



Schrödinger

Schrödinger Capabilities for A&D



Pioneering Digital Chemistry



30+ years of innovation



Over 850 employees worldwide; >40% Ph.D.



>50% of employees dedicated to R&D



~1,785 customers worldwide



Pipeline of 25+ collaborative and proprietary programs

A predict-first approach

Traditional materials design

- Manual materials design
- Candidate materials synthesized and tested over **weeks**

Materials selection or purchase

Candidate synthesis and purification

Property testing



Candidate materials may not meet requirements

Schrödinger digital chemistry platform

- 100Ks of materials tested computationally
- Candidate materials identified digitally over **days**

Model building

Simulations

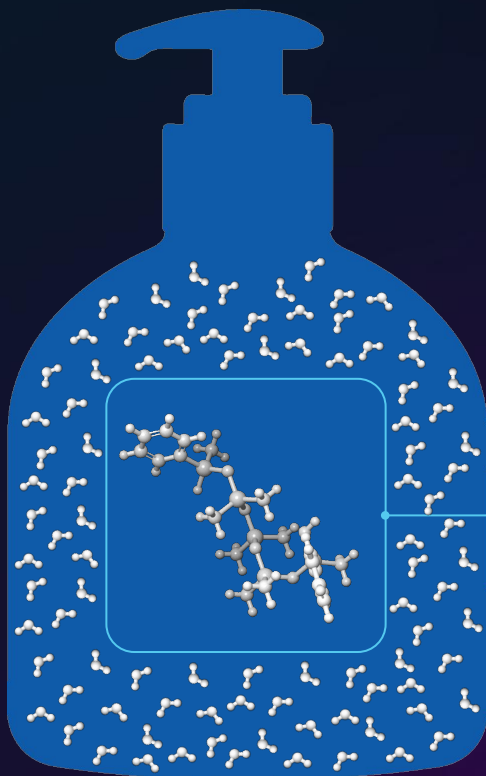
Property predictions

Analysis and screen



Best performing candidate materials with **optimal property profile**

Informed selection



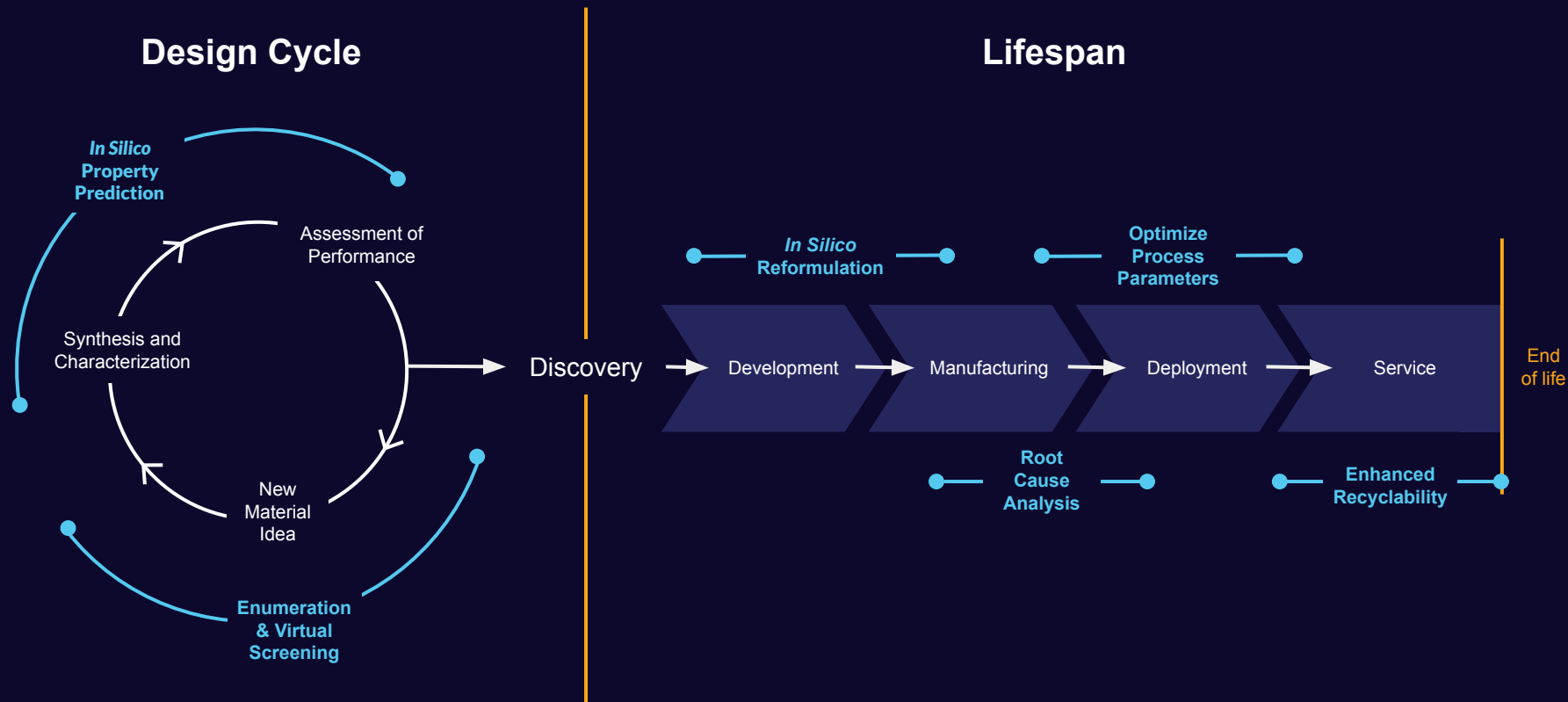
Property / Behavior to optimize, e.g.:

- Miscibility
- Viscosity
- Stability
- Hygroscopicity

Target Property / Behavior



Modeling impact on materials design



Benefits of leveraging digital technology

Less

- **Time** to insights and target solutions
- **Cost** to optimize materials development process
- **Experimental synthesis and testing** of materials with undesirable properties
- **Distance** between teams and expertise areas

More

- **Hypotheses** to test
- **Access** to chemical space
- **Optimization** of multiple property parameters at the same time
- **Dynamic collaboration** in the design process
- **High-quality** materials with desired performance and properties

Synergy between physics-based modeling and machine learning



**Physics-based
modeling**



**Physics &
Machine Learning**

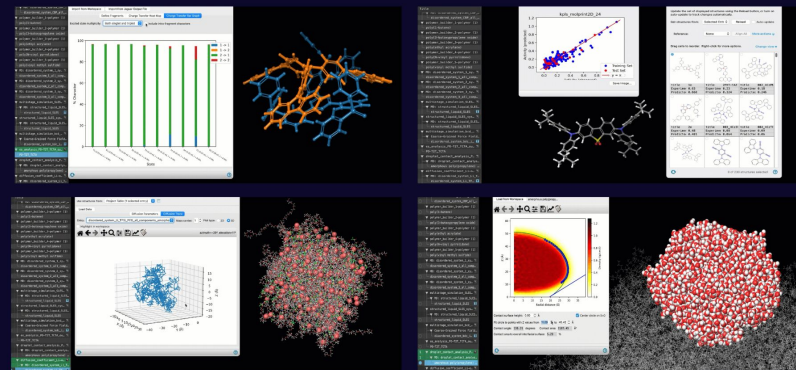
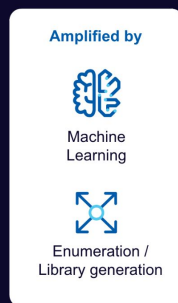
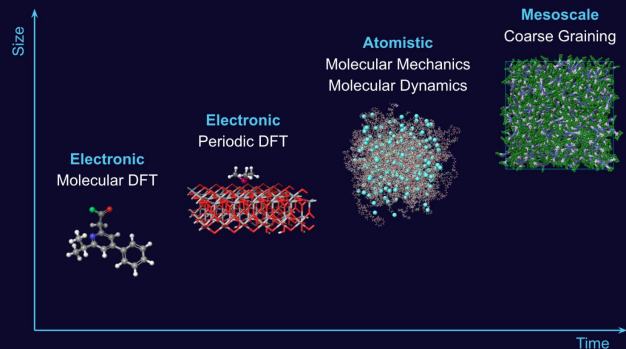
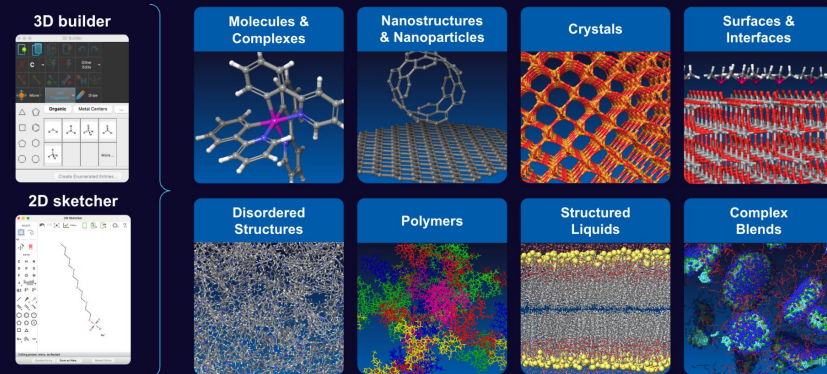
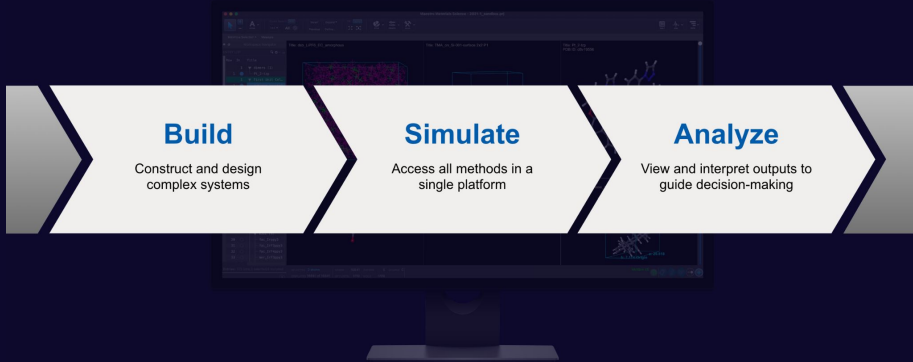
Incorporate physics-based information about materials into practical ML models.

Build targeted ML models to expand the impact of physics-based simulations.

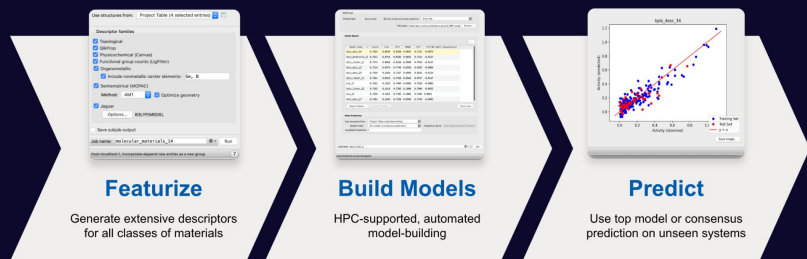


**Machine
learning**

Physics-based modeling



Machine learning



Capabilities for: small molecules, organometallics, polymers, periodic inorganics, and formulations

Small molecules

- Physicochemical, topographical descriptors
- Binary fingerprints (RDKit, Canvas)
- Graph-based convolution neural networks

Polymers

- Taking into account connections between repeat units
- RDKit fingerprints + customized descriptors

Periodic inorganic solids

- Element
- Lattice structure
- Oxidation state
- Intercalation descriptors
- 3D SOAP (with PCA)

Formulations and mixtures

- Composition
- Chemistry of the components
- Experimental/processing conditions

Physics-based descriptors:

- Quantum mechanics
- Auto Reaction Workflow

Physics-based descriptors:

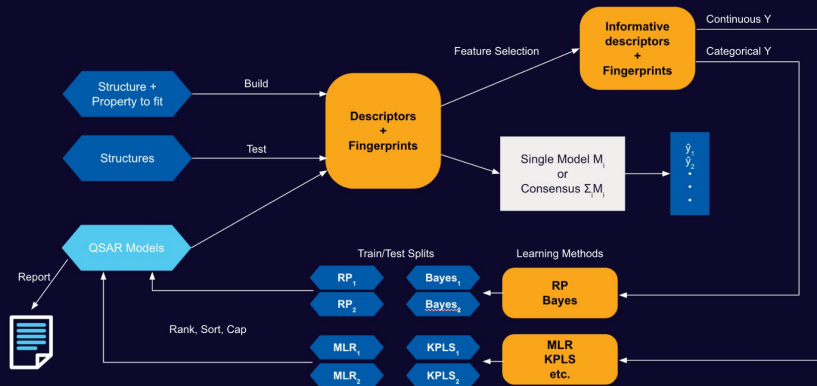
- Molecular dynamics
- Quantum mechanics

Physics-based descriptors:




- Periodic quantum mechanics

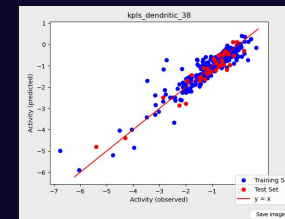
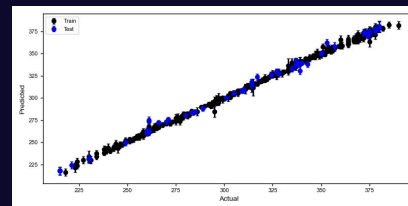
Physics-based descriptors:

- Molecular dynamics



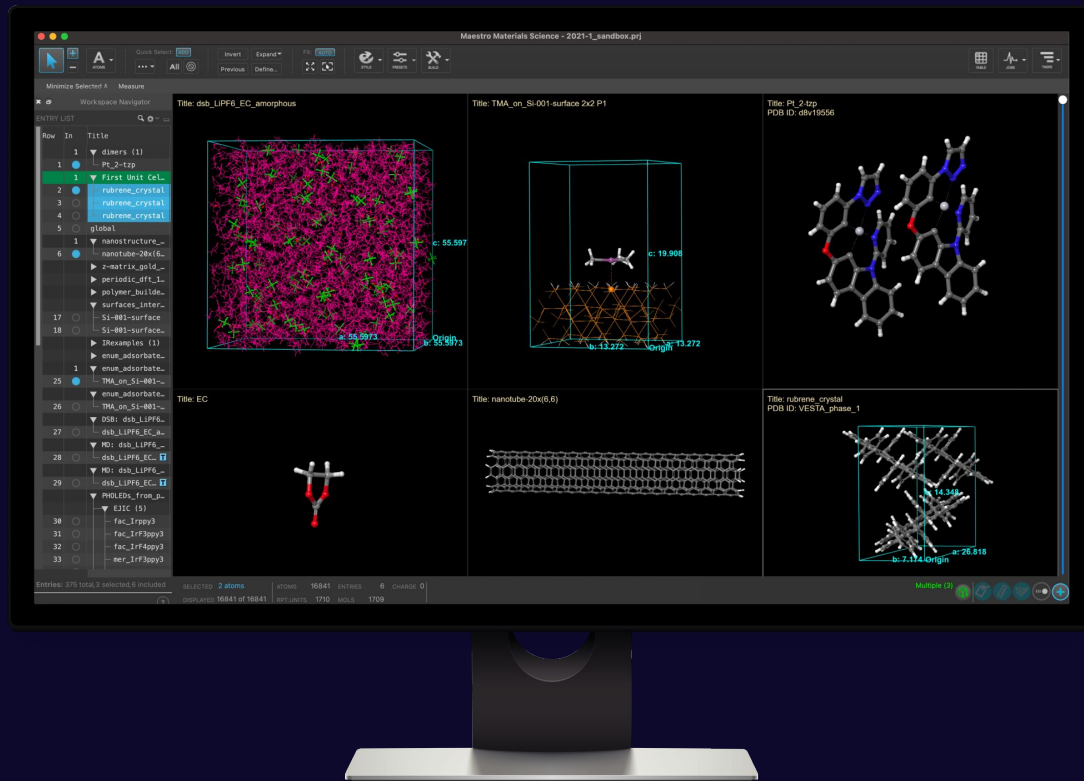
Model Code	Score	S.D.	R ²	RMSE	Q ²	Q ² RM (Null)
kpls_dendritic_38	0.8500	0.3468	0.8584	0.3451	0.9836	-0.0071
kpls_linear_38	0.8319	0.3664	0.8415	0.3778	0.8849	-0.0071
kpls_linear_48	0.8277	0.4017	0.8216	0.3384	0.8488	0.0146
kpls_dendritic_48	0.8159	0.4099	0.8142	0.3912	0.7862	0.0146
kpls_linear_23	0.8039	0.4215	0.8030	0.4084	0.7662	0.0185
kpls_dendritic_23	0.7941	0.4329	0.7921	0.4143	0.7592	0.0185
kpls_radial_21	0.7907	0.4468	0.7836	0.3987	0.7218	-0.0164
kpls_radial_22	0.7833	0.4213	0.8015	0.4255	0.7829	0.0192
kpls_radial_34	0.7805	0.4554	0.7710	0.3895	0.7858	0.0250
kpls_linear_5	0.7793	0.4492	0.7753	0.4219	0.7535	-0.0130

		
title 2	title 344	title 333
Electrica 0.204	Electrica -0.678	Electrica -0.921
Predicted -0.405	Predicted -0.929	Predicted -0.843



User-friendly GUI and comprehensive API

MS Maestro



Python API

Comprehensive API for programmatic interaction with Schrödinger software

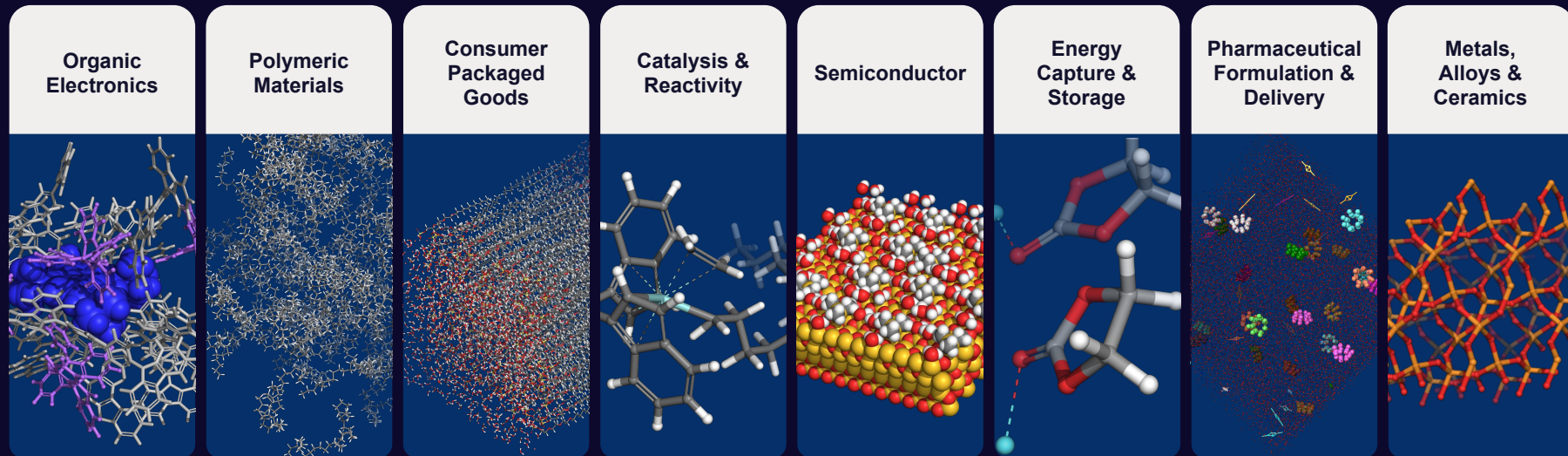
```
➔ ~ export SCHRODINGER=/opt/schrodinger/suites2024-1
➔ ~ $SCHRODINGER/run periodic_dft_gui_dir/qe2mae.py -h
usage: $SCHRODINGER/run periodic_dft_gui_dir/qe2mae.py
       [-h] [-last_only] input_file
```

Converter script from Quantum ESPRESSO output file to Maestro structure file. Copyright Schrödinger, LLC. All rights reserved.

positional arguments:
input_file Quantum ESPRESSO output file (.out, .save.qegz).

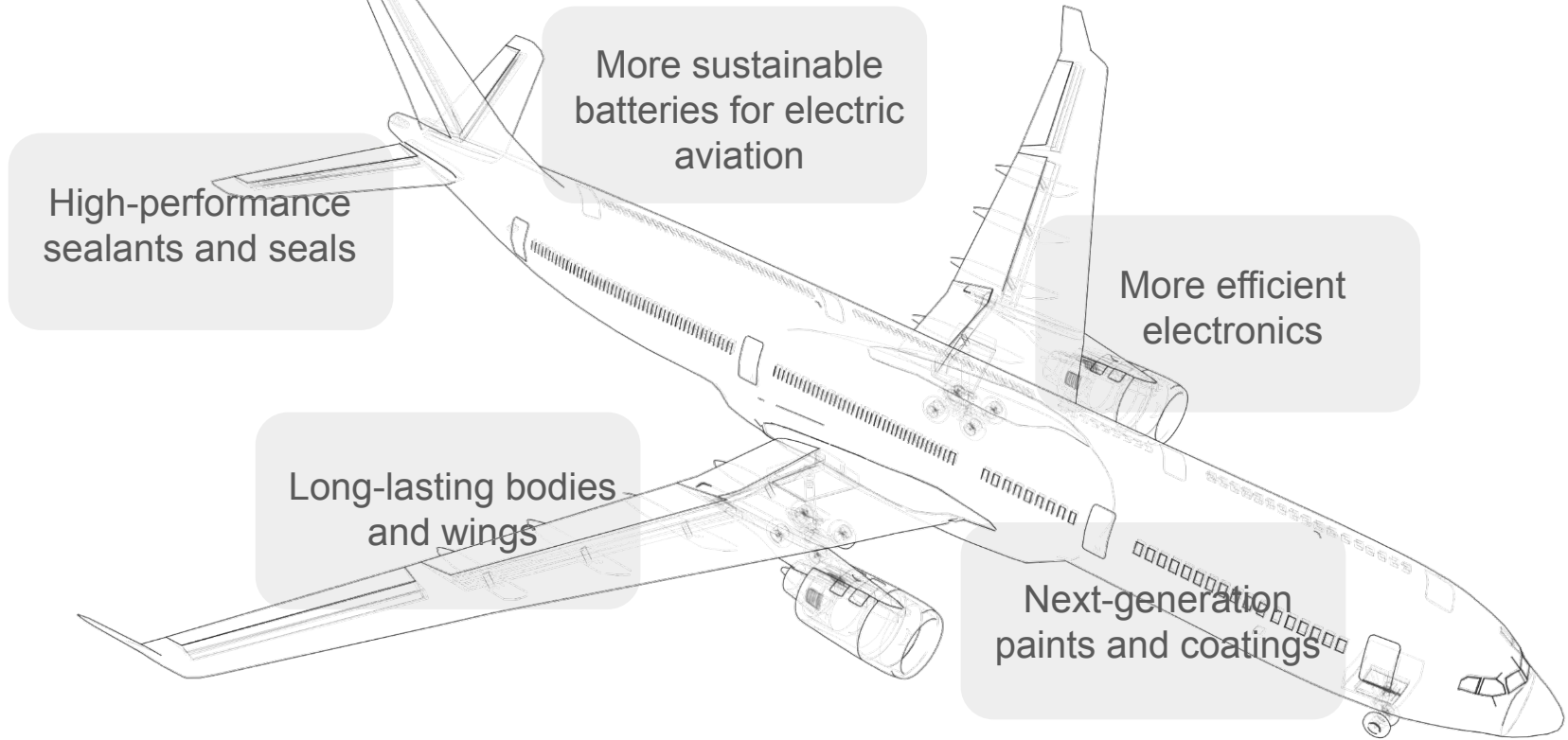
optional arguments:
-h, -help Show this help message and exit.
-last_only Save only last structure. (default: False)

Solutions for all applications



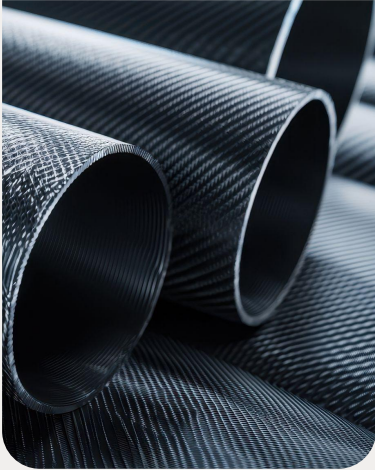
Tailored solutions that reduce cost, reduce risk, shorten timelines

A&D Applications



A&D Applications

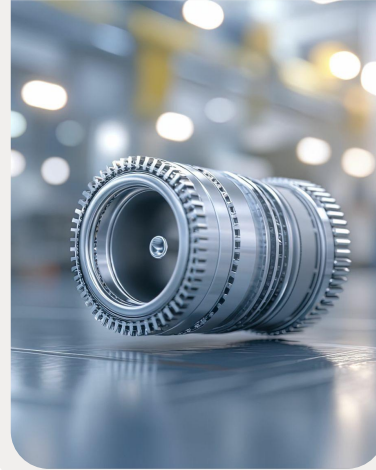
Composites and
ceramics



Lubricants,
fuel additives,
hydraulic fluids



Superalloys

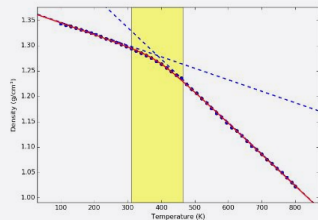


Propellants

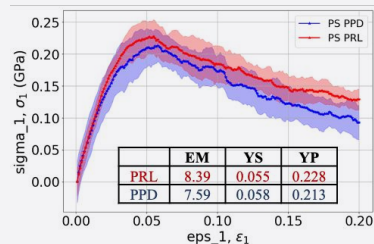


Polymeric materials: select capabilities

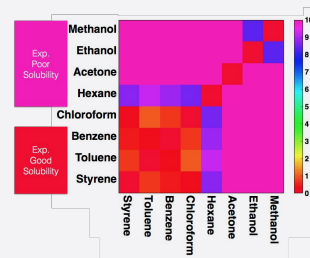
Glass transition temperature



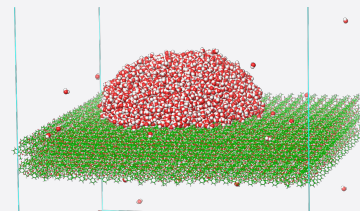
Mechanical response



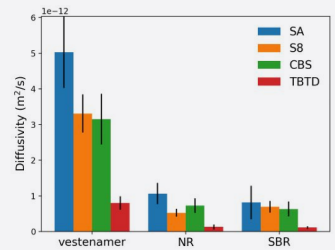
Miscibility and solubility



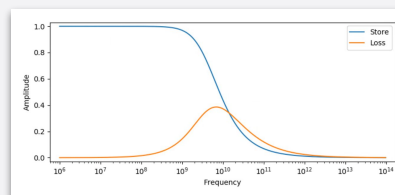
Contact angle



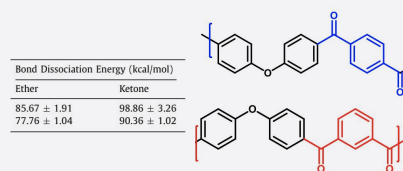
Diffusivity



Dielectric properties

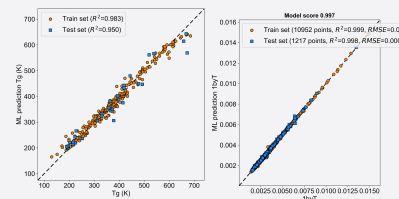


Bond dissociation energy



Croshaw, C. et al. Polymer degradation and stability **2022**, 200, 109968.

ML property prediction



Fast-Tracking Next-Gen Polymers: How SABIC is Leveraging Machine Learning and Physics

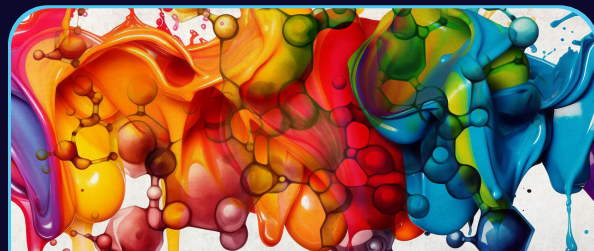


“

With the success of this project, we are now inspired in adopting a ‘computation-first’ approach in our current and future projects.

— Vaidya Ramakrishnan, Sabic

— André van Zyl, Sabic



[LINK TO BLOG](#)

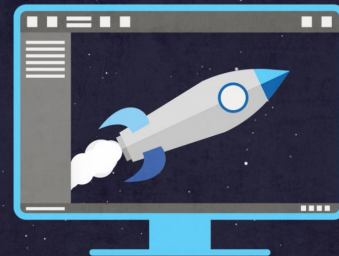
www.extrapolations.com/fast-tracking-next-gen-polymers-how-sabic-is-leveraging-machine-learning-and-physics/

Uncovering Better Materials for the Spacecraft of Tomorrow

“

The advantage of digital simulation is that it can eventually help cut down on the number of new molecules we'd need to synthesize, leading to a more efficient and less resource-intensive iteration cycle.

— Levi Moore, United States Air Force Research Laboratory



LINK TO BLOG

www.extrapolations.com/uncovering-better-materials-for-the-spacecraft-of-tomorrow/

Capabilities: aerospace and defense

Polymers, Composites and Formulations

- ❑ Builders and enumeration (homopolymers, block copolymers, semicrystalline polymers, ladder polymers, carbohydrates/biopolymers, multicomponent mixtures, interfaces, formulations)
- ❑ Methods
 - ❑ All-atom molecular dynamics simulation (OPLS force field)
 - ❑ Coarse-grained simulation
 - ❑ Martini force field (database parameters)
 - ❑ Dissipative particle dynamics (DPD), automated particulation and force field parameterization
- ❑ Physics-based prediction of:
 - ❑ Glass transition temperature (T_g)
 - ❑ Coefficient of thermal expansion (CTE)
 - ❑ Mechanical response (e.g. stress-strain, elastic constants)
 - ❑ Penetrant loading (water, solvent; function of relative humidity and/or temperature)
 - ❑ Evaporation
 - ❑ Diffusivity and migration
 - ❑ Conformational statistics
 - ❑ Dielectric properties (e.g. refractive index, Abbe number, static dielectric constant, complex permittivity)
 - ❑ Wettability (contact angle)
 - ❑ Interaction energy at interface
 - ❑ Clustering/aggregation/additive binding
 - ❑ Viscosity
 - ❑ Thermal conductivity
 - ❑ Surface tension
 - ❑ Miscibility (solubility parameters), solubility of additives/contaminants
 - ❑ Enzyme degradation

Reactivity and Catalysis

- ❑ Cross-linking
 - ❑ Realistic curing simulations
 - ❑ Prediction of gel point
- ❑ Polymer and molecular degradation
 - ❑ Bond dissociation energies
 - ❑ Prediction of decomposition products
- ❑ High energy materials
- ❑ Reaction mechanism elucidation
 - ❑ Energy landscape for reactants, intermediates, and products
 - ❑ Automated transition state search
- ❑ Automated catalyst design
- ❑ Polymerization reaction barriers

Machine Learning

- ❑ Descriptor generation
 - ❑ Molecular descriptors
 - ❑ Polymer descriptors
 - ❑ Formulation descriptors (composition)
- ❑ Pre-trained ML models (e.g. dielectric constant, glass transition temperature)
- ❑ Automated ML model building

Solid-State Materials

- ❑ Builders and enumeration
 - ❑ Crystals (pure inorganics, alloys, additives/dopants)
 - ❑ Slabs and interfaces
- ❑ Physics-based prediction of:
 - ❑ Surface energy
 - ❑ Equilibrium lattice constants
 - ❑ Density of states and band gaps
 - ❑ Mechanical properties (elastic constants / bulk moduli)
 - ❑ Dielectric constants
 - ❑ Ion migration in bulk structures with nudged elastic band (NEB) simulations
 - ❑ Intercalation potential
 - ❑ Defect formation energies with corrections for charged defects
 - ❑ Equation of state predictions
 - ❑ Effective screening medium
- ❑ Microkinetic modeling
- ❑ Reaction mechanism elucidation
 - ❑ Energy landscapes
 - ❑ Automated transition state search

How to work with Schrödinger



Software License

Leverage molecular simulations in-house with extensive Schrödinger support



Contract Research & Development

Leverage Schrödinger scientific and engineering expertise to solve your research challenges and enable your workforce

Contact:

Jorge Avillez, Materials Science Account Manager

jorge.avillez@schrodinger.com