	1. Download data	um structures of 13 different stoichiometries of Mg and Si, whose energy was computed using DFT. Th
in [1]:	dataset was reported in [T. D. Hua (2018)]. It will be obtained from wo	ww.matsml.org. More information on the avaiable datasets can be found at www.matsml.org as well.
.n [1]:	<pre>from matsml.data import Da import os import pandas as pd  # Load data ds_name='crystals_MgSi' data=Datasets(ds_name=ds_r data.load_dataset()</pre>	
	matsML, version 1.0.0  ****  Load requested dataset(s  Data saved in crystals  file_name	n.join(os.getcwd(),str(ds_name),'summary.csv')))
	mg2si_struct_01.vasp mg2si_struct_02.vasp mg2si_struct_03.vasp mg2si_struct_04.vasp mg2si_struct_05.vasp mg2si_struct_30.vasp mgsi_struct_31.vasp mgsi_struct_31.vasp mgsi_struct_32.vasp mgsi_struct_32.vasp	-34.985707 -17.246812 -34.062642 -34.035175  -40.698471 -40.598719
	327 mgsi_struct_33.vasp 328 mgsi_struct_34.vasp  [329 rows x 2 columns]  2. Fingerprint the obtain	-6.706034 -40.362384 ned data
•	learning models of formation	A. Lindmaa, O. Anatole von Lilienfeld, and R. Armiento. <i>Crystal structure representations for machine energies</i> Int. J. Quantum Chem., 115, 1094 (2015)] is an analogy to the Coulomb matrix for molecules, the number of atoms of the structure. We used a similar projection on a set of Gaussian. Keyword for the
	structural and alchemical spa Ewald sum matrix which is de are added up to make the fing	ositions (SOAP) [S. De, A. P. Bartók, G. Csányi, and M. Ceriotti, <i>Comparing molecules and solids acros</i> ce, Phys. Chem. Chem. Phys. <b>18</b> , 13754 (2016)] is a more sophisticated fingerprint. Different from the efined for the whole system, SOAP is defined for each atom. Herein, for simplicity, the atomic fingerprint gerprint for the whole system. In some ML potential, the SOAP fingerprints are used in a different way, The keyword for SOAP in matsML is <b>soap_crystals</b> .
n [2]:	data_loc=os.path.join(os.gn_atoms_max=28	etcwd(),'crystals_MgSi/summary.csv')
		<pre># Intended Tingerprint dimensionality # verbosity, 0 or 1  y':summary,'data_loc':data_loc,'fp_file':'fp_crystals_MgSi_pesm.csv', als','fp_dim':fp_dim,'verbosity':verbosity,'n_atoms_max':n_atoms_max,</pre>
	'fp_type':'soap_crysta' 'species':species}	y':summary,'data_loc':data_loc,'fp_file':'fp_crystals_MgSi_soap.csv', als','fp_dim':fp_dim,'verbosity':verbosity,'n_atoms_max':n_atoms_max,
	<pre>fp_pesm=Fingerprint(data_r fp_pesm.get_fingerprint()  Atomic structure fingerprint     summary     data_loc     species     fp_type</pre>	rinting  /home/huan/work/matsml_examples/ex3_crystals/crystals_MgSi/summary.csv /home/huan/work/matsml_examples/ex3_crystals/crystals_MgSi ['Mg', 'Si'] pesm_crystals
	<pre>fp_file   fp_dim   n_atoms_max   verbosity Read input   num_structs Computing Ewald sum Matri [==</pre>	<pre>fp_crystals_MgSi_pesm.csv 20 28 0 329 ix ] 3%</pre>
	toms.cell.reciprocal() warnings.warn(warning)  [===================================	
	summary data_loc species fp_type fp_file fp_dim n_atoms_max verbosity Read input	<pre>/home/huan/work/matsml_examples/ex3_crystals/crystals_MgSi/summary.csv /home/huan/work/matsml_examples/ex3_crystals/crystals_MgSi ['Mg', 'Si'] soap_crystals fp_crystals_MgSi_soap.csv 20 28 0</pre>
	num_structs Computing SOAP fingerprint [====================================	nt with DScribe
n [3]:	<pre>from matsml.data import Da import os import pandas as pd  # Load data data=Datasets(ds_soap='fp_data.load_dataset()</pre>	atasets _crystals_MgSi_soap', ds_pesm='fp_crystals_MgSi_pesm')
		als_MgSi_soap.csv.gz
n [4]:	<pre># data parameters for lear id_col=['id']</pre>	# this is id column in the fingerprint data
		<pre># this is y columns # other columns that are not id, not x, nor y columns # 90% for training, 15% for validating # way of train/test spliting. Random and more  ile':'fp_crystals_MgSi_pesm.csv','id_col':id_col,'y_cols':y_cols,</pre>
	<pre>'n_trains':n_trains}  data_params_soap={'data_fi    'comment_cols':comment    'n_trains':n_trains}</pre>	t_cols, 'y_scaling':y_scaling, 'x_scaling':x_scaling, 'sampling':sampling,  ile':'fp_crystals_MgSi_soap.csv', 'id_col':id_col, 'y_cols':y_cols,  t_cols, 'y_scaling':y_scaling, 'x_scaling':x_scaling, 'sampling':sampling,
In [5]:	3a. Fully-connected NeuralN  from matsml.models import  # Model parameters layers=[4,4] epochs=2000 nfold_cv=5	
	<pre>model_file='model_nn.pkl' verbosity=0 batch_size=32 loss='mse' activ_funct='selu'</pre>	<pre># Use bias term or not # Name of the model file to be created # Verbosity, 0 or 1 # Default = 32 # Options: "tanh", "relu", and more # options: "Nadam", "Adam", and more</pre>
	<pre>'optimizer':optimizer, 'batch_size':batch_siz # PESM</pre>	<pre>yers, 'activ_funct':activ_funct, 'epochs':epochs, 'nfold_cv':nfold_cv, , 'use_bias':use_bias, 'model_file':model_file, 'loss':loss, ze, 'verbosity':verbosity, 'rmse_cv':False}  ta_params_pesm, model_params=model_params) se)</pre>
	# SOAP	ta_params_soap,model_params=model_params) se)
	<pre>algorithm layers activ_funct epochs optimizer nfold_cv Checking parameters</pre>	<pre>fully connected NeuralNet w/ TensorFlow [4, 4] selu 2000 nadam 5</pre>
	all passed Read data data file data size training size test size x dimensionality y dimensionality	<pre>True  fp_crystals_MgSi_pesm.csv 329 296 (90.0 %) 33 (10.0 %) 19 1</pre>
	y label(s) Scaling x xscaler saved in Scaling y Prepare train/test sets Building model Training model w/ cross cov,rmse_train,rmse_test	['target']  minmax  xscaler.pkl  minmax  random  FCNN  validation  t,rmse_opt: 0 0.059275 0.072458 0.072458
	cv,rmse_train,rmse_test cv,rmse_train,rmse_test cv,rmse_train,rmse_test cv,rmse_train,rmse_test cv,rmse_train,rmse_test Optimal ncv: 3; optimal FCNN trained, now make produced in the company of the com	t,rmse_opt: 1 0.055568 0.068262 0.068262 t,rmse_opt: 2 0.052195 0.066476 0.066476 t,rmse_opt: 3 0.053062 0.066252 0.066252 t,rmse_opt: 4 0.049476 0.075581 0.066252
		= (5.772 & 0.935)
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	edicted value	
	_80 -	
	-120 -120 -100	training, (rmse & $R^2$ ) = (5.772 & 0.935) test, (rmse & $R^2$ ) = (7.392 & 0.925) -80 -60 -40 -20 0 Reference value
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	<pre>x dimensionality y dimensionality y label(s) Scaling x xscaler saved in Scaling y Prepare train/test sets Building model</pre>	275 1 ['target'] minmax xscaler.pkl minmax random FCNN
	Training model w/ cross of cv,rmse_train,rmse_test cv,rmse_train,rmse_test cv,rmse_train,rmse_test cv,rmse_train,rmse_test cv,rmse_train,rmse_test cv,rmse_train,rmse_test Optimal ncv: 3; optim	validation t,rmse_opt: 0 0.008504 0.009348 0.009348 t,rmse_opt: 1 0.009407 0.011897 0.009348 t,rmse_opt: 2 0.003605 0.005141 0.005141 t,rmse_opt: 3 0.003943 0.004369 0.004369 t,rmse_opt: 4 0.004335 0.006089 0.004369 mal NET saved
	unscaling y: minmax rmse training to unscaling y: minmax rmse test	
	test, (rmse & R2) = (0 showing target	
	0	
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	Predicted value - 05 06 06	
	-20 -40	training, (rmse & $R^2$ ) = (0.416 & 1.000)
	-80 -	training, (rmse & $R^2$ ) = (0.416 & 1.000) test, (rmse & $R^2$ ) = (0.768 & 0.999)
	-20 -40 -40 -80 -120 -120 -120 -120 -100  3b. KRR  from matsml.models import  # Model parameters  nfold_cv = 5  model_file = 'model_krr.pl  alpha = [-2,5]  gamma = [-2,5]	test, (rmse & $R^2$ ) = (0.768 & 0.999)  -80    -60    -40    -20
	-20 -40 -80 -120 -120 -120 -120 -100  3b. KRR  from matsml.models import  # Model parameters  nfold_cv = 5 model_file = 'model_krr.p} alpha = [-2,5] gamma = [-2,5] n_grids = 10 kernel = 'rbf'  model_params={'kernel':ker 'gamma':gamma,'n_grids  #PCM model = KRR(data_params=data)	test, (rmse & R <sup>2</sup> ) = (0.768 & 0.999)  -80    -60    -40    -20
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	-20 -40 -80 -120 -120 -120 -120 -120 -120 -120 -12	test, (rmse & R <sup>2</sup> ) = (0.768 & 0.999)  -80
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