Status of Grid Python Toolkit (GPT)

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https://github.com/lehner/gpt

July 31st, 2023 - Lattice 2023

Grid **P**ython **T**oolkit (GPT)

https://github.com/lehner/gpt

- A toolkit for lattice QCD and related theories as well as QIS (a parallel digital quantum computing simulator) and Machine Learning
- Python frontend, C++ backend
- Built on Grid data parallelism (MPI, OpenMP, SIMD, and SIMT)

Initial commit Feb. 2020, 65k lines of C++/Python, >1700 commits so far, 13 contributors

Code co-authors:

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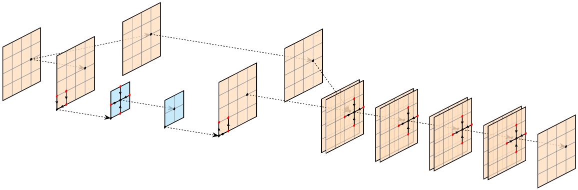
What's new since lattice 2022?

What is new since 2022 (1/3):

- New Machine Learning features such as
  - Adam optimizer
  - gauge-equivariant (local) parallel-transport layers
  - gauge-equivariant (un)pooling layers
  - classical multi-grid blocking layers

  motivated by multi-grid gauge-equivariant models such as arXiv:2304.10438, arXiv:2302.05419 (to appear in PRD)



see also Tilo's talk today at 5pm in Algorithms session.

What is new since 2022 (2/3):

- Efficient general stencil and parallel transport:

```
In [4]: U = g.qcd.gauge.random(grid, rng)
```

```
In [5]: code = []
        for mu in range(4):
            for nu in range(mu):
                code.append((0, -1 if code == [] else 0, 1.0, g.path().f(mu).f(nu).b(mu).b(nu)))
        plaq = g.parallel_transport_matrix(U, code, 1)
```

```
In [6]: print(g.sum(g.trace(plaq(U))).real * 2 / grid.gsites / (3 * 3 * 4))
        print(g.qcd.gauge.plaquette(U))

0.7961959248563635
0.7961959248563635
```

- Twisted Mass Fermions + DSDR term
- Quadruple precision global reduction support via Dekker tuples:

```
grid = g.grid([4,4,4,4], g.double)
```

$$\Rightarrow$$

```
grid = g.grid([4,4,4,4], g.double_quadruple)
```

What is new since 2022 (3/3):

- Performance on LUMI-G and Frontier (1 node):

```
============================================
            Initialized GPT
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============================================
GPT :       6.073338 s :
                       : DWF Dslash Benchmark with
                       :     fdimensions  : [64, 32, 32, 32]
                       :     precision    : single
                       :     Ls           : 12
                       :
GPT :      16.216618 s : 1000 applications of Dhop
                       :     Time to complete            : 3.72 s
                       :     Total performance           : 8926.87 GFlops/s
                       :     Effective memory bandwidth  : 6167.65 GB/s
GPT :      16.217514 s :
                       : DWF Dslash Benchmark with
                       :     fdimensions  : [64, 32, 32, 32]
                       :     precision    : double
                       :     Ls           : 12
                       :
GPT :      27.783497 s : 1000 applications of Dhop
                       :     Time to complete            : 8.45 s
                       :     Total performance           : 3929.23 GFlops/s
                       :     Effective memory bandwidth  : 5429.48 GB/s
============================================
             Finalized GPT
============================================
```

15 TF/s/node possible without inter-GCD communication.
5 TF/s/node in strong scaling up to 64 nodes for $64^3 \times 256$ problem size!

Overview 2020 – 2023

Guiding principles:

- Performance Portability
  common Grid-based framework for current and future (exascale) architectures

- Modularity / Composability
  build up from modular high-performance components, several layers of composability, "composition over parametrization"

Layout and dependencies

Python script / Jupyter notebook

gpt (Python)

- Defines data types and objects (group structures etc.)
- Expression engine (linear algebra)
- Algorithms (Solver, Eigensystem, ...)
- File formats
- Stencils / global data transfers
- QCD, QIS, ML subsystems

cgpt (Python library written in C++)

- Global data transfer system (gpt creates pattern, cgpt optimizes data movement plan)
- Virtual lattices (tensors built from multiple Grid tensors)
- Optimized blocking, linear algebra, and Dirac operators
- Vectorized ranlux-like pRNG (parallel seed through 3xSHA256)

Grid	Eigen	FFTW

The QCD module

Example: Load QCD gauge configuration and test unitarity

```
In [1]: import gpt as g

        U = g.load("ckpoint_lat.IEEE64BIG.1100")

        for mu in range(4):
            g.message("SU3 - Defect: ", g.norm2(U[mu] * g.adj(U[mu]) - g.identity(U[mu])))

        GPT :       1.039211 s : SU3 - Defect:  3.345168726568745e-26
        GPT :       1.094156 s : SU3 - Defect:  3.3476154954606903e-26
        GPT :       1.146703 s : SU3 - Defect:  3.342180010368529e-26
        GPT :       1.199097 s : SU3 - Defect:  3.3423193715873574e-26
```

Here: expression first parsed to a tree in Python (gpt), forwarded as abstract expression to C++ library (cgpt) for evaluation

Example: create a pion propagator on a random gauge field

```
# double-precision 8^4 grid
grid = g.grid([8,8,8,8], g.double)

# pRNG
rng = g.random("seed text")

# random gauge field
U = g.qcd.gauge.random(grid, rng)

# Mobius domain-wall fermion
fermion = g.qcd.fermion.mobius(U, mass=0.1, M5=1.8, b=1.0, c=0.0, Ls=24,
                               boundary_phases=[1,1,1,-1])

# Short-cuts
inv = g.algorithms.inverter
pc = g.qcd.fermion.preconditioner

# even-odd-preconditioned CG solver
slv_5d = inv.preconditioned(pc.eo2_ne(), inv.cg(eps = 1e-4, maxiter = 1000))

# Abstract fermion propagator using this solver
fermion_propagator = fermion.propagator(slv_5d)

# Create point source
src = g.mspincolor(U[0].grid)
g.create.point(src, [0, 0, 0, 0])

# Solve propagator on 12 spin-color components
prop = g( fermion_propagator * src )

# Pion correlator
g.message(g.slice(g.trace(prop * g.adj(prop)), 3))
```

Example: solvers are modular and can be mixed

General design principle: use modularity of python code instead of large number of parameters to configure solvers/algorithms;
Python can also be used in configuration files

```python
# Create an coarse-grid deflated, even-odd preconditioned CG inverter
# (eig is a previously loaded multi-grid eigensystem)
sloppy_light_inverter = g.algorithms.inverter.preconditioned(
    g.qcd.fermion.preconditioner.eo1_ne(parity=g.odd),
    g.algorithms.inverter.sequence(
        g.algorithms.inverter.coarse_deflate(
            eig[1],
            eig[0],
            eig[2],
            block=200,
        ),
        g.algorithms.inverter.split(
            g.algorithms.inverter.cg({"eps": 1e-8, "maxiter": 200}),
            mpi_split=[1,1,1,1],
        ),
    ),
)
```

Further example: Multi-Grid solver

```
def find_near_null_vectors(w, cgrid):
    slv = i.fgmres(eps=1e-3, maxiter=50, restartlen=25, checkres=False)(w)
    basis = g.orthonormalize(
        rng.cnormal([g.lattice(w.grid[0], w.otype[0]) for i in range(30)])
    )
    null = g.lattice(basis[0])
    null[:] = 0
    for b in basis:
        slv(b, null)
    g.qcd.fermion.coarse.split_chiral(basis)
    bm = g.block.map(cgrid, basis)
    bm.orthonormalize()
    bm.check_orthogonality()
    return basis

mg_setup_3lvl = i.multi_grid_setup(
    block_size=[[2, 2, 2, 2], [2, 1, 1, 1]], projector=find_near_null_vectors
)

wrapper_solver = i.fgmres(
    {"eps": 1e-1, "maxiter": 10, "restartlen": 5, "checkres": False}
)
smooth_solver = i.fgmres(
    {"eps": 1e-14, "maxiter": 8, "restartlen": 4, "checkres": False}
)
coarsest_solver = i.fgmres(
    {"eps": 5e-2, "maxiter": 50, "restartlen": 25, "checkres": False}
)

mg_3lvl_kcycle = i.sequence(
     i.coarse_grid(
         wrapper_solver.modified(
             prec=i.sequence(
                 i.coarse_grid(coarsest_solver, *mg_setup_3lvl[1]), smooth_solver
             )
         ),
         *mg_setup_3lvl[0],
     ),
     smooth_solver,
)
```

All algorithms implemented in Python – Example: Euler-Langevin stochastig DGL integrator

```python

class langevin_euler:
    @g.params_convention(epsilon=0.01)
    def __init__(self, rng, params):
        self.rng = rng
        self.eps = params["epsilon"]

    def __call__(self, fields, action):
        gr = action.gradient(fields, fields)
        for d, f in zip(gr, fields):
            f @= g.group.compose(
                -d * self.eps
                + self.rng.normal_element(g.lattice(d)) * (self.eps * 2.0) ** 0.5,
                f,
            )

```

Implemented algorithms:

- BiCGSTAB, CG, CAGCR, FGCR, FGMRES, MR solvers
- Multi-grid, split-grid, mixed-precision, and defect-correcting solver combinations
- Coarse and fine-grid deflation
- Implicitly restarted Arnoldi and Lanczos, power iteration
- Chebyshev polynomials
- All-to-all vector generation
- SAP and even-odd preconditioners
- MSPCG (additive Schwarz)
- Gradient descent, non-linear CG, Adam optimizers
- Runge-Kutta integrators, Wilson flow
- Fourier acceleration
- Coulomb and Landau gauge fixing
- Domain-wall–overlap transformation and MADWF
- Symplectic integrators (leapfrog, OMF2, and OMF4)
- Markov: Metropolis, heatbath, Langevin, (DD-)HMC

Implemented fermion actions:

- Domain-wall fermions: Mobius and zMobius
- Twisted-mass fermions
- Wilson-clover fermions both isotropic and anisotropic (RHQ/Fermilab actions); Open boundary conditions available

Example: stout-smeared heavy-quark Mobius DWF

```
# load configuration
U = g.load(config)
grid = U[0].grid

# smeared gauge link
U_stout = U
for n in range(3):
    U_stout = g.qcd.gauge.smear.stout(U_stout, rho=0.1)

fermion_exact = g.qcd.fermion.mobius(U_stout,{
    "mass": 0.6,
    "M5": 1.0,
    "b": 1.5,
    "c": 0.5,
    "Ls": 12,
    "boundary_phases": [1.0, 1.0, 1.0, -1.0],
})
```

Performance

Benchmark results committed to github

`https://github.com/lehner/gpt/tree/master/benchmarks/reference`

master · gpt / benchmarks / reference /

lehner supermuc-ng timing ...	on Apr 1 · History
..	
bnl_knl	8 months ago
juron	8 months ago
juwels_booster	2 months ago
lrz_supermuc_ng	last month
qpace3	8 months ago
qpace4	4 months ago
stampede2_knl	6 months ago
summit	8 months ago

Rank	System	Cores	Rmax (PFlop/s)	Rpeak (PFlop/s)	Power (kW)
1	**Frontier** - HPE Cray EX235a, AMD Optimized 3rd Generation EPYC 64C 2GHz, AMD Instinct MI250X, Slingshot-11, HPE DOE/SC/Oak Ridge National Laboratory United States	8,699,904	1,194.00	1,679.82	22,703
2	**Supercomputer Fugaku** - Supercomputer Fugaku, A64FX 48C 2.2GHz, Tofu interconnect D, Fujitsu RIKEN Center for Computational Science Japan	7,630,848	442.01	537.21	29,899
3	**LUMI** - HPE Cray EX235a, AMD Optimized 3rd Generation EPYC 64C 2GHz, AMD Instinct MI250X, Slingshot-11, HPE EuroHPC/CSC Finland	2,220,288	309.10	428.70	6,016
4	**Leonardo** - BullSequana XH2000, Xeon Platinum 8358 32C 2.6GHz, NVIDIA A100 SXM4 64 GB, Quad-rail NVIDIA HDR100 Infiniband, Atos EuroHPC/CINECA Italy	1,824,768	238.70	304.47	7,404
5	**Summit** - IBM Power System AC922, IBM POWER9 22C 3.07GHz, NVIDIA Volta GV100, Dual-rail Mellanox EDR Infiniband, IBM DOE/SC/Oak Ridge National Laboratory United States	2,414,592	148.60	200.79	10,096

Results available for GPU and CPU architectures. In the following, focus on Frontier/LUMI-G (AMD MI250X), Juwels/Leonardo booster (NVIDIA A100) and Fugaku/QPace4 (A64FX).

Juwels Booster (node has 4$\times$ A100-40GB): Single-node domain-wall fermion $\not{D}$ operator

```
=============================================
              Initialized GPT
     Copyright (C) 2020 Christoph Lehner
=============================================
GPT :       1.543473 s :
                       : DWF Dslash Benchmark with
                       :     fdimensions  : [64, 32, 32, 32]
                       :     precision    : single
                       :     Ls           : 12
                       :
GPT :       7.958636 s : 1000 applications of Dhop
                       :     Time to complete            : 2.93 s
                       :     Total performance           : 11325.46 GFlops/s
                       :     Effective memory bandwidth  : 7824.86 GB/s
GPT :       7.959499 s :
                       : DWF Dslash Benchmark with
                       :     fdimensions  : [64, 32, 32, 32]
                       :     precision    : double
                       :     Ls           : 12
                       :
GPT :      17.420620 s : 1000 applications of Dhop
                       :     Time to complete            : 5.78 s
                       :     Total performance           : 5749.77 GFlops/s
                       :     Effective memory bandwidth  : 7945.14 GB/s
=============================================
               Finalized GPT
=============================================
```

Compare to HBM bandwidth of 1,555 GB/s per GPU

QPace4 (node has one A64FX): Single-node domain-wall fermion $\not{D}$ operator

```
=============================================
              Initialized GPT
    Copyright (C) 2020 Christoph Lehner
=============================================
GPT :       0.265714 s :
                       : DWF Dslash Benchmark with
                       :     fdimensions  : [24, 24, 24, 24]
                       :     precision    : single
                       :     Ls           : 8
                       :
GPT :      20.218240 s : 1000 applications of Dhop
                       :     Time to complete            : 3.67 s
                       :     Total performance           : 954.90 GFlops/s
                       :     Effective memory bandwidth  : 677.11 GB/s
GPT :      20.218842 s :
                       : DWF Dslash Benchmark with
                       :     fdimensions  : [24, 24, 24, 24]
                       :     precision    : double
                       :     Ls           : 8
                       :
GPT :      45.245379 s : 1000 applications of Dhop
                       :     Time to complete            : 7.36 s
                       :     Total performance           : 475.80 GFlops/s
                       :     Effective memory bandwidth  : 674.77 GB/s
=============================================
               Finalized GPT
=============================================
```

Compare to HBM bandwidth of 1,000 GB/s per A64FX

Juwels Booster (node has 4× A100-40GB): Single-node site-local matrix products

```
============================================
            Initialized GPT
     Copyright (C) 2020 Christoph Lehner
============================================
GPT :       1.589357 s :
                       : Matrix Multiply Benchmark with
                       :     fdimensions  : [48, 48, 48, 128]
                       :     precision    : single
                       :
GPT :      10.985099 s : 10 matrix_multiply
                       :     Object type                 : ot_matrix_color(3)
                       :     Time to complete            : 0.0058 s
                       :     Effective memory bandwidth  : 5271.36 GB/s
                       :
GPT :      16.689329 s : 10 matrix_multiply
                       :     Object type                 : ot_matrix_spin(4)
                       :     Time to complete            : 0.01 s
                       :     Effective memory bandwidth  : 5333.21 GB/s
                       :
GPT :      62.092583 s : 10 matrix_multiply
                       :     Object type                 : ot_matrix_spin_color(4,3)
                       :     Time to complete            : 0.097 s
                       :     Effective memory bandwidth  : 5057.37 GB/s
                       :
```

```
GPT :      62.262581 s :
                       : Matrix Multiply Benchmark with
                       :     fdimensions  : [48, 48, 48, 128]
                       :     precision    : double
                       :
GPT :      72.003471 s : 10 matrix_multiply
                       :     Object type                 : ot_matrix_color(3)
                       :     Time to complete            : 0.012 s
                       :     Effective memory bandwidth  : 5264.01 GB/s
                       :
GPT :      78.174681 s : 10 matrix_multiply
                       :     Object type                 : ot_matrix_spin(4)
                       :     Time to complete            : 0.02 s
                       :     Effective memory bandwidth  : 5439.91 GB/s
                       :
GPT :     128.232979 s : 10 matrix_multiply
                       :     Object type                 : ot_matrix_spin_color(4,3)
                       :     Time to complete            : 0.22 s
                       :     Effective memory bandwidth  : 4416.45 GB/s
                       :
============================================
              Finalized GPT
============================================
```

Compare to HBM bandwidth of 1,555 GB/s per GPU

Juwels Booster (node has 4$\times$ A100-40GB): Inner product (reduction)

```
GPT :      28.406798 s : 100 rank_inner_product
                       :     Object type               : ot_vector_singlet(12)
                       :     Block                     : 4 x 4
                       :     Data resides in           : accelerator
                       :     Performed on              : accelerator
                       :     Time to complete          : 0.13 s
                       :     Effective memory bandwidth  : 4827.16 GB/s
                       :
                       :     rip: timing: unprofiled          = 0.000000e+00 s (=   0.00 %)
                       : rip: timing: rip: view           = 9.706020e-04 s (=   0.70 %)
                       : rip: timing: rip: loop           = 1.369879e-01 s (=  99.30 %)
                       : rip: timing: total               = 1.379585e-01 s (= 100.00 %)
                       :
```

Compare to HBM bandwidth of 1,555 GB/s per GPU

Performance summary

Machine	Operation	Performance	Bandwidth
Frontier	$\not{D}$	9 TF/s	6.2 TB/s
Booster	$\not{D}$	12 TF/s	7.8 TB/s
Booster	ColorMatrix $\times$		5.2 TB/s
Booster	SpinColorMatrix $\times$		5.1 TB/s
Booster	SpinColorVector $\langle \cdot, \cdot \rangle$		4.8 TB/s
QPace4	$\not{D}$	0.95 TF/s	0.68 TB/s
SuperMUC-NG	$\not{D}$	0.72 TF/s	0.51 TB/s

Single-node SP performance of Wilson $\not{D}$ and linear algebra on Juwels Booster (4×A100, HBM BW 1.6 TB/s per A100), Qpace4 (A64FX, HBM BW of 1 TB/s per node), and the SuperMUC-NG (Skylake 8174). The $\not{D}$ performance is inherited from Grid, the linear algebra performance is based on cgpt.

Example applications

RBC ensemble generation

(the generating GPT scripts are linked below; around 200 lines of Python script each)

ID	a^{-1}/GeV	N_f	$L^3 \times T \times L_s$	$b+c$	$m_{\rm res} \times 10^4$	m_π/MeV	m_K/MeV	m_{D_s}/GeV	$m_\pi L$	Code
48I	1.73	2+1	$48^3 \times 96 \times 24$	2	6.1	139	499	–	3.87	CPS
64I	2.35	2+1	$64^3 \times 128 \times 12$	2	3.1	139	507	–	3.77	CPS
96I	2.69	2+1	$96^3 \times 192 \times 12$	2	2.3	132	486	–	4.70	CPS
1	1.73	2+1	$32^3 \times 64 \times 24$	2	6.3	208	513	–	3.85	GPT script
2	1.73	2+1	$24^3 \times 48 \times 32$	2	4.6	284	534	–	3.96	GPT script
3	1.73	2+1	$32^3 \times 64 \times 24$	2	6.5	210	597	–	3.88	GPT script
4	1.74	2+1	$24^3 \times 48 \times 24$	2	6.2	279	534	–	3.84	GPT script
5	1.75	2+1+1	$24^3 \times 48 \times 24$	2	6.7	280	536	1.99	3.84	GPT script
6	1.75	2+1+1	$24^3 \times 48 \times 24$	2	6.7	280	536	1.5	3.84	GPT script
7	1.76	2+1+1	$24^3 \times 48 \times 24$	2	7.9	284	540	1.39	3.88	GPT script
8	2.37	2+1+1	$32^3 \times 64 \times 12$	2	3.0	280	536	1.99	3.88	GPT script
9	2.37	2+1	$32^3 \times 64 \times 12$	2	3.0	281	535	–	3.80	GPT script
A	1.76	2+1	$24^3 \times 48 \times 8$	2	41.5	303	548	–	4.15	GPT script
B	1.73	2+1	$32^3 \times 64 \times 24$	2	6.1	139	499	–	2.58	GPT script
C	1.73	2+1	$64^3 \times 128 \times 24$	2	6.1	139	499	–	5.16	GPT script
D	1.74	2+1	$32^3 \times 64 \times 24$	2	6.2	279	534	–	5.12	GPT script
E	3.50	2+1	$48^3 \times 192 \times 12$, openBC	2	1.4	280	535	–	3.87	GPT script

Further examples

- QED corrections to g-2 HVP and tau decays of RBC/UKQCD
- Ensemble parameters and g-2 HVP (Tuesday talk C.L.)
- g-2 HLbL project of RBC/UKQCD (combined with QLattice)
- Scattering studies in scalar field theory (Bruno et al.)
- Testing stochastic locality with CP(n) models (Bruno, Morandi)

Also applied by BNL and Bielefeld groups for ongoing projects.

Teaching

LGT lecture based on interactive GPT notebooks

(link to lecture)

Chapters:

- Chapter 1: path integral formulation of quantum mechanics (Jupyter Notebook, PDF)
- Chapter 2: Markov Chain Monte Carlo (MCMC) methods (Jupyter Notebook, PDF, last update 09.11. 10:14)
- Chapter 3: statistics of continous variables (Jupyter Notebook, PDF, last update 07.11. 21:00)
- Chapter 4: scalar field theory on a lattice (Jupyter Notebook, PDF, last update 02.12. 10:45)
- Chapter 5: symmetries of fundamental field theories (Jupyter Notebook, PDF, last update 21.11. 18:30)
- Chapter 6: gauge theories on a lattice (Jupyter Notebook, PDF, last update 28.11. 16:30)
- Chapter 7: static quark potential and spectrum of pure QCD (Jupyter Notebook, PDF, last update 03.12. 10:11)
- Chapter 8: strong coupling expansion (Jupyter Notebook, PDF, last update 05.12. 21:11)
- Chapter 9: continuum limit and phase transitions (Jupyter Notebook, PDF, last update 13.12. 10:14)
- Chapter 10: fermions on a lattice (Jupyter Notebook, PDF, last update 19.12. 18:04)
- Chapter 11: symmetries of the Wilson action (Jupyter Notebook, PDF, last update 10.01. 09:35)
- Chapter 12: chiral symmetry on a lattice (Jupyter Notebook, PDF, last update 24.01. 10:00)
- Chapter 13: Hybrid Monte Carlo (HMC) (Jupyter Notebook, PDF, last update 28.01. 09:46)
- Chapter 14: Hadron spectroscopy (Jupyter Notebook, PDF, last update 04.02. 09:56)

The machine learning module

Example: train simple feed-forward network

```
In [ ]: import gpt as g
        grid = g.grid([4, 4, 4], g.double)
        rng = g.random("test")

        # network and training data
        n = g.ml.network.feed_forward([g.ml.layer.nearest_neighbor(grid)] * 2)
        training_input = [rng.uniform_real(g.complex(grid)) for i in range(2)]
        training_output = [rng.uniform_real(g.complex(grid)) for i in range(2)]

        # cost functional
        c = n.cost(training_input, training_output)

        # train network
        W = n.random_weights(rng)
        gd = g.algorithms.optimize.gradient_descent
        gd(maxiter=4000, eps=1e-4, step=0.2)(c)(W, W)
```

The quantum computing module

Example: create and measure a 5-qubit bell state

```python
import gpt as g
from gpt.qis.gate import *

rng = g.random("qis_test")

# initial state with 5 qubits, stored in double-precision
st = g.qis.backends.dynamic.state(rng, 5, precision=g.double)

g.message("Initial state:\n",st)

# prepare Bell-type state
st = (H(0) | CNOT(0,1) | CNOT(0,2) | CNOT(0,3) | CNOT(0,4)) * st

g.message("Bell-type state:\n",st)

# measure
st = M() * st

g.message("After single measurement:\n",st)
g.message("Classically measured bits:\n",st.classical_bit)
```

```
GPT :     197.943668 s : Initial state:
                       :   + (1+0j) |00000>
GPT :     197.949198 s : Bell-type state:
                       :   + (0.7071067811865475+0j) |00000>
                       :  + (0.7071067811865475+0j) |11111>
GPT :     197.951478 s : After single measurement:
                       :   + (1+0j) |11111>
GPT :     197.952545 s : Classically measured bits:
                       :  [1, 1, 1, 1, 1]
```

How to use GPT?

https://github.com/lehner/gpt

Quick Start

The fastest way to try GPT is to install Docker, start a Jupyter notebook server with the latest GPT version by running

```
docker run --rm -p 8888:8888 gptdev/notebook
```

and then open the shown link http://127.0.0.1:8888/?token=<token> in a browser. You should see the tutorials folder pre-installed.

The docker images are automatically generated for each version that passes the CI interface.

CI currently has test coverage of 96%, running on each pushed commit.

Thank you