

Restricted Boltzman Machine Variational parametrisation of the time-evolution operator of periodically driven systems

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Here we explore the use of a Restricted Boltzman Machine to parametrise the Floquet states of harmonically driven qubit. The required complexity of the RBM with the number of Floquet manifolds. Solution of the Floquet spectrum converges from an approximated solution the Rotating Wave Approximation at. The training of the RBM presents all the standar challenges of slow convergency. Combination of loss functions .

Keywords: Floquet, Quantum dynamics, Dressed states, Restricted Boltzman Machine, Machine Learning, Periodic driving, qubit

I. INTRODUCTION

out-of-equilibrium states driven by harmonic forces, transformation of states in . Dynamical decoupling with periodic drivings (several harmonics as in the quantum computing talk I saw), or multiqubit gates by multiple harmonic forces, to floque topological insulators and frequency/time-domain quantum simulations.

The time-evolution operator is key, either to define the time-evolution or for definition of effective Hamiltonians. both of them can be written in terms of the Floquet states. Floquet states perturbation theory, RWA, Bloch-siegart, ... expansion.... All this approximation and general solution are important to understand, for example.

ML representation of quantum states has been recently very active, showing ... and compatibility with on-line learning and experimental realisation, in particular for the control of quantum states in quantum computing architectures control with floquet.... The reduction of the parameters required, reflection on the ... of the physically accessible states of the Hilbert space, corresponding to very restricted subsets, which can be described effectively in none such as MPS, tensor Networks.. Such a relationship between ML and ... is currently an active area of research ..

Harmonically driven systems can be in the frequency space has the as a Hubbard model [?], and such that time-dependent problem can be evaluated using tools of static systems [], which has not been explored sufficiently. Here I study the parametrisation of the Floquet operator using a RBM for the archetypical case of a driven qubit. The RBM is overkill in this case, with other straight numerical diagonalisation of the Floquet Hamiltonian, however it allows to explore the capabilities of, which can be then applied to other more complex systems where exact diagonalisation or cannot be implemented so directly.

The document is as follows. In Section ?? I present the representation of the time-evolution operator in terms of Floquet states. In section ??, presents the Restricted Boltzman Machine representation of the states and the loss functions to evaluate the Floquet spectrum. Section IV shows the representation of Floquet states using

FIG. 1. (a) Schematic energy level structure of a generic quantum system. The basis of states consist of a discrete set of energy states, which define several bands according to the level energy spacing. Inter and intra band coupling is induced by electromagnetic radiation tuned at the corresponding frequencies, as indicated by the coupling terms. The wide variety of physical systems described by this model includes (b) trapped ions [?], (c) superconducting qubits [?] and (d) diamond NV-centres [?].

the RBM. The central result is presented in section ??, where I discuss the evaluation of the Floquet spectrum (eigenvectors and eigenvalues) evaluated using an RBM parametrisation. Discussion of the applications are presented and conclusion are in section...

II. FLOQUET FORMALISM

The openMMF library is developed to calculate the time-evolution operator, $U(t', t)$, $t' > t$, of systems whose Hamiltonian has the form:

$$H = \sum_{i,j} E_{i,j} |i\rangle \langle j| + \sum_{i,j} \sum_{\ell=1}^D \sum_{n \in \mathbb{Z}} V_{i,j}^{\ell,n} e^{in\omega_{\ell}t} |i\rangle \langle j| + \text{h.c.} \quad (1)$$

where D is the dimension of the Hilbert space, $E_{i,j}$ defines the static component of the Hamiltonian H , $V_{i,j}^{\ell,n}$ is the coupling between the states i and j oscillating at frequency $n\omega_{\ell}$ (i.e. the n -th harmonic of the ℓ -th fundamental frequency ω_{ℓ}) and N is the number of incommensurate frequencies.

To calculate the time-evolution operator we generalise the Rotating (or Resonant) Wave Approximation (RWA), taking into account the complex time dependence of eq. (1). For this, we rephrase the problem in terms of building a time-dependent unitary transformation, $U_F(t)$ to a new basis $\{|\bar{i}\rangle\}$, that leads to a *time-independent* and diagonal Hamiltonian, \bar{H} . After applying the standard quantum-mechanical transformation rule to the Schrödinger equation [? ?], this condition

becomes:

$$U_F^\dagger(t) [H(t) - i\hbar\partial_t] U_F(t) = \sum_{\vec{i}} \bar{E}_{\vec{i}} |\vec{i}\rangle \langle \vec{i}| \quad (2)$$

Importantly, in the basis of states defined by this transformation the time evolution operator is diagonal and has the form:

$$\bar{U}(t', t) = \sum_{\vec{i}} e^{-i\bar{E}_{\vec{i}}(t'-t)} |\vec{i}\rangle \langle \vec{i}| \quad (3)$$

which let us to calculate the time evolution operator in the original basis $\{|i\rangle\}$, just by inverting the transformation $U_F(t)$, according to [?]:

$$U(t', t) = U_F(t') \bar{U}(t', t) U_F(t) \quad (4)$$

To formulate a fully defined computational problem, we express the micromotion operator $U_F(t)$ as the multifrequency Fourier series [?]:

$$U_F(t) = \sum_{\vec{n}} U_{i,\vec{i}}^{\vec{n}} e^{-i\vec{\omega} \cdot \vec{n}t} |i\rangle \langle \vec{i}| \quad (5)$$

where $\vec{\omega} = (\omega_1, \omega_2, \dots, \omega_N)$ and \vec{n} is a N -dimensional vector of integers. After plugging this expansion in eq. (2) and performing an integral over time, we obtain a fully defined eigenproblem for the eigenvalues $\bar{E}_{\vec{i}}$ and Fourier components of the unitary transformation $U_{i,\vec{i}}^{\vec{n}}$:

$$\sum_j (E_{i,j} - \hbar\vec{n} \cdot \vec{\omega}) U_{j,\vec{i}}^{\vec{n}} + \sum_j \sum_{\vec{m}} [V_{i,j}^{\vec{m}} U_{j,\vec{i}}^{\vec{n}+\vec{m}} + V_{ji}^{\vec{m}*} U_{j,\vec{i}}^{\vec{m}-\vec{n}}] = \bar{E}_{\vec{i}} U_{i,\vec{i}}^{\vec{n}} \quad (6)$$

where the couplings $V_{i,j}^{\ell,n}$ define $V_{i,j}^{\vec{n}}$ and the vector $\vec{n} = (0, \dots, m, \dots, 0)$ with the value m located at the ℓ -th position. To obtain a finite matrix representation of this problem we truncate the sum over the number of modes of the Fourier expansion eq. (5). Below, in Appendix A, we show an specific example of the shape of the matrix for a bichromatic driven problem.

This formulation to calculate the time-evolution operator is equivalent to the multimode Floquet representation of the Hamiltonian that introduces the extended Hilbert space $|E_i, \vec{n}\rangle$ [? ? ?]. However, the semiclassical description presented here makes emphasis in the experimentally accessible states, which usually are used to express the static part of the Hamiltonian eq. (1).

In this paper we consider the Hamiltonian of qubit system:

$$H = \hbar\omega_0 S_z + \hbar\Omega S_x \cos(\omega t + \phi) \quad (7)$$

In the regime of off-resonant + weak-to-strong driving. More precisely, my numerical results are obtained for the parameters $\omega = 1.7\omega_0$ and a Rabi frequency $\Omega \in 0, 10 \times \omega_0$. Figure presents the energy gap between the dressed states as a function of the Rabi frequency Ω and the eigen states of selected parameters.

The wavefunction has the symmetry: some symmetry

which is used to reduce the number of parameter below.

III. RBM PARAMETRISATION OF THE MICROMOTION OPERATOR

Any wavefunction of the form:

$$|\vec{i}\rangle = \sum_{j,n} u_{j,\vec{i}}^n e^{in\omega t} |j\rangle \quad (8)$$

The coefficients of the expansion can be parametrised using:

$$u_{j,\vec{i}}^n = \sqrt{\frac{P\lambda(\sigma)}{Z}} \exp(\phi_\mu(\sigma)) \quad (9)$$

where

$$P_\kappa(\sigma) = \sum_{\vec{h}} p_\kappa(\sigma, \vec{h}) \quad (10)$$

with

$$p_\kappa(\sigma, \vec{h}) = \exp(\vec{b}_\sigma \cdot \vec{\sigma} + \vec{c}_\sigma \cdot \vec{h} + \vec{h}^t \cdot W_\sigma^{\vec{h}} \cdot \vec{\sigma}) \quad (11)$$

IV. RBM PARAMETRISATION OF FLOQUET STATES

The numerically exact Floquet states (the fourier coefficients of expansion....) straight forward by diagonalising eq [? ?].

the Kull-lil loss function: $k = \sum_i p_i \log \frac{p_i}{\hat{p}_i}$

to train both RBM parametrisation of the amplitude and the phase, I loop swapping one, starting of a random initialization of the RBM parameters.

Typical training problems and parameters. Accuracy.

V. EVALUATING THE FLOQUET SPECTRUM USING ARBM

Finding the full spectrum of quasienergies and the .

As an initial guess for the parameters, we train the RBM to fit the RWA, which can be evaluated in . The second is the definition of a loss function. IN this case we want a that the matrix operation... lead to a diagonal form .we define distance as the difference between the of the values with the corresponding diagonal elementn. The training of this .. shown in ...

As a second form of the loss function is a quantification of the difference between the lefts vectors and the initial vectors. They should only differ in the scale, such . the candidate eigenvalue is chosen as the ratio between ... and Then we evaluate the difference. The training .. suffer similar difficulties taking a long number of steps and requiring a small loss rate.

Combination of the two loss functions during training in a randomly between loss functions. We observe a speed up of the training, improve of the fidelity with the exact, as well an improvement of the numerically exact Floquet spectrum.

VI. DISCUSSION

Loss function with slow learning. Investigation in better loss function as well as dragging tools from ML to speed up ..

The difficulty of training constitutes a tool for characterising physical system as Here we have observed that complex wavefunction require more training effort. application for example to Floquet driven systems.

Application for evaluating the longtime evolution. initial guess functions to improve convergence. Conversely, the training wave function and the distribution/correlation of the coefficients correlated with other criterion of the system..

The application of symmetries and boundary conditions to the Floquet states. Also, this can be readily extended to multimode scaling of multimodedriven system (with uncommensurable frequencies).

RBM parametrisation fits any function.

Floquet states requiring more Fourier components are harder to train.

several ways to define a loss function.

Slow gradient

random selection of criteria similar to ensemble learning

the RWA approximation is a good start generically and evolves towards the solution. speeding up the convergence ML .

More interesting is the construction of the initial guess and restriction of the solutions explored, for example that the amplitude of Floquet manifolds should be small.

here we explored the RBM parametrisation to build the micromotion operator. Other parametrisation can be more efficient for optimisation. Such construction of the initial guess and constraints can be come from using Tensor Networks parametrisation, or ...

VII. CONCLUSION

In this paper we present a premier explorative study of the use of RBM for the parametrisation of Floquet operators, in an archetypical periodically driven system. We obtain that training of the can be done , which is equivalent to the experimentally demonstrated in .. .with online learning of the wavefunction.

The evaluation of the Floquet spectrum is a more difficult task. the initial guess guides the minimum of the defined loss function. simple definitions use the properties of a diagonal matrix and present low gradients . combination of loss function as better, reflection on the ensemble learning combination for other simple architecture of the wave function, eg a NN can lead to for more complex systems than the studied here.

In this work we present a initial exploration of using RBM for Floquet problems. the Floquet states can be parametrised efficiently following similar approaches, even with an alternative fitting of the complex and the wavefunction amplitude. this task can be qualified as easy, rapid from random distribution.

Finding the Floquet states is a harder task. using as initial guess the RWA training . the function has a slow after a fast decline. however a combination of loss functions satisfied by any diagonal matrix or the eigenvectors helps to guide the search. configurationn.. . Perhaps a different . The micromotion operator is the time-evolution operator, then other ML architecture might present better. Also

This starting point for exploration of the use of parametrisation for more complex ...like .. . The numerical effort for the case studied here is overkill, however we explore typical that might be present in other driven quantum systems.

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APPENDIX A: RESTRICTED BOLTZMAN MACHINE PARAMETRISATION OF $u_{j,i}^n$

APPENDIX B: TYPICAL AND NOT SO TYPICAL TRAINING RESULTS

APPENDIX A: TYPICAL EXAMPLE OF THE MATRIX REPRESENTATION OF THE MULTIMODE HAMILTONIAN

A typical shape of the matrix representation of the RHS of eq. (6). Here we consider a static system H_0

driven by the three frequencies: $\omega_1, 2\omega_1, \omega_2$. The integer array describing this set of frequencies must be $(0, 2, 1)$. For the two fundamental frequencies, the num-

ber of Fourier modes in the decomposition of the micro-motion operator is chosen to be $N_F = 3$. With this, the driving of ω_1 and its first harmonic leads to the matrix:

$$\mathcal{H}_1 = \begin{pmatrix} H_0 + 3\hbar\omega_1 & V^{1,1} & V^{1,2} & 0 & 0 & 0 & 0 \\ V^{1,1\dagger} & H_0 + 2\hbar\omega_1 & V^{1,1} & V^{1,2} & 0 & 0 & 0 \\ V^{1,2\dagger} & V^{1,1\dagger} & H_0 + \hbar\omega_1 & V^{1,1} & V^{1,2} & 0 & 0 \\ 0 & V^{1,2\dagger} & V^{1,1\dagger} & H_0 & V^{1,1} & V^{1,2} & 0 \\ 0 & 0 & V^{1,2\dagger} & V^{1,1\dagger} & H_0 - \hbar\omega_1 & V^{1,1} & V^{1,2} \\ 0 & 0 & 0 & V^{1,2\dagger} & V^{1,1\dagger} & H_0 - 2\hbar\omega_1 & V^{1,1} \\ 0 & 0 & 0 & 0 & V^{1,2\dagger} & V^{1,1\dagger} & H_0 - 3\hbar\omega_1 \end{pmatrix}$$

and the full matrix results in:

$$\mathcal{H} = \begin{pmatrix} \mathcal{H}_1 + 3\hbar\omega_2 & \mathcal{V}^{2,1} & 0 & 0 & 0 & 0 & 0 \\ \mathcal{V}^{2,1\dagger} & \mathcal{H}_1 + 2\hbar\omega_2 & \mathcal{V}^{2,1} & 0 & 0 & 0 & 0 \\ 0 & \mathcal{V}^{2,1\dagger} & \mathcal{H}_1 + \hbar\omega_2 & \mathcal{V}^{2,1} & 0 & 0 & 0 \\ 0 & 0 & \mathcal{V}^{2,1\dagger} & \mathcal{H}_1 & \mathcal{V}^{2,1} & 0 & 0 \\ 0 & 0 & 0 & \mathcal{V}^{2,1\dagger} & \mathcal{H}_1 - \hbar\omega_2 & \mathcal{V}^{2,1} & 0 \\ 0 & 0 & 0 & 0 & \mathcal{V}^{2,1\dagger} & \mathcal{H}_1 - 2\hbar\omega_2 & \mathcal{V}^{2,1} \\ 0 & 0 & 0 & 0 & 0 & \mathcal{V}^{2,1\dagger} & \mathcal{H}_1 - 3\hbar\omega_2 \end{pmatrix}$$

with

$$\mathcal{V}^{2,1} = \begin{pmatrix} V^{2,1} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & V^{2,1} & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & V^{2,1} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & V^{2,1} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & V^{2,1} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & V^{2,1} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & V^{2,1} \end{pmatrix}$$

C++ WRAPPER

The library includes wrappers to use with C++. The interfaces to the Fortran subroutines share the name of the aimed function with the appended particle `_C_`. The full set of wrappers are declared in the

file `MultimodeFloquet.h`, which must be included in the C++ source code. As an example we present the C++ codes required to evaluate the time-evolution of a driven qubit. The library distribution includes Fortran and C++ examples.

```
#include <iostream>
#include <complex>
#include <stdio.h>
#include <math.h>
#include <string.h>

using namespace std;
typedef std::complex<double> dcmplx;

#include "MultimodeFloquet.h"

extern "C" int h_floquet_size;
```

```

int main(){

    atom_c id;
    int info,N_;
    int jtotal;
    char name[]      = "qubit";
    char manifold[]  = "U";

    int r,m,l;
    int d_bare,total_frequencies;

    double t1,t2;

    info      = 0;
    jtotal    = 2;
    floquetinit_c(&id,name,&info);

    d_bare = id.d_bare;

    dcmplx * U_AUX = new dcmplx [d_bare*d_bare];

    int nm = 2;
    int * modes_num = new int [nm];

    modes_num[0] = 1;
    modes_num[1] = 1;

    total_frequencies = 0;
    for(r=0;r<nm;r++){
        total_frequencies += modes_num[r];
    }

    mode_c * fields = new mode_c [total_frequencies];

    // --- SET DRIVING PARAMETERS
    fields[0].x      = 0.0;
    fields[0].y      = 0.0;
    fields[0].z      = 2.0;
    fields[0].phi_x  = 0.0;
    fields[0].phi_y  = 0.0;
    fields[0].phi_z  = 0.0;
    fields[0].omega  = 0.0;
    fields[0].N_Floquet = 0;

    fields[1].x      = 4.0;
    fields[1].y      = 0.0;
    fields[1].z      = 0.0;
    fields[1].phi_x  = 0.0;
    fields[1].phi_y  = 0.0;
    fields[1].phi_z  = 0.0;
    fields[1].omega  = 2.0;
    fields[1].N_Floquet = 3;

    // --- SET THE HAMILTONIAN COMPONENTS
    sethamiltoniancomponents_c_
        (&id,&nm,&total_frequencies,modes_num,fields,&info);

```

```

// --- BUILD THE MULTIMODE FLOQUET MATRIX AND FIND ITS SPECTRUM
multimodefloquetmatrix_c_
    (&id,&nm,&total_frequencies,modes_num,fields,&info);

double * e_floquet = new double [h_floquet_size];
dcmplx * U_F = new dcmplx [h_floquet_size*h_floquet_size];

lapack_fulleigenvalues_c_
    (U_F,&h_floquet_size,e_floquet,&info);
// the diagonalization is done with the internal (Fortran)
// Hamiltonian (H_FLOQUET) and the calculated
// U_F is the transformation that diagonalise this Hamiltonian
// On the Fortran side, H_FLOQUET is deallocated after
// diagonalization.

//--- EVALUATE TIME-EVOLUTION OPERATOR IN THE BARE BASIS

N_ = 256;
t1= 0.0;
for(r=1;r<N_;r++){
    t2 = r*100.0/N_;
    multimodetimeevolutionoperator_c_
        (&h_floquet_size,&nm,modes_num,U_F,e_floquet,&d_bare,fields,&t1,&t2,U_AUX,&info);
    for(l=0;l<d_bare*d_bare;l++) p_avg[l] = pow(abs(U_AUX[l]),2);
    write_matrix_c_(p_avg,&d_bare);
}
delete(e_floquet);
delete(U_F);
}

return 0;
}

```
