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Traffic Prediction with Shared Causal Inference in ORAN Computing Continuum

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***Abstract*—Data-driven proactive network optimisation is critical for 5G advanced and 6G, allowing operators to dynamically allocate cellular spectrum reuse in anticipating for demand surges. Current approaches to traffic prediction are largely temporal correlation based. We know causal inference of key factors can help to improve prediction accuracy for spike traffic events and identify pathways to improve services. Current causal inference identify stationary independent variables, but real environments have open challenges: (i) dynamic and heterogeneous causal maps, (ii) cascade partially observable variables, and/or (iii) have coupled / confounding relationships. Currently there is no research that dynamically configures the causal relationship according to emerging real-time data and shares inference outcomes across the data sharing and computing continuum of Open-RAN (ORAN) architecture. Here, we use both real cellular network traffic and social event triggers to perform non-linear causal inference as an rApp: Predictability Improvement (PI), Conditional Mutual Information (CMI), and Convergent Cross Map (CCM). This causal knowledge is then shared across the ORAN to be embedded in traffic prediction xApps: hard causal embedding to Recurrent Neural Network (RNN) and soft causal feature embedding to a Gaussian Processes (GP). The results show a significant accuracy improvement (93-99%) over baseline non-causal correlated prediction (76-94%) and blind multi-variate approaches (87-95%). This work paves the way to causal proactive network optimisation.**

***Index Terms*—causality, machine learning, traffic prediction, social media**

I. Introduction

Traffic prediction is a key determining factor in a network's ability to satisfy consumer demand and maintain Quality-of-Service (QoS) and -Experience (QoE). Traditional traffic prediction approaches have relied on "correlated" regression modeling using auto-regressive moving averages (ARMA), Bayesian Meta-learning [1], Gaussian Processes (GP), and recurrent neural networks (RNN) [2]. In all these cases, we generally either assume a naive model (e.g., it relies on finding raw data correlations) or a guided model (e.g., we insert beliefs on features such as spikes). In general, the challenge is most models cannot predict event triggered spikes, as different events of the same class (e.g., a concert) may produce diversely varying traffic requirements. Furthermore, the space-time diffusion of demand before and after a planned event or during an unplanned flash event (e.g., a protest, disaster, or an emergent phenomenon) is even more unpredictable. Lacking a causal model, our previous work on feature embedded GPs (FE-GP) used spiking features to guide GPs and trade-off average long-term accuracy with traffic spike accuracy [3]. Yet, we know that traffic demand's reasons are complex, vary with event and time, and is not homogeneous. Therefore, offline models that analyse general data, cannot be reliable in forecasting future traffic across diverse urban areas. Without understanding the complex social causal reasons that drive traffic demand, we cannot achieve a dynamic understanding that drives proactive network management.

A. Causality

Causal learning generally deals with a few frameworks [4], including *causal inference*, *causal learning*, and *causal embedding*. In inference, we are generally testing: given two or more data sets, what is the confidence that we have Event (E) $\rightarrow$ Traffic (T) - see Table I. The objective is to disentangle causation from correlation with a certain confidence, under some general statistical assumptions (more on this later). In causal learning, we are interested in a different problem, how can we generally exploring: what are the variables, and what are the causal relationships if any. Here, causal curiosity uses a reinforcement learning agent to explore all action spaces amongst variables and rewards itself by the causal strength it observes as a consequence of experimentation [5].

Understanding causal relations can have a wide range of benefits, beyond explainable AI (XAI) benefits of transparency [6]. Causal embedding is discussed in [4], where we embed pre-established notions of causal structure as a pre-ample to machine learning tasks, reducing the inefficiency of learning spurious associations that do not exist. It can also drive prediction of traffic and lead to anomaly detection [7] and proactive optimisation. These functions are increasingly important in 6G ORAN contexts, where different levels of transparency and explainability is important to diverse stakeholders [8].

1) Causal Traffic Prediction: Current research in causal traffic prediction focus largely on offline causal models that use historical data to build a general causal model. In [9], the classic Granger causal testing is used, under the assumption that a linear relationship exists between variables. In [10], transfer entropy (TE) is used which is the nonlinear version of Granger. Similar studies on both wireless traffic and transportation traffic prediction on a graph network also exist using TE to drive a graph neural network [11].

2) Gap in Knowledge: This research challenge currently un-tackled in traffic prediction are (see Table I):

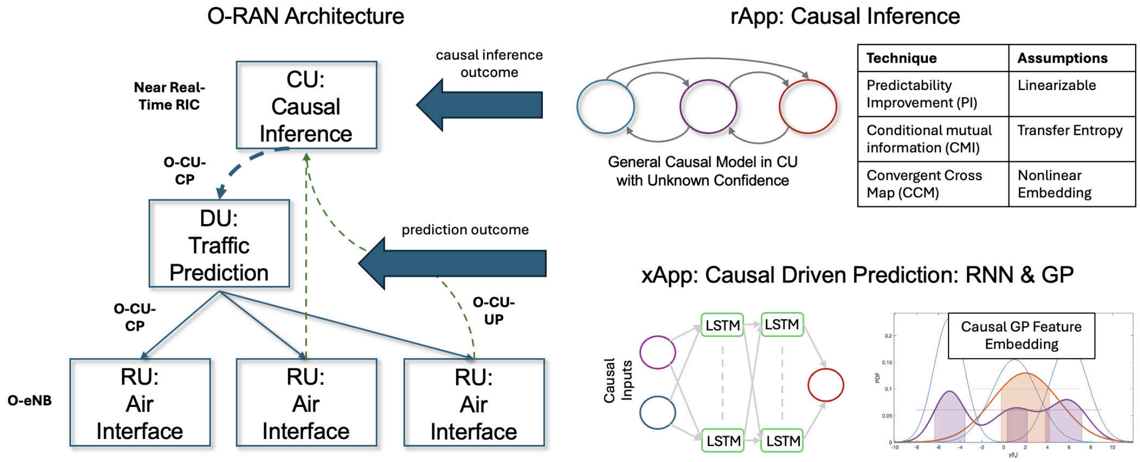


Fig. 1: Causal inference and prediction architecture in ORAN: (left) distribution of inference and prediction tasks across computing continuum, (right) rApp and xApp implementation of LSTM-RNN and GP models.

TABLE I: Causal Tests in Traffic Prediction: E is Physical Event, D is Digital Demand, T is Observed Traffic. *It is worth noting confounding causal knowledge is hard to infer and prove, and here we explore what is a coupled cyclic relationship.*

Test Scenario	Descriptor	Observables	Literature
Direct	E→T	E, T	[9], [10]
Indirect Cascade	E→D→T	E, T	None
Confounding	D↔ E→T, D→T	D, E, T	None

1) Dynamic and Heterogeneous across Network: different events in time and space will have different causal structures that influence traffic (T);
2) Observable State Variables: causal inference can often be challenged by key causal indicators being unobservable and indirect causal relations need to be inferred or learnt;
3) Confounding Variables: variables that affect both other dependent and independent variables. For example, a AR/XR digital event e.g., Pokemon Go, (D) → physical event gathering (E), which both E and D causes further increase to each other and traffic (T).

B. Contributions

To address these gaps, this study focuses on as follows:

1) Designing a general causal inference architecture distributed across the C-RAN computing continuum architecture using rApps and xApps [12];
2) Automated causal inference pipeline that tests different assumptions as a rApp that is slowly updated;
3) Causally distinguish traffic demand from physical events from unusual surge demand from AR/XR demand.
4) Traffic prediction algorithm xApp that ingests rApp causal data to do real-time traffic prediction. We use LSTM RNNs as a performance prediction model, and Gaussian Process (GP) [13] as a probabilistic prediction model with uncertainty outputs.

To be specific, In Section II, we specify the ORAN design and data used. In Section III, we specify the causal inference rApp pipeline that automatically selects the inference result. This is conducted in psuedo-real-time updating only when the test results significant change from previous results. In Section IV, we define the feature embedding GP and RNN framework as an xApp. In Section V, we show the performance results and benchmark against test cases specified in Table1.

II. System Architecture

A. ORAN Planes and Apps

We create a system ORAN compatible architecture such that data sharing enables these applications. A general causal template (see Figure1) (typically logically sits in the access management function of 5G NR) and is responsible for managing traffic prediction and mobility for devices. In real terms, the causal inference as an rApp might sit in the near real-time RIC of the centralised unit (CU) and infers causal relations in quasi real-time. It digests aggregated historic traffic demand data from local Radio Units (RU) via O-CU-UP (user plane) and social media analytics from central service management Cloud-RAN. It then distributes the causal results to relevant Distributed Units (DU) via O-CU-UP (control plane), which operates causal traffic prediction xApp algorithms using techniques of GPs and RNNs, e.g., the causal knowledge feeds into feature embedding [3].

B. Data Curation and Processing

The geographic area we focus on is Greater London area. The time period is selected to be a 2 week period in the last 10 years, as this was the period we had highest quality commercial and purchased data from cellular networks and geo-tagged social media.

1) Cellular Traffic Data (T): The cellular traffic data (T) stream from RUs is shown in Fig.2, which contains both periodic self-predictable elements and spiking elements that

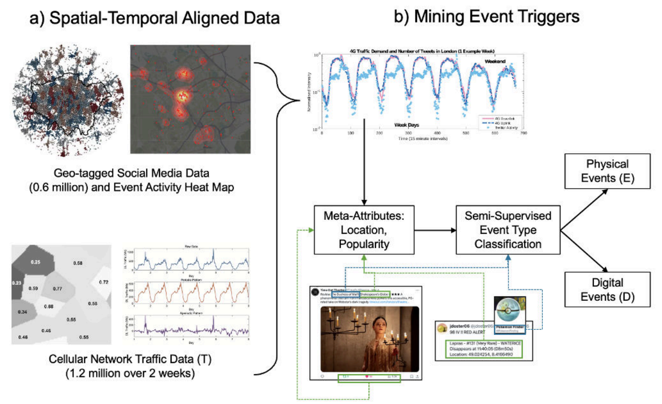


Fig. 2: Big Data Pipeline: (A) cellular and social media raw data, and (B) mining event triggers - two locations are used: Greater London and Milton Keynes.

require causal insight. Over a 2 week period, this is 1.2 million mobile phone Uplink (UL) and Downlink (DL) records, aggregated to the cellular RU level. The time resolution is on a minute basis, aggregated to 15 minute intervals.

2) Social Media Driven Physical Event Data (E) and Digital Demand Data (D): We use from the same time and geography frame as cellular data a large collection of social media Twitter (now called X) data. Approx. 0.6 million geo-tagged Tweets cover a 2 week period with a radius of 40km from London [14]. We also use a secondary location (Milton Keynes 80km north of London) to have secondary demographic distribution to our social data.

We use a number of natural language processing (NLP) techniques (e.g., Latent Dirichlet Allocation to identify from trigger event types from data:

- Major physical events (E) (e.g., concerts, football matches, protests) that can potentially drive digital interaction demand (D) or directly cause traffic spike.
- Major AR/XR digital demands (D) (e.g., rare Pokemon Go event, AR/XR/gaming shows) that can cause traffic spike, and may also cause and be caused by E.

We classify events into classes using supervised learning and the location data usually comes with location data directly or embedded in the text data [15]. A list of E and D events we use are given in Fig.5bottom in the Appendix. We infer the popularity of the events by the number of likes and shares. A brief data processing flow is given in Fig.2 with example data inputs and extracted outputs. Most of the data processing is based on 8 years of previous research [3], [14], [16] and is not the main thrust of this paper.

3) Data Availability: Most of the raw data used is available in a previous data release on Dryad: https://doi.org/10.5061/dryad.35m1f4q.

III. Causal Inference Pipeline

Causal analysis in complex systems with no existing explicit mathematical models is challenging. On the one hand, an end-to-end data analysis between events and traffic demand might exhibit certain confidence in results [10], but one cannot be certain they are reasonable and relate to known social mechanisms. We will leverage on a range of causal inference techniques with proven performance. These are proven through testing on toy non-linear causal systems such as the Rossler attractor dynamics and on real data case studies - and we showcase this in **Appendix**.

We now list the inference methods we have used and detail later how we automatically select the method outputs depending on their result (see Figure3).

A. Nonlinear State Space Inference Approaches

The predictability improvement (PI) causality test is proposed in response to the poor linear assumptions in Granger causality, by reconstructing the time series in multi-dimensional state spaces [17]. In effect, this converts the assumed non-linear dynamic system into a linear manifold, where the Granger causality test can then be applied. The outcome is a direct accept or reject causal link.

A model-free transfer entropy [10] approach is Conditional mutual information (CMI) [18]. Here, discrete random variables (X, Y, Z) with support sets $(\mathcal{X}, \mathcal{Y}, \mathcal{Z})$ define CMI:

$$I(X,Y|Z) = \Sigma_{z\in\mathcal{Z}} p_Z(z) \Sigma_{y\in\mathcal{Y}} \Sigma_{x\in\mathcal{X}} p_{X,Y|Z}(x,y|z) \log \frac{p_Z(z) p_{X,Y,Z}(x,y,z)}{p_{X,Z}(x,z) p_{Y,Z}(y,z)} \quad (1)$$

which estimates the directed information flow from a variable X to another variable Y under the condition of Z. Different from the aforementioned PI hypothesis test, the CMI approach can yield the value of predictability improvement allowing soft causal embedding.

In [19], Convergent Cross Map (CCM) is proposed to detect the causal relationships in nonlinear dynamical systems. Using Takens's theorem, which states that in a time series dynamical system with multi-variables, any single series of one variable of the system can be recovered by the historical series of another variable by high-dimensional state space reconstruction. As such, the causality is defined as the extent to which the time series $[X(t-\eta\tau), ..., X(t-2\tau), X(t-\tau)]$ can be encoded into time series $Y(t)$. The parameter τ here is the time step for the reconstruction while η is the dimension of the reconstruction.

B. Automated Inference Pipeline

We enlist the relative advantages of causal inference techniques discussed above to drive the traffic prediction. We divide the inference outputs into two forms:

- Hard/Blind causal model: where the causal link is accepted or rejected.
- Soft causal model: where each causal link is assigned a predictability improvement value (CMI and CCM).

The pipeline we have designed is shown in Fig.3, which shows how data from different sources combine to drive the causal inference rApp.

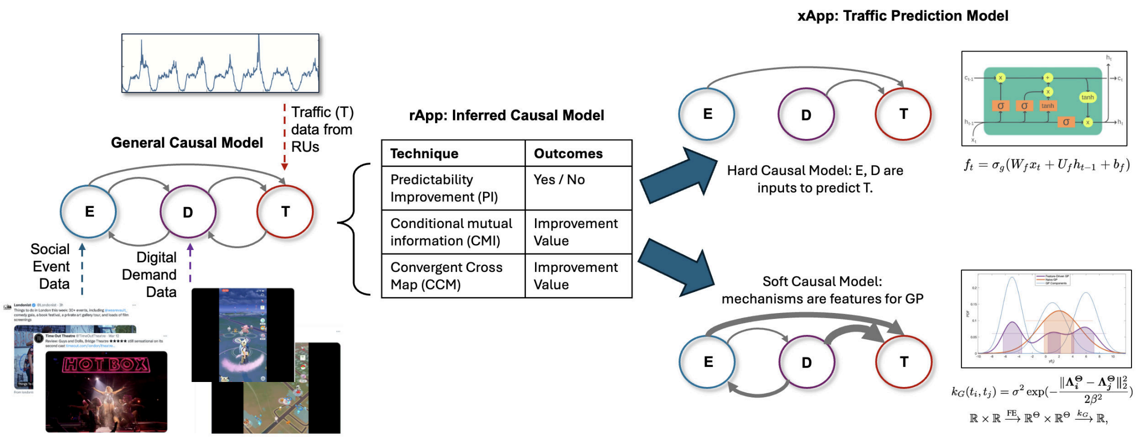


Fig. 3: Causal learning rApp drives LSTM and probabilistic GP prediction tasks as xApps.

IV. Causal Embedding in Traffic Prediction

A. Soft Causal Feature Embedding for GPs

Let us consider a traffic model where the traffic value (T) is assumed to be a noisy GP: $T(t) = f(t) + \epsilon(t)$, where $f(t)$ is the random variable (RV) which follows a distribution given by GP, and ϵ is the additive Gaussian noise with zero mean and variance σ_n^2. In GP, the covariance between every two RVs is quantified by the kernel function which interprets the potential correlation of RVs in a high dimensional space.

1) Gaussian Radial Basis Function for Feature Embedding: Here we use the Gaussian radial basis function (RBF) kernel with a feature embedding (FE) norm [3]:

$$k_G(t_i, t_j) = \sigma^2 \exp(-\frac{\|\boldsymbol{\Lambda_i^\Theta} - \boldsymbol{\Lambda_j^\Theta}\|_2^2}{2\beta^2}) \\ \mathbb{R} \times \mathbb{R} \xrightarrow{\text{FE}} \mathbb{R}^\Theta \times \mathbb{R}^\Theta \xrightarrow{k_G} \mathbb{R}, \tag{2}$$

where $\boldsymbol{\Lambda_l^\Theta}$ is defined as the Θ dimensions weighted feature matrix of the RV at time point t_l:

$$\boldsymbol{\Lambda_l^\Theta} = [w_1\lambda_l^1, w_2\lambda_l^2, ..., w_\Theta\lambda_l^\Theta]^T, \tag{3}$$

where the θ^{th} feature of RV $f(t_l)$ in the matrix is from a feature generator function $h_\theta(.)$:

$$\lambda_l^\theta = h_\theta[T(t_{l-1}), T(t_{l-2}), ..., T(t_{l-L})]. \tag{4}$$

2) Feature Generator using Soft Causal Relationship: In previous work [3], our feature generator $h_\theta(.)$ used the baseline, differential, and fluctuation degree as data-driven features: (1) baseline of the events $(\Sigma_1^i T(t_{l-i}))$, (2) differences in time series values $T(t_{l-i}) - y(t_{l-j})$, and (3) fluctuation degree $\frac{T(t_{l-a})-T(t_{l-b})}{T(t_{l-c})-T(t_{l-d})}$ or the standard deviation of former values.

We advance over previous work by capturing the soft causal relationships. Here we describe an event from three perspectives from Table.I:

1) Direct event causality, i.e. $\alpha\Sigma_1^i E(t_{l-i})$. This feature helps to measure the historical event driven causality with predictability improvement strength α.
2) Indirect cascade causality with D unobservable, i.e. $\Sigma_1^i \alpha \times g(E(t_{l-i}))$, where $\alpha \times g(.)$ models the hidden relation between $E \to D$ and captures the predictability improvement strength.
3) Confounding causality, i.e. $\alpha\Sigma_1^i E(t_{l-i}) + \beta\Sigma_1^j D(t_{l-j})$, where α, β are predictability improvement strengths.

For each previous time point t_i in this model, a posterior distribution component of $T_i(t_f|\boldsymbol{\mathcal{T}_i})$ can be generated. In naive GP, the predicted distribution $T(t_f)$ is also a Gaussian distribution which sums the influence of each previous point on its mean and variance.

In our proposed FE-GP forecasting model, the predicted distribution uses a Gaussian mixed model (GMM). Consider the GMM resultant PDF of $T(t_f)$ is the superposition of every individual distribution components from each $T(t_i)$ and $T(t_f)$ with a normalization coefficient as

$$P(T(t_f)|\boldsymbol{\mathcal{T}}) = \frac{1}{n}\sum_{i=1}^{n} \frac{1}{\sqrt{2\pi\hat{\sigma}_{i,f}^2}} \exp(-\frac{(T_f - \hat{\mu}_{i,f})^2}{2\hat{\sigma}_{i,f}^2}) \tag{5}$$

B. Hard Causal Input Shaping for RNNs

In hard causal input shaping for RNNs, we directly decide which inputs are causally related to traffic (T) and use them to inform the input space. Here we use a 4-layer LSTM network with two full connect layers with 64,128, hidden nodes respectively. We applied next t steps prediction on a 15 minute resolution level using past days as measurements. The input features are:

1) Historical Traffic Data: $T(t_{l-i})$
2) Causal Event or Digital Demand Data: $E(t_{l-j}), D(t_{l-k})$

We achieve a training accuracy benchmark without causal knowledge and compare how much improvement there is by using causal knowledge in Section V.

V. Results and Analysis

A. Benchmark

We first show baseline non-causal prediction results, where we create causal cases but do not leverage on causal information and only use historical traffic to predict future traffic - see TableII. We measure the accuracy of our prediction over the next 1-3 days.

We can see that when the traffic is self-regressive and non-causal, the prediction results are generally above 99.5%. As the causal drivers increase in complexity and create spiking events, we can see the non-causal self-regressive prediction accuracy drops as expected to 76-94%.

TABLE II: Baseline Non-Causal Prediction Results

Test Scenario	Descriptor	Baseline Results using T
Non-Causal	T	GP 99.7% RNN 99.6%
Direct	E→T	GP 92.1% RNN 94.0%
Indirect Cascade	E→D→T	GP 87.8% RNN 88.6%
Confounding	D↔ E→T, D→T	GP 76.5% RNN 85.1%

B. Causal Tests

First we note that in the non-causal baseline, causal analysis will eliminate irrelevant variables and not experience any different performance to baseline.

Referring to TableIII: In the direct causal case E→T, we see a significant improvement by taking into account how E causes spiking behaviour, improving performance from 92-94% to 98-99%. In the indirect cascade case E→D→T, we are unable to observe D. Here from results, we see improved performance from 87-88% to 96-97%. In the confounding case D↔ E→T, and D→T, we are able to observe all. Here from results, we see improved performance from 76-85% to 93-94%.

TABLE III: Causal Prediction Results

Test Scenario	Descriptor	Causal Results
Non-Causal	T	GP 99.7% RNN 99.6%
Direct	E→T	GP 98.8% RNN 99.2%
Indirect Cascade	E→D→T	GP 97.1% RNN 96.5%
Confounding	D↔ E→T, D→T	GP 93.7% RNN 94.2%

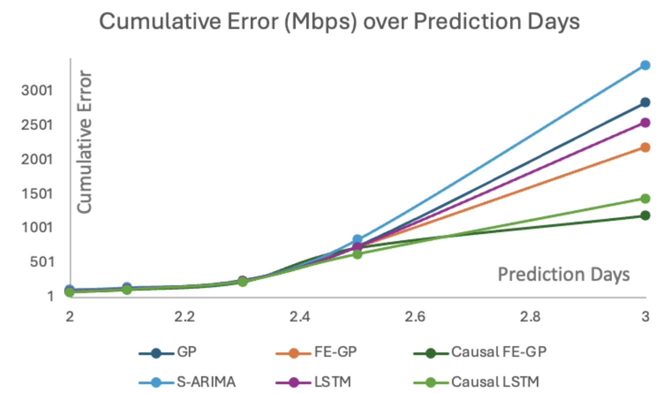
C. Single RU and Multiple RU Performance

We also compare the cumulative error (Mbps) over several days. For a single RU benchmark test, we show in Fig.4top comparisons for naive GPs, GPs with handcrafted features [3], GPs with causal features, Seasonal-ARIMA, LSTM, and causal LSTM. In general we note that causal LSTM slightly out performs causal GPs as a performance model, but the GP has the potential to offer posterior uncertainty distribution which can feed into more probabilistic optimisation models such as Bayesian networks later on.

In Fig.4bottom we show the prediction statistical box-plot for 3 prediction xApps in 3 neighbouring RUs driven by common causal output - demonstrating the potential ORAN continuum architecture implementation envisaged in Fig.1.

D. Testing Against Alternative Approaches

One might argue, why we cannot simply use all interested variables to act as an input for neural network without needing to know causality. Here, there are several arguments:



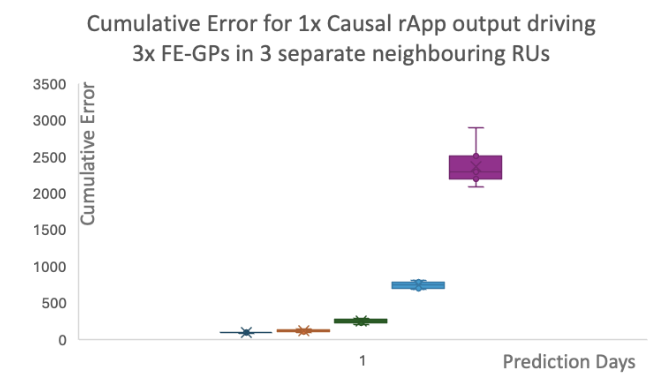


Fig. 4: Cumulative error over prediction future days for: (top) comparison of different causal and non-causal prediction algorithms for a single RU, and (bottom) prediction statistical box-plot for prediction across ORAN computing continuum.

1) Using All Variables without Causal Knowledge: we tested the case of E→T, where we also use D data. Here we suffered a reduced performance from 98-99% to 97-98%, and also caused longer training.
2) Using All Variables without Causal Strengths (Hard/Blind Multi-Variate Approach): we tested the case of D↔ E→T and D→T, where we do need all data but may choose to ignore causal strengths. Here this only applies to the GP case and we suffered a significant reduced performance from 95.7% to 87.2%.
3) Baseline (Using No Variables): this is our original baseline which is significantly worse in complex event driven causal triggers, as shown in TableII.

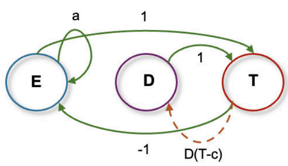
VI. Conclusions and Future Work

In this work, we have dynamically inferred causal traffic generation relationships. We proposed to distribute the causal inference and prediction algorithms across the ORAN as rApp and xApp implementations. Our results show that we can infer cascade acyclic causal relations, with partially unobservable and to a limited extent coupled variables. We then used both hard causal embedding to a LSTM for high prediction performance and soft causal feature embedding to a Gaussian Processes (GP) for uncertainty quantification.

The results show a significant accuracy improvement (93-99%) over baseline non-causal correlated prediction (76-94%) and blind multi-variate approaches (87-95%). This work paves the way to causal proactive network optimisation and orchestration [20].

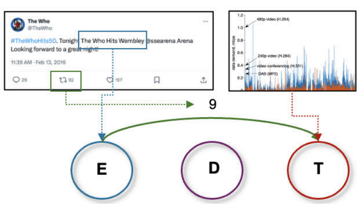
Appendix - Causal Inference Model & Case Study

Toy Causal Model



Technique	Result
Predictability Improvement (PI)	✓
Conditional mutual information (CMI)	0.81
Convergent Cross Map (CCM)	0.53

Data Case Study



Technique	Result
Predictability Improvement (PI)	✓
Conditional mutual information (CMI)	0.87
Convergent Cross Map (CCM)	0.92

Real Event (E) Classes Considered	Digital Demand (D) Classes Considered
Business Operations	Digital Game AR/XR Spawns
Major Entertainment Events	Digital Festivals & Conventions
Major Transport Disruptions	Digital or Electric Outage Events

Fig. 5: Causal inference test cases: (top) toy differential equation model, (bottom) single event triggered case study.

Nonlinear Causal Toy Model: We test our causal inference (e.g., PI, CCM and CMI) on established theoretical coupled differential equation model. Our results show that we can correctly identify causal links in the presence of mixed linear and nonlinear dynamics (Fig.5top), giving us some confidence that these causal inference models are appropriate for coupled/synchronized systems (note this is not equivalent to causal especially in cyclic graphs). In general, the PI method has the most sensitive, while CCM have the longest response lags. In general, we note that cyclic data-driven relations can be more challenging to detect than direct cascade (acyclic) relations.

Data Case Study Example: We test our work against a well known concert at Webley arena (see Fig.5bottom), where NLP is used to mine the event class (see event classes based on previous work [16]), the location, and time, and used to compare against previous times traffic when the event did not exist for causal inference.

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