Learning how to act: making good decisions with machine learning

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In vain the grave, with retrospective Eye, Would from the apparent what conclude the why, Infer the Motive from the Deed, and show That what we chanced, was what we meant, to do.

Alexander Pope

Introduction (3500 words)

My thesis in a sentence: Unifying causal inference with multi-armed bandits.

This thesis contributes to knoweldge by: Introducing a framework connecting causal graphical models with multi-armed bandits as a first step towards a unified approach to estimating the effect of interventions.

My key research questions are:

- To understand and the difference between prediction and causal inference in machine learning and clarify which problems require causal approaches.
- To summarize the key strands of causal inference research from economics and social sciences for the machine learning community
- To make connections between learning to act from observational versus experimental data. In particular, between causal graphical models and multi-armed bandits.

Motivation

Many of the most important questions in science and in our personal lives are about the outcomes of doing something. Will asking people to pay upfront at the doctors reduce long term health expenditure? If we developed a drug to suppress particular genes, could we cure MS and would delaying teen-aged pregnancies improve the outcome for their kids.

These are hard questions because they require more than identifying a pattern in data. Correlation is not causation. Causal inference has proven so difficult that there is barely any consensus on even enduring questions like the returns to education or the long-term consequences of early life events – like teenage pregnancy, where the variables involved are susceptible to human intuition and understanding.

We now live in a world of data. Hours of our lives are spent online, where every click can be recorded, tiny computers and sensors are cheap enough to incorporate into everything and the US Institute of Health is considering if all infants should be genetically sequenced at birth. Such data gives us a window into many aspects of our lives at an unprecedented scale and detail but it is messy, complicated and often generated as a by product of some other purpose. It does not come from the controlled world of a randomised experiment.

The rise of big data sets and powerful computers has seen an explosion in the application of machine learning. From healthcare, to entertainment and self driving cars; machine learning algorithms will transform many industries. It has been suggested that the impressive ability of statistical machine learning to detect complex patterns in huge datasets heralds the end of theory (Reference) and that we may be only a short step from the Singularity, where artifcial intelligence exceeds our own and then grows exponentially.

However, despite the huge advances in specific areas of machine learning (in particular deep learning), machine learning algorithms are effective only within very narrow problem settings. Getting them to generalize to even slightly different problems or datasets remains very challenging. Deciding how we should act or what policies we should implement requires us to be able to predict how a system will behave if we change it. The correlations detected by standard machine learning algorithms do not enable us to do this, no matter how many petabytes of data they are based on. As machine learning algorithms are incorporated into more and more of the decision making processes that shape the world we live it, it is critical to ensure that we understand the distinction between causality and prediction and that we develop techniques for learning how to act that are as effective as those we have for pattern recognition.

What is causality and why do we care? (2000 words)

To explain or to predict [**?**] The two cultures [**?**]

Defining causality

- widely debated in science and philosophy (REFERENCES)
- what is explaination?
- any model that aims to predict the outcome of an action or intervention in a system
- I do not see the distinction between explaination and (causal) prediction. Explaination is all about the ability to compress and to generalize. The more a model can do this, the more we view as providing an understanding of the why.
- mediation?

Identifying when we have a causal problem

Examples of typical machine learning probems. Are they causal?

- Speech recognition (for systems like Siri or Google)
- Machine translation
- Image classification
- Forecasting the weather
- Playing Go
- Identiying spam emails
- Automated essay marking
- Predicting the risk of death in patients with pnumonia.
- Predicting who will re-offend on release from prison
- Predicting which customers will cease to be your customers

- Demand prediction for inventory control
- Predicting who will click on an ad
- Financial trading
- Recommending movies
- Online search
- Self driving cars
- Pricing insurance

What aspects of a problem determine if causal inference is required?

(When is pure prediction useful?)

- To decide between actions we only need to rank them (not estimate their actual effect).
- The predicted outcome in the absence of an intervention provides a single point. We can use this to find which problems are most serious if left alone - and priortise those for modelling changes.
- Any decision we take does not significanly impact the system from which the data was drawn to make it (for repeat decision making)
- Does acting on the result of the prediction change the predictive distribution p(y—x)? Ie change people's behaviour.
- Ethics - ... People's viewpoint on if its ok...

Approaches to causality (1000 words)

Two broad approaches

- Build a model to map the natural behaviour of the system to what will happen for some action
- Take the action and see what happens

The first is causal inference

The second is reinforcement learning

Both generalize from randomized experiment Reinforcment learning to sequential decisions, causal inference to non-experimental conditions

Both approaches involve assumptions the latter that we can group context and actions.

Limitations of causal inference

Limitations of experimets What are the issues with standard randomized experiments?

Causal models (3000 words)

Causal inference aims to infer the outcome of an intervention in a system from data obtained by observing (but not intervening in) the system. To do this we need terminology to describe actions and how we anticipate the system should respond to them. Three key approaches have emerged; counterfactuals, structural equation models and causal bayesian networks. In this chapter we describe these approaches, examine what problems they allow us to solve and the assumptions they rely on and discuss their differences.

Counterfactuals

Counterfactuals (or potential outcomes) are a way of describing distributions under different actions that were developed from the starting point of generalizing randomized experiments.

There are philosophical objections (references) to counterfactuals because of the way the describe alternate universes that were never realized and are not empirically testable (example).

For interventional queries, of the form; what is the is the probaiblity distribution for the variable Y if we intervene to set X = x, and the system is otherwise unchanged? Counterfactuals are a short hand. They say what is the distribution of Y had X = x (regardless of the value X actually took).

Causal graphical models

Although seemingly simplistic, the notion of hard interventions is surprisingly powerful.

A complaint leveled against this view point of causality is that the 'surgery' is too precise and that, in the real world, any intervention will effect many variables (eg Cartwright 2007). However,

Provides an explicit mechinism to map knowelede from one setting to another.

A fully observed causal bayesian network allows asymtoptic point estimates of the causal effect of any intervention (assuming positive density).

Structural Equation models

Comparing and unifying the models

Representation equivelent for interventional queries This means it is straightforward to take the best elements of work done in any of the frameworks. For example, draw a graphical network to determine if a problem is identifiable and which variables we need to adjust for to obtain an unbiased causal estimate. Then use propensity scores or ... to estimate that effect.

Alternatively, make parametric assumptions, to make the problem into a structural equation model.

SWIGs [Richardson and Robins, 2013] [**?**] Causal inference without counterfactuals

What does a causal model give us? Resolving Simpson's paradox

A translator from graphical independence to counter factual statements

Defining causal effects

Summarising the difference between two distributions. There is no one answer. [**?**]

Two key questions (5000 words)

We can rougly categorize the problems studied within causal inference into two groups, causal effect estimation and causal discovery. In causal effect estimation we assume (at least implicitly) that key aspects of the causal graph are known. The goal is then to estimate the causal effect of some action or range of actions. WHERE DOES MEDIATION FIT IN? THIS IS ALREADY HUGE, and is central to 1000 of papers published each year. Causal discovery aims to leverage much broader assumptions to learn the stucture of causal graph from data. THIS IS THE AUTOMATION OF SCIENCE.

Causal Inference

You are willing to assume the causal graph

extremely widely appliled Implicitly accounts 10,000 of studies in phycology, medicine, business, etc.

Identifiability

Definition:asymptopic point estimate is possible, without parametric assumptions

Under what conditions in is the problem solveable

The Do Calculus

Estimation

[?] Review of non-parametric estimation

How well do we actually do with finite datasets?

When is regression causal?

Non identifiable queries

Parametric assumptions

eg linearity

Bounds

Instrumental variables are an example

Causal Discovery

It is possible to infer some aspects of causal structure with very general assumptions. The set of conditional independences in a non-experimental data set indicates some causal structures are more likely than others. In addition, there are subtle asymmetries in the relationship between the joint distribution of cause and effect and the distributions of cause given effect and effect given cause. These clues are the key to causal discovery algorithms, which attempt to learn causal structure from non-experimental data.

You want to learn the graph

Equates to the aim of automating scientific discovery

Increadibly hard

Methods can also be divided into contraint based and search and score

Discovery with Conditional independence

If variables are (conditionally) independent they are unlikely to be directly causally linked.

Discovery with Functional Models

Granger causality

The interventionalist viewpoint (5000 words)

The previous sections all focus on aspects of the question; how can we estimate the effect of an intervention in a system from data collected prior to taking it. There is an obvious alternative. Instead of trying to infer the outcome of an intervention from passive observations we could just do it and see what happens. There are two key differences between observing a system and explicitly intervening in it. Firstly, when we intervene, we can choose which actions to take and thus get some control over which distributions we learn about. Secondly, if we are explicitly choosing interventions, we have a perfect model of the probability that we select each action given any context, allowing us to control confounding bias.

The role of randomization

The interventionalist viewpoint has devloped from the starting point of randomized controlled experiment What is the role of randomization? How do bandits algorithms work despite being only partially randomized? What else can you do to improve randomized studies (variance reduction, lower regret).

Figure showing how randomization breaking any confounding links

Randomization does not ensure target and control group are exactly alike. The more features or variables you include, the more likely that there will be a significant difference across at least one variable. But the within group variance also increases, the net effect is that it becomes harder to draw a conclusion but not more biased.

Limitations of randomization

Limitations of experimentation

Failure to generalize. Transportability, imperfect compliance. Too many contexts.

internal validity Are differences in treatment and control groups down to intervention or the result of bias?

external validity Are the results of the study applicable to the broader population of interest.

Multi armed bandits

Definition

What limitations of randomized experiment does the bandit view address

The exploration/exploitation trade-off

Regret

How do we measure the performance of a bandit algorithm?

Regret

$$R_T(\pi) = \mathbb{E}\left[max_{i\in[k]} \sum_{t=1}^{T} X_{t,i}\right] - \mathbb{E}\left[\sum_{t=1}^{T} X_{t,A(t)}\right] \tag{1}$$

Psuedo-Regret

$$\begin{aligned} R_T(\pi) &= max_{i\in[k]}\mathbb{E}\left[\sum_{t=1}^{T} X_{t,i}\right] - \mathbb{E}\left[\sum_{t=1}^{T} X_{t,A(t)}\right] &(2)\\ &= n\mu_{i^*} - \mathbb{E}\left[\sum_{t=1}^{T} X_{t,A(t)}\right] &(3)\end{aligned}$$

Simple Regret

$$\mu_{i^*} - \mathbb{E}\left[\mu_{\hat{i}^*}\right]. \tag{4}$$

Adversarial Bandits

Key approaches and results

optimisim in the face of uncertainty

The need to add structure

The regret for a bandit problem grows linearly with the number of (sub-optimal) actions. This makes problems with large or infinite actions spaces intractible.

Key extensions

Contexual bandits

Feature selection Is it even more important here? How do algorithms degrade as irrelevent features are added? In the supervised vs the RL setting? What would be a fair comparison?

Markov decision processes

Dynamic Systems

- An explicit model of actions in a partially known system (eg HMM)
- Feynman-Kac Lemma; Solving a PDE can be converted to a stochastic process

Causal Bandits: Unifying the approaches (5000 words)

Extend from my NIPS paper

The framework

Connecting the machinary of causal inference to the bandit problem

For which problem does causal inference help?

Causal bandits with post action feedback

The parallel bandit problem

General graphs

Experiments

Discussion & Future work

Related work

Learning from log data

Conclusions (1000 words)

Open questions

Cycles - a huge issue. Not covered by Pearl,Rubin etc.

Places to look, statistical control theory, etc. any interesting papers along these lines?

Bibliography

[Richardson and Robins, 2013] Richardson, T. S. and Robins, J. M. (2013). Single world intervention graphs (SWIGs): a unification of the counterfactual and graphical approaches to causality.