Handling Missing Data in the Data Science Lifecycle

Lecture Complementary Resources

https://github.com/HatefDastour/DSA_Lecture

Content:

- Lecture Slides
- Lecture Example
- Lecture Activity

Introduction

Opening Example

Cooking and Missing Ingredients

- Imagine you’re cooking a recipe but find that you’re missing key ingredients.
- Just like missing ingredients can ruin a dish, missing data can lead to inaccurate analysis and poor decision-making.

* Image generated by Microsoft Designer.

The Challenge of Missing Data

- Data that is missing or incomplete.

What is Missing Data?

Can You Provide Examples of Missing Data?

- **Reduced Reliability:** Affects the accuracy of analysis.
- **Biased Conclusions:** Can lead to incorrect insights.
- **Model Limitations:** Many machine learning models require complete data.

Why is it a Problem?

Goals of This Lecture

- Understand Missing Data
- Learn Handling Techniques
- Develop Critical Thinking
- Practical Application
- Best Practices

Types of Missing Data

Types of Missing Data

MCAR
Missing Completely at Random

MAR
Missing at Random

MNAR
Missing Not at Random

MCAR: Missing Completely at Random

Definition:

- Data missing **purely by chance**, unrelated to any characteristics or values in the dataset.

Examples:

1. A shipment of completed surveys gets lost in transit.
2. Random power outage causes issues in data collection tools.

MAR: Missing at Random

Definition:

- Missingness **related to observed data**, but not to the missing data itself

Examples:

1. In a public transportation survey, participants who own cars (observed) are more likely to skip questions about bus route preferences.
2. Participants who indicate they work night shifts (observed) are less likely to respond to questions about daytime leisure activities.

MNAR: Missing Not at Random

Definition:

- Missingness directly related to the **unobserved data**

Examples:

1. Individuals with lower savings (unobserved) may be less likely to answer questions about their financial goals.
2. Participants with lower levels of job satisfaction (unobserved) might avoid answering detailed questions about their work environment in an employee survey.

Quiz: Types of Missing Data

1. In a medical study on a new drug, researchers record patients' initial symptom severity (mild, moderate, severe). They notice that patients initially categorized with severe symptoms are more likely to miss follow-up appointments. This is:

A) MCAR $\boxed{\text{B) MAR}}$ C) MNAR

2. In an anonymous online salary survey, the researchers notice that higher-paying job categories have more incomplete responses for the salary question. However, they don't know the actual salaries of those who didn't respond. This represents:

A) MCAR   B) MAR $\boxed{\text{C) MNAR}}$

3. A researcher's computer crashes while working on a dataset, causing random rows to be deleted from the spreadsheet. This scenario is:

$\boxed{\text{A) MCAR}}$ B) MAR   C) MNAR

Identifying Missing Data

Requirements for the Next Part

1. **Have Basic Statistical Knowledge:**
   - Familiar with concepts like *mean*, *median*, and *mode*.

2. **Understand Python Basics:**
   - Basic understanding of *Python* and libraries such as *NumPy* and *Pandas*.

3. **Access to Google Colab:**
   - Have access to *Google Colab* and know the basics of *Jupyter Notebook*.

Lecture Examples

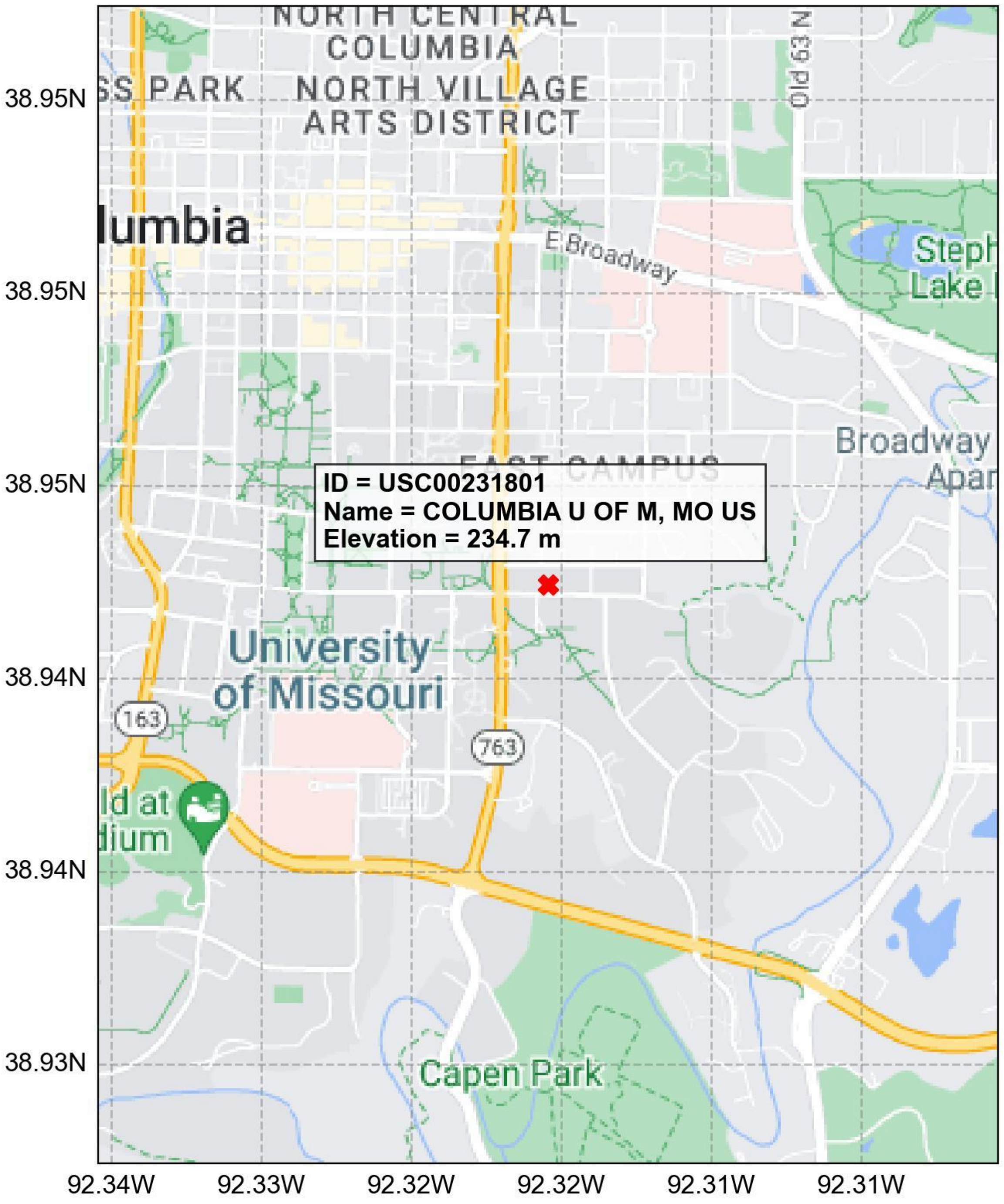
https://github.com/HatefDastour/DSA_Lecture

Lecture_Examples.ipynb

Open in Colab

Weather Data Example (1/3)

- This dataset contains daily temperature readings for Columbia, Missouri, specifically from the **University of Missouri weather station**
- **Data Source:** NCEI Climate Data
- **Period:** October 01, 2024, to October 10, 2024
- **Note:** Some data points have been intentionally removed to create a time series with missing values for educational purposes.



Weather Data Example (2/3)

https://raw.githubusercontent.com/HatefDastour/DSA_Lecture/refs/heads/main/data_files/data_10day_standard_missing.csv

Minimum Daily Temperature (°F)

Maximum Daily Temperature (°F)

	TMIN	TMAX
2024-10-01	49.0	72.0
2024-10-02	44.0	74.0
2024-10-03	NaN	NaN
2024-10-04	NaN	83.0
2024-10-05	62.0	89.0
2024-10-06	NaN	79.0
2024-10-07	47.0	72.0
2024-10-08	NaN	NaN
2024-10-09	46.0	78.0
2024-10-10	49.0	80.0

10 rows × 2 columns

Weather Data Example (3/3)

	TMIN	TMAX
2024-10-01	49.0	72.0
2024-10-02	44.0	74.0
2024-10-03	**NaN**	**NaN**
2024-10-04	**NaN**	83.0
2024-10-05	62.0	89.0
2024-10-06	**NaN**	79.0
2024-10-07	47.0	72.0
2024-10-08	**NaN**	**NaN**
2024-10-09	46.0	78.0
2024-10-10	49.0	80.0

10 rows × 2 columns

	TMIN	TMAX
2024-10-01	False	False
2024-10-02	False	False
2024-10-03	**True**	**True**
2024-10-04	**True**	False
2024-10-05	False	False
2024-10-06	**True**	False
2024-10-07	False	False
2024-10-08	**True**	**True**
2024-10-09	False	False
2024-10-10	False	False

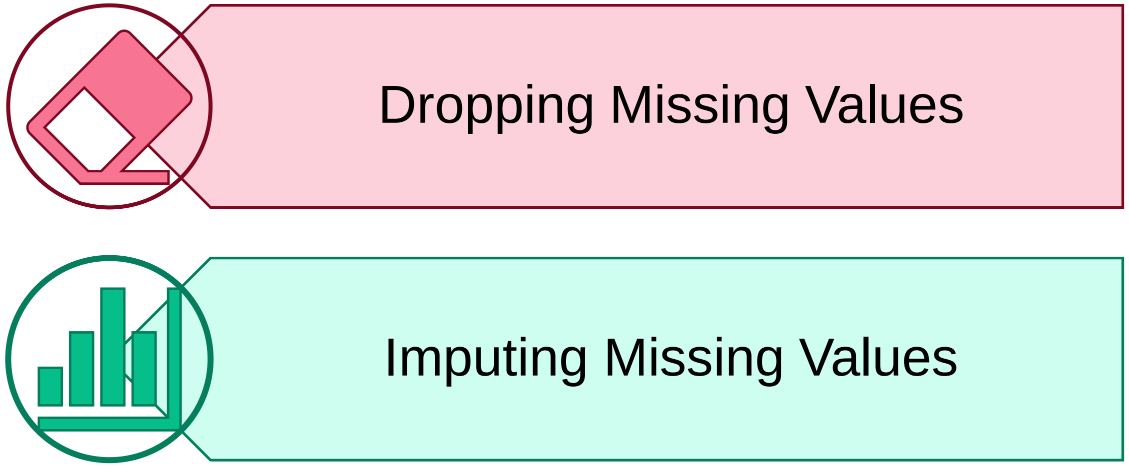
10 rows × 2 columns

Utilizing Pandas' ***isna()*** and ***isnull()*** functions for missing data detection.

Common Methods for Handling Missing Data

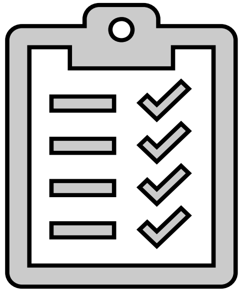
Approaches to Handling Missing Values

When it comes to missing values in datasets, we can take two primary approaches:



Note: In order for these methods to produce appropriate results in most situations, data must be what is known as Missing Completely At Random (**MCAR**).

Dropping Missing Values



Listwise Deletion

- Removes any row with missing data.

Pairwise Deletion

- Uses all available data for each analysis, excluding only the missing values for that specific analysis.

Listwise Deletion: Example

	TMIN	TMAX
2024-10-01	49.0	72.0
2024-10-02	44.0	74.0
2024-10-03	NaN	NaN
2024-10-04	NaN	83.0
2024-10-05	62.0	89.0
2024-10-06	NaN	79.0
2024-10-07	47.0	72.0
2024-10-08	NaN	NaN
2024-10-09	46.0	78.0
2024-10-10	49.0	80.0

10 rows × 2 columns

dropna(how = 'any')

What are the differences?

	TMIN	TMAX
2024-10-01	49.0	72.0
2024-10-02	44.0	74.0
2024-10-05	62.0	89.0
2024-10-07	47.0	72.0
2024-10-09	46.0	78.0
2024-10-10	49.0	80.0

6 rows × 2 columns

Pairwise Deletion: Example

	TMIN	TMAX
2024-10-01	49.0	72.0
2024-10-02	44.0	74.0
2024-10-03	NaN	NaN
2024-10-04	NaN	83.0
2024-10-05	62.0	89.0
2024-10-06	NaN	79.0
2024-10-07	47.0	72.0
2024-10-08	NaN	NaN
2024-10-09	46.0	78.0
2024-10-10	49.0	80.0

10 rows × 2 columns

Excludes NaN values

```
climate_data[ 'TMIN’ ].mean(skipna=True)
climate_data[ ‘TMAX’ ].mean(skipna=True)
```

Using Pairwise Deletion:

- Mean TMIN (using pairwise deletion): 49.50 °F
- Mean TMAX (using pairwise deletion): 78.38 °F

Using Listwise Deletion:

- Mean TMIN (after listwise deletion): 49.50 °F
- Mean TMAX (after listwise deletion): 77.50 °F

Dropping Missing Values: Pros and Cons

- **Pros:** Simple, preserves relationships.
- **Cons:** Reduces sample size, potential for bias.

Listwise Deletion

- **Pros:** Retains more data.
- **Cons:** Inconsistent sample sizes, potential for bias.

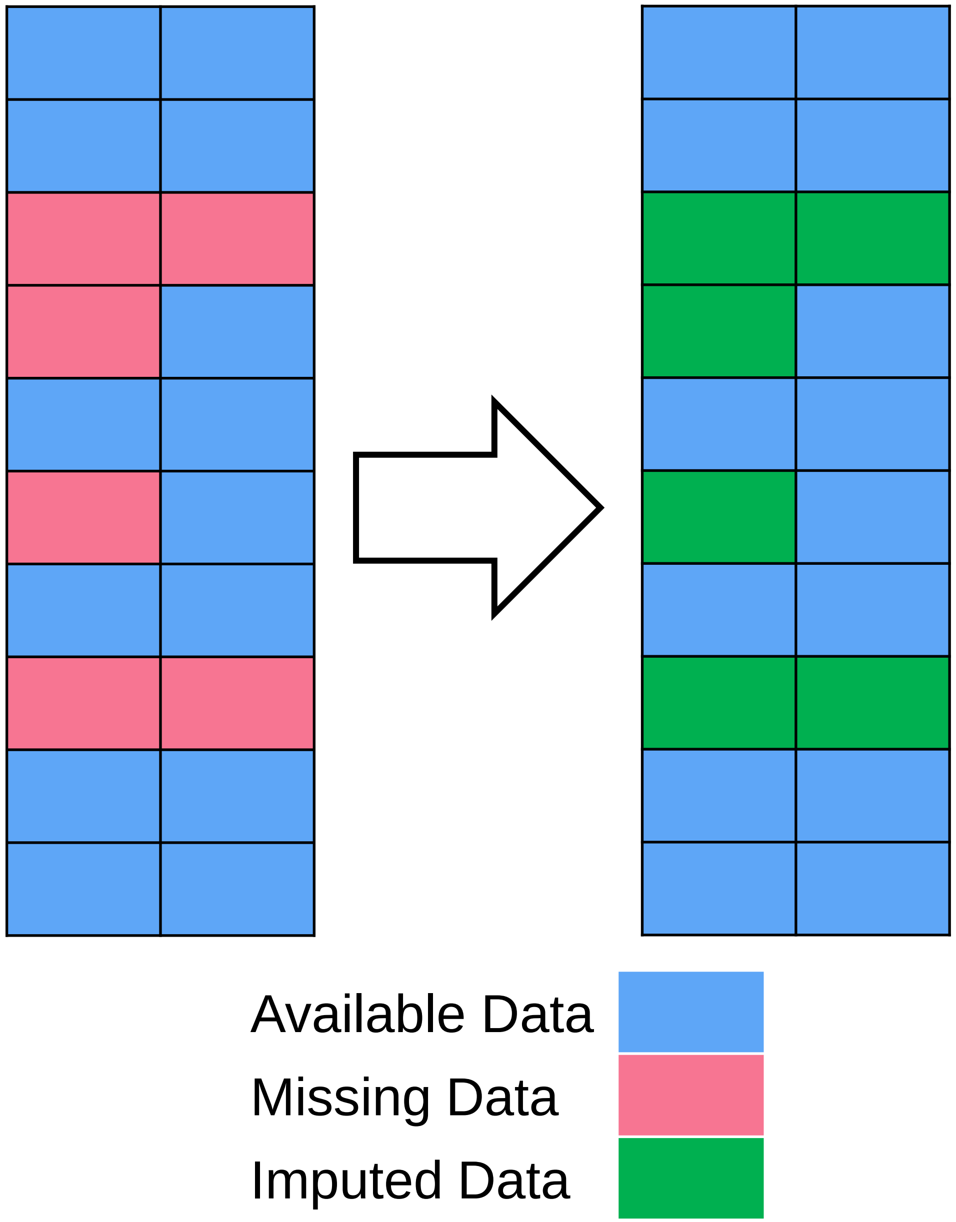
Pairwise Deletion

Imputing Missing Values

- Imputation involves filling in missing values using various techniques.

- This approach helps to maintain sample size and can improve the accuracy of analyses.

Conceptual Figure



Imputation Methods

- **Constant Fill**
- **Forward and Backward Fill**
- **Linear Interpolation**
- Polynomial Interpolation
- Spline Interpolation
- And many more

Constant Fill

Definition: Replaces missing values with a specified constant value (e.g., zero, mean, median, or another meaningful number).

	TMIN
2024-10-01	49.0
2024-10-02	44.0
2024-10-03	**NaN**
2024-10-04	**NaN**
2024-10-05	62.0
2024-10-06	**NaN**
2024-10-07	47.0
2024-10-08	**NaN**
2024-10-09	46.0
2024-10-10	49.0

Constant Fill with a **Constant Value**

	TMIN
2024-10-01	49.0
2024-10-02	44.0
2024-10-03	**Constant Value**
2024-10-04	**Constant Value**
2024-10-05	62.0
2024-10-06	**Constant Value**
2024-10-07	47.0
2024-10-08	**Constant Value**
2024-10-09	46.0
2024-10-10	49.0

Constant Fill – Example (1/2)

	TMIN
2024-10-01	49.0
2024-10-02	44.0
2024-10-03	NaN
2024-10-04	NaN
2024-10-05	62.0
2024-10-06	NaN
2024-10-07	47.0
2024-10-08	NaN
2024-10-09	46.0
2024-10-10	49.0

Constant Fill with **Mean**

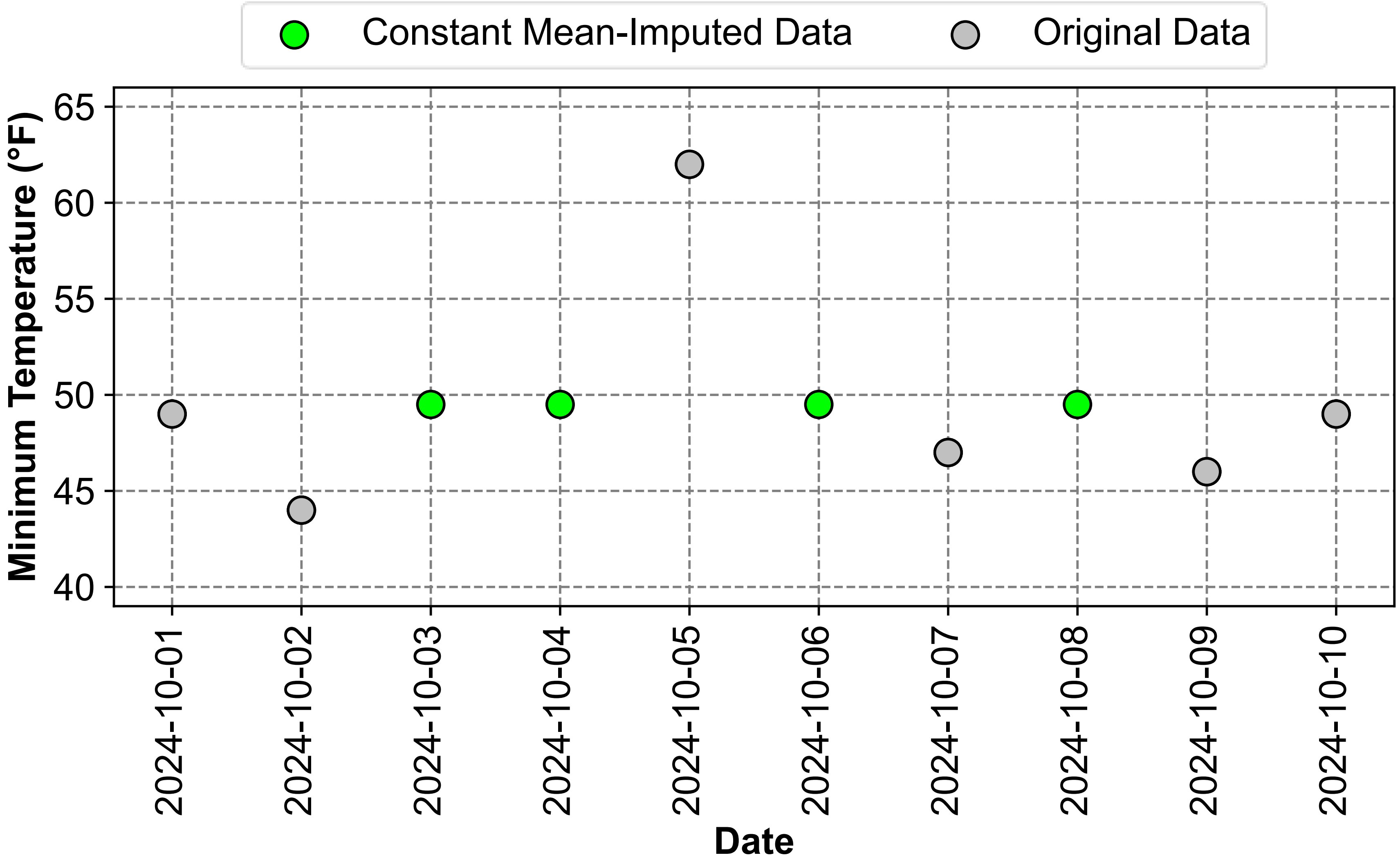
Mean of TMIN = 49.50 °F

	TMIN
2024-10-01	49.0
2024-10-02	44.0
2024-10-03	**49.5**
2024-10-04	**49.5**
2024-10-05	62.0
2024-10-06	**49.5**
2024-10-07	47.0
2024-10-08	**49.5**
2024-10-09	46.0
2024-10-10	49.0

Constant Fill – Example (2/2)

	TMIN
2024-10-01	49.0
2024-10-02	44.0
2024-10-03	49.5
2024-10-04	49.5
2024-10-05	62.0
2024-10-06	49.5
2024-10-07	47.0
2024-10-08	49.5
2024-10-09	46.0
2024-10-10	49.0

Mean of TMIN = 49.50 °F



Constant Fill – Benefits and Considerations

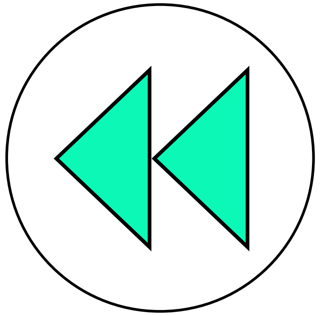
Benefits

- **Simplicity:** Easy to implement and understand
- **Contextual Relevance:** Effective when a default value is logical (e.g., zero for missing income)

Considerations

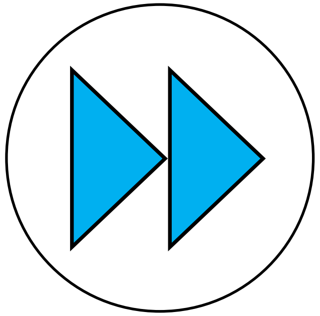
- **Potential Bias:** May not accurately represent the true data distribution
- **Reduced Variability:** Can affect statistical analyses and model performance

Backward Fill and Forward Fill



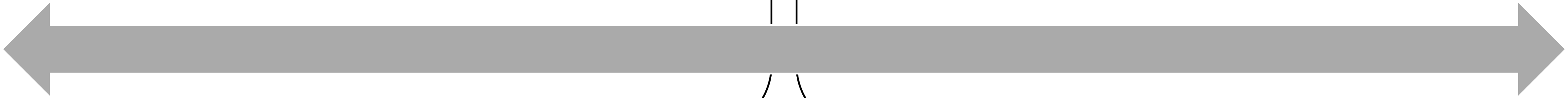
Backward Fill (bfill):

Fills missing values using the next valid observation



Forward Fill (ffill):

Fills missing values using the last valid observation



Backward Fill: Example (1/2)

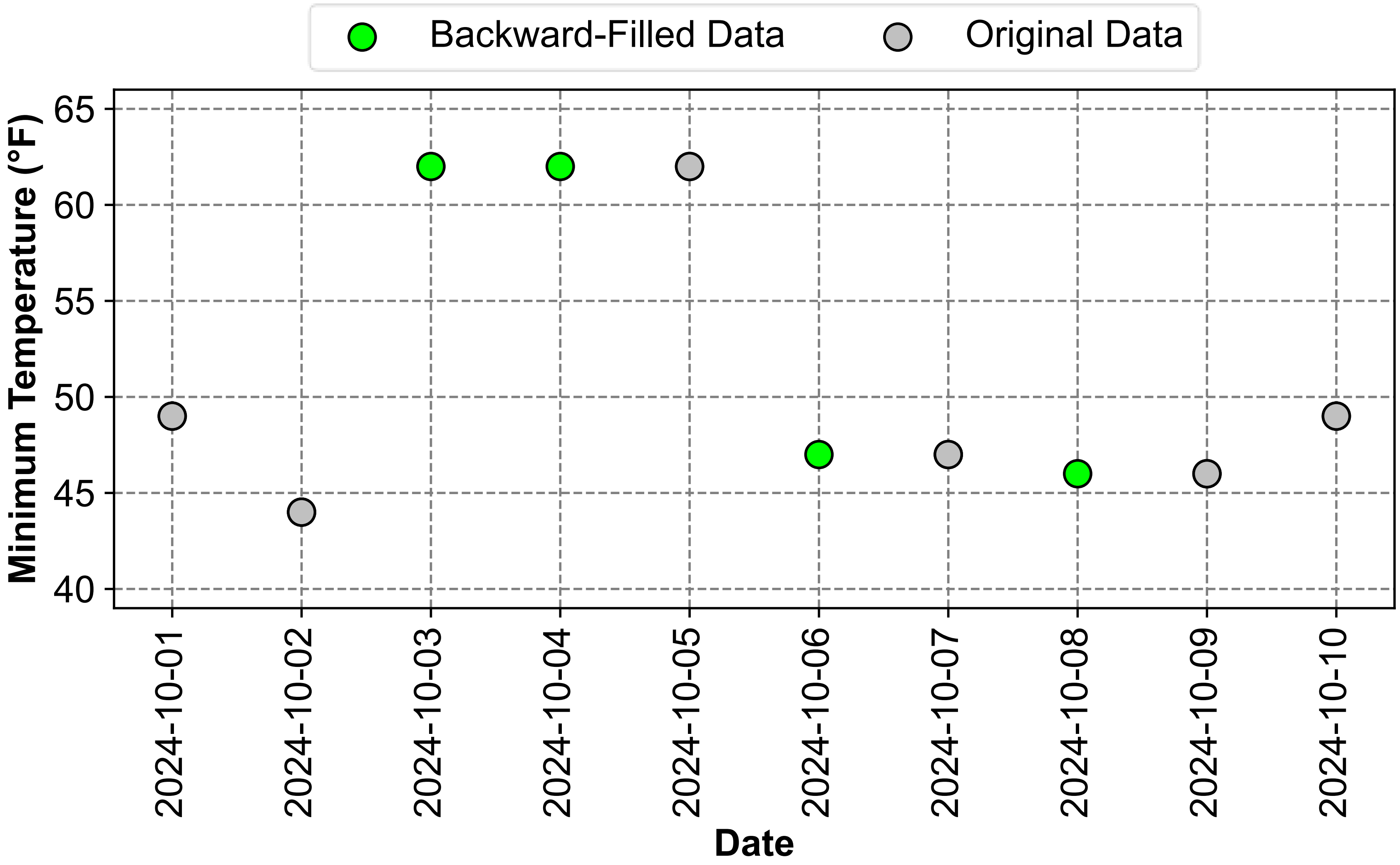
	TMIN
2024-10-01	49.0
2024-10-02	44.0
2024-10-03	**NaN**
2024-10-04	**NaN**
2024-10-05	62.0
2024-10-06	**NaN**
2024-10-07	47.0
2024-10-08	**NaN**
2024-10-09	46.0
2024-10-10	49.0

Backward Fill

	TMIN
2024-10-01	49.0
2024-10-02	44.0
2024-10-03	**62.0**
2024-10-04	**62.0**
2024-10-05	62.0
2024-10-06	**47.0**
2024-10-07	47.0
2024-10-08	**46.0**
2024-10-09	46.0
2024-10-10	49.0

Backward Fill: Example (2/2)

	TMIN
2024-10-01	49.0
2024-10-02	44.0
2024-10-03	**62.0**
2024-10-04	**62.0**
2024-10-05	62.0
2024-10-06	**47.0**
2024-10-07	47.0
2024-10-08	**46.0**
2024-10-09	46.0
2024-10-10	49.0



Forward Fill: Example (1/2)

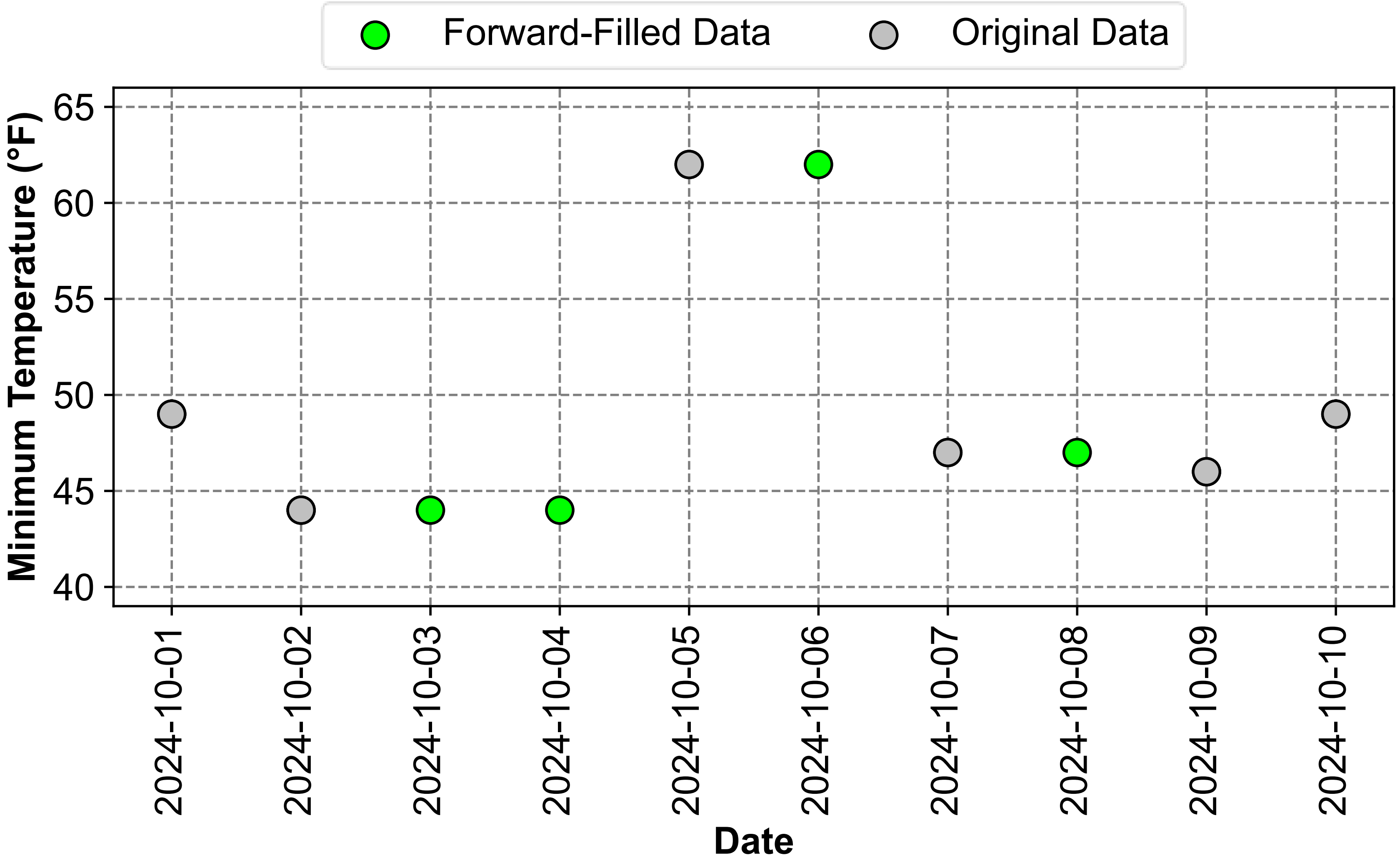
	TMIN
2024-10-01	49.0
2024-10-02	44.0
2024-10-03	NaN
2024-10-04	NaN
2024-10-05	62.0
2024-10-06	NaN
2024-10-07	47.0
2024-10-08	NaN
2024-10-09	46.0
2024-10-10	49.0

Forward Fill

	TMIN
2024-10-01	49.0
2024-10-02	44.0
2024-10-03	**44.0**
2024-10-04	**44.0**
2024-10-05	62.0
2024-10-06	**62.0**
2024-10-07	47.0
2024-10-08	**47.0**
2024-10-09	46.0
2024-10-10	49.0

Forward Fill: Example (2/2)

	TMIN
2024-10-01	49.0
2024-10-02	44.0
2024-10-03	**44.0**
2024-10-04	**44.0**
2024-10-05	62.0
2024-10-06	**62.0**
2024-10-07	47.0
2024-10-08	**47.0**
2024-10-09	46.0
2024-10-10	49.0



Backward Fill and Forward Fill: Benefits and Considerations

Benefits

- **Simplicity:** Easy to implement and understand
- **Time Series Relevance:** Particularly useful for time-based data
- **Preserves Trends:** Maintains data patterns within a series

Considerations

- **Accuracy Limitations:** May not reflect true values, especially for long gaps
- **Directional Bias:** Forward fill favors past data; backward fill favors future data
- **Data Dependency:** Effectiveness relies on the nature and frequency of available data points

Linear Interpolation

What is Linear Interpolation?

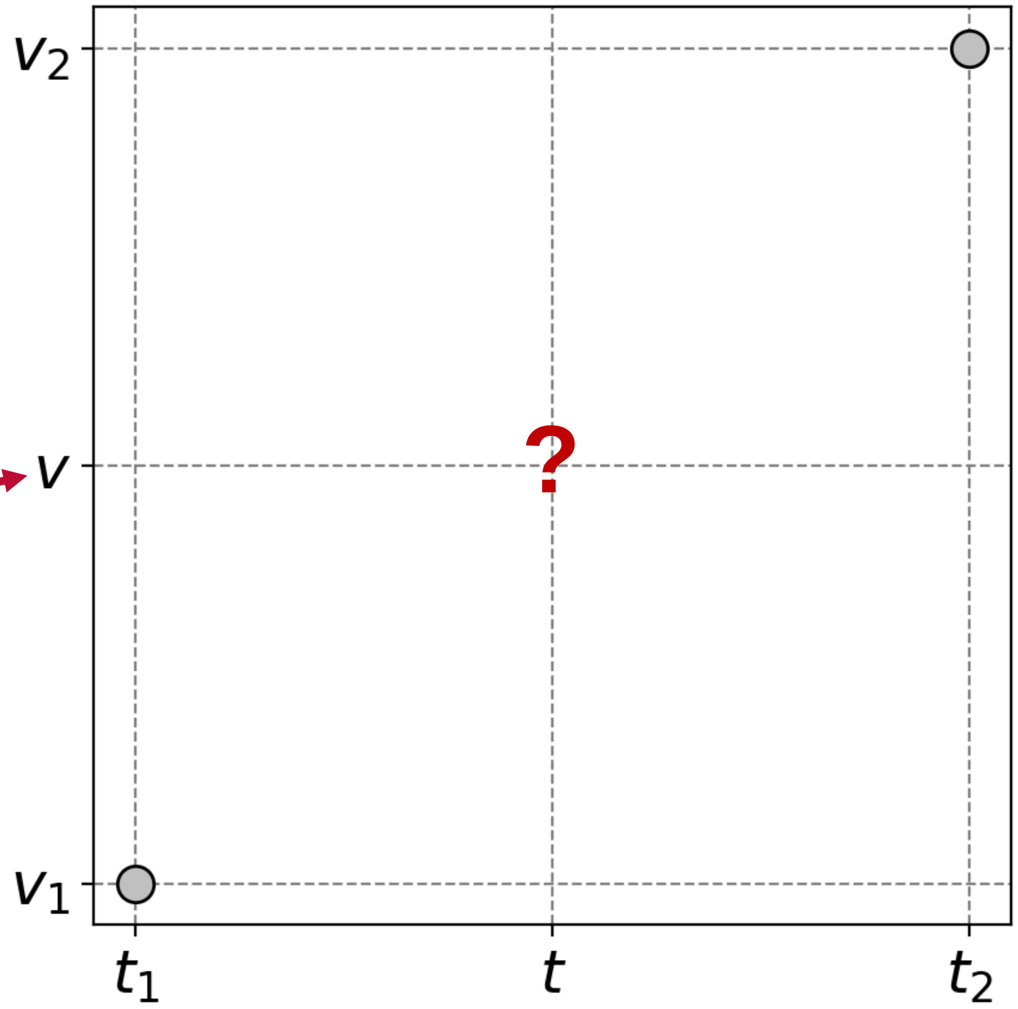
- Linear interpolation estimates missing values in time series data by assuming a straight line between known data points.

Linear Interpolation: Explanation (1/3)

- t_2 is the time of the known point.
- v_2 is the y-value at time t_2

- t is the time for which we want to find the v-value.
- v is the missing value at time t

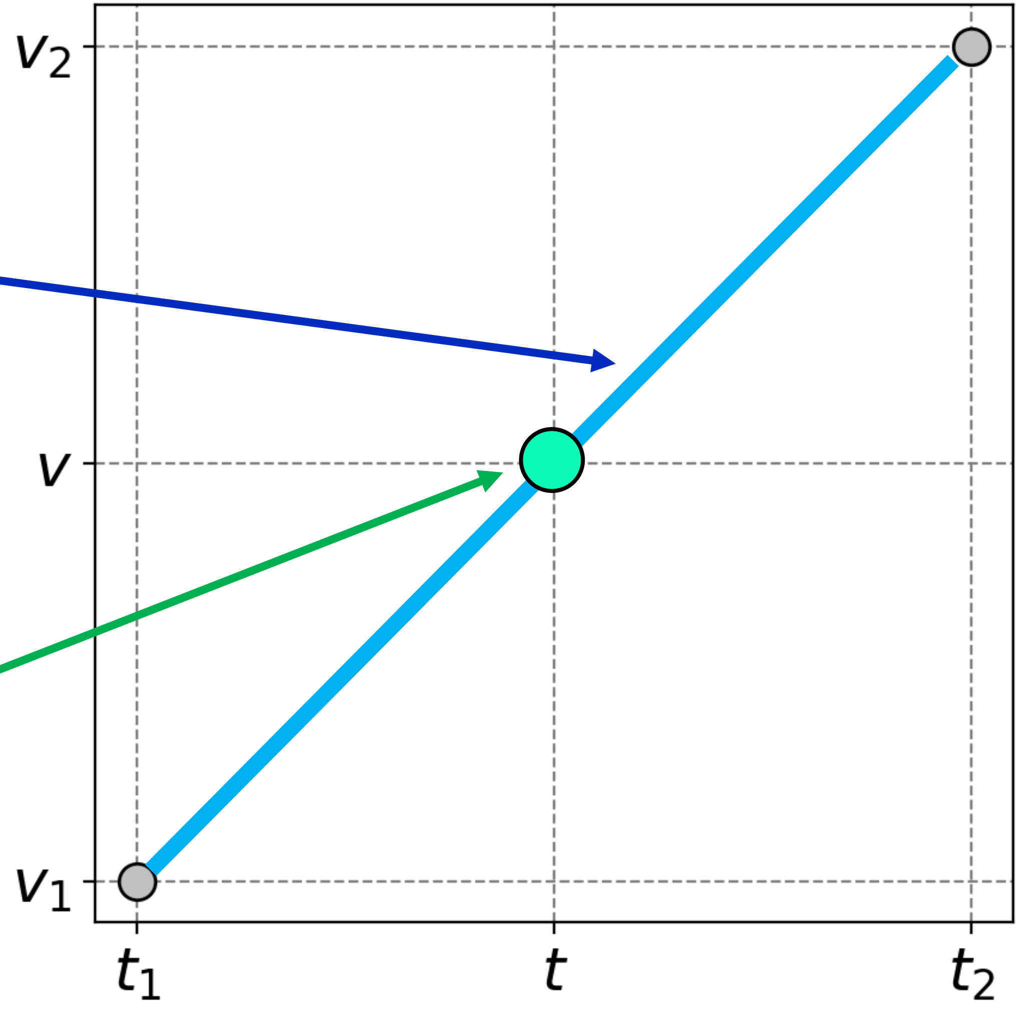
- t_1 is the time of the known point.
- v_1 is the y-value at time t_1.



Linear Interpolation: Explanation (2/3)

A straight line between known adjacent data points

Interpolated Value



Linear Interpolation: Explanation (3/3)

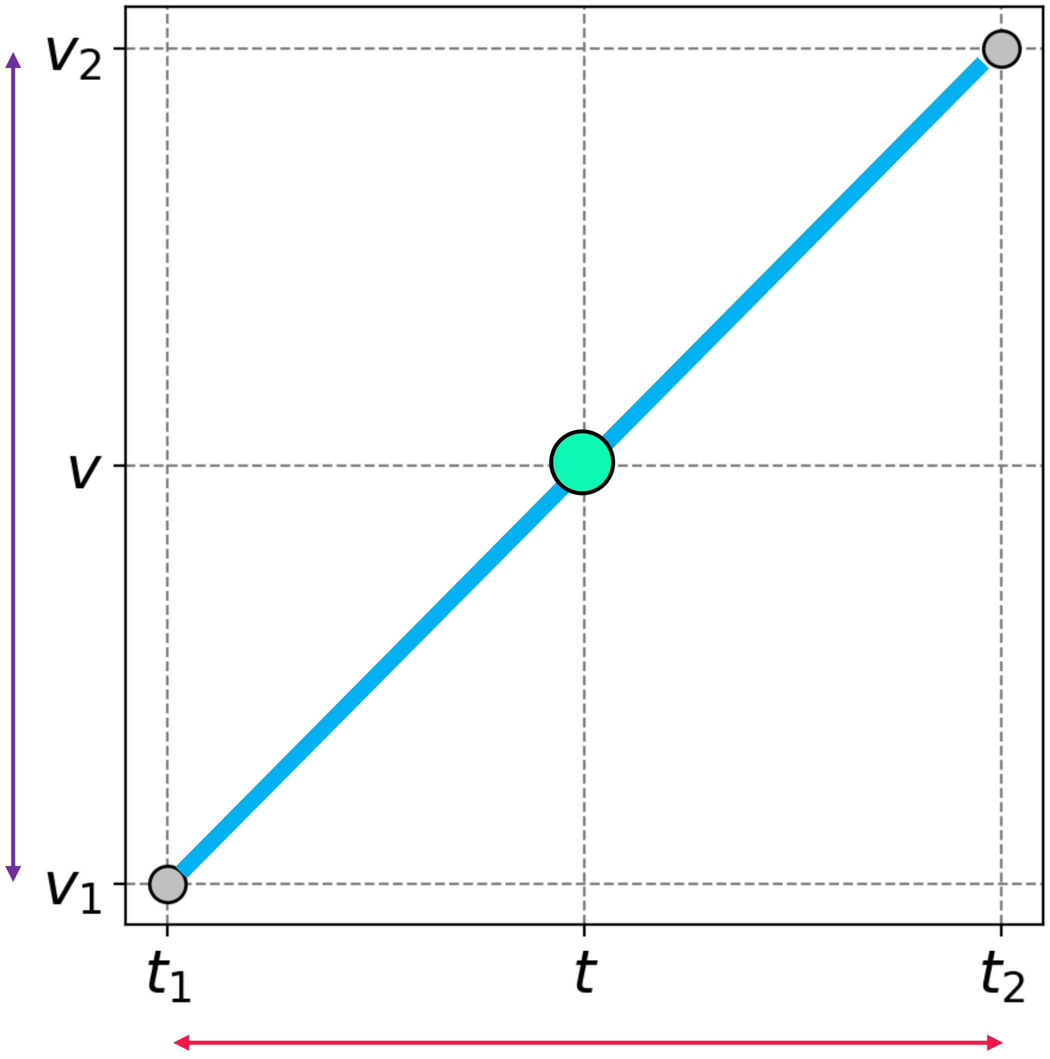
- m is the Slope with

$$m = \frac{(v_2 - v_1)}{(t_2 - t_1)}$$

- Linear Interpolation:

$$v = v_1 + m * (t - t_1)$$

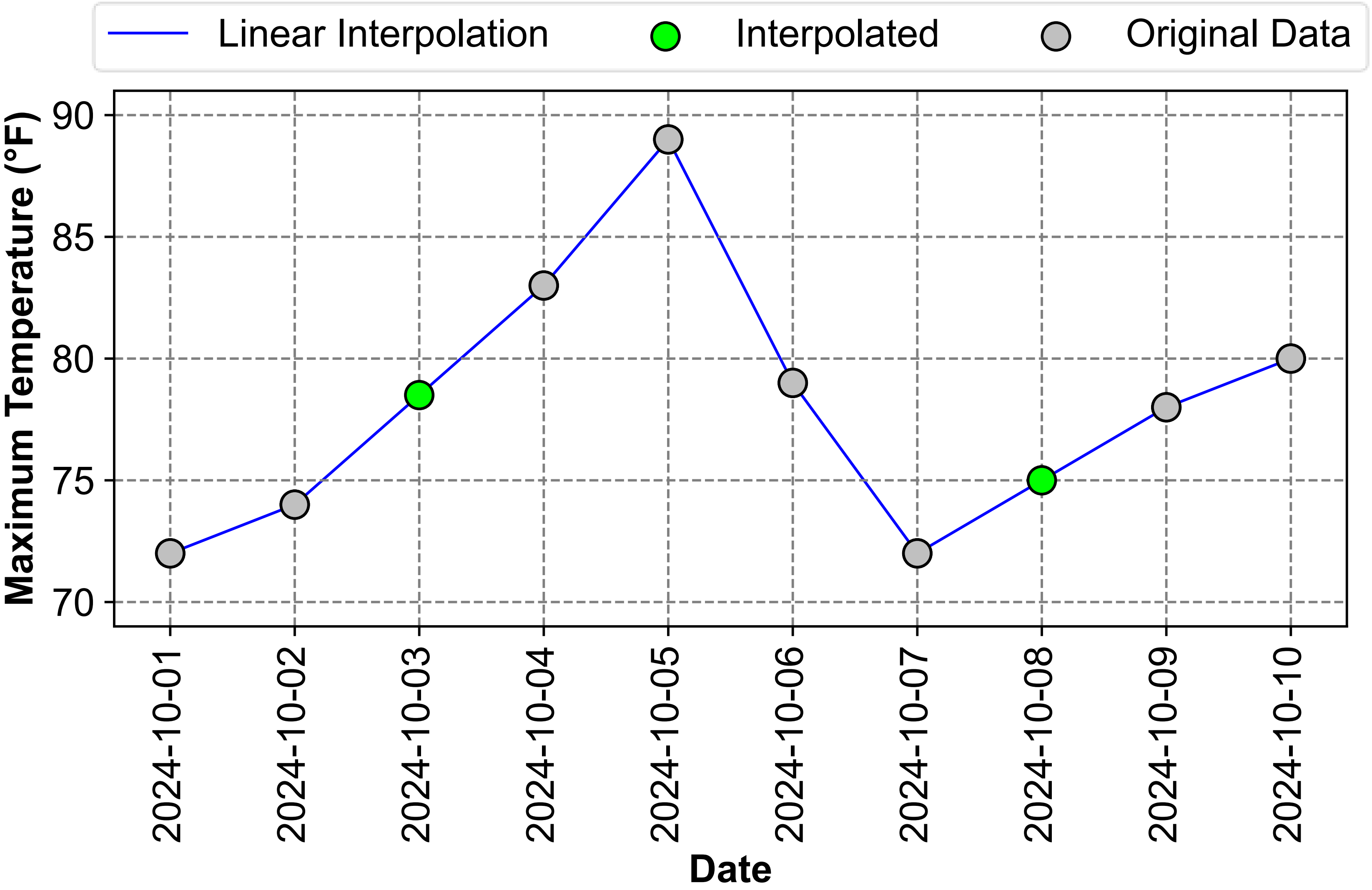
$v_2 - v_1$



$t_2 - t_1$

Linear Interpolation: Example

	TMAX
2024-10-01	72.0
2024-10-02	74.0
2024-10-03	**78.5**
2024-10-04	83.0
2024-10-05	89.0
2024-10-06	79.0
2024-10-07	72.0
2024-10-08	**75.0**
2024-10-09	78.0
2024-10-10	80.0



Linear Interpolation: Benefits and Considerations

Benefits

- **Simplicity:** Easy to understand and implement
- **Computational Efficiency:** Fast to calculate, even for large datasets
- **Predictability:** Results are consistent and easily reproducible

Considerations

- **Accuracy Limitations:** May not capture complex, non-linear relationships
- **Curve Smoothness:** Can result in sharp transitions between data points
- **Boundary Issues:** Doesn't work for missing values at the edges of the dataset.

Lecture Activity

https://github.com/HatefDastour/DSA_Lecture

Lecture_Activity.ipynb

Open in Colab

Thank You

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