CHAPTER

Task 3 -- Answering questions -- General

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Causal mapping produces models you can query to answer questions

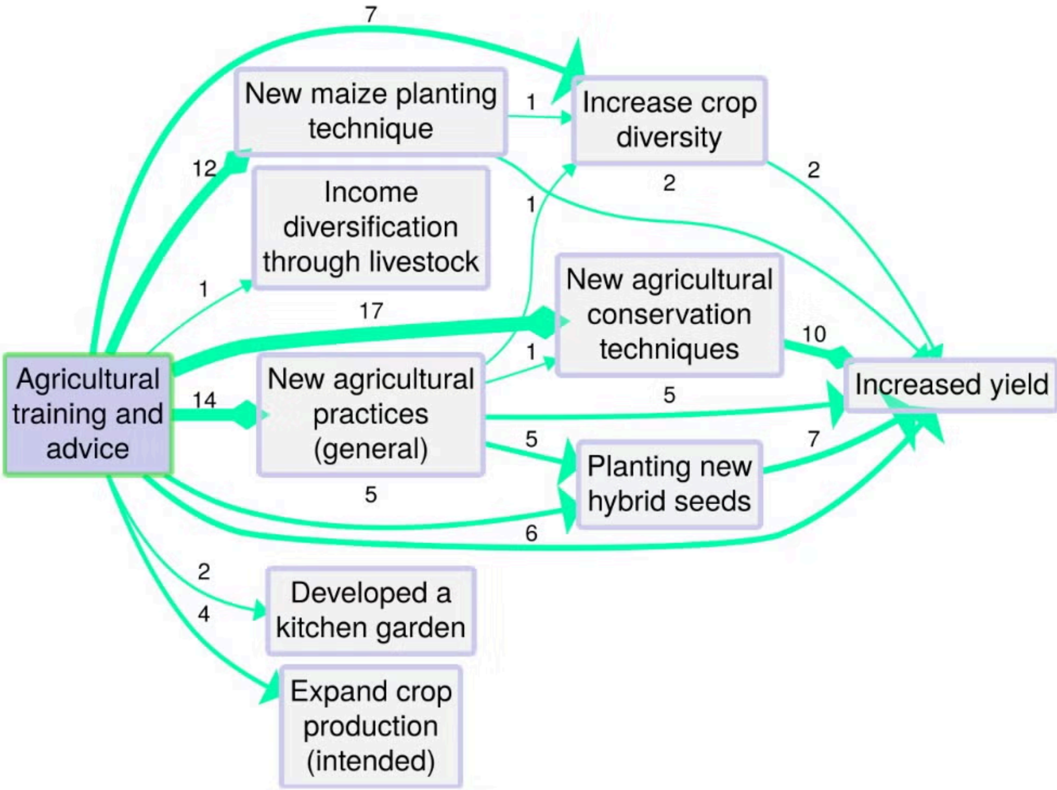
> The fundamental output of causal mapping is a database of causal links. If there are not too many links, this database can be visualised "as-is" in the form of a causal map or network. But usually there are too many links for this to be very useful, so we apply filters.

By applying filters and other algorithms, a causal map can be queried in different ways to answer different questions, for example to simplify it, to trace specific causal paths, to identify significantly different sub-maps for different groups of sources, etc.

As explained on the Causal Mapping website:

"*A global causal map resulting from a research project can contain a large number of links and causal factors. By applying filters and other algorithms, a causal map can be queried in different ways to answer different questions, for example to simplify it, to trace specific causal paths, to identify significantly different sub-maps for different groups of sources, etc.*"

The figure below shows a map from the application Causal Map, showing coded causal statements for a project that provided farmers with agricultural training and advice in order to increase crop yields. The map has been filtered to show only outcomes downstream of the influence factor ‘Agricultural training and advice’. Numbers shown indicate how many times the links were mentioned across all interviews.



Source: BDSR, 2021, p 4

Outputs of QDA

The logic of QDA: you’ve done your analysis, now what?

The result of qualitative data analysis can be understood as, at least, some kind of qualitative theory or model at least of the sources’ beliefs, with at least some possibility of generalising beyond them. But it can be hard to know what to do with the results of an emergent qualitative text analysis. There is no clear decision procedure: we can ask the author, and the answer is: some explanation, i.e. more text. In more reproducible approaches we do get some more structured outputs such as tables of frequencies. Some authors such as Mayring see these kinds of outputs as an important analysis result. QDA software is often used to capture and structure and even make inferences with these kinds of outputs.

In the logic of (non-causal) reproducible QDA, we can do things like this:

- count occurrences of concepts, and use ordinary arithmetic to report eg which of two concepts was more common
- count co-occurrences of two concepts, and construct measures like association between concepts, and more generally combine and query occurrences with boolean logic
- create case/code matrices
- report relationships between sources and concepts, for example to compare codings of one concept for different genders
- reason about concepts, for example to deduce that an occurrence of "lion" is also an occurrence of "mammal", either relying on our implicit understanding of the concepts or through the explicit declaration of a parent-child relationship.

Of course frequency statistics are notoriously unstable, because they depend on our decisions about granularity and chunking. If I have a codebook which has 100 different codes for cats and only 1 code for dogs, we may conclude that dogs were mentioned in the text more often than any other animal-concept even if cat-concepts were mentioned more often in combination. This is one reason why reasoning with these kinds of outputs can never be merely automated. There always has to be a “human in the loop”.

Nevertheless the point is that we can understand the output of QDA coding as some proportion of "more text", which itself needs to be interpreted by humans, and a complementary proportion of machine-readable, structured output which can be used to ask and answer questions (Which are the overarching themes? How much does climate anxiety come up as a theme? Who mentions it most?) at least somewhat independently of human guidance.

QDA logic can also be extended beyond the simple logic of frequencies and occurrences to apply (special kinds of) codes which have additional explicit rules associated with them, such as code weighting (as for example in MaxQDA). This means we can for example apply codes like “somewhat happy” or ‘very unhappy’ which enable us to say that the expression of happiness in one case is stronger than the other, or (if we also allow coding for time) that happiness increases or decreases over time. These extra deductions we can make come free with the (implicit or explicit) underlying ordinal logic of comparison of intensity.

QDA without coding

Coding does not have to be central to qualitative data analysis (Morgan, 2025); (Nguyen-Trung & Nguyen, 2025). ...

References

Morgan (2025). *Query-Based Analysis: A Strategy for Analyzing Qualitative Data Using ChatGPT*.

Nguyen-Trung, & Nguyen (2025). *Narrative-Integrated Thematic Analysis (NITA): AI-Supported Theme Generation Without Coding*. https://doi.org/10.31219/osf.io/7zs9c_v1.

We can reason about causal maps using a logic of evidence

How does causal inference work in a causal *network*?

When is a pathway not just a link?

The logic around how links might combine into pathways and what that means for evaluation, that's the most exciting part. e.g. how might this intervention influence an outcome which might be multiple steps downstream of it?

From

> a -->b

and

> b --> c

what can we conclude about

> a --> c. ?

For example, if the relation --> means "causes", when and under what circumstances can we conclude that a causes c?

Once we know the inference rules for a network, in particular the transitivity rule, we can infer all kinds of useful things about it.

There is a whole library of thinking about causal reasoning within a statistical or probablistic network.

There is less written about qualitative causality within a qualitative causal network.

But our problem is harder again: to reason with what we call a causal map, where the links are about **beliefs about** or **evidence for** a causal connection.

[We can reason about causal maps using a logic of evidence]

We can reason about causal maps using a logic of evidence

(An example of kind-of qualitative causal logic, with a focus on groups: @castellaniCasebasedSystemsMapping])

> From (Powell et al., 2024)

Seen as models of the world, causal maps, like systems maps, are fallible but useful: We can use inference rules (which are explicitly set out in FCMs, SDs, BBNs and CLDs and are implicit in other related approaches), and in particular, transitivity rules, to make deductions about the world.

There are at least three problems of transitivity which we need to think about

1. Given that A influences B and B influences C, does A influence C?
2. Given that P believes that A influences B and P believes that B influences C, does P believe that A influence C?
3. Given that someone believes that A influences B and someone else P believes that B influences C, does someone (who? we? the people?) believe that A influence C?

So if A causes B and B causes C, causal logic might tell us the answer to 1) under what circumstances A causes C.

Seen as models of individuals' causal beliefs, we can arguably use analogous rules to make deductions about what individuals believe, or ought to believe, given what else they believe.

There is a thing called epistemic logic which is a strange shadow of causal logic. Can it help us answer 2 and 3?

But epistemic logic is a strange thing.

If a person P believes that A causes B and B causes C, epistemic logic tells us what P believes about A causing C *if they were a rational person*. Whereas, facts about what people actually do believe is a branch of psychology.

In the last decades, thinkers like Daniel Kahneman have shown that in this sense, humans are so far from rational that it does not make sense even to start off with a rationality assumption and then add some corrections.

It would be great to use causal maps to infer, given a bunch of information about different people's causal beliefs, what they believe about *other* causal connections. That would be really useful. But it is hard.

There is a much easier way to reason with causal maps which is also vital for evaluators: to reason about **evidence**.

[We can reason about causal maps using a logic of evidence]

References

Powell, Copestake, & Remnant (2024). *Causal Mapping for Evaluators*. https://doi.org/10.1177/13563890231196601.

We can reason about causal maps using a logic of evidence

> From (Powell et al., 2024)

Evaluators can break the Janus dilemma and make the best use of causal maps in evaluation by considering causal maps not primarily as models of either beliefs or facts but as repositories of causal evidence. We can use more-or-less explicit rules of deduction, not to make inferences about beliefs, nor directly about the world, but to organise evidence: to ask and answer questions such as:

• Is there any evidence that X influences Z?

• . . . directly, or indirectly?

• . . . if so, how much?

• Is there more or less evidence for any path from X to Z compared to any path from W to Z?

• How many sources mentioned a path from X to Z?

• . . . of these, how many sources were reliable?

We also argue that this is a good way of understanding what evaluators are already doing: gathering and assembling data from different sources about causal connections in order to weigh up the evidence for pathways of particular interest, like the pathways from an intervention to an outcome.

References

Powell, Copestake, & Remnant (2024). *Causal Mapping for Evaluators*. https://doi.org/10.1177/13563890231196601.

Context is critical to the logic of evidence

These questions may depend on a somewhat hidden assumption: that all the causal claims (the links) come from a single context. Such as, in most cases, when all the claims are all agreed on by a group as in participatory systems mapping (PSM). For example, when we wrote "which factors are reported as being causally central?", can we really answer that by simply checking the network? From:

> Factor X is central within these claims

Can we deduce:

> Factor X is claimed to be central

Or, can we go from:

> There are two relatively separate groups of causal claims?

Can we deduce:

> It is claimed that there are two relatively separate groups of causal claims?

In general, no. It is easy to think of counter-examples. If we ask a parents and children about the causal network surrounding family disputes, we might get two relatively separate causal networks with only a little overlap. From this we cannot conclude that these respondents taken together claim that there are two relatively separate systems. It might be that the parents and children indeed are giving information about relatively separate systems about which they each have the best information, or it might be that the two groups are telling conflicting and perhaps incompatible stories.

We could express this as, say, the first axiom of causal mapping:

> If a network of causal evidence from context C has property P, we can conclude that there is evidence that the corresponding causal network has property P, but again only in context C.

P(E(N)) --> E(P(N))

We often assume that contexts are sources and sources are contexts. But this is not always the case. For example one respondent might give two sets of information, one from before losing their job and one set from afterwards, without trying to encode the job loss as a causal factor within the network of claims.

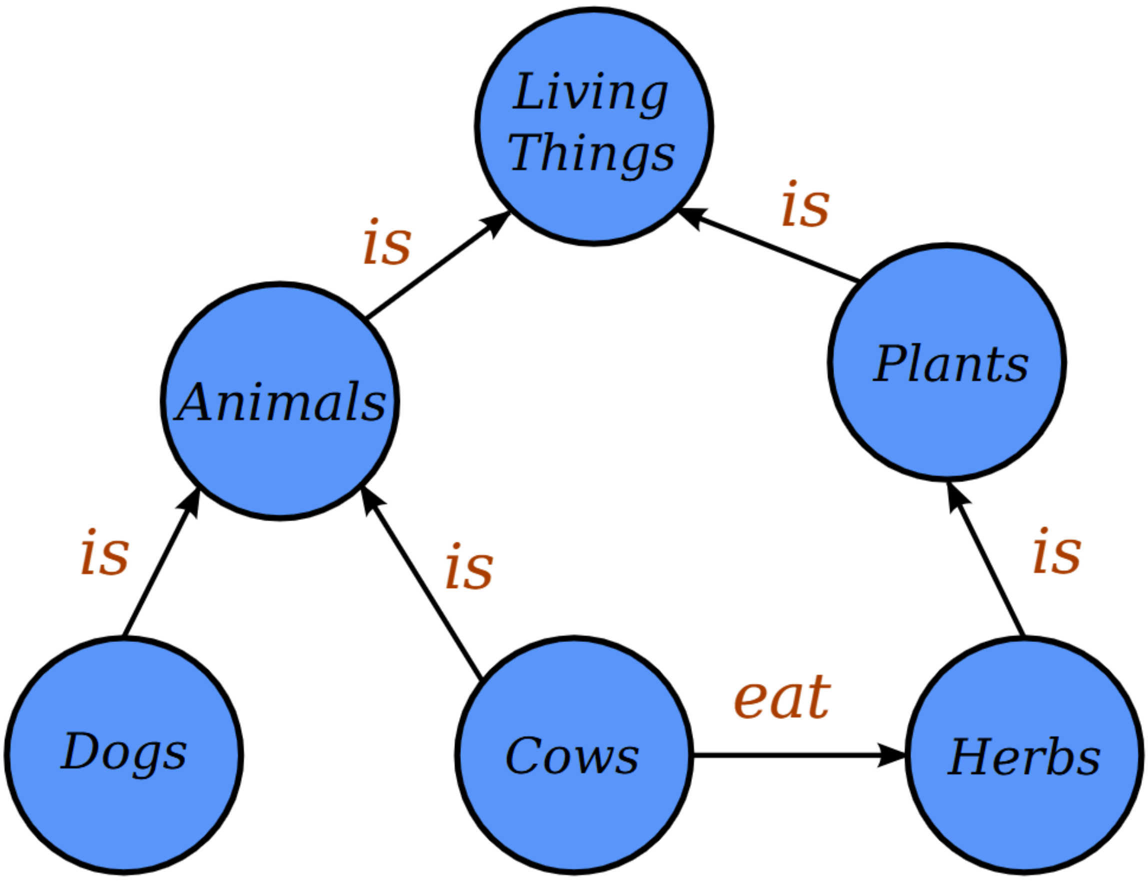
In a PSM workshop, there may be multiple respondents but, as long as they construct a consensus map, these are all treated as one source. Part of the job of the moderator is also to ensure that the claims (evidence) all come from one context, which is the same as saying: we can validly make inferences like those above. I don't know whether PSM moderators actually do this.

You might say "this is all pointless because it depends what you mean by context", and that is exactly true. All we have done is

Causal maps are knowledge graphs, but with wings

What is a Knowledge Graph? 🧠

- A knowledge graph is like a **giant mind map for a computer**. It stores information not as text in a document, but as a network of interconnected facts.
- It's built from two main things: **entities** (the "nodes," representing real-world objects, people, or concepts like "Paris" or "Photosynthesis") and **relationships** (the "edges," describing how these entities are connected, like "is the capital of" or "is a process in").
- A single fact has three parts: **(Subject) --- [Relationship] ---> (Object)**. For example: `(Marie Curie) --- [discovered] ---> (Radium)`.
- Why are knowledge graphs specially useful in the age of AI? 💡
- **They create structure from chaos.** AI can read through millions of pages of unstructured text (like news articles or scientific papers) and pull out these factual triplets. This turns a messy sea of words into an organized, queryable database of knowledge.
- **They enable smarter searching and reasoning.** Instead of just searching for keywords, you can ask complex questions that require understanding the relationships between things. For example, "Which scientists who won a Nobel Prize also discovered an element?" A computer can navigate the graph's connections to find the answer.
- **They provide essential context.** A knowledge graph helps an AI understand that "Apple" in a tech article is a company linked to "Steve Jobs," not the fruit. By looking at its connections, the AI gets the right context, which is crucial for accurate understanding and analysis.



[Image](#) from Wikipedia by Jayarathina - Own work, CC BY-SA 4.0.

Why are Knowledge Graphs (KGs) so useful?

A major benefit of KGs is we can then apply network logic like transitivity rules to answer meaningful questions. For example, if the relation is "works in the same company as", then if we know

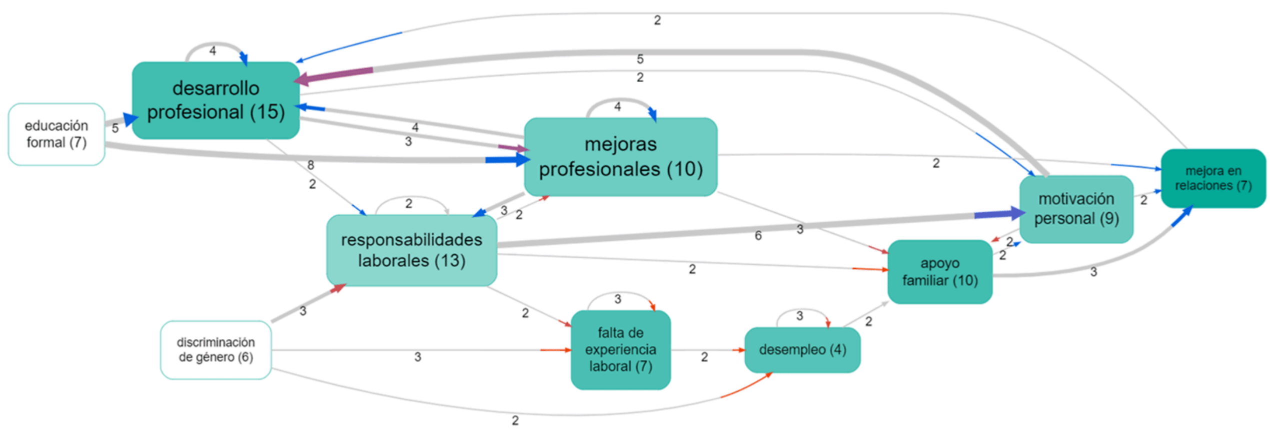
- **A is related to B**
- and
- **B is related to C,**
- then we can conclude
- **A is related to C (A is in the same company as C).**

Challenges with general-purpose knowledge graphs

The trick in **constructing** knowledge graphs is to know what relationship(s) to look for. "belongs to? " "is capital of?" "challenges/undermines?" This can be very difficult to decide. on the fly.

Using network logic to answer queries can be difficult where each different type of relationship may have its own logic. It can be very tricky (though potentially rewarding and useful) to design custom queries to answer specific questions.

Causal mapping gives knowledge graphs wings



A causal map is just a knowledge graph in which there is only one kind of relation: "causes" or "influences". This means:

- It is **much easier to scan and process text data** as we already know what we are looking for.
- We focus on primarily on **exactly the kind of information which is useful for monitoring and evaluation**: what influences what?
- We can **make use of pre-existing logic and queries to help answer common evaluation questions** almost "out of the box". Here we have a whole presentation on *Questions you can answer with causal mapping* which gives plenty of suggestions.

Can only doing causal mapping answer all the questions you might want to ask about a text? Of course not. But it can help answer a lot of the most interesting and important ones.

What about social network analysis?

Yes, social networks can also be constructed as knowledge graphs with just one (or a small number of) relationships, such as "works with".

So can we use causal mapping tools to construct general network graphs?

You might ask if the reverse is also true: can you use causal mapping software like Causal Map to also do your AI-supported knowledge graphing for you? The answer is yes! Concretely, in the new version of Causal Map, version 4, which is arriving very soon, you can manually code any type of link, not just causal, and you can also guide the AI to do this too.

The product of (causal) qualitative coding can be a model you can query

The transitivity trap

> From (Powell et al., 2024)

[Granularity, generalisability and chunking are coding problems for causal mapping too]

Transitivity is perhaps the single most important challenge for causal mapping. Consider the following example. If source P [pig farmer] states ‘I received cash grant compensation for pig diseases [G], so I had more cash [C]’, and source W [wheat farmer] states ‘I had more cash [C], so I bought more seeds [S]’, can we then deduce that pig diseases lead to more cash which leads to more seed (G à C àS), and therefore G à S (there is evidence for an indirect effect of G on S, i.e. that cash grants for pig diseases lead to people buying more seeds)?

The answer is of course that we cannot because the first part only makes sense for pig farmers, and the second part only makes sense for wheat farmers. In general, from G à C (in context P) and C à S (in context W), we can only conclude that G à S in the intersection of the contexts P and W. Correctly making inferences about indirect effects is the key benefit but also the key challenge for any approach which uses causal diagrams or maps, including quantitative approaches (Bollen, 1987).

> For want of a nail the shoe was lost,
>
> For want of a shoe the horse was lost,
>
> For want of a horse the rider was lost,
>
> For want of a rider the battle war lost,
>
> For want of a battle the kingdom was lost,
>
> And all for the want of horseshoe nail.

(Thanks to Gary Goertz for remembering this one!)

Frog thinks: eating salad leads to health (less scurvy), and health (general fitness) leads to better sprinting ability, therefore if I eat this yummy lettuce – AARGH!

One of the key features of causal maps is that you can draw inferences, make deductions, from them. One of the most exciting is to be able to trace causal influences down a chain of causal links. BUT, when you are drawing conclusions from causal maps, beware of the transitivity trap:

from

> B → C

and

> C → E

we can only conclude

> B → E in the intersection of the contexts of 1 and 2

… and in general with any causal mapping, you'll never be sure that these two contexts do intersect. You actually have to look at each chain and think about it, and hope you've been told all the relevant facts.

For example:

If

> Source P [pig farmer]: I received cash grant compensation for pig diseases (G), so I had more cash (C)

and

> Source W [wheat farmer]: I had more cash (C), so I bought more seeds (S)

can we deduce

> G → C → H

and therefore

> G → S

(cash grants for pig diseases lead to people buying more seeds)?

No, we can't, because the first part only makes sense for pig farmers and the second part only makes sense for wheat farmers.

There are thousands of different kinds of transitivity trap. It isn't just a problem across subgroups of people. It can apply for example in different time frames.

If

> Child does well in year 13 (A) → Child has improved academic self-image (C)

and

> Child has improved academic self-image (C) → Child does better in year 9 (D)

can we deduce

> A → C → D

and therefore

> A → D

(child doing well in year 13 leads to child doing well in year 9)?

Of course not - even though these claims might be true of the same child. The problem arises as soon as we generalise one causal factor to apply to different contexts. We have to do this, to make useful knowledge. But there are always pitfalls too.

Not just a problem for causal mapping

This is also true, isn't it, of any synthetic research / literature review?

And in statistics, knowing the effects from B → C and C → E means you can calculate the indirect effect of B on E but not the direct effect. You have to have additional data just for that. This is one source of various so-called paradoxes in statistics.

Can we mitigate the trap with careful elicitation protocols?

Sometimes, we might know that all the information in one particular chain came from the same source, and all this information was explicitly given as a series of explanations of the factor which was initially in focus. But even here, we have to be careful. We might have to ask again, having reached the end of the chain, "did B really influence C which influenced D which influenced E? Was this all part of the same mechanism?" Are we sure we know exactly what we mean by this, and are we sure that our respondents do too?

In any case, part of the point of causal mapping is the synthetic surprises which we can discover by piecing together fragments of causal information which were *not* necessarily provided in this way. This is the situation every evaluator is in when piecing together information from, say, experts for Phase 1 and experts for Phase 2. We just always have to be aware of the transitivity trap.

Transitivity trap, or identity trap?

We can talk about the *identity trap* as more fundamental than the transitivity trap. It comes down to saying, how can you be sure that the way in which this factor is exemplified in one particular context is the same as the way that this similar seeming factor is exemplified in a different context: whether to use "the same" factor to code two different things.

References

Powell, Copestake, & Remnant (2024). *Causal Mapping for Evaluators*. https://doi.org/10.1177/13563890231196601.

