

# Causality and Other Cautionary Tales: “Correlation does not imply Causation”

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First, we will discuss how drawing conclusions about cause and effect from correlations between variables in observational data is risky.

Next, we will consider how to address this by using interventional techniques such as A/B Testing and Reinforcement Learning.

In particular, we will learn about the Azure Personalizer Service, which relies on a form of Reinforcement Learning.

## “Correlation does not imply Causation”

- As ice cream sales increase, the rate of drowning deaths increases sharply.
- Ice cream causes drowning?
- Will banning ice cream prevent drowning?

[https://en.wikipedia.org/wiki/Correlation\\_does\\_not\\_imply\\_causation](https://en.wikipedia.org/wiki/Correlation_does_not_imply_causation)

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You may have heard the saying “Correlation does not imply Causation”.

In fact, there is an entire Wikipedia entry devoted to this phrase:

[https://en.wikipedia.org/wiki/Correlation\\_does\\_not\\_imply\\_causation](https://en.wikipedia.org/wiki/Correlation_does_not_imply_causation)

To paraphrase Wikipedia, “Correlation does not imply Causation” refers to the fact that one cannot legitimately deduce a [cause-and-effect](#) relationship between two [variables](#) solely on the basis of an observed association or [correlation](#) between them.

For example, suppose we observe that ice cream sales and the rate of drowning deaths are correlated – when ice cream sales are low, drowning deaths are low, and when ice cream sales are high, drowning deaths are high.

Can we conclude that there is a cause-and-effect relationship, and that high ice cream sales are causing a high rate of drowning deaths, or vice versa?

If there were a cause-and-effect relationship, with ice cream sales causing drowning deaths, then banning ice cream would indeed help prevent drowning.

Of course, there is no such cause and effect.

The true explanation is that there is a “lurking third variable”, namely the outdoor air temperature. When it is hot out, people buy more ice cream and people swim more, hence drown more.

To tease out whether banning ice cream would actually prevent drowning, we could reason about the causal relationships between ice cream sales, drowning, and outdoor temperature, or we could do an experiment such as banning ice cream.

## “Correlation does not imply Causation”

- Office users who get error messages have lower attrition.
- Does that mean that showing users more error messages will reduce attrition?
- No, these users are heavy users and heavy users have lower attrition.

<https://exp-platform.com/hbr-the-surprising-power-of-online-experiments>

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Just because more error messages is correlated with lower attrition does not mean that showing all users more error messages will reduce attrition.

In this case, the “lurking third variable” is whether the user is a heavy, power user. Such users are more likely to push software to its limits and therefore encounter error messages, but they are also highly invested in the tool and therefore less likely to abandon it.

## “Correlation does not imply Causation”

- Studies showed that women taking hormone replacement therapy (HRT) had **less** coronary heart disease (CHD).
- But later randomized controlled trials showed that HRT led to a small but statistically significant **increase** in the risk of CHD.
- Explanation: women on HRT were more likely to be from higher socioeconomic groups (ABC1), with better-than-average diet and exercise regimens.

[https://en.wikipedia.org/wiki/Correlation\\_does\\_not\\_imply\\_causation](https://en.wikipedia.org/wiki/Correlation_does_not_imply_causation)

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Here the lurking third variable was socioeconomic status. It took an experiment, specifically a “randomized controlled trial” (RCT), to discover that more HRT would actually increase the risk of CHD.

# Observation vs. Experimentation/Intervention - Addressing confounding variables in data analysis

- Simpson's Paradox

The paradoxical conclusion is that **treatment A is more effective when used on small stones, and also when used on large stones**, yet **treatment B is more effective when considering both sizes** at the same time. In this example, the "lurking" variable (or [confounding variable](https://en.wikipedia.org/wiki/Confounding_variable)) is the severity of the case (represented by the doctors' treatment decision trend of favoring B for less severe cases), which was not previously known to be important until its effects were included.

Real success rate data from an *observational* study – *not* a randomized, controlled trial:

Treatment Stone size	Treatment A	Treatment B
Small stones	Group 1 93% (81/87)	Group 2 87% (234/270)
Large stones	Group 3 73% (192/263)	Group 4 69% (55/80)
Both	78% (273/350)	83% (289/350)

[https://en.wikipedia.org/wiki/Simpson's\\_paradox](https://en.wikipedia.org/wiki/Simpson's_paradox)

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Simpson's Paradox is a particularly mind-bending example of how one can be led astray by purely observational data.

One sure remedy is to run an experiment where one intervenes, rather than simply observes. The gold standard is the "randomized, controlled trial."

Treatment A includes all open surgical procedures and Treatment B involves only a small puncture.

"When the less effective treatment (B) is applied more frequently to less severe cases, it can *appear* (incorrectly) to be a more effective treatment."

## Observation vs. Experimentation - Confounding variables in data analysis

- Simpson's Paradox
  - Older people have more pain
  - Older people take more ibuprofen
  - People who take ibuprofen have more pain
    - But if we adjust for age, we can see that ibuprofen helps pain

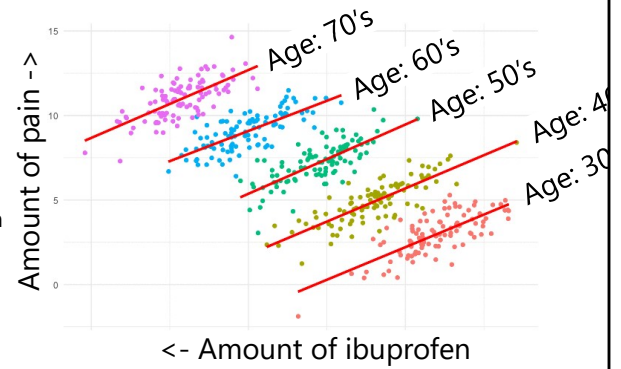
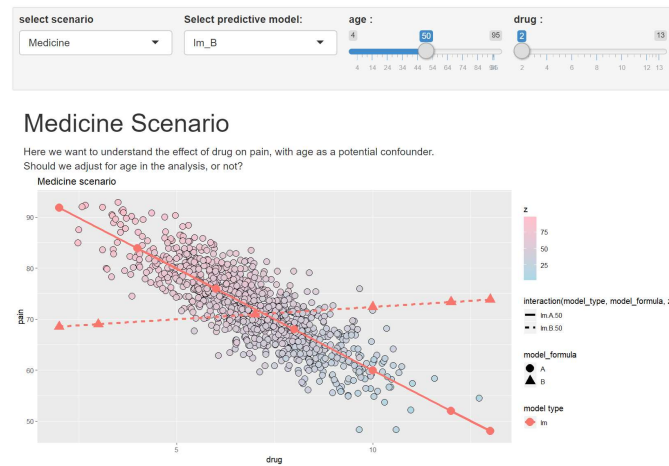


Image credit: [https://en.wikipedia.org/wiki/Simpson's\\_paradox#/media/File:Simpsons\\_paradox\\_-\\_animation.gif](https://en.wikipedia.org/wiki/Simpson's_paradox#/media/File:Simpsons_paradox_-_animation.gif)

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Another example of Simpson's Paradox (note: the data plotted are notional).

# Simpson's Paradox – Interactive Explorer



[https://ml4managers.shinyapps.io/effects\\_of\\_x\\_and\\_z](https://ml4managers.shinyapps.io/effects_of_x_and_z)

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There is an interactive app for exploring Simpson's Paradox at [https://ml4managers.shinyapps.io/effects\\_of\\_x\\_and\\_z/](https://ml4managers.shinyapps.io/effects_of_x_and_z/)

# Online A/B Testing – Successes and Learnings



## • ***A/B testing successes at Bing***

1. In 2012, a simple change to how ad headlines are displayed increased revenue by 12%, corresponding to **\$100 million** annually in the US alone
2. Slightly darker blues and greens in titles and a slightly lighter black in captions boosted revenue by more than **\$10 million** annually
3. A 100-millisecond speedup is worth **\$18 million** in annual incremental revenue

## • ***Learnings***

- **Correlation does not imply Causation**
- **Do lots of experiments!** "At Google and Bing, only about 10% to 20% of experiments generate positive results"
- **Consider the traffic needed to support A/B testing**

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<https://exp-platform.com/hbr-the-surprising-power-of-online-experiments>

Online A/B Testing is a type of randomized controlled trial or experiment.

Given enough user interactions (e.g. web site visits), online A/B testing provides reliable, statistically significant conclusions about cause and effect.



## A/B Testing – Number of events formula

Number of events (Unique Visitors) for an 80% chance of finding a difference:

$$UVs = 16 \times (\text{Variations} + 1) \times \left( \frac{\sqrt{CR \times (1 - CR)}}{CR \times \text{Performance}} \right)^2$$

See <https://julienlenestour.com/maths-behind-minimum-sample-size-ab-testing/>

- **Variations:** the number of NEW variations tested, not including the Control version
- **CR:** the current Conversion Rate of the page(s) tested, i.e. your Baseline Conversion Rate
- **Performance:** the relative increase of the Conversion Rate that your winning variation is seeing. For example, if your Baseline CR is 5% and the CR of your winning variation is 5.5%, then the Variation Performance is 10%, since your variation increases your CR by 10%.
- **UVs:** the minimum sample size to reach for your test to be statistically valid, measured in Unique Visitors tested.

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The key take-away from this formula is that detecting a subtle change in Conversion Rate requires much more data than detecting a larger change.

For example, reliably detecting a 1% increase in Conversion Rate requires 100 time more events than would be required to detect a 10% increase in Conversion Rate.

Mathematically, the number of unique visitors required depends on  $1/(\text{performance}^2)$ , where "performance" is the relative increase in Conversion Rate, e.g. performance = 0.1 for a 10% increase and 0.01 for a 1% increase.

# A/B Testing – Design of Experiments

A/B Test Duration Calculator			
Fill the cells with red background; rest of the cells will update automatically			
Existing Conversion Rate	25%		Number of Visitors
Expected Improvement in Conversion Rate	10.0%	27.5%	80% chance of finding a difference
Number of Variations in Test (including Control)	2		95% chance of finding a difference
			9,600
			15,600

Test Duration Calculator (80%):

[aka.ms/ab-duration](https://aka.ms/ab-duration)

Test Significance Calculator:

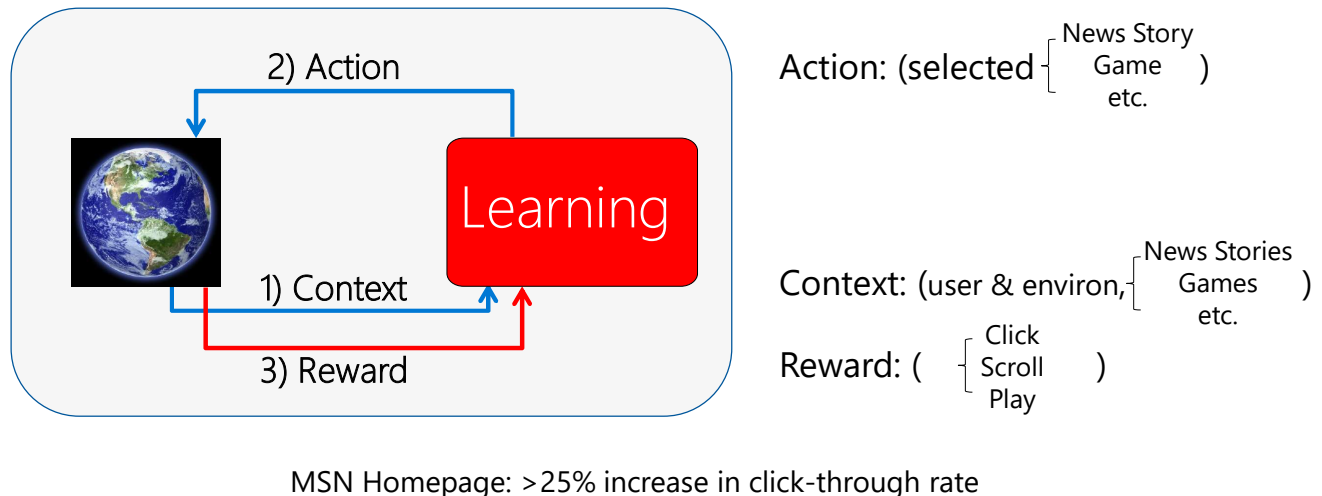
[aka.ms/ab-significance](https://aka.ms/ab-significance)

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Try [aka.ms/ab-duration](https://aka.ms/ab-duration) – first use the default values, and then try changing “**Minimum improvement in conversion rate you want to detect (%)**” from the default of 20% to 2%. Note how the number of days to run the test increases from 28 to **2,800!**

# Online Reinforcement Learning

## - Azure Personalizer Service



Azure Personalizer Service - <https://azure.microsoft.com/en-us/services/cognitive-services/personalizer/>

Azure Personalizer Service continuously and automatically seeks to optimize "reward."

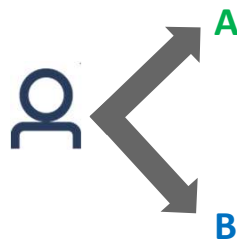
For a given **context** (information about, e.g., a web site visitor, their browser, their approximate location, time of day, day of week, etc.),

Azure Personalizer Service will either recommend the best action learned so far for the context or will recommend a randomly chosen action.

One can configure how often Personalizer recommends a random action, e.g. 20% of the time. This is called the exploration percentage.

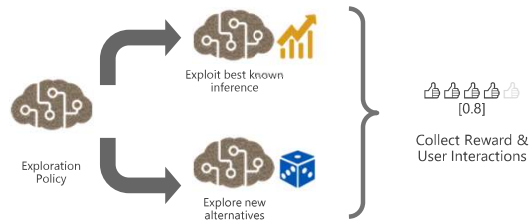
Exploration allows Personalizer to keep learning and adapting as conditions change.

# Online A/B Testing vs. Azure Personalizer



## Traditional A/B Testing:

1. Design an Experiment
2. Test online
3. Repeat



## Azure Personalizer:

1. Online explore and exploit
2. User reactions are logged
3. Automatically improve offline using logged data

With Azure Personalizer “counterfactual evaluation”:

- Run 1,000s of additional offline tests/person/day
- Find levels of performance that can’t be found with simple online A/B testing
  - A/B Testing requires exponentially more traffic when comparing many alternative policies

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Personalizer can use data logged from online exploration to test additional, alternative policies via “offline evaluations”:

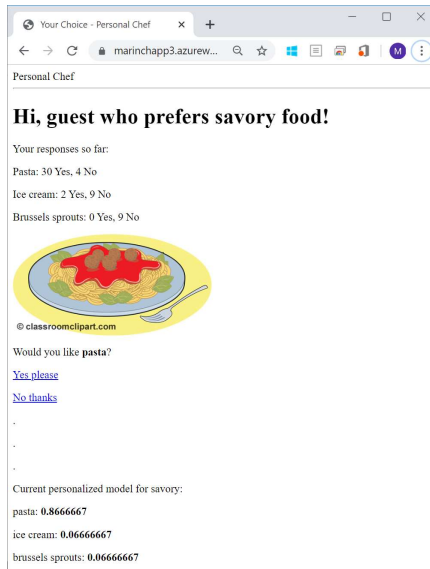
<https://docs.microsoft.com/en-us/azure/cognitive-services/personalizer/concepts-offline-evaluation#how-offline-evaluations-are-done>

Example A/B experiment:

1. Control group (Group A) sees the same text regardless of geographic location
2. Treatment group (Group B) sees one of 10 different versions of the text based on geographic location

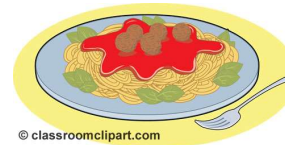
Traditional online A/B testing can only test one policy of assigning versions to locations at a time. Using offline evaluation, Personalizer can test many alternative policies.

## Lab exercise – let's train a Personal Chef!



[aka.ms/personal-chef](https://aka.ms/personal-chef)

Savory



Sweet



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This is a simple example with one binary context feature (savory or sweet preference) and three possible actions (pasta, ice cream, and Brussels sprouts), but Personalizer can handle multiple context features, actions, and action features.

Let's train a personal chef powered by Azure Personalizer Service!

Point your browser to [aka.ms/personal-chef](https://aka.ms/personal-chef)

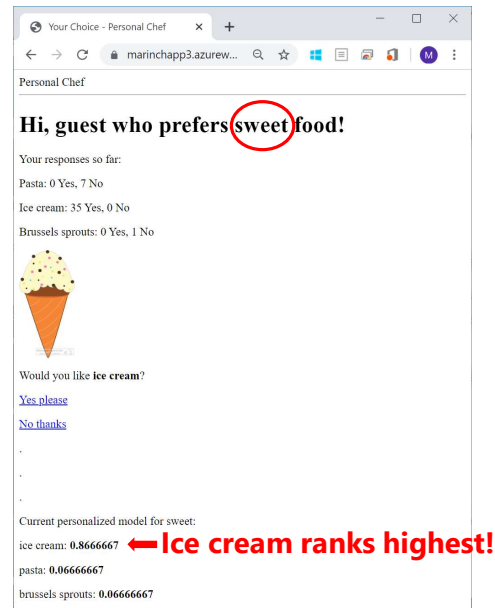
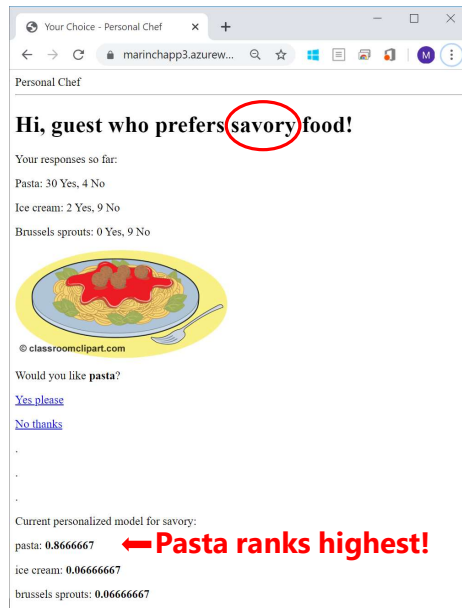
On the first page, "Choose Personalizer Instance," simply click the "Submit" button.

On the next page, choose your food preference, SAVORY or SWEET.

You will be offered either pasta, ice cream, or Brussels sprouts.

Sometimes you will be offered a choice that is not the top ranked choice for your food preference. This is an example of Personalizer exploring alternative actions.

Let's check on [aka.ms/personal-chef](https://aka.ms/personal-chef) ...



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By scrolling to the bottom of the Personal Chef web page, you can see the current personalized rankings.

## Optional: train your own Personalizer instance

- Create and train your own Personalizer instance by following the instructions in the Word document below



Microsoft Word  
Document

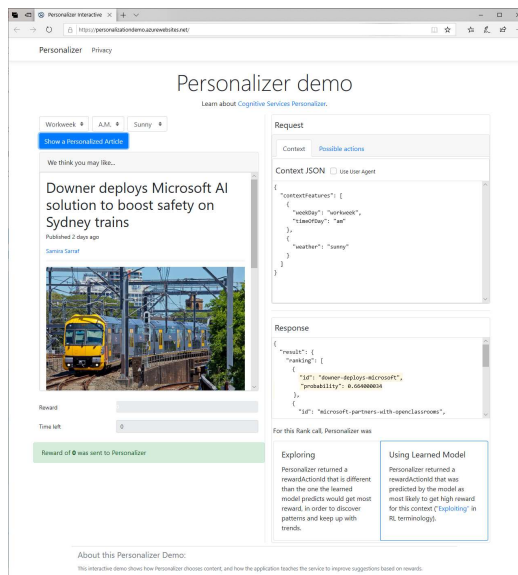


quicklearn.json

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Follow the instructions here if you want to try creating and training your own Personalizer instance from scratch!

# Azure Personalizer Service – Interactive Demo



[aka.ms/personalizer-demo](https://aka.ms/personalizer-demo)

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With this demo, we can peek behind the covers and see the context features and action list sent to Personalizer, along with Personalizer's response.



## Summary

- Correlation does not imply causation
  - Observational data may not tell the whole story – need intervention/experiment
- Online Test duration/required traffic depends strongly on the sensitivity desired
  - Required number of events grows as the square of desired sensitivity
  - Need 100x more traffic to see a 10x smaller effect
- Azure Personalizer automatically learns the best actions to optimize a desired objective (reward)
  - Exponentially more efficient than simple online A/B testing when comparing many personalization policies

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## Resources

- Github repo: <https://github.com/microsoft/datascience4managers>
- Shiny Apps:
  - [https://ml4managers.shinyapps.io/ROC\\_utility/](https://ml4managers.shinyapps.io/ROC_utility/)
  - [https://ml4managers.shinyapps.io/effects\\_of\\_x\\_and\\_z/](https://ml4managers.shinyapps.io/effects_of_x_and_z/)
- Economic Utility Functions Meet ROC Curves: Deciding on a Cutoff Threshold for Binary Classification. Siddarth Ramesh and Robert Horton, MLADS November 14, 2018. <https://resnet.microsoft.com/video/4248>
  - [https://github.com/Azure/utility\\_functions\\_in\\_ROC\\_space](https://github.com/Azure/utility_functions_in_ROC_space)
  - [https://ml4managers.shinyapps.io/ROC\\_utility/](https://ml4managers.shinyapps.io/ROC_utility/)



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## Overloaded Terms in Data Science

- **model**
  - *Statistics*: (data model) a description of a system using mathematical concepts and language (with statistical assumptions about sample generation.)
  - *ML*: (algorithmic model) data generation is a black box; the algorithm is about how to find correlations between features and outcomes.
- **inference**
  - *Statistics*: 'the process of using data analysis to deduce properties of an underlying probability distribution' (to infer properties of the population). ([Wikipedia](#))
  - *ML*: scoring or classifying new cases
- **experiment**
  - *Statistics*: measuring the state or value of a dependent variable when an independent variable is perturbed under controlled conditions in order to establish a cause and effect relationship.
  - *ML*: Try a bunch of algorithms, hyperparameter settings, etc. to see how they affect performance.
- **regression**
  - *English*: 'a return to a former or less developed state.'
  - *Statistics*: (regression toward the mean).
  - *ML*: prediction of a continuous-valued outcome. Contrasted with classification.

Wikipedia: "**regression toward** (or **to** **the mean** is the phenomenon that arises if a [random variable](#) is extreme on its first measurement but closer to the [mean](#) or [average](#) on its second measurement and if it is extreme on its second measurement but closer to the average on its first."

*"Indeed, the statistician David Freedman used to say that if the topic of regression comes up in a criminal or civil trial, the side that must explain regression to the jury will lose the case." - from Thinking, Fast and Slow by Daniel Kahneman*

More terms:

Precision:

Science or engineering: the number of decimal places to which a measurement is made.

Data science: positive predictive value.