ABSTRACT
Data science has the potential to improve business in a variety of verticals. While the lion’s share of data science projects uses a predictive approach, to drive improvements these predictions should become decisions. However, such a two-step approach is not only sub-optimal but might even degrade performance and fail the project. The alternative is to follow a prescriptive framing, where actions are “first citizens” so that the model produces a policy that prescribes an action to take, rather than predicting an outcome. In this paper, we explain why the prescriptive approach is important and provide a step-by-step methodology: the Prescriptive Canvas. The latter aims to improve framing and communication across the project stakeholders including project and data science managers towards a successful business impact.

CCS CONCEPTS
• Computing methodologies → Sequential decision making; Online learning settings.

KEYWORDS
data science, management, framing, machine learning, prescriptive, action, policy, optimization, causal inference, reinforcement learning

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1 PREDICTIVE VS PRESCRIPTIVE
Data science (DS) projects commonly aim to improve business decisions. In this section, we will explain the three-level analytics model that distinguishes between different tasks within data science. We will then show that the predictive approach is more common than the prescriptive one, and explain why the prescriptive approach is better when one aims to improve business decisions.

1.1 The Three Levels of Analytics
There are three levels of data science tasks [15, 21, 28], ordered by increasing value and difficulty, as depicted in Figure 2:

- **Descriptive**: What happened? e.g. What was the average churn over the last 3 months? The result is often a value, chart or dashboard.
- **Predictive**: What will happen? e.g. What is the probability this user will churn? The result is a model that is able to provide predictions.
- **Prescriptive**: What to do? e.g. What should we do to prevent churn? The result is a model that represents a policy: it prescribes actions that optimize the outcome.

The first and the second questions are well understood and even can be automated in some cases[19]. However, the last prescriptive question aims to directly optimize business value [2]. Even though most data science projects aim to improve business decisions, they often solve a forecasting or prediction problem.

To demonstrate this, we analyzed the Kaggle meta-database [25] which describes 5,388 data science competitions. While “forecast” appears in all competition’s descriptions, neither “action”, “policy” nor “decision” appear even once. This again demonstrates the dominance of the predictive framing approach. As an exception, recommendation competitions appeared 11 times. Though the recommendation problem is prescriptive in nature, it is often wrongly framed as a predictive problem [39] and therefore tries to predict future choices or ratings rather than the effect of these recommendations, also known as uplift [13].

1.2 Example: Predictive vs Prescriptive Churn
To demonstrate the difference between predictive and prescriptive approaches, consider the classical problem of churn prevention. A predictive model provides expected churn probabilities, which can be used in a heuristic policy to drive actions, for example targeting users with the highest churn probability. Formally the policy would be \( \pi_{\text{pred}}(x) = I(\hat{y}(x), t) \) where \( t \) is some threshold, \( y \) is churn probability and \( I(a,b) = 1 \) if \( a > b \), otherwise zero. However, the real business goal is to reduce churn, rather than predict it [8]. While the predictive approach targets users that are likely to churn, the prescriptive approach targets users that can be persuaded. Research has shown that the prescriptive approach could be up to 3x more effective than the predictive one[1, 8].

To explain why the prescriptive approach is better, consider that customers that are likely to churn aren’t necessarily easily retained.
Some users will be "lost causes"; they will always churn despite any action, thus targeting these will be a waste of effort. Some other users will be "sleeping dogs"; they would churn because of the action. Perhaps they were already thinking of canceling their subscription, but by contacting them, they churn at that moment. The prescriptive approach aims to correctly predict the effect of the action, and as such, prescribe actions that truly improve churn. Formally, the prescriptive policy would be $\pi^\text{Prescriptive} = I(\tau(x), 0)$ where $\tau(x)$ is the estimated effect of the targeting (the difference in retention probability if targeted or not). We will discuss this kind of approach, called Uplift Modeling in section 2.3.

Note that besides the different views on model output, this also implies choosing correctly the business objective. If a retention desk is measuring success by the amount of retention in the targeted population, a predictive approach would be optimal. However, the latter objective will encourage targeting the "sure things" rather than the "persuadables", thus wasting the targeting budget. However, if the correct business objective will be used, minimizing the overall churn rate, a prescriptive approach will be optimal and likely to impact the true business goals.

1.3 The Prescriptive Problem

The predictive approach goal is to predict as accurate as possible. Formally, minimizing some loss function $\mathcal{L}(\hat{y}, y)$ where $y$ is the true label and $\hat{y}(x)$ is the predicted output based on the input $x$. By contrast, the goal of prescriptive modelling is to find a policy that optimizes some reward by dictating actions. Formally, at each context $x$, the policy $Pr(a) = \pi(x)$ dictates which action $a$ should be taken at which probability, such that reward is maximized: $\pi^\text{Opt} = \arg\max_\pi \mathcal{R}(\pi)$.

The fundamental problem in prescriptive modeling is that we do not know what would have happened if we had acted differently, also known as the counterfactual outcome. In some sense, this could be interpreted as a missing data problem. If we could simulate using a "what-if" [22] model what would have been the counterfactual, we could have used it to find the optimal policy. This also implies that measuring the performance of a prescriptive model offline is harder compared to the predictive approach. Because we don’t know the true counterfactual outcomes, we can’t use them to evaluate candidate policies, as we need to essentially solve the "what-if" problem. As a consequence also model-selection and hyper-parameter optimization are challenging. Nevertheless, there are several approaches to estimate the performance, also known as offline policy evaluation (OPE) [12, 27], and there are some methods for model selection, e.g. [35]. By contrast, in predictive modeling, model selection and hyper-parameter optimization are relatively straightforward via a holdout sample.

To model the counterfactual we need to understand the causal relationship which can be learned from domain experts or using causal discovery techniques [38]. Unfortunately, the data does not explicitly provide us the causal relationships but merely the correlations. How can we distinguish causation from correlation? Understanding the data generating process can help distinguish causation from correlation. This typically is represented in a directed acyclic graph (DAG) of causal dependencies. A simplified example is depicted in Figure 1. In this example, customers are contacted based on their engagement. However, their engagement level is also a precursor of their churn. The relationship between targeting and engagement to churn can be found in the data. In do-calculus language [31], there are two paths from targeting to churn. One is the direct causal dependency we are interested in, and another so-called back door path through engagement. We need to control for the back door path to prevent a biased estimate of the effect of targeting on churn, which could even get the wrong sign. For example, targeting could mistakenly seem as if it increases churn rather than the real effect of decreasing it (also known as the Simpson Paradox). In general, this means that sufficient common causes of both the treatment and the outcome need to be included in the analysis, referred to as backdoor adjustment or controlling for confounding. Other biases could occur, including collider bias, selection bias, and mediators, see [22, 31] for more details.

1.4 Types of Prescriptive Modeling

Prescriptive Analysis holds within it a vast number of modeling frameworks. In this paper, we cannot review these methods fully and direct the reader to the citations. Nevertheless, we would like to give the reader a quick overview to help guide managers and practitioners. In general, there are three sources for prescriptive analysis:

- **Experimentation** - Randomly try actions to determine the cause and effect relationship. This could be a plain A/B test or more advance online methods such as multi-arm bandits (MAB) and contextual bandits (CMAB), where the latter allows also personalization [5, 24, 34]. Online reinforcement learning (RL) is used when a sequence of related actions needs to be optimized.
- **Simulation** - if a trustworthy simulator of the environment is available, such as in the case of video games [29] or operational research [6], optimization can be done using black-box optimization techniques [32], simulated experimentation methods, online RL interacting with the simulation and a Monte-Carlo Tree Search (MCTS) approach [7].

![Figure 1: An example of a DAG in a marketing scenario. The engagement level affects both the targeting (treatment) and the churn probability (outcome), thus it is a confounder. If engagement is not controlled for, a biased effect of targeting on churn would be estimated: e.g. targeting causes churn rather than decreasing it.](image-url)
Offline Data - Observational studies [31] provide ways to leverage existing data to come up with better policies, mainly based on causal inference and recent major advances in offline RL [27]. This is also useful when experimentation and simulation are not achievable. Moreover, recommendation systems (RecSys) are often used when the size of the action space is very large [39]. One technique from the causal inference domain is Uplift Modelling, detailed in 2.3.

In the next section, we will elaborate further on causal inference and observational studies as these are proven to be successful in practice for Marketing and Sales (see Section 2.1 quotes and references within).

2 CAUSAL INFERENCE

2.1 The Benefits of Causal Inference

Causal Inference is the set of techniques that allow inferring the actual causal effect of an action on the outcome [16, 31, 41]. The importance of causal inference was recently publicly recognized as it was at the center of the 2021 Economics Nobel prize [20]. It is considered one of the top ten challenges of DS [40]. The causal framework plays an important role at leading enterprises, for example:

- **LinkedIn** - “At LinkedIn, we proved the usefulness of observational causal studies to the business ...”[4].
- **Uber** - “We have found it invaluable to bring causal inference methods to our work at Uber, as it enables us to solve challenging but critical data science questions that would otherwise be impossible to tackle...”[18].
- **Netflix** - “When A/B experiments are not possible, we rely on quasi-experiments and causal inference methods, especially to measure new marketing and advertising ideas.”[33].
- **Amazon** - “Focusing on causal effect leads to better return on investment (ROI)...”[34].

2.2 Necessary Assumptions for Causal Inference

Applying causal inference on offline data requires three necessary assumptions [22]. These conditions must hold to conceptualize an observational study as a conditionally randomized experiment [22]:

1. **SUTVA** - The values of treatment under comparison correspond to well-defined interventions, and the treatment of one unit does not interfere with other units. It also implies that outcomes of actions are consistent.
2. **No Hidden Confounding** - The conditional probability of receiving every value of treatment depends only on the measured covariates, formally known as **Ignorability**.
3. **Positivity** - The probability of receiving every value of treatment was greater than zero for every decision.

SUTVA means no hidden spillovers: the potential outcomes for a given unit are not influenced by actions on other units. The same action on the same unit is assumed to result in the same outcome. The "No Hidden Confounder" requirement implies that sufficient information should be available about the factors that affect both the treatment and the outcome are known. For example, if a targeting email is sent mainly to people who intend to buy, the effect of the email will be overestimated if it is not adjusted for that intention (see [4] for concrete numerical examples). The positivity requirement implies that every action probability is larger than zero for every decision. For example, if we never send emails to males, we can’t determine the counterfactual predictions of emails for males.

2.3 Uplift Modeling

One specific useful approach to causal inference is uplift modeling [9, 30, 42]. Uplift modeling originates from a typical evaluation metric in marketing: the expected difference in outcome between the treated group and the control group (when the action is binary),
also known as uplift [37]. In the simplest version, one determines the average treatment effect (ATE) of a whole population, but usually, uplift modeling estimates the individual treatment effect (ITE), also known as conditional average treatment effect (CATE). The ITE allows optimal target audience selection: target only people whose predicted effect is positive [10]. If constraints exist such as costs of targeting, one can use optimization techniques to find the overall optimal policy based on the ITE estimations [14]. Determining the uplift performance for many different effect thresholds results in an uplift curve as shown in Figure 3. The two extreme points represent treating no one (A) vs treating everyone (B), two options in a common A/B test. As can be seen, the optimal policy is neither A nor B but somewhere in between. The ITE predictor can improve results compared to treating everyone (B) or no one (A) by utilizing the heterogeneity of the population. Notice that most uplift literature is focused on estimating ITE based on randomized control trials (RCT). To deal with observational data one needs to correct for biases [17].

3 THE PRESCRIPTIVE MODELING CANVAS

In the previous sections, we’ve elaborated on aspects and requirements of prescriptive modeling and the related techniques. It may seem daunting to design a successful prescriptive project. Therefore, we propose a canvas, as shown in Figure 4, to guide conversations between data scientists and business experts. It provides them with a structured checklist, that ensures important information is collected and easily verified.

The canvas follows the recommendation of Microsoft’s Team Data Science Process (TDSP) [3] regarding the first stage of “business-understanding”. It also expands on the “Drivetrain Approach” explained in “Designing Great Data Products” [23], as it emphasizes the levers (actions) that truly modify business results. It also has some similarities with the popular checklist template named the ML canvas [11], by focusing on a clear problem definition from the data scientist’s perspective. However, we combine the business levers with a prescriptive problem definition including actions and policies, and add a clear evaluation plan. The canvas drives questions along the following three dimensions:

1. **Business impact**: The scope of the project, with a definition of success.
2. **Policy definition**: A specification of the problem in such a way that prescriptive methods can be applied.
3. **Policy validation**: Applying and validating the resulting policy.

3.1 Business Impact

The first column in the canvas ensures that the goal of the project, from a business perspective, is clear. It requires (1) a clear metric to optimize, (2) an action that we control, and (3) a decision process.

The key performance indicator (KPI) is the single, aggregated number, to be optimized by the newly created policy. This single metric, also known as the Overall Evaluation Criteria (OEC), forces trade-offs to be made between possible multiple metrics and aligns the organization behind a clear objective [26].

The action is the lever that impacts the KPI. To determine a policy, we need to know which actions can be prescribed. While we put a lot of focus on the action, the policy can only perform a decision, which might not always lead to the decided action due to interfering processes. Investigating that interference allows us to adjust for biases and distinguish between good decisions and good actions.

The policy will change, or replace part of, the current decision process. We first need to know how to integrate our optimal policy. We can also discover which information currently is used in the decision process. These probably make good features for the policy model. They can also indicate possible sources of bias, which will need to be adjusted for.

3.2 Policy Definition

The Policy Definition column maps the business perspective to a data perspective. The resulting formal policy definition allows us to apply prescriptive techniques. Here we construct explicit definitions for (1) units, (2) treatment, and (3) outcomes.

Based on the analysis of the Decision we can define the unit, which is a combination of an entity (like a customer, website visit, subscription) and a decision-moment, the point in time the action is decided. It implies the granularity of the policy, how to define the rows for modeling, and explicitly states the eligibility: which units are included, and which are not.

The policy version of Action is the treatment. Firstly it specifies which actions the policy can prescribe at which granularity. For example, to include calls and emails, but not SMS. But also whether to group them into one treatment “to contact”, or to separate them into different actions. Secondly, it specifies how to map logged observational data to actual treatments. Based on the influences analyzed in the Action section, one might want to exclude certain actions. For example, one can regard calls as treatments, but exclude calls when the customer scheduled such a call. Thus the treatment definition specifies for each unit, which action was observed, and whether the unit can be included.

While the KPI was a single aggregate value, the outcomes defines the metric for each unit that needs to be optimized. If the KPI would be the churn rate, the outcome could be “churned within a month after we decided to call or not”. Note that the outcome is defined as a measurement through time, starting at the decision-moment, for each unit.

3.3 Policy Validation

By specifying the policy validation approach, one firstly ensures that the policy actually can be validated. It will also identify technical work that needs to be done to measure the policy quality, which often can be started before the optimal policy has been created.

First, we translate the outcome to measurable Evaluation Metrics. In the churn case, one might use a 3-month horizon in the policy definition but evaluate with a short-term proxy ‘churned within 1 month’ to reduce delays. The data scientist can verify the relationship between the proxy and the true outcome.

One needs to prepare Tracking, such that taken decisions and actions can be linked to the policy output.

In Compliance we will verify how performed actions correspond to taken decisions. Compliance will not be 100%, as indicated by the previously specified interference. Therefore, the effect of
Figure 4: The Prescriptive Modeling Canvas. Example for churn prevention use-case is in Cyan.

**GOAL**
The company-wide objective.

Which KPI is to be improved?

Decrease total number of churned customers per month.

**OUTCOMES**
The metric per unit to be optimized.

For one specific unit, what outcome is measured? On what timeline?

Requesting to cancel the subscription within 3 months after the decision date.

**EV ALUATION METRICS**
Short term metrics that proxy the KPI.

Which near-term metrics indicate our actions were successful or not?

Requesting to cancel the subscription within 1 month after the decision date.

We also show the running total of the 3-month rate for every past week (up to 3 months).

**ACTION**
The lever, initiated by the business, impacting the KPI.

Which actions will change? Which actions interfere with each other? How do these impact the KPI? Who is performing these actions? Do we always initiate the action?

Customer success agents contact existing customers to proactively support them.

There is a constraint on the number of customers that can be contacted.

The agents also need to onboard new customers, limiting the available time.

**TREATMENT**
The action done to each unit to influence the outcome.

Which actions do we want to prescribe? When are these initiated by us? Which situations should we exclude (not to learn from)?

An agent will call, sms, and/or email the customer.

We exclude units if the customer contacts us, or requests to be contacted, before our outgoing call.

We also exclude units from the training set if they were contacted for other campaigns the past 2 months.

**TRACKING**
How to log decisions and actions?

How can we compare with the current situation?

Each week a selection of customers is made:

- A small random group, to compare against
- The top N from the predictive model
- The top M from the prescriptive model

Customers that have been contacted (either by this campaign or others) in the previous 2 months are excluded.

**COMPLIANCE**
Interference between decision and action.

Are there business rules, systems, domain experts, or other influences that overrule made decisions?

We track when customers didn't accept the call, immediately hung up, had invalid contact details, were skipped due to resource constraints. We also track inbound calls.

**DECISION**
The process of determining the action.

When is the action decided? Who makes the decision? How is the decision made? Which information is used to decide?

Currently a predictive model marks customers as likely to churn. Every week a list of customers to contact is created. The agent contacts customers from this list day by day, in an order he/she decides.

The list is typically longer than possible to contact, to ensure agents don't run out of work.

Sometimes customers file complaints or support tickets that require them to be contacted.

**UNIT**
The definition of entities and decision moments.

On what granularity are decisions made? In the lifetime of an entity, when and how often do we make decisions?

Every current existing customer, on the first day of every week.

Only customers whose renewal date is within 3 months.

Only customers that haven't opted out of being contacted.

No customers that are part of other campaigns.

**DELIVERY**
The method to provide the new decisions.

How? How often? When?

We run predictions every last day of the week at 7 AM, which are delivered to the agents call software through internal ETL processes.

Each expected influence should be measured. This allows to verify the identified processes and one might be able to discover other not yet identified processes that also interfere. The delivery of decisions also needs to be prepared, such that the end-user can act on the prescribed actions. How and when will the policy be applied to new data? Is all the data available at that moment instead of being logged with a delay? How will the end-user be able to consume the decisions, and through which systems?
4 SUMMARY

In this paper, we point out that the predictive approach is the common one in data science, even though it is not the optimal framework for optimizing business goals. We then present the prescriptive approach and emphasized its benefit in optimizing policies which in turn provides better business value. We also explained the challenges in the prescriptive approach, together with an overview of different approaches for prescriptive modeling. Causal inference and specifically uplift modeling were highlighted, as we believe these are underutilized, even though they represent three out of the top ten (3/10) essential most practical methods in DS [28] (Sections 4.8, 4.1 and 4.2, respectively). We finalize the paper with a “Prescriptive Canvas” which aims at helping data science managers, product managers, and practitioners in framing ML projects from a prescriptive perspective, which we strongly believe can help the project’s success probability.

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