

Workshop Outline

Introduction

Modern Data Analysis Teams and Technologies

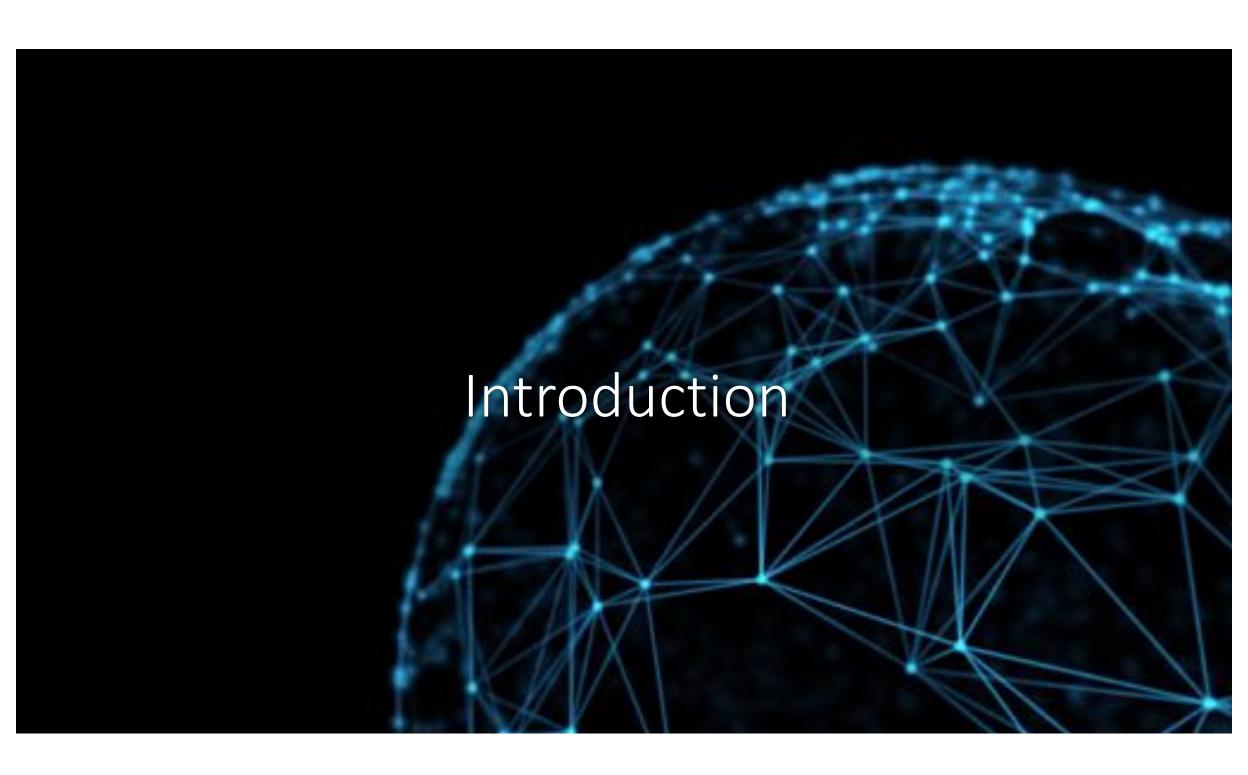
- Modern Teams
- Modern Technologies
- Data Preparation

Analysis

- Machine Learning vs Statistics vs Business Intelligence
- Business Intelligence
- Machine Learning/Al
 - Intro
 - A quick tools discussion
 - Relevant Techniques

Analysis (Cont.)

- Statistics
 - A very quick tools discussion
 - Modern Statistics Controversies and Conversations
 - Your Data, Your Questions
 - Some Relevant Statistical Concepts and Techniques



Armchair analysis



What is (data) analysis?

Some possible answers

Finding patterns in data

Using data to do something (answer a question, help decision-making, predict the future, knowledge discovery)

Describing or explaining your situation (your **system**)

Creating models of your data

(Testing (scientific) hypotheses?)

(Carrying out calculations on data?)



The more complicated the pattern, the more complicated the analysis.



- Typically we want to gain insight into a past, current, possible or general situation.
- For example: grant application situation, grant awarding situation
- We want to be able to: answer questions, describe what happens, explain why it happens, gain new knowledge about the situation.
- More formally: **analysis + synthesis**. A technique used for thousands of years to gain insight into our experiences.

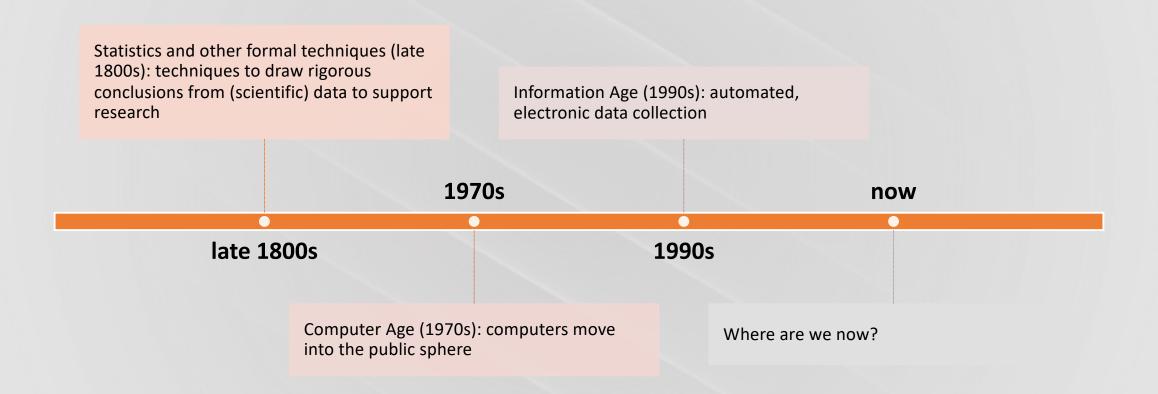
Formal Reasoning Techniques

INDUCTIVE (INFERENTIAL), DEDUCTIVE, ABDUCTIVE, ANALOGICAL REASONING

FURTHER SPECIALIZED TECHNIQUES: THE SCIENTIFIC METHOD, STATISTICAL REASONING, MATHEMATICAL AND COMPUTER MODELLING.

EVIDENCE BASED ANALYSIS. EVIDENCE BASED ANALYSIS MAY BE MORE MORE OR LESS TECHNICAL.

Rise of analysis?



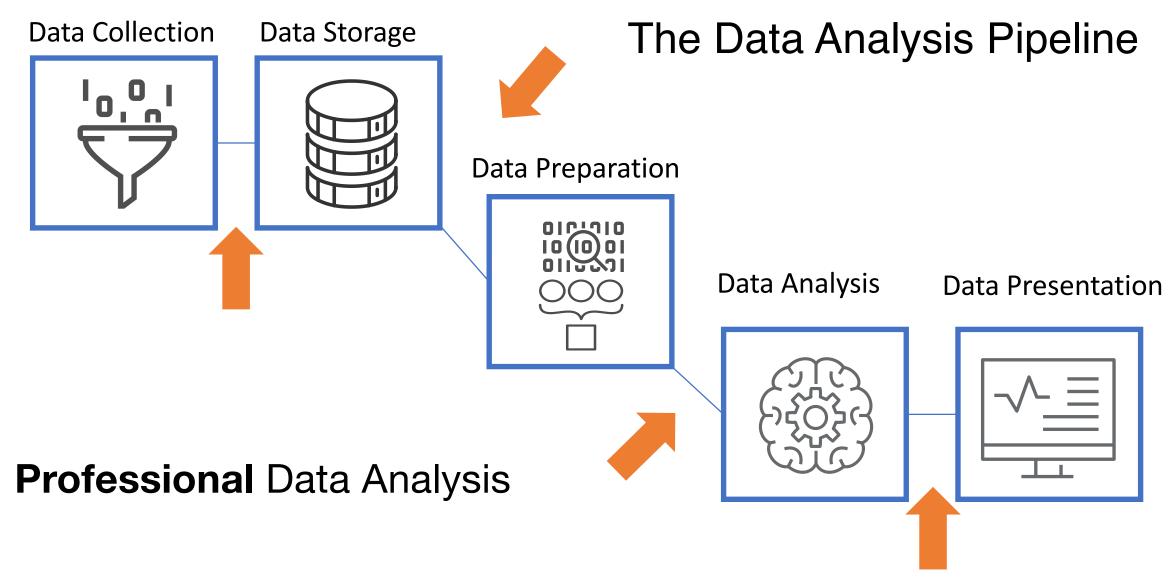
Pre-Digital Age vs The Digital Age

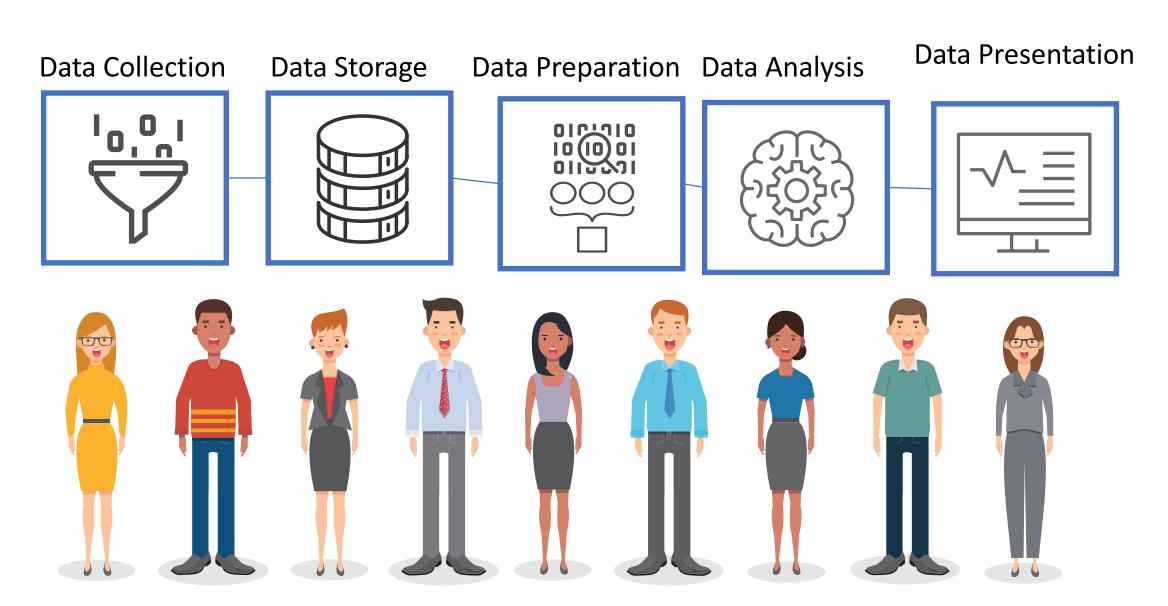
Then: Only people could carry out the activity of analysis and the components of an analysis process

Now: We can distill the essence of an analysis process into an algorithm, and automate the activity of analysis and its supporting process. We have analysis machines.

Then: A given analysis of a situation was typically seen as a one-time, oneoff activity. A single person might carry out 'an analysis' and then move on.

Now: We can expect that we will probably want to repeat variations of the same analysis over and over again on new data that is streaming in on a regular basis





Modern Data Analysis Is A Team Sport

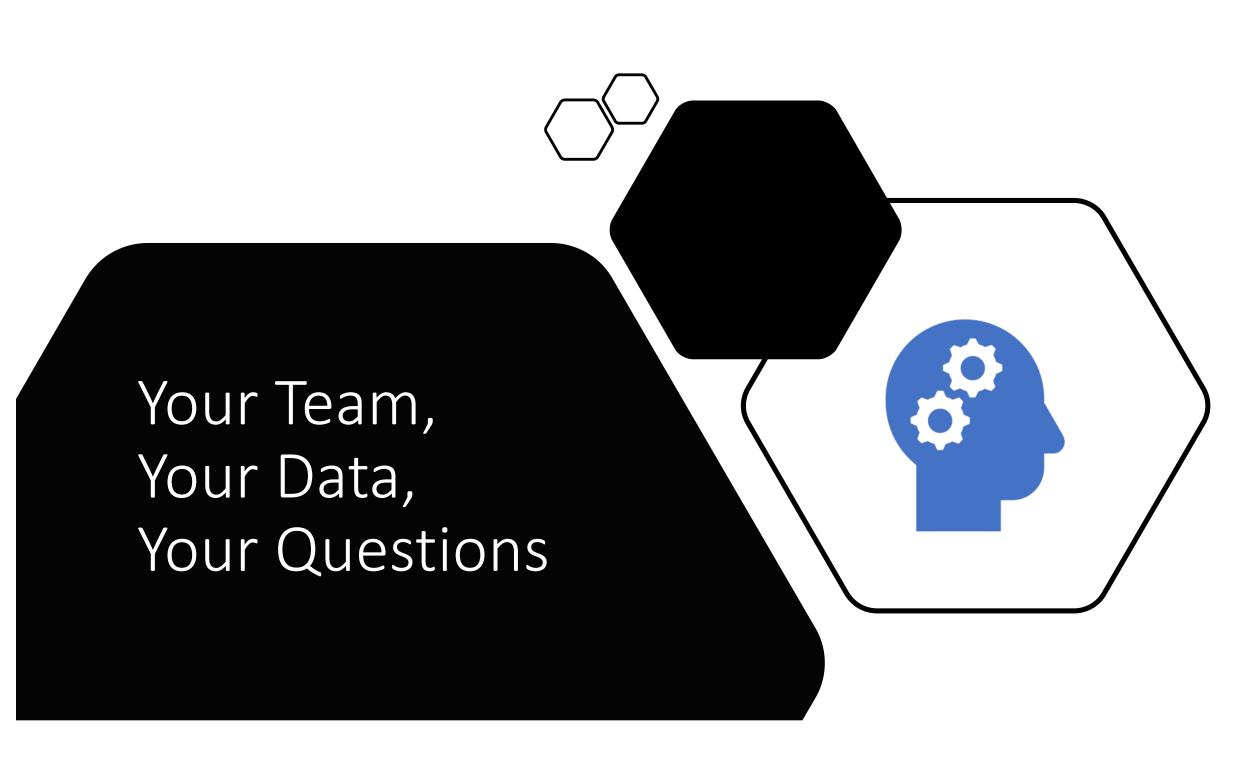


Goals For Today

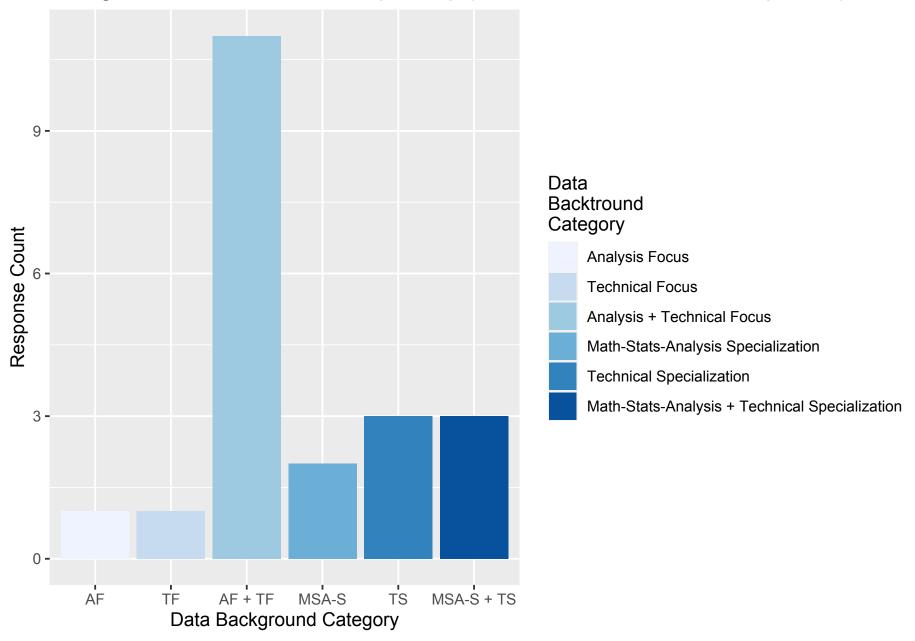
Orient	Orient you towards modern data analysis
Build	Build a picture of the modern analysis landscape - what can modern data analysis DO
Understand	Understand how your work goals can be supported by different aspects of the data analysis landscape
Understand	Understand where your current interests and skillsets position you and your team within this landscape
Gain	Gain a sense of the gaps that might exist between where you are now and where you need to be to achieve analysis goals
Understand	Understand what next steps you need to take to bridge the gap, personally and in a team context
Gain	Gain awareness of resources you can draw on to take the next steps to achieve your goals

Some Useful Analogies

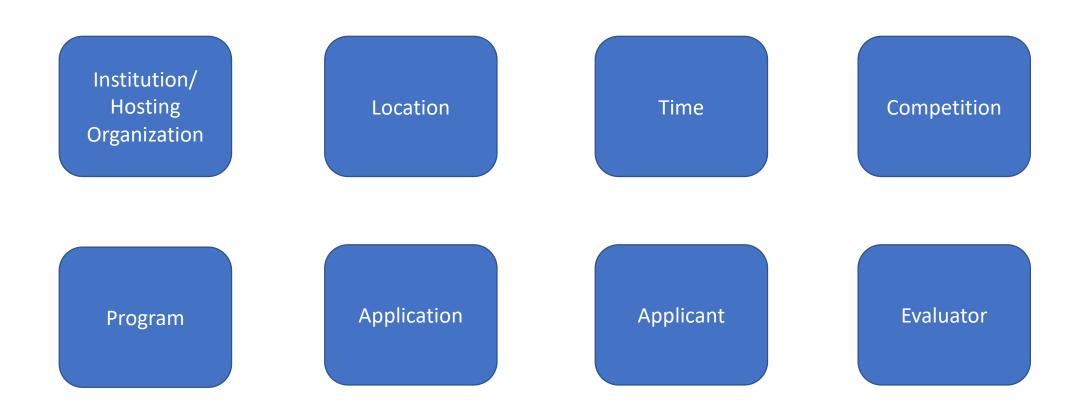
Medicine Cooking **The World of Cars** People who own cars Everyone Home Cook **Amateur** First Aider Car Hobbyist Bake-Sale Folks? **Paramedic** Semi-Pro Racer Semi-Pro Gas Station Mechanic? Doctor: GP, Specialist Chef Nurse Garage Mechanic Pastry Chef **Professional Hospital Director Restaurant Owner Body Shop Specialist**



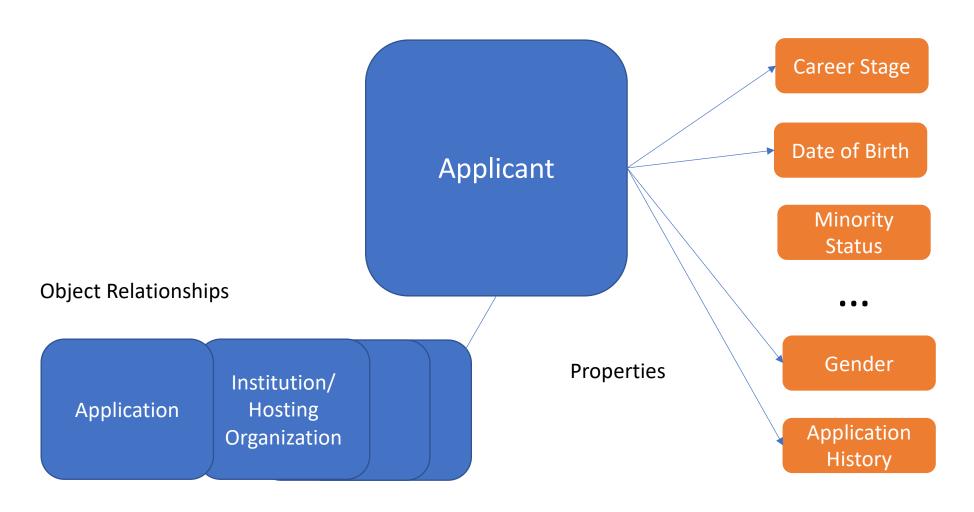
Background of NSERC Workshop Group (Based on Questionnaire Responses)



Key Objects Sketch – NSERC Grants



A Key Object with Properties – NSERC Grants



Topics from Survey: NonStatistical

REPORTING AND DATA PREPARATION

- Any tips for generating reports from data (e.g., my team maintains an Excel "work plan" spreadsheet of our projects. Useful if I can pull reports from this data every quarter or so for senior management).
- Importing data from various sources to use in analysis (e.g. several Excel spreadsheets that are updated monthly/quarterly, websites, etc.)
- Translation of Power BI, tips and short cuts.

REPORTING AND DATA PREPARATION (CONT.)

- Best practices of data preparation for data analysis (i.e. curation, verification, setup, etc.)
- Preparing data sets for analysis

TEXT ANALYSIS + MACHINE LEARNING

- word cloud and keyword analysis. any additional methods to gain insight into data from freeform text entries
- Working with text data
- Data analysis, AI / ML

Topics from Survey: Statistical (I)

POPULATION VS SAMPLE

- statistical techniques to compare period data (e.g., year to year)
- Statistical techniques for population data
- Using significance tests when you've captured the whole population in the dataset

SIGNIFICANCE TESTS

 statistical significance tests which to use for questions commonly asked about NSERC data and how to perform them

SIGNIFICANCE TESTS (CONT.)

- "How to determine statistical significance of findings. For example at NSERC, when is the difference between an application rate and an award rate significant?
- the statuses of grants and scholarships are successful or unsuccessful (analysis of those, how to analyse if the results from two subgroups are statistically different, what approach would you use?)

TOOLS FOR DOING STATS

Statistical tools available in the software.

Topics from Survey: Statistical (II)

MULTI-VARIABLE, MULTI-LEVEL, MULTI-FACTOR, MULTI-PASS!

- What is the best approach for multi-variable analysis. For example at NSERC, intersectional analysis in the context of EDI could have multiple identity factors."
- Advanced analyses techniques (e.g., multi-level regression analyses)

OTHER 'COMPLEX' STATISTIC TOPICS

Complex sampling (e.g., for large-scale surveys)

NON-PARAMETRIC TESTS AND ANALYSIS

- data that we use is often not normal (we usually give more small grants than large grants), what approach would you use for the analysis?"
- ordinal variables in surveys for example (how to analyse if the results from two subgroups are statistically different, what approach would you recommend?)

Meeting you where you are:

If you are already a statistical analysis expert (You laugh in the face of regression analysis and statistical models): Data Engineering, Data Preparation, Data Presentation, Alternatives to statistics (e.g. Machine Learning, Business Intelligence)

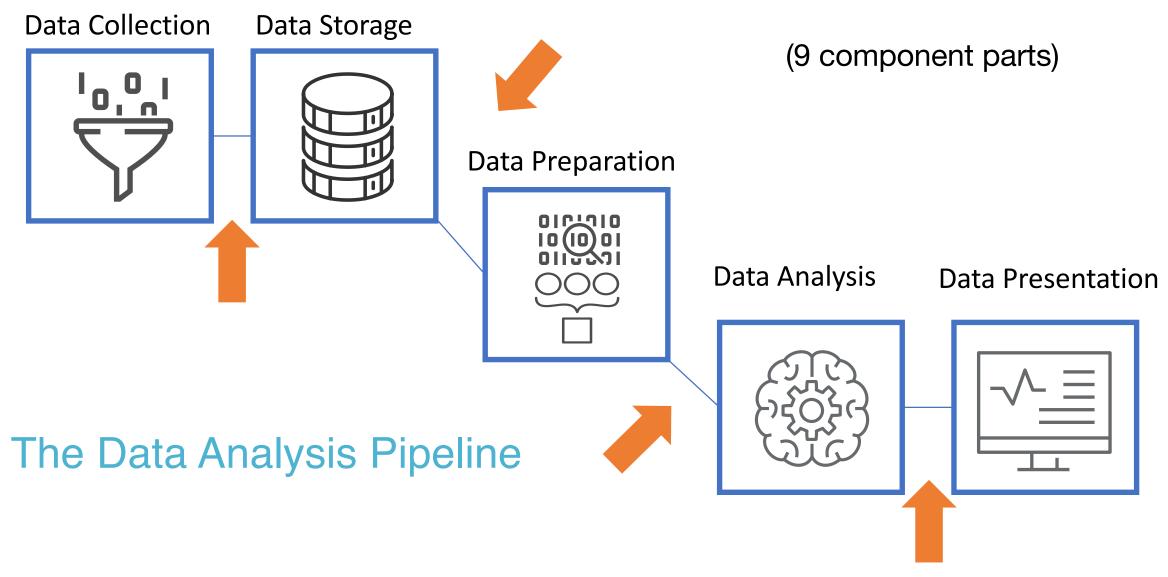
If you are already a programming expert (you eat R packages or Python modules for breakfast): New Analysis Techniques, Modern Data Engineering IT Infrastructure Practices

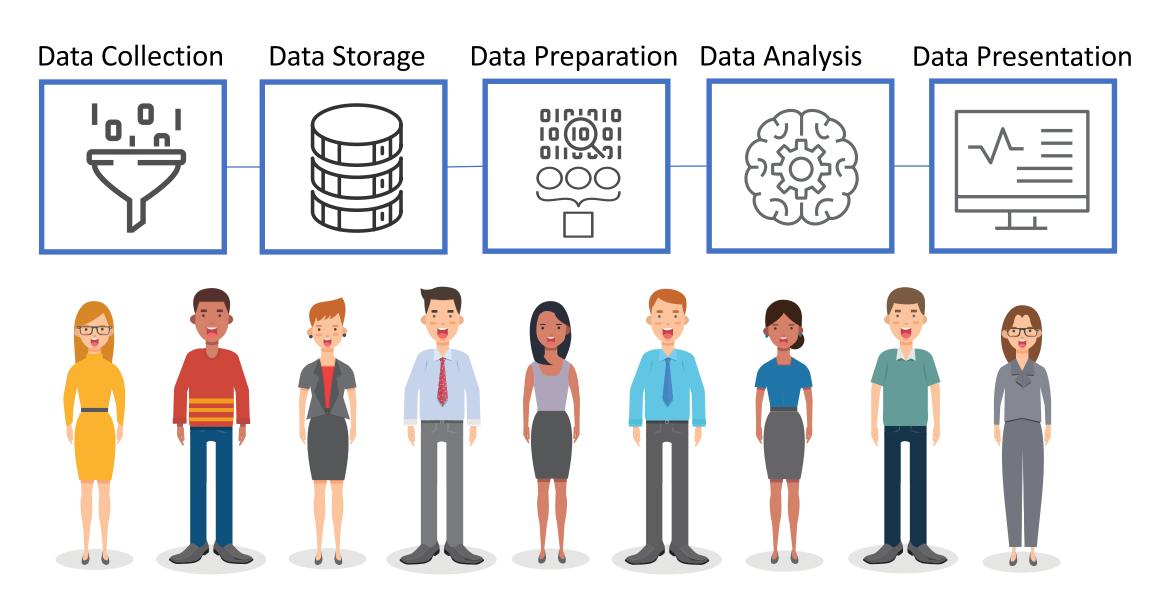
If you are already an IT infrastructure expert (you could stand up sophisticated cloud or on prem fully automated data pipeline systems without breaking a sweat!): An understanding of why the other members of the team are always asking you for such strange things on the IT front!

If you are already a subject matter or organization expert (you know everything there is to know about grant programs and the world of scientific grants): How the other members of the data science team can support your work, the language you need to use talk to them to make sure they give you what you want.

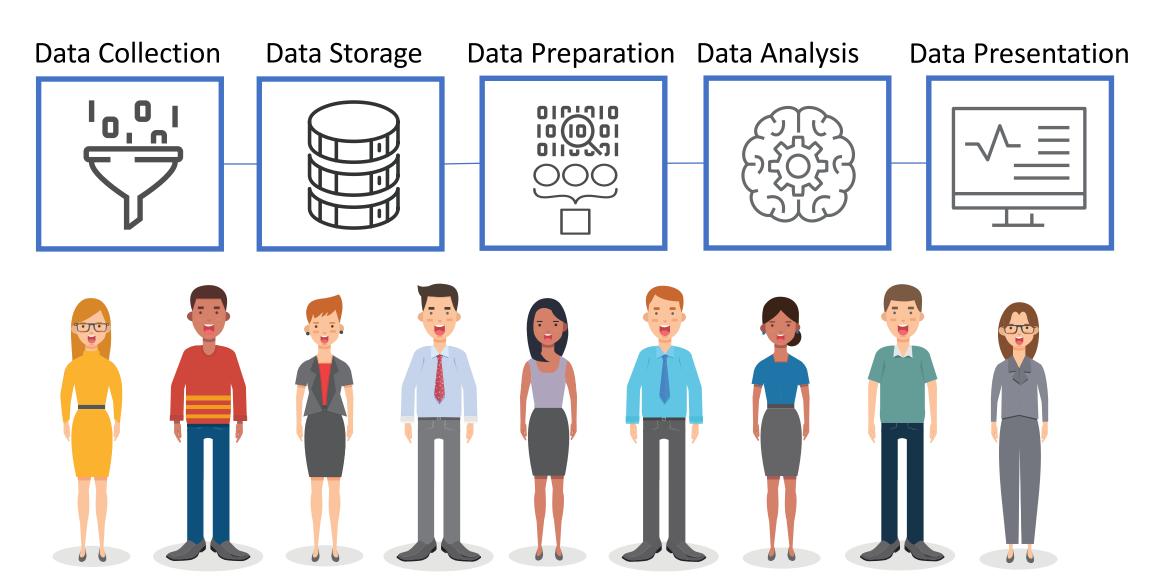
If you're already an expert on techniques, technologies, analysis and the subject (you could be giving this workshop): a shared orientation to modern data analysis that will help you talk to and work with other members of your data science team

Modern Data Analysis Teams and Technologies

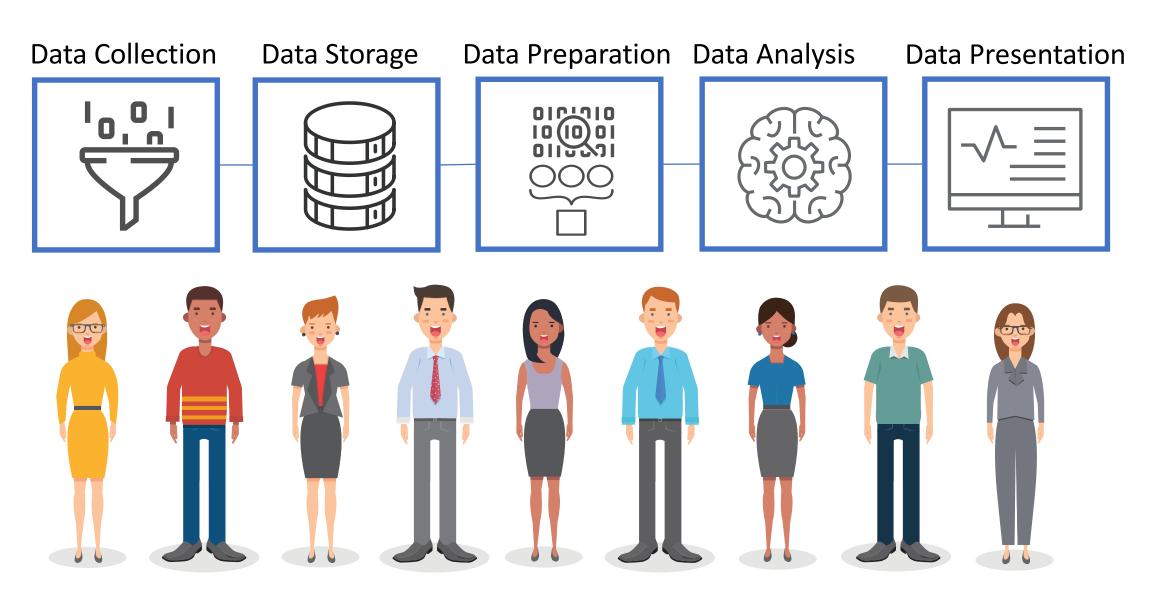




What Roles Support This Pipeline?



~ ratio of other team members to analysts: 10:1



~ ratio of analysis to other activities - 1:10

Data Team Roles (I)

Data engineering: Data infrastructure design and implementation - IT and DevOps heavy

Data collection: design of data collection strategies and implementation of data collection tools

Data architect, Data manager: Data storage and data architecture design and implementation

Data preparation: You work hand in hand with the data collection, data managers and data analysis members of the team to get the data into a state where it is ready for analysis. To automate this you design and implement processes to carry out all of the relevant steps This is a pivotal position on the team

Analysis: You determine what analysis can work with the information you have, and can give insight that is relevant and useful. You design algorithms that can be used to automate these analyses

Data Team Roles (II)

Data Pipeline UX Expert: Interface design, user experience, Data Communication: data visualization, data presentation Subject Matter Expert: Knows a lot about the situation, understands what is important, what data could provide insight, how to interpret and apply the results of the analysis

Business or Organization
Strategy expert: You hold the picture and know where the organization wants to head.
You need to provide this information to the team.

Project Lead: You keep everyone on track and working together

Data Translator: Knows how the different pieces of the pipeline work at a high level, knows something about the subject matter. Good at connecting people and helping them talk to each other.

Where do you fit in?

Here are some preliminary questions to ask yourself:

- 1. What part of the pipeline is most appealing to you?
- 2. Do you like designing OR implementing what someone else has designed? Or both?
- 3. Are you a generalist who likes to know a little bit of everything, or do you like to specialize and become an expert in one thing? (Are you a big picture person or a detail-oriented person)
- 4. Can you currently write computer programs or more generally scripts that tell computers what to do (OR do you want to be able to do so)?
- 5. Do you have a math or statistics background
- 6. Do you like working with IT technologies?
- 7. Do you like to facilitate communication between different members of a team
- 8. Do you have a deep knowledge of your organizations operations or subject matter
- 9. Do you have a deep knowledge of organizational goals? Do you like strategy?

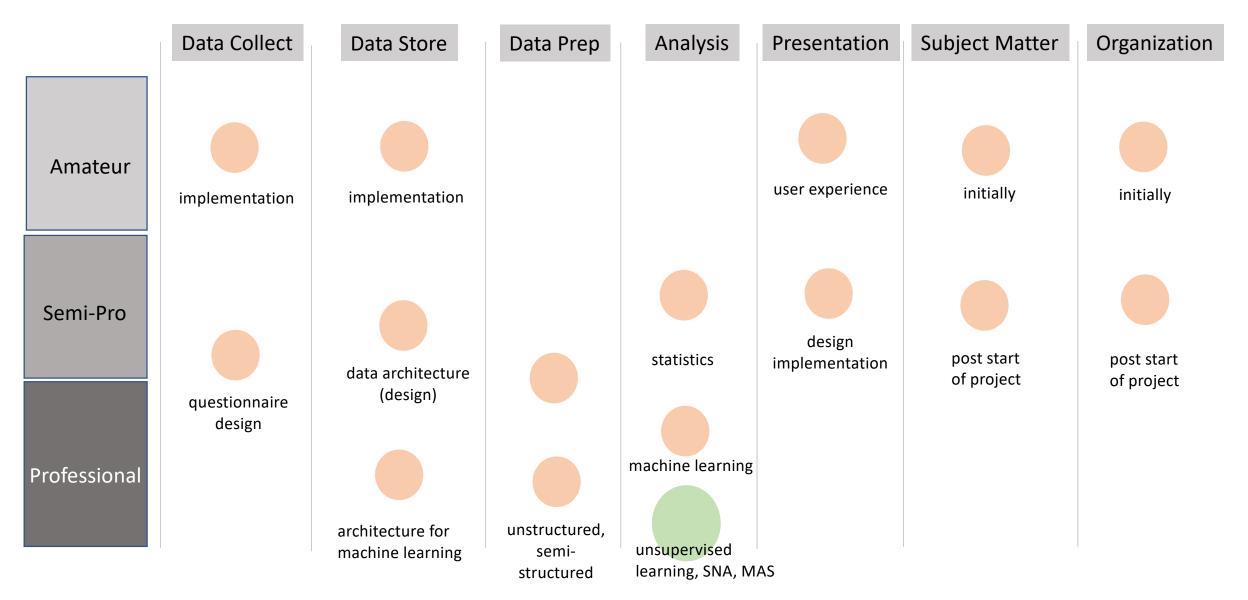
Another way to think about where you fit

	Data Collect	Data Store	Data Prep	Analysis	Presentation	Subject Matter	Organization
Amateur							
Semi-Pro							
Professional							

Generalists vs Specialist: You can't do it all!

Example of a generalist:

multi-purpose, can communicate across lanes,



Generalists vs Specialist: You can't do it all!

Example of a specialist (data engineer)

High quality, fast, deal with tricky situations

	Data Collect	Data Store	Data Prep	Analysis	Presentation	Subject Matter	Organization
Amateur							
Semi-Pro							
Professional							
	implementation	implementation			implementation		

Generalists vs Specialist: You can't do it all!

Example of a specialist (statistician)

	Data Collect	Data Store	Data Prep	Analysis	Presentation	Subject Matter	Organization
Amateur							
Semi-Pro							
Professional				all statistical			
				techniques			I

Full coverage

A team can collectively provide you with full coverage

	Data Collect	Data Store	Data Prep	Analysis	Presentation	Subject Matter	Organization
Amateur							
Semi-Pro							
Professional							



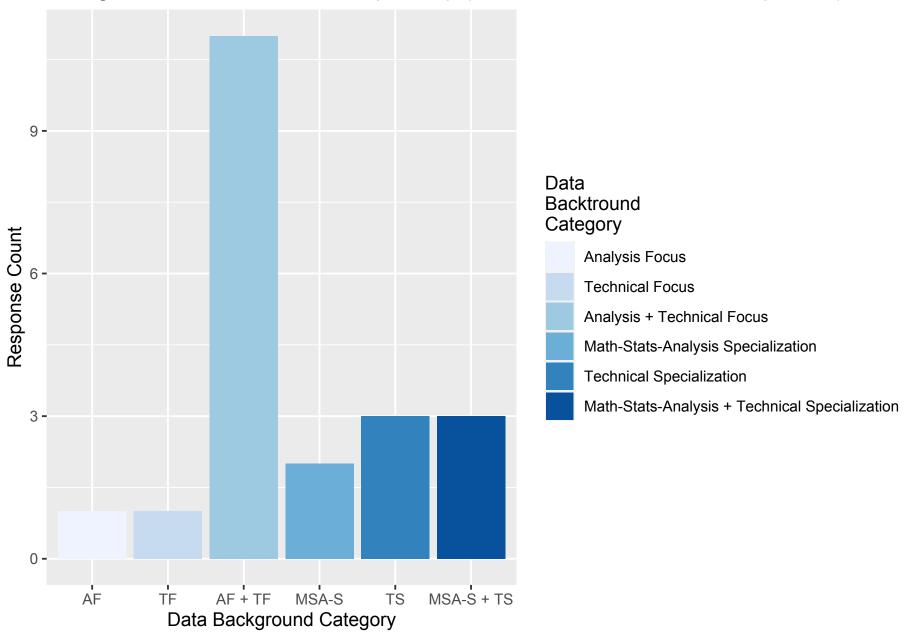
Data Analysis - Why Me???

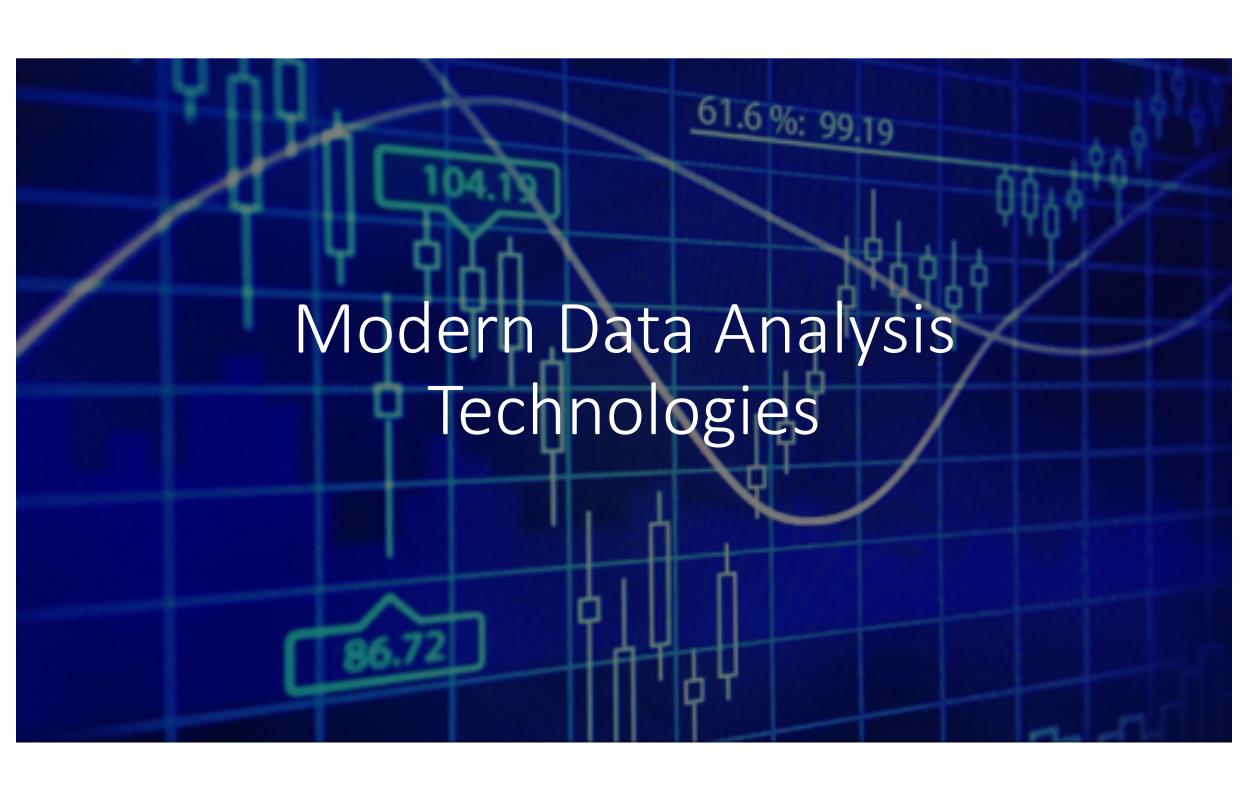
- In general, even if you are not an analyst you must be able to talk to the analysts!
- Data engineer person who is designing the kitchen need to know what the cooks will be doing, who in turn need to know what people want to eat
- Data presenter person who is doing the bodywork on the car – need it to fit on the car, who in turn must deliver a car that the driver likes
- Data Translator!!!

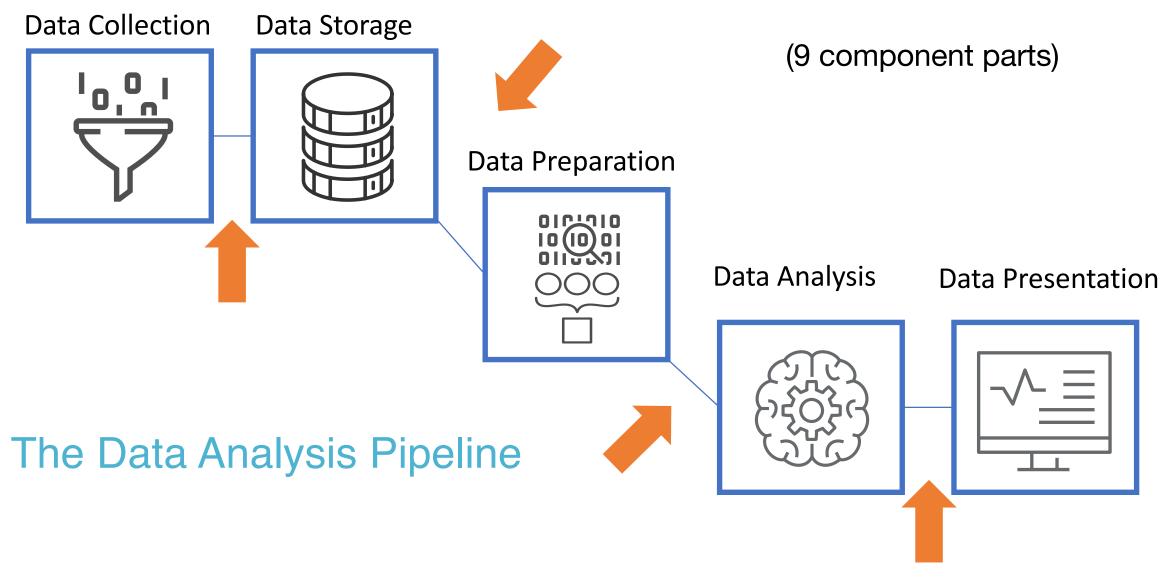
In the end, it's not about the analysis!

- In a professional setting, analysis will not be happening just for the sake of analysis.
- In an applied setting, analysis supports business goals.
- Let's return to our analogies for a moment.
 - Cooking analogy: In the cooking world, the person eating the food is royalty!
 - Car Hobby analogy: Yes, some people work on cars for fun. And some people work on data for fun. BUT in the end it's about the owner/driver of the car
- Don't lose sight of your end goal. Who knows the end goal? DON'T PRESUME THAT THIS IS YOU!
- User Centered Design

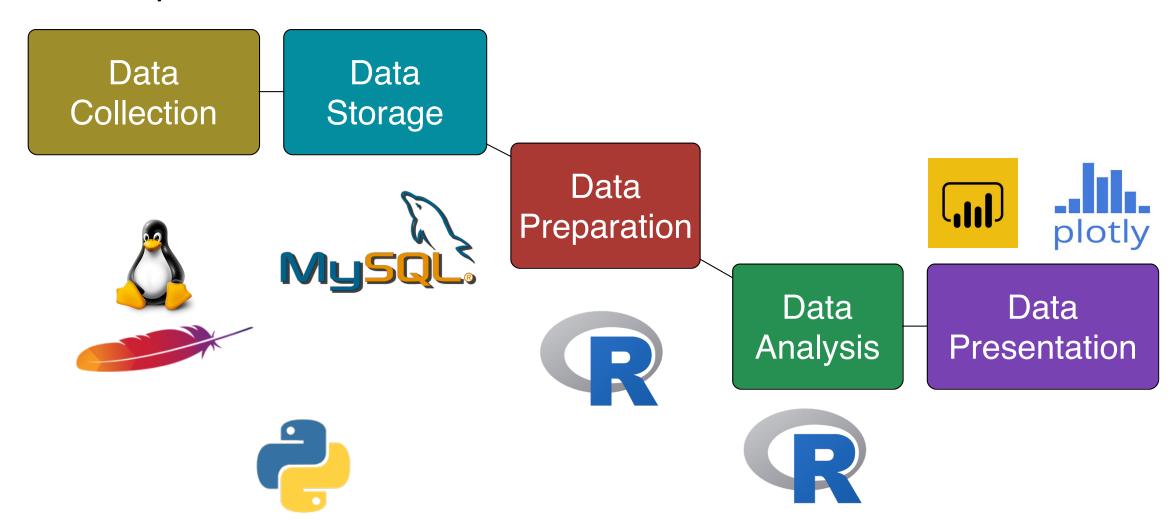
Background of NSERC Workshop Group (Based on Questionnaire Responses)







A Open-Source Driven Data Stack



Typical GoC Data Stack

Data Collection

Data Storage

> Data Preparation

> > Data Analysis

Data Presentation











Data Collection

Data Storage

> Data Preparation













Data Presentation



Data Pipeline Technologies: Amateur Technologies vs Professional Technologies – Compare and Contrast

	On-Premises (LAN)	Public Cloud	Private Cloud
Amateur	Shared Directory + Excel +Power Point + 'Desktop' Access	Piecemeal SaaS – e.g. Data Analysis or Presentation as a	
Semi-Pro	Desktop DataScience: Desktop PowerBI SQL-Lite (Desktop) MS Access Stand-alone In-House DBMS – Read + Write	service Freemium Model End-to-end SaaS	Home Brewed Solutions using Servers stood up on Cloud – e.g. AWS, GCP
Professional	Server Based End-to-End Automated Pipeline Tech: On-Premises Azure, On- Premises IBM RedHat	data pipelines – e.g. COTS Pachyderm or more bespoke: e.g. SaaSCoder	End-to-End Cloud Data Pipeline Infrastructure (Serverless/NoServer): AWS, GCP, Azure





laaS: Infrastructure as a Service



PaaS: Platform as a Service

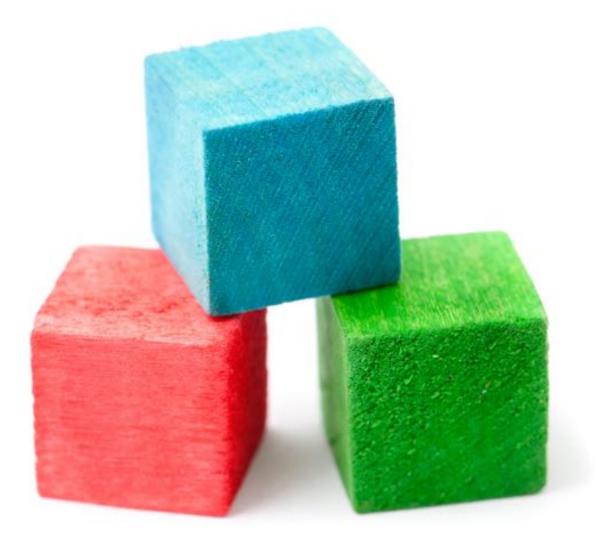


SaaS (AlaaS, DaaS): Software (Al, Data) as a Service

Pipeline Creation Phases

- 1. Research + Design
- 2. Implementation
- 3. Testing
- 4. Production + Management
- 5. Research + Design

Agile!



Pre-Analysis: Data Collection, Structuring and Preparation

Collection: Three Main Data Sources



Recordkeeping



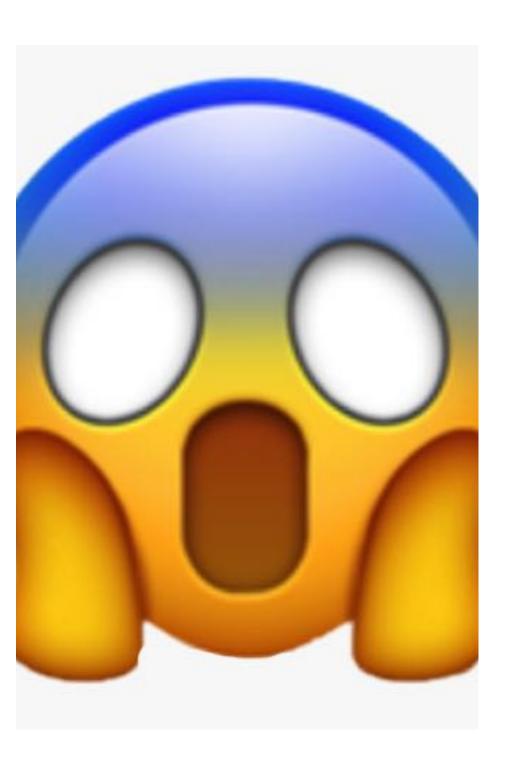
Research



Sensors/Monitoring

Recordkeeping: Primary Focus On Specific Entities





The Curse of Categorical Data

Government data tends to be very heavy on the categories and text data.

Traditional analysis methods:

- were not categorical data heavy
- did not focus on doing complex analyses with (complex) categorical data

This means we need to work harder to come up with good strategies to deal with this type of data (hint – machine learning likes categories)

Research: Focus On Generalizing



Applied Data Analysis and Science

- Scientific data analysis techniques are sometimes relevant only:
 - in a very specific experimental context
 - on certain types of data
- Now that data is so much more prevalent and usable, we need to grow and adapt these techniques
- We need to break out of the 'science mindset'



Decision Support! Immediate and Focused

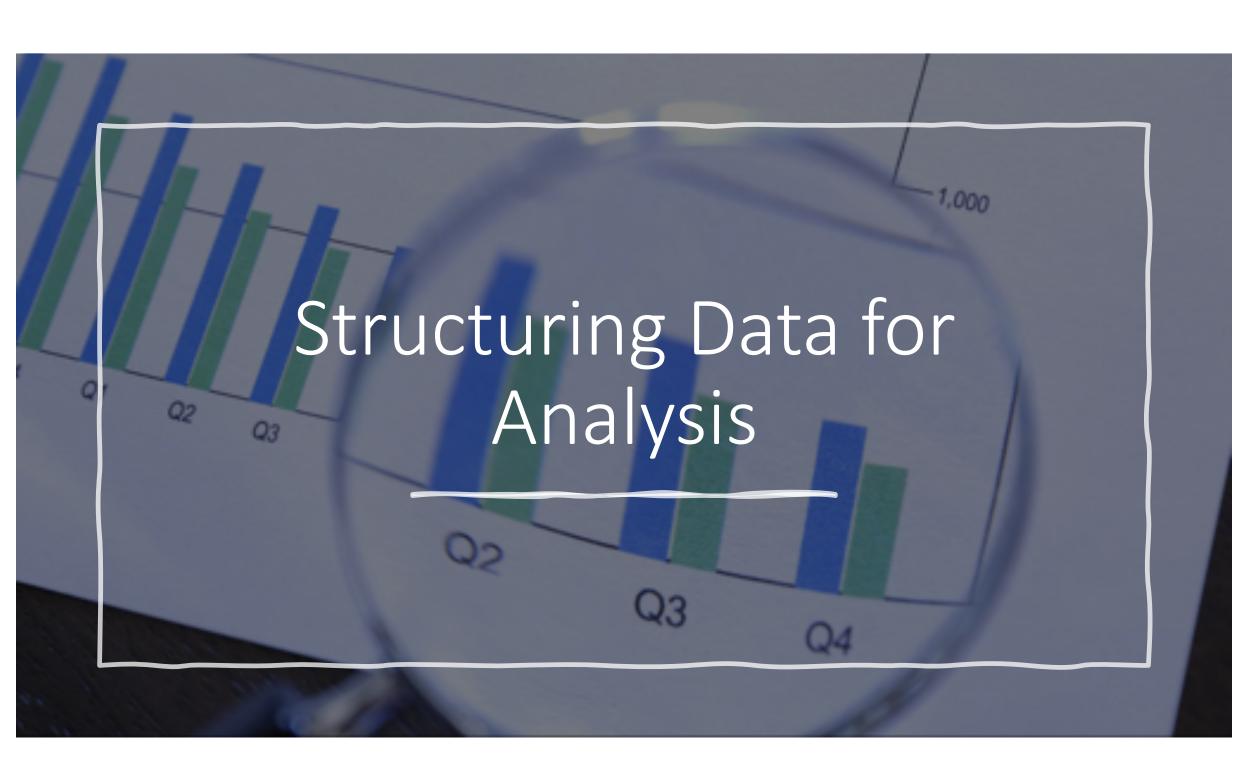


What Is Your Analysis Goal?

- Do you want to:
 - Carry out actions based on what is in your data (maybe not analysis?)
 - gain a deeper understanding of something specific (specific individuals? A specific group?)
 - come to some general conclusions that extend beyond the specific
- Local vs Global
- Here vs Everywhere
- Past/Present vs Future
- Situational Awareness vs Contingency Planning

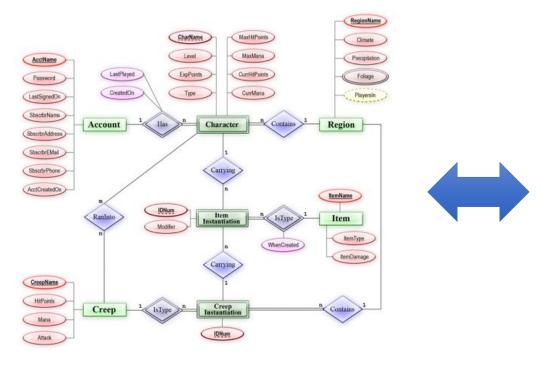






Database vs Flat File

Database



Flat File

	A1	2 6	300	fx season								
Œ	A	B	C	D	E	F	G	н	1		K	L
1	season	size	speed	mxPH	mnO2	CI	NO3	NH4	oPO4	PO4	Chla	a1
2	winter	small	medium	8	9.8	60.8	6.238	578	105	170	50	
3	spring	small	medium	8.35	8	57.75	1.288	370	428.75	558.75	1.3	1.4
4	autumn	small	medium	8.1	11.4	40.02	5.33	346.66699	125.667	187.05701	15.6	3.3
5	spring	small	medium	8.07	4.8	77.364	2.302	98.182	61.182	138.7	1.4	3.3
6	autumn	small	medium	8.06	9	55.35	10.416	233.7	58.222	97.58	10.5	9.3
7	winter	small	high	8.25	13.1	65.75	9.248	430	18.25	56.667	28.4	15.3
8	summer	small	high	8.15	10.3	73.25	1.535	110	61.25	111.75	3.2	2.4
9	autumn	small	high	8.05	10.6	59.067	4.99	205.66701	44.667	77.434	6.9	18.2
10	winter	small	medium	8.7	3.4	21.95	0.886	102.75	36.3	71	5.544	25.4
11	winter	small	high	7.93	9.9	8	1.39	5.8	27.25	46.6	0.8	1
12	spring	small	high	7.7	10.2	8	1.527	21.571	12.75	20.75	0.8	16.6
13	summer	small	high	7.45	11.7	8.69	1.588	18.429	10.667	19	0.6	32.3
14	winter	small	high	7.74	9.6	5	1.223	27.286	12	17	41	43.5
15	summer	small	high	7.72	11.8	6.3	1.47	8	16	15	0.5	31.3
16	winter	small	high	7.9	9.6	3	1.448	46.2	13	61.6	0.3	52.2
17	autumn	small	high	7.55	11.5	4.7	1.32	14.75	4.25	98.25	1.1	69.5
18	winter	small	high	7.78	12	7	1.42	34.333	18.667	50	1.1	46.2
19	spring	small	high	7.61	9.8	7	1.443	31.333	20	57.833	0.4	31.8
20	summer	small	high	7.35	10.4	7	1.718	49	41.5	61.5	0.8	50.6
21	spring	small	medium	7.79	3.2	64	2.822	8777.59961	564.59998	771.59998	4.5	
22	winter	small	medium	7.83	10.7	88	4.825	1729	467.5	586	16	0.000
23	spring	small	high	7.2	9.2	0.8	0.642	81	15.6	18		15.5
24	autumn	small	high	7.75	10.3	32.92	2.942	42	16	40	7.6	23.3
25	winter	small	high	7.62	8.5	11.867	1.715	208.33299	3	27.5	1.7	74.2
26	spring	small	high	7.84	9.4	10.975	1.51	12.5	3	11.5	1.5	1
27	summer	small	high	7.77	10.7	12.536	3.976	58.5	9	44.136	3	4.3
28	winter	small	high	7.09	8.4	10.5	1.572	28	4	13.6	0.5	29.7
29	autumn	small	high	6.8	11.1	9	0.63	20	4	NA.	2.7	30.3
30	winter	small	high	8	9.8	16	0.73	20	26	45	0.8	17.1

Data Integrity



Data Analysis



Rows vs Columns

Columns contain attributes (variables, fields, etc.)

Rows contain objects*

	A1		:	000	fx	season									
5	A	100	B.	C	1	D	L.	1/2		G	Н			K	L
1	season	size		speed	mx	PH	mnO2	CI		NO3	NH4	oPO4	PO4	Chla	a1
2	winter	smal		medium		8	9.8		60.8	6.238	578	105	170	50	
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8	summer	smal		high	_	8.15	10.3		73.25	1.535	110	61.25	111.75	3.2	2
9	autumn	smal		high	-	8.05	10.6		59.067	4.99	205.66701	44.667	77.434	6.9	18.
10	winter	smal		medium		8.7	3.4		21.95	0.886	102.75	36.3	71	5.544	25
11	winter	smal		high		7.93	9.9		8	1.39	5.8	27.25	46.6	0.8	1
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26	spring	smal		high		7.84	9.4		10.975	1.51	12.5	3	11.5	1.5	,
27	summer	smal		high		7.77	10.7		12.536	3.976	58.5	9	44.136	3	
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29	autumn	small		high		6.8	11.1		9	0.63	20	4	NA.	2.7	30
30	winter	smal		high		8	9.8		16	0.73	20	26	45	0.8	17



Rows vs Columns

variable (field) name-

object ID

variable (field) value (datum)

	A1	: 1	300	fx season								
	A	1	C	D	L.	F	G	Н	1 1	1	K	L
-1	season	size	speed	mxPH	mnO2	CI	NO3	NH4	oPO4	PO4	Chla	a1
2	winter	small	medium	8	9.8	60.8	6.238	578	105	170	50	0
3	spring	small	medium	8.35	8	57.75	1.288	370	428.75	558.75	1.3	1.4
4	autumn	small	medium	8.1	11.4	40.02	5.33	346.66699	125.667	187.05701	15.6	3.3
5	spring	small	medium	8.07	4.8	77.364	2.302	98.182	61.182	138.7	1.4	3.1
6	autumn	small	medium	8.06	9	55.35	10.416	233.7	58.222	97.58	10.5	9.2
7	winter	small	high	8.25	13.1	65.75	9.248	430	18.25	56.667	28.4	15.1
8	summer	small	high	8.15	10.3	73.25	1.535	110	61.25	111.75	3.2	2.4
9	autumn	small	high	8.05	10.6	59.067	4.99	205.66701	44.667	77.434	6.9	18.2
10	winter	small	medium	8.7	3.4	21.95	0.886	102.75	36.3	71	5.544	25.4
11	winter	small	high	7.93	9.9	8	1.39	5.8	27.25	46.6	0.8	17
12	spring	small	high	7.7	10.2	8	1.527	21.571	12.75	20.75	0.8	16.6
13	summer	small	high	7.45	11.7	8.69	1.588	18.429	10.667	19	0.6	32.1
14	winter	small	high	7.74	9.6	5	1.223	27.286	12	17	41	43.5
15	summer	small	high	7.72	11.8	6.3	1.47	8	16	15	0.5	31.1
16	winter	small	high	7.9	9.6	3	1.448	46.2	13	61.6	0.3	52.2
17	autumn	small	high	7.55	11.5	4.7	1.32	14.75	4.25	98.25	1.1	69.9
18	winter	small	high	7.78	12	7	1.42	34.333	18.667	50	1.1	46.2
19	spring	small	high	7.61	9.8	7	1.443	31.333	20	57.833	0.4	31.8
20	summer	small	high	7.35	10.4	7	1.718	49	41.5	61.5	0.8	50.6
21	spring	small	medium	7.79	3.2	64	2.822	8777.59961	564.59998	771.59998	4.5	0
22	winter	small	medium	7.83	10.7	88	4.825	1729	467.5	586	16	0
23	spring	small	high	7.2	9.2	0.8	0.642	81	15.6	18	0.5	15.5
24	autumn	small	high	7.75	10.3	32.92	2.942	42	16	40	7.6	23.2
25	Winter	small	high	7.62	8.5	11.867	1.715	208.33299	3	27.5	1.7	74.2
26	spring	small	high	7.84	9.4	10.975	1.51	12.5	3	11.5	1.5	13
27	symmer	small	high	7.77	10.7	12.536	3.976	58.5	9	44.136	3	4.1
28	winter	small	high	7.09	8.4	10.5	1.572	28	4	13.6	0.5	29.7
29	autumn	small	high	6.8	11.1	9	0.63	20	4	NA.	2.7	30.3
30	winter	small	high	8	9.8	16	0.73	20	26	45	0.8	17.1

Recordkeeping





Dataset Shape and Focus

Research: many rows, few columns

	A1	- 1	:	0	0 0	fx	season											
Ŧ	A	1			C	T	D	1 20	E	55	F	G	H	1		K	1	
1	season	size		-3	speed	m	PH .	mnO2	2	CI		NO3	NH4	oPO4	PO4	Chla	a1	
2	winter	small			medium		8	1	9.8		60.8	6.23	8 578	105	170	50		
3	spring	small			medium		8.35		8		57.75	1.28	8 370	428.75	558.75	1.3		1
4	autumn	small	Г		medium		8.1		11.4		40.02	5.3	3 346.66699	125.667	187.05701	15.6		3
5	spring	small			medium		8		4.8		77.364	2.30	2 98.182	61.182	138.7	1.4		3
6	autumn	small			medium													ġ
7	winter	small			high			Ro	COL	-A1	coor	ving:	many	colum	nc for	AL KONA	c	
8	summer	small			high:			116	CUI	uı	vech	ning.	llally	Colum	iis, iev	V IOW	>	4
9	autumn	small			high		- L											18
10	winter	small			medium		8		3.4		21.95	0.88	6 102.79	36.3	71	5.544		25
11	winter	small			high		7.93		9.9		8	1.3	9 5.8	27.25	46.6	0.8		
12	spring	small			high		7.7	8	10.2		8	1.52	7 21.57	12.75	20.75	0.8		16
13	summer	small			high		7.45		11.7		8.69	1.58	8 18.429	10.667	19	0.6		32
14	winter	small			high		7.74	iš.	9.6		5	1.22	3 27.286	12	17	41		43
15	summer	small			high		7.72		11.8		6.3	1.4	7	8 16	15	0.5		31
16	winter	small			high		7.9		9.6		3	1.44	8 46.2	13	61.6	0.3		57
17	autumn	small			high		7.55		11.5		4.7	1.3	2 14.75	4.25	98.25	1.1		65
18	winter	small			high		7.78	ij.	12		7	1.4	2 34.333	18.667	50	1.1		46
19	spring	small			high		7.61		9.8		7	1.44	3 31.333	3 20	57.833	0.4		31
20	summer	small			high		7.35		10.4		7	1.71	8 4	41.5	61.5	0.8		50
21	spring				medium		7.79	į.	3.2		64	2.82	2 8777.5996	564.59998	771.59998	4.5		
22	winter				medium		7.83	l)	10.7		88	4.82	5 1729	467.5	586	16		
23	spring				high		7.2		9.2		0.8	0.64	2 8:	1 15.6	18	0.5		15
24	autumn				high		7.75		10.3		32.92	2.94	2 4	16	40	7.6		23
25	winter				high		7.62		8.5		11.867	1.71	5 208.33299	3	27.5	1.7		74
26	spring				high		7.84		9.4		10.975	1.5	1 12.5	3	11.5	1.5		
27	summer	small			high		7.77		10.7		12.536	3.97	6 58.5	9	44.136	3		.4
28	winter	small		/	high		7.09	ij.	8.4		10.5	1.57	2 21	8 4	13.6	0.5		29
29	autumn				high		6.8		11.1		9	0.6	3 2	0 4	NA.	2.7		30
30	winter	50			high		8	.5	9.8		16	0.7	3 20	26	45	0.8		17

Recordkeeping









Data Preparation

- Data validation + verification
- Data cleaning
- Data transformation
- (Data Exploration?)



Data Preparation

- Data validation + verification
- Data cleaning
- Data transformation
- (Data Exploration?)

Each of these steps may themselves involve data analysis and other techniques

Data Validation + Verification

- Verification: Confirm that the data is correct relative to the dataset
- Validation: Confirm that the data correctly represents the objects
- We determine data cleaning requirements based on the results of our data verification and validation



[3, 10.43, ROUn, golden delicious]

Data Cleaning

?

A question for you: should you clean before you do exploratory analysis?



Some possible issues:

Character encodings

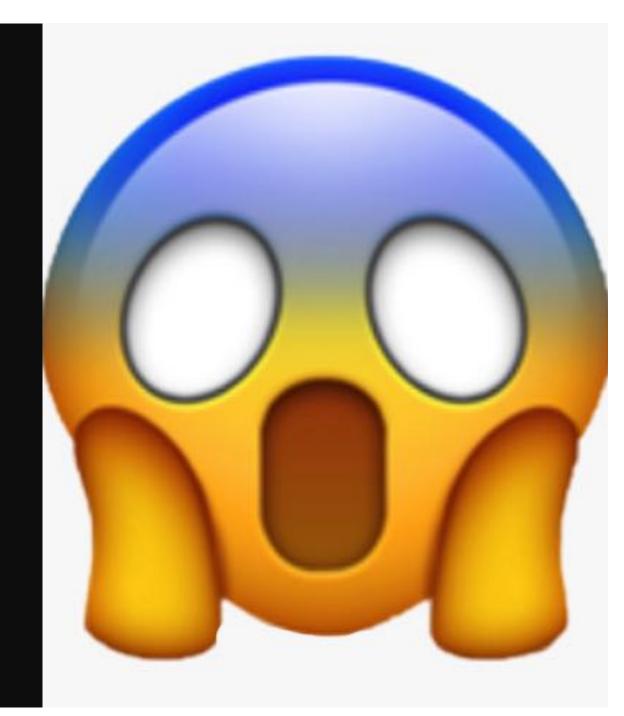
Missing Data

Data collection or entry errors

Systematic errors

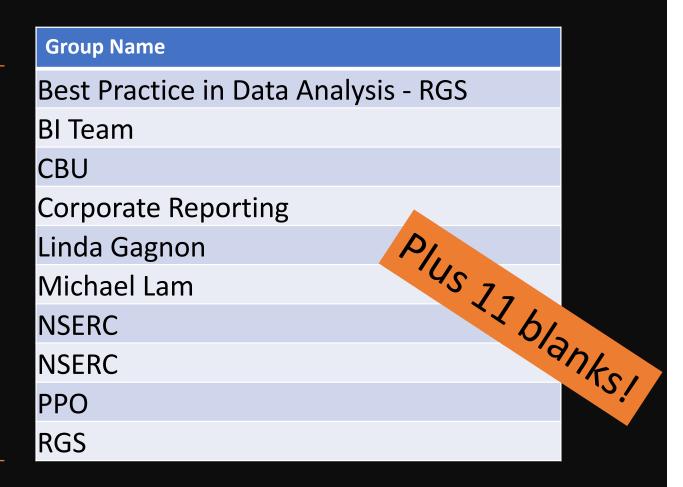
The Curse of Free Text Fields

- The curse of categorical data is made much worse by the curse of free text fields
- If you have a field that is supposed to be categorical but it is a free text field, it is no longer categorical
- You can use machine learning techniques to help to some extent, but this is a case where an ounce or prevention is worth a pound of cure.



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Data Cleaning Bingo

random missing values	outliers	values outside of expected range - numeric	factors incorrectly/iconsiste ntly coded	date/time values in multiple formats
impossible numeric values	leading or trailing white space	badly formatted date/time values	non-random missing values	logical inconsistencies across fields
characters in numeric field	values outside of expected range - date/time	DCB!	inconsistent or no distinction between null, 0,not available, not applicable,missing	possible factors missing
multiple symbols used for missing values	???	fields incorrectly separated in row	blank fields	logical iconsistencies within field
entire blank rows	character encoding issues	duplicate value in unique field	non-factor values in factor	numeric values in character field



Cleaning: Character Encodings

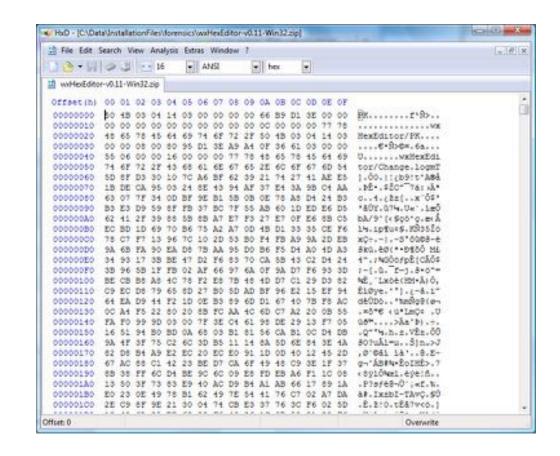
The ASCII code

American Standard Code for Information Interchang

A	SCH	contro	of characters			ASC	ill pr	intabl	e charact	lers:							Exte	nded AS	CII ch	arac	ters			
DEC	HEX	31	MDDIO ASCII	DEC	HEX	Simbolo	DEC	HEX	Simbolo	DEC	HEX	Simpolo	DEC	HEX	Simbolo	DEC	HEX	Simbolo	DEC	HEX	Simbolo	DEC	HEX	Simboli
00	200.	MULL.	(parider rule)	32	2171	espacio	64	416	- 6	96	101	1.6	128	THE .	C	160	400	6	192	din	L	224	100	0
01		90H	únicio encategado)	33			65		A A	97			129		ü	161	415	1	193		+	225		
02		STX	(Inicia Savia)	34	225	-	66		В	56		ь	130		é	162		6	194		-	226		0
03		ETK	(Sin-die texcho)	35			67		C	99			535		à	163			195		-	227		Ò
04		103	(Nn transmission)	36		5	68		D	100		d	132		ä	164	: AM	6	196		-	228	-E-Jan	ő.
95		DNG	(entury)	37		*	69			101			133			165		Ň	997		+	229		0
06		ACK	(activity/edgement)	38			26	411	F	102		· 1	134		- 6	166			126			230		- 10
97		138	(finting)	39		- 4	71		G	103		· ·	135			107			199		A	231		b
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99		HIT	(lab harcsetal)	45	238	- 3	73	435	1	105		- 1	137			169		è	201			255		0
10		LF	(nato de inea)	42			74		- 1	106		1	138			170	AAL	-	202			234		0
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12		FF	Chorm Seatt)	44			76		L	108		1	140		1	172		- %	204			256		
13		CR	(retorno de carro)	45	31%	85	77		M	109		m	545	ton	100	173		1	205	COB		237		Ŷ
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15		52	constraint.	47			79		0	111			543	atri	A	175	ME		207	cm		239	22%	- 4
16		DLE	rigida (m), escape)	48			86		p	612		0	144		É	176			208			240		
17	110	DC1	(device-costrict)	49		1	81		Q	113		a	545		an .	177	416		209	Dith	0	241	711	
38	130	DC2	(device-control 2)	50		2	82		R	114	720	7	546		Æ	178			210		. 6	242	120	
19		DCS	(device cortrol 3)	55		3	83		\$	115			147		6	179	110	T	211		E	245	F	6.
20		DC4	(device control 4)	52		4	84		T	116		1	548		ė.	180		- 1	212	DIR	Ē	244	7-45	
21		MAK	(negative addrouse)	53		5	85		U	117		u	549		. 0	181			213			245		
22		5771	(synchronous idle)	54		6	216		v	110		*	150		0	182		£	214	Dish		246	100	4
23		570	Gend of trans. Stock)	55		7	87		W	119	7779	w	555	0.25	0	183	-		295	D.Th	1	247	FTb	135
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25		ERR	rend of medium)	57			89		¥	121		Ç	153		ô	185		ă.	217			249		
26		SUB	(substitute)	58		- 1	90		. 2	122		2	154		0	186	1		218			250		1.4
27		ESC	(99(909)	59			91		1	123		1	155			187			219			251		
28	tion	FS	(Tile separator)	60			92		1	124		- 2	156	30h		188		1	220			252	10	
29	106	65	Conscio segundori	65			93		1.0	125		- T	157	469	à	189			221	700	-	253	Fig.	
30	HD.	RS	(record separator)	62	101		94		1	126		-	158		*	150			222			254		
31		US	(unit separator)	63		7	95					100000	159		7	191	-		723		•	255	H	
127		DEL	(SAMPLE)	946		7.9	44		-	Bek	SCHool	te com ar	149		1	100	-	.7			A LONG TO SERVICE	244	-	

Encoding: Tools and Strategies

- Use built in options in text editors, browsers
- Command line tools: iconv, recode, vim
- Libraries in R, Python
- Hex editors
- Statistical methods, machine learning!
- (an ounce of prevention...)



Cleaning: Missing Values

What counts as a missing value?

How many missing values

Column-wise?

Row-wise?

Missing randomly (MCAR, MAR) or non-randomly (MNAR)?

Dealing with Missing Values

If percentage is very low (e.g. <= 5%) you might be able to just ignore those rows*

You can try to detect if the data is MNAR instead of MCAR/MAR using statistical tests

If missing values are MCAR/MAR you might be able to ignore them

You might be able to 'impute' the data using statistical modelling techniques

MCAR, MAR, MNAR

Missing Completely At Random (MCAR): Genuinely no pattern to the missing values (think "due to sunspots"

Missing At Random (MAR): Missing values are correlated with another variable you also have.

Missing Not At Random (MNAR): Missing values are correlated with another variable you don't have

Interesting example with NSERC data – fields where people can select "Choose not to reply"

When does imputation make sense?

Cleaning: Other Data Entry Errors

Syntax errors: Capitalization, misspellings

Heaping: people tend to round off measurement values (e.g. hours worked). This results in the data showing up in 'heaps'

Collector bias, sensor error: recording what is expected rather than what is, dealing with badly calibrated sensor

Transforming Data:

- Changing focus
- Summarizing, condensing
- Reshaping
- Adding complexity and abstraction (metrics)



Long vs Wide Format

- A flat file with the same data can be structured in two shapes:
 - Long (Narrow) (Tall)(Stacked)
 - Wide (Unstacked)
- Different analysis *algorithms* require particular shapes
- Presentation of data



Long Format to Wide Format

long

variable name + values _

Group#	Group-Size	Status-Check-Time
1	14	START
1	12	MIDDLE
1	13	END
2	20	START
2	5	MIDDLE
2	6	END
3	6	START
3	8	MIDDLE
3	10	END

— variable name

variable values

wide

Group#	Group-Size-START	Group-Size-MIDDLE	Group-Size-END
1	14	12	13
2	20	5	6
3	6	8	10

Reshaping Data: Tools

- Reshaping your flat file by hand (or in Excel) can be extremely tedious! And error prone!
- This is where tools like R can be extremely helpful and time saving
- Plus automation. Resist the 'manual' short cut!



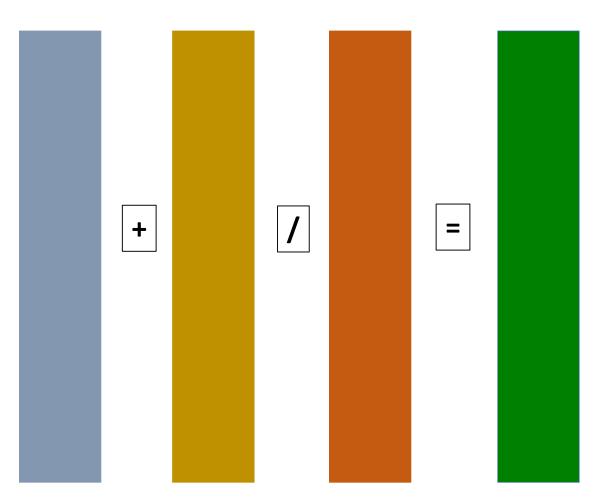
Adding Complexity: Metrics

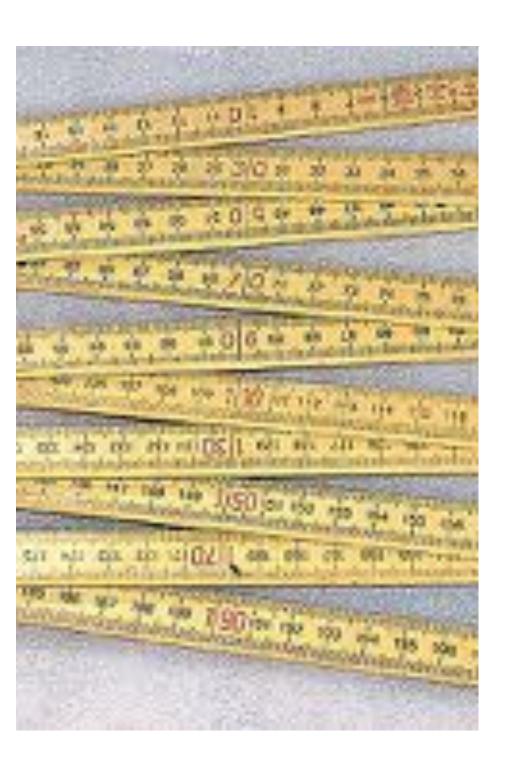
• Measures:

- Concrete properties
- come from taking measurements

• Metrics:

- Built up out of measures
- Quantifies a more abstract concept





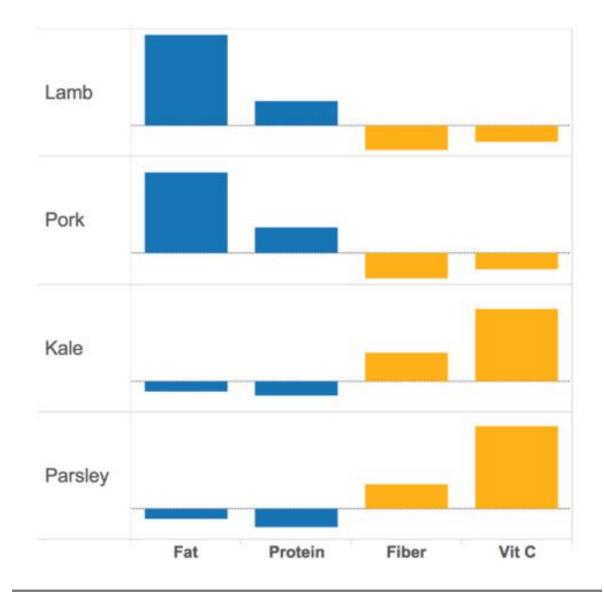
Metrics: Good, Bad, Ugly

- "When a measure becomes a target, it ceases to be a good measure" *Goodhart's Law*
- "The more any quantitative <u>social indicator</u> is used for social decision-making, the more subject it will be to corruption pressures and the more apt it will be to distort and corrupt the social processes it is intended to monitor." *Campbell's* Law

(Surgeons Example)

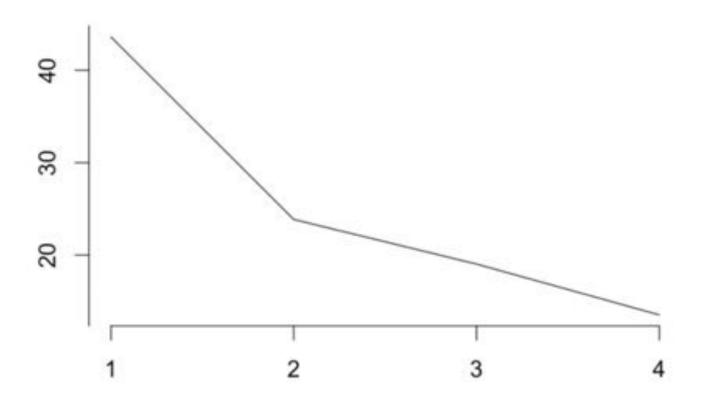
Data Reduction: Principal Components Analysis (PCA)*

- In this example, presence of nutrients appears to be correlated among food items.
- In the (small) sample consisting of Lamb, Pork, Kale, and Parsley, Fat and Protein levels seem in step, as do Fiber and Vitamin C.
- In a larger dataset, the correlations are r = 0.56 and r = 0.57.
- How much could 2 variables explain?



Retaining Principal Components

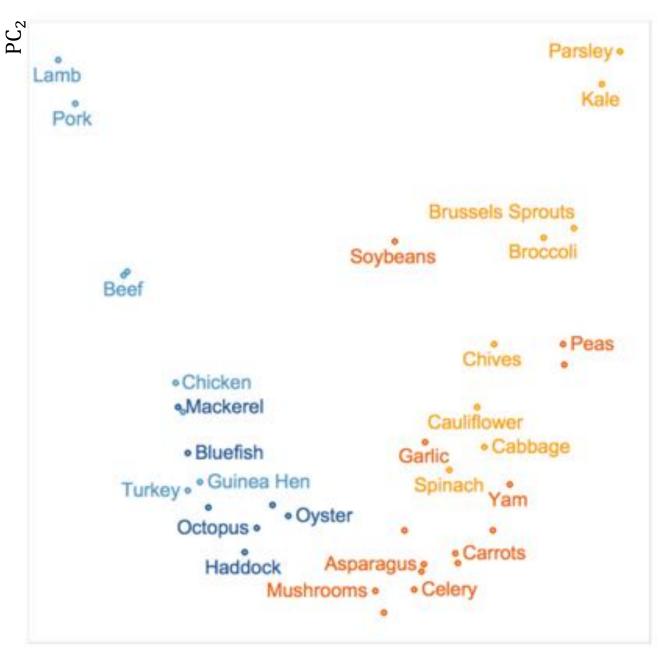
- The proportion of the spread in the data which can be explained by each principal component is shown in the scree plot.
- How many PCs are retained in the analysis?
 - keep the PCs where the cumulative proportion is below some threshold
 - keep the PCs leading to a kink
- Here, 2 PCs \approx 68% of the spread.



PC₁differentiates meats from vegetables

PC₂differentiates **sub-categories** within meats (using *Fat*) and vegetables (using *Vitamin C*).

- Meats are concentrated on the left (low PC₁ values).
- Vegetables are concentrated on the right (high PC₁ values).
- Seafood has lower Fat content (low PC₂ values) and is concentrated at the bottom.
- Non-leafy veggies have lower Vitamin C content (low PC₂ values) and are also bunched at the bottom.



Are we there yet?

