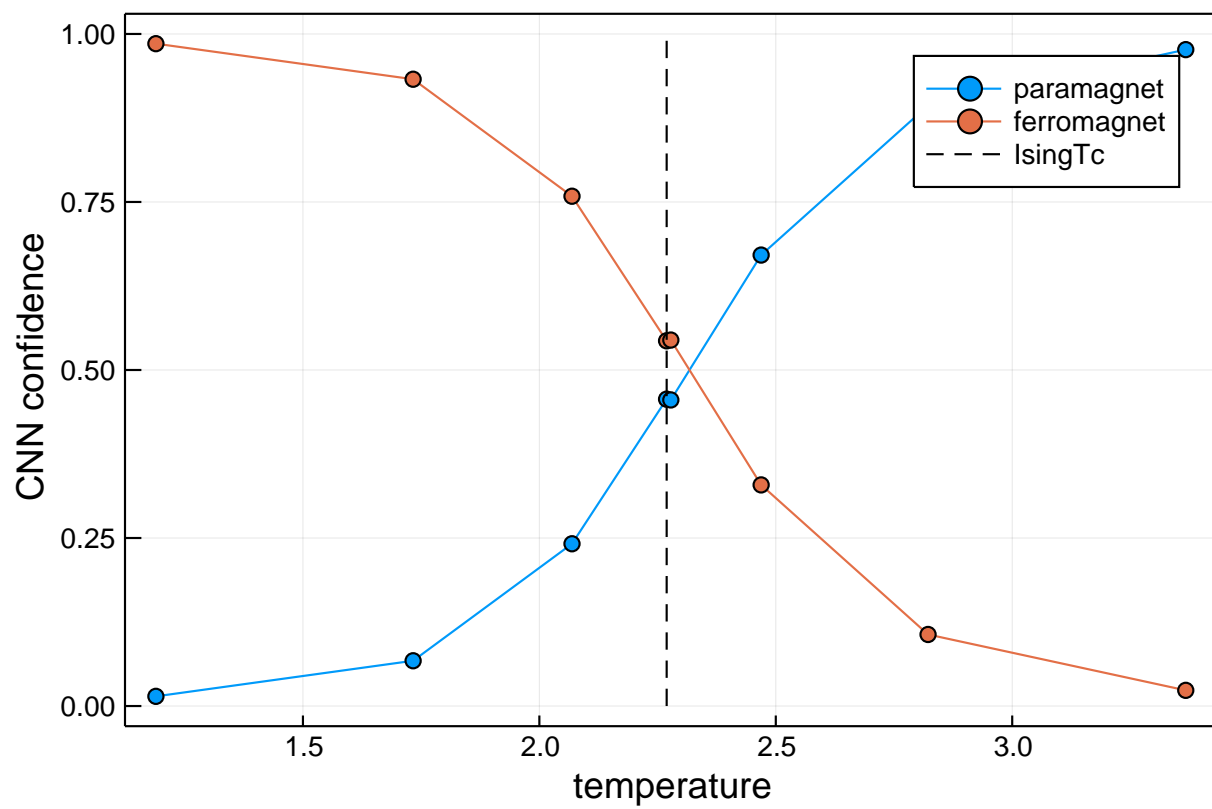


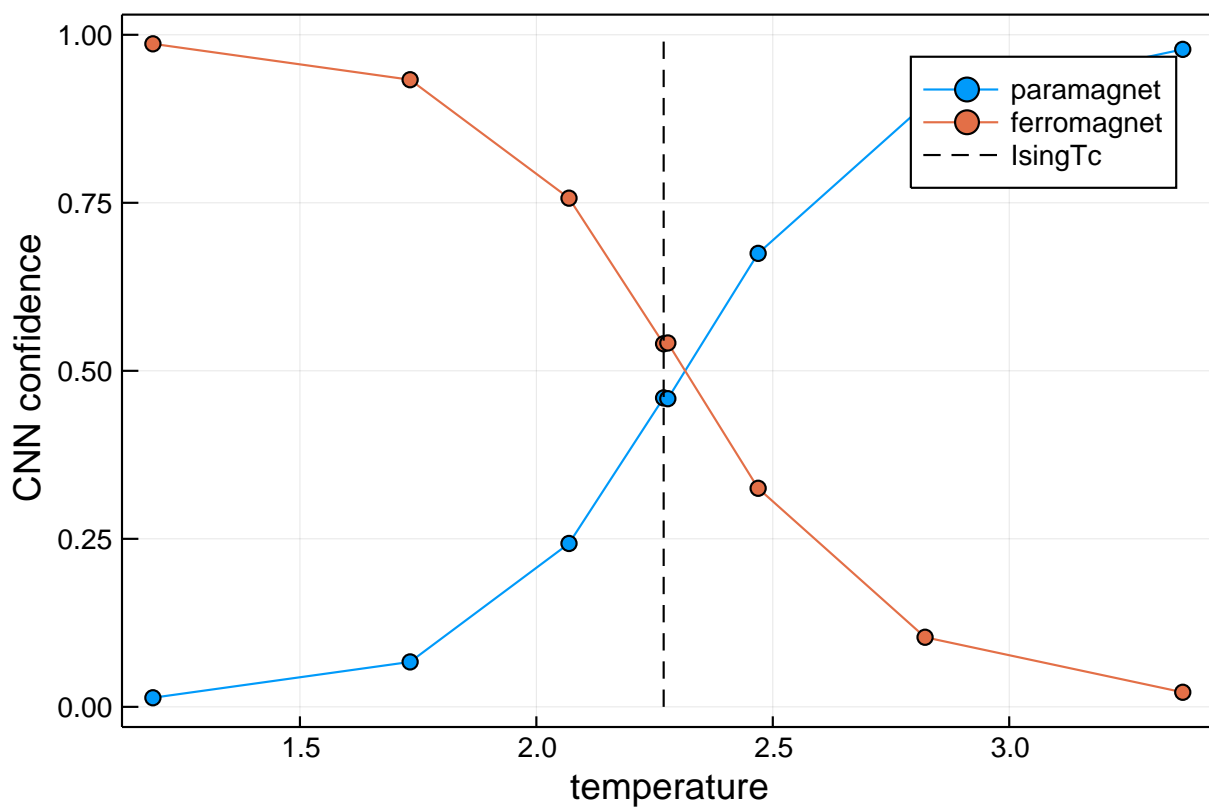
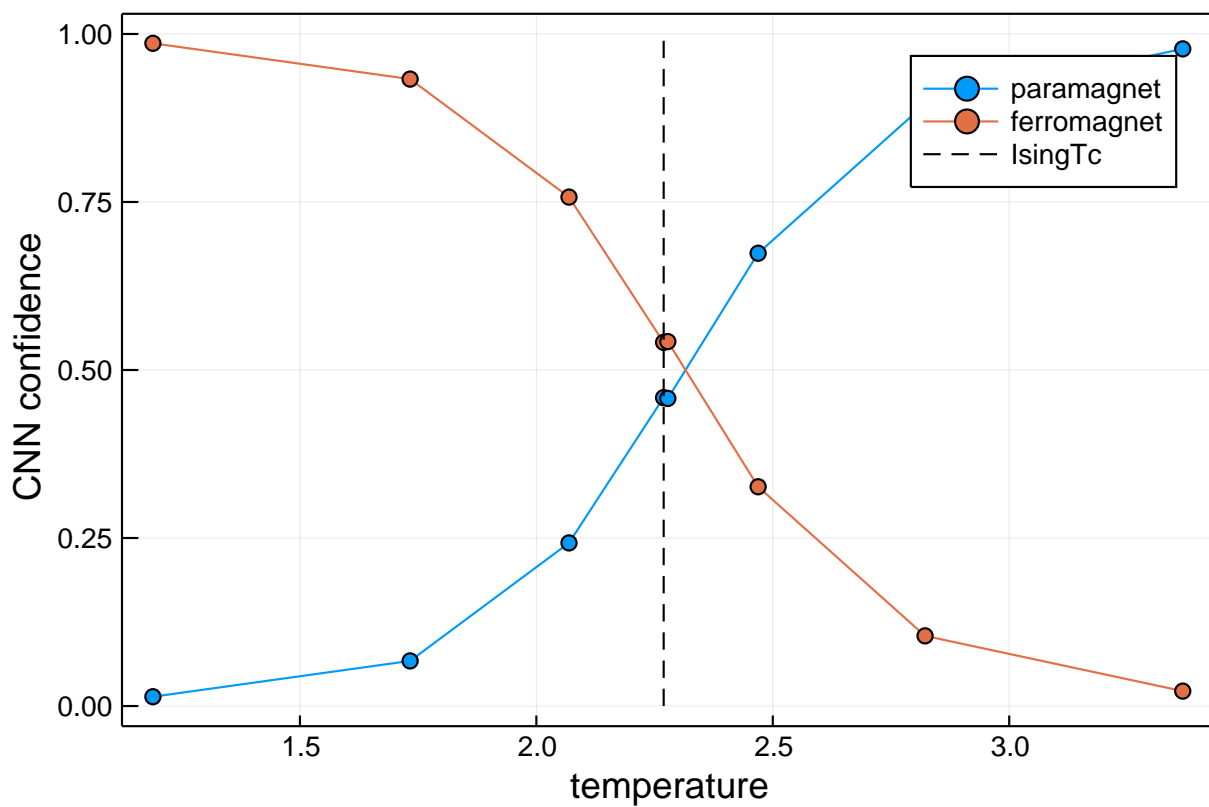


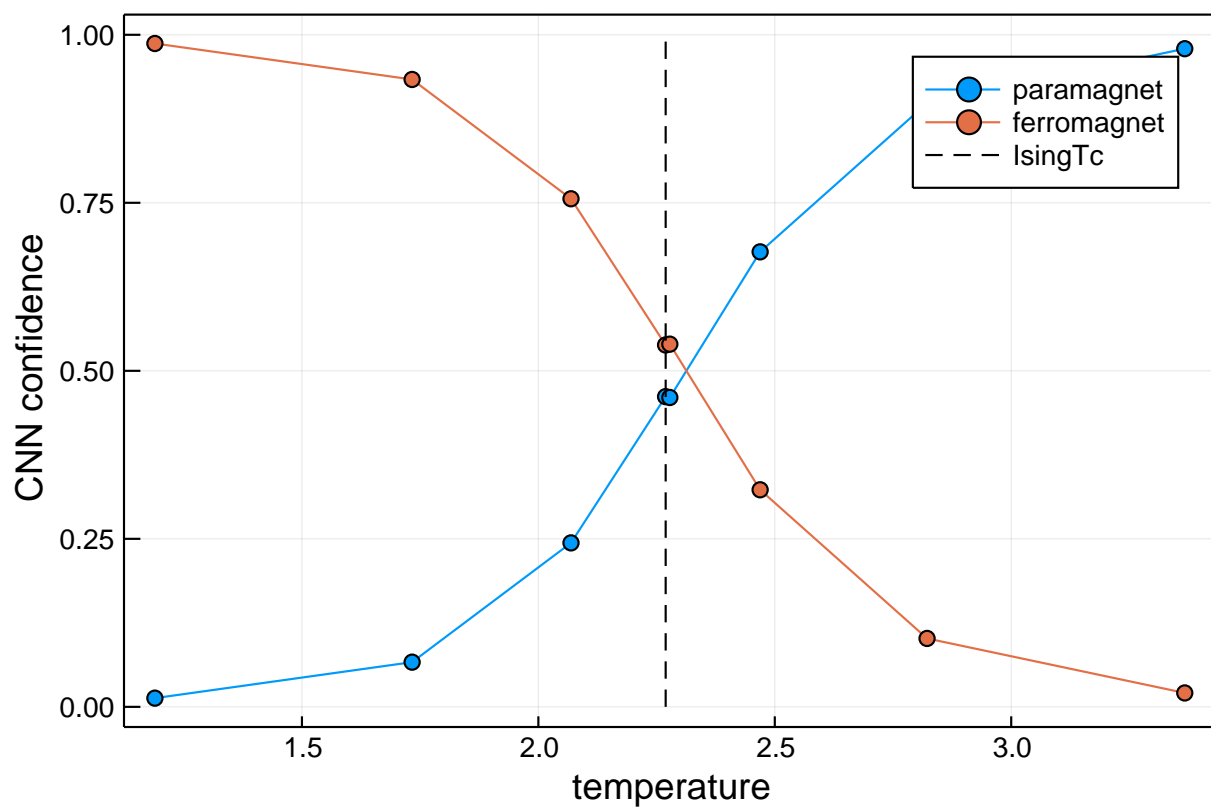
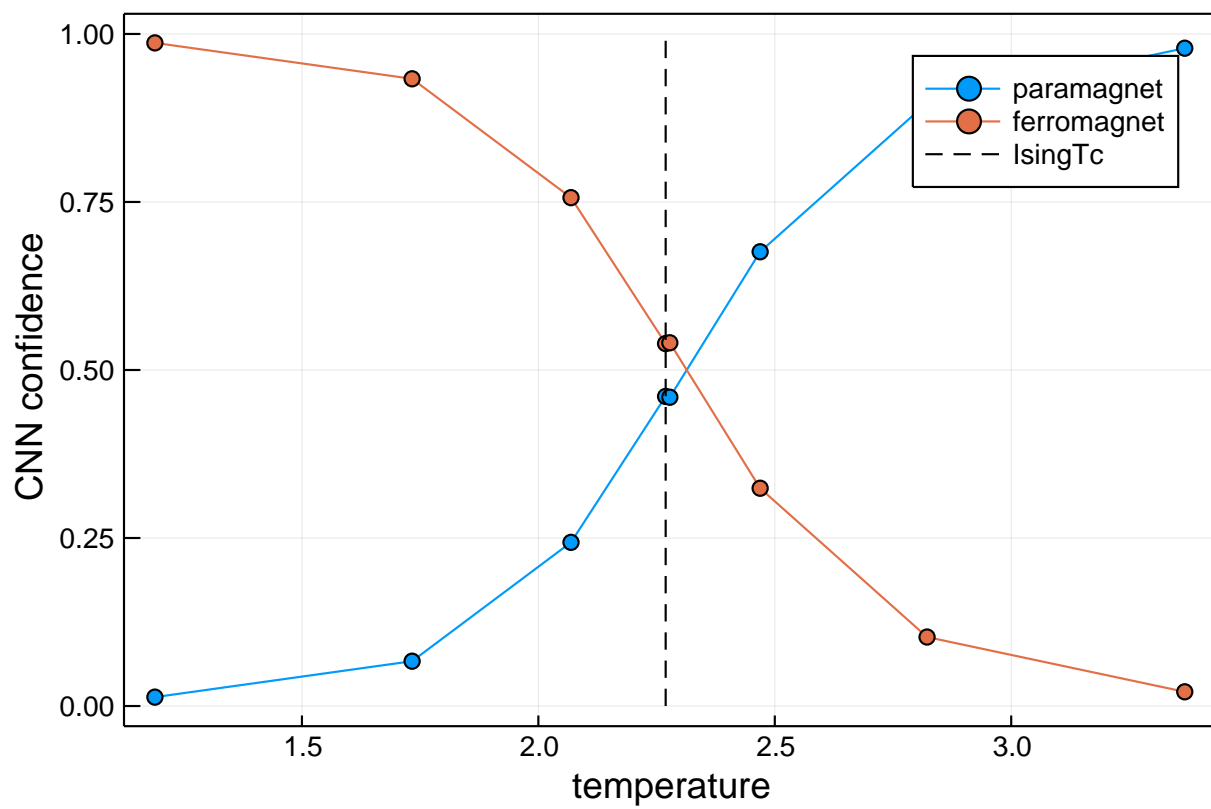


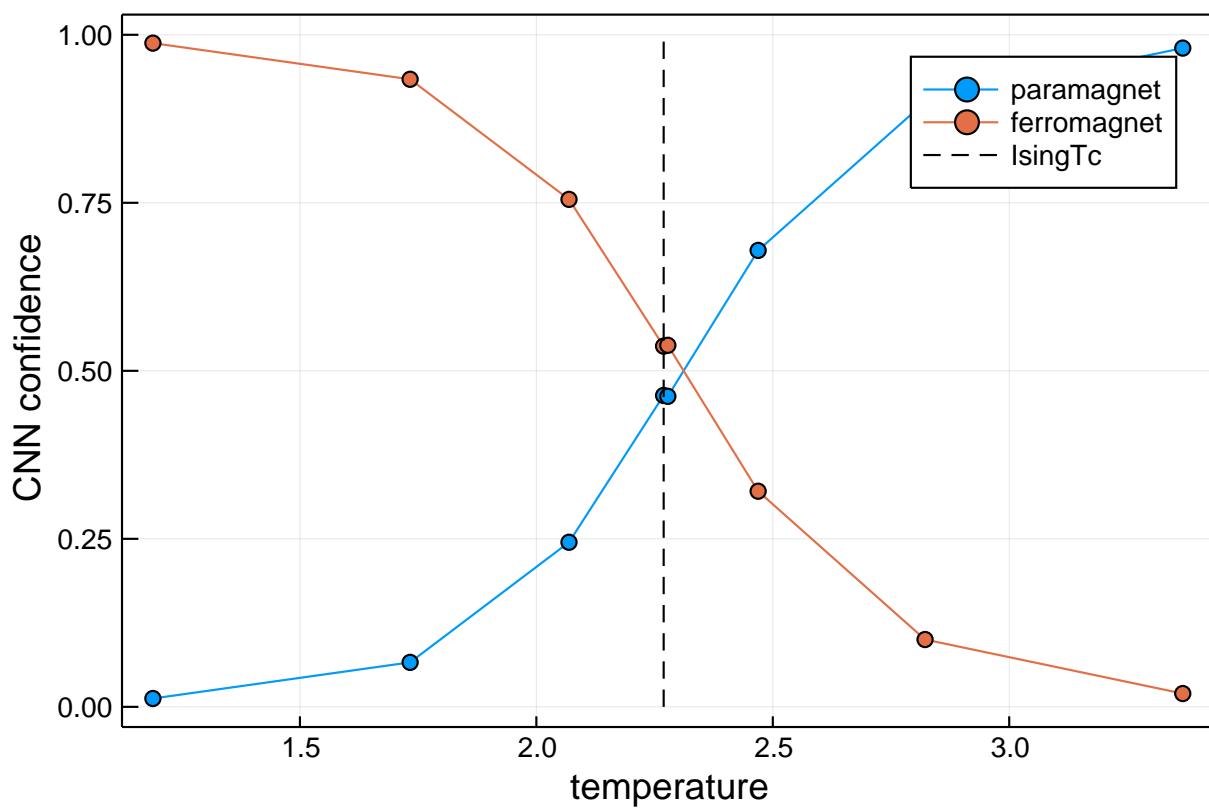
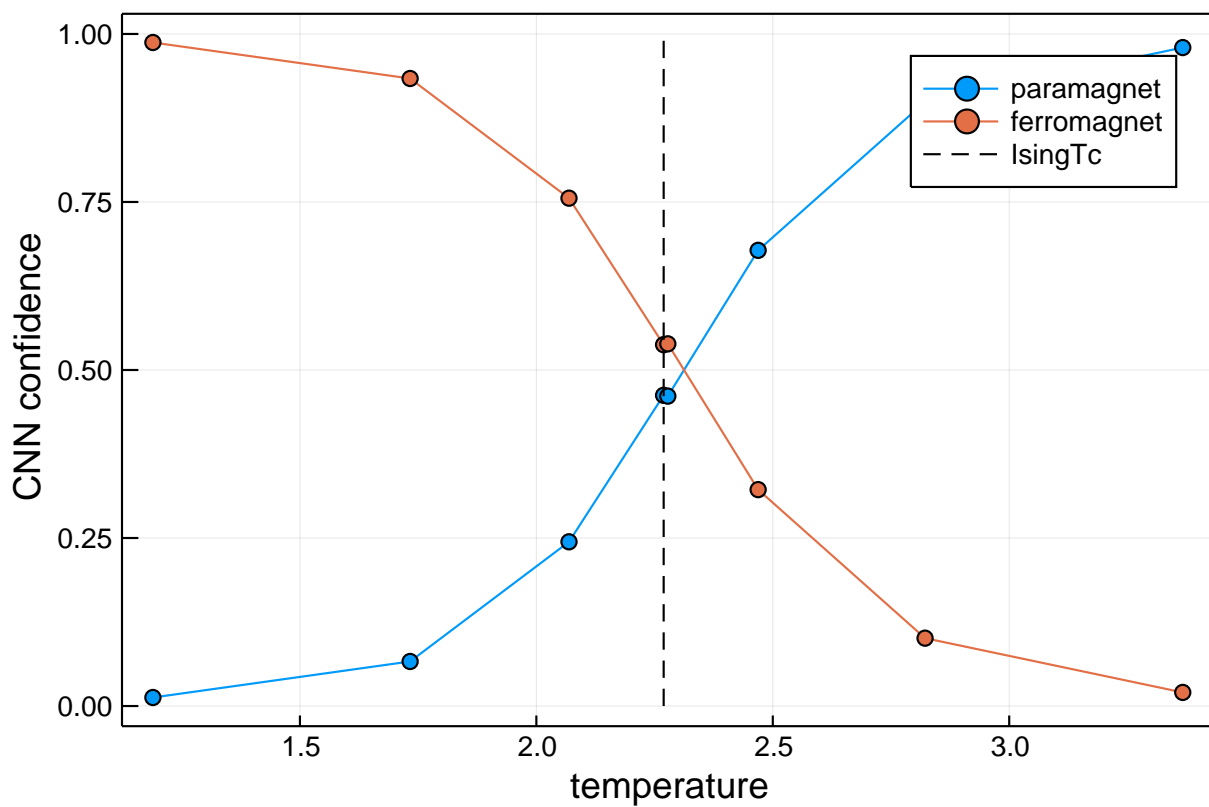


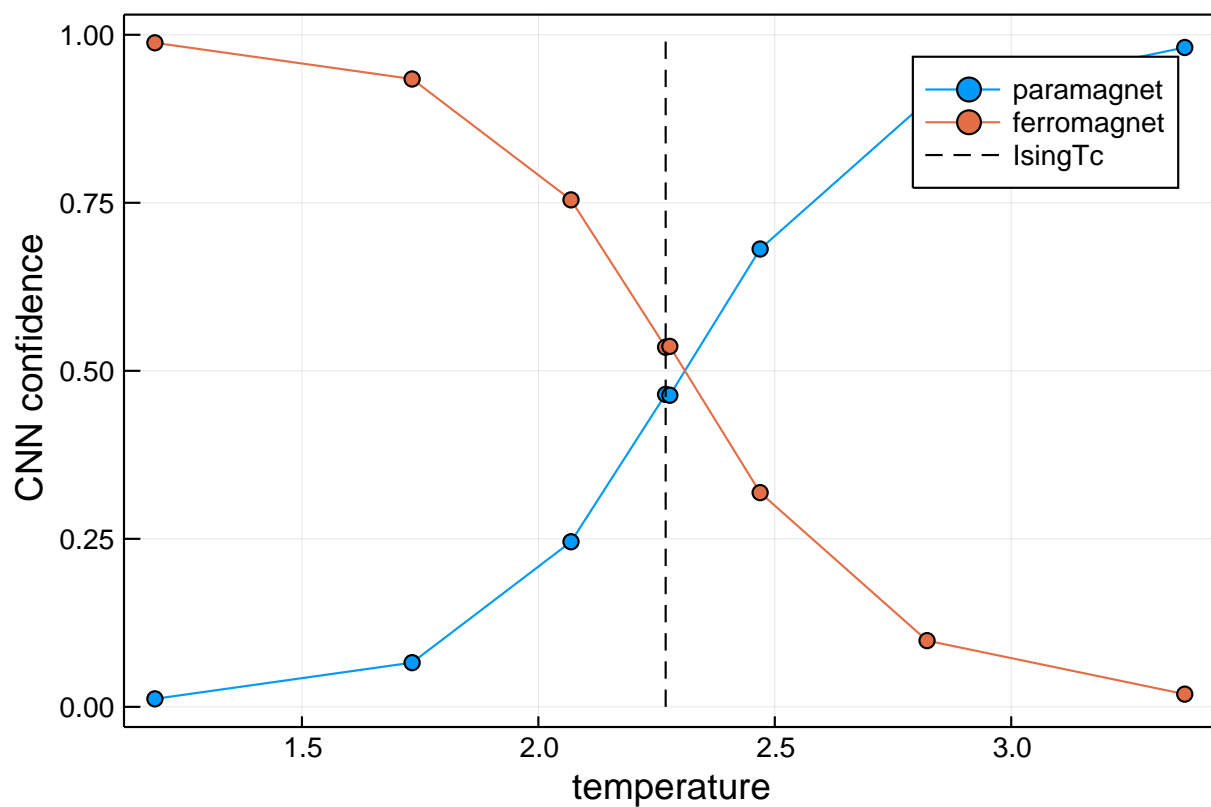
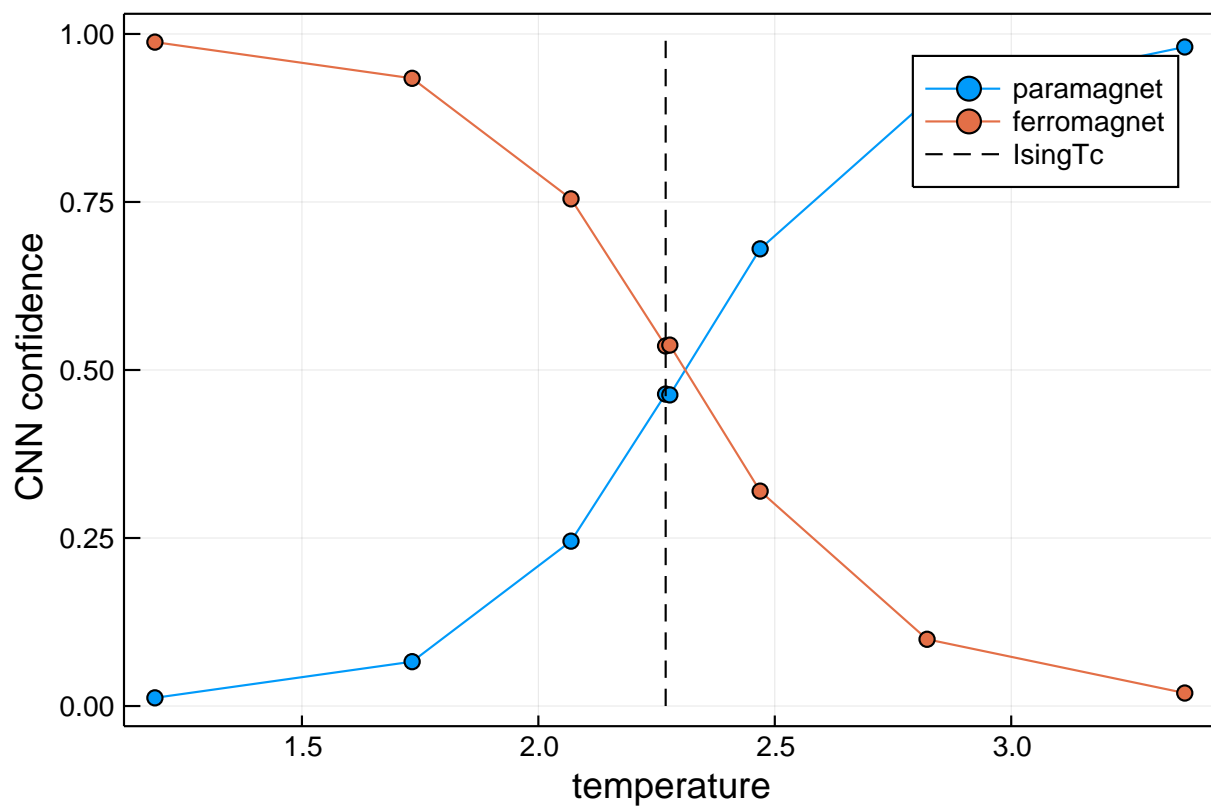


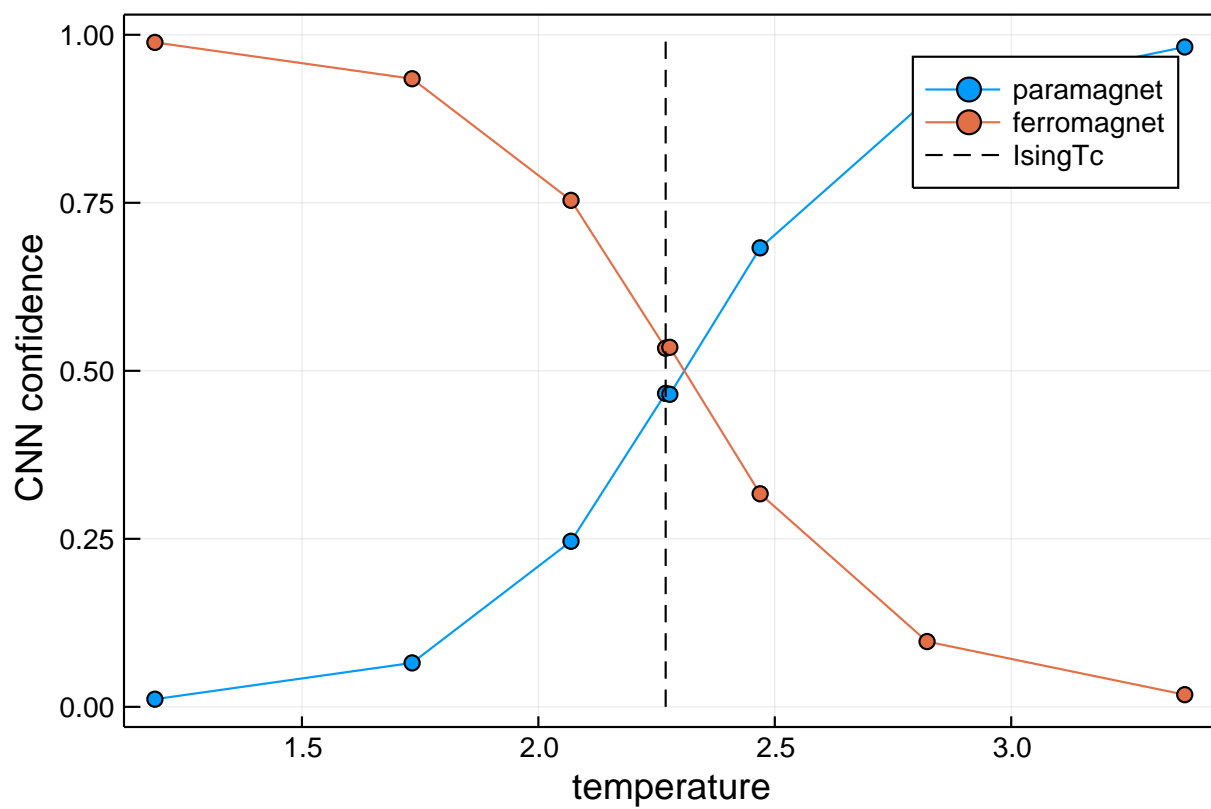
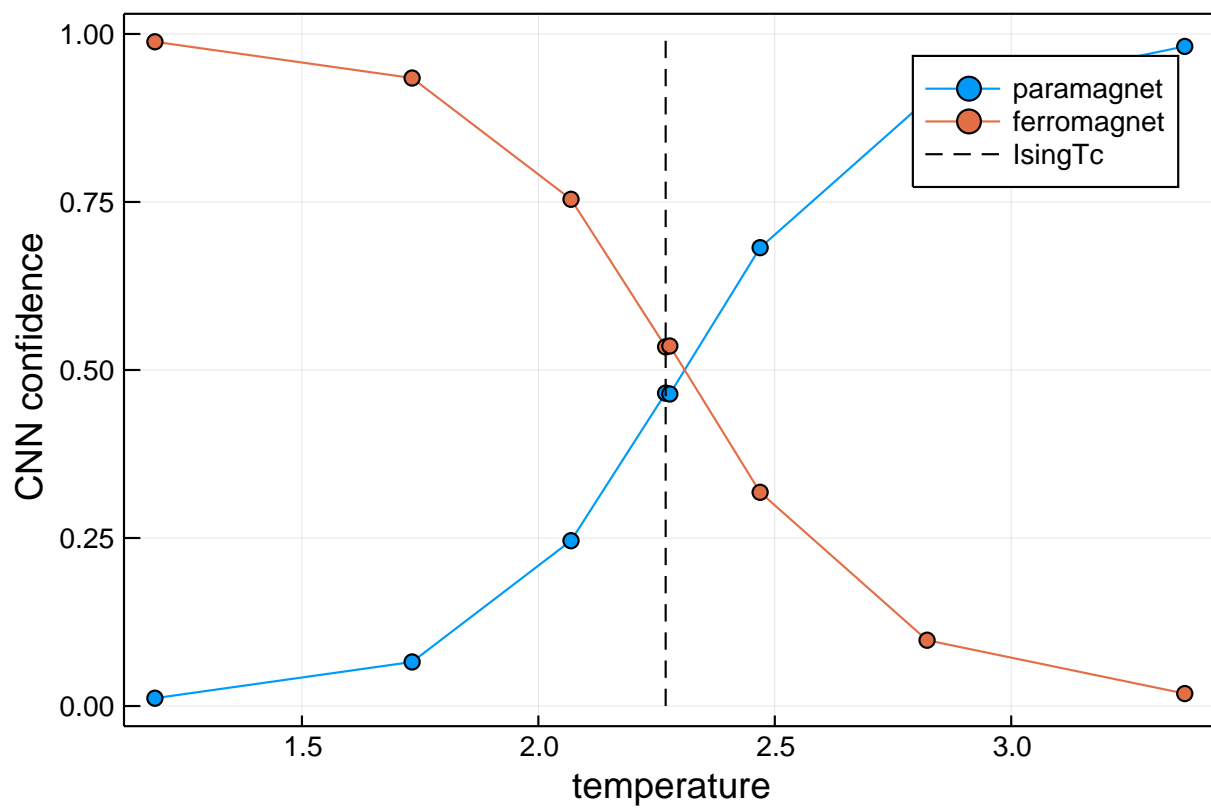


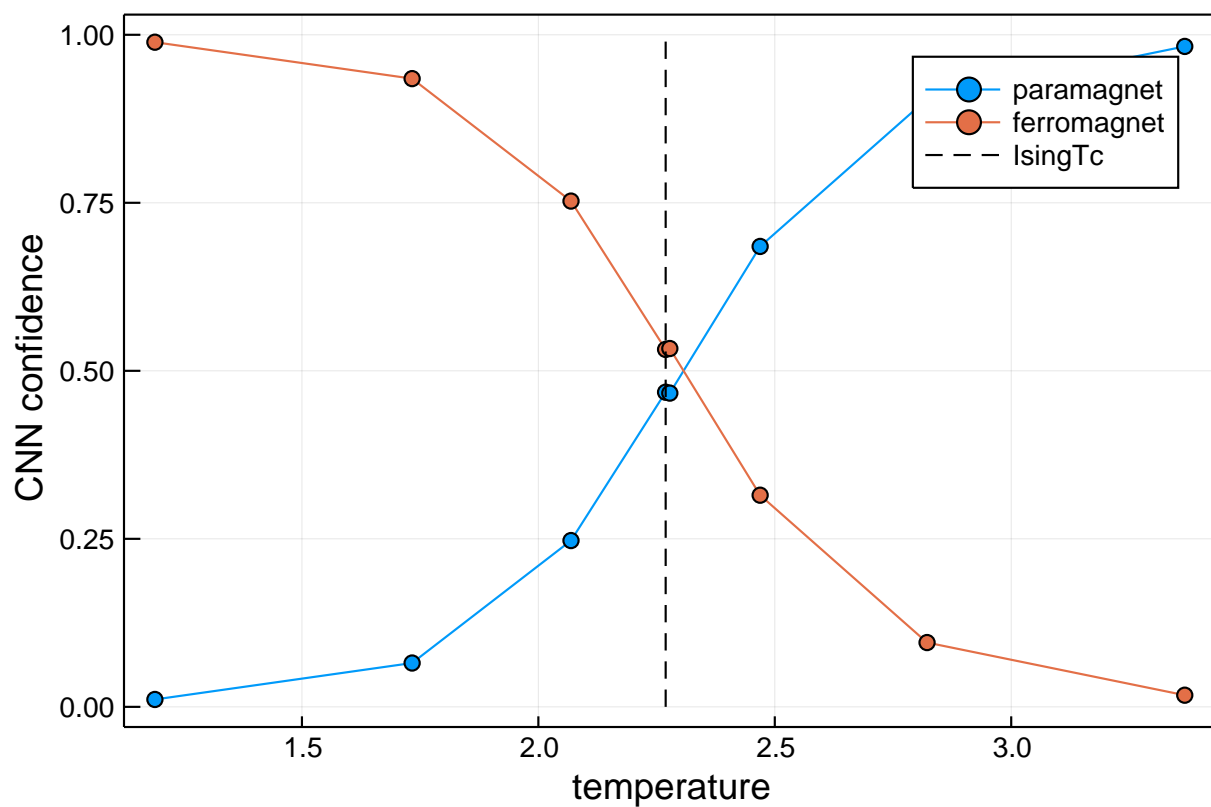
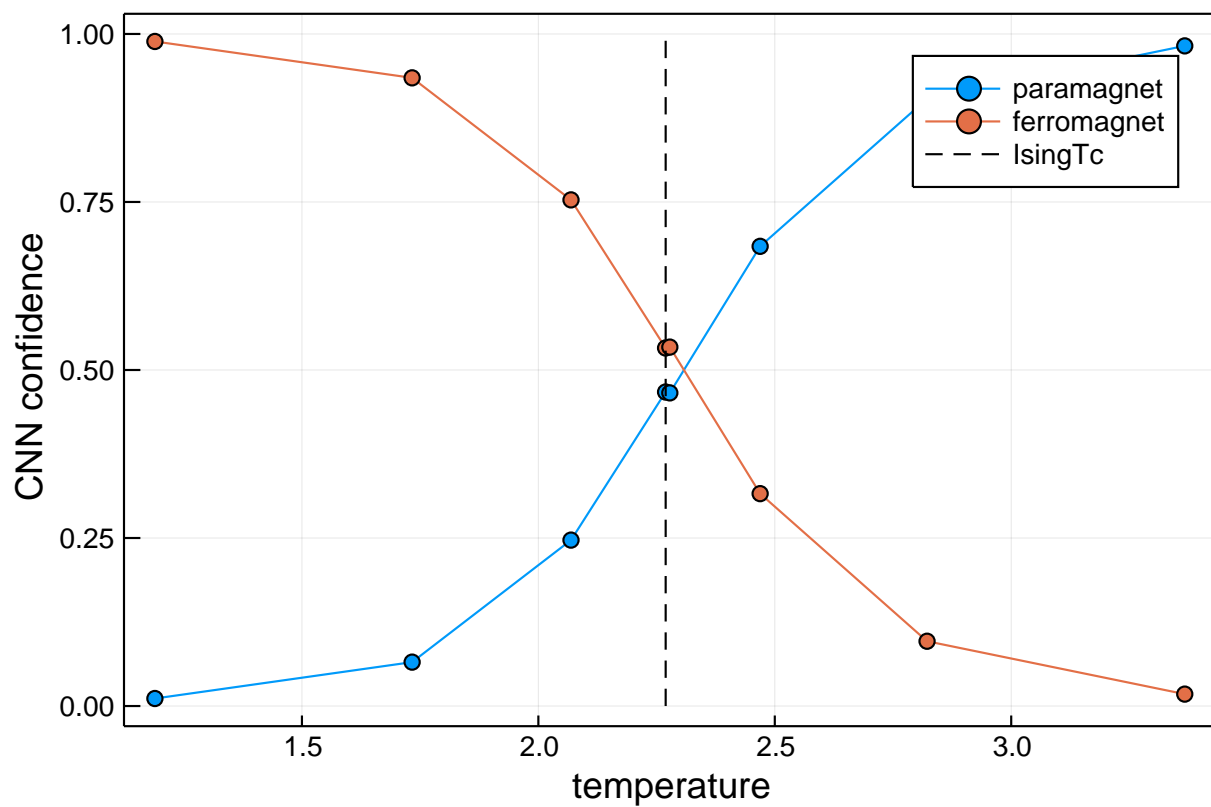


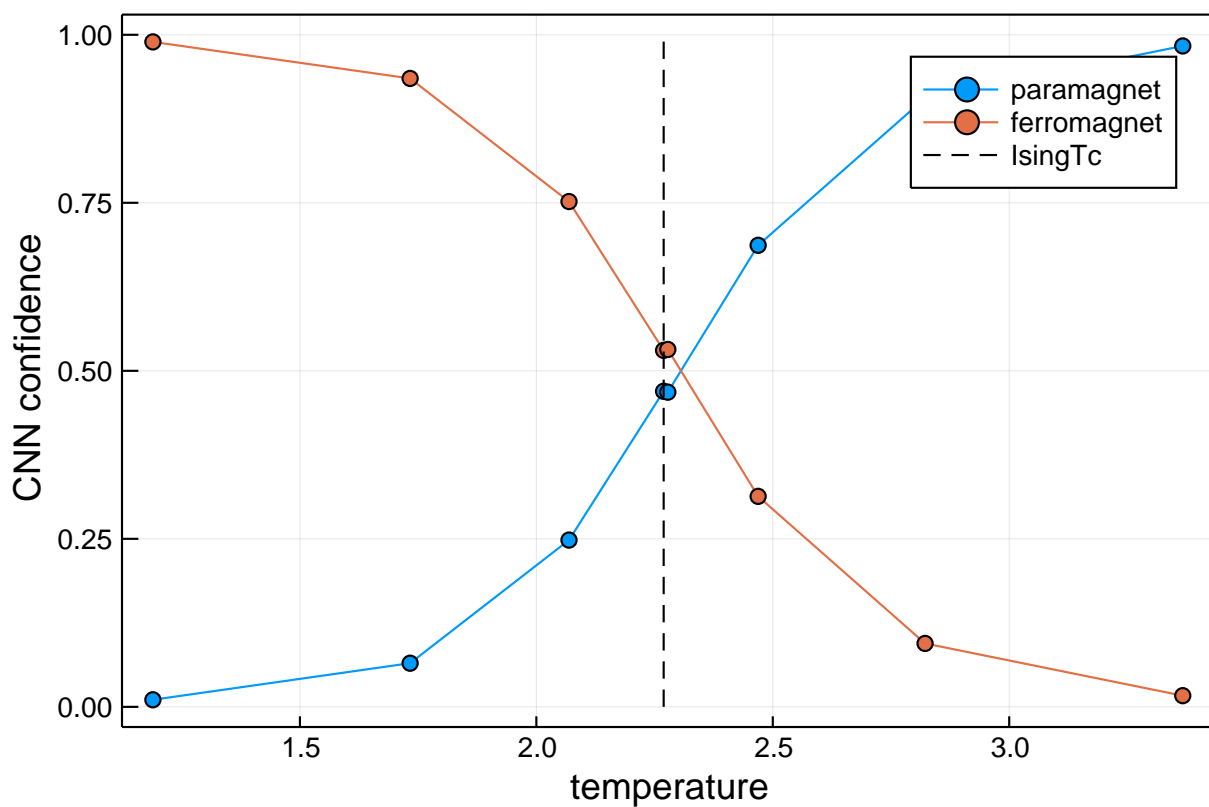
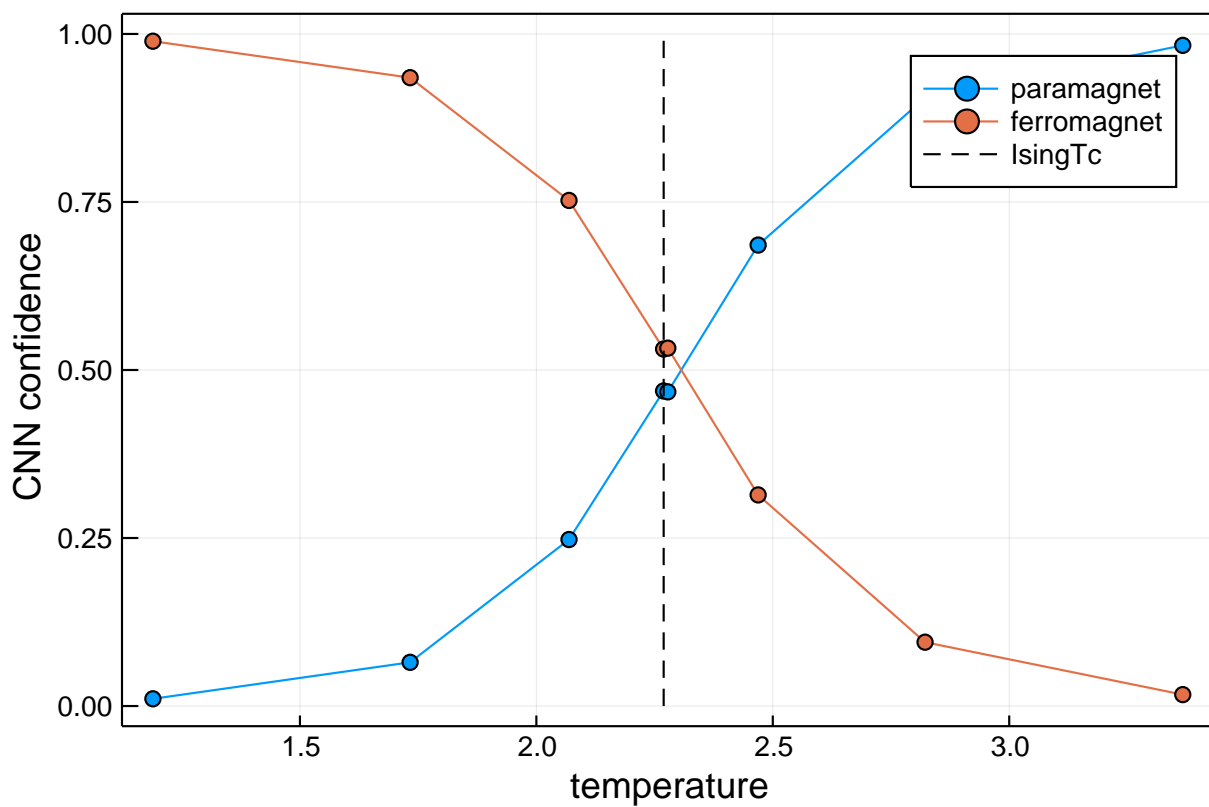


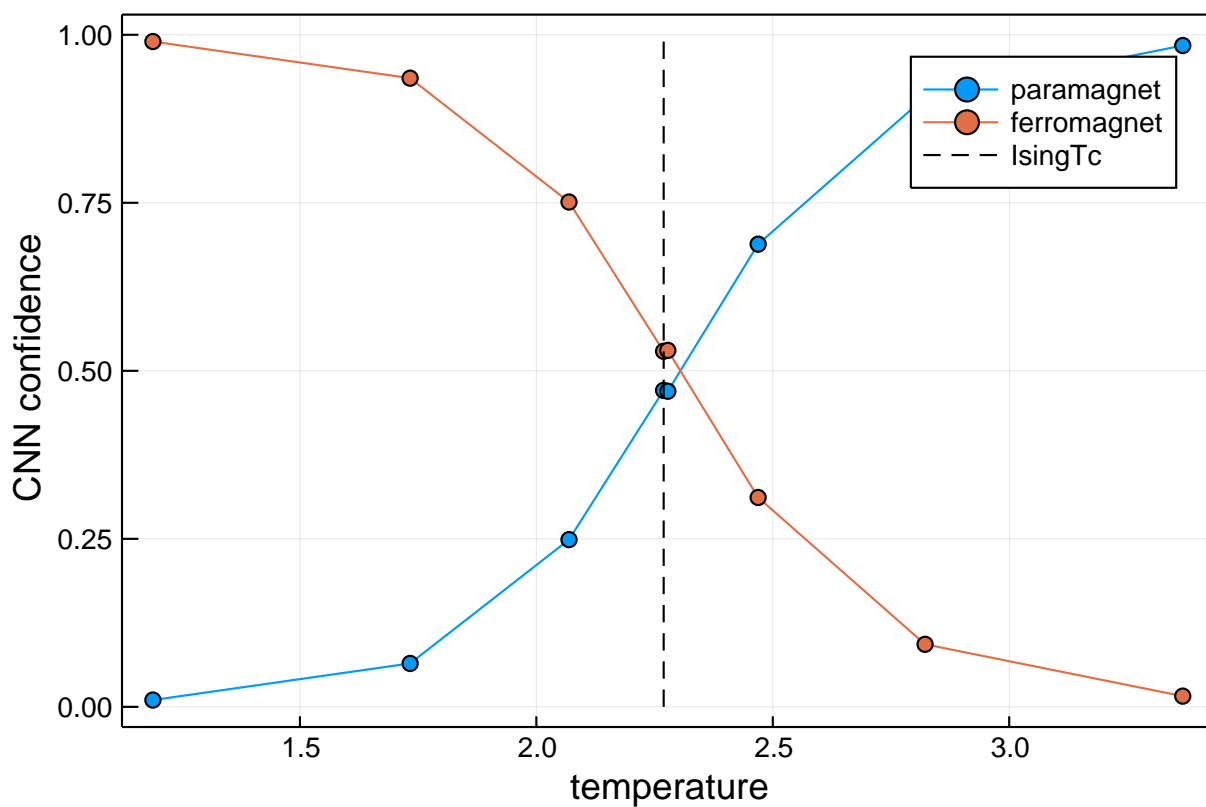
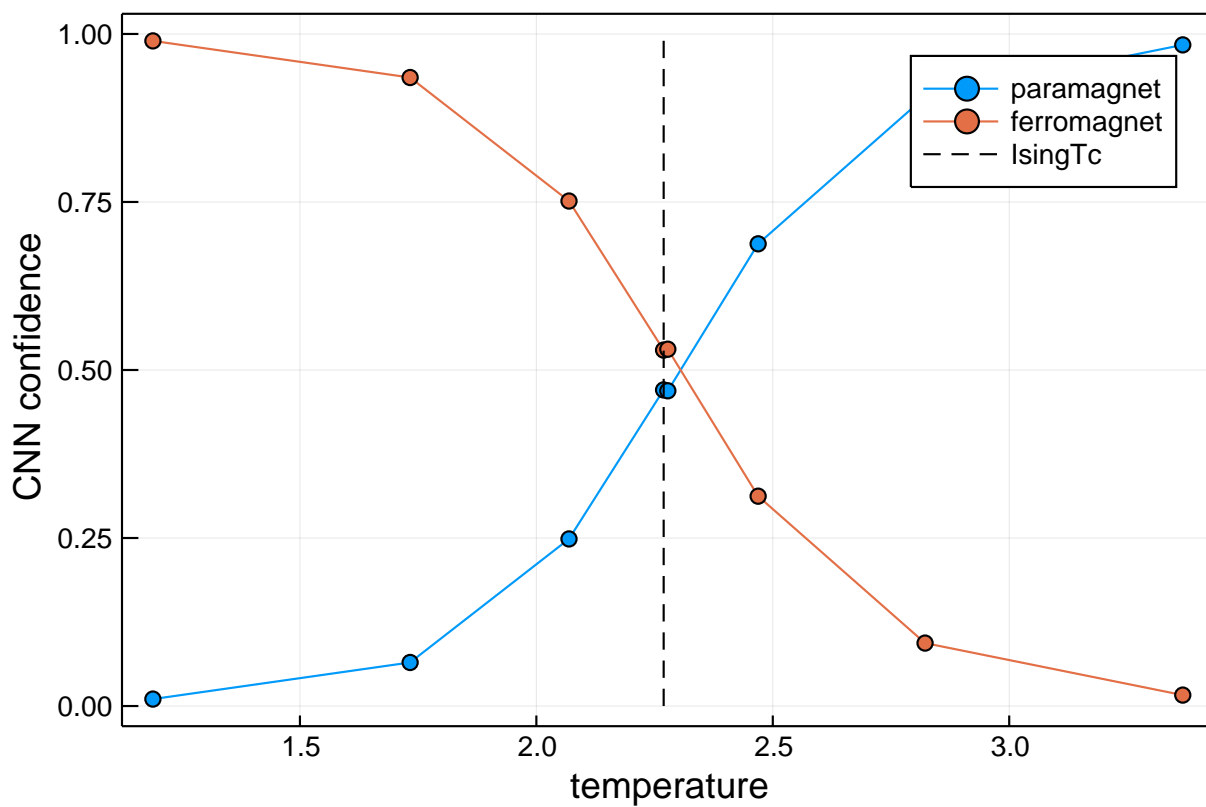


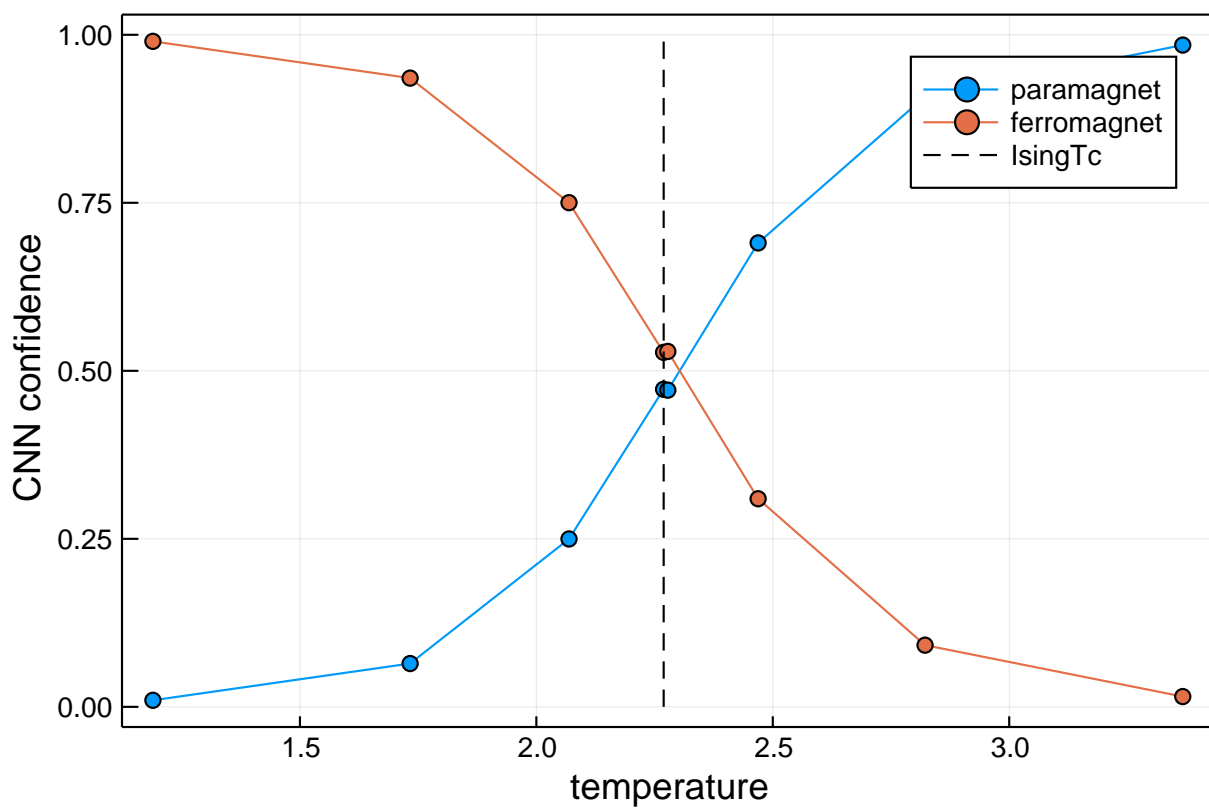
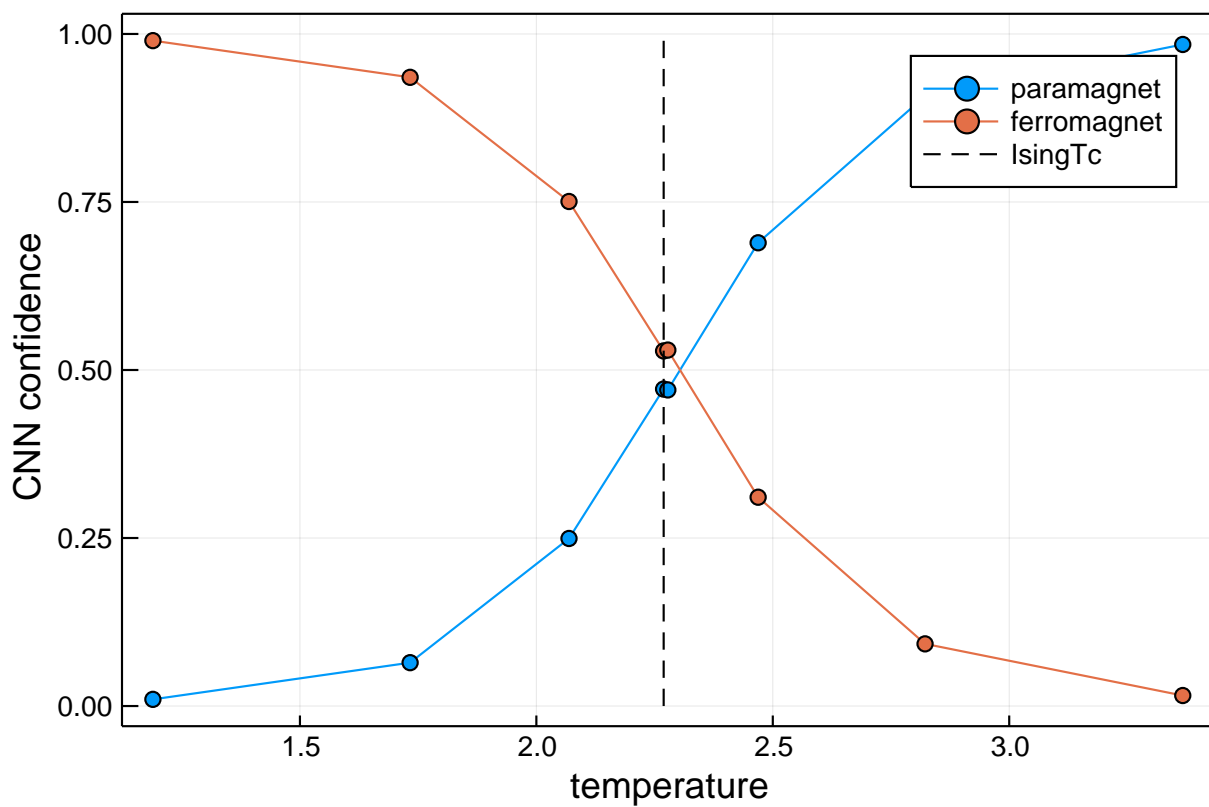


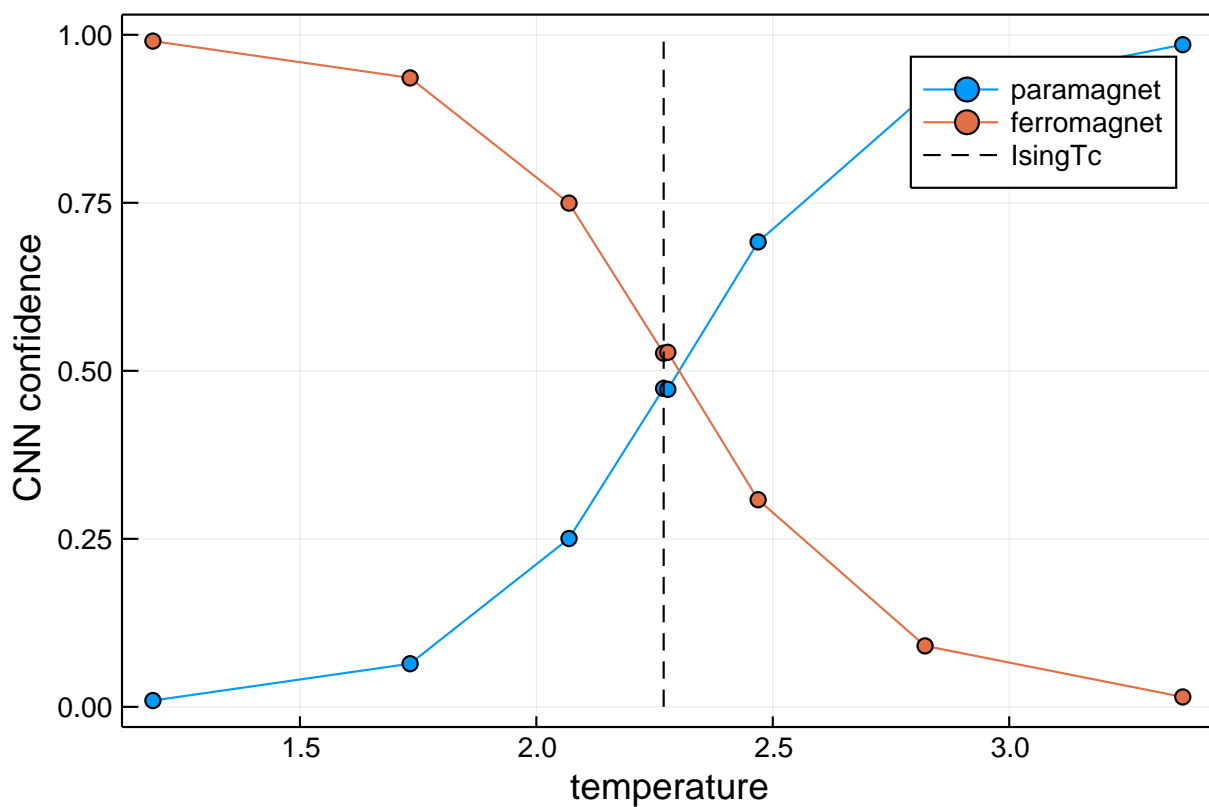
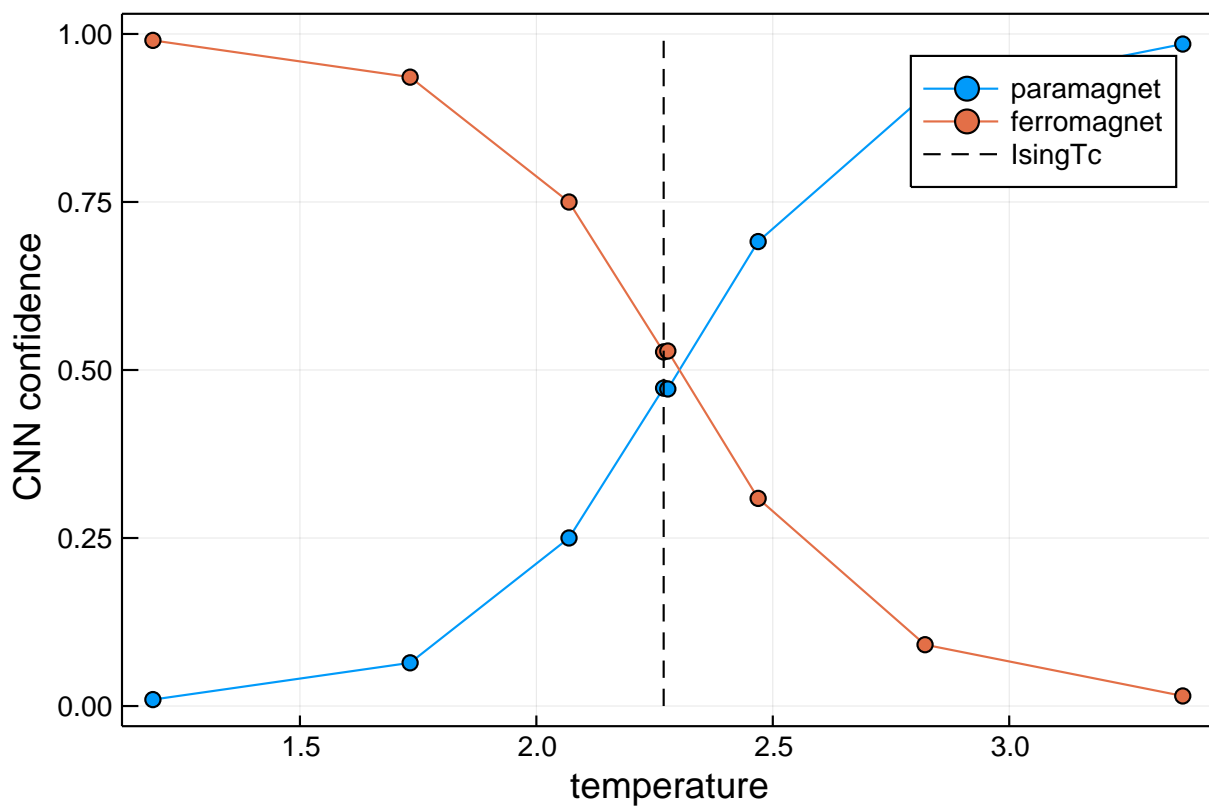


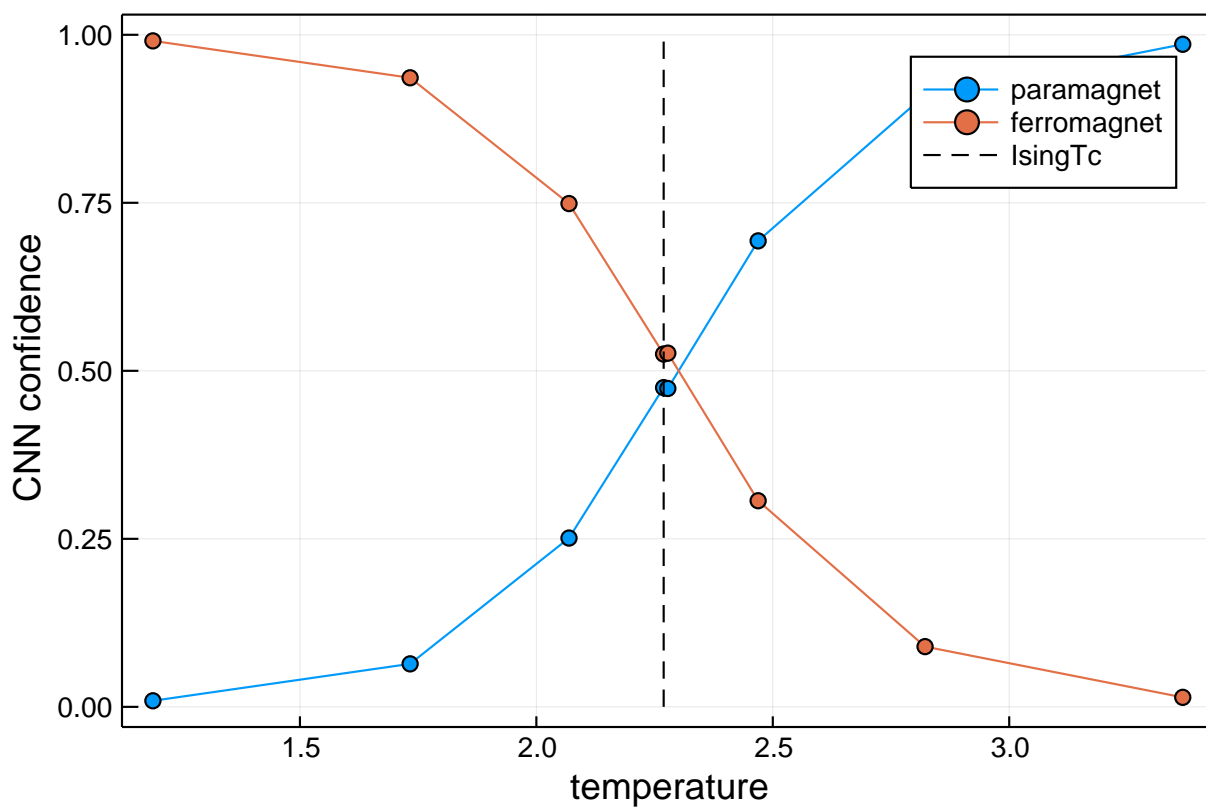
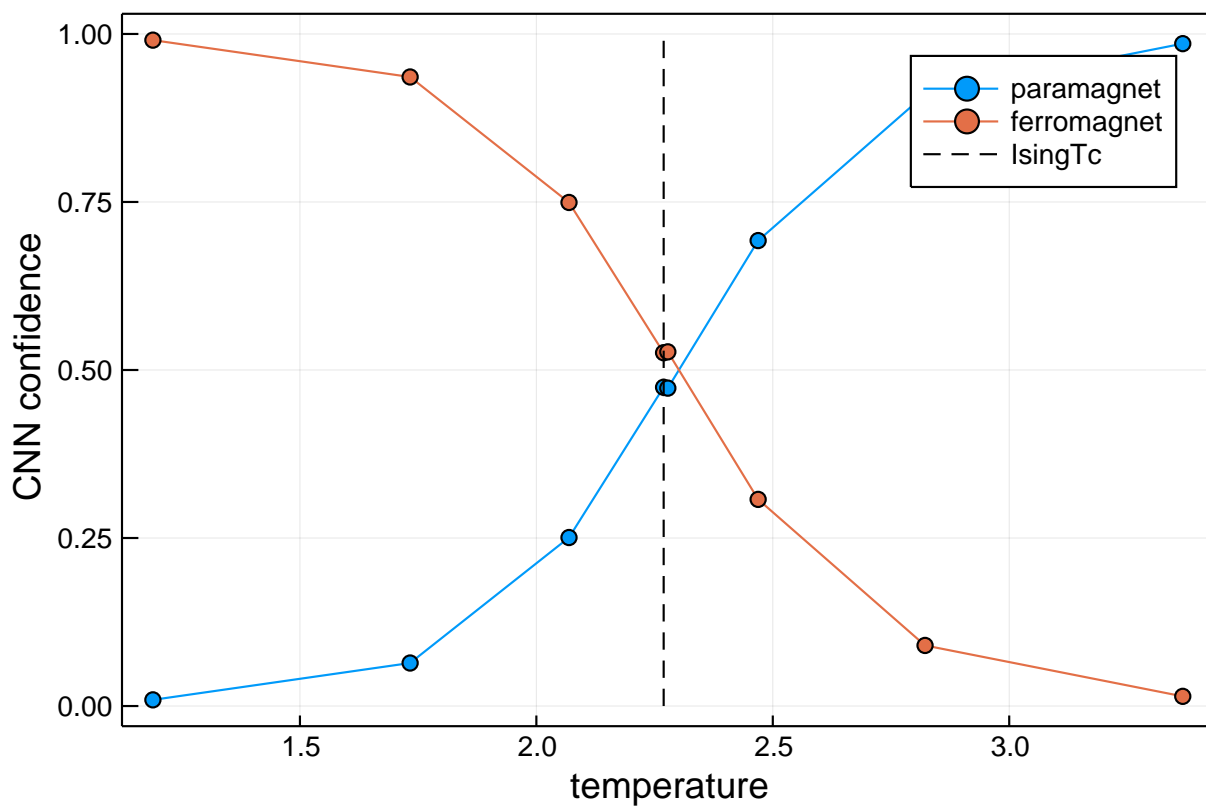


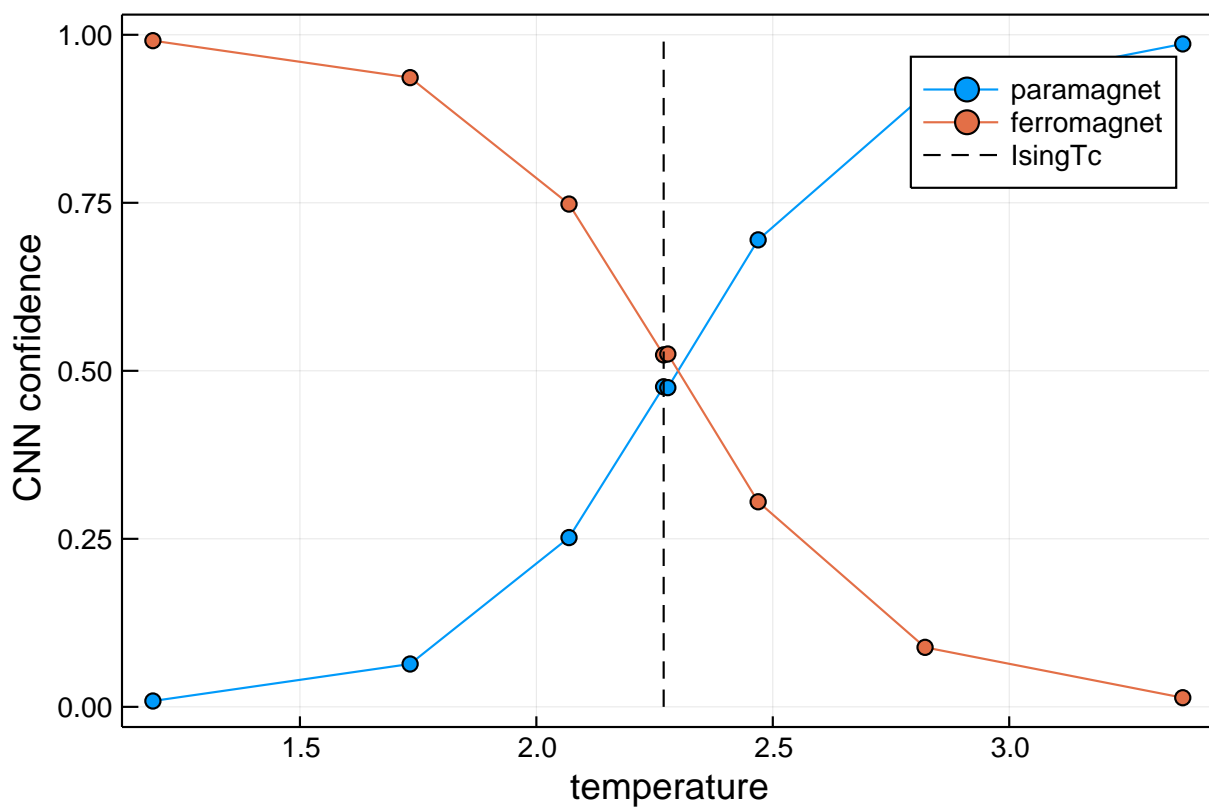
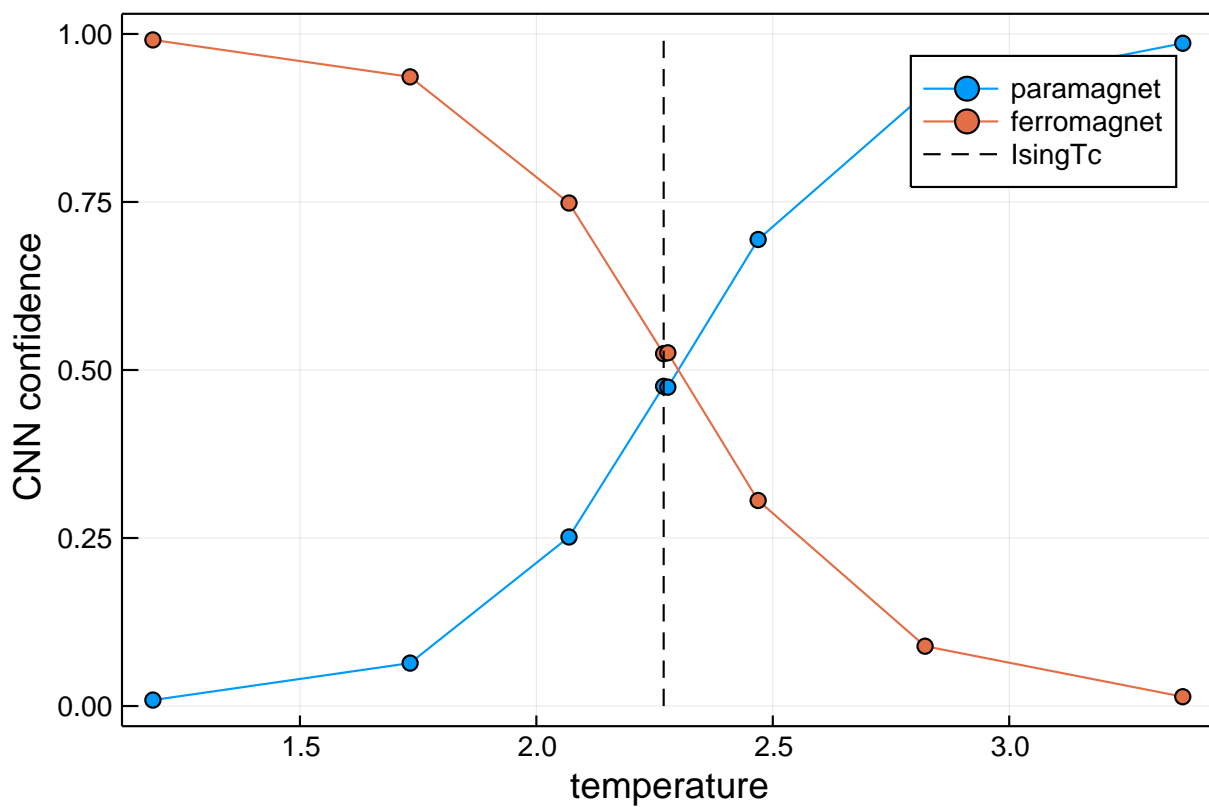


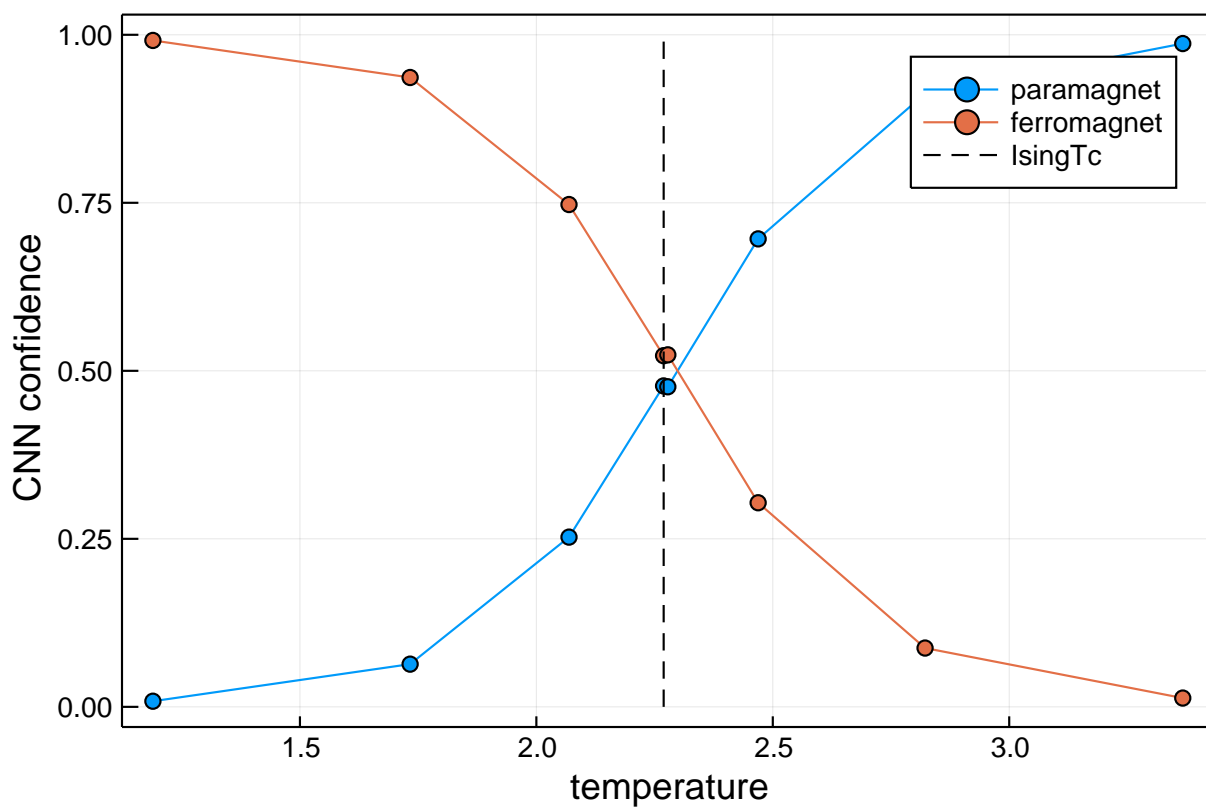
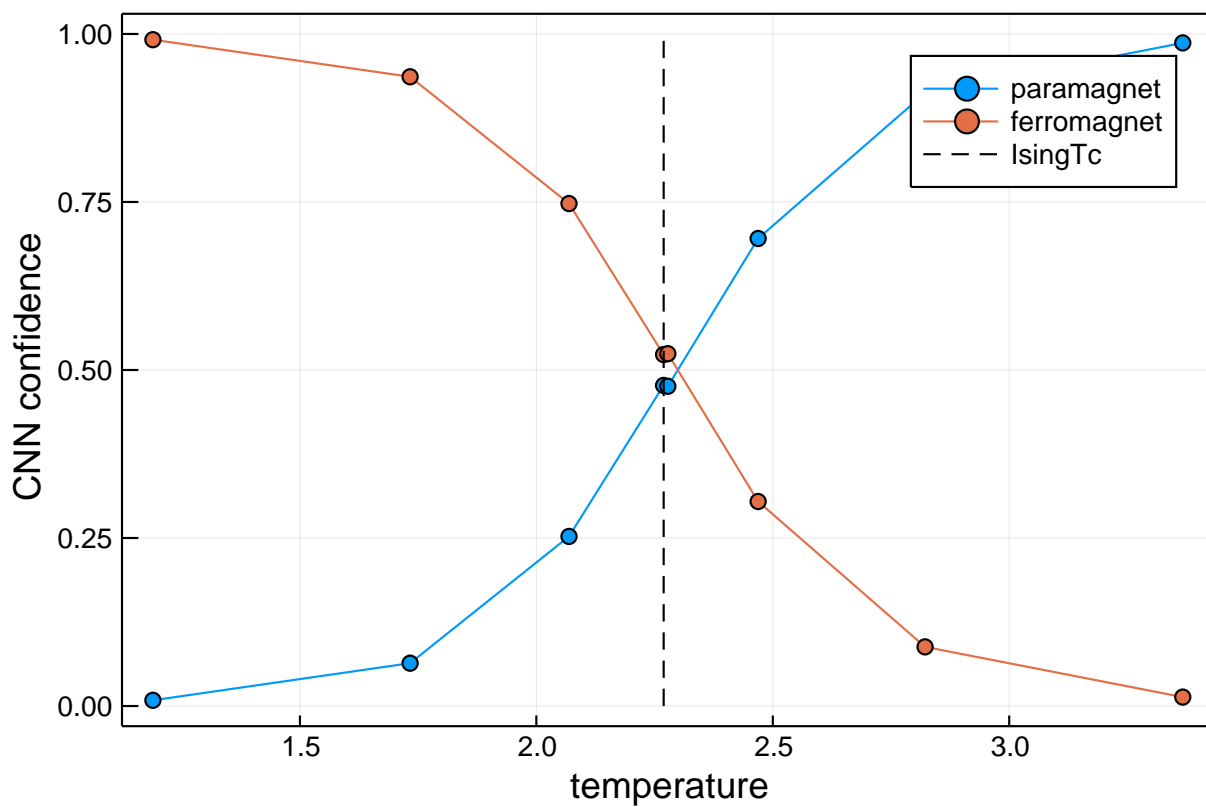


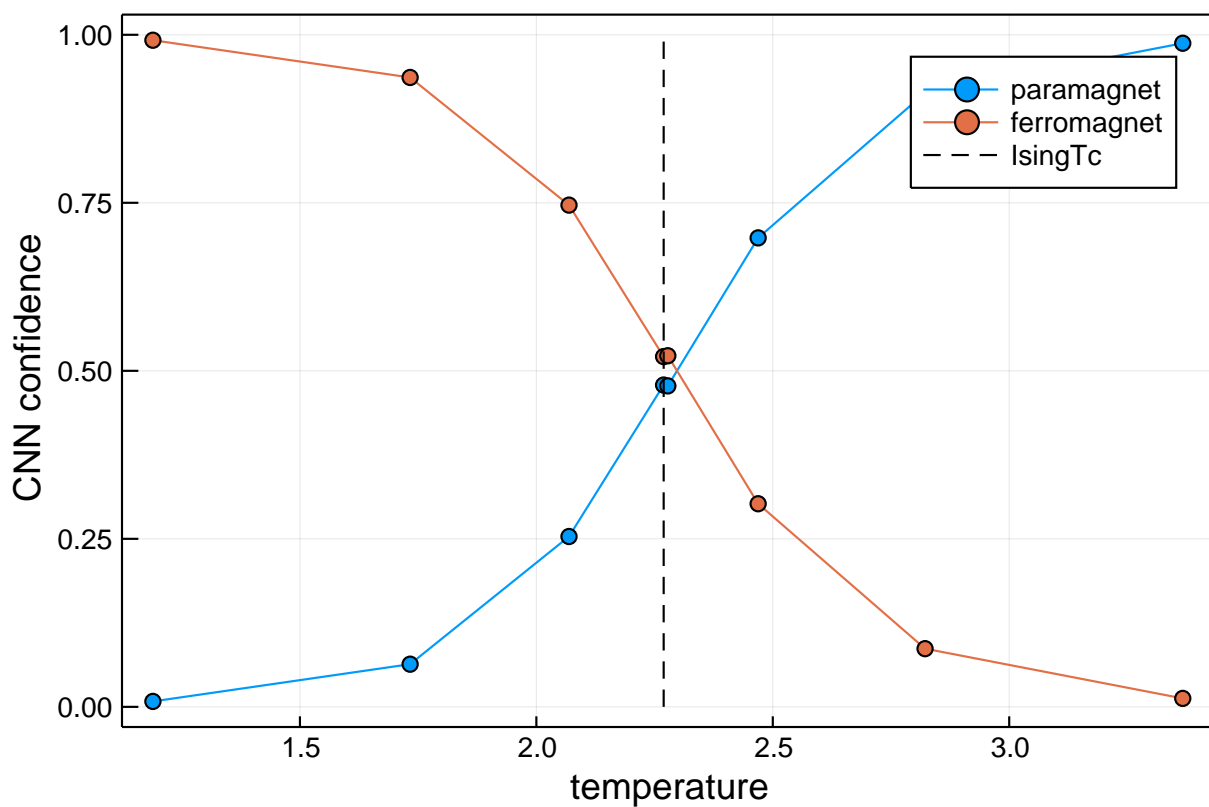
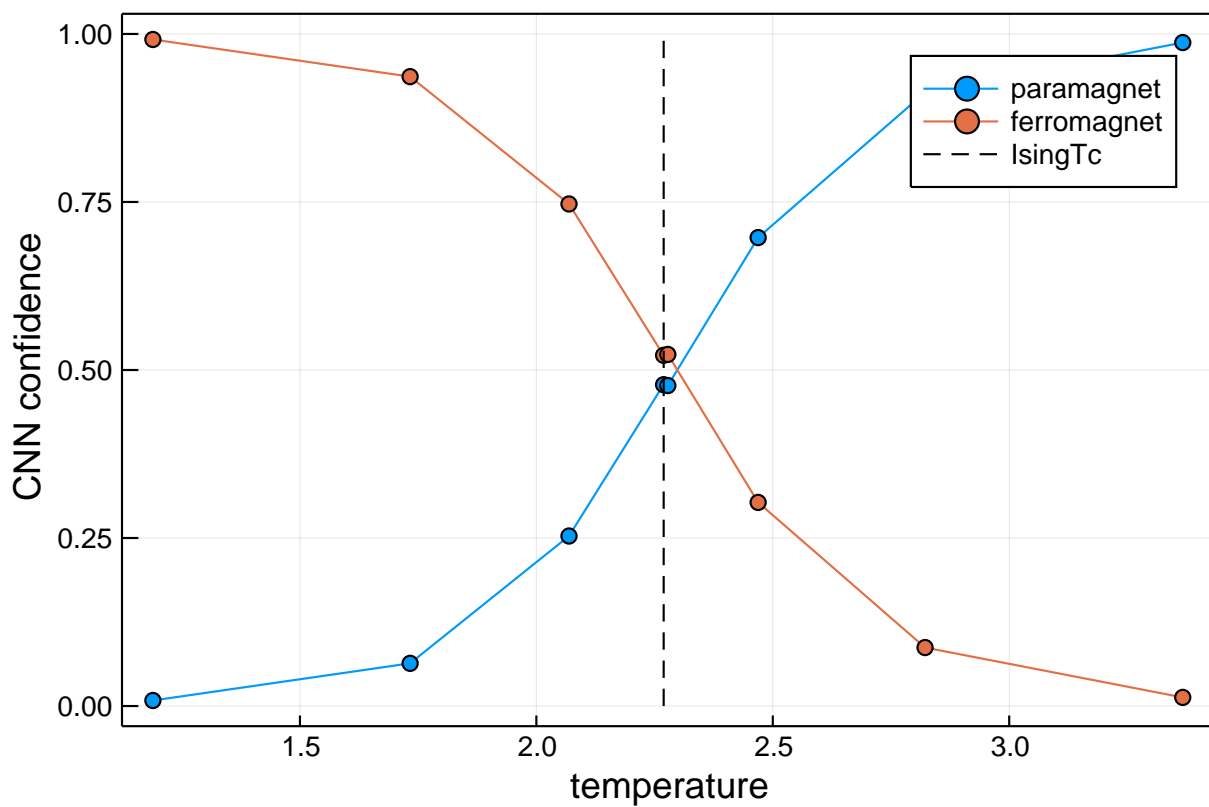


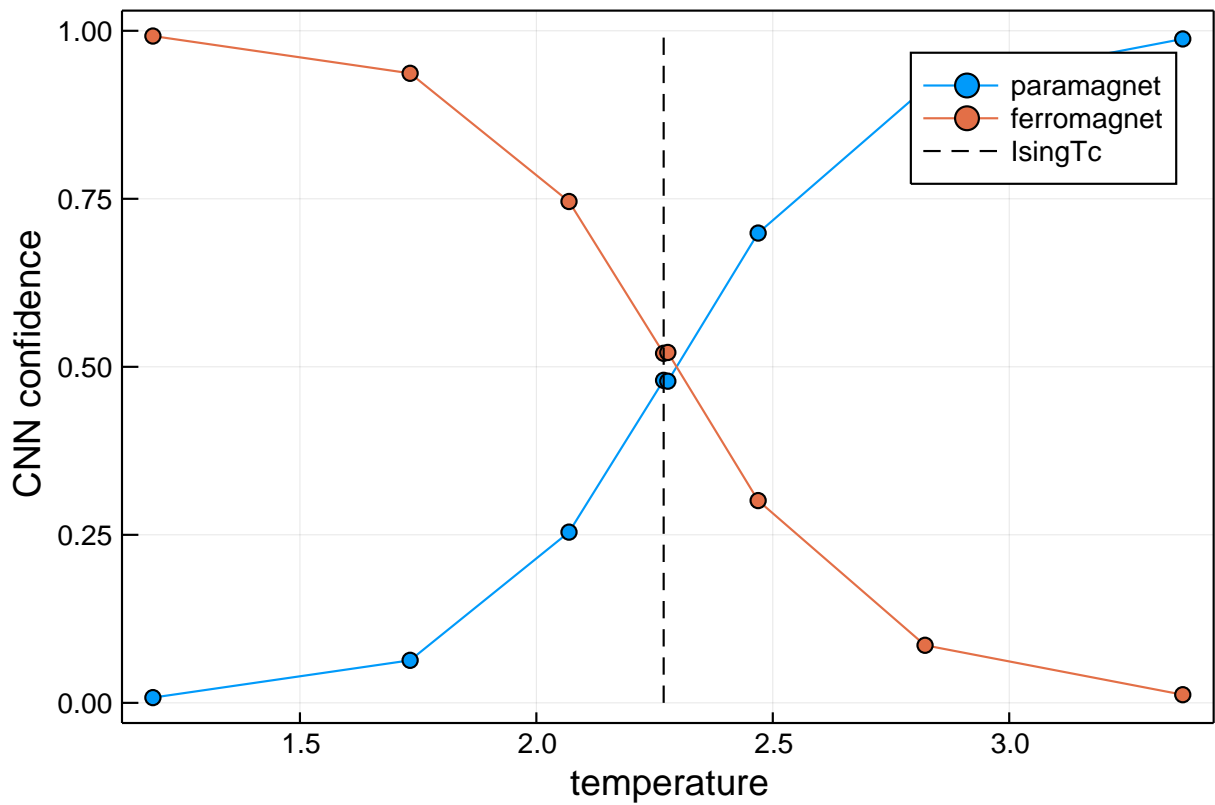
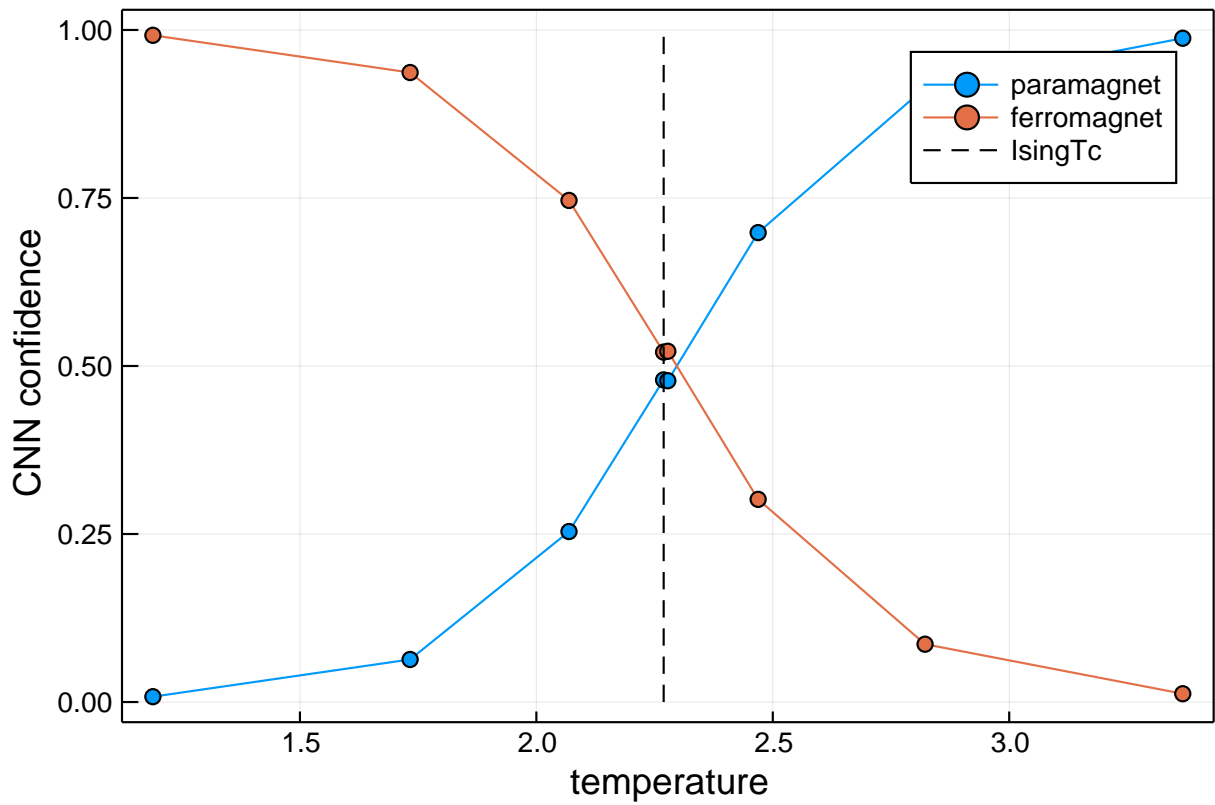












2.1 Appendix

This tutorial is part of the [PhysicsTutorials.jl](https://github.com/PhysicsTutorials/jl) repository.