## **Dimensionality Reduction**

Principal Component Analysis (PCA)

t-Stochastic Neighbor Embedding (t-SNE)

Uniform Manifold Approximation and Projection (UMAP)







Quick review

We've learned several useful methods already. What sorts of things are we now good at?



Quick review

We've learned several useful methods already. What sorts of things are we now good at?

Can I always use these? If not, what are the requirements in order to run these methods?



Quick review

We've learned several useful methods already. What sorts of things are we now good at?

Can I always use these? If not, what are the requirements in order to run these methods?

What should we do if we don't have labels?



# What should we do if we don't have labels?



### Example: Galaxy spectra

SDSS/Galaxy Zoo





### Distant "Lyman Break" Galaxies

Zaroubi et al. 2013





### Distant "Lyman Break" Galaxies

Zaroubi et al. 2013



COSMIC DAWN CENTER

DAWN



COSMIC DAWN



no detection

detection

4, 2022

### Two Fundamental Assumptions for Photometry



### Two Fundamental Assumptions for Photometry

1. If an object is sufficiently well-measured, there is a surjective (one-to-one or many-to-one, but not one-to-many) mapping from photometric fluxes to astrophysical properties



### Two Fundamental Assumptions for Photometry

- 1. If an object is sufficiently well-measured, there is a surjective (one-to-one or many-to-one, but not one-to-many) mapping from photometric fluxes to astrophysical properties.
- 2. Objects with sufficiently similar photometry should be mapped to similar astrophysical properties.



## Approach 1: Color space map using two colors (three bands)

COSMOS2015 catalog, objects at z≈1





## Approach 1: Color space map using two colors (three bands)

COSMOS2015 catalog, objects at z≈1





### Approach 2: Color space map using all bands



### Two Three Fundamental Assumptions for Photometry

- 1. If an object is sufficiently well-measured, there is a surjective (one-to-one or many-to-one, but not one-to-many) mapping from photometric fluxes to astrophysical properties.
- 2. Objects with sufficiently similar photometry should be mapped to similar astrophysical properties.
- 3. We can map objects from the full, n-dimensional space with all bands to a smaller one with many neighbors, and the other two assumptions will continue to hold.



### Two Three Fundamental Assumptions for Photometry

- 1. If an object is sufficiently well-measured, there is a surjective (one-to-one or many-to-one, but not one-to-many) mapping from photometric fluxes to astrophysical properties.
- 2. Objects with sufficiently similar photometry should be mapped to similar astrophysical properties.
- 3. We can map objects from the full, n-dimensional space with all bands to a smaller one with many neighbors, and the other two assumptions will continue to hold.



Can we somehow decide what information is "important" even without labels?

https://setosa.io/ev/principal-component-analysis/





https://setosa.io/ev/principal-component-analysis/





https://setosa.io/ev/principal-component-analysis/





https://setosa.io/ev/principal-component-analysis/





https://setosa.io/ev/principal-component-analysis/





https://setosa.io/ev/principal-component-analysis/





https://setosa.io/ev/principal-component-analysis/



![](_page_24_Picture_3.jpeg)

![](_page_24_Picture_4.jpeg)

https://setosa.io/ev/principal-component-analysis/

![](_page_25_Picture_2.jpeg)

![](_page_25_Picture_3.jpeg)

![](_page_25_Picture_4.jpeg)

https://setosa.io/ev/principal-component-analysis/

![](_page_26_Picture_2.jpeg)

![](_page_26_Figure_3.jpeg)

![](_page_26_Picture_4.jpeg)

https://setosa.io/ev/principal-component-analysis/

![](_page_27_Picture_2.jpeg)

![](_page_27_Figure_3.jpeg)

COSMIC DAWN CENTER

### PCA in 17D

https://setosa.io/ev/principal-component-analysis/

	England	N Ireland	Scotland	Wales
Alcoholic drinks	375	135	458	475
Beverages	57	47	53	73
Carcase meat	245	267	242	227
Cereals	1472	1494	1462	1582
Cheese	105	66	103	103
Confectionery	54	41	62	64
Fats and oils	193	209	184	235
Fish	147	93	122	160
Fresh fruit	1102	674	957	<mark>1</mark> 137
Fresh potatoes	720	1033	566	874
Fresh Veg	253	143	171	265
Other meat	685	586	750	803
Other Veg	488	355	418	570
Processed potatoes	198	187	220	203
Processed Veg	360	334	337	365
Soft drinks	1374	1506	1572	1256
Sugars	156	139	147	175

![](_page_28_Picture_3.jpeg)

### PCA in 17D

#### https://setosa.io/ev/principal-component-analysis/

	England	N Ireland	Scotland	Wales
Alcoholic drinks	375	135	458	475
Beverages	57	47	53	73
Carcase meat	245	267	242	227
Cereals	1472	1494	1462	1582
Cheese	105	66	103	103
Confectionery	54	41	62	64
Fats and oils	193	209	184	235
Fish	147	93	122	160
Fresh fruit	1102	674	957	<mark>1</mark> 137
Fresh potatoes	720	1033	566	874
Fresh Veg	253	143	171	265
Other meat	685	586	750	803
Other Veg	488	355	418	570
Processed potatoes	198	187	220	203
Processed Veg	360	334	337	365
Soft drinks	1374	1506	1572	1256
Sugars	156	139	147	175

![](_page_29_Figure_3.jpeg)

![](_page_29_Figure_4.jpeg)

![](_page_29_Picture_5.jpeg)

1. Standardization

![](_page_30_Picture_2.jpeg)

- 1. Standardization
- 2. Compute covariance matrix

	Cov(x, x)	Cov(x, y)	Cov(x, z)
8	Cov(y, x)	Cov(y,y)	Cov(y, z)
	Cov(z, x)	Cov(z,y)	Cov(z,z)

![](_page_31_Picture_4.jpeg)

- 1. Standardization
- 2. Compute covariance matrix

 $\left[\begin{array}{ccc} Cov(x,x) & Cov(x,y) & Cov(x,z) \\ Cov(y,x) & Cov(y,y) & Cov(y,z) \\ Cov(z,x) & Cov(z,y) & Cov(z,z) \end{array}\right]$ 

3. Compute eigenvectors and eigenvalues

![](_page_32_Picture_5.jpeg)

- 1. Standardization
- 2. Compute covariance matrix

 $\left[\begin{array}{ccc} Cov(x,x) & Cov(x,y) & Cov(x,z) \\ Cov(y,x) & Cov(y,y) & Cov(y,z) \\ Cov(z,x) & Cov(z,y) & Cov(z,z) \end{array}\right]$ 

3. Compute eigenvectors and eigenvalues

4. Discard vectors that are not important enough

![](_page_33_Figure_6.jpeg)

![](_page_33_Picture_7.jpeg)

### Example: Handwritten Digits

MNIST dataset

![](_page_34_Figure_2.jpeg)

![](_page_34_Picture_3.jpeg)

Principal Component Analysis

![](_page_35_Figure_2.jpeg)

### Example: Handwritten Digits

MNIST dataset

![](_page_36_Figure_2.jpeg)

![](_page_36_Picture_3.jpeg)

### Some things aren't linear!

Wikimedia Commons

![](_page_37_Figure_2.jpeg)

![](_page_37_Picture_3.jpeg)

Pezzotti 2019

![](_page_38_Figure_2.jpeg)

![](_page_38_Picture_4.jpeg)

"Fashion MNIST" datasets, t-SNE

![](_page_39_Figure_2.jpeg)

![](_page_39_Picture_3.jpeg)

Wang et al. 2020

![](_page_40_Picture_2.jpeg)

COSMIC DAWN CENTER

## Approach 2: First, make a t-SNE map reducing to two dimensions

COSMOS2015 catalog, objects at z≈1

![](_page_41_Figure_2.jpeg)

![](_page_41_Picture_3.jpeg)

### Approach 2: Similar galaxies are nearby

COSMOS2015 catalog, objects at z≈1

![](_page_42_Figure_2.jpeg)

![](_page_42_Picture_3.jpeg)

### Approach 2: Similar galaxies are nearby

WARNING: positions are neither fixed nor meaningful. Topology is meaningful.

![](_page_43_Figure_2.jpeg)

## Approach 2: Arranging by photometry also calculates other useful things!

COSMOS2015 catalog, objects at z≈1

 $Log_{10}(M_*)$ 

COSMIC DAWN CENTER

DAWN

![](_page_44_Figure_3.jpeg)

### Approach 2: Finding "dead" galaxies

COSMOS2015 catalog, objects at z≈1

![](_page_45_Figure_2.jpeg)

COSMIC DAWN CENTER

DAWN

### Photometric Redshifts Usually Work...

![](_page_46_Figure_1.jpeg)

![](_page_46_Figure_2.jpeg)

![](_page_46_Picture_3.jpeg)

### Photometric Redshifts Usually Work...

Hovis-Afflerbach, Steinhardt et al. 2020

![](_page_47_Figure_2.jpeg)

![](_page_47_Picture_3.jpeg)

![](_page_47_Figure_4.jpeg)

![](_page_48_Figure_0.jpeg)

DAWN

### ...But Not Always!

#### About 5% of objects fail template fitting<sup>1</sup>

Can we identify these objects without comparing with spectroscopy?

Can we fix these objects and determine the correct properties?

![](_page_49_Picture_4.jpeg)

<sup>1</sup>Hildebrandt et al. 2010: 12 photo-z methods tested on objects with 18 bands, between 4.9% and 29% of objects had dz/(1+z) > 0.15