Short-, Medium-, and Long-Term Financial Investments ?

https://www.youtube.com/watch?v=vrex3kcz-H0

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Short-Term Investments

Definition: Investments with a duration of up to 3 years

Examples: Savings accounts, fixed deposits, short-term bonds, treasury bills

Key Characteristics
- High liquidity
- Low risk
- Lower returns

Strategies
- Focus on capital preservation
- Quick access to funds
- Suitable for emergency funds and short-term goals

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Medium-Term Investments

Definition: Investments with a duration of 3 to 10 years

Examples: Corporate bonds, balanced mutual funds, certificates of deposit , Exchange-traded funds (ETFs)

Key Characteristics

- Moderate risk and return
- Balance between growth and income
- Suitable for goals like buying a car, funding education, or a down payment on a home

Strategies

- Diversified portfolio
- Combination of growth and income-focused investments

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Long-Term Investments

Definition: Investments with a duration of 10 years or more

Examples: Stocks, real estate, retirement accounts , IRA), long-term bonds

Key Characteristics

- High (but volatile)
- Potential for higher returns
- Suitable for retirement planning and wealth building

Strategies

- Emphasis on growth
- Compounding returns
- Regular contributions to take advantage of dollar-cost averaging

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Summary Table

Investment Horizon	Key Risks	Typical Return
Short-Term (0–3 yrs)	Low returns, inflation risk, reinvestment risk	Low
Medium-Term (3–7 yrs)	Market volatility, interest rate risk, inflation risk	Moderate
Long-Term (7+ yrs)	Market risk, economic/political risk, liquidity risk	High (but volatile)

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Comparison of Investment Timeframes

- Risk vs. Reward: How risk and potential returns differ across short-, medium-, and long-term investments
- Liquidity: Access to funds over different time horizons
- Tax Considerations: How investment duration affects taxes

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Factors to Consider When Choosing an Investment Timeframe

- Financial goals and timeline
- Risk tolerance
- Income needs
- Market conditions
- Inflation and interest rates

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Case Study Examples

- Short-Term: Saving for a vacation in the next year
- Medium-Term: Planning for a child's education in 5 years
- Long-Term: Building a retirement fund over 30 years

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Common Mistakes to Avoid

- Ignoring inflation in long-term planning
- Taking excessive risk with short-term funds
- Lack of diversification
- Failing to regularly review and adjust the portfolio

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Commonly used Strategy

Don't buy or hold shares blindly

Track your companies regularly

- **Business developments**
- **Management**
- **Results**
- **Future plans**

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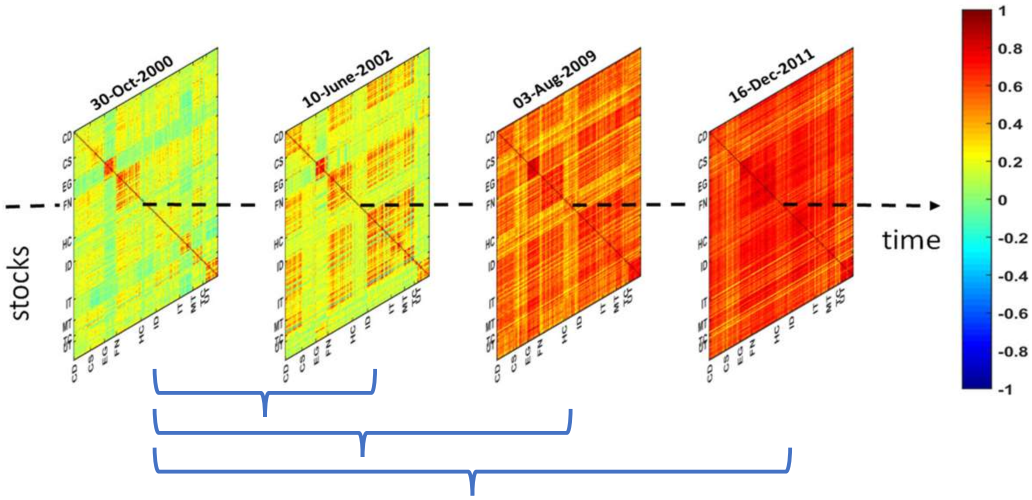
Measure the crash



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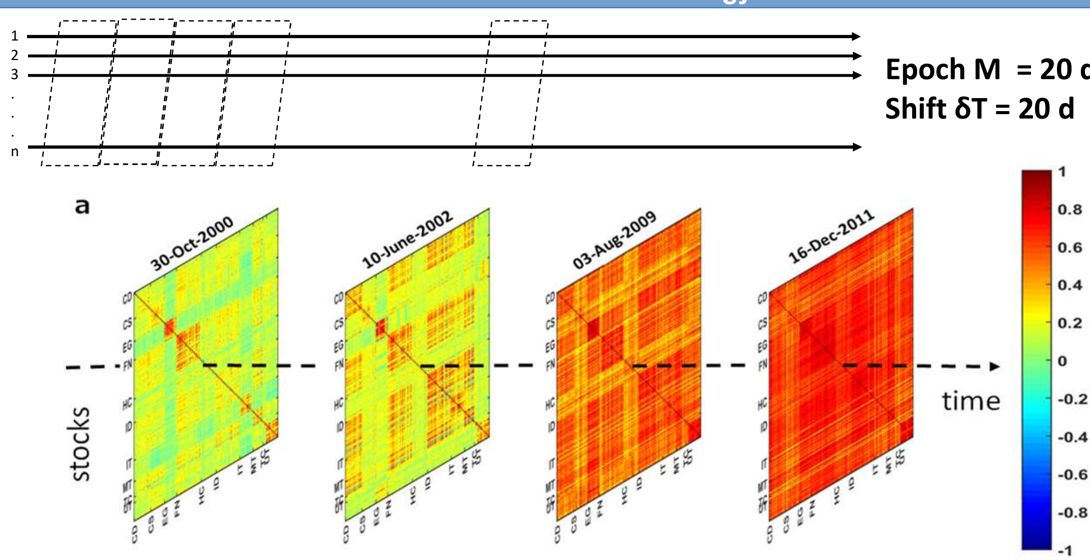
Rolling Cross-Correlation Matrices

Short or Medium Term strategy



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(Dis-) similarity Measure Or Distance

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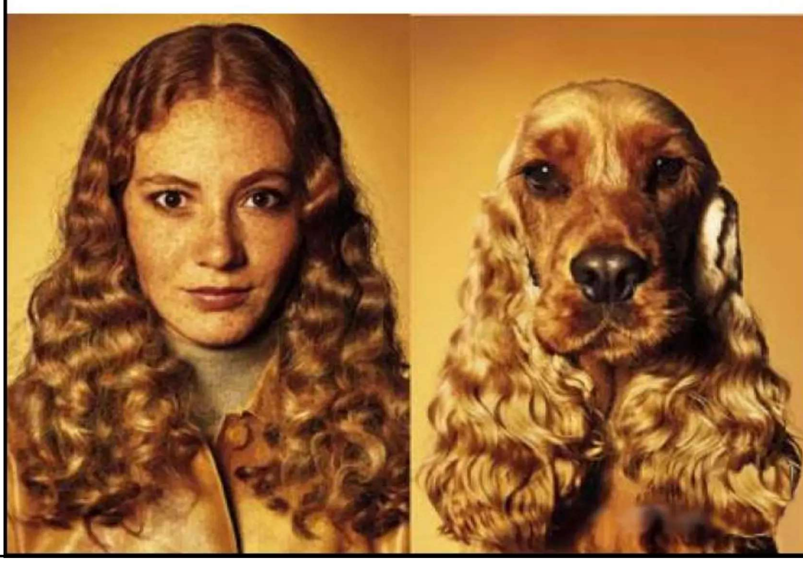
What is Similarity?

The quality or state of being similar; likeness; resemblance; as, a similarity of features.

Webster's Dictionary



Similarity is hard to define, but… "*We know it when we see it*"

The real meaning of similarity is a philosophical question. We will take a more pragmatic approach.

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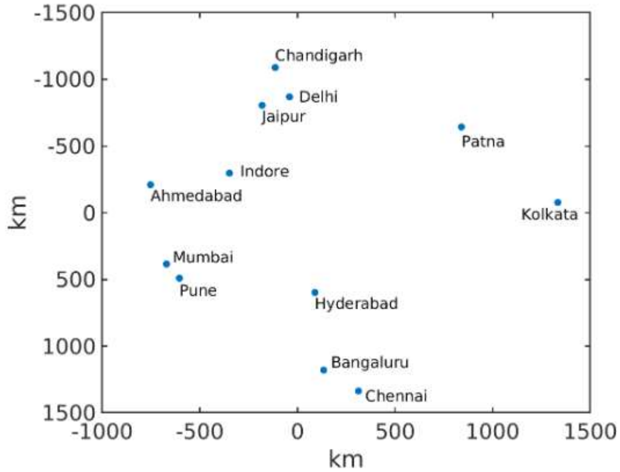
	Ahmedabad	Bangaluru	Mumbai	Kolkata	Chandigarh	Delhi	Hyderabad	Indore	Jaipur	Chennai	Patna	Pune
Ahmedabad	0											
Bangaluru	1490	0										
Mumbai	552	1013	0									
Kolkata	2068	1461	2012	0								
Chandigarh	1157	2296	1645	1721	0							
Delhi	911	2049	1404	1474	248	0						
Hyderabad	1436	563	729	1467	1693	1447	0					
Indore	442	1601	589	1620	1052	806	999	0				
Jaipur	648	2005	1148	1530	507	263	1404	405	0			
Chennai	1821	331	1344	1630	2489	2243	699	1795	2200	0		
Patna	1656	2071	1856	621	1332	1086	1489	1205	1115	2096	0	
Pune	664	826	184	2058	1663	1417	545	623	1371	1157	1738	0



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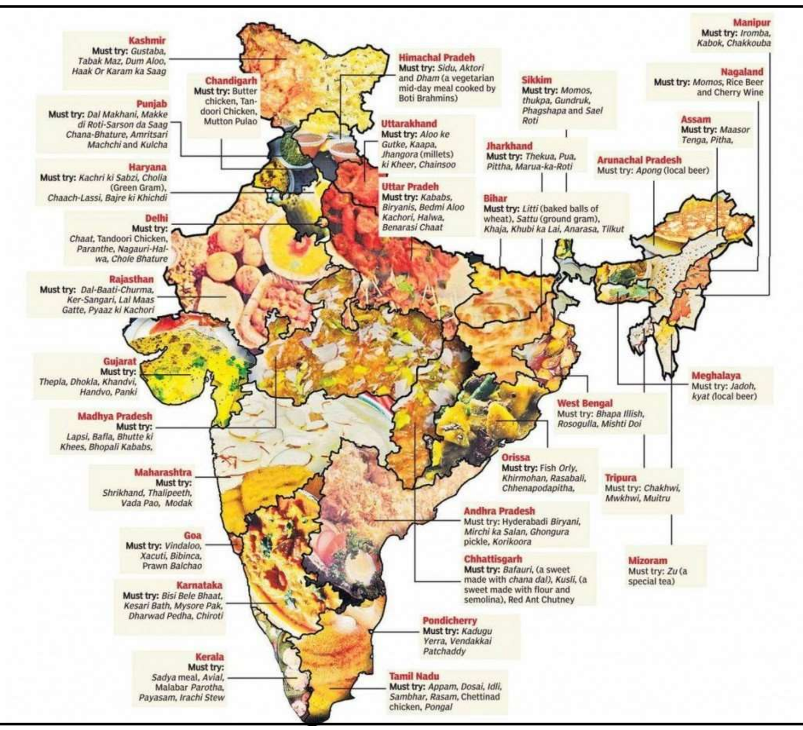

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Similarity and Dissimilarity Measures

- In clustering techniques, similarity (or dissimilarity) is an important measurement.
- Informally, similarity between two objects (e.g., two images, two documents, two records, etc.) is a numerical measure of the degree to which two objects are alike.
- The dissimilarity on the other hand, is another alternative (or opposite) measure of the degree to which two objects are different.
- Both similarity and dissimilarity also termed as proximity.
- Usually, similarity and dissimilarity are non-negative numbers and may range from zero (highly dissimilar (no similar)) to some finite/infinite value (highly similar (no dissimilar)).

Note:
- Frequently, the term distance is used as a synonym for dissimilarity
- In fact, it is used to refer as a special case of dissimilarity.

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Proximity Measures: Single-Attribute

- Consider an object, which is defined by a single attribute A (e.g., length) and the attribute A has n-distinct values $a_1, a_2, \ldots\ldots, a_n$.
- A data structure called "Dissimilarity matrix" is used to store a collection of proximities that are available for all pair of n attribute values.
  - In other words, the Dissimilarity matrix for an attribute A with n values is represented by an $n \times n$ matrix as shown below.

$$\begin{bmatrix} 0 & & & \\ p_{(2,1)} & 0 & & \\ p_{(3,1)} & p_{(3,2)} & 0 & \\ \vdots & \vdots & \vdots & \\ p_{(n,1)} & p_{(n,2)} & \ldots\ldots & 0 \end{bmatrix}_{n \times n}$$

  - Here, $p_{(i,j)}$ denotes the proximity measure between two objects with attribute values a_i and a_j.
- Note: The proximity measure is symmetric, that is, $p_{(i,j)} = p_{(j,i)}$

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Proximity Measure with Interval Scale

- The measure called distance is usually referred to estimate the similarity between two objects defined with interval-scaled attributes.
- We first present a generic formula to express distance d between two objects x and y in n-dimensional space. Suppose, x_i and y_i denote the values of i^{th} attribute of the objects x and y respectively.

$$d(x, y) = \left(\sum_{i=1}^{n} |x_i - y_i|^r\right)^{\frac{1}{r}}$$

- Here, r is any integer value.
- This distance metric most popularly known as Minkowski metric.

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Proximity Measure with Interval Scale

Properties of Minkowski metrics:

1. Non-negativity:
   a. $d(x, y) \geq 0 \; for \; all \; x \; and \; y$
   b. $d(x, y) = 0$ only if $x = y$. This is also called identity condition.

2. Symmetry:
   $d(x, y) = d(y, x) \;\; for \; all \; x \; and \; y$
   This condition ensures that the order in which objects are considered is not important.

3. Transitivity:
   $d(x, z) \leq d(x, y) + d(y, z) \; for \; all \; x \, , y \; and \; z.$
   - This condition has the interpretation that the least distance $d(x, z)$ between objects $x \; and \; z$ is always less than or equal to the sum of the distance between the objects $x \; and \; y$, and between $y \; and \; z$.
   - This property is also termed as Triangle Inequality.

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Proximity Measure with Interval Scale

Depending on the value of r, the distance measure is renamed accordingly.

1. **Manhattan distance (L_1 Norm: r = 1)**

   The Manhattan distance is expressed as

$$d = \sum_{i=1}^{n} |x_i - y_i|$$

where $|\ldots|$ denotes the absolute value. This metric is also alternatively termed as **Taxicals metric, city-block metric**.

Example: x = [7, 3, 5] and y = [3, 2, 6].

The Manhattan distance is $|7 - 3| + |3 - 2| + |5 - 6| = 6.$

- As a special instance of Manhattan distance, when attribute values $\in [0, 1]$ is called Hamming distance.
- Alternatively, Hamming distance is the number of bits that are different between two objects that have only binary values (i.e. between two binary vectors).

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- $X = (1,0,0,0,0,0,0,0,0,0)$
- $Y = (0,0,0,0,0,0,1,0,0,1)$
- $D(x,y) = \sum_{i=1}^{n} |x_i - y_i|$

$= 3$

Hamming distance for 0–1 vectors

x	0	1	0	0	1	0	0	1	0
y	1	0	0	0	0	1	0	1	1

$$L_1(x,y) = \left(\sum_{i=1}^{d} |x_i - y_i|\right) = 5$$

Distance functions between strings

- Strings x and y have **equal length**
- Modification of **Hamming** distance
- Add 1 for all positions that are different

x	c	g	t	a	a	c	g
y	g	a	t	t	a	c	a

Hamming dist. = 4

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Questions

1. Calculate the Manhattan Distance between the points A(3,7) and B(9,2) in a 2D plane.
2. Given three points A(1,4) B(5,6), and C(8,3) find the sum of the Manhattan Distances between A and B, and B and C.
3. Find the Manhattan Distance between the points P(2,5,7) and Q(6,3,9) in a 3-dimensional space.
4. Compare the Manhattan Distances between points X(2,3), Y(8,7), and Z(4,9). Which pair of points has the shortest Manhattan Distance?
5. If a robot moves from point A(1,1) to point B(5,8) on a grid following only horizontal and vertical paths, what is the Manhattan Distance traveled? What would the distance be if the robot had to stop at point C(3,5) along the way?
6. Calculate the Hamming Distance between the binary strings 1011101 and 1001001.
7. Find the Hamming Distance between the DNA sequences AGCT and ACGA.
8. Find the Hamming Distance between the binary strings 11101 and 1001, assuming they must be of equal length by padding the shorter string with leading zeros.

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Proximity Measure with Interval Scale

2. Euclidean Distance (L_2 Norm: $r = 2$)

This metric is same as Euclidean distance between any two points x and y in $\mathcal{R}^n$.

$$d(x, y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}$$

Example: x = [7, 3, 5] and y = [3, 2, 6].

The Euclidean distance between x and y is

$$d(x, y) = \sqrt{(7-3)^2 + (3-2)^2 + (5-6)^2} = \sqrt{18} \approx 2.426$$

Proximity Measure with Interval Scale

3. Chebychev Distance ($L_\propto$ Norm: $r \in \mathcal{R}$)

This metric is defined as

$$d(x, y) = \max_{\forall i}\{|x_i - y_i|\}$$

- We may clearly note the difference between Chebychev metric and Manhattan distance. That is, instead of summing up the absolute difference (in Manhattan distance), we simply take the maximum of the absolute differences (in Chebychev distance). Hence, $L_\propto < L_1$

Example: x = [7, 3, 5] and y = [3, 2, 6].

The Manhattan distance = $|7-3| + |3-2| + |5-6| = 6$.

The chebychev distance = Max $\{|7-3|, |3-2|, |5-6|\} = 4$.

Non-Metric similarity

- In many applications (such as information retrieval) objects are complex and contains a large number of symbolic entities (such as keywords, phrases, etc.).
- To measure the distance between complex objects, it is often desirable to introduce a non-metric similarity function.
- Here, we discuss few such non-metric similarity measurements.

Cosine similarity

Suppose, x and y denote two vectors representing two complex objects. The cosine similarity denoted as $\cos(x, y)$ and defined as

$$\cos(x, y) = \frac{x \cdot y}{\|x\| \cdot \|y\|}$$

- where $x \cdot y$ denotes the vector dot product, namely $x \cdot y = \sum_{i=1}^{n} x_i \cdot y_i$ such that $x = [x_1, x_2, .., x_n]$ and $y = [y_1, y_2, .., y_n]$.
- $\|x\|$ and $\|y\|$ denote the Euclidean norms of vector x and y, respectively (essentially the length of vectors x and y), that is

$$\|x\| = \sqrt{{x_1}^2 + {x_2}^2 + .. + {x_n}^2} \text{ and } \|y\| = \sqrt{{y_1}^2 + {y_2}^2 + .. + {y_n}^2}$$

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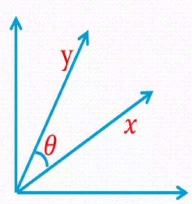
Cosine Similarity

- In fact, cosine similarity essentially is a measure of the (cosine of the) angle between x and y.
- Thus if the cosine similarity is 1, then the angle between x and y is 0° and in this case, x and y are the same except for magnitude.
- On the other hand, if cosine similarity is 0, then the angle between x and y is 90° and they do not share any terms.
- Considering, this cosine similarity can be written equivalently



$$\cos(x, y) = \frac{x \cdot y}{\|x\| \cdot \|y\|} = \frac{x}{\|x\|} \cdot \frac{y}{\|y\|} = \hat{x} \cdot \hat{y}$$

where $\hat{x} = \frac{x}{\|x\|}$ and $\hat{y} = \frac{y}{\|y\|}$. This means that cosine similarity does not take the magnitude of the two vectors into account, when computing similarity.

- It is thus, one way normalized measurement.

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Example: Document Similarity in Search Engines

Imagine you search on Google: **Query**: "machine learning applications in healthcare"

Step 1: Convert text into vectors (e.g., TF-IDF or embeddings)

- Suppose we have two articles in the database:
  - **Doc 1**: "AI and machine learning are transforming healthcare by analyzing patient data."
  - **Doc 2**: "Football players train daily to improve their skills and teamwork."
- After vectorization (simplified for explanation):
- Query vector → **Q = [1, 1, 1, 1, 0, 0];**
- Doc 1 vector → **D1 = [1, 1, 1, 1, 1, 0];**
- Doc 2 vector → **D2 = [0, 0, 0, 0, 0, 1]**

Step 2: Compute cosine similarity

- **Q vs D1:**

$$\text{cosine}(Q, D1) = \frac{4}{\sqrt{4}\cdot\sqrt{5}} \approx 0.89$$

- **Q vs D2:**

$$\text{cosine}(Q, D2) = 0$$

Step 3: Interpretation

- **Doc 1** has a cosine similarity of **0.89** with the query → very relevant.
- **Doc 2** has a cosine similarity of **0** with the query → irrelevant.

So, the search engine will rank **Doc 1** much higher than **Doc 2**.

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Non-Metric Similarity

Example 12.7: Cosine Similarity

Suppose, we are given two documents with count of 10 words in each are shown in the form of vectors x and y as below.

$$x = [3, 2, 0, 5, 0, 0, 0, 2, 0, 0] \text{ and } y = [1, 0, 0, 0, 0, 0, 0, 1, 0, 2]$$

Thus, $x \cdot y = 3*1 + 2*0 + 0*0 + 5*0 + 0*0 + 0*0 + 0*0 + 2*1 + 0*0 + 0*2$
$= 5$

$$||x|| = \sqrt{3^2 + 2^2 + 0 + 5^2 + 0 + 0 + 0 + 2^2 + 0 + 0} = 6.48$$
$$||y|| = \sqrt{1^2 + 0 + 0 + 0 + 0 + 0 + 0 + 1^2 + 0 + 2^2} = 2.24$$
$$\therefore \quad \cos(x, y) = 0.31$$

Extended Jaccard Coefficient

The extended Jaccard coefficient is denoted as EJ and defined as

$$EJ = \frac{x \cdot y}{||x||^2 \cdot ||y||^2 - x \cdot y}$$

- This is also alternatively termed as Tanimoto coefficient and can be used to measure like document similarity.

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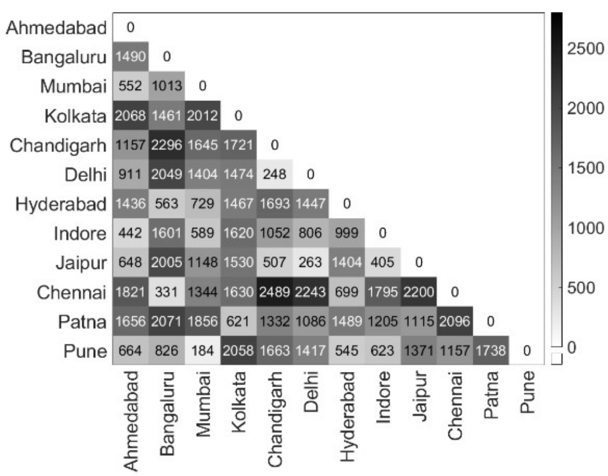
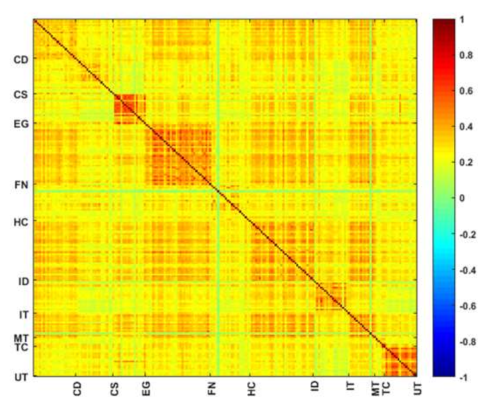
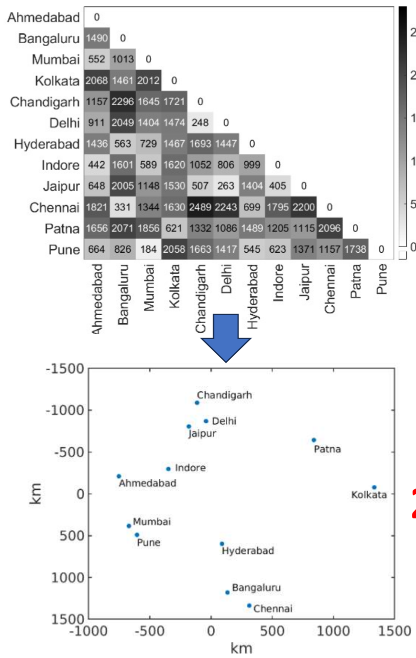
Visualization of Distance matrix

The dimensionality of a Matrix

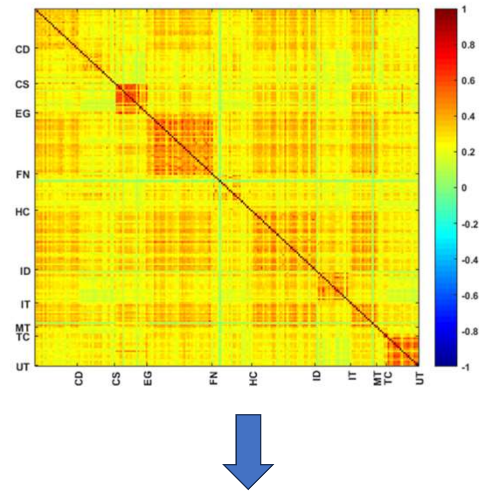




***Dimensionality: O*(N^2)**



2D map



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Introduction to Dimensionality Reduction

What is Dimensionality Reduction?

- Dimensionality reduction refers to techniques used to reduce the number of input variables in a dataset
- It simplifies data analysis and visualization, especially when working with high-dimensional data
- Key techniques: PCA and MDS
- Objective: To retain the essential structure of the data while reducing complexity

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Dimensional reduction techniques

MDS and PCA can both be used for exploratory data analysis and pattern recognition.

Differences: MDS focuses on preserving pairwise distances, while PCA focuses on capturing maximum variance in the data.

MDS works directly with a distance matrix, whereas PCA operates on the original data matrix

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Principal Component Analysis (PCA) Overview

- PCA is a linear algebra technique used to transform high-dimensional data into a set of linearly uncorrelated components
- Purpose
  - Reduce dimensionality while maximizing variance
  - Identify the most important features that contribute to data variance
  - Principal components are linear combinations of the original variables

Data Standardization

Mean center and scale the data so that features contribute equally

Covariance Matrix Computation

Calculate the covariance matrix of the dataset to understand how variables correlate with each other

Eigenvectors and Eigenvalues

Compute eigenvectors and eigenvalues

The eigenvectors form the principal components, and eigenvalues indicate the amount of variance captured by each

Dimensionality Reduction

Select the top k principal components with the largest eigenvalues and project the data into the new space

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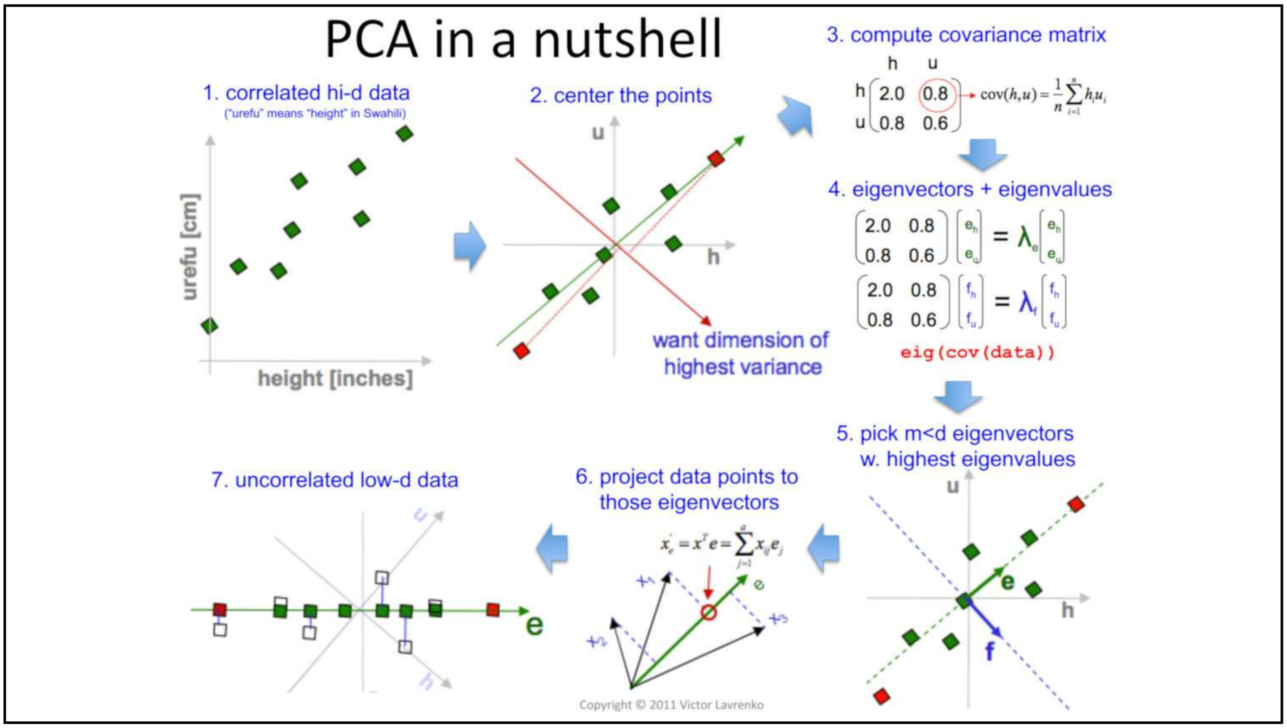

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Multidimensional Scaling (MDS):

Multidimensional Scaling (MDS) is a statistical technique used to visualize the level of similarity or dissimilarity between a set of items. The primary objective of MDS is to place each item in an n-dimensional space such that the pairwise distances between items reflect their observed dissimilarities as closely as possible. There are two main types of MDS: Metric MDS and Non-Metric MDS. These two approaches differ in how they interpret and use the input dissimilarities.

MDS is a non-linear technique for dimensionality reduction that maps data points based on dissimilarities or distances into a **lower-dimensional space**

Purpose

To preserve the pairwise distances between objects in a dataset	Used for both metric and non-metric data	Helps in understanding how objects relate to each other in terms of their similarities or dissimilarities

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Dissimilarity Matrix Calculation

Calculate pairwise dissimilarities between data points

Input can be a precomputed distance matrix

Choose Target Dimensionality

- Typically 2D or 3D, based on how the data needs to be visualized

Optimization

- MDS minimizes a stress function that measures how well the distances in the reduced space approximate the original dissimilarities
- Stress function is minimized to achieve the best fit

Visualize the Data

- The output is a plot where distances between points in the lower-dimensional space reflect their dissimilarities

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Recap: Distance, Dissimilarity and similarity

Distance, dissimilarity and similarity (or proximity) are defined for any pair of objects in any space. In mathematics, a distance function (that gives a distance between two objects) is also called *metric*, satisfying

1. $d(x, y) \geq 0$,
2. $d(x, y) = 0$ if and only if $x = y$,
3. $d(x, y) = d(y, x)$,
4. $d(x, z) \leq d(x, y) + d(y, z)$.

Given a set of dissimilarities, one can ask whether these values are distances and, moreover, whether they can even be interpreted as Euclidean distances

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The data to be analyzed is a collection of M objects (colors, faces, stocks, . . .) on which a *distance function* is defined,

$d_{i,j}$:= distance between i-th and j-th objects.

These distances are the entries of the *dissimilarity matrix*

$$D := \begin{pmatrix} d_{1,1} & d_{1,2} & \cdots & d_{1,M} \\ d_{2,1} & d_{2,2} & \cdots & d_{2,M} \\ \vdots & \vdots & & \vdots \\ d_{M,1} & d_{M,2} & \cdots & d_{M,M} \end{pmatrix}.$$

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Given a dissimilarity (distance) matrix $D = (d_{ij})$, MDS seeks to find $\mathbf{x}_1, \ldots, \mathbf{x}_n \in \mathbb{R}^p$ so that

$$\boxed{d_{ij} \approx \|\mathbf{x}_i - \mathbf{x}_j\|_2 \text{ as close as possible.}}$$

Oftentimes, for some large p, there exists a configuration $\mathbf{x}_1, \ldots, \mathbf{x}_n$ with exact distance match $d_{ij} \equiv \|\mathbf{x}_i - \mathbf{x}_j\|_2$. In such a case the distance d involved is called a Euclidean distance.
There are, however, cases where the dissimilarity is distance, but there exists no configuration in any p with perfect match

$$d_{ij} \neq \|\mathbf{x}_i - \mathbf{x}_j\|_2, \text{ for some } i, j.$$

Such a distance is called non-Euclidean distance.

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Stress Function and Interpretation in MDS

Stress Function is the core concept in MDS that quantifies the difference between the original pairwise dissimilarities and the distances in the low-dimensional space

$$\text{Stress}_D(x_1, x_2, \ldots, x_n) = \sqrt{\sum_{i \neq j = 1,\ldots,n} \left(d_{ij} - \|x_i - x_j\|\right)^2}.$$

Interpretation

- Low stress values indicate that the lower-dimensional representation is a good approximation of the original data
- High stress values suggest poor representation and the need for more dimensions

https://demonstrations.wolfram.com/MultidimensionalScaling/

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Types of MDS:
- **Metric MDS**: Preserves exact distances.
- **Non-Metric MDS**: Preserves the rank order of dissimilarities (ordinal data).

Non-Parametric Multidimensional Scaling (Non-Metric MDS) is a specific form of Multidimensional Scaling (MDS) designed to handle **ordinal** data, where only the **rank order** of dissimilarities is considered important, rather than their exact numerical values. It is a **non-parametric** technique, meaning it does not assume a specific parametric form for the relationship between the original data and the projected distances. The focus is on preserving the **rank order** of the pairwise dissimilarities in the low-dimensional space

- **Focus**: Maintains the rank order of dissimilarities instead of actual distances.
- **Data Type**: Ordinal data where the magnitude of differences is not important, but the order is.
- **Objective**: To place objects in a low-dimensional space such that the rank ordering of distances reflects the rank ordering of the original dissimilarities.

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Non-metric multidimensional scaling (NMDS)

In contrast to metric MDS, non-metric MDS finds both a non-parametric monotonic relationship between the dissimilarities in the item-item matrix and the Euclidean distances between items, and the location of each item in the low-dimensional space.

Let d_{ij} be the dissimilarity between points i, j. Let $\hat{d}_{ij} = \|x_i - x_j\|$ be the Euclidean distance between embedded points x_i, x_j.

Now, for each choice of the embedded points x_i and is a monotonically increasing function f, define the "stress" function:

$$S(x_1, \ldots, x_n; f) = \sqrt{\frac{\sum_{i<j} \left(f(d_{ij}) - \hat{d}_{ij}\right)^2}{\sum_{i<j} \hat{d}_{ij}^2}}.$$

Metric MDS

$$\mathrm{Stress}_D(x_1, x_2, \ldots, x_n) = \sqrt{\sum_{i \neq j = 1, \ldots, n} \left(d_{ij} - \|x_i - x_j\|\right)^2}.$$

The factor of $\sum_{i<j} \hat{d}_{ij}^2$ in the denominator is necessary to prevent a "collapse". Suppose we define instead $S = \sqrt{\sum_{i<j} \left(f(d_{ij}) - \hat{d}_{ij}\right)^2}$, then it can be trivially minimized by setting $f = 0$, then collapse every point to the same point.

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Aspect	Metric MDS	Non-Metric MDS
Data Type	Interval or Ratio	Ordinal
Preservation	Exact distances	Rank order of dissimilarities
Stress Minimization	Linear distances preserved	Monotonic function preserves rank
Application	Geographical or real-world distance mapping	Psychology, sociology

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PCA vs. MDS

Aspect	PCA	MDS
Approach	Linear, focuses on variance.	Non-linear, focuses on distances or dissimilarities.
Data Requirements	Requires metric, numeric data.	Can handle both metric and non-metric data.
Purpose	Reduce dimensionality by maximizing variance explained by the principal components.	Reduce dimensionality by preserving pairwise distances.
Optimization	Eigenvalue decomposition (finds principal components).	Minimizes the stress function (preserves distances).
Output	Principal components, orthogonal axes.	Configuration of points where distances reflect dissimilarities.
Scalability	Handles large datasets efficiently.	Can be computationally intensive with larger datasets.
Interpretation	Principal components are interpretable as directions of maximum variance.	Axes in MDS are not easily interpretable, focus is on distances.
Data Structure	Emphasizes global structure (variance).	Emphasizes local structure (pairwise relationships).

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Use Cases for PCA and MDS

When to use PCA

- You have numeric data, and your goal is to explain as much variance as possible with fewer components
- Example: Feature extraction for predictive modeling, compression of image datasets, or financial analysis

When to use MDS

- You want to preserve pairwise distances or visualize the similarity structure of the data
- Useful for survey analysis, genetic data visualization, and social network analysis where relationships between items matter more than variance

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Visualization Example: PCA vs. MDS

PCA Example: A 2D plot where the first two principal components capture the maximum variance

MDS Example: A 2D plot where the distances between points approximate the original dissimilarities

Key Insight: PCA focuses on variance; MDS focuses on pairwise distance relationships

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Advantages and Limitations

Technique	Advantages	Limitations
PCA	Simple, interpretable, maximizes variance, handles large datasets.	Only linear relationships, sensitive to outliers.
MDS	Non-linear, handles both metric and non-metric data, preserves distances.	Computationally expensive, axes not interpretable.

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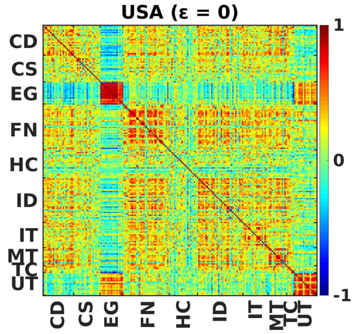
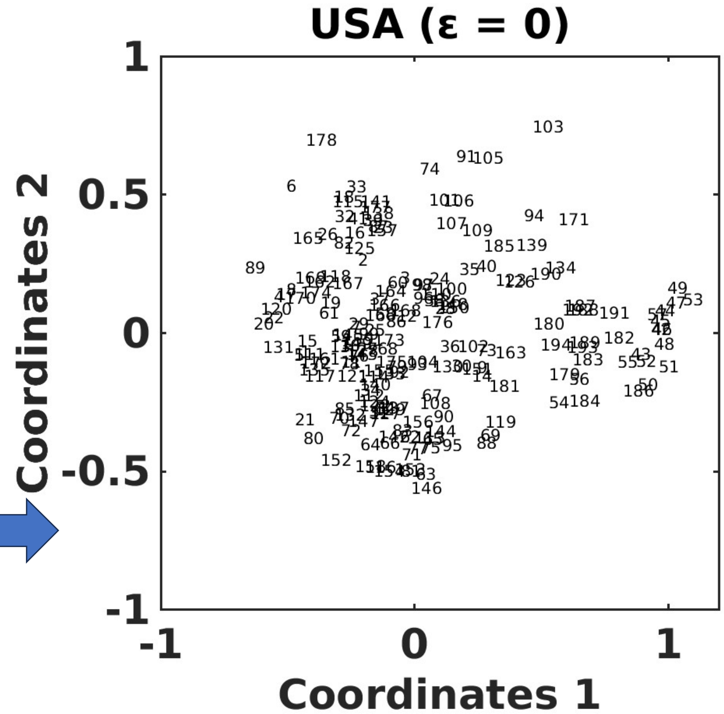


$$d_{ij} = \sqrt{2(1 - C_{ij})}$$



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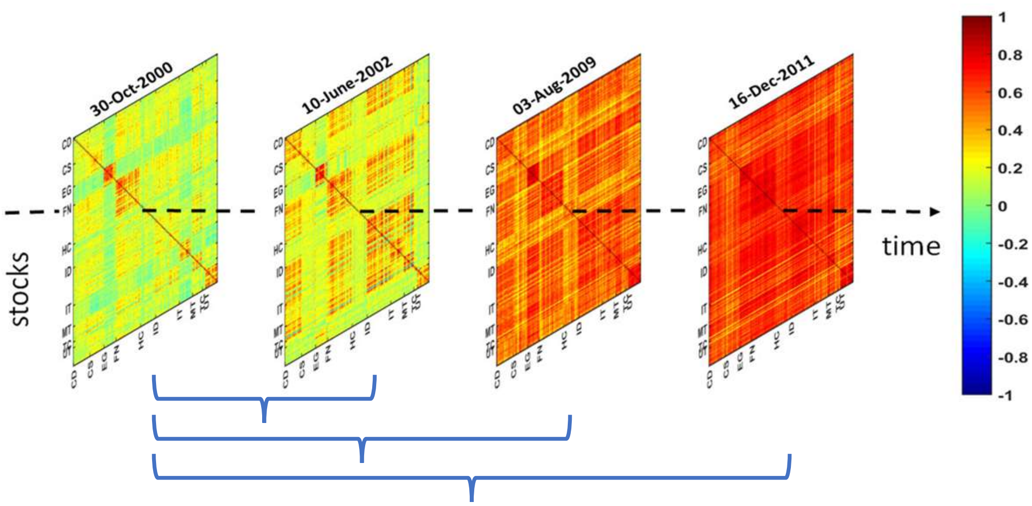

$$\zeta(\tau_1, \tau_2) \equiv \langle |C_{ij}(\tau_1) - C_{ij}(\tau_2)| \rangle$$

where |...| denotes the absolute value and <...> denotes the average over all matrix elements C_{ij}

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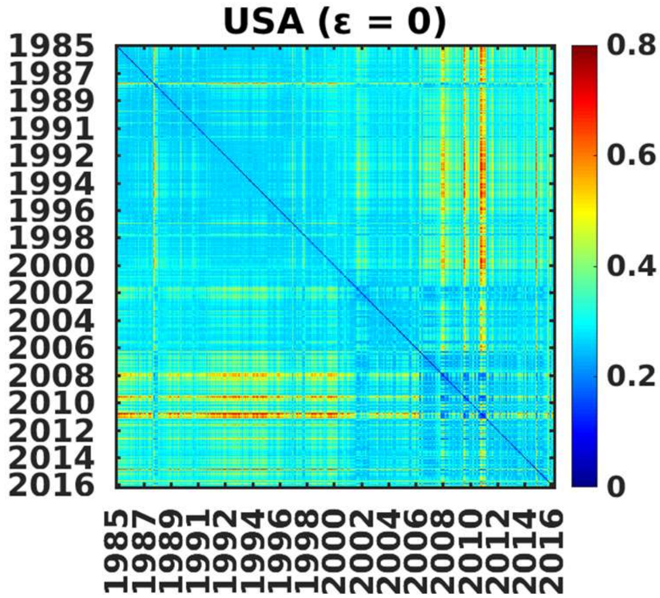
Similarity Matrix of Correlation Frames (1985-2016)



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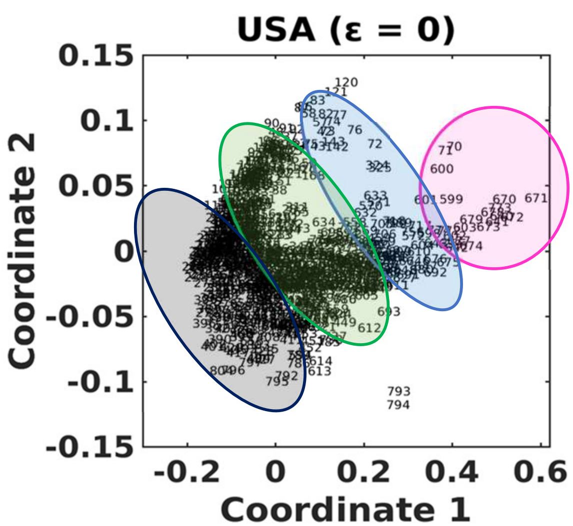
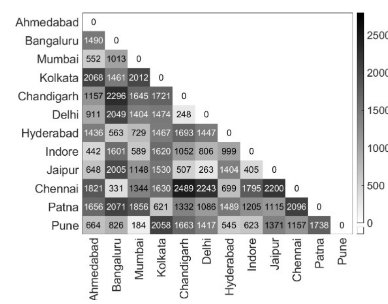
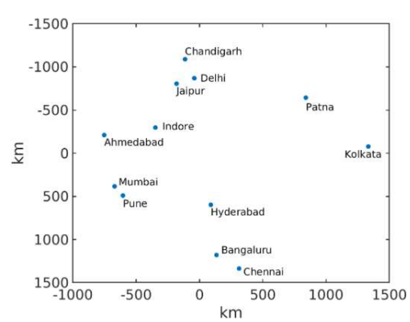
Multi-dimensional scaling (MDS)





	Ahmedabad	Bangaluru	Mumbai	Kolkata	Chandigarh	Delhi	Hyderabad	Indore	Jaipur	Chennai	Patna	Pune
Ahmedabad	0											
Bangaluru	1490	0										
Mumbai	552	1013	0									
Kolkata	2068	1461	2012	0								
Chandigarh	1157	2296	1645	1721	0							
Delhi	911	2049	1404	1474	248	0						
Hyderabad	1436	563	729	1467	1693	1447	0					
Indore	442	1601	589	1620	1052	806	999	0				
Jaipur	648	2005	1148	1530	507	263	1404	405	0			
Chennai	1821	331	1344	1630	2489	2243	699	1795	2200	0		
Patna	1656	2071	1856	621	1332	1086	1489	1205	1115	2096	0	
Pune	664	826	184	2058	1663	1417	545	623	1371	1157	1738	0



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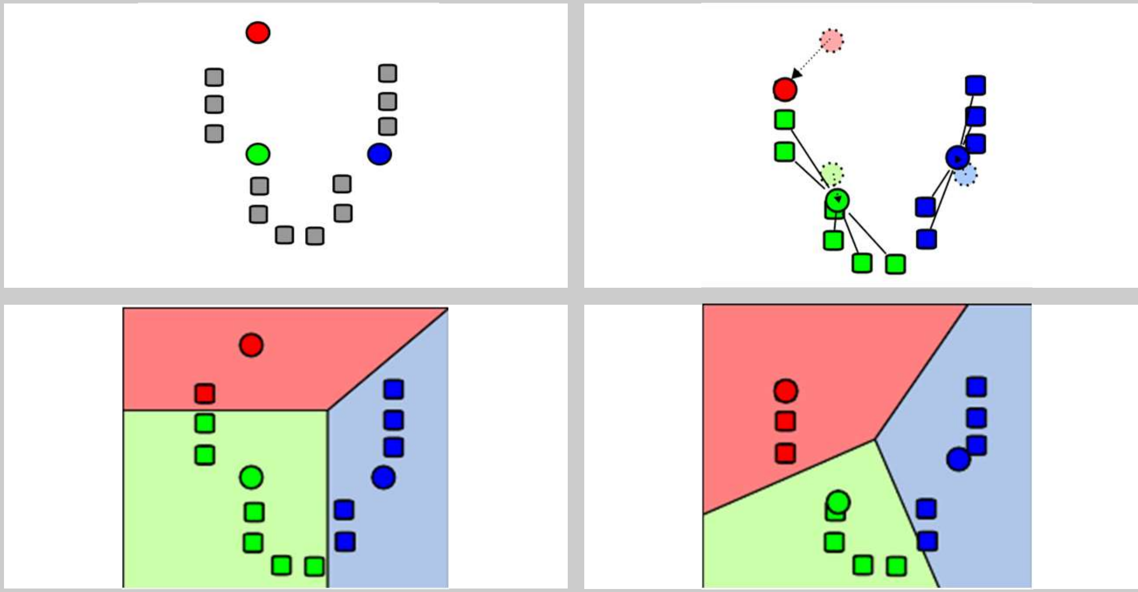
K-means Clustering



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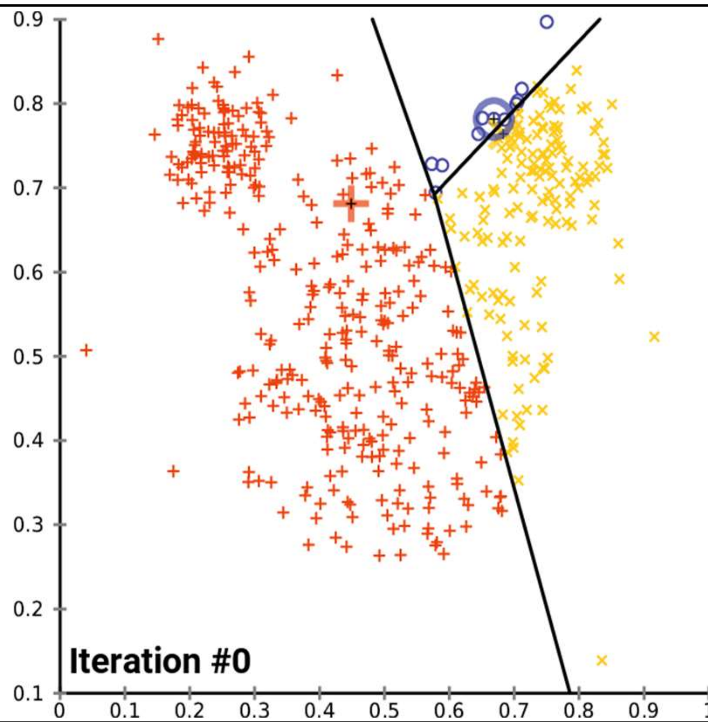

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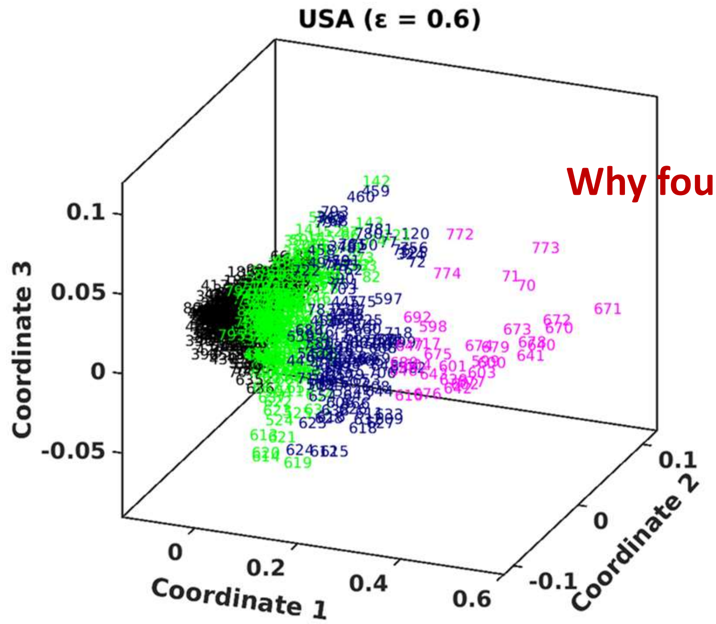
K-means clustering



Why four clusters only?

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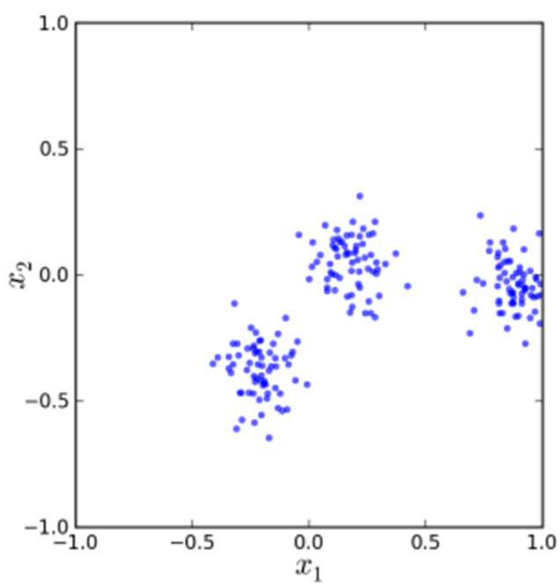
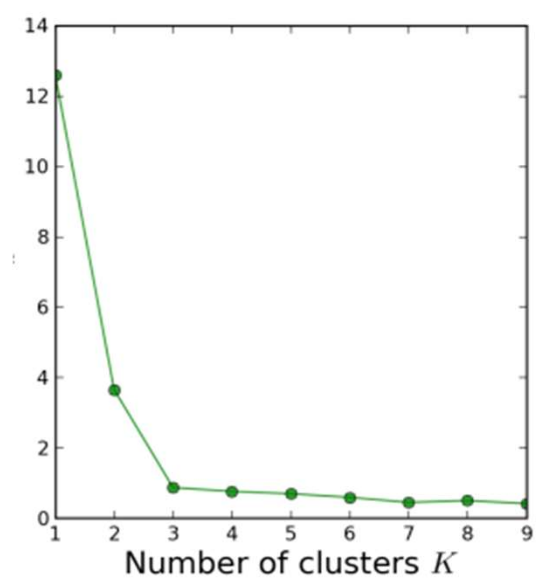
Intra Cluster Distance and elbow point





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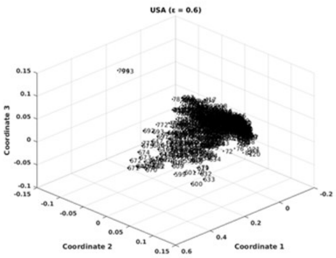
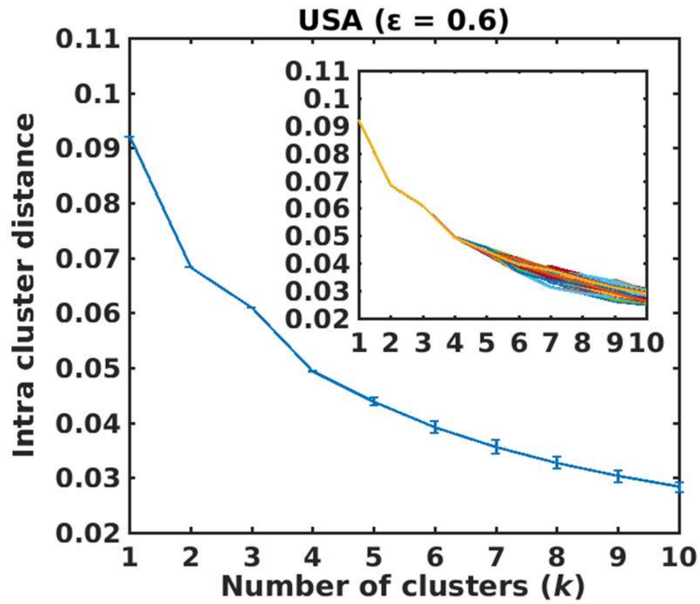

USA (ε = 0.6)
Coordinate 1
Coordinate 2
Coordinate 3


USA (ε = 0.6)
Intra cluster distance
Number of clusters (k)

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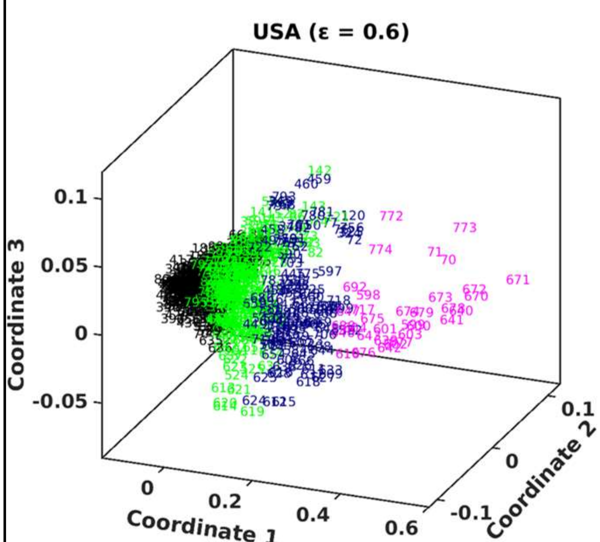
USA (ε = 0.6)
Coordinate 1
Coordinate 2
Coordinate 3

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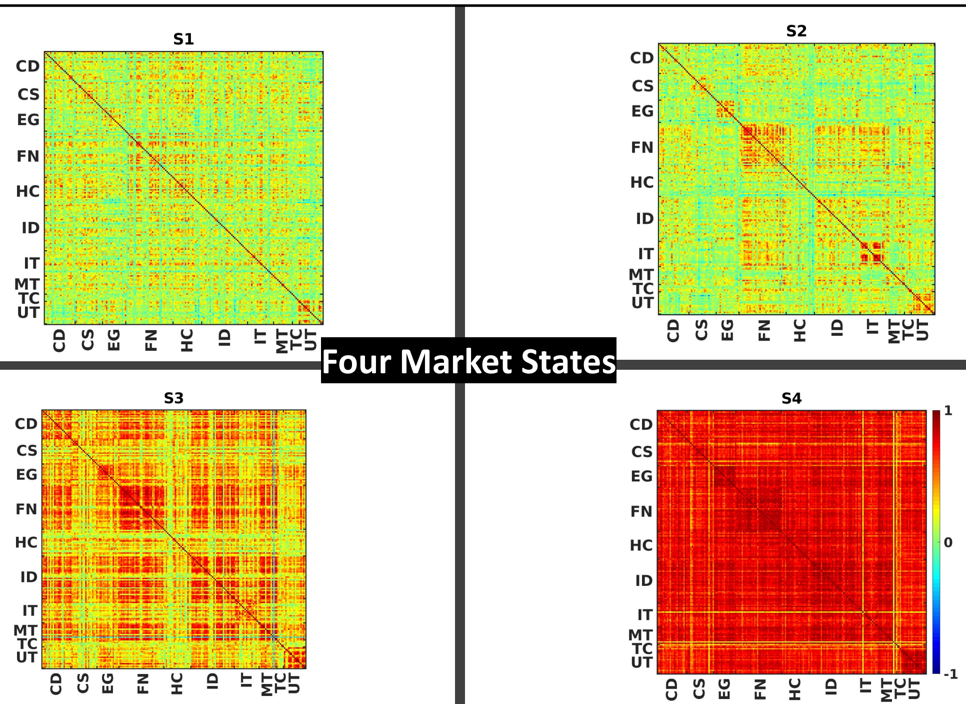
Four Market States



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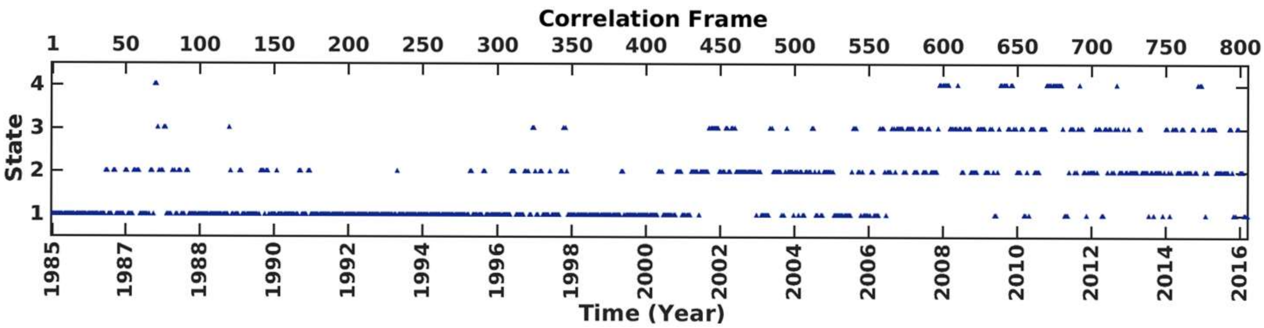
Market States Dynamics



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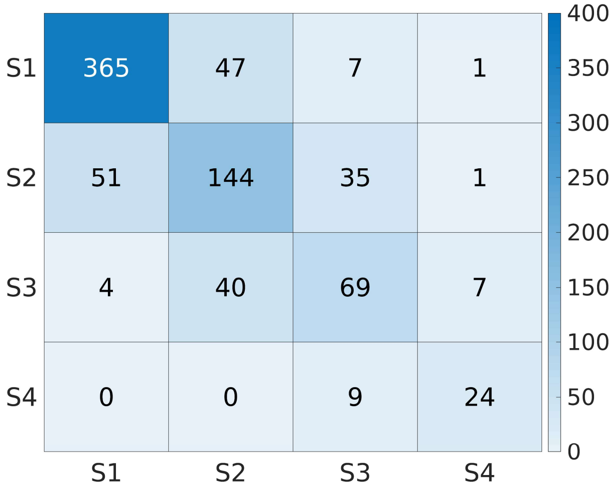

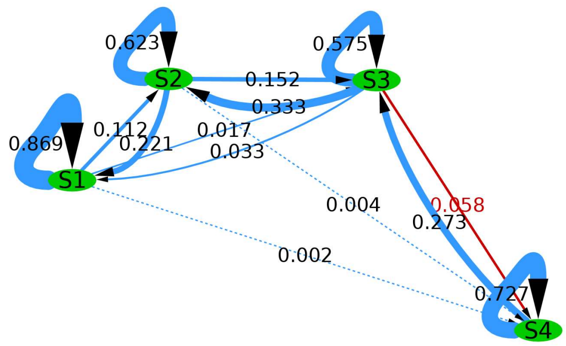

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Thank you

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