Data Preparation

UBCO Master of Data Science – DATA 542

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Lecture 3 - review

Data cleaning

Handling missing values

Data preparation

Prepare data for analysis

- Remove duplicates
- Replace values
- Filter outliers
- Rename Axis
- Binning

Discuss rationales for each action

Data preparation

Prepare data for analysis

- Remove duplicates
- Replace values
- Filter outliers
- Rename Axis
- Binning

- perform better statistics
- balanced dataset
- Null replacement
- string with numbers
- standardize
- Renaming axis → clear or easier data processing
- Transforming: F ↔ C
  inch ↔ cm

Discuss rationales for each action

Question Try It

Question 1: What is `data`?

```
data = pd.DataFrame({'k1': ['one', 'two'] * 3 + ['two'],
                     'k2': [1, 1, 2, 3, 3, 4, 4]})
```

	k1	k2
0	1	1
1	2	1
2	1	2
3	2	3
4	1	3
5	2	4
6	2	4

A)

	k1	k2
0	one	1
1	two	1
2	one	2
3	two	3
4	one	3
5	two	4
6	two	4

B)

	0	1	2	3	4	5	6
k1	one	two	one	two	one	two	two
k2	1	1	2	3	3	4	4

C)

	k1	k2
0	5	1
1	8	1
2	5	2
3	8	3
4	5	3
5	8	4

D)

Duplicates

Investigate duplicates in the data:

```
data = pd.DataFrame(
        {'k1': ['one', 'two'] * 3 + ['two’],
         'k2': [1, 1, 2, 3, 3, 4, 4]})
```

```
data.duplicated(keep=)
```

Returns Boolean value

```
keep argument is by default the first
observation
```

```
keep =‘last’ will return the last observation
```

Duplicates cont.

```
data.duplicated()
```

```
0    False
1    False
2    False
3    False
4    False
5    False
6     True
dtype: bool
```

```
data.duplicated(keep='last')
```

```
0    False
1    False
2    False
3    False
4    False
5     True
6    False
dtype: bool
```

Drop duplicates

Drop duplicate observations in the data, or filter it by each column

```
data.drop_duplicates([column_names], keep)
```

Optional

```
data[‘v1’] = range(7)
data.drop_duplicates(['k1','k2'], keep='last’)
data.drop_duplicates(['k1'], keep='last')
```

	k1	k2	v1
0	one	1	0
1	two	1	1
2	one	2	2
3	two	3	3
4	one	3	4
5	two	4	5
6	two	4	6

	k1	k2	v1
4	one	3	4
6	two	4	6

Replacing values

Replace values using lists or dictionaries

`data.replace(value, replacement)`

`value` and `replacement` can be lists

`data.replace({value:replacement, value:replacement)`

```
data.replace([-999, -1000], np.nan)
data.replace([-999, -1000], [np.nan, 0], inplace=True)
```

Try IT

Use the first dataframe you created and apply duplicate functions we learned. Drop duplicates, and replace values.

Try IT

Question 1: Create the following Dataframe:

Hint: Use `numpy arrays functions for the values`

```
pd.DataFrame()
np.arange()
np.reshape()
```

	one	two	three	four
Ohio	0	1	2	3
Colorado	4	5	6	7
New York	8	9	10	11

Renaming axis indices

Three options to rename axis indices:

	one	two	three	four
Ohio	0	1	2	3
Colorado	4	5	6	7
New York	8	9	10	11

```
data.rename(index=str.title, columns=str.upper)

data.rename(index={‘Ohio': 'INDIANA'},
            columns={'three': 'peekaboo’})

data.rename(index={‘Ohio': 'INDIANA'},
inplace=True)
```

Try It

Renaming axis indices

Create, modify or rename new/existing axis labels with `map` or `rename`

	one	two	three	four
Ohio	0	1	2	3
Colorado	4	5	6	7
New York	8	9	10	11

Inplace assignment:

```
data.columns = data.columns.map(lambda x: x.upper())
```

```
data.index = data.index.map(lambda x: x.upper())
```

Try It

Anonymous Function

Anonymous function is a function that is defined without a name.

Use it as an argument to a higher-order function (a function that takes in other functions as arguments), such as map, filter

`def` keyword => `lambda` keyword

```
lambda arguments: expression
```

```
def double(x):
    return x * 2
```

```
lambda x: x * 2
```

Discretization and Binning

Need for binning into categories, with `pandas cut`

```
pd.cut(data, bins, labels, precision, right)
```

1D array

Bins list
Or an Integer

Optional: Labels list

Optional: Decimal precision

Optional Boolean:
right inclusion/exclusion

```
ages = [20, 22, 25, 27, 21, 23, 37, 31, 61, 45,
41, 32]
```

Binning cont.

```
ages = [20, 22, 25, 27, 21, 23, 37, 31, 61, 45, 41, 32]
```

```
bins = [18,25,35,60,100]
```

```
cats = pd.cut(ages,bins)
```

```
[(18, 25], (18, 25], (18, 25], (25, 35], (18, 25], ..., (25, 35], (60, 100], (35, 60], (35
, 60], (25, 35]]
Length: 12
Categories (4, interval[int64]): [(18, 25] < (25, 35] < (35, 60] < (60, 100]]
```

Right interval inclusion

```
cats = pd.cut(ages,bins, right= False)
```

```
[[18, 25), [18, 25), [25, 35), [25, 35), [18, 25), ..., [25, 35), [60, 100), [35, 60), [35
, 60), [25, 35)]
Length: 12
Categories (4, interval[int64]): [[18, 25) < [25, 35) < [35, 60) < [60, 100)]
```

Changing intervals: Right exclusion

Binning cont.

`Categories` object with attributes `Codes` and `Categories`

```
cats=pd.cut(x=ages,bins=bins,labels=['Youth',
'YoungAdult', 'MiddleAged', 'Senior'])
```

```
cats.categories
```

```
Index(['Youth', 'YoungAdult', 'MiddleAged', 'Senior'], dtype='object')
```

```
cats.codes
```

```
array([0, 0, 0, 1, 0, 0, 2, 1, 3, 2, 2, 1], dtype=int8)
```

```
pd.value_counts(cats)
```

```
Youth         5
MiddleAged    3
YoungAdult    3
Senior        1
dtype: int64
```

Binning cont.

Binning with integers: computes equal-length bins based on the minimum and maximum values in the data

```
data = np.random.rand(20)
pd.cut(data, 4, precision=2)
```

```
Categories (4, interval[float64]): [(0.0049, 0.24] < (0.24, 0.48] < (0.48, 0.72] < (0.72,
0.96]]
```

```
pd.value_counts(cats)

(0.72, 0.96]      9
(0.24, 0.48]      7
(0.48, 0.72]      3
(0.0049, 0.24]    1
dtype: int64
```

1. Try It.
2. Search: what is precision?

Binning cont.

Binning with integers: using qcut for roughly equal sized bins

```
data = np.random.rand(1000)
pd.qcut(data,4, precision = 2)
```

```
Categories (4, interval[float64]): [(-0.00969, 0.24] < (0.24, 0.5] < (0.5, 0.74] < (0.74,
1.0]]
```

```
(0.74, 1.0]          250
(0.5, 0.74]          250
(0.24, 0.5]          250
(-0.00969, 0.24]     250
dtype: int64
```

Try IT

Use the previous slides and Try binning!

Outliers

What is an outlier?

Why should we detect outliers?

What should we do with the outliers?

Outliers

Reasons:

- Data errors (data entry error, measurement error)
- high variations

Outlier types:

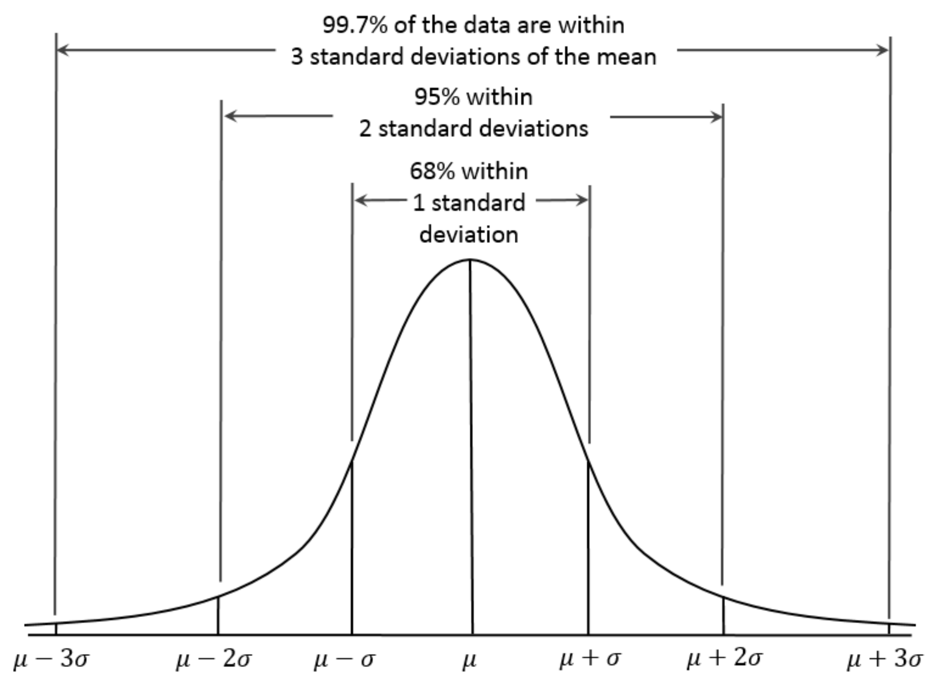
- Univariate
- Multivariate

Methods: Statistical methods and ML methods

- Z-score, Modified Z-Score, Maximum likelihood
- IQR (interquartile range)
- DBScan
- Minkowski error: Reduces the contribution of potential outliers in the training process

Univariate outlier detection with z-score

Z-score: how many standard deviation a data point is from the sample's mean



$$Z = \frac{x - \mu}{\sigma}$$

μ : mean

σ: standard deviation

Some rule of thumb threshold for outliers using z-score is: 2.5, 3, 3.5 or more.

Univariate outlier detection with modified z-score

Good for normal distribution, low dimensional features

Does not work for small number of data points (<12)

Z-score is not robust for small datasets

Modified z-score is less influenced by the outliers and works with median instead of mean in the score

modified z score: "is a standardized score that measures outlier strength or how much a particular score differs from the typical score."

https://www.ibm.com/support/knowledgecenter/en/SS4QC9/com.ibm.solutions.wa_an_overview.2.0.0.doc/modified_z.html

Univariate outlier detection with modified z-score cont.

mean absolute deviation (MeanAD)

median absolute deviation (MAD)

median absolute deviation = median(x - median(x))

Dataset: $X = X_1, X_2, \ldots, X_n$

Median: $median\ X = \bar{X}$

MAD: $MAD = median(|X - \bar{X}|)$

If MAD does equal 0: (X- $\bar{X}$)/(1.253314*MeanAD)

If MAD does not equal 0: (X- $\bar{X}$)/(1.486*MAD)

https://www.ibm.com/support/knowledgecenter/en/SS4QC9/com.ibm.solutions.wa_an_overview.2.0.0.doc/modified_z.html

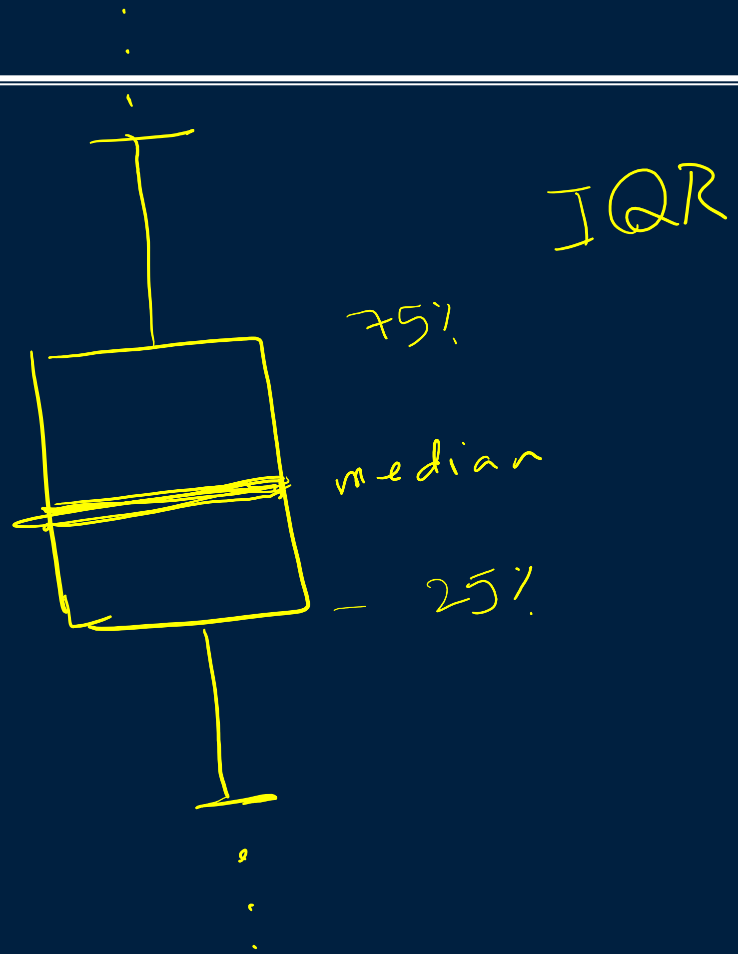
Univariate outlier detection with modified z-score cont.

```
import numpy as np
def outliers_modified_z_score(ys):
		threshold = 3.5
		median_y = np.median(ys)
		median_absolute_deviation_y =  np.median([np.abs(y - median_y) for y in ys])
		modified_z_scores = [0.6745 * (y - median_y) / median_absolute_deviation_y for y in ys]
		return np.where(np.abs(modified_z_scores) > threshold)
```

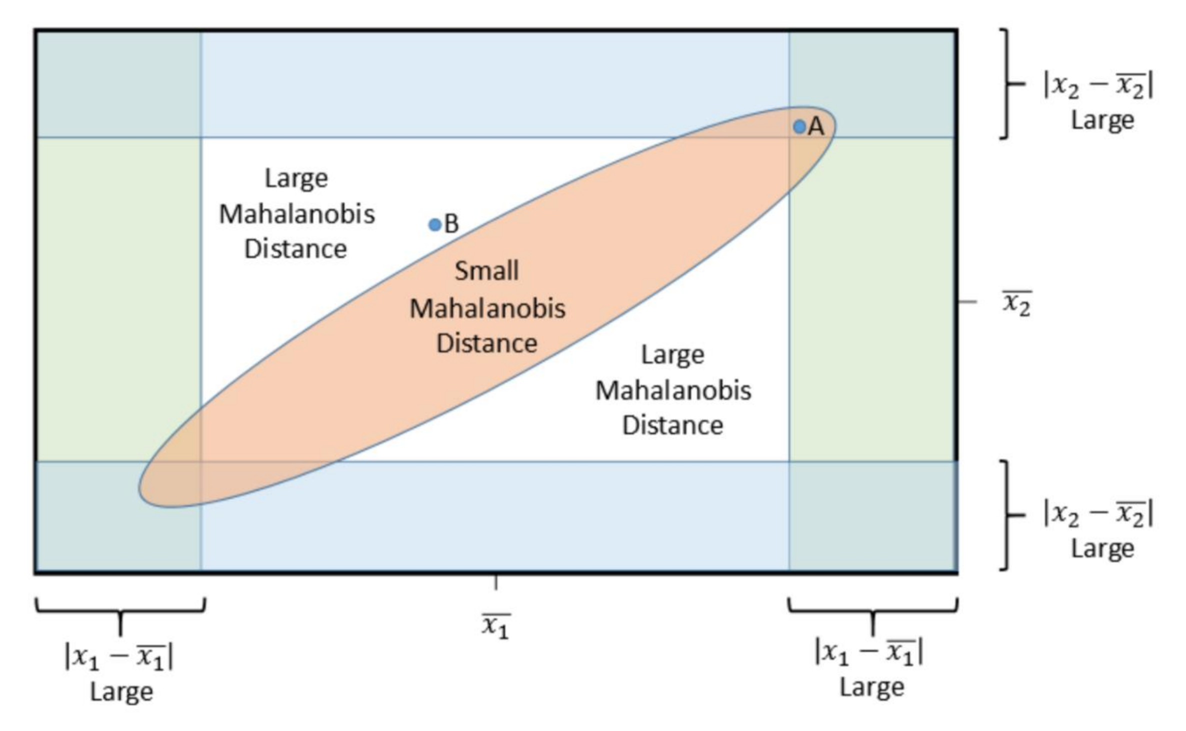
$$MAD = \text{median}\{|x_i - \tilde{x}|\}$$

$$M_i = \frac{0.6745(x_i - \tilde{x})}{MAD}$$

0.6745 is the 0.75th quartile of the standard normal distribution, to which the MAD converges to.

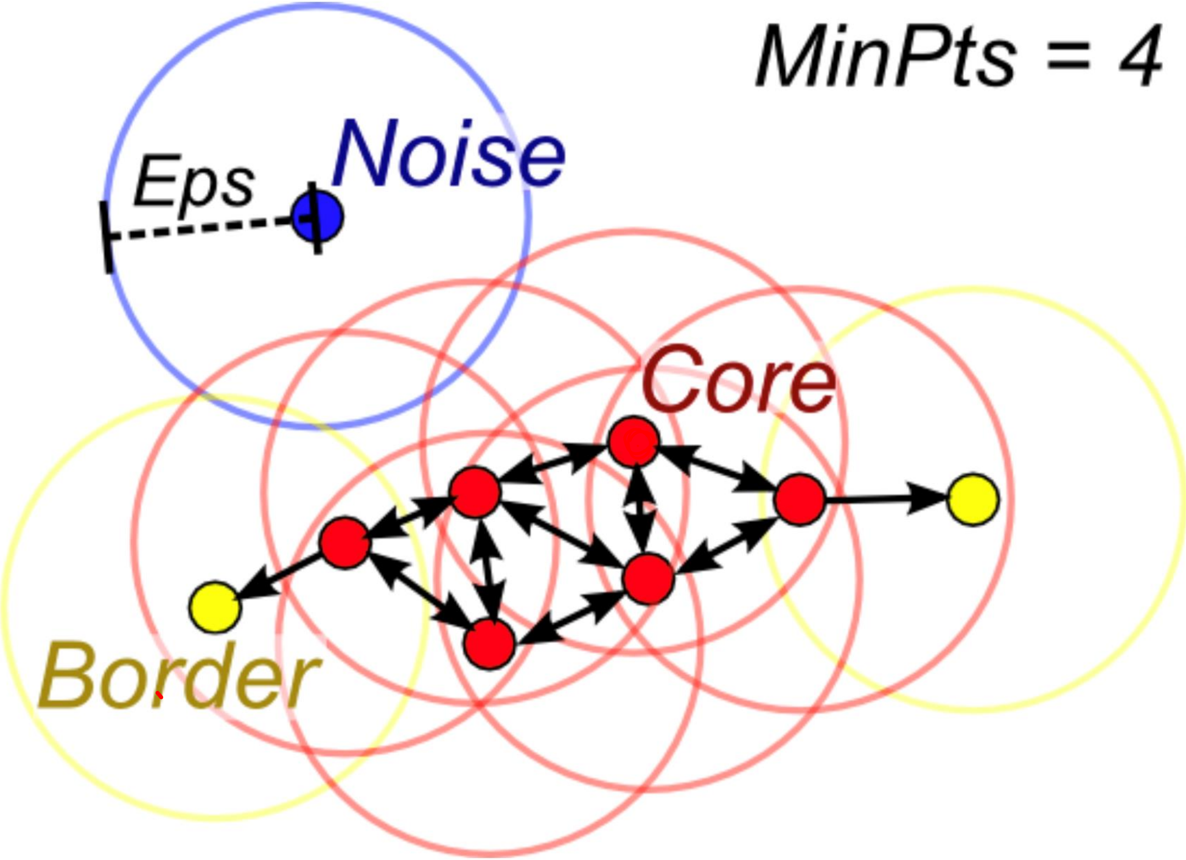

IQR
75%
median
25%

Univariate vs Multivariate Outliers



https://blogs.sas.com/content/iml/2019/03/25/geometry-multivariate-univariate-outliers.html

DBSCAN: Density-Based Spatial Clustering of Applications with Noise



Red: Core Points

Yellow: Border points. Still part of the cluster because it's within epsilon of a core point, but not does not meet the min_points criteria

Blue: Noise point. Not assigned to a cluster

https://medium.com/@elutins/dbscan-what-is-it-when-to-use-it-how-to-use-it-8bd506293818

Lecture 4 learning outcomes

A the end of this lecture you should be able to:

- Perform duplicate removal in Pandas
- Perform axis renaming
- Perform Binning on datasets
- Explain some outlier removal techniques
- Perform outlier detection using z-score

More resources

Outlier detection:

1. Siffer, A., Fouque, P. A., Termier, A., & Largouet, C. (2017, August). Anomaly detection in streams with extreme value theory. In *Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (pp. 1067-1075). ACM.

2. Leys, C., Delacre, M., Mora, Y. L., Lakens, D., & Ley, C. (2019). How to Classify, Detect, and Manage Univariate and Multivariate Outliers, With Emphasis on Pre-Registration. *International Review of Social Psychology*, *32*(1).

3. Rousseeuw, P. J., & Hubert, M. (2011). Robust statistics for outlier detection. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 1(1), 73-79.

4. Chalapathy, R., & Chawla, S. (2019). Deep learning for anomaly detection: A survey. arXiv preprint arXiv:1901.03407.

5. The curse of dimensionality: How to define outliers in high-dimensional data?, https://blogs.sas.com/content/iml/2012/03/23/the-curse-of-dimensionality.html

6. Multivariate location and scatter (MCD algorithm), https://blogs.sas.com/content/iml/2012/02/02/detecting-outliers-in-sas-part-3-multivariate-location-and-scatter.html.

7. Mahalanobis distance, https://blogs.sas.com/content/iml/2012/02/15/what-is-mahalanobis-distance.html

8. https://towardsdatascience.com/a-brief-overview-of-outlier-detection-techniques-1e0b2c19e561

9. https://www.kdnuggets.com/2017/01/3-methods-deal-outliers.html

10. https://towardsdatascience.com/density-based-algorithm-for-outlier-detection-8f278d2f7983

Anonymous Functions in R and Python:

1. https://lukesingham.com/anonymous-functions-in-r-python/

Quick catch up on Pandas DataFrames:

1. https://www.datacamp.com/community/tutorials/pandas-tutorial-dataframe-python

Try it

Discuss how to calculate the MAD. One simple example is given here:

https://www.khanacademy.org/math/statistics-probability/summarizing-quantitative-data/other-measures-of-spread/a/mean-absolute-deviation-mad-review

Try it

Follow the instructions from the following link and implement z-score, modified z-score and IQR:

http://colingorrie.github.io/outlier-detection.html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