

Dealing with missing values

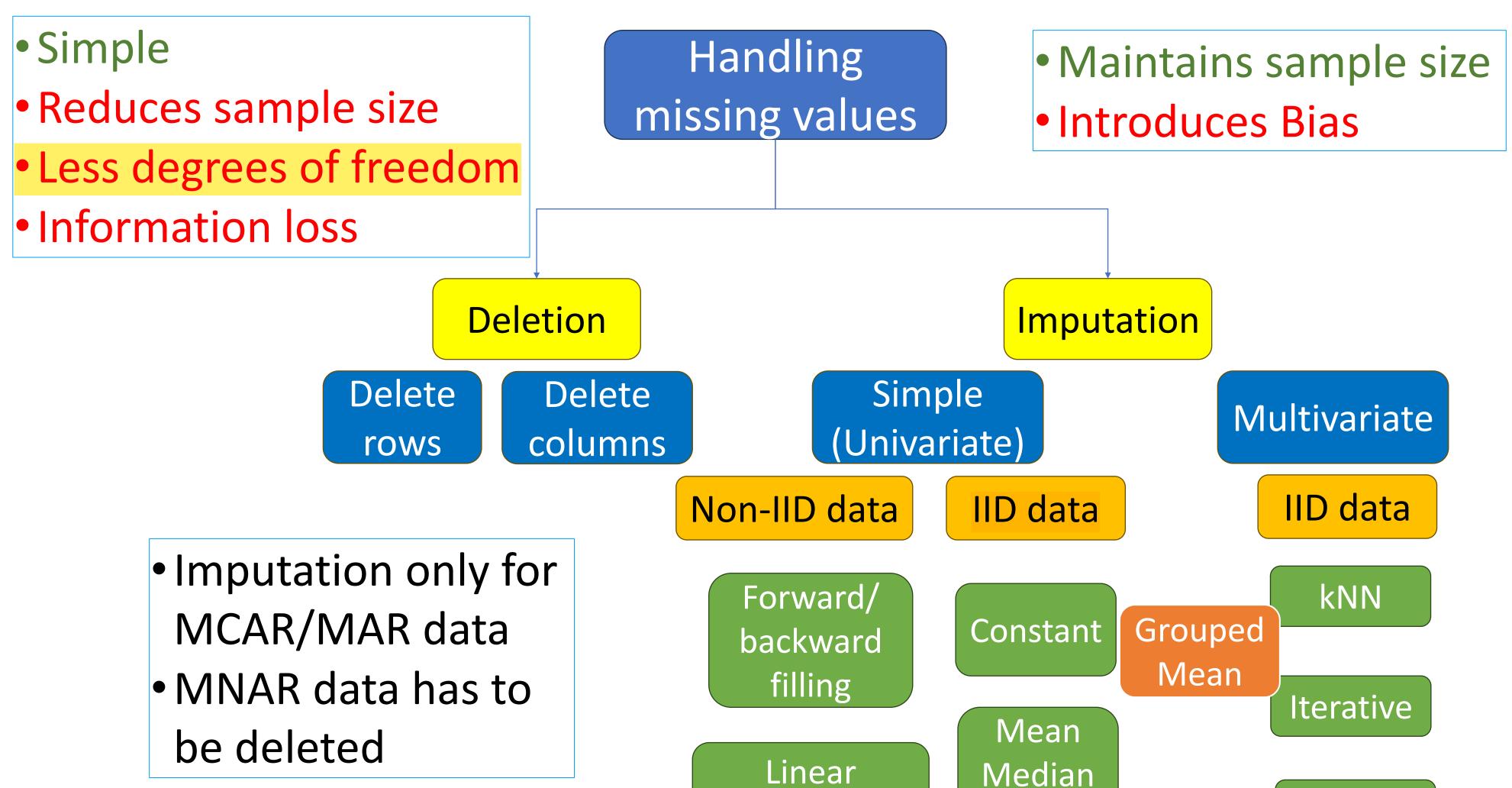
Handling missing values

- Deletion
 - Delete the rows or columns with missing value
- Imputation
 - Replace cells containing missing values with something meaningful
- Imputation is good. But we cannot always impute
 - MNAR data should never be imputed

Types of Missing values

- Missing completely at random (MCAR)
- Missing at Random (MAR)
- Missing not at Random (MNAR)

| | Observed data | Unobserved data | Examples |
|------|---------------|-----------------|---|
| MCAR | No relation | No relation | A random student's answer sheet is missing. Every answer sheet has equal probability of missing |
| MAR | Related | No relation | A student's answer sheet missing because he was absent |
| MNAR | No relation | Related | A student did not answer a question because he did not that study that part |



interpolation

Mode

MICE

Perils of constant imputation

THE WEEK



FEATURE

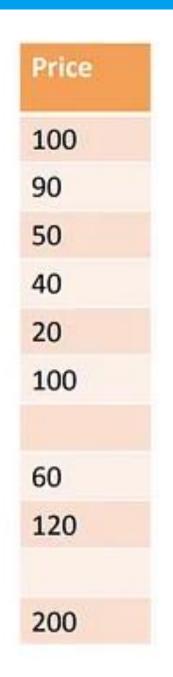
How an internet mapping glitch turned this Kansas farm into digital hell

For a decade, the owners of a Kansas farm have been inundated with accusations that they are online scammers and identity thieves



 Better to create a unknown unmapped feature to investigate separately

Mean Imputation

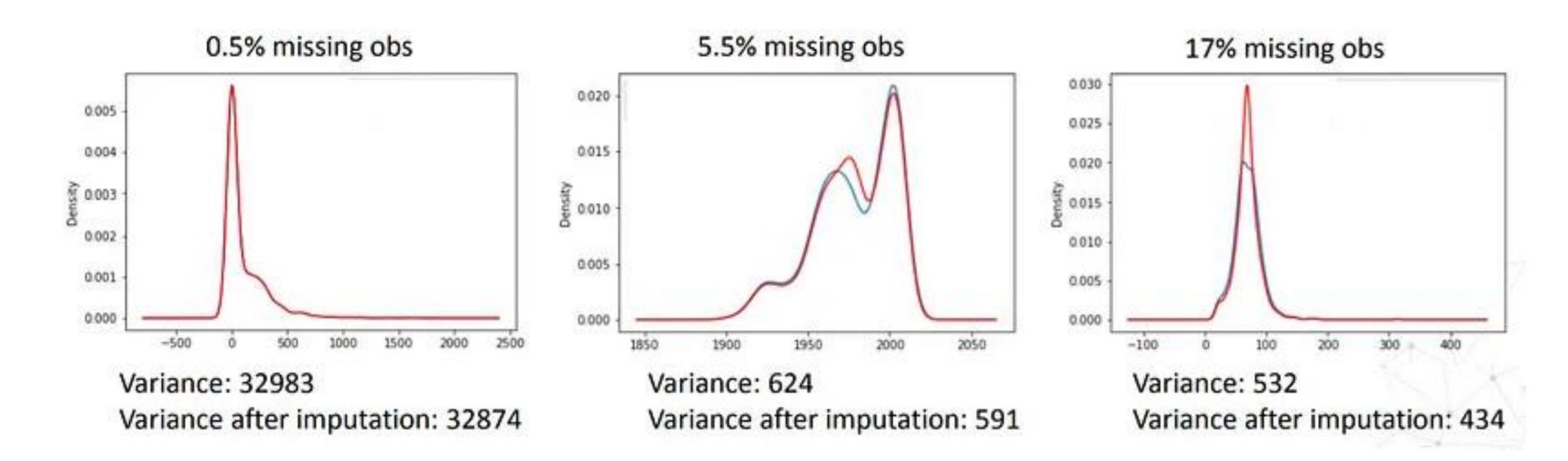


Mean = 86.66

Median = 90

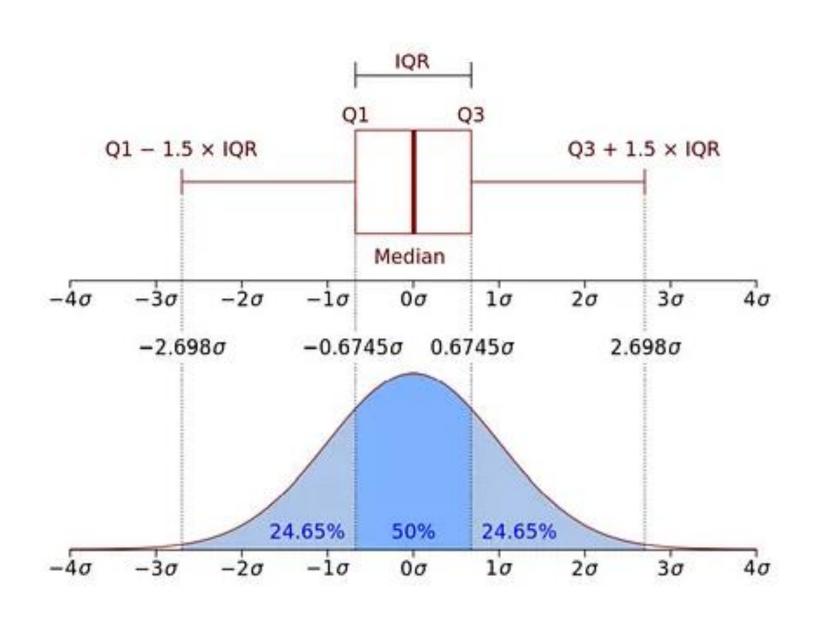
- Assumptions:
- Data is MCAR
- Missing data is mostly same as the rest

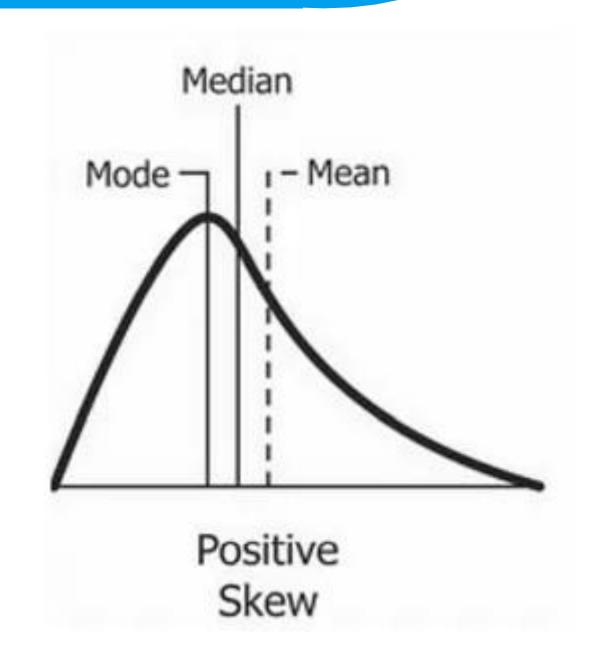
Impact of imputation on variance



•Variance decreases why?

Mean/Median Imputation When?





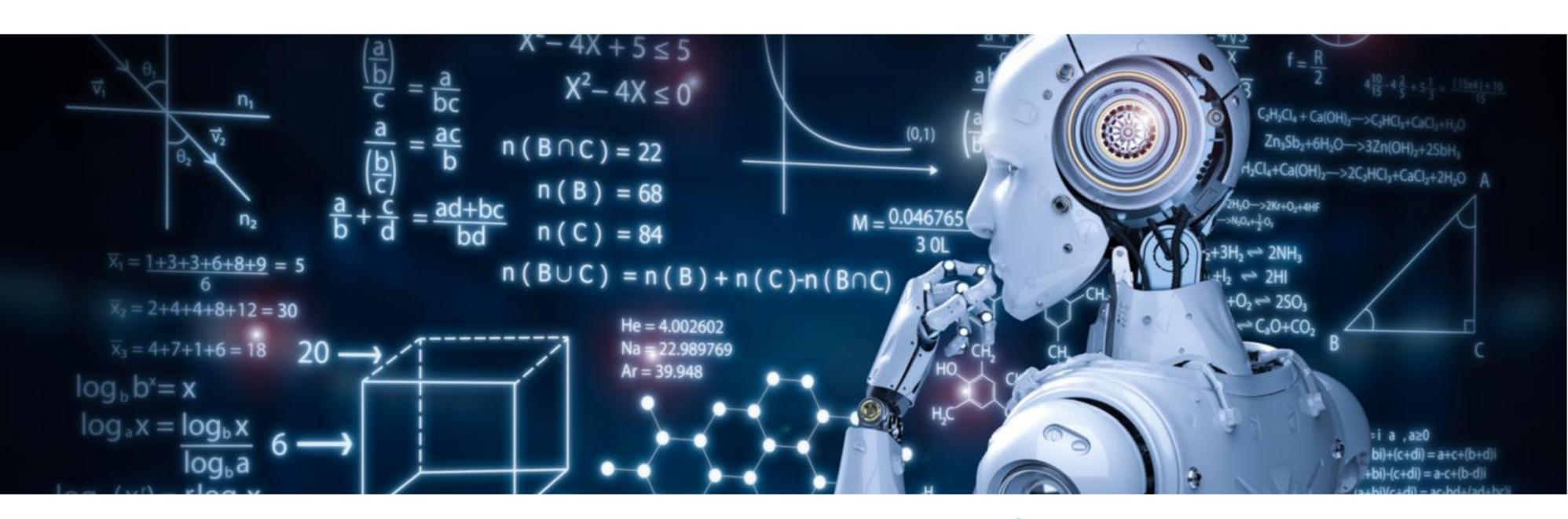
•If a feature is normally distributed, both mean & median imputation are equal

• If a feature is skewed or has many outliers, then median is better

Grouped Mean imputation

| sepal lengt | h ∙sepal width | target |
|-------------|----------------|--------|
| 5.1 | 3.4 | 0 |
| 5.5 | 4.2 | 0 |
| 5.5 | Nan | 1 |
| 5.1 | Nan | 0 |
| 6.6 | 3.0 | 1 |
| 6.7 | Nan | 2 |
| 6.2 | 3.4 | 2 |

- •Sepal width mean = 3.0
- •Setosa Sepal width mean = 2.7
- •Virginica Sepal width mean = 3.2
- •Solution:
- Impute with grouped mean



Imputation using kNN

kNN for Imputation

| HR | ВР | Temp |
|------|-------|------|
| 76.0 | 126.0 | 38.0 |
| 74.0 | 120.0 | NaN |
| 72.0 | 118.0 | 37.5 |
| NaN | 136.0 | 37.0 |
| 77.0 | NaN | 39.0 |

- Logic: Nearest points share similar data
- •kNN Imputation working summary:
- Choose k=3
- Find Euclidean distance between
 - Highlighted row & other rows
- Sort distance like kNN
- Pick the top 3 and average

Catch: Regular Euclidean distance wont work due to Nan

Nan Euclidean distance

•Distance between points (3, Nan, 5) & (1,0,0)

$$\sqrt{\frac{3}{2}\{(3-1)^2+(5-0)^2\}}=6.595453$$

 $d_{xy} = \sqrt{\text{weight } * \text{squared distance from present coordinates}}$

$$weight = \frac{Total\ number\ of\ coordinates}{Number\ of\ present\ coordinates}$$

scikit-learn.org/stable/modules/generated/sklearn.metrics.pairwise.nan euclidean distances.html

Distance between (100, Nan, 0.1) & (110, 0.3, 0.2)

All features should be on same scale

before KNN imputation

kNN Imputation with k=2

| НІ | R | ВР | Temp |
|------|------------|------|------|
| 76. | 0 1 | 26.0 | 38.0 |
| 74.0 | 0 1 | 20.0 | NaN |
| 72.0 | 0 1 | 18.0 | 37.5 |
| Nal | V 1 | 36.0 | 37.0 |
| 77. | 0 | NaN | 39.0 |

HR imputation for highlighted record with Nan adjusted distance

$$\sqrt{\frac{2}{2}} \times \{(136 - 126)^2 + (37 - 38)^2\}$$

$$\sqrt{\frac{2}{1}} \times \{(136 - 120)^2\}$$

$$\sqrt{\frac{2}{2}} \times \{(136 - 118)^2 + (37 - 37.5)^2\}$$

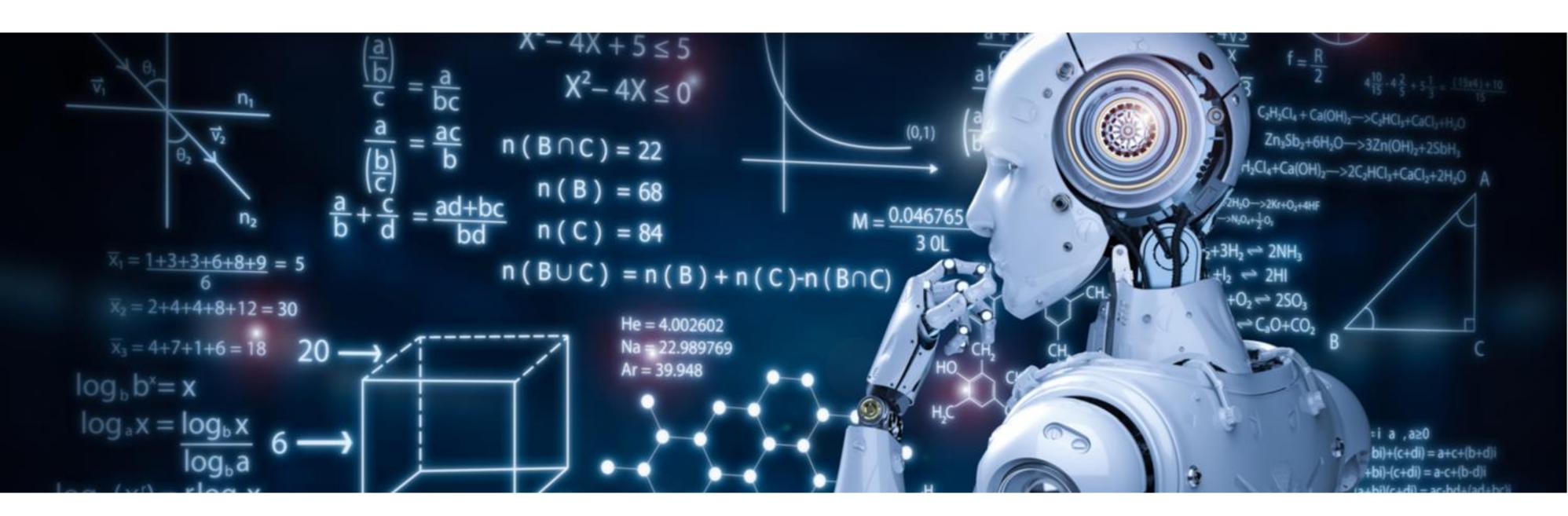
$$\sqrt{\frac{2}{1} \times \{(37 - 39)^2\}}$$

- Sort asc& picktop 2
- Average

kNN imputation considerations

- •If kNN is used for imputation, don't use kNN for classification/regression
 - E.g. Choose RandomForest Regressor for prediction
- Choosing k value for imputation is a part of cross validation

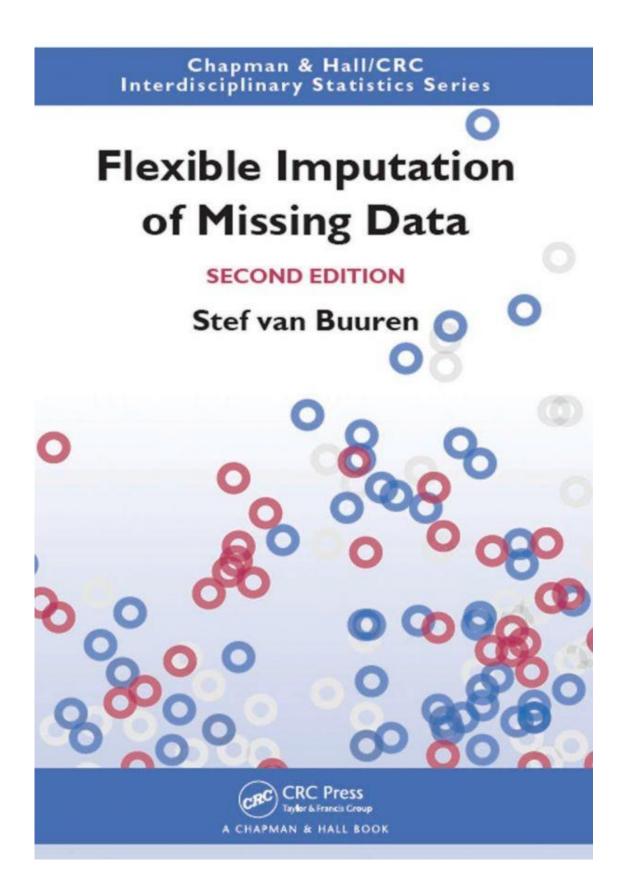
```
imputer = KNNImputer(n_neighbors=2, weights='uniform', metric='nan_euclidean')
imputer.fit_transform(df)
```

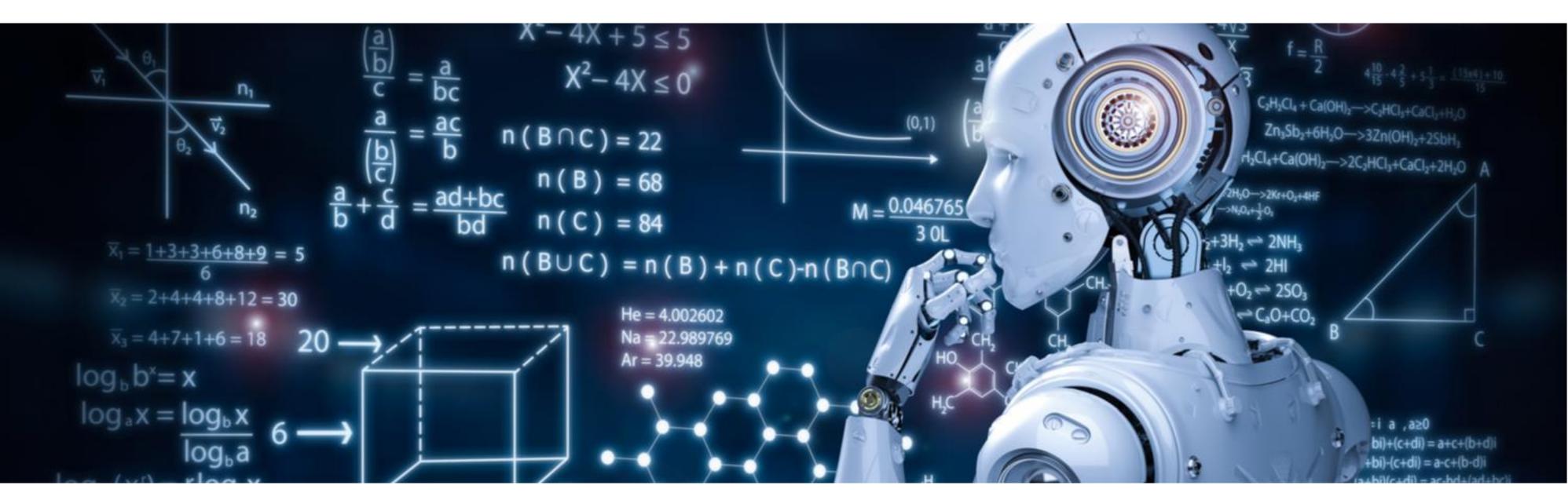


Iterative Imputation

Missing Data: The missing parts

- •Imputation covered in future classes
 - Iterative Imputation,
 - •MICE, MissForest
- Markov Chain Monte Carlo methods (will not be covered)

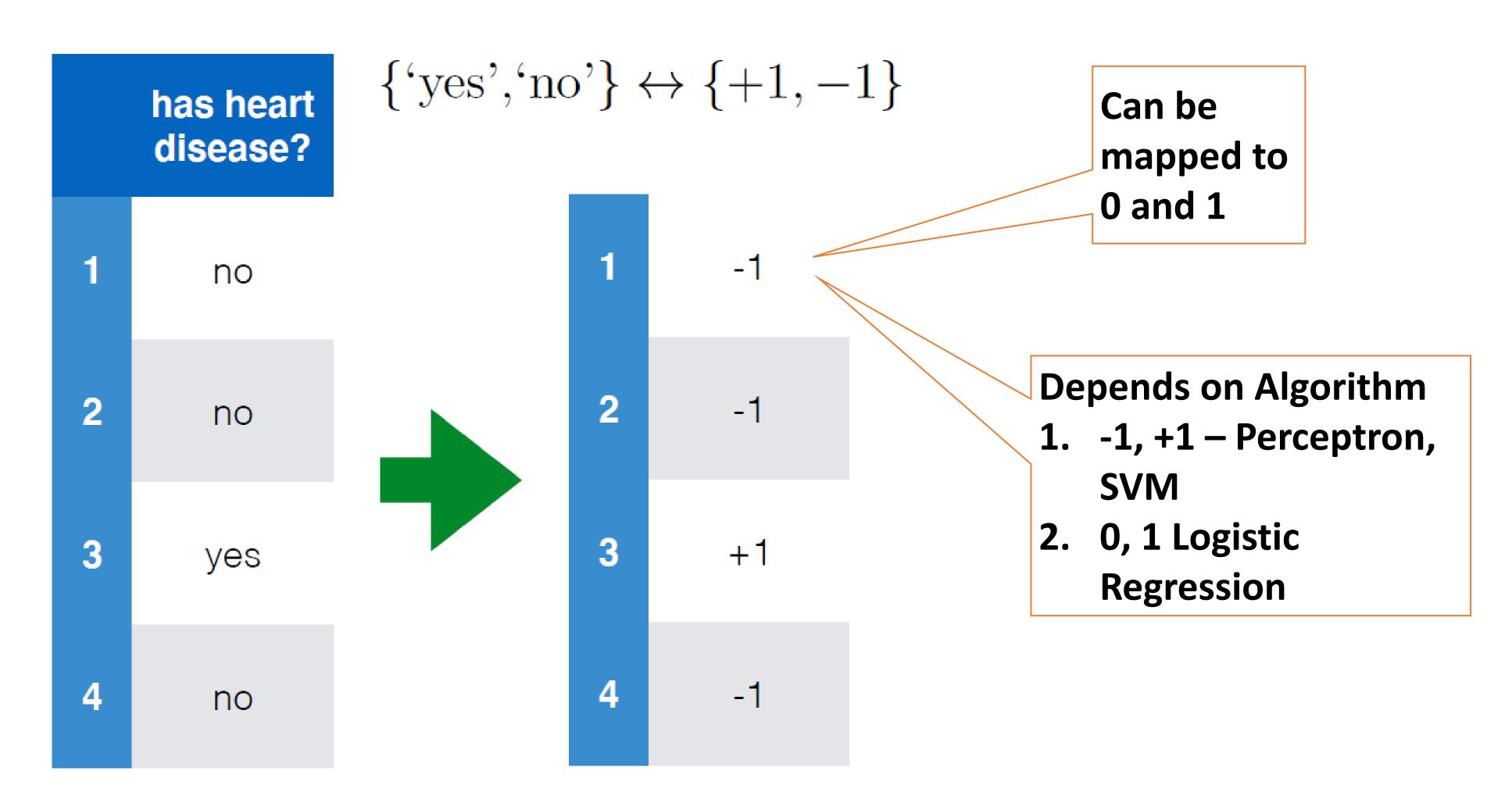




Categorical Variable encoding & imputation

| | has heart disease? | resting heart rate (bpm) | pain? | job | medicines | age | family income (USD) |
|---|-----------------------|--------------------------------|-------|--------|------------------------|-----|---------------------|
| 1 | no | 55 | no | nurse | pain | 40s | 133000 |
| 2 | no | 71 | no | admin | beta blockers, pain | 20s | 34000 |
| 3 | yes | 89 | yes | nurse | beta blockers | 50s | 40000 |
| 4 | no | 67 | no | doctor | none | 50s | 120000 |

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| | resting heart rate (bpm) | | job | medicines | age | family income (USD) | pain? |
|---|--------------------------------|-----|--------|------------------------|-----|---------------------|-------|
| 1 | 55 | no | nurse | pain | 40s | 133000 | Ο |
| 2 | 71 | no | admin | beta blockers, pain | 20s | 34000 | 0 |
| 3 | 89 | yes | nurse | beta blockers | 50s | 40000 | 1 |
| 4 | 67 | no | doctor | none | 50s | 120000 | 0 |

job

nurse

admin

nurse

doctor

- •Ordinal Encoding 1, 2, 3, 4
- Is admin > nurse and doctor
- •Is it a linear scale?
- Binary code 00, 01, 10, 11
- Inadvertently introduced pattern in job

| nurse | 0 | 0 | O |
|---------------|---|---|---|
| admin | O | O | 1 |
| pharmacist | O | 1 | 0 |
| doctor | O | 1 | 1 |
| social worker | 1 | 0 | 0 |

job

nurse

admin

nurse

doctor

- Turn each category into 0/1
- •One hot encode 0001 0010 0100 1000
- No pattern, feature explosion
- Not good for high cardinality

| nurse | 1 | 0 | 0 | 0 | 0 |
|--------------|---|---|---|---|---|
| admin | O | 1 | O | O | 0 |
| pharmacist | O | O | 1 | O | 0 |
| doctor | 0 | 0 | 0 | 1 | 0 |
| ocial worker | 0 | 0 | 0 | 0 | 1 |

medicines

pain

beta blockers, pain

beta blockers

none

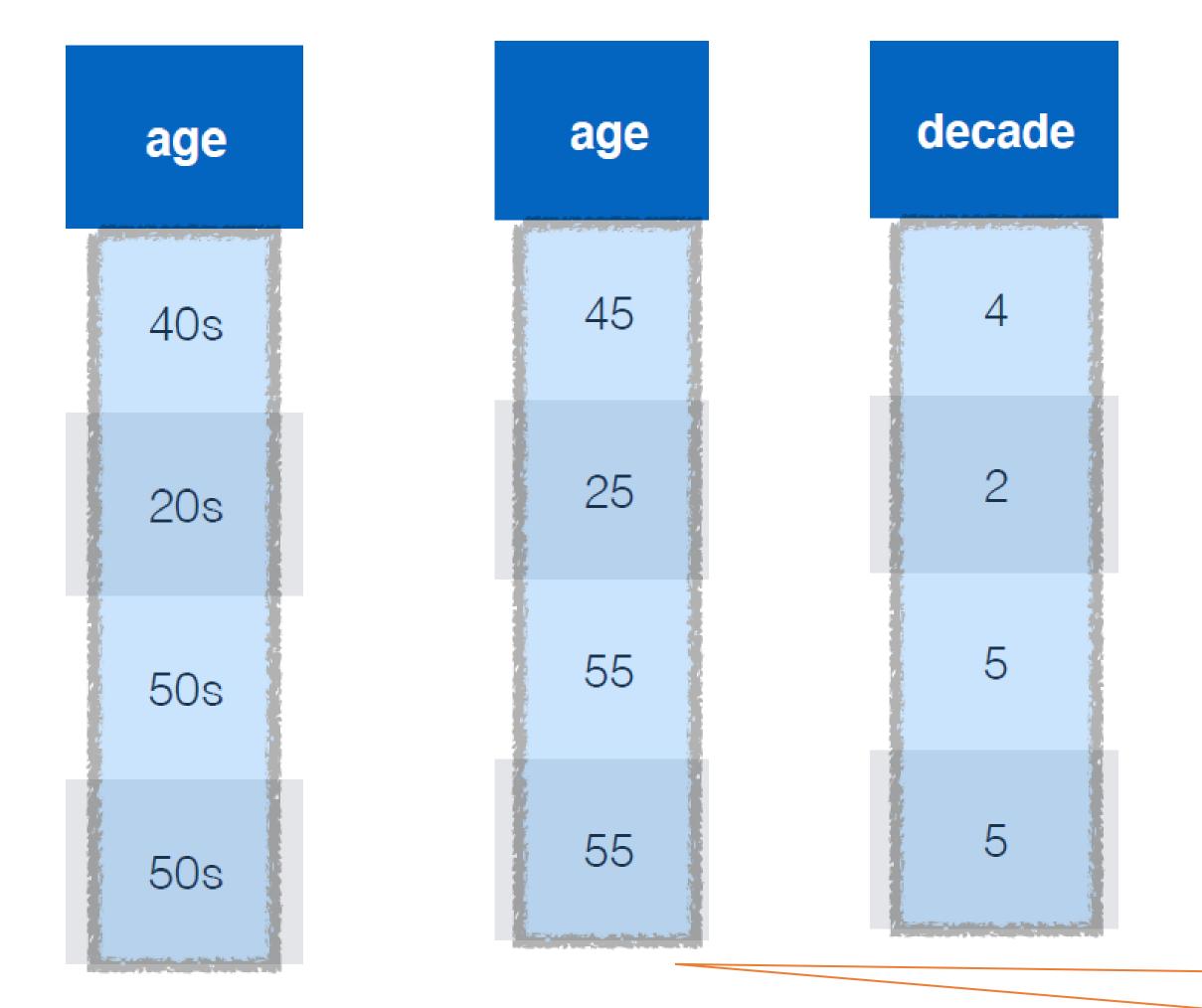
•Should we use one hot encoding?

| pain | 1 | O | O | U |
|----------------------|---|---|---|---|
| pain & beta blockers | 0 | 1 | 0 | 0 |
| beta blockers | 0 | 0 | 1 | 0 |
| no medications | 0 | 0 | O | 1 |

How about Factored encoding?

| pain | 1 | 0 |
|----------------------|---|---|
| pain & beta blockers | 1 | 1 |
| beta blockers | 0 | 1 |
| no medications | 0 | 0 |

•How is it different from binary encoding?



Reminds of IP
Address Geo
location fiasco

Encode Ordinal Data

| Strongly disagree | Disagree | Neutral | Agree | Strongly agree |
|-------------------|----------|---------|-------|----------------|
| 1 | 2 | 3 | 4 | 5 |

- Log Levels
 - •Trace, Debug, Info, Warn, Error, Fatal
 - •Do these map to 1,2,3,4,56?
 - •Or 1,2,5,8,10?

Imputing Categorical Variables

- Cannot do mean/median
- Impute the most frequent value
- Grouped mode
- •Impute the value to be a new category

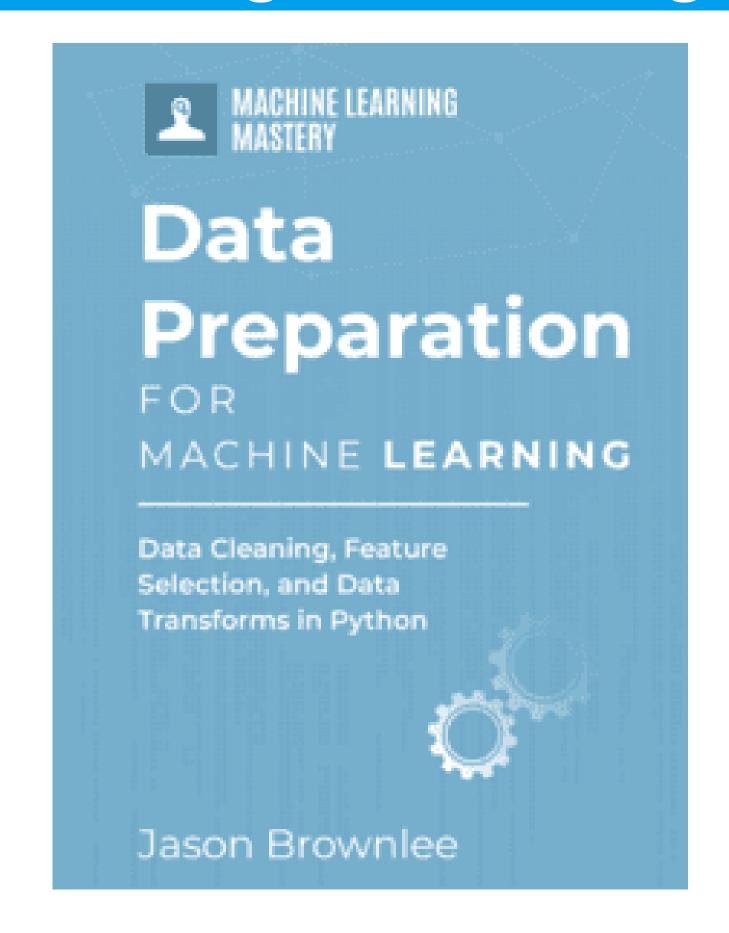
Recap

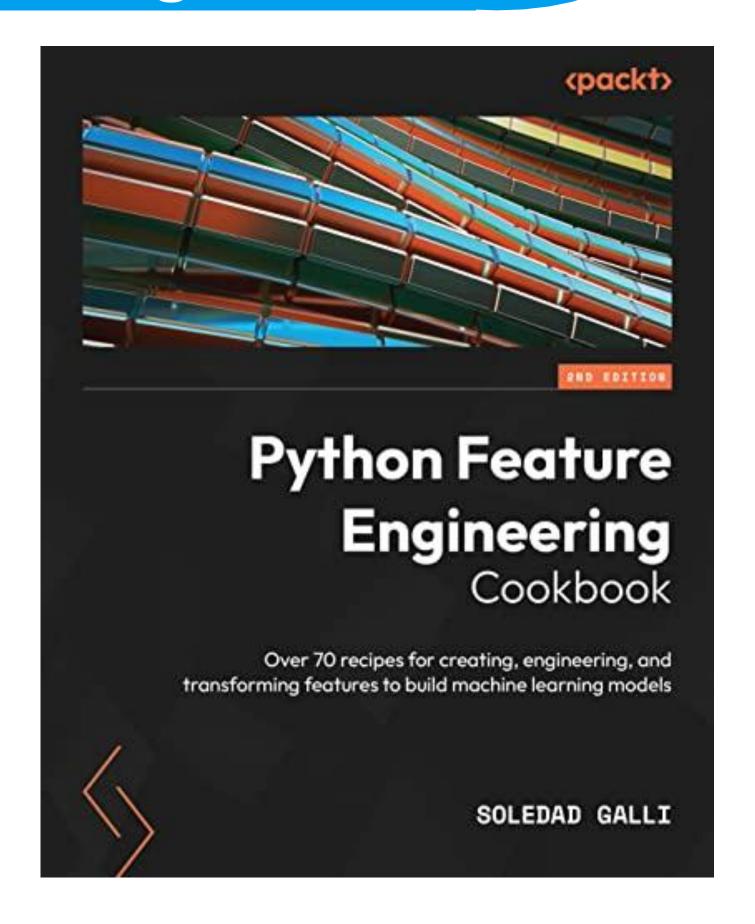
- •kNN Regression
- Data imputation
 - •Univariate Mean, Median, Mode, Grouped Mean
 - •Multivariate kNN (Nan Euclidean distance)
- Encoding transformations for categorical variables
 - Ordinal, Factored, One hot, binary,
- Problem: Imputation first or standardization first?

Solutions: No one right answer

- Some have opined standardize first
- Others: impute with a temporary value first
- Hybrid solution approach (one variation):
 - Grouped mean impute + missing indicator (adds 0/1)
 - Standardize
 - Set Nan again using Missing Indicator, then KNN Impute
- Can use missing indicator as feature for ML prediction

Data cleaning, Feature Engineering books





Data cleaning: Big picture

