JAWS: Auditing Predictive Uncertainty Under Covariate Shift

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Abstract

We propose **JAWS**, a series of wrapper methods for distribution-free uncertainty quantification tasks under covariate shift, centered on the core method **JAW**, the **JA**ckknife+ **W**eighted with data-dependent likelihood-ratio weights. JAWS also includes computationally efficient **A**pproximations of JAW using higher-order influence functions: **JAWA**. Theoretically, we show that JAW relaxes the jackknife+'s assumption of data exchangeability to achieve the same finite-sample coverage guarantee even under covariate shift. JAWA further approaches the JAW guarantee in the limit of either the sample size or the influence function order under common regularity assumptions. Moreover, we propose a general approach to repurposing any distribution-free uncertainty quantification method and its guarantees to the task of risk assessment: a task that estimates the probability that the true label lies within a user-specified interval. We then propose **JAW-R** and **JAWA-R** as the repurposed versions of proposed methods for **R**isk assessment. Practically, JAWS outperform the state-of-the-art predictive inference baselines in a variety of biased real world data sets for both interval-generation and risk-assessment predictive uncertainty auditing tasks.

1 Introduction

Auditing the uncertainty under data shift Principled quantification of predictive uncertainty is crucial for enabling users to calibrate how much they should or should not trust a given prediction [Thiebes et al., 2021, Ghosh et al., 2021, Tomsett et al., 2020, Bhatt et al., 2021]. Uncertainty-based predictor auditing can be considered a type of uncertainty quantification performed *post-hoc*, for example by a regulator without detailed knowledge of a predictor's architecture and with limited resources [Schulam and Saria, 2019]. Data shift poses a major challenge to uncertainty quantification due to violation of the common assumption that the training and test data are exchangeable, or more specifically independent and identically distributed (i.i.d.) [Ovadia et al., 2019, Ulmer et al., 2020, Zhou and Levine, 2021, Chan et al., 2020]. Therefore, it is essential to develop convenient tools for users or regulators to audit predictive uncertainty even when training data is biased.

Predictor auditing: interval generation In this work we distinguish between two types predictive uncertainty auditing. We describe a first type by the task of *interval generation*, which refers to a common goal in the distribution-free uncertainty quantification literature: to generate a predictive interval (or confidence interval) that covers the true label with at least some user-specified probability. For instance, an auditor may wish to generate confidence intervals around a prediction that contain the true label with at least, say 90% probability.

Predictor auditing: risk assessment While predictive interval generation has been a central focus of the distribution-free uncertainty quantification literature, in some applications the converse computation may be more actionable: estimating the probability that a user-specified interval around a

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prediction contains the true label. We describe this type of predictor auditing task as *risk assessment* because a natural type of interval for a user to specify is one defined by a safe or acceptable error threshold around a prediction, where the goal is then to estimate the probability that the true label is within the error threshold (or the "risk" that it is outside the threshold). A concrete example of when such a risk-assessment audit may be more useful to a stakeholder than an interval-generation audit is the setting of chemical or radiation therapy dose prediction for cancer treatment, where administering the correct dosage within $5\% - 10\%$ is safety-critical (see Appendix A.1 for more details). As we will demonstrate, any interval generation method with a distribution-free coverage guarantee can be repurposed for the task of risk assessment with minor modifications (as we will see in Section 3.3).

Coverage We assume a standard regression setup with training data $\{(X_1, Y_1), ..., (X_n, Y_n)\}$ and a test point (X_{n+1}, Y_{n+1}) where $(X_i, Y_i) \in \mathbb{R}^d \times \mathbb{R}$ for all $i \in \{1, ..., n+1\}$. Also, we denote a predictor as $\widehat{\mu} = \mathcal{A}(\{(X_1, Y_1), ..., (X_n, Y_n)\})$, where $\mathcal{A}$ is the algorithm for fitting the model. For predictive or confidence interval (or region) $\widehat{C}^{\text{audit}}_{n,\alpha} : \mathbb{R}^d \to \{\text{subsets of } \mathbb{R}\}$, a *coverage guarantee* aims to give a lower bound to the probability that the interval covers a test point's true label:

$$\mathbb{P}\Big\{Y_{n+1} \in \widehat{C}^{\text{audit}}_{n,\alpha}(X_{n+1}) \geq 1 - \alpha\Big\} \tag{1}$$

The coverage guarantee provides the basis for both interval generation and risk assessment auditing, though it is important to note that in this work we focus on marginal rather than conditional coverage (see [Foygel Barber et al., 2021] for more details on this distinction). Standard conformal prediction methods [Vovk et al., 2005, Shafer and Vovk, 2008, Vovk, 2013] along with the jackknife+ and related methods [Barber et al., 2021], which we refer to together as "predictive inference" methods, provide a framework for generating predictive intervals with finite-sample guaranteed coverage.

Exchangeability Standard conformal prediction and the jackknife+ rely on two crucial notions of *exchangeability*: data exchangeability, that is that the training and test data are all exchangeable (e.g., i.i.d.); and secondly that the model-fitting algorithm $\mathcal{A}$ treats the data symmetrically [Barber et al., 2022]. In common situations of dataset shift, however, the data exchangeability assumption is violated. Empirically, the coverage performance of standard conformal prediction methods can suffer under data shift [Tibshirani et al., 2019, Podkopaev and Ramdas, 2021]. In this work, we build on the jackknife+ method due to its beneficial compromise between the statistical and computational limitations of other conformal prediction methods [Barber et al., 2021]. However, jackknife+ coverage performance can still degrade in the presence of dataset shift, such as shown in Figure 1.

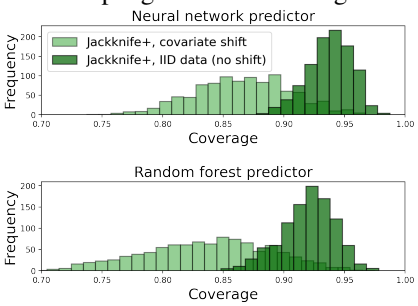


Figure 1: Jackknife+ loses coverage on the airfoil dataset under covariate shift (details in Section 4).

In this work, we develop JAWS, a series of wrapper methods for distribution-free uncertainty quantification under covariate shift. Table 1 gives a summary of key properties (details in Section 3).

Our contributions can summarized as follows:

1. We develop JAW: a jackknife+ method with data-dependent likelihood-ratio weights for uncertainty quantification under covariate shift. We show that JAW achieves the same rigorous, finite-sample coverage guarantee as jackknife+ [Barber et al., 2021] while relaxing the data exchangeability assumption to allow for covariate shift.
2. We develop JAWA: a sequence of computationally efficient approximations to JAW that uses higher-order influence functions to avoid retraining. Under assumptions outlined in Giordano et al. [2019a] regarding the regularity of the data, Hessian of the objective (local strong convexity), and the existence and boundedness of higher order derivatives, we provide an asymptotic guarantee for the JAWA coverage in the limit of either the sample size or influence function order.
3. We propose a general approach to repurposing any distribution-free predictive inference method to the risk assessment task, with rigorous guarantees for the coverage probability estimation. Our approach applies to methods that assume exchangeable data and to methods like JAW and JAWA that allow for covariate shift—JAW-R and JAWA-R refer to the risk assessment versions.
4. We demonstrate superior empirical performance of JAWS over other distribution-free predictive inference baselines on a variety of benchmark datasets under covariate shift.

Table 1: Summary of key properties for JAWS methods (details in Section 3).

Method	Task	Guarantee (under covariate shift)		Avoids retraining
		Finite sample	Asymptotic	
JAW	Interval generation	✓	✓	✗
JAWA	Interval generation	✗	✓	✓
JAW-R	Risk assessment	✓	✓	✗
JAWA-R	Risk assessment	✗	✓	✓

2 Background and related Work

2.1 Standard conformal prediction

Conformal prediction has grown into a broad research field since arising in the 1990s [Vovk et al., 2005, Shafer and Vovk, 2008, Vovk et al., 2009, Vovk, 2013, Burnaev and Vovk, 2014]. With the exchangeability assumptions in Section 1, standard conformal prediction methods generate a score distribution for the data using a function $\mathcal{S} : \mathbb{R}^d \times \mathbb{R} \to \mathbb{R}$ (such as the residual score $\mathcal{S}(X_i, Y_i) = |Y_i - \widehat{\mu}(X_i)|$) to determine the prediction interval. These estimates are *distribution-free* [Lei and Wasserman, 2014, Lei et al., 2018] in that they apply to any exchangeable data distribution.

Split conformal and full conformal are two main types of standard conformal prediction, each bears its own limitation [Vovk et al., 2005, Shafer and Vovk, 2008]. Split conformal generates scores on labeled holdout data and is computationally efficient due to not requiring retraining, but sample splitting to obtain the holdout set can reduce model accuracy [Papadopoulos, 2008, Lei et al., 2018, Vovk, 2012]. On the other hand, full conformal prediction avoids the holdout set requirement, but at the expense of the heavy computational cost of retraining the model on every possible target value (or, in practice, on a fine grid of target values) [Ndiaye and Takeuchi, 2019, Zeni et al., 2020].

2.2 Covariate shift

Under the *covariate shift* assumption, the $Y|X$ distribution is assumed to be the same between training and test data but the marginal X distributions may change [Sugiyama et al., 2007, Shimodaira, 2000]:

$$(X_i, Y_i) \overset{\text{i.i.d.}}{\sim} P_X \times P_{Y|X}, i = 1, ..., n; \qquad (X_{n+1}, Y_{n+1}) \sim \tilde{P}_X \times P_{Y|X}, \text{ independently} \tag{2}$$

Rich literature exist in this domain—see Appendix A.2 for more details. Uncertainty quantification is relatively less explored under covariate shift, though recent work [Ovadia et al., 2019, Zhou and Levine, 2021, Chan et al., 2020] emphasizes its importance, especially in deep learning.

2.3 Conformal prediction under covariate shift and beyond exchangeability

Tibshirani et al. [2019] develop the idea of *weighted exchangeability* for adapting conformal prediction to the covariate shift setting. Random variables $V_1, ..., V_n$ are weighted exchangeable with weight functions $w_1, ..., w_n$ if their joint density f can be factorized as $f(v_1, ..., v_n) = \prod_{i=1}^n w_i(v_i) \cdot g(v_1, ..., v_n)$, where g is independent of ordering on its inputs. For covariate shift as in (2), the data $\{(X_i, Y_i)\}$ are weighted exchangeable with weights given by the likelihood ratio $w(X_i) = \mathrm{d}\tilde{P}_X(X_i)/\mathrm{d}P_X(X_i)$ [Tibshirani et al., 2019].

If $\{V_i\}$ represents a set of scores for standard conformal prediction, then we can represent the empirical distribution of $\{V_i\}$ as $\frac{1}{n+1}\sum_{i=1}^n \delta_{V_i} + \frac{1}{n+1}\delta_\infty$, where δ_{V_i} denotes a point mass at V_i [Barber et al., 2022]. By extension, weighted conformal prediction uses the *weighted* empirical distribution defined as $\sum_{i=1}^n p_i^w(x)\delta_{V_i} + p_{n+1}^w(x)\delta_\infty$, with weights given by

$$p_i^w(x) = \frac{w(X_i)}{\sum_{j=1}^n w(X_j) + w(x)}, i = 1, ..., n, \qquad \text{and} \qquad p_{n+1}^w(x) = \frac{w(x)}{\sum_{j=1}^n w(X_j) + w(x)} \tag{3}$$

where $p_i^w(x)$ can be thought of as a normalized likelihood ratio weight for each $i \in \{1, ..., n+1\}$. Corollary 1 in [Tibshirani et al., 2019] provides the coverage guarantee of weighted conformal prediction that takes the form of (1) but relaxes the exchangeable data assumption to allow for covariate shift. However, weighted split and weighted full conformal inherit the same statistical and computational limitations, respectively, from their standard (exchangeable) variants.

The recent work of [Barber et al., 2022] provides a novel extension of conformal prediction and the jackknife+ to unknown violations of the exchangeability assumption, including "nonexchangeable jackknife+" defined with fixed weights. The key difference between the nonexchangeable jackknife in Barber et al. [2022] and our proposed JAW method is that Barber et al. [2022] use fixed weights to compensate for unknown exchangeability violations (not limited to covariate shift) but at the expense of a bounded but generally nonzero "coverage gap" (drop in guaranteed coverage relative to if the data were exchangeable), whereas our JAW method with data-dependent weights assumes covariate shift but does not suffer from any similar coverage gap. See Appendix A.3 for more details.

2.4 Jackknife+

The jackknife+ [Barber et al., 2021], which is closely related to cross conformal prediction [Vovk et al., 2018], offers a compromise between the statistical limitation of split conformal and the computational limitation of full conformal, at the cost of a slightly weaker coverage guarantee. The jackknife+ predictive interval can most easily be understood as a modification to a predictive interval from the classic jackknife resampling method [Miller, 1974, Steinberger and Leeb, 2018, 2016] that it builds on. For some values $v_1, ..., v_n$, let $\widehat{q}^{-}_{n,\alpha}\{v_i\}$ and $\widehat{q}^{+}_{n,\alpha}\{v_i\}$ respectively denote the level α and $1-\alpha$ quantiles of the empirical distribution $\frac{1}{n+1}\sum_{i=1}^{n}\delta_{v_i} + \frac{1}{n+1}\delta_{-\infty}$. Then, denoting the model trained without the ith point as $\widehat{\mu}_{-i} = \mathcal{A}\big((X_1, Y_1), ..., (X_{i-1}, Y_{i-1}), (X_{i+1}, Y_{i+1}), ..., (X_n, Y_n)\big)$ and the leave-one-out residual $R_i^{LOO} = |Y_i - \widehat{\mu}_{-i}(X_i)|$, the classic jackknife prediction interval is given by

$$\widehat{C}^{\text{jackknife}}_{n,\alpha}(X_{n+1}) = \Big[\widehat{q}^{-}_{n,\alpha}\{\widehat{\mu}(X_{n+1}) - R_i^{LOO}\}, \widehat{q}^{+}_{n,\alpha}\{\widehat{\mu}(X_{n+1}) + R_i^{LOO}\}\Big]. \tag{4}$$

In contrast, we obtain the jackknife+ predictive interval in Barber et al. [2021] by replacing the full model prediction $\widehat{\mu}(X_{n+1})$ in (4) with $\widehat{\mu}_{-i}(X_{n+1})$:

$$\widehat{C}^{\text{jackknife+}}_{n,\alpha}(X_{n+1}) = \Big[\widehat{q}^{-}_{n,\alpha}\{\widehat{\mu}_{-i}(X_{n+1}) - R_i^{LOO}\}, \widehat{q}^{+}_{n,\alpha}\{\widehat{\mu}_{-i}(X_{n+1}) + R_i^{LOO}\}\Big]. \tag{5}$$

[Barber et al., 2021] prove that, with the same exchangeability assumptions as in standard conformal prediction, the jackknife+ prediction interval satisfies

$$\mathbb{P}\{Y_{n+1} \in \widehat{C}^{\text{jackknife+}}_{n,\alpha}(X_{n+1})\} \geq 1 - 2\alpha \tag{6}$$

2.5 Approximating leave-one-out models with higher-order influence functions

Influence functions (IFs) [Cook, 1977] have a long history in robust statistics for estimating the dependence of parameters on sample data, and recently IFs have become more widespread in machine learning for uses including model interpretability Koh and Liang [2017] and approximating classic resampling uncertainty quantification methods including bootstrap [Schulam and Saria, 2019], jackknife, and leave-k-out cross validation [Giordano et al., 2019b] [Giordano et al., 2019a]. In each of these cases IFs enable approximation of the parameters that would be obtained by retraining the model on resampled data by instead estimating the effect of a corresponding reweighting. Alaa and Van Der Schaar [2020] proposed approximating the leave-one-out models required by the jackknife+ with higher-order IFs, but their work assumes exchangeable or i.i.d. train and test data.

Let $\hat{\theta}$ denote the fitted parameters for predictor $\widehat{\mu}$ trained on the full training data. Given Assumptions 1-4 in Giordano et al. [2019a]—which require that $\hat{\theta}$ is a local minimum of the objective function, that the objective is $k+1$ times continuously differentiable with bounded norms, and that the objective is strongly convex in the neighborhood of $\hat{\theta}$—then the k-th order leave-one-out IF refers to the k-th order directional derivative of the model parameters $\hat{\theta}$ with respect to the data weights, in the direction of the leave-one-out change in weights (See A.4 for more details). With each of these kth order leave-one-out IFs for $k \in \{1, ..., K\}$, denoted with condensed notation $\delta^k_{-i}\hat{\theta}$, we can construct a K-th order Taylor series approximation to estimated the leave-one-out model parameters $\hat{\theta}_{-i}$:

$$\hat{\theta}^{\text{IF-}K}_{-i} := \hat{\theta} + \sum_{k=1}^{K} \frac{1}{k!}\delta^k_{-i}\hat{\theta} \tag{7}$$

In this work we implement the algorithm proposed by Giordano et al. [2019a] to compute higher-order IFs, a recursive procedure based on foreward-mode automatic differentiation [Maclaurin et al., 2015] for memory efficiency in computing higher-order directional derivatives. Our introduction of IFs is highly simplified—we refer to Appendix A.4 and to Giordano et al. [2019a] for more details.

3 Proposed approach and theoretical results

3.1 JAW: Jackknife+ weighted with data-dependent weights

We present **JAW**, the **JA**ckknife+ **W**eighted with data-dependent likelihood-ratio weights, defined by the following predictive interval:

$$\widehat{C}^{\text{JAW}}_{n,\alpha}(X_{n+1}) = \left[\widehat{q}^{-}_{n,\alpha}\{p^w_i(X_{n+1}) \cdot \delta_{\widehat{\mu}_{-i}(X_{n+1})-R^{LOO}_i}\},\ \widehat{q}^{+}_{n,\alpha}\{p^w_i(X_{n+1}) \cdot \delta_{\widehat{\mu}_{-i}(X_{n+1})+R^{LOO}_i}\}\right] \tag{8}$$

where $R^{LOO}_i = \left|\widehat{\mu}_{-i}(X_i) - Y_i\right|$, where $\widehat{q}^{-}_{n,\alpha}\{p^w_i(X_{n+1}) \cdot \delta_{\widehat{\mu}_{-i}(X_{n+1})-R^{LOO}_i}\}$ denotes the level α quantile of the empirical distribution $\sum_{i=1}^{n}\left[p^w_i(X_{n+1}) \cdot \delta_{\widehat{\mu}_{-i}(X_{n+1})-R^{LOO}_i}\right] + p^w_{n+1}(X_{n+1}) \cdot \delta_{-\infty}$, where $\widehat{q}^{+}_{n,\alpha}\{p^w_i(X_{n+1}) \cdot \delta_{\widehat{\mu}_{-i}(X_{n+1})+R^{LOO}_i}\}$ is the level $1-\alpha$ quantile for $\sum_{i=1}^{n}\left[p^w_i(X_{n+1}) \cdot \delta_{\widehat{\mu}_{-i}(X_{n+1})+R^{LOO}_i}\right] + p^w_{n+1}(X_{n+1}) \cdot \delta_{\infty}$, and the $p^w_i(X)$ are as defined in (3).

We show that $\widehat{C}^{\text{JAW}}_{n,\alpha}(X_{n+1})$ satisfies the same coverage guarantee as the jackknife+ except relaxing the data exchangeability assumption to allow for covariate shift, which we state formally as follows:

Theorem 1. *With covariate shift between the training and test data, the JAW interval in (8) satisfies*

$$\mathbb{P}\{Y_{n+1} \in \widehat{C}^{\text{JAW}}_{n,\alpha}(X_{n+1})\} \geq 1 - 2\alpha \tag{9}$$

Remark. The results from Tibshirani et al. [2019] do not directly imply Theorem 1. Applying the approach from Tibshirani et al. [2019] to the jackknife+ entails treating $\widehat{\mu}_{-i}(X_{n+1}) \pm R^{LOO}_i$ as implicit nonconformity scores. Tibshirani et al. [2019] assume that the nonconformity scores for the training data $\{V_1, ..., V_n\}$ are weighted exchangeable with the nonconformity score for the test point V_{n+1}. But, observe that for $i \in \{1, ..., n\}$, $\widehat{\mu}_{-i}$ is trained on $n-1$ datapoints, whereas $\widehat{\mu}_{-(n+1)} = \widehat{\mu}$ is trained on n datapoints. Thus, no reweighting can make $\widehat{\mu}_{-i}$ equivalent to $\widehat{\mu}$ in distribution, and therefore $\widehat{\mu}_{-i}(X_{n+1}) \pm R^{LOO}_i$ and $\widehat{\mu}(X_{n+1}) \pm R^{LOO}_{n+1}$ are not weighted exchangeable.

Proof sketch: Our proof technique for Theorem 1 extends the jackknife+ coverage guarantee proof in Barber et al. [2021] to the covariate shift setting for JAW using likelihood ratio weights as in Tibshirani et al. [2019]. The outline is as follows:

1. *Setup*: Following Barber et al. [2021], we define a set of leave-*two*-out models $\{\tilde{\mu}_{-(i,j)}\}$. We then generalize the notion of "strange" points described in Barber et al. [2021] to covariate shift.
2. *Bounding the total normalized weight of strange points*: We establish deterministically that the total normalized weight of strange points cannot exceed 2α.
3. *Weighted exchangeability using the leave-two-out models*: Using the leave-two-out model construction, we leverage weighted exchangeability to show that the probability that a test point $n+1$ is strange is thus bounded by 2α.
4. *Connection to JAW*: Lastly, we show that the JAW interval can only fail to cover the test label value Y_{n+1} if $n+1$ is a strange point.

While JAW assumes access to oracle likelihood ratio weights, in practice this information often has to be estimated. See Appendix D.5 for a discussion and experiments of JAW with estimated weights.

3.2 JAWA: Using higher-order influence functions to approximate JAW without retraining

For computationally efficient JAW **A**pproximations that avoid retraining n leave-one-out models, we propose the JAWA sequence, which approximates the leave-one-out models required by JAW using higher-order influence functions. For each training point $i \in \{1, ..., n\}$, define the K-th order influence function approximation to the leave-one-out refit parameters $\hat{\theta}_{-i}$, obtained from Algorithm 4 in Giordano et al. [2019a], as given by equation (7), and let $\widehat{\mu}^{\text{IF-}K}_{-i}$ be the model with with these approximated parameters $\hat{\theta}^{\text{IF-}K}_{-i}$ for each $i \in \{1, ..., n\}$. Then, the prediction interval for the K-th order JAWA (i.e., for JAWA-K) is given by

$$\begin{aligned}\widehat{C}^{\text{JAWA-}K}_{n,\alpha}(X_{n+1}) = \Big[&\widehat{q}^{-}_{n,\alpha}\{p^w_i(X_{n+1}) \cdot \delta_{\widehat{\mu}^{\text{IF-}K}_{-i}(X_{n+1})-R^{\text{IF-}K,LOO}_i}\},\\ &\widehat{q}^{+}_{n,\alpha}\{p^w_i(X_{n+1}) \cdot \delta_{\widehat{\mu}^{\text{IF-}K}_{-i}(X_{n+1})+R^{\text{IF-}K,LOO}_i}\}\Big]\end{aligned} \tag{10}$$

with $R_i^{\text{IF-}K,LOO} = \left|\widehat{\mu}_{-i}^{\text{IF-}K}(X_i) - Y_i\right|$, quantiles defined analogously to JAW, and $p_i^w(X)$ as in (3).

We now provide an asymptotic coverage guarantee for $\widehat{C}_{n,\alpha}^{\text{JAWA-}K}(X_{n+1})$ that holds either in the limit of the sample size or in the limit of the influence function order, under regularity conditions formally described in Giordano et al. [2019a]. These assumptions concern the regularity and continuity of the training data, local convexity of the objective (or that the Hessian is strongly positive definite), and the existence and boundedness of the objective's 1st through $K+1$th order directional derivatives.

Theorem 2. *Let Assumptions 1 - 4 and either Condition 2 or Condition 4 from Giordano et al. [2019a] hold uniformly for all n. Then, with covariate shift between the training and test data, in either the limit of the training sample size $n \to \infty$ or in the limit of the influence function order $K \to \infty$, the JAWA-K interval in (10) satisfies*

$$\mathbb{P}\{Y_{n+1} \in \widehat{C}_{n,\alpha}^{\text{JAWA-}K}(X_{n+1})\} \geq 1 - 2\alpha \tag{11}$$

We leave the proof to Appendix C.2, but we note that the result follows by combining Propositions 2 and 3 in Giordano et al. [2019a] with the JAW coverage guarantee that we present in Theorem 1.

3.3 Risk assessment under covariate shift

We now propose a general approach to adapting any weighted predictive inference method and associated covariate-shift coverage guarantee to the task of risk assessment, that is, estimating the probability that a true test point's label Y_{n+1} lies within a given arbitrary, finite interval $I = [a_L, a_U]$. We also provide a similar result for uniform-weighted methods that assume exchangeable data, but for brevity we defer the exchangeable data approach and result to Appendix B.1.

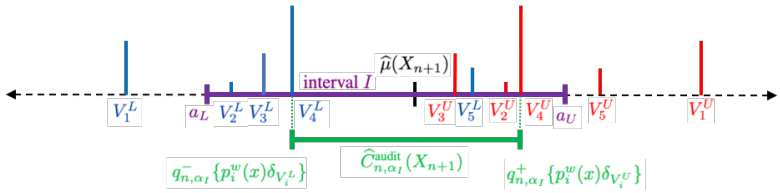


Figure 2: Illustration of terms involved in computing $\alpha_I^{\text{w-audit}}$. The interval $I = [a_L, a_U]$ is shown in violet, the values $\{V_i^L\}$ in blue, the values $\{V_i^U\}$ in red, and the interval $\widehat{C}_{n,\alpha}^{\text{audit}}(X_{n+1})$ in green. Each vertical line at a location V_i on the real line represents a point mass δ_{V_i} with height corresponding to the normalized likelihood ratio weight $p_i^w(x)$.

The key idea is as follows: given I (violet interval in Figure 2), leverage a predictive inference method's weighted predictive *distribution* (blue and red lines in Figure 2; quantiles on this distribution determine predictive intervals) to find the method's largest predictive interval contained in I (green interval in Figure 2), and then to use this predictive interval's target coverage to estimate the coverage of I. That is, for a predictive inference method with data-dependent weights for generating intervals $\widehat{C}_{n,\alpha}^{\text{audit}}(X_{n+1}) = \left[q_{n,\alpha}^{-}\{p_i^w(x)\delta_{V_i^L}\},\ q_{n,\alpha}^{+}\{p_i^w(x)\delta_{V_i^U}\}\right]$ under covariate shift, define $\alpha_I^{\text{w-audit}}$ as

$$\alpha_I^{\text{w-audit}} = \min\left(\left\{\alpha' \ :\ a_L \leq\ q_{n,\alpha'}^{-}\{p_i^w(x)\delta_{V_i^L}\}\ ,\ q_{n,\alpha'}^{+}\{p_i^w(x)\delta_{V_i^U}\} \leq a_U\right\}\right). \tag{12}$$

Then, we estimate the coverage probability for interval I as the predictive inference method's target coverage for the interval corresponding to $\alpha_I^{\text{w-audit}}$:

$$\widehat{p}\{Y_{n+1} \in I\} \geq \begin{cases} 1 - \alpha_I^{\text{w-audit}} & \text{if } \alpha_I^{\text{w-audit}} \text{ exists} \\ 0 & \text{otherwise} \end{cases}. \tag{13}$$

While the target coverage is used in (13), the following theorem gives the worst-case risk assessment guarantee for covariate shift (proof in Appendix C.3; see Appendix B.1 for the analogous exchangeable data result). Corollary 1 in Appendix B.2 and corollary 2 in Appendix B.3 follow from Theorem 3 and give the risk assessment guarantees for JAW-R and JAWA-R respectively.

Theorem 3. *Given a predictive inference method for generating intervals $\widehat{C}_{n,\alpha}^{audit}(X_{n+1}) = \left[q_{n,\alpha}^{-}\{p_i^w(x)\delta_{V_i^L}\},\ q_{n,\alpha}^{+}\{p_i^w(x)\delta_{V_i^U}\}\right]$ with coverage guarantee $\mathbb{P}\{Y_{n+1} \in \widehat{C}_{n,\alpha}^{audit}(X_{n+1})\} \geq$*

$1 - c_1\alpha - c_2$ *under covariate shift where* $c_1, c_2 \geq 0$ *are constants, suppose we are given some arbitrary interval* $I = [a_L, a_U] \subseteq \mathbb{R}$ *(assuming* $a_L \leq a_U$ *WLOG). Define* $\alpha_I^{\text{w-audit}}$ *as follows:*

$$\alpha_I^{\text{w-audit}} = \min\left(\left\{\alpha' \ : \ a_L \leq \ q^-_{n,\alpha'}\{p_i^w(x)\delta_{V_i^L}\} \ , \ q^+_{n,\alpha'}\{p_i^w(x)\delta_{V_i^U}\} \leq a_U\right\}\right). \tag{14}$$

Then, I has coverage given by

$$\mathbb{P}\{Y_{n+1} \in I\} \geq \begin{cases} 1 - c_1\alpha_I^{\text{w-audit}} - c_2 & \text{if } \alpha_I^{\text{w-audit}} \text{ exists and } \alpha_I^{\text{w-audit}} < \frac{1-c_2}{c_1} \\ 0 & \text{otherwise} \end{cases}. \tag{15}$$

4 Experiments[1]

4.1 Datasets and creation of covariate shift

We conduct experiments on five UCI datasets Dua and Graff [2017] with various dimensionality (Table 2): airfoil self-noise, red wine quality prediction [Cortez et al., 2009], wave energy converters, superconductivity [Hamidieh, 2018], and communities and crime [Redmond and Baveja, 2002].

Table 2: Statistics for the UCI datasets. Only the first 2000 samples were used for the wave and superconductivity datasets (for wave, the first 2000 samples of Adelaide data).

Dataset	# of samples	# of features	label range
Airfoil self-noise (airfoil)	1503	5	[103.38, 140.987]
Red wine quality (wine)	1599	11	[3, 8]
Wave energy converters (wave)	2000	48	[1226969, 1449349]
Superconductivity (superconduct)	2000	81	[0.2, 136.0]
Communities and crime (communities)	1994	99	[0, 1]

We use exponential tilting to induce covariate shift on the test data, based on the approach used in Tibshirani et al. [2019]. We first randomly sample 200 points for the training data, and then sample the biased test data from the remaining datapoints that are not used for training with probabilities proportional to exponential tilting weights. See Appendix D.1 for additional details.

4.2 Baselines

Baselines for comparison to JAW We compared JAW to the following baselines:

1. **Naive** estimates are based on training data residuals $|Y_i - \widehat{\mu}(X_i)|$, which suffers from overfitting.
2. **Jackknife** uses the classic Jackknife resampling as in (4).
3. **Jackknife+** follows (5), which replaces the prediction $\widehat{\mu}(X_{n+1})$ in jackknife with $\widehat{\mu}_{-i}(X_{n+1})$.
4. **Jackknife-mm** is a more conservative alternative to the jackknife+ method that guarantees coverage at the $1-\alpha$ level with exchangeable data, but usually with overly-wide intervals.

$$\widehat{C}^{\text{jackknife-mm}}_{n,\alpha}(X_{n+1}) = \left[\min_{i=1,\ldots,n} \widehat{\mu}_{-i}(X_{n+1}) - \widehat{q}^+_{n,\alpha}\{R_i^{LOO}\}, \max_{i=1,\ldots,n} \widehat{\mu}_{-i}(X_{n+1}) + \widehat{q}^+_{n,\alpha}\{R_i^{LOO}\}\right]$$

5. **CV+** (cross validation) similar to jackknife+ except splits data into k portions and replaces the $\widehat{\mu}_{-i}(X_{n+1})$ with $\widehat{\mu}_{-k}(X_{n+1})$, the model trained with the kth subset removed.
6. **Split** method follows the split conformal prediction and use half of the data for training and the other half of the data for generating the nonconformal scores.
7. **Weighted split** version of split conformal with likelihood ratio weights for covariate shift, as in Tibshirani et al. [2019].

Baselines for comparison to JAWA For influence function orders $K \in \{1, 2, 3\}$, we compared the proposed JAWA-K method with K-th order influence function approximations of the jackknife-based baselines that we used as comparisons to JAW—we thus refer to these approximations as IF-K jackknife, IF-K jackknife+, and IF-K jackknife-mm. Each baseline compared to JAWA-K is thus also approximated with the same K-th order leave-one-out influence function models.

[1] Additional experimental analysis and a link to code for all experiments and included in Appendices D and E

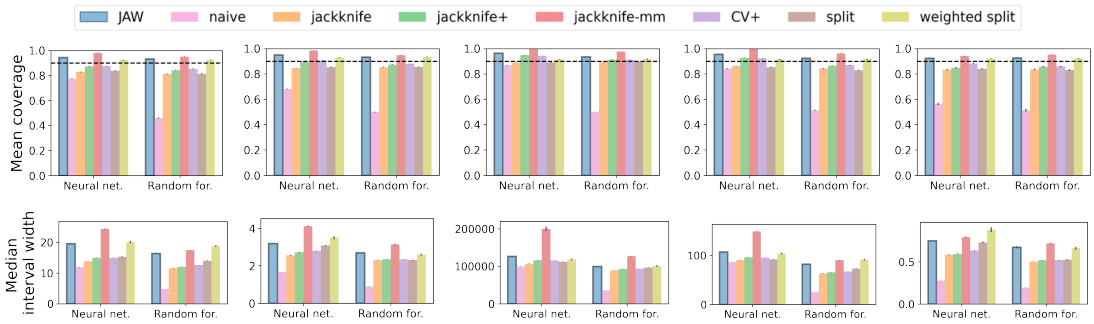
4.3 Experimental results

We report experimental results on the interval generation task for both JAW and JAWA and on the risk assessment task for JAW, compared to baselines. Additional experimental details and supplementary experiments can be found in Appendix D, including for estimated likelihood ratio weights in D.5, ablation study with shift magnitudes in D.6, and coverage histograms in D.9.

4.3.1 Interval generation results for JAW: coverage and interval width

Figure 3 compares JAW and its baselines, firstly regarding mean coverage and secondarily regarding median interval width, on all five UCI datasets for both neural network and random forest predictors, averaged over 200 experimental replicates. See Appendix D.2 for predictor function details. Meeting the target coverage level of $1 - \alpha$ is the primary goal of the interval-generation audit task, but for methods that meet or nearly meet the target coverage level, smaller interval widths are more informative. Additionally, smaller variance in coverage indicates a more reliable or consistent method.

As seen in Figure 3, the JAW predictive interval coverage is above the target level of 0.9 across all datasets, for both random forest and neural network $\widehat{\mu}$ functions, along with the jackknife-mm and weighted split methods. However, JAW's interval widths are generally smaller and thus more informative than those of jackknife-mm (which are often overly large, as noted in Barber et al. [2021]). Weighted split and JAW perform similarly on mean coverage and median interval width (both methods have coverage guarantees under covariate shift), but JAW avoids sample splitting and as a result has lower coverage variance than weighted split for all dataset and predictor conditions (see Appendix D.3), which suggests that JAW's predictive intervals are more reliable.



(a) Airfoil (b) Wine (c) Wave (d) Superconduct (e) Communities

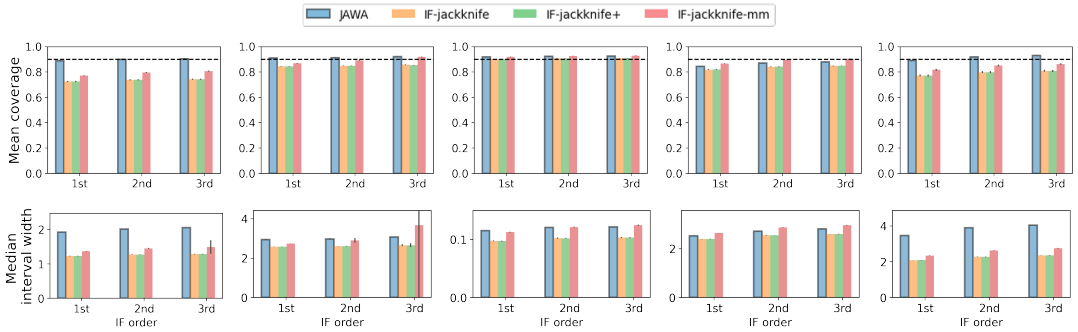
Figure 3: Mean coverage (first row) and median interval width (second row) for neural network and random forest predictors on UCI datasets. Dashed line is the target coverage level ($1 - \alpha$ = 0.9). Error bars show the standard error of 1000 repeated experiments.

4.3.2 Interval generation results for JAWA: coverage and interval width

Figure 4 evaluates JAWA coverage and interval width compared to baselines for IF orders $K \in \{1, 2, 3\}$ with a neural network predictor (see Appendix D.2 for predictor details). As with the JAW experiments, coverage at the target level of $1-\alpha = 0.9$ is the primary goal, while secondarily, smaller intervals are more informative for methods that meet or nearly meet target coverage. For three of the five datasets (airfoil, wine, and communities) JAWA is the only method that consistently reaches or nearly reaches the target coverage level. JAWA and all the baselines perform well on the wave datasets, and in the superconduct dataset JAWA still outperforms approximations of jackknife and jackknife+ for all IF orders. Appendix D.7 provides an an example empirical comparison of JAWA and JAW runtimes, which demonstrates that JAWA can be orders of magnitude faster to compute.

4.3.3 Risk assessment results for JAW: AUC

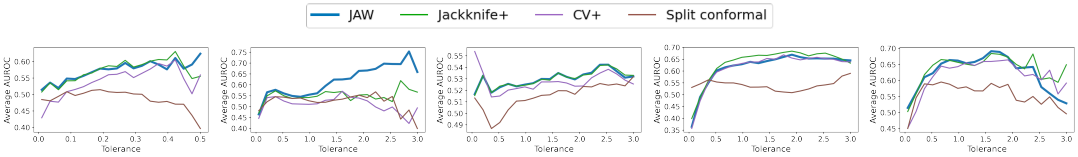
We now turn to the risk-assessment audit task where the goal is to evaluate a method's ability to estimate the coverage probability of a given interval, or to estimate the risk that the true label lies outside some error threshold τ around the original prediction $\widehat{\mu}(X_{n+1})$. Given prediction $\widehat{\mu}(X_{n+1})$ and error threshold τ, define the interval of interest as $I(\widehat{\mu}(X_{n+1}), \tau) = [\widehat{\mu}(X_{n+1}) - \tau,\ \widehat{\mu}(X_{n+1}) + \tau]$.



(a) Airfoil (b) Wine (c) Wave (d) Superconduct (e) Communities

Figure 4: Mean coverage (first row) and median interval width (second row) for JAWA and baselines for influence function orders $K \in \{1, 2, 3\}$. Dashed line is the target coverage level ($1 - \alpha = 0.9$). Error bar shows the standard error of 200 repeated experiments.

Then, the goal is to estimate the probability that $\widehat{\mu}(X_{n+1})$ is correct, i.e., $Y_{n+1} \in I(\widehat{\mu}(X_{n+1}), \tau)$; or incorrect, i.e., $Y_{n+1} \notin I(\widehat{\mu}(X_{n+1}), \tau)$. For four predictive interval-generation methods repurposed to the risk assessment task (JAW-R, jackknife+R, cross validation+R, and split conformal-R), Figure 5 reports the area under the receiver operating characteristic curve (AUROC) for values of τ selected with uniform spacing in the interval $[q^{-}_{n,0.05}\{R_i^{LOO}\},\ q^{+}_{n,0.05}\{R_i^{LOO}\}]$ (between the 0.05 and 0.95 quantiles of the leave-one-out residuals for a dataset) for five repeated experiments with the random forest predictor. Better performing methods have higher overall AUROC values for all values τ.



(a) Airfoil (b) Wine (c) Wave (d) Superconduct (e) Communities

Figure 5: AUROC values for different tolerance levels τ across the three datasets for the random forest predictor, averaged across 5 experiment replicates, with random forest $\widehat{\mu}$. See Appendix D.4 for additional experiments with neural network predictor.

JAW achieves AUROC values comparable to jackknife+ and CV+ for most tolerance levels and datasets. JAW moreover achieves higher AUROC values than its baselines in the wine dataset with the random forest predictor. These results suggest that, for risk assessment, JAW likely performs at least as well as its baselines and may offer a marginal benefit depending on the dataset and predictor.

5 Conclusion and Future Work

In this paper, we develop JAWS, a series of wrapper methods for distribution-free predictive uncertainty auditing tasks when the data exchangeability assumption is violated due to covariate shift. We also propose a general approach to repurposing any distribution-free predictive inference method to the risk assessment task. We provide rigorous finite-sample guarantees for JAW and JAW-R on the interval generation and risk assessment tasks respectively, and analogous asymptotic guarantees for the computationally efficient JAWA and JAWA-R. We moreover demonstrate superior performance of the JAWS series on a variety of datasets. In supplementary experiments we investigate a number of JAWS' limitations: weight estimation can address the assumed access to oracle weights with similar empirical performance (Appendix D.5), and JAW's increased coverage variance with covariate shift can be explained by reduced effective sample size due to importance weighting (Appendix D.6). Additionally, we note that JAW and JAWA share a limitation with weighted conformal prediction [Tibshirani et al., 2019] of potentially producing overly large intervals in extreme covariate shift cases where a test point's normalized likelihood ratio approaches or exceeds α. In the future, we aim to address the problems of reducing coverage variance and improving predictive interval sharpness.

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Checklist

The checklist follows the references. Please read the checklist guidelines carefully for information on how to answer these questions. For each question, change the default **[TODO]** to [Yes] , [No] , or [N/A] . You are strongly encouraged to include a **justification to your answer**, either by referencing the appropriate section of your paper or providing a brief inline description. For example:

- Did you include the license to the code and datasets? [Yes] See Appendix E.
- Did you include the license to the code and datasets? [No] The code and the data are proprietary.
- Did you include the license to the code and datasets? [N/A]

Please do not modify the questions and only use the provided macros for your answers. Note that the Checklist section does not count towards the page limit. In your paper, please delete this instructions block and only keep the Checklist section heading above along with the questions/answers below.

1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes]
   (b) Did you describe the limitations of your work? [Yes] We discuss the limitations of our method in the experiments (Section 4) and the conclusion (Section 5). We aim to resolve them in our future work.
   (c) Did you discuss any potential negative societal impacts of your work? [N/A] Our work are motivated from the predictor auditing perspective, which aims to facilitate more convenient quality estimation of the predictive models for the users and regulators.
   (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes]
2. If you are including theoretical results...
   (a) Did you state the full set of assumptions of all theoretical results? [Yes]
   (b) Did you include complete proofs of all theoretical results? [Yes] We include a proof sketch of Theorem 1 in Section 3.1, and have the full proof of all our theoretical results in Appendix C.
3. If you ran experiments...
   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [Yes] We include an anonymous link to our code repository in the supplemental material, Appendix E.
   (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? [Yes] See Section 4 and Appendix D.
   (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? [Yes] See Figure 3 and Figure 4. We repeat our experiments 1000 times for Figure 3 and 200 times for Figure 4 and report the standard error as error bars.

(d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? [Yes] We include the computational details in the supplemental materials, Appenidx E

4. If you are using existing assets (e.g., code, data, models) or curating/releasing new assets...
   (a) If your work uses existing assets, did you cite the creators? [Yes]
   (b) Did you mention the license of the assets? [N/A]
   (c) Did you include any new assets either in the supplemental material or as a URL? [Yes] We include an anonymous link to our code repository in the supplemental material.
   (d) Did you discuss whether and how consent was obtained from people whose data you're using/curating? [N/A]
   (e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? [N/A]
5. If you used crowdsourcing or conducted research with human subjects...
   (a) Did you include the full text of instructions given to participants and screenshots, if applicable? [N/A]
   (b) Did you describe any potential participant risks, with links to Institutional Review Board (IRB) approvals, if applicable? [N/A]
   (c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? [N/A]