



PUNCC: A Python Library for Predictive UNcertainty Calibration and Conformalization

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Agenda

Introduction

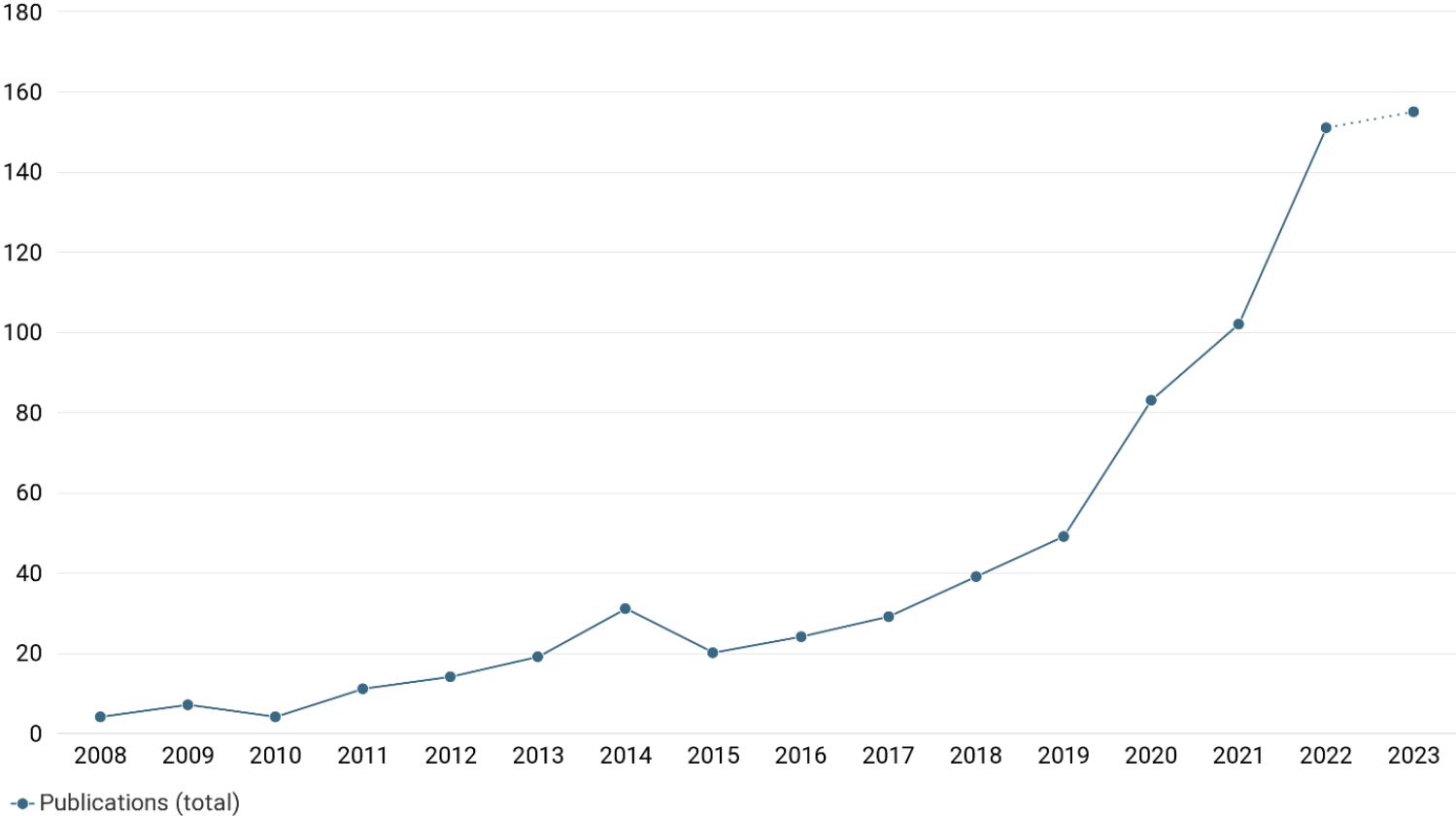
Properties of PUNCC

Experiments

Conclusion

Introduction: context

Publications in each year. (Criteria: see below)



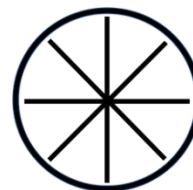
Source: <https://app.dimensions.ai>
Exported: September 01, 2023
Criteria: "Conformal prediction" OR "Conformal Inference" in title and abstract.
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Introduction: context

- Conformal prediction
- Nonexchangeable conformal prediction
- Conformal risk control
- Conformal training
- ...

Introduction: context

Lively open source ecosystem (check awesome-CP for more refs):

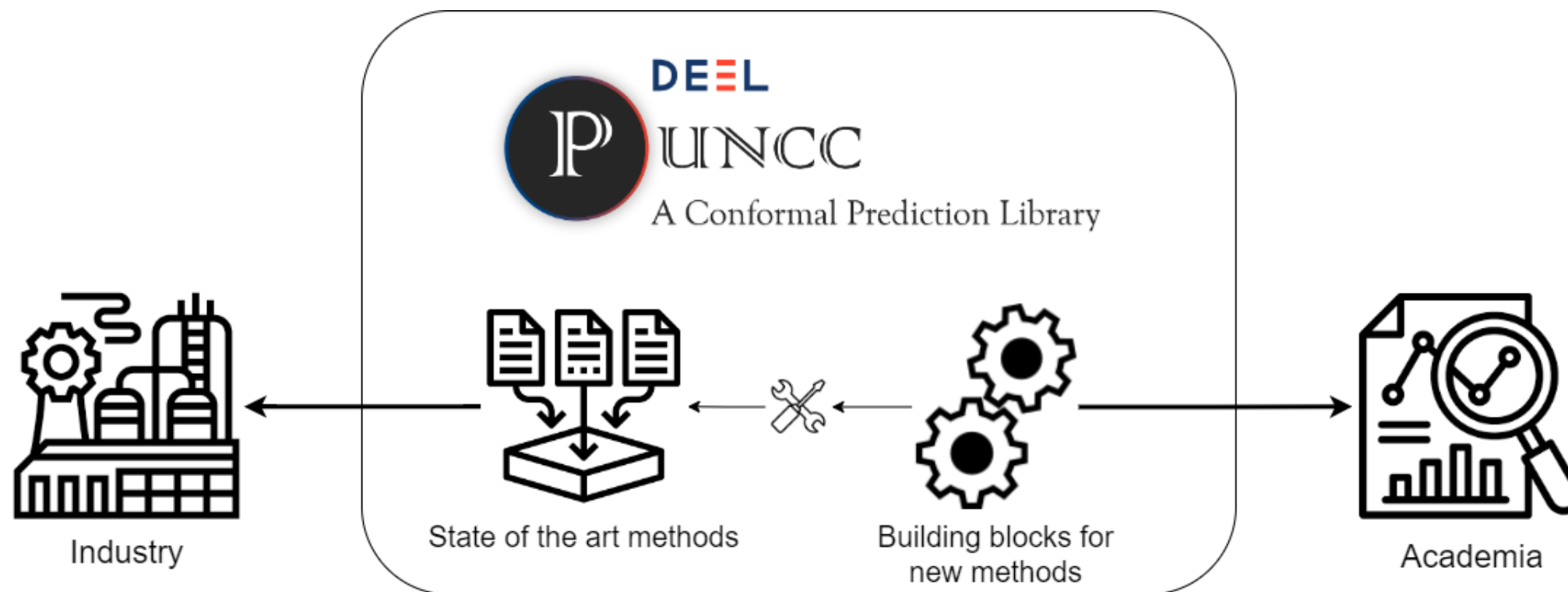


Challenge: maturity vs upgradability

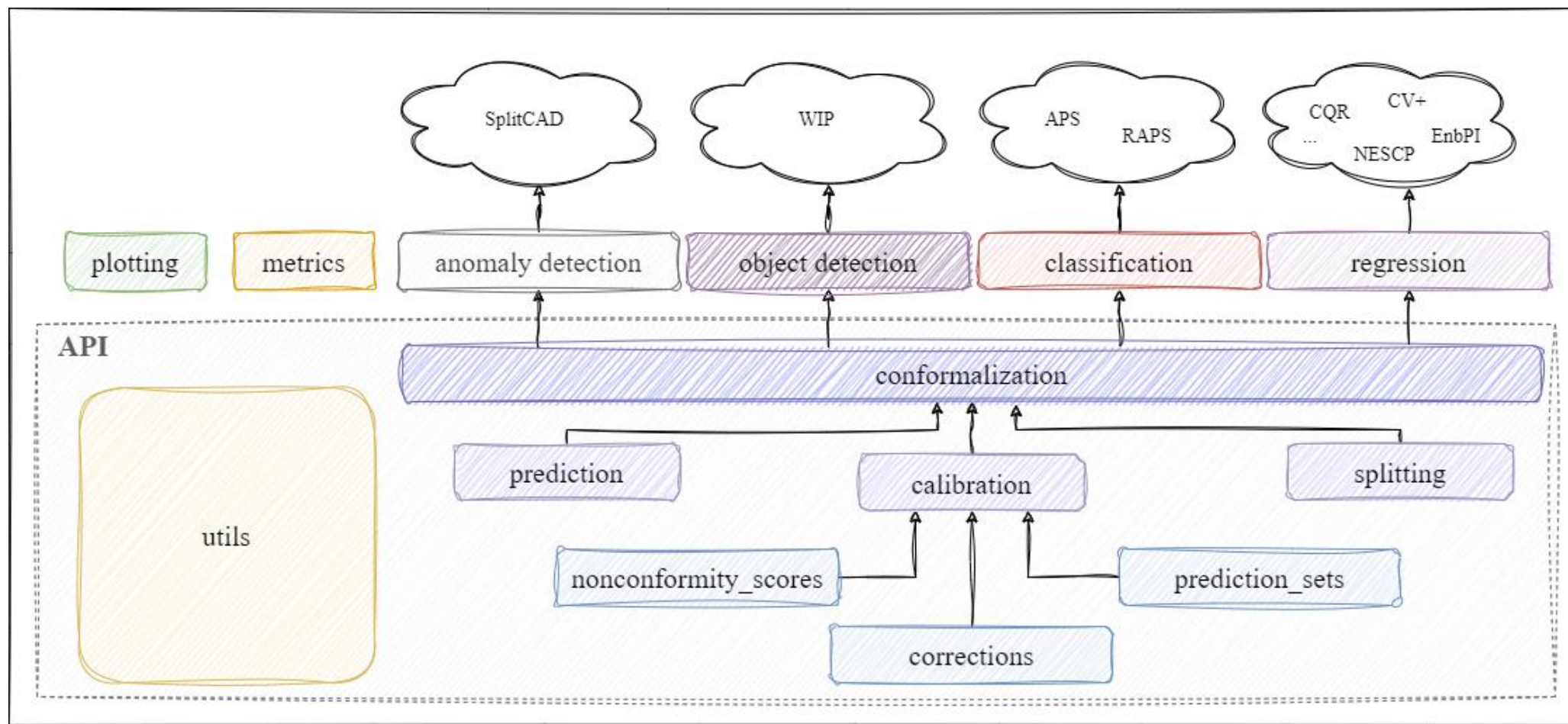
Introduction: PUNCC



Introduction: PUNCC



Introduction: PUNCC



Properties of PUNCC

User-friendliness

Simplicity

Interoperability

Extensivity

Flexibility



Properties of PUNCC: User-friendliness

- Documentation
- Tutorials
- Tests
- Updates and maintenance

Properties of PUNCC: Simplicity

1

```
from deel.puncc.regression import SplitCP, CQR, EnbPI

# ICP
cp_alg = SplitCP(predictor)

# CQR
cp_alg = CQR(predictor)

# EnbPI
cp_alg = EnbPI(predictor, B=30)
```

```
from deel.puncc.classification import APS

cp_alg = APS(predictor)
```

```
from deel.puncc.anomaly_detection import SplitCAD

cp_alg = SplitCAD(predictor)
```

2

```
# Proper training and calibration
cp_alg.fit(X, y)
```

3

```
# Inference
preds = cp_alg.predict(X_new, alpha)
```

❑ Consistent interface and workflow:

1. Initialization
2. Proper training and calibration
3. Inference

❑ Many possible variations (pretrain, calibration, hyper-parameters...)

Properties of PUNCC: Interoperability

- ❑ Support most data types and ML libraries

```
from deel.puncc.api.prediction import BasePredictor

# Definition of a predictor
my_predictor = BasePredictor(my_model)
```



- ❑ Natively support Scikit-learn, TensorFlow, PyTorch, XGBoost, ...

- ❑ Can work on top of UQ libraries too

Properties of PUNCC: Extensivity

- Several sota methods implemented covering different tasks

Conformal Method	Source	Task
<i>Split Conformal Prediction (SCP)</i>	Papadopoulos et al. (2002)	Regression
<i>Locally Adaptive CP (LACP)</i>	Lei et al. (2018)	Regression
<i>Conformalized Quantile Regression (CQR)</i>	Romano et al. (2019)	Regression
<i>Cross-Validation+ (CV+)</i>	Barber et al. (2019)	Regression
<i>Adaptive Prediction Sets (APS)</i>	Romano et al. (2020)	Classification
<i>Regularized Adaptive Prediction Sets (RAPS)</i>	Angelopoulos et al. (2020)	Classification
<i>Ensemble batch Prediction Interval (EnbPI)*</i>	Xu and Xie (2021)	Regression
<i>Weighted Split Conformal Prediction (WSCP)*</i>	Barber et al. (2022)	Regression
<i>Inductive Conformal Anomaly Detection (ICAD)</i>	Laxhammar et al. (2015)	Anomaly detection

- Community oriented: Contributors can easily share their implementations

Properties of PUNCC: Flexibility

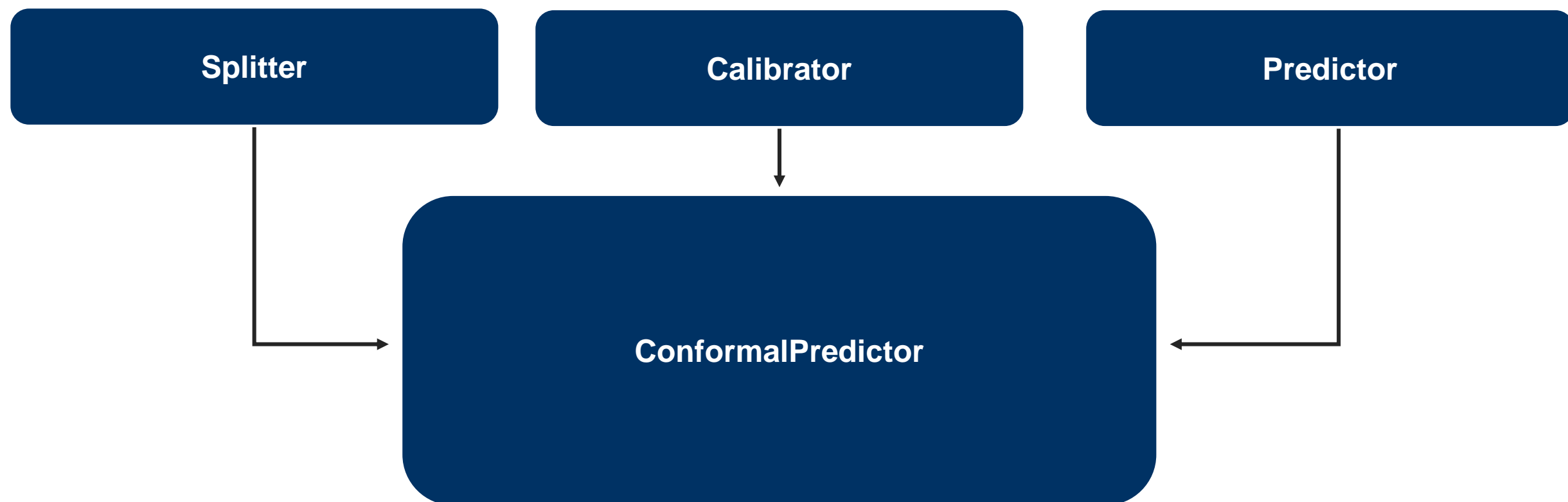
- ❑ Easily design your (own) conformal predictors with the API
 - Custom data attribution for proper training and calibration
 - New nonconformity scores
 - New ways of computing prediction sets
 - (New approaches to adaptively update the sensitivity level)

- ❑ No need to code everything from scratch, just implement what's new

- ❑ Rely on tested and maintained code to build and experiment new algorithms

Properties of PUNCC: Flexibility

□ Example: weighted JKK+ CQR



Properties of PUNCC: Flexibility

□ Example: weighted JKK+ CQR

```
from deel.puncc.api.splitting import KFoldSplitter

# LOO data schemes
cv_splitter = KFoldSplitter(K=n, random_state=0)
```

```
from deel.puncc.api.calibration import BaseCalibrator
from deel.puncc.api.nonconformity_scores import cqr_score
from deel.puncc.api.prediction_sets import cqr_interval

# Define a calibrator from the API
calibrator = BaseCalibrator(nonconf_score_func=cqr_score,
                             pred_set_func=cqr_interval,
                             weight_func=exp_decay)
```

```
from deel.puncc.api.prediction import DualPredictor

# Wrap quantile regressors in predictor
gb_predictor = DualPredictor(models=[regressor_q_low,
                                     regressor_q_hi])
```

```
from deel.puncc.api.conformalization import ConformalPredictor

# Instanciate a conformal prediction object
cp_alg = ConformalPredictor(predictor=gb_predictor,
                             calibrator=calibrator,
                             splitter=cv_splitter,
                             train=True)

# Proper training and calibration
cp_alg.fit(X_train, y_train)

# Conformal inference
preds = cp_alg.predict(X_test, alpha=.1)
```


Experiments



Experiments

□ Experiments using PUNCC

Datasets	Data types	Underlying Models	ML Libraries	CP Methods
California housing prices	Tabular	MLP Xgboost Gradient boosting Nearest neighbors	TensorFlow Pytorch XGBoost Sklearn	SCP LACP CQR/CV+
Imagenette Imagewoof	Images	ResNet-50	TensorFlow	APS RAPS
Elec2	Time series	Linear	Sklearn	OSSCP NESCP EnbPI

Experiments: Metrics

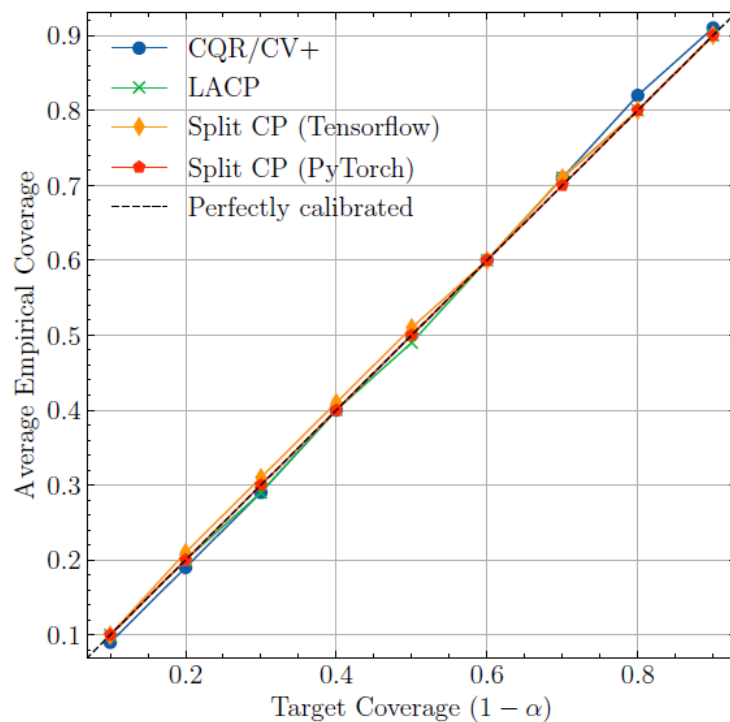


Figure 3: Average coverage gap (across 20 validation folds).

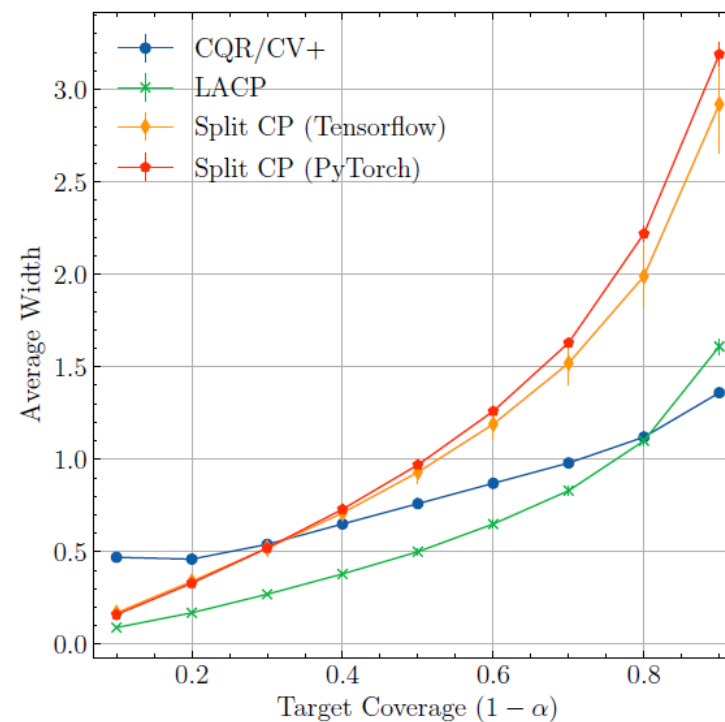


Figure 4: Average empirical size of PIs (across 20 validation folds).

Experiments: Plotting

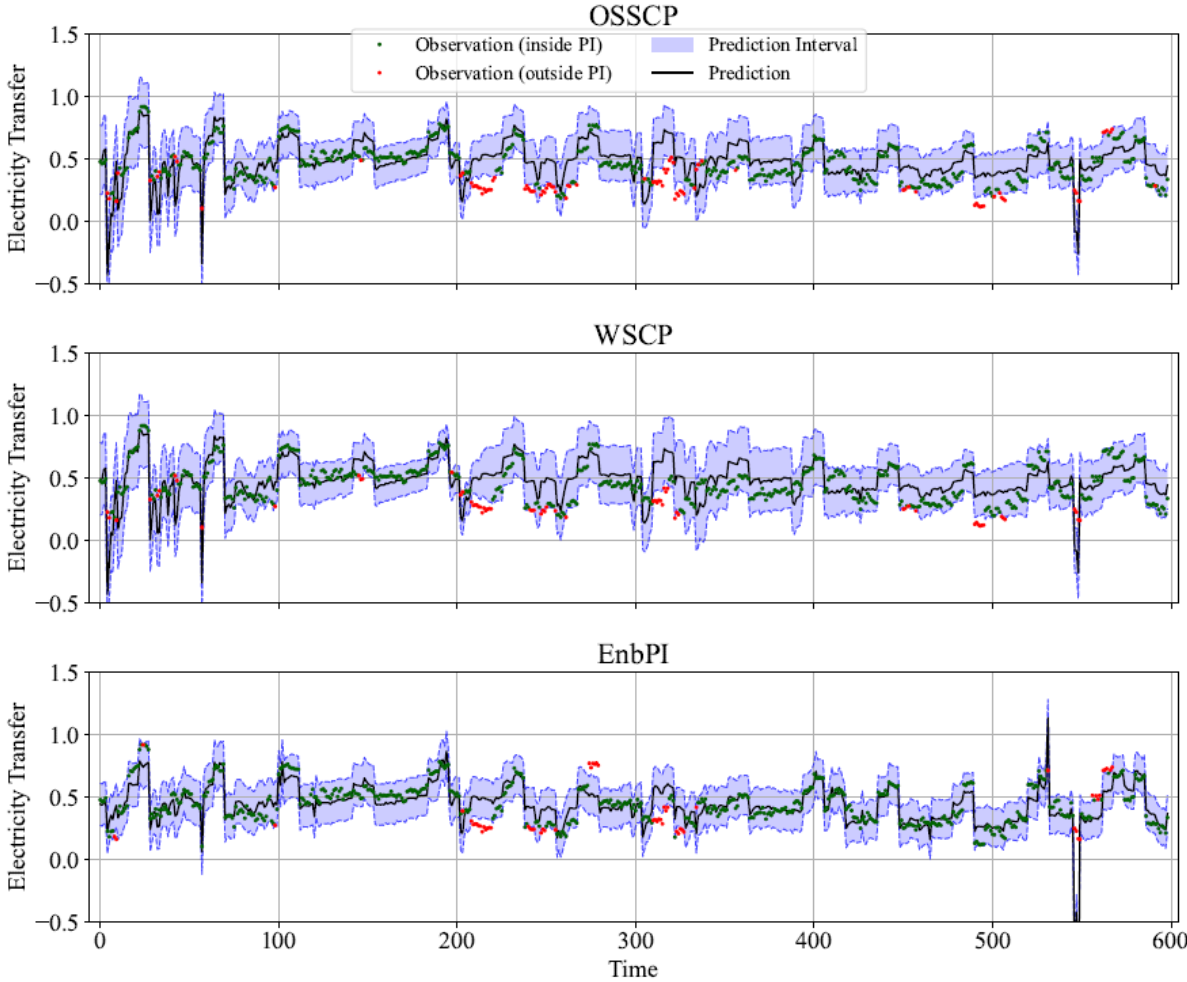


Figure 9: PIs on 600 test samples for three different algorithms (using puncc.plotting).

Conclusion

- ❑ Open-source library in Python for uncertainty quantification based on CP
- ❑ Interoperable with most data types and ML frameworks
- ❑ Collection of state of the art CP-related algorithms
- ❑ Consistent workflow to facilitate learning and benchmarks
- ❑ API to have full control on the design of new/advanced CP procedures

Perspectives

- ❑ Team is expanding !
- ❑ More sota methods
- ❑ Conformal multivariate regression (object detection)
- ❑ Further projects



<https://github.com/deel-ai/puncc>



Properties of PUNCC: Interoperability

- ❑ Easy to use wrapper to conform to API constraints

Example:

RAPS on RandomForestClassifier,
or CatBoostClassifier need logit
predictions

```
from sklearn.ensemble import RandomForestClassifier
from deel.puncc.api.prediction import BasePredictor

# Create a random forest classifier
rf_model = (n_estimators=100, random_state=0)

# Create a wrapper of the random forest model
# to redefine its predict method into logits predictions
class RFPredictor(BasePredictor):
    def predict(self, X, **kwargs):
        return self.model.predict_proba(X, **kwargs)

# Wrap model in the newly created RFPredictor
rf_predictor = RFPredictor(rf_model)
```

- ❑ Can work on top of UQ libraries too