Conformal Prediction in Limit Order Books: Calibration and Uncertainty Quantification of DeepLOB

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Abstract

This paper explores the application of conformal prediction to enhance deep learning models for price prediction in limit order books (LOBs). We employ a conformal wrapper by customizing TorchCP package to calibrate DeepLOB, a popular deep learning architecture for mid-price forecasting. The paper explore different score functions such as Adaptive Prediction Sets (APS), Regularized APS (RAPS), and Soft APS (SAPS) to construct prediction sets, and uses Temperature Scaling for probabilities calibration. The results demonstrate that calibrating DeepLOB can significantly improve its performance, interpretability and reliability, improving accuracy from 75% to 88% when acting only on prediction sets of size one. SAPS method achieves 92% prediction coverage with an average set size of 1.6 reducing Log Loss of the original model from 1.4 to 0.7. This study's results highlight the importance of machine learning calibration to improve models reliability and informativeness for better risk management and more informed algorithmic trading decisions.

Keywords: Conformal Prediction, Limit Order Book, Machine Learning

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1 Introduction

The limit order book (LOB) is an inventory of all outstanding limit orders for a specific financial instrument that is usually arranged by price levels and is updated in real-time as new orders are added, executed, or canceled (Gould et al. [2013]). Understanding and being able to forecast the dynamics of limit order books is crucial for market participants, such as traders, market makers, and regulators O'Hara [2005] and over the years different models have been developed to capture various aspects of limit order books, for example setting the optimal bid and ask based on market depth and order arrival Glosten and Milgrom [1985] and Kyle [1985].

Conventional econometric models, which assume linear correlations and normality of returns, are based on strong assumptions that are not necessarily represented in financial markets. Conversely, deep learning models have shown to be more successful in identifying intricate patterns and nonlinear relationships in high-dimensional LOB data, providing a more adaptable method that sacrifices simplicity and interpretability in favour of fewer assumptions Sirignano and Cont [2019]. The availability of LOB data and computing resources to train deep learning models has led to an upsurge in research output on this area, with DeepLOB being the most influential model (Zhang et al. [2019])..With the use of CNNs, DeepLOB is able to reduce the spatial component of the limit order book (depth) to a single data point, then the temporal component of these data points is then captured by LSTMs, and the output is then passed to a dense layer that makes predictions about the future price direction.

At the same time, there has been an increased attention to probabilistic machine learning, which tries to improve the interpretability and accuracy of model predictions. To provide an example, machine learning practitioners sometimes mistakenly believe that true probabilities are the same as the output of sigmoid and softmax functions, whereas in reality, these functions are just approximations of real probabilities and do not share the same properties of probability distributions. However, when the outputs are well-calibrated, these approximations can be handled with some degree of confidence almost as true probabilities. In contexts like the financial markets, where relying solely on data mining techniques like ROC curves and AUC to validate model performance can be extremely dangerous, as the majority of machine learning models are not well-calibrated, especially as complexity rises Guo et al. [2017]. Some of theses issues can be eased by conformal prediction, a framework for constructing prediction sets with guaranteed coverage under the assumption of exchangeability. The main idea is to assess how well a new example conforms to the previously observed data by minimizing a nonconformity measure, which quantifies the "strangeness" of an example relative to a set of other examples.

Conformal prediction is particularly valuable in financial applications, including LOB prediction, for several reasons:

- Distribution-free guarantees: Financial data often exhibit non-stationary and heavy-tailed distributions, conformal prediction's validity holds without assumptions about the underlying distribution.
- Uncertainty quantification: Conformal prediction provides well-calibrated prediction sets and prediction intervals, which are more informative than a point prediction.
- Model-agnostic approach: Conformal prediction can be applied as a wrapper around any predictive model, without the need to re-train a model whose training can be expensive and time consuming.
- Interpretability: This is a key issue for regulated entities and conformal predictors can provide consistent logits thresholds, which combined with the prediction sets and calibrated probabilities can help to understand better model outputs.

2 Related Work

2.1 Deep Learning in Limit Order Books

Over the past 10 years, the rise in popularity, capacity, and availability of deep learning models has brought significant improvements in mid-price LOB forecasting. Although much success has been registered in the use of LSTM networks due to their capacity to capture long-term dependencies on time series data, newer architectures like Transformers are also showing promising results. Zhang et al. [2019] introduced DeepLOB, an effective hybrid model with convolutional and LSTM layers, which performs better in the mid-price prediction task: the first ones extract spatial characteristics from the LOB, while the second ones record temporal dependencies. In the wake of DeepLOB, dozens of studies introduced similar architectures to try and improve the model of Zhang et al. [2019], such as Tsantekidis et al. [2020] with DeepOB, which deepens the architecture and introduces residual connections; Huang et al. [2021] with AttnLOB, using attention mechanisms to focus only on the most relevant features in the LOB; and Ye et al. [2020] with LOB-Net, using a dual-stream network for processing both order book and order flow information. In this regard, each of these models addresses some particular issues in LOB modeling: the ability to capture multi-scale temporal dynamics, incorporation of a variety of data sources, improvement of feature extraction, and increasing the model's capacity to direct much of its attention toward the most relevant segments of the input data.

2.2 Transformers Architectures

Bilokon et al. [2023] presented a comparative analysis between Transformer architectures and LSTM-based models for the LOB prediction problem. The study shows that transformer-based models achieve very small improvements when it comes to absolute price sequence prediction. For the tasks of predicting price movement and predicting difference sequences, the LSTM-based models yield far more reliable and better performances. A new unique architecture for Transformer-based models, modified for financial prediction, and a new model, DLSTM, are introduced. Based on this result, LSTM-based architectures are more effective for most financial time series prediction applications. Lately, the most favored alternative, as far as time series modeling is concerned, is the Mamba models, first introduced by Gu et al. [2023]. The main innovation of Mamba is this selective state space layer, allowing for the modeling of long-range dependencies within time series. While relatively new in the field, some researchers believe that Mamba models can do better than LSTM networks, as shown by Zhang and Li [2023], although their application in the industry is quite minimal.

2.3 Conformal Prediction in Financial Markets

Conformal prediction is a relatively young field, having been invented by Vovk et al. [2005] in the 2000s, so the relevant literature about its applications in financial markets is scarce. The application of conformal prediction to the calibration of various machine learning models for forecasting energy prices was explored by Amjad and Zhou [2022], and regarding market making, Luetkebohmert et al. [2021] applied conformal prediction to forecast intervals of market makers' net positions. Limit order book analysis based on conformal prediction has been little researched and not well-founded, as most deep learning frameworks do not implement rigorous uncertainty quantification. The present paper fills this gap by investigating how conformal prediction may improve DeepLOB, which became a benchmark model in LOB prediction. Our objectives are to calibrate the model, provide statistically reliable estimates of uncertainty, and evaluate the impact on overall performance.

3 Methodology

3.1 Data

We use the FI-2010 dataset and the LSE dataset , both used in Zhang et al. [2019] as a train and test dataset respectively, for a fair comparison with the original model.

3.1.1 FI-2010 Dataset

The FI-2010 dataset was introduced by Ntakaris et al. [2018]. It includes information from five stocks on the Nasdaq Nordic stock market, spanning ten consecutive trading days and each sample has 40 attributes, which correspond to ten levels of the limit order book (LOB), including volume and bid/ask prices. We make use of the dataset's rolling 5-day standardised version.

3.1.2 London Stock Exchange (LSE) Dataset

One year of data (January 3, 2017 to December 24, 2017) and five equities are covered by the LSE dataset and to avoid bidding times, trading hours are limited to 08:30:00 - 16:00:00 and the dataset is structured similarly to FI-2010, with 40 attributes per timestamp.

3.1.3 Data Preprocessing

We utilise the normalised FI-2010 dataset and apply the same z-score normalisation to the LSE dataset in order to guarantee the model's efficacy under various market circumstances and across different products. Specifically, we feed our model with the 100 most recent LOB states for each of the two datasets, yielding an input shape of (100, 40) for every sample.

To construct our target feature we adopt the method described in Zhang et al. [2019]:
1. Calculate the mean of previous and future k mid-prices:

$$m^{-}(t) = \frac{1}{k}\sum_{i=0}^{k} p_{t-i}, \quad m^{+}(t) = \frac{1}{k}\sum_{i=1}^{k} p_{t+i}$$

2. Compute the percentage change:

$$l_t = \frac{m^{+}(t) - m^{-}(t)}{m^{-}(t)}$$

3. Assign labels based on a threshold α:
   - If $l_t > \alpha$: up (+1)
   - If $l_t < -\alpha$: down (-1)
   - Otherwise: stationary (0)

This method allows us to focus on price direction, simplifying our forecast to a classification task.

3.2 Model

We use the pre-trained model from the original publication Zhang et al. [2019] in this paper. In order to forecast mid-price fluctuations in limit order books, DeepLOB is a hybrid deep neural network that incorporates long short-term memory (LSTM) networks and convolutional neural networks (CNNs).

The model architecture consists of:

- Convolutional layers to extract spatial features from the LOB data
- LSTM layers to capture temporal dependencies
- Fully connected layers for final prediction

3.3 Calibration

Currently, most conformal prediction libraries only accept scikit-learn models, so we implement a conformal prediction wrapper for PyTorch, adjusting the TorchCP library Riquelme et al. [2022]. Since we need to calibrate our model on the output of a softmax function, we employ a class-wise predictor Shi et al. [2013] and explore several conformal score functions:

- Adaptive Prediction Sets (APS) Romano et al. [2020]: APS dynamically adjusts the size of prediction sets based on the difficulty of each instance, while maintaining coverage.
- Regularized Adaptive Prediction Sets (RAPS) Angelopoulos et al. [2022]: An extension of APS, it incorporates a regularization term to balance between coverage and set size in the prediction sets.
- Sorted Adaptive Prediction Sets (SAPS) Huang et al. [2024]: SAPS further generalizes APS by discarding almost all the probability values except for the maximum softmax probability, mitigating the effect of tail probabilities.

4 Evaluation

To evaluate our conformal predictor applied to the DeepLOB model, we employ various metrics to assess both the probabilistic performance and the classification accuracy. We use probabilistic evaluation metrics for hyper-parameters tuning and to study the level calibration against the original model, as well as classification metrics to understand the effect of calibrating the base model on performance (Brier [1950], Good [1952], Murphy [1973], Powers [2011]). We test different metrics to optimize our hyper-parameters making sure the coverage is always met by penalizing values that violate it.

We evaluate two versions of our calibrated model, in one we sample at random from the prediction sets to choose our point prediction, in the other we only take into account sets with a single label. The logic behind this is that, in a real scenario we will not trade if all the labels are present in a prediction set and our strategy will be much more complex when we have two labels.

4.1 Probabilistic Evaluation Metrics

4.1.1 Test Data Coverage

Test data coverage measures the proportion of test samples for which the true label is included in the prediction set. It is defined as:

$$\text{Coverage} = \frac{1}{n}\sum_{i=1}^{n} \not\Vdash\{y_i \in \Gamma^{\epsilon}(X_i)\} \tag{1}$$

where n is the number of test samples, y_i is the true label, and $\Gamma^\epsilon(X_i)$ is the prediction set for sample X_i at significance level ϵ. This metric helps us verify if the conformal predictor is well-calibrated, as the empirical coverage should be close to the desired confidence level $1 - \epsilon$.

4.1.2 Average Set Size

Average set size quantifies the average number of labels in the prediction sets:

$$\text{Average Set Size} = \frac{1}{n} \sum_{i=1}^{n} |\Gamma^\epsilon(X_i)| \tag{2}$$

This metric helps us assess the efficiency of the conformal predictor. A smaller average set size indicates more informative predictions.

4.1.3 Size-1 Set Ratio

This metric measures the proportion of prediction sets containing only one label:

$$\text{Size-1 Set Ratio} = \frac{1}{n} \sum_{i=1}^{n} \mathbb{1}\{|\Gamma^\epsilon(X_i)| = 1\} \tag{3}$$

A higher percentage of sets with just a label indicates higher accuracy resulting in a simpler decision making process.

4.1.4 Brier Score

The Brier score measures the accuracy of probabilistic predictions:

$$\text{Brier Score} = \frac{1}{n} \sum_{i=1}^{n} \sum_{j=1}^{k} (f_{ij} - o_{ij})^2 \tag{4}$$

where f_{ij} is the predicted probability of class j for sample i, and o_{ij} is 1 if the true class of sample i is j, and 0 otherwise. Lower Brier scores indicate better calibrated probabilities.

4.1.5 Log Loss

Log loss, also known as cross-entropy loss, measures the performance of a classification model where the prediction is a probability value between 0 and 1:

$$\text{Log Loss} = -\frac{1}{n} \sum_{i=1}^{n} \sum_{j=1}^{k} y_{ij} \log(p_{ij}) \tag{5}$$

where y_{ij} is 1 if observation i belongs to class j and 0 otherwise, and p_{ij} is the predicted probability. Lower log loss values indicate better performance.

4.2 Classification Evaluation Metrics

4.2.1 Accuracy

Accuracy measures the overall correctness of the model:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{6}$$

4.2.2 Precision

Precision measures the model's ability to avoid labeling negative instances as positive:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{7}$$

4.2.3 Recall

Recall measures the model's ability to find all positive instances:

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{8}$$

4.2.4 F1-Score

F1-Score is the harmonic mean of precision and recall, providing a balanced measure of the model's performance:

$$\text{F1-Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{9}$$

5 Results

5.1 Calibration

We found that across techniques, there were comparable Brier Scores and Log Losses and consistent coverage rates when optimising for either Brier Score (Table 1) or Log Loss (Table 2). On the other hand, the number of singletons dramatically dropped, particularly with greater coverage where, for example, the Size-1 Set Ratio varied between techniques at $\alpha = 0.10$, ranging from 0.087 to 0.097.

On the other hand, we obtained substantially higher proportions of singleton sets when we tuned to minimise the Size-1 Set Ratio (Table 3) and SAPS obtained a Size-1 Set Ratio of 0.631 at $\alpha = 0.10$, although at the expense of slightly greater Brier Scores and Log Losses.

As for score functions, SAPS was the best by far at maximising Size-1 Set Ratio but behaved similarly to the others when fine-tuned on Brier Score and Log Loss. As for our hyper-parameters, we almost always saw Temperatures less than 1, especially when maximizing Size-1 Set Ratio which decreased smaller probabilities and increase larger ones, effectively denoising the output of the original model.

Although single label are more practical, well-calibrated probabilities (as evaluated by Brier Score and Log Loss) are crucial for evaluating model uncertainty. This decision-making utility is prioritised by the Size-1 Set Ratio optimisation, but some probabilistic calibration quality may be lost in the process.

SAPS often provided a good balance in this trade-off such as at $\alpha = 0.20$ when optimizing for Brier Score, SAPS achieved a Size-1 Set Ratio of 0.607, higher than APS (0.473) and RAPS (0.461), while maintaining comparable Brier Scores and Log Losses.

Table 1: Comparison of APS, RAPS, and SAPS across different metrics and alpha values by fine-tuning hyper-parameters to minimize Brier Score Loss.

Alpha	Coverage Rate			Brier Score			Log Loss			Average Size			Size-1 Set Ratio		
	APS	RAPS	SAPS	APS	RAPS	SAPS	APS	RAPS	SAPS	APS	RAPS	SAPS	APS	RAPS	SAPS
0.10	0.925	0.924	0.924	0.129	0.128	0.128	0.703	0.702	0.703	2.116	2.106	2.096	0.092	0.088	0.097
0.15	0.890	0.888	0.890	0.128	0.128	0.128	0.703	0.701	0.703	1.816	1.808	1.803	0.258	0.261	0.270
0.20	0.852	0.853	0.850	0.129	0.129	0.129	0.706	0.703	0.703	1.536	1.541	1.456	0.473	0.461	0.607
0.25	0.815	0.816	0.818	0.129	0.129	0.128	0.704	0.703	0.700	1.269	1.274	1.354	0.731	0.726	0.646

Table 2: Comparison of APS, RAPS, and SAPS across different metrics and alpha values by fine-tuning hyper-parameters to minimize Log Loss.

Alpha	Coverage Rate			Brier Score			Log Loss			Average Size			Size-1 Set Ratio		
	APS	RAPS	SAPS	APS	RAPS	SAPS	APS	RAPS	SAPS	APS	RAPS	SAPS	APS	RAPS	SAPS
0.10	0.924	0.924	0.924	0.128	0.128	0.128	0.701	0.701	0.702	2.106	2.107	2.115	0.095	0.088	0.087
0.15	0.888	0.890	0.889	0.128	0.129	0.128	0.700	0.704	0.701	1.810	1.833	1.808	0.265	0.245	0.264
0.20	0.854	0.854	0.855	0.128	0.128	0.128	0.702	0.699	0.701	1.536	1.544	1.565	0.473	0.460	0.448
0.25	0.814	0.814	0.815	0.128	0.128	0.128	0.700	0.702	0.700	1.259	1.257	1.319	0.741	0.743	0.682

Table 3: Comparison of APS, RAPS, and SAPS across different metrics and alpha values by fine-tuning hyper-parameters to minimize Size-1 Set Ratio.

Alpha	Coverage Rate			Brier Score			Log Loss			Average Size			Size-1 Set Ratio		
	APS	RAPS	SAPS	APS	RAPS	SAPS	APS	RAPS	SAPS	APS	RAPS	SAPS	APS	RAPS	SAPS
0.10	0.923	0.924	0.916	0.160	0.157	0.143	2.065	1.411	0.770	1.987	2.031	1.693	0.222	0.161	0.631
0.15	0.886	0.886	0.882	0.160	0.159	0.166	2.033	1.950	0.863	1.628	1.677	1.517	0.506	0.389	0.725
0.20	0.849	0.851	0.844	0.160	0.155	0.128	2.041	1.231	0.695	1.342	1.377	1.360	0.770	0.694	0.789
0.25	0.812	0.813	0.810	0.160	0.158	0.210	2.064	1.548	1.045	1.189	1.188	1.211	0.876	0.868	0.865

5.2 Forecasting

For the next analysis we will focus on the model $(SAPS, \alpha = 0.1, Temperature = 0.9, \lambda = 0.0007)$ that achieved the highest share of single sets while maintaining low Log Loss and Brier Loss. The comparison between the base DeepLOB model and the conformal model (using SAPS at $\alpha = 0.1$) further illustrates this trade-off (Tables and 5).

The conformal model showed improved calibration metrics with a lower Brier Score (0.1432 vs 0.1454) and a substantially lower Log Loss (0.7701 vs 1.4306). However, only 62.89% of its prediction sets contained a single label, compared to 100% for the base model (Table 4).

In classification performance, the unfiltered conformal model showed similar results to the base model which is expected since we just rely upon the highest logit to chose our label when we have a set size different from one. However, the filtered conformal model, which only makes predictions when the prediction set contains a single label, showed significantly improved performance across all metrics. This highlights the potential for using conformal prediction to abstain from making predictions when uncertainty is high, leading to more reliable forecasts but at the cost of reduced activity.

This analysis underscores the importance of carefully considering the specific requirements of the financial application when applying conformal prediction. If the primary goal is to have well-calibrated probability estimates and a clear representation of uncertainty, optimizing for Brier Score or Log Loss may be preferable. However, if the application requires single-label predictions for immediate decision-making, optimizing for the Size-1 Set Ratio or using a filtered approach may be more appropriate, albeit with some sacrifice in probabilistic calibration quality.

Table 4: Comparison of Calibration Metrics between Base Model and Conformal Model using SAPS at $\alpha = 0.1$.

Metric	**Base Model**	**Conformal Model (SAPS, $\alpha = 0.1$)**
Brier Score	0.1454	0.1432
Log Loss	1.4306	0.7701
Percentage of Prediction Sets of Size 1	100%	62.89%

Table 5: Comparison of Classification Metrics between Base Model, Conformal Model (Unfiltered), and Filtered Conformal Model.

Metric	**Base Model**	**Conformal Model (Unfiltered)**	**Filtered Conformal Model**
Model-Level Accuracy	0.7535	0.7531	0.8767
Label-Level Metrics			
Label 0			
Accuracy	0.8213	0.8212	0.9129
Precision	0.7341	0.7340	0.8695
Recall	0.7523	0.7521	0.8688
F1-Score	0.7431	0.7429	0.8691
Label 1			
Accuracy	0.8554	0.8551	0.9242
Precision	0.8074	0.8065	0.8956
Recall	0.7622	0.7622	0.8969
F1-Score	0.7841	0.7837	0.8962
Label 2			
Accuracy	0.8302	0.8301	0.9163
Precision	0.7204	0.7203	0.8617
Recall	0.7451	0.7451	0.8610
F1-Score	0.7325	0.7324	0.8613

6 Conclusion

This paper demonstrates the advantages of applying conformal prediction to calibrate deep learning models, exemplified by the application to the DeepLOB limit order book forecasting task. By employing methods like Temperature Scaling Adaptive Prediction Sets (APS), Relaxed Adaptive Prediction Sets (RAPS), and Split-Adaptive Prediction Sets (SAPS), we were able to enhance the reliability, interpretability and performance of the DeepLOB model.

When optimized for decision-making simplicity, so by maximising the number of prediction sets of size 1, the conformal model achieved a significant improvement in classification accuracy, increasing from 75.35% for the base DeepLOB model to 87.67% for the filtered conformal model (Table 5).

This study shows how conformal prediction can be used to support a range of tasks in finance, including risk management, market making, and algorithmic trading. More robust and informed decision-making can be facilitated by the prediction sets, which include prediction sets with coverage guarantees by construction. These sets can capture more information that a simple point prediction, such as price direction, volatility and uncertainty.

In conclusion, this work introduces a conformal DeepLOB model and demonstrates an effective application of conformal prediction with deep learning for financial markets and limit order book forecasting.

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