**Huan Tran** The main objective of this example is to demonstrate a generic workflow of materials, involving (1) obtaining a small dataset of molecules and their energy, (2) fingerprint them, and (3) develop some ML models. 1. Download a dataset The dataset contains 10,000 non-equilibrium structures of CH<sub>3</sub>-NH-OH molecules, whose energy was computed using BigDFT package and HGH norm-conserving pseudopotentials. It is available at www.matsml.org. In [1]: from matsml.data import Datasets import pandas as pd import os # Load a dataset dataset name='molecs CH3NHOH 10k' data=Datasets(dataset name=dataset name) data.load\_dataset() # have a look at the content print (pd.read\_csv(os.path.join(os.getcwd(),str(dataset\_name),'summary.csv'))) matsML, version 1.0 Load requested dataset(s) Data saved in molecs CH3NHOH 10k file\_name target CH3NHOH\_00001.xyz -940.288539 CH3NHOH 00002.xyz -940.580380 CH3NHOH 00003.xyz -940.184809 2 3 CH3NHOH 00004.xyz -940.460977 CH3NHOH 00005.xyz -940.579457 . . . . . . 9994 CH3NHOH 09996.xyz -940.286083 9995 CH3NHOH 09997.xyz -940.744461 9996 CH3NHOH 09998.xyz -940.553979 9997 CH3NHOH 09999.xyz -940.650902 9998 CH3NHOH 10000.xyz -940.059079 [9999 rows x 2 columns] 2. Fingerprint the obtained data Two kinds of fingerprints will be demonstrated here 1. Coulomb matrix (CM) [M. Rupp, A. Tkatchenko, K.-R. Müller, and O. Anatole von Lilienfeld, Fast and accurate modeling of molecular atomization energies with machine learning, Phys. Rev. Lett., 108, 058301 (2012)] is perhaps one of the earliest fingerprints used in materials informatics. It was defined as an N imes N matrix for a molecule of N atoms. The key advantage of CM is that it is invariant under rotations and translations, required ro represent materials structure as a whole. However, its size depends on the molecule size, making it not directly usable for machine learning. Normally, the eigenvalues of these matricies are computed and sorted, and then zero padding is used to make fixed-size vectors. Here, we defined a projection of these Coulomb matricies onto a set of Gaussian functions, covering the entire range of the Coulomn matrix element values. The results are also a set of fixed-size fingerprints, which are ready for learning. Keyword for this fingerprint is **pcm\_molecs**. 2. Smooth Overlap of Atomic Positions (SOAP) [S. De, A. P. Bartók, G. Csányi, and M. Ceriotti, Comparing molecules and solids across structural and alchemical space, Phys. Chem. Chem. Phys. 18, 13754 (2016)] is a more sophisticated fingerprint. Keyword for this fingerprint is soap\_molecs. In [2]: from matsml.fingerprint import Fingerprint summary=os.path.join(os.getcwd(),'molecs CH3NHOH 10k/summary.csv') data\_loc=os.path.join(os.getcwd(),'molecs\_CH3NHOH\_10k/') # max number of atoms in all of the structures to be fingerprinted n atoms max=8 fp dim=50# intended fingerprint dimensionality; the final number can be smaller verbosity=0 # verbosity, 0 or 1 species=['C','H', 'N', 'O'] # All the spacies in the datasets, used for SOAP data params pcm={'fp type':'pcm molecs','summary':summary,'data loc':data loc, 'n atoms max':n atoms max,'fp file':'fp pcm.csv','fp dim':fp dim, 'species':species,'verbosity':verbosity} fp pcm=Fingerprint(data params pcm) fp pcm.get fingerprint() # SOAP data params soap={'fp type':'soap molecs','summary':summary,'data loc':data loc, 'species':species,'n atoms max':n atoms max,'fp file':'fp soap.csv', 'fp dim':fp dim,'verbosity':verbosity} fp soap=Fingerprint(data params soap) fp soap.get fingerprint() Atomic structure fingerprinting /home/huan/work/matsml/examples/ex1 pcm-molecs/molecs CH3NHOH 10k/summary.csv /home/huan/work/matsml/examples/ex1\_pcm-molecs/molecs\_CH3NHOH\_10k/ data loc ['C', 'H', 'N', 'O'] species fp type pcm molecs fp file fp pcm.csv fp dim 50 n atoms max verbosity Read input 9999 num structs Computing Coulomb matrix [========= 100% Projecting Coulomb matrix to create fingerprints [=========] 100% Done fingerprinting, results saved in fp pcm.csv Atomic structure fingerprinting /home/huan/work/matsml/examples/ex1 pcm-molecs/molecs CH3NHOH 10k/summary.csv data loc /home/huan/work/matsml/examples/ex1 pcm-molecs/molecs CH3NHOH 10k/ ['C', 'H', 'N', 'O'] species fp\_type soap molecs fp file fp soap.csv fp dim 50 n atoms max verbosity Read input 9999 num structs Computing SOAP fingerprint [=======] 100% Done fingerprinting, results saved in fp\_soap.csv The fingerprinting step is slow. A version of fingerprinted data can also be obtained in case you want to skip this step. Pandas can read gzip files fo no need to unzip them. In [3]: from matsml.data import Datasets import os # Load data data=Datasets(ds1='fp\_molecs\_CH3NHOH\_10k\_pcm',ds2='fp\_molecs\_CH3NHOH\_10k\_soap') data.load\_dataset() print (os.path.isfile('fp\_molecs\_CH3NHOH\_10k\_pcm.csv.gz')) print (os.path.isfile('fp\_molecs\_CH3NHOH\_10k\_soap.csv.gz')) Load requested dataset(s) Data saved in fp molecs CH3NHOH 10k pcm.csv.gz Data saved in fp\_molecs\_CH3NHOH\_10k\_soap.csv.gz True Train some ML models with "fp\_pcm.csv" and "fp\_soap.csv" just created In [4]: # data parameters for learning id\_col=['id'] # column for data ID

y\_cols=['target'] # columns for (one or more) target properties

comment\_cols=[] # comment columns, anything not counted into ID, fingerprints, and target

n\_trains=0.8 # 80% for training, 20% for validating

sampling='random' # method for train/test spliting

x\_scaling='minmax' # method for x scaling

y\_scaling='minmax' # method for y scaling id col=['id'] # column for data ID # Dict of data parameters data\_params\_pcm={'data\_file':'fp\_pcm.csv','id\_col':id\_col,'y\_cols':y\_cols, 'comment\_cols':comment\_cols,'y\_scaling':y\_scaling,'x\_scaling':x\_scaling, 'sampling':sampling,'n\_trains':n\_trains} data params soap={'data file':'fp soap.csv','id col':id col,'y cols':y cols, 'comment cols':comment cols, 'y scaling':y scaling, 'x scaling':x scaling, 'sampling':sampling,'n trains':n trains} In [5]: from matsml.models import FCNN # Model parameters layers=[8,8,8] # Epochs

# Number of folds for cross validation

use\_bias=True # Use bias term or not

model\_file='model\_nn.pkl' # Name of the model file to be created

verbosity=0 # Verbosity, 0 or 1

batch\_size=32 # Default = 22

loss='mse' # list of nodes in hidden layers # Epochs loss='mse' activ\_funct='selu' # Options: "tanh", "relu", and more # Options: "Nadam", "Adam", and more optimizer='nadam' # Dict of model parameters model params={'layers':layers,'activ funct':activ funct,'epochs':epochs, 'nfold cv':nfold cv,'optimizer':optimizer,'use bias':use bias, 'model file':model file, 'loss':loss, 'batch size':batch size, 'verbosity':verbosity,'rmse\_cv':False} # PCM model=FCNN(data\_params=data\_params\_pcm,model\_params=model\_params) model.train() model.plot(pdf\_output=False) model=FCNN(data\_params=data\_params\_soap,model\_params=model\_params) model.train() model.plot(pdf output=False) Learning fingerprinted/featured data fully connected NeuralNet w/ TensorFlow algorithm layers [8, 8, 8] activ\_funct selu 200 epochs nadam optimizer nfold cv Reading data ... data file fp\_pcm.csv data size 9999
training size 7999 (80.0 %)
test size 2000 (20.0 %) 2000 (20.0 30 1 ['target'] x dimensionality y dimensionality y label(s) caling x

xscaler saved in

xscaler.pkl
minmax Scaling x Scaling y Prepare train/test sets random Building model Training model w/ cross validation cv,rmse\_train,rmse\_test,rmse\_opt: 0 0.068174 0.072319 0.072319 cv,rmse\_train,rmse\_test,rmse\_opt: 1 0.064059 0.072494 0.072319 cv,rmse\_train,rmse\_test,rmse\_opt: 2 0.064114 0.063432 0.063432 cv,rmse\_train,rmse\_test,rmse\_opt: 3 0.062374 0.064459 0.063432 cv,rmse\_train,rmse\_test,rmse\_opt: 4 0.062188 0.065128 0.063432 Optimal ncv: 2; optimal NET saved FCNN trained, now make predictions & invert scaling Unscaling y: minmax rmse training 0.113256 target Unscaling y: minmax rmse test target 0.113944 Predictions made & saved in "training.csv" & "test.csv" Plot results in "training.csv" & "test.csv" showing target -939.00-939.25-939.50Predicted value -939.75-940.00 -940.25 -940.50-940.75training, (rmse &  $R^2$ ) = (0.113 & 0.748) test, (rmse &  $R^2$ ) = (0.114 & 0.739) -941.00-941.00940.75940.50940.25940.00939.75939.50939.25939.00Reference value Learning fingerprinted/featured data algorithm fully connected NeuralNet w/ TensorFlow layers [8, 8, 8] activ funct selu epochs 200 optimizer nadam nfold cv Reading data ... data file fp soap.csv data size 9999 7999 (80.0 %) training size 2000 (20.0 %) test size 1050 x dimensionality y dimensionality y label(s) ['target'] Scaling x minmax xscaler saved in xscaler.pkl minmax Scaling y Prepare train/test sets Building model Training model w/ cross validation cv,rmse\_train,rmse\_test,rmse\_opt: 0 0.024478 0.025270 0.025270 cv,rmse\_train,rmse\_test,rmse\_opt: 1 0.019971 0.021035 0.021035 cv,rmse\_train,rmse\_test,rmse\_opt: 2 0.018775 0.019346 0.019346 cv,rmse\_train,rmse\_test,rmse\_opt: 3 0.017142 0.017984 0.017984 cv,rmse train,rmse test,rmse opt: 4 0.019387 0.020291 0.017984 Optimal ncv: 3; optimal NET saved FCNN trained, now make predictions & invert scaling Unscaling y: minmax 0.030649 rmse training target Unscaling y: minmax rmse test target 0.032979 Predictions made & saved in "training.csv" & "test.csv" Plot results in "training.csv" & "test.csv" showing target -939.00-939.25-939.50Predicted value -939.75 -940.00 -940.25 -940.50-940.75training, (rmse &  $R^2$ ) = (0.031 & 0.981) test, (rmse &  $R^2$ ) = (0.033 & 0.979) -941.00-941.00940.75940.50940.25940.00939.75939.50939.25939.00Reference value 4. The same flowwork with the CH<sub>4</sub> dataset In [6]: # Load data data=Datasets(dataset\_name='molecs\_CH4\_10k') data.load\_dataset() print (pd.read\_csv('molecs\_CH4\_10k/summary.csv')) # Fingerprint from matsml.fingerprint import Fingerprint summary=os.path.join(os.getcwd(),'molecs\_CH4\_10k/summary.csv') data\_loc=os.path.join(os.getcwd(),'molecs\_CH4\_10k/') # max number of atoms in all of the structures to be fingerprinted n\_atoms\_max=6 fp\_type='pcm\_molecs' # projected Coulomb matrix for molecules # intended fingerprint dimensionality; the final number can be smaller fp\_dim=100 verbosity=0 # verbosity, 0 or 1 species=['C','H'] # All the spacies in the datasets, used for SOAP data\_params\_pcm={'fp\_type':'pcm\_molecs','summary':summary,'data\_loc':data\_loc, 'n\_atoms\_max':n\_atoms\_max,'fp\_file':'fp\_CH4\_pcm.csv','fp\_dim':fp\_dim, 'species':species,'verbosity':verbosity} fp\_pcm=Fingerprint(data\_params\_pcm) fp\_pcm.get\_fingerprint() data params soap={'fp type':'soap molecs','summary':summary,'data loc':data loc, 'species':species, 'n\_atoms\_max':n\_atoms\_max, 'fp\_file':'fp\_CH4\_soap.csv', 'fp\_dim':fp\_dim,'verbosity':verbosity} fp\_soap=Fingerprint(data\_params\_soap) # Data params y\_cols=['target'] # column for data ID

y\_cols=['target'] # columns for (one or more) target properties
comment\_cols=[] # comment columns, anything not counted into in
n trains=0.8 # comment columns, anything not counted into ID, fingerprints, and target n\_trains=0.8 # 80% for training, 20% for validating
sampling='random' # method for train/test spliting
x\_scaling='minmax' # method for x scaling
y\_scaling='minmax' # method for y scaling # Dict of data parameters data\_params\_CH4\_pcm={'data\_file':'fp\_CH4\_pcm.csv','id\_col':id\_col,'y\_cols':y\_cols, 'comment\_cols':comment\_cols,'y\_scaling':y\_scaling,'x\_scaling':x\_scaling, 'sampling':sampling,'n\_trains':n\_trains} data\_params\_CH4\_soap={'data\_file':'fp\_CH4\_soap.csv','id\_col':id\_col,'y\_cols':y\_cols, 'comment\_cols':comment\_cols,'y\_scaling':y\_scaling,'x\_scaling':x\_scaling, 'sampling':sampling,'n\_trains':n\_trains} # Models with FCNN from matsml.models import FCNN # Model parameters layers=[4,4] # list of nodes in hidden layers epochs=200 # Epochs nfold\_cv=5 # Number of folds for couse\_bias=True # Use bias term or not # Number of folds for cross validation model\_file='model\_nn.pkl' # Name of the model file to be created verbosity=0 # Verbosity, 0 or 1 batch size=32 # Default = 32 batch size=32 # Default = 32loss='mse' activ\_funct='tanh' # Options: "tanh", "relu", and more # options: "Nadam", "Adam", and more optimizer='nadam' # Dict of model parameters model\_params={'layers':layers,'activ\_funct':activ\_funct,'epochs':epochs, 'nfold\_cv':nfold\_cv,'optimizer':optimizer,'use\_bias':use\_bias, 'model\_file':model\_file,'loss':loss,'batch\_size':batch\_size, 'verbosity':verbosity,'rmse\_cv':False} # PCM model=FCNN(data\_params=data\_params\_CH4\_pcm,model\_params=model\_params) model.train() model.plot(pdf\_output=False) model=FCNN(data\_params=data\_params\_CH4\_soap,model\_params=model\_params) model.train() model.plot(pdf\_output=False) Load requested dataset(s) Data saved in molecs CH4 10k file\_name target CH4-00001.xyz -219.537 0 CH4-00002.xyz -219.117 1 CH4-00003.xyz -219.402 2 CH4-00004.xyz -219.155 3 4 CH4-00005.xyz -219.180 . . . . . . 9995 CH4-09996.xyz -219.359 9996 CH4-09997.xyz -219.342 9997 CH4-09998.xyz -218.069 9998 CH4-09999.xyz -219.161 9999 CH4-10000.xyz -219.128 [10000 rows x 2 columns] Atomic structure fingerprinting /home/huan/work/matsml/examples/ex1\_pcm-molecs/molecs\_CH4\_10k/summary.csv summary data loc /home/huan/work/matsml/examples/ex1\_pcm-molecs/molecs\_CH4\_10k/ ['C', 'H'] species fp\_type pcm molecs fp\_file fp\_CH4\_pcm.csv 100 ip dim 6 n atoms max verbosity Read input num structs 10000 Computing Coulomb matrix Projecting Coulomb matrix to create fingerprints [=========] 100% Done fingerprinting, results saved in fp\_CH4\_pcm.csv Atomic structure fingerprinting /home/huan/work/matsml/examples/ex1\_pcm-molecs/molecs\_CH4\_10k/summary.csv data loc /home/huan/work/matsml/examples/ex1\_pcm-molecs/molecs\_CH4\_10k/ species ['C', 'H'] fp\_type soap\_molecs fp\_file fp\_CH4\_soap.csv fp\_dim 100 n atoms max verbosity Read input num structs 10000 Computing SOAP fingerprint Done fingerprinting, results saved in fp\_CH4\_soap.csv Learning fingerprinted/featured data algorithm fully connected NeuralNet w/ TensorFlow layers [4, 4]activ\_funct tanh epochs optimizer nadam nfold cv Reading data ... data file fp\_CH4\_pcm.csv data size 10000 training size 8000 (80.0 %) test size 2000 (20.0 %) x dimensionality y dimensionality y label(s) ['target'] Scaling x minmax xscaler saved in xscaler.pkl Scaling y minmax Prepare train/test sets random Building model Training model w/ cross validation cv,rmse\_train,rmse\_test,rmse\_opt: 0 0.001728 0.001792 0.001792 cv,rmse\_train,rmse\_test,rmse\_opt: 1 0.001823 0.001871 0.001792 cv,rmse\_train,rmse\_test,rmse\_opt: 2 0.002435 0.002473 0.001792 cv,rmse\_train,rmse\_test,rmse\_opt: 3 0.001406 0.001354 0.001354 cv,rmse\_train,rmse\_test,rmse\_opt: 4 0.001378 0.001405 0.001354 Optimal ncv: 3 ; optimal NET saved FCNN trained, now make predictions & invert scaling Unscaling y: minmax rmse training 0.003258 target Unscaling y: minmax rmse test target 0.003258 Predictions made & saved in "training.csv" & "test.csv" Plot results in "training.csv" & "test.csv" showing target -217.5-218.0-218.5Predicted -219.0-219.5training, (rmse &  $R^2$ ) = (0.003 & 1.000) test, (rmse &  $R^2$ ) = (0.003 & 1.000) -219.5-219.0-218.5-218.0Reference value Learning fingerprinted/featured data algorithm fully connected NeuralNet w/ TensorFlow layers [4, 4] activ funct epochs 200 optimizer nadam nfold cv Reading data ... fp CH4 soap.csv data file data size 10000 training size 8000 (80.0 %) test size 2000 (20.0 %) x dimensionality 275 y dimensionality y label(s) ['target'] Scaling x xscaler saved in xscaler.pkl Scaling y Prepare train/test sets Building model Training model w/ cross validation cv,rmse train,rmse test,rmse opt: 0 0.002481 0.002652 0.002652 cv,rmse train,rmse test,rmse opt: 1 0.002453 0.002506 0.002506 cv,rmse train,rmse test,rmse opt: 2 0.002143 0.003453 0.002506 cv,rmse train,rmse test,rmse opt: 3 0.002029 0.002155 0.002155 cv,rmse train,rmse test,rmse opt: 4 0.004519 0.004522 0.002155 Optimal ncv: 3; optimal NET saved FCNN trained, now make predictions & invert scaling Unscaling y: minmax rmse training target Unscaling y: minmax 0.004675 target Predictions made & saved in "training.csv" & "test.csv" Plot results in "training.csv" & "test.csv" showing target -217.5-218.0Predicted value -218.5 -219.0-219.5training, (rmse &  $R^2$ ) = (0.005 & 1.000) test, (rmse &  $R^2$ ) = (0.005 & 1.000) -219.5-219.0-218.5-218.0-217.5Reference value In [ ]:

Example 1: Learning molecules energy