MATH 302 Applied Project: Approximation Theory and Related Applications

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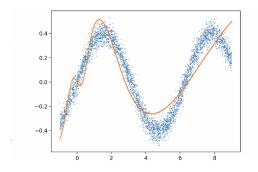


Outline

- Background of approximation theory
 - Discrete least squares approximation
 - Continuous least squares approximation
 - Other techniques (least squares using Legendre/Chebyshev polynomials)
- Research questions
 - How to find the "line" of best fit in practical problems?
 - Can we identify the trends in stocks and make prediction about the trends using least squares approximation?
- Results
 - Market price of gold vs Stock price of a gold mining company
 - Weather forecast
 - Identify the trends in stocks (Original result)
- Summary

Background of approximation theory

- Approximation theory is the branch of mathematics which studies the process of approximating general functions by simple functions such as polynomials.
- It therefore plays a central role in the analysis of numerical methods.



https://gaoxiangluo.github.io/2020/09/27/V isual-and-Rigorous-Proof-of-Universal-Approximation-Theorem-UAT/2020/09/27/V isual-and-Rigorous-Proof-of-Universal-Approximation-Theorem-UAT/2020/09/200/09/

Discrete least squares approximation

Discrete least squares approximation

- Linear least squares
- Polynomial least squares
- Non-polynomials least squares

Discrete least squares approximation (Linear)

Linear least squares

- Data: $(x_1, y_1), (x_2, y_2), \dots, (x_m, y_m)$
- Linear approximation: y = f(x) = ax + b
- Find a, b that minimize the error $E = \sum_{i=1}^{m} (y_i ax_i b)^2$
- For a minimum to occur, we must have $\frac{\partial E}{\partial a} = 0$ and $\frac{\partial E}{\partial b} = 0$
- We have:

$$\frac{\partial E}{\partial a} = \sum_{i=1}^{m} \frac{\partial E}{\partial a} (y_i - ax_i - b)^2 = \sum_{i=1}^{m} (-2x_i)(y_i - ax_i - b) = 0$$

$$\frac{\partial E}{\partial b} = \sum_{i=1}^{m} \frac{\partial E}{\partial b} (y_i - ax_i - b)^2 = \sum_{i=1}^{m} (-2)(y_i - ax_i - b) = 0$$

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P.S. The error term E has the same idea as the **residual vector** we learned on Wednesday.

Definition 7.23 Suppose $\tilde{\mathbf{x}} \in \mathbb{R}^n$ is an approximation to the solution of the linear system defined by $A\mathbf{x} = \mathbf{b}$.

The **residual vector** for $\tilde{\mathbf{x}}$ with respect to this system is $\mathbf{r} = \mathbf{b} - A\tilde{\mathbf{x}}$.

Discrete least squares approximation (Linear)

Linear least squares (continued)

• Using algebra, these equations can be simplified as

$$b\sum_{i=1}^{m} x_i + a\sum_{i=1}^{m} x_i^2 = \sum_{i=1}^{m} x_i y_i$$
$$bm + a\sum_{i=1}^{m} x_i = \sum_{i=1}^{m} y_i,$$

The solution to this system of equations is

$$a = \frac{m \sum_{i=1}^m x_i y_i - \sum_{i=1}^m x_i \sum_{i=1}^m y_i}{m \left(\sum_{i=1}^m x_i^2\right) - \left(\sum_{i=1}^m x_i\right)^2}, b = \frac{\sum_{i=1}^m x_i^2 \sum_{i=1}^m y_i - \sum_{i=1}^m x_i y_i \sum_{i=1}^m x_i}{m \left(\sum_{i=1}^m x_i^2\right) - \left(\sum_{i=1}^m x_i\right)^2}.$$

• Now we get a, b that minimize the error $E = \sum_{i=1}^{m} (y_i - ax_i - b)^2$

Polynomial least squares

- Data: $(x_1, y_1), (x_2, y_2), \dots, (x_m, y_m)$
- Polynomial approximation: $P_n(x) = a_n x^n + a_{n-1} x^{n-1} + \cdots + a_0$ where m will be usually much larger than n and $a_n \neq 0$
- Similarly, we want to minimize

$$E = \sum_{i=1}^{m} (y_i - P_n(x_i))^2 = \sum_{i=1}^{m} \left(y_i - \sum_{j=0}^{n} a_j x_i^j \right)^2$$

with respect to the parameters $a_n, a_{n-1}, \ldots, a_0$

For a minimum to occur, the necessary conditions are

$$\frac{\partial E}{\partial a_k} = 0 \Rightarrow -\sum_{i=1}^m y_i x_i^k + \sum_{j=0}^n a_j \left(\sum_{i=1}^m x_i^{k+j} \right) = 0$$

for
$$k = 0, 1, ..., n$$

Polynomial least squares (continued)

• Using algebra, we get a system of (n+1) equations and (n+1) unknowns

$$\sum_{j=0}^{n} a_j \left(\sum_{i=1}^{m} x_i^{k+j} \right) = \sum_{i=1}^{m} y_i x_i^k$$

for k = 0, 1, ..., n

We can write this system as a matrix equation

$$\mathbf{A}a = \mathbf{b}$$

where a is the unknown vector we are trying to find, and b is the constant vector

Polynomial least squares (continued)

 where a is the unknown vector we are trying to find, and b is the constant vector

$$a = \begin{bmatrix} a_0 \\ a_1 \\ \vdots \\ a_n \end{bmatrix}, b = \begin{bmatrix} \sum_{i=1}^m y_i \\ \sum_{i=1}^m y_i x_i \\ \vdots \\ \sum_{i=1}^m y_i x_i^n \end{bmatrix}$$

and A is an (n+1) by (n+1) symmetric matrix with (kj)th entry A_{kj} , $k=1,2,\ldots,n+1$, $j=1,2,\ldots,n+1$ given by

$$A_{kj} = \sum_{i=1}^{m} x_i^{k+j-2}$$

• The matrix equation Aa = b has a unique solution if the x_i are distinct, and $n \le m - 1$

Non-polynomials least squares

• The method of least squares is not only for polynomials. For example, suppose we want to find the function

$$f(t) = a + bt + c\sin(2\pi t/365) + d\cos(2\pi t/365)$$

that has the best fit to some data $(t_1, T_1), \ldots, (t_m, T_m)$ in the least-squares sense. This function is used in modeling weather temperature data, where t denotes time, and T denotes the temperature.

Similarly, we want to minimize the least squares error term

$$E = \sum_{i=1}^{m} (f(t_i) - T_i)^2 = \sum_{i=1}^{m} \left(a + bt_i + c \sin(\frac{2\pi t_i}{365}) + d \cos(\frac{2\pi t_i}{365}) - T_i \right)^2$$

Non-polynomials least squares (continued)

• We set its partial derivatives with respect to the unknowns a, b, c, d to zero to obtain the following equations:

$$\begin{split} \frac{\partial E}{\partial a} &= 0 \Rightarrow \sum_{i=1}^{m} 2\left(a + bt_i + c\sin\left(\frac{2\pi t_i}{365}\right) + d\cos\left(\frac{2\pi t_i}{365}\right) - T_i\right) = 0 \\ &\Rightarrow \sum_{i=1}^{m} \left(a + bt_i + c\sin\left(\frac{2\pi t_i}{365}\right) + d\cos\left(\frac{2\pi t_i}{365}\right) - T_i\right) = 0, \end{split}$$

$$\frac{\partial E}{\partial b} = 0 \Rightarrow \sum_{i=1}^{m} (2t_i) \left(a + bt_i + c \sin\left(\frac{2\pi t_i}{365}\right) + d\cos\left(\frac{2\pi t_i}{365}\right) - T_i \right) = 0$$
$$\Rightarrow \sum_{i=1}^{m} t_i \left(a + bt_i + c \sin\left(\frac{2\pi t_i}{365}\right) + d\cos\left(\frac{2\pi t_i}{365}\right) - T_i \right) = 0,$$

$$\begin{split} \frac{\partial E}{\partial c} &= 0 \Rightarrow \sum_{i=1}^m \left(2 \sin \left(\frac{2\pi t_i}{365} \right) \right) \left(a + bt_i + c \sin \left(\frac{2\pi t_i}{365} \right) + d \cos \left(\frac{2\pi t_i}{365} \right) - T_i \right) = 0 \\ &\Rightarrow \sum_{i=1}^m \sin \left(\frac{2\pi t_i}{365} \right) \left(a + bt_i + c \sin \left(\frac{2\pi t_i}{365} \right) + d \cos \left(\frac{2\pi t_i}{365} \right) - T_i \right) = 0, \end{split}$$

$$\frac{\partial E}{\partial d} = 0 \Rightarrow \sum_{i=1}^{m} \left(2\cos\left(\frac{2\pi t_i}{365}\right) \right) \left(a + bt_i + c\sin\left(\frac{2\pi t_i}{365}\right) + d\cos\left(\frac{2\pi t_i}{365}\right) - T_i \right) = 0$$

$$\Rightarrow \sum_{i=1}^{m} \cos\left(\frac{2\pi t_i}{365}\right) \left(a + bt_i + c\sin\left(\frac{2\pi t_i}{365}\right) + d\cos\left(\frac{2\pi t_i}{365}\right) - T_i \right) = 0.$$

Non-polynomials least squares (continued)

• Rearranging terms in the above equations, we get a system of four equations and four unknowns:

$$am + b\sum_{i=1}^{m} t_i + c\sum_{i=1}^{m} \sin\left(\frac{2\pi t_i}{365}\right) + d\sum_{i=1}^{m} \cos\left(\frac{2\pi t_i}{365}\right) = \sum_{i=1}^{m} T_i$$

$$a\sum_{i=1}^{m} t_i + b\sum_{i=1}^{m} t_i^2 + c\sum_{i=1}^{m} t_i \sin\left(\frac{2\pi t_i}{365}\right) + d\sum_{i=1}^{m} t_i \cos\left(\frac{2\pi t_i}{365}\right) = \sum_{i=1}^{m} T_i t_i$$

$$a\sum_{i=1}^{m} \sin\left(\frac{2\pi t_i}{365}\right) + b\sum_{i=1}^{m} t_i \sin\left(\frac{2\pi t_i}{365}\right) + c\sum_{i=1}^{m} \sin^2\left(\frac{2\pi t_i}{365}\right) + d\sum_{i=1}^{m} \sin\left(\frac{2\pi t_i}{365}\right) \cos\left(\frac{2\pi t_i}{365}\right)$$

$$= \sum_{i=1}^{m} T_i \sin\left(\frac{2\pi t_i}{365}\right)$$

$$a\sum_{i=1}^{m} \cos\left(\frac{2\pi t_i}{365}\right) + b\sum_{i=1}^{m} t_i \cos\left(\frac{2\pi t_i}{365}\right) + c\sum_{i=1}^{m} \sin\left(\frac{2\pi t_i}{365}\right) \cos\left(\frac{2\pi t_i}{365}\right) + d\sum_{i=1}^{m} \cos^2\left(\frac{2\pi t_i}{365}\right)$$

$$= \sum_{i=1}^{m} T_i \cos\left(\frac{2\pi t_i}{365}\right)$$

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Non-polynomials least squares (continued)

• Using a short-hand notation where we suppress the argument $(\frac{2\pi t_l}{365})$ in the trigonometric functions, and the summation indices, we write the above equations as a matrix equation:

$$\underbrace{ \begin{bmatrix} m & \sum t_i & \sum \sin(\cdot) & \sum \cos(\cdot) \\ \sum t_i & \sum t_i^2 & \sum t_i \sin(\cdot) & \sum t_i \cos(\cdot) \\ \sum \sin(\cdot) & \sum t_i \sin(\cdot) & \sum \sin^2(\cdot) & \sum \sin(\cdot) \cos(\cdot) \\ \sum \cos(\cdot) & \sum t_i \cos(\cdot) & \sum \sin(\cdot) \cos(\cdot) & \sum \cos^2(\cdot) \end{bmatrix}}_{\mathbf{A}} \underbrace{ \begin{bmatrix} a \\ b \\ c \\ d \end{bmatrix}}_{\mathbf{r}} = \underbrace{ \begin{bmatrix} \sum T_i \\ \sum T_i t_i \\ \sum T_i \sin(\cdot) \\ \sum T_i \cos(\cdot) \end{bmatrix}}_{\mathbf{r}}$$

• Solve the equation $\mathbf{A}x = \mathbf{r}$ to get the unknowns a, b, c, d

Continuous least squares approximation

Continuous least squares approximation

- In discrete least squares, our starting point was a set of data points. Here we will start with a continuous function f on [a,b] and answer the following question: how can we find the "best" polynomial $P_n(x) = \sum_{j=0}^n a_j x^j$ of degree at most n, that approximates f on [a,b]?
- As before, "best" polynomial will mean the polynomial that minimizes the least squares error:

$$E = \int_{a}^{b} \left(f(x) - \sum_{j=0}^{n} a_{j} x^{j} \right)^{2} dx$$

Compare this expression with that of the discrete least squares:

$$E = \sum_{i=1}^{m} \left(y_i - \sum_{j=0}^{n} a_j x_i^j \right)^2$$

Continuous least squares approximation

Continuous least squares approximation (continued)

• To minimize E we set $\frac{\partial E}{\partial a_k} = 0$, for k = 0, 1, ..., n, and observe

$$\frac{\partial E}{\partial a_k} = \frac{\partial}{\partial a_k} \left(\int_a^b f^2(x) dx - 2 \int_a^b f(x) \left(\sum_{j=0}^n a_j x^j \right) dx + \int_a^b \left(\sum_{j=0}^n a_j x^j \right)^2 dx \right)$$
$$= -2 \int_a^b f(x) x^k dx + 2 \sum_{j=0}^n a_j \int_a^b x^{j+k} dx = 0,$$

which gives the (n+1) equations for the continuous least squares problem:

$$\sum_{j=0}^{n} a_j \int_a^b x^{j+k} dx = \int_a^b f(x) x^k dx$$

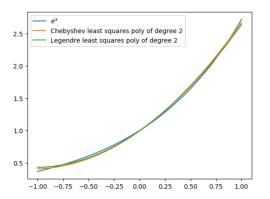
for k = 0, 1, ..., n

• Note that the only unknowns in these equations are the a_j 's, hence this is a linear system of equations.

Other techniques

Other techniques

- Least squares using Legendre polynomials
- Least squares using Chebyshev polynomials



Compare the quadratic approximations obtained by Legendre and Chebyshev polynomials. We can see visually that Chebyshev does a better approximation at the end points of the interval (First Semester Numerical Analysis with Julia, p. 206).

Research questions

Research questions

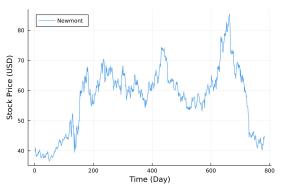
- How to find the "line" of best fit in practical problems?
- Can we identify the trends in stocks and make prediction about the trends using least squares approximation?



https://ohiostate.pressbooks.pub/choosingsources/chapter/purpose-of-research-questions/

A practical problem

- There is an investment considering whether to invest in a gold mining company or not. We want to know how sensitive the company's stock price is to changes in the market price of gold.
- To study this, we could use the least squares method to trace the relationship between those two variables over time onto a scatter plot. This analysis could help us predict the degree to which the stock's price would likely rise or fall for any given change in the price of gold.
- In this project, we trace the stock price of Newmont, which is one of the world's largest gold mining corporations, and the market price of gold from 2019/8/30 to 2022/10/6.



Plotted by Julia



https://finance.yahoo.com/news/newmont-delays-investment-decision-peru-135023690.html

What we understand from the analysis

- The stock price of Newmont rises as the market price of gold goes up.
- The relationship is not simply linear.
- Investors should pay attention to the change of gold price when investing gold mining companies.

Apply non-polynomials least squares to weather forecast

$$f(t) = a + bt + c\sin(\frac{2\pi t}{365}) + d\cos(\frac{2\pi t}{365})$$

- The period T is 365 days.
- The term bt implies "global warming" if b > 0.

How to apply non-polynomials least squares to the stock market

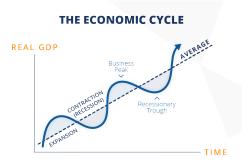
$$f(t) = a + bt + c\sin(\frac{2\pi t}{T}) + d\cos(\frac{2\pi t}{T})$$

Questions we need to answer

- What is the period T in this case? Is it still 365 days?
- What does the term bt represent in the stock market?

To answer the above questions, we need to know

The economic cycle



https://www.fe.training/free-resources/asset-management/stages-of-the-economic-cycle/stages-of-the-ec

 The average length of recessions in the U.S. since World War II has been just around 11 months. U.S. expansions have typically lasted longer than U.S. recessions.

https://www.kiplinger.com/slideshow/investing/t038-s001-recessions-10-facts-you-must-know/index.html. A continuous cont

To answer the above questions, we need to know

- Cyclical stocks:
 Cyclical businesses perform well during economic expansions but typically experience significantly declining sales and profits during recessions.
- Cyclical stocks are generally concentrated in specific industries such as airlines, real estate, and construction.



Now we are able to apply non-polynomials least squares

- We trace the stock price of Lennar, which is the leading homebuilder in the U.S., from 2012/7/2 to 2018/9/27.
- The period *T* is approximately 22 months.
- The term bt shows that the real estate industry develops as the U.S. economy grows (the stock trend is going up).

Now we are able to apply non-polynomials least squares

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- The period *T* is approximately 22 months.
- The term bt shows that the real estate industry develops as the U.S. economy grows (the stock trend is going up).

Some limitations on our approach

- We can only investigate the cyclical stocks.
- The trend in the stock market (e.g., S & P 500) is supposed to be going up or going down (there exists a general trend).
- "Black swan events" may influence the approximation significantly.
- P.S. The limitations are not always a bad thing. Knowing the limitations of a method actually enables us to apply it properly and effectively.

Summary

- Approximation theory
 - Discrete least squares approximation
 - Continuous least squares approximation
 - Other techniques (least squares using Legendre/Chebyshev polynomials)
- Research questions
 - How to find the "line" of best fit in practical problems?
 - Can we identify the trends in stocks and make prediction about the trends using least squares approximation?
- Results
 - The "line" of best fit of gold price vs stock price
 - Weather forecast using non-polynomials least squares
 - Identify the trends in stocks using non-polynomials least squares
- Summary

References

References:

- Numerical Analysis 10E
- First Semester Numerical Analysis with Julia
- Cyclical stocks: https://finbold.com/guide/cyclical-stocks-definition/
- The economic cycle: https://www.kiplinger.com/slideshow/investing/t038-s001-recessions-10-facts-you-must-know/index.html

The end

Thanks for your listening!