Modern Time Series Forecasting Techniques

For Predictive Analytics and Anomaly Detection

1ST EDITION

CHRIS KUO

From Classical Foundations to Cutting-Edge Applications

INNOVATION PRESS

ISBN 979-8-9907810-0-9

First edition: April 2024
Second impression, with minor extensions: May 2024

This book was typeset using LaTeX software. The TeX template acknowledgement:
The *Beautybook* [https://ctan.org/pkg/beautybook?lang=en]
Comprehensive TEX Archive Network (CTAN)

The Innovation Press,
Ann Arbor, MI

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About the author

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Chris Kuo is a writer on Medium.com, also known as 'Dr. Dataman' in the field of data science. He has published in several economic and management journals and is the author of the following data science books (by year):

- *2021 - Modern Time Series Anomaly Detection: With Python and R examples*
- *2022 - The eXplainable A.I.: With Python examples*
- *2022 - Transfer Learning for Image Classification: With Python examples*
- *2023 - The Handbook of Anomaly Detection: Build and modernize your anomaly detection models with examples*
- *2023 - The Handbook of NLP with Gensim: Leverage topic modeling to uncover hidden patterns, themes, and valuable insights within textual data*
- *2024 - Modern Time Series Forecasting: For Predictive Analytics and Anomaly Detection*

To my son, Nathan Kuo,
When you were 5 years old and knew some ABCs,
your mom told you there was an academic journal that has dad's paper.
You eagerly picked it up and wanted to read it as a storybook.
In that moment, I regretted why I had not written a book for you.
Now I dedicate this book to you.
Your dad.

For God so loved the world, that he gave his only begotten Son,
that whosoever believeth in him should not perish,
but have everlasting life. (John 3:16)

Preface

Time series data is ubiquitous in today's world, and its analysis is critical for various applications, such as finance, healthcare, and manufacturing. As the volume and complexity of data continue to grow, innovative techniques are needed to address the challenges of the evolving nature of data and effectively identify anomalies in real time. This book provides an overview of classical time series forecasting and then advances to state-of-the-art time series techniques. The contents within these pages are crafted to inform, inspire, and empower your endeavors.

Sec What this book covers

This book organizes time series models and applications into six meticulously crafted parts. Each part equips you with the knowledge and skills to conduct time series forecasting and anomaly detection. The six parts are:

Part 1: From Prophet to NeuralProphet

Part 2: Getting Probabilistic Forecasts

Part 3: Autoregressive-based Time Series Techniques

Part 4: Tree-based Time Series Techniques

Part 5: Deep into Deep learning-based Time Series Techniques

Part 6: Transformer-based Time Series Techniques

Part 1 starts with Prophet and its successor NeuralProphet because they a intuitive way to model time series data with interpretable results and user-friendly APIs. Both have active communities of users and contributors. **Part 2** teaches you the techniques for forecasting uncertainty. You will be able to build projects with forecasting uncertainty to help your users make more informed decisions and manage risks. **Part 3** and **Part 4** offer theories and applications into Autoregressive Integration Moving Average (ARIMA) modeling and modern tree-based techniques. You will gain valuable insights into algorithmic approaches and their practical implementation. **Part 5** and **Part 6** explore cutting-edge research and sophisticated techniques including deep learning architectures and Transformer-based methods. Therefore Part 1 to Part 6 range from classical models to the modern large foundational models in time series.

Why read this book?

In this book, you will find a wide coverage of methodologies, algorithms, and applications. Whether you're a seasoned data scientist seeking to refine your expertise or a novice eager to embark on your analytical odyssey, this book offers a roadmap tailored to cater to diverse skill levels and objectives. You will emerge equipped with the proficiency and confidence to unravel intricate temporal patterns, harness predictive power, and unlock new horizons of insight across a myriad of domains, from finance and economics to healthcare and beyond.

The writing style of this book is another selling point. Instead of taking a technique as given, this book first describes intuitions and then dives into detail. This book also gives a landscaping view from one idea to the consequent ideas. With the real-world data cases in this book, you will gain a deeper understanding of how time series techniques are applied in diverse domains.

Open-source Python libraries

Another key feature in this book is the integration of open-source Python time series libraries. They include: `Prophet`, `NeuralProphet`, `Darts`, `GluonTS`, `SKtime`, `Pmdarima`. By leveraging these libraries, you can expedite data preprocessing, explore temporal patterns, and deploy sophisticated forecasting algorithms with ease. This integration of these tools in the book let you experience the production efficiency and convenience for your proof-of-concept initiatives.

Who this book is for

Whether you're seeking to enhance your skill set, solve complex problems, or simply satisfy your curiosity, this book offers a compelling journey into the captivating world of time series anomaly detection.

- Data Scientists and Analysts: Professionals who work with time series data and need to identify anomalies for various applications such as finance, cybersecurity, IoT, and healthcare. They will benefit from the practical methodologies and real-world examples provided in the textbook.
- Researchers: Academics and researchers exploring novel approaches to anomaly detection in time series data, seeking a comprehensive reference and practical insights to inform their research endeavors.
- Students: Undergraduate and graduate students studying data science, machine learning, statistics, or related fields, looking to gain expertise in time series analysis and anomaly detection. The book offers a structured learning path with clear explanations and hands-on exercises.
- Industry Practitioners: Engineers, developers, and decision-makers in industries where anomaly detection is crucial for maintaining operations, ensuring quality, and detecting fraud. They will find the book's practical focus and real-world case studies invaluable for enhancing their skills and solving real-world problems.

Sec Recommended prerequisites

- Basic Knowledge of Statistics: Familiarity with concepts such as mean, median, standard deviation, probability distributions, and hypothesis testing will help readers grasp the statistical methods used in anomaly detection.
- Programming Skills: Proficiency in at least one programming language such as Python or R for implementing algorithms, visualizing data, and analyzing results.
- Understanding of Machine Learning: Basic understanding of machine learning concepts including supervised and unsupervised learning algorithms, feature engineering, and model evaluation.
- Prior Exposure to Time Series Data: Some experience working with time series data and understanding its unique characteristics such as trends, seasonality, autocorrelation, and stationarity will aid in comprehending the challenges and techniques discussed in the textbook.

Sec Motivation for writing this book

Traditional time series forecasting methods, such as AutoRegressive Integrated Moving Average (ARIMA), have been widely used for decades. New techniques, such as recurrent neural networks (RNNs), long short-term memory (LSTM) networks, and deep learning architectures, become the new foundations for time series forecasting. Tree-based models including gradient-boosting models and LightGBM (2017) topped the time series forecasting competitions (the M competition in 2020s). Even more, after the arrival of the Transformer model in 2017, new methods including the Temporal Fusion Transformer (2019), and Lag-LLAMA (2024) came to the stage. These techniques are being used in various applications, such as finance, energy, and transportation, to forecast stock prices, electricity demand, and traffic flow.

With these unprecedented developments in time series forecasting techniques and applications, I have been longing to write a book to cover the traditional methods and bridge new techniques. This book covers new techniques developed from 2014 to the present.

The global Pandemic hit in 2019. Many office buildings around the world were closed for one and a half years. I remember the last afternoon before office closure, I rushed to the food truck to get an egg sandwich. I had one bite or two of my egg sandwich between busy meetings. Then the following months the whole world was all working remotely. During that period, we continued to witness notable large language models flourishing. During the Pandemic year, I had a dream. In my dream, I strolled through an empty Times Square. I went into the empty office building to pick up my notes. Then I found my half-finished egg sandwich was still on my desk!

Chris Kuo,
New York City, New York

Contents

1 Introduction

Part

Time series is a sequence of data at equally spaced intervals over time. It is around us in our daily lives. We derive forecasts from the time series data for various purposes. If you meet Mr. P in this story, you may find one or two persons in your life who are just like Mr. P. And you probably agree you also use time series forecasts around the clock in your life. Mr. P is a middle-aged professional living in a busy city. He usually starts his day with a morning jog. He puts on his fitness tracker for jogging. The tracker monitors his heart rate, sleep patterns, activity levels, and other physiological parameters. His doctor told him the forecasts are based on his health data over time. The forecasts tell him if he is on the way to his fitness goals. The forecasts also alert him to any anomalies or irregularities so he can share them with the doctor. Although he does not like too much regulation, he seems enjoying his disciplined life and has convinced his next-door neighbor to join him next month. Mr. P works as an inventory control manager for a fashion sports company. The company designs and produces athletic apparel, footwear, and accessories for sports enthusiasts. Part of his job is to monitor the trend for sales figures, inventory levels, and customer foot traffic. He needs to predict demand and optimize inventory levels for each line of business. His numbers help other departments to plan promotions, allocate resources, and maximize quarterly revenue. He also buys and sells some stocks on his own. He subscribes to a reputable stock forecasting service for investment guidance. He follows certain stocks for his investment decisions. He reads some investment strategies like algorithmic trading or swing trading. But he seems not too active about trading opportunities, though he has a friend who often brags about the revenues in day trading. Talking about Mr. P's passion, everyone knows it is about hiking and photography. He is a serious photographer — his blog has one million followers. He talks about camera basics like DSLR, mirrorless, point-and-shoot, and other kinds of cameras. He talks about aperture, shutter speed, ISO, and where to buy lenses, tripods, memory cards, and so on. But most of all, he enjoys traveling. He often plans vacations to really remote forests for his nice photo shots. Okay, back to time series forecasts. He checks 10-day weather forecasts to plan for his travel. Around our lives we all have one or two persons like Mr. P. Most of all, we all use time series forecasts like Mr. P.

Sec 1.1 Use Forecasts for resource planning and anomaly detection

We need forecasts to have a range of possible values for planning and monitoring purposes. When the actual values are within our predicted range, we will not be surprised because we have planned the best or worst scenarios accordingly. The terms probabilistic forecasting, prediction uncertainty, or prediction intervals are often used interchangeably in time series forecasting. Just like the white and yellow lines on a road to guide traffic, time series forecasts are used to guide business operations across a wide range of industries. In finance and banking, time series forecasting is used for predicting possible values of an asset to help investors make informed decisions. In retail and E-Commerce, time series forecasting is used to guide the optimal inventory levels. In healthcare and pharmaceuticals, time series forecasting helps to predict hospital bed occupancy, disease outbreaks, and medical resource demand.

On the other hand, when the actual values are outside the predicted values, they are called outliers or anomalies. We also want to track the chances of them happening to mitigate risks. Either the forecasts are used for resource planning or anomaly detection or both, the probabilistic forecasts derived from the same time series modeling tool can be applied. Let's see the preceding use cases to see how forecasting helps resource planning and anomaly detection.

1.1.1 Case study 1: Retail inventory management

Story: ABC Retail is a large chain of stores specializing in consumer electronics. With thousands of products and fluctuating demand patterns, optimizing inventory levels is crucial to profitability. Anomalies such as sudden spikes or drops in demand can lead to excess inventory and lost sales opportunities.

Technology innovation: ABC Retail requires techniques that can produce a high level of prediction accuracy for the sales of its products. ABC Retail adopts various advanced forecasting techniques to improve prediction accuracy. The prediction accuracy empowers the company to adjust to market dynamics quickly.

Cost savings: By optimizing inventory levels and minimizing the need for emergency restocking or clearance sales, ABC Retail saves millions of dollars annually in inventory holding costs, markdowns, and lost sales revenue.

Actionable insights: When anomalies are detected, ABC Retail's inventory management team receives real-time alerts and actionable insights. They investigate the root causes of anomalies, such as unexpected surges in demand or supply chain disruptions. Based on their findings, they adjust inventory levels, reorder points, and procurement strategies accordingly to mitigate potential risks and optimize resource allocation.

Additional benefits: By ensuring product availability and minimizing out-of-stock instances, ABC Retail obtains improved Customer Satisfaction, increased loyalty, and repeat purchases.

1.1.2 Case study 2: Electricity demand forecasting

Story: XYZ Power is a utility company responsible for generating and distributing electricity to residential, commercial, and industrial customers. Maintaining a reliable and stable power supply is critical to meet customer demand, avoid blackouts, and optimize operational costs.

Technology innovation: XYZ Power implements advanced time series forecasting techniques combined with anomaly detection algorithms to improve its electricity demand forecasting capabilities. The technology helps the company optimize generation schedules, manage grid stability, and avoid unnecessary expenses associated with overproduction or emergency measures.

Cost savings: By avoiding overproduction and emergency measures, XYZ Power saves millions of dollars annually in fuel costs, maintenance expenses, and penalties associated with capacity shortages or grid imbalances.

Actionable insights: The forecasted demand values are used to establish prediction intervals. Any observed demand data points falling outside these prediction intervals are flagged as anomalies. When anomalies are detected, XYZ Power's grid management team receives real-time alerts. They can investigate the root causes of anomalies, such as unexpected spikes or drops in demand, equipment failures, or network congestion. Based on their findings, they can adjust generation schedules or grid configurations to mitigate potential risks.

Since we have mentioned the use cases of anomaly detection, we shall also address the definitions for anomaly scores.

Sec 1.2 Anomaly score definitions

An anomaly refers to a significant deviation from the expected patterns within the data. These deviations can take various forms, such as sudden spikes, dips, or irregular behavior. An anomaly score quantifies how unusual or deviant a data point is compared to the expected behavior within the time series. The definition of anomaly score can vary based on specific business contexts or requirements. Here we offer the common definitions.

Prediction-interval-based Anomaly Score: A prediction interval estimates a range of values within upper and lower bounds where a certain percentage of data is likely to fall. For example, a 0.99 prediction interval means that 99 percent of the data is expected to lie within the interval. If a data point lies beyond the bounds of the prediction interval, it is considered anomalous. An anomaly score can be defined as 0.0 if the actual value is within the prediction interval, and otherwise 1.0 if it falls outside the interval.

Z-score-based Anomaly Score: This method calculates the anomaly score based on z-scores, which represent the number of standard deviations a data point is away from the mean of the time series. Data points with larger z-scores are considered more anomalous.

$$\text{Anomaly Score at time t} = \frac{(\text{Observed value at t}^{-}\text{Mean of time series})}{\text{Standard deviation of time series}}.$$

Sec 1.3 Model interpretability

This book emphasizes the interpretability of a modeling technique. A model should be transparent and its prediction should be interpretable. A black-box model is less than ideal, as Kuo mentioned in *Explainable A.I.: with Python Examples*, "no one wants to swallow a black pill without knowing what's in it." An important factor is the **trust** in the model. Users will be willing to accept the model prediction as their guidance for actions. Transparency means the model parameters are present, and the model prediction can be decomposed. Users can even do an elementary-school type of addition like A + B + C = the predicted value. Model interpretability often comes with visualization. Users can visualize the key factors and assess their relative significance. For example, a visual exhibit may show that a factor of a model is positively or negatively correlated to the prediction. Users of the model may approve or disapprove of such a relationship through the visual exhibits and gain their confidence in the model.

Sometimes model interpretability can refer to causality because people may want to use the discovered relationships in a model to infer causality, or to approve their hypotheses about the natural world. For example, if there is a spike in the sales volume due to a special promotional event, we may interpret that the high demand is due to the event and may predict demand spikes for similar promotional events in the future.

Sec 1.4 Local models vs. global models

In time series forecasting, a local model deals with a single time series or **univariate time series**. A global model is developed on multiple time series and the parameters are shared by all the time series. The techniques in this book include both local and global modeling techniques. Local models are useful when the patterns and trends in the data are specific to a particular time series, and there is little or no relationship between multiple time series. In this case, a local model can provide accurate forecasts without being influenced by the noise or variability in other time series.

On the other hand, global models are useful when there are common patterns across multiple time series, and the relationships between the time series are important for accurate forecasting. A global model can leverage the shared information across the time series to provide robust forecasts. For example, the sales volume over time of products within the same product category are multiple time series. A global model can be built for all products even when a new product is newly added to the same product category and has no history.

Sec 1.5 A roadmap to learn modern time series forecasting

An important goal of this book is to guide you through the rich landscape of time series forecasting techniques. First, knowing the development journey from classical to advanced techniques is as important as the proficiency of a particular technique. Second, we focus on probabilistic forecasting and multi-period forecasting. This is because many applications require both. Third, we highlight model interpretability for the advantages mentioned in the previous section. Fourth, we emphasize software competency.

We group the modern techniques into six parts to explore their evolution, intricacies, and transformative potential. **Part 1** starts with the Prophet technique because of its intuitive design and ease of use. Then it continues to NeuralProphet to assist you in building more complex models. In **Part 2**, we present four techniques to quantify uncertainty and deliver probabilistic forecasts. They include the Monte Carlo simulation, Quantile regression, Conformal prediction, and Conformalized quantile regression, These techniques are used in later techniques as well. **Part 3** uncovers the power of autoregressive-based techniques, shedding light on their ability to capture temporal dependencies and model dynamic relationships within sequential data. **Part 4** shifts focus to tree-based methodologies, showcasing their effectiveness in handling nonlinear patterns and successes in recent time series competitions. Venturing into the realm of deep learning, **Part 5** explores the depths of neural network architectures, revealing their capacity to learn complex patterns and extract latent features from high-dimensional data. Finally, in **Part 6**, we journey into the realm of transformer-based techniques. You will understand the architectures of the

Transformer-based models and their successes. Together, these six parts offer you a roadmap to learn modern forecasting techniques and apply them to your projects.

Chapter	Chapter content	Prophet/ Neuralprophet	Statmodels	pmdarima	Sktime	lightGBM	Darts	GluonTS
1	Introduction							
2	Prophet	O						
3	NeuralProphet	O						
4	NeuralProphet	O						
5	Change point detection							
6	Monte Carlo							
7	Quantile regression	O						
8	Conformal prediction	O						
9	Conformalized quantile prediction	O						
10	Automatic ARIMA		O	O			O	
11	Data formats	O		O	O		O	O
12	Linear regression						O	O
13	Tree-based Feature engineering					O		O
14	Primary strategies			O	O	O		
15	Tree-based						O	
16	Progression of techniques							
17	Deep learning							O
18	Deep learning							O
19	RNN to Transformer							
20	Temporal fusion transformer						O	
21	Lag-Llama							O

Figure 1.1: Time Series Python Libraries in this book

Sec 1.6 Time series Python libraries

The criteria for adopting the Python libraries in this book are **popularity** and **documentation support**. The time series Python libraries in this book are `statsmodels, pmdarima, sktime, Darts, GluonTS`, and `Autogluon`. All these libraries have active communities and documentation support. Figure 1.1 shows the Python libraries used in this book. Chapters 1, 16, and 19 are survey-type chapters and do not have code examples.

The `statsmodels` library contains all the classical tools and is a popular library for the statistics community. It has fundamental statistical tests, such as t-tests, F-tests, or chi-square tests. On model techniques, it has the most commonly used ordinary least squares (OLS) and generalized linear models (GLM). It includes the classical time series models such as autoregressive integrated moving average (ARIMA), seasonal ARIMA (SARIMA), vector autoregression (VAR), and state space models.

The `pmdarima` library extends the ARIMA modeling capabilities of the `statsmodels` library. It enables users to automatically select the optimal ARIMA and Seasonal ARIMA models. It provides the ability to perform multi-step forecasts. It also includes time-series functions to diagnose the fitted ARIMA models, such as residual analysis, ACF/PACF plots, and Ljung-Box tests.

The `sktime` library is another open-source library that combines many forecasting tools under a unified API. It wraps up a wide range of tools and algorithms for time series forecasting, classification and anomaly detection. Let's see its underlying modules. From `statsmodels`, it includes Holt-Winter's Exponential Smoothing, Theta Forecaster, and ETS. The ETS model is the decomposition model for trend (T), seasonal (S), and an error term (E). From `pmdarima`, it includes ARIMA and AutoARIMA. It also uses the `tbats` library. TBATS stands for Trigonometric seasonality, Box-Cox transformation, ARMA errors, Trend, and Seasonal components. Finally, it also wraps the Prophet forecasters from the `Prophet` library.

The `Darts` Python library is a one-stop shop for time series analysis and forecasting. It provides a comprehensive set of tools and models for building, training, and evaluating time series forecasting models. The Darts library includes implementations of various time series forecasting models and is well-engineered for multi-period probabilistic forecasting. It includes popular forecasting techniques such as linear regression, ARIMA, XGB, GBM, CatBoost, RNN/LSTM/GRU, and Temporal Fusion Transformer (TFT).

The `GluonTS` Python library stands as a pioneering achievement from the Amazon Web Services (AWS) team. By leveraging MXNet and PyTorch, GluonTS empowers users to build complex models such as DeepAR, Transformer-based models, and TFTa. DeepAR is a deep-learning architecture for probabilistic forecasting. Chapter 17: *Deep Learning-based DeepAR for Time Series Probabilistic Forecasting*. GluonTS offers a wide array of techniques from traditional statistical methods to machine-learning algorithms. The "AutoGluon" library is a more general-purpose automatic machine learning (AutoML) framework. In other words, while GluonTS specializes in time series forecasting and probabilistic modeling, AutoGluon is a more general AutoML framework that automates the process of building machine learning models across various tasks, including time series analysis.

The above libraries are covered in Chapter 11: *Time Series Data Formats Made Easy*. All chapters except 1, 16, and 19 require Pandas and Matplotlib. These libraries continue to receive active developments. The above highlights are limited to the time I wrote this book.

Sec 1.7 Model evaluation metrics

This book uses several standard evaluation metrics. The choice of metric depends on the specific requirements of the forecasting task and the characteristics of the time series data. They include MAPE, MAE, MSE, sMAPE, RMSE, and Continuous Ranked Probability Score (CRPS) Since they will be used often throughout the book, we give the definitions here.

1.7.1 Mean Absolute Percentage Error (MAPE)

Mean Absolute Percentage Error (MAPE) provides a measure of the accuracy of a forecasting model in terms of the percentage error relative to the actual values.

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{|F_i - A_i|}{A_i}\right) \times 100\%$$

Where:

- F_t is the forecasted value at time t,
- A_t is the actual value at time t,
- n is the number of observations.

1.7.2 Mean Squared Error (MSE)

Mean Squared Error (MSE) measures the average squared difference between the forecasted values and the actual values. It's a measure of the average squared deviation of the forecasts from the actual values.

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(F_i - A_i)^2$$

MSE is particularly useful because it penalizes larger errors more heavily than smaller errors due to the squaring operation. This property makes it sensitive to outliers and large errors, which can be important in many applications. However, since MSE involves squaring the errors, it's not in the same unit as the original data, which can sometimes make interpretation less intuitive.

1.7.3 Mean Absolute Error (MAE)

Mean Absolute Error (MAE) measures the average absolute difference between the forecasted values and the actual values. It provides a more intuitive measure of error compared to other metrics like MSE because it is in the same unit as the original data.

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|F_i - A_i|$$

MAE is robust to outliers since it does not involve squaring the errors.

1.7.4 Root Mean Squared Error (RMSE)

Root Mean Squared Error (RMSE) measures the square root of the average squared difference between the forecasted values and the actual values. It provides a measure of the typical magnitude of error, and since it's in the same unit as the original data, it's more interpretable than MSE.

$$\text{RMSE} = \sqrt{\text{MSE}}$$

RMSE penalizes larger errors more heavily than smaller errors due to the squaring operation in MSE. Like MSE, RMSE is sensitive to outliers and large errors, making it a useful metric for assessing the overall accuracy of a predictive model.

1.7.5 Symmetric Mean Absolute Percentage Error (sMAPE)

Symmetric Mean Absolute Percentage Error (sMAPE) is a widely used metric for evaluating forecast accuracy. While it is similar to MAPE, it addresses some of the shortcomings of the traditional Mean Absolute Percentage Error (MAPE) by symmetrically handling both overestimations and underestimations. sMAPE is calculated using the following formula:

$$\text{sMAPE} = \frac{1}{n}\sum_{t=1}^{n}\frac{|F_t - A_t|}{(|A_t| + |F_t|)/2} \times 100\%$$

sMAPE is a symmetric measure, meaning it treats under- and over-forecasting equally. In contrast, MAPE can be influenced by the direction of the error, which can make it difficult to compare the performance of models that have different error distributions. sMAPE is less sensitive to extreme values than MAPE. This is because sMAPE scales the errors by the average of the actual and forecasted values, rather than just the actual value as in MAPE.

1.7.6 Continuous Ranked Probability Score (CRPS)

Continuous Ranked Probability Score (CRPS) is an evaluation metric when the forecasts are probabilistic forecasts rather than a point estimate. CRPS ranges from 0 to positive infinity. When the forecasted cumulative distribution function (CDF) perfectly matches the observed outcome, CRPS is zero. We want the CRPS to be as low as possible. The formula for the Continuous Ranked Probability Score (CRPS) is:

$$CRPS(F, y) = \int_{-\infty}^{\infty} [F(x) - h(x \geq y)]^2 \, dx \tag{1.1}$$

Let's break down the components:

- $F(x)$: This term represents the predicted cumulative distribution function (CDF) at each point x. The CDF gives the probability that the observed value will be less than or equal to x.
- $x \geq y$: This is an indicator function that evaluates to 1 if x is greater than or equal to the observed value y, and 0 otherwise. It essentially creates a step function that helps in comparing the predicted CDF with the observed value.
- $h()$: This is the Heaviside step function. It is 1.0 if $x \geq y$, otherwise 0. It defines whether each forecasted probability exceeds the observed outcome.
- $F(x) - h(x \geq y)]$: This term calculates the difference between the predicted CDF and the indicator function. It essentially measures the distance between the predicted cumulative probabilities and the step function representing the observed value.
- $F(x) - h(x \geq y)]^2$: Squaring the difference penalizes larger discrepancies more than smaller ones, ensuring that under- and over-predictions are treated equally.
- $\int_{-\infty}^{\infty}$: This represents the integral over the entire real line, summing up the squared differences across all possible values of x .

CRPS evaluates the alignment between predicted and observed outcomes by comparing their cumulative distribution functions (CDFs). This function measures the probability that the actual value falls below or equals a specific value. Here are the key aspects of CRPS:

- CRPS assesses the consistency of probabilistic forecasts, represented as CDFs, with observed outcomes. It computes the average deviation between predicted cumulative probabilities and actual results.
- It penalizes both under-dispersion (when predicted uncertainty is lower than observed) and over-dispersion (when predicted uncertainty exceeds observation). This dual penalty system enhances CRPS's robustness in evaluating forecast accuracy.
- Unlike metrics focusing solely on point estimates, CRPS evaluates the entirety of the forecast distribution. This characteristic renders it apt for assessing probabilistic forecasts, as it accounts for the entire probability distribution.

We will apply CRPS in Chapter 21: *Lag-Llama for time series forecasting*.

Sec 1.8 Cheat Sheets

This book has developed cheat sheets for quick reference. The cheat sheets summarize essential syntax examples from the chapters in the book. You will benefit from having specialized information at your fingertips. Whether you're a seasoned data scientist or just starting, having a well-curated cheat sheet can significantly enhance your productivity.

Sec 1.9 Download the example code files

The Python notebooks are available for download at

```
https://github.com/dataman-git/modern-time-series
```

If there's an update to the code, it will be updated in the GitHub repository.

Sec 1.10 Data for this book

The datasets for this book cover energy, electricity, retail sales, and selected economic time series. The frequencies include hourly, daily, weekly, and monthly. All the datasets are available on Kaggle.com.

The **Website visitors** dataset [2] has the number of visitors to an academic teaching notes website from Kaggle.com. This dataset has daily counts of page loads, unique visitors, first-time visitors, and returning visitors. The dataset covers the date range from September 14, 2014, to August 19, 2020.

The **Bike-rental** dataset [3] has daily bike rental count records for 2011–2012. It includes other covariates like weather and seasonal information.

The **Hourly Electricity consumption** dataset [4] contains hourly electricity consumption and other covariates like temperature, dew point, heat index, and wind gust.

The **AEP hourly energy** dataset [5] is from the American Electric Power Company, Inc. It has hourly energy consumption data and other covariates.

The **Retail clothing** dataset [6] has monthly retail sales for clothing and clothing accessories.

The **Avocado** dataset [7] has monthly avocado sale volumes and price levels.

The **Store sales** dataset [8] has the sales for the thousands of product families sold at Favorita stores located in Ecuador. The columns include dates, store and product information, promotions, and other related fields.

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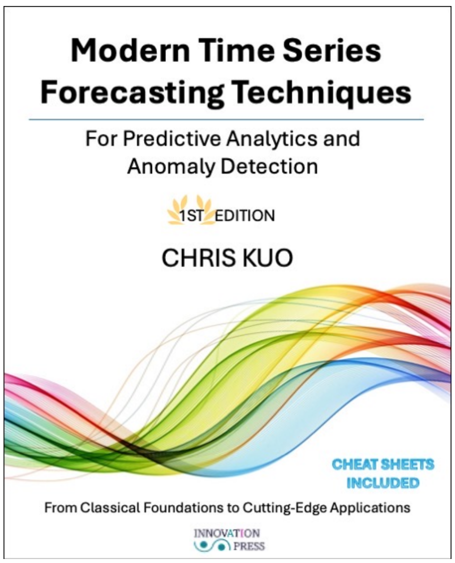
Modern Time Series Forecasting: For Predictive Analytics and Anomaly Detection

2024



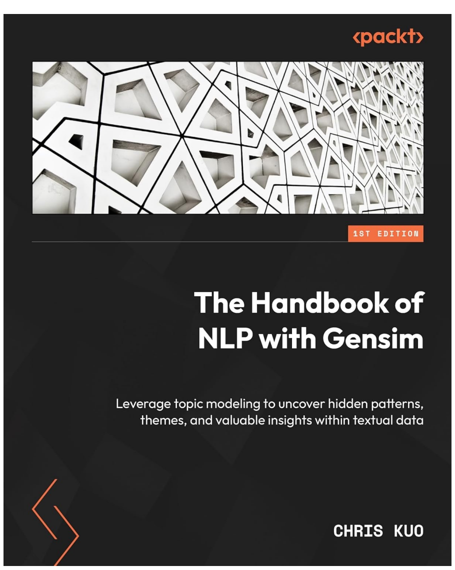
Key features

This book offers a comprehensive exploration of methodologies, algorithms, and practical applications, catering to both seasoned data scientists looking to refine their skills and newcomers eager to begin their analytical journey. Equipped with this resource, you'll confidently decipher intricate temporal patterns and harness predictive capabilities across various domains.

- Part 1: From Prophet to NeuralProphet
- Part 2: Getting probabilistic forecasts
- Part 3: Autoregressive-based Time Series Techniques
- Part 4: Tree-based Time Series Techniques
- Part 5: Deep into Deep learning-based Time Series Techniques
- Part 6: Transformer-based Time Series Techniques

The Handbook of NLP with Gensim: Leverage topic modeling to uncover hidden patterns. https://a.co/d/ifO2LxR

2023



Key features

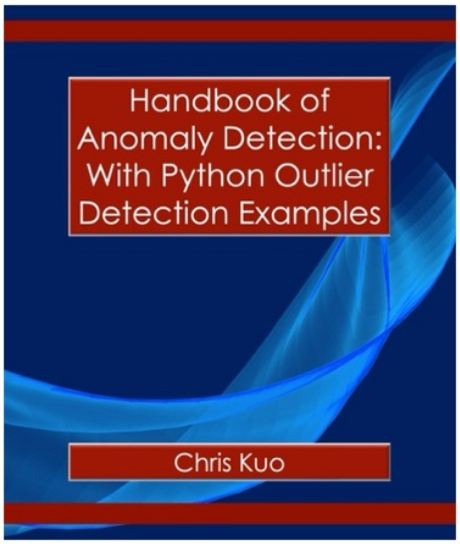
This book demystifies NLP and equips you with hands-on strategies spanning healthcare, e-commerce, finance, and more to enable you to leverage Gensim in real-world scenarios. You'll begin by exploring motives and techniques for extracting text information like bag-of-words, TF-IDF, and word embeddings. This book guides you on topic modeling using methods such as Latent Semantic Analysis (LSA) for dimensionality reduction and discovering latent semantic relationships in text data, Latent Dirichlet Allocation (LDA) for probabilistic topic modeling, and Ensemble LDA to enhance topic modeling stability and accuracy. By the end of this book, you'll have mastered the techniques essential to create applications with Gensim and integrate NLP into your business processes.

Books by Chris Kuo

Handbook of Anomaly Detection: With Python Outlier Detection: Build and modernize your anomaly detection with examples

https://a.co/d/hHuHJEV

2023



Key features

Learn a wide range of proven techniques that cover proximity-based, distribution-based, and ensemble-based algorithms. Enjoy systematic learning of modern techniques through appealing visualization of complex concepts. Become an experienced data scientist in outlier detection by hands-on code examples

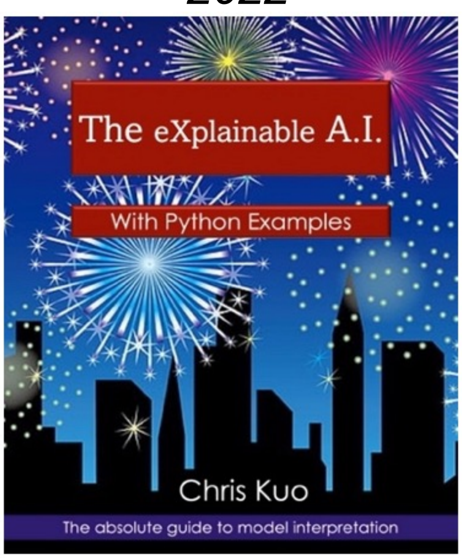
Developer review

"Anomaly detection is a critical technique to identify rare items in risk modeling, security, and healthcare. Dr. Kuo's book provides hands-on guidance on how to use existing tools, such as PyOD, to leverage this technique in your daily data science work. More importantly, this book reviews more than 10 leading detection algorithms, with both algorithm descriptions and detailed code examples." ~ Yue Zhao, Principal Developer of PyOD

The eXplainable A.I.: With Python examples

https://a.co/d/i8htOES

2022



Key features

- Learn algorithms with easy-to-understand examples.
- Learn what explainability A.I. is
- Learn SHAP to explain your machine learning models
- Learn SHAP with H2O Models. Learn SHAP Kernel Explainer
- Learn Microsoft's interpretML
- Learn how to use LIME to explain your models.

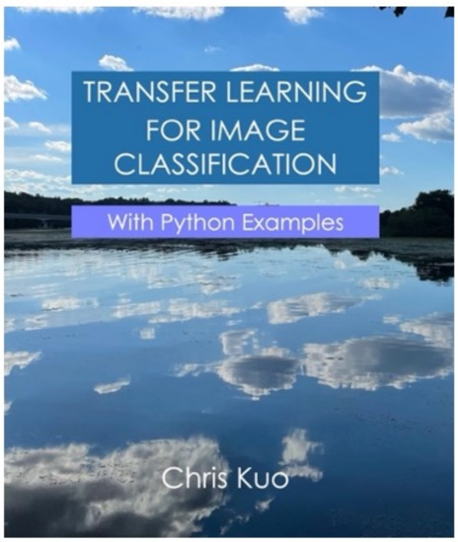
Who this book is for

This book is for anyone who wants to understand model explainability and get your complex machine-learning models adopted. Although the content is extensive, data science professionals who do not have much machine learning background will find this book accessible

Books by Chris Kuo

Transfer Learning for Image Classification: With Python examples. https://a.co/d/e3MuX0e

2022



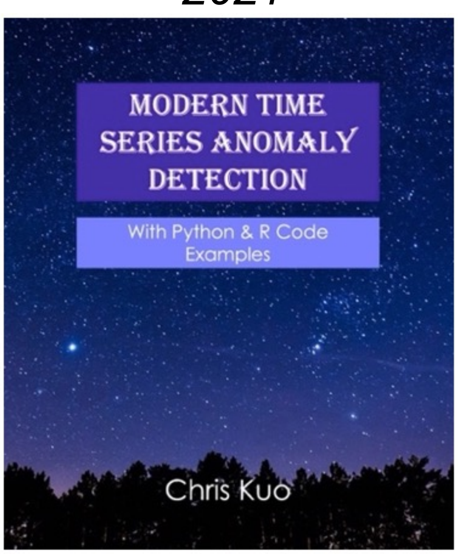
What you will learn

- Learn how deep learning models treat image data.
- Learn what a convolutional neural network (CNN) is.
- Learn each layer of a CNN by visualizing what it sees in an image layer-by-layer
- Learn the development of pre-trained image models
- Learn how to annotate images programmatically and pre-process images for modeling
- Follow Step 1,2,3 in the book to build deep learning models with Keras
- Build a repeatable pipeline to apply transfer learning for any image projects

Book Description

The best way of learning is to understand the motives of a technique and then practice with code examples. Thus, this book explains the reasons, describes a method and then shows the code examples. This book presents large-scale pre-trained image models and how to apply transfer learning techniques to build your models.

2021



Modern Time Series Anomaly Detection: With Python and R examples (Out of stock)

Modern Time Series Forecasting Techniques For Predictive Analytics and Anomaly Detection

This book offers a comprehensive exploration of methodologies, algorithms, and practical applications, catering to both seasoned data scientists looking to refine their skills and newcomers eager to begin their analytical journey. Equipped with this resource, you'll confidently decipher intricate temporal patterns and harness predictive capabilities across various domains.

This book offers unique surveys from classical time series forecasting to state-of-the-art techniques:

- Part 1: From Prophet to NeuralProphet
- Part 2: Getting probabilistic forecasts
- Part 3: Autoregressive-based Time Series Techniques
- Part 4: Tree-based Time Series Techniques
- Part 5: Deep into Deep learning-based Time Series Techniques
- Part 6: Transformer-based Time Series Techniques

WHAT YOU GET IN THE BOOK

- Learning time series techniques comprehensively in a short period
- A roadmap from the classical techniques to modern time series forecasting
- Applying forecasting for resource planning and anomaly detection
- Mastering time series Python libraries
- Hands-on example code
- Cheat Sheets

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