A New Belief

Random Matrix Theory Applied to Deep Belief Signaling Networks

![$I(ABB_{openAIGYM}(GAN; NAS; ME; MLE; AI))$

$Inference = Belief(I(ABB_{openAIGYM}(GAN; NAS; ME; MLE; AI)))$

$Z \rightarrow Inference $

Then, to learn on the inference:

$min_{T}{\sum_{i} \sum_{j} T_{ij} Z_{ij}}$

$\sum_{i} \sum_{j} T_{ij}Z_{ij} + \dfrac{a}{2} ||T||^{2}{F} + |dfrac{a}{2} ||T||^{2}{2}s.t. ||T|| = n$](https://render.githubusercontent.com/render/math?math=%5Cdisplaystyle+%24I%28ABB_%7BopenAIGYM%7D%28GAN%3B+NAS%3B+ME%3B+MLE%3B+AI%29%29%24%0A%0A%24Inference+%3D+Belief%28I%28ABB_%7BopenAIGYM%7D%28GAN%3B+NAS%3B+ME%3B+MLE%3B+AI%29%29%29%24%0A%0A%24Z+%5Crightarrow+Inference+%24%0A%0AThen%2C+to+learn+on+the+inference%3A%0A%0A%24min_%7BT%7D%7B%5Csum_%7Bi%7D+%5Csum_%7Bj%7D+T_%7Bij%7D+Z_%7Bij%7D%7D%24%0A%0A%24%5Csum_%7Bi%7D+%5Csum_%7Bj%7D+T_%7Bij%7DZ_%7Bij%7D+%2B+%5Cdfrac%7Ba%7D%7B2%7D+%7C%7CT%7C%7C%5E%7B2%7D_%7BF%7D+%2B+%5Cdfrac%7Ba%7D%7B2%7D+%7C%7CT%7C%7C%5E%7B2%7D_%7B2%7Ds.t.+%7C%7CT%7C%7C+%3D+n%24)

<img src= "https://render.githubusercontent.com/render/math?math=%5Cdisplaystyle+%24I%28ABB_%7BopenAIGYM%7D%28GAN%3B+NAS%3B+ME%3B+MLE%3B+AI%29%29%24%0A%0A%24Inference+%3D+Belief%28I%28ABB_%7BopenAIGYM%7D%28GAN%3B+NAS%3B+ME%3B+MLE%3B+AI%29%29%29%24%0A%0A%24Z+%5Crightarrow+Inference+%24%0A%0AThen%2C+to+learn+on+the+inference%3A%0A%0A%24min_%7BT%7D%7B%5Csum_%7Bi%7D+%5Csum_%7Bj%7D+T_%7Bij%7D+Z_%7Bij%7D%7D%24%0A%0A%24%5Csum_%7Bi%7D+%5Csum_%7Bj%7D+T_%7Bij%7DZ_%7Bij%7D+%2B+%5Cdfrac%7Ba%7D%7B2%7D+%7C%7CT%7C%7C%5E%7B2%7D_%7BF%7D+%2B+%5Cdfrac%7Ba%7D%7B2%7D+%7C%7CT%7C%7C%5E%7B2%7D_%7B2%7Ds.t.+%7C%7CT%7C%7C+%3D+n%24" alt="$I(ABB_{openAIGYM}(GAN; NAS; ME; MLE; AI))$

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Then, to learn on the inference:

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subject to W being a valid weighted adjacency matrix (non-negative, symmetric, with zero diagonal). In python, we can express this computation:

```
# Run inference on information shared between random populations of...
```

```
belief_prop = bp.random(population, enviornments, neural_architectures:
neural_ode, gan, cnn, rnn; depth: multi, ...)

# Analyze intersection of neural architectures and enviornments (graph
signal processing)
GSP.engine(analysis(union for belief_prop), algo_seq: [forward, backward,
forward])
```

`GSP.engine` can be further optimized through quantum topological search:

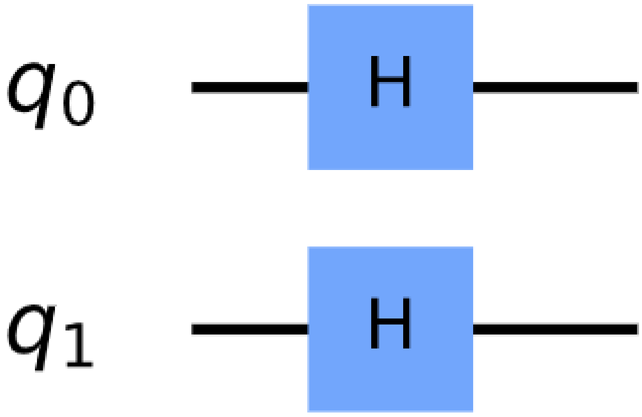
```
# Initialization
import matplotlib.pyplot as plt
import numpy as np

# Importing Qiskit
from qiskit import IBMQ, Aer, QuantumCircuit, ClassicalRegister,
QuantumRegister, execute
from qiskit.providers.ibmq import least_busy
from qiskit.quantum_info import Statevector

# Import basic plot tools
from qiskit.visualization import plot_histogram

# Initialize quantum components
n = 2 # qubits
grover_circuit = QuantumCircuit(n)
grover_circuit = initialize_s(grover_circuit, [0,1])
grover_circuit.draw()

def initialize_s(qc, qubits):
    """Apply a H-gate to 'qubits' in qc"""
    for q in qubits:
        qc.h(q)
    return qc
```



. . . . And so on

See references for quantum computing, graph signal processing, and belief propagation: 📖