A Causal Approach to the Study of TCP Performance

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Communication networks are complex systems whose operation relies on a large number of components that work together to provide services to end users. As the quality of these services depends on different parameters, understanding how each of them impacts the final performance of a service is a challenging but important problem. However, intervening on individual factors to evaluate the impact of the different parameters is often impractical due to the high cost of intervention in a network. It is, therefore, desirable to adopt a formal approach to understand the role of the different parameters and to predict how a change in any of these parameters will impact performance.

The approach of causality pioneered by J. Pearl provides a powerful framework to investigate these questions. Most of the existing theory is non-parametric and does not make any assumption on the nature of the system under study. However, most of the implementations of causal model inference algorithms and most of the examples of usage of a causal model to predict intervention rely on assumptions such linearity, normality, or discrete data.

In this article, we present a methodology to overcome the challenges of working with real-world data and extend the application of causality to complex systems in the area of telecommunication networks, for which assumptions of normality, linearity and discrete data do no hold. Specifically, we study the performance of TCP, which is the prevalent protocol for reliable end-to-end transfer in the Internet. Analytical models of the performance of TCP exist, but they take into account the state of network only and disregard the impact of the application at the sender and the receiver, which often influences TCP performance. To address this point, we take as application the file transfer protocol (FTP), which uses TCP for reliable transfer. Studying a well-understood protocol such as TCP allows us to validate our approach and compare its results to previous studies.

We first present and evaluate our methodology using TCP traffic obtained via network emulation, which allows us to experimentally validate the prediction of an intervention. We then apply the methodology to real-world TCP traffic sent over the Internet. Throughout the article, we compare the causal approach for studying TCP performance to other approaches such as analytical modeling or simulation and and show how they can complement each other.

CCS Concepts: ● **Mathematics of computing** → **Bayesian networks**; **Causal networks**; *Bayesian computation*; ● **Networks** → **Network performance analysis**; *Network performance modeling*; Transport protocols; Network measurement; Public Internet; ● **Computing methodologies** → **Causal reasoning and diagnostics;**

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1. INTRODUCTION

The Internet is an interconnection of many different networks. Each network is only required to offer a very simple service, namely to forward a packet to the next hop toward its final destination. Most of the complex operations are executed in the end-hosts. One example of a protocol executed in the end-hosts is TCP, which offers a reliable data transfer between two end-hosts across the Internet that may loose, delay, or mis-order data. TCP carries the vast majority of today's traffic in the Internet as it is used by application layer protocols such as FTP, HTTP, or mail protocols. For more details we refer the reader to the textbook by Kurose and Ross [2009]. Given the importance of TCP, many studies have tried to model and evaluate the performance of TCP. The performance metric used most often is *throughput*, which is defined as the number of bytes delivered per second to the receiving end-host. As we will see, the throughput of a transfer between two end-hosts depends on various parameters such as the average time for a packet to travel between these two end-hosts, which is commonly referred to as round trip time (RTT), or the loss rate experienced, which expresses the percentage of packets that will not reach the destination but get lost due to events such as temporary resource shortage in the network. Aside from modeling the throughput, one also would like to understand the inter-dependencies that exist between the various parameters that all impact the throughput.

The inference and representation of causal models as Bayesian networks provide very powerful tools that we apply to study the performance of TCP and the relationships between the various parameters. When we represent these relationships via a directed acyclic graph (DAG), interventions on individual parameters can be predicted with simple graphical criteria by using data collected prior to this intervention. As interventions on communication networks are expensive or even impossible to carry out, being able to predict them without the need of performing complex and costly controlled experiments represents an important advantage.

However, various challenges arise when trying to apply the existing methods for causal model inference and for intervention prediction in the case of the transport protocol TCP. Indeed, studying TCP performance involves working with a mix of both discrete and continuous parameters whose distributions cannot in general be approximated by normal distributions. Additionally, their dependences do not follow any known functional form, and in particular are not linear. We believe that the challenges of working with data that are non-linear and not normal are common to many real-world scenarios. As we will see later, tools such as WISE [Tariq et al. 2008] or NANO [Tariq et al. 2009] that were proposed in the context of network traffic to study parameter dependences based on their partial correlation do not give the correct results in such scenarios. In this article, we use the do-calculus [Pearl 2009] and non-parametric estimation of multivariate distributions to develop a simple yet formal approach to estimate the effect of interventions on a system where the assumptions of normality and linearity do not hold. Through this work, we show that even when dealing with more complex systems where many existing implementations of causal model inference would fail because they rely on assumptions that do not hold, the causal theory can be applied and give very good and insightful results provided that the adequate recent tools are used appropriately for inference and estimation.

Our contribution can be summarized as follows.

—We show how to adapt the existing methods for the causal study of real systems whose data are non-linear and not normally distributed.
—To corroborate the soundness of our approach, we perform experiments in a controlled environment where the predictions of interventions can be validated.

—We successfully apply our method to perform the causal study of the performance of TCP used by a file transfer (FTP) application that transmits large amounts of data over the Internet.

—The methods presented are tested and validated through the study of TCP performance, where we illustrate the benefits of adopting a causal approach and ompare it with other approaches.

The theory of causality as developed in Pearl [2009] and Spirtes et al. [2001] is non-parametric, does not make assumptions such as linearity or normality, and is not restricted to discrete data. However, most of the implementations of causal model inference methods (PC, GES, Lingam or FCI implementations in Tetrad, bnt toolbox or Pcalg R package) suppose linearity or normality.[1] Similarly, the examples of predictions of interventions in these works [Pearl 2009; Spirtes et al. 2001] only consider discrete data where probability distribution studies can be simplified by the use of conditional probability tables. Dealing with real data, where these assumptions do not hold, poses a number of challenges.

Section 2 discusses the characteristics of TCP and the parameters that impact its performance while Section 3 shows how to adapt existing methods to the nature of these parameters and overcome the challenges of working with continuous data where no distribution or functional form can be assumed.

Once the framework of our work presented, we evaluate in Section 4 our approach on data obtained using the Mininet emulator. Section 5 presents a case study of the performance of TCP using real data obtained via file transfers over the Internet that illustrates the interest of causal modeling for network performance prediction. Section 6 compares our approach using causal modeling to other approaches discussed in the literature. Conclusions and some directions for future work are presented in Section 7.

2. TCP

2.1. Overview

In this section, we present TCP and the different parameters that are known to impact its performance. We discuss the different constraints inherent to the study of network performance and how they are handled in our work.

TCP is very widely used in the Internet, which makes it easy to collect traces. TCP has been well studied and there is a good understanding of the different factors that influence its throughput performance. However, the efforts to study the performance of TCP analytically or via simulation typically concentrate on capturing the impact of the *network* on TCP performance and ignore the impact of the TCP sender or receiver. On the other hand, studies of real TCP traffic have shown that it is often not the network that determines TCP performance but receiver limitations or sender limitations [Zhang et al. 2002; Siekkinen et al. 2008]. These mechanisms are captured by our model, as we can see later in Figure 4. In the case of receiver limitations, the application at the receiver side is not able to consume data fast enough, in which case the TCP receiver will slow down the sender via flow control. In case of sender limitations, it is the sender that controls the rate to the transmission, which will then determine TCP throughput performance. Another reason for choosing TCP is that we have a long experience studying TCP in the "wild," which helps us interpret and validate the causal graphs we obtain.

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[1]Note that, in the case of the PC algorithm, it is the absence of an independence test for non-linear non-Gaussian data that prevents its usage in our case. In the current release of Tetrad (5.1.0-6), the test from Ramsey [2014] is now available. This test was not present at the beginning of our work and is now under investigation.

TCP is a relatively complex protocol that implements not only mechanisms for error control and recovery of lost packets but also mechanisms to react to network congestion by adapting its sending rate to the load of the network. While we cannot describe these mechanisms in detail, it is important to keep in mind that, at a given moment, the sending rate will be controlled by two parameters, namely the *receiver window* and the *congestion window*. The *receiver window* indicates the quantity of data that the receiver can handle, while the *congestion window* regulates the rate at which the sender can inject packets into the network as a function of the load along the path between the two end-hosts.

2.2. TCP Performance Modeling

In our work, we study the throughput performance experienced by a host that uses TCP. Padhye et al. [1998] were among the first to give a formula that expresses the throughput of TCP as a function of the different parameters, which captures the network and operating conditions. A simplified version of this formula is given by

$$throughput = C \cdot \frac{MSS}{RTT \cdot \sqrt{p}} \tag{1}$$

and will be referred to later in this article as the **PFTK model**. In this equation, *MSS* (maximum segment size) represents the maximum amount of data that can be carried in a single packet, *RTT* (round trip time) represents the time it takes for a packet to traverse the network and its acknowledgement to get back to the sender, p denotes the probability that a loss happens, and C is a constant. The only parameters that can vary dynamically when the state of the network changes are *RTT* and p. As we can see, the throughput depends in a non-linear way on the parameters *RTT* and p. The PFTK model was experimentally validated via real data transfers using TCP among end-hosts located in different parts of the world.

The throughput formula of Equation (1) has some limitations: It assumes that the network congestion is the only limiting factor, that is, it does not consider receiver limitations, it is only valid for the version of TCP that is called TCP Reno, and it assumes that *RTT* and p are independent. Many extensions to the PFTK model have been proposed in Fortin-Parisi and Sericola [2004], Kaj and Olsén [2001], and Sikdar et al. [2001]. The causal method we present in this article does not need to make these assumptions. However, to validate our approach, we focus on TCP Reno because this will allow us to use the PFTK model to interpret our result and compare it with the throughput obtained using Equation (1).

TCP is a protocol implemented in every end host connected to the Internet. The load of the network path between two hosts exchanging data on the Internet is not known a priori. Each TCP sender dynamically estimates parameters that capture the state of the network and adapts the rate at which the data is sent accordingly. In our study, we are interested in TCP performance when dealing with the network variations, without looking into its implementation details. While the parameterization of the TCP implementation and the causal study of TCP performance could be complementary, the methods we propose in this article aim to be applicable to a broader range of systems and do not focus on any particular implementation of TCP.

In addition to the inherent non-linearity of the dependencies of the TCP parameters, another important property is the distribution and the variation of the values of these parameters. The datasets we are working with consist of a mix of discrete and continuous parameters whose values cannot be approximated by normal distributions. These considerations play an important role when working with the densities of the parameters.

2.3. Measuring TCP Performance

Compared to cases such as social science or medical studies, a big advantage of studying network performance is the relative ease with which data can be obtained. While, as in every real-world experiment, not all the variables can be observed, many of them are available, and it is relatively simple to record the traffic at a given point in the network. However, the presence of latent variables is an important concern. Latent variables are variables that are not or cannot be observed but impact more than one of the observed variables.

TCP is a transport protocol that is used by an application to transfer data reliably from the sender to the receiver. In this article, we consider a file transfer (FTP) application where large files are transmitted from the sender to the receiver using TCP. We investigate two scenarios: The first scenario studies the performance in an emulated environment (c.f. Section 4), and the second scenario comprises a real FTP sender at our university to which the receivers from all over the world connect in order to perform file transfers (c.f. Section 5). In both cases, we perform hundreds of file transfers and passively capture all the data packets sent by the FTP sender. All the packets that belong to the transfer of a single file form a **connection** and each connection corresponds to one sample in our dataset.

Once these packet captures made, we perform an offline analysis using the Tstat and Intrabase tools [Mellia et al. 2005; Siekkinen et al. 2005] to extract the values of the key parameters for each of the connections. The full list and description of the parameters can be found in the Appendix C.1. Examples for parameters are loss rate, round-trip time, or receiver window. Since a connection may last for several minutes, the values of the parameters can vary over the lifetime of a connection. For each connection, we compute the *average value* for each parameter. We will come back to the issue of the sampling frequency of the parameters in Section 7, and we discuss the issue of how to choose the set of parameters that are needed to model our system in Section 3.1.4.

As we show in the following sections, using causal graphs to model TCP *at the level of connections* will allow us to obtain a meaningful model that can be used to make predictions about the effect of interventions on the system.

3. CAUSAL METHODS

In this section, we first review some of the existing methods to build a causal graph from observational data, evaluate the performance of the methods that apply to our data, and justify the methodological choices we make. Finally, we show how to use this model to predict the effect of interventions in our system.

3.1. Inference of Causal Models

In our work, we only consider graphical causal models represented by Bayesian networks. Other models, such as structural equation models, exist. However, the use of Bayesian networks presents many advantages, the main one being the existence of simple graphical criteria to infer the mathematical equations to predict the effect of interventions [Pearl 2009; Spirtes et al. 2001]. In addition, the Bayesian networks offer a concise visual presentation of the different causal dependences, which greatly simplifies the understanding and manipulation of complex systems.

3.1.1. Algorithms. Inference algorithms for graphical causal models can be divided roughly into two categories: The score-based ones and the constraint-based ones. The score-based methods solve an optimization problem: The graph is built step by step and the progression is dictated by the optimization of an objective function matching the actual graph with the given data. There has been an important progress in recent years in "exact Bayesian network inference" using score-based approach: the exact posterior

probability of subnetworks (edges, Markov blanket, etc.) is computed to search for the best Bayesian network fitting the input data. Koivisto [2006] and Koivisto and Sood [2004] propose an algorithm with lower than super-exponential complexity in the number of parameters of the system. These algorithms always converge and allow to stop at any moment obtaining a graph with a lower bound on its accuracy. However, in these algorithms, *completeness* is assumed (all the variables are observed), and the parameters have to follow a normal distribution. These hypotheses do not hold in our work.

Constraint-based methods build the graph in two steps. First, an undirected graph (skeleton) is built and in a second step the edges are oriented. The inference of the skeleton starts with a fully connected graph (i.e., a graph in which every vertex is connected to any other vertex). Then we test all the possible independences between the different parameters and remove an edge connecting two vertices when their corresponding parameters are found to be independent. This first phase consists of a series of independence tests. In the PC algorithm [Spirtes and Glymour 1991], the sequence of tests can be optimized to decrease the number of independences to test. In the PC algorithm, we start with a fully connected graph and test all the unconditional independences, removing an edge between two nodes whose corresponding parameters are found independent. For the parameters whose nodes are still adjacent, we test if there exists a conditioning set of size 1 that makes two adjacent nodes independent. If such set exists, we remove the edge connecting the corresponding two nodes; otherwise, the edge is not removed. This step is repeated, increasing the conditioning set size by one at each step, until the size of the conditioning set reaches the maximum degree of the current skeleton (the maximum number of adjacent vertices for a given vertex), which means that no more independence can be found. The second phase, the orientation of the edges, can be performed using two different methods. One method orients the colliders (subgraphs $X - Z - Y$, where X and Y are not adjacent) in a first step and then orients as many edges as possible without creating new colliders or cycles [Pearl 2009] in a second step. The second method, which is implemented in the kPC algorithm, is based on Weakly Additive Noise (WAN) models [Tillman et al. 2009] and tests the independence of residuals by conditioning on their regressor. To determine the orientation of a given undirected edge, the regression from a child on one of his parent leads to a residual independent of its regressor, while this is not the case if the regression is made from a parent on one of its children (assuming the WAN property holds).

When we started our study, we used the Tetrad software [Spirtes et al. 2001] to compare the graphs obtained for score-based methods and for different constraint-based methods. Tetrad implements many algorithms for causal model inference (as Bayesian network) such as the PC [Spirtes and Glymour 1991], GES [Maxwell 2002], or iMAGES [Ramsey et al. 2010] algorithms for Pattern inference, LiNGAM [Hoyer and Hyttinen 2009] for DAG inference, FCI [Spirtes et al. 1995], and FCI extensions for partial ancestral graph (PAG) inference (please refer to Tetrad documentation for an exhaustive list of the algorithms). Some of the proposed algorithms, such as LiNGAM, assumes linearity while for others, such as GES, iMAGES, FCI, or the PC algorithms, it is the Tetrad implementation that assumes either linearity or normality. More precisely, at the time of these tests, no independence test for not normal and not linear data was present. However, despite these limitations, it turned out that constraint-based methods give more informative graphs, which are more in line with our understanding of TCP performance. While these experiments did not prove that score-based methods will not give correct results for our data, we decided to use constraint-based methods for the rest of work.

The performance of the kPC algorithm, which uses non-linear regression, highly depends on the goodness of fit of the regression method used. As the dependencies between the parameters defining TCP performance do not follow any given functional

model, the graphical causal models we obtain with the kPC algorithm suggest that the existing non-linear regression functions could not correctly capture the dependencies as no orientations could be made in most of the cases (we present some of the models obtained with the kPC algorithm in Appendix D.1.6 and Appendix E.1.5). Therefore, we use the method relying on colliders for edge orientation for the rest of work.

It is worth noting that the PC algorithm is able to infer a causal model up to its independence equivalence class (called Markov Equivalence Class and represented by partially directed acyclic graph, PDAG). It often happens that several graphs exist that imply the detected independences (see Section 3.2.1 on the d-separation graphical criterion). As a consequence, the output of the PC algorithm is a graph where only the independences leading to a unique orientation of the edges are present. The other edges are left unoriented. In our work, we use the bnt toolbox implementation of the PC algorithm [Murphy 2001] and select the member of the equivalence class inferred by the PC algorithm based on our knowledge and understanding of TCP networks.

It often happens that domain knowledge informs us on the presence of a causal dependence between two parameters of our model ($X \rightarrow Y$) or, on the opposite, on the absence of a causal dependence between two parameters ($X \not\rightarrow Y$). Such knowledge can be used in the inference of a causal model consistent with both, the detected independences and such knowledge. Meek [1995] presents an algorithm that in the absence of latent variable is able to infer a causal model that is consistent with both, the detected independences and a prior background knowledge. The set of rules presented in Meek [1995] is proved to be sound when no latent variable is present and the graphical causal model can be represented by a DAG, or its Markov Equivalence Class can be represented by PDAG. In the event of latent variables present in the model, the inference of a causal model, where indirect dependencies can be present, is more complex [Spirtes et al. 1995]. However, Borboudakis and Tsamardinos [2012] also propose a set of procedures to make use of prior domain knowledge to infer the Maximum Ancestral Graph that represents the (possibly indirect) dependencies between the parameters of the system that one is trying to model.[2]

3.1.2. Independence Test. The choice of the independence test is essential for inferring the correct graph. In the different implementations of the PC algorithm from Tetrad [Spirtes et al. 2001], bnt toolbox [Murphy 2001] or the Pcalg R package [Kalisch et al. 2012], the Z-Fisher independence criterion is used.[3] The Z-Fisher test assumes linearity and normality of the data. It was shown [Voortman and Druzdzel 2008] that the PC algorithm, with the Z-Fisher criterion, still performs correctly when relaxing the assumption of normality. However, the non-linearity has a strong negative impact on its accuracy. Our own tests on artificially generated data to study the effect of non-linearity and non-normality on the accuracy of the Z-Fisher criterion confirmed these conclusions (see Appendix A for more details).

To better take into account the nature of our data we use a different independence test that takes into consideration the non-linearity of the dependencies between the different parameters and their distributions. The Kernel Conditional Independence test (KCI) from Zhang et al. [2012] defines covariance operators in the Reproducing Kernel Hilbert Spaces (RKHS) corresponding to the parameters being tested and derives a statistic which distribution can be estimated under the hypothesis of independence. This independence test is very similar to the Hilbert Schmidt Independence Criterion (HSIC) [Gretton et al. 2007], the statistics of the two tests being

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[2]Note that this prior domain knowledge can be used in existing implementations of graphical causal model inference algorithms present in tools such as Tetrad or the BayesNet Toolbox.

[3]As mentioned in the footnote 1 (page 2), recent versions of Tetrad implement a test for non-linear and non-normal data that we are currently investigating.

exactly the same in the unconditional case. The use of kernel based independence test was proposed to handle the cases where no formal functional dependence or distribution can be assumed from the data. As we show in Appendix A, the KCI test achieves better performance than the Z-Fisher criterion when tested on our data. However, its implementation has two problems. First, the computation time to perform independence tests with this criterion is much longer than for the Z-Fisher test, in particular to test the conditional independences. Second, the implementation of the KCI test uses matrix operations (Cholesky factorization) that, although theoretically well justified, may fail due to numerical issues. In this case, the test will not return an answer. However, these two problems can be avoided by using datasets of smaller size (or sub-datasets) but at the expense of a possible loss of accuracy.

To solve these two problems, we modified the independence test by including a bootstrap method [Davison and Hinkley 1997], which works as follows. For each independence test of $X \perp Y \mid Z$ (X independent of Y conditionally on Z), we re-sample the dataset (with replacement) and create l new sub-datasets of N samples. The test is performed on each re-sampled sub-dataset (by comparing the p-value to an objective level of significance of the test, often denoted as α), and we accept the independence if a percentage of at least δ of sub-tests detects that the variables are independent. As shown in Appendix B.3, this testing procedure KCI+bootstrap does not decrease the accuracy compared to the KCI test on the full dataset as long as N is large enough. On the other side, it offers a number of very valuable advantages. First, it reduces the computation time and offers an easy and efficient way to parallelize the computation on different machines. Second, it reduces the numerical issues due to Cholesky factorization and, therefore, allows to obtain a more accurate result in cases where the KCI test on the full dataset would simply fail. Also, the bootstrap method offers a way to estimate the confidence in the result of the independence tests.[4]

3.1.3. Study of KCI Test Performance and Choice of Parameters. Appendix B presents a detailed study of the KCI+bootstrap procedure in terms of computation time and accuracy. Here, we briefly summarize the main results that justify our choice of parameters.

Choice of δ, the Threshold Percentage of Accepted Tests. We choose $\delta = 0.5$, which corresponds to comparing the median p-value obtained on all re-sampled sub-datasets to α. The parameter δ is related to the significance level of the sub-tests (α). Its value reflects a trade-off between error of type I and type II: one can increase δ to decrease the risk of type I error (wrongly accepting an independence) with the drawback of increasing the risk of type II error (rejecting a valid independence) or decrease δ to reduce the risk of type II error but increase the risk of type I error.

Choice of the N, the Sub-Dataset Size in the Bootstrap Method. The accuracy is, to some extent, dependent on the variability of the data. If the variation in the dataset is important, more data is required to capture an independence, with a number of observations increasing with the size of the conditioning set. However, increasing the size of the sub-dataset has a strong impact on the computation time. Our experiments showed that, for our system, choosing $N = 400$ yields no degradation in accuracy (which is not the case for values smaller than 400). For $N = 400$, computation time is reasonable, while the computation time increases very fast for larger values. For example, for a conditioning set of size 1, a test with $N = 400$ lasts less than 30s, while for $N = 500$ it already lasts 1 minute (see Figure 9 Appendix B.2.2). Consequently, we choose $N = 400$.

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[4]We did not further investigate this option in our study.

Choice of l, the Number of Repetitions of the Bootstrap Method. While large values of l are often advised in the bootstrap method [Andrews and Buchinsky 2001], the number of repetitions is often dictated in practice by computational constraints. In Table IX of Appendix B.2.2, we present estimations of the computation times for different values of l. Based on these real constraints, we choose $l = 100$. This choice was initially based on preliminary experiments showing that the bootstrap results become stable beyond 100 repetitions. This choice is also confirmed by the results concerning the accuracy (c.f. Appendix B.3, which shows that using $l = 100$, together with $N = 400$, yields the same accuracy of the KCI test on the full dataset).

Additional Remark. The choice of the values for δ, N and l values represents a trade-off between computation time and accuracy. This choice most likely depends on the dataset. Therefore, a learning phase may be necessary to determine the best value for these parameters. As the final goal is to detect the underlying independences between the different variables of the model, the parameters δ, N, and l cannot be fixed through the study of a real case scenario where the independences are not known. To solve this issue, we generated an artificial dataset where the parameters follow distributions similar to the ones of the parameters of the system we are studying and where the dependences are defined based on the knowledge we have of the system that we want to study. This learning phase and its results are presented in Appendix B where, for two different scenarios, the parameterization $N = 400$ and $l = 100$ is validated.

3.1.4. Feature Selection. A last point that we would like to mention briefly concerns the choice of the parameters that will form the nodes of the Bayesian network representing the causal model of our system. It is mainly domain knowledge that will suggest the parameters that impact the performance of the system being studied. In the event where our model does not include a parameter impacting more than one of the parameters being observed, such a parameter is called a *latent variable*. The presence of a latent variable makes the detection of the independence between two parameters more complex. In $X \leftarrow \mathcal{L} \rightarrow Y$, where $\mathcal{L}$ is a latent variable, X and Y might look dependent while they are not. Such a scenario makes a causal study more complex when there are back paths passing through $\mathcal{L}$ (see Section 3.2.2). The causal theory in Pearl [2009] and Spirtes et al. [2001] handles the presence of latent variables. However, as illustrated by the models presented in Figure 18 and Figure 23 in Appendix D.1.4 and Appendix E.1.3, respectively, the detection of latent variables is often complex. In our work, we use domain knowledge to define a set of parameters that forms a system where all the dependences are captured by the observed parameters, leaving ourselves the possibility to extend the list of parameters in the event of a possible latent variable preventing the inference of our system causal model. An example of such scenario is given in Appendix E.1.3.

3.2. Prediction

In this section, we assume that a DAG was obtained, and we summarize the different graphical criteria that are used in our work to estimate intervention from a causal graphical model. We use the notation $do(X = x)$ to represent the intervention that sets variable X to the value x.

3.2.1. D-separation. The d-separation criterion is a graphical criterion to judge, from a graph, the independence between two parameters, represented by their corresponding nodes. D-separation associates the notion of connectedness with dependence. Therefore, if there exists a directed path between two nodes, they are said to be d-connected and their corresponding nodes are dependent. On the other hand, if we condition on one of the nodes of this path, then this node is said to block the path and the parameters are

d-separated by this node. When studying d-separation, an important notion is the one of **collider** (a node where arrows meet head to head). The presence of a collider on a path blocks this path and conditioning on a collider unblocks the path.[5]

3.2.2. Total Effect vs. Direct Effect. In our work, we are interested in predicting the effect an intervention on one of the parameters will have on the system. By intervention, we mean that we isolate a parameter from the effect of any of its ancestors and we manually set its value (*atomic intervention* [Pearl 2009]). An intervention removes the influence of all external parameters on the (set of) parameter(s) of our intervention and fix its (their) distribution(s) according to the nature of the intervention. Only the distributions of the descendants of the parameters fixed by the intervention will be modified, and the ancestors will keep the distributions they were following prior to this intervention. Pearl [2009] calls the effect that an intervention has on all parameters the *total effect*.

On the other hand, one can be interested in the effect that one variable has on another, independently of the influence of any other parameter. This effect is referred to as *direct effect*. In the case of linear dependences, the direct effect can be computed by holding constant all the external variables and regressing Y on X (if interested in the direct effect X → Y). Instead of holding all the external variables constant, we can block their influences by conditioning on a specific set of variables, Z, and obtain the value of the direct of X on Y from the coefficient of the partial regression of X in the regression of Y on X and Z. However, when the assumption of linearity does not hold, the value of this coefficient of regression depends on the value at which Z is fixed. Without this assumption, the formal computation of direct effect is more complex [Pearl 2013]. For this reason, while the study of direct effects could give interesting insights, it is not central to our problem and left for future work.

To estimate the total effect, on a parameter Y, of an intervention on parameter X, we can use the *back-door criterion* or the *front-door criterion* [Pearl 2009]. In this work, we use the back-door criterion defined as follows.

Definition 1 (*Back-door criterion*). A (set of) variable(s) Z is said to satisfy the back-door criterion relative to an ordered pair of variables (X, Y) in a DAG G if:

(1) no node in Z is a descendant of X; and
(2) Z blocks every path between X and Y that contains an arrow into X.

Using the back-door definition, we can now predict the effect of an intervention with the following theorem:

THEOREM 1 (BACK-DOOR ADJUSTMENT). *If a set of variables Z satisfies the back-door criterion relative to (X, Y), then the causal effect of X on Y is identifiable and given by the formula:*

$$P(y \mid do(X = x)) = \sum_z P(Y = y \mid X = x, Z = z)P(Z = z). \qquad (2)$$

3.2.3. Density Estimation. We can see from Equation (2) that the estimation of the distribution of the parameters after an intervention relies on conditional probability densities of the parameters before this intervention. In Equation (2), the variables are assumed to be discrete, which is not the case for all variables in our dataset. In addition, the parameters we consider in our system do not have an a priori distribution nor can they be approximated with a mixture of known distributions such as normal, gamma, beta, and so on (see Appendix C.2 for examples of our parameter distributions

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[5]Intuitively, two independent causes become dependent if one conditions on their common consequence.

and [Nagode and Fajdiga 2011] for an example of an estimation of a univariate distribution with a mixture of pre determined distributions). We address these difficulties using copulae [Jaworski et al. 2010]. Copulae are models to build multivariate densities from their marginals. Some of their properties are summarized hereafter.

The Sklar Theorem stipulates that, if F is a multivariate cumulative distribution function with marginals $(F_1, \ldots, F_n)$, there exists a copula C such that

$$F(x_1, \ldots, x_n) = C(F_1(x_1), \ldots, F_n(x_n)). \tag{3}$$

In the bi-variate case, differentiating Equation (3) gives the following result:

$$f(x_1, x_2) = c(F_1(x_1), F_2(x_2)) f_1(x_1) f_2(x_2), \tag{4}$$

where $f_i(x_i)$ is the probability density function of the marginal F_i and c is the derivative of C. Assuming $f_2(x_2) > 0$ for all x_2, we have

$$f_{X_1|X_2}(x_1, x_2) = c(F_1(x_1), F_2(x_2)) f_1(x_1). \tag{5}$$

For the back-door criterion, we often place ourselves in the case illustrated in Equation (5). When $dim(X_2) > 1$, we use Equation (3) to estimate the multivariate CDF of X_2 and use this estimation in Equation (5).

Copulae, as any model, need to be parameterized and the choice of the copula to model the dependencies between the marginals should be dictated by the real dependencies. In our work, we chose T-copulae, as they better capture the tail dependencies between the parameters influencing the throughput.

The T-copula is an elliptical copula and, in the bi-variate case, is given by

$$C_{\rho,\nu}(u, v) = \int_{-\infty}^{t_\nu^{-1}(u)} \int_{-\infty}^{t_\nu^{-1}(v)} \frac{1}{2\pi(1-\rho^2)^{1/2}} \left(1 + \frac{x^2 - 2\rho xy + y^2}{\nu(1-\rho^2)}\right)^{-\frac{(\nu+2)}{2}} \mathrm{d}x\mathrm{d}y, \tag{6}$$

where ρ is the linearcorrelation coefficient and ν the number of degrees of freedom. One interesting property of the T-copula is the presence of more points (compared to the normal copula for example) in the tail.

The estimation of the marginals, in our work, is done via kernel functions. Once again, the choice of the kernel (normal, triangle, etc.) should be done according to the nature of the parameters we observe. We chose normal kernels, as they give smoother estimations of the marginals that will be the support for future predictions.

4. NETWORK EMULATION

In this section, we validate the approach described in the previous section in the context of network data obtained via emulations. We use the Mininet emulation tool [Lantz et al. 2010], which allows us to make interventions and compare the results to the predictions obtained from the causal graph.

4.1. Mininet Network Emulator

Mininet is a powerful network emulator based on container-based emulation (CBE) [Handigol et al. 2012]. It offers the possibility to run, on a single machine, a realistic network emulation with real kernel, switch, and application code. An emulator makes it easy to recreate different network conditions and manipulate different parameters to control the performance of the network. Mininet gives us access to four parameters to control the delay, the bandwidth, the loss, and the delay jitter of each link connecting two nodes in our network. In addition, each router has a buffer size that can be controlled to obtain different network behaviors.

However, like any emulator, Mininet has its own limitations, which we will discuss later in this section when we present and interpret the results. Nevertheless, using
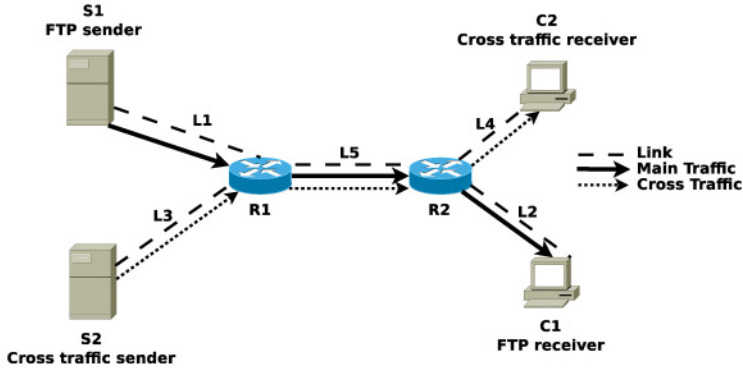
Fig. 1.   Emulated network using Mininet.

Table I. Summary of Mininet Network Emulation Experiments Dataset

Parameter	Definition	Min	Max	Avg	CoV
bw	minimum bandwidth (MBps)	1	25	7.1	0.91
delay	propagation delay (ms)	30	180	86	0.48
queue1	size of **R1** buffer (pkts)	10	400	98	1.10
queue2	size of **R2** buffer (pkts)	10	400	100	0.99
nlac	Narrow Link Available Capacity (kBps)	12	3,070	630	5.00
rwin	Receiver window advertised by **C1** (kB)	74	2,155	288	0.65
bufferingdelay	part of the RTT due to queuing delay (ms)	1	6,760	120	2.40
rtt	Round Trip Time (ms)	84	6,910	310	0.99
timeouts	number of timeouts (units)	0	682	79	1.50
retrscore	fraction of retransmitted packets (no unit)	0	0.61	0.04	5.10
p	fraction of loss events (no unit)	0	0.64	0.04	8.40
nbbytes	number of bytes sent by the server (MB)	6	150	110	0.21
tput	throughput (kBps)	6	1,100	280	0.81

this emulator serves well our purpose, which is validating the application of causal modeling to network performance prediction.

4.2. Experimental Setup

Figure 1 presents the emulated network we use for our experiments. The traffic is recorded at the FTP sender hosted by **S1** using the Tcpdump tool [FreeBSD 2009]. It consists of the different file downloads issued by the client **C1**. The traffic is going through the link **L1**, the router **R1**, the link **L5**, the router **R2,** and the link **L2**, allowing us to manipulate the different parameters along the path. To make the network traffic more realistic, we add a server **S2** serving requests from a client **C2** and generating cross traffic that will interfere with the transfers between **C1** and **S1**.

   Once we have captured the packet trace, we use Tstat [Mellia et al. 2005] and Intrabase [Siekkinen et al. 2005] to compute the different metrics summarized in Table I. The *delay* parameter represents the propagation delay between **S1** and **C1**, that is, the time for a bit to propagate, at a speed close to the speed of light, along the links connecting the two end-hosts. *Delay* does not take into account the impact of buffering. The loss event parameter (*p*) is closely related to the retransmission score (*retrscore*). *Retrscore* represents the fraction of retransmitted packets and is an approximation of the loss probability. Instead, *p* approximates the probability of a loss event. As losses in networks often occur in bursts (buffers, when overflowing, drop
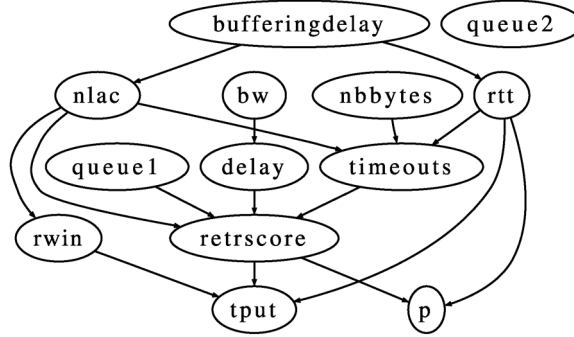
Fig. 2. Causal model inferred by the PC algorithm, with KCI test, for the emulated network traffic.

packets), an important parameter to observe is the occurrence of loss events which is approximated by p.

4.3. Causal Model

The causal graph of our emulated FTP traffic is presented in Figure 2. It was inferred using the PC algorithm with the KCI test, implemented with the bootstrap method (Section 3.1.2), for testing independence. We observe that the graph is globally in good accordance with the domain knowledge of how the different parameters impact the performance of TCP.

We see in Table I that the values of *retrscore* and p are very similar. This is due to the definition of p and a possible limitation of Mininet in the way the packets are dropped: the difference between p and *retrscore* is mainly due to the burstiness of losses happening in the network. Mininet uses internally Netem [Audrius et al. 2011] to simulate losses or the drop of packets by the router, which seems to drop only one packet at the time. This limitation could explain the difference in the orientation found between p and *retrscore* in the model presented in Figure 2 (*retrscore* $\rightarrow p$) and the orientation found in the real case scenario ($p \rightarrow$ *retrscore*, see Figure 4 in Section 5.2).

The models presented in Figures 2 and 4 both indicate that *rtt* impacts p. Such dependence is absent from the PFTK model and would be interesting to study, which we leave for future work. On the other hand, the presence of a causal relationship between p and *retrscore* is quite obvious, while its orientation is harder to explain, in particular when both parameters have very similar variations.

Taking into account the remark made previously about *retrscore* and p, we can see that the *rtt* and *retrscore* are two of the parents of *tput* (*throughput*). The third parent of *tput* is *rwin* (the *Receiver Window*), which, as we mentioned in Section 2.1, represents the capacity of the receiver to handle the quantity of data that is sent by the Server. The PFTK model assumes that the TCP performance is not "receiver limited" and ignores the parameter *rwin* in Equation (1). In the model of Figure 2, all the empirical parameters that are known to impact TCP throughput are correctly detected and shown as the direct parents of *tput*. In Appendix D.1.4, we present in Figure 18 the model obtained using the IC* algorithm [Pearl 2009], which indicates that there are no latent variables between the three parameters, *rtt*, *retrscore*, *rwin*, and the parameter *tput*.

The time a packet needs to cross the network is mainly influenced by the time it spends waiting in buffer queues. This fact is captured by the graph in Figure 2 where the *bufferingdelay* is the unique parent of *rtt*.

Finally, the existence of a dependence between the *Bandwidth* (*bw*) and the *Delay* (*delay*) is clearly the effect of the experiment design. In our simulations, we vary the

Bandwidth and the *Delay* to observe a broader range of situations and the choice of the values for these parameters is not totally random. The dependence found between *bw* and *delay* shows that the experiment setup creates a wrong association between these two parameters. However, it should not influence the validity of the model (the bandwidth is an exogenous parameter). On the other hand, it is interesting to see that the causal model correctly captures this dependence.[6]

4.3.1. Remark on the Z-fisher Criterion. Due to space constraints, the model we obtain with the classical approach that uses the Z-Fisher criterion to test for independence is presented in Figure 16 in Appendix D.1.2. We can see that this model is very different from the one presented in Figure 2, which shows the inadequacy of the Z-Fisher criterion to test for independence in the case of our dataset.

4.4. Predictions

In this section, we validate our approach to predict the effect of an intervention. For this purpose, we compare the prediction we obtain with the back-door criterion (Section 3.2.2) for the dataset Table I (and in the associated graph of Figure 2) to the performance observed in a controlled emulation where the same intervention is actually made. Given the model shown in Figure 2 and the interventions that we can perform, the best parameter to intervene on is the retransmission score (*retrscore*). The retransmission score can be well approximated by the sum of the percentage of packets dropped at the routers R_1 and R_2, a parameter we can manipulate in our emulated network. Our dataset consists of 1,100 connections, out of which only 355 connections experienced a loss. For 353 of these connections, the recorded *retrscore* is 0.01 (1%). As it can be seen from the back-door criterion, Equation (2), it is necessary to have, in our dataset, samples where the values of the parameter we want to set, by intervention, are observed. As the value of 1% for the *retrscore* is the most commonly observed, for this scenario, we will perform an intervention on the loss rate (*retrscore*), set its value to 1%, and estimate the impact of this intervention on the performance of our system (represented by the throughput).

To estimate the distribution of the *throughput* after intervention, we apply the back-door criterion (cf. Equation (2)) with the blocking set $Z = \{nlac, rtt\}$. This criterion ensures the identifiability of the causal effect representing the intervention on the retransmission score and, applying the back-door adjustment, provides us the way to compute the post-intervention distribution of the throughput. The result we obtain is an expected value of the *throughput* post-intervention of 82.67kBps. The one observed prior to the intervention was 280kBps, where most of the connections did not experience any loss.

To validate our approach, we make new experiments with Mininet, where we intervene on the retransmission score that we fix to 1%, which is very easy to configure in Mininet. The other parameters are unchanged and are the same as for the pre-intervention scenario. Now, the average *throughput* we obtain is 98.2kBps. This value is relatively close to the value predicted using the back-door criterion, which validates our approach.

To better appreciate the benefits of the causal approach, we compare it with the "naïve" approach. In the naïve approach, we select in our initial dataset the values of *throughput* corresponding to the observations where 1% of loss was observed, in which case we obtain an expected *throughput* of 133.09kBps. This means that the naïve approach significantly overestimates the post-intervention *throughput*. The

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[6]The experiment was repeated, selecting random values for the parameters of the simulation. The corresponding model is presented in Figure 15 in Appendix D.1.1.
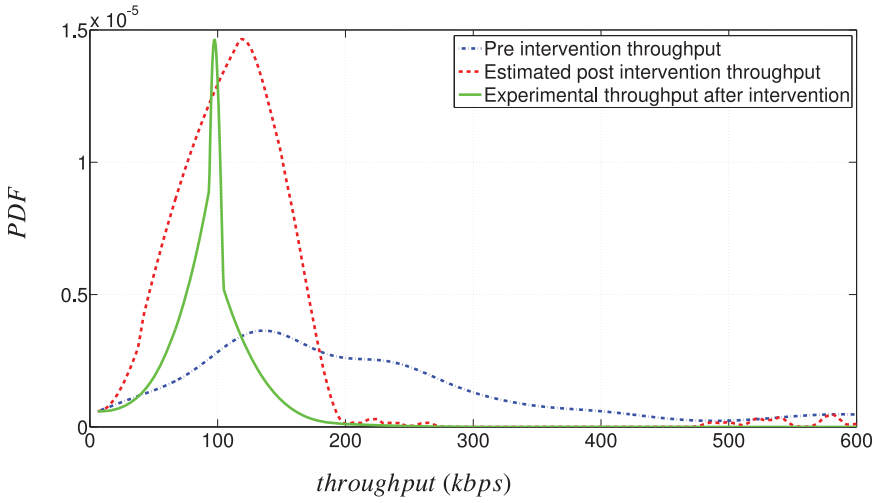
Fig. 3. Effect of an intervention on the retransmission score, on the throughput distribution.

naïve approach is equivalent to conditioning on *retrscore*. However, as we explained in Section 3.2.1, we must condition on non-collider nodes to block paths creating spurious associations (e.g., $tput \leftarrow retrscore \leftarrow ...rtt \rightarrow tput$).

If the back-door paths between *retrscore* and *throughput* are left unblocked, the expected throughput we obtain also takes into account the effect of other variables, such as *rtt* or *nlac*, on *retrscore*. As presented in Section 3.2.2, an intervention on the retransmission score (*retrscore*) consists in isolating *retrscore* from the influence of its direct and remote causes and in fixing its value (or distribution) as defined by the intervention. In this case, the impact of parameters such as *rtt* or *nlac* must still be taken into account, but their impact on the variable of intervention, *retrscore*, is spurious and must be neglected, which is implied by the back-door formula.

This result illustrates the superiority of causal approach over purely statistical ones. A study based on correlation where one, by finding the throughput and retransmission score correlated, would adopt the "naïve approach" to predict the effect of modifying the retransmission score would obtain a wrong result. The causal approach detects and blocks the spurious associations and allows for a correct estimation of the impact of interventions.

Figure 3 presents the probability density functions corresponding to the throughput prior to intervention (in dash-dot line), the post-intervention throughput estimated with the back-door criterion (dashed line) and the throughput observed when we manually modify the loss (solid line). Again, while not perfectly matching, the graph-based prediction (dashed line) and the real density after manual intervention (solid line) show similar shapes. In particular, both densities have a single mode around the same value(~100kBps). The fact that the experimental throughput values after intervention (solid line) show less variance can be explained by the small number of samples available to make the estimation. Also our method to estimate the post-intervention throughput (dashed line) uses normal kernels and a T-copula, which tend to widen and smooth the estimated post-intervention density.

In this section, we have validated the causal method using a network emulation system called Mininet where the prediction of an intervention could be tested. Despite the limitations of Mininet, the prediction we obtain validates our causal approach and demonstrates its usefulness. In the next section, we apply our causal approach to real traffic data sent over the Internet.

Table II. Summary of FTP Traffic Dataset

| Parameter	Definition	Min	Max	Avg	CoV
dist	distance between server and client (km)	14	620	250	0.95
tod	time of the day, beginning of the connection (s)	740	82,000	46,000	0.53
nbbytes	number of bytes sent by the server (MB)	6	60	32	0.51
nlac	Narrow Link Available Capacity (kBps)	48	43,000	5,900	1.70
nbhops	number of hops between client and server (hops)	9	27	11	0.24
rtt	Round-Trip Time (ms)	60	710	270	0.76
bufferingdelay	part of the RTT due to queuing delay (ms)	4.2	470	84	1.20
retrscore	fraction of retransmitted packets (no unit)	0.001	0.01	2e-3	0.92
p	fraction of loss events (no unit)	3e-5	0.01	7e-4	1.30
tor	fraction of *retrscore* due to timeouts (no unit)	0	0.01	6e-4	1.70
rwin	Receiver Window (kB)	11	254	137	0.68
tput	throughput (kBps)	24	928	332	0.77
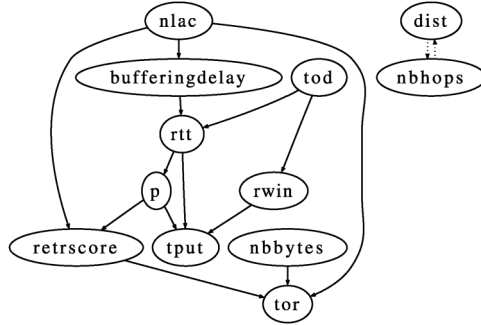
Fig. 4. Causal graph modeling FTP transfers for real traffic.

5. CAUSAL STUDY OF TCP PERFORMANCE UNDER FTP

We set up a real FTP server at our institute where we record all the incoming and outgoing traffic. The FTP clients are machines located somewhere else in Europe that download files from the FTP server. This scenario is more complex than the emulated one because more factors are unobserved, such as all the ones related to buffering and the network load, and observations are also subject to more variations, for example, in the path the packets travel.

5.1. Experimental Setup

In this experiment, we set up an FTP server in EURECOM in the South of France where all the traffic is recorded using the Tcpdump tool. Different receivers from France, Germany, and Spain are downloading several files, of different sizes and at different times, from that server. Using the Tstat and Intrabase tools, we compute from the packet traces the different metrics presented in Table II.

5.2. Causal Model

Using the PC algorithm with the KCI test, implemented with the bootstrap method (Section 3.1.2), we obtain the graph presented in Figure 4.[7] Below we discuss the most important features of the graph.

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[7]For more insights on possible latent variables, we refer the reader to Appendix E.1.3 and Figure 23, which presents the output of the IC* algorithm [Pearl 2009], where we can see that almost all parents of *tput* have marked directed edges, excluding the possibility of latent variables. The model obtained with the FCI (Fast Causal Inference) algorithm [Spirtes et al. 2001] is also presented Figure 24 in Appendix E.1.4.

First, we see that the graph is fully coherent with the domain knowledge of TCP. In particular, the parents of the *tput*, namely *{p,rtt,rwin}*, are the empirical parameters influencing the *throughput* and {*p,rtt*} are present in the PFTK model (*rwin* is not).

Another interesting outcome is that the timeouts, once normalized by the number of packets (*tor*), do not have an impact on the *throughput* (*tput*). Consequently, intervening on this parameter will not lead to a direct improvement of *throughput*. Intervention on a parameter can be seen as disconnecting this parameter from all its parents and creating a new parent that represents our intervention. As there is no path between *tor* and *tput* in the graph $G_{\overline{tor}}$ (the modified graph where all the edges entering the *tor* node are removed), there will be no effect on the throughput if we were to intervene on the *tor* parameter.

The causal graph shows a dependence between the *rtt* and *p*. Such dependence was already detected in the model presented in Figure 2 and mentioned in Section 4.3. The study of this dependence is out of the scope of this article but illustrates the limitations of empirical models such as the PFTK model.

This last point illustrates the advantage of a causal study over a purely statistical or empirical one, such as the model represented in Equation (1). By simply studying the correlations between *p* and *tput* and between *rtt* and *tput*, one would miss the dependence between *rtt* and *p* and obtain biased estimates, as it was the case when studying the intervention on the retransmission score in the emulated network, Section 4.4.

The presence of an isolated subgraph between *dist* and *nbhops* illustrates a remark we made for the emulated experiment. The distance is linked to the propagation delay, which was found not to have any dependence with the *RTT* (see Section 4.3). Similarly, the number of hops, approximating the number of routers traversed along the path from the client to the server, is highly dependent on the distance and does not present important variations in our dataset (see Table II). This remark shows an important factor that will impact the accuracy of the independence tests, and consequently the graph obtained by the PC algorithm: the variations in the values of the observed parameters. We can see from Table II that few losses are observed (*p* and *retrscore*). This means that the PFTK model, which bases its study on network congestion, does not capture mechanisms that often determine the TCP performance. As defined in Section 4.2, *p* represents the probability of a loss event while *retrscore* represents the probability of a packet loss. Given the difference between *p* and *retrscore* and the low values we observe for these two parameters, their relative and absolute variations make it difficult to fully capture their dependence.

The influence of the *time of the day* (*tod*) on the *RTT* (*rtt*) captures the peak hour effect, when the network is heavily loaded. On the other hand, the dependence found between the *time of the day* (*tod*) and the *receiver window* (*rwin*) is more subtle. It can be explained by the fact that a TCP client may implement the receiver window auto-tuning (RWAT) function [Ford et al. 2002] to adapt the size of the receiver window as a function of the bandwidth delay product (BDP), which, in turn, is influenced by the time of the day. However, intuitively we expect that the *tod* should impact the *RTT* and *narrow link available capacity,* which, in turn, would influence the *receiver window*. As the *narrow link available capacity* is computed using the PPRate tool [En-Najjary and Urvoy-Keller 2006], its estimation is less accurate when run at the server side where it can underestimate the path capacity. In this case, the effect that the peak hour (*tod*) has on the path capacity, which, in turn, impacts the receiver window, might not be captured by the estimate of the *nlac* parameter.

The path *nlac→bufferingdelay→rtt→tput* shows again that the buffering delay in routers traversed along the path from the server and the client is the main factor influencing the *RTT* and plays an important role in the TCP Performance.

5.2.1. Remark on Z-Fisher Criteria. Due to space constraints, the model obtained using the Z-Fisher criterion instead of the KCI test is presented in Figure 21 of the Appendix E.1.1. It should be mentioned that, as discussed previously, the model we obtain with the Z-Fisher criterion shows some properties in contradiction with how TCP operates and confirms that this criterion is not able to detect the independences for our dataset.

5.3. Prediction

Having inferred the causal graph of our system, we now demonstrate its usefulness to predict interventions on the three most important variables (see PFTK model, Equation (1)), namely *RTT*, *p*, and *rwin*. It should be noticed that, in this scenario, we cannot directly intervene on the network to validate the results as we could do in for the emulated network (cf. Section 4.4).

5.3.1. Intervening on the Round-Trip Time. From the causal graph presented in Figure 4, we want to predict the effect of manually intervening on the *RTT*. To do so, we use the back-door criterion (cf. Section 3.2.2), which ensures the identifiability of this intervention. There is one trek between *rtt* and *tput* blocked by *tod*.[8] We can apply the back-door adjustment, Theorem 1, with the blocking set $Z = \{tod\}$. As in Section 3.2.3, we use normal kernels to estimate the marginals of the *throughput* (*tput*), the *RTT* (*rtt*), and the *time of the day* (*tod*) and a T-copula to model the conditional probability density function of $f_{tput|rtt,tod}$.

We know from Table II that the value of the *throughput* before intervention has an average value of 332kBps, for an average observed RTT of 270ms. The intervention of setting the RTT value to 100ms gives an expected value of 480kBps, with a standard deviation of 176kBps (compared to 256kBps prior to intervention). This result is good in the sense that it shows that, by decreasing the value of the *RTT* and its variance, we can improve the *throughput* via intervention. We can precisely quantify the expected improvement in the *throughput* if we modify the *RTT*.

The improvement of the *throughput* (*tput*) when decreasing the *RTT* is an expected behavior of TCP performance. However, the naïve approach, which computes the effect of setting the *RTT* to 100ms by selecting observation where this value of *RTT* is observed, would produce an incorrect estimate of the post intervention *throughput*. Figure 5 compares the results of the two methods. The dashed line with cross markers represents the expected value of the *throughput*, for a given value of *RTT*, that will be obtained using *the naïve approach*. The solid line with diamond markers represents the expected value post-intervention computed with the back-door criterion adjustment. We also added the information of the number of samples that were used to compute the different values of the *throughput*.

We see in Figure 5 that the expected value of the *throughput* after intervention is smaller than the value we would obtain with the naïve approach. This result is supported by our causal model, Figure 4, where conditioning on *RTT* to predict the *throughput* also takes into account the effect of the *receiver window* on the *RTT*. As mentioned in Section 4.4, when studying how an intervention on a parameter, *X*, would impact *Y*, all external variables ($\notin \{X, Y\}$) maintain their dependence with *Y* but not via their (possible) dependence with *X*, whose behavior is only dictated by the intervention. Therefore, the impact of the *receiver window* on the *RTT* is spurious and must be neglected, which is done in our approach by the use in the back-door formula

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[8]"A trek between distinct vertices *A* and *B* is an unordered pair of directed paths between *A* and *B* that have the same source, and intersect only at the source" [Spirtes et al. 2001].
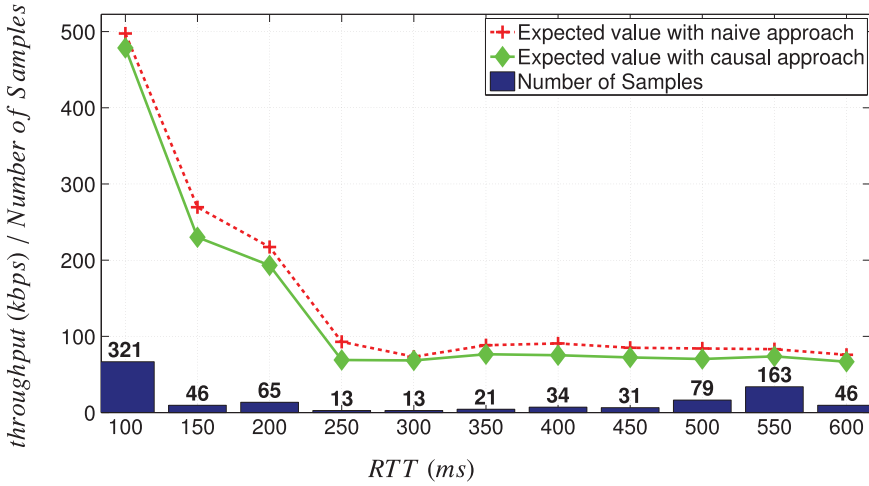
Fig. 5.   Effect of an intervention on the RTT, on the throughput distribution.

and $Z = \{tod\}$. However, this is not the case in the naïve approach that includes the spurious impact of the *receiver window* on the *RTT* and overestimates the effect of an intervention on the *RTT*.

The fact that both curves are quite similar can be explained by the fact that only one variable, the *tod*, is used to block the only back-door passing through *rwin*, which does not have important variations in our dataset. It should be noted that in the field of telecommunications, one should not expect improvements orders of magnitude higher than the ones we observe here due the complexity of the systems, which does not mean that improvements are not useful.[9]

5.3.2. Intervening on Loss Event Frequency. We now predict the effect of an intervention on the loss parameter p. In this case, the blocking set is $Z = \{rtt\}$.

Setting the p parameter to 0.01% allows to achieve an expected *throughput* value of 525.5kBps as compared to a *throughput* value of 332kBps for a value of p of 0.07% prior to intervention.

Figure 6 compares the naïve approach and the causal approach to predict the impact of intervention. Again, we see that the naïve approach overestimates the effect of an intervention on p. We obtain a difference between these two methods, which is slightly bigger than the one observed in Figure 5 when intervening on *RTT*.

5.3.3. Intervening on the Receiver Window. One parameter absent from the the PFTK model, Equation (1), but present in the model Figure 4 is the receiver window. After investigations, we observed that the distribution of the receiver window in our dataset has essentially two peaks around 72kB and 235kB, which reduces the range of interventions we can predict. The average value of the receiver window prior to intervention is 137kB for an average throughput of 332kBps (see Table II). Using the back-door criterion with $Z = \{tod\}$, we could predict the effect of intervening on the receiver window and fix its value to 235kB. This intervention would result in a 9% improvement of the throughput (365kBps) for an increase of 70% in the value of the receiver window. Instead, with a decrease of 70% of *RTT* or p, we predicted an improvement of the throughput of 44% and 58%, respectively. This observation is consistent with our domain knowledge and Intrabase [Siekkinen et al. 2005] result that show that the impact

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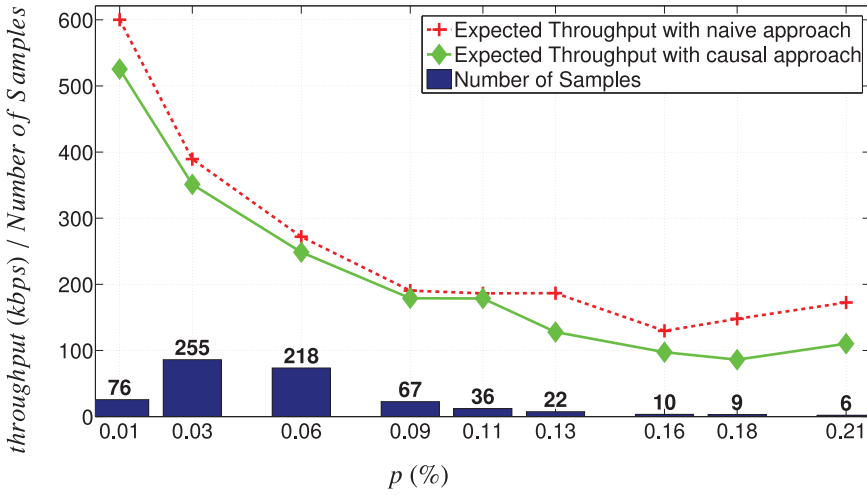[9]Amazon claimed that every 100ms of latency costs it 1% of profit.

Fig. 6.   Effect of an intervention on p, on the throughput distribution.

of the receiver window on the throughput is less important than the one of loss and delay.

This does not imply that an intervention on the receiver window should never be made. To decide on an intervention, an operator must balance benefits and costs. Intervening on the loss or delay means upgrading network equipments or moving their locations, which may be more costly than intervening on the receiver window. Here, we do not have the necessary information to assess the cost (and monetary benefits) of interventions; hence, our goal is not to give generic recommendations on which intervention should be performed. Rather, we provide a formal method to predict the expected gain in term of performance for each intervention. Then, these predictions can be used to decide on the best intervention in terms of cost versus performance gain (and the corresponding economical gain).

5.3.4. Discussion. In this section, we applied the causal approach using the methodology described in earlier sections to the study of TCP performance under real-world FTP connections. Although we cannot fully validate the predictions made in this real-case scenario (since we do not have direct access to the parameters of intervention), the results we obtain are in complete agreement with our understanding of TCP and with the literature. Then, our study shows that, provided that the right tools are used appropriately to cope with the data characteristics (in particular, the use of the KCI test and of copulae to cope with the non-normality of the distributions and non-linearity of the dependences), the causal framework can be very useful to predict the effect of interventions in the network.

6. RELATED WORK

Some of the preliminary results concerning the emulated network and the FTP traffic studies can be found in workshop papers, such as Hours et al. [2014a] and Hours et al. [2014b], respectively. The current version significantly extends both the results and description of the proposed methodology.

To the best of our knowledge, the only previous work applying causal models in the area of computer networks is the WISE system [Tariq et al. 2008]. WISE is a system that estimates a causal graph from network data collected in the core of a content distribution network (CDN) and uses it to predict the impact of configurations changes

(e.g., locations of the servers). Our study differs from WISE in some important aspects. First, when inferring the causal graph, WISE uses the Z-Fisher independence criterion and the definition of "no cause variables." We could observe that the Z-Fisher criterion performs very poorly due to the properties of our dataset, namely non-linearity and non-normality. Adapting the kernel-based conditional independence test [Zhang et al. 2012], we obtain good results with methods requiring less resources than the WISE system. Second, when using the causal model, WISE only uses the graph to reduce the number of regressors when applying knowledge propagation to estimate the post-intervention distribution. In contrast, we adopt a more formal approach based on the works of Pearl [2009] and Spirtes et al. [2001] which allows us to obtain consistent results with fewer resources. When we used non-parametric regression to orient the edges in the kPC algorithm [Tillman et al. 2009], we observed that this approach does not show enough accuracy in modeling the dependencies between the different TCP parameters, while the use of causal graphs and the criteria based on d-separation [Pearl 2009] lead to more accurate results and require fewer resources (please refer to the models inferred by the kPC algorithm presented in Appendixes D.1 and E).

There have been cases where the Internet service providers (ISPs) were found to violate the network neutrality of their users [Dischinger et al. 2008]. Network neutrality means that no application or (subset of) client gets privileged access to any service or resource. In Nano [Tariq et al. 2009], the authors make a causal study of the violation of network neutrality. The challenge in this case is to separate the part of the performance degradation due to the ISP policy from the factors impacting network performance that are not related to the ISP, such as the client OS, its distance from the service, and so on. These parameters are called *confounding factors*. To estimate the causal effect of an ISP on network performance, Nano clusters the confounding factors in bins of similar values and blocks spurious associations. An exhaustive list of confounding factors is made based on domain knowledge. However, Nano does not use a causal graph to block spurious associations. As a consequence, Nano must condition on all possible confounding variables. If one parameter happens to be a collider in a path between another confounding variable and the outcome variable, such conditioning, could create a spurious association. Additionally, Nano uses partial correlation to test for independence inside a bin, which turned out to be inaccurate for our scenario.

The performance of TCP has been modeled extensively. The first model was proposed by Padhye et al. [1998]. This model was based on Markov processes and was extended by other works along the same line that study TCP performance under various conditions (see, e.g., Loiseau et al. [2010] and references therein). However, such models generally limit the number of parameters they include and do not permit to predict the impact of interventions in the system.

In addition, the advantage of our approach comes from the fact that we only use domain knowledge to validate the inferred model, but this knowledge is not needed when inferring this model (apart from choosing the smallest list of parameters able to create a self-explaining system). In the case of the PFTK model, the obtained equation is designed from a deep understanding and study of TCP as well as the implementation of its mechanisms. On the other hand, graphical causal models offer an understanding of the underlying mechanisms (causal dependences), in addition to the effect of interventions, that approaches that blindly mimic the system under study cannot provide [Winstein and Balakrishnan 2013].

In Shah et al. [2007] and Mirza et al. [2007], a statistical approach is used to model TCP performance. However, these models become obsolete when the conditions under which they were built change. Most importantly, these models are highly dependent on the presence of spurious correlations that will be taken into account in the computations and will bias the estimates, as shown in our study (cf. Section 5.3). One important

contribution of causal models comes from their ability to detect spurious associations and the graphical criteria to cancel them. As we could observe for the dependence between the RTT and loss probability, causal models detect the dependencies among the explanatory variables, which, otherwise, would lead to biased estimates of the performance of the system and its evolution post-intervention.

Finally, while the parameters considered in our work rely on a given version of TCP, Sikdar et al. [2001], Kaj and Olsén [2001], and Fortin-Parisi and Sericola [2004] present studies and models of more recent versions of this protocol that should guide the application of the causal methods presented in this article to a broader range of communication network protocols.

7. CONCLUDING DISCUSSION

This article presents a first attempt to use a formal causal approach to study the performance of communication networks. While the theory of causal modeling is well developed and a number of software tools are available to apply it, our work showed that in order to successfully apply these tools, one needs to carefully study the nature of the data and check whether the assumptions made by these tools hold. In our case of network traffic, we need to handle continuous variables that are non-normal and with non-linear dependencies, which entails some challenges. First, using the appropriate tool for independence testing in the PC algorithm was key to infer plausible causal graphs. We adapted the kernel-based conditional independence (KCI) test with a bootstrap method that allows handling all the constraints of our datasets. Second, for the prediction of post-intervention distributions, we introduced the use of copulae to model multidimensional conditional densities in order to adapt the existing methods to our datasets. The use of copulae gave consistent results even when working on a limited amount of data. From this perspective, our study shows that it is possible to use all the methods offered by the causal theory to study complex systems, even if no assumption can be made about the parameters distributions or the functional form of the parameter dependences.

Using an appropriate methodology as described above, we obtained graphs consistent with our domain knowledge that enable very useful intervention predictions. The independences detected with the KCI+bootstrap method lead to graphs that are fully in accordance with our knowledge of the telecommunication network mechanisms. While such knowledge was used to orient the edges that these independences could not orient (the edges for which choosing an orientation does not change the Markov equivalence class), the models we obtain also present dependencies that domain knowledge alone may not be able to uncover (see, e.g., the discussion about the Receiver Window Auto-Tuning mechanism or the dependence between the RTT parameter and the p parameter in Section 5.2).

We first validated our method by verifying the accuracy of the predictions based on our causal approach with controlled emulations (using Mininet). Then, we used our method on real-world traffic generated by the FTP application. We successfully built a causal model of TCP performance and used it to predict the effect on throughput of modifying its three main causes, the RTT, the loss probability and the receiver window. Our results also show the benefits of our causal approach by shedding light on the biased estimates that a correlation based approach would give and by highlighting dependences that would have been missed otherwise.

In telecommunication networks, changes in the architecture, routing policies or content placements represent important costs in term of money and time so that testing interventions is often impossible. Due to the complexity of the system, intervention decisions usually rely on domain knowledge and back-of-the-envelope computations. Our study offers an appealing formal and automatic methodology to estimate much more

precisely the expected effect of an intervention on the system's performance without having to test the intervention in practice. These predictions can then be translated in economical gains (see Thomas et al. [2012] and references therein) and used by an operator to decide on a potential intervention by comparing this gain to the intervention cost that only the operator can quantify.

A limitation of the approach proposed in this paper is that the range of interventions that can be predicted is dependent on the dataset, that is, on the range of values that were observed prior to these interventions (as, e.g., in the case of the intervention on the receiver window, Section 5.3.3). This constitutes a limitation, as we are often interested in predicting the effect of setting a parameter to a value that is not observed. This limitation is inherent to the fact of inferring the model solely from the dataset (for this reason, when leading a causal study, "outliers" are often of great importance as they represent points of interest for predictions). A possible solution to perform intervention predictions in regions not observed in the data is to extend the model to these regions using additional assumptions not drawn from the dataset, but the results accuracy will likely be very sensitive to the assumptions made. We leave investigation of this problem for future work.

We plan to continue our work along to following lines. Causal models can be used for the prediction of intervention plans where more complex and more realistic scenarios (for which we intervene on several parameter distributions simultaneously) can be predicted. Handling those more complex scenarios will require to overcome the difficulties encountered in modeling the conditional probability density functions with many dimensions. One possible approach could be the use of parametric models for approximating the marginals, which extend the range of situations that can be predicted. Another approach relies on Chow-Liu tree [Chow and Liu 1968; Pearl 1988] in combination with the Bayesian network representation of our causal model to estimate our joint probability distribution as a product of second-order conditional probability. This approach could highly benefit from the use of copulae, as seen in Section 3.2.3. However, the presence of continuous variables with several parents (cf. Figure 2 where one node has four parents) might lead to important approximations and loss in accuracy when compared with the joint probability model given by the Bayes chain rule and the underlying Markovian hypothesis.

Another important challenge to address in future work is the sampling frequency of observations. So far, we have represented the parameters of a connection by their average values. However, sub-sampling may impact the inference of the causal model, as it can prevent the detection of dependencies or create non-structural ones. We started to use the Web10G software [Mathis et al. 2003] to continuously observe the variables of the TCP state machine during the duration of a connection, and plan to investigate how these fine-grain data can be use to build more accurate causal models.

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