

Machine-Learning Electron Dynamics with Moment Propagation Theory: Application to Optical **Absorption Spectrum Computation using Real-Time TDDFT**

Introduction

Recent development of real-time time-dependent density functional theory (RT-TDDFT) in maximally-localized Wannier functions (MLWF) gauge [1] and the use of machine learning (ML) for modeling quantum dynamics have motivated us to employ our newly formulated moment propagation theory (MPT) [2] for efficiently simulating quantum dynamics of electrons. Theoretical formalism for the moment propagation is presented and numerical details for using the theoretical formalism for ML models is demonstrated. Results for single molecules and a condensed matter system are presented.

Moments with increasing orders of the position operator with the particle density are

$$\langle x^{a}y^{b}z^{c}\rangle(t) \equiv \iiint x^{a}y^{b}z^{c}n(x,y,z,t)dxdydz$$

Theoretical Formulation

According to time-dependent Schrödinger equation in the single-particle description, the first and second order time derivatives can be written as [2],

 $\frac{d\left\langle x^{a}y^{b}z^{c}\right\rangle \left(t\right)}{dt}=-\frac{i}{2}\int\left[\nabla^{2}\left(x^{a}y^{b}z^{c}\right)n+2\nabla\left(x^{a}y^{b}z^{c}\right)\cdot\nabla\psi\psi^{*}\right]d^{3}r$

The EOM for the moments can be expressed as a function *F* that depends on the moments and their time derivatives:

$$\frac{d^2}{dt^2} \langle x^a y^b z^c \rangle(t) = F(\{\langle x^d y^e z^f \rangle(t)\}, \{\frac{d}{dt} \langle x^d y^e z^f \rangle(t)\})$$

However, it's analytical form is very complicated for the use in first-principles electronic structure theory [2].

Using a simple linear model, the second order time derivatives of the quantum-particle j with the order of moments (a,b,c) is given by

$$\frac{d^2}{dt^2} \langle x^a y^b z^c \rangle_j(t)$$

$$= \sum_k \left(B_{a,b,c}^{j,k} + \sum_{d,e,f} C_{a,b,c,d,e,f}^{j,k} \langle x^d y^e z^f \rangle_k(t) + \sum_{d,e,f} D_{a,b,c,d,e,f}^{j,k} \frac{d}{dt} \langle x^d y^e z^f \rangle_k(t) \right)$$

Using the matrix notation, the moments are represented as

Y defines the moments and their time derivative, as we have

$$\dot{\mathbf{Y}}(t) = \mathbf{A}\mathbf{Y}(t) + \mathbf{H}$$

$$\mathbf{Y}(t) \equiv \begin{bmatrix} \mathbf{X}(t) \\ \dot{\mathbf{X}}(t) \end{bmatrix}$$
$$\mathbf{A} \equiv \begin{bmatrix} \mathbf{0} & \mathbf{I} \\ \mathbf{C} & \mathbf{D} \end{bmatrix}$$
$$\mathbf{E} \equiv \begin{bmatrix} \mathbf{0} \\ \mathbf{B} \end{bmatrix}$$

$$\dot{\mathbf{X}}(t) = \mathbf{C}\mathbf{X}(t) + \mathbf{D}\dot{\mathbf{X}}(t) + \mathbf{B}$$

$$\ddot{\mathbf{X}}(t) = \mathbf{C}\mathbf{X}(t) + \mathbf{D}\dot{\mathbf{X}}(t) + \mathbf{B}$$

$$\mathbf{A}(\iota) = \mathbf{C}\mathbf{A}(\iota) + \mathbf{D}\mathbf{A}(\iota) + \mathbf{D}$$

$$\mathbf{Y}(t) = e^{\mathbf{A}t}\mathbf{V} - \mathbf{A}^{-1}\mathbf{E}$$
$$\mathbf{V} \equiv \mathbf{Y}(0) + \mathbf{A}^{-1}\mathbf{E}$$
$$\mathbf{Y}(t) = \mathbf{P}e^{\mathbf{Q}t}\mathbf{P}^{-1}\mathbf{V} - \mathbf{A}^{-1}\mathbf{E}$$

where P is the eigenvalue Q is the matrix and eigenvector matrix of A.

formulation, unphysical analytical behavior stemming from noises in the ML can be removed conveniently.

Then,

$$i\hbar \frac{d}{dt} |w_l(t)\rangle = \bigg\{$$

Example :

 H_2O

Crystalline Si

$$\langle \mathbf{r} \rangle = \frac{\mathbf{L}}{2\pi} \operatorname{Im} \ln \langle$$
$$/(r - \langle r \rangle)^2 \rangle = -\frac{1}{2\pi} \operatorname{Im} \ln \langle r \rangle \langle r \rangle \langle r \rangle \langle r \rangle \rangle^2 \langle r \rangle \rangle^2 \langle r \rangle \langle r$$

$$\langle (r-\langle r
angle)(r'-\langle r'
angle$$

Dielectric function:

$$\epsilon(\omega) = 1 + \frac{4\pi c}{3\omega}$$

Dipole strength function:

$$S(\omega) = \frac{4\pi\omega}{3c} \operatorname{Tr}$$

Description

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$$L = \alpha * \sum_{i} LM_i^2 + \sum_{i} (y_j - LM(x_j))^2$$

$$\sum_{a,b,c}^{j,k} + \sum_{d,e,f} C_{a,b,c,d,e,f}^{j,k} \left\langle x^{\mathrm{d}} y^{\mathrm{e}} z^{\mathrm{f}} \right\rangle_{k}(t) + \sum_{d,e,f} D_{a,b,c,d,e,f}^{j,k} \frac{d}{dt} \left\langle x^{\mathrm{d}} y^{\mathrm{e}} z^{\mathrm{f}} \right\rangle_{k}(t) \right)$$

