

# OBJECT DETECTION WITH PROBABILISTIC GUARANTEES: A CONFORMAL PREDICTION APPROACH

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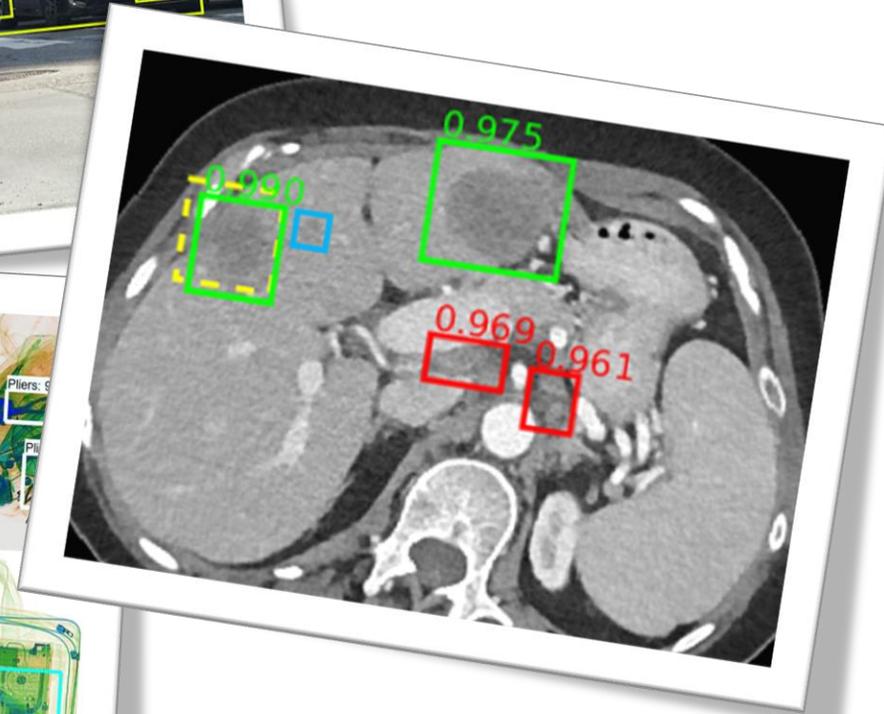
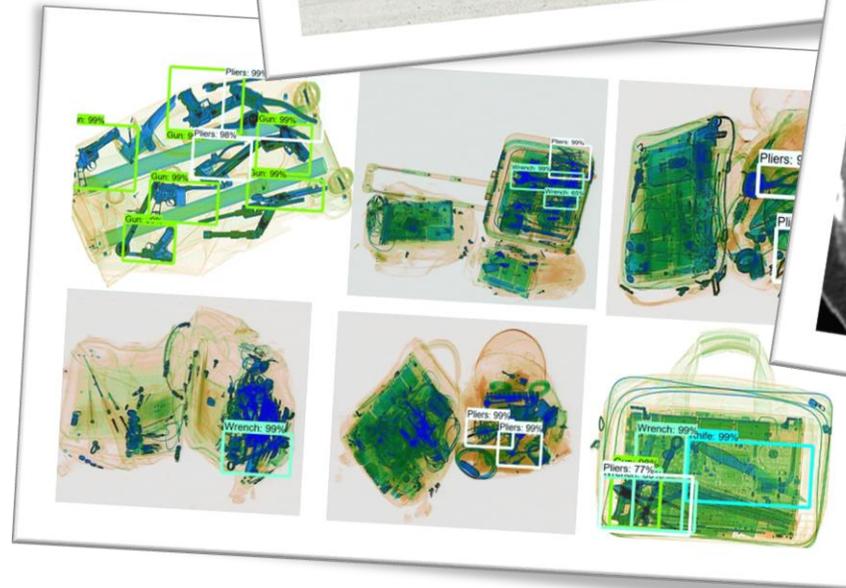
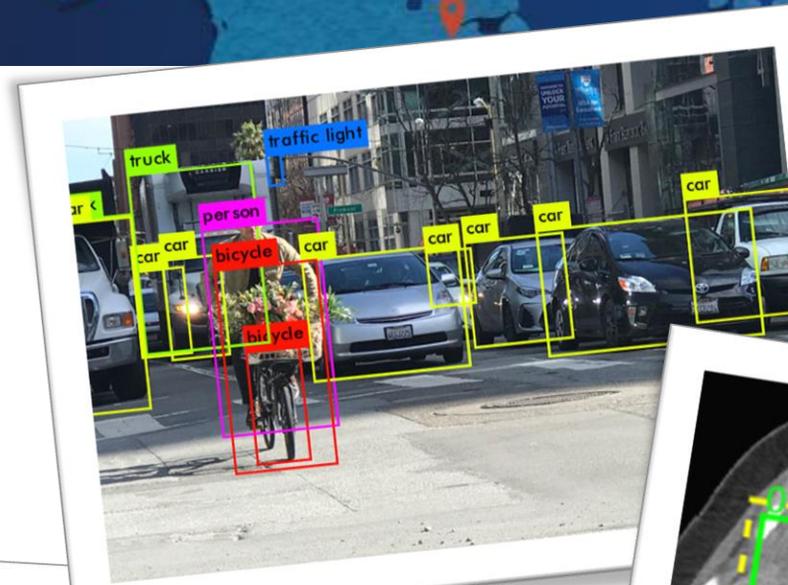
# OBJECT LOCALIZATION

## Object detection

- Classification
- **Localization**  
(focus of this paper)

## Applications

- Autonomous driving
- Medical diagnosis
- Anomaly detection
- etc.



- Uncertainty quantification for object detection

- Deep Ensembles [1]
- Monte-Carlo [2]
- Direct modeling [3]
- Bayesian networks [4]
- Uncertainty Wrapper [5]
- ....

Lack of formal guarantees



- In order to use ML predictions in **safety-critical applications** we need **reliable uncertainty quantification**

- Conformal prediction
- Formal methods
- PAC-Bayes learning
- etc.

Theoretical guarantees



[1] Lyu, Z & al.: Probabilistic object detection via deep ensembles. In: ECCV'20

[2] Deepshikha, K. & al: Monte carlo dropout for modelling uncertainty in object detection (2021), arXiv:2108.03614

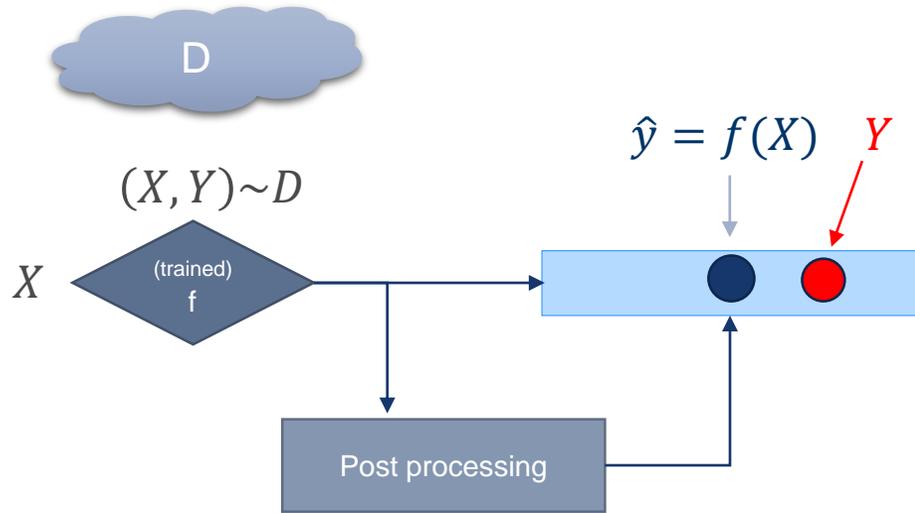
[3] Le, M.T & al :Uncertainty estimation for deep neural object detectors in safety-critical applications. In: ITSC'18

[4] A. Harakeh & al : Estimating and Evaluating Regression Predictive Uncertainty in Deep Object Detectors

[5] Kläs, M., Sembach, L.: Uncertainty wrappers for data-driven models: Increase the transparency of AI/ML-based models through enrichment with dependable situation-aware uncertainty estimates. In: WAISE'19 (2019)

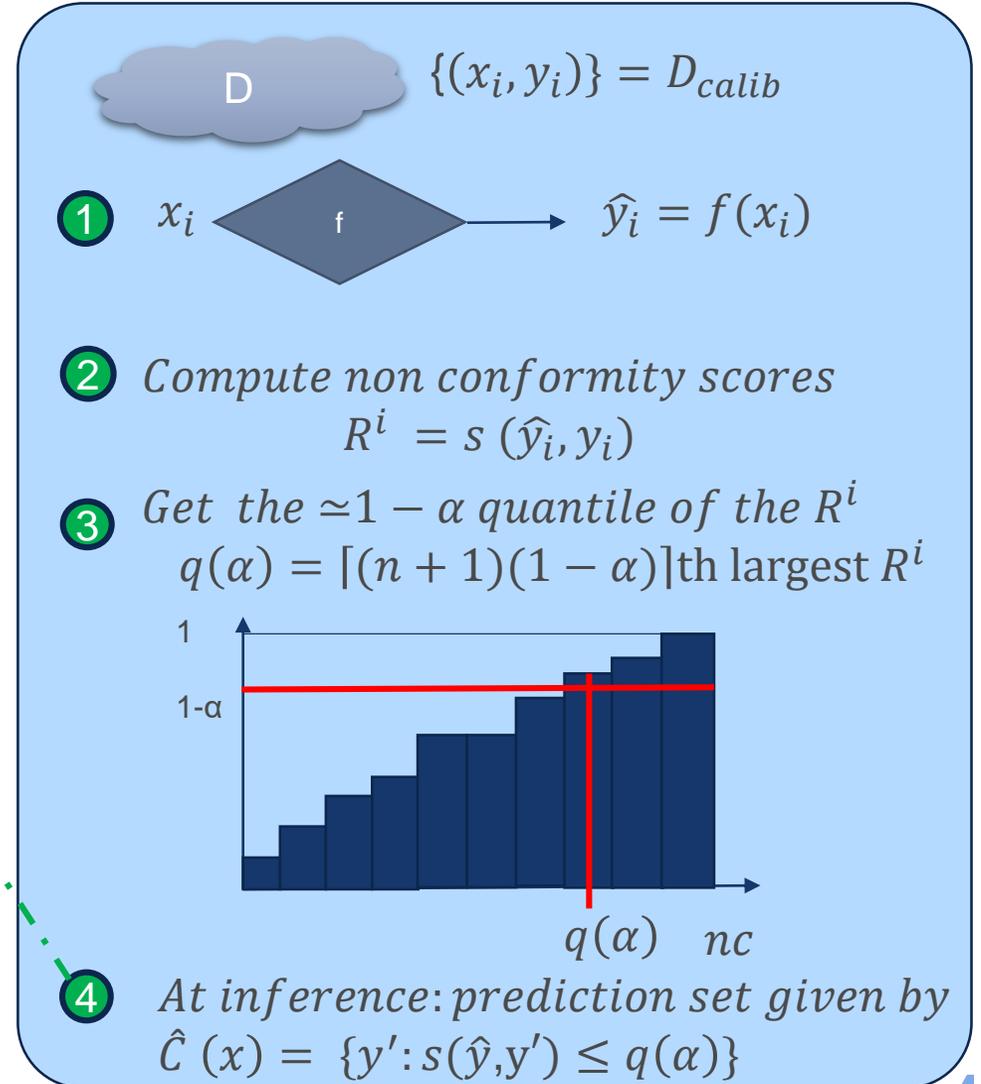
# CONFORMAL PREDICTION

## GENERAL FRAMEWORK



**Conformal prediction [1,2]** = statistical framework that provides a *prediction interval or set* which, at a *desired risk level  $\alpha$* , contains the true value  $Y$ .

[1] Vovk, V., Gammerman, A., and Shafer, G. (2005). *Algorithmic Learning in a Random World*. Springer.  
 [2] Angelopoulos, A.N., Bates, S. (2021). *A gentle introduction to conformal prediction and distribution-free uncertainty quantification*. arXiv:2107.07511



Split Conformal Prediction

# SPLIT CONFORMAL PREDICTION

## TECHNICAL DETAILS (REGRESSION)

2 The **non-conformity scores**  $R^i$  can be defined in various ways, e.g.,

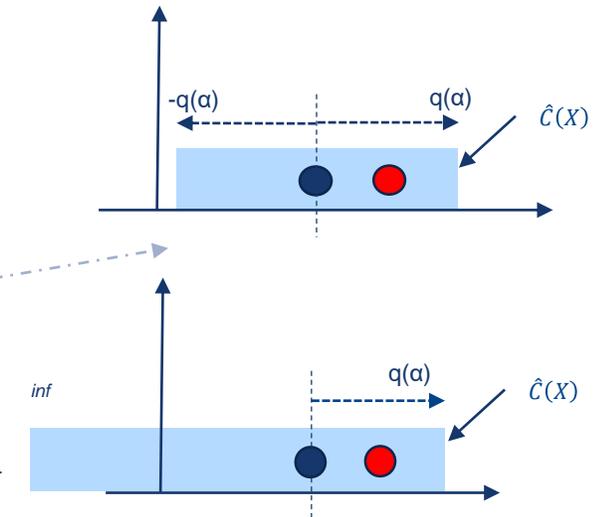
$$R^i = |\hat{y}_i - y_i| \quad \text{Lower and upper bounds}$$

$$R^i = y_i - \hat{y}_i \quad \text{(Tighter) upper bound}$$

4 A **prediction interval**  $\hat{C}(x)$  is built using the  $\approx 1 - \alpha$  quantile  $q(\alpha)$  of the  $R^i$

$$\hat{C}(x) = [\hat{y} - q(\alpha), \hat{y} + q(\alpha)] \quad \text{Lower and upper bounds}$$

$$\hat{C}(x) = (-\infty, \hat{y} + q(\alpha)] \quad \text{(Tighter) upper bound}$$



### Theoretical guarantees [1,2]

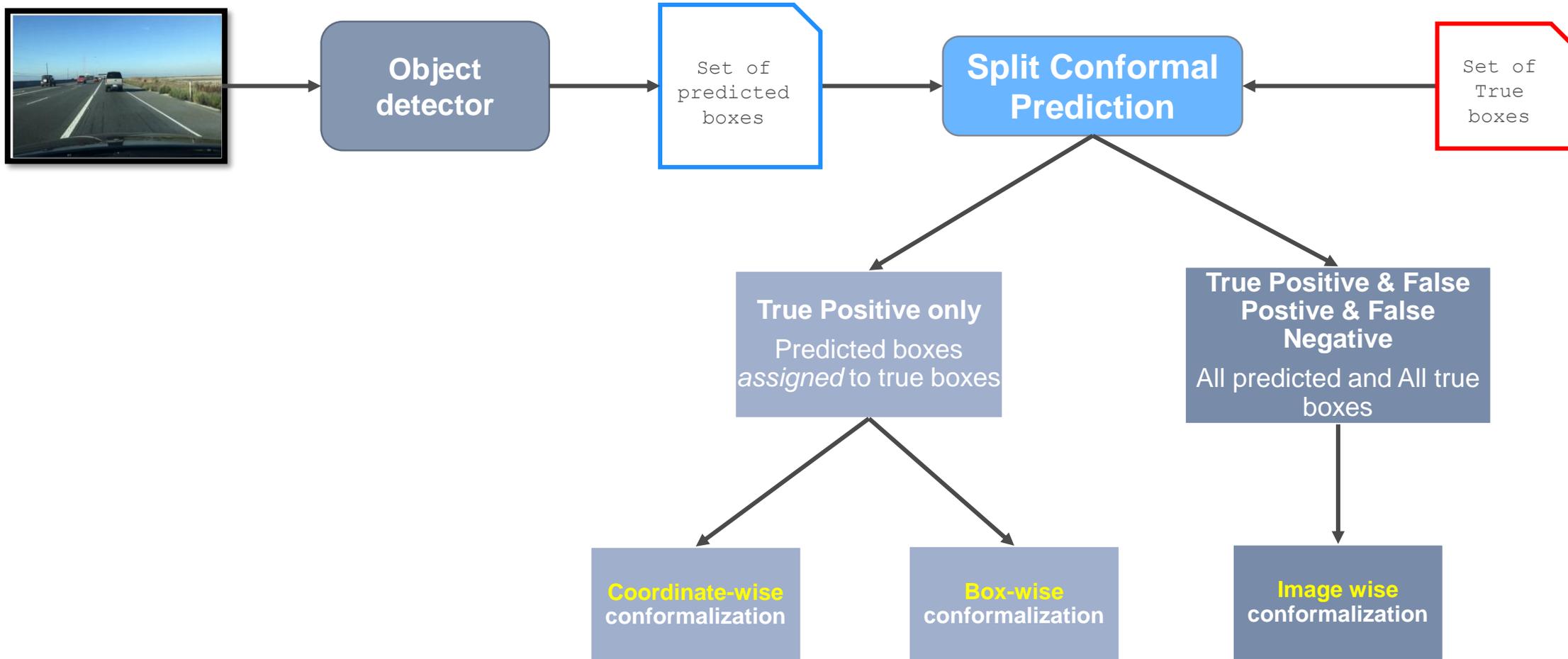
Let  $f$  be any ML model learned on a training set, evaluated on a calibration set, and later applied on some new data point  $(X, Y)$  (inference step). Assume that:

- (i) data from all 3 datasets (training, calibration, inference) are independent;
- (ii) data distributions at calibration and inference steps are identical (can differ from training distribution)

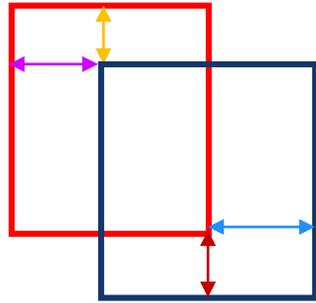
Then, the prediction set  $\hat{C}(X)$  at inference has the desired risk level  $\alpha$  on average:

$$P(Y \in \hat{C}(X)) \geq 1 - \alpha$$

# CONFORMAL OBJECT LOCALIZATION



- Apply Split Conformal to each bounding box **coordinate** independently
- **Objective:** *true coordinate is contained in prediction interval (risk level  $\alpha$ )*



Ex. of non-conformity scores ②

$$R^i = \widehat{x_{min}^i} - x_{min}^i, R^i = \widehat{y_{min}^i} - y_{min}^i$$

$$R^i = x_{max}^i - \widehat{x_{max}^i}, R^i = y_{max}^i - \widehat{y_{max}^i}$$

Computing prediction intervals ④

$$\widehat{C_{x_{min}}^\alpha} = [\widehat{x_{min}} - q_{x_{min}}(\alpha), +\infty]$$

$$\widehat{C_{y_{min}}^\alpha} = [\widehat{y_{min}} - q_{y_{min}}(\alpha), +\infty]$$

$$\widehat{C_{x_{max}}^\alpha} = (-\infty, \widehat{x_{max}} + q_{x_{max}}(\alpha)]$$

$$\widehat{C_{y_{max}}^\alpha} = (-\infty, \widehat{y_{max}} + q_{y_{max}}(\alpha)]$$

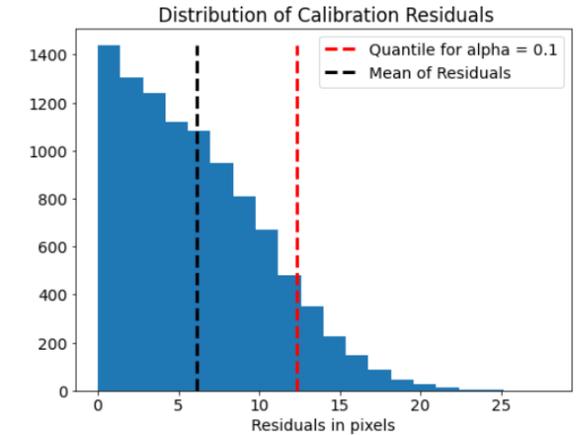
With associated guarantees

$$P(x_{min} \in \widehat{C_{x_{min}}^\alpha}) \geq 1 - \alpha$$

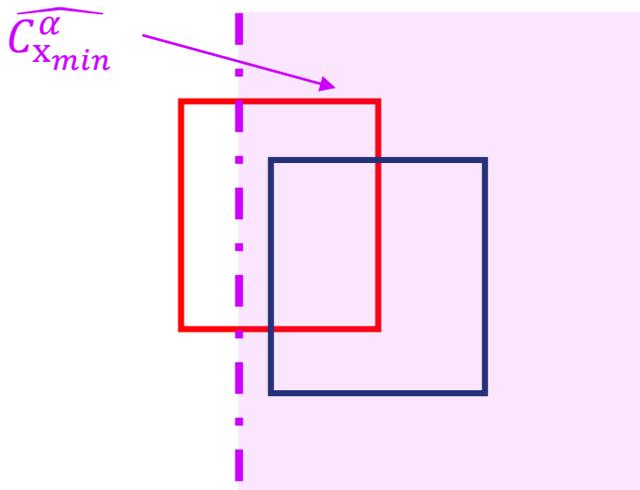
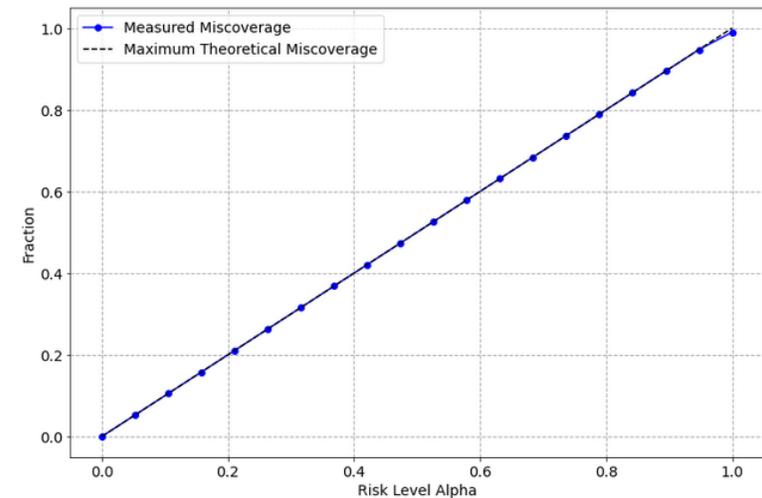
$$P(y_{min} \in \widehat{C_{y_{min}}^\alpha}) \geq 1 - \alpha$$

$$P(x_{max} \in \widehat{C_{x_{max}}^\alpha}) \geq 1 - \alpha$$

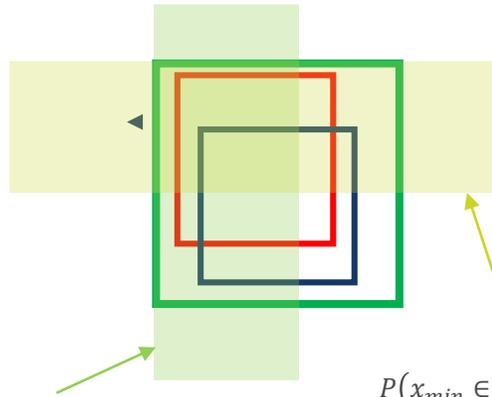
$$P(y_{max} \in \widehat{C_{y_{max}}^\alpha}) \geq 1 - \alpha$$



Miscoverage Curve (Fraction of out of range predictions with Risk Level)

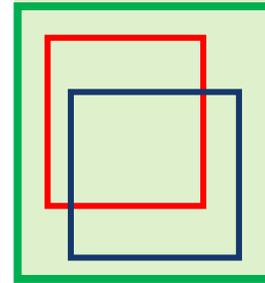


- Apply Split Conformal to each **bounding box** independently
- **Objective:** *true box* contained in *conformalized box* (risk level  $\alpha$ )
  - *Coordinate-wise provides guarantees for each coordinate separately*
  - *With  $\alpha = 1\%$ , our method may fail to identify  $x_{min} / x_{max} / y_{min} / y_{max}$  on 1% of all boxes.*  
 $\Rightarrow$  *At box level: one error can occur on up to 4% of all boxes.*
  - *Must introduce a **multiple-testing correction such as Bonferroni correction.***



$$P(y_{min} \in \widehat{C}_{x_{min}}^\alpha) \geq 1 - \alpha$$

$$P(x_{min} \in \widehat{C}_{y_{min}}^\alpha) \geq 1 - \alpha$$

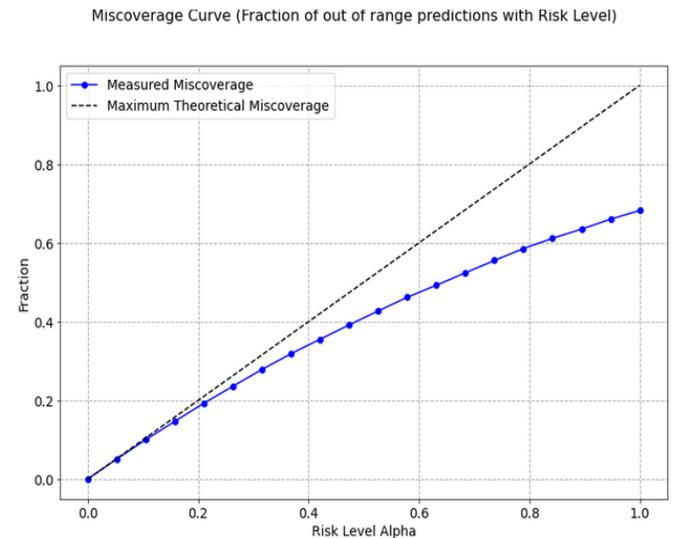
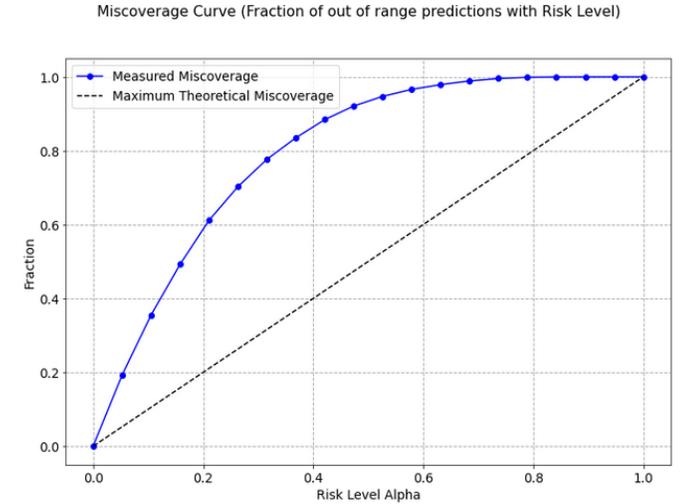


$$P(x_{min} \in \widehat{C}_{BOX}^\alpha) \geq 1 - \alpha$$

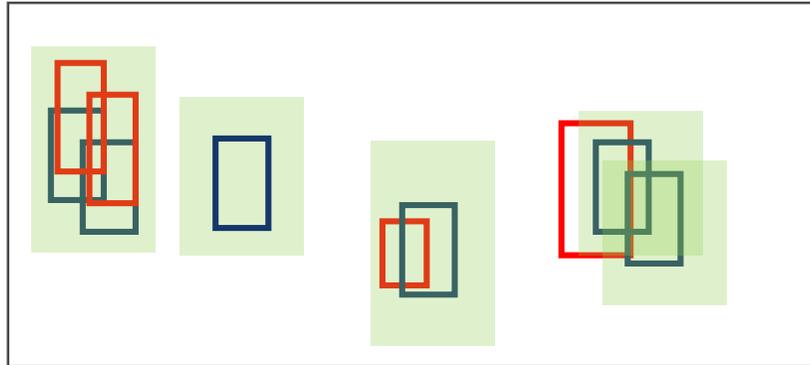
$$P(x_{min} \in \widehat{C}_{x_{min}}) \geq 1 - \alpha/4$$

$$P(y_{min} \in \widehat{C}_{y_{min}}) \geq 1 - \alpha/4$$

- *Bonferroni correction is equivalent to computing conformalization for each coordinate with a risk level of  $\frac{\alpha}{n_{coord}} = \frac{\alpha}{4}$  at step 3*



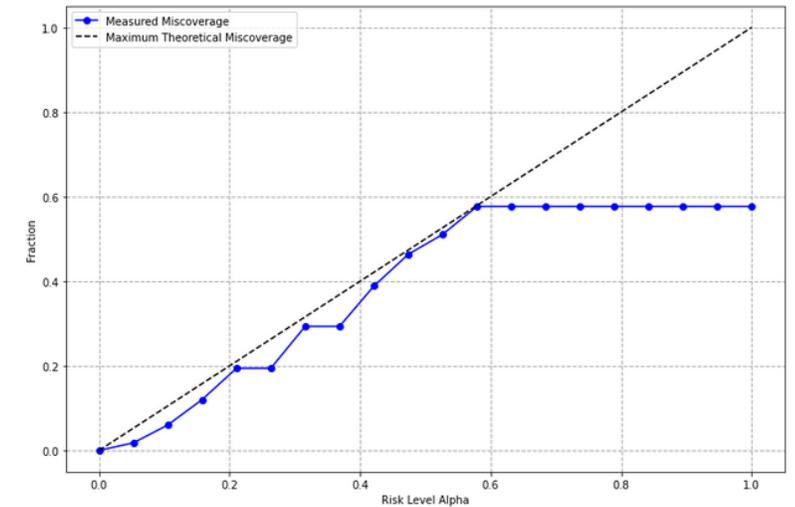
- Apply Split Conformal to each **image** independently
- Objective: *set of true boxes in an image contained in prediction set (risk level  $\alpha$ ).*



$$P(\text{Set TrueBoxes} \in \widehat{C_{set\ BOX}}) \geq 1 - \alpha$$

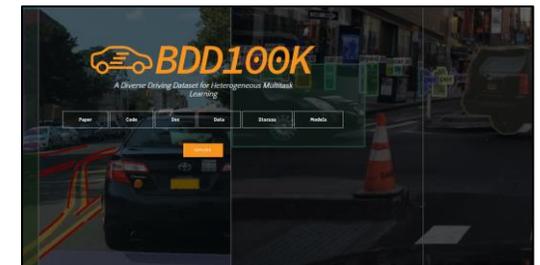
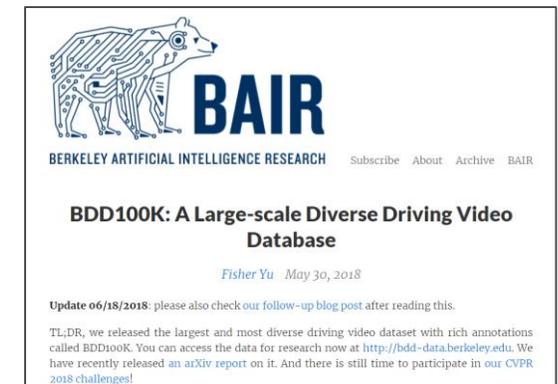
- Custom non-conformity score (step ②) at image level, such as partial or quantile **Hausdorff distance**
  - equivalent to min margin to be added to all predicted boxes to cover all true boxes
- **Advantage:** all true boxes are considered (instead of true positive only)
- **Drawback :** Conservative margins

Miscoverage Curve (Fraction of out of range predictions with Risk Level)



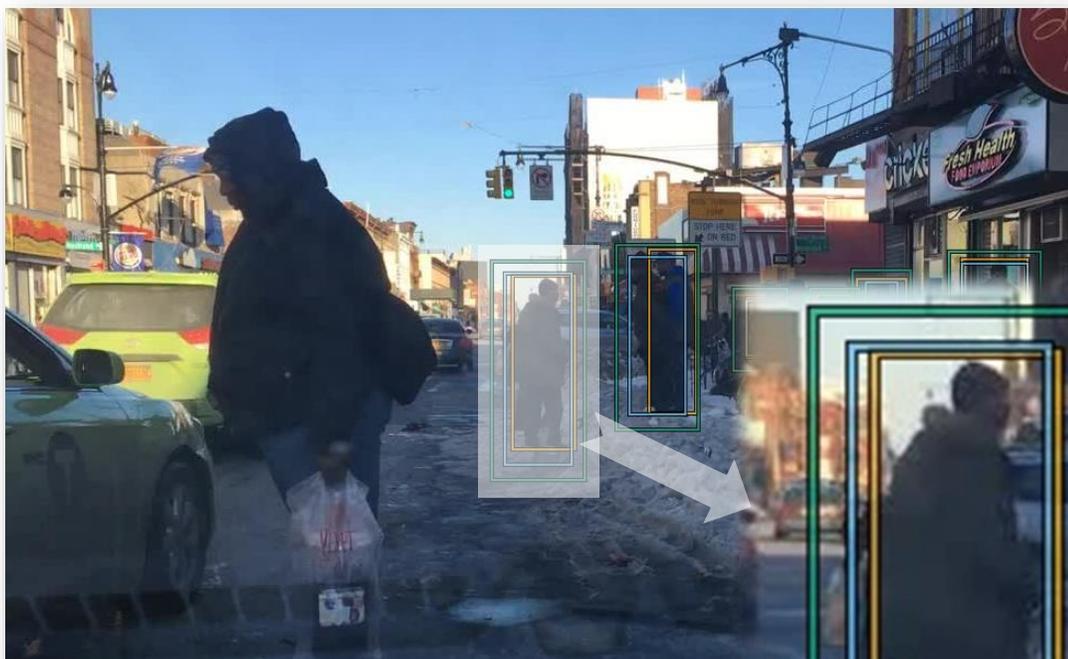
# APPLICATION TO PEDESTRIAN LOCALIZATION SETUP

- Pedestrian detector
  - **Yolo V3** [1] architecture trained on Microsoft COCO
    - Detection threshold: 0.5
    - IoU threshold: 0.5 for ground truth assignment
- Dataset
  - **BDD100k Driving Data** [2]
    - Training Set used for calibration (91349 annotated persons)
    - Validation Set for evaluation (13262 annotated persons)
- Calibration parameters
  - Calibration is performed on **True Positive** detections
  - Risk level  $\alpha=0.1$

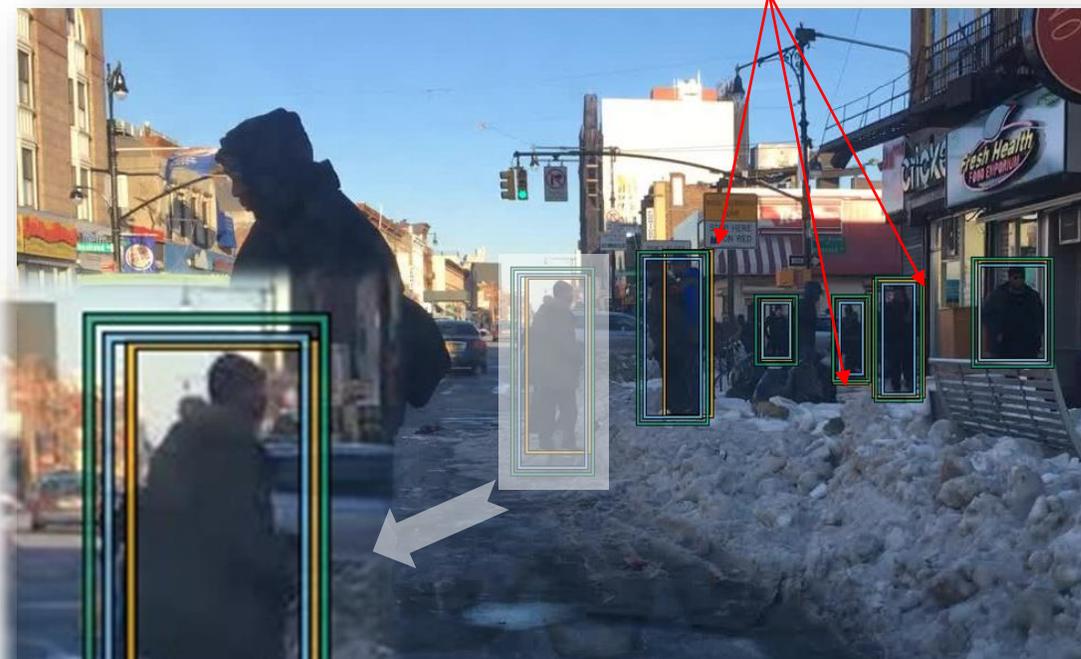


[1] Redmon, J., Farhadi, A.: YOLOv3: An incremental improvement (2018),arXiv:1804.02767  
[2] Yu, F., Xian, W., Chen, Y., Liu, F., Liao, M., Madhavan, V., Darrell, T.:BDD100K: a diverse driving dataset for heterogeneous multitask learning (2018),arXiv:1805.04687

# APPLICATION TO PEDESTRIAN LOCALIZATION BOX-WISE VS COORDINATE-WISE MARGINS



Box-Wise Conformalization

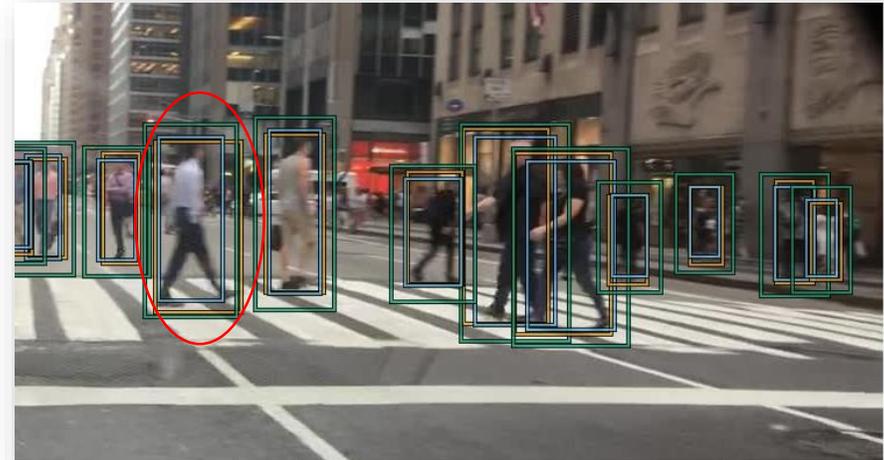
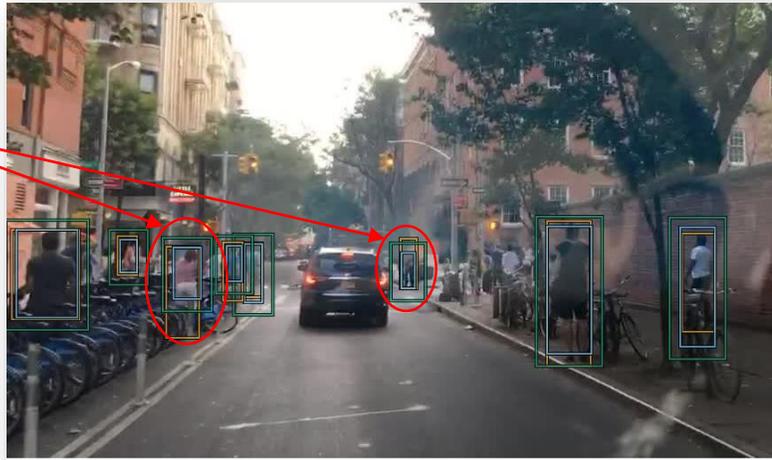


No box-wise guarantee

Coordinate-Wise Conformalization

# APPLICATION TO PEDESTRIAN LOCALIZATION BOX-WISE CONFORMALIZATION

Out of prediction set examples



Out of prediction set : Ground Truth errors identification

False negative: no conformalization

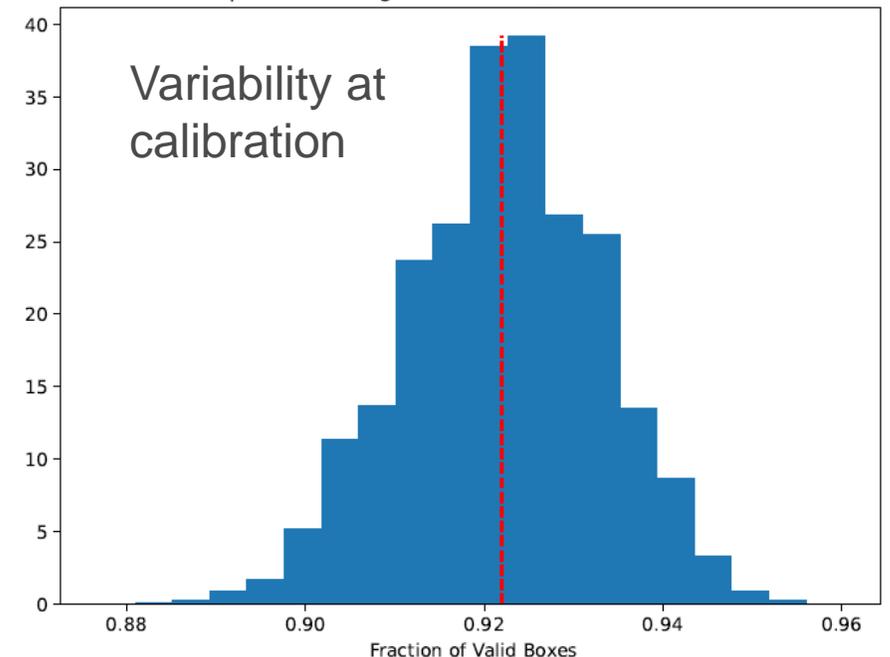




The probabilistic guarantees obtained from Conformal Prediction methods are subject to several **statistical pitfalls** and must be **carefully interpreted!**

- **Guarantees are “on average”** over calibration and test sets
- **Data requirements:** (i) **independence** (ii) **same distribution** for calibration and inference data.

Empirical coverage at box level, for a risk level 0.1



## Conclusions

 **Probabilistic guarantees** for object localization at various levels:

- Coordinate
- Bounding box
- Image

 Demonstration on a **pedestrian detection** use-case.

 Focus on several **statistical pitfalls**

## Future work

 Address the **full object detection problem**

 Study **link** between **probabilistic guarantees** and **safety-related risks** at system-level

 Analyze other **non-conformity scores**

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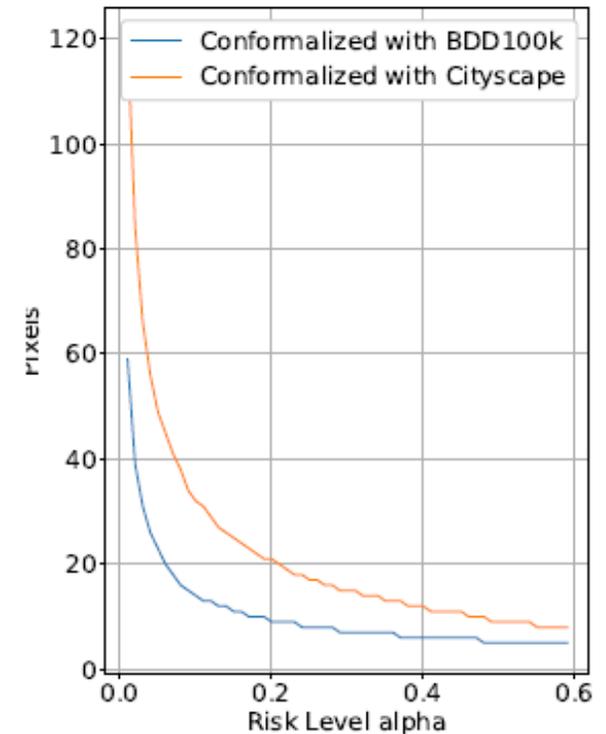
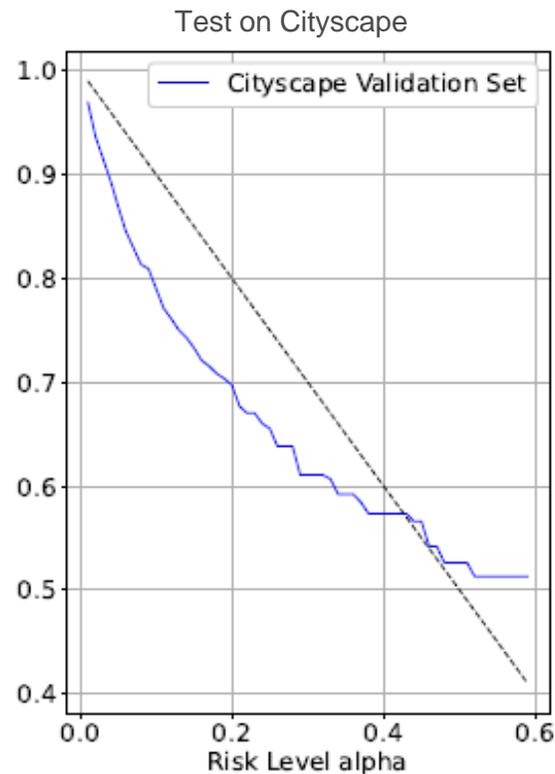
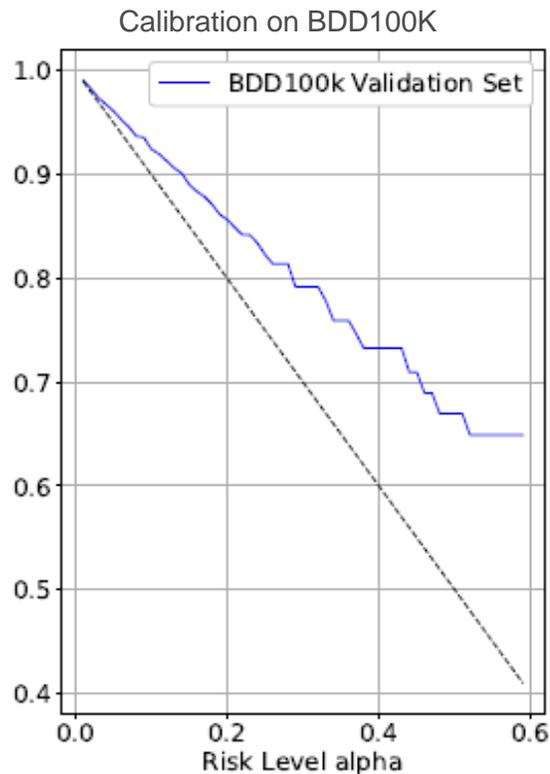
# APPENDIX



# STATISTICAL PITFALLS



Data samples used for calibration and inference must belong to the same data distribution



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