

Announcements

- Readings:
 - In https://github.com/gquer/dsc-96_winter19/blob/master/03_joining_mapping/readings.md
 - By Wednesday Jan. 23 at 6.00pm
 - To gquer@ucsd.edu
 - **Subject:** [DSC 96 W03 SecA|C Journal]: Name LastName
- Titanic [Optional]:
 - add a sentence at the end of the readings W03 email
 - About your results/story
 - What did you discover about the Titanic
 - What did you learn
- Starting next week
 - We'll check class attendance
 - Write me an email if you can not attend one lecture



Data is (still) Messy

Giorgio Quer (adapted from Colin Jemmott)
DSC 96

Much of this is adapted from the outstanding “Quartz Bad Data Guide”

<https://github.com/Quartz/bad-data-guide>

Identifying messy data

- Are the data types correct?
- String type fields are have consistent values?
- No missing values that we don't understand?
- All values look in a reasonable range?

The data was perfect, right? HA!

How do we deal with the messiness we found?

Identifying messy data

- Are the data types correct?
 - Mostly. Did a little convenience conversion
- String type fields are have consistent values?
 - Case Type, Sex, Ethnicity
 - Solutions: Re-map values (calculated field), filter values, etc...
- All values look in a reasonable range?
 - Age
 - Solutions: filter, smooth,...
- No missing values that we don't understand?
 - Age, Time, Search, Arrested,....
 - Solutions: filter, imputation, create a new binary variable

Human entered data

The dog licensing website for Cook County, Illinois gave a text field to type your dog breed into. As a result this database contained at least 250 spellings of Chihuahua!

How can this be fixed?



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How can this be fixed?

One solution: limit choices

SEARCH FOR A BREED

Select A Breed ▲

Affenpinscher

Afghan Hound

Airedale Terrier

Akita ▼

Alaskan Malamute

American English Coonhound

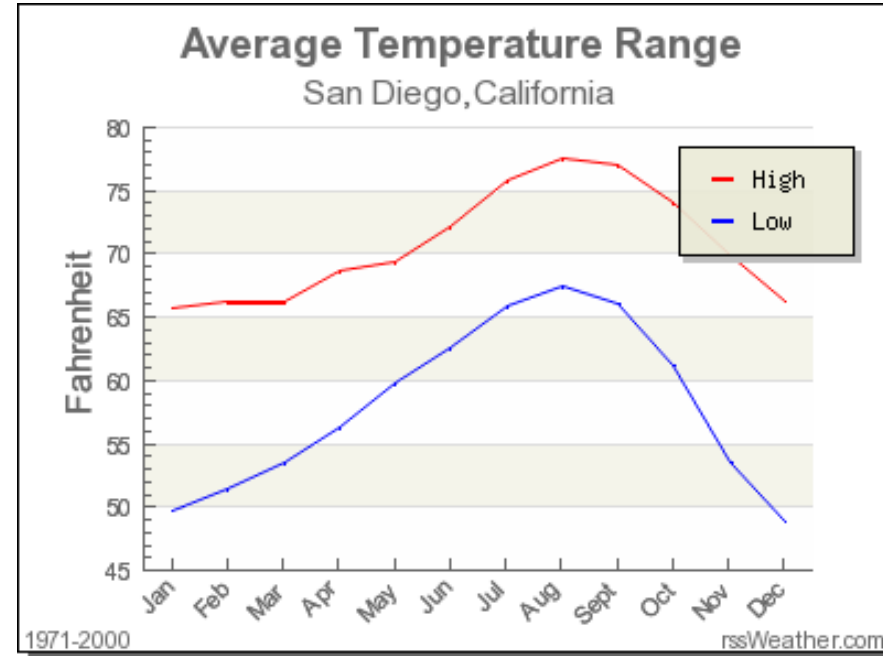
American Eskimo Dog



Non-Stationary Data

The average low temperature in San Diego is 57 F (14 C). If it is July do you need to bring a sweater?

Sheldon graduated from UCSD CSE in 2010 and got an entry level job paying \$60,000. After working his way up, he is now earning \$68,000. That is more money, right?



Outliers and “Incorrect” Values

- Consistently “nonsense” values
 - Is it a product of the data ingestion process? Time field has year 1899? Is it an inferred “default” value?
 - Solution: Change the value to the correct one!
- Abnormal artifacts from the data collection process
 - E.g. unreasonable spikes in recorded ages at round numbers (25, 35, 45)
 - Solution: Try “smoothing” (e.g. binning the ages)
- Unreasonable outliers
 - Data points with unrealistic and highly unreasonable values. E.g. age=200
 - Solution: filter it? Maybe it points to bugs in the data collection? Maybe it’s **real** and you should investigate!

Missing data

vehicle_stops_2016_datasd

stop_id	stop_cause	service_area	subject_race	subject_sex	subject_age	timestamp	stop_date	stop_time	sd_resident	arrested	searched
1308198	Equipment Violation	530	W	M	28	2016-01-01 00:06:00	2016-01-01	0:06	Y	N	N
1308172	Moving Violation	520	B	M	25	2016-01-01 00:10:00	2016-01-01	0:10	N	N	N
1308171	Moving Violation	110	H	F	31	2016-01-01 00:14:00	2016-01-01	0:14			
1308170	Moving Violation	Unknown	W	F	29	2016-01-01 00:16:00	2016-01-01	0:16	N	N	N
1308197	Moving Violation	230	W	M	52	2016-01-01 00:30:00	2016-01-01	0:30	N	N	N
1308200	Moving Violation	710	H	M	24	2016-01-01 00:30:00	2016-01-01	0:30	Y	N	N
1308174	Moving Violation	Unknown	O	M	20	2016-01-01 00:35:00	2016-01-01	0:35	Y	N	N
1308199	Moving Violation	440	H	M	50	2016-01-01 00:45:00	2016-01-01	0:45	Y	N	N
1308979	Moving Violation	310	H	F	25	2016-01-01 01:03:00	2016-01-01	1:03	Y	N	Y
1308965	Moving Violation	240	W	F	23	2016-01-01 01:10:00	2016-01-01	1:10	Y	N	N
1308175	Moving Violation	120	O	M	54	2016-01-01 01:20:00	2016-01-01	1:20	Y	N	N
1308176	Moving Violation	520	W	F	53	2016-01-01 01:39:00	2016-01-01	1:39	Y	N	N
1308177	Moving Violation	520	W	M	35	2016-01-01 01:57:00	2016-01-01	1:57	N	N	N
1308178	Moving Violation	520	W	M	29	2016-01-01 02:00:00	2016-01-01	2:00	N	Y	N
1308180	Moving Violation	510	B	M	38	2016-01-01 03:24:00	2016-01-01	3:24	Y	N	N
1308182	Moving Violation	310	W	M	24	2016-01-01 06:40:00	2016-01-01	6:40	Y	N	N
1308202	Moving Violation	Unknown	W	F	28	2016-01-01 00:15:00	2016-01-01	0:15	Y	N	N

Missing data

- Missing by Design (MD)
 - The field being absent is deterministic.
- Missing Completely at Random (MCAR)
 - The missing value isn't associated to the (actual, unreported) value itself, nor the values in any other fields.
 - The participants with completely observed data are in effect a random sample of all the participants
 - The analysis performed on the data is unbiased
 - Example: additional questions in a survey are posed on a random sample of respondents
- Missing at Random (MAR)
 - A missing value may depend on values of other fields, but not its own
 - Example: service workers are less likely to report income.
- Not Missing at Random (NMAR)
 - A missing value depends on the value of the (actual, unreported) variable that's missing.
 - Example: people with high income are less likely to report income.

Missing data

- See example ipython!

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Null Values: MD, MCAR, MAR, NMAR?

- Attrition due to natural processes?
- Built into the data collection process (intentional)?
- Random issues in (the mechanics of) the data collection process.
- Non-response or refusal

It's very tricky to distinguish between these with certainty!

Can you come up with examples from SDPD dataset?

Null Value Imputation (what to do about them)

- Missing by Design
 - Fill them in? Drop them? Recode the variable?
- Missing Completely at Random (MCAR)
 - Dropping them is ok (if there aren't too many)
- Missing at Random (MAR)
 - Careful! Dropping data will skew your dataset!
 - Replace with mean/mode (perhaps by an associated group)
 - Train a model to replace the missing values
- Not Missing at Random (NMAR)
 - Difficult! Proceed with caution!
 - Train a model to replace the missing values

SD police stop data

1. age:

- how are they distributed?
- What issues you observe? anything strange?
- Divide by sex and age

2. ethnicity:

- which races do you see? Can you rename them?
- which are more represented? should we group them?
- stop vs searched (or arrested): anything conclusion we can see here?

3. time series plot:

- plot by quarter, month, day.. any issue you see?
- Plot by minute?
- are there any abnormality low/high to discuss?

Searched

- Data is Y y N n Null
- Group them: create - group, N n and Null in the same group
- Change format:
 - Create - Calculated Field:
 - IF [Searched (group)]= 'No' THEN 0 ELSE 1 END
- Move to Measures
- Now we can calculate the average !!!

