1	Revealing the Role of Local Octahedral Distortions in	
2	Hybrid Halide Perovskites Through Physical-Informed	
3		Data-Driven Machine Learning
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1 Abstract

Data-driven materials design often encounters challenges from small and imbalanced 2 datasets. The complex structural and physicochemical properties of hybrid halide 3 perovskites, coupled with these limitations, create obstacles for performing feature 4 engineering and extracting key fingerprints. Herein, we employed a physical-informed 5 6 data-driven modeling approach to identify lattice geometric fingerprints, such as the distortion index (DI) and effective coordination number (ECoN), and to establish a 7 robust structure-properties relationship mapping the electronic bandgap, resulting in 8 improved model performance. Lattice compression simulations across multiple phases 9 of MAPbI₃ further confirmed a strong correlation between DI and ECoN with electronic 10 bandgap, validating the robustness of the selected octahedra geometrical fingerprints. 11 By adjusting the *s*-*p* antibonding coupling, the pressure-driven reduction in local 12 octahedral distortion, induced by the anisotropic hydrogen bonding between the 13 14 inorganic framework and organic cation, narrows the electronic bandgap and facilitates 15 the p-p transitions, thereby boosting the transition dipole moment and band-edge absorption. Combining data mining with physical analysis, we have successfully 16 clarified the significant impact of lattice geometry on the electronic properties and 17 identified key octahedral geometric fingerprints for effectively describing the electronic 18 19 bandgap, while also revealed the microphysical mechanisms of local octahedral 20 distortion on the optoelectronic properties of hybrid halide perovskites.

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1 1. Introduction

The efficient harvesting, storage, and utilization of clean energy are fundamental to 2 combating climate change and achieving sustainable development¹⁻⁴. Solar energy, due 3 to its wide availability and low environmental impact, ranks among the most significant 4 renewable energy sources and drives the growing demand for photovoltaic 5 6 technologies⁴. Exploring prospective photovoltaic materials with superior performance and excellent stability for energy production is currently one of the biggest challenges 7 and has attracted significant attention^{5, 6}. Hybrid halide perovskites have emerged as a 8 class of promising candidates for various optoelectronic applications with unique 9 virtues⁷⁻⁹, including excellent optical absorption, highly adjustable bandgap, long 10 carrier diffusion lengths, and low exciton binding energy. Besides, the ease of 11 fabrication, the low-cost of compositional precursors, and the solution processability 12 have dramatically stimulated the development of perovskites solar cells^{10, 11}, with power 13 conversion efficiency (PCEs) had boosted from 3.8%¹² to a certified value of 26.7% in 14 a short time^{13, 14}. Despite unprecedented progress and promising applications, designing 15 and evaluating new photovoltaic materials for further performance enhancement 16 remains challenging, due to the complex diversity of hybrid halide perovskites and 17 limited understanding of the structure-composition-property relationship^{10, 11, 15}. 18

Recently, data-driven material design methodologies based on machine learning 19 (ML), an interdisciplinary field that integrates computer science, mathematics, and 20 material science, have been envisioned as a decisive enabler for accelerating the 21 discovery of various functional materials¹⁶. Machine learning approaches typically 22 adopt a framework that extracts descriptors from the atomic, geometric, and 23 physicochemical properties, and identified several key target properties (e. g., 24 electronic bandgap¹⁷⁻¹⁹, carrier mobility²⁰, and formation energy²¹, etc.) through 25 statistical analysis or learning-based importance analysis as criteria for screening 26 27 candidates for various applications. These descriptors are subsequently employed in machine learning models to establish a rigorous mapping to the target properties, 28 29 enabling the rapid traversal of the vast chemical space and facilitating the screening of

potential candidates. Given the vast chemical space and complex structural, 1 physicochemical properties of hybrid halide perovskites, machine learning has become 2 a powerful tool favored by researchers for accelerating material design^{20, 22, 23}, and it is 3 even directly integrated with high-throughput experiments to optimize the performance 4 and manufacturing of perovskite solar cells. Although the integration of big data, 5 artificial intelligence, and materials modeling aims to achieve a paradigm shift in 6 7 materials design by fast deriving rules and trends from existing data to guide material development without understanding the underlying physical mechanisms, the common 8 issue of small and imbalanced datasets often results in significant sacrifices in accuracy. 9 Feature engineering, which leverages experience to construct appropriate and suitable 10 descriptors or fingerprints instead of relying solely on traditional atomic 11 physicochemical descriptors²², promises to address the prevalent issues. However, 12 13 implementing feature engineering itself presents a significant challenge.

Feature engineering has been employed to extract key descriptors for hybrid halide 14 perovskites, including the electronegativities of constituent elements^{19, 20}, Goldschmidt 15 tolerance factor (TF)¹⁷, and packing factor (PF)^{18, 19}, to effectively establish structure-16 property relationships and accelerate material design. However, the significant impact 17 of lattice geometry on atomic orbital overlap, and consequently on the electronic 18 bandgap²⁴, emphasizes the need for novel and effective geometrical fingerprints. Given 19 20 this, a physical-informed data-driven modeling approach is employed to assess the impact of local octahedra geometric fingerprints on the electronic properties, with the 21 goal of establishing a robust structure-property relationship mapping the electronic 22 23 bandgap and improving machine learning performance. Through feature engineering, we identified key octahedral geometric fingerprints, such as the distortion index (DI) 24 25 and effective coordination number (ECoN), to capture complex trends and correlations within the chemical space of hybrid halide perovskites. Further lattice compression 26 27 simulations across multiple phases (cubic, tetragonal and orthorhombic) of MAPbI₃ demonstrate that the pressure-driven non-monotonic variation of DI and ECoN closely 28 align with the electronic bandgap, highlighting the strong correlation between local 29 octahedral distortion and electronic properties, and validating the interpretability and 30

explainability of machine learning models. By modulating the s-p antibonding coupling, 1 2 the local O_h symmetry of PbI₆ octahedra, reflected in DI and ECoN, shows a strong correlation with the electronic bandgap. Reducing local octahedral distortion facilitates 3 *p-p* transitions, thereby enhancing both the transition dipole moment, carrier mobility, 4 and band-edge absorption. Moreover, the local octahedral distortion primarily 5 originates from anisotropic hydrogen bonding between the inorganic framework and 6 7 NH₃ group in MA⁺ in hybrid halide perovskites. Combining data mining with physical 8 analysis, current study clarified the significant impact of lattice geometry on electronic properties, identified key octahedral geometric fingerprints for describing the electronic 9 bandgap, while also revealed the microphysical mechanisms of local octahedral 10 distortion on the optoelectronic properties of hybrid halide perovskites. 11

12 2. Methodology

13 To systemically validate the capability of the selected configuration feature 14 characteristics for describing the electronic bandgap of hybrid halide perovskites, a variety of classical and advanced machine learning algorithms (13 models) are 15 introduced. These algorithms include Gradient Boosting Regression (GBR), Supporting 16 17 Vector Regression (SVR), Decision Tree (DT), Kernel Ridge Regression (KRR), K-18 Nearest Neighbor (KNN), Artificial Neural Network (ANN), Random Forest (RF), LASSO, extremely Randomized Trees (ExtraTree), Gradient Boosting Decision Tree 19 20 (GBDT), eXtreme Gradient Boosting (XGBoost), Light Gradient Boosting Machine (LightGBM), and Categorical Boosting (CatBoost). To evaluate the accuracy and 21 22 generalization ability of the trained model for all these machine learning algorithms, a 23 10-fold cross-validation was employed. Specifically, to assess the performance of these machine learning models, common metrics: mean absolute error (MAE), mean squared 24 error (MSE), and coefficient of determination (R² score) are unitized in the current study. 25 These metrics are defined as follows: $MAE = \frac{1}{n} \sum_{i=1}^{n} |y_i - \hat{y}_i|$, $MSE = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)$ 26 $(\widehat{y}_i)^2$, and $R^2 = \sum_{i=1}^n (y_i - \widehat{y}_i)^2 / \sum_{i=1}^n (y_i - \overline{y})^2$, where *n* is the number of observations, 27 y_i is the actual observed value of the response variable for the *i*-th observation, $\hat{y_i}$ is the 28 predicted value of the response variable for the *i*-th observation according to the model, 29

and \bar{y} is the mean of the observed values. The SHapley Additive exPlanations (SHAP) method was used to extract and analyze important features of atomic physicochemical and geometric descriptors, revealing their relationship with electronic bandgap.

Furthermore, the formula for electronic bandgap of hybrid halide perovskites was 4 identified using the sure independence screening and sparsifying operator (SISSO) 5 method²⁵, a machine learning method with an exceptional performance on huge-6 7 dimensional space. Initially, 10 features were selected from 36 physical chemistry quantities (Table S1) through Least Absolute Shrinkage and Selection Operator 8 Regression (LASSO) algorithm as the primary features. The feature space was denoted 9 as ϕ_0 and served as the starting point for the SISSO process. A set of algebraic and 10 functional operations (Table S2) were iteratively applied to the initial feature space ϕ_0 11 12 to construct augmented feature spaces with increased dimensionalities. After one, two, and three iterations, three feature spaces ϕ_1 , ϕ_2 , and ϕ_3 were generated, containing 13 370, 411092, and 7.28×10^{10} features, respectively. To identify the formula, an efficient 14 15 dimensionality reduction method, sequential importance sampling (SIS), was unitized to screen the features and identify a subset with the largest correlation with the response. 16 A key hyperparameter to tune was the dimensionality of the solution, i.e., the 17 18 dimensionality of the identified formula represented by D. The fitted regression formula was written as: $y = \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_D x_D$, where y is the response, β_i and x_i are 19 the solved coefficient and feature value for the *i*-th dimension, respectively. To evaluate 20 21 the predictive performance of different dimensionality, cross-validation techniques are implemented. In detail, the training data was divided into ten subsets, and the formula 22 23 was then identified using nine of these subsets, while the remaining subset was reserved to assess the prediction errors $(RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2})$, in which *n* is the number 24 25 of observations, y_i and \hat{y}_i are the actual observed value and the predicted value of the response variable according to the model for the *i*-th observation, respectively. 26

The first-principles calculations were performed using the density-functional theory formalism implemented in the Vienna Ab-initio Simulation Package (VASP)²⁶⁻²⁸. The frozen-core projected augmented wave (PAW) pseudopotentials were employed to

describe the electron-core interactions²⁹. The generalized gradient approximation 1 (GGA) formulated by Perdew, Burke, and Ernzerhof (PBE) was utilized as the 2 exchange-correlation functional³⁰. Electrons taken to be valence are 1s¹ of H, 2s²2p² of 3 C, $2s^22p^3$ of N, $5d^{10}6s^26p^2$ of Pb, and $5s^25p^5$ of I. The effect of van der Waals (vdW) 4 dispersion interactions was estimated with the pairwise D3 three-body dispersion 5 correction proposed by Grimme (DFT-D3)³¹. The electronic wavefunctions were 6 expanded using a plane-wave basis with a cutoff energy of 520 eV, and the sampling of 7 the first Brillouin zone was adopted by applying the Monkhorst-Pack scheme. The cell 8 parameters and atomic positions were fully relaxed until the energy and residual forces 9 on atoms converged to 1×10^{-7} eV and 0.001 eV/Å by applying the conjugate-gradient 10 algorithm, respectively. A reciprocal space sampling with a Γ center of $7 \times 7 \times 7$ k-point 11 mesh of the Brillouin zone was applied in the cubic phase, $5 \times 5 \times 3$ k-mesh for 12 tetragonal and orthorhombic structural optimization. Finer k-point meshes were 13 adopted for the calculations of electronic band structure and projected density of states 14 15 (DOS) for each configuration. The absorption coefficient was defined as $\alpha(\omega) =$ $\frac{\sqrt{2}e}{\hbar c} \left[(\varepsilon_1^2 + \varepsilon_2^2)^{\frac{1}{2}} - \varepsilon_1 \right]^{\frac{1}{2}}$, in which ε_1 and ε_2 represent the real and imaginary parts of the 16 dielectric function, respectively. The crystal lattice free volume was calculated by using 17 the Multiwfn 3.3.9 software³². The transition dipole moments were calculated based on 18 the wavefunction from VASP using VASPKIT code³³. 19

20 3. Results and discussion

3.1 Data-Driven Revelation of the Relationship between Local Octahedral Geometric Fingerprints and Electronic Bandgaps

Although geometric parameters significantly influence the overlap of atomic orbitals and, consequently, the electronic bandgap of hybrid halide perovskites, visualization of dataset achieved from previous high throughput first-principles calculations (**Figure 1a**) reveals unclear trends and periodicities between the extract geometric fingerprints and the electronic bandgap. In detail, the definitions of the selected geometric fingerprints are given in **Table S1**. To ensure the generalizability of the closed structure-property relationship between the geometric features and electronic

bandgap, we selected all types of crystal structures (cubic, tetragonal, and orthorhombic) 1 2 with electronic bandgaps calculated using the PBE functional. Pearson correlation coefficient matrix between pairs of 10 selected fingerprints (e. g. the electronegativity 3 of halide and geometric features), along with the matrix for all features, as illustrated 4 in Figure 1b and S1, respectively. The evaluated low linear correlation coefficients 5 clearly indicate that the nonredundant descriptors are constructed and robust feature 6 engineering is applied. Then, multiple machine learning algorithms are employed to 7 evaluate the impact of the geometrical fingerprints of the local MX₆ octahedra on the 8 electronic bandgap, and four indices are introduced to estimate the prediction errors: 9 coefficient of determination (R^2) , mean absolute error (MAE), mean squared error 10 (MSE). The results shown in Figure 1c and S2, clearly indicates the robustness of the 11 12 newly proposed geometrical fingerprints in predicting electronic properties, with a notable improvement in prediction accuracy across all machine learning models once 13 the geometric features are incorporated. 14



Figure. 1 (a) Data visualization of the electronic bandgap for hybrid halide perovskites based on octahedral geometric parameters. (b) Heat map of the Pearson correlation coefficient matrix among lo selected features. (c) Fitting results comparing actual and predicted electronic bandgap using XGBoost with (Green) and without (Violet) geometrical fingerprints, along with R², MAE, and MSE to estimate the prediction errors. (d) SHAP value plots highlighting the top 10 features identified by XGBoost.

The SHAP method is adopted to interpret the predictions of complex machine 1 2 learning models and to assess the importance and contributions of various fingerprints in predicting the bandgap of hybrid halide perovskites. The SHAP value plots of top 10 3 features (XGBoost), as shown in Figure 1d, highlight that the electronegativity of 4 halide (χ_X) , TF, and PF significantly correlate with the electronic properties. 5 Additionally, bond-angle variance (σ^2) and DI, average bond length (l_{av}), effective 6 coordination number (ECoN), and bond length quadratic elongation ($\langle \lambda \rangle$) of MX₆ 7 octahedra also play a crucial role. χ_X plays the most important role in predicting the 8 9 electronic bandgap, with the increase in the electronegativity from I to F positively affecting the expected bandgap. Higher TF and OF are also associated with a widening 10 of bandgap output, while an increase in the PF shortens the average M-X bond length 11 (l_{av}) and reduces the polyhedral volume (V_{Poly}) , thereby narrowing the bandgap. 12 Interestingly, although both reflect the local distortion of the MX₆ octahedra, the σ^2 has 13 14 a favorable influence, while the DI has a somewhat adverse effect on the bandgap 15 prediction. ECoN of MX₆ octahedra positively contributes to bandgap prediction, while $<\lambda>$ has a negative effect. 16

17 To address the issue of multiple descriptors influencing the electronic bandgap and 18 to enhance the interpretability of the machine learning algorithm, the SISSO approach is employed to identify reliable, low-cost formulas through mathematical operations 19 20 between these features. These formulas describe the relationship between ten primary descriptors and the electronic bandgap, expressed in a nonlinear functional form due to 21 22 the compressed sensing methodology with different feature dimensions (Figure S3). 23 The identified SISSO formula for the electronic bandgap demonstrates promising 24 predictive accuracy compared to DFT calculations, with an RMSE as low as 0.38 eV (Figure S4). Several top 3D descriptor identified by SISSO of ϕ_3 (Table S3): 25 $\frac{\chi_X \times TF}{e^{TF} \times (\chi_X^3 - e^{\chi_X})}, \frac{(OF \times DI) - \chi_X}{\chi_X^3 - e^{\chi_X}}, \frac{TF^3 - e^{TF}}{\chi_X^3 - e^{\chi_X}}, |(\chi_X \times DI) - e^{-PF}| - |e^{-PF} - (DI \times ECoN)|.$ 26 In addition to halide electronegativity (χ_X) , TF, and octahedral factor (OF), and local 27 octahedral geometric parameters: DI, and ECoN, are identified as key descriptors. 28 While machine learning algorithm has highlighted the significant influence of local 29

octahedral geometrical parameters on the electronic structure, the unclear physical understanding drives further exploration of how changes in the local octahedral geometrical parameters affect their electronic structure and optoelectronic properties, particularly in relation to the interaction between the organic cations and metal halide framework.

3.2 Physics-Driven Validation of the Impact of Local Octahedral Geometric
 Fingerprints on the Electronic Structure



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9 Figure. 2 (a) Orbital projected electronic band structure of cubic MAPbI₃. Pressure-induced (b) 10 variation of the electronic bandgap with experimental values from Ref. 26, (c) changes in crystal 11 structure, (d) changes in VBM and CBM, and (e) variation in lattice volume, free volume, 12 polyhedral volume, and MA cation volume. Yellow color in the inset represents the free volume at 13 different pressures.

14 The hybrid nature and soft inorganic framework in organic-inorganic hybrid halide 15 perovskites make their structural alterations and optoelectronic properties susceptible

to external stimuli, thus rendering the lattice compression a powerful tool for 1 2 investigating the impact of local octahedral geometrical parameters on their electronic structure. To further clarify the structure-property relationship, the representative 3 material MAPbI₃ is selected for additional study. The calculated unpressurized orbital-4 projected electronic band structure of cubic MAPbI₃ is shown in Figure 2a, where the 5 valence band maximum (VBM) is dominated by an antibonding hybrid state between 6 7 Pb-6s and I-5p orbitals, while the conduction band minimum (CBM) primarily originates from Pb-6p orbitals, with an electronic bandgap of 1.51 eV. Under pressure, 8 although VBM and CBM remain dominated by a hybrid state between Pb-6s and I-5p 9 orbitals and Pb-6p orbital (Figure S5-S7), respectively, both the crystal structure and 10 electronic structures undergo significant changes, as shown in Figure 2b-c and S5-S7. 11 Notably, the electronic bandgap exhibits a significant red shift under pressure, followed 12 by significant blue shifts. This nonmonotonic variation, where the bandgap initially 13 decreases and then increases with external pressure, well aligns with previous 14 15 experimental observations. Despite that such pressure-induced nonmonotonic behavior is commonly observed in other organic-inorganic hybrid halide perovskites, its atomic-16 level mechanism remains unclear. CBM, primarily originating from the Pb-6p orbital, 17 increases linearly with rising pressure. In contrast, VBM, influenced by an antibonding 18 hybrid state between Pb-6s and I-5p orbitals, initially increases steeply but then slows, 19 20 resulting in a nonmonotonic variation of the electronic bandgap as function of pressure. Interestingly, the electronic bandgap of MAPbI₃ reaches an optimal value of 1.34 eV at 21 ~1.5 GPa, enabling the highest power-to-electricity conversion efficiency (PCE) for 22 23 solar cells, as predicted by the Shockley-Queisser limit.

Regarding structural changes (**Figure 2e**), the significant reduction in lattice volume with increasing pressure is mainly attribute to a notable decrease in free volume, while the relatively rigid MA⁺ and metal halide octahedral structures experience smaller changes. Initially, as shown in **Figure 3a**, the lattice volume reduction is driven by the shortening of Pb-I bond lengths (< 2 GPa), followed by a decrease in Pb-I-Pb bond angles (> 2 GPa). The sharp decline of Pb-I-Pb bond angle (> 2 GPa), reflecting increased global distortion between adjacent octahedra, suggests the occurrence of

significant octahedral tilting or a pressure-induced phase transition. Additionally, the 1 shortening of the Pb-I bond with pressure enhances the coupling between Pb-6s and I-2 5p antibonding orbitals, leading to an increase of VBM (Figure 3b). In contrast, the 3 localized nature of the Pb-6p orbitals makes CBM relatively insensitive to the 4 shortening of the Pb-I bond lengths, resulting in a narrowing of the electronic bandgap. 5 The sharp decrease in the Pb-I-Pb bond angle with pressure (> 2 GPa) causes the 6 partially broken of Pb-I bonding^{24, 34} and the weakening of Pb-6p and I-5s orbital 7 coupling, resulting in the widening the electronic bandgap (Figure 2b). The synergy 8 between Pb-I bonds and Pb-I-Pb bond angles provides a detailed atomic-scale 9 explanation for the nonmonotonic variation of the electronic bandgap with pressure. 10 Given the critical role of the inorganic framework in determining the band-edge 11 electronic structure, understanding its microstructural physical parameters is essential 12 and warrants significant attention³⁵⁻³⁸. 13



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Figure. 3 (a) Variation of average Pb-I bond length (purple) and average Pb-I-Pb bond angle (cyan) as function of pressure. (b) Schematic representation of the bandgap (1) red- and (2) blue-shift as pressure below and exceeds 2 GPa, respectively.

18 The local octahedral geometric parameters of unpressurized MAPbI₃ (Figure 4a), 19 including $\langle \lambda \rangle$, σ^2 , DI, and ECoN, show that the PbI₆ octahedra experience considerable 20 distortion (Figure 4b). In addition to the shape of MA⁺ and hydrogen bonding between 21 NH₃ group with iodine atoms, the lone pair of nonbonding electrons in Pb²⁺ itself will 22 also lower the coordination symmetry of PbI₆ octahedron. However, the lack of 23 consistent correlation between the pressure-driven changes in $\langle \lambda \rangle$ and σ^2 with the

electronic bandgap suggests that they do not strongly correlate with the electronic 1 properties. Fortunately, DI and ECoN of local octahedra are sensitive indicators of 2 microstructure modifications. The non-monotonic variation of the DI with increasing 3 pressure, depicted by the standard deviation of Pb-I bond lengths (Figure S8), closely 4 5 mirrors the pressure-induced changes in the electronic bandgap. Under mild pressure (< 2 GPa), the enhancement of local O_h symmetry in PbI₆ octahedra (Figure 4a) 6 strengthens the s-p antibonding coupling between the lone-pair Pb-6s² with I-5p orbitals, 7 as well as the unoccupied Pb-6p orbitals coupling³⁹, leading to a narrowing of electronic 8 bandgap. However, as the pressure increases beyond 2 GPa, the local O_h symmetry 9 deteriorates (Figure 4b), resulting in the breaking of some Pb-I bond and weakening of 10 the s-p antibonding coupling^{24, 40} and causing an electronic bandgap widening. 11 Moreover, Figure 4b shows that the pressure-induced lattice modifications primarily 12 13 occur along the ac-lattice plane.



Figure. 4 (a) Variation of $\langle \lambda \rangle$, σ^2 , DI, and ECoN (yellow circles) as compared to bandgap (blue square) under pressure. (b) Shape of PbI₆ octahedra under pressure, with the standard PbI₆ octahedra

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1 (green) serving as a benchmark. (c) Variation of total DI, along with axial (DI_{ax}) and equatorial (DI_{eq}) 2 components of PbI₆ octahedra, and (d) average hydrogen bond length ($HB_{N-H \cdot I}$, green circle) and 3 hydrogen bond angle ($\theta_{N-H \cdot I}$, red square) as a function of pressure, respectively.

We define the DI contribution from the PbI₆ octahedron in the equatorial direction 4 5 (ac-lattice plane) as DI_{eq} , while the contribution along the axial direction (b-axis) as 6 DI_{ax}. The matching trends of the overall DI and DI_{eq} under pressure further confirm that the distortion of local octahedron is primarily driven by lattice structure changes along 7 8 the *ac*-lattice plane. Under moderate pressure (≤ 2 GPa), the external force equalizes Pb-I bond lengths in the equatorial direction (Pb-Ieq), significantly reducing DI and, 9 especially DIeq. Meanwhile, stretching or compression of Pb-I bond lengths in the axial 10 direction (Pb-I_{ax}) lead to a noticeable reduction in DI (Figure 4c). As pressure increase 11 exceeds 2 GPa, the Pb atom deviates from the center of PbI₆ octahedron, causing a 12 13 substantial distortion in all Pb-I bond lengths and resulting in a significant increase in both DIeq and DIax. The uneven variation of local octahedral distortion with increasing 14 pressure is closely linked to the interaction between the MA⁺ and the PbI₆ inorganic 15 framework through hydrogen bonding, as shown in the insert of Figure 4d. Among the 16 hydrogen bonds in the Pb-I cage (HB_{N-H···I} < 3 Å), while each iodine atom along the 17 axial direction forms a hydrogen bond with NH₃ group in MA⁺, only some iodine atoms 18 19 along the equatorial direction participates in hydrogen bond formation. Consequently, this hydrogen bonding inhibits the distortion along the axial direction (DIax) but 20 exacerbates it along the equatorial direction (DIeq). The slight elongation of HB_{N-H···I} 21 22 (used as a proxy for hydrogen bond strength) and the stable hydrogen bond angle (θ_{N-1} $H \cap I$) under pressure below 2 GPa suggest a weakening interaction between MA⁺ and the 23 PbI₆ inorganic framework, contributing to a reduction in DI and enhancement of local 24 octahedral symmetry, consistent with previous study⁴¹. Beyond 2 GPa, the distortion 25 26 and shrinkage of Pb-I cage lead to a sharp decrease in HB_{N-H···I} and a corresponding 27 increase in θ_{N-H-I} . Hydrogen bonding between MA⁺ and the PbI₆ inorganic framework plays a crucial role not only in structural stabilization but also in influencing the 28 29 octahedral distortion of the inorganic framework.

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3.3 Influence of Local Octahedral Distortion on Optoelectronic Properties

Figure. 5 Variation of (a) dipole matrix element at the R point and (b) effective mass of electrons
(blue) and holes (yellow) under pressure. (c) Variation of linear absorption spectra, and (d)
corresponding differential absorption spectrum ((I-I₀)/I₀, percentage) as function of pressure. I₀ is
linear absorption spectra under 0 GPa pressure.

In addition to affecting the electronic bandgap, the improvement in local symmetry 7 of PbI₆ octahedra has a significant impact on the optical transitions. According to the 8 Fermi Golden rule⁴², the optical absorption of a semiconductor at photonic energy $\hbar\omega$ 9 is directly correlated with $\frac{2\pi}{\hbar} \int |\langle v | \hat{H} | c \rangle|^2 \frac{2}{8\pi^3} \delta(E_c(\vec{k}) - E_v(\vec{k}) - \hbar \omega) d^3k$, where 10 $\langle v | \hat{H} | c \rangle$ is the transition dipole matrix between the valance band (VB) and conduction 11 band (CB), and the second term corresponds to the joint density of states (JDOS) at $\hbar\omega$. 12 The transition dipole matrix at the R point increases significantly under pressure below 13 2 GPa (Figure 5a and S5-S7), with the transition dipole moment (P^2) at 2 GPa reaching 14 more than twice that at 0 GPa, highlighting the importance of band edges in photon-15 electron interaction. Strong optical transitions at the band edge are known to be 16 17 dominated by *p-p* transitions³⁹, as the lower CBs primarily originate from unoccupied Pb-6p orbitals, while the upper VBs are dominated by hybrid states of I-5p orbitals and 18 19 Pb-6s orbitals (Figure 2a). Enhanced local $O_{\rm h}$ symmetry strengthens the antibonding coupling between Pb-6s and I-5p orbitals and promotes the p-p transitions, leading to 20

an increase in the transition dipole moment (Figure 5a). However, the deterioration of
local O_h symmetry (>2 GPa) weakens the antibonding coupling, resulting in an indirect
bandgap and a sharp decrease in the transition dipole moment.

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Additionally, the improvement of local octahedral symmetry enhances the 4 dispersion of CBM and VBM (Figure 5b), which slightly reduces the effective masses 5 for electron (m_e^*) and hole (m_h^*) , resulting in the improvement of carrier mobility. 6 7 Conversely, as pressure increases (>2 GPa), the breaking of local symmetry weakens band dispersion, leading to heavier effective masses for electrons and holes. 8 9 Furthermore, the pressure-induced modifications in linear absorption spectra primarily occur in the visible light range, which accounts for the most usable portion of the full 10 solar spectrum (Figure 5c-d). The enhancement of transition dipole matrix increases 11 optical absorption in the visible light range (≤ 2 GPa), while the reduction in bandgap 12 causes a significant red-shift in the differential absorption spectrum. However, as 13 pressure exceeds 2 GPa, a broad indirect bandgap and a weaker transition dipole matrix 14 15 leads to an obvious blue-shift, or even a negative peak in the differential absorption spectrum (Figure S7). Consequently, under mild pressure (< 2 GPa), the reduction in 16 octahedral distortion promotes the s-p orbital overlaps and p-p transitions, narrowing 17 the bandgap and enhancing band dispersion, thus increasing visible light absorption. 18 When pressure exceeds 2 GPa, the weakening of *s*-*p* orbital overlap due to increased 19 20 octahedral distortion causes a decline in visible light absorption.

21 While the pressure-driven nonmonotonic variation of the electronic bandgap in cubic MAPbI₃ has been well explained, and the structure-property relationships 22 23 between local octahedral distortion and optoelectronic properties have been established, 24 further verification is needed to confirm its universal applicability. The low-temperature 25 tetragonal and orthorhombic MAPbI₃, which also feature the PbI₆ inorganic framework with voids occupied by MA⁺, serve as suitable candidates for such verification. The 26 27 calculated lattice parameters (Table S4) and electronic bandgap for the tetragonal (Figure S9) and orthorhombic (Figure S10) MAPbI₃ are in good agreement with 28 previous studies^{41, 43-45}. The orbital-projected band structure and projected density of 29 states (PDOS) for these phases under various pressures are displayed in Figure S11-30

S14. Both VBM and CBM of tetragonal (Figure S9) and orthorhombic (Figure S10)
phases MAPbI₃ are similarly composed by a hybrid state between Pb-6s and I-5p orbital
coupling and Pb-6p orbitals, respectively. Furthermore, the crystal lattice free volume
in both tetragonal and orthorhombic phases MAPbI₃ decreases significantly, making a
major contribution to the reduction in lattice volume (Figure S15-S16).

6 3.4 Robustness of Local Octahedral Geometric Fingerprints across Multiple

7 Phases



Figure. 6 (a) Variation of the electronic bandgap (blue circle) and DI (red square) of (a) tetragonal
and (b) orthorhombic MAPbI₃ under pressure, respectively. Total, axial (DI_{ax}), and equatorial (DI_{eq})
distortion index of (c) tetragonal and (d) orthorhombic MAPbI₃, as function of pressure, respectively.

12 Interestingly, both tetragonal and orthorhombic phases MAPbI₃ exhibit a 13 nonmonotonic variation of the bandgap with external pressure, as shown in **Figure 6ab.** Unlike the monotonic variation of Pb-I bond length, Pb-I-Pb bond angle, and $\langle \lambda \rangle$ 14 and σ^2 with pressure (Figure S17-S18), the nonmonotonic changes in DI (Figure 6a-15 16 b) and ECoN (Figure S19-S20) for the PbI₆ octahedra closely align with the pressuredriven evolution of the electronic bandgap. The intrinsic local distortion of the PbI₆ 17 octahedra causes uneven Pb-I bond lengths, resulting in a wide bandgap. Mild external 18 pressure (< 3 GPa) improves the local octahedral symmetry in both tetragonal and 19

orthorhombic MAPbI₃, as reflected by the decrease in DI (Figure 6a-b), leading to a
narrowing of the electronic bandgap. However, as the local octahedral distortion
increases under further compression (> 3 GPa), the electronic bandgap increases rapidly.
The lower the local octahedral distortion, the smaller the electronic bandgap. Moreover,
as shown in Figure S21-S22, the reduction in local octahedral distortion under pressure
in both phases MAPbI₃ enhances the optical absorption in the visible light range.

7 Similar to cubic MAPbI₃, as shown in Figure 6c-d, variation of local octahedral distortion in the tetragonal and orthorhombic phases exhibit strong anisotropy under 8 pressure. Specifically, DIax in both phases follows a monotonic or quasi-monotonic 9 trend with pressure, while the nonmonotonic pressure-driven changes in DIeq 10 correspond to the overall DI trend. Mild external pressure (< 3 GPa) equalizes Pb-I 11 bond lengths along the equatorial direction (Pb-Ieq), significantly reducing the total and 12 equatorial octahedral distortion (DI and DIeg), and narrowing the electronic bandgap. 13 However, pressure-induced deviations of Pb-I bond lengths along the axial direction 14 15 (Pb-Iax) increase the axial distortion (DIax). As Pb atom shifts from the center of PbI6 octahedron (indicated by σ^2) under further compression, both DI_{eq} and DI_{ax} rise sharply, 16 and the resulting breakdown in local octahedral symmetry leads to the electronic 17 bandgap widening. Therefore, irrespective of crystalline phase, the local distortion of 18 19 PbI₆ octahedra, characterized by deviations in Pb-I bond lengths, DI and ECoN, plays 20 a pivotal role in determining the optoelectronic properties of hybrid halide perovskites.

21 **4.** Conclusions

22 To summarize, utilizing physical-informed data-driven machine learning 23 techniques, we have evaluated the impact of lattice geometric fingerprints on the electronic properties in hybrid halide perovskites, extracting robust geometrical 24 25 fingerprints to establish a robust structure-property relationship mapping the electronic bandgap and improve the performance of machine learning models dealing with small 26 27 and imbalanced datasets. In addition to atomic and physicochemical properties descriptors like halide electronegativity and TF, feature engineering identified key 28 29 octahedral geometric fingerprints, such as the DI and ECoN, to effectively capture

complex trends and correlations within chemical space. Furthermore, lattice 1 compression simulations across multiple phases of MAPbI₃ (cubic, tetragonal, and 2 orthorhombic) demonstrate that the pressure-driven non-monotonic variations of DI 3 and ECoN closely aligns with the electronic bandgap, validating the effectiveness of 4 the selected local octahedral geometric fingerprints and confirming the reliability of 5 ML's interpretability and explainability. By adjusting the s-p antibonding coupling, the 6 7 pressure-driven reduction in local octahedral distortion (enhanced local O_h symmetry), induced by the anisotropic hydrogen bonding between the inorganic framework and 8 organic cation, narrows the electronic bandgap and facilitates the *p*-*p* transitions, 9 thereby boosting the transition dipole moment, carrier mobility, and band-edge 10 absorption. Combining data mining with physical analysis, our theoretical 11 investigations has thoroughly examined the significant impact of lattice geometry on 12 electronic properties, successfully identified effective octahedral geometric fingerprints 13 for describing the electronic bandgap, while also revealed the microphysical 14 15 mechanisms of local octahedral distortion on the optoelectronic properties of hybrid halide perovskites. 16

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