Excercises Ch3

April 21, 2025

0.1 Hands-On Data Preprocessing in Python

Learn how to effectively prepare data for successful data analytics

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0.1.1 Chapter 3: Data

Excercise 1

1) From 5 colleagues or classmates ask to provide a definition for the term data.
   a) Report these definitions and indicate the similarity among them.
   b) In your own words, define the all-encompassing definition of data put forth in this chapter.
   c) Indicate the two important aspects of the definition in b.
   d) Compare the 5 definitions of data from your colleagues with the all-encompassing definitions and indicate

a) Colleague Definitions & Similarities Colleague 1: "Numbers and facts collected for analysis" Colleague 2: "Information stored in computers" Colleague 3: "Measurements used to make decisions" Colleague 4: "Observations about the world" Colleague 5: "Raw material for creating knowledge"

Similarities:

All associate data with information collection

3/5 mention analysis or decision-making

None explicitly mention representation or structure

b) All-Encompassing Definition Data: Structured or unstructured representations of objects, events, or their attributes, captured in a reproducible format to enable interpretation and analysis.

c) Two Key Aspects Representation: Data encodes reality in symbolic forms (numbers, text, images)

Purpose: Collected to support reasoning, analysis, or decision-making

d) Comparison vs. Colleague Definitions Colleague Definition | Matches All-Encompassing? | Missing Elements "Numbers and facts" | Partial | Representation format, purpose "Computer-stored info" | Partial | Real-world connection, structure "Measurements" | Closest | Representation diversity “Observations” | Partial | Storage/structured aspect “Raw material” | Partial | Representation method

Excercise 2 For this exercise, we are going to use covid_impact_on_airport_traffic.csv. Answer the following questions. This dataset is from Kaggle.com, use this link to see its page: https://www.kaggle.com/terenceshin/covid19s-impact-on-airport-traffic. The key attribute of this dataset is PercentOfBaseline which shows the ratio of air traffic in the specific day compared to pre-pandemic time (1st Feb to 15th March 2020)

[12]:
```python
import pandas as pd
covid_df = pd.read_excel("covid_impact_on_airport_traffic.xlsx")
covid_df
```

[12]:
```
     AggregationMethod       Date  Version                    AirportName  \
0                Daily 2020-04-03        1                Kingsford Smith
1                Daily 2020-04-13        1                Kingsford Smith
2                Daily 2020-07-10        1                Kingsford Smith
3                Daily 2020-09-02        1                Kingsford Smith
4                Daily 2020-10-31        1                Kingsford Smith
…                  …          …      …                            …
7242             Daily 2020-06-05        1  Seattle-Tacoma International
7243             Daily 2020-10-03        1  Seattle-Tacoma International
7244             Daily 2020-07-16        1  Seattle-Tacoma International
7245             Daily 2020-07-31        1  Seattle-Tacoma International
7246             Daily 2020-08-30        1  Seattle-Tacoma International

      PercentOfBaseline                                 Centroid    City  \
0                    64  POINT(151.180087713813 -33.9459774986125)  Sydney
1                    29  POINT(151.180087713813 -33.9459774986125)  Sydney
2                    54  POINT(151.180087713813 -33.9459774986125)  Sydney
3                    18  POINT(151.180087713813 -33.9459774986125)  Sydney
4                    22  POINT(151.180087713813 -33.9459774986125)  Sydney
…                  …                                          …     …
7242                 80  POINT(-122.308661576118 47.4505828917119)  SeaTac
7243                 55  POINT(-122.308661576118 47.4505828917119)  SeaTac
7244                 76  POINT(-122.308661576118 47.4505828917119)  SeaTac
7245                 69  POINT(-122.308661576118 47.4505828917119)  SeaTac
7246                 68  POINT(-122.308661576118 47.4505828917119)  SeaTac

                State ISO_3166_2                        Country  \
0     New South Wales         AU                      Australia
1     New South Wales         AU                      Australia
2     New South Wales         AU                      Australia
3     New South Wales         AU                      Australia
4     New South Wales         AU                      Australia
…                …        …                             …
7242       Washington      US-WA  United States of America (the)
```

```
7243       Washington      US-WA  United States of America (the)
7244       Washington      US-WA  United States of America (the)
7245       Washington      US-WA  United States of America (the)
7246       Washington      US-WA  United States of America (the)

                                                   Geography
0     POLYGON((151.164354085922 -33.9301772341877, 1…
1     POLYGON((151.164354085922 -33.9301772341877, 1…
2     POLYGON((151.164354085922 -33.9301772341877, 1…
3     POLYGON((151.164354085922 -33.9301772341877, 1…
4     POLYGON((151.164354085922 -33.9301772341877, 1…
…                                                   …
7242  POLYGON((-122.297594547272 47.434474106872, -1…
7243  POLYGON((-122.297594547272 47.434474106872, -1…
7244  POLYGON((-122.297594547272 47.434474106872, -1…
7245  POLYGON((-122.297594547272 47.434474106872, -1…
7246  POLYGON((-122.297594547272 47.434474106872, -1…

[7247 rows x 11 columns]
```

```
a)  What is the best definition of the data object for this dataset?
b)  Are there any attributes in the data that only have one value? Use .unique() function to cl
c)  What type of values do the remaining attributes carry?
d)  How much statistical information the attribute 'PercentOfBaseline' has?
```

Answer:

a) time-series panel data object

[13]:
```python
# b)

single_value_cols = [
    col for col in covid_df.columns
    if len(covid_df[col].unique()) == 1
    ]
print("Single-value columns:", single_value_cols)
```

```
Single-value columns: ['AggregationMethod', 'Version']
```

[14]:
```python
covid_df = covid_df.drop(columns=single_value_cols)
```

[15]:
```python
# c)
print(covid_df.dtypes)

# Key types:
# Date                          interval
# AirportName                    nominal
# PercentOfBaseline                ratio
# Centroid                       nominal
```

```
# City                        nominal
# State                       nominal
# ISO_3166_2                  nominal
# Country                     nominal
# Geography                   nominal
```

```
Date                    datetime64[ns]
AirportName                     object
PercentOfBaseline                int64
Centroid                        object
City                            object
State                           object
ISO_3166_2                      object
Country                         object
Geography                       object
dtype: object
```

[16]:
```
# d)
print(covid_df['PercentOfBaseline'].describe())
```

```
count    7247.000000
mean       66.651442
std        22.134433
min         0.000000
25%        53.000000
50%        67.000000
75%        84.000000
max       100.000000
Name: PercentOfBaseline, dtype: float64
```

Excercise 3 For this exercise, we are going to use US_Accidents.csv. Answer the following questions. This dataset is from Kaggle.com, use this link to see its page: https://www.kaggle.com/sobhanmoosavi/us-accidents. This dataset shows all the car accidents in the US from February 2016 to Dec 2020.

[19]:
```
# import pandas as pd
# pd.read_csv('US_Accidents.csv')
```

```
a)  What is the best definition of the data object for this dataset?
b)  Are there any attributes in the data that only have one value? Use .unique() function to cl
c)  What type of values do the remaining attributes carry?
d)  How much statistical information the numerical attributes of the dataset carry?
e)  Compare the statistical information of the numerical attributes and see if any of them are
```

Answer:

[20]:
```
# skip because detaset too large
```

Excercise 4 For this exercise, we are going to use fatal-police-shootings-data.csv. There are a lot of debates, discussions, dialogues, and protests happening in the US surrounding police killings. The Washington Post has been collecting data on all fatal police shootings in the US. The dataset available to the government and the public alike has date, age, gender, race, location, and other situational information of these fatal police shootings. You can read more about this data on https://www.washingtonpost.com/graphics/investigations/police-shootings-database/, and you can download the last version of the data from https://github.com/washingtonpost/data-police-shootings

[21]:
```
import pandas as pd

fatal_df = pd.read_csv('fatal-police-shootings-data.csv')
fatal_df.head()
```

[21]:
```
   id                name        date   manager_of_death       armed   age  \
0   3          Tim Elliot  2015-01-02               shot         gun  53.0
1   4    Lewis Lee Lembke  2015-01-02               shot         gun  47.0
2   5  John Paul Quintero  2015-01-03  shot and Tasered     unarmed  23.0
3   8     Matthew Hoffman  2015-01-04               shot  toy weapon  32.0
4   9   Michael Rodriguez  2015-01-04               shot    nail gun  39.0

  gender race           city state  signs_of_mental_illness threat_level  \
0      M    A        Shelton    WA                     True       attack
1      M    W          Aloha    OR                    False       attack
2      M    H        Wichita    KS                    False        other
3      M    W  San Francisco    CA                     True       attack
4      M    H          Evans    CO                    False       attack

          flee  body_camera  longitude  latitude  is_geocoding_exact
0  Not fleeing        False   -123.122    47.247                True
1  Not fleeing        False   -122.892    45.487                True
2  Not fleeing        False    -97.281    37.695                True
3  Not fleeing        False   -122.422    37.763                True
4  Not fleeing        False   -104.692    40.384                True
```

```
a)  What is the best definition of the data object for this dataset?
b)  Are there any attributes in the data that only have one value? Use .unique() function to cl
c)  What type of values do the remaining attributes carry?
d)  How much statistical information the numerical attributes of the dataset carry?
e)  Compare the statistical information of the numerical attributes and see if any of them are
```

a) This dataset is a structured event-log data object

[22]:
```
# b)

single_value_cols = [
    col for col in fatal_df.columns
    if fatal_df[col].nunique() == 1
    ]
```

```
single_value_cols
```

[22]: []

[23]:
```
# c)

fatal_df.dtypes

# id                              nominal
# name                           nominal
# date                           interval
# manner_of_death                nominal
# armed                          nominal
# age                           ratio
# gender                         nominal
# race                           nominal
# city                           nominal
# state                          nominal
# signs_of_mental_illness          nominal
# threat_level                   ordinal
# flee                           ordinal
# body_camera                      nominal
# longitude                     interval
# latitude                      interval
# is_geocoding_exact               nominal
```

[23]:
```
id                             int64
name                          object
date                          object
manner_of_death               object
armed                         object
age                          float64
gender                        object
race                          object
city                          object
state                         object
signs_of_mental_illness         bool
threat_level                  object
flee                          object
body_camera                     bool
longitude                    float64
latitude                     float64
is_geocoding_exact              bool
dtype: object
```

[24]:
```python
# d)
fatal_df.describe()
```

[24]:

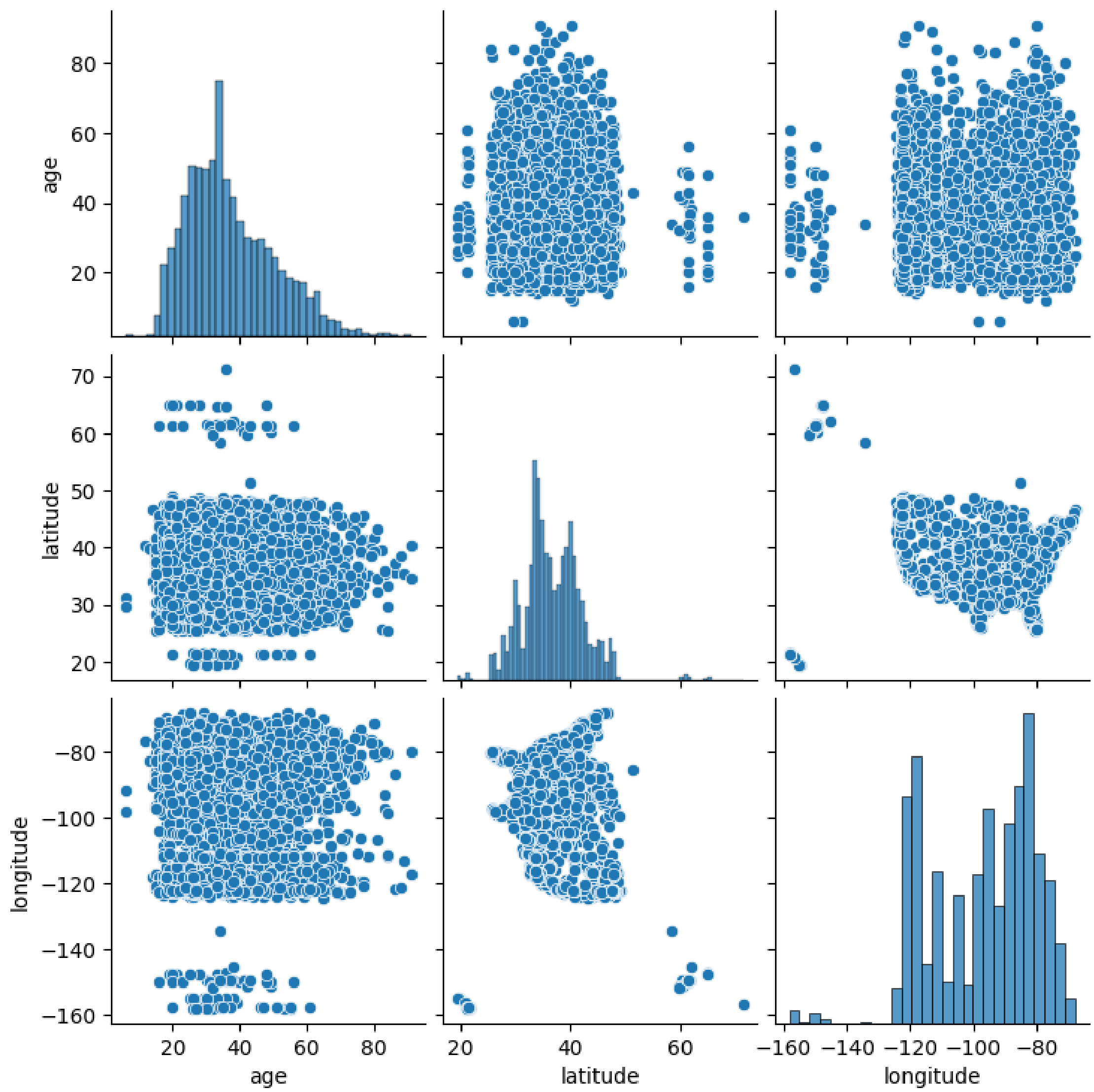
	id	age	longitude	latitude
count	6068.000000	5802.000000	5771.000000	5771.000000
mean	3363.828444	37.160290	-97.238779	36.660617
std	1898.394615	13.039693	16.629397	5.377469
min	3.000000	6.000000	-158.137000	19.498000
25%	1716.750000	27.000000	-112.117000	33.475500
50%	3369.500000	35.000000	-94.386000	36.096000
75%	5019.250000	46.000000	-83.067000	39.986500
max	6629.000000	91.000000	-68.014000	71.301000

[25]:
```python
# e)

fatal_df[['age', 'latitude', 'longitude']].corr()
```

[25]:

	age	latitude	longitude
age	1.000000	-0.014671	0.057657
latitude	-0.014671	1.000000	-0.116595
longitude	0.057657	-0.116595	1.000000

[26]:
```python
import matplotlib.pyplot as plt
import seaborn as sns

sns.pairplot(fatal_df[['age', 'latitude', 'longitude']])
plt.show()
```



Excercise 5 For this exercise, we will be using electricity_prediction.csv. The screenshot below shows the 5 rows of this dataset and a linear regression model created to predict electricity consumption based on the weekday and daily average temperature.

[27]:
```
import pandas as pd

electricity_df = pd.read_csv('electricity_prediction.csv')
electricity_df.head()
```

[27]:

	Date	Weekday	Consumption	Average Temperature
0	1/1/2016	4	2581914	80
1	1/2/2016	5	2663011	77
2	1/3/2016	6	2725351	78

```
3   1/4/2016        0      3092978                   80
4   1/5/2016        1      3231827                   81
```

[28]:
```python
from sklearn.linear_model import LinearRegression

X = electricity_df[['Weekday', 'Average Temperature']]
y = electricity_df['Consumption']

lrm = LinearRegression()
lrm.fit(X, y)

print('intercept ', lrm.intercept_)
print(pd.DataFrame({'Predictor': X.columns, 'coefficient': lrm.coef_}))
```

```
intercept  3074181.495015881
             Predictor   coefficient
0              Weekday -55710.145405
1  Average Temperature  -3476.377056
```

The regression model that is derived from the data is presented below.

`Consumption = 3074181.5- 55710.1 × Weekday-3476.4 ×Average Temperature`

What is the fundamental mistake in this analysis? Describe it and provides possible solutions for it.

Answer:

The primary issue is treating the Weekday variable (0-6) as a continuous/numeric predictor in the linear regression mode. Weekdays are categorical (nominal) variables, not continuous. The model assumes a linear relationship between Weekday and Consumption, implying that the difference between Monday (0) and Tuesday (1) is the same as between Saturday (5) and Sunday (6). This is illogical because weekdays have no inherent numerical meaning (e.g., Sunday isn't "greater than" Monday).

Solution is to treat Weekday as Categorical (One-Hot Encoding)

Excercise 6 For this exercise, we will be using adult.csv. we used this dataset extensively in chapter 1. Read the dataset using Padans and call it adult_df.

[29]:
```python
import pandas as pd

adult_df = pd.read_csv('adult.csv')
```

```
a)  What type of values does the attribute eduction carry?
b)  Run 'adult_df.education.unique()', study the results, and explain what the code does.
c)  Based on your understandings, order the output of the code you ran for b).
d)  Run 'pd.get_dummies(adult_df.education)', study the results, and explain what the code does
e)  Run 'adult_df.sort_values(['education-num']).iloc[1:32561:1200]', study the results and exp
f)  Compare your answer to c) and what you learned from e). Was the order you came up with in 
g)  Education is an ordinal attribute, translating an ordinal attribute from an analytic perspe
```

```
    - 'adult_df.education'
    - 'pd.get_dummies(adult_df.education)'
    - 'adult_df[‘education’]'
h)  Either of the choices has some advantages and some disadvantages. Select which programing c
    - If an ordinal attribute is presented using this programming value representation, no bias
    - If an ordinal attribute is presented using this programming value representation, the dat
    - If an ordinal attribute is presented using this programming value representation, there w
```

Answer:

a) Ordinal

[30]:
```python
# b)

adult_df.education.unique()
```

[30]:
```
array(['Bachelors', 'HS-grad', '11th', 'Masters', '9th', 'Some-college',
       'Assoc-acdm', 'Assoc-voc', '7th-8th', 'Doctorate', 'Prof-school',
       '5th-6th', '10th', '1st-4th', 'Preschool', '12th'], dtype=object)
```

Returns an array of unique values in the education column.

c)

1. Preschool
2. 1st-4th
3. 5th-6th
4. 7th-8th
5. 9th
6. 10th
7. 11th
8. 12th
9. HS-grad
10. Some-college
11. Assoc-acdm
12. Assoc-voc
13. Bachelors
14. Masters
15. Prof-school
16. Doctorate

[31]:
```python
# d)

pd.get_dummies(adult_df.education)
```

[31]:
```
        10th   11th   12th  1st-4th  5th-6th  7th-8th    9th  Assoc-acdm  \
0      False  False  False    False    False    False  False       False
1      False  False  False    False    False    False  False       False
2      False  False  False    False    False    False  False       False
3      False   True  False    False    False    False  False       False
4      False  False  False    False    False    False  False       False
…          …      …      …        …        …        …      …           …
32556  False  False  False    False    False    False  False        True
32557  False  False  False    False    False    False  False       False
32558  False  False  False    False    False    False  False       False
32559  False  False  False    False    False    False  False       False
32560  False  False  False    False    False    False  False       False

       Assoc-voc  Bachelors  Doctorate  HS-grad  Masters  Preschool  \
0          False       True      False    False    False      False
1          False       True      False    False    False      False
2          False      False      False     True    False      False
3          False      False      False    False    False      False
4          False       True      False    False    False      False
…              …          …          …        …        …          …
32556      False      False      False    False    False      False
32557      False      False      False     True    False      False
32558      False      False      False     True    False      False
32559      False      False      False     True    False      False
32560      False      False      False     True    False      False

       Prof-school  Some-college
0            False         False
1            False         False
2            False         False
3            False         False
4            False         False
…                …             …
32556        False         False
32557        False         False
32558        False         False
32559        False         False
32560        False         False

[32561 rows x 16 columns]
```

Performs one-hot encoding, converting each education level to a binary column

[32]:
```
# e)

adult_df.sort_values(['education-num']).iloc[1:32561:1200]
```

[32]:
```
       age     workclass  fnlwgt     education  education-num  \
32432   36       Private  208068     Preschool              1
32467   55       Private  199713           9th              5
2449    25       Private  345121          10th              6
14720   17       Private   99462          11th              7
4862    35       Private   46385       HS-grad              9
29380   25       Private  410240       HS-grad              9
27398   50     State-gov   97778       HS-grad              9
25406   26       Private  122206       HS-grad              9
23272   25       Private  109419       HS-grad              9
21374   44   Federal-gov  320071       HS-grad              9
19242   56       Private  134756       HS-grad              9
17302   60       Private  132529       HS-grad              9
15265   58       Private  126991       HS-grad              9
20514   25     State-gov  108542  Some-college             10
22642   18       Private  266489  Some-college             10
25709   24       Private  186213  Some-college             10
29946   38       Private   64879  Some-college             10
31715   22     State-gov  124942  Some-college             10
29794   47       Private  358465  Some-college             10
11908   26       Private   78424     Assoc-voc             11
1317    35           NaN  327120    Assoc-acdm             12
25132   41     Local-gov  177599     Bachelors             13
14210   54       Private  256908     Bachelors             13
7184    42       Private  168103     Bachelors             13
16832   49       Private  224393     Bachelors             13
17112   46       Private  198774       Masters             14
26083   71  Self-emp-inc   38822       Masters             14
7690    34       Private  228873     Doctorate             16

           marital-status         occupation    relationship  \
32432            Divorced      Other-service   Not-in-family
32467  Married-civ-spouse       Craft-repair         Husband
2449            Separated      Other-service       Own-child
14720       Never-married      Other-service       Own-child
4862   Married-civ-spouse   Transport-moving         Husband
29380       Never-married       Craft-repair       Own-child
27398  Married-civ-spouse    Protective-serv         Husband
25406       Never-married       Craft-repair  Other-relative
23272       Never-married       Adm-clerical       Own-child
21374  Married-civ-spouse       Craft-repair         Husband
19242       Never-married      Other-service   Not-in-family
17302  Married-civ-spouse      Other-service         Husband
```

```
15265            Divorced     Other-service        Unmarried
20514  Married-civ-spouse   Protective-serv          Husband
22642       Never-married   Exec-managerial   Not-in-family
25709  Married-civ-spouse      Tech-support          Husband
29946            Divorced             Sales   Not-in-family
31715       Never-married     Other-service        Own-child
29794            Divorced      Adm-clerical   Not-in-family
11908       Never-married             Sales        Unmarried
1317        Never-married               NaN   Not-in-family
25132            Divorced    Prof-specialty        Unmarried
14210  Married-civ-spouse      Tech-support          Husband
7184   Married-civ-spouse   Exec-managerial          Husband
16832  Married-civ-spouse   Exec-managerial          Husband
17112            Divorced   Exec-managerial        Unmarried
26083  Married-civ-spouse   Exec-managerial          Husband
7690   Married-civ-spouse    Prof-specialty          Husband

                     race     sex  capitalGain  capitalLoss  hoursPerWeek  \
32432               Other    Male            0            0            72
32467               White    Male            0            0            48
2449                White  Female            0            0            25
14720  Amer-Indian-Eskimo  Female            0            0            20
4862                White    Male         5178            0            90
29380               White    Male            0            0            40
27398               White    Male            0            0            40
25406               White    Male            0            0            40
23272               White  Female            0            0            40
21374               White    Male            0            0            40
19242               Black  Female            0            0            40
17302               White    Male            0            0            40
15265               Black  Female            0            0            20
20514               White    Male            0            0            40
22642               White    Male            0            0            50
25709               White    Male            0            0            50
29946               White  Female            0            0            40
31715               White    Male            0            0            45
29794               White  Female            0            0            40
11908               White  Female            0            0            54
1317                White    Male            0            0            55
25132               White  Female            0            0            35
14210               White    Male            0            0            25
7184                White    Male            0            0            40
16832               White    Male            0            0            55
17112               White  Female            0          323            45
26083               White    Male        99999            0            40
7690                White    Male            0            0            45
```

```
        nativeCountry income
32432          Mexico  <=50K
32467   United-States  <=50K
2449    United-States  <=50K
14720   United-States  <=50K
4862    United-States   >50K
29380   United-States  <=50K
27398   United-States  <=50K
25406   United-States  <=50K
23272   United-States  <=50K
21374   United-States   >50K
19242   United-States  <=50K
17302   United-States  <=50K
15265   United-States  <=50K
20514   United-States  <=50K
22642   United-States  <=50K
25709   United-States   >50K
29946   United-States  <=50K
31715   United-States  <=50K
29794   United-States  <=50K
11908   United-States  <=50K
1317    United-States  <=50K
25132   United-States  <=50K
14210   United-States   >50K
7184    United-States   >50K
16832   United-States   >50K
17112   United-States  <=50K
26083   United-States   >50K
7690    United-States   >50K
```

Sorts the DataFrame by education-num (numeric education ranking).

f)

Hypothesis (c): Ordered education levels subjectively.

Reality (e): The correct order is defined by education-num

[34]:
```
adult_df[['education', 'education-num']].drop_duplicates().
 ↪sort_values('education-num')
```

[34]:
```
        education  education-num
224     Preschool              1
160       1st-4th              2
56        5th-6th              3
15        7th-8th              4
6             9th              5
77           10th              6
3            11th              7
```

```
415          12th               8
2          HS-grad              9
10   Some-college              10
14       Assoc-voc             11
13      Assoc-acdm             12
0        Bachelors             13
5          Masters             14
52     Prof-school             15
20       Doctorate             16
```

g)

adult_df.education String

pd.get_dummies(adult_df.education) Boolean (One-hot)

adult_df['education'] String

h)

Advantages/Disadvantages of Representations

String Representation (adult_df.education):

- Statement: "No bias, but algorithms can't use it."
- Pros: Preserves original labels.
- Cons: Cannot be used directly in math models.

One-Hot Encoding (get_dummies):

- Statement: "Algorithms can use it, but data size increases."
- Pros: Works with ML algorithms.
- Cons: Creates many columns; loses ordinality.

Integer Representation (education-num):

- Statement: "No size concerns, but assumes linear bias."
- Pros: Compact; respects order.
- Cons: Implies equal intervals between levels (e.g., "HS-grad → Bachelors" = "Bachelors → Masters").