UC Center for Business Analytics

Why Choose a Master of Science in Business Analytics Program at UC Online?

The University of Cincinnati Online's Master of Science in Business Analytics program is nationally recognized and has a proven track record with placing students at successful, high-profile companies. Predictive Analytics Today named UC as the No.1 MS Data Science school in the country and Quacquarelli Symonds (QS) ranked us 18th globally and 7th nationally among U.S. public universities.

The Master's of Science in Business Analytics online program at UC provides students with expertise in descriptive, predictive, and prescriptive analytics. Many of our graduates are working as data scientists and business analysts at world-leading companies from larger corporations, to startups across the nation.

Note: The MS-Business Analytics program is recognized as a <u>STEM</u> (Science, Technology, Engineering, and Mathematics) program. According to the <u>National Science Teachers Association</u> (NSTA), "A common definition of STEM education [...] is an interdisciplinary approach to learning where rigorous academic concepts are coupled with real-world lessons as students apply science, technology, engineering, and mathematics in contexts that make connections between school, community, work, and the global enterprise enabling the development of STEM literacy and with it the ability to compete in the new economy." UC Online's skilled faculty members bring valuable field experiences to their courses to ensure that students have the skills necessary to excel in STEM positions.

What is Business Analytics?

According to <u>U.S. News</u>, Business Analytics Business "is the science of using data to build mathematical models and arrive at decisions that have value for a company or organization, Bertsimas says. This is relevant in nearly every field, whether it's medicine, technology, retail or real estate".

The University of Cincinnati's online Business Analytics Master's program is designed to achieve several core objectives:

- Put you ahead of the competition when applying to the workforce
- Provide you with the skills and tools needed to collect data and analyze it to influence decisions in an organization
- University of Cincinnati's 100% online program will empower you with core business analytics skills, and technical skills for understanding and implementing descriptive, predictive, and prescriptive analytics

Data Analytics ~ Convert raw data (information) to actionable and useful assessments

At what price should gas be set as a function of time of day/day of week/month/year/stock market/oil price etc... (this would use the IoT, data gathered at the local Speedway pump)

Decide what information is potentially relevant

Collect that data

Apply a model or use ML to draw new (illogical in the current model) relationships Make predictions for future behavior and actions that will optimize results Implement these suggestions

If these operations are conducted with limited or no human interaction it appears to be AI (really an algorithm)

We know this works in some situations

Amazon suggests your next purchase (simple systems)

When it fails it can fail in embarrassing/frustrating ways (automatic phone answering at the insurance company etc.)

Intellectual property issues: Who owns the data, who owns the results of data mining, who owns your choices

All are important to materials/polymer companies, research labs, academics

Types of Data Analytics

Data analytics is broken down into four basic types.

- 1. Descriptive analytics: This describes what has happened over a given period of time. Have the number of views gone up? Are sales stronger this month than last?
- 2. Diagnostic analytics: This focuses more on why something happened. This involves more diverse data inputs and a bit of hypothesizing. Did the weather affect beer sales? Did that latest marketing campaign impact sales?
- 3. Predictive analytics: This moves to what is likely going to happen in the near term. What happened to sales the last time we had a hot summer? How many weather models predict a hot summer this year?
- 4. Prescriptive analytics: This suggests a course of action. If the likelihood of a hot summer is measured as an average of these five weather models is above 58%, we should add an evening shift to the brewery and rent an additional tank to increase output.

https://www.investopedia.com/terms/d/data-analytics.asp

ML

ΑI

Consider obvious problems that might be addressed by this approach:

- -Selection of the best combination of materials for a super-conducting alloy
- -Best metals for advanced manufacturing (rapid prototyping)
- -Processing conditions/compounding for optimizing polymer pipe extrusion
- -Optimize a better heterogeneous catalyst for polypropylene synthesis (once you have the discovery by Ziegler/Natta)

And might not be addressed:

- -Solution to global warming
- -Solution to the plastics waste problem
- -Discovery of room temperature super conductors
- -Invention of the internet
- -Invention of block-copolymers

ML, AI, IoT are hammers, but everything isn't a nail

\$1,670,200,000.00 FY 2022

Machine Learning (ML), Artificial Intelligence (AI), the Internet of Things (IoT)

The world is run on money:

NATIONAL SCIENCE AND TECHNOLOGY COUNCIL

Committee on Science and Technology Enterprise Subcommittee on Networking and Information Technology Research and Development (NITRD) Co-Chair: Kathleen (Kamie) Roberts, NITRD

(DOE/CESER)

Office of Science (DOE/SC)

Chun-Ju (Janey) Hsiao

Susan Gregurick

Peter Lyster

Frank Hearl

Steven Posnack

Security (DHS)

Sridhar Kowdley

Russell Becker

Department of Homeland

Science & Technology Directorate (S&T)

(ONC)

National Institutes of Health (NIH)

Co-Chair: Margaret Martonosi, National Science Foundation (NSF)

Executive Secretary: Nekeja Butler, NCO

National Artificial Intelligence Initiative Office

Director: Lynne E. Parker, OSTP

National Coordination Office for Networking & Information Technology Research & Development Director: Kathleen (Kamie) Roberts

NITRD Subcommittee Member Agencies and Representative (Principal representatives are listed first

Department of Commerce (DOC) National Institute of Standards and Technology (NIST) Elham Tabassi

National Oceanic and Atmospheric Administration (NOAA)

Frank Indiviglio Department of Defense (DOD)

Military Services Air Force Matthew D. Cocuzzi Army Jeffrey D. Singleton

Sandy Landsberg

National Security Agency (NSA) Rita Bush

Office of the Secretary of Defense

Keith A. Krapels Department of Energy (DOE) Artificial Intelligence & Technology Office (DOE/AITO) Pamela K. Isom Jonnie Bradley

National Nuclear Security Thuc T. Hoang

Department of Energy (DOE) (continued) rtment of Justice (DO.D. National Institute of Justice (NIJ) Office of Cybersecurity, Energy Kyle Fox Mark Greene

> Department of State (State) Office of S&T Cooperation

Department of Veterans Affairs National AI Institute (NAII) Gil Alterovitz

Department of Health and Human Services (HHS) Agency for Healthcare Research and Quality (AHRQ) National Aeronautics and Space Administration (NASA) Kathleen B. Loftin

> National Archives and Records Administration (NARA) Hung Nguyen

National Institute for Occupational Safety and Health (NIOSH) National Reconnaissance Office Office of the National Coordinator for Health Information Technology

Thomas Jenkins National Science Foundation Margaret Martonosi Joydip Kundu

Executive Office of the President Office of Management & Budget (OMB) Avital Bar-Shalom

Liuvi Pei Department of the Interior (DOI) U.S. Geological Survey (USGS)

Office of Science and Technology

OTHER PARTICIPATING DEPARTMENTS AND AGENCIES

These Federal departments and agencies participate in NITRD activities and have mission interests in advance networking and IT R&D and applications, but they are not members of the NITRD Subcommittee,

Department of Agriculture (USDA)

Agricultural Research Service (ARS) Agriculture and Food Research Initiative (AFRI) National Institute of Food and Agriculture (NIFA)

Department of Commerce (DOC)

International Trade Administration (ITA) National Telecommunications and Information Administration (NTIA)

United States Census Bureau (Census) U.S. Patent and Trademark Office (USPTO)

Department of Defense (DOD) Defense Health Agency (DHA)

Defense Research and Engineering Network (DREN) Joint Artificial Intelligence Center (JAIC) Military Services Facilities:

Air Force Office of Scientific Research (AFOSR) Army Research Laboratory (ARL) Combat Capabilities Development Command (Army-CCDC)

Command, Control, Computers, Communication Cyber, Intelligence, Surveillance and Reconnaissance Center (Army-C5ISR)

C5ISR Space and Terrestrial Communications Directorate (C5ISR S&TCD) High-Performance Computing Modernization

Program (Army-HPCMP) Naval Research Laboratory (NRL) U.S. Army Medical Research and Development

Command (USAMRDC) Office of the Under Secretary of Defense fo Research and Engineering (OUSD R&E) Test Resource Management Center (TRMC) U.S. Army Corps of Engineers (USACE)

U.S. Cyber Command (USCYBERCOM) Department of Energy (DOE)

Advanced Research Projects Agency-Energy (ARPA-E) Office of Energy Efficiency and Renewable Energy

Office of Electricity (OE) Office of Fossil Energy (FE) Office of Nuclear Energy (NE)

Department of Health and Human Services (HHS) Administration for Community Living (ACL)

Centers for Disease Control and Prevention (CDC) Centers for Medicare and Medicaid Services (CMS) Food and Drug Administration (FDA) Health Resources and Services Administration (HRSA) Indian Health Service (IHS) HHS (continued)

National Cancer Institute (NCI) National Center for Health Statistics (NCHS) Substance Abuse and Mental Health Services Administration (SAMHSA)

Department of Homeland Security Cybersecurity and Infrastructure Security Agency (CIS)

Department of Justice (DOJ) Drug Enforcement Administration (DEA)

Federal Bureau of Investigation (FBI) Department of Labor (DOL)

Bureau of Labor Statistics (BLS) Occupational Safety & Health Administration (OSHA) Department of Transportation (DOT)

Federal Aviation Administration (FAA) Federal Highway Administration (FHWA) Federal Motor Carrier Safety Administration (FMCSA) Federal Railroad Administration (FRA)

Federal Transit Administration (FTA) Intelligent Transportation Systems Joint Program Office (ITS JPO)

Maritime Administration (MARAD) National Highway Traffic Safety Administration (NHTSA)

Pipeline and Hazardous Materials Safety Administration (PHMSA) Department of the Treasury (Treasury)

Department of Veterans Affairs (VA) Environmental Protection Agency (EPA) Federal Communications Commission (FCC) Federal Trade Commission (FTC)

General Services Administration (GSA) Intelligence Advanced Research Projects Activity
(IARPA)

National Maritime Intelligence-Integration Office (NMIO) Office of Director of National Intelligence (ODNI)

National Transportation Safety Board (NTSB) Nuclear Regulatory Commission (NRC) Social Security Administration (SSA)

Note: Any mention in the text of commercial or academic partners in Federal R&D activitie is for information only; it does not imply



The Networking & Information Technology R&D Program and the National Artificial Intelligence Initiative Office

SUPPLEMENT TO THE PRESIDENT'S FY2022 BUDGET

A report by the SUBCOMMITTEE ON NETWORKING AND INFORMATION TECHNOLOGY RESEARCH AND DEVELOPMENT

COMMITTEE ON SCIENCE AND TECHNOLOGY ENTERPRISE

and the

MACHINE LEARNING AND ARTIFICIAL INTELLIGENCE SUBCOMMITTEE COMMITTEE ON TECHNOLOGY

SELECT COMMITTEE ON ARTIFICIAL INTELLIGENCE

NATIONAL SCIENCE AND TECHNOLOGY COUNCIL

December 2021

Materials Informatics

- -Identify superior materials from initial training sets and physics simulation *scikit-learn*; *keras*; *pytorch*
- -Tailor materials data using ML. Take multiple sources, images, diffraction, scattering, spectroscopy, mechanical testing, electrical properties, thermal properties and generate models for materials design
- -High-throughput data acquisition. Synchrotron sources is a chief example. Robotics, DFT.
- -Post process STEM images.
- -Use ML to optimize simulations e.g. modify atomic potential functions or use ML to couple simulations at different length scales (molecular MD, coarse grain MD, Dissipative Particle Dynamics).



learn Install User Guide API Examples Community More -

scikit-learn

Getting Started Release Highlights for 1.0 GitHub

- Simple and efficient tools for predictive data analysis
- Accessible to everybody, and reusable in various contexts
- . Built on NumPy, SciPy, and matplotlib
- Open source, commercially usable BSD license

Classification

Identifying which category an object belongs to.

Applications: Spam detection, image recognition.

Algorithms: SVM, nearest neighbors, random forest, and more...



Dimensionality reduction

Reducing the number of random variables to consider.

Applications: Visualization, Increased efficiency

Algorithms: k-Means, feature selection, non-negative matrix factorization, and



On-going development: What's new

December 2021, scikit-learn 1.0.2 is available for download (Changelog).

October 2021, scikit-learn 1.0.1 is available for download (Changelog).

September 2021, scikit-learn 1.0 is available for download (Changelog).

April 2021, scikit-learn 0.24.2 is available for download (Changelog). January 2021. scikit-learn 0.24.1 is available for

December 2020, scikit-learn 0.24.0 is available

for download (Changelog). August 2020, scikit-learn 0.23.2 is available for

download (Changelog). May 2020. scikit-learn 0.23.1 is available for

download (Changelog) May 2020, scikit-learn 0.23.0 is available for download (Changelog).

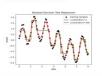
Scikit-learn from 0.23 requires Python 3.6 or

Regression

Predicting a continuous-valued attribute associated with an object.

Applications: Drug response, Stock

Algorithms: SVR, nearest neighbors, random forest, and more...



Model selection

Comparing, validating and choosing parameters and models.

Applications: Improved accuracy via parameter tuning Algorithms: grid search, cross validation, metrics, and more...



About us: See authors and contributing More Machine Learning: Find related projects Questions? See FAQ and stackoverflow

Mailing list: scikit-learn@python.org Gitter: gitter.im/scikit-learn

Twitter: @scikit_learn Twitter (commits): @sklearn_commits

Linkedin: linkedin/scikit-learn

YouTube: youtube.com/scikit-learn Facebook: @scikitlearnofficial

Instagram: @scikitlearnofficial Communication on all channels should respect PSF's code of conduct.

Help us, donate! Cite us!

Clustering

Automatic grouping of similar objects into sets.

Applications: Customer segmentation. Grouping experiment outcomes Algorithms: k-Means, spectral clustering, mean-shift, and more.

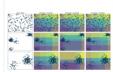


Preprocessing

extraction, and more...

Feature extraction and normalization.

Applications: Transforming input data such as text for use with machine learning algorithms. Algorithms: preprocessing, feature



Who uses scikit-learn?



le use scikit-learn to support leading-edge sic research [...]"





API docs Guides Examples

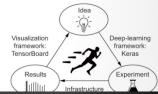


Deep learning for humans.

Keras is an API designed for human beings, not machines. Keras follows best practices for reducing cognitive load: it offers consistent & simple APIs, it minimizes the number of user actions required for common use cases, and it provides clear & actionable error messages. It also has extensive documen

Iterate at the speed of thought.

Keras is the most used deep learning framework among top-5 winning teams on Kaggle. Because Keras makes it easier to run new experiments, it empowers you to try more ideas than your competition, faster And this is how you win.





Exascale machine learning.

Built on top of TensorFlow 2, Keras is an industry-strength framework that can scale to large clusters of GPUs or an entire TPU pod. It's not only possible; it's easy.

Deploy anywhere.

Take advantage of the full deployment capabilities of the TensorFlow platform. You can export Keras models to JavaScript to run directly in the browser, to TF Lite to run on iOS, Android, and embedded devices. It's also easy to serve Keras models as via a web API.

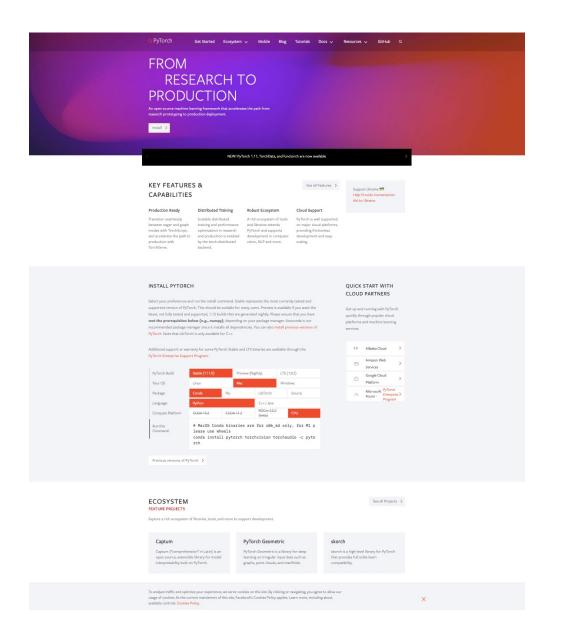


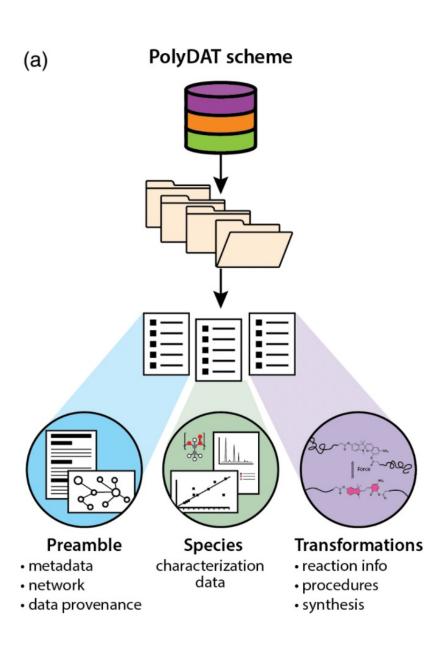


A vast ecosystem.

A Valst ECOSysterm.

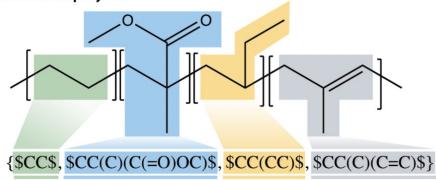
Keras is a central part of the tightly-connected TensorFlow 2 ecosystem, covering every step of the machine learning workflow, from data management to hyperparameter training to deployment solutions.



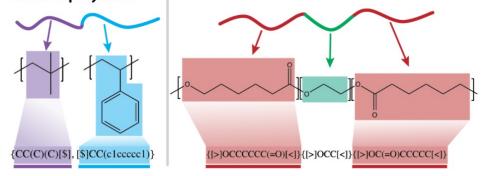


(b) BigSMILES scheme

Random copolymer



Block copolymers



Cencer MM, Moore JS, Assary RS Machine learning for polymeric materials: an introduction Polym. Int. (2021) DOI 10.1002/pi.634

Polymer Genome An informatics platform for polymer property prediction and design using machine learning Home Guide References Sign-in/up Draw Polymer Polymer name, repeat unit, SMILES ... Predict Properties Retrosynthesis

Guide to User Input in Polymer Genome

1. Repeat Unit Guidelines

Polymer Genome accepts the repeat unit representation of polymers as one of the input types. The repeat unit is used both for searching the Polymer Genome database and/or to perform instant machine learning predictions. The polymers composed of the following building blocks are available to use for writing the repeat unit _CH2-, _CH= (must be paired, eg, _CH=CH=), -O, _CS-, _CO-, _NH-, _CGH2-, _CH2S-, _CSH3N-, _CGH3N-, _CP2-, _CP-(must be paired, eg, _CH=CP-), -CHF-, _CC12-, _CC1- (must be paired, eg, _CH=CH2-), _CH2-, _CH2-, _CH3-, _C

Examples of repeat units are CH2-CH2 (polyethylene), NH-CO-NH-C6H4, CH-CH-CH2, etc. Those with chemically unstable bonds (such as NH-NH, CO-CO, CS-CS, O-O) are not allowed, and will be flazeed. The following basic formatting rules should also be followed:

- Element symbols are case sensitive (C, Br, etc.), and numerals are not sub-scripted (CH2, C6H4, etc.).
- Building blocks in a repeat unit must be connected with '-'.
- Spaces are not permitted in a repeat unit.
 CH, CF, CC1, CBr, and CI blocks must be paired.

Create your own repeat unit. Legitimate repeat unit will be converted to an equivalent SMILES.

Polymer repeat unit, ex) CH2-C6H4



2. SMILES Guidelines

SMILES (simplified molecular-input line-entry system) uses short ASCII string to represent the structure of chemical species. Because the SMILES format described here is custom-designed by us for polymers, it is not completely identical to other SMILES formats. Strictly following the rules explained below is crucial for having correct results. Details of the rules are given below, while the SMILES strings of some example polymer blocks and polymers are provided in Table 1.

- Spaces are not permitted in a SMILES string.
- An atom is represented by its respective atomic symbol. In case of 2-character atomic symbol, it is placed between two square brackets [].
- Single bonds are implied by placing atoms next to each other. A double bond is represented by the = symbol while a triple bond is represented by #.
- Hydrogen atoms are suppressed, i.e., the polymer blocks are represented without hydrogen. Polymer Genome interface assumes typical valence
 of each atom type (see Table 2). If enough bonds are not identified by the user through SMILES notation, the dangling bonds will be automatically
 saturated by hydrogen atoms.
- Branches are placed between a pair of round brackets (), and are assumed to attach to the atom right before the opening round bracket (.
- Numbers are used to identify the opening and closing of rings of atoms. For example, in C1CCCC1, the first carbon having a number "1" should
 be connected by a single bond with the last carbon, also having a number "1". Polymer blocks that have multiple rings may be identified by using
 different, consecutive numbers for each ring.
- Atoms in aromatic rings can be specified by lower case letters. As an example, benzene ring can be written as clccccc1 which is equivalent to C(C=C1)=CC=C1.
- A SMILES string used for Polymer Genome represents the repeating unit of a polymer, which has 2 dangling bonds for linking with the next
 repeating units. It is assumed that the repeating unit starts from the first atom of the SMILES string and ends at the last atom of the string. These
 two bonds must be the same due to the periodicity. It can be single, double, or triple, and the type of this bond must be indicated for the first
 atom. For the last atom, this is not needed. As an example, cor represents -CH₂-CH₂-while =cor represents =cB-CE=.
- Atoms other than the first and last can also be assigned as the linking atoms by adding special symbol, [*1. As an example, C(C=C1)=CC=C1

Zhu M-X, Deng T, Dong L, Chen J-M, Dang Z-M Review of machine learning-driven design of polymer-based dielectrics IET Nanodielectrics 5 24-38 (2022).

Evolution Searching (Inverse design method) Generative Model (vs. Discriminative model) Genome Approach

Identify Polymers with a linear notation (fingerprint)
simplified molecular-input line-entry system (SMILES)
Link fingerprint to properties (machine learning from training dataset)

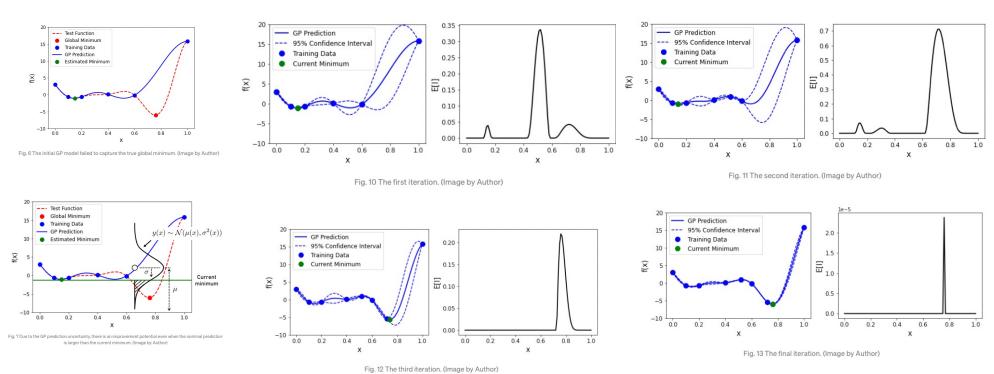
Kernel regression (expected value within range of learned data)

Decision tree (various indications, some missing, predict answer from other examples)

Neural network (deep learning) (predictive modeling, adaptive control, or trained by dataset: take handwritten "0"'s from 1000 people break into pixels, correlate black and white pixels (1 and 0) with presence of 0 to get an overall probability you have a "0")

Zhu M-X, Deng T, Dong L, Chen J-M, Dang Z-M Review of machine learning-driven design of polymer-based dielectrics IET Nanodielectrics **5** 24-38 (2022).

Surrogate model (example gaussian)



Pearson Correlation Coefficient

$$r = rac{\sum \left(x_i - ar{x}
ight)\left(y_i - ar{y}
ight)}{\sqrt{\sum \left(x_i - ar{x}
ight)^2 \sum \left(y_i - ar{y}
ight)^2}}$$

r = correlation coefficient

 x_i = values of the x-variable in a sample

 \bar{x} = mean of the values of the x-variable

 y_i = values of the y-variable in a sample

 $\overline{y}\,\,$ = mean of the values of the y-variable

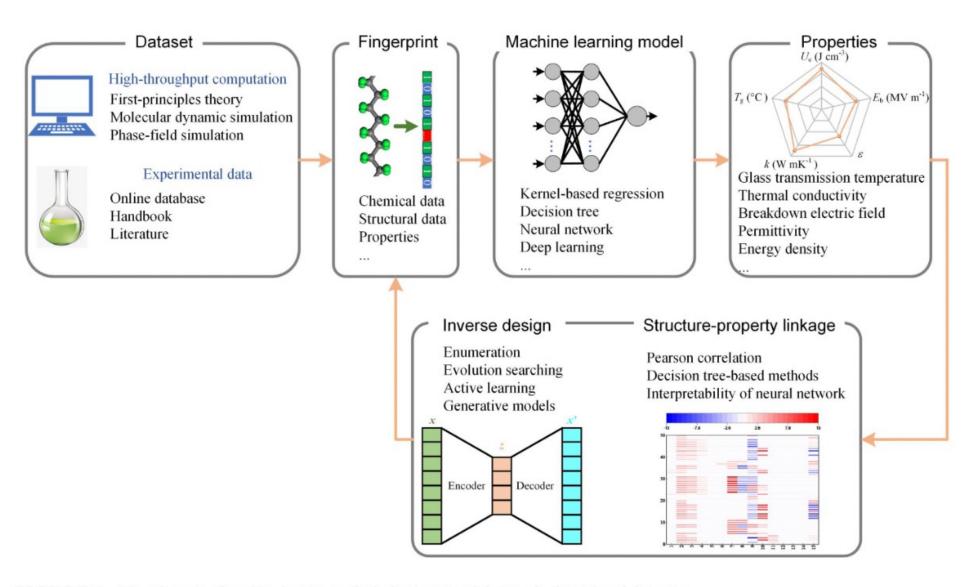
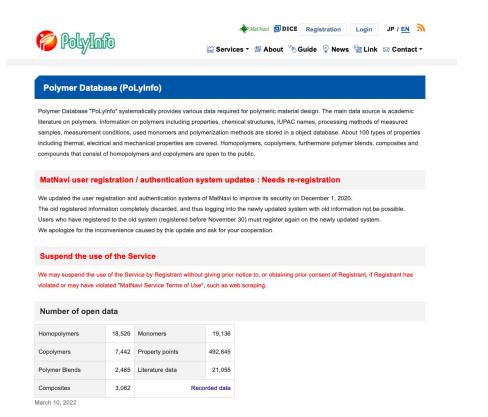
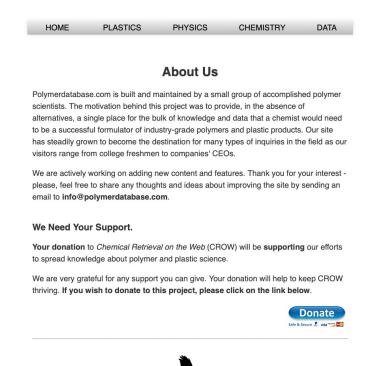


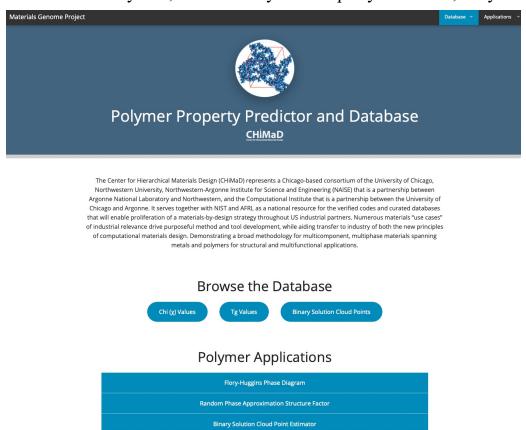
FIGURE 1 The schematic of machine learning methods for the rational design of polymer-based dielectrics

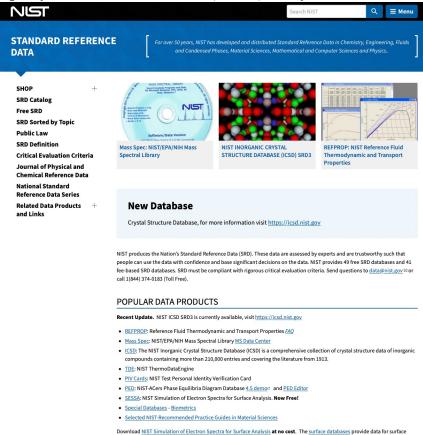
Online libraries, experiments and high-throughput computations PoLyInfo, CROW Polymer Property Database, Polymer Property Predictor, Database (NIST), Polymer Genome





Online libraries, experiments and high-throughput computations PoLyInfo, CROW Polymer Property Database, Polymer Property Predictor, Database (NIST), Polymer Genome

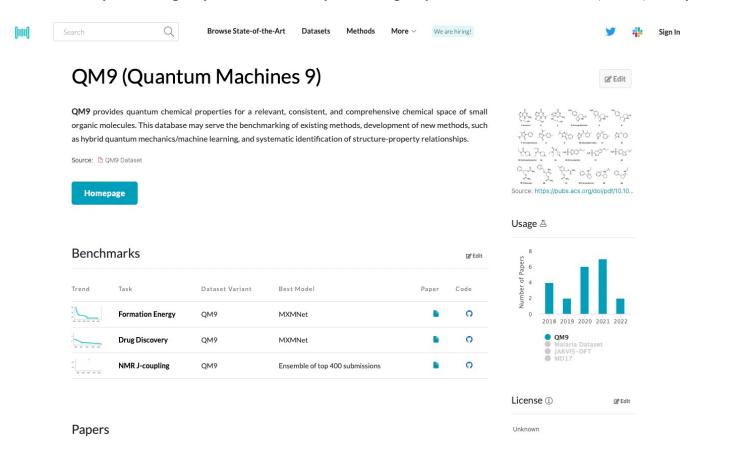




Online libraries, experiments and high-throughput computations PoLyInfo, CROW Polymer Property Database, Polymer Property Predictor, Database (NIST), Polymer Genome

Polymer Genome An informatics platform for polymer property prediction and design using machine learning
Home Guide References Sign-in/up
To make predictions please Sign-in/up.
Draw Polymer Polymer name, repeat unit, SMILES Predict Properties Retrosynthesis
Polymers may be queried either using the drawing tool, or by specifying common names, repeat units or SMILES strings.
Advanced experimental features Copolymer Genome € (Please Sign-in/up)
How it Works? Querying Polymers Join Now

Online libraries, experiments and high-throughput computations PoLyInfo, CROW Polymer Property Database, Polymer Property Predictor, Database (NIST), Polymer Genome



20

Online libraries, experiments and high-throughput computations NanoMine for nanocomposites



NanoMine: an Online Platform of Materials Genome Prediction for Polymer Nanocomposites

Materials science is founded on the processing-structure-properties (p-s-p) paradigm. Understanding of mechanisms have built up over decades leading to a rich tapestry of knowledge which is used to select and design materials for applications. Unlike metallic alloy systems where databases and predictive tools have been built to up and can enable more rapid materials design, the polymer nanocomposite data/design space is considerably less developed due to the heterogeneity of constituent combinations as well as complexity in polymer and interphase behavior.

Because of the complex mechanisms involved in nanocomposite formation and response, and the isolation of data sets from each other, both the fundamental understanding and the discovery of new nanocomposites is Edisonian and excruciatingly slow. We address this issue by creation of a living, open-source data resource for nanocomposites. NanoMine is built on both a schema and an ontology to provide a robustness to the FAIR (findable, accessible, interoperable and reusable) principles. Nanomine also allows for the registration of materials resources, bridging the gap between existing resources and the end users and making those existing resources available for research to material community. The data framework together with the module tools like microstructure characterization and the FEA simulation tools forms the nanocomposite data resource. Searching and visualization tools are being developed for user to query, visualize, and compare their data with the existing data in our system for design purposes. Tools and models utilizing data sciences and optimization concepts are being developed with the goal of data-driven materials design.

Our lab is making continuous efforts to improve the data curation experience by allowing customized Excel templates uploading in the front end and to ensure the data quality in the back end by developing autonomous agents to detect possible errors. We are now transitioning the back end system to a more extensible ontology-based system while maintaining an API to the Material Data Curator developed at NIST under the grand objective of the Materials Genome Initiative (MGI). A corresponding new front end javascript based user interface is also under development with more powerful dynamic features available.

You can access the prototype by clicking the button

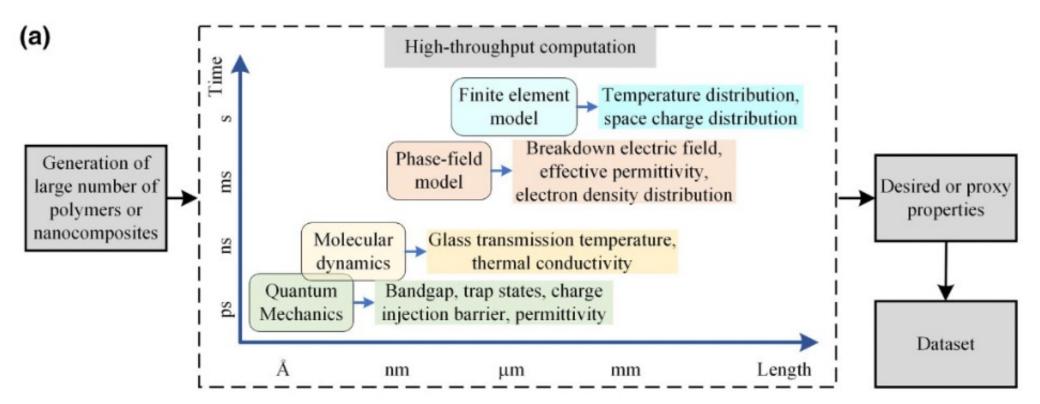
NetID can apply for a Duke Onelink account for access.

Users without a Duke

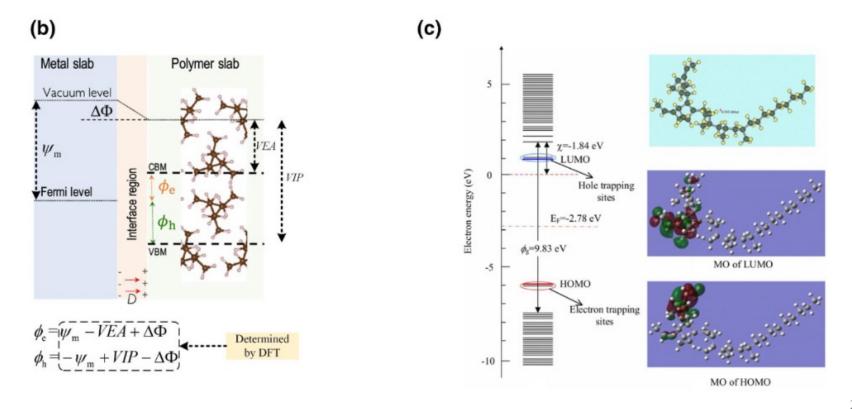
RESEARCH

- Overview
- Materials Genome Prediction (MaterialsMine)
- NanoMine: Online MGI Prediction Platform
- Predicting Polymer Nanocomposite Properties
- ChemProps
- MetaMine
- Polymers and Nanostructured Polymers
- Education Research (NRT)
- Previous Projects

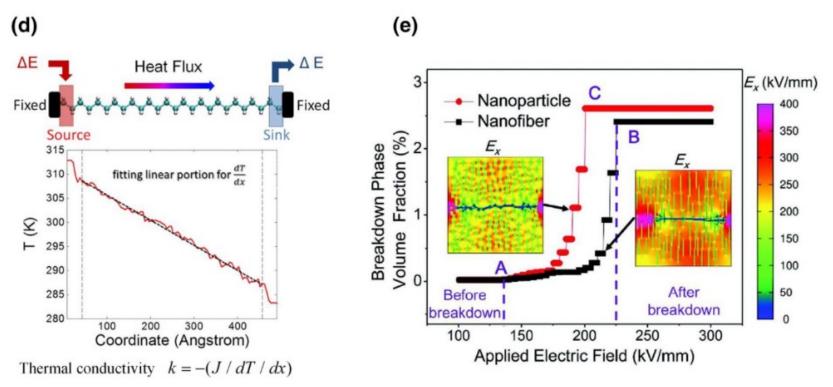
Manual search of the literature High-throughput computations using first principles; MD simulations



Density functional theory (DFT) for charge injection barrier from electrode to polymer, trap depth in polymer; ionic electronic and total dielectric constant



- d) Non-equilibrium molecular dynamics for thermal conductivity
- e) Phase field model for dielectric breakdown in polymer nanocomposites (free energy as a function of composition; composition is subject to diffusion; dynamic model with energy minimization at an interface)



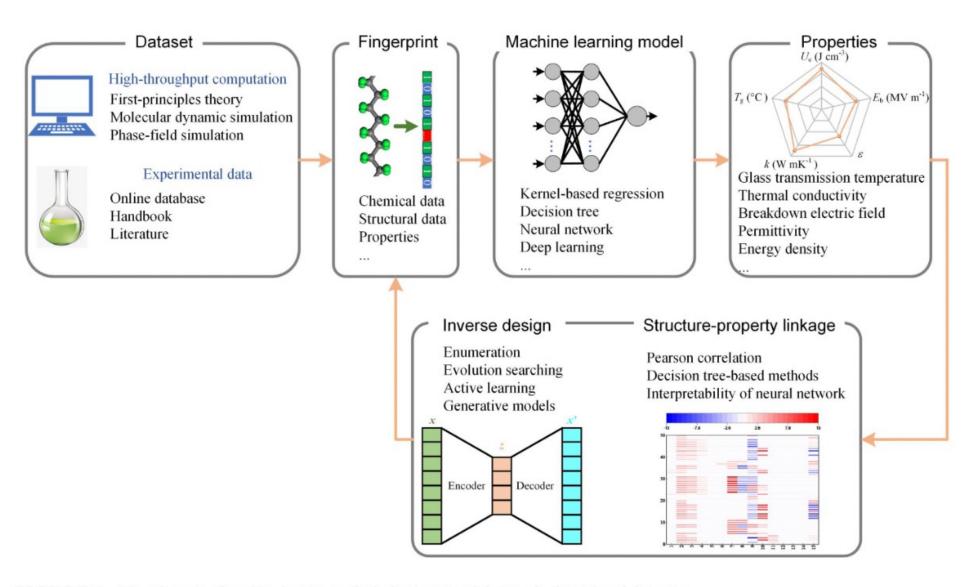


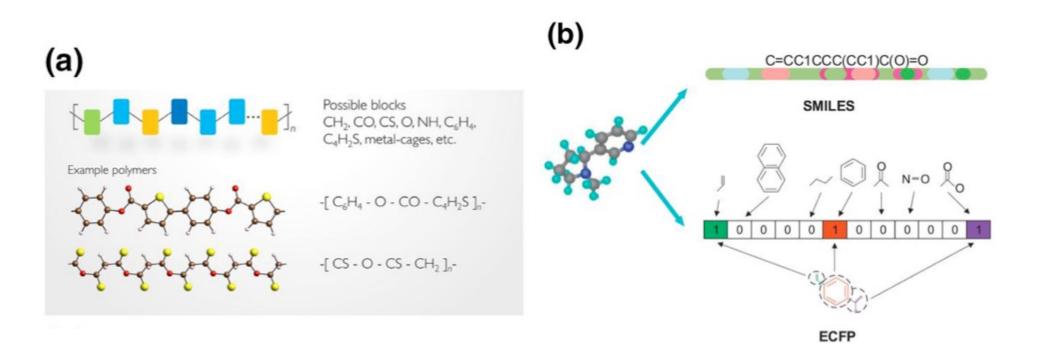
FIGURE 1 The schematic of machine learning methods for the rational design of polymer-based dielectrics

Machine Learning Strategies

Fingerprinting: Numerical representation of the materials in the datasets

Learning: Map between target property and fingerprint

a) Fingerprint based on a group contribution method; b) Simplified Molecular-Input Line-Entry System (SMILES) and Extended-Connectivity Fingerprints (ECFPs)



RDKit converts SMILES to numerical vectors

RDKit: Open-Source Cheminformatics Software

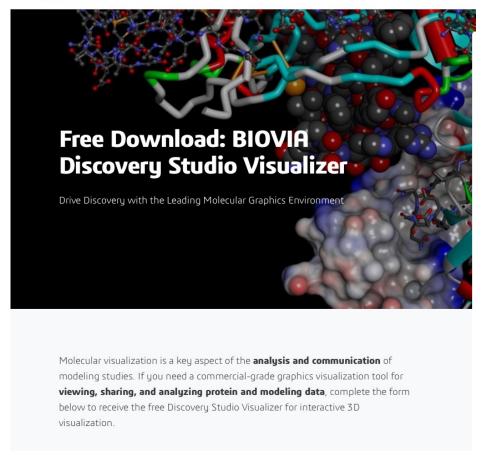
Useful Links

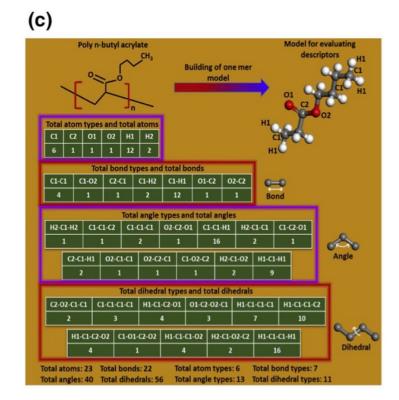
- GitHub page
 - Git source code repository
 - The bug tracker
 - Q&A, Discussion
- Sourceforge page
 - The mailing lists
 - Searchable archive of rdkit-discuss
 - Searchable archive of rdkit-devel
- · RDKit at LinkedIn
- The RDKit Blog
- Online Documentation
 - Python API
 - · C++ API
 - Downloadable version of the full HTML documentation
 - · Japanese translation of the documentation
 - Materials from the 2012 UGM
 - Materials from the 2013 UGM
 - Materials from the 2014 UGM
 - Materials from the 2015 UGM
 - Materials from the 2016 UGM
 - Materials from the 2017 UGM
 - Materials from the 2018 UGM
 - Materials from the 2019 UGM
 - Materials from the 2020 UGM
 - Materials from the 2021 UGM
- Other Stuff
 - · Conda binary packages for the RDKit
 - RDKit Knime nodes
 - recipes for building using the excellent conda package manager Contributed by Riccardo Vianello.
 - o homebrew formula for building on the Mac Contributed by Eddie Cao.



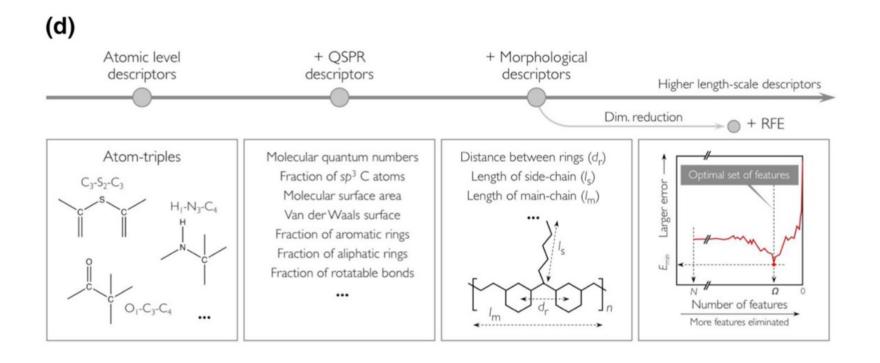
BIOVA gives hierarchical fingerprints

≡ BASSAULT



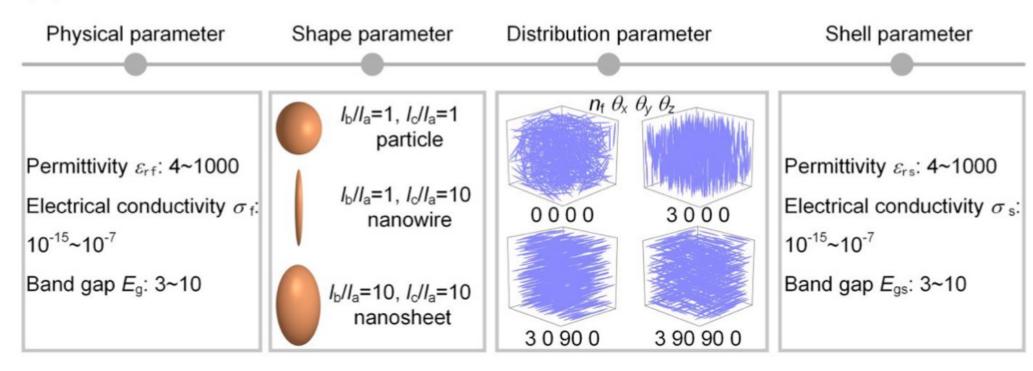


Hierarchical fingerprints

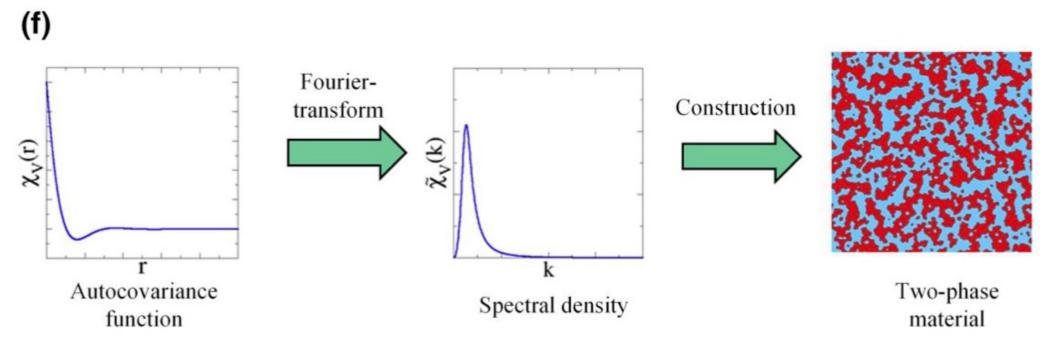


Nanocomposite fingerprint for dielectric properties

(e)



Inverse space nanocomposite fingerprint for structure



Convolutional neural network (CNN)

Neural network (decision tree type algorithm) with classification optimization using matrix multiplication for images to identify patterns, require GPUs.

-Convolution layer (Initial layer, image)

further convolution layers for color, edges, etc.

- -Pooling layer
- -Fully connected (FC) layer (Final layer)



- A. Image (height, width, depth RGB)
- B. Convolution, check if a feature is present such as an "O" using a kernel or filter
- C. Process by rastering across image with dot products resulting in a feature map, activation map or convolution feature

Number of filters; Stride (step of raster); zero padding (background) decides the complexity

For PNCs interfacial regions can be important

This is a major stumbling block

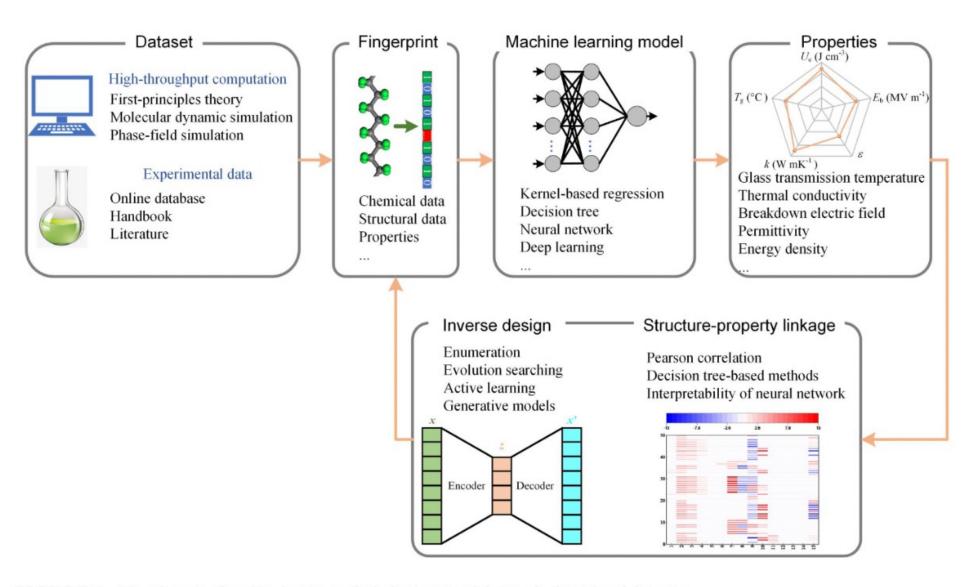


FIGURE 1 The schematic of machine learning methods for the rational design of polymer-based dielectrics

Machine Learning (ML) Algorithm

Fingerprint => ML => Property

Linear and non-linear regression algorithms

Fingerprint ~ property (linear)

Radial basis function: Property $\sim SUM(f(fingerprint-x_c))$

Polynomial: Property $\sim SUM(k_n \text{ fingerprint}^n)$

Kernel based algorithms (alternatives to least squares routines)

Kernel ridge regression (KRR)

Support vector machine (SVM)

Gaussian process regression (GPR)

Artificial neural networks (ANN)

Surrogate model (example gaussian)

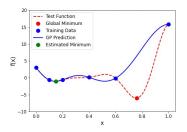


Fig. 6 The initial GP model failed to capture the true global minimum. (Image by Author)

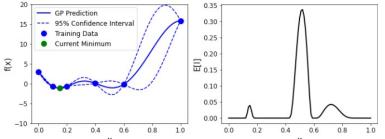


Fig. 10 The first iteration. (Image by Author)

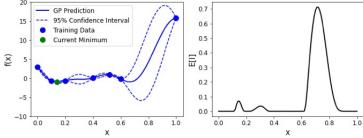


Fig. 11 The second iteration. (Image by Author)

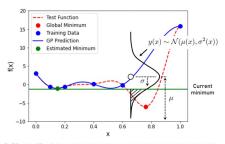


Fig. 7 Due to the GP prediction uncertainty, there is an improvement potential even when the nominal prediction is larger than the current minimum. (Image by Author)

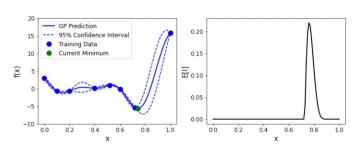


Fig. 12 The third iteration. (Image by Author)

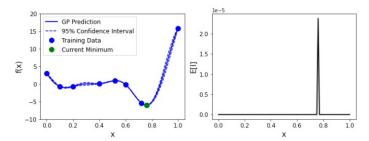
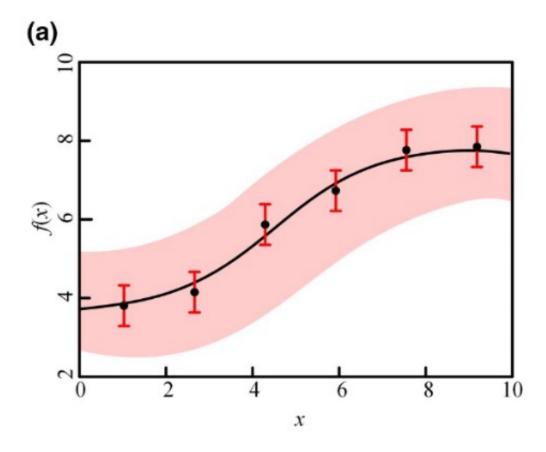


Fig. 13 The final iteration. (Image by Author)

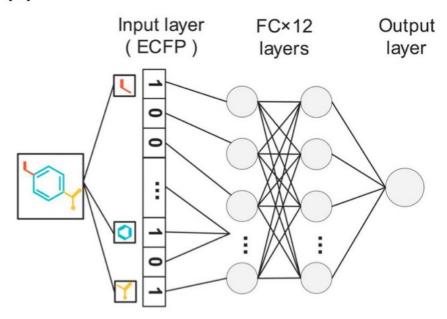
Gaussian process regression



Decision tree algorithms, random forest (RF)

Decision trees with many levels tend to learn irregular patterns By randomly grouping sets from the input fingerprint irregular patterns can be removed

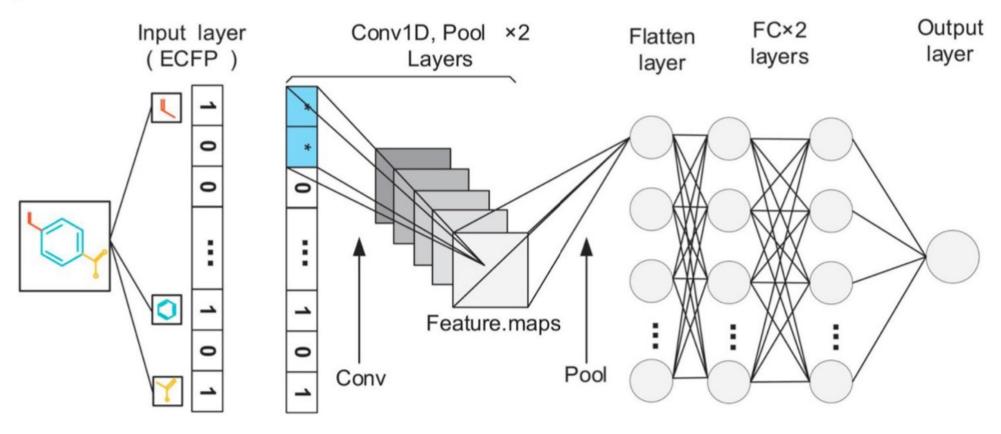
(b)



Artificial neural network

Convolution neural network

(c)



Convolutional neural network (CNN)

Neural network (decision tree type algorithm) with classification optimization using matrix multiplication for images to identify patterns, require GPUs.

- -Convolution layer (Initial layer, image)
 - further convolution layers for color, edges, etc.
- -Pooling layer
- -Fully connected (FC) layer (Final layer)



- A. Image (height, width, depth RGB)
- B. Convolution, check if a feature is present such as an "O" using a kernel or filter
- C. Process by rastering across image with dot products resulting in a feature map, activation map or convolution feature

Number of filters; Stride (step of raster); zero padding (background) decides the complexity

TABLE 1 Comparison of different ML algorithms

ML algorithm	Advantages	Disadvantages		
Linear regression	Simplest method	Neglect of non-linear linkage between descriptors and properties		
KRR, SVM	Low computational cost	Unfeasible for large datasets as the size of the kernel matrix scales quadratically with the number of features		
GPR	The uncertainty for objective values can be well predicted	Requires a manageable dataset size and does not have the capability to train multiple properties in one single model		
RF	Feasible for large datasets and provides an intrinsic metric to evaluate the importance of each descriptor	Might create over-complex trees and cause overfitting		
ANN	Exhibits strong ability to capture non-linear complex relations from large-scale datasets	Requires much more training data, is time-consuming, and lacks interpretability; also called 'black boxes'.		
Deep neural network	Feasible for graphical representations of materials and learns representations with different abstraction levels	Requires much more training data, is time-consuming, and lacks interpretability		

Abbreviations: ANN, artificial neural network; GPR, Gaussian process regression; KRR, kernel ridge regression; ML, machine learning; RF, random forest; SVM, support vector machine.

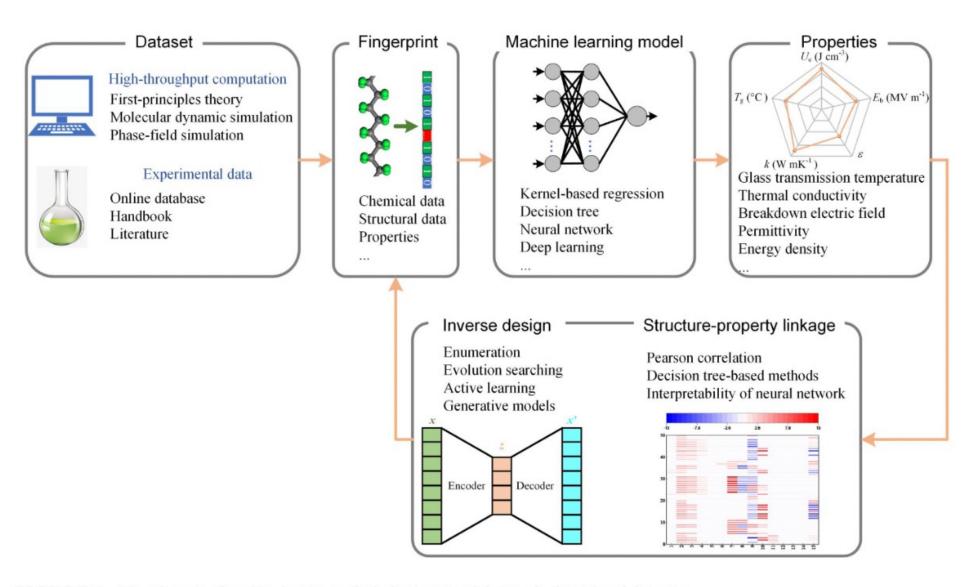
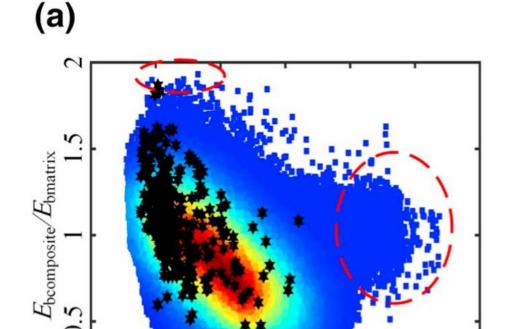


FIGURE 1 The schematic of machine learning methods for the rational design of polymer-based dielectrics

Inverse Design Methods

5

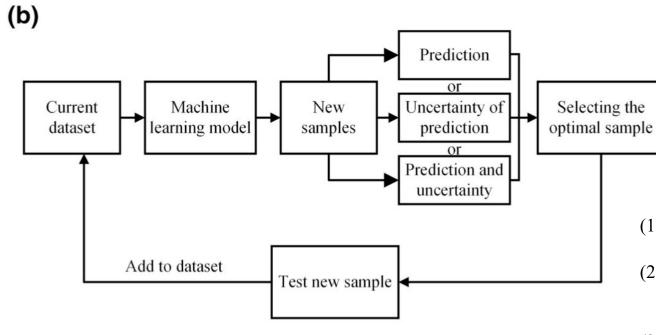


 $\mathcal{E}_{composite}/\mathcal{E}_{matrix}$

Enumeration method, go through each possible solution (complete enumeration) or limit the solutions (incomplete enumeration)

GPR-based ML model used to screen promising polymer nanocomposites with desired permittivity, breakdown strength and energy density, resulting in several kinds of nanocomposites with desired properties

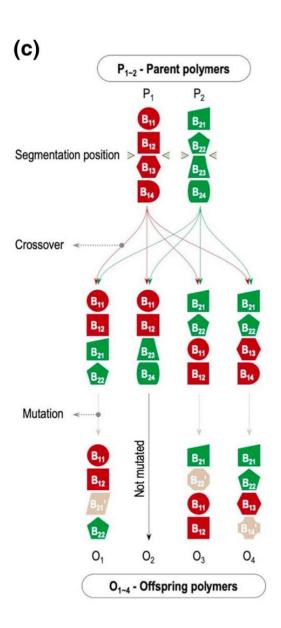
Inverse Design Methods



Choosing the optimal sample requires ML models to provide both prediction and uncertainty values of the target property. As a result, the GPR algorithm and a combination of bootstrapping methods with standard ML algorithms (decision tree, SVM etc.), which can estimate the uncertainty of pre-dictions, are common ML methods in active learning.

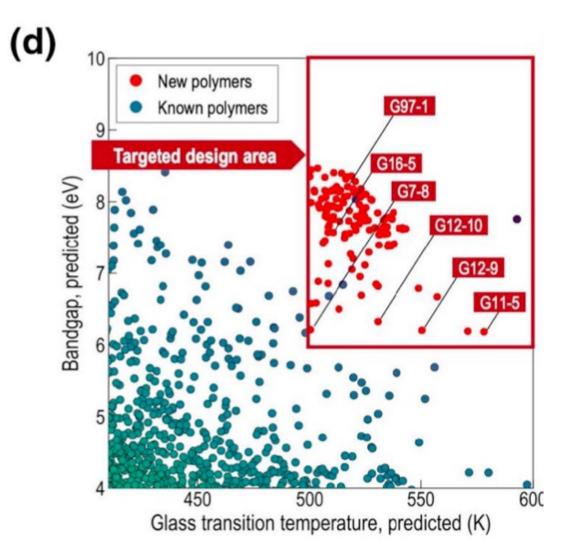
Active learning algorithm

- (1) training the ML-based surrogate model for property prediction,
- (2) selecting the optimal sample based on the prediction results including values and uncertainties, and
- (3) supplementing the optimal sample into training dataset



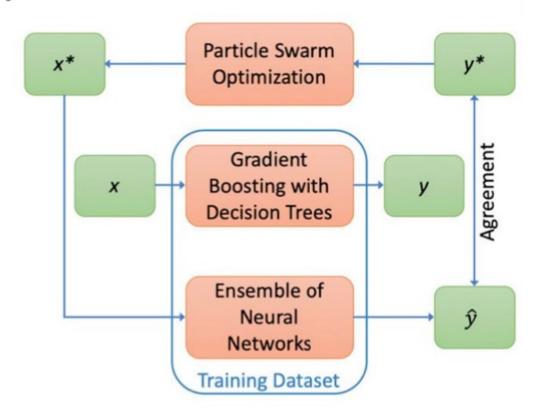
Evolutionary Strategy (ES)

Generic Algorithm



ES completes a structured search through procedures inspired by natural evolution. At each iteration, parameter vectors ('genotypes', fingerprints in the ML) in a population are updated (selection, crossover and mutation in GA; movement of particle in PSO) to generate an offspring, followed by an evaluation of the objection function value.

(e)

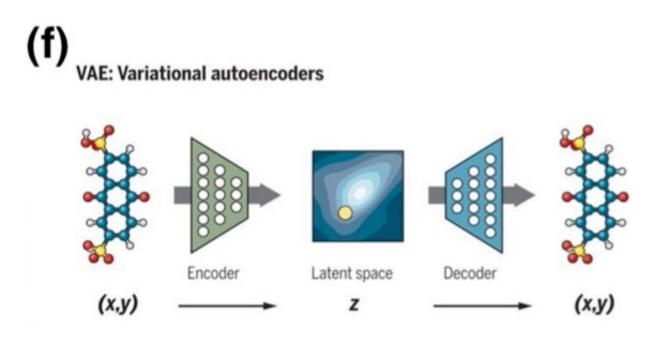


Particle Swarm Optimization (PSO)

Move a particle to improve the situation moving one particle impacts the other particles

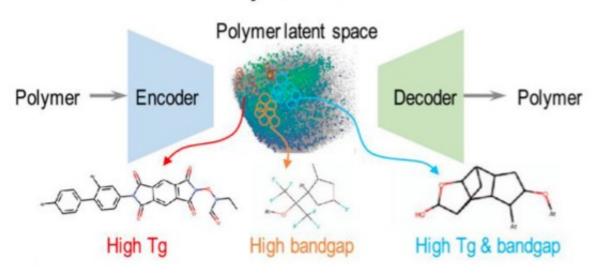
repeat and let the system evolve

Seems similar to a Monte-Carlo/Metropolis simulation Take the known structure, find a relationship to the desired property, then invert that relationship to regenerate the structure, finally you can set the desired property to your target and generate the associated structure (possibly)



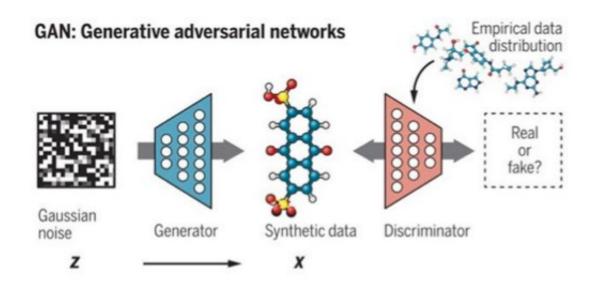
(g)

Polymer SD-VAE



(h)

Generate molecule from desired properties Generate properties from molecule Learn to do this process correctly by repeating





An image generated by a StyleGAN that looks deceptively like a photograph of a real person. This image was generated by a StyleGAN based on an analysis of portraits.



Another GAN deepfake deep learning example

TABLE 2 Some examples of the ML-driven approach applied in designing polymers and nanocomposites

Target property	Data source	Fingerprint	ML model	Inverse design method	Reference
Polymers: Bandgap of the polymer and electron	DFT computation	Hierarchical fingerprint in [53]	GPR	Enumeration	[53]
injection barrier (proxies for breakdown strength)		SMILES in [43]			[43]
Polymers: Bandgap and dielectric constant (proxies for energy density)	DFT computation	Fingerprints based on singles, doubles and triples components	KRR	Enumeration	[22]
Polymers: Frequency-dependent dielectric constant	Experimental data in studies	Hierarchical fingerprint	GPR	Enumeration	[34]
Polymers: Dielectric constant	Experimental data in studies	Hierarchical fingerprint	Interval support vector regression	-	[86]
Polymers: Bandgap, glass transition temperature	perature Experimental data in studies	SMILES	GPR	GA in [102]	[102]
				VAE in [104]	[104]
Polymers: Glass transition temperature	Experimental data in studies	SMILES	GPR	Active learning	[88]
Polymers: Specific heat of polymers	Experimental data	Hierarchical fingerprint constructed using the Materials Studio software	Decision tree	-	[66]
Polymers: Thermal conductivity	MD simulations	SMILES	CNN	-	[25]
Polymers: Thermal conductivity	Online database	SMILES	Bayesian method	Enumeration	[39]
Nanocomposites: Breakdown strength, permittivity and energy density	Experimental data in studies	Descriptor-based fingerprint	GPR	Enumeration	[26]
Nanocomposites: Breakdown strength	Monte Carlo multi-scale simulation	MCR methods	GPR	GA	[79]
Nanocomposites: Energy density	Phase-field simulations	Descriptor-based fingerprint	NN	Enumeration	[60]
Nanocomposites: Thermal conductivity	FEM simulation	2D cross-sectional images	CNN	-	[61]

Abbreviations: CNN, convolutional neural network; DFT, density functional theory; FEM, finite-element model; GA, genetic algorithm; GPR, Gaussian process regression; KRR, kernel ridge regression; MCR, microstructure characterization and reconstruction MD, molecular dynamic; ML, machine learning; NN, neural network; SMILES, Simplified Molecular-Input Line-Entry System; VAE, variational autoencoder.

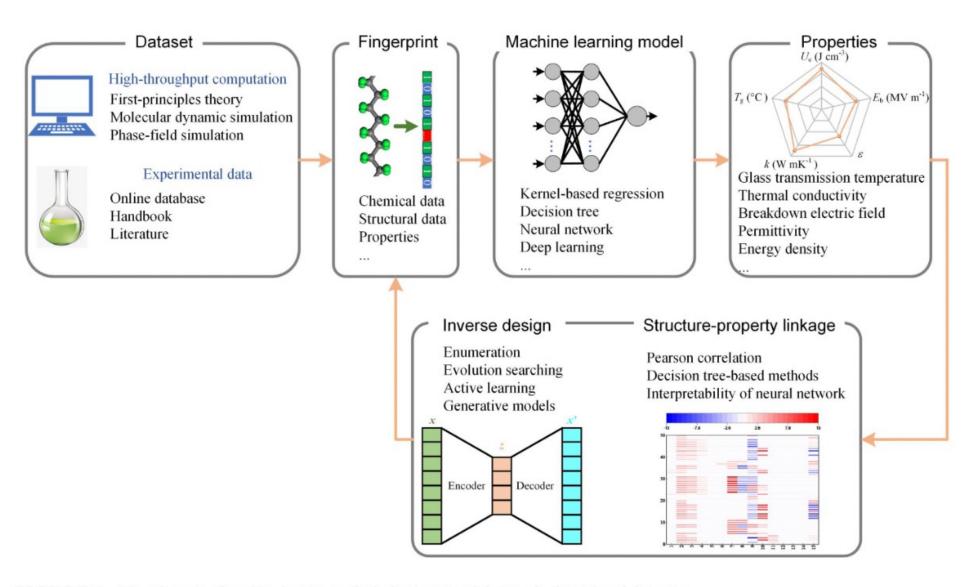
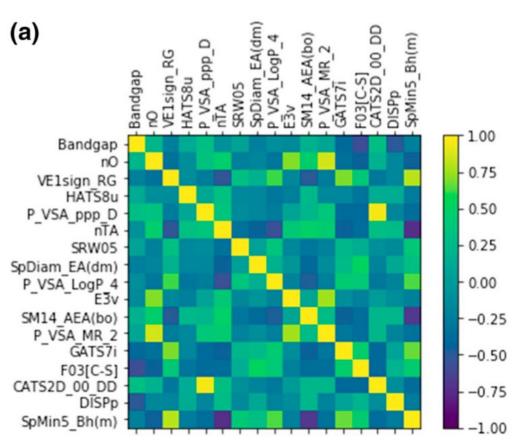


FIGURE 1 The schematic of machine learning methods for the rational design of polymer-based dielectrics

the relevance of features with target properties



Pearson correlation coefficient

$$r = rac{\sum \left(x_i - ar{x}
ight)\left(y_i - ar{y}
ight)}{\sqrt{\sum \left(x_i - ar{x}
ight)^2 \sum \left(y_i - ar{y}
ight)^2}}$$

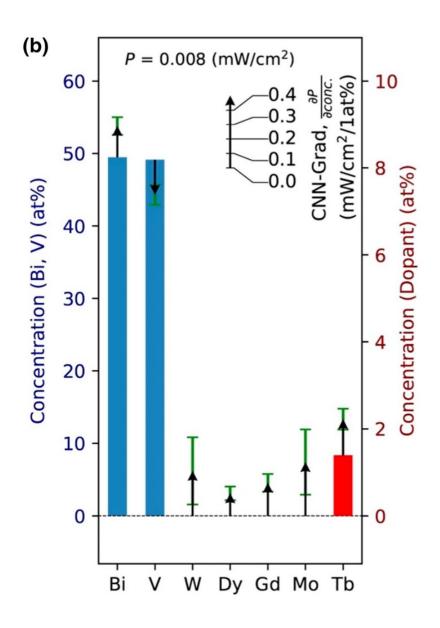
r = correlation coefficient

 x_i = values of the x-variable in a sample

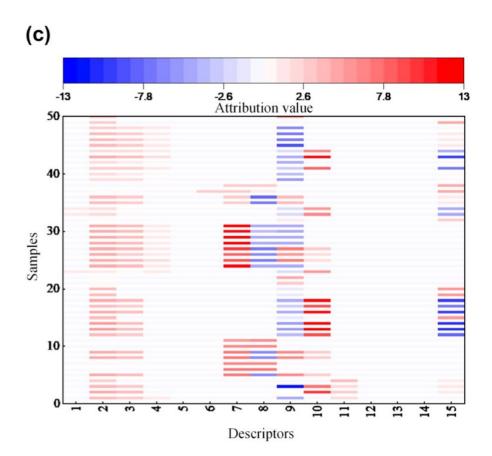
 $ar{x}$ = mean of the values of the x-variable

 y_i = values of the y-variable in a sample

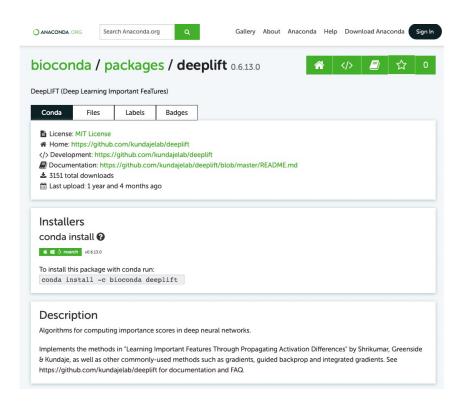
 \overline{y}_{-} = mean of the values of the y-variable



Gradients of convolutional neural networks (CNNs) model



Deep Learning Important FeaTures (DeepLIFT)



9.6 SHAP (SHapley Additive exPlanations)

SHAP (SHapley Additive exPlanations) by Lundberg and Lee (2017)⁶⁹ is a method to explain individual predictions. SHAP is based on the game theoretically optimal Shapley values.

There are two reasons why SHAP got its own chapter and is not a subchapter of Shapley values. First, the SHAP authors proposed KernelSHAP, an alternative, kernel-based estimation approach for Shapley values inspired by local surrogate models. And they proposed TreeSHAP, an efficient estimation approach for tree-based models. Second, SHAP comes with many global interpretation methods based on aggregations of Shapley values. This chapter explains both the new estimation approaches and the global interpretation methods.



Interested in an in-depth, hands-on course on SHAP and Shapley values? Head over to the Shapley course page and get notified once the course is available.

I recommend reading the chapters on Shapley values and local models (LIME) first.

9.6.1 Definition

The goal of SHAP is to explain the prediction of an instance x by computing the contribution of each feature to the prediction. The SHAP explanation method computes Shapley values from coalitional game theory. The feature values of a data instance act as players in a coalition. Shapley values tell us how to fairly distribute the "payout" (= the prediction) among the features. A player can be an individual feature value, e.g. for tabular data. A player can also be a group of feature values. For example to explain an image, pixels can be grouped to superpixels and the prediction distributed among them. One innovation that SHAP brings to the table is that the Shapley value explanation is represented as an additive feature attribution method, a linear model. That view connects LIME and Shapley values. SHAP specifies the explanation as:

$$a(z') = \phi_0 + \sum_{i=1}^{M} \phi_i z'.$$

9 Local Interpretable Model-agnostic Explanations (LIME)

9.1 Introduction

Break-down (BD) plots and Shapley values, introduced in Chapters 6 and 8, respectively, are most suitable for models with a small or moderate number of explanatory variables.

None of those approaches is well-suited for models with a very large number of explanatory variables, because they usually determine non-zero attributions for all variables in the model. However, in domains like, for instance, genomics or image recognition, models with hundreds of thousands, or even millions, of explanatory (input) variables are not uncommon. In such cases, sparse explanations with a small number of variables offer a useful alternative. The most popular example of such sparse explainers is the Local Interpretable Model-agnostic Explanations (LIME) method and its modifications.

The LIME method was originally proposed by Ribeiro, Singh, and Guestrin (2016). The key idea behind it is to locally approximate a black-box model by a simpler glass-box model, which is easier to interpret. In this chapter, we describe this approach.

9.2 Intuition

The intuition behind the LIME method is explained in Figure 9.1. We want to understand the factors that influence a complex black-box model around a single instance of interest (black cross). The coloured areas presented in Figure 9.1 correspond to decision regions for a binary classifier, i.e., they pertain to a prediction of a value of a binary dependent variable. The axes represent the values of two continuous explanatory variables. The coloured areas indicate combinations of values of the two variables for which the model classifies the observation to one of the two classes. To understand the local behavior of the complex model around the point of interest, we generate an artificial dataset, to which we fit a glass-box