Lecture Notes for

Machine Learning in Python

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Preprocessing and Visualization

Class Logistics and Agenda

- Participation/Teams
- Be sure you look at **Lab One**!
- Dataset Selection Now Complete! Probably! … maybe?
- Agenda
  - Finish Pandas Demo with Imputation, *if needed*
  - Data Exploration
  - Data Preprocessing
  - Data Visualization

Class Overview, by topic

Table Data Visualization

Numpy, Pandas, Seaborn
Overviews with some in-depth discussion

Dimension Reduction and Image Processing

Scikit-learn, Scikit Image,
Intuition only, Some mathematics

Linear and Logistic Regression

Numpy, Recreate API for Scikit-learn
Detailed mathematics for simple optimization
intuition for advanced optimization

Neural Networks and Back Prop.

Numpy
Detailed mathematics for NN operations

Wide and Deep Networks

Convolutional Networks

Recurrent Networks

Keras, Tensorflow
Intuition, Detailed implement.

Ethics in Language Models

ConceptNet
Case studies

Last Time

- Datatypes
- Imputation
- Document Features

Feature Type Representation Review

	Attribute	Representation Transformation	Comments
Discrete	Nominal	Any permutation of values one hot encoding	If all employee ID numbers were reassigned, would it make any difference?
Discrete	Ordinal	An order preserving change of values, i.e., new_value = f(old_value) where f is a monotonic function. integer	An attribute encompassing the notion of good, better best can be represented equally well by the values {1, 2, 3} or by { 0.5, 1, 10}.
Continuous	Interval	new_value =a * old_value + b where a and b are constants float	Thus, the Fahrenheit and Celsius temperature scales differ in terms of where their zero value is and the size of a unit (degree).
Continuous	Ratio	new_value = a * old_value float	Length can be measured in meters or feet.

K-Nearest Neighbors Imputation

TID	Pregnant	BMI	Age	Diabetes
1	Y	33.6	41-50	positive
2	N	26.6	31-40	negative
3	Y	23.3	?	positive
4	?	28.1	21-30	negative
5	N	43.1	31-40	positive
6	Y	25.6	21-30	negative
7	Y	31.0	21-30	positive
8	Y	35.3	?	negative
9	N	30.5	51-60	positive
10	Y	37.6	51-60	positive

For K=3, find 3 closest neighbors

TID	Pregnant	BMI	Age	Diabetes	Dist
3	Y	23.3	?	positive	0
6	Y	25.6	21-30	negative	(0+2.3+1)/3
2	N	26.6	31-40	negative	(1+3.3+1)/3
4	?	28.1	21-30	negative	(4.8+1)/2

How to calculate distance?

- Difference for valid features only
- May need to normalize ranges
- Or weight neighbors differently
- Or have min # of valid features
- Euclidean, city-block, etc.

Demo

Start
Pandas demo

DataFrames
Loading
Indexing
Imputing

“if needed”
Pandas demo

- DataFrames
- Loading
- Indexing
- Imputing

03.Data Visualization.ipynb

Data Exploration

What is data exploration?

A preliminary exploration of the data to better understand its characteristics.

- Help **select** the **right tool** for preprocessing or analysis

- Exploratory Data Analysis (EDA) by Dr. John Tukey:
  - The focus was visualization
  - Clustering and anomaly detection were viewed as exploratory techniques

- In our discussion,
  - Summary statistics, aggregations
  - Visualizing summaries

Summary Statistics

- frequency, location, and spread
  - Examples: location by **mean**
    spread by **standard deviation**
- Most summary statistics can be calculated in a single pass through the data

$$\text{sample} \quad \text{mean}(x) = \overline{x} = \frac{1}{m}\sum_{i=1}^{m} x_i$$

$$\begin{array}{c}\text{sample}\\ \text{median}(x)\end{array} = \begin{cases} x_{(r+1)} & \text{if } m \text{ is odd, i.e., } m = 2r+1 \\ \frac{1}{2}(x_{(r)} + x_{(r+1)}) & \text{if } m \text{ is even, i.e., } m = 2r \end{cases}$$

- For nominal data, mode or frequency is most common

Tan, Steinbeck, Kumar

Measures of **Spread**

- **Range** is the difference between the max and min
- The **variance** or standard deviation is the most common measure of the spread of a set of points.

$$\underset{\text{variance}}{\text{sample}}(x) = s_x^2 = \frac{1}{m-1}\sum_{i=1}^{m}(x_i - \overline{x})^2$$

- However, this is also sensitive to outliers, so that other measures are often used.

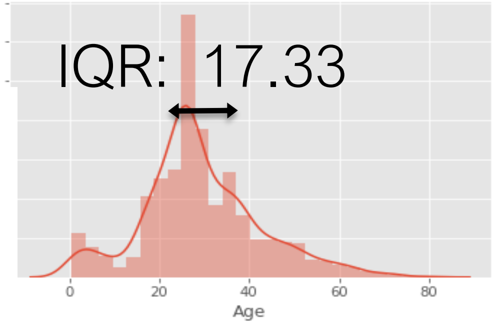
Average Absolute Difference

$$\text{AAD}(x) = \frac{1}{m}\sum_{i=1}^{m}|x_i - \overline{x}|$$

Median Absolute Difference

$$\text{MAD}(x) = median\left(\{|x_1 - \overline{x}|, \ldots, |x_m - \overline{x}|\}\right)$$

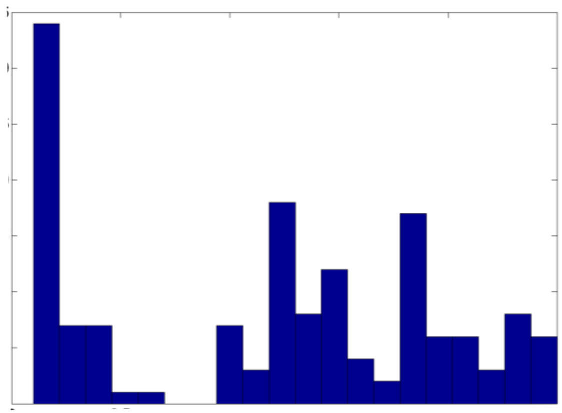
$$\text{interquartile range}(x) = x_{75\%} - x_{25\%}$$



STD: 13.89
AAD: 10.67
MAD: 8.29

Self Test 2a.1

What measure of **spread** is **most appropriate** for the data in the histogram below?



A) Standard Deviation
B) Interquartile Range
C) Median Absolute Difference
D) None of these

Data Preprocessing

Preprocessing

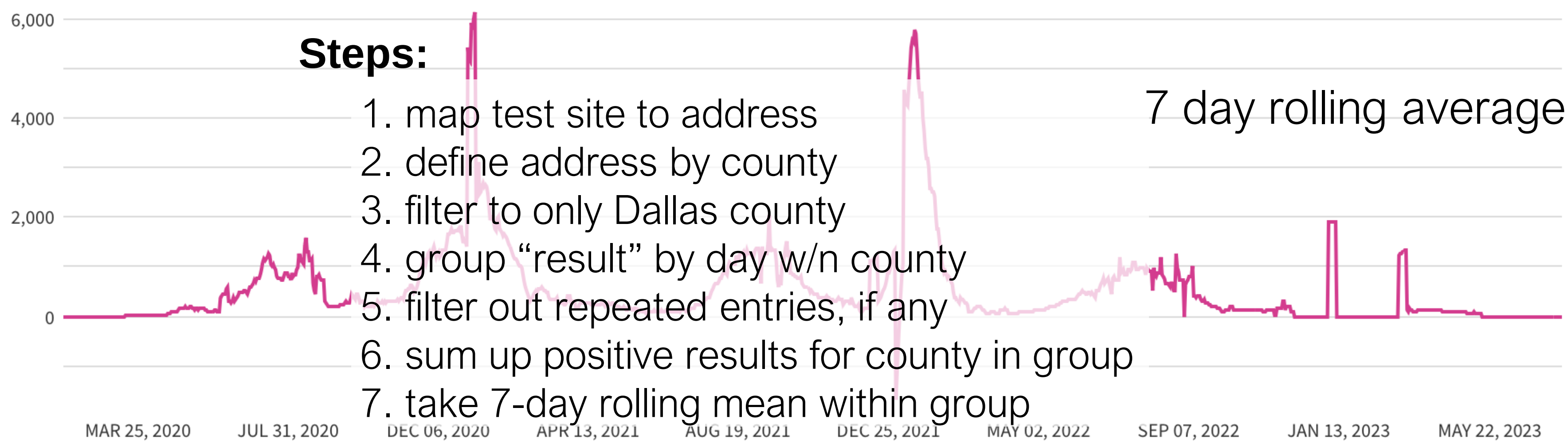
- Common preprocessing techniques:
  - **Aggregation: Combine features/samples**
    - Reduce the number of attributes or objects
    - Aggregated data tends to be more stable
  - **Transformation: Change of scale**
    - Normalize dynamic ranges
    - More numerically stable when combining
  - **Quantization: Make discrete**
    - More stable
    - More semantically meaningful

Preprocessing: Aggregation

COVID Cases in Dallas County
696,581

data/image from [cdc.gov](cdc.gov)

Number of daily cases



Steps:

1. map test site to address
2. define address by county
3. filter to only Dallas county
4. group "result" by day w/n county
5. filter out repeated entries, if any
6. sum up positive results for county in group
7. take 7-day rolling mean within group

7 day rolling average

Mar. 2020

May 2023

How has aggregation has been used to create these plots?

TID	Location	time	test	Probable?
1	test site name	day and hour	test result	yes/no

Preprocessing: Transformation

- Monotonically map one set of values to a set of replacement values
- **Standardization and Normalization**
  - z-scores `df_normalized = (df-df.mean())/(df.std())`
  - min/max `df_normalized = (df-df.min())/(df.max()-df.min())`

Normalization options in scikit-learn:

`preprocessing.maxabs_scale`(X, *[, axis, copy])	Scale each feature to the [-1, 1] range without breaking the sparsity.
`preprocessing.minmax_scale`(X[, ...])	Transform features by scaling each feature to a given range.
`preprocessing.normalize`(X[, norm, axis, ...])	Scale input vectors individually to unit norm (vector length).
`preprocessing.quantile_transform`(X, *[, ...])	Transform features using quantiles information.
`preprocessing.robust_scale`(X, *[, axis, ...])	Standardize a dataset along any axis
`preprocessing.scale`(X, *[, axis, with_mean, ...])	Standardize a dataset along any axis.
`preprocessing.power_transform`(X[, method, ...])	Power transforms are a family of parametric, monotonic transformations that are applied to make data more Gaussian-like.

Attribute Transformation in Python

```
>>> from sklearn import preprocessing
>>> import numpy as np
>>> X = np.array([[ 1., -1.,  2.],
...               [ 2.,  0.,  0.],
...               [ 0.,  1., -1.]])
>>> X_scaled = preprocessing.scale(X)
>>> X_scaled
array([[ 0.  ..., -1.22...,  1.33...],
       [ 1.22...,  0.  ..., -0.26...],
       [-1.22...,  1.22..., -1.06...]])
```

using direct functions

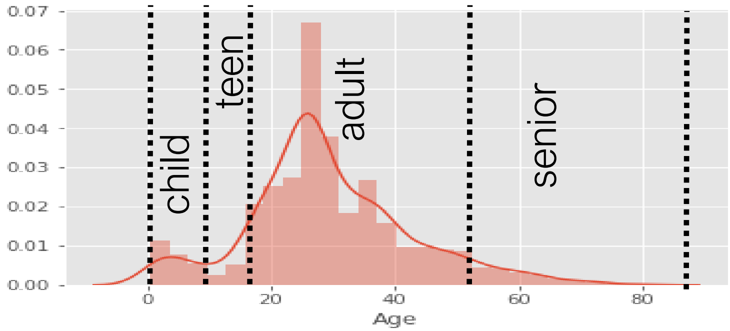
```
>>> scaler = preprocessing.StandardScaler().fit(X)
>>> scaler
StandardScaler(copy=True, with_mean=True, with_std=True)

>>> scaler.mean_
array([ 1. ...,  0. ...,  0.33...])

>>> scaler.std_
array([ 0.81...,  0.81...,  1.24...])

>>> scaler.transform(X)
array([[ 0.  ..., -1.22...,  1.33...],
       [ 1.22...,  0.  ..., -0.26...],
       [-1.22...,  1.22..., -1.06...]])
```

using object oriented approach
Preferred!!

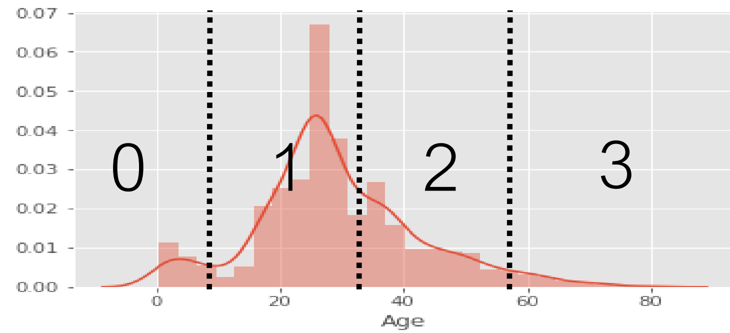
Preprocessing: Quantization

Expert selected

pandas.cut(dataframe.var, [5,10,15])

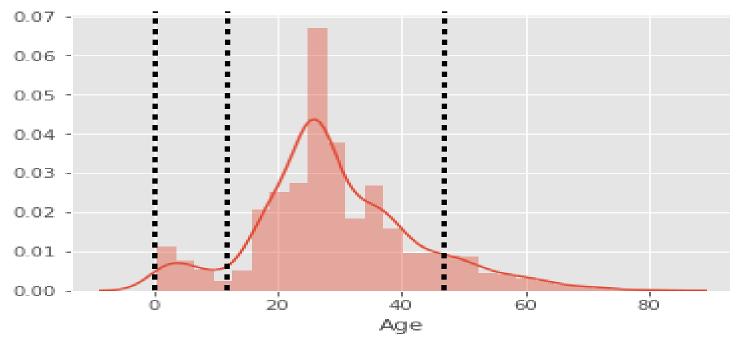


Data



Equal interval width

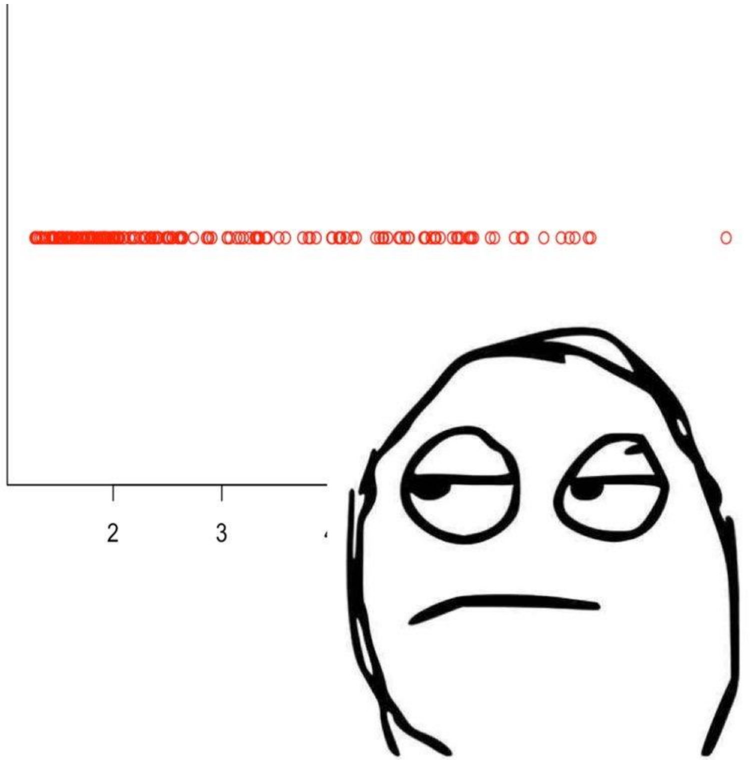
Equal frequency

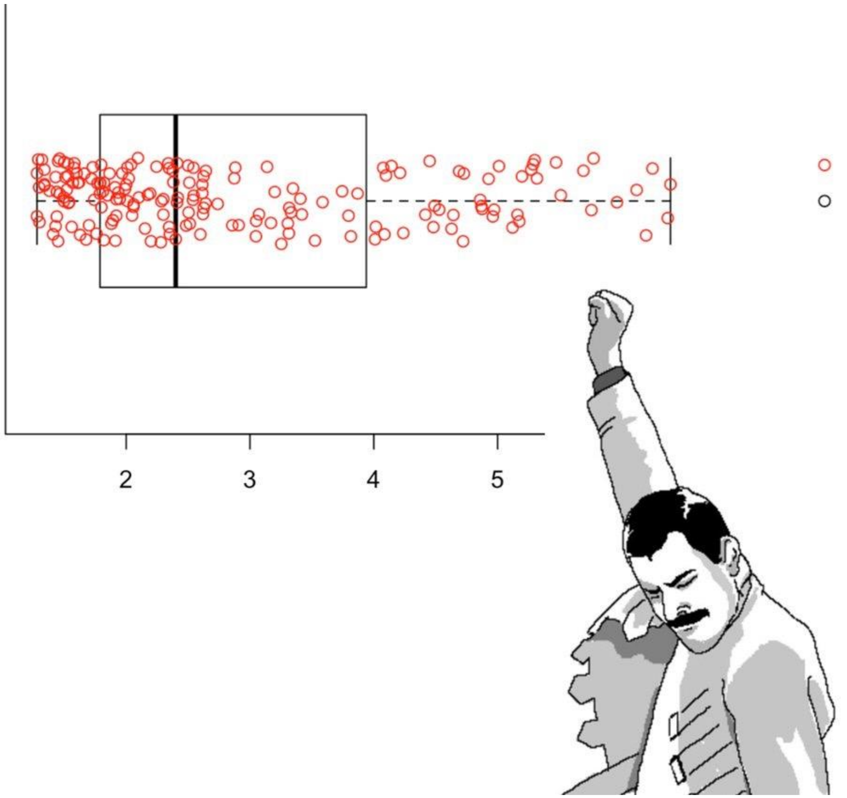


clustering: *e.g.*, K-means

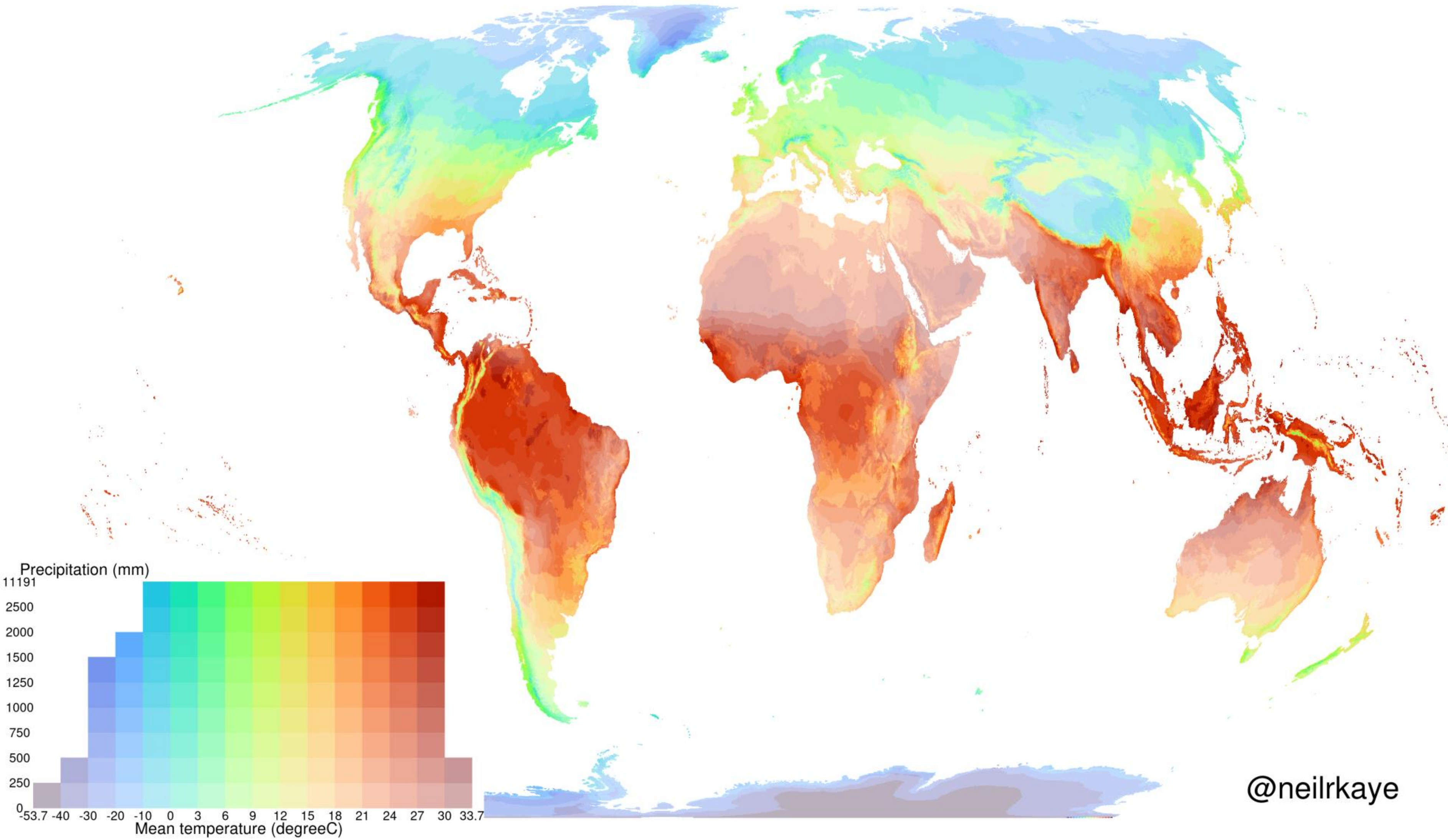
```
num_quantiles = 4
pandas.qcut(dataframe.var, num_quantiles)
```

Data Visualization





Annual mean temperature and precipitation totals (long term average)



Choosing How/What to Visualize?

- Start with a question you want to understand
- Think about the **best plot** to answer the question
  - Do you have the **right data** for visualizing?
  - Do you need to **worry** about the **amount** of data in the plot (aliasing, low samples, etc.)?
  - Can your question be answered **reliably**?
- **Interpret** the visualization: Did it answer the question?
  - **No**: Think of another visual
  - **Kinda**: Ask a follow up question
  - **Yes**: No it didn't, think more critically

Matplotlib

- Python plotting utility
  - Has **low level plotting** functionality
  - Highly **similar to Matlab and R** for plotting
- Extended to be visually more beautiful by
  - **seaborn**: stanford data visualization group

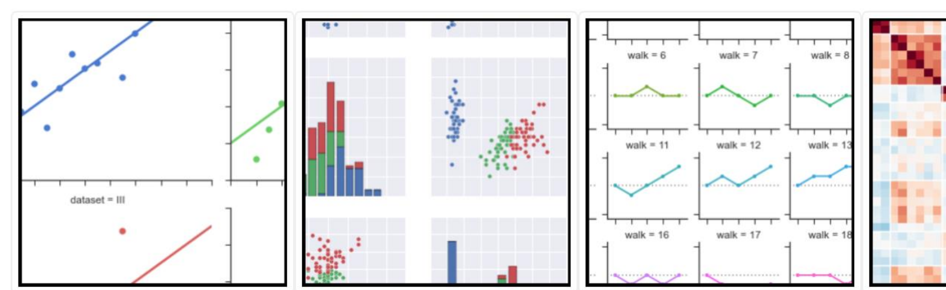
John Hunter (1968-2012)

On August 28 2012, John D. Hunter, the creator of matplotlib, died from complications arising from cancer treatment, after a brief but intense battle with this terrible illness. John is survived by his wife Miriam, his three daughters Rahel, Ava and Clara, his sisters Layne and Mary, and his mother Sarah.

If you have benefited from John's many contributions, please say thanks in the way that would matter most to him. Please consider making a donation to the John Hunter Memorial Fund.

matplotlib

Seaborn: statistical data visualization



Let's look at some graphs

Demo

- You tell me what conclusions we are getting from these graphs
  - Histogram
  - KDE
  - HeatMaps and Correlation
  - Scatter and Scatter Matrix
  - Box / Violin / Swarm

03.Data Visualization.ipynb

Matplotlib

Seaborn

Plotly

Let’s look at some graphs

Demo

03.Data Visualization.ipynb

Other Tutorials:

https://t.co/zNzD8Q8w5E

http://matplotlib.org/examples/index.html

http://stanford.edu/~mwaskom/software/seaborn/index.html

http://pandas.pydata.org/pandas-docs/stable/visualization.html

http://nbviewer.ipython.org/github/mwaskom/seaborn/blob/master/examples/plot
ributions.ipynb

For Next Lecture

- Next Time:
  - Finish Visualization Demo
  - First Town Hall Meeting
- Look at chapter 5 of Python Machine Learning