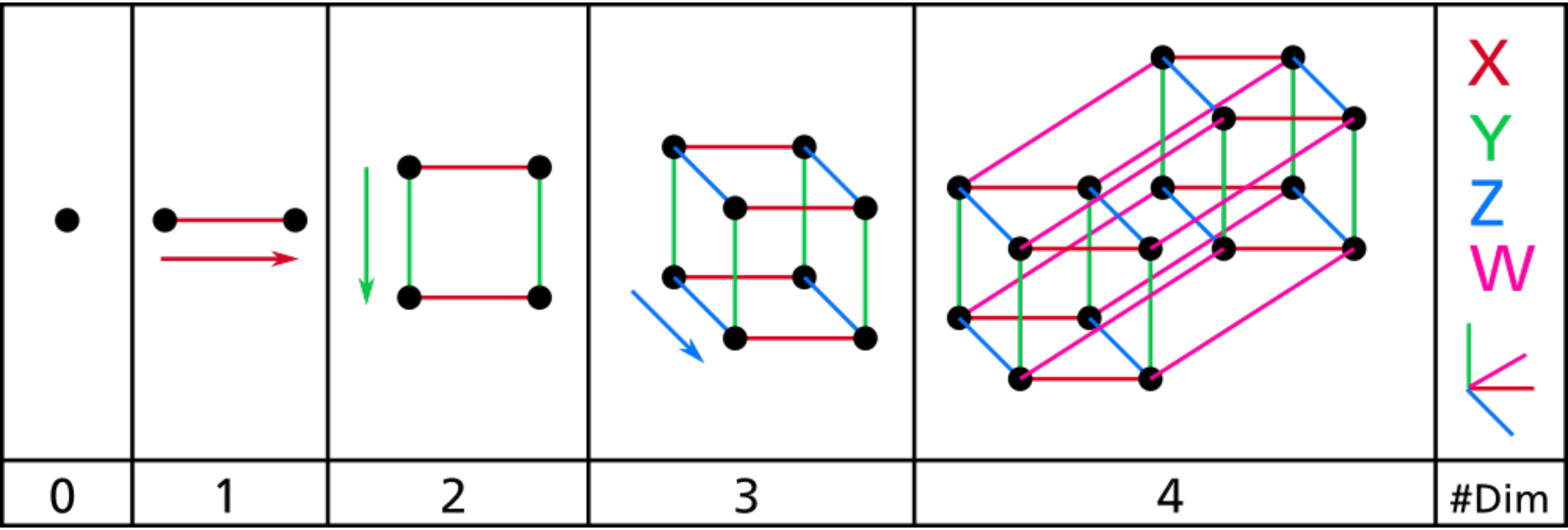
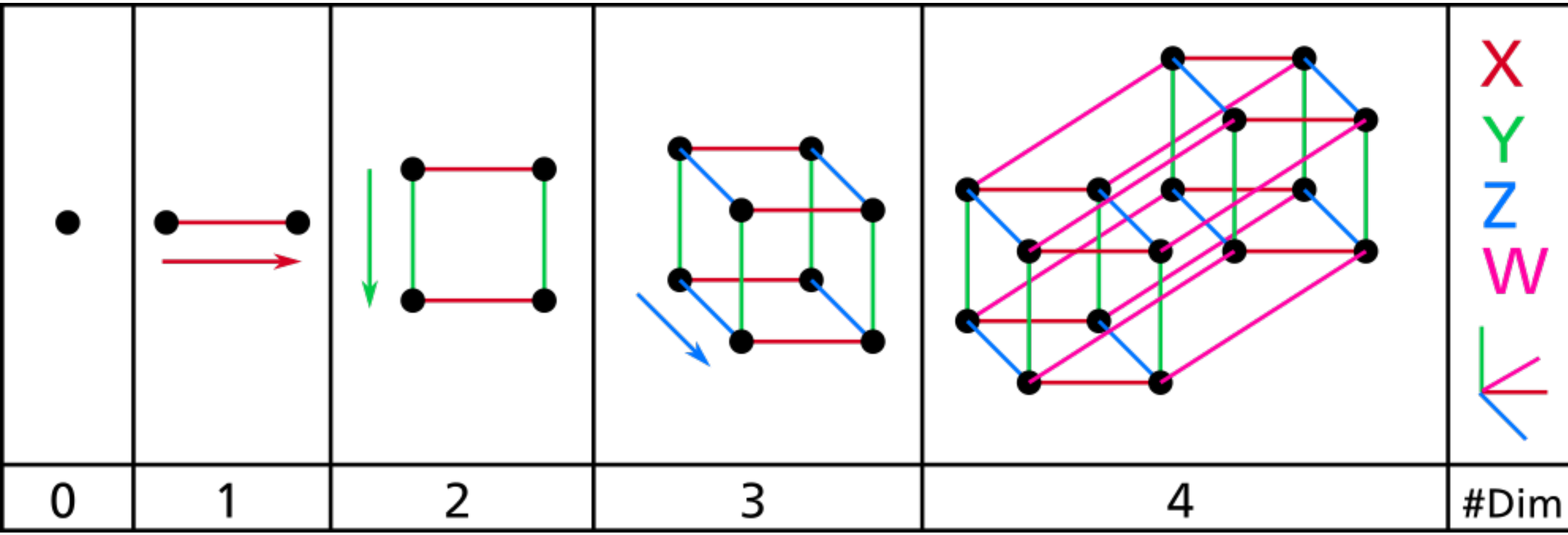
Dimensionality Reduction

Curse of Dimensionality



Curse of Dimensionality

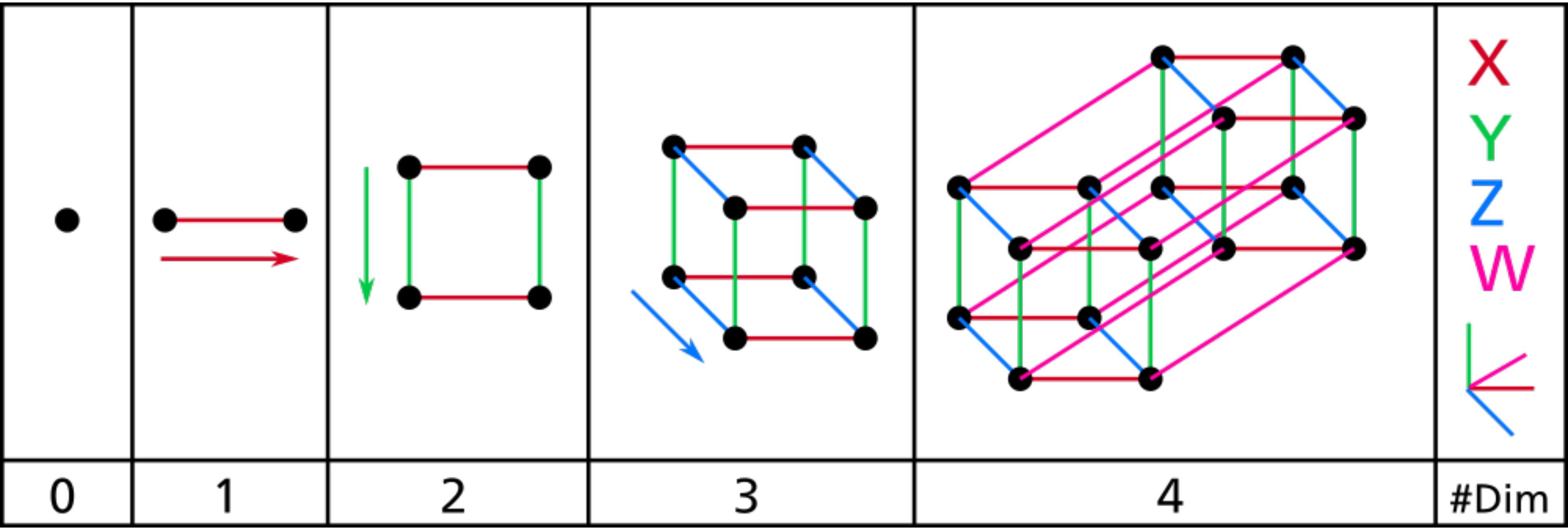


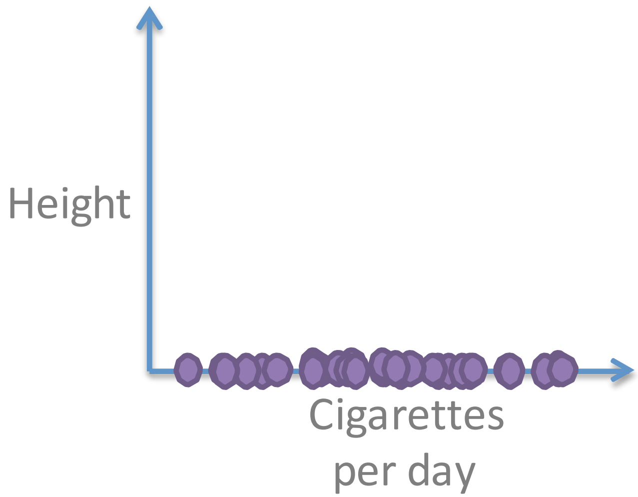
One dimension:

Small space

Being close quite probable

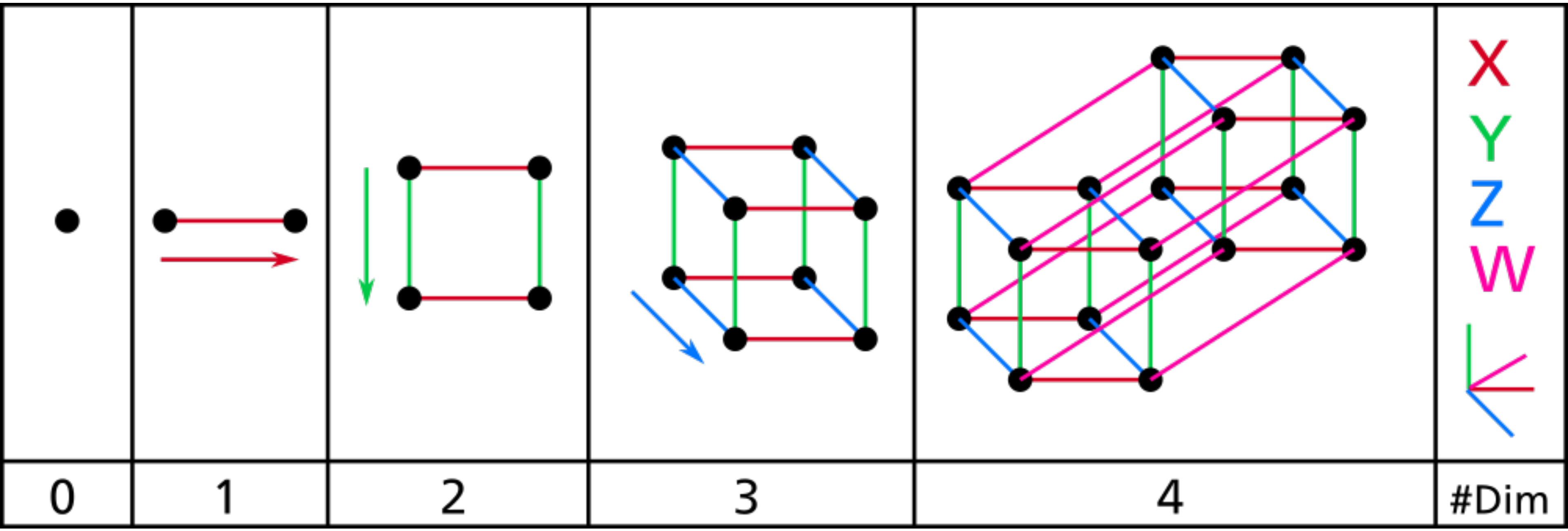
Curse of Dimensionality

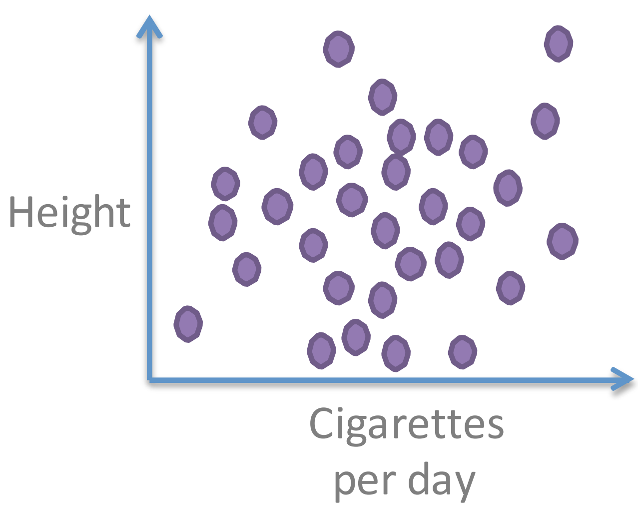




Two dimensions

Curse of Dimensionality



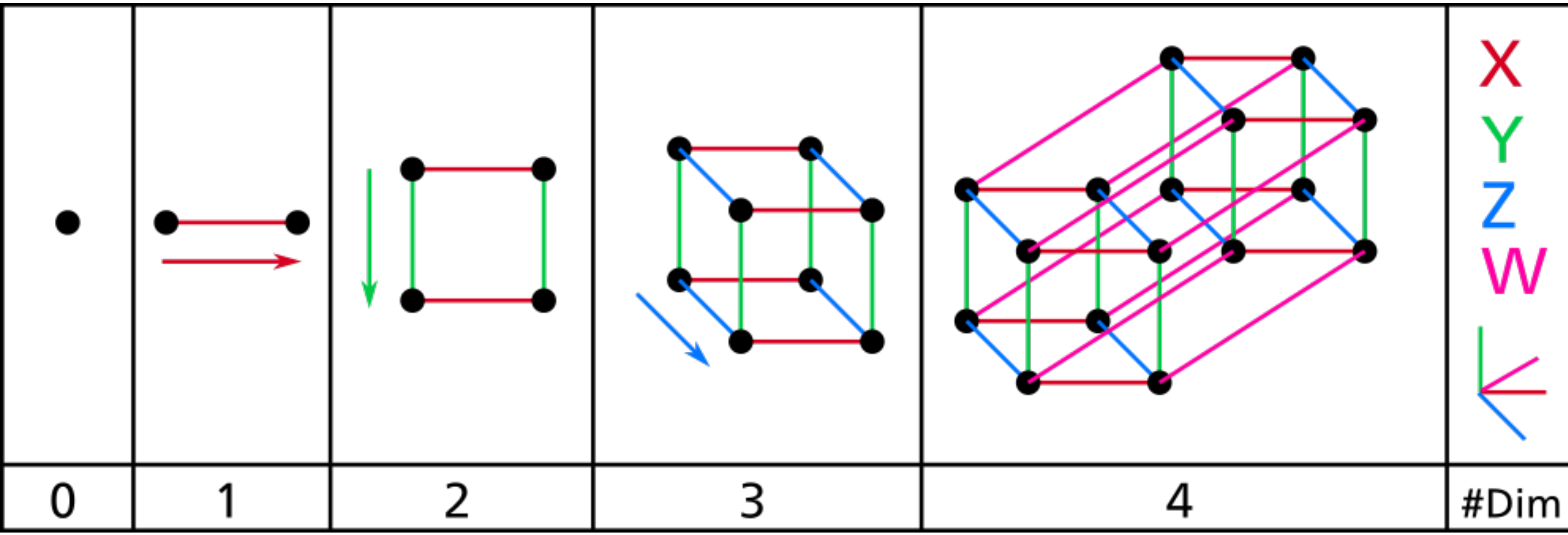


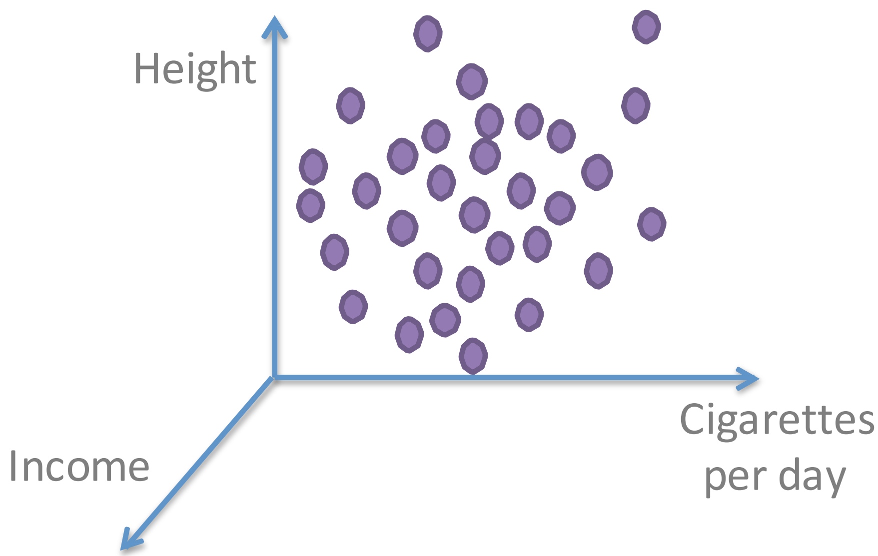
Two dimensions:

More space but still not so much

Being close not improbable

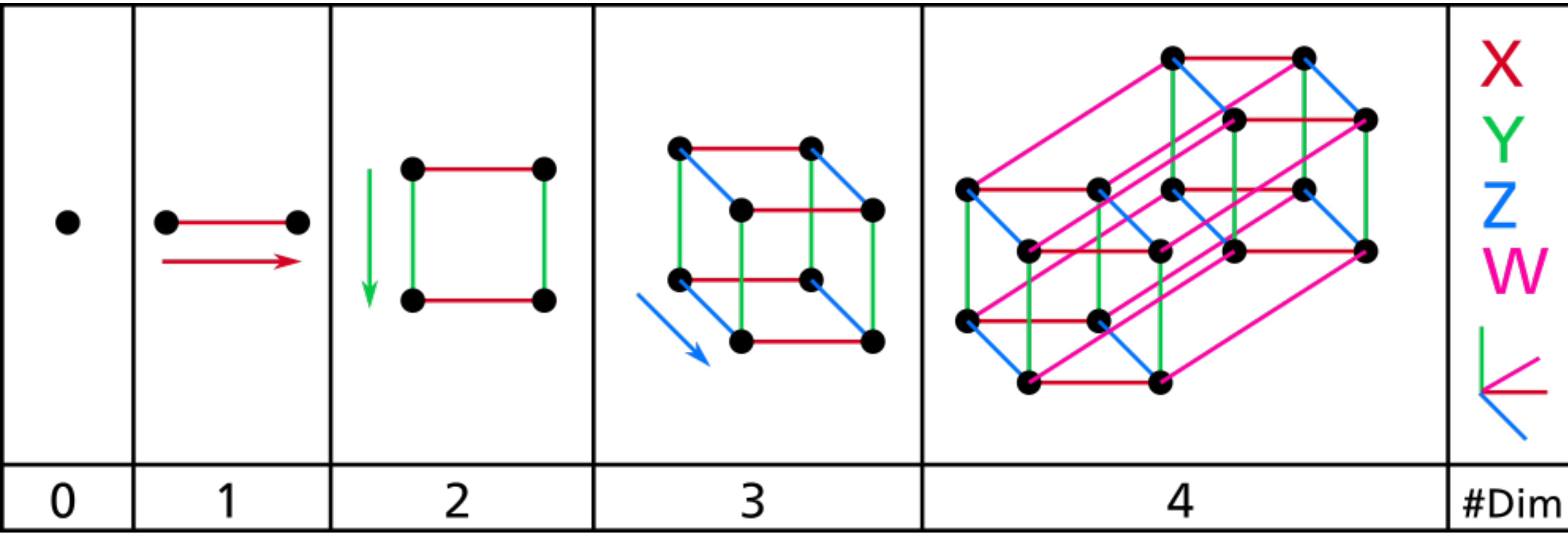
Curse of Dimensionality

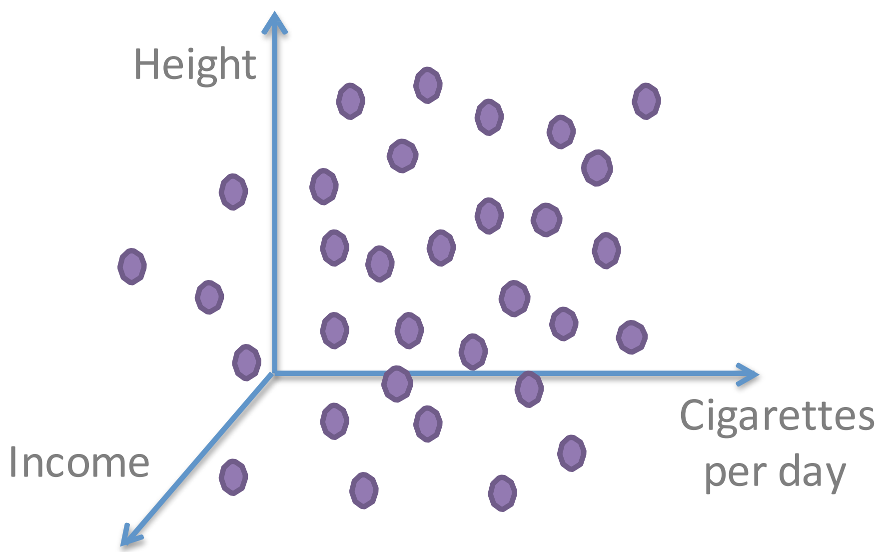




Three dimensions

Curse of Dimensionality



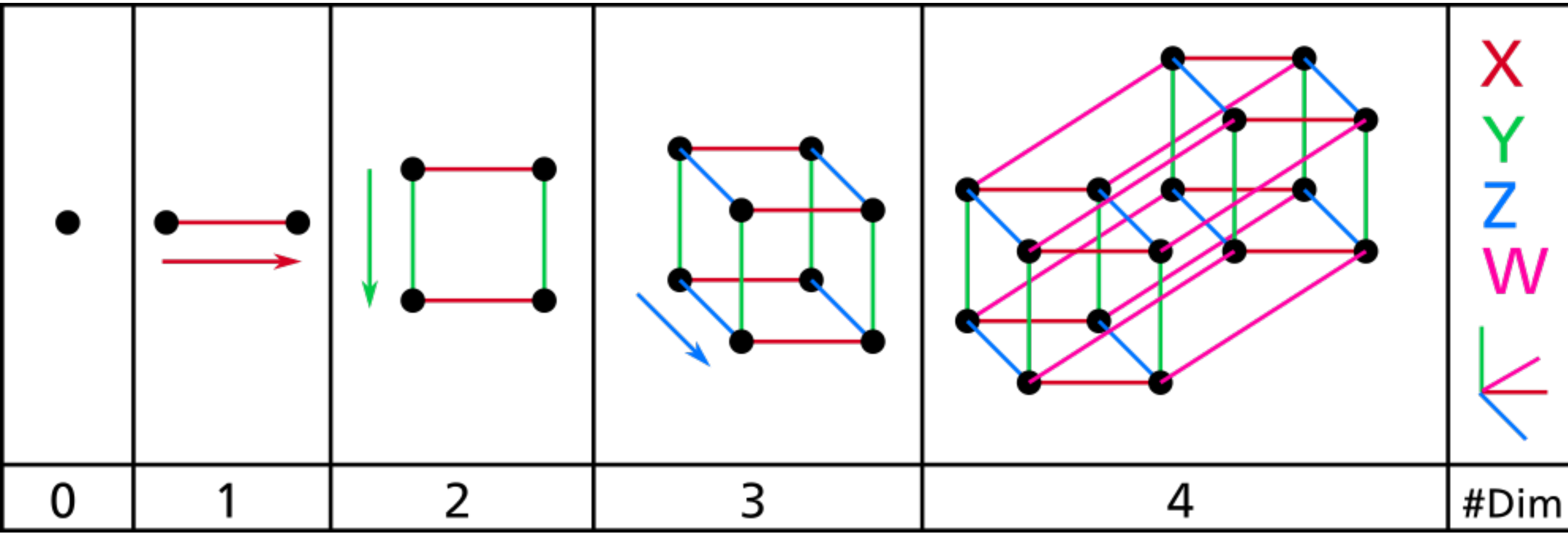


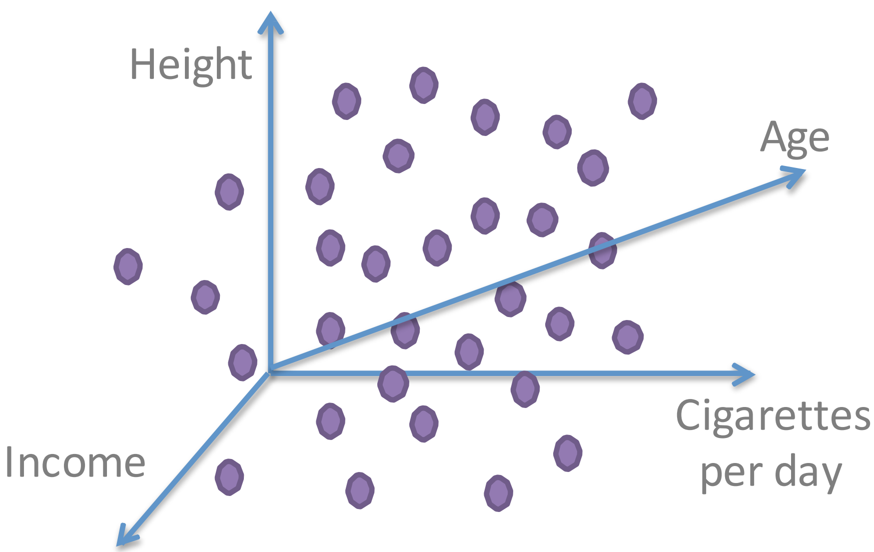
Three dimensions:

Much larger space

Being close less probable

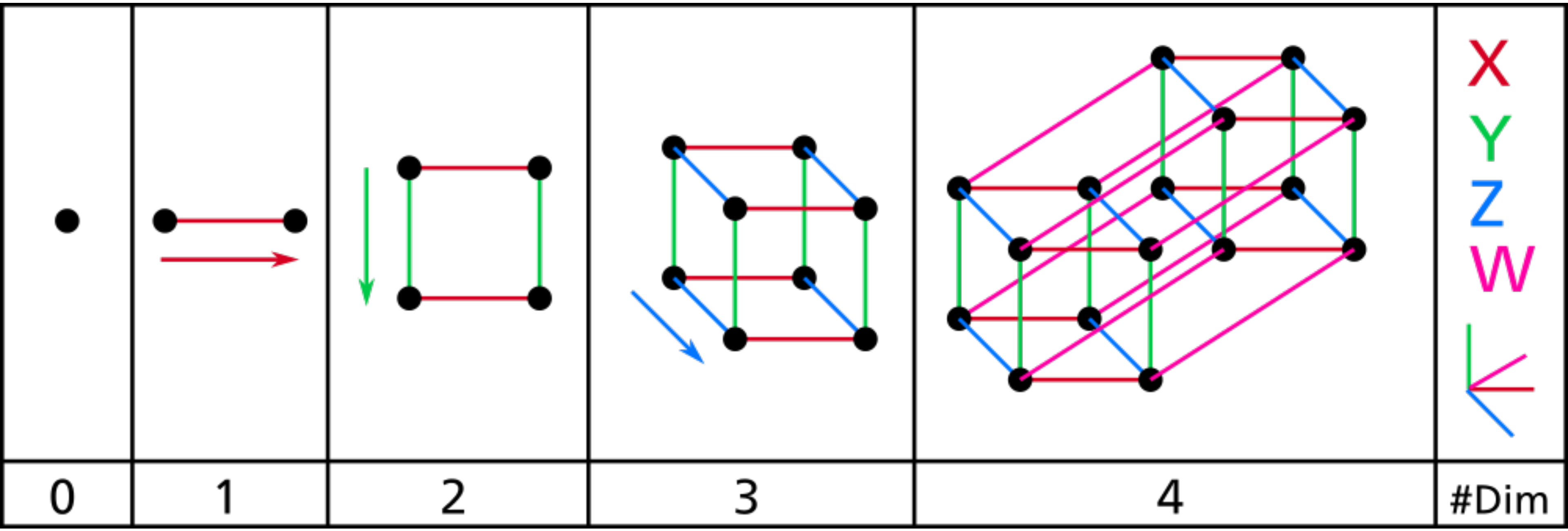
Curse of Dimensionality

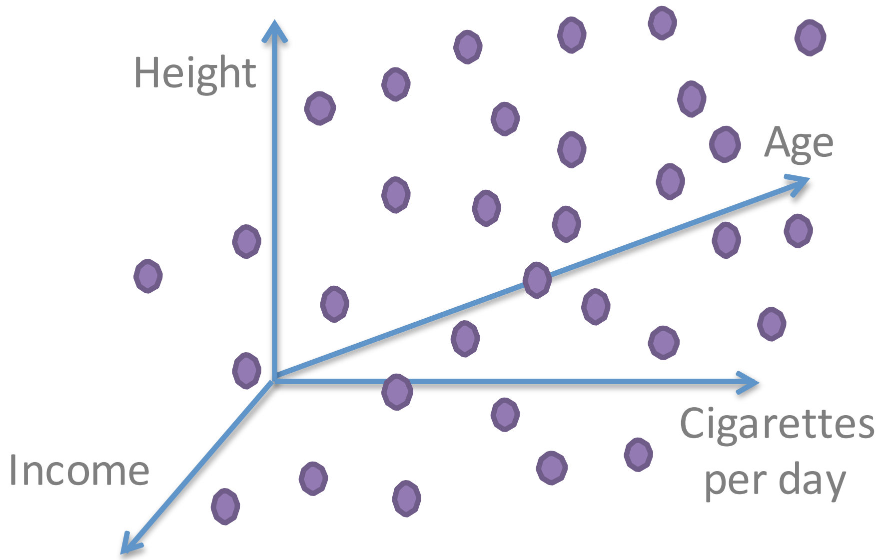




Four dimensions

Curse of Dimensionality



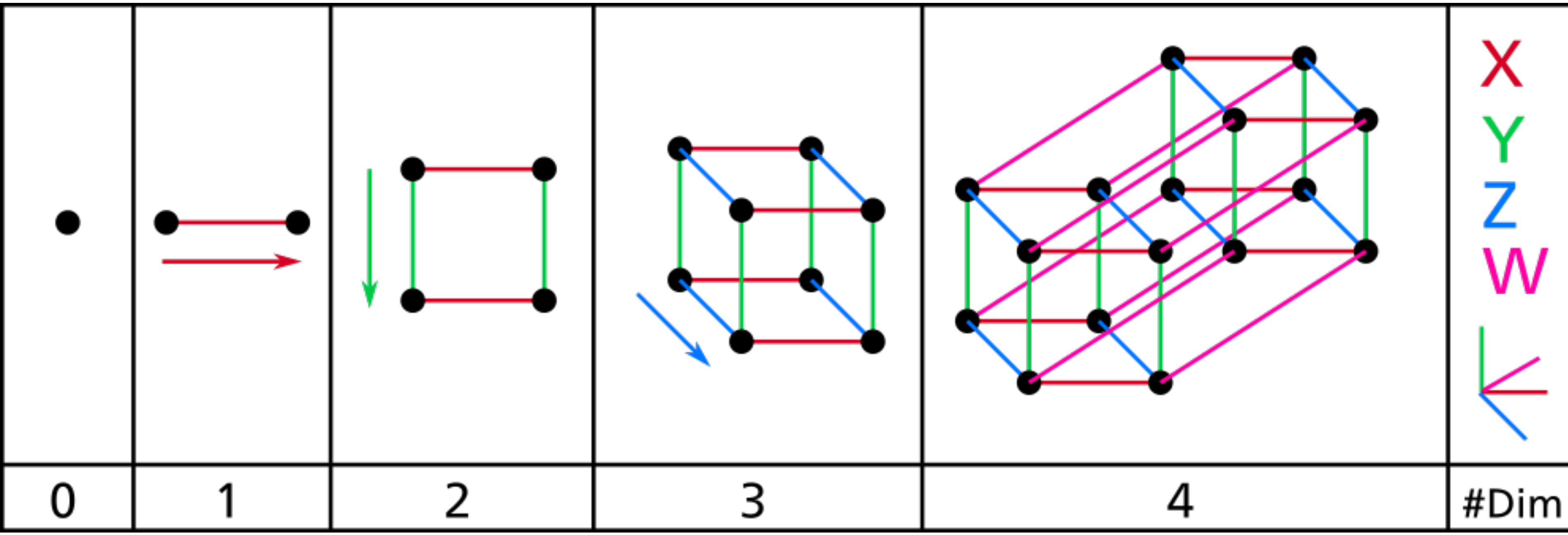


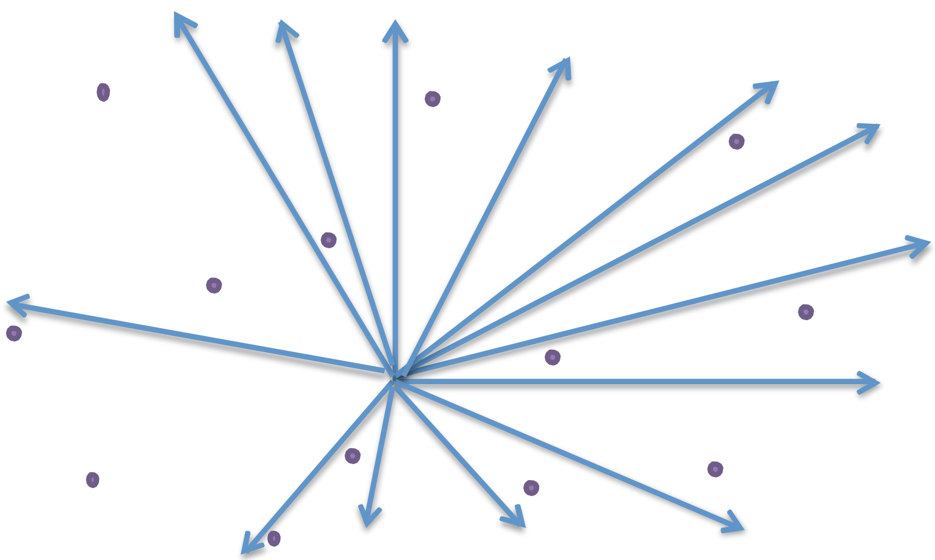
Four dimensions:

omg so much space

Being close quite improbable

Curse of Dimensionality





Thousand dimensions:

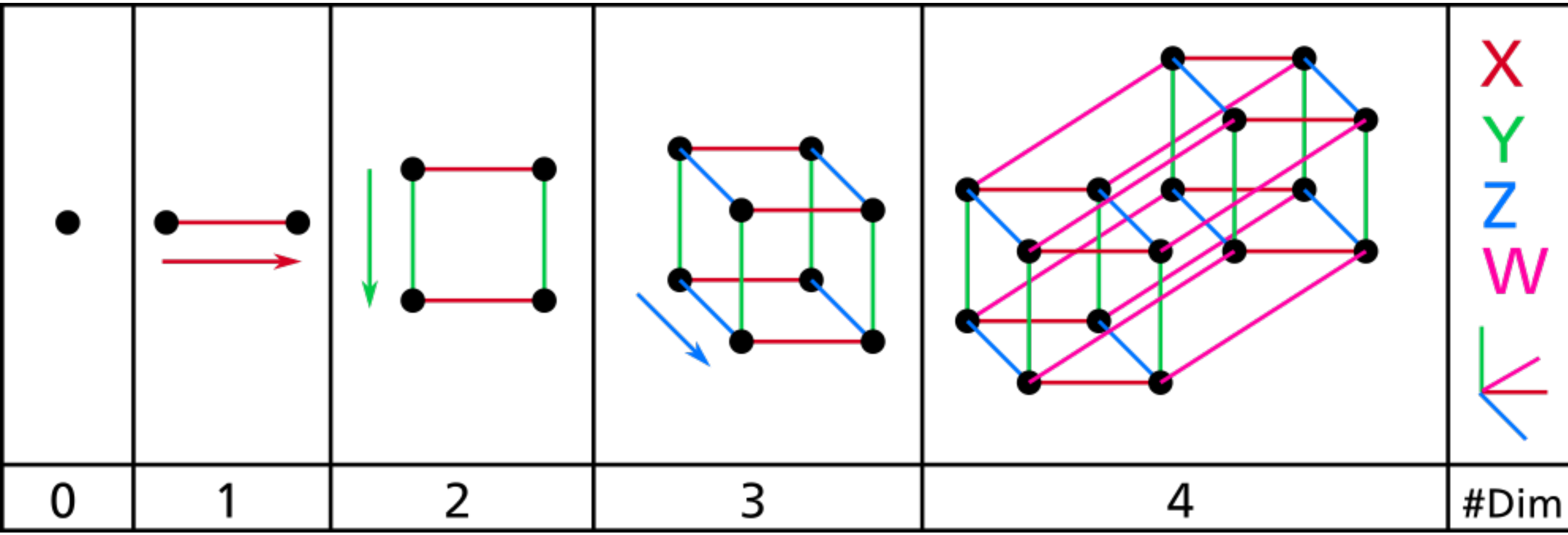
Helloooo... hellooo.. helloo...

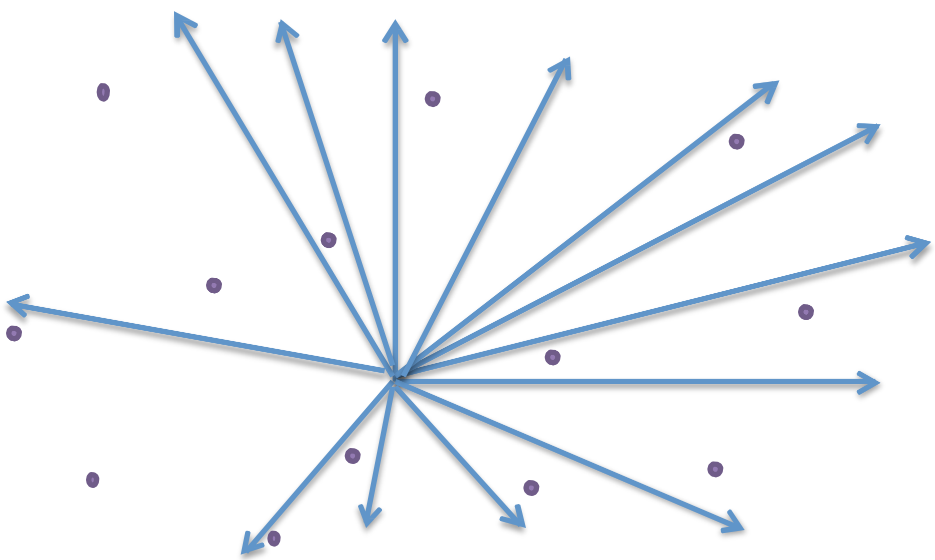
Can anybody hear meee.. mee..

mee.. mee..

So alone....

Curse of Dimensionality





Thousand dimensions:

I specified you with such high resolution, with so much detail, that you don't look like anybody else anymore. You're unique.

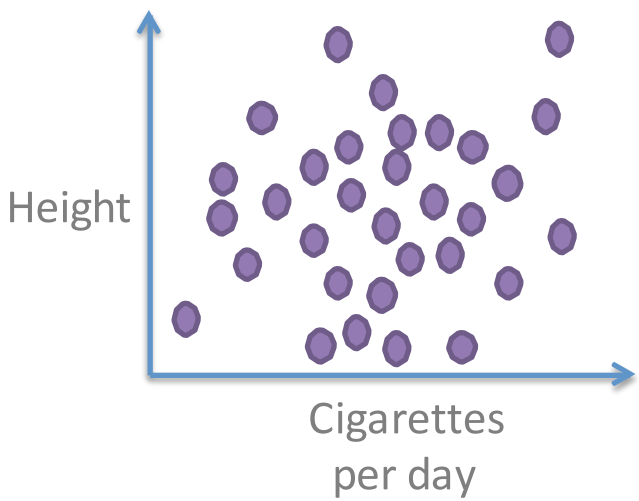
Curse of Dimensionality

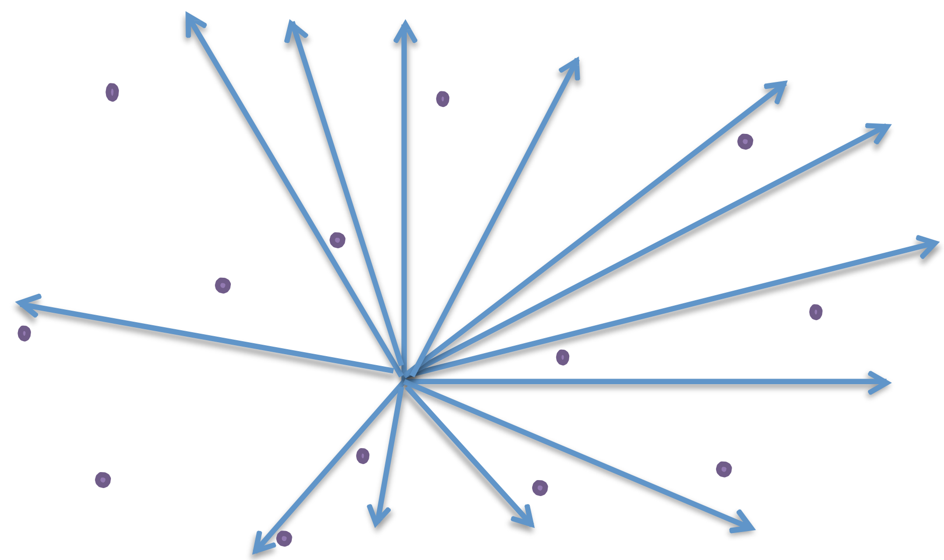
Demonstration of how space grows

(ipython notebook)

Curse of Dimensionality

Classification, clustering and other analysis methods become exponentially difficult with increasing dimensions.

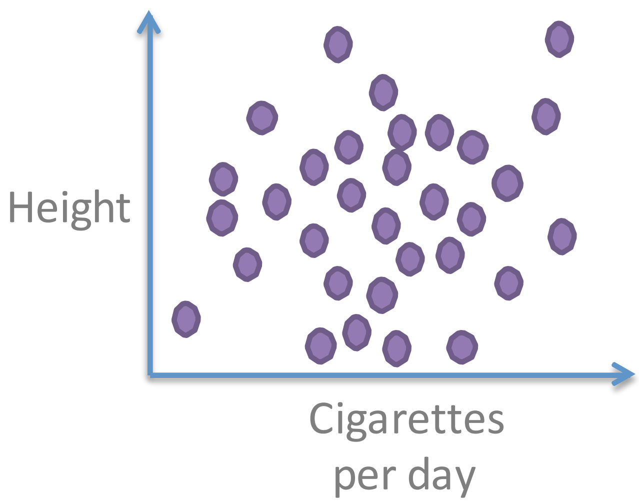


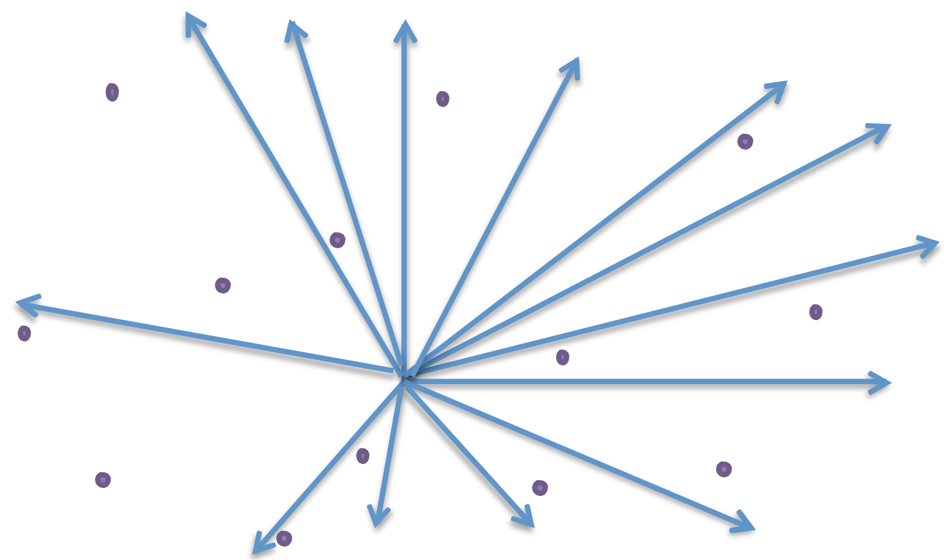


Curse of Dimensionality

Classification, clustering and other analysis methods become exponentially difficult with increasing dimensions.

To understand how to divide that huge space, we need a whole lot more data (usually much more than we do or can have).



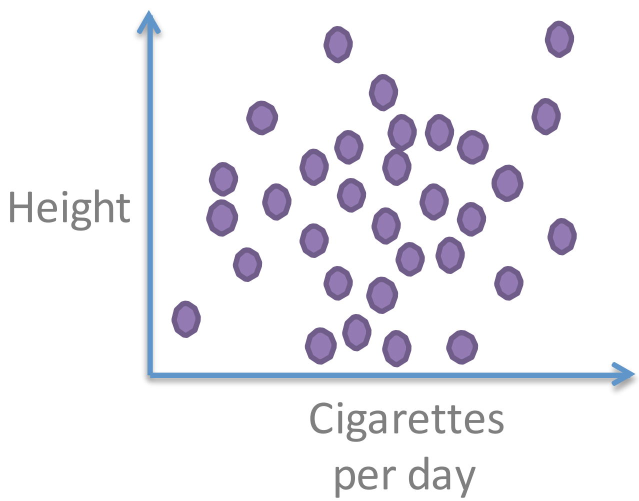


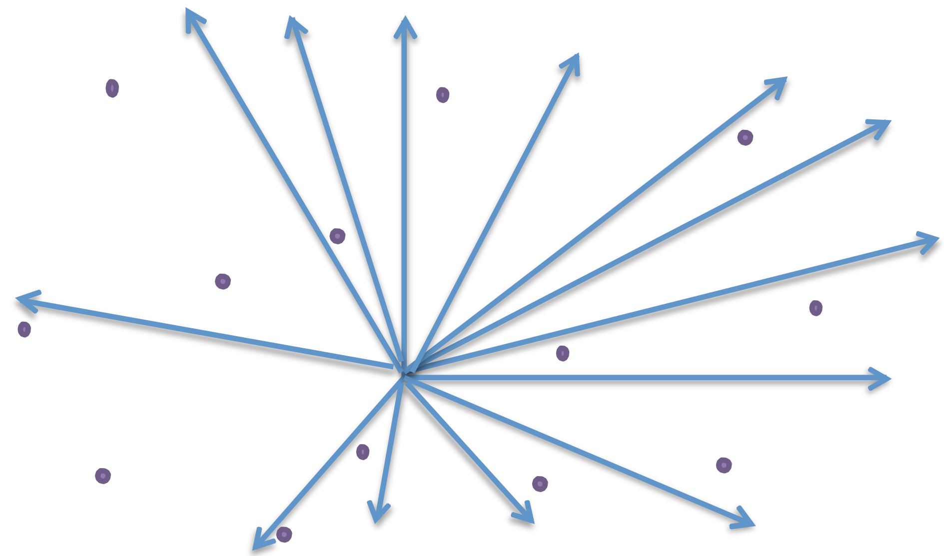
Dimensionality Reduction

Lots of features, lots of data is best. But what if you don't have the luxury of ginormous amounts of data?

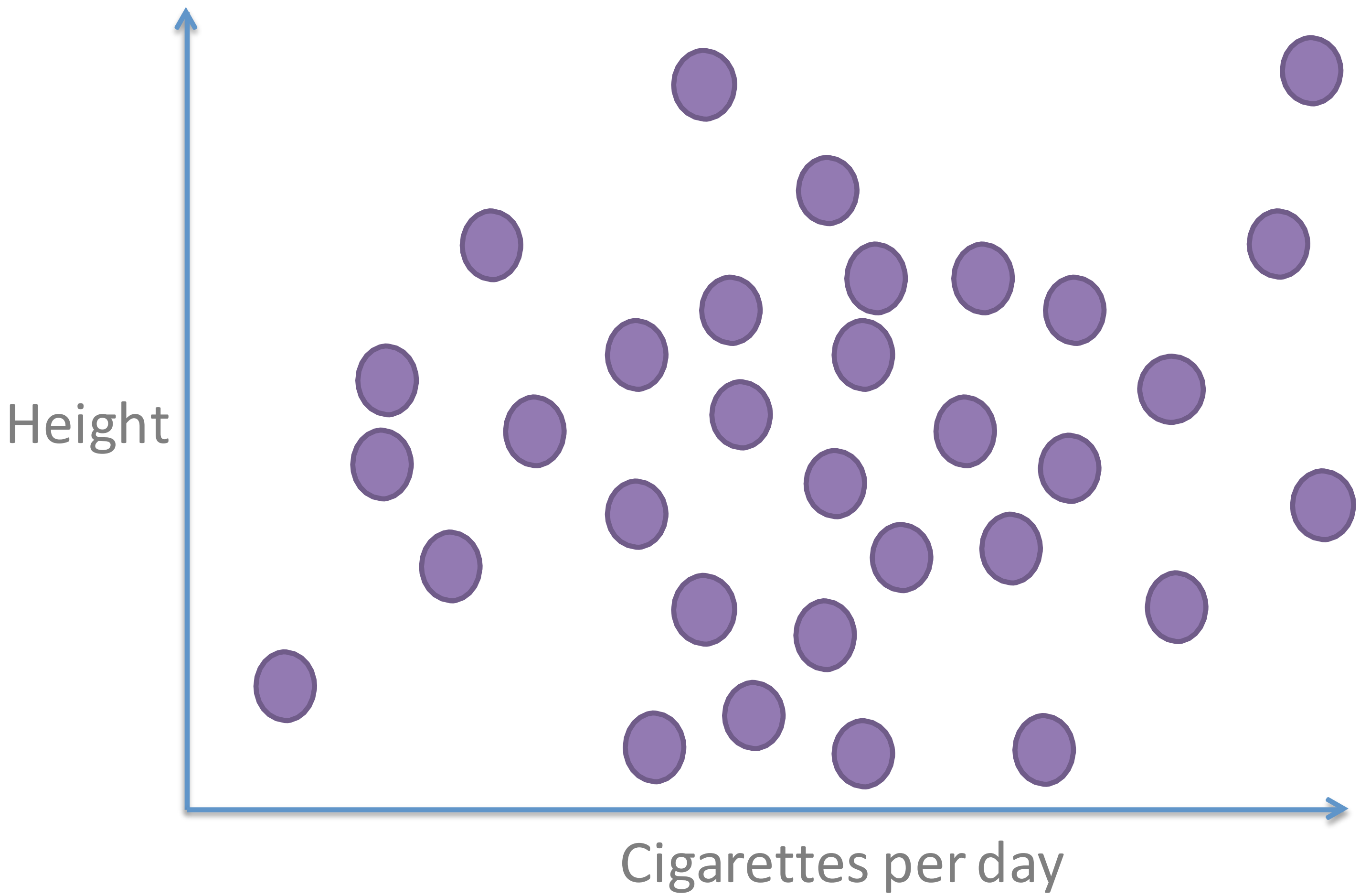
Not all features provide the same amount of information.

We can reduce the dimensions (compress the data) without necessarily losing too much information.



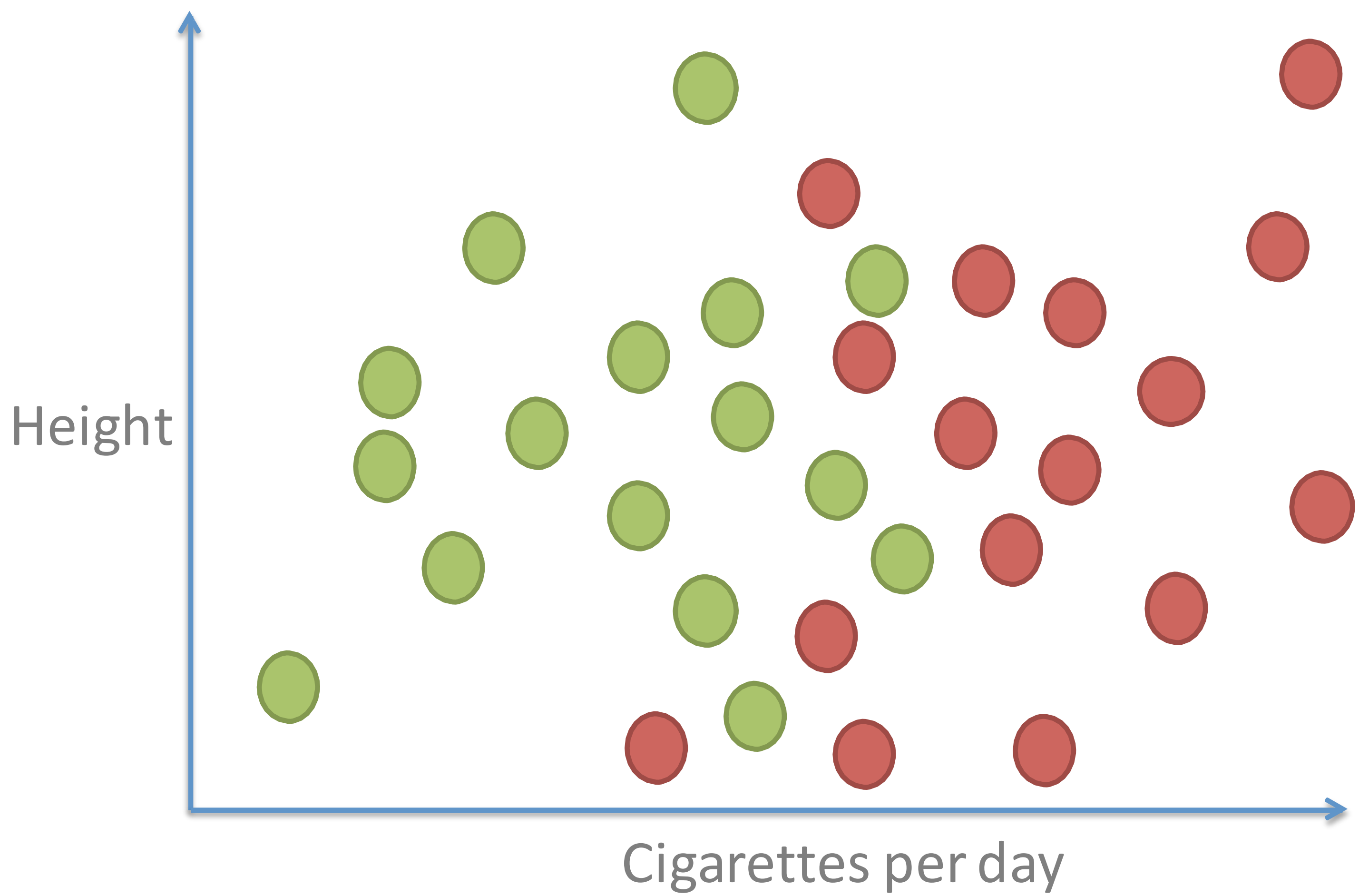


Feature Selection



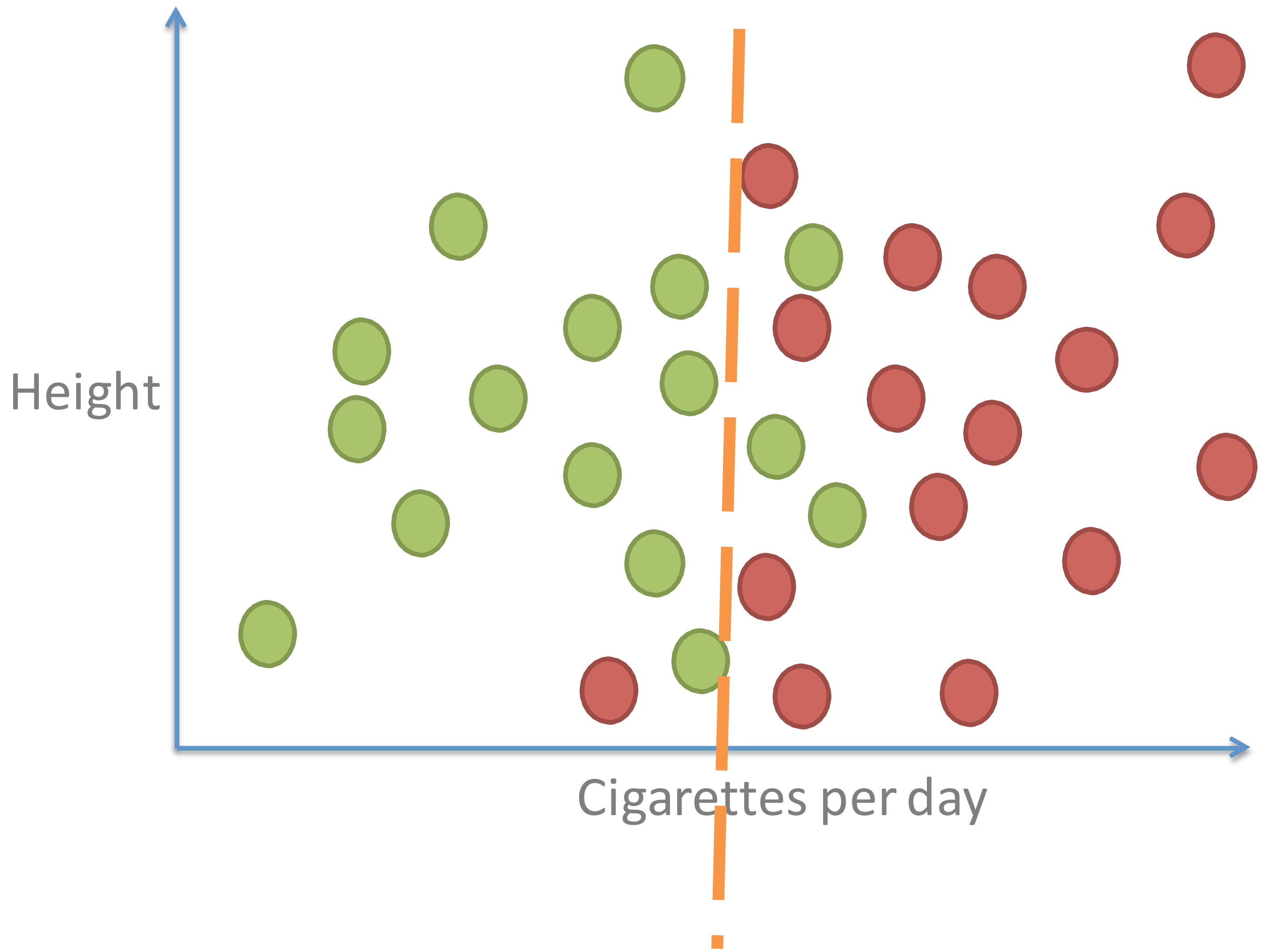
Feature Selection

Healthy / Heart Disease



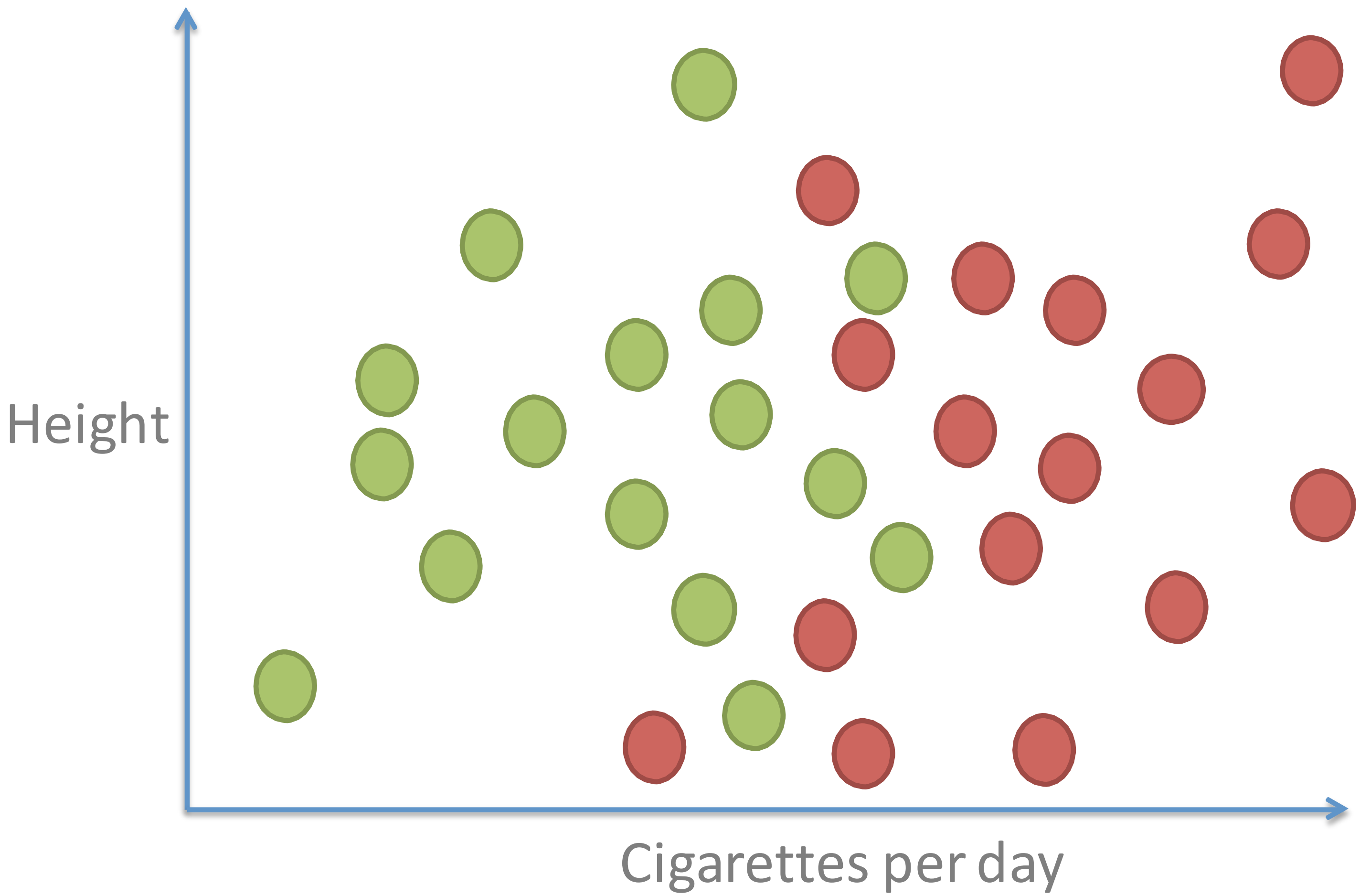
Feature Selection

Healthy / Heart Disease



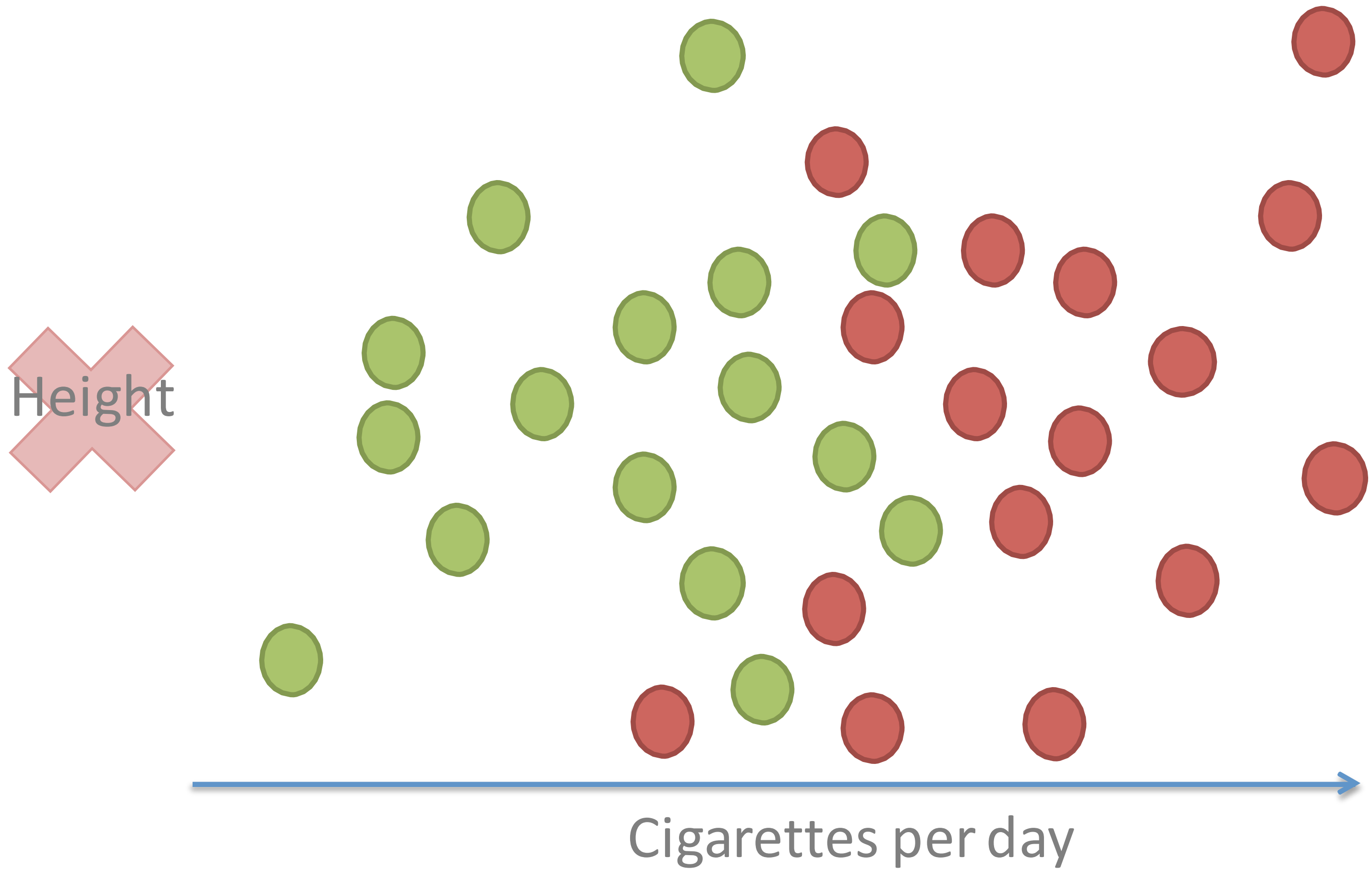
Feature Selection

Healthy / Heart Disease



Feature Selection

Healthy / Heart Disease



Feature Selection

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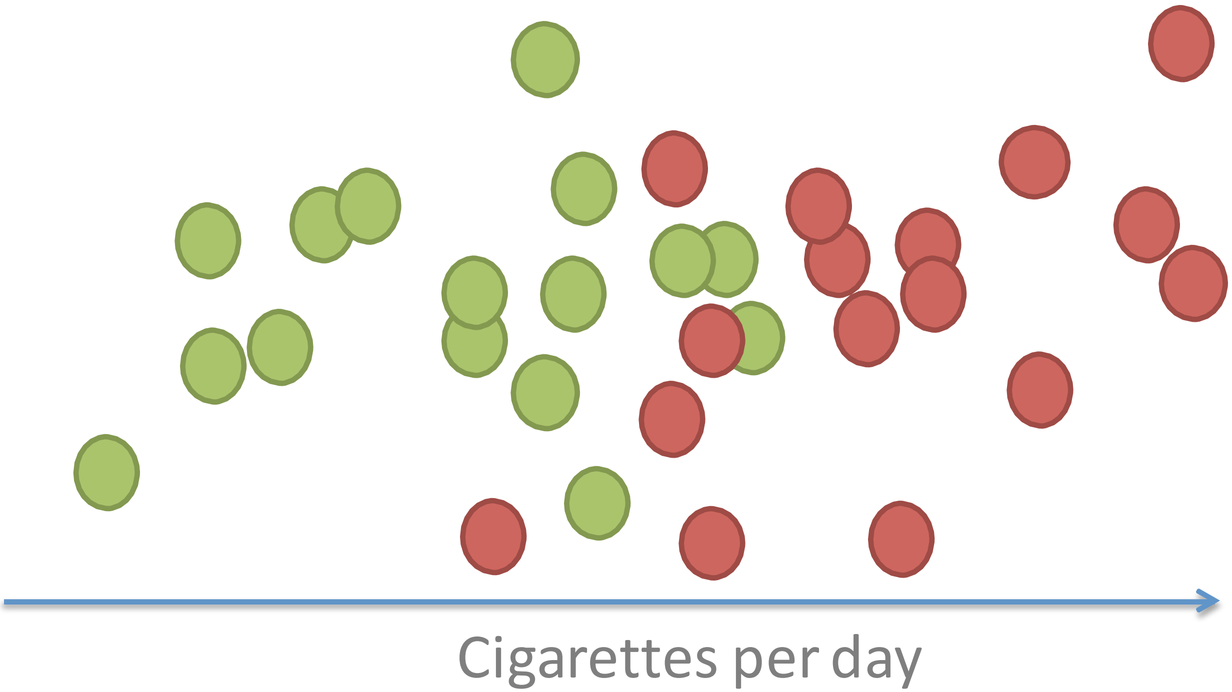
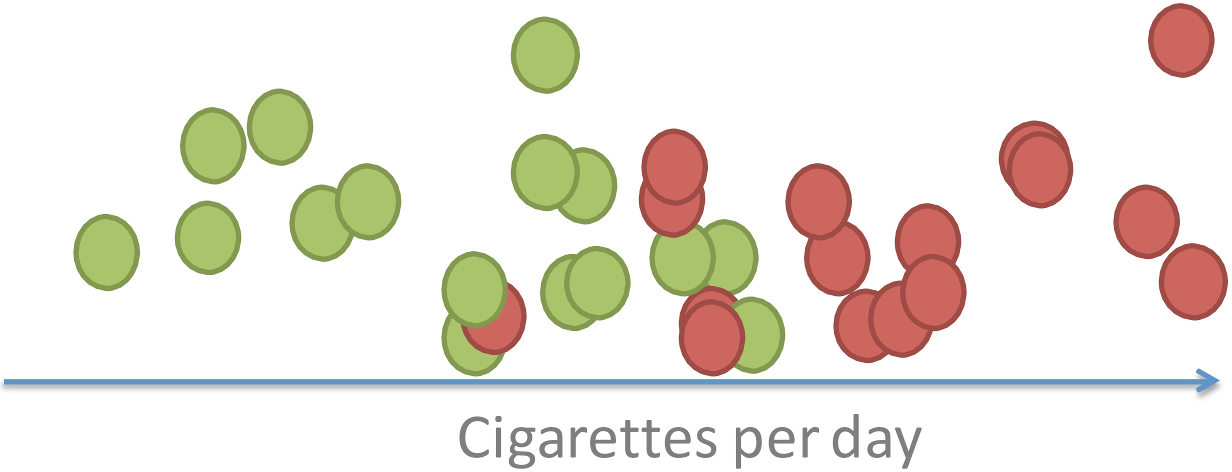


Feature Selection

Healthy / Heart Disease



Feature Selection

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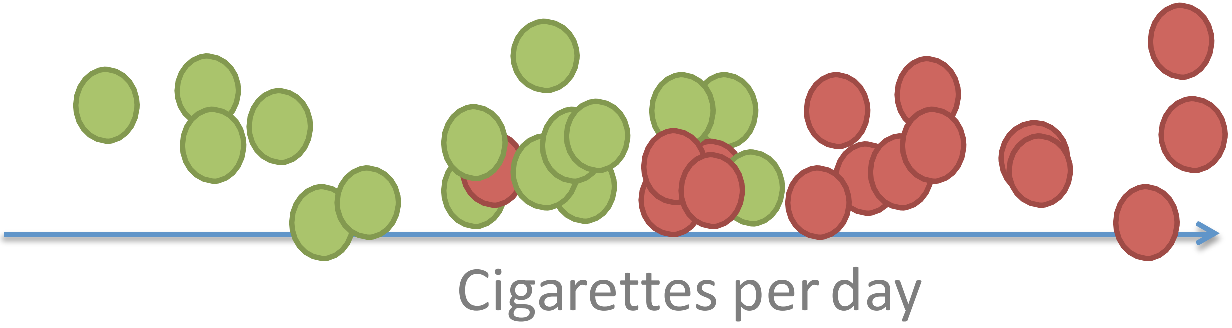
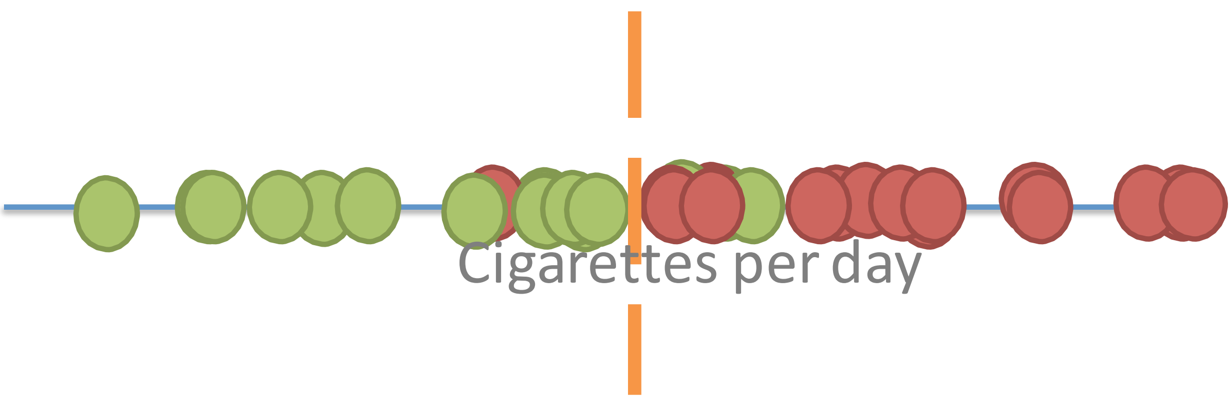


Feature Selection

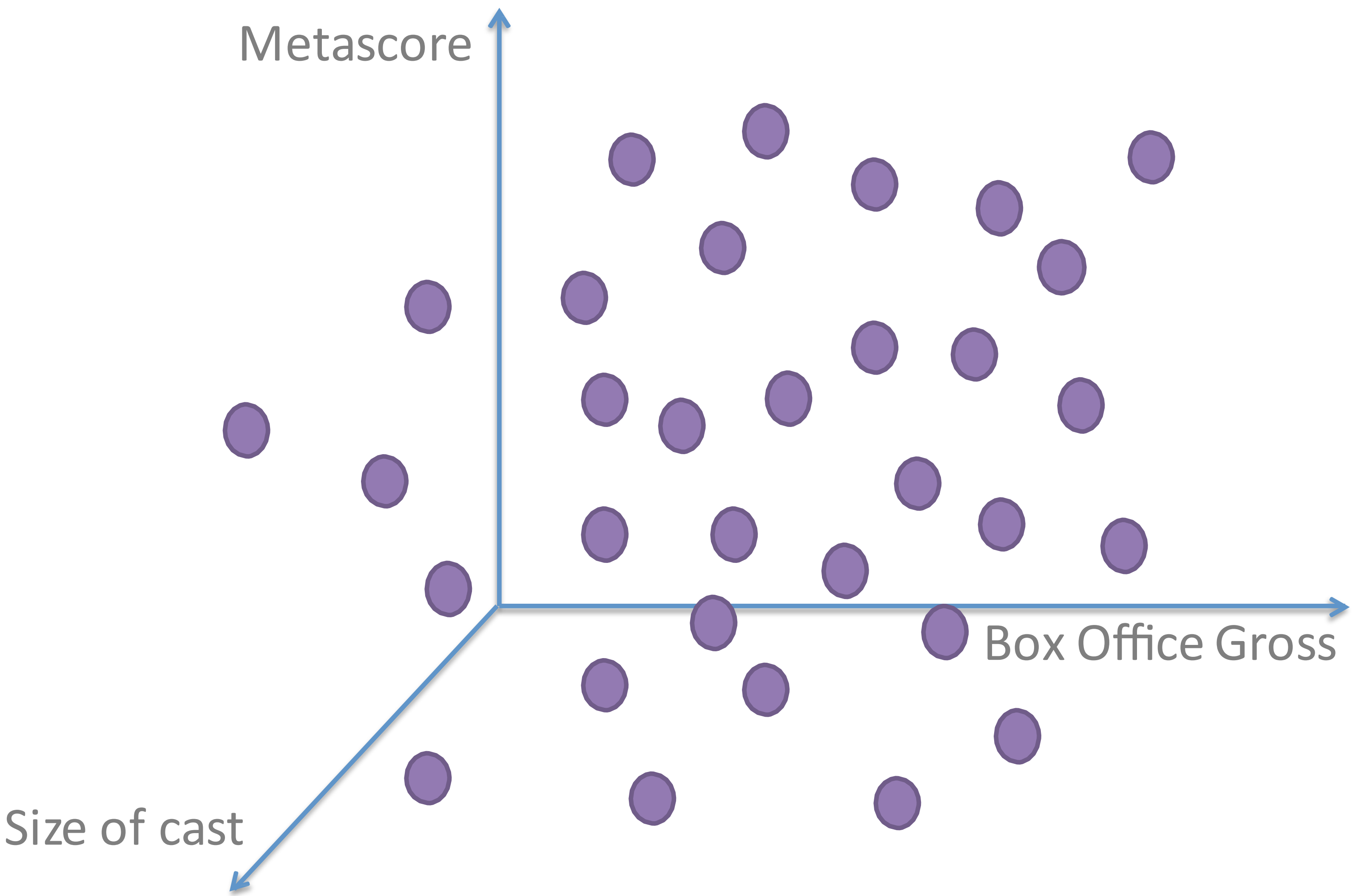
Healthy / Heart Disease

Feature Selection

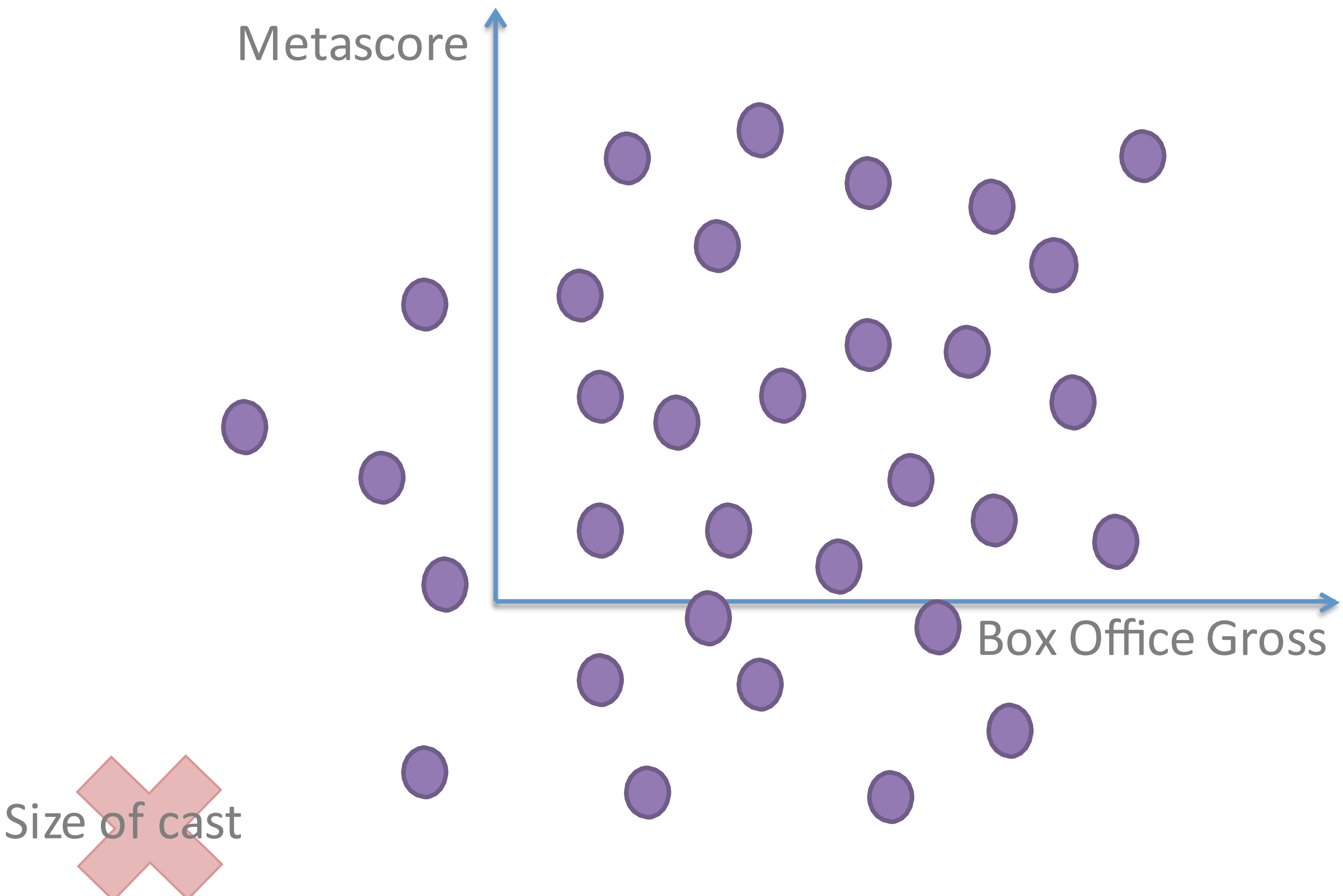
Healthy / Heart Disease



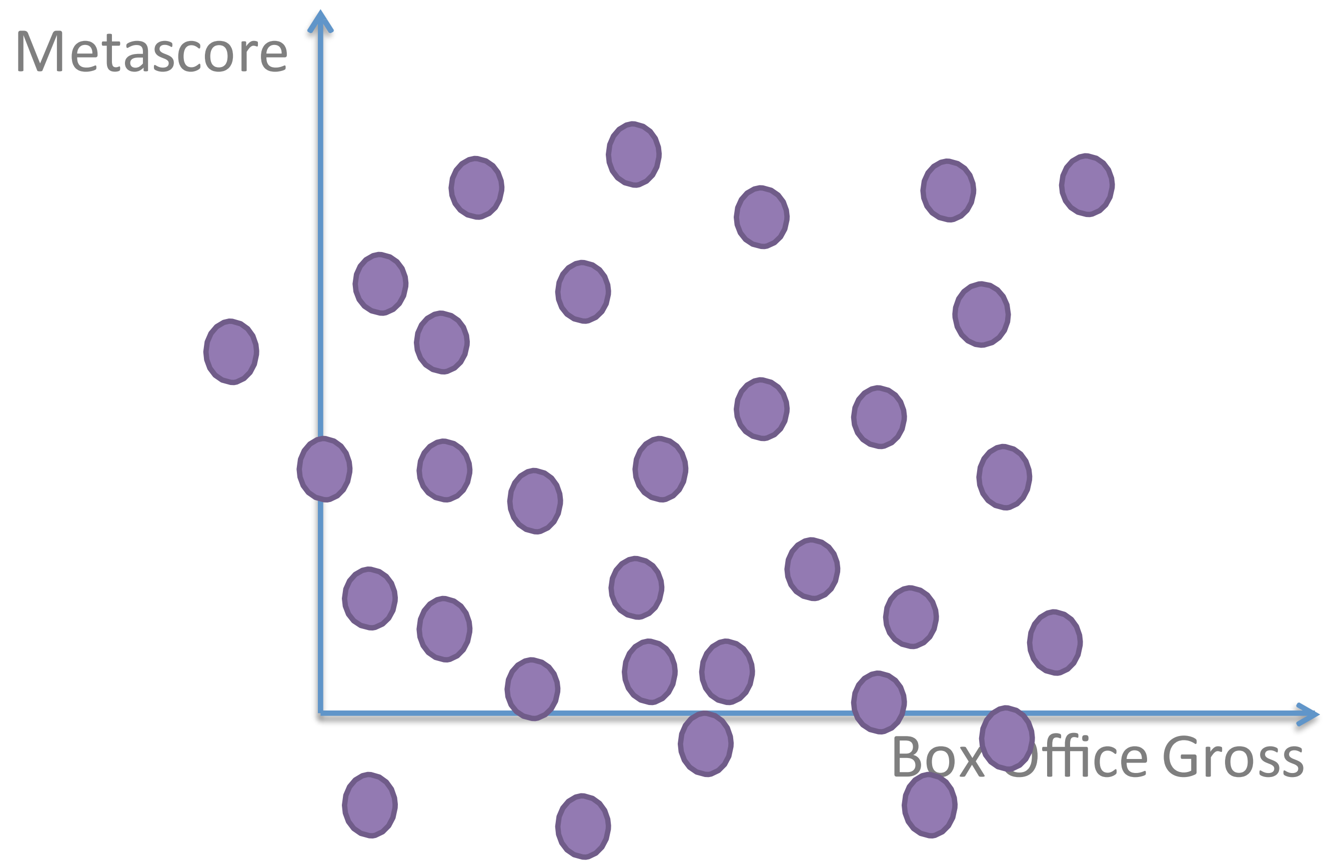
Feature Selection

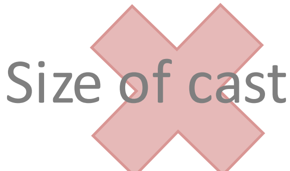


Feature Selection

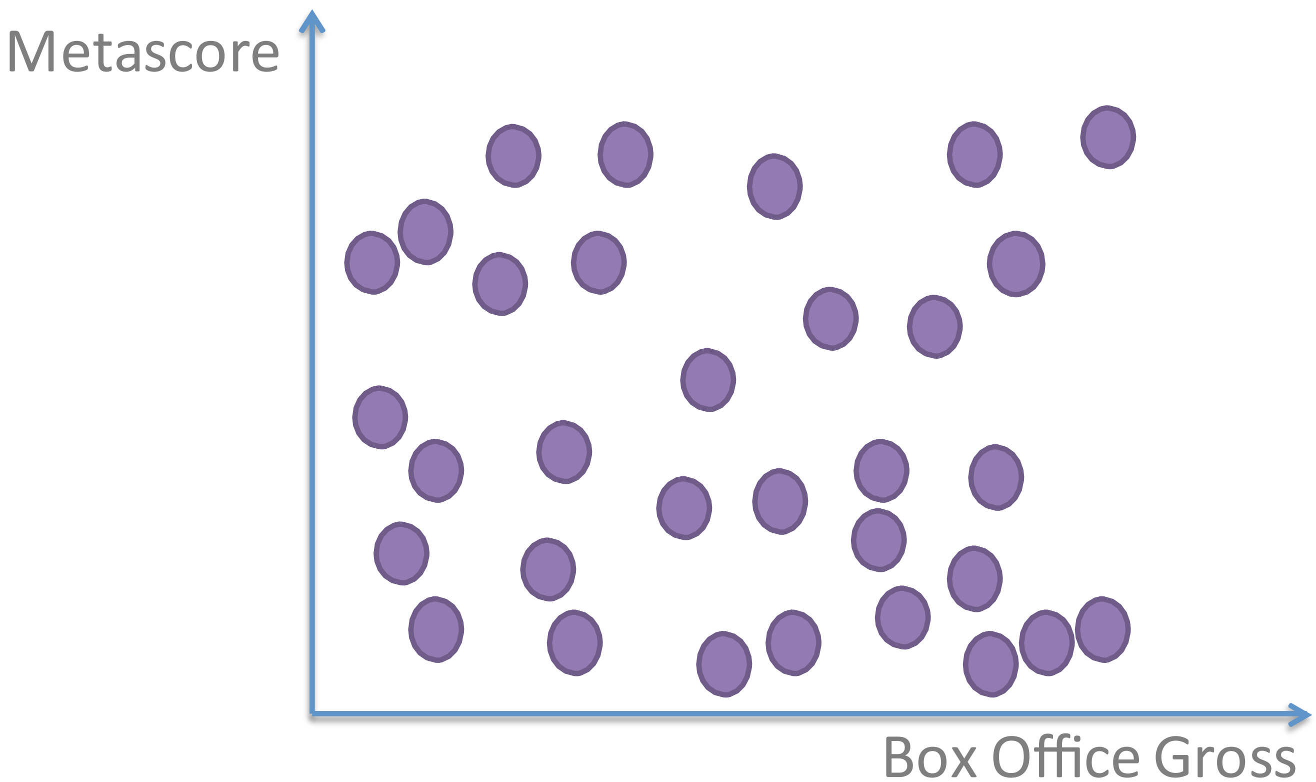


Feature Selection





Feature Selection



Feature Selection

Common Sense

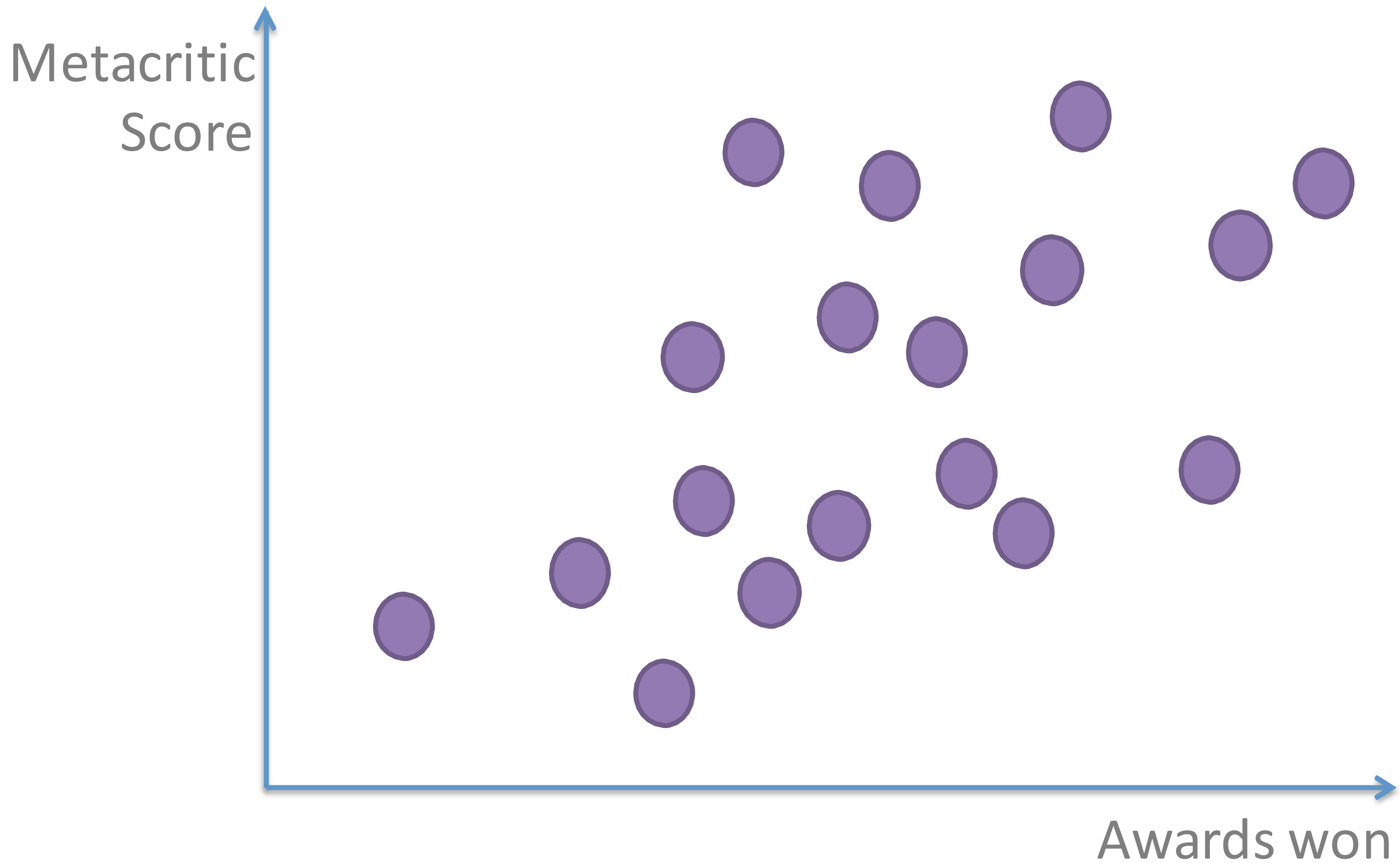
Experiments (remove a feature, fit again, evaluate results)

Regularization (in regression)

Feature scores (chi^2, F-test, etc. : SelectKBest())

Feature Extraction

Do I have to choose the dimensions among existing features?



Feature Extraction

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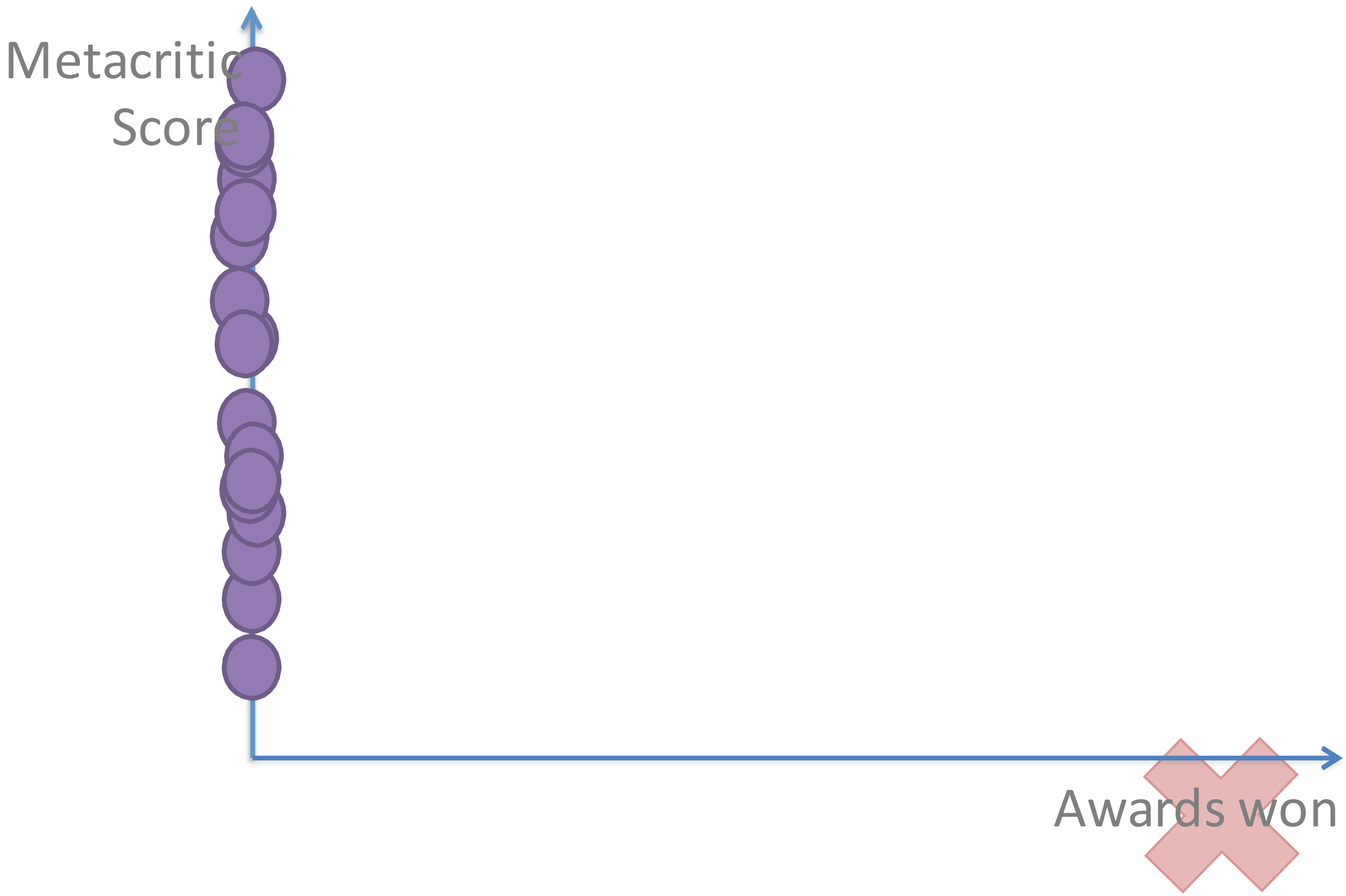
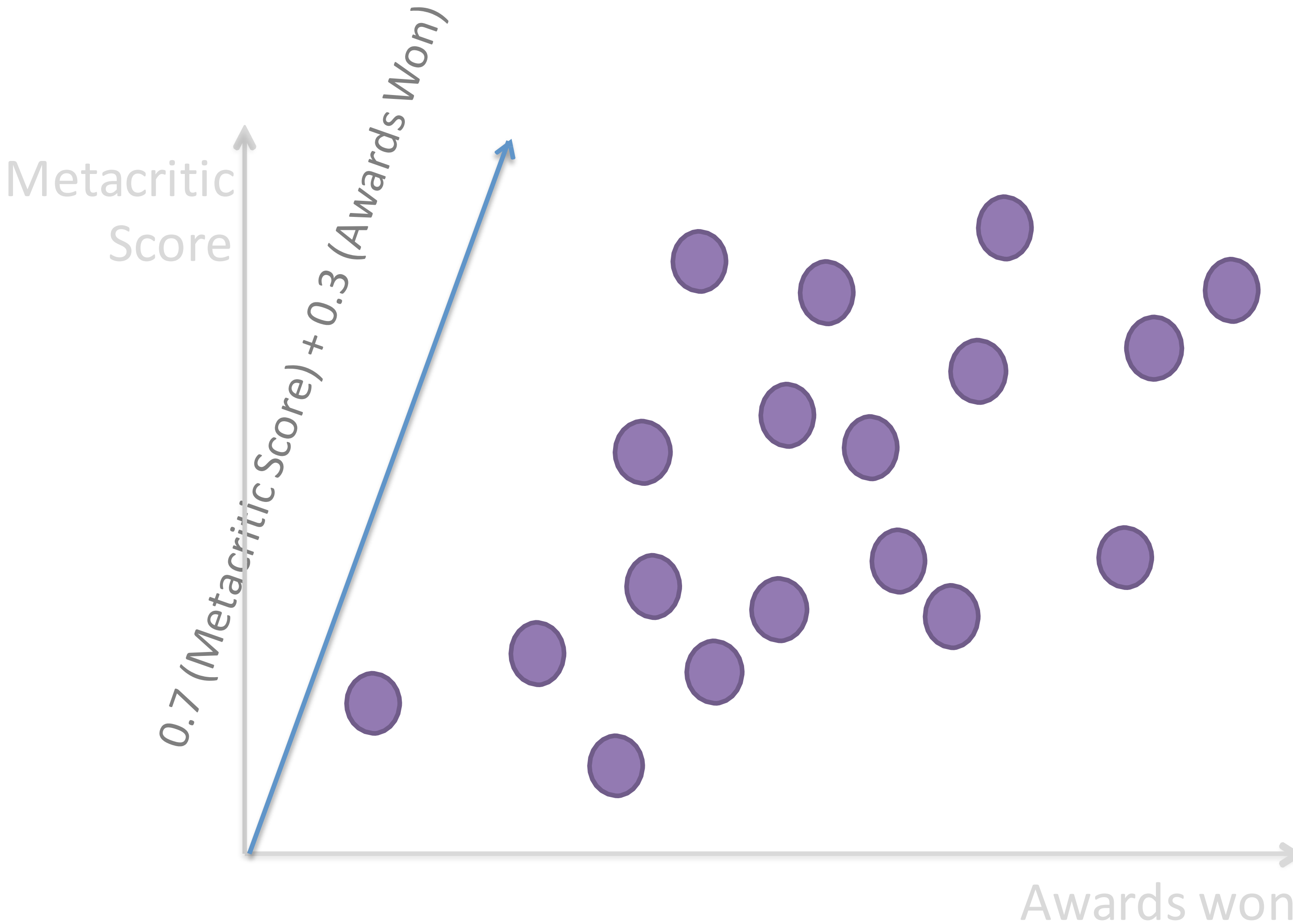
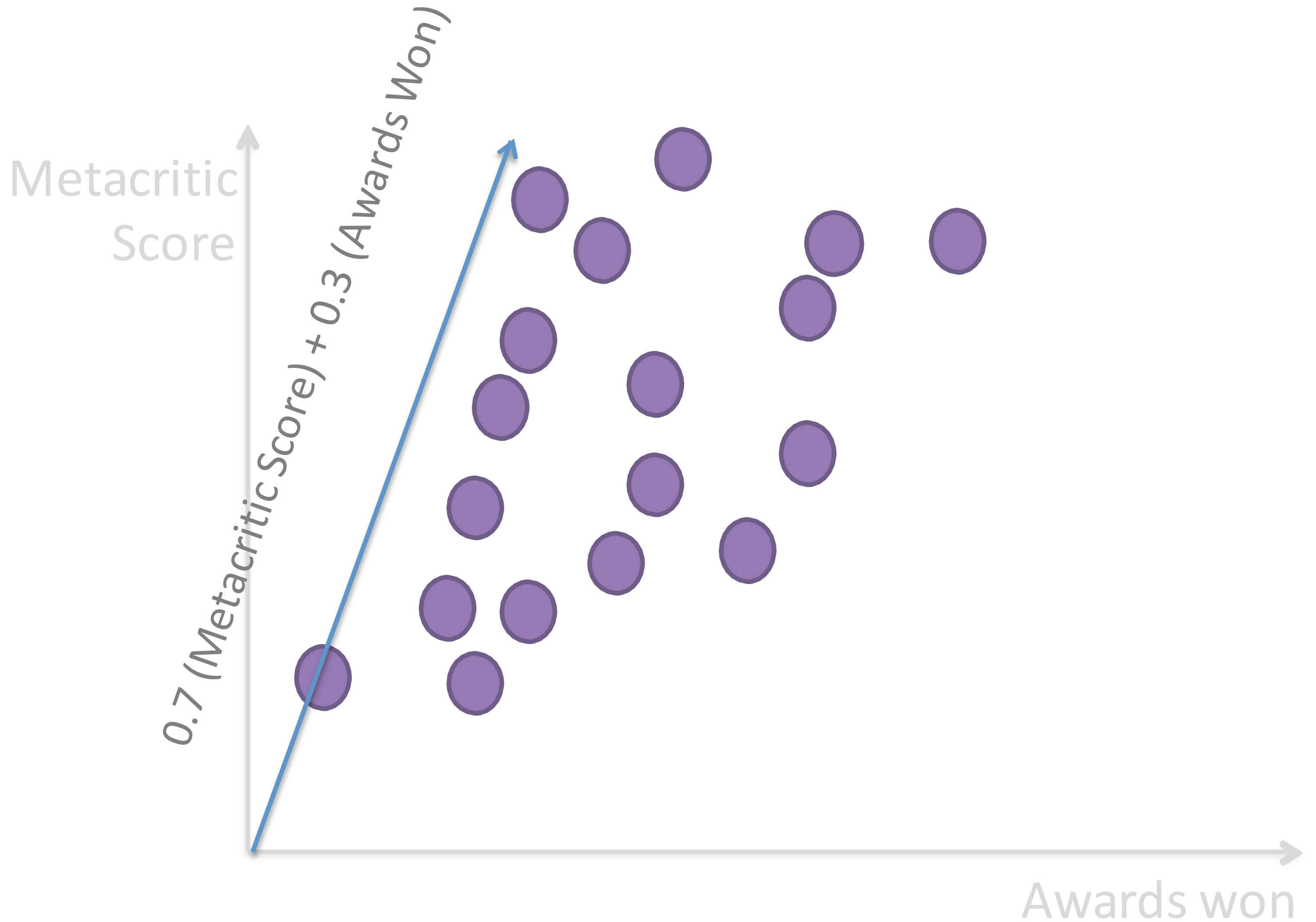


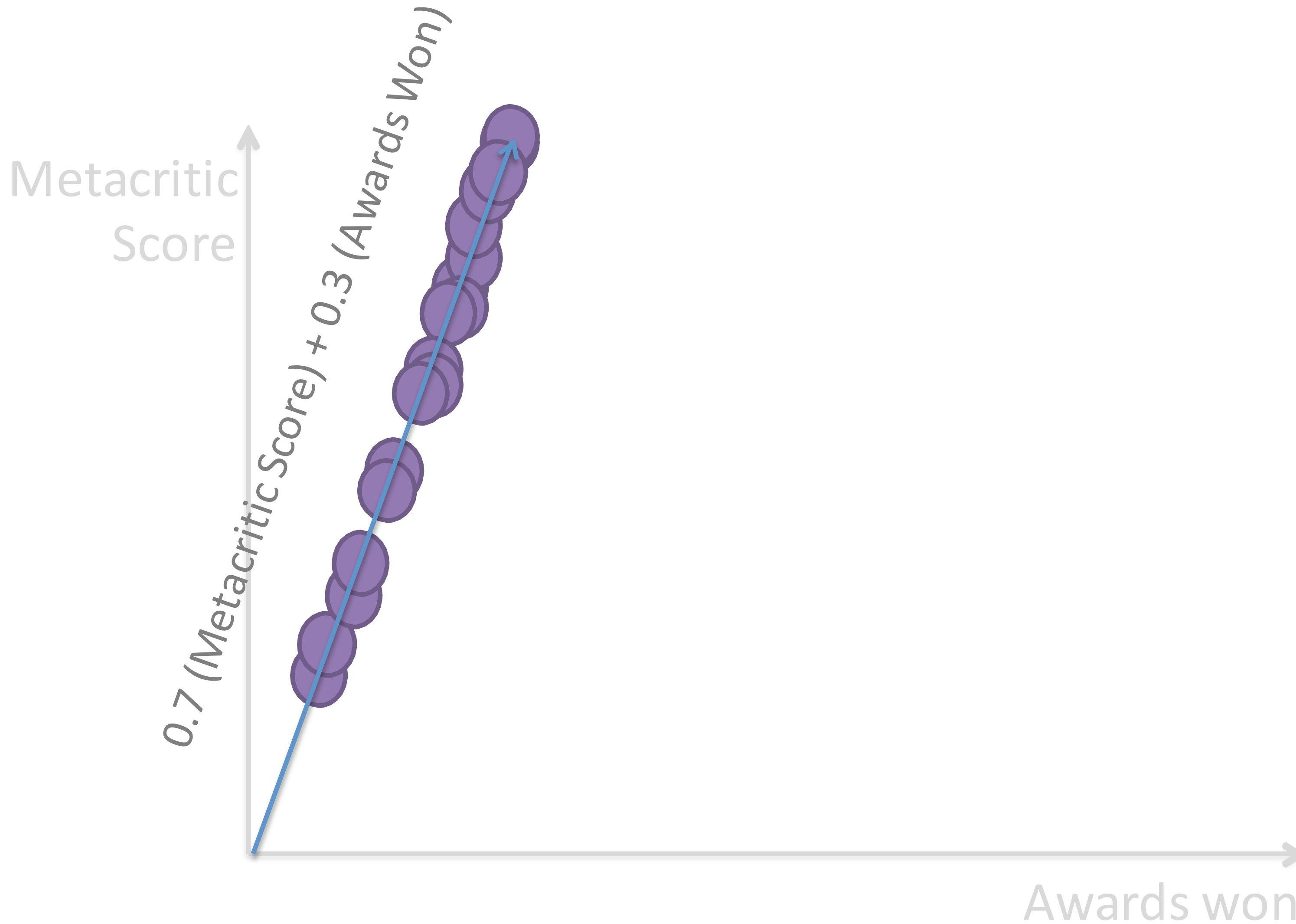
Feature Extraction



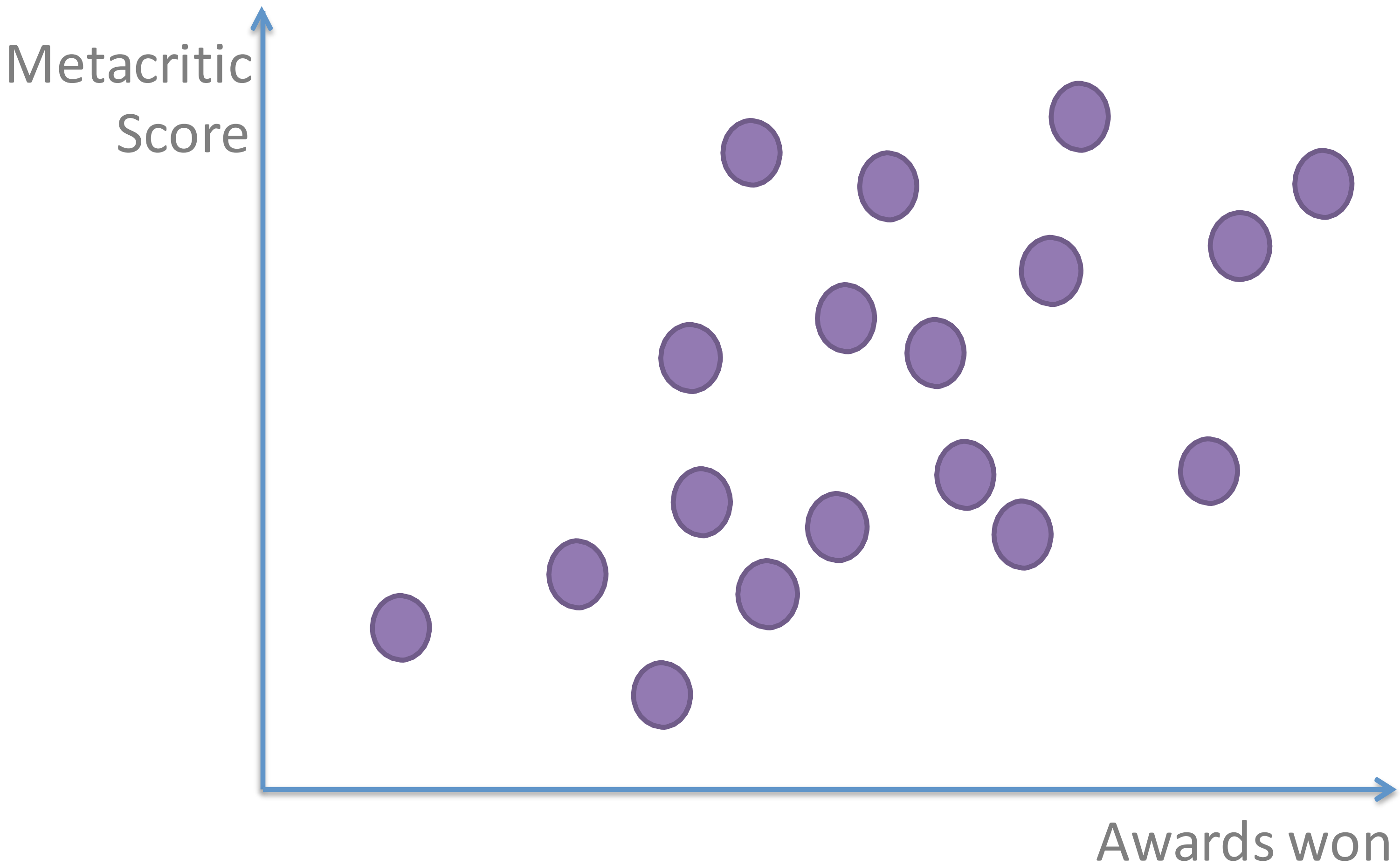
Feature Extraction



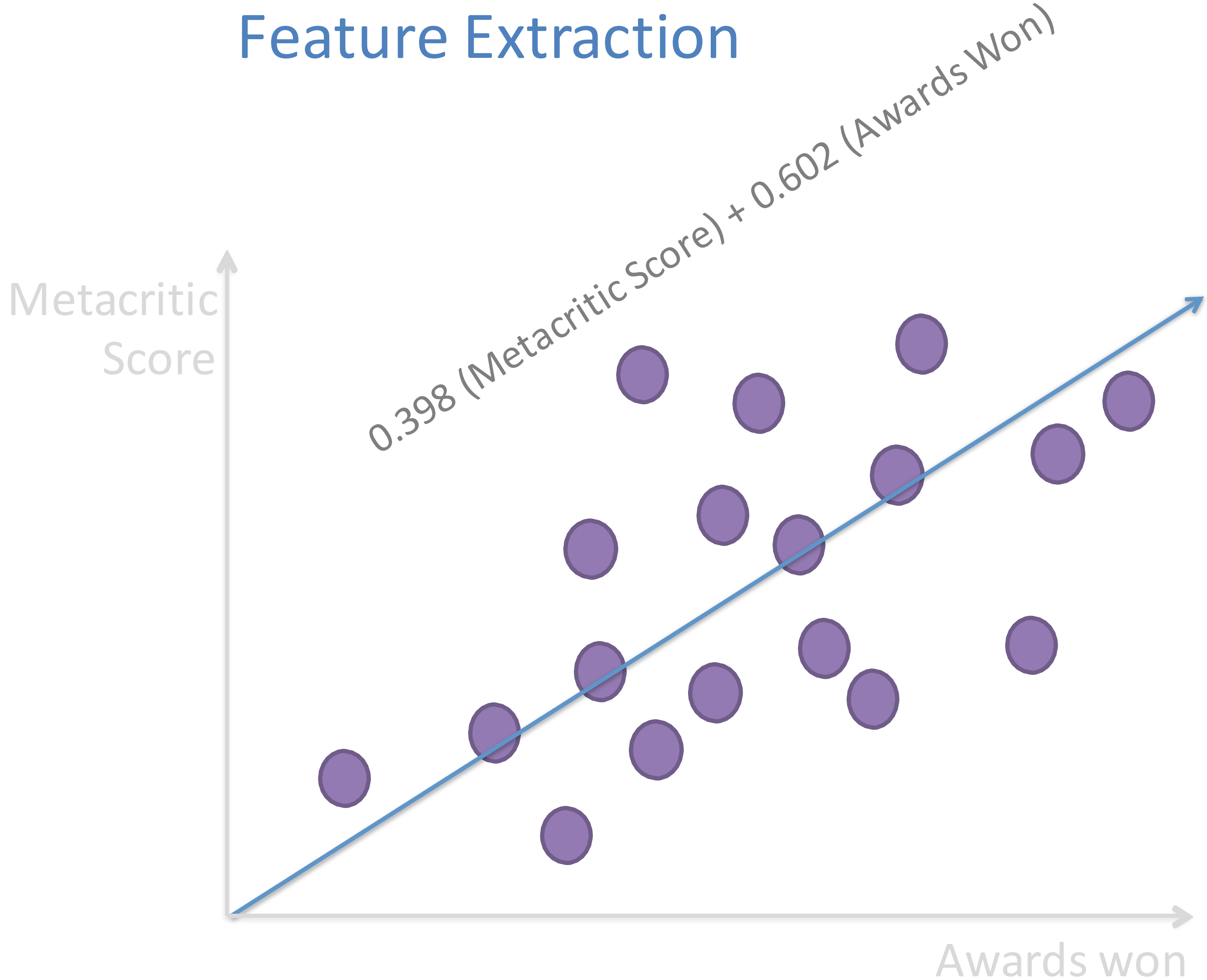
Feature Extraction



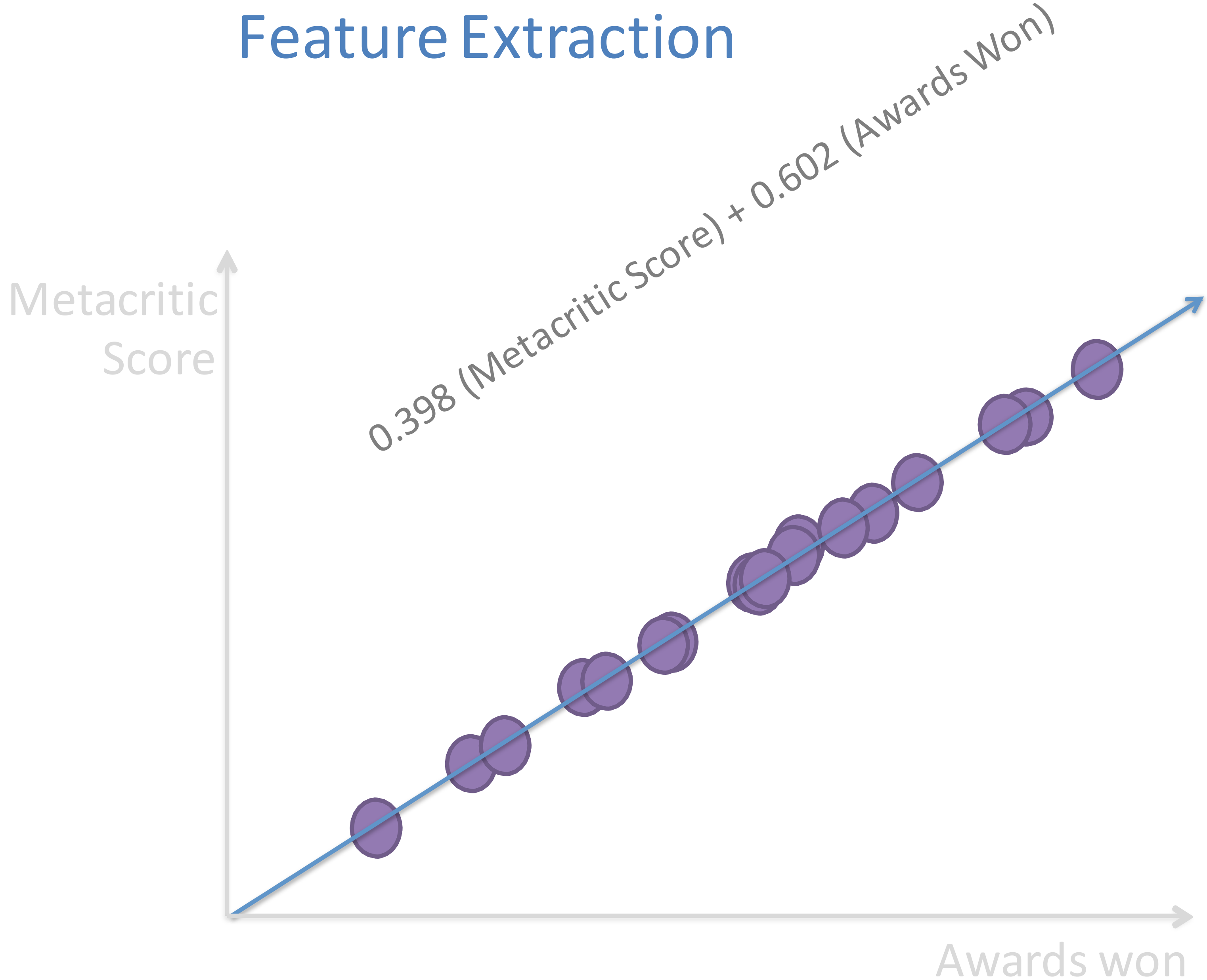
Feature Extraction



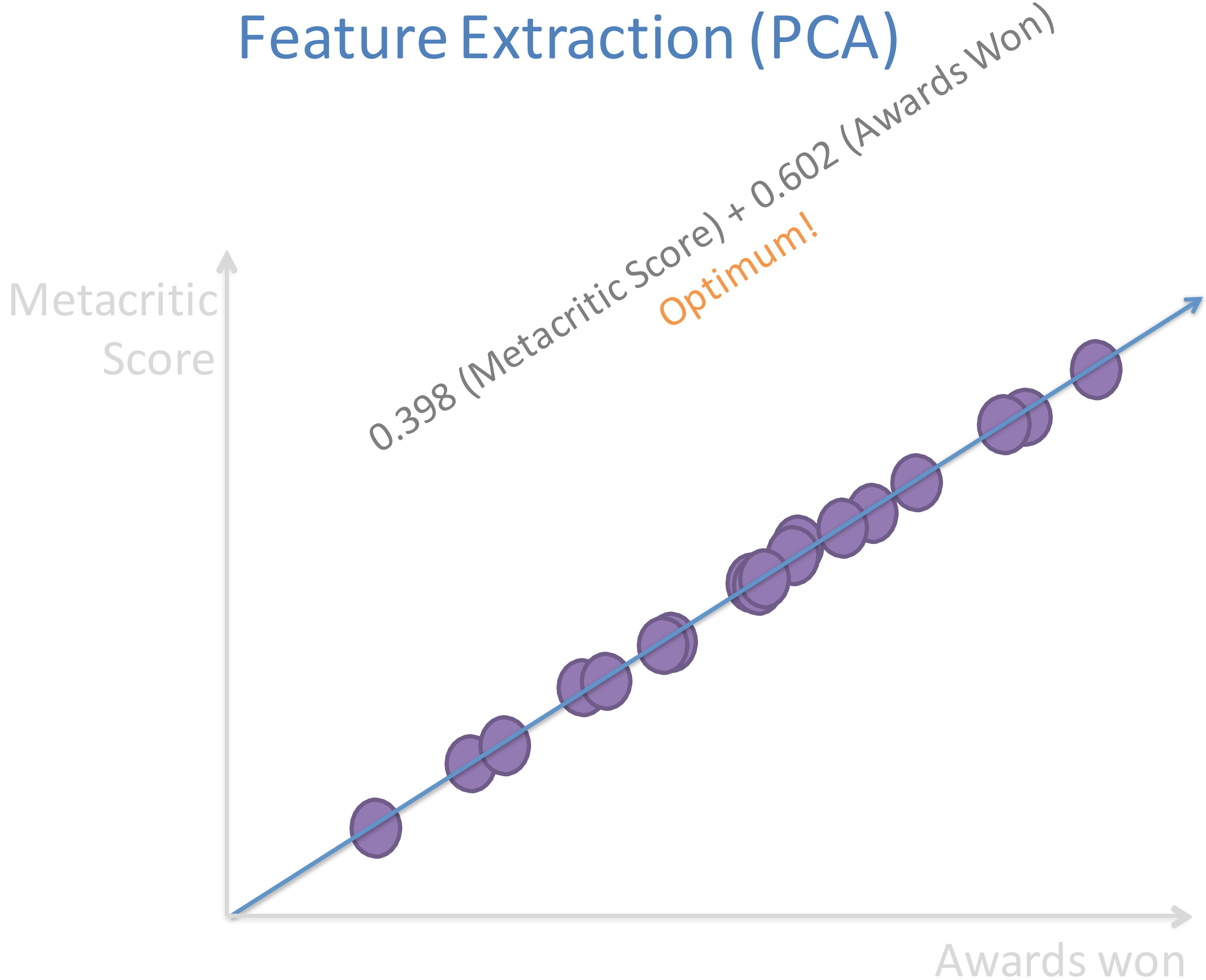
Feature Extraction



Feature Extraction



Feature Extraction (PCA)



Feature Extraction

Advantage: You retain more information
Disadvantage: You lose interpretability

Feature Extraction

Advantage: You retain more information
Disadvantage: You lose interpretability

2D

Oscar_or_not = logit(β_1(Metascore) + β_2(Awards))

Feature Extraction

Advantage: You retain more information
Disadvantage: You lose interpretability

2D

Oscar_or_not = logit(β_1(Metascore) + β_2(Awards))

Feature selection 1D

Oscar_or_not = logit(β_1(Metascore))

Feature Extraction

Advantage: You retain more information

Disadvantage: You lose interpretability

2D

Oscar_or_not = logit(β_1(Metascore) + β_2(Awards))

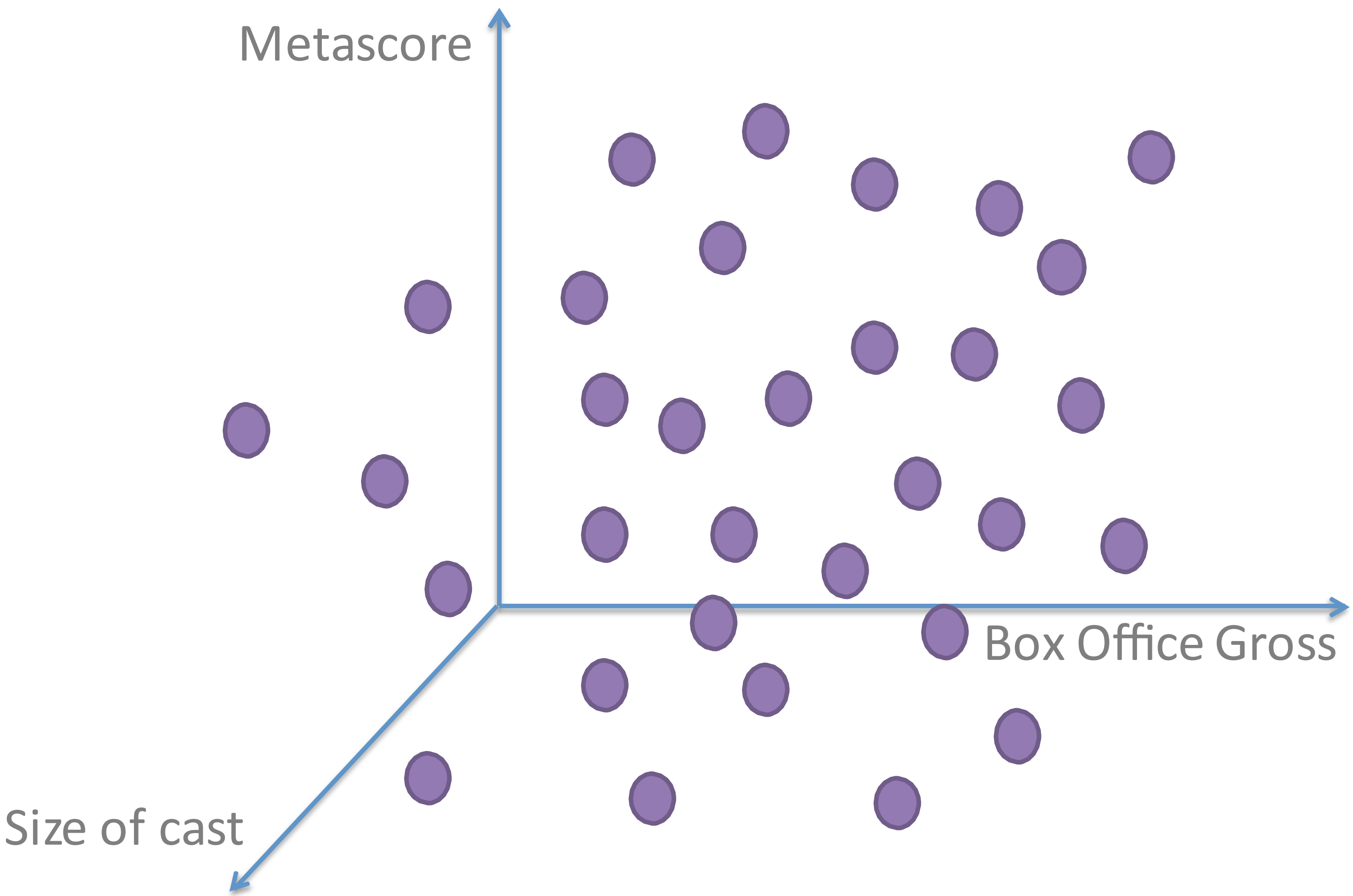
Feature selection 1D

Oscar_or_not = logit(β_1(Metascore))

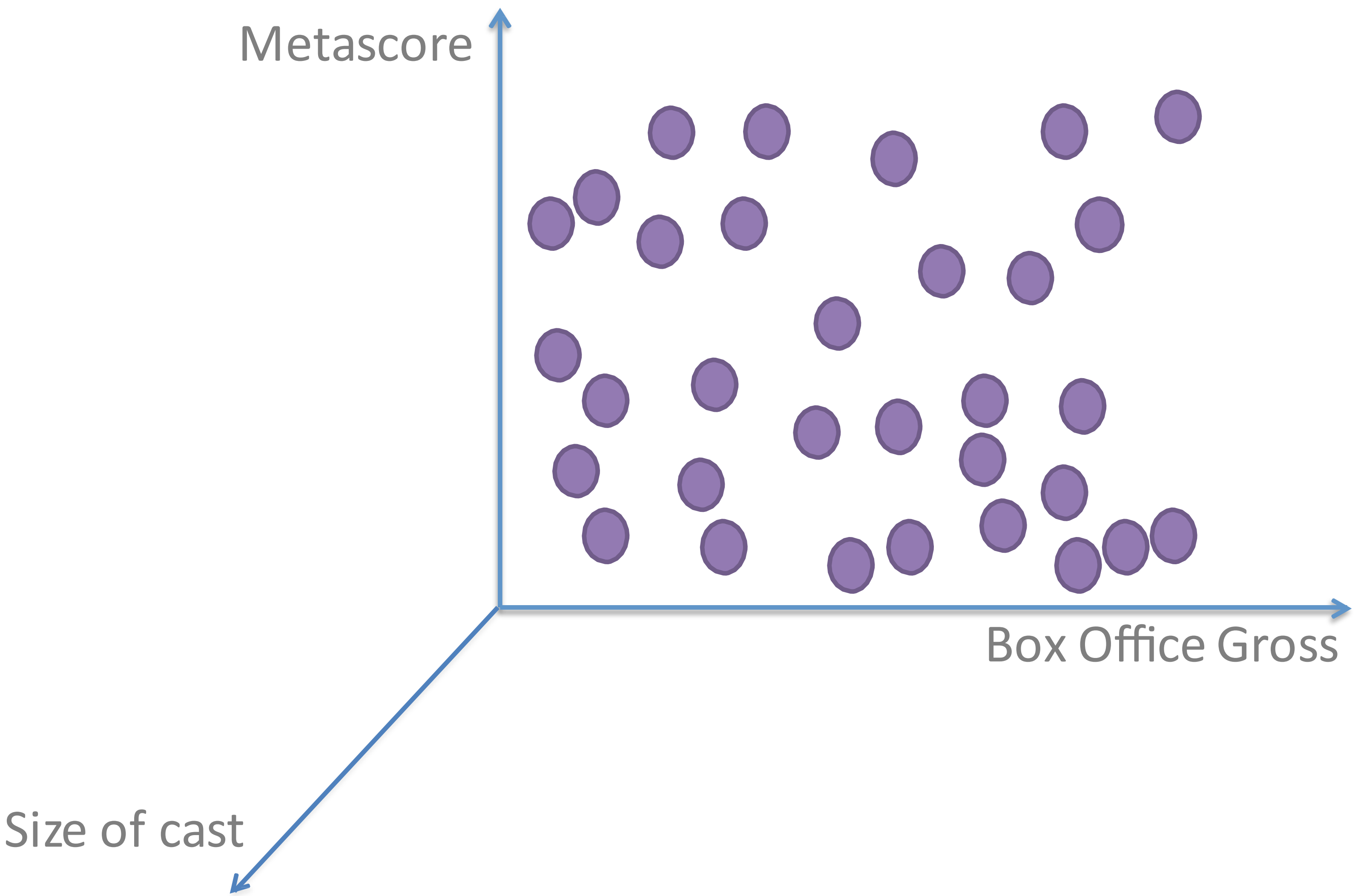
Feature extraction 1D

Oscar_or_not = logit(β_1(0.4*Metascore + 0.6*Awards))

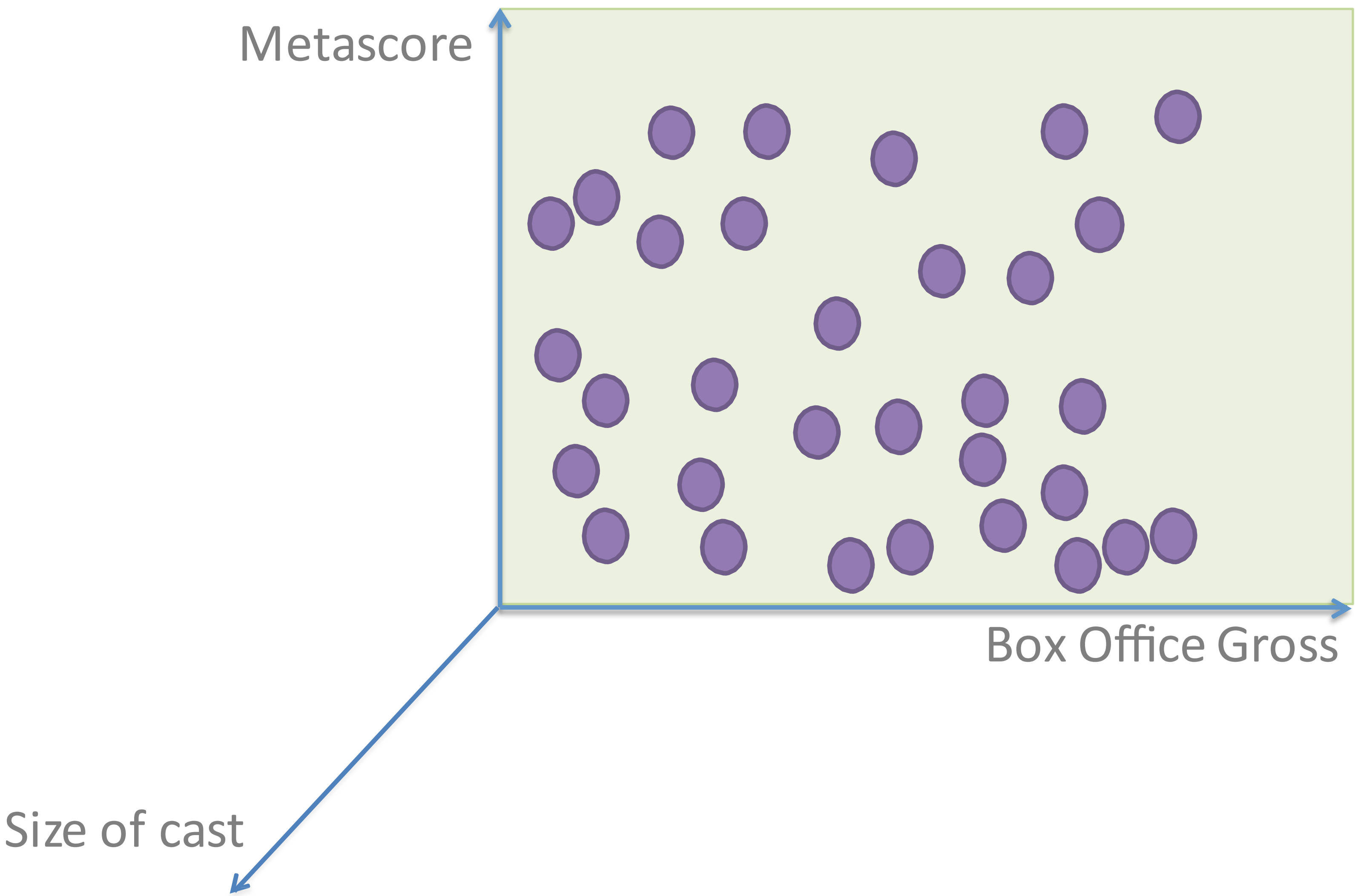
3D → 2D Feature Selection



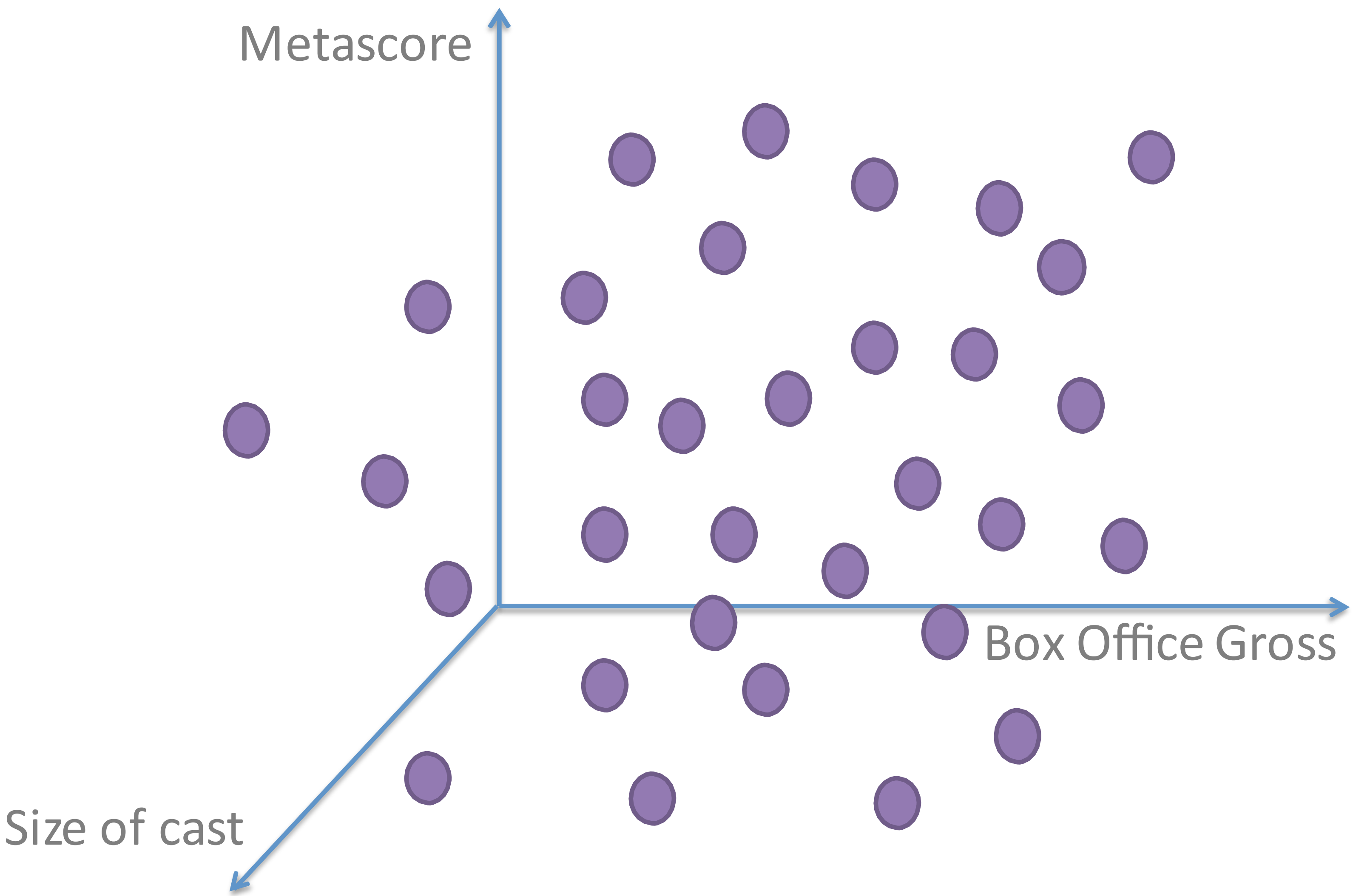
3D → 2D Feature Selection



3D → 2D Feature Selection



3D → 2D Feature Extraction (PCA)



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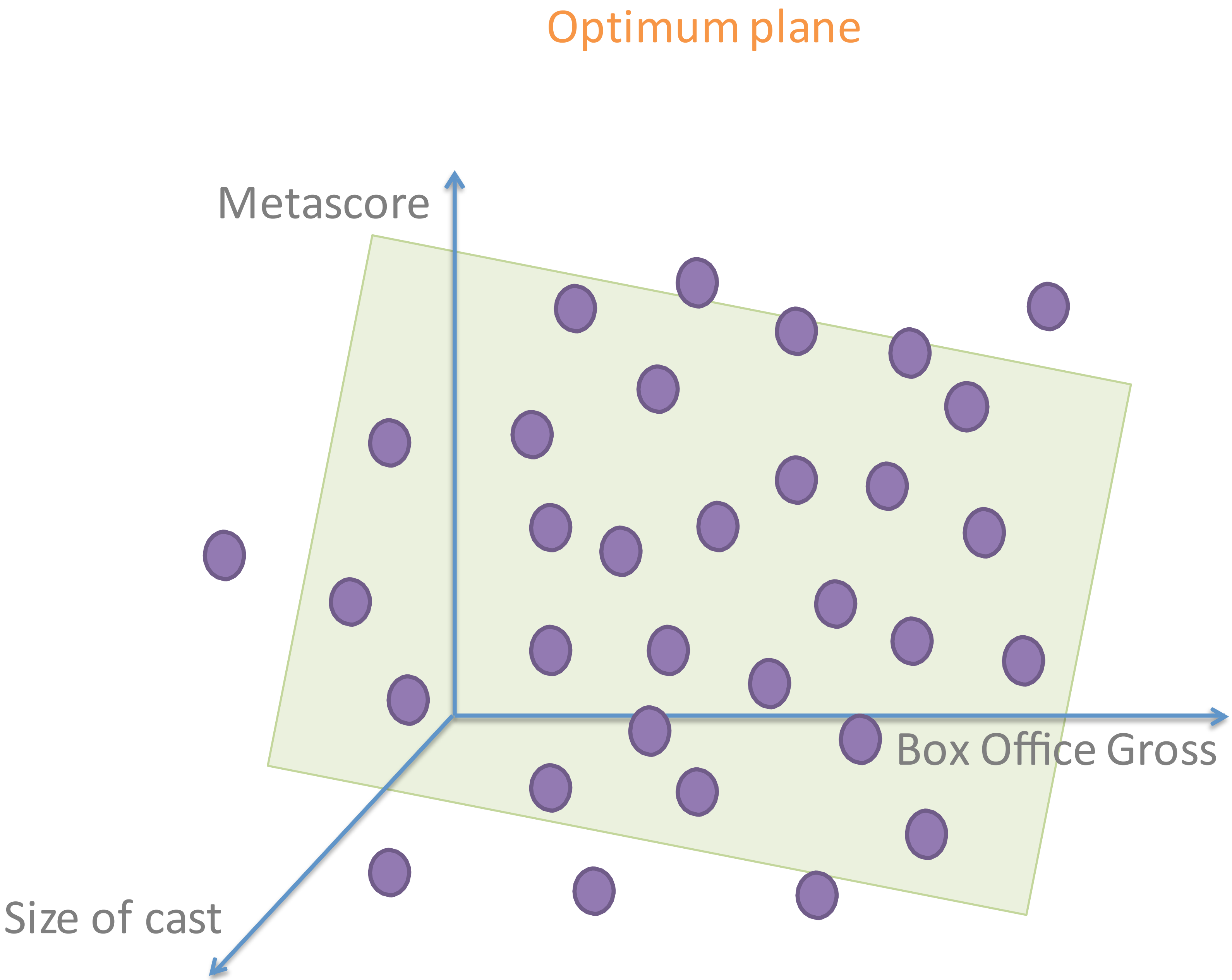

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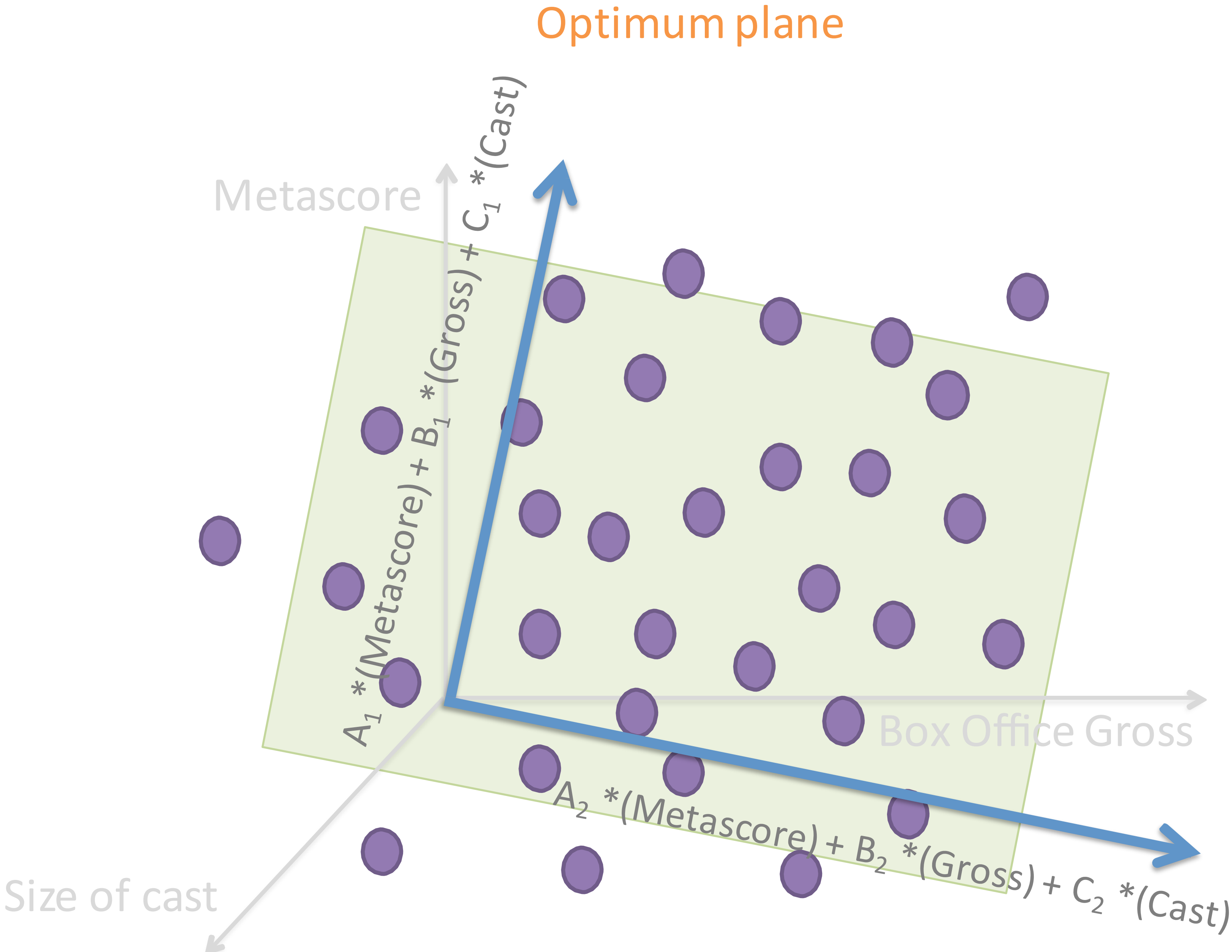

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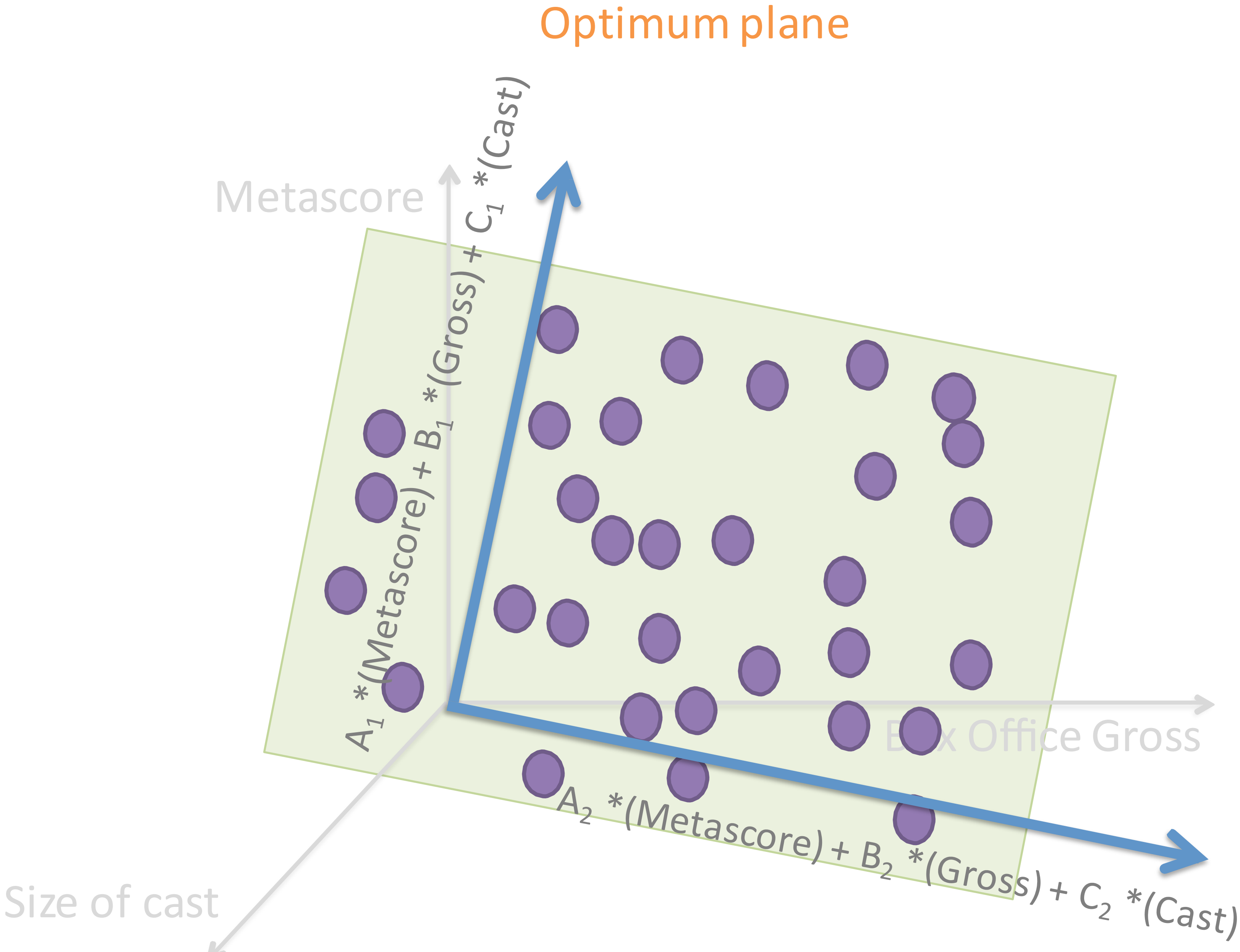

```python
from sklearn.decomposition import PCA

reducer = PCA( n_components = 20 )
reduced_X = reducer.fit_transform(X)
```

How and why to use PCA

Improving your clustering

Improving your classification
(alternative to feature selection)

Visualizing high dimensional data in 2D or 3D

Data compression with little loss

PCA Math

Vectors defining the reduced hyperplane are eigenvectors of the covariance matrix of the features.

Singular Value Decomposition (SVD) is a related decomposition that can be used to solve the PCA problem as well, and with better numeric properties.

(See notebook.)