

Quantum circuit simulation with tensor network contraction

Link to the tutorial repository: <https://github.com/GiggleLiu/tutorial-tensornetwork>

```
1 # check the current environment
2 using Pkg; Pkg.activate("../..") ; Pkg.status()
```



```
Activating project at `~/jcode/tutorial-tensornetwork`
Status `~/jcode/tutorial-tensornetwork/Project.toml`
 [6e4b80f9] BenchmarkTools v1.6.0
 [1f49bdf2] LuxorGraphPlot v0.5.1
 [ebe7aa44] OMEinsum v0.9.2
 [c3e4b0f8] Pluto v0.20.16
 [7f904dfe] PlutoUI v0.7.70
 [123dc426] SymEngine v0.12.0
 [0500ac79] TensorQEC v2.2.0
 [5872b779] Yao v0.9.2
 [9b173c7b] YaoToEinsum v0.2.8 `~/.julia/dev/Yao/lib/YaoToEinsum`
 [37e2e46d] LinearAlgebra v1.11.0
 [9a3f8284] Random v1.11.0
```



```
1 # `PlutoUI` is for control gadgets, e.g. the checkboxes
2 using PlutoUI
```

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```
1 PlutoUI.TableOfContents(aside=false)
```

Tutorial: einsum notation

In this tutorial, we use `OMEinsum.jl` as our default tensor network contractor.

- State of the art performance in optimizing the contraction order
- Has GPU support

```
1 using OMEinsum    # Tensor network contraction backend
```

Specify a tensor network with string literal `ein`

```
code = ab, bc, cd -> ad
1 # '-' separates the input and output tensors
2 # ',' separates the indices of different input tensors
3 # each char represents an index
4
5 code = ein"ab,bc,cd->ad" # using string literal
```

or programmatically


```
1o2, 2o3, 3o4 -> 1o4
1 EinCode([[1,2], [2, 3], [3, 4]], [1, 4]) # alternatively
```

```
▼Vector{Char}[
  1: ▼Char[
    1: 'a'
    2: 'b'
  ]
  2: ▶['b', 'c']
  3: ▶['c', 'd']
]
```

```
1 getixsv(code) # indices for input tensors
```

```
▶['a', 'd']
```

```
1 getiyv(code) # indices for the output tensor
```

variable_dimension =  100

```
label_sizes = ▼Dict{Char, Int64}{
    'a' => 100
    'c' => 100
    'd' => 100
    'b' => 100
}
```

```
1 label_sizes = uniformsize(code, variable_dimension) # define the sizes of the indices
```

Time complexity: $2^{26.575424759098897}$
 Space complexity: $2^{13.287712379549449}$
 Read-write complexity: $2^{15.287712379549449}$

```
1 # Time complexity: number of arithmetic operations
2 # Space complexity: number of elements in the largest tensor
3 # Read-write complexity: number of elemental read-write operations
4 contraction_complexity(code, label_sizes)
```

```
2x2 Matrix{Float64}:
-1.5785  3.0381
 1.84091 -3.8551
```

```
1 code(randn(2, 2), randn(2, 2), randn(2, 2)) # not recommended
```

```
nested_code = ac, cd -> ad
               |
               | ab, bc -> ac
               |
               | ab
               |
               | bc
               |
               | cd
```

```
1 nested_code = ein"(ab,bc),cd->ad" # recommended
```

Time complexity: $2^{20.931568569324174}$
 Space complexity: $2^{13.287712379549449}$
 Read-write complexity: $2^{15.872674880270605}$

```
1 contraction_complexity(nested_code, label_sizes)
```

```
1 using BenchmarkTools # use for benchmark
```

run_benchmark = ☒

```
1 run_benchmark && @btime code(randn(100, 100), randn(100, 100), randn(100, 100)); #
  unoptimized
```

```
> 85.595 ms (38 allocations: 385.55 KiB)
```

```
1 run_benchmark && @btime nested_code(randn(100, 100), randn(100, 100), randn(100,
  100)); # optimized
```

```
> 146.875 μs (165 allocations: 486.31 KiB)
```

Reasons why order matters:

1. Contraction order reduces the computational complexity
2. Binary contraction can make use of BLAS

Contraction order optimization

- Contracting a tensor network is #P-hard, the complexity is $O(2^{\text{tw}(\bar{T})})$, i.e. exponential to the tree width of the line graph of the tensor network hypergraph topology T .
- Optimizing the contraction order is NP-hard

```
1 using Graphs # used for constructing graphs
```

demo_network (generic function with 1 method)

```
1 function demo_network(n::Int; seed=2)
2     # random regular graph
3     g = random_regular_graph(n, 3; seed)
4     # place a matrix on each edge
5     code = EinCode([[e.src, e.dst] for e in edges(g)], Int[])
6     # each input matrix has size 2x2
7     sizes = uniformsize(code, 2)
8     tensors = [randn([sizes[leg] for leg in ix]...) for ix in getixsv(code)]
9     return code, tensors, sizes
10 end
```

```
1 code_r3, tensors_r3, sizes_r3 = demo_network(100);
```

```
1 optcode = optimize_code(
2     code_r3,    # tensor network topology
3     sizes_r3,   # variable sizes
4     TreeSA()    # optimizer
5 );
```

```
cc_r3 = Time complexity: 2^17.347033043146006
      Space complexity: 2^13.0
      Read-write complexity: 2^16.52724790138619
```

```
1 cc_r3 = contraction_complexity(optcode, sizes_r3)
```

For more choices of optimizers, please check: [OMEinsumContractionOrdersBenchmark](#) and [issue](#)

```
1 # reduce the memory cost by slicing
2 sliced_code = slice_code(
3     optcode,
4     sizes_r3,
5     TreeSASlicer(score=ScoreFunction(sc_target=cc_r3.sc-3)) # keep slicing until the
6     space complexity target 'sc_target' is reached.
7 );
```

```
cc_r3_sliced = Time complexity: 2^17.675295499094062
              Space complexity: 2^10.0
              Read-write complexity: 2^17.126623819032357
```

```
1 cc_r3_sliced = contraction_complexity(sliced_code, sizes_r3)
```

Example 1: GHZ state generation circuit

We use [Yao.jl](#) as our default quantum simulation tool.

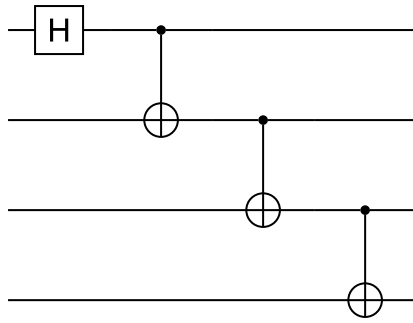
- State of the art performance, has GPU support
- Supports tensor network backend
- Supports noisy channel simulation

```
1 using Yao    # Quantum circuit simulator
```

Let us first define a GHZ state generation circuit.

```
ghz_circuit (generic function with 1 method)
```

```
1 # chain: connect the component gates
2 # put(n, k=>G): place gate G at location k of a n qubits system.
3 # control(n, c, k=>G): place controlled gate G at location k, c is the control qubit
4 ghz_circuit(n) = chain(put(n, 1=>H), [control(n, i-1, i=>X) for i=2:n]...)
```



```
1 vizcircuit(ghz_circuit(4))
```

```
net_ghz = TensorNetwork
          Time complexity: 2^5.807354922057604
          Space complexity: 2^4.0
          Read-write complexity: 2^7.044394119358453
```

```
1 # 1st argument is a Yao circuit
2 # 'initial_state' takes a dictionary
3 # 'final_state' is left unspecified
4 net_ghz = yao2einsum(ghz_circuit(4);
5                     initial_state= Dict(zip(1:4, zeros(Int,4))),
6                     optimizer = TreeSA(ntrials=1) # contraction order optimizer
7 )
```

The tensor network contraction is represented as a binary tree. It contains both the tensor network topology and an optimized contraction order.

```
6x5, 8x6x7 -> 5x6x7x8
├── 6x5x2, 5x1 -> 6x5
│   ├── 2, 6x2x5 -> 6x5x2
│   │   ├── 2
│   │   └── 6x2x5
│   └── 1, 5x1 -> 5x1
│       ├── 1
│       └── 5x1
└── 8x7x4, 7x6x3 -> 8x6x7
    ├── 4, 8x4x7 -> 8x7x4
    │   ├── 4
    │   └── 8x4x7
    └── 3, 7x3x6 -> 7x6x3
        ├── 3
        └── 7x3x6
```

```
1 net_ghz.code # contraction code in (nested) einsum notation
```

```
▼(
  1: :code
  2: :tensors
  3: :label_to_qubit
)
```

```
1 fieldnames(typeof(net_ghz))
```

```
► [[3], [1], [4], [2], [5, 1], [6, 2, 5], [7, 3, 6], [8, 4, 7]]
```

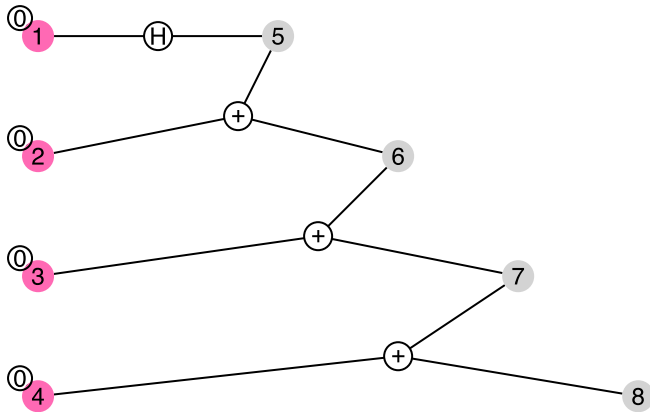
```
1 OMEinsum.getixsv(net_ghz.code) # input tensor labels
```

```
8
```

```
1 length(net_ghz.tensors) # input tensor data
```

► [5, 6, 7, 8]

```
1 OMEinsum.getiyyv(net_ghz.code) # open indices
```



```
1 # red/gray nodes are variables/open variables, transparent nodes are tensors
2 # 0 tensor is defined as: [1, 0]
3 # + tensor is the XOR gate
4 viznet(net_ghz; scale=60)
```

Time complexity: $2^{5.807354922057604}$
Space complexity: $2^{4.0}$
Read-write complexity: $2^{7.044394119358453}$

```
1 contraction_complexity(net_ghz)
```

```
2x2x2x2 Array{ComplexF64, 4}:
[:, :, 1, 1] =
 0.707107+0.0im  0.0+0.0im
 0.0+0.0im  0.0+0.0im

[:, :, 2, 1] =
 0.0+0.0im  0.0+0.0im
 0.0+0.0im  0.0+0.0im

[:, :, 1, 2] =
 0.0+0.0im  0.0+0.0im
 0.0+0.0im  0.0+0.0im

[:, :, 2, 2] =
 0.0+0.0im  0.0+0.0im
 0.0+0.0im  0.707107+0.0im
```

```
1 Yao.contract(net_ghz)
```

Example 2: Simulate quantum supremacy experiments

In this example, we will load the quantum supremacy circuit from the disk, and compute probability of having state $|0\rangle$ by computing $\langle 0|U|0\rangle$, where U is the quantum circuit of interest.

Step 1: circuit loading

Some popular shallow quantum circuits are placed in the `data` folder, they are from [qflex](#) (Ref. qflex datasets, check bottom). To load the circuits to Yao, please use the `YaoCircuitReader` module

provided in file `reader.jl`:

```
1 # circuit reader
2 include("reader.jl"); using YaoCircuitReader: yaocircuit_from_file
```

```
▼String[
  1: "bristlecone_48_1-16-1_0.txt"
  2: "bristlecone_48_1-20-1_0.txt"
  3: "bristlecone_48_1-24-1_0.txt"
  4: "bristlecone_48_1-32-1_0.txt"
  5: "bristlecone_48_1-40-1_0.txt"
  6: "bristlecone_60_1-24-1_0.txt"
  7: "bristlecone_60_1-32-1_0.txt"
  8: "bristlecone_60_1-40-1_0.txt"
  9: "bristlecone_70_1-12-1_0.txt"
 10: "bristlecone_70_1-16-1_0.txt"
 11: "bristlecone_70_1-20-1_0.txt"
 12: "bristlecone_70_1-24-1_0.txt"
 13: "bristlecone_70_1-32-1_0.txt"
 14: "bristlecone_70_1-40-1_0.txt"
 15: "rectangular_11x12_1-16-1_0.txt"
 16: "rectangular_11x12_1-24-1_0.txt"
 17: "rectangular_11x12_1-32-1_0.txt"
 18: "rectangular_11x12_1-40-1_0.txt"
 19: "rectangular_2x2_1-2-1_0.txt"
 20: "rectangular_4x4_1-16-1_0.txt"
 21: "rectangular_6x6_1-16-1_0.txt"
 22: "rectangular_6x6_1-24-1_0.txt"
 23: "rectangular_6x6_1-32-1_0.txt"
 24: "rectangular_7x7_1-32-1_0.txt"
 25: "rectangular_7x7_1-40-1_0.txt"
 26: "rectangular_7x7_1-48-1_0.txt"
 27: "rectangular_8x8_1-24-1_0.txt"
 28: "rectangular_8x8_1-32-1_0.txt"
 29: "rectangular_8x8_1-40-1_0.txt"
 30: "rectangular_8x9_1-24-1_0.txt"
 31: "rectangular_8x9_1-32-1_0.txt"
 32: "rectangular_8x9_1-40-1_0.txt"
 33: "rochester_53_10_0_pABC.txt"
 34: "rochester_53_12_0_pABC.txt"
 35: "rochester_53_16_0_pABC.txt"
 36: "rochester_53_20_0_pABC.txt"
 37: "rochester_53_4_0_pABC.txt"
 38: "rochester_53_8_0_pABC.txt"
 39: "sycamore_53_10_0.txt"
 40: "sycamore_53_12_0.txt"
 41: "sycamore_53_14_0.txt"
 42: "sycamore_53_16_0.txt"
 43: "sycamore_53_18_0.txt"
 44: "sycamore_53_20_0.txt"
 45: "sycamore_53_4_0.txt"
 46: "sycamore_53_5_0.txt"
 47: "sycamore_53_6_0.txt"
 48: "sycamore_53_8_0.txt"
 49: "test.txt"
]
```

```
1 # check available circuits
2 readdir(joinpath(@__DIR__, "data", "circuits"))
```

We load the circuit to Julia with Yao (幺), a high performance quantum simulator.

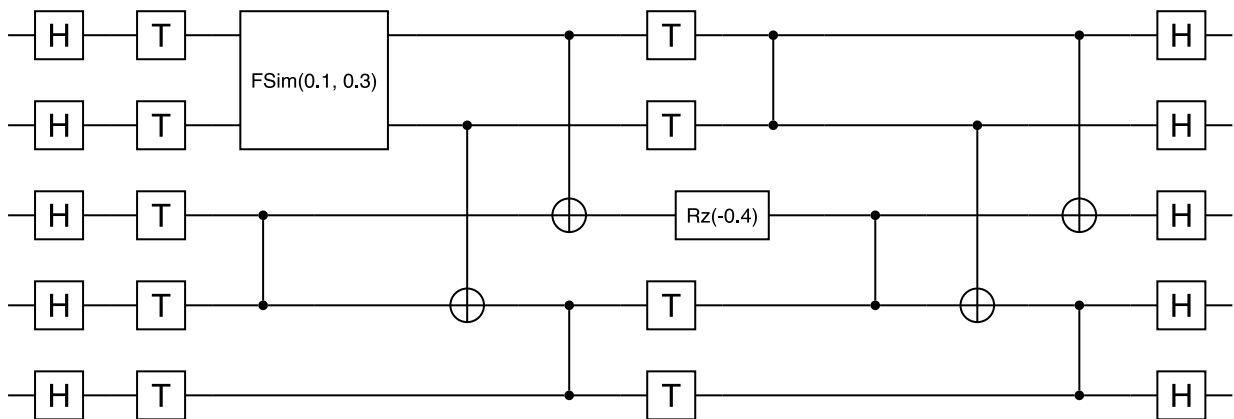
```
filename =
"/Users/liujinguo/jcode/tutorial-tensornetwork/examples/simulation/data/circuits/test.txt"

1 # Hint: please try replacing "test.txt" with "bristlecone_70-12-1_0.txt", a circuit
  with 70 qubits, 12 layers, see what happens
2 filename = joinpath(@__DIR__, "data", "circuits", "test.txt")
```

```
1 c = yaocircuit_from_file(filename); # circuit in Yao's data-format
```

$n = 5$

```
1 n = nqubits(c) # number of qubits
```



```
1 vizcircuit(c)
```

Step 2: construct tensor network

During the conversion, we also specify an optimizer to specify the contraction order.

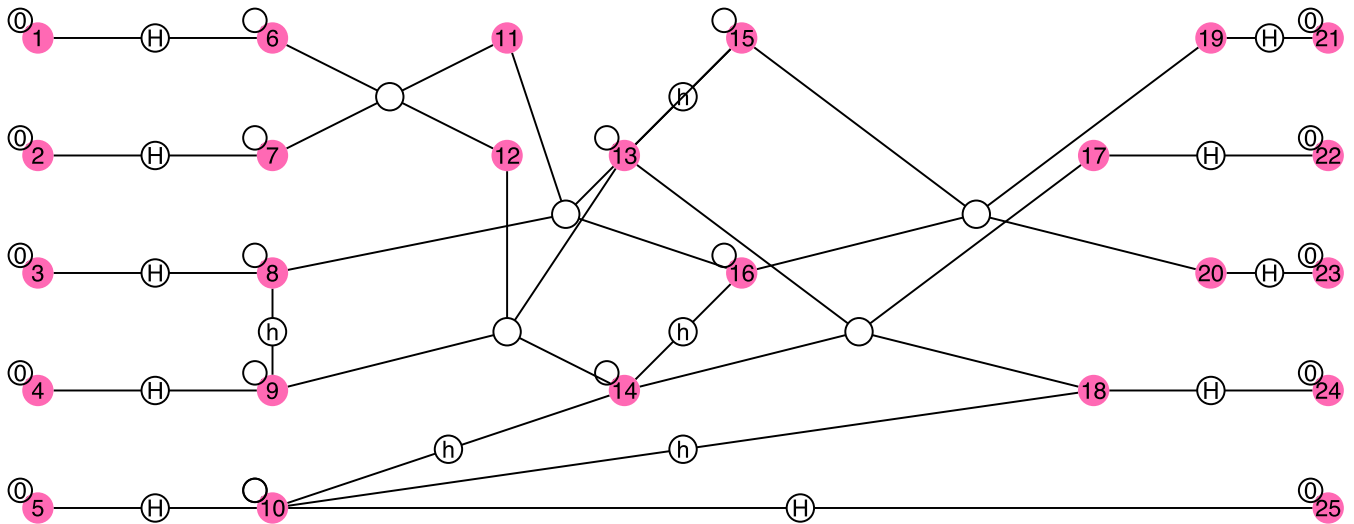
```
net = TensorNetwork
Time complexity:  $2^{8.507794640198696}$ 
Space complexity:  $2^{4.0}$ 
Read-write complexity:  $2^{9.38586240064146}$ 
```

```
1 net = yao2einsum(c;  
2     initial_state= Dict(zip(1:n, zeros(Int,n))),  
3     final_state = Dict(zip(1:n, zeros(Int,n))),  
4     optimizer = TreeSA(ntrials=1) # contraction order optimizer  
5 )
```

Time complexity: $2^{8.507794640198696}$
 Space complexity: $2^{4.0}$
 Read-write complexity: $2^{9.38586240064146}$

```
1 contraction_complexity(net)
```

```
1 using LuxorGraphPlot # Required by visualization extension
```

```

1 # red nodes are variables, transparent nodes are tensors
2 # h = [1 1; 1 -1] is the unnormalized version of Hadamard gate
3 # 0 tensor is defined as: [1, 0]
4 viznet(net; scale=60)

```

The space complexity is the number of elements in the largest intermediate tensor. For tensor network backend, it can be a much smaller number compared with the full amplitude simulation given the circuit is shallow enough. Learn more about contraction order optimizers:

<https://tensorbfs.github.io/OMEinsumContractionOrders.jl/dev/optimizers/>

Step 3: contract the tensor network

If your circuit has space complexity less than 28, the tensor network is probably contractable on your local device. Then please go ahead to check the following box.

contract_network = ☒

```
-0.044451061508327644 + 0.2223855135772236im
```

```
1 contract_network && Yao.contract(net)[ ]
```

The result should be consistent with the exact simulation.

exact_simulate = ☐

```
false
```

```
1 exact_simulate && apply(zero_state(n), c)' * zero_state(n)
```

Example 3: Construct tensor network for computing observables (channel simulation)

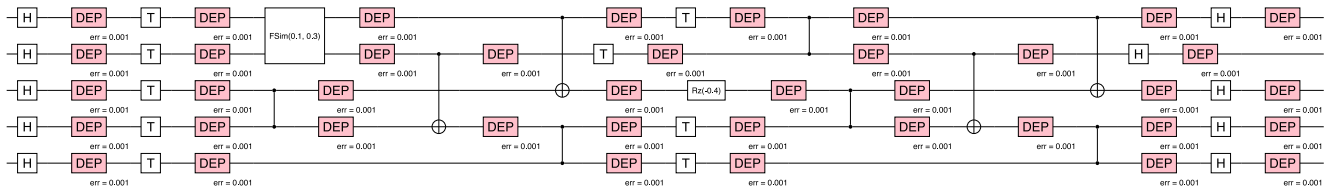
In this example, we show how to compute $\langle \psi | X_1 X_2 | \psi \rangle$ through quantum channel simulation, where $|\psi\rangle = U|0\rangle$, where U is the quantum circuit with interest. During the conversion, we also specify an optimizer to specify the contraction order.

add_depolarizing_noise (generic function with 1 method)

```
1 # add depolarizing noise
2 function add_depolarizing_noise(c::AbstractBlock, depolarizing)
3     Optimise.replace_block(c) do blk
4         if blk isa PutBlock || blk isa ControlBlock
5             rep = chain(blk)
6             for loc in occupied_locs(blk)
7                 push!(rep, put(nqubits(blk), loc=>DepolarizingChannel(1,
8 depolarizing)))
9             end
10            return rep
11        else
12            return blk
13        end
14    end
```

Hint: please change the noise probability see how the result change with it.

```
1 noisy_c = add_depolarizing_noise(c, 0.001);
```



```
1 vizcircuit(noisy_c)
```

```
observable = nqubits: 5
              kron
              └ =>Z
                =>Z
```

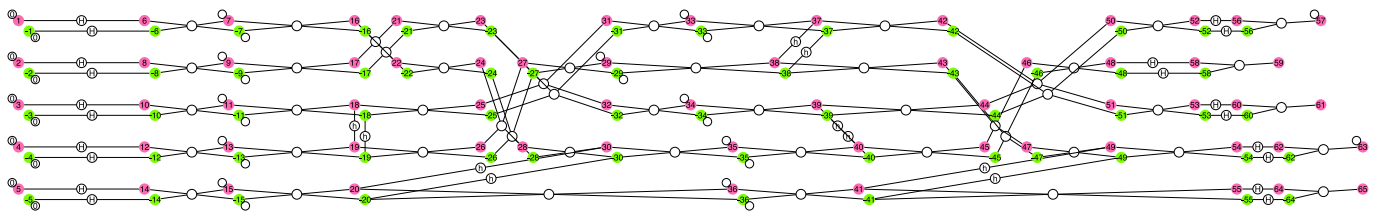
```
1 observable = kron(n, 1=>Z, 4=>Z)
```

```
noisy_net = TensorNetwork
Time complexity: 2^13.023407843140218
Space complexity: 2^8.0
Read-write complexity: 2^12.588011853215086
```

```
1 noisy_net = yao2einsum(noisy_c;
2     initial_state=Dict(zip(1:n, zeros(Int,n))),
3     observable,
4     optimizer = TreeSA(ntrials=1),
5     mode=DensityMatrixMode())
```

```
Time complexity: 2^13.023407843140218
Space complexity: 2^8.0
Read-write complexity: 2^12.588011853215086
```

```
1 contraction_complexity(noisy_net)
```



```
1 # the green dots are dual variables
2 viznet(noisy_net; scale=60)
```

contract_noisy = ☒

0-dimensional Array{ComplexF64, 0}:
0.4464601777319247 + 4.163336342344336e-17im

```
1 contract_noisy && Yao.contract(noisy_net)
```

exact_noisy = ☒

0.446460177731925

```
1 exact_noisy && expect(observable, apply(density_matrix(zero_state(n)), noisy_c))
```

References

- **(qflex datasets)** B. Villalonga, et al., "A flexible high-performance simulator for verifying and benchmarking quantum circuits implemented on real hardware", NPJ Quantum Information 5, 86 (2019)
- **(Efficient simulation of noisy circuits)** Gao, Xun, and Luming Duan. "Efficient classical simulation of noisy quantum computation." arXiv preprint arXiv:1810.03176 (2018).
- **Tutorial page of YaoToEinsum:** <https://docs.yaoquantum.org/dev/man/yaozeinsum.html>

