



2 28<sup>th</sup> August 2024 William Bragg (GR.25) 16.00 – 18:00

- Dr Colin Paterson That can't be right? Making decisions in an uncertain world.
- Medical and Al-themed Articulate



### Today's schedule

Time	Торіс
16:05	Guest Speaker: Dr Colin Paterson
16:55	Food
17:05	Articulate
17:55	Close + Optional Networking at a Pub





### **That can't be right?** Making decisions in an uncertain world.

Dr. Colin Paterson colin.paterson@york.ac.uk

AI^2 : August 2024

### **Bard: A Large Language Model**



#### Who is Colin Paterson at the University of York?

Colin Paterson is a Lecturer in Computer Science at the University of York. He received his PhD in Computer Science from the University of Edinburgh in 1997. His research interests include probabilistic model checking, operational processes, process mining, and control systems engineering. He is also the Director of the Institute for the Governance of Innovation in the Global Economy (IGGI). Here is a summary of his work experience and education:

Education:

- PhD in Computer Science, University of Edinburgh, 1997
- MSc in Computer Science, University of Edinburgh, 1995
- BSc in Computer Science, University of Glasgow, 1993
- Work Experience:
  - Lecturer in Computer Science, University of York, 2022-Present
  - Research Fellow, University of York, 2021-2022
  - Technical Director, RSM Bentley Jennison, 2000-2021

Here are some of his notable publications:

• Paterson, C., & Lane, J. (2000). Probabilistic model checking of real-time systems. IEEE Transactions on Software Engineering, 26(1), 51-65.

• Paterson, C., & Neil, M. (2004). Process mining for business process improvement. IEEE Transactions on Knowledge and Data Engineering, 16(10), 1266-1280.

• Paterson, C., & Holcombe, M. (2008). Control systems engineering with probabilistic model checking. IEEE Transactions on Automatic Control, 53(1), 15-27.

Paterson is a highly respected researcher in the field of computer science. His work has made significant contributions to the areas of probabilistic model checking, operational processes, process mining, and control systems engineering. He is also a passionate educator and mentor, and has made a significant impact on the lives of his students.



### **Bard: A large Language Model**



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Newest publication 15 years old.

#### Photo by Andrea De Santis on Unsplash



Strange timeline!

## My journey





1987 - 96 Co

Coventry University. BEng, PhD Control Systems Engineering. Temporary Lectureship, First RA Post (Leicester)

Failed my A levels and went to work in a large insurance company

1996 - 11

1983

Working in industry. dot-com boom. Technical Director of an IT consultancy. Then self-employed.

2011 - 14

2014 -

Teacher of ICT in secondary schools.

as a computer programmer. Apple ][.

University of York. PhD Computer Science. RA, RF, Lecturer, Senior Lecturer.

### My Work

Assurance of ML for Autonomous Systems in Safety-Critical Applications		Autonomous Systems for the monitoring of forest health	
Identifying unusual behaviours in operational processes	AI	Reimagining Trustworthy Autonomous Systems (TAS) with Young people	
Evacuation planning using Social Media to update models at run-time	Safety	Decision Making under uncertainty for Mobile Autonomous Systems	
Specification of Social Legal Ethical Empathetic and Cultural Requirements for TAS		Co-Director for training SAINTS CDT	

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## Just pick the correct model!



#### CURVE-FITTING METHODS AND THE MESSAGES THEY SEND





### Observation-Enhanced QoS Analysis of Component-Based Systems

Colin Paterson, Radu Calinescu

Abstract—We present a new method for the accurate analysis of the quality-of-service (QoS) properties of component-based systems. Our method takes as input a QoS property of interest and a high-level continuous-time Markov chain (CTMC) model of the analysed system, and refines this CTMC based on observations of the execution times of the system components. The refined CTMC can then be analysed with existing probabilistic model checkers to accurately predict the value of the QoS property. The paper describes the theoretical foundation underlying this model refinement, the tool we developed to automate it, and two case studies that apply our QoS analysis method to a service-based system implemented using public web services and to an IT support system at a large university, respectively. Our experiments show that traditional CTMC-based QoS analysis can produce highly inaccurate results and may lead to invalid engineering and business decisions. In contrast, our new method reduced QoS analysis errors by 84.4–89.6% for the service-based system and by 94.7–97% for the IT support system, significantly lowering the risk of such invalid decisions.

Index Terms—Quality of service, component-based systems, Markov models, probabilistic model checking.

#### **1** INTRODUCTION

Modern software and information systems are often constructed using complex interconnected components [1]. The performance, cost, resource use and other quality-of-service (QoS) properties of these systems underpin in portant engipeer testing the components prior to system integration, from logs of other systems that use the same components, or from the log of the analysed system. The second OMNI activity involves the development of a high-level CTMC model of the system under analysis. This model can be generated om m \_\_\_\_\_\_aral sof ware mod \_\_\_\_\_ch as annotated UML

### OMNI



Fig. 2: High-level abstract CTMC modelling the handling of a request by the web application

P1  $P_{=?}[F^{[0,T]} complete]$ P2  $P_{=?}[\neg arrivals U^{[0,T]} complete]/(1-p_1)$  (7) P3  $P_{=?}[F^{[0,T]} complete] - 2 \cdot P_{=?}[F^{(3,\infty)} complete]$ 



- Modeling Operational Processes
- Probabilistic Models using CTMC
- Assume Exponential Holding Time
- Mathematically convenient
- Formal Verification Mathematical Proof





### **Exponential Distributions**

The cumulative distribution function is given by

$$F(x;\lambda) = egin{cases} 1-e^{-\lambda x} & x\geq 0,\ 0 & x< 0. \end{cases}$$

Average time for kettle to boil = 180s

p(t<180) = 0.63 p(t<240) = 0.74 p(t<10) = 0.05 p(t<1) = 0.006



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### Both of these approximations are learnt from data.



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Figure 3.4: SLA property evaluation using CTMC verification



Figure 3.11: Properties P1-P3 predicted after holding-time modelling (dashed line) vs. actual (continuous line); error<sub>0</sub>, error<sub>1</sub> and error<sub>11</sub> are the prediction errors before OMNI and after each OMNI stage, respectively



### **OMNI**

Models come with assumptions.

If your models don't match your purpose then you can "prove" things which are blatantly untrue.

Averaging is a blunt tool and in safety critical cases it can be dangerous.

"All models are wrong, but some are useful" George Box.

## Just involve experts!





### Using Unstructured Data to Improve the Continuous Planning of Critical Processes Involving Humans



Colin Paterson, Radu Calinescu, Di Wang and Suresh Manandhar Department of Computer Science, University of York, York, UK

Abstract-The success of processes executed in uncertain and changing environments is reliant on the dependable use of relevant information to support continuous planning at runtime. At the core of this planning is a model which, if incorrect, can lead to failures and, in critical processes such as evacuation and disaster relief operations, to harm to humans. Obtaining reliable and timely estimations of model parameters is often difficult, and considerable research effort has been expended to derive methods for updating models at run-time. Typically, these methods use data sources such as system logs, run-time events and sensor readings, which are well structured. However, in many critical processes, the most relevant data are produced by human participants to, and observers of, the process and its environment (e.g., through social media) and is unstructured. For such scenarios we propose COPE, a work-in-progress method for the continuous planning of critical processes involving humans and carried out in uncertain, changing environments. COPE uses a combination of runtime natural-language processing (to update a stochastic model of the target process based on unstructured data) and stochastic model synthesis (to generate Pareto-optimal plans for the process). Preliminary experiments indicate that COPE can support continuous planning effectively for a simulated evacuation operation after a natural disaster. lar





stochastic model of a human-centric critical process by exploiting information encoded in unstructured data streams such as Twitter; and (ii) stochastic model synthesis, to dynamically generate updated Pareto-optimal plans for the process.

#### II. MOTIVATING EXAMPLE

We consider an operation in which a disaster relief team must devise and communicate evacuation plans to people traversing a country to safety after an earthquake that led to shortage food medicine in structure are as





AIM : Plan for evacuating people when there has been a natural disaster and resulting civil unrest.

Context : Rapidly evolving, up to date information on social media.









## Abstract the problem and model as an MDP.











Human in the loop.

### **Advisory AI & Accountability**



Complexity	AI	Human	Outcome	Blame	
Low	Correct	Agree	Success	None	
High	Incorrect	Disagree	Success	None	
High	Incorrect	Agree	Failure	?	
High	Correct	Disagree	Failure	Human	
<b>.</b>	You wouldn't know this?		Causation?	Wh	nen would you ose to disagree with the AI?

## The people problem

#### By Elsa Maishman

BBC News

### A robot broke a seven-year-old boy's finger during a chess match in Moscow last week, Russian news outlets report.

"The robot broke the child's finger," Sergey Lazarev, Moscow Chess Federation President, told Tass news agency. "This is of course bad."

Data from <u>Autonomous Cars, Robotaxis & Sensors 2022–2042</u> reveals for crashed vehicles that were operating in autonomous mode, 81 out of the 83 recorded incidents were caused by a human, either in another vehicle or as a misbehaving pedestrian.

Of 187 reports of autonomous vehicles accidents, just two could be attributed to the poor performance of the systems.





- Designers of AI can focus too much on the technology rather than the wider systems into which they are to be deployed.
- If people don't like the way that a system works they will find a way to work around it invalidating any design assumptions.



## The system relies on getting expert opinion for events which have never happened before.

### Probability as degree of belief :

https://plato.stanford.edu/entries/probability-interpret/#SubPro

How can we incorporate expert opinion when the experts don't know with any certainty?

### Just follow the specification!





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#### From Pluralistic Normative Principles to Autonomous-Agent Rules

Beverley Townsend<sup>1</sup> · Colin Paterson<sup>1</sup> · T. T. Arvind<sup>1</sup> · Gabriel Nemirovsky<sup>1</sup> · Radu Calinescu<sup>1</sup> · Ana Cavalcanti<sup>1</sup> · Ibrahim Habli<sup>1</sup> · Alan Thomas<sup>1</sup>

Received: 29 April 2022 / Accepted: 14 October 2022 / Published online: 29 October 2022 © The Author(s) 2022

#### Abstract

With recent advancements in systems engineering and artificial intelligence, autonomous agents are increasingly being called upon to execute tasks that have normative relevance. These are tasks that directly—and potentially adversely—affect human well-being and demand of the agent a degree of normative-sensitivity and -compliance. Such norms and normative principles are typically of a social, legal, ethical, empathetic, or cultural ('SLEEC') nature. Whereas norms of this type are often





### SLEEC





### **Rule Elicitation Process**

## **SLEEC Concerns**



When the user tells the robot to open the curtains, then the robot should open the curtains.

## Might this rule conflict with another norm?

Norms: SOCIAL LEGAL **ETHICAL EMPATHETIC CULTURAL** 

## **SLEEC Concerns**



When the user tells the robot to open the curtains, then the robot should open the curtains.

When the user tells the robot to open the curtains then the robot should open the curtains, UNLESS the user is 'undressed' in which case the robot does not open the curtains and tells the user 'the curtains cannot be opened while you, the user, are undressed'.

Might this rule conflict with another norm?

SOCIAL LEGAL ETHICAL EMPATHETIC CULTURAL

## **SLEEC Concerns**



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When the user tells the robot to open the curtains then the robot should open the curtains, UNLESS the user is 'undressed' in which case the robot does not open the curtains and tells the user 'the curtains cannot be opened while you, the user, are undressed,' UNLESS the user is 'highly distressed' in which case the robot opens the curtains.

### **SLEEC**



Getting the ground truth can be hard.

Experts often disagree.

Guidance is not consistent.

Can we be sure that our set of objectives and constraints will be accepted in all likely contexts?

### UKRI AI Centre for Doctoral Training in Safe Artificial INtelligence Systems (SAINTS)

The SAINTS CDT is the UK's first multidisciplinary PhD programme focused solely on the safety of artificial intelligence (AI).

Our vision is to train future leaders with the research expertise and skills to ensure that the benefits of AI systems are realised without introducing harm as the systems and their environments evolve.

Research will be focused on the lifelong safety assurance of increasingly autonomous AL systems in dynamic and uncertain

#### Contact us

SAINTS Administration Team SAINTS Centre for Doctoral Training

☑ saints-cdt-admissions
 (ayork.ac.uk)
 ▲ +44 (0)1904 325412





## SAINTS



Life-long safety of AI: Safety-driven design and training for evolving contexts; testing for open and uncertain operating environments; safe retraining and continual learning; proactive monitoring procedures and dynamic safety cases; ongoing assurance of societal and ethical acceptability. Safety of increasingly autonomous AI: Understanding human-AI interaction to design safe joint cognitive systems; the assurance of safe transition between human and AI control; achieving effective human oversight and AI explainability; preserving human autonomy and responsibility.

## **Assuring safety**

Some points to note:

- Safety is not something that can be bolted on after the event.
- Safety is a systems level issue. We can not say a machine learnt algorithm is, in itself, safe.
- We are always working within constraints, and we are looking to develop systems which achieve acceptable levels of safety.





## **Assuring Safety**





We build a safety argument using a structured pattern with explicit assumptions and a specified context.

We use evidence from each stage of the development process to support the claims being made.

Arguments may rely on sub claims and arguments.

### **Decision-Making Framework**



Uncertainty, Time and Trade-offs. Safe Decision-making for mobile Autonomous Systems. Hasan Bin Firoz, Dr. Colin Paterson, Dr. Richard Hawkins



### **Decision-Making Framework**





Designing everyblock requires us to consider the sources, and mitigation strategy, for uncertainty.

Uncertainty, Time and Trade-offs. Safe Decision-making for mobile Autonomous Systems. Hasan Bin Firoz, Dr. Colin Paterson, Dr. Richard Hawkins

#### **Decision-Making Framework**





Decision Matrix							
Action	Safety	Performance	Time				
Accelerate	0.78 – 0.82	0.96 – 0.98	2 sec				
Mt. Speed	0.86 - 0.98	0.78 – 0.95	N/A				
Slow down	0.86 - 0.94	0.85 – 0.89	3 sec				
Stop	0.90 – 0.99	0.76 – 0.81	5 sec				
Action	Safety	Performance	Time				
Accelerate	0.84 – 0.88	0.96 – 0.98	1 sec				
Mt. Speed	0.72 – 0.80	0.78 – 0.95	N/A				
Slow down	0.86 - 0.98	0.86 – 0.88	2 sec				
Stop	0.92 – 0.96	0.75 – 0.80	4 sec				
Action	Safety	Performance	Time				
Accelerate	Invalid	Invalid	N/A				
Mt. Speed	Invalid	Invalid	N/A				
Slow down	0.95 – 0.97	0.85 – 0.87	1 sec				

 $0.96 - 0.98 \quad 0.73 - 0.77$ 

Stop

Uncertainty, Time and Trade-offs. Safe Decision-making for mobile Autonomous Systems. Hasan Bin Firoz, Dr. Colin Paterson, Dr. Richard Hawkins

3 sec



When we're asked to be accountable for the decisions we make we need to understand our decision making process better and the question the assumptions upon which our decisions depend.

Making decisions is hard, justifying them is harder, dealing with the consequences of bad decisions harder still.

## Thank you

Al 'godfather' Yoshua Bengio feels 'lost' over life's work



One of the so-called "godfathers" of Artificial Intelligence (AI) has said he would have prioritised safety over usefulness had he realised the pace at which it would evolve.



**BBC News June 2023** 

## **SLEEC Proxy Mapping**









# Time for a break!



### **Medical and Al Articulate**



### Articulate

- In groups split into 2 play Articulate
- The goal is to explain what the piece of paper says without saying the word(s) on the paper
- The team that guesses right first wins a point (they can have the piece of paper as the counter)



### Next month:

Wednesday 25<sup>th</sup> September Speaker: Xinyi Wang – Brain MRI Segmentation Location: TBC



### Fancy more networking?

#### Head over to the Pub

