



Energy Innovation Summit

Modeling Meets Optimization

Model Building with gurobipy

Jaromil Najman
Senior Developer





Agenda

Model Building Frameworks
gurobipy, Pandas-, and Matrix-API
Integrating Machine Learning



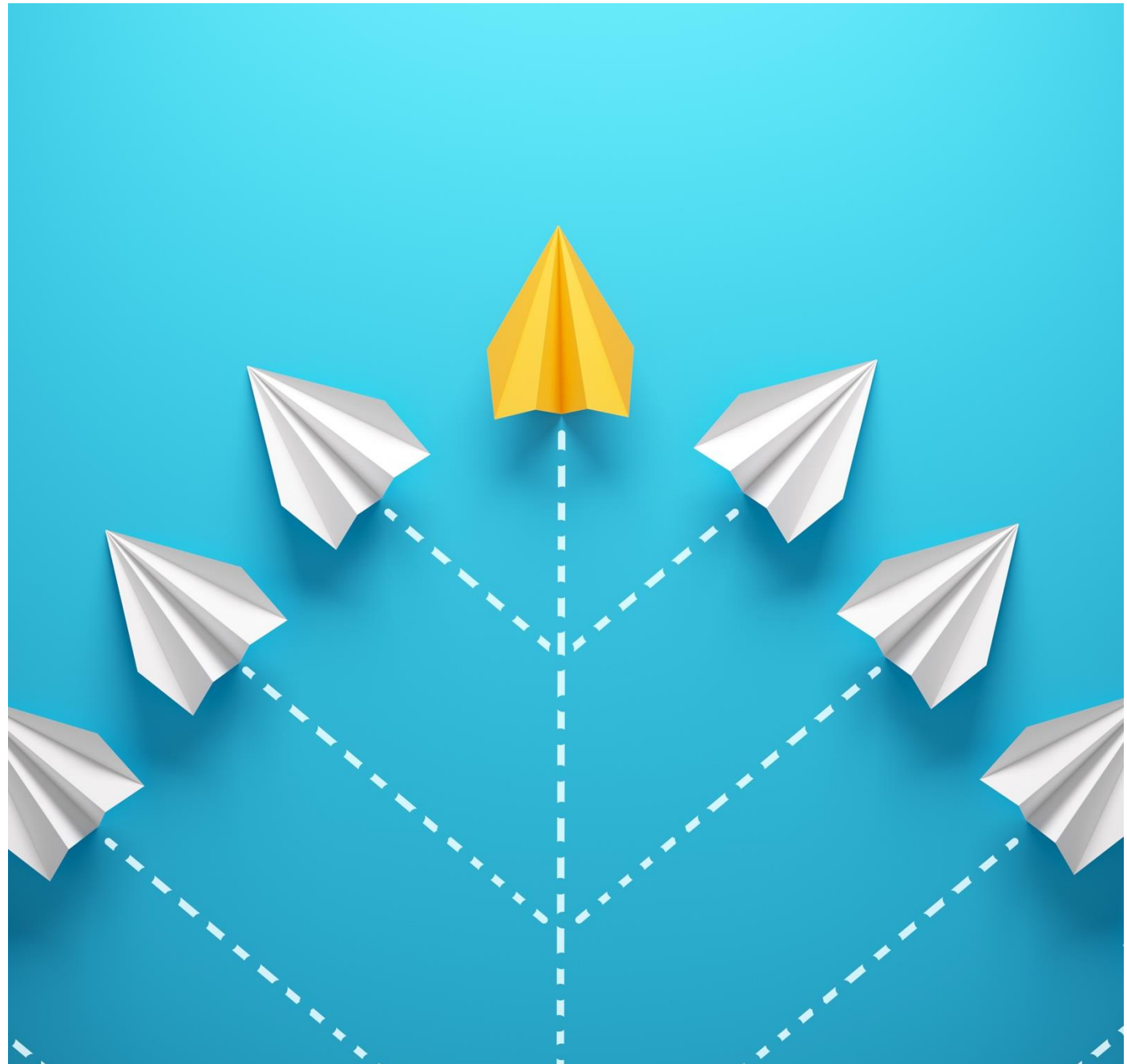
Model Building Frameworks

Making a choice

Energy model generators
PyPSA, oemof, GenX, etc.

Third-party model-building
frameworks
linopy, JuMP, PuLP, Pyomo, etc.

Gurobi's model building APIs
gurobipy, C, C++, C#, Java, Matlab, R



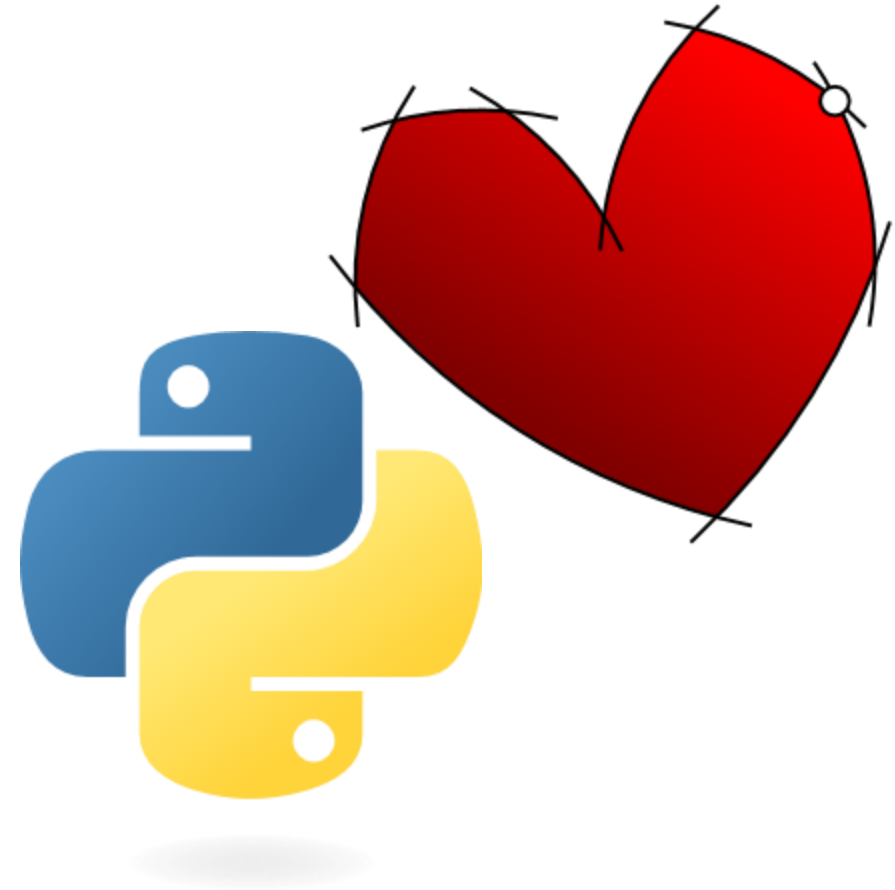
Gurobi has a heart for Python

- Gurobi's Python API "**gurobipy**" was part of the product from the start
- Built for fast and memory efficient model-building in Python
- Most feature-rich API to use the Gurobi Optimizer
- We continue to modernize and improve with every release!

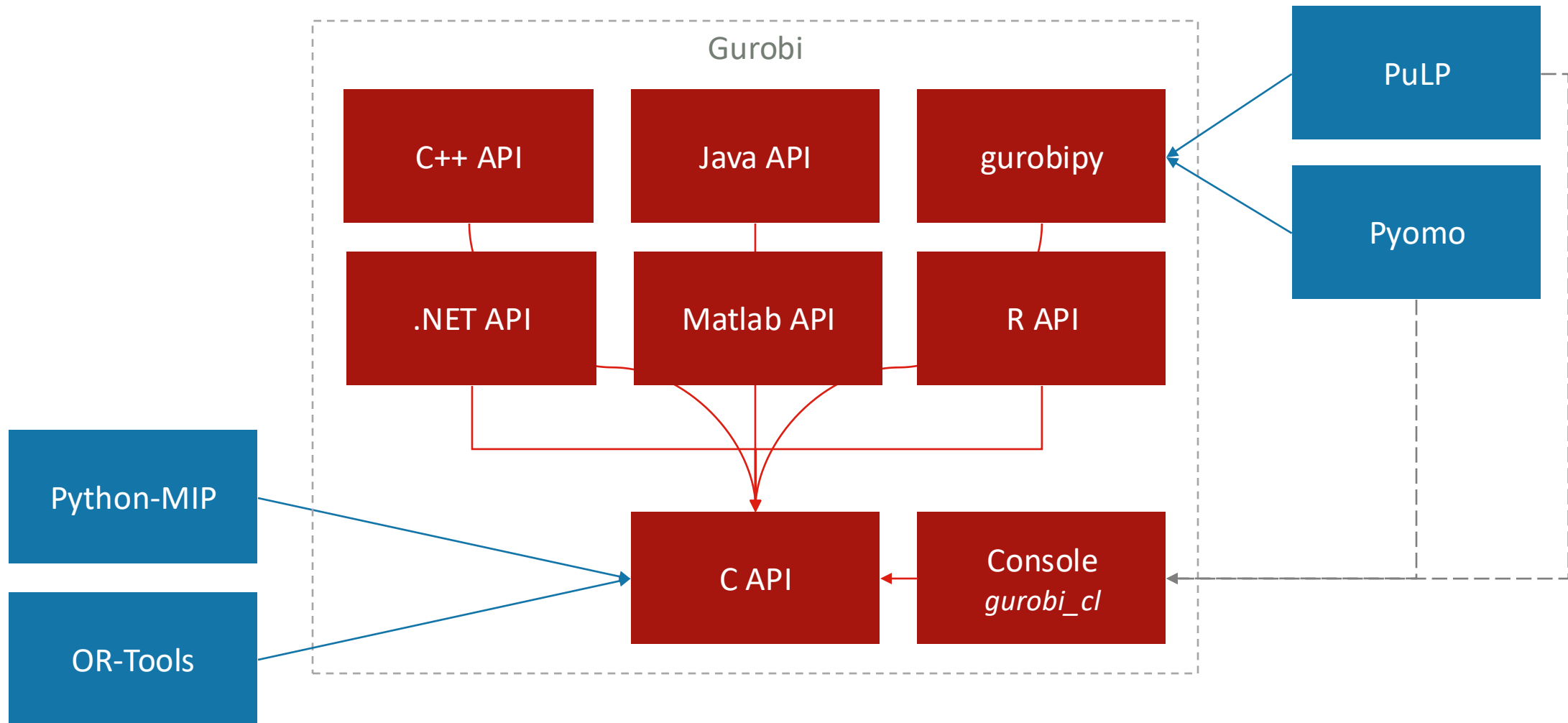
```
pip install gurobipy
```

```
conda install -c gurobi gurobi*
```

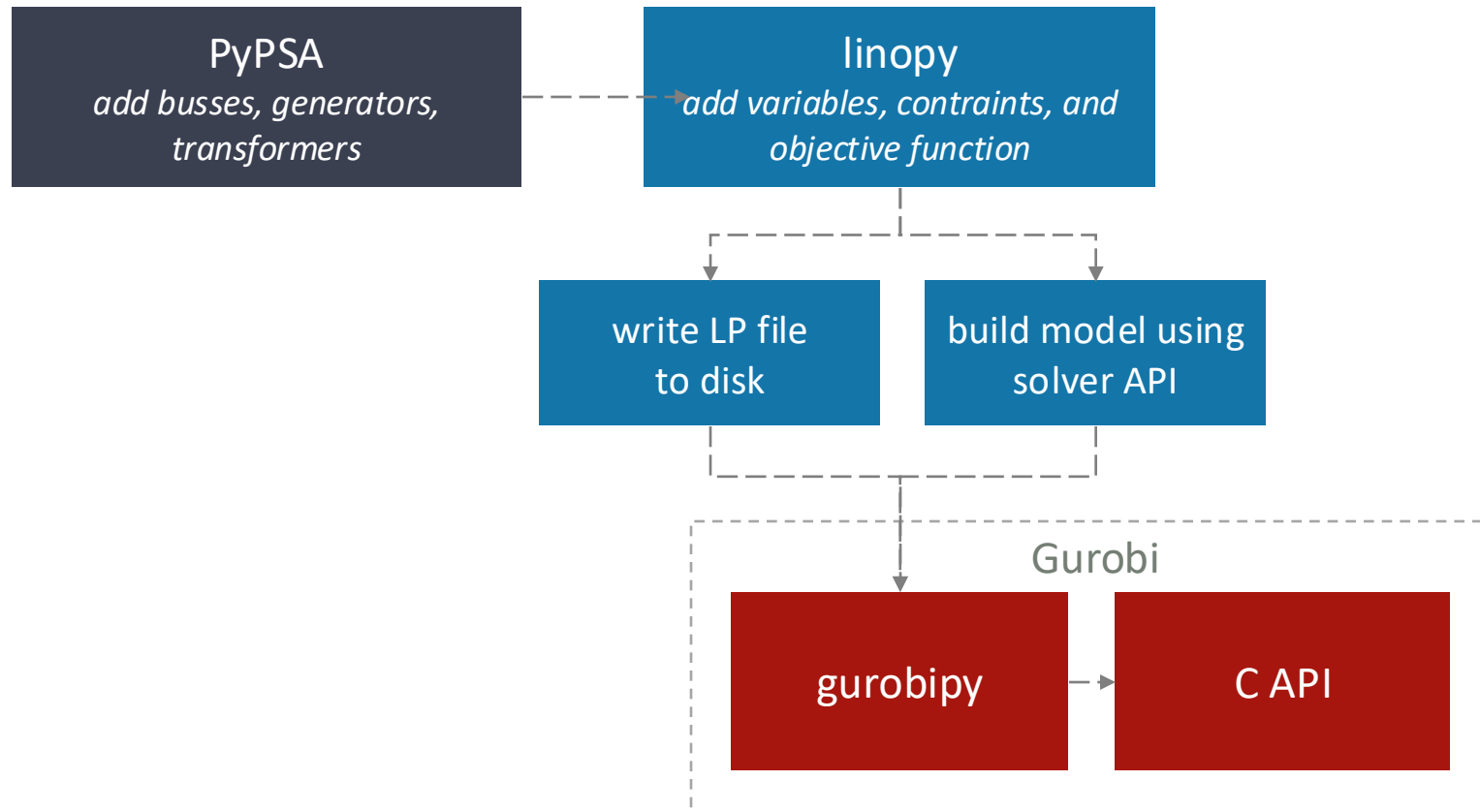
*conda install contains `gurobi_cl`



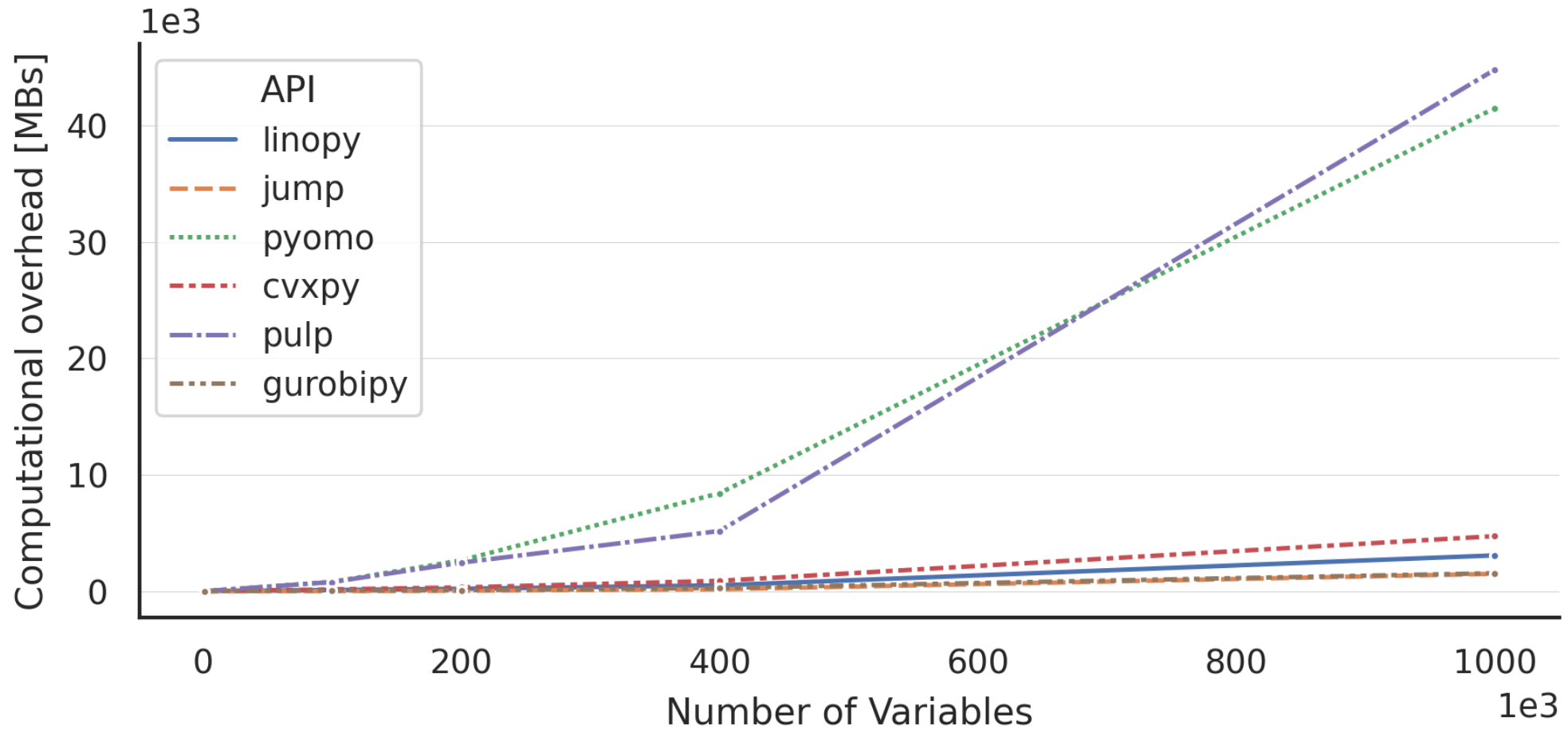
Solvers, APIs and frameworks



Connecting PyPSA to Gurobi

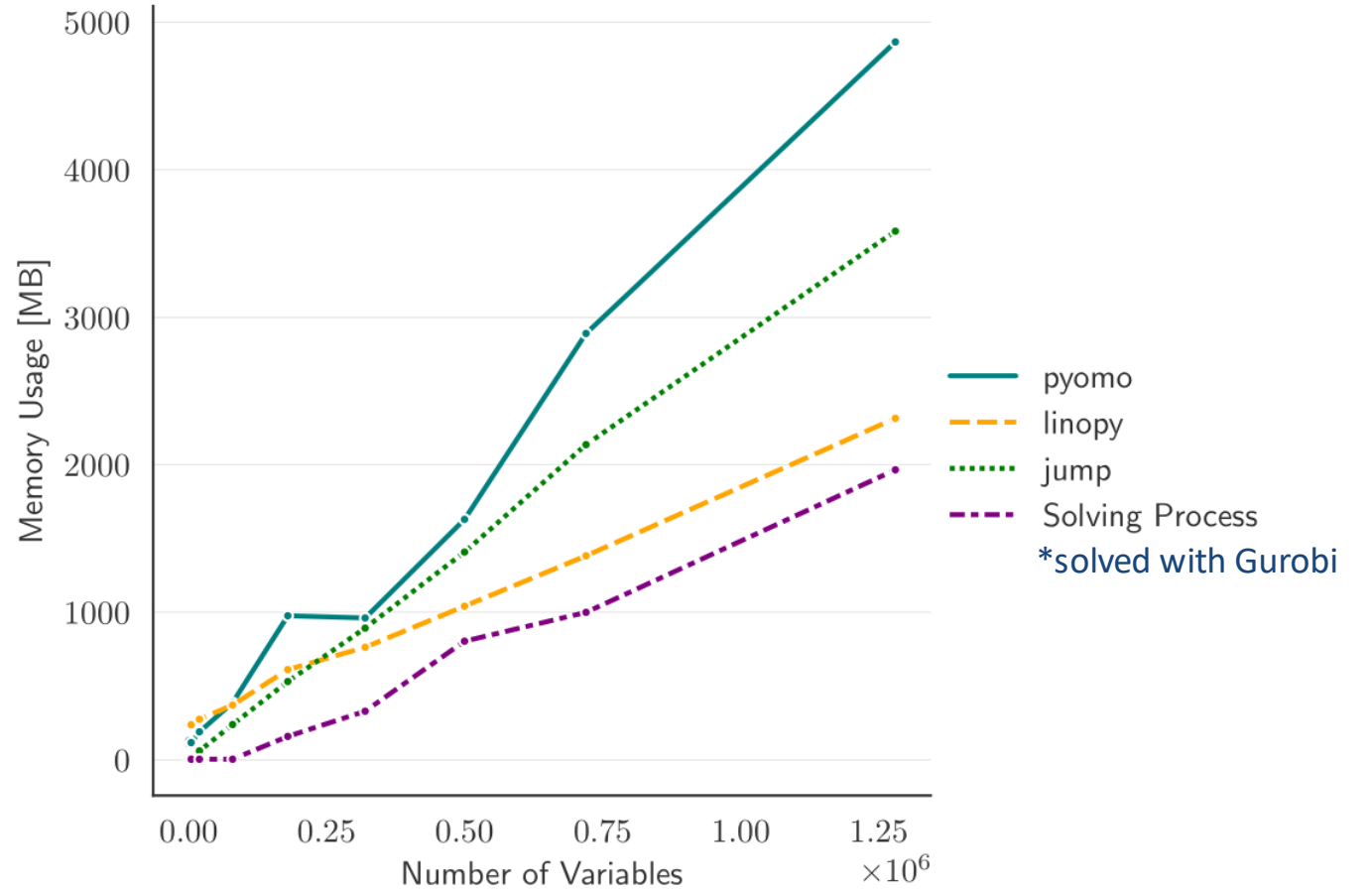
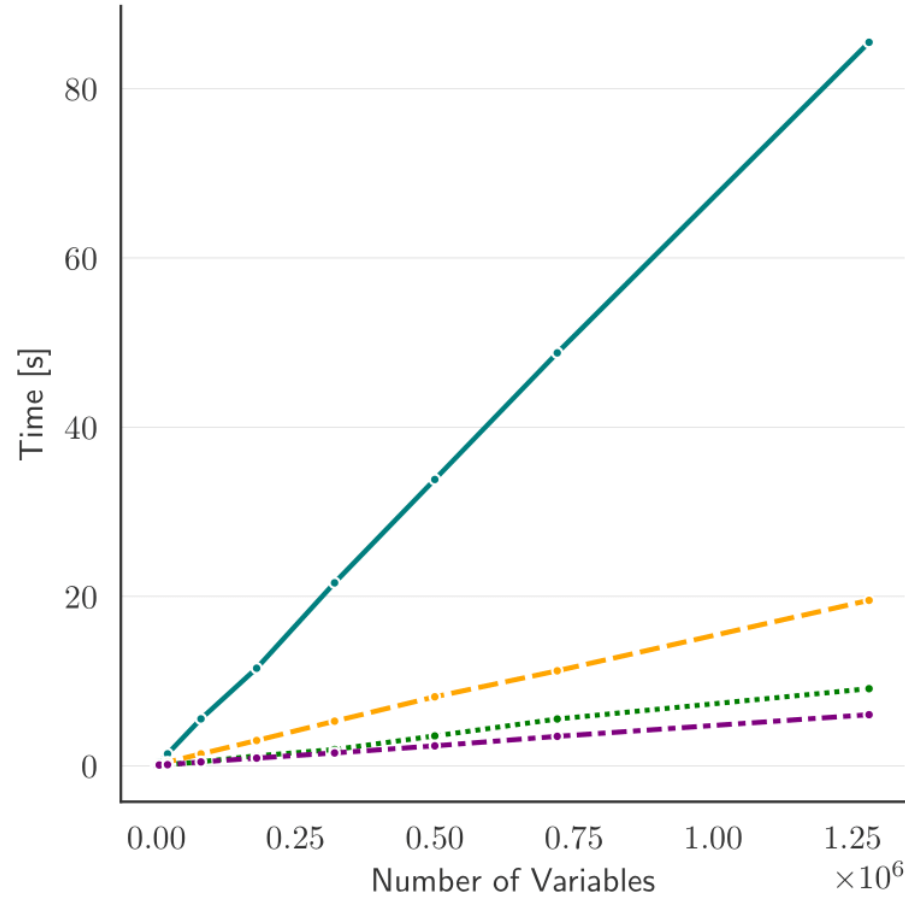


Model building memory efficiency



<https://github.com/pypsa/linopy>

Model building speed



<https://linopy.readthedocs.io/en/latest/benchmark.html>

With or without a modeling framework?

	Modeling framework	Gurobi directly	However...
Support	Depends on community	Commercial support	We do our best and can often help you
Learning curve	Use what you already know	Gurobi-specific API	Very similar to open-source frameworks
Performance	Overhead (memory and time)	Optimal	
Benchmarking	Easy; just one line of code	Need to re-implement models	Benchmark via MPS exports first
Vendor lock-in	With the modeling framework	With Gurobi as a solver	Centralize your optimization logic
Feature set	Limited to what is exposed by framework	Full access to all Gurobi features	

```
import gurobipy as gp
```

Gurobi's Python API

Four major approaches

1) Element-by-element

```
model.addConstrs(  
    output.sum('*', period)  
    >= demand[period]  
    for period in range(nperiods))  
)
```

2) Matrix-friendly API

```
m.addConstr(A @ x <= rhs)
```

3) Pandas integration

```
demand = gppd.add_constrs(  
    m,  
    df['output'].groupby('type').sum(),  
    GRB.GREATER_EQUAL,  
    demand["Period"]  
)
```

4) Machine learning integration

```
lin_reg = make_pipeline(  
    feat_transform, LinearRegression()) lin_reg.fit(X_train,  
y_train)  
...  
pred_constr = add_predictor_constr(  
    m, lin_reg, features, result)
```

Efficient data structures in gurobipy

Tupledicts enable efficient variable and coefficient selection:

```
d = gp.tupledict([(1,2), 'onetwo'], [(1,3), 'onethree'], [(2,3), 'twothree']))
```

```
print(d.select(1, '*')) # prints ['onetwo', 'onethree']
```

```
x = m.addVars([(1,2), (1,3), (2,3)])
```

```
expr = x.sum() # LinExpr: x[1,2] + x[1,3] + x[2,3]
```

```
expr = x.sum('*', 3) # LinExpr: x[1,3] + x[2,3]
```

```
coeff = dict([(1,2), 2.0], [(1,3), 2.1], [(2,3), 3.3])
```

```
expr = x.prod(coeff) # LinExpr: 2.0 x[1,2] + 2.1 x[1,3] + 3.3 x[2,3]
```

```
expr = x.prod(coeff, '*', 3) # LinExpr: 2.1 x[1,3] + 3.3 x[2,3]
```

Efficient data structures in gurobipy

Multidict splits a single dictionary into multiple dictionaries.

```
keys, dict1, dict2 = gp.multidict( {  
    'key1': [1, 2],  
    'key2': [1, 3],  
    'key3': [1, 4] } )
```

Quicksum is a version of the Python sum function that is much more efficient for building large Gurobi expressions.

```
expr = gp.quicksum([2*x, 3*y+1, 4*z*z])  
expr = gp.quicksum(model.getVars())
```

Term-based vs. Matrix-based model building

```
# Term Based
m=gp.Model()
x=m.addVar(ub=1.0)
y=m.addVar(ub=1.0)
z=m.addVar(ub=1.0)
m.setObjective(x*x + 2*y*y + 3*z*z)
m.addConstr(x + 2*y + 3*z >= 4)
m.addConstr(x + y >= 1)
```

```
# Matrix Based
m=gp.Model()
Q=np.diag([1,2,3])
A=np.array([[1,2,3],[1,1,0]])
b=np.array([4,1])
x = m.addMVar(3, ub=1.0)
m.setObjective(x @ Q @ x)
m.addConstr(A@x >= b)
```

gurobipy's matrix-friendly modeling API

- Enables natural model building using matrix-based expressions
- Complements existing capabilities for term-based modeling
- Concepts and semantics lean on NumPy

```
expr1 = A @ x
```

```
expr2 = A @ x + B @ y + z
```

```
expr3 = x @ A @ x + y @ B @ y
```

NumPy



Powerful N-dimensional arrays

Fast and versatile, the NumPy vectorization, indexing, and broadcasting concepts are the de-facto standards of array computing today.

gurobipy-pandas

gurobipy-pandas Convenient wrapper library to connect pandas with gurobipy.



- Efficiently build mathematical optimization models from DataFrames and Series objects.
- Built for experienced pandas users who are familiar with methods to transform, group, and aggregate data stored in DataFrames.
- Some familiarity with optimization modeling is required but does not require deep experience with gurobipy.

```
pip install gurobipy-pandas
```

gurobipy-pandas



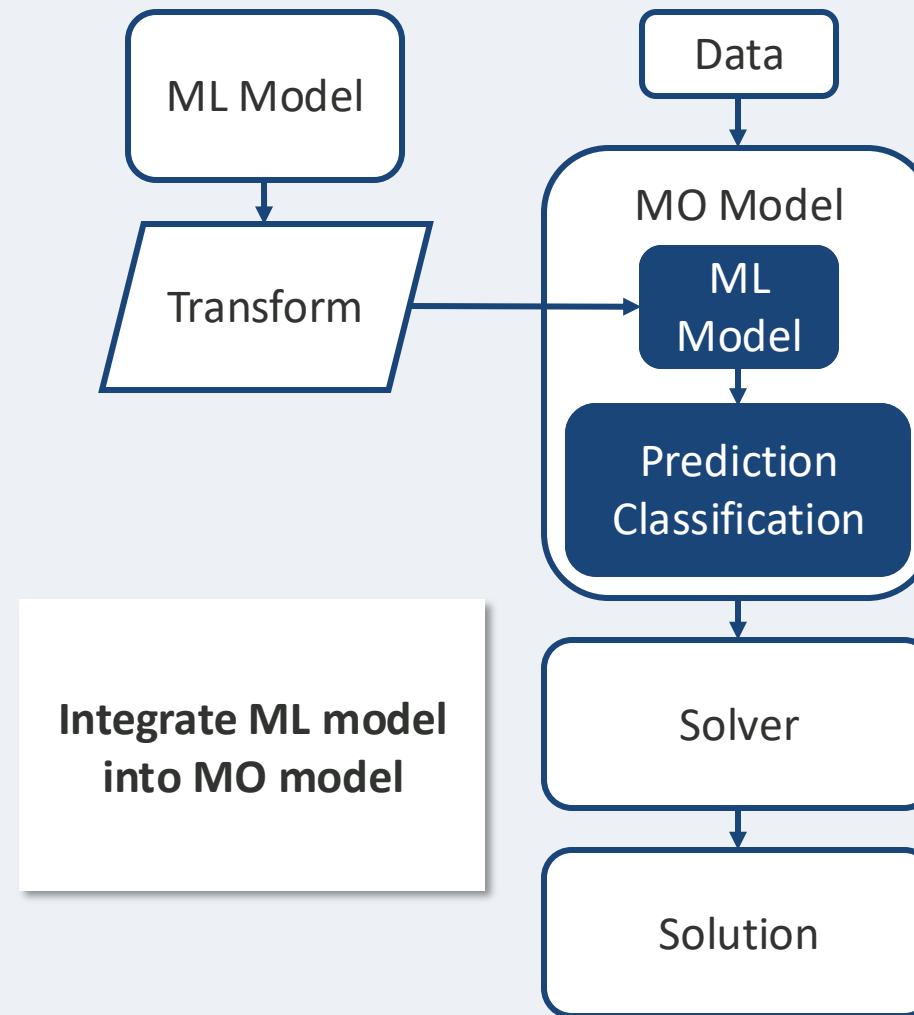
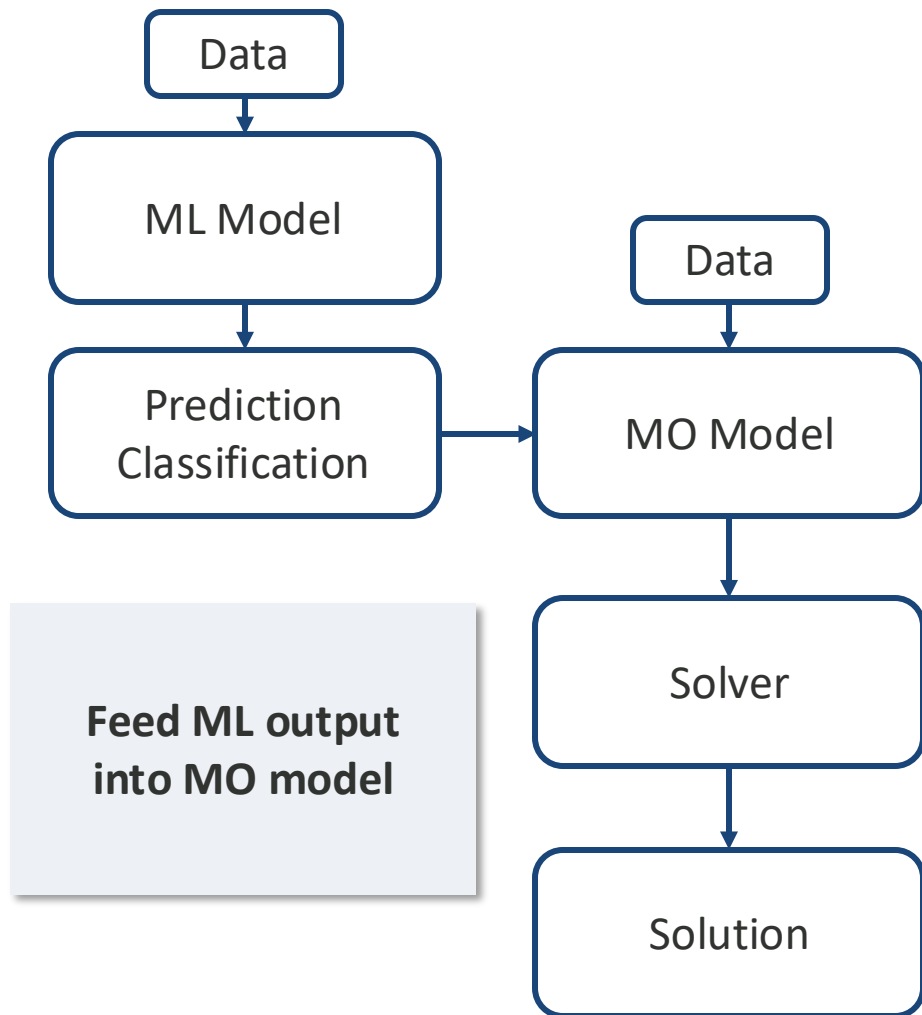
```
df.gppd.add_vars(model, name="output")
    .gppd.add_vars(
        model, vtype=GRB.INTEGER, ub="num_available",
        name="num_active"
    )

df.gppd.add_constrs(
    model,
    "output >= min_output * num_active")
```

Machine Learning and Mathematical Optimization

Joining forces

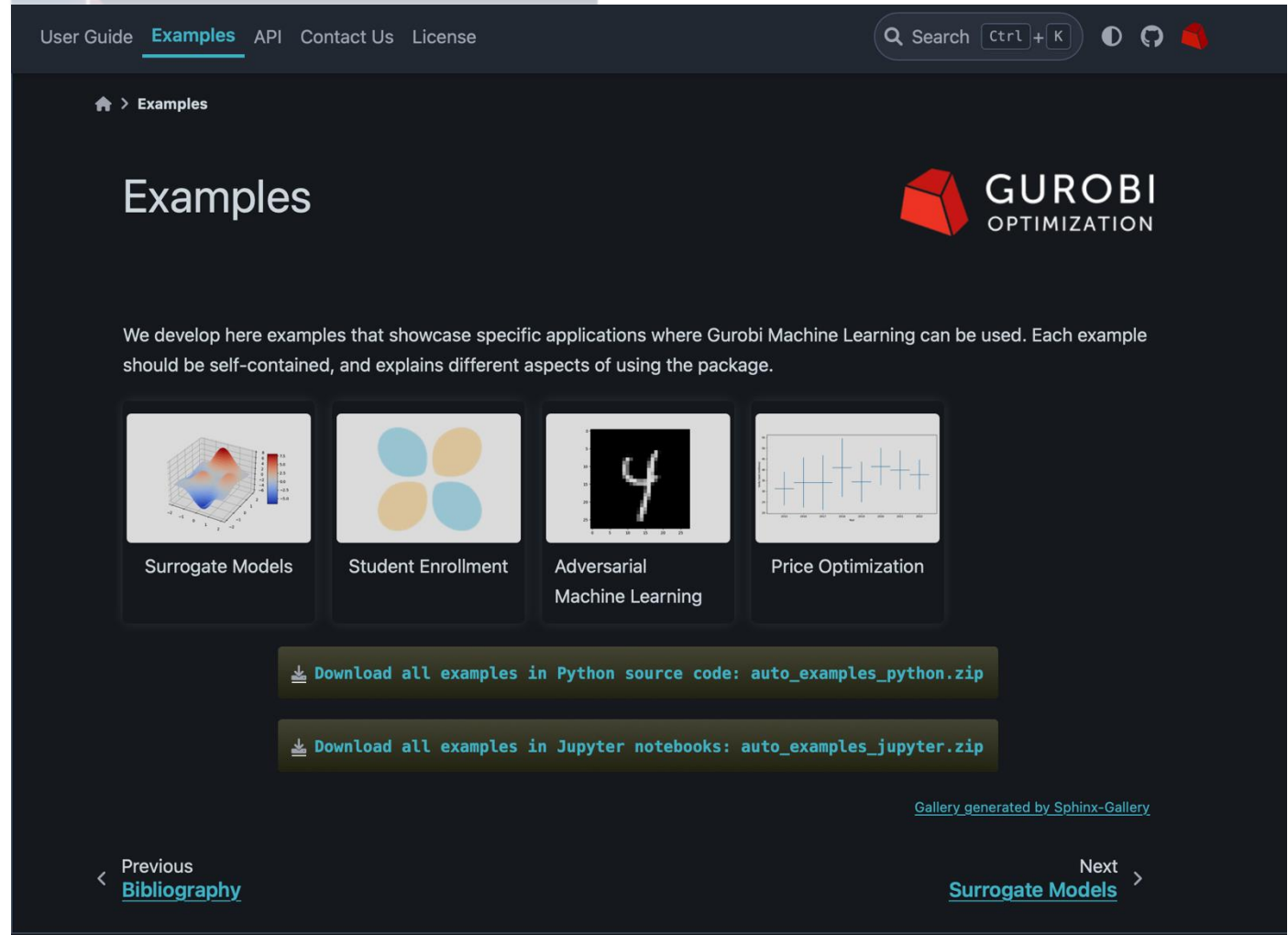
Working hand in hand



Gurobi Machine Learning

Incorporate trained regression models into optimization models

- Input and output of the ML model are decision variables of the optimization
- Feasible solutions of the optimization obey the regressor's input-output relationship
- Supports scikit-learn, LightGBM, XGBoost, Keras, TensorFlow and PyTorch



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Examples

GUROBI
OPTIMIZATION

We develop here examples that showcase specific applications where Gurobi Machine Learning can be used. Each example should be self-contained, and explains different aspects of using the package.

- Surrogate Models
- Student Enrollment
- Adversarial Machine Learning
- Price Optimization

[Download all examples in Python source code: auto_examples_python.zip](#)

[Download all examples in Jupyter notebooks: auto_examples_jupyter.zip](#)

Gallery generated by [Sphinx-Gallery](#)

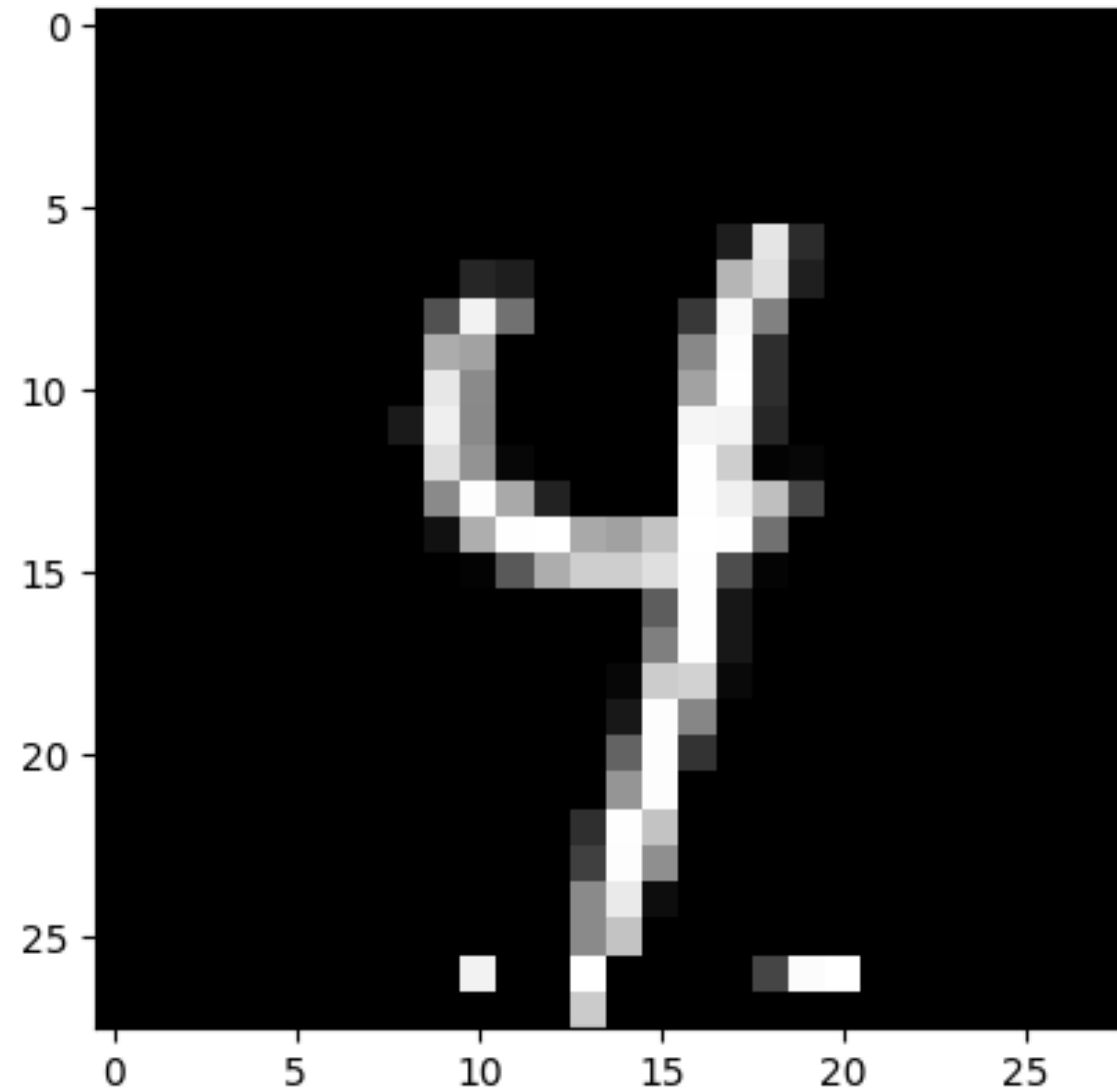
[Previous Bibliography](#) [Next Surrogate Models](#)

Adversarial Learning

Identify the minimum change required to your input data to break your classification model

- Scikit-learn's MLPRegressor classifies handwritten digits
- An optimal solution manipulates a given input as little as possible while causing misclassification
- The letter on the right is classified as 9

[Gurobi - Adversarial Machine Learning](#)



Open-source package to formulate trained ML predictors with Gurobi

```
1 from gurobi_ml import add_predictor_constr
2
3 add_predictor_constr(gp_model, ml_predictor, input_vars, output_vars)
```





A gurobipy speciality: Session boundaries

Session boundaries

An environment that is not disposed, keeps a session active (also blocks a license token). Especially important in interactive environments.

with `gp.Env()` as `env`:

with `gp.Model(env=env)` as `model`:

```
# construct, solve, and post-process `model`
```

```
# ...
```

Alternative

```
...
```

```
model.dispose()
```

```
env.dispose()
```

```
# disposeDefaultEnv() # if environment was not created explicitly before
```

For small models, re-using one environment for a sequence of models is way faster. You can create and manage a **gurobipy** environment with many other model building frameworks.

Questions?

Jaromił Najman
Senior Developer

