Guided Tour of Machine Learning in Finance

Week 3: Unsupervised Learning

Minimum Spanning Trees, Kruskal algorithm, and equity correlation matrices

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Task:

Given a connected weighted graph with N nodes and connection weights d_{ij} , find a minimum spanning tree (MST) - a graph without loops connecting N nodes with N-1 links, such that the total weight of all edges is minimized.

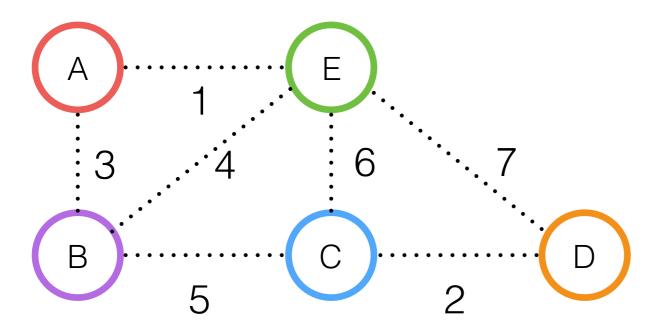
Meaning: from N(N-1)/2 links, select N-1shortest links that span all the nodes without forming loops.

The Kruskal algorithm:

- 1. Find a minimum weight on a graph. Color it in any color (e.g. red)
- 2. Find the minimum uncolored edge that does not cross a colored or a red circuit. Mark this edge by a new color.
- 3. Repeat step 2 until connecting every vertex on the graph. The red edges form a MST.

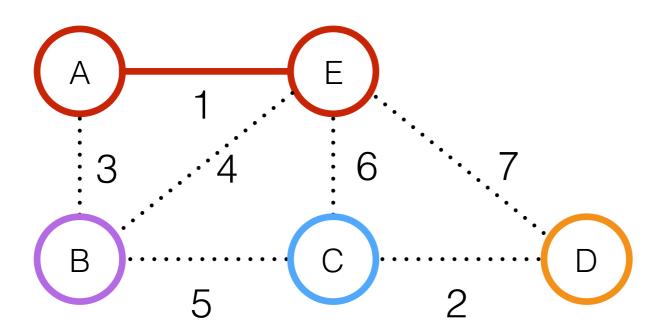
Wikipedia's example (N=5)

Edge	AE	CD	AB	BE	ВС	EC	ED
Weight	1	2	3	4	5	6	7



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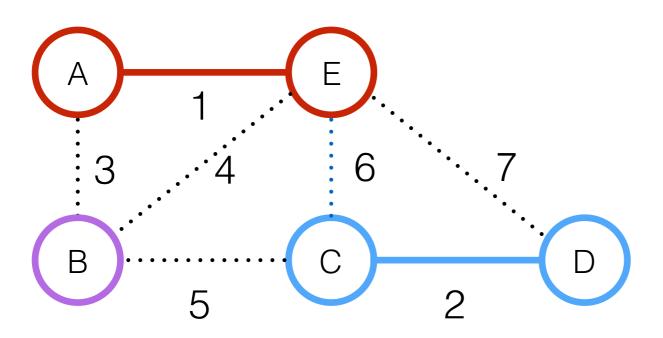
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Select the smallest weight

Wikipedia's example (N = 5)

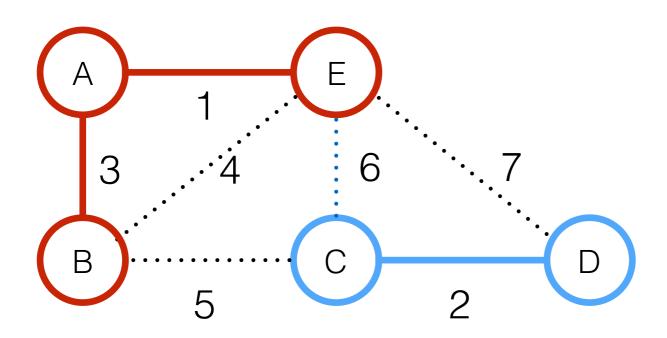
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Select another smallest weight

Wikipedia's example (N=5)

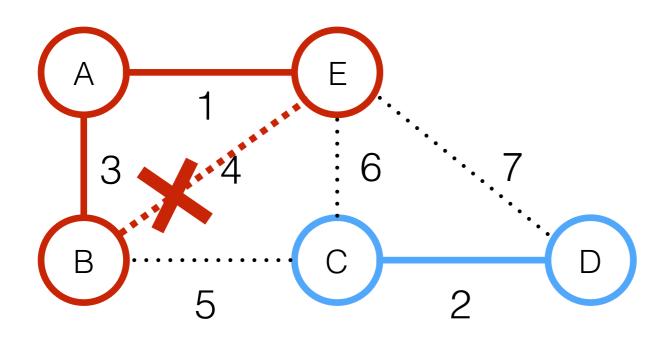
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Select another smallest weight

Wikipedia's example (N = 5)

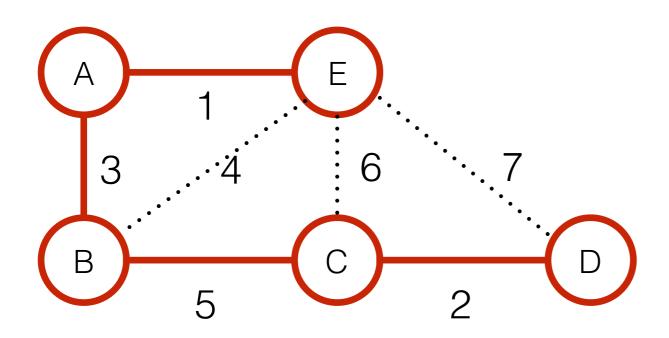
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Weight	1	2	3	4	5	6	7



Selecting BE creates a loop!

Wikipedia's example (N = 5)

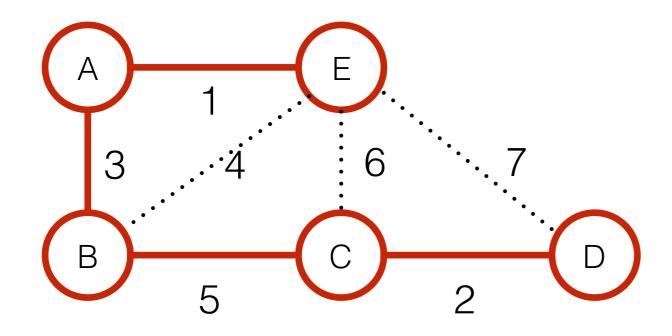
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The minimum spanned tree is completed!

Wikipedia's example (N = 5)

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The minimum spanned tree is completed!

The MST compresses the data representation from $N(N-1)/\sqrt{2}$ parameters to N-1 parameters

Use the MTS to de-noise the empirical distance matrix $D(\Delta t) = \left\{d_{ij}(\Delta t)\right\}_{i,j=1}^N$ (and the correlation matrix $C(\Delta t)$!) matrix by replacing

$$d_{ij} \rightarrow d_{ij}^{<}$$

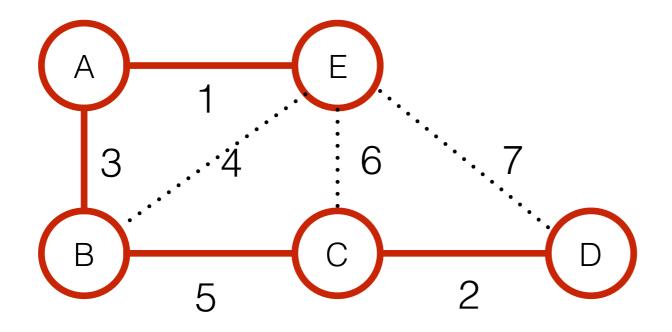
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Maximum distance d_{kl} among single steps in a path from i to j in a MST

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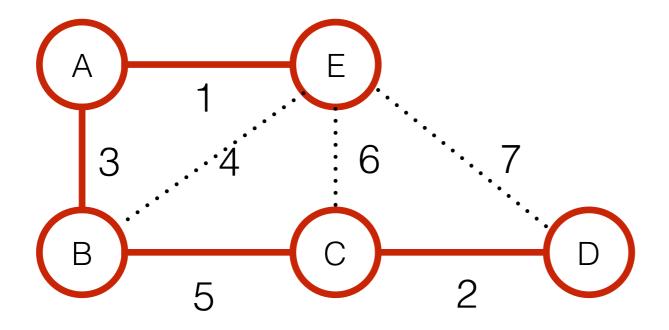


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Edge	AE	CD	AB	BE	ВС	EC	ED
$ d_{ij} $	1	2	3	4	5	6	7
d_{ii}^{ϵ}	1	2	3	3	5	5	5

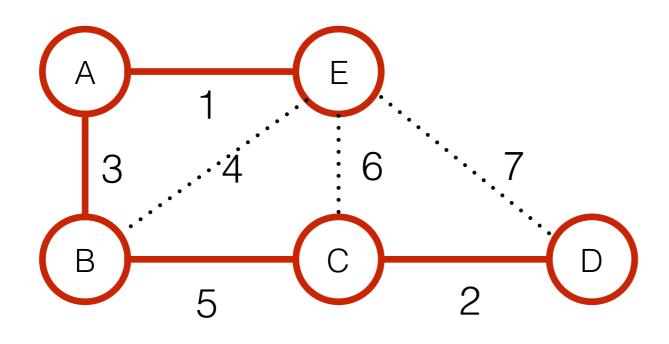


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Maximum distance d_{kl} among single steps in a path from i to j in a MST (the Subdominant Ultrametric Distance)

Edge	AE	CD	AB	BE	ВС	EC	ED
$ d_{ij} $	1	2	3	4	5	6	7
d_{ii}^{ϵ}	1	2	3	3	5	5	5



Ultrametric distance: violates the triangle inequality of an Euclidean metric:

$$d_{ij} \leq \max_{k} \left\{ d_{ik}, d_{kj} \right\}$$

Subdominant Ultrametric - the largest ultrametric among those that are less or equal to $d_{\it ij}$

Application for portfolio optimization

Application for portfolio optimization (E. Pantaleo et al, "When Do Improved Covariance Matrix Estimators Enhance Portfolio Optimization? An empirical study of nine estimators", 2010):

- Applied different filtering techniques to a sample covariance matrix of US stocks
- Compared realized risk for Markowitz-optimal portfolios obtained with different filtered covariance matrices

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 - (i) Sample covariance matrix
 - (ii) Random Matrix Theory (RMT) based filtering
 - (iii) MST and other graph-based filtering

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Results:

- Substantially lower-risk optimal portfolios for the regime $T \ / \ N > 1$ when short sales are allowed
- No significant improvements over the sample covariance matrix when short sales are not allowed, and/or T / N < 1

Control question

Select all correct answers

- 1. A Minimum Spanning Tree (MTS) constructs a graph with N nodes without loops using N-1 links, such that the total weight of all links is **maximized**.
- 2. A Minimum Spanning Tree (MTS) constructs a graph with N nodes without loops using N-1 links, such that the total weight of all links is **minimized**.
- 3. The MST compresses the parametrization of a correlation matrix from N(N-1)/2 parameters to N-1 parameters
- 4. Graph-based filtering of correlation matrices produce lower-risk optimal portfolios for the regime T / N < 1 when short sales are not allowed
- 5. Graph-based filtering of correlation matrices produce lower-risk optimal portfolios for the regime T / N > 1 when short sales are allowed

Correct answers: 2, 3, 5