PROGRAMMING WITH R **ANALYTIC QUESTIONS EXPLORATORY DATA ANALYSIS** DATA REPRESENTATION **VECTORS** DATA FRAMES LOAD DATA **TIDY DATA** STRINGS TRANSFORM DATA **UNSTRUCTURED DATA** MACHINE LEARNING VISUALIZE DATA COMMUNICATE DATA

PROGRAMMING WITH R

variables

control structures

loops

functions

libraries

ANALYTIC QUESTIONS



did you summarize the data?

did you summarize the data? NOT a data analysis



did you report the summaries without interpretation?







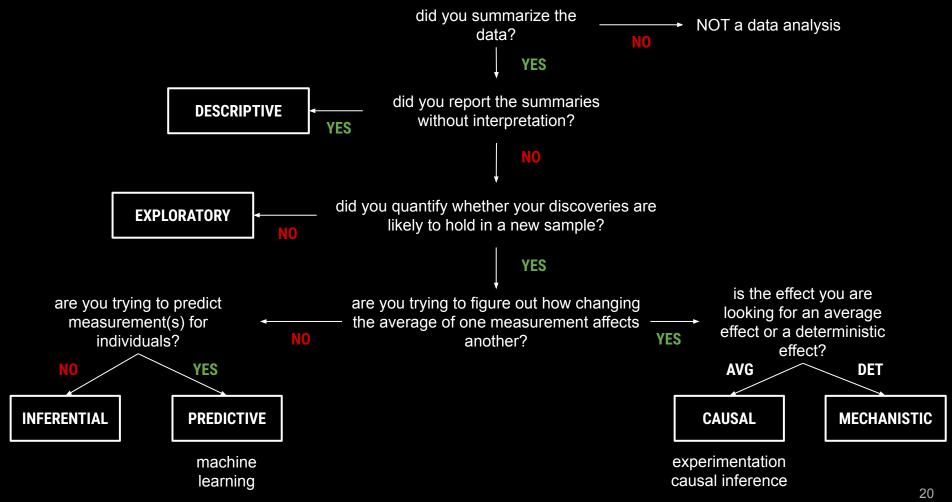


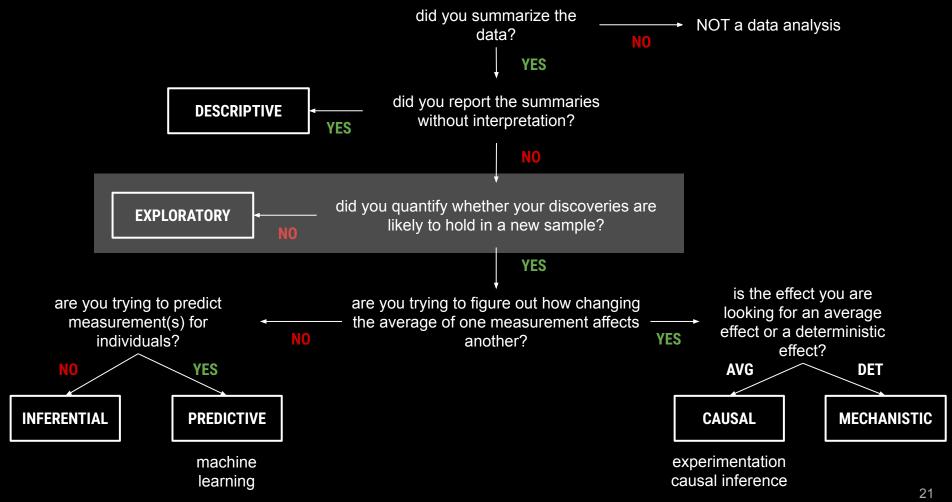












EXPLORATORY DATA ANALYSIS

load











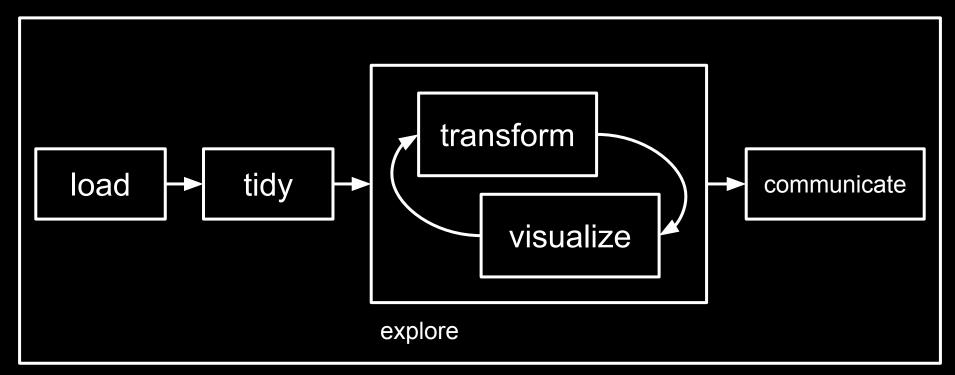








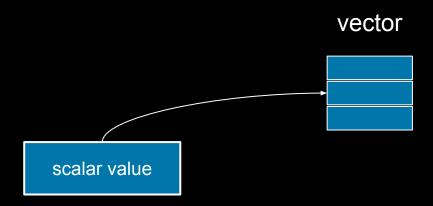
program

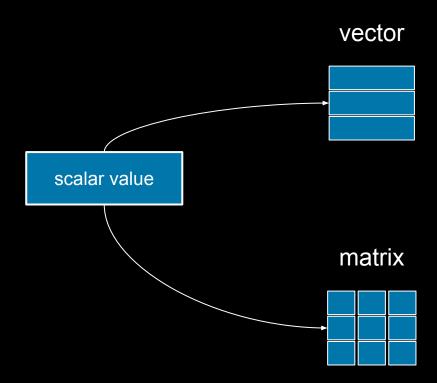


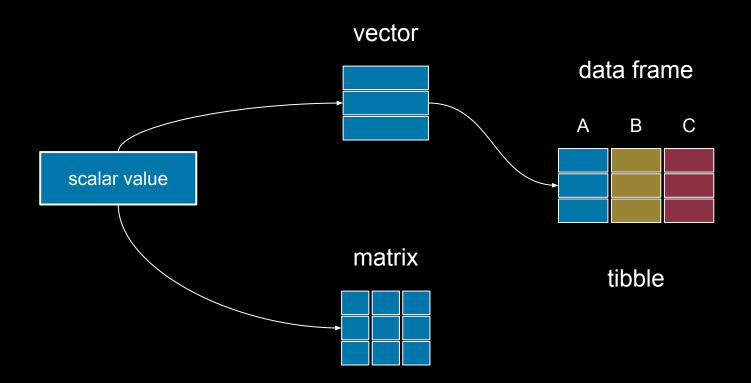
program

DATA REPRESENTATION

scalar value







VECTORS

apple

pear

orange

list of values with the same storage mode

list of values with the same storage mode

character double integer logical

```
v <- c("apple", "pear", "orange")
```

v[1] pear orange

v[2] pear orange

v[3]

apple

pear

orange

weight <- c(91, 75.5, 61, 88.5, 120)

```
weight <- c(91, 75.5, 61, 88.5, 120)
mean(weight)</pre>
```

sum	length	
mean	sort	
median	cumsum	
sd	prod	
var	quantile	
min	abs	
max	range	

91
75.5
61
88.5
120

```
weight_after_diet <-
   c(89.5, 75, 56, 96.5, 115)</pre>
```

weight weight_after_diet 89.5 91 75.5 75 61 56 88.5 96.5 120 115

weight	weight_after_diet		weight_loss	
91		89.5		1.5
75.5		75		0.5
61		56		5
88.5		96.5		-8
120		115		5

```
weight_loss <-
   weight - weight_after_diet</pre>
```

subsetting vectors

weight[1]

```
weight[1]
weight[-1]
```

weight[1]
weight[-1]
weight[2:5]

```
weight[1]
weight[-1]
weight[2:5]
weight[1:length(weight)-1]
```

```
weight[1]
weight[-1]
weight[2:5]
weight[1:length(weight)-1]
weight[c(TRUE, FALSE, TRUE, TRUE, FALSE)]
```

```
weight[1]
weight[-1]
weight[2:5]
weight[1:length(weight)-1]
weight[c(TRUE, FALSE, TRUE, TRUE, FALSE)]
weight[weight > 80]
```

```
weight[1]
weight[-1]
weight[2:5]
weight[1:length(weight)-1]
weight[c(TRUE, FALSE, TRUE, TRUE, FALSE)]
weight[weight > 80]
weight[weight > 80 & weight < 100]</pre>
```

special values

NA NULL NaN Inf -Inf

factors

```
category <- factor(c("heavy", "medium", "light", "medium", "heavy"))</pre>
```

```
category <- factor(c("heavy", "medium", "light", "medium", "heavy"))
levels(weight_category)</pre>
```

```
category <- factor(c("heavy", "medium", "light", "medium", "heavy"))</pre>
levels(weight_category)
category_reordered <- factor(category,</pre>
                               levels = c("light", "medium", "heavy"))
category_ordered <- factor(category,</pre>
                             levels = c("light", "medium", "heavy"),
                             ordered = TRUE)
```

{{ forcats }}

as_factor()

```
fct_reorder
fct_relevel
fct_infreq
fct_rev
fct_lump
```

DATA FRAMES

"apple"

"pear"

"orange"

"apple" TRUE

"pear" TRUE

"orange" FALSE

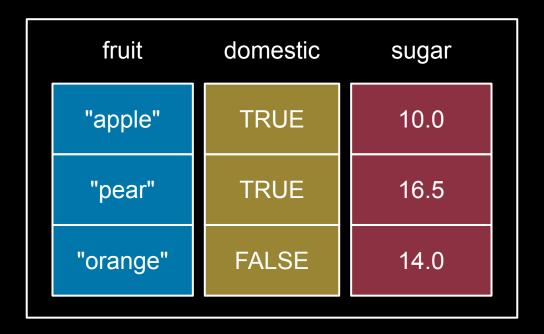
"apple"	TRUE	10.0
"pear"	TRUE	16.5
"orange"	FALSE	14.0

fruit

"apple"	TRUE	10.0
"pear"	TRUE	16.5
"orange"	FALSE	14.0

fruit	domestic	
"apple"	TRUE	10.0
"pear"	TRUE	16.5
"orange"	FALSE	14.0

fruit	domestic	sugar
"apple"	TRUE	10.0
"pear"	TRUE	16.5
"orange"	FALSE	14.0



data frame "fruits"

domestic	sugar
TRUE	10.0
TRUE	16.5
FALSE	14.0
	TRUE

creating data frames

```
data.frame()
read.csv()
```

comma separated values (CSV)

data frame meta data

```
ncol()
nrow()
dim()
colnames()
```

accessing data frames

accessing data frames accessing columns

monty\$prize_door
monty\$contestant_choice
monty\$decision

monty\$prize_door
monty\$contestant_choice
monty\$decision

return a vector

```
monty["prize_door"]
monty["contestant_choice"]
monty["decision"]
```

```
monty["prize_door"]
monty["contestant_choice"]
monty["decision"]
```

return a data frame

```
# multiple columns by name
monty(c("prize_door", "contestant_choice"))
```

```
monty[, 1]  # first column
monty[, 1:2]  # first two columns
monty[, ncol(monty)]  # last column
```

accessing data frames accessing rows

```
monty[1,] # first row
monty[1:10,] # first 10 rows
monty[nrow(monty),] # last row
```

changing columns

monty\$decision <- as.factor(monty\$decision)</pre>

adding columns

```
monty$correct_guess <-
monty$contestant_choice == monty$prize_door</pre>
```

rename columns

colnames(monty)[2] <- "choice"</pre>

subsetting data frames

```
switched <-
monty[monty_hall$decision == "switch, ]</pre>
```

```
switched <-
  monty[
    monty_hall$decision == "switch &
    monty$won == TRUE, ]</pre>
```

subset()

```
subset(monty, decision == "switch")
```

```
subset(
    monty,
    decision == "switch" & won == TRUE
)
```

sorting rows

monty[order(monty\$prize_door),]

saving data frames

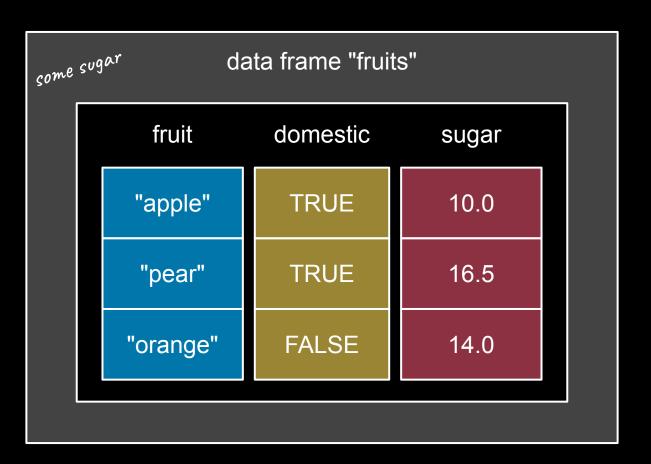
write.csv()

tibbles

{{ tibble }}

data frame "fruits"

"apple" TRUE 10.0	
TDUE 40.5	
"pear" TRUE 16.5	
"orange" FALSE 14.0	



as_tibble()

some sugar

better printing
subsets stay tibbles
better data type guessing
support for extended data types

%!Load Data%!

LOAD DATA



{{ readr }}

```
read_csv()
read_delim()
```

{{ readxl }}

read_excel()

%!Tidy Data%!

TIDY DATA



tidy data

each variable is a column; each column is a variable.

each observation is a row; each row is an observation.

each value is a cell; each cell is a single value.

country	year	cases	population
Afghanistan	1999	745	19987071
Afghanistan	2000	2666	20595360
Brazil	1999	37737	172006362
Brazil	2000	80488	174504898

C	ountry	year	cases	population
Afgha	nistan	1999	745	19987071
Afgha	nistan	2000	2666	20595360
	Brazil	1999	37737	172006362
	Brazil	2000	80488	174504898

variables

country	year	cases	population
Afg it anistan	1000	745	19 >7071
Afg Kanistan	2000	2666	20 >5360
→ Drazil	1999	37737	172 > 6362
→ Drazil	2000	00400	174 >4898

observations

country	year	cases	population
Afgnaristan	O 1999	745	1997071
Afgnaristan	2000	2666	20595360
O 3razil	O 1999	7737	17(20)6362
O 3razil	2000	0488	17(450)4898

values

country	year	type	count
Afghanistan	1999	cases	745
Afghanistan	1999	population	19987071
Afghanistan	2000	cases	2666
Afghanistan	2000	population	20595360
Brazil	1999	cases	37737
Brazil	1999	population	172006362
Brazil	2000	cases	80488
Brazil	2000	population	174504898

longer

country	year	type	count
Afghanistan	1999	cases	745
Afghanistan	1999	population	19987071
Afghanistan	2000	cases	2666
Afghanistan	2000	population	20595360
Brazil	1999	cases	37737
Brazil	1999	population	172006362
Brazil	2000	cases	80488
Brazil	2000	population	174504898

wider

country	cases_1999	cases_2000	pop_1999	pop_2000
Afghanistan	745	2666	19987071	20595360
Brazil	37737	172006362	80488	174504898



country	year	rate
Afghanistan	1999	745 / 19987071
Afghanistan	2000	2666 / 20595360
Brazil	1999	37737 / 172006362
Brazil	2000	80488 / 174504898

tidy

country	year	cases	population
Afghanistan	1999	745	19987071
Afghanistan	2000	2666	20595360
Brazil	1999	37737	172006362
Brazil	2000	80488	174504898

tidy

country	year	cases	population
Afghanistan	1999	745	19987071
Afghanistan	2000	2666	20595360
Brazil	1999	37737	172006362
Brazil	2000	80488	174504898

vector

{{ tidyr }}

pivot_wider()

pivot_longer()

STRINGS

{{ stringr }}

```
str_trim()
str_squish()
```

str_detect()

str_starts()

str_ends()

"Annabel Miller"

"Annabel Miller"

str_starts(txt, "Anna")

"Annabel Miller"

str_ends(txt, "Miller")

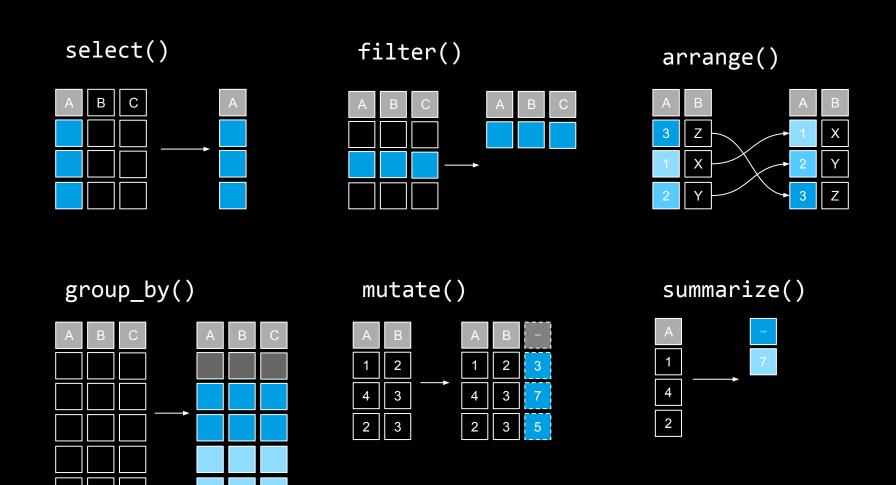
"Annabel Miller"

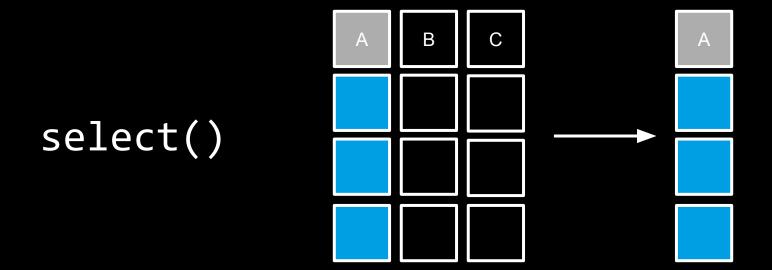
str_detect(txt, "Mill")

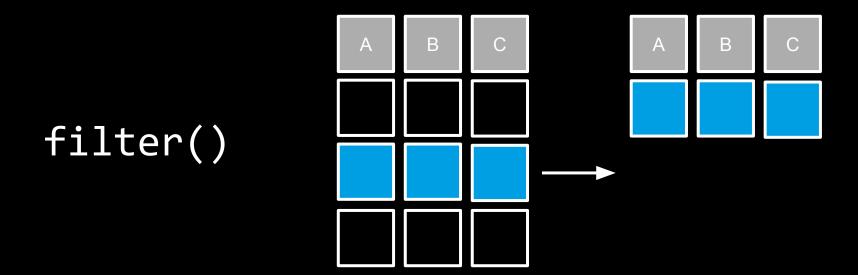
TRANSFORM DATA

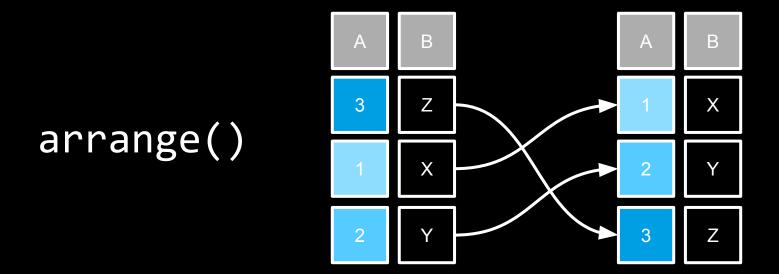
{{ dplyr }}

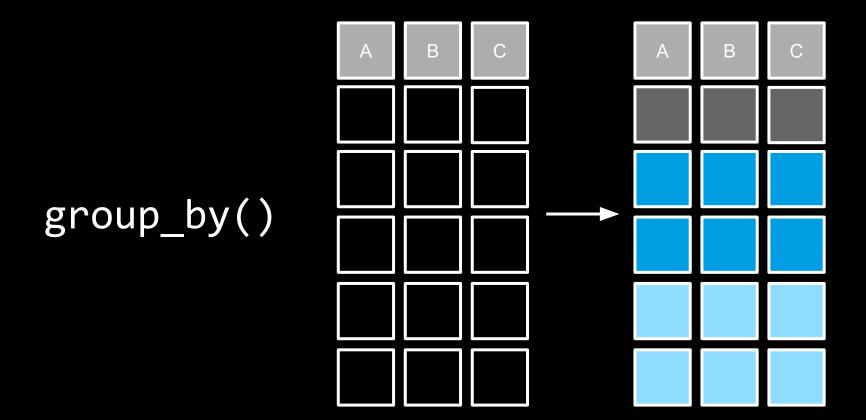
types of transformations





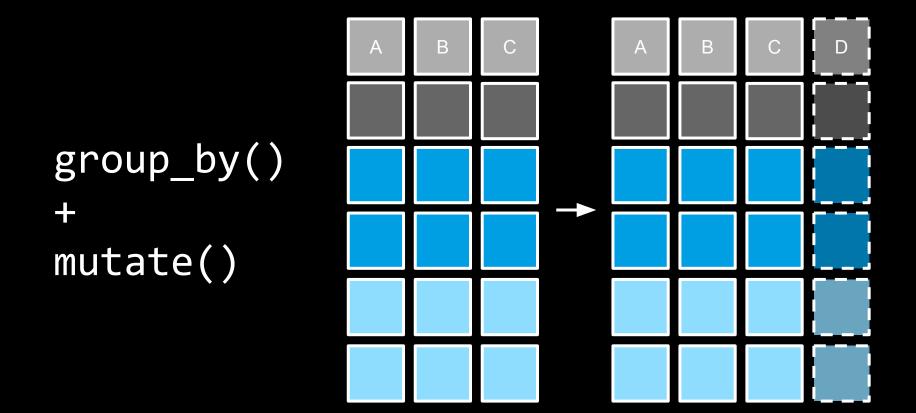


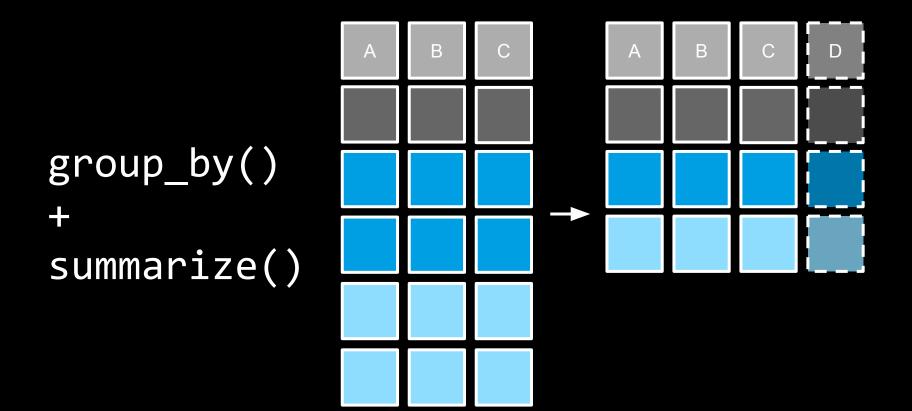




mutate() A B A B SUM 1 2 1 2 3 4 3 7 2 3 5

summarize() A SUM 7 2





joining data

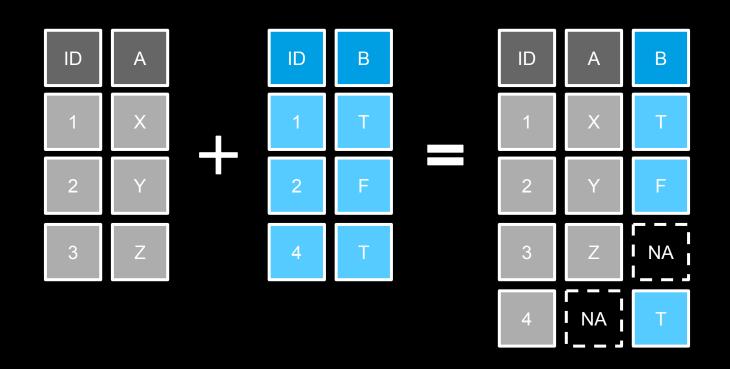
left_join()



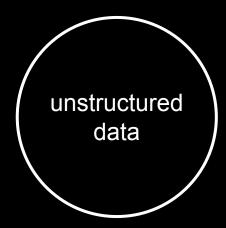
inner_join()

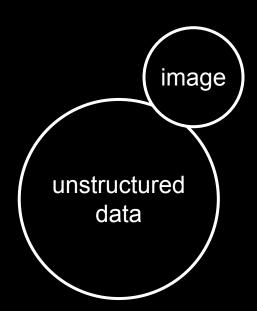


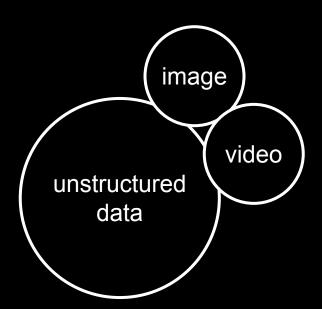


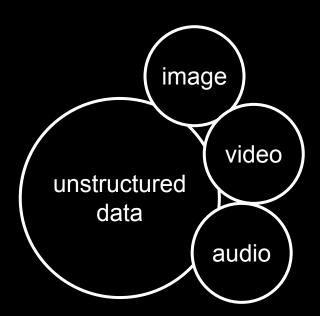


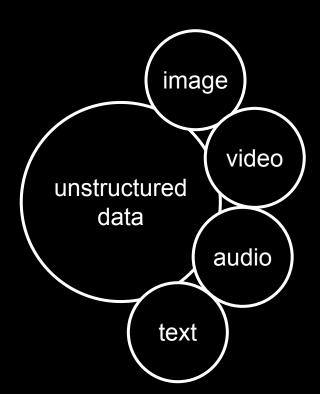
UNSTRUCTURED DATA



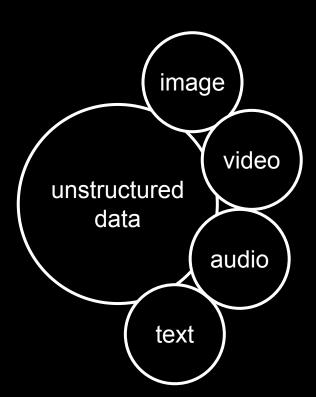




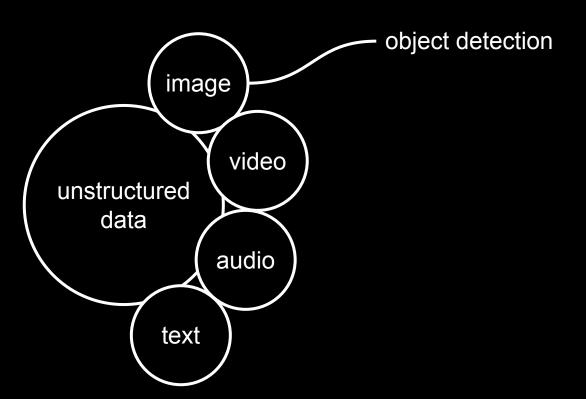




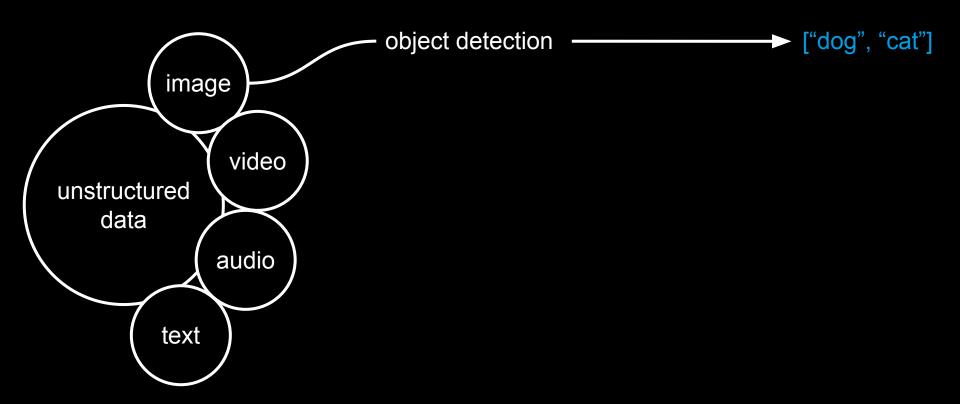
no handles to grab

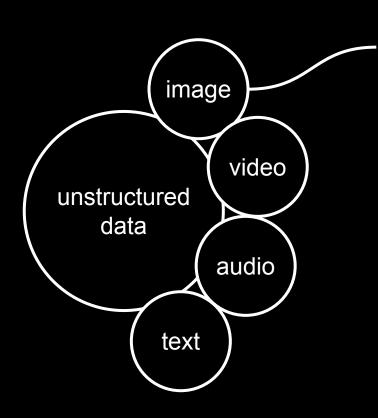


no handles to grab



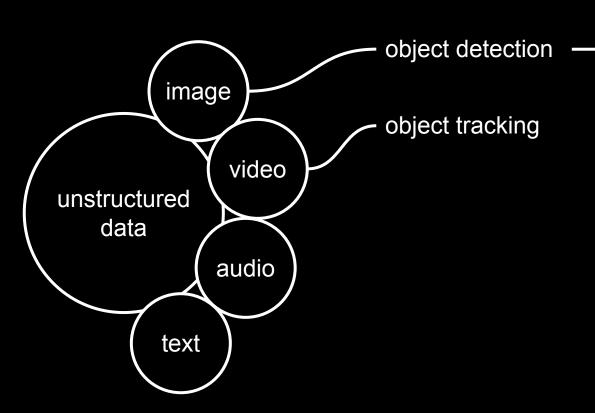
no handles to grab



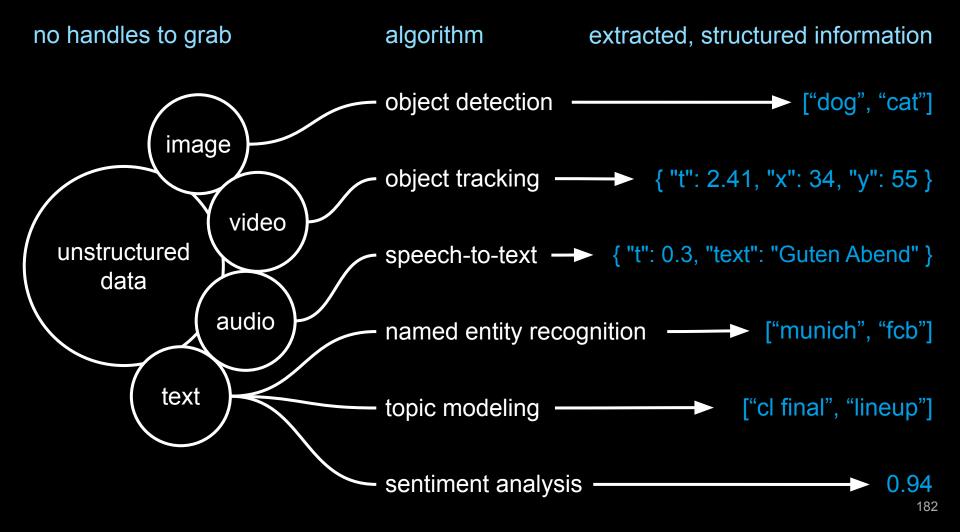


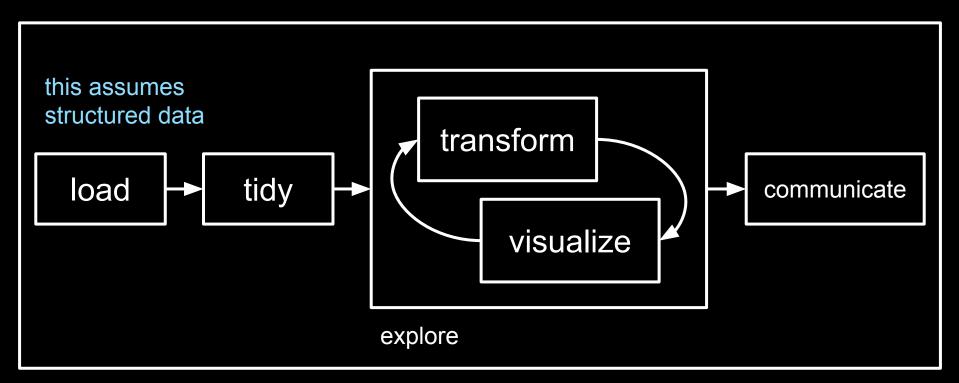
object detection

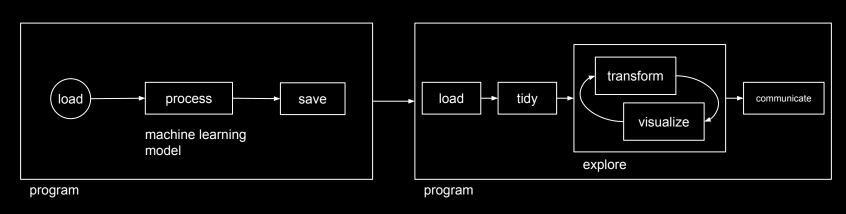
→ ["dog", "cat"]

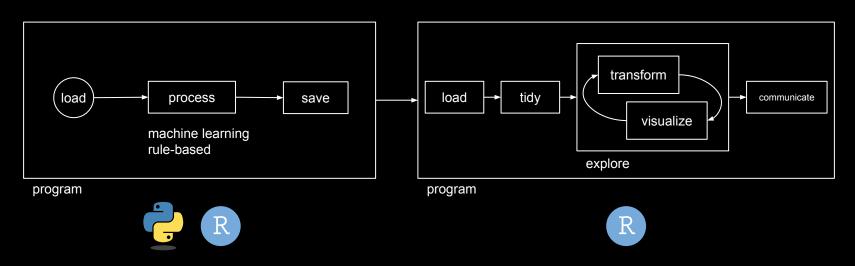


→ ["dog", "cat"]







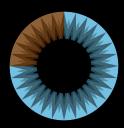


%!Machine Learning%!

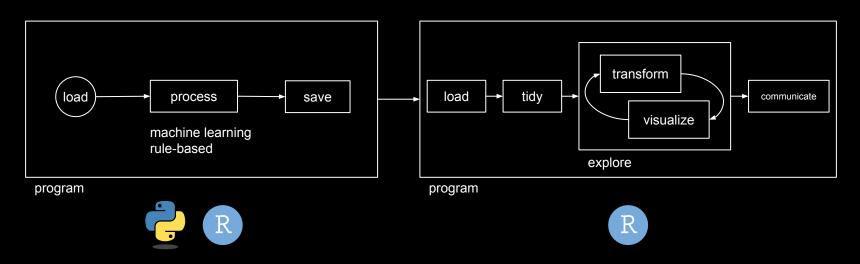
MACHINE LEARNING

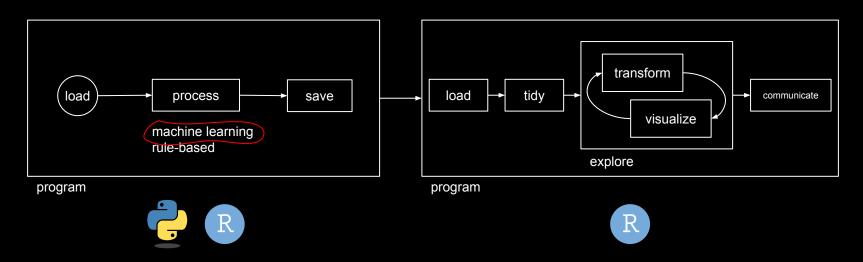


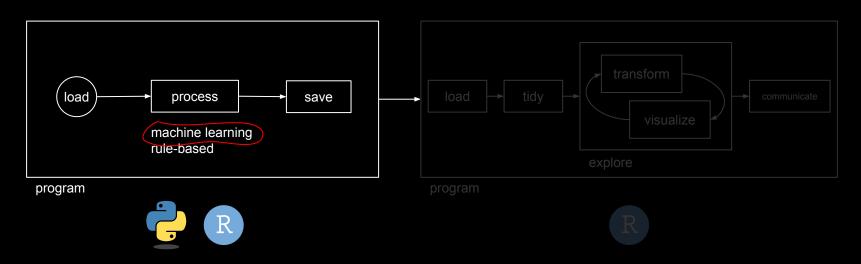
Highly recommended for background information

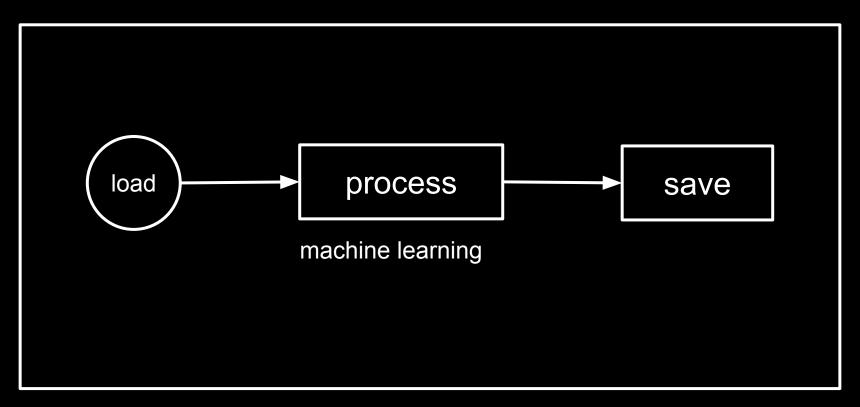


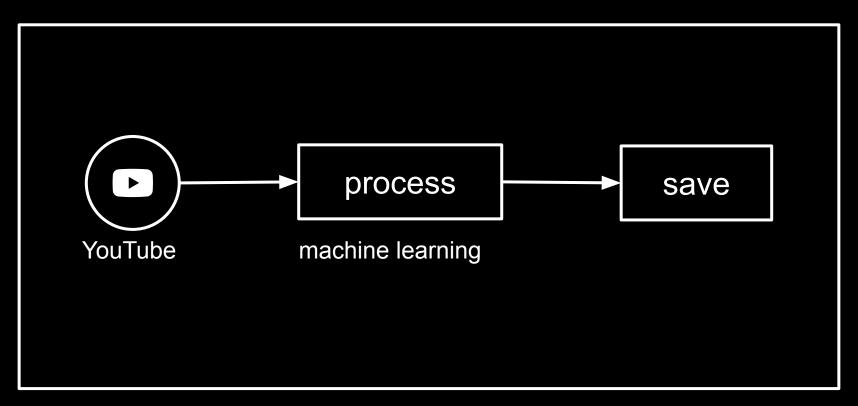
3Blue1Brown's YouTube Course on Neural Networks and Deep Learning

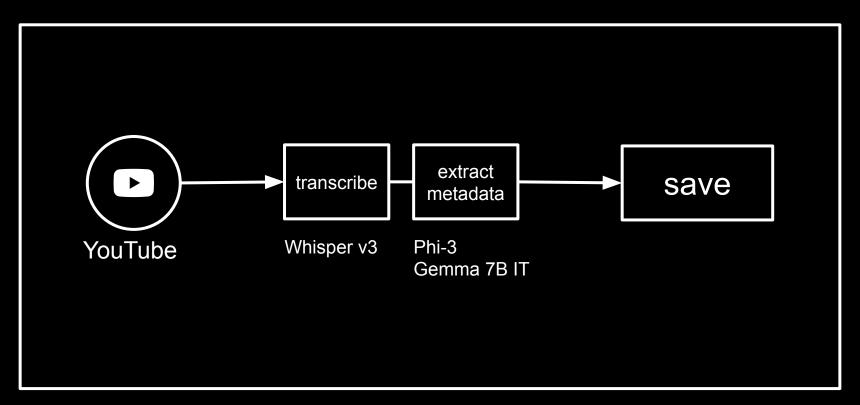


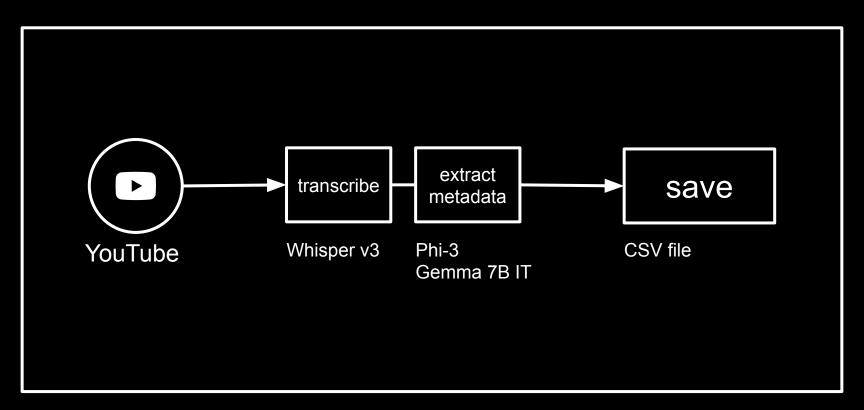












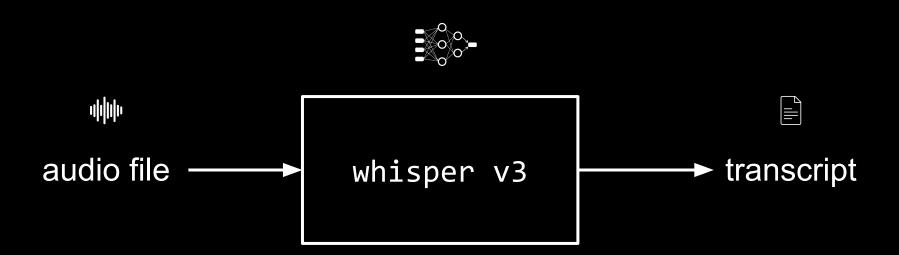
YouTube API

Whisper v3

https://arxiv.org/abs/2212.04356



https://huggingface.co/openai/whisper-large-v3



Large Language Models (LLM)



prediction of next token based on learnt probability distribution



prediction of next token based on learnt probability distribution



(randomness)



prediction of next token based on learnt probability distribution



(randomness)



(filter)

(discriminating, insulting content)



prediction of next token based on learnt probability distribution



(randomness)

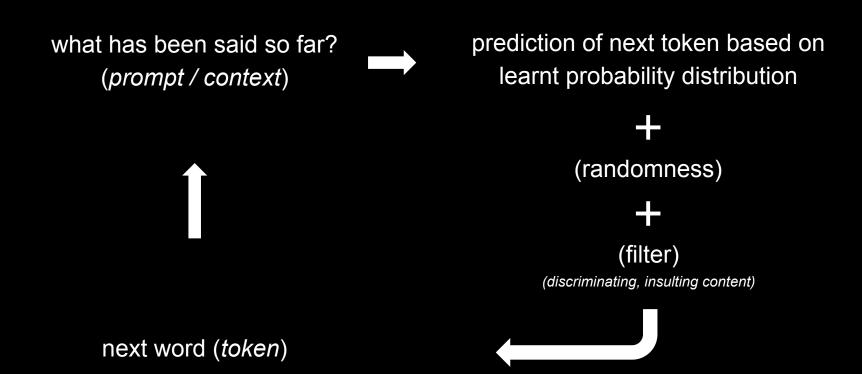


(filter)

(discriminating, insulting content)

next word (token)





PROMPTING



elements of a prompt

```
<instruction>
<context>
<input data>
<output indicator>
```

elements of a prompt

example prompt

<instruction>

<context>

<input data>

<output indicator>

Explain the binary number system.

```
elements of a prompt
```

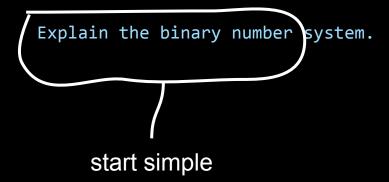
<instruction>

<context>

<input data>

<output indicator>

example prompt



elements of a prompt

<instruction>

<context>

<input data>

<output indicator>

example prompt

You are a friendly tutor and your task is to explain complex concepts as simple as possible.

Explain the binary number system.

elements of a prompt

<instruction>

<context>

<input data>

<output indicator>

example prompt

You are a friendly tutor and your task is to explain complex concepts as simple as possible.

Your answers are never longer than 10 sentences.

Explain the binary number system.

ZERO-SHOT PROMPTING

elements of a prompt

example prompt

<instruction>

<context>

<input data>

<output indicator>

Classify the text into neutral, negative or positive.

Text: "What a great dinner!"

Sentiment:

elements of a prompt

<instruction>

<context>

<input data>

<output indicator>

example prompt

Classify the text into neutral, negative or positive.

Text: "What a great dinner!"
Sentiment:

this will be replaced with data later...

FEW-SHOT PROMPTING

IN-CONTEXT LEARNING

examples in the context to learn from

Extract all references to countries and their continent in the following text using the format from the examples below.

Example 1: "They played the team called 'Die Mannschaft' in the world cup final" Correct answer: Germany, Europe

Example 2: "The Three Lions once again lost to Germany in a semi final" Correct answer: England, Europe, Germany, Europe

Text: "The Selecao was destroyed 1:7 by the DFB selection in their home stadium." Answer:

examples in the context to learn from

Extract all references to countries and their continent in the following text using the format from the examples below.

```
Example 1: "They played the team called 'Die Mannschaft' in the world cup final". Correct answer: Germany, Europe
```

Example 2: "The Three Lions once again lost to Germany in a semi final" Correct answer: England, Europe, Germany, Europe

Text: "The Selecao was destroyed 1:7 by the DFB selection in their home stadium." Answer:

more prompting strategies

```
chain-of-thought (CoT)
self-consistency
generate knowledge prompting
prompt chaining (subtasks)
tree-of-thoughts (ToT)
retrieval-augmented-generation (RAG)
...
```

Phi-3

https://arxiv.org/abs/2404.14219



https://huggingface.co/microsoft/Phi-3-mini-128k-instruct

https://huggingface.co/microsoft/Phi-3-medium-128k-instruct

Gemma 2B / 7B Instruct

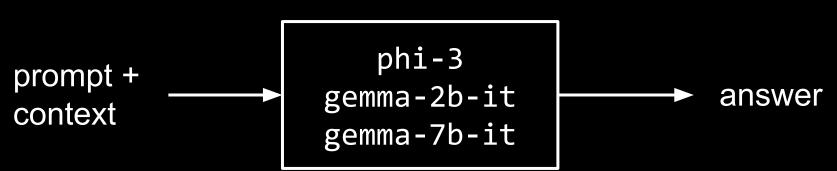
https://arxiv.org/abs/2403.08295



https://huggingface.co/google/gemma-2b-it

https://huggingface.co/google/gemma-7b-it



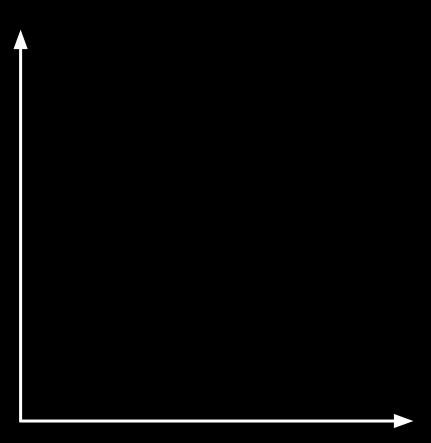


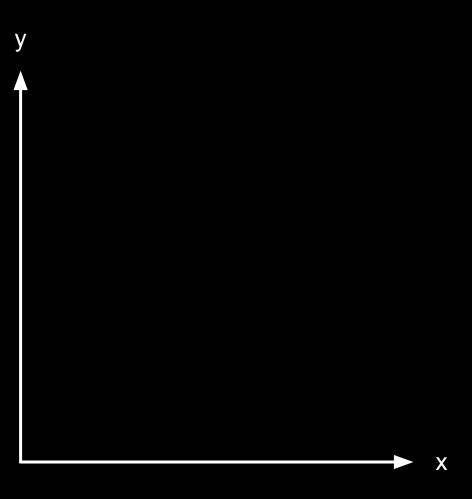
OpenAl GPT-4o

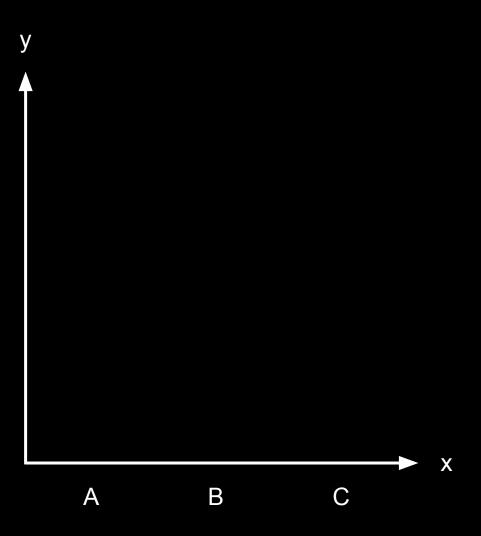
VISUALIZE DATA

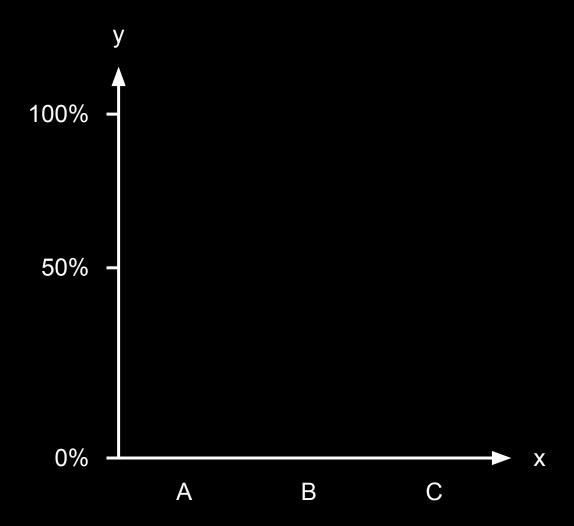
data

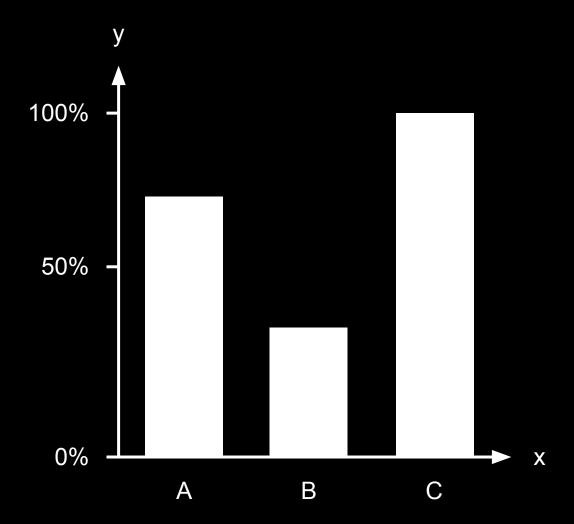
category	pct
А	75
В	33
С	100



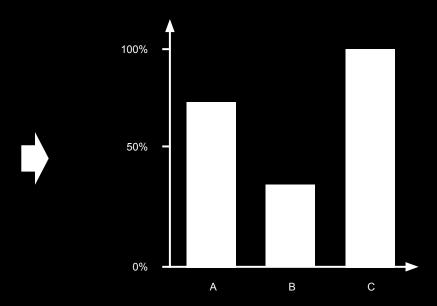








category	pct
Α	75
В	33
С	100

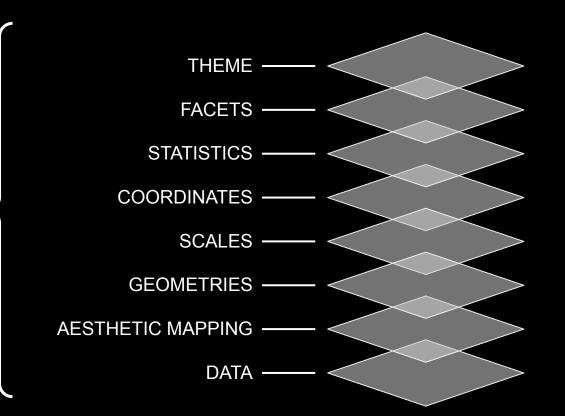


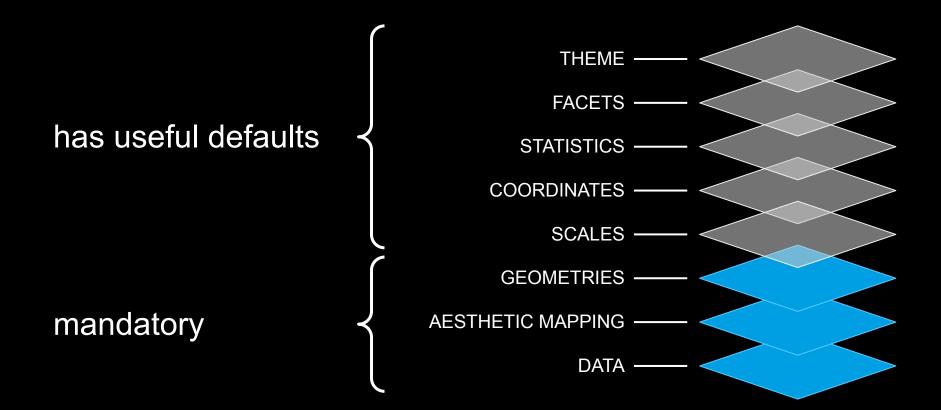
{{ ggplot2 }}

why visualize?

```
{{ ggplot2 }}
grammar of graphics
```

any
data
visualization



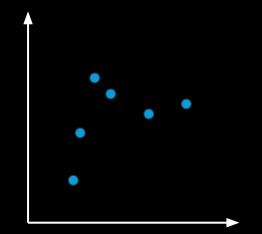


ggplot()

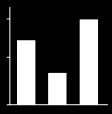
```
ggplot() +
aes()
```

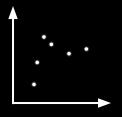
```
ggplot() +
  aes() +
  geom_point()
```

```
ggplot() +
  aes() +
  geom_point()
```

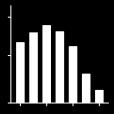


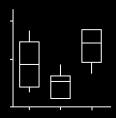
basic plots



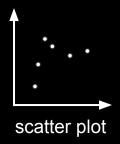


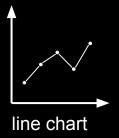




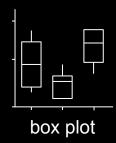








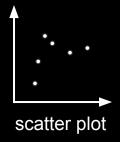




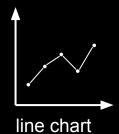
amounts proportions distributions (discrete)



associations patterns



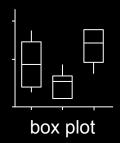
trends developments



distributions (continuous)



compare distributions (continuous)



COMMUNICATE DATA

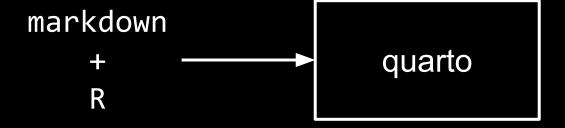
quarto

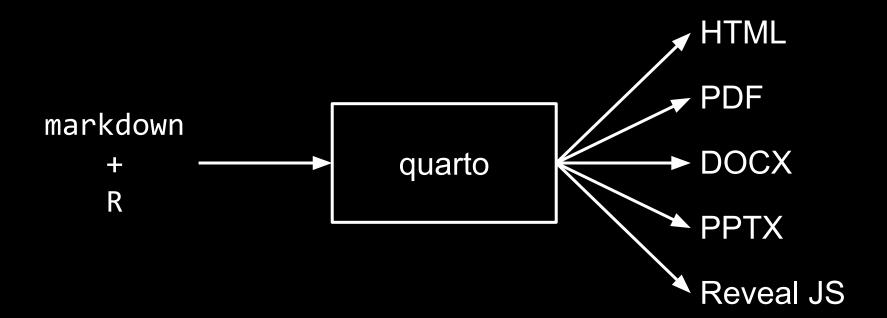
{{ quarto }}

markdown

╅

R





markdown

Heading 1

```
### Heading 2
#### Heading 3
#### Heading 4
```

This is *italic*,
and this **bold**

This is rendered as `code`.

- List item A
- List item B
- List item C

- 1. First
- 2. Second
- 3. Third

![Image title](path/to/image.png)

![Image title](path/to/image.png){width=200}

![Image title](path/to/image.png){#fig-myimage}

For more details see @fig-myimage.

[Linked text](https://quarto.org)

```
```{r}
1 + 1
```

## code options

```
```{r}
#| echo: false
1 + 1
...
```

```
"\" {r}
# | eval: false
x <- 1 + 1</pre>
```

```
#| warning: false
data <- read_csv("data.csv")</pre>
```

figures

```
```{r}
label: fig-tweets-per-user
fig-cap: "Tweets per User"
tweets >
 ggplot() +
 aes(x = screen_name) +
 geom_bar()
. . .
```

```
```{r}
# code-fold: true
# code-summary: "Show code"
tweets >
   ggplot() +
  aes(x = screen_name) +
   geom_bar()
. . .
```

cross references

```
"``{r}
#| label: fig-tweets-per-user
#| fig-cap: "Tweets per User"
...
...
```

In @fig-tweets-per-user you can see an overview of the number of tweets per user in the data set.

```
# Introduction {#sec-introduction}
...
```

Analysis

As stated in @sec-introduction, the goal of this paper is to analyze the user behavior with regard to the content they tweet.

citation & bibliography

https://quarto.org/docs/authoring/citations.html

output formats