

MAPIE

Uncertainty quantification



Valentin
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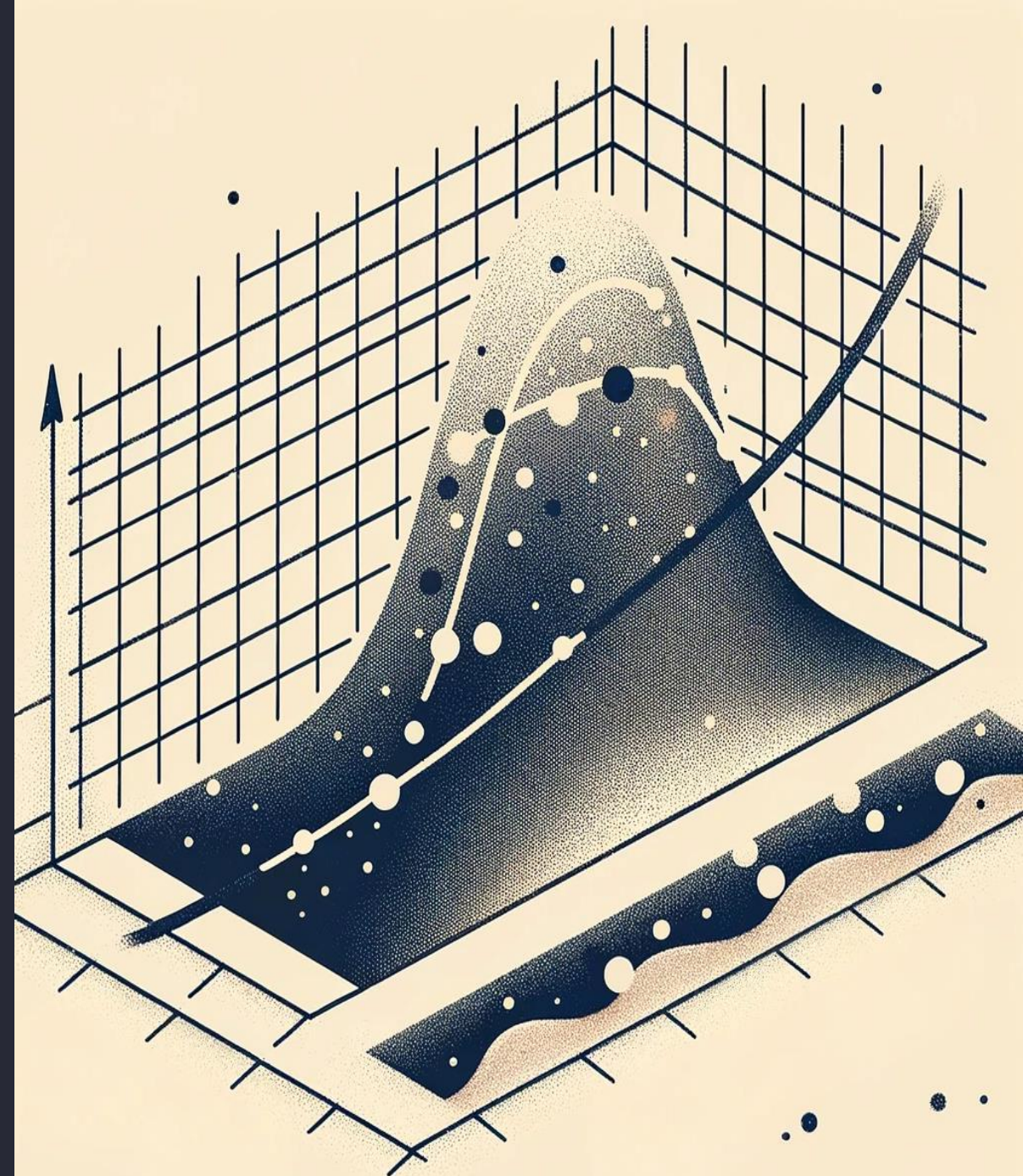
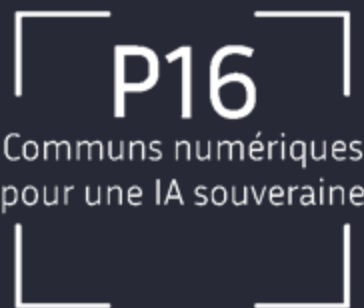
Adrien
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Geoffray
BRELURUT

Campus Cyber, Puteaux, France
P16 Days | October 14th 2025

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Uncertainty quantification with MAPIE

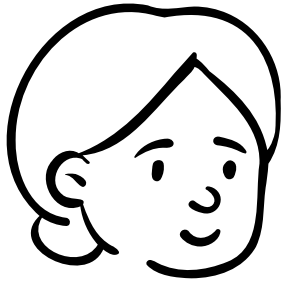
1. Why quantifying uncertainty?
2. Introducing MAPIE
3. What's next?
4. Q&A

Why quantifying uncertainty?



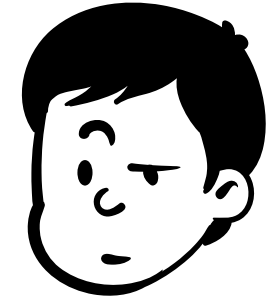
Because wrong expectations lead to wrong decisions...

Model



I predict this is gonna be OK

Business



Just how sure were you, again?





Uncertainty quantification: methods

Conformal prediction is the only method that does not require distribution assumption and provides coverage guarantee.

Family of Methods	Method	Description	Advantages	Disadvantages
Resampling Methods	Bootstrap Jackknife Cross-validation	Use resampling techniques to estimate the uncertainty of model predictions	<ul style="list-style-type: none">- Simple to implement- Efficiently uses available data	<ul style="list-style-type: none">- Can be computationally expensive
Bayesian Methods	Bayesian Inference	Incorporates prior knowledge and updates it with data to estimate model parameters	<ul style="list-style-type: none">- Incorporates uncertainty into the model- Allows incremental updates	<ul style="list-style-type: none">- Can be complex to implement- Can be computationally expensive
	Monte Carlo Dropout Concrete Dropout	Applies dropout during training and testing to estimate prediction uncertainty	<ul style="list-style-type: none">- Simple to implement- More computationally efficient	<ul style="list-style-type: none">- May require hyperparameter tuning- Poorly approximates complex posterior
Uncertainty Quantification Methods	Uncertainty Propagation	Propagates input uncertainties through the model to estimate output uncertainties	<ul style="list-style-type: none">- Allows propagation of uncertainty- Provides a complete estimate of uncertainty	<ul style="list-style-type: none">- Can be complex to implement- Can be computationally expensive
	Confidence Interval	Provides prediction intervals within which the true value is likely to fall	<ul style="list-style-type: none">- Simple to interpret- Provides an estimate of uncertainty	<ul style="list-style-type: none">- Depends on distribution assumptions
	Quantile Regression	Models the conditional quantiles of the response variable	<ul style="list-style-type: none">- Allows modelling of distribution quantiles- Useful for heteroscedastic data	<ul style="list-style-type: none">- Does not provide coverage guarantees- May require specific adjustments
	Calibration	Adjusts the model's predictions to better match the true probabilities	<ul style="list-style-type: none">- Simple to interpret- Allows correction of biases	<ul style="list-style-type: none">- Depends on how the probabilities are discretised, only for classification
	Conformal Prediction	Provides prediction intervals within which the true value is likely to fall, with guaranteed coverage and without distribution assumptions	<ul style="list-style-type: none">- Simple to implement- Provides coverage guarantees- Does not require distribution assumptions- Only require exchangeability data assumption- Is model and use case agnostic	<ul style="list-style-type: none">- Can be conservative- May require specific adjustments to deal with heteroscedasticity



How to explain conformal prediction to your grandmother?



Regression task: age estimation

Model prediction: 24

MAPIE prediction interval: [20, 29]
(with 90% confidence)



Classification task: species identification

Model prediction: zebra

MAPIE prediction set: {zebra, horse}
(with 90% confidence)

MAPIE

Model Agnostic Prediction Interval Estimator

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MAPIE – your go-to package for uncertainty quantification

🤖 What is MAPIE?

MAPIE

MAPIE is an uncertainty quantification package to control the risks associated with AI models.

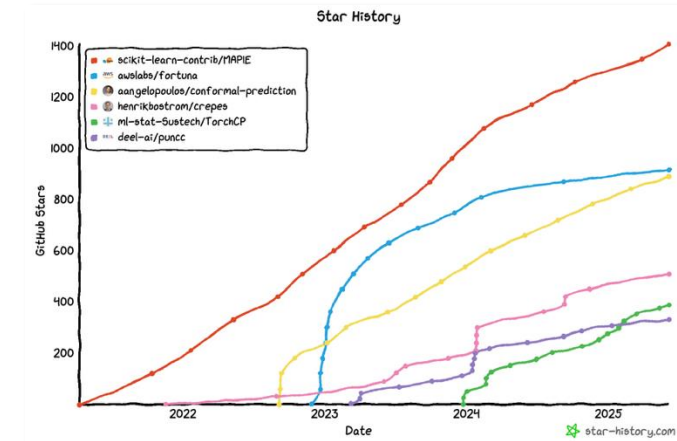
😊 Python package

😊 Open source

😊 Comprehensive documentation

😊 State-of-the-art mathematical guarantees

😊 Integrated into the scikit-learn ecosystem





Multiple facets of MAPIE

Documentation

MAPIE - Model Agnostic Prediction Interval Estimator

Unit tests: passing | codecov: 100% | docs: passing | license: BSD-3-Clause | python: 3.9 | 3.10 | 3.11 | pypi: v1.0.1 | conda-forge: v1.0.1 | release: v1.0.1 | commits since v1.0.1: 7

MAPIE

MAPIE - Model Agnostic Prediction Interval Estimator

🎉 MAPIE v1.0.0 is live! 🎉 You're seeing the documentation of this new version, which introduces major changes to the API. Extensive release notes are available [here](#). You can switch to the documentation of previous versions using the button on the bottom right of ReadTheDoc pages.

MAPIE is an open-source Python library for quantifying uncertainties and controlling the risks of machine learning models.

Regression task: age estimation

Model prediction: 24

MAPIE prediction interval: [20, 29] (with 90% confidence)

Scientific publications

MAPIE: an open-source library for uncertainty quantification

Vianney Taquet¹, Vincent Blot¹, Thomas Morzadec¹, Louis Lacombe¹, Louis Lacombe¹, Thomas Morzadec¹, Arnaud Capitaine^{1,2}, Nicolas Brunel^{1,2}

¹: Quantmetry, 52, rue d'Anjou, 75008, Paris, France
²: Laboratoire de Mathématiques et de Modélisation d'Evry, EN

Abstract

Estimating uncertainties associated with the predictions (ML) models is of crucial importance to assess their reliability. In this submission, we introduce MAPIE (Model Agnostic Prediction Interval Estimator), an open-source Python library that quantifies uncertainties for single-output regression and multi-class classification tasks. MAPIE implements conformal prediction methods, allows computing uncertainties with strong theoretical guarantees on and with mild assumptions on the model or on the underlying data. MAPIE is hosted on scikit-learn-contrib and is fully compatible with scikit-learn.

Proceedings of Machine Learning Research 2041-33, 2023 Conformal and Probabilistic Prediction with Applications

Flexible and Systematic Uncertainty Estimation with Conformal Prediction via the MAPIE library

Thibault Cordier¹, Vincent Blot^{1,2}, Louis Lacombe¹, Thomas Morzadec¹, Arnaud Capitaine^{1,2}, Nicolas Brunel^{1,2}

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Editor: Harris Papadopoulos, Khuong An Nguyen, Henrik Boström and Lars Carlsson

Abstract

Conformal prediction (CP) is an attractive theoretical framework for estimating the un-

Blog articles

Uncertainty, quantified. MAPIE v1 is here.

Grégoire Marlin · 7 min read · May 25, 2023

<https://medium.com/capgemini-invent-lab/uncertainty-quantified-mapie-v1-is-here-b0d0f953b5ac>

Quantifying LLMs Uncertainty with Confidence Scores

Fautin Puybelle · 8 min read · 22 hours ago

<https://medium.com/capgemini-invent-lab/quantifying-llms-uncertainty-with-confidence-scores-6bb8a6712aa0>

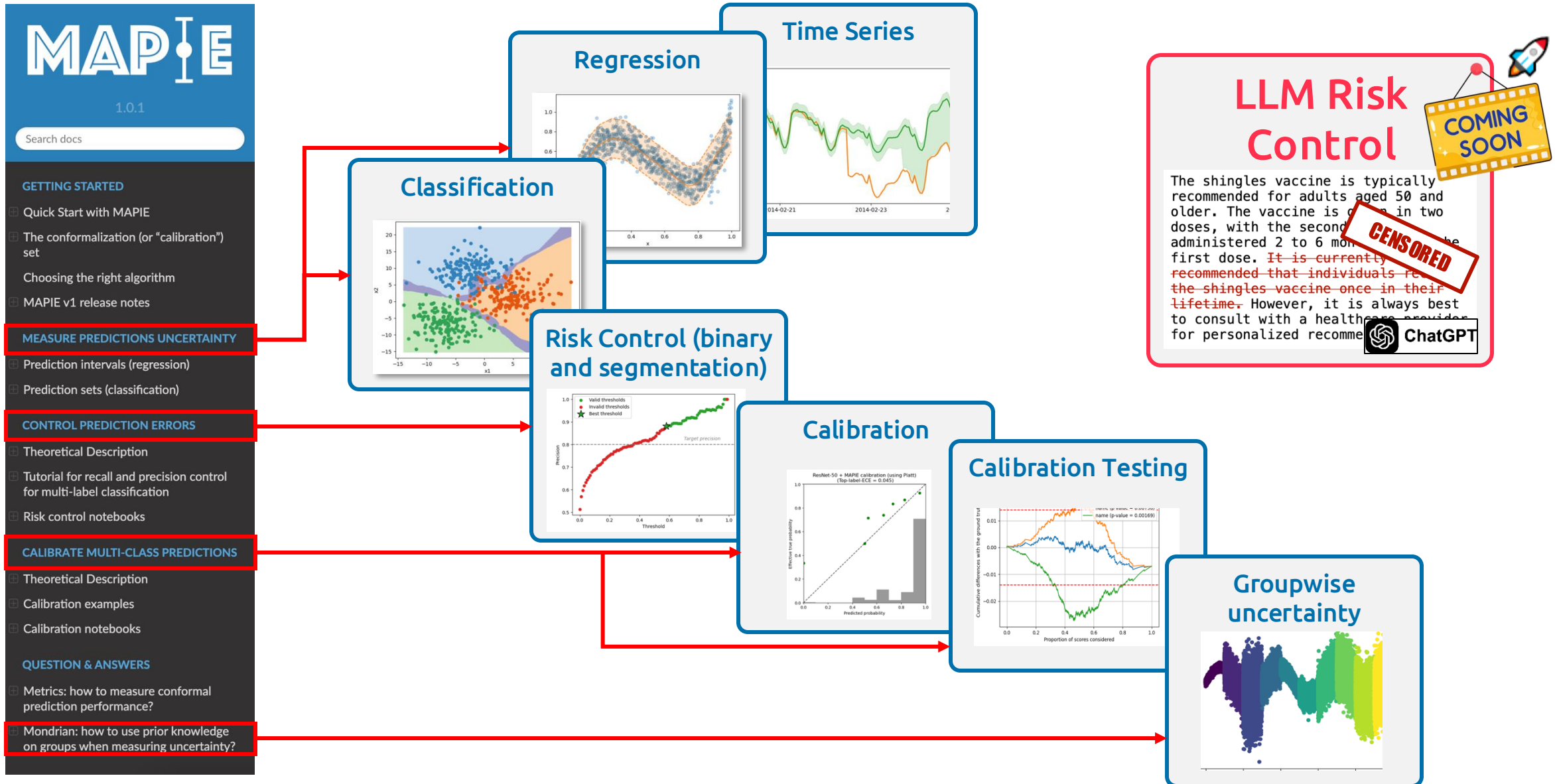
Quantifying LLMs Uncertainty with Conformal Predictions

Grégoire Marlin · 10 min read · 2 hours ago

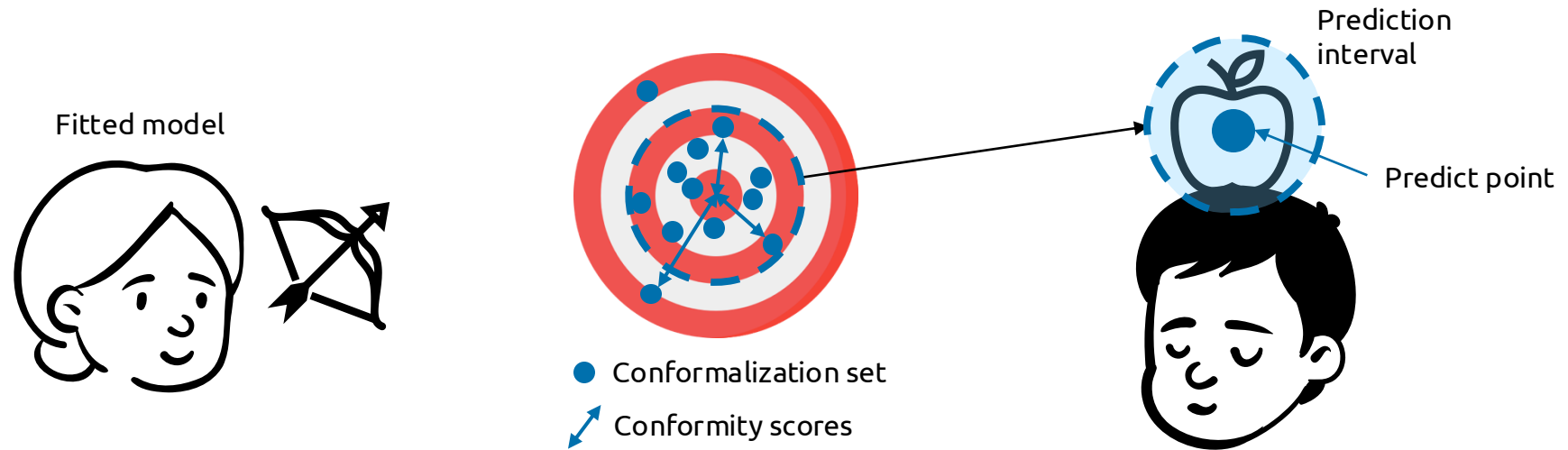
<https://medium.com/capgemini-invent-lab/quantifying-llms-uncertainty-with-conformal-predictions-567870e63e00>



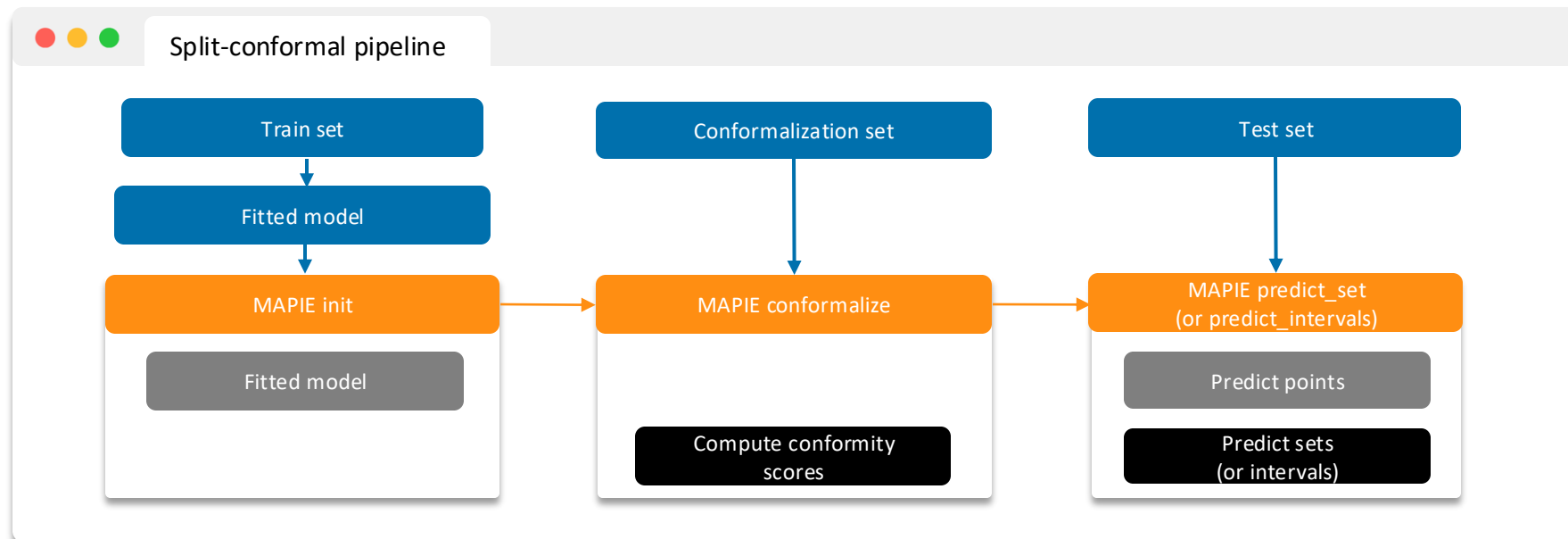
ANY data science problem? MAPIE is here to help



Conformal prediction in three steps



**Prefitted
model**



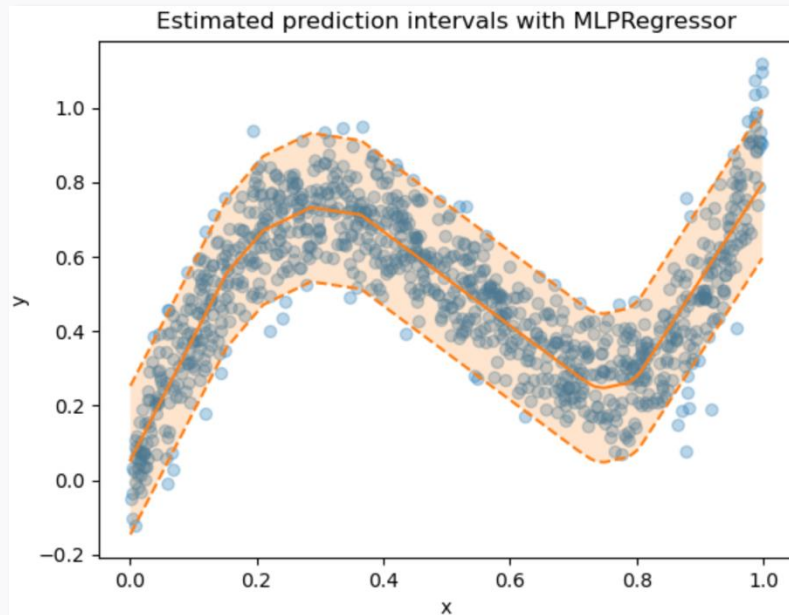


Practical code snippets

Regression

```
regressor = MLPRegressor(activation="relu", random_state=RANDOM_STATE)
regressor.fit(X_train, y_train)

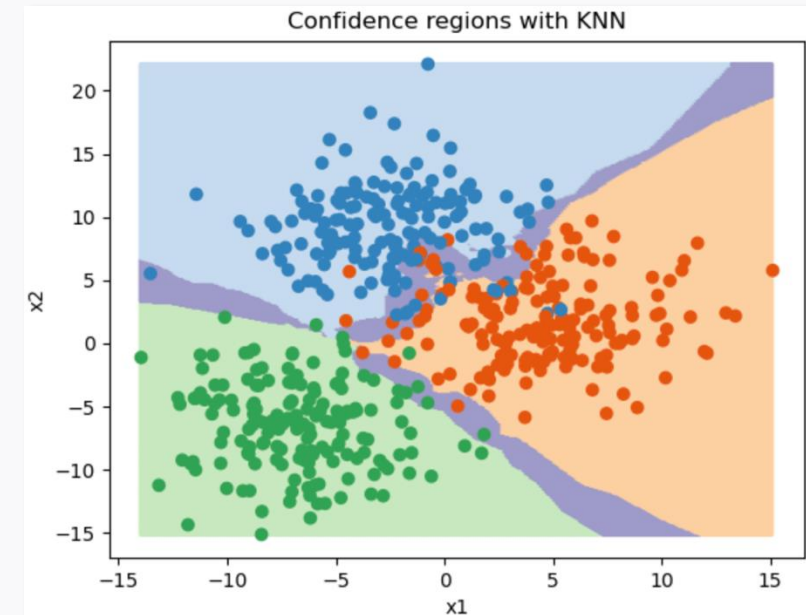
confidence_level = 0.95
mapie_regressor = SplitConformalRegressor(
    estimator=regressor, confidence_level=confidence_level, prefit=True
)
mapie_regressor.conformalize(X_conformalize, y_conformalize)
y_pred, y_pred_interval = mapie_regressor.predict_interval(X_test)
```



Classification

```
classifier = KNeighborsClassifier(n_neighbors=10)
classifier.fit(X_train, y_train)

confidence_level = 0.95
mapie_classifier = SplitConformalClassifier(
    estimator=classifier, confidence_level=confidence_level, prefit=True
)
mapie_classifier.conformalize(X_conformalize, y_conformalize)
y_pred, y_pred_set = mapie_classifier.predict_set(X_test)
```



What's next ?





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MAPIE roadmap

Focused improvements and exciting new directions!

What's new

- **MAPIE v1:** major release to enhance usability
 -  *Reworked documentation*
 -  *New, modular API*
 -  *Updated dependencies*
 -  *Comprehensive release notes*
- **MAPIE v1.1:** first iteration of risk control for binary classification
- **France 2030 support:** 1 engineer from Inria to help improve the library



Priorities

- **Risk control:** further develop the binary classification setting, to enable controlling LLM-based systems
- **Adaptivity:** Focus on conditional coverage (VS marginal coverage)

Next up

- Exchangeability hypothesis testing
- Feedback and suggestions welcome!



MAPIE team & contributors

MAPIE Team



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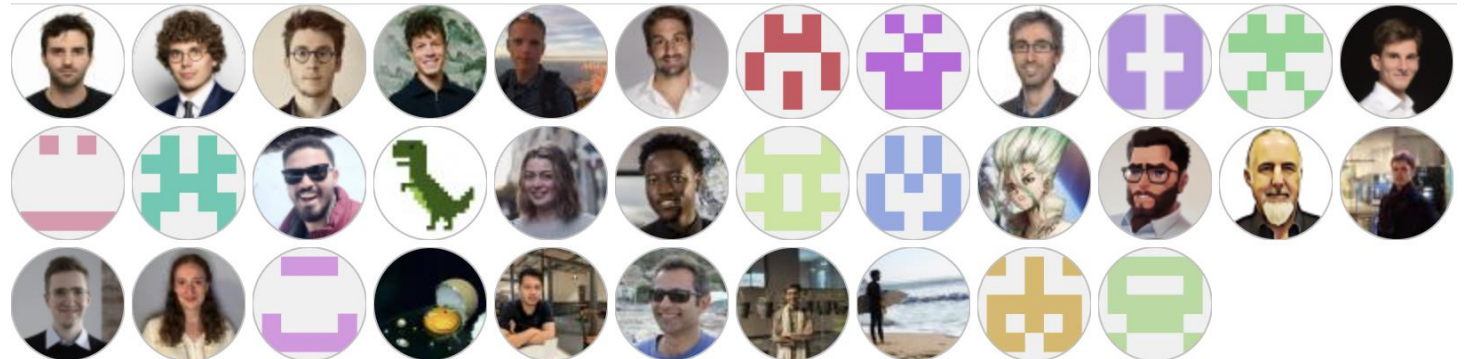


Hassan
Maissoro

Affiliations and Financial Supports

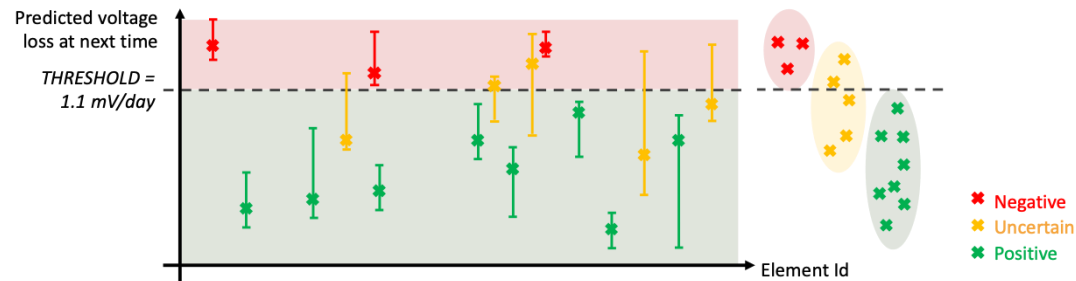


Contributors of MAPIE



They use MAPIE

Focus on faulty battery detection



Conformalized Quantile Regression: Capture noise variability (heteroscedasticity)

Focus on predicting price movements



Segmentation of plane identification in pictures



- Classic detection
- Uncertainty area
- 90% of the plane on average

Q&A

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