第 13 章CHAPTER 13用折線圖進行預測Forecasting with Line Graphs

預測的做法很古老。即使是 5,000
年前的埃及法老也依賴占卜師、骨頭、內臟等，誰能忘記公元前 1400 年左右在德爾斐神諭中湧現的宗教熱情呢？如果你想要一個很酷的複習，並且喜歡漫畫書和六塊腹肌（誰不喜歡呢！），看看電影《300》——電影中有一個真正史詩般的場景，被下藥的年輕女孩受到醜陋、扭曲、腐敗的屍體般的祭司——埃弗爾家族的“鼓勵”，發表神論聲明，將把列奧尼達國王和 300 名英雄送去，最終在溫泉關戰役中光榮地死去。一個真正壯觀的預測例子！（注意：該視頻是 NSFW。

The practice of forecasting is ancient. Even Pharaohs of Egypt 5,000 years ago relied on soothsayers, bones, entrails, and the like, and who can forget the religious fervor that sprung up around 1400 BC at the Oracle of Delphi? If you want a cool refresher and like comic books and six-pack abs (and who doesn’t!), take a look at the movie 300—there is a truly epic scene in the movie where the drugged-up young girl is “encouraged” by the ugly, twisted, corrupt corpse-like priests—the Ephors—to make the Oracular pronouncement that will be sending King Leonidas and the 300 heroes to their eventual glorious deaths in the Battle of Thermopylae. A truly spectacular example of forecasting! (Note: That video is NSFW.)

今天（幸運的是），我們不再需要給人們下藥來獲得我們的預測。AI 的預測使用者體驗設計模式實際上看起來非常簡單且幾乎平凡。大多數情況下，它顯示為實線折線圖，顯示實際收集的數據，後面跟著顯示預測值的虛線（見圖 13.1）。

Today (fortunately), we no longer need to drug people to get our predictions. The Forecasting UX for AI design pattern actually looks quite simple and almost mundane. Most often, it shows up as a line graph in a solid line showing the actual collected data followed by a dashed line showing the forecasted value (see Figure 13.1).

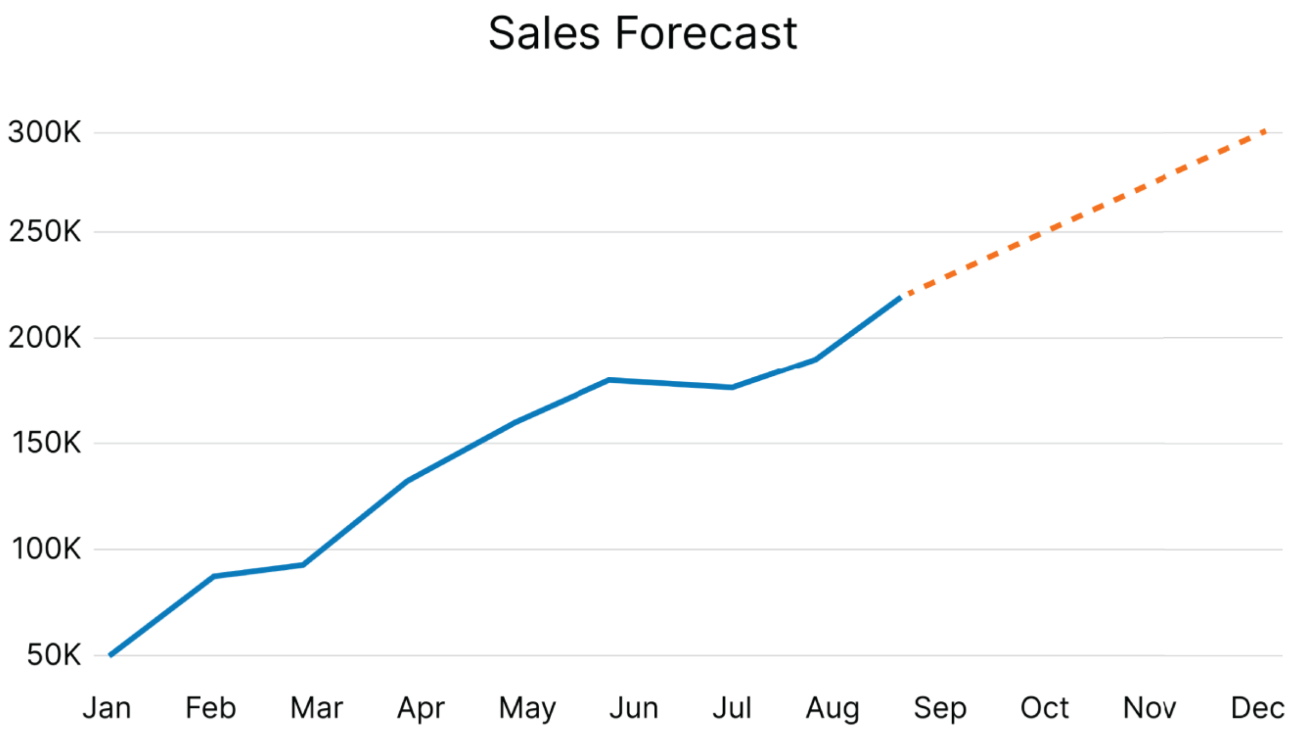

圖 13.1 圖表上的典型預測

Figure 13.1 Typical forecast on a graph

來源：'作者' / 經 exceljet 許可轉載 / https://exceljet.net/charts/line-chart-actual-with-forecast

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或者，除了虛線之外，您還可以放置一條垂直的 “ 現在 ” 線，作為一種 “ 您在這裡 ” 標記來指示當前日期和時間，以及一個 “ 置信區間 ” 圓錐體（稍後會詳細介紹）。圖 13.2 顯示了溫差預報中這兩種技術的範例。

Optionally, in addition to the dashed line, you may drop a vertical “ now ” line as well, as a sort of “ you are here ” marker to indicate the current date and time, and a “ confidence interval ” cone (more on that later). Figure 13.2 shows an example of both techniques in a temperature differential forecast.

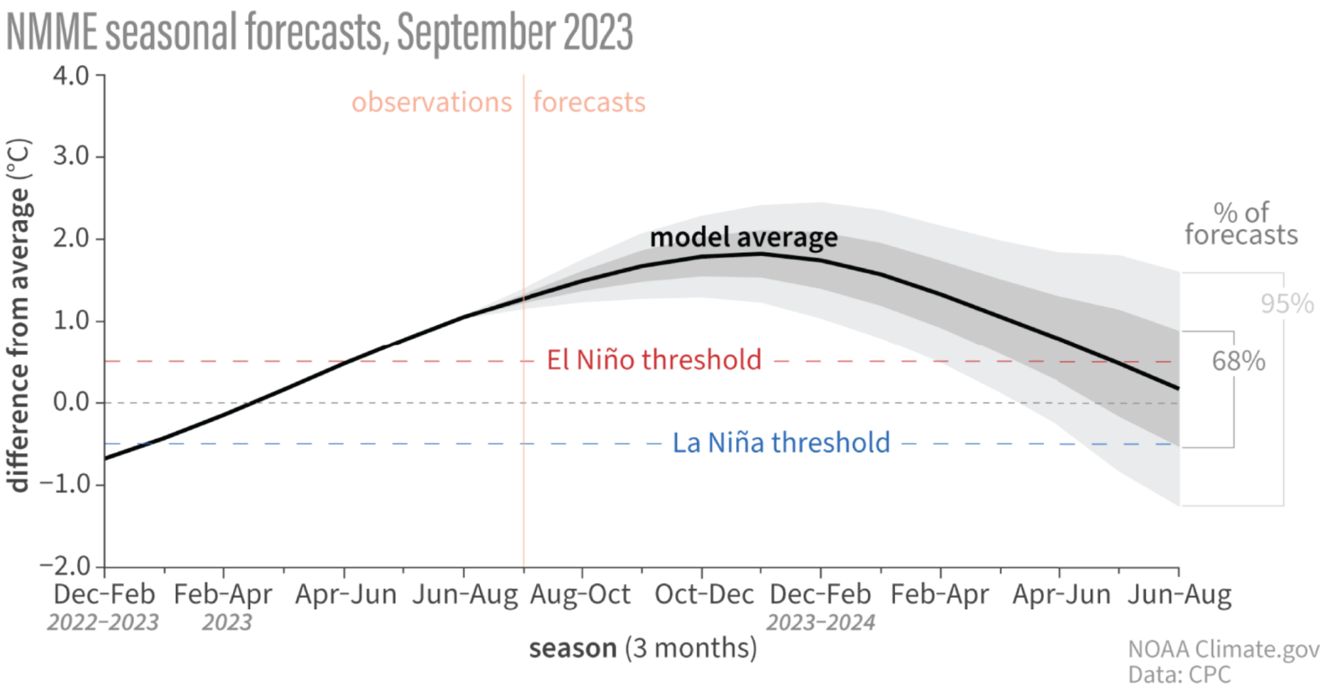

圖 13.2 溫度預報圖中的 now 線和兩個置信區間

Figure 13.2 The now line and two confidence intervals in a temperature forecast graph

資料來源：'author' / 美國國家海洋和大氣管理局 / 公共領域 / https://www.climate.gov/media/15588

Source: ‘ author ’ / National Oceanic and Atmospheric Administration / Public domain / https://www.climate.gov/media/15588

作為使用者體驗設計師或研究人員，您為什麼要關心預測介面的設計？簡而言之，這是人工智慧最重要的用途之一。除了預測銷售和天氣之外，您還可以使用這個簡單的界面設計模式來預測飲食計劃、產品需求、股市表現、農作物生長或管道生鏽、化糞池裝滿需要多長時間，或者全球變暖殺死我們所有人......希望你明白了。（我們將在本章末尾的練習中嘗試這一點。

Why should you, as a UX designer or researcher, care about the design of forecasting interfaces? Simply put, it ’ s one of the most important uses of AI. In addition to forecasting sales and weather, you can use this simple interface design pattern to forecast weight loss/gain on a diet plan, product demand, stock market performance, how long it takes for crops to grow or a pipe to rust, or a septic tank to fill, or for global warming to kill us all … Hopefully, you get the idea. (We will try this out in an exercise at the end of the chapter.)

現在讓我們深入研究預測的細節。為此，我們必須進入數學軌道，但我向你保證，這些概念非常簡單，今天花 10 分鐘將使您能夠在未來 10
年的職業生涯中與同事進行更好的對話。

Now let ’ s dig into the finer points of forecasting. For this, we ’ ll have to get into the orbit of planet Math, but I assure you, the concepts are quite simple, and an investment of 10 minutes today will empower you to have better conversations with your colleagues for the next 10 years of your career.

線性迴歸

Linear Regression

最重要的預測技術之一是線性迴歸。從本質上講，這個想法很簡單：在可用數據點上畫一條直線。然後，您可以使用這條線來預測任何 X 的 Y 值;不需要人工智慧！這方面的數學實際上非常簡單;在我們穿過資料點的線後，我們測量從每個資料點到結果線的距離，稱為殘差。直觀地，很容易看出最適合的線與所有數據點的距離最小。這些距離（殘差）通常被平方以刪除負號，因此您正在測量到線 （1） 的絕對距離。見圖 13.3。

One of the most important forecasting techniques is linear regression. Essentially, the idea is simple: Draw a straight line through the available data points. Then, you can use this line to predict the value of Y for any X; no AI is required! The math for this is actually pretty straightforward; after we put a line through the data points, we measure the distance from each data point to the resulting line, called a residual. Intuitively, it is easy to see that the line that fits best will have the smallest distances from all the data points. These distances (residuals) are typically squared to remove the negative sign, so you are measuring the absolute distance to the line (1). See Figure 13.3.

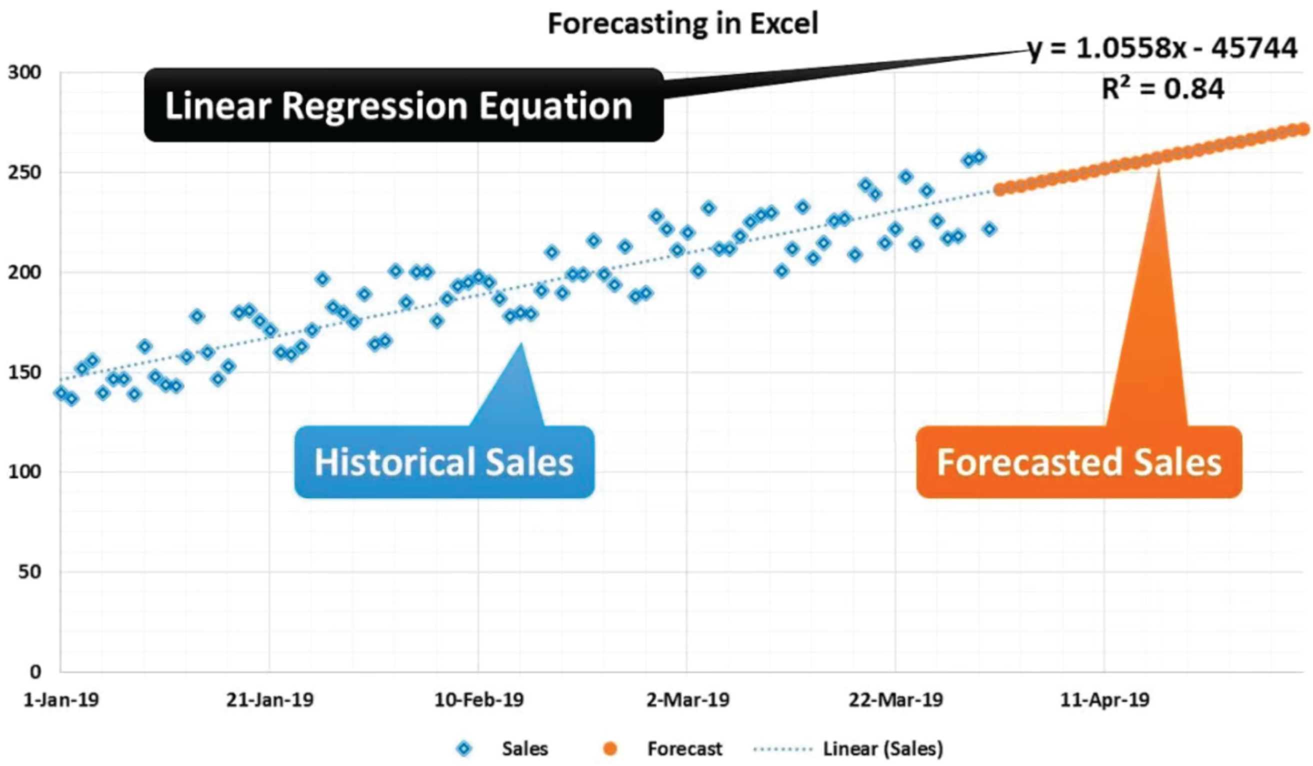

圖 13.3 線性迴歸預測範例

Figure 13.3 Example of a linear regression forecast

來源：'author'/ 經 Youtube 許可轉載 / https://youtu.be/8iqzFQ_nZI8?si=MJrhk59_b-oPyY4F

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R 平方

R-Squared

作為預測效果的代理，我們可以使用標準衡量我們繪製的線與現有數據點的匹配程度。在圖 13.4 中，我們可以直觀地看到線 A（左）比線 B（右）對資料點的擬合「更寬鬆」。

As a proxy to how well the forecast will work, we can use a standard measure of how well the line we drew matches the existing data points. In Figure 13.4, we can intuitively see that the line A (left) is a “ looser ” fit to the data points than the line B (on the right).

這種 “ 適應度 ” 可以用數學來衡量，稱為 R 平方，是一個介於 0 和 1 之間的數字。同樣，不需要花哨的人工智慧;數學非常簡單，並且在許多 YouTube

視頻中以有趣且易於理解的方式進行了解釋 （2）。

This “ fitness ” can be measured mathematically and is called R-squared, which is a number between 0 and 1. Again, no fancy AI is needed; the math is pretty straightforward and is explained in many YouTube videos in an entertaining and accessible manner (2).

關於 R 平方，需要了解的重要一點是，它越接近
1，擬合就越好，因此，它可能會產生更好的預測。相反，R 平方數越低（例如，R
平方越接近 0），擬合度越差，因此我們的預測就越不可信。R
平方很容易使用，因為它是線性的：0.8 的 R 平方是 0.4 的 R 平方的兩倍。（我意識到這有點令人困惑：平方變量是線性的，這就是為什麼我想我應該指出這一點。

The important thing to understand about R-squared is that the closer it is to 1, the better the fit and, therefore, it presumably yields a better forecast. In contrast, the lower the R-squared number (e.g., the closer the R-squared is to 0), the worse the fit and, therefore, the less trustworthy our prediction is. R-squared is easy to work with because it is linear: R-squared of 0.8 is twice as good as R-squared of 0.4. (I realize this is somewhat confusing: a squared variable is linear, which is why I thought I ’ d point that out.)

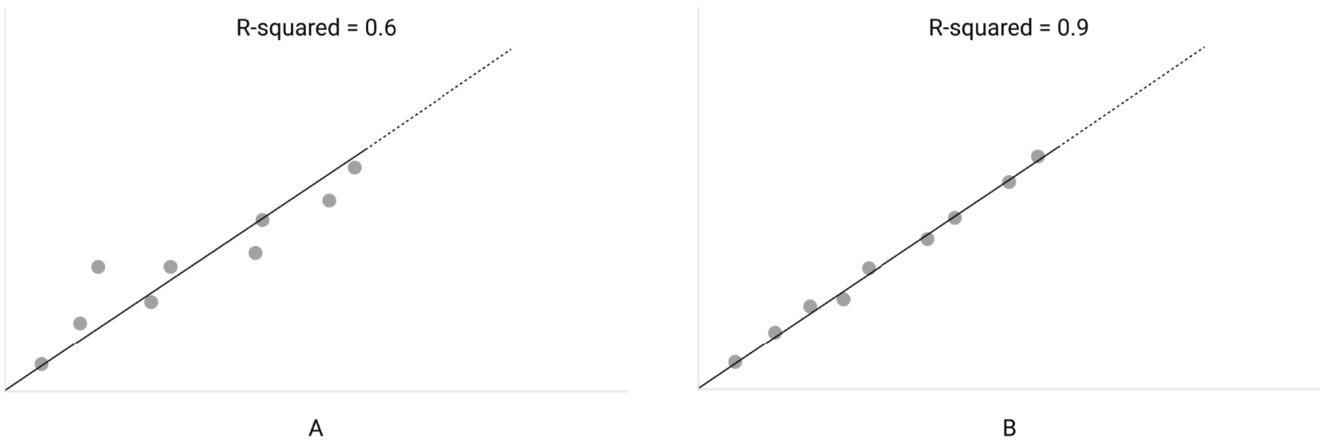

圖 13.4 R 平方是衡量線與數據點擬合程度的指標

Figure 13.4 R-squared is a measure of how well the line fits the data points

為了協助您的客戶了解預測的擬合程度，您可以顯示帶有置信區間的虛線預測線，這有點像最近「修復」的狗的「恥辱錐」。我們已經在預測厄爾尼諾溫度變化的圖表中使用的章節前面看到了置信區間（圖 13.2）。置信區間的陰影區域標記了線（或狗）可能去的地方的假定限制。我們預測得越遠，我們引入的不確定性就越大，從而為線的移動創造了更大的可

能空間。當然，預測不是一門精確的科學，因此置信區間（作為大多數狗的錐體）更像是一個想法而不是一個規則。因此，它旨在作為概率的視覺指示，而不是未來一定會實現的事情。然而，置信區間（見圖 13.5）確實為預測的可能“ 優點 ”提供了有用、直觀的視覺指南（3）。

To help your customer see how well the prediction fits, you can show the dashed forecast line with the confidence interval—which is kind of like a “ cone of shame ” for a dog who has been recently “ fixed. ” We have already seen a confidence interval earlier in the chapter used in the graph predicting the El Ni ñ o temperature change (Figure 13.2). The shaded area of the confidence interval marks the supposed limits of where the line (or the dog) may go. The further out we forecast, the more uncertainty we introduce, creating a larger possible space for the line to move. Of course, forecasting is not an exact science, so the confidence interval (as a cone with most dogs) is more of an idea than a rule. It is, therefore, meant to be a visual indication of probability, not something that is necessarily going to come true in the future. However, the confidence interval (see Figure 13.5) does provide a helpful, intuitive visual guide as to the possible “ goodness ” of the forecast (3).

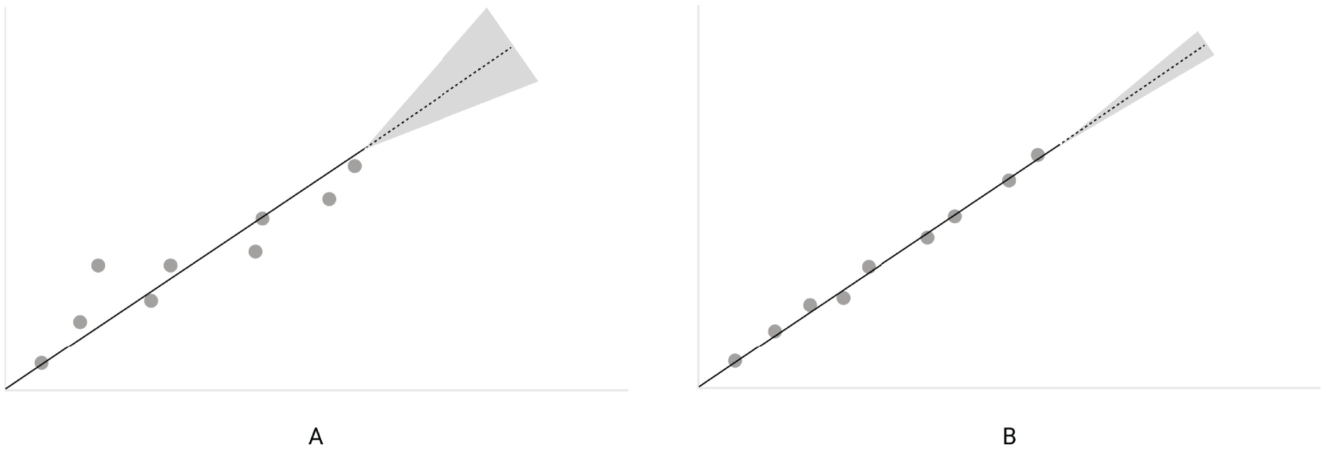

圖 13.5 置信區間為觀眾提供了預測可能的「優點」的提示。（與圖13.4比較）

Figure 13.5 The confidence interval gives the viewer a hint of a possible “ goodness ” of a forecast. (Compare with Figure 13.4)

請注意，對於圖 A（左圖），資料點的間距離線更遠，因此預測的確定性較差（圓錐體更寬），而不是圖 B（右圖），其中所有點都非常靠近線排列，這讓我們非常有信心這種趨勢將持續下去;因此，置信區間較小（圓錐體較窄）。當然，置信區間也具有嚴格的數學意義（估計值的平均值加上或減去該估計值的變異），這超出了本書的範圍。

Note that for graph A (on the left), the data points are spaced further away from the line, so the forecast is less certain (the cone is wider), than it is in graph B (on the right), where all of the points line up very close to the line, giving us high confidence that this trend will continue; thus, the confidence interval is smaller (the cone is narrower). Naturally, the confidence interval also has a strict mathematical meaning (the mean value of your estimate plus or minus the variation in that estimate), which is beyond the scope of this book.

R 與 R 平方

R vs. R-Squared

R 平方的一個潛在缺點是它不指示方向（更高或更低）;我們所知道的只是絕對的區別。您可能還記得我們在第 5 章中對準確性的討論，“ 價值矩陣——人工智能準確性是胡說八道。這就是使用者體驗必須採取的措施」，有時超調可能比低於預測產生更高的後果，因此在那些時候，您確實需要考慮差異的方向。

One potential disadvantage of R-squared is that it does not indicate the direction (higher or lower); all we know is the absolute difference. As you might recall from our discussion of accuracy in Chapter 5, “ Value Matrix—AI Accuracy Is Bullshit. Here's What UX Must Do About It, ” sometimes overshooting can have much higher consequences than undershooting your forecast, and so in those times, you really do want to account for the direction of the difference.

便條

NOTE

例如，想像一下，您正在預測前往北極的 1 個月旅程需要多少食物。您認為預測誤差的兩個方向會產生相同的結果嗎？如果你高估了食物的數量，你會攜帶一些額外的牛肉乾 1,000 英里，這是一個相對較小的不便。如果你低估了食物的數量，你的探險隊就會挨餓，每個人都可能死去。

Imagine, for example, that you are forecasting how much food you would need for a 1-month journey to the North Pole. Do you think that both directions of a forecast error will have the same consequence? If you overestimate the amount of food, you will carry some extra beef jerky 1,000 miles, a relatively minor inconvenience. If you underestimate the amount of food, your expedition will starve and everyone may die.

R-Squared
不適合預測超調/低調產生不同貨幣或人道主義影響的情況，因此您可以只使用
R。您如何知道您的特定用例代表什麼場合？嗯，很自然地，你會問你的
PM、中小企業和客戶，再次證明了 Richard Saul Wurman 的格言：

R-Squared is unsuitable for the occasions where the forecasting over/undershooting has a different monetary or humanitarian impact, so you can just use R. How do you know what occasion your specific use case represents? Well, naturally, you would ask your PMs, SMEs, and customers, once again proving Richard Saul Wurman ’ s maxim:

While most professions make a living with their knowledge, UX people make a living through their ignorance

—Richard Saul Wurman

當然，這意味著用戶體驗問題的質量很重要。事實上，這就是本章的目的：為您提供提出正確問題所需的工具。

Meaning, of course, that the quality of UX questions matters. This is, in fact, the purpose of this chapter: to equip you with the tools you need to ask the right questions.

利用 AI 進行預測

Forecasting with AI

你可能會說，「這一切都很好，但你沒有告訴我們任何關於人工智慧如何幫助我們進行預測的資訊。這一切都只是高中數學！這是真的。在許多情況下，提出更好的問題意味著從您的數據科學同事那裡了解預測算法到底有多複雜。

You might say, “ All this is well and good, but you did not tell us anything about how AI could help us with forecasting. It was all just high school math! ” That is true. In many cases, asking better questions means sussing out from your data science colleagues just how sophisticated the prediction algorithm really is.

便條

NOTE

大多數時候，您會發現簡單的數學效果很好，而使用 AI/ML
方法只會讓事情變得複雜。乃。（參見 David Andrzejewski 在第 2
章「選擇正確用例的重要性」中的側邊欄。

Most times, you will find simple math works just fine, and using AI/ML methods will only complicate things. Really. (See David Andrzejewski ’ s sidebar in Chapter 2, “ The Importance of Picking the Right Use Case. ”)

然而，有幾種關鍵的預測技術以折線圖的形式顯示，其中 AI/ML 方法幾乎是創建準確預測的唯一方法。我對其中兩個有最個人的經驗：非線性回歸和季節性。接下來讓我們介紹這兩個。

However, there are several key forecasting techniques shown as line graphs, where AI/ML methods are pretty much the only way to create an accurate forecast. I have the most personal experience with two of them: nonlinear regression and seasonality. Let ’ s cover those two next.

非線性迴歸

Nonlinear Regression

雖然近期預測通常可以通過直線和簡單的數學來近似：

While a near-term prediction can often be approximated via a straight line and simple math:

便條

NOTE

自然界中很少有事物在整個數據範圍內具有真正的線性關係。

Few things in nature have a true linear relationship across the entire spectrum of data.

例如，圖 13.6 顯示了產品中氯降解的圖表，該圖表與產品在架子上停留的時間的函數有關，該圖表來自一篇關於非線性回歸技術的論文 （4）。

For example, Figure 13.6 shows a graph of chlorine degradation in a product as a function of the time it spent sitting on a shelf from a paper on nonlinear regression techniques (4).

雖然我們當然可以通過這些數據點畫一條直線，但很明顯，直線並不適合。在這種情況下，我們將在非線性回歸方面做得更好。基本上，對於線性和非線性迴歸，相同的考慮因素都適用，只不過圖表不是直線，而是一條更複雜的曲線，具有更複雜的方程，最適合資料點並提供最高的 R 平方。最佳擬合方程式通常由某種 AI/ML
演算法確定，該演算法會嘗試各種標準方程式方法來確定哪個方程式會產生最佳擬合。

While we can certainly put a straight line through these data points, it should be fairly obvious that a straight line will not be a great fit. This is a case where we will do much better with nonlinear regression. Essentially, for both linear and nonlinear regression, the same considerations apply, except the graph is not a straight line but a more complex curve with a more complex equation that best fits the data points and provides the highest R-squared. The best-fit equation is usually determined by some kind of AI/ML algorithm, which tries various standard equation approaches to determine which equation creates the best fit.

這篇論文詳細介紹了各種技術，所以我建議完整閱讀。然而，對於不想進入數學領域的使用者體驗設計師來說，主要要點是，如圖 13.7 所示，多個不同的方程式可能（幾乎）同樣有效，您應該與您的資料科學和工程同事合作使用 AI/ML 方法找出最適合的非線性模型。

The paper goes into a great deal of detail regarding various techniques, so I recommend reading it in its entirety. However, the main takeaway for UX designers who do not want to get into math is that, as shown in Figure 13.7, multiple different equations might work (nearly) equally well, and you should work with your data science and engineering colleagues on the AI/ML approaches to figure out the best fit nonlinear model.

您還需要了解用例。僅僅因為模型很好地擬合了數據，並不意味著該模型是預測下一個數據點的正確模型。圖 13.8 顯示了一個不幸的例子，該模型雖然很好地擬合了現有數據，但與系統中實際發生的情況不符：這條曲線預測氯的量會隨著儲存時間的延長而增加，這是一種明顯的“ 幻覺 ”。

You also need to understand the use case. Just because the model fits the data well, that does not mean the model is the correct one for predicting the next data point. Figure 13.8 shows one unfortunate example where the model, while fitting the existing data well, does not match what physically happens in the system: This curve is predicting that the amount of chlorine will increase with prolonged storage time, an obvious “ hallucination. ”

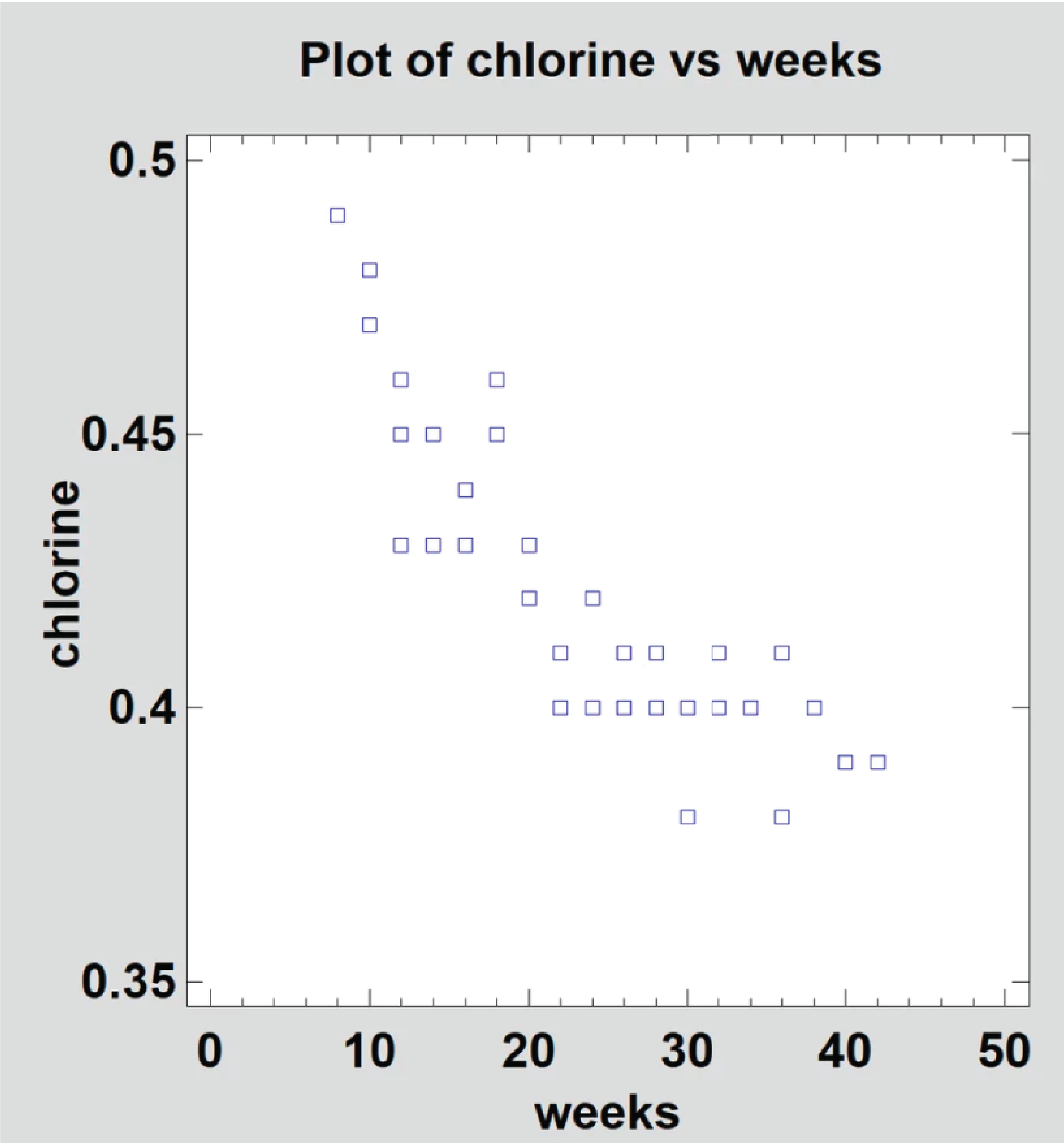

圖 13.6 產品中的氯降解隨時間變化是非線性函數

Figure 13.6 Chlorine degradation in a product as a function of the time is a nonlinear function

資料來源：'作者' / 經 Statgraphics Technologies 許可轉載 / https://www.statgraphics.com/blog/nonlinear_regression

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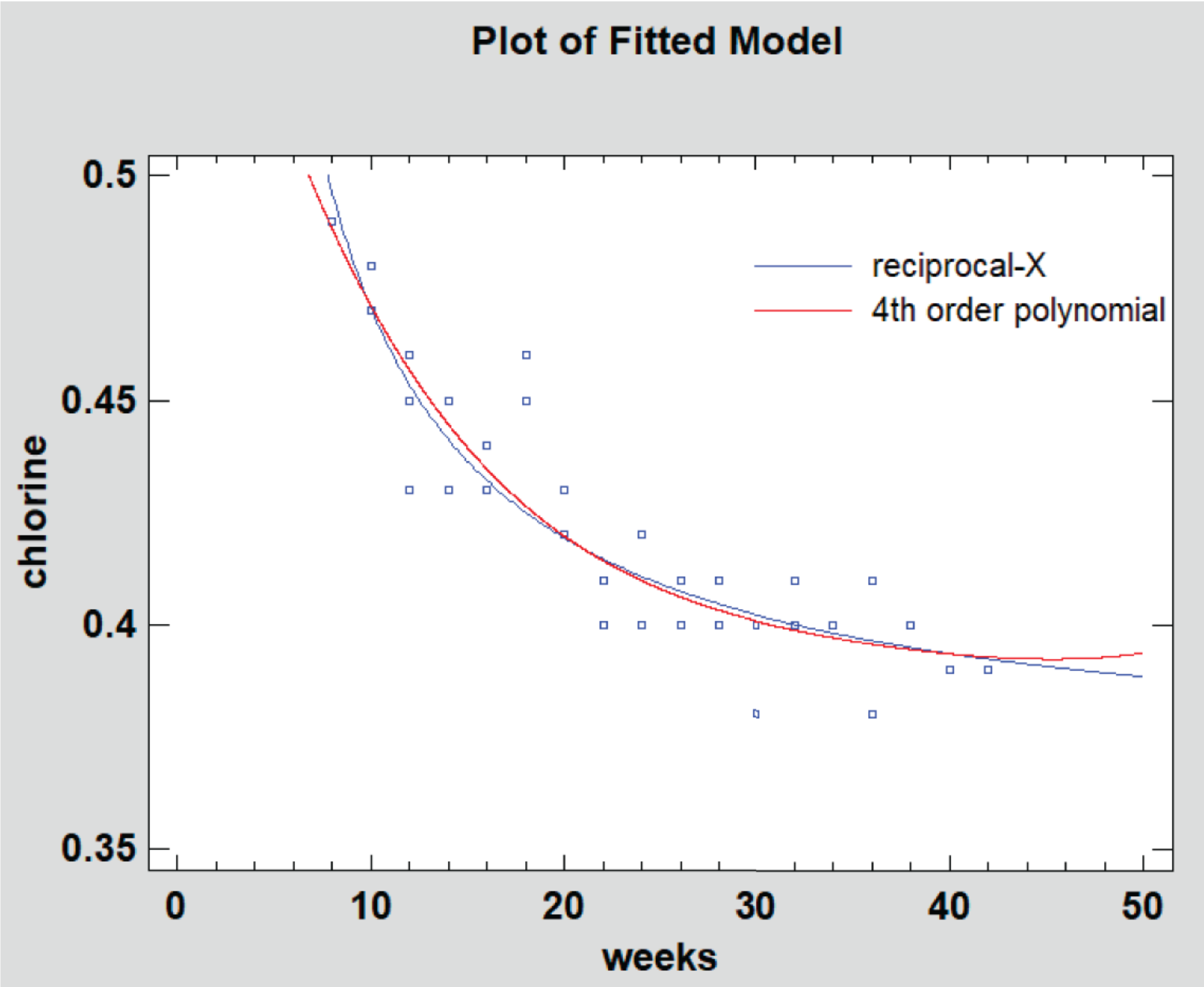

圖 13.7 多個方程式可能幾乎同樣有效。您需要了解用例才能選擇最好的用例

Figure 13.7 Multiple equations might work almost equally well. You need to understand the use case to pick the best one

資料來源：'作者' / 經 Statgraphics Technologies 許可轉載 / https://www.statgraphics.com/blog/nonlinear_regression

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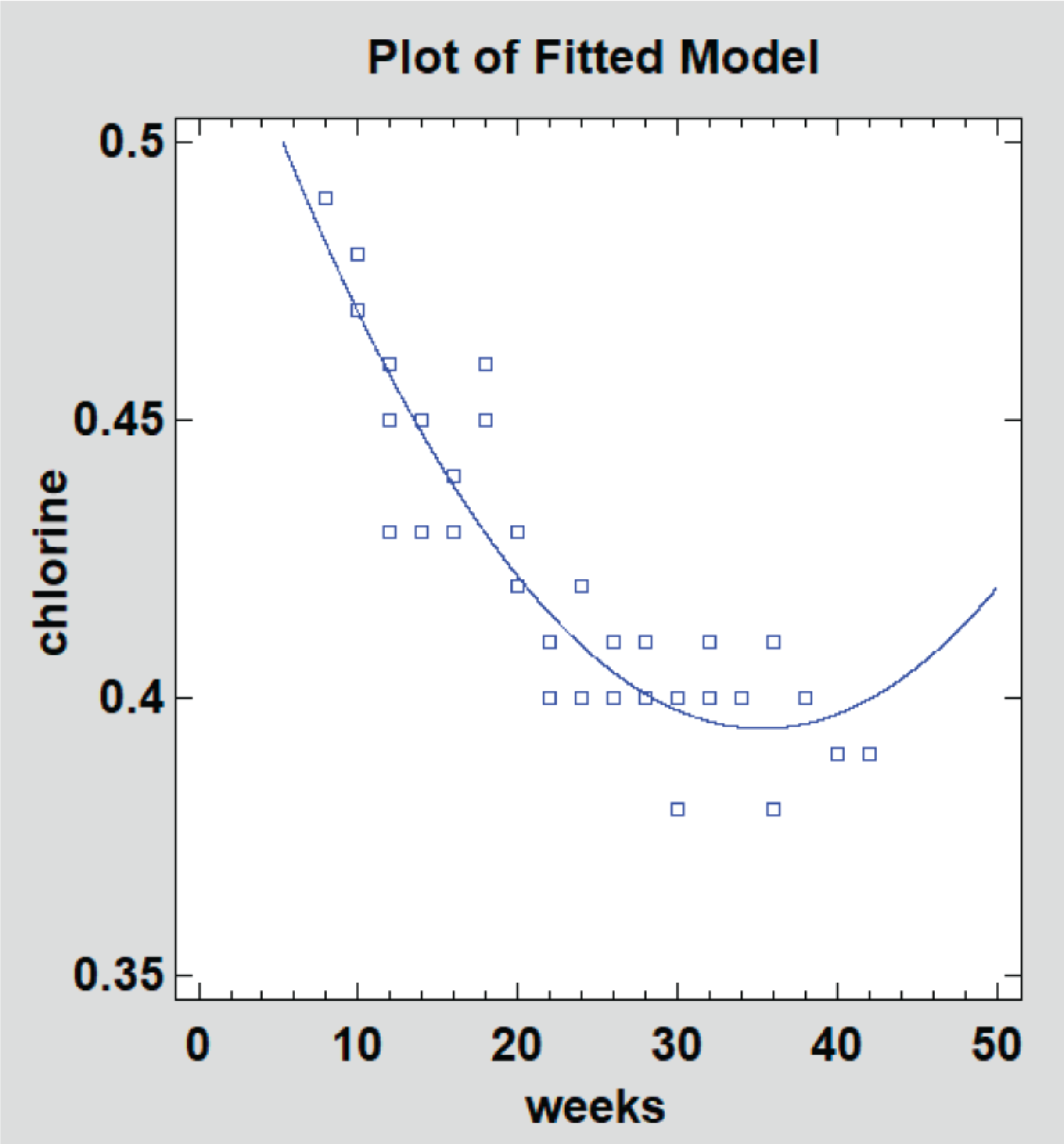

圖 13.8 並非所有符合資料的曲線都符合使用案例。這張圖顯示，氯的含量會隨著儲存時間的延長而增加，這是一種明顯的「幻覺」

Figure 13.8 Not all curves that fit the data match the use case. This graph shows that the amount of chlorine will increase with prolonged storage time, an obvious " hallucination "

資料來源：'作者' / 經 Statgraphics Technologies 許可轉載 / https://www.statgraphics.com/blog/nonlinear_regression

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便條

NOTE

作為從事非線性迴歸預測的使用者體驗設計師，向資料科學家、中小企業和客戶提出好問題以確定曲線是否與物理現實相符，以幫助團隊避免像圖 13.8 中的情況一樣，這是您工作的一部分。

As a UX designer working on nonlinear regression forecasting, it is part of your job to ask good questions of data scientists, SMEs, and customers to determine if the curve matches physical reality in order to help the team avoid situations like the one in Figure 13.8.

季節性

Seasonality

考慮典型的網站流量：它在周一至週五的工作時間達到高峰，並在每晚和週末下降。除了典型的每週變化外，還有電子商務網站需求增加的高峰期。對於美國電子商務網站來說，這些日子是每年都會發生的黑色星期五、網路星期一、假日、勞動節等（見圖 13.9）。

Consider typical website traffic: it peaks Monday – Friday during working hours and drops off every night and on weekends. In addition to the typical weekly variation, there are peak times of increased demand for e-commerce websites. For U.S. e-commerce websites, those are days such as Black Friday, Cyber Monday, holidays, Labor Day, etc., which occur every year (see Figure 13.9).

這種類型的變化稱為季節性，使用典型的非線性迴歸方法很難預測。考慮此類變化並做出準確需求預測的唯一好方法是收集大量數據並將其提供給 ML 模型。幸運的是，ML 在這種情況下通常運作良好。

This type of variation is called seasonality, and it is very difficult to predict using typical nonlinear regression methods. The only good way to account for this type of variation and make accurate demand forecasts is to collect a bunch of data and feed it to an ML model. Fortunately, ML usually works quite well in this case.

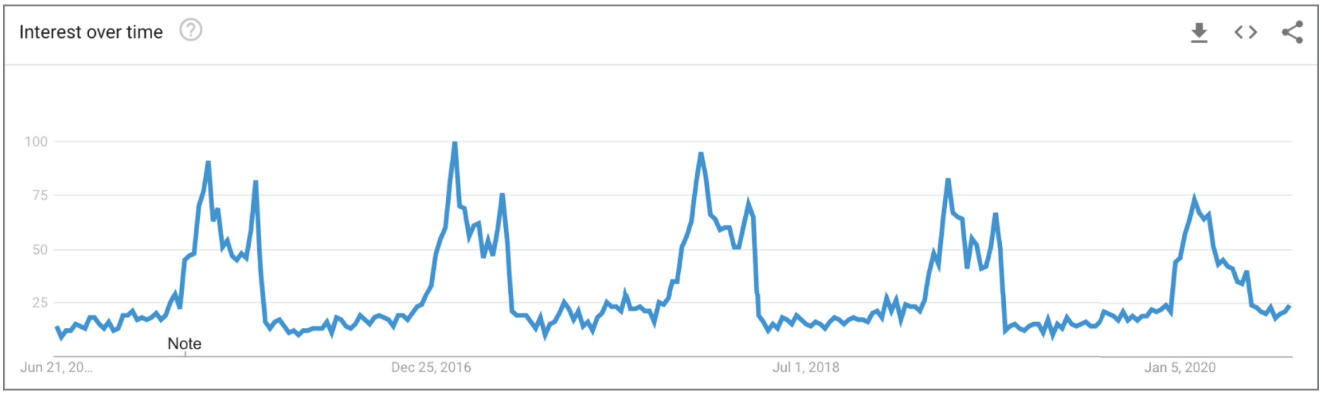


圖 13.9 季節性範例

Figure 13.9 Example of seasonality

資料來源：作者/經 Search Engine Journal 許可轉載id_0000。

Source: author / reproduced with permission of Search Engine Journal./ https://www.searchenginejournal.com/seo-seasonality-overcoming-dips-during-slow-season/372742

同樣，作為設計師，您的工作是了解驅動季節性的潛在力量，以便您可以就團隊預測演算法的品質和限制提出好問題。不僅要記住每週，還要記住每月和每年的季節性，以便模型的預測最能描述現實。詢問過度和不足是否會產生相同的後果——大多數情況下，它們不會！

Again, as a designer, it is your job to understand the underlying forces that drive seasonality so that you can ask good questions about the quality and limitations of your team ’ s prediction algorithm. Keep in mind not only the weekly but also monthly and yearly seasonality so that the model ’ s predictions best describe reality. Ask if overshooting and undershooting will have the same consequences—most often, they will not!

便條

NOTE

例如，如果您高估了網路星期一的流量，您的 AWS 帳單會略高。如果您低估流量，您的整個網站將崩潰，刪除購物車和搜索會話信息，並且每中斷一分鐘就讓您損失數百萬美元。

For example, if you overestimate Cyber Monday traffic, your AWS bill will be slightly higher. If you underestimate the traffic, your whole website will crash, erasing shopping carts and search session information, and costing you millions for every minute of outage.

一旦您完成了功課並覺得您很好地理解了現實生活中的模型並預測了後果，請與您的工程和數據科學同事進行高質量的討論。詢問建立預測模型使用了多少資料：一週的數據還是幾週的數據？該模型是否考慮了黑色星期五等年度趨勢？確保您收集的資料符合使用案例的季節性要求，並且每個人都對目標不足/超調的後果達成共識，並相應地調整模型。

Once you complete your homework and feel that you understand the real-life model and forecast consequences well, set up a quality discussion with your engineering and data science colleagues. Ask about how much data was used to build the forecast model: one week ’ s worth of data or several? Does the model account for yearly trends such as Black Friday? Make sure the data you are collecting meets the seasonality requirements of your use case and that everyone is on the same page with regard to the consequences of under/overshooting your target and adjust the model accordingly.

預測彙總變數

Forecasting an Aggregate Variable

最後，讓我們談談一個用例，其中折線圖不是預測的絕佳選擇。例如，如果我們要繪製一個最好用長條圖描述的聚合變數（例如某物的每日交易量），則預測也應該是長條圖。圖 13.10 和圖 13.11 顯示了一個使用人工智能系統預測每週用水需求模式的示例。

Finally, let ’ s talk about a use case where a line graph will not be a great option for the forecast. For example, if we are plotting an aggregate variable (like the daily volume of something) that is best described as a bar graph, the forecast should also be a bar graph. Figures 13.10 and 13.11 show an example where the AI system is used to forecast the weekly water demand pattern.

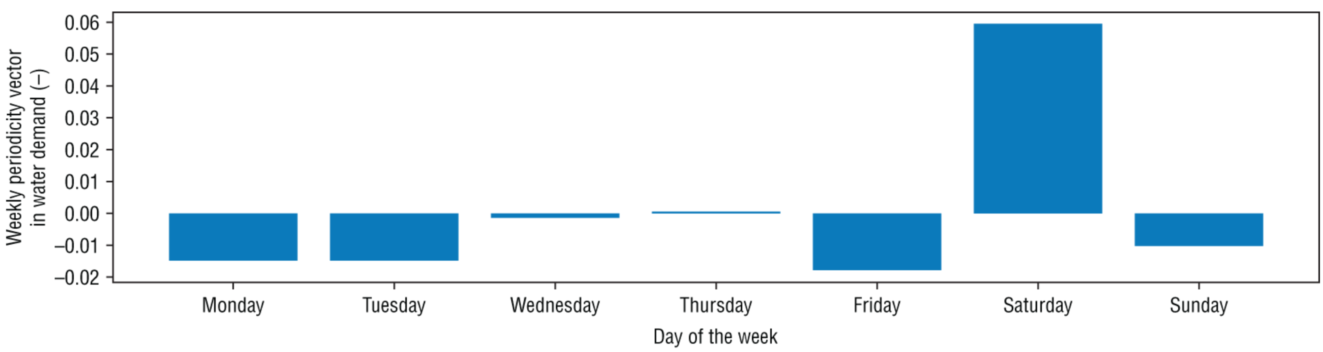


圖 13.10 聚合變數最好使用長條圖顯示

Figure 13.10 Aggregate variable is best displayed with a bar graph

資料來源：作者 / 施普林格自然 / CC BY 4.0 / https://www.nature.com/articles/s41598-022-17177-0

Source: author / Springer Nature / CC BY 4.0 / https://www.nature.com/articles/s41598-022-17177-0

在此用例中使用折線圖並不是一個好的選擇;條形圖要好得多，因為我們使用了一個聚合變量：每日總用水量。請注意，此範例示範了我們在上一節中提到的強烈每週季節性。

Using a line graph for this use case would not be a great choice; a bar chart is much better because we are using an aggregate variable: total daily water consumption. Note that this example demonstrates the strong weekly seasonality we touched upon in the previous section.

這種預測的用例是什麼？如果你能準確預測對水的需求，你可以使用更便宜的方法來抽水，比如在晚上把水抽到高儲水箱以節省電費，或者使用更便宜、更可靠但速度較慢的小容量泵來提高效率並降低成本。此預測的另一個價值是簡單地知道您有足夠的水來滿足選民的需求。

What ’ s the use case for this kind of prediction? If you can accurately forecast the demand for water, you can use cheaper methods to pump it, like pumping it to a high storage tank at night to save on the electrical bill, or using a cheaper and more reliable but slower low-volume pump to increase efficiency and decrease cost. Another value of this forecast is simply knowing that you have enough water to meet the needs of your constituents.

現在，如果您的系統只是計算平均一周的數據並預測下週的相同數量，這將非常簡單，並且不需要人工智慧參與。然而，更現實的模型可能包括每年的季節性;也許人們在夏季或某些假期前後使用更多的水。基於人工智慧的模型可以幫助更準確地預測季節性需求。

Now, if your system simply calculated the average week ’ s worth of data and forecasted the same amounts for next week, that would be pretty straightforward, and no AI would need to be involved. However, a more realistic model might include yearly seasonality; perhaps people use more water in the summer or around certain holidays. An AI-based model can help forecast seasonal demand more accurately.

當我們訓練模型來考慮環境因素時，事情會變得更加有趣。回想一下，在第 2 章中，我們討論瞭如何使用智慧灌溉系統來減少生長植物的用水量。一個「知道」各種植物每日澆水

需求並可以考慮降水（雨、霧、露水等）以及溫度和濕度等環境因素的人工智慧模型對於預測農作物田的總澆水需求非常有用。像這樣的模型可用於在保持作物產量的同時將用水量保持在最低限度，從而實現利潤最大化（同時還可以減少水資源浪費和抽水成本，遵守行業法規，並減少全球變暖）。

Things get even more interesting when we train the model to account for environmental factors. Recall that in Chapter 2 we discussed how a smart irrigation system can be used to reduce water consumption in growing plants. An AI model that “ knows ” the daily watering requirements of various plants and that can take into account environmental factors such as precipitation (rain, fog, dew, etc.), as well as temperature and humidity, would be very useful in forecasting the total watering needs for a field of crops. A model such as this could be used to keep water consumption at the minimum while maintaining crop yield, thereby maximizing profit (while also reducing water waste and pumping costs, complying with industry regulations, and reducing global warming).

漂亮，不是嗎？

Nifty, no?

在圖 13.11 中，實際用水量以深色條標示。較輕的條形代表我們的 AI
模型產生的需求預測。

In Figure 13.11, the actual water consumption is marked in dark bars. Lighter bars represent the demand forecast produced by our AI model.

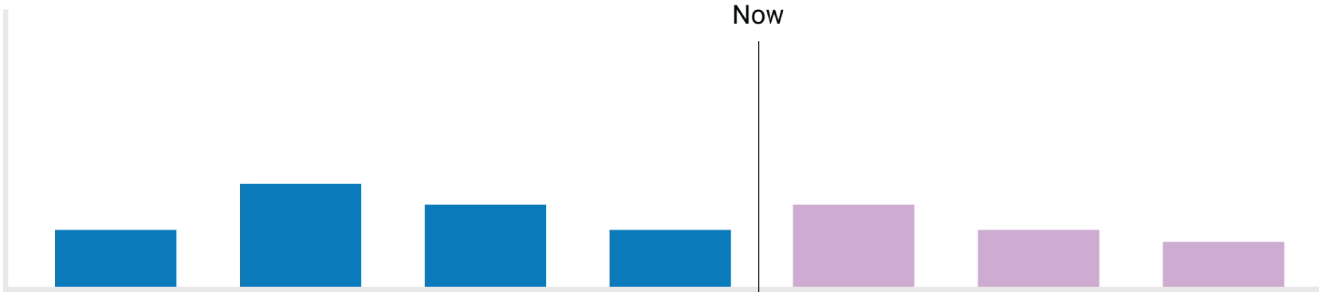


圖 13.11 彙總變數的複雜季節性預測

Figure 13.11 Complex seasonal forecast for an aggregate variable

最後的話

Final Words

在本章中，我們詳細介紹了基於折線圖和聚合變量的預測。雖然預測本身的圖片通常很簡單（虛線圖或條形圖），但將其視為“簡單”將是一個錯誤。有許多細微差別需要考慮;實地研究和與同事的高質量對話是絕對必須的。

In this chapter, we have covered line-graph and aggregate variable-based forecasting in some detail. While the picture of the forecast itself is often straightforward (a dashed line or bar chart), treating it as “simple” would be a mistake. There are many nuances to consider; field research and quality conversations with your colleagues are an absolute must.

作為使用者體驗設計師，您不需要深入了解可能涉及的所有複雜數學。但是，如果您對所涉及的概念有一定的了解，您的工作會更容易，專案成果也會好得多。了解更多關於各種統計預測方法的信息將幫助您最大限度地提高對團隊的價值，並提高您作為用戶體驗設計師的效率。

As a UX designer, you don't need a deep understanding of all of the complex math that could be involved. However, your work will be easier and project outcomes will be far better if you have some understanding of the concepts involved. Learning more about various statistical forecasting methods will help you maximize your value to the team and increase your effectiveness as a UX designer.

正如羅伯特·謝克利（Robert Sheckley）在他無與倫比的短篇小說《問一個愚蠢的問題》（Ask a Foolish Question）中說得那麼好（5）：

As Robert Sheckley said so well in his incomparable short story, “Ask a Foolish Question”(5):

In order to ask a [good] question you must already know most of the answer

—Robert Sheckley

設計練習：設計您自己的預測 UI

Design Exercise: Design Your Own Forecasting UI

1. 想出三種不同的方法來使用預測來幫助在您自己的專案中顯示預測。您想要預測哪些變數以及為什麼？預測將如何影響客戶的決策？這些預測是高調好還是低調好？何？Come up with three different ways you can use forecasting to help display predictions in your own project. What variables would you want to forecast and why? How would the forecast affect your customers' decisions? Is it better to overshoot or undershoot these predictions? Why?

2. 想一想您可以為專案預測的三個不同的彙總變數。訓練此類模型時，最好包含哪些因素？您有哪些現成的數據？您還需要哪些資料？您需要與誰交談才能弄清楚如何獲取丟失的數據？（請記住，您可以隨時從向 ChatGPT 尋求幫助開始！Think of three different aggregate variables you can forecast for your project. What factors would be ideal to include when training such a model? What data do you have readily available? What data do you still need? Who do you need to talk with in order to figure out how to get the missing data? (Remember, you can always start by asking ChatGPT for help!)

如果您需要靈感，請看以下範例。在完成自己的設計練習之前，不要繼續下一章。

If you need inspiration, look at the following example. Do not proceed to the next chapter until you complete your own design exercise.

設計練習範例：生命時鐘預測

Design Exercise Example: Life Clock Forecasting

很容易想像我們如何在 Life Clock/Life Copilot 用例中利用預測——整個應用程式基本上是一台預測機器，用於計算用戶何時死亡！當用戶養成更健康的習慣時，我們也會相應地更新預測，以幫助盡可能長時間地延長健康壽命。因此，預測在我們的應用程式設計中起著關鍵作用。到目前為止，我們一直使用實際日期作為預測里程碑（例如，請參閱第 7 章和第 8 章的設計練習）。對於這個設計練習，讓我們嘗試使用置信區間的折線圖預測，為了多樣性，讓我們在水平方向的全螢幕上進行（見圖 13.12）。

It is easy to imagine how we can utilize forecasting in the Life Clock/Life Copilot use case—the entire app is basically a forecasting machine for figuring out when the user will die! We also update the forecast accordingly as the user implements the healthier habits to help extend healthy life for as long as possible. Thus, forecasting plays a pivotal role in our app design. So far we ’ ve been using the actual date as a forecast milestone (see design exercises for Chapters 7 and 8, for example). For this design exercise, let ’ s try out the line graph forecast with a confidence interval, and just for variety, let ’ s do it on a full screen in a horizontal orientation (see Figure 13.12).

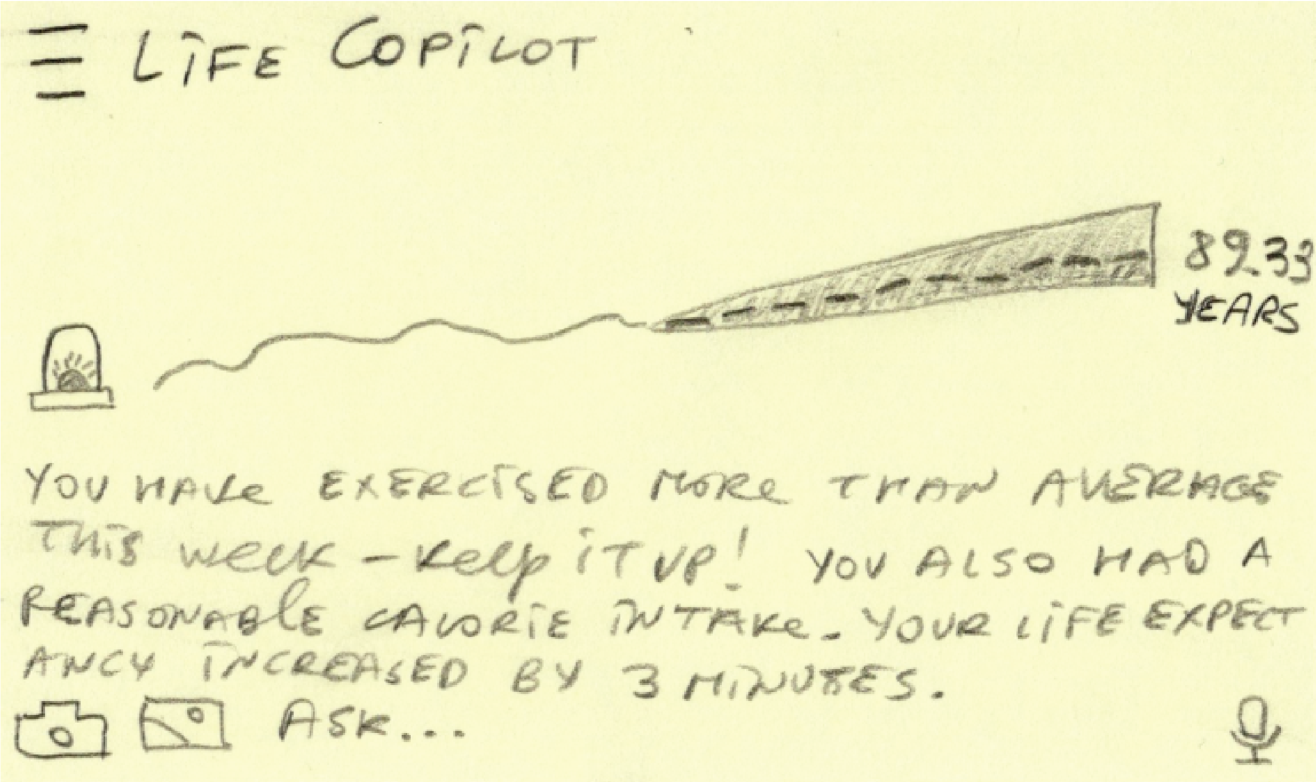


圖 13.12 具有置信區間的折線圖預測

Figure 13.12 Line graph forecast with a confidence interval

顯然，我們應用程式的用戶應該關心他們的壽命，因此也許該應用程式可以每週進行一次“ 簽到 ”，人工智慧會顯示此類圖表並解釋預期壽命預測與上週相比的變化。也許通過看到他們在過去一周的選擇對他們預計壽命的直接影響，用戶會受到啟發，在下週做出更好的選擇。用戶是否關心我們的預測是否錯誤？好吧，顯然生命越多越好，但如果我們在任一方向上休息幾年，可能沒有人會那麼在意——畢竟，基因和事故之類的東西在我們實際死亡的日期中發揮了很大的作用。因此，在這種情況下，積極地對待我們預測的影響可能是可以的。畢竟，當用戶死後，如果你預測他們還能再活兩年，他們不太可能起訴你！

Clearly the users of our app are expected to care about their longevity, so maybe the app can do a weekly “ check-in ” where the AI shows this type of graph and explains the life expectancy forecast changes from last week. Perhaps by seeing the immediate impact of their choices during the past week on their projected longevity, the users will be inspired to make even better choices next week. Do users care if we are mistaken in our prediction? Well, clearly more life is better, but if we are off a few years in either direction no one will likely care that much—after all, genes and things like accidents play a large part in the actual date of our demise. Thus, being aggressive about the impact of our prediction might be okay in this case. After all, when the user is dead, they are unlikely to sue you if you predicted that they would live for another two years!

現在來談談彙總變數。雖然我們一直將預期壽命預測顯示為折線圖，指向用戶在地球上死亡的遙遠未來，但從每日總體中來說，增加或減去的預期壽命效應實際上是一個總體變量。不僅如此，每天增加或減少的生活還受到多個總變量的影響：卡路里攝入量和運動量。讓我們建立一個簡單的行動線框圖，顯示一周內的所有三個匯總指標（卡路里攝取量、運動量、終生增加/減少），並附有「現在線」和四天預測（見圖 13.13）。

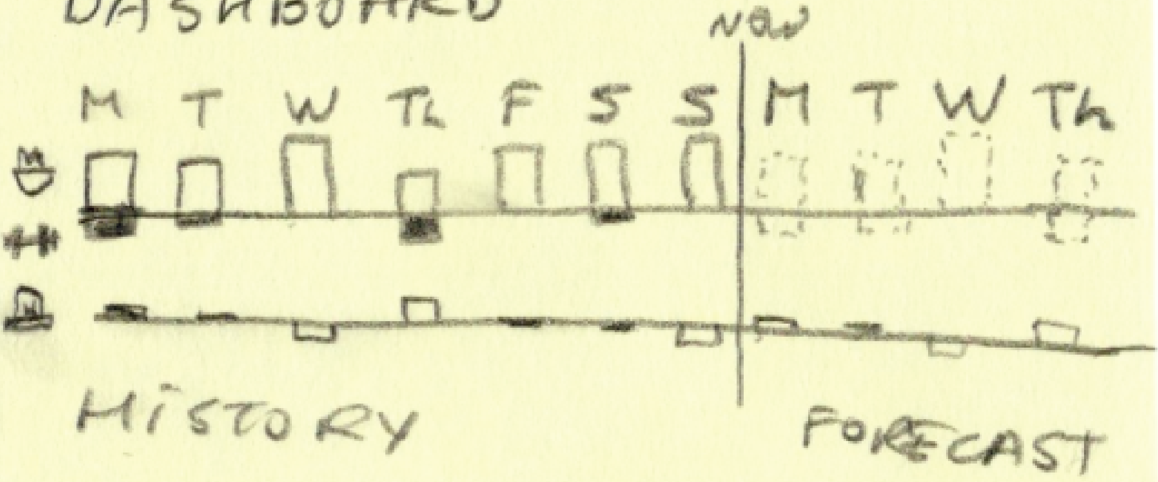
Now on to the aggregate variables. While we have been showing the life expectancy forecast as a line graph that points into a distant future of the user ’ s earthly demise, in daily aggregate, the added or subtracted life expectancy effect is actually an aggregate variable. Not only that, but life added or subtracted each day is influenced by multiple aggregate variables: calorie intake and exercise. Let ’ s create a simple mobile wireframe that shows all three aggregate metrics (calorie intake, exercise, lifetime increase/decrease) for a week with a “ now line ” and a four-day forecast (see Figure 13.13).

每個指標都是每日彙總，因此將它們顯示為長條圖非常有意義。還要注意每天出現的週期性——週一和週四大量鍛煉，週三、週五、週六和週日暴飲暴食。看到圖表的預測部分重複的每週模式可能非常有效地改變人的行為並說服他們，例如，避免每週與好友酗酒，而是在周三和周五去健身房。

Each of the metrics is a daily aggregate, so it makes perfect sense to show them as bar charts. Note also the emerging periodicity of each day—lots of exercise on Mondays and Thursdays, and binge eating on Wednesdays, Fridays, Saturdays, and Sundays. Seeing that weekly pattern repeated in the forecast section of the graph might be very effective in changing the person ’ s behavior and persuade them, for example, to avoid weekly binge drinking with their buddies and instead to go to the gym on Wednesdays and Fridays.

LIFE COPILOT

DASHBOARD



Ask...

圖 13.13 一周的總計指標（卡路里攝入量、運動量、終生增加/減少），帶有“ 現在線 ” 和四天預測

Figure 13.13 Aggregate metrics (calorie intake, exercise, lifetime increase/decrease) for a week with a “ now line ” and a four-day forecast

最後一點：雖然營養顯然起著重要作用，但很難以總體方式表示。也許我們可以嘗試顯示飽和脂肪、蛋白質、鈉和其他微量營養素的類似聚合條形圖？我會說“ 是的 ”，但首先我會研究我們已有的線框圖如何與客戶產生共鳴。（更多關於以 RITE 方式進行 AI 用戶研究的 UX 的信息，請參閱本書的第 3 部分。

One final note: While nutrition clearly plays a big role, it is harder to represent in an aggregate way. Perhaps we can experiment with showing similar aggregate bar graphs for saturated fat, protein, sodium, and other micronutrients? I ’ d say “ yes, ” but first I would research how the wireframes we already have resonate with customers. (More on doing UX for AI user research the RITE way in Part 3 of this book.)

現在輪到你了！花 10
分鐘繪製您自己的預測設計草圖。在完成練習之前不要繼續下一章。

Now it ’ s your turn! Take 10 minutes to sketch your own designs for forecasting. Do not proceed to the next chapter until you finish the exercise.

參考

References

1. 1. youtu.be/nk2CQITm_eo?si=0fgAnCW5PYH_5G3d1. youtu.be/nk2CQITm_eo?si=0fgAnCW5PYH_5G3d
2. 2.
www.youtube.com/watch?v=bMccdk8EdGo2. www.youtube.com/watch?v=bMccdk8EdGo
3. 3. 艾莉森，R.（2013）。如何繪製預測和信賴區間。SAS 學習帖子 https://blogs.sas.com/content/sastraining/2013/12/19/how-to-plot-a-forecast-and-confidence-interval3. Allison, R. (2013). How to plot a forecast and confidence interval. SAS Learning Post. https://blogs.sas.com/content/sastraining/2013/12/19/how-to-plot-a-forecast-and-confidence-interval

4. 4. 波爾赫穆斯，N.（2018）。擬合非線性迴歸模型。統計圖形。https://www.statgraphics.com/blog/nonlinear_regression4.　　Polhemus, N. (2018). Fitting nonlinear regression model. Statgraphics. https://www.statgraphics.com/blog/nonlinear_regression

5. 5. 謝克利，R.（2010）。問一個愚蠢的問題（古騰堡計劃電子書）。www.gutenberg.org/files/33854/33854-h/33854-h.htm5.　　Sheckley, R. (2010). Ask a Foolish Question (The Project Gutenberg e-Book). www.gutenberg.org/files/33854/33854-h/33854-h.htm