# INFO 2950: Intro to Data Science

Lecture 6 2023-09-11



# Agenda

#### 1. Time series

- a. Time series data
- b. Line plots

#### 2. Regressions

- a. Motivation
- b. Notation
- c. Interpretation

• Data where one axis denotes time



• Data where one axis (one column) denotes time





- Data where one axis (one column) denotes time
- Each row = one "time step"

one time step {
another time step {

Time	Υ
2010	0
2011	3
	• • •

- Most meaningful when data is aggregated so that each "time step":
  - 1. Is regularly spaced (e.g. daily, monthly, quarterly data) chronologically

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  - 4. Deals with missing values

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  - Has corresponding data per time step
  - Is unique
  - Deals with missing values
- "Daily Temperature Data": each time step represents one day.

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- "Daily Temperature Data": each time step represents one day. How many temperatures do we expect for each day?

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     chronologically
  - Has corresponding data per time step
  - Is unique
  - Deals with missing values
- "Daily Temperature Data": each time step represents one day. How many temperatures do we expect for each day?
   1 (i.e., unique per time step)!

# A dataframe called daily\_temps\_df

	day	time_of_measurement	temperature
0	2022-09-10	high	82
1	2022-09-10	low	62
2	2022-09-11	high	69
3	2022-09-11	low	62
4	2022-09-12	high	77
5	2022-09-13	high	69
6	2022-09-13	low	56
7	2022-09-14	high	74
8	2022-09-14	low	50

# How do we get array data types?

type (a) or a.dtype?

	day	time_of_measurement	temperature
0	2022-09-10	high	82
1	2022-09-10	low	62
2	2022-09-11	high	69
3	2022-09-11	low	62
4	2022-09-12	high	77
5	2022-09-13	high	69
6	2022-09-13	low	56
7	2022-09-14	high	74
8	2022-09-14	low	50

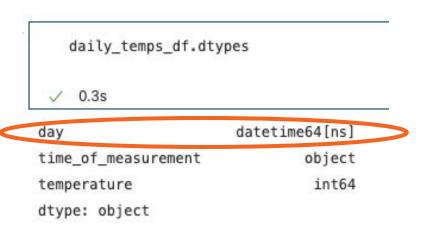
## How do we get array data types?

# a.dtype is what we want for each array a!

	day	time_of_measurement	temperature
0	2022-09-10	high	82
1	2022-09-10	low	62
2	2022-09-11	high	69
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5	2022-09-13	high	69
6	2022-09-13	low	56
7	2022-09-14	high	74
8	2022-09-14	low	50

# daily\_temps\_df has date type data

	day	time_of_measurement	temperature
0	2022-09-10	high	82
1	2022-09-10	low	62
2	2022-09-11	high	69
3	2022-09-11	low	62
4	2022-09-12	high	77
5	2022-09-13	high	69
6	2022-09-13	low	56
7	2022-09-14	high	74
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#### slate

@PleaseBeGneiss

excel: is that a date?

me: 57.39 is very much not a date

excel: strong date vibes to me

me: h-how

excel: fixed it

me: 57/39/2020?

excel: you're welcome

11:23 AM · Nov 17, 2020



#### slate

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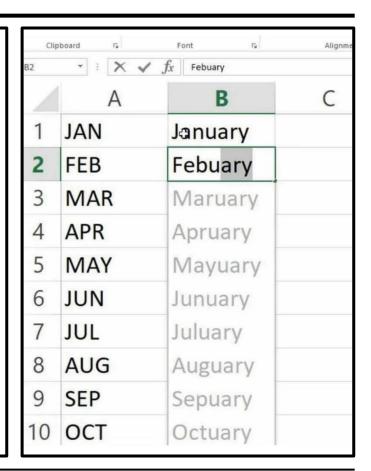
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excel: you're welcome

11:23 AM · Nov 17, 2020



### Date issues in the wild?

#### Date issues in the wild?

- Non-standard formatting around the world
  - month/day vs. day/month (Sep 10th vs. Oct 9th)
  - Even if the same ordering, -YYYY vs. .YY vs. ,Year
     (09-10-2023 vs. 09.10.23 vs. September 10th, 2023)
  - Leading zeroes (09-10-2023 vs. 9-10-2023)

#### Date issues in the wild?

- Non-standard formatting around the world
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  - Even if the same ordering, -YYYY vs. .YY vs. ,Year
     (09-10-2023 vs. 09.10.23 vs. September 10th, 2023)
  - Leading zeroes (09-10-2023 vs. 9-10-2023)
- Sorting is annoying (e.g. sorting "Monday" thru
   "Friday" is alphabetical, not in MTWThF order)
  - MM-DD-YY: "12-31-2023" < "9-10-2023"</li>
  - DD-MM-YY: "01-12-2023" < "31-9-2023"</li>

#### Now throw in *time* too...

- Hours:minutes:seconds? HH:MM:SS?
- Are all clock measurements of a millisecond identical?
- What about tracking time zones?
- What about when exactly daylight savings time happens? What about leap years?
- What if you generate data while flying over the international date line?
- ...

# Is the day before Saturday always Friday?

### No!

#### Samoa jumps forward in time

Published 9-May-2011. Changed 1-Sep-2011

Samoa will switch time zones by redrawing the international dateline.

The change will occur at midnight on December 29, 2011, taking the Pacific island nation straight into December 31, 2011. Neighboring American Samoa will remain on the eastern side of the dateline, resulting in a time difference of a whole day between the two territories, which are a mere 30 miles apart.

Any guesses why Samoa did this?

#### Samoa jumps forward in time

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Prime Minister Tuilaepa Sailele Malielegaoi maintains that this constricts Samoa's economy: "In doing business with New Zealand and Australia, we're losing out on two working days a week," he told the government newspaper *Sivali*. "While it's Friday here, it's Saturday in New Zealand, and when we're at church on Sunday, they're already conducting business in Sydney and Brisbane."

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# Moral of the story

- Do not try to be clever when dealing with dates & times yourself
- Professionals have dealt with this for *years*; you should **rely on packages** they've written for this



Everytime I call in datetime for python.

## Data types for dates

- If you have any time-related data, USE DATETIME!
  - Lessens confusion (Sep 10th vs. Oct 9th)
  - Sorts correctly, plots in correct order
  - Allows you to extract important parts of your time data (e.g., month, day, day of week, etc.) & format as desired

# Data types for dates

Convert from string to datetime in pandas:

```
daily_temps_df["day"]=pd.to_datetime(daily_temps_df["day"])
```

	day	time_of_measurement	temperature
0	2022-09-10	high	82
1	2022-09-10	low	62
2	2022-09-11	high	69
3	2022-09-11	low	62
4	2022-09-12	high	77
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- Is regularly spaced (e.g. daily, monthly, quarterly data) chronologically
- Has corresponding data per time step
- Is unique
- Deals with missing values

ure	tempera	time_of_measurement	day	
82		high	2022-09-10	0
62		low	2022-09-10	1
69		high	2022-09-11	2
62		low	2022-09-11	3
77		high	2022-09-12	4
69		high	2022-09-13	5
56		low	2022-09-13	6
74		high	2022-09-14	7
50		low	2022-09-14	8

Datetime default of YYYY-MM-DD (even if accidentally string) sorts chronologically!

- Is regularly spaced (e.g. daily, monthly, quarterly data) chronologically
- Has corresponding data per time step
- Is unique
- Deals with missing values

	temperature	time_of_measurement	day	
	82	high	2022-09-10	0
	62	low	2022-09-10	1
	69	high	2022-09-11	2
	62	low	2022-09-11	3
	77	high	2022-09-12	4
	69	high	2022-09-13	5
	56	low	2022-09-13	6
	74	high	2022-09-14	7
ŕ	50	low	2022-09-14	8

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- Is regularly spaced (e.g. daily, monthly, quarterly data) chronologically
- Has corresponding data per time step
- Is unique
- Deals with missing values

# Aggregate daily\_temps\_df: 1 daily avg temp

	day	time_of_measurement	temperature
0	2022-09-10	high	82
1	2022-09-10	low	62
2	2022-09-11	high	69
3	2022-09-11	low	62
4	2022-09-12	high	77
5	2022-09-13	high	69
6	2022-09-13	low	56
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8	2022-09-14	low	50

# What SQL code yields this new table of averaged daily temperatures?

table name: daily\_temps\_df

	day	time_of_measurement	temperature
0	2022-09-10	high	82
1	2022-09-10	low	62
2	2022-09-11	high	69
3	2022-09-11	low	62
4	2022-09-12	high	77
5	2022-09-13	high	69
6	2022-09-13	low	56
7	2022-09-14	high	74
8	2022-09-14	low	50



	day	avg(temperature)
0	2022-09-10	72.0
1	2022-09-11	65.5
2	2022-09-12	77.0
3	2022-09-13	62.5
4	2022-09-14	62.0

SELECT

FROM daily\_temps\_df\_

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7	2022-09-14	high	74
8	2022-09-14	low	50

SELECT day, AVG(temperature) FROM daily\_temps\_df GROUP BY day

# Is this a meaningful time series now?

day		avg(temperature)	
0	2022-09-10	72.0	
1	2022-09-11	65.5	
2	2022-09-12	77.0	
3	2022-09-13	62.5	
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SELECT day, AVG(temperature) FROM daily\_temps\_df GROUP BY day

# Is this a meaningful time series now?

aggregated so that each "time step":

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	day	avg(temperature) 72.0	
0	2022-09-10	72.0	
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2	2022-09-12	77.0	
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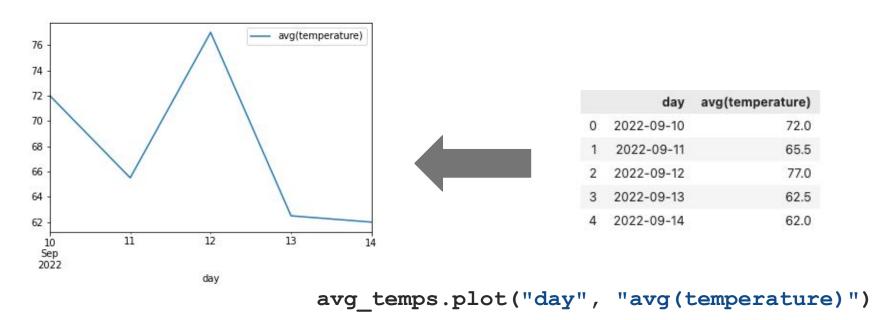
SELECT day, AVG(temperature) FROM daily\_temps\_df GROUP BY day

#### Let's plot the time series!

		day	avg(temperature) 72.0 65.5	
	0	2022-09-10	72.0	
	1	2022-09-11	65.5	
	2	2022-09-12	77.0	
	3	2022-09-13	62.5	
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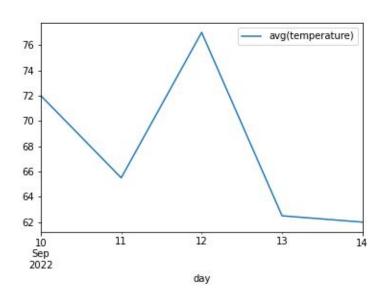
```
avg_temps.plot("day", "avg(temperature)")
```

#### Let's plot the time series!



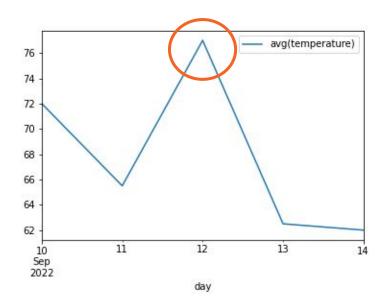
40

# Are there any outliers here?



	day	avg(temperature)
0	2022-09-10	72.0
1	2022-09-11	65.5
2	2022-09-12	77.0
3	2022-09-13	62.5
4	2022-09-14	62.0

#### Are there any outliers here? Maybe...



	day	avg(temperature)
0	2022-09-10	72.0
1	2022-09-11	65.5
2	2022-09-12	77.0
3	2022-09-13	62.5
4	2022-09-14	62.0

Domain knowledge?

#### Let's look back at our original data...

#### table name: daily\_temps\_df

	day	time_of_measurement	temperature
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1	2022-09-10	low	62
2	2022-09-11	high	69
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Anything weird?

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	day	time_of_measurement	temperature
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1	2022-09-11	65.5		
2	2022-09-12	77.0		
3	2022-09-13	62.5		
4	2022-09-14	62.0		

Anything weird?

# Let's look only at temperature highs.

#### table name: daily\_temps\_df

	day	time_of_measurement	temperature
0	2022-09-10	high	82
1	2022-09-10	low	62
2	2022-09-11	high	69
3	2022-09-11	low	62
4	2022-09-12	high	77
5	2022-09-13	high	69
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6	2022-09-13	low	56
7	2022-09-14	high	74
8	2022-09-14	low	50



daily\_temps\_df[\_ "high"]

82

69

77

69

74

table	name:	daily	temi	ps di	f
tabic	manne.	uuiiy_		93_U	,

	day	time_of_measurement	temperature
0	2022-09-10	high	82
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5	2022-09-13	high	69
6	2022-09-13	low	56
7	2022-09-14	high	74
8	2022-09-14	low	50



Need to grab the correct column (by re-invoking the df)

table name: daily temps df

	day	time_of_measurement	temperature
0	2022-09-10	high	82
1	2022-09-10	low	62
2	2022-09-11	high	69
3	2022-09-11	low	62
4	2022-09-12	high	77
5	2022-09-13	high	69
6	2022-09-13	low	56
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8	2022-09-14	low	50





Don't forget to use quotes for the column name

table name: daily\_temps\_df

	day	time_of_measurement	temperature
0	2022-09-10	high	82
1	2022-09-10	low	62
2	2022-09-11	high	69
3	2022-09-11	low	62
4	2022-09-12	high	77
5	2022-09-13	high	69
6	2022-09-13	low	56
7	2022-09-14	high	74
8	2022-09-14	low	50



daily temps df[daily temps df['time of measurement']



Double equals in Pandas, Single equals in SQL

table name: daily_t	emps dt
---------------------	---------

	day	time_of_measurement	temperature
0	2022-09-10	high	82
1	2022-09-10	low	62
2	2022-09-11	high	69
3	2022-09-11	low	62
4	2022-09-12	high	77
5	2022-09-13	high	69
6	2022-09-13	low	56
7	2022-09-14	high	74
8	2022-09-14	low	50



daily\_temps\_df[daily\_temps\_df['time\_of\_measurement'] == "high"]

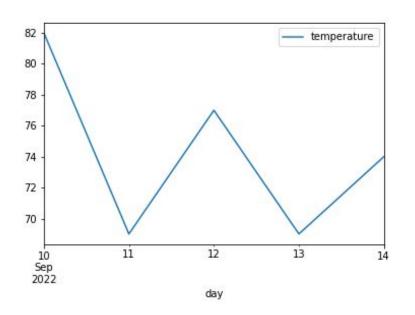
The output of the code in [] yields: [True, False, True, False, True, False, True, False]

	table r	name: daily_ter	nps_df
	day	time_of_measurement	
)	2022-09-10	high	82
1	2022-09-10	low	62
2	2022-09-11	high	69
3	2022-09-11	low	62
ļ	2022-09-12	high	77
5	2022-09-13	high	69
6	2022-09-13	low	56
7	2022-09-14	high	74
8	2022-09-14	low	50

daily\_temps\_df[daily\_temps\_df['time\_of\_measurement'] == "high"]

daily\_tempts\_df[[True, False, True, False, True, Frue, False, True, False]] restricts to only the rows corresponding to True

#### What do the highs look like?



	day	time_of_measurement	temperature
0	2022-09-10	high	82
2	2022-09-11	high	69
4	2022-09-12	high	77
5	2022-09-13	high	69
7	2022-09-14	high	74

high\_temps.plot("day", "temperature")

# Now let's look at the lows only.

#### table name: daily\_temps\_df

	day	time_of_measurement	temperature
0	2022-09-10	high	82
1	2022-09-10	low	62
2	2022-09-11	high	69
3	2022-09-11	low	62
4	2022-09-12	high	77
5	2022-09-13	high	69
6	2022-09-13	low	56
7	2022-09-14	high	74
8	2022-09-14	low	50

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5	2022-09-13	high	69
6	2022-09-13	low	56
7	2022-09-14	high	74
8	2022-09-14	low	50



day time_of_measurement temperate	ure
1 2022-09-10 low	62
3 2022-09-11 low	62
6 2022-09-13 low	56
8 2022-09-14 low	50

low\_temps = daily\_temps\_df[daily\_temps\_df['time\_of\_measurement'] == "low"]

#### Now let's look at the lows only.

table name: daily\_temps\_df

	day	time_of_measurement	temperature
0	2022-09-10	high	82
1	2022-09-10	low	62
2	2022-09-11	high	69
3	2022-09-11	low	62
4	2022-09-12	high	77
5	2022-09-13	high	69
6	2022-09-13	low	56
7	2022-09-14	high	74
8	2022-09-14	low	50





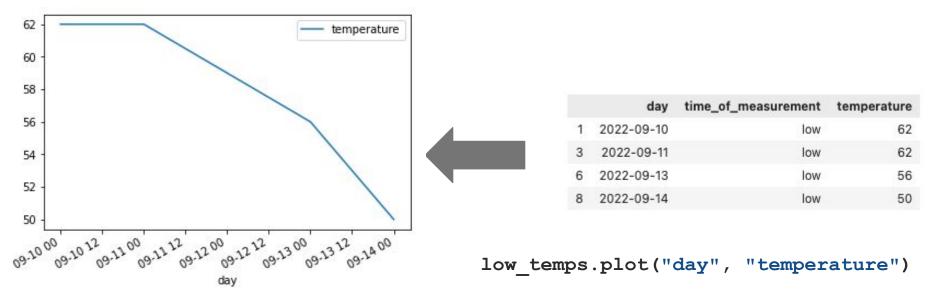
low\_temps = daily\_temps\_df[daily\_temps\_df['time\_of\_measurement'] == "low"]

# What happens when we plot the lows?

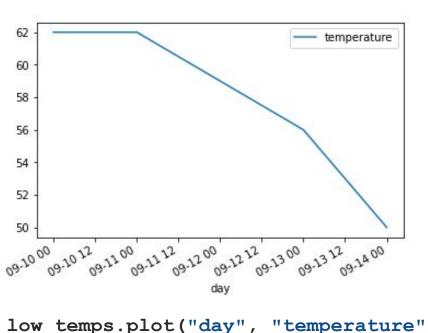
	day	time_of_measurement	temperature
1	2022-09-10	low	62
3	2022-09-11	low	62
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8	2022-09-14	low	50

#### What happens when we plot the lows?

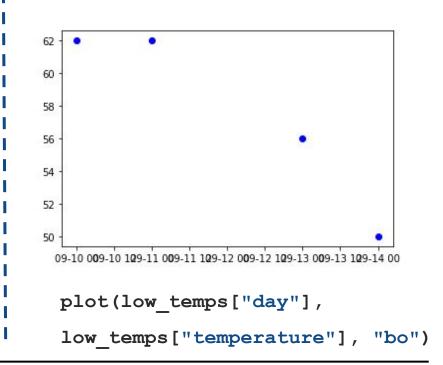
Is this expected behavior?



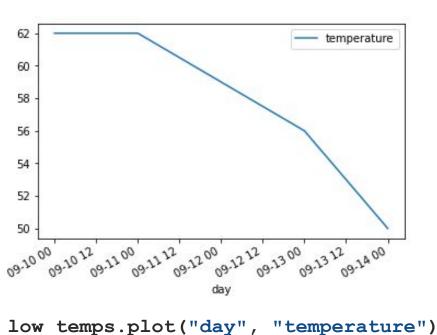
#### Missing data can be easy to miss!

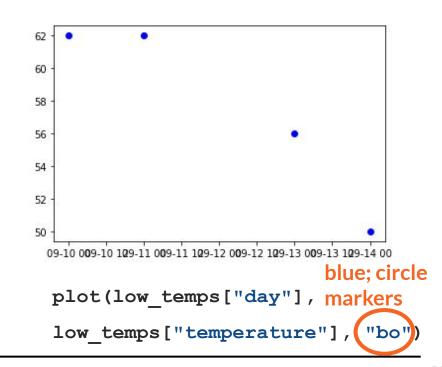


low temps.plot("day", "temperature")



#### Missing data can be easy to miss!





# How do we make daily\_temps\_df meaningful?

	day	time_of_measurement	temperature
0	2022-09-10	high	82
1	2022-09-10	low	62
2	2022-09-11	high	69
3	2022-09-11	low	62
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7	2022-09-14	high	74
8	2022-09-14	low	50

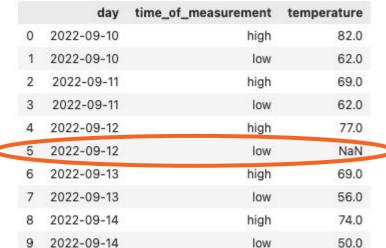
aggregated so that each "time step":

- Is regularly spaced (e.g. daily, monthly, quarterly data) chronologically
- Has corresponding data per time step
- Is unique
- Deals with missing values

# Back to the original data. What if we include missingness using NaNs?

table name: daily\_temps\_df

	day	time_of_measurement	temperature
0	2022-09-10	high	82
1	2022-09-10	low	62
2	2022-09-11	high	69
3	2022-09-11	low	62
4	2022-09-12	high	77
5	2022-09-13	high	69
6	2022-09-13	low	56
7	2022-09-14	high	74
8	2022-09-14	low	50



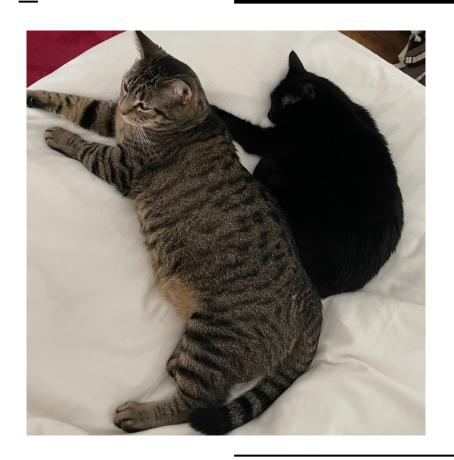
# Back to the original data. What if we include missingness using NaNs?

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8	2022-09-14	low	50

	day	time_of_measurement	temperature
0	2022-09-10	high	82.0
1	2022-09-10	low	62.0
2	2022-09-11	high	69.0
3	2022-09-11	low	62.0
4	2022-09-12	high	77.0
5	2022-09-12	low	NaN
6	2022-09-13	high	69.0
7	2022-09-13	low	56.0
8	2022-09-14	high	74.0
9	2022-09-14	low	50.0

Could use something like pd.concat to manually add in missing rows of data



#### conCATenated

	day	time_of_measurement	temperature
0	2022-09-10	high	82.0
1	2022-09-10	low	62.0
2	2022-09-11	high	69.0
3	2022-09-11	low	62.0
4	2022-09-12	high	77.0
5	2022-09-12	low	NaN
6	2022-09-13	high	69.0
7	2022-09-13	low	56.0
8	2022-09-14	high	74.0
9	2022-09-14	low	50.0

# How to include missingness? (SQL's Version)

SELECT a.day, a.time\_of\_measurement, b.temperature
FROM

(SELECT \* FROM (SELECT distinct day FROM
daily\_temps\_df) CROSS JOIN (SELECT distinct
time\_of\_measurement FROM daily\_temps\_df)) as a

LEFT JOIN daily\_temps\_df as b

ON a.day=b.day AND
a.time\_of\_measurement=b.time\_of\_measurement

ORDER BY a.day

	day	time_of_measurement	temperature
0	2022-09-10	high	82.0
1	2022-09-10	low	62.0
2	2022-09-11	high	69.0
3	2022-09-11	low	62.0
4	2022-09-12	high	77.0
5	2022-09-12	low	NaN
6	2022-09-13	high	69.0
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# What are pros of cons of including NaN?

	day	time_of_measurement	temperature
0	2022-09-10	high	82.0
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6	2022-09-13	high	69.0
7	2022-09-13	low	56.0
8	2022-09-14	high	74.0
9	2022-09-14	low	50.0

# What are pros of cons of including NaN?

#### • Pros:

- easier to tell which values are missing
- consistent number
   of rows no matter
   how you slice data
- Cons: now you need to deal with NaN

	day	time_of_measurement	temperature
0	2022-09-10	high	82.0
1	2022-09-10	low	62.0
2	2022-09-11	high	69.0
3	2022-09-11	low	62.0
4	2022-09-12	high	77.0
5	2022-09-12	low	NaN
6	2022-09-13	high	69.0
7	2022-09-13	low	56.0
8	2022-09-14	high	74.0
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# What happens if we plot time series with NaN?

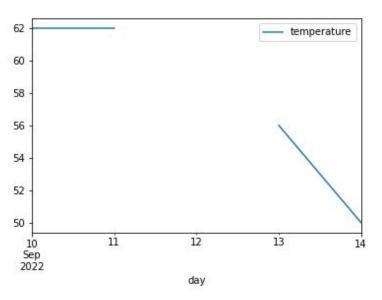
(Lows only)

	day	time_of_measurement	temperature
1	2022-09-10	low	62
3	2022-09-11	low	62
6	2022-09-13	low	56
8	2022-09-14	low	50

# What happens if we plot time series with NaN?

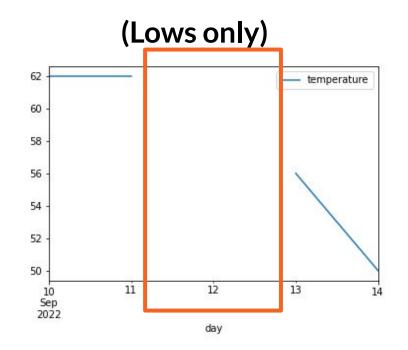
# day time\_of\_measurement temperature 1 2022-09-10 low 62 3 2022-09-11 low 62 6 2022-09-13 low 56 8 2022-09-14 low 50

#### (Lows only)



#### What happens if we plot time series with NaN?

If you ever see a missing chunk in your plots, CHECK FOR NaNS



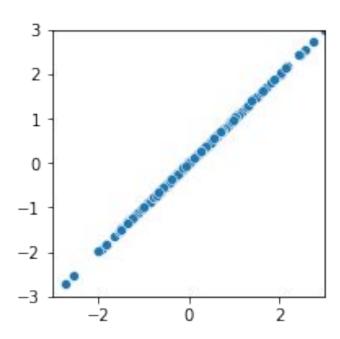
#### **Takeaways on Time Series:**

- 1. Make sure your dates are in datetime type
- 2. Make sure your time series data are meaningful: check for inconsistencies
- 3. Have a plan for how to deal with missing data: explain why they're not in the data, substitute with another value, impute a value, etc. (more later in course)

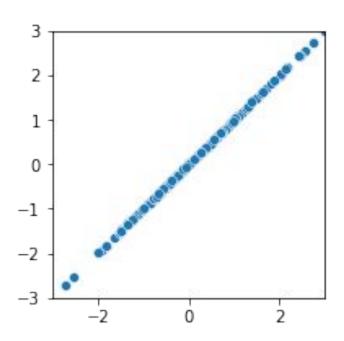
#### 1 min break



#### Refresher: what is the covariance here?



#### Refresher: what is the covariance here?



1. (The axes match here — both X and Y go from -3 to 3, unlike Lec 5 slide 68)

## Last time: how to measure the extent that X, Y move together?

Covariance (measures direction of X, Y relationship)	Correlation (also measures strength of X, Y relationship)
$\Sigma_i (X_i - \overline{X})(Y_i - \overline{Y}) / N$	$Cov(X,Y)/(\sigma_x \sigma_y)$

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Covariance (measures direction of X, Y relationship)	Correlation (also measures strength of X, Y relationship)
$\Sigma_i (X_i - \overline{X})(Y_i - \overline{Y}) / N$	$Cov(X,Y)/(\sigma_x\sigma_y)$
Doesn't normalize X, Y	Normalizes to deal with different X, Y scales
Between - $\infty$ and $\infty$	Between -1 and 1
Has interpretable units (X*Y)	Is unitless

- Recall that Cov and Corr are symmetric
  - $\circ$  Cov(X,Y) = Cov(Y,X)
  - $\circ$  Corr(X,Y) = Corr(Y,X)

- Recall that Cov and Corr are symmetric
  - $\circ$  Cov(X,Y) = Cov(Y,X)
  - $\circ$  Corr(X,Y) = Corr(Y,X)
- But what if you want to measure how one variable (X) affects another variable (Y)?

 Cov and Corr each summarizes the relationship between X and Y into a single number

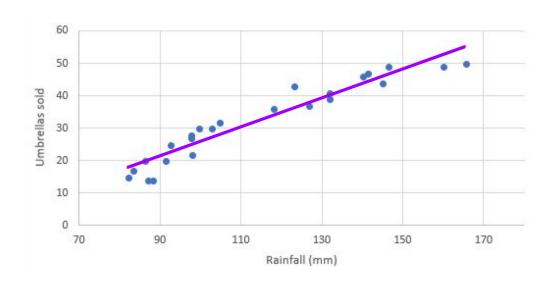
- Cov and Corr each summarizes the relationship between X and Y into a single number
- But what if you want more information about a X→Y relationship than just a single summary statistic?

#### Regression

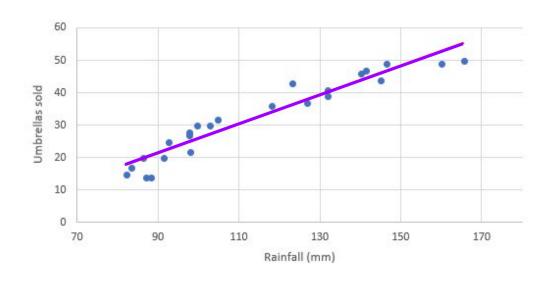
- Why do we use regressions?
- If I give you a regression line, what can we do with it?

#### Regression

- Why do we use regressions?
- If I give you a regression line, what can we do with it?
- This week: regression on one variable
- Next week: regression on multiple variables

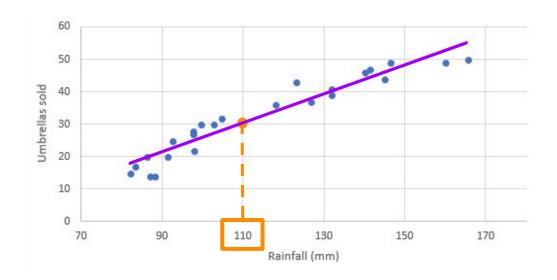


1. Ability to make predictions

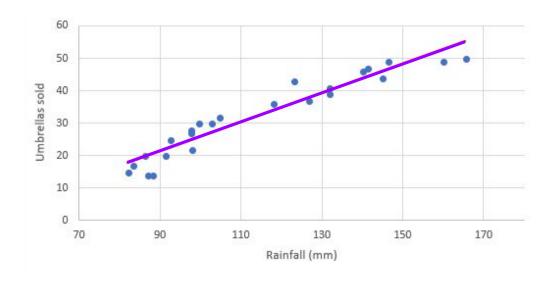


## 1. Ability to make predictions

Today there was 110mm of rainfall, so I expect to sell 30 umbrellas

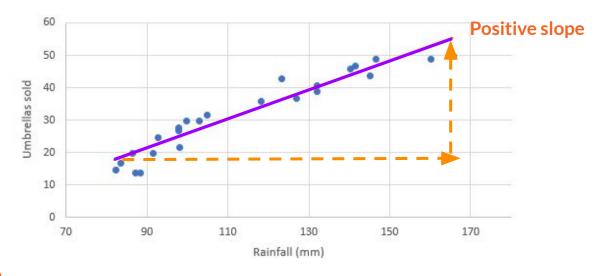


2. Summarize relationship between variables

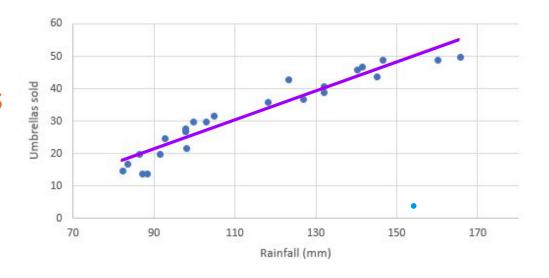


# 2. Summarize relationship between variables

When there is more rain, sales of umbrellas increase. Each additional mm of rain corresponds to an extra 0.45 umbrellas we expect to be sold.

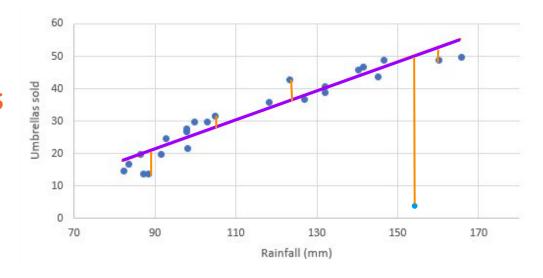


3. Inspect outliers and other oddities



### 3. Inspect outliers and other oddities

We only had one day with 155mm rain, but that day everyone was indoors for an all-day conference so we barely sold any umbrellas.



#### **Regression motivations**

- 1. Make predictions
- 2. Summarize relationship between variables
- 3. Inspect outliers and other oddities

**But how?** 

#### **Regression motivations**

Input

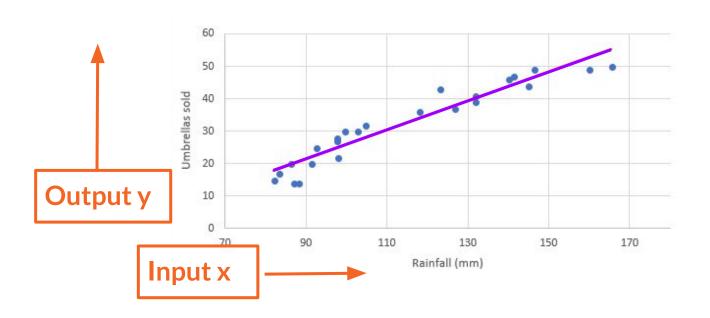
**Output** 

- 1. Make predictions
- 2. Summarize relationship between variables
- 3. Inspect outliers and other oddities

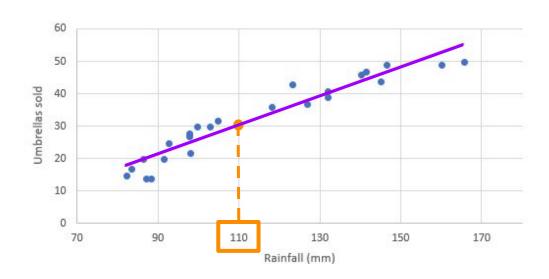
**But how?** 

#### Regressions: what are they?

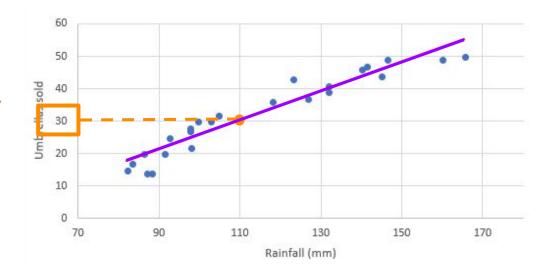
- A regression is given an input (x) and predicts an output (y)
- [input, output] are also known as...
  - [independent, dependent]
  - [endogenous, exogenous]
  - [regressor, regressand]



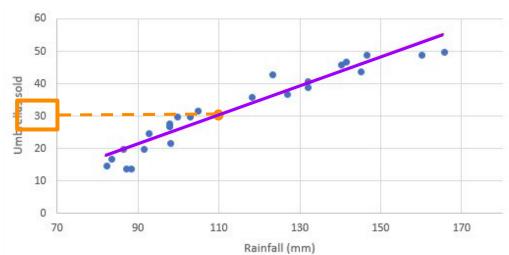
For the *input* 110 mm of rain we expect the *output* 30 umbrellas sold



We could predict rainfall given umbrella sales, by swapping input/output.



We could predict rainfall given umbrella sales, by swapping input/output.



But, you should be upfront with what your main data question is. Are you studying the effect of umbrella sales on rainfall, or the effect of rainfall on umbrella sales?

#### Components of a regression

English: • output = intercept + slope \* input

Math:  $\bullet$   $y = \alpha + \beta \cdot x$ 

Math shorthand:  $\bullet$   $\vee$   $\sim$   $\times$ 

#### Components of a regression

English:

• output = intercept + slope \* input

• y =  $\alpha$  +  $\beta$  · x

Math shorthand:

what would y be if x = 0. (sometimes x=0 is nonsensical)

#### Components of a regression

English: • output = intercept + slope \* input

Math:  $\bullet$   $y = a + \beta / x$ 

Math shorthand:  $\bullet$   $\mathsf{y}$   $\sim$   $\mathsf{x}$ 

unit change in x leads to  $\beta$  unit change in y, regardless of where you start with x

#### Is y~x the same as x~y?

English: • output = intercept + slope \* input

Math:  $\bullet$   $y = a + \beta \cdot x$ 

Math shorthand:  $\bullet$   $\mathsf{Y}$   $\sim$   $\mathsf{X}$ 

#### Is y~x the same as x~y?

English:

output = intercept + slope \* input

Math:

v = a + B · x

Math shorthand: 

y ~ x

One extra mm of rain corresponds to 0.45 more umbrellas being sold.

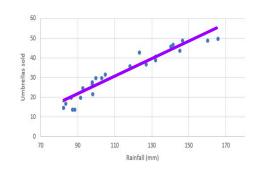
Does one extra umbrella being sold correspond to 0.45mm more rain? No!

- Recall that Cov and Corr are symmetric and distill statistical summary into a single number
- Regression is asymmetric and distills statistical summary into a line

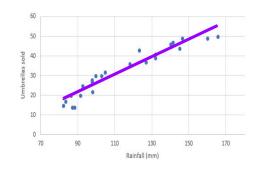
#### 1 min break & attendance



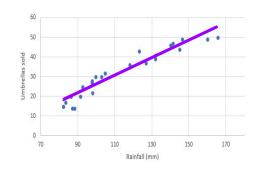
tinyurl.com/2r4wmheh



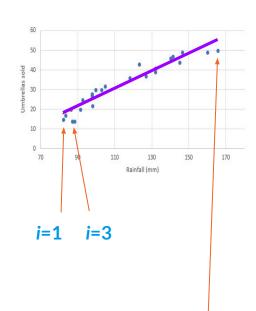
We have a set of **points** that we want to draw a linear regression line through. That line will have form  $y = \alpha + \beta x$ 



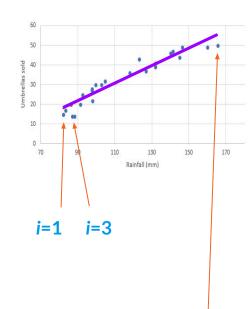
- We have a set of **points** that we want to draw a linear regression line through. That line will have form  $y = \alpha + \beta x$ 
  - (Today, let's assume I'm just giving you a regression line, so  $\alpha$  and  $\beta$  are known)



- We have a set of **points** that we want to draw a linear regression line through. That line will have form  $y = \alpha + \beta x$
- But, that form doesn't describe the points themselves because they aren't necessarily on the regression line



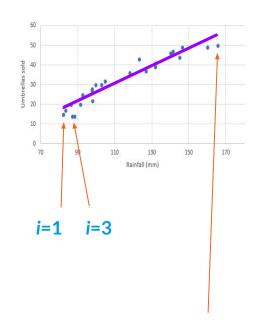
- We have a set of **points** that we want to draw a linear regression line through. That line will have form y = α + βx
- We need to talk about each individual point i



- We have a set of points that we want to draw a linear regression line through. That line will have form y = α + βx
- We need to talk about each individual point i

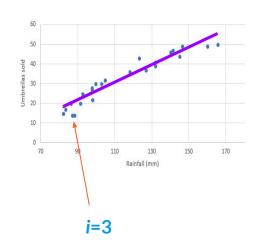
Remember: any time you see math i's, think of them as rows in a dataframe!

i	X	Y
1	78	18
2	83	14

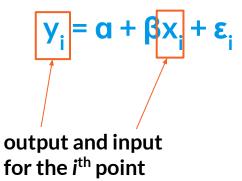


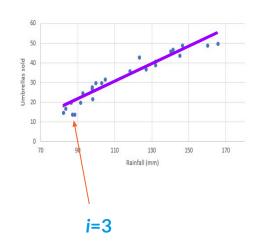
- Regression line:  $y = \alpha + \beta x$
- Underlying relationship for each point:

$$y_i = \alpha + \beta x_i + \epsilon_i$$

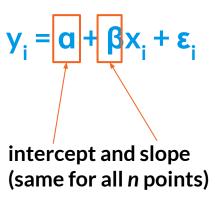


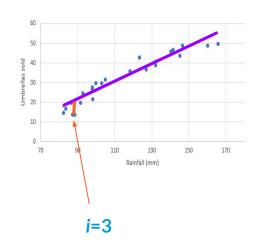
- Regression line:  $y = \alpha + \beta x$
- Underlying relationship for each point:





- Regression line:  $y = a + \beta x$
- Underlying relationship for each point:

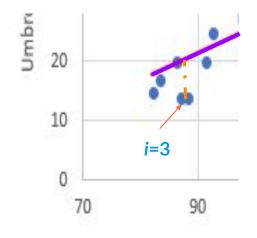


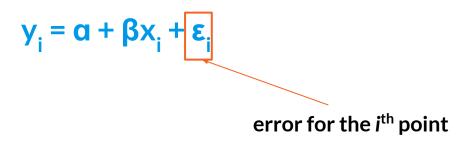


- Regression line:  $y = a + \beta x$
- Underlying relationship for each point:

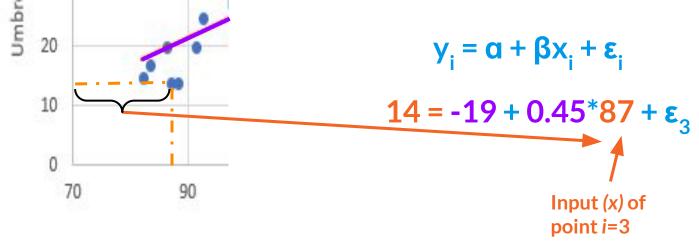
$$y_i = \alpha + \beta x_i + \epsilon_i$$
error for the  $i^{th}$  point

- Regression line:  $y = a + \beta x$
- Underlying relationship for each point:

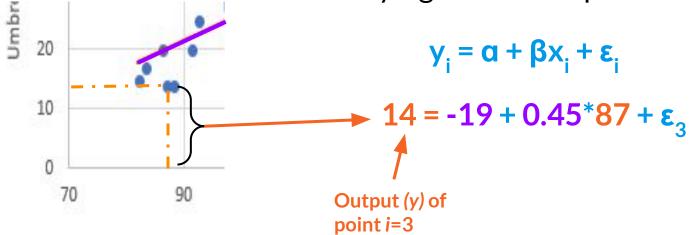




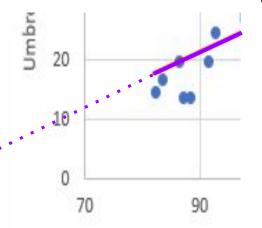
- Regression line:  $y = a + \beta x$
- Underlying relationship for each point:



- Regression line:  $y = a + \beta x$
- Underlying relationship for each point:



- Regression line:  $y = a + \beta x$
- Underlying relationship for each point:

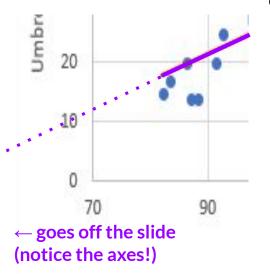


$$y_i = \alpha + \beta x_i + \epsilon_i$$

$$14 = -19 + 0.45*87 + \epsilon_3$$
Theorem (y value if x = 0).

Intercept (y value if x = 0). Does -19 look right?

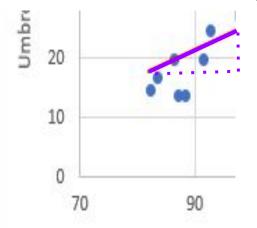
- Regression line:  $y = a + \beta x$
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$$y_i = \alpha + \beta x_i + \epsilon_i$$

$$14 = -19 + 0.45*87 + \epsilon_3$$
Intercept (y value if x = 0).

- Regression line:  $y = a + \beta x$
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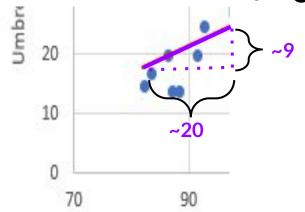


$$y_i = \alpha + \beta x_i + \epsilon_i$$

14 = -19 + 0.45\*87 +  $\epsilon_3$ 

Slope (rise over run): Does positive 0.45 seem right?

- Regression line:  $y = a + \beta x$
- Underlying relationship for each point:

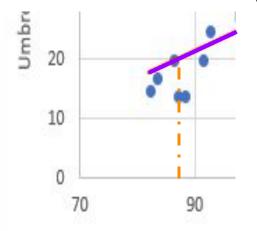


$$y_i = \alpha + \beta x_i + \epsilon_i$$

14 = -19 + 0.45\*87 +  $\epsilon_3$ 

Slope (rise over run):
9/20 = 0.45

- Regression line:  $y = \alpha + \beta x$
- Underlying relationship for each point:



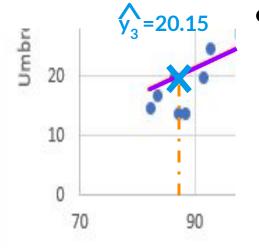
$$y_i = \alpha + \beta x_i + \epsilon_i$$

$$14 = -19 + 0.45*87 + \epsilon_3$$

What if we look along the purple regression line for expected output, given input 87?



Underlying relationship for each point:

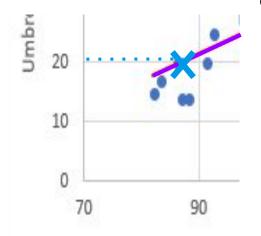


$$y_i = \alpha + \beta x_i + \epsilon_i$$

$$14 = -19 + 0.45*87 + \epsilon_3$$

Our prediction for how many umbrella sales there should be if rainfall is x<sub>3</sub> millimeters

- Regression line:  $y = a + \beta x$
- Underlying relationship for each point:



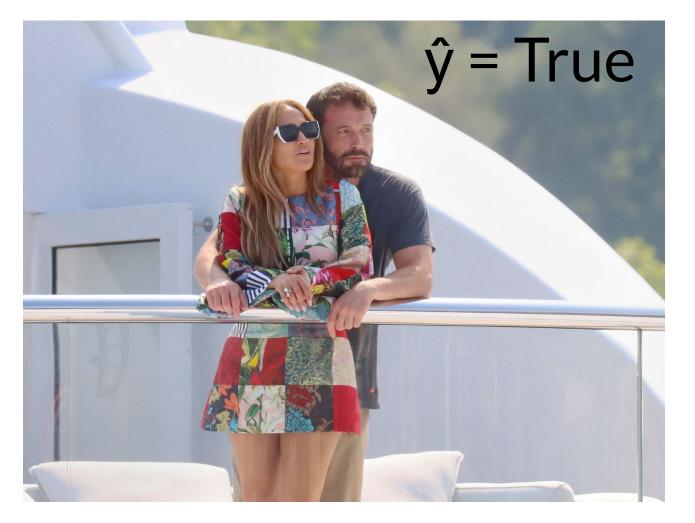
$$y_i = \alpha + \beta x_i + \epsilon_i$$

$$14 = -19 + 0.45*87 + \epsilon_3$$

$$\alpha + \beta x_3 = y_3 = 20.15$$







- Regression line:  $y = a + \beta x$
- Underlying relationship for each point:

$$y_i = \alpha + \beta x_i + \epsilon_i$$

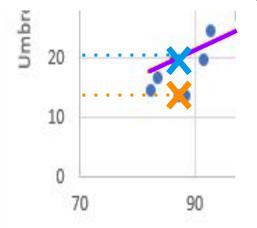
i	x	у
1	78	18
2	83	14

- Regression line:  $y = a + \beta x$
- Underlying relationship for each point:

$$y_i = \alpha + \beta x_i + \epsilon_i$$

i	x	у	ŷ
1	78	18	-19+0.45*78
2	83	14	-19+0.45*83

- Regression line:  $y = a + \beta x$
- Underlying relationship for each point:



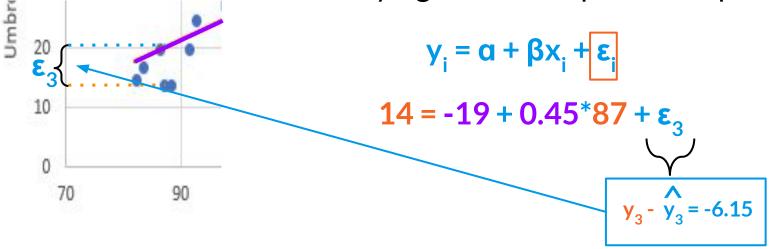
$$y_i = \alpha + \beta x_i + \epsilon_i$$

$$14 = -19 + 0.45*87 + \epsilon_3$$

$$y_3 = 14$$

$$y_3 = 20.15$$

- Regression line:  $y = a + \beta x$
- Underlying relationship for each point:



- Regression line:  $y = a + \beta x$
- Underlying relationship for each point:

$$y_i = \alpha + \beta x_i + \epsilon$$

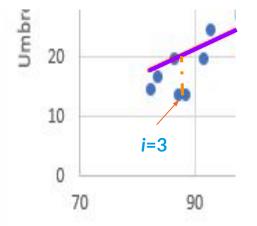
i	x	у	ŷ
1	78	18	-19+0.45*78 = 16.10
2	83	14	-19+0.45*83 = 18.35

- Regression line:  $y = a + \beta x$
- Underlying relationship for each point:

$$y_i = \alpha + \beta x_i + \epsilon_i$$

i	x	у	ŷ	8
1	78	18	-19+0.45*78 = 16.10	18 - 16.10
2	83	14	-19+0.45*83 = 18.35	14 - 18.35
•••				

- Regression line:  $y = a + \beta x$
- Underlying relationship for each point:

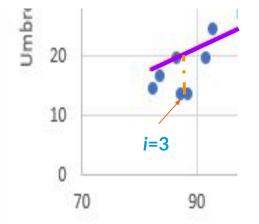


$$y_i = \alpha + \beta x_i + \epsilon_i$$

$$14 = -19 + 0.45*87 + \epsilon_3$$

Error: how wrong was our prediction? Is -6.15 a lot or a little?

- Regression line:  $y = a + \beta x$
- Underlying relationship for each point:

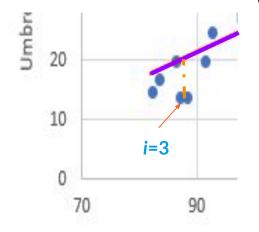


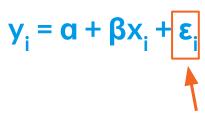
$$y_i = \alpha + \beta x_i + \epsilon_i$$

$$14 = -19 + 0.45*87 + \epsilon_3$$

Error: how wrong was our prediction? Is -6.15 a lot or a little? Error close to 0 is ideal

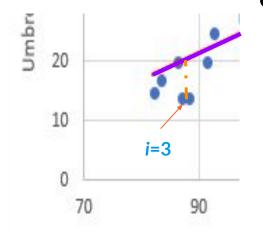
- Regression line:  $y = a + \beta x$
- Underlying relationship for each point:





KEY INSIGHT: we want to minimize abs(error) across all of our points *i* 

- Regression line:  $y = a + \beta x$
- Underlying relationship for each point:



$$y_i = \alpha + \beta x_i + \epsilon_i$$

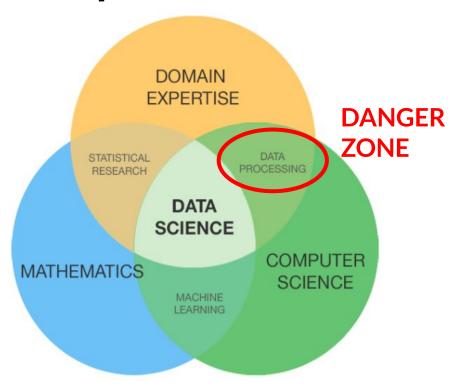
Next class: how we can use minimizing error to find the

regression line (and get  $\alpha$  and  $\beta$ )

# **Regression motivations** → **interpretations**

- 1. Summarize relationship between variables
- 2. Make predictions
- 3. Inspect outliers and other oddities

# Why interpret?



• Model:  $y = a + \beta x$ 

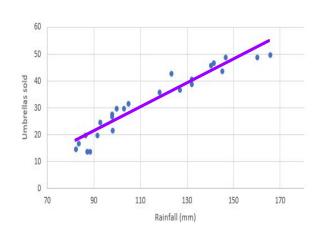
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- 1 unit increase in x corresponds to a β unit increase/decrease in y
  - Why do we say "corresponds to"? Because we don't know if it's causal
  - Why do we say "increase/decrease"?
     Because it depends on the sign of β

# **Regression motivations** → **interpretations**

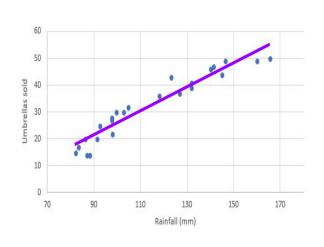
1. Summarize relationship between variables:



Make predictions:

**Inspect oddities / outliers:** 

# **Regression motivations** → **interpretations**



1. Summarize relationship between variables:

Our model shows a positive relationship between rain and sales of umbrellas; specifically, each additional mm of rain corresponds to an extra 0.45 umbrellas we expect to be sold.

Make predictions:

**Inspect oddities / outliers:** 

#### Common task in data science job

- You are a data scientist at a dairy bar
- You need to write an email to your boss that interprets a regression that you recently ran
  - x: Days (2023-08-12 to 2023-09-12)
  - y: Ice Cream Sales (# units sold)
  - Regression model: y = 100 3x

# Regression interpretations: summarize relationship

x = millimeters of rainfall

y = umbrellas sold

y = -19 + 0.45x

# Summarize relationship between variables:

Our model shows a positive relationship between rain and sales of umbrellas; specifically, each additional mm of rain corresponds to an extra 0.45 umbrellas we expect to be sold. x = days (2023-08-12 to 2023-09-12) y = # ice cream units sold y = 100 - 3x

Summarize relationship between variables:

\_\_\_\_\_

## Regression interpretations: summarize relationship

x = millimeters of rainfall

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x = days (2023-08-12 to 2023-09-12)

y = # ice cream units sold

y = 100 - 3x

# Summarize relationship between variables:

Our model shows a negative relationship between days and sales of ice cream; specifically, each additional day that goes by (benchmarked where x=0 means Aug 12, 2023) corresponds to 3 fewer ice cream units we expect to be sold.

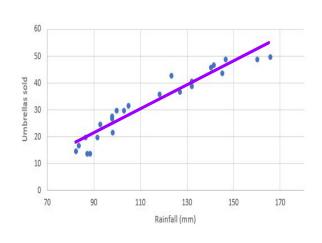
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- "For variable x = [some number], we expect variable y = [the model's predicted number]."

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     This is a prediction, not a certainty!
- For x = 0, we expect y = a

## **Regression motivations** → **interpretations**



- 1. Summarize relationship between variables:
  - Our model shows a positive correlation between rain and sales of umbrellas; specifically, each additional mm of rain corresponds to an extra 0.45 umbrellas we expect to be sold.
- 2. Make predictions: This model indicates that at the annual Ithaca average of 110mm of rainfall, we should expect to sell 30 umbrellas.
- 3. Inspect oddities / outliers:

#### Regression interpretations: make predictions

x = millimeters of rainfall

y = umbrellas sold

y = -19 + 0.45x

#### Make predictions:

This model indicates that at the annual Ithaca average of 110mm of rainfall, we should expect to sell 30 umbrellas; however, if we have no rainfall, we expect to sell -19 umbrellas?!

x = days (2023-08-12 to 2023-09-12) y = # ice cream units sold y = 100 - 3x

Make prediction(s):

### Regression interpretations: make predictions

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#### Make predictions:

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x = days (2023-08-12 to 2023-09-12)

y = # ice cream units sold

y = 100 - 3x

#### Make predictions:

This model indicates that for one day after Aug 12, 2023, we expect to sell 97 ice cream units. It indicates that 30 days after Aug 12, 2023, we expect to sell 10 ice cream units.

It indicates that 100 days after Aug 12, 2023, we expect to sell -200 ice cream units?!

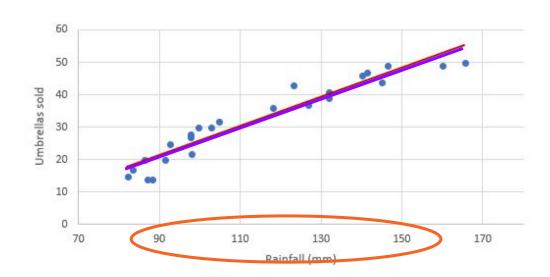
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- When are regression results non-sensical?
  - We want to avoid extrapolating beyond the "scope of the model"

### Interpret regressions: oddities

- When are regression results non-sensical?
  - We want to avoid extrapolating beyond the "scope of the model"
- Are there outliers in the data?
  - Are there explanations for them?
  - Should they be captured by a different model (e.g. quadratic instead of linear)?

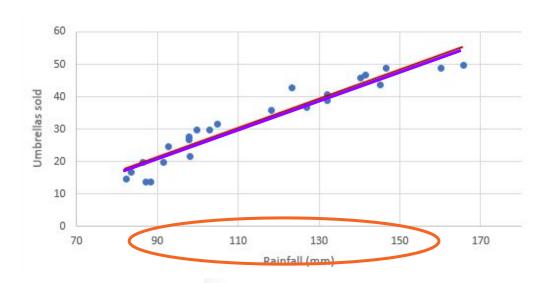


https://en.wikipedia.org > wiki > Meteorological\_histor...

#### Meteorological history of Hurricane Katrina - Wikipedia

Hurricane Katrina was an extremely destructive Category 5 hurricane that affected the ... causing 1.97–6.69 inches (50–170 mm) of rain in 12 hours, ...

Formation · First Landfall · Gulf of Mexico · Second and third landfalls



# Use domain knowledge to check if your data make sense!

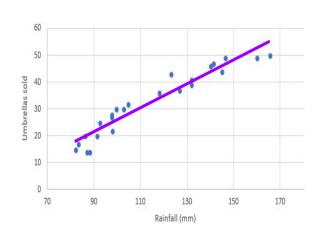
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- 2. Make predictions: This model indicates that at the annual Ithaca average of 110mm of rainfall, we should expect to sell 30 umbrellas.
- 3. Inspect oddities / outliers: We expect this model to hold between for rainfall amounts between 80-170mm, but cannot extrapolate further.

#### Regression interpretations: note oddities

x = millimeters of rainfall

y = umbrellas sold

y = -19 + 0.45x

#### Inspect oddities / outliers:

We expect this model to hold between for rainfall amounts between 80-120mm, but cannot extrapolate further.

x = days (2023-08-12 to 2023-09-12)

y = # ice cream units sold

y = 100 - 3x

Inspect oddities / outliers:

159

#### Regression interpretations: note oddities

x = millimeters of rainfall

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x = days (2023-08-12 to 2023-09-12)

y = # ice cream units sold

y = 100 - 3x

#### Inspect oddities / outliers:

We expect this model to hold between 2023-08-12 \* and 33.3 days after that day, but cannot extrapolate further since otherwise we predict negative sold units.

\*Maybe it holds beforehand; need more domain knowledge! Slope is probably positive from early summer to Aug.

#### Regression interpretations: note oddities

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y = umbrellas sold

y = -19 + 0.45x

#### Inspect oddities / outliers:

We expect this model to hold between for rainfall amounts between 80-120mm, but cannot extrapolate further.

x = days (2023-08-12 to 2023-09-12)y = # ice cream units sold

y = 100 - 3x

Note: we can't inspect outliers here since I haven't given you any of the underlying x, y data for each individual data point i