

Approaching coupled-cluster accuracy for molecular electronic structures with multi-task learning

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Machine learning plays an important role in quantum chemistry, providing fast-to-evaluate predictive models for various properties of molecules; however, most existing machine learning models for molecular electronic properties use density functional theory (DFT) databases as ground truth in training, and their prediction accuracy cannot surpass that of DFT. In this work we developed a unified machine learning method for electronic structures of organic molecules using the gold-standard CCSD(T) calculations as training data. Tested on hydrocarbon molecules, our model outperforms DFT with several widely used hybrid and double-hybrid functionals in terms of both computational cost and prediction accuracy of various quantum chemical properties. We apply the model to aromatic compounds and semiconducting polymers, evaluating both ground- and excited-state properties. The results demonstrate the model's accuracy and generalization capability to complex systems that cannot be calculated using CCSD(T)-level methods due to scaling.

Computational methods for molecular and condensed matter systems play essential roles in physics, chemistry and materials science, which can reveal underlying mechanisms of diverse physical phenomena and accelerate materials design¹. Among various types of computational methods, quantum chemistry calculations of electronic structures are usually the bottleneck, limiting the computational speed and scalability². In recent years, machine learning methods have been successfully applied to accelerate molecular dynamics simulations and improve their accuracy in many application scenarios³. Particularly, machine-learned inter-atomic potentials can predict energy and force of molecular systems with much lower computational costs than quantum chemistry methods^{4–7}. Indeed, recent advances in universal machine-learned potentials enable large-scale molecular dynamics simulation with the complexity of realistic physical systems^{8–11}. In addition to machine-learned inter-atomic potentials, rapid advances also

appear in another promising direction, namely, the machine learning density functional, which focuses on further improving the energy prediction towards chemical accuracy (1 kcal mol⁻¹)^{12,13}.

Aside from energy and force, other electronic properties that explicitly involve the electron degrees of freedom are also essential in molecular simulations¹⁴. In the past few years, machine learning methods have also been extended to electronic structure of molecules, predicting various electronic properties such as electric multipole moments^{15–17}, electron population¹⁸, excited-state properties^{19,20}, and the electronic band structure of condensed matter^{21,22}. Most of these methods take the density functional theory (DFT) results as the training data, and use neural networks to fit the single-configurational representation (either the Kohn–Sham Hamiltonian or molecular orbitals) of the DFT calculations^{15,19,21,23}. Along with the rapid advances of machine learning techniques, the neural network predictions match the DFT

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results increasingly well, approaching chemical accuracy^{8,16}. However, as a mean-field-level theory, DFT calculations themselves induce a systematic error that is usually several times larger than the chemical accuracy²⁴, limiting the overall accuracy of the machine learning model trained on DFT datasets.

By comparison, the correlated wavefunction method CCSD(T) is considered the gold-standard in quantum chemistry²⁵. It provides high-accuracy predictions on various molecular properties. Unfortunately, the computational cost of CCSD(T) calculations scales unfavorably with system size. It can therefore only handle small molecules with up to hundreds of electrons. This urges the combination of CCSD(T) with machine learning methods, which, together, can potentially have both high accuracy and low computational cost. However, the above-mentioned machine learning methods that directly fit the single-configurational representation of the DFT calculations cannot be directly applied to the CCSD(T) training data. This is because CCSD(T) does not provide either Kohn–Sham Hamiltonians or single-body electronic wavefunctions due to the many-body quantum entanglement nature of its representation.

In this work we develop a unified multi-task machine learning method for molecular electronic structures. Instead of focusing solely on energy, our method also provides accurate predictions for various electronic properties. By contrast to machine learning models trained on DFT datasets, our method learns from CCSD(T)-accuracy training data. The method incorporates the E3-equivariant neural network (E3NN)^{4,26}, in which vectors and tensors are involved in the message-passing step. For brevity we refer to our method as multi-task electronic Hamiltonian network (MEHnet). Using hydrocarbon organic molecules as a testbed, our method predicts molecular energy within chemical accuracy as compared with both CCSD(T) calculations and experiments. It also predicts various properties such as electric dipole and quadrupole moments, atomic charge, bond order, energy gap and electric polarizability with better accuracy than B3LYP, one of the most widely used hybrid DFT functionals²⁷. Our trained model shows robust generalization capability from small molecules in the training dataset (molecular weight < 100 unified atomic mass unit) to larger molecules such as naphthalene and even semiconducting polymers (molecular weight up to several thousands). Systematically predicting multiple electronic properties using a single model with local DFT computational speed, the method provides a high-performance tool for computational chemistry and a promising framework for machine learning electronic structure calculations.

Results

Computational workflow

In this section we briefly describe the theoretical background and model architecture of the MEHnet method (see Methods for details). We basically use a neural network to simulate the non-local exchange-correlation interactions of a many-body system. A physics-informed approach is then used to predict multiple properties from the output of a single neural network.

Given an input atomic configuration, our goal is to acquire an effective single-body Hamiltonian matrix that is then used to predict quantum chemical properties from physics principles (Fig. 1a). First, a fast-to-evaluate single-configurational method such as DFT or Hartree–Fock is used to obtain a mean-field effective Hamiltonian, \mathbf{F}' . Note that \mathbf{F}' is easy and fast to compute, but its accuracy is relatively low. We will use \mathbf{F}' as the starting point of our machine learning model, and the total effective Hamiltonian of the system $\mathbf{H}^{\text{eff}} = \mathbf{F}' + \mathbf{V}^\theta$ is obtained by adding the machine learning correction term \mathbf{V}^θ . In the current formalism, \mathbf{F}' is obtained from a local DFT calculation, and it contains only a local-exchange-correlation contribution, and the correction term \mathbf{V}^θ would account for the non-local exchange-correlation effects. Generally, the non-local exchange-correlation effects can be captured in CCSD(T) calculations. However, as mentioned before, the

computational costs of CCSD(T) methods are formidably high for large systems. The essence of our machine learning method is to obtain the non-local exchange-correlation effects from a neural network, whose computational cost scales only linearly with system size.

To obtain the machine learning correction term, we build a neural network model to predict \mathbf{V}^θ . The workflow consists of the input, convolutional and output layers. The input layer takes atomic configurations as input, encoding them into the node features $\mathbf{x}_{i,\text{in}}$ for atom information, and edge features $\mathbf{f}_{I,J,\text{in}}$ for bond information (I, J are indices of atoms). The E3NN framework is employed for the convolutional layer (Fig. 1b; see Methods for details) due to its good performance in predicting molecular properties⁴. The convolutional layer outputs $\mathbf{x}_{i,\text{out}}$ and $\mathbf{f}_{I,J,\text{out}}$, which encode E3-equivariant features of atoms and bonds, as well as their atomic environment. The equivariant machine learning correction Hamiltonian \mathbf{V}^θ is then constructed using $\mathbf{x}_{i,\text{out}}$ and $\mathbf{f}_{I,J,\text{out}}$ in the output layer. The effective electronic structure of a molecule is obtained by solving the eigenvalue equations of the total Hamiltonian $\mathbf{H}^{\text{eff}} = \mathbf{F}' + \mathbf{V}^\theta$, giving ϵ_i , the i th energy level, and \mathbf{c}^i , the corresponding molecular orbital represented on atomic orbital basis set.

Multiple learning tasks

Our scheme aims to predict multiple observable molecular properties (more than just energy). To achieve reduced computational costs, we do not include information about the entire electronic Hilbert space as learning targets. MEHnet is instead trained on a series of molecular properties to capture their shared underlying representation, that is, the effective single-body Hamiltonian \mathbf{H}^{eff} . The corresponding single-body energy levels and molecular orbitals are used to evaluate a series of ground-state properties O_g according to the rules of quantum mechanics:

$$O_g^{\text{MEHnet}} = f_{O_g}(\{\epsilon_i\}, \{\mathbf{c}^i\}), \quad O_g = E, \vec{p}, \mathbf{Q}, C_I, B_{IJ}, \quad (1)$$

where O_g goes through the ground-state energy (E), the electric dipole (\vec{p}) and quadrupole (\mathbf{Q}) moments, the Mulliken atomic charge²⁸ of each atom C_I , and Mayer bond order²⁹ of each pair of atoms B_{IJ} . We also evaluate the energy gap (first excitation energy, E_g) and static electric polarizability α :

$$\begin{aligned} E_g^{\text{MEHnet}} &= f_{E_g}(\{\epsilon_i\}, \{\mathbf{c}^i\}, \mathbf{G}), \\ \alpha^{\text{MEHnet}} &= f_\alpha(\{\epsilon_i\}, \{\mathbf{c}^i\}, \mathbf{T}). \end{aligned} \quad (2)$$

In principle, the ground-state electronic structure does not contain the information on the energy gap and electric polarizability. We therefore use the model-output correction terms \mathbf{G} (energy gap correction) and \mathbf{T} (dielectric screening matrix) to account for the information on excited states and the linear response, respectively. We provide more details on the function forms of f_{O_g} , f_{E_g} and f_α in the Methods. Note that these properties are all derived from the underlying electronic structure, so they are internally related. Multi-task learning methods can therefore utilize these relations to mutually enhance the model's generalization capability.

The goal of our multi-task learning is to predict the properties listed above with coupled-cluster accuracy. Hence, the total loss function L_{Total} for each molecule is constructed as follows:

$$\begin{aligned} L_{\text{Total}} &= l_V + \sum_{O \in O_g \cup \{E_g, \alpha\}} l_O, \\ l_O &= w_O \times \text{MSEloss}(O^{\text{MEHnet}}, O^{\text{label}}), \\ l_V &= \frac{w_V}{N_{\text{basis}}^2} \sum_{I\mu, J\nu} |V_{I\mu, J\nu}^\theta|^2. \end{aligned} \quad (3)$$

Here, for each property O , l_O is the the mean-square error loss between O^{MEHnet} and O^{label} , the MEHnet predictions (equations (1) and (2)) and

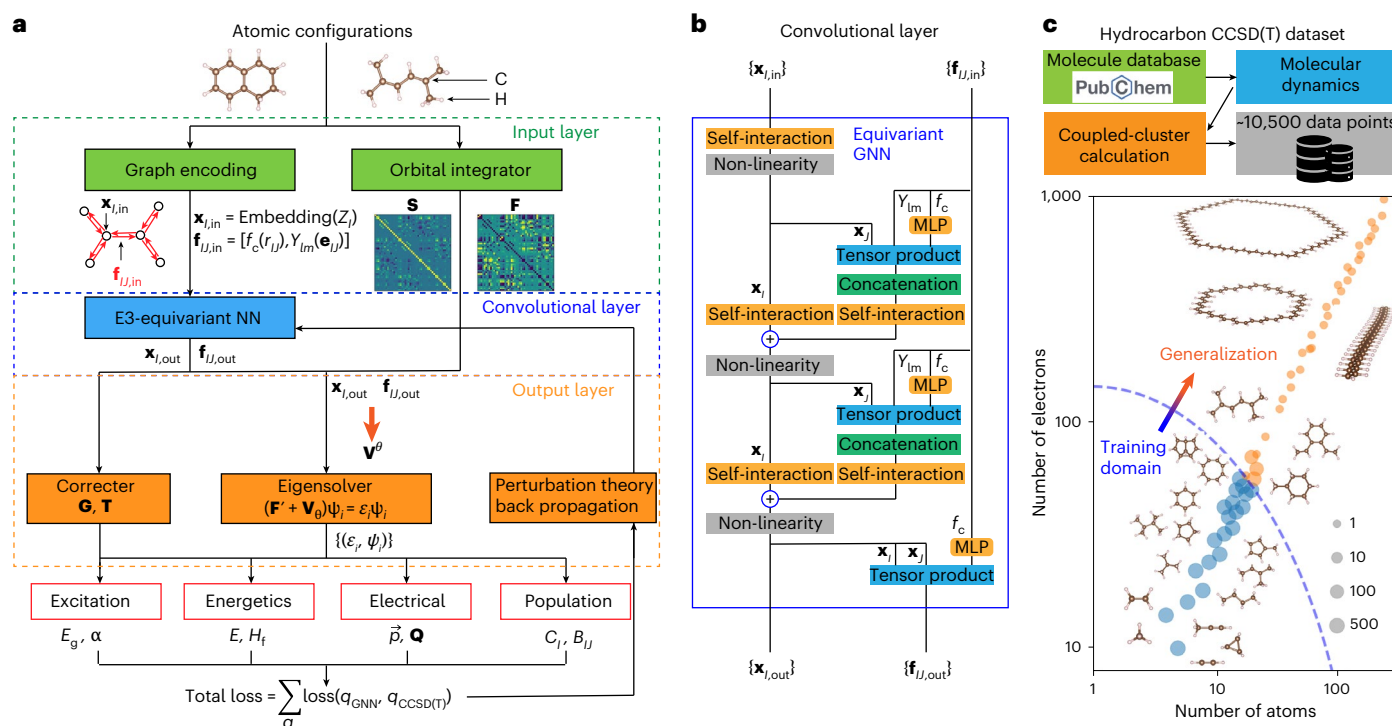


Fig. 1 | Schematic of the MEHnet electronic structure workflow.

a, Computation graph of the MEHnet method that predicts multiple quantum chemical properties from atomic configurations inputs. The computational graph consists of an input layer (green blocks), convolutional layer (blue block) and output layer (orange blocks). **b**, Model architecture of the E3-equivariant NN with two layers of graph convolution. The output contains both node feature $\mathbf{x}_{i,\text{out}}$ and edge feature $\mathbf{f}_{i,j,\text{out}}$. **c**, Training and testing dataset generation. Each dot

represents molecules with the same chemical formula, and is plotted to show the number of electrons and atoms. The blue and orange colors correspond to molecules in the training and generalization domains, respectively. The model is trained with small molecules, and is subsequently tested with large molecules. The dot size reflects the number of conformers and/or vibrational configurations with the same chemical formula in the dataset (from 1 to 500, in log scale).

coupled-cluster labels in the training dataset, respectively. Meanwhile, l_V is a regularization that penalizes large correction matrix \mathbf{V}^θ , whereas N_{basis} is the total number of basis functions in the molecule. The weights w_V and w_O are hyperparameters whose values are listed in the Methods. The weights are chosen to balance the training tasks so that the training errors of all tasks decrease to satisfactory levels. Minimizing L_{Total} requires the back-propagation through the diagonalization of \mathbf{H}^{eff} (that is, calculating $\partial \varepsilon_i / \partial \mathbf{H}^{\text{eff}}$ and $\partial \mathbf{c}^i / \partial \mathbf{H}^{\text{eff}}$), which is numerically unstable with direct numerical differentiation. To overcome this issue, we derive customized back-propagation schemes for each property using perturbation theory in quantum mechanics (see Methods for details), giving

$$\begin{aligned} \nabla_{\theta} \varepsilon_i &= (\mathbf{c}^i)^\dagger (\nabla_{\theta} \mathbf{V}^\theta) \mathbf{c}^i \\ \nabla_{\theta} \mathbf{c}^i &= \sum_{p \neq i} \frac{(\mathbf{c}^p)^\dagger (\nabla_{\theta} \mathbf{V}^\theta) \mathbf{c}^i}{\varepsilon_i - \varepsilon_p} \mathbf{c}^p. \end{aligned} \quad (4)$$

When evaluating the gradients of properties in equations (1) and (2) using the chain rule, terms that analytically cancel each other are removed in the numerical evaluation, making the scheme numerically stable.

Atomic configurations of molecules in our training dataset are generated by the workflow shown in Fig. 1c. Our dataset covers various classes of hydrocarbons (saturated, unsaturated, alicyclic and aromatic) and molecular structures (linear, branched and cyclic), containing both stable and metastable conformers with diverse types of carbon-carbon bonds (single, double, triple and conjugated π -bonds; see Supplementary Section 1). Coupled-cluster calculations are implemented for various hydrocarbon molecules. The MEHnet model is

trained on small-molecules training dataset (training domain; Fig. 1c). The model is then tested on both small molecules in the training domain but outside the training dataset (in-domain validation) and larger molecules outside the training domain (out-of-domain validation).

Benchmark of model performance

We then benchmark the performance of the MEHnet model and display potential applications of the model in systems of practical importance. The following discussions focus on close-shell hydrocarbon molecules (except for the QM9 version of MEHnet that we will describe later).

The model's generalization capability from small to large molecules is essential for its usefulness on complex systems for which coupled-cluster calculations cannot be implemented on current computational platforms due to their formidable computational costs. To test the generalization capability and data efficiency of our model, we train the model with a varying training dataset size, N_{train} , which ranges from 10 to 7,440 atomic configurations of hydrocarbon molecules. The testing root-mean-square error (RMSE, absolute error in atomic units) of different trained properties exhibits a decreasing trend when the training dataset size increases (Fig. 2a), indicating effective model generalization. Notably, the energy error has the fastest drops with a slope of -0.38 (meaning that the testing error $\propto N_{\text{train}}^{-0.38}$). In comparison, some of the recently developed advanced machine learning potentials (that directly learn energies and their derivatives, such as the potentials in refs. 4,8) exhibit lower slopes of about -0.25 . This implies a potential advantage of the multi-task method: as a multi-task method learns different molecular properties through a shared representation (the electronic structure), the domain information learned from one property can help the model's generalization on predicting other properties³⁰, providing improved data efficiency.

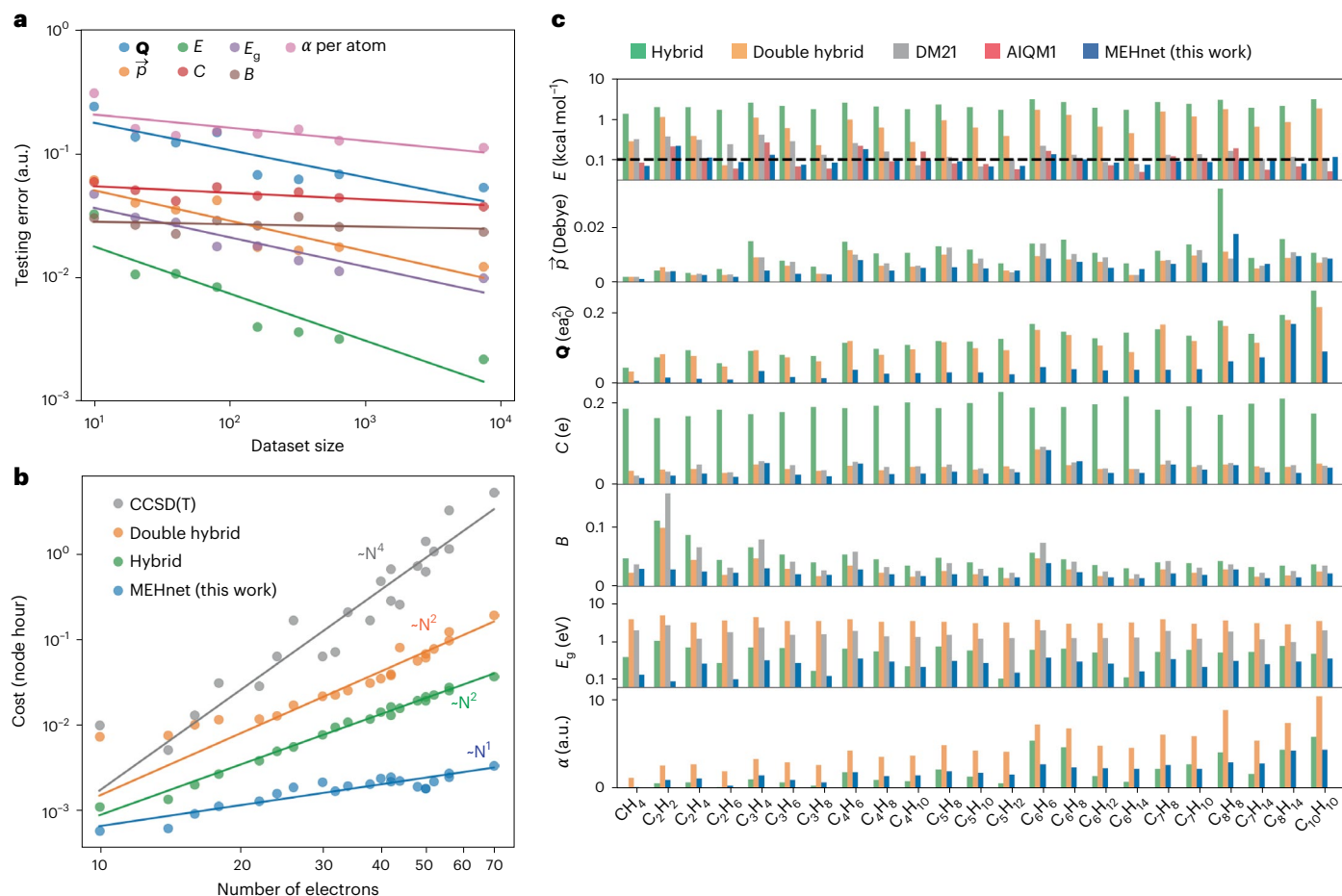


Fig. 2 | Benchmark of the model performance on the testing dataset.

a, Testing RMSE of different quantities as a function of training dataset size. **b**, Computational costs of different methods plotted against the number of electrons. The computational cost is measured as the calculation time (node hour) on a single Intel Xeon Platinum 8260 CPU node with 48 cores with sufficient memory for all calculations. The scaling deviates from the theoretical asymptotic scaling N^7 for CCSD(T), because the parallelization efficiency is higher for larger molecules. In principle, the N^7 scaling for CCSD(T) would appear in the large N

limit. **c**, Prediction RMSE of the energy (E per atom, reference to separate atoms), electric dipole moment (\vec{p}), electric quadrupole moment (\mathbf{Q}), Mulliken atomic charge (C), Mayer bond order (B), energy gap (first excitation energy, E_g) and static electric polarizability (α , a.u. means atomic unit) with respect to the coupled-cluster results. The MEHnet method is compared with the B3LYP hybrid functional, DSD-PBEP86 double-hybrid functional³¹, DM21 machine learning functional¹² and AIQM1 machine learning potential¹¹.

We then benchmark the computational costs and prediction accuracy of our model trained on 7,440 atomic configurations with 70 different molecules, which will be used in the rest of this paper. The MEHnet method exhibits smaller computational cost and slower scaling with system size, as compared with the hybrid functional, double-hybrid functional³¹ and the CCSD(T) method (Fig. 2b). Compared to the hybrid functional, our method avoids the expensive calculation of the exact exchange, thus substantially reducing computational cost²⁷. Using the gold-standard CCSD(T) calculation as a reference, the prediction accuracy of the MEHnet method on various molecular properties is compared with that of several popular functionals and existing machine learning methods (Fig. 2c and Table 1). The comparison is implemented on both the in-domain (ID) and out-of-domain (OOD) testing dataset of hydrocarbon molecules. Note that although the B3LYP hybrid functional is widely used, it is known to exhibit certain failure modes in hydrocarbon molecules³², we therefore include several other high-performance hybrid and double-hybrid functionals^{32,33} with DFT-D3 correction³⁴ in the comparison (Supplementary Section 2).

The MEHnet predictions consistently exhibit smaller RMSEs than the hybrid (B3LYP and B3PW91³⁵), double-hybrid (DSD-PBEP86³¹ and PWPB95³⁶) and DM21¹² functionals on most molecular properties (Table 1, with the exception of the electric dipole moment on the OOD

dataset, for which DSD-PBEP86 gives the smallest RMSE). Remarkably, the RMSE of the combination energy predicted by MEHnet is about $0.1 \text{ kcal mol}^{-1}$ ($\sim 4 \text{ meV}$) per atom in both the ID and OOD datasets. Our method exhibits a similar combination energy RMSE to the AIQM1 machine learning potential, which features energy predictions within chemical accuracy. These results confirm that MEHnet's predictions on reaction energies can approach quantum chemical accuracy (assuming that on average 1 mole of molecules in reactants contain ~ 10 moles of atoms). Note that the B3LYP functional (with the def2-SVP basis set) exhibits large RMSEs for Mulliken charge mainly because of the basis set error³⁷. Although using a large basis set for the B3LYP Mulliken charge gives a much smaller error, the MEHnet model still gives better overall accuracy (Supplementary Fig. 3).

Aside from the ground-state properties, MEHnet also provides the excited-state property E_g and linear response property α with better overall accuracy than other methods (Table 1). For intensive quantities (E per atom, C , B and E_g), the errors are on a similar level for molecules with different sizes; for extensive quantities (\vec{p} , \mathbf{Q} , α), there is a trend of increasing error with increasing system size, because the absolute values of these quantities themselves increase with system size. Furthermore, the MEHnet model gives similar prediction accuracy among different classes of hydrocarbons such as alkanes, alkenes, alkynes and

Table 1 | Benchmark of MEHnet model's RMSE in predicting different quantum chemical properties on the ID testing dataset and OOD testing dataset with respect to the coupled-cluster calculations

RMSE	(ID/OOD)	Hybrid		Double	Hybrid	ML		
	Unit	B3LYP	B3PW91	DSD-PBEP86	PWPB95	DM21	AIQM1	MEHnet (ours)
Energy (per atom)	kcal mol ⁻¹	2.20/2.41	2.03/2.73	0.94/1.20	1.64/1.98	0.22/0.11	0.13/0.06	0.11/0.10
Dipole	Debye	0.06/0.06	0.06/0.04	0.03/0.03	0.07/0.05	0.04/0.04	–	0.03/0.04
Quadrupole	ea ₀ ²	0.12/0.21	0.32/0.51	0.11/0.18	0.10/0.14	–	–	0.03/0.12
Atomic charge	e	0.19/0.20	0.16/0.16	0.04/0.05	0.05/0.05	0.05/0.04	–	0.04/0.03
Bond order	–	0.05/0.03	0.06/0.04	0.04/0.02	0.06/0.03	0.06/0.03	–	0.02/0.02
Bandgap	eV	0.59/0.63	0.65/0.54	3.71/3.26	2.19/1.98	1.71/1.47	–	0.26/0.31
Polarizability	a.u.	2.22/4.32	2.53/4.72	4.74/8.05	–	–	–	1.85/3.91

The numbers in the table are ID/OOD RMSE. Other DFT and machine learning methods are compared. We leave some of the spaces blank when the method does not directly output the quantity for fair comparison.

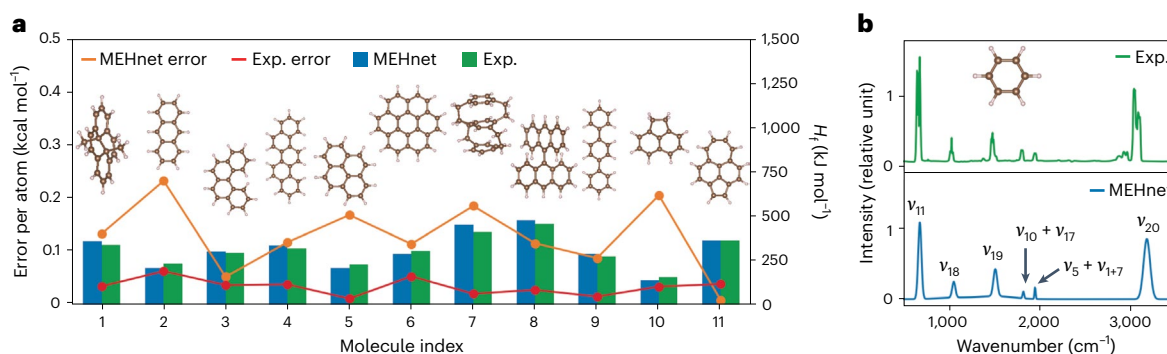


Fig. 3 | Validation of the MEHnet's predictions on gas phase aromatic hydrocarbon molecules, as compared with experimental results. a, Standard enthalpy of formation. The MEHnet predictions and experimental values from ref. 38 (right axis) are compared for 11 molecules (see Supplementary Table 2 for details). The difference between the MEHnet method and experimental values

are shown by the orange line, and the experimental uncertainty is shown by the red line (left axis). **b**, Infrared spectrum of benzene. The experimental data is from the NIST Chemistry WebBook⁵⁴. Vibration modes corresponding to the peaks are labeled following the convention in ref. 55.

arenes (Supplementary Fig. 1), suggesting consistent generalizability in the hydrocarbon chemical space.

Aromatic molecules

Hydrocarbon molecules have a vast structural space, including various types of local atomic environments. To further examine the model's generalization capability in more complex structures, we apply MEHnet to a series of aromatic hydrocarbon molecules synthesized in experiments³⁸. The gas phase standard enthalpy of formation H_f is an essential thermochemical property of molecules that can be accurately measured in experiments. In this regard, we use the MEHnet model to predict H_f of various aromatic molecules in a comprehensive experimental review paper (ref. 38). The MEHnet predictions on H_f are well consistent with experiments on all molecules, and their difference is only around -0.1 – 0.2 kcal mol⁻¹ per atom (Fig. 3a). Note that the MEHnet prediction error is on the same order of magnitude as the experimental error bar (though numerically larger), indicating high prediction accuracy.

In addition to thermochemical properties, MEHnet can also predict spectral properties (Fig. 3b and Supplementary Fig. 4). Infrared spectra, especially, reflect essential information on molecular vibrational modes and their interaction with light. In a past work on machine learning electronic structure¹⁶, the predicted peak intensity is usually inconsistent with the experiment. In comparison, the MEHnet predictions on both the peak positions and intensity agree well with experimental results in several common hydrocarbon molecules, and it also provides both the fundamental bands and combination bands known as benzene fingers in the infrared spectrum. The good consistency of peak intensity is attributed to accurate predictions on the

transition dipole moments that determine the intensity of light–matter interaction. See Supplementary Section 3 for details on calculating the infrared spectrum, as well as the calculated infrared spectra for several other molecules.

Large-scale semiconducting polymers

Aside from small molecules, we also apply MEHnet to semiconducting polymers comprising hundreds of atoms, which are difficult to calculate by rigorous correlated methods such as CCSD(T). The essential electronic properties of semiconducting polymers originate from the conjugated π -bonds with delocalized molecular orbitals. As the delocalized molecular orbitals extend through the whole molecule (Fig. 4a), the polymers' electronic properties also involve long-range correlation, making it challenging for machine learning methods. It is therefore important to examine whether MEHnet can capture semiconducting polymers' electronic properties involving delocalized molecular orbitals.

Three kinds of semiconducting polymers: *trans*-polyacetylene (t-PA), cyclic polyacetylene (c-PA) and polyphenylene (PPP) are studied using MEHnet. The model correctly captures the delocalized π -bond feature of frontier orbitals, that is, the highest occupied molecular orbital (HOMO) and lowest unoccupied molecular orbital (LUMO) (Fig. 4a). Various important electronic properties of semiconducting polymers depend on the chain length, including the energy gap E_g and polarizability α . We calculate such chain-length dependence (up to more than 400 atoms) using the MEHnet model (Fig. 4b,c). One can see that E_g is larger for shorter oligomers and converges to a smaller value for long chains. This is in analogy to the size effect on the energy

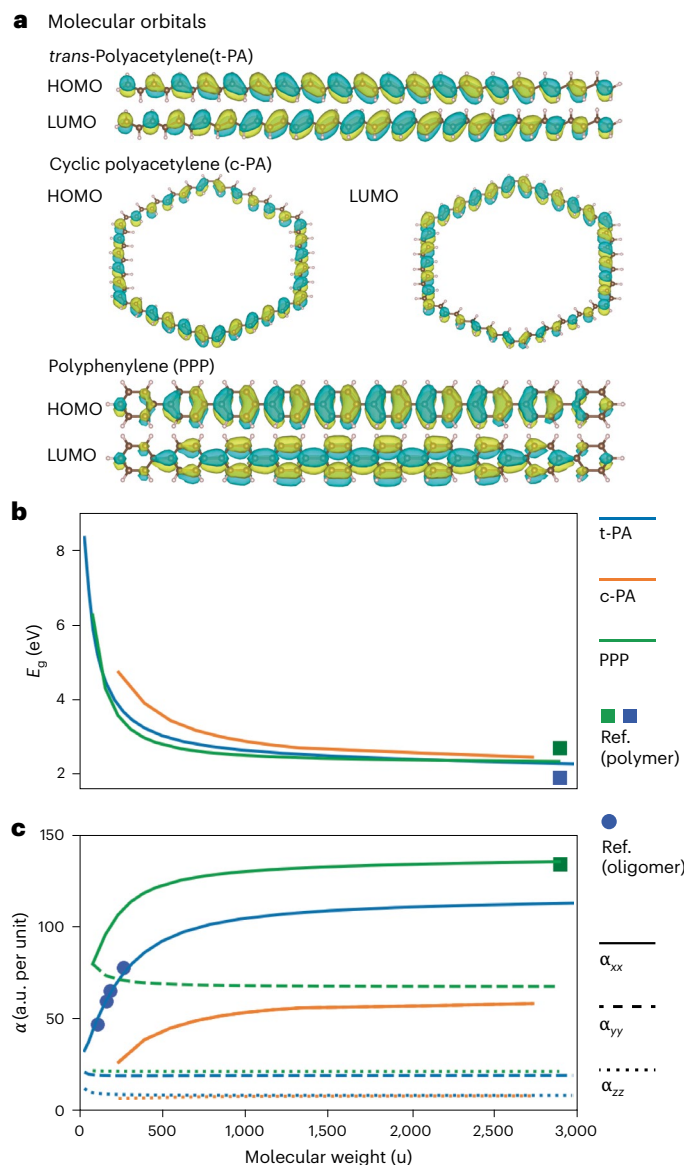


Fig. 4 | MEHnet predictions for the electronic properties of semiconducting polymers. **a**, Atomic structure and HOMO and LUMO wavefunctions of t-PA, polyphenylene PPP and c-PA. The wavefunctions are visualized by isosurfaces at the level of $\pm 0.04 \text{ \AA}^{-3/2}$ (positive isosurface colored blue and negative isosurface colored yellow). **b,c**, Energy gap (**b**) and static electric polarizability (**c**) of t-PA (blue lines), PPP (green lines) and c-PA (orange lines) with different polymer chain length. Longitudinal polarizability α_{xx} , horizontal polarizability α_{yy} and vertical polarizability α_{zz} are shown as solid, dashed and dotted lines, respectively. Squares (blue for t-PA and green for PPP) represent literature values for polymers in experiments^{39,40} and correlated calculations⁴¹, whereas blue dots represent literature values for t-PA oligomers from the MP2 correlated calculations⁴².

gap of quantum dots and quantum wells. The converged energy gap for long t-PA and PPP polymers calculated by MEHnet are in reasonable agreement with the experimental values (relative errors within 10%)^{39,40}, which are shown as squares in Fig. 4b. The longitudinal static electric polarizability α_{xx} (per monomer) is positively related to the polymer chain length. This is because in longer chains, more delocalized electron distributions can have larger displacements under an external electric field. The predicted α_{xx} for t-PA oligomers and PPP polymers are in perfect agreement with previous correlated calculations using the high-accuracy MP2 method^{41,42} (Fig. 4c). The chain-length-dependent E_g and α of c-PA, to the best of our knowledge, have not been reported. We provide their values as a prediction to be examined by future work.

QM9 version of MEHnet

Although the results in this paper mainly focus on hydrocarbons, our method is readily applicable to systems with different elements. To examine the generality of our method to the chemical space beyond hydrocarbons, we trained an MEHnet model on 10,000 molecules randomly sampled from the QM9 dataset⁴³—a common quantum chemistry database including molecules comprising H, C, N, O and F atoms. The model is then tested on 4,000 other molecules randomly sampled from the QM9 dataset (see Table 2 and Supplementary Fig. 5). The prediction accuracy on the QM9 testing dataset is even better than that in the case of hydrocarbons (Table 1), suggesting that our method can be applied to more general cases with various types of elements (refer to Supplementary Section 4 for details on the benchmark of the QM9 version).

Discussion

The current MEHnet scheme has several limitations: it is not readily applicable to periodic crystals, open shell molecules or molecules with strong multi-reference character.

In principle, our approach can also be generalized to extended systems, where the periodic boundary condition (PBC) is applied. The band structure and Bloch wavefunction can then be obtained by solving the eigenvalue problem for each wave vector \vec{k} after a Fourier transformation from the real space to the reciprocal space. Although the CCSD(T) method for training data generation does not directly support PBC, one can use CCSD(T) calculations for finite atom clusters (that is, a truncated and possibly passivated supercell) to train the model and subsequently use the model to predict the properties of extended systems. Alternatively, the training data of extended systems can be generated by high-accuracy methods other than CCSD(T), such as double-hybrid DFT, which allows for PBC. Aside from CCSD(T), our scheme can also use other high-level quantum chemistry methods to generate the training labels of molecule properties. Quantum chemistry methods can be selected according to the desired accuracy and the character of systems under consideration.

Note that the results of CCSD(T) calculations may not be consistently accurate for all molecules. Some of the polyaromatic hydrocarbons are more multi-reference in nature (although it is rare for the molecules studied in this paper; see Supplementary Section 5), so that the CCSD(T) calculations themselves exhibit larger errors for these molecules than for other molecules. As all of our training and testing data take CCSD(T) as the ground truth, our model cannot capture the strong multi-reference effects that are not captured by CCSD(T). One possible way to adapt the workflow to systems with strong multi-reference nature is by using the multi-reference configuration interaction method⁴⁴ to generate the training dataset. It is also possible to include one-particle reduced density matrix as an output descriptor of the MEHnet model to better describe electronic structure with strong multi-reference nature, as demonstrated in refs. 16. The one-particle reduced density matrix contains complete information on ground-state single-body properties for both single- and multi-reference systems. Adapting the MEHnet method to more comprehensive datasets can produce a general-purpose electronic structure predictor, which is left for future work.

Methods

Graph encoding of atomic configuration

The input layer takes atomic configurations as input, including the information on atomic numbers (Z_1, Z_2, \dots, Z_n) and atomic coordinates ($\vec{r}_1, \vec{r}_2, \dots, \vec{r}_n$) of an n -atom system. A molecular graph is constructed, in which atoms are mapped to graph nodes, whereas bonds between atoms (neighboring atoms within a cut-off radius $r_{\text{cut}} = 2 \text{ \AA}$) are mapped to graph edges. The atomic numbers Z_i of input elements are encoded as node features $\mathbf{x}_{i,\text{in}}$ by one-hot embedding. The atomic coordinates are encoded as edge features $\mathbf{f}_{j,\text{in}} \equiv [f_c(r_{ij}), Y_{lm}(\hat{e}_{ij})]$, where $f_c(r) \equiv \frac{1}{2} [\cos(\pi \frac{r}{r_{\text{cut}}}) + 1]$ is a smooth cut-off function reflecting the

Table 2 | RMSE of the QM9 version of MEHnet model on the testing dataset of 4,000 randomly sampled configurations in the QM9 dataset

Property	E per atom	p	Q	C	B	E_g	α
Unit	kcal mol ⁻¹	Debye	a.u.	e	–	eV	a.u.
RMSE	0.07	0.03	0.04	0.03	0.04	0.25	1.19

The dash indicates that the bond order B has no unit.

bond length $r_{ij} \equiv |\vec{r}_i - \vec{r}_j|$, and $Y_{lm}(\vec{e}_{ij})$ is the spherical harmonic functions acting on the unit vector $\vec{e}_{ij} \equiv \frac{\vec{r}_i - \vec{r}_j}{|\vec{r}_i - \vec{r}_j|}$ representing the bond orientation²⁶. We include Y_{lm} tensors up to $l = 2$. The electron wavefunction is represented using an atomic orbital basis set $\{\phi_{I,\mu}\}$ (ref. 45), where I is the index of atom and μ is the index of atomic orbital basis function.

BP86 single-body effective Hamiltonian

A quantum chemistry calculation⁴⁶ (the orbital integrator block in Fig. 1a) is then used to evaluate the single-body effective Hamiltonian $F_{\mu,\nu}$ and overlap matrix $S_{\mu,\nu} \equiv \langle \phi_{I,\mu} | \phi_{J,\nu} \rangle$ in the non-orthogonal atomic orbital representation, where $I\mu$ is the row index and $J\nu$ is the column index. The S and F matrices are evaluated by the ORCA quantum chemistry program package⁴⁶ (v.5.0.4) with the quick-to-evaluate BP86 local density functional⁴⁷ and the medium-sized cc-pVDZ basis set⁴⁵. As the hydrocarbon molecules we study are all close-shell molecules, we use spin-restricted DFT calculations to obtain F . We also assume the neural network correction term V^θ is spin-independent as well. Namely, the spin-up and -down molecular orbitals and energy levels are the same, and all molecular orbitals are either doubly occupied or vacant.

The total BP86 energy E_{BP86} equals the molecular orbital energy $2 \sum_{i=1}^{n_e/2} \epsilon_i$ (where ϵ_i is the i th molecular orbital energy level and n_e is the number of electrons) plus a many-body energy E_{MB} :

$$E_{BP86} = 2 \sum_{i=1}^{n_e/2} \epsilon_i + E_{MB} \quad (5)$$

E_{MB} originates from the double-counting of the electron–electron interaction in the band structure energy and can be obtained from the output of the ORCA BP86 DFT calculation. The Lowdin-symmetrized Kohn–Sham Hamiltonian⁴⁸ is then obtained as

$$\mathbf{F}' \equiv \mathbf{S}^{-1/2} \mathbf{F} \mathbf{S}^{-1/2} + \frac{E_{MB}}{n_e} \mathbf{I}, \quad (6)$$

where the last term is an identity shift to account for the many-body energy term. In this case, the direct summation of molecular orbital energies given by F' equals:

$$\begin{aligned} 2 \sum_{i=1}^{n_e/2} \text{eig}_i(\mathbf{F}') &= 2 \sum_{i=1}^{n_e/2} \text{eig}_i \left(\mathbf{S}^{-1/2} \mathbf{F} \mathbf{S}^{-1/2} + \frac{E_{MB}}{n_e} \mathbf{I} \right) \\ &= 2 \sum_{i=1}^{n_e/2} \left[\text{eig}_i(\mathbf{S}^{-1/2} \mathbf{F} \mathbf{S}^{-1/2}) + \frac{E_{MB}}{n_e} \right] \\ &= 2 \sum_{i=1}^{n_e/2} \epsilon_i + E_{MB}, \end{aligned} \quad (7)$$

where eig_i is a function that returns the i th lowest eigenvalue of a matrix, and we use the fact that the energy level ϵ_i is the eigenvalue of the Lowdin-symmetrized Hamiltonian $\text{eig}_i(\mathbf{S}^{-1/2} \mathbf{F} \mathbf{S}^{-1/2})$ (ref. 48). After this transformation, the Kohn–Sham effective Hamiltonian F' already includes the many-body energy E_{MB} , and the total electronic energy is just the summation of molecular orbital energies. Adding the E_{MB} term does not change the eigenfunction and relative energy levels, and thus all other properties are unchanged.

Architecture of the convolutional layer

In the convolutional layer, the input feature first goes through a $N_{\text{species}} \times N_{\text{species}}$ linear transformation (the first self-interaction block, N_{species} is the number of different elements in the system) and an activation layer (the first non-linearity block). All activation layers in MEHnet are tanh functions applied to scalar features. The input features then go through the first-step convolution, where the fully connected tensor product (the first tensor product block) of node feature \mathbf{x}_l and the spherical Harmonic components of all connected edge features \mathbf{f}_{lj} are mapped to an irreducible representation '8 × 0e + 8 × 1o + 8 × 2e' (denoted as Irreps1), meaning there are eight even scalars, eight odd vectors and eight even rank-2 tensors. Weights in the fully connected tensor product are from a multilayer perceptron (the first multilayer perceptron (MLP) block), taking $f_c(r_{ij})$ as input. All MLP blocks in Fig. 1b have a $1 \times 16 \times 16 \times 16 \times N_w$ structure and tanh activation function, where N_w is the number of weights in the tensor product. Then, in the concatenation block, tensor products from different edges \mathbf{f}_{lj} connected to the node l are summed to a new node feature on l . The new node features then go through a linear transformation (self-interaction block) that maps to Irreps1. In all of the self-interaction layers, linear combinations are only applied to features with the same tensor order. The new node features are added to the original node features, before undergoing the linear transformation to complete the first-step of the convolution process. The second-step convolution has the same architecture. The only difference is that the second tensor product block takes input node features of Irreps1 and output features of '8 × 0e + 8 × 0o + 8 × 1e + 8 × 1o + 8 × 2e + 8 × 2o' (denoted as Irreps2). The output of the self-interaction blocks is also Irreps2. After another activation function, the node features are output as $\mathbf{x}_{l,\text{out}}$. Another tensor product is applied to the node features of the two endpoints of each edge to attain the output bond feature $\mathbf{f}_{j,\text{out}}$; this output also has a dimension of Irreps2, with weight parameters from the MLP taking $f_c(r_{ij})$ as input.

Finally, the output features are used to construct the correction matrix V^θ . The neural network correction matrix is as follows:

$$V_{\mu,\nu}^\theta = \begin{cases} [V_{\text{node}}(\mathbf{x}_{l,\text{out}})]_{\mu,\nu} & \text{if } l = J \\ \frac{1}{2} [V_{\text{edge}}(\mathbf{f}_{j,\text{out}})]_{\mu,\nu} + \frac{1}{2} [V_{\text{edge}}(\mathbf{f}_{l,\text{out}})]_{\nu,\mu} & \text{if } l \neq J \end{cases} \quad (8)$$

where $V_{\text{node}}(\mathbf{x}_{l,\text{out}})$ is a $N_l \times N_l$ symmetric matrix rearranged from node features $\mathbf{x}_{l,\text{out}}$, whereas $V_{\text{edge}}(\mathbf{f}_{j,\text{out}})$ is a $N_j \times N_j$ matrix obtained from edge features $\mathbf{f}_{j,\text{out}}$. Here N_l and N_j are the numbers of basis functions of the atom l, j . Note that the output matrices V^θ are Hermitian and equivariant under rotation according to the transformation rule of the basis set $\{\phi_{I,\mu}\}$. $V_{\text{node}}(\mathbf{x}_{l,\text{out}})$ first applies a linear layer from the input dimension of Irreps2 to the output dimension Irreps(l)⁸², where:

$$\text{Irreps}(l) = \begin{cases} (2 \times 0e + 1 \times 1o) & \text{if } l \text{ is H} \\ (3 \times 0e + 2 \times 1o + 1 \times 2e) & \text{if } l \text{ is C} \end{cases} \quad (9)$$

The output dimension corresponds to the irreducible representation of the block diagonal terms of the Hamiltonian of the cc-pVDZ basis set. The output is then arranged into the $N_l \times N_l$ matrix form, $V_{l,\text{out}}$, according to the Wigner–Eckart theorem²², and symmetrized to obtain $V_{\text{node}}(\mathbf{x}_{l,\text{out}}) = \frac{\lambda_V}{2} (V_{l,\text{out}} + V_{l,\text{out}}^T)$; λ_V is a constant hyperparameter and is set to 0.2 for our model. Similarly, the off-diagonal term $V_{\text{edge}}(\mathbf{f}_{j,\text{out}})$ in equation (8) applies a linear layer from the input dimension of Irreps2 to the output the dimension Irreps(l, j), which equals the direct product of Irreps(l) and Irreps(j). The outputs are then arranged into the $N_l \times N_j$ matrix and multiplied by λ_V , giving $V_{\text{edge}}(\mathbf{f}_{j,\text{out}})$.

Furthermore, the energy gap correction term G is obtained from a $8 \times 32 \times 3$ MLP that takes the even scalars of $\mathbf{x}_{l,\text{out}}$ as input and outputs a three-component scalar array, $\mathbf{g}_{r0,1,2}$, with tanh activation. The first component is for attention pooling:

$$\mathbf{G}_K = \sum_I \frac{e^{g_{I,0}}}{\sum_J e^{g_{J,0}}} g_{I,K}, \quad K = 1, 2, \quad (10)$$

giving the two-component bandgap correction term \mathbf{G} . The polarizability correction term, the screening matrix \mathbf{T} is obtained from the edge features $\mathbf{f}_{j,\text{out}}$ going through a Irreps2 to $32 \times 0e + 1 \times 2e$ linear layer, a tanh activation layer, and a $32 \times 0e + 1 \times 2e$ to $1 \times 0e + 1 \times 2e$ linear layer. The $1 \times 0e + 1 \times 2e$ array is then multiplied by a factor λ_T (set to 0.01 in our case) and rearranged into the six independent components of the symmetric matrix, \mathbf{T} .

Evaluating molecular properties

Using \mathbf{H}^{eff} , the electronic structure is evaluated by Schrodinger equation $\mathbf{H}^{\text{eff}} \mathbf{c}^i = \epsilon_i \mathbf{c}^i$, and the molecular orbitals are $|\psi_i\rangle = \sum_{I,\mu} \tilde{c}_{I,\mu}^i |\phi_{I,\mu}\rangle$, $\mathbf{c}^i = \mathbf{S}^{-1/2} \tilde{\mathbf{c}}^i$. The ground-state properties in equation (1) are evaluated from the electronic structure from physics principles, that is, refs. 28,29:

$$\begin{aligned} E^{\text{MEHnet}} &= E_{\text{NN}} + 2 \sum_{i=1}^{n_e/2} \epsilon_i \\ \vec{p}^{\text{MEHnet}} &= -2e \sum_{i=1}^{n_e/2} \sum_{\mu,\nu} (\tilde{c}_{I,\mu}^i)^* \tilde{c}_{J,\nu}^i \langle \phi_{I,\mu} | \hat{r} | \phi_{J,\nu} \rangle \\ \mathbf{Q}^{\text{MEHnet}} &= -2e \sum_{i=1}^{n_e/2} \sum_{\mu,\nu} (\tilde{c}_{I,\mu}^i)^* \tilde{c}_{J,\nu}^i \langle \phi_{I,\mu} | \hat{r} \hat{r} | \phi_{J,\nu} \rangle \\ C_I^{\text{MEHnet}} &= e \left[Z_I - 2 \sum_{i=1}^{n_e/2} \sum_{J,\mu,\nu} (\tilde{c}_{I,\mu}^i)^* \tilde{c}_{J,\nu}^i S_{I\mu,J\nu} \right] \\ B_{IJ}^{\text{MEHnet}} &= 4 \sum_{i,j=1}^{n_e/2} \sum_{K,L,\mu,\nu,\sigma} (\tilde{c}_{K,\mu}^i)^* \tilde{c}_{I,\mu}^i S_{K\mu,L\nu} (\tilde{c}_{L,\sigma}^j)^* \tilde{c}_{J,\nu}^j S_{L\sigma,I\mu} \end{aligned} \quad (11)$$

where E_{NN} is the Coulomb repulsion energy between nuclei, and e and \hat{r} are the electron charge and position operator, respectively.

Besides, using the ground-state electronic structure, E_g can be roughly estimated as $\epsilon_{n_e/2+1} - \epsilon_{n_e/2}$, the HOMO–LUMO gap. However, in principle, the ground-state electronic structure (ϵ_n, \mathbf{c}^n) does not contain the information on excited states (once a electron is excited, ϵ_n and \mathbf{c}^n undergo relaxation and become different). We therefore use MEHnet to output two correction terms G_1 and G_2 ; E_g is then evaluated as a linear transformation of the HOMO–LUMO gap using G_1 and G_2 as the coefficients:

$$E_g^{\text{MEHnet}} = (1 + G_1)(\epsilon_{n_e/2+1} - \epsilon_{n_e/2}) + G_2 \quad (12)$$

Evaluation of the static electric polarizability is done in two steps. First, we evaluate the single-particle polarizability α_0 using perturbation theory:

$$\alpha_0 = 2e^2 \sum_{a=n_e/2+1}^{N_{\text{basis}}} \sum_{i=1}^{n_e/2} \frac{\vec{r}_{a\mathbf{i}} \vec{r}_{i\mathbf{a}}}{\epsilon_a - \epsilon_i} \quad (13)$$

where N_{basis} is the number of basis functions of the molecule, and $\vec{r}_{i\mathbf{a}} \equiv \sum_{\mu,\nu} (\tilde{c}_{I,\mu}^a)^* \tilde{c}_{J,\nu}^i \langle \phi_{I,\mu} | \hat{r} | \phi_{J,\nu} \rangle$. However, the single-particle approximation used in equation (13) does not consider the electric screening effect from electron–electron interaction. We use MEHnet to output a screening matrix T and evaluate the corrected polarizability α as follow:

$$\alpha^{\text{MEHnet}} = (\mathbf{I} + \alpha_0 \mathbf{T})^{-1} \alpha_0. \quad (14)$$

We evaluate the gas phase standard enthalpy of formation of molecules in Fig. 3 using atomic configurations relaxed by the BP86 functional with cc-pVDZ basis set. The total energy at the relaxed atomic configuration is then calculated by the MEHnet. The zero-point

energy (ZPE) and thermal vibration, rotation, and translation energy at $T = 298.15$ K are also calculated by the BP86 functional with cc-pVDZ basis set implemented in ORCA. The ZPE is corrected by the optimal scaling factor of 1.0393 according to Ref. 49. Summing all energy terms give the inner energy U , and the enthalpy is evaluated as $H \simeq U + k_B T$ (k_B is the Boltzmann constant), where we use the ideal gas law. To obtain the standard enthalpy of formation, we subtract the reference state enthalpy of graphite and hydrogen gas at standard condition. The reference enthalpy for each carbon and hydrogen atom are determined as -38.04634 a.u. and -0.57545 a.u., respectively, using CCSD(T) calculation with cc-pVTZ basis set combined with measured standard enthalpy of formation of atomic carbon, atomic hydrogen, and benzene. Atomic configurations of semiconducting polymers in Fig. 4 are relaxed using the Preferred Potential v.5.0.0 (ref. 6,7).

Perturbation theory-based back-propagation

In MEHnet training, gradient of the loss function to the model parameters needs to be calculated. Gradient back-propagation schemes are well-developed for all computation steps, with the exception of solving the Schrodinger equation. The gradients are numerically unstable when there are near-degenerate energy levels, which is usually the case in molecules. Here we first use quantum perturbation theory to obtain the first-order change of energy levels and molecular orbitals:

$$\begin{aligned} \delta \epsilon_i &= (\mathbf{c}^i)^\dagger \delta \mathbf{H}^{\text{eff}} \mathbf{c}^i \\ \delta \mathbf{c}^i &= \sum_{p \neq i} \frac{(\mathbf{c}^p)^\dagger \delta \mathbf{H}^{\text{eff}} \mathbf{c}^i}{\epsilon_i - \epsilon_p} \mathbf{c}^p \end{aligned} \quad (15)$$

We then have the gradients to model parameters as equation (4). Using these equations, we derive the gradients of each molecule properties in equation (11), as follows:

$$\begin{aligned} \nabla_{\theta} f_E &= 2 \sum_{i=1}^{n_e/2} \nabla V_{ii} \\ \nabla_{\theta} f_{\vec{p}} &= -4e \sum_{i=1}^{n_e/2} \sum_{a=n_e/2+1}^{N_{\text{basis}}} \text{Re} \frac{\nabla V_{ai}}{\epsilon_i - \epsilon_a} \langle \psi_i | \hat{r} | \psi_a \rangle \\ \nabla_{\theta} f_{\mathbf{Q}} &= -4e \sum_{i=1}^{n_e/2} \sum_{a=n_e/2+1}^{N_{\text{basis}}} \text{Re} \frac{\nabla V_{ai}}{\epsilon_i - \epsilon_a} \langle \psi_i | \hat{r} \hat{r} | \psi_a \rangle \\ \nabla_{\theta} f_{C_i} &= -4e \sum_{i=1}^{n_e/2} \sum_{a=n_e/2+1}^{N_{\text{basis}}} \text{Re} \frac{\nabla V_{ai} (\tilde{\mathbf{c}}^i)^\dagger (\mathbf{I} \mathbf{S}) \mathbf{c}^a}{\epsilon_i - \epsilon_a} \\ \nabla_{\theta} f_{B_{ij}} &= 4 \sum_{i=1}^{n_e/2} \sum_{a=n_e/2+1}^{N_{\text{basis}}} \text{Re} \frac{\nabla V_{ai}}{\epsilon_i - \epsilon_a} \\ &\quad \times (\tilde{\mathbf{c}}^i)^\dagger (\mathbf{S} \mathbf{I} \mathbf{P} \mathbf{S} \mathbf{I} + \mathbf{S} \mathbf{I} \mathbf{P} \mathbf{S} \mathbf{I}) \mathbf{c}^a \end{aligned} \quad (16)$$

where $\nabla V_{ai} \equiv (\mathbf{c}^a)^\dagger (\nabla_{\theta} \mathbf{V}^{\theta}) \mathbf{c}^i$, the $N_{\text{basis}} \times N_{\text{basis}}$ matrix \mathbf{I}_j is identity in the block diagonal part of atom j and zero elsewhere. Meanwhile, we define $\mathbf{P} \equiv 2 \sum_{i=1}^{n_e/2} \tilde{\mathbf{c}}^i (\tilde{\mathbf{c}}^i)^\dagger$. The essential method to avoid numerical instability is to remove terms that can be proved to cancel each other out. Taking $\nabla_{\theta} f_{\vec{p}}$ as an example: in equation (4), the summation over p goes through all states except i . But as the summed formula in equation (16) is antisymmetric to i and a , the terms for which a ranges from 1 to $n_e/2$ cancel each other out. Only terms for which a ranges from $n_e/2 + 1$ to N_{basis} have a non-zero contribution to the final gradient. Therefore, i is always occupied, and a is always unoccupied in the summation. As close-shell molecules have a finite bandgap, ϵ_i and ϵ_a are not close to each other in any term of the summation, so evaluating equation (16) is numerically stable.

Similarly, the gradients of E_g and α are as follow:

$$\begin{aligned} \nabla_{\theta} f_{E_g} &= (1 + G_1) [\nabla V_{n_e/2+1, n_e/2+1} - \nabla V_{n_e/2, n_e/2}] \\ &\quad + (\epsilon_{n_e/2+1} - \epsilon_{n_e/2}) \nabla_{\theta} G_1 + \nabla_{\theta} G_2 \end{aligned} \quad (17)$$

To calculate the gradient of α , we first evaluate the gradient of α_0 , and then derive $\nabla_{\theta} f_{\alpha}$ using the chain rule:

$$\begin{aligned} \nabla_{\theta} \alpha_0 &= 2e^2 \sum_{a=n_e/2+1}^{N_{\text{basis}}} \sum_{i=1}^{n_e/2} \text{Re} \left\{ \frac{\vec{r}_{ai} \vec{r}_{ia} (\nabla V_{ii} - \nabla V_{aa})}{(\epsilon_a - \epsilon_i)^2} \right. \\ &\quad \left. - 2 \sum_{p \neq a, i} \frac{\vec{r}_{ai}}{(\epsilon_a - \epsilon_i)} \left[\frac{\vec{r}_{ip} \nabla V_{pa}}{(\epsilon_p - \epsilon_a)} + \frac{\vec{r}_{pa} \nabla V_{ai}}{(\epsilon_p - \epsilon_i)} \right] \right\} \quad (18) \\ \nabla_{\theta} f_{\alpha} &= (\mathbf{I} + \alpha_0 \mathbf{T})^{-1} (\nabla_{\theta} \alpha_0) (\mathbf{I} - \mathbf{T} \alpha) \\ &\quad - \alpha_0 (\nabla_{\theta} \mathbf{T}) (\mathbf{I} + \alpha_0 \mathbf{T})^{-1} \alpha \end{aligned}$$

The above equations give gradients of all terms in the loss function expressed by gradients to the direct outputs of the MEHnet, $\nabla_{\theta} \mathbf{V}^{\theta}$, $\nabla_{\theta} \mathbf{G}$ and $\nabla_{\theta} \mathbf{T}$.

Dataset generation

First, 85 small hydrocarbon molecule structures are collected from the PubChem database⁵⁰. The training domain (out-of-domain testing dataset) includes 20 (3) different chemical formula correspond to the horizontal axis labels of the first 20 (last 3) columns in Fig. 2c. Each chemical formula includes up to five different molecules (conformers) taken from the PubChem database. The total number of molecules (conformers) in the training domain and out-of-domain testing dataset is 70 and 15, respectively. The full list of molecules and the number of atomic configurations for each molecule are listed in Supplementary Table 1. Refer to Supplementary Section 1 for a discussion on the principles of selecting these molecules, and their diversity.

Molecular dynamics simulation with TeaNet interatomic potential^{6,7} is then performed for each molecule structure to sample an ensemble of atomic configurations. The molecular dynamics simulation uses Preferred Potential v.4.0.0 (ref. 10) at a temperature of 2,000 K, which enables large bond distortion but does not break the bonds. The initial velocity is set as a Maxwell Boltzmann distribution with the same temperature. Langevin NVT dynamics is used with the friction factor of 0.001 fs⁻¹ and timestep of 2 fs. The TeaNet potential run for 100,000 steps for each chemical formula, and one atomic configuration is sampled every 200 timesteps in the molecular dynamics trajectory; 500 configurations (including the initial equilibrium configuration) are sampled for each chemical formula in the training domain; three-quarters of the 10,000 configurations are sampled to form the training dataset, and the remaining one-quarter forms the in-domain testing dataset. The out-of-domain testing dataset contains 500 configurations. Note that as we aim to include structures out of equilibrium positions, geometric relaxation is not needed before CCSD(T) calculation (otherwise all structures will relax back to the equilibrium positions).

A CCSD(T) calculation with the cc-pVTZ basis set is then implemented in ORCA⁴⁶ for each selected configuration, giving the training labels of total energy, electric dipole and quadrupole moment, Mulliken atomic charge, and Mayer bond order. An EOM-CCSD calculation⁵¹ with the cc-pVDZ basis set is then implemented to obtain the first excitation energy (energy gap). Finally, we conduct a polarizability calculation with the CCSD and cc-pVDZ basis set. The overlap matrix S and starting-point effective Hamiltonian F is obtained from a BP86 DFT calculations with the cc-pVDZ basis set.

Model training

The weight parameters in the loss function is listed as follow: $w_V = 0.1$, $w_E = 1$, $w_p = 0.2$, $w_Q = 0.01$, $w_C = 0.01$, $w_B = 0.02$, $w_E = 0.2$, $w_{\alpha} = 3 \times 10^{-5}$. All quantities are in atomic unit. The model training is implemented by full gradient descend (FGD) with Adam optimizer. For the finally deployed model (7,440 training data points), it is first trained on 1,240 data points sampled from the whole training dataset for 5,000 FGD steps with initial learning rate of 0.01. The learning rate is decayed by

a constant factor $\gamma_1 = 10^{-1/10}$ per 500 steps. The model is then trained on the whole dataset with 7,440 data points for 6,000 FGD steps with a learning rate of 0.001. For other models trained on smaller dataset in Fig. 2a in the main text, the model is trained for 3,000 FGD steps with initial learning rate of 0.01 decayed by $\gamma_2 = 10^{-1/6}$ per 500 steps. As the model trained on 640 data points do not converge in the 3,000-step training, we implement a 10,000-step training, with an initial learning rate of 0.01 that decays by γ_1 every 500 steps in the first 5,000 steps and keeps constant at the last 5,000 steps.

Data availability

Raw computational data files and the training and testing datasets are available with this manuscript through FigShare at <https://doi.org/10.6084/m9.figshare.25762212> (ref. 52). Source Data are provided with this paper.

Code availability

The source code to generate the training dataset, train the MEHnet model, and apply the trained MEHnet model to hydrocarbon molecules has been deposited into a publicly available GitHub repository at <https://github.com/htang113/Multi-task-electronic> (ref. 53), and is also available in the Supplementary Software. The repository contains two branches: the branch v.1.6 is for all results of hydrocarbon molecules in this paper, and the branch v.2.0 is for the benchmark on the QM9 dataset.

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Author contributions

All authors contributed to the discussions of theory and results and to writing the manuscript. J.L. designed and guided the project and formulated the research goals. H.T., H.X., B.X. and W.H. designed and developed the computational method and code package, generated the quantum chemistry dataset, implemented the machine learning training and applications, and did data analysis and visualization. A.H. initiated the theme and formulated the research goals. Y.W., F.L. and P.S. provided important comments for the paper.

Competing interests

The authors declare no competing interests.

Additional information

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