Similarity Based Modeling

Advantages:

- Easier than 1st Principles, uses empirical data
- No *a priori* assumptions required

Limitations:

- Model is only as good as available data
- Model estimates do not extrapolate beyond the range of the training data
- Does not explicitly incorporate time
  - New technology (Sequential Similarity Based Modeling) extends modeling into time domain

When is SBM Particularly Advantageous?

Fundamental 1st principles are arduous or impossible to discover

Nonlinear phenomena drive the system

System may undergo graceful aging or undetermined evolution

Data are readily available to characterize the system

Data beyond the range of the training data are characteristic of abnormal operation

Condition monitoring applications exhibit all of these properties

Characteristics of Similarity Based Modeling

SBM does not attempt to explicitly relate one variable to another

Modeling is accomplished via pattern reconstruction

Patterns represent current operational state and normal operational states

- Current pattern is a vector containing current sensor measurements
- Training patterns consist of vectors containing sensor data collected during periods of normal operation

Characteristics of Similarity Based Modeling

Pattern reconstruction

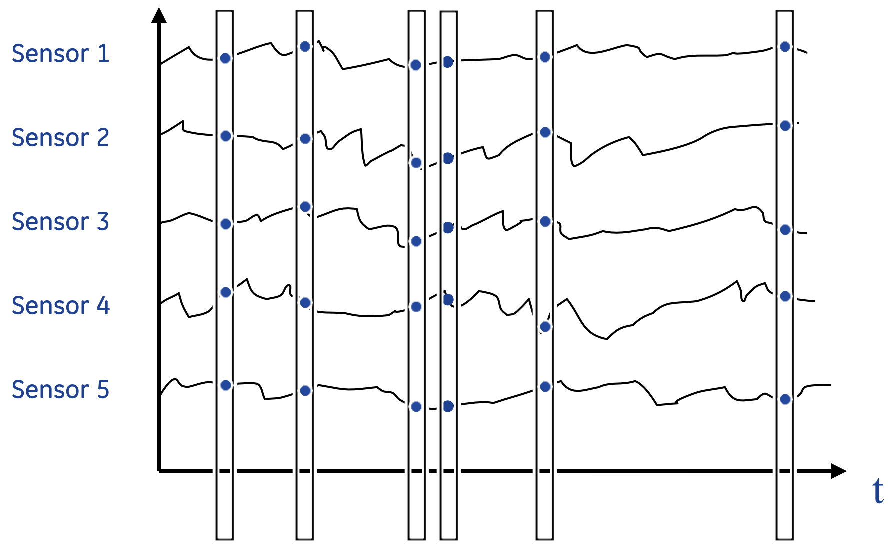
- Similarity between current vector and each training vector is calculated
- Similarities are combined to generate an estimate vector
- Estimate vector represents the expected operating state

Goal is to capture normal variation under all operating conditions

- Thereby exposing abnormal behavior
- Analyze abnormal behavior to identify cause

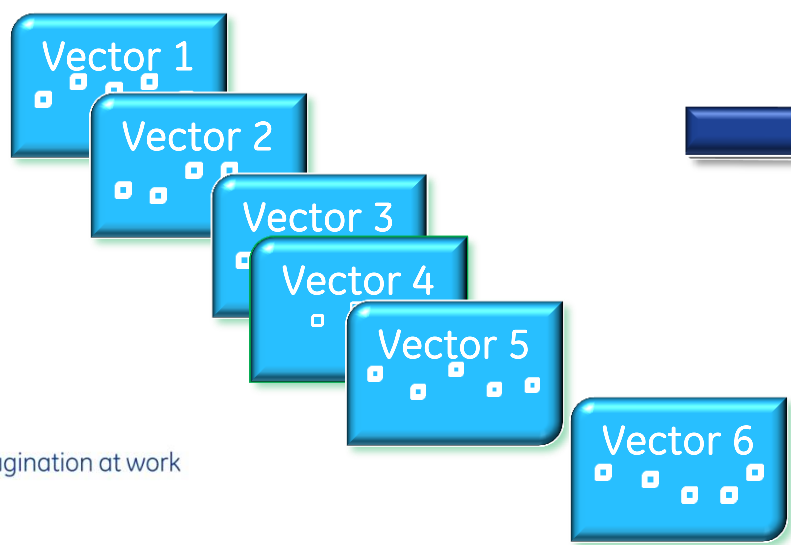
imagination at work

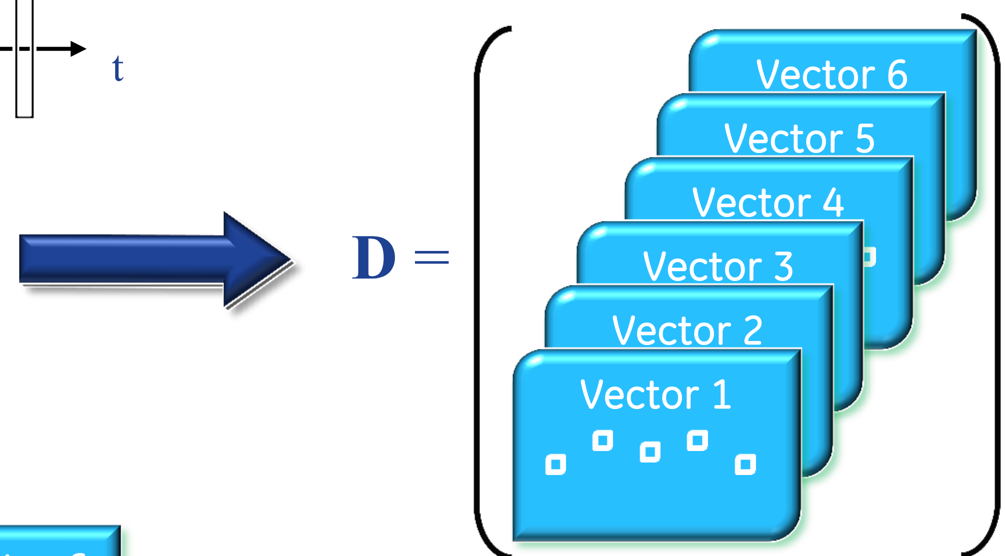
SBM Employs Pattern Reconstruction



The selected vectors define the SBM "State Matrix"

Model estimates are generated using combinations of these vectors





imagination at work

The Math Behind the SBM Modeling Process

Off-line (training)

1 Select patterns from reference data (Y) to form a state matrix (D)

2 Calculate and invert the interpolation matrix (G)

On-line (estimate generation)

3 Calculate similarity of input (x_{in}) to patterns in the state matrix (D)

4 Transform similarities (a) into weights (w_0) – then normalize (w)

5 Generate an estimate by linearly combining patterns and weights

1) $\mathbf{Y} \Rightarrow \mathbf{D}$ 2) $\mathbf{G}^{-1} = (\mathbf{D}^t \otimes \mathbf{D})^{-1}$ 3) $\mathbf{a} = \mathbf{D}^t \otimes \mathbf{x}_{in}$ 4) $\mathbf{w}_0 = \mathbf{G}^{-1} \cdot \mathbf{a},\ \mathbf{w} = \dfrac{\mathbf{w}_0}{\sum \mathbf{w}_0}$ 5) $\hat{\mathbf{x}}_{in} = \mathbf{D} \cdot \mathbf{w}$

The Similarity Operator

Similarity Operator ($V1 \otimes V2$)

- Nonlinear function that returns a scalar measure of the 'similarity' between two vectors
- Similarity attains a maximum value (1) when the two vectors are identical ($V1 = V2$)
- Similarity decreases as the distance between the vectors increases ($V1 \otimes V2 \sim 1 / \| V1 - V2 \|$)

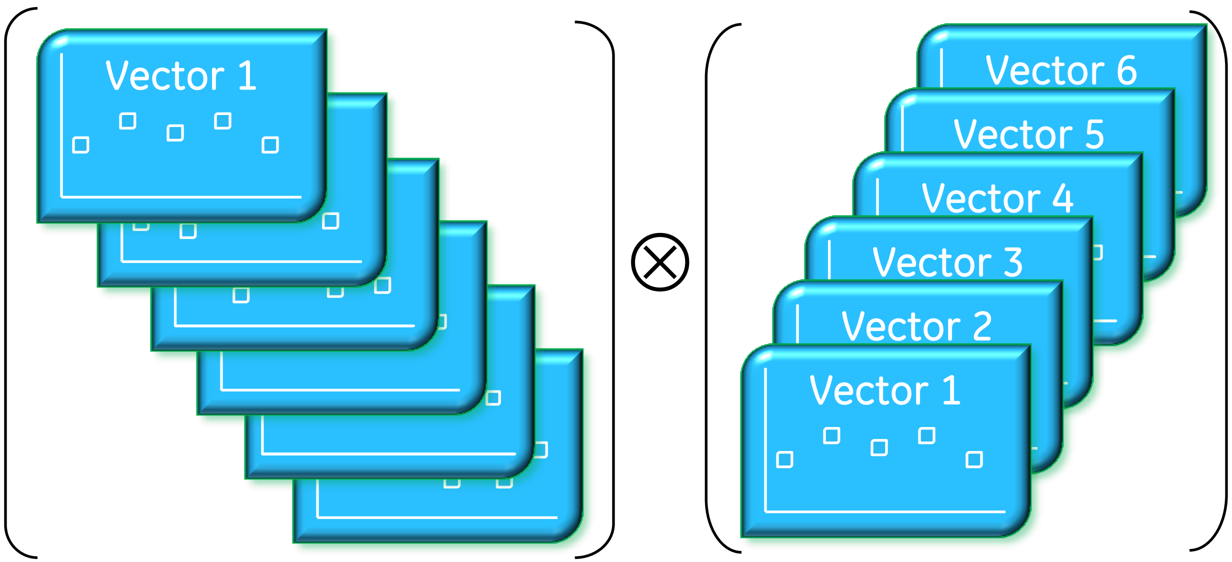
Extended operator returns the similarity of all vector combinations in a matrix

Operators tailored to specific applications

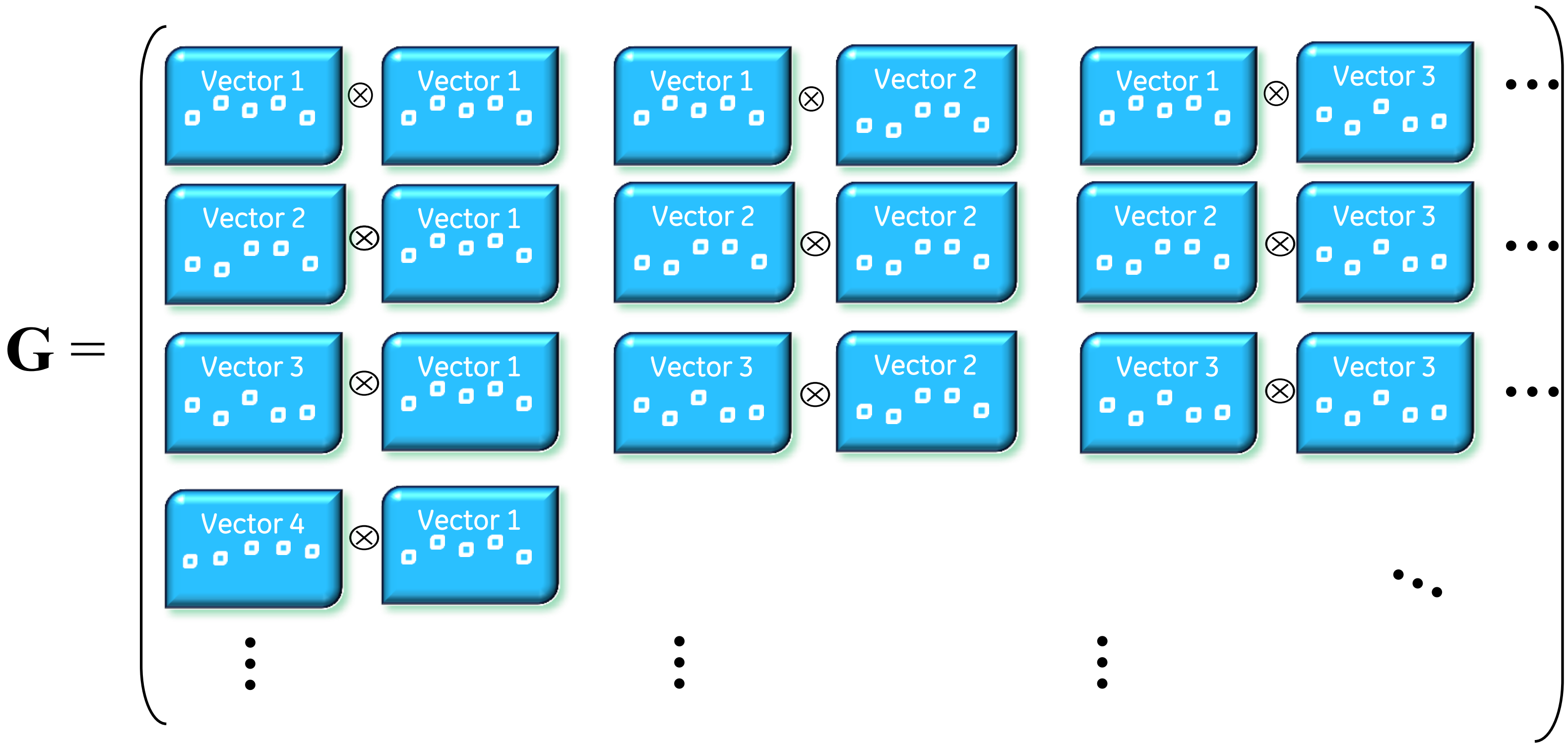
- SSCOP2 for autoassociative modeling
- SSCOP3 for inferential modeling

Pattern Reconstruction in Action

Generate the interpolation matrix (**G**) by calculating the similarity between all combinations of vectors stored in **D**…

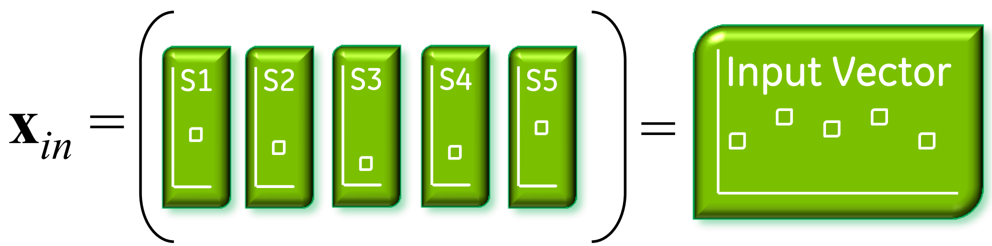


Interpolation Matrix



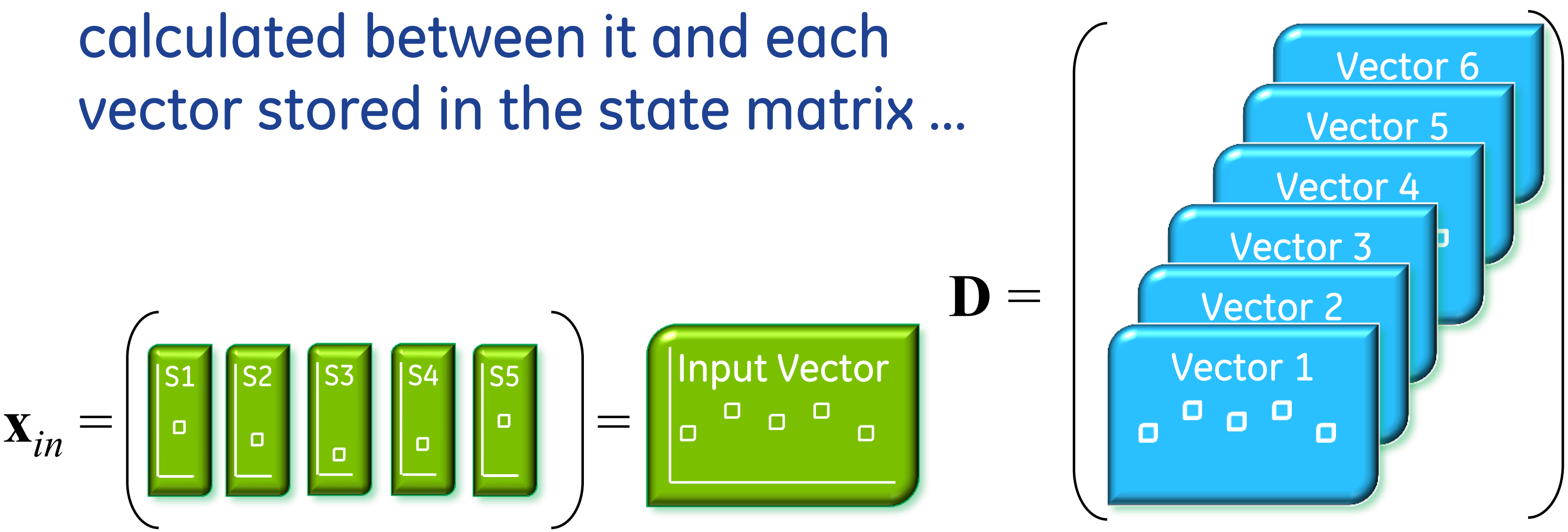
Collect Current Measurements of All Signals

At a point in time, an input vector ($\mathbf{x}_{in}$) is constructed from a single measurement of each sensor in the model…



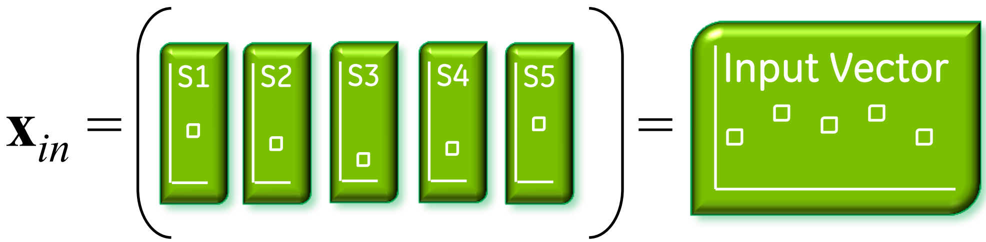
Calculate Similarity to Normal States

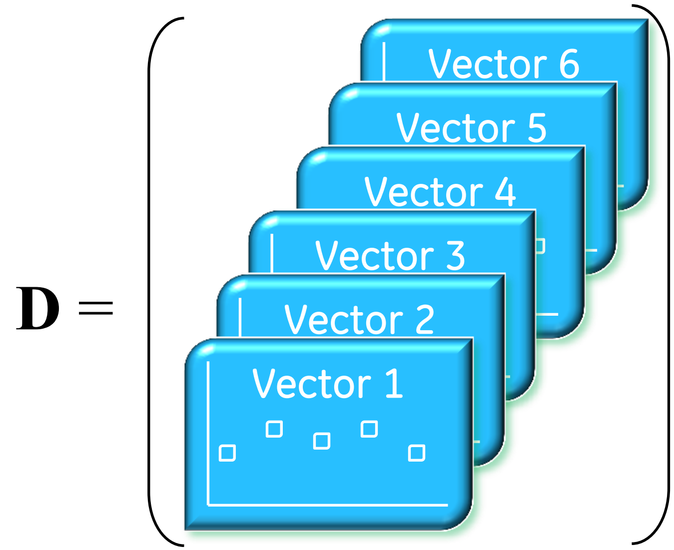
Given a state matrix (**D**), the similarity of the input vector is calculated between it and each vector stored in the state matrix …

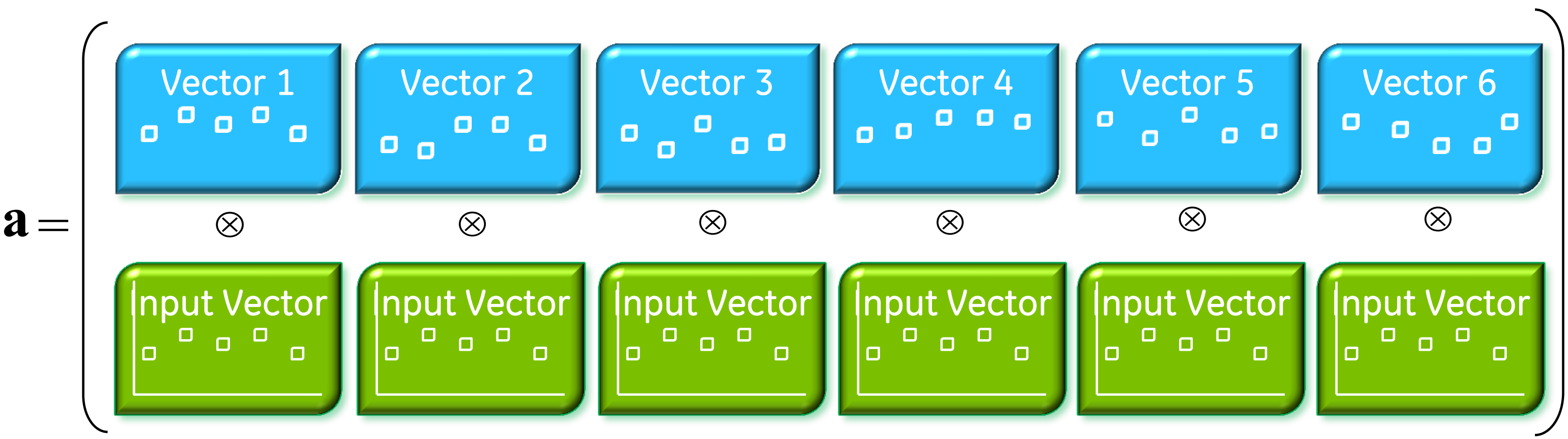


Similarity Vector

This produces the similarity vector (**a**), which has the same number of elements as the number of training vectors (patterns) stored in the state matrix…







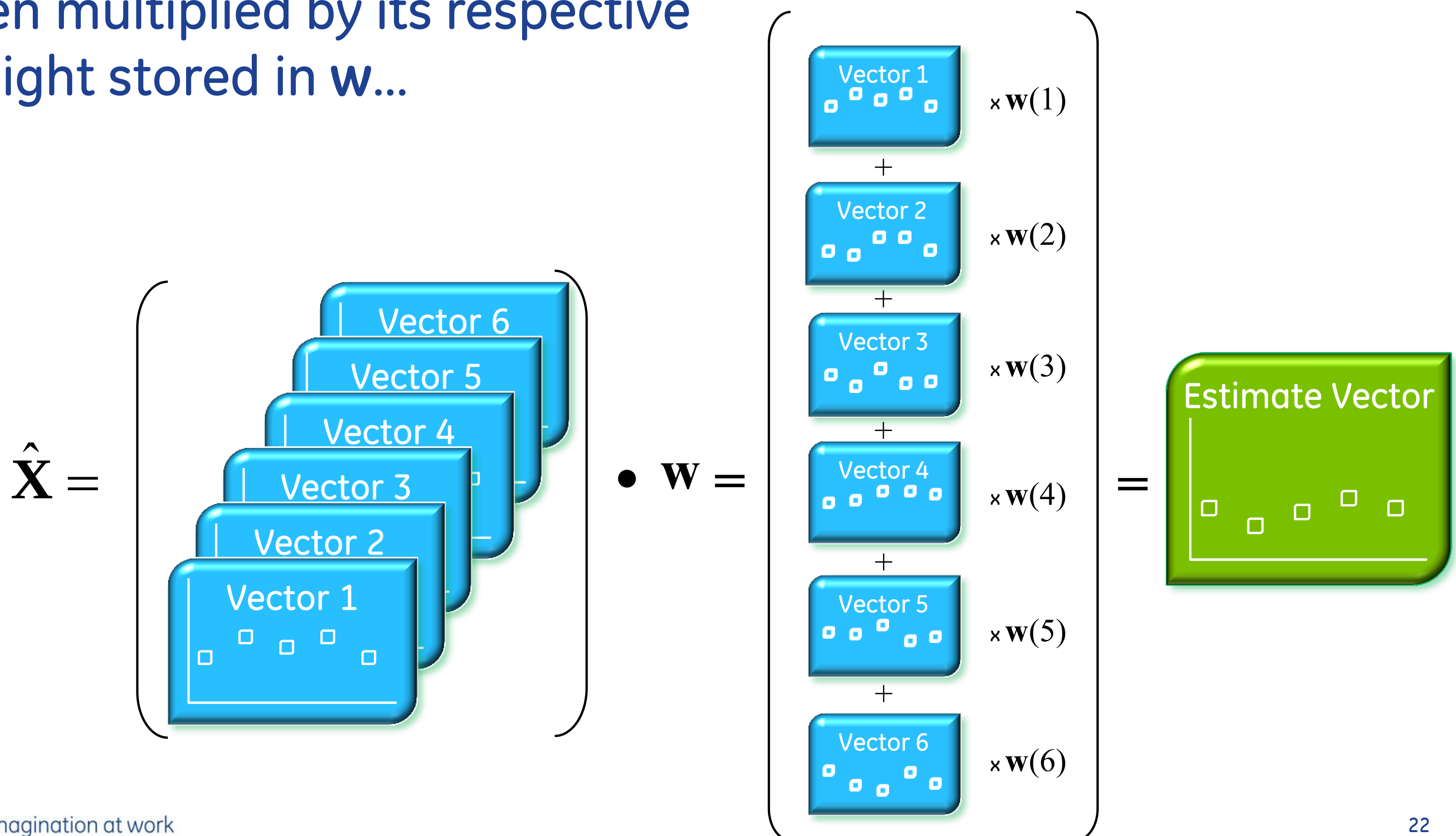
Obtain Weights for Each Training Vector

The similarity vector is transformed into a vector of weights (**w**)…

$$\mathbf{w}_0 = \mathbf{G}^{-1} \bullet \mathbf{a} \qquad \mathbf{w} = \frac{\mathbf{w}_0}{\sum \mathbf{w}_0}$$

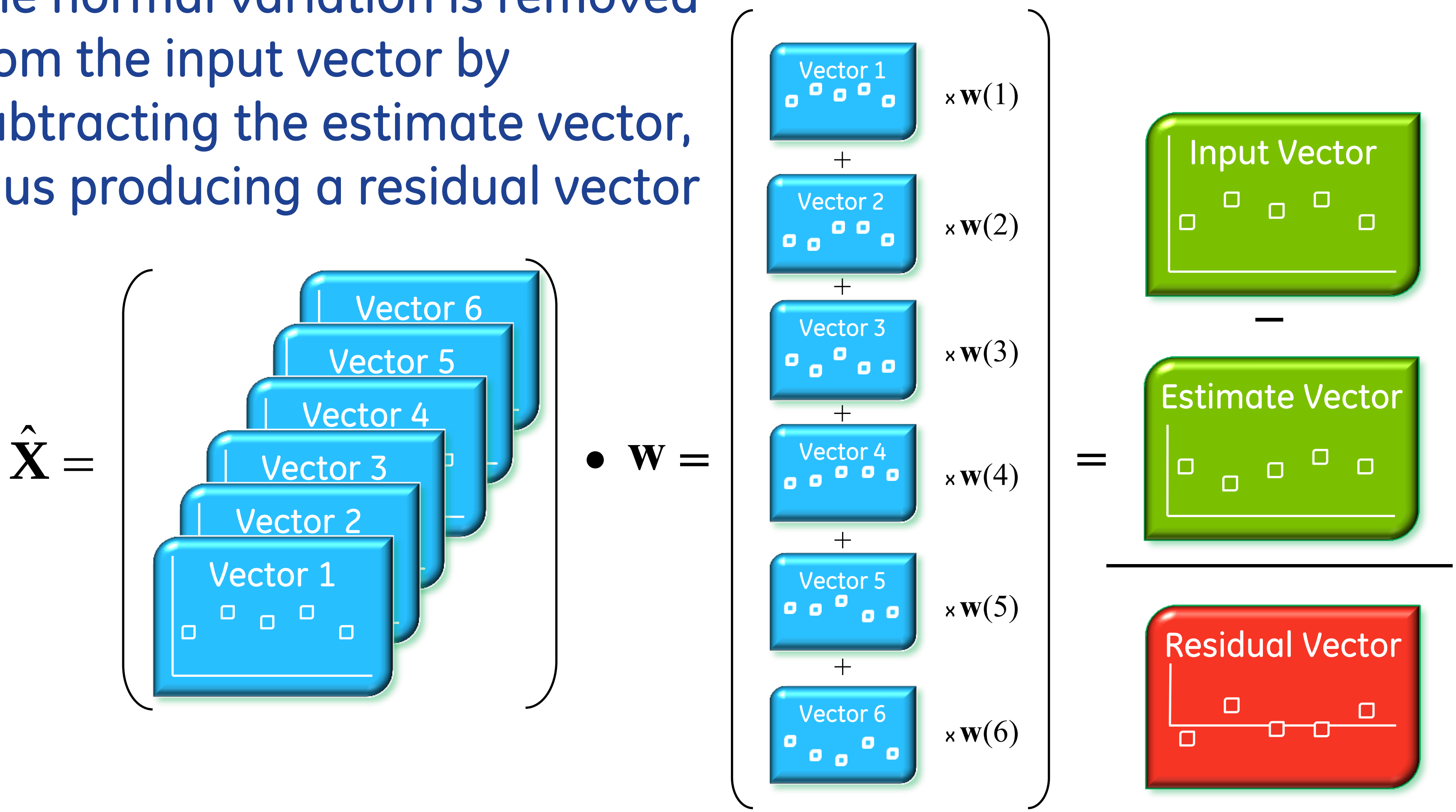
Calculate the Estimate Vector

Each vector in the state matrix is then multiplied by its respective weight stored in **w**…



Calculate the Residual Vector

The normal variation is removed from the input vector by subtracting the estimate vector, thus producing a residual vector



Two-Dimensional Example

Two-Dimensional Example

D =

X	Y
1	0.101
10	0.722
19	0.722
28	0.278
37	-0.200
46	-0.682
55	-0.691
64	-0.094
73	0.467
82	0.932
91	0.602
100	-0.180