

# Introduction to Causality

AI4ER MRes Workshop



# Schedule

1-2pm: Introduction to Causality lecture and discussion

2-2.15pm: break

2.15-3.15pm: Practical Causal inference lecture/discussion, followed by going through the notebook examples and questions

3.15-3.45pm: Tea/informal questions and discussion

3.45-4.15pm: Causal discovery lecture and discussion

4.15-4.45pm: Working through the code and trying on some synthetic data

4.45pm-5pm: Wrap up and homework!

# First - what is causality?

- Thoughts?
- What do we mean when we say 'causal relationship'?

It is a big question...

# Definitions of causality

## Counterfactual theory of causality (David Hume, David Lewis)

- We define causation as a counterfactual relation.
  - Hume (18th century): “where, if the first object had not been, the second never had existed.”
  - Lewis (1973): “An event E causally depends on C if, and only if, (i) if C had occurred, then E would have occurred, and (ii) if C had not occurred, then E would not have occurred.”
- What do we think?

# Probabilistic causality

- Our previous definition is narrow.
- It does not allow for causation that increases the probability of something...it only allows for binary/deterministic cause and effect.



- We need probabilistic causality to cope with this.
- $P(\text{lung cancer} \mid \text{smoking}) > P(\text{lung cancer})$
- We need extra conditions too...temporality, for example.

# Now we have a feel for causality...

- Why do we care about it?
- Why is it particularly important for machine learners to know about it?

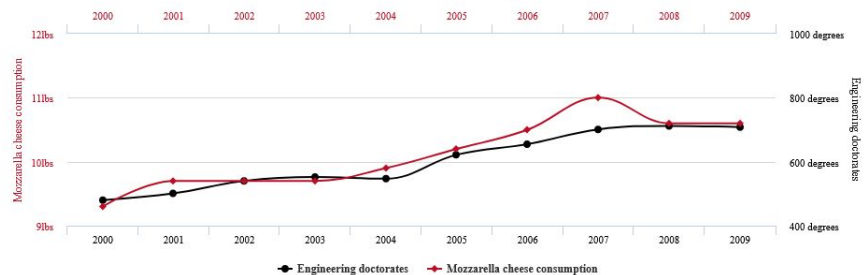
# Correlation does not amount to causation!

## Per capita consumption of mozzarella cheese

correlates with

## Civil engineering doctorates awarded

Correlation: 95.86% ( $r=0.958648$ )



Data sources: U.S. Department of Agriculture and National Science Foundation

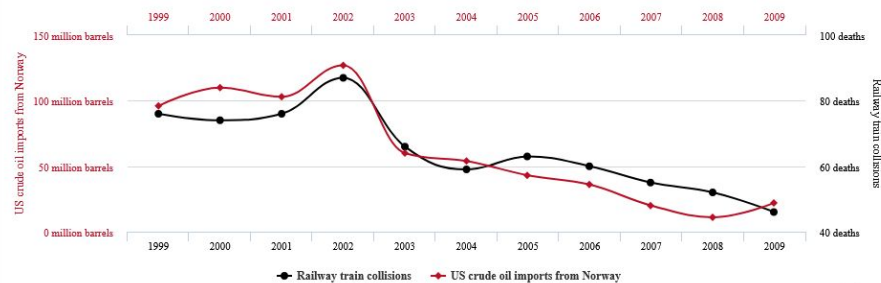
tylervigen.com

## US crude oil imports from Norway

correlates with

## Drivers killed in collision with railway train

Correlation: 95.43% ( $r=0.954509$ )



Data sources: Dept. of Energy and Centers for Disease Control & Prevention

tylervigen.com

Source: <https://www.tylervigen.com/spurious-correlations>



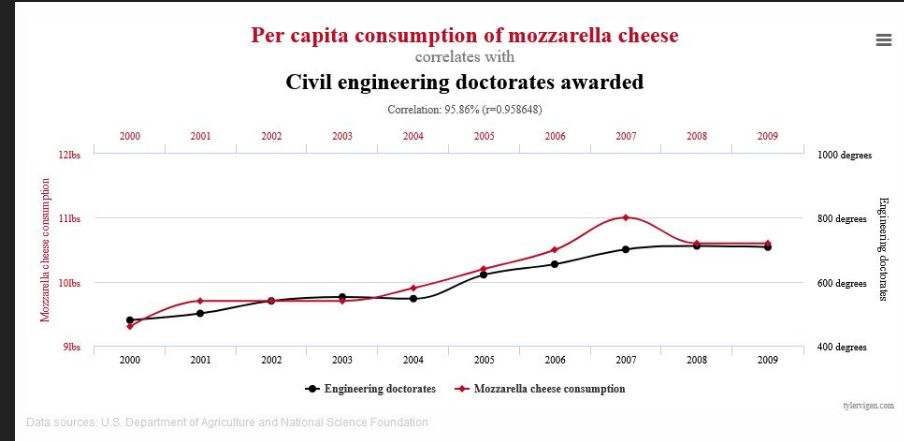


# The key point is that ML is based on **correlations!**

- Linear regression, neural networks, transformers...all work based on correlations.
- And they work (sometimes) (amazingly) well!
- **This is often fine!!!**

# For prediction, this is basically fine!

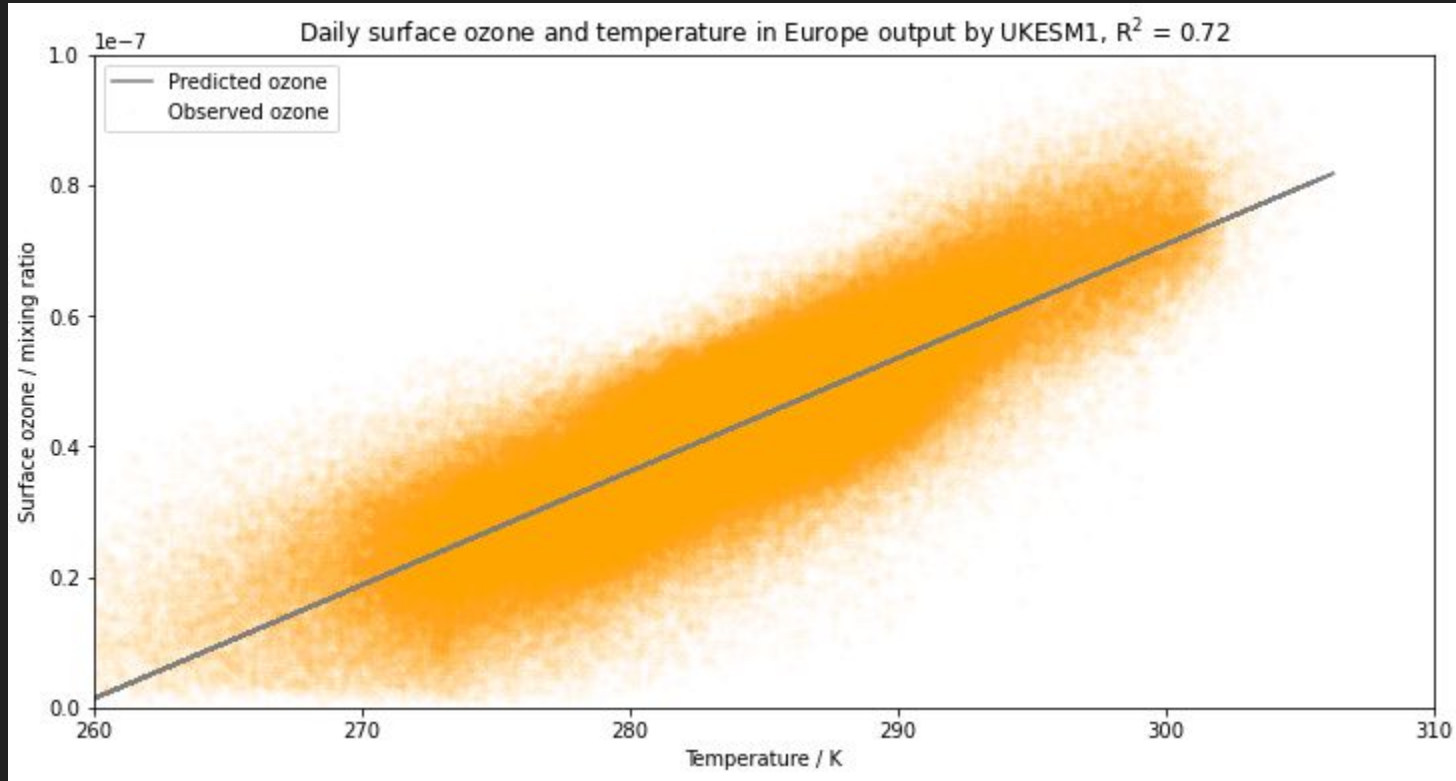
- If we are **only** interested in making predictions, this is usually ok.
- We do all the usual business of retrieving and cleaning a large dataset, making sure it is representative of our test data, optimisation, etc. etc.
- We can train our model, make predictions and they will probably be fine...



# However!

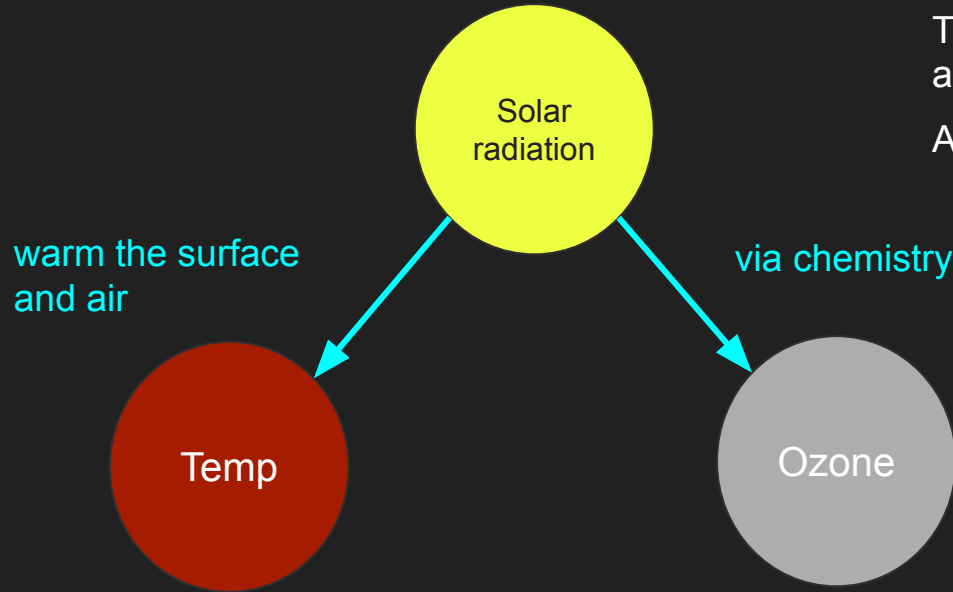
- If we want to do more than prediction on a very similar test set, we are going to run into problems.
- In an ideal world, what else might we like to do with our models other than prediction? What are the most **useful** 'models' of the world that you know of? What do they give us?

# Can we **predict** ozone pollution from temperature?



Mmmm, what a lovely ML model...

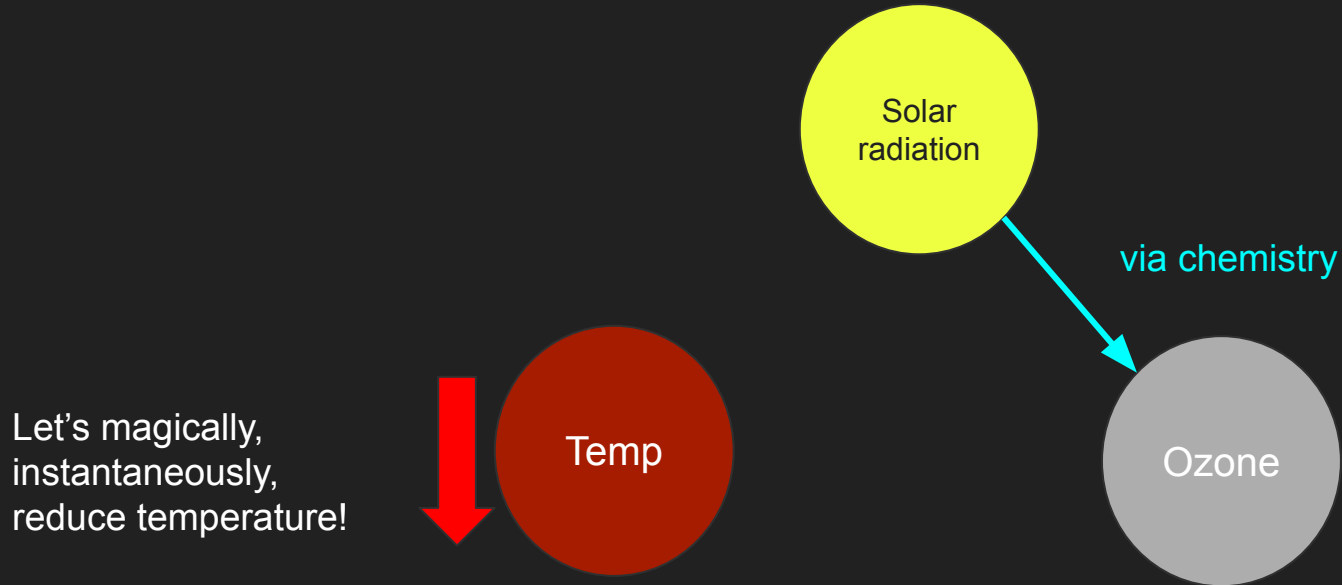
# What if we actually want to **intervene**, to reduce ozone?



This sort of diagram is known as a **Directed Acyclic Graph**  
Arrows denote a causal effect

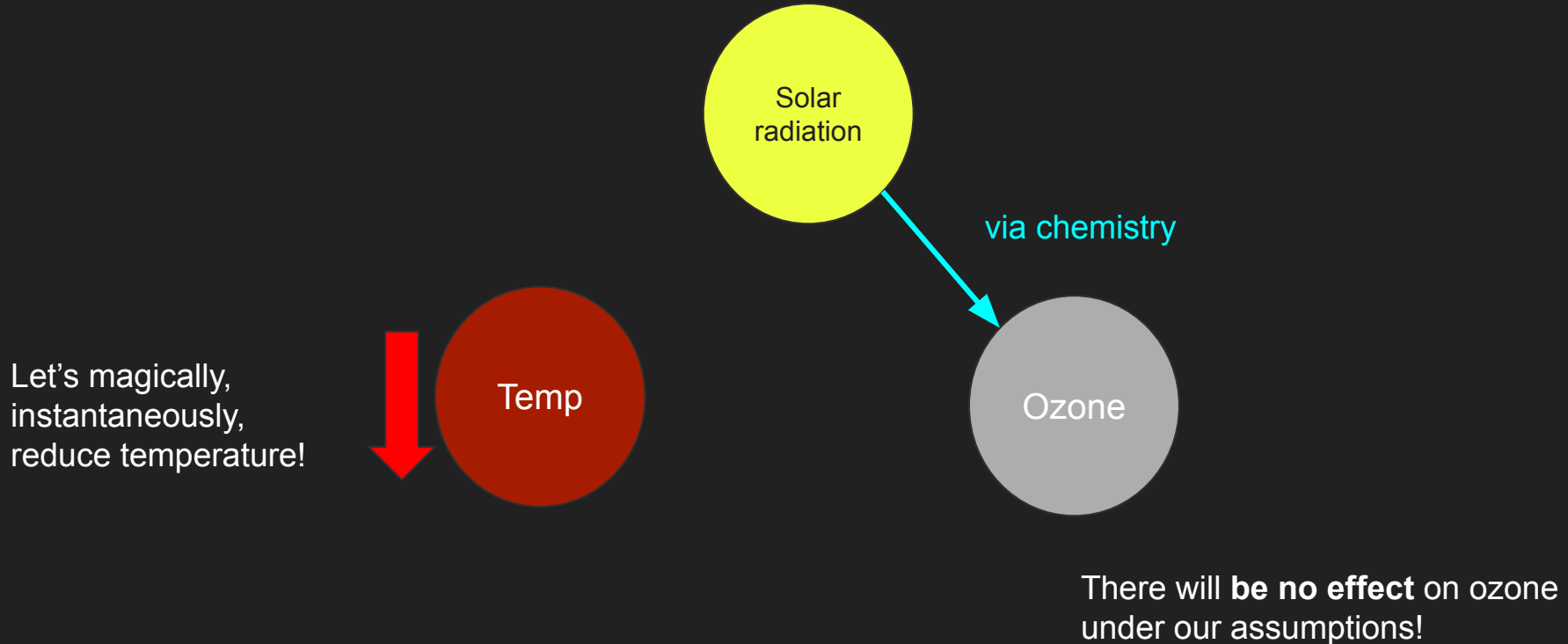
This leads to temperature and ozone being **well correlated**; but there is no causal link!

Let's follow the 'advice' of our ML model...

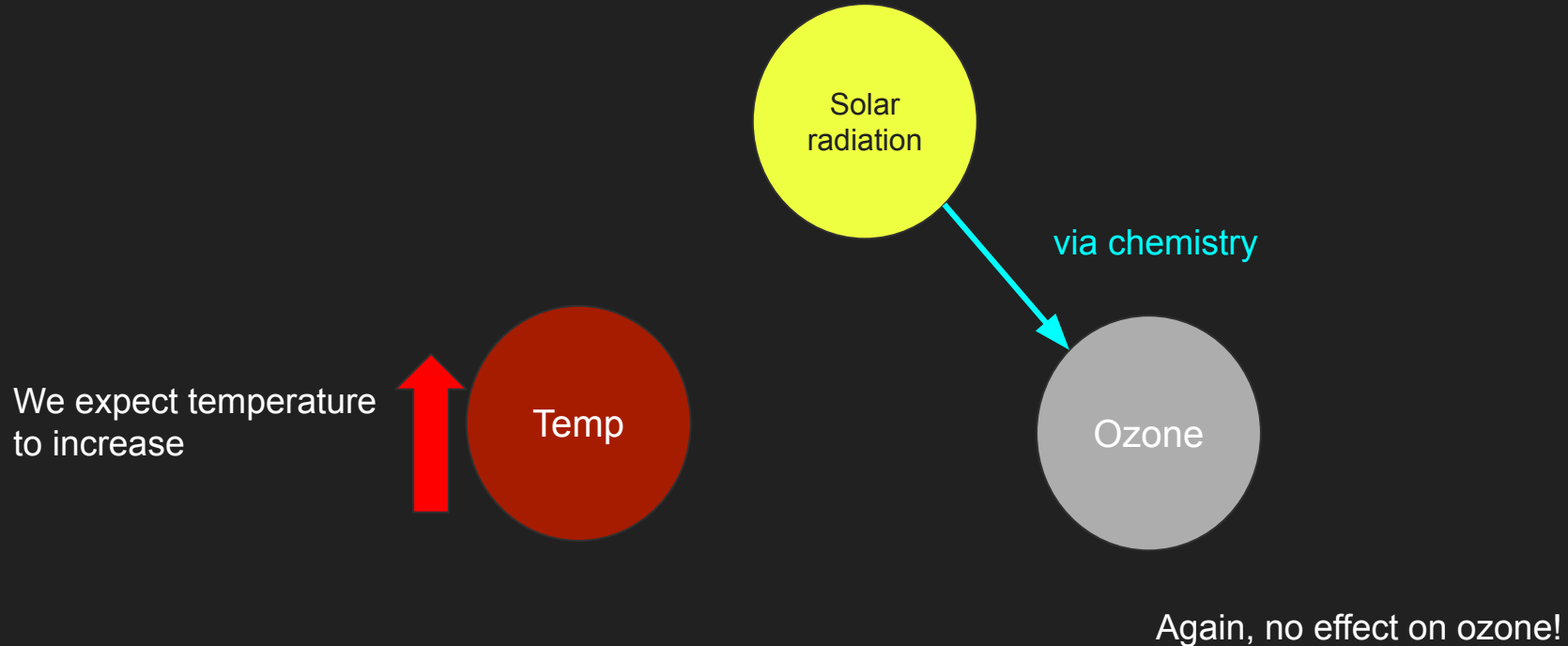


What do we think will happen to ozone?

# Let's follow the 'advice' of our ML model...



Or perhaps more pertinently, what might happen under climate change?





# The four tiers of (data) science

## 1. **Description** (*data science*)

- a. What is happening? What does the data show?

## 2. **Prediction** (*data science/ML*)

- a. Can we predict what will happen next?
- b. Can we **predict Y given X**?

## 3. **Causation** (*science/maybe ML!*)

- a. **Why** did this happen?
- b. What would happen to **Y** if we change **X**? (**intervention**)

## 4. *Explanation* (*science*)

- a. *What is the mechanism for this phenomenon?*
- b. *How do we evaluate if this is the correct mechanism?*

## Overall...

- Causation is important if we are interested in making interventions!
- Causation may help us make out of distribution predictions
- It helps us get closer to traditional science, particularly understanding mechanisms and why things happen! This is the basis for understanding the world.

Thoughts?