

# Membership constraints

CLEANING DATA IN PYTHON



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## Chapter 2 - Text and categorical data problems

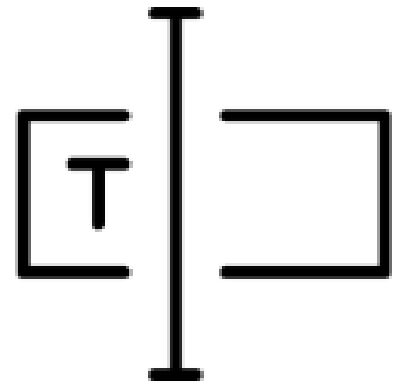
# Categories and membership constraints

Predefined finite set of categories

Type of data	Example values	Numeric representation
Marriage Status	unmarried , married	0 , 1
Household Income Category	0-20K , 20-40K , ...	0 , 1 , ..
Loan Status	default , payed , no_loan	0 , 1 , 2

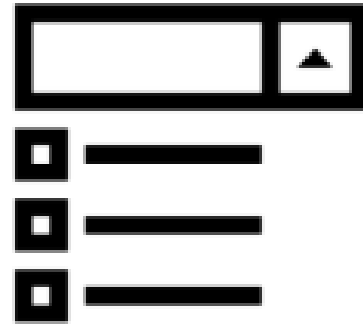
*Marriage status can **only** be* unmarried \_or\_ married

# Why could we have these problems?



*Free text*

Or



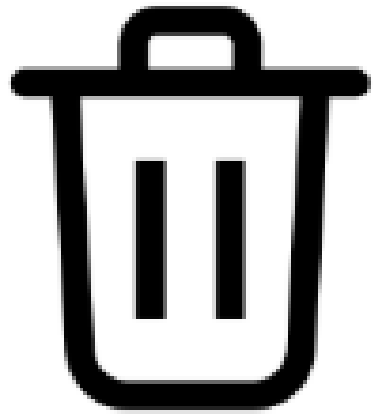
*Dropdowns*

***Data Entry Errors***

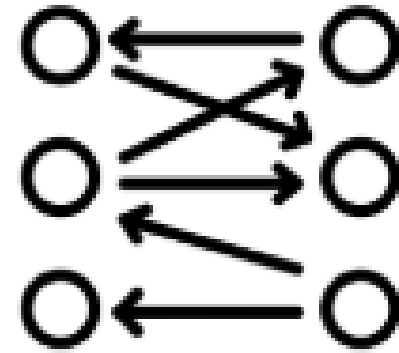


***Parsing Errors***

# How do we treat these problems?



***Dropping  
Data***



***Remapping  
Categories***



***Inferring  
Categories***

# An example

```
# Read study data and print it
study_data = pd.read_csv('study.csv')
study_data
```

	name	birthday	blood_type
1	Beth	2019-10-20	B-
2	Ignatius	2020-07-08	A-
3	Paul	2019-08-12	O+
4	Helen	2019-03-17	O-
5	Jennifer	2019-12-17	Z+
6	Kennedy	2020-04-27	A+
7	Keith	2019-04-19	AB+

```
# Correct possible blood types
categories
```

	blood_type
1	O-
2	O+
3	A-
4	A+
5	B+
6	B-
7	AB+
8	AB-

# An example

```
# Read study data and print it
study_data = pd.read_csv('study.csv')
study_data
```

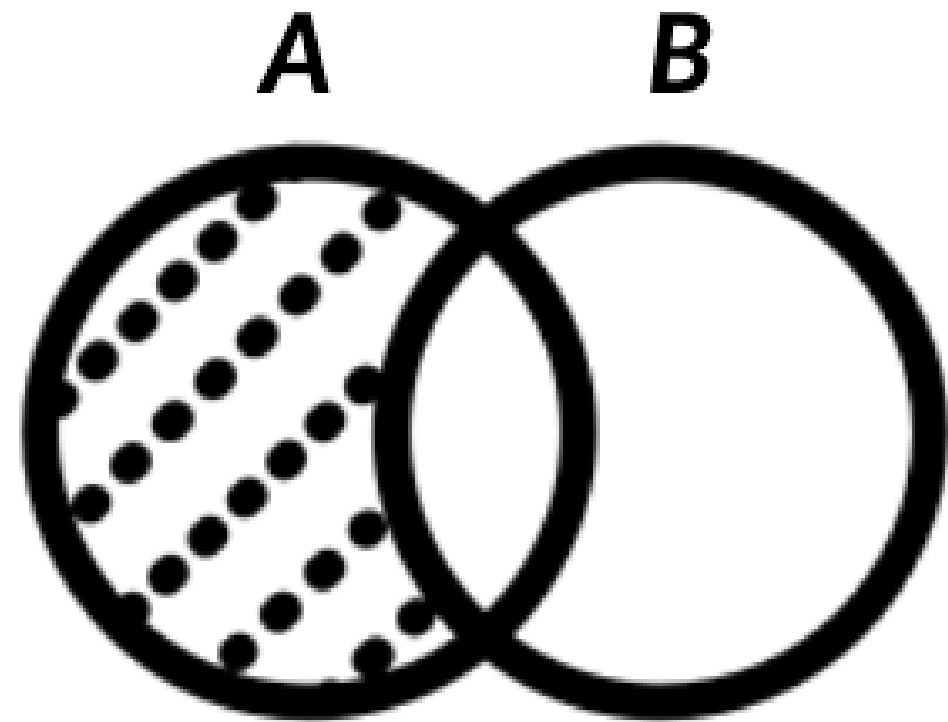
	name	birthday	blood_type
1	Beth	2019-10-20	B-
2	Ignatius	2020-07-08	A-
3	Paul	2019-08-12	O+
4	Helen	2019-03-17	O-
5	Jennifer	2019-12-17	Z+ <--
6	Kennedy	2020-04-27	A+
7	Keith	2019-04-19	AB+

```
# Correct possible blood types
categories
```

	blood_type
1	O-
2	O+
3	A-
4	A+
5	B+
6	B-
7	AB+
8	AB-

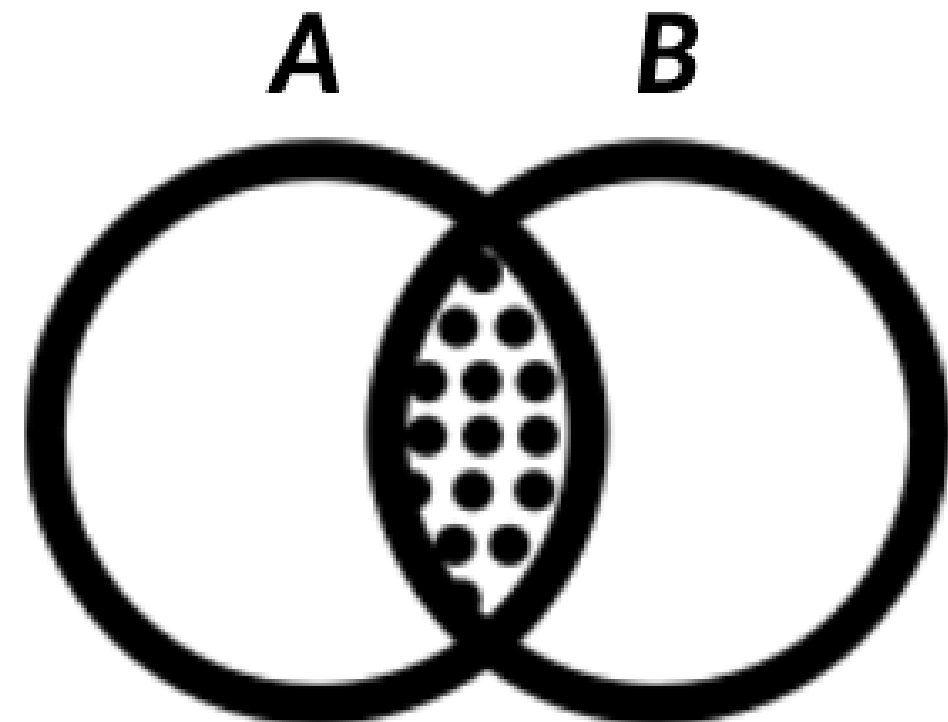
# A note on joins

## *Anti Joins*



*What is in A and not in B*

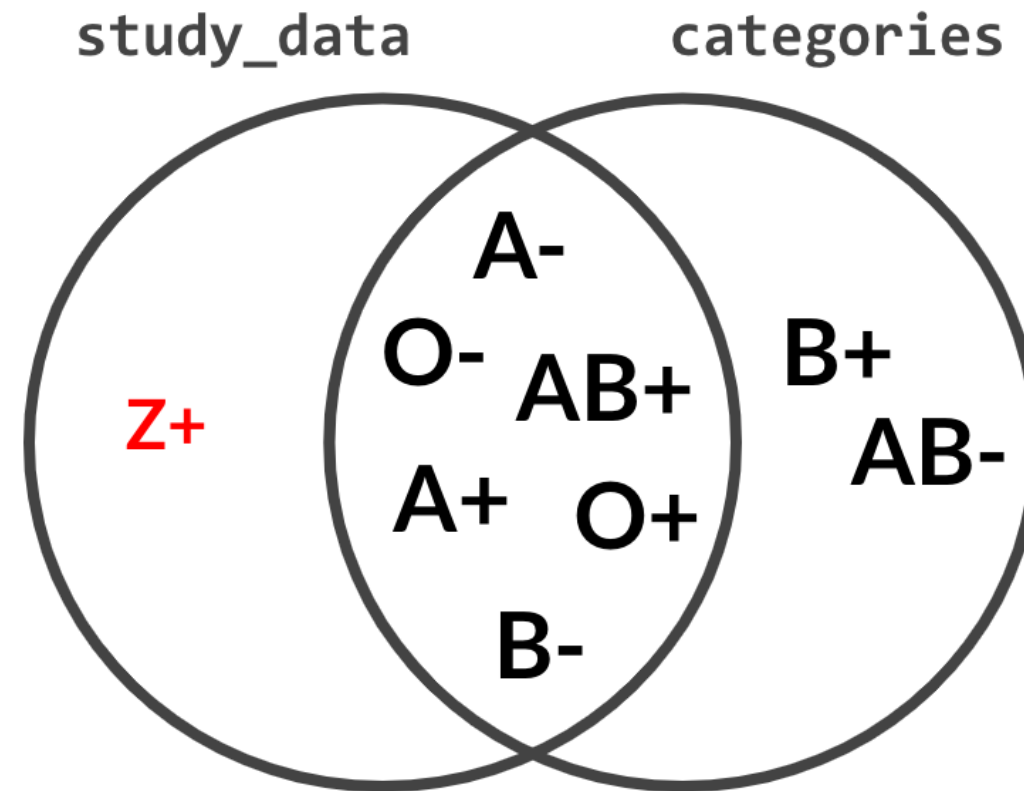
## *Inner Joins*



*What is in both A and B*



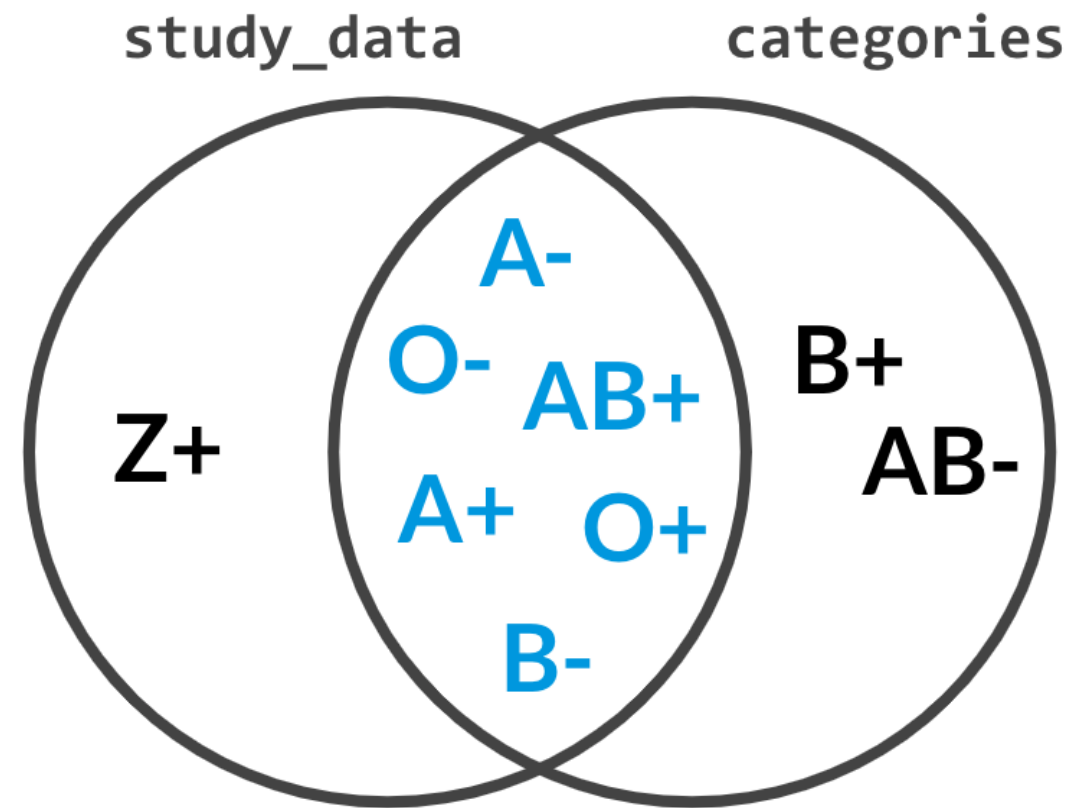
# A left anti join on blood types



*What is in study\_data only*

*Returns only rows  
containing Z+*

# An inner join on blood types



*What is in `study_data` and `categories` only*

*Returns all the rows except those  
containing **Z+**, **B+** and **AB-***

# Finding inconsistent categories

```
inconsistent_categories = set(study_data['blood_type']).difference(categories['blood_type'])  
print(inconsistent_categories)
```

```
{'Z+'}
```

```
# Get and print rows with inconsistent categories  
inconsistent_rows = study_data['blood_type'].isin(inconsistent_categories)  
study_data[inconsistent_rows]
```

```
   name  birthday blood_type  
5 Jennifer 2019-12-17      Z+
```

# Dropping inconsistent categories

```
inconsistent_categories = set(study_data['blood_type']).difference(categories['blood_type'])
inconsistent_rows = study_data['blood_type'].isin(inconsistent_categories)
inconsistent_data = study_data[inconsistent_rows]
# Drop inconsistent categories and get consistent data only
consistent_data = study_data[~inconsistent_rows]
```

	name	birthday	blood_type
1	Beth	2019-10-20	B-
2	Ignatius	2020-07-08	A-
3	Paul	2019-08-12	O+
4	Helen	2019-03-17	O-
...	...	...	...

**Let's practice!**  
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# Categorical variables

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# What type of errors could we have?

## I) Value inconsistency

- *Inconsistent fields:* 'married' , 'Married' , 'UNMARRIED' , 'not married' ..
- *\_Trailing white spaces:* \_ 'married ' , ' married ' ..

## II) Collapsing too many categories to few

- *Creating new groups:* 0-20K , 20-40K categories ... from continuous household income data
- *Mapping groups to new ones:* Mapping household income categories to 2 'rich' , 'poor'

## III) Making sure data is of type category (seen in Chapter 1)

# Value consistency

**Capitalization:** 'married', 'Married', 'UNMARRIED', 'unmarried' ..

```
# Get marriage status column
marriage_status = demographics['marriage_status']
marriage_status.value_counts()
```

```
unmarried    352
married      268
MARRIED      204
UNMARRIED    176
dtype: int64
```



# Value consistency

```
# Get value counts on DataFrame  
marriage_status.groupby('marriage_status').count()
```

	household_income	gender
marriage_status		
MARRIED	204	204
UNMARRIED	176	176
married	268	268
unmarried	352	352

# Value consistency

```
# Capitalize
```

```
marriage_status['marriage_status'] = marriage_status['marriage_status'].str.upper()  
marriage_status['marriage_status'].value_counts()
```

```
UNMARRIED    528  
MARRIED      472
```

```
# Lowercase
```

```
marriage_status['marriage_status'] = marriage_status['marriage_status'].str.lower()  
marriage_status['marriage_status'].value_counts()
```

```
unmarried    528  
married      472
```

# Value consistency

**Trailing spaces:** 'married ', 'married', 'unmarried', ' unmarried' ..

```
# Get marriage status column
marriage_status = demographics['marriage_status']
marriage_status.value_counts()
```

```
unmarried    352
unmarried    268
married      204
married      176
dtype: int64
```

# Value consistency

```
# Strip all spaces
demographics = demographics['marriage_status'].str.strip()
demographics['marriage_status'].value_counts()
```

```
unmarried    528
married      472
```

# Collapsing data into categories

*Create categories out of data:* `income_group` column from `income` column.

```
# Using qcut()
import pandas as pd
group_names = ['0-200K', '200K-500K', '500K+']
demographics['income_group'] = pd.qcut(demographics['household_income'], q = 3,
                                       labels = group_names)

# Print income_group column
demographics[['income_group', 'household_income']]
```

```
   category  household_income
0  200K-500K      189243
1    500K+      778533
..
```

# Collapsing data into categories

*Create categories out of data:* `income_group` column from `income` column.

```
# Using cut() - create category ranges and names
ranges = [0,200000,500000,np.inf]
group_names = ['0-200K', '200K-500K', '500K+']
# Create income group column
demographics['income_group'] = pd.cut(demographics['household_income'], bins=ranges,
                                      labels=group_names)
demographics[['income_group', 'household_income']]
```

	category	Income
0	0-200K	189243
1	500K+	778533

# Collapsing data into categories

***Map categories to fewer ones:*** reducing categories in categorical column.

operating\_system column is: 'Microsoft', 'MacOS', 'IOS', 'Android', 'Linux'

operating\_system column should become: 'DesktopOS', 'MobileOS'

```
# Create mapping dictionary and replace
mapping = {'Microsoft': 'DesktopOS', 'MacOS': 'DesktopOS', 'Linux': 'DesktopOS',
          'IOS': 'MobileOS', 'Android': 'MobileOS'}
devices['operating_system'] = devices['operating_system'].replace(mapping)
devices['operating_system'].unique()
```

```
array(['DesktopOS', 'MobileOS'], dtype=object)
```

**Let's practice!**  
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# Cleaning text data

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# What is text data?

Type of data	Example values
Names	Alex , Sara ...
Phone numbers	+96171679912 ...
Emails	`adel@datacamp.com`..
Passwords	...

## Common text data problems

1) *Data inconsistency:*

+96171679912 or 0096171679912 or ..?

2) *Fixed length violations:*

Passwords needs to be at least 8 characters

3) *Typos:*

+961.71.679912

# Example

```
phones = pd.read_csv('phones.csv')  
print(phones)
```

	Full name	Phone number
0	Noelani A. Gray	001-702-397-5143
1	Myles Z. Gomez	001-329-485-0540
2	Gil B. Silva	001-195-492-2338
3	Prescott D. Hardin	+1-297-996-4904
4	Benedict G. Valdez	001-969-820-3536
5	Reece M. Andrews	4138
6	Hayfa E. Keith	001-536-175-8444
7	Hedley I. Logan	001-681-552-1823
8	Jack W. Carrillo	001-910-323-5265
9	Lionel M. Davis	001-143-119-9210

# Example

```
phones = pd.read_csv('phones.csv')  
print(phones)
```

	Full name	Phone number	
0	Noelani A. Gray	001-702-397-5143	
1	Myles Z. Gomez	001-329-485-0540	
2	Gil B. Silva	001-195-492-2338	
3	Prescott D. Hardin	+1-297-996-4904	<-- Inconsistent data format
4	Benedict G. Valdez	001-969-820-3536	
5	Reece M. Andrews	4138	<-- Length violation
6	Hayfa E. Keith	001-536-175-8444	
7	Hedley I. Logan	001-681-552-1823	
8	Jack W. Carrillo	001-910-323-5265	
9	Lionel M. Davis	001-143-119-9210	

# Example

```
phones = pd.read_csv('phones.csv')  
print(phones)
```

	Full name	Phone number
0	Noelani A. Gray	0017023975143
1	Myles Z. Gomez	0013294850540
2	Gil B. Silva	0011954922338
3	Prescott D. Hardin	0012979964904
4	Benedict G. Valdez	0019698203536
5	Reece M. Andrews	NaN
6	Hayfa E. Keith	0015361758444
7	Hedley I. Logan	0016815521823
8	Jack W. Carrillo	0019103235265
9	Lionel M. Davis	0011431199210

# Fixing the phone number column

```
# Replace "+" with "00"
phones["Phone number"] = phones["Phone number"].str.replace("+", "00")
phones
```

	Full name	Phone number
0	Noelani A. Gray	001-702-397-5143
1	Myles Z. Gomez	001-329-485-0540
2	Gil B. Silva	001-195-492-2338
3	Prescott D. Hardin	001-297-996-4904
4	Benedict G. Valdez	001-969-820-3536
5	Reece M. Andrews	4138
6	Hayfa E. Keith	001-536-175-8444
7	Hedley I. Logan	001-681-552-1823
8	Jack W. Carrillo	001-910-323-5265
9	Lionel M. Davis	001-143-119-9210

# Fixing the phone number column

```
# Replace "-" with nothing
phones["Phone number"] = phones["Phone number"].str.replace("-", "")
phones
```

	Full name	Phone number
0	Noelani A. Gray	0017023975143
1	Myles Z. Gomez	0013294850540
2	Gil B. Silva	0011954922338
3	Prescott D. Hardin	0012979964904
4	Benedict G. Valdez	0019698203536
5	Reece M. Andrews	4138
6	Hayfa E. Keith	0015361758444
7	Hedley I. Logan	0016815521823
8	Jack W. Carrillo	0019103235265
9	Lionel M. Davis	0011431199210

# Fixing the phone number column

```
# Replace phone numbers with lower than 10 digits to NaN
digits = phones['Phone number'].str.len()
phones.loc[digits < 10, "Phone number"] = np.nan
phones
```

	Full name	Phone number
0	Noelani A. Gray	0017023975143
1	Myles Z. Gomez	0013294850540
2	Gil B. Silva	0011954922338
3	Prescott D. Hardin	0012979964904
4	Benedict G. Valdez	0019698203536
5	Reece M. Andrews	NaN
6	Hayfa E. Keith	0015361758444
7	Hedley I. Logan	0016815521823
8	Jack W. Carrillo	0019103235265
9	Lionel M. Davis	0011431199210



# Fixing the phone number column

```
# Find length of each row in Phone number column
sanity_check = phone['Phone number'].str.len()
```

```
# Assert minmum phone number length is 10
assert sanity_check.min() >= 10
```

```
# Assert all numbers do not have "+" or "-"
assert phone['Phone number'].str.contains("+|-").any() == False
```

***Remember,*** `assert` *returns nothing if the condition passes*

# But what about more complicated examples?

```
phones.head()
```

	Full name	Phone number
0	Olga Robinson	+(01706)-25891
1	Justina Kim	+0500-571437
2	Tamekah Henson	+0800-1111
3	Miranda Solis	+07058-879063
4	Caldwell Gilliam	+(016977)-8424

*Supercharged control + F*

# Regular expressions in action

```
# Replace letters with nothing
phones['Phone number'] = phones['Phone number'].str.replace(r'\D+', '')
phones.head()
```

	Full name	Phone number
0	Olga Robinson	0170625891
1	Justina Kim	0500571437
2	Tamekah Henson	08001111
3	Miranda Solis	07058879063
4	Caldwell Gilliam	0169778424

**Let's practice!**  
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