



An Illustrative Explanation to Dynamic Time Warping

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Getting Started

Dynamic Time Warping (DTW) is a way to compare two temporal- sequences that do not sync up perfectly. It calculate the optimal matching between two sequences in many domains such as speech recognition, data mining, financial markets, etc. It's commonly used in data mining to measure the similarity between two time-series.

In this post, we will go over the mathematics behind DTW. Illustrative examples are provided to better understand the concept. If you are not interested in the math behind it, please jump to the Formulation section.

Formulation

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$$X = x[1], x[2], \dots, x[i], \dots, x[n]$$

$$Y = y[1], y[2], \dots, y[j], \dots, y[m]$$

The sequences X and Y can be arranged to form an n -by- m grid, where each point (i, j) is the alignment between $x[i]$ and $y[j]$.

A warping path W maps the elements of X and Y to minimize the distance between them. W is a sequence of points in the grid. We will see an example of the warping path later.

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Warping Path and DTW distance

The Optimal path to (i_k, j_k) can be computed by:

$$D_{min}(i_k, j_k) = \min_{i_{k-1}, j_{k-1}} D_{min}(i_{k-1}, j_{k-1}) + d(i_k, j_k)$$

where d is the Euclidean distance. Then, the overall DTW distance is calculated as

$$D = \sum_k d(i_k, j_k)$$

Restrictions on the Warping function

The warping path is found using a dynamic programming algorithm to align two sequences. Going through all possible paths is "combinatorically explosive" [1]. Therefore, for efficiency, it is important to limit the number of possible warping paths. The following constraints are outlined:

- **Boundary Condition:** This constraint ensures that the warping path begins with the start points of both signals and terminates with their endpoints.

$$i_1 = 1, i_k = n \quad \text{and} \quad j_1 = 1, j_k = m$$

- **Monotonicity condition:** This constraint preserves the time order of points (not going back in time).

$$i_{t-1} \leq i_t \quad \text{and} \quad j_{t-1} \leq j_t$$

- **Continuity (step size) condition:** This constraint transitions to adjacent points in time (not jumping

$$i_t - i_{t-1} \leq 1 \quad \text{and} \quad j_t - j_{t-1} \leq 1$$

In addition to the above three constraints, there are other conditions for an allowable warping path:

- **Warping window condition:** Allowable points can fall within a given warping window of width ω (a parameter)

$$|i_t - j_t| \leq \omega$$

- **Slope condition:** The warping path can be constrained by restricting the slope, and consequently avoiding extreme movements in one direction.

An acceptable warping path has combinations of **these** constraints:

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- Horizontal moves: $(i, j) \rightarrow (i, j+1)$
- Vertical moves: $(i, j) \rightarrow (i+1, j)$
- Diagonal moves: $(i, j) \rightarrow (i+1, j+1)$

Implementation

Let's import all python packages we need

```
import pandas as pd
import numpy as np

# Plotting Packages
import matplotlib.pyplot as plt
import seaborn as sbn

# Configuring Matplotlib
import matplotlib as mpl
mpl.rcParams['figure.dpi'] = 300
savefig_options = dict(format="png", dpi=300, bbox_inches='tight')

# Computation packages
from scipy.spatial.distance import euclidean
from fastdtw import fastdtw
```

Let's define a method to compute the accumulated cost of the optimal dynamic time warp path. The cost matrix uses the Euclidean distance between every two points. The methods to compute the Euclidean distance matrix and accumulated cost matrix are defined below:

```
1 def compute_euclidean_distance_matrix(x, y) -> np.array:
```

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```

2     """Calculate distance matrix
3     This method calculates the pairwise Euclidean distance between two sequences.
4     The sequences can have different lengths.
5     """
6     dist = np.zeros((len(y), len(x)))
7     for i in range(len(y)):
8         for j in range(len(x)):
9             dist[i,j] = (x[j]-y[i])**2
10    return dist

```

dtw_compute_euclidean_distance_matrix.py hosted with ❤ by GitHub

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```

1  def compute_accumulated_cost_matrix(x, y) -> np.
2      """Compute accumulated cost matrix for warp path using Euclidean distance
3      """
4      distances = compute_euclidean_distance_matrix(x, y)
5
6      # Initialization
7      cost = np.zeros((len(y), len(x)))
8      cost[0,0] = distances[0,0]
9
10     for i in range(1, len(y)):
11         cost[i, 0] = distances[i, 0] + cost[i-1, 0]
12
13     for j in range(1, len(x)):
14         cost[0, j] = distances[0, j] + cost[0, j-1]
15
16     # Accumulated warp path cost
17     for i in range(1, len(y)):
18         for j in range(1, len(x)):
19             cost[i, j] = min(
20                 cost[i-1, j],    # insertion
21                 cost[i, j-1],    # deletion
22                 cost[i-1, j-1]   # match
23             ) + distances[i, j]
24
25     return cost

```

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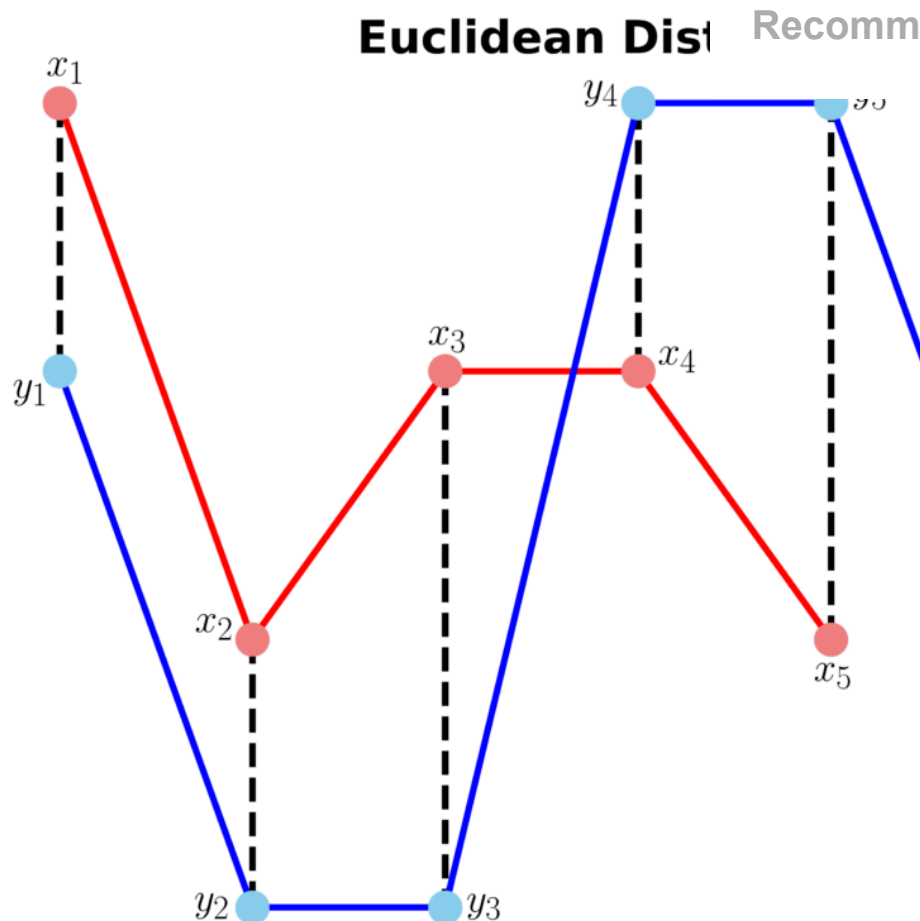
Example 1

In this example, we have two sequences x and y with different lengths.

```
# Create two sequences
x = [3, 1, 2, 2, 1]
y = [2, 0, 0, 3, 3, 1, 0]
```

We cannot calculate the Euclidean distance between x and y since they don't have equal lengths.

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Example 1: Euclidean distance between x and y (is it possible? 🤔) (In

Compute DTW distance and warp pat

Many Python packages calculate the DTW by just prc sequences and the type of distance (usually Euclidean

popular Python implementation of DTW that is FastDTW which is an approximate DTW algorithm with lower time and memory complexities [2].

```
dtw_distance, warp_path = fastdtw(x, y, dist=euclidean)
```

Note that we are using SciPy's distance function *Euclidean* that we imported earlier. For a better understanding of the warping path, we can compute the accumulated cost matrix and plot it as a heatmap. The following code will plot a heatmap of the cost matrix.

```
cost_matrix = compute_accumulated_cost_matrix(x, y)

1  fig, ax = plt.subplots(figsize=(12, 8))
2  ax = sns.heatmap(cost_matrix, annot=True, square=True, linewidths=0.5)
3  ax.invert_yaxis()
4
5  # Get the warp path in x and y directions
6  path_x = [p[0] for p in warp_path]
7  path_y = [p[1] for p in warp_path]
8
9  # Align the path from the center of each cell
10 path_xx = [x+0.5 for x in path_x]
11 path_yy = [y+0.5 for y in path_y]
12
13 ax.plot(path_xx, path_yy, color='blue', linewidth=3, alpha=0.2)
14
15 fig.savefig("ex1_heatmap.png", **savefig_options)
```

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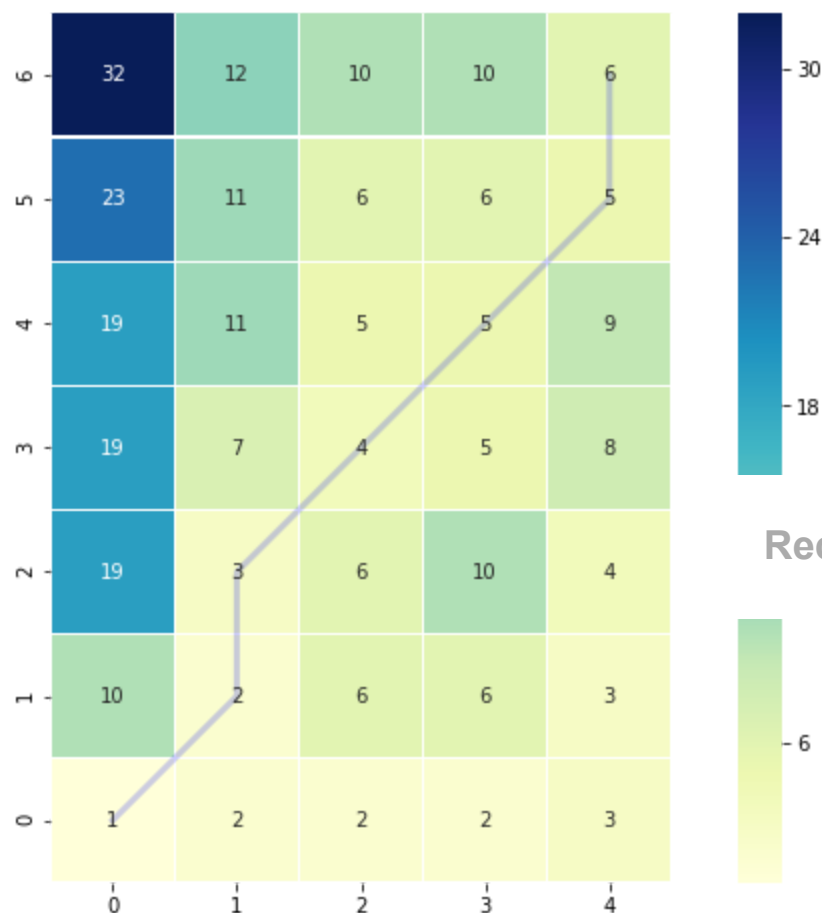
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Example 1: Accumulated cost matrix and warping path (Image b)

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The color bar shows the cost of each point in the grid
 the warp path (blue line) is going through the lowest c
 Let's see the DTW distance and the warping path by
 variables.

```
>>> DTW distance: 6.0
```

```
>>> Warp path: [(0, 0), (1, 1), (1, 2), (2, 3), (3, 4)]
```

The warping path starts at point (0, 0) and ends at (4,
 Let's also calculate the accumulated cost most using
 defined earlier and compare the values with the heatr

```
cost_matrix = compute_accumulated_cost_matrix(x, y)
print(np.flipud(cost_matrix)) # Flipping the cost matr
```



```
>>> [[32. 12. 10. 10. 6.]
      [23. 11. 6. 6. 5.]
      [19. 11. 5. 5. 9.]
      [19. 7. 4. 5. 8.]
      [19. 3. 6. 10. 4.]
      [10. 2. 6. 6. 3.]
      [ 1. 2. 2. 2. 3.]]
```

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The cost matrix is printed above has simi

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Now let's plot the two sequences and connect the ma
code to plot the DTW distance between x and y is giv

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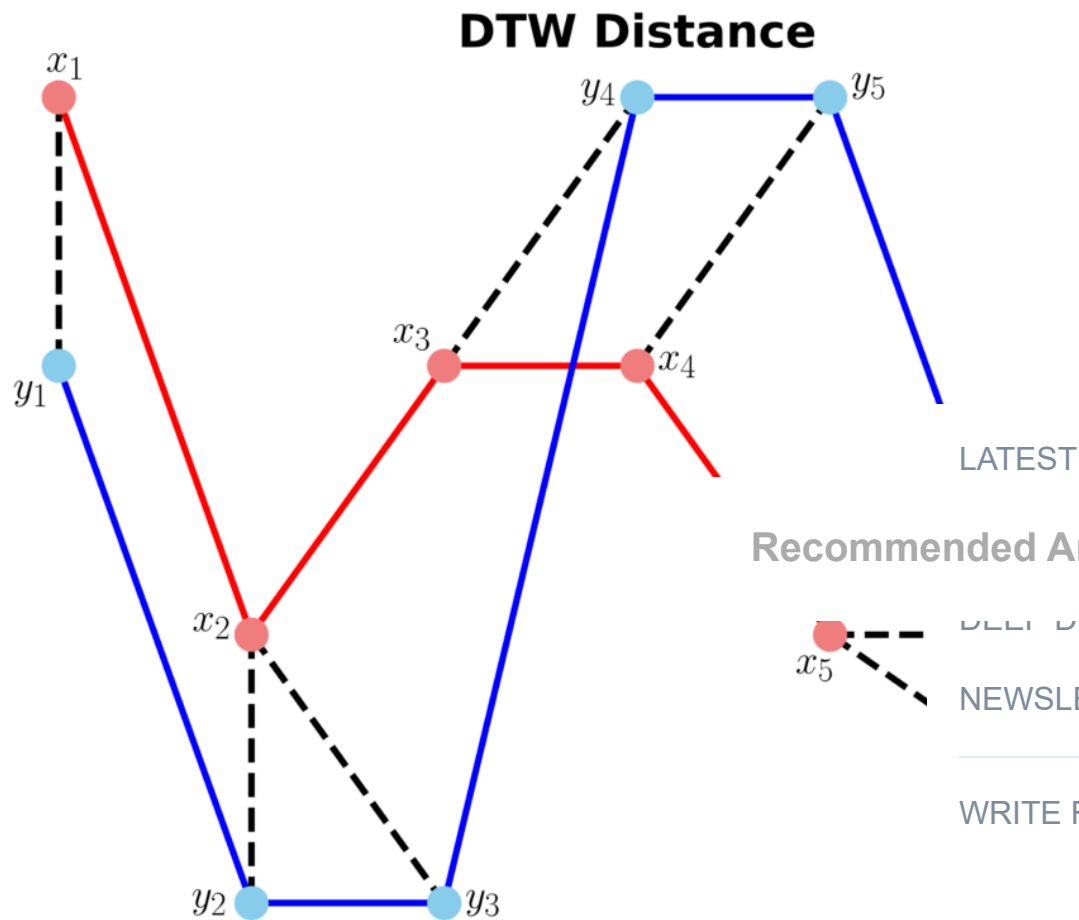
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```
1  fig, ax = plt.subplots(figsize=(14, 10))
2
3  # Remove the border and axes ticks
4  fig.patch.set_visible(False)
5  ax.axis('off')
6
7  for [map_x, map_y] in warp_path:
8      ax.plot([map_x, map_y], [x[map_x], y[map_y]], '--k', linewidth=2)
9
10 ax.plot(x, '-ro', label='x', linewidth=4, markersize=20, markerfacecolor='r')
11 ax.plot(y, '-bo', label='y', linewidth=4, markersize=20, markerfacecolor='b')
12 ax.set_title("DTW Distance", fontsize=28, fontweight="bold")
13
14 fig.savefig("ex1_dtw_distance.png", **savefig_options)
```

dtw_ex1_dtw_plot.py hosted with ❤ by GitHub



Example 2

In this example, we will use two sinusoidal signals and be matched by calculating the DTW distance between

```
1 time1 = np.linspace(start=0, stop=1, num=50)
2 time2 = time1[0:40]
3
4 x1 = 3 * np.sin(np.pi * time1) + 1.5 * np.sin(4*np.pi * time1)
5 x2 = 3 * np.sin(np.pi * time2 + 0.5) + 1.5 * np.sin(4*np.pi * time2)
```

dtw_ex2.py hosted with ❤ by GitHub

Just like Example 1, let's calculate the DTW distance for x_1 and x_2 signals using FastDTW package.

```
distance, warp_path = fastdtw(x1, x2, dist=euclidean)
```

```
1  fig, ax = plt.subplots(figsize=(16, 12))
2
3  # Remove the border and axes ticks
4  fig.patch.set_visible(False)
5  ax.axis('off')
6
7  for [map_x, map_y] in warp_path:
8      ax.plot([map_x, map_y], [x1[map_x], x2[map_y]], '-k')
9
10 ax.plot(x1, color='blue', marker='o', markersize=10)
11 ax.plot(x2, color='red', marker='o', markersize=10)
12 ax.tick_params(axis="both", which="major", labelsize=10,
13               direction="in", top=False, bottom=False, left=False, right=False)
14 fig.savefig("ex2_dtw_distance.png", **savefig_options)
```

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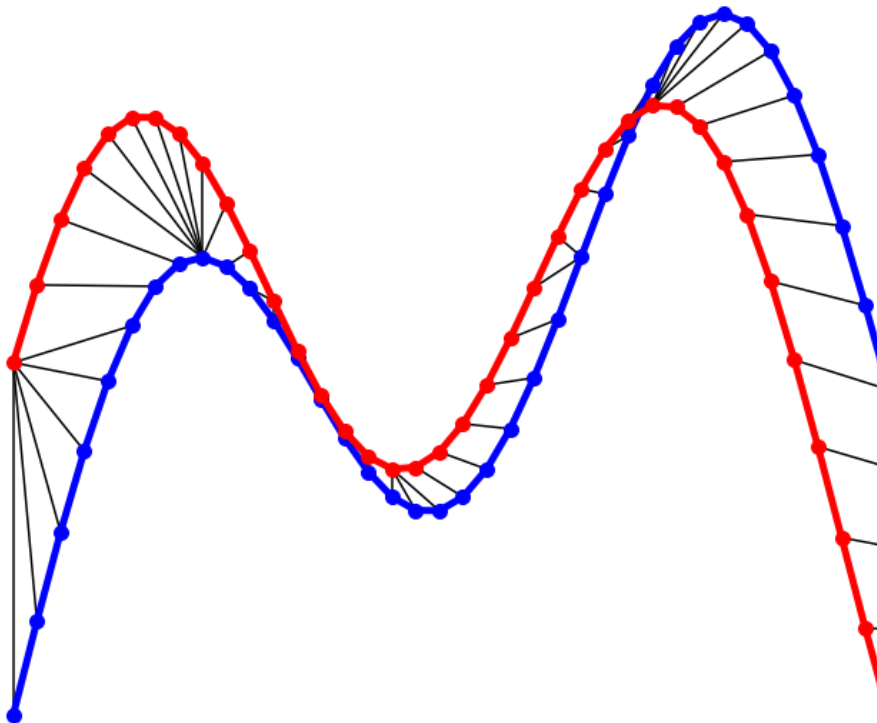
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Example 2: DTW distance between x1 and x2 (Image by Au)

As can be seen in above figure, the DTW distance between the two signals is particularly powerful when the signals have similar patterns. The extrema (maximum and minimum points) between the two signals are correctly mapped. Moreover, unlike Euclidean distance, we may see many-to-one mapping when DTW distance is used, particularly if the two signals have different lengths.

You may spot an issue with dynamic time warping from [LATEST](#)

Can you guess what it is?

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The issue is around the head and tail of time-series time match. This is because the DTW algorithm cannot afford invariance for at the endpoints. In short, the effect of 1 difference at the sequence endpoints will tend to contribute disproportionately to the estimated similarity[3].

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Conclusion

DTW is an algorithm to find an optimal alignment between sequences and a useful distance metric to have in our technique is useful when we are working with two non-linear sequences, particularly if one sequence is a non-linear stretched/compressed version of the other. The warping path is a combination of "ches" starts from the head of two sequences and ends with

You can find the Jupyter notebook for this blog post [here](#) reading!

Thanks for reading! 📖

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References

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[1] Donald J. Berndt and James Clifford, [Using Dynamic Time Warping to Find Patterns in Time Series](#), 3rd International Conference on Knowledge Discovery and Data Mining

[2] Salvador, S. and P. Chan, [FastDTW: Toward accurate and fast DTW in linear time and space](#) (2007), Intelligent Data Mining

[3] Diego Furtado Silva, *et al.*, [On the effect of endpoint alignment on time warping](#) (2016), SIGKDD Workshop on Mining and Learning from Time Series

Useful Links

[1] <https://nipunbatra.github.io/blog/ml/2014/05/01/dtw/>

[2] <https://databricks.com/blog/2019/04/30/understanding-dynamic-time-warping.html>

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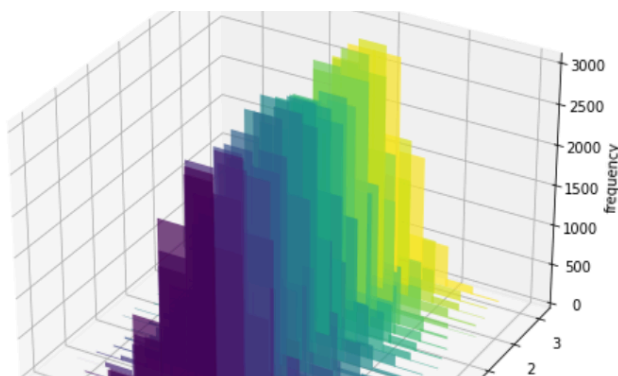
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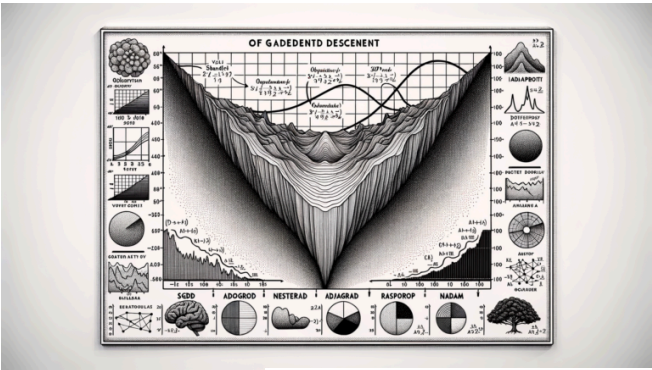
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