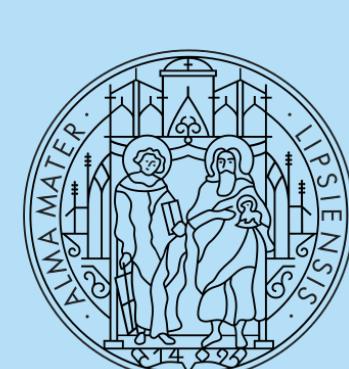


Strain-induced bandgap transition in III-V semiconductors

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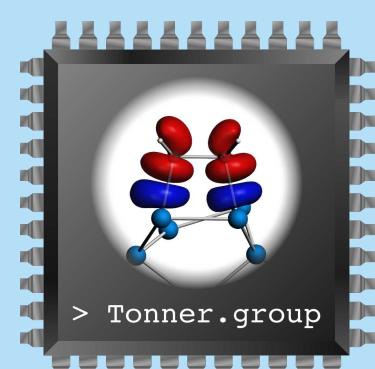


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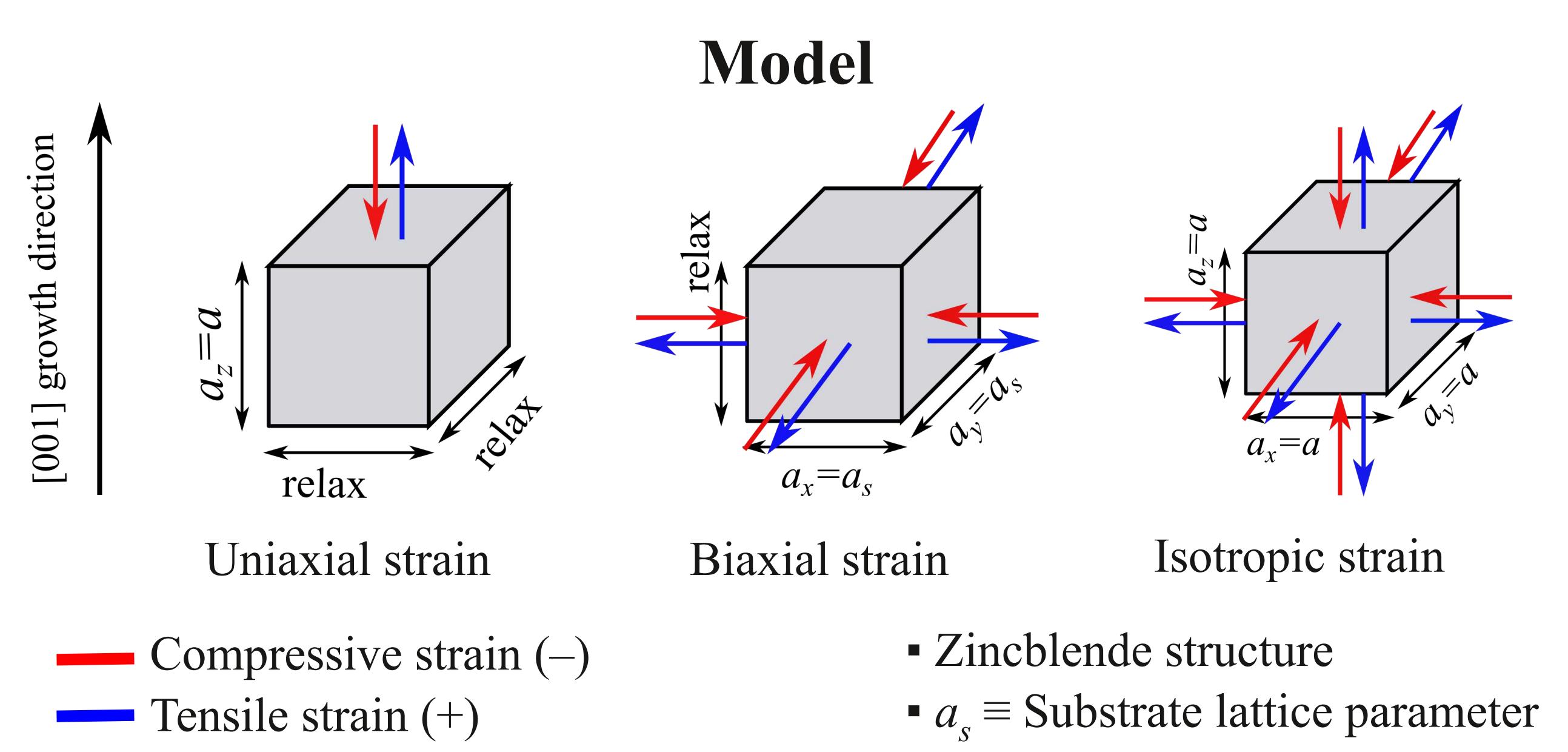


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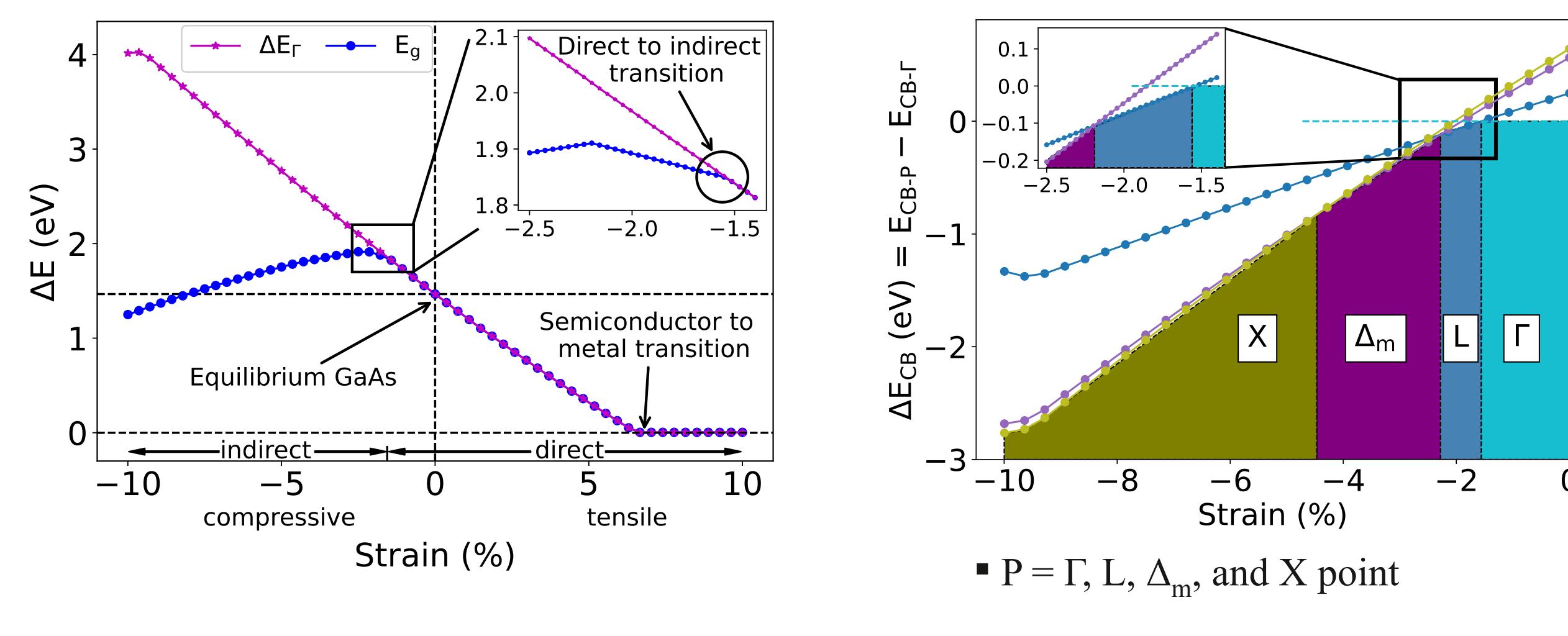
Introduction

The modification of bandgaps in III-V semiconductors is of strong interest for optoelectronic applications. Varying the relative composition is one of the major strategies to tailor the bandgap in compound semiconductors. Strain can be used further to fine-tune. In combination, they can be used to customize the bandgaps over a wide range of values and induce the transition in the nature of bandgaps. Here, we establish a predictive *ab initio* approach based on density functional theory (DFT) to analyze the mutual correlation of composition, strain, and the bandgap of material in multinary III-V semiconductors.



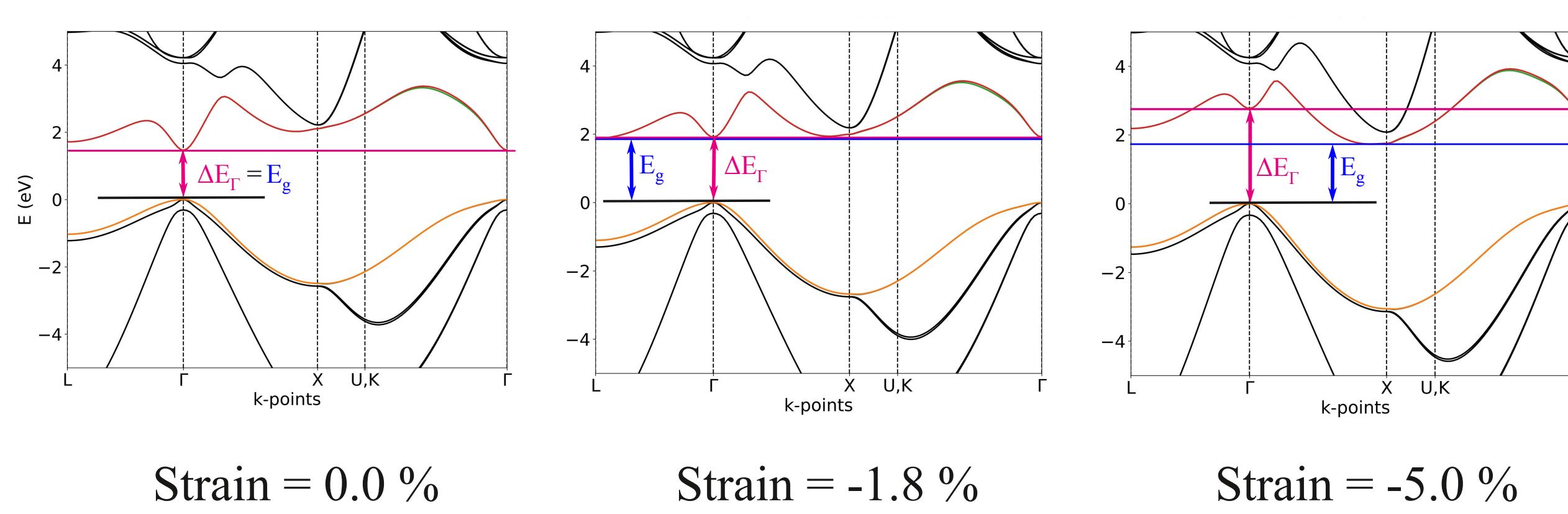
Binary system

• Strain-bandgap relationship in GaAs under isotropic strain

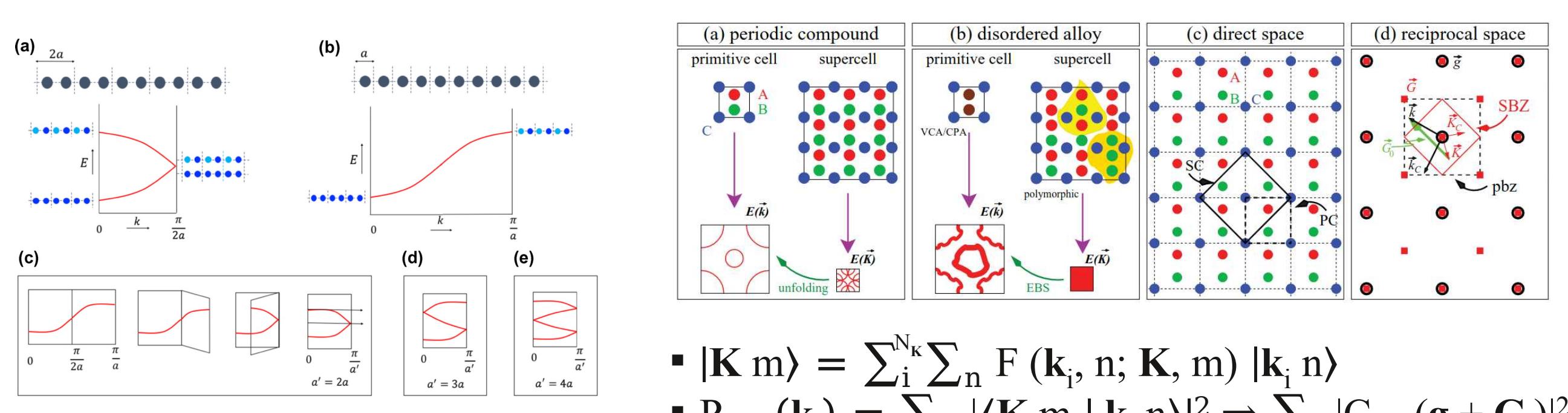


▪ Valence band maxima stays at the Γ point throughout

• Evolution of GaAs band structure under compressive strain



Band folding [1, 2]



Summary

- Bandgap nature in multinary system using Bloch spectral weight
- Efficient sampling in multinary system using machine learning
- Composition-strain-bandgap map: bandgap phase diagram [5]
- Direct-indirect transition in the bandgap nature under strain

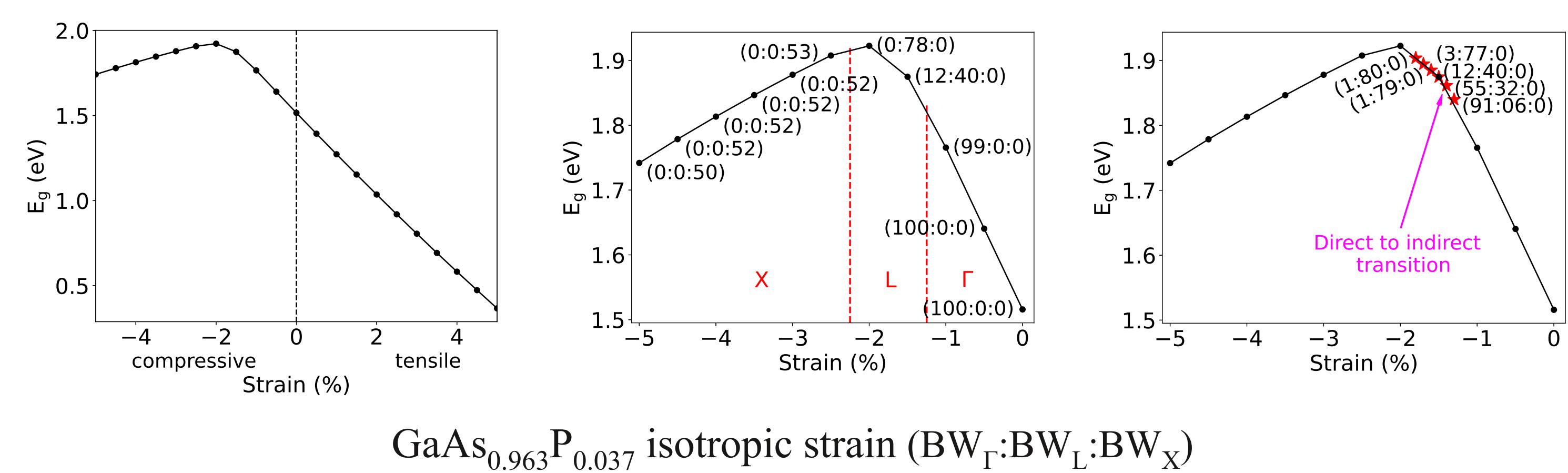
Ternary system

• Challenge

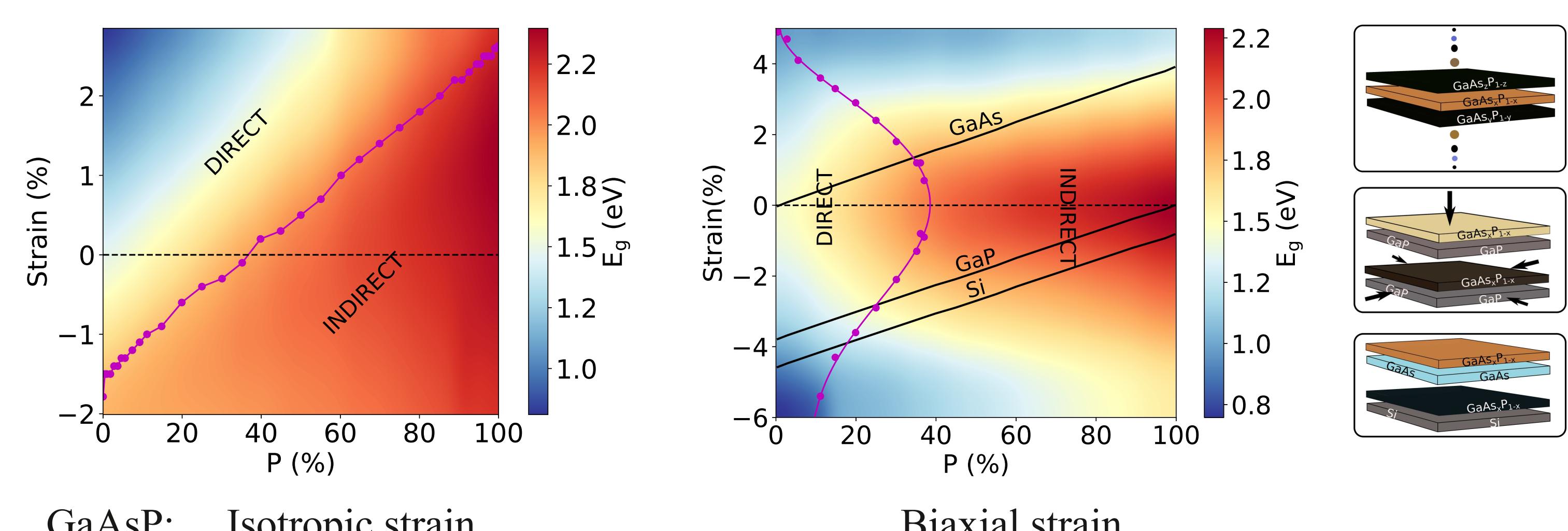
- Supercell: band folding \Rightarrow bandgap magnitude ✓; bandgap nature ✗

• Determining nature of bandgap using Bloch spectral weight

- Compare the Bloch spectral weights (BW) for conduction band at Γ , L, and X points



• Composition-strain-bandgap relationship: bandgap phase diagram



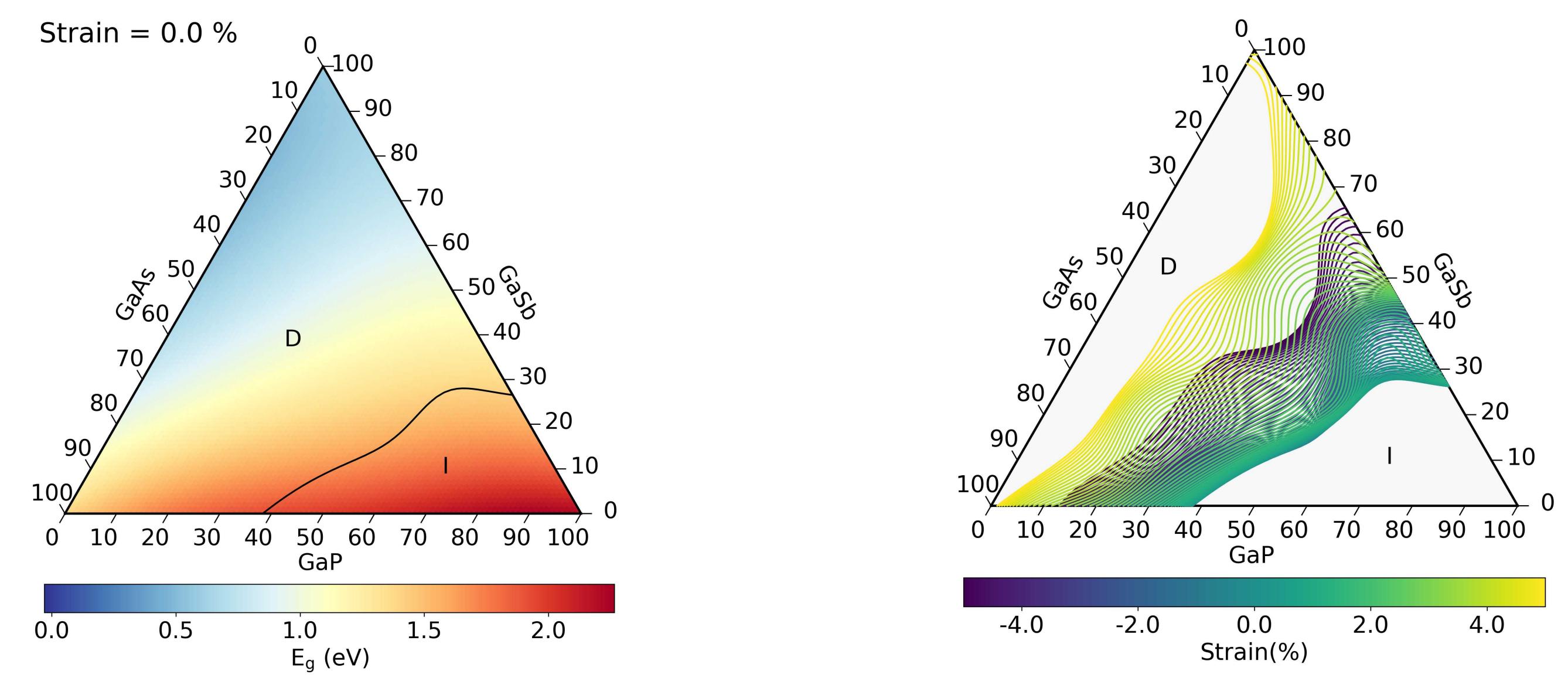
Quaternary system

• Challenge

- Large composition-strain space \Rightarrow sampling is not efficient with DFT calculations only

• Combining DFT with machine learning

- | | |
|-----------------------------------------------------------------|---------------------------------------|
| ▪ Model : support vector machine (radial basis function kernel) | ▪ Bandgap magnitude : r2_score = 0.99 |
| ▪ Training set : 3892 DFT data | ▪ Bandgap nature : accuracy = 0.95 |
| ▪ Features : composition, strain | |



Computational details

- | | |
|-----------------------------------------------------------------------|-----------------------------------------------------------------------|
| ▪ Periodic DFT : VASP-5.4.4, PAW basis set | ▪ Primitive cell : $11 \times 11 \times 11$ Γ -centered k-mesh |
| ▪ Geometry opt. : PBE-D3(BJ), 550 eV | ▪ Supercell : $6 \times 6 \times 6$, SQS [3], Γ -only |
| ▪ Electronic prop. : TB09, 450 eV, SOC | ▪ Bloch weight : band unfolding [4] |
| ▪ Convergence : 10^{-6} eV energy, 10^{-2} eV/ \AA force | ▪ ML model : SVM(rbf) |

Outlook

- $A_x B_{1-x} C_y D_{1-y}$, $AB_x C_y D_z E_{1-x-y-z}$, WZ structure, II-VI systems

Acknowledgements

- HRZ Marburg, HLR Frankfurt, ZIH Dresden, HLR Stuttgart

References

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- [3] A. van de Walle et al., Calphad 42, 13 (2013)
- [4] O. Rubel et al., Phys. Rev. B 90, 115202 (2014)
- [5] <https://bmondal94.github.io/Bandgap-Phase-Diagram>, 2022