

Xopt: Flexible Black Box Optimization of Simulations and Experiments

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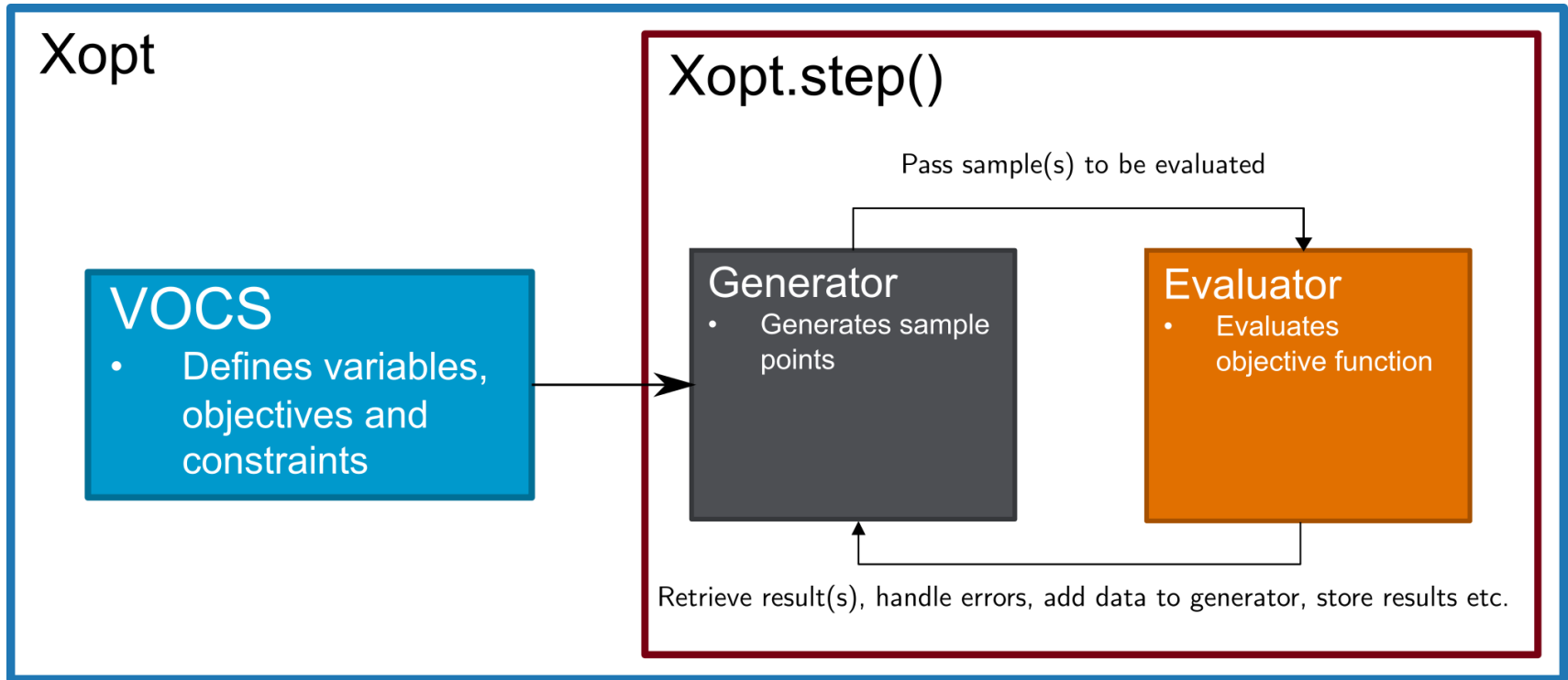
NATIONAL
ACCELERATOR
LABORATORY

What is Xopt?

- Flexible **framework** for optimization of arbitrary problems using python
- **Independent** of problem type (simulation or experiment)
- **Independent** of optimization algorithm + easy to incorporate custom algorithms
- **Easy to use** text interface and/or advanced customized use for professionals

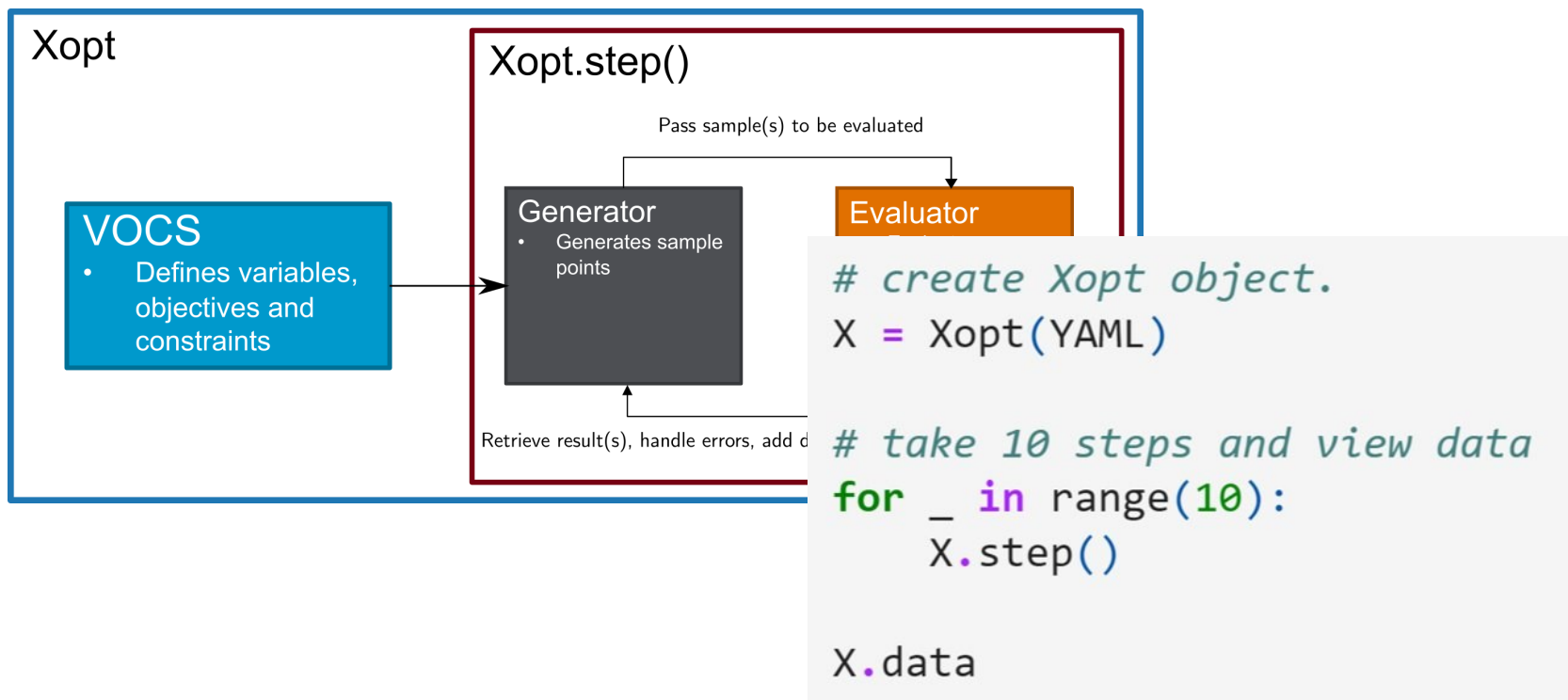


<https://github.com/ChristopherMayes/Xopt>



Note: this process can also be done asynchronously

Xopt usage



Via YAML file (validated by pydantic):

```
xopt:
  max_evaluations: 6400

generator:
  name: cnsiga
  population_size: 64
  population_file: test.csv
  output_path: .

evaluator:
  function: xopt.resources.test_functions.tnk.evaluate_TNK
  function_kwargs:
    raise_probability: 0.1

vocs:
  variables:
    x1: [0, 3.14159]
    x2: [0, 3.14159]
  objectives: {y1: MINIMIZE, y2: MINIMIZE}
  constraints:
    c1: [GREATER_THAN, 0]
    c2: [LESS_THAN, 0.5]
  linked_variables: {x9: x1}
  constants: {a: dummy_constant}
```

Via python code:

```
evaluator = Evaluator(...)
generator = CNSGAGenerator(...)
vocs = MyVOCS(...)
```

```
X = Xopt(
    evaluator=evaluator,
    generator=generator,
    vocs=vocs
)
```

Evaluator specification

- Python function must accept/return dicts
- Input dict must have **at least** the keys specified in vocs variables/constants (see next slide)
 - You can include extra keyword args if needed!
- Output dict must have **at least** the keys specified in objectives/constraints (see next slide)
 - The function can output extra keys to be tracked!
- Functions can be defined at the module level and passed via string if they are in PYTHONPATH, they can also be passed inside the same python file (use `__main__.my_function`)
- Evaluators inherit directly from `python concurrent.futures` so you can use this for parallel evaluation (see /xopt/docs/examples/basic/xopt_parallel)

```
xopt:
  max_evaluations: 6400

generator:
  name: test_functions.tnk.evaluate_TNK
  popsize: 100
  evaluate(inputs: dict) -> dict
  output_path: .

evaluator:
  function: xopt.resources.test_functions.tnk.evaluate_TNK
  function_kwargs:
    raise_probability: 0.1

vocs:
  variables:
    x1: [0, 3.14159]
    x2: [0, 3.14159]
  objectives: {y1: MINIMIZE, y2: MINIMIZE}
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Evaluate function

- Python function must accept/return dicts
- Input dict must have **at least** the keys specified in vocs variables/constants (see next slide)
 - You can include extra keyword args if needed!
- Output dict must have **at least** the keys specified in objectives/constraints (see next slide)
 - The function can output extra keys to be tracked!

```
evaluate(inputs: dict) -> dict
```

```
from epics import caget, caput, cainfo
import time

outputs = ["XRMS", "YRMS"]
def make_epics_measurement(input_dict):
    # set inputs
    for name, val in input_dict.items():
        caput(name, val)

    # wait for inputs to settle
    time.sleep(1)

    # get output values, current time
    output_dict = caget_many(outputs)
    output_dict["time"] = time.time()

    # compute geometric avg of beamsizes
    output_dict["RMS"] = (
        output_dict["XRMS"]*\
        output_dict["YRMS"]
    )**0.5

    return output_dict
```

- Variables: input domain limits and names
- Objectives: objective names and goals (minimize/maximize)
- Constraints: constraint names and conditions (greater than/less than)
- Constants: constant values

```
xopt:
  max_evaluations: 6400

generator:
  name: cnsqa
  population_size: 64
  population_file: test.csv
  output_path: .

evaluator:
  function: xopt.resources.test_functions.tnk.evaluate_TNK
  function_kwargs:
    raise_probability: 0.1

vocs:
  variables:
    x1: [0, 3.14159]
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```


Generator specification

- Use built-in generators by name

- optimization algorithms:
 - `cmsga` Continuous NSGA-II with constraints.
 - `bayesian_optimization` Single objective Bayesian optimization (w/ or w/o constraints, serial or parallel).
 - `mobo` Multi-objective Bayesian optimization (w/ or w/o constraints, serial or parallel).
 - `bayesian_exploration` Bayesian exploration.
- sampling algorithms:
 - `random_sampler`

- Each generator has its own specific options

- Locate the default options in the docs or via

```
from xopt.utils import get_generator_and_defaults
gen, options = get_generator_and_defaults("upper_confidence_bound")
print(yaml.dump(options.dict()))
```

```
acq:
  beta: 2.0
  monte_carlo_samples: 512
  proximal_lengthscales: null
model:
  use_conservative_prior_lengthscales: false
  use_conservative_prior_mean: false
  use_low_noise_prior: false
n_initial: 3
optim:
  num_restarts: 5
  raw_samples: 20
  sequential: true
```

```
xopt:
  max_evaluations: 6400

generator:
  name: cmsga
  population_size: 64
  population_file: test.csv
  output_path: .

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```

- Data is stored by xopt in the `data` attribute
- Set `dump_file` in xopt options to dump data and xopt config to yaml file after every evaluation step
- Dump file can be used to restart xopt

```
# view the data
X.data
```

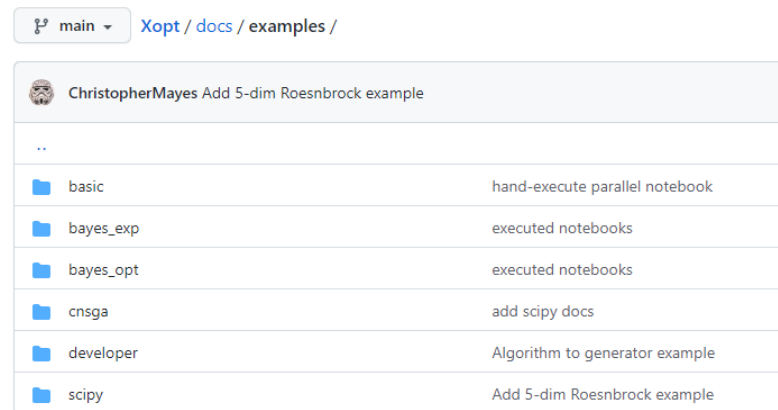
	x1	x2	y1	y2	c1	c2	some_array	xopt_error	xopt_error_str	a
1	1.000000	0.750000	1.000000	0.750000	0.626888	0.312500	[1, 2, 3]	False		NaN
2	0.750000	1.000000	0.750000	1.000000	0.626888	0.312500	[1, 2, 3]	False		NaN
3	0.796389	0.807321	0.796389	0.807321	0.186596	0.182292	[1, 2, 3]	False		dummy_constant
4	0.871085	0.943368	0.871085	0.943368	0.568348	0.334279	[1, 2, 3]	False		dummy_constant
5	1.067732	0.797750	1.067732	0.797750	0.843056	0.410974	[1, 2, 3]	False		dummy_constant
6	0.995019	0.879029	0.995019	0.879029	0.707805	0.388707	[1, 2, 3]	False		dummy_constant
7	0.803822	1.022336	0.803822	1.022336	0.724145	0.365142	[1, 2, 3]	False		dummy_constant
8	0.656282	0.952071	0.656282	0.952071	0.434474	0.228792	[1, 2, 3]	False		dummy_constant
9	0.566763	0.935263	0.566763	0.935263	0.271920	0.193911	[1, 2, 3]	False		dummy_constant
10	0.547152	1.008562	0.547152	1.008562	0.326474	0.260859	[1, 2, 3]	False		dummy_constant
11	0.617813	1.081140	0.617813	1.081140	0.594283	0.351603	[1, 2, 3]	False		dummy_constant
12	0.491363	1.027666	0.491363	1.027666	0.231751	0.278506	[1, 2, 3]	False		dummy_constant

```
xopt:
  dump_file: dump.yaml
```

```
In 3 1 config = yaml.safe_load(open("dump.yaml"))
      2 X2 = Xopt(config)
      3 print(X2.options)
      4 print(X2.generator)
      5 print(X2.evaluator)
```

Tips and Tricks

- **Look at the examples in docs/examples !!!!**
- Get creative with the evaluate function to track variables/outputs.
- Ask for invite to #xopt channel
- Always looking for help!



Example Application: LCLS FEL Power Characterization

- **Proximal biasing** to reduce exploration step size and **constraints** to prevent charge loss.
- **Custom evaluate function** captures 80th percentile FEL power over 100 shots.
- Data stored in Pandas DataFrame objects, exported to text file with Xopt configuration
- FEL sensitivity is captured in the GP model lengthscales inside the generator object.
- Entirely executed from an **interactive Jupyter notebook**.

