

# MACHINE LEARNING APPROACH TO QUANTUM MECHANICS

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**MEDICINE IS A SCIENCE OF  
UNCERTAINTY AND AN ART OF  
PROBABILITY.**

**William Osler**

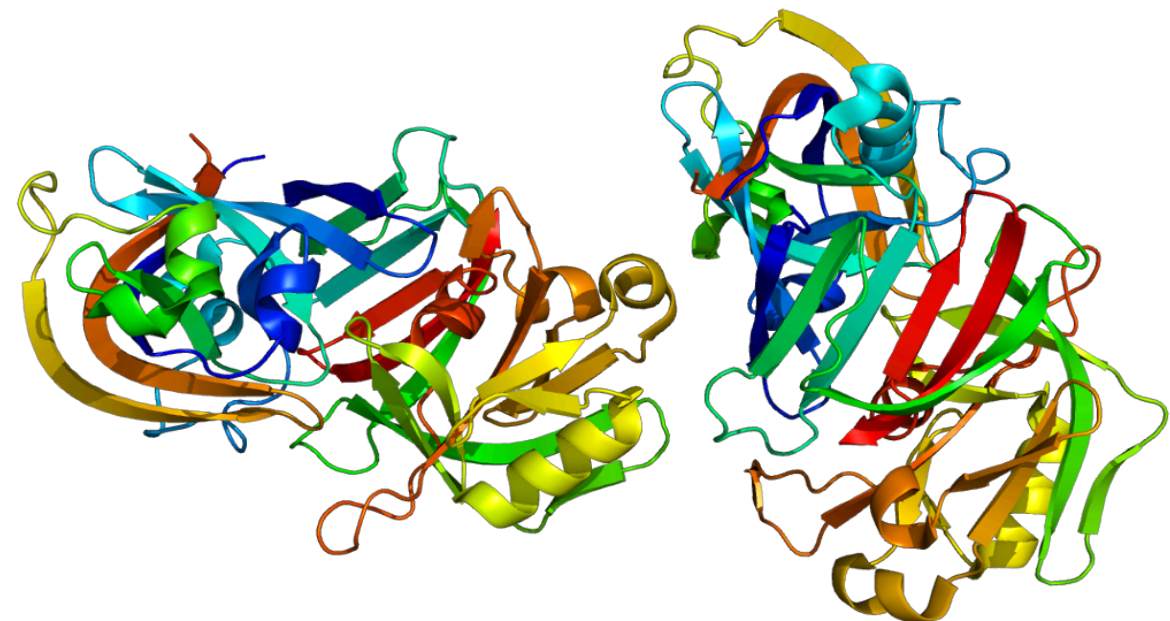
## PHARMACEUTICAL R&D COSTS NOW EXCEED \$2.87B

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# TAXOL: A SUCCESS STORY

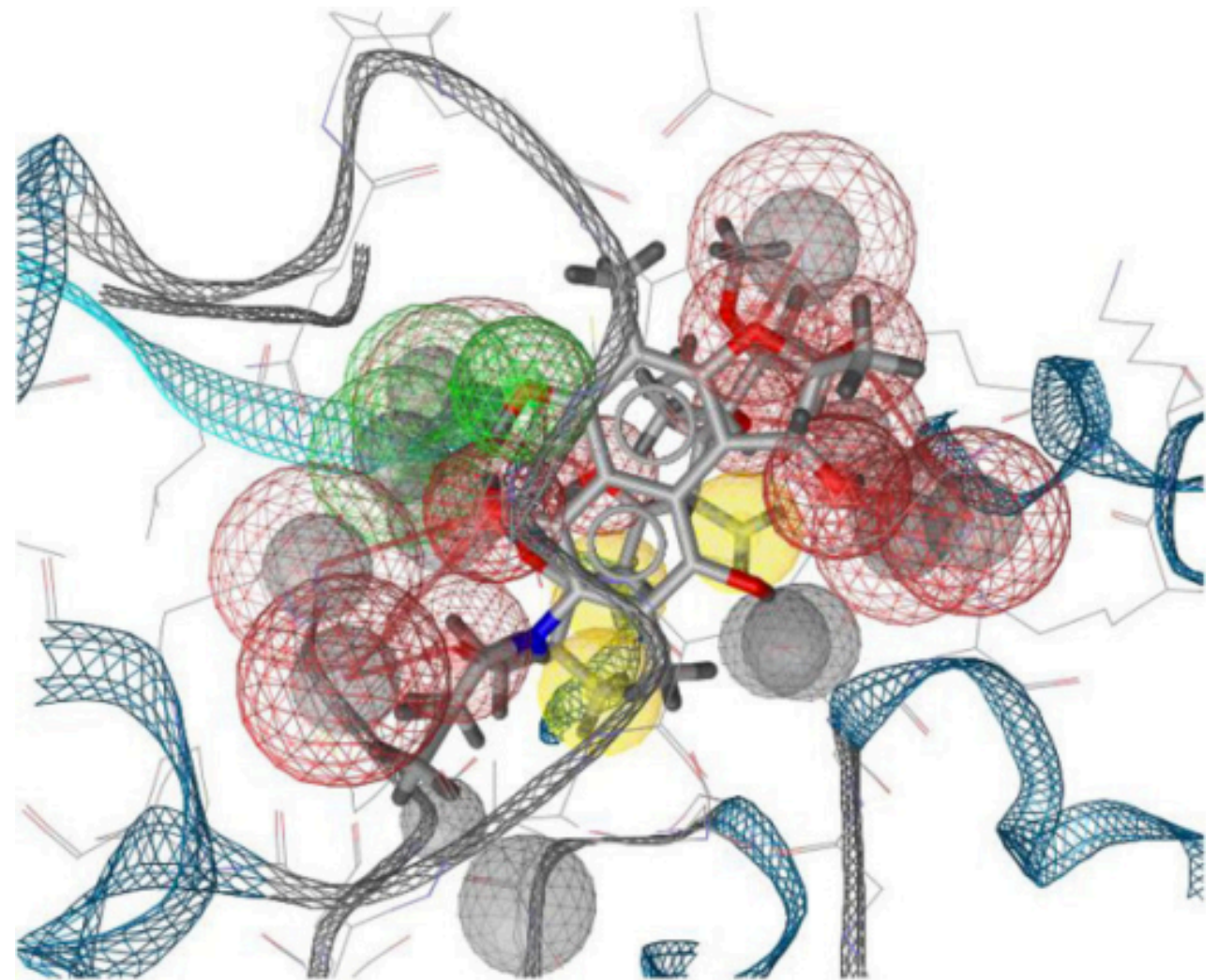
- ▶ In the second half of the 20th century, researchers realized the need for systemic treatments for different types of cancer
- ▶ A new NCI institution funded such screening programs
- ▶ Welcome Taxol
- ▶ To date, Taxol is the best-selling cancer drug ever manufactured





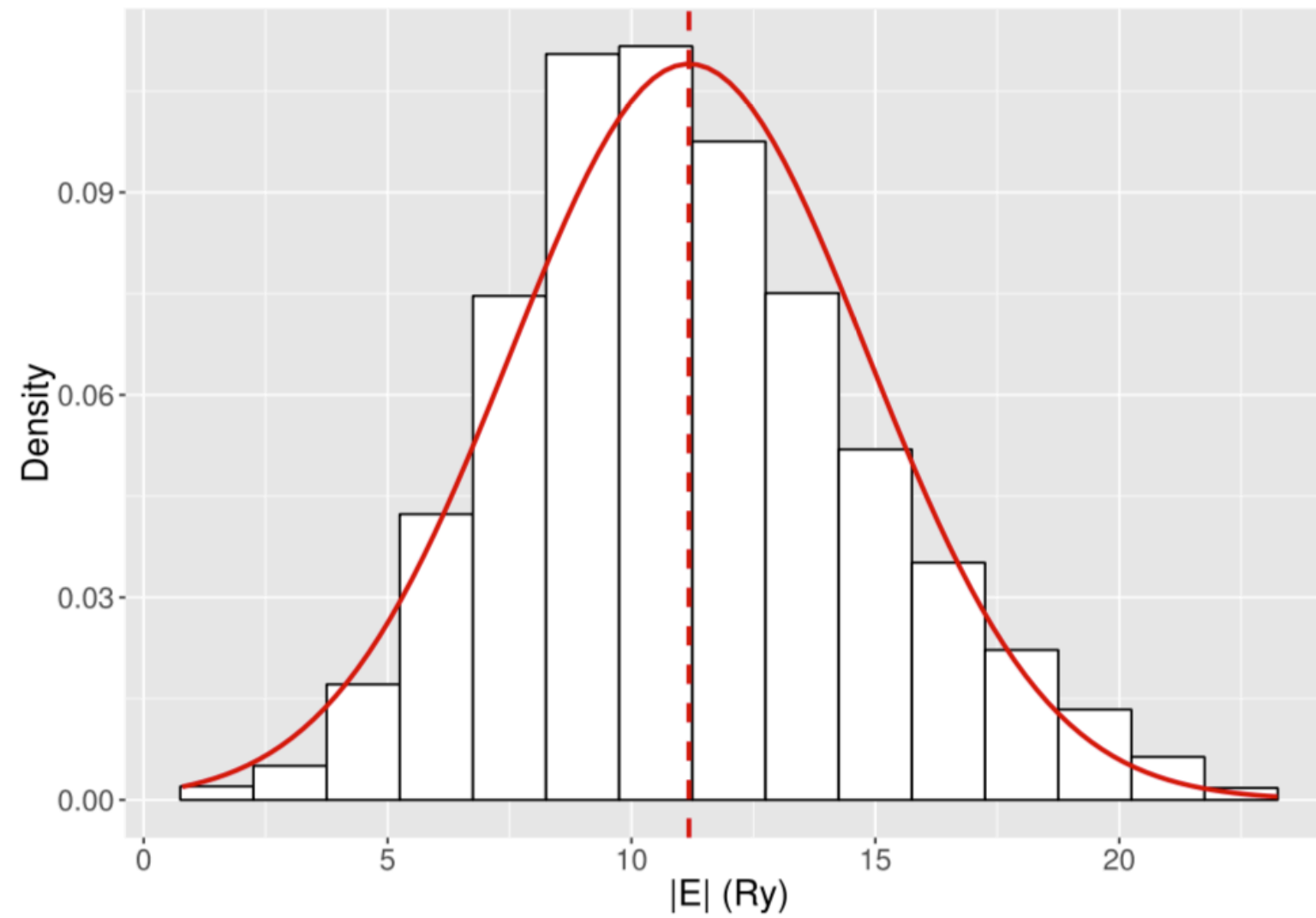
## OUTLINE

- ▶ Describe Data
- ▶ Visualizations
- ▶ Models
- ▶ Parameter Tuning
- ▶ Results





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```



### IDENTIFY AND DESIGN

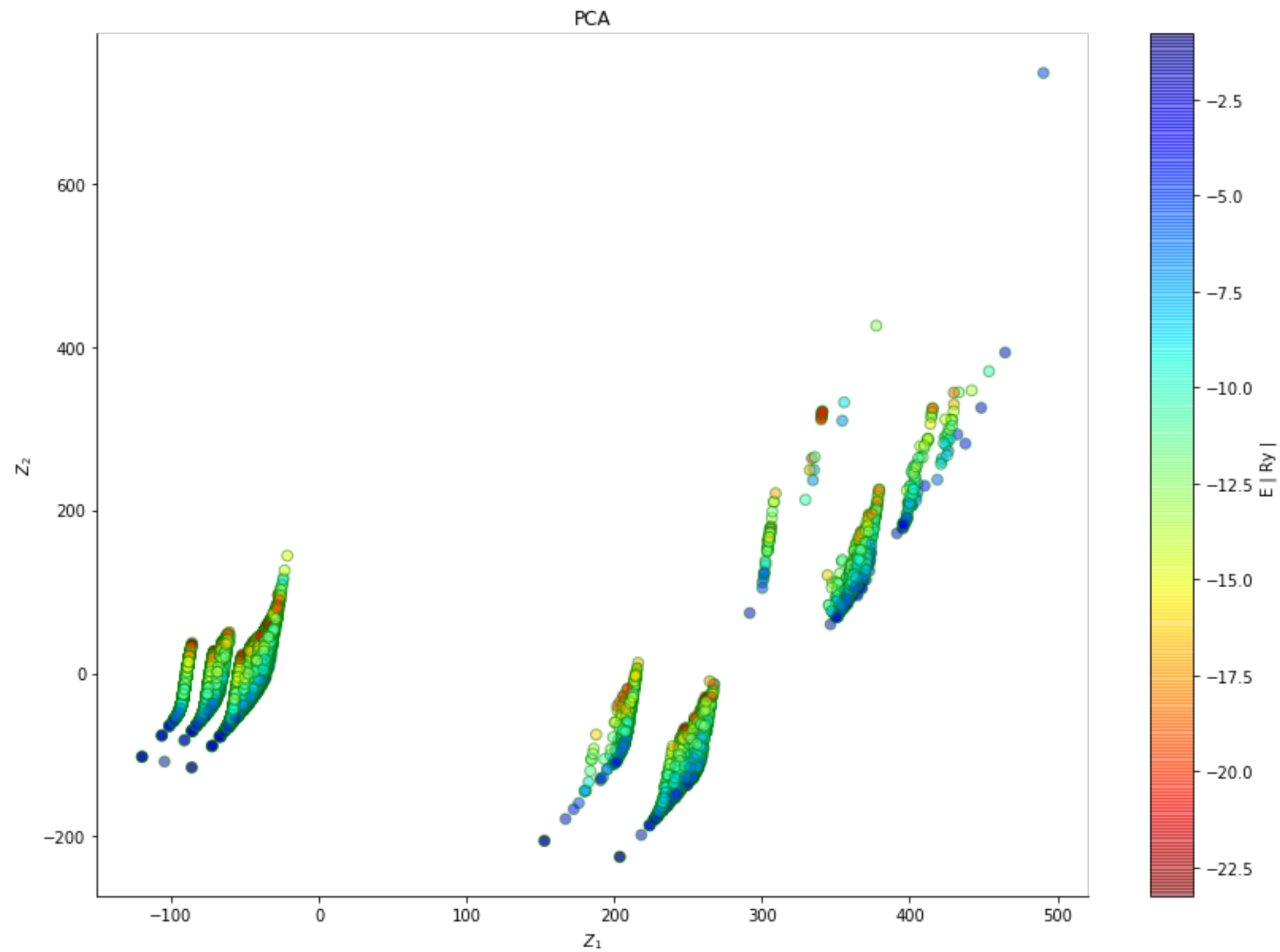
- ▶ Chemical & electrical properties
- ▶ Quantum mechanics
- ▶ Coulomb Matrix
- ▶ Computationally expensive

$$C_{IJ} = \begin{cases} 0.5 Z_I^{2.4} & I = J \\ \frac{Z_I Z_J}{|\mathbf{R}_I - \mathbf{R}_J|} & I \neq J \end{cases}$$

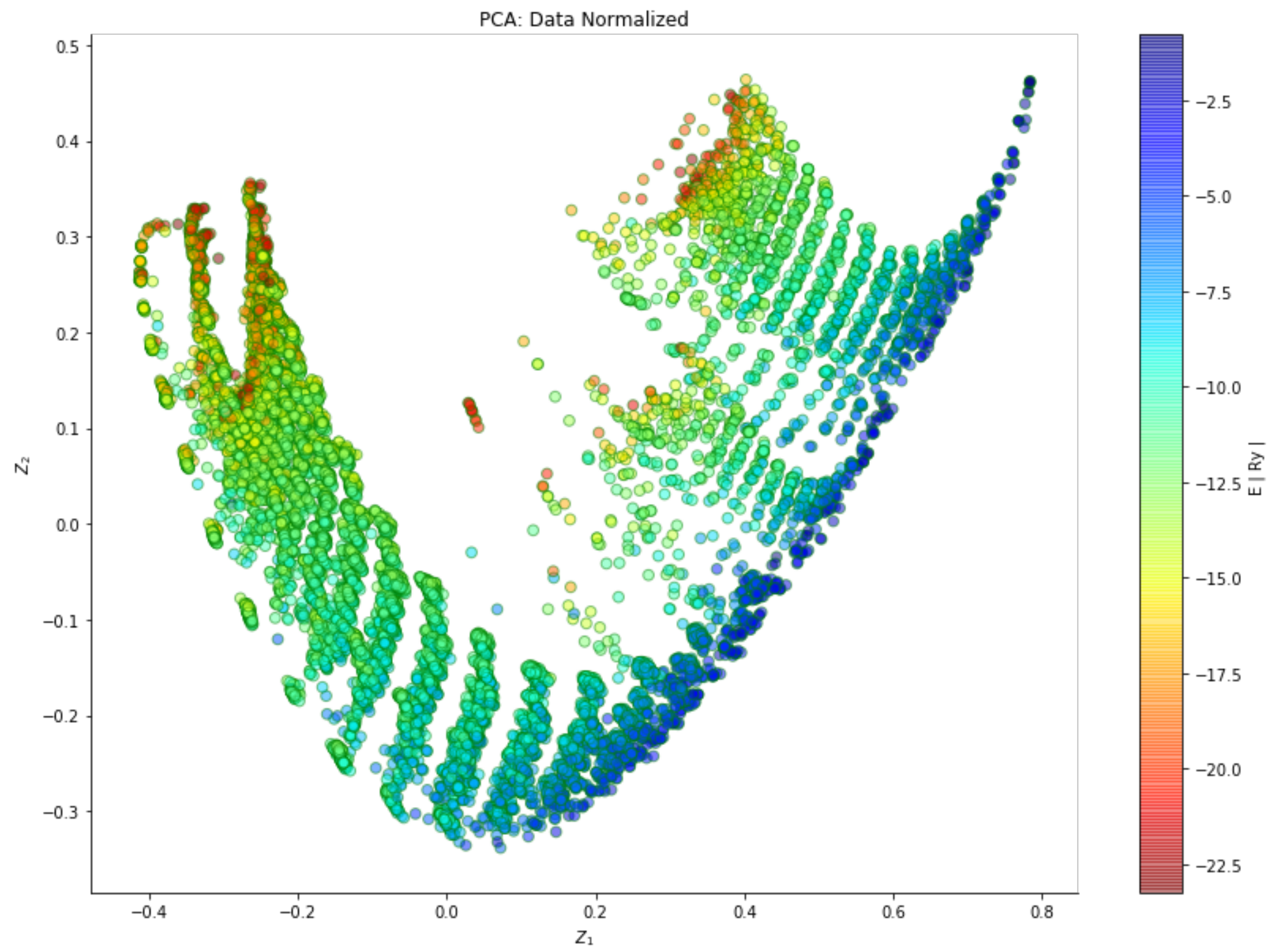
- ▶ Electronic state simulations via Density Functional Theory
- ▶ B. Himmetoglu (2016) [Tree based machine learning framework for predicting ground state energies of molecules](#)
  - ▶ Data available on [Kaggle](#) / [GitHub](#)
  - ▶ Objective: Predict Enthalpy of Atomization Energy



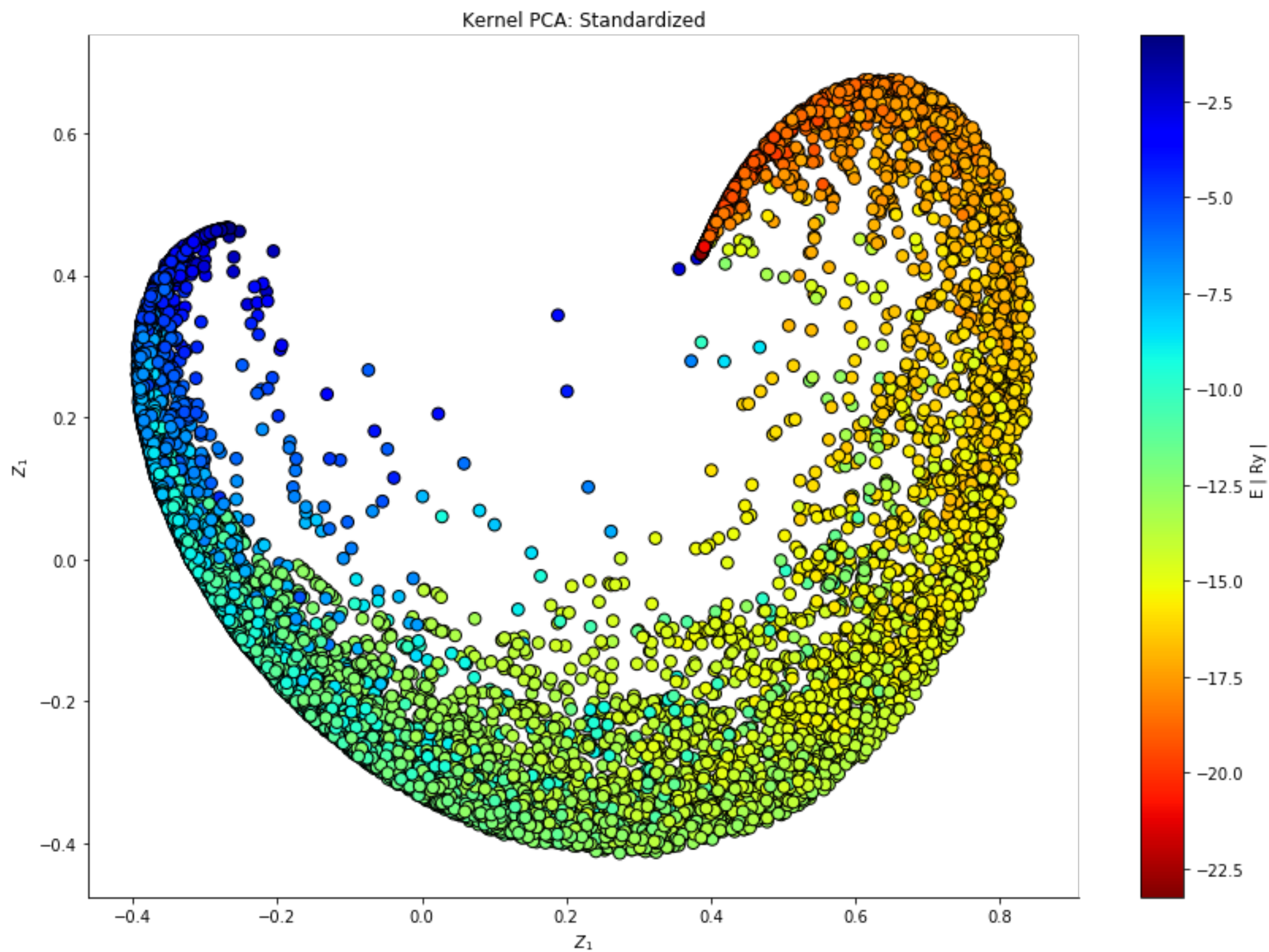
# VISUALIZATION: PCA



# VISUALIZATION: PCA (NORMALIZED)

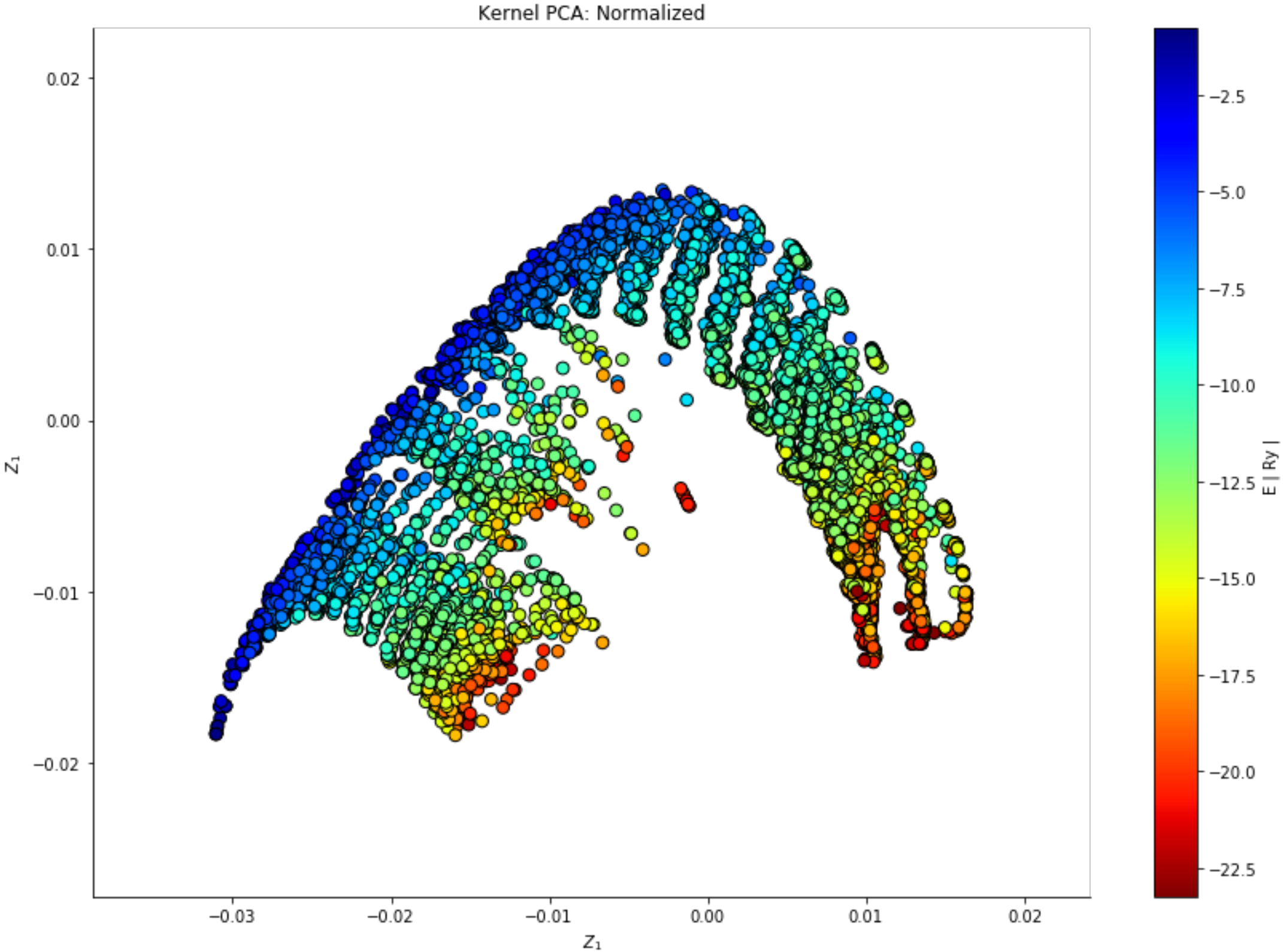


## VISUALIZATION: KERNEL PCA (STANDARDIZED)

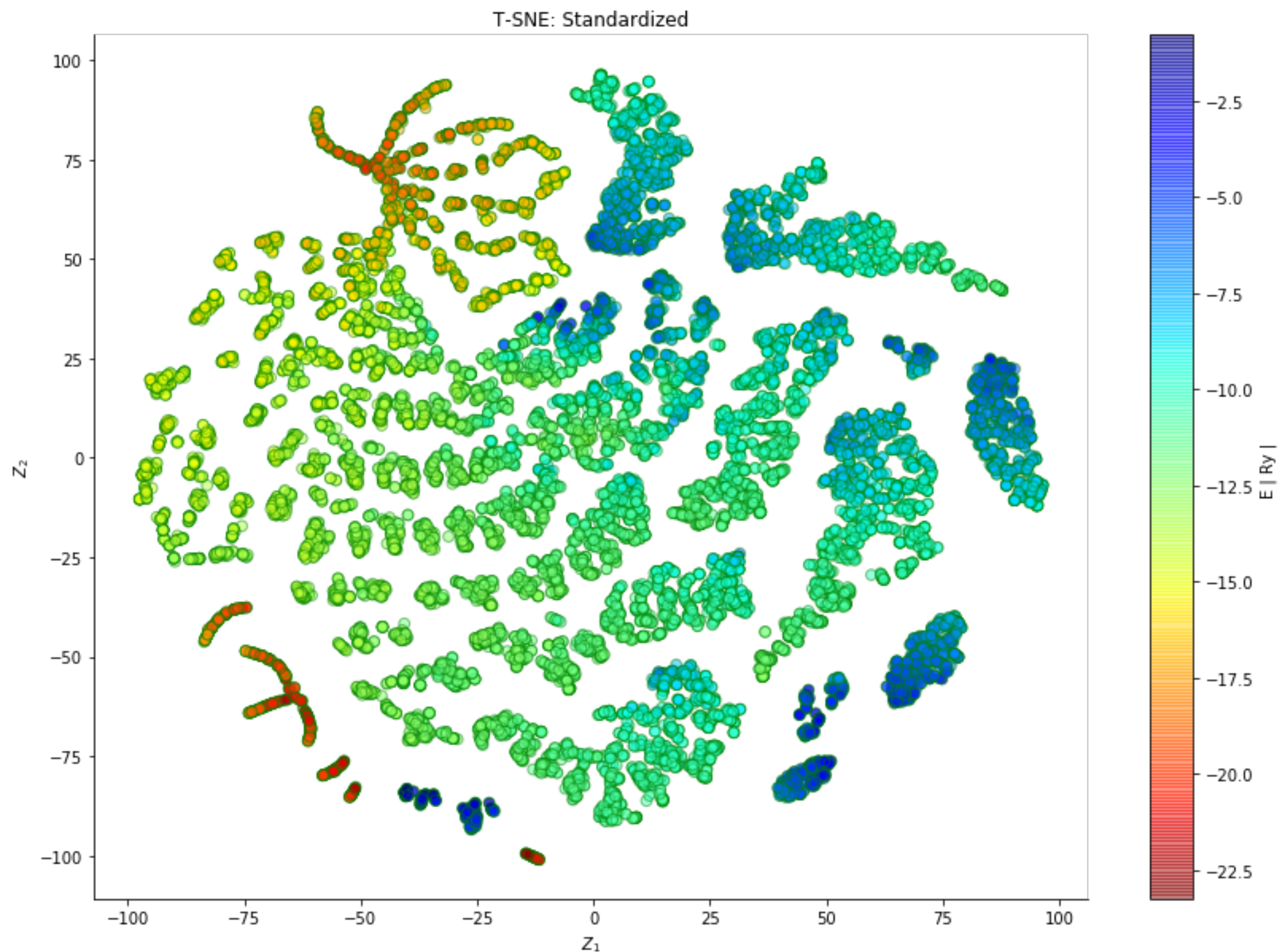




# VISUALIZATION: KERNEL PCA (NORMALIZED)



# VISUALIZATION: T-SNE (STANDARDIZED)





- ▶ Linear Regression
- ▶ Boosted Regression Models
- ▶ Ensemble Models

## PARAMETER TUNING

- ▶ Literature - optimal?
- ▶ Grid Search
- ▶ Manual Tuning
  - ▶ Trial and error/intuition

	R	$\eta$	$\gamma$	MD	CST	MCW
$\lambda^{(i)}$	600	0.0156	0.0	16	0.4	10
$C_{IJ}^{(i)}$	400	0.0625	0.0	6	0.2	10

# MODELS: RESULTS

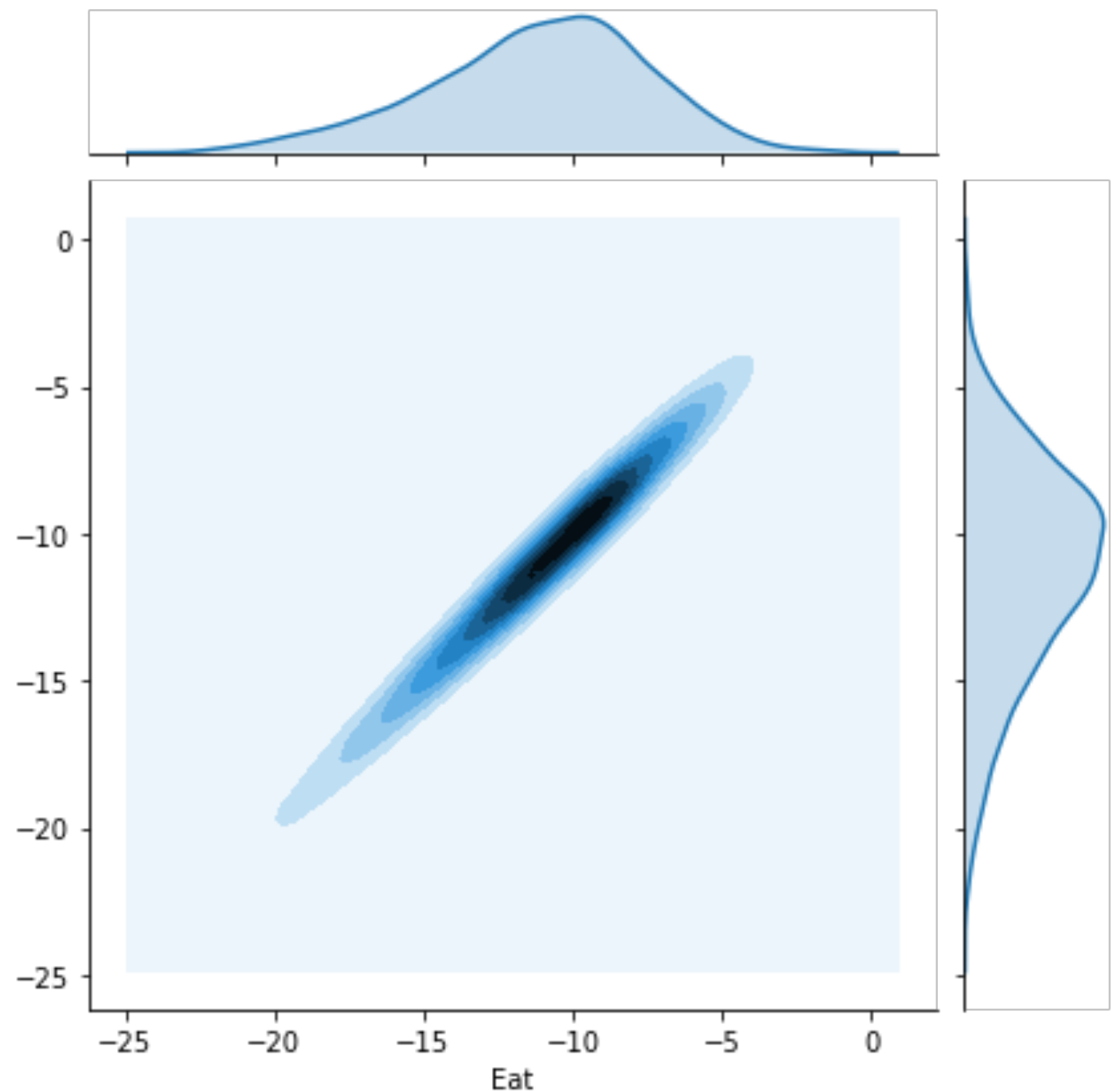
## PREVIOUS MODEL

▶ RMSE: 36.63

MODEL TYPE	RMSE[Ry]	TEST SCORE	RMSE [kcal/mol]
LightGBM	0.00505493	0.99963	1.588
XGBoost	0.00522919	0.99957	1.636
Gradient Boosting	0.09485	0.9993	29.682
Extra Tree	0.12229	0.9989	38.268
Bagging	0.148732	0.9983	46.543
Random Forest	0.284132	0.994	88.914
K-Nearest Neighbors (k=3)	0.547451	0.9776	171.314
Linear Regression (PCA)	0.809693	0.9509	253.378
Elastic Net	0.882564	0.9417	276.182
Passive Aggressive	1.022587	0.922	319.999
Support Vector Machine Regression	1.698415	0.7848	531.487
Linear Regression (Kernel PCA)	3.3874	0.1439	1060.023
Linear Regression	116.05917	-1004.0646	36318.519

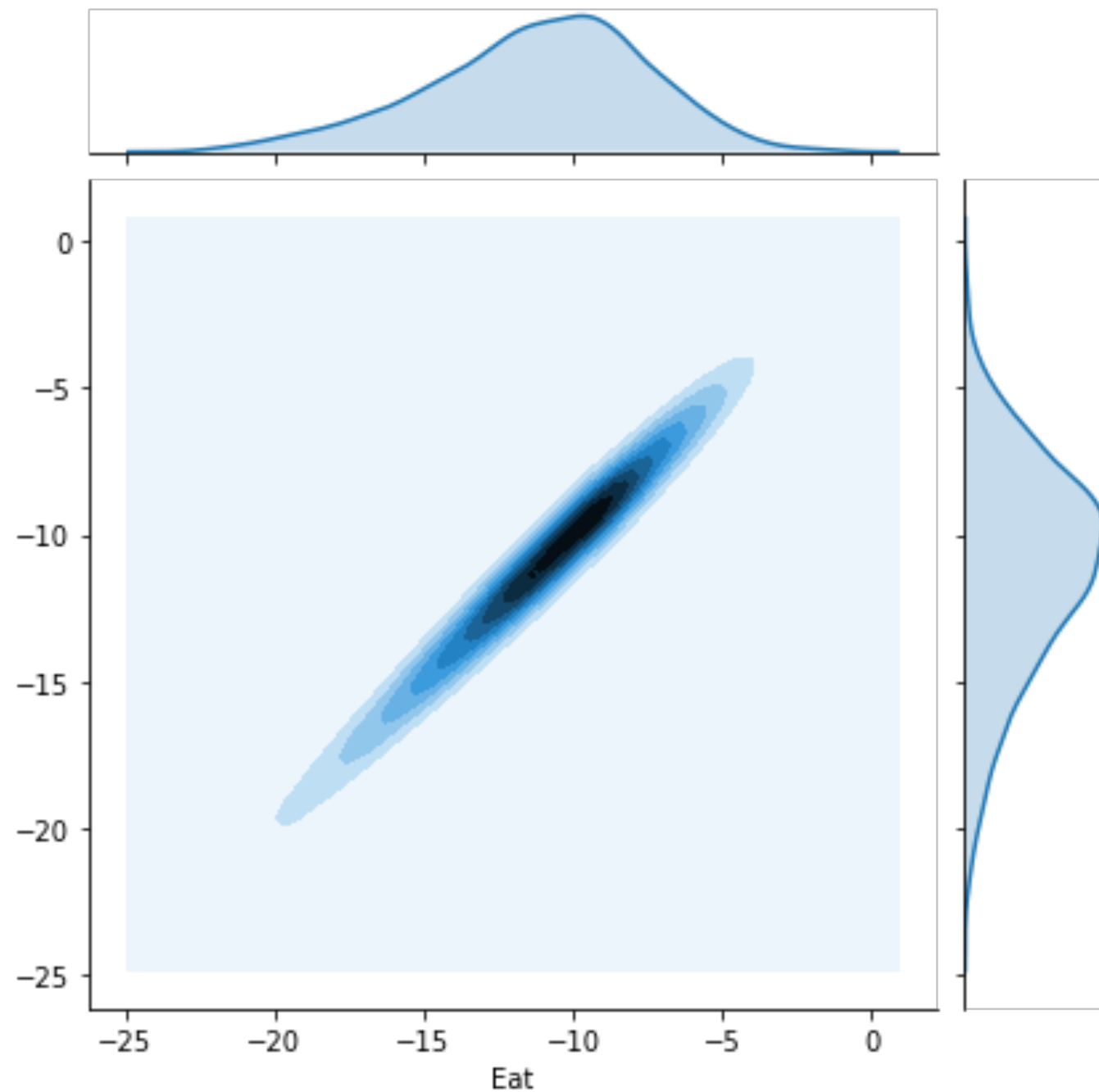
## PARAMETERS

- ▶ `booster = gbd`
- ▶ `learning_rate = 0.09`
- ▶ `reg_alpha = 0.115`
- ▶ `reg_lambda = 0.58`
- ▶ `max_depth=8`
- ▶ `num_leaves=17`
- ▶ `subsample = 0.6`
- ▶ `gamma = 0.001`
- ▶ `eval_metric = rmse`



## PARAMETERS

- ▶ `booster = gbd`
- ▶ `learning_rate = 0.09`
- ▶ `num_leaves = 100`
- ▶ `reg_alpha, reg_lambda = 0`
- ▶ `min_child_samples = 7`
- ▶ `min_child_weight = 1`
- ▶ `base_score = 0.5`
- ▶ `eval_metric = l2`



- ▶ WHY ARE XGBOOST/LIGHTGBM SO FAST?
- ▶ SHORTCOMINGS

# Q&A