

# data cleaning principles

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[bit.ly/datacleaning2023](https://bit.ly/datacleaning2023)



Tidy data are all alike,  
but every messy dataset  
is messy in its own way.

– Hadley Wickham

If I clean up [Medicare] data ...  
does any of the knowledge I gain ...  
apply to the processing of RNA-seq data?

– Roger Peng

# Data Mishaps Night

Join us for the first inaugural Data Mishaps Night!  
We will feature a lineup of data mistake stories with  
a focus on the human aspect of data work and  
lessons learned the hard way.



Caitlin Hudon & Laura Ellis  
[dataMishapsNight.com](http://dataMishapsNight.com)

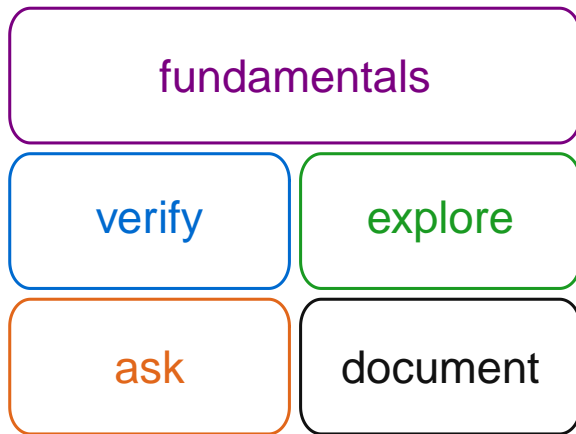
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- ▶ embarrassing
- ▶ needs context
- ▶ doesn't feel like progress

# Data cleaning

- ▶ tedious
- ▶ embarrassing
- ▶ needs context
- ▶ doesn't feel like progress
- ▶ requires creativity
- ▶ requires coding prowess
- ▶ source of many problems

# Data cleaning principles



## fundamentals

1. Don't clean data when you're tired or hungry.

(paraphrasing Ghazal Gulati)



## fundamentals

2. Don't trust anyone (even yourself)

## fundamentals

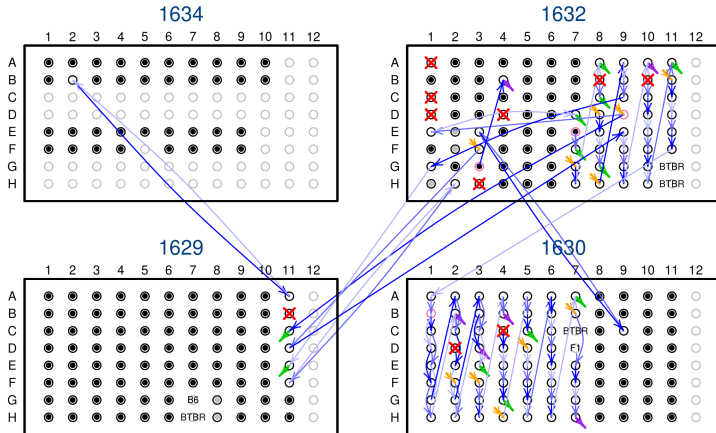
### 2. Don't trust anyone (even yourself)

“my motto is ‘trust no one’  
...except maybe @kwbroman?”

– Jenny Bryan

# fundamentals

3. Think about what might have gone wrong and how it might be revealed



doi:10/gpfzs8

# fundamentals

## 4. Use care in merging

	A	B	C	D	E	F	G		
1	id	glucose.0	glucose.5	glucose.15	glucose.30	insulin.0	insulin.5		
2	DO-221	145.742786	206.452638	216.640608	299.55501	0.74455	2.0264		
3	DO-222								
4	DO-223		A	B	C	D	E	F	G
5	DO-224	1	id	glucose.0	insulin.0	glucose.5	insulin.5	glucose.15	insulin.15
6	DO-225	2	DO-321	66.839405	0.04	246.685995	0.04	305.26214	0.04
7	DO-226	3	DO-322	98.12509	0.51185	246.25574	1.4062	301.8201	2.828
8	DO-227	4	DO-323	94.68305	1.7812	448.1068	1.0248	521.61894	1.02725
9	DO-228	5	DO-324	121.051535	0.0882	407.355505	0.63475	470.541525	0.8195
10	DO-229	6	DO-325	122.95695	0.19155	298.193665	0.6467	323.148455	0.40515
11	DO-230	7	DO-326	201.447755	0.7454	386.51887	0.6081	654.99799	1.07225
		8	DO-327	130.025425	0.0509	477.302675	0.166	610.49733	0.4842
		9	DO-328	143.60919	0.23435	438.88705	0.70505	406.249135	0.2498
		10	DO-329	125.29262	0.04	543.74634	1.7366	520.205245	0.8498
		11	DO-330	135.61874	0.91275	393.03416	3.73095	454.62209	1.7325

## fundamentals

### 5. Dates & categories suck

Principle:

a fundamental truth that guides our thinking

# fundamentals

## 5. Dates & categories suck

verify

## 6. Check that distinct things are distinct

	A	B	C	D	E	F	G
1	WiscID	ID	NEOID	Fem_CA	Fem_lmax	Fem_lmin	Fem_J
2	F2.C1W.F.1248	1248	NEO183	0.7524	0.1427	0.1006	0.2433
3	F2.C1W.M.1250	1250	NEO184	0.7669	0.1556	0.09652	0.2521
4	F2.C1W.F.1251	1251	NEO185	0.7613	0.1549	0.09659	0.2515
5	F2.C1W.F.1254	1254	NEO186	0.7475	0.1503	0.08603	0.2363
6	F2.C1W.M.1257	1257	NEO187	0.8197	0.1849	0.1056	0.2905
7	F2.___.F.715	715	NEO764	0.6017	0.09662	0.05969	0.1563
8	F2.___.F.751	751	NEO765	0.7273	0.1304	0.08735	0.2178
9	F2.___.F.1251	1251	NEO766	0.6675	0.1157	0.07814	0.1938
10	F2.___.M.1340	1340	NEO768	0.6656	0.1387	0.08122	0.2199
11	F2.C1W.M.739	739	NEO779	0.9336	0.2828	0.1628	0.4456



verify

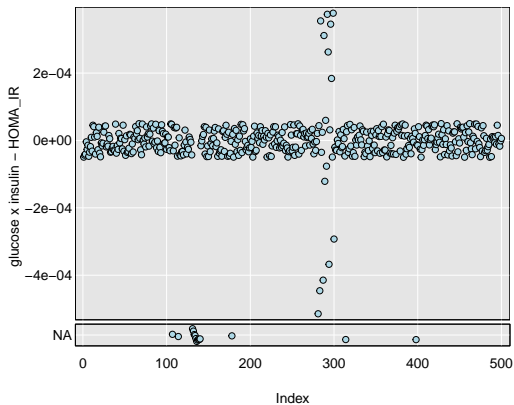
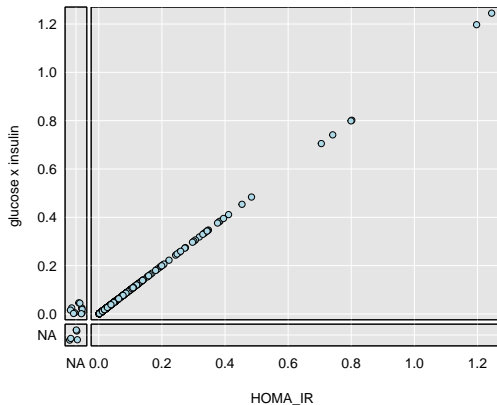
## 7. Check that matching things match

	A	B	C	D
1	id	sex	n_gen	age_days
2	F20.25	M	20	75
3	F21.30	M	21	75
4	F21.68	M	21	71
5	F22.52	M	22	73
6	F21.71	F	22	63
7	F22.116	F	22	57
8	F21.F20.9.M5	M	20	82
9	F21.F20.18.M5	M	20	77
10	F20.26	M	20	75
11	F21.62	M	21	72

	A	B	C	D
1	id	sex	age_at_dosing	n_gen
2	F22.69	F	67	22
3	F22.106	F	69	22
4	F22.70	F	67	22
5	F22.107	F	69	22
6	F21.71	F	65	21
7	F22.116	F	62	22
8	F22.73	F	65	22
9	F22.117	F	62	22
10	F21.108	F	62	21
11	F22.118	F	59	22

verify

## 8. Check calculations

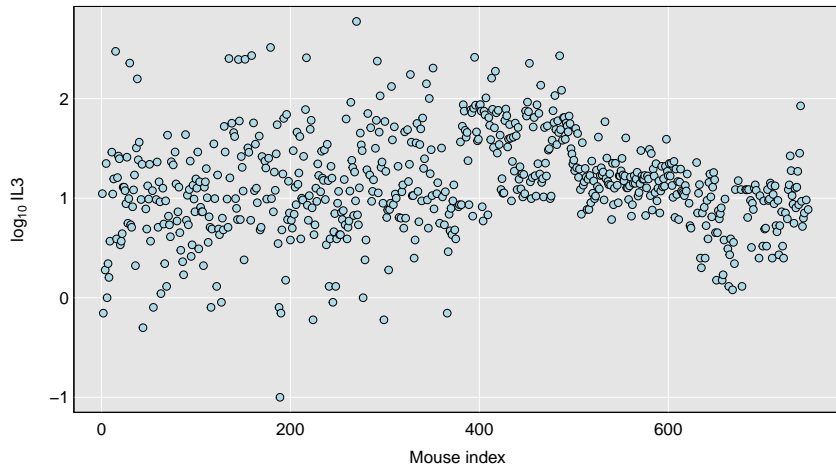


verify

9. Look for other instances of a problem

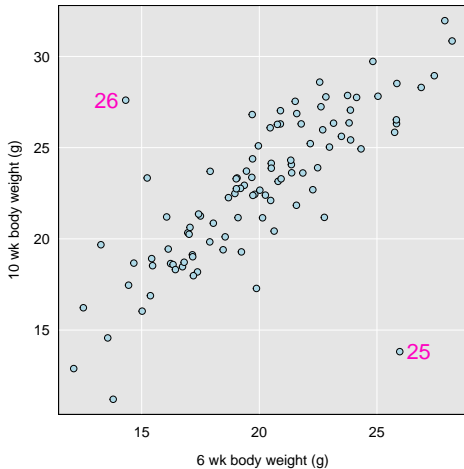
explore

## 10. Make lots of plots



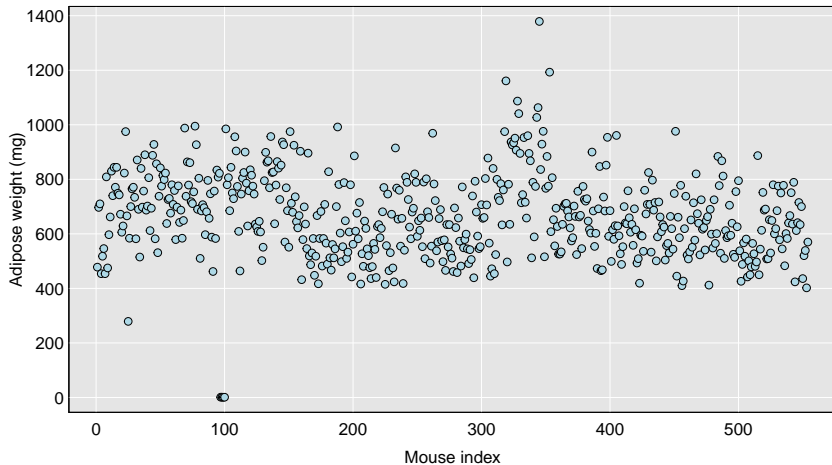
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explore

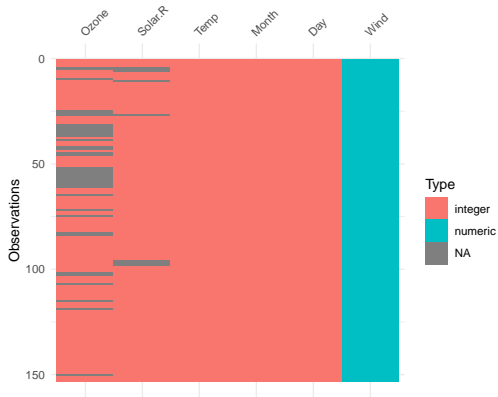
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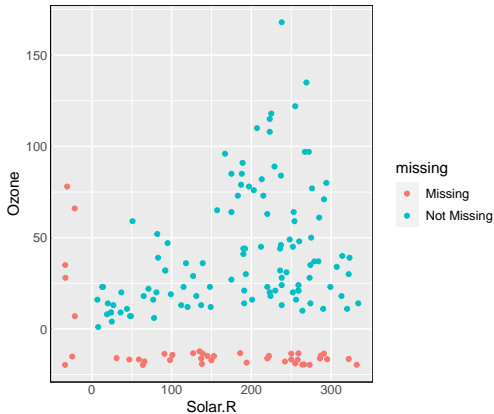
# explore

## 11. Look at missing value patterns

{visdat}

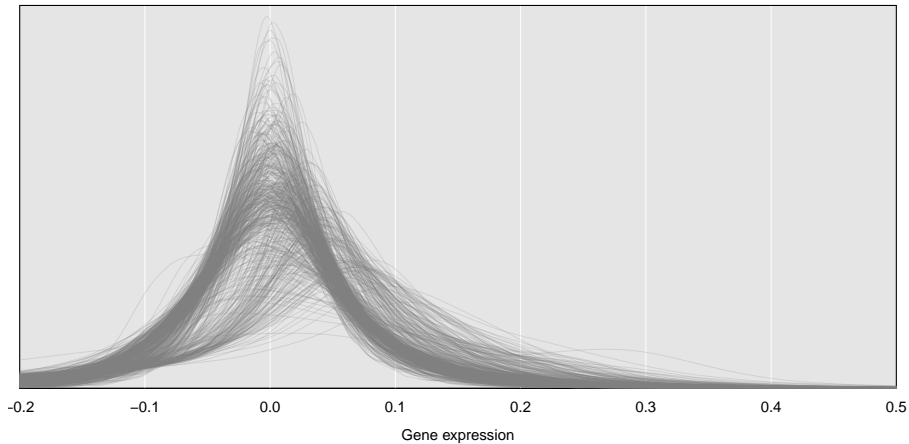


{naniar}



explore

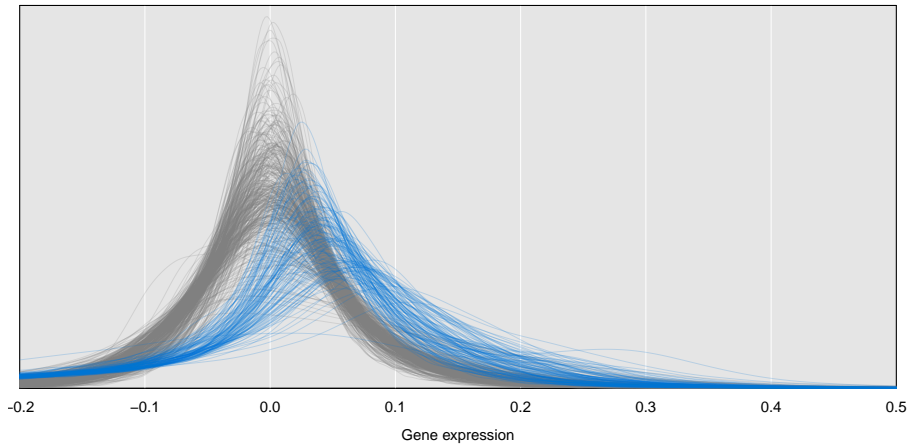
12. With massive data,  
make more plots not fewer





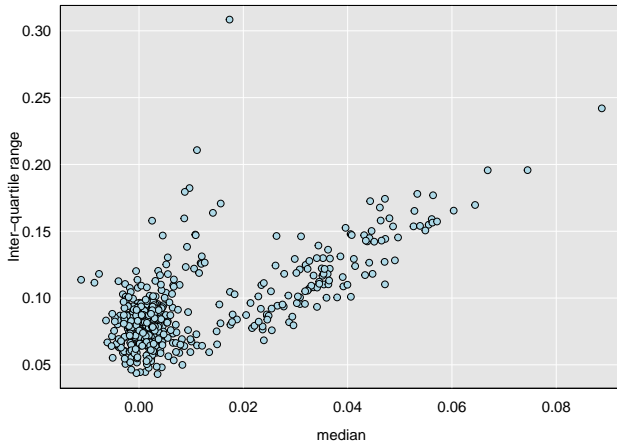
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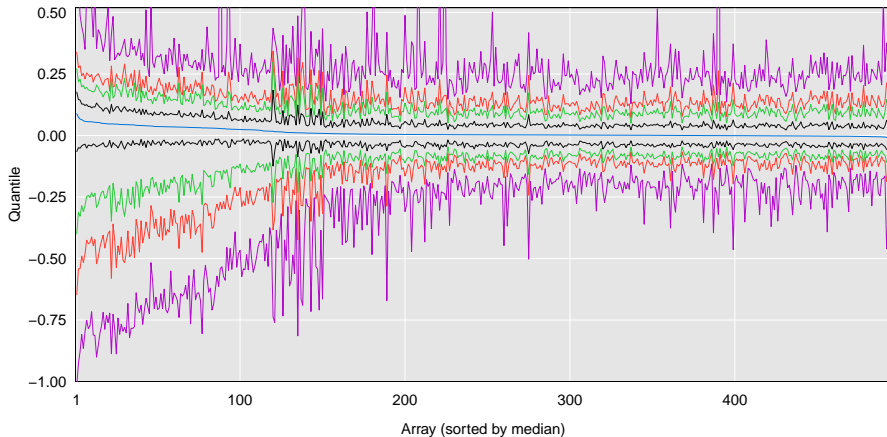
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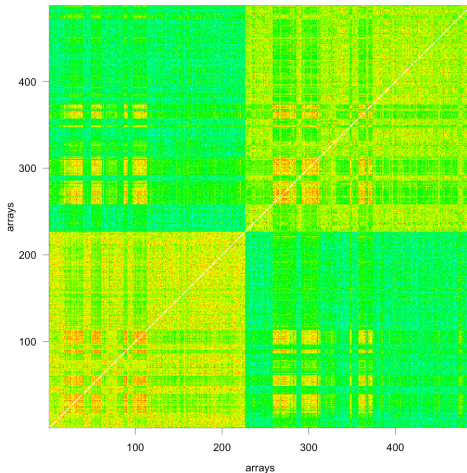
explore

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make more plots not fewer



explore

### 13. Follow up all artifacts



ask

## 14. Ask questions

When were the data gathered?

How, and by whom?

Was the data gathered in batches?

How were the data files created?

Was any calibration or normalization done?

ask

## 15. Ask for the primary data

	A	B	C	D	E	F	G	H
1	MouseNum	Wean Date	Assay Date	Weight	Glucose	Insulin	Trigly	HOMA
2	Mouse3001	6/22/2005	8/18/2005	47.3	617	11.7	175.1	321.9
3	Mouse3002	6/22/2005	8/18/2005	51	256.5	50.6	97.6	576.6
4	Mouse3003	6/22/2005	8/18/2005	50.6	274.9	52.5	160.5	641.3
5	Mouse3004	6/22/2005	8/18/2005	46	615.1	9	238.7	246
6	Mouse3005	6/30/2005	b	42.4	NA	NA	102.3	587.1
7	Mouse3006	6/30/2005	b	39.7	NA	NA	209.4	338.7
8	Mouse3007	6/30/2005	b	36.9	NA	NA	69.8	140.6
9	Mouse3008	6/30/2005	b	50	195.5	45.3	142.1	393.4
10	Mouse3009	6/30/2005	b	40.1	569.4	12.4	411	312.9
11	Mouse3010	6/30/2005	b	40.7	593.8	15.6	333.6	411.8

ask

16. Ask for metadata

“What the heck is ‘FAD\_NAD SI 8.3\_3.3G’?”

ask

## 16. Ask for metadata

	A	B	C	D
1	name	plot_name	group	description
2	mouse	Mouse	demographic	Animal identifier
3	sex	Sex	demographic	Male (M) or Female (F)
4	sac_date	Date of sac	demographic	Date mouse was sacrificed
5	partial_inflation	Partial inflation	clinical	Indicates if mouse showed partial pancreatic inflation
6	coat_color	Coat color	demographic	Coat color, by visual inspection
7	crumblers	Crumblers	clinical	Indicates if mouse stored food in their bedding
8	diet_days	Days on diet	clinical	Number of days on high-fat diet



ask

## 17. Ask why data are missing

Assay failed?

Below detection limit?

Viewed as outliers?

Subjects dropped out?

## document

### 18. Create checklists & pipelines

- ☐ Percent missing genotypes
- ☐ Sample duplicates
- ☐ Sex and X/Y genotypes
- ☐ Heterozygosity
- ☐ Genotype frequencies
- ☐ Crossover counts
- ☐ Genotyping error rates

### Gough project diagnostics

Karl Broman, 3 March 2014

#### Combine genotypes and phenotypes

I've combined the initial genotypes (using the re-clustered genotypes for plates 14-16) with the well-behaved portion of the re-run genotypes. I'm focusing on 36813 markers that are informative (though, as we'll see, there are still a lot of badly behaved and basically non-informative markers that need to be removed). I've combined data on replicate samples, to give one set of genotype calls for each sample.

There are 1497 genotyped mice and 1464 phenotyped mice. All of the mice in the phenotype data have genotypes, but there are 33 genotyped mice with no phenotypes, including 3 Gough mice and 30 F2 progeny.

document

20. Expect to recheck

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6. Verify that distinct things are distinct
7. Verify that matching things match
8. Check calculations
9. Look for other instances of problems

## explore

10. Make lots of plots
11. Look at missing value patterns
12. With big data make more plots
13. Follow up all artifacts

## ask

14. Ask questions
15. Ask for the primary data
16. Ask for metadata
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## document

18. Create checklists & pipelines
19. Document not just what but why
20. Expect to recheck

I will let the data speak for itself  
when it cleans itself.

— Allison Reichel

Slides: [bit.ly/datacleaning2023](https://bit.ly/datacleaning2023)

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