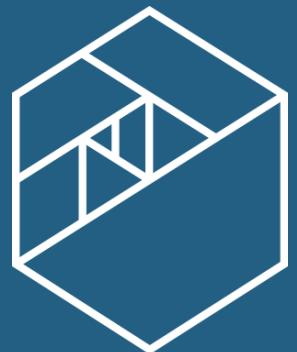


Learning from Text: Natural Language Processing with Python

ODSC East
May 2, 2017

Michelle L. Gill, Ph.D.
Senior Data Scientist, Metis
michelle@thisismetis.com

@modernscientist, michellelynngill.com

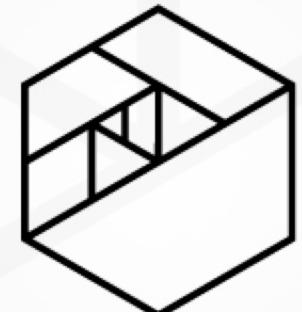


METIS

Metis Data Science Training

- Data Science Bootcamp
 - 12 Week, In-Person
 - New York, San Francisco, Chicago, Seattle
- Corporate Training
 - Python for Data Science
 - Machine Learning
 - Natural Language Processing
 - Spark
- Evening Professional Development Courses
- Explore Data Science Online Training

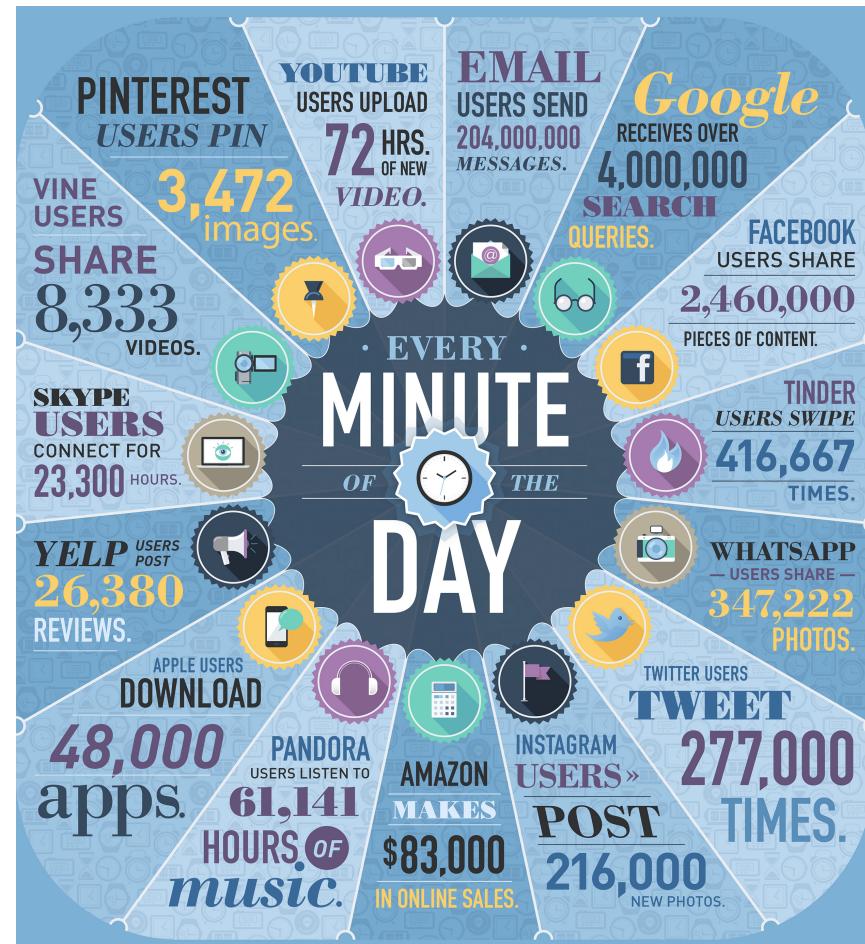
thisismetis.com



Data Generated Each Minute

Much of this data is text

- Email
- Text messages
- News articles
- Blogs
- Twitter
- Reviews
- 204,000,000 Emails
- 4,000,000 Google Search Queries
- 277,000 Tweets
- 26,380 Yelp Reviews



<https://www.domo.com/blog/2014/04/data-never-sleeps-2-0/>



How is this Useful?

- Information retrieval
- Classification and clustering
- Sentiment analysis
- Recommendation systems



How to Represent Text?

Answer

For machine learning tasks
structured, numeric data is desired

Problem

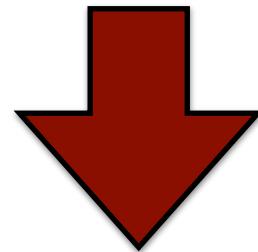
Text is unstructured and
contains limited numeric values



Creating Numerical Features

- Split text into words
(tokenization)

“This is an example”



[This, is, an, example]



Creating Numerical Features

- Split text into words
(tokenization)
- Numerically encode words
(one-hot encoding)

This	= [1, 0, 0, 0]
is	= [0, 1, 0, 0]
an	= [0, 0, 1, 0]
example	= [0, 0, 0, 1]



Creating Numerical Features

- Split text into words
(tokenization)
- Numerically encode words
(one-hot encoding)
- Represent documents by their numerical tokens

	This	is	an	example
Doc 1	1	1	1	1
Doc 2	1	1	0	0
Doc 3	0	1	1	0



Creating Numerical Features with Python

Code

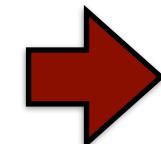
```
import pandas as pd
from sklearn.feature_extraction.text
    import CountVectorizer

corpus = ['This is the first document.',
          'This is the second document.',
          'And the third one.']

cv = CountVectorizer()
X = cv.fit_transform(corpus)
pd.DataFrame(X.toarray(),
              columns=cv.get_feature_names())
```

Output

	and	document	first	is	one	second	the	third	this	
0	0		1	1	1	0	0	1	0	1
1	0		1	0	1	0	1	1	0	1
2	1		0	0	0	1	0	1	1	0



Count Vectorizer



Is That All?

- How much information is contained in a word?
- Can more information be gained?
- What assumptions are being made?



Preprocessing Text

- How to tokenize: single word? multiple words?
- Remove: capital letters, punctuation, common words
- Word order and co-occurrence
- Convert to roots: running --> ran
- Misspellings
- Different languages
- Weight words equally or differently?



Preprocessing Examples

- Common words (stop words)
 - the, I, a

```
ex = CountVectorizer(stop_words='english')
x = ex.fit_transform(['this is an example with stop words'])
pd.DataFrame(x.toarray(), columns = ex.get_feature_names())
```

example	stop	words
1	1	1

- Word roots (stemming)
 - run, running

```
import nltk
stemmer = nltk.stem.porter.PorterStemmer()
print stemmer.stem('run')
run
print stemmer.stem('running')
run
```

- Word order (n-grams)
 - The movie was not good
 - New York Times

```
text = ['this is a bigram example']
bigram_vectorizer = CountVectorizer(ngram_range=(2,2))
X = bigram_vectorizer.fit_transform(text)
pd.DataFrame(X.toarray(), columns=bigram_vectorizer.get_feature_names())
```

bigram example	is bigram	this is
1	1	1



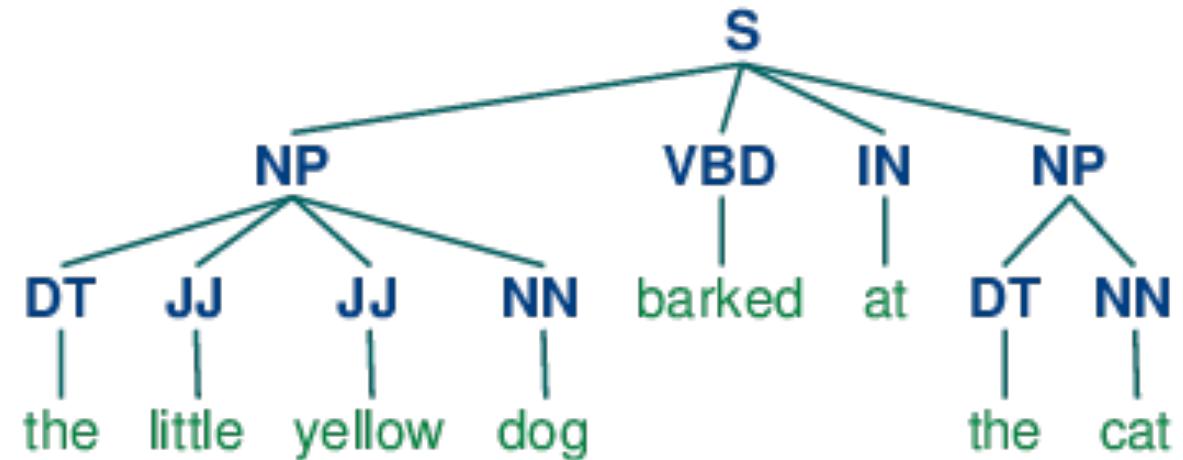
Other Preprocessing Considerations

- Presupposition: implicit assumptions
 - Jane no longer writes fiction (Jane once wrote fiction)
- Word relationships:
 - Substitution: red and blue, Saturday and Sunday
 - Co-occurrences: car and drive
- Sparsity
 - High dimensionality
 - Similarity and meaning



Other Preprocessing Considerations

- Chunking segments and labels multi-token sequences
- Like parts-of-speech tagging with sentence structure included



Practice Preprocessing

Walkthrough

01_Text_Preprocessing_Walkthrough

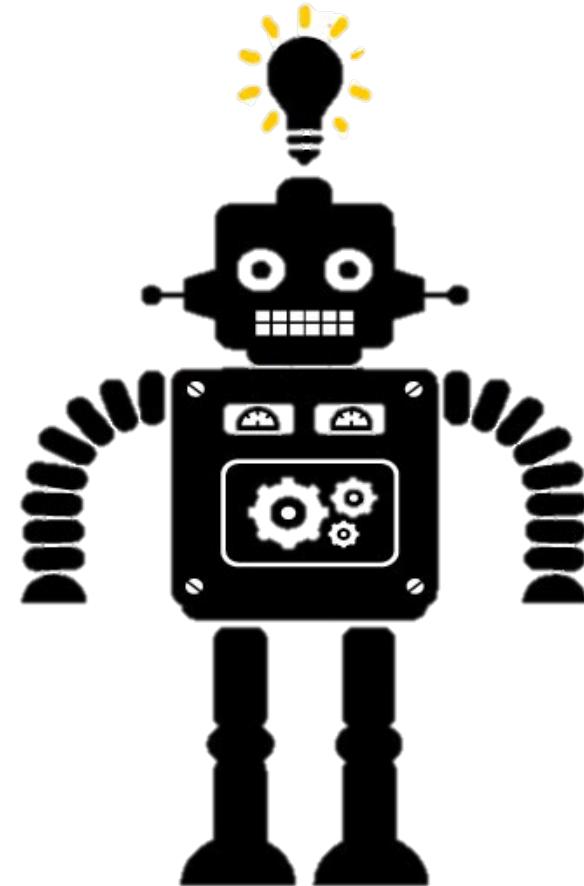
Exercises

02_Text_Preprocessing_Exercises



What is Machine Learning?

Machine learning allows computers to learn and infer from data.



Types of Machine Learning

Supervised

Data points have known outcome (prediction)

- **Regression**: predict continuous value
- **Classification**: predict categorical value

Unsupervised

Data points have unknown outcome (find structure)

- **Clustering**: group observations
- **Dimensionality reduction**: reduce features



Machine Learning Vocabulary

- Features
- Observations
- Labels



sepal length	sepal width	petal length	petal width	species
6.7	3.0	5.2	2.3	virginica
6.4	2.8	5.6	2.1	virginica
4.6	3.4	1.4	0.3	setosa
6.9	3.1	4.9	1.5	versicolor
4.4	2.9	1.4	0.2	setosa
4.8	3.0	1.4	0.1	setosa
5.9	3.0	5.1	1.8	virginica
5.4	3.9	1.3	0.4	setosa
4.9	3.0	1.4	0.2	setosa
5.4	3.4	1.7	0.2	setosa



Machine Learning Vocabulary

- Features
- Observations
- Labels



sepal length	sepal width	petal length	petal width	species
6.7	3.0	5.2	2.3	virginica
6.4	2.8	5.6	2.1	virginica
4.6	3.4	1.4	0.3	setosa
6.9	3.1	4.9	1.5	versicolor
4.4	2.9	1.4	0.2	setosa
4.8	3.0	1.4	0.1	setosa
5.9	3.0	5.1	1.8	virginica
5.4	3.9	1.3	0.4	setosa
4.9	3.0	1.4	0.2	setosa
5.4	3.4	1.7	0.2	setosa



Machine Learning Vocabulary

- Features
- Observations
- Labels

sepal length	sepal width	petal length	petal width	species
6.7	3.0	5.2	2.3	virginica
6.4	2.8	5.6	2.1	virginica
4.6	3.4	1.4	0.3	setosa
6.9	3.1	4.9	1.5	versicolor
4.4	2.9	1.4	0.2	setosa
4.8	3.0	1.4	0.1	setosa
5.9	3.0	5.1	1.8	virginica
5.4	3.9	1.3	0.4	setosa
4.9	3.0	1.4	0.2	setosa
5.4	3.4	1.7	0.2	setosa



What are the Text Features?

- Tokenized words
- N-Grams
- Parts-of-speech tags
- Chunks
- Syntactic structure
- etc.



Text Classification

- Want to predict a categorical variable
 - Example: Predict if an email is spam or not
- Given
 - X: Email text
 - Y: Spam or not spam
- Goal: Build model that predicts if a new email is spam or not



Many Choices for Model Algorithm

- Logistic regression
- Naive Bayes
- Support vector machines
- Random forest
- Boosting



Supervised Modeling Process

- Have historical email data with spam/not spam labels
- Preprocess the email text data
 - Tokenize
 - Remove stop words
 - Stem or lemmatize
 - Count vectorize
- Use this numerical dataset in a classification algorithm
- Given a new email, process the same way and predict



Practice Machine Learning

Walkthrough

03_Classification_Walkthrough

Exercises

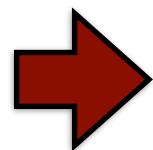
04_Text_Classification_Exercises



Beyond Count Vectorizer

Problems with binary values or word count:

- Binary counts can be too simplistic
- High counts can dominate--especially for high frequency words or long documents
- Each word is treated equally--some terms might be more important than others



Want a metric that takes these issues into consideration



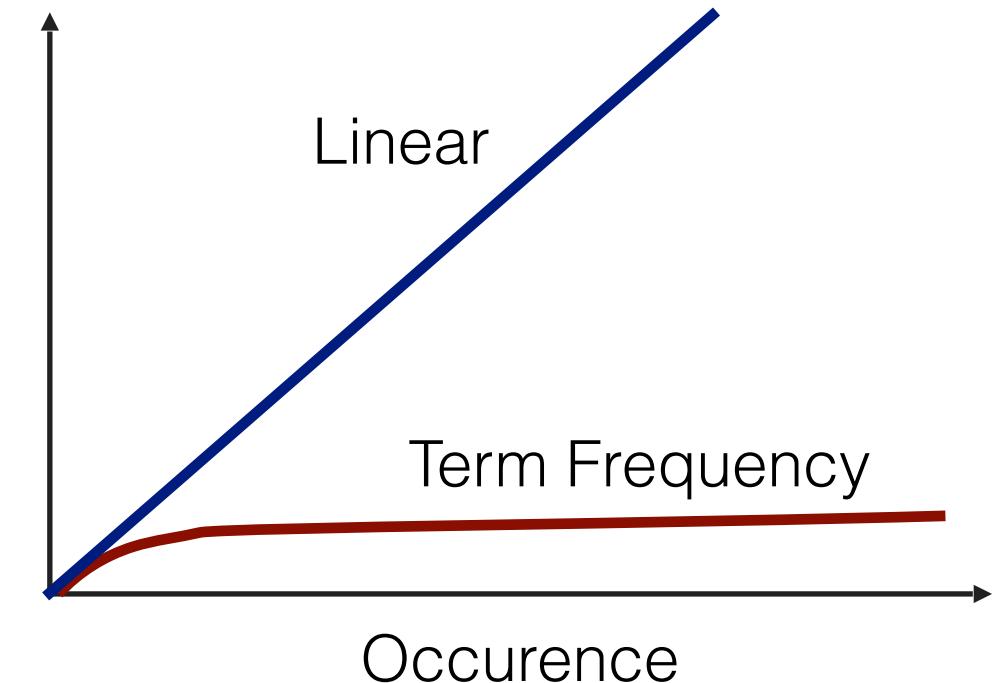
Term Frequency (TF)

- Alternative to binary values or counting word appearance

- Balance count with a transformation:

$$tf = \log(x + 1)$$

x = term occurrence



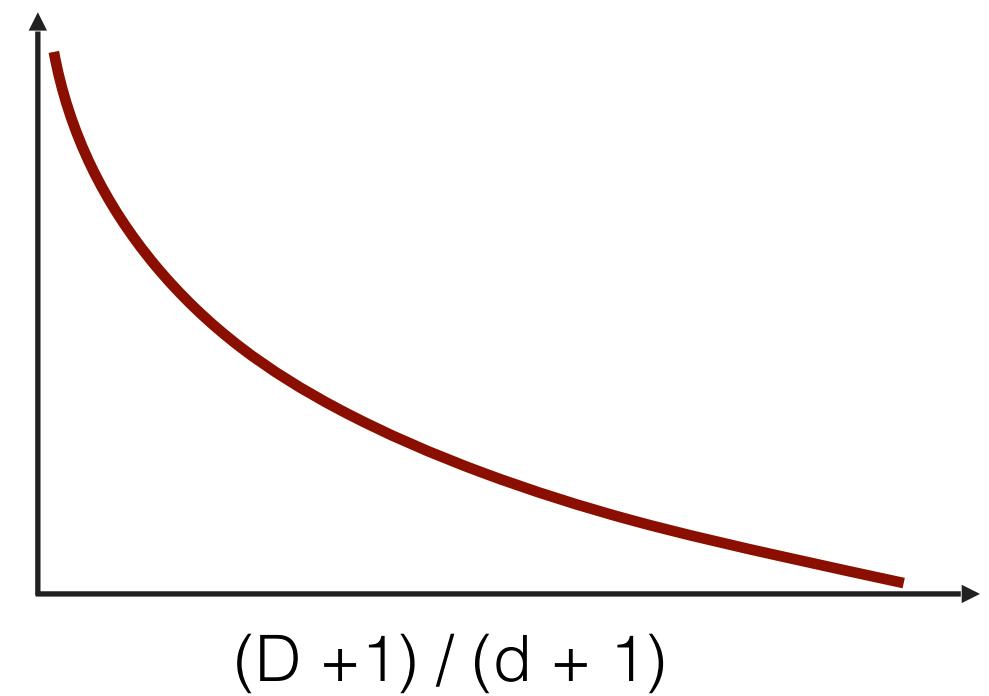
Inverse Document Frequency (IDF)

- Also want to increase weight of words appearing in only a few documents
- Calculate inverse document frequency:

$$\text{idf} = \log(D + 1 / d + 1)$$

D = total documents

d = documents containing word

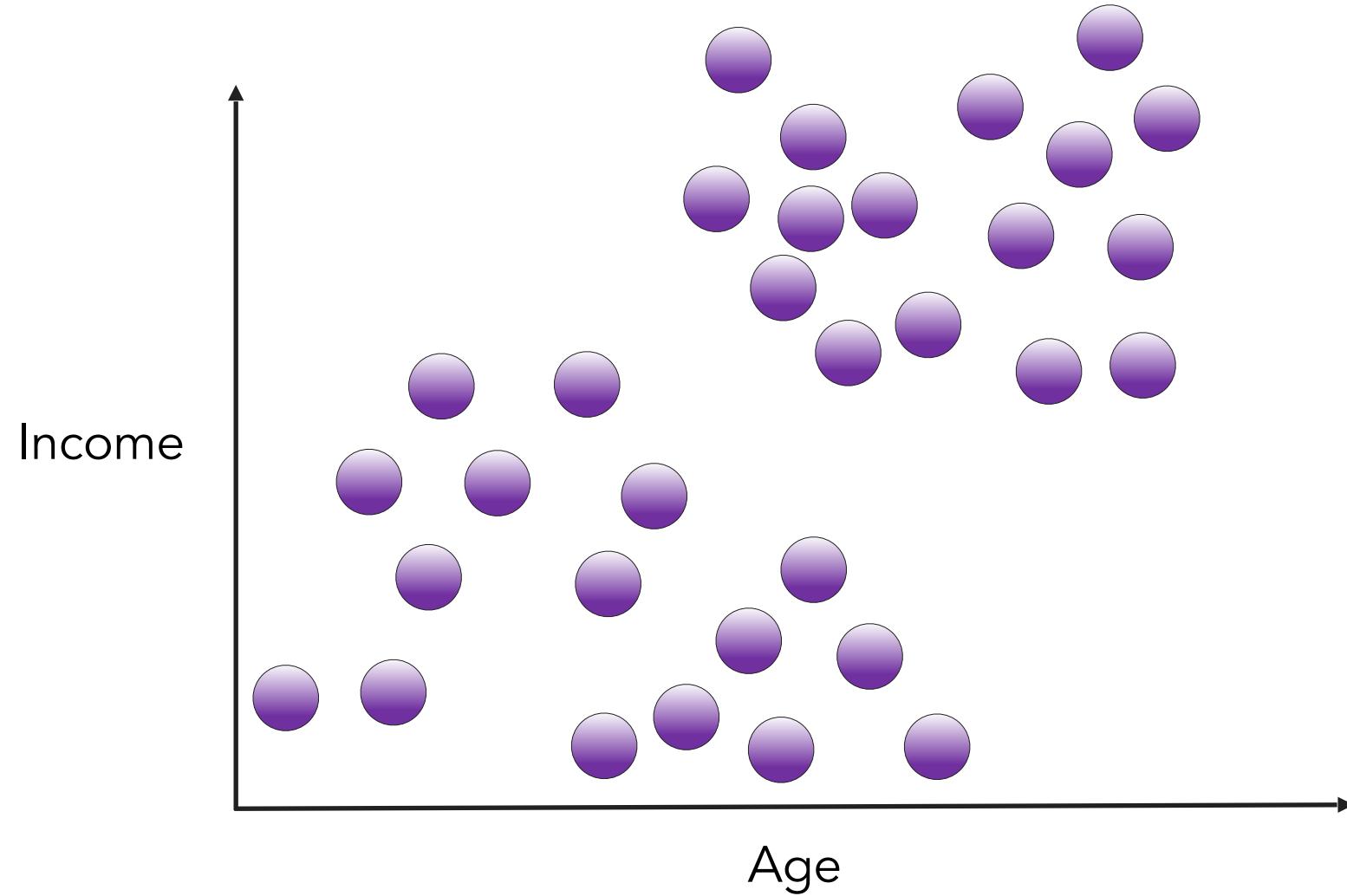


Practice TF-IDF

- Complete question 4 from the previous exercises
(04_Text_Classification_Exercises)
- We will discuss the syntax briefly within the exercise

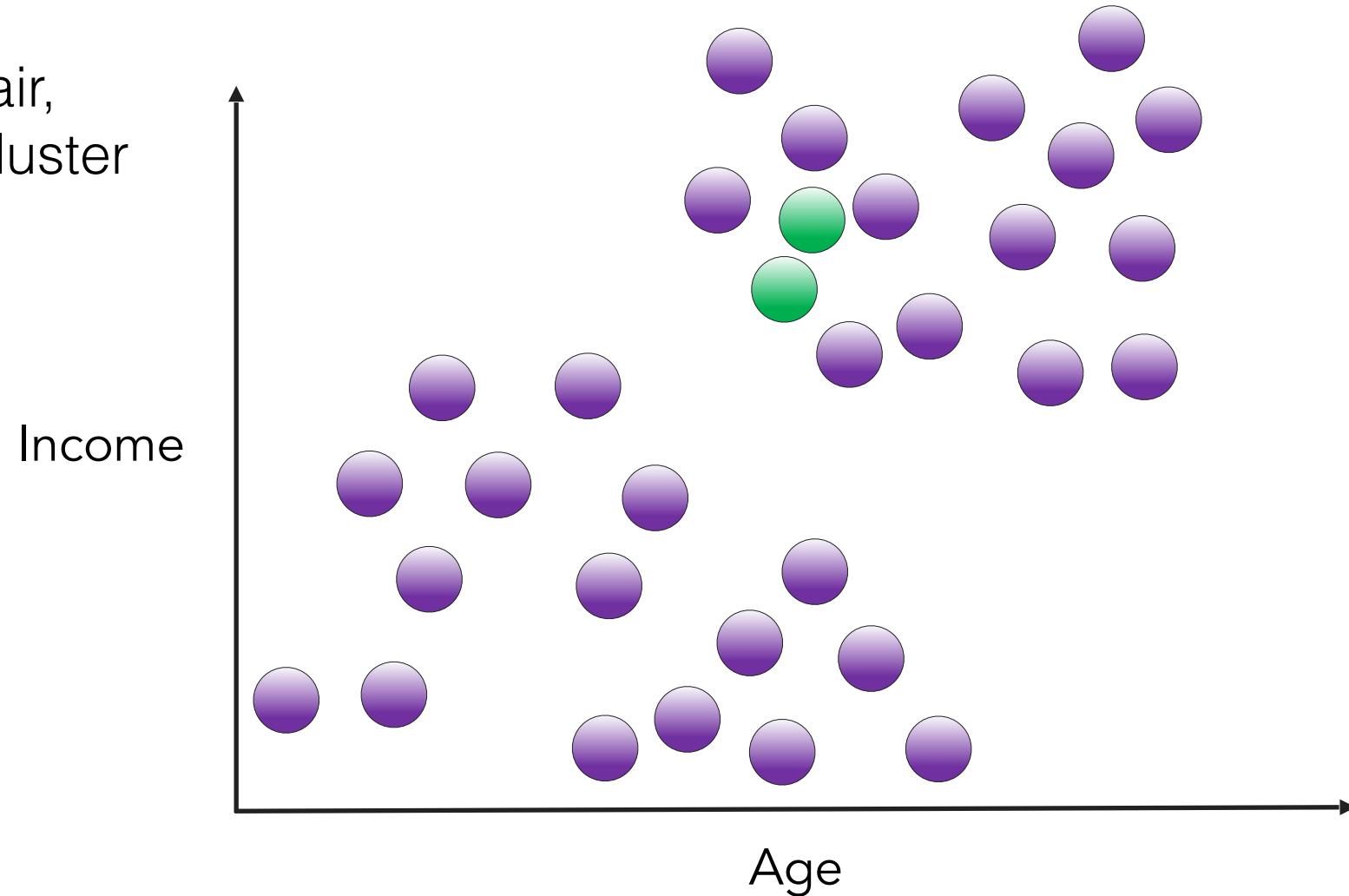


Clustering



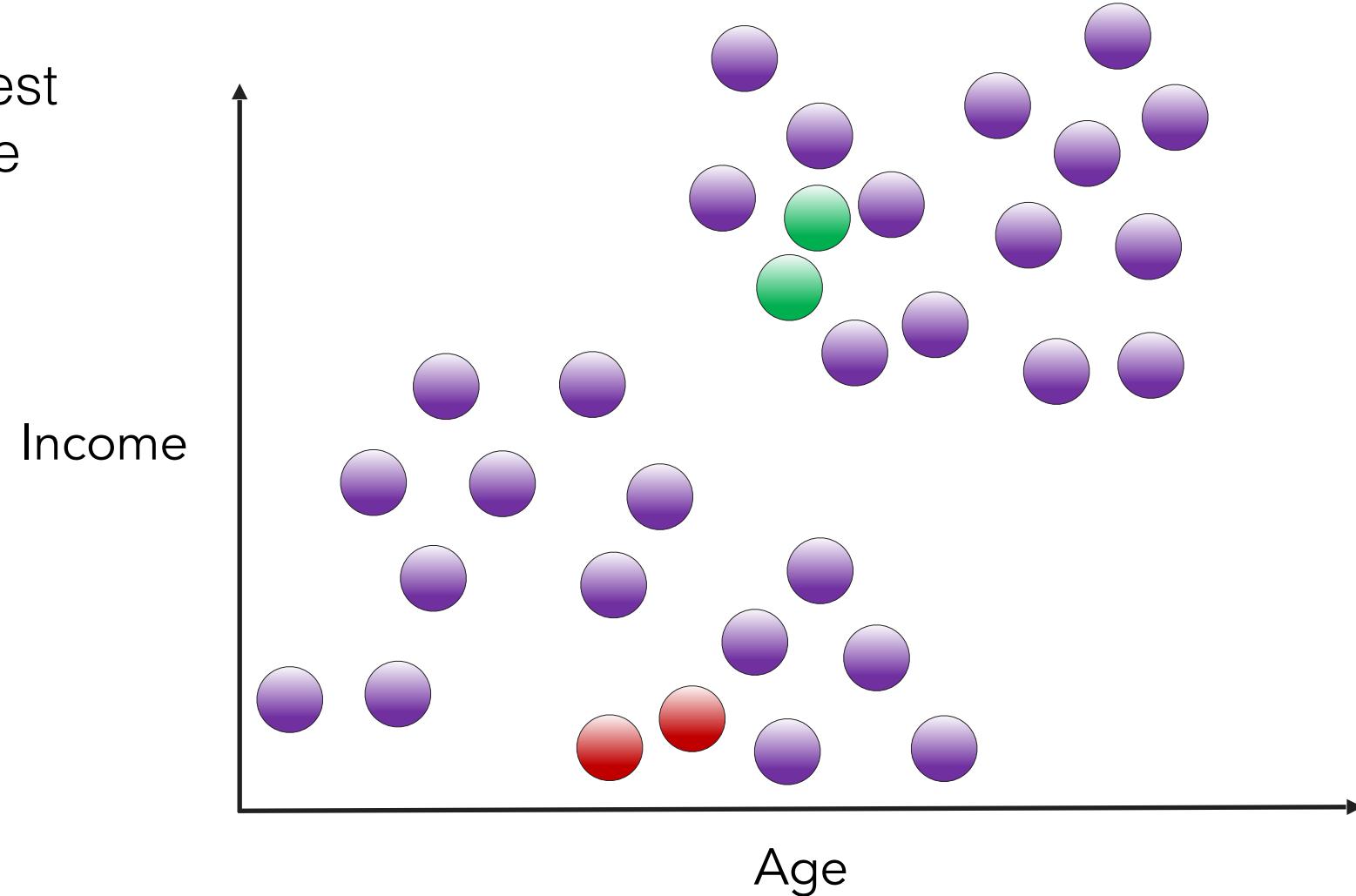
Clustering

Find closest pair,
merge into a cluster



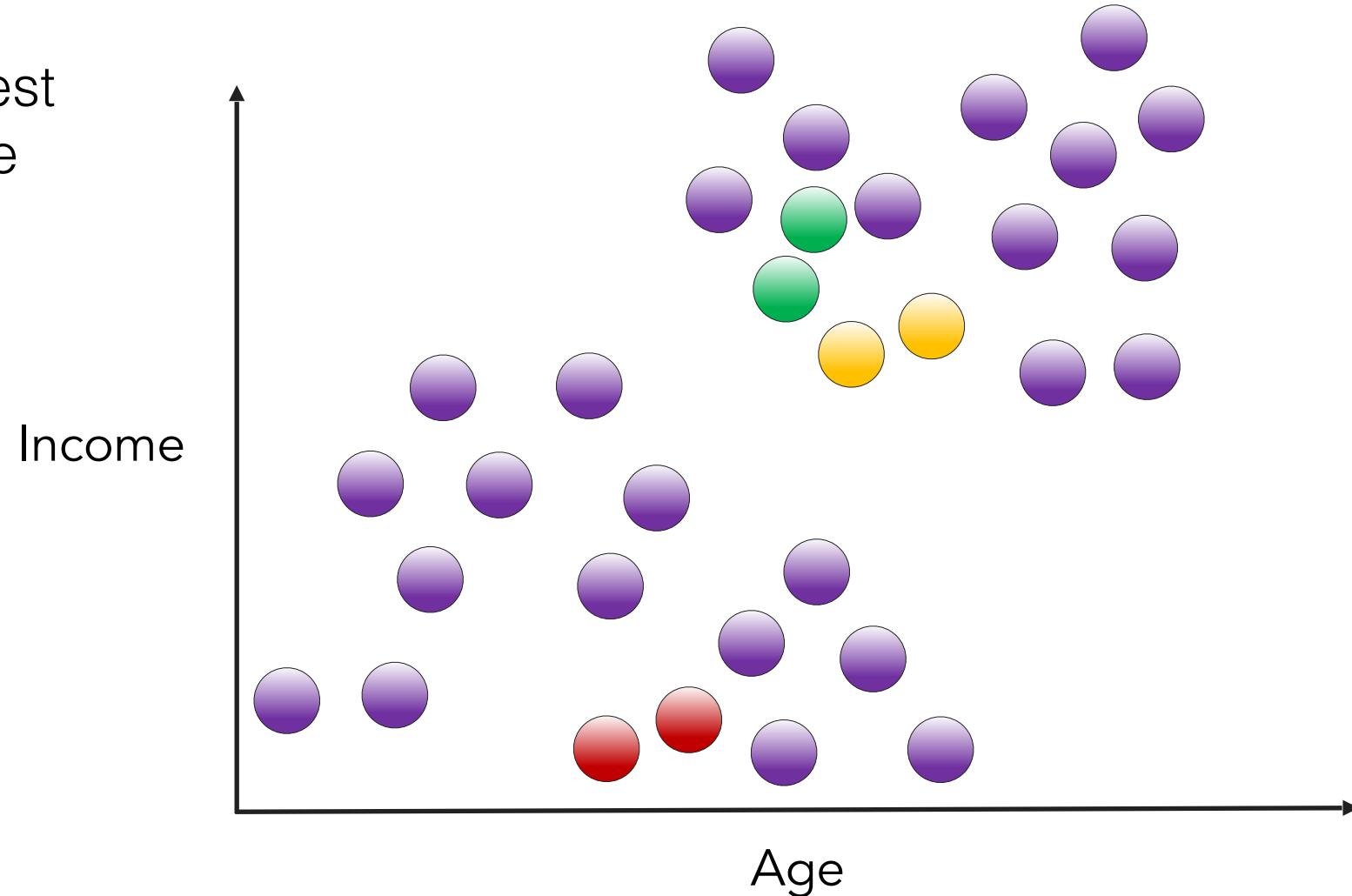
Clustering

Find next closest pair and merge



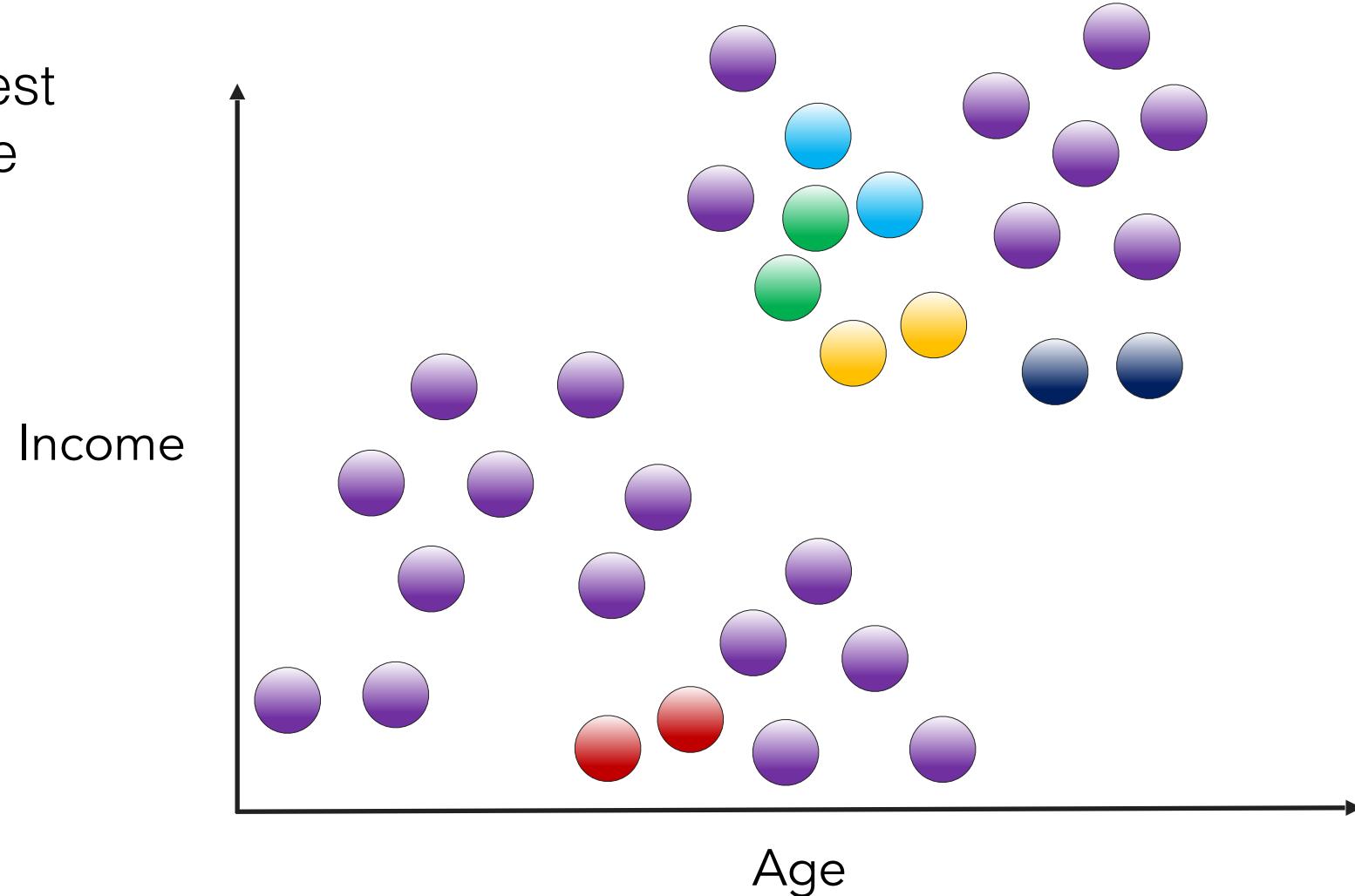
Clustering

Find next closest pair and merge



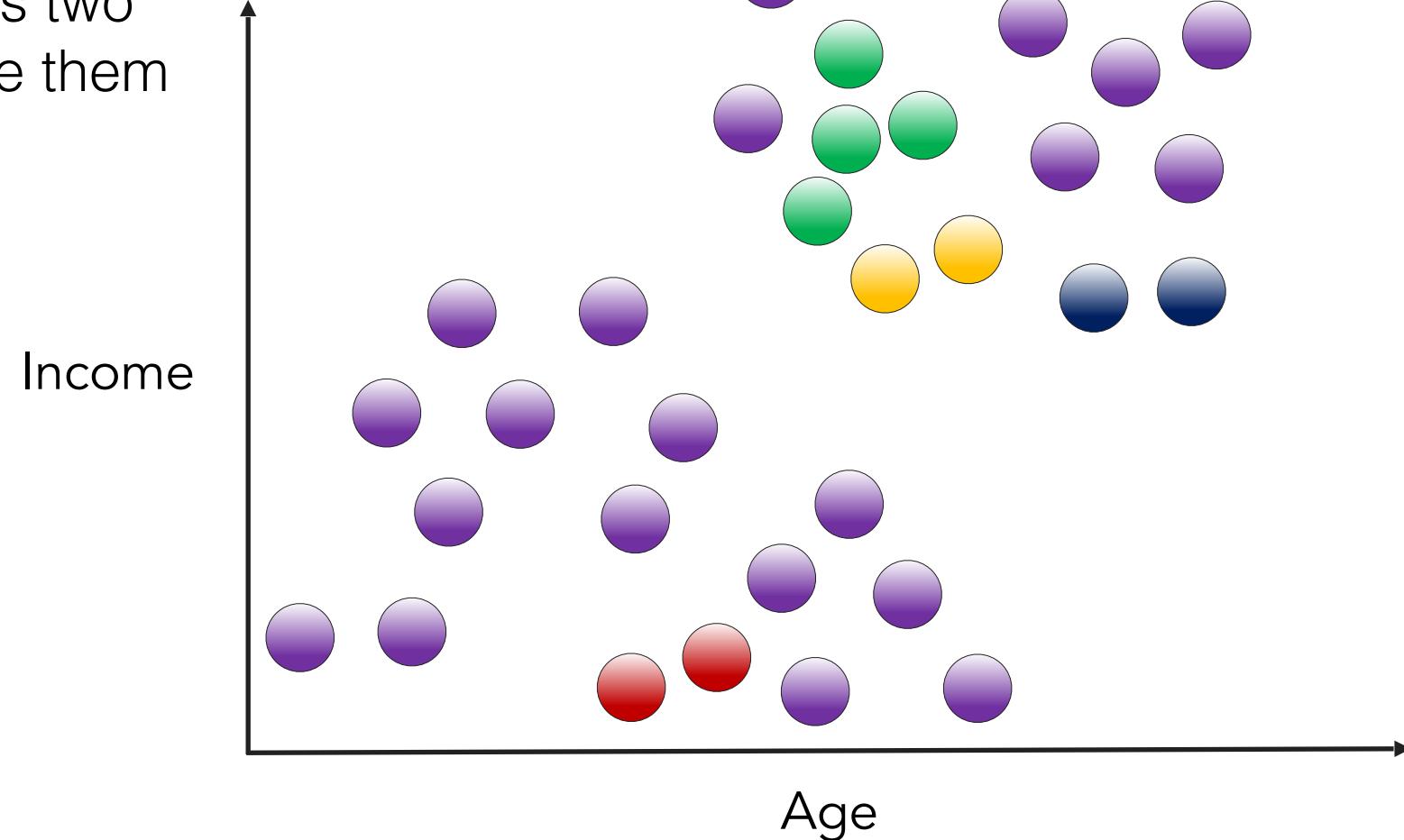
Clustering

Find next closest pair and merge



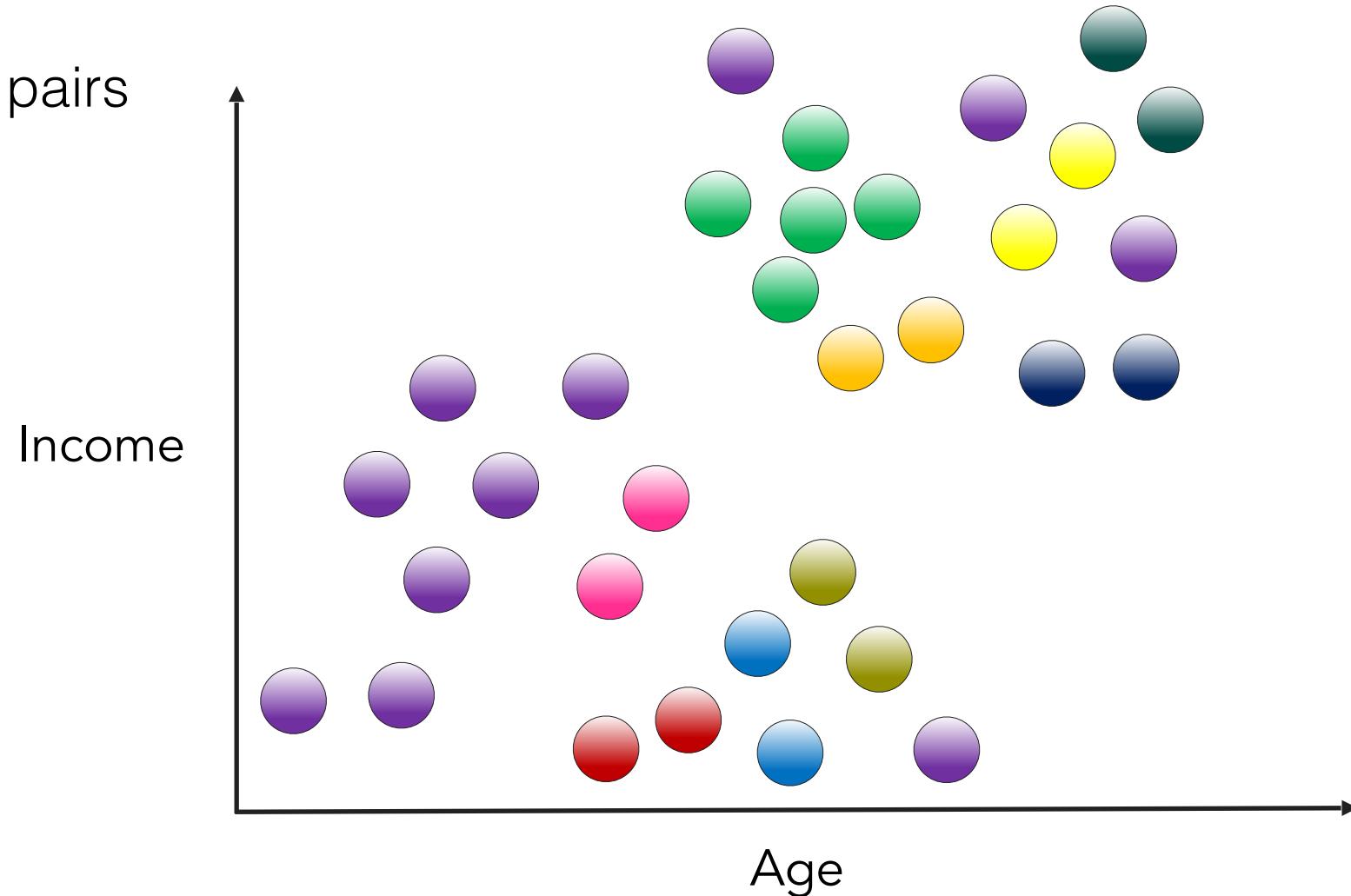
Clustering

If closest pair is two clusters, merge them



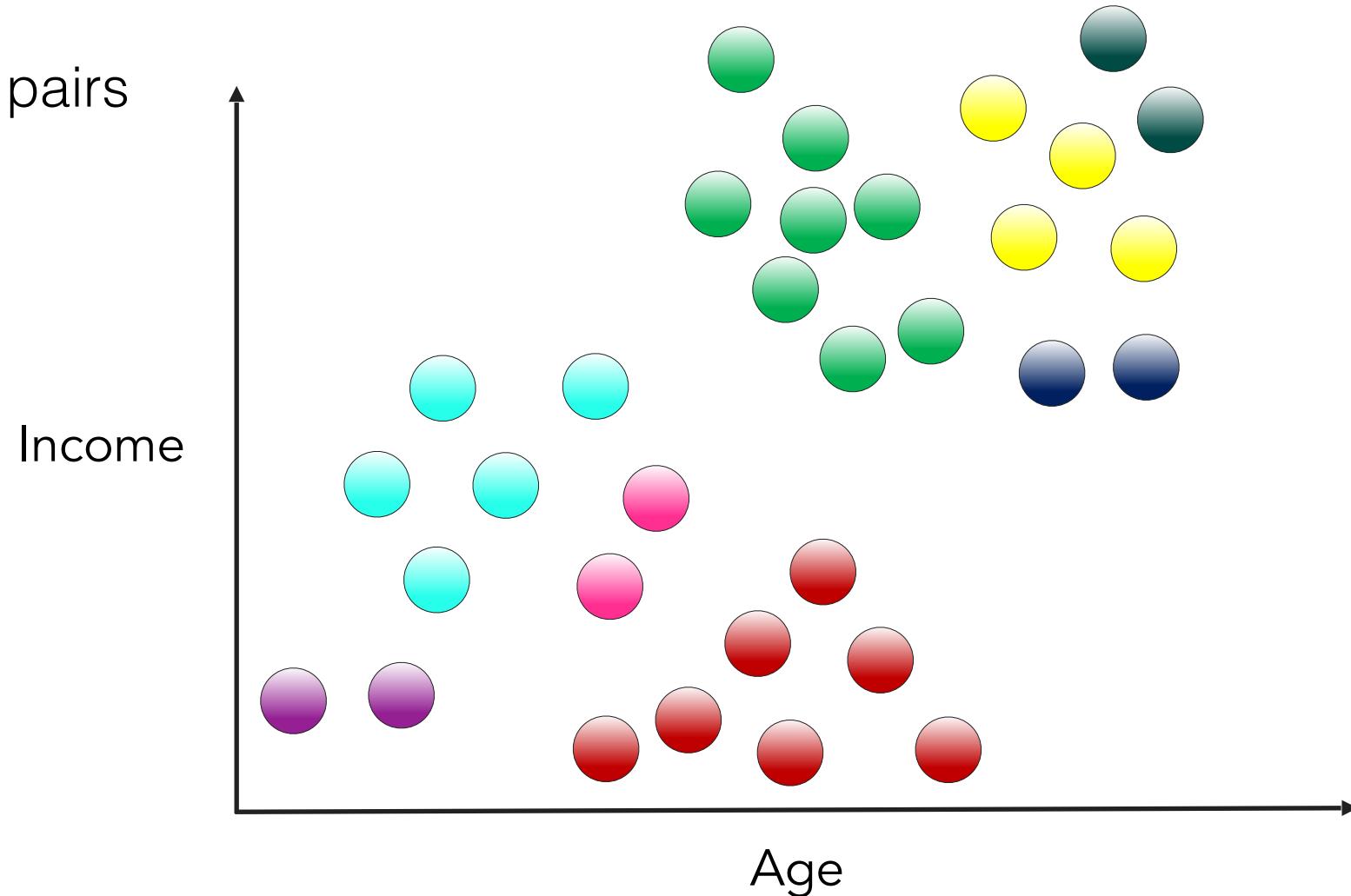
Clustering

Keep merging pairs
and clusters



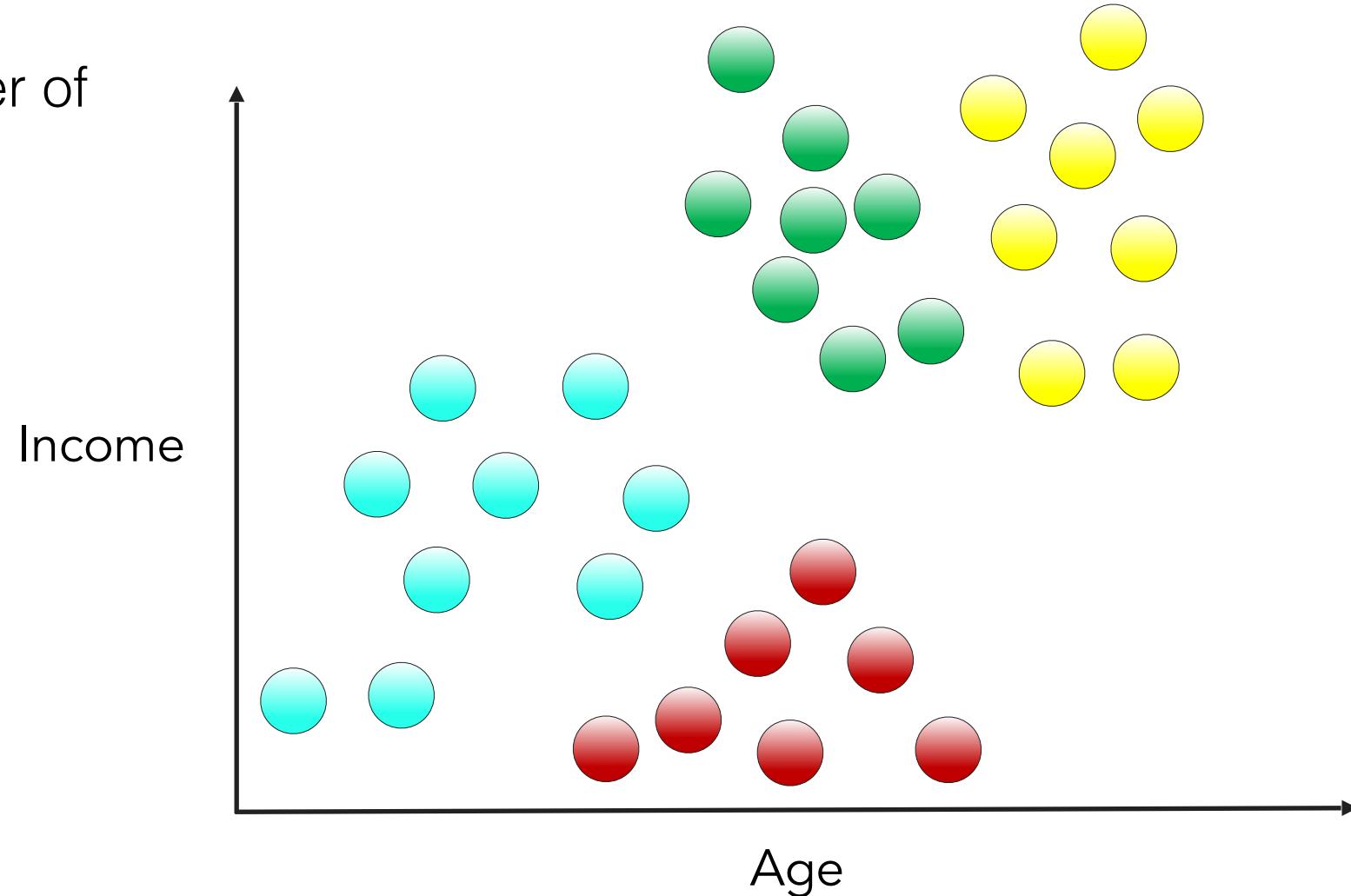
Clustering

Keep merging pairs
and clusters



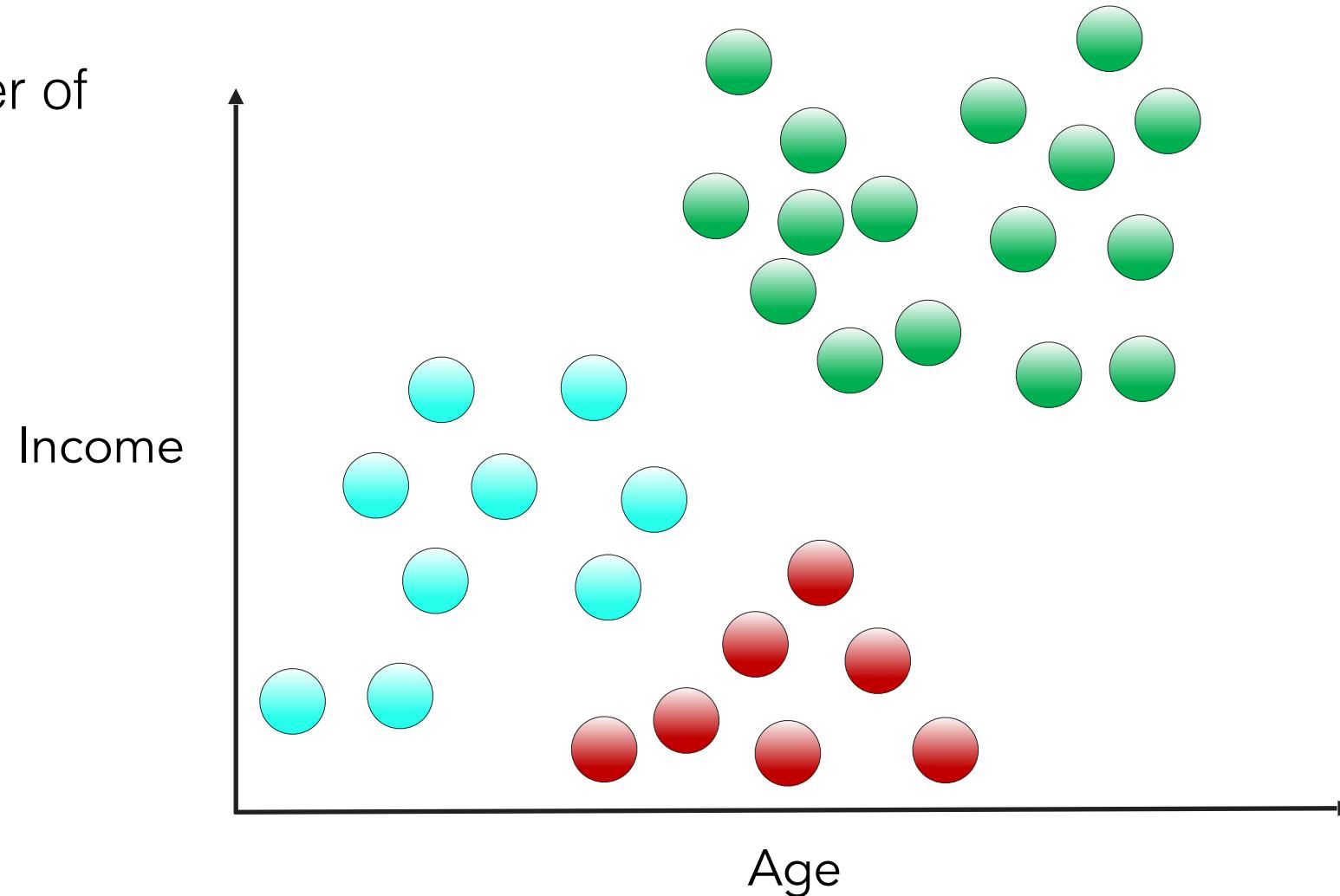
Clustering

Current number of clusters = 4



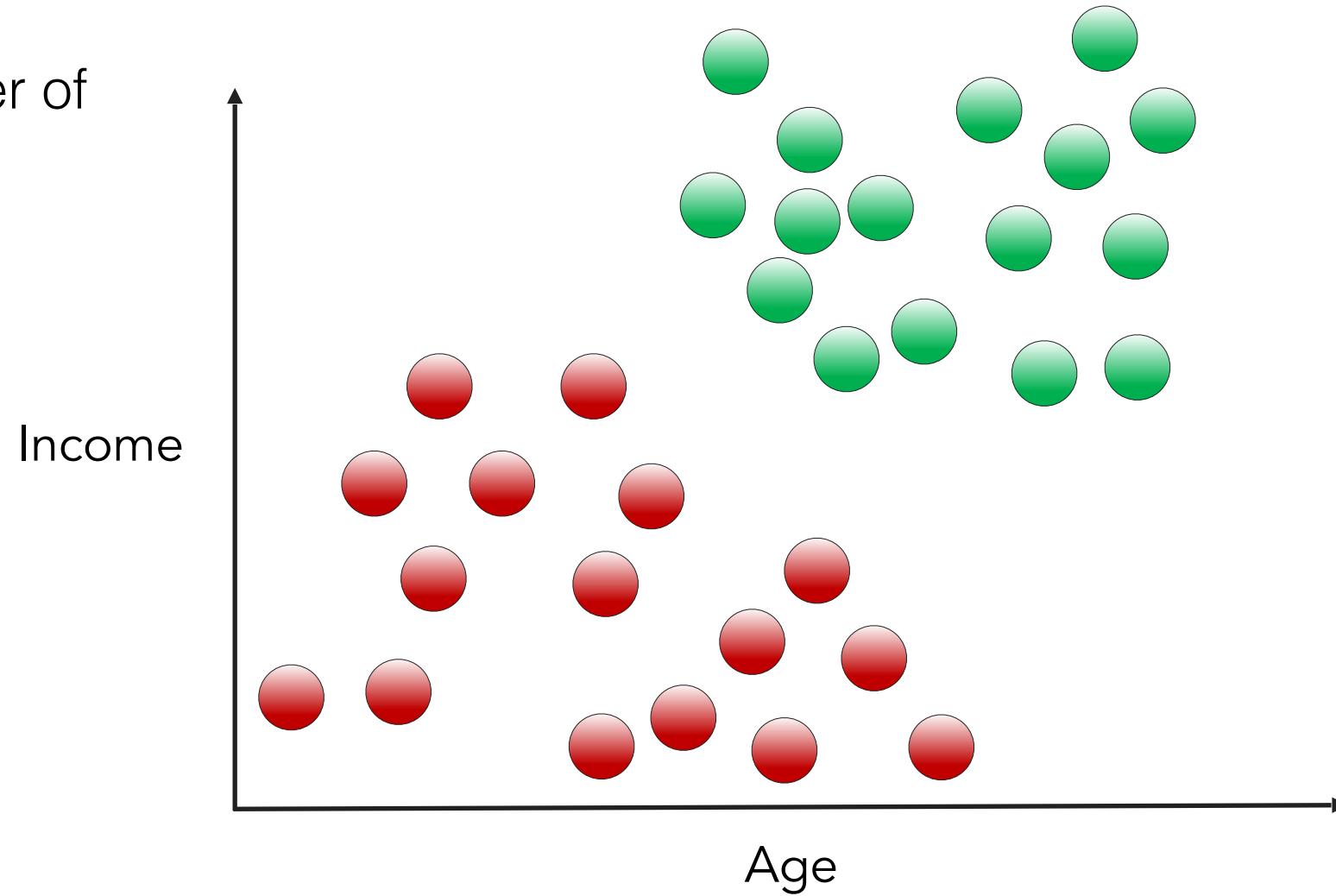
Clustering

Current number of clusters = 3



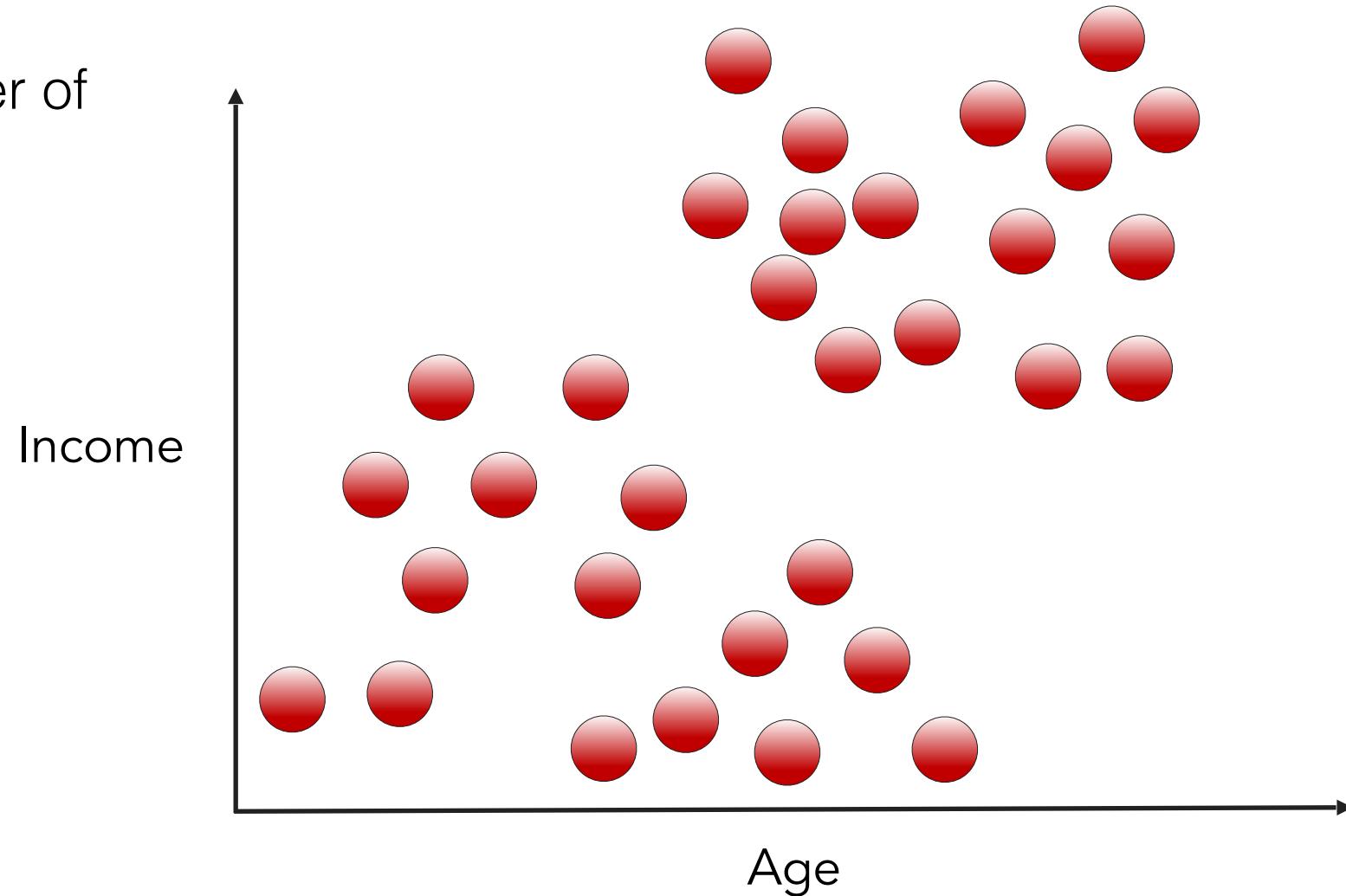
Clustering

Current number of clusters = 2



Clustering

Current number of clusters = 1



When to Stop Clustering?

Condition 1

Correct number of clusters is reached

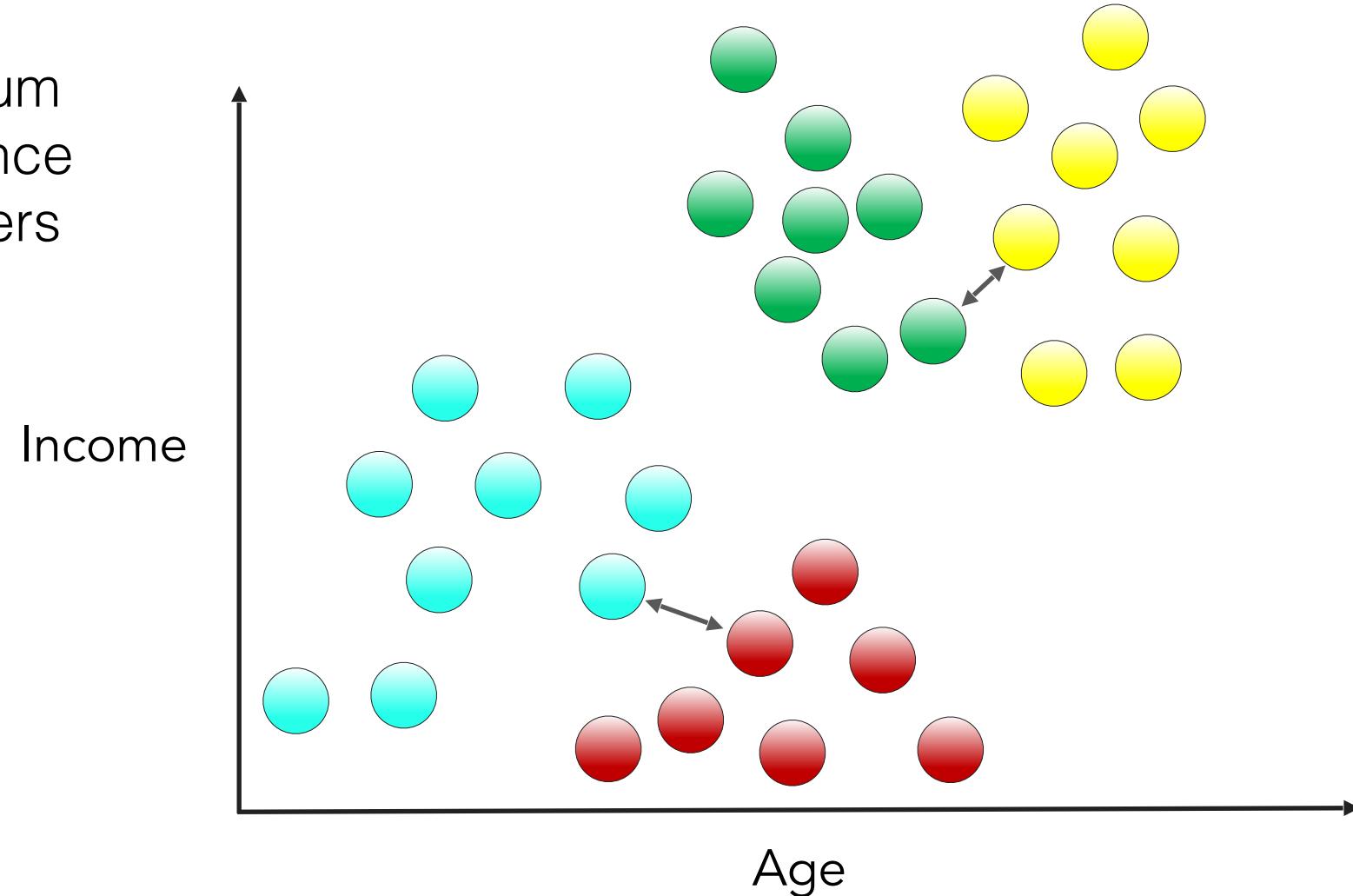
Condition 2

Cluster linkage (distance) reaches a set value



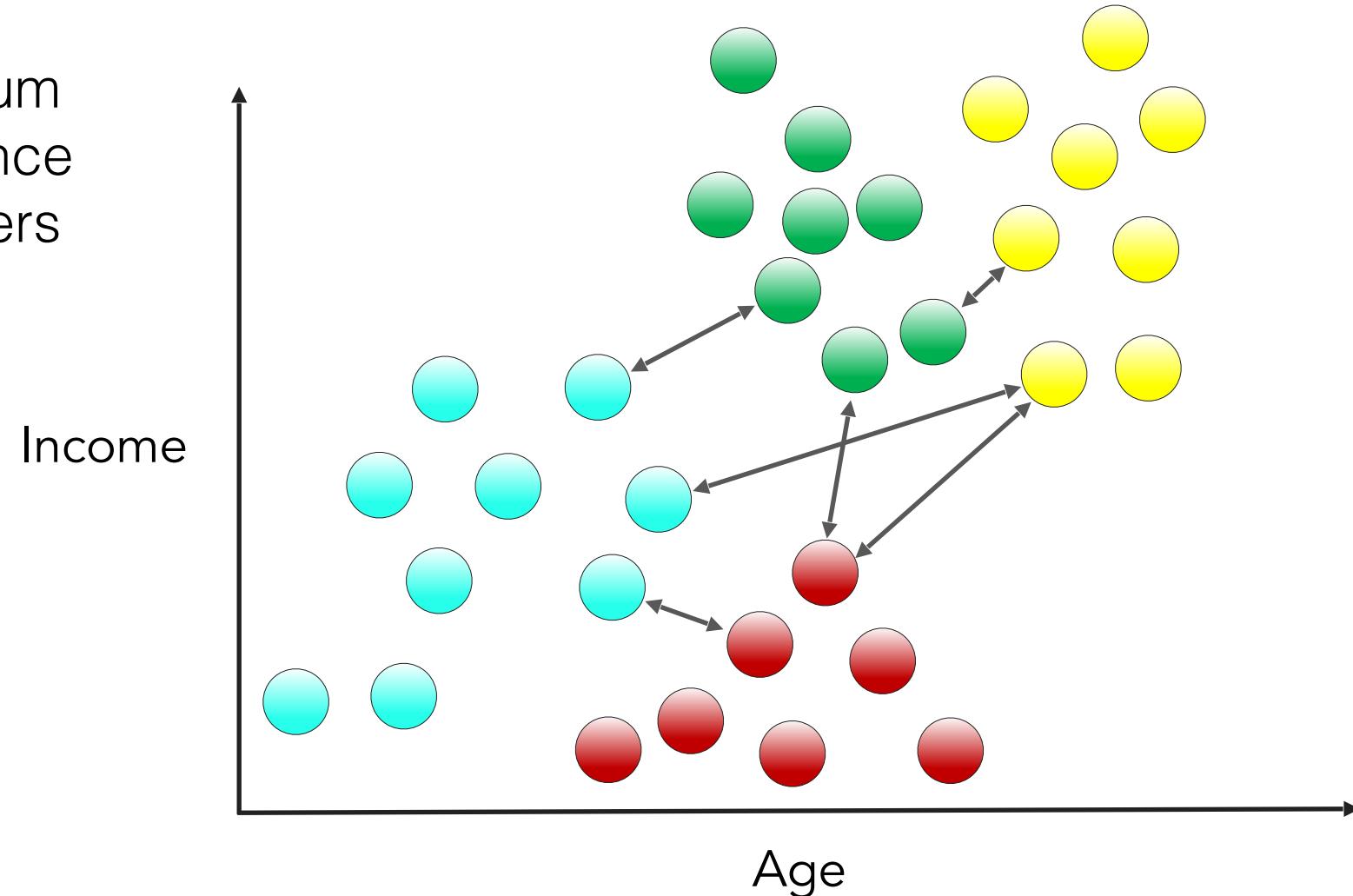
Cluster Linkage

Single: minimum pairwise distance between clusters



Cluster Linkage

Single: minimum pairwise distance between clusters

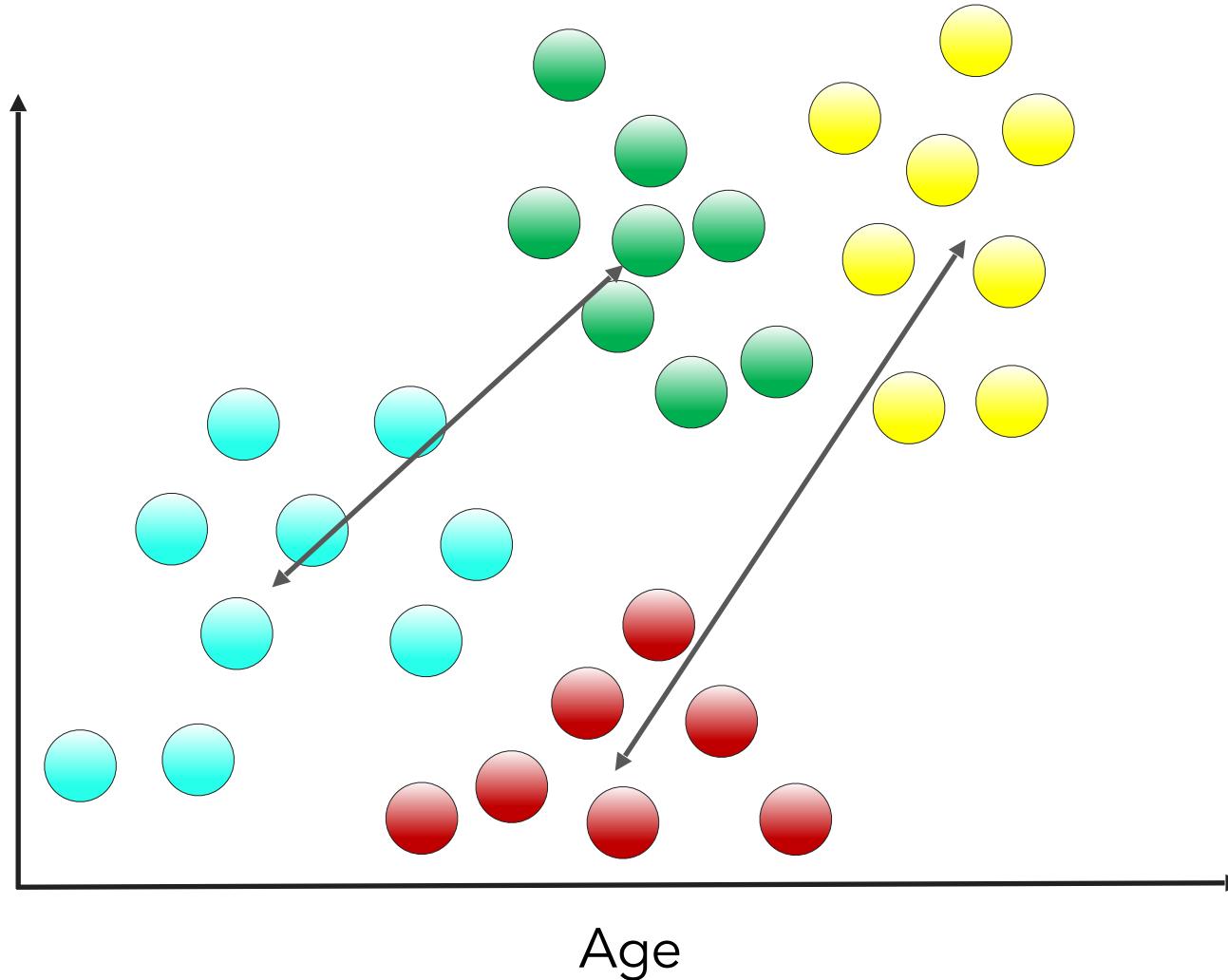


Cluster Linkage

Average: average pairwise distance between clusters

Income

Age

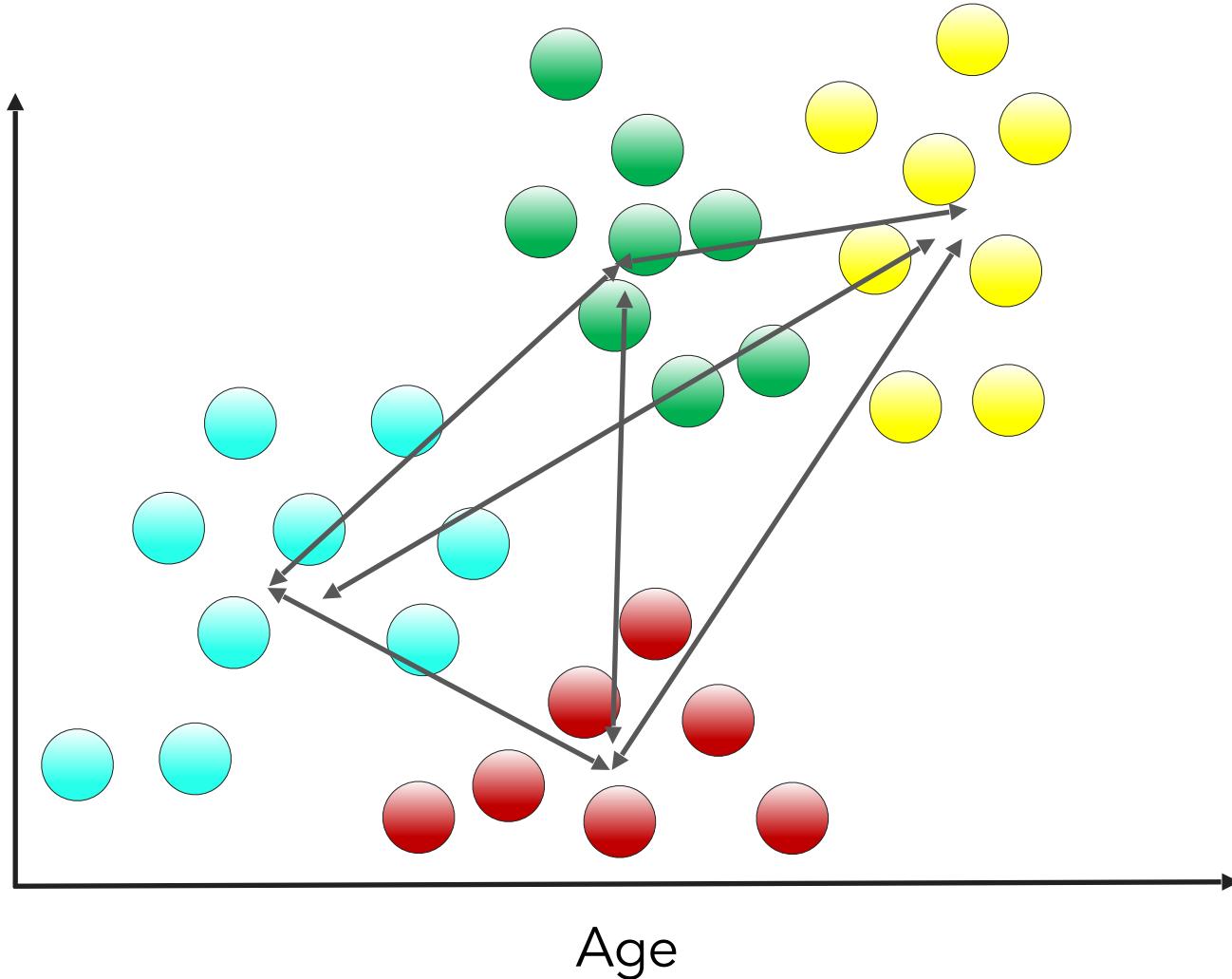


Cluster Linkage

Average: average pairwise distance between clusters

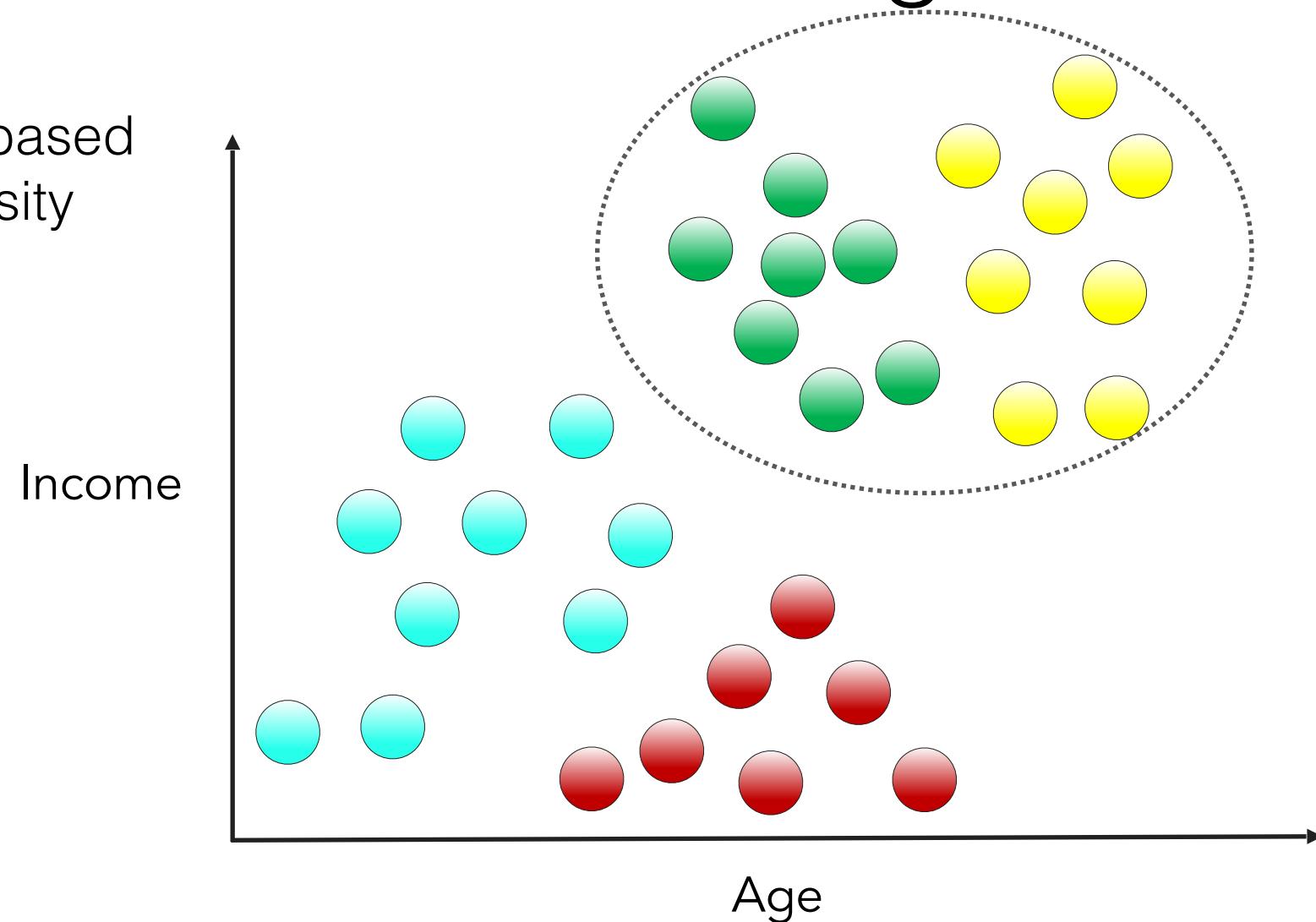
Income

Age

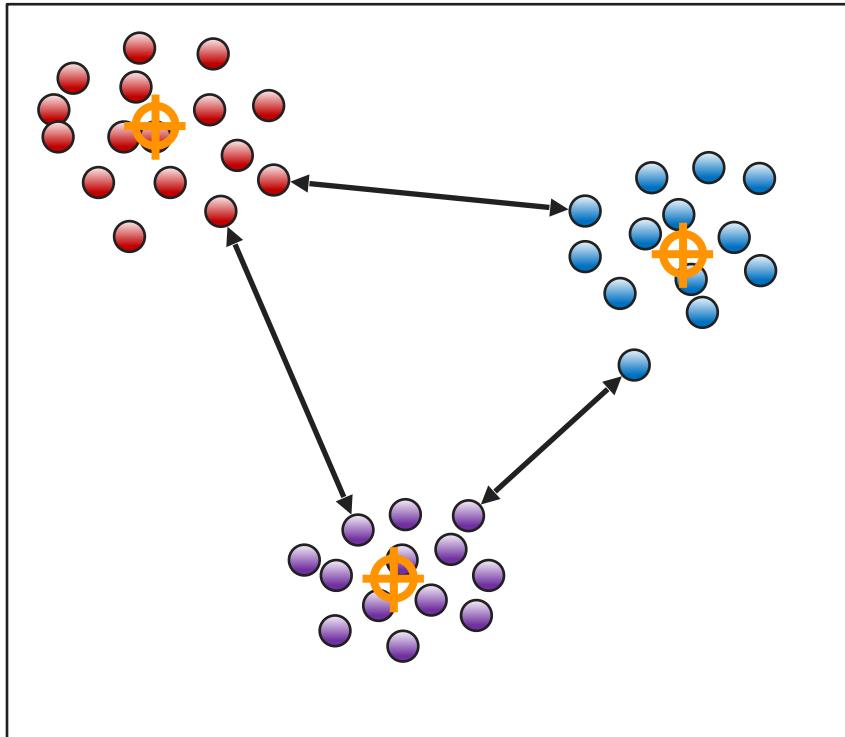


Cluster Linkage

Ward: merge based
on cluster density
(inertia)



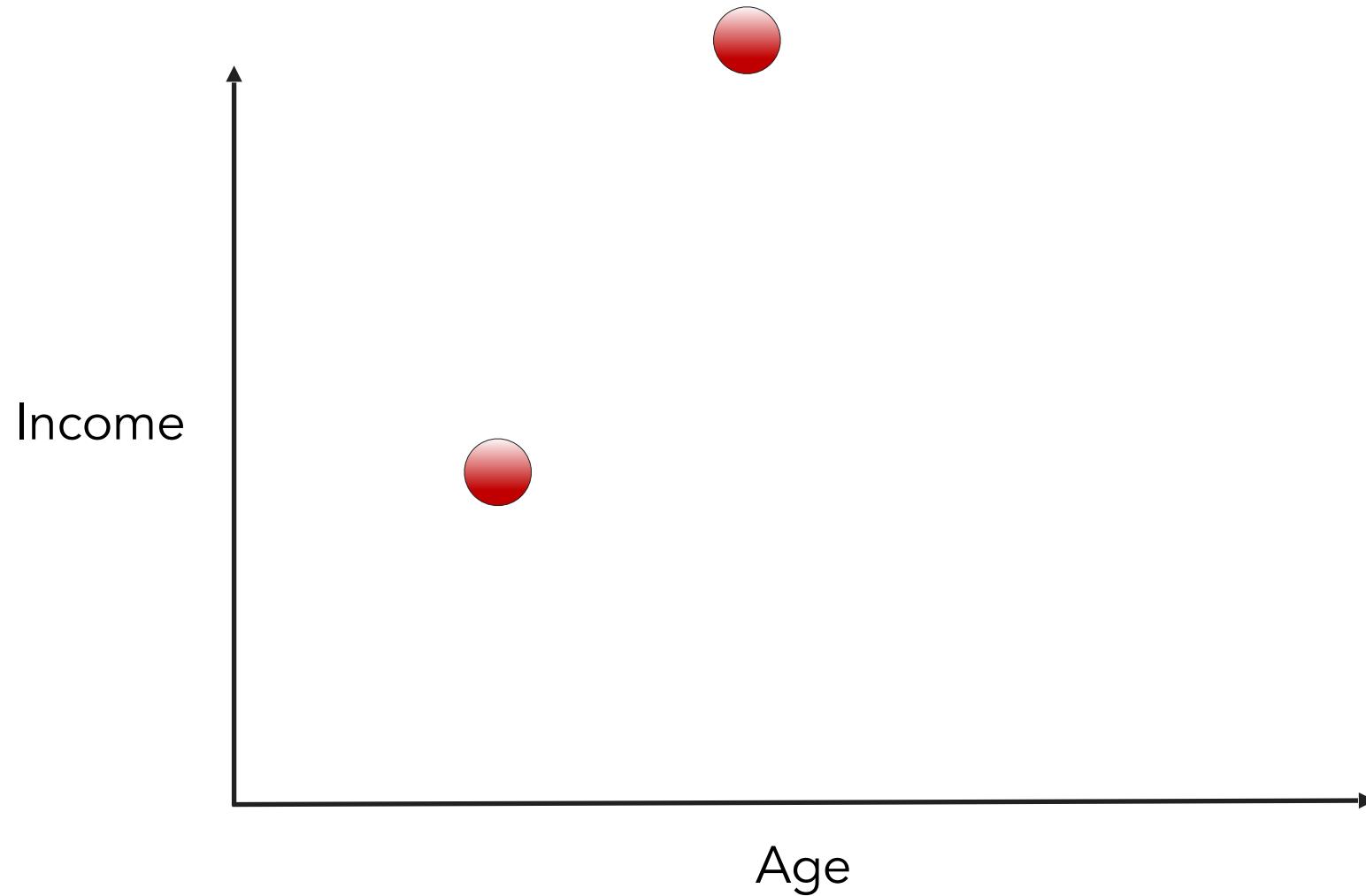
Distance Metrics



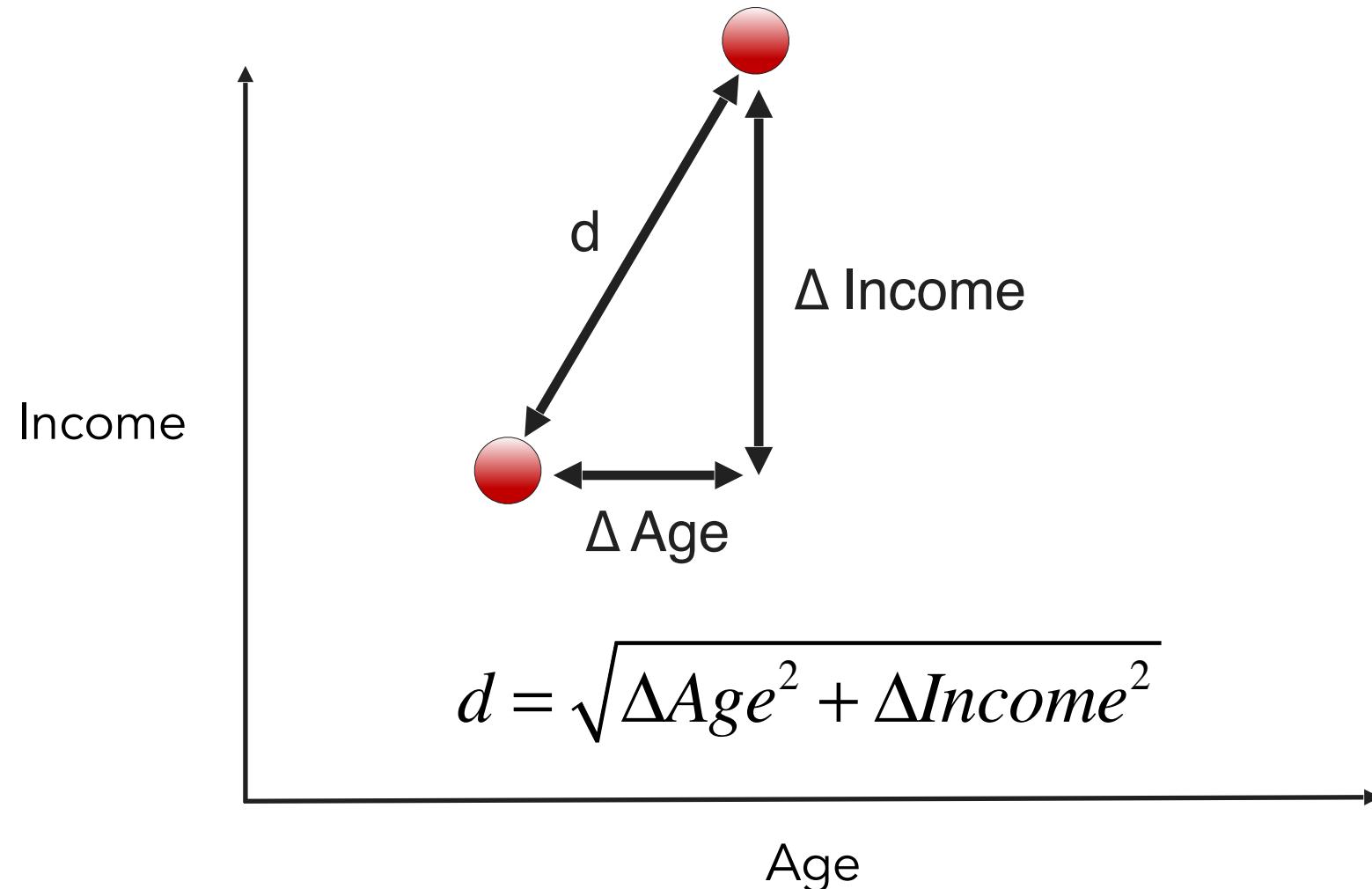
- Clustering requires measuring distance between observations
- Choice of distance metric is extremely important to clustering success



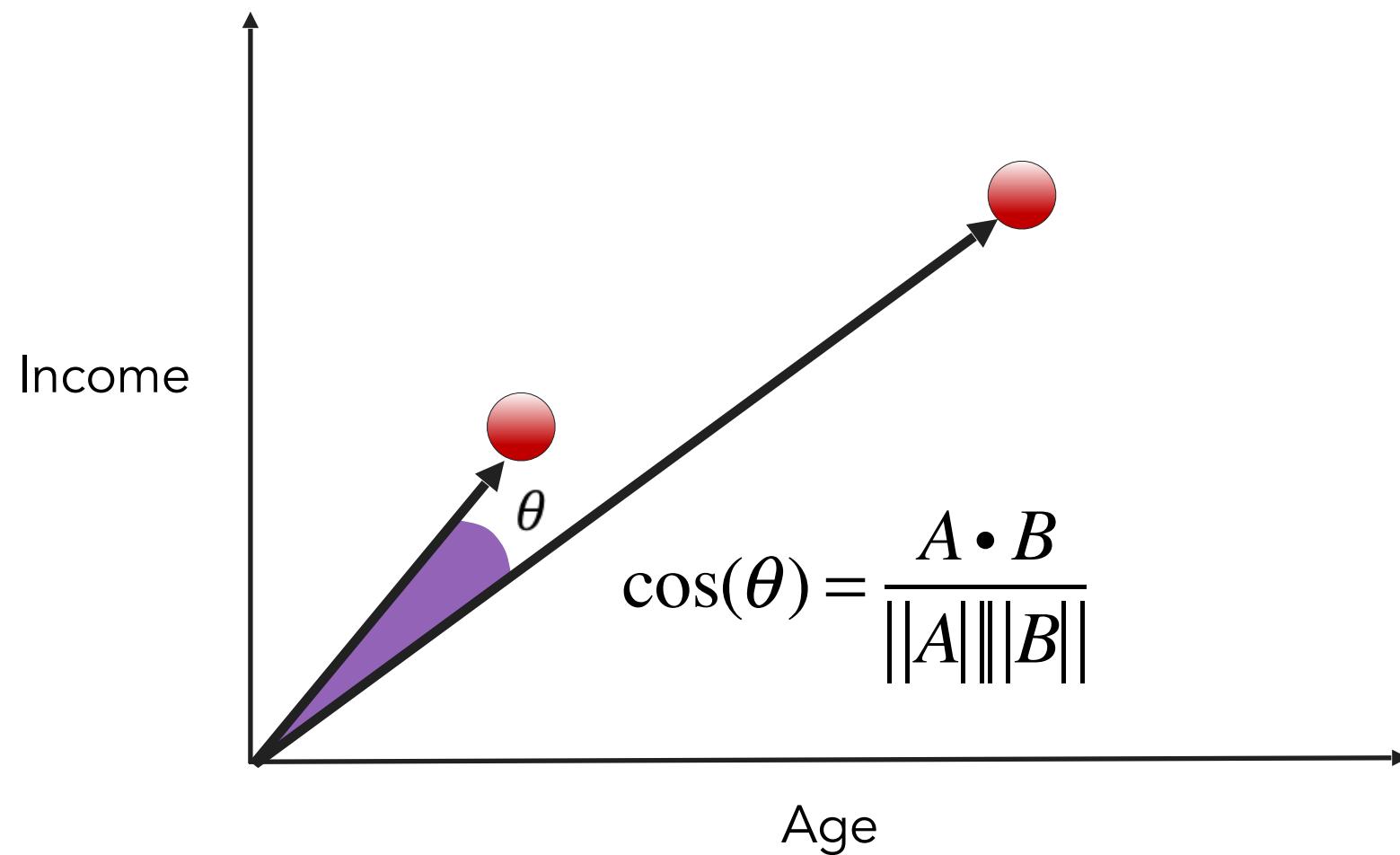
Distance Metrics



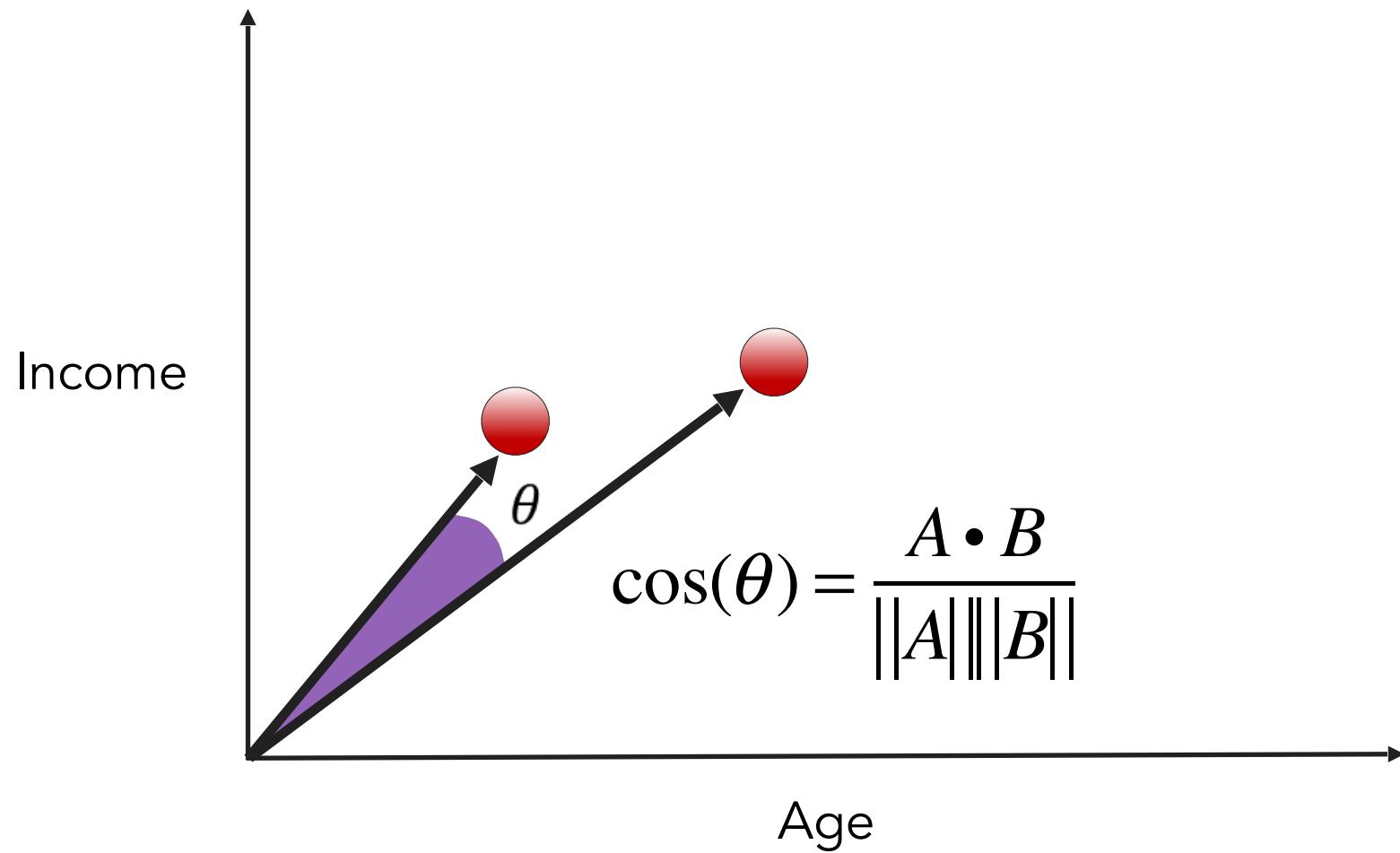
Euclidean Distance



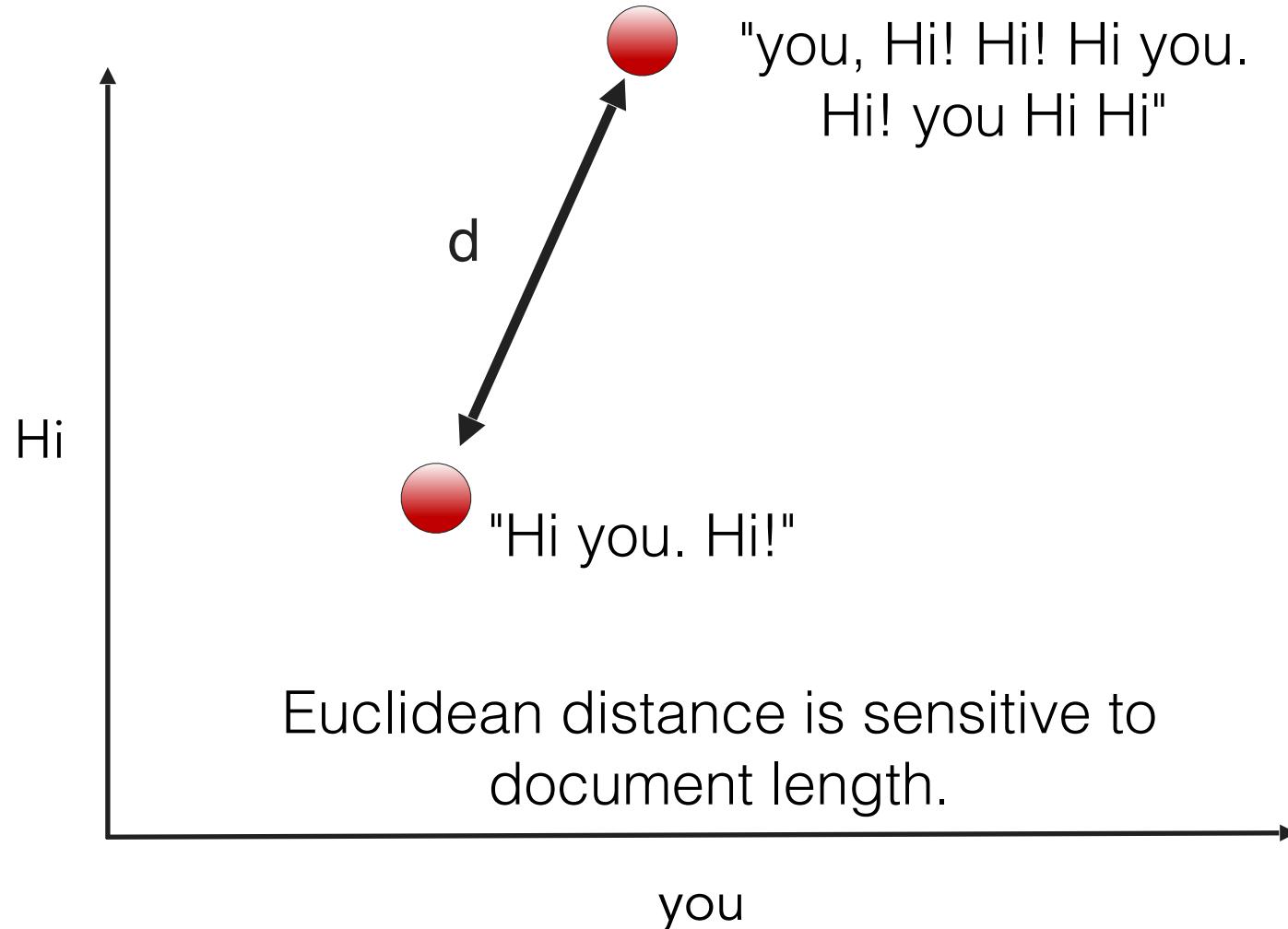
Cosine Distance



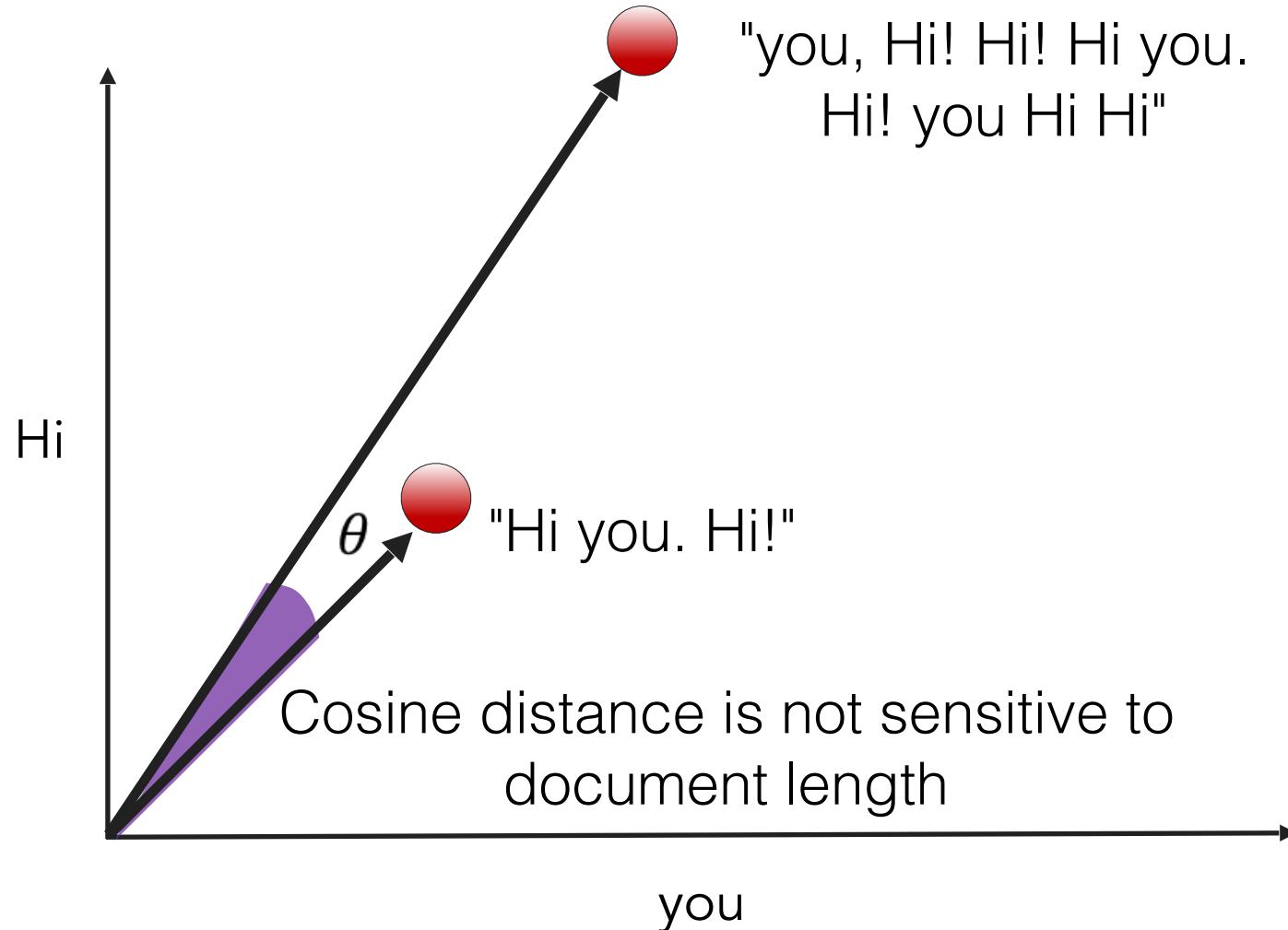
Cosine Distance



Distance Metrics for Text



Distance Metrics for Text



Practice Clustering

Walkthrough

05_Hierarchical_Clustering_Walkthrough

Exercises

06_Hierarchical_Clustering_Exercises



Topic Modeling



- Goal: Discover topics in a large collection of documents
- For example, articles arranged by topic on a news site



Document Structure



- Assume a document is a distribution of topics
- An article can be 30% business, 30% tech, 40% science



Topic Structure

- Assume a topic is a distribution over words
- Topic 1 is about sports so it uses “game” and “team” frequently
- Topic 2 can also use the words “team” or “game” but less frequently than topic 1

Topic 1		Topic 2		Topic 3	
term	weight	term	weight	term	weight
game	0.014	space	0.021	drive	0.021
team	0.011	nasa	0.006	card	0.015
hockey	0.009	earth	0.006	system	0.013
play	0.008	henry	0.005	scsi	0.012
games	0.007	launch	0.004	hard	0.011



The Goal

Topics

gene 0.04
dna 0.02
genetic 0.01
...

life 0.02
evolve 0.01
organism 0.01
...

brain 0.04
neuron 0.02
nerve 0.01
...

data 0.02
number 0.02
computer 0.01
...

Documents

Seeking Life's Bare (Genetic) Necessities

COLD SPRING HARBOR, NEW YORK—How many genes does an organism need to survive? Last week at the genome meeting here,* two genome researchers with radically different approaches presented complementary views of the basic genes needed for life. One research team, using computer analyses to compare known genomes, concluded that today's organisms can be sustained with just 250 genes, and that the earliest life forms required a mere 128 genes. The other researcher mapped genes in a simple parasite and estimated that for this organism, 800 genes are plenty to do the job—but that anything short of 100 wouldn't be enough.

Although the numbers don't match precisely, those predictions

* Genome Mapping and Sequencing, Cold Spring Harbor, New York, May 8 to 12.

"are not all that far apart," especially in comparison to the 75,000 genes in the human genome, notes Siv Andersson of Uppsala University in Sweden. "We arrived at the 800 number, but coming up with a consensus answer may be more than just a genetic numbers game; particularly as more and more genomes are completely mapped and sequenced. "It may be a way of organizing any newly sequenced genome," explains Arcady Mushegian, a computational molecular biologist at the National Center for Biotechnology Information (NCBI) in Bethesda, Maryland. Comparing all

genes in common between the two

organisms, he found that they share 22 genes.

Genes needed for最基本生存

~22 genes

冗余基因移除

~4 genes

保守基因移除

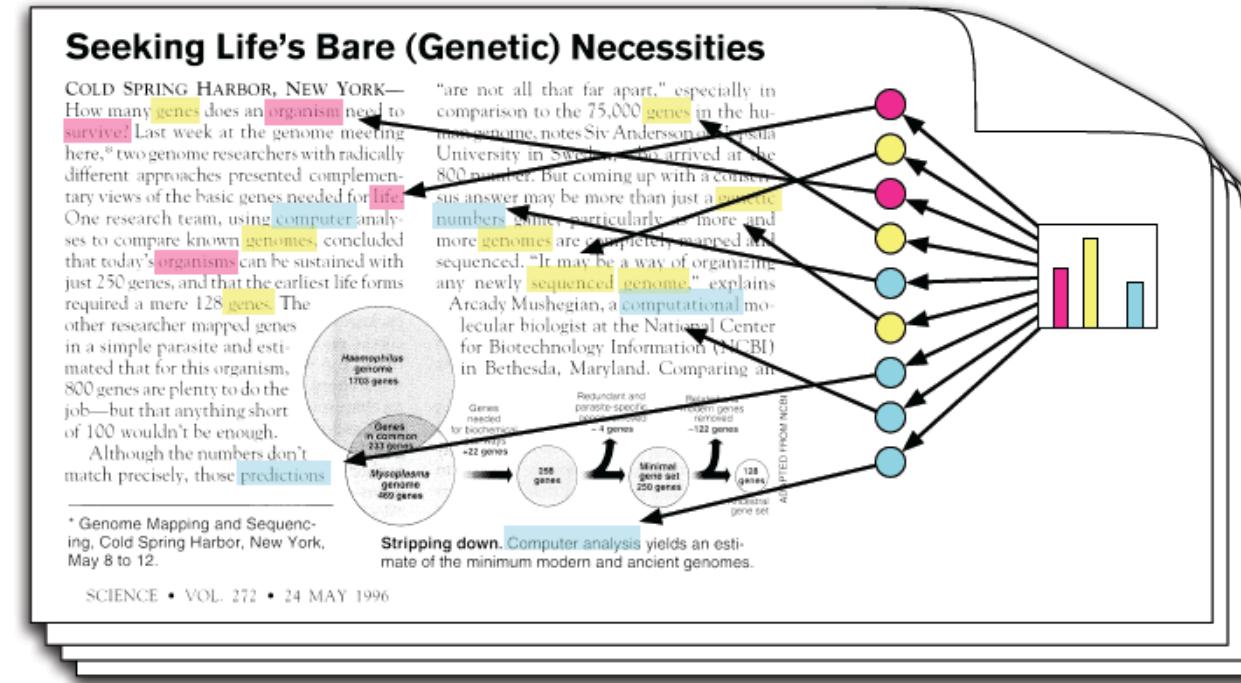
~122 genes

保守基因集

~128 genes

保守基因集

Topic proportions and assignments



- Find document topic distribution
- Based on topic word distribution



Latent Dirichlet Allocation (LDA)

- Generative model: models how the data is generated
- Assume a set of topics shared by all documents
- To create a document:
 - Generate a topic from the document topic distribution
 - Generate a word from that topic
- Repeat



How is LDA Used?

- Assume a set of documents were generated in this way
- Reverse the generative process to understand topics in a given document
- We won't go into the math
- Let's practice in Python



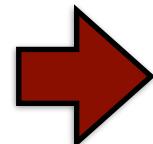
Practice Topic Modeling

- We will complete the first part of 07_LDA_Walkthrough_and_Exercises together
- Then answer the remaining questions

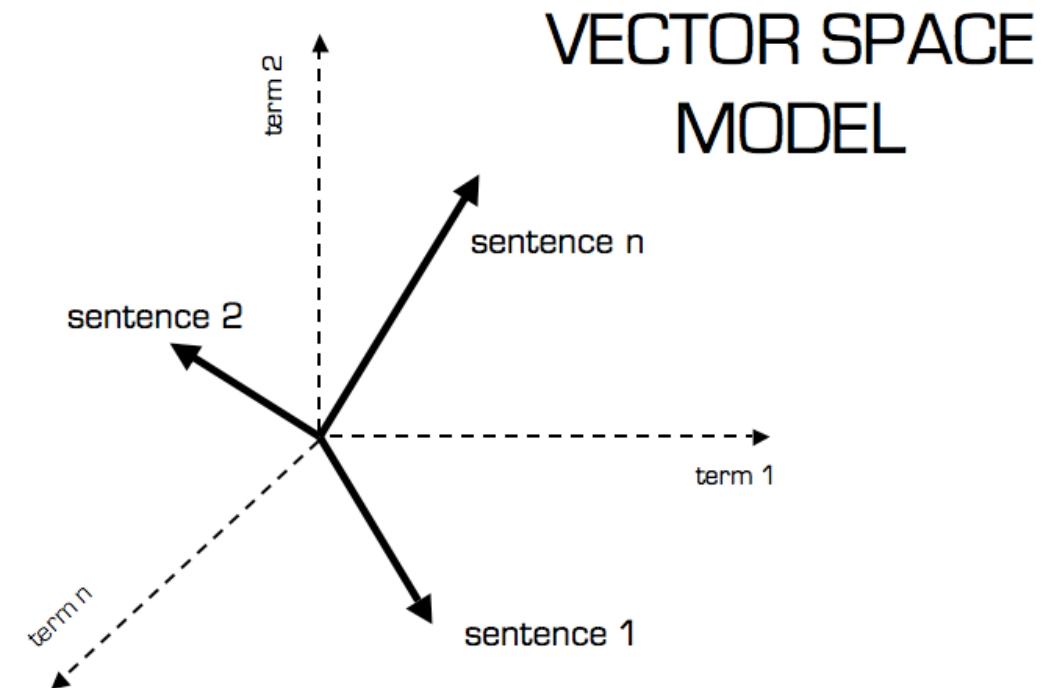


Deep Learning with Text

- **Problem:** taxonomy count increases dramatically with document size
- **Solution:** use a neural network to create a numerical representation (vector) for each word



Word2Vec



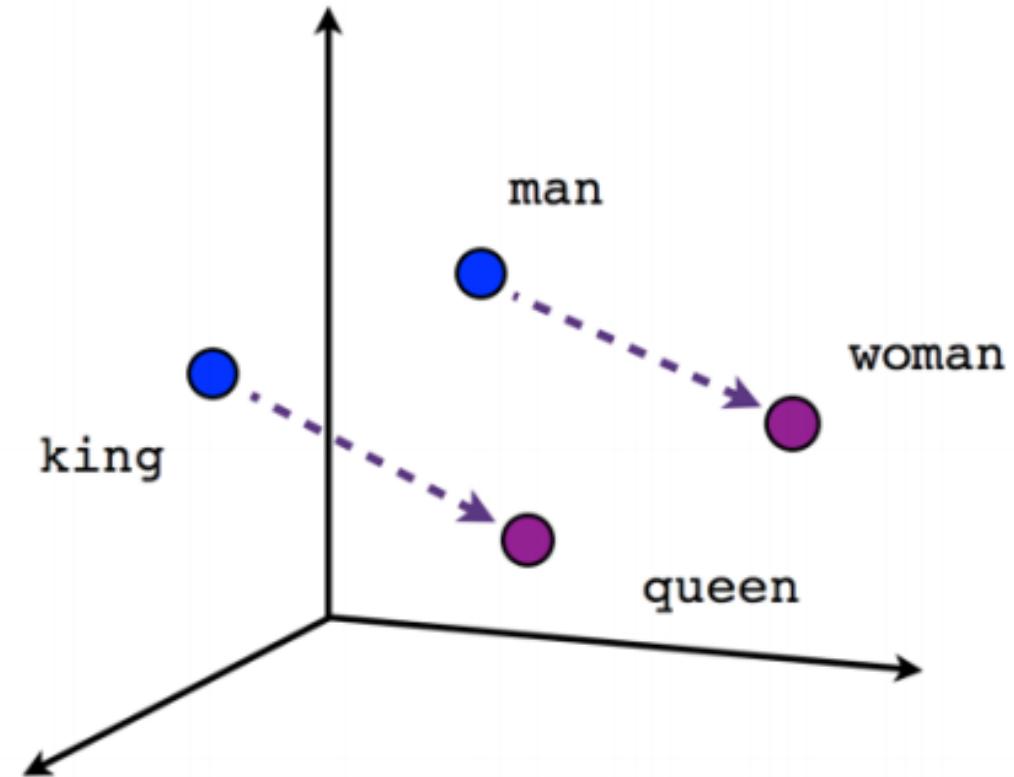
Word Embeddings with Word2Vec

- Word vectors can be used to understand relationships between words

- For example:

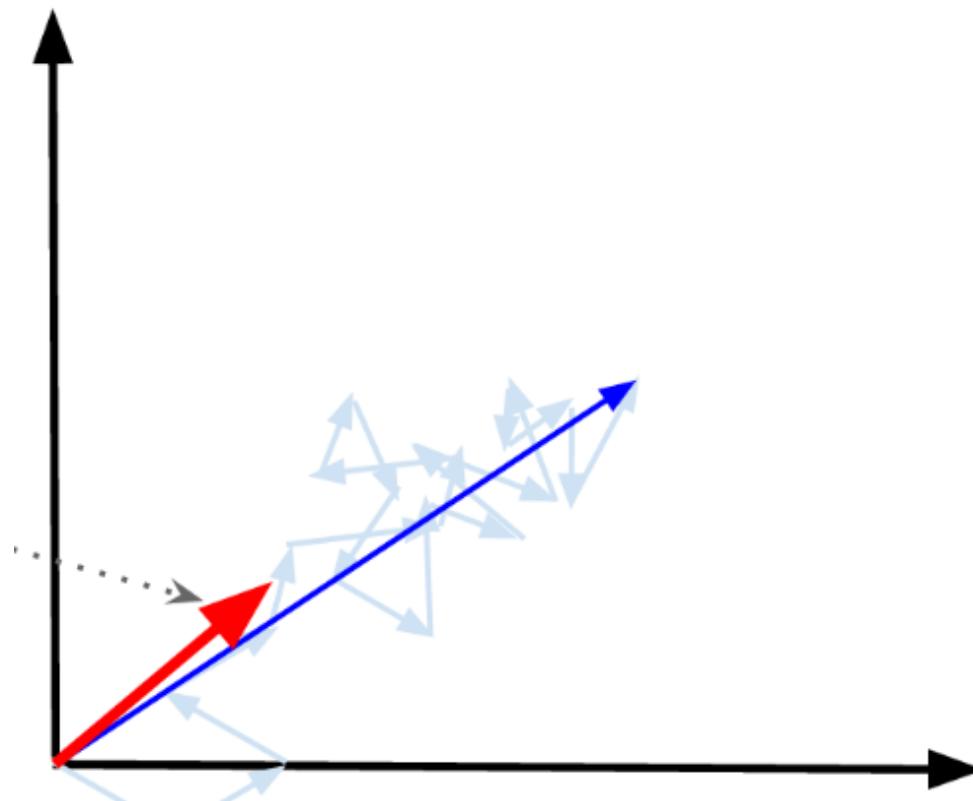
man --> woman

king --> queen



How Can We Use Word2Vec?

- Vectors can be combined to create features for documents
- Neural network requires large training set--Google, *et. al.* provide pre-trained version



Practice Word2Vec

- We will complete the first part of
08_Word2Vec_Walkthrough_and_Exercises together
- Then answer the remaining questions



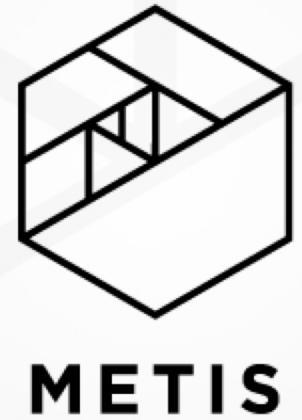
Thank You

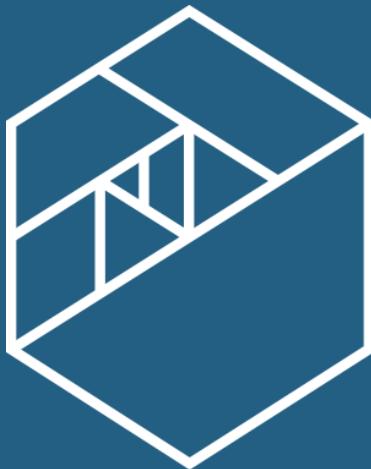
Contacting me:

- michelle@thisismetis.com
- @modernscientist
- michellelynngill.com
- github.com/mlgill

Contacting Metis:

- @thisismetis
- thisismetis.com





METIS